LOST IN THE MAZE: OVERCOMING CONTEXT LIMITATIONS IN LONG-HORIZON INFORMATION SEEKING

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ABSTRACT

Long-horizon information seeking tasks require iteratively searching the web over long trajectories and synthesizing information across many sources, and is a key capability to enable powerful applications like deep research systems. In this work, we show that popular information-seeking frameworks struggle to scale to long trajectories primarily due to context mismanagement—they accumulate long, noisy content, hit context window and tool budgets, or stop early. We introduce SLIM (**S**imple **L**ightweight **I**nformation **M**anagement), a simple framework that separates retrieval into distinct search and browse tools and periodically summarizes the trajectory, keeping context concise while enabling longer, more focused searches. On long-horizon tasks, SLIM achieves comparable accuracy at substantially lower cost and with far fewer tool calls than strong open-source baselines across multiple base models. Specifically, with o3 as the base model, SLIM achieves 55% on BrowseComp and 31% on HLE, outperforming all open-source frameworks by 7 and 3 absolute points, respectively, while incurring 5x fewer tool calls. Finally, we release an automated fine-grained trajectory analysis pipeline and error taxonomy for characterizing long-horizon information-seeking frameworks; SLIM exhibits less hallucination and fewer unfocused searches than prior systems. We hope our analysis framework and simple tool design inform future long-horizon agents.

1 INTRODUCTION

Long-horizon information-seeking tasks involve performing searches over long horizon and reasoning over many sources, and requires powerful systems that can explore diverse sources and leverage tools effectively. This core capability to reason over long-horizon serve as the foundation for exciting applications such as deep research (OpenAI, 2025; Google, 2025; xAI, 2025). Due to its immense potential in solving complex tasks, long-horizon systems been a key focus in the community, eliciting the development of many proprietary and open-source frameworks. For example, HuggingFace Open Deep Research (HF-ODR; Roucher et al., 2025) and GPT Researcher (GPT-R; Elovic, 2023) opts for complex multi-agent orchestration while SEARCH-O1 (Li et al., 2025b) uses a single-agent system. However, despite numerous implementations of these systems, they often fail to get the right answers in long-trajectory information-seeking settings and there are no systematic approaches to analyze their trajectories and identify the failure modes.

In this work, we first analyze existing frameworks by examining their trajectory outcomes on BrowseComp (Wei et al., 2025), a challenging long-horizon search benchmark. Our analysis shows that these frameworks still struggle with long-trajectory tasks, failing to achieve more than 50% accuracy—most of the failures are due to hitting either the context window limit, running out of tool budget, or stopping prematurely.

We attribute these failure modes to poor context management that can fill the context window often with noisy information that derails long search trajectories. The limited context restricts the number of turns in each trajectory, resulting in incomplete information gathering. To overcome these limitations, we design SLIM (**S**imple **L**ightweight **I**nformation **M**anagement), a framework with three simple yet powerful components—search, browse, and summarization—that effectively manage the context size of long-horizon systems. The simple tool design allows LLMs to interleave searching for diverse information and browsing promising pages without spending unnecessary tool calls on noisy search results. Furthermore, the summarization module acts as a general-purpose context manager that

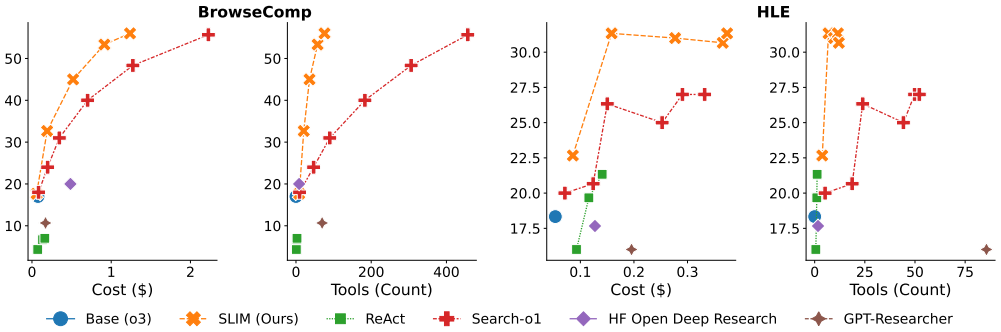

Figure 1: With o3 as the base model, SLIM achieves better performance than existing frameworks on both BrowseComp and HLE while using more than 5x fewer tool calls and lower overall costs, which accounts for LLM token usage and tool costs.

can reduce long trajectories into more condensed summaries. These design choices combine to allow the system to scale to longer trajectories while maintaining a concise context and reduced tool costs. Under a comparable cost budget, with o3 as the base model, SLIM significantly outperforms previous best open-source frameworks by 7 and 4 points on BrowseComp and HLE, respectively, while requiring only 25% of the tool calls (Figure 1).

Finally, we introduce an automated trajectory-level analysis pipeline that provides fine-grained insights to long-horizon frameworks. To characterize mistakes made by these systems, we develop an error taxonomy identifying common failure modes. Our analysis reveals that SLIM's advantage stems from its robustness to failure modes such as hallucinations and unfocused and generic searches. We hope our analysis pipeline, error taxonomy, and careful design choices in SLIM can serve as a foundation for understanding and improving long-horizon information-seeking systems.

2 PRELIMINARIES: LONG-HORIZON INFORMATION SEEKING

Previous information-seeking tasks, such as open-domain question answering, are relatively simple and straightforward as the queries are often factoid questions that are easy to answer with a single source of data (Joshi et al., 2017; Kwiatkowski et al., 2019; Petroni et al., 2021). As a result, these tasks can be mostly solved with static retrieval-augmented generation (RAG) systems that leverage at most a few retrieval steps (Lewis et al., 2020; Izacard et al., 2023; Shi et al., 2024), and do not showcase the challenges of realistic, long-horizon deep research settings.

In contrast, we study long-horizon tasks with complex queries that require extensive searches to gather the necessary information and reasoning over different sources to synthesize the answer. In this section, we formalize the task, describe the datasets for studying long-horizon information-seeking, and review some previous long-horizon systems.

2.1 TASK FORMULATION

We formalize long-horizon information-seeking tasks as follows: given a query q, a corpus of documents $\mathcal{D}$, the system needs to perform a sequence of tool calls to find relevant information from $\mathcal{D}$ and output a final answer o, which is checked against the annotated groundtruth answer a. A critical component of the system is the design of its tools and how it interacts with the corpus; each tool is a function $\mathcal{T}_i(x) \rightarrow y$ that maps arbitrary system-generated inputs x to arbitrary outputs y.

Furthermore, agentic systems are often controlled by a tool budget T, which is the maximum number of tool calls they are allowed to use in any trajectory. The tool budget T also corresponds to the maximum number of turns in a trajectory, as each turn corresponds to one tool call or action.[1]. Thus, how to manage the input context to the underlying LLM across many tool uses and turns is another critical design choice in long-horizon systems.

[1]Some architectures, such as the CodeAgent (Wang et al., 2024) used in HF-ODR, allow for parallel tool calls in one step, but we found that this does not occur in our long-horizon settings.

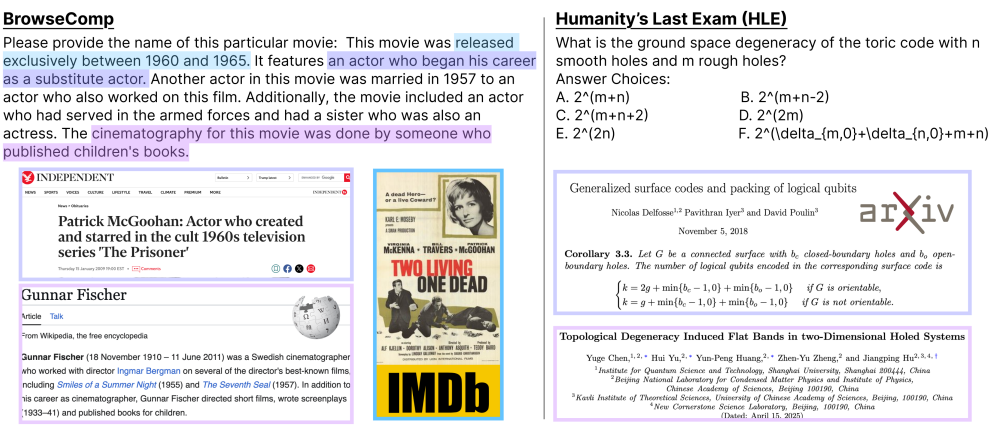

Figure 2: Example queries and their relevant documents for BrowseComp (Wei et al., 2025) and HLE (Phan et al., 2025).

In long-horizon information-seeking settings, $\mathcal{D}$ is often set as the web due to the diversity and complexity of the queries, and each document $d_i = (u_i, t_i, c_i)$ is a tuple of its URL, title, and content. In practice, long-horizon systems typically use search engines $\mathcal{R}(q) \to \{(t_i, u_i)\}_1^n$ to obtain a list of n web pages with their titles and URLs most relevant to the search query q. Furthermore, a scraping operation $\mathcal{S}(u_i) \to c_i$ is necessary to obtain the full content of any URL as search engines only provide a list of URLs, but scraping is slow and noisy in practice.

In traditional QA settings, since the retrieval tool only needs to be called once due to the simplicity of the queries and the corpus (i.e., Wikipedia) is relatively small, the retrieval function returns the full list of documents and their contents $\mathcal{R}_{\texttt{wiki}}(q) \to \{(t_i, c_i)\}_1^n$. As a result, many existing long-horizon systems follow a similar design, where the retrieval tool is a single search engine call and scraping all returned documents. However, the complexity of long-horizon information-seeking tasks requires multiple rounds of tool calls to gather the necessary information. As we will demonstrate empirically later, this naive tool design leads to severe context limitations, where the system is overwhelmed by long, noisy content, motivating the design of more efficient tool interfaces for long-horizon systems.

2.2 Datasets

We select two datasets with naturally difficult queries that require long-trajectory searches. These datasets also have verifiable answers, which ensures the reliability of subsequent analyses. For evaluation, we sample a random subset of 300 instances from each dataset due to the expensive costs of running long-horizon systems. An example query from each dataset is shown in Figure 2.

BrowseComp (Wei et al., 2025) consists of challenging queries targeting hard-to-find information. BrowseComp tests one of the core capabilities of long-horizon systems—the ability to exhaustively search the web over long trajectories and collect the necessary information. These queries were rigorously validated by humans that even with access to the web, they cannot be solved within 10 minutes of searching. The answers are short and straightforward, resulting in reliable evaluation.

Humanity's Last Exam (HLE; Phan et al., 2025) tests across multiple domains and often require domain-specific knowledge and reasoning skills. These expert domains span across a wide range of topics, such as biology, mathematics, and physics. HLE tests the ability of long-horizon systems leverage the web to find helpful information that can aid reasoning-heavy problems. Similar to BrowseComp, the answers are easily verifiable due to their short lengths.

2.3 Existing Approaches

We briefly describe some popular approaches to information-seeking and deep research, ranging from simple single-LLM frameworks to complex multi-agent systems. We summarize the differences between these frameworks in Table 1; more details are in §A.1.

Table 1: Comparison of SLIM with existing frameworks. In contrast to previous works that bundle search and browsing search results into *one* retrieval tool, we separate it into two distinct tools.

Framework	Architecture	# Tools	Tools	Input to LLM Context	Summarization
REACT	Single-agent	1	Retrieval	All search results	-
SEARCH-O1	Single-agent	1	Retrieval	All search results	Retrieved content
HF-ODR	Multi-agent	11	Search, Browse, Python, ...	Selected search results	Search agent result
GPT-R	Multi-agent	1	Retrieval	All search results	Retrieved content
SLIM (ours)	Single-agent	2	Search, Browse	Selected search results	Task trajectory

REACT (Yao et al., 2023) is a simple framework that allows an LLM agent to alternate between thinking and acting, allowing tool calling across many turns. Following the original work, our implementation gives the LLM access to a single retrieval tool—given a query, the tool returns a list of top 10 results along with their web contents. All search results are then concatenated and appended to the agent context for subsequent steps. When the LLM chooses not to use the search tool, the final output is used for evaluation. Our experiments vary the maximum number of turns in each trajectory.

SEARCH-O1 (Li et al., 2025b) builds upon REACT with an additional "reason-in-document" step, where an LLM summarizes the search results and their contents before appending the results to the agent's input context. Although the summary step reduces context length for the main LLM compared to using full search result, this approach still uses a large amount of scrape operations in each search step, and summarization incurs a large amount of LLM token usage. We vary the maximum number of turns in each trajectory.

HuggingFace OpenDeepResearch (HF-ODR; Roucher et al., 2025) leverages a hierarchical structure consisting of a manager agent and a search agent. The manager agent calls the search agent to perform detailed searches, and the search agent iteratively interacts with a search engine and a browser, and returns a summary of its searches. The manager agent may use the summary to issue more queries or output the final answer. We use the default settings, which fixes the maximum number of turns for the manager and search agent to be 20.

GPT-Researcher (GPT-R; Elovic, 2023) is a complex multi-agent system where each agent has distinct roles: a research conductor that orchestrates the search process, a report generator that creates the report, a context manager that summarizes search results, and a source curator that selects relevant sources from scraped pages. The system uses a deep researcher agent that acts as a search tree node, spawning multiple children nodes with these same components. We use the default setting, which fixes the number of depths of the search tree to be 2 and the breath of search at each depth to be 4.

3 FAILURE MODES OF EXISTING APPROACHES

Despite recent progress, we still know little about how individual components in these systems perform, or fail. To study behavior on long-horizon tasks, we focus on BrowseComp, which naturally induces extended, multi-step search trajectories. For this task, the final outcome can reveal the overall performance of each framework as well as its relationship with the context window limitation and tool budget constraints. For this analysis, we let the framework run up to a fixed number of iterations and output an answer. We categorize the final outcome in Table 2.

Table 2: Categorization of different search outcomes and their descriptions

Outcome	**Description**
Correct	The system outputs the correct answer
Exceed context	The system exceeds LLM's context window, falling back to not using any tools
Exceed budget	The system exceeds the tool calling or iteration budget
Early stopping	The system outputs an incorrect answer before reaching the iteration budget
Misc. error	Due to uncontrollable factors (e.g., API content filters) the system outputs an error message

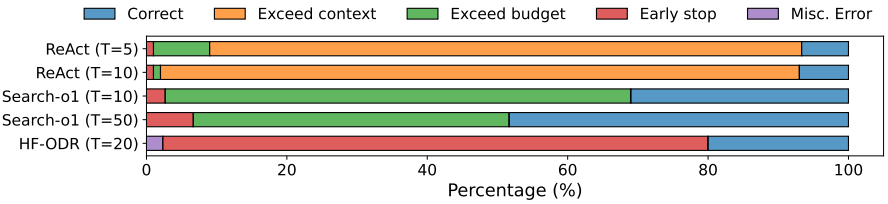

Figure 3: Each framework exhibit distinct outcome trends—REACT predominantly runs out of context window, while SEARCH-O1 is often limited by the tool budget (T). We exclude GPT-R due to its predefined workflow—the outcome can only be either correct or incorrect.

For this analysis, we consider different tool budgets for REACT and SEARCH-O1, and use the default 20 turns for HF-ODR, without loss of generality. We observe that context window limitations and tool budgets are the main bottlenecks for existing approaches in Figure 3, and each framework exhibits distinct patterns.

Specifically, REACT often hit the context window limit over a long trajectory due to the large amount of text returned by each search call. As a result, it cannot effectively scale to long trajectories and make full use of its tool budgets. SEARCH-O1 failure cases are almost entirely due to exceeding the tool budget, which suggests increasing the tool budget may potentially lead to better performance. However, such an increase is non-trivial without incurring a significant amount of cost—each retrieval step in SEARCH-O1 involves scraping all search results, even though only a fraction of these results are relevant, leading to a large amount of LLM token consumption during the summarization step.

Finally, we observe that HF-ODR often prematurely terminates due to the manager agent's inability to leverage its search agent across multiple steps. The root cause of these failure modes is bad context management—either exceeding context and tool budgets or stopping too early. In the next section we explore how to substantially improve deep research frameworks through better context management.

4 OUR FRAMEWORK: SLIM

A key takeaway from our analysis is that long-trajectory tasks require **scaling up the number of turns and tool calls while keeping the context concise to avoid hitting the context window limit**. Specifically, search results are often noisy and irrelevant to the answer, so filling up the context with content from all search results can lead to noisy context and unnecessary tool costs. Motivated by these observations, we introduce SLIM (**S**imple **L**ightweight **I**nformation **M**anagement) with two key principles: (1) using simple and flexible tools for LLMs to interact with, and (2) minimizing the amount of noisy information presented to the model and keeping the context concise during exploration. An overview of SLIM in comparison to existing frameworks are shown in Figure 4.

Concretely, SLIM adopts three simple yet powerful components—search, browse, and summarization—to effectively manage the context and scale the number of turns.

Search tool $\mathcal{R}$. As the main vehicle for exploring the web, SLIM uses a simple and fast interface for the search tool. Specifically, the search tool only returns the top k search results from a search engine, where each search result consists of a title, an URL, and a short snippet of its content. A crucial difference with previous frameworks is that previous work often bundles the search and browse functionality and return the full content for all search results, and relies on the main LLM to discern relevant context. In comparison, our search tool only returns a short snippet of each result, keeping the output concise and avoiding waste of context and tool use on irrelevant content.

Browse tool $\mathcal{B}$. Our browse tool is designed to complement the search tool by allowing the LLM to dig deeper into promising search results. Specifically, the browse tool $\mathcal{B}(u, q) \rightarrow \max_{c_i \in c} \texttt{sim}(c_i, q)$ returns the most relevant section of the content c from the URL u to the query q. Notably, this design enables the LLM to select the most relevant search result and choose a subset of the content that best matches the specific information it is looking for. As a result, our browse tool is significantly more

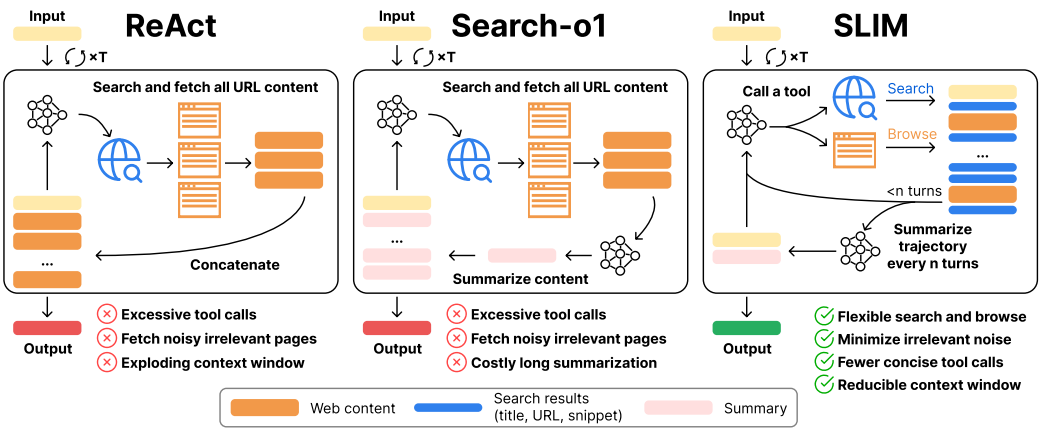

Figure 4: Compared to REACT and SEARCH-O1, the cooperation between search, browse, and summarization modules allows SLIM to accumulate much shorter context length and less noisy information after exploring the same amount of searches.

efficient and cheaper than previous frameworks that exhaustively browse all search results in terms of both the scraping operations and the amount of new tokens introduced to the context.

Summarization module $\mathcal{S}$. Despite the brevity of each tool response, agent context inevitably grows as it explores over a long horizon of searches. To maintain a concise context while retaining the effective exploration history, we introduce a summarization module that periodically compresses the LLM context. We find a simple heuristic sufficient: we summarize the entire conversation history after every n turns of tool calls and replace the trajectory with the summary. This crucially differs from previous works where summarization is solely applied to search results at each turn.

Finally, we combine these components into a single framework by allowing the underlying LLM to call either the search or the browse tools at every turn. Then, the summarization module compresses the entire conversation every n turns to reduce the amount of noise. Our implementation uses Google[2] as the search tool, crawl4ai[3] as the browse tool, and the same LLM as the agent model for summarization. More details and an example of the agent trajectory can be found in §A.4.

5 RESULTS

We use o3, o4-mini, and Claude-4-Sonnet as our base models. For each instance, we evaluate the system's performance as well as the number of tool calls and tokens used. The number of tool calls consider both the search API and browse/scraping operations. For the number of tokens, we take a weighted sum of the LLM input and output tokens across all turns. We exclude cached input tokens in total tokens count due to the fact that practical systems are implemented with caching mechanisms in long-trajectory tasks with many turns and shared context. For each dataset we record results averaged over all instances. More details on the experimental setup can be found in §A.5.

We present the main results with o3 as the base model in Table 3. Under the same cost, SLIM achieves significant improvements over SEARCH-O1, the best performing open-source framework, by 7 points on BrowseComp and 3 points on HLE. The difference is more pronounced when controlling for cost—SLIM can scale to 150 turns while using less total cost and reaching higher performance than SEARCH-O1 that can only scale to 50 turns. Furthermore, SLIM uses significantly fewer tool calls—less than 25% of the tool calls used by SEARCH-O1—suggesting that SLIM can leverage tools much more efficiently. The performance-cost comparisons of these systems are shown in Figure 1.

We also show results with different base models—o4-mini in Figure 5 and Claude-4-Sonnet in Figure 6. SLIM consistently achieves the highest performance across these models and all datasets compared to other frameworks, suggesting that our simple design generalizes well to models of

[2] https://serper.dev/
[3] https://github.com/unclecode/crawl4ai

Table 3: Main results with o3 as the base model. All results are macro-averaged across test instances. The number of tokens is shown in 10,000s. The cost is shown in US dollars. T denotes the maximum number of turns in each trajectory. For reference only, † marks deep research systems that underwent task-specific training. Numbers are from the original reports (OpenAI, 2025; xAI, 2025; Qiao et al., 2025; Li et al., 2025c), and are not directly comparable due to different subsets of test instances used.

		BrowseComp				HLE			
	T	Score (↑)	Tokens (↓)	Tools (↓)	Cost (↓)	Score (↑)	Tokens (↓)	Tools (↓)	Cost (↓)
o3 (no search)	-	17.0	3.8	0.0	0.08	18.3	2.7	0.0	0.05
REACT	1	4.3	3.6	1.0	0.07	16.0	4.6	0.6	0.09
	5	6.7	6.6	2.2	0.13	19.7	5.8	1.1	0.12
	10	7.0	8.0	2.8	0.16	21.3	7.0	1.2	0.14
SEARCH-O1	1	18.0	3.8	9.5	0.08	20.0	3.3	5.2	0.07
	5	24.0	8.0	46.9	0.20	20.7	5.4	18.7	0.12
	10	31.0	13.7	89.8	0.35	26.3	6.6	23.9	0.15
	25	40.0	27.8	183.2	0.70	25.0	10.9	44.2	0.25
	50	48.3	51.5	306.2	1.27	27.0	12.6	49.8	0.29
	100	55.7	93.3	456.7	2.23	27.0	14.5	52.2	0.33
HF-ODR	20	20.0	24.1	8.4	0.49	17.7	6.4	1.7	0.13
GPT-R	-	10.7	5.8	69.5	0.17	16.0	6.4	85.6	0.20
SLIM	10	17.7	2.7	8.7	0.06	22.7	4.2	3.8	0.09
	25	32.7	9.0	20.7	0.19	**31.3**	7.7	6.9	0.16
	50	45.0	25.0	36.0	0.52	31.0	13.6	9.7	0.28
	100	53.3	44.1	57.4	0.91	**31.3**	18.4	11.6	0.37
	150	**56.0**	59.8	75.9	1.24	30.7	17.9	12.0	0.37
OpenAI DR†	-	51.5	-	-	-	26.6	-	-	-
Grok-4†	-	44.9	-	-	-	38.6	-	-	-
WebS-30B†	-	37.3	-	-	-	28.8	-	-	-
WebT-32B†	-	15.8	-	-	-	-	-	-	-

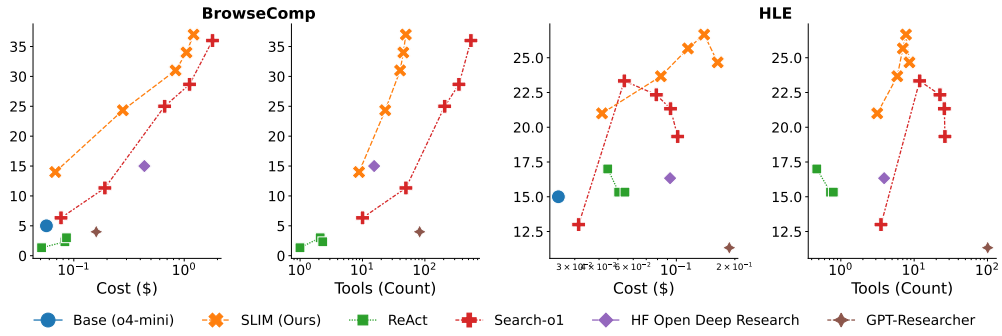

Figure 5: With o4-mini as the base model, SLIM consistently outperforms other baselines on BrowseComp while using fewer tool calls and lower overall costs. On HLE, SLIM can achieve overall higher performance and use fewer tool calls.

different sizes and training strategies. Furthermore, our effective context management also results in fewer tool calls and often lower overall costs compared to the baselines. SLIM also shows consistent trend across all three base models whereas certain framework only works well under certain models (e.g., HF-ODR only achieving competitive performance with Claude). Overall, this is strong evidence that SLIM serves as an effective framework for long-horizon tasks.

6 FINE-GRAINED TRAJECTORY-LEVEL ANALYSIS

6.1 TRAJECTORY-LEVEL ERROR TAXONOMY

To understand how SLIM improves over other systems at a deeper level, we hope to go beyond analysis based solely on outcome, and focus on characterizing the mistakes that a system makes over the course of its long search *trajectories*. To this end, we first develop a shared taxonomy of common failure modes by manually examining individual trajectories from the compared systems on BrowseComp.

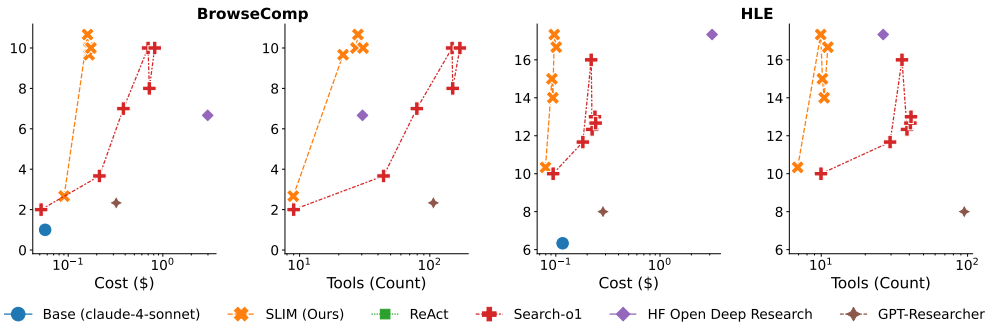

Figure 6: With Claude-4-Sonnet as the base model, SLIM consistently outperforms other baselines on BrowseComp while using fewer tool calls and lower overall costs. On HLE, SLIM can achieve overall higher performance and use fewer tool calls.

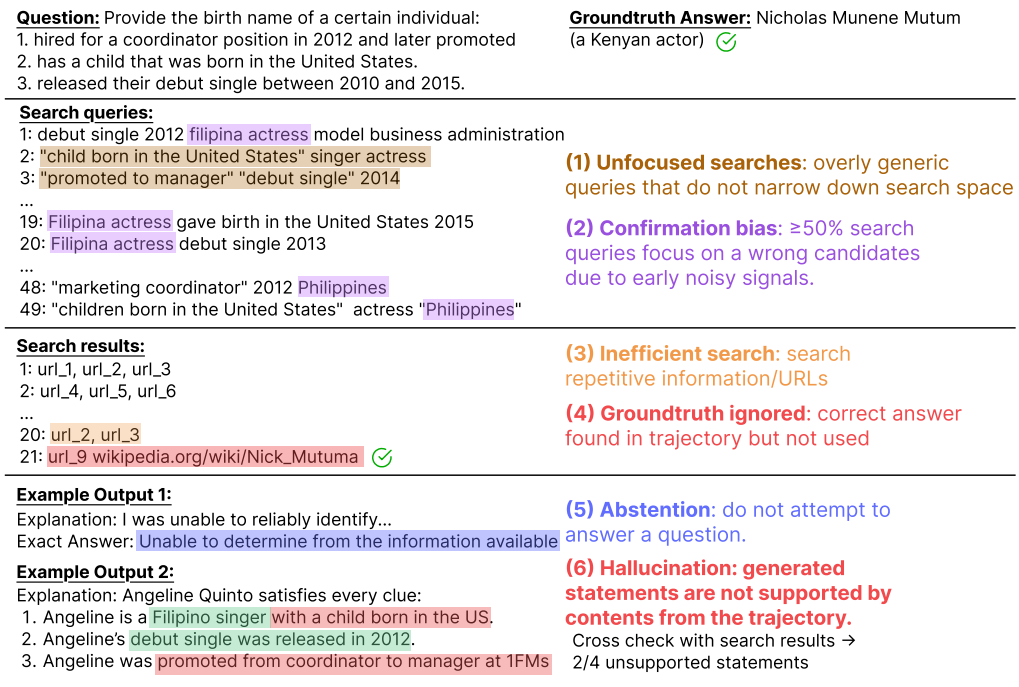

Figure 7: Examples of each trajectory-level failure mode on a BrowseComp sample.

Then based on the taxonomy, we develop an automated error analysis pipeline that annotates each trajectory with the failure modes using a mix of rule-based heuristics and LLM-as-a-judge approaches.

We present examples of each failure mode in the taxonomy in Figure 7. We also include detailed definitions of these failure modes and how we construct the error analysis pipeline in §A.3.

6.2 Analysis of Trajectory-level Failure Modes

For fair comparison, we analyze all frameworks under a similar cost budget. For each framework we choose the setting with closest cost to SLIM with 150 iterations, according to Table 3. The distribution of trajectory-level errors are shown in Table 4. We first observe that SLIM's advantage in performance could be attributed to the notably reduced number of unfocused searches and hallucination rate. Since SLIM can issue more search queries due to its relatively low cost compared to other frameworks that consume longer context for search and browsing, it is able to conduct wider and more diverse searches, with only 37.0% trajectories exhibiting unfocused searches whereas other frameworks observe this in more than 40% of their trajectories.

Table 4: The percentage of trajectory that observe each failure mode.

Framework	Turn Budget	Correct	Confirm Bias	Unfocused Search	Inefficient Search	Abstention	Answer Ignored	Hallucinate
REACT	10	7.0	32.7	54.0	3.9	1.0	0.7	40.0
SEARCH-O1	50	48.3	21.0	42.0	7.2	4.3	23.0	45.2
HF-ODR	20	20.0	15.7	44.3	43.9	32.0	0.0	95.9
GPT-R	-	10.7	25.7	73.3	-	12.3	-	-
SLIM	150	56.0	19.7	37.0	7.6	27.3	27.3	19.1

Furthermore, SLIM carefully manages the amount of information added to the context and minimizes the amount of noise, leading to an overall lower hallucination rate of only 14.5% compared to the next lowest of 40% from REACT. In contrast, frameworks that consume significantly more cost at issuing search queries—such as HF-ODR—are more prone to hallucination since they often resort to their parametric knowledge to answer the question.

Notably, despite the improvements on these two axes and an overall higher correct ratio, SLIM still suffers from high confirmation bias and abstention, and is more prone to ignoring the groundtruth answers. We leave these improvements to future work, and hope that our trajectory-level analysis can be a useful tool for improving long-horizon systems in more interpretable and concrete ways.

7 RELATED WORK

Deep research. Recently, the community has taken great interests in deep research systems due to their potential to solve complex tasks—there have been several efforts across both industry (OpenAI, 2025; Google, 2025; xAI, 2025; Nguyen et al., 2025) and open-source communities (Wu et al., 2025a; Du et al., 2025; Sun et al., 2025, *inter alia*). They are often evaluated through long-horizon search trajectories tasks that also require complex reasoning (Wei et al., 2025; Phan et al., 2025). Other benchmarks evaluate the long-form generation capabilities of systems (Du et al., 2025).

Furthermore, between the opaque proprietary systems and increasingly complex open-source systems, there is little understanding on the underlying behavior of long-horizon systems and how they fail in practice. In this work, we aim to fill this gap by introducing a error taxonomy for long-horizon systems and an automatic error analysis pipeline. Finally, in contrast to existing open-source approaches that are growing increasingly more complex, we show that a simple approach with carefully designed tools can achieve better performance with fewer tool calls.

Reinforcement learning for long-horizon systems. There have been considerable efforts in improving search agents through reinforcement learning (Li et al., 2025c; Zheng et al., 2025; Chen et al., 2025; Li et al., 2025a; Wu et al., 2025b, *inter alia*). A popular approach is to synthetically generate question-answer pairs that require long-horizon search trajectories (Xia et al., 2025; Tao et al., 2025). Other works focuses on comparing different training objectives (Jin et al., 2025b;a). However, critical analysis of the error modes and comparison of different frameworks are still lacking.

8 CONCLUSION

In this work, we propose SLIM, a simple yet effective long-horizon information-seeking framework that address context limitations prevalent in existing systems. We show that SLIM consistently achieves the highest performance across different base models and datasets compared to other frameworks while using fewer tool calls and lower overall costs, suggesting that our simple enables better long-horizon information-seeking.

We then develop an automated error analysis pipeline to characterize the failure modes of long-horizon systems. Our analysis shows that SLIM is more resistant to failure modes such as unfocused search and hallucination. We hope our framework and analysis pipeline can serve as a useful tool for the community to understand and improve long-horizon systems.

Ethics Statement

This work studies the behavior of long-horizon information-seeking systems, and how to improve them through better design choices. Although there are no direct ethical concerns, we acknowledge that the web and LLMs are complex systems that can be used for harmful purposes.

Reproducibility Statement

We submit our code and data in the Supplemental Material, which includes everything needed to reproduce our results. We plan to release the code and data publicly after the review process.

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A APPENDIX

A.1 EXISTING FRAMEWORKS

REACT (Yao et al., 2023) is a simple framework that allows an LLM agent to alternate between thinking and acting. This framework allows the agent to use tool calls across many turns. Following the original work's knowledge-intensive task settings, our implementation gives the LLM access to a single search tool—given a query, the tool returns a list of top 10 search results, from a search engine, along with their web contents. The search results are then concatenated and appended to the agent context for subsequent steps. When the LLM chooses not to use the search tool, the final output is used for evaluation.

In our implementation, we vary the maximum number of turns in each trajectory from 1 to 10. Consistently with SLIM, we use Google as the search engine, accessed through the Serper API, which returns a list of top 10 search results. Each search result contains a title, an URL, and a short snippet of the content. After obtaining the top 10 search results, we emulate previous RAG approaches by scraping all search result URLs and concatenate their content. Similar to SLIM, we use crawl4ai to scrape web pages. We truncate each scraped document to at most 10,000 characters, which corresponds to roughly 1,000 tokens.

We notice that REACT often hit the context window limit as the retrieval results are often too long. When the LLM API call fails due to the context window limit, we fallback to not using any tools and just ask the base LLM to answer the question. As a result, we only experiment with up to 10 turns, where the framework already falls back to not using any tools for most queries. A sketch of the framework is shown in Alg. 1.

SEARCH-O1 (Li et al., 2025b) builds upon REACT with an additional "reason-in-document" step, where an LLM summarizes the list of top 10 search results and their contents before appending the results to the agent's input context. Although the summary added to the agent context is relatively short compared to the full search result, this approach still uses a large amount of browse calls in each search step, and the summarization steps incur a large amount of LLM token usage. In our setting, we vary the maximum number of turns in each trajectory from 1 to up to 100 turns.

Similar to REACT, the retrieval tool at each step is consisted of a single Serper API call, followed by multiple scraping operations. We adopt the code from the original implementation[4], which uses BeautifulSoup[5] to scrape the search result URLs. In this implementation, the scraping operation will extract part of the web content that best matches the short snippet returned by the search engine. The matching is done by simply computing the F1 scores between the snippet and sentences in the web page. Subsequently, the context is filled up with at most 2,500 characters from the web page. Then, all context from the search results are concatenated and appended to the agent context for the summarization step.

It's important to note that the scraping operation is relatively expensive due to the network latency, resulting in long running time for the framework. A sketch of the framework is shown in Alg. 2.

HuggingFace OpenDeepResearch (HF-ODR; Roucher et al., 2025) leverages a hierarchical structure consisting of a manager agent and a search agent. The manager agent calls the search agent to perform detailed searches, and the search agent iteratively interacts with the search engine and a simulated browser to gather information. When the search agent concludes its searches, it generates a summary of its searches and returns it to the manager agent. The manager agent may use the summary to issue additional queries or output the final answer. Furthermore, another key feature of HF-ODR is its access to additional tools, such as a Python interpreter. We use the default settings[6], which fixes the maximum number of turns for the manager and search agent to be 20. A sketch of the framework is shown in Alg. 3. Specific descriptions of each tool can be found in Appendix A.2.

[4] https://github.com/RUC-NLPIR/Search-o1

[5] https://beautiful-soup-4.readthedocs.io/en/latest/

[6] https://github.com/huggingface/smolagents/tree/main/examples/open_deep_research

GPT-Researcher (GPT-R; Elovic, 2023) is a complex multi-agent system where each agent has distinct roles. Specifically, the system consists of a researcher conductor that orchestrates the search process, a report generator that generates the final report at the end of the search process, a context manager that summarizes search results, and a source curator that selects relevant sources from scraped web pages. Finally, GPT-R uses a deep researcher agent that acts as the node of a search tree, where each node is able to spawn multiple children nodes, each of which is a system with the previously described components. We use the default settings of the framework[7], which fixes the number of depths of the search tree to be 2 and the breath of search at each depth to be 4. A sketch of the framework is shown in Alg. 4.

Algorithm 1: ReAct

Data: Task input x, LLM θ, maximum number of turns T
Function *search(q)*:
  return *(title$_i$, url$_i$, snippet$_i$)*$_{i=1}^{k}$;
Function *visit(u, q)*:
  $D \leftarrow \text{scrape}(u)$;
  return $D[:10000]$;
Result: Task output y
Turn $t \leftarrow 1$;
Context $C \leftarrow \{x\}$;
$\mathcal{T} \leftarrow \{\text{search}\}$;
while $t < T$ **do**
  $o_t \leftarrow \theta(C; \mathcal{T})$; `/* LLM may only call the search tool */`
  switch o_t **do**
    case *search* **do**
      $R \leftarrow \text{search}(o_t)$; `/* Perform search */`
      $C \leftarrow C \cup \{o_t\}$; `/* Visit every search result and append */`
      for $(t_i, u_i, s_i) \in R$ **do**
        $C \leftarrow C \cup \text{visit}(u_i, s_i)$
    case *Final Answer* **do**
      return o_t;
  $t \leftarrow t + 1$;
return $\theta(C; \textit{final answer})$;

A.2 HuggingFace Open Deep Research Tools

HF-ODR is a hierarchical framework that consists of a manager agent and a search agent. The manager agent has access to the following tools:

1. **Search Agent**: an agent that will search the internet to answer a question.
2. **Visualizer**: given the path to a downloaded image, it will call and LLM to answer questions about the image.
3. **Text Inspector**: given the path to a downloaded text file, it will call and LLM to answer questions about the text.

The search agent has access to the following tools:

1. **Google Search**: a search engine that will search the internet to answer a question. This tool uses Serper API in the backend.
2. **Visit Tool**: visit a URL and render the page in HTML as in a browser.
3. **Page Up**: navigate the current page by scrolling up.
4. **Page Down**: navigate the current page by scrolling down.

[7] https://github.com/assafelovic/gpt-researcher

Algorithm 2: Search-o1

Data: Task input x, LLM θ, maximum number of turns T, summary interval n
Function *search(q)*:
  return *(title$_i$, url$_i$, snippet$_i$)*$_{i=1}^{k}$;
Function *visit(u, q)*:
  $D \leftarrow \text{scrape}(u)$;
  $D \leftarrow \text{split}(D) = \{d_i\}_{i=1}^{m}$;
  if $q = \emptyset$ then **return** $d' \leftarrow d_1$;
  else $d' \leftarrow \arg\max_{d_i \in D} \text{F1}(d_i, q)$;
  return d';
Result: Task output y
Turn $t \leftarrow 1$;
Context $C \leftarrow \{x\}$;
$\mathcal{T} \leftarrow \{\text{search}\}$;
while $t < T$ **do**
  $o_t \leftarrow \theta(C; \mathcal{T})$; `/* LLM may only call the search tool */`
  switch o_t **do**
    case *search* **do**
      $R \leftarrow \text{search}(o_t)$; `/* Perform search */`
      $l \leftarrow \text{length}(C)$;
      $D \leftarrow \{c_i\}_{i=l-5}^{l}$;
      for $(t_i, u_i, s_i) \in R$ **do**
        $D \leftarrow D \cup \text{visit}(u_i, s_i)$; `/* Visit every search result */`
      $C \leftarrow C \cup \{o_t, \theta(D; \text{summarize})\}$;
    case *Final Answer* **do**
      return o_t;
  $t \leftarrow t + 1$;
return $\theta(C; \textit{final answer})$;

5. **Finder Tool**: find a text in the current page.
6. **Find Next**: find the next occurrence of the text in the current page.
7. **Archive Search**: search the archives for information.
8. **Text Inspector**: given the path to a downloaded text file, it will call and LLM to answer questions about the text.

Detailed descriptions of each tool can be found in the original implementation[8].

A.3 Trajectory-Level Analysis

In this subsection, we describe how we annotate each trajectory with the failure modes. For LLM-as-a-judge approaches, we use `o3-2025-04-16` as the judge model. In each of the following LLM-as-a-judge approaches, we use the same judge model, and force the model to generate its response in a json format for easy parsing. We find that existing frontier LLMs are powerful enough to reliably check for simple yes/no questions and output them in a json format.

Confirmation bias. Confirmation bias occurs when the system finds a potential candidate that is incorrect in its search process, and subsequently spends the majority of its search budget on the same candidate without considering other options, leading to a lack of exploration in the search space. To this end, we first collect all the search queries that the system has made and then use an LLM to check if the search queries overly focus on a single wrong candidate. The judge model is given access

[8] `https://github.com/huggingface/smolagents/blob/main/src/smolagents/default_tools.py`

Algorithm 3: HuggingFace Open Deep Research

Data: Task input x, LLM θ, maximum number of turns for search and main agents T_s and T_m, respectively, and planning interval p

web_tools ← {Search, Visit, Page Up, Page Down, Finder, Find Next, Archive Search, Text Inspector};
main_tools ← {search_agent, Visualize, Text Inspector};
Function *plan(q, c)*:
  /* Prompt the LLM to generate a plan */
  return $\theta(q, c; \textit{plan})$;
Function *search_agent(q)*:
  $P \leftarrow \text{plan}(q, \emptyset)$;
  $C \leftarrow \{q, P\}$;
  $t \leftarrow 1$;
  while $t < T_s$ **do**
    if $t \mod p = 0$ **then**
      $P \leftarrow \text{plan}(q, C)$;
      $C \leftarrow C \cup \{P\}$;
    $o_t \leftarrow \theta(C; \text{web\_tools})$;
    if $type(o_t) = \textit{final\_answer}$ **then**
      return o_t;
    /* do the tool call, see A.2 for tool details */
    $C \leftarrow C \cup \{o_t, \text{tool}(o_t)\}$;
    $t \leftarrow t + 1$;
  return $\theta(C; \textit{final answer})$;
Result: Task output y
Turn $t \leftarrow 1$;
$P \leftarrow \text{plan}(x, \emptyset)$;
Context $C \leftarrow \{x, P\}$;
/* the main agent plans and calls the search agent */
while $t < T_m$ **do**
  if $t \mod p = 0$ **then**
    $P \leftarrow \text{plan}(x, C)$;
    $C \leftarrow C \cup \{P\}$;
  $o_t \leftarrow \theta(C; \text{main\_tools})$;
  if $type(o_t) = \textit{final\_answer}$ **then**
    return o_t;
  $C \leftarrow C \cup \{o_t, \text{tool}(o_t)\}$;
  $t \leftarrow t + 1$;
return $\theta(C; \textit{final answer})$;

to the groundtruth answer and the search queries, so it's able to determine if the search queries are relevant to the groundtruth answer and the similarities between different search queries. We consider a trajectory to have confirmation bias if a majority of the search queries are similar to each other, and focuses on a single wrong candidate. The prompt used for confirmation bias detection is shown in Table 5.

Unfocused search. Unfocused search occurs when the system generates overly generic search queries that are not useful for narrowing down the search space—the system cannot make any progress towards finding useful information. To this end, we first collect all the search queries that the system has made and then use an LLM to check if the search queries are generic and not useful for narrowing down the search space. We consider a trajectory to have unfocused search if a majority of the search queries are overly generic and not useful for narrowing down the search space. The prompt used for unfocused search detection is shown in Table 6.

Algorithm 4: GPT-Researcher

Data: Task input x, LLM θ, research depth D, research breadth B, summary interval n
Function *search(q)*:
  return *(title$_i$, url$_i$, snippet$_i$)*$_{i=1}^{k}$;
Function *visit(u, q)*:
  $D \leftarrow \text{scrape}(u)$;
  $D \leftarrow \text{split}(D) = \{d_i\}_{i=1}^{m}$;
  if $q = \emptyset$ then **return** $d' \leftarrow d_1$;
  else $d' \leftarrow \arg\max_{d_i \in D} \text{F1}(d_i, q)$;
  return d';
Function *plan(q)*:
  /* Prompt the LLM to generate a list of queries */
  $R \leftarrow \text{search}(q)$;
  return $\theta(x, R; \textit{plan})$;
Function *conduct_research(q)*:
  /* Conduct research on one query by generating subqueries and retrieve and scrape */
  $Q \leftarrow \text{plan}(q)$;
  $R \leftarrow \emptyset$;
  for $q_i \in Q$ **do**
    for $t_i, u_i, s_i \in \textit{search}(q_i)$ **do**
      $r_i \leftarrow \text{visit}(u_i, s_i)$;
      $R \leftarrow R \cup r_i$;
  return $\theta(x, R; \textit{process})$;
Function *deep_research(q, d)*:
  /* Recursively plan and conduct research */
  $Q \leftarrow \text{plan}(q)$;
  $R \leftarrow \emptyset$;
  for $q_i \in Q$ **do**
    $r_i \leftarrow \text{conduct\_research}(q_i)$;
    /* Prompt the LLM to generate takeaways and follow up questions */
    $q_i' \leftarrow \theta(r_i; \text{process})$;
    if $d < D$ **then**
      $R \leftarrow R \cup \text{deep\_research}(q_i', d+1)$;
  return R;
Result: Task output y
Turn $t \leftarrow 1$;
Context $C \leftarrow \{x\}$;
$P \leftarrow \text{plan}(x)$;
$R \leftarrow \text{deep\_research}(P, 1)$;
return $\theta(R; \textit{write report})$;

Inefficient tool usage. Inefficient tool usage occurs when the system does not discover new information with its tool calls, and is therefore wasting its tool budget. Specifically, we use URLs as a proxy for the information discovered by the system—a tool call that only return URLs seen in previous search results is considered as a waste of tool budget. We use a simple heuristic for this analysis—iterate over all search calls made in the trajectory and keep track of seen URLs. Then, we report the percentage of search calls that only return URLs seen in previous search results.

Groundtruth ignored. Groundtruth ignored occurs when the system encounters the correct answer in its search process, but does not use it to answer the question. One possible explanation is that the system is distracted by other noisy information in its context, preventing it from correctly identifying

Prompt for Confirmation Bias Detection
You are a helpful assistant that can analyze the trajectory of an information-seeking agent. You are given the search history of an agent and the correct answer for the question given to the agent. You should analyze the search history and determine if the agent spends more than half of the tool calls searching for the same incorrect answer. That is, the agent continues searching for the same topic even though it's not the correct answer, and spends half or more of its tool calls on these searches. Output your final conclusion with your reasoning and a single word: 'yes' if the agent spends more than half of its tool calls on the same incorrect answer or 'no' if the agent does not. **Reasoning:** explain what the agent did, and if it did or did not focus its searches on a wrong answer. **Conclusion:** "yes" or "no". **Search queries:** `<search-queries>` **The correct answer is:** `<correct-answer>`

Table 5: System prompt used for detecting confirmation bias in agent trajectories

Prompt for Unfocused Search Detection
You are a helpful assistant that can analyze the trajectory of an information-seeking agent. You are given the search history of an agent and the correct answer for the question given to the agent. You should analyze the search history and determine if the search queries are too broad. That is, the agent spends more than half of its tool calls on searches that are too generic and not specific enough to the question, and does not use enough tool calls to properly narrow down the search space by either eliminating wrong answers or verifying the correct answer. Output your final conclusion with your reasoning and a single word: 'yes' if the searches are too broad or 'no' if the searches are focused enough. **Reasoning:** explain what the agent did, and if it did or did not use tool calls to properly narrow down the search space. **Conclusion:** "yes" or "no". **Search queries:** `<search-queries>`

Table 6: System prompt used for detecting unfocused search in agent trajectories

the groundtruth. We employ a simple approach for this analysis—we check if the groundtruth answer is present in any of the tool responses. We employ a LLM judge to enable fuzzy matching between the groundtruth answer and the tool responses. The prompt used for groundtruth ignored detection is shown in Table 7. We iterate over all tool calls and use this check to determine if any tool responses contain the groundtruth answer. We terminate the iteration if we find a tool response that contains the groundtruth answer, and report the percentage trajectories where at least one tool response contains the groundtruth answer.

Giving up. Giving up occurs when the system does not attempt to answer the question due to the lack of information in its context. Existing LLMs can often refuse to answer the question if it is not confident in answering the question, but this behavior is not desirable for information-seeking agents that could leverage additional tool calls to find the necessary information. We use a simple LLM judge to check if the system attempted to answer the question. The prompt used for giving up detection is shown in Table 8.

Hallucination. Hallucination occurs when the system generates information that is not supported by the information it has discovered in its search process. In deep research systems, it is not desirable to hallucinate information, as it could result in incorrect and misleading answers and thus affect the trustworthiness of the system. Inspired by previous works(Rashkin et al., 2023; Bohnet et al., 2022; Gao et al., 2023), we check if the system hallucinates information by first decomposing the model's explanation into a set of atomic claims. Then, we iterate through all the tool responses from the search process and check if the tool responses support all the claims. As long as one tool response support a claim, we consider the system to not have hallucinated that claim. In the end, we report the average percentage of unsupported claims in across trajectories. The prompt used for decomposing the model's explanation into a set of atomic claims is shown in Table 9, and the prompt

Prompt for Groundtruth Ignored Detection
You are a helpful assistant that can analyze the trajectory of an information-seeking agent. You are given a list of webpages and the correct answer for the question given to the agent. You should analyze the web contents and determine if it contains the correct answer. The correct answer is considered to be found if there are some context in the search results that is either a direct or near-exact match to the correct answer. Output your final conclusion with your reasoning and a single word: 'yes' if the content contains the correct answer or 'no' if the content does not contain the correct answer. **Reasoning:** explain if the web content contains the correct answer. **Conclusion:** "yes" or "no". `<tool-responses>` **The correct answer is:** `<correct-answer>`

Table 7: System prompt used for detecting groundtruth ignored in agent trajectories

Prompt for Giving Up Detection
You are a helpful assistant that can analyze the final output of an information-seeking agent. You are to check if the agent decides that it cannot find the correct answer. For example, if the explanation states that it cannot find enough relevant information to answer the question, or if the response is simply empty or "I don't know", then the agent did not attempt to answer the question. Output your final conclusion with a single word "yes" if the agent decides it did not find enough information to answer the question or "no" otherwise. **Conclusion:** "yes" or "no". **Final output:** `<final-output>`

Table 8: System prompt used for detecting giving up in agent trajectories

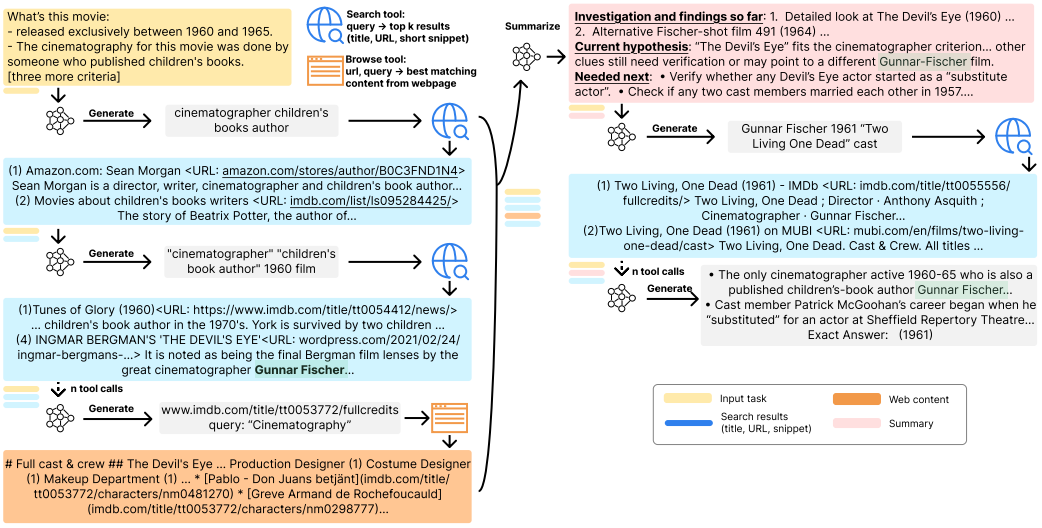

Figure 8: An example of a SLIM trajectory.

used for hallucination detection is shown in Table 10. These prompts are derived from previous works that show LLMs can reliably decompose texts into a set of atomic claims and check if claims are supported by a piece of text—they also achieve high agreement with human judges (Gao et al., 2023; Kamoi et al., 2023; Yen et al., 2025).

A.4 SLIM DETAILS

We show an example of a SLIM trajectory in Figure 8. Furthermore, a sketch of the framework is shown in Alg. 5.

Prompt for Decomposing Explanation into Atomic Claims

Read the given explanation and generate a list of atomic claims that are supported by the explanation. Atomic claims that are basic facts that cannot be further broken down. Generate at most 10 claims for the explanation.
Use the following as an example:

```
Explanation:  Searching UFCStats for featherweight bouts
where the loser landed 14 of 83 significant strikes (16.87 %)
and went 0-for-4 on takedowns returns the fight Myles Jury
vs. Ricky Glenn at UFC 219: Cyborg vs Holm (30 Dec 2017).
• Ricky Glenn (nickname "The Gladiator"|a synonym
for swordsman)
was the loser: sig. strikes 14/83 (16.87 %), takedowns 0/4.
• Both fighters (Jury 29, Glenn 28) were under 35 and
are American.
• The referee was John McCarthy, whose first event for
the UFC was in 1994.
Thus, the MMA event is UFC 219: Cyborg vs Holm.

Exact Answer: UFC 219: Cyborg vs Holm

Confidence: 75%
```

Atomic Claims:
- Ricky Glenn was the loser
- Ricky Glenn was nicknamed ”The Gladiator”
- The sig. strike rate of Ricky Glenn was 14/83 (16.87- The takedown rate of Ricky Glenn was 0/4
- Jury was age 29
- Glenn was age 28
- Jury is American
- Glenn is American
- The referee was John McCarthy
- John McCarthy’s first event for the UFC was in 1994

Output the atomic claims in the form of a json list.

Table 9: System prompt used for decomposing the model’s explanation into a set of atomic claims

Prompt for Hallucination Detection

You are a helpful assistant that can analyze the trajectory of an information-seeking agent. You are given a list of webpages and a list of claims made by the agent. You should analyze the web contents to determine if each claim is supported by the web content. A claim is supported by the web content if its factual information is mostly supported by the web content, and is not contradicted by the web content. Output your final conclusion with a list of claims that are supported by the web content. Output the list in the form of a json list, and you only need to write the index of the supported claims in the list and nothing else.
Webpages: `<webpages>`
Atomic Claims: `<atomic-claims>`

Table 10: System prompt used for detecting hallucination in agent trajectories

A.5 Experimental Details

We use o3, o4-mini, and Claude-4-Sonnet as our base models. To calculate the cost, we use the prices listed in Table 11, which are obtained from respective websites `https://platform.openai.com/docs/models/o3`, `https://platform.openai.com/docs/models/o4-mini`, `https://claude.com/pricing#api`, `https://www.firecrawl.dev/pricing`.

To calculate the token cost, we take a weight sum of the token usage across all LLM calls: non-cached input tokens plus 4 times the total output tokens, and multiply the results by price per token. We

Algorithm 5: SLIM

Data: Task input x, LLM θ, maximum number of turns T, summary interval n
Function *search(q)*:
  return *(title$_i$, url$_i$, snippet$_i$)*$_{i=1}^{k}$;
Function *visit(u, q)*:
  $D \leftarrow \text{scrape}(u)$;
  $D \leftarrow \text{split}(D) = \{d_i\}_{i=1}^{m}$;
  if $q = \emptyset$ then **return** $d' \leftarrow d_1$;
  else $d' \leftarrow \arg\max_{d_i \in D} \text{ROUGE-L}(d_i, q)$;
  return d';
Result: Task output y
Turn $t \leftarrow 1$;
Context $C \leftarrow \{x\}$;
$\mathcal{T} \leftarrow \{\text{search}, \text{visit}\}$;
while $t < T$ **do**
  if $t \mod n = 0$ **then**
    $C \leftarrow \theta(C; \text{summarize})$; `/* Summarize every n turns */`
  $o_t \leftarrow \theta(C; \mathcal{T})$;
  switch o_t **do**
    case *search* **do**
      $q_t \leftarrow o_t$;
      $C \leftarrow C \cup \{o_t, \text{search}(q_t)\}$;
    case *visit* **do**
      $u_t, s_t \leftarrow o_t$;
      $C \leftarrow C \cup \{o_t, \text{visit}(u_t, s_t)\}$;
    case *Final Answer* **do**
      return o_t;
  $t \leftarrow t + 1$;
return $\theta(C; \textit{final answer})$;

exclude cached tokens from the calculation because in practice, long-horizon systems are expected to have a large amount of cached tokens and system implementation that takes advantage of caching. Then, for the total cost, we add in the number of search API and scrape URL operations, multiplied by their respective prices.

Table 11: Pricing for different components. Numbers are obtained from respective websites:

	Cost
o3	\$2.0 / M token
o4-mini	\$1.1 / M token
Claude-4-Sonnet	\$3.0 / M token
Google search	\$0.5 / K query
Scrape URL	\$0.83 / K query

A.6 ADDITIONAL RESULTS

Here we provide the concrete results for SLIM with different base models—o4-mini is shown in Table 12, and Claude-4-Sonnet is shown in Table 13.

Table 12: Main results with o4-mini as the base model. All results are macro-averaged across test instances. The number of tokens is shown in 10,000s. The cost is shown in US dollars. T denotes the maximum number of turns in each trajectory.

		BrowseComp				**HLE**			
	T	Score (↑)	Tokens (↓)	Tools (↓)	Cost (↓)	Score (↑)	Tokens (↓)	Tools (↓)	Cost (↓)
o4	-	5.0	5.1	0.0	0.06	15.0	2.2	0.0	0.02
REACT	1	1.3	4.6	1.0	0.05	17.0	4.0	0.5	0.04
	5	3.0	7.7	2.1	0.09	15.3	4.6	0.7	0.05
	10	2.3	7.4	2.3	0.08	15.3	4.9	0.8	0.05
SEARCH-O1	1	6.3	6.2	10.0	0.08	13.0	2.6	3.5	0.03
	5	11.3	13.8	49.7	0.19	23.3	4.0	11.9	0.05
	25	25.0	45.4	207.7	0.66	22.3	5.5	22.5	0.08
	50	28.7	76.1	351.5	1.12	19.3	7.3	26.3	0.10
	100	36.0	124.4	546.7	1.80	21.3	6.6	25.8	0.09
HF-ODR	20	15.0	38.9	15.4	0.44	16.3	8.3	3.9	0.09
GPT-R	-	4.0	8.5	82.5	0.16	11.3	9.7	100.8	0.19
SLIM	10	14.0	5.7	8.8	0.07	21.0	3.6	3.1	0.04
	25	24.3	24.0	23.2	0.28	23.7	7.2	5.9	0.08
	50	31.0	73.7	40.1	0.83	25.7	10.0	7.0	0.11
	100	34.0	92.9	45.2	1.05	26.7	12.2	7.7	0.14
	150	**37.0**	107.8	49.5	1.22	**24.7**	14.4	8.6	0.16

Table 13: Main results with Claude-4-Sonnet as the base model. All results are macro-averaged across test instances. The number of tokens is shown in 10,000s. The cost is shown in US dollars. T denotes the maximum number of turns in each trajectory.

		BrowseComp				**HLE**			
	T	Score (↑)	Tokens (↓)	Tools (↓)	Cost (↓)	Score (↑)	Tokens (↓)	Tools (↓)	Cost (↓)
Claude-4-Sonnet	-	1.0	1.9	0.0	0.06	6.3	3.9	0.0	0.12
REACT	1	0.3	0.0	0.0	0.00	8.3	0.0	0.0	0.00
	5	0.3	0.0	0.0	0.00	8.3	0.0	0.0	0.00
	10	0.3	0.0	0.0	0.00	8.0	0.0	0.0	0.00
SEARCH-O1	1	2.0	1.5	9.0	0.05	10.0	2.9	10.0	0.09
	5	3.7	6.0	44.1	0.21	11.7	5.3	29.5	0.18
	10	7.0	10.7	79.5	0.38	16.0	6.3	35.6	0.22
	25	8.0	20.1	149.9	0.72	13.0	6.8	41.1	0.24
	50	10.0	22.9	170.3	0.82	12.7	7.0	40.7	0.24
	100	10.0	19.4	148.3	0.70	12.3	6.4	38.5	0.22
HF-ODR	20	6.7	98.8	30.4	2.98	17.3	105.0	26.5	3.16
GPT-R	-	2.3	7.9	106.5	0.32	8.0	6.9	94.9	0.28
SLIM	10	2.7	2.8	8.9	0.09	10.3	2.5	6.9	0.08
	25	9.7	5.1	21.6	0.17	15.0	2.8	10.2	0.09
	50	10.0	5.0	27.1	0.16	17.3	3.0	9.9	0.10
	100	**10.7**	4.8	28.1	0.16	14.0	2.9	10.5	0.09
	150	10.0	5.2	30.7	0.17	**16.7**	3.1	11.1	0.10