

PRINTS: Reward Modeling for Long-Horizon Information Seeking

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Abstract

Information-seeking is a core capability for AI agents, requiring them to gather and reason over tool-generated information across long trajectories. However, such multi-step information-seeking tasks remain challenging for agents backed by language models. While process reward models (PRMs) can guide agents by ranking candidate steps at test-time, existing PRMs, designed for short reasoning with binary judgment, cannot capture richer dimensions of information-seeking steps, such as tool interactions and reasoning over tool outputs, nor handle the rapidly growing context in long-horizon tasks. To address these limitations, we introduce PRINTS, a generative PRM trained with dual capabilities: (1) dense scoring based on the PRM’s reasoning across multiple step quality dimensions (e.g., interpretation of tool outputs, tool call informativeness) and (2) trajectory summarization that compresses the growing context while preserving essential information for step evaluation. Extensive evaluations across FRAMES, GAIA (levels 1-3), and WebWalkerQA (easy-hard) benchmarks on multiple models, along with ablations, reveal that best-of- n sampling with PRINTS enhances information-seeking abilities of open-source models as well as specialized agents, matching or surpassing the performance of frontier models with a much smaller backbone agent and outperforming other strong reward modeling baselines.¹

1. Introduction

A long-standing goal in artificial intelligence has been to develop agents that can answer novel queries by intelligently seeking information (Bachman et al., 2016; Yuan et al., 2020), thereby enabling them to tackle challenging

tasks in mathematics (Liu et al., 2025a;b), software engineering (Yang et al., 2025b; Pan et al., 2024), and research (Li et al., 2025b; Wu et al., 2025a). Large Language Models (LLMs) have shown promise as agents for such tasks when equipped with frameworks like ReAct (Yao et al., 2023), which interleaves LLM reasoning with external tool interactions. However, long-horizon information-seeking tasks, which require agents to gather and synthesize information across multiple steps (Su et al., 2025; Shao et al., 2025), remain challenging, even for recent LLMs with tool-use training, performing far below human-level (Mialon et al., 2024; Wei et al., 2025). While finetuning LLMs as information-seeking agents has shown promise (Li et al., 2025b; Wu et al., 2025a; Tao et al., 2025), it is limited to specific model families and is highly computationally demanding (Gao et al., 2025). An alternative way to boost a variety of agents is to build reward models (e.g., as done for math reasoning and instruction following (Wang et al., 2024a; Zou et al., 2025)). These models approximate the expected reward of a step or sequence of steps, enabling test-time scaling by ranking and selecting higher-quality actions or trajectories to successfully tackle long-horizon tasks. Specifically, Process Reward Models (PRMs) (Zou et al., 2025; Choudhury, 2025; Chae et al., 2025) offer a promising model-agnostic way of improving performance, scoring the quality of each of an agent’s steps.

While past work has developed PRMs for tasks such as mathematics and logical reasoning, these methods are insufficient for long-horizon information-seeking tasks for two critical reasons. (1) **Tool-Reasoning Evaluation Granularity**: existing PRMs evaluate short reasoning units in isolation, typically one- to two-sentence logical or mathematical inferences (Xiong et al., 2025; Zhao et al., 2025), providing binary judgments based on logical/math validity. In contrast, long-horizon information-seeking requires jointly evaluating a complete trajectory step, which encompasses a reasoning step combined with tool interactions (e.g., web search, web browsing, code execution). Moreover, step quality depends on multiple factors (e.g., interpretation of tool outputs, tool call informativeness, plan for next action) that coarse feedback cannot capture, increasing the granularity of the guidance needed to effectively steer agents toward good trajectories. (2) **Context Accumulation**: existing PRMs cannot manage the ever-growing reasoning context

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¹Code available at <https://github.com/G-JWLee/PRInTS>

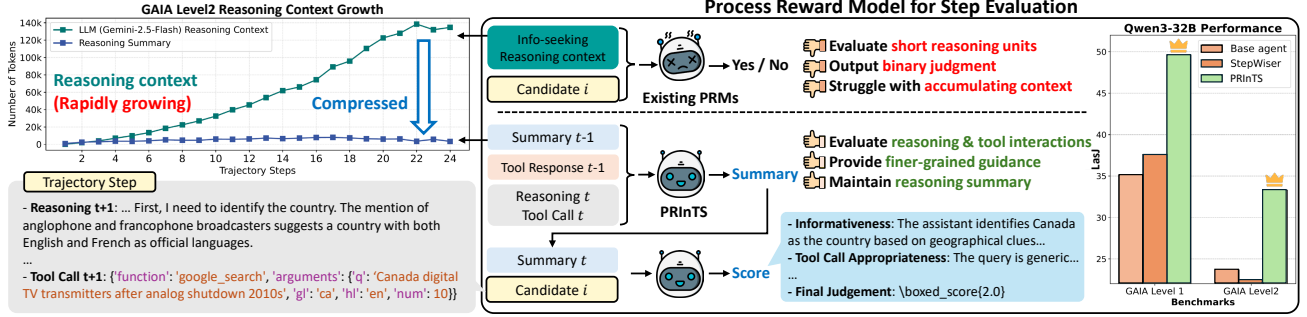


Figure 1. Comparison between existing PRMs and PRINTS. **Top:** Existing PRMs are limited for long-horizon information-seeking as they evaluate a short reasoning unit (e.g., one-to-two-sentence inferences) with coarse feedback, which cannot capture multi-faceted quality factors from tool interactions. They also struggle with rapidly accumulating reasoning context (left). **Bottom:** In contrast, PRINTS evaluates a complete trajectory step (reasoning + tool interactions), considers multiple trajectory step quality dimensions to produce dense scores for finer-grained guidance at each step, and maintains compact trajectory summaries that keep key information for the evaluation.

that arises over multiple trajectory steps. As illustrated in Figure 1 (Top-left), the information-seeking trajectory – interleaving reasoning steps, tool calls, and tool call outputs – grows rapidly as tool responses at each step introduce lengthy, noisy content, creating computational overhead. Furthermore, recent studies show that models struggle to process long, accumulated contexts (Tang et al., 2025; Yen et al., 2025; Kuratov et al., 2024), resulting in noisy evaluations. This necessitates compressing trajectories into compact forms instead of processing entire historical contexts.

Our work aims to fill these gaps by introducing **Progress Reward** via **Information gain** scoring and **Trajectory Summarization** (PRINTS), a novel generative PRM for long-horizon information-seeking tasks. PRINTS is a unified model jointly trained with two key abilities to address both the need for fine-grained guidance and the challenge of context accumulation. These two abilities are learned jointly within the same PRM. First, PRINTS acts as a scorer that evaluates candidate next trajectory steps by generating Chain-of-Thought (Wei et al., 2022) analyses across multiple quality dimensions and outputting dense scores derived from this generative reasoning, as illustrated in (Figure 1 (Bottom)). Crucially, we frame step evaluation as information gain estimation that quantifies how much each trajectory step increases the probability of reaching the correct answer. This formulation enables training via reinforcement learning with information gain estimation and preference prediction objectives, providing richer reward signals that account for the multi-faceted quality of trajectory steps. At test-time, PRINTS evaluates n candidate next steps, selecting the step expected to yield the greatest information gain. Second, PRINTS simultaneously functions as a summarizer that recursively generates and updates a compact trajectory summary at each step. PRINTS compresses the query, previous summary, latest tool response, and current step into an updated summary that captures essential findings and plans up to the current timestep (Figure 1 (Bottom)). This keeps

input length bounded, as shown in Figure 1 (Bottom-left), while preserving information for subsequent evaluation.

To equip PRINTS with these dual capabilities, we first design preference and summary data that can produce supervision signals needed to train the scoring and summarization components. Specifically, our annotation pipeline (Figure 3) uses Monte Carlo rollouts (Wang et al., 2024a; Setlur et al., 2025) to estimate information gain scores and construct preference trajectory step pairs, and generates compact trajectory summaries for each step. Next, we use this annotated data to train PRINTS via reinforcement learning for scoring ability with two complementary rewards: (1) a **Score Reward** that teaches the model to analyze the trajectory step quality and estimate the step’s information gain score, and (2) a **Comparison Reward** that teaches the model to assign higher scores to preferred trajectory steps by learning from pairwise preferences. These rewards enable the model to capture the multi-faceted quality of the trajectory step and perform dense step-level evaluation. We jointly train PRINTS via supervised fine-tuning for summarization that recursively updates the trajectory summary based on the previous summary and most recent reasoning context at each step, directly addressing the context accumulation challenge while preserving key information needed for step-level evaluation. Together, this pipeline enables PRINTS to serve as a unified PRM capable of both managing long, noisy trajectories and providing fine-grained test-time guidance.

We validate our approach across three distinct LLMs used as information-seeking agents: Qwen3-32B (Yang et al., 2025a), Tongyi DeepResearch-30B-A3B (Li et al., 2025a) – a specialized information-seeking agent – and Gemini-2.5-Flash (Gemini Team, 2025), evaluated on three long-horizon information-seeking benchmarks: FRAMES, GAIA, and WebWalkerQA. The experimental results show that PRINTS, a 4B PRM, consistently provides test-time gains across diverse agents – Qwen3-32B by 9.3%,

DeepResearch-30B-A3B by 3.9%, and Gemini-2.5-Flash by 4.0% absolute average accuracy – without fine-tuning the underlying models. Unlike existing PRMs, which obtain diminished and inconsistent gains as agents become stronger, PRINTS continues to deliver substantial improvements. Notably, on GAIA (levels 1-3) (Mialon et al., 2024), PRINTS raises DeepResearch-30B-A3B from 61.9% to 64.4% in our implementation, enabling the 30B agent augmented with the 4B PRM to match the performance of OpenAI DeepResearch (67.4%) and DeepSeek-V3.1-671B (63.1%) (Li et al., 2025a). Furthermore, our ablation studies reveal that providing compressed summaries outperforms using raw trajectories as input context, showing that context management is essential for accurate step-level evaluation in long-horizon tasks. Overall, our approach enhances information-seeking abilities of pretrained open-source models as well as specialized agents, showing strong generalizability.

2. Related Work

Large Language Models (LLM) as Agents. LLMs have been increasingly adopted as agents through frameworks such as ReAct (Yao et al., 2023), which integrates reasoning with external tool interactions to solve complex tasks (Deng et al., 2025; Wu et al., 2025c). To facilitate effective information-seeking behaviors that require multiple reasoning steps and tool interactions to reach a final answer, recent studies (Li et al., 2025b; Tao et al., 2025; Li et al., 2025a) aim to improve the intrinsic quality of information-seeking trajectories. For instance, both WebSailor (Li et al., 2025b), WebShaper (Tao et al., 2025), DeepResearch (Li et al., 2025a) agents synthesize large-scale QA training data by injecting uncertainty into structured knowledge to teach LLMs to reduce the search space by discovering unknown variables. However, training LLMs for long-horizon tasks shares key limitations: (1) it requires substantial supervision (MiroMind AI Team, 2025; Li et al., 2025a) and (2) it requires access to model weights, which poses challenges for generalization whenever the underlying model changes. We empirically show that PRINTS enhances agent performance, indicating that test-time guidance and agent fine-tuning are orthogonal yet mutually beneficial directions for improving information-seeking capabilities.

Reward Models for Reasoning. To measure reasoning quality, Outcome Reward Models (ORMs) are used to predict the correctness of complete reasoning trajectories (Kim et al., 2024; Pan et al., 2024). Consequently, ORMs cannot provide finer-grained, step-wise guidance over partial trajectories. Process Reward Models (PRMs) address this limitation by evaluating and assigning rewards for individual steps (Ton et al., 2024; He et al., 2025; Chen et al., 2025). Recent advancements cast PRMs as generative judges (Wang et al., 2024b; Whitehouse et al., 2025; He

et al., 2025) that generate justifications for step scores and have achieved strong performance in mathematics (Zhao et al., 2025; Xiong et al., 2025; Wang et al., 2024a), finance (Zhou et al., 2025), and agentic tasks (Chae et al., 2025; Choudhury, 2025). In contrast to these existing PRM approaches that rank the validity of relatively short reasoning snippets and struggle with managing growing contexts, PRINTS is equipped with jointly evaluating reasoning with tool interactions, planning for subsequent actions across multiple dimensions of “information gain” in tandem with a compact trajectory summarization mechanism, inspired by approaches that compress reasoning histories and have shown success in context length reduction (Wu et al., 2025c; Kang et al., 2025; Ye et al., 2025).

3. PRINTS: Progress Reward via Information Gain Score and Trajectory Summarization

We start by introducing the framework that quantifies and annotates the quality of each trajectory step – a reasoning step combined with a tool call – followed by reinforcement learning that uses these annotations to train PRINTS as a scorer (Section 3.2). Next, we describe our approach for generating compact summaries of long interaction trajectories, and explain how these summaries are used to train the same PRINTS as a summarizer (Section 3.3). The overall design of PRINTS is illustrated in Figure 2.

3.1. Preliminaries

To tackle long-horizon information-seeking problems, we adopt the agentic ReAct (Yao et al., 2023) paradigm, where a Large Language Model (LLM) acts as an agent that interleaves reasoning with tool-based action toward the goal of answering query q (Tao et al., 2025; Li et al., 2025a). At each timestep t , the agent may generate intermediate reasoning s_t based on the current context and then predict the subsequent action a_t , i.e., calls to external tools, such as web search, web browsing, and code execution, to acquire new information. The resulting tool response o_t is observed and added to the context, which informs the agent’s reasoning at timestep $t + 1$. Figure 2 (Left) visually shows this tool interaction process: s_t, a_t, o_t correspond to reasoning, tool call, tool response at timestep t . This process repeats until timestep T , when the agent submits its answer o_T . The task is successful if o_T matches the ground-truth answer a^* . The accumulated reasoning context up to timestep t , referred to as the information-seeking trajectory, is defined as:

$$H_t = (s_1, a_1, o_1, s_2, a_2, o_2, \dots, s_t, a_t, o_t) \quad (1)$$

Specifically, the agent π generates the next reasoning step and tool call conditioned on the query and information-seeking trajectory, i.e., $s_t, a_t \sim \pi(\cdot | q, H_{t-1})$. Then the tool call is executed to get the tool response o_t . This in-

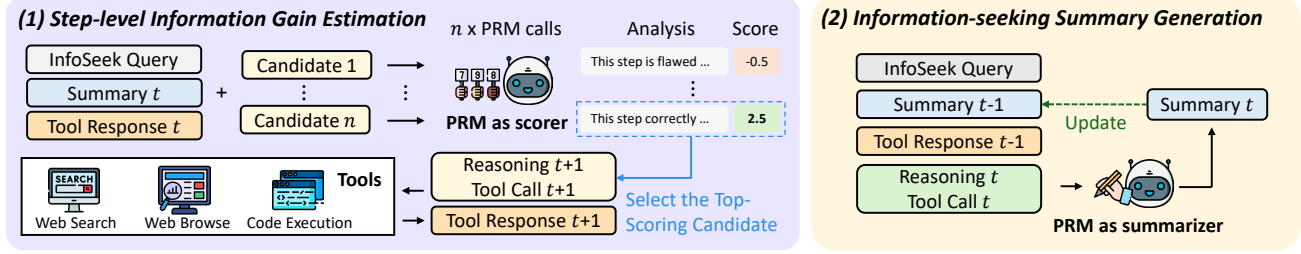


Figure 2. **Overview of PRINTS.** **Left:** PRINTS functions as a scorer, evaluating agent’s multiple candidate next trajectory steps based on the summarized context and current tool response. It generates an analysis and a dense score for each candidate, selecting the top-scoring one to guide the agent’s information-seeking. **Right:** PRINTS acts as a summarizer, recursively updating a compact information-seeking trajectory summary to keep input length bounded and preserve key information for its subsequent score evaluation.

terleaving of reasoning and action has shown success in long-horizon information-seeking tasks (Li et al., 2025b; Gao et al., 2025; Li et al., 2025a), and thus we adopt this setting. However, applying PRMs to guide long-horizon information seeking of the agent faces two key challenges: trajectory steps contain substantially richer content than traditional steps, requiring multi-dimensional evaluation beyond simple correctness, and the accumulated context H_t grows rapidly, producing a long, noisy input context, which makes it difficult to identify evaluation evidence. Thus, we next introduce our data annotation and train pipeline, which equips PRINTS with two core capabilities: (1) dense step-level scoring for fine-grained guidance, and (2) trajectory summarization for effective step-level evaluation under a rapidly accumulating input context.

3.2. Step-level Information Gain Estimation

Information Gain Score. To train a Process Reward Model (PRM) for long-horizon information seeking, we need to measure how much each reasoning step and tool call contributes towards reaching the correct answer. To this end, we define information gain of the current step as the change in expected likelihood of arriving at the correct answer before and after taking the current step (Rao & III, 2018; Prasad et al., 2023; Wang et al., 2024a). This local evaluation quantifies the marginal improvement in task success contributed by the current step. Specifically, for a reasoning step and tool call (s_t, a_t) preceded by information-seeking trajectory prefix, H_{t-1} , we use Monte Carlo estimation (Wang et al., 2024a; Xiong et al., 2025; Setlur et al., 2025) by executing M rollouts until their final answers are produced and compute the mean accuracy:

$$m_t = \frac{\sum_{j=1}^M \mathbb{1}(o_{T_j}^{(j)} = a^*)}{M}, \quad (2)$$

where $o_{T_j}^{(j)} \sim \pi(\cdot | q, H_{t-1}, s_t, a_t)$ is the final answer from rollout j , which terminates at timestep T_j . The information gain score g_t is then computed as:

$$g_t = (m_t - m_{t-1}) \times M/2, \quad (3)$$

which quantifies how much (s_t, a_t) contributes to the successful completion of the task. We scale by $M/2$ to obtain scores in the range $[-M/2, M/2]$. A positive g_t indicates that the current step (s_t, a_t) increases the probability of reaching the correct answer – for example, through logically coherent reasoning or a tool call that resolves uncertainties – whereas a g_t lower than zero indicates that the current step reduces the probability, e.g., by making unverified assumptions or invoking an irrelevant tool call.

Trajectory Score Annotations. While prior approaches annotate individual trajectory steps in isolation (Xiong et al., 2025; Wang et al., 2024a) or use imitation learning to learn directly from precomputed step-level scores (Wang et al., 2024a), Whitehouse et al. (2025) demonstrates that pairwise preference learning is effective for training robust judge models. We extend this by automatically constructing preference pairs grounded in information gain scores, then training PRINTS with complementary objectives – a score reward for information gain estimation and a comparison reward for preference prediction – as illustrated in Figure 3 (Top).

During the M rollouts performed to calculate g_t , the LLM generates a set of M unique next trajectory steps $\{s_{t+1}^{(j)}, a_{t+1}^{(j)}\}_{j=1}^M$ and the corresponding final answer predictions $\{o_{T_j}^{(j)} \sim \pi(\cdot | q, H_t, s_{t+1}^{(j)}, a_{t+1}^{(j)})\}_{j=1}^M$. As shown in Figure 3 (Top-left), to construct a candidate preference pair, we first select one trajectory step that (1) leads to a successful final answer and (2) achieves the shortest successful trajectory, assuming this step has the highest potential to be both effective and efficient among the M rollouts. A second trajectory step is then randomly sampled from the remaining steps, assuming that it provides a contrasting, less effective reasoning (i.e., one that either leads to an incorrect answer or reaches the correct answer through a longer trajectory).

Next, we annotate the information gain scores of this candidate preference pair by treating each trajectory step as a new starting point and running M rollouts to estimate their respective mean accuracies and information gain scores. After annotation, the winning and losing labels are reassigned

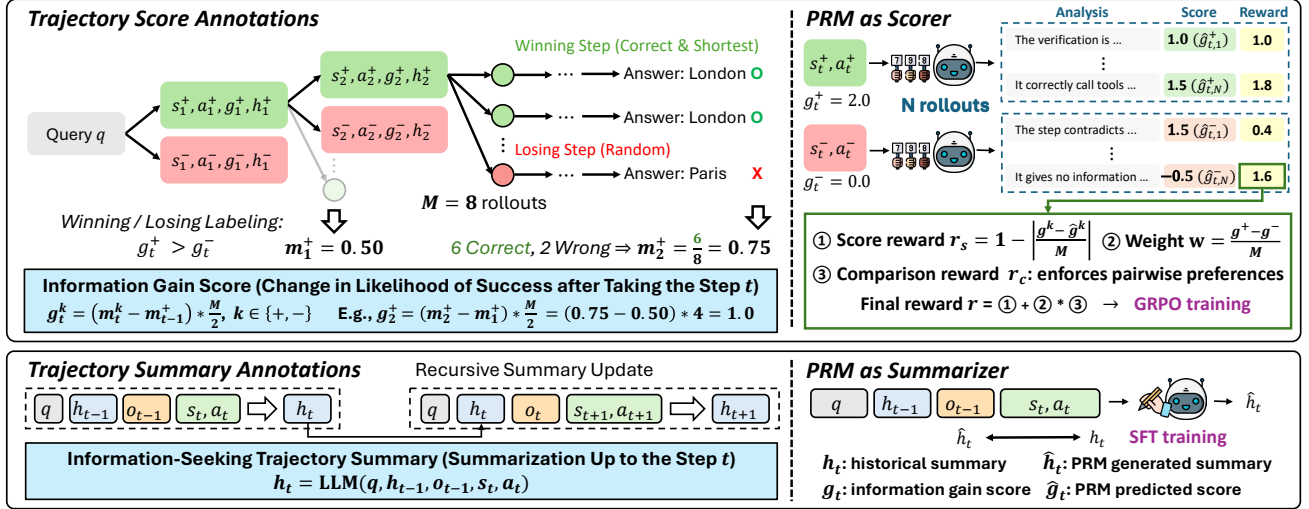


Figure 3. **PRINTS: data annotation and training pipeline.** **Top:** For each trajectory step, we estimate the information gain score via Monte Carlo rollouts as the change in mean answer accuracy before and after the step. Then we construct winning-losing step pairs based on these scores (left). Preference pair examples are shown in Figure 7. Then we train PRINTS as a scorer via GRPO on these pairs (right). The final reward combines a score reward for accurate prediction, a comparison reward for pairwise preference learning, and an adaptive weight to mitigate noisy annotations. **Bottom:** Each step is annotated with a compact, recursively updated trajectory summary capturing essential findings and plans up to the step (left). The same PRM is jointly trained as a summarizer via SFT on this summary data (right).

based on the actual information gain scores: the step with the higher score becomes the true winning sample (s_{t+1}^+, a_{t+1}^+) , while the other becomes the losing sample (s_{t+1}^-, a_{t+1}^-) . The winning step then serves as the starting point for generating the next pair at step $t + 2$. This contrastive labeling ensures that PRINTS learns relative preferences between trajectory steps grounded in empirically estimated improvements.

Training the PRM as a Scorer. The core function of PRINTS is to assess information-seeking trajectory step quality and assign higher scores to steps expected to yield greater information gain. To this end, we train PRINTS to evaluate the trajectory step quality by predicting information gain scores. Given a query q , trajectory summary h_{t-1} (introduce in Section 3.3 below), the latest tool response o_{t-1} , and trajectory step (s_t, a_t) , PRINTS generates a Chain-of-Thought analysis and outputs a scalar score prediction \hat{g}_t :

$$\hat{g}_t = f_I(q, h_{t-1}, o_{t-1}, s_t, a_t), \quad (4)$$

where f_I denotes PRINTS that works as an information gain scorer function. We train this scoring capability using GRPO (Shao et al., 2024) with the following rewards: (1) a score reward (r_s) that targets minimizing the discrepancy between the predicted score (\hat{g}_t) and the ground-truth score (g_t), and (2) a comparison reward (r_c) that enforces pairwise preferences derived from annotated pairs:

$$r_s^k = 1 - \left| \frac{g^k - \hat{g}^k}{M} \right|, r_c = \frac{1}{N} \sum_{j=1}^N y^k \cdot \text{sign}(\hat{g}^k - \hat{g}_j^{\bar{k}}) \quad (5)$$

where $\text{sign}(x) = \begin{cases} +1, & x \geq 0 \\ -1, & x < 0 \end{cases}$, $k \in \{+, -\}$ indicates

the winning or losing sample, $y^+ = 1$ and $y^- = -1$ for comparison direction, \bar{k} denotes its counterpart, N is the number of rollouts, and $\hat{g}_j^{\bar{k}}$ is the predicted score of j -th rollout from the counterpart. For simplicity, we omit rollout- and step-level indices, which do not affect the underlying formulation of the scores. The comparison reward ensures PRINTS learns to distinguish better from worse reasoning paths, while the score reward provides fine-grained feedback on estimation accuracy. Finally, we combine the two rewards into a single scalar per rollout with an adaptive weight based on the ground-truth score margin:

$$r^k = r_s^k + w * r_c^k, w = \frac{g^+ - g^-}{M}, \quad (6)$$

where w is the comparison reward weight set for each pair. This adaptive weighting addresses noise in the automatically annotated preference pairs. Pairs with large score margins between winning and losing samples ($g^+ - g^-$) are more reliably ranked and receive higher comparison weights, while pairs with small margins receive lower weights, as they may reflect annotation noise rather than true preference (Prasad et al., 2024). This weighting scheme amplifies strong preference signals while mitigating the impact of noisy annotations. The combined reward thus encourages PRINTS both to estimate absolute scores accurately and to learn robust preferences in information-seeking trajectories.

3.3. Information-seeking Summary Generation

Trajectory Summary Annotations. Another core challenge in building a PRM for information-seeking agents is the rapidly growing context (Figure 1 Top-left) of lengthy and noisy reasoning and tool interactions. This context explosion hinders PRMs from efficient processing and results in noise and distraction in quality evaluation. To this end, we further extract a concise summary of the information-seeking trajectory of each trajectory step (s_t, a_t) . This summary, h_t , captures the essential findings and plan development up to timestep t . As illustrated in Figure 3 (Bottom-left), each summary is recursively updated and generated by an LLM, incorporating the previous summary h_{t-1} , the latest tool response o_{t-1} , and the current trajectory step (s_t, a_t) (i.e., $h_t = \text{LLM}(q, h_{t-1}, o_{t-1}, s_t, a_t)$). This recursive formulation ensures that h_t maintains a compressed form of the entire trajectory H_t , with a bounded input length.

Training the PRM as a Summarizer. To enable efficient processing of the reasoning context during the score estimation, PRINTS is trained to generate concise summaries that retain only the essential context:

$$\hat{h}_t = f_S(q, h_{t-1}, o_{t-1}, s_t, a_t), \quad (7)$$

where f_S is PRINTS that works as a summarization function, and \hat{h}_t is the summary generated by PRINTS. We use supervised fine-tuning (SFT) on the annotated summaries h_t of trajectory steps, which allows PRINTS to learn effective summarization by imitating the provided annotations.

4. Experiments

4.1. Experimental Setup

Models. To evaluate the efficacy and generalizability of PRINTS, we use three distinct LLMs: Qwen3-32B (Yang et al., 2025a), an open-source model with strong reasoning capability; Gemini-2.5-Flash (Gemini Team, 2025), a closed-source frontier model; and Tongyi DeepResearch-30B-A3B (Li et al., 2025a), a recently developed agent specifically optimized for long-horizon information-seeking tasks. We instantiate ReAct-based agents using these LLMs and evaluate them using the Inspect-Eval (AI Security Institute, 2024) evaluation environment. Further details on the evaluation environment are provided in Section A.

Evaluation Benchmarks. Following recent work on long-horizon information-seeking agents (Gao et al., 2025; Li et al., 2025c;a), we assess the effectiveness of PRM-guided reasoning on three benchmarks: FRAMES (Krishna et al., 2025), GAIA (Mialon et al., 2024), and WebWalkerQA (Wu et al., 2025b). GAIA evaluates general assistant capabilities on complex retrieval and multi-step reasoning tasks

spanning three difficulty levels (Level 1-3). WebWalkerQA requires agents to traverse webpages to gather evidence across Easy-Hard levels. FRAMES contains factual and reasoning-intensive queries that require multiple retrieval steps. For Qwen3-32B and DeepResearch agent, we evaluate across FRAMES, GAIA, and WebWalkerQA. For Gemini-2.5-Flash, we evaluate on GAIA. Further explanations of these benchmarks are provided in Section A.

Evaluation Metric. Following past work (Gao et al., 2025; Li et al., 2025c;a), we adopt the LLM-as-Judge (LasJ) paradigm to measure benchmark performance, which is a standard approach in long-horizon information-seeking research. We use GPT-5 to judge the correctness of final answers. All results are reported using Avg@3, defined as the mean accuracy over three independent runs.

Baselines. We compare PRINTS againsts three categories of baselines: **(1) Base agent:** this directly uses the LLM’s information-seeking abilities without any PRM guidance. This serves as a reference to measure the test-time improvement achieved by PRM-based guidance. **(2) Intrinsic reasoning heuristics:** we include widely used reasoning quality heuristics, including confidence (Ghasemabadi et al., 2025), relevance (Wan et al., 2025), and verbal-progress. **(3) Existing PRMs:** we compare with existing PRMs: GenPRM-7B (Zhao et al., 2025), Web-Shepherd-8B (Chae et al., 2025), StepWiser (Xiong et al., 2025). To provide a controlled comparison, we follow StepWiser’s training protocol to reimplement StepWiser using our annotated data and Qwen3-4B model, adapting it to long-horizon information-seeking tasks. This setup allows us to directly demonstrate the contributions of PRINTS’s design; dense comparative scoring and compact trajectory summarization. Further details of the baseline are provided in Section A.

Implementation Details. Our dataset consists of $\sim 2k$ preference trajectory step pairs with score and summary annotations drawn from publicly available web-agent training corpora (MiroMind Data Team, 2025). We use Qwen3-32B to generate both the information gain score and summary annotation for each step with Monte Carlo rollouts $M = 8$. PRINTS is instantiated as Qwen3-4B and trained with an alternating SFT-GRPO schedule, where one epoch of SFT for the summarization objective is followed by a period of GRPO training for the scoring objective with GRPO rollouts $N = 4$. This SFT-GRPO cycle is repeated iteratively throughout training, enabling PRINTS to jointly acquire summarization and scoring abilities. At test-time, all baselines and PRINTS evaluate sets of candidate next steps output by LLMs, performing best-of- n guided search with $n = 4$. Further details can be found in Section A.

Method	FRAMES	GAIA			WebWalkerQA			Avg.
		Level 1	Level 2	Level 3	Easy	Medium	Hard	
Base agent	49.3	35.1	23.7	11.1	30.1	26.9	30.3	29.5
Confidence	55.7	36.8	24.4	<u>16.7</u>	31.7	31.3	32.9	32.8
Relevance	<u>56.3</u>	34.2	20.5	8.3	<u>33.3</u>	29.5	32.5	30.7
Verbal-progress	45.0	35.9	21.2	13.9	27.6	30.2	34.2	29.7
GenPRM-7B	50.0	32.5	<u>25.7</u>	<u>16.7</u>	<u>33.3</u>	<u>32.8</u>	<u>34.6</u>	32.2
Web-Shepherd-8B	49.0	<u>38.5</u>	23.7	5.5	28.5	31.8	33.3	30.0
StepWiser	51.3	37.6	22.4	8.3	31.7	31.8	33.8	31.0
PRINTS	58.7	49.6	33.3	19.4	39.8	33.3	37.3	38.8

Table 1. Comparison of step quality evaluation methods on Qwen3-32B across information-seeking benchmarks. We adopt the LLM-as-Judge (LasJ) metric and report Avg@3. The best and the second best results are in **bold** and underline, respectively. PRINTS delivers consistent gains all benchmarks, whereas the second-best baseline varies.

Method	FRAMES	GAIA			WebWalkerQA			Avg.
		Level 1	Level 2	Level 3	Easy	Medium	Hard	
Base agent	79.3	68.4	61.6	<u>41.7</u>	61.8	59.5	68.0	62.9
Confidence	61.3	60.7	47.5	25.0	63.4	62.0	64.9	55.0
Relevance	81.3	70.1	63.5	33.3	<u>66.7</u>	62.8	66.7	63.5
Verbal-progress	82.3	<u>69.2</u>	60.9	<u>41.7</u>	63.4	<u>63.8</u>	68.4	<u>64.2</u>
GenPRM-7B	79.0	70.1	<u>64.1</u>	38.9	60.2	<u>63.8</u>	<u>68.9</u>	63.6
Web-Shepherd-8B	79.7	<u>69.2</u>	61.5	36.1	62.6	62.3	67.1	62.6
StepWiser	81.0	70.1	60.9	36.1	65.0	61.8	64.9	62.8
PRINTS	<u>81.7</u>	<u>69.2</u>	65.4	44.5	70.7	65.9	70.1	66.8

Table 2. Comparison of step quality evaluation methods on Tongyi DeepResearch-30B-A3B across information-seeking benchmarks. We adopt the LLM-as-Judge (LasJ) metric and report Avg@3. The best and the second best results are in **bold** and underline, respectively. The results show that PRINTS enhances the performance of strong information-seeking agents.

4.2. Results and Discussion

PRINTS substantially outperforms existing PRMs on foundation models. Table 1 presents long-horizon information-seeking task results using the open-source Qwen3-32B as the LLM agent. Across all benchmarks, including FRAMES, GAIA, and WebWalkerQA, PRINTS consistently achieves substantial gains over the base agent. For instance, on GAIA Level 1 and 2, PRINTS surpasses the base agent by 14.5% and 9.6% absolute accuracy, respectively, whereas other baselines yield only marginal improvements or sometimes even reduce performance. Although StepWiser is trained on the same annotated dataset as PRINTS, it provides only a 1.5% absolute average accuracy gain (cf. 9.3% improvement with PRINTS). This illustrates the limitation of binary correctness signals, which provide only coarse supervision and fail to capture multiple quality dimensions that influence the usefulness of a trajectory step in long-horizon information seeking. However, even baselines that generate richer outputs do not bridge this gap. Verbal-progress – which produces scalar progress esti-

mates – and Web-Shepherd – which generates and evaluates multi-item checklists – both offer more expressive signals than binary labels but still fall short, adding marginal gains of 0.2% and 0.5% absolute average accuracy respectively. This shows that having continuous scores alone does not guarantee effective test-time guidance. In contrast, PRINTS is trained to produce multi-factor analyses and a dense comparative score grounded in both information-gain estimation and pairwise preference learning. This design choice enables it to identify subtle yet important quality differences between candidate steps and select the most informative next step, leading to better information-seeking behavior.

PRINTS improves highly performant information-seeking agents. In Table 2, we evaluate PRINTS on the specialized information-seeking agent DeepResearch-30B-A3B, specifically optimized for and achieves high performance in long-horizon information-gain tasks through extensive fine-tuning. The results show that adding PRINTS to this strong information-seeking agent consistently achieves

Method	GAIA			Avg.
	Level 1	Level 2	Level 3	
Base agent	58.1	42.3	19.5	40.0
Relevance	58.1	44.9	19.5	40.8
Verbal-progress	60.7	44.2	16.7	40.5
GenPRM-7B	56.4	44.9	11.1	37.5
Web-Shepherd-8B	59.8	46.2	16.7	40.9
StepWiser	60.7	44.3	19.5	41.5
PRINTS	61.5	45.5	25.0	44.0

Table 3. **PRINTS shows strong generalization to the frontier LLM (Gemini).** We adopt the LLM-as-Judge (LasJ) metric and report Avg@3 comparing with other step quality evaluation methods on Gemini-2.5-Flash.

performance gains across benchmarks, surpassing the base agent by 3.9% absolute average accuracy, while no other baselines come close to achieving notable improvements, with the strongest one improving performance by only 1.3% absolute average accuracy. It is also noteworthy that PRINTS improves on the challenging subsets, such as GAIA Level 3 and WebWalkerQA Hard. Moreover, on GAIA, PRINTS lifts DeepResearch-30B-A3B from 61.9% to 64.4% average accuracy, enabling the 30B agent augmented with the 4B PRM to reach competitive performance with OpenAI DeepResearch (67.4%) and surpass DeepSeek-V3.1-671B (63.1%).² Specialized information-seeking agents (Wu et al., 2025a; Li et al., 2025b;c) require a large-scale dataset (10k-100k+ samples), substantial computational costs for tool interactions and multi-step rollouts during online reinforcement learning, which is especially challenging as different samples have different trajectory lengths to provide the outcome reward signal for training agents (Gao et al., 2025). Despite these agents undergoing resource-intensive training, applying PRINTS further improves this strong information-seeking agent, surpassing its original performance with training only a small 4B model that either does not require a large dataset (2k+ pair samples) or long-horizon rollouts and tool interactions during training. These findings demonstrate that even highly optimized information-seeking agents can benefit from the step-level guidance provided by PRINTS, pushing their performance to the limit in a cost- and data-effective manner.

PRINTS also generalizes to frontier LLMs. To further demonstrate the versatility of our approach, we use the closed-source Gemini-2.5-Flash as the LLM agent, as shown in Table 3. PRINTS provides 4.0% absolute average accuracy gain, whereas the second-best method improves performance by only 1.5%. On the most challenging subset, GAIA Level 3, PRINTS yields the largest

²See Section A for details on reporting frontier model results.

Input Context	FRAMES	GAIA		Avg.
		Level 1	Level 2	
H_{-1} :	56.3	44.5	25.7	42.2
H_{-2} :	61.0	44.5	26.9	44.1
H_{-4} :	57.0	37.6	25.0	39.9
H_t	55.7	38.5	24.4	39.5
h_t (Ours)	58.7	49.6	33.3	47.2

Table 4. **Effectiveness of context compression.** Comparison of input context representations for PRM on Qwen3-32B across information-seeking tasks. H_{-1} , H_{-2} , and H_{-4} : provide the most recent one, two, and four trajectory steps from the full trajectory H_t , while h_t uses the trajectory summary from PRINTS. Our approach (h_t) shows better scoring ability by retaining essential information for step evaluation in a compact summary.

improvement among all baselines (+5.5%), showing its strength on long-horizon reasoning tasks. Overall, our results indicate that PRINTS provides effective test-time guidance, improving the information-seeking behavior of both open-source LLMs, closed-source LLMs, and information-seeking agents, which shows strong versatility and generalizability without modifying or retraining underlying LLMs.

4.3. Analysis and Ablations

Summarization ability contributes to better scoring ability. To validate the effectiveness of compressed information-seeking trajectory representations for accurate step-level scoring, we compare our summarization approach against several alternatives: providing only the most recent one, two, or four trajectory steps as input context (H_{-1} , H_{-2} , H_{-4}), and providing the full trajectory H_t . We evaluate on Qwen3-32B across FRAMES and GAIA. Since the performance on GAIA Level 3 is low (see Table 1), we only use Levels 1 and 2. Results in Table 4 show that our summary-based approach achieves the best or second-best performance across benchmarks, outperforming the full raw-history baseline by 7.7% absolute average accuracy.

Notably, providing more raw history does not improve performance. H_{-2} outperforms both H_{-1} (insufficient context), H_{-4} , and H_t (excessive, noisy context). This demonstrates that accumulated raw context becomes a bottleneck – longer histories introduce noise and irrelevant information that hinder the PRM from identifying key information, distracting step-level evaluation. In contrast, our summarization compresses entire trajectories into compact representations that preserve key information while filtering out noise and maintaining bounded input length, enabling more accurate scoring even as trajectories grow arbitrarily long.

Complementary rewards improve step-level evaluation. We analyze the contribution of each reward component

Reward Design	FRAMES	GAIA		Avg.
		Level 1	Level 2	
$r = r_s$ (score-only)	57.0	43.6	32.0	44.2
$r = r_c$ (comparison-only)	58.7	41.9	28.8	43.1
$r = r_s + r_c$ (combination)	60.3	47.0	31.4	46.2
$r = r_s + w \cdot r_c$ (Ours)	58.7	49.6	33.3	47.2

Table 5. **Impact of reward components.** Experiments with reward components on PRM performance across information-seeking tasks evaluated with Qwen3-32B. Combining the score reward with comparison reward ($r_s + r_c$) leads to better step evaluation, with further improvement when mitigating noise in preference pairs through the adaptive weight ($r_s + w \cdot r_c$).

in Equation (6). Following the setup from the previous ablation, we evaluate on Qwen3-32B across FRAMES, GAIA Levels 1, and 2. As shown in Table 5, combining the score and comparison rewards ($r_s + r_c$) yields substantially better performance than using either component alone, leading to 2.0% and 3.1% absolute average accuracy gains compared to using the score reward (r_s) and comparison reward (r_c), respectively. This indicates that information-gain estimation and preference prediction capture complementary aspects of the quality of an information-seeking trajectory step, underscoring the benefit of our pairwise annotation strategy over prior work that labels individual steps in isolation (Xiong et al., 2025; Wang et al., 2024a). Furthermore, incorporating the adaptive weight ($r_s + w \cdot r_c$) yields 1.0% additional absolute average accuracy gain over the naive combination. This is because the adaptive weight mitigates noise in preference pairs. Pairs with small information gain score differences are inherently noisier, as they may reflect annotation variance rather than true quality differences. Thus, these pairs receive lower weights, while pairs with clear margins are weighted higher, leading to more stable learning. Overall, adaptive weighting provides a simple and cost-efficient way of leveraging existing annotated preference pairs.

PRINTS scales effectively with test-time compute. In order to evaluate how PRINTS benefits from additional test-time compute, we conduct best-of- n scaling experiments with varying numbers of candidate steps ($n \in \{1, 2, 4, 8, 16\}$) on GAIA Level 2 using Qwen3-32B, as shown in Figure 4. PRINTS exhibits strong scaling behavior, achieving 2.5%, 3.8%, 8.9% absolute accuracy gains at $n = 2, 4, 8$, respectively, demonstrating that PRINTS reliably identifies higher-quality steps within large candidate sets. However, performance declines at $n = 16$, which we attribute to over-exploration: we observe that the PRM increasingly selects uncertainty-resolving steps even when correct answers already appear among candidates. Consequently, the agent continues exploring until it reaches the maximum step budget, failing to output an answer despite having generated one

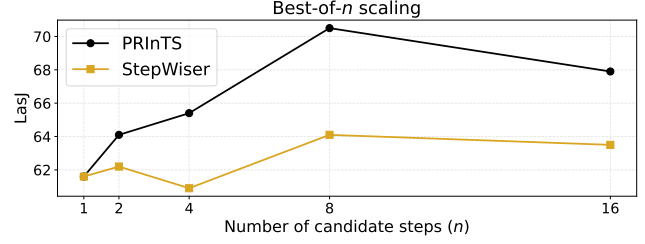


Figure 4. **Scaling test-time compute.** Best-of- n test-time scaling results on GAIA Level 2 using Qwen3-32B. PRINTS benefits from additional test-time compute by identifying higher-quality steps from n candidates.

earlier. In contrast, StepWiser provides only marginal and inconsistent improvements under scaling. This difference in scaling efficiency further validates that PRINTS’s design of information-gain estimation and preference prediction captures subtle quality differences between steps, enabling fine-grained guidance for long-horizon information-seeking.

5. Conclusion

In this paper, we introduce PRINTS, a generative PRM for long-horizon information seeking. PRINTS unifies information gain scoring with recursive trajectory summarization, enabling fine-grained step-level evaluation under rapidly accumulating context from agents. To equip PRINTS with these dual capabilities, we develop an annotation pipeline that constructs preference step pairs with information gain scores and summaries, and we jointly train PRINTS through alternating schedule of supervised fine-tuning for summarization and reinforcement learning for scoring. We validate PRINTS on three distinct agents, including a strong information-seeking agent, and comprehensive experiments demonstrate that PRINTS consistently enhances the information-seeking abilities of these agents, showcasing its high versatility. Notably, PRINTS pushes the performance of the frontier information-seeking agents beyond their original performance, showing that test-time guidance can be a powerful complement to agent fine-tuning while remaining robust to changes in underlying models.

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A. Details of Experimental Setups

Tool Implementation Details. We conduct all experiments within the Inspect-Eval evaluation framework ([AI Security Institute, 2024](#)), which fully supports the ReAct paradigm ([Yao et al., 2023](#)) for multi-turn reasoning and tool interactions necessary for complex information-seeking tasks. The framework provides access to a comprehensive set of external tools:

- **Web Search:** We utilize the Serper search API to retrieve up-to-date web content for search queries.
- **Web Browsing:** The framework includes built-in browser automation tools, supporting essential web interaction functions such as browsing with URLs, clicking, scrolling down/up, typing, etc.

- **Code Execution:** The framework also supports built-in Python and Bash code execution environments.

In this evaluation framework, agents use these tools to interact with external sources to search and synthesize information to solve given information-seeking questions.

Evaluation Benchmarks. We provide in-depth explanations of the long-horizon information-seeking benchmarks used in our experiments. (1) GAIA (Mialon et al., 2024) evaluates the ability to act as a general AI assistant on complex retrieval and reasoning tasks spanning three difficulty levels. Following prior work (Li et al., 2025c; Gao et al., 2025; Kang et al., 2025), we use 103 questions from the text-only validation subset. (2) WebWalkerQA (Wu et al., 2025b) focuses on web-based reasoning, requiring agents to traverse webpages to locate target information across three difficulty levels. We evaluate on 247 English questions. (3) FRAMES (Krishna et al., 2025) provides factual and reasoning-intensive queries to assess both retrieval and reasoning capabilities. We use a subset that consists of 300 samples that are randomly selected from the original dataset.

Baselines. In this section, we provide a more detailed explanation of the baselines.

- **GenPRM-7B** (Zhao et al., 2025) is a generative PRM originally designed for mathematical reasoning. It produces Chain-of-Thought rationales with a binary verdict (yes / no) indicating whether the current step is correct. We follow their prompt format and ask GenPRM to verify the correctness of a trajectory step and explain why the step is judged correct or incorrect.
- **Web-Shepherd-8B** (Chae et al., 2025) generates a task-specific checklist that decomposes a task into key subgoals and evaluates agentic trajectories based on it. Specifically, it assigns coarse feedback labels (Yes / No / In progress) for each checklist item for evaluation. We also follow their prompt formats to generate a checklist for a given information-seeking task and evaluate each trajectory step relative to that checklist.
- **StepWiser** (Xiong et al., 2025) trains a generative PRM using GRPO with binary rewards, where each step is labeled as effective or ineffective. For implementation, we follow the *Relative Effective Reward Thresholding* in the paper to re-annotate our training dataset: a step receives a positive label if the ratio between the current and previous mean accuracies exceeds the threshold (0.7), and a negative label otherwise. Using this binary supervision, we train Qwen3-4B for 4 epochs to build StepWiser PRM.
- **Confidence** (Ghasemabadi et al., 2025; Fu et al., 2025; Prabhudesai et al., 2025; Wang et al., 2025) estimates reasoning quality based on the model’s certainty. Following

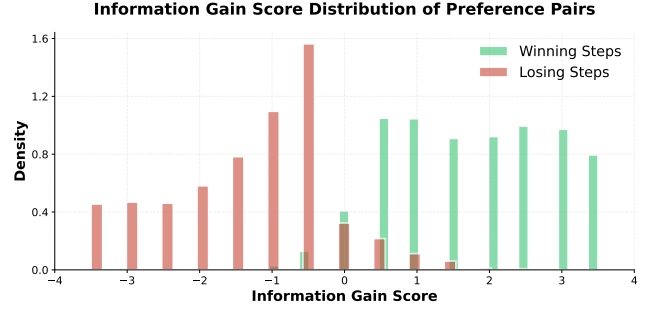


Figure 5. Distribution of annotated information gain scores.

the confidence definition in recent work (Ghasemabadi et al., 2025; Fu et al., 2025), we calculate confidence by taking the negative average log-probability of the top-10 most likely tokens at each position across all generated tokens in the reasoning step, and then averaging these scores across all token positions. Higher scores indicate lower uncertainty.

- **Relevance** (Wan et al., 2025) measures the coherence between the current step and the preceding context. Specifically, it uses the Jaccard similarity between the current step and the accumulated past steps. A higher similarity indicates better contextual coherence.
- **Verbal progress** is a zero-shot baseline that assesses progress toward the final answer by prompting Qwen3-4B to estimate how close the current reasoning state is to completing the task. The model is asked to output a scalar that ranges from 1 to 5 based on the textual content of the current step and its information-seeking trajectory. A higher score indicates that the current reasoning state is close to the final answer.

Train Configurations. We train PRINTS using Qwen3-4B with an alternating SFT-GRPO schedule over four cycles, where each cycle consists of one SFT epoch for summarization followed by one GRPO epoch for scoring, to jointly acquire both abilities. For the SFT stage, we use a batch size of 128 and a learning rate of 1e-6. For the GRPO stage, we execute $N = 4$ rollouts and use a batch size of 128 and a learning rate of 1e-6. Such alternating optimization allows the model to continuously refine its summarization ability while simultaneously improving its scoring accuracy on reasoning quality. This iterative schedule ensures both modules evolve synergistically, stabilizing training and preventing either skill from degrading over time.

Data Annotations. We construct our annotated data from 4,344 information-seeking questions, comprising 720 questions used to train information-seeking agents from the Alibaba group (Wu et al., 2025a; Li et al., 2025b; Tao et al., 2025), and 3,624 questions from the Miroverse-v0.1

dataset (MiroMind Data Team, 2025), a large-scale agent dataset covering multi-hop QA, web navigation, and scientific reasoning tasks. For the score annotation process, we execute $M = 8$ rollouts per trajectory step to estimate the mean accuracy and information gain score. We discard steps that are either too easy ($m_t = 1$) or too hard ($m_t = 0$), resulting in 2,294 preference pairs used for training.

As shown in Figure 5, our annotation pipeline produces well-balanced information gain score distributions across the full score range. This balanced distribution ensures that PRINTS learns to estimate diverse trajectory step quality, from harmful steps that reduce success probability to highly effective steps that substantially advance toward the correct answer. Moreover, the distributions of winning and losing steps exhibit clear separation. This clear separation validates the effectiveness of our preference pair construction and using this as training signals for PRINTS to output dense and comparative scores.

Frontier Model Performance. For the performance of frontier models on the GAIA benchmark, we follow the reported results (OpenAI DeepResearch: 67.4% and DeepSeek-V3.1-671B: 63.1%) in the DeepResearch-30B-A3B paper (Li et al., 2025a) and use these reported numbers as reference points when evaluating improvements brought by integrating PRINTS into DeepResearch-30B-A3B.

B. Additional Experiments

PRINTS as Summarizer. To validate our design of jointly training scoring and summarization within a single model, we compare PRINTS against a variant that uses separate models for each capability. Specifically, we train a PRM using only GRPO for scoring without SFT for summarization, and pair it with Qwen3-32B – the same model we use for summary annotation – to generate summaries at test-time. As shown in 6, PRINTS, which is jointly trained as both scorer and summarizer through our alternating SFT-GRPO schedule, outperforms this separated design. This demonstrates that the two abilities are complementary and that our alternating training schedule enables seamless integration of these abilities. We hypothesize that this benefit arises from positive transfer between the two objectives. As both abilities operate on the same input (i.e., query, preceding summary, latest tool response, current trajectory step), learning to distill essential information during SFT directly aids GRPO optimization by highlighting the most relevant factors for quality evaluation.

Dataset Scaling To further validate that PRINTS is a cost-efficient way of improving information-seeking behaviors of agents without fine-tuning them, we conduct an ablation study on the training dataset scaling. As shown

Method	FRAMES	GAIA		Avg.
		Level 1	Level 2	
Qwen3-32B	54.7	44.5	29.5	42.9
PRINTS	58.7	49.6	33.3	47.2

Table 6. Ablation study of summarizer. The Qwen3-32B approach utilizes Qwen3-32B as a summarizer and employs the PRM trained solely as a scorer. PRINTS that simultaneously acts as a summarizer and scorer shows better performance, showing that two abilities are complementary.

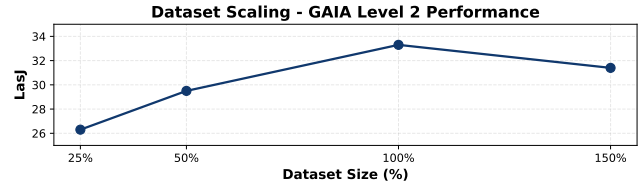


Figure 6. Dataset scaling. Experiments on the impact of dataset scaling on GAIA Level 2 using Qwen3-32B. Training PRINTS shows strong sample efficiency, achieving performance gain using only 50% (~1k samples) of our annotation data.

in Figure 6, using only 50% (i.e., ~ 1 k samples) of our annotation data still achieves 29.5 accuracy in GAIA Level 2, surpassing the base agent approach by training a relatively lightweight model (4B). The scaling curve saturates beyond 100%, indicating that our ~ 2 k preference pairs represent a data-efficient point. This demonstrates strong sample efficiency compared to fine-tuning agents, which typically require 10k-100k samples and expensive long-horizon rollouts using relatively larger models, requiring substantial computational resources.

Winning / Losing Pair Examples

InfoSeek Query

An individual held positions at St John's College, Cambridge, first ending in 1815 and then from 1815 to 1839, totaling 37 years of tenure. This person authored "The Elements of Algebra (1795)" and bequeathed a library of nearly 4,500 books in classics, history, mathematics, theology, and travel (17th–19th centuries). Starting from 1820, they held a position with the role of Chief Justice, administering an area, but the name of this position is unknown. What is the name of this position?

- Reasoning: 'Okay, so the user is asking for the name of the position held by an individual starting in **1820** as Chief Justice, but the name of the position is unknown. The Google search results indicate that the author is **James Wood**, who was active from 1795 to 1839. The second organic result mentions that **James Wood was a Fellow of St John's College, Cambridge**, from 1795 to 1839 ...'
- Tool Call: {'function': 'google_search', 'arguments': {'q': 'James Wood St John's College Cambridge position 1820 Chief Justice'}}

Winning Reasoning Step (s_3^+) & Tool Call (a_3^+)

- **✓ Precise temporal and institutional anchors:** key identifiers from the reasoning narrow down the search space effectively.
- **Overall accuracy:** $0.75 (m_2^+) \rightarrow 1.00 (m_3^+)$
- **Score (g_3^+):** + 2.0

- Reasoning: 'Okay, so the search results indicate that "The Elements of Algebra" from 1795 was authored by James Wood. The second and third results mention James Wood (1760–1839) as the author, and it's associated with Cambridge. So the person in the question is **James Wood**. Now, **he was at St John's College, Cambridge** ...'
- Tool Call: {'function': 'google_search', 'arguments': {'q': 'James Wood Cambridge Chief Justice position'}}

Losing Reasoning (s_3^-) & Tool Call (a_3^-)

- **✗ Misalignment between reasoning & tool call:** No mention of "St John's College" or "1820" in the search query.
- **Overall accuracy:** $0.75 (m_2^+) \rightarrow 0.675 (m_3^-)$
- **Score (g_3^-):** - 1.0

InfoSeek Query

What is the name of the city where, in July 1965, the director of the 2020 documentary that includes archival footage from the 1960s and focuses on the composer who wrote the soundtrack for the 1963 B movie "Run Home Slow" participated in an event?

- Reasoning: 'Okay, so the 2020 documentary about Frank Zappa is called "Zappa" and it's directed by Alex Winter. Now, the question is about the city where Alex Winter participated in an event in July 1965... **But given that Alex Winter wasn't born yet in 1965 (born in 1961, according to my knowledge), that seems impossible.** Wait, I must have made a mistake. **Let me confirm Alex Winter's birth year. Let me check Alex Winter's birth year.** I can do a quick search for "Alex Winter birth date".'
- Tool Call: {'function': 'google_search', 'arguments': {'q': 'Alex Winter birth date'}}

Winning Reasoning Step (s_2^+) & Tool Call (a_2^+)

- **✓ Verified assumptions before pivoting:** when things seemed contradictory, fact-checks the key premise rather than making leaps.
- **Overall accuracy:** $0.50 (m_1^+) \rightarrow 0.875 (m_2^+)$
- **Score (g_2^+):** + 1.5

- Reasoning: 'Okay, the 2020 Frank Zappa documentary is titled "Zappa" and directed by Alex Winter. Now I need to find out if the director, Alex Winter, participated in an event in July 1965... **Alex Winter was born in 1969, according to some of my prior knowledge, so he wouldn't have been alive in 1965... Therefore, there must be a mistake in the question's phrasing. Let me proceed with that assumption...** Let me search for "Run Home Slow 1965 premiere location".'
- Tool Call: {'function': 'google_search', 'arguments': {'q': 'Run Home Slow 1965 premiere location'}}

Losing Reasoning (s_2^-) & Tool Call (a_2^-)

- **✗ Made unverified assumptions:** Assumed the question be wrong and switched to a completely different person without verification.
- **Overall accuracy:** $0.50 (m_1^+) \rightarrow 0.00 (m_2^-)$
- **Score (g_2^-):** - 2.0

Figure 7. Examples of preference pairs constructed by our annotation pipeline.

Prompt Template for PRM as Scorer

Instruction:

You are given a user information seeking problem. Your task is to act as an impartial judge and evaluate how well the "Current Reasoning Step" contributes to solving the user's problem based on the problem description and historical reasoning context. It is OK that the current step does not contain any tool call response.

REASONING EVALUATION RULES:

- As you evaluate, develop and refine your assessment criteria based on the specific requirements of this problem type and reasoning context. Think carefully about how to assess the quality of the current reasoning step. Your thinking should include your evaluation criteria, explaining how the step aligns with or deviates from your expectations.
- Finally, assign the reasoning step a score from -4 to 4, using either an integer or a decimal with up to 0.1 precision. A higher score should indicate a higher-quality response.

[Input]:

Information Seeking Problem
{problem}

Historical Reasoning Trace Summary
{historical_summary}

Previous Tool Response
{previous_tool_response}

Current Reasoning Step
{current_reasoning}

[Output format]:

1. Criteria Development: [Identify the key evaluation criteria relevant for evaluating this reasoning step. Consider factors such as: logical validity and coherence of the step, tool call appropriateness and argument quality (whether too general or too narrow), consistency with user problem, historical reasoning trace summary, and previous tool response, informative/progress toward final answer, confidence and uncertainty expression, etc. Briefly explain why your selected criteria are critical for this particular evaluation.]
2. Analysis: [Always provide a step-by-step analysis here. First, briefly state the goal of the current reasoning step. Second, systematically evaluate the step against each of your identified criteria above. For each criterion, assess how well the step performs and explain your reasoning. If errors or deficiencies are found, clearly explain what is wrong and why. If the step performs well on a criterion, explain why it succeeds.]
3. Final Judgment: [Provide the final judgment within `\boxed_score{}`. Examples: `\boxed_score{-3.0}` or `\boxed_score{3.5}`.]

Figure 8. Input prompt for PRINTS when the model is trained with GRPO for scoring ability and acts as a scorer at test-time.

Prompt Template for PRM as Summarizer

Instruction:

You are a reasoning trace summarizer for multi-step information seeking problems. Your task is to incrementally build a concise summary of an information-seeking process. Your summary should capture the process's state of knowledge, uncertainty, hypothesis, and next actions.

Input Sources:

- # Information Seeking Problem - the original user question.
- # Historical Reasoning Trace Summary - the accumulated summary built from all previous reasoning steps and tool responses.
- # Previous Tool Response - the tool response from the immediately preceding step (not yet incorporated into Historical Summary).
- # Current Reasoning Step - the reasoning and tool interaction from the current step (not the complete reasoning trace).

SUMMARIZATION RULES:

- Keep essential information from the Previous Tool Response and Current Reasoning Step needed for the next action.
- Incorporate what the current process believes, suspects, verifies, or is planning further verification.
- For the Current Reasoning Step's action, summarize tool name and key parameters.
- Preserve the Historical Reasoning Trace Summary unless explicitly contradicted or superseded. Justify any removals.
- Do NOT infer or invent missing information. It is normal for reasoning to be incomplete.
- Output the COMPLETE updated summary.

[Input]:

Information Seeking Problem
{problem}

Historical Reasoning Trace Summary
{historical_summary}

Previous Tool Response
{previous_tool_response}

Current Reasoning Step
{current_reasoning}

[Output format]:

1. Analysis: [In 3-5 sentences, explain what key information from Previous Tool Response and Current Reasoning Step is being added, what (if anything) from Historical Summary is being removed or updated and why, and why the resulting summary is sufficient for next steps.]
2. Updated Summary: [Provide the complete summary within \boxed_summary\{\}\} containing:
 - **Confirmed Knowledge**: Verified facts.
 - **Uncertainty**: What remains unknown.
 - **Previous Hypotheses**: Abandoned hypotheses (if relevant).
 - **Previous Action**: Previous tool calls with key parameters in the Historical Reasoning Trace Summary.
 - **Current Hypothesis**: Current working hypothesis in the Current Reasoning Step and Historical Reasoning Trace Summary.
 - **Current Action**: Most recent tool call with key parameters in the Current Reasoning Step.]

Figure 9. Input prompt for PRINTS when the model is trained with SFT for summarization ability and acts as a summarizer at test-time.

Step-level Score Evaluation

InfoSeek Query

Who composed the song that was performed by a rooster and a hamster in separate animated videos at separate tempos with different lyrics? Answer using the format First name Last name.

Best Agent Trajectory Step

- Reasoning: 'Okay, let's try to figure out this question. First, I need to recall if there's any well-known song that fits this description. The mention of a rooster and a hamster makes me think of children's songs or maybe something from a cartoon. **But I'm not immediately recalling a specific song.** Maybe I should break it down. **The key elements here are: composed a song, performed by a rooster and a hamster, separate animated videos, different tempos and lyrics...** Since I'm stuck, maybe I should use the available tools to search for the answer. The user has provided a Google search function. Let me try that. I'll use the google_search function with the query: "song performed by rooster and hamster animated videos different tempos composer". Let's see what comes up...'
- Tool Call: {'function': 'google_search', 'arguments': {'q': 'song performed by rooster and hamster animated videos different tempos composer'}}

PRInTS score evaluation

...

1. **Criteria Development**: ...
2. **Analysis**:
 - **Logical Validity**: The assistant correctly identifies the problem's key elements (rooster/hamster, animated videos, different tempos/lyrics) and considers plausible angles (children's songs, educational videos, viral content). This demonstrates a structured approach.
 - **Tool Call Appropriateness**: The Google search query is specific and tailored to the problem, making it a strong tool call. The query includes all critical details (e.g., "rooster and hamster," "different tempos," "composer").
 - **Progress Toward Answer**: The step is progressively moving toward the answer by combining analysis with targeted research. The assistant avoids vague assumptions and instead focuses on actionable steps.
 - **Confidence in Uncertainty**: The assistant acknowledges uncertainty (e.g., "I'm not immediately recalling a specific song") and uses the tool to resolve it, which is appropriate.

3. **Final Judgment**: The assistant's reasoning is well-structured, logically valid, and appropriately uses a tool call to address the problem. The step balances analytical thinking with practical action.

\boxed_score{2.0}



Worst Agent Trajectory Step

- Reasoning: 'Okay, let's tackle this question step by step. ...I recall that "The Yellow Song" by The Yellow Album Leaf is a song where a rooster and a hamster perform the song in different animated versions. The rooster's version is faster, and the hamster's is slower. The lyrics are also slightly different between the two. The composer of this song is likely the same as the artist, The Yellow Album Leaf. But wait, The Yellow Album Leaf is a project by Ben Schneider. **Let me confirm that. A quick search in my mind: yes, Ben Schneider is the creator and composer behind The Yellow Album Leaf.** The song in question is part of their "Yellow Album" series, which includes various characters and their own versions of songs. So, the answer should be Ben Schneider. Let me make sure there's no other composer associated with that specific song. Since The Yellow Album Leaf is his project, and he composes the songs, it's safe to attribute the composition to him. Therefore, the first name is Ben and the last name is Schneider
- Tool Call: {'function': 'submit', 'arguments': {'answer': 'Ben Schneider'}}

PRInTS score evaluation

...

1. **Criteria Development**: ...
2. **Analysis**:
 - **Logical Validity**: The assistant assumes the song is "The Yellow Song" by *The Yellow Album Leaf* without confirming its existence or relevance to the described scenario. This leap in logic is unsupported by evidence.
 - **Evidence-Based Conclusion**: The assistant relies on unverified memory (e.g., "Ben Schneider is the creator of The Yellow Album Leaf") without citing any sources or references. This undermines the reliability of the answer.
 - **Relevance to Problem**: The reasoning focuses on a specific project but fails to address the core question directly. The connection between the described scenario and the song/composer is unclear.
 - **Confidence in Answer**: The assistant presents the answer with certainty, despite the lack of evidence. This overconfidence is problematic in an information-seeking context.

3. **Final Judgment**: The reasoning step is speculative and lacks evidence, making it unsuitable for solving the problem. The conclusion is not justified by the provided information.

\boxed_score{-2.0}



Figure 10. PRINTS step-level evaluation examples on a GAIA query. Among four candidate steps, we show the highest-scoring (top) and lowest-scoring (bottom) steps. The high-quality step acknowledges uncertainty and initiates an appropriate tool call to gather missing information, while the low-quality step makes unverified assumptions and confidently produces an unsupported answer without evidence.