PokeeResearch: Effective Deep Research via Reinforcement Learning from AI Feedback and Robust Reasoning Scaffold

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Abstract

Tool-augmented large language models (LLMs) are emerging as deep research agents—systems that decompose complex queries, retrieve external evidence, and synthesize grounded responses. Yet current agents remain limited by shallow retrieval, weak alignment metrics, and brittle tool-use behavior. We introduce PokeeResearch-7B, a 7B-parameter deep research agent built under a unified reinforcement learning framework for robustness, alignment, and scalability. PokeeResearch-7B is trained by a Reinforcement Learning from AI Feedback (RLAIF) framework to optimize policies using LLM-based reward signals that capture factual accuracy, citation faithfulness, and instruction adherence. A chain-of-thought-driven multi-call reasoning scaffold further enhances robustness through adaptive recovery from tool failures and self-verification on generated answers. At test time, multiple research threads are executed independently and synthesized to produce the best answer. Among 10 popular deep research benchmarks, PokeeResearch-7B achieves state-of-the-art performance among 7B-scale deep research agents. This highlights that careful reinforcement learning and reasoning design can produce efficient, resilient, and research-grade AI agents. The model and inference code is open-sourced under Apache 2.0 license at https://github.com/Pokee-AI/PokeeResearchOSS.

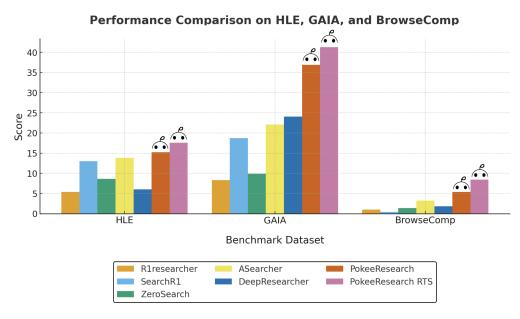


Figure 1: Performance on HLE, GAIA and BrowseComp among 7B-scale deep research models.

1 Introduction

With their ability to use tools for complex, open-domain tasks, tool-augmented large language models (LLMs) are increasingly deployed as deep research agents, *i.e.*, systems capable of gathering, reasoning over, and

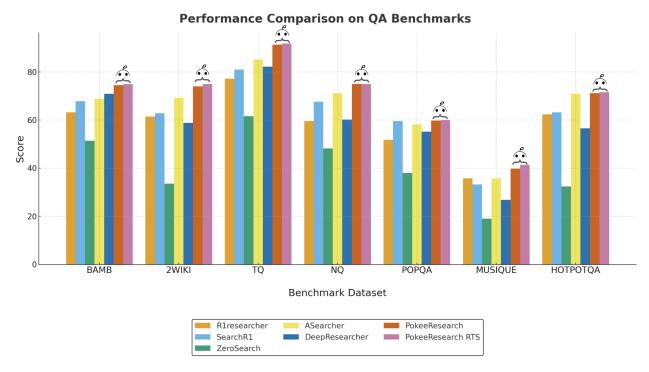


Figure 2: Performance on 7 QA Benchmarks among 7B-scale deep research models.

synthesizing evidence from diverse sources to provide well-grounded answers to sophisticated queries. A typical deep research workflow requires an agent to decompose the user's query, identify relevant external information, and synthesize it into a coherent, verifiable response.

Recent progress in deep research agents has been driven by two parallel directions: (1) the development of smaller, cost-efficient LLM backbones suitable for scalable deployment [SJM⁺25, JZY⁺25, SQG⁺25, GFX⁺25, ZFH⁺25, WZA⁺25]; and (2) the design of training recipes that interleave reasoning with external actions [TT25, Tea25, LJD⁺25]. Despite these advances, existing agents remain constrained by several key limitations. First, most training pipelines still depend on token-overlap metrics such as F1 or ROUGE [WZA⁺25, DCL⁺25, MHF⁺25, LZY⁺25], which correlate weakly with human judgments of usefulness, factual grounding, and instruction adherence. Moreover, current agents exhibit brittle tool-use behavior: a single malformed function call, fetch error, or transient API failure can derail an entire trajectory, with little opportunity for self-correction [SWY⁺25, XHJ⁺25, SMPN25]. In addition, plausible research threads can miss critical information, producing misleading inferences and therefore incorrect answers, especially for challenging questions.

To address these challenges, we introduce PokeeResearch-7B, a 7-billion-parameter deep research agent developed under a unified reinforcement learning framework optimized for reliability, human alignment, and practical deployment. Our contributions center on three core innovations:

- Human Value-Driven Training Pipeline: We enhance agent alignment with Reinforcement Learning from AI Feedback (RLAIF) instantiated with the REINFORCE Leave-One-Out (RLOO) algorithm [KvHW19, ACG+24]. RLAIF provides rich, LLM-based reward signals calibrated to human values, including factual accuracy, citation faithfulness, and instruction compliance. RLOO offers unbiased gradient estimation in an on-policy fashion for policy improvement. This algorithm distinguishes itself from algorithms that are only approximately on-policy and follow a biased gradient direction, such as the PPO family of algorithms.
- Robust Reasoning Scaffold: To enhance the robustness of our deep research agent, we employ three complementary techniques. Self-correction: Rather than blindly executing potentially malformed tool calls, the agent proactively diagnoses errors and suggests corrections. Self-verification: The agent incorporates an answer verification step that filters out easily detectable false outputs. Research threads synthesis: To improve answer accuracy on challenging questions at test time, the agent launches multiple independent

research threads in parallel. These research threads are jointly analyzed and synthesized by the agent to produce the final answer.

Together, these design choices yield a deep research agent that (1) optimizes directly for human-salient dimensions of answer quality rather than surface overlap; and (2) maintains robustness across imperfect models through adaptive, verifiable reasoning. At 7B scale, PokeeResearch-7B demonstrates that carefully engineered reinforcement learning and reasoning scaffolds can produce research-grade agents that are both cost-efficient and resilient in open-domain settings. We show in 10 benchmarks that PokeeResearch-7B presents state-of-the-art performance among 7B-size deep research agents.

2 Related Work

In this section, we give a review of existing benchmarks for deep research and summarize recent progress in building deep research agents.

Information Seeking Benchmarks. The development of sophisticated information retrieval agents has necessitated increasingly complex evaluation benchmarks. Traditional datasets such as Natural Questions [KPR+19] and TriviaQA [JCWZ17] primarily assess single-hop reasoning, which can often be addressed using parametric knowledge or simple query sequences. Their multi-step extensions, including HotpotQA [YQZ+18] and Musique [TBKS22], evaluate structured multi-hop reasoning but remain insufficiently challenging for advanced agents. Recent evaluation frameworks have evolved to present more nuanced challenges: GAIA [MFW+23] introduces real-world complexity requiring sophisticated reasoning chains, while WebWalkerQA [WYJ+25] emphasizes dynamic web navigation skills. The BrowseComp suite [WSP+25, ZLY+25] establishes standardized metrics for web browsing competency across multiple languages. At the frontier of evaluation difficulty, Humanity's Last Exam [PGH+25] presents multi-modal challenges that push the boundaries of current capabilities, with state-of-the-art agents achieving merely 25.4% success rates.

Information Seeking Agents. Recent advances in large language models—particularly commercial agents such as DeepResearch [Ope25] and Grok-3 [x.a25]—have driven significant progress in automated information-seeking agents. However, the proprietary nature of these models limits scientific understanding and hinders reproducibility. The open research community has responded with agents like WebDancer [WLF+25], WebThinker [LJD+25], and R1-Searcher [SJM+25], which leverage the ReAct reasoning framework [YZY+23] but exhibit performance limitations on demanding benchmarks. Training paradigms remain an active area of investigation: traditional supervised fine-tuning approaches often suffer from poor generalization in dynamic environments [ZZW+25, ZDZ+25], while reinforcement learning methodologies [JZY+25, SLW+25, ZFH+25, MHF+25, TWG+25] show promise for developing adaptive exploration strategies despite challenges in stability and sample efficiency. Recent innovations include StepSearch's process-supervised RL approach [WZA+25], Tool-star's hierarchical reward framework combining SFT initialization with multi-tool RL optimization [DCL+25], and WebSailor's trajectory filtering methodology followed by reasoning-focused RL fine-tuning [LZY+25].

3 Method

In this section, we first describe the deep research workflow of PokeeResearch-7B. Then, we describe the tools provided to the agent and the training pipeline. Finally, we provide our reward design for the training algorithm and test time design for our agent.

3.1 Deep Research Workflow

The deep research workflow runs in research-verification cycles. Upon receiving a research question from the user, the agent initiates a research thread, where the agent alternates between research mode and verification mode, starting in research mode.

Research Mode. The research mode is a multi-turn process. In each turn, the agent produces a textual response that either (1) issues a tool call enclosed by the special tags <tool_call> and </tool_call> to gather necessary information to answer the question; or (2) provides an answer enclosed by <answer> and </answer>. If a tool call is generated, the corresponding tool is executed and the tool call response

is returned to the agent. Then, the research process continues. We point out that as long as the tags <tool_call> and </tool_call> is produced, our agent does not simply terminate the research whenever tool call fails. Instead, the agent continues to experiment with new tool calls until either success or turn limit is reached. Finally, if an answer is generated, the agent transitions to verification mode.

Verification Mode. In this mode, the agent examines the entire research thread to assess whether the generated answer is correct. If the verification succeeds, the thread ends. Otherwise, the agent re-enters research mode to continue refinement. This research–verification cycle repeats until the context limit is reached or the verification approves the answer.

Unlike most prior works, where the research thread concludes with answer generation, our framework introduces the additional answer verification step in which the agent evaluates its own answer. This step can effectively prevent several observed common failures: (1) the agent's answer does not fully address all aspects of the question; (2) the agent produces an answer despite insufficient supporting evidence; and/or (3) the agent's reasoning contains simple logical errors that could be easily detected. We hypothesize that such failure modes can be identified during self-verification, owing to the generation–verification gap of large language models $[SZE^+24]$.

3.2 Tools and Training Pipeline

Tools. In our design, we enable the agent to interact with the web to efficiently gather information by equipping it with a set of specialized tools. Here, each tool targets distinct functionalities in the research process, from initial discovery to relevant information extraction.

- Web Searching Tool: We provide Serper [Ser25] to our agent to find information over the Internet. This tool takes a list of string queries as input and searches for information related to it through Google. Afterwards, the tool returns a structured list of results, including URLs and descriptive snippets, for each query. This allows the agent to survey the landscape of available information and constantly identify promising sources for further investigation;
- Web Reading Tool: We also provide Jina Reader [Jin25] to our agent to allow it to read through the search results. This tool takes a list of URLs as input and returns a concise summary of the primary content from each corresponding webpage. These summaries provide a quick and high-level understanding of a webpage, helping the agent determine if a deeper analysis of the page is warranted.

Training Data and Algorithm. In our training pipeline, we adopt the MiroRL-GenQA dataset [TT25], which features complicated question-answer pairs. These questions are non-trivial and require multi-turn research to address. For a fair experiment setup, no training data from the benchmarks is used in testing.

To train our agent, we use the RLOO algorithm [KvHW19, ACG⁺24]. This is a true on-policy algorithm and the parameter update follows an unbiased policy gradient estimate. It achieves a lower variance compared to the classic REINFORCE algorithm by drawing more than one samples from the same start state. Formally, in our problem setting, given the current policy π parameterized by θ , for prompt x, the algorithm samples k i.i.d. completions $\{y^{(i)}\}_{i=1}^k \sim \pi_{\theta}(\cdot \mid x)$ and obtain their rewards R(x,y). For each sample, form a leave-one-out baseline [KvHW19]:

$$b_i = \frac{1}{k-1} \sum_{j \neq i} R(x, y^{(j)}).$$

Then compute the advantage:

$$A_i = R(x, y^{(i)}) - b_i.$$

RLOO updates policy parameters θ following

$$\theta \leftarrow \theta + \alpha \frac{1}{k} \sum_{i=1}^{k} A_i \nabla \log \pi_{\theta} (y^{(i)} | x),$$

where α is a step size parameter. This update follows the direction of an unbiased policy gradient estimate $\frac{1}{k} \sum_{i=1}^{k} A_i \nabla \log \pi_{\theta}(y^{(i)} | x)$.

In words, RLOO operates by sampling multiple completions per prompt from the *current* policy and using a *leave-one-out* baseline formed from the other samples. This centering removes any effect of a prompt-level constant shift in rewards, yielding an unbiased gradient estimate with lower variance $[ACG^{+}24]$. To align with

the special workflow of our agent outlined in Section 3.1, during training, the agent receives a large positive reward (see Section 3.3 for more details) if the agent generates an answer in the research thread and the answer is correct; if the agent's response follows the right format, the agent receives a small positive reward; otherwise, it receives a reward of zero. The agent's goal is to maximize the reward across all user questions.

RLOO can be related to the well-known Group Relative Policy Optimization (GRPO) algorithm [SWZ⁺24]. Like RLOO, GRPO also samples multiple completions per prompt and obtains advantages by subtracting rewards by the mean of rewards of completions (GRPO subtracts rewards by the mean of rewards of ALL completions, introducing a small bias in the policy gradient estimate, which should not be a concern as the bias is multiplicative). Unlike RLOO, GRPO 1) uses a surrogate advantage by dividing the original advantages by the standard deviation of the rewards, and 2) applies a PPO-style update. The standard deviation normalization rescales updates based on within-group dispersion, making the parameter update a biased one; moreover, GRPO employs multiple updates per batch and applies clipping and KL regularization as in PPO, making it only approximately on-policy. In our experiments, we found that the standard deviation normalization often results in performance collapsing when training for long enough time. We also observed that RLOO demonstrates faster learning progress, possibly due to its true on-policy nature.

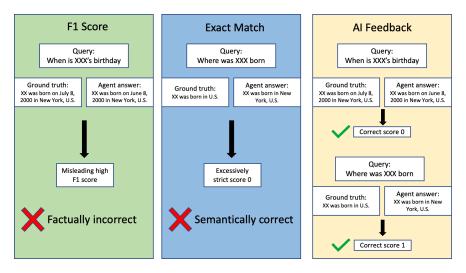


Figure 3: Illustration of the advantages of AI feedback over traditional lexical metrics.

3.3 Reward Design

Our reward design mainly focuses on answer correctness, which can be measured through three complementary evaluation approaches: F1 score, Exact Match (EM), and AI feedback. Each metric provides distinct signals on the quality of an answer, and we explore their relative merits in our empirical analysis.

- F1 Score: The F1 score measures the harmonic mean of precision and recall between the set of tokens in the generated answer and the ground truth (see Section A for formal definition). This token-level metric provides a nuanced assessment of content overlap, rewarding answers that are substantially correct even if they are not lexically identical to the ground truth. The F1-based reward is denoted as $R_{\rm F1}$.
- Exact Match (EM): The Exact Match metric is a stricter binary evaluation that awards a score of 1 if the normalized predicted answer is identical to any of the provided ground-truth answers, and 0 otherwise. Although less flexible than F1, it serves as a clear indicator of complete accuracy. We denote this reward as $R_{\rm EM}$.
- AI Feedback: To address the limitations of purely lexical metrics (see Remark 1 below), we introduce an AI feedback approach. Here, we leverage an external LLM as an impartial judge to assess whether the agent's answer is semantically equivalent to the ground truth. The judge model is provided with both the ground truth and the agent's answer and returns a binary judgment indicating semantic correctness. This approach captures nuanced semantic information that token-level metrics may miss. We denote the AI reward as $R_{\rm AI}$.

In our experiments, we adopt AI feedback plus a small format reward as our reward signal during training. The AI feedback directly aligns with our ultimate goal of producing semantically correct answers and the format reward helps adherence to the required output format.

Remark 1 (On the Advantages of AI Feedback) Although lexical metrics such as F1 score and EM provide valuable signals, they exhibit inherent limitations that motivate our emphasis on AI feedback. The token level F1 score, despite its flexibility, can produce misleadingly high scores for factually incorrect answers that share substantial token overlap with the ground truth. For instance, as shown on the left-hand side of Figure 3, the two answers differ by only one word, but the agent's answer would be factually incorrect if the query asks for the birthday of the object. In contrast, EM suffers from excessive strictness, penalizing semantically correct answers that are not identical to the ground truth. In the middle of Figure 3, EM would judge the agent's answer as incorrect because it differs from the ground truth, despite the additional information is accurate. The AI-based approach addresses these limitations by directly optimizing for semantic correctness, which is our ultimate objective. This alignment between the reward signal and the desired outcome mitigates reward hacking behaviors and provides more reliable training signals for complex reasoning tasks.

3.4 Test Time Design

In our preliminary experiments, we observed that running multiple independent research threads can yield divergent answers, particularly for challenging questions. In such cases, the correct answer typically appeared in only one or two threads, if at all. Interestingly, the threads leading to incorrect answers often seemed reasonable when viewed in isolation but became less convincing when compared against those producing the correct answer. This discrepancy can arise, for example, when a thread misses key information—leading the agent to form a plausible yet incomplete inference—while another thread happens to retrieve the missing information.

Motivated by this observation, we hypothesize that introducing a synthesis stage to evaluate and compare multiple research threads can enhance overall accuracy. Specifically, for each question, the agent launches n independent research threads in parallel. Each thread is subsequently summarized by our model to preserve only the essential findings and reasoning steps. These summaries are then jointly analyzed by our model, which synthesizes the evidence and determines the final answer. We refer to this approach as $Research\ Threads\ Synthesis\ (RTS)$.

4 Experiments

In this section, we describe our empirical analysis in detail.

4.1 Experiment Setup

Benchmarks. In our experiments, we test the performance of PokeeResearch-7B in the following popular benchmarks. Due to the limitations of the base model we choose, we only evaluate on the text-only versions of the following benchmarks.

- Natural Questions (NQ) [KPR⁺19]: A large-scale question-answering dataset derived from real Google search queries, testing the agent's ability to answer factoid questions using Wikipedia articles.
- TriviaQA [JCWZ17]: A reading comprehension dataset containing trivia questions paired with evidence documents, evaluating the agent's capacity to locate and extract relevant information from web sources.
- PopQA: A dataset focused on questions about popular entities and topics, assessing the agent's performance on queries requiring up-to-date knowledge from current web content.
- HotpotQA [YQZ⁺18]: A multi-hop reasoning dataset requiring the agent to gather and synthesize information from multiple documents to answer complex questions.
- 2WikiMultiHopQA [HNSA20]: A challenging benchmark designed specifically for multi-hop reasoning over Wikipedia, where answering requires connecting information across multiple articles.
- Musique [TBKS22]: A multi-hop question-answering benchmark that tests compositional reasoning abilities, requiring the agent to perform sequential information gathering and inference steps.

- Bamboogle (BAMB) [PZM⁺22]: A dataset containing questions that cannot be answered using the model's parametric knowledge alone, necessitating active web search and information retrieval.
- GAIA [MFW⁺23]: A benchmark presenting real-world complexity with sophisticated reasoning chains, evaluating the agent's ability to handle realistic, challenging research tasks.
- BrowseComp [WSP+25]: A standardized evaluation suite for web browsing competency, testing the agent's ability to navigate and extract information from dynamic web pages across multiple languages.
- Human's Last Exam [PGH⁺25] A comprehensive benchmark assessing an agent's general reasoning, factual
 recall, and multi-domain understanding, serving as a holistic test of advanced language and reasoning
 capabilities.

Baselines. We compare our approach against several recent deep research agents: R1-Searcher [SJM⁺25], Search-R1 [JZY⁺25], ZeroSearch [SQG⁺25], ASearcher [GFX⁺25], and DeepResearcher [ZFH⁺25]. These agents employ various combinations of web searching, reading, and browsing tools. All baselines use Qwen2.5-7B (Base or Instruct)¹ as their backbone model, matching ours for a fair comparison. We use Serper for search across all methods, and ASearcher additionally uses Jina for webpage reading, consistent with our approach. We note that other deep research works, such as [LLZ⁺25, LJD⁺25], employ larger models or longer context lengths. We exclude them from consideration to ensure a fair comparison.

Training Details. We use Qwen2.5-7B-Instruct [Tea24] as our backbone model, which is a powerful open-source LLM that has been instruction-tuned on a large corpus of human-generated data. The model is fine-tuned using the RLOO algorithm. We fine-tine the backbone model for 140 steps. For each step, the model is trained using a batch of 64 questions and the number of independent research threads used by the RLOO algorithm is 8. We set the maximum number of interaction turns to 100, allowing the agent to iteratively refine its research process. The learning rate is 3e-6. The context limit is 32768. No entropy or KL regularization is applied.

Evaluation Details. We construct our test dataset by randomly sampling 125 text-only questions from each benchmark, except for GAIA, which contains only 103 text-only questions. This results in a total of 1,228 questions. For each question and each agent (except for our agent with RTS) under evaluation, we run four research threads independently, with the context limit being 32768. If a research thread produces an answer, we submit both the generated answer and the corresponding ground-truth answer to a Gemini-Flash-2.5-Lite model, which judges whether the generated answer is correct. Formally, the accuracy for a given question—agent pair is defined as:

accuracy
$$\doteq \frac{\text{\# research threads where the answer is correct}}{4}$$

We report the mean accuracy across all questions within each benchmark (mean@4).

For our agent with RTS, we perform four independent runs, each consisting of four independent research threads. The final answer in each run is derived by synthesizing the outputs of the four threads. This answer is then sent to the judge, and accuracy is calculated in the same manner.

4.2 Results and Analysis

We compare our deep research agent, with and without RTS, against the baselines. For RTS, we experimented with four research threads. Table 1 summarizes the results. Both versions of our agent outperform all baselines across all benchmarks (mean@4). The improvement from RTS is especially notable on challenging benchmarks such as HLE, GAIA, and BrowseComp, while its effect is minor on other benchmarks, which are relatively simpler.

Upon inspection, we also find that our self-verification is helpful in improving the answer correctness. Below, we provide an excerpt on how it helps PokeeResearch-7B to correct an initially inaccurate response. In this example, after finding the initial answer, the agent enters the verification mode, and determines the initial answer is incorrect based on the retrieved information and its own judgment. Afterwards, it re-enters the research mode, and manages to find out the correct one with additional tool calls. The complete log of this is detailed in Section B of the appendix.

¹When agents report results for both versions, we use the better-performing one.

Method	HLE	GAIA	BrowseComp
R1searcher	5.4	8.3	1.0
SearchR1	13.0	18.7	0.4
ZeroSearch	8.6	9.9	1.4
ASearcher	13.8	22.1	3.2
DeepResearcher	6.0	24.03	1.8
PokeeResearch	15.2	36.9	5.4
PokeeResearch-RTS	17.6	41.3	8.4

Method	BAMB	2WIKI	$\mathbf{T}\mathbf{Q}$	NQ	POPQA	MUSIQUE	HOTPOTQA
R1searcher	63.2	61.4	77.2	59.6	51.8	35.8	62.4
SearchR1	67.8	62.8	81.0	67.6	59.6	33.2	63.2
ZeroSearch	51.4	33.6	61.6	48.2	38.0	19.0	32.4
ASearcher	68.8	69.2	85.2	71.2	58.2	35.8	71.0
DeepResearcher	71.0	58.8	82.2	60.2	55.2	26.8	56.6
PokeeResearch	74.5	74.0	91.3	75.1	59.8	39.8	71.2
PokeeResearch-RTS	75.0	75.0	91.8	75.0	60.0	41.4	71.6

Table 1: Performance comparison of deep research agents built on open-sourced 7B models across prevalent benchmarks.

Question

In one of Walter Scott's Waverley' novels what was The Heart of Midlothian?

Response

<think>

The Heart of Midlothian is a character or a setting in one of Walter Scott's Waverley novels. I need to find out which novel it is from and its significance in the story.

</think>

<tool call>

{"name": "web_search", "arguments": {"query_list": ["The Heart of Midlothian in Walter Scott's Waverley novels", "Walter Scott Waverley novel The Heart of Midlothian character"]}}

$</tool_call>$

user

<tool_response>

• • • • • •

.

<answer> In Walter Scott's Waverley novel "The Heart of Midlothian," The Heart of Midlothian refers to the Old Tolbooth prison in Edinburgh, and the novel's plot follows the journey of a young woman named Jeanie Deans from Edinburgh to London to seek a royal pardon for her sister, who is accused of murdering her newborn baby.

</answer>

user

You have provided an answer.

##The verification mode starts##.
assistant

<verification>

I need to verify if the answer satisfies all the conditions in the question. The question asked about what "The Heart of Midlothian" was in one of Walter Scott's Waverley novels. The answer provided information about the novel's

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plot and the significance of the title. However, it does not explicitly state
that "The Heart of Midlothian" is the title of the novel. The answer should
have clearly stated that "The Heart of Midlothian" is the title of the novel,
and it refers to the Old Tolbooth prison in Edinburgh.
 </re>
 <verification_result>
INCORRECT
 </re>
The answer is verified to be incorrect. Please incorporate the feedback from
the verification mode and re-enter the research mode.
##The research mode starts##.
assistant
<think>
. . . . . . .
<answer>
In Walter Scott's Waverley novel "The Heart of Midlothian," the title refers
to the Old Tolbooth prison in Edinburgh, which was at the center of the
Scottish county of Midlothian during that time. The novel's plot is set in
motion by the Porteous Riots in Edinburgh and follows the journey of a young
woman named Jeanie Deans from Edinburgh to London to seek a royal pardon for
her sister, who is accused of murdering her newborn baby. The novel is
considered by some to be Scott's best work. </answer>
user You have provided an answer.
##The verification mode starts##.
assistant
 <verification>
I need to verify if the answer satisfies all the conditions in the question.
The question asked about what "The Heart of Midlothian" was in one of Walter
Scott's Waverley novels. The answer provided that "The Heart of Midlothian" is
the title of the novel and gave context about its significance, the plot, and
the author's perspective on the work. The answer correctly identifies the
title and provides relevant information about the novel.
 </re>
 <verification_result>
CORRECT
 </re>
```

5 Conclusion

We introduced PokeeResearch-7B, a 7-billion-parameter deep research agent built under a unified reinforcement learning framework to advance the reliability, alignment, and scalability of tool-augmented LLMs. By integrating Reinforcement Learning from AI Feedback (RLAIF) with RLOO, PokeeResearch-7B optimizes directly for human-salient dimensions such as factual accuracy, citation faithfulness, and instruction adherence. Complemented by a chain-of-thought-driven multi-call reasoning scaffold, the model demonstrates robust and adaptive tool use, enabling it to diagnose, recover from, and mitigate common failure modes in dynamic research environments.

Empirically, PokeeResearch-7B achieves state-of-the-art performance among 7B-scale deep research agents across ten open-domain benchmarks, validating the effectiveness of its design in both reasoning quality and operational resilience. More broadly, our results highlight that reliability and alignment—not just scale—are central to progress in research-grade AI agents. We believe PokeeResearch-7B represents a step toward a new generation of autonomous, verifiable, and human-aligned research agents, and we hope its principles inspire future work in scalable, self-correcting LLM-based reasoning.

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Appendix

A Definition of Metrics

For completeness, we include the definition of the F1 score and EM here.

• F1 Score: The F1 score measures the harmonic mean of precision and recall between the set of tokens in the generated answer and the ground truth. Before comparison, both texts are normalized by converting to lowercase and removing punctuation. Let G and T denote the sets of tokens of the generated answer and the ground truth, respectively. Define $C \doteq G \cap T$. Then, precision is defined as $P \doteq |C|/|G|$, and recall is defined as $R \doteq |C|/|T|$. We compute the word-level F1 score as follows,

$$F_1(G,T) \doteq \frac{2PR}{P+R}.\tag{1}$$

This approach provides a nuanced assessment of content overlap, rewarding answers that are substantially correct even if they are not lexically identical to the ground truth.

• Exact Match: The Exact Match (EM) reward is a stricter evaluation metric. This binary measure awards a score of 1 if the normalized predicted answer is identical to any of the ground-truth answers, and 0 otherwise. Although less flexible than the F1 score, it serves as a clear indicator of complete accuracy.

B Complete Log for the Example of Self-Verification

Below is the complete log of the example provided in Section 4.

In one of Walter Scott's Waverley' novels what was The Heart of Midlothian?

```
<think>
The Heart of Midlothian is a character or a setting in one of Walter Scott's
Waverley novels. I need to find out which novel it is from and its
significance in the story.
</think>
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Edinburgh mob in the ..." }, { "url ": "https://
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"https://www.biblio.com/booksearch/author/sir-walter-scott/title/the-heart-of
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Midlothian. Author: Sir Walter Scott. Illustrated by MM. Overall: Very good.
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..."}, {"url": "https://www.abebooks.com/book-
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series. "}, {"url": "https://www.barnesandnoble.com/w/the-heart-of-
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century; she was renowned as an example of an honest, upright, sincere, highly
religious person. "}, {"url": "https://en.wikipedia.org/wiki/
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www.ebsco.com/research-starters/literature-and-writing/heart-
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Butler, Jeanie's betrothed \u00b7 Geordie Robertson (George Staunton),
..." } , { "url ": "https://literariness.org/
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letter confirms inspiration for The Heart of Midlothian", "description": "It
is already known that Jeanie Deans, the central character in Sir Walter
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..."}]}]
</tool_response>
assistant
```

<think>

From the search results, I can confirm that "The Heart of Midlothian" is the seventh novel in Sir Walter Scott's Waverley series, published in 1818. The main character is Jeanie Deans, who is a sister of a filicide and is determined to save her sister's life by traveling to London. She is a central figure in the novel, known for her honesty, upright character, and religious devotion.

</think>

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user

<tool response>

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pseudonym " Jedediah Cleishbotham, Schoolmaster and Parish-clerk of
Gandercleugh." The novel's plot is set in motion by the Porteous Riots in
Edinburgh and follows the journey of a young woman from Edinburgh to London to
seek a royal pardon for her sister, who is accused of murdering her newborn
baby. The novel is considered by some to be Scott's best work. The title
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assistant

<think>

The Heart of Midlothian is the seventh novel in Sir Walter Scott's Waverley Novels series, published on July 25, 1818. The novel's plot is set in motion by the Porteous Riots in Edinburgh and follows the journey of a young woman named Jeanie Deans from Edinburgh to London to seek a royal pardon for her sister, who is accused of murdering her newborn baby. The novel is considered by some to be Scott's best work. The title "The Heart of Midlothian" refers to the Old Tolbooth prison in Edinburgh, which was at the center of the Scottish county of Midlothian during that time.

</think>

<answer> In Walter Scott's Waverley novel "The Heart of Midlothian," The Heart of Midlothian refers to the Old Tolbooth prison in Edinburgh, and the novel's plot follows the journey of a young woman named Jeanie Deans from Edinburgh to London to seek a royal pardon for her sister, who is accused of murdering her newborn baby.

</answer>

user

You have provided an answer.

##The verification mode starts##.

assistant

<verification>

I need to verify if the answer satisfies all the conditions in the question. The question asked about what "The Heart of Midlothian" was in one of Walter Scott's Waverley novels. The answer provided information about the novel's plot and the significance of the title. However, it does not explicitly state that "The Heart of Midlothian" is the title of the novel. The answer should have clearly stated that "The Heart of Midlothian" is the title of the novel, and it refers to the Old Tolbooth prison in Edinburgh.

</re>

<verification_result>

INCORRECT

</re>

user The answer is verified to be incorrect. Please incorporate the feedback from the verification mode and re-enter the research mode.

```
##The research mode starts##.
assistant
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I need to restate that "The Heart of Midlothian" is the title of the novel and
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Gandercleugh." The novel's plot is set in motion by the Porteous Riots in
Edinburgh and follows the journey of a young woman from Edinburgh to London to
seek a royal pardon for her sister, who is accused of murdering her newborn
baby. The novel is considered by some to be Scott's best work. The title
itself refers to the Old Tolbooth prison in Edinburgh, which was at the center
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assistant
<think>
I need to restate that "The Heart of Midlothian" is the title of the novel and
provide more context about its significance.
</think>
<answer>
In Walter Scott's Waverley novel "The Heart of Midlothian," the title refers
to the Old Tolbooth prison in Edinburgh, which was at the center of the
Scottish county of Midlothian during that time. The novel's plot is set in
motion by the Porteous Riots in Edinburgh and follows the journey of a young
woman named Jeanie Deans from Edinburgh to London to seek a royal pardon for
her sister, who is accused of murdering her newborn baby. The novel is
considered by some to be Scott's best work.
</answer>
user
You have provided an answer.
##The verification mode starts##.
assistant
 <verification>
I need to verify if the answer satisfies all the conditions in the question.
The question asked about what "The Heart of Midlothian" was in one of Walter
Scott's Waverley novels. The answer provided that "The Heart of Midlothian" is
the title of the novel and gave context about its significance, the plot, and
the author's perspective on the work. The answer correctly identifies the
title and provides relevant information about the novel.
 </re>
 <verification_result>
CORRECT
 </re>
```