SSRL: Self-Search Reinforcement Learning

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ABSTRACT

We investigate the potential of large language models (LLMs) to serve as efficient simulators for agentic search tasks in reinforcement learning (RL), thereby reducing dependence on costly interactions with external search engines. To this end, we first quantify the intrinsic search capability of LLMs via structured prompting and repeated sampling, which we term Self-Search. Our results reveal that LLMs exhibit strong scaling behavior with respect to the inference budget, achieving high pass@k on question-answering benchmarks, including the challenging BrowseComp task. Building on these observations, we introduce Self-Search RL (SSRL), which enhances LLMs' Self-Search capability through format-based and rule-based rewards. SSRL enables models to iteratively refine their knowledge utilization internally, without requiring access to external tools. Empirical evaluations demonstrate that SSRL-trained policy models provide a cost-effective and stable environment for search-driven RL training, reducing reliance on external search engines and facilitating robust sim-to-real transfer. We draw the following conclusions: 1) LLMs possess world knowledge that can be effectively elicited to achieve high performance; 2) SSRL demonstrates the potential of leveraging internal knowledge to reduce hallucination; 3) SSRL-trained models integrate seamlessly with external search engines without additional effort. Our findings highlight the potential of LLMs to support more scalable RL agent training.

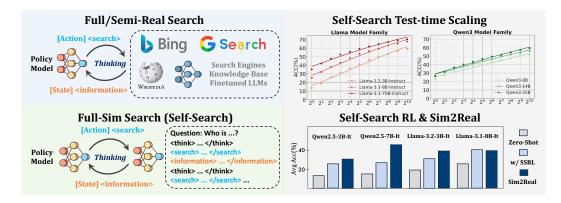


Figure 1: Left: Prior methods like Search-R1 (Jin et al., 2025b) and ZeroSearch (Sun et al., 2025) rely on external sources (e.g., search engines, knowledge bases, or fine-tuned LLMs), representing full or semi-real search. We propose full-sim search, where a policy model generates information internally (Self-Search). Right: Self-Search with test-time scaling shows strong pass@k performance as compute increases. Self-Search Reinforcement Learning (SSRL) further boosts results across models and tasks, especially with sim-to-real generalization.

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1 Introduction

Recently, Reinforcement Learning (RL) with verifiable rewards has substantially improved the reasoning abilities of Large Language Models (LLMs) in complex mathematical problem-solving (OpenAI, 2024; DeepSeek-AI, 2025; Petrov et al., 2025) and code generation (El-Kishky et al., 2025; Cui et al., 2025a), leading to the emergence of Large Reasoning Models (LRMs) (Xu et al., 2025). Beyond mathematics and coding, numerous studies have explored the application of RL to LLMs in agentic contexts such as tool learning (Qian et al., 2025; Feng et al., 2025). These approaches enable LLMs to learn to invoke external tools such as web search engines, perform actions, and observe states within real-world environments. Although recent models like Search-R1 (Jin et al., 2025b) and Kimi V2 (Team et al., 2025) have achieved strong performance on various benchmarks, interacting with real web search engines remains costly (Sun et al., 2025), especially given the large number of rollouts and multi-turn tool calls required during RL training. In fact, due to pre-training on massive web-scale corpora (Brown et al., 2020; Liu et al., 2024; Yang et al., 2025b), LLMs can often answer questions involving world knowledge. Some studies also suggest that LLMs can serve as world models by providing state information in response to given actions (Li et al., 2023; Hao et al., 2023; Gu et al., 2024; Tang et al., 2024). For example, recent work on ZeroSearch (Sun et al., 2025) demonstrates that a fine-tuned LLM can effectively replace web search, providing stable and reliable knowledge. This finding indicates that the cost of search RL can be significantly reduced by adopting a semi-real setting. Inspired by recent advances in unsupervised RL like TTRL (Zuo et al., 2025), we explore self-search RL within fully simulated RL settings (noted as *full-sim*), where no real search is used during training. Specifically, we focus on two key research questions: 1) What is the performance limit of LLMs on search-based QA tasks using only internal knowledge? 2) Can full-sim search RL enable effective sim-to-real transfer with real web search during inference?

First, we investigate whether an LLM can generate both queries and information based on the knowledge embedded in its parameters, effectively simulating querying external search engines. To this end, we assess the intrinsic search capabilities of LLMs on benchmarks that require web searching by prompting the model to simulate the search process within a single generation trajectory using multi-turn, tool-formatted outputs. Extensive sampling demonstrates that LLMs encode substantial world knowledge within their parameters, yielding high predictive pass@k scores that follow a scaling law. However, reliably extracting the optimal answer remains challenging, underscoring the gap between latent knowledge and actionable retrieval. To address this challenge and explore the potential of full-sim search RL for sim-to-real transfer, we study the potential of Self-Search Reinforcement Learning (SSRL) which enhances the self-search abilities of LLMs through format-based and rule-based rewards, enabling autonomous refinement of internal knowledge utilization without relying on external searches. Our experiments show that models trained with SSRL not only outperform previous search API-based RL baselines, such as Search-R1 and ZeroSearch, across various benchmarks, but also serve as cost-effective, implicit world knowledge provider, thus reducing hallucination, for search-driven question answering. Moreover, this approach reduces dependence on external search engines and opens new avenues for sim-to-real generalization, enabling skills acquired through self-search to transfer robustly to online settings with real web access.

In summary, our work demonstrates that LLMs hold significant potential as simulator of the web, a resource that can be leveraged for search-driven tasks without the need for external queries. By systematically quantifying and enhancing this self-search capability with SSRL, we pave the way for more autonomous and scalable LLM agents (Leike et al., 2018; Gao et al., 2025).

Takeaways

- 1. LLMs can serve as simulator of world knowledge, exhibiting varying upper bounds across different model families on challenging search-based benchmarks. (§ 2.4)
- 2. Achieving the upper performance bound of Self-Search remains challenging; current methods, such as voting, are insufficient for reliably selecting optimal outputs. (§ 2.5)
- 3. By relying on feedback from the policy model itself, Self-Search RL (SSRL) can achieve superior performance compared to training with external search engines.(§ 3.4.1)
- 4. Models trained with SSRL can be seamlessly adapted to real search scenarios without additional effort, providing preliminary evidence for sim-to-real transfer. (§ 3.4.2)

2 Inference-time Scaling of Self-Search

2.1 TASK FORMULATION

Formulation of pass@k. We consider the problem of answering information-seeking queries using only the internal knowledge of an LLM, without access to external retrieval tools such as web search engines or databases. We generate K samples for problem i, and we calculate the number of accurate responses C_i . We compute pass@k using the formula below:

$$\operatorname{pass@k} = \frac{1}{\# \text{ of problems}} \sum_{i=1}^{\# \text{ of problems}} \left(1 - \frac{\binom{K - C_i}{k}}{\binom{K}{k}} \right), \tag{1}$$

where correctness is defined according to the evaluation standard of the underlying benchmark (e.g., exact match, top-k accuracy, or task-specific criteria). This setup allows us to estimate the intrinsic upper bound of the model's internalized search capabilities, independent of any external retriever.

Formulation of Scaling Law. We present a detailed formulation of the scaling law for test-time self-search. Following Brown et al. (2024), we define an explicit function to simulate the correlation between the number of samples K and the coverage c. We model the log of c as a function of k using:

$$\log c \approx ak^b,\tag{2}$$

where a, b are fitted model parameters. We exponentiate each side to have a straightforward prediction of the coverage c. That is:

$$c \approx \exp(ak^b).$$
 (3)

2.2 PROMPT DESIGN

Following Jin et al. (2025a), we use an unbiased instruction without any hints for reflection. The instruction just teaches LLMs to think step by step. The prompt template is shown in Table 1.

Prompt Template

Answer the given question. You must conduct reasoning inside <think> and </think> first every time you get new information. After reasoning, if you find you lack some knowledge, you can call a search engine by <search> query </search>, and you should return the top searched results between <information> and </information>. You can search as many times as you want. For multi-hop QA, you can break it down into pieces and search one by one. If you find no further external knowledge needed, you can directly provide the answer inside <answer> and </answer> without detailed illustrations. For example, <answer> Beijing </answer>. Question:

Table 1: Prompt template. The question is appended at the end during training and inference.

Our iterative reasoning framework follows a structured process where the model first expresses its initial thoughts within <think>...</think> tags. When the model identifies missing information necessary for solving the problem, it formulates search queries within <search>...</search> tags. The model then auto-regressively generates relevant information to address these queries, which is incorporated within <information>...</information> tags. This cycle of thinking, searching, and information gathering continues iteratively until the model arrives at a final answer. While this approach shares similarities with traditional multi-turn search systems, it fundamentally differs in its implementation: rather than conducting genuine iterative interactions with external systems, our method employs a Chain-of-Thought (Wei et al., 2023) process where the language model auto-regressively generates the entire reasoning trajectory in a single forward pass, including thoughts, search queries, and retrieved information. This design enables efficient self-contained search while maintaining the structured exploration benefits of iterative search processes.

2.3 EXPERIMENTAL SETUP

Benchmarks. We evaluate across seven benchmarks spanning three categories of question-answering tasks: 1) General Question Answering, which tests factual knowledge retrieval using

Knowledge Type	Benchmark	Time	Construction	Targeted Task	Source
Factual	TriviaQA	2017	Manual	General QA	Wikipedia + Web
	Natural Questions	2019	Manual	General QA	Wikipedia
	SimpleQA	2024	Manual	Factual QA	General knowledge
Reason	HotpotQA	2018	Manual	Multi-hop QA	Wikipedia
	2WikiMultiHopQA	2020	Semi-automated	Multi-hop QA	Wikipedia + Wikidata
	BamBoogle	2022	Manual	Multi-hop QA	Wikipedia
	MuSiQue	2022	Automated	Multi-hop QA	Wikipedia
Web browsing	BrowseComp	2025	Manual	Search and Browse	Open Web

Table 2: Benchmark concerning search. Most benchmarks are constructed manually, except 2Wiki-MultiHopQA and MuSiQue. Most of the benchmarks are designed for QA initially.

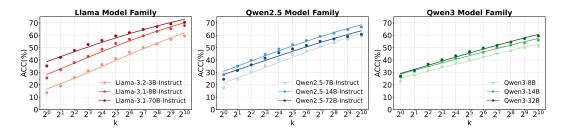


Figure 2: The scaling curves of repeated sampling averaged on six benchmarks within three model families (Qwen2.5, Llama, and Qwen3). It indicates predictive performance gains, where average MAE for different families is 1.42%, 1.45%, and 0.95%, respectively.

Natural Questions (Kwiatkowski et al., 2019) and TriviaQA (Joshi et al., 2017); 2) Multi-hop Question Answering, which requires reasoning across multiple pieces of information through HotpotQA (Yang et al., 2018), Musique (Trivedi et al., 2022), Bamboogle (Press et al., 2023), and 2Wiki-MultiHopQA (Ho et al., 2020); and 3) Vague Question Answering, which evaluates information synthesis from various vague restrictions using BrowseComp (Wei et al., 2025). This comprehensive evaluation framework captures capabilities ranging from direct knowledge retrieval to complex reasoning and information integration, providing a robust assessment of model performance across varied question-answering scenarios. Benchmark details are listed in Table 2.

Models. To ensure comprehensive evaluation of the effects of repeated sampling, we conduct experiments across three model families: Qwen2.5 (Qwen et al., 2025), Llama3 (including Llama-3.1 and Llama-3.2) (Grattafiori et al., 2024), and Qwen3 (Yang et al., 2025a). We test models spanning a wide range of parameter scales from 0.6B to 72B. To ensure a fair comparison across all experiments, we maintain consistent sampling parameters with temperature set to 0.7, top-k to -1, top-p to 0.95, and max token to 8192. The instruction used is shown in Appendix A.1.1.

2.4 Performance Evaluation

Predictive Performance Improves with Sample Size. As shown in Figure 2 and Figure 3, we observe consistent and predictive performance improvements across all benchmarks as the number of samples increases. Notably, on Bamboogle, Llama-3.1-8B-Instruct achieves 87.2% accuracy for pass@1024, a **150%** improvement over pass@1 performance. These substantial gains are evident across all three model families (Qwen2.5, Llama, and Qwen3), with the Llama series showing particularly pronounced benefits. Figure 3 shows performance on BrowseComp, a benchmark characterized by difficult search requirements but straightforward verification. While GPT-40 with search achieves only 1.9% and o1 scores 10%, Self-Search yields surprising results: Qwen2.5-14B-Instruct and Llama-3.1-8B-Instruct surpass o1's performance when given sufficient samples. This finding suggests that LLMs possess substantial internal knowledge that can be effectively leveraged through repeated sampling, even in the absence of external information sources. Analysis of the

upper bound further highlights the strong potential of LLMs to provide information in response to given search actions. More details are provided in Appendix A.2.

Llama Outperforms Qwen, Contrary to Prior Reasoning Tasks. Previous works (Gandhi et al., 2025; Liu et al., 2025b; Wang et al., 2025a) have shown that Qwen models (including Qwen2.5 and Qwen3) possess stronger priors in mathematical reasoning and achieve greater improvements than Llama models in reinforcement learning settings. However, our findings indicate that Llama models outperform Qwen models in the Self-Search setting with respect to priors for world knowledge, as demonstrated in Figure 2 and Figure 3. This observation suggests that self-search ability and reasoning priors are not strongly correlated. We will further explore the utilization of knowledge and reasoning in Section 2.5.1.

Performance Gap Narrows Between Large and Small Models with More Sampling. Remarkably, our results demonstrate that smaller models can achieve performance comparable to models with

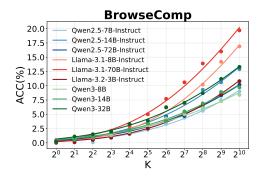


Figure 3: TTS on BrowseComp leads to consistent performance gains within all models. It indicates predictive performance gains, with average MAE for the LLaMA, Qwen 2.5, and Qwen 3 families at 0.34 %, 0.22 %, and 0.26 %, respectively.

nearly $10 \times$ more parameters by leveraging repeated sampling, as measured by pass@k. For example, on TriviaQA with 1024 samples, Llama-3.1-8B-Instruct achieves a score of 81.2%, while Llama-3.1-70B-Instruct achieves 81.4%, a negligible difference despite the substantial gap in model size. This finding is consistent with previous studies (Snell et al., 2024; Liu et al., 2025a).

2.5 FURTHER ANALYSIS

2.5.1 IS MORE REASONING ALWAYS BETTER?

Experimental Setup. As discussed in Section 2.4, we observe inconsistent results on the agentic search benchmark of reasoning and instruction models, e.g., Qwen3 vs Qwen2.5 and Llama. In this section, we begin by analyzing the utilization efficiency of thinking tokens in Qwen3 models, followed by a comparison of two types of sequential scaling: multi-turn search and multi-turn reflection. Additional case studies are provided in Table 19. For implementation of token comparison, we don't truncate when the decoding response reaches a predefined threshold to restrict the response length of LLMs since it may harm the ability of LLMs. Instead, we generate K responses and sum up the tokens used, and compared them under the same token budget.

Inefficient Utilization of Thinking Tokens. Qwen3 models support both "thinking" and "no thinking" modes (Yang et al., 2025b), allowing manual adjustment of the number of thinking tokens before the model produces a final answer. To investigate the influence of increasing thinking tokens in Self-Search settings, we conduct a comparative study evaluating the impact of whether enabling the thinking process during inference. We only count the token used out of search>...
search>..., <information>...
/information>, and <answer>...
/answer> for comparison of thinking token. As presented in Figure 4, the results demonstrate that as the number of assigned tokens increases, long CoT reasoning doesn't yield a better performance, contradictory to what is observed in complex math questions. This is probably attributed to that the solution to agentic search mainly relies on the usage of knowledge, either internal or external, rather than solely thinking. These findings indicate that short-CoT should be preferred in Self-Search settings to maximize token efficiency.

Multi-Turn Self-Search Hurts Performance. Following the established approach in search agent literature (Jin et al., 2025a; Sun et al., 2025) that formalizes search as a multi-turn process, we perform Self-Search for each rollout. Upon generating a search query, we prompt the model to provide relevant information for that query, incorporate this information into the reasoning context,

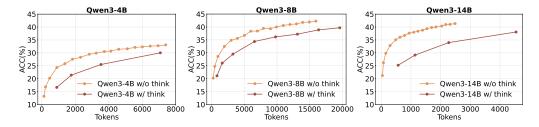


Figure 4: The performance of various sizes of Qwen3 averaged on six benchmarks, when enabled forced-thinking or not. The x-axis is measured by the number of tokens used by thinking solely.

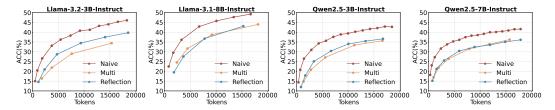


Figure 5: The performance of Repeated Sampling of Self-Search, Multi-turn Self-Search, and Self-Search with Reflection measured under the same token budget across four models.

and continue the iterative reasoning process until reaching a final decision. We denote the number of such interactions as N. The instruction for LLMs to provide relevant information is listed in Appendix A.1.2. Since our approach eliminates the need for external search engines (Google, Bing, etc.), we avoid API costs and inference budget constraints typically associated with online search. Therefore, we set N=10 to ensure sufficient iterations for every sample to converge to a final answer. As shown in Figure 5, when measured by tokens consumed, naive repeated sampling shows better performance and a steady performance growth, further highlighting the upper bound of LLMs themselves as an implicit simulator of world knowledge.

Self-Search with Reflection Hurts Performance. The "Aha Moment", introduced by Deepseek-R1 (DeepSeek-AI, 2025), demonstrates emergent reflection and exploration capabilities in LLMs, particularly in math and code generation. To investigate whether this reflective behavior extends to information search tasks without external sources, we incorporate reflection-triggering phrases into our sampling process. Specifically, we append "Wait, wait, wait" after each generated response to encourage the model to reconsider and explore alternative reasoning paths. Figure 5 presents the experimental results. We also find that under the same token budget, reflection doesn't yield a better performance measured by pass@k compared with naive repeated sampling.

In conclusion, we find that increasing the number of thinking tokens and incorporating multi-turn generation are not always beneficial in Self-Search settings. This suggests that knowledge utilization may be more advantageous than reasoning in these scenarios. Further investigation is warranted, particularly in the context of language models as world models (Hao et al., 2023; Gu et al., 2024).

2.5.2 MAJORITY VOTING VS. PASS@K

In the above experiment, we found that LLMs exhibit a high performance ceiling in search and question-answering tasks. However, it remains challenging to identify the correct answer from a set of candidate responses, despite the correct answer being present, when the ground truth is unknown (Brown et al., 2024). This suggests that repeated sampling represents the upper limit of Test-Time Scaling (TTS), and further evaluation of alternative TTS strategies is necessary.

Majority voting is widely thought of as a simple but effective method to integrate with Test-time Scaling (Zuo et al., 2025). To investigate whether the performance transfers to knowledge-intensive tasks, we employ the maj@k metric.

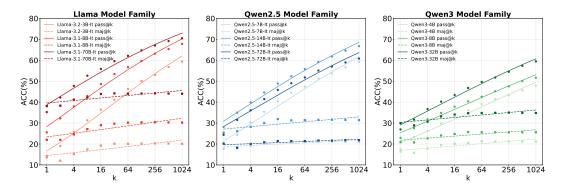


Figure 6: Majority voting results of different models averaged on six benchmarks.

In essence, maj@k evaluates to 1 when the most frequently occurring answer among K samples matches the ground truth, and 0 otherwise. The instruction for the majority voting experiments is detailed in Appendix A.1.1. We show the results in Figure 6. Our experiments reveal that even as we increase the number of responses k for majority voting, we observe only marginal performance improvements. This limited scaling behavior suggests that naive majority voting may be insufficient for search tasks, where incorrect answers might consistently appear across multiple samples. These findings indicate that LLMs have the potential to become world models, but the world knowledge presented is vague, and how to provide precise knowledge is still a challenging task.

3 SSRL: Self-Search Reinforcement Learning

In this section, we employ reinforcement learning (RL) to enable LLMs to export world knowledge from their own parameters. We examine the effectiveness of the policy model as a simulator of world knowledge in Self-Search RL, as well as its performance in Sim2Real and TTRL settings.

3.1 TASK DEFINITION

We formulate the RL objective for LLM-based search agent utilizing external search engines as:

$$\max_{\pi_{\theta}} \mathbb{E}_{x \sim D, y \sim \pi_{\theta}(\cdot|x;R)} [r_{\phi}(x,y)] - \beta \mathbb{D}_{KL} [\pi_{\theta}(y|x;R)||\pi_{\text{ref}}(y|x;R)], \tag{4}$$

where π_{θ} denotes the policy model, π_{ref} represents the reference model, r_{ϕ} is the reward function, R represents retrieved information, and \mathbb{D}_{KL} denotes the KL divergence regularization term with coefficient β . In our approach, since the model auto-regressively retrieves knowledge from its internal parameters rather than external sources, the retrieved information R follows the same distribution as π_{θ} . This Self-Search mechanism allows us to simplify the objective function to:

$$\max_{\pi_{\theta}} \mathbb{E}_{x \sim D, y \sim \pi_{\theta}(\cdot|x)}[r_{\phi}(x, y)] - \beta \mathbb{D}_{KL}[\pi_{\theta}(y|x)||\pi_{\text{ref}}(y|x)], \tag{5}$$

where π_{θ} simultaneously functions as both the reasoning policy model and the internal search engine. We primarily leverage GRPO (Shao et al., 2024) as our training algorithm, while also experimenting with alternative RL algorithms, including PPO (Schulman et al., 2017), Reinforce++ (Hu et al., 2025), DAPO (Yu et al., 2025), and KL-Cov (Cui et al., 2025b) to validate the robustness.

3.2 Training Methodology

Information Token Mask Previous research (Jin et al., 2025b; Sun et al., 2025) demonstrates that masking information tokens from external search engines helps stabilize training and improve performance. However, in Self-Search, the retrieved information originates from the model's own generation process rather than external sources, raising questions about whether information masking remains beneficial in this context. To investigate this, we conduct comparative experiments under two conditions: training with complete reasoning trajectories versus training with information-masked trajectories. For implementation, we extract all the tokens embraced by <information> and

</information> and mask them for loss calculation. Our results reveal that information masking continues to enhance performance even when the information is self-generated by the model. We show our detailed experiments in Section 3.5.1.

Reward Modeling Following DeepSeek-AI (2025); Yu et al. (2025), we employ a composite reward function with two signals: format reward and outcome reward. We directly use the accuracy of the model's final prediction as the outcome reward, computed using the following rule:

$$R(\hat{y},y) = \begin{cases} 1, & \text{is_equivalent}(\hat{y},y) \\ -1, & \text{otherwise} \end{cases} \tag{6}$$

where y is the ground-truth answer and \hat{y} is the predicted answer.

Since our iterative search process requires models to decompose complex questions into manageable sub-problems, with each iteration focusing on searching for specific information and incrementally building toward the final answer, maintaining a structured output format is crucial for effective reasoning. To address this requirement, we introduce a format reward that ensures adherence to the prescribed reasoning structure, detailed in Appendix C. This format reward guides the model to produce well-organized, multi-step reasoning trajectories.

The final reward combines both components as:

$$r_{\phi}(y_{i},y) = \begin{cases} 1 & \text{if is_equivalent}(\hat{y},y) \land f_{\text{format}}(y) = \text{True}, \\ 1 - \lambda_{f} & \text{if is_equivalent}(\hat{y},y) \land f_{\text{format}}(y) = \text{False}, \\ \lambda_{f} & \text{if !is_equivalent}(\hat{y},y) \land f_{\text{format}}(y) = \text{True}, \\ 0 & \text{if !is_equivalent}(\hat{y},y) \land f_{\text{format}}(y) = \text{False}, \end{cases}$$
 (7)

where we set $\lambda_f = 0.1$ to prioritize correctness while maintaining structured reasoning, following (Wang et al., 2025b).

3.3 EXPERIMENTAL SETUP

Benchmarks We conduct evaluation across six of the benchmarks described in Section 2.3. We exclude BrowseComp from evaluation due to its exceptional difficulty and limited availability of training data. To ensure fair comparison with existing baselines, we adopt the same validation sets used by Sun et al. (2025). Our evaluation employs EM, where a prediction is considered correct only when it matches the ground truth answer precisely. This strict evaluation criterion ensures robust assessment of model performance.

Baselines To evaluate the effectiveness of Self-Search, we compare our model with the following methods: **Vanilla Prompt Methods:** It includes Direct Prompt and CoT; **RAG-based Methods:** This category includes standard RAG and Search-o1 (Li et al., 2025b); **RL-based Methods:** This category includes R1, Search-R1 (Jin et al., 2025b), and ZeroSearch (Sun et al., 2025). We conduct offline evaluations of our models while enabling online testing for baseline methods where applicable. To ensure fair comparison in online settings, we limit the number of retrieved passages to 3 across all RAG-based approaches. For vanilla prompt methods, we employ instruction-tuned models as they demonstrate superior prompt-following capabilities. The implementation details of baselines are listed in Appendix B.2.1.

Training Setups We conduct our RL experiments primarily on the Llama model family, specifically Llama-3.2-3B (Base/Instruct) and Llama-3.1-8B (Base/Instruct), selected based on their demonstrated effectiveness under repeated sampling conditions. We use the combination of the training dataset of NQ and HotpotQA, as in previous work, to ensure a mix of general QA and multi-hop QA. Our training framework primarily utilizes GRPO as the default algorithm, while also experimenting with alternative approaches, including PPO and REINFORCE++, to validate the robustness of our findings. All training is conducted on a single node equipped with 8 NVIDIA A800 GPUs. For GRPO, the training configuration includes a batch size of 256, a learning rate of 1e-6, and 62 warmup steps across all experiments. The max response length is 4096 across all models in our experiments. For policy optimization, we set the temperature to 1.0 and generate 5 rollouts per prompt and apply a KL divergence coefficient of 0.001. We train each model for 5 epochs and select

Model	Search	Gene	ral QA		Multi-H	op QA		Avg
Wiodel	Engine	NQ	$\overline{\mathbf{TQ}}$	HotpotQA	Musique	2Wiki	Bamboogle	8
LLaMA-3.2-3B								
Direct Answer	Ø/-	16.2	29.6	12.6	2.0	9.2	8.0	12.9
CoT	Ø/-	26.2	44.4	16.0	5.8	10.2	21.6	20.7
RAG	Ø/G	30.0	57.6	23.4	9.6	17.6	11.2	24.9
Search-o1	Ø/ G	24.2	48.4	19.4	6.0	17.4	32.0	24.6
R1-Base	-/-	28.4	44.2	22.8	7.0	28.4	11.1	23.7
R1-Instruct	-/-	35.0	52.2	21.6	11.4	17.8	20.8	26.5
Search-R1-Base	W/G	41.2	60.0	29.6	13.6	31.6	19.4	32.6
Search-R1-Instruct	W/ Ğ	37.6	53.6	21.0	8.8	20.4	27.8	28.2
ZeroSearch-Base	∞/Ğ	43.4	63.8	32.2	13.8	35.6	15.3	34.0
ZeroSearch-Instruct	∞/Ğ	40.2	58.0	22.8	10.4	21.4	18.1	28.5
SELF-SEARCH-BASE	-/-	35.0	45.8	28.2	14.2	29.6	30.2	30.5
SELF-SEARCH-INSTRUCT	-/-	43.8	58.4	25.0	14.2	31.6	38.4	35.2
			LLaN	/IA-3.1-8B				
Direct Answer	Ø/-	21.2	52.8	21.0	3.2	8.0	23.8	21.7
CoT	Ø/-	23.0	46.6	18.8	8.8	17.6	35.2	25.0
RAG	Ø/G	40.8	62.8	37.0	22.4	34.0	38.4	39.2
Search-o1	Ø/G	26.8	37.2	21.0	9.2	23.6	25.6	23.9
R1-Base	-/-	21.0	48.8	23.0	5.4	28.0	5.6	22.0
R1-Instruct	-/-	39.2	59.8	30.4	18.2	36.8	47.2	38.6
Search-R1-Base	W/G	41.0	62.6	40.0	25.0	37.8	36.1	40.4
Search-R1-Instruct	W/Ğ	39.6	59.6	36.8	19.6	34.8	31.9	37.1
ZeroSearch-Base	ø/Ğ	38.2	52.4	26.0	9.6	28.4	12.5	27.9
ZeroSearch-Instruct	ø/Ğ	48.2	68.2	36.6	19.6	36.2	40.3	41.5
SELF-SEARCH-BASE	-/-	41.0	49.6	30.0	18.4	34.4	32.8	34.4
SELF-SEARCH-INSTRUCT	-/-	48.0	62.6	34.4	24.2	35.2	54.4	43.1

Table 3: Main results of our trained models on the six benchmarks measured by EM. The column **Search Engine** refers to the external search engine used in the training stage and the evaluation stage. We use \emptyset to denote that the baseline does not undergo the stage and "-" to denote using internal knowledge. We use ∞ to denote the Simulation LLM and W to denote Wikipedia for simplification. We use G to denote Google. The largest score of each model is denoted using **bold**.

the checkpoint with the highest average validation accuracy for final evaluation, ensuring optimal performance while preventing overfitting. For all the evaluation, we set the temperature to 0.0. The implementation details of other algorithms are listed in Appendix B.2.2

3.4 Performance Evaluation

3.4.1 SELF-SEARCH RL

We present the main experimental results in Table 3 and show the case studies in Appendix (Table 28 and Table 29). We also experiment on the Qwen series, and the results of Qwen2.5 and Qwen3 are listed in Appendix B.3.1 and Appendix B.3.2. The results reveals several key insights:

SSRL achieves superior performance. Our results demonstrate that models trained with autoregressive internal retrieval consistently outperform those relying on external search engines, whether using other LLMs or Google Search. We also observe a better performance compared with R1-like models, which are trained with the naive CoT prompt. These findings suggest that through well-designed instruction and reward, language models can effectively function as both reasoners and knowledge retrievers simultaneously, successfully extracting relevant information from their internal parametric knowledge without external dependencies.

Instruction models more effectively utilize internal knowledge. When trained on identical data for the same duration, instruction-tuned models achieve significantly better performance than their base counterparts, suggesting that additional knowledge operations may be incorporated during supervised fine-tuning. However, this advantage appears to be context-dependent: while instruction-tuned models excel at leveraging internal knowledge, base models demonstrate superior performance when external information sources are available. This finding implies that different optimization strategies are required for internal versus external knowledge utilization.

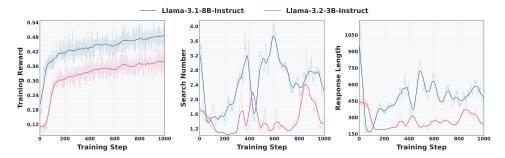


Figure 7: The training curves of Llama-3.2-3B-Instruct and Llama-3.1-8B-Instruct. The first figure is the training reward. The second figure is the response length, and the third figure is the number of searches included in the response.



Figure 8: The training curve of Llama-3.1-8B-Instruct using SSRL and ZeroSearch. The first figure is the time used during training. The second figure is the training reward on the same training step, and the third figure is the training reward consuming the same time.

Larger models show better self-search performance. Figure 7 presents the training curves for both models. We observe steady growth in training reward throughout the process. During the early training stage, both response length and search count decrease as the models adapt to the format reward constraints. In later stages, Llama-3.1-8B-Instruct develops more sophisticated strategies, learning to decompose questions and employ self-reflection to enhance performance, thus yielding a better performance on our benchmarks.

SSRL is more efficient and robust. Figure 8 presents the training curves for ZeroSearch and SSRL. Compared to ZeroSearch, SSRL demonstrates substantially improved training efficiency, achieving a 5.53× reduction in training time. Additionally, SSRL exhibits steady reward growth throughout training without collapse, indicating robust performance. Although SSRL shows relatively lower training rewards than ZeroSearch during early training stages due to limited external knowledge, its superior efficiency and robustness compensate for this initial disadvantage.

3.4.2 SIM2REAL GENERALIZATION

Although SSRL achieves strong results on static benchmarks, the inherent knowledge within these models remains fixed, which limits their applicability to real-world scenarios. In this work, we investigate whether SSRL can generalize to real-time search settings. Since our trained model follows the exact format specifications of Search-R1 (Jin et al., 2025b), we can seamlessly integrate real search capabilities. We refer to this setting as sim-to-real generalization, following terminology from prior work in Robotics RL (Kaspar et al., 2020; Da et al., 2025).

Replacing Simulated Search with Real Search We replace model-generated information with results of actual searches from Google Search or local corpora, substituting up to K self-generated responses, where K represents the maximum turns used by Jin et al. (2025b). To ensure compatibility, we post-process the retrieved information using rule-based modifications that remove patterns absent

Model	Gene	ral QA		Multi-H	op QA		$\mathbf{A}\mathbf{v}\mathbf{g}$
1110401	\overline{NQ}	\mathbf{TQ}	HotpotQA	Musique	2Wiki	Bamboogle	
		I	LLaMA-3.2-3I	B-Instruct			
Zero-shot CoT	26.2	44.4	16.0	5.8	10.2	21.6	20.7
SSRL	43.8	58.4	25.0	14.2	31.6	38.4	35.2
Sim2Real (K=1)	44.4	63.4	34.8	17.2	37.8	42.4	40.0
Sim2Real (K =3)	44.8	63.0	35.4	19.4	41.8	47.2	41.9
Sim2Real (All)	44.0	61.6	35.2	20.8	42.8	46.4	41.8
		I	LLaMA-3.1-8I	B-Instruct			
Zero-shot CoT	23.0	46.6	18.8	8.8	17.6	35.2	25.0
SSRL	48.0	62.6	34.4	24.2	35.2	$\bf 54.4$	43.1
Sim2Real(K=1)	39.4	55.8	$\overline{34.0}$	26.8	39.8	<u>53.6</u>	41.6
Sim2Real (K=3)	33.2	50.6	29.7	23.4	39.2	36.6	35.5
Sim2Real (All)	39.6	54.6	34.6	25.0	36.8	50.4	40.2
			Qwen2.5-3B-	Instruct			
Zero-shot CoT	15.0	33.6	16.2	3.6	18.0	12.8	14.7
SSRL	23.6	41.0	22.4	10.4	26.0	32.8	26.0
Sim2Real(K=1)	35.2	44.0	22.0	14.8	36.6	26.4	29.8
Sim2Real (K=3)	37.8	51.6	26.4	22.4	36.8	21.6	32.8
Sim2Real (All)	37.8	51.4	27.4	22.4	36.4	22.4	33 .0
			Qwen2.5-7B-	Instruct			
Zero-shot CoT	12.8	35.6	16.2	6.6	22.6	24.0	17.4
SSRL	31.4	44.4	26.0	11.8	31.0	36.8	30.2
Sim2Real (K=1)	38.4	58.0	35.6	18.4	36.0	41.6	38.0
Sim2Real (K =3)	43.8	64.4	42.0	29.4	$\bf 53.4$	54.5	47.9
Sim2Real (All)	41.8	65.0	43.2	28.6	50.4	52.0	46.8

Table 4: Performance of Sim2Real Search Generalization. The largest score is denoted using **bold**. The second largest score is denoted using <u>underline</u>.

from our training data. Table 4 and Figure 9 present our experimental results. Performance consistently improves with an increasing number of maximum turns across all models except Llama-3.1-8B-Instruct. Furthermore, compared to Search-R1 and ZeroSearch baselines, SSRL-based models under Sim2Real settings generally achieve superior performance with less online searching across various benchmarks. These findings demonstrate that search agents trained exclusively on internal knowledge can effectively leverage external knowledge sources when format alignment is maintained, thereby reducing training costs and improving efficiency. Case study is in Table 30.

Combining Simulated Search with Real Search Our findings demonstrate that LLMs possess substantial internal knowledge, suggesting they should search externally only when necessary. Based on this insight, we propose an entropy-guided search strategy. For each generated sequence, we analyze the entropy trend of the initial search query: increasing entropy indicates model uncertainty, triggering external search; otherwise, we rely on internal knowledge. We use Sim2Real (All) as our baseline for fair comparison and always use external search for the first query based on the performance gains shown in Table 4 (see Appendix B.3.6 for ablation studies on first-search importance). We present our results in Table 5. The entropy-guided approach reduces search frequency by 20-42%, yielding substantial

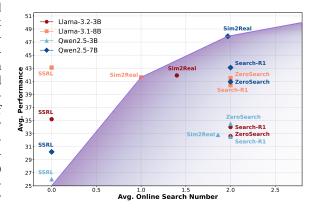


Figure 9: Pareto frontier illustrating the trade-off between performance and the number of real searches across different models. The Sim2Real models are evaluated using the maximum score within Sim2Real (K=1), Sim2Real (K=3) for fair comparison.

Model	Gene	ralQA		Multi-H	opQA		Avg	Avg. Search	
Wodel	NQ	TQ	HotpotQA	A Musique 2Wiki Bamboogle		Bamboogle	11.6	Avg. Search	
			LLaMA-3.2	-3B-Instruc	t				
Sim2Real (All)	44.0	61.6	35.2	20.8	42.8	46.4	41.8	1.9	
Entropy-guided Search	45.2	62.4	34.6	18.6	40.0	46.4	41.2	1.5	
			LLaMA-3.1	-8B-Instruc	t				
Sim2Real-guided Search (All)	39.6	54.6	34.6	25.0	36.8	50.4	40.2	2.6	
Entropy	43.2	56.2	33.4	26.8	40.8	49.6	41.7	1.5	
			Qwen2.5-3	B-Instruct					
Sim2Real (All)	37.8	51.4	27.4	22.4	36.4	22.4	33.0	3.0	
Entropy-guided Search	36.4	54.4	30.4	19.6	36.8	25.6	33.9	1.8	
Qwen2.5-7B-Instruct									
Sim2Real (All)	41.8	65.0	43.2	28.6	50.4	52.0	46.8	2.6	
Entropy-guided Search	40.6	63.4	39.0	23.8	45.4	48.0	43.4	1.9	

Table 5: The performance of LLaMA and Qwen2.5 models when using either full or entropy-based selection over the real search engine. The average search number is the average number of search> used during generation, i.e., online search plus self-search, if exists.

cost savings while maintaining performance comparable to full external search. As we observe above, though Llama-3.1-8B-Instruct fails under Sim2Real (K=3), it achives better performance than Sim2Real (All), indicating that Llama-3.1-8B-Instruct is hard to leverage external information easily, which may be attributed to the gap between self-search gathered information and external one. These results reinforce our key finding: LLMs can effectively leverage their internal knowledge when they possess relevant information and know how to access it, making external search unnecessary in many cases.

3.4.3 TEST-TIME RL

Considering unsupervised RL algorithms, e.g., TTRL, (Zuo et al., 2025), show great potential in math and code generation, we are curious about its generalization to Self-Search. We conduct experiments on the Llama series, using the dataset consisting of NQ, TQ, HotpotQA, MusiQue, Bamboogle, 2WikiMultiHopQA, and BrowseComp ¹. The implementation details are listed in Appendix B.2.3. To ensure thorough analysis, we performed ablation studies both with and without information masking, while maintaining the format reward component, which remains essential for label voting mechanisms.

We measure the results using EM and show the experimental results in Table 6. We observe a better performance when trained with TTRL compared with GRPO. For Llama-3.2-3B-Instruct, the average performance is improved by 59%. This phenomenon indicates the generalization of TTRL across domains and model families. When using TTRL, we find that training without the information mask yields slightly better results, which contradicts RLVR. Surprisingly, we find that simply applying TTRL on the combined benchmarks results in a substantial improvement on BrowseComp, even without external search engines. The accuracy curve on BrowseComp is presented in Figure 13, and the final performance metrics are summarized in Table 7.

There is an interesting observation that smaller models achieve higher scores on Browsecomp through TTRL, and when we delve into the cases, we find that these models prefer to point out an entity at first and check if it meets all the requirements, which is opposite to the search-and-answer paradigm.

Models	BrowseComp
WebSailor-3B	2.0
Qwen2.5-3B-Instruct (TTRL)	3.9
Qwen2.5-3B-Instruct (TTRL-Sim2Real)	1.4
Llama-3.2-3B-Instruct (TTRL)	6.2
Llama-3.2-3B-Instruct (TTRL-Sim2Real)	4.1

Table 7: Performance on BrowseComp.

This further strengthens our opinion that LLMs contain information that once elicited, it can be applied to solve extremely complex questions.

¹For WebSailor, we sample 250 records from BrowseComp and evaluate them using a substring match. A response of WebSailor is considered right only if the generated prediction is in the ground truth or the ground truth is in the prediction.

Algorithm	Gene	ralQA		Multi-H	IopQA		Avg
Angor tumin	NQ	$\mathbf{T}\mathbf{Q}$	HotpotQA	Musique	2Wiki	Bamboogle	2116
		I	LaMA-3.2-3I	B-Instruct			
GRPO	43.8	58.4	25.0	14.2	31.6	38.4	35.2
TTRL (w/o info)	58.6	76.4	47.2	37.2	59.4	57.6	56.1
Δ	+14.8	+18.0	+22.2	+23.0	+27.8	+19.2	+20.9
	$\uparrow 33.8\%$	$\uparrow 30.8\%$	↑ 88.8%	$\uparrow 162.0\%$	$\uparrow 87.9\%$	$\uparrow 50.0\%$	$\uparrow 59.4\%$
TTRL (w/ info)	57.4	74.0	45.2	36.4	60.2	56.0	54.9
Δ	+13.6	+15.6	+20.2	+22.2	+28.6	+17.6	+19.7
	$\uparrow 31.1\%$	$\uparrow 26.7\%$	$\uparrow 80.8\%$	$\uparrow 156.3\%$	$\uparrow 90.5\%$	$\uparrow 45.8\%$	$\uparrow 56.0\%$
		I	LaMA-3.1-8I	B-Instruct			
GRPO	48.0	62.6	34.4	24.2	35.2	54.4	43.1
TTRL (w/o info)	43.0	64.0	35.6	27.2	47.0	52.0	44.8
Δ	-5.0	+1.4	+1.2	+3.0	+11.8	-2.4	+1.7
	↓ 10.4%	$\uparrow 2.2\%$	$\uparrow 3.5\%$	↑ 12.4%	$\uparrow 33.5\%$	$\downarrow 4.4\%$	$\uparrow 3.9\%$
TTRL (w/ info)	49.2	67.4	35.4	40.2	48.2	52.0	48.7
Δ	+1.2	+4.8	+1.0	+16.0	+13.0	-2.4	+5.6
	$\uparrow 2.5\%$	$\uparrow 7.7\%$	$\uparrow 2.9\%$	$\uparrow 66.1\%$	$\uparrow 36.9\%$	$\downarrow 4.4\%$	$\uparrow 13.0\%$
			Qwen-2.5-3B	-Instruct			
GRPO	23.6	41.0	22.4	10.4	26.0	32.8	26.0
TTRL (w/o info)	39.2	59.8	37.8	23.8	51.2	49.4	43.5
Δ	+13.2	+18.8	+15.4	+13.4	+25.2	+16.6	+17.5
	$\uparrow 55.9\%$	$\uparrow 45.9\%$	$\uparrow 68.8\%$	$\uparrow 128.8\%$	$\uparrow 96.9\%$	↑ 50.6%	$\uparrow 67.3\%$
TTRL (w/ info)	31.8	58.0	33.6	22.0	49.0	48.8	40.5
Δ	+8.2	+17.0	+11.2	+11.6	+23.0	+16.0	+14.5
	$\uparrow 34.7\%$	$\uparrow 41.5\%$	$\uparrow 50.0\%$	$\uparrow 111.5\%$	$\uparrow 88.5\%$	↑ 48.8%	$\uparrow 55.8\%$
			Qwen-2.5-7B	-Instruct			
GRPO	31.4	44.4	26.0	11.8	31.0	36.8	30.2
TTRL (w/o info)	40.6	63.2	40.4	28.8	53.2	64.0	48.4
Δ	+9.2	+18.8	+14.4	+17.0	+22.2	+27.2	+18.2
	↑ 29.3%	† 42.3%	↑ 55.4%	↑ 144.1%	↑ 71.6%	↑ 73.9%	↑ 60.3%
TTRL (w/ info)	34.6	54.8	32.6	20.2	43.0	50.4	39.3
Δ	+3.2	+10.4	+6.6	+8.4	+12.0	+13.6	+9.1
	↑ 10.2%	† 23.4%	$\uparrow 25.4\%$	↑ 71.2%	↑ 38.7%	† 36.7%	↑ 30.1%
			1			1	

Table 6: The performance of Llama and Qwen trained with TTRL and GRPO. w/o info and w/ info indicate without information mask and with information mask, respectively. The largest value is denoted using **bold**.

We also experiment on Sim2Real on TTRL-trained models, and we show the results in Table 8. Though TTRL achieves better performance compared with RLVR, it introduces biases where models over-relying on its internal knowledge and are hard to adapt to real environments easily. We find that almost all queries are finished using one search query, even for BroweseComp. Therefore, in one-turn generation, the web search engine can't provide flexible information as the LLMs do. Moreover, we observe that TTRL-trained models prefer to select a candidate answer and verify it rather than search based on the question sequentially. We also find that it collapses frequently than RLVR, which is attributed to the unexpected deterministic behavior of policy models. We provide a case study in Table 31.

3.5 FURTHER DISCUSSIONS

3.5.1 Benefits of Information Masking

Since all retrieved information originates from the reasoning model itself, jointly training the model on both the reasoning process and information generation represents a natural optimization strategy. To test the effectiveness of training full trajectories, we conduct experiments for training with and without information masking during the learning process. Figure 10 presents comparative results. The experimental results demonstrate that information masking consistently enhances model performance across benchmarks. Analysis of the training dynamics, which is listed in Appendix B.3.3, reveals that masking information tokens during training encourages the model to generate more com-

Model	Gene	ralQA		Multi-H	opQA		Avg	
1,10 (101	\overline{NQ}	$\overline{\mathbf{TQ}}$	$\overline{ ext{HotpotQA}}$	Musique	2Wiki	Bamboogle	8	
LLaMA-3.2-3B-Instruct								
TTRL Sim2Real	58.6 56.6	76.4 74.8	47.2 46.0	37.2 36.0	59.4 59.0	57.6 54.4	56.1 54.5	
			Qwen2.5-	3B-Instruc	t			
TTRL Sim2Real	39.2 39.8	59.8 61.2	37.8 40.2	23.8 22.8	51.2 51.8	49.4 41.6	43.5 42.9	

Table 8: Performance of Sim2Real Search Generalization on TTRL.

prehensive and detailed reasoning trajectories. The enhanced capability provides a compelling explanation for the consistent performance improvements observed across diverse question-answering tasks. By preventing the model from simply copying retrieved information during training, the masking strategy forces deeper engagement with the reasoning process itself, ultimately leading to more robust problem-solving abilities at inference time.

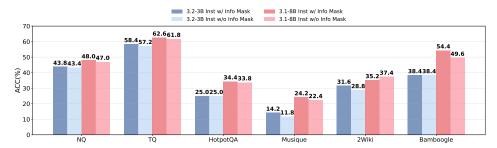


Figure 10: The performance of Llama-3.2-3B-Instruct and Llama-3.1-8B-Instruct when trained with and without the information mask.

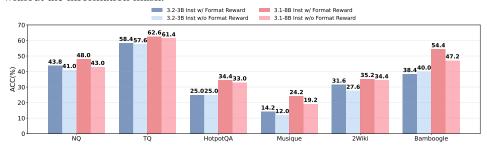


Figure 11: The performance of Llama-3.2-3B-Instruct and Llama-3.1-8B-Instruct when trained with and without format reward. All of the models are trained with an information mask.

3.5.2 IMPACT OF FORMAT-BASED REWARD

To effectively elicit the dual capabilities of language models as both reasoners and internal search engines, we design a format reward that enforces adherence to our structured reasoning framework. This reward component ensures that models consistently follow the prescribed format of thinking, searching, and information gathering throughout their reasoning process. We evaluate the effectiveness of format reward through ablation studies comparing models trained with and without this component. Figure 11 presents the comparative results, demonstrating that format reward consistently improves performance for both base and instruction-tuned models across all benchmarks. These findings highlight that structured output formatting is crucial for successfully combining reasoning and search capabilities within a single model. The format reward acts as a critical scaffolding mechanism, guiding the model to maintain organized reasoning trajectories that facilitate effective internal knowledge retrieval. Without this structural guidance, models tend to produce less coherent reasoning paths that underutilize their internal search capabilities, resulting in degraded overall per-

Algorithm	Gene	ralQA		Multi-H	IopQA		Avg	
Aligorithm	NQ	\mathbf{TQ}	$\overline{\text{HotpotQA}}$	Musique	2Wiki	Bamboogle	21.48	
LLaMA-3.2-3B-Instruct								
GRPO	43.8	58.4	25.0	14.2	31.6	38.4	35.2	
GRPO (Freezing)	28.6	46.6	15.8	5.6	13.8	20.8	21.9	
Δ	-15.2	-11.8	-9.2	-8.6	-17.8	-17.6	-13.3	
	$\downarrow 34.7\%$	$\downarrow 20.2\%$	$\downarrow 36.8\%$	$\downarrow 60.6\%$	$\downarrow 56.3\%$	$\downarrow 45.8\%$	$\downarrow 37.8\%$	
		I	LaMA-3.1-8E	B-Instruct				
GRPO	48.0	62.6	34.4	24.2	35.2	54.4	43.1	
GRPO (Freezing)	24.4	46.6	15.4	7.6	17.2	23.2	22.4	
Δ	-23.6	-16.0	-19.0	-16.6	-18.0	-31.2	-20.7	
	$\downarrow 49.2\%$	$\downarrow 25.6\%$	$\downarrow 55.2\%$	$\downarrow 68.6\%$	$\downarrow 51.1\%$	$\downarrow 57.4\%$	$\downarrow 48.0\%$	
			Qwen-2.5-3B-	Instruct				
GRPO	23.6	41.0	22.4	10.4	26.0	32.8	26.0	
GRPO (Freezing)	9.8	18.4	7.4	5.0	7.5	12.8	10.2	
Δ	-13.8	-22.6	-15.0	-5.4	-18.5	-20.0	-15.8	
	$\downarrow 58.5\%$	$\downarrow 55.1\%$	$\downarrow 67.0\%$	$\downarrow 51.9\%$	$\downarrow 71.2\%$	$\downarrow 61.0\%$	$\downarrow 60.8\%$	
	Qwen-2.5-7B-Instruct							
GRPO	31.4	44.4	26.0	11.8	31.0	36.8	30.2	
GRPO (Freezing)	15.6	37.4	15.0	7.2	15.2	23.2	22.6	
Δ	-15.8	-7.0	-11.0	-4.6	-15.8	-13.6	-7.6	
	$\downarrow 50.3\%$	$\downarrow 15.8\%$	$\downarrow 42.3\%$	$\downarrow 39.0\%$	$\downarrow 51.0\%$	↓ 37.0%	$\downarrow 25.2\%$	

Table 9: Performance of Llama and Qwen2.5 with on-policy GRPO compared to freezing policy.

Algorithm	Gene	ralQA		Multi-H	opQA		Avg
111891101111	NQ	\mathbf{TQ}	HotpotQA	Musique	2Wiki	Bamboogle	8
			LLaMA-3.2-3	B-Instruct			
GRPO	43.8	58.4	25.0	14.2	31.6	38.4	35.2
DAPO	44.6	58.0	26.8	12.8	26.6	38.4	34.5
KL-Cov	41.8	58.6	24.6	12.4	28.6	38.4	34.1
REINFORCE++	42.2	55.8	25.6	12.6	32.0	30.8	33.2
PPO	35.0	55.8	21.8	11.4	29.6	30.4	30.7
			LLaMA-3.1-8	B-Instruct			
GRPO	48.0	62.6	34.4	24.2	35.2	54.4	43.1
DAPO	48.6	63.8	34.4	21.6	39.2	52.0	43.3
KL-Cov	44.8	63.6	32.6	22.8	37.4	52.8	42.3
REINFORCE++	46.2	64.4	33.4	18.4	43.2	36.4	40.3
PPO	37.4	58.4	27.0	17.0	38.4	37.4	36.2

Table 10: The performance of Llama-3.2-3B-Instruct and Llama-3.1-8B-Instruct when trained with different RL algorithms. All of the models are trained with an information mask and a format reward.

formance. Also, we observe a drastic response length growth without format reward, which indicates that format reward stabilizes the training process.

3.5.3 IMPORTANCE OF ON-POLICY SELF-SEARCH

In previous work such as ZeroSearch (Sun et al., 2025), the fine-tuned LLM serves as an information provider. In contrast, we treat the policy model as an implicit simulator of world knowledge to supply information in above sections, which not only simplifies training but also significantly reduces training costs, particularly those associated with multi-turn rollouts.

To gain a comprehensive understanding, we examine two settings: one in which the information provider is the policy itself, and another in which the provider is the zero-step policy (i.e., a frozen policy). An information mask and a formatted reward are applied throughout all training procedures. We conduct experiments on four models from two different model families to evaluate their generalization capabilities. The results, presented in Table 9, reveal a dramatic collapse after approximately 100 training steps, with training rewards either remaining stagnant or decreasing sharply. We also observe significant performance degradation when using a frozen LLM as the information provider.

Terminology	Explanation	Example
Full-Real Search	Search external real engines like RAG or Google.	Search-R1 (Jin et al., 2025b)
Semi-Real Search	Search external simulated engines like LLMs.	ZeroSearch (Sun et al., 2025)
Full-Sim Search	Search internal engines, e.g., implicitly retrieving information from embedded knowledge.	SELF-SEARCH
Sim2Real Search	Train with Full-Sim Search but inference with external real engines, such as Google Search or Bing.	SELF-SEARCH

Table 11: We display key concepts discussed in this paper. The terminology we mentioned above is the approach of search used during training and inference.

3.5.4 Compatibility with RL Algorithms

We present the performances when training models with different algorithms, including PPO, GRPO, Reinforce++, DAPO, and KL-Conv. We use Llama-3.2-3B-Instruct and Llama-3.1-8B-Instruct as our backbones. The implementation details is listed in Appendix B.2.2. We present our results in Table 10. We observe a non-trivial performance gap between different training algorithms, with GRPO-based algorithms, e.g., GRPO, DAPO, etc, performs better than PPO and RE-INFORCE++. The superior performance of PPO is also observed in Sun et al. (2025), which proves the effectiveness of repeated rollouts for search agent training. It is worth noting that when trained with online engines like Google, the repeated rollouts will lead to greater cost. However, since we train models totally offline, more rolloouts may result in better performance without additional cost.

4 RELATED WORK

4.1 REINFORCEMENT LEARNING WITH SEARCH ENGINES

Reinforcement Learning (RL) has emerged as a powerful approach for enhancing the reasoning capabilities of LLMs (DeepSeek-AI, 2025; Cui et al., 2025a; OpenAI, 2024). RL-trained reasoning models, which utilize either process rewards or outcome rewards, demonstrate remarkable performance on complex tasks such as math and code generation through self-reflection and exploration. Several recent works have explored applying RL to improve the performance of LLM-based search agents. Search-R1 (Jin et al., 2025a) employs RL to train models for iterative searches in a local text corpus with retrievers like e5. Similarly, ReSearch (Chen et al., 2025) leverages outcome rewards exclusively to enhance LLMs' ability to seek additional information during reasoning processes. However, these approaches are limited by their reliance on textual corpora, such as Wikipedia, which is static and inadequately represents the complexity and noise inherent in real-world online search environments. To address these limitations, Zheng et al. (2025) introduced online-search RL coupled with a browse agent, aligning trained models with web search engines like Google and Bing. While this approach yields superior performance, the training process demands extensive API calls for RL algorithms such as Group Relative Policy Optimization (GRPO) (Shao et al., 2024), resulting in substantial API costs. As a cost-effective alternative, ZeroSearch (Sun et al., 2025) proposes using an LLM as a search engine simulator to create a synthetic online search environment, significantly reducing computational overhead while maintaining comparable or superior performance. However, considering the huge amount of training data, the potential of LLMs to serve as a search world model has not been widely explored. In particular, the upper bounds of LLMs as world models for reinforcement learning in agentic search remain unknown.

4.2 Large Language Models as Search Engines

With the advancement of LLMs, a novel paradigm called generative search has emerged, offering users flexible, multi-grained information through generation rather than traditional matching-based retrieval (Li et al., 2024b; 2025c). Current research on using LLMs as search engines primarily explores two approaches. The first, generative retrieval (Tay et al., 2022; Wang et al., 2022; Li et al., 2024c), directly generates document identifiers without explicit matching, with each identifier

corresponding to a specific document in the corpus. These methods operate under the assumption that LLMs have memorized the corpus, effectively functioning as an implicit knowledge base (Long et al., 2024). The second, reliable response generation, employs LLMs to summarize retrieved items, such as papers (Gao et al., 2023) and web pages (Qin et al., 2023), and generates user-centric responses as search results (Shen et al., 2023). These methods address key limitations of traditional information retrieval systems, such as rigid document granularity and relevance matching, while providing better flexibility, efficiency, and creativity for real-world applications (Li et al., 2024a; Ding et al., 2025). According to these applications, LLMs have the potential to serve as world models, providing knowledge for keyword-based searches on world knowledge. However, there has been limited exploration of using LLMs as textual world models in agentic reinforcement learning.

4.3 Inference-time Scaling of LLMs and Agents

Repeated Sampling refers to the practice of generating multiple candidate outputs from the same prompt using probabilistic sampling. Brown et al. (2024) find that the coverage of correct answers scales substantially with the number of repeated samples. This finding is further corroborated by Yue et al. (2025), who demonstrate that increasing sample numbers significantly improves the percentage of correct answers captured, even on challenging benchmarks such as AIME. Similar scaling effects have been observed in code generation tasks (Li et al., 2025a). Beyond simple repeated sampling, these approaches can be enhanced through integration with verification mechanisms. Best-of-N sampling (Liu et al., 2025a; Qiu et al., 2024) and majority voting (Zuo et al., 2025) both leverage multiple samples with different selection criteria to achieve superior performance compared to single greedy decoding. Despite these advances in reasoning and generation tasks, the effectiveness of repeated sampling strategies in information retrieval and search contexts remains underexplored.

On the other hand, recent developments in TTS have also revealed a vast and largely unexplored design space in language-based and embodied agent systems. Zhu et al. (2025) systematically explored various TTS strategies for language agents, demonstrating the effectiveness of parallel sampling, reflective revision, and diversified rollouts. Furthermore, agents such as web agents exhibit superior adaptive behaviors like exploration and backtracking, substantially outperforming traditional per-step scaling methods when applying scaling test-time interaction (TTI) (Shen et al., 2025). In addition to language agents, Yang et al. (2025c) introduced a GUI Test-time Scaling Agent (GTA1), leveraging concurrent sampling and evaluation to significantly enhance robustness in graphical user interface (GUI) interaction tasks without relying on extensive lookahead. Complementing these strategies, Lifshitz et al. (2025) presented Multi-Agent Verification (MAV), where multiple aspect verifiers collaboratively evaluate outputs, significantly boosting overall agent performance. Collectively, these recent studies highlight diverse approaches to TTS in agent-based systems, underscoring the potential of both compute allocation and interaction strategies to enhance adaptive and robust agent behaviors across varied environments.

5 CONCLUSION

In conclusion, our study establishes that LLMs possess untapped capacity as implicit world models for search-driven tasks, often containing the necessary knowledge to answer complex queries internally. While reliably extracting this knowledge remains difficult, our proposed Self-Search Reinforcement Learning (SSRL) method significantly enhances self-search abilities, outperforming search API-based baselines and enabling robust sim-to-real transfer. These findings suggest a promising path toward more autonomous and scalable LLM agents that can operate effectively without reliance on external search engines.

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A INFERENCE-TIME SCALING OF SELF-SEARCH

A.1 PROMPTS

A.1.1 Instructions for Repeated Sampling

We use the instruction in Table 12 for repeated sampling.

Answer the given question. You must conduct reasoning inside <think> and </think> first every time you get new information. After reasoning, if you find you lack some knowledge, you can call a search engine by <search> query </search>, and it will return the top searched results between <information> and </information>. You can search as many times as you want. If you find no further external knowledge needed, you can directly provide the answer inside <answer> and </answer> without detailed illustrations. For example, <answer> Beijing </answer>. Question:

Table 12: Instruction for repeated sampling.

A.1.2 Instructions for LLM Providing Information

We use the instruction in Table 13 when querying LLM to provide information.

Given a query, you need to imitate the style of the following demos and generate five useful documents for the query.

[EXAMPLE]

You should generate documents that can help the user find the answer. Each document should contain about 30 words. You must directly output the English documents and not output any other texts.

Query: query Useful Output:

Table 13: Instruction for LLM providing information.

A.2 DETAILED RESULTS

We introduce the results of repeated sampling of seven benchmarks, across 16 models, in Figure 12. We also list the simulated parameters for each model in Table 14 and comparison of actual vs. fitted values, residuals, and relative errors for every model across different k values in Table 15, 16, 17

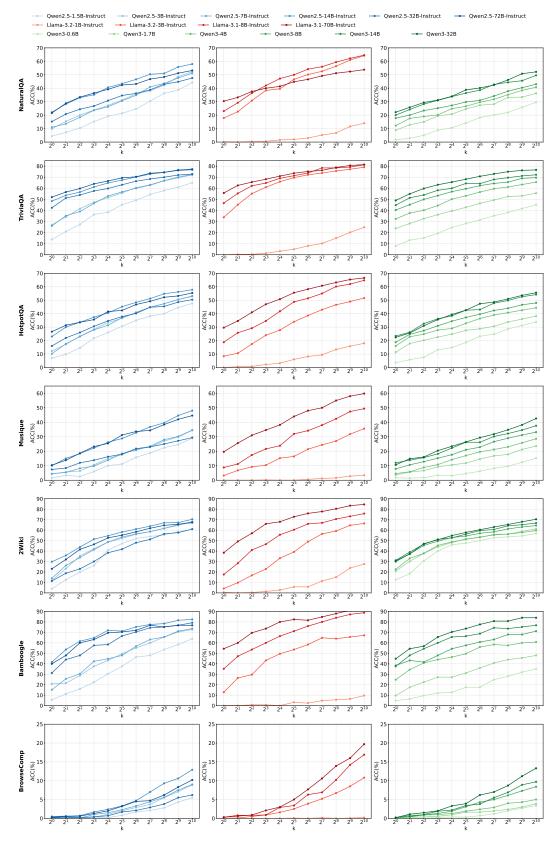


Figure 12: The results of repeated sampling of seven benchmarks

Model	a	b	R^2	RMSE	MAE
Llama-3.2-3B-Instruct Llama-3.1-8B-Instruct Llama-3.1-70B-Instruct	-1.793 -1.263 -0.950	-0.191 -0.183 -0.159	0.986 0.987 0.976	1.745% $1.541%$ $1.688%$	1.583% 1.267% 1.415%
Qwen3-8B Qwen3-14B Qwen3-32B	-1.370 -1.249 -1.232	-0.111 -0.117 -0.130	0.984 0.984 0.989	1.115% $1.184%$ $1.073%$	$0.906\% \ 0.987\% \ 0.949\%$
Qwen2.5-7B-Instruct Qwen2.5-14B-Instruct Qwen2.5-72B-Instruct	-1.533 -1.174 -1.259	-0.167 -0.163 -0.148	0.978 0.989 0.970	1.932% $1.265%$ $1.984%$	1.674% $1.029%$ $1.660%$

Table 14: Fitting performance metrics for Llama and Qwen series models (RMSE and MAE are in percentage)

	Llama-3.2-3B-Instruct					Llama-3.1-8B-Instruct			Llama-3.1-70B-Instruct			
K	Actual	Fitted	Residual	Rel. Error (%)	Actual	Fitted	Residual	Rel. Error (%)	Actual	Fitted	Residual	Rel. Error (%)
2^{0}	13.50	16.64	-3.14	23.26	25.53	28.27	-2.74	10.73	35.23	38.69	-3.45	9.80
2^1	19.00	20.78	-1.78	9.35	32.20	32.87	-0.67	2.09	42.20	42.72	-0.52	1.24
2^2	25.88	25.24	0.64	2.49	37.97	37.54	0.43	1.12	47.77	46.69	1.07	2.24
2^3	31.32	29.92	1.40	4.45	42.93	42.20	0.74	1.71	52.63	50.56	2.07	3.93
2^{4}	36.36	34.74	1.62	4.44	48.63	46.78	1.86	3.82	55.83	54.30	1.54	2.75
2^{5}	41.16	39.60	1.56	3.79	53.37	51.22	2.15	4.03	59.53	57.88	1.66	2.78
2^{6}	46.28	44.41	1.87	4.04	56.73	55.47	1.26	2.22	62.13	61.28	0.85	1.37
2^7	50.04	49.10	0.94	1.87	59.60	59.52	0.08	0.14	64.73	64.50	0.24	0.36
2^{8}	52.96	53.62	-0.66	1.25	63.17	63.32	-0.15	0.24	67.03	67.52	-0.49	0.73
2^{9}	56.72	57.92	-1.20	2.12	65.33	66.87	-1.53	2.35	69.17	70.35	-1.18	1.71
2^{10}	59.36	61.97	-2.61	4.40	67.83	70.16	-2.33	3.43	70.50	72.98	-2.48	3.52

Table 15: Comparison of actual vs. fitted values, residuals, and relative errors for three Llama models across different K values.

A.3 CASE STUDIES

A.3.1 Case Study for Qwen3 with/without Thinking

We show a case study for Qwen3 with/without thinking mode in Table 18. When enabling thinking, the model will spend many tokens for reasoning at the beginning.

A.3.2 Case Study for Multi-turn and Reflection Repeated Sampling

We show the case study for multi-turn and reflection-based repeated sampling in Table 19.

B SELF-SEARCH REINFORCEMENT LEARNING

B.1 PROMPTS

We list the instruction used for direct reasoning in Table 20, the instruction for RAG in table 21, and the instruction for R1-like model training in Table 22.

B.2 IMPLEMENTATION DETAILS

B.2.1 BASELINE IMPLEMENTATION

Direct Answer and CoT We show the instruction used in Appendix B.1 and A.1.1 respectively. We set the temperature to 0.0 for consistent evaluation.

RAG We use the instruction listed in Appendix B.1. We use Jina and Google search. We set the temperature to 0.0 for consistent evaluation.

	Qwen3-8B					Qwen3-14B				Qwen2.5-7B-Instruct			
K	Actual	Fitted	Residual	Rel. Error (%)	Actual	Fitted	Residual	Rel. Error (%)	Actual	Fitted	Residual	Rel. Error (%)	
2^{0}	22.92	25.42	-2.50	10.90	26.28	28.69	-2.41	9.15	17.60	21.58	-3.98	22.63	
2^1	27.56	28.14	-0.58	2.09	30.92	31.62	-0.70	2.26	24.33	25.51	-1.18	4.83	
2^2	31.80	30.91	0.89	2.79	35.40	34.59	0.81	2.29	30.40	29.61	0.79	2.61	
2^3	34.84	33.73	1.11	3.20	38.96	37.57	1.39	3.56	35.40	33.81	1.59	4.50	
2^{4}	37.84	36.56	1.28	3.39	41.40	40.55	0.85	2.04	40.43	38.05	2.38	5.89	
2^{5}	40.40	39.39	1.01	2.50	45.16	43.51	1.65	3.65	44.43	42.28	2.16	4.85	
2^{6}	42.56	42.21	0.35	0.82	46.32	46.43	-0.11	0.23	47.43	46.44	1.00	2.10	
2^{7}	45.20	45.00	0.20	0.44	49.88	49.29	0.59	1.18	51.23	50.49	0.74	1.45	
2^{8}	47.52	47.75	-0.23	0.48	52.04	52.09	-0.05	0.09	53.77	54.39	-0.63	1.17	
2^{9}	50.04	50.44	-0.40	0.80	53.84	54.80	-0.96	1.79	56.67	58.13	-1.46	2.58	
2^{10}	51.64	53.07	-1.43	2.76	56.08	57.44	-1.36	2.42	59.17	61.67	-2.50	4.23	

Table 16: Comparison of actual vs. fitted values, residuals, and relative errors for Qwen3-8B, Qwen3-14B, and Qwen2.5-7B-Instruct.

		2.5-14B-In	struct	Qwen2.5-72B-Instruct				Qwen3-32B				
K	Actual	Fitted	Residual	Rel. Error (%)	Actual	Fitted	Residual	Rel. Error (%)	Actual	Fitted	Residual	Rel. Error (%)
2^{0}	28.10	30.91	-2.81	10.01	24.40	28.39	-3.99	16.34	26.96	29.16	-2.20	8.17
2^1	34.97	35.05	-0.09	0.25	31.50	32.09	-0.59	1.88	31.68	32.44	-0.76	2.39
2^2	39.83	39.22	0.62	1.55	36.10	35.85	0.25	0.69	36.64	35.75	0.89	2.43
2^3	44.57	43.35	1.22	2.73	41.47	39.62	1.85	4.45	40.24	39.07	1.17	2.91
2^4	48.87	47.41	1.46	2.98	45.83	43.36	2.47	5.39	43.44	42.37	1.07	2.45
2^5	52.37	51.35	1.01	1.94	49.03	47.04	1.99	4.06	46.76	45.64	1.12	2.41
2^{6}	55.83	55.15	0.68	1.22	51.80	50.63	1.17	2.26	49.64	48.83	0.81	1.62
2^7	59.17	58.78	0.39	0.65	55.10	54.10	1.00	1.81	51.76	51.95	-0.19	0.37
2^8	61.80	62.22	-0.42	0.68	57.00	57.44	-0.44	0.77	54.48	54.97	-0.49	0.91
2^9	64.60	65.46	-0.86	1.34	58.97	60.63	-1.66	2.82	57.36	57.89	-0.53	0.92
2^{10}	66.73	68.50	-1.77	2.65	60.80	63.66	-2.86	4.70	59.48	60.69	-1.21	2.03

Table 17: Comparison of actual vs. fitted values, residuals, and relative errors for Qwen2.5-14B-Instruct, Qwen2.5-72B-Instruct, and Qwen3-32B.

R1 We use the instruction listed in Appendix B.1. We train for up to 5 epochs, and we stop training if any collapse is observed, including response length and training accuracy. We select the checkpoint with the best performance. The training batch size is 256, and the learning rate is 1e-6. We use a KL loss coef of 0.001. We train our models based on GRPO, and for each prompt, we generate 5 responses. For evaluation, we use temperature = 0.0.

ZeroSearch We use the instruction listed in Appendix A.1.1. We use the same setting as R1. The max turn is 2. The simulation LLM is Simulation_LLM_google_14B. The start threshold is 0.0, and the end threshold is 0.5.

Search-R1 We use the same setting as R1. When training, we use e5 as the retriever and Wikipedia as the corpus. When testing, we use Google Search for consistent comparison.

B.2.2 OTHER ALGORITHM IMPLEMENTATION

PPO We train for up to 5 epochs, and we stop training if any collapse is observed, including response length and training accuracy. We select the checkpoint with the best performance. The training batch size is 256, and the learning rate is 1e-6. We use a KL loss coef of 0.001. The learning rate for the critic model is 1e-5. We use a standard GAE as our advantage estimator, with $\gamma=1.0$ and $\lambda=1.0$.

REINFORCE++ We train for up to 5 epochs, and we stop training if any collapse is observed, including response length and training accuracy. We select the checkpoint with the best performance. The training batch size is 256, and the learning rate is 1e-6. We use a KL loss coef of 0.001.

DAPO We train for up to 5 epochs, and we stop training if any collapse is observed, including response length and training accuracy. We select the checkpoint with the best performance. The

Question: Who is the mother of the director of film Polish-Russian War (Film)?

Golden Answer: Małgorzata Braunek Extracted Answer: Elżbieta Munk

Thinking Process (With Thinking):

<think> Okay, let's see. The question is asking for the mother of the director of the film "Polish-Russian War." First, I need to figure out who directed that film. But wait, I don't remember any film specifically called "Polish-Russian War." Maybe it's known by a different title in English? Sometimes movies have different names in different countries.

Alternatively, maybe it's a historical film about the Polish-Russian conflicts. Let me think. There are several conflicts between Poland and Russia, like the Polish-Soviet War in the early 20th century. Could the film be about that? Maybe the user is referring to a film like "The Battle of Somosierra," but that's a different conflict. Hmm.

Wait, perhaps the user is referring to a Polish film. Maybe the director is someone well-known. Let me try to search for the film "Polish-Russian War" to find the director. If I can find the director, then I can look up their mother.

So, first step: search for "Polish-Russian War film director." Let's see what comes up. If there's a film by that name, I can get the director's name. If not, maybe there's confusion with the title. Alternatively, maybe it's a documentary or a less-known film.

•••

So first, I need to search for "Polish-Russian War film director" to get the correct director's name.

<search> Polish-Russian War film director </search>

<information> 1. "Bitwa Warszawska" (1975) directed by Andrzej Munk - focuses on the Polish-Soviet War. 2. "The First Echelon" (1968) directed by Georgy Yungvald-Khilkevich - Soviet film about Polish-Soviet War. 3. "The War" (2015) directed by Andrzej Munk - Polish film about the Polish-Soviet War. </information>

<search> Andrzej Munk mother </search>

<information> 1. Andrzej Munk's mother was Elżbieta Munk, a Jewish woman from Warsaw who perished in the Holocaust. </information>

<search> Georgy Yungvald-Khilkevich mother </search>

<information> 1. Limited information found; focus on his career in Soviet cinema.

<answer> Elżbieta Munk </answer>

Thinking Process (Without Thinking):

To answer the question, I first need to identify the director of the film *Polish-Russian War* and then determine who their mother is. Let me start by finding out who directed the film.

<search> Who directed the film Polish-Russian War? </search>

<information> 1. The film "Polish-Russian War" (also known as "Polsko-Rosyjska Wojna") was directed by Andrzej Wajda. 2. Andrzej Wajda was a renowned Polish film director, screenwriter, and actor, known for his contributions to Polish cinema.

Now that I know the director is Andrzej Wajda, I can proceed to find out who his mother was.

<search> Who was the mother of Andrzej Wajda? </search>

<information> 1. Andrzej Wajda's mother was Jadwiga Wajda (née Bujak). 2. Jadwiga Wajda was a Polish teacher and a significant influence in Andrzej Wajda's early life.
</information>

<answer> Jadwiga Wajda </answer>

Table 18: Case study for Qwen3-32B with thinking and without thinking.

Question: Were Scott Derrickson and Ed Wood of the same nationality?

Golden Answer: yes

Extracted Answer: No, Scott Derrickson and Ed Wood are not of the same nationality, with Derrickson being Canadian and Wood being American.

Thinking Process (Multi):

<think> I need to consider the nationality of Scott Derrickson and Ed Wood to determine if they are of the same nationality. Scott Derrickson is known for directing movies like "Doctor Strange" and "The Exorcism of Emily Rose". Ed Wood is known for directing cult classic films like "Plan 9 from Outer Space". To find their nationalities, I'll need to look into their birthplaces.

<search> Scott Derrickson nationality </search>

<information> Doc 1: Scott Derrickson is a Canadian film director, screenwriter, and producer known for directing Marvel's Doctor Strange, released in 2016. Doc 2: Born in 1966, Derrickson grew up in Ontario, Canada, before pursuing a career in filmmaking. His background in animation and visual effects influenced his work. Doc 3: Derrickson's work often explores the intersection of faith and science. He co-created the TV series Eureka and wrote the screenplay for The Exorcism of Emily Rose. Doc 4: As a director, Derrickson's films often combine supernatural and psychological elements. His work has been praised for its unique visual style and atmospheric tension. Doc 5: Derrickson's production company, Film Science, has produced several films and TV series. He continues to explore the boundaries of storytelling through his work.

<think> Now that I know Scott Derrickson is Canadian, I'll look into Ed Wood's nationality.
</think>

<search> Ed Wood nationality </search>

<information> Doc 1: Ed Wood is an American filmmaker known for his low-budget horror and sci-fi films, including the cult classic Plan 9 from Outer Space. Doc 2: As a pioneer in the low-budget film industry, Wood's work often featured unique and bizarre storylines, captivating a niche audience. Doc 3: Born in Poughkeepsie, New York, Ed Wood began making films as a teenager and developed a passion for storytelling and filmmaking. Doc 4: Wood's most famous film, Plan 9 from Outer Space, is often cited as one of the worst films ever made, but also as a cult classic. Doc 5: Ed Wood's life and career have been the subject of numerous documentaries and books, exploring his legacy as a filmmaker and outsider artist.

<answer> No, Scott Derrickson and Ed Wood are not of the same nationality, with Derrickson being Canadian and Wood being American. </answer>

Thinking Process (Reflection):

<think> I need to determine the nationality of Scott Derrickson and Ed Wood to compare
them. </think>

<search> Scott Derrickson nationality </search>

<information> Scott Derrickson is an American film director, screenwriter, and cinematographer. He was born in the United States. </information>

<search> Ed Wood nationality </search>

<information> Ed Wood was an American film director, screenwriter, and actor. He was
born in the United States. </information>

<answer> Yes, Scott Derrickson and Ed Wood are of the same nationality. They are both American. </answer>

wait, wait, wait

<search> nationality American </search>

<information> Americans are people born or citizens of the United States.
</information>

<search> nationality same </search>

<information> The terms "same" and "nationality" typically refer to identical or similar
ethnic or cultural identity. </information>

<answer> Yes, Scott Derrickson and Ed Wood are of the same nationality. They are both
American. </answer>

Table 19: Case study for Multi-turn and reflective Repeated Sampling.

Answer the given question. Provide the answer inside <answer> and </answer> without any additional information. For example, <answer> Beijing </answer>.

Table 20: Instruction for Direct Reason.

You are a knowledgeable assistant that utilizes the provided documents to answer the user's question accurately.

Question: question Documents: documents Guidelines:

- Analyze the provided documents to extract relevant information. Synthesize the information to formulate a coherent and accurate answer.
- Ensure that your response directly addresses the user's question using the information from the documents.

Table 21: Instruction for RAG.

training batch size is 256, and the learning rate is 1e-6. We don't use a KL loss. The low clip ratio is 0.2, and the high clip ratio is 0.28. We filter groups based on accuracy.

KL-Cov We train for up to 5 epochs, and we stop training if any collapse is observed, including response length and training accuracy. We select the checkpoint with the best performance. The training batch size is 256, and the learning rate is 1e-6. We don't use a KL loss. We use a k-percent of 0.2.

B.2.3 TTRL

We set the max prompt length to 1024, and the max response length to 3076. The batch size is 8, and for each prompt, we rollout 32 times. The rollout temperature is set at 0.6. We use a learning rate of 5e-7 and a warm up step of 62. We remove the use of KL loss as in the original paper. We train for 80 epochs and stop when the performance converges.

B.3 ABLATION STUDIES

B.3.1 MODEL FAMILY COMPARISON

Since Qwen is widely regarded as a stronger base model than Llama in math or code tasks, we aim to find out whether the conclusion holds when it relies on internal knowledge to answer the knowledge-intensive questions. We also use the default setting for training Qwen. All the training consists of the format, reward, and information token mask. The experimental results is listed in Table 23. Though we still observe the same training pattern as in Llama, for example, the scaling effect and the superior ability of instruct models, the absolute performance is relatively lower than Llama series, indicating that the ability of Qwen to serve as a simulator of world knowledge is not as good as Llama. The finding con-

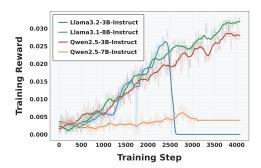


Figure 13: The performance of TTRL of various models on BrowseComp.

Answer the given question. Provide the answer inside <answer> and </answer>. For example, <answer> Beijing </answer>. Let's search step by step. You can break the question into pieces and answer one by one.

Table 22: Instruction for R1 Training.

Model	Gene	ralQA		Multi-H	opQA		Avg	
1/10401	NQ	NQ TQ Hotpor		Musique	2Wiki	Bamboogle	8	
	Qwen2.5-3B-Instruct							
Search-R1-base	40.6	60.0	29.2	11.2	32.0	12.5	30.9	
Search-R1-inst	35.8	55.8	33.2	7.6	26.0	12.5	28.5	
ZeroSearch-base	43.0	61.6	33.8	13.0	34.6	13.9	33.3	
ZeroSearch-inst	41.4	57.4	27.4	30.0	9.8	11.1	29.5	
SELF-SEARCH-BASE	26.2	38.0	21.8	8.4	30.2	24.0	24.8	
SELF-SEARCH-INSTRUCT	23.6	41.0	22.4	10.4	26.0	32.8	26.0	
		Qw	m ven 2.5-7B-Inst	truct				
Search-R1-Base	43.4	61.4	31.2	18.2	35.2	27.8	36.2	
Search-R1-Instruct	42.4	63.4	32.8	17.4	33.2	26.4	35.9	
ZeroSearch-Base	42.4	66.4	32.0	34.0	18.0	33.3	37.7	
ZeroSearch-Instruct	43.6	65.2	34.6	18.4	35.2	27.8	37.5	
SELF-SEARCH-BASE	28.8	44.2	25.0	11.4	30.4	35.2	29.0	
SELF-SEARCH-INSTRUCT	31.4	44.4	26.0	11.8	31.0	36.8	30.2	

Table 23: The performance of Qwen2.5 models on General QA and Multi-Hop QA tasks.

Model	Gene	ralQA		Multi-H	opQA		Avg	
1,10 401	\overline{NQ}	$\mathbf{T}\mathbf{Q}$	HotpotQA	Musique	2Wiki	Bamboogle	8	
Qwen2.5								
Qwen2.5-3B-Instruct	23.6	41.0	22.4	10.4	26.0	32.8	26.0	
Qwen2.5-7B-Instruct	31.4	44.4	26.0	11.8	31.0	36.8	30.2	
	Qwen3							
Qwen3-4B	22.0	37.4	21.8	7.6	24.2	34.4	24.7	
Qwen3-8B	27.0	45.2	27.0	10.8	31.8	36.0	29.6	

Table 24: The performance of Qwen2.5 and Qwen3 models on General QA and Multi-Hop QA tasks.

tradicts the trend in reasoning tasks, such as math and code generation, where Qwen is always thought of as the best base model to start.

B.3.2 COMPARISON BETWEEN GENERAL MODELS AND REASONING MODELS

LRMs show expressive performance on reasoning tasks like math and code generation. However, few work continues to train LRMs to adapt to other fields. To have a thorough overview, we compare the RL performance between general models and reasoning models. We use Qwen2.5 and Qwen3 for a comparison. The experimental results is shown in Table 24. We find that the performance of Qwen3 is generally lower than Qwen2.5. Recall in Figure 2, the upper bound of Qwen3 is also lower than Qwen2.5. These findings indicate that reasoning models trained with too much math or code generation data may be hard to transfer to other domains easily. We also notice an inferior instruction-following ability during our training process, resulting in a decreasing search number, which drops to 0 at a later training stage. However, this may also be attributed to the format reward of a certain prompt, which contradicts the initial tool call format of the Qwen3 series.

B.3.3 Dynamics of Training with and without Information Mask

We show the training dynamics with and without the information mask in Figure 14. The experimental results demonstrate that the information mask significantly enhances the model's search behavior activity. This indicates that the information mask mechanism encourages the model to perform more search operations, potentially improving the model's reasoning capabilities in complex tasks.

B.3.4 GROUP SIZE ABLATION

For GRPO, we set the group size to 5 as in Jin et al. (2025b). In this part, we ablate on the impact of group size on the training dynamics and final performance. We train for 5 epochs and stop when the final performance converges, and select the checkpoints with the largest validation score. We use the default setting as mentioned above. We experiment on Qwen2.5-3B-Instruct and Llama-3.2-

Model	Gene	ralQA		$\operatorname{Multi-Hop}\mathbf{Q}\mathbf{A}$					
1110401	$\overline{\mathbf{NQ}}$	$\overline{\mathrm{TQ}}$	$\overline{ ext{HotpotQA}}$	HotpotQA Musique		Bamboogle	\mathbf{Avg}		
LLaMA-3.2-3B-Instruct									
Group Size = 5 Group Size = 10	43.8 44.0	58.4 57.8	25.0 27.0	14.2 12.0	31.6 31.4	38.4 40.8	35.2 35.5		
			Qwen2.5-3B	-Instruct					
Group Size = 5 Group Size = 10	$23.6 \\ 26.2$	41.0 37.8	$22.4 \\ 22.6$	10.4 8.4	$26.0 \\ 27.0$	32.8 24.8	26.0 24.5		

Table 25: The performance of LLaMA and Qwen2.5 models trained with different group sizes.

3B-Instruct. We show the training curve in Figure 14 and the results in Table 25. We observe a comparable performance when trained with a larger group size, but a faster convergence rate.

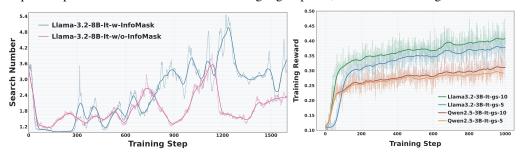


Figure 14: Left: Comparison of the search number with and without information mask on Llama-3.1-8B-Instruct. Right: Group size comparison.

B.3.5 ADDITIONAL BENCHMARKS

For a comprehensive evaluation of self-contained search, we further evaluate on SimpleQA with Offline Search, Online Search (We drop out K=3 for simplification), and Entropy-guided Search. We sample 200 records from SimpleQA. The results are listed in Table 27. We find that leveraging internal knowledge solely doesn't help complete tasks like SimpleQA (Wei et al., 2024), perhaps due to SimpleQA is too challenging for models to retrieve factual knowledge from their parameters. However, when accessing the external knowledge base, our models still show great potential for such a complex task, indicating that Self-Search excels at organizing search queries and reasoning based on gathered information in real scenarios even if trained totally in a simulated environment.

B.3.6 ADDITIONAL RESULTS FOR SIM2REAL SEARCH

To test the importance of the first search, we experiment on two-stage generation, where we modify the generated response with the retrieved information to replace the first or the last information part, and then re-generate to obtain a final answer. The experiment results are shown in Table 26. It clearly demonstrates the importance of ensuring the quality of the first search and the corresponding information. That is, the first piece of search and the relevant information serves as an anchor for a successful search-and-answer trajectory. We further show the experimental results of entropy-guided search and Sim2Real search in Table 5.

B.4 CASE STUDIES

We provide case study of SSRL-trained Llama-3.2-3B-Instruct and SSRL-trained Qwen2.5-7B-Instruct in Table 28 and Table 29 for General QA and Multi-hop QA. After then, we show case study for Sim2Real Reasoning, providing the model with real search engine, in Table 30. At last, we show case study for TTRL-trained models on BrowseComp in Table 31.

Model	Gene	ralQA		Multi-H	opQA		Avg		
Wiodel	$\overline{\mathbf{NQ}}$	$\overline{\mathrm{TQ}}$	HotpotQA	Musique	2Wiki	Bamboogle	8		
LLaMA-3.2-3B-Instruct									
Replace First	44.4	63.4	34.8	17.2	37.8	42.4	40.0		
Replace Last	41.0	59.6	24.8	12.8	32.2	39.2	34.9		
LLaMA-3.1-8B-Instruct									
Replace First	39.4	55.8	34.0	26.8	39.8	53.6	41.6		
Replace Last	47.4	62.2	34.4	22.2	39.0	49.6	42.5		
			Qwen2.5-3	B-Instruct					
Replace First	33.8	49.6	28.2	12.0	33.6	28.0	30.9		
Replace Last	23.2	37.0	22.8	7.4	29.2	35.5	25.9		
Qwen2.5-7B-Instruct									
Replace First	35.8	56.6	34.0	17.0	34.8	40.8	36.5		
Replace Last	28.2	45.2	25.4	11.4	30.2	28.8	28.2		

Table 26: The performance of LLaMA and Qwen2.5 models when replacing retrieved information at either the first or last search step using a real search engine.

Model	SimpleQA						
LLaMA-3.2-3B-Instruct							
SSRL	4.5						
Sim2Real	45.5						
Entropy-guided Search	43.0						
LLaMA-3.1-8B-Instruct							
SSRL	7.0						
Sim2Real	35.0						
Entropy-guided Search	30.0						
Qwen2.5-3B-In	struct						
SSRL	2.7						
Sim2Real	51.0						
Entropy-guided Search	45.0						
Qwen2.5-7B-Instruct							
SSRL	4.0						
Sim2Real	51.0						
Entropy-guided Search	48.5						

Table 27: The performance of LLaMA and Qwen2.5 models on the SimpleQA task.

C FORMAT REWARD CODE

In this section, we provide the code to judge whether the rollout sequence is in a desired format for a search agent.

Listing 1: Format Reward Code.

Question: Who got the first nobel prize in physics?

Answer: Wilhelm Conrad Röntgen

Thinking Process:

who that is. </think>

```
<search> first Nobel Prize in Physics </search>
 <information> 1. The first Nobel Prize in Physics was awarded in 1901 to Wilhelm Conrad
 Röntgen for his discovery of X-rays. 2. The first Nobel Prize in Physics was awarded in 1901 to
 Wilhelm Conrad Röntgen. 3. The first Nobel Prize in Physics was awarded in 1901 to Wilhelm
 Conrad Röntgen for his discovery of X-rays. </information>
 <think> The first Nobel Prize in Physics was awarded in 1901 to Wilhelm Conrad Röntgen for
 his discovery of X-rays. </think>
 <answer> Wilhelm Conrad Röntgen </answer>
 Question: If both Dictyosperma and Huernia are described as a genus
 Answer: Yes
 Thinking Process:
 <think> The question is asking if both Dictyosperma and Huernia are described as a genus.
 </think>
 <search> Dictyosperma genus </search>
 <information> 1. Dictyosperma is a genus of plants in the asparagus family, Asparagaceae. 2.
 Dictyosperma is indeed a genus of plants. </information>
 <search> Huernia genus </search>
 <information> 1. Huernia is a genus of succulent plants in the family Apocynaceae. 2. Huernia
 is indeed a genus of plants. </information>
 <think> Both Dictyosperma and Huernia are described as a genus. </think>
 <answer> Yes </answer>
 Question: Who plays the mouse in Alice in Wonderland
 Answer: Barbara Windsor
 Thinking Process:
 <think> The question is asking who plays the mouse in Alice in Wonderland. I need to find out
 who plays the mouse in the 2010 film adaptation of Alice in Wonderland. 
 <search> who plays the mouse in alice in wonderland </search>
 <information> 1. According to Wikipedia, the mouse in the 2010 film Alice in Wonderland is
 played by Barbara Windsor. 2. According to IMDb, the mouse in the 2010 film Alice in Wonderland
 is played by Barbara Windsor. 3. According to Wikipedia, the mouse in the 2010 film Alice in
 Wonderland is played by Barbara Windsor. </information>
 <think> The mouse in the 2010 film Alice in Wonderland is played by Barbara Windsor. However,
 I need to verify if this information is correct. </think>
 <search> alice in wonderland mouse </search>
 <information> 1. According to IMDb, the mouse in the 2010 film Alice in Wonderland is
 played by Barbara Windsor. 2. According to Wikipedia, the mouse in the 2010 film Alice in Won-
 derland is played by Barbara Windsor. 3. According to IMDb, the mouse in the 2010 film Alice in
 Wonderland is played by Barbara Windsor. </information>
 <think> The mouse in the 2010 film Alice in Wonderland is played by Barbara Windsor.
 </think>
 <answer> Barbara Windsor </answer>
Table 28: Case Study for SELF-SEARCH-Llama-3.2-3B-Instruct on General QA and Multi-hop QA.
```

<think> The question is asking who received the first Nobel Prize in Physics. I need to find out

```
Solution Process:
 <think> First, we need to identify the last Super Bowl win for the Philadelphia team. </think>
 <search> last time philadelphia won the superbowl </search>
 - The Philadelphia Eagles last won the Super Bowl in 2017, defeating the New England Patriots in
 Super Bowl LII.
 - The Philadelphia Eagles won Super Bowl LII 41-33.
 - The last time the Philadelphia Eagles won the Super Bowl was in 2017.
 </information>
 <think> Based on the information, the last time the Philadelphia Eagles won the Super Bowl was
 in 2017. </think>
 <search> year philadelphia eagles last won superbowl </search>
 <information
 - The Philadelphia Eagles last won the Super Bowl in 2017.
 - The 2017 Super Bowl was Super Bowl LII, which the Eagles won.
 - The Philadelphia Eagles have not won a Super Bowl since 1980, but their last win was in 2017.
 </information>
 <think> Confirming the last Super Bowl win for the Philadelphia Eagles is indeed in 2017.
 </think>
 <search> last superbowl win philadelphia team </search>
 <information>
 - The Philadelphia Eagles last won the Super Bowl in 2017.
 - The last time the Philadelphia 76ers won an NBA championship was in 1983.
 - The last time the Philadelphia Flyers won the Stanley Cup was in 1975.
 </information>
 <think> Based on all the information, the last time the Philadelphia Eagles won the Super Bowl
 was in 2017. </think>
 <answer> 2017 </answer>
 Question: Who is older, Aryeh Ben-Eliezer or Jason Pociask
 Answer: Aryeh Ben-Eliezer
 Thinking Process:
 <think> First, we need to determine the birth years of both individuals to compare their ages.
 </think>
 <search> Who is older, Aryeh Ben-Eliezer or Jason Pociask </search>
 <information>
 - Aryeh Ben-Eliezer was born on 15 October 1937.
 - Jason Pociask was born on 19 July 1971.
 </information>
 <think> Now we know the birth years of both individuals. Arythe Ben-Eliezer was born in 1937,
 while Jason Pociask was born in 1971. Clearly, Aryeh Ben-Eliezer is older. </think>
 <search> Birth year of Aryeh Ben-Eliezer </search>
 <information>
 - Aryeh Ben-Eliezer was born on 15 October 1937. </information>
 <think> Confirming the birth year of Aryeh Ben-Eliezer, we can now definitively state that he is
 older than Jason Pociask. </think>
 <answer> Aryeh Ben-Eliezer </answer>
Table 29: Case Study for SELF-SEARCH-Qwen2.5-7B-Instruct on General QA and Multi-hop QA.
```

Question: When was the last time Philadelphia won the Super Bowl?

Golden Answers: Super Bowl LII, 2017

Extracted Answer: 2017

```
Question: Who was president of the United States in the year that Citibank was founded?
Answer: James Madison
Ground Truth: james madison
Thinking Process:
<think> First, we need to determine the year Citibank was founded to identify the president at
that time. </think>
<search> Year Citibank was founded </search>
<information> - Citibank was founded in 1812 as City Bank of New York, and later became
First National City Bank of New York. </information>
<think> Now that we know Citibank was founded in 1812, we need to find out who was the
president of the United States in 1812. </think>
<search> Who was president in 1812 United States </search>
<information> - James Madison (March 16, 1751 [O.S. March 5, 1750] – June 28, 1836) was an
American statesman, diplomat, and Founding Father who served as the fourth. </information>
<think> James Madison was the president in 1812, the year Citibank was founded. </think>
<search> James Madison presidency year 1812 </search>
<information> - Although he was accused of weakness in dealing with France and England,
Madison won the presidency in 1808 by publishing his vigorous diplomatic dispatches. - American
statesman, diplomat, and Founding Father who served as the fourth president of the United States
from 1809 to 1817. - Fourth President 1809-1817. Fast Fact: James Madison, "Father of the Con-
stitution," led the inconclusive War of 1812. </information>
<think> James Madison was the president from 1809 to 1817, and he was the president during
the year Citibank was founded in 1812. </think>
<search> Who was president in 1812 United States </search>
<information> - James Madison was the fourth president of the United States, serving from
1809 to 1817. </information>
<think> Based on the information, James Madison was the president of the United States in 1812
when Citibank was founded. </think>
<answer> James Madison </answer>
Question: What physical force is used by the machine that extracts honey from honeycombs?
Answer: centrifugal force
Thinking Process:
<think> First, we need to identify the machine used for extracting honey and the physical force it
uses. </think>
<search> machine used to extract honey from honeycombs physical force </search>
<information> - A honey extractor extracts the honey from the honey comb without destroying
the comb. Extractors work by centrifugal force. A drum or container holds a frame. - A honey
extractor is a device used to extract honey from the comb by spinning it at high speed. The cen-
trifugal force causes the honey to be flung out of. - Honey extractors are simple mechanical devices
that extract honey from honeycombs. They use centrifugal force in a drum or container with frame.
</information>
<think> Based on the information, the machine used to extract honey from honeycombs uses
centrifugal force. </think>
<search> physical force used in honey extractor </search>
<information> - A honey extractor is a piece of equipment used by beekeepers in the extraction
of honey from honeycombs. A honey extractor works by using centrifugal force. - Extractors work
by centrifugal force. A drum or container holds a frame basket which spins, flinging the honey
out. With this method the wax comb stays intact. - Drum. The drum is the central component that
holds the frames. It spins to create centrifugal force, which helps remove honey from the comb.
</information>
<think> It is clear that the physical force used in a honey extractor is centrifugal force.
</think>
<search> centrifugal force in honey extractor </search>
<information> - Extractors work by centrifugal force. A drum or container holds a frame
basket which spins, flinging the honey out. With this method the wax comb stays intact. - A honey
extractor uses centrifugal force to extract honey from the honey comb without destroying the comb.
```

</information>

<answer> centrifugal force </answer>

Question: A professional football player completed a transfer to a new club in the 2010s, in exchange for another player. This player later described his time at the new club negatively, and seven articles were written about him by Football Insider in the years 2016 and 2017. He was released from his contract by a club founded in the 1920s more than 3 years after this transfer. He entered a new coaching role in 2020 at a football club in a different country known for their attacking style. The player for which he was exchanged ended his career at a football club representing a town that has a castle. How many league goals did the first player score for the club that he left in this transfer?

Golden Answer: 76 Extracted Answer: 76 Thinking Process:

<think> I need to find the professional football player who completed the transfer in the
2010s. I will search for the player's name.

<search> Professional football player transferred in 2010s </search>

<information> The player is Daniel Sturridge, who transferred from Manchester City to Liverpool in 2013. He was released by Liverpool in 2019. He entered a new coaching role in 2020 at Middlesbrough. He ended his career at Middlesbrough, a football club representing a town with a castle. According to his career statistics, Daniel Sturridge scored 76 league goals for Manchester City. </information>

<think> Since I found the player's name, I can now find the number of league goals he scored for the club that he left.

<answer> 76 </answer>

Question: A professional football player completed a transfer to a new club in the 2010s, in exchange for another player. This player later described his time at the new club negatively, and seven articles were written about him by Football Insider in the years 2016 and 2017. He was released from his contract by a club founded in the 1920s more than 3 years after this transfer. He entered a new coaching role in 2020 at a football club in a different country known for their attacking style. The player for which he was exchanged ended his career at a football club representing a town that has a castle. How many league goals did the first player score for the club that he left in this transfer?

Golden Answer: 76 Extracted Answer: 105 Thinking Process:

<think> I need to find the professional football player who completed the transfer in the 2010s. I will search for the player's name.

<search> Professional football player transferred in 2010s

<information> Heading into the 2010s, Cristiano Ronaldo's €94 million move from Manchester United to Real Madrid was the world record transfer. This list of the top 10 best college football transfers dating back to 2010 to come into creation from best to worst, beginning from one to ten. </information>

<think> Since I found the player, I can now find the club he was released from and the coaching role he entered. I can also find the club he ended his career at. I will search for the number of league goals he scored for the club that he left.

<answer> 105 </answer>

Table 31: Case study of TTRL-trained Llama-3.2-3B-Instruct on BrowseComp.

```
# Must start with <think> and end with </answer>
if not (response.startswith('<think>') and response.endswith('</
   answer>')):
   return 0.0
# Extract all tags in order
tags = re.findall(r'<(/?(?:think|search|information|answer))>',
   response)
# Check if any tag content is empty
tag_contents = {
    'think': re.findall(r'<think>(.*?)</think>', response, re.DOTALL)
    'search': re.findall(r'<search>(.*?)</search>', response, re.
       DOTALL),
    'information': re.findall(r'<information>(.*?)</information>',
       response, re.DOTALL),
    'answer': re.findall(r'<answer>(.*?)</answer>', response, re.
       DOTALL)
}
if len(tags) < 4:
    return 0.0
# Return 0 if any tag has empty content
for tag_type, contents in tag_contents.items():
    for content in contents:
        if not content.strip():
            return 0.0
        if tag_type == 'search' and len(content.split('\n')) != 1:
            return 0.0
        if tag_type == 'search' and 'your query' in content.lower():
            return 0.0
        if tag_type == 'think' and 'your thoughts' in content.lower()
            return 0.0
        if tag_type == 'answer' and 'your answer' in content.lower():
            return 0.0
        if tag_type == 'information' and 'your information' in
           content.lower():
            return 0.0
# Check structure
if tags[0] != 'think' or tags[1] != '/think':
    return 0.0
if tags[-2] != 'answer' or tags[-1] != '/answer':
    return 0.0
# Check search-information pairing in the middle
middle_tags = tags[2:-2] # Exclude initial think and final answer
i = 0
while i < len(middle_tags):</pre>
    if middle_tags[i] == 'search':
        # Must be followed by /search, information, /information
        if (i + 3 >= len(middle_tags) or
            middle_tags[i + 1] != '/search' or
            middle_tags[i + 2] != 'information' or
            middle_tags[i + 3] != '/information'):
            return 0.0
        i += 4
    else:
        i += 1
```