

RAG-R1 : INCENTIVIZE THE SEARCH AND REASONING CAPABILITIES OF LLMs THROUGH MULTI-QUERY PARALLELISM

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ABSTRACT

Large Language Models (LLMs) have demonstrated remarkable capabilities across various tasks, while they remain prone to generating hallucinated or outdated responses due to their static internal knowledge. Recent advancements in Retrieval-Augmented Generation (RAG) methods have explored enhancing models’ search and reasoning capabilities through reinforcement learning (RL). Although these methods demonstrate promising results, they face challenges in training stability and encounter issues such as substantial inference time and restricted capabilities due to the single-query mode. In this paper, we propose RAG-R1, a novel training framework designed to enable LLMs to adaptively leverage internal and external knowledge during the reasoning process. We further expand the generation and retrieval processes within the framework from single-query mode to multi-query parallelism, aimed at reducing inference time and enhancing the model’s capabilities. Extensive experiments on seven question-answering benchmarks demonstrate that our method outperforms the strongest baseline by up to 13.2% and decreases inference time by 11.1%. The code and model checkpoints are available at <https://github.com/inclusionAI/AgenticLearning/tree/main/RAG-R1>.

1 INTRODUCTION

Large Language Models (LLMs) (Zhao et al., 2025; et al., 2025b) have demonstrated remarkable capabilities in various domains, including mathematical reasoning, question answering, and code generation. However, the knowledge encoded in these models is static, limiting their adaptability. As a result, LLMs are susceptible to producing hallucinated or outdated responses (Ji et al., 2023; Shuster et al., 2021; Asai et al., 2023) when dealing with complex or real-time issues, compromising their reliability. Therefore, it is essential to equip LLMs with access to external knowledge to ensure more accurate and grounded responses.

Retrieval-Augmented Generation (RAG) (Gao et al., 2024; Fan et al., 2024) is a widely adopted approach to address this issue, broadening the model’s capability boundaries by integrating external knowledge into the generation process. Early efforts (Shao et al., 2023; Ram et al., 2023a) in this area focused on prompt-based strategies that guide LLMs through question decomposition, query rewriting and multi-turn retrieval. While effective, these approaches are limited by prompt engineering. Recent advances (Trivedi et al., 2023; Li et al., 2025; Asai et al., 2023; Guan et al., 2025; Wang et al., 2025) have increasingly emphasized the integration of reasoning capabilities within RAG. These approaches combine RAG with Chain of Thought (CoT) for step-by-step retrieval, or automatically generate intermediate retrieval chains that incorporate reasoning and employ Supervised Fine-Tuning (SFT) to enable learning of retrieval and reasoning. However, new insights (Chu et al., 2025) indicate that these methods may cause models to memorize solution paths, thus constraining their generalization to novel scenarios.

Recently, reinforcement learning (RL) (Schulman et al., 2017) has demonstrated great potential in improving LLM performance by enhancing the reasoning capability. Reasoning models such as OpenAI-o1 (et al., 2024b) and Deepseek-R1 (et al., 2025b) indicate that utilizing RL with outcome-

based rewards can enhance the model’s performance in mathematical and logical reasoning tasks. Within this paradigm, several works have explored enhancing the model’s search ability during reasoning through RL. R1-Searcher (Song et al., 2025) proposes a novel two-stage outcome-based RL approach designed to enhance the search capability of LLMs. Search-R1 (Jin et al., 2025) introduces a novel RL framework that enables LLMs to interact with search engines in an interleaved manner with their own reasoning. Despite significant improvements, these RL-based methods struggle with stable training due to the restricted capabilities of cold-start models (et al., 2025b). Furthermore, existing methods generate only a single search query whenever external retrieval is required, which presents two significant challenges: (1) **Substantial Retrieval Iterations and Inference Time**: The model generally requires multi-turn interleaved reasoning and search in single-query mode, particularly when dealing with multi-hop reasoning problems. This results in increased inference time, hindering its applicability in real-world scenarios. (2) **Restricted External Knowledge**: In single-query mode, the limited knowledge acquired from retrieval restricts the model’s ability to thoroughly explore the extent of its reasoning capability during training, thereby impacting its overall performance.

To address the aforementioned challenges, we propose RAG-R1, a novel training framework that enables LLMs to adaptively leverage internal and external knowledge during the reasoning process and improves the reasoning ability to answer questions correctly. We further expand the generation and retrieval processes within the framework from single-query mode to multi-query parallelism to reduce the model’s inference time and enhance its capabilities. Specifically, the training framework contains two stages, i.e., Format Learning Supervised Fine-Tuning and Retrieval-Augmented Reinforcement Learning. In the first stage, we thoughtfully generate samples that integrate reasoning and search to equip LLMs with the ability to adaptively leverage internal and external knowledge during the reasoning process and response in a think-then-search format. In the second stage, we employ outcome-based RL with a retrieval environment to improve the model’s ability to reason and dynamically retrieve external knowledge to answer questions correctly. Building upon the training framework, we expand the generation and retrieval processes from single-query mode to multi-query parallelism. This approach reduces retrieval rounds and inference time, supplying the model with more comprehensive and diverse information and ultimately boosting its performance.

We conduct extensive experiments based on Qwen2.5-7B-Instruct (et al., 2024a) to verify the effectiveness of our proposed method. The results demonstrate its effectiveness, which achieves state-of-the-art performance on seven question answering benchmarks. In particular, our method utilizing multiple-query parallelism outperforms the strongest baseline by up to 13.2% and decreases inference time by 11.1%.

The contributions of this work are summarized as follows:

- We propose RAG-R1, a novel training framework that empowers LLMs with the ability to adaptively leverage internal and external knowledge during the reasoning process and improves the reasoning ability to answer questions correctly.
- We further expand the generation and retrieval processes within the framework from single-query mode to multi-query parallelism, which not only reduces retrieval rounds and inference time of the model, but also further boosting its performance.
- Extensive experiments demonstrate the effectiveness of our proposed method, which achieves state-of-the-art performance on seven question answering benchmarks and significantly decreases retrieval rounds and inference time.

2 RELATED WORK

Retrieval-Augmented Generation RAG enhances LLMs outputs by integrating external information with internal knowledge. Initial RAG methods employed static pipelines, coupling retrieved documents with LLMs via prompt engineering (Shi et al., 2023; Ram et al., 2023b; Lin et al., 2023; Korikov et al., 2024) to control generation. While effective for information-sourcing tasks, these approaches struggle with complex, multi-faceted queries requiring iterative retrieval. Subsequent research developed dynamic RAG frameworks (Jeong et al., 2024) that utilize LLM feedback for adaptive retrieval and generation control. Complementary efforts have focused on improving knowledge representation of retrieved documents (Edge et al., 2024; Guo et al., 2025) from augmentation

perspectives. Most recently, advances (Jin et al., 2025; Li et al., 2025; Song et al., 2025; Sun et al., 2025; Wu et al., 2025) demonstrate significant scalability potential by training interaction trajectories to optimize LLM’s use of search engines for complex problem-solving queries. Following these advances, our method further enhances the interaction between LLMs and retrievers by leveraging LLM’s reasoning abilities.

Learning to Search Recent advances in Learning to Search have evolved from static query and generation template via SFT to dynamic and reward-driven search using RL. SFT-based approaches have demonstrated success in improving LLM capabilities in instruction following (Dong et al., 2024b;a; Li et al., 2024), robustness (Dong et al., 2024c), and domain-specific adaptation (Zhang et al., 2024). However, these methods are limited by a tendency to memorize solution paths, which constrains generalization and scalability. RL-based methods (et al., 2024b; 2025b; Shao et al., 2024; et al., 2025a) offer a promising alternative by enabling autonomous reasoning and decision-making. Recent works (Li et al., 2025; Song et al., 2025; Jin et al., 2025) further integrate LLMs into real-time search workflows, allowing interaction with live search engines. Although these methods support autonomous search engine invocation, the efficacy of search-as-a-tool remains underexplored. To address this, our approach introduces a two-stage training framework that enables parallel query generation, with the aim of retrieving more comprehensive and diverse document contexts.

3 TRAINING FRAMEWORK

In this section, we introduce the RAG-R1 training framework, which aims to empower LLMs with the ability to adaptively leverage internal and external knowledge during reasoning through two stages, i.e., Format Learning Supervised Fine-Tuning and Retrieval-Augmented Reinforcement Learning. Specifically, in the first stage, we thoughtfully generate samples that integrate reasoning and search, segmenting them into four categories. We then apply SFT based on these segmented samples to teach LLMs generating responses in a think-then-search format and enable it to leverage internal and external knowledge adaptively. In the second stage, we conduct data selection and employ outcome-based RL with a retrieval environment to enhance the model’s ability to reason and dynamically retrieve external knowledge to answer questions correctly. The overall framework is shown in Figure 1.

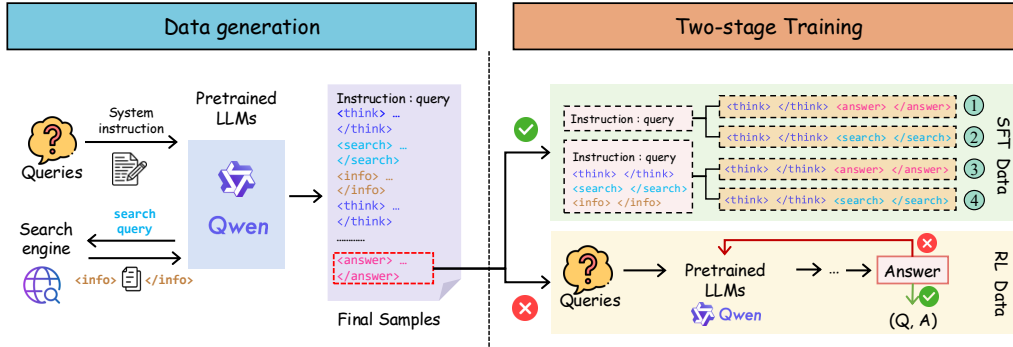


Figure 1: Overall framework of our proposed method.

3.1 FORMAT LEARNING SUPERVISED FINE-TUNING

3.1.1 SFT DATA GENERATION

To equip LLMs with the ability to adaptively leverage internal and external knowledge during reasoning and response in a think-then-search format, we first generate samples that integrate reasoning and search. Specifically, the system instruction guides the LLM to perform reasoning between `<think>` and `</think>` whenever it receives new information. After completing the reasoning process, the LLM can generate search query between the designated search call tokens, `<search>` and `</search>`, whenever external retrieval is necessary. The system will subsequently extract the

search query and request an external search engine to retrieve relevant documents. The retrieved information is then appended to the existing sequence, enclosed within special retrieval tokens, `<information>` and `</information>`, providing additional context for the next generation step. This process continues iteratively until reaching the maximum number of retrieval or the model generates a final answer enclosed within the special answer tokens, `<answer>` and `</answer>`. The system instruction follows Jin et al. (2025) and is shown in Table 1.

Table 1: System instruction of SFT data generation.

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 your 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: `question`

We use Qwen2.5-72B-Instruct (et al., 2024a) as the generation model and employ a portion of the HotpotQA (Yang et al., 2018) training dataset for generation tasks.

3.1.2 SFT DATA SEGMENTATION AND TRAINING

After generating the samples, we selected those with correct answers and segment them into four categories according to specific segmentation points. As illustrated in Figure 1, we segment the samples at corresponding points whenever the model needs to perform reasoning or retrieval, thereby preventing the model from generating retrieval documents. In this manner, a complete sample might be split into multiple smaller samples, which can then be classified into four distinct categories.

By employing the first and second categories of samples, we train the model to respond by adaptively leveraging internal and external knowledge, respectively. In contrast, by utilizing the third and fourth categories of samples, we expect the model to perform reasoning and generate subsequent steps primarily based on external knowledge. Notably, the output section of the samples does not include retrieved documents, which aids in preventing the model from generating hallucinations.

After segmentation, we use these samples to perform SFT to teach the model generating responses in a think-then-search format and enable it to leverage internal and external knowledge adaptively. This stage aims to develop a highly capable model that can respond in a think-then-search format, serving as a cold-start model to enhance the stability of the subsequent RL training stage.

3.2 RETRIEVAL-AUGMENTED REINFORCEMENT LEARNING

3.2.1 RL DATA SELECTION

After Format Learning SFT, we obtain a model that can adaptively leverage internal and external knowledge during the reasoning process and response in a think-then-search format. To further enhance the model’s reasoning ability and enable it to answer questions accurately, we begin with data selection to identify challenging yet answerable questions suitable for RL.

Specifically, we select the samples that generate incorrect answers in Section 3.1.1. The questions of these samples present a relative challenge to the model. We subsequently filter out samples that are inherently unanswerable due to incomplete data retrieval or model limitations. We implement stochastic sampling for Qwen2.5-72B-Instruct with the sampling temperature of 1.2 and the maximum number of retrieval to 10. For each question, we conduct up to 10 rollouts and retain only samples containing at least one correct solution. Finally, we obtain 2488 samples which are challenging yet answerable and randomly selected 25% of the correctly answered samples in Section 3.1.1 to construct the final training dataset.

3.2.2 RL WITH RETRIEVAL

We extend reinforcement learning to utilize an external retrieval system. The RL objective function utilizing an external retrieval system \mathcal{R} can be represented as follows:

$$\max_{\pi_{\theta}} \mathbb{E}_{x \sim D, y \sim \pi_{\theta}(\cdot|x; \mathcal{R})} [r_{\phi}(x, y)] - \beta \mathbb{D}_{KL}[\pi_{\theta}(y|x; \mathcal{R}) || \pi_{ref}(y|x; \mathcal{R})] \quad (1)$$

where π_{θ} and π_{ref} represent the policy model and the reference model, respectively, both of which are initialized from the SFT model, r_{ϕ} is the reward function and \mathbb{D}_{KL} is KL-divergence. x denote input samples drawn from the dataset D , and y represent the generated outputs which is sampled from the policy model π_{θ} and retrieved from the retrieval system \mathcal{R} . The rollout process follows the same procedure detailed in Section 3.1.1. We employ the Proximal Policy Optimization (PPO) (Schulman et al., 2017) algorithm to optimize the policy model, which is widely used in reinforcement learning due to its efficiency and reliability.

Retrieval Masked Loss In our framework, the rollout sequence consists of both LLM-generated tokens and retrieved tokens from the external retrieval system. To prevent retrieved tokens from interfering with the inherent reasoning and generation capabilities of the model, we implement a masked loss for these tokens. By computing the policy gradient objective exclusively on the LLM-generated tokens and excluding the retrieved content from optimization, this approach stabilizes training while preserving the adaptability and benefits of retrieval-augmented generation.

Reward Modeling The reward function serves as the primary training signal, which decides the optimization direction of RL. Inspired by et al. (2025b), we adopt a rule-based reward system that includes final answer rewards to assess the accuracy of responses. For instance, in factual reasoning tasks, we adopt rule-based criteria such as exact string matching (EM) to evaluate correctness:

$$r_{\phi}(x, y) = EM(a_{pre}, a_{gold}) \quad (2)$$

where a_{pre} represents the extracted final answer from response y and a_{gold} denotes the ground truth answer. We avoid incorporating format rewards because the SFT model has already learned to respond in a think-then-search format. Furthermore, following et al. (2025b), we do not apply neural reward models to avoid reward hacking and additional computational cost.

Utilizing the SFT model, which can adaptively leverage internal and external knowledge, as the cold-start model improves the stability of RL training. Furthermore, by incorporating retrieval into outcome-based RL, we improve the model’s reasoning capability and its ability to dynamically access external knowledge to accurately answer questions.

4 MULTI-QUERY PARALLELISM

By enabling the model to adaptively leveraging internal and external knowledge during reasoning, the capability boundaries of the model are significantly extended. However, existing methods generate only a single search query whenever external retrieval is required, which results in substantial retrieval iterations and limited knowledge acquired from retrieval. To enhance inference efficiency and the model’s capabilities, we further expand the generation and retrieval process within the framework from single-query mode to multi-query parallelism.

Specifically, we guide the model to generate multiple search queries whenever external retrieval is required. The external retrieval system then performs parallel searches with these queries and returns the results to the model in a JSON format, ensuring clear alignment between the search queries and the retrieved documents. Compared to single-query retrieval, multi-query parallel retrieval decreases the total number of retrievals needed, while maintaining comparable time for each retrieval. This approach is particularly beneficial for comparison-type questions, allowing for improved inference efficiency without compromising the model’s effectiveness. Moreover, by generating multiple search queries for parallel retrieval, the model can obtain more comprehensive and diverse information in a single interaction, which aids in subsequent decision-making. This enriched information acquisition further broadens the model’s capability boundaries, thereby augmenting its overall effectiveness.

Table 2 illustrates the system instructions for generating multiple search queries. We restrict the model to generate at most three parallel search queries simultaneously. The retrieval system returns the results in a JSON format which contains:

- **query**: A list of search queries generated by the model.
- **documents**: A list containing the retrieved documents corresponding to the search queries.

Utilizing the above format allows the model to recognize the alignment between search queries and retrieved documents. The remaining aspects of the training process are consistent with those outlined in Section 3. More case studies are available in Appendix B

Table 2: System instruction for generating multiple search queries.

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_1,query_2 `</search>` and it will return the top searched results for each query between `<information>` and `</information>`. You can search as many times as your want, using up to three queries each time. 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: `question`

5 EXPERIMENTS

5.1 EXPERIMENTAL SETTINGS

Datasets and Evaluation Metrics We evaluate our models on seven benchmark datasets: (1) **General Question Answering**: NQ (Kwiatkowski et al., 2019), TriviaQA (Joshi et al., 2017), and PopQA (Mallen et al., 2023). (2) **Multi-Hop Question Answering**: HotpotQA (Yang et al., 2018), 2WikiMultiHopQA (Ho et al., 2020), Musique (Trivedi et al., 2022), and Bamboogle (Press et al., 2023). HotpotQA is in-domain benchmark since a portion of its training sets is used for training while others serve as out-of-domain benchmarks to assess our model’s generalization capabilities. For evaluation metric, we utilize Exact Match (EM) following Yu et al. (2024).

Baselines We compare our method against the following baselines: (1) **Naive Generation**: Generating answers directly without retrieval. (2) **Standard RAG**: Traditional retrieval-augmented generation systems. (3) **RAG-CoT Methods**: Integration of retrieval-augmented generation with chain-of-thought prompts, such as IRCot (Trivedi et al., 2023) and Search-o1 (Li et al., 2025). (4) **RAG-RL Methods**: Utilizing reinforcement learning to allow the model to autonomously perform retrieval during inference, such as Search-R1 (Jin et al., 2025) and R1-Searcher (Song et al., 2025).

Implementation Details We utilize Qwen-2.5-7B-Instruct as the backbone models for our training and all baselines. For retrieval, we use the English Wikipedia provided by KILT (Petroni et al., 2021) in 2019 as retrieval corpus, segmented into 100-word passages with appended titles, totaling 29 million passages. We employ BGE-large-en-v1.5 (Chen et al., 2023) as the text retriever and set the number of retrieved passages to 3 across all retrieval-based methods to ensure fair comparison. The maximum number of retrieval is set to 4. More details on the experimental settings are provided in Appendix A.

Table 3: Performance comparisons on QA benchmarks under the EM metric. The best and second best results are **bold** and underlined, respectively.

Methods	General QA			Multi-Hop QA				Avg.
	NQ	PopQA	TriviaQA	HotpotQA	2Wiki	Musique	Bamboogle	
Direct Inference	0.132	0.148	0.360	0.183	0.236	0.031	0.080	0.167
Standard RAG	0.328	0.353	0.476	0.284	0.253	0.048	0.152	0.271
IRCoT	0.183	0.328	0.434	0.276	0.356	0.060	0.144	0.254
Search-o1	0.277	0.294	0.474	0.348	0.384	0.107	0.296	0.311
Search-R1	0.387	0.422	0.531	0.377	0.351	0.135	0.376	0.368
R1-Searcher	0.404	0.410	0.522	0.442	<u>0.513</u>	0.158	0.368	0.402
RAG-R1-sq	0.429	0.477	0.599	0.474	0.481	<u>0.181</u>	0.432	0.439
RAG-R1-mq	<u>0.423</u>	0.479	0.608	0.495	0.556	0.192	0.432	0.455

5.2 MAIN RESULTS

The main results comparing RAG-R1 with baseline methods across the seven datasets are presented in Table 3. RAG-R1-sq denotes our method operating in single-query mode while RAG-R1-mq represent the overall framework incorporating multi-query parallelism. From the results, we can obtain the following key observations:

- **Significant improvements across all datasets** Our method achieves significant improvements compared to all baseline methods across both General QA and multi-hop QA benchmarks, including both CoT-based methods and RL-based methods. Specifically, RAG-R1-mq outperforms the best RL-based method R1-Searcher by 13.2% across all datasets. These results demonstrate that our approach enables the model to effectively utilize both internal and external knowledge throughout the reasoning process.
- **Effectiveness of Multi-query Parallelism** RAG-R1-mq outperforms all RL-based approaches that generate a single search query whenever external retrieval is required, including our own RAG-R1-sq. This highlights that multi-query parallelism not only boosts inference efficiency but also effectively utilizes comprehensive and diverse information for reasoning, thereby improving the model’s performance. Further details are available in Section 6.2.
- **Excellent generalization Ability** Despite utilizing only a subset of the HotpotQA training data, our models achieve significant improvements on in-domain datasets and exhibit excellent generalization capabilities across out-of-domain datasets, such as 2WikiMultiHopQA and Musique. This demonstrates that our models have effectively learned to reason and retrieve information for diverse questions, which proves the effectiveness of our approach across various scenarios requiring retrieval. Moreover, it can effectively extend to online search, as detailed in Section 6.3.

Table 4: Ablation study of SFT, RL and RL Data Selection.

Methods	HotpotQA	2Wiki	Musique	Bamboogle	Avg.
RAG-R1-sq	0.474	0.481	0.181	0.432	0.392
RAG-R1-sq <i>w/o SFT</i>	0.415	0.406	0.138	0.312	0.318
RAG-R1-sq <i>w/o RL</i>	0.425	0.433	0.150	0.368	0.344
RAG-R1-sq <i>w/o Filter</i>	0.452	0.442	0.159	0.408	0.365
RAG-R1-mq	0.495	0.556	0.192	0.432	0.419
RAG-R1-mq <i>w/o SFT</i>	0.413	0.423	0.129	0.392	0.339
RAG-R1-mq <i>w/o RL</i>	0.427	0.490	0.143	0.424	0.371
RAG-R1-mq <i>w/o Filter</i>	0.491	0.543	0.186	0.424	0.411

Table 5: Average time and retrieval count of different methods.

Methods	HotpotQA		2Wiki		Avg.	
	Time	RC	Time	RC	Time	RC
Search-R1	7.79	2.44	8.90	3.01	8.35	2.73
R1-Searcher	10.98	2.31	10.93	2.40	10.96	2.36
RAG-R1-sq	7.69	2.13	8.72	2.93	8.21	2.53
RAG-R1-mq	6.72	1.87	8.11	2.42	7.42	2.15

6 FURTHER ANALYSIS

6.1 ABLATION STUDY

To validate the effectiveness of our proposed training framework, we conduct a comprehensive ablation analysis of its key design elements.

SFT and RL As shown in Table 4, *w/o SFT* removes the initial format learning SFT while *w/o RL* removes the entire RL training stage. The results demonstrate the necessity and effectiveness of both

SFT and RL in our training framework, which together improve the model’s performance. Specifically, *w/o SFT* struggles to leverage internal and external knowledge, resulting in decreased performance. In contrast, *w/o RL* restricts the model’s capability to correctly answer questions through reasoning. The considerable improvement achieved through RL highlight its ability to significantly enhance the model’s capability.

RL Data Selection We further validate the effectiveness of data selection during the RL process. We trained the models using all samples with incorrect answers and 25% of the samples with correct answers in Section 3.1.1, denoted as RAG-R1-sq *w/o Filter* and RAG-R1-mq *w/o Filter* respectively. The decline in performance indicates that careful data selection plays a crucial role in enhancing the effectiveness of RL training. Unanswerable samples do not facilitate the model’s improvement and may even detrimentally impact the training process.

6.2 EFFECTS OF MULTI-QUERY PARALLELISM

As shown in Table 5, we record the average inference time (in seconds) and average retrieval count for different methods on HotpotQA and 2WikiMultiHopQA using A100 GPUs without employing any inference acceleration technique. The results show that RAG-R1-mq achieves the lowest inference time and retrieval count, indicating that multi-query parallelism can significantly enhance the efficiency of the model. Furthermore, according to Table 3, our approach incorporating multi-query parallelism achieves the highest accuracy, demonstrating its effectiveness in enhancing the model’s capabilities. By comparing the responses of single-query mode and multi-query parallelism, we find that the improvement in effectiveness mainly comes from two aspects: (1) Multi-query parallelism reduces the number of retrieval while obtaining the correct answer, whereas single-query often fails to find the answer due to the limitation on the maximum number of retrieval. (2) Multi-query parallelism is capable of rewriting the query based on all existing information and conducting an additional retrieval when no effective information is found, whereas single-query mode lacks this ability. More case studies can be found in Appendix B. Consequently, multi-query parallelism not only boosts the model’s inference efficiency but also expands the boundaries of its capabilities.

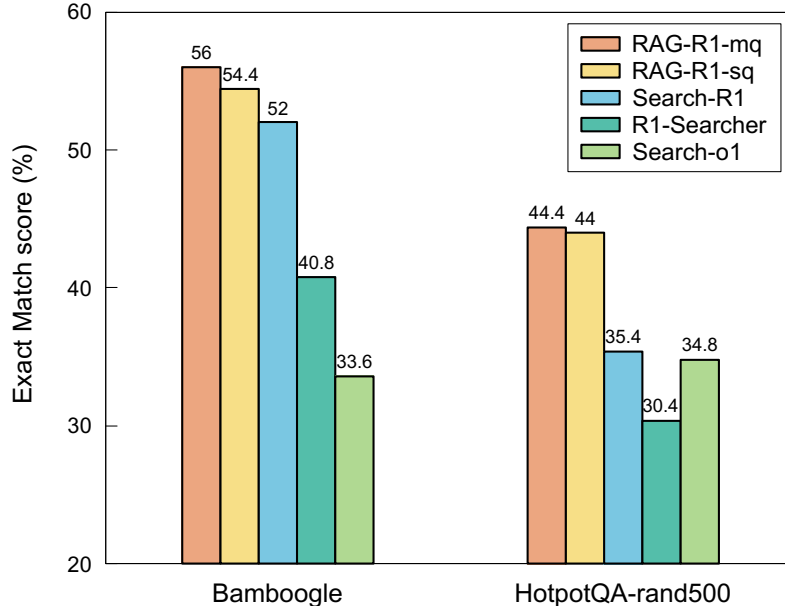


Figure 2: Performance comparisons of our models and baselines in online search scenarios.

6.3 GENERALIZATION TO ONLINE SEARCH

Considering training efficiency and cost, we employ a local dense embedding retrieval system utilizing Wikipedia as a static external retrieval corpus throughout the training process. This contrasts

with most real-world applications, which depend on online web search. To demonstrate the generalization capability of RAG-R1 in such scenarios, we assess our models’ performance on two benchmarks: Bamboogle and a randomly selected set of 500 samples from HotpotQA, utilizing online web search—a setting not encountered during training. Specifically, during inference, whenever retrieval is necessary, we leverage the Google API to perform real-time web searches and obtain relevant web pages. Subsequently, we utilize BeautifulSoup4 to scrape information from these pages and employ GPT-4o-mini to generate concise summaries, which are then incorporated into the reasoning process. As illustrated in Figure 2, RAG-R1-mq achieves the best EM score among all compared methods, highlighting its strong adaptability to online search scenarios. These findings suggest that our approach equips the model to dynamically retrieve information during the reasoning process, rather than merely memorizing response formats.

7 CONCLUSION

In this paper, we propose RAG-R1, a novel training framework that enables LLMs to adaptively leverage internal and external knowledge during the reasoning process and improves the reasoning ability to answer questions correctly. We further expand the generation and retrieval processes within the framework from single-query mode to multi-query parallelism to reduce the model’s inference time and enhance its capabilities. Extensive experiments on seven question answering benchmarks demonstrate the effectiveness of our method. In particular, our method utilizing multiple-query parallelism outperforms the strongest baseline by up to 13.2% and decreases inference time by 11.1%. Additionally, we conduct a comprehensive ablation analysis of its key design elements to assess the effectiveness of each component.

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A IMPLEMENTATION DETAILS

We utilize Qwen-2.5-7B-Instruct as the backbone models for our training and all baseline models. For retrieval, we use the English Wikipedia provided by KILT (Petroni et al., 2021) in 2019 as retrieval corpus, segmented into 100-word passages with appended titles, totaling 29 million passages. We employ BGE-large-en-v1.5 (Chen et al., 2023) as the text retriever and set the number of retrieved passages to 3 across all retrieval-based methods to ensure fair comparison. The maximum number of retrieval is set to 4.

In Format Learning SFT, we collect 18994 samples for single-query training and 19303 samples for multi-query parallelism training. We set the input length to 8192 and the output length to 2048. We perform full-parameter SFT for 5 epochs and chose the checkpoint with the lowest validation loss for evaluation and subsequent RL training.

In Retrieval-Augmented RL, we collect 5022 samples for single-query training and 7015 samples for multi-query parallelism training. We split 95% of all the samples into a training set and used the remaining as a validation set. For the PPO variant, we set the learning rate of the policy LLM to $1e-6$ and that of the value LLM to $1e-5$. The training step is 500, with warm-up ratios of 0.285 and 0.015 for the policy and value models, respectively. We use Generalized Advantage Estimation (GAE) (Schulman et al., 2018) with parameters $\lambda = 1$ and $\gamma = 1$. All the trainings are conducted on a single node with 8 A100 GPUs. We configure the batch settings as follows: a total batch size of 512, a mini-batch size of 128, and a micro-batch size of 32. The maximum sequence length is 8,192 tokens, with a maximum response length of 500 and retrieved content lengths set to a maximum of 1000 tokens for each search query.

For evaluation, we set the maximum number of retrieval to 5, with a maximum response length of 1024 and the temperature setting of 0.7. The evaluation metric employed is Exact Match (EM).

B CASE STUDY

Table 6: Comparison of the format for single-query and multi-query parallelism

Question: Which magazine was started first Arthur's Magazine or First for Women?
Ground Truth: Arthur's Magazine
Single-query: <think> To determine which magazine was started first between Arthur's Magazine and First for Women, I need to find the founding years of both magazines. </think> <search> founding year of Arthur's Magazine </search> <information> Doc 1: Arthur (magazine) moved Arthur's headquarters from Los Angeles to New York, the seat of North America's publishing industry. On March 6, 2011, Jay Babcock announced that the magazine would cease to exist in any form as of March 15, 2011, though its archive and store would remain active for an unspecified period thereafter.. </information> ----- <think> From the search results, I found that Arthur's Magazine was published from 1844 to 1846. Now, I need to find the founding year of First for Women. </think> <search> founding year of First for Women magazine </search> <information> Doc 1: First for Women - Wikipedia First for Women is an American women's interest magazine published by Bauer Media Group. It was founded in 1978 and is based in New York City. The magazine focuses on topics such as health, beauty, relationships, and personal finance. It is known for its practical advice and real-life stories. First for Women has a circulation of over 1 million readers and is available in both print and ... </information> ----- <think> First for Women was founded in 1978. Comparing the founding years, Arthur's Magazine (1844) is clearly older than First for Women (1978). </think> <answer> Arthur's Magazine </answer>
Multiple-query parallelism: <think> To determine which magazine was started first, I need to compare the founding years of both "Arthur's Magazine" and "First for Women." </think> <search> Arthur's Magazine founding year, First for Women founding year </search> <information> { "query": ["Arthur's Magazine founding year", "First for Women founding year"], "documents": ["Doc 1: Arthur's Magazine Arthur's Magazine Arthur's Magazine (1844-1846) was an American literary periodical published in Philadelphia in the 19th century. Edited by Ti...", "Doc 1: First woman firsts Doc 2: First for Women First for Women First for Women is a woman's magazine published by Bauer Media Group in the USA. The magazine was started in 1989. It is based in Englewood Cliffs, New Jersey..."]} </information> ----- <think> From the search results: - "Arthur's Magazine" was published from 1844 to 1846. - "First for Women" was started in 1989. Therefore, "Arthur's Magazine" was started first. </think> <answer> Arthur's Magazine </answer>

Table 7: Comparison of the effectiveness between single-query and multi-query parallelism

<p>Question: Are both Dictyosperma, and Huernia described as a genus?</p> <hr/> <p>Ground Truth: Yes</p> <hr/> <p>Single-query: <code><think></code> To determine if both Dictyosperma and Huernia are described as genera, I need to verify the taxonomic classification of each. <code></think></code> <code><search></code> Dictyosperma genus <code></search></code> <code><information></code> Doc 1: Dictyospermum Dictyospermum Dictyospermum is a genus of monocotyledonous flowering plants in the dayflower family, first described in 1849. It is native to Africa ... <code></information></code> ----- <code><think></code> The search results indicate that Dictyosperma is not clearly identified as a genus in the provided information. It seems to be referred to as "Polyspatha" in the context of species. I will need to conduct another search specifically for "Dictyosperma" to confirm its status as a genus. <code></think></code> <code><search></code> Huernia genus <code></search></code> <code><information></code> Doc 1: Huernia have shown the genus to be monophyletic, and most closely related to the genus "Tavaresia", and to a widespread branch of stapeliads comprising the genera "Orbea", "Piaranthus" and "Stapelia" ... <code></information></code> ----- <code><think></code> The search results confirm that Huernia is indeed described as a genus, with its first description dating back to 1810. Now, I need to confirm the status of Dictyosperma. <code></think></code> <code><search></code> Dictyosperma genus <code></search></code> <code><information></code> Doc 1: Dictyospermum Dictyospermum Dictyospermum is a genus of monocotyledonous flowering plants in the dayflower family, first described in 1849. It is native to Africa ... <code></information></code> ----- <code><think></code> The search results do not provide clear evidence that Dictyosperma is a genus. Instead, it seems to be associated with the genus Polyspatha. Given the information available, I cannot confirm that both Dictyosperma and Huernia are described as genera. <code></think></code> <code><answer></code> No <code></answer></code> </p>	<p>Multiple-query parallelism: <code><think></code> To determine if both Dictyosperma and Huernia are described as genera, I need to verify their taxonomic status. <code></think></code> <code><search></code> Dictyosperma genus, Huernia genus <code></search></code> <code><information></code> <pre>{ "query": ["Dictyosperma genus", "Huernia genus"], "documents": ["Doc 1: Dictyospermum Dictyospermum Dictyospermum is a genus of monocotyledonous flowering plants in the dayflower family, first described in 1849. It is native to Africa ...", "Doc 1: Huernia have shown the genus to be monophyletic, and most closely related to the genus "Tavaresia", and to a widespread branch of stapeliads comprising the genera "Orbea", "Piaranthus" and "Stapelia" ..."] }</pre> <code></information></code> ----- <code><think></code> From the search results, it appears that: - Dictyosperma is not explicitly mentioned as a genus, but there is a genus named Dictyospermum, which might be a similar spelling. - Huernia is indeed described as a genus within the family Apocynaceae, subfamily Asclepiadoideae. I should confirm the status of Dictyosperma. <code></think></code> </p>
---	--

<search> **Dictyosperma plant** </search>

<information>

```
{  "query": [  
    "Dictyosperma plant",  
  ],
```

```
  "documents": [  
    "Doc 1: Dictyoloma Dictyoloma Dictyoloma is a genus of flowering plants that belongs to  
the family Rutaceae ...",  
  ] }  
</information>
```

<think> Based on the additional search, Dictyosperma is confirmed to be a monotypic genus of
flowering plant in the palm family, found in the Mascarene Islands.

Both Dictyosperma and Huernia are described as genera. </think>

<answer> **Yes** </answer>
