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MASKSEARCH: A Universal Pre-Training Framework to Enhance Agentic Search Capability

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Abstract

Retrieval-Augmented Language Models (RALMs) represent a classic paradigm where models enhance generative capabilities using external knowledge retrieved via a specialized module. Recent advancements in Agent techniques enable Large Language Models (LLMs) to autonomously utilize tools for retrieval, planning, and reasoning. While existing training-based methods show promise, their agentic abilities are limited by inherent characteristics of the task-specific data used during training. To further enhance the universal search capability of agents, we propose a novel pre-training framework, **MASKSEARCH**. In the pre-training stage, we introduce the Retrieval Augmented Mask Prediction (RAMP) task, where the model learns to leverage search tools to fill masked spans on a large number of pre-training data, thus acquiring universal retrieval and reasoning capabilities for LLMs. After that, the model is trained on downstream tasks to achieve further improvement. We apply both Supervised Fine-tuning (SFT) and Reinforcement Learning (RL) for training. For SFT, we combine agent-based and distillation-based methods to generate training data, starting with a multi-agent system consisting of a planner, rewriter, observer, and followed by a self-evolving teacher model. While for RL, we employ DAPO as the training framework and adopt a hybrid reward system consisting of answer rewards and format rewards. Additionally, we introduce a curriculum learning approach that allows the model to learn progressively from easier to more challenging instances based on the number of masked spans. We evaluate the effectiveness of our framework in the scenario of open-domain multi-hop question answering. Through extensive experiments, we demonstrate that MASKSEARCH significantly enhances the performance of LLM-based search agents on both in-domain and out-of-domain downstream tasks. Code is available at `https://github.com/Alibaba-NLP/MaskSearch`.

1 Introduction

Large Language Models (LLMs) [1–4] demonstrate strong performance across a variety of tasks by leveraging vast internal knowledge [5–7], but suffer from hallucinations and often fall short in effectively addressing domain-specific or real-time tasks [8, 9]. Retrieval-Augmented Language Models (RALMs) [10, 9, 11] have been proposed to enhance LLMs by incorporating external knowledge, where a retrieval mechanism fetches information relevant to the input to augment the model's generation. While this approach has been successful, the separation of retrieval and generation limits the model's adaptability, preventing it from proactively acquiring information needed for multi-step tasks.

[†] Equal Contribution. This work was done during Weiqi Wu and Xin Guan's internship at Tongyi Lab, Alibaba Group.

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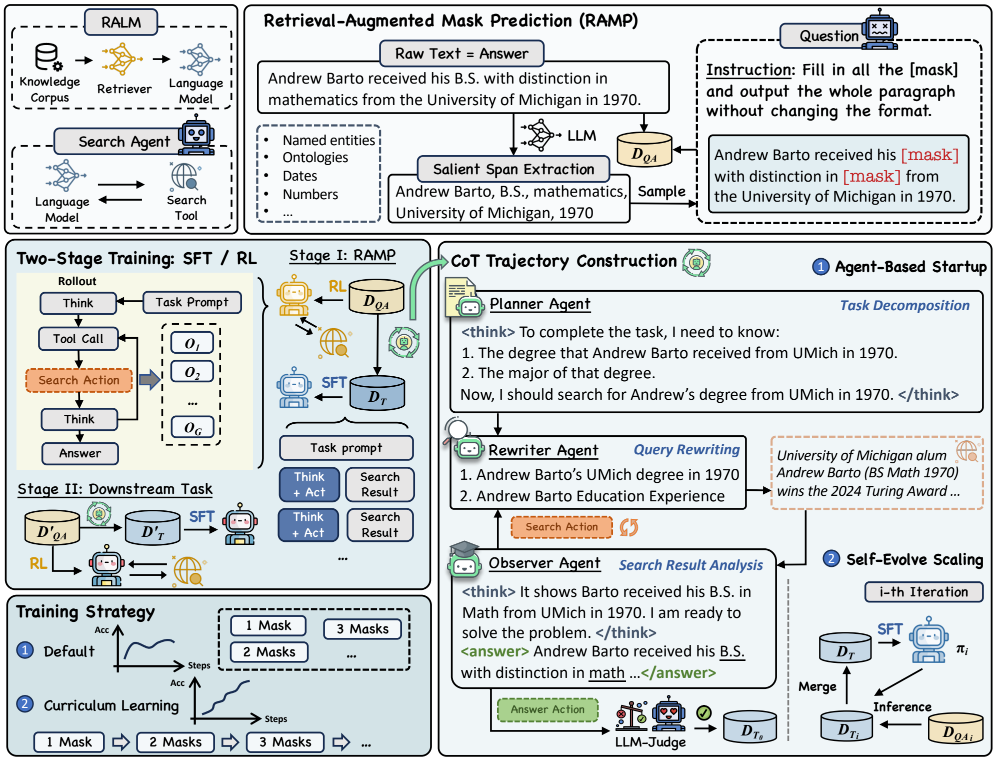
RALM
Knowledge Corpus
Retriever
Language Model
Search Agent
Language Model
Search Tool
Retrieval-Augmented Mask Prediction (RAMP)
Raw Text = Answer
Andrew Barto received his B.S. with distinction in mathematics from the University of Michigan in 1970.
Named entities
Ontologies
Dates
Numbers
...
LLM
Salient Span Extraction
Andrew Barto, B.S., mathematics, University of Michigan, 1970
Sample
D_{QA}
Question
Instruction: Fill in all the [mask] and output the whole paragraph without changing the format.
Andrew Barto received his [mask] with distinction in [mask] from the University of Michigan in 1970.
Two-Stage Training: SFT / RL
Rollout
Think
Task Prompt
Tool Call
Search Action
Think
Answer
o_1
o_2
...
o_G
Stage I: RAMP
RL
D_{QA}
SFT
D_T
Task prompt
Think + Act
Search Result
Think + Act
Search Result
...
Stage II: Downstream Task
D'_{QA}
D'_T
SFT
RL
Training Strategy
① Default
Acc
Steps
② Curriculum Learning
Acc
Steps
1 Mask
3 Masks
2 Masks
...
1 Mask
2 Masks
3 Masks
...
CoT Trajectory Construction
① Agent-Based Startup
Planner Agent
Task Decomposition
<think> To complete the task, I need to know:
1. The degree that Andrew Barto received from UMich in 1970.
2. The major of that degree.
Now, I should search for Andrew's degree from UMich in 1970. </think>
Rewriter Agent
Query Rewriting
1. Andrew Barto's UMich degree in 1970
2. Andrew Barto Education Experience
University of Michigan alum Andrew Barto (BS Math 1970) wins the 2024 Turing Award ...
Search Action
Observer Agent
Search Result Analysis
<think> It shows Barto received his B.S. in Math from UMich in 1970. I am ready to solve the problem. </think>
<answer> Andrew Barto received his B.S. with distinction in math ...</answer>
Answer Action
LLM-Judge
D_{T_0}
② Self-Evolve Scaling
i-th Iteration
D_T
SFT
π_i
Merge
Inference
D_{T_i}
D_{QA_i}

Figure 1: Overview of MASKSEARCH, a pre-training framework to incentivize the agentic RAG capabilities of LLMs. Based on the Retrieval-Augmented Mask Prediction (RAMP) task, models can be trained via SFT or RL to acquire generalizable abilities before downstream task training.

With autonomous AI agents gaining momentum, a new paradigm has emerged—agents leveraging search engines as tools while employing agentic strategies such as planning, reasoning, reflection, and multi-agent collaboration to enhance their problem-solving capabilities. While prompt-based workflows have been widely used [12], they suffer from inefficiency and a lack of flexibility. Training an LLM-based search agent offers a more promising solution [13], yet current methods primarily rely on task-specific data, which limits the ability to generalize across a broader range of tasks.

Previous research on Masked Language Models (MLM) [11, 14] has proved that models' memory, understanding and generation capabilities can be effectively incentivized through nearly infinite, diverse and verifiable data. By allowing models to think and utilize search tools to fill in the masks instead of solely based on the given context, we can further enhance their tool usage and reasoning abilities. Building on these insights, we propose **MASKSEARCH**, a universal pre-training framework designed to enhance the agentic search capabilities of LLMs within a unified model architecture. The model is trained on a theoretically infinitely scalable task named Retrieval-Augmented Mask Prediction (RAMP), where it learns to fill in masked spans by performing multi-step search and reasoning as illustrated in Figure 1. The task requires general capabilities of task decomposition, search tool utilization and observation-based reasoning, which are highly transferable to downstream tasks such as open-domain question answering.

Both Supervised Fine-tuning (SFT) and Reinforcement Learning (RL) can be used for training on RAMP. To construct the SFT dataset, we propose a method that combines agent-based and distillation-based approaches to generate Chain-of-Thought (CoT) trajectories that can solve the RAMP task. Initially, a multi-agent system involving a planner, rewriter, and observer agent is utilized to synthesize reasoning data. Subsequently, we adopt an iterative self-evolutionary distillation strategy, using an increasingly fine-tuned model to generate the next partition of the dataset. For RL, we employ the Dynamic Sampling Policy Optimization (DAPO) algorithm [15] to optimize the model's search and reasoning process with a hybrid reward system including rule-based format rewards and model-based answer rewards. In addition, we introduce a curriculum learning method based on the number of masks, enabling the model to learn progressively from easier to more difficult scenarios.

Extensive analysis shows that incorporating RAMP as the pre-training task yields significant performance enhancements across a variety of open-domain question-answering datasets. It not only provides a stable improvement in recall scores for the in-domain downstream task but also achieves pronounced gains on out-of-domain benchmarks. We also validate the scalability of MASKSEARCH by constructing a 10M pertaining dataset for SFT. Furthermore, despite the fact that RL is not typically used for pre-training, our experiments indicate that it achieves impressive performance gains through pre-training. It even demonstrates a greater potential to optimize model performance, achieving higher upper limits after post-training compared to using SFT. These findings highlight the effectiveness of MASKSEARCH in enhancing the general agentic search capabilities of LLMs, regardless of their size, type, or the specific training method employed.

2 Related Work

Retrieval-Augmented Generation RAG is a powerful approach to bridging the gap between static model parameters and dynamic external knowledge [8, 16, 17, 9]. By incorporating an external retrieval module, LLMs can generate responses with real-time or domain-specific [18, 19] data, thereby mitigating issues like hallucinations [20, 21] and outdated facts. Early advances demonstrate that coupling neural retrievers with language models improves factual accuracy in tasks such as open-domain question answering [9, 11]. Recent studies have advanced RAG by embedding autonomous AI agents into the RAG workflow [22–24], leveraging the advantage of agent frameworks like planning, reflection and multi-agent collaboration [25].

Agent The advent of LLM-based agents marks a revolutionary transformation in the AI domain. These agents can autonomously plan, reason, utilize tools, and retain memory while interacting with dynamic environments, thereby being capable of handling complex tasks such as web search [26, 27] and operations [28], creative writing [29], and travel planning [30]. In addition to realizing LLM agents through prompt engineering [31–34], recent research has also focused on optimizing and training these agent skills in an end-to-end manner [35, 36]. We aim to integrate this idea into the training of RALM, enabling RALM to more autonomously retrieve knowledge and enhance its understanding, reasoning and generation capabilities.

Reasoning LLM Improving reasoning capabilities in LLMs has become a central focus to push the frontier of coherence and consistency in complex problem-solving. The advent of Large Reasoning Models (LRMs) [37, 2, 38] demonstrates the effectiveness of inference-time scaling [39, 40] and multi-step reasoning [41, 42, 33] mechanisms. Hence, smaller models can also tackle complex tasks in a series of logical steps rather than attempting to provide solutions in a single step. Apart from well-designed prompt-based methods [12, 43, 44] and Supervised Fine-tuning (SFT) [45–47], where even small models show competitive performance on multi-step reasoning [48–50], Reinforcement Learning (RL) has been proved to be effective for models to gain more advanced reasoning capabilities [15, 13, 2], which has now become a mainstream training method.

3 MASKSEARCH

3.1 Preliminary

We define Retrieval-Augmented Mask Prediction (RAMP) as the pre-training task of MASKSEARCH. It involves predicting the masked spans in an input context sequence x that contains n masked spans, by proactively retrieving relevant information from an external knowledge corpus D using a search tool $\mathcal{R}$. To train an LLM-based search agent π_θ, which is parameterized by θ and initialized from a pre-trained base model to take a strong starting point, there are two primary methods: Supervised Fine-tuning (SFT) and Reinforcement Learning (RL).

Supervised Fine-tuning (SFT) Let π_t be an advanced implementation capable of multi-step agentic RAG and reasoning. The goal of SFT is to train π_θ on a dataset $\mathbb{D}_t$, where each instance consists of Chain-of-Thought (CoT) data $y_t = \pi_t(x)$. Here, y_t represents the reasoning trace generated by π_t to solve the RAMP task through searching and reasoning. During training, we treat the search results as a latent variable by masking the retrieved tokens and focusing on optimizing the model response.

The optimization process can be formulated as:

$$\pi_\theta \leftarrow \arg\min_{\pi} \mathbb{E}_{(x,y_t)\sim\mathbb{D}_t} \left[\mathcal{L}(\pi_\theta(x, D), y_t)\right] \tag{1}$$

Reinforcement Learning (RL) We follow the paradigm of Search R1 [13], which incorporates the search engine $\mathcal{R}$ into the RL process for optimization. The optimization objective is formulated as:

$$\max_{\pi_\theta} \mathbb{E}_{x\sim\mathcal{D}, y\sim\pi_\theta(\cdot|x;\mathcal{R})} \left[r_\phi(x, y)\right] - \beta\mathbb{D}_{\text{KL}} \left[\pi_\theta(y \mid x; \mathcal{R}) \,||\, \pi_{\text{ref}}(y \mid x; \mathcal{R})\right], \tag{2}$$

where π_θ is the policy model, π_{ref} is the reference model, r_ϕ is the reward function and $\mathbb{D}_{\text{KL}}$ is KL-divergence measure. We employ the Dynamic Sampling Policy Optimization (DAPO) RL algorithms [15], and mask the retrieved tokens from the search engine during gradient computation as well. Details can be found in Appendix E.

3.2 Retrieval-Augmented Mask Prediction (RAMP)

Question-Answer Generation We leverage Wikipedia as our data source to build RAMP to ensure comprehensive and diverse domain coverage. Since the answers naturally originate from the unmasked portions of the original paragraphs, our task is to design a method for selectively masking spans in the paragraphs, with a focus on spans that require deeper reasoning and knowledge retrieval, rather than simple local context understanding.

Salient Span Extraction Salient Span Masking [51, 11] is a critical strategy for creating challenging tasks, where the masked spans require world knowledge to predict. instead of solely local context. We broaden the definition of salient spans to include not only named entities and dates, but also ontologies, specific terms, and numerical values.

Qwen-Turbo [1] is utilized to extract salient spans. After extracting the spans, we randomly select k spans (where $0 < k < 5$) and replace them with a mask token [mask]. This ensures the CoT trajectories remain manageable and focused while still offering sufficient challenge. The model then predicts the original content of the masked spans based on the context x.

3.3 CoT Trajactory Construction

Supervised Fine-tuning (SFT) on CoTs is the most direct way to enable multi-step reasoning. This involves generating reasoning traces that guide the model through solving the RAMP task. There are typically two ways to synthesize data: (1) agent-based, prompting a model to complete the task, and (2) distillation-based, using a stronger model to generate traces directly. We propose a hybrid approach for constructing CoT data that combines the two approaches, and construct a 10M CoT dataset (14B tokens) to validate the scalability of MASKSEARCH as a pre-training framework.

Agent-Based Startup Initially, we orchestrate a synthesizing process involving planning, search, and reflection, supported by a multi-agent system, as shown in Figure 1. The **Planner Agent** first analyzes the overall task and breaks it into sub-tasks, generating an initial search query. The **Rewriter Agent** refines the generated query for improved knowledge retrieval and calls the search tool. The **Observer Agent** reviews the search results and steps taken, determining whether the task can be resolved or if additional steps are needed, updating the process until the final answer is obtained. Each agent is instructed with a few-shot prompt, as detailed in Appendix D. The final answer is evaluated by LLM-as-Judge and only trajectories that correctly fill all the masks are curated in $\mathbb{D}_0$.

Self-Evolve Distillation To rapidly scale up the dataset while maintaining high data quality, we utilize an iterative generation strategy by using a trained teacher model π_t instead of the multi-agent method. During the j-th iteration, the current dataset $\mathbb{D}_j$ is used to fine-tune the model $\pi_{\theta_{j-1}}$, resulting in an updated policy π_{θ_j}. This updated policy incorporates the reasoning traces and search strategies learned from $\mathbb{D}_j$. The updated policy π_{θ_j} is then employed as the new teacher model $\pi_{t_{j+1}}$, which is used to synthesize the next iteration of the dataset $\mathbb{D}_{j+1}$.

$$\pi_{\theta_j} \leftarrow \arg\min_{\pi} \mathbb{E}_{(x,y_t)\sim\mathbb{D}_j} \left[\mathcal{L}(\pi_{\theta_j}(x, D), y_t)\right], \quad \pi_{t_{j+1}} \leftarrow \pi_{\theta_j} \tag{3}$$

$$\mathbb{D}_{j+1} \leftarrow \{(x, y_t) \mid y_t = \pi_{t_{j+1}}(x, D)\}, \quad \mathbb{D}_t \leftarrow \{\mathbb{D}_0, \ldots, \mathbb{D}_{j+1}\} \tag{4}$$

This iterative approach ensures that the model continuously learns from increasingly complex and diverse reasoning traces, as each iteration builds on the improved capabilities of the previous one.

3.4 RL Reward Design

Reward signals are essential in RL, guiding the direction of model optimization. Our hybrid reward system consists of two components: a format reward and an answer reward, each contributing 50% to a total score of 1:

$$r_\phi(x, y) = 0.5R_f(y) + 0.5R_a(\hat{y}, y_{pre}) \tag{5}$$

where $\hat{y}$ is the ground truth answer, y is the response and y_{pre} is the extracted final answer from y. The format reward R_f evaluates the response of the policy model to ensure it conforms to the specified answer format. It uses string matching to check whether the response contains special symbols that distinguish the various inference stages. If the response meets the format criteria, it is awarded 1 point; otherwise, it receives 0.

For the answer reward R_a, we explore various reward functions to identify the optimal one for optimization:

1) **Token-level Recall Reward**: We set token-level Recall TR as the reward metric.

2) **Token-level Recall with Answer Length Penalty Reward** (Penalty-based Reward): Recall Reward often lead to reward hacking. To address this, we introduce the penalty for the answer length, defined by the following:

$$R_a(\hat{y}, y_{pre}) = TR(\hat{y}, y_{pre}) - \alpha(\min(\max(\log_2\left(\frac{|y_{pre}|}{\beta \times |\hat{y}|}\right), 0), \gamma)) \tag{6}$$

where α, β, γ are parameters that adjust the strictness of the length penalty, set to 0.2, 8, and 4.

3) **Model-Based Reward**: We utilize the Qwen2.5-72B-Instruct model as a judge, evaluating the consistency between generated answers and standard answers, assigning a score of 0 or 1.

3.5 Curriculum Learning

Curriculum learning is a training strategy that sorts training samples by difficulty and presents them to the model in an incremental manner. In the context of our RAMP task, the number of masked spans k serves as the primary metric for difficulty. Instead of random sampling, the curriculum learning method starts with simpler tasks containing fewer masked spans and progressively introduces more complex tasks with a higher number of masked spans. This approach allows the model to first learn fundamental reasoning skills and gradually build up its capabilities to handle more challenging scenarios. By following this curriculum, the model can better adapt to the increasing complexity of the tasks, leading to improved performance and more robust reasoning abilities.

$$\pi_\theta \leftarrow \arg\min_{\pi} \mathbb{E}_{(x,y_t)\sim\mathbb{D}_{t_k}} \left[\mathcal{L}(\pi_\theta(x, D), y_t)\right], \quad \text{for } k \text{ in } \{1, 2, 3, 4\} \tag{7}$$

4 Experiment Setup

Models We conduct experiments with two series of foundation models: (1) **QWEN2.5** [1]: QWEN2.5-1.5B, QWEN2.5-3B and QWEN2.5-7B; (2) **LLAMA3** [3]: LLAMA-3.2-1B, LLaMa-3.2-3B and LLAMA-3.1-8B. To generate CoT trajectories for Supervised Fine-tuning, we use QWEN-MAX to build the multi-agent system as well as filter the correct trajectories. For self-evolve distillation, we fine-tune with QWEN2.5-7B when the size of the curated dataset reaches 250K, 500K and 1M. We use the instruct models for RL, as base models often fail to follow the instructions. The detailed training setups can be found in Appendix A.

Table 1: Test datasets used in the experiment. Datasets marked with † use their development split as the test set.

Dataset	Hops	#Test
HotpotQA†[52]	2	7405
FanoutQA†[53]	avg. 7	310
Musique†[54]	2-4	2417
2WikiMultiHopQA †[55]	2-4	12576
Bamboogle [56]	2	125
FreshQA [57]	1-2	374

Datasets In our study, we employ a variety of datasets to evaluate the performance of our proposed training task, as presented in Table 1. For the downstream task, we select HotpotQA [52] as a representative challenge. During the SFT phase, we utilize the agent-based method to synthesize and filter 58K correct CoT trajectories for training data. For out-of-domain testing, we first evaluate the

Table 2: Evaluation results of different methods on various open-domain question answering datasets. Bold and underlined indicate the best and the second best results.

Methods	Pre-Training	Post-Training	HotpotQA	FanoutQA	Musique	2Wiki	Bamboogle	FreshQA	Avg.
Qwen2.5-1.5B									
RAG-PE	✗	✗	29.45	27.37	12.07	37.32	22.93	41.19	28.37
Agent-PE	✗	✗	48.74	36.15	28.87	49.72	58.87	63.27	47.60
Distilled Search-R1	✗	SFT	64.13	47.76	35.02	76.45	63.87	68.12	59.22
Search-R1	✗	RL	61.72	42.68	35.63	64.40	64.59	74.44	57.24
MaskSearch	SFT	SFT	67.58	**53.18**	38.58	**81.13**	**75.65**	75.47	65.27
	RL	SFT	66.23	45.61	40.55	71.77	73.79	75.91	62.31
	SFT	RL	65.95	48.64	40.36	72.00	72.67	73.54	62.19
	RL	RL	**71.02**	49.73	**40.59**	76.03	73.60	**81.08**	**65.34**
Qwen2.5-3B									
RAG-PE	✗	✗	38.37	41.48	20.78	51.14	37.60	61.55	41.82
Agent-PE	✗	✗	51.17	49.82	25.27	58.14	56.40	67.80	48.10
Distilled Search-R1	✗	SFT	67.38	54.00	38.20	79.76	68.05	77.59	64.17
Search-R1	✗	RL	69.03	48.55	39.08	78.85	72.53	76.78	64.14
MaskSearch	SFT	SFT	69.30	**56.03**	40.12	**82.36**	74.52	79.84	67.03
	RL	SFT	68.23	55.85	39.48	81.72	73.87	77.58	66.12
	SFT	RL	69.03	54.55	39.08	79.85	72.53	76.78	65.30
	RL	RL	**73.08**	53.02	**44.48**	80.43	**80.13**	**85.07**	**69.37**
Qwen2.5-7B									
RAG-PE	✗	✗	43.55	51.92	25.05	53.86	44.60	64.40	47.23
Agent-PE	✗	✗	61.75	55.69	34.25	68.77	63.25	75.81	58.25
Distilled Search-R1	✗	SFT	69.55	57.24	41.06	83.84	73.07	78.97	67.29
Search-R1	✗	RL	70.59	56.25	41.29	80.50	79.33	78.46	67.74
MaskSearch	SFT	SFT	70.44	**60.85**	41.76	**84.65**	80.13	**81.12**	69.83
	RL	SFT	70.84	56.29	41.90	83.38	78.53	78.93	68.31
	SFT	RL	71.69	57.69	42.23	81.25	81.87	75.42	68.36
	RL	RL	**75.61**	58.96	**45.54**	82.10	**83.00**	80.85	**71.01**

model on a range of multi-hop question-answering tasks, including FanoutQA [53], Musique [54] and 2WikiMultiHopQA [55]. Furthermore, we use the data without false premises in FreshQA [57] to evaluate its performance on single-hop reasoning questions. We report token-level Recall as the evaluation metric. Specifically, it segments the generated text and the golden text into token lists and calculates the ratio of common tokens between model-generated responses and ground truth.

Baselines We compare our method against the following baselines with retrieval: (1) **RAG-PE**: The model generates a response based on retrieval results; (2) **Agent-PE**: As elaborated in Section 3.3, it leverages advanced prompt-based techniques to handle complex reasoning tasks; (3) **Distilled Search-R1**: The model is directly fine-tuned on the downstream data, i.e., 58K CoT trajectories from HotpotQA; (4) **Search R1** [13]: The model is directly trained using reinforcement learning on the downstream data from HotpotQA until its performance on the validation set converges.

5 Experimental Results

5.1 Main Results

First-stage training of the RAMP task benefits LLM-based search agents. As shown in Table 2, our proposed MaskSearch, which incorporates RAMP as the pre-training stage, significantly enhances the model performance across multiple open-domain question-answering datasets. In the in-domain dataset, i.e., HotpotQA, RAMP provides a stable improvement in the model's recall score. On out-of-domain datasets, the improvement is even more pronounced. For instance, on the Bamboogle dataset, the Qwen2.15-1.5B model achieves a substantial increase of **11.78** compared to post-training only, while the LLaMA model sees an impressive gain of **15.12** [3]. Moreover, smaller models (e.g., Qwen2.5-1.5B) can perform comparably to larger models on a variety of tasks. This proves that RAMP, as a scalable learning signal, can help models better strengthen their abilities to decompose problems and interact with search tools.

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[3] LLaMA results in Appendix C.

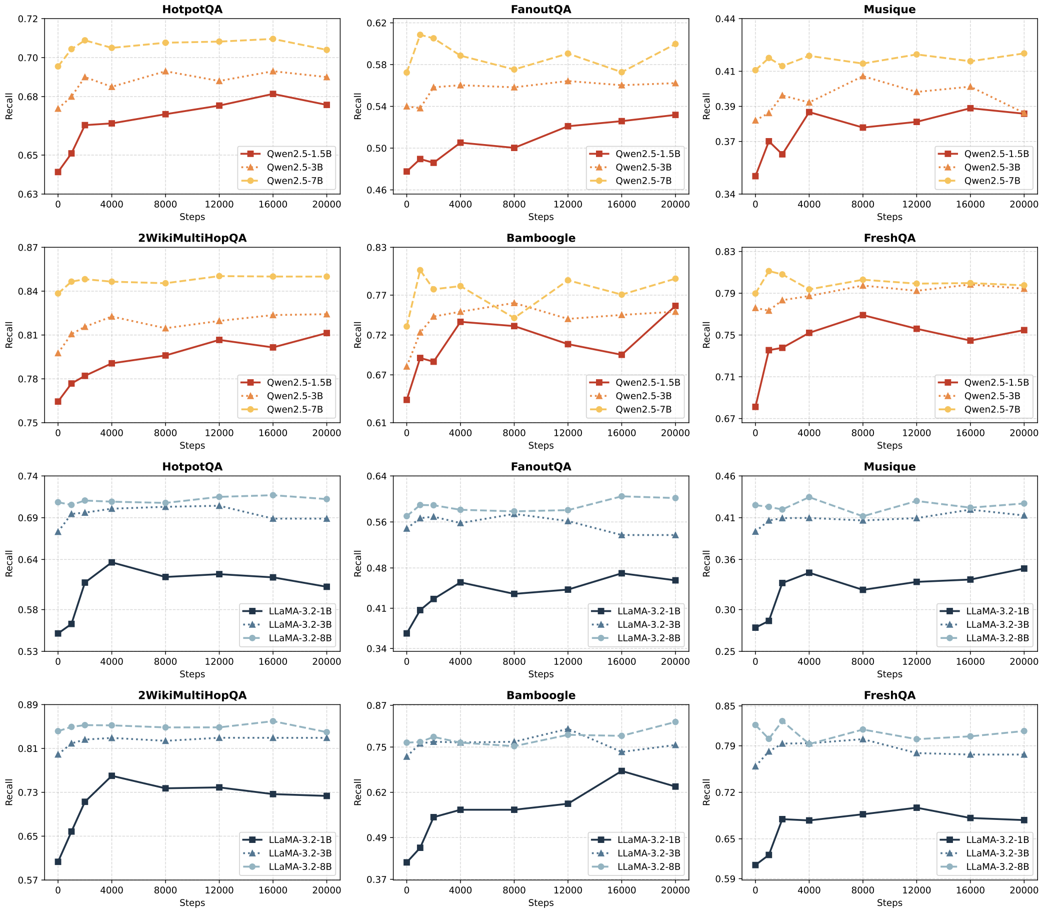


Figure 2: Scaling Performance of SFT with respect to training steps on RAMP. The results obtained at training step 0 align precisely with those of the *Direct SFT* baseline, which is directly fine-tuned on the 58K CoT trajectories derived from HotpotQA.

RL offers higher performance gains on RAMP compared with SFT. While SFT proves to be effective in improving search agent performance, RL demonstrates the potential to achieve even higher upper limits when applied to RAMP tasks. The combination of RL with RAMP shows better gains over SFT alone, especially in the in-domain dataset HotpotQA, where an improvement of 3 to 5 points is achieved on different-scale models, suggesting that RL can better optimize the model for the specific nuances and challenges presented by the retrieval-augmented prompting process. This finding highlights the importance of exploring advanced training techniques like RL to fully exploit the benefits of RAMP in enhancing RALM performance.

5.2 Scaling Performance

To verify the scaling potential of MASKSEARCH as a pre-training task, we conducted experiments using models trained with different numbers of steps in the first stage and evaluated their performance after subsequent finetuning on the downstream task. Our experiments in Figure 2 reveal that small models (1B, 1.5B) demonstrate significant improvements in performance after undergoing the pre-training phase. This indicates that the RAMP task is effective in enhancing the agentic search capabilities of models. For larger models, scaling up the dataset size is also effective, but the performance gains are not as pronounced as those observed with smaller models. This can be attributed to the fact that the data used for training the 7B model is generated through a self-evolution process, which may lack diversity and complexity compared to its own prediction. Therefore, the quality and diversity of the training data are critical factors in determining the upper limit of the model's performance during SFT.

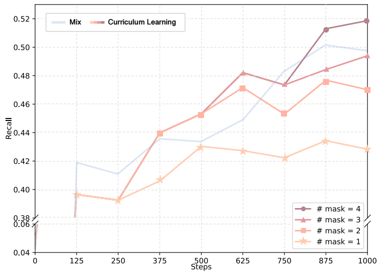


Figure 3: Performance on the dev set while finetuning with varying numbers of masks.

Table 3: Average recall of different training strategies on the test datasets.

Model	**w/ RAMP**		**w/o RAMP**
	CL	**Mix**	
	Qwen		
Qwen2.5-1.5B	54.06	**55.36**	52.54
Qwen2.5-7B	**65.42**	65.36	64.35
	LLaMA		
LLaMA-3.2-1B	**55.93**	53.67	52.98
LLaMA-3.1-8B	64.93	**65.57**	64.21

5.3 Supervised Curriculum Learning

In this section, we delve deeper into the effectiveness of curriculum learning in the context of RAMP and downstream task training via SFT. We sample 10K data from RAMP for each number of masked spans and 6K from HotpotQA to maintain an appropriate ratio between pre-training and downstream tasks. Additionally, 500 QA pairs are sampled from the remaining RAMP data as a validation set, with 100 data points for each number of masked spans. As illustrated in Figure 3, we observe a clear trend where increasing the number of masked spans leads to significant performance improvements on the validation set. Although the initial performance lags behind, the curriculum learning approach ultimately outperforms the mixed training strategy, which is the default training method that mixes all the data together. The advantage observed in the validation set has the potential to carry over to the downstream tasks after fine-tuning. As shown in Table 3, CL outperforms the mixed training strategy when using the Qwen2.5-7B and LLaMA-3.2-1B models, indicating that the approach can generalize across different model architectures.

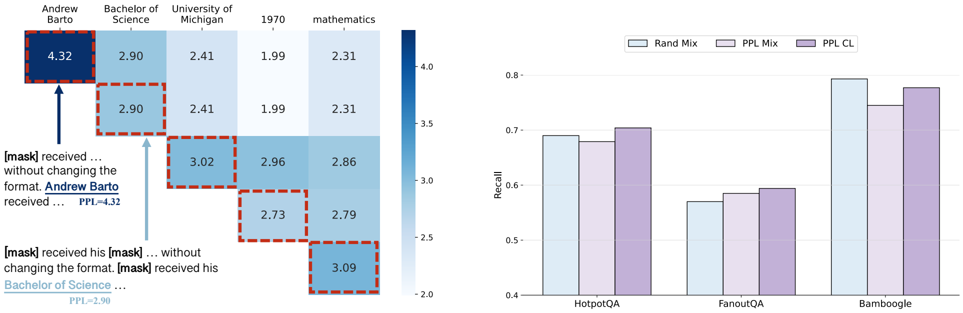
6 Discussion

In this section, we conduct an in-depth discussion of the critical factors of RAMP and its training process to offer a comprehensive exploration of our approach. A case study is presented in the Appendix F to provide further insights into the practical application of our method.

6.1 Masking Strategy

We delve into the impact of masking methods on the RAMP task. Beyond salient span masking, numerous prior studies have investigated the effects of selecting more challenging masks in Masked Language Modeling (MLM), including using Pointwise Mutual Information (PMI) and Perplexity (PPL) to evaluate the difficulty of masked spans. For autoregressive models, we explore the PPL-based masking strategy depicted in Figure 4(a). We measure the difficulty of a masked span to a model by calculating the perplexity, i.e., loss of the span, as it restores the masked span in the original context following the instruction. Specifically, we greedily select the span with the highest PPL among all unmasked salient spans until the required number of masks is met. To validate this strategy against the original random masking strategy, we prepare a 40K RAMP dataset for SFT using our agent-based trajectory construction method and sample 6K HotPotQA trajectories for training in the second stage.

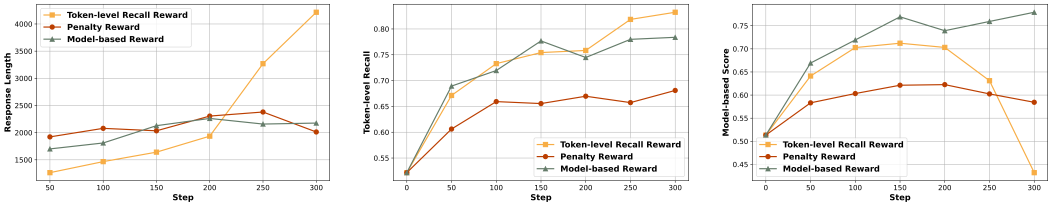
As shown in Figure 4(b), the PPL-based masking strategy yields a performance boost on the FanoutQA dataset, underscoring the efficacy of selecting more challenging masks. However, the experimental outcomes on the HotpotQA and Bamboogle datasets imply that merely augmenting the difficulty of the masked spans may result in a decline in performance. This suggests that the model may not have genuinely mastered the tasks due to its increased difficulty. On the other hand, curriculum learning, which progressively escalates the complexity of the training tasks, proves to be advantageous. After the second stage of training, the model demonstrates enhanced performance across all three datasets, highlighting its effectiveness in enhancing the model's learning progress to tackle intricate tasks.



(a) PPL-based Masking Strategy.

(b) Downstream Performance.

Figure 4: Exploring RAMP with PPL-based masking strategy. The subfigure (a) illustrates the computation of perplexity for the unmasked spans in each round. The subfigure (b) indicates the effect of the PPL-based masking strategy on downstream test sets along with CL.



(a) Response Length

(b) Token-level Recall

(c) Model-based Score

Figure 5: Exploring Different Answer Reward Designs. These figures present the performance of the Qwen-7b model on the development set during RL training. The subfigure (a) illustrates the length of responses generated by the model. The subfigure (b) displays the metric based on token-level recall. The subfigure (c) details the metric assessed using the Qwen-72b model as a judge.

6.2 Performance with Different RL Reward

We study the impact of different RL rewards on model performance, as discussed in section 3.4. The results are shown in Figure 5, model trained with the token-level recall reward hacks the metric by adding a lot of irrelevant information to the answer, significantly increasing the length of the response. This results in a notable decline in actual performance compared to other RL rewards under model-based evaluation. While penalty-based reward can substantially reduce answer length, performance is still affected and the model still can hack within the constraint of limited answer length by employing enumeration in our observation. Model-based reward offer significant improvements of 34.71 and 19.48 over the other two reward methods, effectively addressing issues of reward hacking and demonstrating remarkable stability and effectiveness in RL training. These advantages ultimately led us to adopt the model-based reward approach for training.

7 Conclusion

In this paper, we introduce a novel framework MASKSEARCH for enhancing the agentic search capabilities of LLMs, specifically through a two-stage training approach. Our method, built around the Retrieval-Augmented Mask Prediction (RAMP) pre-training task, enables models to autonomously perform multi-step search and reasoning to fill in masked spans, fostering a deeper integration of external knowledge. We demonstrate that by using both Supervised Fine-tuning (SFT) and Reinforcement Learning (RL), along with curriculum learning. Our framework leads to substantial performance improvements across both in-domain and out-of-domain open-domain question answering tasks, compared to the baselines. Overall, our work underscores the potential of pre-training in advancing the field of multi-hop reasoning and retrieval-augmented tasks, offering a scalable, transferable framework that enhances the capabilities of LLM-based search agents regardless of model size, architecture, or training methods.

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A Training Settings

Supervised Fine-tuning During the Continuous Pre-Training (CPT) phase of the scaling experiment, we ensure a global batch size of 1024. For models with 1B, 1.5B, and 3B parameters, we use a distributed training setup with 16 nodes and 8 H20 GPUs per node. For models with 7B and 8B parameters, we use a distributed training setup with 32 nodes and 8 GPUs per node. Each model is trained for 2 epochs with a learning rate set to 4×10^{-5}. For downstream task training, we use a global batch size of 64 with a learning rate set to 1×10^{-5}, training on 8 GPUs per node.

Reinforcement Learning For DAPO training, we configure the batch size to 16, set the policy model learning rate to 1×10^{-6}, and sample 16 responses per prompt. The training for the CPT and downstream tasks is performed on 8 H20 GPUs over 1 epoch and early stops training when there is no better result on the development set for 150 steps. We use the instruct models for RL, as base models often fail to follow the instructions.

B Detailed Comparison with Existing RALMs

MaskSearchintroduces several innovations that distinguish it from prior work in the field of Retrieval-Augmented Language Models (RALMs) and search-enhanced reasoning models. Firstly, in terms of the number of retrieval tokens, MaskSearchoperates with an effectively infinite retrieval space, which is a significant departure from traditional models that are limited by the size of their pre-defined retrieval corpora. Secondly, MaskSearchemploys a single-model architecture, in contrast to the dual-model setups of traditional RALMs. This simplification not only reduces computational overhead but also enhances the coherence and consistency of the reasoning process. By interacting with a search engine in agentic style, MaskSearchsupports multi-step reasoning, a capability that is not present in most of the models listed in the table. This feature is crucial for handling complex queries that require the integration of information from multiple sources and cannot be solved in a single step.

Table 4: Comparison with existing RALMs and search-enhanced reasoning models. E2E is short for end-to-end.

	# Retrieval Tokens	**# Models**	**Retriever**	**Multi-Step**
KNN-LM [58]	$O(10^9)$	2	Transformer (Frozen)	✗
REALM [11]	$O(10^9)$	2	BERT (2-Stage E2E)	✗
RAG [9]	$O(10^9)$	2	DPR (E2E)	✗
Retro [59]	$O(10^{12})$	2	BERT (Frozen)	✗
Atlas [60]	$O(10^{10})$	2	Contriever (E2E)	✗
IC-RALM [10]	$O(10^8)$	2	BM25	✗
RADIT [46]	$O(10^{11})$	2	DRAGON+ (Separate)	✗
Search-R1 [13]	∞	1	LLM (1-Stage RL)	✓
MaskSearch	∞	1	LLM (2-Stage E2E)	✓

The work most similar to MaskSearchis Search-R1, but there are several key differences that set MaskSearchapart. While both models operate with an effectively infinite retrieval space and support multi-step reasoning, MaskSearchemploys a two-stage end-to-end training process that can be adapted to both SFT and RL. This contrasts with Search-R1, which uses a single-stage reinforcement learning approach for its retriever. The two-stage end-to-end training in MaskSearchallows for more general optimization of the agent capabilities, leading to better integration with the LLM and improved performance.

C Results for LLaMA Models

In this section, we present the results of our experiments conducted on varying sizes of LLaMA models. Our experiments were specifically carried out on the SFT, as is shown in Table 5. The main findings are summarized as follows:

Significant Performance Improvement over Baselines Similar to Qwen models, our experiments demonstrated that the MaskSearchframework achieved substantial performance improvements across multiple datasets compared to existing methods. On the LLaMA-3.2-1B model, MaskSearchachieved an average performance improvement of nearly 10 points over the next best method (Distilled Search-R1). This significant enhancement highlights the effectiveness of MASKSEARCHin improving search capabilities.

Scalability Across Model Sizes The MASKSEARCHframework showed consistent performance improvements across different sizes of LLaMA models, ranging from 1B to 8B parameters. However, the extent of improvement for the SFT stage depends on the capability gaps between the distilled model and the student model, which is also observed with the Qwen series.

Transferability among Different Model Series The MASKSEARCHframework showed strong transferability among different architectures of models, as we utilize data generated by the Qwen-series model but still achieve significant performance improvements for LLaMA models. This demonstrates the framework's ability to leverage data from different sources and adapt to different model architectures, further enhancing its applicability in diverse research and development scenarios.

Table 5: Complete results of LLaMA models.

Methods	Pre-Training	Post-Training	HotpotQA	FanoutQA	Musique	2Wiki	Bamboogle	FreshQA	Avg.
				LLaMA-3.2-1B					
RAG-PE	✗	✗	20.00	29.91	9.03	40.15	13.23	42.74	32.51
Agent-PE	✗	✗	37.51	31.73	19.14	45.96	32.22	57.24	37.30
Distilled Search-R1	✗	SFT	55.15	36.62	27.84	60.32	41.87	61.05	47.14
MASKSEARCH	SFT	SFT	63.66	45.50	34.41	76.01	56.99	67.77	57.40
				LLaMA-3.2-3B					
RAG-PE	34.00	48.84	15.44	53.79	46.35	63.33	48.63		
Agent-PE	51.90	37.17	42.66	71.44	48.46	58.06	51.61		
Distilled Search-R1	✗	SFT	67.31	54.86	39.33	79.91	72.25	75.91	64.93
MASKSEARCH	SFT	SFT	70.31	57.40	40.67	82.39	76.52	80.00	67.88
				LLaMA-3.1-8B					
RAG-PE	36.67	52.38	19.74	51.52	51.04	63.33	50.06		
Agent-PE	59.70	52.30	41.12	77.09	59.69	71.85	60.29		
Distilled Search-R1	✗	SFT	70.85	57.01	42.50	84.15	76.27	82.13	68.82
MASKSEARCH	SFT	SFT	71.70	60.46	42.20	85.98	78.22	80.42	69.83

D Prompt Demonstration

This section presents the prompts used for agent-based reasoning trajectories construction, including the planner agent, rewriter agent, observer agent and LLM-Judge.

Table 6: Prompt for Agent-Based CoT trajectory construction.

Planner Agent

Your task is to provide the steps for solving a multi-hop search problem.
The output format should be: "`<think>` {Overall thought process} `</think>` `<search>` [{"query": "query", "intent": 1}] `</search>` "; query should be in sentence format.

Here are some examples:

Question: What is the undergraduate school of the director of the movie "Sense and Sensibility"?
Thought: `<think>` To answer this question, I will take the following steps:
1. First, find out who directed the movie "Sense and Sensibility".
2. Investigate the educational background of the director, particularly their undergraduate school.
3. Identify the specific institution where the director completed their undergraduate studies.
Now, I will start with the first step and search for the director of the movie "Sense and Sensibility". `</think>`
`<search>` [{"query": "Who is the director of the movie 'Sense and Sensibility'?", "intent": 1}] `</search>`

Continued on next page

Table 6: Prompt for Agent-Based CoT trajectory construction.

Question: When did the birthplace of the performer of Live and Beyond become the capital of the state where Knowles is located?
Thought: `<think>` To determine when the birthplace of the performer of Live and Beyond became the capital of the state where Knowles is located, I will take the following steps:
1. First, identify who the performer of Live and Beyond is.
2. Then find out the birthplace of this performer.
3. Next, search for which state Knowles is from.
4. Finally, determine when the birth city of the performer of Live and Beyond became the capital of Knowles' state.
Now, I will start with the first step and search online to determine who the performer of Live and Beyond is. `</think>`
`<search>` [{"query": "Find out who the performer of Live and Beyond is", "intent": 1}] `</search>`

Question: {input}
Thought:

Rewriter Agent

Given a piece of content containing queries to search, your task is to rewrite the queries in order to obtain more comprehensive search results. Please provide at least three rewritten queries. The output format should be the following JSON structure:
{"queries": ["query 1", "query 2", "query 3"]}

Here are some examples:

Content: `<think>` To find out which undergraduate school the director of the movie "Sense and Sensibility" attended, I will take the following steps:
1. First, determine who the director of the movie "Sense and Sensibility" is.
2. Then, search for educational background of this director, particularly undergraduate education.
Now, I'll proceed with the first step by using online searches to identify the director of the movie "Sense and Sensibility". `</think>`
`<search>` [{"query": "Find out who the director of the movie 'Sense and Sensibility' is", "intent": 1}] `</search>`
Rewritten Queries:
{"queries": ["Sense and Sensibility director", "Sense and Sensibility 1995 director", "Sense and Sensibility Filmmaker"]}

Content: `<think>` After analyzing the search results in detail, I concluded that the director of the movie "Sense and Sensibility" is Ang Lee. Therefore, I will proceed with the next step, where I need to search for his detailed undergraduate education. `</think>`
`<search>` [{"query": "Search for the undergraduate school of Ang Lee", "intent": 1}] `</search>`
Rewritten Queries:
{"queries": ["Ang Lee education background", "Ang Lee undergraduate school", "Ang Lee biography"]}

Content: {input}
Rewritten Queries:

Observer Agent

Given a multi-hop search problem, the steps already taken, and the search results obtained from the last executed step, your task is to:
1. Carefully analyze the search results to determine if they resolve the previous step, and provide a summary.

Continued on next page

Table 6: Prompt for Agent-Based CoT trajectory construction.

2. Update the execution steps and propose new steps based on the search results. You may encounter the following scenarios:

a. If the current search results are sufficient to arrive at the Final Answer to the problem, provide the final answer directly. Use the format: "`<think>` {thought process} `</think>` `<answer>` {answer} `</answer>` ". Please strictly adhere to this format.

b. If the current search results resolve the previous step, proceed according to the original plan and provide the next new step. Use the format: "`<think>` {thought process} `</think>` `<search>` [{"query": "query", "intent": 1}] `</search>` "; the query should be in sentence format.

c. If the current search results do not resolve the previous step, reflect on and update the previous execution steps based on the search results. Use the format: "`<think>` {reflection} `</think>` `<search>` [{"query": "query", "intent": 1}] `</search>` "; the query should be in sentence format.

d. If after multiple reflections (at least twice), the search still fails to resolve the issue, supplement based on your knowledge and provide the next new step. Use the format: "`<think>` {thought process} `</think>` `<search>` [{"query": "query", "intent": 1}] `</search>` "; the query should be in sentence format.

Below are some examples:

Question: What is the undergraduate school of the director of the movie "Sense and Sensibility"?
Thought: `<think>` To find out the undergraduate school of the director of the movie "Sense and Sensibility", I will take the following steps:
1. First, determine who directed the movie "Sense and Sensibility".
2. Then, search for this director’s educational background, focusing on undergraduate education.
I will now begin with step one by searching online to identify the director of the movie "Sense and Sensibility". `</think>`
`<search>` [{"query": "Find out who directed the movie ’Sense and Sensibility’", "intent": 1}] `</search>`
Observation: `<information>`
1. The movie "Sense and Sensibility" was released in 1995 and is directed by Ang Lee, a renowned director known for his work in both Eastern and Western cinema.
2. Ang Lee is recognized for directing major films such as "Crouching Tiger, Hidden Dragon" and "Life of Pi".
3. Ang Lee’s background in filmmaking and storytelling has earned him multiple Academy Awards and international acclaim. `</information>`
Thought: `<think>` After a detailed analysis of the search results, I concluded that Ang Lee is the director of the movie "Sense and Sensibility". Thus, I will proceed to the next step and search for Ang Lee’s educational background, focusing on his undergraduate education. `</think>`
`<search>` [{"query": "Search for the undergraduate school of Ang Lee", "intent": 1}] `</search>`

Question: What is the undergraduate school of the director of the movie "Sense and Sensibility"?
Thought: `<think>` To find out the undergraduate school of the director of the movie "Sense and Sensibility", I will take the following steps:
1. First, determine who directed the movie "Sense and Sensibility".
2. Then, search for this director’s educational background, focusing on undergraduate education.
I will now begin with step one by searching online to identify the director of the movie "Sense and Sensibility". `</think>`
`<search>` [{"query": "Find out who directed the movie "Sense and Sensibility", "intent": 1}] `</search>`
Thought: `<think>` After a detailed analysis of the search results, I concluded that Ang Lee is the director of the movie "Sense and Sensibility". Thus, I will proceed to the next step and search for Ang Lee’s educational background, focusing on his undergraduate education. `</think>`
`<search>` [{"query": "Search for the undergraduate school of Ang Lee", "intent": 1}] `</search>` **Observation**: `<information>`

Continued on next page

Table 6: Prompt for Agent-Based CoT trajectory construction.

1. Ang Lee graduated from the National Taiwan College of Arts in 1975 and then came to the U.S. to receive a B.F.A. Degree in Theatre/Theater Direction at the University of Illinois at Urbana-Champaign, and a Masters Degree in Film Production at New York University.
2. After high school Lee attended the Taiwan Academy of Art, where he became interested in acting. He moved to the United States in 1978 to study theater at the University of Illinois at Urbana-Champaign. `</information>`

Thought: `<think>` After a thorough analysis of the search results, I found out that Ang Lee graduated from the National Taiwan University with a degree in French literature, as well as a B.F.A. Degree from the University of Illinois at Urbana-Champaign, therefore, the answer is `</think>` `<answer>` National Taiwan College of Arts and University of Illinois at Urbana-Champaign. `</answer>`

Question: Who is the director of the suspense drama that premiered on MBC?
Thought: `<think>` To solve this problem, I need to follow a few steps in my search:
1. First, I need to identify which suspense drama premiered on MBC.
2. Then, I will look up who directed that suspense drama.
First, I will search for recent suspense dramas that premiered on MBC. `</think>`
`<search>` [{ "query": "What recent suspense dramas premiered on MBC?", "intent": 1}] `</search>`
Observation: `<information>` 1. Premiering soon! A 12-episode suspense drama is coming, starring Wang Zhiwen and Yu Ai... From the trailer, 'The Vanishing Elephant' combines suspense and comedy, bringing an amusing story with humor and absurdity.
2. Chen Weiting's suspense drama is airing, featuring time travel and criminal investigation, with top actors like award-winning actors joining."
3. The best 10 suspense dramas of the past 4 years, with 'The Big Squad' at the bottom. Though the series is framed as a historical drama, it unfolds as a large-scale suspense espionage drama.
4. Premiering soon! An 18-episode suspense drama is coming, starring Sun Li, with a strong cast. However, recent suspense dramas such as 'Dim Flames' and 'Rebirth' have not been well-received.
5. Lee Jong-suk's return! New drama 'The Black Lawyer' premiered on MBC, achieving high viewership. The story is a suspenseful crime drama about a vulnerable lawyer who is framed and battles powerful forces.
6. The top 10 suspense dramas to watch in 2024, featuring leading actors like Liao Fan, Duan Yihong, and Zhang Songwen...
7. Premiering tonight! Another suspenseful drama is coming! 'Thirteen Years in Dust' will air on iQIYI's Mist Theater, starring Chen Jianbin and Chen Xiao.
8. Chen Weiting's new drama 'The Sun and Stars' debuted with impressive suspenseful plotlines.
`</information>`
Thought: `<think>` From the search results, I found several relevant pieces of information:
1. The suspense drama 'The Black Lawyer' premiered on MBC, starring Lee Jong-suk and Im Yoon-ah, and it is a crime suspense drama.
2. The premiere of 'The Black Lawyer' achieved high ratings, telling a story about a vulnerable lawyer who is framed and fights back against powerful figures.
3. However, the search results did not provide the director's information for 'The Black Lawyer.'
Filter out unrelated content: The search results also mention suspense dramas on other platforms like iQIYI and Mist Theater, and other non-MBC dramas, such as 'The Sun and Stars.' These are not directly related to the question and can be excluded.
Current progress summary: Based on the retrieved information, 'The Black Lawyer' is a recent suspense drama premiered on MBC, but the director's information is still missing.
Next plan: I will continue with the second step of my plan, searching for the director of 'The Black Lawyer.' `</think>`
`<search>` [{"query": "Who is the director of 'The Black Lawyer'?", "intent": 1}] `</search>`
Question: {input}
Thought: {thought}
Observation: {observation}

Continued on next page

Table 6: Prompt for Agent-Based CoT trajectory construction.

Thought:

LLM-Judge

Given the correct answer to a question, determine if the modelś response is correct. If correct, output "correct"; if incorrect, output "incorrect". Do not include unrelated content.

Question: {question}
Correct Answer: {answer}
Model Response: {model_response}

E Reinforcement Learning

E.1 Training Template

Table 7: Training template. The question is appended at the end during RL training and inference.

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>` xxx `</answer>` .
Question:

As illustrated in Table 7, during the RL process, we follow [13] by utilizing a multi-round interactive template to guide the reasoning of the policy model. Specifically, the model engages in internal reasoning within the <think> tag, where it analyzes the problem and assesses the information collected. If additional evidence is required, the search query is refined within the <search> tag. Once sufficient information is gathered, the answer is provided within the <answer> tag.

E.2 RL Algorithms Detail

DAPO with Search Engine Decouple Clip and Dynamic sAmpling Policy Optimization (DAPO) [15] is an advanced RL algorithm that enhances the Group Relative Policy Optimization (GRPO) [61] by incorporating techniques such as dynamic sampling and token-level policy gradient loss. DAPO samples a group of outputs $\{o_i\}_{i=1}^{G}$ for each question q paired with the answer a, and optimizes the policy model via the following objective function:

$$\begin{aligned}\mathcal{J}_{\text{DAPO}}(\theta) = \; & \mathbb{E}_{(q,a)\sim\mathcal{D},\{o_i\}_{i=1}^{G}\sim\pi_{\theta_{\text{old}}}(\cdot|q)} \\ & \left[\frac{1}{\sum_{i=1}^{G}|o_i|}\sum_{i=1}^{G}\sum_{t=1}^{|o_i|}\min\left(r_{i,t}(\theta)\hat{A}_{i,t},\ \text{clip}\left(r_{i,t}(\theta),1-\varepsilon_{\text{low}},1+\varepsilon_{\text{high}}\right)\hat{A}_{i,t}\right)\right]\end{aligned} \tag{8}$$

where

$$r_{i,t}(\theta) = \frac{\pi_{\theta}(o_{i,t} \mid q, o_{i,<t}; \mathcal{R})}{\pi_{\theta_{\text{old}}}(o_{i,t} \mid q, o_{i,<t}); \mathcal{R})}, \qquad \hat{A}_{i,t} = \frac{R_i - \text{mean}(\{R_i\}_{i=1}^{G})}{\text{std}(\{R_i\}_{i=1}^{G})}. \tag{9}$$

Here, $\mathcal{R}$ is the search engine, $\hat{A}_{i,t}$ represent the advantage, ε_{low} and $\varepsilon_{\text{high}}$ are hyperparameters where we set 0.2 and 0.28 respectively. Additionally, DAPO removes KL Divergence to stabilize the generation of long-cot. We mask the retrieved tokens from the search engine, ensuring the policy gradient objective is computed only over LLM-generated tokens.

E.3 Model-based Reward Prompt

Table 8: Prompt for model-based reward design.

Reward Model

Please evaluate whether the model's response is correct based on the given question, standard answer, and the model's predicted answer. Your task is to rate the result as: **Correct** or **Incorrect**.

Correct Responses

Here are examples of **Correct** responses:
Question: What are Barack Obama's children's names?
Standard Answer: Malia Obama and Sasha Obama
Model Prediction 1: Malia Obama and Sasha Obama
Model Prediction 2: Malia and Sasha
Model Prediction 3: Most people would say Malia and Sasha, but I'm not sure and need to confirm.
Model Prediction 4: Barack Obama has two daughters, Malia Ann and Natasha Marian, but they are commonly known as Malia Obama and Sasha Obama. These responses are **Correct** because:
They fully include the important information from the standard answer.
They do not contain any information that contradicts the standard answer.
Only the semantic content is considered; language (English or Chinese), case, punctuation, grammar, and order are not important.
The presence of vague statements or guesses is acceptable, as long as the standard answer is included and there is no incorrect or contradictory information.

Incorrect Responses

Here are examples of **Incorrect** responses: Question: What are Barack Obama's children's names?
Standard Answer: Malia Obama and Sasha Obama
Model Prediction 1: Malia
Model Prediction 2: Malia, Sasha, Susan, and Sasha Obama or Malia Obama, or Natasha Marian, or Einstein
Model Prediction 3: Although I don't know their exact names, I can say that Barack Obama has two children.
Model Prediction 4: You might be thinking of Bessie and Olivia. But you should check the latest references for detailed information. Is that the correct answer?
Model Prediction 5: Barack Obama's children These responses are **Incorrect** because: They contain factual statements that contradict the standard answer.
The answer is empty, restates the question.
The answer lists multiple answers, restates the answer.

Special Notes

Please note the following:
The standard answer may contain multiple aspects of the question's response, and within the same aspect, there may be multiple different descriptions, all of which are correct and are given within the same parentheses, connected by commas. For example, consider the question ”What is the name of the social media platforms purchased by Elon Musk?”:
Predicted answers ”Twitter,” ”Twitter, X,” and ”X” are all **Correct**.
For standard answers that contain responses to multiple aspects of the question, the model must provide answers to all aspects to be considered correct; otherwise, it is directly judged as **Incorrect**. There is no such output as **Partially Correct**. These answers will be given in different parentheses. For example, consider the question ”Who are the original members of the band The Beatles?”:
Predicted answers ”John Lennon, Paul McCartney, George Harrison, Ringo Starr” that include all answers are considered **Correct**.

Continued on next page

Table 8: Prompt for model-based reward design.

Predicted answers like ”John Lennon, Paul McCartney” that do not include all answers are considered **Incorrect**.

Additional Guidelines

Also, pay special attention to the following:
For questions with numerical standard answers, the predicted answer should match the standard answer. For example, consider the question ”What is the total length of the Jinshan Railway Huangpujiang Special Bridge in meters?”:
Predicted answers ”3518,” ”3518.1,” and ”3518.17” are all **Correct**.
Predicted answers ”3520” and ”3600” are all **Incorrect**.
If the model’s prediction does not directly answer the question and attempts to bypass or fails to directly provide the standard answer, it is considered an **Incorrect** answer.
If the standard answer contains more information than the question, the predicted answer only needs to include the information mentioned in the question.
If it is obvious from the question that the predicted answer has omitted information, it is considered **Correct**.
If it is clear that different translation versions of a name refer to the same person, they are also considered **Correct**.
You should focus more on the match between the standard answer and the model’s prediction, rather than whether the standard answer is correct.

Example Question

Here is a new example question. Please rate the predicted answer as one of the following:
Question: {question}
Standard Answer: {target}
Predicted Answer: {predicted answer}
Only return the option represented by **Correct** or **Incorrect**, that is, only return A or B, without adding any other text.

F RAMP Case Study

We illustrate how the model acquires the ability to retrieve and reason using the Retrieval-Augmented Mask Prediction Task (RAMP) through a case study presented in Table 9. In this example, information about the league, team, and university that David Henry Hoelscher is associated with is masked. The model autonomously utilizes the search engine to reason and fill in the missing information.

Initially, the model establishes a search plan, which includes details about the individual’s career, team, and university. In the first step, it retrieves information related to his career and team. After acquiring the initial search results, the model identifies the league associated with the individual based on the retrieved data and initiates another search to confirm the team he played for. Following the second search, the model successfully infers his team affiliation and discovers that the previous search results include his college information. It then requests another search to verify this data. Upon completing the third search, the search agent effectively gathers all required information and fills in the masks.

Through the RAMP task, the model not only learns to perform retrievals but also masters the use of retrieved information for further reasoning and verification until the complete answer is obtained.

Table 9: RAMP Case.

Question
David Hoelscher David Henry Hoelscher (born November 27, 1975) is a former American football defensive tackle. He played one game in the [mask] for the [mask] in 1998. He played college football at [mask]. Fill in all the [mask] and output the whole paragraph without changing its format.
Response

Continued on next page

Table 9: RAMP Case.

<think> To fill in the blanks in the provided sentence about David Hoelscher, I will perform the following searches:
1. First, search for David Hoelscher's brief NFL career to determine the specific league and team he played for in 1998.
2. Then confirm the name of the college where he played football before entering the NFL.
Now, I will start with the first step and search for David Hoelscher's NFL career details.
</think>
<search> [{"query": "David Hoelscher one game NFL" "David Henry Hoelscher NFL team 1998" "David Hoelscher defensive tackle one game in 1998", "intent": 1}]
</search>
<information>
1. David Hoelscher, , - Career Stats - NFL - CBSSports.com: Get the latest career stats for David Hoelscher of the on CBS Sports.
2. David Hoelscher, , - 2021-22 Game Log - NFL - CBSSports.com: Get up-to-date stats for every game played by David Hoelscher during the 2021-22 NFL season on CBS Sports.
3. David Hoelscher Stats, News and Video - DE | NFL.com: David Hoelscher DE Player Info Height 6-6 Weight 261 Arms Hands Experience 2 College Eastern Kentucky.
4. David Hoelscher - 2021-22 - Esports - Florida Southern College: David Hoelscher. Class Freshman. Hometown Orchard Park, N.Y.
5. David Hoelscher | American Football Database - Fandom: American football defensive tackle in the National Football League for the Washington Redskins. He played college football at Eastern Kentucky University.
</information>
<think> After finding out that David Hoelscher is indeed associated with the National Football League (NFL) and a specific team, I will now confirm the name of the team he played for in 1998 when he played one game.
</think>
<search> [{"query": "David Hoelscher one game in 1998 NFL team" "Which team did David Hoelscher play for in one game in 1998" "David Hoelscher NFL team when he played college football at Eastern Kentucky", "intent": 1}]
</search>
<information>
1. David Hoelscher 1998 Game Log | StatMuse: David Hoelscher's game log for the 1998 NFL regular season and playoffs. TEAM, W, L, T, PCT. Eagles NFL 2024 Betting. Best Record ATS · Chargers. 12-5-1.
2. David Hoelscher Stats, News and Video - DE | NFL.com: David Hoelscher DE Player Info Height 6-6 Weight 261 Arms Hands Experience 2 College Eastern Kentucky.
3. David Hoelscher - Washington Redskins Defensive Lineman: David Hoelscher played 1 season for the Redskins. He played but didn't record a tackle.
4. Colonels in the NFL - Eastern Kentucky University Athletics: Colonels in the NFL; David Hoelscher (1994-97), Washington Redskins (1998); Joe Hollingsworth (1946-47), Pittsburgh Steelers (1949-51); Tyrone
5. David Hoelscher Pro Football Stats, Position, College, Draft: DAVID HOELSCHER; 1998 Washington Redskins (NFL), 91, DT, 1, 0; 1999 Frankfurt Galaxy (NFLE), 91, RDT-RDE.
</information>
<think> After confirming that David Hoelscher played for the Washington Redskins in 1998, I will now verify if there is any additional confirmation needed about the college he attended before entering the NFL, which was mentioned as Eastern Kentucky in the previous searches.
</think>
<search> [{"query": "David Hoelscher college football" "Which college did David Hoelscher play football before entering the NFL?" "David Hoelscher defensive tackle college", "intent": 1}]
</search>
<information>
1. David Hoelscher Pro Football Stats, Position, College, Draft: DAVID HOELSCHER. Hoelscher, David Henry Height: 6-6 Weight: 256. Born: November 27, 1975 Coldwater, OH High School: Versailles (OH). Year, College, Status. 1994.

Continued on next page

Table 9: RAMP Case.

2. HOELSCHER; 1994, Eastern Kentucky, Roster; 1995, Eastern Kentucky, Roster; 1996, Eastern Kentucky, Roster; 1997, Eastern Kentucky, Played.
3. David Hoelscher - 2021-22 - Esports - Florida Southern College: David Hoelscher. Class Freshman. Hometown Orchard Park, N.Y.. Prev School Athletics. 111 Lake Hollingsworth Drive | Lakeland FL 33801 | 863-680-4245.
4.David Hoelscher Stats, Height, Weight, Position, Draft, College: Position: DE; Born: November 27, 1975 in Coldwater, OH; College: Eastern Kentucky; Weighted Career AV (100-95-): 0 (17977th overall since 1960); High School:.
5. David Hoelscher | American Football Database - Fandom: He played college football at Eastern Kentucky University. Stub icon, This biographical article relating to an American football defensive lineman born in the.
`</information>`
`<think>` After verifying the college where David Hoelscher played football, I can now complete the original statement.
`</think>`
`<answer>` David Hoelscher David Henry Hoelscher (born November 27, 1975) is a former American football defensive tackle. He played one game in the National Football League for the Washington Redskins in 1998. He played college football at Eastern Kentucky University.
`</answer>`

G Broader Impacts

As an exploration in the field of Search Agents, MASKSEARCH has the following impacts:

- Provides a general pre-training method for Search Agent: MASKSEARCH introduces the Retrieval Augmented Mask Prediction Pre-training Task, pioneering the enhancement of an agent's retrieval and reasoning capabilities during the pre-training stage. This offers new perspectives for future developments in agent technology.
- Applications in Various RAG Fields: As a general pre-training task, it can be broadly applied to RAG applications across different knowledge domains.
- Negative social impacts: There are no negative social impacts foreseen.

H Limitations

Despite the empirical success and intuitive motivation of our approach, there are several limitations that warrant further investigation. First, we employ only a search tool for knowledge retrieval to adhere to the concept of RALM. However, agents are capable of utilizing a diverse array of tools, and we believe that the RAMP task could be generalized to incorporate the use of multiple tools. Future work could explore the diversity of toolset, potentially expanding the application scope beyond open-domain QA to other scenarios. Furthermore, while our method has demonstrated promising results, a more in-depth theoretical analysis is necessary to fully understand the factors contributing to its effectiveness.

I Data Ethics Statement

In this paper, we conduct experiments using publicly available datasets, including Hotpot, FanoutQA, Musique, 2WikiMultiHopQA, Bamboogle, and FreshQA, in accordance with their respective usage terms and conditions.