

MA-RAG: MULTI-AGENT RETRIEVAL-AUGMENTED GENERATION VIA COLLABORATIVE CHAIN-OF-THOUGHT REASONING

Thang Nguyen & Peter Chin & Yu-Wing Tai

Dartmouth College

{thangnv.th, peter.chin, yu-wing.tai}@dartmouth.edu

ABSTRACT

We present MA-RAG, a Multi-Agent framework for Retrieval-Augmented Generation (RAG) that addresses the inherent ambiguities and reasoning challenges in complex information-seeking tasks. Unlike conventional RAG methods that rely on end-to-end fine-tuning or isolated component enhancements, MA-RAG orchestrates a collaborative set of specialized AI agents: Planner, Step Definer, Extractor, and QA Agents, each responsible for a distinct stage of the RAG pipeline. By decomposing tasks into subtasks such as query disambiguation, evidence extraction, and answer synthesis, and enabling agents to communicate intermediate reasoning via chain-of-thought prompting, MA-RAG progressively refines retrieval and synthesis while maintaining modular interpretability. Extensive experiments on multi-hop and ambiguous QA benchmarks, including NQ, HotpotQA, 2WikimQA, and TriviaQA, demonstrate that MA-RAG significantly outperforms standalone LLMs and existing RAG methods across all model scales. Notably, even a small LLaMA3-8B model equipped with MA-RAG surpasses larger standalone LLMs, while larger variants (LLaMA3-70B and GPT-4o-mini) set new state-of-the-art results on challenging multi-hop datasets. Ablation studies reveal that both the planner and extractor agents are critical for multi-hop reasoning, and that high-capacity models are especially important for the QA agent to synthesize answers effectively. Beyond general-domain QA, MA-RAG generalizes to specialized domains such as medical QA, achieving competitive performance against domain-specific models without any domain-specific fine-tuning. Our results highlight the effectiveness of collaborative, modular reasoning in retrieval-augmented systems: MA-RAG not only improves answer accuracy and robustness but also provides interpretable intermediate reasoning steps, establishing a new paradigm for efficient and reliable multi-agent RAG¹.

1 INTRODUCTION

Recent advances in natural language processing have driven the development of Retrieval-Augmented Generation (RAG) models, which aim to enhance the factual accuracy and contextual relevance of generated text by integrating external knowledge sources (Lewis et al., 2020; Guu et al., 2020; Izacard & Grave, 2021; Lin et al., 2024). These systems address core limitations of Large Language Models (LLMs), such as outdated knowledge (Zhang et al., 2023b; Kasai et al., 2023) and poor generalization to domain-specific queries (Siriwardhana et al., 2023; Xiong et al., 2024), by retrieving top- k documents from an external corpus (Formal et al., 2022; Izacard et al., 2022; Wang et al., 2022a) to ground the model’s output in relevant evidence.

Prior research in RAG has largely concentrated on optimizing three key components—retrieval, augmentation, and generation (Gao et al., 2024; Fan et al., 2024) (Figure 1(a)). Retrieval strategies span sparse methods (Jones, 1972; Robertson & Zaragoza, 2009) and dense retrieval (Reimers & Gurevych, 2019; Karpukhin et al., 2020), each with respective weaknesses such as lexical gaps (Berger et al., 2000) or retrieval failure on out-of-distribution and multi-hop queries (Dai et al.,

¹Our code is available at <https://github.com/thangylvp/MA-RAG>

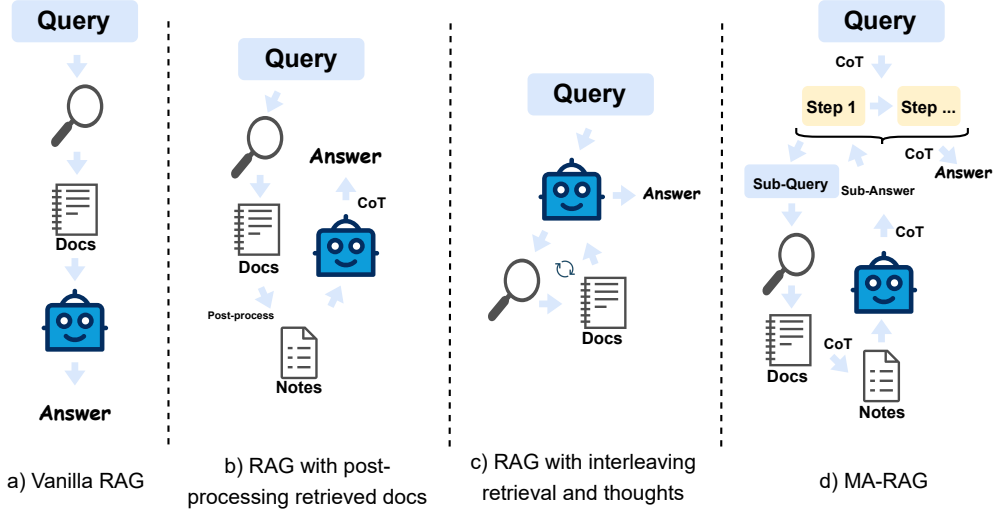


Figure 1: **Architectural Comparison of MA-RAG and Prior RAG Methods.** **a)** A naive RAG system performs one-shot retrieval followed by direct answer generation. **b)** Enhanced systems incorporate post-retrieval processing such as document re-ranking or summarization. **c)** Iterative systems interleave retrieval and reasoning via query rewriting or multi-step refinement, yet often lack explicit modularity and planning. **d)** In contrast, MA-RAG adopts a collaborative multi-agent architecture where specialized agents handle distinct stages of the RAG pipeline, such as query disambiguation, targeted evidence extraction, and answer synthesis, using chain-of-thought reasoning. Agents are invoked dynamically and on demand, enabling fine-grained document analysis and step-by-step resolution of ambiguities, resulting in a more robust, interpretable, and efficient retrieval-to-generation process.

2023). Augmentation methods often rely on post-retrieval processing such as re-ranking or document summarization (Chen et al., 2020; Glass et al., 2022; Ma et al., 2024) (Figure 1(b)) to improve input quality for the LLM, but add latency and may still fail to filter irrelevant or misleading evidence. More sophisticated approaches introduce iterative retrieval or query rewriting (Jiang et al., 2023b; Asai et al., 2024) (Figure 1(c)), but commonly assume the input query is well-formed and overlook the broader reasoning process across the pipeline. Across retrieval, augmentation, and generation, most existing methods treat components in isolation, failing to resolve ambiguities and reasoning gaps that span multiple stages, such as vague queries, incomplete retrievals, or scattered evidence, ultimately limiting robustness and transparency in complex QA scenarios.

To address these challenges, we propose **MA-RAG**, a modular, *training-free* Multi-Agent framework that performs step-by-step reasoning across the entire RAG pipeline (Figure 1(d)). MA-RAG views the RAG process as a collaborative effort among specialized agents, each responsible for a specific subtask such as query disambiguation and task decomposition (Planner), document retrieval (Step Definer and Retrieval Tool), evidence extraction (Extractor), and answer synthesis (QA Agent). Rather than invoking all agents uniformly, MA-RAG adopts an *on-demand* strategy, calling only the necessary agents depending on the ambiguity and complexity at each step. Each agent is guided by chain-of-thought prompting, enabling explicit intermediate reasoning that improves interpretability and task alignment. For instance, agents can decompose an underspecified query into concrete sub-questions, retrieve documents tailored to each subtask, distill targeted evidence from multiple sources, and compose coherent answers by integrating dispersed information.

This multi-agent design not only improves robustness to ambiguous and multi-hop questions, but also provides fine-grained control over the information flow in RAG, all without requiring model fine-tuning. Empirically, MA-RAG achieves new state-of-the-art performance on multiple open-domain QA benchmarks, including NQ, HotpotQA, TriviaQA, and 2WikimQA, consistently outperforming both standalone LLMs and strong RAG baselines across model scales. Ablation studies further reveal the importance of the modular architecture: the planner agent is essential for multi-hop reasoning, while the extractor agent significantly improves grounding by filtering irrelevant content. Moreover, our analysis shows that model size matters most for answer generation, planning and evidence extraction, while lighter-weight models can be effectively used for retrieval components,

enabling more efficient deployments. These results highlight the effectiveness and flexibility of our multi-agent framework in tackling complex QA tasks without additional supervision or domain-specific training.

Our key contributions are as follows:

- We introduce **MA-RAG**, a modular multi-agent framework that performs reasoning-driven RAG via *structured collaboration* between agents, enabling fine-grained handling of ambiguity and complex queries.
- MA-RAG operates entirely without model fine-tuning, offering a general and adaptable solution that outperforms or matches strong baselines across multiple QA datasets and LLM backends.
- Through agent-specific chain-of-thought reasoning, MA-RAG provides *interpretable intermediate steps* and demonstrates strong *generalization* to specialized domains, such as biomedical QA, without requiring domain-specific fine-tuning.

2 RELATED WORKS

Large Language Models (LLMs) have driven significant advancements in recent years. Starting with GPT-1 (Radford et al., 2018) on the Transformer architecture (Vaswani et al., 2017), subsequent models such as GPT-2 (Radford et al., 2019), GPT-3 (Brown et al., 2020), and GPT-4 (OpenAI, 2024) have greatly enhanced capabilities in text understanding and generation. Beyond GPT, models including Mistral (Jiang et al., 2023a), Gemini (Gemini Team, 2023), and LLaMA (Touvron et al., 2023a), Touvron et al. (2023b)) show strong performance across tasks such as question answering and entity recognition (Zhao et al., 2023). LLM training involves unsupervised pre-training, supervised fine-tuning, and alignment with human feedback, yet domain-specific challenges remain (Kandpal et al., 2023). Techniques such as PEFT (Houlsby et al., 2019a) improve fine-tuning efficiency, while prompt-based learning (Lester et al., 2021; Li & Liang, 2021), adapters (Houlsby et al., 2019b; Fu et al., 2021; Wang et al., 2022b; He et al., 2022), and reparameterization methods (Hu et al., 2022; Edalati et al., 2022; Dettmers et al., 2023) selectively adjust parameters for improved performance. Additionally, recent studies (Wei et al., 2024; Java et al., 2025) highlight the importance of evaluating factuality and retrieval efficiency in short-form and deep research scenarios.

Retrieval-Augmented Generation (RAG) enhances LLM performance by integrating external knowledge via document retrieval (Lewis et al., 2020; Guu et al., 2020). Challenges remain in determining what, when, and how to retrieve (Gao et al., 2024). Early methods incorporate retrieval into next-token prediction (Khandelwal et al., 2020; Ram et al., 2023; Liu et al., 2024b) or use end-to-end pipelines (Guu et al., 2020; Borgeaud et al., 2022; Izacard et al., 2023; Zhang et al., 2024a), while others study knowledge representation and retrieval robustness (Xu et al., 2024; Sarthi et al., 2024). Supervised and contrastive approaches often face scalability and domain transfer limitations (Dai et al., 2023; Zhang et al., 2023b; Shi et al., 2024). Structured retrieval methods include HippoRAG (Gutiérrez et al., 2024), which leverages knowledge graphs. Recent research focuses on tighter retrieval-reasoning integration. RA-DIT (Lin et al., 2024) tunes LLMs for context use and retrievers for relevance independently. Speculative RAG (Wang et al., 2025) drafts answers with a specialist LM and verifies with a generalist LM. CD-LM (Li et al., 2025b) improves inference via chunk-level retrieval, while Auto-GDA (Leemann et al., 2025) addresses domain adaptation with synthetic data. Graph-based methods such as ToG-2 (Ma et al., 2025) and SubgraphRAG (Li et al., 2025a) utilize subgraph structures to enhance retrieval. Reinforcement learning approaches optimize retrieval and generation via episodic memory (Shinn et al., 2023), policy optimization (Kulkarni et al., 2024), evidence citation (Menick et al., 2022), and reflection-based refinement (Asai et al., 2024; Zhou et al., 2023; Gao et al., 2025). Recent open-source agentic retrieval frameworks, such as Open Deep Search (Alzubi et al., 2025a), further demonstrate the potential of lightweight reasoning agents for democratized, structured search. Compared to prior agent-based RAG systems, our MA-RAG provides a training-free, efficient, and interpretable solution.

LLM-based Agentic Systems coordinate multiple specialized agents to solve complex tasks through structured interaction (Guo et al., 2024). Agents operate in diverse environments, including sandboxed, physical, or abstract settings (Hong et al., 2024; Mao et al., 2025; Park et al., 2023), and assume predefined, emergent, or data-driven roles (Du et al., 2024; Xiong et al., 2023). Communication follows cooperative, competitive, or debate-based paradigms through centralized or decen-

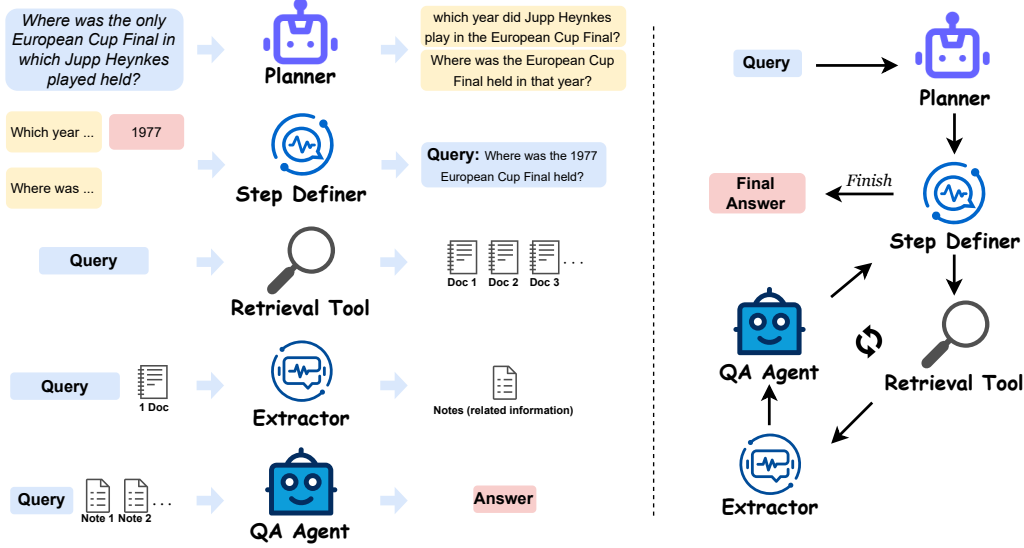


Figure 2: **Overview of MA-RAG.** MA-RAG is a training-free, multi-agent RAG framework that decomposes complex queries into interpretable steps through collaborative reasoning. The left panel shows individual components and their I/O interfaces; the right panel illustrates the overall iterative workflow. A **Planner Agent** first breaks down the input query into a high-level reasoning plan. For each step, a **Step Definer Agent** generates a detailed subquery based on the step goal, original question, and prior outputs. This subquery is processed by the **Retrieval Tool** to fetch top-ranked documents, which are then refined by the **Extractor Agent** to retain only step-relevant content. The **QA Agent** synthesizes the final answer for each step using the filtered evidence and subquery. MA-RAG iterates through these steps until the full reasoning path is complete.

tralized channels (Liu et al., 2024c; Hong et al., 2024). Capabilities are developed via environmental feedback, memory retrieval, or self-evolution (Wang et al., 2023; 2024; do Nascimento et al., 2023; Zhang et al., 2023a; Chen et al., 2024a;b). Recent work has extended agentic designs to RAG. For example, Agentic RAG for time series (Ravuru et al., 2024) uses hierarchical agent routing, while ColLEX (Schneider et al., 2025) enables multimodal retrieval via vision-language agents. MA-RAG differs by employing lightweight, specialized agents that collaborate through chain-of-thought reasoning, improving transparency and performance in complex QA settings without fine-tuning.

3 METHOD

In this section, we introduce MA-RAG, our proposed multi-agent framework for retrieval-augmented generation. We begin by formalizing the RAG problem setting, and then describe our multi-agent approach designed to improve both retrieval and reasoning.

Preliminaries Retrieval-augmented generation leverages a large corpus of documents or contexts—such as Wikipedia—to provide grounded knowledge for question answering. Given a query q and a corpus \mathcal{C} , a dense retriever \mathcal{R} retrieves the top- k relevant contexts $C_q = \{c_1, \dots, c_k\}$. In standard RAG pipelines, a large language model (LLM) generates the answer based on a prompt that includes the query and the retrieved documents:

$$y = \text{LLM}(\text{Prompt}_{\text{gen}}(q, C_q)),$$

where $\text{Prompt}_{\text{gen}}$ is a prompting template that provides instructions and structures the input for the LLM. This paradigm allows the LLM to produce answers grounded in retrieved evidence, thereby reducing hallucinations (Huang et al., 2023).

3.1 MULTI-AGENT SYSTEM FOR RETRIEVAL-AUGMENTED GENERATION (MA-RAG)

While advances in long-context LLMs (Liu et al., 2025) suggest potential to bypass retrieval altogether, practical limitations remain: effective context utilization is still far below advertised limits (Modarressi et al., 2025), and processing long sequences significantly increases inference cost and

latency. More importantly, RAG is not merely a workaround for context size—it is a framework for extending LLMs’ factual coverage by dynamically incorporating external knowledge. We emphasize a system-level perspective: RAG should be treated as a pipeline for complex, knowledge-intensive reasoning, not just improved generation.

Two persistent challenges degrade RAG performance. First, *retrieval mismatch* arises from semantic gaps between user queries and corpus content due to ambiguity, domain shift, or granularity differences. Second, *context inefficiency* stems from naively appending all retrieved passages, which inflates input length and model attention without guaranteeing relevance (Liu et al., 2024a). Moreover, document chunking introduces trade-offs: larger chunks preserve context but increase noise; smaller ones lose coherence.

To address these challenges, we propose **MA-RAG**, a lightweight, training-free multi-agent RAG framework that decomposes complex queries into structured reasoning steps and coordinates specialized agents for high-precision retrieval and generation. Figure 2 presents an overview of the system, which includes four collaborating agents and one retrieval module.

Planner Agent. The Planner analyzes the input query q to perform query disambiguation and task decomposition. It identifies ambiguities or underspecified elements and reformulates them into clearer sub-questions if needed. For complex or multi-hop queries, it produces a structured plan $P = \{s_1, s_2, \dots, s_n\}$, where each s_i denotes a reasoning subtask. The number of reasoning steps is determined by the Planner, and at each step the system performs a Retrieve \rightarrow Answer RAG process using a sub-query refined by the Step Definer. Breaking down questions into simpler, targeted sub-queries enables more precise retrieval, and our empirical results across benchmarks validate this design. The Planner is guided by chain-of-thought prompting with few-shot examples, ensuring interpretable step-wise decomposition that supports grounded reasoning in downstream modules.

Step Definer Agent. Each abstract step s_i is made executable by the step definer, which generates a detailed subquery tailored for retrieval. This agent conditions on the original query q , the plan P , the current step s_i , and accumulated history $H_{i-1} = \{(s_1, a_1), \dots, (s_{i-1}, a_{i-1})\}$. By grounding the subquery in context and prior answers, the step definer bridges high-level intent and low-level execution, enabling precise and relevant document retrieval.

Retrieval Tool. We use a dense retrieval module built on FAISS (Johnson et al., 2021) for fast, scalable search over large corpora. Texts are preprocessed into chunks and embedded using a pretrained encoder. At inference, the subquery is encoded into a vector and matched against the index via inner product. The top- k relevant passages are returned, enabling dynamic, on-demand knowledge augmentation at each step.

Extractor Agent. Retrieved passages often contain redundant or irrelevant content. Instead of appending entire chunks, the Extractor selects and aggregates sentences or spans directly aligned with the current subquery. This not only filters out noise and mitigates the lost-in-the-middle issue (Liu et al., 2024a), but also enables effective evidence aggregation by combining complementary information from multiple sources into a concise evidence set for the QA agent. To avoid context overflow in multi-hop queries, the Extractor summarizes relevant content at each step, and only the step-level query with the extracted summary or answer is passed forward. This preserves continuity while keeping context concise and efficient, ultimately supporting more accurate and informed answer generation.

Question Answering Agent. Given the step-specific query and filtered evidence, the QA agent synthesizes an answer using in-context learning. It produces a response a_i for each step s_i , which is passed to the next iteration. Once all steps are completed, the final answer is assembled and returned to the user.

A key feature of MA-RAG is its dynamic and modular agent invocation. Rather than executing a fixed pipeline, the system orchestrates agents on demand based on the structure of the reasoning plan. The **Planner Agent** is invoked once at the beginning to generate a high-level plan. Subsequently, for each step s_i , the system triggers the **Step Definer Agent** to produce a detailed subquery, which is then passed to the **Retrieval Tool** and the **Extractor Agent** in sequence. The extracted evidence is sent to the **QA Agent**, which returns the answer a_i . This answer is added to the history H_i , and the next iteration begins. The system maintains state throughout the reasoning trajectory, allowing each agent to condition on the evolving context. This modular design enables flexible, step-by-step

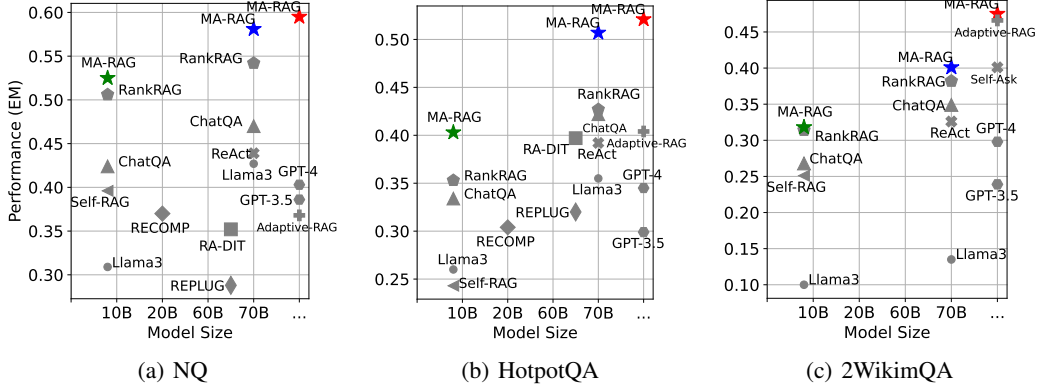


Figure 3: Exact Match (EM) performance of MA-RAG and baseline methods on NQ, HotpotQA, and 2WikimQA. The green star indicates MA-RAG with LLaMA3-8B, the blue star indicates MA-RAG with LLaMA3-70B, and the red star indicates MA-RAG with GPT-4o-mini. Across all datasets, MA-RAG consistently outperforms baseline methods using the same model size, demonstrating the effectiveness of our multi-agent reasoning approach.

execution and supports adaptive reasoning over complex, multi-hop queries without requiring all agents to be active simultaneously. The complete implementation and agent communication details are provided in Appendix.

4 EXPERIMENTS

Datasets. We evaluate MA-RAG on two tasks: *Open-domain Question Answering* and *Fact Verification*. For open-domain QA, we use four widely adopted benchmarks: Natural Questions (NQ) (Kwiatkowski et al., 2019), TriviaQA (Joshi et al., 2017), HotpotQA (Yang et al., 2018), and 2WikimQA (Ho et al., 2020). Among them, NQ and TriviaQA consist primarily of single-hop questions, while HotpotQA and 2WikimQA require multi-hop reasoning across multiple evidence sources. For fact verification, we use FEVER (Thorne et al., 2018) as our primary benchmark.

While we include results on TriviaQA and FEVER for completeness, these datasets may be sub-optimal for evaluating the effectiveness of RAG methods. In particular, GPT-4 can already achieve strong performance on these benchmarks, 84.8 EM and 87.7 Acc respectively, even without retrieval augmentation. This is because their questions often do not require external knowledge retrieval, making them less suitable for assessing the benefits of retrieval-augmented approaches.

Baselines. For question-answering, we consider baseline LLMs without RAG include GPT-3.5-turbo (OpenAI, 2022), GPT-4 (OpenAI, 2024), Llama3-Instruct 8B (Meta, 2024), and Llama3-Instruct 70B (Meta, 2024). We also consider baselines in RAG include Atlas (Izacard et al., 2023), Recomp (Xu et al., 2024), Replug (Shi et al., 2024), Ra-dit (Lin et al., 2024), Self-RAG (Asai et al., 2024), ChatQA-1.5 (Liu et al., 2024b), RankRAG (Yu et al., 2024)², Adaptive-RAG (Jeong et al., 2024), ReAct (Yao et al., 2023), Self-Ask (Press et al., 2023), and Smart-RAG (Gao et al., 2025).

Evaluation Metrics. For *Open-domain QA* tasks, we use *Exact Match (EM)* as the main metric for comparison, while we use *Accuracy (Acc)* for *Fact verification*.

Implementation Details. For NQ, HotpotQA, TriviaQA, and FEVER, we use the split from KILT benchmark (Petroni et al., 2021). We use Wikipedia corpus preprocessed by Karpukhin et al. (2020). We use gte-multilingual (Zhang et al., 2024b) as our retrieval model. We use different LLMs to build MA-RAG in different size, from small LLMs with 8B parameters (Meta, 2024) to middle size LLMs with 70B parameters (Meta, 2024) to black box LLMs (OpenAI, 2024).

²By the time of submission, RankRAG had not released any models. The reported results are therefore directly copied from their paper.

Table 1: Ablation study with MA-RAG using 70B LLM: evaluating the impact of planner and extractor agents on MA-RAG performance across single-hop and multi-hop QA benchmarks.

Task	NQ	TriviaQA	HotpotQA	2WikimQA	FEVER
MA-RAG (Llama3-70B)	58.1	85.4	50.7	43.1	93.1
- w/o Extractor	53.4	82.1	43.4	38.2	89.2
- w/o Planer	57.9	80.3	36.2	26.4	91.3

4.1 RESULTS

Figure 3 provides a visual comparison between MA-RAG and several baseline models across multiple datasets. The full numerical results with additional discussion are available in the Appendix. Key observations from our experiments include:

MA-RAG outperforms standalone LLMs without retrieval. Our results show that MA-RAG significantly enhances the performance of base LLMs when combined with retrieval-augmented reasoning. For instance, while Llama3-70B and GPT-4 achieve accuracy scores of 42.7 and 40.3 on NQ, respectively, MA-RAG (Llama3-8B) already surpasses these models with a score of 52.5, and MA-RAG (GPT-4o-mini) achieves an even higher score of 59.5. Similar improvements are observed across other datasets, including HotpotQA and 2WikimQA, where MA-RAG demonstrates a substantial advantage in handling complex, knowledge-intensive questions. These results underline that retrieval-augmented reasoning, supported by a multi-agent framework, outperforms standalone LLMs that rely solely on their internal knowledge base.

MA-RAG outperforms existing RAG models. At the 8B scale, MA-RAG consistently outperforms several strong baseline models, such as ChatQA-1.5 8B and RankRAG 8B. Despite using models of comparable size, MA-RAG (Llama3-8B) achieves superior exact match (EM) scores on NQ, HotpotQA, and 2WikimQA, showcasing the effectiveness of our multi-agent architecture in optimizing retrieval and reasoning. Even when compared to larger retrieval models like RA-DIT 65B and REPLUG 65B, MA-RAG (8B) demonstrates consistently better performance across all tasks, indicating that our approach is more effective at leveraging external knowledge while maintaining efficiency.

When scaling up to larger models, MA-RAG (Llama3-70B and GPT-4o-mini) outperforms the strongest 70B-scale models, such as ChatQA-1.5 70B and RankRAG 70B, setting new state-of-the-art results on multiple benchmarks. Notably, MA-RAG achieves a score of 59.5 on NQ, 87.2 on TriviaQA, 52.1 on HotpotQA, and 47.5 on 2WikimQA. In particular, on more challenging, multi-hop, and long-tailed datasets like HotpotQA and 2WikimQA, MA-RAG demonstrates significant gains over previous methods. These improvements suggest that the fine-grained query decomposition and passage extraction capabilities inherent in MA-RAG are particularly advantageous in handling complex retrieval conditions. A key strength of our modular design is that the number of steps in MA-RAG is dynamically determined by the planner based on question complexity, with multi-hop questions resulting in more steps and LLM calls. For example, on HotpotQA, MA-RAG averages 2.3 steps per question, while on NQ, which is mostly single-hop, it averages 1.4 steps. Overall, these results highlight the critical role of multi-agent coordination in improving open-domain QA performance, emphasizing that the integration of specialized agents for different reasoning steps leads to more effective and efficient utilization of external knowledge sources.

4.2 ABLATION STUDY

Impact of Agents. To understand each agent’s contribution, we conduct an ablation study by removing either the Extractor or Planner from MA-RAG. Table 1 reports performance across five QA benchmarks. Without the Extractor, retrieved documents are fed directly into the prompt, leading to consistent performance drops and highlighting its role in refining input and grounding responses. Removing the Planner reduces MA-RAG to a single-turn RAG system with document filtering but no query decomposition. While it still performs well on simpler, single-hop datasets, it struggles with multi-hop questions requiring structured reasoning. The largest performance drop occurs on multi-hop datasets, emphasizing the Planner’s importance in guiding complex reasoning. These results show both agents are essential: the Extractor enhances precision, and the Planner enables effective reasoning across diverse question types.

Table 2: Ablation study on LLMs’ size: evaluating the impact of replacing individual agents with Llama3-8B in a 70B-based MA-RAG system on multi-hop QA.

Planner	Step definer	Extractor	QA	HotpotQA	2WikimQA
Llama3-70B	Llama3-70B	Llama3-70B	Llama3-70B	50.7	43.1
Llama3-70B	Llama3-70B	Llama3-70B	Llama3-8B	49.7	34.5
Llama3-70B	Llama3-70B	Llama3-8B	Llama3-70B	49.4	39.8
Llama3-70B	Llama3-8B	Llama3-70B	Llama3-70B	49.9	42.5
Llama3-8B	Llama3-70B	Llama3-70B	Llama3-70B	49.2	39.1

Impact of LLMs. To assess the effect of model size on different agents in our multi-agent system, we conduct an ablation study where each agent is individually replaced with an LLaMA3-8B model while keeping the others as LLaMA3-70B. This isolates the impact of LLM capacity across agents on two multi-hop datasets: HotpotQA and 2WikimQA (Table 2). Replacing the QA agent consistently causes the largest performance drop, especially on 2WikimQA, suggesting that high-capacity models are crucial for final answer generation. Substituting the Planner or Extractor also leads to clear declines, with the Extractor highlighting the challenge of identifying relevant evidence in complex retrieval. The Planner’s ability to generate effective reasoning plans is similarly sensitive to model capacity. In contrast, reducing the Step Definer has only marginal impact, indicating its structured role is less dependent on large models.

In summary, for multi-hop QA tasks like HotpotQA and 2WikimQA, it is critical to allocate larger models to the QA, planner and extractor agents to maintain performance. Smaller models can be used for step definer with minimal loss, enabling more efficient resource allocation in practice.

Other Domains We further assess the generalizability of our method by conducting experiments in other domains. Specifically, we evaluate MA-RAG on medical benchmark datasets, including PubmedQA and MedMCQA. We follow the setup in Xiong et al. (2024), using MedCPT (Jin et al., 2023) as the retrieval model and deploying MedCorp (Xiong et al., 2024) as the corpus.

The experimental results of MA-RAG and the baselines are shown in Table 3. We compare MA-RAG with various RAG baseline models, including Mixtral (Jiang et al., 2024), Llama2-70B (Touvron et al., 2023b), Meditron-70B (Chen et al., 2023), PMC-Llama 13B (Wu et al., 2024), ChatQA-1.5 (Liu et al., 2024b), RankRAG (Yu et al., 2024), GPT-3.5 (OpenAI, 2022), and GPT-4-0613 (OpenAI, 2024), under identical settings. MA-RAG demonstrates strong performance in the medical domain, despite *not being fine-tuned on biomedical data*. Notably, MA-RAG with Llama3-70B outperforms domain-specific models such as Meditron 70B and PMC-LLaMA 13B, achieving performance comparable to GPT-4. When using GPT-4o-mini, MA-RAG surpasses all baselines, including GPT-4-0613 and RankRAG 70B. These results underscore the generalizability of MA-RAG to specialized domains through modular reasoning and chain-of-thought coordination, *without the need for domain-specific fine-tuning*.

Case Study Table 4 presents a case study from the 2WikimQA dataset. Given a complex query, our model first generates a plan and solves the problem step by step. Even though each sub-query is detailed and single-hop, the retrieved documents remain noisy, and the extractor agent selectively retains only the relevant information. To ensure a fair comparison, we report results generated exclusively by 70B models. Our main results are based on Llama3-70B, and for reference, we also include direct answers from Llama3-70B without RAG. Comparisons with RankRAG are not provided, as it is not open source. Additional examples can be found in the Appendix.

Table 4: A case study on the 2WikiMQA dataset. The **blue** texts represent the ground truth answer or correct outputs, while **red** texts denote distractors or wrong outputs, and **green** texts stand for evidences. Note that none of the retrieved documents contain the correct answer directly. All experiments are conducted under the same setting, using the same corpus (Karpukhin et al., 2020) and the same retrieval model (Zhang et al., 2024b).

Q: Who is Edward De Vere, 17th Earl Of Oxford's paternal grandfather? Correct Answer: John de Vere, 15th Earl of Oxford	
MA-RAG 70B	<p>Plan: ["Identify Edward De Vere, 17th Earl of Oxford's father", "Determine the name of Edward De Vere, 17th Earl of Oxford's paternal grandfather based on the father's name."] Step 1 (Identify Edward De Vere, 17th Earl of Oxford's father)</p> <p>Step query: Who is Edward De Vere, 17th Earl of Oxford's father?</p> <p>Retrieved DocIDs: 129772, 6127861, 129773, 14010350, 12540430</p> <p>Extracted Information: <i>doc-129772:</i> [No related information about his father.], <i>doc-6127861:</i> [No related information about his father.], <i>doc-129773:</i> [Edward De Vere, 17th Earl of Oxford's father is John de Vere, 16th Earl of Oxford. This is evidenced by the passage stating, "De Vere was the only son of John de Vere, 16th Earl of Oxford."], <i>doc-14010350:</i> [No related information about his father.], <i>doc-12540430:</i> [No related information about his father.]</p> <p>Step Answer: The question asks for the identity of Edward De Vere's father. The relevant document doc-129773 clearly states that Edward De Vere, 17th Earl of Oxford, is the son of John de Vere, 16th Earl of Oxford. Other documents do not provide additional information about his father.</p> <p>Step 2 (Determine the name of Edward De Vere, 17th Earl of Oxford's paternal grandfather based on the father's name.)</p> <p>Step query: Who was the father of John de Vere, 16th Earl of Oxford?</p> <p>Retrieved DocIDs: 6127862, 6127858, 17870603, 12540430, 14010350</p> <p>Extracted Information: <i>doc-6127862:</i> [John de Vere, 16th Earl of Oxford was born to John de Vere, 15th Earl of Oxford.], <i>doc-6127858:</i> [John de Vere, 16th Earl of Oxford (1516 – 3 August 1562) was born to John de Vere, 15th Earl of Oxford.], <i>doc-17870603:</i> [No related information.], <i>doc-14010350:</i> [No related information about his father.], <i>doc-14010350:</i> [No related information about his father.]</p> <p>Step Answer: The relevant documents indicate that John de Vere, 15th Earl of Oxford is the father of John de Vere, 16th Earl of Oxford</p> <p>Answer: John de Vere, 15th Earl of Oxford</p>
Llama3-70B	<p>Answer: Edward De Vere, 17th Earl of Oxford's paternal grandfather is John De Vere, 13th Earl of Oxford.</p>
ChatQA 70B	<p>Query: Who is Edward De Vere, 17th Earl Of Oxford's paternal grandfather?</p> <p>Retrieved Docs:</p> <p>Doc-129772: Edward de Vere, 17th Earl of Oxford Edward de Vere, 17th Earl of Oxford (; 12 April 155024 June 1604) was an English peer and courtier of the Elizabethan era. Oxford was heir to the second oldest earldom in the kingdom, a court favourite for a time, ...</p> <p>Doc-17870603: De Vere family The de Vere family were an English aristocratic family who derived their surname from Ver (department Manche, commune Coutances, canton Gavray), in Lower Normandy, France. The family's Norman founder in England, Aubrey (Albericus) de Vere ...</p> <p>Doc-6127861: son, Edward de Vere, 17th Earl of Oxford, and a daughter, Mary de Vere. Margery died on 2 December 1568. After his death in Oxford, he was buried in Castle Hedingham, Essex, on 31 August 1562...</p> <p>Doc-129778: was placed in the household of Sir William Cecil, her secretary of state and chief advisor. At 12, de Vere had become the 17th Earl of Oxford, Lord Great Chamberlain of England, and heir to an estate whose annual income ...</p> <p>Doc-129773: proposed for the authorship of Shakespeare's works. De Vere was the only son of John de Vere, 16th Earl of Oxford, and Margery Golding. After the death of his father in 1562, he became a ward of Queen Elizabeth and was sent to live in the household ...</p> <p>Answer: John de Vere, 16th Earl of Oxford</p>
ReAct (70B)	<p>Query: Who is Edward De Vere, 17th Earl Of Oxford's paternal grandfather?</p> <p>AI Messages: Retrieve(query=paternal grandfather of Edward De Vere, 17th Earl of Oxford)</p> <p>Retrieve documents:</p> <p>Doc-129772: Edward de Vere, 17th Earl of Oxford Edward de Vere, 17th Earl of Oxford (; 12 April 155024 June 1604) was an English peer and courtier of the Elizabethan era. Oxford was heir to the second oldest earldom in the kingdom, a court favourite for a time ...</p> <p>Doc-6127861: son, Edward de Vere, 17th Earl of Oxford, and a daughter, Mary de Vere. Margery died on 2 December 1568. After his death in Oxford, he was buried in Castle Hedingham, Essex, on 31 August 1562. The Earl was known as a sportsman, ...</p> <p>Doc-17870603: De Vere family The de Vere family were an English aristocratic family who derived their surname from Ver (department Manche, commune Coutances, canton Gavray), in Lower Normandy, France. The family's Norman founder in England, Aubrey (Albericus) de Vere...</p> <p>Doc-129773: proposed for the authorship of Shakespeare's works. De Vere was the only son of John de Vere, 16th Earl of Oxford, and Margery Golding. After the death of his father in 1562, he became a ward of Queen Elizabeth and was sent to ...</p> <p>Doc-6393404: Kirke and granddaughter of Aurelian Townshend. They had five children: Since he had no surviving sons and as no other suitable claimant came forward, he became the last de Vere Earl of Oxford, one of the longest-lived titles in the peerage of England; the first de Vere ...</p> <p>Answer: John de Vere, 16th Earl of Oxford , was the paternal grandfather of Edward De Vere, 17th Earl of Oxford.</p>

MA-RAG with Internet Access. We further evaluated MA-RAG with web access by integrating Google Search as the retrieval engine on the SimpleQA benchmark (Wei et al., 2024). Results in the Appendix show that MA-RAG achieves strong performance (GPT-4o: 40.1% versus MA-RAG (GPT-4o-mini, web): 86.4%), demonstrating its flexibility and competitive accuracy among recent web-enabled systems.

Discussions. MA-RAG's multi-agent design, while improving reasoning and interpretability, introduces additional runtime and token overhead. Each agent invocation involves separate prompts and responses, which can increase latency and inference cost, especially for complex queries requiring multiple reasoning steps. Although agents are called on demand to reduce unnecessary computation, the workflow remains more resource-intensive than single-pass or standalone RAG systems. On single-hop datasets, MA-RAG achieves an average response time of about 2.2 seconds using GPT-4o-mini, while on multi-hop questions the response time increases to about 4.1 seconds. We believe this latency remains acceptable for real-world use, especially given the significant performance gains achieved. Our ablation study also shows that not all agents require large models, suggesting that assigning resource-efficient agents to different subtasks is a promising direction.

5 CONCLUSION

We present MA-RAG, a novel multi-agent framework for Retrieval-Augmented Generation that recasts the RAG pipeline as a coordinated reasoning process among specialized agents. Each agent, responsible for planning, retrieval, extraction, or generation, uses chain-of-thought prompting to enable structured and context-sensitive query resolution. Unlike prior work that tunes individual

components or requires supervised training, MA-RAG is entirely training-free and generalizes well across domains and question types. Empirical results on five open-domain and multi-hop QA benchmarks show that MA-RAG outperforms strong LLMs and state-of-the-art RAG baselines, achieving new best results on several datasets. Ablation studies confirm the importance of the planner and extractor: the former decomposes complex queries, while the latter improves retrieval precision. Strategic allocation of model capacity across agents yields further gains in both performance and efficiency. Together, these findings highlight the potential of modular, agent-based reasoning as a scalable and adaptable approach to improving retrieval-augmented generation.

REFERENCES

- Salaheddin Alzubi, Creston Brooks, Purva Chiniya, Edoardo Contente, Chiara von Gerlach, Lucas Irwin, Yihan Jiang, Arda Kaz, Windsor Nguyen, Sewoong Oh, Himanshu Tyagi, and Pramod Viswanath. Open deep search: Democratizing search with open-source reasoning agents. *arXiv preprint arXiv:2503.20201*, 2025a. URL <https://arxiv.org/abs/2503.20201>.
- Salaheddin Alzubi, Creston Brooks, Purva Chiniya, Edoardo Contente, Chiara von Gerlach, Lucas Irwin, Yihan Jiang, Arda Kaz, Windsor Nguyen, Sewoong Oh, Himanshu Tyagi, and Pramod Viswanath. Open deep search: Democratizing search with open-source reasoning agents. *arXiv preprint arXiv:2503.20201*, 2025b.
- Akari Asai, Zeqiu Wu, Yizhong Wang, Avirup Sil, and Hannaneh Hajishirzi. Self-RAG: Learning to retrieve, generate, and critique through self-reflection. In *International Conference on Learning Representations (ICLR)*, 2024.
- Adam Berger, Rich Caruana, David Cohn, Dayne Freitag, and Vibhu Mittal. Bridging the lexical chasm: statistical approaches to answer-finding. In *Proceedings of the 23rd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, pp. 192–199, 2000.
- Sebastian Borgeaud, Arthur Mensch, Jordan Hoffmann, Trevor Cai, Eliza Rutherford, Katie Millican, George Bm Van Den Driessche, Jean-Baptiste Lespiau, Bogdan Damoc, Aidan Clark, Diego De Las Casas, Aurelia Guy, Jacob Menick, Roman Ring, Tom Hennigan, Saffron Huang, Loren Maggiore, Chris Jones, Albin Cassirer, Andy Brock, Michela Paganini, Geoffrey Irving, Oriol Vinyals, Simon Osindero, Karen Simonyan, Jack Rae, Erich Elsen, and Laurent Sifre. Improving language models by retrieving from trillions of tokens. In *International Conference on Machine Learning*, pp. 2206–2240, 2022.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. In *Advances in Neural Information Processing Systems*, volume 33, pp. 1877–1901, 2020.
- Dongmei Chen, Sheng Zhang, Xin Zhang, and Kaijing Yang. Cross-lingual passage re-ranking with alignment augmented multilingual BERT. *IEEE Access*, 8:213232–213243, 2020.
- Guangyao Chen, Siwei Dong, Yu Shu, Ge Zhang, Jaward Sesay, Börje Karlsson, Jie Fu, and Yemin Shi. Autoagents: A framework for automatic agent generation. In *Proceedings of the International Joint Conference on Artificial Intelligence, IJCAI*, 2024a.
- Weize Chen, Yusheng Su, Jingwei Zuo, Cheng Yang, Chenfei Yuan, Chi-Min Chan, Heyang Yu, Yaxi Lu, Yi-Hsin Hung, Chen Qian, Yujia Qin, Xin Cong, Ruobing Xie, Zhiyuan Liu, Maosong Sun, and Jie Zhou. Agentverse: Facilitating multi-agent collaboration and exploring emergent behaviors. In *The International Conference on Learning Representations, ICLR*, 2024b.
- Zeming Chen, Alejandro Hernández Cano, Angelika Romanou, Antoine Bonnet, Kyle Matoba, Francesco Salvi, Matteo Pagliardini, Simin Fan, Andreas Köpf, Amirkeivan Mohtashami, Alexandre Sallinen, Alireza Sakhaeirad, Vinitra Swamy, Igor Krawczuk, Deniz Bayazit, Axel Marmet,

-
- Syrielle Montariol, Mary-Anne Hartley, Martin Jaggi, and Antoine Bosselut. Meditron-70b: Scaling medical pretraining for large language models. *arXiv preprint arXiv:2311.16079*, 2023.
- Zhuyun Dai, Vincent Y. Zhao, Ji Ma, Yi Luan, Jianmo Ni, Jing Lu, Anton Bakalov, Kelvin Guu, Keith B. Hall, and Ming-Wei Chang. Promptagator: Few-shot dense retrieval from 8 examples. In *International Conference on Learning Representations (ICLR)*, 2023.
- Tim Dettmers, Artidoro Pagnoni, Ari Holtzman, and Luke Zettlemoyer. Qlora: Efficient finetuning of quantized llms. In *Advances in Neural Information Processing Systems*, 2023.
- Nathalia Moraes do Nascimento, Paulo S. C. Alencar, and Donald D. Cowan. Self-adaptive large language model (llm)-based multiagent systems. In *IEEE International Conference on Autonomic Computing and Self-Organizing Systems, ACSOS*, 2023.
- Yilun Du, Shuang Li, Antonio Torralba, Joshua B. Tenenbaum, and Igor Mordatch. Improving factuality and reasoning in language models through multiagent debate. In *The International Conference on Machine Learning, ICML*, 2024.
- Ali Edalati, Marzieh Tahaei, Ivan Kobzyev, Vahid Partovi Nia, James J. Clark, and Mehdi Rezagholizadeh. Krona: Parameter efficient tuning with kronecker adapter. *arXiv preprint arXiv:2212.10650*, 2022.
- Wenqi Fan, Yujuan Ding, Liangbo Ning, Shijie Wang, Hengyun Li, Dawei Yin, Tat-Seng Chua, and Qing Li. A survey on rag meeting llms: Towards retrieval-augmented large language models. In *Proceedings of the ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, 2024.
- Thibault Formal, Carlos Lassance, Benjamin Piwowarski, and Stéphane Clinchant. From distillation to hard negative sampling: Making sparse neural ir models more effective. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pp. 2353–2359, 2022.
- Cheng Fu, Hanxian Huang, Xinyun Chen, Yuandong Tian, and Jishen Zhao. Learn-to-share: A hardware-friendly transfer learning framework exploiting computation and parameter sharing. In *Proceedings of the 38th International Conference on Machine Learning*, volume 139, pp. 3469–3479, 2021.
- Jingsheng Gao, Linxu Li, Ke Ji, Weiyuan Li, Yixin Lian, yuzhuo fu, and Bin Dai. SmartRAG: Jointly learn RAG-related tasks from the environment feedback. In *The International Conference on Learning Representations, ICLR*, 2025.
- Yunfan Gao, Yun Xiong, Xinyu Gao, Kangxiang Jia, Jinliu Pan, Yuxi Bi, Yi Dai, Jiawei Sun, Meng Wang, and Haofen Wang. Retrieval-augmented generation for large language models: A survey. *arXiv preprint arXiv:2312.10997*, 2024.
- Google Gemini Team. Gemini: A family of highly capable multimodal models. *arXiv preprint arXiv:2312.11805*, 2023.
- Michael Glass, Gaetano Rossiello, Md Faisal Mahbub Chowdhury, Ankita Naik, Pengshan Cai, and Alfio Gliozzo. Re2G: Retrieve, rerank, generate. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 2701–2715, 2022.
- Taicheng Guo, Xiuying Chen, Yaqi Wang, Ruidi Chang, Shichao Pei, Nitesh V. Chawla, Olaf Wiest, and Xiangliang Zhang. Large language model based multi-agents: A survey of progress and challenges. In *Proceedings of the International Joint Conference on Artificial Intelligence, IJCAI*, 2024.
- Bernal Jiménez Gutiérrez, Yiheng Shu, Yu Gu, Michihiro Yasunaga, and Yu Su. Hipporag: Neurobiologically inspired long-term memory for large language models. *arXiv preprint arXiv:2405.14831*, 2024.
- Kelvin Guu, Kenton Lee, Zora Tung, Panupong Pasupat, and Ming-Wei Chang. Realm: retrieval-augmented language model pre-training. In *International Conference on Machine Learning*, 2020.

-
- Junxian He, Chunting Zhou, Xuezhe Ma, Taylor Berg-Kirkpatrick, and Graham Neubig. Towards a unified view of parameter-efficient transfer learning. In *International Conference on Learning Representations (ICLR)*, 2022.
- Xanh Ho, Anh-Khoa Duong Nguyen, Saku Sugawara, and Akiko Aizawa. Constructing A multi-hop QA dataset for comprehensive evaluation of reasoning steps. In *Proceedings of the International Conference on Computational Linguistics, COLING*, 2020.
- Sirui Hong, Mingchen Zhuge, Jonathan Chen, Xiawu Zheng, Yuheng Cheng, Jinlin Wang, Ceyao Zhang, Zili Wang, Steven Ka Shing Yau, Zijuan Lin, Liyang Zhou, Chenyu Ran, Lingfeng Xiao, Chenglin Wu, and Jürgen Schmidhuber. Metagpt: Meta programming for A multi-agent collaborative framework. In *The International Conference on Learning Representations, ICLR*, 2024.
- Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin De Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. Parameter-efficient transfer learning for NLP. In *International Conference on Machine Learning*, volume 97, pp. 2790–2799, 2019a.
- Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin De Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. Parameter-efficient transfer learning for NLP. In *International Conference on Machine Learning*, volume 97, pp. 2790–2799, 2019b.
- Edward J Hu, yelong shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. LoRA: Low-rank adaptation of large language models. In *International Conference on Learning Representations (ICLR)*, 2022.
- Lei Huang, Weijiang Yu, Weitao Ma, Weihong Zhong, Zhangyin Feng, Haotian Wang, Qianglong Chen, Weihua Peng, Xiaocheng Feng, Bing Qin, and Ting Liu. A survey on hallucination in large language models: Principles, taxonomy, challenges, and open questions. *arXiv preprint arXiv:2311.05232*, 2023.
- Gautier Izacard and Edouard Grave. Leveraging passage retrieval with generative models for open domain question answering. In *European Chapter of the Association for Computational Linguistics (EACL)*, pp. 874–880, 2021.
- Gautier Izacard, Mathilde Caron, Lucas Hosseini, Sebastian Riedel, Piotr Bojanowski, Armand Joulin, and Edouard Grave. Unsupervised dense information retrieval with contrastive learning. *Transactions on Machine Learning Research*, 2022.
- Gautier Izacard, Patrick Lewis, Maria Lomeli, Lucas Hosseini, Fabio Petroni, Timo Schick, Jane Dwivedi-Yu, Armand Joulin, Sebastian Riedel, and Edouard Grave. Atlas: Few-shot learning with retrieval augmented language models. *Journal of Machine Learning Research*, pp. 1–43, 2023.
- Abhinav Java, Ashmit Khandelwal, Sukruta Midigeshi, Aaron Halfaker, Amit Deshpande, Navin Goyal, Ankur Gupta, Nagarajan Natarajan, and Amit Sharma. Characterizing deep research: A benchmark and formal definition. *arXiv preprint arXiv:2508.04183*, 2025. URL <https://arxiv.org/abs/2508.04183>.
- Soyeon Jeong, Jinheon Baek, Sukmin Cho, Sung Ju Hwang, and Jong Park. Adaptive-rag: Learning to adapt retrieval-augmented large language models through question complexity. In *Proceedings of the Conference of the North American Chapter of the Association for Computational Linguistics, NAACL*, 2024.
- Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, L  lio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timoth  e Lacroix, and William El Sayed. Mistral 7b. *arXiv preprint arXiv:2310.06825*, 2023a.
- Albert Q. Jiang, Alexandre Sablayrolles, Antoine Roux, Arthur Mensch, Blanche Savary, and et al. Mixtral of experts. *arXiv preprint arXiv:2401.04088*, 2024.

-
- Zhengbao Jiang, Frank F. Xu, Luyu Gao, Zhiqing Sun, Qian Liu, Jane Dwivedi-Yu, Yiming Yang, Jamie Callan, and Graham Neubig. Active retrieval augmented generation. In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), *Proceedings of the Conference on Empirical Methods in Natural Language Processing, EMNLP*, 2023b.
- Qiao Jin, Bhuwan Dhingra, Zhengping Liu, William Cohen, and Xinghua Lu. PubMedQA: A dataset for biomedical research question answering. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pp. 2567–2577, 2019.
- Qiao Jin, Won Kim, Qingyu Chen, Donald C Comeau, Lana Yeganova, W John Wilbur, and Zhiyong Lu. Medcpt: Contrastive pre-trained transformers with large-scale pubmed search logs for zero-shot biomedical information retrieval. *Bioinformatics*, pp. btad651, 2023.
- Jeff Johnson, Matthijs Douze, and Hervé Jégou. Billion-scale similarity search with gpus. *IEEE Transactions on Big Data*, 7(3):535–547, 2021.
- Karen Spärck Jones. A statistical interpretation of term specificity and its application in retrieval. *Journal of documentation*, 28(1):11–21, 1972.
- Mandar Joshi, Eunsol Choi, Daniel Weld, and Luke Zettlemoyer. TriviaQA: A large scale distantly supervised challenge dataset for reading comprehension. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 1601–1611, 2017.
- Nikhil Kandpal, Haikang Deng, Adam Roberts, Eric Wallace, and Colin Raffel. Large language models struggle to learn long-tail knowledge. In *International Conference on Machine Learning*, volume 202, pp. 15696–15707, 2023.
- Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. Dense passage retrieval for open-domain question answering. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 6769–6781, 2020.
- Jungo Kasai, Keisuke Sakaguchi, yoichi takahashi, Ronan Le Bras, Akari Asai, Xinyan Velocity Yu, Dragomir Radev, Noah A. Smith, Yejin Choi, and Kentaro Inui. Realtime QA: What’s the answer right now? In *Neural Information Processing Systems Datasets and Benchmarks Track*, 2023.
- Urvashi Khandelwal, Omer Levy, Dan Jurafsky, Luke Zettlemoyer, and Mike Lewis. Generalization through memorization: Nearest neighbor language models. In *International Conference on Learning Representations (ICLR)*, 2020.
- Mandar Kulkarni, Praveen Tangarajan, Kyung Kim, and Anusua Trivedi. Reinforcement learning for optimizing rag for domain chatbots. *arXiv preprint arXiv:2401.06800*, 2024.
- Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. Natural questions: A benchmark for question answering research. *Transactions of the Association for Computational Linguistics*, 7:452–466, 2019.
- Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph E. Gonzalez, Hao Zhang, and Ion Stoica. Efficient memory management for large language model serving with pagedattention. In *Proceedings of the ACM SIGOPS 29th Symposium on Operating Systems Principles*, 2023.
- Tobias Leemann, Periklis Petridis, Giuseppe Vietri, Dionysis Manousakas, Aaron Roth, and Sergul Aydore. Auto-GDA: Automatic domain adaptation for efficient grounding verification in retrieval-augmented generation. In *The International Conference on Learning Representations, ICLR*, 2025.
- Brian Lester, Rami Al-Rfou, and Noah Constant. The power of scale for parameter-efficient prompt tuning. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing, EMNLP*, pp. 3045–3059, 2021.

-
- Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. Retrieval-augmented generation for knowledge-intensive nlp tasks. In *Advances in Neural Information Processing Systems*, volume 33, pp. 9459–9474, 2020.
- Mufei Li, Siqi Miao, and Pan Li. Simple is effective: The roles of graphs and large language models in knowledge-graph-based retrieval-augmented generation. In *The Thirteenth International Conference on Learning Representations*, 2025a. URL <https://openreview.net/forum?id=JvkuZZ0407>.
- Xiang Lisa Li and Percy Liang. Prefix-tuning: Optimizing continuous prompts for generation. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, 2021.
- Yanhong Li, Karen Livescu, and Jiawei Zhou. Chunk-distilled language modeling. In *The International Conference on Learning Representations, ICLR*, 2025b.
- Xi Victoria Lin, Xilun Chen, Mingda Chen, Weijia Shi, Maria Lomeli, Richard James, Pedro Rodriguez, Jacob Kahn, Gergely Szilvasy, Mike Lewis, Luke Zettlemoyer, and Wen tau Yih. RA-DIT: Retrieval-augmented dual instruction tuning. In *International Conference on Learning Representations (ICLR)*, 2024.
- Jiaheng Liu, Dawei Zhu, Zhiqi Bai, Yancheng He, Huanxuan Liao, Haoran Que, Zekun Wang, Chenchen Zhang, Ge Zhang, Jiebin Zhang, Yuanxing Zhang, Zhuo Chen, Hangyu Guo, Shilong Li, Ziqiang Liu, Yong Shan, Yifan Song, Jiayi Tian, Wenhao Wu, Zhejiang Zhou, Ruijie Zhu, Junlan Feng, Yang Gao, Shizhu He, Zhoujun Li, Tianyu Liu, Fanyu Meng, Wenbo Su, Yingshui Tan, Zili Wang, Jian Yang, Wei Ye, Bo Zheng, Wangchunshu Zhou, Wenhao Huang, Sujian Li, and Zhaoxiang Zhang. A comprehensive survey on long context language modeling. *arXiv preprint arXiv:2503.17407*, 2025.
- Nelson F. Liu, Kevin Lin, John Hewitt, Ashwin Paranjape, Michele Bevilacqua, Fabio Petroni, and Percy Liang. Lost in the middle: How language models use long contexts. *Transactions of the Association for Computational Linguistics*, 12:157–173, 2024a.
- Zihan Liu, Wei Ping, Rajarshi Roy, Peng Xu, Chankyu Lee, Mohammad Shoeybi, and Bryan Catanzaro. Chatqa: Surpassing gpt-4 on conversational qa and rag. *arXiv preprint arXiv:2401.10225*, 2024b.
- Zijun Liu, Yanzhe Zhang, Peng Li, Yang Liu, and Diyi Yang. A dynamic llm-powered agent network for task-oriented agent collaboration. *arXiv preprint arXiv:2310.02170*, 2024c.
- Shengjie Ma, Chengjin Xu, Xuhui Jiang, Muzhi Li, Huaren Qu, Cehao Yang, Jiaxin Mao, and Jian Guo. Think-on-graph 2.0: Deep and faithful large language model reasoning with knowledge-guided retrieval augmented generation. In *The International Conference on Learning Representations, ICLR*, 2025.
- Xueguang Ma, Liang Wang, Nan Yang, Furu Wei, and Jimmy Lin. Fine-tuning llama for multi-stage text retrieval. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pp. 2421–2425, 2024.
- Shaoguang Mao, Yuzhe Cai, Yan Xia, Wenshan Wu, Xun Wang, Fengyi Wang, Qiang Guan, Tao Ge, and Furu Wei. ALYMPICS: LLM agents meet game theory. In *Proceedings of the International Conference on Computational Linguistics*, 2025.
- Jacob Menick, Maja Trebacz, Vladimir Mikulik, John Aslanides, Francis Song, Martin Chadwick, Mia Glaese, Susannah Young, Lucy Campbell-Gillingham, Geoffrey Irving, and Nat McAleese. Teaching language models to support answers with verified quotes. *arXiv preprint arXiv:2203.11147*, 2022.
- Meta. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.

-
- Ali Modarressi, Hanieh Deilamsalehy, Franck Dernoncourt, Trung Bui, Ryan A. Rossi, Seunghyun Yoon, and Hinrich Schütze. Nolima: Long-context evaluation beyond literal matching. *arXiv preprint arXiv:2502.05167*, 2025.
- OpenAI. Introducing chatgpt. 2022. URL <https://openai.com/index/chatgpt/>.
- OpenAI. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2024.
- Ankit Pal, Logesh Kumar Umapathi, and Malaikannan Sankarasubbu. Medmcqa: A large-scale multi-subject multi-choice dataset for medical domain question answering. In *Proceedings of the Conference on Health, Inference, and Learning*, volume 174 of *Proceedings of Machine Learning Research*, pp. 248–260, 2022.
- Joon Sung Park, Joseph C. O’Brien, Carrie Jun Cai, Meredith Ringel Morris, Percy Liang, and Michael S. Bernstein. Generative agents: Interactive simulacra of human behavior. In *Proceedings of the Annual ACM Symposium on User Interface Software and Technology, UIST*, 2023.
- Fabio Petroni, Aleksandra Piktus, Angela Fan, Patrick Lewis, Majid Yazdani, Nicola De Cao, James Thorne, Yacine Jernite, Vladimir Karpukhin, Jean Maillard, Vassilis Plachouras, Tim Rocktäschel, and Sebastian Riedel. KILT: a benchmark for knowledge intensive language tasks. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 2523–2544, June 2021.
- Ofir Press, Muru Zhang, Sewon Min, Ludwig Schmidt, Noah A. Smith, and Mike Lewis. Measuring and narrowing the compositionality gap in language models. In *Findings of the Association for Computational Linguistics: EMNLP*, 2023.
- Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. Improving language understanding by generative pre-training. In *Advances in Neural Information Processing Systems*, 2018.
- Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners. 2019.
- Ori Ram, Yoav Levine, Itay Dalmedigos, Dor Muhlgay, Amnon Shashua, Kevin Leyton-Brown, and Yoav Shoham. In-context retrieval-augmented language models. *Transactions of the Association for Computational Linguistics*, pp. 1316–1331, 2023.
- Chidaksh Ravuru, Sakhinana Sagar Srinivas, and Venkataramana Runkana. Agentic retrieval-augmented generation for time series analysis. *arXiv preprint arXiv:2408.14484*, 2024.
- Nils Reimers and Iryna Gurevych. Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pp. 3982–3992, 2019.
- Stephen Robertson and Hugo Zaragoza. The probabilistic relevance framework: Bm25 and beyond. *Foundations and Trends® in Information Retrieval*, 3(4):333–389, 2009.
- Parth Sarthi, Salman Abdullah, Aditi Tuli, Shubh Khanna, Anna Goldie, and Christopher D Manning. RAPTOR: Recursive abstractive processing for tree-organized retrieval. In *International Conference on Learning Representations (ICLR)*, 2024.
- Florian Schneider, Narges Baba Ahmadi, Niloufar Baba Ahmadi, Iris Vogel, Martin Semmann, and Chris Biemann. Collex – a multimodal agentic rag system enabling interactive exploration of scientific collections. *arXiv preprint arXiv:2504.07643*, 2025.
- Weijia Shi, Sewon Min, Michihiro Yasunaga, Minjoon Seo, Richard James, Mike Lewis, Luke Zettlemoyer, and Wen-tau Yih. REPLUG: Retrieval-augmented black-box language models. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pp. 8364–8377, June 2024.

-
- Noah Shinn, Federico Cassano, Ashwin Gopinath, Karthik Narasimhan, and Shunyu Yao. Reflexion: language agents with verbal reinforcement learning. In *Advances in Neural Information Processing Systems*, volume 36, pp. 8634–8652, 2023.
- Shamane Siriwardhana, Rivindu Weerasekera, Elliott Wen, Tharindu Kaluarachchi, Rajib Rana, and Suranga Nanayakkara. Improving the domain adaptation of retrieval augmented generation (RAG) models for open domain question answering. *Transactions of the Association for Computational Linguistics*, pp. 1–17, 2023.
- James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. FEVER: a large-scale dataset for fact extraction and VERification. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pp. 809–819, 2018.
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023a.
- Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, and et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023b.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in Neural Information Processing Systems*, volume 30, 2017.
- Kexin Wang, Nandan Thakur, Nils Reimers, and Iryna Gurevych. GPL: Generative pseudo labeling for unsupervised domain adaptation of dense retrieval. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 2345–2360, 2022a.
- Kuan Wang, Yadong Lu, Michael Santacrose, Yeyun Gong, Chao Zhang, and Yelong Shen. Adapting LLM agents through communication. *arXiv preprint arXiv:2310.01444*, 2023.
- Lei Wang, Chen Ma, Xueyang Feng, Zeyu Zhang, Hao Yang, Jingsen Zhang, Zhiyuan Chen, Jiakai Tang, Xu Chen, Yankai Lin, Wayne Xin Zhao, Zhewei Wei, and Jirong Wen. A survey on large language model based autonomous agents. *Frontiers of Computer Science*, 2024.
- Yaqing Wang, Sahaj Agarwal, Subhabrata Mukherjee, Xiaodong Liu, Jing Gao, Ahmed Hassan Awadallah, and Jianfeng Gao. AdaMix: Mixture-of-adaptations for parameter-efficient model tuning. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pp. 5744–5760, 2022b.
- Zilong Wang, Zifeng Wang, Long Le, Steven Zheng, Swaroop Mishra, Vincent Perot, Yuwei Zhang, Anush Mattapalli, Ankur Taly, Jingbo Shang, Chen-Yu Lee, and Tomas Pfister. Speculative RAG: Enhancing retrieval augmented generation through drafting. In *The International Conference on Learning Representations, ICLR*, 2025.
- Jason Wei, Nguyen Karina, Hyung Won Chung, Yunxin Joy Jiao, Spencer Papay, Amelia Glaese, John Schulman, and William Fedus. Measuring short-form factuality in large language models. *arXiv preprint arXiv:2411.04368*, 2024.
- Chaoyi Wu, Weixiong Lin, Xiaoman Zhang, Ya Zhang, Weidi Xie, and Yanfeng Wang. PMC-LLaMA: toward building open-source language models for medicine. *Journal of the American Medical Informatics Association*, 2024.
- Guangzhi Xiong, Qiao Jin, Zhiyong Lu, and Aidong Zhang. Benchmarking retrieval-augmented generation for medicine. In *Findings of the Association for Computational Linguistics, ACL*, 2024.

-
- Kai Xiong, Xiao Ding, Yixin Cao, Ting Liu, and Bing Qin. Examining inter-consistency of large language models collaboration: An in-depth analysis via debate. In *Findings of the Association for Computational Linguistics: EMNLP*, 2023.
- Fangyuan Xu, Weijia Shi, and Eunsol Choi. RECOMP: improving retrieval-augmented lms with context compression and selective augmentation. In *International Conference on Learning Representations (ICLR)*, 2024.
- Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William W. Cohen, Ruslan Salakhutdinov, and Christopher D. Manning. Hotpotqa: A dataset for diverse, explainable multi-hop question answering. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, 2018.
- Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik R. Narasimhan, and Yuan Cao. React: Synergizing reasoning and acting in language models. In *The International Conference on Learning Representations, ICLR*, 2023.
- Yue Yu, Wei Ping, Zihan Liu, Boxin Wang, Jiaxuan You, Chao Zhang, Mohammad Shoeybi, and Bryan Catanzaro. Rankrag: Unifying context ranking with retrieval-augmented generation in llms. *arXiv preprint arXiv:2407.02485*, 2024.
- Ceyao Zhang, Kaijie Yang, Siyi Hu, Zihao Wang, Guanghe Li, Yihang Sun, Cheng Zhang, Zhaowei Zhang, Anji Liu, Song-Chun Zhu, Xiaojun Chang, Junge Zhang, Feng Yin, Yitao Liang, and Yaodong Yang. Proagent: Building proactive cooperative AI with large language models. *arXiv preprint arXiv:2308.11339*, 2023a.
- Peitian Zhang, Shitao Xiao, Zheng Liu, Zhicheng Dou, and Jian-Yun Nie. Retrieve anything to augment large language models. *arXiv preprint arXiv:2310.07554*, 2023b.
- Tianjun Zhang, Shishir G. Patil, Naman Jain, Sheng Shen, Matei Zaharia, Ion Stoica, and Joseph E. Gonzalez. Raft: Adapting language model to domain specific rag. *arXiv preprint arXiv:2403.10131*, 2024a.
- Xin Zhang, Yanzhao Zhang, Dingkun Long, Wen Xie, Ziqi Dai, Jialong Tang, Huan Lin, Baosong Yang, Pengjun Xie, Fei Huang, Meishan Zhang, Wenjie Li, and Min Zhang. mgte: Generalized long-context text representation and reranking models for multilingual text retrieval. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing, EMNLP*, 2024b.
- Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, Yifan Du, Chen Yang, Yushuo Chen, Zhipeng Chen, Jinhao Jiang, Ruiyang Ren, Yifan Li, Xinyu Tang, Zikang Liu, Peiyu Liu, Jian-Yun Nie, and Ji-Rong Wen. A survey of large language models. *arXiv preprint arXiv:2303.18223*, 2023.
- Yujia Zhou, Zhicheng Dou, and Ji-Rong Wen. Enhancing generative retrieval with reinforcement learning from relevance feedback. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pp. 12481–12490, 2023.

A APPENDIX

A.1 DETAILS OF EXPERIMENTAL DATASET

A.1.1 MAIN EXPERIMENTS

We evaluate our method on five publicly available QA benchmarks that cover both single-hop and multi-hop reasoning.

- **Natural Questions (NQ)** (Kwiatkowski et al., 2019) consists of real user queries from Google Search, where answers are short spans extracted from Wikipedia articles. We use 2837 questions from the development set in the KILT benchmark (Petroni et al., 2021) for evaluation.
- **TriviaQA** (Joshi et al., 2017) includes challenging trivia questions written by trivia enthusiasts, paired with independently collected evidence documents. We use 5359 questions from the development set in the KILT benchmark (Petroni et al., 2021) for evaluation.
- **HotpotQA** (Yang et al., 2018) is a multi-hop QA dataset that requires reasoning over multiple Wikipedia articles to answer complex questions. We use 5600 questions from the development set in the KILT benchmark (Petroni et al., 2021) for evaluation.
- **2WikiMultiHopQA (2WikimQA)** (Ho et al., 2020) is a multi-hop dataset featuring questions grounded in two distinct Wikipedia entities, designed to evaluate a model’s ability to retrieve and reason across multiple sources.
- **FEVER** (Thorne et al., 2018) is a fact verification benchmark in which models must determine whether a claim is supported, refuted, or unverifiable based on evidence retrieved from Wikipedia. We use 10444 questions from the development set in the KILT benchmark (Petroni et al., 2021) for evaluation.

A.1.2 MEDICAL BENCHMARKS

We use two dataset in medical domain to test our method.

- **MedMCQA** (Pal et al., 2022) is a multiple-choice QA dataset based on Indian medical entrance exams. We use its 4,183-question development set for evaluation.
- **PubmedQA** (Jin et al., 2019) is a biomedical QA dataset of 1,000 yes/no/maybe questions derived from PubMed abstracts.

A.2 EXPERIMENT RESULTS

Table 5: **Results of MA-RAG and baselines on different datasets.** Results unavailable in public reports are marked as “-”. We use NQ, TriviaQA, HotpotQA, and FEVER from the KILT benchmark (Petroni et al., 2021). We report accuracy for the FEVER dataset and exact match for the others.

Task	NQ	TriviaQA	HotpotQA	2WikimQA	FEVER
Metric	EM	EM	EM	EM	Acc
<i>Without Retrieval-augmented Generation</i>					
Llama3-Instruct 8B (2024)	30.9	70.7	26.0	9.6	88.9
Llama3-Instruct 70B (2024)	42.7	82.4	35.5	13.5	91.4
GPT-3.5-turbo-1106 (2022)	38.6	82.9	29.9	23.9	82.7
GPT-4-0613 (2024)	40.3	84.8	34.5	29.8	87.7
<i>With Retrieval-augmented Generation</i>					
SmartRAG 7B (2025)	-	-	26.0	-	-
Atlas 11B (2023)	26.7	56.9	34.7	-	77.0
RECOMP 20B (2024)	37.0	59.0	30.4	-	-
REPLUG 65B (2024)	28.8	72.6	32.0	-	73.3
RA-DIT 65B (2024)	35.2	75.4	39.7	-	80.7
Self-RAG 8B (2024)	39.6	78.2	24.3	25.1	-
ChatQA-1.5 8B (2024b)	42.4	81.0	33.4	26.8	90.9
ChatQA-1.5 70B (2024b)	47.0	85.6	42.2	34.9	92.7
RankRAG 8B (2024)	50.6	82.9	35.3	31.4	92.0
RankRAG 70B (2024)	54.2	<u>86.5</u>	42.7	38.2	93.8
ReAct (70B) (2023)	43.9	84.5	39.2	32.6	92.0
Adaptive-RAG (GPT-3.5) (2024)	36.8	-	40.4	<u>46.6</u>	-
Self-Ask (GPT-3) (2023)	-	-	-	40.1	-
<i>Ours</i>					
MA-RAG (Llama3-8B)	52.5	82.6	40.3	31.8	91.4
MA-RAG (Llama3-70B)	<u>58.1</u>	85.4	<u>50.7</u>	43.1	93.1
MA-RAG (GPT-4o-mini)	59.5	87.2	52.1	47.5	<u>93.3</u>

MA-RAG achieves competitive performance on both TriviaQA and FEVER, with GPT-4o-mini reaching 87.2 EM and 93.3 accuracy, respectively, on par with or surpassing strong finetuned baselines such as RankRAG. Notably, unlike these methods, MA-RAG is fully training-free, relying solely on agent-based reasoning and chain-of-thought prompting without any gradient-based updates to the underlying LLMs. However, we caution that these benchmarks may not fully reflect the advantages of retrieval-augmented methods. Strong LLMs like GPT-4 already perform well without external retrieval (e.g., 84.8 EM on TriviaQA and 87.7 accuracy on FEVER), likely due to the fact that many questions are either single-hop or already aligned with the model’s pretraining data. We include these results for completeness but emphasize that more complex, multi-hop datasets provide a better testbed for evaluating retrieval and reasoning capabilities.

A.3 MA-RAG WITH INTERNET ACCESS

To further evaluate the capabilities of MA-RAG in practical information-seeking scenarios, we conducted additional experiments by granting MA-RAG access to real-time web search. Specifically, we integrated Google Search as the external retrieval engine and evaluated on the SimpleQA benchmark (Wei et al., 2024). This dataset is designed to assess factual question-answering abilities of frontier models *without* access to the web. It contains questions that often require up-to-date or obscure knowledge, making it a challenging benchmark for retrieval-augmented systems. We enabled MA-RAG to retrieve evidence via Google Search, replacing the retrieval tool with this search engine.

Results. As shown in Table 6, MA-RAG achieved an accuracy of 86.4% on SimpleQA, demonstrating a significant improvement over GPT-4o (40.1%) and the GPT-4o-mini baseline when equipped with web access. While DeepSeek-R1 (82.4%) performs significantly better than GPT-4o alone, our MA-RAG (GPT-4o-mini, web) results show that multi-agent reasoning substantially boosts performance. Although our current results are still below ODS-v2/ODS-v1+DeepSeek-R1* (Alzubi et al., 2025b), MA-RAG outperforms ODS-v1+Llama3.1-70B (Alzubi et al., 2025b). We believe that the performance gap largely depends on the reasoning model used. Additionally, we highlight that Perplexity Deep Research is a closed-source system without an arXiv paper or public report. These findings suggest that MA-RAG’s combination of multi-agent reasoning and web integration is also highly effective for open-domain factual QA.

Table 6: SimpleQA results (Accuracy) for recent systems. * indicates models allowed to access the internet.

Method	SimpleQA (%)
Qwen 2.5	9.1
Llama3.1-70B	20.4
Claude 3.5 Sonnet	28.9
GPT-4o	40.1
DeepSeek-R1	82.4
Perplexity Deep Research*	93.9
ODS-v1+Llama3.1-70B*	83.4
ODS-v2+DeepSeek-R1*	88.3
ODS-v1+DeepSeek-R1*	87.7
MA-RAG (GPT-4o-mini, web)*	86.4

Note: MA-RAG here is evaluated with live Google Search. All other results are as reported in prior work or reproduced using public checkpoints.

A.4 IMPLEMENTATION DETAILS

We use 8 NVIDIA A6000 GPUs for LLM inference and employ vLLM (Kwon et al., 2023) to enable efficient generation.

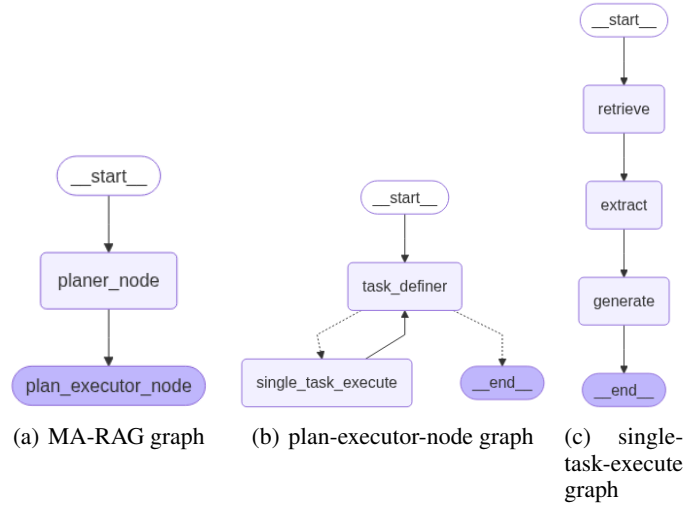


Figure 4: **MA-RAG** graph representations in Langchain.

A.5 WORKFLOWS

We implement MA-RAG using LangChain and LangGraph³, where agents communicate through structured JSON messages. Each agent is represented as a node in the graph, and edges determine the next agent to execute based on the current state. The overall graph structure representing the architecture of MA-RAG is shown in Figure 4. For modularity and clarity, we define separate subgraphs for core components, including the planner, the plan executor, and the RAG pipeline.

A.5.1 AGENT COMMUNICATION

In LangChain’s LangGraph framework, multi-agent workflows are modeled as directed graphs where each node corresponds to an agent, and edges define the flow of control based on task outcomes or states. These nodes operate on a shared mutable object called the Graph State, a dictionary that holds the information exchanged across agents. As agents act on this state, they append or modify fields to propagate reasoning, inputs, and outputs throughout the pipeline.

In MA-RAG, we define multiple GraphState schemas using Python’s TypedDict to ensure consistency and clarity in communication between agents. Each sub-state corresponds to a key stage in the pipeline. Below we describe each one individually.

QAAnswerState. Stores outputs from the QA agent for each subtask.

```

1 class QAAnswerState(TypedDict):
2     analysis: str
3     answer: str
4     success: str
5     rating: int

```

PlanState. Represents the planner’s output plan and rationale.

```

1 class PlanState(TypedDict):
2     analysis: str
3     step: List[str]

```

StepTaskState. Encodes detailed instructions for individual subtasks.

```

1 class StepTaskState(TypedDict):
2     type: str

```

³<https://www.langchain.com/>

```
3 task: str
```

PlanSummaryState. Summarizes results after plan execution.

```
1 class PlanSummaryState(TypedDict):
2     output: str
3     answer: str
4     score: int
```

PlanExecState. Captures the full state of executing a plan, including inputs, intermediate outputs, and notes.

```
1 class PlanExecState(TypedDict):
2     original_question: str
3     plan: List[str]
4     step_question: Annotated[List[StepTaskState], operator.add]
5     step_output: Annotated[List[QAAnswerState], operator.add]
6     step_docs_ids: Annotated[List[List[str]], operator.add]
7     step_notes: Annotated[List[List[str]], operator.add]
8     plan_summary: PlanSummaryState
9     stop: bool = False
```

RagState. Manages state during single-step RAG execution.

```
1 class RagState(TypedDict):
2     question: str
3     documents: List[str]
4     doc_ids: List[str]
5     notes: List[str]
6     final_raw_answer: QAAnswerState
```

GraphState. The top-level state object that coordinates the MA-RAG pipeline.

```
1 class GraphState(TypedDict):
2     original_question: str
3     plan: List[str]
4     past_exp: Annotated[List[PlanExecState], operator.add]
5     final_answer: str
```

Each agent in MA-RAG reads from and writes to specific fields in these structured states. For example, the Planner agent sets the `plan`, the Step Definer appends to `step_question`, the Extractor populates `step_notes`, and the QA agent writes the `step_output`. This modular design enables interpretable multi-agent reasoning and seamless communication across the pipeline.

A.6 BORDER IMPACTS

MA-RAG offers a flexible and interpretable framework for retrieval-augmented generation, which may prove valuable in domains requiring accurate, grounded, and explainable information access. Its modular design allows for fine-grained reasoning steps and clearer attribution of retrieved content, which could support applications in fields like education, healthcare, and research. At the same time, as with any system built on large language models, care must be taken when deploying MA-RAG in high-stakes environments. Even with structured reasoning, the generated outputs may reflect limitations of the underlying LLM or retrieved documents, potentially leading to overconfident or misleading conclusions. As the system enables multi-step reasoning and synthesis, ensuring transparency in intermediate steps and incorporating human oversight remain important considerations for responsible use.

A.7 PROMPT FORMATS

A.7.1 PLANNER AGENT

System: You are tasked with assisting users in generating structured plans for answering questions. Your goal is to deconstruct a query into manageable, simpler components. For each question, perform these tasks:

*Analysis: Identify the core components of the question, emphasizing the key elements and context needed for a comprehensive understanding. Determine whether the question is straightforward or requires multiple steps to provide an accurate answer.

*Plan Creation:

- Break down the question into smaller, simpler questions by reasoning that lead to the final answer. Ensure those steps are non overlap.
- Ensure each step is clear and logically sequenced.
- Each step is a question to search, or to aggregate output from previous steps. Do not verify previous step.

Notes:

- Put your output in a list of string, each string describe a sub-task

User: {Question}

A.7.2 STEP DEFINER AGENT

System: Given a plan, the current step, and the results from finished steps, decide the task for this step. Output the type of task and the query. The query need to be in detail, include all of information from previous step's results in the query if it maked, especially for aggregate task. Be concise.

User:

Plan: {plan}

Current step: {cur_step}

Results of finished steps:
{memory}

A.7.3 EXTRACTOR AGENT

System: Summarize and extract all relevant information from the provided passages based on the given question. Remove all irrelevant information. Think step-by-step.

****Identify Key Elements****: Read the question carefully to determine what specific information is being requested.

****Analyze Passages****: Review the passages thoroughly to find any segments that contain information relevant to the question.

****Extract Relevant Information****: Highlight or note down sentences, phrases, or words from the passages that relate to the question.

****Remove Irrelevant Details****: Ensure that all extracted information is relevant to the question, eliminating any unnecessary or unrelated content.

Output Format

- Output a list of notes. Each note contains related information from the passage, and each note is clear, standalone.

Notes

- Avoiding any irrelevant details.
- If a piece of information is mentioned in multiple places, include it only once.
- If there are no related information, output: No related information from this document.

User:

Passage: passage

Query: question?

A.7.4 QUESTION-ANSWERING AGENT

System: You are an assistant for question-answering tasks. Use the following process to deliver concise and precise answers based on the retrieved context.

1. Analyze Carefully: Begin by thoroughly analyzing both the question and the provided context.
2. Identify Core Details: Focus on identifying the essential names, terms, or details that directly answer the question. Disregard any irrelevant information.
3. Provide a Concise Answer:
 - Remove redundant words and extraneous details.
 - Present the answer by listing only the necessary names, terms, or very brief facts that are crucial for answering the question.
4. Clarity and Accuracy: Ensure that your answer is clear and maintains the original meaning of the information provided.
5. Consensus: If the contexts are not consensus, pick one which is the most logical, consensus, or confident.

User:

Retrieved information: context

Question: question

A.8 CASE STUDY

A.8.1 HOTPOTQA

Table 7: A case study on the HotpotQA dataset. The **blue** texts represent the ground truth answer or correct outputs, while **red** texts denote distractors or wrong outputs, and **green** texts stand for evidences. Note that none of the retrieved documents contain the correct answer directly. All experiments are conducted under the same setting, using the same corpus (Karpukhin et al., 2020) and the same retrieval model (Zhang et al., 2024b).

Q: What role did Thomas Doherty play in sitcom based on the Israeli series "North Star"? Correct Answer: Sean	
MA-RAG 70B	<p>Plan: ["Identify the sitcom based on the Israeli series North Star.", "Determine the character role played by Thomas Doherty in that sitcom."] Step 1 (Identify the sitcom based on the Israeli series North Star.) Step query: What is the name of the sitcom that is based on the Israeli series 'North Star'? Retrieved DocIDs: 19587422, 19587424, 14539692, 19587423, 17716638 Extracted Information: <i>doc-19587422:</i> [No related information from this document.], <i>doc-19587424:</i> [No related information from this document.], <i>doc-14539692:</i> [No related information from this document.], <i>doc-19587423:</i> [The sitcom based on the Israeli series 'North Star' is titled "The Lodge." This is evidenced by the passage stating, "The British Disney Channel produces an adapted under the title 'The Lodge' (working title: 'North Star')."], <i>doc-17716638:</i> [No related information from this document.] Step Answer: The question asks for the name of a sitcom that is based on the Israeli series 'North Star'. The relevant document (doc-19587423) clearly states that the sitcom is titled "The Lodge". The other documents do not provide any relevant information. Therefore, the answer is straightforward based on the retrieved context. Step 2 (Determine the character role played by Thomas Doherty in that sitcom.) Step query: What character role does Thomas Doherty play in the sitcom "The Lodge"? Retrieved DocIDs: 20322850, 19608218, 20322852, 20322851, 19608221 Extracted Information: <i>doc-20322850:</i> [Thomas Doherty plays the character role of Sean in the British musical comedy-drama, The Lodge. This is directly stated in the passage where it mentions his best-known roles.], <i>doc-19608218:</i> [Thomas Doherty stars in the role of a character in the TV series The Lodge. The passage does not specify the name of his character or the details of his role], <i>doc-20322852:</i> [Thomas Doherty plays the role of Sean in the sitcom The Lodge. This is evidenced by the passage stating, offered the role of Sean in 'The Lodge'], <i>doc-20322851:</i> [No related information from this document], <i>doc-19608221:</i> [No related information from this document] Step Answer: The question asks for the character role of Thomas Doherty in "The Lodge". The relevant documents consistently indicate that he plays the character named Sean. Therefore, the answer is straightforward based on the retrieved context. Answer: Sean</p>
Llama3-70B	<p>Answer: Thomas Doherty played the role of Jasper in the sitcom "High Fidelity", which is based on the Israeli series "North Star."</p>
ChatQA 70B	<p>Query: What role did Thomas Doherty play in sitcom based on the Israeli series "North Star"? Retrieved Docs: Doc-20322850: Thomas Doherty (actor) Thomas Doherty (born 21 April 1995) is a Scottish actor, best known for his roles as Harry Hook in Disney Channel's "Descendants 2" and as Sean in the British musical comedy-drama, "The Lodge". Doherty was born and raised in Edinburgh, Scotland. He has an older brother and younger sister, and his parents were both in the banking business. Doherty began acting at the age of 5 and also played football. Doherty joined Lothian Youth Arts and Musicals Company and played a variety of roles, including his debut as Disney's Aladdin. Doherty attended Royal High School in Edinburgh. Doc-8474610: Tommy Doherty Thomas Edward Doherty (born 17 March 1979 in Bristol) is a Northern Ireland international footballer who plays as a midfielder. Doherty started his career at Bristol City, making 189 league appearances in nine years before moving to Queens Park Rangers in 2005. He joined Wycombe on loan from QPR in September 2006 and was named in the PFA League Two Team of the Year for the 2006–07 season. He was also named the supporters official player of the year. In the summer of 2007 Wycombe tried to sign him but for many reasons a deal was never agreed. Doc-12942841: them. The show was canceled after one season owing to poor ratings. She also starred in the popular British sitcom ""Bo! in the USA"", a brain child of Leigh Francis. In the show, she plays herself being randomly harassed by Avid Merrión (Francis), who claims they are lovers. The show aired in October 2006 on the British Channel 4, and she appeared in several episodes. During 2007, Doherty appeared in two television projects. She first appeared in ""Kiss Me Deadly: A Jacob Keane Assignment"" for the Here TV network and followed up with a starring role in the holiday film Doc-1423761: to the stage, making a disastrous start in John Phillips' ""Man on the Moon"" (1975). In 1977, he returned to his birthplace, Halifax, Nova Scotia, and started playing legitimate roles, including Shakespeare, at the Neptune Theatre under the tutelage of John Neville. This led to television work, beginning with a variety program, ""Denny's Sho*"", which ran for one season in 1978. He went on to host and voice parts in the children's program, ""Theodore Tugboat"", and to act in various series, including twenty-two episodes of the drama ""Pit Pony"". Doherty also performed with the New Mamas and the Papas (see Doc-7852137: Tom Doherty Tom Doherty (born April 23, 1935) is an American publisher, and the founder of science fiction and fantasy book publisher Tor Books. After working as a book salesman in the 1950s and 1960s, Doherty became publisher of Tempo Books in 1972; in 1975, he became, in addition, publisher of another company also owned by Grosset Dunlap, the science fiction imprint Ace Books. In 1980 he left Ace to found his own company, Tor Books. Tor became a subsidiary of St. Martin's Press in 1987; both are now subsidiaries of Holtzbrinck Publishers, ultimately owned by the Macmillan Publishers. Answer: Thomas Doherty played the role of Harry Hook in the sitcom based on the Israeli series North Star.</p>
ReAct (70B)	<p>Query: What role did Thomas Doherty play in sitcom based on the Israeli series "North Star"? AI Messages: Retrieve(query="Thomas Doherty sitcom North Star role") Retrieve documents: Doc-20322850: Thomas Doherty (actor) Thomas Doherty (born 21 April 1995) is a Scottish actor, best known for his roles as Harry Hook in Disney Channel's "Descendants 2" and as Sean in the British musical comedy-drama, "The Lodge". Doherty was born and raised in Edinburgh, Scotland. He has an older brother and younger sister, and his parents were both in the banking business. Doherty began acting at the age of 5 and also played football. Doherty joined Lothian Youth Arts and Musicals Company and played a variety of roles, including his debut as Disney's Aladdin. Doherty attended Royal High School in Edinburgh. Doc-1423761: to the stage, making a disastrous start in John Phillips' ""Man on the Moon"" (1975). In 1977, he returned to his birthplace, Halifax, Nova Scotia, and started playing legitimate roles, including Shakespeare, at the Neptune Theatre under the tutelage of John Neville. This led to television work, beginning with a variety program, ""Denny's Sho*"", which ran for one season in 1978. He went on to host and voice parts in the children's program, ""Theodore Tugboat"", and to act in various series, including twenty-two episodes of the drama ""Pit Pony"". Doherty also performed with the New Mamas and the Papas (see Doc-18484135: After high school, Doherty attended The MGA Academy of Performing Arts in Edinburgh, Scotland. He graduated after studying music theatre at MGA Academy in July 2015 and immediately signed a contract with Olivia Bell Management in London. Doherty was trained in acting, singing, and various types of dance including contemporary, hip hop, jazz, tap and ballet. After graduating from The MGA Academy of Performing Arts in the summer of 2015, Doherty began waiting tables in Edinburgh at Tigerlilly restaurant. On his days off, Doherty split his time between auditioning for ""The Lodge"" and working with the Edinburgh Fringe. Doherty was Doc-18484135: Tommy Doherty Thomas Edward Doherty (born 17 March 1979 in Bristol) is a Northern Ireland international footballer who plays as a midfielder. Doherty started his career at Bristol City, making 189 league appearances in nine years before moving to Queens Park Rangers in 2005. He joined Wycombe on loan from QPR in September 2006 and was named in the PFA League Two Team of the Year for the 2006–07 season. He was also named the supporters official player of the year. In the summer of 2007 Wycombe tried to sign him but for many reasons a deal was never agreed. Doc-2573069: of Harbour Master, as well as the voice-overs of the characters, in ""Theodore Tugboat"", a CBC Television children's show chronicling the ""lives"" of vessels in a busy harbour loosely based upon Halifax Harbour. In 1999, he also played Charley McGinnis in 22 episodes of the CBC Television series ""Pit Pony"". In 2004, Doherty appeared on Sharon, Lois Bram's 25th Anniversary Concert special, ""25 Years of Skinnamarink"", that aired on CBC on January 1, 2004. He sang two songs with the trio: "California Dreamin'" and "Who Put the Bomp?" One of his last appearances was in the Canadian TV series Answer: Thomas Doherty played the role of Brandon in the sitcom based on the Israeli series "North Star", which is the series "High Desert".</p>

A.8.2 2WIKIMQA

Table 8: A case study on the 2WikimQA dataset. The blue texts represent the ground truth answer or correct outputs, while red texts denote distractors or wrong outputs, and green texts stand for evidences. Note that none of the retrieved documents contain the correct answer directly. All experiments are conducted under the same setting, using the same corpus (Karpukhin et al., 2020) and the same retrieval model (Zhang et al., 2024b).

Q: When was the company that published Woman's Century founded? Correct Answer: October 27, 1893	
MA-RAG 70B	<p>Plan: ["Identify the publisher of 'Woman's Century'.", "Determine the founding date of the identified publisher."] Step 1 (Identify the publisher of 'Woman's Century'.) Step query: Identify the publisher of the magazine 'Woman's Century' Retrieved DocIDs: 18191569, 18191576, 3964891, 12413254, 9717742 Extracted Information: doc-18191569: [The magazine Woman's Century was published by the National Council of Women of Canada (NCWC). This is evidenced by the statement: Woman's Century was the official organ of the National Council of Women of Canada (NCWC).], doc-18191576: [The magazine 'Woman's Century' was published by the National Council of Women of Canada (NCWC). This is evidenced by the statement: Woman's Century was the official organ of the National Council of Women of Canada (NCWC).], doc-3964891: [No related information from this document.], doc-12413254: [The magazine Woman's Century was published by the NCWC (National Council of Women of Canada). This is evidenced by the phrase Between 1914 and 1921 the NCWC published the monthly journal 'Woman's Century'.], doc-9717742: [No related information from this document.] Step Answer: National Council of Women of Canada (NCWC) Step 2 (Determine the founding date of the identified publisher.) Step query: What is the founding date of the National Council of Women of Canada (NCWC)? Retrieved DocIDs: 12413249, 12413257, 17476996, 6878896, 20577251 Extracted Information: doc-12413249: [The National Council of Women of Canada (NCWC) was founded on October 27, 1893, in Toronto, Ontario. This is relevant as it directly answers the question regarding the founding date of the organization.], doc-12413257: [No related information from this document.], doc-17476996: [The National Council of Women of Canada (NCWC) was established in 1894, as indicated by the passage stating, "the Local Council was established in 1894 as the local chapter of the National Council of Women of Canada (NCWC)."], doc-6878896: [The National Council of Women of Canada was founded in 1893. This information is directly stated in the passage.], doc-20577251: [No related information from this document] Step Answer: The question asks for the founding date of the National Council of Women of Canada (NCWC). The relevant documents indicate conflicting information: one states it was founded on October 27, 1893, while another mentions 1894. However, multiple documents confirm the 1893 date, making it the more reliable answer. Answer: October 27, 1893</p>
Llama3-70B	<p>Answer: The company that published Woman's Century, initially called the "Woman's Century Club", later Woman's Century Magazine or just 'Woman's Century', is uncertain but it's known that Woman's Century Club itself predates the magazine as the club was formed in 1891, in Jacksonville, Florida."</p>
ChatQA 70B	<p>Query: When was the company that published Woman's Century founded? Retrieved Docs: Doc-18191576: Citations Sources Woman's Century Woman's Century was the official organ of the National Council of Women of Canada (NCWC), published in Toronto between 1913 and 1921. The magazine was relatively conservative, and supported World War I, but stood up for women's rights and universal suffrage. The founder of "Woman's Century" was Jessie Campbell MacIver. She had come to Canada from Scotland with her husband, a lawyer, and five children. She became involved in the National Council of Women. The first issue of "Woman's Century" appeared in May 1913. It was largely produced out of MacIver's home, with the help of Doc-18191569: Woman's Century Woman's Century was the official organ of the National Council of Women of Canada (NCWC), published in Toronto between 1913 and 1921. The magazine was relatively conservative, and supported World War I, but stood up for women's rights and universal suffrage. The founder of "Woman's Century" was Jessie Campbell MacIver. She had come to Canada from Scotland with her husband, a lawyer, and five children. She became involved in the National Council of Women. The first issue of "Woman's Century" appeared in May 1913. It was largely produced out of MacIver's home, with the help of her husband Doc-3964891: The Century Magazine The Century Magazine was first published in the United States in 1881 by The Century Company of New York City, which had been bought in that year by Roswell Smith and renamed by him after the Century Association. It was the successor of "Scribner's Monthly Magazine" and ceased publication in 1930. In 1921, "The Cambridge History of English and American Literature" summarized the early history of the magazine: The magazine was very successful during the 19th century, most notably for the aforementioned series of articles about the American Civil War, which ran for three years during the Doc-12413254: also authorized through race-based arguments that linked White women's enfranchisement to the need to protect the nation from "racial degeneration." Between 1914 and 1921 the NCWC published the monthly journal "Woman's Century". The purpose was to educate women about public issues and the reforms that were needed, and to provide a forum for discussion by different women's groups. The title page described it as "A journal of education and progress for Canadian women." The monthly journal was modeled on successful British and American feminist periodicals. It was one of the very few women's rights journals published in Canada. In 1918, Doc-18227076: eight-page weekly paper created and managed by the Women's Centennial Executive Committee of Philadelphia. It was "devoted to the Industrial interest of women" by promoting choice, equal pay for equal work, and greater financial and social autonomy. The New Century Club was a woman's organization that was established in 1877 to improve the lives of women. It had committees for working women, municipal affairs and self-education. Rather than portraying the opinions of the "radical" viewpoints of some of its members, the Hallowell, its first president, said that they only "whispered... [the] logic of suffrage." As the organization evolved, the moved Answer: The company that published Woman's Century was founded in 1881.</p>
ReAct (70B)	<p>Query: When was the company that published Woman's Century founded? AI Messages: Retrieve(query="Woman's Century publication company founding date") Retrieve documents: Doc-18191576: Citations Sources Woman's Century Woman's Century was the official organ of the National Council of Women of Canada (NCWC), published in Toronto between 1913 and 1921. The magazine was relatively conservative, and supported World War I, but stood up for women's rights and universal suffrage. The founder of "Woman's Century" was Jessie Campbell MacIver. She had come to Canada from Scotland with her husband, a lawyer, and five children. She became involved in the National Council of Women. The first issue of "Woman's Century" appeared in May 1913. It was largely produced out of MacIver's home, with the help of Doc-18191569: Woman's Century Woman's Century was the official organ of the National Council of Women of Canada (NCWC), published in Toronto between 1913 and 1921. The magazine was relatively conservative, and supported World War I, but stood up for women's rights and universal suffrage. The founder of "Woman's Century" was Jessie Campbell MacIver. She had come to Canada from Scotland with her husband, a lawyer, and five children. She became involved in the National Council of Women. The first issue of "Woman's Century" appeared in May 1913. It was largely produced out of MacIver's home, with the help of her husband Doc-3964891: The Century Magazine The Century Magazine was first published in the United States in 1881 by The Century Company of New York City, which had been bought in that year by Roswell Smith and renamed by him after the Century Association. It was the successor of "Scribner's Monthly Magazine" and ceased publication in 1930. In 1921, "The Cambridge History of English and American Literature" summarized the early history of the magazine: The magazine was very successful during the 19th century, most notably for the aforementioned series of articles about the American Civil War, which ran for three years during the Doc-18227076: eight-page weekly paper created and managed by the Women's Centennial Executive Committee of Philadelphia. It was "devoted to the Industrial interest of women" by promoting choice, equal pay for equal work, and greater financial and social autonomy. The New Century Club was a woman's organization that was established in 1877 to improve the lives of women. It had committees for working women, municipal affairs and self-education. Rather than portraying the opinions of the "radical" viewpoints of some of its members, the Hallowell, its first president, said that they only "whispered... [the] logic of suffrage." As the organization evolved, the moved Doc-12741329: in 1847 and the Philadelphia Female Anti-Slavery Society in the 1850s. She helped found the Pennsylvania Woman Suffrage Association in 1869, and she was its first corresponding secretary. At the Philadelphia Centennial Exposition of 1876, Turner was a leader of the Women's Congress and distributed the newspaper "New Century for Women" that she wrote and edited at the Women's Pavilion. The New Century Club women's club was founded in Philadelphia in 1877 following a stirring paper that Turner delivered at the Women's Congress. Turner was the president from 1879 to 1881 and the first corresponding secretary of the literary, social Answer: The company that published Woman's Century was founded in 1881 in New York City.</p>

A.9 LLM USAGE DECLARATION

We declare that large language models (LLMs) were used in limited and specific capacities in this work. Specifically, LLMs such as LLaMA3 (8B and 70B) and GPT-4o-mini were used as components within the MA-RAG framework for retrieval-augmented reasoning. In addition to framework development, LLMs were employed for grammar checking and language refinement of the manuscript. All core technical contributions, experimental design, analysis, and conclusions presented in this work are entirely our own. The use of LLMs did not influence the scientific methodology, results interpretation, or technical contributions of this research.