

Optimizing Retrieval for RAG via Reinforced Contrastive Learning

Jiawei Zhou Lei Chen

The Hong Kong University of Science and Technology
The Hong Kong University of Science and Technology (Guangzhou)
{jzhoubu, leichen}@connect.ust.hk

Abstract

As retrieval-augmented generation (RAG) becomes increasingly widespread, the role of information retrieval (IR) is shifting from retrieving information for human users to retrieving contextual knowledge for artificial intelligence (AI) systems, where relevance becomes difficult to define or annotate beforehand. To address this challenge, we propose **R3**, a **R**etrieval framework optimized for **R**AG through trial-and-feedback **R**einforced contrastive learning. Unlike prior approaches that rely on annotated or synthetic data for supervised fine-tuning, R3 enables the retriever to dynamically explore and optimize relevance within the RAG environment. During training, the retrieved results interact with the environment to produce contrastive signals that automatically guide the retriever’s self-improvement. Extensive experiments across diverse tasks demonstrate that R3 improves RAG performance by 5.2% over the original retriever and surpasses state-of-the-art retrievers by 4.9%, while achieving comparable results to LLM-augmented retrieval and RAG systems built on post-trained or instruction-tuned LLMs. It is both efficient and practical, requiring only 4 GPUs and completing training within a single day.

1 Introduction

Retrieval-augmented generation (RAG) [1, 2, 3] is a well-established paradigm that integrates large language models (LLMs) [4] with information retrieval (IR) [5] to access external knowledge. Recently, RAG has rapidly evolved into a foundation for a new wave of advanced AI applications [6]. Examples include web-browsing agents [7, 8] that interact with live web content, conversational chatbots [9, 10, 11] that integrate retrieval to enable knowledge-grounded and emotionally aware dialogue, and DeepResearch assistants [12, 13, 14] that autonomously analyze and synthesize information across multiple sources to produce comprehensive reports.

These RAG applications signify a fundamental shift in the role of retrieval, from search for humans to search for AI. As illustrated in Figure 1, traditional **IR** searches information for human users, where relevance is pre-defined as superficial similarity to ensure interpretability [15, 16], so that human users can instantly grasp the underlying relations. In contrast, **RAG** searches knowledge for AI systems, which can efficiently process and reason over vast amounts of information and are designed to handle diverse and evolving tasks. The retriever functions as an internal component within a RAG environment that encompasses tasks, workflows, LLMs, and other components, making relevance more environment-dependent, hard to pre-define, and necessary to explore.

Existing RAG applications have several retrieval options. Some leverage search engine APIs, which are convenient but expensive, difficult to scale, and cannot be further optimized [17]. Others deploy neural retrievers locally. However, directly applying these off-the-shelf retrievers can suffer from **gap between IR and RAG**. Studies have shown that traditional IR often retrieve semantically related but unhelpful content [18, 19, 20], LLM-generated documents [21], or misleading evidence [22], all of

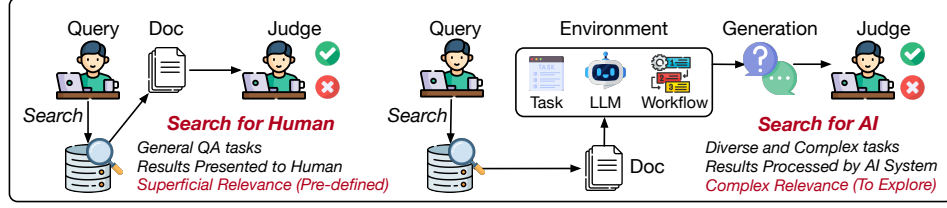


Figure 1: Comparison of traditional IR setting and RAG setting.

which can degrade RAG performance. Furthermore, Cuconasu et al. [23, 24] demonstrate that while traditional IR retrieves documents containing the correct answer, these documents do not necessarily improve RAG performance. Additionally, related findings have emerged in the study of LLM faithfulness, where teams from Anthropic [25] and Apple [26] found that chain-of-thought prompts often fail to reflect the actual reasoning process of LLMs, and even advanced LLMs sometimes fail to follow explicit instructions. These observations reveal a key challenge in RAG: there is no universal prior knowledge of context engineering that applies across all RAG environments. As a result, the context engineering process often diverges from human intuition and can only be refined through practice within environment.

In addition to the studies mentioned above, we further examine this gap through empirical experiments presented in Appendix C, where we evaluate the varying capabilities of different retrievers (unsupervised, supervised, and SOTA) on tasks of varying complexity in both IR and RAG settings. In IR, we examine whether the retriever can retrieve documents containing the answer, while in RAG, we assess whether the retrieved document can prompt the LLM to generate the correct answer. The results reveal two key findings. **Finding 1: Better IR performance does not always lead to better RAG performance, especially when a task shift occurs.** For QA tasks, we observe that higher accuracy in IR settings generally correlates with better RAG performance. However, this trend does not hold for non-QA tasks. For example, on PubHealth, a vanilla DPR_{MS} outperforms a SOTA retriever in RAG settings, despite being weaker in IR metrics. Similarly, on ARC, the unsupervised CONTRIEVER achieves the best RAG performance, outperforming its supervised counterparts. **Finding 2: Substantial room for improvement in retrieval within the RAG system.** We find that although most required knowledge already exists in the datastore, each retriever succeeds on only a subset of queries. For example, on NQ, 77% of queries can be answered by at least one retriever via RAG, yet the best single retriever covers only 43%. This gap reveals significant untapped potential in the datastore and underscores the need for stronger retrieval in RAG.

To bridge the gap from IR to RAG, we propose **R3**, a **R**etrieval framework optimized for **R**AG in a **R**einforced manner. Unlike prior works that **learn pre-defined relevance via supervised fine-tuning (SFT)** through annotation or synthetic data, R3 aims to **explore relevance via reinforcement learning (RL)** within the RAG environment. Within this framework, we introduce reinforced contrastive learning (RCL) as the core training paradigm, where contrastive relational data are explored during training rather than pre-annotated in datasets. Specifically, R3 follows the standard RAG workflow: it retrieves documents and incorporates them as context for LLM generation. Based on the generation outcomes, the retrieved documents are labeled as positive or negative with respect to the query, and contrastive learning objective is applied to optimize the retriever accordingly. Extensive experiments demonstrate that R3 enables retrievers to effectively adapt from IR to RAG, achieving an average 5.2% improvement in 1-shot accuracy and consistently outperforming SOTA retrievers as well as LLM-empowered retrieval methods.

Our contributions are summarized as follows:

1. We identify and analyze the relevance gap between traditional IR and RAG settings, supported by evidence from prior studies across diverse domains as well as our own empirical findings.
2. We propose R3, a retrieval framework optimized for RAG in a reinforced manner, enabling retrievers to automatically explore and self-improve within RAG environments.
3. R3 is simple, effective, and efficient: it requires only modest computational resources for training while achieving significant performance improvements across multiple benchmarks. It consistently outperforms RAG frameworks based on state-of-the-art off-the-shelf retrievers and, in several tasks, matches the performance of systems employing post-trained or instruction-tuned LLMs, making it a impactful advancement for contemporary RAG applications.

2 Related Works

The Evolution of Information Retrieval. Information retrieval has long been a core mechanism for various applications. The field began with heuristic approaches such as TF-IDF and BM25 [27], which have been widely adopted in both research and industry. As the field progressed, the advent of neural networks gave rise to neural retrieval [28]. Yet, these models still heavily relied on training data annotated using BM25 and manual validation [29, 30], leading to superficial relevance.

In recent years, however, the rise of RAG has exposed the gap between search for humans and search for AI. This shift has prompted efforts to optimize retrieval models specifically for RAG. Early work in this direction focus on learning-free methods, such as using LLMs or heuristics to determine when to retrieve [31, 32], performing adaptive retrieval with reasoning [33, 34, 35], or decomposing and refining complex queries [36, 37]. Other research explored learning-based approaches, where retrievers are optimized jointly [2, 38] or separately [39, 40] with LLMs, using unsupervised objective like prefix language modeling [40], or supervised objective that maximize question-answer generation likelihood [41]. Despite their successes, these methods often come with high computational costs and focus primarily on general relevance, with limited consideration of specific RAG environments.

Beyond conventional RAG systems that search context for LLMs, there are many more complex, real-world environments where retrieval must interact with other intelligent components to address emerging challenges. For example, searching multi-modal data to improve multi-modal LLM reasoning [42, 43], retrieving MCP services for agents [44], or searching action modules or planning for robot embodiment [45, 46]. All of these emerging and advanced applications highlight complex environment-specific relevance. Our method, in line with this area, provides a solution by efficiently training specialized retrievers tailored to a specific environment for applications.

Contrastive Learning versus Reinforced Contrastive Learning. Contrastive learning (CL) [47, 48] is a well-established method used to train bi-encoder retrievers by pulling representations of positive pairs closer and pushing negatives apart [28, 49]. CL relies on contrastive labels, which define the positive or negative relationship between pair-wise data. These relational data (i.e., positive and negative query–document pairs) can be obtained through annotation [29], extracted from the web [50, 51], or, more recently, synthesized using LLMs [52, 53]. While these contrastive labels provide effective training signals, they are inherently defined at the data level, making them difficult to transfer across different environments when needed. If components such as tasks, LLMs, or workflows within the environment change, these labels often lose effectiveness and require reconstructed. We further introduce **Reinforced Contrastive Learning (RCL)**, which distinguishes itself from conventional CL by constructing contrastive signals on-the-fly in a trial-and-feedback manner. Simply put, traditional CL involves SFT on annotated data to learn pre-defined relevance, while RCL leverages RL to explore proper relevance that suit the specific search environment. Our framework follows RCL paradigm, enabling versatility and automatic generalization to any RAG environment.

3 Methodology

In this section, we introduce **R3**, a framework that optimizes **R**etrieval for **R**AG via **R**einforced contrastive learning. While our idea is straightforward, it presents several challenges. In the following sections, we detail the problem setup (§3.1), the solution to the first challenge, which addresses the on-policy retrieval issue (§3.2), the solution to the second challenge, which focuses on mitigating the cost of autoregressive generation (§3.3), and the reinforced contrastive learning (§3.4).

3.1 Problem Setup

A RAG framework typically consists of:

- Retriever \mathcal{R}_θ parameterized by θ ;
- Datastore \mathcal{D} containing a vast number of documents d ;
- User query q , and the corresponding answers a , if provided;
- RAG environment env to the retriever, which refers to everything surrounding the retriever within the RAG system, such as LLM \mathcal{G} , task instructions, and specific workflows, etc.;
- Scoring function $S(\cdot)$ that evaluates the quality of the generated response.

The downstream RAG pipeline generally follows:

1. Retrieve the top- k relevant documents from the \mathcal{D} based on q , with a relevance function f_θ :

$$\{\hat{d}\}_k = \mathcal{R}_\theta(q, \mathcal{D}, k) \triangleq \underset{d \in \mathcal{D}}{\operatorname{argmax}}_k f_\theta(q, d)$$

2. Generate response based on the retrieved documents and the RAG environment. We use $\mathcal{G}(\cdot)$, abbreviated from $\mathcal{G}_{env}(\cdot)$, to denote the generation process within env :

$$\hat{y} = \mathcal{G}(q, \{\hat{d}\}_k)$$

3. Scoring the quality of the generation \hat{y} . In our setup, we measure whether the generation contains the answer:

$$S(\hat{y}) = \begin{cases} 1 & \text{if } \hat{y} \text{ contain } a, \\ 0 & \text{otherwise.} \end{cases}$$

Optimization Goal. Given a datastore and a RAG environment, R3 aims to optimize the retrieval relevance to minimize the generation scores for all training queries:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmax}} \sum_{\forall q} S(\hat{y} \mid \mathcal{R}_\theta, q, \mathcal{D}, \mathcal{G}_{env})$$

RL Formulation. From a RL perspective, the query q and datastore \mathcal{D} can be viewed as the state, the policy is represented by the bi-encoder θ and the action involves embedding the data into the appropriate representation. During training, the policy generates embeddings based on the current state, which then interact with the env to produce a reward through S . The policy θ is optimized to maximize this reward. Despite this formulation differing from mainstream RL [54, 55], where explicit state transitions are typically involved, we still conceptualize it as a variant of RL, as it adheres to the principles of trial-and-feedback and contrasts with conventional SFT.

Training Overview. Our training consists of three steps: (i) on-policy retrieval that conduct search during training with its latest parameters (§3.2); (ii) approximated LLM generation based on the retrieved documents (§3.3); (iii) reinforced contrastive learning to optimize the retriever (§3.4). Steps (i) and (ii) present practical challenges, which we address in the next section. Both are essential to enable effective reinforced contrastive learning. An illustration of our framework is depicted in Figure 2.

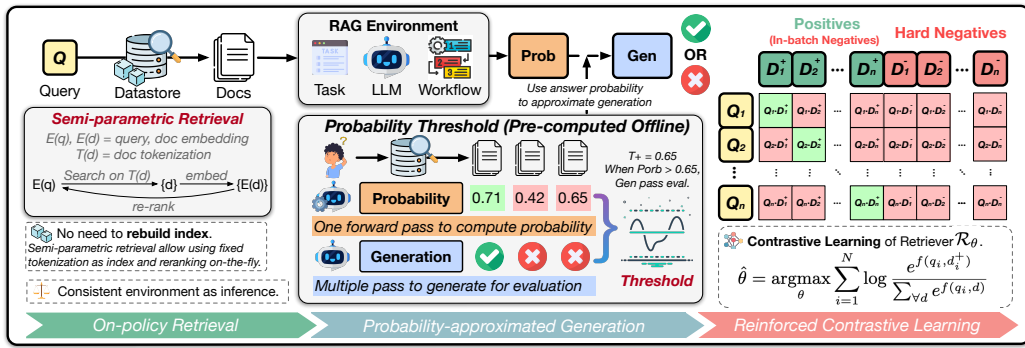


Figure 2: Illustration of the R3 training process.

3.2 On-Policy Retrieval

In this step, given a query q , we use the on-policy retriever to retrieve the top- k relevant documents. The main challenge in this stage concerns the retrieval index.

Challenge of Index Staleness. As is well known, the retrieval index is typically the embedding of the datastore, denoted as $E_\theta(\mathcal{D})$. During training, as the \mathcal{R}_θ parameters update from $\theta \rightarrow \theta'$, the index must be updated accordingly, from $E_\theta(\mathcal{D}) \rightarrow E_{\theta'}(\mathcal{D})$, where $|\mathcal{D}| \gg 1$. Otherwise, the index becomes stale, leading to mismatches between the query and document embeddings. However,

frequently re-embedding a large datastore is computationally expensive and often unaffordable in practice. Fundamentally, this challenge stems from the coupling between retrieval index and model parameters θ .

Prior solutions alleviate index staleness by periodically rebuilding the index [2, 40] or freezing the document encoder during training [41, 38]. While shorter re-index intervals are observed to yield better results [56], longer intervals are often chosen to reduce re-indexing costs. Although these strategies alleviate index staleness to some extent, residual staleness remains and ultimately limits the effectiveness of retriever training.

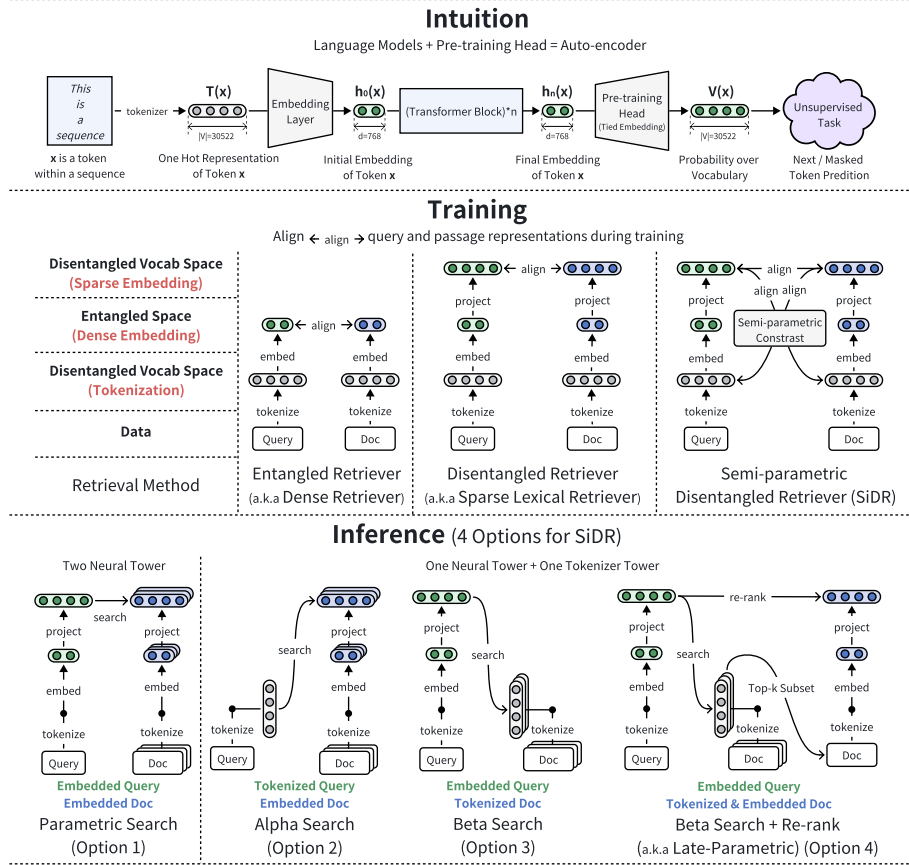


Figure 3: Overview illustration of SiDR.

Our Solution. We adopt our recently proposed semi-parametric retriever architecture SiDR [57], which is designed to address this issue.

Revisiting SiDR. Figure 3 illustrates the core idea of SiDR. Intuitively, a language model together with its pre-training head can be viewed as an auto-encoder that encodes one-hot token representations $T(x) \in \{0, 1\}^{|V|}$ into softmax vocabulary probabilities $V(x) \in (0, 1)^{|V|}$ to predict masked or next tokens. Inspired by this, SiDR aligns bag-of-token representation with sparse embeddings so that, at downstream, the embedded query can directly search over tokenized documents, thereby decoupling the index from parameters θ .

Specifically, SiDR builds upon a BERT-based models with three simple modifications to its pre-training head: (i) replacing the softmax with elu1p activation; (ii) aggregating token representations via max pooling; and (iii) applying top- k sparsification. Given a sequence X , SiDR embeds it into a $|V|$ -dimensional sparse embedding which we refer to $E_\theta(X) \in (0, +\infty)^{|V|}$. During training, SiDR applies contrastive learning across three channels: $E_\theta(q)$ with $E_\theta(d)$, $T(q)$ with $E_\theta(d)$, $E_\theta(q)$ with $T(d)$. In this setup, it succeeds in using $E_\theta(q)$ to search over bag-of-token index $T(\mathcal{D})$. We expand on SiDR in more detail in Appendix D.

On-policy Retrieval. During R3 training, we adopt the late parametric mechanism of SiDR (shown as option 4), which first retrieves the top- m documents using the bag-of-tokens index $T(\mathcal{D})$, and then embeds these documents for re-ranking. This process can be formulated as:

$$\begin{aligned}\{\hat{d}\}_m &= \mathcal{R}_\theta(E_\theta(q), T(\mathcal{D}), m) \\ \{\hat{d}\}_k &= \mathcal{R}_\theta(E_\theta(q), E_\theta(\{\hat{d}\}_m), k)\end{aligned}$$

To reduce training costs, we set $m = k = 20$ in our experiments. Additional ablation studies and comparisons on re-indexing solutions are provided in Section 5.1.

3.3 Probability-approximated Generation

Following on-policy retrieval, we obtain the retrieved set $\{\hat{d}\}_k$ for each query, denoted as $\hat{\mathcal{D}}_q$. The goal of the LLM forward step is to divide this set into a positive pool $\hat{\mathcal{D}}_q^+$ and a negative pool $\hat{\mathcal{D}}_q^-$, based on the RAG outcome. Below, we outline the key challenges involved in this step.

Challenge of Online Autoregressive Generation. During training, the online generation process \mathcal{G} is computationally expensive and slow due to the overhead of autoregressive decoding.

Solution. While a promising solution is to generate responses on-the-fly and verify them with either human-in-the-loop in the loop [58] or a larger proprietary LLM as a judge [59, 60], this approach incurs substantial computational cost, potentially slowing down training and reducing the accessibility of our method. As a more practical solution, we pre-compute a probability threshold offline and use it to approximate autoregressive generation online. This relies on the weak assumption that a higher conditional probability $P(y | x)$ corresponds to a greater likelihood of generating y , where x is the input to the LLM. Further discussion on this assumption is provided in Appendix F. Below, we present the details of our solution.

Offline Computation of Probability Threshold. We follow the standard RAG pipeline described in Section 3.1. For each training query q , we retrieve the top-100 documents, denoted as the initial retrieved set \mathcal{D}_q . For each $d_i \in \mathcal{D}_q$, we compute the joint probability $P(y | x)$ of generating the ground truth response y given the input prompt x , where x consists of the query, one retrieved document, and the instruction.

$$x = \text{Prompt}_{task}(q, d_i); \quad P(y | q, d_i) = P(y | x) = \prod_{\forall t_i \in y} P_\phi(t_i | t_{<i}, x)$$

We then generate responses $\hat{y} = \mathcal{G}(x)$. Based on whether \hat{y} passes the evaluation, we partition the initial retrieved set \mathcal{D}_q into a positive pool \mathcal{D}_q^+ and a negative pool \mathcal{D}_q^- . We set $k = 100$ and discard any query for which either pool is empty. We define the probability thresholds for positives and negatives as \mathcal{T}^+ and \mathcal{T}^- , respectively.

$$\mathcal{T}_q^+ = \max\{P(y | q, d) | \forall d \in \mathcal{D}_q^-\}; \quad \mathcal{T}_q^- = \min\{P(y | q, d) | \forall d \in \mathcal{D}_q^+\}$$

Online Identification of Positives and Negatives. During online training, given a query q , we retrieve the top- k documents as the in-training retrieved set $\hat{\mathcal{D}}_q$. For each $\hat{d}_i \in \hat{\mathcal{D}}_q$, we compute $P(y | q, \hat{d}_i)$ and classify it as positive or negative based on the offline thresholds.

$$\hat{d}_i \in \begin{cases} \hat{\mathcal{D}}_q^+, & \text{if } P(y | q, \hat{d}_i) > \mathcal{T}_q^+ \\ \hat{\mathcal{D}}_q^-, & \text{if } P(y | q, \hat{d}_i) < \mathcal{T}_q^- \\ \text{Discarded,} & \text{else} \end{cases}$$

In plain terms, if using \hat{d}_i leads to a higher probability of generating y than any $d \in \mathcal{D}_q^-$, then \hat{d}_i is considered positive. Conversely, if its probability is lower than any $d \in \mathcal{D}_q^+$, then \hat{d}_i is considered negative. Otherwise, \hat{d}_i is discarded. If $\hat{\mathcal{D}}_q^-$ or $\hat{\mathcal{D}}_q^+$ is empty, we fall back to the initial set \mathcal{D}_q^- or \mathcal{D}_q^+ .

Sampling. In practice, we iterate through the retrieved documents in descending order of retrieval relevance. For each document \hat{d}_i , we apply the LLM forward pass to classify it as positive, negative, or discard it. This process continues until the first negative document is identified, which we designate as the hard negative \hat{d}^- . We then randomly sample one positive document \hat{d}^+ from $\hat{\mathcal{D}}_q^+$. If either

\hat{d}^+ or \hat{d}^- is unavailable, we fall back to sampling from the initial pool \mathcal{D}_q^+ or \mathcal{D}_q^- , respectively. We evaluate alternative sampling strategies in Appendix E and find that this strategy consistently achieves the best performance.

Other Details. For closed-set tasks where the response is a single token, we directly compare next-token probabilities to classify \hat{d}_i . If the gold choice token has a higher probability than other options, \hat{d}_i is considered as positive; otherwise, negative. For queries q with multiple gold responses y , each y is treated as a separate entry. If \hat{d}_i succeeds on at least one, it is considered positive; otherwise negative. To avoid redundant computation, we cache all $P(y | q, \hat{d}_i)$ for reuse.

3.4 Reinforced Contrastive Learning

Following on-policy retrieval and probability-approximated generation, we obtain the in-training retrieved positive document \hat{d}_i^+ and negative documents \hat{d}_i^- for the training query q . In the final step, we apply contrastive learning to these pairs.

Our training objective follows S1DR to preserve its compatibility with late parametric retrieval (i.e., retrieving documents from a bag-of-tokens index and then re-ranking). Given a batch B of N samples, each sample contains a query q_i , a positive document d_i^+ , and a negative document d_i^- . The semi-parametric contrastive loss is defined as:

$$L(q, d) = - \sum_{i=1}^N \left(\log \underbrace{\frac{e^{f(q_i, d_i^+)}}{\sum_{\forall d \in B} e^{f(q_i, d)}}}_{\text{q-to-d}} + \log \underbrace{\frac{e^{f(d_i^+, q_i)}}{\sum_{\forall q \in B} e^{f(d_i^+, q)}}}_{\text{d-to-q}} \right)$$

The final loss integrates contrastive loss of both parametric and semi-parametric components:

$$\begin{aligned} L_{\text{para}}(q, d) &= L(E_{\theta}(q), E_{\theta}(d)) \\ L_{\text{semi-para}}(q, d) &= L(E_{\theta}(q), T(d))/2 + L(T(q), E_{\theta}(d))/2 \\ L_{\text{final}}(q, d) &= L_{\text{para}}(q, d) + L_{\text{semi-para}}(q, d) \end{aligned}$$

4 Experiments

4.1 Experimental Setup

Tasks and Datasets. We evaluate R3 on five public RAG benchmarks. For free-form generation, we utilize Natural Questions (NQ; Kwiatkowski et al., 2019), TriviaQA (TQA; Joshi et al., 2017), and HotpotQA [62], three well-established open-domain QA datasets. For closed-set generation, we employ the PubHealth [63] dataset for fact-checking tasks, and the ARC-Challenge [64] dataset for multiple-choice reasoning. More details can be found in Appendix A.

We exclude long-form generation datasets as we use the probability of continuation to approximate RAG performance, which may not align well with such tasks. Additionally, certain datasets, such as PopQA [65], which only offer a test split, are also excluded.

Evaluation Metrics. Following previous works [66, 65], we use accuracy on the test set as our evaluation metric. In the traditional IR setting, accuracy reflects whether the retrieved documents contain the answer, while in the RAG setting, it is determined by whether the generated output contains the answer. Since our training uses only one document in context, whereas prior work typically uses ten, we report accuracy under both 1-shot and 10-shot settings for comparison.

Implementation Details. Our RAG system employs the LLM Llama3-8b [67] with the retriever S1DR_{MS} [57] that trained on MS MARCO dataset [30]. For experiments on NQ, since certain baselines are trained on its training split, we additionally train S1DR_{MS} on NQ before applying our method. By default, we use the same English Wikipedia datastore and prompt as those open-sourced by SELF-RAG, detailed in Appendix K. For HotpotQA, we use the official datastore provided with the dataset. During training, we train the retriever for each dataset for 80 epochs, aligning with the training duration used for S1DR_{MS}. We use a batch size of 128 and an AdamW optimizer [68] with a learning rate of 2×10^{-5} . The training process is divided into two phases: the first half involves a warm-up phase using initial retrieved positives and negatives, while the second half transitions to in-training retrieval, using the in-training positives and negatives. During inference, we set the

maximum number of generated token to be 100 for free-form generation while 20 for closed-set generation. Our experiments are conducted with 4 NVIDIA GPUs. Both offline RAG preparation and online RAG training take less than one day, depending on the number of queries in the datasets. We leverage vLLM [69] to accelerate offline generation.

Baselines. We consider the below baselines: (1) *Standard RAG*: RAG frameworks using Llama3-8B and SOTA retrievers E5 [51] and CONTRIEVER_{MS} [49]. (2) *Improving IR for RAG*: RAG frameworks with tuning retriever or advanced retrieval strategies enhanced by LLM. Strategy-based methods include ADAPTIVE-RAG [33] and IR-CoT [35], which adapt retrieval based on question complexity or LLM reasoning, as well as DRAGIN [31], FLARE [32], and SEAKR [34], which dynamically retrieve or selectively integrate external information guided by LLMs. For learning-based method, we compare against REPLUG [40], which tunes only the retriever while frozen the LLM. (3) *Improving LLM for RAG*: RAG frameworks that tune the LLM, typically requiring more computation than tuning the retriever. We compare with SELF-RAG [66], which trains the LLM to decide when to retrieve and to self-verify its answers, and with RA-DIT [41], which jointly tunes both the retriever and the LLM. We include LLM-tuning methods in the comparison to illustrate the relative improvement from tuning the retriever. (4) *Transferring to other LLMs*: We compare the RAG framework using different LLMs, such as Llama3-Instruct_{8B} [67], Phi-3-mini-4k-instruct_{3.8B} [70], Mistral-Instruct_{7B} [71], along with SiDR_{MS} before and after tuning. This setup is designed to evaluate whether the learned in-context relevance transfers across different LLMs. Further model details are provided in Appendix B.

4.2 Main Results

Table 1: Main results of R3 and other RAG baselines. **Bold**: best RAG method by only improving IR. Δ : improvement or decline; \blacktriangle : baseline for below methods to compare; \dagger : reproduction by other works; \ddagger : our reproduction; \spadesuit : LLM-enhanced retrieval process.

Task Type (→)		Free-form												Closed-set					
Dataset (→)		NQ			TriviaQA			HotpotQA			PubHealth			ARC-C					
Method (↓)	Metrics (→)	1-shot	10-shot	Δ	1-shot	10-shot	Δ	1-shot	Δ	1-shot	Δ	10-shot	Δ	1-shot	Δ	10-shot	Δ		
Standard RAG																			
† Llama3 _{8B} + SiDR		42.2	▲	42.1	▲	62.0	▲	62.5	▲	39.1	▲	63.5	▲	64.9	▲	56.9	▲	57.5	▲
† Llama3 _{8B} + CONTRIEVER _{MS}		36.5	-5.7	38.3	-3.8	60.7	-1.3	60.6	-1.9	37.2	-1.9	63.1	-0.4	62.9	-2.0	58.1	+1.2	58.9	+1.4
† Llama3 _{8B} + E5		43.2	+1.0	41.8	-0.3	63.2	+1.2	61.4	-1.1	35.7	-3.4	64.7	+1.2	63.7	-1.2	58.0	+1.1	58.1	+0.6
Improving IR for RAG																			
♠ ADAPTIVE-RAG _{TS-XXL-11B} (15-shot) [33]	–	–	47.4	+5.3	–	–	57.2	-5.3	46.8	+7.7	–	–	–	–	–	–	–	–	
† IR-CoT _{Llama3-3.1-8B-Instruct} (15-shot) [35]	–	–	47.8	+5.7	–	–	60.8	-1.7	43.8	+4.7	–	–	–	–	–	–	–	–	
† DRAGIN _{Llama3-3.1-8B-Instruct} (15-shot) [31]	–	–	48.0	+5.9	–	–	66.6	+4.1	43.0	+3.9	–	–	–	–	–	–	–	–	
† SEAKR _{Llama3-3.1-8B-Instruct} (15-shot) [34]	–	–	40.6	-1.5	–	–	65.6	+3.1	42.4	+3.3	–	–	–	–	–	–	–	–	
♠ FLARE _{Llama3-3.1-8B-Instruct} (15-shot) [32]	–	–	45.0	+2.9	–	–	64.8	+2.3	37.2	-1.9	–	–	–	–	–	–	–	–	
‡ REPLUG _{Llama2-7B} (3-shot) [72]	–	–	–	–	–	–	–	–	–	–	–	41.7	-23.2	–	–	–	47.2	-10.3	
R3 _{Llama3-3.8B} (Ours)		47.8	+5.6	48.2	+6.1	65.8	+3.8	66.2	+3.7	47.1	+8.0	69.5	+6.0	69.3	+4.4	59.2	+2.3	59.4	+1.9
Improving LLM for RAG																			
Llama3-Instruct _{8B} + SiDR		47.2	+5.0	54.7	+12.6	65.2	+3.2	73.3	+10.8	49.0	+9.9	67.2	+3.7	71.8	+6.9	72.3	+15.2	75.4	+18.0
SELF-RAG _{Llama2-7B} [66]	–	–	–	–	–	–	–	66.4	+3.9	–	–	–	–	72.4	+7.5	–	–	67.3	+9.8
‡ SELF-RAG _{Mistral-7B} [73]	–	–	–	–	–	–	–	64.8	+2.3	–	–	–	–	72.4	+7.5	–	–	74.9	+17.4
‡ SELF-RAG _{Llama3-8B} [74]	–	–	–	–	–	–	–	56.4	-6.1	–	–	–	–	67.8	+2.9	–	–	58.0	+0.5
‡ SELF-RAG _{Llama3-8B} + SiDR		38.5	-3.7	38.0	-4.1	51.0	-11.0	57.7	-4.8	–	–	64.2	+0.7	64.0	-0.9	58.9	+2.0	59.1	+1.6
RA-DIT _{Llama-65B} (5-shot) [41]	–	–	–	43.9	+1.8	–	–	75.1	+12.6	40.7	+1.6	–	–	–	–	–	–	–	–
Transferring R3 to other LLM																			
Llama3-Instruct _{8B} + SiDR		45.2	▲	52.7	▲	65.2	▲	73.3	▲	49.0	▲	67.2	▲	71.8	▲	72.3	▲	75.4	▲
Llama3-Instruct _{8B} + R3		48.8	+3.6	56.5	+3.8	65.6	+0.4	73.8	+0.5	50.7	+1.7	65.2	-2.0	66.1	-5.7	71.8	-0.5	75.1	-0.3
Phi-3-mini-4k-instruct _{3.8B} + SiDR		44.1	▲	50.7	▲	64.6	▲	69.2	▲	44.1	▲	48.2	▲	57.6	▲	84.5	▲	84.7	▲
Phi-3-mini-4k-instruct _{3.8B} + R3		46.6	+2.5	52.4	+1.7	65.6	+1.0	70.4	+1.2	45.7	+1.6	45.3	-2.9	54.4	-3.2	85.1	+0.6	84.2	-0.5
Mistral-Instruct _{7B} + SiDR		43.9	▲	48.8	▲	58.2	▲	57.1	▲	42.4	▲	50.1	▲	57.4	▲	69.8	▲	71.2	▲
Mistral-Instruct _{7B} + R3		46.1	+2.2	51.7	+2.9	59.8	+1.6	57.6	+0.5	41.8	-0.6	46.7	-3.4	54.6	-2.8	69.2	-0.6	70.6	-0.6

Table 1 presents results of R3 and other RAG methods, with key findings summarized below:

Reinforced contrastive learning effectively improves the retriever within RAG environments. Unlike CONTRIEVER_{MS} and E5, which rely on extensive pre-training and SFT, R3 tunes SiDR with only four GPUs in one day. This efficient setup yields an average improvement of 5.2% over the original SiDR_{MS} and outperforms other SOTA retrievers by 4.9% under the 1-shot setting. On PubHealth, the gain reaches 6%, which even instruction-tuned LLMs fail to match. These results demonstrate that learning retrieval tailored to the specific RAG environment in an RL manner is more effective than SFT with massive paired data that is unaware of the RAG environment. In Appendix I, we show that improving the retriever for RAG can degrade its performance in traditional IR settings, highlighting the gap between IR and RAG.

Tuning a small retriever can yield improvements on par with tuning a LLM. Reproductions of SELF-RAG from other works [74, 73] and our own experiments have shown inconsistent gains. This suggests that, despite substantial training costs, improving RAG through LLM tuning requires heavy customization and lacks generalizability. In contrast, tuning a smaller retriever can achieve comparable or even superior results to RAG-oriented or instruction-tuned 8B LLMs on certain datasets. Importantly, improving retriever complements improving LLM without conflict, offering a more efficient and controllable path for improving RAG systems.

Learned relevance can be transferred to other LLMs across domains but not across tasks. Our results show that R3, trained with Llama3-8B, also improves performance when paired with other LLMs, such as Llama3-Instruct-8B, Phi-3-mini-4k-instruct, and Mistral-Instruct, on QA tasks across different benchmarks. However, this transferability does not consistently extend to non-QA tasks. Given that the original S1DR is trained on a QA dataset, the current observations suggest that the learned relevance to be robust for transfer across domains within the same task, but not across tasks. This also reflects a broader phenomenon: while different LLMs may require similar documents for general QA tasks, these requirements diverge significantly for more complex tasks, such as fact-checking and complex reasoning. This highlights the importance of learning retrieval tailored to the specific RAG environment. Rather than viewing this as a limitation, we see it as evidence that R3 is capable of capturing environment-specific relevance.

5 Analysis

5.1 Ablation Study

Compared to prior works, our main differences include (i) construct contrastive on-the-fly (ii) employing contrastive objective instead of KL divergence objective, and (iii) using late parametric to avoid periodic re-indexing. We systematically analyze these factors in this section. Note that our ablation experiments on NQ are conducted with the initial retriever S1DR_{MS}, and thus differs from the main experiment setup.

Contrastive Learning versus Reinforced Contrastive Learning. In the warm-up stage, we use documents retrieved offline from the initial retrieval pool. During the training stage, we apply RCL using documents retrieved online with the current parameters (i.e., on-policy). We conduct an ablation study on NQ and PubHealth under three settings: *[offline-only]* uses only the offline retrieved pool offline, which can be considered as conventional CL; *[online-only]* skips the warm-up and relies solely on online on-policy retrieval; our full method *[offline+online]* uses both offline warm-up and online on-policy retrieval, which refers to RCL with both positive and negative pools guaranteed.

As shown in Figure 4, using either *[offline-only]* or *[online-only]* alone results in suboptimal performance, while *[offline+online]* leads to the best results. These observations demonstrate that both off-policy contrastive labels obtained through conventional CL and on-policy contrastive labels identified via RCL during training can improve the retriever. However, combining both approaches delivers the best results. This supports findings from our prior work [57], which show that a warm-up phase with static contrastive labels helps the retriever initially align with environment-specific relevance, and on-policy retrieval further refines it by continuously mining more effective contrastive labels during training, thereby deepening the retriever’s alignment with the environment.

Contrastive Objective versus KL-Divergence Objective. We also evaluate a variant of our method that replaces contrastive learning objective with KL divergence, denoted as *[offline+online(KL)]*. KL divergence has been adopted in prior work [40, 2] to align query-document relevance with generation likelihood. Our results show that while KL divergence yields initial improvements, these gains quickly plateau and remain consistently lower than those achieved by our contrastive approach. KL-based alignment is easier to implement but provides a more rigid and less adaptive learning signal. In contrast, contrastive learning continuously supplies effective positives and negatives based on the current retriever state, enabling ongoing improvement throughout training.

We believe KL divergence underperforms in this context because the generation likelihood distribution of LLMs is inherently hard to capture by bi-encoder. Many studies in knowledge distillation [75, 76] have attempted to use small bi-encoders to approximate fine-grained ranking signals, typically provided by cross-encoders or LLMs, but have consistently found that such models struggle to capture these signals effectively. This limitation has led to the widespread adoption of the retrieve-then-rerank paradigm in both academic and industrial settings.

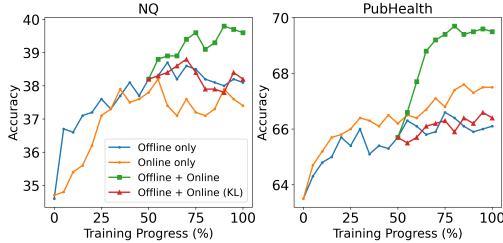


Figure 4: Ablation of offline and online learning.

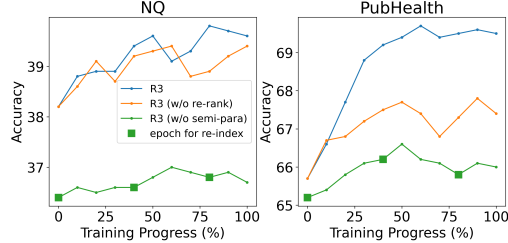


Figure 5: Ablation on re-indexing strategies.

Late Parametric versus Periodic Re-indexing. Another key distinction between our method and prior approaches lies in how we address index staleness. While previous works periodically rebuild the index during training, we adopt a late parametric mechanism from S1DR to avoid frequent re-indexing. Below, we compare these strategies for handling index staleness. *[R3 (w/o re-rank)]* refers to performing retrieval directly on the bag-of-tokens index without subsequent re-ranking. This reduces computational cost but results in suboptimal retrieval accuracy. *[R3 (w/o semi-para)]* denotes the removal of the entire semi-parametric design, falling back to periodic re-indexing as done in prior work. In our setup, the index is rebuilt three times during training. More details are provided in Appendix H.

As shown in Figure 5, our results indicate that while periodic re-indexing *R3 (w/o semi-para)* provides some improvement, it is significantly less effective than the semi-parametric design. The late parametric approach not only yields better performance but also reduces training cost and simplifies implementation. Compared to direct retrieval on the bag-of-tokens index, the late parametric design provides higher-quality positive and negative examples to improve. This advantage is particularly evident on the PubHealth dataset, where R3 shows a much larger improvement over *R3 (w/o re-rank)*.

5.2 Cost-Effectiveness Analysis

The main training cost comes from LLM forward passes to compute probability $P(y | q, d)$ for previously unseen documents. In Table 2, we report the number of such documents processed during training. Each query involves between 14 and 128 unseen documents, depending on the task. We observe a positive correlation between the number of processed documents and the performance gain of R3. Notably, PubHealth encounters most unseen documents and yields the largest improvement, suggesting a greater gap between the initial and learned retriever.

	NQ	TriviaQA	PubHealth	ARC
nDoc	34	18	128	14
Improv.	+5.6%	+3.8%	+6.0%	+2.3%

Table 2: Number of documents requiring probability computation and corresponding improvement.

Together with the transferability results in Table 1, this motivates further analysis. In Appendix G, we show that R3 learns LLM-specific relevance on PubHealth. We find that transferability improves initially but then declines steadily during training, even as RAG performance continues to rise. This suggests that the retriever becomes more specialized for the target LLM (Llama3-8B), reducing its generalization to other LLMs. This pattern reflects a broader trend: while LLMs may share similar relevance preferences for general QA tasks, they might diverge in specialized domains and complex tasks, highlighting the need to tune retrievers for each specific RAG environment.

6 Conclusion

In this work, we demonstrate the relevance gap between IR and RAG. To address this gap, we introduce R3, a RAG framework that optimizes retrieval for a given RAG environment in a RL manner. Our results show that RCL, which constructs on-policy contrastive signals on-the-fly, significantly improves a retriever within a specific RAG environment, outperforming state-of-the-art off-the-shelf retrievers and LLM-augmented retrieval, while performing comparably to RAG systems with post-trained or instruction-tuned 8B LLMs. These findings highlight the substantial potential of our approach to enhance RAG systems through effective retrieval learning.

Limitations

Our work explores optimizing retrieval for RAG in a reinforcement learning manner, but several limitations remain. First, the current experimental setup focuses on a vanilla RAG workflow, where only one document is retrieved as context. We believe this idea can naturally extend to more complex workflows, as long as the online learning process remains computationally feasible. Second, the current reward function is constrained by its reliance on short answers and string matching. During training, we also observe that performance is sensitive to how positive and negative examples are defined. A more stable and generalizable reward or evaluation function, such as using an LLM-as-a-Judge, could further improve reliability. Lastly, our current foundation model is based on BERT, which is relatively outdated. We expect that incorporating more advanced LLM-based encoders could greatly broaden the applicability and potential of this framework.

Broader Impact and Future Work

In this section, we discuss the broader societal impact of our work and its potential influence on other areas and advanced applications.

RAG Application Safety. Our work could be deployed in complex environments where retrieval is learned to affect AI behavior and safety. The retrieval module can learn to retrieve contextual information, few-shot examples, instructions, or existing chain-of-thought prompts that guide LLMs toward more reliable outputs, or conversely be intentionally misused to generate harmful content, mislead users, or surface inappropriate material. We acknowledge this potential for malicious use and encourage responsible deployment and safeguard mechanisms in practice.

Scaling with Learned Sparsity. The success of different areas can be unified under the paradigm of *Scaling with Learned Sparsity*. For example, LLM pre-training leverages Mixture-of-Experts (MoE) to scale up the parameter space, improving effectiveness while sparsely activating modules at inference time to ensure efficiency. RAG can be viewed as scaling knowledge coverage by integrating external databases, while sparsely activating specific data partitions through the retrieval function. Similarly, a line of sparse retrieval studies [77, 78, 79] can be regarded as scaling the representation space to enhance representational capacity and allviate the limitations [80] of embedding models, while sparsely activating dimensions to guarantee search efficiency.

	MoE	RAG	Sparse Retrieval
Area	Pre-training	Inference	Representation Learning
Scaling	Parameter Space	Knowledge Space	Representation Space
Sparsely Activate	Neural Modules	Data Partitions	Dimensions

Table 3: Overview of scaling with learned sparsity paradigms.

Looking forward, we believe that future AI systems will inevitably require learning to scale along certain axes while simultaneously learning sparsity over them. Our two works, SiDR and R3, demonstrate how to learn sparsity and how such sparsity can further be utilized to improve the large-scale complex systems within which they operate, offering preliminary insights in this direction.

Multi-modal RAG (Searching Cross-modal Context). Beyond document retrieval, emerging AI search systems increasingly involve multimodal data such as images and videos. Unlike query–document pairs, where lexical relevance can often serve as a reasonable heuristic, constructing effective relevance pairs for cross-modal data is far more challenging due to the high cost of annotation and the lack of explicit alignment signals. This direction highlights opportunities for framework that can automatically obtain contrastive labels through interaction or feedback signals, a principle that aligns with the learning dynamics explored in our work.

AI Search (Searching Functions, Tools, MCP, and Agents). Recent progress in agentic frameworks, where AI agents learn to call functions, tools, MCP services, or interact with other agents, has largely relied on online reinforcement learning to manage a small pool of available operations. As the pool of callable components continues to grow, learning effective representations of these components for retrieval will become crucial for scalable and efficient decision-making. In such settings, the proposed reinforced contrastive learning offers one possible direction for enabling search and coordination across a large pool of functions, tools, and agents.

References

- [1] Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. Retrieval-augmented generation for knowledge-intensive nlp tasks. *Advances in Neural Information Processing Systems*, 33:9459–9474, 2020.
- [2] Kelvin Guu, Kenton Lee, Zora Tung, Panupong Pasupat, and Mingwei Chang. Retrieval augmented language model pre-training. In *International conference on machine learning*, pages 3929–3938. PMLR, 2020.
- [3] Yunfan Gao, Yun Xiong, Xinyu Gao, Kangxiang Jia, Jinliu Pan, Yuxi Bi, Yi Dai, Jiawei Sun, and Haofen Wang. Retrieval-augmented generation for large language models: A survey. *arXiv preprint arXiv:2312.10997*, 2023.
- [4] Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, et al. A survey of large language models. *arXiv preprint arXiv:2303.18223*, 2023.
- [5] Christopher D Manning. *An introduction to information retrieval*. Cambridge university press, 2009.
- [6] Aditi Singh, Abul Ehtesham, Saket Kumar, and Tala Talaei Khoei. Agentic retrieval-augmented generation: A survey on agentic rag. *arXiv preprint arXiv:2501.09136*, 2025.
- [7] Zhepei Wei, Wenlin Yao, Yao Liu, Weizhi Zhang, Qin Lu, Liang Qiu, Changlong Yu, Puyang Xu, Chao Zhang, Bing Yin, et al. Webagent-r1: Training web agents via end-to-end multi-turn reinforcement learning. *arXiv preprint arXiv:2505.16421*, 2025.
- [8] Xueyu Hu, Tao Xiong, Biao Yi, Zishu Wei, Ruixuan Xiao, Yurun Chen, Jiasheng Ye, Meiling Tao, Xiangxin Zhou, Ziyu Zhao, et al. Os agents: A survey on mllm-based agents for computer, phone and browser use, 2024.
- [9] Le Huang, Hengzhi Lan, Zijun Sun, Chuan Shi, and Ting Bai. Emotional rag: Enhancing role-playing agents through emotional retrieval. In *2024 IEEE International Conference on Knowledge Graph (ICKG)*, pages 120–127. IEEE, 2024.
- [10] Zihan Liu, Wei Ping, Rajarshi Roy, Peng Xu, Chankyu Lee, Mohammad Shoeybi, and Bryan Catanzaro. Chatqa: Surpassing gpt-4 on conversational qa and rag. *Advances in Neural Information Processing Systems*, 37:15416–15459, 2024.
- [11] Mandar Kulkarni, Praveen Tangarajan, Kyung Kim, and Anusua Trivedi. Reinforcement learning for optimizing rag for domain chatbots. *arXiv preprint arXiv:2401.06800*, 2024.
- [12] Yuxiang Zheng, Dayuan Fu, Xiangkun Hu, Xiaojie Cai, Lyumanshan Ye, Pengrui Lu, and Pengfei Liu. Deepresearcher: Scaling deep research via reinforcement learning in real-world environments. *arXiv preprint arXiv:2504.03160*, 2025.
- [13] Zile Qiao, Guoxin Chen, Xuanzhong Chen, Donglei Yu, Wenbiao Yin, Xinyu Wang, Zhen Zhang, Baixuan Li, Huifeng Yin, Kuan Li, et al. Webresearcher: Unleashing unbounded reasoning capability in long-horizon agents. *arXiv preprint arXiv:2509.13309*, 2025.
- [14] Zijian Li, Xin Guan, Bo Zhang, Shen Huang, Houquan Zhou, Shaopeng Lai, Ming Yan, Yong Jiang, Pengjun Xie, Fei Huang, et al. Webweaver: Structuring web-scale evidence with dynamic outlines for open-ended deep research. *arXiv preprint arXiv:2509.13312*, 2025.
- [15] Hang Li, Jun Xu, et al. Semantic matching in search. *Foundations and Trends® in Information Retrieval*, 7(5):343–469, 2014.
- [16] Avishek Anand, Lijun Lyu, Maximilian Idahl, Yumeng Wang, Jonas Wallat, and Zijian Zhang. Explainable information retrieval: A survey. *arXiv preprint arXiv:2211.02405*, 2022.
- [17] Hao Sun, Zile Qiao, Jiayan Guo, Xuanbo Fan, Yingyan Hou, Yong Jiang, Pengjun Xie, Yan Zhang, Fei Huang, and Jingren Zhou. Zerosearch: Incentivize the search capability of llms without searching. *arXiv preprint arXiv:2505.04588*, 2025.

- [18] Siye Wu, Jian Xie, Jiangjie Chen, Tinghui Zhu, Kai Zhang, and Yanghua Xiao. How easily do irrelevant inputs skew the responses of large language models? *arXiv preprint arXiv:2404.03302*, 2024.
- [19] Viktor Moskvoretskii, Maria Lysyuk, Mikhail Salnikov, Nikolay Ivanov, Sergey Pletenev, Daria Galimzianova, Nikita Krayko, Vasily Konovalov, Irina Nikishina, and Alexander Panchenko. Adaptive retrieval without self-knowledge? bringing uncertainty back home. *arXiv preprint arXiv:2501.12835*, 2025.
- [20] Yuhao Wang, Ruiyang Ren, Junyi Li, Wayne Xin Zhao, Jing Liu, and Ji-Rong Wen. Rear: A relevance-aware retrieval-augmented framework for open-domain question answering. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 5613–5626, 2024.
- [21] Sunhao Dai, Yuqi Zhou, Liang Pang, Weihao Liu, Xiaolin Hu, Yong Liu, Xiao Zhang, and Jun Xu. Llm may dominate information access: Neural retrievers are biased towards llm-generated texts. *arXiv preprint arXiv:2310.20501*, 2023.
- [22] Linda Zeng, Rithwik Gupta, Divij Motwani, Diji Yang, and Yi Zhang. Worse than zero-shot? a fact-checking dataset for evaluating the robustness of rag against misleading retrievals. *arXiv preprint arXiv:2502.16101*, 2025.
- [23] Florin Cuconasu, Giovanni Trappolini, Federico Siciliano, Simone Filice, Cesare Campagnano, Yoelle Maarek, Nicola Tonellotto, and Fabrizio Silvestri. The power of noise: Redefining retrieval for rag systems. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 719–729, 2024.
- [24] Florin Cuconasu, Giovanni Trappolini, Federico Siciliano, Simone Filice, Cesare Campagnano, Yoelle Maarek, Nicola Tonellotto, Fabrizio Silvestri, et al. Rethinking relevance: How noise and distractors impact retrieval-augmented generation. In *CEUR WORKSHOP PROCEEDINGS*, volume 3802, pages 95–98. CEUR-WS, 2024.
- [25] Yanda Chen, Joe Benton, Ansh Radhakrishnan, Jonathan Uesato, Carson Denison, John Schulman, Arushi Somani, Peter Hase, Misha Wagner, Fabien Roger, et al. Reasoning models don’t always say what they think. *arXiv preprint arXiv:2505.05410*, 2025.
- [26] Parshin Shojaee, Iman Mirzadeh, Keivan Alizadeh, Maxwell Horton, Samy Bengio, and Mehrdad Farajtabar. The illusion of thinking: Understanding the strengths and limitations of reasoning models via the lens of problem complexity. *arXiv preprint arXiv:2506.06941*, 2025.
- [27] Stephen Robertson, Hugo Zaragoza, et al. The probabilistic relevance framework: Bm25 and beyond. *Foundations and Trends® in Information Retrieval*, 3(4):333–389, 2009.
- [28] 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)*, pages 6769–6781, 2020.
- [29] Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, et al. Natural questions: a benchmark for question answering research. *Transactions of the Association for Computational Linguistics*, 7:453–466, 2019.
- [30] Payal Bajaj, Daniel Campos, Nick Craswell, Li Deng, Jianfeng Gao, Xiaodong Liu, Rangan Majumder, Andrew McNamara, Bhaskar Mitra, Tri Nguyen, et al. Ms marco: A human generated machine reading comprehension dataset. *arXiv preprint arXiv:1611.09268*, 2016.
- [31] Weihang Su, Yichen Tang, Qingyao Ai, Zhijing Wu, and Yiqun Liu. Dragin: Dynamic retrieval augmented generation based on the information needs of large language models. *arXiv preprint arXiv:2403.10081*, 2024.

- [32] Zhengbao Jiang, Frank 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, editors, *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 7969–7992, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.emnlp-main.495. URL <https://aclanthology.org/2023.emnlp-main.495>.
- [33] Soyeong Jeong, Jinheon Baek, Sukmin Cho, Sung Ju Hwang, and Jong C Park. Adaptive-rag: Learning to adapt retrieval-augmented large language models through question complexity. *arXiv preprint arXiv:2403.14403*, 2024.
- [34] Zijun Yao, Weijian Qi, Liangming Pan, Shulin Cao, Linmei Hu, Weichuan Liu, Lei Hou, and Juanzi Li. Seagr: Self-aware knowledge retrieval for adaptive retrieval augmented generation. *arXiv preprint arXiv:2406.19215*, 2024.
- [35] Harsh Trivedi, Niranjan Balasubramanian, Tushar Khot, and Ashish Sabharwal. Interleaving retrieval with chain-of-thought reasoning for knowledge-intensive multi-step questions. *arXiv preprint arXiv:2212.10509*, 2022.
- [36] Ran Xu, Wenqi Shi, Yuchen Zhuang, Yue Yu, Joyce C Ho, Haoyu Wang, and Carl Yang. Collab-rag: Boosting retrieval-augmented generation for complex question answering via white-box and black-box llm collaboration. *arXiv preprint arXiv:2504.04915*, 2025.
- [37] Chi-Min Chan, Chunpu Xu, Ruibin Yuan, Hongyin Luo, Wei Xue, Yike Guo, and Jie Fu. Rq-rag: Learning to refine queries for retrieval augmented generation. *arXiv preprint arXiv:2404.00610*, 2024.
- [38] 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*, 24(251): 1–43, 2023.
- [39] Sebastian Borgeaud, Arthur Mensch, Jordan Hoffmann, Trevor Cai, Eliza Rutherford, Katie Millican, George Bm Van Den Driessche, Jean-Baptiste Lespiau, Bogdan Damoc, Aidan Clark, et al. Improving language models by retrieving from trillions of tokens. In *International conference on machine learning*, pages 2206–2240. PMLR, 2022.
- [40] Weijia Shi, Sewon Min, Michihiro Yasunaga, Minjoon Seo, Rich James, Mike Lewis, Luke Zettlemoyer, and Wen-tau Yih. Replug: Retrieval-augmented black-box language models. *arXiv preprint arXiv:2301.12652*, 2023.
- [41] Xi Victoria Lin, Xilun Chen, Mingda Chen, Weijia Shi, Maria Lomeli, Richard James, Pedro Rodriguez, Jacob Kahn, Gergely Szilvasy, Mike Lewis, et al. Ra-dit: Retrieval-augmented dual instruction tuning. In *The Twelfth International Conference on Learning Representations*, 2023.
- [42] Jianhao Yuan, Shuyang Sun, Daniel Omeiza, Bo Zhao, Paul Newman, Lars Kunze, and Matthew Gadd. Rag-driver: Generalisable driving explanations with retrieval-augmented in-context learning in multi-modal large language model. *arXiv preprint arXiv:2402.10828*, 2024.
- [43] Navve Wasserman, Roi Pony, Oshri Naparstek, Adi Raz Goldfarb, Eli Schwartz, Udi Barzelay, and Leonid Karlinsky. Real-mm-rag: A real-world multi-modal retrieval benchmark. *arXiv preprint arXiv:2502.12342*, 2025.
- [44] Guozhao Mo, Wenliang Zhong, Jiawei Chen, Xuanang Chen, Yaojie Lu, Hongyu Lin, Ben He, Xianpei Han, and Le Sun. Livemcpbench: Can agents navigate an ocean of mcp tools? *arXiv preprint arXiv:2508.01780*, 2025.
- [45] Quanting Xie, So Yeon Min, Pengliang Ji, Yue Yang, Tianyi Zhang, Kedi Xu, Aarav Bajaj, Ruslan Salakhutdinov, Matthew Johnson-Roberson, and Yonatan Bisk. Embodied-rag: General non-parametric embodied memory for retrieval and generation. *arXiv preprint arXiv:2409.18313*, 2024.

- [46] Weiye Xu, Min Wang, Wengang Zhou, and Houqiang Li. P-rag: Progressive retrieval augmented generation for planning on embodied everyday task. In *Proceedings of the 32nd ACM International Conference on Multimedia*, pages 6969–6978, 2024.
- [47] Phuc H Le-Khac, Graham Healy, and Alan F Smeaton. Contrastive representation learning: A framework and review. *Ieee Access*, 8:193907–193934, 2020.
- [48] Ashish Jaiswal, Ashwin Ramesh Babu, Mohammad Zaki Zadeh, Debapriya Banerjee, and Fillia Makedon. A survey on contrastive self-supervised learning. *Technologies*, 9(1):2, 2020.
- [49] Gautier Izacard, Mathilde Caron, Lucas Hosseini, Sebastian Riedel, Piotr Bojanowski, Armand Joulin, and Edouard Grave. Towards unsupervised dense information retrieval with contrastive learning. *arXiv preprint arXiv:2112.09118*, 2021.
- [50] Jiawei Zhou, Xiaoguang Li, Lifeng Shang, Lan Luo, Ke Zhan, Enrui Hu, Xinyu Zhang, Hao Jiang, Zhao Cao, Fan Yu, et al. Hyperlink-induced pre-training for passage retrieval in open-domain question answering. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7135–7146, 2022.
- [51] Liang Wang, Nan Yang, Xiaolong Huang, Binxing Jiao, Linjun Yang, Daxin Jiang, Rangan Majumder, and Furu Wei. Text embeddings by weakly-supervised contrastive pre-training. *arXiv preprint arXiv:2212.03533*, 2022.
- [52] Yanzhao Zhang, Mingxin Li, Dingkun Long, Xin Zhang, Huan Lin, Baosong Yang, Pengjun Xie, An Yang, Dayiheng Liu, Junyang Lin, et al. Qwen3 embedding: Advancing text embedding and reranking through foundation models. *arXiv preprint arXiv:2506.05176*, 2025.
- [53] Liang Wang, Nan Yang, Xiaolong Huang, Linjun Yang, Rangan Majumder, and Furu Wei. Multilingual e5 text embeddings: A technical report. *arXiv preprint arXiv:2402.05672*, 2024.
- [54] Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D Manning, Stefano Ermon, and Chelsea Finn. Direct preference optimization: Your language model is secretly a reward model. *Advances in neural information processing systems*, 36:53728–53741, 2023.
- [55] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.
- [56] Lee Xiong, Chenyan Xiong, Ye Li, Kwok-Fung Tang, Jialin Liu, Paul Bennett, Junaid Ahmed, and Arnold Overwijk. Approximate nearest neighbor negative contrastive learning for dense text retrieval. *arXiv preprint arXiv:2007.00808*, 2020.
- [57] Jiawei Zhou, Li Dong, Furu Wei, and Lei Chen. Semi-parametric retrieval via binary token index. *arXiv preprint arXiv:2405.01924*, 2024.
- [58] Yu Bai, Yukai Miao, Li Chen, Dawei Wang, Dan Li, Yanyu Ren, Hongtao Xie, Ce Yang, and Xuhui Cai. Pistis-rag: Enhancing retrieval-augmented generation with human feedback. *arXiv preprint arXiv:2407.00072*, 2024.
- [59] Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.
- [60] Jiawei Gu, Xuhui Jiang, Zhichao Shi, Hexiang Tan, Xuehao Zhai, Chengjin Xu, Wei Li, Yinghan Shen, Shengjie Ma, Honghao Liu, et al. A survey on llm-as-a-judge. *arXiv preprint arXiv:2411.15594*, 2024.
- [61] Mandar Joshi, Eunsol Choi, Daniel S 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)*, pages 1601–1611, 2017.
- [62] 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. *arXiv preprint arXiv:1809.09600*, 2018.

- [63] Neema Kotonya and Francesca Toni. Explainable automated fact-checking for public health claims. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 7740–7754, 2020.
- [64] Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. Think you have solved question answering? try arc, the ai2 reasoning challenge. *arXiv preprint arXiv:1803.05457*, 2018.
- [65] Alex Troy Mallen, Akari Asai, Victor Zhong, Rajarshi Das, Daniel Khashabi, and Hannaneh Hajishirzi. When not to trust language models: Investigating effectiveness of parametric and non-parametric memories. In *The 61st Annual Meeting Of The Association For Computational Linguistics*, 2023.
- [66] Akari Asai, Zeqiu Wu, Yizhong Wang, Avirup Sil, and Hannaneh Hajishirzi. Self-rag: Learning to retrieve, generate, and critique through self-reflection. *arXiv preprint arXiv:2310.11511*, 2023.
- [67] Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, et al. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.
- [68] Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. In *International Conference on Learning Representations*, 2018.
- [69] 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.
- [70] Marah Abdin, Jyoti Aneja, Hany Awadalla, Ahmed Awadallah, Ammar Ahmad Awan, Nguyen Bach, Amit Bahree, Arash Bakhtiari, Jianmin Bao, Harkirat Behl, et al. Phi-3 technical report: A highly capable language model locally on your phone. *arXiv preprint arXiv:2404.14219*, 2024.
- [71] Albert Q Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, et al. Mistral 7b. *arXiv preprint arXiv:2310.06825*, 2023.
- [72] Shengbin Yue, Siyuan Wang, Wei Chen, Xuanjing Huang, and Zhongyu Wei. Synergistic multi-agent framework with trajectory learning for knowledge-intensive tasks. *arXiv preprint arXiv:2407.09893*, 2024.
- [73] Zilong Wang, Zifeng Wang, Long Le, Huaixiu Steven Zheng, Swaroop Mishra, Vincent Perot, Yuwei Zhang, Anush Mattapalli, Ankur Taly, Jingbo Shang, et al. Speculative rag: Enhancing retrieval augmented generation through drafting. *arXiv preprint arXiv:2407.08223*, 2024.
- [74] Xuanwang Zhang, Yun-Ze Song, Yidong Wang, Shuyun Tang, Xinfeng Li, Zhengran Zeng, Zhen Wu, Wei Ye, Wenyuan Xu, Yue Zhang, et al. Raglab: A modular and research-oriented unified framework for retrieval-augmented generation. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 408–418, 2024.
- [75] Jianping Gou, Baosheng Yu, Stephen J Maybank, and Dacheng Tao. Knowledge distillation: A survey. *International Journal of Computer Vision*, 129:1789–1819, 2021.
- [76] Gautier Izacard and Edouard Grave. Distilling knowledge from reader to retriever for question answering. *arXiv preprint arXiv:2012.04584*, 2020.
- [77] Thibault Formal, Benjamin Piwowarski, and Stéphane Clinchant. Splade: Sparse lexical and expansion model for first stage ranking. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 2288–2292, 2021.

- [78] Yang Bai, Xiaoguang Li, Gang Wang, Chaoliang Zhang, Lifeng Shang, Jun Xu, Zhaowei Wang, Fangshan Wang, and Qun Liu. Sparterm: Learning term-based sparse representation for fast text retrieval. *arXiv preprint arXiv:2010.00768*, 2020.
- [79] Tao Shen, Xiubo Geng, Chongyang Tao, Can Xu, Xiaolong Huang, Binxing Jiao, Linjun Yang, and Daxin Jiang. Lexmae: Lexicon-bottlenecked pretraining for large-scale retrieval. *arXiv preprint arXiv:2208.14754*, 2022.
- [80] Orion Weller, Michael Boratko, Iftekhar Naim, and Jinhyuk Lee. On the theoretical limitations of embedding-based retrieval. *arXiv preprint arXiv:2508.21038*, 2025.
- [81] Guillaume Wenzek, Marie-Anne Lachaux, Alexis Conneau, Vishrav Chaudhary, Francisco Guzmán, Armand Joulin, and Edouard Grave. Ccnet: Extracting high quality monolingual datasets from web crawl data. *arXiv preprint arXiv:1911.00359*, 2019.
- [82] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, 2019.
- [83] Jiawei Zhou, Xiaoguang Li, Lifeng Shang, Xin Jiang, Qun Liu, and Lei Chen. Retrieval-based disentangled representation learning with natural language supervision. *arXiv preprint arXiv:2212.07699*, 2022.
- [84] Jinming Nian, Zhiyuan Peng, Qifan Wang, and Yi Fang. W-rag: Weakly supervised dense retrieval in rag for open-domain question answering. *arXiv preprint arXiv:2408.08444*, 2024.
- [85] Zixuan Ke, Weize Kong, Cheng Li, Mingyang Zhang, Qiaozhu Mei, and Michael Bendersky. Bridging the preference gap between retrievers and LLMs. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 10438–10451, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-long.562. URL <https://aclanthology.org/2024.acl-long.562/>.
- [86] 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.

A Details of Datasets

We present details of datasets as follows.

- Natural Questions (NQ; [Kwiatkowski et al., 2019](#)) is a widely used open-domain QA dataset constructed from Wikipedia. The questions originate from Google search queries, and the answers are text spans within Wikipedia passages. This dataset consists of queries with one or more answer strings, requiring RAG systems to generate responses based on factual knowledge.
- TriviaQA (TQA; [Joshi et al., 2017](#)) is a challenging QA dataset that comprises question-answer pairs curated by trivia enthusiasts along with independently gathered evidence documents.
- HotpotQA [\[62\]](#) is a multi-hop question answering dataset that requires reasoning over multiple Wikipedia paragraphs to answer factoid questions.
- PubHealth [\[63\]](#) is a fact-checking task that focuses on verifying health claims across a variety of biomedical topics.
- ARC-Challenge [\[64\]](#) is a multiple-choice reasoning dataset consisting of science exam questions for grades 3 to 9.

B Details of Models

B.1 Retrieval Model (IR)

- E5 [51] is a state-of-the-art dense retriever that pre-trained on millions of weakly related text pairs from the Web. The unsupervised version of this model is denoted as E5-unsup. This model undergoes further fine-tuning on natural language inference (NLI) datasets, as well as the Natural Questions and MS MARCO datasets, to enhance its capabilities in downstream applications. The fine-tuned version is denoted as E5.
- CONTRIEVER [49] is a widely-used dense retriever pre-trained unsupervised on Wikipedia data and CCNet [81]. The unsupervised version of this model is denoted as CONTRIEVER. It is further fine-tuned on the MS MARCO dataset to enhance its retrieval performance, with the fine-tuned version denoted as CONTRIEVER_{MS}.
- DPR [28] is a widely used dense passage retriever initialized with a BERT-based uncased encoder [82], and fine-tuned on downstream dataset. Specifically, DPR_{MS} is fine-tuned on the MS MARCO dataset, DPR_{NQ} on the NQ dataset, and DPR_{TQA} on the TriviaQA dataset.
- S1DR [57] is a semi-parametric sparse retriever that supports using both embeddings and tokenization as index. This nature allows for in-training retrieval, where the model’s parameters dynamically update while the retrieval index remains fixed. The model is initialized with a BERT-based uncased encoder [82] and fine-tuned exclusively on single dataset depending on the variant: S1DR_{MS} is fine-tuned on the MS MARCO dataset, S1DR_{NQ} on the NQ dataset, and S1DR_{TQA} on the TriviaQA dataset.

All the above retrieval methods are initialized with a BERT-based encoder, which contains approximately 200 million (0.2B) parameters.

B.2 Large Language Model (LLM)

- Llama3_{8B} [67] is a variant of the latest Llama3 model series with 8 billion parameters.
- Llama3-Instruct_{8B} [67] builds upon the Llama3_{8B} by undergoing a post-training stage in which the model is specifically tuned to follow instructions and align with human preferences to improve specific capabilities.
- Phi-3-mini-4k-instruct_{3,8B} [70] is a lightweight widely-used LLM with 3.8 billion parameters, trained on the Phi-3 dataset featuring synthetic and high-quality filtered web data, focused on reasoning and quality.
- Mistral-Instruct_{7B} [71]. We use Mistral-7B-Instruct-v0.3 LLM which is an instruct fine-tuned version of the Mistral-7B-v0.3.

B.3 Retrieval-augmented Generation Framework (RAG)

- ADAPTIVE-RAG [33] is a RAG framework that adapts the retrieval strategy based on question complexity where simple questions are answered without retrieval and complex ones trigger a multi-step process involving iterative interaction between the retriever and the LLM.
- IR-CoT [35] is a RAG framework designed for multi-hop question answering. It interleaves retrieval with intermediate steps in chain-of-thought (CoT) reasoning.
- FLARE [32] is a RAG framework that enhances LLM performance by selectively integrating external knowledge. It monitors token-level generation probabilities to detect uncertainty and triggers retrieval when needed during generation.
- DRAGIN [31] is a RAG framework that, similar to FLARE, monitors token-level probabilities during generation to detect uncertainty.
- SEAKR [34] is a RAG framework that reduces hallucinations by leveraging self-aware uncertainty. It monitors the LLM’s internal signals and triggers retrieval only when high uncertainty is detected during generation.

For the above four baselines, we adopt the reproductions and reported results from Moskvoretskii et al. [19].

- REPLUG [40] is a RAG framework using GPT-3 and CONTRIEVER. The retriever is specifically trained to use the first 128 tokens of a sequence as queries, with the goal of retrieving documents that maximize the probability of generating the subsequent 128 tokens when these retrieved documents are prepended to the query.
- SELF-RAG [66] is a RAG framework designed to improve response quality by enabling on-demand retrieval and incorporating self-reflection mechanisms.

The reproductions by Wang et al. [73] and Zhang et al. [74], SELF-RAG_{Mistral-7B} and SELF-RAG_{Llama3-8B} respectively, involve tuning Mistral-7B and Llama3-8B as base language models using the open-source data provided by SELF-RAG. Our reproduction, SELF-RAG_{Llama3-8B}+SiDR_{MS}, utilizes the SELF-RAG_{Llama3-8B} checkpoint from Zhang et al. [74] as LLM, while employing the same retriever SiDR_{MS} and adapting it to our downstream setup.

- RA-DIT [41] is a RAG framework that separately fine-tunes the LLM to better utilize retrieved information and the retriever to align with the LLM’s preferences.

C Preliminary Study

Table 4: Accuracy in IR and RAG settings using Llama3-8b with top-1 retrieved document in-context; **Bold**: best performance; Δ : **improvement** or **decline** compared to SiDR_{MS}; §: has been trained in-domain.

Dataset (\rightarrow)	NQ				TriviaQA				PubHealth		ARC-C	
	IR	Δ	RAG	Δ	IR	Δ	RAG	Δ	RAG	Δ	RAG	Δ
<i>Unsupervised Pre-training</i>												
Contriever	23.6	-15.5	30.9	-3.5	37.2	-18.9	56.6	-5.4	61.8	-1.7	58.6	+1.7
E5-unsup	30.8	-8.3	33.4	-1.0	39.5	-16.6	54.3	-7.7	62.9	-0.6	58.3	+1.4
<i>Supervised on MSMARCO</i>												
DPR _{MS}	38.9	-0.2	34.9	+0.5	43.7	-12.4	55.2	-6.8	64.5	+1.0	56.3	-0.6
SiDR _{MS}	39.1	—	34.4	—	56.1	—	62.0	—	63.5	—	56.9	—
<i>Supervised on NQ</i>												
DPR _{NQ}	‡43.5	+4.4	‡38.5	+4.1	39.4	-16.7	55.9	-6.1	62.9	-0.6	56.6	-0.3
SiDR _{NQ}	‡49.5	+10.4	‡42.7	+8.3	47.4	-8.7	59.8	-2.2	63.5	—	57.1	+0.2
<i>Supervised on TQA</i>												
DPR _{TQA}	32.1	-7.0	32.9	-1.5	‡55.4	-0.7	‡61.1	-0.9	63.1	-0.4	56.7	-0.2
SiDR _{TQA}	30.6	-8.5	32.9	-1.5	‡56.9	+0.8	‡63.6	+1.6	61.1	-2.4	58.6	+1.7
<i>Pre-training + Supervised on Multiple Datasets</i>												
Contriever _{MS}	41.5	+2.4	36.5	+2.1	53.5	-2.6	60.7	-1.3	63.1	-0.4	58.1	+1.2
E5	‡58.0	+18.9	‡43.2	+8.8	58.7	+2.6	63.2	+1.2	64.7	+1.2	58.0	+1.1
Upper-bound	65.9		77.6		78.5		80.3		92.1		71.5	

In Table 4, we report the performance of several off-the-shelf retrievers across multiple datasets, covering both IR and RAG scenarios. The datasets include QA benchmarks such as NQ and TQA, and non-QA benchmarks such as PubHealth and ARC, as detailed in Appendix A. The evaluated retrievers include the dense retriever DPR, the sparse retriever SiDR, and unsupervised models such as CONTRIEVER and E5-unsup, along with their supervised counterpart. Model details are provided in Appendix B. The evaluation metric is described in Section 4.1, where the IR measure evaluates whether the retrieved document contains the answer, and the RAG measure evaluates whether the retrieved document can prompt the LLM to generate the answer. We benchmark all models using SiDR_{MS} as the base retriever, which also serves as the backbone of our proposed method. The results reveal two key findings.

Finding 1: Better IR performance does not always lead to better RAG performance, especially when a task shift occurs. For QA tasks, we observe that higher accuracy in IR settings generally correlates with better RAG performance. However, this trend does not hold for non-QA tasks. For example, on PubHealth, a vanilla DPR_{MS} outperforms a SOTA retriever in RAG settings, despite being weaker in IR metrics. Similarly, on ARC, the unsupervised CONTRIEVER achieves the best RAG performance, outperforming its supervised counterparts.

Finding 2: Substantial room for improvement in retrieval within the RAG system. We find that although most required knowledge already exists in the datastore, each retriever succeeds on only a subset of queries. For example, on NQ, 77% of queries can be answered by at least one retriever via RAG, yet the best single retriever covers only 43%. This gap reveals significant untapped potential in the datastore and underscores the need for stronger retrieval in RAG.

D Revisiting Semi-parametric Disentangled Retriever (SiDR)

This section can be considered an expanded version of Section 3.2, where we discuss SiDR in more detail.

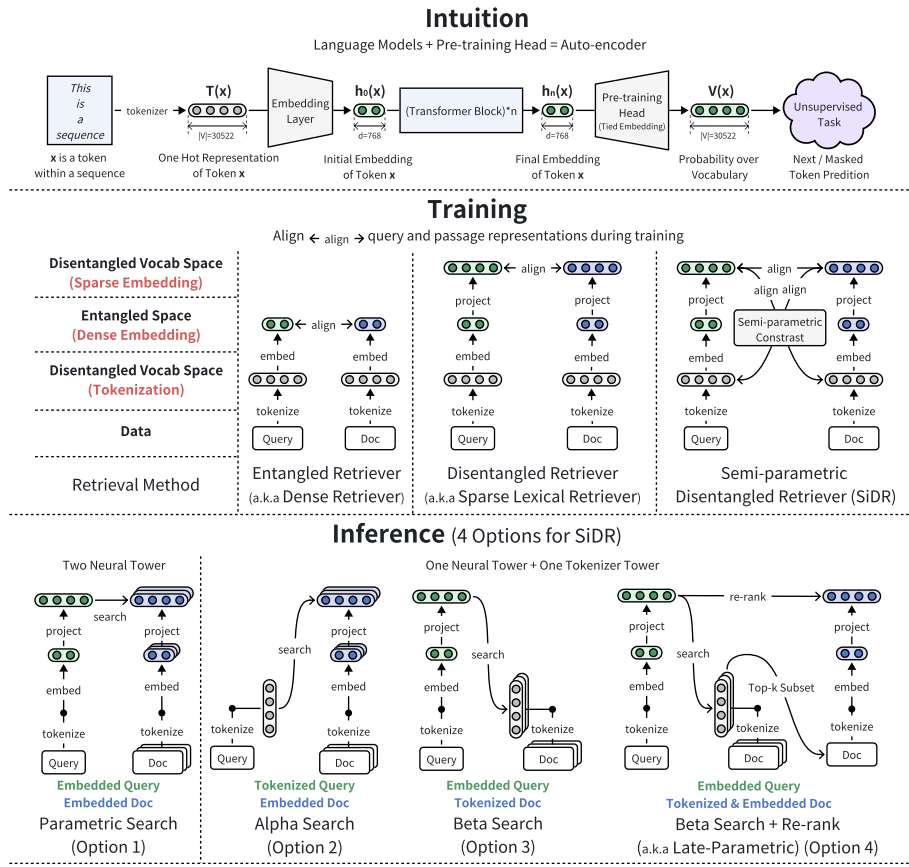


Figure 6: Overview illustration of SiDR.

Background: Challenge of Index Staleness. As is well known, the retrieval index is typically the embedding of the datastore, denoted as $E_\theta(\mathcal{D})$. During training, as the \mathcal{R}_θ parameters update from $\theta \rightarrow \theta'$, the index must be updated accordingly, from $E_\theta(\mathcal{D}) \rightarrow E_{\theta'}(\mathcal{D})$, where $|\mathcal{D}| \gg 1$. Otherwise, the index becomes stale, leading to mismatches between the query and document embeddings. However, frequently re-embedding a large datastore is computationally expensive and often unaffordable in practice. Fundamentally, this challenge stems from the coupling between retrieval index and model parameters θ .

Intuition of SiDR. Intuitively, a language model (LM), together with its pre-training head, can be viewed as an auto-encoder. Let's use BERT as an example. Given an input sequence X , a specific token x can be represented as a one-hot vector $T(x) \in \{0, 1\}^{|V|}$, where $|V| = 30522$ is the size of the BERT vocabulary V . These tokens are then processed by the embedding layer to yield a d -dimensional hidden state $H_0(x)$, where $d = 768$. After passing through 12 transformer blocks, the token representations interact with the contextualized token representations, resulting in the final token representation from the last layer, denoted as $H_n(x)$. The $H_n(x)$ of a masked token is then further processed by the masked language model head (MLMH) to yield a probability distribution $V(x) \in (0, 1)^{|V|}$ over the vocabulary space, used to predict the masked token.

Given a sequence X , SiDR embeds it into a $|V|$ -dimensional sparse embedding, denoted as $E_\theta(X) \in (0, +\infty)^{|V|}$. SiDR builds upon a BERT-based model with three simple modifications to its pre-

training head: (i) replacing the softmax activation with `elu1p`; (ii) aggregating token representations via max pooling; and (iii) applying top- k sparsification.

Inspired by the auto-encoder property, we are curious whether output sparse embedding can be aligned with input tokenization to yield better features. Specifically, during training, SiDR applies contrastive learning across three channels: $E_\theta(q)$ with $E_\theta(d)$, $T(q)$ with $E_\theta(d)$, and $E_\theta(q)$ with $T(d)$. In this training setup, we find that SiDR successfully uses $E_\theta(q)$ to search over the bag-of-token index $T(\mathcal{D})$, as illustrated in Figure 6 with Option 3 (Beta Search) and Option 4 (Beta Search + Re-rank). This provides an opportunity to use a non-parametric bag-of-token index as a frozen proxy for retrieval during the retriever’s training loop, thereby bypassing the re-indexing issue.

On-policy Retrieval. During R3 training, we adopt the late parametric mechanism of SiDR (shown as option 4), which first retrieves the top- m documents using the bag-of-tokens index $T(\mathcal{D})$, and then embeds these documents for re-ranking. This process can be formulated as:

$$\begin{aligned}\{\hat{d}\}_m &= \mathcal{R}_\theta(E_\theta(q), T(\mathcal{D}), m) \\ \{\hat{d}\}_k &= \mathcal{R}_\theta(E_\theta(q), E_\theta(\{\hat{d}\}_m), k)\end{aligned}$$

To reduce training costs, we set $m = k = 20$ in our experiments.

Other Applications of SiDR. Besides using the bag-of-token index to enable on-policy training in R3 (i.e., $E_\theta(q)$ searches over $T(\mathcal{D})$), SiDR offers additional advantages. For example, it facilitates conventional search, where the sparse embedding of the query searches over the sparse embeddings of the documents, enabling efficient search via inverted indexing and improving interpretability. Additionally, it can further reduce online query embedding time by using the bag-of-token representation of the query (i.e., $T(q)$ searches over $E_\theta(\mathcal{D})$), a method known as alpha search [83].

E Sampling Strategies

We report the performance using SiDR_{MS} as the initial retriever under the 1-shot setting. The sampling strategy plays a crucial role in forming effective contrastive pairs during training. In this section, we compare our current sampling method against two alternatives:

- **Current (A):** Most-relevant negative + randomly selected positive
- **Alternative (B):** Randomly selected negative + randomly selected positive
- **Alternative (C):** Most-relevant negative + most-relevant positive

Table 5 reports the RAG performance on NQ and PubHealth under each strategy.

Table 5: Impact of sampling strategies on RAG performance using SiDR_{MS} as the initial retriever.

Strategy	NQ	PubHealth
A	39.8	69.5
B	38.7	68.7
C	39.2	69.0

Overall, the current strategy (A) achieves the best performance on both datasets. We hypothesize that incorporating the most-relevant negative increases training difficulty and encourages more discriminative learning, while introducing randomness in positive sampling promotes generalization. These findings are consistent with observations from prior retrieval learning studies (e.g., DPR), where the choice of hard negatives has a substantial impact on performance, whereas positive selection tends to be less critical.

F Assumption on Probability and Generation

Given that our training relies on the conditional probability of the ground-truth response y given input x , denoted as $P(y | x)$, as a signal for identifying positive and negative documents, we now investigate whether higher values of $P(y | x)$ correlate with improved RAG performance (i.e., better generation of y).

Table 6: Results of RAG framework using top-1 and top-10 documents in context, sorted by retrieval relevance and joint probability of responses.

Task Type (\rightarrow)		Free-form				Closed-set			
Dataset (\rightarrow)		NQ		TriviaQA		PubHealth		ARC-C	
Method (\downarrow)	Metrics (\rightarrow)	1-shot	10-shot	1-shot	10-shot	1-shot	10-shot	1-shot	10-shot
Llama3 _{8B} + SiDR _{MS} (doc with top relevance)		49.1	51.4	65.3	67.2	65.2	67.4	58.1	57.3
Llama3 _{8B} + SiDR _{MS} (doc with top $P(y x)$)		85.1	76.2	88.7	84.2	87.4	77.4	95.6	83.6

For each dataset, we sample 1,000 training instances. For each query, we retrieve the top 100 documents, and evaluate RAG performance using only the top-1 and top-10 documents, selected either by retrieval relevance or by $P(y | x)$. The results, presented in Table 6, show that $P(y | x)$ is predictive of final RAG accuracy. Moreover, the strong performance obtained when using documents ranked by $P(y | x)$ highlights untapped potential of the datastore, a potential that current retrieval methods fail to fully leverage.

To our knowledge, using $P(y | x)$ to identify positives and negatives is a rough yet resource-efficient solution that could cover most existing knowledge-intensive tasks, aligning with their evaluation metrics that often utilize string matching. However, it may not be suitable for long-form generation, which requires different evaluation strategies. We believe it is possible to customize the identification of positive and negative examples based on the specific needs of each task. Ideally, if computational cost is not a concern or resources are sufficient, a strong proprietary LLM like GPT-4 can be used for identification on-the-fly.

G LLM-Specific Relevance

In Table 2, we observe that PubHealth requires significantly more online probability computations and yields larger improvements compared to other datasets. Combined with the transferability results in Table 1, we hypothesize that R3 may succeed in learning LLM-specific relevance on this task. While this enables strong task-specific performance, it also limits the retriever’s generalization ability across LLMs. To further examine this hypothesis, we report both effectiveness and transferability metrics throughout the online training process of R3 on PubHealth.

Table 7: Effectiveness and transferability during different stages of online training on PubHealth.

On-policy Training Progress	0%	25%	50%	75%	100%
RAG Effectiveness	65.7	67.7	68.8	69.4	69.5
Transfer to Llama3-8B-Instruct	66.7	67.1	67.0	66.1	65.2
Transfer to Mistral-7B-Instruct	49.8	50.4	48.2	47.7	46.7

We observe that while transferability initially increases, it steadily declines as training progresses, even as task-specific RAG performance continues to improve. This trend indicates that the retriever is learning a relevance function increasingly specialized for the target LLM. Although this improves retrieval quality for the specific LLM, it comes at the cost of generalization to others. This reflects a broader phenomenon: while LLMs may share similar relevance preferences for general tasks such as QA, their needs diverge more significantly in specialized domains like fact-checking. These results underscore the value of end-to-end retrieval learning for RAG.

H Late Parametric vs. Periodic Re-indexing

A key distinction between our work and prior practices lies in our use of the late parametric mechanism to avoid re-indexing during training. In this section, we systematically evaluate these in-training retrieval approaches.

Baseline. We present ablation studies on different in-training retrieval approaches: (i) R3 employs the late parametric method as proposed in SiDR, which uses a bag-of-token index for first-stage retrieval and re-ranks the top-20 documents on-the-fly using up-to-date parameters. (ii) R3 (w/o re-rank) employs the bag-of-token index for retrieval, similar to the late parametric method but without the

re-ranking process. This setup aims to assess the costs associated with re-ranking during training. (iii) R3 (w/o semi-para) involves periodic re-indexing using the most recently built but outdated index for retrieval, an in-training retrieval method that commonly used in prior studies. In this setup, we employ DPR_{MS} as the initial retriever. We avoid using SiDR_{MS} , which has high-dimensional embeddings of 30,522, in stark contrast to DPR’s 768 dimensions. This significant discrepancy prevents our GPU cards from allocating the parametric index for SiDR_{MS} , although they manage DPR effectively.

Training. All models undergo the similar training pipeline: they are trained for 80 epochs with the first 40 epochs as a warm-up and the last 40 conducting in-training retrieval. They differ only in their in-training retrieval strategies: both R3 and R3 (w/o re-rank) do not require re-indexing; R3 (w/o semi-para) requires rebuilding index at every 15 epochs (around 5k steps), a rebuild interval commonly used in previous research [56], resulting in a total of three rebuilds.

Results. We present the RAG accuracy on NQ and PubHealth test splits during in-training retrieval, with results reported every four epochs, as depicted in Figure 7. For the re-ranking setup, significant improvements are observed in the PubHealth data when re-ranking is employed, whereas the NQ dataset shows only minor improvements. Given that the costs associated with re-ranking are manageable in our setup, we continue to implement it. Regarding re-indexing, our findings indicate that despite requiring significant time and resources, it fails to yield improvements comparable to those of the late parametric approach and significantly lags behind. We attribute this to index staleness, where query embeddings must optimize against outdated document embeddings, rendering the learning process less effective. On the other hand, as presented in the study by Zhou et al. [57], by re-ranking the top-20 retrieved documents, the late parametric method can recover more than 90% of the performance of a full parametric search across different tasks, representing a minor compromise. This also partially explains why the late parametric approach outperforms periodic re-indexing.

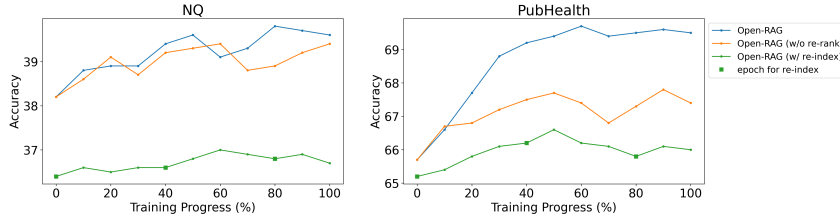


Figure 7: RAG accuracy of different in-training retrieval approaches.

I Inconsistencies between IR and RAG Settings

I.1 Performance Changes in IR Scenarios after Tuning

Table 8: Performance changes before and after tuning the retriever using the R3 approach.

Dataset (→)		NQ		TriviaQA	
Method (↓)	Metrics (→)	IR	RAG	IR	RAG
Llama3 _{8B} + SiDR_{MS}		39.1	34.4	56.1	62.0
Llama3 _{8B} + R3 (SiDR_{MS})		40.8 (+1.7)	39.8 (+5.4)	53.9 (-2.2)	65.8 (+3.8)
Llama3 _{8B} + SiDR_{NQ}		49.5	42.7	—	—
Llama3 _{8B} + R3 (SiDR_{NQ})		47.1 (-2.4)	44.1 (+1.4)	—	—

We evaluate the performance of our retriever in both IR and RAG scenarios before and after tuning. Note that the retriever we use for NQ is SiDR_{MS} , which does not access the NQ training split, unlike the version used in the main experiments. In IR scenarios, we measure top-1 retrieval accuracy by checking whether the top-1 retrieved document contains the answer. In RAG scenarios, we measure accuracy using a single document in the context window, evaluating whether the generated response contains the correct answer.

Our results indicate that while R3 tunes the retriever to improve RAG performance, it results in inconsistent performance on traditional IR performance, with some degradation observed on certain

datasets. This highlights a long-standing issue in the IR evaluation pipeline: a document containing the answer does not necessarily imply that it effectively addresses the query, and conversely, a document not containing the answer does not mean it is irrelevant or unhelpful.

Our conclusion also aligns with the findings and observations of other research. Cuconasu et al. [23] find that including more answer-containing documents in the context negatively impacts RAG performance. Similarly, Nian et al. [84] observe that traditional relevance definitions for IR tasks do not enhance RAG response quality. Additional research emphasizes the need for further learning to bridge the preference gap [85] or re-ranking [86] for off-the-shelf retrievers to improve RAG performance.

I.2 Case Study

In this section, we present a case study using the NQ dataset where each query has a list of answer strings. This case study is designed to further explore the inconsistency issues inherent in RAG implementations. We specifically examine two scenarios: (i) cases where the retrieved document contains the correct answer but fails to produce the correct RAG output, and (ii) instances where the retrieved document does not directly address the query, yet the RAG model manages to generate the correct answer nonetheless. To enhance our analysis, we also ask GPT-4 to judge whether the documents address the question, helping readers quickly grasp the key issue.

In Figure 8, we present examples where RAG outputs the correct answer, even though the retrieved document neither contains the answer nor is considered to address the question by GPT-4. In both cases, the document fails to provide the correct answer or relevant clues, yet RAG is still able to generate the correct response. We believe this is a common phenomenon, as LLMs possess a wealth of internal knowledge, particularly for public knowledge questions. In general, an incorrect or imperfect retrieved document is insufficient to mislead the LLM into producing an incorrect output.

In Figure 9, we present examples where RAG fails to output the correct answer, even though the retrieved document contains the correct answer or GPT-4 considers the document as addressing the question. In the first case, the document does not address the query, and the LLM tends to extract key phrases, such as the title, as the response, ignoring the query. In the second case, the document contains information that addresses the query, and the LLM generates the correct answer, but the answer’s alias name is not included in the pre-defined answer candidates, leading to a failure in the RAG scenario. These inconsistencies can be driven by many factors, including the LLM, instruction prompt, evaluation metrics, and relevance. All of these factors are intertwined, and we believe that end-to-end data-driven learning is more effective than analyzing their interplay in isolation.

J Examples of Generation

For free-form generation tasks, we assess whether the generation contains any of the given answers. For closed-set generation tasks, we measure whether the generation contains the answers. Below are examples that illustrate how different generations pass (1) or fail (0) the evaluation.

K Prompt Formats

We demonstrate our prompts for different tasks such as OpenQA, fact-checking, and multi-choice reasoning in Figures 12, 13, and 14, respectively.

=====	Question =====
Who plays Big Momma in Big Momma's House?	
=====	Answers =====
['Ella Mitchell', 'Martin Lawrence']	
=====	Document =====
Bounce with Me	
Jermaine Dupri, Jagged Edge and Da Brat. Brief clips from "Big Momma's House" are also included. Bounce with Me "Bounce with Me" is a single by American rapper Lil' Bow Wow featuring Xscape. It is Lil' Bow Wow's debut single, taken from his debut album "Beware of Dog". The single samples "Love Serenade (Part II)" by Barry White. It spent nine weeks at number 1 on the U.S. Rap Chart and number 20 on "Billboard" Hot 100. The song was featured in the film "Big Momma's House" and the trailer of "Hardball".	
=====	Generation =====
[1] Martin Lawrence	
=====	GPT4 Judgement =====
No, the document does not address the question. The document talks about the song "Bounce with Me" and its connection to the movie Big Momma's House, but it doesn't mention who plays Big Momma in the movie. The answer to the question is Martin Lawrence, who plays the character of Big Momma in Big Momma's House.	

=====	Question =====
Who sang "Buddy, Can You Spare a Dime?"	
=====	Answers =====
['Rudy Vallee', 'Bing Crosby']	
=====	Document =====
Brother, Can You Spare a Dime?	
Brother, Can You Spare a Dime? "Brother, Can You Spare a Dime?", also sung as "Buddy, Can You Spare a Dime?", is one of the best-known American songs of the Great Depression. Written in 1930 by lyricist E. Y. "Yip" Harburg and composer Jay Gorney, "Brother, Can You Spare a Dime?" was part of the 1932 musical revue "Americana"; the melody is based on a Russian-Jewish lullaby Gorney's mother had sung to him as a child. It was considered by Republicans to be anti-capitalist propaganda, and almost dropped from the show; attempts were made to ban it from the radio.	
=====	Generation =====
The song "Brother, Can You Spare a Dime?" was written by E. Y. "Yip" Harburg and Jay Gorney . It was first performed by Bing Crosby in 1932.	
=====	GPT4 Judgement =====
The document provides information about the song "Brother, Can You Spare a Dime?" (also referred to as "Buddy, Can You Spare a Dime?") and its origins, but it does not directly answer the question of who sang it. The document focuses more on the history of the song and its cultural significance.	
To answer your question: The song has been performed by several artists, including Bing Crosby, Al Jolson, and Barbra Streisand, among others.	

Figure 8: Example of RAG output correct answers while the retrieved document does not contain the correct answer, nor does GPT-4 consider the document address the question.

```

===== Question =====
When was The Hitchhiker's Guide to the Galaxy made?
===== Answers =====
['1978', '2005']
===== Document =====
The Hitchhiker's Guide to the Galaxy (radio series)
The original series was the recipient of a number of awards including the Imperial Tobacco
Award (1978), The Sony Award (1979), The Society of Authors/Pye Awards Best Programme for
Young People (1980) and the Mark Time Awards 'Grand Master Award' (Adams) and 'Hall of Fame
' (1998). It was the only radio show ever to be nominated for the Hugo science fiction
awards, in 1979, in the 'Best Dramatic Presentation' category. As a result of the series,
Douglas Adams was inducted into the Radio Academy's Hall of Fame. In November 2003, two
years after Adams's death and 23 years after the ...

===== Generation =====
[1] The Hitchhiker's Guide to the Galaxy (radio series)
===== GPT4 Judgement =====
No, the document does not directly address the query of when The Hitchhiker's Guide to the
Galaxy was made. It provides information about the radio series, its awards, and
recognition but does not specify the year of its creation or first broadcast.

The original radio series of The Hitchhiker's Guide to the Galaxy first aired in 1978.

```

```

===== Question =====
Who ordered the Forbidden City to be built?
===== Answers =====
['Zhu Di']
===== Document =====
History of the Forbidden City
The site of the Forbidden City was situated on the Imperial city during the Mongol Yuan
Dynasty. After the collapse of the Yuan Dynasty, the Hongwu Emperor of the Ming Dynasty
moved the capital from Beijing in the north to Nanjing in the south, and in 1369 ordered
that the Yuan palaces be razed. His son Zhu Di was created Prince of Yan with his seat in
Beijing. In 1402, Zhu Di usurped the throne and became the Yongle Emperor. He made Beijing
a secondary capital of the Ming empire ...

===== Generation =====
The Yongle Emperor ordered the forbidden city to be built.
===== GPT4 Judgement =====
Yes, the document addresses the query. It mentions that Zhu Di, who later became the Yongle
Emperor, ordered the construction of the Forbidden City. The passage describes how he
moved the capital to Beijing and commissioned the building of the Forbidden City in 1406.

```

Figure 9: Example of RAG failing to output the correct answer while the retrieved document contains the correct answer or GPT-4 considers the document as addressing the question.

```

===== Question =====
Who is the sister of for king and country?
===== Answers =====
['Rebecca St. James']
===== Generation 1 =====
Rebecca St. James

### Explanation:
Rebecca St. James is the sister of for king and country. She is a Christian recording
artist and speaker. The Smallbones are the younger brothers of Rebecca St. James, and the
brothers-in-law of Jacob Fink, former bassist for the band Foster the People. They were
raised with another sister, Libby, and three other brothers, Ben, Dan, and Josh. On

===== Output 1 =====
Eval(Generation): 1
===== Generation 2 =====
Courtney Helm

### Explanation:
Courtney Helm is the sister of for king and country.

===== Output 2 =====
Eval(Generation): 0

```

Figure 10: Examples of generations and their evaluation results for free-form tasks.


```

===== Question =====
Study: Vaccine for Breast, Ovarian Cancer Has Potential.
===== Answers =====
True
===== Generation 1 =====
True

### Explanation:
The study is about a vaccine for breast and ovarian cancer. The vaccine is
===== Output 1 =====
Eval(Generation): 1
===== Generation 2 =====
False

### Explanation:
The statement is false because the vaccine is not for breast and ovarian cancer.
===== Output 2 =====
Eval(Generation): 0

```

Figure 11: Examples of generations and their evaluation results for close-set tasks.

```

===== Prompt (OpenQA) =====
### Paragraph:
[1] For King & Country (band)
Their father was a music promoter, and Joel recalls, "going to these rock concerts, sitting
on my father\'s shoulders, plugging my ears...Honestly, in a lot of ways I feel like music
chose me and as I grew older, I made a clear decision to fully lean into it." The
Smallbones are the younger brothers of Christian recording artist and speaker Rebecca St.
James, and the brothers-in-law of Jacob Fink, former bassist for the band Foster the People
. They were raised with another sister, Libby, and three other brothers, Ben, Dan, and Josh
. On ...

### Instruction:
Who is the sister of for king and country?

### Response:
===== Continuation =====
Rebecca St. James
===== Generation =====
Rebecca St. James

### Explanation:
Rebecca St. James is the sister of for king and country. She is a Christian recording
artist and speaker. The Smallbones are the younger brothers of Rebecca St. James, and the
brothers-in-law of Jacob Fink, former bassist for the band Foster the People. They were
raised with another sister, Libby, and three other brothers, Ben, Dan, and Josh. On
===== Output =====
Probability: P('Rebecca St. James'|prompt) = 0.595
Eval(Generation): 1

```

Figure 12: Example prompt and outcomes of each step for NQ and TQA dataset.

```

===== Prompt (Fact Checking) =====
Below is an instruction that describes a task. Write a response that appropriately
completes the request.

### Paragraph:
[1] Gustav Gaudernack
potential of dendritic cells (DCs) and in 2005, Gaudernack's group published results from a
phase I/II clinical trial in prostate cancer patients using autologous DCs loaded with
tumor mRNA as a vaccine. This study demonstrated that vaccination with autologous DCs
transfected with mRNA derived from three prostate cancer cell lines was safe and an
improved clinical outcome was significantly related to immune responses against the vaccine
. Furthermore, Gaudernack and colleagues initiated a phase I/II clinical trial for
treatment of malignant melanoma with autologous tumor-mRNA transfected DC vaccines. These
data clearly demonstrated vaccine-specific immune responses with a broad specter of ...

### Instruction:
Is the following statement correct or not? Say true if it's correct; otherwise say false.

### Input:
Study: Vaccine for Breast, Ovarian Cancer Has Potential

### Response:
===== Continuation =====
True
===== Generation =====
true

### Explanation:
The study is about a vaccine for breast and ovarian cancer. The study has ...
===== Output =====
P('true' |prompt) = 0.116
P('false'|prompt) = 0.109
Eval(Generation): 1

```

Figure 13: Example prompt and outcomes of each step for the Pubhealth dataset.

```

===== Prompt (Multi-choice Reasoning) =====
Below is an instruction that describes a task. Write a response that appropriately
completes the request.

### Paragraph:
[1] Rheumatic fever
Rheumatic fever may occur following an infection of the throat by the bacterium "
Streptococcus pyogenes". If the infection is untreated rheumatic fever can occur in up to
three percent of people. The underlying mechanism is believed to involve the production of
antibodies against a person's own tissues. Due to their genetics, some people are more
likely to get the disease when exposed to the bacteria than others. Other risk factors
include malnutrition and poverty. Diagnosis of RF is often based on the presence of signs
and symptoms in combination with evidence of a recent streptococcal infection. Treating
people who have strep ...

### Instruction:
Given four answer candidates, A, B, C and D, choose the best answer choice.

### Input:
Which factor will most likely cause a person to develop a fever?
A: a leg muscle relaxing after exercise
B: a bacterial population in the bloodstream
C: several viral particles on the skin
D: carbohydrates being digested in the stomach

### Response:
===== Continuation =====
B
===== Generation =====
B

### Explanation:
The bacteria Streptococcus pyogenes is a common cause of throat
===== Output =====
P('A'|prompt) = 0.121
P('B'|prompt) = 0.309
P('C'|prompt) = 0.061
P('D'|prompt) = 0.100
Eval(Generation): 1

```

Figure 14: Example prompt and outcomes of each step for the ARC-Challenge dataset.