CL-RAG: Bridging the Gap in Retrieval-Augmented Generation with Curriculum Learning

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Abstract

Retrieval-Augmented Generation (RAG) is an effective method to enhance the capabilities of large language models (LLMs). Existing methods focus on optimizing the retriever or generator in the RAG system by directly utilizing the top-k retrieved documents. However, the documents effectiveness are various significantly across user queries, *i.e.* some documents provide valuable knowledge while others totally lack critical information. It hinders the retriever and generator's adaptation during training. Inspired by human cognitive learning, curriculum learning trains models using samples progressing from easy to difficult, thus enhancing their generalization ability, and we integrate this effective paradigm to the training of the RAG system. In this paper, we propose a multi-stage Curriculum Learning based RAG system training framework, named CL-RAG. We first construct training data with multiple difficulty levels for the retriever and generator separately through sample evolution. Then, we train the model in stages based on the curriculum learning approach, thereby optimizing the overall performance and generalization of the RAG system more effectively. Our CL-RAG framework demonstrates consistent effectiveness across four open-domain QA datasets, achieving performance gains of 2% to 4% over multiple advanced methods.

1 Introduction

Large language models (LLMs) have demonstrated remarkable capabilities in a wide range of Natural Language Processing (NLP) tasks (Brown et al., 2020; Anil et al., 2023; Dubey et al., 2024), but they still constrained by the limitations of the knowledge embedded within their internal parameters (Roberts et al., 2020; Kandpal et al., 2023; Gao et al., 2023). Retrieval-Augmented Generation (RAG) addresses this limitation by leveraging additional knowledge retrieved from external knowledge bases. By retrieving relevant documents and incorporating them

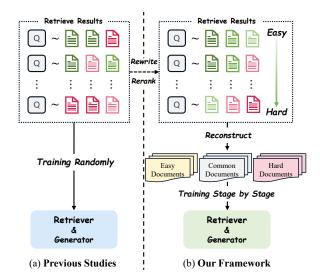


Figure 1: Comparison between our method and previous studies, where green represents documents that are conducive to model responses, while red indicates documents that are useless or even detrimental to model responses. Figure 1(a) illustrates the previous method, which randomly samples documents of varying quality without considering the difficulty order of the documents. Figure 1(b), in contrast, presents our approach, which focuses on reordering and combining documents based on their difficulty levels for stage-by-stage training.

as contextual input, RAG has significantly enhanced the capabilities of existing large models in tasks such as Open-Domain Question Answering (Izacard et al., 2023; Shi et al., 2023; Yoran et al., 2023; Lin et al., 2023; Fang et al., 2024) and Natural Language Modeling (Borgeaud et al., 2022; Ram et al., 2023; Zhang et al., 2024). The overall performance of the RAG system depends on the quality of the retrieved documents and the LLMs' ability to utilize these documents. Therefore, how to retrieve better documents and how to better utilize the retrieved documents are of vital importance in RAG research.

Existing efforts to enhance RAG systems have

focused on: (1) Utilizing LLMs to evaluate document quality and guide retriever training (Shi et al., 2023; Zhang et al., 2024); (2) Training Retrieval-Augmented Language Models (RALMs) that can better utilize documents (Izacard and Grave, 2020; Yoran et al., 2023; Fang et al., 2024), or a combination of both (Lin et al., 2023) to enhance the overall performance of the RAG system. However, given a specific query, these researches directly use the top-k retrieved documents as training samples and randomly input them into the model for training, as shown in Figure 1(a). This approach neglects the substantial quality variations among retrieved documents, where the top-k documents for different queries may vary greatly in quality: some provide valuable knowledge while others lack critical information or even contain misleading content. These discrepancies pose varying learning challenges for the retriever and generator during training.

Inspired by cognitive science studies (Elman, 1993; Rohde and Plaut, 1999) that humans can benefit from a easy-to-difficult learning sequence, the curriculum learning (Bengio et al., 2009) suggests that deep learning models trained by the gradual introduction of more challenging samples in subsequent stages. Previous studies (Guo et al., 2018; Hacohen and Weinshall, 2019; Xu et al., 2020) have demonstrated that this easy-to-difficult strategy can effectively enhance the generalization ability of models. Therefore, we propose that the training of the RAG system should also adhere to this paradigm, which has been neglected in previous works. To bridge this gap, we propose a sample evolution strategy to construct document data with different levels of difficulty and further train the retriever and generator based on the idea of curriculum learning, as demonstrated in Figure 1(b).

In this work, we propose a Curriculum Learning based training framework for the RAG system, named CL-RAG. To the best of our knowledge, we are the first to integrate the idea of human imitation learning with RAG training, which can effectively enhance the generalization and stability of the RAG system. Specifically, we first focus on the training of the generator, constructing multiple difficulty levels of documents by rewriting queryenhanced golden documents or counterfactual distractor documents. Then we finetune a RALM in a stage-by-stage manner according to the order of difficulty. For the training of the retriever, we propose to use the well-trained RALM to assess the quality of documents and rerank them. We then construct

document data from easy to difficult by gradually reducing the ranking gap between sampled documents, and propose a hierarchical training strategy to finetune the retriever.

As a result, CL-RAG bring two advantages to RAG system: (1) For the generator, CL-RAG systematically transition it from merely extracting information to effectively countering potential distracting noise within documents. (2) For the retriever, CL-RAG train it in stages to progressively distinguish documents with obvious differences and then distinguish those with only slight differences. This progressive training framework has led to an overall performance and generalization improvement of the RAG system. Our contributions can be concluded as follows:

- We propose the CL-RAG training framework for the RAG system based on the concept of curriculum learning. To the best of our knowledge, this is one of the first times that CL strategy has been applied to optimize RAG systems.
- We defined the document difficulty levels for the retriever and generator based on the concept of curriculum learning and designed a complete method for constructing enhanced documents.
- We evaluated our CL-RAG framework on four popular datasets, demonstrating consistent performance gains of 2% to 4% over multiple advanced methods, thereby highlighting the superiority of our approach.

2 Related Work

2.1 Retrieval-augmented Generation

Using documents retrieved from extended knowledge bases to enhance the capabilities of large language models (LLMs) has been proven effective in NLP tasks, including language modeling (Borgeaud et al., 2022; Ram et al., 2023; Zhang et al., 2024) and question answering (Izacard et al., 2023; Shi et al., 2023; Yoran et al., 2023; Lin et al., 2023; Fang et al., 2024). Specifically, a Retrieval-Augmented Generator (RAG) system takes a query as input and uses a retriever to retrieve relevant documents from an external knowledge base. Then, it combines the documents with the query and feeds them into the LLM to make up for the LLM's own lack of knowledge.

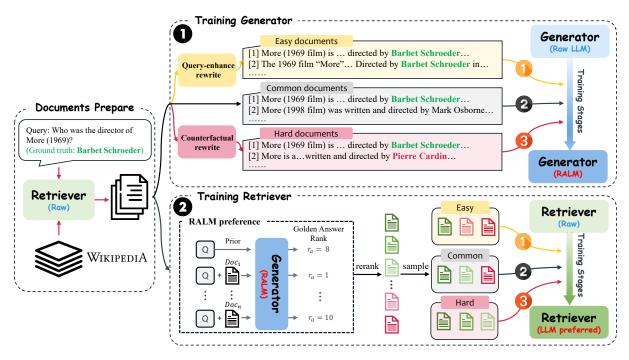


Figure 2: **The overview of our CL-RAG training framework,** which has into two continuous phases: (1) Training Generator: We construct multiple difficulty levels of documents and then finetune a RALM in a stage-by-stage manner. (2) Training Retriever: We use the well-trained RALM to assess documents and rerank them. We then construct document data from easy to difficult, and finetune the retriever in a stage-by-stage manner.

Optimization of the RAG system focuses on two main areas: improving the retriever and enhancing the generator (LLM) to the RALM. Replug (Shi et al., 2023) uses KL divergence to align retriever results with LLM preferences. LLM-Embedder (Zhang et al., 2024) employs a distillation objective based on LLM rankings. These methods train the retriever to better match LLM preferences. For generator, FiD (Izacard and Grave, 2020) finetunes LLM to handle retrieved documents and queries, addressing irrelevant information. Other studies introduce noise to improve LLM robustness (Yoran et al., 2023; Fang et al., 2024). Combining the strengths of both approaches, RA-DIT (Lin et al., 2023) uses modular training to optimize the retriever and LLM separately, enhancing overall RAG system performance.

2.2 Curriculum Learning

Curriculum Learning (CL) is a machine learning strategy that mimics human learning by training models gradually, starting with simpler tasks and progressing to more complex ones. It aims to improve the model's generalization ability and accelerate its convergence speed. Early studies have extensively investigated CL in computer vision domain and have demonstrated its advantages in train-

ing deep models (Guo et al., 2018; Hacohen and Weinshall, 2019). In the NLP domain, Xu et al. (2020) first explore and validate the effectiveness of CL in the context of finetuning LMs on Natural Language Understanding (NLU) tasks. Their framework achieved general performance improvements across various NLU tasks, including Machine Reading Comprehension (MRC) and Natural Language Inference (NLI). In terms of retrievers, recent research has shown that by gradually increasing the difficulty of sampled data, CL can also bring significant performance improvements in the training of embedders (Zhu et al., 2022; Zeng et al., 2022; He et al., 2023).

3 Methodology

In this section, we will provide a detailed introduction to our CL-RAG training framework. We first briefly introduce the RAG pipeline in Section 3.1. Then, in Sections 3.2 and 3.3, we present the curriculum learning methods we propose for RALM training and retriever training, respectively. An overview of our CL-RAG training framework is given in Figure 2.

3.1 Preliminary

The RAG system combines a **Retriever** that retrieves query-relevant documents from external data bases with a **Generator** (LLM) that synthesizes responses from retrieved documents.

Retriever Given a query q, the Retriever aims to retrieve documents $\{d_1, d_2, ..., d_n\}$ relevant to the query from an external knowledge base \mathcal{D} . In this work, we employ a dense retriever. Specifically, we use a dual encoder to encode the input query q and the documents d into E(q) and E(d). The similarity between them is defined by cosine similarity, which serves as the score for document retrieval:

$$score_i = cos(E(q), E(d_i)).$$

Typically, we select the top-k documents with the highest scores as the input to the generator.

Generator Given the top-k retrieved documents, the goal of the Generator (LLM) is to utilize these external documents to better answer the question. Generally, the retrieved documents are concatenated with the query q as contextual information, and then fed into the Generator to produce the answer:

$$Output = LLM(d_1 \oplus d_2 \oplus ... \oplus d_k, q).$$

In this paper, we employ a raw retriever to retrieve n relevant documents. For generator (LLM) training, we construct curriculum-ordered data from easy to difficult examples by applying data augmentation and document rewriting to top-k retrieved documents. Subsequently, for retriever training, we leverage the finetuned generator (RALM) to assess the quality of n retrieved documents. We then perform reranking and sampling to construct curriculum-ordered training data to train the retriever to align with RALM's preference.

3.2 Curriculum Learning for RALM

In this section, we will present the data construction process for training the RALM, along with the corresponding curriculum learning framework.

To construct data with increasing difficulty for curriculum learning, we first categorize and construct documents of various difficulty levels. Previous work (Yoran et al., 2023; Fang et al., 2024) has considered data augmentation and constructed documents with *relevant noise*, *irrelevant noise*, and *counterfactual noise*. However, they neglected

Rewrite Documents

Rewrite Golden Documents

Instruction: Please rewrite the given text to make it better assist in answering the provided question.

Question: Who was the director of More (1969)?

Original text(100+ tokens): More (1969 film) More is an English-language drama-romance film written and directed by Barbet Schroeder, in his theatrical feature film directorial debut, released in 1969......

Rewritten Text (20 tokens): The 1969 film "More" is directed by Barbet Schroeder in his directorial debut.

Rewrite Counterfactual Documents

Instruction: Make false modifications to the facts(country, region, year, etc.) in the given text and rewrite the text while maintaining the similar quotation marks. You don't need to consider whether the rewritten object is a real person or object.

Original text: More (1969 film) More is an English-language drama-romance film written and directed by Barbet Schroeder, in his theatrical feature film directorial debut, released in 1969... Rewritten Text: More is a French-language drama-romance film written and directed by Pierre Cardin, in his theatrical feature film directorial debut...

Figure 3: Case of document rewriting, including query-enhanced document rewriting and counterfactual document rewriting. The highlighted green text represents the keywords within the document that aid in addressing the question, while the highlighted red text signifies wrong knowledge.

to include simple documents that definitely contain the correct answers, which is essential during the initial training stage for the model to learn the fundamental ability to answer questions from documents that contain the answers.

We first classify documents into three levels of difficulty: Easy, Common, and Hard. The Easy level contains at least two documents with correct answers to ensure the model can acquire preliminary answer extraction capabilities. The Common level follows the original retrieved documents, which may not contain the exact correct answers, thereby training the model's ability to infer answers using documents of average quality. The Hard level includes the most challenging documents for the model, potentially containing irrelevant or even harmful noise, which trains the model's ability to counteract disruptive information.

Since the retriever's results may not always include the correct answers, to construct the documents for Easy level, we use the documents provided for the corresponding questions in the MRQA reading comprehension task (Fisch et al., 2019) as the golden documents to ensure that they contain the exact correct answers. Meanwhile, we rewrite the golden document as shown in Figure 3 to obtain document that better meet the model's needs. Com-

pared to using only the golden document, using both the golden document and its rewritten version ensures that there are at least two documents containing answers within the top-k documents, which helps train the model's ability to extract consistent information from multiple documents. We complete the total number of documents to k using the original retrieved documents.

For Common level, we directly use the *top-k* documents from the retriever's results. Unlike documents in Easy level, these may not contain the correct answers and have more noise related to the questions, which may increase the difficulty for the model to answer the questions.

For Hard level, we randomly select a document from the top-k and replace it with retrieved document from other questions or perform counterfactual rewriting as shown in Figure 3. This introduces irrelevant and counterfactual noise, which represents the most challenging type of documents for the model, aiming to train the model's robustness against various types of real-world data.

During the training phase, data from the three difficulty levels are fed into the model in sequence to conduct Supervised Fine-Tuning (SFT). Through the curriculum learning approach that progresses from easy to difficult, the model is gradually trained to extract answers from documents and to resist the interference of distracting documents.

3.3 Curriculum Learning for Retriever

In this section, we will introduce our retriever training strategy. It initially employs a well-trained RALM to rerank documents and constructs data through stratified sampling. Subsequently, the retriever is trained in stages using a curriculum learning approach to align with the RALM.

We first employ the trained RALM to assess documents, thereby eliciting its preferences for them. Differs from that in Lin et al. (2023), which relies on the raw LLM, utilizing RALM for evaluation provides a more effective means of differentiating between high-quality and low-quality documents.

Previous researchers (Shi et al., 2023; Zhang et al., 2024) assess document quality based on the probability of the model generating the correct answer and the improvement in decoding rank, respectively. However, using either method alone has its limitation: the probability of generating the correct answer can be unstable when the input documents are diverse, and the decoding rank cannot finely distinguish between good and bad documents

when the model itself is capable of generating the correct answer, i.e., when most of the input documents have a decoding rank of 1 for the correct answer.

To address these limitations, we propose using the improvement in decoding rank as a coarse measure of document quality, and then using the probability of generating the correct answer to finely rank documents with the same decoding rank improvement. This helps us obtain a reranked list of retrieved documents:

$$\mathcal{D}_{rerank} = \{d_1, d_2, ..., d_n\}.$$

Next, we construct data with different difficulty levels for curriculum learning, aiming to first train the retriever to distinguish documents with obvious quality gaps and then train it to distinguish documents with slightly quality differences. Specifically, we divide \mathcal{D}_{rerank} into three groups $\{\mathcal{D}_1, \mathcal{D}_2, \mathcal{D}_3\}$ based on the ranking order from RALM. These groups contain documents in the ranges $[1, n_1]$, $[n_1, n_2]$, and $[n_2, n]$, respectively, representing good documents, sub-optimal documents, and hard negative documents. During training stages, we sample k_1 , k_2 , and k_3 documents from each of the three groups, while $k_1 + k_2 + k_3 =$ k, and gradually increase k_1 and decrease k_2 and k_3 , narrowing the quality gap between the sampled documents. We have also designed a tiered loss function to better fit our approach:

$$\mathcal{L}(q, \mathcal{D}_k) = -\sum_{d_{i,j} \in \mathcal{D}_k} \sum_{j>i} \frac{j-i}{n-1} log(\frac{e^{s_i}}{e^{s_i} + e^{s_j}}),$$

where \mathcal{D}_k denotes a subset of k documents selected from \mathcal{D} , n represents the total number of documents involved in the ranking, and i,j are the ranks of the documents, s_i denotes the similarity score between the query q and the document d_i . We start by distinguishing documents with obvious quality differences and gradually move to distinguishing documents with slight quality differences. This stage-by-stage approach helps bridge the gap between the original retriever and the retriever aligned with RALM preferences.

4 Experiments

4.1 Experimental Setting

4.1.1 Datasets

We first evaluated our complete training framework under the standard open-domain questionanswering (QA) setting. Subsequently, we assessed

Method	N	Q	Trivi	aQA	PopQA		HotpotQA		Avg.	
Method	EM	F1								
$Llama3_{8B}$	39.51	53.37	72.74	81.80	46.07	52.16	25.23	39.46	45.89	56.70
			With	RALM	Trainir	g				
RAAT	31.65	40.39	71.84	77.02	38.49	41.87	22.16	30.26	41.04	47.39
$RALM_{golden}$	42.90	52.30	79.55	83.84	50.06	52.45	31.25	41.96	50.94	57.64
$RALM_{top5}$	48.15	58.95	80.32	85.05	57.58	60.13	36.57	48.46	55.66	63.15
RetRobust	47.83	58.60	81.25	85.96	57.51	60.31	37.02	48.99	55.90	63.47
$RALM_{CL}(Ours)$	<u>51.53</u>	<u>61.19</u>	<u>82.93</u>	<u>87.59</u>	<u>59.71</u>	<u>62.28</u>	<u>38.14</u>	<u>50.22</u>	<u>58.08</u>	<u>65.32</u>
			With R	etriever	r Train	ing				
RA-DIT	49.52	59.94	76.62	81.10	61.73	64.47	36.14	47.82	56.00	63.33
Replug	52.52	62.28	76.86	81.59	63.75	66.35	37.75	49.22	57.72	64.86
$LLM ext{-}Emebedder$	51.85	61.41	82.60	87.20	64.24	66.69	38.80	50.51	59.37	66.45
CL- $RAG(Ours)$	53.01	62.51	82.97	87.57	66.63	69.12	39.11	51.19	60.43	67.60

Table 1: Experimental results for EM and F1 scores(%) on four open-domain QA datasets compared with multiple baselines in RALM or Retriever training. " $RALM_{CL}$ " refers to the RALM trained with CL strategy.

the robustness of the RALM within our training pipeline under a setting with added noise.

Open-domain QA We considered four opendomain QA datasets: single-hop question datasets Natural Questions (NQ) (Kwiatkowski et al., 2019), TriviaQA (Joshi et al., 2017), and PopQA (Mallen et al., 2023), as well as the multi-hop question dataset **HotpotQA** (Yang et al., 2018). For each dataset, we employed Contriever-MSMARCO (Izacard et al., 2021) as the retriever. Following previous settings (Asai et al., 2024), for NQ, TriviaQA, and HotpotQA, we retrieved the corresponding documents from the 2018 Wikipedia corpus provided by Izacard et al. (2023). For PopQA, we retrieved the documents from the 2020 Wikipedia corpus. Noting that PopQA only contains a test set, which we split into two non-overlapping parts for training and testing, respectively. We utilized datasets from the KILT benchmark (Petroni et al., 2021), more detailed information about the datasets is provided in Appendix A.

Robustness Test To evaluate the robustness of the RALM in our framework, we artificially introduced irrelevant and counterfactual documents into the retrieved document sets. Specifically, for each question and its retrieved documents in the test set, we generated test data with irrelevant noise by randomly replacing one of the retrieved documents with a document retrieved for a different question. Additionally, we created test data with counterfactual noise by randomly rewriting one of the retrieved documents in a counterfactual manner. The test sets obtained through these two methods

will be used separately to assess the model's robustness against irrelevant and counterfactual noise.

4.1.2 Evaluation Metrics

We employ Exact Match (EM) and F1 score as evaluation metrics. Specifically, EM assesses whether the model-generated answers are identical to the correct answers. Meanwhile, the F1 score integrates Precision and Recall to measure the accuracy and coverage of the model in generating answers.

4.1.3 Baselines

We utilized several training methods for RALM and Retriever as baselines, and firstly evaluated the performance of all the RALM training methods: (1)RAAT: Fang et al. (2024) enhances the robustness of RALMs through adversarial training. (2)RALM_{top5}: The most basic approach in RALM training by directly employing the *top*-5 retrieved documents. (3)RALM_{golden}: Lin et al. (2023) added the golden document to the retrieved documents to train the RALM. (4)RetRobust: Yoran et al. (2023) randomly injected irrelevant and counterfactual documents into the retrieved documents to expose the model to diverse types of noise during training.

Then, we continued to assess the performance of retrievers on the best-performing RALM: (1)**Replug**: Shi et al. (2023) minimized the KL divergence between the score of retriever's and the model's preference distribution to train a retriever that better aligns with the LLM. (2)**RA-DIT**: Lin et al. (2023) combined the method of finetuning the retriever using KL divergence and finetuning

Method	Irrel	evant	Counterfactual			
Method	EM	F1	EM	F1		
$Llama3_{8B}$	44.10	54.79	44.32	54.55		
RAAT	39.17	45.38	39.27	45.65		
$RALM_{golden}$	49.36	56.07	48.25	54.73		
$RALM_{top5}$	53.48	61.05	53.63	61.13		
RetRobust	53.85	61.43	54.16	61.77		
$RALM_{CL}$	56.17	63.42	56.21	63.47		

Table 2: Experimental results on robustness test(%) over irrelevant and counterfactual documents. We report the average results on each dataset here, and the complete results are provided in Appendix C.

the RALM with retrieved documents that include golden documents as context. (3)**LLM-Embedder**: Zhang et al. (2024) defines the quality of document *d* based on how much it improves the correct answer's ranking in LLM's response and proposes a fine-grained hierarchical loss function for training.

4.1.4 Implementation Details

RLAM Training We trained our model based on LLaMA3-8B-Instruct (Dubey et al., 2024), using five retrieved documents. We randomly selected 1500 samples from the training sets of four datasets, totaling 6000 samples, and conducted LoRA finetuning based on LLaMA Factory (Zheng et al., 2024), with the LoRA rank set to 8, a learning rate of 1e-4, a gradient accumulation step of 8, and a warmup ratio of 0.1. All experiments were conducted on a A800 80G GPU card.

Retriever Training We trained our model based on Contriever-MSMARCO (Izacard et al., 2021). By randomly sampling from the training sets of four datasets, we constructed a retriever training set comprising 100,000 samples. We set the number of input retrieved documents k to 5, the learning rate of 1e-5, the number of epochs to 3, and the batch size to 64. For our three-stage curriculum learning settings, the number of reranked documents n is set to 20. $n_1 = [1, 3, 5]$ for each training epoch and n_2 is set consistently to 15. The sampling parameters for each stage are $k_1 = [1, 3, 5]$, $k_2 = [2, 2, 0]$, and $k_3 = [2, 0, 0]$.

4.2 Main Results

The overall results are shown in Table 1, where the <u>underlined</u> and **boldface** items indicate the best results under each setting. We notify that the training of all methods adhered to a unified model and settings, and were tested under a 0-shot setting, with the prompts provided in the Appendix B.

With RALM Training The results in the upper half of Table 1 demonstrate that our training method achieves better performance than previous methods across all test sets, thereby validating the effectiveness of our approach. It is noted that the model trained with the RAAT method performs worse than the baseline model. This is because its training data follows the setting of $\{d_{golden} \oplus d_{noise}\}$. While this setting trains the model to be robust against noise, the inclusion of golden documents in all data deviates from the conventional RAG setup, resulting in poorer performance under the standard setting. Training using documents that contain a golden document can enhance the model's basic performance, i.e., its ability to extract correct answers from documents. However, due to the limitations of the retriever, the retrieved documents may not always contain the necessary information to answer the question. Therefore, training solely for answer extraction is insufficient. It is also necessary to further train the model to infer answers from more complex documents. RetRobust considers a more complex setting by accounting for both irrelevant document noise and counterfactual document noise. However, it neglects the incorporation of golden documents, which are beneficial in the early stages of model training. In contrast, our proposed method considers all types of document combinations, thereby enabling the model to adapt to the diverse documents generated by retrieval. Therefore, it achieves the best performance, with improvements of 2.18% in the average EM score and 1.85% in the average F1 score.

With Retriever Training In the settings that incorporate retriever training, our method also achieves the best average performance. As shown in the lower half of Table 1, RA-DIT utilizes the model from its experimental setting, namely $RALM_{top5}$, while the other methods all employ the best-performing $RALM_{CL}$. We found that on datasets where LLM itself performs well, such as TriviaQA, the gains from further improving the retriever's performance are minimal. However, for datasets like PopQA, which involve questions about specific entities, enhancing the retriever enables it to more accurately fetch entity-related documents, resulting in a significant boost in performance.

Method	Avg.						
Method	R@1	R@5	R@10				
Baseline	44.35	67.40	74.26				
Replug	49.10	72.32	78.43				
w/o~RALM	43.82	67.25	74.25				
$LLM ext{-}Embedder$	49.45	71.48	77.78				
w/o~RALM	47.78	69.78	76.29				
CL-RAG	50.40	73.29	79.55				
w/o~RALM	48.55	70.71	77.33				

Table 3: Experimental results on Recall rates(%) for retrievers trained with different methods. "Baseline" refers to the retrieval results of the raw retriever and "w/o RALM" indicates using the raw LLM without employing the well-trained RALM. Detailed results for each dataset are provided in Appendix D.

4.3 Robustness Test

To demonstrate the superiority of our RALM in combating noise, we also conducted tests under document settings that included noise. The results are shown in Table 2. Under the influence of document noise, the performance of all models declined to some extent. The impact of irrelevant document noise was comparable to that of counterfactual noise. The experimental results show that our model maintained its leading performance even when different types of noise were added.

4.4 Further Study of Retriever Training

To demonstrate that using the trained RALM to guide the finetuning of the retriever is superior, we compared the retrieval results of the retriever finetuned with the raw LLM preferences to those finetuned with the preferences of RALM. We reported the recall rate of correct answers in the retrieved documents in Table 3. The experimental results show that finetuning with the preferences of RALM generally outperforms finetuning with the raw LLM preferences. We observed that Replug, which assesses document quality based on answer probability, led to a significant drop in recall rate. This is because when the LLM itself is capable of providing the correct answer, using answer probability as a criterion to judge the quality of documents becomes unstable. In contrast, the trained RALM has a higher ability to discern documents and can more accurately differentiate between good and bad ones. The experiments on final answer generation are provided in Appendix D. It is worth emphasizing that even when the same trained RALM is used for guidance, our method

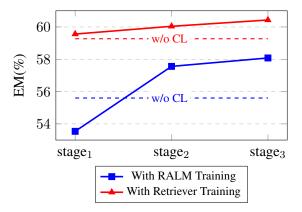


Figure 4: **Ablation studies for our CL-RAG framework(%).** We report the average EM scores and the complete results are provided in Appendix E.

still maintains a leading position.

4.5 Ablation Study

To systematically elucidate the contribution of each training stage to the overall performance, we conducted an ablation study. Specifically, we evaluated the intermediate models generated at each stage of our CL-RAG framework in a stage-by-stage manner. This approach allows us to more explicitly discern the contribution of each training stage to the overall performance. The experimental results are presented in Figure 4, where $stage_1$, $stage_2$, and $stage_3$ refer to the training phases involving simple, common, and hard samples, respectively. We observed that the performance of both the retriever and the generator steadily improves as the training stages progress. Furthermore, the removal of the curriculum learning strategy resulted in a significant performance decline, indicating that neglecting the difficulty order of training samples leads to sub-optimal training outcomes.

5 Conclusion

In this study, we introduce CL-RAG, a curriculum learning-based training framework designed for the RAG system. To the best of our knowledge, it's one of the first time that the idea of human imitation learning is integrated with RAG training, which can effectively enhance the generalization and stability of the RAG system. Experiments on four opendomain question answering datasets provide substantial evidence of the framework's effectiveness. Additionally, separate experiments conducted on the retriever and the generator have demonstrated the significant enhancements our method brings to each individual part.

Limitations

Despite its effectiveness, CL-RAG still has certain limitations. First, the LLM preference measurement based on the probability or ranking of decoding correct answers may have advantages in open-domain question answering data, but it may be unstable in long text generation. Second, our framework only involves a single iteration of training between the RALM and the retriever, that is, training the RALM first and then the retriever. More refined iterative methods, such as iteration after each difficulty level training stage, still need further exploration.

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A Datasets Details

Table 4 shows details of the datasets we used, where the data volumes for RALM and Retriever represent the amounts used for training each respective component.

B Inference Prompt

During the inference stage of all models, we used the same prompt to ensure fairness. As shown in Table 5, paragraph represents the retrieved document, and instruction represents the query. Finally, we extracted the content following "Answer:" in the model's response as the final answer.

Dataset		Test		
	Total	RALM	Retriever	Total
NQ	87372	1500	30000	2837
TriviaQA	61844	1500	30000	5359
PopQA	10000	1500	10000	4267
HotpotQA	88869	1500	30000	5600

Table 4: Details of the datasets we used.

Prompt

System Prompt: Answer the following questions with two to three words. Your answer must be

formatted as follows: Answer: <your answer>

User Prompt: The following contexts will help you answer the question.

{paragraph}

Question: {instruction}

Table 5: Prompt for LLM inference.

C Complete Results of Robustness Test

Complete results are shown in Table 6.

D Further Study of Retriever Training

D.1 Complete Results of Retriever Training

Complete document retrieval results are shown in Table 7 and Table 8. The final results on QA datasets are provided in Table 9.

D.2 Case Study of Documents Evaluation

Table 10 presents the case study comparing the document evaluation result of the base LLM and the RALM. The result indicate that for some documents containing implicit knowledge required for answering questions, the base LLM may generate erroneous judgments, whereas the trained RALM is more capable of distinguishing the quality of documents. This also highlights the necessity of the iterative process of training the RALM first and then training the retriever, as the trained RALM and the base LLM may no longer share the same preferences for documents. Separate training may lead to suboptimal final outcomes.

E Complete Results of Ablation Study

Complete results of the ablation study are shown in Table 11.

Method	N	NQ		TriviaQA		PopQA		otQA	Avg.		
Method	EM	F1	EM	F1	EM	F1	EM	F1	EM	F1	
With irrelevant documents											
$Llama3_{8B}$	38.56	51.72	71.28	80.61	42.68	48.85	23.89	37.99	44.10	54.79	
RAAT	30.31	38.65	69.34	74.61	35.90	39.29	21.13	28.96	39.17	45.38	
$RALM_{golden}$	41.49	50.92	78.52	83.10	46.97	49.44	30.46	40.80	49.36	56.07	
$RALM_{top5}$	46.32	57.35	78.66	83.52	53.60	56.33	35.32	47.01	53.48	61.05	
RetRobust	46.56	57.17	79.57	84.42	54.28	57.17	35.00	46.95	53.85	61.43	
$RALM_{CL}$	50.30	59.89	81.48	86.31	56.13	59.05	36.75	48.43	56.17	63.42	
With counter	factual	docume	ents								
$\overline{Llama3_{8B}}$	38.10	50.78	72.53	80.93	42.49	48.52	24.16	37.95	44.32	54.55	
RAAT	30.60	39.16	70.23	75.40	34.92	38.59	21.32	29.43	39.27	45.65	
$RALM_{golden}$	40.08	49.03	77.52	81.90	45.58	48.07	29.82	39.92	48.25	54.73	
$RALM_{top5}$	46.18	56.88	79.10	83.88	53.88	56.66	35.34	47.10	53.63	61.13	
RetRobust	46.56	57.47	80.39	85.13	53.90	57.04	35.80	47.42	54.16	61.77	
$RALM_{CL}$	50.16	59.82	81.74	86.55	55.89	58.68	37.04	48.82	56.21	63.47	

Table 6: Complete results on robustness test(%).

Method		NQ		TriviaQA				
Methou	R@1	R@5	R@10	R@1	R@5	R@10		
Baseline	43.64	72.75	81.00	65.56	88.25	93.30		
Replug	48.43	75.54	83.22	66.50	88.59	93.13		
w/o~RALM	45.29	73.60	81.32	56.13	80.26	86.29		
$\overline{LLM\text{-}Embedder}$	46.60	73.56	82.16	68.20	88.68	92.47		
w/o~RALM	44.77	72.01	80.12	67.41	88.27	92.90		
CL- RAG	48.82	75.33	83.33	68.59	89.86	93.91		
w/o~RALM	46.11	72.26	80.61	69.26	89.00	93.22		

Table 7: Retrieve results of Natural Questions and TriviaQA.

Method		PopQA	L	HotpotQA			
Methou	R@1	R@5	R@10	R@1	R@5	R@10	
Baseline	43.03	66.51	73.56	25.16	42.07	49.14	
Replug	54.79	80.50	86.15	26.68	44.63	51.23	
w/o~RALM	50.55	76.49	83.90	23.30	38.64	45.48	
$\overline{LLM\text{-}Embedder}$	54.68	79.17	85.66	28.30	44.52	50.82	
w/o~RALM	51.54	75.72	82.05	27.41	43.13	50.07	
CL- RAG	55.26	81.53	87.18	28.91	46.45	53.79	
w/o~RALM	51.84	78.04	84.77	26.98	43.55	50.73	

Table 8: Retrieve results of PopQA and HotpotQA.

Method	NQ		Trivi	TriviaQA		PopQA		HotpotQA		Avg.	
	EM	F1	EM	F1	EM	F1	EM	F1	EM	F1	
LLM- $Emebedder$	52.10	61.53	83.03	87.72	65.24	67.88	38.86	50.91	59.81	67.01	
Replug	52.73	62.42	83.17	87.67	66.16	68.75	38.73	50.33	60.20	67.29	
CL- RAG	53.01	62.51	82.97	87.57	66.63	69.12	39.11	51.19	60.43	67.60	

Table 9: Final results on QA datasets when all retrievers are trained to align with the preferences of $RALM_{CL}$.(%)

Question: Who scored a film based on a 1961 science fiction novel by Stanislaw Lem?

Answer: Cliff Martinez

Retrieved Document

Stanisław Lem

(Poland, Germany, and the Soviet Union). Franz Rottensteiner, Lem's former agent abroad, had this to say about Lem's reception on international markets: His best-known novels include "Solaris" (1961), "His Master's Voice" ("Głos pana", 1968), and the late "Fiasco" ("Fiasko", 1987). "Solaris" was made into a film in 1968 by Russian director Boris Nirenburg, a film in 1972 by Russian director Andrei Tarkovsky—which won a Special Jury Prize at the Cannes Film Festival in 1972—and an American film in 2002 by Steven Soderbergh. "Solaris" is not the only work of Lem's to be filmed.

Raw LLM preference

Answer probably: 0.002 Answer rank: 1417

Well-trained RALM preference

Answer probably: 0.73

Answer rank: 1

Table 10: An example of document evaluation.

Method	N	Q	Trivi	iaQA	Pop	QA	Hotp	otQA	A	vg.
Michiga	EM	F1	EM	F1	EM	F1	EM	F1	EM	F1
With RAL	M Trai	ning								
w/o CL	49.31	59.37	80.34	85.38	57.65	60.47	35.11	46.94	55.60	63.04
$stage_1$	46.32	56.26	81.77	85.99	53.29	55.79	32.77	43.79	53.54	60.46
$stage_2$	51.22	60.73	83.12	87.50	58.54	61.52	37.36	49.13	57.56	64.72
$RALM_{CL}$	51.53	61.19	82.93	87.59	59.71	62.28	38.14	50.22	58.08	65.32
$\overline{With\ Retr}$	iever Tr	$\overline{raining}$								
w/o CL	52.13	61.42	82.48	87.11	64.26	66.70	38.20	50.13	59.27	66.34
$stage_1$	52.66	62.11	82.96	87.67	63.67	66.14	38.94	50.89	59.56	66.70
$stage_2$	52.98	62.39	83.04	87.49	65.10	67.53	39.05	51.26	60.04	67.17
CL- RAG	53.01	62.51	82.97	87.57	66.63	69.12	39.11	51.19	60.43	67.60

Table 11: Complete results of ablation study(%).