Query Rewriting for Retrieval-Augmented Large Language Models

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Abstract

Large Language Models (LLMs) play a powerful Reader of the Retrieve-then-Read pipeline, making great progress in knowledge-based open-domain tasks. This work introduces a new framework, Rewrite-Retrieve-Read that improves the retrieval-augmented method from the perspective of the query rewriting. Prior studies mostly contribute to adapt the retriever or stimulate the reader. Different from them, our approach pay attention of the query adaptation. Because the original query can not be always optimal to retrieve for the LLM, especially in the real world. (1) We first prompt an LLM to rewrite the queries, then conduct retrieval-augmented reading. (2) We further apply a small language model as a trainable rewriter, which rewrite the search query to cater to the frozen retriever and the LLM reader. To fine-tune the rewriter, we first use a pseudo data to conduct supervised warm-up training. Then the Retrieve-then-Read pipeline is modeled as a reinforcement learning context. The rewriter is further trained as a policy model by maximize the reward of the pipeline performance. Evaluation is performed on two downstream tasks, open-domain QA and multiple choice. Our framework is proved effective and scalable.

1 Introduction

Large Language Models (LLMs) have emerged remarkable abilities for human language processing with extraordinary scalability and adaptability (Ouyang et al., 2022; Brown et al., 2020; Chowdhery et al., 2022). These advancements makes it possible to leverage LLM interfaces as an off-the-shelf widely-applicable assistant. However, powerful LLMs such as ChatGPT still have to face the problem of hallucination (Yao et al., 2023; Bang et al., 2023). Trained on large-scale corpora, LLMs often meet standards of fluency and readability. But whether the generated sentences are consistent

with the real word needs further validation, as all abilities of LLMs are from the data-driven training but the perception of the reality. Therefore, knowledge injection can be applied to augment LLMs for knowledge-intensive situation, like open-domain Question Answering.

Retrieve-then-read (Lewis et al., 2020b; Karpukhin et al., 2020; Izacard et al., 2022) has proved to be an effective pipeline. Take the opendomain Question Answering task (open-domain QA) as an example, a retriever first searches for related documents for a question. Then a reader receives the question and the documents as context, and gives an answer. Earlier works strengthen the retrieve algorithm (Wu et al., 2022; Izacard et al., 2021) or jointly fine-tuning the reader model (Lewis et al., 2020b; Guu et al., 2020; Izacard et al., 2022) for performance gains. More recently, with a powerful but black-box LLM serving as the reader, the optimization leans more on the LLM-oriented adaptation: (1) The retriever can be adapted to cater to the fixed LLM (Shi et al., 2023). By using a feedback from the LLM as a training objective, the retrieval model is tuned for more suitable LLM inputs, e.g. useful documents for the LLM reader. (2) Another idea relies on the design of interactions between the retriever and LLM reader (Yao et al., 2023; Khattab et al., 2022), especially when the retriever is also frozen. The Retrieve-then-read rotation could be repeated for decoupling complex requests. The reader refers to the retrieved context and the next query to retrieve is from the LLM feedback. Further, in the sophisticated pipeline design, the LLM demonstrations can also be bootstrapped from the retriever. However, there are still problems remaining to be solved: (1) These approaches focus on the adaptation of the pipeline adaptation and overlook the guery adaptation. The guery is either original from dataset or directly determined by the LLM feedback, thus is always fixed. This

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may limit the performance and leave burdens to works on retriever adaptation and prompt design. (2) To eliminate the hallucination, some queries need real-time knowledge check. But training a dense retrieve model relied on the maintenance of the search index, which maybe not that flexible to transfer to web search.

This paper proposes to rewrite the query for retrieve-then-read pipeline. The main idea is a novel tuneable pipeline for complex queries that achieve performance gains from the query perspective. Our retrieve-then-read framework adopts Bing search engine as the retriever and ChatGPT as the reader. Firstly, we integrate query rewriting into the pipeline by prompting ChatGPT. By this few-shot rewriting, the performance of reader is improved. Then we go further to fine-tune query rewriting. A rewriter is added before the retriever, which is a trainable model. The positive samples in the training set are gathered as a self-supervised rewriting training set. On this training set, the rewriter is warmed-up, serving as a baseline. We follow the reinforcement learning scheme and use the reader feedback to tune the rewriter.

To evaluate the proposed method, experiments are conducted on open-domain QA (HotpotQA, TriviaQA) and multi-choice QA (JEC-QA, gaokao) tasks.

The contributions can be summarized as follows: (1) We introduce a novel retrieval-augmented scheme with a trainable query rewriter. (2) A training method is proposed to adapt the query to the frozen retriever and back-box reader.

2 Related Work

2.1 Retrieval-augmented Methods

When language models deal with task that requires backup of knowledge injection, a retriever can be leveraged as a knowledge interface. It is because the training objectives of language models follow the linguistics rules rather than the aim of building a knowledge base. Thus, a retriever that provide external knowledge, like common sense or real-time news, can support background and eliminate the hallucination.

Earlier studies use sparse retriever like BM25 (Robertson et al., 2009) or dense retriever in front of a pre-trained language model. DPR (Karpukhin et al., 2020) proposes an end-to-end open-domain QA system: a dense passage retriever on the basis of BERT (Devlin et al., 2019), and another BERT

to extract answers from each retrieved passages. While evaluating each answers, the passages are also re-ranked. RAG (Lewis et al., 2020b) steps further on generation tasks. It adopts BERT-based DRP and a BART (Lewis et al., 2020a) as a answer generator. Retrieved documents being treated as a latent variable, the answer can be generated using each documents or all of them. Similarly, EMDR² (Sachan et al., 2021) applies expectation-maximization algorithm to marginalize over multiple retrieved documents. The latent variable estimates are used to update the parameter of the retriever and the reader.

Under the competition with large language modes, recent work manages to use a retriever to compensate the reduction of parameter size. Atlas follows EMDR² framework. By jointly training the retriever and the reader, Atlas (Izacard et al., 2022) shows few-shot performance on par with 540B PalM (Chowdhery et al., 2022) but is 50x smaller. RETRO (Borgeaud et al., 2022) is enhanced by retrieving on a large-scale corpus at pre-training stage. Using 25× fewer parameters, RETRO shows comparable performance to GPT-3 (Brown et al., 2020).

2.2 Cooperate with black-box LLMs

Large Language Models, such as ChatGPT (Ouyang et al., 2022), Codex (Chen et al., 2021), PaLM (Chowdhery et al., 2022), emerge impressive natural language processing ability as well as remarkable scalability. This leads to a tendency to embrace LLMs on a wide range of NLP tasks. However, LLMs are only accessable as a blackbox in most cases, which is because (1) Some like ChatGPT is not open-source and keep private from users; (2) The large parameter scale requires computational resources that is not affordable for users. This constraint means nothing is available except inputs and outputs.

Existing studies have proved that LLMs abilities can be better leveraged by carefully designed prompt methods. GenRead (Yu et al., 2023) prompts an LLM to generate context documents instead of deploying a retriever. It shows that LLMs can retrieve from internal knowledge by prompting. ReAct (Yao et al., 2023) combines the Chain-of-Thought (CoT) (Wei et al., 2022; Wang et al., 2022) and inter-actions with Wikipedia web API. Only relying on prompt construction, ReAct provides novel baselines for interactive tasks. Demon-

strate—Search—Predict (Khattab et al., 2022) is a sophisticated pipelines between an LLM and a retriever. Unlike ReAct, DSP integrates prompts for demonstration bootstrap besides multi-hop breakdown and retrieve.

Despite the powerful ability in the zero/few-shot setting, the behaviour of LLMs sometimes needs adjustments. A feasible approach is to append trainable small models in front of or after the LLM. The small models, as a part of the parameters of the system, can be fine-tuned for optimization. Re-Plug (Shi et al., 2023) is proposed to fine-tune the retrieve model to enhance the frozen LLM in the retrieve-then-read pipeline. The retriever is trained under the LLM's supervision, thus is supposed to retrieve documents that best for the LLM. With the same purpose, Directional Stimulus Prompting (Li et al., 2023) deploys a small model to provide the LLM with stimulus (e.g., keywords for summarization, or dialogue actions for response generation), which is updated according to the LLM reward.

Different from the inspiring work mentioned above, our proposed pipeline add a rewriter model in front, which is of trainable size. We explore a noval enhancement for retrieval-augmented LLM by reconstructing the seach query.

3 Methodology

We present rewrite-retrieve-read, a pipeline that improve the retrieval-augment LLM from the perspective of query rewriting. Figure 1 shows an overview. The pipeline consists of three steps. (1) A rewriter R_{θ} , performing sequence-to-sequence generation. (2) A frozen retriever RM, which we use Bing search engine for convenience. (3) A frozen reader LM, ChatGPT. This task can be formulated as follows. Given a knowledge-intensive benchmark (i.e., open-domain QA), $D = \{(x,y)_i\}, i=0,1,2,\ldots,N, x$ (a question) is input to the pipeline, y_i is the expected output (the correct answer). x is firstly rewritten as \tilde{x} . Then the retriever retrieves a set of documents doc. And the reader reads [doc, x] and predicts the output \hat{y} .

3.1 Query Rewriting

We first introduce to rewrite search query by prompting the LLM. Related word has proved that retrieval augmentation can cause misleading and compromise the language model (Mallen et al., 2022), especially for parametric knowledge. In step (1), a straightforward method is to ask the

LLM to generate queries to search for information that is potentially needed. The prompt encourages the LLM to reason, and the output can be none, or one or more queries to search.

3.2 Trainable Rewriter

However, total reliance on a frozen LLM has shown some drawbacks. Reasoning errors or invalid search hinders better performance (Yao et al., 2023). On the other hand, tasks like open-domain QA not severe data scarcity and have training set, which can be leveraged to support fine-tuning. Hence, we further propose to utilize a trainable small language model to take over the rewriting step.

3.2.1 Rewriter Warm-up

To build this pipeline, we first use pseudo data to train a warm-up rewriter, then apply reinforcement learning to optimize the policy model. The task, query rewriting, is quite different from the pretraining objective of sequence-to-sequence models. So we perform a supervised training for the rewriter as a warm-up baseline before the reinforcement learning. The data is from the generation of an LLM. First, we prompt the LLM to rewrite the original question x. Here we use a human-written prompt line just for a baseline performance of the rewriter. The the retriever searches the rewritten queries \tilde{x} . The retrieved background passages and the original question, [doc, x] are fed into the reader. Then the samples that get the correct answers are collected as the pseudo training data, which can be denoted as $\tilde{D} = \{(x, \tilde{x}) | \hat{y} = y\}$. We fine-tune the rewriter on \tilde{D} with the standard log-likelihood as the training objective, denoted as

$$\mathcal{L}_{ll} = -\sum_{t} log p_{\theta}(\hat{x}_{t} \mid \tilde{x}_{< t}, x).$$
 (1)

The rewriter model after warm-up shows modest performance, which depends on the pseudo data quality and rewriter capability. Highly relying on the human-written prompt line, \tilde{x} can be suboptimal. The relative small scale of the rewriter size is also a limitation of the performance after the warm-up.

3.2.2 Reinforcement Learning

To further fine-tune the rewriter to cater to the LLM reader, we adopt policy gradient reinforcement learning framework.

Task Formulation. In the context of reinforcement learning, the rewriter optimization is for-

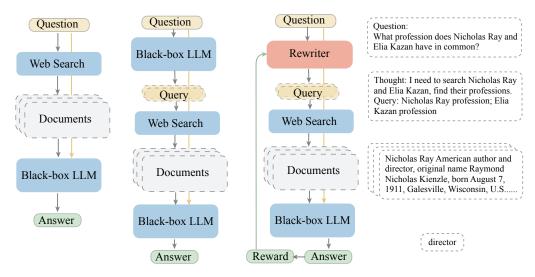


Figure 1: Overview of our proposed pipeline. From left to right, we show standard *retrieve-then-read* method, LLM as a query rewriter and *rewrite-retrieve-read* pipeline with a trainable rewriter.

mulated as a Markov Decision Process 5-tuple $\langle \mathcal{S}, \mathcal{A}, P, R, \gamma \rangle$. (1) The state space \mathcal{S} is a finite set limited by the vocabulary and the sequence length. (2) The action space A is equals to the vocabulary. (3) The transition probability P is determined by the policy network, which is the rewriter model R_{θ} . (4) The reward function gives a reward value that depends on the current state. The policy gradient is derived from rewards, used as the training objective. (5) γ denotes the discount factor. More specifically, the warm-up rewriter R_{θ} is the initial policy model π_0 . At each step t, the action a_t is to generate the next token \hat{x}_t based on the observation of the present state, $s_t = [x, \hat{\tilde{x}}_{\leq t}]$. When the generation is stopped by selecting the End-Of-Sentence token, one episode is ended. After finishing the retrieval and reading, a reward is computed by evaluating the final output, i.e. the prediction of the reader.

Policy Optimization. We adopt Proximal Policy Optimization (PPO) (Schulman et al., 2017), following (Ramamurthy et al., 2022). Maximization of the expectation of the reward is formulated as

$$\max_{\theta} \mathbb{E}_{\hat{x} \sim p_{\theta}(\cdot|x)}[R(x, \hat{x})],$$

$$\max_{\theta} \mathbb{E}_{(s_{t}, a_{t}) \sim \pi_{\theta'}}[\min\{r_{t, \theta} A^{\theta'}(s_{t}, a_{t});$$

$$\operatorname{clip}(r_{t, \theta}, 1 - \varepsilon, 1 + \varepsilon) A^{\theta'}(s_{t}, a_{t})\}],$$

$$r_{t, \theta} = \frac{p_{\theta}(a_{t} \mid s_{t})}{p_{\theta'}(a_{t} \mid s_{t})},$$

$$(2)$$

where θ' is the temporarily fixed policy for sampling and θ is updated. A value network V_{ϕ} is initialized from the policy network π_{θ} . The reward is formulated as an advantage function based on

the estimation of V_{ϕ} .

$$\delta_{t} = r\left(s_{t}, a_{t}\right) + V_{\phi}\left(s_{t+1}\right) - V_{\phi}\left(s_{t}\right),$$

$$\hat{A}_{t}^{\theta}\left(s_{t}, a_{t}\right) = \sum_{t'=0}^{\infty} \lambda^{t'} \delta_{t+t'},$$
(3)

where λ is the bias-variance trade-off parameter of Generalized Advantage Estimation (GAE) (Schulman et al., 2015).

The reward represents the quality of the generated queries, which needs to be consistent with the final evaluation of the task, denoted as R_{lm} . R_{lm} is fed to the retriever and the reader for a final prediction \hat{y} . The reward is a combination of the measures of \hat{y} compared to the golden label y (e.g., exact match and F_1 of the predicted answers). Besides, a KL-divergence regularization is added to prevent the model from deviating too far from the initialization (Ramamurthy et al., 2022; Ziegler et al., 2019).

$$R\left(s_{t}, a_{t}, y\right) = R_{lm}(\hat{\tilde{x}}, y) - \beta \text{KL}\left(\pi_{\theta} \| \pi_{0}\right). \tag{4}$$

The final loss function is composed of policy loss and value loss.

$$\mathcal{L}_{\theta} = -\frac{1}{|\mathcal{S}|T} \sum_{\tau \in \mathcal{S}} \sum_{t=0}^{T} \min(r_{t,\theta} A^{\theta'}, \operatorname{clip} A^{\theta'}),$$

$$\mathcal{L}_{\phi} = \frac{1}{|\mathcal{S}|T} \sum_{\tau \in \mathcal{S}} \sum_{t=0}^{T} (V_{\phi}(s_t) - R_t)^2,$$

$$\mathcal{L}_{ppo} = \mathcal{L}_{\theta} + \lambda_v \mathcal{L}_{\phi}.$$
(5)

Here S denotes the sampled set, T is for step numbers. In our implementation, the rewriter for English task is initialized a pre-trained T5 in the size of Large (770M). For Chinese task, we use mT5-large (1.2B).

3.3 Retriever and Reader

The Retriever & Reader are the frozen modules of our pipeline. We adopt effective and convenient implementations.

Retriever. As the retriever we use a web search engine. It requires no FAISS index construction like dense retriever, nor candidates like training set. But it allows for a wide knowledge scope and realtime factuality. With Bing API, the retrieval are performed in two approaches. (1) For all retrieved web pages, we concatenate the snippets that are related sentences selected by Bing. This method similar to use a search engine in an browser, input a query and Enter, then collect the texts shown on the search result page. (2) For all retrieved web pages, we request the URLs and parser to get all the texts. This is similar to clicking into each items on the search result page. Then we use BM25 to reduce the document length, keeping those with higher BM25 scores with the query.

Reader. ChatGPT ¹ is considered as the reader It predicts the output by the method of few-shot in-context learning. The prompt follows the formulation of *[instruction, demonstrations, input]*, where the input is *[doc, x]*. We use straightforward instructions and 1-3 random examples, mainly for the task-specific output format illustration. It has been proved that both the phrasing of prompt lines (Zhang et al., 2023a) and the selection of demonstrations shows effects on the in-context learning performance (Su et al., 2022; Zhang et al., 2023b). As it is not the focus of this work, we pay no more attention on prompt editing.

4 Experiments

4.1 Tasks

4.1.1 Open-domain QA

(1) HotPotQA (Yang et al., 2018) consists of complex questions that require multi-hop reasoning. In other words, the questions are often indirect, which is consistent with our motivation of query rewriting. (2) AmbigNQ (Min et al., 2020) provides a disambiguated version of Natural Questions (NQ) (Kwiatkowski et al., 2019). For each

ambiguous questions in NQ, minimal constraints are added to break it into several similar but specific questions. (3) PopQA (Mallen et al., 2022) includes long-tail distributions as it samples more low-popularity knowledge than other popular QA tasks. Retrieval is even more significant on this benchmark, because non-parametric memory complements parametric memory.

Open-domain QA can be formulated as $\{(q, a)_i\}$. The evaluation metrics are Exact Match (EM) and F_1 scores. In the step of reinforcement learning, the reward is a weighted sum of EM, F_1 , and an indicator for if the retrieved content hits the answer.

$$h = \begin{cases} 1 & y \text{ in } doc, \\ -1 & else \end{cases}$$

$$\mathcal{R}_{lm} = EM + \lambda_f F_1 + \lambda_h h.$$

$$(6)$$

4.1.2 Multi-choice QA

Inspired by AGIEval (Zhong et al., 2023), we utilize human standardized exam problems. (1) We selected subjects that are less dependent on in-domain information. For example, to solve a math problem or a passage reading comprehension problem, the students may analyze the problem description or the passage. But for a history question, the students may make more efforts on recalling their knowledge. We construct our Chinese gaokao set with the subsets of history, geography, biology and physics of AGIEval. (2) JEC-QA-KB Zhong et al. (2020) consists of multiple choice problems in National Judicial Examination of China, which is also partially included in AGIEval (Zhong et al., 2023). (3) Massive Multi-task Language Understanding (MMLU) (Hendrycks et al., 2021) is also exam questions datasets in 4 categories: humanities, STEM, social sciences and other.

Multi-choice QA can be formulated as $\{(q,a)_i\}, q = [q', \{c_j\}]$, where c denotes the choices. The question along with choices are rewritten into search queries. The answer is one or more options, e.g., A,C. The EM and F_1 scores are reported as metrics and used to derive the reward.

$$\mathcal{R}_{lm} = EM + \lambda_f F_1. \tag{7}$$

4.2 Baselines

Following settings are evaluated to supports our methods. (1) **Reader**: The standard in-context learning without any augmentations. (2) **Retrieve-then-read**: The standard retrieval-augmented method. Retrieved documents are concatenated

¹gpt-3.5-turbo

with the question. (3) **LLM as a frozen rewriter**: The ChatGPT works as a frozen rewriter. In the rewriting process, we prompt ChatGPT to reason and generate queries by few-shot in-context learning. (4) **Rewrite-retrieve-read**: After fine-tuning of the rewriter, the output queries are used in retriever and the reader. Table 1 presents prompt forms.

reader
Answer the question in the following format, end the
answer with '**'. {demonstration} Question: $\{x\}$

retrieve-then-read & rewrite-retrieve-read

Answer the question in the following format, end the answer with '**'. {demonstration} Question: $\{doc\}$ {x} Answer:

LLM as a frozen rewriter

Open-domain QA: Think step by step to answer this question, and provide search engine queries for knowledge that you need. Split the queries with ';' and end the queries with '**'. {demonstration} Question: {x} Answer:

Multi-choice QA: Provide a better search query for web search engine to answer the given question, end the queries with '**'. {demonstration} Question: $\{x\}$ Answer:

Table 1: Prompt lines used for the LLM reader.

4.3 Results and Analysis

The main results are shown in Table 2. Query rewriting leads to performance advantages on all tasks, and rewriter fine-tuning further improves scores on HotPotQA. In addition, we analyze retrieval methods and reader ability. Table 3 presents contents selection with BM25 recalls better documents than snippets, but query rewriting make progress with both. We also collect the samples for which the retriever manages to find documents that contain their gold answers. Their scores shows the ability of the reader, also is the upper bound score.

5 Conclusion

This paper introduces *Rewrite-Retrieve-Read* pipeline, where a query rewriting step is added for retrieval augmentation. This approach is applicable for adopting a frozen large language model as the reader and a real-time web search engine as the retriever. Further, we propose to apply a tuneable language model the rewriter, which can be trained to cater to the frozen retriever and reader. Evaluation

Model	EM	\mathbf{F}_1	
HotPotQA			
Reader	32.36	43.05	
Retrieve-then-read	30.47	41.34	
LLM rewriter	32.80	43.85	
Rewrite-retrieve-read	33.70	44.87	
AmbigNQ			
Reader	42.10	53.05	
Retrieve-then-read	45.80	58.50	
LLM rewriter	46.50	58.95	
PopQA			
Reader	41.94	44.61	
Retrieve-then-read	43.20	47.53	
LLM rewriter	46.00	49.74	
Model	gaokao	JEC	
Reader	48.3	21.1	
Retrieve-then-read	55.81	24.4	
LLM rewriter	58.18	28.4	
MMLU			
	Human.	STEM	Other
Reader	75.60	58.80	69.00
Retrieve-then-read	76.70	63.30	70.00
LLM rewriter	77.00	63.50	72.60

Table 2: Metrics of open-domain QA and multi-choice QA.

Model	EM	\mathbf{F}_1	hit
Reader	42.10	53.05	_
Retrieve-then-read			
w/ snippet	38.70	50.50	61.1
w/ BM25	45.80	58.50	76.4
w/ BM25+filter	57.54	69.58	100
LLM rewriter			
w/ snippet	39.80	52.64	63.5
w/ BM25	46.50	58.95	77.5
w/ BM25+filter	58.40	69.45	100

Table 3: Analysis on AmbigNQ.

on open-domian QA and multi-choice QA shows the effectiveness of query rewriting. Our work proposes novel retrieval-augmented LLM framework and provides new baselines for integrating trainable module into black-box LLMs.

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A Appendix

This is a section in the appendix.