

# RETA-LLM: A Retrieval-Augmented Large Language Model Toolkit

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## Abstract

Although Large Language Models (LLMs) have demonstrated extraordinary capabilities in many domains, they still have a tendency to hallucinate and generate fictitious responses to user requests. This problem can be alleviated by augmenting LLMs with information retrieval (IR) systems (also known as retrieval-augmented LLMs). Applying this strategy, LLMs can generate more factual texts in response to user input according to the relevant content retrieved by IR systems from external corpora as references. In addition, by incorporating external knowledge, retrieval-augmented LLMs can answer in-domain questions that cannot be answered by solely relying on the world knowledge stored in parameters. To support research in this area and facilitate the development of retrieval-augmented LLM systems, we develop RETA-LLM, a RETreival-Augmented LLM toolkit. In RETA-LLM, we create a complete pipeline to help researchers and users build their customized in-domain LLM-based systems. Compared with previous retrieval-augmented LLM systems, RETA-LLM provides more plug-and-play modules to support better interaction between IR systems and LLMs, including request rewriting, document retrieval, passage extraction, answer generation, and fact checking modules. Our toolkit is publicly available at <https://github.com/RUC-GSAI/YuLan-IR/tree/main/RETA-LLM>.

## 1 Introduction

Large language models (LLMs) have attracted increasing attention from both research community and industry (Brown et al., 2020; OpenAI, 2023; Ouyang et al., 2022; Touvron et al., 2023; Chowdhery et al., 2022; Zhao et al., 2023; Zeng et al., 2022). With tremendous world knowledge stored in parameters (Petroni et al., 2019; Roberts et al., 2020; Jiang et al., 2020) and the Reinforcement Learning

from Human Feedback (RLHF) techniques (Christian et al., 2017; Ziegler et al., 2019), LLMs can generate helpful, detailed, and polite texts in response to user inputs. Many studies have demonstrated LLMs’ extraordinary abilities in various areas, including nature language processing (Moslem et al., 2023), information retrieval (Sun et al., 2023; Wang et al., 2023; Mao et al., 2023), and recommendation (Hou et al., 2023; Zhang et al., 2023).

However, LLMs still tend to hallucinate and sometimes generate texts opposite to facts (Zhou et al., 2021; Zhao et al., 2023). To tackle these problems, researchers have proposed a new paradigm to strengthen LLMs with information retrieval systems (retrieval-augmented LLMs) (Shi et al., 2023; Jiang et al., 2023; Nakano et al., 2022), which enables LLMs to retrieve relevant contents from an external repository (knowledge corpus) to generate texts based on them. It has been verified that retrieval-augmented LLMs can generate texts in response to user input with fewer hallucinations (Nakano et al., 2022). Furthermore, by incorporating customized private data resources, retrieval-augmented LLMs can respond to in-domain queries that cannot be answered by LLMs trained with public data.

To support research in this area and help users build their own in-domain LLM-based systems, we devise RETA-LLM, a RETreival-Augmented LLM toolkit. Different from previous general LLM-enhanced toolkits such as LangChain,<sup>1</sup> RETA-LLM focuses on the retrieval-augmented LLMs and provides more plug-in modules. Typically, retrieval-augmented LLMs use a retrieve-and-generate strategy with two modules: First, they retrieve documents or passages based on user request (**document retrieval** module); then, they generate answers utilizing these relevant documents as references (**answer generation** module). In addition,

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<sup>1</sup>LangChain, <https://github.com/hwchase17/langchain>

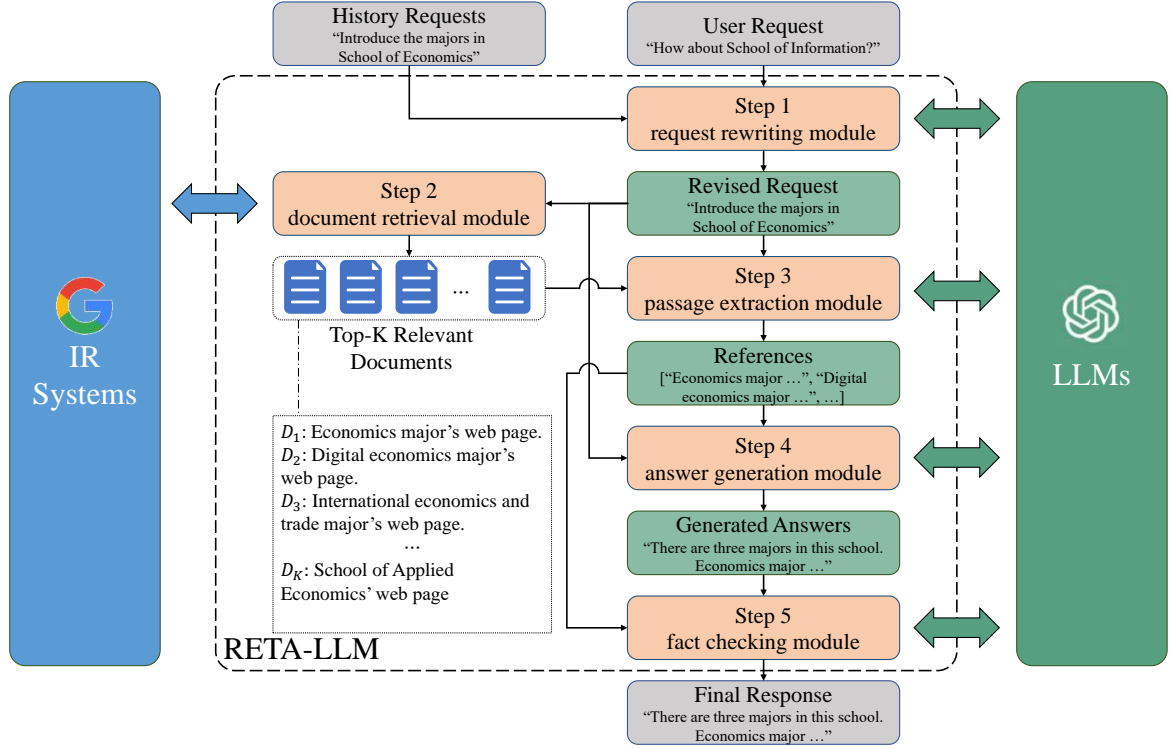


Figure 1: The RETA-LLM framework. Examples are taken from an intelligent university information seeking system powered by RETA-LLM.

tion to these two basic modules, our RETA-LLM provides three optional modules: (1) a **request rewriting** module to make user’s current request more complete and clear; (2) a **passage extraction** module to extract relevant passages or fragments from the whole retrieved document contents; and (3) a **fact checking** module to verify whether there exist factual errors in the generated answers. These optional modules can make the interaction between IR systems and LLMs more effective and smooth. The disentanglement between LLMs and IR systems in our RETA-LLM is more thorough, which makes the customization of search engines and LLMs more convenient. Furthermore, to make the usage easier, we provide a complete and ready-to-use pipeline for researchers and users to build their RETA-LLM toolkits based on their own repository for in-domain LLM-based systems from scratch.

RETA-LLM is part of YuLan, a open source LLM initiative proposed by Gaoling School of Artificial Intelligence, Renmin University of China. RETA-LLM is still under development and there are many issues that need to be solved with great efforts. We sincerely welcome contributions on this open source toolkit.

## 2 RETA-LLM Framework

As aforementioned, compared with Langchain, which is a common LLM-augmented toolkit, our RETA-LLM toolkit focuses specifically on retrieval-augmented LLMs. We provide five plug-in modules in RETA-LLM to interact with LLMs and IR systems. The modules include request rewriting, document retrieval, passage extraction, answer generation, and fact checking modules. The framework of our RETA-LLM is shown in Figure 1. The workflow of RETA-LLM is as follows:

First, RETA-LLM uses the request rewriting module to revise the current user request to make it complete and clear. Because users can issue a series of questions to the RETA-LLM, the semantics of the current user request may be incomplete. For example, A user may ask “How about the School of Information?” while the historical request is “Introduce the majors in School of Economics”. In this case, the precise meaning of the user is “Introduce the majors in School of Information”. Since LLMs have shown remarkable abilities in rewriting queries in conversational dense retrieval (Mao et al., 2023), we feed the current user request and the previous conversation histories to LLMs to perform rewriting.

Then, RETA-LLM uses the document retrieval module to retrieve relevant documents from the external corpus based on the revised user request. The document retrieval module is the module connected to the IR system. It retrieves relevant documents from the external knowledge corpus and returns top- $K$  of them. The  $K$  is set to 3 in our default configuration. We provide a default dense retriever in our repository. The detailed description can be found in the next section.

Next, RETA-LLM uses the passage extraction module to extract fragments related to the user request from the retrieved documents to form the references. Because of the input length limitations (typically 2048 or 4096 tokens) of LLMs, it is impossible to directly concatenate the contents of all top- $K$  relevant document contents as references for them to generate answers. Trivial methods by truncating the document contents may lose important information in them. Therefore, we reuse the LLMs themselves to extract related fragments from retrieved documents based on the revised request. Since the length of one document may also exceed the limitations, we apply the sliding window strategy to extract fragments step by step. The sliding window size and step are set to 512 and 256 in our default configuration. These fragments are then concatenated together as the references.

Besides, RETA-LLM uses the answer generation module to generate answers for the user request. As previous researches (Nakano et al., 2022; Shi et al., 2023; Jiang et al., 2023) suggest, by feeding the references retrieved from the external corpus, LLMs can generate more factual answers.

Finally, RETA-LLM uses the fact checking module to verify whether the generated answers contain factual mistakes and output final responses for the user request. Though providing additional evidence for generation, LLMs may also hallucinate (Nakano et al., 2022). It is necessary to devise a module to conduct further fact verification. Because of the strong natural language understanding abilities of LLMs, we feed the references and generated answers to them to make judgments. Therefore, RETA-LLM can decide whether to output the generated answers or just say “*I cannot answer this question*”.

Noticed that all the inputs to the LLMs are wrapped in instructions or prompts. As shown in Figure 1, we disentangle the IR systems and LLMs entirely in our RETA-LLM. This separate design

in our RETA-LLM leads users can customize their personal search engines and LLMs.

### 3 RETA-LLM Usage Pipeline

To make the toolkit more convenient for personal usage, we provide a complete pipeline to build in-domain LLM-based system based on html resources. The pipeline is as follows:

First, RETA-LLM uses Beautiful Soup package to convert the raw html files into json data in our **HTML Converter**.<sup>2</sup>

Second, RETA-LLM follows the implementation of disentangled-retriever (Zhan et al., 2022) to build dense indexes and to conduct domain adaption from the converted json data in our **Index Builder**.<sup>3</sup> Specifically, our method supports unsupervised training of dense retrieval models on local document collections, enabling the model to learn domain-specific knowledge in advance. Compared with the retrieval module in the popular LangChain library, our retrieval method has two advantages: (1) the model learns knowledge within the domain of local documents, enabling it to match queries more accurately, and (2) our method does not segment text, thus avoiding any negative impact on the overall semantic information of the text. We also provide a sparse retriever applying faiss (Johnson et al., 2019) package to build sparse indexes.<sup>4</sup> Otherwise, users can also use their customized search engines as the document retrieval module.

Third, users need to prepare LLMs for question answering. For LLM loading and responding, we provide the template for Alpaca (Taori et al., 2023),<sup>5</sup> YuLan,<sup>6</sup> ChatGLM (Zeng et al., 2022; Du et al., 2022), and GPT-3.5 API (Ouyang et al., 2022).<sup>7</sup> If users use other LLMs, they can edit the codes and configurations in our toolkit.

Finally, users can start their own RETA-LLM services using streamlit package.<sup>8</sup>

More details about the usage pipeline can be found on our Github repository.

<sup>2</sup>Beautiful Soup, <https://beautiful-soup-4.readthedocs.io/en/latest/>

<sup>3</sup>disentangled-retriever, <https://github.com/jingtaozhan/disentangled-retriever>

<sup>4</sup>Faiss, <https://github.com/facebookresearch/faiss>

<sup>5</sup>Alpaca, [https://github.com/tatsu-lab/stanford\\_alpaca](https://github.com/tatsu-lab/stanford_alpaca)

<sup>6</sup>YuLan, <https://github.com/RUC-GSAI/YuLan-Chat>

<sup>7</sup>OpenAI’s API, <https://api.openai.com/v1/completions>

<sup>8</sup>streamlit, <https://github.com/streamlit/streamlit>



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Figure 2: A case in RUC-enrollment-assistant system.

## 4 A RETA-LLM Service Case

Based on the RETA-LLM and the usage pipeline, we use the web pages on Renmin University of China’s enrollment online platform,<sup>9</sup> to build an RUC-enrollment-assistant system. The system uses a dense document retrieval module and adopts YuLan-13B as the backbone LLM. A using case is shown in 2. By enhancing the IR systems, LLMs can answer in-domain questions which cannot be answered by their own knowledge.

## 5 Conclusion and Future Work

In this paper, we propose RETA-LLM to facilitate research and development of retrieval-augmented LLMs. We provide five independent modules: request rewriting, document retrieval, passage extraction, answer generation, and fact checking modules in our toolkit. Furthermore, we provide a pipeline to help users build their in-domain LLM-based systems. In the future, we are going to include more retrieval-augmented LLM strategies such as active retrieval augmented generation (Jiang et al., 2023). Besides, we plan to make RETA-LLM more modularized and configurable.

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<sup>9</sup>Renmin University of China’s enrollment online platform, <https://rdzs.ruc.edu.cn>



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