CRUD-RAG: A Comprehensive Chinese Benchmark for Retrieval-Augmented Generation of Large Language Models

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Retrieval-Augmented Generation (RAG) is a technique that enhances the capabilities of large language models (LLMs) by incorporating external knowledge sources. This method addresses common LLM limitations, including outdated information and the tendency to produce inaccurate "hallucinated" content. However, the evaluation of RAG systems is challenging, as existing benchmarks are limited in scope and diversity. Most of the current benchmarks predominantly assess question-answering applications, overlooking the broader spectrum of situations where RAG could prove advantageous. Moreover, they only evaluate the performance of the LLM component of the RAG pipeline in the experiments, and neglect the influence of the retrieval component and the external knowledge database. To address these issues, this paper constructs a large-scale and more comprehensive benchmark, and evaluates all the components of RAG systems in various RAG application scenarios. Specifically, we have categorized the range of RAG applications into four distinct types—Create, Read, Update, and Delete (CRUD), each representing a unique use case. "Create" refers to scenarios requiring the generation of original, varied content. "Read" involves responding to intricate questions in knowledge-intensive situations. "Update" focuses on revising and rectifying inaccuracies or inconsistencies in pre-existing texts. "Delete" pertains to the task of summarizing extensive texts into more concise forms. For each of these CRUD categories, we have developed comprehensive datasets to evaluate the performance of RAG systems. We also analyze the effects of various components of the RAG system, such as the retriever, the context length, the knowledge base construction, and the LLM. Finally, we provide useful insights for optimizing the RAG technology for different scenarios[1].

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[1]The source code is available at GitHub:https://github.com/IAAR-Shanghai/CRUD_RAG

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ACM 0004-5411/2018/8-ART111
https://doi.org/XXXXXXX.XXXXXXX

CCS Concepts: • **Do Not Use This Code → Generate the Correct Terms for Your Paper**; *Generate the Correct Terms for Your Paper*; Generate the Correct Terms for Your Paper; Generate the Correct Terms for Your Paper.

Additional Key Words and Phrases: Do, Not, Us, This, Code, Put, the, Correct, Terms, for, Your, Paper

ACM Reference Format:
Yuanjie Lyu, Zhiyu Li, Simin Niu, Feiyu Xiong, Bo Tang, Wenjin Wang, Hao Wu, Huanyong Liu, Tong Xu, and Enhong Chen. 2018. CRUD-RAG: A Comprehensive Chinese Benchmark for Retrieval-Augmented Generation of Large Language Models. *J. ACM* 37, 4, Article 111 (August 2018), 26 pages. https://doi.org/XXXXXXX.XXXXXXX

1 INTRODUCTION

Retrieval-augmented generation (RAG) is an advanced technique that leverages external knowledge sources to enhance the text generation capabilities of large language models(LLMs). It retrieves relevant paragraphs from a corpus based on the input, and feeds them to the LLMs along with the input. With the help of external knowledge, LLMs can generate more accurate and credible answers, and effectively address the challenges such as outdated knowledge [14], hallucinations [17, 28], and lack of domain expertise [24, 37]. Therefore, RAG technology is attracting increasing attention.

Although the effectiveness of retrieval-augmented strategies has been proven through extensive practice, their implementation still requires a significant amount of tuning. The overall performance of the RAG system is affected by multiple factors, such as retrieval model, external knowledge base construction, and the language model. Therefore, automatic evaluation of RAG systems is crucial. Currently, there are only a few existing benchmarks for evaluating RAG performance. These benchmarks can be classified into two types: reference-required and reference-free evaluation. Reference-free evaluation frameworks, such as RAGAS [9] and ARES [35], measure the contextual relevance, faithfulness, and informativeness of the content generated by the RAG system. Given that these frameworks do not rely on ground truth references for evaluation, they are limited to evaluating the consistency of the generated text with the retrieved context. However, this approach becomes unreliable if the retrieved external information is of poor quality. Consequently, reference-required evaluations remain the predominant method for appraising RAG systems. Existing benchmarks for reference-required evaluations, such as RGB [5] and NQ [21]. do have their limitations.

First, they all rely on question answering tasks to measure the performance of RAG systems. Question answering is not the only application scenario of RAG, an optimization strategy that is effective for question answering may not work well for other scenarios. Therefore, these benchmarks may not reflect the generalizability of RAG systems. Second, current evaluations usually focus on the LLMs part of the RAG pipeline, and ignore the retrieval model and the external knowledge base. These components are also crucial for the RAG system, as they determine the quality and relevance of the retrieved paragraphs and the external knowledge. Hence, none of the benchmarks can provide a comprehensive evaluation of the RAG system.

To evaluate the performance of RAG in different application scenarios, we need a comprehensive benchmark that covers more than just the question answering task. Lewis et al. [23] argue that the core of the RAG systems is they interactive way of combining LLMs with external knowledge sources. And following [20], we can group any interaction with external knowledge sources into four basic actions: create, read, update, and delete, which are also known as CRUD actions. Therefore, we can use the CRUD framework to classify the RAG systems' application scenarios. As shown in Figure 1, each CRUD category demonstrates different capabilities of the RAG system: In "**CREATE**", the system improves the input text by adding relevant information from external sources, making creative outputs such as poetry, stories, or code. In "**READ**", the system uses external knowledge

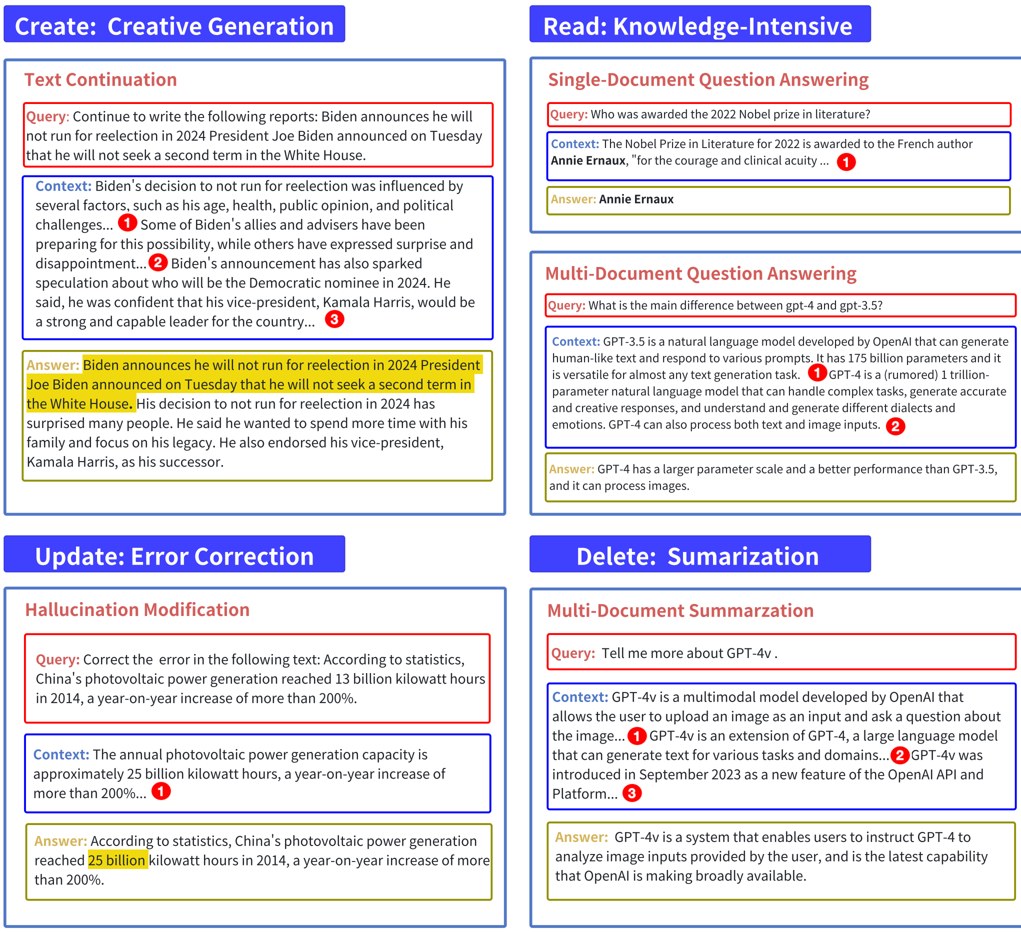

Fig. 1. We have classified the application scenarios of RAG into four primary aspects: Create, Read, Update, and Delete. The figure provides an illustrative example for each category, showcasing the wide-ranging potential of RAG technology.

retrieval to answer questions, solving problems in question-answering, dialogue, and reasoning, and increasing understanding of the input text. In "**UPDATE**", the system fixes errors in the input text using retrieved content, correcting spelling, grammar, or factual mistakes to make the text better. In "**DELETE**", the system simplifies the input by improving retrieval results, removing unnecessary details, and doing tasks like text summarization or simplification.

To evaluate the RAG system in these four scenarios, we introduce CRUD-RAG, a large-scale and comprehensive Chinese RAG benchmark. CRUD-RAG consists of four evaluation tasks: text continuation, question answering (with single-document and multi-document questions), hallucination modification, and open-domain multi-document summarization, which respectively correspond to the CRUD-RAG classification of RAG application scenarios. We constructed CRUD-RAG by crawling the latest high-quality news data from major news websites in China, which were not seen by the LLMs during training. We then created corresponding datasets for each scenario based on these news data. In the experiments, we systematically evaluate the RAG system's performance on our CRUD-RAG benchmark. We also investigate various factors that affect the RAG system, such as the context length, the chunk size, the embedding model, the retrieval algorithms and the LLM. Based on our experimental results, we provide some valuable suggestions for building effective RAG systems.

The contributions of this paper are:

- **A comprehensive evaluation system**: Our system covers not only question answering, but also create, read, update, and delete (CRUD) of RAG applications.
- **High-quality evaluation datasets**: We constructed diverse datasets for different evaluation tasks, based on the application scenarios of RAG. These tasks include text continuation, multi-document summarization, question answering and hallucination modification.
- **Extensive experiments**: we performed extensive experiments on our own benchmark, using various metrics to measure the performance of RAG systems. Based on our experiments, we offered useful guidance for future researchers and RAG system developers.

2 RELATED WORK

2.1 RAG: A Neural Text Generation Framework that Combines Retrieval and Generation

LLMs excel in text generation but also confront challenges such as outdated knowledge and the generation of hallucinatory content [4, 14, 34]. In response to these challenges, RAG, also referred to as RALM (Retrieval-Augmented Language Models), incorporate external knowledge to generate responses characterized by enhanced accuracy and realism [33, 38]. This is particularly critical in domains that heavily depend on precision and reliability, including but not limited to the legal, medical, and financial sectors.

Conventional RAG systems adhere to a standardized workflow encompassing indexing, retrieval, and generation phases [23, 29]. The indexing phase encompasses data cleansing, extraction, transformation into plain text, segmentation, and indexing, utilizing embedding models to transform text fragments into vector representations [1, 13]. In the retrieval phase, the system computes similarity scores based on the user's query to select the most pertinent text fragments. In the generation phase, the query and selected documents are amalgamated into prompts, facilitating the LLMs in generating a response. While this method is straightforward, it encounters challenges related to retrieval quality, generation quality, and enhancement processes [16, 18].

In response to these challenges, researchers concentrate on the enhancement of the retriever, a task that can be categorized into three key aspects: pre-retrieval processing, retrieval model optimization, and post-retrieval processing [15]. Pre-retrieval processing encompasses data transformer to enhance text standardization, ensuring factual accuracy, optimizing index structures, adjusting block sizes, and rewriting query [2, 12, 40, 42]. Retrieval model optimization entails the fine-tuning of domain-specific embedding models and the application of dynamic embedding techniques [7, 47]. Post-retrieval processing minimizes context length through reranking and compression operations, aiming to emphasize critical information, diminish noise interference, and enhance integration and utilization by the generator [30, 43, 44].

Furthermore, to enhance the precision and efficiency of the generator when handling retrieval content, scholars have undertaken a series of optimization measures. As an illustration, researchers have devised methods such as Chain-of-Note (CON) for the generator [46]. CON generates continuous reading notes to comprehensively evaluate the relevance of retrieved documents to the posed question, integrating this information to produce precise final responses. This approach further enhances the capability of RAG in managing retrieval information, guaranteeing the production of responses that are simultaneously accurate and pertinent. In specific domains, such as medical and

Table 1. Relate Work.

Method	Dataset	Scale	Evaluation Metrics	Evaluation Method	Application Field	Ref.	Lang.
[22]	Based on LangChain Python documentation QA dataset	86	Accuracy of answer, Faithfulness of response to the retrieved document	Evaluating retrieval and generation consistency	General QA scenarios (**R**ead)	Yes	EN
[22]	PDF documents containing tables and charts	5	Accuracy of answer, Faithfulness of response to the retrieved document	Evaluating retrieval and generation consistency	Semi-structured data scenarios (**R**ead)	Yes	EN
[26]	Query and responses (with citations)	1450	Fluency, Perceived utility, Citation recall and precision	Human evaluation	Citation (**R**ead)	Yes	EN
[32]	Questions, answers and contexts	200	Categorization ability, Logical/Mathematical reasoning, Complex question solving, Summarization ability	Accuracy	Financial services, Legal, Business (**R**ead, **D**elete)	Yes	EN
[5]	LLM-generated dataset	1000	Noise robustness, Negative rejection, Information integration, Counterfactual robustness	Self-devised metrics	General, especially news domain (**R**ead, **U**pdate)	Yes	CN EN
[11]	–	–	Context relevance, Groundedness, Answer relevance	Analyzing the RAG triad	General (**C**reate, **R**ead)	No	–
[9]	–	–	Faithfulness, Answer relevance, Context relevance	Automated evaluation using LLM prompts	General (**C**reate, **R**ead)	No	–
[35]	LLM-generated dataset	150	Context relevance, Answer faithfulness, Answer relevance	Generating custom LLM judges for each component of a RAG system	General (**C**reate, **R**ead)	No	EN
Ours	LLM-generated dataset	36166	ROUGE, BLEU, bertScore, RAGQuestEval	Evaluating retrieval and generation consistency	General (**C**reate, **R**ead **U**pdate, **D**elete)	Yes	CN

legal, models undergo fine-tuning to enhance the generator's performance within those particular fields [6, 19, 45]. Through the implementation of these methods, the generator can more effectively process retrieved information and furnish responses that are more accurate and relevant.

2.2 RAG Benchmark: Evaluation Datasets and Methods for Retrieval-Augmented Generation

When investigating the development and optimization of RAG, the effective evaluation of their performance becomes a fundamental concern. LangChain provides benchmark tasks, such as LangChain Docs Q&A and Semi-structured Reports [22], designed to assess various RAG architectures. These datasets are constructed from snapshots of Python documentation and PDFs containing tables and charts. They emphasize the model's capability to handle structured and semi-structured data. Evaluation standards encompass the accuracy of answers and the faithfulness of model responses. Utilizing large models for question-answering generation has emerged as a prevalent approach in building evaluation datasets. For instance, RGB [5] creates its evaluation dataset by gathering recent news reports and employing LLM to generate relevant events, questions, and answers. Conversely, ARES [35]. relies on generating synthetic queries and answers, leveraging the FLAN-T5 XXL model. These methods not only showcase the RAG system's proficiency in handling real-time data but also illustrate the utility of automation and synthetic data in the evaluation process. For evaluating the capabilities of models across various professional domains, the Instruct-Benchmark-Tester dataset encompasses a range of question types, with a particular focus on financial services, legal, and intricate business scenarios [32].

Depending on whether the evaluation phase incorporates ground truth, metrics of existing evaluation methods can be categorized into those necessitating reference and those not requiring it. Reference-required evaluation methods gauge the accuracy and robustness of the RAG by contrasting model-generated answers with factual benchmarks. As an example, RAG-Instruct-Benchmark-Tester [32] employs accuracy score as an evaluation metric, a widely acknowledged measure of model performance that assesses the extent to which model-generated answers align

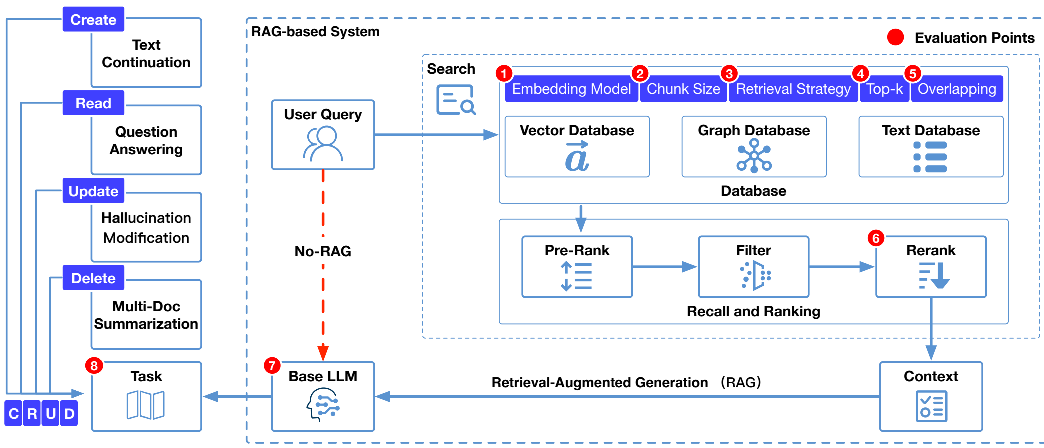

Fig. 2. Illustration of CRUD-RAG, our comprehensive Chinese benchmark for RAG. It classifies the RAG application scenarios into four categories: create, read, update, and delete. For each category, we created appropriate evaluation tasks and datasets. In the experiments, we evaluated various components of the RAG system using our benchmarks.

with reference answers. The primary objective of RGB [5] is to evaluate whether large models can effectively utilize external documents to acquire knowledge and generate accurate answers. Its evaluation metrics encompass accuracy, rejection rate, error detection rate, and correction rate. Tonic Validate incorporates metrics such as answer similarity score, retrieval precision, augmentation precision, accuracy, and answer consistency [10].

Reference-free evaluation methods, including TruLens-Eval [11], RAGAS [9], and ARES [35], provide distinct viewpoints for evaluating the performance of RAG systems, particularly concerning context relevance, answer faithfulness, and answer relevance. TruLens-Eval [11] introduces the RAG Triad as an innovative approach to evaluate hallucination issues within the RAG architecture, encompassing context relevance, groundedness, and answer relevance. RAGAS [9], serving as a reference-free evaluation framework, concentrates on assessing the retrieval system's capacity to identify pertinent and concentrated context passages, along with the LLMs' proficiency in faithfully and accurately leveraging these passages. In contrast to RAGAS, which depends on a predefined set of heuristically crafted prompts, ARES generates tailored LLMs judges for each aspect of a RAG pipeline, leading to a substantial enhancement in evaluation precision and accuracy when compared to existing methods such as RAGAS. Furthermore, ARES [35] employs prediction-powered inference to offer statistical assurances for its scoring, generating confidence intervals. ARES emphasizes three evaluation scores: context relevance, answer faithfulness, and answer relevance, highlighting the importance of a proficient RAG system in identifying relevant contexts and producing both faithful and relevant answers. Regarding evaluation methods, [26] places an emphasis on assessing the credibility and accuracy of responses generated by generative search engines through manual inspection. Nonetheless, manual evaluation possesses drawbacks, including high costs and challenges in scalability. Hence, rule-based evaluation metrics such as accuracy, exact match, rouge, or self-devised metrics like rejection rate, error detection rate, and correction rate continue to be widely adopted in the field. Furthermore, employing large language models for evaluation closely approximates manual evaluation outcomes.

3 CRUD-RAG: A COMPREHENSIVE CHINESE BENCHMARK FOR RAG

As we discussed earlier, implementing RAG effectively requires careful tuning of multiple components, such as the retrieval model, the knowledge corpus, the language model, and the query formulation. Therefore, we need a framework that can evaluate the RAG system automatically. This framework would enable us to examine how these components affect the system's performance, and provide us with useful insights for improving and innovating the system.

However, The current RAG benchmarks have several drawbacks: they only evaluate question answering tasks, ignoring other diverse application of RAG. The optimization strategy for question answering tasks may not suit other tasks; And in the evaluation experiment, current RAG benchmarks only account for the large language model component in the RAG pipeline, disregarding the vital roles of retrieval database construction and retrieval.

To address the shortcomings of previous benchmarks, we introduce CRUD-RAG, a comprehensive Chinese benchmark for RAG. Figure 2 illustrates the features of our CRUD-RAG benchmark. It classifies the application scenarios of RAG into four categories: Create, Read, Update, Delete, and constructs appropriate evaluation tasks and datasets for each category. Besides, in the experiments, we will assess the impact of various components of RAG, such as chunk size, retrieval strategy, top-k, LLM, etc., on all tasks.

In the following section, we will describe the evaluation tasks and the datasets that we designed for each RAG application scenario type.

3.1 News Collection

As mentioned above, the existing benchmarks for evaluating RAG systems are mainly constructed for question answering tasks. Therefore, the datasets, such as NQ [21] and RGB [5], are also tailored for this type of task. Hence, we need to construct new datasets.

We argue that the latest news data is the most suitable choice for creating a RAG evaluation dataset. Unlike other types of data, such as encyclopedias, questions, or conversations, the latest news data prevent the model from generating answers directly from its own knowledge base. Instead, the model has to use external documents to generate content. This allows us to evaluate the performance of the overall RAG pipeline, rather than just the model's generation capabilities. Moreover, the latest news data offer rich and diverse topics and content, which can test the model's performance and adaptability in various domains and situations.

Therefore, we select news as the base of our datasets. To ensure the authenticity and currency of the datasets, we collected nearly $300,000$ of historical news articles from major Chinese news websites published after July 2023, which were unseen by the LLMs during the training phase. Based on the news corpus we collected, we constructed our datasets for three tasks, namely open-domain multi-document summarization, text continuation, and question answering.

3.2 Open-domain Multi-document Summarization: RAG Application in "Delete"

In the "Delete" scenario of RAG application, the RAG system retrieves key information from external sources based on the input text, and eliminates redundancy and irrelevance, to generate concise summaries. A suitable task for evaluating this scenario is multi-document summarization, which aims to generate a brief and coherent summary from a set of related documents. For the news data we collect, this task involves retrieving major media reports on a news event, and summarizing the background, process, and results of the event.

However, constructing such a dataset is extremely challenging. First, news articles retrieved based on events may not be fully relevant, requiring manual filtration to identify the correct and pertinent documents. Then, when generating summaries from these documents, it is essential

Table 2. The composition of our dataset.

Dataset Name	Dataset Size	Components	Evaluation objectives
Text Continuation	10,728	An initial part of an article, followed by its extension or completion.	Evaluate the RAG system's performance in "Create" scenarios(Creative generation).
Question Answering (1-document)	3,199	A collection of question-answer pairs, where the answer is directly extractable from a document passage.	Evaluate the RAG system's performance in "Read" scenarios(Knowledge-intensive application).
Question Answering (2-document)	3,192	A collection of question-answer pairs, where the answer **requires synthesis of information from 2 different document sources**.	The objective is the same as 1-document QA, but it also examines **the reasoning ability of combining 2 documents**.
Question Answering (3-document)	3,189	A collection of question-answer pairs, where the answer **requires synthesis of information from 3 different document sources**.	The objective is the same as 1-document QA, but it also examines **the reasoning ability of combining 3 documents**.
Hallucination Modification	5,130	Some sentences containing errors, and the sentence with the errors fixed.	Evaluate the RAG system's performance in "Update" scenarios(Error correction application).
Multi-Doc Summarization	10,728	A one-sentence headline of an article, followed by a brief summary of the article.	Evaluate the RAG system's performance in "Delete" scenarios(Summarization).
Retrieval Database	86,834	As the knowledge base for the RAG system, we expect the RAG system to retrieve relevant content from the knowledge base to address the above tasks.	———

to eliminate a significant amount of redundant information, retaining only the most important content. These tasks require manual annotation, which consumes substantial time and financial resources, and often result in too much superfluous information.

Fortunately, we can use an existing method, which construct a multi-document summary dataset in reverse [27]. Figure 3 shows the construction process of multi-document summarization. In particular, our dataset construction process is as follows:

- Instead of generating event summaries based on multiple related news content, we first acquire a news article from a high-quality corpus, and annotate its summary and events.
- Then, we search for external reference materials related to the current news by using the event text, ensuring they are connected but not overly similar. We conduct extensive searches to gather sufficient information to reconstruct the summary of the selected news.
- In this manner, the reference literature we collect, along with the summary of the current news, collectively form a dataset of multi-document summarization.

Specifically, we first select $10,000$ news articles d from our high-quality news corpus D, and then use GPT-4 to generate summaries and events for each article. Next, we use the events as keywords, and search for the most relevant 10 news articles on Baidu, excluding any data that is too similar to the original article. We repeat this process for all the articles, and add the expanded articles to our news corpus, removing the $10,000$ articles d simultaneously. The new news corpus $D - d + E$ serves as our retrieval corpus, and we expect the model to use the events and relevant information from the retrieval corpus to generate summary for the articles d.

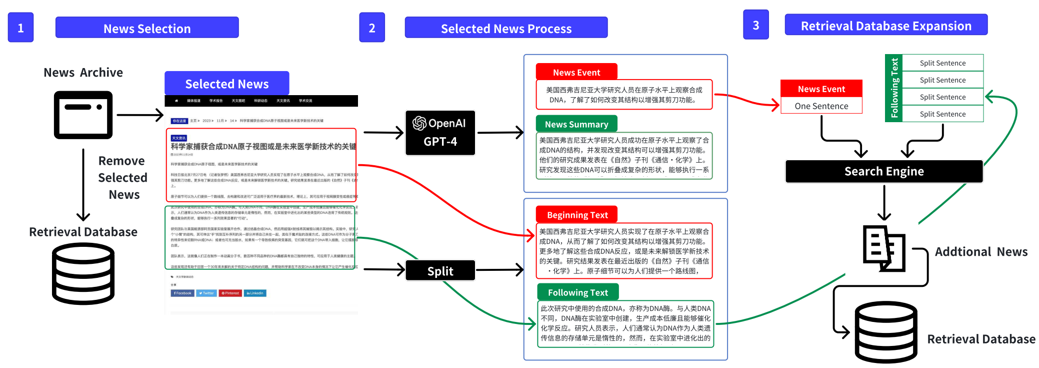

Fig. 3. The dataset construction pipeline for text continuation and open-domain multi-document summarization task.

3.3 Text continuation: RAG Application in "Create"

RAG is useful not only for "Delete", where it retrieves and summarizes key information from massive texts, but also for "Create". In this scenario, RAG systems show strong creativity by expanding existing texts, and we take the text continuation task as an evaluation. The text continuation task aims to automatically produce coherent and relevant subsequent content based on the beginning of the text, making the text more complete and vivid.

To construct the continuation task dataset, we follow the same method as the summary task dataset. Figure 3 shows the construction process of text continuation. Specifically, we select a news article from a high-quality corpus and use jieba, a specialized Chinese word segmentation tool, to split it into sentences. Then, we divide the article into two equal parts: the first half serves as the input and the second half as the output of the continuation dataset. We expect the model to use RAG technology to retrieve relevant information from the document library and generate a continuation that is coherent, informative, and consistent with the input and output.

To ensure that the retrieval database covers the real continuation text, we use Baidu search engine to find external documents and add them to the database. The continuation text differs from the event text in that it consists of multiple sentences. Therefore, we split the continuation text into paragraphs by sentences and retrieve relevant documents for each paragraph using search engine. This way, we guarantee that the retrieval database contains most of the information to reconstruct the continuation text.

3.4 Question Answering: RAG Application in "Read"

Another application scenario of RAG is to use external knowledge bases to enhance the question-answering capabilities of large language models, which can be applied to various knowledge-intensive tasks. Currently, there are many evaluation benchmarks to measure the performance of RAG in this scenario, and multiple question answering datasets have been created.

However, the existing question answering datasets also have some limitations. On the one hand, some datasets (such as NQ and WEBQA) are outdated, and may have been covered by large language models in the pre-training stage, which reduces the advantage of RAG systems. On the other hand, some datasets (such as RGB) only contain some factual questions, which can be directly extracted from the retrieved texts, without requiring complex reasoning over multiple texts, which poses

Fig. 4. The dataset construction pipeline for multi-document(inferential) question answering task.

less challenge to RAG systems. The most recent LLMs capture enough knowledge to rival human performance across a wide variety of question answering benchmarks [3].

To overcome these limitations, we build a large-scale question answering dataset, which is divided into two parts: single-document and multi-document question answering. Single-document question answering focuses on factual questions that ask for specific details in the news, such as the location or the main characters of an event. Multi-document question answering, on the other hand, involves inferential and critical thinking questions that require readers to reason across multiple news paragraphs, such as comparing and contrasting two events or assessing their impact.

For the single-document question answering task, we follow the dataset construction process of the previous RGB benchmark [5]. We first select news articles from our collected high-quality corpus. Then we use prompts to make ChatGPT generate questions and answers for each article. For example, for a report on "The 2023 Nobel Prize", ChatGPT will generate the question "Who was awarded the 2023 Nobel Prize for Physiology and Medicine?" and provide key information for answering it.

For the multi-document question answering task, constructing a reasoning question that requires the synthesis of multiple documents is not trivial. Simply using a prompt to force ChatGPT to generate the question is ineffective, because creating such a multi-document QA dataset is a complex reasoning task in itself. Therefore, we adopt Chain-of-Thought (CoT) technology [41] to enhance ChatGPT. We guide the model to build the dataset gradually through multiple reasoning steps. Figure 4 illustrates our specific process for building a two-document question answering dataset using ChatGPT. We will explain it in detail:

(1) **Retrieve multiple connected news**, which should cover the same event, but offer different perspectives or information.
(2) **Identify the common elements between different reports**, such as the event they report on, and ensure they are relevant.

(3) **Distinguish the differences between news articles**. While keeping the connection between reports, we analyze the differences between each report. This step requires comprehensive understanding and analysis from multiple angles, and avoids generating questions that can be answered from a single paragraph.
(4) **Generate question based on different focus points**, which should require integrating information from multiple sources to answer.
(5) **Reconstruct the question based on the contact point**. Based on the connections in the reports, refine the questions, ensuring the inherent logical connection, and avoiding superficial combinations. The questions should be logically linked, rather than physically juxtaposed. For example, instead of simply asking 'Describe the history of World War II and explain the basic principles of quantum physics, a question like 'How did the technological and political environment during World War II foster the development of quantum physics?' should be formulated, where the parts are interdependent or have causal relationships.

We constructed two types of multi-document question answering datasets with different levels of difficulty: one requires reasoning from 2 documents to answer the question, and the other is more challenging and requires reasoning from 3 documents to answer the question.

3.5 Hallucination Modification: RAG Application in "Update"

Besides the three scenarios mentioned above, the RAG framework can also be used to correct errors in the text. This involves using the RAG framework to access relevant information from external sources, identify and correct errors in the text, and maintain the accuracy of the text content.

We construct a hallucination modification dataset using the open-source large-scale dataset UHGEval [25]. UHGEval instructs the model to generate continuations that contain hallucinations for a given news text. It utilizes GPT-4 for automatic annotation and human evaluation to identify and mark segments in the text containing hallucinations. In our approach, we input the hallucination text along with the corresponding annotations from the dataset. Subsequently, GPT-4 is employed to rectify the hallucinations, resulting in the production of the text without any hallucinatory elements. Finally, real news continuations will be included in the document retrieval database.

The RAG system's experimental results on this dataset can confirm if the system can retrieve the real news information from the document database based on the input text, which consists of the beginning text and the hallucination continuation text, and then correct the hallucination text to generate the text without hallucination.

3.6 Evaluation Method

The aim of this benchmark is to evaluate how well RAG systems can retrieve relevant documents, and use them to generate sensible responses. Therefore, we adopt an end-to-end evaluation method, which directly compares the similarity between the model output and the reference answers.

Evaluating the performance of RAG systems requires choosing appropriate evaluation metrics. We considered the previous evaluation metrics for text generation, **ROUGE** and **BLEU**, which are both based on word overlap. ROUGE mainly counts the recall rate on n-gram, while BLEU mainly counts the precision rate on n-gram. However, BLEU and ROUGE are word overlap-based accuracy metrics that depend on the overall expression of the text, and do not capture the accuracy of the particular key information in the text. Therefore, they may not reflect the factual consistency of a text well, especially for long texts. To alleviate this issue, recent work [8, 36, 39] has proposed new evaluation metrics for abstractive summarization evaluation. These metrics are based on the intuition that if you ask questions about the summary and the original document, you will get

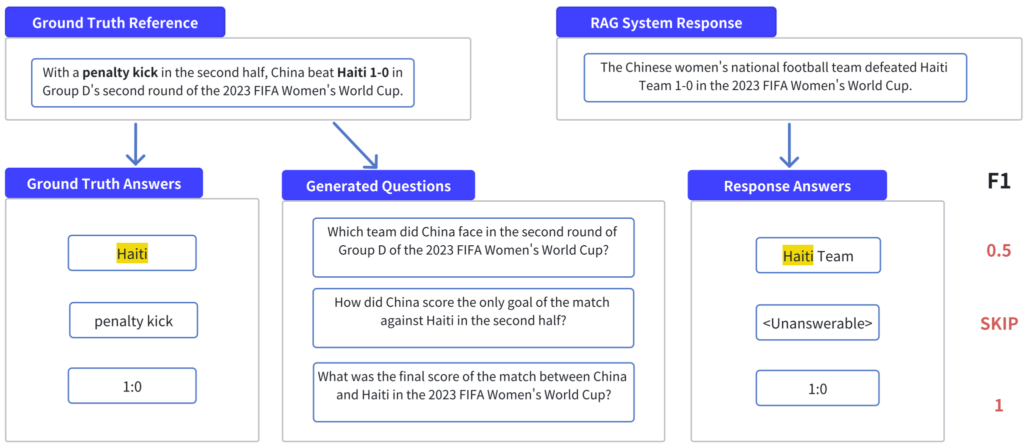

Fig. 5. Overview of RAGQuestEval. A set of questions is generated based on the ground truth references. The questions are then answered using both the ground truth and the response. For the recall score of RAGQuestEval, we calculate the ratio of answerable questions to all questions(in this case, recall = 2/3). For the precision score of RAGQuestEval, corresponding answers are compared using a similarity function and averaged across questions(in this case, precision = (0.5 + 1) / 2 = 0.75). The recall metric of RAGQuestEval indicates how much of the key information in the ground truth reference is included in the generated text, while the precision metric of RAGQuestEval indicates how correct the recalled key information is.

a similar answer if the summary realistically matches the original document. They evaluate the accuracy of each local piece of key information in the summary.

We also consider question answering-based metrics to evaluate the factual accuracy of generation. In this paper, we examine **QuestEval** [36], a metric that improves the correlation with human judgments over previous metrics in their extensive experiments. QuestEval evaluates the factual consistency between the generated text and the source document, which is mainly used for text summarization tasks. Therefore, it does not require any ground truth reference. However, for RAG systems, the retrieved texts may be irrelevant or incorrect, so consistency with them is not a valid criterion. Instead, we use this metric to measure how well the generated text matches the ground-truth reference. We call this metric **RAGQuestEval**. We will explain this metric in detail.

Let GT and GM be two sequences of tokens, where GT denotes the ground truth references and GM the corresponding evaluated generations. First, we generate a series of questions from the ground truth references GT using the QuestEval method, which extracts entities and noun phrases from the text. The goal of **RAGQuestEval** is to check if the generated text includes and conveys correctly all the key information from the ground truth reference.

Next, we answer these questions using both real references and model-generated text. If the question is unanswerable, the model returns "<Unanswerable>".

Finally, we calculate two scores to evaluate the quality of the generated text: recall and precision.

Recall. Recall is the ratio of answerable questions to all questions. This score shows how much information in the ground truth reference is captured by the text generated by the RAG system. A higher recall means that the generated text covers more information from the reference.

$$\text{Recall}(GT, GM) = \frac{1}{|Q_G(GT)|} \sum_{(q,r) \in Q_G(GT)} \mathbb{I}[Q_A(GM, q) \neq <\text{Unanswerable}>] \tag{1}$$

In the above equation, Q_G is the question generator and Q_A is the question answerer.

Precision. Precision is the average answer similarity of all questions, excluding the unanswerable ones. We use the token level F1 score to measure the answer similarity, which is a standard metric for evaluating factoid question answering models. Higher precision means that the generated text is more accurate and consistent with the reference.

$$\mathrm{Prec}(GT, GM) = \frac{1}{|Q_G(GT)|} \sum_{(q,r) \in Q_G(GT)} F1\left(Q_A(GM, q), r\right) \tag{2}$$

4 EXPERIMENT

The current evaluation of RAG Benchmark only focuses on the large language model component in the RAG pipeline, and overlooks the importance of retrieval database construction and retriever. To address this gap, we examine how different aspects of RAG systems affect their performance in our benchmark. We also discuss some possible ways to improve existing RAG systems.

4.1 Experimental Settings

In this section, we will introduce the components of the RAG system, and describe how we conduct experiments to evaluate their impact on system performance. The RAG system consists of the following components:

- **Chunk size**: The RAG system splits the external knowledge into chunks of a certain length and stores them in a vector database. The chunk size affects the retrieval accuracy and the completeness of the context.
- **Chunk overlap**: Chunk overlap refers to the shared tokens between two consecutive text chunks and is used to ensure semantic coherence when chunking.
- **Embedding model**: The RAG system converts the text chunks and the user's query into vectors using an embedding model or other methods. The embedding model affects the quality and relevance of the context.
- **Retriever**: The RAG system uses a retriever to find the top-k vectors most similar to the query vector in the vector database and fetches the corresponding text chunks. The retriever affects the richness and diversity of the context.
- **Top-k**: This is the number of text chunks that the RAG system retrieves for each query, which serve as the context part of the LLMs prompts. The top-k influences the size of the context that the model receives.
- **Large language model**: The RAG system inputs the context and the query to an LLM to generate the answer. The LLM affects the correctness and rationality of the answer.

We use the following settings as the basic version of our RAG system: chunk size: 128, chunk overlap: 0%, embedding model: bge-base, retriever: dense retriever, top-k: 8, and LLM: GPT-3.5. In the experiments, we change one component at a time and evaluate the results on different tasks. We compare the following values for each component:

- Chunk size: 64, 128, 256, 512.
- Chunk overlap: 0%, 10%, 30%, 50%, 70%.
- Embedding model: m3e-base, bge-base, stella-base, gte-base.
- Retriever: dense, bm25, hybrid, hybrid+rerank.
- Top-k: 2, 4, 6, 8, 10.
- Base LLMs: GPT-3.5, GPT-4, ChatGLM2-6B, Baichuan2-13B, Qwen-7B, Qwen-14B.

In the experiments, we use two types of evaluation metrics: The overall semantic similarity metrics(bleu, rouge-L, and bertScore) measure how closely the generated content matches the

Table 3. The experimental results for evaluating different chunk size in our benchmark. We use two types of evaluation metrics: The overall semantic similarity metrics(bleu, rouge-L, and bertScore) and the key information metric(RAGQuestEval).

task name	chunk size	topk	bleu	rouge-L	bertScore	RAGQuestEval		length
						precision	recall	
text continuation	64	16	3.42	17.67	83.94	26.09	23.39	345.8
	128	8	3.66	17.78	83.99	26.96	24.68	367.6
	256	4	4.21	17.93	**84.17**	28.86	25.99	403.0
	512	2	**5.12**	**18.81**	83.57	**30.91**	**28.27**	413.2
summarization	64	16	**24.60**	33.78	88.07	**68.29**	43.98	184.2
	128	8	23.69	33.53	88.49	68.06	46.18	205.9
	256	4	22.97	**33.85**	88.83	67.87	48.66	219.9
	512	2	21.08	33.23	**88.89**	66.43	**50.31**	243.6
question answering 1-document	64	16	37.50	55.45	83.02	48.31	68.62	71.5
	128	8	**39.76**	**57.24**	83.81	52.67	70.82	73.3
	256	4	38.43	56.20	**84.02**	**52.83**	**72.21**	79.6
	512	2	36.51	54.64	82.72	51.26	68.65	84.1
question answering 2-document	64	16	19.86	34.80	86.14	37.77	52.60	143.1
	128	8	22.75	37.25	87.16	42.93	56.73	149.8
	256	4	**24.38**	39.36	88.18	48.45	61.75	164.5
	512	2	24.05	**39.69**	**88.22**	**49.24**	**63.37**	176.7
question answering 3-document	64	16	18.55	33.39	86.85	34.91	47.95	146.1
	128	8	21.05	35.04	87.81	40.32	51.37	156.6
	256	4	**21.63**	36.03	88.10	42.55	53.80	171.2
	512	2	21.40	**36.55**	**88.38**	**44.28**	**57.38**	183.6
hallucination modification	64	16	**34.20**	**54.90**	**81.14**	64.98	80.96	60.7
	128	8	32.35	53.04	80.49	**65.07**	80.85	64.8
	256	4	31.48	51.76	80.15	64.93	**80.99**	67.7
	512	2	30.35	50.50	79.66	64.83	79.17	66.6

reference content in terms of meaning and fluency; and the key information metric(RAGQuestEval) measure how well the generated content captures and presents the key information from the reference content.

4.2 Analyzing the Impact of Chunk Size on RAG Performance in Different Tasks

Chunking is the process of dividing a document into chunks of a fixed length, and then converting each chunk into a vector and storing it in an index. This creates an external knowledge index. Chunk size is a crucial parameter that varies depending on the corpus characteristics. If the chunk is too small or too large, it can reduce the search accuracy or omit important content. Hence, finding the optimal chunk size is vital for ensuring the search accuracy and relevance, and enabling the LLMs to generate appropriate responses. Our experiments reveal that different RAG tasks correspond to different optimal chunk sizes.

Text Continuation: The experimental results in Table 3 demonstrate that larger chunk size can significantly improve the overall semantic similarity measures (bleu, rouge-L, bertScore). Besides, the RAGQuestEval metrics, which reflect the precision and recall rate of key information, follow a consistent pattern. This indicates that larger blocks preserve the original document's structure, which is crucial for creative tasks such as text continuation. Smaller chunks, on the other hand, result in fragmented and semantically incoherent content, which impairs the ability of large models to understand and generate engaging content.

Open-Domain Multi-Document Summarization: We observe some intriguing patterns in the experimental results. Firstly, we discover that larger chunk size not only substantially increase the length of the generated text, but also cause a notable drop in the bleu score, while the rouge-L and bertScore remain almost unchanged. This implies that larger chunks can preserve more original text information, but also introduce some semantic redundancy. Secondly, for the RAGQuestEval metric that evaluates key information, we found that a larger chunk size considerably enhances the recall of key information, but also lowers the precision of key information.

We hypothesize that this is because larger blocks enable the retrieval of more relevant content without breaking the article structure, thus improving the recall of key information. However, larger blocks also make the summarization task more challenging, as more fine-grained selection is required from the more relevant information, leading to lower precision of key information.generated text, which may not be a good thing for the summary.

Question Answering: For single-document QA, larger blocks will reduce both recall and precision score of key information. The task only requires extracting information from a sub-paragraph of a single document, and the answer may be in a specific sentence. Therefore, smaller chunks are more suitable, as excessive content will make the extraction harder for the model.

For multi-document QA, the results are different from those of single-document QA. Larger blocks can significantly improve the recall and precision of key information, as well as the semantic similarity of the generated and reference answers. This is because larger blocks retain the original structure of the article, which is crucial for reasoning understanding tasks, and fragmented information is not conducive to reasoning.

Hallucination Modification: For the hallucination modification task, the results are similar to those of the single-document QA task. Smaller blocks can significantly improve the semantic similarity metrics, such as BLEU score. This indicates that in the hallucination dataset created by UHGEval, the hallucination information often pertains to only one sentence, which is a mistake at the word or entity level, and does not require the comprehension of long text. Hence, there is no need to understand the whole document, only the relevant portions can be retrieved and modified.

4.3 Analyzing the Impact of Chunk Overlap on RAG Performance in Different Tasks

Chunk overlap is the number of tokens that two adjacent chunks share. To keep the text semantics coherent, adjacent chunks have some overlap. Chunk overlap determines the size of this overlap. This splitting method meets the maximum length limit of LLMs and maintains the semantic connection between adjacent chunks. Suitable chunk size and overlap can enhance the fluency and coherence of large language models for long texts. We will show how the chunk overlap rate affects the system performance for different tasks in the Table 4.

Text Continuation: With an increase in chunk overlap, we observe significant enhancements in the metrics that evaluate the alignment of generated text with a reference answer (BLEU, ROUGE, and BERTScore). The RAGQuestEval metric, which evaluates the accuracy and completeness of important information, also improves. These results indicate that a greater chunk overlap is beneficial for preserving the flow of ideas in the text, which is essential for tasks that require generating new, creative content.

Open-Domain Multi-Document Summarization: During summarization tasks, all evaluation metrics show a slight improvement as chunk overlap grows. Interestingly, despite assumptions that more overlap might reduce the variety of context information available, this does not result in a lower rate of recalling important information. In fact, the best performance in terms of recall

Table 4. The experimental results for evaluating different chunk overlap values in our benchmark.

task name	chunk overlap(%)	bleu	rouge-L	bertScore	RAGQuestEval		length
					precision	recall	
text continuation	0	3.66	17.78	83.99	26.96	24.68	367.6
	10	3.86	17.84	84.03	27.18	24.21	359.2
	30	3.91	17.92	**84.12**	28.21	24.72	367.0
	50	3.94	17.86	84.01	**28.34**	24.48	365.4
	70	**4.03**	**17.95**	84.04	27.64	**25.32**	364.0
summarization	0	23.69	33.53	88.49	68.06	46.18	205.9
	10	23.54	33.59	88.35	**68.67**	46.16	208. 4
	30	23.74	33.58	88.41	68.02	46.08	203.3
	50	24.05	33.99	88.62	68.61	46.64	204.2
	70	**24.49**	**34.29**	**88.71**	68.45	**47.08**	201.8
question answering 1-document	0	**39.76**	57.24	83.81	52.67	70.82	73. 3
	10	39.36	**57.59**	83.77	51.87	71.36	73. 3
	30	39.43	57.40	83.87	53.30	72.74	73.5
	50	39.31	57.27	**84.14**	53.85	73.63	74.6
	70	38.46	57.01	84.10	**54.06**	**73.94**	75.5
question answering 2-document	0	22.75	37.25	87.16	42.93	56.73	149.8
	10	23.41	37.72	87.33	43.18	56.50	149.4
	30	23.02	37.37	87.24	43.64	58.25	149.4
	50	23.65	38.33	87.61	43.98	59.21	152.2
	70	**23.69**	**38.51**	**87.76**	**44.84**	**59.53**	152.2
question answering 3-document	0	21.05	35.04	87.81	40.32	51.37	156.6
	10	21.08	**35.56**	87.57	41.62	50.74	154.6
	30	21.39	35.49	87.78	40.96	51.33	155.9
	50	**21.60**	35.48	87.83	**41.91**	**51.97**	157.4
	70	21.10	35.11	**87.95**	41.39	51.58	158.9
hallucination modification	0	32.35	53.04	80.49	65.07	80.85	64.8
	10	32.57	53.29	80.51	65.30	**81.36**	63.9
	30	**33.72**	**53.98**	**80.69**	64.53	80.91	63.6
	50	32.58	52.92	80.49	65.07	80.18	65.7
	70	31.77	52.13	80.12	**65.80**	81.06	66.9

occurs at a chunk overlap of 70%. This could mean that a larger overlap allows the model to focus more on the main points and ignore less relevant or redundant information.

Question Answering: The consistency of meanings across diffierent chunks is especially important in question answering tasks. Data shows that as chunk overlap increases, the metrics of precision and recall of key information improve significantly in the single-document question answering task. A similar improvement is evident for two-document question answering. However, for three-document question answering, the enhancements are more modest. This might be because these tasks require a wealth of context, and a large chunk overlap could cut down on the context available.

Hallucination Modification: Changes in chunk overlap have a minimal effect on the performance metrics for tasks that involve correcting hallucinations. This is likely due to the errors in these tasks typically being specific to individual entities or words, making the consistency of the chunks less impactful.

Table 5. The experimental results for evaluating different retrievers in our benchmark.

task name	retriever name	bleu	rouge-L	bertScore	RAGQuestEval		length
					precision	recall	
text continuation	BM25	3.51	17.56	83.83	**27.25**	23.70	370.5
	Dense	3.66	**17.78**	**83.99**	26.96	**24.68**	367.6
	Hybrid	**3.69**	17.69	83.97	27.24	24.01	362.4
	Hybrid+Rerank	3.55	17.55	83.90	26.69	24.02	370.3
summarization	BM25	**25.19**	33.77	87.82	**70.78**	44.30	190.4
	Dense	23.69	33.53	**88.49**	68.06	46.18	205.9
	Hybrid	24.21	33.81	88.24	68.70	45.63	199.8
	Hybrid+Rerank	24.33	**33.90**	88.48	68.34	**46.41**	200.2
question answering 1-document	BM25	39.91	57.33	83.36	51.90	69.17	69.6
	Dense	39.76	57.24	83.81	52.67	70.82	73.3
	Hybrid	39.67	57.38	84.06	52.71	70.83	70.8
	Hybrid+Rerank	**40.63**	**58.26**	**84.68**	**54.60**	**73.92**	72.8
question answering 2-document	BM25	**24.61**	38.31	86.86	42.26	54.56	138.4
	Dense	22.75	37.25	87.16	42.93	56.73	149.8
	Hybrid	24.03	38.43	87.30	45.67	58.01	144.6
	Hybrid+Rerank	24.53	**38.91**	**87.89**	**47.18**	**58.12**	151.7
question answering 3-document	BM25	20.98	34.33	87.02	37.04	48.53	147.6
	Dense	21.05	35.04	87.81	40.32	51.37	156.6
	Hybrid	21.35	35.34	87.66	41.07	51.09	150.8
	Hybrid+Rerank	**21.74**	**35.88**	**88.21**	**41.59**	**52.84**	157.1
hallucination modification	BM25	**33.09**	**54.21**	**80.86**	64.80	79.90	59.0
	Dense	32.35	53.04	80.49	65.07	80.85	64.8
	Hybrid	32.22	52.92	80.57	**66.30**	**81.03**	63.4
	Hybrid+Rerank	32.62	53.01	80.62	65.57	80.82	64.9

4.4 Analyzing the Impact of Retriever on RAG Performance in Different Tasks

A retriever is a key component of the RAG pipeline, which finds relevant documents from a large database based on the user input, and provides contextual information for the large model. There are two main types of retrievers: **Keyword-based search-sparse retrieval algorithms**, which use keywords and their frequencies to compute the relevance between documents and queries. Common sparse retrieval algorithms include TF-IDF and BM25. BM25 is an enhanced TF-IDF method, which accounts for factors such as the length and position of words in the document. **Dense retrieval algorithms**, which use deep learning models to encode documents and queries into low-dimensional vectors, and then measure the cosine similarity between them. This method can capture the semantic and contextual information of words, and improve the retrieval performance.

In order to combine the advantages of both types of retrievers, we can fuse their retrieval results and randomly sample k from them as contexts for LLMs(**Hybrid**). Alternatively, we can also use a re-ranking model to re-rank the fused retrieval results, and then select the top-k ones as the context of LLMs(**Hybrid+Rerank**). In our experiments, we employ the bge-rank as the rerank model.

Text Continuation: As Table 5 displays, dense retriever outperforms BM25. Compared to the keyword-based algorithm, the modern vector search can capture the semantic and contextual information of words, and greatly enhance the retrieval performance. Thus, in the RAG pipeline, the generation results using dense retriever are also better. However, the RAG system using BM25 also performs well. In terms of the precision of key information, BM25 even exceeds Dense retriever. This suggests that in the continuation task, which is a creative task, BM25 can retrieve content that is highly relevant to the user's intention, but may overlook some details.

Open-Domain Multi-Document Summarization: On the overall semantic similarity metric, BM25 outperforms dense retriever. On the QuestEval metric, BM25 surpasses dense retriever in terms of key information precision, but slightly trails behind in key information recall. If the retrieved content contains a lot of irrelevant information, the model-generated summary may have errors or redundancies. BM25 retrieved content usually matches the user's intention better, but sometimes may miss some important information. Therefore, BM25 is slightly weaker than dense retriever in key information recall, but excels in key information accuracy. Besides, hybrid retrieval algorithms presumably combine the advantages of both, and the RAG system generates content with suitable precision and recall.

Question Answering: In question answering, we find that dense retriever has a more obvious advantage over BM25, when dealing with reasoning questions that require synthesizing multiple documents. In question answering tasks that require considering three documents, Dense retriever not only surpasses BM25 in all the overall semantic similarity metrics, but also achieves a significant improvement in key information precision and recall. This indicates that question answering retrieval is more difficult than text continuation and other tasks, especially reasoning question answering, which requires a higher level of semantic understanding, and simple keyword retrieval algorithms may not be sufficient. We also found that the Hybrid+Rerank algorithm, which combines and re-ranks the results of both algorithms, improves on all evaluation metrics. This suggests that this is a better retrieval algorithm for question answering tasks.

Hallucination Modification: Consistent with the conclusion of summarization, BM25 retriever performs slightly better than dense retriever, and the hybrid retrieval algorithm presumably combines the advantages of both. For RAG tasks such as hallucination modification, which require precise retrieval of highly relevant content, BM25 shows greater advantages. Moreover, BM25 requires less computational resource then dense retriever. This indicates that different RAG tasks require different retrieval algorithms

4.5 Analyzing the Impact of Embedding Model on RAG Performance in Different Tasks

Most RAG systems use vector similarity-based algorithms as retrievers. Therefore, the embedding model that converts document blocks into vectors is crucial for the retrieval effect. We tested various embedding models optimized for retrieval tasks and compared their performance in the RAG system. We evaluated several embedding models with similar parameter sizes. According to [31], the embedding models' performance on the retrieval task should follow the order of gte > stella > bge > m3e. Our benchmark confirmed this order, but with some variations.

For creative tasks like continuation, the relevance of the retrieved content was often ambiguous. Thus, we noticed that the performance difference between the embedding models was small.

However, for question answering tasks that required precise localization of relevant documents, we found that m3e-base performed much worse than gte-base. This matched the finding of [31].

More importantly, for the hallucination modification task, m3e-base, which ranked the lowest on the retrieval benchmark, outperformed the other models on all metrics. This implies that m3e-base is better at retrieving relevant content for tasks that correct entity-level errors in the text.

These results further show that the retrieval benchmark may not be fully appropriate for RAG. In general, question answering tasks that need accurate localization of relevant documents can use the retrieval benchmark to select models.

Table 6. The experimental results for evaluating different embedding models in our benchmark.

task name	embedding name	bleu	rouge-L	bertScore	RAGQuestEval		length
					precision	recall	
text continuation	m3e-base	3.59	17.55	83.76	27.30	23.73	350.0
	bge-base	3.66	17.78	83.99	26.96	**24.68**	367.6
	stella-base	3.73	17.67	**84.05**	**28.78**	24.65	366.6
	gte-base	**3.76**	**17.80**	84.03	27.35	24.18	362.1
summarization	m3e-base	22.91	33.23	88.31	68.58	46.02	210.5
	bge-base	23.69	**33.53**	88.49	68.06	46.18	205.9
	stella-base	**23.50**	33.50	88.58	**68.22**	46.56	205.5
	gte-base	22.87	33.46	**88.58**	68.10	**47.13**	211.1
question answering 1-document	m3e-base	38.81	56.49	83.41	50.18	69.72	75.2
	bge-base	**39.76**	57.24	83.81	52.67	70.82	73.3
	stella-base	39.58	**57.28**	**83.91**	**53.13**	71.74	73.9
	gte-base	39.58	57.19	83.90	52.39	**71.97**	76.5
question answering 2-document	m3e-base	22.32	36.81	86.91	42.97	55.67	148.4
	bge-base	22.75	37.25	87.16	42.93	56.73	149.8
	stella-base	**23.39**	**37.75**	87.37	**44.83**	**58.00**	149.5
	gte-base	23.20	37.59	**87.48**	43.99	57.58	151.5
question answering 3-document	m3e-base	20.72	34.78	87.43	39.57	50.88	154.3
	bge-base	21.05	35.04	87.81	40.32	**51.37**	156.6
	stella-base	**21.26**	35.27	**87.81**	**41.41**	50.42	154.4
	gte-base	21.15	**35.59**	87.86	40.18	51.11	157.2
hallucination modification	m3e-base	**32.83**	**53.27**	**80.78**	**65.87**	**81.69**	64.5
	bge-base	32.35	53.04	80.49	65.07	80.85	64.8
	stella-base	32.34	52.96	80.59	65.74	81.50	65.2
	gte-base	31.69	52.46	80.40	65.35	80.69	64.5

4.6 Analyzing the Impact of Top-k on RAG Performance in Different Tasks

The RAG system converts the user's query into a vector using the same embedding model as the vector database. Then, it searches the index for the top-k most similar vectors to the query vector , and retrieves the corresponding text blocks from the database. These text blocks serve as the context for the LLM prompt. The amount of information that the model receives depends on the size of k. We will show how the amount of context information affects the system performance for different tasks in the Table 7.

Text Continuation: Text continuation is a highly creative task. Table 7 shows that increasing top-k improves both the overall semantic similarity metrics (bertScore, bleu and rouge-L) and the RAGQuestEval metrics. The recall metric of RAGQuestEval shows how much key information from the reference is included in the generated text, while the precision metric shows how correct and relevant that information is. We found that higher top-k values lead to higher recall and precision scores, indicating that the generated text contains more and better key information. We attribute this to the increased diversity and accuracy of the generated text from more documents.

Open-Domain Multi-Document Summarization: Increasing the top-k value leads to longer and lower-quality summaries. The rouge-L and bertScore metrics stay almost the same, but the bleu metric drops significantly, indicating less similarity between the summaries and the references. The top-k value also affects the key information metrics. Higher top-k values increase the recall

Table 7. The experimental results for evaluating different top-k values in our benchmark.

task name	topk	bleu	rouge-L	bertScore	RAGQuestEval		length
					precision	recall	
text continuation	2	2.89	17.20	83.60	25.35	23.14	367.0
	4	3.34	17.49	83.80	26.66	23.54	369.3
	6	3.53	17.64	83.81	**27.66**	24.32	375.4
	8	3.66	17.78	83.99	26.96	24.68	367.6
	10	**3.91**	**17.84**	**84.01**	27.61	**25.00**	355.7
summarization	2	**26.86**	**33.87**	87.34	**70.08**	42.21	161.0
	4	24.78	33.62	87.95	68.91	44.19	185.6
	6	23.71	33.36	88.16	68.28	45.08	198.6
	8	23.69	33.53	88.49	68.06	46.18	205.9
	10	23.62	33.56	**88.51**	68.17	**46.70**	208.3
question answering 1-document	2	39.13	56.26	82.57	50.81	65.80	67.7
	4	39.47	56.58	83.39	52.14	69.53	70.6
	6	39.40	56.86	83.81	52.60	70.80	72.5
	8	**39.76**	**57.24**	83.81	52.67	**70.82**	73.3
	10	38.84	56.52	**83.93**	**53.67**	70.31	74.1
question answering 2-document	2	21.65	35.16	84.72	36.91	47.41	126.5
	4	22.33	36.68	86.39	41.15	52.78	139.5
	6	**23.04**	37.43	87.01	43.29	55.47	143.7
	8	22.75	37.25	87.16	42.93	56.73	149.8
	10	22.90	**37.63**	**87.43**	**43.88**	**57.34**	153.4
question answering 3-document	2	19.27	32.57	85.65	33.70	43.90	136.3
	4	20.23	34.21	86.93	37.26	48.35	145.5
	6	20.73	34.95	87.66	39.59	51.03	151.3
	8	**21.05**	**35.04**	87.81	40.32	51.37	156.6
	10	20.61	35.01	**88.02**	**40.90**	**52.11**	162.5
hallucination modification	2	32.12	53.00	**80.54**	64.95	79.24	59.6
	4	**32.50**	52.94	80.53	**65.18**	79.34	60.2
	6	32.32	52.70	80.36	64.48	79.27	61.8
	8	32.35	**53.04**	80.49	65.07	80.85	64.8
	10	31.30	51.71	80.09	64.84	**80.90**	68.3

scores, meaning more key information is included, but decrease the precision scores, meaning more errors or redundancies are present.

Question Answering: For single-document QA, increasing top-k has little impact on the semantic similarity metric, but improves the RAGQuestEval metrics, which measure the accuracy and recall of key information. Higher top-k values lead to higher recall and precision scores, especially when the retrieved content is small. This is because more documents can confirm the answer multiple times.

For multi-document QA (2-document and 3-document), increasing top-k significantly improves the recall and precision scores, as there are more chances to retrieve two relevant and complementary documents. More documents can also provide additional information, which helps to bridge the knowledge gap between documents and give more comprehensive answers. The results of 2-document and 3-document question answering are similar.

Hallucination Modification: The top-k value has little effect on the semantic similarity metrics (bleu, rouge and bertScore) and the key information metric (RAGQuestEval). They only drop sharply when the top-k is too large. This is because, in our hallucination modification dataset, correcting the wrong information only requires a small amount of context, and the model has a certain anti-interference ability in the hallucination modification task, so the top-k value is not a decisive factor.

4.7 Analyzing the Impact of LLM on RAG Performance in Different Tasks

The core of the RAG system is a large language model (LLM), which can generate accurate and fluent answers based on the user's question and the retrieved information. In this paper, we conducted experiments on several commonly used LLMs and showed their performance on our benchmark.

Text Continuation: The experimental results show that the larger the model parameters, the better the performance. GPT-4 surpassed other large models in all tasks, demonstrating its powerful generation ability.

Open-Domain Multi-Document Summarization: GPT-4 also excelled in the summary generation task. It achieved higher scores than other models on the overall semantic accuracy metric, as well as the key information recall and precision metric. Moreover, the summary generated by GPT-4 was relatively concise, avoiding redundant information. GPT-4 is the most suitable model for this task.

Question Answering: For single-document QA, which only require extracting relevant information from a sentence in the text, this task is relatively simple. Qwen and Baichuan2 even outperformed GPT series models. However, for multi-document QA that require comprehensive understanding of multiple documents, GPT-4 was far ahead of other models, showing its excellent knowledge fusion ability. Baichuan2-13B model also performed better than GPT-3.5, indicating its potential.

Hallucination Modification: We found that some models generated text that was too long, introducing redundant information. The hallucination modification task only requires modifying the hallucination information, retaining other information, and not introducing irrelevant information. Therefore, ChatGLM2, Qwen-7B, Baichuan2 did not complete this task well.

In summary, the GPT-4-0613 model performed excellently on most tasks and evaluation metrics, proving that it is a powerful LLM. Qwen-7B and Qwen-14B models also performed well, especially in the text continuation and summary generation tasks. Baichuan2-13B model was very competitive with GPT-4 in the QA task, deserving more investigation.

4.8 Suggestions on how to optimize your RAG system

Using the benchmark we constructed, we systematically evaluated the impact of each component in the RAG system in various application scenarios. Subsequently, we offer some suggestions for future researchers aiming to optimize the performance of the RAG system. Table 9 summarizes our recommendations

The **top-k** value is a crucial parameter for the RAG system, as it determines how many documents are retrieved for each query. Depending on the scenario, the optimal top-k value may vary. For instance, in creative content generation tasks, such as text continuation, a larger top-k value is preferable. This allows the LLMs to access more diverse and relevant knowledge, resulting in richer

Table 8. The experimental results for evaluating different large language models in our benchmark.

task name	model name	bleu	rouge-L	bertScore	RAGQuestEval		length
					precision	recall	
text continuation	ChatGLM2-6B	2.06	13.35	68.51	20.68	15.44	363.3
	Qwen-7B	**7.10**	15.31	77.94	28.06	18.44	159.6
	Baichuan2-13B	3.97	14.21	71.75	28.62	22.95	358.4
	Qwen-14B	5.70	18.48	82.97	27.89	21.68	240.1
	GPT-3.5-turbo	3.66	17.78	83.99	26.96	24.68	367.6
	GPT-4-0613	5.58	**19.47**	**84.91**	**30.34**	**28.02**	369.8
summarization	ChatGLM2-6B	17.09	28.16	83.00	58.94	40.35	228.1
	Qwen-7B	28.30	30.21	84.26	67.62	40.03	240.5
	Baichuan2-13B	24.49	32.49	85.64	65.96	42.53	179.5
	Qwen-14B	**32.51**	33.33	85.62	68.94	40.57	139.1
	GPT-3.5-turbo	23.69	33.53	88.49	68.06	46.18	205.9
	GPT-4-0613	24.54	**35.91**	**89.39**	**71.24**	**50.53**	194.6
question answering 1-document	ChatGLM2-6B	29.11	47.57	79.59	50.06	69.35	90.8
	Qwen-7B	39.63	56.71	82.64	51.77	72.02	68.8
	Baichuan2-13B	35.40	53.85	83.59	**54.35**	**76.92**	91.3
	Qwen-14B	37.95	55.13	83.25	53.03	73.92	73.8
	GPT-3.5-turbo	**39.76**	**57.24**	**83.81**	52.67	70.82	73.3
	GPT-4-0613	33.87	51.42	80.92	53.14	62.39	95.9
question answering 2-document	ChatGLM2-6B	15.15	29.12	82.30	37.61	51.51	193.4
	Qwen-7B	22.61	36.07	85.84	42.32	56.26	157.6
	Baichuan2-13B	20.32	35.56	87.49	45.01	61.47	208.8
	Qwen-14B	21.11	34.97	85.87	42.23	56.59	151.1
	GPT-3.5-turbo	**22.75**	**37.25**	87.16	42.93	56.73	149.8
	GPT-4-0613	20.38	36.08	**88.10**	**49.56**	**62.56**	223.0
question answering 3-document	ChatGLM2-6B	14.01	27.71	83.42	35.60	45.28	204.1
	Qwen-7B	**21.63**	33.42	86.31	39.14	50.55	160.6
	Baichuan2-13B	18.30	33.34	88.08	41.35	55.75	227.5
	Qwen-14B	19.83	33.33	86.93	42.01	51.70	161.2
	GPT-3.5-turbo	21.05	**35.04**	87.81	40.32	51.37	156.6
	GPT-4-0613	19.11	34.58	**88.88**	**48.24**	**56.48**	235.1
hallucination modification	ChatGLM2-6B	13.51	28.70	71.26	59.63	73.02	176.0
	Qwen-7B	22.87	38.10	73.52	60.00	73.72	172.5
	Baichuan2-13B	10.56	27.28	68.90	54.42	67.47	124.8
	Qwen-14B	33.78	51.90	79.49	67.05	**84.08**	89.7
	GPT-3.5-turbo	32.35	53.04	80.49	65.07	80.85	64.8
	GPT-4-0613	**36.69**	**55.70**	**81.27**	**69.18**	82.06	63.5

and more accurate content. However, this also comes with a higher computational cost. In summary tasks, a moderate top-k value can strike a balance between precision and recall of information. For scenarios that require high precision, a smaller top-k value is recommended, while for scenarios that require high recall, a larger top-k value is recommended. In single-document QA, it is still recommended to use a large top-k value, which means that the answer can be determined multiple times. In QA tasks that involve reasoning across multiple documents, a larger top-k value can

Table 9. Recommendations for Adjusting RAG System Key Parameters Based on Different Tasks

Scenario	**top-k**	**Chunk Size**	**Chunk overlap**	**Retriever**	**LLM**
Create: Creative Content Generation	Larger, to access diverse knowledge	Larger, to preserve article structure	Larger, to maintain semantic coherence	Dense algorithm for semantic understanding	Qwen-14B for cost-effective high-quality text
Delete: Summarization	Moderate, for precision-recall balance	Smaller for more recall, larger for more precision	Larger, to maintain semantic coherence	BM25 for precise content, Dense algorithm for more recall	Qwen-14B for high-quality summaries
Read: Single-document QA	Larger, for repeated determination	Moderate, for pinpointing short answers	Larger, to maintain semantic coherence	Hybrid + rerank for enhanced performance	Baichuan2-13B for GPT-4-like performance
Read: Multi-document QA	Larger, for retrieving complementary articles	Larger, for article completeness	Larger, to maintain semantic coherence	Hybrid + rerank for enhanced performance	Baichuan2-13B for GPT-4-like performance
Update: Error Correction	Smaller, for high precision tasks	Larger, to avoid breaking article structure	Smaller, error correction tasks are not sensitive to semantic coherence	BM25 for precise content generation	GPT-4 or alternatives depending on cost

help to retrieve two related and complementary articles, thus enhancing the question answering performance.

The **chunk size** is also an important factor when building the vector index for external knowledge. For creative scenarios, such as content generation, we suggest using a larger chunk size to preserve the structure of the article and avoid affecting the performance of the RAG system. For summary scenarios, a smaller chunk size can be used if more information is desired to be recalled; however, if the precision of the generated content is more important, a larger chunk size is still recommended to avoid destroying the structure of the article. In factual question answering scenarios, a smaller chunk size is beneficial for finding the answer in a short sentence. For reasoning tasks, a larger chunk size can ensure the article completeness and enhance the reasoning ability.

The **chunk overlap** is the shared content between two adjacent chunks, and chunk overlap is key to maintaining the coherence of semantics in LLMs when dealing with long texts. Experiments show that for creative generation, summarization, and question answering scenarios, the semantic consistency between chunks is very important, so a large chunk overlap value should be maintained. However, for error correction scenarios, the semantic consistency between chunks is relatively unimportant, and a smaller chunk overlap value can be considered.

When choosing an **embedding** model, you can refer to the mteb leaderboard [31], which shows the performance of different embedding models on retrieval tasks. However, the actual performance of the RAG system may differ from the leaderboard, so you need to evaluate and adjust according to the specific scenario.

When choosing a **retrieval algorithm**, BM25 has the advantage of saving computational resources compared to dense retrievers, and since it is a keyword-based algorithm, it can usually retrieve very relevant documents. However, keyword-based algorithms perform poorly in capturing semantics and may miss some relevant content. Therefore, we suggest using BM25 for tasks that require precise content generation, such as hallucination modification and summarization.

However, BM25 may not be suitable for tasks that require semantic understanding, such as question answering and creative generation, and we recommend using dense algorithms based on deep learning embeddings instead.

Moreover, the hybrid algorithm that combines dense and BM25 retriever has very limited improvement on the overall quality of the generated results. However, by using a rerank model to reorder the retrieval results and then inputting them into LLMs, the performance of almost all tasks improved, especially for reasoning tasks. Therefore, we suggest trying to use the hybrid algorithm + rerank retrieval mode when the conditions permit, which can achieve better performance in the RAG system.

When choosing a **large language model**, GPT-4 model is undoubtedly the most advanced model at present. However, due to the high cost of invoking GPT-4, we may need to consider some open-source alternatives. According to our experimental results, Qwen-14B model has shown similar performance to GPT-4 in the two tasks of text continuation and summary generation, and can generate high-quality creative and summarizing texts. And in the QA task, Baichuan2-13B model also showed a level close to GPT-4, and can generate accurate and fluent answers. Therefore, we can choose the suitable large language model according to different tasks and cost requirements.

5 CONCLUSION

In this paper, we have introduced an innovative framework (CRUD-RAG) for evaluating retrieval-augmented generation (RAG) systems that is both comprehensive and scenario-specific. Our unique categorization of text generation tasks into the CRUD—Create, Read, Update, and Delete—types provides a structured approach to assess the capabilities and limitations of RAG systems in handling a variety of textual contexts. To facilitate this evaluation, we have meticulously constructed large-scale datasets for each CRUD category, which are tailored to challenge and reflect the performance of RAG systems under different operational conditions. Through rigorous experimental comparisons, we have demonstrated that RAG systems can significantly enhance the quality of generated content by effectively incorporating information from external knowledge sources.

Our study delves into the intricate balance required in the fine-tuning process of RAG systems, highlighting the importance of optimizing the retrieval model, context length, construction of the knowledge base, and the deployment of the underlying large language model to achieve the best results. The insights provided by our findings offer a valuable roadmap for researchers and practitioners in the field, guiding them in the development and refinement of RAG systems. We believe that the methodologies and results presented in this paper will spur further exploration and innovation in the realm of RAG technologies. Our work aims to catalyze advancements in text generation applications, pushing the envelope of what is possible with the integration of retrieval mechanisms and language models. It is our hope that this contribution will serve as a cornerstone for future research endeavors, fostering the creation of more intelligent, adaptive, and context-aware generative systems.

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