# RAGEval: Scenario Specific RAG Evaluation Dataset Generation Framework

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## **Abstract**

Retrieval-Augmented Generation (RAG) systems have demonstrated their advantages in alleviating the hallucination of Large Language Models (LLMs). Existing RAG benchmarks mainly focus on evaluating whether LLMs can correctly answer the general knowledge. However, they are unable to evaluate the effectiveness of the RAG system in dealing with the data from different vertical domains. This paper introduces RAGEval, a framework for automatically generating evaluation datasets to evaluate the knowledge usage ability of different LLMs in different scenarios. Specifically, RAGEval summarizes a schema from seed documents, applies the configurations to generate diverse documents, and constructs questionanswering pairs according to both articles and configurations. We propose three novel metrics, Completeness, Hallucination, and Irrelevance, to carefully evaluate the responses generated by LLMs. By benchmarking RAG models in vertical domains, RAGEval has the ability to better evaluate the knowledge usage ability of LLMs, which avoids the confusion regarding the source of knowledge in answering question in existing QA datasets-whether it comes from parameterized memory or retrieval.

### 1 Introduction

Large language models (LLMs) have achieved impressive advancements in natural language processing (NLP) tasks. However, LLMs still suffer from the hallucination problem (Zhang et al., 2023), which leads to generating factual errors in their responses. To alleviate the problem, lots of researchers (Gao et al., 2023b; Asai et al., 2024) have advocated for employing Retrieval-Augmented Generation (RAG) models to help LLMs produce more accurate responses. However, benchmarking

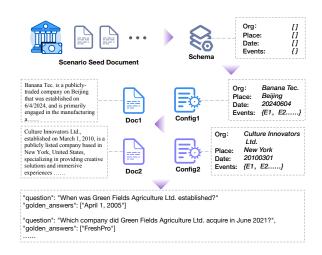


Figure 1: RAGEval Framework.

the effectiveness of RAG models is still challenging (Chen et al., 2024).

Existing RAG benchmarks mainly focus on the question-answering tasks (Joshi et al., 2017; Nguyen et al., 2017; Kwiatkowski et al., 2019), which evaluates the factual correctness in answering questions in general domains. Nevertheless, these benchmarks usually face challenges in assessing the reliability of RAG models, especially for vertical domains, such as finance, healthcare, and legal (Bruckhaus, 2024). Building the RAG benchmarks for different domains is the most straightforward way to deal with the problem. However, due to the privacy of user data, it is challenging to curate high-quality and diverse datasets for evaluating the effectiveness of RAG models across different domains.

This paper introduces **RAGEval**, a universal framework designed to automatically generate scenario-specific RAG evaluation cases in various vertical domains. Specifically, RAGEval begins by collecting a small set of domain-specific documents to summarize a schema, which is created by analyzing the factual information, thus encapsulating the essential domain-specific knowledge. Then within

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the constraints of certain rules, RAGEval generates different configurations according to this schema. These configurations are further leveraged to generate diverse documents. Finally, both generated documents and configurations are used to generate questions. The triples of question, reference, and answer are then used to evaluate the RAG effectiveness.

To completely evaluate the RAG effectiveness on the generated data, our work focuses on evaluating the quality of model responses from three dimensions, Completeness, Hallucination, and Irrelevance, regardless of the String EM metric (Yu et al., 2023). For each question-answer pair, the framework identifies and summarizes the essential factual points, referred to as key points, based on which we propose novel evaluation metrics that focus more on factual accuracy.

#### 2 Related Work

The landscape of question-answering (QA) and RAG evaluation has evolved significantly in recent years. Traditional open-domain QA benchmarks such as HotpotQA (Yang et al., 2018), TriviaQA (Joshi et al., 2017), MS Marco (Nguyen et al., 2017), Natural Questions (Kwiatkowski et al., 2019), 2WikiMultiHopQA (Ho et al., 2020), and KILT (Petroni et al., 2021) have long served as foundational datasets. However, these benchmarks face limitations in evaluating modern RAG systems, including potential data leakage and inadequate assessment of nuanced outputs.

Addressing these shortcomings, a new generation of RAG-specific benchmarks has emerged. RGB (Chen et al., 2024) assesses LLMs' ability to leverage retrieved information, focusing on noise robustness and information integration. CRUD-RAG (Lyu et al., 2024) expands the scope by categorizing RAG applications into Create, Read, Update, and Delete operations. CRAG (Yang et al., 2024) increases domain coverage and introduces mock APIs to simulate real-world retrieval scenarios. MultiHop-RAG (Tang and Yang, 2024) focuses on complex queries requiring multi-hop reasoning across multiple documents.

While these benchmarks offer valuable insights, they are still confined to predefined domains. Our approach aims to address this limitation by providing a framework that offers higher contextual agility, allowing for the design of domain-specific factual queries. This facilitates the fine-tuning of

the entire RAG system, ensuring better alignment with the unique demands of each application scenario.

Traditional RAG evaluation relied on established NLP metrics like F1, BLEU, ROUGE-L, and EM for answer generation while using Hit Rate, MRR, and NDCG for retrieval assessment (Liu, 2023; Nguyen, 2023). However, these metrics lack the nuance needed for evaluating RAG's generative capabilities.

More recent approaches incorporate LLMs in the evaluation process. RAGAS (Es et al., 2024) and ARES (Saad-Falcon et al., 2023) use LLM-generated data to evaluate contextual relevance, faithfulness, and informativeness, without relying on ground truth references. RGB (Chen et al., 2024) introduces task-oriented metrics focusing on noise robustness, negative rejection, information integration, and counterfactual robustness.

Contemporary frameworks employ a combination of metrics to assess both retrieval and generation capabilities (Gao et al., 2023a). These methods often use general quality scores to evaluate RAG performance across information retrieval and generation stages, with some introducing automated LLM-based evaluation to reduce human evaluation costs (Liu et al., 2023).

Our work builds on these advancements by introducing three keypoint-based evaluation metrics and two adapted retrieval metrics, aiming to provide a more comprehensive assessment of the RAG pipeline.

# 3 Method

Building a close-domain Retrieval-Augmented Generation (RAG) evaluation dataset poses two significant challenges. First, collecting and annotating vertical documents is prohibitively expensive due to the sensitive nature of these documents and the specialized knowledge required for their analysis. Second, unlike open-domain QA tasks, which typically require models to generate relatively short answers, vertical-domain answers tend to be much more comprehensive and detailed, complicating their evaluation.

To address these challenges, RAGEval employs a "schema-configuration-document-QAR-keypoint" pipeline, thereby emphasizing the utilization of factual information and enhancing the robustness of answer estimation to improve the accuracy and reliability of the evaluation process. We describe

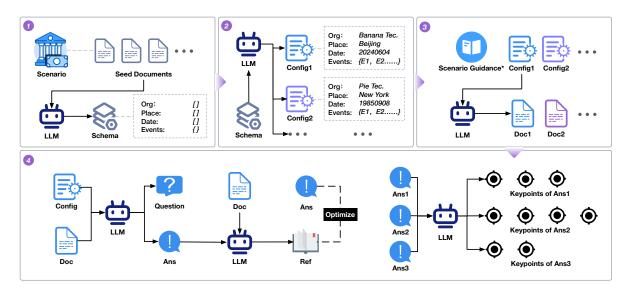


Figure 2: RAGEval Progress.

the components of this pipeline in detail in the following sub-sections.

## 3.1 Stage 1: Schema Summary

In domain-specific scenarios, texts typically adhere to a common knowledge framework, regardless of their stylistic variations. This framework, represented by a schema S, encapsulates the overall coverage of factual information in documents. The schema includes key elements such as organization, type, events, date, and place, summarizing the characteristic information of the scenario. To derive this schema, we employ LLMs to perform inductive reasoning based on a small set of seed texts. Although these seed texts may share the same type, they can vary greatly in style and specific factual content. For instance, financial reports might cover diverse industries from internet technology to food processing. This approach ensures the validity and comprehensiveness of the derived schema, enhancing the controllability of text generation and enabling the production of coherent, domain-appropriate content that aligns with the structural patterns of specific document types.

# 3.2 Stage 2: Document Generation

Generating virtual texts with rich factual information, logical coherence, and internal consistency is crucial for creating effective evaluation datasets. To achieve this, we first generate configurations  $\mathcal C$  derived from the schema  $\mathcal S$  established in Stage 1, rather than immediately producing the text. These configurations directly correspond to the types and content of factual information, serving as a refer-

ence and constraint for text generation. This approach ensures that information across different parts of the document remains more consistent with the configuration.

To generate these configurations, we employ a hybrid approach combining rule-based and LLMbased methods to assign values to the schema elements. Rule-based value generation employs programmatic algorithms to create or select values, ensuring high accuracy, factual consistency, and efficiency, particularly for structured data like dates or categorical information. This approach is especially useful for schema elements with limited options or those requiring strict formatting. Complementing this, we leverage LLMs to generate more complex or diverse content. LLMs excel at creating varied and nuanced information, particularly for elements that require natural language understanding or creativity, such as detailed descriptions or complex relational information. This method allows us to produce a wide range of high-quality, diverse configurations. For instance, in the domain of financial reports, our configurations cover numerous sectors, including "agriculture," "aviation," and "construction." In total, we have 20 different business domains in our documents.

Using the following strategy, we cast the factual information in a configuration  $\mathcal C$  into a document  $\mathcal D$ : we integrate configuration details into a structured narrative format appropriate to the domain, incorporating domain-specific prior knowledge to ensure accuracy and contextual relevance. For medical records, this involves guidance on the structure and content, including categories of diseases, ensuring

the inclusion of necessary fields such as "patient information, medical history, examination results, diagnosis, treatment plan, and follow-up". To mitigate hallucination issues in legal documents, the model only generates references to legal articles by their number, ensuring correct citations are added later. In financial reports, we provide a summary of the company to the model to ensure continuity. Financial documents often contain multiple chapters; thus, we use three sections: "Financial Report, Corporate Governance, Environmental and Social Responsibility" to cover various aspects. Given the complexity of financial events, we manually divide the configuration into the above three sections. We then provide these sections to GPT-40 to generate the relevant parts of the document. This prevents repeated overall summaries and maintains content flow. Finally, the three sections are concatenated to form a complete financial report.

# 3.3 Stage 3: QRA Generation

In this subsection, we describe the process of generating Question-Reference-Answer (QRA) triples using the given documents  $\mathcal{D}$  and configurations  $\mathcal{C}$ . The motivation behind this stage is to create a comprehensive evaluation framework that tests various aspects of information retrieval and reasoning capabilities.

In this subsection, we describe the process of generating Question-Reference-Answer (QRA) triples using the given documents  $\mathcal{D}$  and configurations  $\mathcal{C}$ . The motivation behind this stage is to create a comprehensive evaluation framework that tests various aspects of information retrieval and reasoning capabilities.

Utilizing Configurations for Questions and Initial Answers Generation. We leverage the configurations C to guide the generation of questions and initial answers. The configurations are embedded within the prompts to ensure that the generated questions are specific and the answers are precise. As shown in Table 6, we address seven types of questions: factual questions, multi-hop reasoning questions, summarization questions, multidocument questions, and others. This diverse set of question types is designed to evaluate different facets of language understanding and information processing. The input to the GPT-40 model includes detailed instructions and a few examples for each question type, which are tailored according to the configurations. This results in questions Q and initial answers A that are more targeted and accurate. Specific prompts and examples are detailed in the appendices.

Extracting References. Our goal is to capture all pertinent references to support the answers comprehensively. Using the constructed questions  $\mathcal{Q}$  and initial answers  $\mathcal{A}$ , we extract relevant information fragments (references)  $\mathcal{R}$  from the articles by utilizing an extracting prompt. In the prompt, we emphasize the importance of grounding answers in the source material to ensure reliability and traceability. This step enhances the comprehensiveness and accuracy of the answers by ensuring they are well-supported by the source documents. The constraints and rules applied during this extraction phase ensure that the references are relevant and directly support the answers, leading to more precise and comprehensive QRA triples.

Optimizing Answers and References. Optimizing answers is crucial to ensure accuracy and alignment with the provided references  $\mathcal{R}$ , thereby minimizing misinformation and enhancing the reliability of the generated content. The refinement process follows these principles: If the references  $\mathcal{R}$  contain content not present in the initial answers A, we supplement the answers accordingly. Conversely, if the initial answers A contain content not found in the references  $\mathcal{R}$ , we first check the article for any overlooked references. If such references are found, we add them to the reference set and keep the answer unchanged. If no corresponding references are found, we remove the irrelevant content from the answer. This approach addresses the issue of hallucinations that may arise during the answer generation process, ensuring that the final answers are both accurate and well-supported by the references  $\mathcal{R}$ .

Generating Keypoints. In our evaluation framework, assessing answers is not merely about correctness or keyword matching but about identifying the critical information contained in the responses. To facilitate this, we generate keypoints from the standard answers  $\mathcal{A}$  for each question  $\mathcal{Q}$ .

To generate these keypoints, we employ a predefined prompt for the GPT-40 model, which supports both Chinese and English. The prompt is designed using in-context learning, providing examples of keypoint extraction across different domains and question types. This includes cases where the answer is unanswerable, and the keypoints reflect that appropriately. Typically, responses are distilled into 3-5 keypoints, encompassing indispensable factual information, relevant inferences, and final

conclusions necessary to answer the question.

By extracting these keypoints, we ensure that our evaluation is grounded in clearly defined and relevant information, enhancing the precision and reliability of the subsequent metrics calculation.

### 3.4 DRAGONBall Dataset

Leveraging the aforementioned generation method, we construct the DRAGONBall dataset, which stands for **D**iverse **RAG Omni-B**enchmark for **All** domains. This dataset encompasses a wide array of texts and related RAG questions across three critical domains: finance, law, and medical. Moreover, the dataset includes both Chinese and English texts, providing a comprehensive resource for multilingual and domain-specific research.

For document generation, the dataset includes texts from 20 different corporate domains in finance, with one randomly selected text per domain; 10 different legal domains, with two randomly selected texts per domain; and 19 major medical categories, each with two subcategories and one randomly selected text per major category. This ensures a balanced number of human-evaluated documents across finance, law, and medical domains.

In Table 1, we present a detailed breakdown of the DRAGONBall dataset. The first section of the table shows the distribution of documents across the three domains (finance, legal, and medical) in both Chinese (CN) and English (EN), with an equal number of documents for each language. The second section categorizes the types of questions included in the dataset, providing percentages for each type. The third section details the distribution of the number of reference documents used in answering the questions, reflecting the complexity and variability of the dataset. In total, the dataset comprises 6711 questions.

To ensure the high quality of the QRA triples, we first consider the balance and diversity among the different question types, and then we remove homogeneous and meaningless questions. For example, if the number of unanswerable questions is insufficient, we supplement them according to the article. Second, we eliminate redundant references and answer statements and correct logical reasoning errors in the answers to ensure the dataset quality.

Domain	Language	<b>Document Count</b>
Finance	CN & EN	40 & 40
Legal	CN & EN	30 & 30
Medical	CN & EN	38 & 38

<b>Question Type</b>	Percentage
Information Integration	22.34%
Factual	19.49%
Multi-hop Reasoning	16.15%
Summary	17.40%
Numerical Comparison	10.51%
Time-series	7.15%
Irrelevant/Unanswerable	6.96%

<b>Reference Document Count</b>	Percentage
0 Documents	6.35%
1 Document	20.82%
2 Documents	46.64%
3 Documents	7.09%
4 Documents	4.56%
More than 4	14.54%

Table 1: Distribution of Documents and Question Types in the DRAGONBALL Dataset, in total, we have 6711 questions.

## 3.5 Evaluation Metrics for RAG Systems

In this work, we propose a comprehensive evaluation framework for RAG systems, considering both retrieval and generation components.

We define multiple metrics to evaluate the model's effectiveness and efficiency in the retrieval phase. These metrics are specifically designed for RAG systems, taking into account the need for generation in the presence of incomplete and noisy information.

## 3.5.1 Retrieval Metrics

**Recall.** We introduce the RAG Retrieval Recall metric to evaluate the effectiveness of the retrieval process in matching ground truth references. The Recall is formally defined as

$$Recall = \frac{1}{n} \sum_{i=1}^{n} \mathbb{I}(M(G_i, \mathcal{R})), \tag{1}$$

where n is the total number of ground truth references,  $G_i$  denotes the i-th ground truth reference,

 $\mathcal{R} = \{R_1, R_2, \dots, R_k\}$  represents the set of retrieved references,  $M(G_i, \mathcal{R})$  is a boolean function that returns true if all sentences in  $G_i$  are found in at least one reference in  $\mathcal{R}$ , and false otherwise, and  $\mathbb{I}(\cdot)$  is the indicator function, returning 1 if the condition is true and 0 otherwise.

This metric assesses the alignment between retrieved and ground truth references at the sentence level. A ground truth reference is considered successfully recalled if all its constituent sentences are present in at least one of the retrieved references.

Effective Information Rate (EIR). This metric quantifies the proportion of relevant information within the retrieved passages, ensuring that the retrieval process is both accurate and efficient in terms of information content. It is calculated as

$$EIR = \frac{\sum_{i=1}^{m} |G_i \cap R_t|}{\sum_{j=1}^{k} |R_j|},$$
 (2)

where  $G_i$  is the i-th ground truth reference,  $R_t$  is the set of total retrieved passages, m is the number of ground truth references successfully matched,  $|G_i \cap R_t|$  represents the number of words in the intersection of the i-th ground truth reference and the concatenated retrieved passages  $R_t$ , calculated only if  $G_i$  is matched in  $R_t$ ,  $|R_j|$  represents the total number of words in the j-th retrieved passage, and k is the total number of retrieved passages.

To calculate  $|G_i \cap R_t|$  at the sentence level, follow these steps: 1. Divide  $G_i$  into individual sentences. 2. For each sentence in  $G_i$ , check if it matches any sentence in  $R_t$ . 3. Calculate the number of words in the matched sentences. 4. Sum the number of words from all matched sentences to get  $|G_i \cap R_t|$ . This ensures that the overlap is calculated based on sentence-level matches, providing a more granular and accurate measure of relevant information within the retrieved passages.

## 3.5.2 Generation Metrics

For the generation component, we introduce novel metrics tailored for RAG evaluation. These metrics provide a comprehensive evaluation of the quality and reliability of generated answers.

**Completeness.** Completeness measures how well the generated answer captures the key information from the ground truth. We employ a large language model (LLM) to generate a set of key points  $K = \{k_1, k_2, \ldots, k_n\}$  from the ground truth. The Completeness score is then calculated as the proportion of key points semantically covered by the

generated answer A:

$$Comp(A, K) = \frac{1}{|K|} \sum_{i=1}^{n} \mathbb{1}[A \text{ covers } k_i], \qquad (3)$$

where  $\mathbb{1}[\cdot]$  is an indicator function that evaluates to 1 if the generated answer A semantically covers the key point  $k_i$ , and 0 otherwise. Here, "covers" means that the generated answer contains information consistent with and correctly representing the key point. Specifically, for a key point to be considered covered, the generated answer must not only include the relevant information but also present it accurately without contradictions or factual errors.

**Hallucination.** Hallucination identifies instances where the content contradicts key points, highlighting potential inaccuracies. The Hallucination score is calculated as

$$\operatorname{Hallu}(A, K) = \frac{1}{|K|} \sum_{i=1}^{n} \mathbb{1}[A \text{ contradicts } k_i], \qquad (4)$$

where  $\mathbb{1}[\cdot]$  is an indicator function that evaluates to 1 if the generated answer A contradicts the key point  $k_i$ , and 0 otherwise.

**Irrelevancy.** Irrelevancy assesses the proportion of key points from the ground truth that are neither covered nor contradicted by the generated answer. Irrelevancy quantifies the proportion of key points neither covered nor contradicted, indicating areas where the answer fails to engage with relevant information. The Irrelevancy score is calculated as

$$Irr(A, K) = 1 - Comp(A, K) - Hallu(A, K).$$
 (5)

These metrics—Completeness, Hallucination, and Irrelevancy—together pinpoint specific strengths and weaknesses of RAG models, ensuring generated answers are informative, accurate, and relevant, thereby enhancing their overall quality and trustworthiness.

## 4 Quality Assessment

In this section, we introduce the human verification process used to assess the quality of the generated dataset and the evaluation. The assessment is divided into three main tasks: QAR and generated documents quality assessment, and the validation of automated evaluation.

**QAR Quality Assessment.** We ask annotators to assess the quality of the QARs by scoring the correctness of the QARs generated under different

- 5: The response is completely correct and fluent.
- 4: The response is correct but includes redundant information.
- **3**: Most of the response is correct.
- **2**: About half of the response is correct.
- 1: A small part of the response is correct, or there are logical errors.
- **0**: The response is irrelevant or completely incorrect.

Figure 3: QAR quality scoring criteria.

configurations, according to the standards listed in Figure 3. We randomly select 10 samples per question type for every language and domain, resulting in 420 samples in total for annotation. When scoring, annotators are provided with the document, question, question type, generated response, and references. The results from Table 2 indicate that the QAR quality scores are consistently high across different domains, with slight variations between languages. Specifically, the combined proportion of scores 4 and 5 for all domains is approximately 95% or higher. This suggests that our approach maintains a high standard of accuracy and fluency in QARs.

**Generated Document Quality Assessment.** We evaluate the quality of the documents generated using RAGEval by comparing them with documents generated using baseline methods, which include zero-shot prompting (to ask the LLM to generate the document given only a domain prompt) and one-shot prompting (to ask the LLM to generate the document given a domain prompt and a sample document). We randomly select 20, 20, and 19 generated documents for finance, legal, and medical domain for both language, respectively, and pack each document with 2 baseline documents generated by zero- and one-shot prompting into one group for comparison. Annotators are asked to rank the documents in each group in terms of clarity, safety, richness, and conformity, as defined in Figure 4, with ties allowed. Results shown in Figure 5 demonstrate that our method consistently outperforms zero-shot and one-shot methods across all criteria, particularly in safety, clarity, conformity, and richness. Specifically, for the Chinese and English datasets across the three aspects of richness, clarity, and safety, our method ranks first in over 85% of the cases. This demonstrates the effectiveness of our approach in generating high-quality articles with diverse and rich content without com**Safety**: Avoidance of real-world sensitive informa-

Clarity: Clear and specific information.

Conformity: Resemblance to real documents like

financial reports or medical records.

**Richness**: Depth and breadth of information.

Figure 4: Document quality comparison criteria.

	Finance	Law	Medical
CN	4.94	4.81	4.76
EN	4.84	4.79	4.87

Table 2: QAR quality human review scores by domain.

promising safety and clarity.

Validation of Automated Evaluation. To validate the consistency between LLM and human evaluations, we compare the completeness, hallucination, and irrelevance metrics reported by the LLM with those reported by humans. We use the same 420 examples from the QAR quality assessment and ask human annotators to judge the answers from Baichuan-2-7B-chat. We then calculate the metrics and compare them with LLM-annotated results. Results in Figure 6 show that the machine and human evaluations show a high degree of alignment in all metrics, with absolute differences less than 0.015. This validates the reliability of our automated evaluation metrics and confirms their consistency with human judgment.

In summary, the human evaluation results highlight the robustness and effectiveness of our method in generating accurate, safe, and rich content across various domains, as well as the reliability of our automated evaluation metrics in reflecting human judgment.

# 5 Experiment

# 5.1 Main Setting

We conduct main experiments following a classic pipeline, which consists of text chunking, passage retrieving and generation to estimate different modules in an RAG system.

In our main experiments, we utilize a retrieval model with the following hyperparameters: the TopK retrieved documents is set to 5, the retrieval batch size is 256, and we enable the use of fp16 precision for the retrieval model to optimize performance. The maximum length for the retrieval query

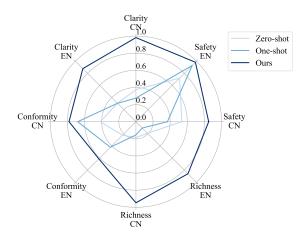


Figure 5: Document generation comparison by domain.

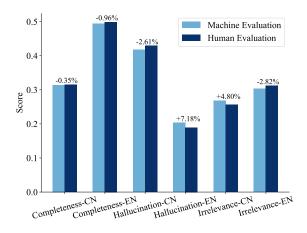


Figure 6: Automated metric validation results.

is capped at 128 tokens. The default chunk size is set to 512 without overlaps; we also add meta-information about the basic information, such as the name of the company, patient, etc., to add the success rate of the retrieval process. For the generation phase, the maximum input length for the query generator is set to 4096 tokens, and the generator processes batches of 5. The generation parameters include a maximum of 256 new tokens per output.

We use the model's default generation configurations, such as temperature, TopP, etc. When the model does not have default generation configurations, the hugging face's default generation configurations will be applied. ChatGPT series models' temperature and TopP were set to 0.2 and 1.0, generating one response per query. More details can be found in the released code.

#### **5.2 RAG Performance Evaluation**

We conducted experiments from the following perspective.

Generation Performance Comparison. The

experiment aims to compare the performance of 9 popular open/close-sourced generation models with different parameter sizes, including MiniCPM-2B-sft (Hu et al., 2024), Phi3-mini (Abdin et al., 2024), Baichuan-2-7B (Yang et al., 2023), Llama3-8B-Instruct (AI@Meta, 2024), Qwen1.5-7B/14B-chat (Bai et al., 2023), Qwen2-7B-Instruct (Bai et al., 2023), GPT-3.5-Turbo, and GPT-4o.

We use the same input prompt to compare the outputs of the different generation models. We chose the first 50 questions of all question types for each domain and language to be evaluated, for example, 350 questions in total for each domain.

# 5.3 Generation Performance Comparison

The overall experimental results of the different generation models are shown in Table 3.

It can be observed that, based on the Rouge-L metric, Baichuan-2-7B-chat achieved the best performance with scores of 0.3262 (CN) and 0.3039 (EN), while GPT-40 performed almost the worst with scores of 0.1527 (CN) and 0.2190 (EN). This contradicts our intuition—according to Chatbot Arena (Chiang et al., 2024) and OpenCompass (Contributors, 2023), GPT-40 is one of the best models in terms of overall performance. Therefore, we can infer that sparse metrics like Rouge-L, which are based on word frequency statistics, do not accurately reflect model capabilities and the effectiveness of the RAG system in RAG scenarios.

Compared to Rouge-L, GPT-40 performed better on the Completeness, Hallucination, and Irrelevance metrics, proving that our proposed keypoints-based evaluation metrics can indeed better and more comprehensively reflect model performance in RAG scenarios. Specifically, GPT-40 achieved the highest Completeness scores of 0.5187 (CN) and 0.6845 (EN), and the lowest Irrelevance score in English at 0.1520.

From our detailed analysis, several critical insights can be drawn:

1. The 2B model MiniCPM-2B achieved remarkable results, particularly in Chinese, where it scored 0.4114 in Completeness. This score surpassed even larger models like Baichuan-2-7B-chat and Qwen1.5-7B-chat, which scored 0.4009 and 0.3983 respectively. In English, MiniCPM-2B's performance was equally impressive, with a Completeness score of 0.5484, nearly matching Baichuan-2-7B-chat's 0.5498. These results provide compelling evidence that 2B models have sufficient potential to exceed the performance of

Table 3: Overall Model Performance Results.(Without irrelevant result)

Model	Completeness $(\uparrow)$		Hallucination $(\downarrow)$		Irrelevance $(\downarrow)$		Rouge-L (†)	
Nouci	CN	EN	CN	EN	CN	EN	CN	EN
MiniCPM-2B-sft	0.4114	0.5484	0.4080	0.2115	0.1803	0.2401	0.2773	0.2505
Baichuan-2-7B-chat	0.4009	0.5498	0.4181	0.2212	0.1809	0.2290	0.3262	0.3039
Qwen1.5-7B-chat	0.3983	0.5704	0.4058	0.1953	0.1957	0.2340	0.2040	0.1862
Qwen2-7B-Instruct	0.4564	0.6052	0.3829	0.1955	0.1596	0.1988	0.2035	0.2182
Llama3-8B-Instruct	0.4427	0.6524	0.3888	0.1582	0.1679	0.1894	0.1982	0.2406
Qwen1.5-14B-chat	0.4926	0.6053	0.3440	0.1795	0.1630	0.2152	0.2611	0.2330
GPT3.5-Turbo	0.4774	0.6540	0.3601	0.1901	0.1626	0.1556	0.2309	0.2563
GPT-40	0.5187	0.6845	0.2797	0.1636	0.1972	0.1520	0.1527	0.2190

Table 4: Retrieve Model Performance Results.

		Reti	rieve		Generation					
Model	Reca	dl (†)	EIR	R (†)	Comple	teness (†)	Hallucii	nation $(\downarrow)$	Irreleva	ance (↓)
	CN	EN	CN	EN	CN	EN	CN	EN	CN	EN
BM25	0.7662	0.6717	0.0470	0.1162	0.6316	0.6649	0.2441	0.1264	0.1242	0.2087
GTE-Large	0.5760	0.7542	0.0362	0.1372	0.5337	0.6921	0.2851	0.1042	0.1813	0.2037
BGE-Large	0.6881	0.7321	0.0465	0.1362	0.5780	0.7077	0.2794	0.1129	0.1426	0.1795
BGE-M3	0.8387	0.6928	0.0541	0.1243	0.6980	0.6556	0.2004	0.1254	0.1010	0.2190

models with substantially more parameters in RAG tasks.

- 2. Among the four models in the 7B-8B range, Llama3-8B-Instruct demonstrated significant advantages. In the English evaluation, it led other models with the highest score of 0.6524. In the Chinese evaluation, although slightly lower than Qwen2-7B-Instruct's 0.4564, Llama3-8B-Instruct still performed excellently with a close score of 0.4427. These results strongly demonstrate the superiority of the Llama3-8B-Instruct model across both languages.
- 3. Model Size Impact: In comparing models of the same series with different parameter sizes, Qwen1.5-14B-chat clearly outperformed Qwen1.5-7B-chat. The 14B model recorded higher Completeness scores of 0.4926 (CN) and 0.6053 (EN), demonstrating that larger parameter sizes normally perform better in RAG questions.
- 4. Best Performing Open-Source Models: Among all the tested open-source models, Qwen1.5-14B-chat exhibited the best performance in Chinese, with a Completeness score of 0.4926, while Llama3-8B-Instruct performed best in English with a score of 0.6524.
- 5. GPT-40 Performance: Although GPT-40 currently shows the best performance overall, the gap

with the top-performing open-source models is not substantial. Specifically, in Chinese, GPT-4o's Completeness score of 0.5187 in Chinese is only 0.0261 higher than Qwen1.5-14B-chat's score of 0.4926. In English, GPT-4o's Completeness score of 0.6845 is only 0.0321 higher than Llama3-8B-Instruct's score of 0.6524. This suggests that open-source models have the potential to close the performance gap with further advancements.

## 5.4 Retrieval Performance Comparison

Our experiments were conducted using the Llama3-8B-Instruct model on the Dragonball finance dataset, with evaluations performed in both Chinese and English. The BGE-Large model was deployed with language-specific versions for Chinese and English. All other parameters were consistent with the previous experimental setup.

Table 4 presents the performance results of various retrieval models on both Chinese (CN) and English (EN) datasets. The primary metrics evaluated include Recall, Expected Information Retrieval (EIR), Signal-to-Noise Ratio (SNR), Completeness, Hallucination, and Irrelevance.

In the English setting, the GTE-Large model demonstrated superior performance across several key metrics. It achieved a Recall of 0.7542, and

Table 5:	TopK &	Chunk-TopK	Performance	Results.

		Retr	ieve				Gener	ation		
Settings	Reca	ıll (†)	EIR	R (†)	Comple	teness (†)	Hallucii	nation (\bigcup)	Irreleva	ance (↓)
	CN	EN	CN	EN	CN	EN	CN	EN	CN	EN
					TopK					
2	0.4667	0.5685	0.0764	0.2491	0.5004	0.5682	0.3226	0.1693	0.1770	0.2625
4	0.6362	0.6976	0.0553	0.1591	0.5517	0.6503	0.3127	0.1303	0.1352	0.2194
6	0.7259	0.7542	0.0408	0.1182	0.5835	0.7087	0.2974	0.1227	0.1191	0.1686
				(	Chunk-Top	K				
128-8	0.5031	0.5472	0.0884	0.2222	0.4549	0.6683	0.2861	0.1168	0.2591	0.2148
256-4	0.4393	0.6161	0.0824	0.2628	0.4855	0.6509	0.3196	0.1241	0.1944	0.2250
512-2	0.4667	0.5685	0.0764	0.2491	0.4932	0.5609	0.3195	0.1635	0.1873	0.2756

EIR of 0.1372, indicating its robustness in retrieving relevant information with minimal noise. However, this model's performance in the Chinese setting was suboptimal, with significantly lower Recall of 0.5760.

Conversely, in the Chinese setting, the BGE-M3 model achieved the highest overall performance. It recorded the best Recall of 0.8387 and Completeness of 0.6980, along with a leading EIR of 0.0501. Additionally, BGE-M3 exhibited the lowest Hallucination rate of 0.2711 and Irrelevance rate of 0.1085, suggesting a balanced and reliable retrieval capability in the Chinese context.

These results highlight the importance of language-specific optimization in retrieval models. The consistent performance patterns observed in both retrieval and generation metrics reinforce the validity of our evaluation framework. This indicates that the metrics designed for the retrieval phase are effective predictors of generation phase outcomes since higher Recall and EIR scores can usually result in better completeness and hallucination scores.

### 5.5 Hyperparameter Comparison

Our experiments, conducted using the Llama3-8B-Instruct model on the Dragonball finance dataset, evaluated the impact of common RAG (Retrieval-Augmented Generation) settings, specifically TopK retrieval and chunk size, on model performance in both Chinese and English. The results, summarized in Table 5, highlight several key observations and insights:

# 5.5.1 TopK Retrieval Observations

1. **Recall Improvement with Higher TopK**: - As expected, Recall improved with higher TopK val-

ues. Specifically, Recall increased from 0.4667 at TopK=2 to 0.7259 at TopK=6 in Chinese, and from 0.5685 at TopK=2 to 0.7542 at TopK=6 in English.

These improvements suggest that higher TopK values enable the model to retrieve more relevant information, crucial for enhancing overall retrieval effectiveness.

2. Generation Metrics Improve with Increased Recall: The improvements in Recall due to increased TopK values are reflected in the generation metrics, demonstrating a positive correlation between retrieval performance and generation quality. For Chinese, Completeness improved significantly from 0.5004 at TopK=2 to 0.5835 at TopK=6. Similarly, for English, Completeness rose from 0.5682 at TopK=2 to 0.7087 at TopK=6. These results indicate that retrieving more relevant documents (higher TopK) leads to more complete and accurate responses, with reduced hallucination, highlighting the direct impact of improved retrieval on generation quality.

# 5.5.2 Chunk Size Impact

- 1. **Optimal Chunk Size Varies by Language**: From Table 5, we observe that the optimal chunk size varies between Chinese and English. For Chinese, the 128-8 setting (128 tokens, 8 chunks) performed best in Recall (0.5031) and EIR (0.0884), while for English, the 256-4 setting achieved the highest Recall (0.6161) and EIR (0.2628). This suggests that the ideal chunk size may be language-dependent, with Chinese benefiting from smaller, more numerous chunks, and English from slightly larger chunks.
- 2. **Trade-offs in Generation Metrics**: Interestingly, the best retrieval performance doesn't always translate to the best generation metrics. For

Chinese, the 512-2 setting achieved the highest Completeness (0.4932) despite lower Recall, while for English, the 128-8 setting led in Completeness (0.6683). Hallucination rates were lowest with the 128-8 setting for both languages (0.2861 for CN, 0.1168 for EN), indicating that more, smaller chunks may help reduce hallucination.

3. Balancing Retrieval and Generation Performance: The results highlight the complex relationship between chunk size, retrieval performance, and generation quality. While smaller chunks (128-8) generally led to better retrieval metrics and lower hallucination, larger chunks sometimes improved completeness. This suggests that the optimal chunk size should be chosen based on the specific requirements of the task, balancing between retrieval accuracy, generation completeness, and hallucination reduction.

The varying performance across different chunk sizes and languages underscores the importance of careful tuning in retrieval-augmented generation systems. It also highlights the need for a holistic approach that considers both retrieval and generation metrics when optimizing such systems.

#### 6 Conclusion

This paper introduces RAGEval, a novel framework for automatically generating and scenario-specific datasets to assess the capabilities of RAG systems. Our approach addresses the limitations of existing benchmarks by focusing on factual accuracy and scenario-specific knowledge, which are crucial in industries like finance, healthcare, and legal sectors. Our experimental results demonstrate that the new metrics we designed provide a more comprehensive and accurate assessment of model performance in RAG scenarios compared to conventional metrics. Notably, while GPT-40 showed superior performance overall, the gap with top-performing open-source models was relatively small. This suggests significant potential for improvement in opensource models. Future work could focus on extending the framework to more diverse domains and exploring ways to further minimize the performance gap between open-source and proprietary models in RAG scenarios.

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# A Appendix

```
"procuratorate": ""
  },
"chiefJudge": "",
 "chiefJudge": "",
"judge": "",
"clerk": "",
"defendant": {
"name": "",
"gender": "",
"birthdate": "",
"residence": "",
"ethnicity": "",
"occupation": ""
}.
 },
"defenseLawyer": {
   "name": "",
   "lawFirm": ""
  },
"caseProcess": [
     {
    "event": "Case Filing and Investigation",
    "date": ""
     "event": "Detention Measures Taken",
"date": ""
     "event": "Criminal Detention",
"date": ""
     {
    "event": "Arrest",
    "date": ""
     }
   "criminalFacts": [
   {
  "crimeName": "",
  "details": [
      {
"timePeriod": "",
"behavior": "",
"evidence": ""
   }
  "legalProcedure": {
  "judgmentDate": "",
  "judgmentResult": [
    {
  "crimeName": "",
  "sentence": "",
  "antencingConsi
       "sentencingConsiderations": ""
   ]
```

Figure 7: A schema example of Law domain.

```
{
       "courtAndProcuratorate": {
    "court": "Ashton, Clarksville, Court",
    "procuratorate": "Ashton, Clarksville, Procuratorate"
       },
"chiefJudge": "M. Gray",
"judge": "H. Torres",
"clerk": "A. Brown",
       "clerk": "A. Brown",
"defendant": {
    "name": "J. Gonzalez",
    "gender": "female",
    "birthdate": "15th, June, 1999",
    "residence": "53, Bayside street, Clarksville",
    "ethnicity": "Hispanic",
    "occupation": "Senior Inspector, Clarksville Tax Department"
       },
"defenseLawyer": {
    "name": "M. Smith",
    "lawFirm": "Clarksville Legal Associates"
       },
"caseProcess": [
               {
                        "event": "Case Filing and Investigation",
"date": "1st March 2023"
                },
                        "event": "Detention Measures Taken",
"date": "5th March 2023"
                        "event": "Criminal Detention",
"date": "10th March 2023"
                },
                        "event": "Arrest",
"date": "12th March 2023"
               }
        ],
"criminalFacts": [
                        "crimeName": "Crime of Bending the Law for Personal Gain",
                        "details": [
                               {
                                       "timePeriod": "January 2022 - December 2022",
"behavior": "J. Gonzalez utilized her position as Senior Inspector in ...",
"evidence": "Email correspondences between J. Gonzalez and ..."
                               }
                       ]
                }
       "crimeName": "Crime of Bending the Law for Personal Gain",
"sentence": "5 years of fixed-term imprisonment",
"sentencingConsiderations": "The defendant's position of trust ..."
                       }
               ]
      }
}
```

Figure 8: A config example of Law domain.

```
"qa_fact_based": [
              {
                     "Question Type": "Factual Question", "Question": "According to the court judgment of Ashton, Clarksville, Court, what was the
          judgment date?",
                            "Date of Judgment: 15th May 2023"
                      'Answer": "15th May 2023."
             }
         qa_multi_hop": [
                     "Question Type": "Multi-hop Reasoning Question",
"Question": "According to the judgment of Ashton, Clarksville, Court, how many instances
          of bending the law for personal gain did J. Gonzalez commit?",
                           "The Crime of Bending the Law for Personal Gain by the defendant, J. Gonzalez,
        occurred over a span of one year, from January 2022 to December 2022.",
"During this period, J. Gonzalez exploited her position as a Senior Inspector within
        the Clarksville Tax Department to manipulate tax audits, reports, and reduce penalty fees for several conspiring local businesses in exchange for substantial financial bribes.",
                              In March 2022, J. Gonzalez revised the tax records for Sunrise Construction Inc.,
        are march 2022, J. Gonzalez revised the tax receives or Sumrise Construction incommendation of reducing their tax liability after receiving a bribe of $50,000.",

"In exchange for $30,000, J. Gonzalez facilitated the undue reduction of penalty fees levied on Downtown Boutique Ltd. for late tax submissions.",

"The most egregious of the offenses occurred in November 2022, when J. Gonzalez
         disclosed sensitive and confidential information about ongoing tax investigations to executives
        at Riven Pharmaceuticals, securing a bribe of $45,000."
                     "Answer": "According to the judgment, J. Gonzalez committed four instances of bending
        the law for personal gain: manipulating tax audits and reports, altering tax records, reducing penalty fees, and providing confidential information."
         qa_summary": [
              {
        "Question Type": "Summary Question",
"Summary Content": "Facts of the crime",
"Question": "According to the judgment of Ashton, Clarksville, Court, summarize the facts of J. Gonzalez's crimes.",
                     "ref": [
                           "The Crime of Bending the Law for Personal Gain by the defendant, J. Gonzalez,
        occurred over a span of one year, from January 2022 to December 2022.",
"During this period, J. Gonzalez exploited her position as a Senior Inspector within the Clarksville Tax Department to manipulate tax audits, reports, and reduce penalty fees for
        several conspiring local businesses in exchange for substantial financial bribes.",

"In March 2022, J. Gonzalez revised the tax records for Sunrise Construction Inc.,
drastically reducing their tax liability after receiving a bribe of $50,000.",
         "In exchange for $30,000, J. Gonzalez facilitated the undue reduction of penalty fees levied on Downtown Boutique Ltd. for late tax submissions.",

"The most egregious of the offenses occurred in November 2022, when J. Gonzalez
         disclosed sensitive and confidential information about ongoing tax investigations to executives
        at Riven Pharmaceuticals, securing a bribe of $45,000."
                     "Answer": "J. Gonzalez, a Senior Inspector at the Clarksville Tax Department,
        the crime of bending the law for personal gain. From January 2022 to December 2022, she manipulated tax audits and reports in exchange for bribes from multiple local businesses. In March 2022, she altered tax records to reduce the tax liability for Sunrise Construction Inc. after receiving $50,000. In August 2022, she reduced penalty fees for late tax submission of Downtown Boutique Ltd. in exchange for $30,000. In November 2022, she provided confidential
         information about ongoing tax investigations to Riven Pharmaceuticals in exchange for $45,000."
       ٦
}
```

Figure 9: A QAR example of Law domain.

Table 6: RAG Question Types and Their Definitions

<b>Question Type</b>	Definition
	Single-document QA
Factual	Questions targeting specific details within a reference (e.g., a company's profit in a report, a verdict in a legal case, or symptoms in a medical record) to test RAG's retrieval accuracy.
Summarization	Questions that require comprehensive answers, covering all relevant information, to mainly evaluate the recall rate of RAG retrieval.
Multi-hop Reasoning	Questions that involve logical relationships among events and details within a document, forming a reasoning chain, to assess RAG's logical reasoning ability.
	Multi-document QA
Information Integration	Questions that need information from two documents combined, typically containing distinct information fragments, to test cross-document retrieval accuracy.
Numerical Comparison	Questions requiring RAG to find and compare data fragments to draw conclusions, focusing on the model's summarizing ability.
Temporal Sequence	Questions requiring RAG to determine the chronological order of events from information fragments, testing the model's temporal reasoning skills.
	Unanswerable Questions
Unanswerable	Questions arising from potential information loss during the schema-to- article generation, where no corresponding information fragment exists or the information is insufficient for an answer.