Self-adaptive Multimodal Retrieval-Augmented Generation

Wenjia Zhai

Unaffiliated zhaiwenjia0311@163.com

Abstract

Traditional Retrieval-Augmented Generation (RAG) methods are limited by their reliance on a fixed number of retrieved documents, often resulting in incomplete or noisy information that undermines task performance. Although recent adaptive approaches alleviated these problems, their application in intricate and real-world multimodal tasks remains limited. To address these, we propose a new approach called Self-adaptive Multimodal Retrieval-Augmented Generation (SAM-RAG), tailored specifically for multimodal contexts. SAM-RAG not only dynamically filters relevant documents based on the input query, including image captions when needed, but also verifies the quality of both the retrieved documents and the output. Extensive experimental results show that SAM-RAG surpasses existing state-of-the-art methods in both retrieval accuracy and response generation. By further ablation experiments and effectiveness analysis, SAM-RAG maintains high recall quality while improving overall task performance in multimodal RAG task. Our codes are available at https://github.com/SAM-RAG/SAM RAG.

1 Introduction

Recent advances in large language models (LLMs) have significantly improved various natural language processing tasks (Manikandan et al., 2023; OpenAI et al., 2024; Ouyang et al., 2022; Touvron et al., 2023; Anil et al., 2023), including question answering (Tan et al., 2023). In addition, LLMs have begun to cross modal boundaries, exhibiting potential in various multimodal tasks such as visual comprehension (Pan et al., 2022) and code generation (Wang et al., 2024).

However, challenges remain, including the generation of false information (hallucination) (Li et al., 2022) and difficulties in knowledge updating (Zhang et al., 2023), which hinder the applicability of a wider variety. To address these challenges,

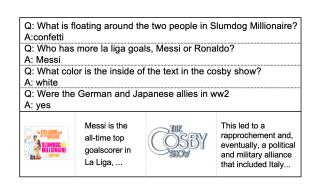


Figure 1: Some questions rely on visual information, which make text-only retrieval unfeasible. These questions require retrieving and reasoning over visual context.

Retrieval-Augmented Generation (RAG) (Lewis et al., 2020) has been proposed, positing that documents semantically similar to a query likely contain the information needed to answer that query. By leveraging the in-context learning capabilities of LLMs, RAG enhances the likelihood of accurate responses from semantically related document retrievals while effectively reducing hallucinations and facilitating knowledge acquisition (Li et al., 2024). As RAG technology evolves, it gradually expands into the multimodal domain, achieving progress in tasks involving texts (Wu et al., 2024), images (Pan et al., 2022), etc., an example of multimodal RAG task is shown in Figure 1.

RAG, while advantageous, encounters substantial obstacles, especially regarding adaptability (Zhao et al., 2024). RAG's reliance on a fixed number of retrieved documents often results in retrieval omissions or excessive noise, negatively impacting performance, while it also lacks a mechanism to verify its generated responses. To address these challenges, adaptive RAG frameworks have been introduced, enabling dynamic adjustments based on task-specific needs, which greatly improve RAG performance in various tasks. However, research on adaptive RAG in multimodal contexts remains limited.

To this end, we propose Self-Adaptive Multimodal Retrieval-Augmented Generation (SAM-RAG), the first adaptive multimodal RAG framework capable of proactively selecting relevant data and self-evaluating generated responses. By employing knowledge distillation from state-ofthe-art models to a smaller multimodal LLM, we ensure superior performance in multimodal tasks. SAM-RAG defines three essential criteria: relevance, usefulness, and support. In the course of processing queries, SAM-RAG assesses each set of retrieval outcomes separately, identifying pertinent data after retrieval, then generates a preliminary response based on these relevant contexts and assesses their contribution to response generation. Ultimately, the framework conducts a thorough evaluation of the query, contexts, and response. This process ensures that the generated answer is thoroughly substantiated by the provided contexts, thereby significantly reducing the occurrence of hallucinations.

We set up a series of experiments and introduce various baselines to evaluate our method. The experimental results indicate that SAM-RAG significantly outperforms the previous state-of-the-art framework like MuRAG (Chen et al., 2022) and other baselines in multimodal RAG tasks, demonstrating its robust capabilities in multimodal retrieval and generation. The ablation study evaluates the rationale and effectiveness of the three verifications, while the analysis of retrieval effectiveness underscores the importance of dynamic retrieval in enhancing performance. Additionally, the case study offers concrete examples demonstrating how each verification individually and collectively improves retrieval accuracy and the quality of answer generation.

The SAM-RAG framework integrates dynamic retrieval, relevance verification, and multi-stage answer validation to optimize multimodal tasks, ensuring accurate and supported answers while minimizing hallucinations. The process involves modality alignment, document retrieval, and iterative verifications for relevance, usability, and support, enhancing both output quality and model robustness. In summary, the contributions of this paper are as follows:

 SAM-RAG introduces a dynamic multimodal RAG framework, enhancing relevant document selection while minimizing unnecessary retrievals;

- It uses three key verification criteria relevance, usability, and support to improve retrieval accuracy and answer quality;
- Experiments show SAM-RAG's superior performance over state-of-the-art models, especially in multimodal tasks.

2 Related Works

2.1 Retrieval-Augmented Generation

RAG improved the relevance and accuracy of generated responses by incorporating external knowledge into language models. Early research focused on the text modality. Re2G (Glass et al., 2022) combined BM25 with deep learning retrieval, UPRISE (Cheng et al., 2023) introduced a prompt retriever to enhance the zero-shot capabilities of large language models, and QOQA (Koo et al., 2024) refined the retrieval performance through query regeneration. However, these methods relied on a fixed number of retrieval results, limiting adaptability to specific tasks. SAM-RAG overcomes this limitation by using adaptive retrieval, dynamically assessing recalled documents to improve response generation.

2.2 Multimodal Retrieval-Augmented Generation

A key area of RAG research is multimodal contexts, integrating various formats such as texts (Wu et al., 2024), images (Pan et al., 2022), tables (Dong et al., 2024), and audio (Xu et al., 2019), with Visual Question Answering (VQA) being a significant focus (Ishmam et al., 2024). The main distinction between multimodal and textual RAG tasks is the necessity to unify diverse modalities into a single representation, known as modality alignment. Current LLMs exhibit superior reasoning, analysis, and generation capabilities by leveraging large-scale internet corpora, often outperforming visual and other modalities in these tasks (Jin et al., 2024). Thus, in multimodal RAG, a common approach involves converting non-textual modalities into text representations using a modality converter, thereby utilizing LLM's strengths in text processing (Zhao et al., 2023). Frameworks such as RA-VQA (Lin and Byrne, 2022) used object detection to create multiple textual representations from images for standard RAG operations, while other approaches like MMHQA-ICL (Liu et al., 2023) and UniM-MQA (Luo et al., 2023) combined text, tabular, and visual data to align with text-based RAG techniques. This paper specifically focuses on texts and images, incorporating these methods to extract image information effectively.

2.3 Adaptive Retrieval-Augmented Generation

The quality of retrieval significantly impacts RAG performance, as irrelevant or incorrect documents often cause "hallucinations" (Huang et al., 2023b). The conventional RAG relies on a fixed number of documents, which can miss crucial information or introduce irrelevant text. The conventional RAG also lacks verification mechanisms for generated answers. Adaptive RAG frameworks, such as Self-Improve (Huang et al., 2023a) and Self-Refine (Madaan et al., 2023), used feedback loops for error correction. Self-Correction (Welleck et al., 2023) and Self-Reasoning (Xia et al., 2024) further enhanced retrieval quality via reasoning. Self-RAG (Asai et al., 2024) improved adaptability by using on-demand retrieval and reflection. SAM-RAG builds on these ideas, introducing active screening and reflection mechanisms in the multimodal domain, creating a more dynamic retrieval process and advancing multimodal RAG applications.

3 Method

In this study, we propose a novel multimodal RAG framework, SAM-RAG, as illustrated in Figure 2. SAM-RAG is designed to actively select multimodal data pertinent to the query for answer generation and to validate the generated responses from multiple perspectives, thereby ensuring the quality and reliability of the output.

3.1 Task Definition

Formally, the RAG task involves constructing a retrieval database from a document collection $D = \{d_1, d_2, \ldots, d_n\}$ using a retriever \mathcal{R} . For a set of queries $Q = \{q_1, \ldots, q_m\}$, the retriever identifies a relevant document set $D_{rel} = \{d_1, \ldots, d_k\}$ for each query q, generating a sequence of s tokens $A = [a_1, \ldots, a_s]$ as the answer. Here, k (k < n) is typically a predefined number for retrieval.

The multimodal RAG task typically involves the following steps: First, a modality converter \mathcal{P} transforms information in other modalities into a format that the language model \mathcal{L} can interpret, integrating it with textual data for retrieval. Next, for each query q, the retriever \mathcal{R} identifies the relevant information D_{rel} . Finally, the language model \mathcal{L}

generates a sequence of s tokens $[a_1, \ldots, a_s]$ as a response to the query q, based on the retrieved information. The modules \mathcal{P} and \mathcal{L} are often combined into a single module \mathcal{M} to streamline the entire process.

3.2 Embedding Model

In the RAG framework, the quality of retrieval results is critical to overall performance (Salemi and Zamani, 2024). To enhance the recall rate of \mathcal{R} , we optimize its representational capabilities through contrastive learning.

For a given query q, the supporting documents for the official answers constitute the positive sample set D_{pos} , resulting in positive query-document pairs (Q, D_{pos}) . The remaining documents form the negative sample set D_{neg} . We employ dense passage retrieval (DPR) (Karpukhin et al., 2020) to rank the negative document collection D_{neg} and randomly select 10 samples from the top 50 samples, thereby creating negative query-document pairs (Q, D_{neg}) . This process culminates in a dataset of approximately 240k entries, with each query paired with corresponding a positive document d_{pos} and a negative document d_{neg} , used to finetune the model \mathcal{R} .

We optimize the performance of \mathcal{R} using the InfoNCE loss function (He et al., 2020), as shown in Equation 1, where D_{pos} represents the supporting documents for the answers, and τ is the temperature hyperparameter. The goal is to minimize ℓ between positive and negative samples.

$$\ell = -\log \frac{\exp \left(\mathbf{Q} \cdot \mathbf{D}_{pos} / \tau\right)}{\sum \exp \left(\mathbf{Q} \cdot \mathbf{D} / \tau\right)}$$
(1)

3.3 Multimodal Knowledge Distillation

Knowledge distillation transfers knowledge from a high-performance model (teacher) to a simpler model (student), enhancing the student's performance while reducing complexity (Yang et al., 2024). In LLMs, this technique effectively passes capabilities from larger models to smaller ones (Jin et al., 2024; Gu et al., 2024; Li et al., 2023). We use **GPT** $\mathcal G$ to generate instruction-tuning data that improves our local model $\mathcal M$ (Peng et al., 2023), refining its reasoning and generation skills. By leveraging chain-of-thought reasoning (Wei et al., 2022), we retain inference processes of $\mathcal G$ for effective model distillation.

The data preparation for model distillation proceeds as follows. First, query-specific captions D_{sc}

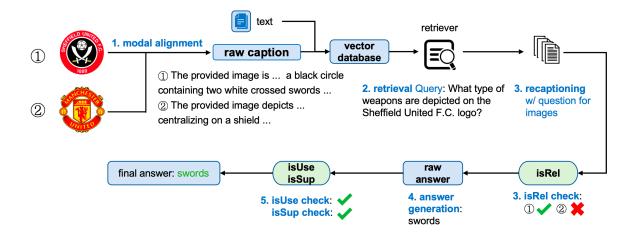


Figure 2: The illustration of SAM-RAG pipeline. If the documents are visual, they will be converted to textual captions, vectorized and stored with textual documents. When a retrieval is performed, documents are processed in batch based on semantic similarity. If a caption is in a batch, its coressponding image will be recaptioned with the query.

are generated by \mathcal{G} for query-image pairs $\{q, d_{pos}\}$, and only the reasoning processes where the generated answers A match the standard answers are retained. Next, **isRel** is inferred using query-document pairs $\{q, d \mid d \in D_{sc}, D_t\}$, keeping reasoning processes with **isRel** =True. To improve efficiency, the negative set D_{neg} is ranked using DPR, and documents equal in number to the positive samples are randomly selected and inferenced from the top 10 ranked by similarity. The reasoning processes where **isRel** =False are retained. Coarse answers A are then generated from the filtered D_{pos} , retaining reasoning processes where the conclusions align with the standard answers.

After generating A, isUse =? is inferred based on the set $\{q, d, A \mid d \in \{D_{sc}, D_t\}\}$. Using the same method as for isRel, positive and negative samples with consistent inference results are retained. Finally, isSup =? is inferred. Similar to isRel, for negative samples, reasoning processes where isSup =False are kept. While for positive samples, those with inference results of either True or Partial are retained.

3.4 SAM-RAG

The components of the SAM-RAG framework, as illustrated in Figure 2, are described. The overall process of executing multimodal RAG tasks is divided into five steps: **modality alignment**, **document retrieval**, **relevance verification**, **answer generation**, and **answer verification**. Image information from the entire document corpus is first

aligned with the text modality. Upon receiving a query, document retrieval is performed. The retrieved results are then ranked by similarity, and each is assessed for relevance to the query, with only the relevant results being retained. Based on the relevant documents, the framework generates A. The validity of the generated answer is subsequently verified, and if confirmed, the answer is returned, concluding the retrieval process. The core innovation of this method lies in the introduction of three key verification mechanisms, as shown in Table 1. Prompts are listed in Appendix B.

3.4.1 Modality Alignment

Raw captions d_{rc} are first generated using **GPT**, referred to as \mathcal{G} , without being tailored to specific queries. These captions are produced under constraints based on image titles. Since the raw captions are not specific to the queries, d_{rc} may omit key information relevant to the queries. Therefore, d_{rc} is used exclusively for indexing and similarity calculations. The generated D_{rc} , along with the original textual documents D_t , is then input into the embedding model \mathcal{R} for vectorization, preparing for query retrieval.

3.4.2 Document Retrieval

For a given query q, scores for the document corpus D are obtained using DPR (Karpukhin et al., 2020), and the results are sorted in descending order of similarity scores for the next step.

Verification	Definition	Input	Output	Action
isRel	If $oldsymbol{d}$ is related to $oldsymbol{q}$	q, d	TRUE	$\mathcal{F} \leftarrow TRUE, \mathbf{C} \leftarrow \mathbf{C} \cup \{d\}$
			FALSE	continueed
isUse	If $m{A}$ accurately responded query $m{q}$	q, A	TRUE	proceeded to isSup
			FALSE	regenerated \overline{A}
isSup	If $oldsymbol{A}$ supported by $oldsymbol{C}$	q, A, C	TRUE	returned A
			Partial	$\mathcal{F} \leftarrow FALSE$
			FALSE	$\mathcal{F} \leftarrow$ FALSE, clear $oldsymbol{C}$

Table 1: Explanation of each verification, its definition, inputs, outputs and corresponding actions.

3.4.3 Relevance Verification

To track the retrieval status, a flag \mathcal{F} is initialized to False, and a storage space C is created to hold relevant information. The retrieved documents are processed in batches, where the relevance of each retrieved text document d_t to the query is directly assessed using the relevance verification isRel (refer to Figure 2 and Table 1, top row). If an image d_i is retrieved instead, a question-specific caption d_{sc} is generated based on the query, and its relevance is evaluated accordingly. When isRel =True, the relevant information is stored in C, and \mathcal{F} is updated to True. After processing a batch, if isRel =False, the next batch is processed; otherwise, the retrieval process is paused, and the next stage is initiated.

3.4.4 Answer Generation

The context C generated in the previous stage, along with the query q, is utilized by the model \mathcal{M} to produce a coarse answer A through an autoregressive generation method. Subsequently, the generated answer A undergoes a verification process to evaluate its relevance and support.

3.4.5 Answer Verification

In this stage, is Use verification process (refer to Figure 2 and Table 1, second row), is introduced to determine whether the generated answer A effectively addresses the query. If | isUse |=True, the next step will involve evaluating the support of A using | isSup | (refer to Figure 2 and Table 1, third row); otherwise, A is regenerated based on C. The purpose of |isSup| is to confirm that A is adequately supported by C, thereby preventing situations where A lacks support from D_{rel} . If **isSup** =True, it is indicated that A fulfills the task requirements, and A is returned, concluding the retrieval process. If | isSup | =False, it signifies that A is unsupported by \overline{C} , prompting a reset of both C and $\mathcal F$ to return to the first stage for further retrieval. If | isSup |=Partial, it suggests incomplete support information, leading to the retention of C

while resetting \mathcal{F} , and returning to the first stage to continue the retrieval. The objective of this stage is to ensure that the final output aligns with task requirements and minimizes the risk of potential hallucinations.

Through the aforementioned design, the SAM-RAG method ensures effective retrieval while minimizing the risk of generating misleading answers, thereby safeguarding the quality of the final output. To enhance the model's stability and the reliability of the results, we incorporate the Chain-of-Thought method (Wei et al., 2022) into each verification process and the answer generation step. Furthermore, we can implement the self-consistency strategy (Wang et al., 2023) to further bolster robustness.

4 Experiments

4.1 Dataset

In this study, the MultimodalQA dataset (Talmor et al.) is used as a benchmark to evaluate the performance of the SAM-RAG framework. This dataset comprises multimodal question-answering inputs, including texts, images, and tables. To facilitate a fair comparison with the leading multimodal RAG model, MuRAG (Chen et al., 2022), the experiments focus exclusively on the TextQ and ImageQ categories of questions within the MultimodalQA dataset.

4.2 Metrics

F1 score and exact match (EM) metrics (Rajpurkar et al., 2016) are employed to evaluate the quality of the generated answers. Additionally, two metrics are used to evaluate retrieval performance: Recall@N (as defined in Equation 2) and a newly introduced metric, the average retrieval number (ARN), which measures the average number of documents retrieved to generate the final answer, providing a more nuanced assessment of retrieval efficiency in SAM-RAG.

Evaluation	Text		Image		All
Metrics	F1	\mathbf{EM}	F1	EM	\mathbf{EM}
MuRAG	56.10	49.70	56.50	56.50	51.40
$\overline{\mathbf{RAG}(\mathcal{R} + \mathcal{M})}$	35.47	32.44	33.56	30.95	32.12
$RAG(\mathcal{R}^* + \mathcal{M})$	40.82	38.85	36.20	33.81	37.75
$RAG(\mathcal{R} + \mathcal{M}^*)$	42.86	41.66	39.26	37.62	40.77
$RAG(\mathcal{R}^* + \mathcal{M}^*)$	52.31	51.18	46.20	44.29	47.97
$\overline{\mathbf{SAM\text{-}RAG}(\mathcal{R}^* + \mathcal{M})}$	40.49	39.25	39.54	38.57	39.10
$\mathbf{SAM\text{-}RAG}(\mathcal{R}^* + \mathcal{M}^*)$	54.35	52.74	54.13	52.38	52.66
$\overline{\mathbf{RAG}(\mathcal{R} + \mathcal{G})}$	60.92	58.88	54.11	50.47	57.04
$\mathbf{RAG}(\mathcal{R}^* + \mathcal{G})$	66.64	65.49	59.09	57.62	63.92
$\mathbf{SAM\text{-}RAG}(\mathcal{R}^* + \mathcal{G})$	71.03	70.10	80.51	79.98	72.26

Table 2: Multimodal test-set synthesis evaluation results. "RAG" means conventional RAG with retrieval top k as 8. \mathcal{R} and \mathcal{M} indicate model is not finetuned; \mathcal{R}^* and \mathcal{M}^* indicate model is finetuned; \mathcal{G} indicates model is **GPT**.

$$recall@N = \begin{cases} 1, & \text{if } \mathbf{D}_{pos} \subseteq \mathcal{R}_{q_i}(\mathbf{D}) \\ 0, & \text{otherwise} \end{cases}$$
 (2)

4.3 Experimental Settings

The experimental setup involves the finetuning of both the embedding model \mathcal{R} and the vision-language model \mathcal{M} , alongside generation and inference tasks using either \mathcal{M} or \mathcal{G} . Finetuning is performed on a single NVIDIA A100 80GB GPU, with the server running Ubuntu Server 20.04 LTS.

For the embedding model, bge-base-en-v1.5¹ (Xiao et al., 2024) is used, finetuned using the FlagEmbedding framework² (Xiao et al., 2023). Key hyperparameters include a learning rate of 1e-5, 5 training epochs, and a batch size of 64. The vision-language model \mathcal{M} , LLaVA-v1.5-7b³ (Liu et al., 2024), is finetuned via the LLaMA-Factory framework⁴ (Zheng et al., 2024) using LoRA (Hu et al., 2022). The setup includes a learning rate of 1e-4, 5 epochs, a batch size of 1, and 8 gradient accumulation steps, with AdamW (Loshchilov, 2017) as the optimizer.

During data generation and inference, \mathcal{G}^5 is utilized, with a temperature parameter set to 1.2 to ensure response diversity, and is further used to finetune \mathcal{M} and conduct inference tasks.

4.4 Main Results

The experimental results, summarized in Table 2, demonstrate that SAM-RAG achieves superior performance across all evaluated tasks, significantly outperforming baseline models, including the state-of-the-art MuRAG. Below, we provide a detailed analysis of the performance improvements and insights gained from the comparisons.

1. **Overall Performance**: Across both text and image tasks, SAM-RAG delivers higher F1 and EM scores compared to baseline methods. These improvements underscore the effectiveness of the dynamic retrieval and generation mechanisms of SAM-RAG. The roles of key components, **isRel**, **isUse** and **isSup**, are further analyzed in the ablation study (4.5) and illustrated through case studies (4.7, Figure 4). Additional case examples are provided in Appendix A.

2. Performance Comparison with Baselines:

Table 2 (top) demonstrates that fine-tuning the retrieval model \mathcal{R} or the VLM \mathcal{M} improves multimodal RAG performance. However, fine-tuning \mathcal{M} provides more substantial gains. This suggests that the baseline retrieval model \mathcal{R} is already sufficiently optimized, leading to smaller performance improvements from fine-tuning. In contrast, optimizing \mathcal{M} directly enhances the model's ability to process multimodal data. Notably, the fine-tuned $\mathbf{RAG}(\mathcal{R}^* + \mathcal{M}^*)$ shows slightly lower performance than MuRAG, despite differences in the volume of training data.

¹https://huggingface.co/BAAI/bge-base-en-v1.5

²https://github.com/FlagOpen/FlagEmbedding

³https://huggingface.co/llava-hf/llava-1.5-7b-hf

⁴https://github.com/hiyouga/LLaMA-Factory

⁵**GPT** version: GPT-40-2024-05-13

- 3. SAM-RAG vs. Conventional RAG: As shown in Table 2 (middle), SAM-RAG consistently outperforms conventional RAG methods. By dynamically retrieving documents until relevant information is found, SAM-RAG avoids the limitations of fixed retrieval strategies. Fine-tuning the retrieval model $\mathcal R$ speeds up document retrieval but does not significantly impact overall performance, as the strength of SAM-RAG lies in leveraging the fine-tuned $\mathcal M$. The results indicate that fine-tuning $\mathcal M$ leads to the most notable performance improvements in SAM-RAG, especially for multimodal tasks.
- 4. **Effect of GPT Integration**: Table 2 (bottom) highlights the substantial performance gains from integration of \mathcal{G} into the SAM-RAG and conventional RAG frameworks. Models incorporating \mathcal{G} outperform all other configurations, underscoring \mathcal{G} 's advanced reasoning and understanding abilities. SAM-RAG combined with \mathcal{G} shows the most significant improvements, particularly in visual tasks, where it exceeds textual performance. This suggests that the SAM-RAG framework, when paired with \mathcal{G} , achieves a deeper understanding of visual content than other approaches.

4.5 Ablation Study

Experiment	F1	Δ F1	EM	Δ EM
MuRAG	_	-	51.40	-20.86
RAG	64.99	-8.20	63.92	-8.84
W/ isRel	65.62	-7.57	64.96	-7.30
WO/ isSup	68.56	-4.63	67.07	-5.69
WO/ isUse	69.05	-4.14	67.99	-4.27
W/ all	73.19	-	72.26	-

Table 3: Effect of different verification combinations. "RAG" indicates conventional RAG pipeline.

 Δ : The difference is between the best value and the corresponding value.

To validate the effectiveness of each component of SAM-RAG, a series of ablation studies are performed that check the performance of the framework after removing each component, as shown in Table 3. The results indicate that, compared to conventional RAG, the introduction of distinct verification, particularly isRel and isSup, leads to notable improvements in both F1 and EM

scores. Specifically, although introducing <code>isRel</code> only brings minimal improvement, the subsequent introduction of <code>isUse</code> and <code>isSup</code> makes a greater impact. When all verifications are combined (labeled "with all"), the EM score rises to the maximum value, reflecting an improvement of more than 20% compared to the performance of MuRAG. This finding suggests that simultaneous consideration of relevance (<code>isRel</code>), support (<code>isSup</code>), and usability (<code>isUse</code>) allows the model to effectively filter the most valuable information for the generation of answers, significantly improving the quality of the output.

The introduction of even a single verification leads to an increase in the model's EM score, demonstrating that each criterion contributes uniquely to optimization. However, the results indicate that the most substantial improvements occur when multiple verifications are employed in combination. This suggests that integrating various verification mechanisms can comprehensively optimize information retrieval and generation processes, thereby minimizing the impact of irrelevant or low-quality information.

4.6 Analysis of Retrieval Effectiveness

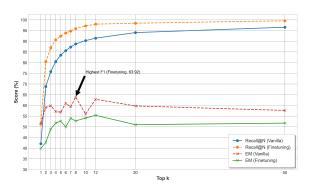


Figure 3: Effect of the Different Retrieval Numbers on Recall@N and EM.

To assess retrieval effectiveness, we analyzed the top-performing SAM-RAG and conventional RAG models, as shown in Figure 3 and Table 4. The results indicate that \mathcal{R}^* consistently outperforms \mathcal{R} in Recall@N across all top k values, suggesting that fine-tuning the embeddings improves relevant context retrieval. Table 2 further shows that the EM scores for \mathcal{R}^* are generally higher than for \mathcal{R} . Notably, at a top k of 8, the EM score surpasses all scores of \mathcal{R} by nearly 20%, suggesting that fine-tuning \mathcal{R} benefits more from a moderate number of retrievals, while too many retrievals may intro-

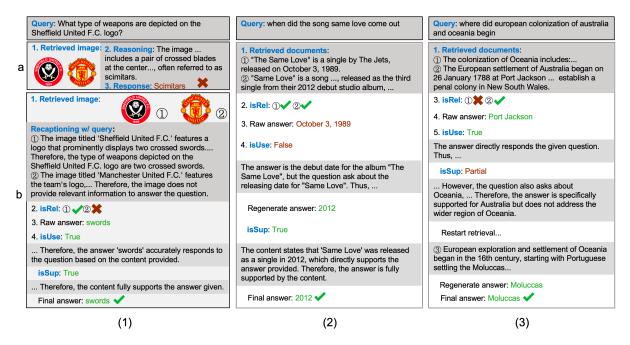


Figure 4: Complete real cases. (1) is a comparison between (a) convntional RAG and (b) SAM-RAG. (2) is a case where **isUse** is False. (3) is a case where **isSup** is Partial. For simplicity, only two visual documents are displayed.

duce noise. Unlike conventional RAG, which often retrieves more documents than needed thus introduces irrelevant content, SAM-RAG's recall numbers closely match the "Gold Reference" values and yield higher EM scores for both text and image retrieval. This suggests that SAM-RAG effectively retrieves relevant information while reducing noise, resulting in more accurate and higher-quality outputs.

Evaluation	Te	ext	Image		
Metrics	EM	ARN	\mathbf{EM}	ARN	
Gold Reference	-	1.55	-	1.00	
conventional RAG	65.69	7	57.62	7	
SAM-RAG	70.01	1.77	80.00	1.24	

Table 4: Multimodal test-set synthesis evaluation results and recall@N analysis.

"Gold Reference" means the texts and images which are labeled as "supporting context"; "ARN" means the average number of retrieved documents for the answers.

4.7 Case Study

To intuitively illustrate the effectiveness of SAM-RAG, we present selected examples in Figure 4. The left panel contrasts the standard RAG pipeline with SAM-RAG. In (a), the conventional RAG retriever \mathcal{R} retrieves multiple documents, but despite including relevant content (e.g., the Sheffield United F.C. logo), \mathcal{M} is misled by irrelevant infor-

mation, resulting in incorrect generation. In (b), SAM-RAG mitigates this problem by filtering irrelevant documents through **isRel**, ensuring that \mathcal{M} focuses only on relevant information, leading to accurate generation based on essential content like d_{sc} .

The middle panel highlights how \mathcal{M} uses the isUse to review its generated answer. Initially, \mathcal{M} produces an incorrect response but recognizes the error and self-corrects, generating the correct answer.

In the right panel, after initial verifications, the $\begin{tabular}{l} \textbf{isSup} \end{tabular}$ identifies a gap between the content and the generated answer. This prompts $\mathcal R$ to retrieve additional information, enabling a more complete and accurate response.

This work presents SAM-RAG, a novel multimodal RAG framework that filters and analyzes retrieved content. SAM-RAG converts image documents into text, then assesses their relevance to the query. Once relevant documents are identified, it generates initial answers and evaluates how these documents contribute to the answer generation, determining if they fully support it. Experimental results show that SAM-RAG outperforms current state-of-the-art models on benchmark datasets.

5 Limitations

The SAM-RAG framework, while innovative in its approach to multimodal retrieval-augmented generation, is not without limitations.

One notable limitation is the potential for biased outputs, which can arise from the training data used for the underlying models. If the data contains historical biases or unrepresentative samples, the SAM-RAG system may inadvertently generate responses that unfair narratives, impacting its effectiveness and fairness.

Additionally, the reliance on large language models poses significant data privacy challenges. Given that these models are trained on extensive datasets, there is a risk that sensitive or personally identifiable information could be inadvertently incorporated into the responses. If not properly managed, this could lead to privacy breaches or the dissemination of confidential information, raising ethical concerns about data handling and user trust.

Moreover, the framework's complexity can also introduce safety issues. The multi-step processes involved in retrieval, relevance verification, and answer generation may not always guarantee that the final output aligns perfectly with task requirements, potentially leading to misleading or hallucinated information. This underscores the need for rigorous validation mechanisms to ensure the reliability of generated answers.

References

Rohan Anil, Andrew M. Dai, Orhan Firat, Melvin Johnson, Dmitry Lepikhin, Alexandre Passos, Siamak Shakeri, Emanuel Taropa, Paige Bailey, Zhifeng Chen, Eric Chu, Jonathan H. Clark, Laurent El Shafey, Yanping Huang, Kathy Meier-Hellstern, Gaurav Mishra, Erica Moreira, Mark Omernick, Kevin Robinson, Sebastian Ruder, Yi Tay, Kefan Xiao, Yuanzhong Xu, Yujing Zhang, Gustavo Hernandez Abrego, Junwhan Ahn, Jacob Austin, Paul Barham, Jan Botha, James Bradbury, Siddhartha Brahma, Kevin Brooks, Michele Catasta, Yong Cheng, Colin Cherry, Christopher A. Choquette-Choo, Aakanksha Chowdhery, Clément Crepy, Shachi Dave, Mostafa Dehghani, Sunipa Dev, Jacob Devlin, Mark Díaz, Nan Du, Ethan Dyer, Vlad Feinberg, Fangxiaoyu Feng, Vlad Fienber, Markus Freitag, Xavier Garcia, Sebastian Gehrmann, Lucas Gonzalez, Guy Gur-Ari, Steven Hand, Hadi Hashemi, Le Hou, Joshua Howland, Andrea Hu, Jeffrey Hui, Jeremy Hurwitz, Michael Isard, Abe Ittycheriah, Matthew Jagielski, Wenhao Jia, Kathleen Kenealy, Maxim Krikun, Sneha Kudugunta, Chang Lan, Katherine Lee, Benjamin Lee, Eric Li, Music Li, Wei Li, YaGuang Li, Jian Li, Hyeontaek Lim, Hanzhao Lin, Zhongtao Liu, Frederick Liu, Marcello Maggioni, Aroma Mahendru, Joshua Maynez, Vedant Misra, Maysam Moussalem, Zachary Nado, John Nham, Eric Ni, Andrew Nystrom, Alicia Parrish, Marie Pellat, Martin Polacek, Alex Polozov, Reiner Pope, Siyuan Qiao, Emily Reif, Bryan Richter, Parker Riley, Alex Castro Ros, Aurko Roy, Brennan Saeta, Rajkumar Samuel, Renee Shelby, Ambrose Slone, Daniel Smilkov, David R. So, Daniel Sohn, Simon Tokumine, Dasha Valter, Vijay Vasudevan, Kiran Vodrahalli, Xuezhi Wang, Pidong Wang, Zirui Wang, Tao Wang, John Wieting, Yuhuai Wu, Kelvin Xu, Yunhan Xu, Linting Xue, Pengcheng Yin, Jiahui Yu, Qiao Zhang, Steven Zheng, Ce Zheng, Weikang Zhou, Denny Zhou, Slav Petrov, and Yonghui Wu. 2023. Palm 2 technical report. Preprint, arXiv:2305.10403.

Akari Asai, Zeqiu Wu, Yizhong Wang, Avirup Sil, and Hannaneh Hajishirzi. 2024. Self-RAG: Learning to retrieve, generate, and critique through self-reflection. In <u>The Twelfth International Conference</u> on Learning Representations.

Wenhu Chen, Hexiang Hu, Xi Chen, Pat Verga, and William Cohen. 2022. Murag: Multimodal retrieval-augmented generator for open question answering over images and text. In <u>Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing</u>, pages 5558–5570.

Daixuan Cheng, Shaohan Huang, Junyu Bi, Yuefeng Zhan, Jianfeng Liu, Yujing Wang, Hao Sun, Furu Wei, Weiwei Deng, and Qi Zhang. 2023. UPRISE: Universal prompt retrieval for improving zero-shot evaluation. In Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, pages 12318–12337, Singapore. Association for Computational Linguistics.

Haoyu Dong, Haochen Wang, Anda Zhou, and Yue Hu. 2024. Ttc-quali: A text-table-chart dataset for multimodal quantity alignment. In <u>Proceedings of the 17th ACM International Conference on Web Search and Data Mining</u>, pages 181–189.

Michael Glass, Gaetano Rossiello, Md Faisal Mahbub Chowdhury, Ankita Naik, Pengshan Cai, and Alfio Gliozzo. 2022. Re2G: Retrieve, rerank, generate. In Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 2701–2715, Seattle, United States. Association for Computational Linguistics.

Yuxian Gu, Li Dong, Furu Wei, and Minlie Huang. 2024. MiniLLM: Knowledge distillation of large language models. In The Twelfth International Conference on Learning Representations.

Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. 2020. Momentum contrast for unsupervised visual representation learning. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pages 9729–9738.

- Edward J Hu, yelong shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. 2022. LoRA: Low-rank adaptation of large language models. In <u>International Conference on Learning Representations</u>.
- Jiaxin Huang, Shixiang Gu, Le Hou, Yuexin Wu, Xuezhi Wang, Hongkun Yu, and Jiawei Han. 2023a. Large language models can self-improve. In Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, pages 1051–1068, Singapore. Association for Computational Linguistics.
- Lei Huang, Weijiang Yu, Weitao Ma, Weihong Zhong, Zhangyin Feng, Haotian Wang, Qianglong Chen, Weihua Peng, Xiaocheng Feng, Bing Qin, et al. 2023b. A survey on hallucination in large language models: Principles, taxonomy, challenges, and open questions. arXiv preprint arXiv:2311.05232.
- Md Farhan Ishmam, Md Sakib Hossain Shovon, Muhammad Firoz Mridha, and Nilanjan Dey. 2024. From image to language: A critical analysis of visual question answering (vqa) approaches, challenges, and opportunities. Information Fusion, page 102270.
- Yizhang Jin, Jian Li, Yexin Liu, Tianjun Gu, Kai Wu, Zhengkai Jiang, Muyang He, Bo Zhao, Xin Tan, Zhenye Gan, Yabiao Wang, Chengjie Wang, and Lizhuang Ma. 2024. Efficient multimodal large language models: A survey. Preprint, arXiv:2405.10739.
- Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. 2020. Dense passage retrieval for opendomain question answering. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 6769–6781, Online. Association for Computational Linguistics.
- Hamin Koo, Minseon Kim, and Sung Ju Hwang. 2024. Optimizing query generation for enhanced document retrieval in rag. arXiv preprint arXiv:2407.12325.
- Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. 2020. Retrieval-augmented generation for knowledge-intensive nlp tasks. In Advances in Neural Information Processing Systems, volume 33, pages 9459–9474. Curran Associates, Inc.
- Huayang Li, Yixuan Su, Deng Cai, Yan Wang, and Lemao Liu. 2022. A survey on retrieval-augmented text generation. Preprint, arXiv:2202.01110.
- Jiarui Li, Ye Yuan, and Zehua Zhang. 2024. Enhancing llm factual accuracy with rag to counter hallucinations: A case study on domain-specific queries in private knowledge-bases. ArXiv, abs/2403.10446.

- Lei Li, Yongfeng Zhang, and Li Chen. 2023.

 Prompt distillation for efficient llm-based recommendation. In Proceedings of the 32nd ACM International Conference on Information and Knowledge Management, pages 1348–1357.
- Weizhe Lin and Bill Byrne. 2022. Retrieval augmented visual question answering with outside knowledge. In Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing, pages 11238–11254, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. 2024. Visual instruction tuning. Advances in neural information processing systems, 36.
- Weihao Liu, Fangyu Lei, Tongxu Luo, Jiahe Lei, Shizhu He, Jun Zhao, and Kang Liu. 2023. Mmhqa-icl: Multimodal in-context learning for hybrid question answering over text, tables and images. Preprint, arXiv:2309.04790.
- I Loshchilov. 2017. Decoupled weight decay regularization. arXiv preprint arXiv:1711.05101.
- Haohao Luo, Ying Shen, and Yang Deng. 2023. Unifying text, tables, and images for multimodal question answering. In <u>Findings of the Association for Computational Linguistics</u>: <u>EMNLP 2023</u>, pages 9355–9367, Singapore. Association for Computational Linguistics.
- Aman Madaan, Niket Tandon, Prakhar Gupta, Skyler Hallinan, Luyu Gao, Sarah Wiegreffe, Uri Alon, Nouha Dziri, Shrimai Prabhumoye, Yiming Yang, Shashank Gupta, Bodhisattwa Prasad Majumder, Katherine Hermann, Sean Welleck, Amir Yazdanbakhsh, and Peter Clark. 2023. Self-refine: Iterative refinement with self-feedback. In Advances in Neural Information Processing Systems, volume 36, pages 46534–46594. Curran Associates, Inc.
- Hariharan Manikandan, Yiding Jiang, and J Zico Kolter. 2023. Language models are weak learners. Advances in Neural Information Processing Systems, 36:50907–50931.
- OpenAI, Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, Red Avila, Igor Babuschkin, Suchir Balaji, Valerie Balcom, Paul Baltescu, Haiming Bao, Mohammad Bavarian, Jeff Belgum, Irwan Bello, Jake Berdine, Gabriel Bernadett-Shapiro, Christopher Berner, Lenny Bogdonoff, Oleg Boiko, Madelaine Boyd, Anna-Luisa Brakman, Greg Brockman, Tim Brooks, Miles Brundage, Kevin Button, Trevor Cai, Rosie Campbell, Andrew Cann, Brittany Carey, Chelsea Carlson, Rory Carmichael, Brooke Chan, Che Chang, Fotis Chantzis, Derek Chen, Sully Chen, Ruby Chen, Jason Chen, Mark Chen, Ben Chess, Chester Cho, Casey Chu, Hyung Won Chung, Dave Cummings, Jeremiah Currier, Yunxing Dai, Cory Decareaux, Thomas Degry, Noah Deutsch,

Damien Deville, Arka Dhar, David Dohan, Steve Dowling, Sheila Dunning, Adrien Ecoffet, Atty Eleti, Tyna Eloundou, David Farhi, Liam Fedus, Niko Felix, Simón Posada Fishman, Juston Forte, Isabella Fulford, Leo Gao, Elie Georges, Christian Gibson, Vik Goel, Tarun Gogineni, Gabriel Goh, Rapha Gontijo-Lopes, Jonathan Gordon, Morgan Grafstein, Scott Gray, Ryan Greene, Joshua Gross, Shixiang Shane Gu, Yufei Guo, Chris Hallacy, Jesse Han, Jeff Harris, Yuchen He, Mike Heaton, Johannes Heidecke, Chris Hesse, Alan Hickey, Wade Hickey, Peter Hoeschele, Brandon Houghton, Kenny Hsu, Shengli Hu, Xin Hu, Joost Huizinga, Shantanu Jain, Shawn Jain, Joanne Jang, Angela Jiang, Roger Jiang, Haozhun Jin, Denny Jin, Shino Jomoto, Billie Jonn, Heewoo Jun, Tomer Kaftan, Łukasz Kaiser, Ali Kamali, Ingmar Kanitscheider, Nitish Shirish Keskar, Tabarak Khan, Logan Kilpatrick, Jong Wook Kim, Christina Kim, Yongjik Kim, Jan Hendrik Kirchner, Jamie Kiros, Matt Knight, Daniel Kokotajlo, Łukasz Kondraciuk, Andrew Kondrich, Aris Konstantinidis, Kyle Kosic, Gretchen Krueger, Vishal Kuo, Michael Lampe, Ikai Lan, Teddy Lee, Jan Leike, Jade Leung, Daniel Levy, Chak Ming Li, Rachel Lim, Molly Lin, Stephanie Lin, Mateusz Litwin, Theresa Lopez, Ryan Lowe, Patricia Lue, Anna Makanju, Kim Malfacini, Sam Manning, Todor Markov, Yaniv Markovski, Bianca Martin, Katie Mayer, Andrew Mayne, Bob McGrew, Scott Mayer McKinney, Christine McLeavey, Paul McMillan, Jake McNeil, David Medina, Aalok Mehta, Jacob Menick, Luke Metz, Andrey Mishchenko, Pamela Mishkin, Vinnie Monaco, Evan Morikawa, Daniel Mossing, Tong Mu, Mira Murati, Oleg Murk, David Mély, Ashvin Nair, Reiichiro Nakano, Rajeev Nayak, Arvind Neelakantan, Richard Ngo, Hyeonwoo Noh, Long Ouyang, Cullen O'Keefe, Jakub Pachocki, Alex Paino, Joe Palermo, Ashley Pantuliano, Giambattista Parascandolo, Joel Parish, Emy Parparita, Alex Passos, Mikhail Pavlov, Andrew Peng, Adam Perelman, Filipe de Avila Belbute Peres, Michael Petrov, Henrique Ponde de Oliveira Pinto, Michael, Pokorny, Michelle Pokrass, Vitchyr H. Pong, Tolly Powell, Alethea Power, Boris Power, Elizabeth Proehl, Raul Puri, Alec Radford, Jack Rae, Aditya Ramesh, Cameron Raymond, Francis Real, Kendra Rimbach, Carl Ross, Bob Rotsted, Henri Roussez, Nick Ryder, Mario Saltarelli, Ted Sanders, Shibani Santurkar, Girish Sastry, Heather Schmidt, David Schnurr, John Schulman, Daniel Selsam, Kyla Sheppard, Toki Sherbakov, Jessica Shieh, Sarah Shoker, Pranav Shyam, Szymon Sidor, Eric Sigler, Maddie Simens, Jordan Sitkin, Katarina Slama, Ian Sohl, Benjamin Sokolowsky, Yang Song, Natalie Staudacher, Felipe Petroski Such, Natalie Summers, Ilya Sutskever, Jie Tang, Nikolas Tezak, Madeleine B. Thompson, Phil Tillet, Amin Tootoonchian, Elizabeth Tseng, Preston Tuggle, Nick Turley, Jerry Tworek, Juan Felipe Cerón Uribe, Andrea Vallone, Arun Vijayvergiya, Chelsea Voss, Carroll Wainwright, Justin Jay Wang, Alvin Wang, Ben Wang, Jonathan Ward, Jason Wei, CJ Weinmann, Akila Welihinda, Peter Welinder, Jiayi Weng, Lilian Weng, Matt Wiethoff, Dave Willner, Clemens Winter, Samuel Wolrich, Hannah Wong,

- Lauren Workman, Sherwin Wu, Jeff Wu, Michael Wu, Kai Xiao, Tao Xu, Sarah Yoo, Kevin Yu, Qiming Yuan, Wojciech Zaremba, Rowan Zellers, Chong Zhang, Marvin Zhang, Shengjia Zhao, Tianhao Zheng, Juntang Zhuang, William Zhuk, and Barret Zoph. 2024. Gpt-4 technical report. Preprint, arXiv:2303.08774.
- Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. 2022. Training language models to follow instructions with human feedback. Advances in neural information processing systems, 35:27730–27744.
- Haiwei Pan, Shuning He, Kejia Zhang, Bo Qu, Chunling Chen, and Kun Shi. 2022. Amam: an attention-based multimodal alignment model for medical visual question answering. Knowledge-Based Systems, 255:109763.
- Baolin Peng, Chunyuan Li, Pengcheng He, Michel Galley, and Jianfeng Gao. 2023. Instruction tuning with gpt-4. Preprint, arXiv:2304.03277.
- Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. Squad: 100,000+ questions for machine comprehension of text. In <u>Proceedings</u> of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 2383–2392.
- Alireza Salemi and Hamed Zamani. 2024. Evaluating retrieval quality in retrieval-augmented generation. In Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR '24, page 2395–2400, New York, NY, USA. Association for Computing Machinery.
- Alon Talmor, Ori Yoran, Amnon Catav, Dan Lahav, Yizhong Wang, Akari Asai, Gabriel Ilharco, Hannaneh Hajishirzi, and Jonathan Berant. Multimodalqa: complex question answering over text, tables and images. In International Conference on Learning Representations.
- Yiming Tan, Dehai Min, Yu Li, Wenbo Li, Nan Hu, Yongrui Chen, and Guilin Qi. 2023. Can chatgpt replace traditional kbqa models? an in-depth analysis of the question answering performance of the gpt llm family. In <u>International Semantic Web Conference</u>, pages 348–367. Springer.
- Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023. Llama 2: Open foundation and fine-tuned chat models. arXiv preprint arXiv:2307.09288.
- Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc V Le, Ed H. Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. 2023. Self-consistency improves chain of thought reasoning in language models. In The Eleventh International Conference on Learning Representations.

- Zora Zhiruo Wang, Akari Asai, Xinyan Velocity Yu, Frank F. Xu, Yiqing Xie, Graham Neubig, and Daniel Fried. 2024. Coderag-bench: Can retrieval augment code generation? Preprint, arXiv:2406.14497.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. 2022. Chain-of-thought prompting elicits reasoning in large language models. Advances in neural information processing systems, 35:24824–24837.
- Sean Welleck, Ximing Lu, Peter West, Faeze Brahman, Tianxiao Shen, Daniel Khashabi, and Yejin Choi. 2023. Generating sequences by learning to self-correct. In The Eleventh International Conference on Learning Representations.
- Shangyu Wu, Ying Xiong, Yufei Cui, Haolun Wu, Can Chen, Ye Yuan, Lianming Huang, Xue Liu, Tei-Wei Kuo, Nan Guan, et al. 2024. Retrieval-augmented generation for natural language processing: A survey. arXiv preprint arXiv:2407.13193.
- Yuan Xia, Jingbo Zhou, Zhenhui Shi, Jun Chen, and Haifeng Huang. 2024. Improving retrieval augmented language model with self-reasoning. Preprint, arXiv:2407.19813.
- Shitao Xiao, Zheng Liu, Peitian Zhang, and Niklas Muennighoff. 2023. C-pack: Packaged resources to advance general chinese embedding. Preprint, arXiv:2309.07597.
- Shitao Xiao, Zheng Liu, Peitian Zhang, Niklas Muennighoff, Defu Lian, and Jian-Yun Nie. 2024. Cpack: Packed resources for general chinese embeddings. In Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 641–649.
- Haiyang Xu, Hui Zhang, Kun Han, Yun Wang, Yiping Peng, and Xiangang Li. 2019. Learning alignment for multimodal emotion recognition from speech.
- Chuanpeng Yang, Wang Lu, Yao Zhu, Yidong Wang, Qian Chen, Chenlong Gao, Bingjie Yan, and Yiqiang Chen. 2024. Survey on knowledge distillation for large language models: Methods, evaluation, and application. arXiv preprint arXiv:2407.01885.
- Zihan Zhang, Meng Fang, Ling Chen, Mohammad-Reza Namazi-Rad, and Jun Wang. 2023. How do large language models capture the ever-changing world knowledge? a review of recent advances. In Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, pages 8289–8311, Singapore. Association for Computational Linguistics.
- Penghao Zhao, Hailin Zhang, Qinhan Yu, Zhengren Wang, Yunteng Geng, Fangcheng Fu, Ling Yang, Wentao Zhang, Jie Jiang, and Bin Cui. 2024. Retrieval-augmented generation for ai-generated content: A survey. Preprint, arXiv:2402.19473.

- Ruochen Zhao, Hailin Chen, Weishi Wang, Fangkai Jiao, Xuan Long Do, Chengwei Qin, Bosheng Ding, Xiaobao Guo, Minzhi Li, Xingxuan Li, and Shafiq Joty. 2023. Retrieving multimodal information for augmented generation: A survey. In Findings of the Association for Computational Linguistics: EMNLP 2023, pages 4736–4756, Singapore. Association for Computational Linguistics.
- Yaowei Zheng, Richong Zhang, Junhao Zhang, Yanhan Ye, Zheyan Luo, Zhangchi Feng, and Yongqiang Ma. 2024. Llamafactory: Unified efficient finetuning of 100+ language models. In Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 3: System Demonstrations), Bangkok, Thailand. Association for Computational Linguistics.

Appendix

A Typical Cases

Due to the black box nature of an LLM, here the typical cases are not analytic or explanatory.

A.1 isRel

A.1.1 Positive

Retrieved image: (Figure. A1)



Figure A1: Image title: Kentucky Derby

Question: What animals race in the Kentucky Derby?

isRel Response: {'Reasoning': 'The image of the Kentucky Derby prominently features horses racing on a track with a crowd watching from the stands. The Kentucky Derby is a well-known horse racing event, which is explicitly illustrated by the horses visible in the image. This visual directly connects to the question by showcasing the animals, horses, that race in the Kentucky Derby. Therefore, the image content answers the question satisfactorily.', 'Response': 'True'}

 $\mathsf{found} \to True$

Continue searching until the end of current batch...

A.1.2 Negative

Retrieved image: (Figure. A2)



Figure A2: Image title: Daria

Question: What object is in front of Felicia Day's face?

isRel Response: {'Reasoning': "The image title is 'Daria,' which refers to a character from an animated series, and it visually features a character with glasses. The question asks about an object in front of Felicia Day's face which is unrelated to either the 'Daria' series or its content. The image does not depict Felicia Day, and there is no visible object in front of a character's face named Felicia Day here. Therefore, there is no relation between the image titled 'Daria' and the question about Felicia Day.", 'Response': 'False'}

Continue searching...

A.2 isUse

A.2.1 Positive

Question: What is the name of the final album released by the Christian rock band that formed in the mid 1980s at Kentucky Christian University in Grayson, Kentucky?

Supporting Context: Adios: The Greatest Hits is the final album released by Christian rock band Audio Adrenaline, and their second Greatest Hits album.

Draft answer: Adios: The Greatest Hits

isUse Response: {'Reasoning': "The answer 'Adios: The Greatest Hits' correctly identifies the name of the final album released by the Christian rock band Audio Adrenaline, as mentioned in the source content. The content specifies that 'Adios: The Greatest Hits' is the final album, aligning logically with the requirement to name the final album in the question. Additionally, the band, although not explicitly mentioned in the answer, is implicitly known from the context of the content and relevant to the question. Both the format and logical consistency criteria are met.", 'Response': 'True'}

Proceed to isSup...

A.2.2 Negative

Question: are all of the songs in mamma mia here we go again by abba

Supporting Context: Mamma Mia! Here We Go Again was announced on May 19, 2017, with a release date of July 20, 2018. It was written and directed by Ol Parker. On September 27, 2017, Benny Andersson confirmed 3 ABBA songs that would be featured in the film: "When I Kissed the Teacher," "I Wonder (Departure)," and "Angeleyes." "I Wonder (Departure)" was cut from the film, but is included on the soundtrack album.

Draft answer: No

isUse Response: {'Reasoning': "The answer 'No' implies that not all songs in 'Mamma Mia! Here We Go Again' are by ABBA, but the content does not explicitly affirm this, nor does it list songs by artists other than ABBA. Although it mentions some ABBA songs included in the film, it lacks specific information about non-ABBA songs. Thus, without specific supporting content to verify that not all songs are by ABBA, the answer cannot be logically consistent with the provided information.", 'Response': 'False'}

Regenerate answer...

A.3 isSup

A.3.1 Postive

Question: what are flying monkeys in wizard of oz called

Supporting Context: Winged monkeys (often referred to in adaptations and popular culture as flying monkeys) are fictional characters created by American author L. Frank Baum in his classic children's novel The Wonderful Wizard of Oz (1900). The winged monkeys are exactly what the name implies: jungle monkeys with powerful bird-like feathered wings attached to their shoulders which allow them to fly. They are most notable from the famous 1939 musical movie by MGM. Ever since, they have taken their own place in popular culture, regularly referenced in comedic or ironic situations as a source of evil or fear.

Draft answer: winged monkeys

isSup Response: {'Reasoning': "The content specifies that the characters in 'The Wonderful Wizard of Oz' referred to as flying monkeys in adaptations and popular culture, are originally called 'winged monkeys' in the novel. Hence, the given answer aligns correctly with the content.", 'Response': 'True'}

Return the answer

A.3.2 Partial

Question: who was first offered the part of columbo

Supporting Context: In 1968, the same play was made into a two-hour television movie that aired on NBC. The writers suggested Lee J. Cobb and Bing Crosby for the role of Columbo, but Cobb was unavailable and Crosby turned it down because he felt it would take too much time away from the golf links. Director Richard Irving convinced Levinson and Link that Falk, who wanted the role, could pull it off even though he was much younger than the writers had in mind.

Draft answer: Lee J. Cobb

isSup Response: {'Reasoning': "The content mentions that Lee J. Cobb was suggested by the writers for the role of Columbo, indicating that he was among the first choices for the role. However, it doesn't clearly state he was formally offered the part, as Bert Freed was the first actor to portray Columbo. Since it's indicated Freed already played the role and Lee J. Cobb was just suggested later, the interpretation of 'offered' here could be nuanced. Given this ambiguity but based on the information that Cobb was suggested, the content supports that proposition within this context.", 'Response': 'Partial'}

Reset draft answer and restart searching on next batch...

A.3.3 Negative

Question: who was considered the father of the blues

Supporting Context: McKinley Morganfield (April 4, 1913 April 30, 1983), known professionally as Muddy Waters, was an American blues singer-songwriter and musician who is often cited as the "father of modern Chicago blues", and an important figure on the post-war blues scene. His style of playing has been described as "raining down Delta beatitude".

Draft answer: McKinley Morganfield

isSup Response: {'Reasoning': "The content states that McKinley Morganfield, known as Muddy Waters, is "often cited as the 'father of modern Chicago blues'," which specifically refers to his influence on the Chicago blues subgenre. However, the question asks who is considered the "father of the blues" in a general sense, which typically implies a foundational figure for the entire blues genre, not just a subgenre. Therefore, while Muddy Waters is a significant figure in blues, the content does not fully support the answer that he is the "father of the blues" overall; it only supports his title within the context of "modern Chicago blues." Thus, the answer "McKinley Morganfield" is not supported by the content for the broader question.", 'Response': 'False'}

Reset content storage C and restart searching on next batch...

B Prompt template

B.1 isRel

""" You are an expert in reading comprehension and logical reasoning. Your task is to determine whether a given piece of text is related to a specific question.

Consider the following inputs:

- 1. Content: {A piece of text provided to you.}
- 2. Title: {The title relevant to the text.}
- 3. Question: {A specific question that may or may not be related to the text.}

Your response should include:

- 1. Reasoning: A step-by-step explanation of how you analyzed the text to determine if it is related to the question.
- 2. Response: A value ('True' or 'False') indicating whether the text is related to the question.

```
- **True**: The text is related and can help answer the question.
```

- **False**: The text is not related to the question.

Format your output as a JSON object:

```
Schema
```

```
"Reasoning": "Step-by-step reasoning explaining why the text is or isn't related to the question.",
"Response": "True"/"False"
```

Example:

- 1. Content: 'Photosynthesis is the process by which darkblue plants and some other organisms use sunlight to synthesize foods with the help of chlorophyll. The process converts carbon dioxide and water into glucose and oxygen.'
- 2. Title: 'Photosynthesis'
- 3. Question: 'What is the main product of cellular respiration?'

Output:

"Reasoning": "The question asks about the main product of cellular respiration, which is a process that converts glucose into energy, carbon dioxide, and water. The text provided discusses photosynthesis, a different process that converts carbon dioxide and water into glucose and oxygen. Since the text does not address cellular respiration, it is not related to the question.", "Response": "False"

1. Content: 'Cellular respiration is a set of metabolic reactions and processes that

take place in the cells of organisms to convert biochemical energy from nutrients into adenosine triphosphate (ATP), and then release waste products.'

- 2. Title: 'Cellular Respiration'
- 3. Question: 'What is the main product of cellular respiration?'

Output:

"Reasoning": "The question asks about the main product of cellular respiration. The text directly discusses cellular respiration and mentions that it converts nutrients into ATP, which is the main product of the process. Therefore, the text is related to the question.", "Response": "True"

}

"""

B.2 QA prompt

"You are an expert in knowledge extraction, problem-solving, and reading comprehension. You excel at identifying key information and providing concise answers.

Given the following inputs:

- 1. Content: {Relevant content that may contain the answer to the question.}
- 2. Question: {A specific question related to the content.}

Your task is to answer the question based on the provided content. The answer should be as simple as possible, typically an entity or a timestamp.

Your response should only contain the answer itself. Do not explain, provide notes, or include any additional text, punctuation, or preposition (e.g., 'on', 'at'), or articles (e.g., 'a', 'an', 'the') unless absolutely necessary.

Output should be in the following JSON format:

```
{
"Reasoning": "A step-by-step solution trace explaining the reasoning behind the answer.",
"Response": "The answer itself, as simple as possible."
}

Example:
```

1. Content: 'The capital of France, known for its art, culture, and history, is Paris.' 2. Question: 'What is the capital of France?'

```
Output:
```

```
{
"Reasoning": "The content directly states that the capital of France is Paris.", "Response":
"Paris"
}
```

- 1. Content: 'The American Civil War ended on April 9, 1865, when General Robert E. Lee surrendered to General Ulysses S. Grant.'
- 2. Question: 'When did the American Civil War end?'

```
Output:
{
"Reasoning": "The content provides a specific date for the end of the American Civil War.",
"Response": "April 9 1865"
}
```

B.3 isSup

"""You are an expert in critical analysis, problem-solving, and comprehension. You excel at evaluating the relationship between content and answers.

Given the following inputs:

- 1. Content: {A content specific to the question, describing the content of the image or text.}
- 2. Question: {A specific question.}
- 3. Answer: {The provided answer to the question.}

Your task is to assess whether the content supports the given answer based on the question.

Please evaluate the support level of the content for the answer according to the following levels:

- 1. True: The answer is fully supported by the content.
- 2. Partial: The answer is partially supported by the content; it may be incomplete or not entirely accurate but contains some correct elements.
- 3. False: The answer is not supported by the content or is contradicted by it.

After evaluating, provide your verification and an explanation for your choice.

```
Output should be in the following JSON format:
{
"Reasoning": "A brief explanation of why the content fully, partially, or does not support the answer.",
"Response": "True" / "Partial" / "False"
}
Example:
```

- 1. Content: "Tokyo is one of the most populous cities in the world and serves as the political, economic, and cultural center of Japan. The city is home to the Japanese government and the Imperial Palace."
- 2. Question: "What is the capital of Japan?"
- 3. Answer: "Tokyo."

Output: { "Reasoning": "The content clearly states that Tokyo is the political center of Japan and houses the government, fully supporting the answer that Tokyo is the capital of Japan.", "Response": "True" }

- 1. Content: "World War II, which began in 1939, was a global conflict that involved most of the world's nations. The war saw the rise and fall of major powers and resulted in significant geopolitical changes. The conflict formally ended with the unconditional surrender of Germany in May 1945, followed by the surrender of Japan in September 1945."
- 2. Question: "What year did World War II end?"
- 3. Answer: "1944."

Output:

"Reasoning": "The content provides information that World War II ended in 1945, contradicting the given answer of 1944. Therefore, the content does not support the answer.", "Response": "False" }

- 1. Content: "The Amazon Rainforest, covering approximately 5.5 million square kilometers, is often referred to as the 'lungs of the Earth.' It plays a critical role in regulating the global climate by absorbing large amounts of carbon dioxide. The rainforest is home to an incredible diversity of flora and fauna, many of which are endemic to the region."
- 2. Question: "How much area does the Amazon Rainforest cover?"
- 3. Answer: "The Amazon Rainforest plays a crucial role in regulating the global climate."

Output:

{

"Reasoning": "The answer correctly mentions the role of the Amazon Rainforest in climate regulation, but it does not address the specific question about the area it covers. Therefore, the answer is only partially supported by the content.",

```
"Response": "Partial"
}
```

,,,,,,

B.4 isUse

"""You are an expert in critical analysis, problem-solving, and comprehension.

Your task is to evaluate whether a given answer appropriately addresses a specific question based on the provided content.

Given the following inputs:

- 1. Content: {The source material from which the answer is derived.}
- 2. Question: {A specific question that needs to be answered.}

3. Answer: {The provided answer in response to the question.}

Your goal is to determine whether the answer is appropriate by considering the following criteria:

- 1. **Format Accuracy**: The answer should be in the expected format. For example, if the question asks for a date, the answer should be presented in a date format.
- 2. **Logical Consistency**: The answer must be logically correct and align with the information provided in the content.

After your evaluation, provide a detailed explanation of your reasoning, breaking it down step by step, and offer a clear conclusion.

Your output should be in the following JSON format:

```
{
"Reasoning": "A comprehensive explanation of whether the answer meets the expected format and logical criteria, supported by specific references to the content.",
"Response": "True" / "False"
}

Examples:
```

- 1. Content: 'Mount Everest, located in the Himalayas on the border between Nepal and the Tibet Autonomous Region of China, is the highest mountain in the world, with a peak that reaches 8,848 meters (29,029 feet) above sea level.'
- 2. Question: What is the height of the highest mountain in the world?
- 3. Answer: 8,848 meters

Output:

"Reasoning": "The answer correctly identifies the height of Mount Everest as 8,848 meters, which is both in the expected numerical format and logically consistent with the provided content.",

```
"Response": "True" }
```

- 1. Content: 'The Nile River, which flows through northeastern Africa, is considered one of the longest rivers in the world, with a length of approximately 6,650 kilometers (4,130 miles). The river is a major waterway for countries such as Egypt and Sudan.'
- 2. Question: How many countries does the Nile River flow through?
- 3. Answer: The Nile River is 6,650 kilometers long.

Output:

"Reasoning": "The answer mentions the length of the Nile River but fails to address the question, which asks for the number of countries the river flows through. The answer is neither in the expected format nor logically consistent with the question.",

```
"Response": "False" }
```

.....

B.5 Image inference prompt

"""You are an expert at problem solving, knowledge extraction, and reading comprehension. You excel at identifying requirements, breaking tasks down, and solving problems step-by-step.

Given the following inputs:

```
    Title: {Title of the context}
    Question: {A given question}
```

Your objective is to determine whether the image content is directly related to answering the question. If the image and title are relevant, you should provide a thorough, step-by-step reasoning that clearly demonstrates the connection between the image content and the question. If the image is not relevant, explain why there is no connection.

Please follow these steps:

- 1. **Analyze the Title and Image**: Assess the image content based on the title and determine its relevance to the question.
- 2. **Develop Reasoning**: If the image is relevant, provide a detailed and logical explanation of how the image content answers the question. If irrelevant, explain the lack of connection between the image and the question.
- 3. **Conclude with a Response**: Clearly state whether the image is relevant ('True') or irrelevant ('False') to the question.

Your output should adhere to the following JSON schema:

```
Schema

{
"Reasoning": "A detailed and logical step-by-step explanation of why the image content is or is not related to the question.",
"Response": "True" / "False"
}

Examples

1. Title: 'The Cosby Show'
2. Question: 'What color is the inside of the text in The Cosby Show?'

Output:
{
```

"Reasoning": "The image titled 'The Cosby Show' prominently displays the show's title. The inside of the text is white, standing out against a darker background. This contrast enhances visibility and aligns with the show's branding, making the title easily recognizable. The use of white inside the text reflects the cultural significance of the show's branding.",

```
"Response": "True"
}

1. Title: 'Mercy (TV series)'
2. Question: 'Is the background to the Person of Interest (TV series) poster colored or colorless?'

Output:
{
"Reasoning": "The image titled 'Mercy (TV series)' features a grayscale background, depicting a cityscape or a map-like layout. The only color in the image is a red triangular symbol, with the rest of the design focusing on muted tones. The colorless background reinforces the show's themes of surveillance and intrigue, creating a serious and dramatic tone. Therefore, the background is predominantly colorless. However, the question asking about the Person of Interest (TV series) poster, not about the Mercy (TV series), so the image does not seem to be related to the question.",
"Response": "False"
}
```

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