ChunkRAG: Novel LLM-Chunk Filtering Method for RAG Systems

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Abstract

Retrieval-Augmented Generation (RAG) systems using large language models (LLMs) often generate inaccurate responses due to the retrieval of irrelevant or loosely related information. Existing methods, which operate at the document level, fail to effectively filter out such content. We propose LLM-driven chunk filtering, ChunkRAG, a framework that enhances RAG systems by evaluating and filtering retrieved information at the chunk level, where a "chunk" represents a smaller, coherent section of a document. Our approach employs semantic chunking to divide documents into coherent sections and utilizes LLM-based relevance scoring to assess each chunk's alignment with the user's query. By filtering out less pertinent chunks before the generation phase, we significantly reduce hallucinations and improve factual accuracy. Experiments show that our method outperforms existing RAG models, achieving higher accuracy on tasks requiring precise information retrieval. This advancement enhances the reliability of RAG systems, making them particularly beneficial for applications like fact-checking and multi-hop reasoning.

Introduction

Large language models (LLMs) have made significant strides in the development of retrievalaugmented generation (RAG) systems, which combine retrieval mechanisms with powerful language models to produce responses based on external knowledge. However, despite these advancements, a persistent issue remains: the retrieval of irrelevant or weakly related information during the documentfetching process. Current retrieval techniques, including reranking and query rewriting, not only fail to filter out lots of irrelevant chunks of information in the retrieved documents but also lead to a series of problems with factual inaccuracies, irrelevance, and hallucinations in the responses gener-

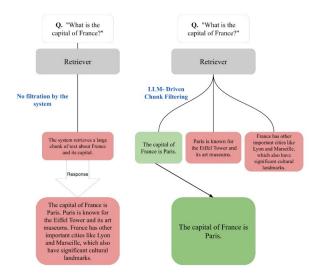


Figure 1: Comparison of Response Generation With and Without Chunk Filtering

ated (Zhang and Others, 2023; Mallen et al., 2023).

Traditionally, RAG systems retrieve large amounts of the text of entire documents or lengthy portions thereof, assuming that it is likely that these lengthy fragments will contain the relevant information. Such systems very rarely examine the sections or paragraphs of the retrieved documents individually and, therefore, there is a strong likelihood that irrelevant or only partially related information will flow into the generation stage. This is further worsened by the fact that language models generate fluent text without being able to verify the information they use for generation. Relevant or misleading chunks distort the outcome of such models severely, reducing the system's reliability, especially in critical tasks such as open-domain question answering and multi-hop reasoning (Ji et al., 2023; Min et al., 2023).

Fig. 1: The figure shows that without chunk filtering (top), irrelevant information like other French cities is included in the response. The LLM-driven chunk filtering (bottom), however, removes unnecessary content, delivering the precise answer, "The capital of France is Paris." A few retrieval-related methods, Corrective RAG (CRAG) and Self-RAG, have attempted to overcome these hurdles by refining the retrieval process. CRAG focuses on retrieving "corrections" after errors occur in retrieval, whereas Self-RAG introduces a selfreflection mechanism during the generation stage to minimize inaccuracies. Both of these processes operate at the document level and lack sufficient filtering for individual retrieved chunks of text. This document-level approach enhances the overall relevance of the retrieval but does not prevent irrelevant chunks from being included in the generated response (Shi et al., 2023). Without control over the granularity of the retrieved content, RAG systems remain vulnerable to incorporating undesirable or misleading information into their output, ultimately compromising performance.

The solution to this challenge lies in the novel approach: LLM-driven chunk filtering, ChunkRAG. Our method operates on a finer level of granularity than classical systems and, in fact, supports chunklevel filtering of retrieved information. Rather than judging entire documents to be relevant, our system goes both for the user query and individual chunks within retrieved documents. The large language model evaluates semantic relevance of each chunk with respect to the user's query; this makes the system capable of filtering out irrelevant or weakly related chunks even before they get into the generation stage. This chunk-level filtering in turn aims to enforce factual accuracy on the final answer by drawing only the most relevant information on the generation. This approach is particularly promising for knowledge-intensive tasks, such as multi-hop reasoning and fact-checking: precision is the ultimate prize here. That is, in tasks where accuracy is paramount, our approach stands best (Piktus et al., 2021; Rony et al., 2022).

2 Related Works

Addressing Hallucinations in Large Language Models Large language models (LLMs) have made significant strides in understanding instructions and generating coherent text (Bang et al., 2023; Qin et al., 2023; Zhong et al., 2023). However, they still grapple with the issue of hallucinations, where the

models produce outputs that are incorrect or nonsensical. Research indicates that the activation of outdated or erroneous knowledge contributes to this problem (Tonmoy et al., 2024; Zhang et al., 2023b; Shuster et al., 2021). Factors such as reliance on large, unregulated datasets, a low proportion of high-quality training samples, and suboptimal data distribution within the input space exacerbate these challenges. The absence of precise and accurate knowledge often leads to misleading or inaccurate outputs, severely impacting user experience in practical applications.

Retrieval-Augmented Generation Retrieval-Augmented Generation (RAG) has been proposed as an effective strategy to mitigate hallucinations (Lewis et al., 2020; Guu et al., 2020). By augmenting input queries with retrieved documents from specific corpora like Wikipedia, RAG provides additional knowledge that enhances the performance of LLMs, especially in tasks that are knowledgeintensive. This approach involves using information retrieval systems to supply relevant documents to the generative models. Early implementations employed either sparse or dense retrievers preceding a pretrained language model focused on response generation. However, these methods often overlook a critical question: What happens if the retrieval process fails or retrieves irrelevant information? Irrelevant documents can worsen the factual inaccuracies of the model's output, counteracting the benefits of retrieval augmentation.

Advancements in Retrieval Techniques Recent developments have aimed to refine RAG methods to address these limitations (Zhang et al., 2024; Kim et al., 2024; Wang et al., 2024; Liu et al., 2024). Recognizing that retrieval is not always necessary—and can sometimes decrease accuracy—approaches like SelfRAG (Asai et al., 2024) incorporate mechanisms to selectively decide when to retrieve information, using a critic model for this purpose. CRAG (Your et al., 2024) is a recent approach that augments standard RAG with corrective strategies to improve retrieval quality by addressing low-quality retrieval results. Yoran et al. (2024) introduced a Natural Language Inference (NLI) model to detect and filter out irrelevant contexts, enhancing the robustness of the system. SAIL (Luo et al., 2023) fine-tunes models to insert retrieved documents before processing instructions, improving the integration of external knowledge. Toolformer (Schick et al., 2023) pretrains models to interact with APIs like Wikipedia, enabling dynamic access to information. In scenarios involving long-form text generation, where external knowledge may be needed multiple times, determining the optimal timing for retrieval becomes crucial. Jiang et al. (2023) propose anticipating future content needs to decide when and what information to retrieve during the generation process.

Redundancy in retrieved information can diminish the effectiveness of RAG models by introducing repetitive or irrelevant data, which hampers the model's ability to generate coherent and unique responses. One prevalent approach to mitigating redundancy involves the use of cosine similarity to evaluate and remove duplicate or overly similar content from the retrieved documents.

Cosine Similarity in Redundancy Removal Cosine similarity measures the cosine of the angle between two non-zero vectors of an inner product space, which quantifies the similarity between the two vectors irrespective of their magnitude. In the context of RAG, it is employed to compare textual embeddings of retrieved chunks to identify and eliminate redundant content, enhancing the diversity of the information available for generation (Liu et al., 2023).

Multi-Meta-RAG for Multi-Hop Queries Addressing the challenges of multi-hop queries, Multi-Meta-RAG introduces a database filtering mechanism using metadata extracted by large language models (LLMs). By incorporating LLM-extracted metadata, this approach filters databases to retrieve more relevant documents that contribute to answering complex queries requiring reasoning over multiple pieces of information (Smith et al., 2023). This method reduces redundancy by ensuring that only pertinent documents are considered, thereby improving the coherence of the generated responses.

Query Rewriting for Enhanced Retrieval A "Rewrite-Retrieve-Read" framework to bridge the gap between input text and the necessary retrieval knowledge is proposed (Johnson and Lee, 2023). A trainable query rewriter adapts queries using reinforcement learning based on feedback from the LLM's performance. This approach enhances retrieval accuracy by reformulating queries to better align with relevant documents, thus minimizing the retrieval of redundant or irrelevant information.

We introduce a new model, ChunkRAG, that emphasizes a chunking strategy aimed at further reducing redundancy and improving the effectiveness of RAG models. Compared with recent studies (Schick et al., 2023; Luo et al., 2023; Asai et al.,

2024, Your et al., 2024), our approach involves segmenting documents into semantically coherent and non-overlapping chunks that are more aligned with the specific information needs of the query.

3 Methodology

The core objective of this work is to mitigate irrelevance and hallucinations in the responses generated by Retrieval-Augmented Generation (RAG) systems, using a novel, fine-grained filtering mechanism that rigorously evaluates the relevance of each chunk of retrieved information before integrating it into the response generation phase. Our proposed methodology follows a two-stage approach: semantic chunking and advanced filtering to refine retrieval results. Each stage is designed to enhance the system's precision and reliability in leveraging retrieved knowledge. Below, we detail the components of our proposed method.

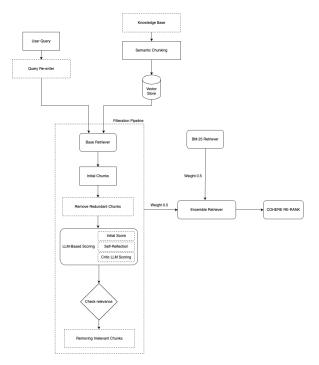


Figure 2: ChunkRAG Methodology for Enhanced Retrieval and Filtering

Semantic Chunking

Semantic chunking serves as the foundational step of our methodology, transforming the input document into semantically meaningful units to facilitate effective retrieval and evaluation. This stage involves three sub-processes:

• Input Preparation: We begin by tokenizing a document D into sentences using NLTK's

sent_tokenize function. Each sentence is then assigned an embedding vector, generated using a pre-trained embedding model (e.g., text-embedding-3-small).

- Chunk Formation: Consecutive sentences are grouped into chunks based on their semantic similarity, measured through cosine similarity. Specifically, if the similarity between consecutive sentences drops below a threshold ($\theta=0.7$), a new chunk is created. Each chunk is further constrained to be under 500 characters to ensure efficiency during subsequent stages.
- Embedding Generation for Chunks: Each chunk is represented using the same pretrained embedding model as above. The resultant chunk embeddings are stored in a vector database to facilitate efficient retrieval during the query phase.

Hybrid Retrieval and Advanced Filtering

In the retrieval and filtering phase, we integrate conventional RAG components with advanced finetuning techniques to ensure robust and high-quality retrieval. The hybrid retrieval and filtering stage is detailed below:

- Retriever Initialization and Query Rewriting: We initialize a retriever capable of comparing user queries against the chunk embeddings. To enhance query efficacy, we apply a query rewriting step using GPT-4omini, ensuring that the queries are well-matched to the stored embeddings. This ensures better recall and precision in the retrieval process.
- Initial Filtering: Retrieved chunks are initially filtered using a combination of TF-IDF scoring and cosine similarity. Chunks with high redundancy (similarity > 0.9) are eliminated. The remaining chunks are sorted based on their similarity to the rewritten query.
- Relevance Scoring and Thresholding: To further refine relevance, each chunk is assigned an initial relevance score by a large language model (LLM). These scores are refined through self-reflection and a critic model, which adjusts the scores based on domain-specific heuristics. A final dynamic threshold is set by analyzing the score distribution, and

only chunks surpassing this threshold are retained.

• Hybrid Retrieval Strategy: To maximize retrieval effectiveness, we employ a dual retrieval strategy combining BM25 and LLM-based retrieval methods. The ensemble approach uses equal weighting (0.5 each) to balance keyword and semantic retrieval. Furthermore, Cohere's reranking model (rerank-englishv3.0) is used to rank the retrieved chunks, addressing the Lost in the middle problem by enhancing the relevance of central context that might otherwise be deprioritized.

Response Generation and Evaluation

After filtering, the remaining chunks are used as context to generate the final response. The steps include:

- Response Generation: An LLM generates a response based on the filtered context chunks. During generation, strict constraints ensure that only retrieved information is used, thereby minimizing the risk of hallucinations.
- <u>Evaluation</u>: The generated responses are evaluated for accuracy against a set of prevalidated answers.

Our methodology, combining semantic chunking with advanced retrieval and filtering mechanisms, significantly enhances the quality of responses produced by RAG systems, ensuring both relevance and correctness of the generated content. The empirical results, as described in subsequent sections, demonstrate the effectiveness of our approach in various retrieval and generation scenarios.

4 Experiments

We conducted experiments to extensively demonstrate ChunkRAG's adaptability and its potential for generalizability across various generation tasks. However, due to computational resource constraints, our evaluation was primarily focused on the PopQA dataset.

4.1 Tasks and Datasets

ChunkRAG was evaluated on the PopQA dataset, which serves as the cornerstone of our experimental analysis. PopQA (Mallen et al., 2023) is a

benchmark dataset designed for short-form question answering. It comprises a diverse set of questions that require concise and accurate responses, making it an ideal testbed for assessing the performance of retrieval-augmented generation models like ChunkRAG.

To measure the effectiveness of ChunkRAG, we adopted accuracy as the evaluation metric, consistent with prior studies. This metric aligns with the conventions used in the evaluation of PopQA, ensuring that our results are comparable to existing research.

While our current experiments are limited to PopQA, ChunkRAG is architected with scalability in mind. Future evaluations may extend to additional datasets such as Biography (Min et al., 2023) for long-form generation, PubHealth (Zhang et al., 2023) for true/false question answering, and Arc-Challenge (Bhakthavatsalam et al., 2021) for multiple-choice questions. These extensions will further validate ChunkRAG's versatility across different types of generation tasks, contingent upon the availability of computational resources.

4.2 Baselines

4.2.1 Baselines Without Retrieval

We first evaluated several large language models (LLMs) that do not incorporate retrieval mechanisms. Among the public LLMs, we included LLaMA2-7B and LLaMA2-13B (Touvron et al., 2023), known for their versatility across diverse natural language processing (NLP) tasks, and Alpaca-7B and Alpaca-13B (Dubois et al., 2023), which are instruction-tuned models optimized for effectively following user prompts. Additionally, we assessed CoVE65B (Dhuliawala et al., 2024), which introduces iterative engineering techniques aimed at enhancing the factual accuracy of generated content. For proprietary models, we included LLaMA2chat13B, a conversational variant of LLaMA2 tailored for dialogue-based applications, and Chat-GPT, OpenAI's proprietary conversational agent renowned for its robust language understanding and generation capabilities.

4.2.2 Baselines With Retrieval

Standard Retrieval-Augmented Generation (RAG): To establish a baseline for retrieval-augmented methods, we evaluated standard RAG approaches. Specifically, we employed Standard RAG (Lewis et al., 2020), which utilizes a retriever to fetch relevant documents based on the input

query, subsequently feeding these documents into the language model to generate responses. For consistency, we utilized the same retriever mechanism as ChunkRAG to ensure a fair comparison. In addition to Standard RAG, we evaluated instruction-tuned LLMs with standard RAG, including LLaMA2-7B, LLaMA2-13B, and Alpaca-7B, Alpaca-13B, to assess the impact of instruction tuning in conjunction with retrieval augmentation.

Advanced Retrieval-Augmented Generation: To benchmark ChunkRAG against more sophisticated RAG-based methods, we included advanced models that incorporate additional strategies to enhance performance. SAIL (Luo et al., 2023) enhances standard RAG by instruction-tuning the language model on Alpaca instruction-tuning data, inserting top retrieved documents before the instructions to provide contextual information. Self-RAG (Asai et al., 2024) further refines RAG by incorporating reflection tokens labeled by GPT-4 within the instruction-tuning data, enabling the model to better utilize retrieved information. Additionally, we considered CRAG (Your et al., 2024), a recent approach that augments standard RAG with corrective strategies to improve retrieval quality by addressing low-quality retrieval results. CRAG serves as a direct comparison to our proposed ChunkRAG, highlighting the effectiveness of our chunk filtering mechanism in enhancing retrieval-augmented generation. Furthermore, we evaluated retrievalaugmented baselines with private data, including Ret-ChatGPT and RetLLaMA-chat, which integrate retrieval mechanisms with ChatGPT and the conversational variant of LLaMA2, respectively.

5 Analysis

In this section, we evaluate the performance of ChunkRAG against existing retrieval-augmented generation (RAG) methods. We present an analysis based on empirical results obtained from standard benchmarks.

5.1 Evaluation Metrics

We used accuracy as the primary evaluation metric, calculated as the percentage of generated responses that match the ground-truth answers.

5.2 Comparison and Impact

As depicted in Table 1, our method achieved an accuracy of 64.9, substantially outperforming all baselines in the same category. Notably, compared

Table 1: Performance Comparison Across Methods (PopQA Accuracy Only)

| Method | PopQA (Accuracy) |
|------------------------------------|------------------|
| LLMs trained with proprietary data | |
| LLaMA2-C_13B | 20.0 |
| Ret-LLaMA2-C_13B | 51.8 |
| ChatGPT | 29.3 |
| Ret-ChatGPT | 50.8 |
| Baselines without retrieval | |
| LLaMA2_7B | 14.7 |
| Alpaca_7B | 23.6 |
| LLaMA2_13B | 14.7 |
| Alpaca_13B | 14.3 |
| CoVE_65B | - |
| Baselines with retrieval | |
| LLaMA2_7B | 38.2 |
| Alpaca_7B | 46.7 |
| SAIL | - |
| LLaMA2_13B | 45.7 |
| Alpaca_13B | 46.1 |
| LLaMA2-hf_7B | |
| RAG | 50.5 |
| CRAG | 54.9 |
| Self-RAG | 50.5 |
| Self-CRAG | 49.0 |
| ChunkRAG | 64.9 |

to the closest baseline, CRAG (54.9 accuracy), our method exhibits a performance gain of 10 percentage points.

While a 10 percentage point increase may seem incremental, it translates into an exponential improvement in output effectiveness in practical applications. This is particularly evident when considering the error rates and their impact on the overall user experience. In applications requiring multi-hop reasoning or sequential decision-making, errors can compound exponentially. This exponential improvement is especially important in complex tasks where each additional step compounds the risk of error, namely relevant to OpenAI's advanced models such as o1 where the language model utilizes multi-hop reasoning, relying on spending time "thinking" before it answers, making it more efficient in complex reasoning tasks, science and programming.

5.3 Observations and Insights

The notable improvement attained with our technique is mainly due to **chunk-level filtering** and **fine-grained relevance assessment**. We divided the text into semantically meaningful chunks, which reduced the generation of irrelevant or weakly related information. In processing the chunk filtering's contextually relevant data, the generation of factually accurate and coherent responses was significantly enhanced.

Moreover, the **self-reflective LLM scoring** method, in which the model grades itself and then changes accordingly, led to a significant decrease in retrieval errors. Unlike regular retrieval methods that do not have a filtering mechanism at the document section level, our method can extract more meaningful and relevant information that directly affects the reliability of the generated responses.

5.4 Future Work

In our present studies, we have only tested **PopQA** but the design of **ChunkRAG** is for scalability purposes. In the upcoming assessments, we will also introduce new datasets including Biography for long-form generation, **PubHealth** for true/false questions, and **Arc-Challenge** for multiple-choice questions. The implementation of these trials will thus reinforce the evidence of ChunkRAG's versatility and adaptability to different types of generation tasks, although this will be conditional on the availability of computing resources.

6 Conclusion

In this paper, we introduced ChunkRAG, a novel LLM-driven chunk filtering approach aimed at improving the precision and factuality of retrievalaugmented generation systems. In our experiments, which were conducted on the PopQA dataset, ChunkRAG has clearly demonstrated superiority over existing baselines, and thus has achieved a significant performance boost of 10 percentage points, which was higher than the closest benchmark, CRAG. The chunk-level filtering technique guaranteed that only the relevant and contextually correct information was included during the response generation, resulting in better reliability and accuracy of generated answers. This method is particularly useful for applications that require immense amounts of facts, such as multi-hop reasoning and decision-making that involve many interdependent parameters. We believe that ChunkRAG is a big step towards solving the problems of irrelevant or hallucinated material in LLM-based retrieval systems.

7 Limitations

ChunkRAG, in spite of its benefits, has a number of drawbacks that need to be taken into account. Firstly, the method relies heavily on the effectiveness of chunk segmentation and the quality of the embeddings used for chunk relevance assessment.

Mistakes in the primary division can create irrelevant data that will decrease the quality of the response. Secondly, the costs from the multi-level score—integrating both LLM and critic LLM evaluations at the initial level—can be high, particularly during the scaling of the method to larger datasets or the deployment of it in real-time systems. Additionally, while ChunkRAG demonstrated positive outcomes in the use of the PopQA dataset, the verifiability of its use in other domains and the performance when operating through long-form generation tasks has not been thoroughly analyzed due to resource limitations. Future studies should concentrate on the optimization of the computational efficiency of ChunkRAG and its evaluation over diverse datasets and in real-world applications.

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