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. 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.

1 Introduction

Large language models (LLMs) have made significant strides in the development of retrieval-augmented 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 document-fetching 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 generated (Zhang and Others, 2023; Mallen et al., 2023).

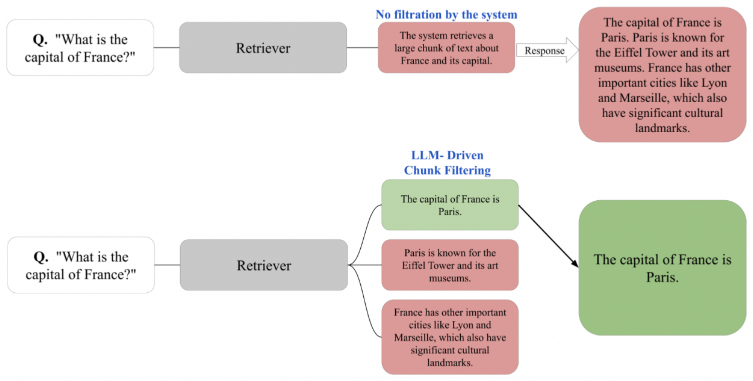
No filtration by the system
Q. "What is the capital of France?"
Retriever
The system retrieves a large chunk of text about France and its capital.
Response
The capital of France is Paris. Paris is known for the Eiffel Tower and its art museums. France has other important cities like Lyon and Marseille, which also have significant cultural landmarks.
LLM- Driven Chunk Filtering
Q. "What is the capital of France?"
Retriever
The capital of France is Paris.
Paris is known for the Eiffel Tower and its art museums.
France has other important cities like Lyon and Marseille, which also have significant cultural landmarks.
The capital of France is Paris.

Figure 1: Flowchart

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. Moreover, 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 consequently distort the outcome of such models severely, reducing the system's reliability, especially in critical applications 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 sophisticating retrieval. CRAG focuses on retrieving "corrections" post-hoc to the errors that occur in retrieval, whereas Self-RAG injects self-reflection into the generation stage itself to avoid inaccuracies. Both of these processes occur at the document level and lack filtering sufficient enough for individual retrieved chunks of text. This document-level method enhances the broader relevance of the retrieval but does nothing to prevent irrelevant chunks from rolling over into the generated response (Shi et al., 2023). Lack of control over the granularity of the content retrieved makes RAG systems vulnerable to including undesirable or misleading information in their output, thus ultimately nullifying the 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 chunk-level 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 Literature Review

Redundancy in retrieved information can diminish the effectiveness of Retrieval-Augmented Generation 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: The paper titled "Query Rewriting for Retrieval-Augmented Large Language Models" proposes a "Rewrite-Retrieve-Read" framework to bridge the gap between input text and the necessary retrieval knowledge (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.

Self-RAG: Learning through Self-Reflection: Self-RAG puts forth a framework that enhances LLM quality and factuality through on-demand retrieval and self-reflection (Li et al., 2023). It trains the model to adaptively retrieve passages, generate text, and reflect on its own outputs using special tokens called reflection tokens. This method allows the model to critique and refine its responses, reducing redundancy by discouraging the inclusion of irrelevant or repetitive information.

We introduce a new model, ChunkRAG that emphasizes an innovative chunking strategy aimed at further reducing redundancy and improving the effectiveness of RAG models. Our approach involves segmenting documents into semantically coherent and non-overlapping chunks that are more aligned with the specific information needs of the query.

Despite advancements in Retrieval-Augmented Generation systems like RAG, CRAG, Self-RAG, and Self-CRAG, limitations persist in effectively retrieving and utilizing relevant information due to fixed size chunking, static relevance thresholds, and single-pass relevance scoring. Our approach addresses these issues through several key innovations: implementing semantic chunking for topically coherent chunks, employing LLM-based query rewriting to refine user queries, introducing advanced LLM-based relevance scoring with self-reflection and a critic LLM for more accurate assessments, utilizing dynamic threshold determination to adaptively filter relevant information, and incorporating initial filtering methods to improve efficiency by reducing redundancy and prioritizing chunks. These enhancements collectively surpass traditional models by providing more precise retrieval and contextually appropriate answers, leading to significant improvements in performance as demonstrated by standard evaluation metrics.

3 Methodology

The primary aim of this work is to reduce the irrelevance and hallucinations in the responses generated by RAG systems by implementing a novel, fine-grained filtering process that evaluates the relevance of each chunk of retrieved information before it is used in the response generation phase.

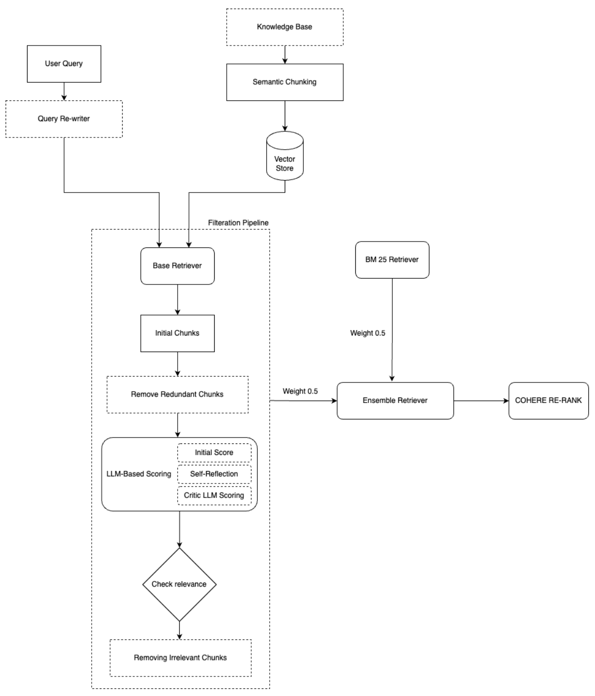

Figure 2: Methodology

Semantic Chunking

The initial step in the methodology involves breaking down the document into semantically coherent chunks, referred to as semantic chunking. This approach ensures that each chunk contains closely related information, improving the relevance of retrieval operations.

Sentence Tokenization:

Each document is split into sentences using NLTK's `sent_tokenize` function. This tokenization step enables the text to be processed at a more granular level.

Sentence Embeddings Generation:

Sentence embeddings are generated using OpenAI's 'text-embedding-3-small' model. Each sentence is transformed into a numerical vector representation, capturing its semantic meaning.

Similarity Calculation:

Cosine similarity is calculated between the embeddings of consecutive sentences. The similarity scores help determine how semantically related consecutive sentences are. If the similarity score drops below a predefined threshold (e.g., 0.7), it indicates a shift in topic.

Chunk Boundary Identification:

Based on similarity scores, chunk boundaries are identified at points where the similarity drops below the threshold, suggesting a change in topic.

Chunk Creation:

Sentences are grouped into chunks based on the identified boundaries. Each chunk is kept within a maximum length (e.g., 500 characters) to ensure semantic coherence and manageability.

Vector Store Creation

To facilitate efficient similarity-based retrieval, chunk embeddings are stored in a vector store:

Embedding Chunks:

Each chunk is embedded using the same embedding model ('text-embedding-3-small'), resulting in numerical vector representations of the chunks.

Storing in Vector Store:

The embeddings are stored in a Chroma vector store, which allows for efficient similarity search operations during retrieval.

Retriever Initialization:

A retriever is initialized to perform similarity-based searches. This retriever compares the embeddings of a query with those of the stored chunks to find the most relevant chunks.

Query Rewriting

To enhance retrieval performance, the user's query is rewritten without changing its original intent:

LLM-Based Rewriting:

A Language Model (LLM), such as GPT-4o-mini, is used to rewrite the query. A prompt guides the LLM to produce an improved version of the query that enhances retrieval effectiveness.

Initial Filtering Method

To improve efficiency and ensure relevance, initial filtering methods are applied before computationally expensive scoring operations:

Remove Redundant Chunks:

Duplicate or highly similar chunks are eliminated using TF-IDF vectorization and cosine similarity measures to reduce redundancy.

Semantic Similarity Sorting:

The remaining chunks are sorted based on their similarity to the query, prioritizing more relevant chunks for subsequent processing.

Advanced LLM-Based Relevance Scoring

To assess the relevance of each chunk more accurately:

Initial LLM Scoring:

The primary LLM assigns an initial relevance score to each chunk using a predefined prompt.

Self-Reflection:

The LLM reflects on its initial score and adjusts it if necessary to catch potential misjudgments.

Critic LLM Scoring:

A second LLM, termed as a critic, independently evaluates each chunk and assigns its own score to validate the initial assessment.

Final Score Calculation:

The final relevance score is obtained by averaging the initial, reflected, and critic scores to enhance accuracy and reliability.

Dynamic Threshold Determination

Instead of using a fixed threshold, a dynamic threshold is determined:

LLM-Based Threshold Determination:

The LLM analyzes the distribution of final scores and suggests an optimal threshold for chunk relevance.

Threshold Application:

Chunks with scores above the threshold are retained for answer generation.

Hybrid Retrieval and Re-Ranking

BM25 Retriever: In parallel, a BM25 retriever is implemented to capture keyword-based retrieval. BM25 retriever is combined using an ensemble approach with equal weights (0.5 each).

Re-ranking Chunks:

Cohere's reranking model ('rerank-english-v3.0') is applied to rank the chunks with relevance to deal with **Lost in the middle** problem.

Answer Generation

To generate the final answer for the user's query:

Context Compilation:

The filtered chunks are compiled to form the context used by the LLM.

Answer Generation with LLM:

The LLM generates a concise answer based on the compiled context and the user's original question using a prompt that ensures the answer is based solely on the provided context.

Evaluation

The system's performance is evaluated using the accuracy metrics. The response generated by the LLM using the retriever is compared with the ground-truth (predetermined correct answer).

The comparison includes both exact and semantically correct answers. An evaluation LLM compares ground-truth and the generated answer and flags it either correct or incorrect.

The accuracy is calculated using:

$$\text{Accuracy} = \frac{\text{Correct Answers}}{\text{Total Questions}} \tag{1}$$

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 LLaMA2-chat13B, a conversational variant of LLaMA2 tailored for dialogue-based applications, and ChatGPT, 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 retrieval-augmented baselines with private data, including Ret-ChatGPT and RetLLaMA-chat, which integrate retrieval mechanisms with ChatGPT and the conversational variant of LLaMA2, respectively. We also assessed Perplexity.ai, an InstructGPT-based production search system that leverages retrieval-augmented techniques for generating accurate and relevant responses.

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.

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**

5.1 Evaluation Metrics

We used accuracy as the primary evaluation metric, calculated as the percentage of generated responses that exactly match the ground-truth answers. Additionally, we considered semantic accuracy, where responses that are semantically equivalent to the ground truth (as evaluated by an LLM-based semantic similarity checker) are also counted as correct.

$$\text{Accuracy} = \frac{\text{Correct Answers}}{\text{Total Questions}} \tag{2}$$

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 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.

5.3 Multi-Step Processes

In applications requiring multi-hop reasoning or sequential decision-making, errors can compound exponentially. The probability of the system providing correct answers across multiple steps is given by:

$$P(\text{correct over } n \text{ steps}) = (\text{accuracy})^n \tag{3}$$

As the number of steps increases, the gap between the success probabilities widens exponentially. For a 3-step process, our method's success rate is 66% higher than CRAG's. 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.

5.4 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.

5.5 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 retrieval-augmented 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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