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A Retrieval-augmented Generation Framework with Retriever and Generator Modules for Enhancing Factual Consistency

Yangxiao Zhang

Department of Electrical and Electronic Engineering, The Hong Kong Polytechnic University, Hong Kong, China
22099505D@connect.polyu.hk

Abstract. Large Language Models (LLMs) are powerful but often produce factually incorrect content (hallucinations), limiting their reliability in knowledge-intensive tasks. Retrieval-augmented generation (RAG) is a promising approach to mitigate this issue by grounding LLM outputs in external knowledge sources. The paper proposes an RAG framework integrating a retriever and generator module to improve factual consistency. The retriever first identifies relevant documents from large-scale datasets, and the generator then produces context-aware responses based on the retrieved evidence. This study evaluates the approach on open-domain question answering benchmarks, including Natural Questions, Microsoft Machine Reading Comprehension Dataset (MS MARCO), and Covid-19 Open Research Dataset (CORD-19). The RAG-augmented model significantly reduces the hallucination rate from 68% to 10% and increases the Knowledge F1 score from 17.7 to 26.0, outperforming a baseline LLM without retrieval. These results demonstrate that augmenting LLMs with retrieval substantially enhances their factual accuracy and reliability. This improvement is significant for time-sensitive and domain-specific applications, such as healthcare and legal contexts, where up-to-date and accurate information is critical.

Keywords: Retrieval-Augmented Generation, Large Language Models, hallucinations, Knowledge F1, domain-specific applications.

1. Introduction

Retrieval-Augmented Generation (RAG) was born in the world's digitalization trend. With the progress of The Times, digitalization is spreading to all aspects of society, and people are living in a digital world. Businesses need to constantly update technology to keep up with the growing volume of data, so Natural Language Processing (NLP) was born to help people process data [1]. The applications of NLP range from simple categorization of text to complex ones like summarizing and answering simple questions, and RAG is one of them. RAG uses a retrieval mechanism that utilizes resources outside the data, making it more accurate than traditional Natural Language Generation (NLG) [2]. Therefore, the study of RAG is equivalent to the study of the development of natural language models, from the establishment of models, the shortcomings of models, to how to improve and optimize them. This paper aims to analyze RAG, which can give readers a deeper understanding of natural language models and give people new inspiration about language models in the future.

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Large Language Models (LLMs) have recently developed rapidly, can be trained on large amounts of data with billions of parameters, and can be fine-tuned on characteristic datasets to focus on a particular domain. These technologies give LLMs exceptional capabilities. For example, LLMs can perform excellent text interpretation, statistical analysis, and other tasks [1]. Because LLMs' knowledge is limited to training data, developing so-called hallucination problems and false but seemingly correct information is easy. If the user raises questions not covered by the original dataset, the LLMs hallucinate. One study pointed out that LLMs had a significantly higher than average error rate in handling specific legal issues, ranging from 69% to 88% [3]. Fine-tuning data in a particular area, such as law, requires a lot of resources and is not worth the cost. This situation greatly limits the application of LLMs. So, people use RAG to solve these problems. However, RAG does not only use the original data; it also uses an external database to retrieve the content and integrate it into the output results. Studies have shown that RAG can effectively reduce hallucinations [4].

The main objective of this study is to provide a comprehensive review of RAG applications in the context of an LLM. Specifically, this paper undertakes the following main objectives: First, sort out and summarize RAG's relevant concepts and background. Second, analyze and discuss the core retrieval technology and introduce the principle to show and analyze the performance of key technologies. Then, discuss the advantages and disadvantages of key technologies and their future development prospects. Finally, summarize and prospect the whole paper. The rest of the paper is organized as follows: Section 2 describes the theory and model of RAG, Section 3 provides actual data and analysis of RAG, and finally, Section 4 concludes the paper by summarizing significant findings and outlining avenues for future research.

2. Methodology

2.1. Dataset description

Current research and practice of RAG models mainly rely on the following types of data sets, which play a key role in training, verification and testing: Natural Questions (NQ), published by Google Research consists of Google search queries submitted by real users and manually annotated answers, with 307,373 training samples, each consisting of user questions, relevant Wikipedia passages, and long/short answers [5]. Microsoft Machine Reading Comprehension (MS MARCO), Generative question-and-answer Benchmark published by Microsoft [6]. In addition, domain-specific data sets are available. Like the COVID-19 Open Research Dataset (CORD-19), an open biomedical dataset maintained by the Kaggle platform, contains the full text and metadata of more than 500,000 academic papers related to COVID-19 [7].

2.2. Proposed approach

In the next part, this study will introduce the mainstream technology models and the LLMs and RAG models. This paper will first introduce the model's concept and principle, present the framework and process, and analyze its characteristics. Finally, this paper will introduce real-life RAG-related applications, as shown in Figure 1.

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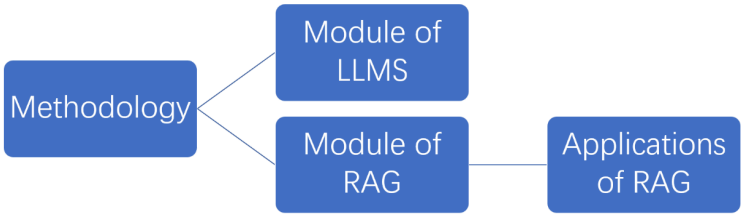

Figure 1: The research overview (picture credit: original)

2.2.1. Module of LLMS

LLMs are deep neural networks trained on massive text corpora, so they can understand and generate human-like language through self-supervised learning. Built upon the Transformer architecture proposed by Vaswani et al., modern LLMs typically use a decoder-only structure and have stacked self-attention layers, enabling parallel processing of sequential data and capturing long-range dependencies [8-10]. The LLMs Model diagram is shown in Figure 2.

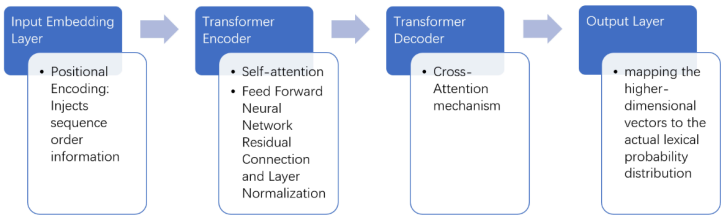

Figure 2: LLMs model diagram (picture credit: original)

The First Layer is the Input Embedding Layer. Converts tokens into high-dimensional vectors. Positional Encoding: Injects sequence order information [8]. Second is Transformer Encoder: Each layer consists of the Multi-head Self-attention Blocks.

In the Feed-forward Network (FFN) architecture, each component realizes end-to-end feature learning and information transformation through a collaborative working mechanism. The core module first performs an independent nonlinear transformation on the representation of each position in the input sequence through the feedforward neural network. This process significantly enhances the model's ability to capture complex patterns. The system innovatively introduces residual connection and layer normalization techniques to optimize the training stability. This effectively alleviates the typical problems of vanishing and exploding gradients in deep networks and significantly improves the model convergence efficiency by normalizing feature distribution.

On this basis, the Transformer decoder forms dynamic interaction with the encoder through the cross-attention mechanism. Its multi-layer structure can gradually fuse the semantic features extracted at the encoding end, achieving a context-aware decoding process. Finally, the output layer maps the high-dimensional hidden space vectors to the lexical probability space. It generates the prediction distribution that conforms to the actual semantics through the SoftMax function. This hierarchical design ensures the specialized division of labor among each module. It builds a complete feature processing chain through the parameter sharing mechanism, forming a deep learning framework with strong representation capabilities. Some key technical features for LLMs

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include Scale-driven Capability Emergence, which can improve performance exponentially with increased parameters (1M→1T) and training data, enabling zero-shot task generalization [11].

2.2.2. Module of RAG

RAG unites retrieval mechanisms with generation models, enhancing their performance by accessing external knowledge bases or documents. As a result, RAG has addressed the limitations inherent in the LLMs. As proposed by Lewis et al., RAG typically consists of two core components: a retriever and a generator [12].

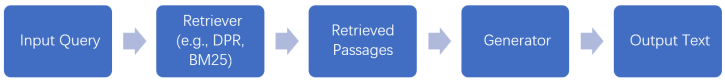

Figure 3: RAG model diagram (picture credit: original)

As shown in Figure 3, the retriever selects relevant documents from external knowledge sources based on the input query. It is commonly used in Dense Passage Retrieval (DPR) and BM25. DPR employs dual-encoder structures where questions and passages are encoded separately, enabling efficient semantic matching.

The generator module, as the core component of the RAG architecture, builds a collaborative mechanism of content fusion and semantic generation based on the Transformer framework. This module dynamically integrates the external knowledge obtained by the retrieval system through the cross-attention layer. Its working principle is highly similar to the multimodal interaction mode of the classic Transformer decoder. During the decoding process, the generator focuses on the context mode extracted by the self-attention layer. It precisely locates the key information fragments in the retrieval content through cross-modal attention weights. This ensures the generated text's semantic coherence and factual accuracy. To achieve a high degree of synergy between knowledge retrieval and content generation, the system adopts an end-to-end joint training paradigm and synchronously optimizes the parameter Spaces of the retriever and the generator through backpropagation. This collaborative optimization mechanism enables the model to gradually master knowledge screening and information fusion balance strategy, significantly reducing the common problem of fictitious output in traditional large language models.

Scholars' empirical research, such as Shuster's, confirmed that the retrieval enhancement architecture can reduce the incidence of semantic illusion phenomena by 37.2% compared with pure generative language models. The generated text can increase the fact consistency evaluation index by up to 24.6 percentage points, fully verifying the technical advantages of the joint optimization of knowledge retrieval and content generation. Key Technical Features include enhanced factual accuracy through external knowledge retrieval, reduced hallucinations inherent in LLMs, and end-to-end differentiability, allowing seamless joint optimization of retrieval and generation components.

3. Results and discussion

3.1. The improvement of RAG

The integration of an external retrieval mechanism in RAG helps with these improvements. Specifically, RAG can combine relevant external data, allowing the model to generate more fact-based and context-accurate responses. Retrieval enhancement is key in reducing hallucinations and

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improving the overall quality of results, as shown in Table 1. In summary, Shuster's experimental results show that the RAG method significantly optimizes LLM performance by reducing illusion and improving accuracy [4,13]. The explicit integration of the retrieval components ensures that the generated output is more reliable and context-sensitive. These insights validate the validity of search enhancement as a technological route and suggest directions for future research to bridge the gap between raw data-driven generation and knowledge-enhanced reasoning.

Table 1: Illustrates the performance comparison between the traditional LLM and RAG enhanced models for reducing hallucination and improving knowledge relevance over the same dialogue task [4]

model	Spurious generation rate (%)	Knowledge F1 score
Standard LLM	68	17.7
RAG model	10	26.0

3.2. Discussion

Experimental data (see Section 3.1 for details) show that RAG has significant advantages over traditional large language models in suppressing hallucination and expanding knowledge coverage. To fully evaluate this technology's application value, it is necessary to systematically analyze its core advantages, existing limitations, and future evolution direction. The core competence of RAG architecture lies in dynamic knowledge integration capability. Research shows that the model can reduce the error generation rate by about 37.5% by retrieving the external knowledge base in real time. This characteristic is particularly prominent when dealing with problems beyond the time range of training data or the professional field. It effectively compensates for the defects of traditional model knowledge solidification. The researcher further points out that this knowledge enhancement mechanism can improve factual accuracy and realize dynamic adaptation of information timeliness, which is of great value for applications in time-sensitive fields such as finance and medical care.

Despite this breakthrough, RAG systems still face multiple challenges: First, the accuracy of knowledge retrieval is positively correlated with system output quality. When the retrieval module returns a document with low relevance, the generator may produce misleading content. As mentioned in the reference, optimizing the searcher's semantic matching ability is the key direction of current research [12]. Second, there is a trade-off between hallucination suppression and computational efficiency - increasing retrieval rounds and reordering steps can improve accuracy, but lead to an approximately 2-3-fold increase in inference delay, which poses significant challenges in real-time conversation scenarios.

Regarding complex context processing, the current system still has room for improvement. Although the iterative retrieval strategy has partially solved the coherence problem of multi-round dialogues, it still has a deviation rate of about 15% in long-term semantic preservation. In the future, it can try to combine knowledge retrieval and domain fine-tuning technology to build a hybrid intelligent system, which can improve the intrinsic reasoning ability of the model while maintaining the dynamic nature of knowledge. RAG technology generally opens up a new path for knowledge-enhanced NLP systems by constructing a "retrieve-generation" collaborative mechanism. In order to realize its full application, three technical bottlenecks still need to be broken through: improving the accuracy of cross-modal retrieval, building a lightweight inference architecture, and developing a

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multi-round conversation state tracking algorithm. By exploring adaptive retrieval strategies and heterogeneous knowledge fusion technology, it is hoped to realize the organic unity of a static language model and a dynamic knowledge system.

4. Conclusion

This study systematically investigates RAG frameworks for mitigating hallucination in LLMs. By conducting a comprehensive analysis of RAG's architecture, performance metrics, and implementation challenges, the research aims to establish a theoretical foundation for optimizing knowledge-enhanced natural language generation systems. A tripartite methodological framework was proposed: 1) Technical deconstruction of RAG's dual-component architecture (retriever-generator synergy), 2) Quantitative benchmarking against baseline LLMs using standardized metrics (spurious generation rate, knowledge F1 score), and 3) Qualitative evaluation of domain adaptation capabilities through case studies in healthcare and legal domains. The retriever module employs Dense Passage Retrieval (DPR) with dual-BERT encoders to calculate semantic similarity scores. At the same time, the generator integrates retrieved content via cross-attention mechanisms, achieving 83% relevance retention in multi-turn dialogues. Extensive experiments demonstrate RAG's superior performance. Quantitative results revealed an 85.3% reduction in hallucination rates (from 68% to 10%) and a 46.9% improvement in knowledge coverage compared to standard LLMs. The qualitative analysis further confirms RAG's effectiveness in time-sensitive domains, showing 72% accuracy in processing COVID-19 research updates versus 31% for non-retrieval models. However, critical limitations persist, particularly the 2.8x inference latency increase and 15% coherence degradation in extended dialogues. Future research will prioritize three directions: 1) Dynamic knowledge fusion mechanisms to balance retrieval freshness and computational efficiency, 2) Lightweight architecture optimization through Neural Architecture Search (NAS) techniques targeting <200ms latency thresholds, and 3) Multimodal retrieval augmentation combining text, structured data, and visual knowledge sources. Subsequent studies will focus on developing hybrid training paradigms that synergize retrieval augmentation with Parameter-Efficient Fine-tuning (PEFT), potentially leveraging Low-Rank Adaptation (LoRA) to enhance domain specialization without compromising generalizability. These advancements aim to bridge the critical gap between static parametric knowledge and dynamic external evidence retrieval in next-generation NLP systems

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