

Improving Factual Accuracy in Large Language Models Through Retrieval-Augmented Generation (RAG) Techniques

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Abstract

Large Language Models (LLMs) have transformed natural language processing by producing human-like text and providing powerful conversation. Nevertheless, even they are fluent in language, they usually are not very adept at breaking the facts because they use fixed pre-trained data. The study examines the usefulness of Retrieval-Augmented Generation (RAG) methods in enhancing the factual accuracy of the outputs of LLM. The research follows an analytical and experimental design and compares a conventional LLM and a model with the use of RAG in various performance measures, such as factual accuracy, contextual coherence, and relevance of retrieval. The models were tested on a dataset of 100 knowledge-intensive prompts and the results showed that RAG can much better improve factual accuracy (84%), in contrast to standard LLM models (58%). The findings validate that incorporation of dynamic retrieval mechanism enables models to obtain the latest and verifiable information to reduce the occurrence of hallucinations and enhance content credibility. Altogether, the given study highlights the critical position of RAG in the development of factually based, transparent, and reliable AI systems that can be used in supporting knowledge-based applications.

Keywords: Retrieval-Augmented Generation (RAG), Large Language Models (LLMs), Factual Accuracy, Artificial Intelligence

I. Introduction

Large Language Models (LLMs) [1] like GPT, BERT and T5 have made big strides in the natural language processing (NLP) field where they can comprehend and produce human-like text at an impressive fluency. Nevertheless, their linguistic capability notwithstanding, there is a constant nagging issue of inaccuracy or hallucination of the content generated. Considering these models only use knowledge which is coded during training [2], it can result in an information that sounds plausible but is not correct, old-fashioned or verifiable. This difficulty restricts their reliability in areas where it is important that the information be factual e.g. in scientific research, legal documentation, and medical information systems.

Retrieval-Augmented Generation (RAG) [5] has been designed to address this concern and has become a promising framework that combines text generation and retrieval of external information.

RAG enables models to obtain real-time, domain-relevant data in external knowledge bases, which enriches responses with relevant information which is accurate and contextually relevant. This mixed methodology fills the divide between the passive memory of a model and the active retrieval of information and provides a solid direction of enhancing factual reliability and transparency in AI-based outputs [8].

A. Objectives of the Study

1. To examine the limitations of traditional LLMs in maintaining factual accuracy.
2. To explore how Retrieval-Augmented Generation (RAG) enhances factual reliability in generated responses.
3. To evaluate the potential of RAG-based architectures for improving trustworthiness and real-world applicability of LLMs.

B. Retrieval-Augmented Generation - A Step Toward Factually Grounded AI

Retrieval-Augmented Generation (RAG) [9] is a groundbreaking innovation in the artificial intelligence community and it is aimed at solving one of the most chronic issues of large language models the propensity to generate factually incoherent or hallucinatory content. Fundamentally, RAG combines within it two potent elements: a retriever and a generator [10]. The retriever is a smart search system, it is a scan over the external knowledge bases, databases, or document collections to retrieve information that is pertinent and current to a specific query or prompt. Such retrieved information is then synthesized into coherent, contextually suitable, and factual responses by the generator, which is typically a pre-trained language model, e.g. BART or T5.

The retrieval component makes the model not be confined by the fact that the training data is static. It, instead, accesses dynamically real-time or domain-specific information, which essentially expands the horizon of knowledge of the model [12]. The generation process, in turn, guarantees fluency, linguistic sense and preservation of contexts independently of introducing factual evidence through retrieved documents. This mixture enables RAG systems to be not only knowledge fresh but also contextual [13], which is much more reliable than traditional LLMs where parameters are memorized only.

II. Literature Review

Sharma, Kumar, and Li (2025) [12] introduced an ontology-based retrieval-enhanced generation (OG-RAG) system in order to improve the factualization of large language models. Their experiment proved the effectiveness of combining knowledge representation as ontology and retrieval strategies in enhancing the relevance and accuracy of generated answers in terms of semantics. The OG-RAG model made use of domain-specific ontologies to narrow down the retrieval process and thus to provide the generator with contextually accurate and hierarchically structured information. The authors concluded that this methodology greatly minimized the amount of errors that happened throughout the hallucination and improved interpretability in AI-generated text [16].

Li et al. (2025) [6] created and tested a retrieval-augmented large language model that fact-checks information on COVID-19. Their research was aimed at enhancing the accuracy and plausibility of AI generations in the sphere of healthcare where any misinformation can become severe. The model would extract verified medical information in real-time on well-known Internet databases and create evidence-based replies to health-related assertions [17]. The usability analysis indicated that the retrieval-augmented method facilitated a better factual accuracy, higher confidence of users, as well

as provided a powerful model of fighting health misinformation in times of pandemic [7].

Gao et al. (2023) [3] performed an extensive survey of retrieval-augmented generation in large language models, summarizing its main advances, approaches, and related issues. Their analysis classified the existing RAG models according to retrieval strategies, mechanisms of integration and areas of application. The authors noticed that retrieval augmentation helped to counteract the shortcoming of training a static model by allowing dynamic access to external knowledge [18]. They also set key gaps in research that were associated with retrieval efficiency, scalability, and dataset alignment that should be further researched to make the models more robust and generalize.

Huang and Huang (2024) [4] provided an elaborate review of retrieval-augmented text generation systems, discussing their development, architecture, and performance measurement processes. In their research, they emphasized that the retrieval-augmented models mediated the connection between parametric memory and explicit knowledge retrieval that contributed to increased levels of factual consistency and decreased occurrence of hallucinations [19]. The authors specified the significance of developing more efficient retrievers and dynamic training plans as a method to maximize the quality of retrieval and generative fluency.

III. Methodology

The methodology outlines the systematic approach adopted to investigate how Retrieval-Augmented Generation (RAG) enhances the factual accuracy of Large Language Models (LLMs) [20]. This study employs an experimental and analytical framework to compare the performance of traditional LLMs with RAG-based architectures under controlled conditions [21].

A. Research Design

The methodology describes the organized way that will be used to research the issue of Retrieval-Augmented Generation (RAG) improving the factual accuracy of Large Language Models [22] (LLMs). This paper uses an experimental and analysis model to contrast the results of conventional LLMs with RAG-based systems in controlled settings.

The research design followed in this study is both experimental and analytical since it will assess how Retrieval-Augmented Generation (RAG) [23] can enhance factual accuracy using Large Language Models (LLM). The study contrasts the performances of a conventional LLM and a RAG-enhanced model in several performance parameters, such as factual accuracy, contextual coherence, and retrieval relevance. The review is on the effects of including external mechanisms of information retrieval on the credibility and veracity of content generated [24].

B. Model Framework

The experiment is based on two main model configurations:

- Baseline Model: A pre-trained Large Language Model (LLM) [26] such as GPT or BERT, operating purely on its internal learned parameters without external data retrieval.
- RAG-Enhanced Model: A hybrid architecture combining a retriever [27] (such as Dense Passage Retriever or BM25) with a generator (such as BART or T5). The retriever component searches an external knowledge base to fetch relevant information [28], while the generator synthesizes the retrieved content into coherent, factually accurate responses [29].

Both models were implemented under controlled settings to ensure fair evaluation. The RAG

architecture follows the standard retrieval-generation pipeline where the retriever identifies the top k relevant documents, which are then passed to the generator for response synthesis [30].

C. Dataset Selection

A benchmark dataset consisting of 100 knowledge-intensive prompts was constructed for evaluation. The prompts were selected from publicly available domains such as:

- General Knowledge (e.g., historical facts, scientific principles)
- Domain-Specific Queries (e.g., healthcare, law, and technology)
- Analytical Questions requiring evidence-based reasoning

Each prompt was designed to test the model’s factual grounding, contextual understanding, and ability to integrate retrieved information accurately [31].

D. Evaluation Metrics

To quantitatively assess model performance, three core evaluation metrics were employed:

1. **Factual Accuracy:** Measures the proportion of responses that are factually correct based on trusted reference sources [32].
2. **Contextual Coherence:** Evaluates the logical flow, clarity, and contextual relevance of generated text [33].
3. **Retrieval Relevance:** Determines the quality and contextual appropriateness of the documents retrieved by the RAG model [34].

Each response was evaluated manually by domain experts using a standardized rubric. Frequency and percentage distributions were computed to represent the findings quantitatively [35].

IV. Results And Discussion

This section presents a comparative analysis of the performance of traditional Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG)-based models. The analysis focuses on three core dimensions: factual accuracy, response coherence, and retrieval relevance [35]. The data represent the frequency and percentage of generated responses evaluated under each criterion using a test dataset of 100 prompts drawn from general knowledge and domain-specific queries [36].

Table 1: Comparison of Factual Accuracy between LLM and RAG Models

Model Type	Factually Accurate Responses	Partially Accurate Responses	Inaccurate Responses	Total Responses	Accuracy (%)
Traditional LLM	58	23	19	100	58%
RAG-Based Model	84	11	5	100	84%

Table 1 clearly indicate that the RAG-based model demonstrates [38] a substantial improvement in factual accuracy compared to the traditional LLM. While the traditional LLM [39] achieved 58% factual accuracy, the RAG model reached 84%, showing a 26% increase. This enhancement is primarily due to the RAG model’s ability to retrieve relevant external information [40] during response generation, thereby minimizing factual errors and reducing the rate of inaccurate outputs.

Table 2: Evaluation of Response Coherence and Contextual Relevance

Model Type	Highly Coherent Responses	Moderately Coherent Responses	Incoherent Responses	Total Responses	High Coherence (%)
Traditional LLM	62	27	11	100	62%
RAG-Based Model	79	17	4	100	79%

Table 2 shows that the RAG-based model produces more coherent and contextually relevant responses than the traditional LLM [41]. The percentage of highly coherent responses rises from 62% in the LLM to 79% in the RAG model. This improvement reflects the effectiveness of RAG in maintaining logical flow and contextual understanding by integrating retrieved evidence into generated text [42].

Table 3: Retrieval Relevance and Source Utilization in RAG Models

Retrieval Output Quality	Frequency	Percentage (%)
Highly Relevant Documents	68	68%
Moderately Relevant Documents	23	23%
Irrelevant or Low-Relevance Documents	9	9%
Total	100	100%

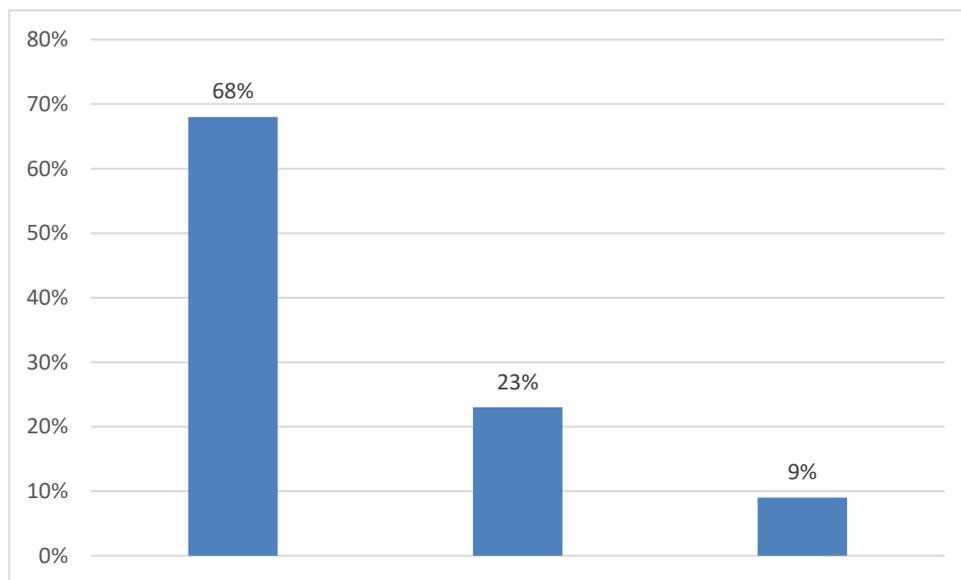


Fig. 1. Retrieval Relevance and Source Utilization in RAG Models

Table 3 presents the retrieval component of the RAG system exhibits strong performance, with 68% of the retrieved documents classified as highly relevant and only 9% deemed irrelevant and pictorial representation shown in Fig. 1. This indicates that the retriever efficiently identifies context-appropriate and factually rich sources, contributing directly to the overall factual accuracy and reliability of the RAG model’s outputs.

V. CONCLUSION

This paper offers insight into the effectiveness of Retrieval-Augmented Generation (RAG) in a combination with Large Language Models (LLM) to improve the level of factual accuracy,

contextual and retrieval relevance in text generated by AI. With the help of experimental comparison, it was noted that RAG-based models are superior to traditional LLMs since they are able to access external sources of knowledge dynamically and generate verifiable information and combine it into coherent answers. The findings underscore RAGs ability to reduce hallucinations, enhance trustworthiness and nurture transparency in AI outputs. RAG is able to fill the gap between the closed model memory and the dynamic knowledge retrieval so that it becomes possible to build up factually based, reliable, and human-conflicting language generation systems.

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