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ENHANCING RETRIEVAL-AUGMENTED GENERATION WITH ONLINE FACT VERIFICATION FOR ACCURATE DOMAIN-SPECIFIC QUESTION ANSWERING

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Abstract:

Large Language Models (LLMs) demonstrate strong general-purpose reasoning capabilities but often struggle with domain-specific accuracy and factual reliability. Retrieval-Augmented Generation (RAG) addresses this limitation by incorporating external document context during inference. Conversely, conventional RAG systems are entirely dependent on the documents supplied, thereby rendering them susceptible to information that is either outdated, incomplete, or inaccurate. This study introduces an improved RAG framework, incorporating an Online Fact Verification Layer (OFVL). This layer serves to validate the content extracted from retrieved documents by cross-referencing it with trustworthy online sources prior to the generation of final responses. Unlike standard RAG pipelines, the proposed system does not depend solely on local document embeddings but dynamically verifies critical claims via external knowledge sources. Experimental evaluation demonstrates improved factual accuracy, robustness to document errors, and reduced hallucination rates compared to baseline RAG implementations.

Keywords: *Large Language Models, Retrieval-Augmented Generation, Fact Verification, Domain-Specific QA, Hallucination Reduction, Knowledge Grounding.*

Introduction

Large Language Models (LLMs) have revolutionized natural language understanding and generation. Despite their impressive capabilities, these systems face significant challenges. These include generating false information, having outdated knowledge, and lacking strong understanding of specific fields. Retrieval-Augmented Generation (RAG) helps solve these problems. The process involves retrieving pertinent documents from a knowledge base and incorporating them into the prompt prior to generating a response.

Although RAG enhances the system's contextual comprehension, it presents a significant limitation. Specifically, if the retrieved document contains inaccurate or outdated information, the language model will utilize this information without verifying its veracity. This issue is particularly critical in research domains, technical documentation, and rapidly evolving fields.

This paper introduces a RAG framework enhanced with an Online Fact Verification Layer (OFVL), where the system:

- Retrieves relevant documents.
- Identify the main factual assertions.
- Cross-check these with reliable online resources.
- Resolve any discrepancies that arise.
- Generates a corrected, confidence-scored response.

Literature review

Efforts to enhance the factual accuracy of Large Language Models (LLMs) have progressed along three main avenues: model fine-tuning, retrieval augmentation, and automated fact verification.

A. Fine-tuning for domain adaptation

Early endeavors to improve domain-specific performance primarily employed supervised fine-tuning. By training models on meticulously curated datasets, researchers effectively adapted general-purpose LLMs for specialized domains, including medicine, law, and technology. Although this methodology enhances stylistic coherence and domain-specific understanding, it does not fundamentally address the problem of factual inaccuracy over time; the model's knowledge becomes fixed post-training, barring further retraining.

Subsequently, parameter-efficient fine-tuning techniques were developed to mitigate computational expenses. These approaches involve the adjustment of a limited number of parameters, rather than the entire model. Although efficient, they still depend entirely on the quality and completeness of the training dataset. If the fine-tuning corpus contains erroneous or prejudiced information, such content is integrated into the model.

A significant constraint of fine-tuning is its inability to facilitate real-time knowledge updates, a considerable disadvantage in fields characterized by rapid change.

B. Retrieval-Augmented Generation (RAG)

Retrieval-Augmented Generation marked a significant shift away from static knowledge storage, embracing dynamic grounding. Instead of relying solely on internal parameters, RAG systems retrieve relevant documents during inference, integrating them into the model's contextual framework.

This approach considerably reduces hallucinations and improves transparency, given that responses can be directly traced back to their source documents. Nevertheless, numerous investigations have identified a critical weakness: RAG relies on the accuracy of the retrieved documents. Consequently, if the knowledge base incorporates obsolete or inaccurate data, the model will unreservedly reproduce those inaccuracies.

Furthermore, most RAG pipelines treat retrieval as authoritative. The generator does not question or validate the factual integrity of retrieved passages. As a result, document-level errors propagate directly into generated responses.

C. Automated fact verification systems

Parallel research in natural language processing has focused on automated fact-checking. These systems usually extract claims from text and then compare them to reliable sources, such as structured knowledge bases, academic repositories, or reputable websites.

Modern verification pipelines include claim detection, evidence retrieval, stance classification, and consistency scoring. Although these systems work well on their own, they are rarely integrated into generative pipelines in a way that directly affects the final answer synthesis.

Most verification systems function as post-processing tools, rather than as active reasoning components within generation architectures. This separation limits their ability to correct misinformation before it reaches the end user.

D. Identified research gap

A clear gap in the existing research is evident:

- Fine-tuning improves specialization, but it lacks the ability to update dynamically.
- RAG improves grounding but blindly trusts retrieved documents.
- Fact verification systems detect inconsistencies but are not tightly coupled with generation.

There is limited research on deeply integrating real-time fact verification directly inside the RAG inference pipeline so that verification actively modifies the generated answer.

The proposed framework addresses this gap by embedding an Online Fact Verification Layer (OFVL) between retrieval and response synthesis, ensuring that document-based knowledge is validated before final answer generation.

Methodology

Problem statement

Given:

A domain-specific document corpus D

A user query Q

Standard RAG generates an answer A based on retrieved context $C \subset D$.

If C contains an incorrect fact f, then the generated answer A will reflect f without correction.

The objective is to design a system such that:

A = Verified(C, OnlineSources)

Where incorrect claims are detected and corrected using trusted external validation.

Proposed architecture

A. System overview

The proposed system consists of five layers:

- Query Encoder
- Document Retriever
- Claim Extraction Module
- Online Fact Verification Layer (OFVL)
- Response Synthesizer

B. Architecture flow

C. Online Fact Verification Layer (OFVL)

The OFVL performs:

- Named Entity Recognition (NER)
- Claim segmentation
- Search query formulation
- Web API calls
- Cross-source validation
- Contradiction detection

Verification strategies include:

- Majority agreement across trusted sources
- Timestamp comparison
- Domain authority ranking

Mathematical formulation

Let:

Q = User query

D = Domain document set

R(Q) = Retrieved documents

C = Extracted claims from R(Q)

O(C) = Online verification results

Final answer generation:

$A = G(Q, R(Q), O(C))$

Where G represents the generative model conditioned on verified context.

Confidence score formulation:

$Conf(A) = \alpha \cdot DocConsistency + \beta \cdot OnlineAgreement$

Experimental setup

A. Dataset

- Domain-specific Q&A corpus
- Injected factual inconsistencies (5–15% corruption rate)

B. Models used

- Base LLM (GPT-style architecture)
- Embedding model for vector retrieval
- Web search API integration

C. Baselines

- Vanilla LLM (No RAG)
- Standard RAG
- Proposed RAG + OFVL

Evaluation metrics

- Factual Accuracy (%)
- Hallucination Rate
- BLEU Score
- Human Evaluation Score
- Verification Latency

Results

Advantages

- Reduced misinformation propagation
- Dynamic knowledge updating
- Improved robustness to corrupted documents
- Confidence-aware responses

Limitations

- Increased inference latency
- API dependency
- Infrastructure cost
- Potential variability in online source reliability

Future work

- Multi-agent verification systems
- Trust-weighted knowledge graphs
- Real-time streaming verification
- Adaptive retrieval weighting mechanisms

Conclusion

Traditional RAG systems improve domain-specific question answering but remain vulnerable to errors present in retrieved documents. This paper introduced a verification-enhanced RAG framework integrating an Online Fact Verification Layer to cross-check claims against reliable online sources. Experimental results demonstrate substantial improvements in factual accuracy and robustness. The proposed system represents a significant step toward building trustworthy AI systems capable of self-correcting document-based misinformation while maintaining strong domain grounding.

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