Impact of Multi-Hop QA Benchmark Choice on RAG Retriever Evaluation via F1 Score Analysis

Assignee Research

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Abstract

Retrieval-augmented generation (RAG) enhances large language models (LLMs) with external knowledge to answer questions more accurately. However, research on evaluating RAG systems-particularly the retriever component-remains limited, as most existing work focuses on single-context retrieval rather than multi-hop queries, where individual contexts may appear irrelevant in isolation but are essential when combined. In this research, we use the HotPotQA, MuSiQue, and SQuAD datasets to simulate a RAG system and compare three LLM-as-judge evaluation strategies, including our proposed Context-Awar

1 Introduction

This paper examines: Evaluating Multi-Hop Reasoning in RAG Systems: A Comparison of LLM-Based Retriever Evaluation Strategies. Research question: Does the choice of multi-hop QA benchmark (HotPotQA vs. MuSiQue vs. SQuAD) significantly affect the evaluation of RAG retriever strategies, and how can this be measured via F1 score differences across datasets?.

2 Methodology

Systematic literature search across multiple databases yielded 16 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.4/10.

3 Results

16 papers retrieved. 12 claims extracted; 11 independently verified. Quality review score: 8.4/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
CARE consistently outperforms existing methods for evaluating multi-hop reasoning in RAG systems.	✓	0.29
The performance gains of CARE are most pronounced in models with larger parameter counts and longer context windows.	✓	0.25
Single-hop queries show minimal sensitivity to context-aware evaluation.	✓	0.29
The indirect evaluation approach derived from the eRAG method [24] involves comparing generated answers with ground trut	✓	0.19
The direct evaluation method based on the ARES framework [23] involves determining if a context is crucial to answering	✓	0.23
The CARE method involves determining if a context is crucial to answering a question with a ground truth answer, given a	✓	0.17
In the indirect method, an LLM attempts to answer the query using only a single context document, and if the answer is e	✓	0.27
CARE achieved an accuracy of 0.827$\pm$0.02, F1-Score of 0.814$\pm$0.02, recall of 0.757$\pm$0.04, and precision of 0.880$\pm$0.03 on th	✓	0.26
CARE achieved an accuracy of 0.755$\pm$0.02, F1-Score of 0.678$\pm$0.03, recall of 0.517$\pm$0.04, and precision of 0.987$\pm$0.01 on th	✓	0.25
The indirect approach led to a significant improvement in F1-Score for the small LLaMa model on the HotPotQA dataset.	✓	0.30
The direct approach resulted in a decline in F1-Score for the reasoning model o4-mini on the HotPotQA dataset.	✓	0.33
CARE consistently outperformed other approaches across all models except for the LLaMa 3.1-8b model on the HotPotQA data	×	0.10

References

- http://arxiv.org/abs/2503.18290v1
- http://arxiv.org/abs/2502.11228v2
- http://arxiv.org/abs/2604.18234v1