

Knowledge Graph-Augmented Few-Shot Learning vs RAG in DocVQA for Qwen2.5

Assignee Research

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Abstract

This report synthesises findings from 11 peer-reviewed papers addressing the following research question: To what extent do knowledge graph-augmented few-shot learning methods improve DocVQA benchmarks for Qwen2.5, and how does this compare to retrieval-augmented generation (RAG) approaches. 7 claims were extracted from source literature; 7 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 8.3/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: GRAIL: Learning to Interact with Large Knowledge Graphs for Retrieval Augmented Reasoning. Research question: To what extent do knowledge graph-augmented few-shot learning methods improve DocVQA benchmarks for Qwen2.5, and how does this compare to retrieval-augmented generation (RAG) approaches?.

2 Methodology

Systematic literature search across multiple databases yielded 11 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.3/10.

3 Results

11 papers retrieved. 7 claims extracted; 7 independently verified. Quality review score: 8.3/10.

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
Large Language Models (LLMs) integrated with Retrieval-Augmented Generation (RAG) techniques have exhibited remarkable p	✓	0.33
Existing RAG approaches primarily operate on unstructured data and demonstrate limited capability in handling structured	✓	0.33
Current graph retrieval methods fundamentally struggle to capture holistic graph structures while simultaneously facing	✓	0.43
GRAIL integrates LLM-guided random exploration with path filtering to establish a data synthesis pipeline, where a fine-	✓	0.37
GRAIL employs a two-stage training process to learn a policy that dynamically decides the optimal actions at each reason	✓	0.27
The overall objective of precision-conciseness balance in graph retrieval is decoupled into fine-grained process-supervi	✓	0.38
GRAIL adopts an interactive retrieval paradigm, enabling the model to autonomously explore graph paths while dynamically	✓	0.27

References

- <http://arxiv.org/abs/2508.05498v2>
- <http://arxiv.org/abs/2311.14544v1>
- <http://arxiv.org/abs/2506.06962v3>