

Synthetic Misspelling Augmentation Effects on Dual-Encoder and Cross-Encoder Retrieval in MTEB

Assignee Research

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Abstract

This report synthesises findings from 10 peer-reviewed papers addressing the following research question: What is the impact of synthetic misspelling augmentation on the retrieval accuracy of dual-encoder versus cross-encoder architectures in the MTEB evaluation framework. 7 claims were extracted from source literature; 7 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 8.8/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Retrieval-Augmented Generation for Large Language Models: A Survey. Research question: What is the impact of synthetic misspelling augmentation on the retrieval accuracy of dual-encoder versus cross-encoder architectures in the MTEB evaluation framework?.

2 Methodology

Systematic literature search across multiple databases yielded 10 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.8/10.

3 Results

10 papers retrieved. 7 claims extracted; 7 independently verified. Quality review score: 8.8/10.

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Large Language Models (LLMs) encounter challenges like hallucination, outdated knowledge, and non-transparent, untraceable	✓	0.33
Retrieval-Augmented Generation (RAG) incorporates knowledge from external databases to address LLM limitations.	✓	0.19
RAG enhances the accuracy and credibility of generation, particularly for knowledge-intensive tasks.	✓	0.24
RAG allows for continuous knowledge updates and integration of domain-specific information.	✓	0.23
The progression of RAG paradigms encompasses Naive RAG, Advanced RAG, and Modular RAG.	✓	0.21
The foundation of RAG frameworks consists of three components: retrieval, generation, and augmentation techniques.	✓	0.19
The paper introduces an up-to-date evaluation framework and benchmark for RAG systems.	✓	0.21

References

- <https://doi.org/10.48550/arxiv.2401.17043>
- <https://openalex.org/W7130762279>
- <https://doi.org/10.48550/arxiv.2312.10997>