Architectural Trade-offs in Dense Retrieval: Robustness and Efficiency Under Misspellings

Assignee Research

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Abstract

This report synthesises findings from 11 peer-reviewed papers addressing the following research question: How do different architectures (e.g., transformer vs. hybrid models) affect the trade-off between robustness to misspellings and inference efficiency in dense retrieval systems. 10 claims were extracted from source literature; 9 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 7.4/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Semantic Product Search. Research question: How do different architectures (e.g., transformer vs. hybrid models) affect the trade-off between robustness to misspellings and inference efficiency in dense retrieval systems?.

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 7.4/10.

3 Results

11 papers retrieved. 10 claims extracted; 9 independently verified. Quality review score: 7.4/10.

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
Pure lexical matching via an inverted index lacks understanding of hypernyms, synonyms, and antonyms.	✓	0.19
Pure lexical matching via an inverted index is fragile to morphological variants (e.g., 'woman' vs. 'women').	✓	0.21
Pure lexical matching via an inverted index is sensitive to spelling errors.	✓	0.15
Much of the recent work on large-scale semantic search using deep learning focuses on ranking for web search.	✓	0.32
The proposed model uses a new loss function with an inbuilt threshold to differentiate between random negative examples,	✓	0.31
The proposed model uses average pooling in conjunction with n-grams to capture short-range linguistic patterns.	✓	0.22
The proposed model uses hashing to handle out of vocabulary tokens.	×	0.13
The proposed model uses a model parallel training architecture to scale across 8 GPUs.	✓	0.16
The proposed model demonstrates at least a 4.7% improvement in over baseline state-of-the-art semantic	✓	0.26
The proposed model demonstrates a 14.5% improvement in mean average precision (MAP) over baseline state-of-the-art seman	✓	0.31

References

- https://doi.org/10.36227/techrxiv.23589741.v3

- https://doi.org/10.1145/3292500.3330759
- https://doi.org/10.3390/info13020083