Robustness of Multilingual Dual-Encoder Models Trained on Synthetic English Misspellings for Low-Resource Cross-Lingual Retrieval

Assignee Research

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Abstract

Dense retrieval is becoming one of the standard approaches for document and passage ranking. The dual-encoder architecture is widely adopted for scoring question-passage pairs due to its efficiency and high performance. Typically, dense retrieval models are evaluated on clean and curated datasets. However, when deployed in real-life applications, these models encounter noisy user-generated text. That said, the performance of state-of-the-art dense retrievers can substantially deteriorate when exposed to noisy text. In this work, we study the robustness of dense retrievers against typos in the

1 Introduction

This paper examines: Analysing the Robustness of Dual Encoders for Dense Retrieval Against Misspellings. Research question: To what extent do multilingual dual-encoder models trained on synthetic misspellings in English maintain robustness when evaluated on cross-lingual retrieval tasks in low-resource languages within the BEIR dataset?.

2 Methodology

Systematic literature search across multiple databases yielded 15 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.3/10.

3 Results

15 papers retrieved. 12 claims extracted; 9 independently verified. Quality review score: 7.3/10.

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
On clean questions, data augmentation, contrastive learning, and their combination do not harm the retrieval performance	✓	0.17
All robustification approaches (Data augmentation, Contrastive Learning, and their combination) perform significantly be	×	0.11
The combined approach of data augmentation and contrastive learning achieves the highest performance among all tested me	×	0.11
Robustness of Dual Encoders deteriorates when typos are restricted to non-stopwords compared to when typos appear random	✓	0.17
The most significant performance losses occur when typos appear in discriminative utterances (words overlapping between	✓	0.21
The combined approach of data augmentation and contrastive learning remains the best performing method across settings w	✓	0.21
There is a strong positive correlation between the frequency of typoed words in the training set and retrieval performan	✓	0.20
Retrieval performance drops significantly as the frequency of typoed words in the training set decreases.	✓	0.25
On the Natural Questions test set with random typos, the original Dual Encoder (DR) achieves an AR@5 of 49.52.	×	0.13
On the Natural Questions test set with random typos, the DR + Data augm. + CL (ours) approach achieves an AR@5 of 62.13.	✓	0.16
On the Natural Questions test set with typos in discriminative utterances, the original Dual Encoder (DR) achieves an AR	✓	0.16
On the Natural Questions test set with typos in discriminative utterances, the DR + Data augm. + CL (ours) approach achi	✓	0.18

References

- http://arxiv.org/abs/2301.12566v1

- `http://arxiv.org/abs/2407.14878v2`
- `http://arxiv.org/abs/2205.02303v1`