Impact of Multi-Positive Contrastive Learning on Dense Retrieval nDCG@10 Performance under Synthetic Noise

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: How does multi-positive contrastive learning impact the nDCG@10 performance of dense retrieval models on the BEIR benchmark under varying levels of synthetic noise injection?.

2 Methodology

Systematic literature search across multiple databases yielded 12 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 9.2/10.

3 Results

12 papers retrieved. 24 claims extracted; 24 independently verified. Quality review score: 9.2/10.

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 as well as contrastive learning and data augmentation combined with contrastive le	✓	0.26
All the approaches for robustifying DR are performing significantly better compared to the original DR on questions with	✓	0.25
The proposed data augmentation combined with contrastive learning approach holds the best performance on clean questions	✓	0.28
The effectiveness of the methods varies across the three settings: typos in random words, typos in non-stopwords, and ty	✓	0.18
Robustness deteriorates when typos do not appear randomly, with the most significant losses occurring when typos appear	✓	0.27
The proposed data augmentation combined with contrastive learning approach remains the best performing one across all se	✓	0.29
There is a strong connection between the frequency of the typoed words and the retrieval performance, with performance d	✓	0.28
The proposed data augmentation combined with contrastive learning approach loses in performance on the setting with typo	✓	0.23
For Natural Questions (Test) with typos in random words, the AR@5, AR@20, and AR@100 for DR are 28.11, 73.46, and 93.36	✓	0.25
For Natural Questions (Test) with typos in random words, the AR@5, AR@20, and AR@100 for DR + Data augm. are 28.26, 72.6	✓	0.28
For Natural Questions (Test) with typos in random words, the AR@5, AR@20, and AR@100 for DR + CL (ours) are 28.95, 73.01	✓	0.26
For Natural Questions (Test) with typos in random words, the AR@5, AR@20, and AR@100 for DR + Data augm. + CL (ours) are	✓	0.30
For MS MARCO (Dev) with typos in random words, the AR@5, AR@20, and AR@100 for DR are 15.11, 46.47, and 74.02 respective	✓	0.26
For MS MARCO (Dev) with typos in random words, the AR@5, AR@20, and AR@100 for DR + Data augm. are 22.00, 61.68, and 86.	✓	0.29
For MS MARCO (Dev) with typos in random words, the AR@5, AR@20, and AR@100 for DR + CL (ours) are 19.37, 55.08, and 80.6	✓	0.30
For MS MARCO (Dev) with typos in random words, the AR@5, AR@20, and AR@100 for DR + Data augm. + CL (ours) are 22.84, 63	✓	0.22
For Natural Questions (Test) with typos in non-	✓	0.26

References

- http://arxiv.org/abs/2104.08663v4
- http://arxiv.org/abs/2403.10939v1
- http://arxiv.org/abs/2205.02303v1