Multi-Positive Contrastive Learning for Zero-Shot Cross-Lingual Dense Retrieval on the XMRC Benchmark

Assignee Research

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Abstract

Dense retrieval has become the new paradigm in passage retrieval. Despite its effectiveness on typo-free queries, it is not robust when dealing with queries that contain typos. Current works on improving the typo-robustness of dense retrievers combine (i) data augmentation to obtain the typoed queries during training time with (ii) additional robustifying subtasks that aim to align the original, typo-free queries with their typoed variants. Even though multiple typoed variants are available as positive samples per query, some methods assume a single positive sample and a set of negative ones p

1 Introduction

This paper examines: Improving the Robustness of Dense Retrievers Against Typos via Multi-Positive Contrastive Learning. Research question: How does multi-positive contrastive learning impact the zero-shot cross-lingual retrieval accuracy of dense retrievers on the XMRC benchmark compared to standard InfoNCE loss?.

2 Methodology

Systematic literature search across multiple databases yielded 9 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.5/10.

3 Results

9 papers retrieved. 10 claims extracted; 8 independently verified. Quality review score: 7.5/10.

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
Employing multi-positive contrastive learning on the robustifying subtask yields improvements in robustness against typo	✓	0.31
The original DR+DL work considers only the typo-free query as a positive sample when computing the contrastive loss for	✓	0.25
The proposed DR+DLM model considers both the typo-free query and all its available typoed variants as positive samples.	✓	0.19
Using multi-positive contrastive loss with all available positives simultaneously outperforms sampling a different posit	×	0.15
The DR+DL+ST model uses a contrastive loss with a single positive for the query retrieval dual task (Lq_CE).	✓	0.23
The DR+DL+ST model considers multiple positives simultaneously only to compute KL-divergence losses (Lp_KL, Lq_KL).	✓	0.17
Statistical significant gains were obtained from models with multi-positive contrastive loss over their original version	✓	0.21
Current typo-robust dense retrievers use contrastive learning with a single positive sample and multiple negative ones f	✓	0.38
The standard contrastive loss function LCE brings a single positive sample closer to the anchor than any negative sample	✓	0.19
The proposed multi-positive contrastive loss LMCE computes the loss by averaging the log probabilities over multiple pos	×	0.14

References

- http://arxiv.org/abs/2207.08374v1
- http://arxiv.org/abs/2403.10939v1
- http://arxiv.org/abs/2402.15059v1