Comparative Performance of Query-Augmented versus Passage-Augmented Cross-Lingual Dense Retrieval on Low-Resource MTrQA Subsets

Assignee Research

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Abstract

Effective cross-lingual dense retrieval methods that rely on multilingual pre-trained language models (PLMs) need to be trained to encompass both the relevance matching task and the cross-language alignment task. However, cross-lingual data for training is often scarcely available. In this paper, rather than using more cross-lingual data for training, we propose to use cross-lingual query generation to augment passage representations with queries in languages other than the original passage language. These augmented representations are used at inference time so that the representation can enco

1 Introduction

This paper examines: Augmenting Passage Representations with Query Generation for Enhanced Cross-Lingual Dense Retrieval. Research question: How does the performance of query-augmented cross-lingual dense retrieval models compare to passage-augmented approaches on low-resource language subsets of the MTrQA benchmark?.

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 7.2/10.

3 Results

15 papers retrieved. 27 claims extracted; 17 independently verified. Quality review score: 7.2/10.

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
The training set contains annotated relevant passage-query pairs, and the development set contains 2,000 passage-answer	×	0.15
Queries in the train and dev sets are in seven languages: Arabic (Ar), Bengali (Bn), Finnish (Fi), Japanese (Ja), Korean	×	0.15
Passages in the dataset are in English.	×	0.05
The corpus contains approximately 18 million passages.	×	0.06
Zero-shot models were trained only on the English subset of the NQ dataset.	✓	0.18
The augmentation ratio was set to α=0.01 for augmenting passage embeddings in the reported experiments.	×	0.14
The xDR model initialized with mBERT achieved an average R@2kt score of 44.1, outperforming the XLM-R initialized model	×	0.14
Applying xQG augmentation to the XLM-R xDR model improved the average R@2kt score from 27.5 to 29.8.	✓	0.16
The improvement of the XLM-R xDR model with xQG (score 29.8) over its baseline (score 27.5) is statistically significant	✓	0.21
Applying xQG augmentation to the mBERT xDR model improved the average R@2kt score from 44.1 to 46.2.	×	0.14
The improvement of the mBERT xDR model with xQG (score 46.2) over its baseline (score 44.1) is statistically significant	✓	0.19
The zero-shot mBERT model achieved an average R@2kt score of 33.0.	✓	0.18
Combining xQG with the zero-shot mBERT model improved the average R@2kt score from 33.0 to 36.0.	✓	0.16
The improvement of the zero-shot mBERT model with xQG is statistically significant with $p < 0.05$.	✓	0.21
xQG improved almost all models across all languages, with the exception of mBERT's R@2kt for Japanese (Ja).	×	0.13
xQG improved almost all models across all languages, with the exception of mBERT's R@5kt for Finnish (Fi).	×	0.13
mBERT performs better than XLM-R for both R@2kt and R@5kt metrics.	✓	0.19
Using 4 or more generated queries results in statistically significant improvements for R@2kt and R@5kt metrics.	✓	0.20
The XLM-R + xQG model achieved an average R@2kt score of 29.8.	✓	0.15

References

- http://arxiv.org/abs/2408.11942v1
- http://arxiv.org/abs/2305.03950v1
- http://arxiv.org/abs/2301.12566v1