Cross-lingual Query vs. Passage Generation for Dense Retriever Alignment in TyDiQA-GoldP

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 cross-lingual query generation approach compare to cross-lingual passage generation in terms of enhancing the alignment capabilities of dense retrievers, as measured by cross-lingual retrieval accuracy on TyDiQA-GoldP with varying degrees of passage and query language divergence?.

2 Methodology

Systematic literature search across multiple databases yielded 13 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

13 papers retrieved. 25 claims extracted; 18 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
The training set contains annotated relevant passage-query pairs.	×	0.13
The dev set contains 2,000 passage-answer pairs.	×	0.14
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.	✓	0.16
The xDR model initialized with mBERT achieved an average R@2kt score of 44.1.	✓	0.18
The xDR model initialized with XLM-R achieved an average R@2kt score of 27.5.	✓	0.18
The xQG passage embedding augmentation improved the XLM-R xDR average R@2kt score to 29.8.	✓	0.22
The improvement of XLM-R with xQG (29.8 vs 27.5) is statistically significant with $p < 0.05$.	×	0.15
The xQG passage embedding augmentation improved the mBERT xDR average R@2kt score to 46.2.	✓	0.21
The improvement of mBERT with xQG (46.2 vs 44.1) is statistically significant with $p < 0.05$.	×	0.14
The zero-shot mBERT model achieved an average R@2kt score of 33.0.	✓	0.19
The zero-shot mBERT model combined with xQG achieved an average R@2kt score of 36.0.	✓	0.22
The improvement of zero-shot mBERT with xQG is statistically significant with $p < 0.05$.	✓	0.21
xQG improves almost all models across all languages except for mBERT's R@2kt for Japanese (Ja).	✓	0.21
xQG improves almost all models across all languages except for mBERT's R@5kt for Finnish (Fi).	✓	0.21
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.	✓	0.21
CORA employs a generator to facilitate retrieval training data mining.	✓	0.21
Sentri proposes a single encoder and self-training.	✓	0.16
DR.DECR utilizes parallel queries and sentences for cross-lingual knowledge distillation.	✓	0.21

References

- http://arxiv.org/abs/2303.14991v1
- http://arxiv.org/abs/2408.11942v1
- http://arxiv.org/abs/2305.03950v1