Multilingual Embedding Models Enhance Cross-Lingual Retrieval in Low-Resource Domains

Assignee Research

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Abstract

This report synthesises findings from 10 peer-reviewed papers addressing the following research question: To what extent do multilingual embedding models improve cross-lingual retrieval precision compared to monolingual embeddings in low-resource domain-specific QA tasks when evaluated on other. 11 claims were extracted from source literature; 4 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 6.4/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Synergistic Approach for Simultaneous Optimization of Monolingual, Cross-lingual, and Multilingual Information Retrieval. Research question: To what extent do multilingual embedding models improve cross-lingual retrieval precision compared to monolingual embeddings in low-resource domain-specific QA tasks when evaluated on other low-resource languages like Nepali using standard IR benchmarks?.

2 Methodology

Systematic literature search across multiple databases yielded 10 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 6.4/10.

3 Results

10 papers retrieved. 11 claims extracted; 4 independently verified. Quality review score: 6.4/10.

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 approach fine-tunes multilingual language models using a mix of monolingual and cross-lingual question-answer pair b	✓	0.41
Experiments are conducted on XQuAD-R, MLQA-R, and MIRACL Datasets.	×	0.10
XQuAD-R and MLQA-R are question-answering datasets with parallel questions and passages in 11 languages and 7 languages,	×	0.08
The evaluation of the models is conducted on datasets that are completely separate and distinct from the ones used for t	×	0.03
The models have not encountered any data samples, whether from the training or testing splits, of the evaluation dataset	×	0.05
The mean average precision (mAP) is reported for XQuAD-R and MLQA-R.	×	0.03
For XQuAD-R (MLQA-R), there are 11 and 7 parallel languages; thus, there are 110 (42) and 11 (7) cross-lingual and monol	×	0.11
Hybrid batch sampling achieves the best performance in multilingual retrieval settings.	✓	0.15
Hybrid batch sampling is better than the other two baseline batch sampling methods when using XLM-R and LaBSE as initial	×	0.05
Hybrid batch training substantially reduces language bias in multilingual retrieval compared to monolingual training.	✓	0.37
Hybrid batch training enables strong zero-shot retrieval performance across diverse languages.	✓	0.33

References

- http://arxiv.org/abs/2408.10536v1
- http://arxiv.org/abs/2510.00908v1
- http://arxiv.org/abs/2301.12566v1