

Adversarial Cross-Lingual Perturbations in Multilingual Retrieval with LaBSE on XQuAD

Assignee Research

May 31, 2026

Abstract

This report synthesises findings from 12 peer-reviewed papers addressing the following research question: How does adversarial cross-lingual perturbation affect the performance of multilingual models like LaBSE on the XQuAD benchmark when evaluated using MA-DPR versus cosine similarity. Information retrieval across different languages is an increasingly important challenge in natural language processing. Recent approaches based on multilingual pre-trained language models have achieved remarkable success, yet they often optimize for either monolingual. 11 claims were extracted from source literature; 3 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 5.5/10. 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: How does adversarial cross-lingual perturbation affect the performance of multilingual models like LaBSE on the XQuAD benchmark when evaluated using MA-DPR versus cosine similarity?.

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 5.5/10.

3 Results

12 papers retrieved. 11 claims extracted; 3 independently verified. Quality review score: 5.5/10.

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 approach fine-tunes multilingual language models using a mix of monolingual and cross-lingual question-answer pairs	✓	0.40
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,	×	0.05
The evaluation of the models is conducted on datasets that are completely separate and distinct from the ones used for training	×	0.03
The models have not encountered any data samples, whether from the training or testing splits, of the evaluation dataset	×	0.04
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 monolingual	×	0.10
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.	✓	0.39
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/2205.15744v2>