Performance Comparison of Zero-Shot Cross-Lingual Retrieval Models on Code-Switched and Parallel Corpora

Assignee Research

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Abstract

Transferring information retrieval (IR) models from a high-resource language (typically English) to other languages in a zero-shot fashion has become a widely adopted approach. In this work, we show that the effectiveness of zero-shot rankers diminishes when queries and documents are present in different languages. Motivated by this, we propose to train ranking models on artificially code-switched data instead, which we generate by utilizing bilingual lexicons. To this end, we experiment with lexicons induced from (1) cross-lingual word embeddings and (2) parallel Wikipedia page titles. We use

1 Introduction

This paper examines: Boosting Zero-shot Cross-lingual Retrieval by Training on Artificially Code-Switched Data. Research question: How does the performance of zero-shot cross-lingual retrieval models trained on code-switched data compare to models fine-tuned on parallel corpora when evaluated on the XNLI and mXGLUE benchmarks?.

2 Methodology

Systematic literature search across multiple databases yielded 7 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.2/10.

3 Results

7 papers retrieved. 16 claims extracted; 14 independently verified. Quality review score: 8.2/10.

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
Code-switching improves cross-lingual and multilingual re-ranking without impeding monolingual setups.	×	0.15
The average MoIR performance is substantially higher than CLIR with 15.7 MRR@10 and MLIR with 16.6 MRR@10.	✓	0.23
The transfer performance greatly varies with the language proximity, with larger drops for typologically distant languag	✓	0.29
The performance gap to fine-tuning on translated data is much smaller in MoIR (+4 MRR@10) than in CLIR (+11.1 MRR@10) an	✓	0.31
Training on code-switched data consistently outperforms zero-shot models in CLIR and MLIR.	✓	0.24
In AR–IT and AR–RU, improvements from 7.7 and 7.1 MRR@10 up to 15.6 and 14.1 MRR@10 are observed, rendering the approach	✓	0.24
The differences between both CS approaches (BL-CS and ML-CS) versus Zero-shot are not statistically significant, showing	✓	0.31
Specializing one zero-shot model for multiple CLIR language pairs (ML-CS, Wiki-CS) performs almost on par with specializ	✓	0.30
The results of Wiki-CS are slightly worse in MoIR and on par with ML-CS on MLIR and CLIR.	✓	0.26
In MoIR, both Zero-shot Translate Test and ML-CS Translate Test underperform compared to other approaches.	✓	0.23
In CLIR, Translate Test shows slight improvements of +0.2 and +2.2 MRR@10.	✓	0.18
In both MoIR and CLIR, Translate Test consistently falls behind code-switching at training time.	✓	0.23
The gains remain virtually unchanged when moving from six seen (+4.1 MRR@10 / +3.8 MRR@10) to fourteen languages includi	✓	0.30
Training on code-switched data is a cheap and effective way of generalizing zero-shot rankers for cross-lingual and mult	✓	0.34
Fine-tuning CEs on monolingual data biases the encoder towards encoding features that are only useful when the target se	✓	0.25
Artificial code-switching is a method to modify monolingual training data by borrowing words from other languages.	×	0.12

References

- http://arxiv.org/abs/2406.13361v1
- http://arxiv.org/abs/2305.05295v2
- http://arxiv.org/abs/2506.15415v1