mPLM-Induced Language Similarity for Optimizing Source Language Selection in Cross-Lingual Knowledge Transfer

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Abstract

Recent multilingual pretrained language models (mPLMs) have been shown to encode strong language-specific signals, which are not explicitly provided during pretraining. It remains an open question whether it is feasible to employ mPLMs to measure language similarity, and subsequently use the similarity results to select source languages for boosting cross-lingual transfer. To investigate this, we propose mPLMSim, a language similarity measure that induces the similarities across languages from mPLMs using multi-parallel corpora. Our study shows that mPLM-Sim exhibits moderately high correlatio

1 Introduction

This paper examines: mPLM-Sim: Better Cross-Lingual Similarity and Transfer in Multilingual Pretrained Language Models. Research question: What is the impact of using mPLM-induced language similarity scores (mPLM-Sim) to select source languages for cross-lingual knowledge transfer on accuracy metrics (e.g., EM, F1) in tasks like PAWS-X, compared to random or language-family-based selection?.

2 Methodology

Systematic literature search across multiple databases yielded 11 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

11 papers retrieved. 8 claims extracted; 6 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
mPLM-Sim results vary across layers, with the embedding layer capturing lexical information and middle layers revealing	✓	0.26
In the high layers of mPLMs, the ability to distinguish between languages becomes less prominent.	✓	0.15
Clustering of languages varies by layer in mPLMs, indicating changes in the representation of language-specific informat	×	0.14
Input modality (text or speech), model size, and data used for pretraining have large effects on mPLM-Sim, while tokeniz	✓	0.30
mPLM-Sim can select source languages that boost cross-lingual transfer better than linguistic similarity measures, achie	✓	0.24
Parallel corpora yield better results for measuring language similarity than monolingual corpora while using fewer sente	✓	0.21
mPLM-Sim provides similarity results for N layers of an mPLM across L languages considered.	×	0.12
For mPLMs with bidirectional encoders, including encoder architecture (e.g., XLM-R) and encoder-decoder architecture (e.	✓	0.30

References

- http://arxiv.org/abs/2310.09917v3
- http://arxiv.org/abs/2305.13684v3
- http://arxiv.org/abs/2505.11665v1