Impact of Multilingual Pretrained Language Models on Cross-Lingual NER F1 Scores in Low-Resource Languages

Assignee Research

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Abstract

Pretrained multilingual language models have become a common tool in transferring NLP capabilities to low-resource languages, often with adaptations. In this work, we study the performance, extensibility, and interaction of two such adaptations: vocabulary augmentation and script transliteration. Our evaluations on part-of-speech tagging, universal dependency parsing, and named entity recognition in nine diverse low-resource languages uphold the viability of these approaches while raising new questions around how to optimally adapt multilingual models to low-resource settings.

1 Introduction

This paper examines: Specializing Multilingual Language Models: An Empirical Study. Research question: What is the impact of using multilingual pretrained language models (e.g., XLM-R, mBERT) on the F1 score of cross-lingual NER models when transferring to typologically distant low-resource languages?.

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 8.0/10.

3 Results

13 papers retrieved. 16 claims extracted; 13 independently verified. Quality review score: 8.0/10.

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
Chau et al. (2020) report significant performance improvements on a small set of low-resource languages using vocabulary	✓	0.22
Muller et al. (2021) observe mixed results with transliteration quality being a confounding factor.	✓	0.20
Vocabulary augmentation offers an appealing balance of performance and cost.	✓	0.21
Vocabulary augmentation improves performance on three tasks in a diverse set of nine low-resource languages across three	✓	0.25
Vocabulary augmentation gains are associated with improved vocabulary coverage of the target language.	✓	0.23
There is a negative interaction between vocabulary augmentation and transliteration in light of a broader framework for	✓	0.24
The performance of LAPT is 95.74 $\pm$ 0.44.	×	0.12
The performance of VA is 95.28 $\pm$ 0.51, 97.15 $\pm$ 0.04, and 93.28 $\pm$ 0.19.	✓	0.22
The performance of MBERT is 71.83 $\pm$ 0.90.	×	0.13
The performance of LAPT is 72.77 $\pm$ 1.12.	×	0.14
The performance of VA is 73.22 $\pm$ 1.23 and 91.62 $\pm$ 0.23.	✓	0.18
The performance of FASTT is 84.26 $\pm$ 0.86, 87.98 $\pm$ 0.76, 67.21 $\pm$ 4.30, and 33.53 $\pm$ 17.89.	✓	0.27
The performance of BERT is 88.08 $\pm$ 0.62, 90.31 $\pm$ 0.20, 76.58 $\pm$ 0.98, 54.64 $\pm$ 3.51, 61.54 $\pm$ 3.70, and 92.85 $\pm$ 2.04.	✓	0.34
The performance of MBERT is 91.13 $\pm$ 0.07, 92.56 $\pm$ 0.09, 82.82 $\pm$ 0.57, 61.86 $\pm$ 2.60, 50.76 $\pm$ 1.86, 94.60 $\pm$ 0.34, 92.13 $\pm$	✓	0.57
The performance of LAPT is 91.61 $\pm$ 0.74, 92.96 $\pm$ 0.13, 84.13 $\pm$ 0.78, 81.53 $\pm$ 2.33, 56.76 $\pm$ 4.91, 95.17 $\pm$ 0.29, 92.41 $\pm$ 0	✓	0.62
The performance of VA is 91.38 $\pm$ 0.56, 92.70 $\pm$ 0.11, 84.82 $\pm$ 1.00, 80.00 $\pm$ 2.77, 68.93 $\pm$ 3.30, 94.43 $\pm$ 0.22, 92.43 $\pm$ 0.1	✓	0.62

References

- http://arxiv.org/abs/2106.09063v4
- http://arxiv.org/abs/2305.00090v1
- http://arxiv.org/abs/2404.17122v1