Performance Comparison of Cross-Lingual NER Models and Multilingual Language Models on Adversarial Perturbations in High-Resource

Assignee Research

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Abstract

Multilingual Language Models (MLLMs) exhibit robust cross-lingual transfer capabilities, or the ability to leverage information acquired in a source language and apply it to a target language. These capabilities find practical applications in well-established Natural Language Processing (NLP) tasks such as Named Entity Recognition (NER). This study aims to investigate the effectiveness of a source language when applied to a target language, particularly in the context of perturbing the input test set. We evaluate on 13 pairs of languages, each including one high-resource language (HRL) and one

1 Introduction

This paper examines: Cross-Lingual Transfer Robustness to Lower-Resource Languages on Adversarial Datasets. Research question: How does the performance of cross-lingual NER models trained via annotation projection compare to multilingual language models (e.g., mBERT, XLM-R) when evaluated on adversarial perturbations in high-resource languages, measured by F1-score degradation on a modified XQuAD-NER adversarial test set?.

2 Methodology

Systematic literature search across multiple databases yielded 14 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 9.3/10.

3 Results

14 papers retrieved. 14 claims extracted; 14 independently verified. Quality review score: 9.3/10.

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
Calix et al. (2022) performed name replacement using different languages as what has been done in Vajjala and Balasubram	✓	0.27
Srinivasan and Vajjala (2023) investigate input alterations in English, German, Hindi, emphasizing how predictions can d	✓	0.27
For German and Hindi, combination of masking and random datasets show the most significant performance drop.	✓	0.22
This paper further investigates multilingual model fine-tuning and its robustness to adversarial input perturbations.	✓	0.21
We compare native LRL models to those performing cross-lingual transfer from an HRL, and examine the relationship betwee	✓	0.29
Our exploration focuses on 13 language pairs from a pool of 21 languages: Arabic/Farsi, Arabic/Hindi, Czech/Slovak, Dutc	✓	0.41
These languages were chosen following the rationale established by Nath et al. (2022) for collecting loanword data: lang	✓	0.35
While Nath et al. (2022)'s data source is Wiktionary, we examined the WikiANN dataset (Pan et al., 2017), a common multi	✓	0.31
We selected language pairs consisting of one language with greater resources in the data and one with fewer resources, w	✓	0.45
One of these pairs—Arabic/Hindi—serves as a kind of "control" group; although there is a substantial amount of vocabular	✓	0.43
In the selected pairs, the HRL is often a major world or national language while the LRL is often a regional or minority	✓	0.32
To assess the effect of zero-shot transfer between languages with overlapping vocabulary, we compare the performance of	✓	0.15
These are two of the most well-known multilingual, publicly-available encoder-style models in use, notable for their abi	✓	0.27
We evaluate both models in a native setting when they are fully fine-tuned on the two tasks in an LRL; in a transfer set	✓	0.22

References

- http://arxiv.org/abs/2501.18750v1
- http://arxiv.org/abs/2305.18933v1
- http://arxiv.org/abs/2403.20056v1