Performance of Multimodal Language Models in Cross-Lingual NER for Low-Resource Languages with Noisy Data

Assignee Research

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Abstract

Cross-lingual Named Entity Recognition (NER) leverages knowledge transfer between languages to identify and classify named entities, making it particularly useful for low-resource languages. We show that the data-based cross-lingual transfer method is an effective technique for crosslingual NER and can outperform multilingual language models for low-resource languages. This paper introduces two key enhancements to the annotation projection step in cross-lingual NER for low-resource languages. First, we explore refining word alignments using back-translation to improve accuracy. Second, we pres

1 Introduction

This paper examines: Revisiting Projection-based Data Transfer for Cross-Lingual Named Entity Recognition in Low-Resource Languages. Research question: How do multimodal language models (e.g., CLIP, Flamingo) perform in cross-lingual NER tasks compared to text-only teacher-student frameworks when evaluated on low-resource languages with noisy unlabeled data?.

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 8.2/10.

3 Results

12 papers retrieved. 16 claims extracted; 13 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
The evaluation was performed across a total of 57 languages using the XTREME (39 languages) and MasakhaNER2 datasets (18	✓	0.16
The heuristic word-to-word alignment-based approach by Garca-Ferrero et al. (2022) was reimplemented and enhanced with	✓	0.26
The EasyProject method uses back-translation of labelled source sentences with the NLLB-200-3.3B model for annotation pr	✓	0.21
The XLM-R-Large model, fine-tuned on the English split of the CONLL2003, was used as the source model and for target can	✓	0.17
MISC entities predicted by the XLM-R-Large model were ignored in the first set of experiments as this class does not exi	✓	0.23
SimAlign and non-finetuned AWESoME neural aligners with default settings were used for computing word-to-word alignments	×	0.14
All models were sourced from the HF Hub, including ychenNLP/nllb-200-3.3B-easyproject, facebook/nllb-200-3.3B, and Faceb	✓	0.21
The evaluation metrics were influenced by both translation quality and the performance of the NER models.	×	0.12
The same models for translation and source labelling were employed throughout all experiments for a fair and consistent	✓	0.16
The greedy approximation algorithm was used for tasks involving the proposed integer linear programming (ILP) formulatio	✓	0.19
Candidate matching methods consistently deliver strong performance, with the proposed n-gram candidates extraction provi	✓	0.21
The NER model-based extraction (N) method is mentioned but not fully described in the provided text.	×	0.06
Projection-based data transfer can outperform multilingual language models for low-resource languages in cross-lingual N	✓	0.34
The paper introduces two key enhancements to the annotation projection step: refining word alignments using back-transla	✓	0.33
Data-based methods automate labelling through translation and annotation projection processes, leveraging multilingual l	✓	0.28
Translate-test and translate-train are two approaches for categorization in cross-lingual NER.	✓	0.19

References

- http://arxiv.org/abs/2508.09516v1
- http://arxiv.org/abs/2501.18750v1
- http://arxiv.org/abs/2106.09063v4