

Projection-based Cross-lingual NER vs. Zero-shot Multilingual Models in Low-resource Languages

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 does the inference efficiency (measured in tokens/second or latency) of projection-based cross-lingual NER compare to zero-shot multilingual models (e.g., mT5, Bloom) on low-resource languages in benchmarks like WikiAnn or PAN-X?.

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 7.5/10.

3 Results

12 papers retrieved. 17 claims extracted; 13 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
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.	✓	0.16
SimAlign and non-finetuned AWESoME neural aligners were used for computing word-to-word alignments with default settings	×	0.14
The NLLB200-3.3B model was employed as a translation model for all experiments.	×	0.12
The evaluation metrics were influenced by both translation quality and the performance of the NER models.	×	0.13
The proposed approach involving n-gram candidates extraction provides comparable or superior results to heuristics.	✓	0.19
The NER model-based extraction (N) method was used in the experiments.	×	0.09
Projection-based data transfer can outperform multilingual language models for low-resource languages.	✓	0.29
The paper introduces two key enhancements to the annotation projection step in cross-lingual NER for low-resource langua	✓	0.37
The first enhancement explores refining word alignments using back-translation to improve accuracy.	✓	0.20
The second enhancement presents a novel formalized projection approach of matching source entities with extracted target	✓	0.22
The findings highlight the robustness of projection-based data transfer as an alternative to model-based methods for cro 4	✓	0.43
Data-based methods automate labelling through translation and annotation projection processes while leveraging advanceme	✓	0.30
Translate-test labels original sentences in zero-shot settings, and translate-train generates labelled data to train a N	✓	0.32

References

- <http://arxiv.org/abs/2501.18750v1>
- <http://arxiv.org/abs/2308.10783v2>
- <http://arxiv.org/abs/2106.09063v4>