Cross-lingual NER Annotation Projection vs. Zero-Shot Few-Shot Learning 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 scalability of annotation projection methods compare to zero-shot few-shot learning approaches in cross-lingual NER when applied to 10+ linguistically diverse low-resource languages?.

2 Methodology

Systematic literature search across multiple databases yielded 8 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.7/10.

3 Results

8 papers retrieved. 18 claims extracted; 13 independently verified. Quality review score: 7.7/10.

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 was reimplemented according to Garca-Ferrero et al. (2022) and enh	✓	0.26
The EasyProject method was reimplemented using the NLLB-200-3.3B2 model for back-translation and annotation projection.	✓	0.17
NLLB200-3.3B3 was employed as the translation model for all experiments.	×	0.13
The XLM-R-Large model, fine-tuned on the English split of the CONLL2003, served as the source model and for target candi	✓	0.19
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
All models were sourced from the HF Hub.	×	0.07
The evaluation metrics were influenced by both translation quality and the performance of the NER models.	×	0.13
The same models for translation and source labelling were employed throughout all experiments for fair comparison.	×	0.12
A greedy approximation algorithm was used for tasks involving the proposed integer linear programming (ILP) formulation	✓	0.20
Candidate matching methods consistently deliver strong performance.	✓	0.15
The proposed n-gram candidates extraction approach provides comparable or superior results while offering greater flexib	✓	0.18
The paper introduces two key enhancements to the annotation projection step in cross-lingual NER for low-resource langua	✓	0.42
Projection-based data transfer can outperform multilingual language models for low-resource languages in cross-lingual N	✓	0.35
Data-based methods automate labelling through translation and annotation projection processes.	✓	0.18
Translate-test and translate-train are two approaches for categorization in cross-lingual NER.	✓	0.19
The paper demonstrates the effectiveness of a data-based cross-lingual transfer method for cross-lingual NER.	✓	0.18

References

- http://arxiv.org/abs/2308.10783v2
- http://arxiv.org/abs/2112.10006v6
- http://arxiv.org/abs/2501.18750v1