Performance Gap in Cross-Lingual NER: Label Projection vs. Teacher-Student Learning

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: What is the performance gap between label projection methods and teacher-student learning on low-resource languages in cross-lingual NER evaluations?.

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 7.8/10.

3 Results

13 papers retrieved. 24 claims extracted; 19 independently verified. Quality review score: 7.8/10.

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 and MasakhaNER2 datasets.	×	0.12
The evaluation encompasses the full pipeline, considering both translation and source NER model performance.	✓	0.20
The heuristic word-to-word alignment-based approach was reimplemented according to Garca-Ferrero et al. (2022).	✓	0.23
The heuristic was enhanced by introducing a word count ratio threshold of 0.8 to better handle misaligned unitary words.	✓	0.18
The EasyProject method performs back-translation of labelled source sentences using the NLLB-200-3.3B model.	✓	0.24
NLLB200-3.3B was employed as a translation model for all experiments.	×	0.12
The XLM-R-Large model, fine-tuned on the English split of the CONLL2003, served as both the source model and for target	✓	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 are from the HF Hub.	×	0.11
The evaluation involved full pipelines, resulting in metrics influenced by both translation quality and the performance	✓	0.15
The same models were employed for translation and source labelling throughout all experiments.	×	0.14
The greedy approximation algorithm was utilized for tasks involving the proposed integer linear programming (ILP) formul	✓	0.20
Candidate matching methods consistently deliver strong performance.	✓	0.15
The proposed approach involving n-gram candidates extraction provides comparable or superior results while offering grea	✓	0.22
The paper introduces two key enhancements to the annotation projection step in cross-lingual NER for low-resource langua	✓	0.38
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	✓	0.23
Projection-based data transfer can outperform	✓	0.21

References

- http://arxiv.org/abs/2106.09063v4
- http://arxiv.org/abs/2004.12440v2
- http://arxiv.org/abs/2501.18750v1