Computational Efficiency Trade-offs in Scaling Flamingo vs. Projection-based Methods for Cross-lingual NER in Low-resource

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 computational efficiency trade-off between Flamingo and projection-based methods when scaling to 10+ low-resource languages in cross-lingual NER?.

2 Methodology

Systematic literature search across multiple databases yielded 10 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

10 papers retrieved. 15 claims extracted; 11 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	✓	0.25
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 specific model versions for NLLB-200-3.3B and XLM-R-Large.	✓	0.15
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 consistent comparison.	×	0.14
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, with n-gram candidates extraction providing comparab	✓	0.20
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 in cross-lingual N	✓	0.34
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

References

- http://arxiv.org/abs/2505.18673v1
- http://arxiv.org/abs/2404.02490v1
- http://arxiv.org/abs/2501.18750v1