

Typological Feature Integration in Budget-Xfer for Cross-Lingual NER Robustness in African Languages

Assignee Research

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Abstract

Cross-lingual transfer learning enables NLP for low-resource languages by leveraging labeled data from higher-resource sources, yet existing comparisons of source language selection strategies do not control for total training data, confounding language selection effects with data quantity effects. We introduce Budget-Xfer, a framework that formulates multi-source cross-lingual transfer as a budget-constrained resource allocation problem. Given a fixed annotation budget B , our framework jointly optimizes which source languages to include and how much data to allocate from each. We evaluate fou

1 Introduction

This paper examines: Budget-Xfer: Budget-Constrained Source Language Selection for Cross-Lingual Transfer to African Languages. Research question: What is the impact of incorporating typological features into Budget-Xfer’s source language selection on the robustness of cross-lingual NER models when transferring to out-of-domain African 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 7.4/10.

3 Results

8 papers retrieved. 9 claims extracted; 7 independently verified. Quality review score: 7.4/10.

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
cosine_gap predicts cross-lingual transfer with a correlation coefficient (ρ) of 0.4–0.6.	×	0.10
FLORES-200 provides 1,012 parallel sentences per language.	×	0.13
MasakhaNER 2.0 provides entity-annotated data in 20 African languages with standard categories (PER, ORG, LOC, DATE).	✓	0.20
AfriSenti covers 14 African languages with three classes (positive, negative, neutral).	✓	0.17
The evaluation metric for NER is entity-level F1 (micro-averaged) computed with seqeval.	✓	0.20
The evaluation metric for sentiment analysis is weighted F1 to account for class imbalance.	✓	0.18
Multi-source transfer significantly outperforms single-source transfer with Cohen’s d effect sizes ranging from 0.80 to	✓	0.23
Among multi-source strategies, differences are modest and non-significant.	✓	0.25
Random selection outperforms similarity-based selection for NER but not sentiment analysis.	✓	0.20

References

- <http://arxiv.org/abs/2603.27651v1>
- <http://arxiv.org/abs/2503.19979v1>
- <http://arxiv.org/abs/2501.18750v1>