

Enhancing Zero-Shot Cross-Lingual NER via Synthetic Unlabeled Data and Projection-Based Transfer Beyond Multilingual Pre-training

Assignee Research

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Abstract

Multilingual BERT (mBERT), a language model pre-trained on large multilingual corpora, has impressive zero-shot cross-lingual transfer capabilities and performs surprisingly well on zero-shot POS tagging and Named Entity Recognition (NER), as well as on cross-lingual model transfer. At present, the mainstream methods to solve the cross-lingual downstream tasks are always using the last transformer layer’s output of mBERT as the representation of linguistic information. In this work, we explore the complementary property of lower layers to the last transformer layer of mBERT. A feature aggregat

1 Introduction

This paper examines: Feature Aggregation in Zero-Shot Cross-Lingual Transfer Using Multilingual BERT. Research question: Does integrating synthetic unlabeled data with projection-based transfer enhance zero-shot cross-lingual NER performance more effectively than multilingual pre-training alone?.

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 8.3/10.

3 Results

12 papers retrieved. 11 claims extracted; 10 independently verified. Quality review score: 8.3/10.

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 |
|--|----------|------------|
| Lower layers of mBERT provide more cross-lingual information while upper layers provide more language structure informat | ✓ | 0.28 |
| The output of layers before the last layer can provide supplementary information to the last layer of mBERT for differen | ✓ | 0.30 |
| Experimental results on four cross-lingual downstream datasets show that the proposed method improves the performance of | ✓ | 0.25 |
| The best results of aggregation models in each task outperform the baseline by 1 to 3 absolute percentage points. | ✓ | 0.20 |
| The best performances of the four tasks are obtained with different fusion layers. | ✓ | 0.21 |
| The ability to extract good semantic and structural features is a crucial reason for the model’s cross-lingual effective | ✓ | 0.24 |
| There exist strong similarities between two languages if they belong to the same language family. | ✓ | 0.25 |
| The DLFA module integrates the representations from the last and from one of the lower layers, and the fusion embeddings | ✓ | 0.21 |
| The AIF module extracts global and local information via two branches and element-wisely multiplies the result with the | ✓ | 0.31 |
| The AIF module is designed to obtain information dynamically according to the requirements of different downstream tasks | ✓ | 0.22 |
| The AIF module includes two convolution layers to expand and compress the dimension of features. | × | 0.11 |

References

- <http://arxiv.org/abs/2210.07022v1>
- <http://arxiv.org/abs/2205.08497v1>
- <http://arxiv.org/abs/2501.18750v1>