Multimodal Intermediate Tasks for Zero-Shot Cross-Lingual Transfer Accuracy in XNLI Versus Text-Only Baselines

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: What is the impact of multimodal intermediate tasks (e.g., image-text alignment) on zero-shot cross-lingual transfer accuracy in XNLI compared to text-only intermediate tasks?.

2 Methodology

Systematic literature search across multiple databases yielded 15 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.5/10.

3 Results

15 papers retrieved. 17 claims extracted; 16 independently verified. Quality review score: 8.5/10.

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
Lower layers of mBERT provide more cross-lingual information while upper layers provide more language structure informat	✓	0.29
The output of layers before the last layer can provide supplementary information to the last layer of mBERT for differen	✓	0.31
The optimal dynamic equilibrium between cross-lingual capability and language-structured ability of mBERT is discussed.	✓	0.26
A feature aggregation module based on an attention mechanism is designed to fuse information from two transformer layers	✓	0.24
Experimental results on four cross-lingual downstream datasets show that the method improves the performance of mBERT on	✓	0.31
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 then the fusion embed	✓	0.22
The representation generated from transformers in mBERT is a tensor with the dimension as B $\times$ T $\times$ E, in which B is the b	✓	0.30
The AIF module extracts global and local information via two branches and element-wisely multiplies the result with the	✓	0.30
The AIF module is designed to obtain information dynamically according to the requirements of different downstream tasks	✓	0.22
The AIF's structure is inspired by SENet, which expanded and compressed the dimension of features in hope of getting a m	✓	0.16
There are two convolution layers in the AIF module.	✓	0.18
The module's input is set as W $\in$ RB$\times$T $\times$E.	×	0.11
There are two contextual aggregation branches in the AIF module.	✓	0.17

References

- http://arxiv.org/abs/2309.10891v1
- http://arxiv.org/abs/2403.10499v1
- http://arxiv.org/abs/2205.08497v1