Scaling Translated Parallel Data in Label-Aware Contrastive Learning for Flan-T5 Cross-Lingual Alignment on XLMR

Assignee Research

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Abstract

Cross-language pre-trained models such as multilingual BERT (mBERT) have achieved significant performance in various cross-lingual downstream NLP tasks. This paper proposes a multi-level contrastive learning (ML-CTL) framework to further improve the cross-lingual ability of pre-trained models. The proposed method uses translated parallel data to encourage the model to generate similar semantic embeddings for different languages. However, unlike the sentence-level alignment used in most previous studies, in this paper, we explicitly integrate the word-level information of each pair of parallel

1 Introduction

This paper examines: Multi-Level Contrastive Learning for Cross-Lingual Alignment. Research question: Does scaling the amount of translated parallel data used in label-aware multi-level contrastive learning proportionally improve the cross-lingual alignment of Flan-T5 models on the XLMR benchmark, evaluated via downstream NLI task performance?.

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 8.1/10.

3 Results

8 papers retrieved. 13 claims extracted; 11 independently verified. Quality review score: 8.1/10.

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
mBERT (base) achieved scores of 65.4, 81.9, 70.3, 62.2, 56.7, and 38.7 on various benchmarks.	✓	0.23
XLM achieved scores of 69.1, 80.9, 70.1, 61.2, 56.8, and 32.6 on various benchmarks.	×	0.14
MMTE achieved scores of 67.4, 81.3, 72.3, 58.3, 59.8, and 37.9 on various benchmarks.	✓	0.15
ML-CTL-CZ (ours) achieved scores of 67.8, 85.3, 72.3, 62.9, 78.4, and 43.4 on various benchmarks.	✓	0.21
info-snt achieved scores of 66.255, 84.092, 71.544, 62.157, 76.426, and 41.148 on various benchmarks.	✓	0.27
CZ-snt achieved scores of 66.862, 84.485, 71.733, 62.337, 77.403, and 41.751 on various benchmarks.	✓	0.26
ML-CTL-CZ achieved scores of 67.750, 85.321, 72.289, 62.865, 78.440, and 43.389 on various benchmarks.	✓	0.27
ML-CTL-CZ has the optimal cross-lingual ability as the distribution of its tokens has better intra-class compactness and	✓	0.22
The transfer ability of the basic model (mBERT) and ML-CTL-CZ outperforms on multiple zero-shot cross-lingual downstream	✓	0.39
The es+ in the denominator sets a lower bound 0 for infoNCE loss.	✓	0.27
CZ-NCE loss is modified to keep the loss value away from zero during most of the training time.	✓	0.21
The learning goal of CZ-NCE is the same as infoNCE.	✓	0.19
CZ-NCE is effective on alleviating the disturbance of the float-point error.	×	0.13

References

- http://arxiv.org/abs/2205.03656v2
- http://arxiv.org/abs/2202.13083v1
- http://arxiv.org/abs/2506.15415v1