Inference Efficiency of Multilingual Models in Domain-Specific vs. General Fine-Tuning for Zero-Shot Cross-Lingual Transfer

Assignee Research

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Abstract

Pre-trained multilingual language models show significant performance gains for zero-shot cross-lingual model transfer on a wide range of natural language understanding (NLU) tasks. Previously, for zero-shot cross-lingual evaluation, pre-trained models are only fine-tuned on English data and tested on a variety of target languages. In this paper, we do cross-lingual evaluation on various NLU tasks (sentence classification, sequence labeling, question answering) using prompt-tuning and compare it with fine-tuning. The results show that prompt tuning achieves much better cross-lingual transfer t

1 Introduction

This paper examines: Prompt-Tuning Can Be Much Better Than Fine-Tuning on Cross-lingual Understanding With Multilingual Language Models. Research question: How does the inference efficiency (latency, memory usage) of multilingual models change when fine-tuned on domain-specific versus general intermediate tasks for zero-shot cross-lingual transfer, as measured on the XTREME-R benchmark?.

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 8.5/10.

3 Results

12 papers retrieved. 9 claims extracted; 8 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
Fine-tuning on large pre-trained language models leads to strong performance on downstream tasks, however, it is memory-	✓	0.28
Prompt tuning can be better than fine-tuning when the model size is not extremely large (10 billion parameters).	✓	0.24
Prex-tuning (Li and Liang, 2021) obtains comparable performance for natural language generation tasks.	✓	0.25
Liu et al. (2022) shows prompt tuning can be matched to fine-tuning on language understanding tasks even at hard sequenc	✓	0.28
The framework demonstrates strong cross-lingual results with only 0.1% to 0.3% additional prompt parameters as compared	✓	0.23
Prompt length is set to 16 or 32 and tuned on the English validation set.	✓	0.25
XLM-R-LARGE achieves stronger performance than mBERT.	×	0.13
Fine-tuning results in Table 1 show that XLM-R-LARGE achieves 78.8% accuracy on XNLI, 87.9% accuracy on PAWS-X, 74.4% F1	✓	0.19
Prompt tuning results in Table 1 show that XLM-R-LARGE achieves 79.9% accuracy on XNLI, 88.4% accuracy on PAWS-X, 75.4%	✓	0.21

References

- http://arxiv.org/abs/2104.08645v2
- http://arxiv.org/abs/2005.13013v2
- http://arxiv.org/abs/2210.12360v2