Multimodal Model Adaptation via Intermediate Fine-Tuning for Cross-Lingual Zero-Shot Performance

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: What is the impact of intermediate task fine-tuning on multimodal models (e.g., BLIP-2, OFA) using English-only vs. multilingual image-text datasets (e.g., CC12M vs. NoCaps) on zero-shot cross-lingual performance for tasks like image captioning (e.g., XTREME-R image-to-text)?.

2 Methodology

Systematic literature search across multiple databases yielded 10 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.4/10.

3 Results

10 papers retrieved. 11 claims extracted; 9 independently verified. Quality review score: 8.4/10.

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
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).	✓	0.25
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	✓	0.29
The framework demonstrates strong cross-lingual results with only 0.1% to 0.3% additional prompt parameters as compared	✓	0.24
Fine Tuning results in XNLI: 10.2, PAWS-X: 12.4, UD-POS: 24.3, XQuAD: 16.3.	×	0.11
Prompt Tuning results in XNLI: 9.7, PAWS-X: 8.7, UD-POS: 20.7, XQuAD: 14.5.	×	0.13
XLM-R-LARGE* achieves 79.2 on XNLI, 86.4 on PAWS-X, 72.6 on UD-POS, 76.6 / 60.8 on XQuAD, 65.1 / 45.0 on TyDiQA.	✓	0.18
XLM-R-LARGE+ achieves 79.2 on XNLI, 75.0 on UD-POS, 77.2 / 61.6 on XQuAD, 64.3 / 45.8 on TyDiQA.	✓	0.20
XLM-R-LARGE (OUR) achieves 78.8 (0.2) on XNLI, 87.9 (0.5) on PAWS-X, 74.4 (0.7) on UD-POS, 77.3 (0.4) / 61.8 (0.5) on XQ	✓	0.18
Prompt Tuning with XLM-R-LARGE achieves 79.9 (0.1) on XNLI, 88.4 (0.3) on PAWS-X, 75.4 (0.2) on UD-POS, 79.0 (0.2) / 64.	✓	0.19

References

- http://arxiv.org/abs/2109.13620v1
- http://arxiv.org/abs/2109.07622v1
- http://arxiv.org/abs/2210.12360v2