

Early-Layer LoRA Depth Effects on Cross-Lingual Consistency in Lugha-Llama

Assignee Research

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Abstract

This report synthesises findings from 12 peer-reviewed papers addressing the following research question: What is the impact of varying the depth of early-layer LoRA fine-tuning in TLI on the cross-lingual consistency of Lugha-Llama, measured by XLM-R's accuracy on the XTREME-R benchmark for Swahili and other low-resource languages?. 16 claims were extracted from source literature; 5 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 5.5/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Adapting Pre-trained Language Models to African Languages via Multilingual Adaptive Fine-Tuning. Research question: What is the impact of varying the depth of early-layer LoRA fine-tuning in TLI on the cross-lingual consistency of Lugha-Llama, measured by XLM-R's accuracy on the XTREME-R benchmark for Swahili and other low-resource languages?.

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 5.5/10.

3 Results

12 papers retrieved. 16 claims extracted; 5 independently verified. Quality review score: 5.5/10.

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
Multilingual PLMs are often trained on about 100 languages due to the curse of multilinguality and non-availability of p	×	0.12
Language adaptive fine-tuning (LAFT) involves fine-tuning a multilingual PLM on monolingual texts in the target language	✓	0.36
Adapting a model to each target language individually using LAFT takes large disk space.	✓	0.21
Adapting a model to each target language individually limits the cross-lingual transfer abilities of the resulting model	✓	0.26
AfriBERTa was trained from scratch on 11 African languages.	×	0.13
A newly created Lingala (lin) news topic classification dataset contains 1,536 training sentences, 220 development sente	×	0.03
A newly created Naija (pcm) news topic classification dataset contains 1,165 training sentences, 167 development sentenc	×	0.03
A newly created Malagasy (mlg) news topic classification dataset contains 3,905 training sentences, 559 development sent	×	0.03
A newly created Somali (som) news topic classification dataset contains 10,072 training sentences, 1,440 development sen	×	0.03
A newly created isiZulu (zul) news topic classification dataset contains 2,961 training sentences, 424 development sente	×	0.03
An existing Amharic (amh) news topic classification dataset contains 36,029 training sentences, 5,147 development senten	×	0.03
The XLM-R-large model has 550M parameters.	×	0.04
The AfriBERTa model has 126M parameters.	×	0.04
The XLM-R-base model has 270M parameters.	×	0.09
The proposed approach is competitive with applying LAFT on individual languages while requiring significantly less disk	✓	0.25
The adapted PLM improves the zero-shot cross-lingual transfer abilities of parameter efficient fine-tuning methods.	✓	0.24

References

- <http://arxiv.org/abs/2104.07412v2>
- <http://arxiv.org/abs/2506.15415v1>
- <http://arxiv.org/abs/2204.06487v3>