What is the impact of adaptive LoRA rank distribution on the robustness of federated fine-tuning against non-IID label shifts

Assignee Research

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Abstract

Federated Learning (FL) has recently been applied to the parameter-efficient fine-tuning of Large Language Models (LLMs). While promising, it raises significant challenges due to the heterogeneous resources and data distributions of clients. This study introduces FlexLoRA, a simple yet effective aggregation scheme for LLM fine-tuning, which mitigates the "bucket effect" in traditional FL that restricts the potential of clients with ample resources by tying them to the capabilities of the least-resourced participants. FlexLoRA allows for dynamic adjustment of local LoRA ranks, fostering the d

1 Introduction

This paper examines: Federated Fine-tuning of Large Language Models under Heterogeneous Tasks and Client Resources. Research question: What is the impact of adaptive LoRA rank distribution on the robustness of federated fine-tuning against non-IID label shifts when evaluated on the GLUE RTE and MNLI benchmarks?.

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 7.8/10.

3 Results

15 papers retrieved. 12 claims extracted; 12 independently verified. Quality review score: 7.8/10.

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
Federated Learning (FL) has recently been applied to the parameter-efficient fine-tuning of Large Language Models (LLMs)	✓	0.30
FL raises significant challenges due to the heterogeneous resources and data distributions of clients.	✓	0.25
FlexLoRA is a simple yet effective aggregation scheme for LLM fine-tuning.	✓	0.25
FlexLoRA mitigates the 'bucket effect' in traditional FL that restricts the potential of clients with ample resources by	✓	0.33
FlexLoRA allows for dynamic adjustment of local LoRA ranks.	✓	0.23
FlexLoRA fosters the development of a global model imbued with broader, less task-specific knowledge.	✓	0.23
FlexLoRA synthesizes a full-size LoRA weight from individual client contributions and employs Singular Value Decompositi	✓	0.28
FlexLoRA fully leverages heterogeneous client resources.	✓	0.27
Experiments involving thousands of clients performing heterogeneous NLP tasks and client resources validate the efficacy	✓	0.34
The federated global model achieves consistently better improvement over SOTA FL methods in downstream NLP task performa	✓	0.34
FlexLoRA's practicality is further underscored by theoretical analysis and its seamless integration with existing LoRA-b	✓	0.30
FlexLoRA offers a path toward cross-device, privacy-preserving federated tuning for LLMs.	✓	0.21

References

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