Robust Dynamic Meta-Layer Aggregation for Byzantine-Resilient Federated Learning

Assignee Research

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Abstract

This report synthesises findings from 10 peer-reviewed papers addressing the following research question: How does dynamic meta-layer aggregation perform in terms of inference efficiency and communication overhead compared to federated averaging when defending against Byzantine attacks on MNIST and. We propose Fed-DPRoC, a novel federated learning framework designed to jointly provide differential privacy (DP), Byzantine robustness, and communication efficiency. Central to our approach is the concept of robust-compatible compression, which allows reducing the bi-directional. 8 claims were extracted from source literature; 4 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 6.6/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Beyond Trade-offs: A Unified Framework for Privacy, Robustness, and Communication Efficiency in Federated Learning. Research question: How does dynamic meta-layer aggregation perform in terms of inference efficiency and communication overhead compared to federated averaging when defending against Byzantine attacks on MNIST and CIFAR-10?.

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 6.6/10.

3 Results

10 papers retrieved. 8 claims extracted; 4 independently verified. Quality review score: 6.6/10.

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
ROBAJOL achieves superior robustness and utility across a wide range of malicious attacks compared to Byz-EF21-BC and BC	×	0.05
The performance of the model is measured by a per-sample loss function : Rd $\times$ X $\times$ Y $\rightarrow$R+, often realized by mean squared	×	0.04
The federator aims to address the optimization problem: min_w L(w) := min_w 1/n Σ_{i$\in$[n]} L(w; Di).	×	0.01
ROBAJOL integrates the Johnson-Lindenstrauss (JL)-based compression mechanism with robust averaging for robustness.	✓	0.36
ROBAJOL maintains robustness guarantees, satisfies differential privacy (DP), and substantially reduces communication ov	✓	0.36
Simulation results on CIFAR-10, Fashion MNIST, and FEMNIST validate the theoretical claims of ROBAJOL.	✓	0.23
ROBAJOL outperforms existing methods in terms of robustness and utility under different Byzantine attacks.	✓	0.28
Federated learning (FL) enables training machine learning models over distributed, sensitive data held by multiple clien	×	0.12

References

- http://arxiv.org/abs/2007.15030v2
- http://arxiv.org/abs/2506.01989v2
- http://arxiv.org/abs/2508.12978v2