Dynamic Knowledge Messenger Scaling in Federated Learning for Distributed Code Generation

Assignee Research

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Abstract

This report synthesises findings from 8 peer-reviewed papers addressing the following research question: How does dynamic knowledge messenger capacity scaling in federated learning impact model convergence speed and inference efficiency in distributed code generation tasks, as measured by. Medical AI faces challenges in privacy-preserving collaborative learning while ensuring fairness across heterogeneous healthcare institutions. Current federated learning approaches suffer from static architectures, slow convergence (45-73 rounds), fairness gaps marginalizing. 20 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 2.8/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Beyond Static Knowledge Messengers: Towards Adaptive, Fair, and Scalable Federated Learning for Medical AI. Research question: How does dynamic knowledge messenger capacity scaling in federated learning impact model convergence speed and inference efficiency in distributed code generation tasks, as measured by rounds-to-convergence and tokens-per-second throughput on the HumanEval benchmark?.

2 Methodology

Systematic literature search across multiple databases yielded 8 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 2.8/10.

3 Results

8 papers retrieved. 20 claims extracted; 0 independently verified. Quality review score: 2.8/10.

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
First-generation federated learning methods like FedAvg struggle with statistical heterogeneity inherent in medical data	×	0.05
Different hospitals serve distinct patient populations with varying disease prevalence, demographic characteristics, and	×	0.03
SCAFFOLD introduced control variates to handle heterogeneous local updates in federated learning.	×	0.04
FedProx added proximal regularization to maintain global coherence in federated learning.	×	0.03
FedNova normalized averaging to handle training heterogeneity where different institutions perform varying numbers of lo	×	0.04
pFedMe employed Moreau envelopes for personalization in federated learning.	×	0.04
FedRep partitioned models into global representation and local parameters for personalized federated learning.	×	0.04
Statistical heterogeneity in medical data causes accuracy to drop 15-25% compared to IID scenarios when using FedAvg and	×	0.06
Recent improvements through FedProx proximal regularization and SCAFFOLD variance reduction provide marginal benefits wh	×	0.02
Personalized approaches including pFedMe, FedRep, and Ditto improve adaptation to local data characteristics but sacrifi	×	0.03
Performance gains for personalized federated learning approaches plateau at 2-4%.	×	0.08
Personalized federated learning approaches require 3-5x computational overhead compared to standard methods.	×	0.06
Single modality data integration has limited clinical value compared to multi-modal integration.	×	0.11
EHR integration in current systems has a 23% failure rate due to incompatible systems.	×	0.04
Genomics data processing in current federated learning systems is privacy-incompatible and lacks secure computation.	×	0.06
Current sensor data processing in federated learning is limited to batch-only processing, posing real-time challenges.	×	0.07
The proposed AFFL algorithm integrates dynamic messenger scaling with equity-preserving collaboration.	×	0.03
The MedFedBench benchmark suite provides standardized evaluation across healthcare-specific dimensions.	×	0.15
The work includes a detailed economic impact	×	0.05

References

- http://arxiv.org/abs/2209.05395v1
- http://arxiv.org/abs/2510.06259v2
- http://arxiv.org/abs/2511.12188v1