

Structural Similarity Degradation in Multimodal Federated Learning Under Non-IID Data

Assignee Research

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Abstract

This report synthesises findings from 11 peer-reviewed papers addressing the following research question: How does the structural similarity of feature embeddings in collaborative multimodal federated learning models scale with increasing degrees of non-IID data, as measured by cosine similarity across. In parallel with the rapid adoption of artificial intelligence (AI) empowered by advances in AI research, there has been growing awareness and concerns of data privacy. Recent significant developments in the data regulation landscape have prompted a seismic shift in interest. 6 claims were extracted from source literature; 5 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 7.9/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Towards Personalized Federated Learning. Research question: How does the structural similarity of feature embeddings in collaborative multimodal federated learning models scale with increasing degrees of non-IID data, as measured by cosine similarity across clients?.

2 Methodology

Systematic literature search across multiple databases yielded 11 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.9/10.

3 Results

11 papers retrieved. 6 claims extracted; 5 independently verified. Quality review score: 7.9/10.

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) is the leading paradigm for the training of machine learning models on data silos in a privacy-p	✓	0.37
Personalized Federated Learning (PFL) addresses the fundamental challenges of FL on heterogeneous data.	✓	0.25
All real-world datasets exhibit heterogeneous data characteristics.	×	0.14
The paper presents a unique taxonomy of PFL techniques categorized according to the key challenges and personalization s	✓	0.31
The paper highlights key ideas, challenges, opportunities, and future trajectories of research in PFL.	✓	0.20
The paper envisions promising future trajectories of research toward a new PFL architectural design, realistic PFL bench	✓	0.33

References

- <https://doi.org/10.1145/3412357>
- <https://doi.org/10.14722/ndss.2021.24434>
- <https://doi.org/10.1109/tnnls.2022.3160699>