Non-IID Data Distribution and Robustness of Federated Learning Against Label-Flipping Attacks in IoT Cybersecurity

Assignee Research

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Abstract

This report synthesises findings from 7 peer-reviewed papers addressing the following research question: What is the impact of non-IID data distribution on the robustness of federated learning models against label-flipping attacks in IoT cybersecurity applications. We present a federated learning approach for learning a client adaptable, robust model when data is non-identically and non-independently distributed (non-IID) across clients. By simulating heterogeneous clients, we show that adding learned client-specific conditioning improves. 20 claims were extracted from source literature; 2 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.8/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Client Adaptation improves Federated Learning with Simulated Non-IID Clients. Research question: What is the impact of non-IID data distribution on the robustness of federated learning models against label-flipping attacks in IoT cybersecurity applications?.

2 Methodology

Systematic literature search across multiple databases yielded 7 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.8/10.

3 Results

7 papers retrieved. 20 claims extracted; 2 independently verified. Quality review score: 3.8/10.

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
The proposed scheme was evaluated using two datasets: one based on audio data and one on image data.	×	0.05
The two datasets cover imbalanced and balanced data as well as binary and multi-class tasks.	×	0.05
Pre-trained networks were used as feature extractors to provide features for a classifier.	×	0.02
The performance of a classifier utilizing client adaptation through conditional gated activation units was investigated.	✓	0.19
The effect of client adaptation was contrasted with a standard feed-forward neural network with rectified linear units w	×	0.08
Clients with non-IID features were simulated by clustering the embedding features.	×	0.14
The level of client heterogeneity was controlled by shuffling a certain percentage of the sample client assignments.	×	0.05
A shuffling proportion of 0.0 corresponds to maximally non-IID clients.	✓	0.17
A shuffling proportion of 1.0 corresponds to completely random assignment of samples to clients.	×	0.03
Experiment I used data from the Freesound Database (FSD) Kaggle 2018 dataset.	×	0.03
FSD contains approximately 11k audio clips from 41 different classes.	×	0.01
Experiment II used the CIFAR-10 dataset, featuring 32x32 resolution natural images from ten different classes.	×	0.02
In Experiment I, a binary problem was constructed from the FSD by subdividing the labels into a positive class of audio	×	0.04
FSD as a whole has a total of 273 examples of the cough label.	×	0.03
A pre-trained MobileNet called YamNet was used to obtain embeddings for the audio data.	×	0.03
Federated learning is often preferable to training a model in a centralized manner due to privacy concerns.	×	0.11
Learning in a decentralized manner poses new problems for training neural networks, especially with highly heterogeneous	×	0.04
Audio collected by personal mobile devices is an example of highly sensitive data.	×	0.04
A federated learning approach is well-suited for scenarios where data does not leave the person's phone.	×	0.11
Data from smartphones can be class imbalanced and have diverging feature distributions between clients	×	0.05

References

- http://arxiv.org/abs/2104.09994v3
- http://arxiv.org/abs/2007.04806v1
- http://arxiv.org/abs/2412.18507v1