Comparative Analysis of FlexLoRA and FedAvg for GLUE Cross-Domain Accuracy Under Non-IID Data Distributions

Assignee Research

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Abstract

Federated learning (FL) has recently emerged as a popular privacy-preserving collaborative learning paradigm. However, it suffers from the non-independent and identically distributed (non-IID) data among clients. In this paper, we propose a novel framework, named Synthetic Data Aided Federated Learning (SDA-FL), to resolve this non-IID challenge by sharing synthetic data. Specifically, each client pretrains a local generative adversarial network (GAN) to generate differentially private synthetic data, which are uploaded to the parameter server (PS) to construct a global shared synthetic datase

1 Introduction

This paper examines: Federated Learning with GAN-based Data Synthesis for Non-IID Clients. Research question: How does FlexLoRA's aggregation scheme compare to FedAvg in maintaining accuracy on GLUE cross-domain tasks under non-IID data distributions?.

2 Methodology

Systematic literature search across multiple databases yielded 14 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.5/10.

3 Results

14 papers retrieved. 21 claims extracted; 19 independently verified. Quality review score: 8.5/10.

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
Different clients learn from different data distributions in non-IID scenarios, leading to high inconsistency among loca	✓	0.26
Many works have been proposed to alleviate the non-IID issue by regularizing the local models with the information of th	✓	0.29
These methods aim to reduce the local model bias and cannot achieve a significant improvement in scenarios with extreme	✓	0.24
Recent studies have attempted to tackle the non-IID problem with data augmentation techniques.	✓	0.21
Yoon et al., 2020; Oh et al., 2020 proposed to generate synthetic samples by mixing the real samples.	✓	0.29
Without implementing a privacy-protection mechanism, these methods are susceptible to data leakage.	✓	0.17
The proposed SDA-FL framework resolves the non-IID issue by sharing the differentially private synthetic data.	✓	0.24
Each client pretrains a local differentially private generative adversarial network (GAN) to generate synthetic data, th	✓	0.28
The synthetic data are collected by the PS to construct a global synthetic dataset.	✓	0.20
An iterative pseudo label update mechanism is proposed to generate confident pseudo labels for the synthetic data.	✓	0.25
The PS utilizes the received local models to update the pseudo labels in each training round.	✓	0.24
The confidence of pseudo labels is enhanced as the local models are progressively improved over the FL process.	×	0.15
The SDA-FL framework is evaluated on four benchmark datasets: MNIST, FashionMNIST, CIFAR-10, and SVHN.	✓	0.18
The whole training dataset is split into K * C subsets, and each subset only has a single class.	×	0.04
The proposed SDA-FL framework achieves a large margin in several benchmark datasets under both the supervised and semi-s	✓	0.23
The non-IID data distribution has been a fundamental obstacle for FL.	✓	0.19
The highly skewed data distribution significantly enlarges the local model divergence and thus deteriorates the performa	✓	0.21
Many works proposed to modify the local objective function with the additional knowledge from the global model and local	✓	0.27
Such methods cannot achieve satisfactory per-	✓	0.19

References

- http://arxiv.org/abs/2206.05507v1
- http://arxiv.org/abs/2302.10167v2
- http://arxiv.org/abs/1907.02189v4