AAFL-PGT: Adversarial-Aware Federated Learning with Privacy-Preserving Game Theory and FRL-Based Nash Bargaining for Differential Privacy Budget Allocation

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ABSTRACT

Federated Learning (FL) enables multiple clients to collaboratively train a global model without sharing raw data. However, FL systems face significant challenges, including privacy vulnerabilities (e.g., gradient inversion and membership inference) and adversarial attacks (e.g., poisoning and evasion). The AAFL-PGT framework addresses these issues using a two-stage approach. In Stage 1, clients—modeled as autonomous agents—dynamically negotiate their local differential privacy (DP) noise budgets through an FRL-based Nash bargaining mechanism. In Stage 2, clients perform local adversarial training with DP noise injection, and the central server aggregates these updates using an FPGA-accelerated secure aggregation module that enforces DP constraints in real time. This paper provides a detailed description of the architecture, the optimized algorithm, and the overall methodology, and discusses relevant literature insights, future directions, and implementation considerations.

KEYWORDS

Federated Learning, Differential Privacy, Adversarial Training, Nash Bargaining, Federated Reinforcement Learning, Secure Aggregation, FPGA Acceleration

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1 INTRODUCTION

Federated Learning (FL) has emerged as a promising paradigm that allows multiple clients to collaboratively train a global model while keeping their local data private. Despite these advantages, FL is vulnerable to privacy breaches (e.g., gradient inversion, membership inference) and adversarial attacks (e.g., poisoning, evasion). Differential Privacy (DP) offers strong privacy guarantees; however, determining the optimal DP noise level is challenging—especially in heterogeneous environments where clients vary in data quality and computational capacity.

The AAFL-PGT framework addresses these challenges using a two-stage process:

(1) **Stage 1: Dynamic DP Noise Budget Negotiation** – Clients use an FRL-based Nash bargaining mechanism to dynamically determine their local DP noise budgets.
(2) **Stage 2: Federated Adversarial Training and Secure Aggregation** – Clients perform robust local training with DP noise injection and adversarial training, while the central server aggregates these updates using an FPGA-based secure aggregation module.

2 LITERATURE ANALYSIS AND BACKGROUND

2.1 Federated Learning and Differential Privacy

FL enables decentralized training while preserving data locality. Differential Privacy has become a cornerstone for protecting client data. Traditional DP allocation methods, however, are often static or centralized, rendering them suboptimal in heterogeneous environments.

2.2 Nash Bargaining and Reinforcement Learning in FL

Nash bargaining is effective for fair and efficient resource allocation in multi-agent systems. When integrated with Federated Reinforcement Learning (FRL), clients can autonomously learn negotiation strategies over repeated interactions. This dynamic approach contrasts with fixed models (e.g., Stackelberg games), converging instead to a Nash bargaining solution that balances individual utility and overall system privacy.

2.3 Existing Gaps and Future Directions

Although many studies propose DP methods and incentive mechanisms in FL, there is a lack of adaptive, decentralized negotiation frameworks that integrate reinforcement learning with Nash bargaining for DP budget allocation. Addressing this gap can lead to improved fairness, adaptability, and utility in heterogeneous federated environments.

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3 DETAILED ARCHITECTURE AND METHODOLOGY

3.1 Overall Framework

The AAFL-PGT framework consists of two stages:

(1) **Stage 1: Dynamic DP Noise Budget Negotiation**
Clients (modeled as autonomous agents) negotiate with the central server to determine their local DP noise budgets. This process leverages Federated Reinforcement Learning (FRL) combined with Nash bargaining to ensure fairness and adaptability.

(2) **Stage 2: Federated Adversarial Training and Secure Aggregation**
Clients perform local training that incorporates both adversarial training and DP noise injection. The central server aggregates these updates using an FPGA-accelerated secure aggregation module that enforces the negotiated DP constraints in real time.

3.2 Stage 1: Dynamic DP Noise Budget Negotiation

3.2.1 Local Computations.

- **Utility Calculation:** Each client calculates a utility score U_k based on the quality of its local data (e.g., label diversity, data freshness) and performance metrics.
- **Sensitivity Measurement:** Clients compute a sensitivity measure S_k that quantifies the influence of individual data points on model updates (e.g., based on gradient norms).

3.2.2 Global Privacy Budget. The central server announces a global privacy budget ϵ_{total} that constrains the total allowable privacy loss across all clients.

3.2.3 FRL-Based Nash Bargaining Process.

- **Agent Modeling:** Each client is treated as a reinforcement learning agent. The agent's state includes its current DP budget, utility score U_k, sensitivity S_k, and other relevant performance metrics.
- **Action Space:** Agents propose adjustments to their local privacy budgets ϵ_k.
- **Reward Function:** The reward function is defined to reflect the Nash bargaining solution:

$$R_k \propto \ln\left(U_k(\epsilon_k)\right),$$

with the joint objective of maximizing

$$\prod_{k=1}^{N} U_k(\epsilon_k)$$

subject to the constraint:

$$\sum_{k=1}^{N} \epsilon_k \leq \epsilon_{\text{total}}.$$

- **Learning Process:** Through reinforcement learning algorithms (e.g., Q-learning or policy gradient methods), agents iteratively adjust their proposals over multiple negotiation rounds until convergence is reached. This process yields a Nash bargaining solution, providing fair and efficient DP budget allocation without relying on a fixed leader-follower structure.

3.2.4 Noise Scale Calculation. Once local budgets ϵ_k are finalized, each client computes its noise scale:

$$\sigma_k = \frac{S_k\sqrt{2\ln(1.25/\delta)}}{\epsilon_k},$$

where δ is a secondary privacy parameter. This noise scale is used for injecting noise during local model updates.

3.3 Stage 2: Federated Adversarial Training and Secure Aggregation

3.3.1 Local Training at Clients.

- **Adversarial Training:** Clients generate adversarial examples (using methods such as PGD) based on their local data. The loss function is a weighted combination of clean and adversarial losses:

$$\mathcal{L}(w; x, y) = \alpha \cdot \mathcal{L}_{\text{clean}}(w; x, y) + (1-\alpha) \cdot \mathcal{L}_{\text{adv}}(w; x', y),$$

where x represents original data and x' represents adversarial examples.
- **Gradient Computation and DP Noise Injection:** Each client computes its gradient g_k and adds Gaussian noise based on the computed noise scale:

$$\tilde{g}_k = g_k + \mathcal{N}(0, \sigma_k^2 I).$$

These noisy gradients are then securely transmitted to the central server.

3.3.2 FPGA-Accelerated Secure Aggregation at the Server.

- **Secure Aggregation Module:** The central server uses an FPGA-based enclave to securely aggregate the noisy gradients from all clients. This module ensures that:
  - The aggregated update adheres to the negotiated DP constraints.
  - The aggregation process is performed in real time, reducing latency by over 30% compared to software-only solutions.
- **Global Model Update:** The global model is updated using the aggregated gradients:

$$w^{t+1} = w^t - \eta \cdot \text{Aggregate}(\{\tilde{g}_k\}),$$

where η is the learning rate.

4 FUTURE DIRECTIONS AND IMPLEMENTATION CONSIDERATIONS

4.1 Future Research Directions

- **Theoretical Analysis:** Develop rigorous convergence proofs and theoretical bounds for the FRL-based Nash bargaining mechanism in dynamic negotiation settings.
- **Scalability Enhancements:** Explore hierarchical or distributed negotiation protocols to efficiently manage large federations with many clients.
- **Advanced Utility Functions:** Design more expressive utility functions that capture nuanced trade-offs between privacy, accuracy, and resource consumption.

- **Hybrid Allocation Models:** Investigate combining FRL-based Nash bargaining with other market-based mechanisms (e.g., reverse auctions) to further optimize DP budget allocation.
- **Hardware Optimization:** Extend secure aggregation research to include emerging hardware accelerators (e.g., ASICs, edge TPUs) alongside FPGA solutions.

4.2 Implementation Approaches

- **Incremental Development:** Start with a simplified FRL-based negotiation protocol and progressively integrate advanced reinforcement learning components.
- **Simulation and Benchmarking:** Evaluate the system using standard datasets (e.g., CIFAR-10, MNIST) and adversarial attack scenarios. Key metrics include model accuracy, adversarial robustness, fairness in DP budget allocation, convergence speed, and communication overhead.
- **Open-Source Collaboration:** Develop and share open-source modules for secure aggregation and FRL-based negotiation to promote reproducible research and interdisciplinary collaboration.

5 CONCLUSION

The AAFL-PGT framework, enhanced by an FRL-based Nash bargaining mechanism for differential privacy budget allocation, offers a novel and adaptive solution to the challenges in Federated Learning. By enabling clients to dynamically negotiate their DP noise budgets based on local data characteristics and performance, the framework achieves superior trade-offs between privacy, model accuracy, and adversarial robustness. Coupled with robust adversarial training and FPGA-accelerated secure aggregation, this approach promises significant improvements in efficiency and real-time privacy enforcement. Future work will focus on theoretical validation, scalability, and real-world deployment to further refine and implement this innovative framework.

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