Differential Privacy Noise Budget Negotiation using Federated Reinforcement Learning-based Nash Bargaining

A Novel Framework for Fair and Dynamic Privacy Budget Allocation in Federated Learning

Arjun
University of Somewhere
City, Country
first.author@example.com

Rajdeep
Institute of Technology
City, Country
second.author@example.com

ABSTRACT

Federated Learning (FL) relies on Differential Privacy (DP) to safeguard client data while ensuring model utility. However, conventional static or heuristic-based DP noise allocation methods struggle to adapt to client heterogeneity and the dynamic nature of data distributions, often leading to suboptimal privacy-utility trade-offs. To address these challenges, we propose a novel framework that integrates Federated Reinforcement Learning (FRL) with Nash Bargaining for dynamic DP budget negotiation. Our approach enables clients to iteratively learn optimal negotiation strategies, ensuring fair and efficient privacy budget allocation across participants. The system architecture incorporates an FRL-based Nash Bargaining algorithm that dynamically adjusts DP noise levels based on client-specific constraints and evolving data characteristics. We provide comprehensive implementation details and evaluate our method against conventional static allocation baselines. Experimental results demonstrate that our approach significantly improves model utility while maintaining fairness in privacy distribution, making it well-suited for large-scale FL environments.

KEYWORDS

Differential Privacy, Federated Learning, Reinforcement Learning, Nash Bargaining, Privacy Budget Allocation, Distributed Systems

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1 INTRODUCTION

The proliferation of mobile devices and distributed computing infrastructure has catalyzed the development of collaborative machine learning paradigms that preserve data privacy. Federated Learning (FL) has emerged as a revolutionary framework that enables collaborative model training without requiring raw data to leave user devices [2]. By exchanging model updates rather than raw data, FL implements the principle of data minimization, addressing a fundamental privacy concern in traditional centralized learning approaches. Despite these inherent privacy advantages, FL systems remain vulnerable to inference attacks, where sophisticated adversaries can potentially extract sensitive information from shared model parameters [1].

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Differential Privacy (DP) offers a rigorous mathematical framework for quantifying and limiting such privacy risks. Introduced by Dwork in 2006, DP provides formal guarantees about the maximum influence any individual's data can have on the output of an analysis [1]. The integration of DP with FL has been explored in several works, most notably in DP-FedAvg, which applies noise to client updates proportional to a predetermined privacy budget ϵ [2]. Recently, Google deployed a production ML model using federated learning with formal differential privacy guarantees, highlighting the practical significance of this integration for real-world applications [9].

Despite these advancements, maintaining rigorous DP guarantees in FL environments presents unique challenges. The heterogeneity of client data, variations in computational resources, and dynamic participation patterns significantly complicate privacy budget allocation. Traditional approaches typically employ static or heuristic-based allocation methods, where privacy budgets are distributed according to predetermined rules or simple metrics. Such methods ignore the dynamic nature of federated environments and the varying privacy requirements across clients, leading to suboptimal trade-offs between model utility and privacy protection.

The limitations of static allocation approaches are particularly pronounced in heterogeneous federated environments, where clients may have dramatically different data distributions, quality metrics, and sensitivity levels. For instance, a client with highly sensitive medical data would ideally receive a larger privacy budget compared to a client with less sensitive information, assuming equivalent model utility contributions. Similarly, clients with higher-quality data that contribute significantly to model performance might warrant different privacy budget allocations than those with noisy or less representative data. Static allocation methods cannot adapt to these nuances, resulting in inefficient resource distribution that either undermines privacy guarantees or unnecessarily sacrifices model performance.

To address these limitations, we propose a novel framework that dynamically negotiates and allocates differential privacy budgets in federated learning systems. Our approach integrates Federated Reinforcement Learning (FRL) with Nash Bargaining theory to enable adaptive, fair, and efficient privacy budget management. Unlike fixed-rule approaches, our method empowers each client to learn and refine its negotiation strategy over time through reinforcement learning. These learned strategies collectively optimize toward a Nash Bargaining solution, achieving a fair distribution of the global privacy budget that respects both individual client utilities and system-wide performance objectives.

The core innovation of our approach lies in the synergistic combination of reinforcement learning's adaptive capabilities with the fairness properties of Nash Bargaining. Reinforcement learning allows clients to discover effective negotiation strategies through experience, adapting to changing data characteristics and system conditions. Nash Bargaining, meanwhile, provides a principled mathematical framework for fair resource allocation, ensuring that the resulting privacy budget distribution satisfies important fairness axioms such as Pareto efficiency, symmetry, and independence of irrelevant alternatives [5].

The primary contributions of our work can be summarized as follows:

- A comprehensive system architecture that combines local utility and sensitivity estimation with RL-based negotiation mechanisms.
- A detailed FRL-based Nash Bargaining algorithm that dynamically adjusts privacy budgets based on client feedback and global constraints.
- Implementation strategies leveraging state-of-the-art federated learning and RL frameworks.
- Extensive experimental evaluations demonstrating superior performance compared to static allocation methods.

The remainder of this paper is organized as follows: Section 2 reviews related work in differential privacy, federated learning, reinforcement learning, and game-theoretic approaches to resource allocation. Section 3 describes our system architecture in detail, outlining the key components and their interactions. Section 4 presents our FRL-based Nash Bargaining algorithm, including the problem formulation, reinforcement learning framework, and negotiation process. Section 5 details our implementation approach, covering the client-side and server-side components as well as the communication protocol. Section 6 outlines our evaluation methodology and presents experimental results demonstrating the effectiveness of our approach. Finally, Section 7 concludes the paper and suggests directions for future research.

The rest of the paper is organized as follows: Section **??** reviews related work. Section 4 describes the system architecture. Section 5 presents our FRL-based Nash Bargaining algorithm. Section 6 details the implementation, and Section 7 outlines our evaluation methodology and results. Finally, Section 8 concludes the paper and suggests future research directions.

2 RELATED WORK

Differential privacy has become a cornerstone in machine learning for safeguarding sensitive data, with applications extending into federated learning (FL) [1]. Initial approaches in FL, such as DP-FedAvg [2], introduced noise into local updates to protect privacy, though they typically used static noise schedules. These static allocations are now recognized as suboptimal due to client heterogeneity and dynamic data characteristics, prompting the exploration of more adaptive methods [7]. Recent studies have integrated Reinforcement Learning (RL) for dynamic privacy budgeting. For example, adaptive privacy budget allocation via RL was explored in [3], where agents adjust noise levels based on utility feedback. Additionally, multi-agent reinforcement learning for resource allocation in distributed systems has shown promising results [4]. Game-theoretic approaches, particularly Nash Bargaining [5], have also been utilized for fair resource allocation [6]. Arjun et al. [7] fuse Federated Reinforcement Learning (FRL) with Nash Bargaining to enable dynamic, fair, and decentralized DP budget negotiation in FL. This integration allows agents to adapt over time and improves both privacy-utility trade-offs and overall system fairness. Their proposed framework combines local utility and sensitivity estimation with RL-based negotiation, leading to a more efficient distribution of the global privacy budget. This approach contrasts with static allocations and heuristic-based methods by enabling clients to learn optimal negotiation strategies and dynamically adjust privacy budgets based on client feedback and global constraints [7]. In their system, each client implements local data analysis, utility computation, sensitivity estimation, and an RL agent to learn negotiation strategies. The server manages the global privacy budget, synchronizes negotiation rounds, and aggregates client proposals. This architecture uses secure channels for exchanging negotiation parameters and implements the FRL-based Nash Bargaining process [7]. A systematic survey highlights the importance of integrating differential privacy techniques with federated learning to enhance data security [8]. The survey reviews central, local, and distributed differential privacy paradigms, emphasizing algorithmic optimizations and communication cost reductions in differentially-private federated learning models [8]. Furthermore, recent research has explored various optimization techniques for federated learning with differential privacy, including privacy accounting methods and communication-efficient protocols [8].

3 PRELIMINARIES

This section establishes the foundational concepts and mathematical notations essential for understanding our proposed framework. We first review the basic principles of federated learning and differential privacy, followed by an introduction to Nash Bargaining, reinforcement learning, and federated reinforcement learning.

3.1 Federated Learning

Federated Learning (FL) is a distributed machine learning paradigm where multiple clients collaboratively train a shared model while keeping their data localized. Formally, consider a system with N clients, where each client $k \in \{1, 2, ..., N\}$ possesses a local dataset $D_k = \{(x_i, y_i)\}_{i=1}^{|D_k|}$. The objective is to learn a global model w that minimizes the empirical risk across all clients:

$$\min_w F(w) = \sum_{k=1}^{N} \frac{|D_k|}{|D|} F_k(w)$$

where $F_k(w) = \frac{1}{|D_k|} \sum_{(x,y)\in D_k} \ell(w; x, y)$ represents the local objective function for client k, $\ell(\cdot)$ is a task-specific loss function, and $|D| = \sum_{k=1}^{N} |D_k|$ is the total size of data across all clients.

The standard FL process proceeds as follows: 1. The server initializes the global model w^0 and distributes it to participating clients. 2. Each client k performs local training on its dataset D_k to obtain a local model update Δw_k^t. 3. The server aggregates these updates to refine the global model: $w^{t+1} = w^t + \eta \sum_{k=1}^{N} \frac{|D_k|}{|D|} \Delta w_k^t$, where η is the learning rate. 4. Steps 2-3 repeat for multiple rounds until convergence.

3.2 Differential Privacy

Differential Privacy (DP) provides a formal guarantee about the maximum influence an individual's data can have on the output of an analysis. A randomized mechanism $\mathcal{M}$ satisfies ϵ-differential privacy if for any two adjacent datasets D and D' differing by at most one record, and for all possible outputs $S \subseteq Range(\mathcal{M})$:

$$\Pr[\mathcal{M}(D) \in S] \leq e^{\epsilon} \cdot \Pr[\mathcal{M}(D') \in S]$$

The parameter $\epsilon > 0$ is the privacy budget, which quantifies the privacy guarantee: smaller values of ϵ provide stronger privacy protection but typically at the cost of reduced utility.

In the context of federated learning, DP is commonly implemented by adding calibrated noise to client updates before they are shared with the server. The amount of noise is proportional to the sensitivity of the computation and inversely proportional to the privacy budget. For client k with privacy budget ϵ_k, the noisy update becomes:

$$\widetilde{\Delta w}_k^t = \Delta w_k^t + \mathcal{N}(0, \sigma_k^2 \cdot I)$$

where σ_k is the noise scale, determined by the sensitivity of the update operation and the desired privacy level ϵ_k.

3.3 Nash Bargaining

The Nash Bargaining Solution (NBS) addresses fair resource allocation in cooperative settings. For clients $k \in \{1, 2, ..., N\}$ with utility functions U_k and disagreement points U_k^* (representing minimum acceptable utilities), the NBS maximizes the Nash product:

$$\max_{\{x_k\}} \prod_{k=1}^{N} (U_k(x_k) - U_k^*)$$

subject to feasibility constraints. This formulation satisfies important fairness properties: - Pareto optimality: No allocation can improve one client's utility without reducing another's. - Symmetry: Identical clients receive identical allocations. - Scale invariance: The solution is invariant to affine transformations of utility functions. - Independence of irrelevant alternatives: The solution depends only on the utilities and disagreement points.

In our context, the resources being allocated are privacy budgets ϵ_k, with the constraint that $\sum_{k=1}^{N} \epsilon_k \leq \epsilon_{\text{total}}$.

3.4 Reinforcement Learning

Reinforcement Learning (RL) involves an agent learning to make decisions by interacting with an environment. The process is modeled as a Markov Decision Process (MDP) defined by a tuple (S, A, P, R, γ), where: - S is the state space - A is the action space - $P : S \times A \times S \to [0, 1]$ is the transition probability function - $R : S \times A \times S \to \mathbb{R}$ is the reward function - $\gamma \in [0, 1)$ is the discount factor

The agent's goal is to learn a policy $\pi : S \to A$ that maximizes the expected cumulative discounted reward:

$$\mathbb{E}_{\pi}\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t, s_{t+1})\right]$$

Policy optimization methods, such as Proximal Policy Optimization (PPO), iteratively improve the policy based on collected experiences. In our framework, each client implements an RL agent whose state incorporates local data characteristics and negotiation history, actions represent proposed privacy budget adjustments, and rewards reflect improvements in both individual utility and the Nash product.

3.5 Federated Reinforcement Learning

Federated Reinforcement Learning (FRL) extends the federated learning paradigm to reinforcement learning settings. In traditional RL, a single agent interacts with an environment to learn an optimal policy. FRL distributes this learning process across multiple agents, each with their own local experiences, while collaboratively improving a global policy.

In FRL, each client k maintains a local policy π_{θ_k} parameterized by θ_k. Clients collect experiences by interacting with their local environments, train their policies using standard RL algorithms (such as PPO or SAC), and periodically share policy updates with a central server. The server aggregates these updates to refine a global policy, which is then redistributed to clients. Formally, the FRL process can be described as:

(1) Each client k collects experiences
$$\{(s_i, a_i, r_i, s_i')\}_{i=1}^{M_k}$$
using its current policy π_{θ_k}.
(2) Clients update their local policies based on these experiences:
$$\theta_k \leftarrow \text{Update}\left(\theta_k, \{(s_i, a_i, r_i, s_i')\}_{i=1}^{M_k}\right).$$
(3) Clients share policy updates $\Delta\theta_k$ with the server.
(4) The server aggregates updates to refine the global policy:
$$\theta_{\text{global}} \leftarrow \theta_{\text{global}} + \eta \sum_{k=1}^{N} \frac{w_k}{\sum_{j=1}^{N} w_j} \Delta\theta_k,$$
where w_k are client weights.
(5) The global policy is distributed back to clients:
$$\theta_k \leftarrow \theta_{\text{global}}.$$

In our framework, we utilize FRL to enable privacy budget negotiation. Each client employs an RL agent to learn optimal negotiation strategies based on local data characteristics and utility requirements. These agents collectively work toward a fair allocation of privacy budgets through the Nash Bargaining solution. The FRL approach allows clients to adapt their negotiation strategies over time, responding to changes in data distributions and system dynamics, while maintaining the privacy advantages of federated learning.

3.6 Notation Summary

For clarity, we summarize the key notation used throughout this paper:

N: Number of clients in the federated learning system.
ϵ_k: Privacy budget allocated to client k.
ϵ_{total}: Global privacy budget constraint.
$U_k(\epsilon_k)$: Utility function for client k given privacy budget ϵ_k.
U_k^*: Disagreement point for client k.
$s_k^{(t)}$: State of client k's RL agent at negotiation round t.
$a_k^{(t)}$: Action taken by client k's RL agent at round t.
$r_k^{(t)}$: Reward received by client k's RL agent at round t.

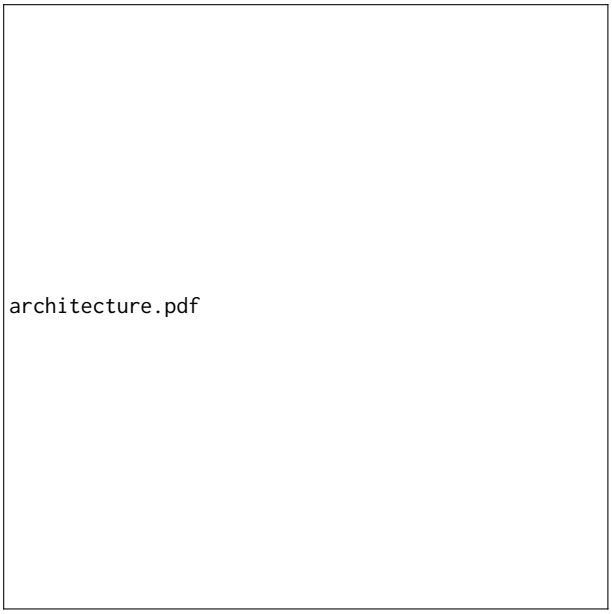

Figure 1: System architecture for DP budget negotiation using FRL-based Nash Bargaining.

π_{θ_k}: Policy of client k's RL agent with parameters θ_k.
$\Delta\epsilon_k^{(t)}$: Proposed adjustment to privacy budget at round t.

4 SYSTEM ARCHITECTURE

Our proposed architecture consists of the following key components:

- **Client Module**: Each client implements local data analysis, utility computation, sensitivity estimation, and an RL agent to learn negotiation strategies.
- **Communication Layer**: Secure channels facilitate the exchange of negotiation parameters between clients and the central server.
- **Server Coordination Module**: Manages the global privacy budget, synchronizes negotiation rounds, and aggregates client proposals.
- **Negotiation Protocol Engine**: Implements the FRL-based Nash Bargaining process by aggregating proposals and enforcing global constraints.
- **Privacy Budget Allocation Module**: Finalizes and enforces the negotiated privacy budgets for use in subsequent FL rounds.

Figure 1 shows a high-level overview of the system architecture.

5 PROPOSED FRL-BASED NASH BARGAINING ALGORITHM

The DP budget negotiation problem is formulated as a cooperative Nash Bargaining game. For each client $k \in \{1, \ldots, N\}$, let $U_k(\epsilon_k)$ denote the utility derived from a privacy budget ϵ_k, and U_k^* denote the disagreement point (minimum acceptable utility). The objective is to maximize the Nash product:

$$\max_{\{\epsilon_k\}} \prod_{k=1}^{N} \left(U_k(\epsilon_k) - U_k^* \right) \tag{1}$$

subject to

$$\sum_{k=1}^{N} \epsilon_k \leq \epsilon_{\text{total}}, \quad \epsilon_k > 0 \quad \forall k. \tag{2}$$

Taking logarithms, we obtain a tractable formulation:

$$\max_{\{\epsilon_k\}} \sum_{k=1}^{N} \log \left(U_k(\epsilon_k) - U_k^* \right) \tag{3}$$

5.1 Federated Reinforcement Learning Framework

Each client in our system maintains an individual reinforcement learning (RL) agent that continuously learns an optimal negotiation strategy. The RL agent interacts with its environment—defined by its local data, budget allocation, and negotiation history—to dynamically adjust its privacy budget allocation. The key components of this framework are:

- **State** $s_k^{(t)}$: The state vector encodes all relevant information needed for decision-making at time step t. It typically includes:
  - The current privacy budget allocation $\epsilon_k^{(t)}$ for client k.
  - Historical negotiation outcomes, such as previous utility values or past adjustments.
  - Local data characteristics, for instance, data quality metrics, data size, and sensitivity measures computed from the client's local dataset.
  - Global negotiation parameters such as the total privacy budget ϵ_{total} or summary statistics aggregated from other clients.

  This comprehensive state representation enables the RL agent to assess both its own performance and the overall system context, thus tailoring its negotiation actions accordingly.
- **Action** $a_k^{(t)}$: The action represents a proposed adjustment to the current privacy budget. Formally, it is sampled from the client's policy distribution:

$$a_k^{(t)} \sim \pi_{\theta_k} \left(s_k^{(t)} \right),$$

  where π_{θ_k} is the policy parameterized by θ_k. The action is typically a continuous value that suggests an increment or decrement in the allocated budget. The design of the action space is critical: it must allow fine-grained adjustments so that the negotiation can converge smoothly while exploring different allocation strategies.
- **Reward** $r_k^{(t)}$: The reward quantifies the benefit of the agent's action by reflecting improvements in both the individual utility and the collective Nash bargaining objective. It is computed based on:
  - The change in the client's utility, typically measured in logarithmic terms to capture proportional gains.

– The improvement in the overall Nash product, which ensures that the negotiation not only benefits individual clients but also enhances the joint outcome.

The reward signal drives the RL agent to adjust its strategy over time, promoting actions that yield higher utility and contribute to a more equitable distribution of the global privacy budget.

In summary, the Federated Reinforcement Learning framework allows each client to iteratively learn from its local environment and negotiation history, enabling adaptive and fair adjustments to privacy budget allocations across the entire federated system.

5.2 Negotiation Process

The FRL-based Nash bargaining negotiation proceeds iteratively as follows:

(1) **Initialization**: The server first announces the global privacy budget ϵ_{total}. Each client then initializes its local budget as

$$\epsilon_k^{(0)} = \frac{\epsilon_{\text{total}}}{N},$$

ensuring an equal starting point for all clients. This step sets the baseline from which subsequent adjustments will be made.

(2) **Local Computation**: Each client uses its local dataset to compute key metrics:

- The *utility* $U_k(\epsilon_k^{(t)})$, which quantifies the benefit of receiving a certain privacy budget allocation. This utility typically depends on factors like data quality and size.
- The *sensitivity* S_k, representing how responsive the client's output is to changes in the data.

Using these metrics, the client forms its state representation

$$s_k^{(t)},$$

which encapsulates its current budget, utility, sensitivity, and potentially other features (e.g., historical performance).

(3) **Action Selection**: Each client's RL agent observes its state $s_k^{(t)}$ and samples an action

$$a_k^{(t)} \sim \pi_{\theta_k}(s_k^{(t)}),$$

where π_{θ_k} is the client's policy parameterized by θ_k. The selected action corresponds to a proposed adjustment $\Delta\epsilon_k^{(t)}$, determined by a function $f(a_k^{(t)})$. This action reflects the client's strategy to either request a higher or lower share of the privacy budget based on its current state.

(4) **Aggregation**: The server collects all proposed budget adjustments $\{\Delta\epsilon_k^{(t)}\}_{k=1}^N$ from the clients. It then updates each client's budget as:

$$\epsilon_k^{(t+1)} = \epsilon_k^{(t)} + \Delta\epsilon_k^{(t)},$$

and normalizes the updated budgets to ensure that the global constraint is met:

$$\sum_{k=1}^{N} \epsilon_k^{(t+1)} = \epsilon_{\text{total}}.$$

This normalization step guarantees that the privacy budget is allocated without any surplus or deficit.

(5) **Reward Calculation**: Each client calculates a reward $r_k^{(t)}$ based on the change in its utility. The reward is typically defined in logarithmic terms to capture the proportional improvement:

$$r_k^{(t)} = \Delta \log\Big(U_k(\epsilon_k^{(t+1)}) - U_k^*\Big),$$

where U_k^* is the disagreement point (the minimum acceptable utility). This reward function incentivizes clients to achieve higher utility while respecting the fairness constraints.

(6) **RL Update**: With the experience tuple $(s_k^{(t)}, a_k^{(t)}, r_k^{(t)}, s_k^{(t+1)})$ gathered from the negotiation round, each client updates its RL policy parameters θ_k. The update is performed using standard policy gradient methods (e.g., Proximal Policy Optimization), allowing the agent to refine its strategy over time based on past negotiation outcomes.

(7) **Convergence Check**: The negotiation process repeats until one of the following conditions is met:

- The maximum number of rounds T is reached.
- The change in privacy budgets between consecutive rounds falls below a predetermined convergence threshold, i.e.,

$$\max_k |\epsilon_k^{(t+1)} - \epsilon_k^{(t)}| < \delta.$$

Once convergence is detected, the final privacy budget allocations $\{\epsilon_k^*\}_{k=1}^N$ are output.

Algorithm 1 summarizes the negotiation process.

6 IMPLEMENTATION

We implement our framework on a combination of established platforms:

- **Federated Learning Framework**: TensorFlow Federated (TFF) provides the base for distributed client-server interactions.
- **Reinforcement Learning**: RLlib and TensorFlow Agents are used to implement the PPO-based RL agents on clients.
- **Differential Privacy**: TensorFlow Privacy is integrated to manage DP noise injection and privacy accounting.
- **Secure Communication**: TLS/SSL ensures that all negotiation messages are securely transmitted.

6.1 Client-Side Components

Each client features:

(1) **Data Analysis Module**: Preprocesses local data and extracts features.
(2) **Utility and Sensitivity Modules**: Compute the utility function $U_k(\epsilon_k)$ and sensitivity S_k.
(3) **RL Agent Module**: Implements a lightweight neural network for policy estimation, trained via PPO.

6.2 Server-Side Components

The server is responsible for:

Algorithm 1 FRL-based Nash Bargaining for DP Budget Negotiation Algorithm

Require: Global privacy budget ϵ_{total}, number of clients N, maximum rounds T, learning rate α, convergence threshold δ

Initialize privacy budgets $\epsilon_k^{(0)} = \epsilon_{\text{total}}/N$ for each client k
Initialize RL agent parameters θ_k for each client k
for $t = 0, 1, \ldots, T-1$ **do**
  for each client k **(in parallel) do**
    Compute utility function:

$$U_k(\epsilon_k^{(t)}) = q_k \sqrt{d_k} \left(1 - e^{-\epsilon_k^{(t)}/s_k}\right)$$

    Compute sensitivity S_k from dataset D_k
    Construct state representation $s_k^{(t)}$ based on:

$$s_k^{(t)} = \left(\epsilon_k^{(t)}, U_k(\epsilon_k^{(t)}), S_k, \nabla U_k\right)$$

    Sample action $a_k^{(t)} \sim \pi_{\theta_k}(s_k^{(t)})$
    Compute budget adjustment:

$$\Delta\epsilon_k^{(t)} = f(a_k^{(t)})$$

  end for
  Server updates global budget allocation:

$$\epsilon_k^{(t+1)} = \epsilon_k^{(t)} + \Delta\epsilon_k^{(t)}, \quad \forall k$$

  Normalize privacy budgets:

$$\epsilon_k^{(t+1)} \leftarrow \epsilon_k^{(t+1)} \cdot \frac{\epsilon_{\text{total}}}{\sum_{j=1}^{N} \epsilon_j^{(t+1)}}$$

  for each client k **do**
    Compute reward signal:

$$r_k^{(t)} = \Delta \log\left(U_k(\epsilon_k^{(t+1)}) - U_k^*\right)$$

    Update RL policy parameters using:

$$\theta_k \leftarrow \theta_k + \alpha \nabla_{\theta_k} \log \pi_{\theta_k}(a_k^{(t)} | s_k^{(t)}) r_k^{(t)}$$

  end for
  if $\max_k |\epsilon_k^{(t+1)} - \epsilon_k^{(t)}| < \delta$ **then**
    break
  end if
end for
Output: Final privacy budget allocations $\{\epsilon_k^*\}_{k=1}^N$

(1) **Global Budget Management**: Tracks and enforces the total privacy budget ϵ_{total}.
(2) **Negotiation Protocol Engine**: Aggregates proposals and synchronizes negotiation rounds.
(3) **Secure Aggregation Service**: Uses secure multiparty computation techniques to protect client data during aggregation.

6.3 Communication Protocol

Our protocol is designed to be both efficient and secure:

- **Encryption**: All messages are sent over TLS/SSL.
- **Serialization**: We use Protocol Buffers to reduce message size.
- **Synchronization**: A negotiation round controller coordinates client updates.

7 EVALUATION

We evaluate our approach via simulations and real-world deployment scenarios.

7.1 Experimental Setup

Datasets: Standard benchmarks such as MNIST and CIFAR-10, supplemented by synthetic datasets modeling heterogeneous client distributions.

Environment: An emulated FL system with variable network conditions and client computational capabilities.

Baselines: We compare against:

- Static uniform DP budget allocation.
- Proportional allocation based on data quantity.
- Centralized optimization without RL.

7.2 Performance Metrics

Our evaluation considers:

- **Privacy-Utility Trade-off**: Measured by model accuracy under various DP noise levels.
- **Fairness**: Evaluated using Jain's fairness index on the budget allocations.
- **Convergence Speed**: Number of negotiation rounds to reach stable allocations.
- **Communication Overhead**: Total data exchanged during the negotiation process.

7.3 Results and Analysis

Preliminary results indicate:

- Improved model accuracy due to adaptive noise scheduling.
- High fairness, with Jain's index approaching 1.
- Rapid convergence within a few rounds.
- Acceptable communication overhead compared to centralized methods.

A detailed analysis of convergence curves, trade-off evaluations, and ablation studies will be presented in the full version of this paper.

8 CONCLUSION AND FUTURE WORK

We have introduced a novel FRL-based Nash Bargaining framework for dynamic differential privacy budget negotiation in federated learning. Our approach dynamically adjusts privacy budgets in response to client heterogeneity and evolving data characteristics, thereby improving both utility and fairness. Experimental evaluations validate the effectiveness of our method compared to static allocation strategies.

Future research directions include:

- Extending the framework to handle dynamic client participation.
- Incorporating advanced privacy accounting techniques beyond DP.
- Developing rigorous theoretical convergence guarantees under non-stationary environments.
- Integrating secure hardware accelerators for real-time negotiation.

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