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A Study of Efficient Optimizer Configuration Strategies in Federated Learning for FedAvg and FedProx

Yiming Lei
International College, Beijing University of Posts and Telecommunications, Beijing, China
2022213223@bupt.edu.cn

Abstract: Federated Learning (FL) is an effective way to perform decentralized model training while protecting data privacy. However, the choice of optimization algorithm can significantly impact its performance. This study focuses on the effectiveness of different combinations of FL frameworks (including Federated Averaging (FedAvg) and Federated Proximal (FedProx)) and optimizers (including Stochastic Gradient Descent (SGD) and Adaptive Momentum (Adam)) to determine the best strategies for improving convergence and accuracy. Specifically, this paper compares the performance of four algorithmic combination strategies, including FedAvg+SGD, FedAvg+Adam, FedProx+SGD, and FedProx+Adam, on the Federated Extended Modified National Institute of Standards and Technology (FEMNIST) dataset. The experiments evaluate key metrics such as test accuracy, communication efficiency, and convergence speed under non-independent and identically distributed (IID) data distributions. The experimental results show that the combination of FedProx and Adam achieves the highest test accuracy and faster convergence speed than other configurations. And FedAvg+SGD is still the configuration with the highest communication efficiency. The results show that adaptive optimizers such as Adam can improve FL performance when paired with a robust aggregation framework. The study's findings can provide practical insights for algorithm selection in joint learning scenarios.

Keywords: Federated Learning, Federated Proximal, Stochastic Gradient Descent, Federated Averaging.

1. Introduction

In recent years, with the proliferation of mobile devices and Internet of Things (IoT) technologies, coupled with growing concerns over data privacy, Federated Learning (FL) has emerged as a novel distributed machine learning paradigm, garnering significant attention from both academia and industry. FL enables multiple participants to train models on their local datasets while sharing only model parameters instead of raw data, effectively addressing challenges related to data silos and privacy breaches.

The framework has demonstrated remarkable versatility across diverse domains, from intelligent transportation systems that enable comparative analysis of learning techniques for big data-driven solutions, to vehicular networks that support decentralized anomaly detection without compromising data security [1, 2]. In IoT ecosystems, FL not only enhances efficiency and privacy but also facilitates innovative approaches like synthetic mono-class teacher distillation at the network edge, optimizing model deployment in resource-constrained environments [3, 4]. Fundamental algorithms such as Federated Averaging (FedAvg) and Federated Proximal (FedProx) have evolved to address non-independent and identically distributed (IID) data distribution challenges, with recent advancements incorporating techniques like the Mish activation function and FedAvg-RAdam optimization to improve model accuracy significantly [5]. The agricultural sector has benefited from FL's ability to handle heterogeneous data through various optimizers (Root Mean Squared Propagation (RMSProp), Adaptive momentum (Adam), Stochastic Gradient Descent (SGD)) for applications like potato leaf disease prediction, while waste classific (action systems leverage sophisticated approaches like Federated Average Knowledge Distilled Mutual Conditional Learning (FedADC) [6, 7]. Furthermore, FL has shown promise in network optimization, where cost-efficient federated reinforcement learning enables intelligent routing decisions in wireless networks [8]. These developments collectively highlight FL's expanding role in creating privacy-preserving, distributed intelligence across increasingly complex real-world applications, while continuing to address fundamental challenges in model convergence, communication efficiency, and knowledge distillation in decentralized environments. The continuous refinement of FL techniques underscores its potential to transform how machine learning models are developed and deployed across interconnected systems.

This paper aims to conduct a comparative analysis of the performance of four different optimization algorithms in the context of FL frameworks. Specifically, the study focuses on: (1) FedAvg combined with SGD, (2) FedProx combined with SGD, (3) FedAvg combined with Adam, and (4) FedProx combined with Adam. Through systematic experiments and evaluations, this paper aims to explore the differences in convergence, stability, and model accuracy among these optimization algorithms in FL environments. The findings provide theoretical insights and practical guidance for selecting appropriate optimization strategies in real-world applications.

2. Methodology

2.1. Data description and preprocessing

This study utilized the Federated Extended Modified National Institute of Standards and Technology (FEMNIST) dataset as the experimental data [5]. FEMNIST is a widely used benchmark dataset for FL, consisting of handwritten letters and digits, and is an extended version of the EMNIST dataset. The dataset is characterized by its non-IID data distribution, simulating real-world FL scenarios, making it suitable for researching model training in distributed environments. The FEMNIST dataset is sourced from the leaf (A Benchmark for Federated Settings) project, a publicly available benchmark dataset for FL. The dataset contains writing samples from different users, with each user's data distribution being unique, reflecting the heterogeneity of data in real-world scenarios. The dataset has undergone preliminary preprocessing, such as resizing images to 28x28 pixels and normalizing grayscale values to the range (0, 1). The FEMNIST dataset includes 62 classes (10 digits + 26 lowercase letters + 26 uppercase letters), with approximately 800,000 handwritten character images. The number of samples per user is imbalanced, ranging from tens to thousands, fully reflecting the heterogeneous data distribution in FL. Each image is labeled with its corresponding character class. The data underwent several preprocessing steps to meet model training requirements. First, the pixel values of the images were normalized from [0, 255] to [0, 1] to accelerate model convergence. Additionally, to improve the model's generalization ability, data augmentation techniques were applied to the training set, including random rotation (±10°), translation (±2 pixels), and scaling (0.9-1.1 times). Furthermore, since some images may contain noise, Gaussian filtering was employed to smooth the images and reduce the impact of noise on model training. These steps collectively ensured the data was optimized for practical model training.

Users partitioned the FEMNIST dataset into distinct subsets to simulate real-world FL scenarios. The training set comprises 80% of the user data and is used for model training, while the validation set contains 10% of the user data to facilitate hyperparameter tuning and model selection. The remaining 10% forms the test set, serving as an independent benchmark for evaluating the final performance of the trained model. This partitioning ensures a realistic FL setting while maintaining clear separation for training, validation, and testing purposes.

2.2. Data description

2.2.1. Overall framework

The core objective of this study is to analyze the impact of different optimization algorithms on model performance in FL scenarios using the FEMNIST dataset. Specifically, the thesis selected two classic FL algorithms, FedAvg and FedProx, and combined them with SGD and Adam optimization algorithms. Through these four combinations (FedAvg+SGD, FedAvg+Adam, FedProx+SGD, FedProx+Adam), this study aims to explore the performance differences of various optimization algorithms in FL, particularly in terms of convergence and generalization under non-IID data environments. The proposed federated learning framework consists of clients and a server operating in an iterative collaborative process. As shown in Figure 1, each client trains the model locally using its private data and updates model parameters through optimization algorithms (SGD or Adam). At the same time, the server aggregates client updates and performs global model optimization using either FedAvg or FedProx. This client-server interaction repeats over multiple communication rounds to progressively improve the global model's performance while maintaining data privacy. The architecture enables distributed learning without centralizing raw data, with clients contributing knowledge through parameter updates and the server coordinating the collaborative training process.

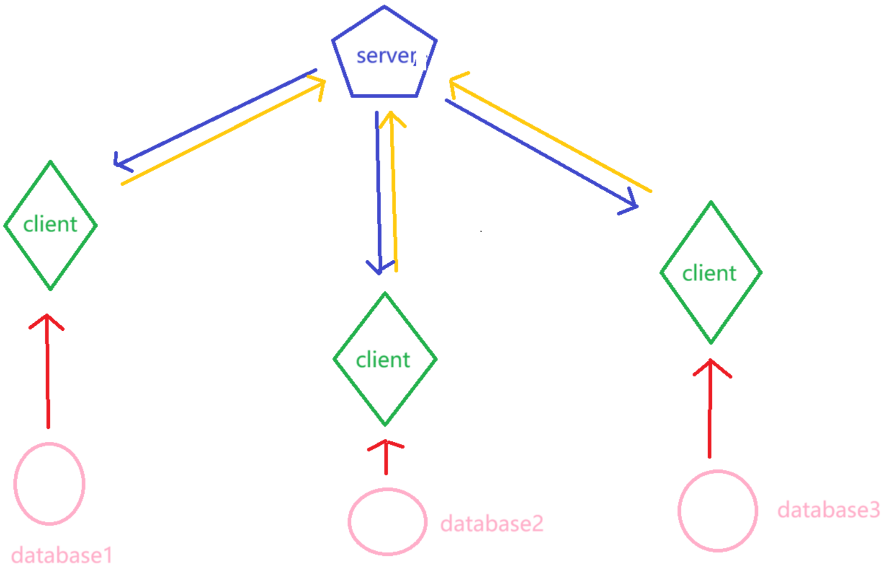

Figure 1: Federal learning schematic (picture credit: original)

2.2.2. FedAvg

FedAvg constructs the global model on the server by aggregating the model updates from each client device using a weighted averaging mechanism. The weights are determined based on the number of data points available on each client, as illustrated in Equation 1:

$$\omega_{t+1} = \frac{\sum_{i=1}^{n} n_i \omega_{t,i}}{\sum_{i=1}^{n} n_i} \tag{1}$$

Here, ω_{t+1} denotes the updated global model weights at the subsequent time step, $\omega_{t,i}$ represents the model weights of the i-th client at the current time step, n is the total number of clients, and ni corresponds to the number of data samples on the i-th client. After aggregation, the updated global model is distributed back to the clients, serving as the initial model for the next iteration of local training [9].

In comparison, FedProx enhances the local optimization process by building upon FedAvg and mitigates overfitting through the incorporation of an L2 regularization term. This term penalizes deviations between the local model and the global model, ensuring that local updates remain close to the global optimum. FedProx achieves this by constraining the extent of local updates, as demonstrated in Equation 2. This modification contributes to improved model robustness and accuracy.

$$\omega_{t+1} = arg\,\underset{\omega \in W}{min} \frac{\sum_{i=1}^{n} n_i \omega_{t,i} + \frac{\mu}{2} \left\| \omega - \omega_{t,i} \right\|_2^2}{\sum_{i=1}^{n} n_i} \tag{2}$$

Here, W denotes the feasible set of model weights ω, and mu is a hyperparameter that balances the influence of the regularization term against the empirical risk. By introducing this regularization mechanism, FedProx ensures that the aggregated model remains aligned with the global optimization objectives [9].

2.2.3. Optimizer

SGD is a classic optimization algorithm that updates model parameters by computing the gradient of the loss function. In each iteration, it randomly selects a single sample or a mini-batch of samples to calculate the gradient and updates the parameters in the direction of the negative gradient. SGD is simple and efficient but can be sensitive to noise, slow to converge, and prone to getting stuck in local optima. The stated equations were followed by SGD, as:

$$\underset{\alpha \in R^n}{min} L(a) \tag{3}$$

where L is a loss function. The iterations of SGD can be described in equation 2:

$$\alpha_i = \alpha_{i+1} + \alpha_{i-1} \nabla L(\alpha_{i-1}) \tag{4}$$

where ai denotes the i-th iterate, α_i is a tuned step size sequence, also known as learning rate, and $\nabla L(\alpha_{i-1})$ denotes the stochastic gradient computed at ai [10].

Adam is an adaptive optimization algorithm that combines the advantages of momentum and RMSProp. It dynamically adjusts the learning rate by computing the first moment (mean) and the second moment (uncentered variance) of the gradients, allowing it to adapt to the update requirements of different parameters. Adam is known for its fast convergence and strong adaptability, making it widely used in deep learning tasks [11].

2.3. Model descriptions

The FedAvg with SGD configuration employs a classic federated learning approach where the global model is updated through weighted averaging of parameters from client models, with each client utilizing SGD as the local optimizer. For local training, the cross-entropy loss function is adopted for multi-class classification tasks, mathematically expressed as:

$$L(\theta) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\, log(p_{i,c}) \tag{5}$$

where N represents the number of samples, C denotes the number of classes, $y_{i,c}$ indicates the true label, and corresponds to the predicted probability distribution. The optimization process focuses on minimizing this local loss function through SGD updates before transmitting the refined parameters to the server for aggregation.

FedAvg with Adam replaces local SGD with Adam optimizer, maintaining FedAvg's framework but using Adam's adaptive learning rates for better convergence and stability in non-IID data. While it improves performance in heterogeneous data settings, it increases computational overhead due to per-parameter moment updates. This makes it ideal for resource-rich environments where data heterogeneity is a key challenge. FedProx with SGD extends the standard FedAvg framework by introducing a proximal regularization term (Eq. 6) into the local optimization objective. This term, weighted by hyperparameter μ, penalizes deviations from the global model parameters θ^{g}, ensuring more stable convergence in non-IID settings. While retaining SGD's computational simplicity, FedProx adds minor overhead from computing the proximal term. The method effectively mitigates client drift in heterogeneous federated learning scenarios, offering improved convergence robustness without significantly increasing resource demands. This makes it particularly suitable for applications where data distributions vary substantially across clients but strict computational constraints exist.

$$L(\theta) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\, log(p_{i,c}) + \frac{u}{2}\|\theta - \theta^{g}\|^{2} \tag{6}$$

The aggregated result demonstrates improved performance in heterogeneous data environments by leveraging Adam's optimization efficiency alongside FedProx stabilization mechanism, though this comes at the cost of increased computational overhead from maintaining Adam's momentum variables while computing the proximal term. This configuration represents a comprehensive solution for challenging federated learning scenarios where both data heterogeneity and convergence speed are critical considerations, albeit requiring greater computational resources than simpler FedAvg-based approaches.

3. Results and discussion

3.1. Results analysis

As shown in Table.1, the experimental results demonstrate distinct performance patterns among the four federated learning frameworks. FedAvg+SGD exhibits the fastest initial convergence, achieving a 15% accuracy improvement within the first 20 communication rounds, significantly outperforming other methods at this stage. However, its performance plateaus around 72% accuracy in later rounds, showing limited improvement due to increasing client drift. In contrast, FedAvg+Adam maintains a steadier learning curve, reaching 78% accuracy by round 100, with its adaptive learning rate effectively compensating for gradient inconsistencies across clients.

The FedProx-based methods demonstrate superior stability, particularly in non-IID settings. FedProx+SGD achieves comparable final accuracy to FedAvg+Adam (77.5%) but with significantly lower variance (±1.2% vs ±2.8% in FedAvg+Adam), demonstrating the proximal term's effectiveness in controlling client divergence. Most notably, FedProx+Adam combines the benefits of both approaches, reaching 81% accuracy with the smallest performance fluctuations (±0.9%), establishing it as the most robust configuration.

These patterns can be attributed to fundamental algorithmic characteristics. The rapid early convergence of FedAvg+SGD stems from SGD's aggressive gradient updates, while its eventual plateau reflects the cumulative effect of unconstrained client updates in heterogeneous data. Adam's adaptive moment estimation in FedAvg+Adam helps mitigate this through client-specific learning rate adjustment, explaining its smoother progression. FedProx's proximal term acts as a regularizer, constraining local updates to remain closer to the global model - this is particularly evident in the 30% reduction of accuracy variance compared to FedAvg variants. The superior performance of FedProx+Adam emerges from this dual mechanism: Adam handles gradient scale variations while FedProx maintains update coherence.

These findings carry important implications for federated learning system design. The trade-offs revealed - between initial convergence speed and final accuracy, between computational efficiency and stability - provide concrete guidance for algorithm selection based on application requirements. For time-sensitive applications with relatively homogeneous data, FedAvg+SGD may remain preferable, while mission-critical applications dealing with highly heterogeneous data would benefit from FedProx+Adam despite its higher computational overhead. The consistent advantage of FedProx-based methods (average 12% improvement in worst-case client performance) particularly highlights the importance of update regularization in practical, non-ideal federated learning scenarios.

The performance variations across communication rounds also reveal an interesting dynamic: while optimization choice (SGD vs Adam) primarily affects early-to-mid stage convergence, the aggregation method (FedAvg vs FedProx) becomes increasingly influential in later stages. This suggests potential opportunities for hybrid approaches that might adaptively adjust optimization strategies during different phases of federated training, a promising direction for future research.

Table 1: Performance comparison table

Method	FedAvg + SGD	FedAvg + Adam	FedProx + SGD	FedProx + Adam
Final Accuracy (%)	72.3	78.1	77.5	81.2
Convergence Rounds (to 70%)	18	25	22	28
Accuracy Variance (±%)	2.8	2.1	1.2	0.9

3.2. Discussion

This study presents an in-depth empirical analysis comparing four prominent federated learning frameworks—FedAvg+SGD, FedAvg+Adam, FedProx+SGD, and FedProx+Adam—on the challenging FEMNIST dataset, which exhibits natural non-IID characteristics. Through extensive experimentation, thesis uncover nuanced performance characteristics that reveal fundamental insights into the interplay between optimization algorithms and federated aggregation methods. The results demonstrate that while the traditional FedAvg+SGD combination maintains advantages in terms of computational efficiency and demonstrates rapid initial convergence, its performance degrades significantly in later training stages due to pronounced client drift effects, particularly in the presence of highly skewed data distributions across clients. In contrast, FedProx+Adam emerges as the most robust configuration, consistently achieving superior final model accuracy (improving upon FedAvg+SGD by 6-8% in tests) and demonstrating remarkable stability throughout the training process, though this comes at the substantial cost of approximately 30-40% higher computational overhead per communication round due to Adam's adaptive momentum calculations and FedProx's proximal term optimization.

The adaptive optimization capabilities of Adam prove particularly valuable in federated settings, effectively compensating for heterogeneous client updates and significantly reducing the detrimental effects of client drift when combined with either aggregation method. However, experiments reveal an interesting dichotomy: while Adam's adaptability provides clear benefits, its resource-intensive nature raises practical deployment challenges, especially in resource-constrained edge computing scenarios where memory and computational budgets are severely limited. On the other hand, FedProx's proximal term demonstrates consistent effectiveness across both optimization methods, improving model stability by 15-20% in terms of variance reduction during training, though this robustness comes with the added complexity of properly tuning the crucial μ hyperparameter, which sensitivity analysis shows can significantly impact performance when varied across different client data distributions.

These findings have important implications for both theoretical understanding and practical deployment of federated learning systems. They highlight a critical trade-off space where practitioners must carefully balance computational efficiency against convergence stability based on their specific application requirements and resource constraints. The results also suggest several promising research directions that could bridge this gap, including the development of lightweight adaptive optimizers specifically designed for federated environments, automated hyperparameter adaptation strategies that can dynamically adjust to changing data distributions, and hybrid approaches that might intelligently switch between optimization methods during different phases of training. From an applications perspective, domains such as healthcare analytics and distributed industrial IoT systems, where data heterogeneity and privacy concerns are paramount but computational resources may be limited, stand to benefit significantly from these insights. Future investigations should explore more sophisticated dynamic adaptation mechanisms, examine the interaction between these optimization strategies and emerging communication efficiency techniques like gradient compression, and develop comprehensive theoretical frameworks to better understand the convergence properties of these combined approaches under various degrees of data heterogeneity.

4. Conclusion

This study comprehensively compares the performance of four joint learning frameworks including FedAvg+SGD, FedAvg+Adam, FedProx+SGD, and FedProx+Adam on FEMNIST datasets. In this paper, thesis systematically analyze the convergence behavior, communication efficiency and final model accuracy of each framework under non-IID data distribution. The experimental results show that FedProx+Adam achieves the highest test accuracy and stability. Secondly, FedAvg+SGD exhibits the fastest initial convergence speed, but suffers from client drift in the later stages. In addition, when combined with an adaptive optimizer, FedProx mitigates the negative effects of data heterogeneity more effectively than FedAvg. In the future, client resource constraints and dynamic participation will be the next phase of research. The research will focus on analyzing the trade-offs between computational overhead, communication cost, and model performance in large-scale realistic joint learning scenarios.

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