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pLFL: A Lightweight Federated Learning Framework for Credit Risk Prediction

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Abstract. A significant challenge faced by numerous small- and medium-sized banks in the field of credit risk prediction lies in the limitations of available data, high non-performing loan ratios, and stringent data privacy regulations. Federated learning (FL) offers a promising solution by enabling collaborative model training across multiple institutions without the need to share sensitive data, thus safeguarding privacy while enhancing the accuracy of credit risk predictions. This study focuses on borrower default prediction as a practical application scenario for small- and medium-sized banks and introduces a lightweight federated learning framework (pLFL) designed to optimize model performance. The proposed framework integrates an enhanced tADA data preprocessing technique with an improved pFed aggregation algorithm, effectively addressing the aforementioned challenges. To evaluate the efficacy of the pLFL framework, experiments were conducted on two real-world datasets. The results demonstrate substantial performance improvements: on the credit card dataset, the F1 score of the model increased to 81.5%, with Precision reaching 91.5%. On the Lending Club Loan Data dataset, communication overhead was significantly reduced, and the global model's convergence rate accelerated to 1.8 times its original speed. Furthermore, the pLFL framework incorporates parameter quantization and asynchronous communication strategies to minimize system resource consumption, underscoring its practicality for small- and medium-sized financial institutions. This research presents an efficient and privacy-preserving solution for credit risk prediction in the financial sector, particularly in scenarios requiring cross-institutional collaboration with heterogeneous data distributions.

Keywords: Federated Learning, Credit Risk, Lightweight, Risk Prediction

1 Introduction

Credit risk prediction is an essential tool for financial institutions, particularly banks, in managing credit risk and optimizing loan decisions. Traditional methods of credit risk assessment often rely on inductive reasoning[1], with mathematical and statistical analyses being conducted on carefully selected, hypothesis-driven data. These methods typically focus on the structural features of the data, with inferences and decisions being made based on model assumptions. In contrast, modern advanced methods emphasize data-driven approaches, in which patterns are automatically learned from the data to adapt to its complexity and nonlinearity. Compared to traditional methods, data-driven models offer greater flexibility and adaptability, as they are capable of extracting underlying patterns from noisy, nonlinear, and heterogeneous data, often yielding superior predictive performance in practice. However, regardless of whether traditional or modern methods are used, both are highly dependent on the quality and quantity of data. The availability of better-quality data allows models to capture real-world risk characteristics more accurately, thereby improving the reliability of predictions. Therefore, data availability is crucial for financial institutions; a scarcity of data often leads to a decline in predictive performance, which in turn affects the quality of decision-making.

For small and medium-sized financial institutions, particularly small and medium-sized banks that account for over 85% of the market in China, data scarcity and privacy protection are the primary challenges faced[2]. Although cross-institutional data sharing has the potential to significantly improve the performance of credit risk prediction models, it is often impeded by barriers stemming from the financial industry's sensitivity to data privacy, control, and legal risks. To address this, federated learning, an emerging distributed learning approach, is proposed as a solution.

Federated learning allows multiple parties to collaboratively train a model without exchanging raw data, sharing only model parameter updates, thereby reducing the risk of data leakage[3]. This approach not only improves the feasibility of cross-institutional collaboration but also ensures compliance with data protection regulations (such as GDPR). However, several challenges remain in the practical application of federated learning: the issue of data imbalance in credit risk prediction tasks, particularly the scarcity of default samples, which may be exacerbated in federated learning environments[4]; second, data heterogeneity across institutions may affect the generalization ability of the global model; furthermore, the communication overhead resulting from frequent model updates and parameter exchanges may lead to inefficiencies in training, particularly in resource-constrained small and medium-sized financial institutions.

To address the challenges outlined above, this study proposes a lightweight federated learning framework, termed pLFL, designed to enhance both the accuracy of credit risk prediction and the efficiency of model training through carefully crafted methodologies. The pLFL framework incorporates an improved tADA sampling technique to mitigate issues arising from data imbalance, thereby significantly boosting model performance. At the central server, the framework employs the pFed aggregation algorithm, which adjusts the weights of participating clients to counteract the effects of data heterogeneity. To reduce communication overhead, pLFL leverages parameter quantization techniques to compress model parameters, coupled with an asynchronous communication strategy that substantially accelerates training processes. The key contributions of this paper are summarized as follows:

- Improved tADA data preprocessing method:To address the pervasive issue of data imbalance in credit datasets, this study introduces an enhanced sampling approach based on the ADASYS algorithm, referred to as the tADA method. This improved technique strategically adjusts sample boundaries and cluster weights to maximize the utility of imbalanced samples, thereby mitigating the adverse effects of data imbalance on model training. Consequently, the proposed method significantly enhances the model's ability to accurately identify minority class instances, particularly defaulting customers.
- Dynamically weighted pFed aggregation algorithm: In response to the data heterogeneity issue in federated learning, the pFed algorithm, based on the FedProx algorithm, is proposed. By dynamically adjusting the weight assigned to each participant in the global model update, the pFed algorithm enhances model stability and generalization ability, while reducing the detrimental effects of data heterogeneity on training performance.
- Novel pLFL Lightweight Framework: To enhance the overall training efficiency of federated learning, a parameter quantization and asynchronous communication strategy has been introduced. Specifically, the model parameters are quantized after local training, converting 32-bit floating-point values into 8-bit integers, thereby reducing the communication overhead during model uploads. Additionally, the asynchronous communication strategy embedded within the pFed aggregation algorithm mitigates the training delay caused by speed discrepancies between devices, further boosting training efficiency.

This lightweight federated learning framework offers an efficient and scalable solution for credit risk prediction in financial institutions, particularly in cross-institutional collaboration scenarios where data privacy must be ensured. By leveraging carefully designed preprocessing methods, optimization algorithms, and a lightweight architecture, the proposed framework demonstrates significant advantages in addressing the complexities inherent in financial data.

2 Related Work

2.1 Credit risk prediction

Credit risk prediction is one of the core challenges faced by financial institutions, particularly banks. With the evolution of financial markets, risk prediction has become an integral part of financial risk management. In recent years, both domestic and international research has primarily focused on the optimization and exploration of various predictive models. Early credit risk prediction models were predominantly based on statistical methods, such as regression analysis and discriminant analysis. Meyer et al.[5] were the first to apply logistic regression (LR) to the financial sector, demonstrating its superiority over discriminant analysis. Sami et al. [6] introduced a time-effect enhanced logistic regression model, which also performed well in predicting bank credit risks. However, with the rise of artificial intelligence, machine learning has gradually replaced traditional statistical methods. Xu et al.[7] employed random forests (RF) for credit risk modeling, achieving significant predictive performance. Hsieh et al. [8] enhanced prediction accuracy by integrating multiple classifiers, while Xiao et al. [9] proposed a supervised clustering model that outperformed single classifiers. As a representative AI method, neural networks have also made groundbreaking advances in credit risk prediction. Chen et al. [10] evaluated credit risk using a multi-layer perceptron (MLP) model, demonstrating excellent accuracy and stability. Kim et al. [11] employed deep dense neural networks, surpassing traditional machine learning methods with their automatic feature extraction capabilities. Su et al.[12] proposed a hybrid neural network credit scoring model, which showed advantages in improving prediction effectiveness. As the demand for model performance has increased, ensemble models have become a research trend in credit risk prediction. For example, Zhu et al.[13] proposed the RS-MultiBoosting enhanced hybrid ensemble method, which significantly improved the accuracy of small and medium-sized enterprise credit risk prediction. Wang et al. [14] combined CNN and LSTM in the LSTM-CNN model, significantly improving prediction performance by integrating behavioral and temporal features, further validating the method's advantages in credit risk prediction.

However, model performance is not solely influenced by algorithms; data quality and quantity are equally critical[15]. Small and medium-sized banks often face challenges related to insufficient and low-quality data, which significantly impacts model performance. Additionally, data privacy protection laws and considerations regarding corporate competitiveness have restricted the progress of data sharing.

2.2 Lightweight federated learning

Federated Learning (FL), as a distributed machine learning approach, operates as follows (see Fig. 1): The central server first selects clients and the machine learning model, which is then distributed to the clients for local training. The clients return their trained results to the server, which aggregates the updates and sends the new model for the next round of training, continuing until the predefined number of iterations or performance targets are reached.

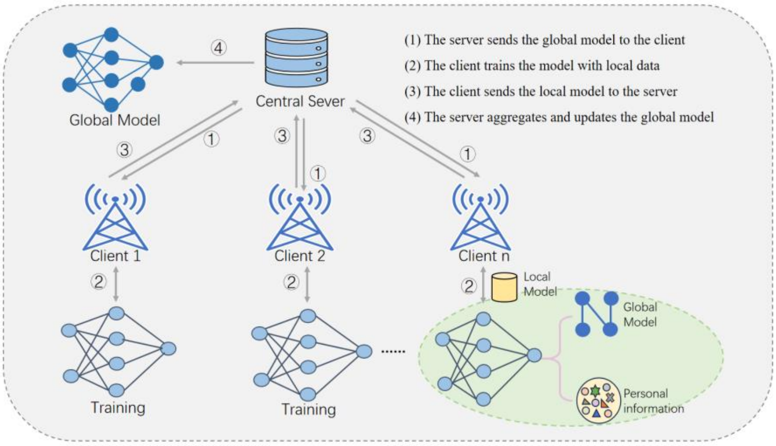

Fig. 1. Federated learning training process

Research in federated learning can be categorized into three main directions. Firstly, at the client-side, the focus is on addressing issues of data heterogeneity and imbalance, optimizing data preprocessing (such as feature selection and data augmentation), and enhancing the accuracy and robustness of local training using either deep learning or traditional algorithms. Secondly, at the server-side, optimizing model aggregation algorithms is critical. The traditional FedAvg algorithm has evolved into methods like FedProx and FedSGD to handle data distribution heterogeneity and improve the generalization capability of the global model. Lastly, the frequent communication requirements incur high costs and privacy risks. Consequently, researchers often employ techniques such as pruning and quantization to reduce communication overhead while incorporating methods like differential privacy, homomorphic encryption, and multi-party secure computation to ensure data privacy and security.

The emergence of Lightweight Federated Learning (LFL) addresses the technical challenges of federated learning in resource-constrained environments[16]. Traditional FL relies on frequent synchronization between clients and servers, leading to significant communication overhead when there are numerous participants or large-scale models. Moreover, the high computational demands of model training pose a bottleneck for resource-limited devices, such as mobile devices and edge nodes. The core objective of LFL is to reduce resource demands through model simplification, communication optimization, and computational efficiency. Lightweight techniques, such as pruning, quantization, and knowledge distillation, are employed: pruning reduces storage and computational burden by eliminating redundant parameters; quantization converts high-precision floating-point numbers to low-precision integers; and knowledge distillation enables smaller models to learn from larger ones, maintaining performance while reducing computational needs. Communication optimization strategies, such as gradient compression, sparse synchronization, and local update frequency adjustment, effectively reduce communication overhead between devices. Through these techniques, LFL significantly enhances the scalability and practical applicability of FL.

As federated learning gradually finds applications in the financial services sector, related research has been steadily increasing. Initially, researchers explored how to simplify model structures to maintain strong performance while adapting to hardware limitations of devices. For instance, Guo et al.[17] demonstrated the advantages of lightweight models by compressing client-side CNN model parameters for distributed anomaly detection in logs. Subsequently, research focused on applying LFL in various scenarios such as IoT and edge computing. For example, Yan et al.[18] proposed the Heroes framework for heterogeneous edge networks. In 2024, Qi et al.[19] presented the first comprehensive review of LFL.

While existing research has demonstrated the potential of LFL in real-world scenarios, there remains a significant gap in the literature regarding its application to financial domains, particularly in the context of real credit datasets from small- and medium-sized financial institutions. Moreover, current federated learning frameworks suffer from excessive parameter exchange, leading to inefficiencies in communication, as well as substantial computational constraints. To bridge this gap, this study investigates how LFL can be leveraged to develop an efficient credit risk prediction model by integrating real-world credit data from financial institutions of varying scales, thereby addressing both communication bottlenecks and computational limitations.

3 Methodology

3.1 Client –tADA algorithm

In the field of credit risk prediction, data imbalance is a pervasive issue. The uneven distribution of samples can skew the predictions of various models, including federated learning-based classifiers, towards the majority class, undermining model robustness. In federated learning scenarios, data imbalance may also arise during communication between participating clients and the server. If not promptly addressed, this imbalance can degrade the performance of local models on each client, thereby compromising the overall performance of the global model and potentially leading to the failure of federated learning- based model training[20].

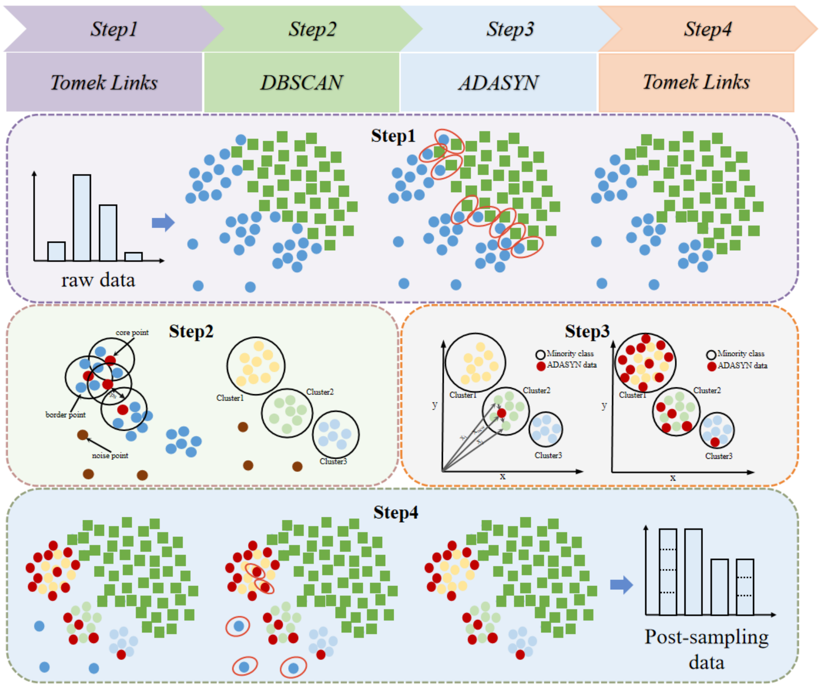

Fig. 2. Principles of the tADA algorithm

To construct a high-quality dataset with balanced intra- class and inter-class distributions, thereby improving the performance of credit risk prediction models on minority classes, this paper proposes an innovative approach by enhancing the tADA algorithm with ADASYS. The key workflow is illustrated in Fig. 2, and the core steps are outlined as follows:

a) Noise Filtering and Minority Class Sample Optimi -zation:. To enhance the quality of minority class samples, the TomekLinks algorithm[21] is first employed to filter out noise. TomekLinks identifies and removes nearest neighbor pairs between classes, effectively eliminating noisy data points that could negatively impact model training. This process generates a refined set of minority class samples, which serve as the input for subsequent clustering steps. The procedure can be formally described as follows:

$$\text{Tomeks}(x_i, x_j) \ \text{ if } \ \|x_i\text{-}x_j\| = \min||x_i - x_j||(x_j \in x_{minority}) \tag{1}$$

where x_i and x_j represent minority class samples, and $x_{minority}$ denotes the set of minority class samples after noise filtering.

b) Clustering and Sample Grouping:. Building upon the noise-filtered minority class samples, the DBSCAN clustering algorithm[22] is applied to partition the minority class samples into distinct sub-clusters, thereby improving the data's representational capacity. DBSCAN identifies clusters based on density connectivity, with the parameters ϵ(neighborhood radius) and MinPts(minimum number of points) determining cluster formation. The resulting sub-clusters are used as input for the subsequent oversampling step. The process can be expressed as:

$$\text{DBSCAN}(x_{minority}, \epsilon, \text{MinPts}) \tag{2}$$

where $x_{minority}$ is the noise-filtered minority class sample set.

c) Oversampling and Weight Optimization:. On the clustered minority sub-classes, the ADASYN algorithm[23] is utilized for oversampling, prioritizing the generation of synthetic samples for hard-to-classify instances and assigning greater attention to high-impact samples. The weight for each minority sample x_i is calculated as follows:

$$\omega(x_i) = \frac{1}{k_i} \sum_{j \in \varkappa_k(x_i)} || x_i - x_j|| \tag{3}$$

where $\omega(x_i)$represents the weight of minority sample x_i, and $\varkappa_k(x_i)$ is the number of nearest neighbors. Based on these weights, ADASYN generates synthetic samples, particularly for challenging minority class instances. The output of this step is a synthetic sample set $x_{synthetic}$, with minority class information, which contributes to constructing a balanced intra-class and inter-class dataset.

d) Post-Oversampling Noise Filtering and Sample Refinement:. Finally, the TomekLinks algorithm is reapplied to the oversampled minority class set $x_{synthetic}$ to remove overlapping samples and noise introduced during the ADASYN process. This refinement step optimizes the final dataset, ensuring minimal noise and overlap. The resulting dataset, denoted as $x_{synthetic}'$, is a balanced, high-quality synthetic dataset ready for model training. The process is described as:

$$\text{Tomeks}(x_i, x_j) \text{ if } \|x_i - x_j\| = \min||x_i - x_j||(x_j \in x_{synthetic}) \tag{4}$$

where $x_{synthetic}$ represents the synthetic sample set generated in the previous step.

3.2 Server – pFed aggregation

Despite the significant improvements brought by tADA in client-side data preprocessing, data heterogeneity and communication efficiency between clients and the central server remain critical challenges affecting the performance of the global model in a FL environment [24]. Thus, optimizing the aggregation algorithm at the server side is crucial. FedProx partially addresses the non-IID data issue by introducing a regularization term to mitigate the divergence between local and global models [25]. However, it does not fully resolve the heterogeneity problem.To further alleviate the impact of data heterogeneity, this study proposes an improved federated optimization algorithm, pFed, based on FedProx. The proposed method not only mitigates the slow convergence of the global model caused by increasing local update iterations under non-IID settings but also enhances the overall predictive accuracy by improving server-side optimization flexibility. The specific workflow of pFed is presented in Algorithm 1. The key idea is to incorporate dynamic weight aggregation during global optimization, which effectively accounts for the local data characteristics of each participating client, reducing the adverse effects of data heterogeneity. Additionally, an asynchronous communication strategy[26] is employed to prevent straggler devices from slowing down global updates, thereby improving the overall convergence efficiency. In the context of credit risk prediction, pFed effectively mitigates challenges posed by non-IID data distributions.The introduction of dynamic weights α_{κ} in pFed is guided by two critical factors:

1) Device-Specific Data Volume (n_k):. Devices with larger local datasets contribute more significantly to global model updates[27]. Therefore, higher aggregation weights are assigned to these devices, reflecting their greater importance in the learning process.

2) Update Magnitude Penalization (Δw_k):. A larger update magnitude from a device may indicate substantial divergence between its local data distribution and the global model, potentially introducing instability. To counteract this, a penalization mechanism is introduced to limit excessive updates, thereby reducing noise and improving the stability of global model aggregation. This adaptive weight computation strategy balances the contributions of different devices, mitigating the impact of non-IID distributions.

In federated learning, asynchronous communication refers to a mechanism where clients independently complete local training and upload model updates without waiting for other devices to finish. The server maintains a priority queue based on local data quality and computational capacity, allowing clients to submit model updates at any time. Consequently, each client's update is immediately integrated into the global model without being delayed by slower devices.

Let θ_t represent the global model parameters at time step, and let $\Delta\theta_t$ denote the local model update from client k. The asynchronous update process as follows:

$$\theta_{t+1}=\theta_t+\alpha\sum_{k=1}^{k}\omega_k\Delta\theta_k \quad (5)$$

where:

θ_{t+1} epresents the global model parameters at time t+1,

α is the global learning rate,

ω_k denotes the weight assigned to client k,

$\Delta\theta_k$ is the local model update uploaded by client k.

In this asynchronous setting, client k can upload its model updates at any given time, and the global model is updated dynamically upon receiving new contributions. This strategy offers three distinct advantages:

- Higher Device Utilization: Asynchronous updates eliminate the need for the server to wait for all clients to complete local training before aggregation. Instead, it continuously integrates updates as they arrive. This mechanism better accommodates real-world device heterogeneity (e.g., varying computational power and network latency), improving overall system efficiency.

- Faster Global Model Updates: Since the server does not need to synchronize updates across all clients, the global model can be updated more frequently, accelerating convergence, particularly in large-scale FL scenarios.
- Enhanced Robustness: The asynchronous update mechanism reduces reliance on strict client synchronization, ensuring that the system remains operational even if some devices become unresponsive . This enhances the robustness of the FL framework.

Algorithm 1 Asynchronous pFed

Require: K (Total devices), T (Max iterations), μ(Proximal term weight), γ (Learning rate), w^0(Initial global model), N (Total data points across devices), p_k (Probability of device k beings selected), k = 1,..., N

Initialize: Server maintains global model w^t and a queue Q for receiving model updates asynchronously.

for t = 0,...,T - 1 **do**

Server selects a subset S_t of devices at random, where each device k is chosen with probability p_k.

Server sends global model w^t to all selected devices S_t.

for all device $k \in S_t$, **(in parallel) do**

Solve the local optimization problem:

$$w_k^{t+1} \approx \underset{w}{\operatorname{argmin}} F_k(w) + \frac{\mu}{2} \| w - w^t \|^2$$

where $F_k(w)$ is the local loss function on device k.

Compute the model delta:

$$\Delta w_k = w_k^{t+1} - w^t$$

Upload (Δw_k , n_k , $||\Delta w_k||$) to the server.

end for

while Server receives (Δw_k , n_k , $||\Delta w_k||$) from devices asynchronously **do**

Compute the dynamic aggregation weight:

$$\alpha_k = \frac{\frac{n_k}{N}}{1 + \| \Delta w_k \|}$$

Incrementally update the global model:

$$w^{t+1} = w^t + \gamma \cdot \alpha_k \cdot \Delta w_k$$

end while

Optionally: Broadcast updated global model w^{t+1} to devices.

end for

3.3 pLFL framework

Although pFed partially addresses the issues arising from device speed discrepancies through asynchronous communication, the challenge of further reducing communication overhead and improving efficiency for resource-constrained devices remains. To this end, this paper proposes the adoption of a lightweight federated learning framework, pLFL, aimed at mitigating this overhead. The term "lightweight" is specifically embodied in two aspects(Fig. 3): On the one hand, during interactions between the client and server, parameter quantization[28] is employed. After local model training is completed, a post-training quantization process is applied, reducing the model parameters from 32-bit floating-point values to 8-bit integers to minimize upload communication costs. Upon receiving the 8-bit integer parameters, the central server then dequantizes them back to 32-bit floating-point values for global aggregation. On the other, in synchronous federated learning, each training round requires waiting for all participating devices to finish uploading their models before aggregation can occur. Due to the variance in device resources and training data, faster devices must wait for slower ones, significantly hindering the efficiency of federated learning. However, in asynchronous federated learning, the model aggregation server immediately performs global aggregation once a minimal set of local models has been collected, thus avoiding the delays caused by slower devices.

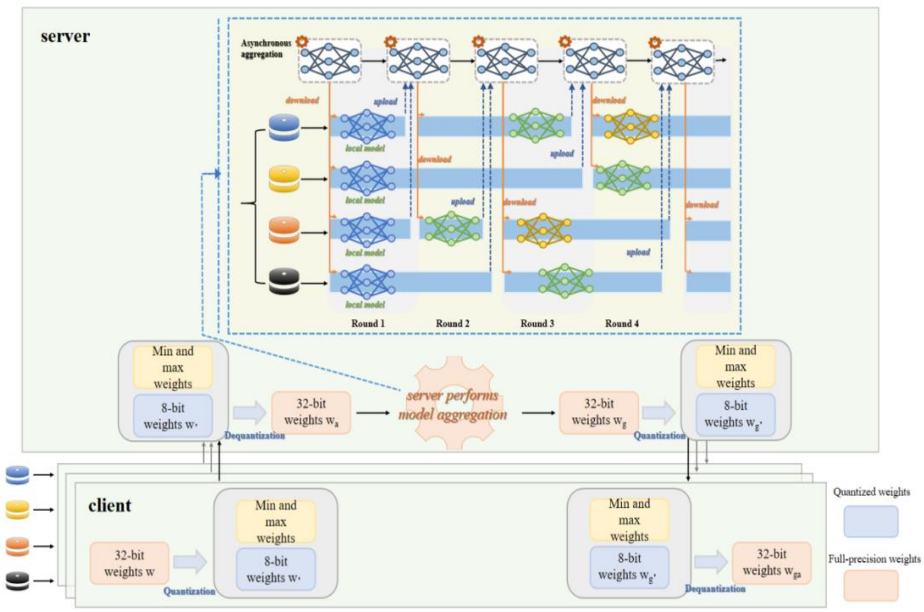

Fig. 3. pLFL framework

4 Experiment

This section presents the experimental results of the credit risk prediction model, pLFL, based on the federated learning framework. The model integrates the tADA algorithm, pFed aggregation, and a lightweight federated learning architecture. To assess the effectiveness of the proposed approach, extensive experimental analysis was conducted on two real-world publicly available credit risk datasets. The evaluation metrics include prediction accuracy, recall, precision, and F1 score, among others.

4.1 Data Source and Data Preprocessing

This experiment utilizes two publicly available credit risk datasets: Credit Card, sourced from Kaggle, and Lending Club Loan Data, obtained from a peer-to-peer lending platform in the United States.

Credit Card dataset. comprises anonymized transaction data from European cardholders and includes a variety of financial transactions of varying scales and complexities. Its primary purpose is to evaluate model performance in real-world scenarios. This dataset features transactions that occurred over two days, with a total of 284,807 transactions, of which only 492 were defaults. The ratio of positive to negative samples is approximately 578:1, creating a highly imbalanced dataset where the negative class (defaults) accounts for 0.172% of all transactions.

Lending Club Loan dataset. spans loan data from 2007 to 2015, containing approximately 890,000 observations. It includes real-world information on individual borrowers, such as age, gender, employment type, housing status, savings, checking accounts, credit amount, loan term, and loan purpose. The ratio of positive to negative samples in this dataset is approximately 7:1.

In this study, to address the issue of class imbalance in credit risk prediction, standard preprocessing steps were applied to the datasets, including missing value imputation, outlier detection, feature normalization. Missing values were filled using mean or median imputation, and outliers were identified and removed using boxplots and Z-Score methods. Numerical features were standardized using Min-Max normalization, while categorical features were encoded using one-hot encoding. Subsequently, tADA sampling was performed on the training data to ensure that the resulting distribution aligned with the training requirements of the model.

4.2 Experimental Setup

The dataset was partitioned into training, testing, and validation sets at a ratio of 6:2:2. To thoroughly evaluate the effectiveness of the proposed method, a comparison was made with several traditional baseline models. For a fair comparison, all models were trained under the same hardware conditions (RTX 3090, CUDA 11.8) using the open-source machine learning framework PyTorch. During federated training, we configured the number of clients to be 10, with a random selection rate of $\varepsilon = (0.3, 0.6)$. The training was conducted over 50 communication rounds, with a maximum of 5 local epochs per round. Additionally, an early stopping strategy was employed to prevent overfitting and ensure efficient training.

4.3 Evaluation Metrics

We employed a set of standard metrics to assess the performance of the model: Accuracy, Recall, Precision, and F1 Score. These four key metrics serve as a comprehensive summary of performance for any classification task. True Positive (TP): Instances correctly predicted as the positive class by the model. For example, if a sample is actually positive and the model also predicts it as positive, it is a true positive. True Negative (TN): Instances correctly predicted as the negative class by the model. If a sample is actually negative and the model predicts it as negative, it is a true negative. False Positive (FP): Instances incorrectly predicted as the positive class by the model. False Negative (FN): Instances incorrectly predicted as the negative class by the model.

Based on these classification outcomes, the following evaluation metrics are defined:Describes the proportion of correct predictions out of the total predictions made.Recall: Describes the proportion of actual positive instances that were correctly classified as positive.Precision: Describes the proportion of correctly classified positive instances out of all instances predicted as positive.F1 Score: The harmonic mean of Recall and Precision, combining the balance between the two. It is particularly useful for evaluating model performance in imbalanced class problems.The definitions of the metrics used are as follows:

$$\mathrm{Accuracy} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{FP}+\mathrm{TN}+\mathrm{FN}} \tag{6}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{7}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{8}$$

$$F_1 = \frac{2\times(\mathrm{Precision}\times\mathrm{Recall})}{\mathrm{Precision}+\mathrm{Recall}} \tag{9}$$

4.4 Results

a) Comparative Analysis of tADA Algorithm on Data Imbalance Issues： . We compared six traditional sampling methods with the tADA algorithm. Fig. 4 presents a detailed comparison of all the methods. Although tADA slightly lags behind in terms of Precision for some models, it consistently outperforms the others in F1-Score and ROC-AUC, indicating that the algorithm is more effective at distinguishing between positive and negative samples in imbalanced datasets.

b) Advantages of the pFed Algorithm Over Traditional Methods：. To evaluate the performance of different aggregation algorithms under varying data distribution conditions, we conducted experiments using the Lending Club Loan Data dataset, which has a relatively low sample imbalance rate. The results are summarized in Table 1. Since pFed is an improved version of FedProx, we primarily focus on the comparison between these two algorithms.The experimental results indicate that, under the non-independent and identically distributed (Non-IID，ε=0.3) data setting, the pFed algorithm outperforms FedProx in both accuracy (increasing from 0.889 to 0.902) and convergence speed (reducing training time by 47%). These findings underscore the advantages of pFed in addressing data heterogeneity and its potential for more efficient training in federated learning environments.

c) Performance of pLFL on Real-World Datasets：. Table 2 presents a clear illustration of the exceptional performance of the pLFL framework across two real-world datasets. The results indicate that, despite a reduction in the model's parameter Scale, the proposed pLFL method continues to achieve outstanding performance across various metrics. Specifically, the pLFL model exceeds 90% accuracy and achieves F1 scores above 80% on both datasets. Moreover, the quantization and asynchronous communication within the pLFL framework significantly enhances its performance, particularly in terms of ROC_AUC and recall. These results demonstrate the feasibility and effectiveness of pLFL for applications in small to medium-sized financial institutions.

Table 1. Comparison of the Lending Club Loan dataset under three distribution settings

Dataset	Data distribution	Method	Precision	Convergence speed
Lending Club Loan Data	IID	FedAvg	**0.802**	62
		FedProx	0.775	78（0.79×）
		pFed	0.792	**42（1.48×）**
	Non-IID (ε=0.3)	FedAvg	0.722	78
		FedProx	0.789	86（0.91×）
		pFed	**0.801**	**45（1.73×）**
	Non-IID (ε=0.6)	FedAvg	0.732	94
		FedProx	0.794	107（0.88×）
		pFed	**0.798**	**52（1.81×）**

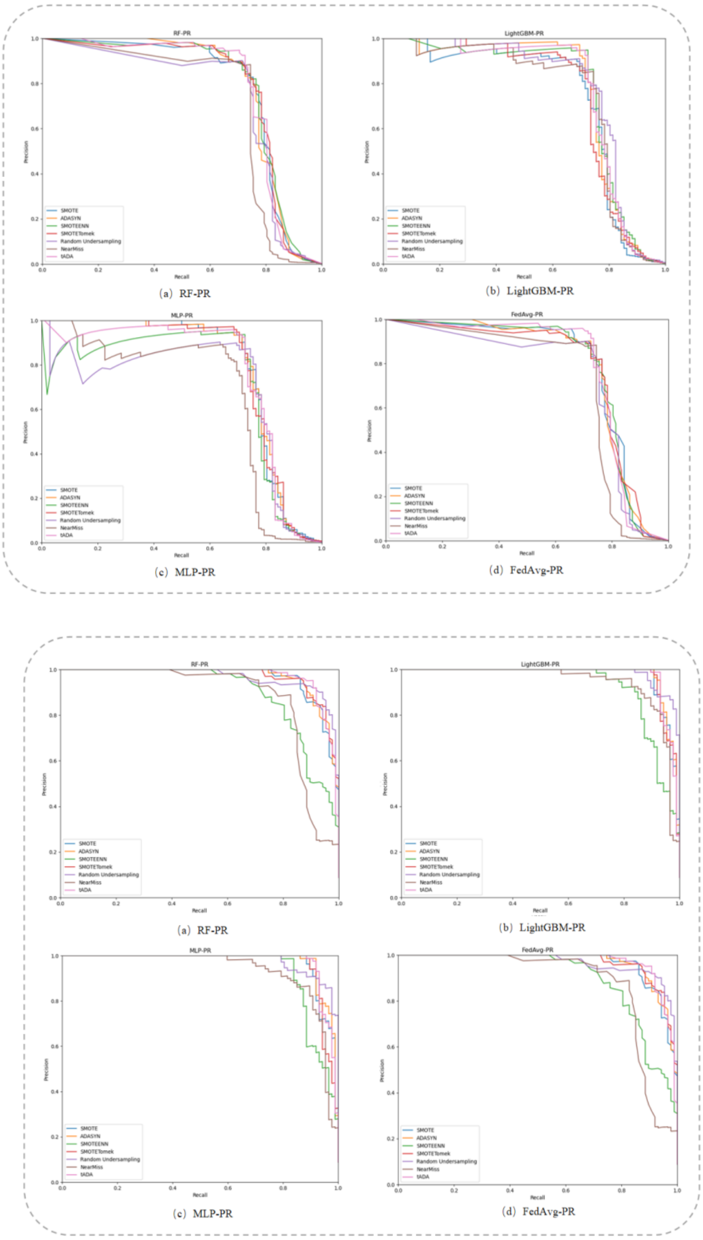

Fig. 4. The PR plots of the two datasets in different models using each sampling method

Table 2. Comparison of pLFL(ours) with other methods

Dataset	Method	Approach	Overall Metrics			
			Precision	Recall	F1_Score	ROC_AUC
Credit Card	FedAvg	No Quant/Async	0.743	0.641	0.685	0.863
	FedAvg	Quant/Asyn	0.717	0.643	0.679	**0.884**
	FedProx	No Quant/Async	0.645	**0.655**	0.694	0.877
	FedSGD	No Quant/Async	0.675	0.634	0.679	0.845
	Scaffold	No Quant/Async	0.733	0.618	0.681	0.859
	pFed	No Quant/Async	0.741	0.649	0.675	0.824
	PLFL(pFed)	Quant/Async	**0.815**	0.650	**0.715**	0.878
Lending Club Loan Data	FedAvg	No Quant/Async	0.748	0.665	0.657	0.863
	FedAvg	Quant/Asyn	0.731	0.676	0.665	0.858
	FedProx	No Quant/Async	0.759	0.683	0.681	0.860
	FedSGD	No Quant/Async	0.741	0.625	0.639	0.867
	Scaffold	No Quant/Async	0.704	0.616	0.633	0.832
	pFed	No Quant/Async	**0.714**	0.690	0.709	0.829
	PLFL(pFed)	Quant/Async	0.802	**0.697**	**0.714**	**0.882**

5 Conclusion

This paper introduces a lightweight federated learning- based credit risk prediction model, pLFL, which integrates the tADA algorithm and the pFed optimization method to effectively address challenges such as data imbalance, heterogeneity, and communication overhead. By employing data balancing and dynamic aggregation optimization strategies at the client level, the proposed approach achieves both high predictive accuracy and system efficiency. Extensive experiments on real-world credit datasets validate the effectiveness of the proposed method.Furthermore, the experimental findings highlight that smaller financial institutions, by leveraging a lightweight federated learning framework and collaborating with other entities, can significantly enhance their application potential and adaptability in resource-constrained environments. This provides these institutions with a more competitive and robust solution for credit risk prediction.

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