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Original Article

Federated Learning for Cross-Institution Credit Scoring under Privacy Constraints

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ABSTRACT

In recent years, credit scoring has become a critical tool for financial institutions to assess the creditworthiness of individuals and businesses. However, accurate credit scoring often requires access to large, diverse datasets from multiple institutions, which raises significant privacy and regulatory challenges. This paper proposes a federated learning framework for cross-institution credit scoring that enables collaborative model training without sharing raw data, thereby preserving user privacy under stringent regulatory constraints. Our approach incorporates privacy-enhancing techniques such as differential privacy and secure aggregation to mitigate data leakage risks. Experimental results on real-world credit datasets demonstrate that the proposed federated model achieves comparable accuracy to centralized training while adhering to privacy requirements. The study highlights the potential of federated learning to revolutionize credit scoring by enabling secure, scalable, and privacy-compliant cooperation among financial institutions.

KEYWORDS

Federated Learning, Credit Scoring, Privacy Preservation, Cross-Institution Collaboration, Differential Privacy, Secure Aggregation, Financial Technology (Fintech), Machine Learning, Data Privacy, Regulatory Compliance.

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1. INTRODUCTION

1.1. Background on credit scoring and its importance

Credit scoring is a fundamental component of the modern financial ecosystem, serving as a crucial mechanism for lenders to evaluate the creditworthiness of borrowers. By analyzing historical financial behavior, repayment records, and various socio-economic factors, credit scoring models help financial institutions assess the risk associated with lending to individuals or businesses. Effective credit scoring enables lenders to make informed decisions, reduce default rates, and optimize resource allocation. Beyond lending, credit scores influence interest rates, credit limits, and even access to financial products, impacting the broader economy and individual financial inclusion. As the demand for reliable credit risk assessment grows, developing accurate and fair credit scoring models becomes increasingly essential for both financial institutions and consumers.

1.2. Challenges in credit scoring across multiple institutions

Despite its importance, credit scoring faces significant challenges when applied across multiple institutions. Financial institutions often operate in silos, each maintaining proprietary datasets that reflect their unique customer base. These datasets can vary in size, quality, and feature composition, leading to data heterogeneity that complicates collaborative modeling. Moreover, pooling data from multiple institutions can yield more robust models with better generalization, yet direct data sharing is typically restricted by competitive concerns, data privacy laws, and security risks. Inter-institution collaboration is further hindered by the lack of standardized data formats and privacy-preserving infrastructure, limiting the ability to leverage the collective intelligence of the financial ecosystem. As a result, credit scoring models trained in isolation may suffer from limited coverage and potential biases, undermining their accuracy and fairness.

1.3. Privacy concerns and regulatory constraints

The financial sector is subject to stringent privacy regulations designed to protect sensitive customer information. Laws such as the General Data Protection Regulation (GDPR) in Europe, the California Consumer Privacy Act (CCPA) in the United States, and similar frameworks worldwide impose strict constraints on the collection, storage, and sharing of personal data. These regulations mandate transparency, user consent, and data minimization, making cross-institutional data sharing highly challenging. Privacy concerns are not limited to legal compliance; customers increasingly demand control over their personal information and expect institutions to safeguard their data against breaches and misuse. Consequently, any collaborative approach to credit scoring must balance the need for data-driven insights with rigorous privacy protections, ensuring that no raw or personally identifiable information is exposed during the model training process.

1.4. Motivation for using federated learning (FL)

Federated learning emerges as a promising solution to the dilemma of collaborative credit scoring under privacy constraints. FL is a decentralized machine learning paradigm that enables multiple parties to jointly train a model without exchanging raw data. Instead, each institution trains a local model on its private data and only shares encrypted or aggregated model updates with a

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central server or coordinator. This approach inherently addresses privacy concerns by keeping sensitive data local, reducing the risk of data leakage and regulatory violations. Additionally, FL supports heterogeneous data distributions and diverse institutional infrastructures, making it suitable for cross-institution collaboration. By leveraging federated learning, financial institutions can collectively build more accurate and robust credit scoring models while preserving customer privacy and complying with regulatory standards, ultimately enhancing trust and cooperation in the financial sector.

1.5. Contributions of this paper

This paper presents a novel federated learning framework tailored for cross-institution credit scoring that rigorously addresses privacy constraints. The primary contributions include the design of a federated architecture optimized for heterogeneous financial datasets, integration of advanced privacy-preserving mechanisms such as differential privacy and secure aggregation, and comprehensive evaluation on real-world credit scoring data. We demonstrate that the proposed federated approach achieves competitive predictive performance compared to traditional centralized models, while significantly reducing privacy risks. Additionally, the paper analyzes the impact of privacy parameters on model accuracy and investigates fairness across different demographic groups. By bridging the gap between privacy and collaboration in financial machine learning, our work lays a foundation for scalable and privacy-compliant credit scoring systems that can benefit multiple stakeholders in the financial ecosystem.

2. RELATED WORK

2.1. Traditional credit scoring methods

Traditional credit scoring methods have evolved significantly over the past decades, starting from simple statistical models to sophisticated machine learning techniques. Early approaches often relied on linear regression and logistic regression models, which utilized a limited set of financial indicators to predict default risk. These models were favored for their interpretability and ease of implementation. Over time, more complex models such as decision trees, random forests, and gradient boosting machines gained prominence due to their superior predictive power. Recently, deep learning models have been explored for credit scoring to capture non-linear relationships and high-dimensional data features. However, these methods generally require access to centralized and comprehensive datasets, limiting their application in multi-institution scenarios. Additionally, the use of traditional models often neglects privacy considerations and regulatory compliance, posing challenges for broader deployment in privacy-sensitive environments.

2.2. Privacy-preserving machine learning in finance

Privacy-preserving machine learning (PPML) has attracted considerable attention in the financial domain due to the sensitive nature of financial data. Techniques such as homomorphic encryption, secure multiparty computation, and differential privacy have been proposed to enable collaborative analytics without exposing raw data. Homomorphic encryption allows computation on encrypted data, but it is often computationally expensive. Secure multiparty computation enables

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parties to jointly compute functions over their inputs while keeping those inputs private, but it can be complex to scale. Differential privacy provides strong mathematical guarantees by adding noise to the data or model parameters, balancing privacy with utility. In finance, PPML has been applied to fraud detection, risk assessment, and credit scoring to comply with data protection laws while facilitating collaborative insights. However, these methods often require trade-offs between privacy, accuracy, and computational efficiency, highlighting the need for integrated frameworks like federated learning.

2.3. Federated learning fundamentals and applications

Federated learning is a distributed machine learning paradigm that enables multiple clients to collaboratively train a shared model while keeping their training data decentralized. Initially introduced by Google for mobile devices, FL has expanded into various domains including healthcare, IoT, and finance. The fundamental principle involves iterative rounds where each client trains a local model on its data and sends model updates—not raw data—to a central server, which aggregates these updates to form a global model. This process preserves data privacy and reduces communication overhead. Key challenges in FL include handling data heterogeneity, ensuring convergence, and implementing privacy-enhancing techniques. Applications of FL span personalized recommendation systems, medical diagnosis, and fraud detection, demonstrating its versatility. In finance, FL holds the potential to overcome traditional barriers to collaboration by allowing institutions to benefit from shared learning without compromising data security.

2.4. Existing work on FL in credit scoring and finance

Recent research has explored the application of federated learning specifically for credit scoring and broader financial services. Several studies have demonstrated that FL can effectively combine knowledge from disparate financial datasets, improving prediction accuracy while adhering to privacy constraints. For example, federated frameworks have been developed to jointly train credit risk models across banks, leveraging data diversity without exposing individual customer records. These works often incorporate secure aggregation protocols and differential privacy to enhance data protection. Additionally, FL has been applied to detect fraudulent transactions, perform anti-money laundering activities, and conduct collaborative risk management. Despite promising results, challenges remain in addressing model fairness, communication efficiency, and scalability in large financial networks. Our work builds upon this foundation by proposing a comprehensive federated learning system designed to handle the unique privacy and operational challenges of cross-institution credit scoring.

3. PROBLEM DEFINITION

3.1. Cross-institution credit scoring scenario

In the contemporary financial landscape, credit scoring often requires collaboration across multiple financial institutions to improve model robustness and predictive accuracy. Each institution maintains its own private customer datasets, which vary significantly in size, features, and data distribution due to differences in client demographics, lending products, and operational practices.

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The cross-institution credit scoring scenario envisions a setting where these disparate institutions jointly contribute to building a comprehensive credit scoring model without sharing raw customer data. This collaborative environment aims to leverage the diverse, yet complementary information held by each institution, thereby capturing a broader representation of borrower behavior and risk factors. Such cooperation can lead to improved generalization of credit risk models, enabling institutions to better identify potential defaulters, reduce biases, and ultimately support more inclusive lending decisions. However, this scenario also introduces complexities related to data privacy, regulatory compliance, and technical interoperability, which must be rigorously addressed.

3.2. Privacy constraints and regulatory requirements (e.g., GDPR, CCPA)

Financial data is highly sensitive, and its handling is tightly regulated by a variety of privacy laws worldwide, which impose strict obligations on data controllers and processors. Regulations such as the General Data Protection Regulation (GDPR) in the European Union and the California Consumer Privacy Act (CCPA) in the United States set stringent requirements on how personal data can be collected, processed, and shared. These laws mandate transparency, consent from data subjects, data minimization, and impose rights such as the ability to access, correct, or delete personal data. In the context of cross-institution credit scoring, these constraints prohibit the sharing of raw, personally identifiable information between entities without explicit consent or adequate anonymization. Failure to comply with these regulations can lead to severe penalties and reputational damage. Therefore, any collaborative model training framework must be designed to ensure compliance by maintaining data locality, preventing leakage of sensitive information, and implementing technical safeguards that enforce privacy guarantees throughout the learning lifecycle.

3.3. Goals: accurate, fair, and privacy-preserving credit scoring

The core objectives in developing a cross-institution credit scoring system revolve around achieving three intertwined goals: accuracy, fairness, and privacy preservation. Accuracy is paramount because the effectiveness of credit scoring directly influences lending decisions and financial outcomes; models must reliably predict default risk across diverse populations and financial products. Fairness is equally critical, ensuring that the scoring model does not propagate or exacerbate biases against particular demographic or socio-economic groups, which is vital for ethical and regulatory compliance. Privacy preservation is a non-negotiable requirement due to the sensitivity of financial data and regulatory mandates; the system must guarantee that individual-level data never leaves the custody of the originating institution. Balancing these goals is challenging, as privacy-preserving techniques can sometimes degrade model performance or introduce biases. The ideal solution must therefore integrate advanced methodologies that enable collaborative learning while upholding data privacy and fairness, without compromising predictive accuracy.

4. FEDERATED LEARNING FRAMEWORK FOR CREDIT SCORING

4.1. Architecture overview

The federated learning framework proposed for cross-institution credit scoring consists of a decentralized, collaborative model training architecture designed to respect data privacy and

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regulatory constraints. At its core, multiple participating institutions (clients) maintain their private credit datasets locally and independently train credit scoring models on their respective data. Rather than sharing raw data, clients transmit only model updates, such as gradients or parameter changes, to a central coordinating server. This server aggregates the received updates to construct a global model that embodies knowledge from all institutions. The aggregated model is then redistributed to clients for further local training, initiating an iterative process until the model converges. The architecture integrates privacy-enhancing technologies such as secure aggregation to ensure that individual updates cannot be reverse-engineered, and differential privacy mechanisms to add statistical noise that protects sensitive information. The system is designed to be scalable, robust to data heterogeneity, and compliant with regulatory standards, providing a practical solution for collaborative credit scoring.

4.2. Data distribution and heterogeneity across institutions

In a federated credit scoring setting, data heterogeneity manifests in both feature space and label distribution, reflecting the distinct operational environments of participating institutions. Some banks might focus on personal loans, while others specialize in mortgages or small business lending, leading to variation in data attributes and risk factors. The number of samples and the distribution of credit outcomes (e.g., default vs non-default) can differ significantly, contributing to statistical heterogeneity. Furthermore, institutions may collect different sets of features or use varied encoding schemes, adding to feature heterogeneity. This non-i.i.d. (independent and identically distributed) nature of data poses a significant challenge for federated learning, as conventional aggregation techniques may not perform optimally when data distributions diverge. Effective federated credit scoring frameworks must incorporate strategies to handle heterogeneity, such as personalized model components, weighted aggregation based on data quality, or domain adaptation techniques, to ensure that the global model accurately represents the collective knowledge while respecting individual institutional contexts.

4.3. Model design (e.g., neural networks, gradient boosting)

The design of the credit scoring model within a federated framework is critical to balancing predictive performance and computational efficiency. Traditional credit scoring has often relied on tree-based ensemble methods such as gradient boosting machines (GBMs) due to their interpretability and strong performance on tabular financial data. However, GBMs pose challenges in federated settings because they typically require centralized data for training. Neural networks, particularly feed forward architectures, offer greater flexibility for federated training since they can be optimized via gradient descent and support incremental updates. Recent advances in federated learning also explore hybrid architectures combining neural networks with tree-based methods or incorporating attention mechanisms to capture complex feature interactions. The chosen model must accommodate the resource constraints of participating institutions, be robust to data heterogeneity, and support privacy-preserving training mechanisms. Additionally, explainability remains important in credit scoring to meet regulatory transparency requirements, necessitating model designs that balance complexity with interpretability.

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4.4. Privacy-preserving techniques (e.g., differential privacy, secure aggregation)

Privacy preservation is foundational to federated learning for credit scoring, necessitating a suite of technical safeguards to protect sensitive data. Differential privacy (DP) introduces controlled noise into model updates or outputs to obscure the contribution of any single data point, providing quantifiable privacy guarantees. Applying DP in federated learning involves carefully tuning noise levels to maintain model utility while preventing inference attacks. Secure aggregation protocols enable the central server to aggregate encrypted model updates from multiple clients without accessing individual updates, ensuring that no single institution's data or model parameters can be isolated or exposed. Complementary methods include homomorphic encryption, which allows computations on encrypted data, and trusted execution environments, which secure computations on hardware-level. Together, these techniques create a multi-layered defense that mitigates risks of data leakage, inference attacks, and regulatory non-compliance, allowing institutions to collaborate confidently on credit scoring models.

4.5. Communication protocol and aggregation methods

Efficient communication and aggregation protocols are vital in federated learning due to the distributed nature of the system and the potentially large number of participating institutions. Communication involves iterative exchanges of model parameters or gradients between clients and the central server, often over unreliable or bandwidth-limited networks. Protocols must optimize for minimal communication overhead while maintaining synchronization and model convergence. Techniques such as update compression, quantization, and asynchronous updates can reduce communication costs. The aggregation method, typically a weighted averaging of client updates, must account for variations in dataset sizes and quality across institutions. More sophisticated aggregation strategies include adaptive weighting based on model performance, robustness to adversarial updates, and incorporation of fairness metrics. These methods aim to produce a global model that fairly and accurately represents the diverse datasets while mitigating the influence of noisy or biased updates. The communication and aggregation design ultimately impact the system's scalability, convergence speed, and privacy guarantees.

5. IMPLEMENTATION DETAILS

5.1. Dataset description and preprocessing

The foundation of any credit scoring model is the underlying dataset, which typically consists of borrower profiles, financial transaction histories, loan repayment records, and demographic attributes. For this federated learning framework, we utilize datasets sourced from multiple financial institutions, each containing distinct, institution-specific customer data. These datasets often vary in feature representation and data quality, necessitating thorough preprocessing to ensure compatibility for federated training. Preprocessing steps include data cleaning to handle missing or inconsistent entries, normalization or standardization of numerical features, and encoding of categorical variables using methods such as one-hot encoding or embeddings. Additionally, feature alignment across institutions is crucial; common features must be identified and standardized to enable meaningful aggregation of model updates. To simulate realistic federated conditions, data partitions are

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maintained locally at each institution, and preprocessing pipelines are deployed independently, preserving data privacy while ensuring the data's suitability for machine learning.

5.2. Training setup across institutions

The federated training setup involves multiple institutions acting as clients, each training local models on their respective private datasets. These local training processes follow synchronized rounds coordinated by a central server, which aggregates model updates to refine a global model. Training parameters, such as learning rate, batch size, and number of local epochs per round, are carefully selected to balance convergence speed with computational load on client devices. Given the heterogeneity in data size and distribution, weighting mechanisms are incorporated during aggregation to ensure that institutions with larger or higher-quality datasets contribute proportionally to the global model. Robust communication protocols are established to handle intermittent connectivity and latency, ensuring fault tolerance. Additionally, hardware and software environments at client sites are configured to support the computational requirements of local training while safeguarding sensitive data through encryption and secure enclaves where applicable.

5.3. Privacy mechanism parameters

Implementing privacy-preserving mechanisms within federated learning requires careful calibration of parameters to achieve an optimal trade-off between data privacy and model utility. Differential privacy is parameterized by a privacy budget (epsilon), which quantifies the level of privacy protection; smaller epsilon values offer stronger privacy guarantees but may introduce more noise, potentially degrading model performance. The noise addition process is designed to obscure individual data contributions during local model updates or global aggregation. Secure aggregation protocols are configured to cryptographically mask individual updates, preventing the central server or adversaries from accessing raw model gradients. Parameters such as encryption key sizes, aggregation threshold values, and noise distribution types (e.g., Gaussian or Laplace) are tailored based on threat models and regulatory requirements. The system monitors privacy leakage risks continuously, adjusting parameters dynamically to maintain compliance without excessively compromising predictive accuracy.

5.4. Evaluation metrics (accuracy, AUC, fairness, privacy leakage)

Evaluating the federated credit scoring framework demands a comprehensive set of metrics that capture both predictive performance and privacy guarantees. Accuracy and Area Under the Receiver Operating Characteristic Curve (AUC-ROC) are standard metrics used to assess the model's ability to correctly classify borrowers as defaulters or non-defaulters, reflecting overall predictive power. Given the critical importance of fairness in financial decision-making, fairness metrics such as demographic parity, equal opportunity, and disparate impact are calculated to detect and mitigate biases across demographic groups. Privacy leakage is assessed through empirical privacy audits and theoretical bounds derived from differential privacy parameters, measuring the potential exposure of individual data points during training. Additional metrics include convergence speed,

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communication overhead, and computational efficiency, which provide insights into the practical viability of the federated learning system in real-world deployments.

6. EXPERIMENTAL RESULTS

6.1. Performance comparison: Federated learning vs centralized vs local models

The experimental evaluation compares the federated learning framework against traditional centralized and isolated local modeling approaches. Centralized models, trained on aggregated data pooled from all institutions, typically achieve the highest predictive accuracy due to access to the full dataset, but at the cost of violating privacy constraints. Local models, trained independently at each institution, maintain privacy but often suffer from limited generalization and biased predictions due to smaller, institution-specific datasets. Federated learning strikes a balance by enabling collaborative training without raw data sharing. Results demonstrate that federated models achieve performance close to centralized models, substantially outperforming local models in terms of accuracy and AUC. This improvement validates the efficacy of federated learning in leveraging distributed data while respecting privacy, providing a practical alternative for cross-institution credit scoring.

6.2. Impact of privacy constraints on model accuracy

Integrating privacy-preserving mechanisms, especially differential privacy, introduces noise that can impact the accuracy of federated credit scoring models. Experimental results explore how varying the privacy budget affects model performance, showing that stricter privacy guarantees (lower epsilon) typically reduce accuracy due to increased noise. However, the decline is often gradual, and by tuning noise parameters and training protocols, federated learning can maintain acceptable predictive performance within regulatory-compliant privacy limits. The experiments highlight the delicate trade-off between privacy and utility, emphasizing the need for carefully designed privacy mechanisms that minimize performance degradation while protecting sensitive financial data.

6.3. Robustness and fairness analysis

Robustness of the federated learning framework is evaluated by assessing model stability under varying data heterogeneity and client participation scenarios, including cases of intermittent client dropout or adversarial updates. The analysis confirms that the system can maintain stable convergence and reliable credit scoring despite such challenges. Fairness analysis examines whether the federated model introduces or mitigates biases against protected groups defined by race, gender, or socio-economic status. Results indicate that federated learning can improve fairness by leveraging diverse datasets, but also caution that privacy noise and aggregation strategies may inadvertently affect fairness metrics. These findings underscore the importance of integrating fairness-aware algorithms and continuous monitoring within the federated learning lifecycle.

6.4. Communication cost and scalability analysis

Communication overhead is a critical factor influencing the feasibility of federated learning in real-world financial networks. The experiments measure the volume of data exchanged during model

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updates and the frequency of communication rounds, demonstrating that communication-efficient protocols such as update compression and sparse transmission significantly reduce bandwidth requirements. Scalability tests involving increasing numbers of institutions show that the framework maintains reasonable convergence times and resource utilization, confirming its suitability for large-scale deployments. Nonetheless, the analysis identifies bottlenecks related to network reliability and synchronization, suggesting areas for further optimization to enhance scalability and reduce latency in federated credit scoring systems.

7. DISCUSSION

7.1. Benefits of federated learning for cross-institution credit scoring

Federated learning offers transformative benefits for credit scoring across institutions by enabling collaborative model development without compromising data privacy. It enhances model accuracy by aggregating knowledge from diverse datasets, thus capturing broader borrower behavior and reducing biases inherent in isolated models. Privacy-preserving protocols foster trust among financial institutions and customers by ensuring compliance with data protection laws, mitigating risks of data breaches and unauthorized sharing. Moreover, federated learning facilitates innovation in credit scoring by allowing institutions to experiment with advanced machine learning techniques collaboratively. The approach promotes financial inclusion by enabling better risk assessment for underserved populations while preserving individual privacy, ultimately leading to more equitable lending practices.

7.2. Limitations and challenges (e.g., data heterogeneity, system complexity)

Despite its advantages, federated learning for credit scoring faces significant limitations and challenges. Data heterogeneity across institutions can impair model convergence and degrade performance if not properly addressed through adaptive aggregation or personalized models. System complexity increases with the need for secure communication channels, synchronization protocols, and privacy mechanisms, requiring sophisticated infrastructure and expertise. Privacy-preserving techniques may introduce computational overhead and reduce model accuracy due to noise addition. Additionally, real-world deployment must contend with legal ambiguities, data governance policies, and potential adversarial behaviors such as model poisoning. These challenges necessitate ongoing research and development to refine federated learning frameworks and ensure their practical viability in the financial sector.

7.3. Regulatory and ethical considerations

Regulatory compliance remains a central consideration in deploying federated credit scoring systems. Institutions must navigate evolving data protection laws that vary across jurisdictions, ensuring that collaborative model training respects consent requirements, data subject rights, and auditability standards. Ethical considerations include preventing algorithmic biases that could reinforce systemic discrimination and ensuring transparency in automated credit decisions. Federated learning frameworks should incorporate explainability features to facilitate regulatory scrutiny and customer trust. Furthermore, mechanisms for accountability and redress must be

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established to address potential harms arising from model errors or privacy breaches. Balancing innovation with ethical responsibility and legal adherence is crucial for sustainable adoption of federated learning in finance.

7.4. Future research directions

Future research in federated credit scoring should focus on enhancing robustness to data heterogeneity through personalized federated learning techniques and domain adaptation methods. Exploring hybrid models that combine the interpretability of traditional credit scoring with the flexibility of deep learning could improve acceptance in regulated environments. Advances in privacy-preserving technologies, such as improved differential privacy algorithms and lightweight secure computation protocols, will further mitigate privacy-utility trade-offs. Additionally, research into fairness-aware federated learning algorithms can help ensure equitable outcomes across diverse populations. Investigating decentralized federated architectures without central servers may enhance resilience and trust. Lastly, empirical studies on large-scale deployments will provide valuable insights into operational challenges and guide the development of best practices for federated learning in the financial industry.

8. CONCLUSION

This paper has explored the application of federated learning as a novel and effective approach to cross-institution credit scoring under stringent privacy constraints. By enabling multiple financial institutions to collaboratively train credit scoring models without sharing sensitive raw data, federated learning addresses the pressing challenges posed by data privacy regulations such as GDPR and CCPA, while enhancing predictive performance beyond isolated local models. Our framework demonstrates how privacy-preserving techniques, including differential privacy and secure aggregation, can be seamlessly integrated to safeguard individual customer information without substantially compromising accuracy. Experimental results highlight that federated learning achieves comparable predictive performance to centralized approaches and significantly outperforms local models trained independently by individual institutions. Furthermore, the framework shows promise in improving fairness by leveraging diverse datasets, although it also underscores the complexity introduced by privacy mechanisms in maintaining unbiased decision-making. Communication-efficient protocols ensure the system's scalability and feasibility across distributed institutional environments. Despite these advantages, the paper acknowledges persistent challenges such as data heterogeneity, system complexity, and the balance between privacy and model utility, which require further research and optimization. The implications for financial institutions are profound: federated learning paves the way for secure, compliant, and collaborative credit risk assessment that can enhance lending decisions while protecting customer privacy. For policymakers, the findings emphasize the importance of fostering regulatory frameworks that support innovative privacy-preserving technologies without stifling financial innovation. Ethical considerations around fairness, transparency, and accountability remain critical, necessitating continued vigilance and methodological advancements. Looking ahead, future work should focus on refining personalized federated learning techniques, improving privacy-utility trade-offs, and developing fairness-aware

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algorithms to ensure equitable outcomes. This research establishes federated learning as a promising paradigm for the financial industry, balancing the dual imperatives of data privacy and model effectiveness, and sets a foundation for responsible, scalable, and collaborative credit scoring in an increasingly interconnected and regulated digital economy.

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