Personal Credit Score Generator using Federated Learning for Financial Stress Management

Ravneet Kaur[1], Seema Wazarkar[1], Rohit Jain[1], Ripul Ahuja[1], Ishit Bajaj[1], and Saloni Bali[1]

Thapar Institute of Engineering and Technology, Patiala, Punjab, India
{ravneet.kaur1, seema.wazarkar}@thapar.edu

Abstract. Credit risk management is an essential activity to avoid financial stress beforehand. Multiple subjective and quantitative factors such as balance, payments, etc. are used to predict credit risks. The prevailing advancements in Artificial Intelligence have led to the advent of machine learning to generate effective predictive models by using user data. Utilization of data from multiple sources at different locations is useful to create better models. However, data sharing is challenging as it the privacy of users' sensitive data at risk and incurs huge communication costs. Federated learning is a technique in which an algorithm is trained across numerous decentralized edge devices or servers without sharing original local data samples. In this research work, all the data furnishers participate with personal credit data, and the model is trained on the data silos of multiple financial institutions and banks without even seeing the data rather than the traditional method of sending all the data by data furnishers to the Data Bureaus and then doing analysis. Users of the proposed framework will utilize federated learning to generate credit scores without relying on data suppliers to deliver information. FedAvg method with Stochastic gradient descent classification performs optimally in the proposed system. Prior knowledge of the credit score is useful to plan and optimally handle the credit risks to avoid financial stress efficiently.

Keywords: Federated Learning · Artificial Intelligence · Machine Learning · Credit Risk · Distributed Servers, · Privacy Preserving

1 Introduction

According to the current lifestyle changes mental health is being affected by multiple types of stressors such as academic and career growth, family responsibilities, physical health conditions, financial and social conditions, etc. In current times, it is essential to identify efficient ways to handle such stressful situations by planning day to day tasks wisely. Credit risk management is an essential activity for every individual in financial planning. It helps in avoiding high financial stress in the future [3]. Various subjective and quantitative factors are used to predict credit risks. The prevailing advancements in artificial intelligence has led to the advent of machine learning to generate effective predictive models by using customer data from financial organizations. Better models can be created by using data from multiple institutions.

But sharing of data from multiple institutions puts the privacy of users' data at risk and incurs huge communicationcosts.

Federated learning is a technology where an algorithm is trained across multiple decentralized edge devices or servers, with each device keeping its data locally rather than sharing it. Unlike traditional centralized machine learning, which requires all data to be collected on a single server, federated learning operates without pooling the data together. This method also differs from traditional decentralized approaches, which often assume data is evenly distributed among participants. By allowing multiple entities to collaborate on a shared, powerfulmodel without exchanging data, federated learning addresses key concerns such as data privacy, security, data ownership, and access to diverse datasets.

Promisingly, developments in federated learning enable secure and international credit scoring, and through this research work, a model has been introduced where data need not travel to a model for the analysis rather the model is sent to different data silos, and an aggregated model is built. Hence, in this research work, all the data furnishers with individual's data of credit will participate and model will be trained on the data silos of all the financial institutions/ banks without even seeing the data. A federated learning-based approach is developed that enables the institutions to collaboratively create a shared prediction model while ensuring that all data remains within each institution. This approach eliminates the need for cloud storage, thereby decentralizing the machine learning process. The users can use it to generate personalized credit scores forcustomers rather than relying on data suppliers to deliver information to them.

Federated Learning (FL) technology focuses on privacy-preserving collaborative machine learning, where data remains with its original providers. This approach allows multiple organizations to collaboratively train a shared machine learning model without the need to transfer data between them. In practice, when training a scorecard model, significant time is often required for parameter tuning to avoid multicollinearity among variables. This process ensures that the model coefficients are non-negative, which helps maintain the interpretability and robustness of the scorecard.

The idea of credit assessment and its methods have rapidly advanced since the 1950s, helped by the growth of knowledge and technology to keep up with the rise in consumer demand following the introduction of credit cards. Advanced technologies like data mining, machine learning, and AI have been a huge help in developing new models that guarantee greater accuracy when predicting a person's risk performance [11]. To address the current issues with credit scoring, experts suggest using an artificial intelligence-based federated credit evaluation platform. In order to integrate diverse data sources and create high-dimensional digital representations of consumers, it makes use of a cutting-edge machine learning engine.

Our contribution is to design the framework for personal credit score generation to identify credit score risk. It will help to plan and reduce financial stress in the future. Furthermore, to suggest optimal machine learning and aggregation models to gain approximately similar scores to real-world scores provided by agencies. The framework has five essential parts: a unified credit score, information fusion, privacy protection, cognitive modeling, and representation learning. The main benefit of federated AI is to guarantee data confidentiality, in which case no local data is purposefully transmitted outside for machine learning. However, re-identification of an individual based on high dimensional feature matching is possible. To strike a balance between privacy and data value, experts suggest using user-level differentially private representations [4]. In order to capture the sensitivities of consumer data and determine the degree of representation learning while obtaining acceptable performance for credit scoring, our federated AI uses cutting-edge neural network architecture.

The rest of the paper has been structured as follows. Section 2 presents the works related to the applicability of Federated learning and its need in practice. Section 3 presents the proposed federated learning approach for credit scoring. Section 4 focuses on the experimental results obtained using federated learning. Finally, section 5 concludes the paper.

2 Related Work and Need Analysis

Traditional machine learning necessitates massive storage devices for data transport and storage, as well as significant processing power to train a huge quantity of data kept in a single location. To solve all of these challenges, a privacy-based credit scoring system based on Federated Learning is required.
According to Kawa et al. [8], financial institutions used to use a traditional approach to create a credit risk rating that took into account a variety of quantitative and subjective variables. This strategy proved to be reactive rather than proactive. As a result, it was necessary to create reasonably accurate quantitative prediction models, which could be accomplished using the Federated Learning method.
Likewise, Shingi et al.[11] developed machine learning models for banking applications, but the security of sensitive customer data remains a critical concern. Due to strict legislative regulations, sharing this data with other organizations is prohibited. Additionally, the loan dataset used in their work was highly imbalanced, with far fewer samples of defaults compared to repaid loans. These challenges make it difficult for the default prediction system to effectively learnand predict default patterns.
Also, the existing machine learning approaches for automating this process have relied on training models using data from within the same organization. However, in today's world, classifying loan applications based solely on internal organizational data is neither sufficient nor practical.
A comprehensive review was conducted by Yin et al. [14] to review different privacy-preserving techniques in federated learning providing a taxonomy as well as future research aspects. Some privacy leakage risks relevant to federated learning were discussed to foster future development. Likewise,

Rathika and Pushparaj [10] discussed the application of federated learning in credit card scoring, highlighting privacy preservation methods.
Truex et al. [12] proposed a novel federated learning system that provides formal privacy guarantees using secure computation techniques. Similarly, He et al. [7] proposed a decentralized credit scoring technique using vertical federated learning to securely leverage multi-source information. Abadi et al. [1] introduced Starlit, a scalable privacy-preserving federated learning mechanism designed to enhance financial fraud detection. Xu et al. [13] presented HybridAlpha, an approach that combines federated learning with privacy preservation mechanisms to handle participant dropout. Fang et al. [6] proposed a scheme for federated learning that ensures strong privacy preservation while maintaining model utility

2.1 Why Federated Learning and Related Algorithms

By gathering data from many banks, machine learning models can be enhanced with more data. The following considerations make centralised data collection an untenable solution:

- For commercial reasons, banks would be reluctant to disclose their private information to outside parties.
- Concerns with the security and administration of training data at the facility.
- It is challenging to transfer huge amounts of data over an expensive or unstable network.

The above-mentioned causes make centralised data storage susceptible in today's world of growing privacy concerns. A novel technique to machine learning called federated learning keeps all training data within the client. Instead of sharing data, the client computes weight changes using data that is accessible locally. This type of machine learning involves collaboration amongst several clients, who divide the training process. Storing all the training data locally on each device, without needing centralization, allows devices to collaboratively build a shared model.
In comparison to traditional machine learning techniques, federated learning has more independent and uniformly dispersed data. Devices used for federated learning may have lesser throughput, increased latency, and sporadic availability. As a result, the Federated Averaging Algorithm (FedAvg) [5], which communicates 10–100 times less than the federated version of Stochastic Gradient Descent, is introduced. Additionally, through random rotation and quantization compressing the model updates, the uploading costs are decreased by a further 100x. Federated learning significantly minimizes privacy and security risks by limiting the attack surface to just the device, rather than both the device and the cloud. Instead of sending data from all banks to a central server for algorithmic processing, federated learning allows for decentralized data usage while still enabling effective training. Due to potential data breach vulnerabilities and other commercial problems, this is not a workable solution. Data collection in one location can raise the likelihood and scale of assaults.

We suggest using federated learning to analyse credit risk. A centrally approved institution serves as the system's central server in the proposed design, coordinating with the federation of clients, or bank servers, where major portion of the work is done.
An initialised model is available on the server to start. In Federated Learning, some clients are chosen at random to enhance the model. Since there are just a few number of banks in India, we suggest choosing all of the customers for each iteration in order to develop the model. This will allow us to take into account every bank and create a system that is consistent across all of them. Each client receives the server's most recent model. Each client uses its own local data to train the model. The server then receives and aggregates all of the model updates. The aggregate is added to the central model, which is then delivered to customers for additional rounds. Repeating this technique results in convergence.
FedAvg [9] [5] is the most well-known federated optimizer. In this method, a coordinating server works with participating data controllers to coordinate federated averaging rounds. The following lists the steps of the algorithm:

- Model is started by the coordinating server, referred to as the coordinator.
- For a training cycle, coordinator chooses at random a subset of data-holders.
- The coordinator hands the chosen runners the global model.
- After obtaining global model, the runners alter the parameters locally before being sent to the coordinator.
- Coordinator has the responsibility to average the model parameters for each model that has been obtained from the training round's runners.
- The process is repeated until a stopping requirement is satisfied.

An important feature of this method is its expansion of the Federated Stochastic Gradient Descent (FedSGD) method. FedSGD averages the local model gradients over rounds. Of course, the approach's drawback is the high frequency of communication required for model convergence between the coordinating server and clients. Contrarily, for FedAvg a minimum number of training epochs are required before average is computed which indeed leads to computation cut down. According to the "small communication, huge computation", FedAvg is predominantly considered as CPU-bound and FedSGD is primarily Input-Output bound. Even though approach enables us to scale FedAvg to large data volumes, thereis high possibility of local models diverging among rounds thereby over-fitting to the local data. Therefore, there needs to be a balance between count of trainingepochs (local) and FedAvg training rounds.

3 Proposed Approach

The proposed methodology is designed for the development of an effective federated learning-based privacy-preserving framework for personal credit score generation to avoid financial risk and ultimately financial stress. The proposed framework has been described in Figure 1.

Model Building and Training on Duet

- Model is developed by the data scientist and sent on the duet server of the clients that get trained.

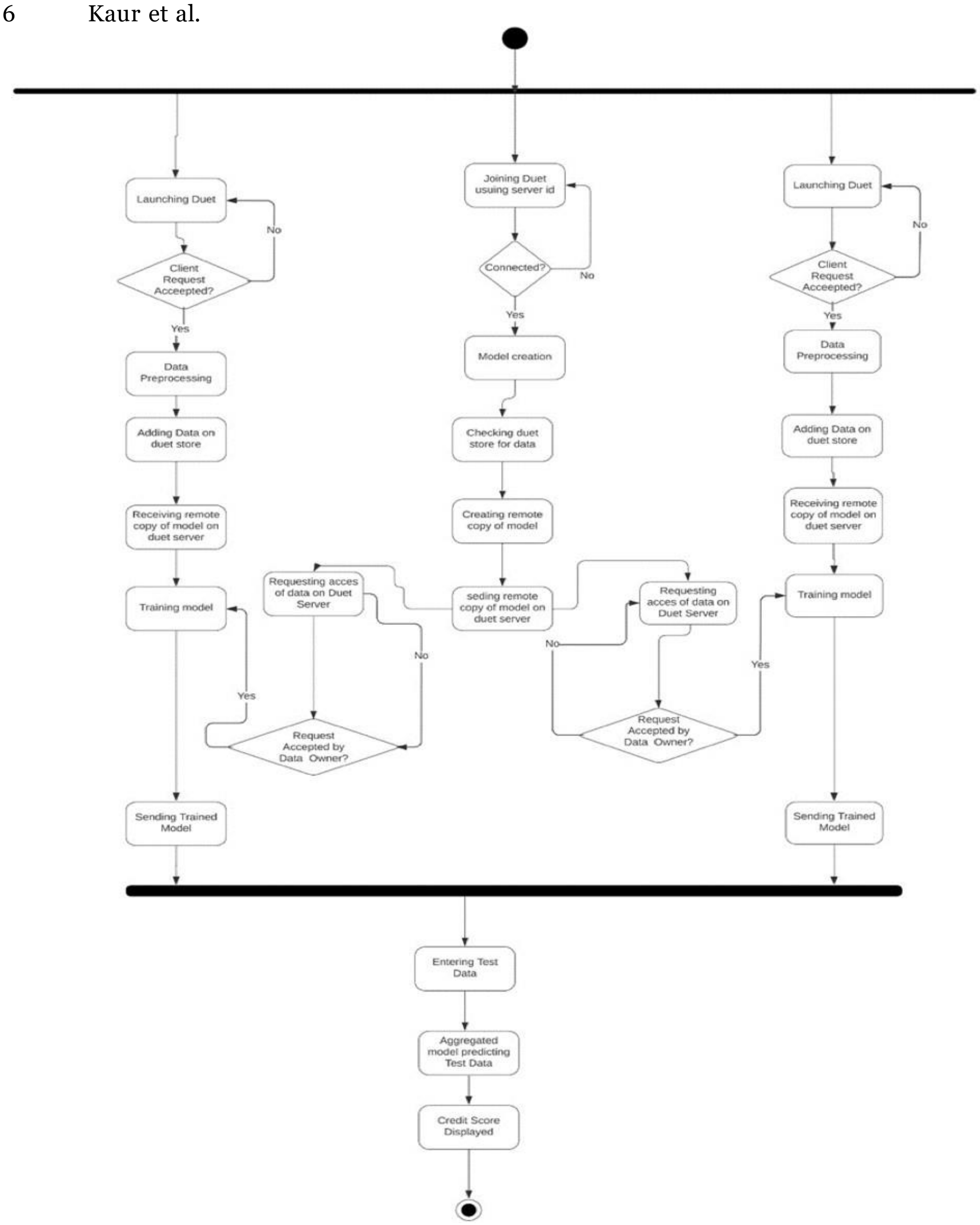

Fig. 1. Proposed Framework

- Each client at the server receives the most recent model. Each client uses its own local data to train the model.
- After that, the server receives and aggregates all of the model updates.
- Aggregate is added to the central model, which is then delivered to customers for additional rounds. Repeating this technique results in convergence.

Testing Model

- A model is started by the coordinating server, referred to as the coordinator.
- For a training cycle, coordinator chooses at random a subset of data-holders.
- The coordinator hands the chosen runners the global model.

– After obtaining the global model, the runners locally alter its parameters before sending it back to the coordinator.
– The coordinator takes the model parameters each runner gave during the training round and averages them.
– The process is repeated until a stopping requirement is satisfied.

After model is trained, model will be tested on the validation dataset and accuracy will be calculated.

3.1 Dataset

American Express Official dataset [2] from the kaggle was selected for credit scoring. The dataset involves instance of hackathon conducted by the Amex. The dataset is intended to predict the probability of a customer to be the defaulter for not paying their credit card bills. In this research work, the said dataset has been used for computing credit score privately using federated learning. As the features of the dataset was large (384 features), PCA was applied for dimensionality reduction to improve the model performance and decrease the model computations.
For a detailed explanation, a sequence diagram (Figure 2) has been constructed to show how the connections are first established between the data owners and data scientist and how the model is aggregated, updated and used for predicting the credit score of an individual.

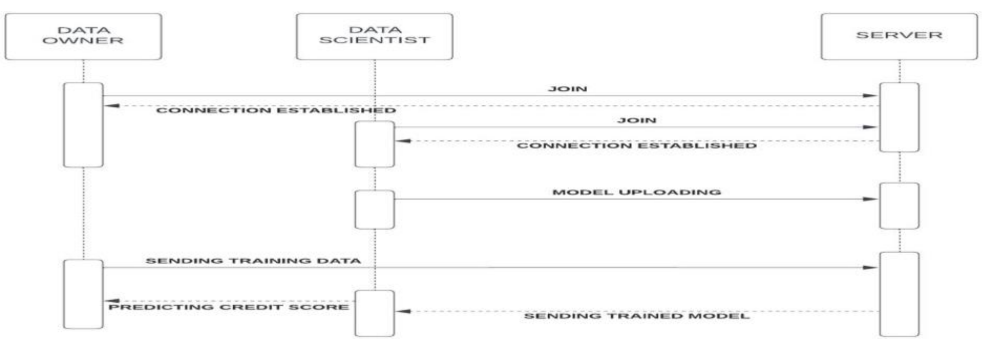

Fig. 2. Sequence Diagram depicting the connections and aggregation of model

4 Results and Discussion

This section involves the demonstration of the results obtained after bringing the proposed model into practice.

4.1 Experimental Setup

– The model created in the research work need to be set up on the DataOwner's PC as well as the DataScientist's PC.
– First we have to first start duet on the DataOwner's side and on starting we will be getting a duet ID.
– This ID would be required by the DataScientist.

- When DataScientist will enter the DataOwner's Id, it will get a client ID.
- After entering this Client ID at the DataOwner's end the connection is established and now the DataOwner can send its local model gradients to the Data Scientist for aggregation.

Procedural Workflow of the model has been demonstrated in Figure 3.

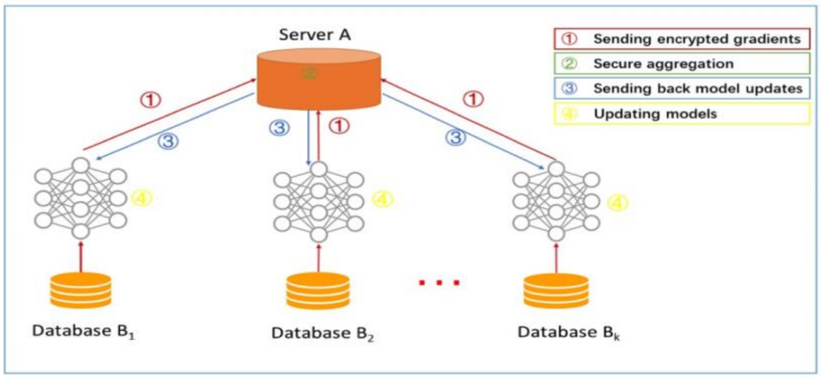

Fig. 3. Procedural Workflow of the model

- The model will be trained locally on the local dataset.
- The global server will get the local model parameters.
- In the global server the aggregation of the parameters is done securely.
- The updated models are then delivered back to the local models for local model updating.
- After that the model is updated for the final prediction.
- At the last the prediction can be made by the user by inserting the details.

In the present work, two algorithms have been used for the credit scoring namely, Duet and FedAvg.
Duet: In the algorithm, initially the connection is established between data owner and data scientist and the model is sent to data owners server and the weights are returned to data owners. The weights from different data owners is combined for the final model and predictions are made.
FedAvg: In this approach, the central model is made and the workers/data owners are selected randomly from all data owners. Model is trained from those workers and combined privately. The model trained is sent to data owners again after a certain period of time, say 15 days to get trained on new dataset by owner and hence, the global model is updated.

4.2 Results and Discussions

American Express Official dataset from the kaggle hackathon conducted by the Amex for the credit scoring has been used for training and testing. We used this dataset for the computing credit score privately using federated learning. As the features of the dataset was large, PCA was applied for dimensionality reduction to improve the model performance and decrease the model computations. Table 1 is used to represent the performance evaluation of the method. After train-

Table 1. Performance evaluation using different performance parameters

Parameter	Value
Root Mean Square Error (RMSE)	26.090
Mean Square Error (MSE)	68.738
Mean Absolute Error (MAE)	24.493
R-Squared Error (R2)	0.92665

ing the model, testing is performed using the test file present in the American Express Kaggle Dataset. The input parameters in the test set include credit-limit, credit-score, previous defaults, age. The computed credit score is to be tested i.e. the result of the test data is computed in the form of credit score. The performance parameters like Mean Absolute Error, Mean Squared Error, Root Mean Squared Error, R-Squared are evaluated. Performance evaluation on some of the test cases after applying PCA dimensionality reduction are as tabulated in Table 2. Alongside, F-score was calculated for both local and FedAvg Model, the comparison of which is shown in Figure 4.

Table 2. Test cases

Input Features after applying PCA	**Predicted Credit Score by Fed- erated LearningModel**	**Predicted Score by Machine Learning Model**	**Credit Score by Bureau**
[453, 633]	569.065	573.232	543
[435, 702]	752.0283	753.245	745
[494, 683]	763.04827	759.433	778
[513, 653]	701.10028	698.934	712
[482, 667]	581.52026	590.237	564

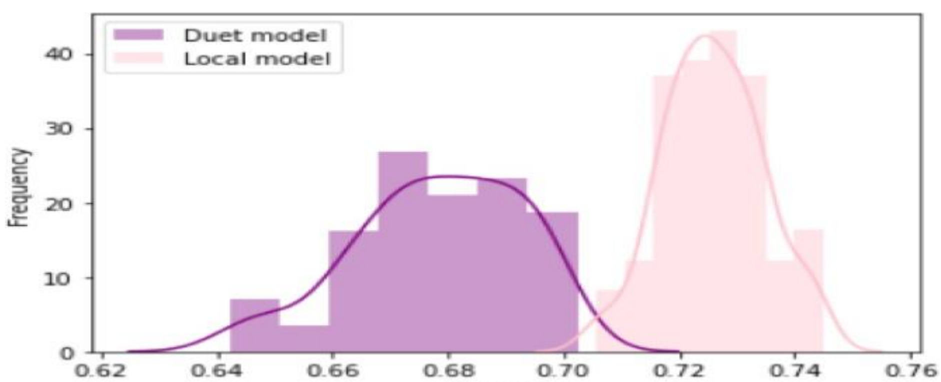

Fig. 4. F-score performance of local and FedAvg Model

From the experiment analysis, itwas inferred that machine learning model when compared to the federated learning model may work a bit better but the major concern with machine learning models is that the privacy of individuals is often at risk. Also, the FedAvg model works closely with the best machine learning model when tested and can be used for optimization of our model.

When comparing Duet and FedAvg, Duet is an efficient method when the testing of the federated Learning model is to be carried out. PCA helps a lot in reducing the computation time when the dataset is large. The combined model work well when weights from different owner models are combined and further credit score losses are reduced.

The proposed framework has limitations as follows: 1. Multiple financial organizations need to be involved. 2. Local models will required to train at those financial institutions. 3. Original data will not be available at server if required.

5 Conclusion

In the proposed Federated Learning framework, Credit Score Prediction is performed using Federated learning through two approaches i.e. Duet and FedAvg. In the first scenario, a local server using duet was created and the data was shared from the data owner machine to the data scientist machine and model was trained on the shared data. Duet was not an optimal option since it is generally used for testing purpose. Therefore, the focus was shifted to FedAvg method using Stochastic gradient descent classification model which resulted in better outcomes similar to real-world scenario. In the FedAvg method, a minimum number of training epochs was set, and then averaging was taken which saved the computation and thus helped with large data volume as in real-world scenarios for credit score prediction for individual financial planning to reduce financial stress in the future.

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