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Application of Compressed Sensing in Federated Learning

Lei Fang[1,*] and Yucheng Ge[2]

[1] Communications Engineering, Chongqing University Of Posts And Telecommunications, Chongqing, China
[2] Mechanical Engineering, Tianjin Sino-German University of Applied Sciences, Tianjin, China

*Corresponding author: 2279385@brunel.ac.uk

Abstract:

Compressed sensing, as an important signal processing technology, uses the sparsity or structure of the signal to reconstruct the original signal with samples much lower than the traditional sampling rate. Federated learning (FL), as a distributed machine learning method that allows model training without sharing sensitive data, provides an effective way to share knowledge across devices and organizations. Combining compressed sensing with federated learning has potential synergistic advantages, which can not only achieve efficient information extraction and transmission, but also protect personal privacy data. This paper aims to explore how compressed sensing technology can be applied to federated learning to accelerate the model training process, improve model accuracy, and ensure data privacy. By deeply studying this field, this paper reveals the potential applications, challenges and future development directions of compressed sensing in the federated learning environment, and promotes further innovation and application in the field of federated learning. Through comprehensive experiments and analysis, this paper provides insights into the integration of compressed sensing within federated learning frameworks, highlighting its role in optimizing communication efficiency and resource utilization.

Keywords: Compressive Sensing; Federated Learning; Data privacy.

1. Introduction

With the rapid development of big data and artificial intelligence, protecting data privacy and security has become an important topic in modern machine learning. Traditional centralized machine learning methods require data to be aggregated to a central server for processing, which undoubtedly increases the risk of data leakage, especially in sensitive fields such as medicine and finance. Therefore, federated learning (FL) came into being. As a decentralized learning method, it allows multiple devices to jointly train models without sharing data, ensuring the privacy of data. However, federated learning still faces many challenges in practical applications, especially the high communication cost and non-IID.

The core of federated learning is to avoid privacy leakage by transmitting model parameters rather

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than data to the server for aggregation. However, the frequent communication needs between multiple devices lead to huge bandwidth consumption, especially when the number of participating devices increases. This problem is particularly prominent. To this end, many scholars have proposed various optimization algorithms to reduce communication costs. For example, McMahan et al. [1] proposed a communication-efficient federated learning algorithm that achieves efficient model learning by reducing data transmission between the client and the server. In addition, the research of Reddi et al. [2] pointed out that by optimizing the problem of inconsistent learning speeds between clients, the convergence speed of the model can be effectively improved.

Although these optimization methods have alleviated the communication problem in federated learning to a certain extent, data heterogeneity is still a key challenge to be solved. The non-IID distribution of client data will lead to a decline in global model performance. In response to this, Khaled et al. [3] proposed a distributed convex optimization algorithm that performs well in complex distributed systems, especially when processing large-scale data, the convergence speed is significantly improved. These studies provide strong theoretical support for our understanding and solution of the challenges in federated learning.

In terms of solving the communication cost problem in federated learning, compressed sensing (CS) technology provides a new idea. Compressed sensing reconstructs signals from data far lower than the traditional sampling rate by utilizing the sparsity of signals, thereby significantly reducing the amount of data transmission. Candes and Wakin [4] systematically introduced the principles of compressed sensing in their research and demonstrated its potential in data reconstruction and signal acquisition. Baraniuk et al. [5] further expanded this theory and proposed a model-based compressed sensing method that significantly improved the efficiency of signal processing. By combining compressed sensing technology, the communication overhead in federated learning can be greatly reduced, while the accuracy of the model can also be guaranteed [6,7].

In the face of the problems of privacy and communication efficiency, Ye Liu et al. [8] proposed Cepe-FL technology, which combines compressed sensing and adaptive compression technology to effectively solve the communication overhead and privacy protection problems in federated learning, and significantly reduce the communication cost while ensuring the accuracy of the model.

The main contribution of this paper is to sort out and summarize these research results in detail, and systematically analyze the advantages and disadvantages of different technologies and their application scenarios. In particular, the advantages of compressed sensing technology in reducing communication costs and its combination with existing federated learning optimization algorithms. This paper also looks forward to possible future research directions, including how to optimize and promote these technologies in more complex application scenarios to cope with higher computing and communication.

2. Organization of the Text

2.1 Compressed sensing(CS)

CS relies on two principles: sparsity, which pertains to the signals of interest, and incoherence, which pertains to the sensing modality [9].

2.1.1 Sparsity

Sparsity refers to the property that the “information rate” of a continuous-time signal may be much smaller than predicted by its bandwidth, or that a discrete-time signal depends on a number of degrees of freedom that is much smaller than its (finite) length. More precisely, CS exploits the fact that many signals are sparse or compressible when expressed in an appropriate basis [9].

2.1.2 Incoherence

Incoherence expands the duality between time and frequency and expresses that the incoherence in $\varnothing$ must be spread out in the domain from which they were obtained, just as a Dirac or spike in the time domain spreads out in the frequency domain. In other words, incoherence indicates that unlike the signal of interest, the sampled/sensed waveform in $\varnothing$ [9].

In summary, CS is a very simple and efficient signal acquisition protocol that, unlike traditional sampling theorems, samples at a low rate and later uses computational power to reconstruct the signal from a seemingly incomplete set of measurements.

2.2 Federated Learning

Federated Learning is a distributed machine learning method that allows multiple devices to collaboratively train global models without sharing data. In this way, federated learning can fully utilize the local computing power of each client while protecting data privacy. An important feature of federated learning is its decentralized training mechanism. The client updates the model locally, and the server is only responsible for aggregating the model parameters of each client. This method avoids the direct transmission of sensitive data, thereby enhancing data privacy protection.

However, federated learning faces several challenging issues, including non-IID data and high communication cost. Since the data distribution of each client is often uneven, this will lead to decreased training efficiency and accuracy of the global model.To address these challenges, many optimization methods have been proposed, such as the distributed deep learning algorithm proposed by Miao Y et al. [8] that makes communication more efficient and effectively reduces the data transmission between the client and the server. In addition, algorithms such as FedProx and FedAvg partially alleviate the problems caused by data heterogeneity by adjusting the client's model update method.

2.3 Integration of Compressed Sensing and Federated Learning

The integration of compressed sensing with federated learning offers new approaches to address high communication costs and data heterogeneity. By applying compressed sensing to model transmission in federated learning, clients can significantly reduce the amount of data that needs to be transmitted without compromising model performance, thus lowering communication overhead. One of the key challenges in federated learning is the substantial bandwidth burden caused by frequent communication between the server and a large number of clients. Compressed sensing effectively reduces data transmission by compressing model parameters.

For example, Miao et al. [8] explored the combination of compressed sensing with contrastive learning (MCFL-CS), as shown in Fig 1, where compressed sensing reduces the transmission of model parameters while differential privacy techniques protect data security. Experimental results demonstrate that this approach not only reduces communication costs but also significantly improves model accuracy in federated learning, particularly in non-IID data environments.

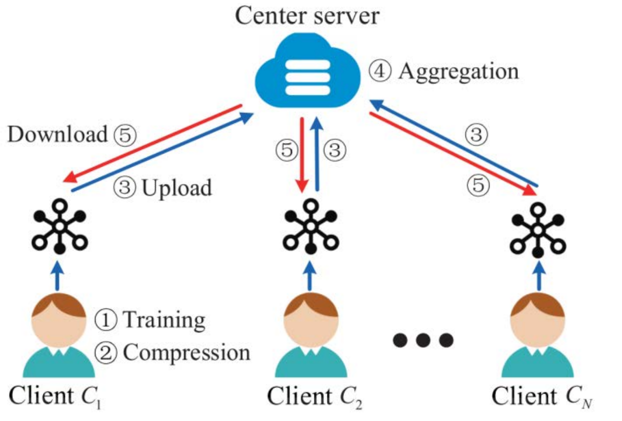

Fig 1: System model of the MCFL-CS scheme [8].

Compressed sensing is also used for node selection optimization to enhance computational efficiency in federated learning. For instance, Islam et al [9]. proposed a compressed sensing method based on sparse regularization, which reduces communication and computational overhead during model updates by selecting important nodes. This method not only accelerates model convergence but also shows greater stability in non-IID data environments.

3. Analysis of Experimental Results

In this section, this paper conducts a detailed analysis of the practical performance of compressed sensing technology in federated learning, focusing primarily on the optimization of communication costs, performance improvement under non-IID data, and the balance between local training rounds and communication efficiency [10]. Through a comprehensive analysis of various experiments, this paper demonstrates that compressed sensing effectively alleviates the common challenges of high communication costs and data heterogeneity in federated learning.

3.1 Optimization of Communication Costs through Compressed Sensing

Communication costs represent a major bottleneck in federated learning, particularly in large-scale distributed training involving multiple devices. During each round of communication, clients and servers need to frequently exchange large amounts of model updates, resulting in extremely high bandwidth demands. Compressed sensing technology significantly reduces the amount of data transmitted per communication round by compressing model parameters. In several experiments, compressed sensing has been shown to reduce communication costs by up to 95% while maintaining model accuracy [6,8].

This effect is especially notable in resource-constrained devices and network environments, such as mobile devices and edge computing. In these scenarios, communication bandwidth is often limited, and frequent data transmission can lead to severe latency and high communication costs. By applying compressed sensing, clients can compress their model updates before uploading, greatly reducing the amount of data transmitted. This not only improves overall system efficiency but also lowers the reliance on high bandwidth. In particular, in scenarios with large data volumes and many devices, such as in smart healthcare and financial risk management, compressed sensing paves the way for the application of federated learning.

3.2 Improvement of Model Performance in Non-IID Data

Non-IID data environments are another significant chal-

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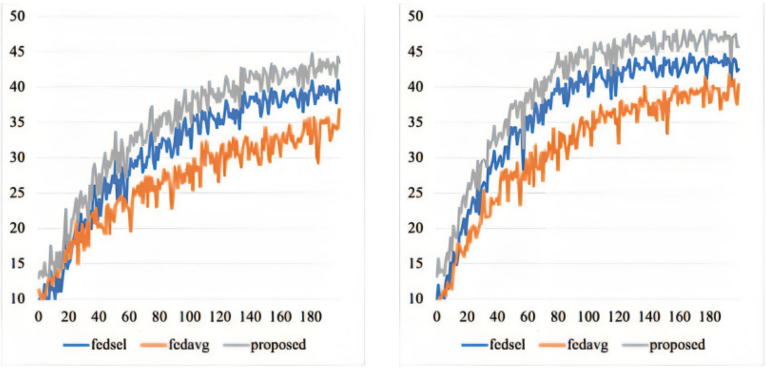
lenge faced by federated learning. In traditional federated learning, models generally assume that data across clients are independently and identically distributed (IID). However, in real-world applications, data across different clients are often unevenly distributed. This data heterogeneity can slow down model convergence and even affect the final model accuracy.

By integrating compressed sensing, federated learning frameworks demonstrate enhanced adaptability to non-IID data [11,12]. By removing unnecessary information and retaining only key features, compressed sensing effectively mitigates the impact of non-uniform data distribution on the global model. Experimental results show that federated learning with compressed sensing achieves approximately 3% to 5% improvements in model accuracy across multiple benchmark datasets. This improvement is particularly evident in image classification tasks. For instance, in the CIFAR-10 and Fashion-MNIST datasets, models utilizing compressed sensing show significant accuracy improvements compared to the traditional FedAvg algorithm. This demonstrates that compressed sensing not only optimizes communication but also enhances model performance in non-IID data environments.

Table 1. Test Accuracy Rankings Across Four Datasets. Results in bold indicate the best performance.

FL algorithms	MNIST	Fashion-MNIST	CIFAR-10	SVHN
MCFL-CS	99.4%	88.6%	70.2%	88.9%
FedAvg	98.4%	82.9%	66.3%	85.7%
FedProx	97.4%	83.6%	66.9%	85.8%
MOON	99.1%	85.4%	69.1%	87.6%
SOLO	90.9%	79.0%	46.3%	80.6%

Additionally, compressed sensing technology reduces the amount of data in model updates, mitigating the bias issues caused by uneven data distribution. This makes the overall performance of federated learning more stable and efficient in real-world applications with high data variability. Figure 2 shows two methods for testing the accuracy of CNN models in multi round communication on the CIFAR-10 dataset.



(a) (b)

Fig 2: Test accuracy of the CNN model on the CIFAR-10 dataset over multiple communication rounds under FedAvg, Fedpns, and the proposed method. Heterogeneity ratios are σ = 0.3 (a) and 0.5 (b)[9].

3.3 Balance of local training rounds with communication efficiency

Adaptive compressed sensing is a technology that combines adaptability and compressed sensing to reduce data redundancy and improve data transmission efficiency during signal collection and transmission. In adaptive compressed sensing, the data collection process dynamically adjusts parameters according to the structure and content of the observed data in order to retain useful information to the maximum extent and remove redundant information during the transmission process. This makes data transmission more efficient, saving transmission bandwidth and storage space.

In this paper, Miao Y [8] and others used compression technology to significantly reduce the communication overhead in federated learning. Experiments show that compared with the traditional FedAvg method, the communication overhead can be reduced by up to 76.2% while maintaining similar model accuracy. And it leads to enhanced privacy protection: since the model parameters are transmitted after compression, the attacker cannot directly restore the original local updates, especially in the absence of compressed base dictionary. Therefore, Cepe-FL significantly reduces the success rate of membership inference attacks, and the inference success rate under white-box attacks is reduced by 20%. Through dictionary learning and adaptive compression, Cepe-FL can still effectively restore model parameters even under large compression ratios, thereby maintaining model performance and improving model reconstruction accuracy.

Suitable for a variety of data distribution scenarios: Experimental results show that Cepe-FL performs well in both IID (independent and identically distributed) and non-IID data scenarios, and its accuracy and communication efficiency have significant advantages over other existing communication efficient methods.

In summary, Cepe-FL combines compressed sensing and adaptive compression technology to effectively solve the communication overhead and privacy protection issues in federated learning, and significantly reduces communication costs while ensuring model accuracy.

3.4 Efficient communication and privacy enhancement through adaptive compressed sensing

Adaptive compressed sensing is a technology that combines adaptability and compressed sensing to reduce data redundancy and improve data transmission efficiency during signal collection and transmission. In adaptive compressed sensing, the data collection process dynamically adjusts parameters according to the structure and content of the observed data in order to retain useful information to the maximum extent and remove redundant information during the transmission process. This makes data transmission more efficient, saving transmission bandwidth and storage space.

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In summary, Cepe-FL combines compressed sensing and adaptive compression technology to effectively solve the communication overhead and privacy protection issues in federated learning, and significantly reduces communication costs while ensuring model accuracy.

4. Challenges and prospects

Although the combination of compressed sensing technology and federated learning has shown remarkable results in solving the problems of high communication cost and data heterogeneity, it still faces some challenges.

First, data heterogeneity remains a core problem in federated learning. When client data is unevenly distributed, although compressed sensing can reduce the amount of transmitted data, excessive compression may lead to information loss, thereby affecting the accuracy of the global model. Especially in scenarios with highly uneven data distribution, the performance of the model may not reach the ideal level.

Secondly, the integration problem of model updates is also an urgent challenge that needs to be solved. When the number of clients increases, how to effectively integrate the model updates of each client to ensure the stability of the global model remains a difficulty. Although compressed sensing can significantly reduce the amount of data transmission, extreme pruning and compression of model parameters may bring more uncertainty in large-scale systems, which places higher requirements on the robustness of federated learning.

Looking to the future, further optimizing the combination of compressed sensing and federated learning is a direction worthy of in-depth study. First, smarter compression algorithms can be explored to achieve the best results under different tasks and data sets by adaptively adjusting the compression ratio. In addition, further strengthening the privacy protection mechanism is also a research focus. In the future, data security can be improved by combining compressed sensing and differential privacy technology

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[13].

Finally, with the rapid development of the Internet of Things and edge computing, how to efficiently deploy federated learning technology in resource-constrained environments will also be the focus of future research. Compressed sensing technology provides effective communication optimization solutions for these scenarios. In the future, more in-depth technology combinations can be used to promote the application and development of federated learning in more practical scenarios.

5. Conclusion

This article reviews the application of compressed sensing technology in federated learning, focusing on analyzing how to reduce communication costs through compressed sensing technology and improve the model performance of federated learning in non-IID data environments. Through the summary and analysis of multiple related studies, this paper explores the advantages of combining compressed sensing with federated learning, especially the potential in dealing with high communication overhead and data heterogeneity. Combined with existing experimental results, compressed sensing technology significantly improves the efficiency and scalability of federated learning by reducing data transmission between the client and the server.

Overall, compressed sensing provides an effective solution to solve the communication bottleneck in federated learning. Experiments show that without sacrificing model accuracy, compressed sensing can significantly reduce bandwidth requirements and show greater robustness in the face of uneven data distribution. Despite this, compression and pruning of model parameters may still cause a certain amount of information loss, especially when data heterogeneity is high, which is still a problem that needs to be overcome in future research.

In the future, with the development of emerging technologies such as the Internet of Things and edge computing, the application scenarios of federated learning will become more widespread. How to further optimize the combination of compressed sensing and federated learning in these resource-constrained environments will be the focus of future research. In addition, the development of intelligent compression algorithms, the combination of differential privacy and compressed sensing, and their promotion and application in large-scale systems are all key directions to promote the development of federated learning technology. Through further technical optimization, compressed sensing is expected to provide more efficient solutions for a wide range of applications of federated learning.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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