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A Survey of Clustering Federated Learning in Heterogeneous Data Scenarios

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Abstract: Federated learning, as a collaborative training paradigm that preserves raw data privacy, offers an effective solution for data protection concerns. However, its practical implementation faces significant challenges due to data heterogeneity. This heterogeneity manifests as non-independent and identically distributed (non-IID) data across participating entities, resulting in degraded model performance, slower convergence rates, and training instability. While conventional federated learning approaches—including parameter averaging, knowledge distillation, and personalization techniques—offer certain advantages, their efficacy remains limited in severely heterogeneous environments. This survey systematically examines research advancements in clustered federated learning for addressing data heterogeneity challenges, encompassing fundamental principles, model architecture development, and algorithmic implementations. We provide a detailed analysis of innovative algorithms ranging from IFCA to FedGroup, and from FCL-GNN to FedAC, highlighting their technical contributions and applicable scenarios. Furthermore, we explore emerging research directions including clustering interpretability, multi-source heterogeneous information fusion, dynamic clustering mechanisms, and resource-aware optimization. Clustered federated learning effectively enhances model performance and convergence efficiency while maintaining privacy by grouping participants with similar data distributions into clusters and training specialized models for each cluster. With ongoing technological progress, clustered federated learning shows promise for achieving an optimal balance between privacy preservation and learning efficiency in critical domains such as healthcare and finance, thereby contributing to the sustainable development of artificial intelligence technologies.

Keywords: Clustering Federated Learning; Data Heterogeneity; Federated Learning; Non-Independent and Identically Distributed (Non-IID).

1. Introduction

Federated Learning (FL) refers to a learning paradigm in which multiple participants collaborate to train a common model without sharing their raw data. Federated learning has significant implications for data privacy protection and security, making research and optimization of federated learning an important direction in the field of artificial intelligence research [1].

Federated learning represents an important balance point between data privacy protection and model performance. Both data privacy and model effectiveness are related to the training process and the data distribution of participants. Data heterogeneity affects the convergence and generalization capabilities of the model, leading to decreased model performance, unstable training processes, and other issues [2]. Therefore, optimization of federated learning in heterogeneous data scenarios can provide important basis for data privacy protection, model performance improvement, and convergence efficiency optimization. Additionally, traditional federated learning methods have some problems; they typically employ strategies based on model parameter averaging and global aggregation for optimization, but these strategies often cannot accurately address the challenges posed by data heterogeneity, resulting in decreased model performance and reduced training efficiency. Therefore, seeking a more effective federated learning method for heterogeneous scenarios is very necessary [3]. With the development of clustering algorithms and personalized federated learning technologies, federated learning methods based on clustering are gradually becoming a research hotspot [4]. In particular, in recent years, the application of clustering federated learning in heterogeneous data scenarios [5] has provided new ideas and methods for federated learning optimization, and the model performance and stability have also been significantly improved [6].

The main purpose of federated learning research is to protect data privacy while improving model training efficiency and performance, optimizing model convergence speed and generalization capabilities, reducing communication overhead and consumption of computational resources, and providing important references for multi-party data collaboration. Federated learning may suffer from model performance degradation due to data heterogeneity, so understanding how to address data heterogeneity can guide researchers in algorithm design decisions, thereby avoiding unnecessary performance loss and resource waste [7]. Optimization of federated learning under data heterogeneity can also solve the problem of unbalanced data distribution at the initial stage of model design, avoiding training failures and inefficiencies, while also discovering new model optimization strategies, improving the practicality and scalability of federated learning. Clustering federated learning has broad potential in practical applications, and research on clustering federated learning in heterogeneous data scenarios can help researchers and engineers optimize system design and improve training effects and model performance. Data heterogeneity may lead to training failures

or model bias, thereby increasing computational costs. Clustering federated learning can prevent this from happening, saving computational resources and communication bandwidth.

2. Traditional Federated Learning Methods

Federated learning is a distributed machine learning paradigm that allows multiple participants to obtain a common model through collaborative training without sharing their raw data. This learning method not only protects data privacy but also fully utilizes distributed data resources, improving model training efficiency and performance. With the enhancement of data privacy protection awareness and the improvement of relevant regulations, federated learning has become an important research direction in the field of artificial intelligence. Traditional federated learning methods mainly include parameter averaging-based methods, knowledge distillation-based methods, and personalized federated learning methods. These methods optimize the federated learning process through different mechanisms, improving model performance and addressing data heterogeneity challenges. This section will introduce in detail the basic principles, typical algorithms, and advantages and disadvantages of these three types of traditional federated learning methods.

2.1. Parameter Averaging-Based Methods

Parameter averaging is the most basic method in federated learning. Its core idea is to generate a global model by weighted averaging of the parameters of locally trained models from various participants. The Federated Averaging (FedAvg) algorithm proposed by McMahan et al. has become a classic algorithm in federated learning [8]. The workflow of this algorithm includes: the central server initializes the global model and distributes it to the participants; participants train the model using their local data; participants upload the updated model parameters; the server performs weighted averaging on the received parameters, generates a new global model, and redistributes it. The main advantages of FedAvg lie in its simple implementation and high communication efficiency, effectively reducing communication overhead.

However, in heterogeneous data scenarios, the FedAvg algorithm faces problems such as slow convergence or even non-convergence. To address this challenge, researchers have proposed various improved versions. The FedProx algorithm improves the stability of the algorithm on non-IID data by adding a proximal term to the local objective function of the client, limiting the deviation between the local model and the global model [9]. Another innovation is the partial model averaging framework, which reduces the model difference problem by selectively averaging model parameters, more effectively minimizing global loss [10].

In addition, decentralized federated averaging algorithms eliminate the central server, allowing clients to communicate only with neighbors, reducing the risk of network congestion and enhancing system privacy protection [11]. These parameter averaging-based methods provide a basic framework for federated learning, but still face challenges in severely heterogeneous data scenarios, prompting researchers to explore more innovative methods.

2.2. Knowledge Distillation-Based Methods

Knowledge distillation-based federated learning methods achieve collaborative learning by transferring model outputs rather than model parameters, providing new ideas for solving model heterogeneity and communication efficiency problems. Knowledge distillation aims to transfer knowledge from a complex model (teacher model) to a simple model (student model). In a federated learning environment, knowledge distillation allows participants to share model predictions or feature representations, improving the level of privacy protection and supporting heterogeneous model architectures.

In FedMD [12], each participant first trains their local model using a public dataset, then uploads the model's predictions on the public data to the server. The server aggregates these predictions, generates a set of "soft labels", and returns them to the participants. Participants train their models using these soft labels along with their local data, acquiring knowledge from other participants without directly accessing their data or model parameters. As research deepened, more innovative methods were proposed. The communication-efficient federated distillation method (FedKD) proposed by Liu et al. [13] significantly reduced communication while maintaining model performance through adaptive mutual knowledge distillation and dynamic gradient compression techniques. Another innovation is the selective knowledge sharing federated distillation method (Selective-FD), which addresses the problem of knowledge sharing errors caused by data distribution differences and lack of well-trained teacher models by identifying accurate and precise knowledge [14].

Knowledge distillation-based federated learning methods provide a flexible and more privacy-protected way of collaborative learning, particularly suitable for scenarios where participants use different model architectures. However, these methods typically require a certain amount of public data as a medium and may experience information loss during the knowledge distillation process, which are challenges that still need to be addressed.

2.3. Personalization-Based Methods

Personalization-based federated learning methods aim to solve the problem of performance degradation of traditional global models in heterogeneous data scenarios by training customized models for each participant, balancing global knowledge with local characteristics. As research deepens, personalized federated learning has become a hot topic, with meta-learning-based methods showing great potential.

Meta-Learning, also known as "learning to learn," aims to quickly adapt to new tasks through learning experiences from multiple tasks. In federated learning, meta-learning views each participant's data as a separate task and achieves personalization by learning an initial model that can quickly adapt to the data distribution of each participant. Model-Agnostic Meta-Learning (MAML) is a classic meta-learning algorithm proposed by Finn et al. [15]. It learns model initialization parameters that can quickly adapt to new tasks, providing a theoretical foundation for personalization in federated learning.

Recent research has further expanded the application of meta-learning in federated learning. Vettoruzzo et al. proposed a personalized federated learning framework based on context modulation and meta-learning, introducing federated modulators that learn context information from data batches and dynamically adjust the activation functions of the

base model [16]. In domain-specific applications, Liu et al. proposed the Federated Meta Reinforcement Learning (FMRL) framework, specifically designed for personalized tasks, providing new solutions for autonomous driving, robotics, and other fields [17].

Personalization-based federated learning methods, especially those combined with meta-learning, provide an effective approach to solving data heterogeneity problems. However, these methods typically have higher computational complexity and require careful design of the learning process and parameters. How to improve computational efficiency while maintaining personalized performance remains a direction worth exploring.

3. Clustering Federated Learning Methods in Heterogeneous Data Scenarios

3.1. Clustering Federated Learning

Although federated learning achieves distributed model training while protecting data privacy, it faces problems such as model performance degradation, slow convergence speed, and training instability in heterogeneous data scenarios. Data heterogeneity mainly manifests as non-independent and identically distributed (Non-IID) data, including label distribution shift, feature distribution shift, and imbalance in sample quantity [18]. Traditional federated learning methods such as FedAvg typically train only one global model, which is difficult to adapt to the data characteristics of different participants, resulting in increased differences between local models and the global model, thereby affecting model performance [19].

Clustered Federated Learning (CFL) is an innovative method that handles data heterogeneity by grouping participants. Compared to traditional federated learning, the core idea of CFL is to group participants with similar data distributions into the same cluster and train a dedicated model for each cluster, thereby better capturing the data characteristics of different participants [20]. This method can significantly improve the performance of federated learning in heterogeneous data scenarios without sacrificing data privacy. Research shows that CFL can effectively mitigate the negative impact of data heterogeneity on model training, improving model convergence speed and accuracy [21].

Key advantages of clustering federated learning include: (1) Improved model performance: By training different models for different clusters, CFL can better adapt to the data characteristics of each participant, reducing the differences between the global model and local data, thereby improving model accuracy; (2) Enhanced convergence speed: Grouping based on data distribution similarity can accelerate the model convergence process, reducing the number of training rounds and computational overhead; (3) Enhanced personalization: Training dedicated models for different clusters can provide a higher degree of personalized service, meeting the specific needs of different participants.

3.2. Construction of Clustering Federated Learning Models

The construction of a clustering federated learning model mainly involves four key steps. First, participant feature representation is the process of extracting representative features from the behavior and data of participants. Common methods include utilizing model parameters or gradients, model performance metrics, and data distribution features [22]. Among these, model parameters provide direct behavioral representation, while data distribution features reflect the essential characteristics of the data.

Second, similarity metrics define how to evaluate the degree of similarity between participants, mainly including Euclidean distance, cosine similarity, and decomposition similarity [23]. These measurement methods each have advantages according to different application scenarios and data characteristics, such as cosine similarity which is particularly suitable for high-dimensional feature spaces.

Third, the choice of clustering algorithm determines how to group participants. Common algorithms include K-means, hierarchical clustering, expectation-maximization algorithm, and adaptive clustering [24]. The selection of clustering algorithms should comprehensively consider data characteristics, computational complexity, and clustering quality requirements.

Finally, intra-cluster model training determines how to train models within each cluster, including independent training, knowledge sharing training, and hierarchical training strategies [25]. This step directly affects the performance and degree of personalization of the final model and is a crucial link in the CFL framework.

These four steps are interrelated and together form an effective clustering federated learning framework for handling heterogeneous data scenarios.

3.3. Clustering-Based Federated Learning Methods

As research deepens, clustering-based federated learning methods continue to emerge, showing diversified development trends. These methods propose innovative solutions for different scenarios and needs.

Iterative Federated Clustering Algorithm (IFCA) is a representative CFL method proposed by Ghosh et al. in 2020 [20]. IFCA alternately estimates the cluster identification of participants and optimizes the model parameters of each cluster through an iterative process. Specifically, IFCA first initializes a model for each cluster, and then in each iteration: (1) validates the local data of participants with models from various clusters, selecting the cluster corresponding to the best-performing model as the cluster identification for that participant; (2) for each determined cluster, aggregates model updates from all participants within that cluster to form a new cluster model. IFCA theoretically proved its convergence and demonstrated good performance in experiments. However, IFCA relies on appropriate initialization and pre-set number of clusters, which may be limited in practical applications.

FedGroup is an efficient clustering federated learning framework proposed by Duan et al. [25], with its main innovation being a decomposition data-driven similarity measurement method. FedGroup first groups participants based on the similarity of their optimization directions, and then conducts model training based on the clustering results. The method specifically introduces ternary cosine similarity (TCS) and Euclidean distance decomposition (EDC) similarity metrics, which can effectively handle the clustering problem of high-dimensional low-sample (HDLSS) parameter update data. Additionally, FedGroup also implements a cold-start mechanism for new participants, improving the framework's scalability and practicality.

FCL-GNN is a graph neural network-based clustering

federated learning method [26] that uses graph neural networks to learn similarity relationships between participants. FCL-GNN views participants as nodes in a graph, with the similarity between participants as the weight of edges, capturing complex relationship structures through graph neural networks, thereby achieving more accurate clustering. This method is particularly suitable for heterogeneous and dynamically changing federated learning environments, capable of adapting to changes in network topology and data distribution.

Recently, the FedAC framework proposed an adaptive clustering method [12], addressing issues in existing CFL methods such as insufficient integration of global and intra-cluster knowledge, lack of efficient online model similarity metrics, and fixed number of clusters. FedAC effectively integrates global knowledge and intra-cluster learning by decoupling neural networks and using different aggregation methods for each submodule; introduces an efficient online model similarity metric based on dimensionality reduction; and designs a cluster number fine-tuning module, improving adaptability and scalability in complex heterogeneous environments. Experiments show that FedAC demonstrates significant performance improvements compared to baseline methods.

SR-FCA is an improved IFCA algorithm proposed by Vardhan et al. [27], which addresses limitations of IFCA such as the need for appropriate initialization and pre-set number of clusters. SR-FCA initially treats each participant as a separate cluster, and then gradually refines cluster estimates by exploring similar participants belonging to the same cluster. This method does not require prior knowledge of the number of clusters and can adaptively discover the clustering structure of participants, improving the practicality and robustness of the algorithm.

Overall, clustering-based federated learning methods effectively alleviate the challenges brought by data heterogeneity by identifying and utilizing similarities between participants, providing feasible solutions for the application of federated learning in complex scenarios. With continuous technological development, clustering federated learning will continue to evolve toward more efficient, robust, and personalized directions.

4. Future Challenges and Prospects

Although clustering federated learning has made significant progress in dealing with data heterogeneity, it still faces several challenges that need to be addressed urgently.

First, the explainability of clustering results constrains the credibility and transparency of the system. Due to the complexity and uncertainty of the clustering process, it is difficult to explain why specific participants are assigned to certain clusters. This "black box" characteristic limits its application in fields requiring high transparency [28]. Recent research, such as the explainable personalized federated learning framework proposed by Qin et al., provides new ideas for improving system explainability by introducing transparent feature attribution mechanisms [29].

Multi-source heterogeneous information fusion is another important challenge. Traditional clustering federated learning mainly focuses on data distribution characteristics, but in practical applications, there are also system heterogeneity factors such as device computing power and communication bandwidth. Yang et al.'s FedPRL framework addresses both data and system heterogeneity by optimizing resource allocation and participant selection through reinforcement learning [30]. Additionally, multimodal federated learning, by fusing data from different modalities (such as images, text, and audio), is particularly suitable for handling modality-missing scenarios [31].

In dynamic environments, the data distribution and system status of participants may change over time, requiring the development of efficient dynamic clustering mechanisms. The FedRC framework addresses various distribution shift problems through robust clustering techniques [32], while the adaptive clustering method proposed by FedAC improves system flexibility by dynamically adjusting the number of clusters [33]. Future research should focus on incremental clustering algorithms and federated continual learning methods to enhance the adaptability of systems in dynamic environments.

Resource awareness and communication efficiency are critical for practical deployment, especially in Internet of Things and edge computing environments. Multi-edge clustering and edge AI heterogeneous federated learning architectures achieve efficient global learning through AI-driven node communication [34], while knowledge distillation techniques such as the FedKD framework significantly reduce communication overhead [35]. Efficient architectures combining model compression, gradient quantization, and selective participation techniques, as well as joint selection methods for modalities and clients, will be important research directions in the future [36].

Smart agriculture is an emerging application where clustering federated learning shows great potential. By grouping farms with similar environmental or resource conditions, it enables more efficient and privacy-preserving model training for tasks such as pest prediction and irrigation planning [37].

With technological advances and deeper research, clustering federated learning is expected to achieve a better balance between privacy protection, resource optimization, and performance improvement, providing stronger support for intelligent applications in different fields.

5. Conclusion

The existence of data heterogeneity severely affects the performance of federated learning and has become a major issue for participant collaboration and model training. If deep learning can effectively address data heterogeneity, the challenges brought by federated learning will be greatly reduced, therefore there is an urgent need to develop clustering federated learning methods with better performance. This paper summarizes existing clustering-based federated learning methods and introduces the construction process of clustering federated learning models. Finally, it discusses the challenges of existing methods and proposes interesting research directions for the future. There is still enormous development potential in the direction of clustering federated learning in heterogeneous data scenarios.

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