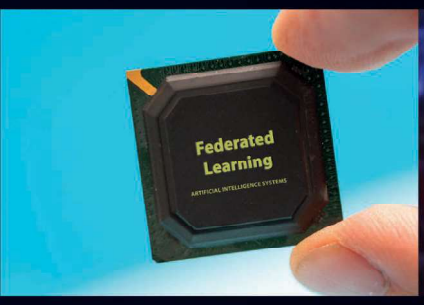
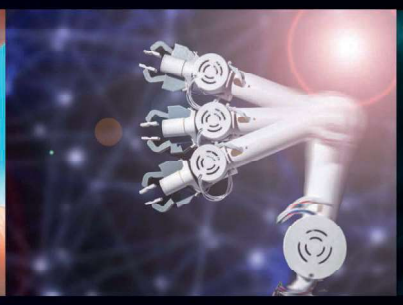
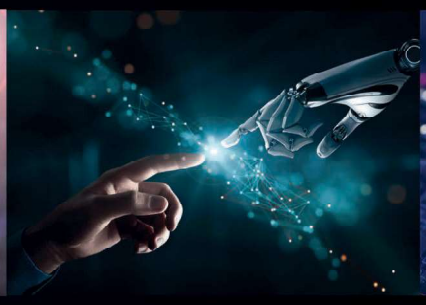
Federated Learning

Foundations and Applications

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Chapter 1

Federated learning at a glance

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1.1 Introduction

Society 5.0 [1] has focused on the integration of technology with different aspects of societal applications including healthcare, agriculture, retail, and transportation. Internet of Things [2], cloud computing [3], edge computing [4], and data analytics are integrated to provide smart solutions for the society. The machine learning (ML) [5] and deep learning (DL) [6] algorithms are used for data analysis. The ML algorithms can be classified into supervised, unsupervised, semi-supervised, and reinforcement learning, which are briefly discussed as follows [7]:

- **Supervised learning:** The supervised ML algorithm learns from a labeled dataset. In a labeled dataset, there exists a pair between each input and the corresponding output (target). The algorithm learns patterns from the labeled data and aims to learn a mapping function to predict the target or output for unseen input values. Logistic regression, decision tree, support vector machine, etc., are examples of supervised ML algorithms.
- **Unsupervised learning:** In this case, the dataset is unlabeled, and the algorithm finds hidden patterns, structures, and relationships within the data. K-means clustering, hierarchical clustering, etc., are examples of unsupervised ML algorithms.
- **Semi-supervised learning:** Semi-supervised learning falls between the categories of supervised and unsupervised learning algorithms. In case of semi-supervised learning, dataset contains a small amount of labeled data and a large amount of unlabeled data, and the algorithm needs to learn from the dataset. If there is a scarcity of labeled dataset, semi-supervised ML can be used.
- **Reinforcement learning:** In reinforcement learning, the algorithm learns through the interaction with the environment and receiving rewards or penalties. The algorithm learns decision-making based on maximizing the collected rewards over time. An automated robot is an example of reinforcement learning, where a robot learns to navigate an environment.

Apart from ML, the DL algorithms are also popular for data analysis, especially, in case of large number of samples. For big data analysis, DL plays a significant role. DL is a subset of ML, where multi-layered neural networks are used for simulating complex decision-making ability of the human brain. Traditional ML algorithms use simple neural networks with one of the two layers of computation, whereas DL models use three or more layers of computation. DL models use artificial neural networks (ANNs) [8] with multiple layers for data analysis and complex pattern learning. DL algorithms are based on the structure and function of the human brain, where interconnected neurons are used for information processing. DL algorithms are suitable for image recognition, natural language processing, speech recognition, etc. There are various DL models such as gated recurrent unit (GRU), multilayer perceptron (MLP), long short-term memory (LSTM), etc.

1.1.1 Why is federated learning needed?

As DL models for large-scale data analysis require high computational resources, cloud servers are mainly used to execute DL models. However, entire data transmission and storage inside the cloud may raise several issues such as high network traffic, high latency, and security concerns. Further, collaborative learning is significant for accurate prediction. *Federated learning* has come with the solutions towards these challenges. The use of federated learning with edge/fog computing [9,10] can result in efficient data analysis in terms of accuracy, latency, etc. Federated learning [11–13] is a collaborative model training approach where the local models are used for analyzing local data, and the clients and the server exchange model parameters between them for updating the model.

Federated Learning. https://doi.org/10.1016/B978-0-44-344433-3.00006-X

Definition of federated learning: Federated Learning is defined as a machine learning technique, where a model is trained across multiple decentralized devices or servers, containing local data, without exchanging the raw data. Each device trains a local model using its own dataset and sends only model updates (gradients or weights) to a central server or among themselves, to build an improved global model by aggregating the local model updates. Federated learning improves data privacy protection and security by keeping sensitive data localized.

The basic diagram of federated learning (FL) is presented in Fig. 1.1. In the figure, four nodes are considered which have their local datasets. Each node k receives global model parameters from the server, and trains its local model (M_k) using own dataset D_k. After training, each node sends the local model update (w_k) to the server. The server aggregates the received model updates to generate the aggregated global model update (w_g). If there are K nodes and federated averaging is used for aggregation, then the aggregated global model update is given as $\frac{1}{K}\sum_{k=1}^{K} w_k$. In the figure, the number of nodes is four, thus, $K = 4$.

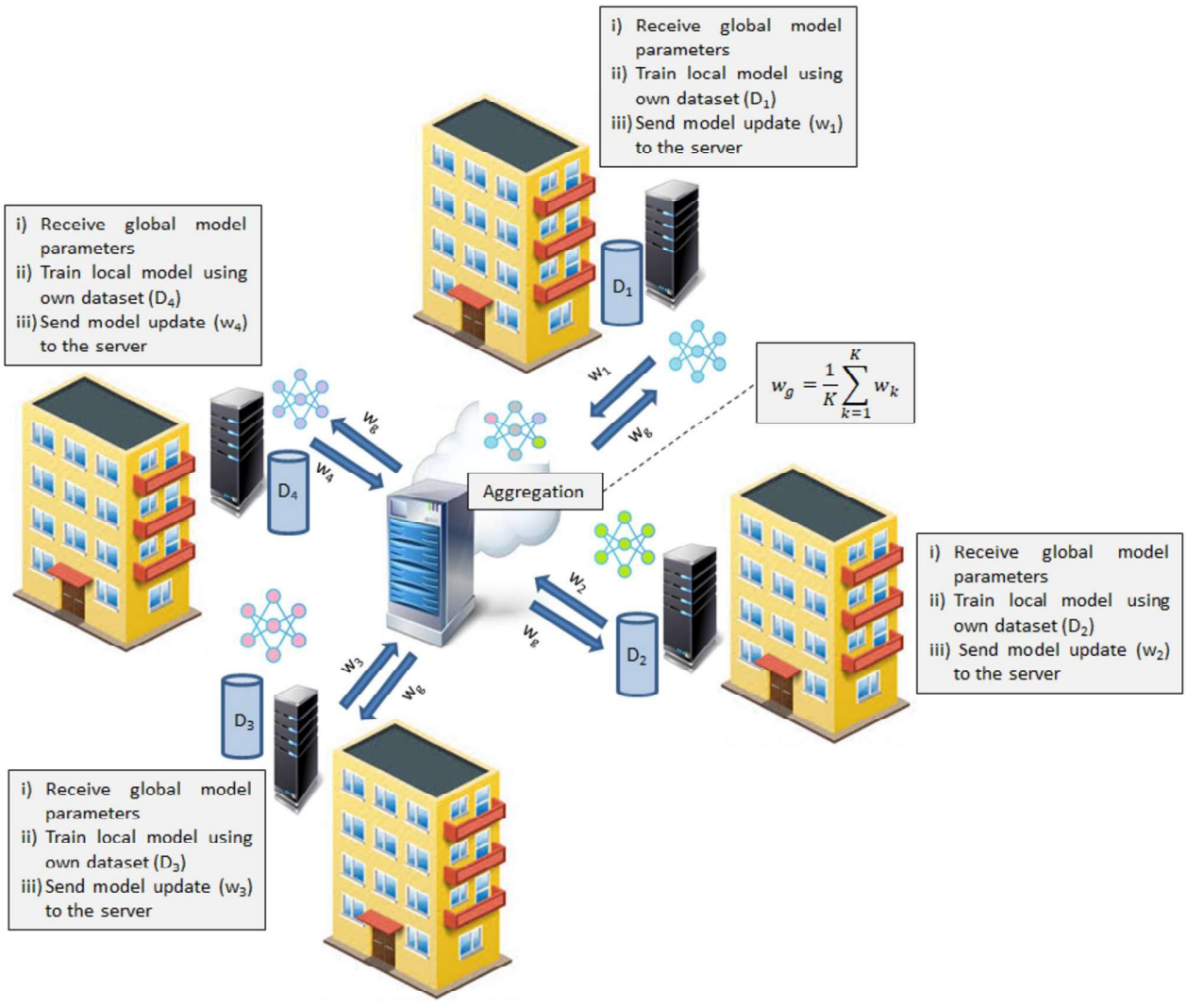

FIGURE 1.1 Federated learning framework with four nodes.

1.1.2 Characteristics of FL

The characteristics of FL are briefly stated as follows:

- **Data localization, decentralization, and privacy protection:** In FL, the raw data is stored inside the clients, and not shared to protect data privacy. Only, the local model updates are transmitted to the server.
- **Collaborative training and aggregation:** The clients share their local model updates with the server that aggregates the received updates to build the global model. Hence, multiple clients collaboratively train a shared global model in FL.
- **Heterogeneity:** FL deals with heterogeneous devices with heterogeneous data.
- **Efficient communication:** As FL is based on the exchange of model updates between the clients and the server, communication should be efficient, and network connectivity should be good enough for smooth execution of the FL process.
- **Distributed learning:** As each client locally trains its model and only updates are shared, FL is a distributed learning model. However, FL can handle both independent and identically distributed (IID) and non-independent and non-identically distributed (non-IID) datasets, stored inside the clients.
- **Scalability:** As training is enabled on vast and distributed datasets, FL can scale a large number of clients.

In FL, local data analysis is performed that enhances data privacy protection. Further, the collaborative learning improves prediction accuracy. In Section 1.2, we discuss on different types of FL. After that, we discuss on various applications of FL in Section 1.3. The research challenges of FL are stated in Section 1.4. The chapter concludes in Section 1.5.

1.2 Types of FL architectures

The FL architectures can be classified according to the following two dimensions [2]:

- Networking structure
- Data partitioning

1.2.1 Networking structure-based FL classification

Based on the networking structure, FL is classified into the following two types:

- Centralized federated learning (CFL)
- Decentralized federated learning (DFL)

In CFL [14], the server shares the global model parameters with the clients. Based on the global model parameters, clients train their local models using their local datasets. The locally trained model updates are shared with the server. The server, after receiving all updates to the model, aggregates them to build the global model. The global model update is then shared with the clients. This process is continued for a number of rounds until a global model with minimal loss is generated.

In decentralized federated learning (DFL) [14], clients form a network among themselves using a ring or mesh topology and share model updates with their neighbors to build the global model.

1.2.2 Data partitioning-based FL classification

Based on the data partitioning process, FL can be classified into three types:

- Horizontal FL (HFL)
- Vertical FL (VFL)
- Federated Transfer Learning (FTL)

In HFL [2], local datasets stored within the clients have the same feature space but different sample spaces. The clients use the same ML/DL model for local training. After training, local model updates are masked using encryption or differential privacy to enhance security, if required, before sharing with the server. The server aggregates the received updates and builds the global model. The global model update is shared with the clients. This process is repeated until a global model with minimal loss is developed.

In VFL [2], the client data sets have the same sample space but different feature spaces. An entity alignment method is used to collect the overlapped data samples of the clients. The data samples are combined to train a global model using encryption.

In FTL [2], the features from different feature spaces are transferred to the same representation to be used for training data aggregated from multiple clients. FTL is suitable where the sample size as well as feature space both differ. For data privacy protection and enhanced security, masking is used for gradient encryption. Depending on the combined updates from the clients, the server performs model learning through aggregation to find a global model update with minimal loss.

1.3 Applications of FL

FL has several application areas, including healthcare, agriculture, mobile applications, and autonomous vehicles [12,14–16]—some of them are discussed below.

1.3.1 Healthcare

FL provides collaborative model training with data privacy protection. As healthcare data is highly sensitive and confidential, FL plays a vital role in healthcare applications such as medical image analysis, activity recognition, disease detection, and electronic health records analysis [17–19]. The Internet of Medical Things (IoMT) devices collect patients' health-related data. The patients' datasets are used for local model training, and the model updates are shared with the central server for aggregation. The aggregated global model update is then shared with the clients. Fig. 1.2 shows an FL-based healthcare system, where three hospitals have their own datasets containing patients' health records. The three hospitals serve as three clients and train their local models using local datasets and share the local model updates with the server. The central server aggregates the received model updates and builds the global model. The global model update is shared with the hospitals. In [20], FL was used for the diagnosis of COVID-19. In [21–23], the use of FL for medical image analysis was illustrated. FL also demonstrated its efficacy in human activity recognition [19,24]. Recently, privacy-aware FL, incentive-based FL, and personalized FL, have become popular in FL-based smart healthcare systems [17,25]. For privacy-enhanced FL, differential privacy [26] has become popular. The artificial noise is added to the dataset for protecting data privacy. The noise can also be added to the model gradients or weights during transmission of model updates. In conventional FL, all IoMT devices participate in the FL process. This may not be possible in real-life scenarios due to the lack of willingness of the participants, because of limited computing resources, bandwidth requirements, etc. As a solution, incentive-based FL [17] method has come to incentivize the participants in the FL process based on the contribution, reputation, and resource allocation. As FL produces a global model after aggregation, personalized healthcare [17] is a challenge. To solve this issue, the devices can download the global model and train the personalized local models. It is also important to deal with label heterogeneity in FL for personalized healthcare.

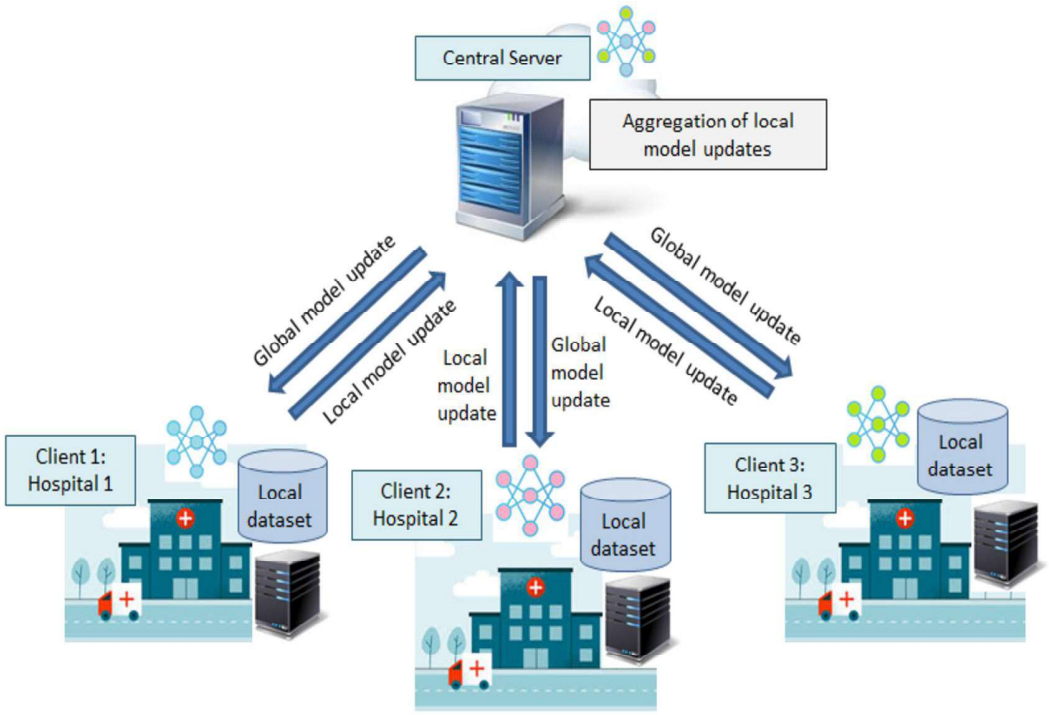

FIGURE 1.2 Federated learning-based healthcare system.

1.3.2 Agriculture

Smart agriculture is an emerging domain, especially in countries where agriculture plays a vital role in the economy. Soil properties, environmental properties of different regions vary; further, the unique soil features, farmers' information, and land-related information are sensitive and confidential. Hence, FL also has a vital application in smart agriculture [27]. Soil health monitoring, moisture prediction, irrigation management, etc., are various applications of smart agriculture, in which FL can play a vital role to provide accurate decision-making through collaborative learning with privacy protection [9,10]. FL plays a significant role in soil health monitoring, crop yield prediction, irrigation management, etc. The farms have their local datasets, which are used for local model training. The local model weights are aggregated by the central server to build the global model [10,14,28]. The global model update is shared with the farms. Fig. 1.3 shows an FL-based agricultural system. In the figure, three agricultural farms are shown as three clients, which have own datasets containing the data regrading the agricultural land, soil parameters, and environmental parameters. The three farms train their local models using own datasets and share the local model updates with the server. The central server aggregates the received model updates and builds the global model. The global model update is shared with the farms. The farms can also collaborate using DFL to build a global model [14]. For enhancing security, blockchain is integrated with FL for smart agriculture in [28]. In [10,28], FL was used for soil moisture monitoring and irrigation decision-making. In [9,14], FL was used to predict crop yields. In [29], FL played a significant role in image-based crop disease detection. In [30], FL was used in soil spectroscopy. For soil fertility prediction, FL was used in [31]. Agriculture is one of the pillars of socio-economic development of most of the countries. FL can play a crucial role in smart sustainable agricultural practices to improve the overall economic growth of the countries.

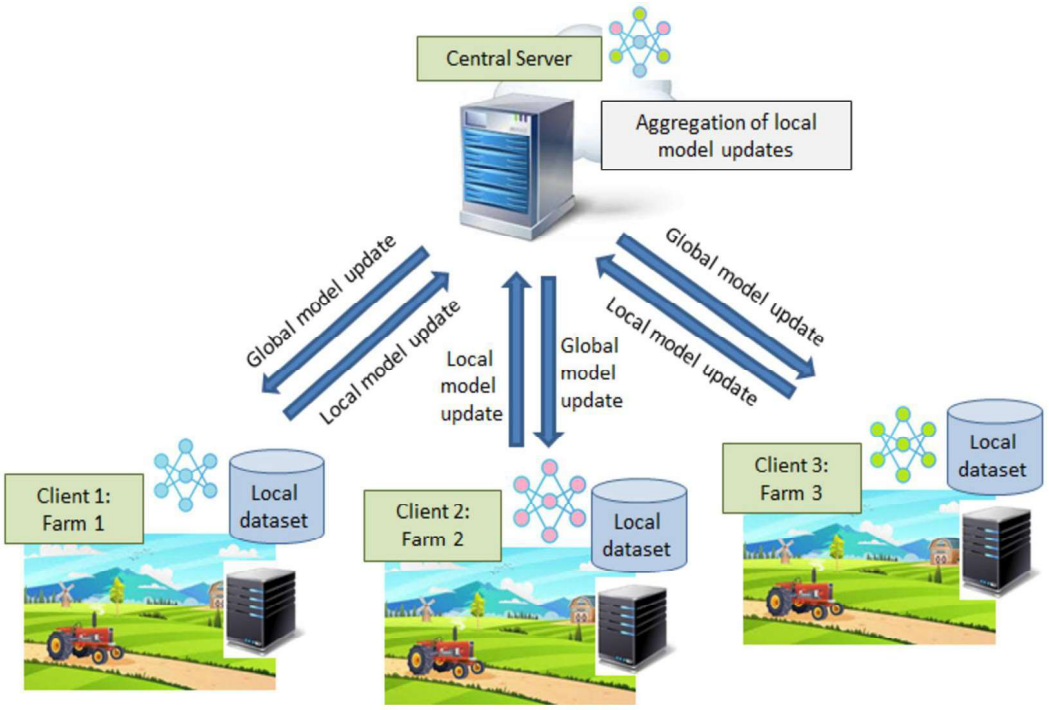

FIGURE 1.3 Federated learning-based agricultural system.

1.3.3 Mobile applications

The smartphones have several applications such as image recognition, speech recognition, recommendation applications, predictive text, etc. Smartphone users' data is highly confidential; hence, FL can play a crucial role in mobile applications [15]. Accurate prediction and recommendation can be performed without sharing raw data if FL is used in various mobile applications. The mobile devices have application-specific personal datasets of the users, which are used for local model training. The local model updates are aggregated by the edge server or cloud server to build the global model. The mobile

devices download the global model parameters. The mobile devices can build their personalized models also by training their local models using the downloaded global model parameters. In [32], a system is proposed to provide federated learning as a service (FLaaS) by enabling third party applications to build decentralized, privacy-aware, and collaborative ML models. The use of FL for latency-sensitive mobility applications is highlighted in [33]. In [34], an FL-based advertising platform was proposed to recommend mobile applications based on ecosystems. Mobile applications for health monitoring and activity recognition have also become popular nowadays for smart and healthy lifestyle recommendations. In [35], mobile-cloud FL framework was discussed for mobile applications with a case study on activity recognition. In [36], the use of FL in mobile health applications was demonstrated. Like physical health, mental health also plays a significant role in the general health and fitness of a person. In [37], FL was used for mental health monitoring. FL can also play significant roles for music and movie recommendation applications [38,39].

1.3.4 Autonomous vehicles

Road navigation and decision-making are vital for autonomous vehicles. FL can be used for autonomous vehicles to build an accurate decision-making model without sharing raw driving data with the central server. FL-based vehicular network [40] can perform road traffic prediction and select the optimal route to the destination. For connected and autonomous vehicles, CFL and DFL both have gained popularity [41]. In [42], FL was used for object detection in autonomous vehicles. In [43], FL was used in autonomous driving vehicles to provide end-to-end on-device ML. In [44], a blockchain-based decentralized FL framework was proposed for privacy-enhanced vehicular communication networking. Privacy is a critical issue of vehicular edge computing (VEC). In [45], FL was used for autonomous driving by protecting data privacy through collaborative model training using edge computing server without raw data sharing. In [46], deep FL was used for autonomous driving. In this work, the authors considered decentralized peer-to-peer model and proposed a federated autonomous driving network. In [47], Byzantine-Fault-Tolerant privacy-aware DFL was proposed for autonomous vehicles. This work also used peer-to-peer network to form a DFL framework. In [40], FL with genetic algorithm was used for optimal route selection in edge computing-based vehicular network.

1.3.5 Intrusion detection

To build a robust intrusion detection model [48], FL can play an important role. The network traffic data from different sources can be used separately for the local models' training, and the updates can be aggregated to build a robust intrusion detection model, without sharing raw data. In [49], the use of FL for intrusion detection was studied in detail with a discussion on the existing approaches. In [50,51], the authors illustrated the use of FL for intrusion detection. There are several challenges still remain such as communication overhead, non-IID data, resource management in low-power IoT devices, and federated poisoning attacks [50]. In [52], the use of FL for intrusion detection in IoT were discussed. In [53], FL-based intrusion detection was proposed for smart agriculture. Future research directions of FL-based intrusion detection systems include the use of edge computing, secure channels, encryption standards, model heterogeneity and interpretability, and efficient handling of non-IID data [50].

Beyond the various types of FL applications discussed above, there are some other areas also where FL can play an important role, such as smart grids, robotics, financial sectors, etc. For energy optimization and predicting demands in smart grids without affecting users' privacy, FL can be used [54]. For swarm robotics, FL can be used [55,56]. It will permit the robots to learn from each other's experiences and improve their performance. For personalized financial services without sharing raw data and prevention of frauds, an FL-based model can play an important role. As no raw data is shared, users' data is protected. Further, an accurate decision-making model can be built through collaboration among various financial organizations [16]. FL can be also used with edge computing [9] to provide an accurate decision-making framework for various real-time applications, where response time needs to be minimal. The FL and edge computing-based frameworks for various applications are studied in several research works [9,10,57].

1.4 Challenges of FL

Though FL provides privacy-aware and accurate prediction and recommendation models, there are several challenges of FL [13,14,29,58]. In this section, we highlight some of the significant issues of FL, which need to be taken care of.

1.4.1 Communication overhead

In FL, the model updates are transmitted between the clients and the server in case of CFL, and among the clients in DFL. Hence, a high communication overhead is involved in both CFL and DFL [58]. Therefore, a subset of client selection at each round along with a periodic updates exchange process can be used to reduce the communication overhead. The number of communication rounds in FL can also be reduced to diminish the communication overhead. However, there should be a trade-off between the communication overhead and the prediction accuracy in that case, so that the model's performance does not degrade. Hence, developing a communication-efficient FL framework is a significant challenge of FL.

1.4.2 Heterogeneity

System heterogeneity and data heterogeneity are two crucial issues of FL [58]. The clients participating in the FL process have different configurations in terms of memory, processing ability, storage, network bandwidth, battery life, etc. Further, the local data contained by the clients also differ in terms of sample space and feature space. The non-identical distribution of the datasets across the participating clients creates a major impact on the model's performance. Further, class imbalance issues in the local datasets, the limited number of samples in the local datasets, etc., also create bottlenecks in the performance of the model.

1.4.3 Resource limitation of clients

The clients can have limited resources in terms of processing ability, memory, storage, battery power, etc. As FL is a collaborative process, the resource limitation of the clients may cause performance degradation. This problem is known as the Straggler effect [59]. Clients with limited resources may slow down during the execution of DL models. As a result, the entire process becomes slow, and the performance of the model is degraded.

1.4.4 Privacy and security

Though, FL avoids raw data sharing, and protects data privacy, there is still a probability of gradient information leakage during the exchange of model updates. Further, a malicious client can affect the entire process. The attacks can be introduced by one or more compromised clients or a compromised server. Various types of attacks are possible in FL, such as model poisoning attacks, backdoor attacks, data poisoning attacks, and membership inference attacks [29]. By identifying malicious participants, data poisoning attacks can be prevented [29]. On the other hand, the rejection of local models based on error rate and loss function, can prevent model poisoning attacks [29]. The backdoor attacks can be prevented using weak differential privacy [29]. Finally, homomorphic encryption, differential privacy, and a trusted execution environment can prevent membership inference attacks [29]. In [60], federated graph anomaly detection can be performed for training high-quality graph anomaly detection models through collaboration on distributed graph data.

Though the challenges are critical, various research is going on to address them. One-shot FL [29] can be used to reduce communication overhead. In one-shot FL, the global model is learned in a single round of communication. Federated offloading, lightweight local models, etc., can be used to deal with the issue of resource limitations of the clients. Hessian-weighted aggregation [61] can address the issue of statistically heterogeneous data. Resource-aware clustering can address the issue of heterogeneous participants in FL [62]. Incentive mechanisms can also help to overcome various issues by providing rewards to the participating nodes based on their performance. Integration of quantum computing with FL is also an emerging future research direction [63].

1.5 Conclusion

This chapter provides a brief overview of federated learning. At first, we have provided an overview of machine learning and deep learning in this chapter. Then, the requirements of federated learning are briefly demonstrated. The characteristics, types, and applications of federated learning are discussed in detail. Finally, the research challenges of federated learning are discussed, and the future research solutions to address the challenges are also briefly mentioned in the chapter.

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