Handling Data Heterogeneity in Federated Learning via Knowledge Fusion

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Abstract
Federated learning (FL) supports distributed training of a global machine learning model across multiple clients with the help from a central server. The local dataset held by each client is never exchanged in FL, so the local dataset privacy is protected. Although FL is increasingly popular, data heterogeneity across different clients leads to the client model drift issue and results in model performance degradation and poor model fairness. To address the issue, we design Federated learning with global-local Knowledge Fusion (FedKF) scheme in this paper. The key idea in FedKF is to let the server return the global knowledge to be fused with the local knowledge in each training round so that the local model can be regularized towards the global optima. Thus, the client model drift issue can be mitigated. In FedKF, we first propose the active-inactive model aggregation technique that supports a precise global knowledge representation. Then, we propose a data-free knowledge distillation (KD) approach to facilitate the KD from the global model to the local model while the local model can still learn the local knowledge (embedded in the local dataset) simultaneously, thereby realizing the global-local knowledge fusion process. The theoretical analysis and intensive experiments demonstrate that FedKF achieves high model performance, high fairness, and privacy-preserving simultaneously. The project source codes will be released on GitHub after the paper review.

1 Introduction
Deep learning is addicted to large high-qualified training data. The training data is often dispersed over a set of data owners (i.e., clients). The traditional central machine learning (ML) training approach requires clients to upload their local data to a central server. However, clients may be reluctant to share their local data with any other entities (e.g., the central server) since their local data (e.g., commercial valuable data, personal biometric data) is highly privacy-sensitive. To alleviate the security concerns, federated learning (FL) [15] is proposed to support distributed local training via using a central server for model aggregation. In FL, since the local data never leaves a client, the client data privacy can be preserved. In recent years, FL has attracted intensive research efforts from both academia and industry (e.g., [27][39]).

The most famous FL algorithm is FedAvg [28]. In one round of FedAvg training, a central server sends the global model weight to a portion of distributed clients (i.e., active clients). Then, each client trains the model using the local data. Next, each client sends the new model weight to the central server, which is responsible for computing the new aggregated averaged model. Afterward, the server sends the new global model to some re-selected active clients to start the next round of
FedAvg training. After numerous rounds of training, the ML model can be well trained. Each client can exploit the well-trained ML model for different applications.

Although FL technique constantly gains popularity, one problem rooted in FL is that the heterogeneity of data across different clients can lead to significant model performance (i.e., test accuracy) degradation [14, 35, 34]. For example, multiple hospitals would like to collaboratively train a disease diagnosis ML model via FL. Each hospital collects patient data independently, so their datasets are unbalanced and non-IID (i.e., heterogeneous). One hospital might have few/no data samples belonging to a certain disease class. When each hospital trains the model locally, its local objective may be far from the global objective. Thus, the averaged global model can be away from the global optima. This phenomenon is called client model drift in some literatures [21, 23, 40, 36], which leads to the poor model performance of the global model.

Except for poor model performance, data heterogeneity may also lead to poor model fairness. Consider a disease diagnosis ML model is trained by multiple different hospitals (that collect patient data in different geographical areas with different race populations) via FL. The FL-trained ML model can achieve high averaged model performance, but it may have large model performance variance across different hospitals (when testing on their local patient datasets). If so, the ML model has biases against certain geographical areas (i.e., geographical discrimination) and race populations (i.e., race discrimination). To mitigate such a model bias issue, the FL-trained ML model should also achieve high fairness, which can be measured by the degree of uniformity in model performance across different clients. The considered concept of fairness is also named accuracy parity [22].

In this paper, we design Federated learning with global-local Knowledge Fusion (FedKF) scheme that aims to achieve both high model performance and high model fairness in heterogeneous FL. The key idea in FedKF is to let the server return some global knowledge to shepherd the local client training so that the local model will be regularized towards the global optima, thereby reducing client model drift issue in each training round. On the server side, to precisely represent the global knowledge in each training round, we design T1 (active-inactive model aggregation technique) for the global model aggregation. On the client side, the T1-aggregated model’s training dataset is absent, making it hard to transfer the knowledge from the T1-aggregated model (teacher network) to each local model (student network). To tackle this challenge, we develop T2 (global-local knowledge fusion technique) to support knowledge fusion on the client side. In T2, a generator is trained to generate the imitated pseudo-samples to facilitate the knowledge distillation (KD) from the teacher network to the student network while the student can still learn the local knowledge (embedded in the local dataset) simultaneously. In this way, global-local knowledge fusion process is realized.

The main contributions of this paper are summarized as follows.

- We make the first step forward to design a privacy-preserving FL scheme that achieves both high (i.e., over FedAvg) model performance and high fairness in heterogeneous FL.
- We propose two techniques T1 (active-inactive model aggregation technique) and T2 (global-local knowledge fusion technique) used in FedKF. Both T1 and T2 can help to improve model performance and model fairness in heterogeneous FL.
- We theoretically prove that FedKF can directly turn out to be a good solution to achieve high model performance and high fairness in heterogeneous agnostic FL. Thus, FedKF has much broader impacts in reality.
- Intensive experiments demonstrate that FedKF outperforms all previous solutions (in terms of the three performance metrics, communication efficiency, and robustness). The superiority of FedKF is more significant with an increasing degree of data heterogeneity.

2 Related Work

To handle data heterogeneity in FL, several solutions have been proposed. The previous solutions can be classified as two categories: model performance-based [40, 25, 23, 21, 20, 36] and multiple-objective optimization-based [22, 12]. They are analyzed as follows.

The model performance-based solutions merely consider improving the model accuracy in heterogeneous FL. These solutions include FedGen [40], CCVR [25], FedDF [23], FedProx [21], MOON [20], FedGKD [36]. FedGen and CCVR require each client to share additional local dataset information (e.g., local label count information and local dataset or mean and covariance of local features for
each class) to the central server. Compared with FedAvg, the two solutions suffer from additional information leakage, resulting in a security level downgrade. Besides, FedDF and FedProx assume there are additional proxy data available on the central server for ensemble distillation. Such a strong assumption makes them impractical since the proxy data is unavailable in most cases. For MOON and FedGKD, their performances are good on less heterogeneous data, but their performances decrease dramatically as data heterogeneity increases. Note that none of solutions in this category are fairness-aware in their initial design.

The multiple-objective optimization-based solutions aim to optimize multiple objectives such as model performance, fairness, robustness, etc. These solutions include q-FFL [22] and FedMGDA+. The fairness gain of q-FFL and FedMGDA+ is obtained by sacrificing model performance, so they cannot achieve a better model performance than FedAvg in theory. For example, when setting the reweighting parameter \( q \) to 0 in q-FFL, it reduces to FedAvg. If \( q \) > 0, the model performance of q-FFL is worse than FedAvg.

Table 1 exhibits the comparison among different previous solutions and FedKF. FedKF shows the superiority over all previous solutions. Compared with q-FFL and FedMGDA+, FedKF achieves model fairness gain without sacrificing the model performance.

| Solutions                | Over FedAvg Model Performance | Fairness-Aware | No Proxy Data Required | No Additional Info. Leakage |
|-------------------------|-------------------------------|----------------|------------------------|-----------------------------|
| Model performance-based |                               |                |                        |                             |
| FedAvg [28]             | ●                            | ○              | ●                      | ●                           |
| FedGen [40]             | ○                            | ●              | ●                      | ○                           |
| CCVR [25]               | ●                            | ○              | ●                      | ●                           |
| FedDF [23]              | ●                            | ○              | ●                      | ●                           |
| FedProx [21]            | ●                            | ○              | ●                      | ●                           |
| MOON [20]               | ●                            | ○              | ●                      | ●                           |
| FedGKD [36]             | ●                            | ○              | ●                      | ●                           |
| Multiple-objective optimization-based |                       |                |                        |                             |
| q-FFL [22]              |                               | ○              | ●                      | ●                           |
| FedMGDA+ [12]           |                               | ○              | ●                      | ●                           |
| FedKF (ours)            | ●                            | ●              | ●                      | ●                           |

3 Preliminaries and Problem Statement

In this section, we first introduce some background knowledge. Then, the formal problem statement is presented.

3.1 Preliminaries

**Federated Learning.** FL is a distributed machine learning setting where a group of clients jointly train a high-quality centralized model without requiring clients to share their local private data [15]. However, FL faces practical challenges from data heterogeneity [21], in that user data from real-world is usually non-IID distributed, which inherently induces deflected local optimum [14].

A variety of efforts have been made to tackle data heterogeneity, mainly from two complementary perspectives. One focuses on stabilizing local training, by regulating the deviation of local models from a global model over the parameter space [21] [14] [40]. This approach may not fully leverage the underlying knowledge across user models, whose diversity suggests informative structural differences of their local data and thus deserves more investigation. Another aims to improve the efficacy of model aggregation [35] [5], among which knowledge distillation has emerged as an effective solution [19] [23]. Suppose that there are \( K \) clients jointly to train a ML model in FL. For the \( k \)-th client, it stores a local dataset \( D_k \). FL aims to learning a global model weight \( w \) over the dataset \( D = \bigcup \{ D_k \}_{k=1}^{K} \). Let \( \mathcal{N} \) be the local model and \( \mathcal{L} \) be the loss function. Accordingly, the objective of FL is to solve the following optimization problem [28]:

\[
\min_{w \in \mathbb{R}^d} f(w) = \sum_{k=1}^{K} p_k F_k(w),
\]

where \( p_k = n_k / \sum_{k=1}^{K} n_k \), \( n_k = |D_k| \) and \( F_k(w) \) represents the local objective function at the \( k \)-th client. It is given by \( F_k(w) = \frac{1}{n_k} \sum_{(x^i,y^i) \in D_k} \mathcal{L}(N(w; x^i), y^i) \).
Knowledge Distillation. Knowledge distillation (KD) technique enables a student model to learn from one or multiple teacher models [9] [7]. KD supports the student model compression, while enable the student model to inherit knowledge distilled from teacher(s). The classic KD techniques (e.g., [9] [23]) requires a proxy dataset during the distillation. To eliminate the requirement for the proxy dataset, data-free KD is proposed [24] [2] [6]. A popular solution for data-free KD is to use the idea of generative adversarial networks (GANs) [2]. A generator is trained to produce imitated training data (to replace the original training dataset) used for KD.

3.2 Problem Statement

Problem Setup. Suppose that there are $K$ clients jointly to train a classification model using FL. For the $k$-th client, it stores a local dataset $D_k$. We consider the local datasets are unbalanced and non-IID (i.e., heterogeneous). Next, we define the following three metrics to facilitate our problem description.

Definition 1 (Averaged Model Performance) The averaged model performance (AMP) of model $w$ (denoted as $AMP_w$) is defined as the accuracy of model $w$ on the global test dataset $D = \bigcup\{D'_k\}_{k=1}^K$. Let $a_{w}^k$ ($k = 1, \ldots, K$) represent the test accuracy of model $w$ on $k$-th client’s local test dataset $D'_k$. $AMP_w$ can also be computed as $AMP_w = \frac{\sum_{k=1}^{K} p_k a_{w}^k}{\sum_{k=1}^{K} |D'_k|}$, where $p_k = |D'_k|/\sum_{k=1}^{K} |D'_k|$.

Definition 2 (Fairness Metric) The fairness metric (FM) of model $w$ (denoted as $FM_w$) is defined as $FM_w = \text{Var}(a_{1}^w, \ldots, a_{K}^w)$, where $\text{Var}$ denotes the variance. It is given by $\text{Var} = \frac{1}{K} \sum_{k=1}^{K} (a_{w}^k - \overline{a_{w}})^2$, where $\overline{a_{w}} = \frac{1}{K} \sum_{k=1}^{K} a_{w}^k$. A smaller $FM_w$ indicates a fairer model $w$.

Definition 3 (Worst-case Local Performance) The worst-case local performance (WLP) of model $w$ (denoted as $WLP_w$) is defined as $WLP_w = \min\{a_{w}^1, \ldots, a_{w}^K\}$.

WLP as Joint Performance Metric. According to Definitions (1)-(3), WLP metric can be treated as measuring the joint performance of AMP and FM. On one hand, given the fixed AMP, a larger WLP tends to indicate a more uniform distribution of local performance (i.e., smaller FM) across clients. On the other hand, given the fixed FM, a larger WLP tends to imply a model with a higher AMP. To better explain why WLP can be treated as a joint performance metric, a numerical example is provided.

Suppose that there are three models $w_1$, $w_2$, and $w_3$ trained over three clients via FL. Their parameter configurations are shown in Table 2. For $w_1$ and $w_2$, it holds that $AMP_{w_1} = AMP_{w_2}$. Since $WLP_{w_1} < WLP_{w_2}$, we have $FM_{w_1} > FM_{w_2}$. For $w_1$ and $w_3$, it holds that $FM_{w_1} = FM_{w_3}$. Since $WLP_{w_1} < WLP_{w_3}$, we have $AMP_{w_1} < AMP_{w_3}$.

Table 2: An numerical example.

| Client 1 | Client 2 | Client 3 | AMP   | FM    | WLP  |
|----------|----------|----------|-------|-------|------|
| $a_{w_1}^1 = 0.6$ | $a_{w_2}^1 = 0.7$ | $a_{w_3}^1 = 0.8$ | 0.7   | 0.667 | 0.6  |
| $a_{w_2}^2 = 0.65$ | $a_{w_3}^2 = 0.65$ | $a_{w_3}^2 = 0.8$ | 0.7   | 0.05  | 0.65 |
| $a_{w_3}^3 = 0.7$ | $a_{w_3}^3 = 0.8$ | $a_{w_3}^3 = 0.9$ | 0.8   | 0.667 | 0.7  |

Definition 4 (Privacy-Preserving) We say an FL scheme is privacy-preserving if it follows the same security principle as FedAvg: for each client, only its model weight can be sent to other entities (e.g., server), and no information about local data can be shared directly.

Design Goals. In this paper, we aim to design a privacy-preserving FL scheme FedKF that can increase AMP while reducing FM. Thus, FedKF can achieve high global performance and fairness simultaneously. If both AMP and FM are jointly considered, FedKF should keep WLP as large as possible.

4 FedKF Design

In this section, we first overview FedKF and two developed key techniques. Then, we introduce T2 (global-local knowledge fusion technique) used in FedKF.
4.1 FedKF & Key Techniques Overview

**FedKF.** An overview of FedKF is illustrated in Fig. 1. In FedKF, the server maintains $K$ different cache slots for storing the latest local models. In each training round, only the selected active clients need to upload their local models to the server. Thus, the $k$-th cache slot stores the local model uploaded from $k$-th client in the most recent training round when $k$-th client is selected to be active. Informally, FedKF can be described as follows.

Step 0: In the last step of the training round $t - 1$, the server aggregates all active clients’ uploaded local models to get the active clients aggregated (ACA) model. Meanwhile, FedKF aggregates both active and inactive clients’ cached models in the cache slots to get the overall clients aggregated (OCA) model. In this step, active and inactive refer to the clients’ state in round $t - 1$.

Step 1: In the training round $t$, a portion of clients are selected as active clients. Let $\{a_1, \ldots, a_m\}$ denote the IDs of the selected clients. Let $\tau$ represent the selection rate. It follows that $m = \tau K$. Then, the server broadcasts the ACA model and the OCA model to all active clients.

Step 2: On receipt of the two models from the server, each active client treats the ACA model as the student model $w^S$ and treats OCA model as the teacher model $w^T$.

Step 3: FedKF employs the data-free KD technique to distill the knowledge of the teacher model to the student model. Meanwhile, the local dataset of each active client is used to train the student model. Therefore, both the global knowledge (embedded in the teacher model) and local knowledge (embedded in the local dataset) are fused and transferred to the student model.

Step 4: After global-local knowledge fusion, all active clients upload their local student models to the server. Each client’s student model serves as the latest local model.

Step 5: Based on the received active clients’ local models, the server updates the weights in the corresponding cache slots. The inactive clients’ cache slots remain the same. Then, the server re-computes the ACA model and COA model. Next, if the model is well trained, then terminates; otherwise, go to Step 1.

When the training is finished, the OCA model (not the ACA model) is used as the final model to be used.

**Two Key Techniques.** In FedKF, two key techniques are developed.

- **T1:** We develop an active-inactive model aggregation technique to generate an OCA model that represents the global knowledge precisely.
- **T2:** We develop the global-local knowledge fusion technique to enable the local model learn both the global knowledge (embedded in the teacher model) and the local knowledge (embedded in the local dataset).
For most previous solutions (e.g., FedAvg), only active clients’ model weights are aggregated to generate the global model in each round. In contrast, in T1 (active-inactive model aggregation technique), both active clients’ model weights and inactive clients’ cached model weights are aggregated to represent the global knowledge. Hence, T1 supports a more precise global knowledge representation. T1 is a simple yet precise approach to generate the global model. It is orthogonal to many previous solutions (e.g., FedAVg, FedProx), so T1 can also be used in these solutions to improve their performance. In Section 4.2-4.5, T2 (global-local knowledge fusion technique) is elaborated.

4.2 Data-Free Knowledge Distillation

Knowledge distillation (KD) technique enables a student model to learn from one or multiple teacher models [9, 7]. KD supports the student model compression while enabling the student model to inherit knowledge distilled from teacher(s). The classic KD solutions (e.g., [9, 23]) require a proxy dataset during the distillation. However, in FL, the exchange of dataset is prohibited due to the security concerns. Accordingly, FedKF employs the idea of data-free KD [24, 2, 6] to eliminate the requirement for the proxy dataset on the client side. In data-free KD, a generator can be trained and then used for generating the imitated training samples. The imitated training samples are expected to be close to the real training samples that are used to train the teacher model. Therefore, once they are used to train the student model, the knowledge of the teacher model is distilled to the student model in a data-free manner.

4.3 Loss Functions for Training Generator

To facilitate the description, we first describe the following parameters. Let \( G \) be the generator. On input a set of random noise vectors \( \{z^i\}_{i=1}^N \), the generator outputs samples \( \{x^i_G\}_{i=1}^N \). It is given by \( x^i_G = G(\theta; z^i) \), where \( \theta \) is the weight of \( G \). On input \( \{x^i_G\}_{i=1}^N \), the teacher model can output the logit outputs \( \{l^i_T\}_{i=1}^N \), where \( l^i_T = \mathcal{N}(w^T; x^i_G) \) (\( \mathcal{N} \) represents a neural network-induced function) and \( l^i_T = \{l^i_c\}_{c=1}^C \) (\( C \) is the number of classes). On input the logit outputs to the softmax function, it outputs a set of probability vectors \( \{p^i_T\}_{i=1}^N \), where \( p^i_T = \{p^i_c\}_{c=1}^C \) in which each entry represent the probability that the input sample \( x^i_G \) being classified as a certain class. The probability classified as class \( c \) is given by \( p^i_c = \exp(l^i_c)/\sum_{c=1}^C \exp(l^i_c) \). Based on the above definitions, the loss functions for training the generator are introduced as follows.

Cross Entropy Loss Function. The pseudo-sample \( x^i_G \) should enforce one entry in \( p^i_T \) to be close to 1 and other entries to be close to 0. Let \( |C| \) represent the set \( \{1, \ldots, C\} \). The pseudo-label \( \hat{y}^i \in [C] \) for \( x^i_G \) is calculated by \( \hat{y}^i = \arg\max(p^i_1, \ldots, p^i_C) \). The cross entropy loss function is defined as

\[
\mathcal{L}_{CE} = -\frac{1}{n} \sum_{i=1}^n \log p^i_{\hat{y}^i}.
\] (1)

If \( \mathcal{L}_{CE} \) is minimized, then a generated sample can be classified into one specific class with significantly high probability. This phenomenon occurs when real samples are used for training.

Information Entropy Loss Function. In order to force the generator to generate samples covering all classes, the information entropy loss is used to measure the uniformity of the class distribution. For the generated samples \( \{x^i_G\}_{i=1}^N \), their information entropy loss can be defined as

\[
\mathcal{L}_{IE} = \sum_{c=1}^C \tilde{p}_c \log \tilde{p}_c,
\] (2)

where \( \tilde{p}_c = \frac{1}{n} \sum_{i=1}^n p^i_c \). When \( \mathcal{L}_{IE} \) moves to the minimum, the generator \( G \) tends to generate samples for each class with roughly the same probability. Thus, minimizing the information entropy loss can result in a training sample set in which the number of samples for each class is roughly the same.

Activation Loss Function. It is observed that the real training sample’s feature vector tends to receive higher activation value. Thus, the activation loss function is defined as

\[
\mathcal{L}_A = -\frac{1}{n} \sum_{i=1}^n \|\hat{y}^i_T\|_1,
\] (3)

6
where $\mathbf{f}_i^t$ is the feature vector extracted from $x_i^t$ by the teacher model and $\|\cdot\|_1$ is the $l_1$ norm.

**Total Loss Function.** By taking the above three loss functions into consideration, the total loss function for the generator training is given by

$$L_G = L_{IE} + \lambda_1 L_{CE} + \lambda_2 L_A,$$

where $\lambda_1$ and $\lambda_2$ are hyper parameters for balancing the three loss functions.

### 4.4 Loss Functions for Training Student Model

The student model is trained by $\text{T2}$ (data-free KD-local training technique). The used loss functions are introduced as follows.

**KL Loss Function.** FedKF uses the imitated training samples generated by generator $\mathcal{G}$ to distill the knowledge from the teacher model (embedding the global knowledge) to the student model. Meanwhile, the local dataset (embedding the local knowledge) is used to train the student model.

On input a set of random noise vectors $\{z^i\}_{i=1}^{n_k}$, the samples generated by the generator are $\{x_i^G\}_{i=1}^{n_k}$, where $x_i^G = \mathcal{G}(\theta; z^i)$. On input the samples $\{x_i^G\}_{i=1}^{n_k}$ to the teacher model $w^T$ and the student model $w^S$ simultaneously, the logit outputs of $w^T$ and $w^S$ are $\{\mathcal{N}(w^T; x_i^G)\}_{i=1}^{n_k}$ and $\{\mathcal{N}(w^S; x_i^G)\}_{i=1}^{n_k}$, respectively. We define the knowledge distillation loss as

$$L_{KL} = \frac{1}{n_k} \sum_{i=1}^{n_k} \text{KL} \left( \sigma \left( \mathcal{N}(w^T; x_i^G) \right), \sigma \left( \mathcal{N}(w^S; x_i^G) \right) \right),$$

where $\sigma$ is the softmax function and KL stands for Kullback–Leibler divergence [17]. When minimizing $L_{KL}$, the student model is moving closer to the teacher model (i.e., learning the global knowledge).

**Cross Entropy Loss Function.** The outputs of the student model over local data instances $\{x^i\}_{i=1}^{n_k}$ are $\{\mathcal{N}(w^S; x^i)\}_{i=1}^{n_k}$. We define objective function of local optimization as

$$L_{CE} = \frac{1}{n_k} \sum_{i=1}^{n_k} \text{CE} \left( \sigma \left( \mathcal{N}(w^S; x^i) \right), y^i \right),$$

where CE stands for cross entropy and $y^i$ is the ground-truth label of $x^i$. When minimizing $L_{CE}$, the student model is learning the local knowledge (embedded in the local dataset).

**Total Loss Function.** The total loss function for global-local knowledge fusion is given as

$$L_S = L_{CE} + \gamma L_{KD},$$

where $\gamma$ is a hyper parameter for balancing the two loss functions. When minimizing $L_S$, the global-local knowledge is fused to the student model.

### 4.5 FedKF Training Algorithm

The detailed FedKF training algorithm is shown in Algorithm [1]. In step s1 and s2, the server initializes ACA model (i.e., student model) weight $w^S$, OCA model (i.e., teacher model) weight $w^T$, and all weights in the cache slots with $w_0$. In step s3, there are $m$ selected active clients in $t$-th round denoted as $\mathcal{S}_t$. In step s4, $k$-th client executes ClientUpdate and uploads the latest local weight $w^k_i$ to the server. In step s5, the $k$-th weight $w^k_i$ in the cached slot is replaced by $w^k_i$. In step s6, after all active clients upload the local weights, the server aggregates all active clients’ local weights and gets the updated $w^T$ and $w^S$. In step s7, when the training is finished, the OCA model (not the ACA model) is used as the final model to be used. In step c5, given a set of noise vectors $\{z^i\}_{i=1}^{B}$, the generator weight $\theta$ is updated via minimizing $L_G$. In step c6, given a set of noise vectors $\{z^i\}_{i=1}^{M}$ and a batch of local instances $b$, the student network weight $w^S$ is updated via minimizing $L_S$. Note that in step c6, the global knowledge (embedded in the teacher network) and local knowledge (embedded in local dataset) is fused and transferred to the updated local model.

### 5 FedKF Analysis

In this section, we analyze FedKF from four aspects: why high AMP, why high fairness, why privacy-preserving, and its relationship with agnostic FL.
Algorithm 1: FedKF Training. The parameter $K$ is the number of total clients; $m$ is the number of active clients; $\mathbf{w}^k$ is the model weight in the $k$-th cache slot; $T$ is the number of global rounds; $E$ is the number of local epochs; $B$ is the local batch size; $D_k$ is the local dataset of $k$-th client; $\beta$ and $\eta$ are the learning rate.

Server executes:

1. Initialize $w_0$
2. for round $t = 1, 2, \ldots, T$
   1. for each client $k \in S_t$ in parallel do
      1. $w^k_t \leftarrow \text{ClientUpdate}(k, w^T_{t-1}, w^S_{t-1})$
   2. end for
3. $w^T_t \leftarrow \frac{1}{\sum_{k=1}^m |D_k|} \sum_{k=1}^K |D_k| \mathbf{w}^k$
4. $w^S_t \leftarrow \frac{1}{\sum_{k \in S_t} |D_k|} \sum_{k \in S_t} |D_k| \mathbf{w}^k$

ClientUpdate($k, w^T, w^S$): // Execute on client $k$

1. Initialize $\theta_0$
2. $\theta \leftarrow \theta_0$
3. $B \leftarrow$ (split $D_k$ into batches of size $B$)
4. for each local epoch $i = 1, 2, \ldots, E$
   1. for each batch $b \in B$ do
      1. Randomly generate a batch of noise vectors: $Z = \{z^i\}_{i=1}^B$
      2. $\theta \leftarrow \theta - \beta \cdot \nabla \mathcal{L}_G(\theta, \mathbf{w}^T, Z)$ // Update generator weight via minimizing $\mathcal{L}_G$
      3. $w^S \leftarrow w^S - \eta \cdot \nabla \mathcal{L}_S(\theta, \mathbf{w}^T, w^S, Z, b)$ // Update student model weight via minimizing $\mathcal{L}_S$
   2. end for
5. end for
6. return $w^S$ to the server as the updated local model

5.1 Why High Average Model Performance

There are two techniques contributed to the high AMP of FedKF.

**T1 Helps to Improve AMP.** On the server side, in the final used model generation (in the last step of training), most previous solutions use the active clients aggregated (ACA) model. Since ACA only aggregates a small portion of clients, it could lead to a large AMP degradation. In contrast, when T1 is used to generate the final model to be used in the last step of training, it aggregates a model that contains more precise global knowledge learned during FL. Thus, T1 can significantly increase AMP of FedKF.

**T2 Helps to improve AMP.** In FedAvg, the AMP degradation is caused by the client model drift issue when training on heterogeneous data. To improve AMP, FedKF uses T2 to address the client model drift issue. On the client side, when performing local training, each client learns the global knowledge at the same time. T2 can regularize the local model training by jointly considering both global and local knowledge. It can avoid model overfitting towards local datasets. Thus, the client model drift issue is alleviated and AMP of FedKF is boosted by using T2.

5.2 Why High Fairness

There are two techniques contributed to the high fairness of FedKF.

**T1 Helps to Improve Fairness.** On the server side, in the final used model generation (in the last step of training), most previous solutions use the active clients aggregated (ACA) model. Because ACA only aggregates a small portion of clients, it could generate a model that is biased towards only the active clients. Although the inactive clients in the last round may also join the training process in some previous rounds, the last round of aggregation plays a more important role in generating the final used model. Thus, ACA model has a poor fairness. On the contrary, if T1 is used to generate the final model to be used, both the inactive and the active clients are taken into consideration, leading to a fairer model.
**T2 Helps to Improve Fairness.** In FedAvg, the local model is trained only on local dataset, so the local model could be overfitted on each local dataset. It leads to different degrees of overfitting on different clients. Hence, the AMP variations could be very large and the model fairness could be low. In contrast, T2 can be used to avoid model overfitting towards local datasets since both global knowledge (embedded in the teacher network) and local knowledge (embedded in the local dataset) are fused to generate the new local model. Therefore, T2 can help FedKF to achieve a higher model fairness.

5.3 Why Privacy-Preserving

In each FedKF training round, there are two information flows exchanged between the server and each client. First, the server needs to send two models (i.e., teacher model and student model) to each client. Second, each client needs to send the updated local model to the server after the global-local knowledge fusion. Hence, no information about the local data is shared directly. According to Definition [3], FedKF is privacy-preserving.

5.4 Relationship with Agnostic FL

The traditional FL is to optimize the model on the global distribution. In practice, the target distribution can be very different from the real target distribution in use. To improve the applicability of FL, agnostic federated learning (AFL) is proposed [29]. AFL aims to optimize the model performance on any possible target distribution formed by a mixture of the client distributions. Thus, AFL better captures the reality and it significantly expands the applicability of FL.

The mathematical description of AFL is presented as follows. Let $\text{Dis}_k$ denote the local data distribution of $k$-th client. The global distribution $\bar{\text{U}}$ is denoted as $\bar{\text{U}} = \sum_{k=1}^{K} \frac{n_k}{n} \text{Dis}_k$, where $n_k$ represents the number of $k$-th client’s local samples. It follows that $n = \sum_{k=1}^{K} n_k$. In AFL, the target distribution $\bar{\text{U}}$ can be modeled as an unknown mixture of the distributions $\text{Dis}_k (k = 1, \ldots, K)$. That is, $\bar{\text{U}} = \sum_{k=1}^{K} \hat{p}_k \text{Dis}_k$, where $\hat{p}_k$ is the weight of $k$-th client. It holds that $\sum_{k=1}^{K} \hat{p}_k = 1$.

AFL aims to optimize the model performance on $\bar{\text{U}} = \sum_{k=1}^{K} \hat{p}_k \text{Dis}_k$ for any possible choices of $\hat{p}_k (k = 1, \ldots, K)$.

For a model trained by using AFL, it may be used for many different agnostic target domains. Each agnostic target domain represents a distinct use case. A good model in AFL is expected to have both high AMP and high fairness in heterogeneous AFL. In the following, we theoretically prove that a model trained by FedKF can directly have both high AMP and high fairness in heterogeneous AFL.

**Lemma 5.1** We denote by $\text{w}$ a trained model via using FedKF. In heterogeneous FL with FedKF, let $\Omega = \{\text{Dis}_1, \ldots, \text{Dis}_K\}$ represent a set of the client distributions, where $\text{Dis}_k$ is the distribution for $k$-th client. $\text{WL}_w^\Omega$ denotes the worst-case local performance on $\Omega$. Suppose that $\text{w}$ is used for an arbitrary agnostic domain $\bar{\text{U}}$, let $MP_{\text{w}}^{\bar{\text{U}}}$ be the model performance on the agnostic domain $\bar{\text{U}}$. It holds that $MP_{\text{w}}^{\bar{\text{U}}} \geq \text{WL}_w^\Omega$.

**Proof:** Let $a^k_w$ represent the test accuracy on distribution $\text{Dis}_k (k = 1, \ldots, K)$. Then, $\text{WL}_w^\Omega$ is given by $\text{WL}_w^\Omega = \min\{a^1_w, \ldots, a^K_w\}$.

For $MP_{\text{w}}^{\bar{\text{U}}}$, we have $MP_{\text{w}}^{\bar{\text{U}}} = \sum_{k=1}^{K} \hat{p}_k a^k_w$. According to Eq. (9), $\text{WL}_w^\Omega$ is the lower bound for $a^k_w (k = 1, \ldots, K)$. Thus, substituting $a^k_w (k = 1, \ldots, K)$ to be $\text{WL}_w^\Omega$ in Eq. (10), it holds that $MP_{\text{w}}^{\bar{\text{U}}} \geq \sum_{k=1}^{K} \hat{p}_k \text{WL}_w^\Omega$.
Theorem 5.1 We denote by $w$ a trained model via using FedKF. Suppose that there are multiple (e.g., $Q$) arbitrary agnostic target domains $\hat{U}_i$ ($i = 1, \ldots, Q$). Let $WLP_{\hat{U}_i}^{w}$ be the worst-case performance on these agnostic target domains, where $\hat{\Omega} = \{\hat{U}_1, \ldots, \hat{U}_Q\}$. It holds that

$$WLP_{\hat{U}_i}^{w} \geq WLP_{\hat{\Omega}}^{w}, \quad (11)$$

where the definition of $WLP_{\hat{\Omega}}^{w}$ can be found in Lemma 5.1.

Proof: According to Lemma 5.1, it holds that $MP_{\hat{U}_i}^{w} \geq WLP_{\hat{\Omega}}^{w}$ for any $i \in [Q]$. Since $WLP_{\hat{U}_i}^{w} = \min\{MP_{\hat{U}_1}^{w}, \ldots, MP_{\hat{U}_M}^{w}\}$, we have $WLP_{\hat{U}_i}^{w} \geq WLP_{\hat{\Omega}}^{w}$. □

According to Theorem 5.1, the WLP of a model trained by FedKF in heterogeneous FL is the lower bound of the WLP when the model is used for heterogeneous AFL. Given the fact that WLP metric tends to measure the joint performance of AMP and FM, so FedKF directly turns out to be a good solution to achieve high AMP and high fairness simultaneously in heterogeneous AFL. Accordingly, FedKF has much broader impacts since AFL significantly expands the applicability of FL.

6 Experiments

This section first introduces the experiment setup. Then, the experimental results are reported.

6.1 Experiment Setup

Solutions in Comparison. We compare FedKF with previous FL algorithms including FedAvg [28], FedProx [21], FedGKD [36], and q-FFL [22]. For q-FFL, we use FedAvg as its optimization method and it is also called q-FedAvg in [22]. A more detailed review of these solutions can be found in Section 2. Note that $T1$ is orthogonal to FedAvg, FedProx, and FedGKD, so $T1$ can also be used in these solutions to improve their performance. These upgraded solutions are named FedAvg+$T1$, FedProx+$T1$, and FedGKD+$T1$, respectively. We also compare FedKF with these upgraded solutions.

Datasets. We conduct experiments on three datasets including CIFAR-10, CIFAR-100 [16] and EMNIST [4]. For EMNIST, we only use a subset of the dataset by randomly sampling 10% from each class. Each client’s local dataset is split into 80% training set and 20% testing set randomly. Following previous works [23] [40] [20] [36], we use Dirichlet distribution to model heterogeneous data. The Dirichlet distribution $\text{Dir}_K(\alpha)$ has a adjustable concentration parameter $\alpha$. A smaller $\alpha$ implies a higher data heterogeneity across different clients. Fig. 2 shows statistical heterogeneity among clients on CIFAR-10 dataset with different concentration parameter $\alpha$.

Implementation & Training Details. The proposed FedKF and solutions in comparison are all implemented in PyTorch [30] and evaluated on a Linux server with two TITAN RTX GPUs. For

Figure 2: Visualization of statistical heterogeneity among clients on CIFAR-10 dataset with different $\alpha$. The size of scattered points is proportional to the number of training samples for a label available on the client.
The optimizer used in training the generator and the student network are Adam and SGD, respectively.

Table 3-5 show the performance metrics (i.e., AMP, FM, and WLP) of

\[ \text{compare with } q-FFL, \text{ we tune } q-FFL's \text{ parameter } \gamma \text{ from } \{0.00001, 0.0001, 0.001, 0.01, 0.1, 1\}. \text{ The best } \lambda_1 \text{ for CIFAR-10, CIFAR-100 and EMNIST are } 0.01, 0.01 \text{ and } 0.1 \text{, respectively. For FedKF’s parameter } \gamma, \text{ when using CIFAR-10 with } \alpha = 1 \text{, we set } \gamma = 0.001. \text{ In all other cases, } \gamma \text{ is fixed at } 1. \]

To compare with FedProx, we tune FedProx’s parameter \( \mu \) from \( \{0.00001, 0.0001, 0.001, 0.01, 0.1, 1\} \) and report the best result. For FedProx, the best \( \mu \) for CIFAR-10, CIFAR-100, and EMNIST are 0.001, 0.0001, and 0.001, respectively. To compare with FedGD, following [36], we set the default buffer size as 5. For FedGKD, we tune FedGKD’s parameter \( \gamma \) from \( \{0.001, 0.01, 0.1, 0.2, 0.5, 1\} \). The best \( \gamma \) for CIFAR-10, CIFAR-100, and EMNIST are 0.2, 0.2, and 0.001, respectively. To compare with q-FFL, we tune q-FFL’s parameter \( q \) from \{0.00001, 0.0001, 0.001, 0.01, 0.1, 1\}. The best \( q \) for CIFAR-10, CIFAR-100, and EMNIST are 0.00001, 0.0001, and 0.0001, respectively.

6.2 Experimental Results

Performance Metrics. Table 3 shows the performance metrics (i.e., AMP, FM, and WLP) of different solutions for three degrees of data heterogeneity (\( \alpha = 1, 0.1, 0.01 \)). In the tables, for each test case, the best result is marked as bold font and the second best is marked using underline. We have the following five findings.

- **F1**: FedKF performance is the best when \( \alpha = 0.1 \) and 0.01 on both CIFRA-10 and CIFAR-100 datasets. When using CIFAR-10 (with \( \alpha = 1 \), AMP, FM, and WLP of FedKF ranks either 1st or 2nd among all 8 solutions in comparison. When using CIFAR-100 with \( \alpha = 1 \), both AMP and WLP metrics are the best, while FM ranks 2nd.
Table 5: Performances of different solutions on EMNIST.

| Solutions          | α = 1          | α = 0.1        | α = 0.01       |
|--------------------|----------------|----------------|---------------|
|                    | AMP (%) | FM (x10^{-4}) | WLP (%)  | AMP (%) | FM (x10^{-4}) | WLP (%)  | AMP (%) | FM (x10^{-4}) | WLP (%)  |
| FedAvg             | 84.42 ± 0.54 | 1.876 ± 0.127 | 73.91 ± 0.53 | 76.64 ± 0.43 | 7.554 ± 0.429 | 57.67 ± 0.36 | 62.61 ± 0.38 | 3.318 ± 0.186 | 18.81 ± 0.00 |
| FedProx            | 85.02 ± 0.51 | 1.670 ± 0.176 | 74.78 ± 0.48 | 77.48 ± 0.38 | 6.291 ± 0.313 | 57.06 ± 0.28 | 62.97 ± 0.41 | 3.591 ± 0.191 | 18.81 ± 0.00 |
| FedGKD             | 84.82 ± 0.63 | 1.354 ± 0.119 | 78.26 ± 0.45 | 77.24 ± 0.51 | 6.103 ± 0.481 | 58.28 ± 0.41 | 63.41 ± 0.46 | 3.662 ± 0.138 | 18.81 ± 0.00 |
| q-FFL              | 84.03 ± 0.65 | 0.733 ± 0.058 | 79.28 ± 0.58 | 76.92 ± 0.62 | 4.697 ± 0.252 | 64.22 ± 0.44 | 62.46 ± 0.61 | 3.196 ± 0.166 | 18.75 ± 0.06 |
| FedAvg+T1          | 84.66 ± 0.39 | 1.093 ± 0.082 | 78.10 ± 0.34 | 79.03 ± 0.36 | 4.504 ± 0.224 | 65.14 ± 0.27 | 66.21 ± 0.32 | 2.033 ± 0.147 | 33.66 ± 0.15 |
| FedProx+T1         | 84.82 ± 0.33 | 1.184 ± 0.097 | 78.18 ± 0.41 | 79.63 ± 0.29 | 3.650 ± 0.237 | 66.26 ± 0.34 | 65.81 ± 0.27 | 2.348 ± 0.165 | 30.21 ± 0.24 |
| FedGKD+T1          | 84.70 ± 0.47 | 0.747 ± 0.083 | 78.26 ± 0.42 | 78.71 ± 0.44 | 3.683 ± 0.243 | 65.03 ± 0.41 | 65.77 ± 0.38 | 2.372 ± 0.178 | 31.25 ± 0.12 |
| FedKF (ours)       | 86.42 ± 0.36 | 0.943 ± 0.074 | 80.00 ± 0.37 | 82.63 ± 0.31 | 2.629 ± 0.175 | 70.64 ± 0.29 | 71.73 ± 0.34 | 2.328 ± 0.132 | 38.64 ± 0.18 |

Figure 3: FedKF performance v.s. number of communication rounds using CIFAR-10 dataset.

- **F2:** For all α values on EMNIST dataset, FedKF’s FM ranks either 1st or 2nd while AMP and WLP are always the best.
- **F3:** One limitation of FedKF is that its performance gains are marginal when dealing with less heterogeneous data (i.e., α = 1).
- **F4:** The superiority of FedKF (over other solutions) is generally more obvious with a decreasing of α (i.e., higher data heterogeneity). For example, on CIFAR-100, FedKF’s WLP is (35.78%-34.48%)=1.3% better than the second best solution when α = 1, whereas it is (11.80%-5.14%)=6.66% better than the second best solution when α = 0.01. Hence, FedKF is especially good at dealing with highly heterogeneous data.
- **F5:** The previous solutions (when equipped with T1) usually have better performance than their original ones. For example, when using CIFAR-10 with α = 0.01, AMP of FedAvg is increased from 36.24% to 45.34%.
**Communication Efficiency.** As shown in Fig. 3, FedKF has a faster learning speed (i.e., has higher communication efficiency) than other solutions when $\alpha = 0.1$ and 0.01. It is shown that the superiority of FedKF (in terms of communication efficiency) is more significant with a decreasing $\alpha$ (i.e., higher data heterogeneity).

**Robustness.** It can be found from Fig. 3 that FedKF is more robust than other solutions (in terms of the performance stability) during FL. As shown in Fig. 3, the fluctuation amplitude of performance metrics in FedAvg, FedGKD, and $q$-FFL is generally increasing with a decreasing $\alpha$. However, FedKF exhibits a relatively smooth learning curve of the three metrics for all $\alpha$ values.

7 Conclusion

In this paper, we have developed FedKF to handle data heterogeneity in FL. Two novel techniques are developed to achieve the precise global knowledge representation and global-local knowledge fusion, by which the local model drift issue can be alleviated. We theoretically prove that FedKF can directly turn out to be a good solution in heterogeneous agnostic FL. Hence, FedKF has much broader impacts since AFL better captures the reality. According to theoretical analysis and experimental results, FedKF achieves the three design goals (high model performance, high model fairness, and privacy-preserving) simultaneously.

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