

FedCache: A Knowledge Cache-driven Federated Learning Architecture for Personalized Edge Intelligence

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Abstract—Edge Intelligence (EI) allows Artificial Intelligence (AI) applications to run at the edge, where data analysis and decision-making can be performed in real-time and close to data sources. To protect data privacy and unify data silos distributed among end devices in EI, Federated Learning (FL) is proposed for collaborative training of shared AI models across multiple devices without compromising data privacy. However, the prevailing FL approaches cannot guarantee model generalization and adaptation on heterogeneous clients. Recently, Personalized Federated Learning (PFL) has drawn growing awareness in EI, as it enables a productive balance between local-specific training requirements inherent in devices and global-generalized optimization objectives for satisfactory performance. However, most existing PFL methods are based on the Parameters Interaction-based Architecture (PIA) represented by FedAvg, which suffers from unaffordable communication burdens due to large-scale parameters transmission between devices and the edge server. In contrast, Logits Interaction-based Architecture (LIA) allows to update model parameters with logits transfer and gains the advantages of communication lightweight and heterogeneous on-device model allowance compared to PIA. Nevertheless, previous LIA methods attempt to achieve satisfactory performance either relying on unrealistic public datasets or increasing communication overhead for additional information transmission other than logits. To tackle this dilemma, we propose a knowledge cache-driven PFL architecture, named FedCache, which reserves a knowledge cache on the server for fetching personalized knowledge from the samples with similar hashes to each given on-device sample. During the training phase, ensemble distillation is applied to on-device models for constructive optimization with personalized knowledge transferred from the server-side knowledge cache. Empirical experiments on four datasets demonstrate that FedCache achieves comparable performance with state-of-art PFL approaches, with more than two orders of magnitude improvements in communication efficiency. Our code and DEMO are available at <https://github.com/wuzhiyuan2000/FedCache>.

Index Terms—Edge computing, personalized federated learning, knowledge distillation, communication efficiency

1 INTRODUCTION

EDGE Intelligence (EI) is an emerging technology for the marriage of edge computing and Artificial Intelligence (AI), enabling real-time data analysis and decision-making close to data sources instead of relying solely on

the cloud [1]. With the proliferation of mobile devices and the unprecedented amount of data generated by ubiquitous devices, EI is playing an increasingly important role in many areas such as unmanned vehicles [2], smart homes [3], recommender systems [4], etc. However, conventional centralized EI paradigms require uploading raw data for training pervasive AI models, raising privacy concerns about sensitive data leakage.

Federated Learning (FL) is a privacy-preserving distributed learning paradigm that enables multiple data owners to collaboratively train AI models without sharing owners' private data. Due to the benefits of data localization and privacy protection, FL has shown great potential in various EI applications, such as healthcare [5], smart transportation [6], industrial manufacturing [7], etc. Unfortunately, the prevailing FL approaches [8], [9] require all participating devices (named clients) to share a uniform model, which is extremely difficult to deploy and generalize to all devices because of the inherent characteristics of device variation in terms of data heterogeneity, resources limitation, task differentiation, etc [10], [11]. Recent studies pay much attention to Personalized Federated Learning (PFL) [11] for addressing the differential training challenges in EI via building personalized models for individual devices, as shown in Fig. 1. However, most PFL approaches [12]–[14]

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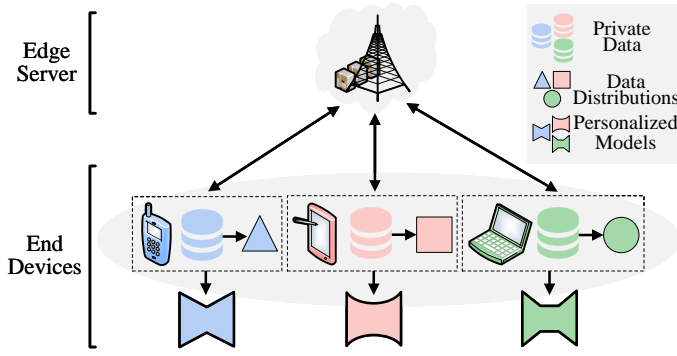


Fig. 1. Schematic diagram of personalized federated learning for edge intelligence.

adopt the Parameters Interaction-based Architecture (PIA) represented by FedAvg [8], which requires homogeneity of on-device model architectures and imposes tremendous communication burden caused by large-scale parameters exchange between clients and the server for bandwidth-limited devices [15], [16].

Furthermore, by applying knowledge distillation technology [17]–[19] to PFL, a series of communication-lightweight and heterogeneous model-allowable PFL architectures with logits (usually called knowledge) exchange instead of interacting model parameters are put forward. These architectures, which we call Logits Interaction-based Architecture (LIA), bring the benefits of saving orders of magnitude of communication overhead and training models with heterogeneous architectures. Related literatures [16], [20]–[23] fall into two types of architectures based on the granularity of the interacted logits during training: Class-grained Logits Interaction-based Architecture (CLIA) and Sample-grained Logits Interaction-based Architecture (SLIA). Thereinto, SLIA is drawn more attention since it allows for fine-grained interaction of logits for performance guarantee. However, existing methods based on SLIA endeavor to achieve satisfactory performance either relying on additional client-side training on unrealistic public datasets [20], [21], or requiring the transfer of embedded features with non-negligible sizes in addition to logits [22], [24]. They appear to be unfriendly to devices by reason of the induction of intensive computation, tremendous communication, or public datasets reliance, making them unsuitable for practical applications in EI [25].

In this paper, we develop a novel device-friendly PFL architecture that is suitable for EI, named knowledge cache-driven FL architecture (FedCache). In contrast to prior architectures, FedCache reserves a knowledge cache on the server to store the latest knowledge associated with each private sample, and applies a customized knowledge cache-driven personalized distillation technique for on-device model training. During the initialization process, all private samples on clients are encoded into hashes via a deep pre-trained neural network, so as to discern the relational degree among samples in a privacy-preserving manner. During the training process, each on-device model is optimized via personalized knowledge distillation over the ensemble of

relevant knowledge whose corresponding hashes are the R -nearest neighbors of the hash of the given sample to be optimized on, which is fetched from the server-side knowledge cache. To our best knowledge, FedCache is the **first Sample-grained Logits Interaction-based Architecture (SLIA) dispensed with features transmission and public datasets**, ensuring the satisfactory performance of on-device models while meeting the practical limitations of EI.

In general, we summarize the contributions of our proposed FedCache as follows:

- **Device Friendliness.** FedCache is a device-friendly architecture that enables only small-scale ensemble logits to be transferred between clients and the server during training without needing public datasets. Meanwhile, FedCache supports collaborative training on devices with heterogeneous models.
- **Scalability.** FedCache is a highly scalable architecture for large-scale devices since it eliminates the need to keep a cumbersome global model on the server and also enables asynchronous training, effectively reducing the server-side computation and client-server synchronization consumption.
- **Effectiveness.** FedCache is compared with state-of-art PFL methods with various architectures on four common datasets. Results confirm that FedCache achieves performance comparable to benchmark algorithms while improving communication efficiency by two orders of magnitude.

2 RELATED WORK

2.1 Federated Learning for Personalized Edge Intelligence

As a uniform shared model cannot accommodate multiple clients with diverse tasks and capabilities [10], [26], personalization techniques in FL are needed to adapt clients-side individualized requirements. Specifically, federated multi-task learning in edge computing [13], [22] allows clients to train personalized neural networks to accommodate the differentiated data distribution in their respective tasks. [14] retains historical personalized models on devices, allowing current models to distill knowledge from previous models for personalized EI. [27] leverages a source-free unsupervised domain adaptation approach to adapt large source-domain models to target data on devices, while adopting lite residual hypothesis transfer to save the storage overhead during the adaptation process. In addition, [28] considers the personalization of accuracy targets on clients and uses adaptive learning rates to allow clients that reach the target to exit in advance for saving resources.

Unlike prior works, we focus on the architecture design of PFL to enable efficient communication as well as asynchronous training, while also supporting heterogeneous on-device models without requiring public datasets, aiming to bridge the gap between PFL and practical applications in EI.

2.2 Knowledge Distillation in Federated Edge Learning

As noted in [25], knowledge distillation has emerged as an important technique for addressing challenges in federated edge learning. [23], [29] leverage knowledge distillation

as a communication protocol for exchanging model representations among devices and the edge server, enabling communication-efficient training over heterogeneous models. [30], [31] transfer knowledge from edge models to differentiated on-device models in FL under device heterogeneity. [14], [22] conduct distillation-based personalized FL optimization over on-device models to support personalized EI.

However, the above approaches cannot achieve satisfactory performance in a device-friendly manner, since they either need features/model parameters transfer or rely on public data during the training process. In contrast, our Fed-Cache architecture solves all the above-mentioned problems and enables practical use in personalized EI.

3 PRELIMINARY AND MOTIVATION

3.1 Background and Notations

We investigate PFL for EI, where distributed devices (named clients) collaboratively train C -class classification models coordinated by an edge server (named the server) while keeping private data on devices. We assume that K clients participate in PFL, and each client $k \in \{1, 2, \dots, K\}$ occupies a private dataset $\mathcal{D}^k := \bigcup_{i=1}^{N^k} \{(X_i^k, y_i^k)\}$, where N^k is the number of samples in \mathcal{D}^k , and X_i^k, y_i^k are the i -th data and label in \mathcal{D}^k , respectively. Each device k owns a personalized model $M^k := (W^k, f^k)$ with possible different model parameters or architectures, where W^k is the model parameters of M^k and $f^k(\cdot)$ is the non-linear mapping determined by M^k . The goal of each device is to improve the User model Accuracy (UA) [13] of its personalized model on its private data as much as possible. The optimization objective of the PFL system is to maximize the Maximum Average UA (MAUA) of all clients, that is to achieve generally satisfactory performance on each client. The main notations and descriptions can be referred to TABLE 1.

3.2 Practical Limitations in Edge Intelligence

We summarize the main practical limitations that PFL architectures need to overcome when deploying in EI:

- **Device Heterogeneity.** Considering the different hardware configurations of end devices such as CPU, memory resources, and energy status, personalized models need to be adopted among devices to fit their specific characteristics [32], [33].
- **Communication Efficiency.** Due to the limited wireless network bandwidth between edge servers and end devices, they are not capable of large-scale communication [16], [32].
- **Data Privacy.** Devices are reluctant to share their local data with edge servers because of privacy concerns or data protection regulations [34], [35]. Hence, it is difficult to obtain information about users' local data.
- **Asynchronous Optimization.** The high synchronization overhead caused by varying computation tasks, capabilities, and communication delays of different devices impedes model update [36], [37].

TABLE 1
Main notations with descriptions.

Notation	Description
C	The number of classes
K	The number of clients
\mathcal{D}^k	The local dataset of client k
X_i^k	The i -th sample of \mathcal{D}^k
y_i^k	The label of X_i^k
N^k	The number of samples in \mathcal{D}^k
M^k	The personalized model on client k
W^k	The model parameters of M^k
f^k	The non-linear mapping determined by M^k
f^h	The hash mapping determined by a pre-trained deep neural network
L_{CE}	The cross-entropy loss
KL	The Kullback-Leibler divergence loss
σ_0	The softmax mapping
LI	The label-to-index pairs
IK	The index-to-knowledge pairs
IH	The index-to-hash pairs
IR	The index relations pairs
KC	The knowledge cache
R	The number of related samples in KC
h_i^k	The hash value of X_i^k
z_i^k	The knowledge of X_i^k
$(zr_i^k)_s$	The s -th knowledge fetched for the given sample index (k, i)
\bar{zT}_i^k	The ensembled fetched knowledge for the given sample index (k, i)
J^k	The optimization objective of M^k

3.3 Overview of PFL Architectures

3.3.1 PFL Architecture based on Parameters Interaction

For Parameters Interaction-based Architecture (PIA), each client periodically uploads locally-trained model parameters to the server and updates the local model with the server-downloaded model parameters obtained from aggregating local models. In PFL with PIA, clients tend to upload only part of its model parameters to preserve local adaptation capabilities [13], [14]. Therefore, filtered parameters aggregation weighted by local sample numbers is performed on the server side, that is:

$$W^* = \frac{N^k}{\sum_{l=1}^K N^l} \cdot \text{filter}(W^k), \quad (1)$$

where $\text{filter}(\cdot)$ filters out partial on-device model parameters to be uploaded to the server, and W^* represents the aggregated model parameters on the server.

Although PIA can preserve the personalization capabilities of on-device models by filtering model parameters, transmitting large-scale parameters for aggregation is still too costly for devices with limited communication resources [16], [32]. Besides, PIA requires strong homogeneity of on-

device model architectures during the aggregation process, which is difficult to realize for heterogeneous devices with differentiated hardware-related constraints [38], [39].

3.3.2 PFL Architecture based on Logits Interaction

For Logits Interaction-based Architecture (LIA), each client performs distillation-based optimization on the global logits downloaded from the server, without parameters transmission during training [22]–[24], [29], [40], [41]. Depending on the granularity of interacted logits, existing PFL architectures can be divided into two categories: class-grained logits interaction and sample-grained logits interaction.

1) Class-grained Logits Interaction-based Architecture (CLIA). For CLIA, the output of each sample X_i^k from client k needs to approach the global average logits calculated by all samples with the same label y_i^k from all other clients except client k [23], that is:

$$\arg \min_{W^k} \sum_{(X_i^k, y_i^k) \in \mathcal{D}^k} [L_{CE}(\sigma_0(f^k(X_i^k)), y_i^k) + \gamma \cdot L_{CE}(\sigma_0(f^k(X_i^k)), \sigma_0(\frac{\sum_{l=1}^K F^{l, y_i^k} - F^{k, y_i^k}}{K-1}))], \quad (2)$$

where $\sigma_0(\cdot)$ is the softmax mapping, and $L_{CE}(\cdot)$ denotes the cross-entropy loss. F^{l, y_i^k} is the average logits calculated by the samples with the same label y_i^k in client l , i.e.

$$F^{l, y_i^k} = \frac{E}{(X_i^k, y_i^k) \in \mathcal{D}^k \wedge y_i^k = y_i^k} f^k(X_i^k). \quad (3)$$

Although CLIA supports model heterogeneity with lightweight communication, it only enables C types of logits to be learned by each client. As clients learn very little additional server-side information compared to standalone, this PFL design is prone to reaching a performance limit.

2) Sample-grained Logits Interaction-based Architecture (SLIA). For SLIA, the number of logits learned by on-device models are related to the number of samples [22], [24], [29], [40], [41]. Such architecture generally requires inevitable compromises of importing public datasets or increasing communication overhead, and can be classified into two forms.

- **SLIA with Features Exchange (SLIA-FE).** In SLIA-FE, the model parameters of client k are divided into the feature extractor part W_e^k and the predictor part W_p^k , where the prediction mapping of the feature extractor is denoted as $f_e^k(\cdot)$. The server keeps only a large-scale classifier W^S with the corresponding prediction mapping $f^S(\cdot)$. Typically, the model on the server is updated with a linear combination of cross-entropy loss $L_{CE}(\cdot)$ and Kullback-Leibler divergence loss $KL(\cdot)$ depending on clients-side uploaded features and logits [22], [24], [40], which can be expressed as follows:

$$\arg \min_{W^S} \sum_{(X_i^k, y_i^k) \in \mathcal{D}^k} [L_{CE}(\sigma_0(f^S(\underbrace{f_e^k(X_i^k)}_{\text{uploaded features}})), y_i^k) + \lambda \cdot KL(\sigma_0(f^S(\underbrace{f_e^k(X_i^k)}_{\text{uploaded features}})) || \sigma_1(\underbrace{f^k(X_i^k)}_{\text{uploaded logits}}))], \quad (4)$$

where $\sigma_1(\cdot)$ is the transform mapping for local logits. Contrastively, client k performs local model param-

eters update with the server-side downloaded global logits, and optimizes the following loss function:

$$\arg \min_{W^k} \sum_{(X_i^k, y_i^k) \in \mathcal{D}^k} [L_{CE}(\sigma_0(f^k(X_i^k)), y_i^k) + \mu \cdot KL(\sigma_0(f^k(X_i^k)) || \sigma_2(\underbrace{f^S(\underbrace{f_e^k(X_i^k)}_{\text{uploaded features}})}_{\text{downloaded global logits}}))], \quad (5)$$

where $\sigma_2(\cdot)$ is the transform mapping for global logits. Although SLIA-FE allows for heterogeneous on-device models without parameters transmission, participants need to agree on the feature dimensionality. Besides, since the feature dimensionality of high-resolution images and long sequential data is often high, the overhead of features transmission is still significant for devices.

- **SLIA with Public Dataset (SLIA-PD).** For SLIA-PD, client k aims to approach the average logits of all clients on a given sample (X_i^O, y_i^O) in the public dataset \mathcal{D}^O [29], [41], that is:

$$\arg \min_{W^k} \sum_{(X_i^O, y_i^O) \in \mathcal{D}^O} L_{CE}(\sigma_0(f^k(X_i^O)), \sigma_0(\frac{1}{K} \sum_l \frac{f^l(X_i^O)}{U})), \quad (6)$$

where U is a hyper-parameter that controls the distribution of ensembled logits. We claim that SLIA-PD not only further relaxes the constraints on model architectures across clients, but also enables exchanges of only logits with minuscule sizes during training, resulting in significantly lower communication overhead compared to previously mentioned architectures. However, SLIA-PD relies on a public dataset whose distribution should be close to private data on clients [42]. As it is unlikely to collect satisfactory public data without knowing data distribution of clients, this architecture is impractical in reality.

3.4 Motivation

From the above analysis, we can conclude that existing PFL architectures cannot realize well-satisfied trade-offs among system performance, resource efficiency and without relying on public datasets, even if LIA gains advantages of remarkably reducing communication burden and tolerating heterogeneous models training over frequently-used PIA. Motivated by the analysis above about PFL architectures, we attempt to answer the following question: **how can a personalized federated learning architecture be designed to allow only logits transmission during the training process without the need for a public dataset, meanwhile significantly outperforming class-grained logits interaction-based architecture?** Concisely, our answer is to develop a knowledge cache-driven federated learning architecture with personalized distillation to optimize local models on clients.

To optimize on-device models via knowledge distillation, we propose to keep a knowledge cache on the server, which enables to fetch relevant personalized knowledge for each sample. Specifically, the server-side knowledge

TABLE 2

Comparison of FedCache with other PFL architectures in terms of model heterogeneity supportability, communication efficiency, dependency on public data, whether enable asynchronous optimization, and communication protocol.

Architecture	Model Hetero. Supportability	Comm. Efficiency	No Dependency on Public Data	Asynchronous Optimization	Communication Protocol
PIA	Partial Hetero.	Low	Yes	No	Model Parameters
CLIA	Complete Hetero.	High	Yes	No	Class-grained Logits
SLIA-FE	Complete Hetero. with Features Dim. Agreement	Medium	Yes	Yes	Sample-grained Features and Logits
SLIA-PD	Complete Hetero.	High	No	No	Sample-grained Logits
FedCache	Complete Hetero.	High	Yes	Yes	Sample-grained Logits

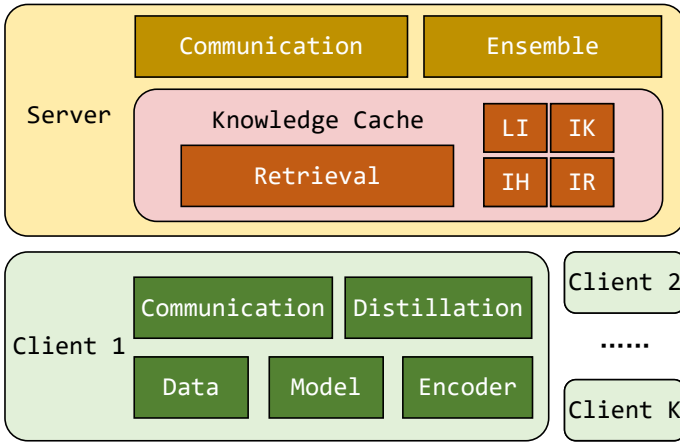
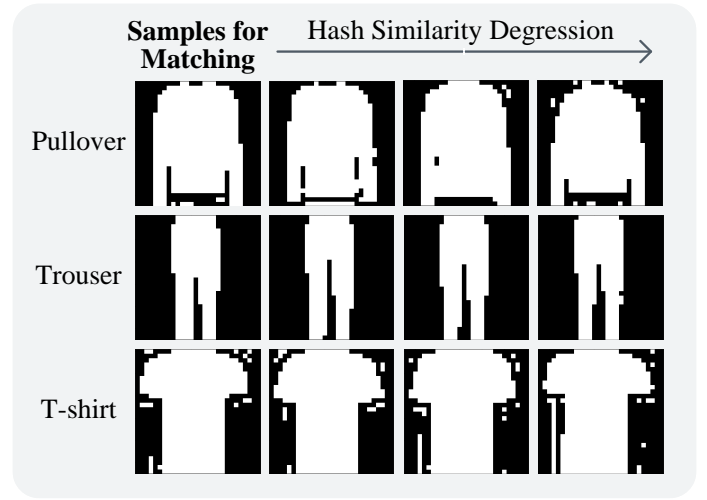


Fig. 2. Functional module diagram of FedCache.

cache keeps track of the latest knowledge of samples and leverages an information retrieval mechanism to search out the most relevant knowledge for each sample from cached knowledge. The searched knowledge from other clients is accompanied by reliable and effectual relevant representations, and is transferred to clients from which the sample originated for constructive distillation-based optimization. On this basis, sample-grained logits interaction can be realized between the server and clients to ensure that on-device models learn sufficient personalized knowledge.

Based on the above insights, FedCache is proposed, whose comparisons with other FL architectures are shown in TABLE 2. Compared to existing architectures, FedCache supports transferring sample-level logits without the assistance of public datasets during training, achieving superior performance compared to CLIA and overcoming the drawbacks of previous SLIA. In addition, FedCache is a device-friendly architecture that enables complete model heterogeneity among clients, unlike other existing approaches either requiring partial model homogeneity or agreeing on the same feature dimension. What is more, FedCache also supports asynchronous interaction of logits required for PFL systems with devices of different capabilities, since it does not need to synchronously aggregate logits from different

Fig. 3. Sample matching results on FashionMNIST dataset with $R = 3$.

clients unlike previous methods [23], [29], [41].

4 KNOWLEDGE CACHE-DRIVEN PERSONALIZED FEDERATED LEARNING

4.1 System Design

The functional module diagram of FedCache is displayed in Fig. 2, which consists of a server with three functional modules: (server-client) communication, (knowledge) ensemble, knowledge cache; and K clients with five functional modules: (client-server) communication, (knowledge) distillation, data, model, and (sample) encoder. Specifically, the ensemble module combines the fetched knowledge from the knowledge cache to obtain personalized knowledge to be distilled over clients; the knowledge cache module is our designed self-organizing knowledge storage structure that facilitates fetching each client's relevant knowledge on the server side; the model module extracts knowledge from local data, and conducts model updates under the guidance of the distillation module; in addition, the encoder module encodes private data into hashes to initialize the knowledge cache.

During the initialization phase, the generated hash codes on clients are uploaded to the server in a single pass. Then, HNSW [43] is then performed in the server-side knowledge cache, aiming to retrieve R most relevant samples for matching each sample measured by cosine similarity of hash values. Fig. 3 displays the sample matching results on FashionMNIST [44] dataset. As shown, the matched samples are very similar to the original sample, making the knowledge extracted from them beneficial to client-side distillation on the original sample. During the training phase, each logits and index of private samples are uploaded to the server in each communication round. Then, R best-matching knowledge with the highest hash similarity in the knowledge cache for each sample is fetched based on the pre-established similarity relations, followed by knowledge ensemble and then knowledge communication to corresponding clients for local distillation. As the distillation phase only relies on highly relevant knowledge of clients' respective private data, the resulting model is locally adaptable and powerful for personalization tasks. We will introduce the key procedures of FedCache in the subsequent subsections.

4.2 Knowledge Cache

The knowledge cache on the server is proposed to asynchronously fetch relevant knowledge for an arbitrary local sample with controllable computation complexity, where the corresponding hash values of samples from which relevant knowledge is extracted should be one of the R -nearest neighbors of the hash value of the original sample. Guided by the above design, we preserve multiple pairs in the knowledge cache, including label-to-index pairs (LI), index-to-knowledge pairs (IK), index-to-hash pairs (IH), and index relations pairs (IR), where each pair enables mapping the first element to the second element. On this basis, the knowledge cache is of two main phases: initialization and training.

The initialization process includes the following steps:

- **Pairs initialization.** The uploaded hash value h_i^k corresponding to each sample index (k, i) is stored in IH . In addition, indexes are added to LI according to their corresponding label classes, and the knowledge corresponding to each given index is initialized to zeros in IK , i.e.

$$IH(k, i) \leftarrow h_i^k, \quad (7)$$

$$LI(y_i^k) \leftarrow LI(y_i^k) \cup \{(k, i)\}, \quad (8)$$

$$IK(k, i) \leftarrow \underbrace{(0, \dots, 0)}_{C \text{ zeros}}. \quad (9)$$

As LI only allows relations to be built within the sample index range of the same label class, it is expected that the number of candidate samples used for matching will be reduced, improving the computation efficiency of the relations establishment in the following step.

- **Build relations.** For each given sample index (k, i) , we relate it to R indexes $\{(l_1, j_1), (l_2, j_2), \dots, (l_R, j_R)\}$ whose hash values have the greatest cosine similarity

to the hash value of the given sample among all the candidate hashes, i.e.

$$\begin{aligned} & \arg \max_{(l_1, j_1), (l_2, j_2), \dots, (l_R, j_R)} \sum_{m=1}^R \cos(IH(k, i), IH(l_m, j_m)), \\ & s.t. \begin{cases} l_{n_1} \neq l_{n_2} \vee j_{n_1} \neq j_{n_2}, \forall n_1, n_2 \wedge n_1 \neq n_2, \\ (k, i) \in LI(y^*) \wedge (l_m, j_m) \in LI(y^*), \exists y^*, \\ n_1, n_2, m \in \{1, 2, \dots, R\}, \\ y^* \in \{1, 2, \dots, C\}, \end{cases} \end{aligned} \quad (10)$$

during which HNSW [43] is adopted to achieve the R -nearest neighbors retrieval. Then, the retrieved results related to each sample index are saved in IR for subsequent access, i.e.

$$IR(k, i) \leftarrow \{(l_1, j_1), (l_2, j_2), \dots, (l_R, j_R)\} \quad (11)$$

During the training process, the following steps should be performed for each given sample index:

- **Knowledge fetching.** The most relevant knowledge can be fetched in the knowledge cache KC based on a provided sample index: for a newly uploaded sample index (k, i) , the corresponding knowledge is obtained and returned according to 1) IR which stores relevant sample indexes of (k, i) , and 2) IK which transforms relevant indexes to knowledge, that is:

$$KC(h_i^k; k, i) = IK(IR(k, i)). \quad (12)$$

As knowledge fetching requires only the clients requesting knowledge to be online, clients can asynchronously perform fetched knowledge-based optimization.

- **Knowledge update.** $IK(k, i)$ is updated with the knowledge z_i^k corresponding to the given sample index (k, i) , so that the latest knowledge can be fetched on the next access, i.e.

$$IK(k, i) \leftarrow z_i^k. \quad (13)$$

4.3 Knowledge Cache-driven Personalized Distillation

We optimize on-device models with personalized federated distillation, where knowledge of samples similar to each client's private data is fetched from the knowledge cache. On this basis, each client performs ensemble distillation on fetched knowledge for constructive optimization of on-device models. Specifically, a pre-trained deep neural network $f^h(\cdot)$ is adopted as an encoder to generate the hash values of samples on clients during initialization, i.e.

$$h_i^k = f^h(X_i^k), \quad (14)$$

and such hash values with corresponding sample indexes and labels are uploaded to the server for initializing the knowledge cache according to Eq. (7, 8, 9, 10, 11).

During training on each given sample (X_i^k, y_i^k) , client k first extracts knowledge z_i^k on X_i^k , and then uploads z_i^k with corresponding sample index (k, i) to the server, where:

$$z_i^k = f^k(X_i^k). \quad (15)$$

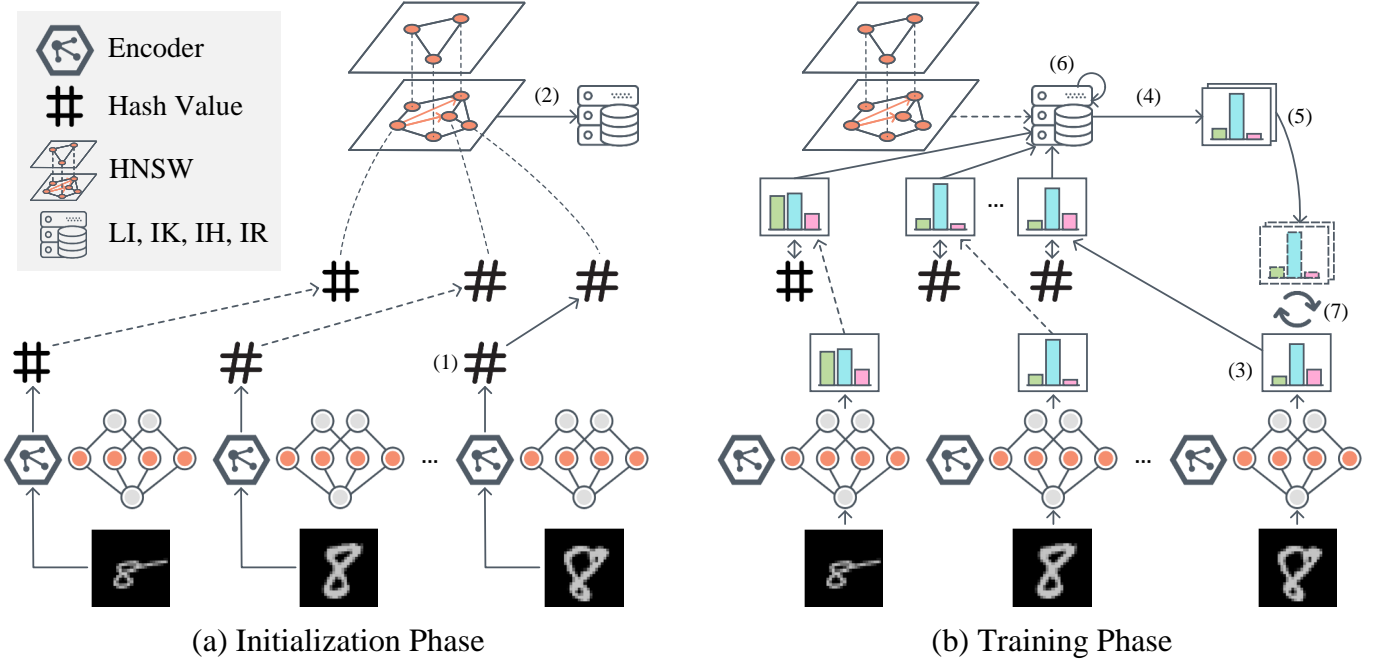


Fig. 4. Overview of executing procedure of FedCache. (1) Hash encoding and uploading. (2) Knowledge cache initialization. (3) Knowledge extraction and uploading. (4) Knowledge fetching. (5) Knowledge ensemble and distributing. (6) Knowledge update. (7) Knowledge acceptance and distillation.

Then, the R knowledge related to sample index (k, i) is fetched from the knowledge cache KC according to Eq. (12), that is,

$$(zr_i^k)_1, (zr_i^k)_2, \dots, (zr_i^k)_R = KC(h_i^k; k, i), \quad (16)$$

where $(zr_i^k)_s$ is the s -th knowledge fetched for the given sample index (k, i) . The fetched knowledge is ensembled in an average manner, which can be expressed as:

$$\bar{zr}_i^k = \frac{1}{R} \sum_{s=1}^R (zr_i^k)_s. \quad (17)$$

Subsequently, the ensembled knowledge is distributed to client k for performing distillation-based local model optimization, which is defined as follows:

$$\begin{aligned} & \arg \min_{W^k} J^k(W^k) \\ &= \arg \min_{W^k} \sum_{(X_i^k, y_i^k) \in \mathcal{D}^k} [L_{CE}(\tau(f^k(X_i^k)), y_i^k) \\ & \quad + \beta \cdot KL(\tau(f^k(X_i^k)) || \tau(\bar{zr}_i^k))]. \end{aligned} \quad (18)$$

4.4 Formal Description of FedCache

The overview of executing procedure of FedCache is shown in Fig. 4, and the execution processes of FedCache on client k and the server are respectively formulated in Algorithms 1 and 2. From the overall perspective, we allow personalized local models on devices to distill ensembled knowledge on the samples similar to private data with the assistance of the server-side knowledge cache. Specifically, FedCache consists of the following steps:

- **Hash Encoding and Uploading.** For each sample from a given client, a hash value is encoded based

on the pre-trained local encoder according to Eq. (14), (Algorithm 1, line 3). This hash value is uploaded to the server along with the corresponding label and sample index (Algorithm 1, line 4). As the encoder is a deep pre-trained neural network with a large number of superimposed non-linear mapping and the dimensionality of the output code is much smaller than that of data, sharing hash values with the server is privacy-preserving.

- **Knowledge Cache Initialization.** The server accepts the uploaded information from clients (Algorithm 2, line 3) and establishes relations between sample indexes in the knowledge cache according to Eq. (7, 8, 9, 10, 11), such that each sample can be indexed to R -related samples (Algorithm 2, line 4-6).
- **Knowledge Extraction and Uploading.** Clients extract logits (Algorithm 1, line 9) and upload logits with corresponding sample indexes to the server (Algorithm 1, line 10). This step is an alternative to the parameters/features uploading step of PIA and SLIA-FE. As the size of the logits and sample indexes are several orders of magnitude smaller than that of the model parameters or features, the communication burden can be significantly reduced.
- **Knowledge Fetching.** The server accepts the sample indexes uploaded by the clients (Algorithm 2, line 10), and fetches R -nearest matching knowledge from the knowledge cache based on pre-established sample index relations (Algorithm 2, line 11).
- **Knowledge Ensemble and Distributing.** The fetched knowledge is ensembled on the server according to Eq. (17) (Algorithm 2, line 12), and is

Algorithm 1: FedCache on Client k .

```

1 //Initialization process
2 foreach  $(X_i^k, y_i^k) \in \mathcal{D}^k$  do
3    $h_i^k \leftarrow f^h(X_i^k)$ 
4   Upload  $h_i^k$  with index  $(k, i)$  and label  $y_i^k$  to the
   server
5 end
6 //Training process
7 repeat
8   foreach  $(X_i^k, y_i^k) \in \mathcal{D}^k$  do
9      $z_i^k \leftarrow f^k(X_i^k)$ 
10    Upload  $z_i^k$  with index  $(k, i)$  to the server
11    Download averaged ensemble knowledge
     $\bar{zr}_i^k$  from the server
12     $W^k \leftarrow W^k - lr \cdot \nabla_{W^k} J^k(W^k)$ 
13    ▷ Optimize Eq. (18)
14  end
15 until Training stop;

```

subsequently distributed to corresponding clients (Algorithm 2, line 13).

- **Knowledge Update.** The stored knowledge in the knowledge cache is updated based on the newly-uploaded knowledge (in Algorithm 2, line 10) according to Eq. (13). (Algorithm 2, line 14)
- **Knowledge Acceptance and Distillation.** The clients receive the ensembled knowledge distributed from the server (Algorithm 1, line 11) and optimize client-side local models according to Eq. (18) (Algorithm 1, lines 12-13). This step is also communication-efficient since only logits are transferred between the server and clients.

5 EXPERIMENTS

5.1 Experimental Setup

5.1.1 Datasets and Preprocessing

We conduct experiments on four common datasets, MNIST [45], FashionMNIST [44], CIFAR-10 [46] and CINIC-10 [47]. In all of our experiments, we partition each dataset into 300 non-independent identically distributed copies for training and testing on $K = 300$ different clients as referred to [48], and the hyper-parameter α that controls the degree of data heterogeneity is set to 1.0. Each client runs locally for one epoch before model aggregation or feature/knowledge transfer.

5.1.2 Benchmarks and Criteria

To fully demonstrate the effectiveness of FedCache, we compare it with the state-of-art PFL methods with various architectures, including FMTL [13] and pFedMe [12] based on PIA, FedDKC [24] and FedICT [22] based on SLIA-FE, and FD [23] based on CLIA. Among all the architectures, SLIA-PD is discarded because of its impractical reliance on public datasets. The precision of benchmark algorithms is measured by Maximum Average User model Accuracy

Algorithm 2: FedCache on the Server.

```

1 //Initialization process
2 repeat
3   Receive  $h_i^k$  with index  $(k, i)$  and label  $y_i^k$  from
   client  $k$ 
4   Update  $LI, IK, IH$  according to Eq. (7, 8, 9)
5 until Receive all indexes  $(k, i)$  from  $K$  clients;
6 Build relations via HNSW [43] according to Eq. (10)
   and Eq. (11)
7 //Training process
8 repeat
9   foreach  $(k, i)$  do
10    Receive  $(k, i)$  and  $z_i^k$  from client  $k$ 
11    Fetch  $R$  related knowledge from the
    knowledge cache according to Eq. (16) and
    Eq. (12)
12    Obtain ensembled fetched knowledge  $\bar{zr}_i^k$ 
    according to Eq. (17)
13    Send  $\bar{zr}_i^k$  to client  $k$ 
14    Update knowledge cache according to Eq.
    (13)
15  end
16 until Training stop;

```

TABLE 3

The $acc@$ used in different experiments to measure system communication overhead.

Model Setting	Dataset			
	MNIST	Fashion MNIST	CIFAR-10	CINIC-10
Model Homo.	87@	77@	43@	40@
Model Hetero.	83@	77@	41@	41@

TABLE 4

Main configurations of four adopted models. The height and width of the input images are noted as H and W , respectively.

Model	Notation	Feat. Shape	Params
ResNet-small	A_1^C	$H \times W \times 16$	76.2K
ResNet-medium	A_2^C		171.2K
ResNet-large	A_3^C		266.1K
ResNet-server	A^S		588.2K

[13] (MAUA). Moreover, we denote the communication overhead to reach a given average UA acc as $acc@$, measuring system communication efficiency with different $acc@$ according to the actual system performance, as shown in TABLE 3. We also calculate the speed-up ratio of each method by comparing the ratio of communication overhead between the one with the highest communication overhead of all benchmark algorithms and this method under the

TABLE 5

MAUA (%), communication overhead and communication efficiency speed-up ratio on homogeneous on-device models. Some methods are unable to calculate the communication overhead with corresponding speed-up ratios as they cannot achieve the MAUA in TABLE 3 under given experimental settings, and their corresponding items are denoted by -. The same as below.

Dataset	Method	Model		Metric		
		Client	Server	MAUA (%)	Comm. (G)	Speed-up Ratio
MNIST	pFedMe	A_3^C	A_3^C	94.89	13.25	$\times 1.0$
	MTFL		A_3^C	95.59	7.77	$\times 1.7$
	FedDKC		A^S	89.62	9.13	$\times 1.5$
	FedICT		A^S	84.62	-	-
	FD		-	84.19	-	-
	FedCache		-	87.77	0.99	$\times 13.4$
FashionMNIST	pFedMe	A_3^C	A_3^C	81.57	20.71	$\times 1.0$
	MTFL		A_3^C	83.92	12.33	$\times 1.7$
	FedDKC		A^S	78.24	8.43	$\times 2.5$
	FedICT		A^S	76.90	13.34	$\times 1.6$
	FD		-	76.32	-	-
	FedCache		-	77.71	0.08	$\times 258.9$
CIFAR-10	pFedMe	A_3^C	A_3^C	37.49	-	-
	MTFL		A_3^C	43.43	52.99	$\times 1.0$
	FedDKC		A^S	45.87	11.46	$\times 4.6$
	FedICT		A^S	43.61	10.69	$\times 5.0$
	FD		-	42.77	-	-
	FedCache		-	44.42	0.19	$\times 278.9$
CINIC-10	pFedMe	A_3^C	A_3^C	31.65	-	-
	MTFL		A_3^C	34.09	-	-
	FedDKC		A^S	43.95	4.12	$\times 1.3$
	FedICT		A^S	42.79	5.50	$\times 1.0$
	FD		-	39.36	-	-
	FedCache		-	40.45	0.07	$\times 78.6$

same experimental settings. In addition, our MAUA results are obtained in a reasonable training time, when the algorithm reaches convergence or the total communication overhead reaches the given limitation, such as 55G and 19G for CIFAR-10 and CINIC-10 datasets, respectively.

5.1.3 Models

For the deep pre-trained encoder, we adopt MobileNetV3 [49] pre-trained on ImageNet [50], with the last fully connected layer removed. In addition, we consider 4 different model architectures, where $\{A_1^C, A_2^C, A_3^C\}$ are for clients, and A^S is for the server, and the main configurations of four adopted models are shown in TABLE 4. It is worth noting that the model on the server does not contain the foremost Conv+Batch+ReLU layers to fit the training requirements of [24], [25]. Moreover, both client-side model homogeneity and heterogeneity are considered in our experiments. Specifically, for the experiments with homogeneous models, we compare FedCache with all aforementioned benchmark algorithms, and all clients adopt the model architecture A_3^C . For the experiments with heterogeneous models, FedCache only compares with the benchmarks that support model heterogeneity among clients, including FedDKC, FedICT and FD, and clients with residuals of index mod 3 of 0, 1

and 2 are assigned with model architectures A_1^C , A_2^C and A_3^C respectively.

5.1.4 Hyper-parameter Settings

We adopt stochastic gradient descent with a learning rate of 0.01 and a batch size of 8 in all the experiments. In addition, the hyper-parameters of benchmark algorithms are set as follows:

- For pFedMe, we set $\eta = 0.005$, $\lambda = 15$ and $\beta = 1$ according to [12].
- For MTFL, we adopt the FedAvg optimization strategy [13], with other hyper-parameters following the default setting in [51].
- For FedDKC, we adopt KKR as the knowledge refinement strategy, with $\beta = 1.5$ and $T = 0.12$ according to [24].
- For FedICT, we adopt the similarity-based LKA strategy, with $\beta = \lambda = \mu = 1.5$ and $T = 3.0$ according to [22].
- For FD, no individualized hyper-parameters are required [23].

Finally, for our proposed FedCache, we set $\beta = 1.5$ and $R = 16$. The impact of hyper-parameters on system performance will be investigated in the ablation study.

TABLE 6
MAUA (%), communication overhead and communication efficiency speed-up ratio on heterogeneous on-device models.

Dataset	Method	Model		Metric		
		Client	Server	MAUA (%)	Comm. (G)	Speed-up Ratio
MNIST	FedDKC	A_1^C, A_2^C, A_3^C	A^S	85.38	10.53	$\times 1.0$
	FedICT		-	80.53	-	-
	FD			79.90	-	-
	FedCache			83.94	0.10	$\times 105.3$
FashionMNIST	FedDKC	A_1^C, A_2^C, A_3^C	A^S	77.96	12.64	$\times 1.0$
	FedICT		-	76.11	-	-
	FD			75.57	-	-
	FedCache			77.26	0.08	$\times 158.0$
CIFAR-10	FedDKC	A_1^C, A_2^C, A_3^C	A^S	44.53	4.58	$\times 1.2$
	FedICT		-	43.96	5.35	$\times 1.0$
	FD			40.40	-	-
	FedCache			41.59	0.05	$\times 107.0$
CINIC-10	FedDKC	A_1^C, A_2^C, A_3^C	A^S	44.80	4.12	$\times 1.3$
	FedICT		-	43.40	5.50	$\times 1.0$
	FD			40.76	-	-
	FedCache			41.71	0.07	$\times 78.6$

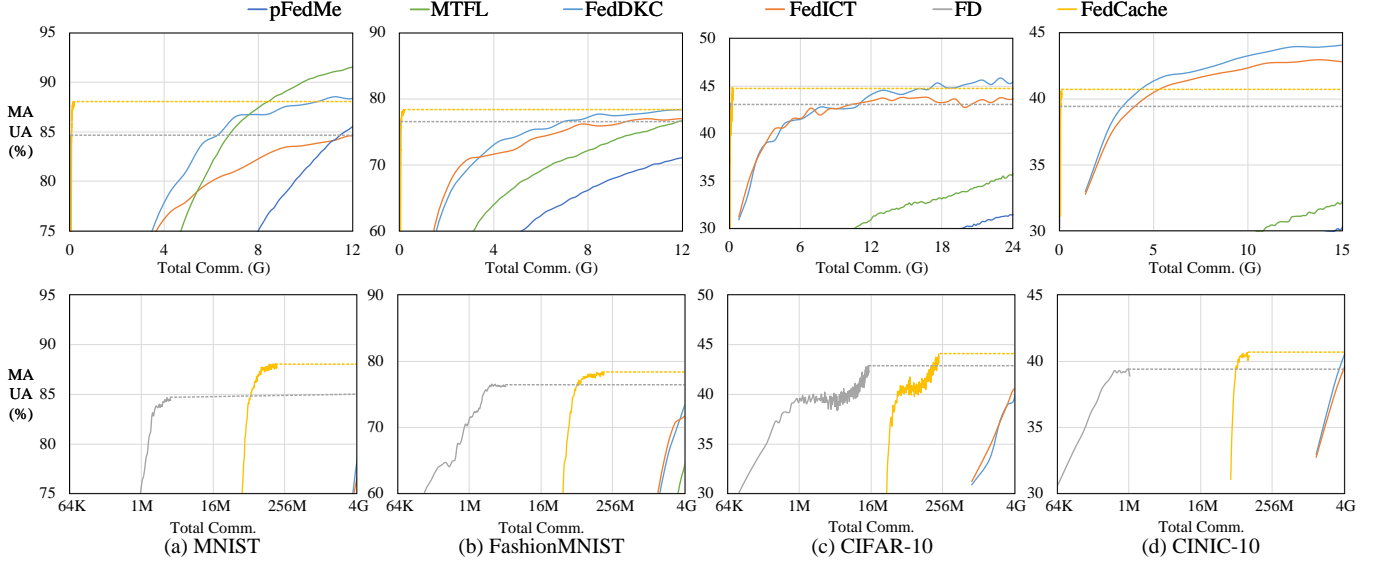


Fig. 5. MAUA (%) per unit of communication overhead in experiments with homogeneous models. Dashed lines indicate the extension of algorithms beyond convergence to the maximum MAUA over communication overheads. The same as below.

5.2 Results

5.2.1 Performance on Homogeneous Models

TABLE 5 displays MAUA and communication overhead of FedCache compared to all considered benchmarks on different datasets, and the MAUA performance per unit of communication overhead is shown in Fig. 5. As can be seen from TABLE 5, FedCache achieves 77.71%, 44.42%, and 40.45% MAUA on FashionMNIST, CIFAR-10, and CINIC-10 datasets, respectively, which are comparable to the considered benchmark algorithms. Meanwhile, according to the criteria described in 5.1.2, the total communication

overhead of FedCache over the three datasets mentioned above are all less than 0.20G, and the speed-up ratios of FedCache are all over $\times 78$, which enable the communication efficiency to be much higher than existing methods with previous architectures. This is because FedCache adopts a lightweight communication protocol with only logits and hash values being transferred, and does not transmit model parameters as well as features with relatively large sizes. Moreover, the efficient communication of FedCache can be further verified in Fig. 5, where our method exhibits a much steeper convergence curve than FedDKC, FedICT, pFedMe, and MTFL. We can also observe in Fig. 5 that compared

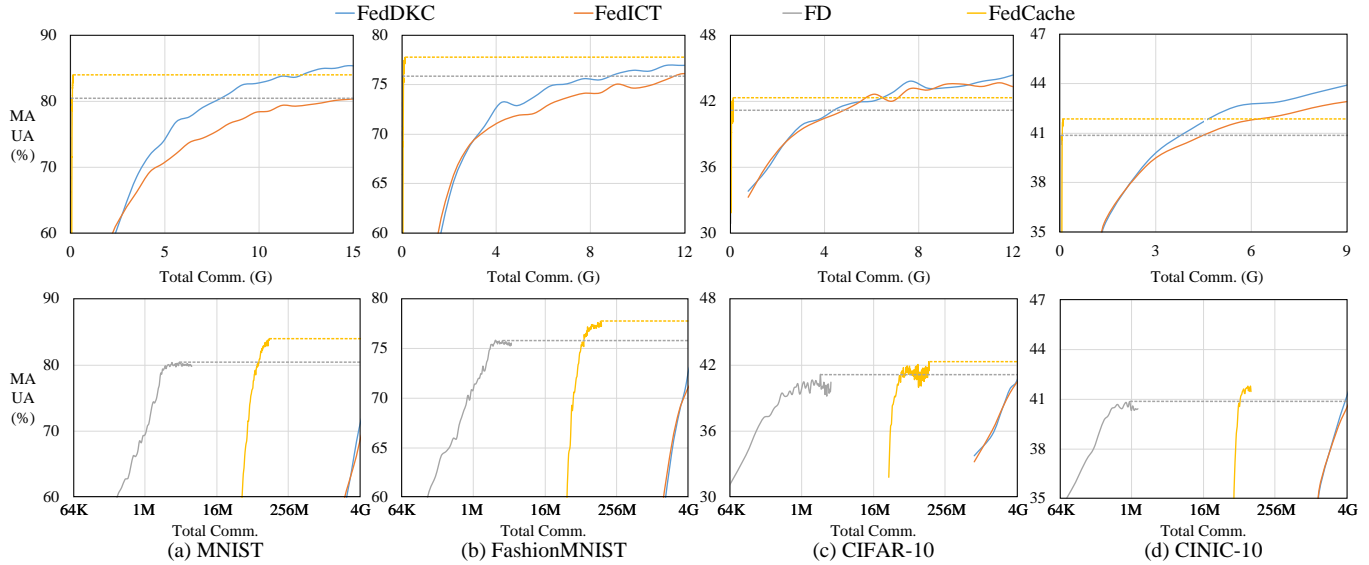


Fig. 6. MAUA (%) per unit of communication overhead in experiments with heterogeneous models.

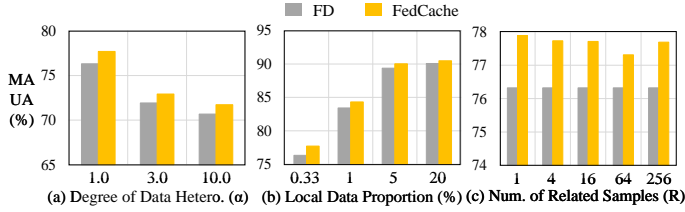


Fig. 7. The impact of the degree of data heterogeneity, local data proportion, and the number of related samples on the performance of FedCache.

TABLE 7
Performance of FedCache and FD with different α .

Method	Degree of Data Heterogeneity		
	$\alpha=1.0$	$\alpha=3.0$	$\alpha=10.0$
FD	76.32	71.92	70.67
FedCache	77.71	72.92	71.73

TABLE 8
Performance of FedCache and FD with different average local sample proportions.

Method	Average Local Sample Proportion			
	0.33%	1%	5%	20%
FD	76.32	83.41	89.37	90.07
FedCache	77.71	84.32	90.03	90.47

to communication-efficient FD, FedCache achieves significantly higher MAUA, achieving satisfactory system performance while maintaining communication efficiency orders of magnitude higher than other benchmark algorithms. The reason is that FedCache is an SLIA architecture rather than CLIA, where enriched knowledge can be utilized to

TABLE 9
Performance of FedCache and FD with different R .

Method	MAUA(%)
FD	76.32
FedCache ($R=1$)	77.89
FedCache ($R=4$)	77.73
FedCache ($R=16$)	77.71
FedCache ($R=64$)	77.31
FedCache ($R=256$)	77.69

obtain significantly more information for on-device model constructive optimization, thus possessing performance superiority.

5.2.2 Performance on Heterogeneous Models

TABLE 6 shows the comparison of FedCache with benchmark algorithms that support model heterogeneity on clients. Likewise, we can conclude that FedCache achieves comparable MAUA to considered benchmarks, but with extremely high communication efficiency due to the elimination of feature transfer compared with FedDKC and FedICT. Similar to section 5.2.1, FedCache obtains a convergence curve in Fig. 6 that is capped above FD, which indicates that FedCache gains better system performance than FD. This further confirms the superiority of our proposed FedCache architecture over heterogeneous models.

6 ABLATION STUDY

6.1 Ablation Settings

In this section, we conduct the ablation study to investigate how the degree of data heterogeneity, the proportion of local samples, and the number of related samples affect system performance. All ablation experiments are evaluated on the FashionMNIST dataset, with the same settings adopted for

TABLE 10
Comparison of the computation complexity of PFL architectures. N^P represents the number of samples in the public dataset. F represents the scale of transmitted features.

	PIA	SLIA-FE	SLIA-PD	CLIA	FedCache
End Devices	$rN^k \cdot O(W^k)$	$rN^k \cdot O(W^k)$	$r(N^k + N^P) \cdot O(W^k)$	$rN^k \cdot O(W^k)$	$rN^k \cdot O(W^k)$
Edge Server	$rK \cdot O(W^S)$	$r \sum_{k=1}^K N^k \cdot O(W^S)$	$rN^P K \cdot O(C)$	$rK \cdot O(C^2)$	$R \sum_{k=1}^K N^k \log \sum_{k=1}^K N^k \cdot O(F)$ $+ rR \sum_{k=1}^K N^k \cdot O(C)$

experiments with homogeneous models in section 5.2.1 by default. The performance of all algorithms is measured by MAUA (%) in the following subsections.

6.2 Results

6.2.1 Impact of Degree of Data Heterogeneity

To explore the effect of data heterogeneity on the performance of FedCache, we set the hyper-parameter α to different values $\alpha \in \{1.0, 3.0, 10.0\}$ to control the degree of data heterogeneity, and compare the performance of FedCache with FD, with the results shown in TABLE 7 and Fig. 7 (a). It can be seen that FedCache consistently outperforms FD despite the skewness of local data distributions, reflecting the adaptability of our method to different data environments.

6.2.2 Impact of Local Data Proportion

To investigate the performance of FedCache with different percentages of local data to the overall data, we control the number of different local samples to $\{0.33\%, 1\%, 5\%, 20\%\}$ of the whole dataset, and compare the performance of FedCache with FD, with the results shown in TABLE 8 and Fig. 7 (b). We can observe that the performance of both FD and FedCache improves as the local sample share of clients increases. Still, FedCache always outperforms FD, which confirms the superior performance of our FedCache with varying percentages of local data from a single client.

6.2.3 Impact of Number of Related Samples

To evaluate the performance of FedCache with different numbers of related samples, we set $R \in \{1, 4, 16, 64, 256\}$ and compare the performance of FedCache with FD with the aforementioned R settings, with the results shown in TABLE 9 and Fig. 7 (c). It can be seen that our method consistently outperforms FD in different R settings. This indicates that FedCache is robust to the choice of related samples and can achieve satisfactory performance consistently.

7 DISCUSSION

7.1 Analysis on Computation Complexity

We compare the communication complexity of FedCache with other PFL architectures in TABLE 10. On the device side, FedCache has the identical computation complexity as PIA, SLIA-FE and CLIA, since their computation all mainly focuses on on-device models' forward propagation on local data. As there is no need for local training based on public

datasets, FedCache has lower computation complexity on the device side compared to SLIA-PD. On the server side, the computation overhead of FedCache mainly consists of establishing relations among samples through R -nearest neighbors retrieval and integrating relevant knowledge of a given sample index in each round. The server-side computation complexity comparison between FedCache and PIA depends on the scale of model parameters and the average number of local samples per client. In our experiments on four datasets with $R = 16$, $r > 100$, hundreds of samples held on a single client and the parameter size $> 50K$, the server-side computation complexity of FedCache is much smaller than that of PIA. Since FedCache converges better than PIA in empirical experiments, the superiority of computation overhead of FedCache over PIA will be pronounced in reality. In addition, we claim that the server-side computation complexity of FedCache is much smaller than that of SLIA-FE and SLIA-PD. The reason for the former is that FedCache doesn't require forward propagation on server-side model training for each sample. While the reason for the latter is that the average size of private data per client is much smaller than that of public datasets in practice. Although CLIA achieves relatively-low server-side computation complexity over FedCache, it pays the price of significantly reduced knowledge enrichment, resulting in poor performance confirmed by empirical experiments in section 5, so FedCache still possesses an irreplaceable superiority over CLIA in terms of balancing computation overhead and system performance.

7.2 Limitations

We analyze that the limitations of FedCache are threefold. One limitation of FedCache is that it conducts knowledge distillation on device-side models only based on knowledge associated with local samples, but neglects knowledge learning for global generalization. As a result, it is only suitable for personalization tasks rather than general tasks that require global generalization capabilities. The generalization performance of FedCache can be improved when introducing additional information, such as partial global parameters or global public data. Another limitation is that we apply our method only to conventional image classification problems in our experiments, and additional research on data encoding strategies, hash correlation measures for serialized data and other non-image structured data are also meaningful for FedCache. In addition, limited by the exe-

cution procedure of HNSW [43], FedCache cannot support PFL with incremental data. By considering and addressing the above limitations, FedCache can further enhance its effectiveness in a wider range of applications.

8 CONCLUSION

In this paper, we propose FedCache, a novel federated learning architecture tailored for personalized edge intelligence. FedCache designs a knowledge cache on the server for storing newly-extracted knowledge uploaded by clients and fetching correlatively personalized knowledge from samples with similar hashes to the specified private data. On this basis, ensemble distillation is performed on device-side local models for personalized constructive optimization. To our best knowledge, FedCache is the first architecture for personalized federated learning that enables sample-grained logits interaction without features transmission or public datasets. Empirical experiments show that FedCache achieves comparable accuracy with state-of-the-art personalized federated learning methods with various architectures, meanwhile reducing communication costs by two orders of magnitude.

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