FedProc: Prototypical Contrastive Federated Learning on Non-IID data

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Abstract

Federated learning allows multiple clients to collaborate to train high-performance deep learning models while keeping the training data locally. However, when the local data of all clients are non-independent and identically distributed (i.e., non-IID), it is challenging to implement this form of efficient collaborative learning. Although significant efforts have been dedicated to addressing this challenge, the effect on the image classification task is still not satisfactory. In this paper, we propose FedProc: prototypical contrastive federated learning, which is a simple and effective federated learning framework. The key idea is to utilize the prototypes as global knowledge to correct the local training of each client. We design a local network architecture and a global prototypical contrastive loss to regulate the training of local models, which makes local objectives consistent with the global optima. Eventually, the converged global model obtains a good performance on non-IID data. Experimental results show that, compared to state-of-the-art federated learning methods, FedProc improves the accuracy by 1.6% ~ 7.9% with acceptable computation cost.

1 Introduction

Federated learning (FL), as a promising machine learning approach, has enabled distributed clients to collaboratively train a global model without accessing their data by sharing their local model parameters for aggregation. This approach effectively mitigates privacy concerns in situations where raw data cannot be gathered into a central server for legal or privacy reasons. Serving as a communication-efficient and privacy-preserving learning scheme, FL has shown its potential to facilitate real-world applications, including medical image analysis (Kaisiss et al. 2020, Kumar et al. 2021), biometrics analysis (Aggarwal, Zhou, and Jain 2021), and object detection (Liu et al. 2020), etc.

FL has been shown to work well on the independent and identically distributed (IID) data. However, in practice, the data held by different clients usually has a highly skewed distribution. Specifically, the local dataset of each client is non-independent and identically distributed (non-IID), which can result in a significant decrease in the performance of FL (Zhao et al. 2018, Kairouz et al. 2019). This unbalanced data distribution will bring about a drift of local model training in each client, making the local objective far from the global optima. How to mitigate the adverse effects of non-IID data for FL is still an open question.

A variety of efforts have been made to tackle non-IID data issues, mainly from two complementary perspectives: one aims to improve the efficacy of model aggregation, such as FedNova (Wang et al. 2020b), FedMA (Wang et al. 2020a), FedAvgM (Hsu, Qi, and Brown 2019). Another focuses on stabilizing the local training phase by regulating the deviation of the local models from a global model over the parameter space, such as MOON (Li, He, and Song 2021), FedProx (Li et al. 2020a, 2020b), SCAFFOLD (Karimireddy et al. 2019). However, whether in the model aggregation phase or local training phase, these approaches do not take full advantage of the underlying knowledge provided by each client. As shown in the experiments (see Section 4), the accuracy and computation efficiency of these approaches still have plenty of room for improvement.

Observing the challenge in the presence of non-IID data and the limitations of the prior arts, in this paper, we propose a prototypical contrastive federated learning framework, dubbed as FedProc. Inspired by the prototypical contrastive learning (Li et al. 2020a), we innovatively introduce prototypes into federated learning for fully utilizing the knowledge of each client to correct the local training. A prototype is defined as the mean vectors for the representations in each class (Snell, Swersky, and Zemel 2017). Specifically, the server first obtains the global class-prototypes by gathering the class-prototypes of the client and broadcasts them to clients as global knowledge to correct local training. Then, the clients use our elaborate local network architecture and loss function to regulate the training of local models, which makes local objectives consistent with the global optima. This approach forces each sample of the client to be pulled toward the global prototype of its class and pushed away from the global prototypes of other classes, such that the classification performance of the local network would be improved. In summary, FedProc is a simple and effective federated learning framework that addresses the non-IID data issues from a new perspective of prototype-based contrastive learning.

We experimentally evaluate the performance of FedProc on multiple image classification datasets, including CIFAR-10, CIFAR-100, and Tiny-ImageNet. FedProc significantly outperforms the state-of-the-art federated learn-
nations of local distributions (Deng, Kamani, and Mahdavi and designing robust algorithms against different combina-
Fallah, Mokhtari, and Ozdaglar 2020; Hanzely et al. 2020) non-IID data setting, such as personalizing the local
In addition, there are also other FL studies related to (W ang et al. 2020a), FedA vgM (Hsu, Qi, and Brown 2019).
Another aims to improve the efficacy of model aggre-
Karimireddy et al. 2019). With acceptable computation cost, FedProc improves accuracy by 1.6% on the CIFAR-10
dataset, and even more than 7% on the CIFAR-100 and Tiny-ImageNet datasets. As a highlight, on the CIFAR-100
dataset with 100 clients, FedProc achieves 70.6% top-1 accu-
We summarize our contributions as follows:
- We propose a novel federated learning framework to address
assess the non-IID data issues. The framework introduces
the global class-prototypes to correct the local training,
yielding a good classification performance.
- We design a hybrid local network architecture and a
global prototypical contrastive loss to make use of the un-
derlying knowledge provided by global class-prototypes.
The careful designs of the local network and the loss
function enable FedProc to achieve a good performance.
- We implement FedProc, and do extensive experiments on
different datasets. The results demonstrate that FedProc
significantly outperforms the state-of-the-art in terms of
both inference accuracy and computational efficiency.

2背景与相关工作
2.1联邦学习
Federated Learning (FL) is first proposed as a decentralized machine learning paradigm (McMahan et al. 2017), which is executed by following a typical four-step protocol illustrated in Figure 1. 1) The server randomly initializes the parameters of the global model and sends them to each client. 2) When receiving the global model, each client updates the model based on their local training data using stochastic gradient descent (SGD). 3) The selected clients upload their local model parameters back to the server. 4) The server averages the model parameters to produce a global model for the training of the next round. These steps are repeated until convergence is achieved.

Subsequent work along this line tackles different challenges faced by FL, including heterogeneity (Sattler et al. 2019), Briggs, Fan, and Andras 2020, Huang et al. 2021b), privacy (Truex et al. 2019, Wang et al. 2019), communication efficiency (Luping, Wei, and Bo 2019, Asad et al. 2021, Bouacida et al. 2021), and convergence analysis (Huang et al. 2021a, Jin et al. 2020). Specifically, a wealth of work has been proposed to handle the non-IID issues, mainly from two complementary perspectives: one focuses on stabilizing the local training phase, such as MOON (Li, He, and Song 2021), FedProx (Li et al. 2020b), SCAFFOLD (Karimireddy et al. 2019). Another aims to improve the efficacy of model aggregation, such as FedNova (Wang et al. 2020b), FedMA (Wang et al. 2020a), FedAvgM (Hsu, Qi, and Brown 2019). In addition, there are also other FL studies related to non-IID data setting, such as personalizing the local models for each client (T Dinh, Tran, and Nguyen 2020, Fallah, Mokhtari, and Ozdaglar 2020, Hanzely et al. 2020) and designing robust algorithms against different combinations of local distributions (Deng, Kamani, and Mahdavi 2019).

2.2对比学习
Contrastive learning has shown great promise in unsupervised representation learning (Chen et al. 2020, He et al. 2020). The key idea is to learn an embedding space where samples from the same instance are pulled closer (i.e., positive pairs) and samples from different instances are pushed apart (i.e., negative pairs). Supervised contrastive learning (Khosla et al. 2020) is an extension to contrastive learning by incorporating the label information to compose positive and negative images. A recent work (Wang et al. 2021) improved the quality of learning features using supervised contrastive learning to solve the long-tail distribution problem in classification tasks. Later, there emerges prototypical contrastive learning (Li et al. 2020a), which is an unsupervised feature learning method that bridges contrastive learning with clustering. Different from prior work, we design a local network architecture and a loss function tailored for federated learning to address the non-IID data issues from a perspective of supervised contrastive learning.

2.3对比学习在联邦学习
Contrastive learning in federated learning has recently emerged as an effective approach to tackle the non-IID issue. Some existing works (Zhang et al. 2020, van Berlo, Saeed, and Ozcelebi 2020) focus on the unsupervised learning setting. They use a contrastive loss to compare the representations of different images in order to make full use of the enormous unlabeled data on distributed edge devices. MOON (Li, He, and Song 2021) is based on the design of model-based comparative learning to solve non-IID data problems. This model-level comparative learning is performed by comparing the representations of different model learning, and the local update is corrected by maximizing the consistency between the current local model learning representation and the global model learning representation. However, in this paper, we focus on the supervised learning.
Figure 2: T-SNE visualizations of hidden vectors on CIFAR-10. Figure (a) and (b) show the SOLO representations at Client $C_1$ and $C_2$, respectively. Figure (c) shows global representation distribution. Figure (d) and (e) show the FedProc representations at Client $C_1$ and $C_2$, respectively. SOLO: A baseline approach where each client trains a model only by inputting its local data without federated learning.

setting, and we introduce prototypes to address the issues of inconsistency in the embedding space for each client.

3 Prototypical Contrastive Federated Learning

3.1 Problem Statement

FedProc involves $m$ clients (denoted as $C_1, ..., C_m$), where $C_i$ has a local dataset $D_i = \{(x_j, y_j)\}_{j=1}^{N(i)}$, where $x_j \in \mathbb{R}^P$ is the $P$-dimensional feature vector of a sample, and $y_j \in 1, 2, ..., K$ (a multi-classification learning task) is the corresponding label of $x_j$, and $N(i)$ is the sample number in dataset $D_i$. Our goal is to learn a machine learning model $w$ over the dataset $D = \bigcup_{i=1}^{m} D_i$ with the help of a central server, while the raw data are not exchanged. The objective is to solve

$$\arg \min_w \mathcal{L}(w) = \sum_{i=1}^{m} \frac{|D_i|}{|D|} L_i(w) \quad (1)$$

where $L_i(w) = \mathbb{E}_{(x, y) \sim D_i}[\ell_i(w; (x, y))]$ is the empirical loss of $C_i$, and $\ell_i(w; (x, y))$ is the loss function.

3.2 Motivation

We now discuss the observations that motivate the correction of local training. We begin by investigating the feature distribution of hidden layers of local network architecture during the training. For that, we give a baseline approach named SOLO, where each client trains a model only by inputting its local data without federated learning. Specifically, we use SOLO to train models based on the different clients’ local data that are carefully designed for learning better representations, which boosts the classification performance of the local network. Using the above insight, we present FedProc, a simple and effective FL framework based on FedAvg (McMahan et al. 2017). Our main changes happen in the local training phase, where the local network architecture and the loss function are carefully designed for learning better representations, which makes the local objective of each client consistent with the global optima. To demonstrate the efficacy of this idea, we run the FedProc on the above local data of clients $C_1$ and $C_2$, and show the feature distributions of images in Figure 2(d) and Figure 2(e). We find that the points with the same class in the two clients are constrained to the same domain centered in the global class-prototype. Moreover, the distribution of the points in clients $C_1$ and $C_2$ both match with the global distribution shown in Figure 2(c).

3.3 Method

Using the above insight, we present FedProc, a simple and effective FL framework based on FedAvg (McMahan et al. 2017). Our main changes happen in the local training phase, where the local network architecture and the loss function are carefully designed for learning better representations, which boosts the classification performance of the local network. The overall federated learning algorithm is shown in Algorithm 1. In the following, we present the local network architecture, the local objectives, and global prototypical contrastive loss.

Local Network Architecture Figure 3 describes the overview of the proposed local network architecture. The local network is comprised of three modules: a base encoder, a projection head, and an output layer. Firstly, the base encoder extracts representation $r$ from input $x$. Then, the projection head maps the representation $r$ into a vector representation $z \in \mathbb{R}^Q$, which is used to compute a global prototypical contrastive loss $\ell_{gpc}$ (will be illustrated in Eq. 4). Noth that, we use a multiple-layer perception (MLP) with one hidden layer to implement the projection head, which is helpful in improving the representation ability of the layer before it (Chen et al. 2020). At last, by inputting the image representation $z$, the output layer (i.e., a single linear layer $f_e(\cdot)$) predicts the class-wise logits $s \in \mathbb{R}^K$, which are used to compute the cross-entropy loss $\ell_{ce}$.

For ease of presentation, with model weight $w$, we use $w_e$ to represent the weight of the feature extraction network, which is composed of the base encoder and the projection head, and $w_c$ to represent the weight of the output layer.
Correspondingly, \( f_c(w_c; \cdot) : \mathbb{R}^P \rightarrow \mathbb{R}^Q \) (with learnable parameters \( w_c \)) represents the feature extraction network, and \( f_c(w_c; \cdot) : \mathbb{R}^Q \rightarrow \mathbb{R}^K \) (with learnable parameters \( w_r \)) represents the output layer network. That is, \( z = f_c(w_c; x) \) is the mapped representation of input \( x \), and \( s = f_c(w_c; z) \) is the prediction vector of the representation \( z \).

**Local Objective** The loss function of our local network is composed of two parts. The first part is our proposed global prototypical contrastive loss term \( \ell_{gpc} \). This term makes the local network learn an embedding space that has the property of intra-class compactness and inter-class separability. The second part is a typical cross-entropy loss \( \ell_{ce} \) for classifier learning, which can be benefited from the above embedding space. Inspired by cumulative learning [Zhou et al. 2020], we introduce a coefficient \( \alpha \) for adjusting the weights of the two terms during the local training phase. Concretely, the number of total communication rounds is denoted as \( T \), and the current round is \( t \), \( \alpha \) is calculated by \( \alpha = 1 - \frac{t}{T} \).

The final loss function for the network is:

\[
\ell = \alpha \cdot \ell_{gpc} + (1 - \alpha) \cdot \ell_{ce}
\]  

This method makes the local learning to be progressively transitioned from feature learning to classifier learning with the increased rounds. The local objective to minimize

\[
L_i(w) = E_{(x,y) \sim D_i}[\alpha \cdot \ell_{gpc}(w^t_c; (x, y)) + (1 - \alpha) \cdot \ell_{ce}(w^t_c; (x, y))]
\]  

In the local training, each client updates the model based on their local training data using stochastic gradient descent (SGD), while the objective is defined in Eq. (3).

**Global Prototypical Contrastive Loss** To make the global class-prototypes serve as the knowledge to correct each client’s local training, we propose a global prototypical contrastive loss \( \ell_{gpc} \). This loss forces each sample of the client to be close to the global prototype of its class and far away from the global prototypes of other classes. We define the global prototypical contrastive loss as

\[
\ell_{gpc} = -\log \frac{\exp(sim(z_j, c_{i,k}))}{\sum_{k'} \exp(sim(z_j, c_{i,k'}))}
\]  

Figure 3: Overview of the local network architecture in FedProc. The feature extraction network (including the base encoder and the projection head) extracts the representation \( z \), which is used to calculate the global prototypical contrastive loss \( \ell_{gpc} \). By inputting the representation \( z \), the output layer \( f_c(\cdot) \) predicts the class-wise logits \( s \), which are used to compute the cross-entropy loss \( \ell_{ce} \). A coefficient \( \alpha \) is introduced to adjust the weights of the two loss functions during the local training.

Algorithm 1: The FedProc framework

- **Input:** local datasets \( D_i \), number of communication rounds \( T \), number of local epochs \( E \), number of classes \( K \), number of clients \( m \), learning rate \( \eta \).
- **Output:** The final model \( w^T \).

```python
1: Server executes:
2: initialize \( w^0 \), \( c^0 \)
3: for \( t = 0, 1, \ldots, T - 1 \) do
4:   for \( i = 1, 2, \ldots, m \) in parallel do
5:     send the global model \( w^t \) to \( C_i \)
6:     send the global class-prototypes \( c^t \) to \( C_i \)
7:     \( w^{t+1}_i \leftarrow\) ClientLocalTraining \((i, t, w^t, c^t)\)
8:   end for
9:   \( c^{t+1} \leftarrow \frac{1}{m} \sum_{i=1}^{m} c^{t+1}_i \)
10: \( w^{t+1} \leftarrow \sum_{i=1}^{m} \frac{|D_i|}{|D|} w^{t+1}_i \)
11: end for
12: return \( w^T \)
13: ClientLocalTraining \((i, t, w^t, c^t)\):
14: \((w^t_{c_i}, w^t_{c_j}) \leftarrow w^t\)
15: for epoch = 1, 2, \ldots, \( E \) do
16:   for each batch \( b = \{x_j, y_j\} \) of \( D_i \) do
17:     \( z_j \leftarrow f_c(w^t_{c_i}; x_j)\)
18:     \( \ell_{gpc} \leftarrow -\log \frac{\exp(sim(z_j, c^{t+1}_j))}{\sum_{k'} \exp(sim(z_j, c^{t+1}_{i,k'}))}\)
19:     \( s_j \leftarrow f_c(w^t_{c_j}; z_j)\)
20:     \( \ell_{ce} \leftarrow CrossEntropyLoss(y_j, s_j)\)
21:     \( \alpha \leftarrow 1 - \frac{t}{T}\)
22:     \( \ell \leftarrow \alpha \cdot \ell_{gpc} + (1 - \alpha) \cdot \ell_{ce}\)
23:     \( w^{t+1}_i \leftarrow w^t_i - \eta \nabla \ell\)
24:   end for
25: end for
26: \((w^{t+1}_{c_i}, w^{t+1}_{c_j}) \leftarrow w^{t+1}_i\)
27: for \( k = 1, 2, \ldots, K \) do
28:   \( c^{t+1}_{i,k} \leftarrow \frac{1}{|D_i|} \sum_{(x_j, y_j) \in D_i} f_c(w^{t+1}_{c_i}; x_j)\)
29: end for
30: \( c^{t+1}_i \leftarrow \{c^{t+1}_{i,1}, c^{t+1}_{i,2}, \ldots, c^{t+1}_{i,K}\}\)
31: return \( w^{t+1}_i, c^{t+1}_i \) to server
```
where \( \text{sim}(z_j, c_{i,k}) = \frac{z_j^T c_{i,k}}{\|z_j\|_2 \|c_{i,k}\|_2} \) is the cosine similarity, and \( z_j \) is the representation extracted by the feature extraction network when inputting \( x_j \). Not that, \( c_{i,k} \) (resp. \( c_{i,kr} \)) denotes the mean representation of the samples belonging to class \( k \) (resp. other classes except for class \( k \)) in the client \( C_i \). The prototype \( c_{i,k} \in \mathbb{R}^W \) is formulated as

\[
c_{i,k} = \frac{1}{|D_i^k|} \sum_{(x,y) \in D_i^k} f_c(w_c; x)
\]

where \( D_i^k \) is the data of class \( k \) in the client \( C_i \).

4 Experiment

We implemented FedProc by PyTorch and ran experiments on the machines running Ubuntu 18.04 and equipped with two NVIDIA GeForce RTX 3090 GPUs and an Intel(R) Core(TM) i9-10900K CPU. To demonstrate the superiority of our work, we compare with the state-of-the-art federated learning algorithms, including 1) MOON (Li, He, and Song 2021), 2) FedAvg (McMahan et al. 2017), 3) FedProx (Li et al. 2020b), 4) SCAFFOLD (Karimireddy et al. 2019), and SOLO. Recall that SOLO is a baseline approach where each client trains a model with its local data without federated learning. In the following experiments, unless explicitly stated, all comparisons with the prior arts used reported results from respective papers.

4.1 Experimental Setup

We conduct experiments over three standard datasets: CIFAR-10 (60,000 images with 10 classes), CIFAR-100 (60,000 images with 100 classes), and Tiny-ImageNet (100,000 images with 200 classes). For a fair comparison, we use the same modules in the local network for all approaches. As in the previous work (Li, He, and Song 2021), we use a simple CNN model as the base encoder for CIFAR-10 and use ResNet-50 (He et al. 2016) as the base encoder for CIFAR-100 and Tiny-ImageNet. Note that the simple CNN model has two 5x5 convolution layers followed by 2x2 max pooling and two fully connected layers with ReLU activation. For all datasets, the projection head consists of a 2-layer MLP with an output size of 256, and the output layer is just a single linear layer. We use Dirichlet distribution to generate the non-IID data distribution as previous studies (Wang et al. 2020a; Yurochkin et al. 2019). Specifically, we draw \( p_k^j \sim \text{DirN}(\beta) \) from a Dirichlet distribution and allocate a \( p_k^j \) proportion of the instances of class \( k \) to client \( C_i \), where \( \beta \) is a concentration parameter controlling the identiﬁcalness among clients. Table 1 lists the default conﬁguration of our work.

### Table 1: The default conﬁguration of our work

| Parameter                  | Default value |
|----------------------------|---------------|
| Learning rate \((\eta)\)   | 0.01(CIFAR-10) |
| Number of clients \((m)\)  | 64            |
| Number of communication rounds \((T)\) | 100          |
| Number of local epochs \((E)\) | 10           |
| Concentration parameter \((\beta)\) | 0.5          |

4.2 Accuracy Results

Table 2 lists the top-1 test accuracy of all methods. SOLO shows the worst result among all methods, which demonstrates the advantages of federated learning. FedAvg is the first FL framework that uses cross-entropy loss to train the local network, which can be regarded as a baseline for FL. The other FL framework including SCAFFOLD, FedProx, and MOON are designed to address the non-IID data issue. Since FedAvg does not make any optimization for the non-IID setting, the accuracy of FedAvg is relatively low among all FL algorithms. Furthermore, SCAFFOLD is proposed to improve the accuracy on the CIFAR-10, but it has much worse results on CIFAR-100 and Tiny-ImageNet than FedAvg. For FedProx, its accuracy is very close to that of FedAvg. It is because that FedProx makes only minor modiﬁcations on the FedAvg by using re-parameterization techniques. MOON presents a model contrastive federated learning, which compares the representations learned by different models. This approach outperforms FedAvg by 1.3% \( \sim \) 3% accuracy on the different datasets. As for our method (FedProc), we can observe that its accuracy results are always better than those of other methods for all datasets. Specifically, our method outperforms MOON by 1.6% \( \sim \) 7.9% on the different datasets. It is indicated that our method (prototype contrastive federated learning) can effectively correct the local training. Next, we explore the impact of different parameters on accuracy.

**Impact of number of communication rounds** \((T)\) Figure 3 shows the accuracy in each round during the training. We find that FedProc achieves the best performance at the end of the training. Further, the curves in Figure 3 show that FedProc improves the accuracy at the expense of the slow convergence speed. This is because feature learning plays a critical role at the beginning of training, and then classifier learning gradually dominates the training. In other words, FedProc learns better representations in the early stages of the training, which can beneﬁt the classiﬁer learning in the later stages.

**Impact of number of local epochs** \((E)\) Figure 4 shows the accuracy as the number of local epoch increases during the training. We find that the accuracy of most of the meth-
ods is the highest when the number of local epochs $E = 10$. This is because that, when $E$ is small, the local network cannot be fully trained. But, when $E > 10$, there is over-fitting in the local training on the skewed data, which leads to a reduction in the accuracy of the global model.

**Impact of data heterogeneity ($\beta$)** To assess the impact of the data heterogeneity on the accuracy, we ran the experiments on heterogeneous data by varying the concentration parameter $\beta$ of the Dirichlet distribution on the CIFAR100 dataset. A smaller $\beta$ indicates a more skewed data distribution. The results in Table 3 shows that FedProc consistently achieves the best accuracy with all levels of imbalance. Specifically, FedProc outperforms MOON by 7.6% accuracy when $\beta = 5$. When the data distributions are highly heterogeneous ($\beta = 0.5, 0.1$), FedProc still outperformed MOON by 7.1% and 4.9% accuracy, respectively. This result verifies our motivations, since the advantage of FedProc benefits from the introduction of class prototypes, which serve as global knowledge to correct the local training. In contrast, other methods do not make full use of the underlying knowledge, such as the global class-prototypes.

**Impact of coefficient in loss function ($\alpha$)** In this work, we use the coefficient $\alpha$ to adjust the weights of the feature learning and classifier learning during the local training. To demonstrate the superiority of our method, we design a two-stage federated learning inspired by two-stage work (Khosla et al. 2020). This method trains the features by $\ell_{gpc}$ loss in the first stage and then fixed the features to train classifiers in the second stage. As shown in Table 4, the accuracy of our method is evidently higher than that of the two-stage training method. It is because that the training with two stages breaks the compatibility between feature learning and classifier learning. To validate the efficacy of the setting method of $\alpha$, we re-run FedProc when fixing $\alpha = 0.5$. Obviously, the results in this setting are worse than

![Figure 4: The top-1 test accuracy with different number of communication rounds ($T$).](image)

![Figure 5: The top-1 test accuracy with different number of local epochs ($E$).](image)

| Table 3: The top-1 test accuracy with $\beta = 5, 0.5, 0.1$. |
|-----------------|---------|---------|---------|
| Method          | $\beta = 5$ | $\beta = 0.5$ | $\beta = 0.1$ |
| SOLO            | 26.6%   | 22.3%   | 15.9%   |
| FedAvg          | 65.7%   | 64.5%   | 62.5%   |
| SCAFFOLD        | 55.0%   | 52.5%   | 47.3%   |
| FedProx         | 64.9%   | 64.6%   | 62.9%   |
| MOON            | 68.0%   | 67.5%   | 64.0%   |
| FedProc         | 75.6%   | 74.6%   | 68.9%   |

| Table 4: The top-1 accuracy with different kinds of loss objective. |
|-----------------|---------|---------|---------|
| Method          | CIFAR-10 | CIFAR-100 | Tiny-ImageNet |
| Two-stage FL    | 65.10%   | 67.50%   | 24.70%   |
| FedProc ($\alpha = 0.5$) | 66.30%   | 68.90%   | 30.20%   |
| FedProc         | **70.70%**   | **74.60%** | **35.40%** |

![Image]
ours. When $\alpha = 1 - \frac{1}{T}$, FedProc learns better representations in the early stages of the training, making it have the greater classification capacity in the later stages.

### 4.3 Computation Cost

To make a fair comparison, we measure the computation cost of all the above methods under the same machines. Table 5 shows the average training time per round. We can observe that the average training time of FedAvg is the lowest of all. The reason is, FedProx, MOON, and FedProc introduce additional loss items based on FedAvg, and SCAFFOLD introduces additional control variables for the server and clients. We also find that the average training time of FedProc on CIFAR-10 and CIFAR-100 is nearly the same as most of the methods (e.g., SCAFFOLD and FedProx). As a highlight, FedProc on Tiny-ImageNet is superior to other methods (except FedAvg). We can conclude that FedProc has more advantages in the computation cost as the volume of data and the scale of local networks increases.

### 4.4 Scalability

In order to demonstrate the scalability of FedProc, we ran the experiments on CIFAR-100 with a large number of clients. As in the previous work [Li, He, and Song [2021]], the number of clients ($m$) is set to 50 (with sampling rate $\gamma = 1$) and 100 (with sampling rate $\gamma = 0.2$). Note that $\gamma = 0.2$ means that 20 clients out of 100 clients are randomly selected to participate in the training in each round (refer to FedAvg [McMahan et al. [2017]] for client sampling technology). The results in Table 6 and Figure 6 demonstrate the excellent scalability of FedProc, whose accuracy is far higher than those of the other methods. In particular, our method outperforms MOON by 9.3% accuracy when the number of rounds $T = 200$ and the number of clients $m = 50$. The excellent scalability of FedProc is due to the introduction of prototypical contrastive learning. This improvement makes local objectives of each client consistent with the global optima, such that the performance of FedProc will not be affected as the number of clients increases.

### 5 Conclusion

This paper proposes prototypical contrastive federated learning (FedProc), a simple and effective federated learning framework to tackle non-IID data issue. FedProc introduces class prototypes as global knowledge to correct the local training in federated learning. Technically, we design a local network architecture and global prototypical contrastive loss to make local objectives consistent with the global optima, yielding a good classification performance of the global model. Extensive experiments on multiple datasets demonstrate the advantage of FedProc on non-IID data.
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