An Empirical Study of Personalized Federated Learning

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Abstract
Federated learning is a distributed machine learning approach in which a single server and multiple clients collaboratively build machine learning models without sharing datasets on clients. A challenging issue of federated learning is data heterogeneity (i.e., data distributions may differ across clients). To cope with this issue, numerous federated learning methods aim at personalized federated learning and build optimized models for clients. Whereas existing studies empirically evaluated their own methods, the experimental settings (e.g., comparison methods, datasets, and client setting) in these studies differ from each other, and it is unclear which personalized federate learning method achieves the best performance and how much progress can be made by using these methods instead of standard (i.e., non-personalized) federated learning. In this paper, we benchmark the performance of existing personalized federated learning through comprehensive experiments to evaluate the characteristics of each method. Our experimental study shows that (1) there are no champion methods, (2) large data heterogeneity often leads to high accurate predictions, and (3) standard federated learning methods (e.g. FedAvg) with fine-tuning often outperform personalized federated learning methods. We open our benchmark tool FedBench for researchers to conduct experimental studies with various experimental settings.

1 Introduction
Federated learning has emerged as a distributed machine learning approach in which a single server and multiple clients collaboratively build machine learning models without sharing datasets on clients in order to reduce privacy risks and communication traffic [28]. Its general procedure consists of two steps: (1) client training, in which clients train models on their local data and send their trained models to the server, and (2) model aggregation, in which the server aggregates those models to build a global model and distributes the global model to the clients. Due to its effectiveness in a distributed scenario, federated learning has received considerable attention from research communities and numerous methods have been proposed [4, 6, 18, 10, 13, 20, 36, 37, 38].

One of the main challenges in federated learning lies on data heterogeneity: clients have local data that differ in distributions’, i.e., they do not conform to the property of independent and identically distributed (IID) random variables. This causes difficulty in learning a single global model that is optimal for all clients. It was reported that, in typical federated learning methods, model parameters of a global model are divergent when each client has non-IID local data [20, 21]. To deal with this issue, a recent trend resorts to personalized federated learning, which aims to build personalized models that are optimized for clients [2, 5, 19, 23, 25, 27, 33, 35, 59].

Motivation. While empirical evaluations are available in existing studies, the experimental settings (e.g., comparison methods, datasets, and client settings) in these studies differ from each other.
Despite a comprehensive comparison and analysis of non-personalized federated learning methods on non-IID data [17], to the best of our knowledge, a comprehensive comparison and analysis of personalized federated learning methods have not been conducted yet. Hence the following three questions remain unanswered:

- Which personalized federated learning method performs the best?
- Do personalized federated learning methods perform better than non-personalized federated learning methods?
- How does the experimental setting affect the model performance?

Contributions. In this paper, we benchmark the performance of various personalized federated learning methods in comprehensive experimental studies. For future method development, we summarize several key findings of our study:

- **There are no champion methods**: none of the existing state-of-the-art personalized federated learning methods outperform the others in all the cases.
- **Fine-tuning works well for data heterogeneity**: standard federated learning methods with fine-tuning are able to build highly accurate personalized models, which are not evaluated fairly in existing studies.
- **Large data heterogeneity often leads to high accuracy**: the larger the degree of data heterogeneity, the more accurate the personalized federated learning methods are.

To foster future work, we develop FedBench, a Jupyter notebook-based tool, which supports performing easily experimental studies with various methods, experimental settings, and datasets. FedBench is publicly available at [https://github.com/OnizukaLab/FedBench](https://github.com/OnizukaLab/FedBench) under the MIT licence.

2 Preliminaries on Personalized Federated Learning

2.1 Problem Formulation

We describe the problem formulation of personalized federated learning. Consider a server and a set of clients which collaboratively build personalized models of clients. Let S denote the set of clients. |S| is the number of clients. We use a subscript $i$ for the index of the $i$-th client. $D_i$ denotes the local data of client $i$. $n_i$ denotes the number of data samples (e.g., records, images, and texts). $N$ denotes the sum of $n_i$ across all the clients. $x_i$ and $y_i$ are the features and the labels of samples contained in the local data of client $i$, respectively. $T$ and $E$ are the total numbers of global communication rounds and local training rounds, respectively, where global communication refers to the communication between the server and the clients during training and local training refers to the training of each client’s model using its local data.

In standard federated learning, a server and clients aim to create a single global model $w_g$. We define standard federated learning as the following optimization problem:

$$\min_{w_g \in \mathbb{R}^d} \sum_{i=1}^{\vert S \vert} \mathcal{T}_i(w_g),$$

(1)

where $\mathcal{T}_i$ is the objective for client $i$ and is defined as follows:

$$\mathcal{T}_i(w) = \frac{1}{n_i} \sum_{(x_i, y_i) \in D_i} f_i(x_i, y_i, w),$$

(2)

where $f_i$ is a loss function.

In personalized federated learning, a server and clients aim to create a personalized model $w_p$ for each client. We define personalized federated learning as the following optimization problem:

$$\min_{\{w_{p_1}, \ldots, w_{p_{\vert S \vert}}\} \in \mathbb{R}^d} \sum_{i=1}^{\vert S \vert} \mathcal{T}_i(w_{p_i}),$$

(3)

where $w_{p_i}$ is the personalized model of client $i$. 

2
Table 1: Summary of federated learning methods. Model splitting indicates that the server and each client train a part of the model. Model update regularization is a technique by which the personalized model trained by each client will not stray too far from the global model.

| Method                        | FedAvg | FedProx | HypCluster | FML | FedMe | LG-FedAvg | FedPer | FedRep | Ditto | pFedMe |
|-------------------------------|--------|---------|------------|-----|-------|-----------|--------|--------|-------|--------|
| Personalization               | x      | x       | ✓          | ✓   | ✓     | ✓         | ✓      | ✓      | ✓     | ✓      |
| Clustering                    | x      | x       | ✓          | ✓   | ✓     | ✓         | x      | x      | x     | x      |
| Deep mutual learning          | x      | x       | ✓          | ✓   | ✓     | ✓         | x      | x      | x     | x      |
| Model splitting               | x      | x       | x          | x   | x     | ✓         | ✓      | x      | x     | x      |
| Model update regularization   | x      | ✓       | x          | x   | x     | ✓         | x      | ✓      | ✓     | ✓      |

2.2 Representative Federated Learning Methods

We introduce a set of representative federated learning methods which are evaluated in this paper. The characteristics are summarized in Table 1.

**Standard federated learning.** The basic method on federated learning is FedAvg [28], which aggregates all the trained models of the clients by averaging their model parameters to build a single global model. FedProx [20] utilizes a regularization term in its loss function so that the clients’ trained models will not significantly differ from the global model.

**Personalized federated learning.** Hypcluster [25] is a method that divides the set of clients into groups and creates a model for each group. Federated mutual learning (FML) [33] and FedMe [27] use deep mutual learning [40], which is a machine learning method by which multiple models are trained to imitate each other’s output. In FML, each client trains its own personalized model independently and a generalized model is trained collaboratively. In FedMe, each client trains its own personalized model and other clients’ personalized models, depending on a clustering. In LG-FedAvg [23], FedPer [2], and FedRep [5], the server and each client train a part of the model. These methods combine the server’s and the clients’ sub-models for training and inference. In LG-FedAvg, the clients train the input part of the model, and the server trains the output part of the model. In FedPer and FedRep, the clients train the output part of the model, and the server trains the input part of the model. In Ditto [19] and pFedMe [35], the personalized models of the clients do not stray too far from the global model. Ditto updates the personalized models based on the difference between the model parameters of the global model and those of the personalized models, while pFedMe employs Moreau envelopes as the clients’ regularized loss functions to facilitate convergence analysis.

3 Experimental Design Dimensions

In federated learning, datasets, client, and training settings affect the performance of learning methods. To evaluate the performance of existing methods and understand their characteristics, we consider the following three design dimensions in this study.

**Number of clients.** The number of clients may significantly differ, depending on the use case we target. For example, the number of the clients may be around 10 for small institutions, while the number of the clients may be 100 or even more for mobile devices. As the number of clients increases, it becomes more difficult to aggregate models on the server, resulting in less accuracy. Therefore, a robust method for varying numbers of clients is desirable.

**Total number of data samples.** Like the number of clients, the total number of data samples also depends on the use case, and the performances of federated learning methods may differ when we vary the total number of data samples. Even if the server is aware of the numbers of data samples of the clients, it is challenging to select an optimal method. A robust method for different numbers of data samples is desirable. To this end, it is necessary to evaluate how the performances of existing methods vary with the total number of data samples.

**Degree of data heterogeneity.** As the degree of data heterogeneity increases, the accuracy of non-personalized federated learning decreases, while personalized federated learning rather improves accuracy because it allows the construction of a model that fits each client. Previous studies have not comprehensively evaluated this impact on the performance of personalized federated learning methods. In this paper, we compare and discuss the accuracies of existing methods by varying the degree of data heterogeneity.
Table 2: Data statistics. Total size and test size indicate the numbers of data samples in the entire dataset and the test data of the dataset, respectively. Other measures are statistics of local datasets.

| Datasets     | Total size | Test size | Mean  | SD     | Max  | Min  |
|--------------|------------|-----------|-------|--------|------|------|
| FEMNIST      | 749,068    | 77,483    | 220.3 | 85.20  | 465  | 19   |
| Shakespeare  | 517,106    | 103,477   | 3,616.1| 6,832.37| 41,305| 3    |
| Sent140      | 74,589     | 7,895     | 80.5  | 40.02  | 549  | 50   |
| MNIST        | 70,000     | 10,000    | 3,450.0| 1,050.17| 5,534| 1,354|
| CIFAR-10     | 60,000     | 10,000    | 2,950.0| 1,233.60| 6,043| 1,360|

4 Experiments

In this section, we introduce experimental configurations and report our experimental results. To answer the questions described in Section 1, we perform the following experiments: (1) To evaluate the performance of personalized and non-personalized federated learning methods, we compare the methods in terms of accuracy, convergence speed, communication traffic, and training time. (2) To evaluate the impact of experimental settings on accuracy, we conduct experiments by varying the number of clients, the total number of data samples, and the degree of data heterogeneity described in Section 3.

To simplify the experiments, we used Pytorch to create a virtual client and the server on a single GPU machine. Experiments were performed on a Linux server with NVIDIA Tesla V100 SXM2 GPU (16GB) and Intel Xeon Gold 6148 Processor CPU (384GB).

4.1 Experimental Setup

Datasets, tasks, and models. We use five datasets: FEMNIST, Shakespeare, Sent140, MNIST, and CIFAR-10, which are often used in previous studies [4, 5, 16, 20, 25, 28, 36]. FEMNIST, Shakespeare, and Sent140 are originally separated for federated learning. While since MNIST and CIFAR-10 are not separated, we need to divide these two datasets synthetically.

FEMNIST [3] includes images of handwritten characters with 62 labels, and is divided into 3,400 sub-datasets of writers. Shakespeare [20] includes lines in “The Complete Works of William Shakespeare”, and is divided into 143 sub-datasets of actors. Sent140 [3] includes the text of tweets with 2 labels, either positive sentiment or negative sentiment. This dataset is divided into 660,120 sub-datasets of twitter users, and we use 927 sub-datasets with more than 50 tweets in the experiment. MNIST [15] includes images of handwritten characters with 10 labels. CIFAR-10 [14] includes photo images with 10 labels. We divide MNIST and CIFAR-10 into sub-datasets using the Dirichlet distribution as in [36]. Table 2 shows the statistics of the above datasets. We note that we randomly divide MNIST and CIFAR-10 in each test, so the statistics of them are the values in a single test.

In tasks and models, we follow the previous studies [4, 5, 16, 20, 25, 28, 31, 36]. In task settings, we conduct an image classification task for FEMNIST, MNIST, and CIFAR-10. For Shakespeare, we conduct a next-character prediction that infers the next characters after given sentences. For Sent140, we conduct a binary classification that categorizes whether a tweet is a positive or negative sentiment. We use different models for each task following the existing works [31, 36, 5]. For FEMNIST and MNIST we use CNN, and for Shakespeare we use LSTM. For CIFAR-10, we use VGG with the same modification reported in [36]. For Sent140, we use a pre-trained 300-dimensional GloVe embedding [30] and train RNN with an LSTM module.

Client and training setting. We vary several parameters for clients and training: the number of clients, the total number of data samples, and the degree of data heterogeneity. The number of clients, |S|, is selected from {5, 10, 20, 100}. We change the total number of data samples using a ratio D to the entire dataset (i.e., the total number of data samples is D · N), whose range is {0.25, 0.5, 0.75, 0.1}. To change the degree of data heterogeneity, we use a parameter αlabel to control the degree of heterogeneity for the labels on the clients. αlabel is selected from {0.1, 0.5, 1.0, 5.0}. The default values of |S|, D, and αlabel are 20, 1.0, and 0.5, respectively.

The five datasets are pre-partitioned into training and test data. In FEMNIST, Shakespeare, and Sent140, we randomly select |S| sub-datasets as local data. In MNIST and CIFAR-10, we randomly divide the whole train and test data into |S| local data. The distributions of test and train data follow...
the same Dirichlet distribution. We split the training data into 7 : 3 for FEMNIST, Shakespeare, and 
Sent140, and into 8 : 2 for MNIST and CIFAR-10. The two splits are used for training and validation, 
respectively. We select 1,000 unlabeled data from the training data for FedMe, and the unlabeled data 
is excluded from the training data.

We set the number of global communication rounds to be 300, 200, 500, 100, and 100 for FEMNIST, 
MNIST, CIFAR-10, Shakespeare, and Sent140, respectively. We set the local epoch \( E \) to be 2 for 
all the settings. All the clients participate in each global communication round following recent 
studies \[2, 33, 36\]. We conduct training and test five times and report mean and standard deviation 
(std) of accuracy over five times of experiments with different clients.

Methods and hyperparameter tuning. We compare three types of methods: (1) non-personalized 
federated learning methods, (2) personalized federated learning methods, and (3) non-federated 
learning methods. For (1), we use FedAvg and Fedprox; for (2), we use HypCluster, FML, FedMe, 
LG-FedAvg, FedPer, FedRep, Ditto, and pFedMe; for (3), we use Local Data Only, in which 
clients build their models on their local data, and Centralized, in which a server collects local data 
from all clients (centralized can be considered as an oracle). We use fine-tuning on each client 
for FedAvg, Fedprox, HypCluster, FedMe, and Centralized after building their models. In FML, 
LG-FedAvg, FedPer, FedRep, Ditto, and pFedMe, we do not use fine-tuning because techniques 
similar to fine-tuning are included in these methods.

We describe hyperparameter tuning. The learning rate is selected from 
\[\{10^{-3}, 10^{-2.5}, 10^{-2}, \ldots, 10^{0.5}\}\] and optimized for each method on default parameters. The 
optimized learning rate is used in the experiment of impact of the experimental setup. The 
optimization method is SGD (stochastic gradient descent) with momentum 0.9 and weight decay 
\(10^{-4}\). The batch sizes of FEMNIST, MNIST, CIFAR-10, Shakespeare, and Sent140 are 20, 20, 40, 
10, and 4, respectively. Hyperparameters specific to each method is described in the supplementary 
file.

4.2 Performance Comparison

We compare the methods in terms of accuracy, convergence speed, training speed, and communica-
tions traffic in the default parameter setting. In this experiment, we have the two findings:

**Finding 1.** No method consistently outperforms the other methods in all the datasets.

**Finding 2.** Only a few state-of-the-art personalized methods outperform standard federated 
learning methods.

Accuracy. Table 3 shows the accuracy and average ranking of each method. We note that the standard 
deviations of FEMNIST, Shakespeare, and Sent140 are relatively large because the clients differ in 
each test (we randomly select 20 clients from the set of clients). From Table 3, we can see that the 
most accurate method is FedMe+FT for FEMNIST, Ditto for Shakespeare, Hypcluster for Sent140, 
FedAvg+FT for MNIST, and FedMe+FT for CIFAR-10. From this result, we find that none of the 
existing state-of-the-art personalized federated learning methods outperform the others in all the 
datasets.

We can also see that FedMe+FT has the highest average rank. On the other hand, the other personal-
ized federated learning methods have lower average ranks than the standard federated learning 
methods such as FedAvg and FedProx with fine-tuning. From this result, we can find that only a few 
state-of-the-art personalized methods outperform standard federated learning methods, and those 
with fine-tuning are often sufficient to deal with data heterogeneity.

Convergence speed. Figure 1 shows the validation accuracy of each global communication round. 
The validation accuracy is the average accuracy at each epoch of the five experiments. Since each 
client evaluates its model by its own validation data after training its model and before aggregating 
models, the accuracy of each method is equivalent to that after fine-tuning.
We evaluate run time on the training phase in each method. Figure 2 shows the training time. Since each method exchanges models between the server and client, communications traffic is compared by the size of model parameters sent per global communication round. Figure 4 shows the communications traffic.

From Figure 1 we can see that FedAvg and Ditto are stable and converge quickly for all datasets. On the other hand, we can see that FedMe has the highest average rank but loses in convergence speed to FedAvg and Ditto. From this result, we can find that the methods with the highest accuracy and the fastest convergence are different.

Training time. We evaluate run time on the training phase in each method. Figure 2 shows the average run time per global communication round. We note that the run time is the average of ten global communication rounds.

From Figure 2 we can see that FedAvg has the smallest training time for all datasets. FedMe and Ditto have a large training time than the other methods. pFedMe spends similar training time to the other methods on FEMNIST and Sent140, while it spends much larger time than the other methods on Shakespeare, MNIST, and CIFAR-10. pFedMe has large training time for clients, so when the volume of local data increases, its training time increases.

Communications traffic. We evaluate communications traffic on the training phase in each method. Since each method exchanges models between the server and client, communications traffic is compared by the size of model parameters sent per global communication round. Figure 4 shows the communications traffic per global communication round.
As the number of clients increases, it becomes more difficult to aggregate the model on the server, resulting in decreasing accuracy. FedAvg+FT has the highest average rank for MNIST, and Ditto has the highest average rank for CIFAR-10. This result indicates that the larger number of clients is more challenging, while we can design robust methods for different number of clients.

### 4.3 Impact of Experimental Settings on Accuracy

In this section, we compare the accuracy of each method in different experimental settings.

**Impact of the number of clients.** Table 5 shows the accuracy of varying the number of clients.

From Table 5, we can see that the accuracy decreases significantly as the number of clients increases. As the number of clients increases, it becomes more difficult to aggregate the model on the server, resulting in decreasing accuracy. FedAvg+FT has the highest average rank for MNIST, and Ditto has the highest average rank for CIFAR-10. This result indicates that the larger number of clients is more challenging, while we can design robust methods for different number of clients.

**Impact of the total number of data samples.** Table 6 shows the accuracy when we vary the total number of data samples.
From Table 6, we can see that the accuracy decreases as the total number of data samples decreases. This is because clients do not have sufficient data samples to train their models when the number of data samples is small. The ranks of methods do not change much, so the number of data samples does not significantly impact deciding the superiority of methods.

**Impact of the degree of data heterogeneity.** Table 7 shows the accuracy when we vary the degree of data heterogeneity. A smaller $\alpha_{\text{label}}$ indicates a larger degree of data heterogeneity.

Finding 3. The larger the degree of data heterogeneity, the more accurate the personalized federated learning methods are.

From Table 7, we can see that the accuracy of FedAvg and FedProx decreases as the degree of data heterogeneity increases. On the other hand, we can see that the accuracy of personalized federated learning methods tends to increase as the degree of data heterogeneity increases. As the degree of data heterogeneity increases, the clients can easily build their personalized models that fit their local data. We can find that data heterogeneity works positively for personalized federated learning.

We can also see that FedAvg+FT and FedProx+FT have the highest average rank on MNIST, and FedMe+FT has the highest average rank on CIFAR-10. This result indicates that the standard federated learning methods with fine-tuning are often sufficient to deal with the data heterogeneity.

**4.4 Summary of Experimental Results**

We summarize the results of the above experimental study. First, there is a trade-off between accuracy, communication traffic, and training time. For example, FedMe is accurate in various experimental settings but reports large communication traffic and training time. Second, the standard federated learning methods with fine-tuning can deal well with data heterogeneity. In particular, for easy-to-learn datasets such as MNIST, they outperform the personalized federated learning methods. Finally, for a small number of clients, a large total number of data samples, or a large degree of heterogeneity, we observed higher accuracies of federated learning methods. These characteristics should be considered when developing and evaluating new federated learning methods.
5 Conclusions, Limitations, and Future Work

We evaluated personalized federated learning in various experimental settings. The experimental results showed several key findings: First, no method consistently outperformed the others in all the datasets. Second, the large degree of data heterogeneity improved the accuracy of personalized federated learning methods. Third, standard federated learning with fine-tuning was accurate compared with most personalized federated learning methods. We opened our Jupyter notebook-based tool FedBench to facilitate experimental studies.

This study has three limitations. First, despite 17 methods (ten federated learning, four variants, and three non-federated learning methods) and five datasets were used in this study, which are comprehensive compared with previous ones, we also note that there are numerous other federated learning methods (e.g., [1][8][9][12][26][29][34][37][39] and datasets (e.g., DigitFive and Office-Caltech10 [22], PROSTATE [24], Flicker mammal [11], and FLCKER-AES and REAL-CUR [32]). Second, to study the impact of the data heterogeneity, we controlled the label distribution skew but did not investigate the impact of other types of skews, such as quantity skew, in which each client has a different number of data samples, and feature distribution skew, in which the clients’ data share the same labels but vary in features. Third, we varied the number of clients, the total number of data samples, and the degree of data heterogeneity, whereas other parameters, such as client participant ratio, the number of local epochs, and model architectures, were not varied.

As future work, we plan to enrich our benchmark tool by addressing the above limitations and find further insights. We hope that our benchmark tool and experimental results help to develop and evaluate new federated learning methods.

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A Dataset statistics

Detailed statistics for the datasets used in our experiments are shown in Table 8.

| Dataset       | Size (Train/Test) | Mean (Train/Test) | SD (Train/Test) | Max (Train/Test) | Min (Train/Test) |
|---------------|-------------------|-------------------|-----------------|-----------------|-----------------|
| FEMNIST       | 671,585/77,483    | 197.53/22.79      | 6.69/8.51       | 418/47          | 16/3            |
| Shakespeare   | 413,629/103,477   | 2,892.51/723.62   | 5,465.89/1,366.48 | 33,044/8,261   | 2/1             |
| MNIST         | 59,000/10,000     | 2,950.00/500.00   | 896.15/154.09   | 4725/809        | 1,334/220       |
| CIFAR-10      | 49,000/10,000     | 2,450.00/500.00   | 1,024.66/208.95 | 5,018/1,025     | 1,131/229       |

B Model architectures

The details of the model used in our experiments are shown in Tables 9–13.

| Layer         | Output Shape | Trainable Parameters | Activation | Hyperparameters               |
|---------------|--------------|----------------------|------------|-------------------------------|
| Input         | (28, 28, 1)  | 0                    | -          |                               |
| Conv2d        | (26, 26, 32) | 320                  | -          | kernel size = 3; strides=(1, 1) |
| Conv2d        | (24, 24, 64) | 18496                | -          | kernel size = 3; strides=(1, 1) |
| MaxPool2d     | (12, 12, 64) | 0                    | -          | pool size= (2, 2)             |
| Dropout       | (12, 12, 64) | 0                    | -          | p = 0.25                      |
| Flatten       | 9216         | 0                    | -          |                               |
| Linear        | 128          | 1179776              | ReLU       |                               |
| Dropout       | 128          | 0                    | -          | p = 0.5                       |
| Linear        | 62           | 7998                 | Softmax    |                               |

| Layer         | Output Shape | Trainable Parameters | Activation | Hyperparameters               |
|---------------|--------------|----------------------|------------|-------------------------------|
| Input         | 80           | 0                    | -          |                               |
| Embedding     | (80, 8)      | 720                  | -          |                               |
| LSTM          | (80, 256)    | 798720               | -          | number of layers = 2          |
| Linear        | 90           | 23130                | Softmax    |                               |

C Hyper-parameters setting

We show the hyper-parameters that we used in our experimental study. We generally follow the hyper-parameter settings of original papers that each method has been proposed.

All methods. The common hyper-parameters of all methods are listed as follows:

- Momentum: 0.9
- Weight decay: $10^{-4}$
- Max norm of the gradients: 20
- Batch size
  - For FEMNIST: 20
  - For Shakespeare: 20
  - For Sent140: 40
  - For MNIST: 10
  - For CIFAR-10: 4
- Learning rate: See Table 14
Table 11: Model architectures for Sent140.

| Layer        | Output Shape | Trainable Parameters | Activation | Hyperparameters |
|--------------|--------------|----------------------|------------|-----------------|
| Input        | (25)         | 0                    | -          | -               |
| Embedding    | (300, 25)    | 0                    | -          | -               |
| LSTM         | (300, 128)   | 79360                | -          | number of layers = 1 |
| Linear       | (300, 10)    | 1290                 | ReLU       | -               |
| Dropout      | (300, 10)    | 0                    | -          | p = 0.5         |
| Linear       | 2            | 22                   | Softmax    | -               |

Table 12: Model architectures for MNIST.

| Layer        | Output Shape | Trainable Parameters | Activation | Hyperparameters |
|--------------|--------------|----------------------|------------|-----------------|
| Input        | (28, 28, 1)  | 0                    | -          | -               |
| Conv2d       | (26, 26, 32) | 320                  | -          | kernel size = 3; strides=(1, 1) |
| Conv2d       | (24, 24, 64) | 18,496               | -          | kernel size = 3; strides=(1, 1) |
| MaxPool2d    | (12, 12, 64) | 0                    | -          | pool size=(2, 2) |
| Dropout      | (12, 12, 64) | 0                    | -          | p = 0.25        |
| Flatten      | 9,216        | 0                    | -          | -               |
| Linear       | 128          | 1,179,776            | ReLU       | -               |
| Dropout      | 128          | 0                    | -          | p = 0.5         |
| Linear       | 10           | 1,290                | Softmax    | -               |

We here note that the learning rates were tuned in \( \{10^{-3}, 10^{-2.5}, 10^{-2}, 10^{-1.5}, 10^{-1}, 10^{0.5}, 10^{0}, 10^{0.5}\}\) for each dataset and method.

The followings are the method-specific hyper-parameters.

**FedProx.** The hyper-parameters of FedProx are listed as follows:

- Parameter to control the regularization term \( \mu: 0.001 \)

**HypCluster.** The hyper-parameters of HypCluster are listed as follows:

- The number of clusters \( k: 2 \)

**FedMe.** The hyper-parameters of FedMe are listed as follows:

- The numbers of global communication rounds to increase the number of clusters
  - For FEMNIST: 150, 225, and 275
  - For Shakespeare: 50, 75, and 90
  - For Sent140: 25, 50, and 75
  - For MNIST: 50, 100, and 150
  - For CIFAR-10: 250, 375, and 450
- The number of unlabeled data: 1000

**LG-FedAvg.** The hyper-parameters of LG-FedAvg are listed as follows:

- Sub-models of the server and the clients
  - For FEMNIST, Shakespeare, Sent140, and MNIST
    - **Server:** The last linear layer
    - **Clients:** The all layers except for the last linear layer
  - For CIFAR-10
    - **Server:** The all linear layers
    - **Clients:** The all convolutional layers

**FedPer.** The hyper-parameters of FedPer are listed as follows:

- Sub-models of the server and the clients
Table 13: Model architectures for CIFAR-10.

| Layer       | Output Shape | Trainable Parameters | Activation | Hyperparameters |
|-------------|--------------|----------------------|------------|-----------------|
| Input       | (32, 32, 3)  | 0                    | -          | -               |
| Conv2d      | (32, 32, 64) | 1,792                | ReLU       | kernel size = 3; strides=(1, 1) |
| Conv2d      | (32, 32, 64) | 36,928               | ReLU       | kernel size = 3; strides=(1, 1) |
| MaxPool2d   | (16, 16, 64) | 0                    | -          | pool size= (2, 2) |
| Conv2d      | (16, 16, 128)| 73,856               | ReLU       | kernel size = 3; strides=(1, 1) |
| Conv2d      | (16, 16, 128)| 147,584              | ReLU       | kernel size = 3; strides=(1, 1) |
| MaxPool2d   | (8, 8, 128)  | 0                    | -          | pool size= (2, 2) |
| Conv2d      | (8, 8, 256)  | 295,168              | ReLU       | kernel size = 3; strides=(1, 1) |
| Conv2d      | (8, 8, 256)  | 590,080              | ReLU       | kernel size = 3; strides=(1, 1) |
| MaxPool2d   | (4, 4, 256)  | 0                    | -          | pool size= (2, 2) |
| Conv2d      | (4, 4, 512)  | 1,180,160            | ReLU       | kernel size = 3; strides=(1, 1) |
| Conv2d      | (4, 4, 512)  | 2,359,808            | ReLU       | kernel size = 3; strides=(1, 1) |
| MaxPool2d   | (2, 2, 512)  | 0                    | -          | pool size= (2, 2) |
| Conv2d      | (2, 2, 512)  | 2,359,808            | ReLU       | kernel size = 3; strides=(1, 1) |
| Conv2d      | (2, 2, 512)  | 2,359,808            | ReLU       | kernel size = 3; strides=(1, 1) |
| MaxPool2d   | (1, 1, 512)  | 0                    | -          | pool size= (2, 2) |
| Dropout     | 512          | 0                    | -          | p = 0.5         |
| Linear      | 512          | 262,656              | ReLU       | -               |
| Dropout     | 512          | 0                    | -          | p = 0.5         |
| Linear      | 512          | 262,656              | ReLU       | -               |
| Linear      | 10           | 5,130                | Softmax    | -               |

Table 14: The optimal learning rates.

|                      | FEMNIST | Shakespeare | Sent140 | MNIST | CIFAR-10 |
|----------------------|---------|-------------|---------|-------|----------|
| FedAvg               | 10^-2   | 10^-4       | 10^-4   | 10^-2 | 10^-2    |
| FedProx              | 10^-2   | 10^-0.5     | 10^-1   | 10^-2.5| 10^-2    |
| HypCluster           | 10^-1.5 | 10^-3       | 10^-1.5 | 10^-2.5| 10^-2    |
| FML                  | 10^-2   | 10^-0.5     | 10^-0.5 | 10^-2.5| 10^-2    |
| FedMe                | 10^-2   | 10^-1.5     | 10^-2.5 | 10^-3  | 10^-2    |
| LG-FedAvg            | 10^-3   | 10^-0.5     | 10^-2.5 | 10^-2  | 10^-2    |
| FedPer               | 10^-1.5 | 10^-1.5     | 10^-2   | 10^-2.5| 10^-2    |
| FedRep               | 10^-1.5 | 10^-1       | 10^-1   | 10^-2.5| 10^-2.5  |
| Ditto                | 10^-2   | 10^-0.5     | 10^-2.5 | 10^-3  | 10^-1.5  |
| pFedMe               | 10^-2   | 10^-1       | 10^-1.5 | 10^-2  | 10^-2.5  |
| Local Data Only      | 10^-2.5 | 10^-0.5     | 10^-2   | 10^-2.5| 10^-2    |
| Centralized          | 10^-2.5 | 10^-1       | 10^-2   | 10^-3  | 10^-2    |

- For FEMNIST, Shakespeare, Sent140, and MNIST
  Server: The all layers except for the last linear layer
  Clients: The last linear layer
- For CIFAR-10
  Server: The all convolutional layers
  Clients: The all linear layers

**FedRep.** The hyper-parameters of FedRep are listed as follows:

- The number of epochs to train sub-models: 2 for each of sub-models
- Sub-models of the server and the clients
  - For FEMNIST, Shakespeare, Sent140, and MNIST
    Server: The all layers except for the last linear layer
    Clients: The last linear layer
  - For CIFAR-10
    Server: The all convolutional layers
    Clients: The all linear layers
**Ditto.** The hyper-parameters of Ditto are listed as follows:

- Parameter to control the interpolation between global and personalized models $\lambda$: 0.75

**pFedMe.** The hyper-parameters of pFedMe are listed as follows:

- Parameter to control the regularization term $\lambda$: 15
- The number of repetitions of batch trains $K$: 5