Meta-learning and Personalization layer in Federated learning

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Abstract. Federated learning systems are confronted with two challenges: systemic and statistical. Non-IID data is acknowledged to be a primary component in causing statistical challenges. To address the federated learning system's substantial performance loss on non-IID data, we offer the `FedMeta-Per` algorithm (which combines meta-learning methods and personalization layer approaches into a federated learning system). In terms of performance and personalization, `FedMeta-Per` has been shown in experiments to outperform typical federated learning algorithm, algorithms using personalization layer techniques and algorithms using meta-learning in system optimization.

Keywords: Federated learning · non-IID · Meta-learning · Personalization layer

1 Introduction

In the era of the Internet of Things, facing a huge amount of data at edge devices generated every second, the centralized training process presents many disadvantages. First, data at edge devices often contains sensitive information about users. When it has to be transmitted to a server for training a machine learning model, this information can be exposed, seriously affecting data privacy. Second, the cost of transmitting information between the server and the clients is very expensive because a large amount of data must be transferred to the server. Third, the server must have large computing power and storage to conduct the training process.

Edge computing [12] was born to push the computation and storage of data from the server to clients or edge devices, reducing the load on the server. Furthermore, the computation is moved to or near the data generation site, which saves huge amounts of communication costs and reduces computational latency. Not only that, the process of exchanging data between the server and the clients no longer takes place, greatly increasing the user's data privacy.

Based on the idea of edge computing, *federated learning* (FL) [18] was born to protect user data privacy by allowing machine learning models to be trained on separate datasets that are distributed across edge devices. Specifically, the

goal of the FL system is to find a global parameter w_G^* such that the system error is minimized:

$$w_G^* = \arg\min_{w_G} f_{global}(w_G)$$
$$= \arg\min_{w_G} \frac{1}{n} \sum_{i=1}^{n} f_{local}(w_i) \tag{1}$$

where, n is the number of clients participating in the system, f_{global} is the error of the whole system, $f_{local}(w_i)$ is the error of the client i when it uses the parameter w_i.

This training method not only inherits the benefits of edge computing (lowering hardware costs and latency, increasing data security), but also has the potential to increase personalization for each user. However, the clients participating in the system are often heterogeneous in terms of storage and computing capacity. The data distributed across these clients is also not uniformly distributed (non-IID). This creates two main challenges of an FL system: the Systemic Challenge and the Statistical Challenge [15]. As for the statistical challenge, [21] research indicates that FL's traditional algorithm - Federated Averaging (`FedAvg`) suffers from severe performance loss on non-IID data.

Task. This study aims to partially solve the statistical problem. Specifically, we improve the performance as well as the personalization per user of the FL system on non-IID data in the supervised learning problem by meta-learning (ML) algorithms [9] and personalization layer (PL) technique.

Contribution. The study proposes the `FedMeta-Per` algorithm, a combination of ML algorithms (`MAML` [7], `Meta-SGD` [16]) and PL techniques (`FedPer` [1], `LG-FedAvg` [17]), which helps to increase accuracy and personalize for each user. Experimentally, the research shows the effectiveness in increasing the accuracy as well as the personalization of the proposed algorithm compared with the algorithm `FedAvg`; algorithms that incorporate ML into FL [3] (`FedMeta(MAML)`, `FedMeta(Meta-SGD)`) and algorithms that use PL (`FedPer`) on a FL system of 50 users, containing the data of two datasets MNIST [5] and CIFAR-10 [13] respectively.

2   Related Work

Since the `FedAvg` algorithm was first introduced in 2017, a lot of work has been done to improve the accuracy of the system on non-IID data. Here, the study reviews a few typical works in the realization of this goal.

Meta-learning - based approach. ML is a new learning method that allows the learning model to gain experience by performing many different tasks in the same task distribution. This results in ML models being able to adapt quickly to new tasks after only a few training steps with limited training data. This is an important discovery, playing a role in bringing machine learning closer to human learning [8].

In the context of non-IID data, each user, with different needs, generates datasets with very different distributions. If we consider each user as a task, training the global model on a set of users (FL system) is equivalent to training the machine learning model on a task distribution (ML approach). Research [3] proposes framework `FedMeta` and experimentally illustrates by two algorithms `FedMeta(MAML)`, `FedMeta(Meta-SGD)`. The results show that the global model has fast adaptability and faster convergence than `FedAvg` on the LEAF dataset [2]. Study [6] proposes the combination of `MAML` on the CIFAR-10 dataset, and study [11] proposes the combination of `Reptile` [19] on the EMNIST-62 dataset [4] to the FL system, to increase personalization for each client.

An FL system, on the other hand, will have new clients over time. One downside for systems that use ML in training is that they treat clients that have been around for a long time in the system and those that have just joined the system equally. Therefore, although global models are able to adapt quickly to new data, their performance can be further improved.

Personalization layer-based approach. To capture the data properties, which are highly personalized for different users, dividing the deep neural network into personalization layers and base layers and maintaining the personalization layers at each client (base layers will be co-trained by the clients) is suggested. Accordingly, study [1] proposes the `FedPer` algorithm with the idea of maintaining fully-connected layers of the deep neural network at the clients with the goal of increasing personalization. Experimentally, `FedPer` achieved much higher results than `FedAvg` when tested on the data sets CIFAR-10 and CIFAR-100. In addition, study [17] with the algorithm `LG-FedAvg` proposes to maintain the feature extraction layers of the deep neural network at the clients with the goal of capturing the features of each different client. The results obtained are even better than `FedPer` in most cases when testing on a system consisting of 10 to 100 users containing data from the data sets CIFAR-10, CIFAR- 100, and Omniglot [14].

The similarity between these two methods lies in the training base layers. These layers are trained and synthesized using the `FedAvg` algorithm. Therefore, they are not able to adapt quickly to the new data set. In addition, during the inference phase, the `FedPer` algorithm takes the average of the parameters of the personalization layers and then combines them with the parameters of the base layers to conduct the test. The parameters of the personalization layers, which are highly personalized, are now averaged, which can cause the classification efficiency to be significantly reduced when the data is strong non-IID. The algorithm `LG-FedAvg` proposes performing an ensemble test between personalization layers. However, only personalization layers trained on the same data as the test data will really perform well. Therefore, in some cases, ensemble test results are not high because there are too many personalization layers that have never worked with the same data as the data during the test.

3   Proposed Method

The proposed method of this study is a combination of maintaining personalization layers at the edge device of the algorithm `FedPer` and using meta-learning in training base layers of the model. With this combination, the research aims at two goals: (1) - Fast adaptability on new dataset of ML algorithms, (2) - High personalization ability of PL techniques.

Fast adaption. As mentioned above, the base layers of algorithms using PL techniques are not really strong because they are trained on the `FedAvg` algorithm, which leads to them being slow to adapt to the new data sets. The training of base layers by ML algorithms is expected to provide these base layers with the ability to quickly adapt to the data set of clients, overcoming the disadvantages of algorithms using PL techniques.

High personalization. The personalization of the FL system combined with ML comes from the fact that the system allows the global model to perform a fine-tune on part of the client data before going into testing on the rest of the client data. Allowing the FL system to maintain a portion of the deep neural network (personalization layers) on each client also greatly increases the ability to personalize each user. Here, our algorithm proposes a combination of the two methods of personalization enhancement mentioned above, which is expected to further increase the personalization of the FL system.

Specifically, the deep neural network is divided into two parts: the base layers include feature extraction layers, and the personalization layers contain fully-connected layers. The base layers are trained against two ML algorithms (`MAML` and `Meta-SGD`). The personalization layers are maintained by separate clients. With this combination, we call our proposed algorithm `FedMeta-Per`.

Algorithm 1 FedMeta-Per (Server)

1: Initialize w_B^0 for MAML or (w_B^0, α_B^0) for Meta-SGD
2: **for** $t = 0, 1, 2, ...$ **do**
3:      Sample a subset C_t of m clients
4:      **for** $c_i \in C_t$ **do**
5:          $w_{B(i)}^{t+1} \leftarrow \text{ModelTrainingMAML}(c_i, w_B^t)$ for MAML
6:          $(w_{B(i)}^{t+1}, \alpha_{B(i)}^{t+1}) \leftarrow \text{ModelTrainingMetaSGD}(c_i, w_B^t, \alpha_B^t)$ for Meta-SGD

7:
8:      $n_i = \left| \mathcal{D}_{train(i)}^{query} \right|, N_m = \sum_{i=0}^m n_i$
9:      Aggregate $w_B^{t+1} = \sum_{i=0}^m \frac{n_i}{N_m} w_{B(i)}^{t+1}$ for MAML
10:      Aggregate $(w_B^{t+1}, \alpha_B^{t+1}) = \sum_{i=0}^m \frac{n_i}{N_m} (w_i^{t+1}, \alpha_{B(i)}^{t+1})$ for Meta-SGD

Training phase. On the server, the algorithm 1 is implemented to coordinate the training activities. These operations include: parameter initialization of base layers; distributing this parameter to clients; synthesizing the parameters of the new global base layers. This process is summarized in Table 1. For

the `MAML` algorithm, the base layers parameters include only part of the global model parameters (w_B^t at round t). Meanwhile, the parameter of the `Meta-SGD` algorithm's base layers contains an extra part of the learning rate at each client (α_B^t at round t), which is the same size as w_B^t. This learning rate value will be well explained in the training process of the clients. These values will be distributed to a subset C_t of m clients to conduct distributed training. The clients then train on their own dataset and return the parameters of the base layers ($w_{B(i)}^{t+1}$ for `MAML` and $(w_{B(i)}^{t+1}, \alpha_{B(i)}^{t+1})$ for `Meta-SGD` at round t) to the server. The parameters of the new base layers are summarized as follows:

$$\text{MAML: } w_B^{t+1} = \sum_{i=0}^{m} \frac{n_i}{N_m} w_{B(i)}^{t+1} \tag{2}$$

$$\text{Meta-SGD: } (w_B^{t+1}, \alpha_B^{t+1}) = \sum_{i=0}^{m} \frac{n_i}{N_m} (w_i^{t+1}, \alpha_{B(i)}^{t+1}) \tag{3}$$

where, n_i is the number of data samples of the client's query set $c_i \in C_t$, N_m is the total number of data samples on the query set of m of the client participating in global training.

Table 1: Server activity summary at round t^{th}

	Algorithm	
	MAML	Meta-SGD
Send	w_B^t	(w_B^t, α_B^t)
Receive	Weights: $w_{B(i)}^{t+1}, i \in [1,m]$	Parameters: $(w_{B(i)}^{t+1}, \alpha_{B(i)}^{t+1}), i \in [1,m]$
Aggregate	w_B^{t+1}	$(w_B^{t+1}, \alpha_B^{t+1})$

Either algorithm 2 or algorithm 3, is implemented at the clients, corresponding to the training methods of the type `MAML` and `Meta-SGD`. To train the model on bilevel optimization-based ML algorithms , the client data is divided into support set ($\mathcal{D}_{train(i)}^{support}$) and query set ($\mathcal{D}_{train(i)}^{query}$). The training steps at the client include: merging parameters of base layers and personalization layers to form complete model parameters; performing training according to ML algorithms; new model parameter resolution.

Specifically, for clients that train on the `MAML` algorithm, at the tth step of the global training process, client c_i will receive an initialization weight w_B^t of the base layers sent by the server. Next, c_i merges the weight of the base layers w_B^t with the weight of the personalization layers $w_{P(i)}^t$ to get the weight of the complete model w_i^t . w_i^t is then trained as follows:

$$\text{Train: } \hat{w}_i^{t+1} \leftarrow w_i^t - \alpha \nabla_{w_i^t} f_{local} \left(w_i^t, \mathcal{D}_{train(i)}^{support} \right) \tag{4}$$

Algorithm 2 FedMeta-Per (MAML Client)

1: **ModelTrainingMAML**(c_i, w_B^t)**:**
2: Sample support set $\mathcal{D}_{train(i)}^{support}$ and query set $\mathcal{D}_{train(i)}^{query}$
3: **if** $t = 0$ **then**
4:     Initialize $w_{P(i)}^t$
5: **else**
6:     Load $w_{P(i)}^t$ from the external memory
7: $w_i^t \leftarrow w_B^t \bigoplus w_{P(i)}^t$ ▷ Merge w_B^t and $w_{P(i)}^t$ to form w_i^t
8: Training:

$$\hat{w}_i^{t+1} \leftarrow w_i^t - \alpha \nabla_{w_i^t} f_{local}\left(w_i^t, \mathcal{D}_{train(i)}^{support}\right)$$

$$w_i^{t+1} \leftarrow w_i^t - \beta \nabla_{w_i^t} f_{local}\left(\hat{w}_i^{t+1}, \mathcal{D}_{train(i)}^{query}\right)$$

9: $w_{B(i)}^{t+1}, w_{P(i)}^{t+1} \leftarrow w_i^{t+1}$ ▷ Resolve w_i^{t+1} to form $w_{B(i)}^{t+1}$ and $w_{P(i)}^{t+1}$
10: Send $w_{B(i)}^{t+1}$ to server and store $w_{P(i)}^{t+1}$

$$\text{Meta-train: } w_i^{t+1} \leftarrow w_i^t - \beta \nabla_{w_i^t} f_{local}\left(\hat{w}_i^{t+1}, \mathcal{D}_{train(i)}^{query}\right) \tag{5}$$

where, $\alpha, \beta \in [0, 1]$ are the learning rates.

For clients that use the `Meta-SGD` algorithm in training, the base layers of the deep neural network include two parameters: the weight of the base layers w_B^t and the learning rate of the base layers α_B^t; personalization layers of the network include two parameters $w_{P(i)}^t$ and $\alpha_{P(i)}^t$ (same size as $w_{P(i))}^t$). Parameter merging also takes place between the parameters of base layers and personalization layers to form the complete parameter set w_i^t and α_i^t. It should be noted that `Meta-SGD` configures α as a learning rate array of the size of the model weight and treats α as a trainable parameter. Thus, the algorithm performs element-wise multiplication between α and the derivative of the error function in Equation 6 and performs the derivative with respect to α in Equation 7.

$$\text{Train: } \hat{w}_i^{t+1} \leftarrow w_i^t - \alpha_i^t \circ \nabla_{w_i^t} f_{local}\left(w_i^t, \mathcal{D}_{train(i)}^{support}\right) \tag{6}$$

$$\text{Meta-train: } (w_i^{t+1}, \alpha_i^{t+1}) \leftarrow (w_i^t, \alpha_i^t) - \beta \nabla_{(w_i^t, \alpha_i^t)} f_{local}\left(\hat{w}_i^{t+1}, \mathcal{D}_{train(i)}^{query}\right) \tag{7}$$

Inference phase. Based on the testing process of study [17], we divide users into two types: local clients and new clients. For local clients, the personalization layers are reused to achieve a high degree of personalization. For new clients, we do not use ensemble testing techniques as suggested by study [17], but rather use each of the previously built personalization layers combined with base layers to operate on the new dataset. During the fine-tuning process, the client selects the parameter set with the smallest error. Then use this set of parameters to process test data.

Algorithm 3 FedMeta-Per (Meta-SGD Client)

1: **ModelTrainingMetaSGD**(c_i, w_B^t, α_B^t):
2: Sample support set $\mathcal{D}_{train(i)}^{support}$ and query set $\mathcal{D}_{train(i)}^{query}$
3: **if** $t = 0$ **then**
4:     Initialize $(w_{P(i)}^t, \alpha_{P(i)}^t)$
5: **else**
6:     Load $(w_{P(i)}^t, \alpha_{P(i)}^t)$ from the external memory
7: $w_i^t \leftarrow w_B^t \bigoplus w_{P(i)}^t$ ▷ Merge w_B^t and $w_{P(i)}^t$ to form w_i^t
8: $\alpha_i^t \leftarrow \alpha_B^t \bigoplus \alpha_{P(i)}^t$ ▷ Merge α_B^t and $\alpha_{P(i)}^t$ to form α_i^t
9: Training:
$$\hat{w}_i^{t+1} \leftarrow w_i^t - \alpha_i^t \circ \nabla_{w_i^t} f_{local}\left(w_i^t, \mathcal{D}_{train(i)}^{support}\right)$$

$$(w_i^{t+1}, \alpha_i^{t+1}) \leftarrow (w_i^t, \alpha_i^t) - \beta \nabla_{(w_i^t, \alpha_i^t)} f_{local}\left(\hat{w}_i^{t+1}, \mathcal{D}_{train(i)}^{query}\right)$$

10: $w_{B(i)}^{t+1}, w_{P(i)}^{t+1} \leftarrow w_i^{t+1}$ ▷ Resolve w_i^{t+1} to form $w_{B(i)}^{t+1}$ và $w_{P(i)}^{t+1}$
11: $\alpha_{B(i)}^{t+1}, \alpha_{P(i)}^{t+1} \leftarrow \alpha_i^{t+1}$ ▷ Resolve α_i^{t+1} to form $\alpha_{B(i)}^{t+1}$ và $\alpha_{P(i)}^{t+1}$
12: Send $(w_{B(i)}^{t+1}, \alpha_B^{t+1})$ to server and store $(w_{P(i)}^{t+1}, \alpha_{P(i)}^{t+1})$

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4   Numerical Experiments

Dataset. This study uses 50 clients for training (containing 75% of the data) and 50 clients for testing (containing 25% of the data). The clients contain the data from the two datasets, MNIST [5] and CIFAR-10 [13], respectively. To simulate Non-IID data, each client is configured to contain only 2/10 labels. The amount of data between clients is uneven (see Table 2). During testing, each local user has the same data distribution as that of a training client; each new user has a data distribution that is completely different from the data distribution of all the clients participating in the training. At each client, the data is divided into a support set (containing 20% of the data) and a query set (containing 80% of the data).

Table 2: Statistics on MNIST and CIFAR-10 (non-IID data)

Dataset	#clients	#samples	#classes	#samples/client				#classes/client
				min	mean	std	max	
MNIST	50	69,909	10	135	1,398	1,424	5,201	2
CIFAR-10	50	52,497	10	506	1,049	250	1,986	2

Metrics. The study evaluates the model through the following metrics: accuracy in correlation with all data points (acc_{micro}), accuracy in correlation with all clients (acc_{macro}) and F1-score ($F1_{macro}$).

Experiments. This study performs centralized and distributed experiments on the same model architecture. For distributed training, the study experimented on `FedAvg`, `FedPer`, `FedMeta(MAML)`, `FedMeta(Meta-SGD)`. The results are compared with the proposed algorithm `FedMeta-Per`. For a fair comparison, the study allows the global model obtained by the `FedAvg` and `FedPer` algorithms to perform a fine-tune one or several times on the client's support set during the inference phase. This is the idea of `FedAvgMeta` and `FedPerMeta`. Details of the experimental settings can be found in Appendix A.

5   Results & Discussion

Centralized & Decentralized. The results of centralized training and distributed training (`FedAvg` on IID and non-IID data) are presented in Table 3. It is easy to see that the centralized training model achieves higher results on all metrics. Results obtained on `FedAvg` (IID data) are 7% to 8% lower because the global model captures the features indirectly (through parametric averaging at the server). However, when the input data is non-IID, the metrics decrease from 7% to 13% on MNIST and do not reach convergence on CIFAR-10. Metrics on non-IID data also differ quite a lot (3% - 6% on MNIST and 3% - 4% on CIFAR-10) compared to differences on IID data (less than 1%). This proves that the uneven data distribution across the clients has adversely affected the classification quality.

Table 3: Classification results (%) of centralized and decentralized (FedAvg on IID and non-IID data) using MNIST and CIFAR-10 datasets. Best results per metrics are boldfaced.

		acc_{micro}	acc_{macro}	$F1_{macro}$
MNIST	Centralized	**97.07**	-	**97.04**
	FedAvg (IID data)	90.36	90.34±2.24	90.12±2.29
	FedAvg (local client)	85.03	82.14±14.76	79.43±16.83
	FedAvg (new client)	83.92	81.69±19.71	77.66±22.54
CIFAR-10	Centralized	**61.91**	-	**61.72**
	FedAvg (IID data)	53.83	53.83±3.14	53±3.21
	FedAvg (local client)	19.02	19.29±25.11	16.85±23.92
	FedAvg (new client)	24.63	24.83±22.57	20.52±20.45

Convergence ability. The results on metrics of `FedMeta-Per` and the algorithms used in the comparison are presented in Table 4. To solve the problem of non-IID data, the technique of fine-tuning localizes the FL system in a simple form (algorithm `FedAvgMeta`), in order to improve the adaptability and personalization of the model on the new data sets. However, the results obtained in Table 4 as well as in Fig. 2 are not very satisfactory (low convergence on the MNIST dataset and not on the CIFAR-10 dataset). The reason for `FedAvgMeta`

not converging is that the adaptability of the global model to the new dataset is very low. The PL technique is also used in the form of two algorithms, `FedPer` and `FedPerMeta`. However, the results obtained are even worse than `FedAvg` and `FedAvgMeta`. This is understandable given that the model architecture used by study [1] is a pre-trained network `MobileNet-v1` [10], a more complex deep neural network than this study (see Appendix A.1). This also proves that using the PL technique is not enough for handling non-IID data.

Table 4: Classification results (%) of FedAvg, FedPer and FedMeta-Per using MNIST and CIFAR-10 datasets. Best results per metrics are boldfaced.
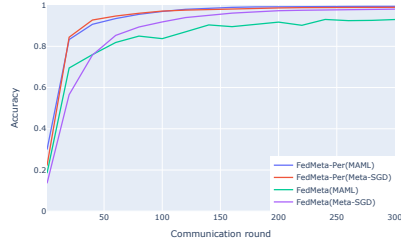
		CIFAR-10			MNIST		
		acc_{micro}	acc_{macro}	$F1_{macro}$	acc_{micro}	acc_{macro}	$F1_{macro}$
local client	FedAvg	19.02	19.29±25.11	16.85±23.92	85.03	82.14±14.76	79.43±16.83
	FedPer	13.22	12.99±19.39	10.52±14.91	77.29	75.48±14.84	72.32±15.99
	FedAvgMeta	40.3	38.47±31.52	33.81±30.61	84.84	81.56±16.68	78.31±19.8
	FedPerMeta	18.57	17.48±22.55	14.54±18.67	75.91	74.11±16.2	71.22±16.77
	FedMeta(MAML)	69.02	68.76±14.86	61.14±20	92.99	91.14±5.99	90.16±6.28
	FedMeta(Meta-SGD)	78.63	78.73±11.59	72.87±18.31	98.02	96.35±4.62	95.80±5.51
	FedMeta-Per(MAML)	**86.6**	**86.52±6.31**	**85.33±6.77**	**99.37**	**99.12±1.29**	**98.94±1.6**
	FedMeta-Per(Meta-SGD)	85.61	85.68±7.22	85.08±7.32	98.92	98.15±3.32	98.20±2.94
new client	FedAvg	24.63	24.83±22.57	20.52±20.45	83.92	81.69±19.71	77.66±22.54
	FedPer	14.4	14.52±20.15	10.66±13.79	78.3	76.19±18.79	72.72±19.3
	FedAvgMeta	43.39	43.54±18	35.14±17.22	84.34	82.37±17.42	78.78±19.31
	FedPerMeta	13.33	13.57±19.62	10.05±13.17	77.47	75.56±20.33	72.60±21.37
	FedMeta(MAML)	61.69	61.64±12.49	50.76±19.2	92.96	91.88±5.88	90.02±7.34
	FedMeta(Meta-SGD)	68.36	67.89±15.11	60.24±21.52	96.39	93.53±8.39	89.31±14.56
	FedMeta-Per(MAML)	64.22	63.70±12.29	53.68±19.06	93.6	93.57±5.58	91.83±6.43
	FedMeta-Per(Meta-SGD)	**69.97**	**69.13±14.63**	**62.42±20.94**	**96.62**	**95.88±3.58**	**94.85±4.61**

When comparing the convergence ability of `FedMeta` and `FedMeta-Per`, the fact that both algorithms have the participation of ML and have similarities in the convergence process (Fig. 1) shows that ML has a certain impact on the FL system.

The ability of ML in the proposed algorithm in comparison with algorithms `FedAvg`, `FedAvgMeta`, `FedPer`, and `FedPerMeta` is shown in Fig. 2. Accordingly, ML provides the system with fast adaptability on new clients, leading to `FedMeta-Per` convergence much faster than the old algorithms, reaching convergence thresholds of about 60%-85% on CIFAR-10 and about a 20% improvement in accuracy on MNIST. More specifically, this convergence comes from performing a single fine-tune step on 20% of the data at the client, once again demonstrating the very fast adaptability of the FL-ML system.

In addition, thanks to the construction of good personalization layers, the testing process on local clients also achieves a higher degree of convergence when comparing the proposed algorithm with `FedMeta` (Fig. 1). However, in the face of a strange data distribution of new clients, these two algorithms have almost equivalent convergence ability.
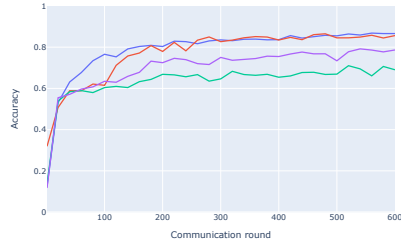
Personalization ability. Observing the standard deviation of the algorithms `FedMeta`, `FedAvg` and `FedPer` in Table 4, we can see the standard devia-
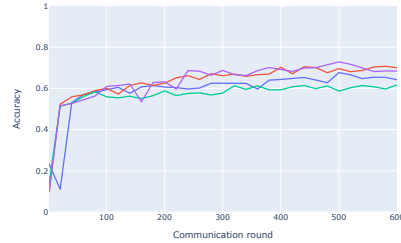
(a) MNIST, local client
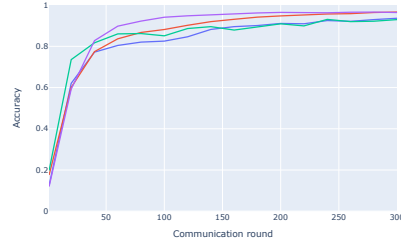
(b) MNIST, new client

(c) CIFAR-10, local client

(d) CIFAR-10, new client

Fig. 1: acc_{micro} of FedMeta-Per and FedMeta. The end result and convergence of FedMeta-Per is significantly higher than that of FedMeta on local clients. On new clients, even though FedMeta-Per reaches a higher value, the difference in convergence is not so great.

tion in the results of `FedMeta` is much smaller than the rest of the algorithms. It shows that the personalization of the FL system has been improved many times thanks to the training of ML algorithms as well as the fine-tuning execution on the support set to capture the characteristics of a new data set. However, as mentioned above, this ability can be completely improved. With new suggestions during the inference phase, `FedMeta-Per` further reduces the standard deviations on the scales. Specifically, after combining the fine-tuning of the model with the support set of local data and maintaining the personalization layer for each client, the standard deviation of the local clients decreases from 4% to 14% on CIFAR-10 and from 1% to 5% on MNIST while the averages are still superior. On new clients, the mean values are higher but the standard deviation, in some cases, is not actually smaller than the previous algorithms. This is because the personalization layers in the deep neural network of new clients have not really matched that user yet. However, over time, when new clients participate in one or a few steps of global training, they will build up good personalization layers for themselves, resulting in the metrics reaching the same value as local clients.

(a) MNIST, local client

(b) MNIST, new client

(c) CIFAR-10, local client

(d) CIFAR-10, new client

Fig. 2: acc_{micro} of FedMeta-Per, FedAvg, FedAvgMeta, FedPer and FedPerMeta. FedMeta-Per's convergence and accuracy outperform the rest of the algorithms.

6   Conclusion

Through the research process, we combine ML algorithms and PL techniques into the FL system, to improve the accuracy as well as the ability to personalize the machine learning model for each user of the system on non-IID data. Experimentally, we prove the effectiveness of the proposed algorithm `FedMeta-Per` compared with algorithms `FedAvg`, `FedPer`, and `FedMeta` over 50 users with two datasets, CIFAR-10 and MNIST. In which, it can be explained that achieving high results is based on two inherited factors: (1) - Fast adaptability to new data set of the proposed algorithm inherited from ML algorithms, (2) - High personalization ability for each user inherited from personalization layers of PL technique and model fine-tuning on the support set of ML algorithms.

In the future, bilevel optimization-based algorithms (`FO-MAML` [7], `iMAML` [20], `Reptile`) can be integrated into the system. The search and clustering of users so that each user finds the best set of partial parameters should also be further studied to increase the performance of the system. In addition, the issue of information security between the server and the client should also be considered to make the system more practical.

A   Experimental Details

A.1   Model Architecture

The study uses two simple models for feature extraction and data classification for the CIFAR-10 and MNIST datasets.

CIFAR-10. The model takes input images of size $(32 \times 32 \times 3)$. Two convolution layers (kernel of size (5×5), channel numbers of 6 and 16 respectively) are used for feature extraction. Following each convolution layer is a `MaxPooing` layer of size (2×2). The classifier consists of three linear layers whose outputs are 120, 84 and 10 respectively. The activation functions used are `ReLU` and `Softmax`.

MNIST. The model receives flattened input images of size (1×784). Use two linear layers with outputs of 100 and 10, respectively. The activation functions used are `ReLU` and `Softmax`.

A.2   Hyper-parameters Searching

The hyper-parameters of the FL system of the study include: the number of clients participating in training in a global training step ($\#clients/round$), number of local training steps ($\#epochs$), number of global training steps ($\#rounds$), amount of data in a data batch ($batch\_size$), number of personalization layers for algorithms using PL techniques ($\#per\_layers$) and the learning rates used in the optimization of deep neural networks by mini batch gradient descent.

To accommodate the limited configuration client hardware in the Horizontal FL scenario, we limits $\#epochs = 1$ and $batch\_size = 32$. From the survey of FL experiments in recent studies, the number of clients participating in global training was selected as 2, 5, and 10, respectively. In which, $\#clients/round = 5$ gives a higher result and consumes an acceptable computational cost. The study maintains a base layer and a personalization layer for the neural network of the MNIST dataset. For the deep learning network used for the set CIFAR-10, $\#per\_layers \in \{1, 2, 3\}$ (calculated from the last linear layer). Experimental results show that using the last linear layer as the personalization layer and the remaining deep layers as the base layers gives the best results. The learning rates are searched in the range $(10^{-5}, 0.01)$ and are presented in Table 5.

Table 5: Tuning learning rate for algorithms. Empty cells indicate that hyper-parameters cannot be found for the model to converge.

	CIFAR-10	MNIST
FedAvg, FedAvgMeta	-	10^{-5}
FedPer, FedPerMeta	-	10^{-5}
FedMeta(MAML) (α, β)	$(0.01, 0.001)$	$(0.001, 0.001)$
FedMeta(Meta-SGD)(α, β)	$(0.001, 0.001)$	$(0.001, 5 \times 10^{-4})$
FedMeta-Per(MAML)(α, β)	$(0.001, 0.005)$	$(0.001, 0.001)$
FedMeta-Per(Meta-SGD)(α, β)	$(0.01, 0.01)$	$(0.001, 5 \times 10^{-4})$

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