Federated Learning with Adaptive Batchnorm for Personalized Healthcare

Wang Lu\textsuperscript{1}, Jindong Wang\textsuperscript{2}, Yiqiang Chen\textsuperscript{1}, Xin Qin\textsuperscript{1}, Tao Qin\textsuperscript{2}

\textsuperscript{1} Institute of Computing Technology, Chinese Academy of Sciences
\textsuperscript{2} Microsoft Research Asia
luwang@ict.ac.cn, jindong.wang@microsoft.com, Code: http://transferlearning.xyz

Abstract
There is a growing interest in applying machine learning techniques for healthcare. Recently, federated machine learning (FL) is gaining popularity since it allows researchers to train powerful models without compromising data privacy and security. However, the performance of existing FL approaches often deteriorates when encountering non-iid situations where there exist distribution gaps among clients, and few previous efforts focus on personalization in healthcare. In this article, we propose AdaFed to tackle domain shifts and obtain personalized models for local clients. AdaFed learns the similarity between clients via the statistics of the batch normalization layers while preserving the specificity of each client with different local batch normalization. Comprehensive experiments on five healthcare benchmarks demonstrate that AdaFed achieves better accuracy compared to state-of-the-art methods (e.g., 10\%+ accuracy improvement for PAMAP2) with faster convergence speed.

Introduction
Machine learning has been widely adopted in many applications in people’s daily life. Specifically for healthcare, researchers can build models to predict health status by leveraging health-related data, such as activity sensors, images, and other health information. To achieve satisfying performance, machine learning healthcare applications often require sufficient client data for model training. However, with the increasing awareness of privacy and security, more governments and organizations enforce the protection of personal data via different regulations (Inkster 2018; Voigt and Von dem Bussche 2017). In this situation, federated learning (FL) (Yang et al. 2019) came into being to build powerful machine learning models with data privacy well-protected. Personalization is often important in healthcare applications since different individuals, hospitals or countries usually have different demographics, lifestyles, and other health-related characteristics (Xu et al. 2021). Therefore, we are more interested in achieving better personalized healthcare, i.e., building models for each client to preserve their specific information while harnessing the commonalities using federated learning. As shown in Figure 1, there are three different clients A, B, and C with different statistics of data distributions (e.g., the adult A and the child B may have different lifestyles and activity patterns). Even if federated learning can be performed in the standard way, the non-iid nature of their data cannot be easily handled. This will severely limit the performance of existing federated learning algorithms.

The popular FL algorithm, FedAvg (McMahan et al. 2017), has demonstrated superior performance in many situations (Ching et al. 2018; Zhu et al. 2020). However, FedAvg is unable to deal with non-iid data among different clients since it directly averages the parameters of models coming from all participating clients (Li et al. 2019). There are some algorithms for this non-iid situation. FedProx (Li et al. 2020) is designed for non-iid data. However, it learns a unique model for all clients, which means that it is unable to obtain personalized models for clients. FedHealth (Chen et al. 2020), another work for personalized healthcare, needs access to a large public dataset, which is often impossible in real applications. FedBN (Li et al. 2021) handles the non-iid issue by learning local batch normalization layers for each client but ignores the similarities across clients that can be used to boost the personalization. In a nutshell, it is challenging to achieve personalization in federated learning.

In this article, we propose AdaFed, a federated learning algorithm via adaptive batch normalization for personalized healthcare. Specifically, AdaFed learns the similarities among clients with the help of a pre-trained model that is...
easy to obtain. The similarities are determined by the distances of the data distributions, which can be calculated via the statistical values of the layers’ outputs of the pre-trained network. After obtaining the similarities, the server averages the models’ parameters in a personalized way and generates a unique model for each client. Each client preserves its own batch normalization and updates the model with a momentum method. In this way, AdaFed can cope with the non-iid issue in federated learning. AdaFed is extensible and can be deployed to many healthcare applications.

Our contributions are as follows:

1. We propose AdaFed, a federated learning algorithm via adaptive batch normalization for personalized healthcare, which can aggregate the information from different clients without compromising privacy and security, and learn personalized models for each client.
2. We evaluate the performance of AdaFed in five public healthcare datasets across time series and image modalities. Experiments demonstrate that our AdaFed achieves significantly better performance than state-of-the-art methods in all datasets.
3. AdaFed reduces the number of rounds and speeds up the convergence to some extent. Moreover, some experimental results illustrate AdaFed may be able to reduce communication costs with little performance degradation via increasing local iterations and decreasing global communications.

Related Work

Machine Learning and Healthcare

With the rapid development of perception and computing technology, people can make use of machine learning to help doctors diagnose and assist doctors in the operation, etc. Machine learning even can make disease warnings via daily behavior supervision. For instance, certain activities in daily life reflect early signals of some cognitive diseases. Through daily observation of gait changes and finger flexibility, the machine can tell people whether they are suffering from Parkinson (Chen et al. 2017).

Unfortunately, a successful healthcare application needs a large amount of labeled data of persons. However, in real applications, data are often separate and few people are willing to disclose their private data. In addition, an increasing number of regulations, such as (Inkster 2018; Voigt and Von dem Bussche 2017), hold back the leakages of data.

Federated Learning

Federated learning is a usual way to combine each client’s information while protecting data privacy and security. It was first proposed by Google (McMahan et al. 2017), where they proposed FedAvg to train machine learning models via aggregating distributed mobile phones’ information without exchanging data. The key idea is to replace direct data exchanges with model parameter-related exchanges. FedAvg is able to resolve the data islanding problems.

Though FedAvg works well in many situations, it may still suffer in the non-iid data and fail to build personalized models for each client (Smith et al. 2017; Khodak, Balcan, and Talwalkar 2019). FedProx (Li et al. 2020) tackled data non-iid by allowing partial information aggregation and adding a proximal term to FedAvg. (Yeganeh et al. 2020) aggregated the models of the clients with weights computed via $L_1$ distance among client models’ parameters. These works focus on a common model shared by all clients while some other works try to obtain a unique model for each client. (Arivazhagan et al. 2019) exchanged information of base layers and preserved personalization layer to combat the ill-effects of non-iid. (T Dinh, Tran, and Nguyen 2020) utilized Moreau envelopes as clients’ regularized loss function and decoupled personalized model optimization from the global model learning in a bi-level problem stylized for personalized FL. (Yu, Bagdasaryan, and Shmatikov 2020) evaluated three techniques for local adaptation of federated models: fine-tuning, multi-task learning, and knowledge distillation. Two works most relevant to our method are FedHealth (Chen et al. 2020) and FedBN (Li et al. 2021). FedHealth needs to share some datasets in all clients while FedBN used local batch normalization to alleviate the feature shift before averaging models.

Batch Normalization

Batch Normalization (BN) (Ioffe and Szegedy 2015) is an important component of deep learning. Batch Normalization improves the performance of the model and has a natural advantage in dealing with domain shifts. Li et al. (2018) proposed an adaptive BN for domain adaptation where they learned domain-specific BN layers. Nowadays, researchers have explored many effects of BN, especially in transfer learning (Segù, Tonioni, and Tombari 2020). FedBN (Li et al. 2021) is one of few applications of BN in the field of FL field. However, FedBN does still not make full use of BN properties, and it does not consider the similarities among the clients.

Method

Problem Formulation

In federated learning, there are $N$ different clients (organizations or users), denoted as $\{C_1, C_2, \ldots, C_N\}$ and each client has its own dataset, i.e. $\{D_1, D_2, \ldots, D_N\}$. Each dataset $D_i = \{(x_{ij}, y_{ij})\}_{j=1}^{n_i}$ contains two parts, i.e. a train dataset $D_i^{tr} = \{(x_{ij}^{tr}, y_{ij}^{tr})\}_{j=1}^{n_i^{tr}}$ and a test dataset $D_i^{te} = \{(x_{ij}^{te}, y_{ij}^{te})\}_{j=1}^{n_i^{te}}$. Obviously, $n_i = n_i^{tr} + n_i^{te}$ and $D_i = D_i^{tr} \cup D_i^{te}$. All of the datasets have different distributions, i.e. $P(D_i) \neq P(D_j)$. Each client has its own model denoted as $f_i$. Our goal is to aggregate information of all clients to learn a good model $f$ for each client on its local dataset $D_i$ without private data leakage:

$$\min_{\{f_i\}_{i=1}^N} \frac{1}{N} \sum_{i=1}^{N} \frac{1}{n_i^{tr}} \sum_{j=1}^{n_i^{tr}} \ell(f_i(x_{ij}^{tr}), y_{ij}^{tr}),$$

where $\ell$ is a loss function.
Motivation

There are mainly two challenges for personalized healthcare: data islanding and personalization. Following FedAvg (McMahan et al. 2017) and some other traditional federated learning methods (Cao, Xu, and Huang 2021, Cao, Jia, and Gong 2021), it is easy to cope with the first challenge. Personalization is a must in many applications, especially in healthcare. It is better to train a unique model in each client for personalization. However, one client often lacks enough data to train a model with high accuracy in federated learning. In addition, clients do not have access to the data of other clients. Overall, it is a challenge that how to achieve personalization to obtain high accuracy in federated learning. As mentioned in (Wang et al. 2019), batch normalization (BN) layers contain sufficient statistics (including mean and standard deviation) of features (outputs of layers). Therefore, BN has been utilized to represent distributions of training data indirectly in many works (Li et al. 2018, Chang et al. 2019). We mainly use BN to represent the distributions of clients. Therefore, on the one hand, we utilize local BN to preserve clients’ feature distributions. On the other hand, we also use BN-related statistics to calculate the similarity between clients for better personalization with weighted aggregation.

Our Approach: AdaFed

In this paper, we propose AdaFed (Adaptive Federated Learning) to achieve accurate personal healthcare via adaptive batch normalization without compromising data privacy and security. Figure 2 gives an overview of its structure. Without loss of generality, we assume there are three clients, which can be extended to more general cases. The structure mainly contains five steps:

1. The server distributes the pre-trained model to each client.
2. Each client computes statistics of the outputs of specific layers according to local data.
3. The server obtains the client similarities denoted by weight matrix $\mathbf{W}$ to guide aggregation.
4. Each client updates its own model with the local train data and pushes their models to the server.
5. The server aggregates models and obtains $N$ models delivered to $N$ clients respectively.

For stability and simplicity, we only calculate $\mathbf{W}$ once and we show that computing once is enough to achieve acceptable performance in experiments. Note that all processes do not involve the direct transmission of data, so AdaFed avoids the leakage of private data and ensures security. The keys of AdaFed are obtaining $\mathbf{W}$ and aggregating the models. We will introduce how to compute $\mathbf{W}$ after describing the process of model aggregation.

We denote the parameters of each model $f_i$ as $\theta_i = \phi_i \cup \psi_i$, where $\phi_i$ corresponds to the parameters of BN layers specific to each client and $\psi_i$ is the parameters of the other layers (colored blocks in Figure 3). $\mathbf{W}$ is an $N \times N$ matrix, which describes the similarities among the clients. $w_{ij} \in [0, 1]$ represents the similarity between client $i$ and client $j$: the larger $w_{ij}$ is, the more similar the two clients are.

Figure 3 demonstrates the process of model aggregation. As shown in Figure 3, $\phi_i$ is particular while $\psi_i$ is computed according to $w_i$, where $w_i$ means the $i$–th row of $\mathbf{W}$, and $\psi_i = \{\psi_{ij}\}_{j=1}^{N}$, $\phi_i$ is BN parameters which are not shared across clients while $\psi_i$ is other parameters which are shared. Let $\theta_i^t = \phi_i^t \cup \psi_i^t$ represents the parameters of the model from client $i$ in the round $t$. After updating $\theta_i^t$ with the local data from the $i$–th client, we obtain updated parameters $\theta_i^{t+1} = \phi_i^{t+1} \cup \psi_i^{t+1}$. We use the $*$ notation to denote updated parameters. Then, for aggregation on the server, we have the following updating strategy:

\[
\begin{align*}
\phi_i^{t+1} &= \phi_i^{t*} \\
\psi_i^{t+1} &= \sum_{j=1}^{N} w_{ij} \psi_j^{t*}. 
\end{align*}
\]

The overall process of AdaFed is described in Algorithm 1. In next sections, we will introduce how to compute the weight matrix $\mathbf{W}$.

Evaluate Weights

In this section, we will evaluate the weights with a pre-trained model $f$ and propose two alternatives to compute the weights. We mainly rely on the feature output statistics of clients’ data in the pre-trained network to compute weights.

We denote with $l \in \{1, 2, \cdots, L\}$ in superscript notations the different batch normalization layers in the model. And $z_i^l$ represents the input of $l$–th batch normalization layer.
Algorithm 1: AdaFed

**Input:** A pre-trained model \( f \), data of \( N \) clients \( \{D_i\}_{i=1}^N \), \( \lambda \)

**Output:** Client models \( \{f_i\}_{i=1}^N \)

1. Distribute \( f \) to each client
2. Each client computes its statistics \((\mu_i, \sigma_i)\), where \( \mu_i \) represents the mean values while \( \sigma_i \) represents the co-variance matrices. Push \((\mu_i, \sigma_i)\) to the server
3. Compute \( W \) according to the statistics
4. Update clients’ model with local data. Push updated parameter \( \{\theta_t^i\}_{i=1}^N \) to the server
5. Update \( \{\theta_{t+1}^i\}_{i=1}^N \) according to Eq. (2) and distribute them to the corresponding clients
6. Repeat steps 4 ~ 5 until convergence or maximum round reached

in the \( i \)-th client. The input of the classification layer in the \( i \)-th client is denoted as \( z^i \) which represents the domain features. We assume \( z^{i,l} \) is a matrix, \( z^{i,l}_{c_i,1 \times s_i,l} \) where \( c_i,l \) corresponds to the channel number while \( s_i,l \) is the product of the other dimensions. Similarly, \( z^i = z^{i,1} \). We feed \( D_i \) into \( f \), and we can obtain \( z^{i,l}_{c_i,1 \times s_i,l} \). Obviously, \( s_i,l = e \times n_i \) where \( e \) is an integer. Now, try to compute statistics on the channels, and we treat \( z^{i,l} \) as a Gaussian distribution. For the \( l \)-th layer of the \( i \)-th client, it is easy to obtain its distribution parameters, \( N(\mu^{i,l}, \sigma^{i,l}) \). We only compute statistics of inputs of BN layers. And the BN statistics of the \( i \)-th client is formulated as:

\[
(\mu_i, \sigma_i) = [(\mu^{i,1}, \sigma^{i,1}), (\mu^{i,2}, \sigma^{i,2}), \cdots, (\mu^{i,L}, \sigma^{i,L})].
\]

(3)

Now we can calculate the similarity between two clients. It is popular to adopt the Wasserstein distance to calculate the distance between two Gaussian distributions:

\[
W_2^2(N(\mu^{i,l}, \sigma^{i,l}), N(\mu^{j,l}, \sigma^{j,l})) = ||\mu^{i,l} - \mu^{j,l}||^2 + \text{tr}(\sigma^{i,l} + \sigma^{j,l} - 2((\sigma^{i,l})^{1/2} \sigma^{j,l} (\sigma^{i,l})^{1/2})^{1/2}),
\]

(4)

where \( \text{tr} \) is the trace of the matrix. Obviously, it is costly and difficult to perform efficient calculations. Similar to BN, we perform approximations and consider that each channel is independent of each other. Therefore, \( \sigma^{i,l} \) is a diagonal matrix, i.e. \( \sigma^{i,l} = \text{Diag}(\sigma^{i,l}) \). Therefore, we compute the approximation of Wasserstein distance as:

\[
W_2^2(N(\mu^{i,l}, \sigma^{i,l}), N(\mu^{j,l}, \sigma^{j,l})) = ||\mu^{i,l} - \mu^{j,l}||^2 + ||\sqrt{\sigma^{i,l}} - \sqrt{\sigma^{j,l}}||^2.
\]

(5)

Thus, the distance between two clients \( i, j \) is computed as:

\[
d_{i,j} = \sum_{l=1}^{L} W_2^2(N(\mu^{i,l}, \sigma^{i,l}), N(\mu^{j,l}, \sigma^{j,l}))
\]

\[
= \sum_{l=1}^{L} (||\mu^{i,l} - \mu^{j,l}||^2 + ||\sqrt{\sigma^{i,l}} - \sqrt{\sigma^{j,l}}||^2)^{1/2}.
\]

(6)

Large \( d_{i,j} \) means the distribution distance between the \( i \)-th client and the \( j \)-th client is large. Therefore, the larger \( d_{i,j} \) is, the less similar two clients are, which means the smaller \( w_{i,j} \) is. And we set \( w_{i,j} \) as the inverse of \( d_{i,j} \), i.e. \( w_{i,j} = 1/d_{i,j}, j \neq i \). Normalize \( w_i \) and we have

\[
w_{i,j} = \frac{\tilde{w}_{i,j}}{\sum_{j=1,j \neq i}^{N} \tilde{w}_{i,j}}, \quad \text{where} \ j \neq i
\]

(7)

For stability in training, we take \( \psi(t) \) into account for \( \psi(t+1) \). We update \( \psi(t+1) \) in a moving average style, and we set \( w_{i,i} = \lambda \). Therefore,

\[
w_{i,j} = \begin{cases}
\lambda, & i = j, \\
(1 - \lambda) \times \tilde{w}_{i,j}, & i \neq j.
\end{cases}
\]

(8)

We denote this weighting method as the original AdaFed. Similarly, we can obtain the corresponding \( W \) using only the last layer \( z^i \) and we denote this variant as d-AdaFed.

Discussion

In some extreme cases, there may not exist a pre-trained model. In this situation, we can evaluate weights with models trained from several rounds of FedBN (Li et al. 2021).

![Figure 4: Running mean, running var of a BN layer and the inputs statistics of the corresponding layer in a client model.](image)

As we can see from Figure 4, the running mean of the BN layer has a positive correlation with the statistical mean of the corresponding layer’s inputs. And the variance has a similar relationship. From this, we can use running means and running variances of the BN layers instead of the statistics respectively. Therefore, we can perform several rounds of FedBN (Li et al. 2021) which preserves local batch normalization, and utilize parameters of BN layers replacing the statistics when there does not exist a pre-trained model. We denote this variant as f-AdaFed.

Experiments

We evaluate the performance of AdaFed on five healthcare datasets in time series and image modalities. The statistical information of each dataset is shown in Table I.

Datasets

**PAMAP2.** We adopt a public human activity recognition dataset called PAMAP2 (Reiss and Stricker 2012). The
PAMAP2 dataset contains data of 18 different physical activities, performed by 9 subjects wearing 3 inertial measurement units and a heart rate monitor. We use data of 3 inertial measurement units which are collected at a constant rate of 100Hz to form data containing 27 channels. We exploit the sliding window technique and filter out 10 classes of data. In order to construct the problem situation in AdaFed, we use the Dirichlet distribution as in (Yurochkin et al. 2019) to create disjoint non-iid splits. client training data. Figure 5(a) visualizes how samples are distributed among 20 clients. In each client, half of the data are used to train and the remaining data are for testing as in (Li et al. 2021).

COVID-19. We also adopt a public COVID-19 posterior-anterior chest radiography images dataset (Sait et al. 2020). This is a combined curated dataset of COVID-19 Chest X-ray images obtained by collating 15 public datasets and it contains 9,208 instances of four classes (1,281 COVID-19 X-Rays, 3,270 Normal X-Rays, 1,656 viral-pneumonia X-Rays, and 3,001 bacterial-pneumonia X-Rays) in total. In order to construct the problem situation in AdaFed, we split the dataset similar to PAMAP. Figure 5(b) visualizes how samples are distributed among 20 clients for COVID-19. Note that this dataset is more unbalanced in classes which is an ideal testbed to test the performance under label shift (i.e., imbalanced class distribution for different clients). In each client, half of the data are used to train and the remaining data are for testing.

MedMNist. MedMNIST (Yang, Shi, and Ni 2021; Yang et al. 2021) is a large-scale MNIST-like collection of standardized biomedical images, including 12 datasets for 2D and 6 datasets for 3D. All images are $28 \times 28$ (2D) or $28 \times 28 \times 28$ (3D). We choose 3 datasets which have most classes from 12 2D datasets: OrganAMNIST, OrganCMNIST, OrganSMNIST (Bilic et al. 2019; Xu et al. 2019). These three datasets are all about Abdominal CT images and all contain 11 classes. There are 58,850, 23,660 and 25,221 samples respectively. As operations in PAMAP, each dataset is split into 20 clients with Dirichlet distributions and Figure 5(c) visualizes how samples are distributed for OrganAMNIST.

In each client, half of the data are used to train and the remaining data are for testing.

Implementations Details and Comparison Methods

For PAMAP2, we adopt a CNN for training and predicting. The network is composed of two convolutional layers, two pooling layers, two batch normalization layers, and two fully connected layers. For three MedMNIST datasets, we all adopt LeNet5 (LeCun et al. 1998). For COVID-19, we adopt Alexnet (Krizhevsky, Sutskever, and Hinton 2012). We use a three-layer fully connected neural network as the classifier with two BN layers after the first two fully connected layers following (Li et al. 2021). For model training, we use the cross-entropy loss and SGD optimizer with a learning rate of $10^{-3}$. If not specified, our default setting for local update epochs is $E = 1$ where $E$ means training epochs in one round. And we set $\lambda = 0.5$ for our method, since we can see that $\lambda$ has few influences on accuracy and it only affects convergence speeds in the appendix. In addition, we randomly select 20% of the data to train a model of the same architecture as the pre-trained model. We run three trials to record the average results.

We compare three extensions of our method with five methods including common FL methods and some FL methods designed for non-iid data:

- **Base**: Each client uses local data to train its local models without federated learning.
- **FedAvg** (McMahan et al. 2017): The server aggregates all client models without any particular operations for non-iid data.
- **FedProx** (Li et al. 2020): Allow partial information aggregation and add a proximal term to FedAvg.
- **FedPer** (Arrivazhagan et al. 2019): Each client preserves some local layers.
- **FedBN** (Li et al. 2021): Each client preserves the local batch normalization.

Classification Accuracy

The classification results for each client on PAMAP2 are shown in Table 2. From these results, we have the following observations: 1) Our method achieves the best results on average. It is obvious that our method significantly outperforms other methods with a remarkable improvement (over 10% on average). 2) In some clients, the base method achieves the best test accuracy. As it can be seen from Figure 5(a) the distributions on the clients are very inconsistent, which inevitably leads to the various difficulty levels in different clients.

| Dataset          | Type             | #Class | #Sample   |
|------------------|------------------|--------|-----------|
| PAMAP            | Sensor-based time series | 18     | 3,850,505 |
| COVID-19         | Image            | 4      | 9,208     |
| OrganAMNIST      | Image            | 11     | 58,850    |
| OrganCMNIST      | Image            | 11     | 23,660    |
| OrganSMNIST      | Image            | 11     | 25,221    |

Table 1: Statistical information of five datasets.
Table 2: Activity recognition results on PAMAP2. Bold and underline means the best and second-best results, respectively.

| Dataset | Client 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|---------|---------|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| FedAvg | 77.43 avg | | | | | | | | | | | | | | | | | | | |
| FedBN | 77.55 avg | | | | | | | | | | | | | | | | | | | |
| FedProx | 77.02 | | | | | | | | | | | | | | | | | | | |
| FedPer | 79.15 | | | | | | | | | | | | | | | | | | | |
| AdaFed | 77.20 | | | | | | | | | | | | | | | | | | | |

Table 3: Accuracy on MedMNIST. Bold and underline means the best and second-best results, respectively.

| Dataset | Client 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|---------|---------|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Base | 48.35 | | | | | | | | | | | | | | | | | | | |
| FedAvg | 80.03 | | | | | | | | | | | | | | | | | | | |
| FedBN | 96.06 | | | | | | | | | | | | | | | | | | | |
| FedProx | 80.37 | | | | | | | | | | | | | | | | | | | |
| FedPer | 83.22 | | | | | | | | | | | | | | | | | | | |
| AdaFed | 77.56 | | | | | | | | | | | | | | | | | | | |

Figure 6: Average accuracy of 20 clients on COVID-19.

designed for the feature shifts while our experiments are mainly set in the label shifts.

The classification results for each client on three MedMNIST datasets are shown in Table 3. From these results, we have the following observations: 1) Our method significantly outperforms other methods with a remarkable improvement (over 3.5% on average). 2) For all these three benchmarks, Base achieves the worst average accuracy, which demonstrates Base without communicating with each other does not have enough information for these relatively difficult tasks. 3) FedBN achieves the second best results on all three benchmarks. This could be because there exist feature shifts among clients.

The classification results for each client on COVID-19 are shown in Figure 6. From these results, we have the following observations: 1) Our method achieves the best average accuracy which outperforms the second-best method FedPer by 6.3% on average accuracy. 2) FedBN gets the worst results. This demonstrates that FedBN is not good at dealing with label shifts where label distributions of each client are different, which is a challenging situation. FedBN does not consider the similarities among different clients. From Figure 5(b), we can see that label shifts are serious in COVID-19 since it only has four classes.

Analysis and discussion

We consider the influence of data splits and local iterations in this section. As shown in Figure 7(a), we evaluate Fedavg and AdaFed on three MedMNIST benchmarks with two different splits: \( \alpha = 0.1 \) and \( \alpha = 0.05 \) respectively. Smaller \( \alpha \) means distributions among clients are more different from each other. Figure 7(a) demonstrates that the performance of Fedavg which does not consider data non-iid will drop when encountering clients with greater different distributions while our method is not affected much by the degree of data non-iid, which means our method may be more robust. Figure 7(b) shows the influence of local iterations and total rounds on FedBN and our method. It is obvious that FedBN drops seriously with more local iterations and fewer communication rounds while our method declines slowly, which means when limiting communication costs, our method may be more effective.
Ablation Study

Effects of Weighting. To demonstrate the effect of weighting which considers the similarities among different clients, we compare the average accuracy on PAMAP2 and COVID-19 between the experiments with and without it. Without weighting, our method degenerates to FedBN. From Figure 8(a), we can see that our method performs much better than FedBN which does not include the weighting part. Moreover, from Figure 8(b), we can see our method performs better than FedBN on all clients. These results demonstrate that our method with weighting can cope with the label shifts while FedBN cannot deal with this situation, which means our method is more effective and robust.

Effects of Preserving Local Batch Normalization. We illustrate the importance of preserving local batch normalization. Figure 8(c) shows the average accuracy between the experiments with preserving local batch normalization and the experiments with sharing common batch normalization while Figure 8(d) shows the results on each client. LBN means preserving local batch normalization while SBN means sharing common batch normalization. Obviously, the improvements are not particularly significant compared with weighting. This may be caused by there mainly exist the label shifts in our experiments while preserving local batch normalization is for the feature shifts. However, our method still has a slight improvement, indicating its superiority.

Different Implementations of Our methods In Method section, we propose three implementations of our method: AdaFed, d-AdaFed, and f-AdaFed. The main differences among them are how to calculate W. In Figure 9(a) and Figure 9(b) we can see that all three implementations achieve better average accuracy on both PAMAP2 and COVID compared with FedAvg and FedBN. In addition, f-AdaFed performs slightly worse than the other two variants, which may be because it only utilizes weighting during half rounds for fairness and the other half are for obtaining W.

Parameter Sensitivity and Convergence

AdaFed involves three parameters: local epochs, client number, and λ. We only show results of client number due to space limit and more results can are in the appendix. From Figure 10(a), we can see that our method still achieves acceptable results. When the client numbers increase, our method goes down which may be due to that few data in local clients make the weight estimation inaccurate. And we may take f-AdaFed instead. The results reveal that AdaFed is more effective and robust than other methods under different parameters in most cases.

We also study the convergence of our method. From Figure 10(b), we can see our method almost convergences in the 10th round. And in the actual experiments, 20 rounds are enough for our method while FedBN needs over 400 rounds.

Conclusions and Future Work

In this article, we proposed AdaFed, a weighted federated transfer learning algorithm via batch normalization for personalized healthcare. AdaFed aggregates the data from different organizations without compromising privacy and security and achieves relatively personalized model learning through combining considering similarities and preserving local batch normalization. Experiments have evaluated the effectiveness of AdaFed. In the future, we plan to apply AdaFed to more personalized and flexible healthcare. And we will consider better ways to calculate and update similarities among clients.
References

Arivazhagan, M. G.; Aggarwal, V.; Singh, A. K.; and Choudhary, S. 2019. Federated learning with personalization layers. arXiv preprint arXiv:1912.00818.

Bilic, P.; Christ, P. F.; Vorontsov, E.; Chlebus, G.; Chen, H.; Dou, Q.; Fu, C.-W.; Han, X.; Heng, P.-A.; Hesser, J.; et al. 2019. The liver tumor segmentation benchmark (lits). arXiv preprint arXiv:1901.04056.

Cao, X.; Jia, J.; and Gong, N. Z. 2021. Provably Secure Federated Learning against Malicious Clients. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 35, 6885–6893.

Chang, W.-G.; You, T.; Seo, S.; Kwak, S.; and Han, B. 2019. Domain-specific batch normalization for unsupervised domain adaptation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 7354–7362.

Chen, Y.; Qin, X.; Wang, J.; Yu, C.; and Gao, W. 2020. Fedhealth: A federated transfer learning framework for wearable healthcare. IEEE Intelligent Systems, 35(4): 83–93.

Chen, Y.; Yang, X.; Chen, B.; Miao, C.; and Yu, H. 2017. PdAssist: Objective and quantified symptom assessment of Parkinson’s disease via smartphone. In 2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 939–945. IEEE.

Ching, T.; Himmelstein, D. S.; Beaulieu-Jones, B. K.; Kalinin, A. A.; Do, B. T.; Way, G. P.; Ferrero, E.; Agapow, P.-M.; Zietz, M.; Hoffman, M. M.; et al. 2018. Opportunities and obstacles for deep learning in biology and medicine. Journal of The Royal Society Interface, 15(141): 20170387.

Gao, H.; Xu, A.; and Huang, H. 2021. On the Convergence of Communication-Efficient Local SGD for Federated Learning. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 35, 7510–7518.

Inkster, N. 2018. China’s cyber power. Routledge.

Ioffe, S.; and Szegedy, C. 2015. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In International conference on machine learning, 448–456. PMLR.

Khodak, M.; Balcan, M.-F. F.; and Talwalkar, A. S. 2019. Adaptive Gradient-Based Meta-Learning Methods. In Advances in Neural Information Processing Systems, volume 32, 5917–5928.

Krizhevsky, A.; Sutskever, I.; and Hinton, G. E. 2012. Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems, volume 25, 1097–1105.

LeCun, Y.; Bottou, L.; Bengio, Y.; and Haffner, P. 1998. Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11): 2278–2324.

Li, T.; Sahu, A. K.; Zaheer, M.; Sanjabi, M.; Talwalkar, A.; and Smith, V. 2020. Federated Optimization in Heterogeneous Networks. In Proceedings of Machine Learning and Systems 2020, MLSys 2020, Austin, TX, USA, March 2-4, 2020. mlsys.org.

Li, X.; Huang, K.; Yang, W.; Wang, S.; and Zhang, Z. 2019. On the Convergence of FedAvg on Non-IID Data. In International Conference on Learning Representations.

Li, X.; Jiang, M.; Zhang, X.; Kamp, M.; and Dou, Q. 2021. FedBN: Federated Learning on Non-IID Features via Local Batch Normalization. In International Conference on Learning Representations (ICLR).

Li, Y.; Wang, N.; Shi, J.; Hou, X.; and Liu, J. 2018. Adaptive batch normalization for practical domain adaptation. Pattern Recognition, 80: 109–117.

McMahan, B.; Moore, E.; Ramage, D.; Hampson, S.; and yArcas, B. A. 2017. Communication-efficient learning of deep networks from decentralized data. In Artificial Intelligence and Statistics, 1273–1282. PMLR.

Reiss, A.; and Stricker, D. 2012. Introducing a new benchmarked dataset for activity monitoring. In 2012 16th International Symposium on Wearable Computers, 108–109. IEEE.

Sait, U.; Lal, K. G.; Prajapati, S.; Bhaumik, R.; Kumar, T.; Sanjana, S.; and Bhalla, K. 2020. Curated Dataset for COVID-19 Posterior-Anterior Chest Radiography Images (X-Rays). Mendeley Data, 1.

Segù, M.; Tonioni, A.; and Tombari, F. 2020. Batch Normalization Embeddings for Deep Domain Generalization. arXiv preprint arXiv:2011.12672.

Smith, V.; Chiang, C.-K.; Sanjabi, M.; and Talwalkar, A. 2017. Federated multi-task learning. In Proceedings of the 31st International Conference on Neural Information Processing Systems, 4427–4437.

T Dinh, C.; Tran, N.; and Nguyen, T. D. 2020. Personalized Federated Learning with Moreau Envelopes. In Advances in Neural Information Processing Systems, volume 33.

Voigt, P.; and Von dem Bussche, A. 2017. The eu general data protection regulation (gdpr). A Practical Guide, 1st Ed., Cham: Springer International Publishing, 10: 3152676.

Wang, X.; Jin, Y.; Long, M.; Wang, J.; and Jordan, M. I. 2019. Transferable Normalization: Towards Improving Transferability of Deep Neural Networks. In Advances in Neural Information Processing Systems, volume 32, 1953–1963.

Xu, J.; Glicksberg, B. S.; Su, C.; Walker, P.; Bian, J.; and Wang, F. 2021. Federated learning for healthcare informatics. Journal of Healthcare Informatics Research, 5(1): 1–19.

Xu, X.; Zhou, F.; Liu, B.; Fu, D.; and Bai, X. 2019. Efficient multiple organ localization in CT image using 3D region proposal network. IEEE transactions on medical imaging, 38(8): 1885–1898.

Yang, J.; Shi, R.; and Ni, B. 2021. MedMNIST Classification Decathlon: A Lightweight AutoML Benchmark for Medical Image Analysis. In IEEE 18th International Symposium on Biomedical Imaging (ISBI), 191–195.

Yang, J.; Shi, R.; Wei, D.; Liu, Z.; Zhao, L.; Ke, B.; Pfister, H.; and Ni, B. 2021. MedMNIST v2: A Large-Scale Lightweight Benchark for 2D and 3D Biomedical Image Classification. arXiv preprint arXiv:2008.#TODO.
Yang, Q.; Liu, Y.; Chen, T.; and Tong, Y. 2019. Federated machine learning: Concept and applications. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 10(2): 1–19.

Yeganeh, Y.; Farshad, A.; Navab, N.; and Albarqouni, S. 2020. Inverse Distance Aggregation for Federated Learning with Non-IID Data. In *Domain Adaptation and Representation Transfer, and Distributed and Collaborative Learning*, 150–159. Springer.

Yu, T.; Bagdasaryan, E.; and Shmatikov, V. 2020. Salvaging federated learning by local adaptation. *arXiv preprint arXiv:2002.04758*.

Yurochkin, M.; Agarwal, M.; Ghosh, S.; Greenewald, K.; Hoang, N.; and Khazaeni, Y. 2019. Bayesian nonparametric federated learning of neural networks. In *International Conference on Machine Learning*, 7252–7261. PMLR.

Zhu, W.; Xie, L.; Han, J.; and Guo, X. 2020. The application of deep learning in cancer prognosis prediction. *Cancers*, 12(3): 603.

### Dataset splits

Figure 11(a) shows how samples are distributed for OrganCMNIST while Figure 11(b) shows how samples are distributed for OrganSMNIST.

![Figure 11](image)

Figure 11: The number of samples per class allocated to each client (indicated by dot size).

### Parameter Sensitivity

In this section, we evaluate the parameter sensitivity of AdaFed. Our method is affected by three parameters: local epochs, client number, and $\lambda$. Client number has been analyzed in the paper and we analyze the rest here. We change one parameter and fix the other parameters.

In Figure 12(a), we can see our method is best and it is descending with local epochs increasing, which may be caused that we keep the total number of the epochs unchanged and the communication among the clients is insufficient. Figure 12(b)-12(c) demonstrates $\lambda$ slightly affects the average accuracy of our method while it can change the convergence rate. The results reveal that AdaFed is more effective and robust than other methods under different parameters in most cases.

![Figure 12](image)

Figure 12: Influence of different hyper-parameters.