Federated Multi-Mini-Batch: An Efficient Training Approach to Federated Learning in Non-IID Environments

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Abstract

Federated learning has faced performance and network communication challenges, especially in the environments where the data is not independent and identically distributed (IID) across the clients. To address the former challenge, we introduce the federated-centralized concordance property and show that the federated single-mini-batch training approach can achieve comparable performance as the corresponding centralized training in the Non-IID environments. To deal with the latter, we present the federated multi-mini-batch approach and illustrate that it can establish a trade-off between the performance and communication efficiency and outperforms federated averaging in the Non-IID settings.

1. Introduction

Federated learning (Konečný et al., 2015; 2016; McMahan et al., 2017) is a distributed learning approach that enables multiple parties (clients) to learn a shared (global) model without moving their local data off-site. In federated learning, most of the training is performed by the clients and an aggregation strategy is employed by a central server to iteratively update the global model. The privacy-preserving nature of federated learning has made it popular for applications such as healthcare data analysis (Sheller et al., 2018; Brisimi et al., 2018; Chen et al., 2020) and mobile keyboard prediction (Hard et al., 2018; Yang et al., 2018), in which access to data is impossible due to strict privacy policies.

Federated averaging (FedAvg) (McMahan et al., 2017) is a communication-efficient approach to federated learning, which aims to reach an accurate global model with an efficient number of communication rounds between the clients and the server. The main idea behind FedAvg is to perform a large number of local updates in the clients and then take a simple weighted average over the local model parameters on the server. FedAvg can dramatically reduce the number of communication rounds if the data is independent and identically distributed (IID) across the clients.

However, federated learning faces performance and network communication challenges when it comes to Non-IID settings and FedAvg as the training approach (Zhao et al., 2018; Jeong et al., 2018; Li et al., 2019; Hsieh et al., 2019; Sattler et al., 2019; Li et al., 2020; Wang et al., 2020b; Briggs et al., 2020). The global model trained by FedAvg might not converge to the optimum in Non-IID environments, and consequently, federated training might not provide comparable performance as it does for IID settings. Moreover, FedAvg might still require a large number of communication rounds to achieve target performance in Non-IID configurations.

In this paper, we introduce the federated-centralized concordance property (Section 3), which is directly related to the performance challenge in Non-IID environments. The property states that the federated (global) model trained by a set of clients on their local data is similar to the centralized trained on the aggregated data. If a federated training approach holds this property, it can achieve comparable performance as the corresponding centralized training regardless of the data and sample distribution across the clients. We experimentally show that the federated single mini-batch (FedSMB) approach (Sections 3) can train federated models that are concordant with the centralized model, and as a result, it has the potential to tackle the performance challenge in Non-IID settings (section 4).

To address the communication challenge, we present fed-


**Federated Multi-Mini-Batch (FedMMB)** as a generalization of FedSMB (Section 3). The main idea behind FedMMB is to decouple the batch size from the batch count and to allow for specifying the number of batches for training the local models at the clients (the number of local updates) independent of the batch size. This decoupling is not possible with FedAvg, where a single hyperparameter determines both the batch size and the batch count. Our simulation results illustrate that FedMMB can provide a trade-off between the performance and communication efficiency by controlling the number of local updates on the clients (Sections 4.2 and 4.3). Moreover, FedMMB attains higher performance than FedAvg in the Non-IID environments (Section 4.3).

### 2. Preliminaries

**Gradient descent** is the most widely used optimization method for training neural network models. In each iteration $i$, the gradient $\nabla$ of the loss function $F$ of the model $M$ characterized by the parameters (weights) $W_i$ are computed by minimizing $F$ on subset $S_i$ of the training samples in the dataset. Then, the model parameters are updated in the opposite direction of the gradient values. The learning rate $\eta$ specifies the step size of the update (Ruder, 2016).

\[
W_{i+1} = W_i - \eta \nabla F(W_i; S_i) \tag{1}
\]

There are different variants of gradient descent depending on how the samples of the training dataset are employed to update the model parameters. In **full gradient descent (FGD)**, all samples are leveraged to compute the gradients; **stochastic gradient descent (SGD)** calculates the gradients using a single randomly selected sample of the training dataset; **mini-batch gradient descent (MBGD)** optimizes the loss function on a random small batch of samples (Hinton et al., 2012; Bottou, 2012). For large neural networks, trained on very large datasets, MBGD is typically the best choice because it is computationally efficient (Hinton et al., 2012).

A neural network model can be trained in a centralized or distributed (including federated) environment. In centralized training, the whole dataset is located at a single site, and the model is iteratively trained on the dataset using one of the variants of gradient descent. **Epoch** indicates the number of iterations required to employ all samples of the dataset for training.

**Federated learning** is a privacy-preserving approach to learning a global model from the data distributed across multiple clients. Federated learning can be conducted in a **cross-device or cross-silo setting** (Kairouz et al., 2019). The former involves a huge number of mobile or edge devices as clients, whereas there is a small number of clients (e.g., dozens of medical centers) for training in the latter setting. We assume that the clients have different training samples but use the same form of a neural network model; additionally, all clients are selected to participate in the training process in each communication round.

In each iteration $i$ of the federated training, all $K$ clients obtain the global model parameters $W^g_i$ from the server and set the weights of their local model to $W^j_i$. Next, each client $j$ computes the local model parameters $W^j_{ij}$ by optimizing the loss function $F$ on $n^j_{ij}$ samples from its local data using one of the variants of gradient descent. Afterwards, the server receives the local parameters from the clients and calculates the global model parameters for the next iteration by taking the weighted average over the local parameters:

\[
W^g_{i+1} = \frac{\sum_{i=1}^{K} n^j_{ij} W^j_{ij}}{\sum_{j=1}^{K} n^j_{ij}} \tag{2}
\]

Each iteration of the federated training updates the global model parameters once and requires one communication round between each client and the server. Therefore, iteration and communication round are used interchangeably in the federated environment. However, the clients might update their local model parameters once or multiple times in each iteration depending on the variant of gradient descent they employ for local optimization.

**FedAvg algorithm** employs MBGD in the clients, aiming to reduce the number of communication rounds by performing more local updates at the clients. In FedAvg, each client $j$ updates its local model parameters $\mu_j = E[\frac{\sum_{i=1}^{K} n^j_{ij}}{n_j}]$ times, where $E$ is the number of local epochs, $B$ is the batch size, and $N_j$ is the number of samples in the training set of client $j$. The server then aggregates the local model parameters using the weighted average over the local parameters as above.
In other words, the clients run the MBGD algorithm $E$ times on the local data before sending the local model parameters to the server. The theoretical analysis on the convergence of FedAvg in the Non-IID settings shows that FedAvg with $E > 1$ and full batch might not converge to the optimum (Li et al., 2019).

**Data distribution** (i.e., feature and label distribution) across the clients can be IID or Non-IID. In the former, the training sets of the clients have similar (homogeneous) data distributions while in the latter, the data is heterogeneously distributed across the clients. The sample distribution among the clients might be balanced or imbalanced. In the balanced distribution, the sample sizes of the clients are alike, whereas the clients have very different sample sizes in the imbalanced distribution. Hsieh et al. (Hsieh et al., 2019) empirically show that data heterogeneity makes accurate federated learning very challenging, and the level of heterogeneity plays a major role in the problem. In this study, we focus on the Non-IID label distribution and mainly balanced sample distribution.

### 3. Method

In this section, we define an empirical property called federated-centralized concordance, and describe the FedSMB training approach and its generalization, FedMMB approach, which can fulfill the performance and network communication challenges in federated learning, respectively.

#### 3.1. Federated-centralized concordance

Consider the federated and centralized settings as follows:

The federated setting contains $K$ clients in which each client $j$ possesses training dataset $D_j$ with sample size $N_j$. In iteration $i$, the clients collaboratively train a federated (global) model $M^g$ characterized by weights $W^g_i$. In the centralized environment, the dataset $D$ with $N$ samples is the same as the aggregation of the training datasets of the clients, i.e., $D = \sum_{j=1}^{K} D_j$ and $N = \sum_{j=1}^{K} N_j$. The centralized model $M^c$ characterized by weights $W^c_i$ is iteratively trained on the dataset. $M^g$ and $M^c$ have the same form and are initialized with the same weights. Both environments employ the same loss function $F$ to optimize the model, and the same learning rate $\eta$ to update the model. The models are evaluated on the test dataset $D'$. $\ell^g_i$ and $\ell^c_i$ indicate the loss value of $M^g$ and $M^c$ on $D'$ in iteration $i$, respectively.

The federated-centralized concordance property: The federated model $M^g$ trained on the distributed datasets of the clients ($D_j$, $1 \leq j \leq K$) is similar to the centralized model $M^c$ trained on the aggregated dataset $D$ if the discordance (dissimilarity) value $\delta$ between the federated and centralized models is less than a very small value $\epsilon$. The discordance

$$\delta = \frac{\sum_{i=1}^{I_{\text{max}}} (\ell^g_i - \ell^c_i)^2}{I_{\text{max}}} \quad (3)$$

where $I_{\text{max}}$ is large enough for both models to converge.

Given that, a federated training approach is concordant with a centralized training approach on the dataset $D$ if the models trained by the approaches are concordant independent of the data and sample distribution across the clients provided that $D = \sum_{j=1}^{K} D_j$. The practical application of this property is that if a federated approach holds the property, it can provide comparable performance as the corresponding centralized approach even in Non-IID environments, and as a result, these environments are not challenging for the federated approach from the performance perspective.

**FedSMB** is a training approach, where the clients train the...
model on a single mini-batch from their local dataset instead of the whole in each communication round. In the next section, we experimentally show that the federated models from FedSMB with $K$ clients and batch size $B$ are similar to those from the centralized training using MBGD with batch size $B'=B \times K$ under the following assumptions: (1) FedSMB and MBGD use a relatively small learning rate, (2) the neural network model is convolutional or fully-connected and does not use any regularization such as batch normalization or random dropout, and (3) the sample distribution across the clients is balanced.

3.2. FedMMB

Although FedSMB can potentially meet the performance challenge, it suffers from a practical limitation: it is not communication-efficient, requiring a large number of communication rounds to achieve target performance. To tackle this issue, the FedMMB approach (Algorithm 1) generalizes FedSMB by specifying the number of batches (hyperparameter $C$) that clients should employ to locally train the model separate from the batch size (hyperparameter $B$).

In the initial step, the server initializes the global model; moreover, each client $j$ shuffles its local dataset of size $N_j$ and splits it into $\left\lceil \frac{N_j}{B} \right\rceil$ batches of size $B$ (except the last one whose size might be less than $B$). In the first iteration, the clients train the global model on the first $C$ batches from their dataset, updating the model parameters $C$ times. Afterwards, each client $j$ sends the updated model as well as the number of samples used for training ($n_{ij}^l$) to the server. The server takes the weighted average over the local models from the clients to compute the new global model. Likewise, the clients train the model on the second $C$ batches of their dataset in the second iteration, and the training process is repeated for a pre-specified number of iterations. The client shuffles and splits its dataset every $\left\lceil \frac{N_j}{B \times C} \right\rceil$ iteration.

The batch size and the number of batches used to perform local updates in each iteration can dramatically affect the performance and network efficiency in the federated environments (especially Non-IID ones). In FedAvg, they are coupled to each other because a single hyperparameter (i.e. batch size) determines both. FedMMB decouples the batch size from the batch count by using a separate hyperparameter for each of them. This decoupling enables FedMMB to control the number of local updates in the clients separate from the batch size. Given that, FedMMB can provide a trade-off between the performance and communication efficiency in various Non-IID environments (Section 4.2).

4. Results

We first show that the FedSMB can train models that are concordant with the centralized MBGD models considering the underlying assumptions (e.g. small learning rates or balanced sample distribution). To this end, we leverage the MNIST (LeCun et al., 2010) and Fashion-MNIST (FMNIST) (Xiao et al., 2017) as datasets, which include 70000 gray-scale images (60000 for training and 10000 for testing) of shape 28x28 as well as 10 label values. Following (McMahan et al., 2017), we train two different neural network models\(^1\) on the datasets: (1) a fully-connected neural network with two hidden layers of size 200 and (2) a convolutional neural network containing two 5x5 convolutional layers, each followed by a 2x2 max-pooling layer. The convolutional layers have 32 and 64 filters, respectively. The second max-pooling layer is followed by a fully-connected layer of size 512. In the models, the fully-connected layers use ReLU while the output layer utilizes the softmax activation function. We refer to the models as 2FNN and 3CFNN, respectively.

We also evaluate FedMMB (and FedSMB) as its special case using a more complex model and the CIFAR-10 dataset (Krizhevsky et al., 2009). The CIFAR-10 dataset contains 60000 color images (50000 train and 10000 test samples) of shape 32x32 and 10 class labels. We augment the train images by randomly flipping left/right and adjusting the brightness, contrast, saturation, and hue. The train size is doubled after augmentation. The model consists of three 3x3 convolutional layers with 128, 256, and 512 filters, respectively. Each convolutional layer is followed by a 2x2 max-pooling layer. The third max-pooling layer is followed by a fully-connected layer of size 1024. The convolutional and fully-connected layers employ ReLU whereas the output layer has softmax as the activation function. We call this model 4CFNN.

To compare FedMMB with FedAvg, we employ 4CFNN and CIFAR-10 as well as the VGG16 model (Simonyan & Zisserman, 2015) and the HAM10000 dataset (Tschandl et al., 2018). HAM10000 is an imbalanced dataset, comprising 10015 dermatoscopic skin lesion images of seven classes: Melanocytic nevi (6705), Melanoma (1113), Benign keratosis (1099), Basal cell carcinoma (514), Actinic keratoses (327), Vascular lesions (142), and Dermatofibroma (115)\(^2\). The original resolution of the images is 600x450 but we downsampled them to 200x150 to reduce the number of model parameters. VGG16 is a deep neural network model containing 13 convolutional and two fully-connected layers (TensorFlow implementation). The model contains $\approx$ 82 million trainable parameters in our case.

We distribute the MNIST, FMNIST, and CIFAR-10 datasets\(^1\). All models are implemented in TensorFlow/Keras (Abadi et al., 2016; Chollet et al., 2021) and use SGD optimizer and categorical cross-entropy loss function.

\(^1\)The numbers inside parentheses indicate the number of samples from each class.
across the clients in two different ways: IID and Non-IID. In the former, the distribution of the label values is similar among the clients, and each client has samples from all ten labels. In the latter, the clients have heterogeneous label distributions. For the IID case, we first shuffle the dataset, and then split it into $K$ partitions with the same sample size, and give each partition to one of the $K$ clients. In the Non-IID configuration, we have parameter $L$, which indicates the number of unique labels per client and determines the level of the label distribution heterogeneity across the clients. For instance, $L = 2$ results in a Non-IID setting, where each client only contains the samples from two labels. For

![Figure 1. Similarity between the federated models from FedSMB and those from the centralized training with MBGD ($\eta = 0.01$).](image1)

![Figure 2. FedSMB training for the 4CFNN model on the CIFAR-10 dataset ($\eta = 0.08$, $K = 10$, $B = 10$, $B' = 100$).](image2)
Table 4. Communication rounds | maximum accuracy associated with the scenarios in Figure 3.

| FeedMMB on 4CFNN-CIFAR-10 | C=5 | C=20 | C=50 |
|---------------------------|-----|------|------|
| IID                       | 2471 | 0.7383 | 761 | 0.7456 | 341 | 0.7508 |
| Non-IID-4                 | 2171 | 0.7295 | 931 | 0.7284 | 701 | 0.7230 |
| Non-IID-2                 | 3241 | 0.7260 | 1591 | 0.6906 | 1281 | 0.6591 |

According to Figures 1 and 2, the loss and accuracy curves for the centralized and federated models are similar to each other; additionally, FeedSMB can reach the accuracy of the centralized training regardless of the label distribution among the clients (Tables 2 and 3). However, it might need a large number of communication rounds to this end even in the IID setting, which implies FeedSMB is not a communication-efficient approach (Figure 2).

We also compute the discordance value $\delta$ between the federated and centralized models for each federated scenario (Tables 2 and 3). We consider $\epsilon = 0.01$ as the concordance threshold, i.e. the federated model is concordant with the centralized model if $\delta$ is less than 0.01. We observe that the discordance $\delta$ between the federated and centralized model is $7 \times 10^{-3}$ in the worst case (the higher discordance value in 4CFNN-CIFAR-10 is partly due to the higher learning rate used to train the models). These results indicate that the federated training with $K$ clients and batch size $B$ using FeedSMB and the centralized training with batch size $B' = B \times K$ using MBGD provide concordant models.

4.2. FeedMMB

To investigate the efficiency of FeedMMB, we employ a setting similar to the FeedSMB case using the 4CFNN model, the CIFAR-10 dataset, 10 clients with batch size of 10, and the best accuracy from the centralized training (0.7456) as the baseline. We train the model using different values of $C$ (batch count) under the IID, Non-IID-2 (severely Non-IID label distribution), and Non-IID-4 (moderately Non-IID label distribution) scenarios (Figure 3 and Table 4).

In the IID configuration, FeedMMB can achieve the accuracy of the baseline using high batch count values $(C=20, 50)$. Additionally, the larger batch count $(C=50)$ requires fewer
communication rounds to this end. Thus, increasing the batch count of FedMMB in the IID environment makes the approach more communication-efficient without compromising the accuracy.

In the Non-IID scenarios, FedMMB never reaches the baseline accuracy. In the moderately Non-IID label distribution scenario, all three batch count values achieve a similar accuracy (0.7295, 0.7284, 0.7230 for \( C = 5, 20, 50 \)), and higher batch counts need fewer communication rounds to this end. In the severely Non-IID label distribution case, lower batch counts achieve better accuracy (0.7260 vs. 0.6906 vs. 0.6591) but with more network communication overhead.

In summary, FedMMB with large \( C \) values is a realistic choice for the IID environment because it can save a huge number of communication rounds without negatively affecting the accuracy. For the Non-IID environments, FedMMB can establish a trade-off between the accuracy and communication efficiency through the batch count hyperparameter. In scenarios where the accuracy has priority over the communication efficiency, smaller batch count values can be used. Otherwise, a larger batch count is a better choice because it can considerably reduce the network communication overhead. In general, the best value of \( C \) can be determined based on the target performance and the label distribution across the clients.

### 4.3. FedMMB versus FedAvg

We compare the performance of FedMMB with FedAvg using 4CFNN and VGG16 as models and CIFAR-10 and HAM10000 as datasets (Figure 4 and Table 5). We first train 4CFNN on CIFAR-10 in a federated configuration with \( K = 10 \) clients, batch size \( B = 10 \), and the Non-IID-2 scenario using FedMMB (\( C = 20, \eta = 0.05 \)) and FedAvg (\( E = 1, \eta = 0.02 \)). We use a lower learning rate for FedAvg because the model diverges for the higher learning rates.

FedMMB and FedAvg achieve the maximum accuracy of 0.6906 and 0.6564, respectively, indicating that FedMMB outperforms FedAvg in terms of accuracy in the Non-IID scenario (Table 5a). These results are consistent with those from subsection 4.2 regarding the relationship between the number of local updates and the maximum achievable accuracy in the severely Non-IID label distribution case assuming the same batch size. With batch size of 10, FedMMB and FedAvg client \( j \) performs \( \mu_j = 20 \) and \( \mu_j = \frac{10000}{10} = 1000 \) local updates per iteration, respectively (10000 is the sample size of each client). The approach with a lower number of local updates reaches a higher accuracy.

We test FedAvg with larger batch sizes of \( B = 100 \) and \( B = 500 \) (\( E = 1, \eta = 0.05 \)) to perform fewer (\( \mu_j = 100 \) and \( \mu_j = 20 \)) local updates per iteration (Figure 4a and Table 5a). FedAvg reaches the maximum accuracy of 0.6663 and 0.6654 for \( B = 100 \) and \( B = 500 \), respectively, which is a small improvement over FedAvg with batch size \( B = 10 \) (0.6564). Comparing the accuracy of FedMMB (\( C = 20 \) and \( B = 10 \)) to FedAvg with \( B = 500 \) (\( \approx 0.6906 \) vs. \( \approx 0.6654 \)) highlights the importance of decoupling the batch size from the batch count (the main idea behind FedMMB). While both approaches perform the same number of local updates on the clients (\( \mu_j = 20 \)), FedMMB achieves better accuracy because it employs a smaller batch size without affecting the batch count, which is not possible in FedAvg.

We also train VGG16 on the HAM10000 dataset to evaluate the performance of FedMMB and FedAvg on a deeper neural network and a real-world, imbalanced dataset. We use the same batch size (\( B = 25 \)) and learning rate (\( \eta = 0.001 \)) for both approaches. The batch count is 20 for FedMMB, while the number of local epochs is 1 in FedAvg. We randomly split the dataset into the train set (8012 images) and the test set (2003 images). For the Non-IID scenario, we partition the train set among three clients (2367 samples of two classes, 3376 sample from five classes, and 2269 images from two classes) (Figure 5). Notice that class Melanocytic nevi is still the majority class in all clients and sample distribution is imbalanced across the clients. We refer to this scenario as HAM-Non-IID. We use AUC (Area Under the receiver operating characteristic Curve), a common performance metric for classification tasks on imbalanced datasets, to compare the performance of the approaches in the HAM-Non-IID scenario.

According to Figure 4b and Table 5b, FedMMB reaches higher AUC value than FedAvg in the HAM-Non-IID scenario (maximum AUC of 0.7431 versus 0.6931). Similar to the 4CFNN-CIFAR-10 case, the large number of local updates in the FedAVG clients adversely affects the performance in the Non-IID setting. These results emphasize the importance of controlling the local updates on the clients, the capability that FedMMB offers through the batch count hyperparameter. Given that, FedMMB is a flexible approach that can provide desirable performance or communication efficiency in the Non-IID environments with various degree of (label) heterogeneity.

### 5. Conclusion

In this paper, we address two main challenges of the federated learning in Non-IID environments: performance and network communication efficiency. With respect to the performance challenge, we introduce the federated-centralized concordance property and show that the FedSMB approach can train federated models that are concordant with the corresponding centralized models, and therefore, it can achieve comparable performance in the Non-IID environments and has the potential to overcome the performance challenge in the Non-IID settings.
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![Graph](image)

**Figure 4.** Comparison between FedMMB and FedAvg: FedMMB outperforms FedAvg in terms of accuracy (a) and AUC (b) on the 4CFNN-CIFAR-10 and VGG16-HAM10000 model-dataset pairs, respectively. The dashed line indicates the baseline accuracy or AUC. In (a), $\eta = 0.02$ for FedAvg with $B = 10$ and $\eta = 0.05$ for the other scenarios; $K = 10$ for all scenarios. In (b), $K = 3$ and $\eta = 0.001$ for all scenario.

| (a) 4CFNN-CIFAR-10 | (b) VGG16-HAM10000 |
|---|---|
| **Table 5. Communication rounds and maximum accuracy or AUC corresponding to the scenarios from Figure 4** | **Table 5. Communication rounds and maximum accuracy or AUC corresponding to the scenarios from Figure 4** |
| **Communication rounds** | **Accuracy** | **Communication rounds** | **AUC** |
| FedMMB ($B=10$, $C=20$) | 1591 | 0.6906 | FedMMB ($B=25$, $C=20$) | 241 | 0.7431 |
| FedAvg ($B=10$, $E=1$) | 1441 | 0.6564 | FedAvg ($B=25$, $E=1$) | 216 | 0.6931 |
| FedAvg ($B=100$, $E=1$) | 1361 | 0.6663 | FedAvg ($B=500$, $E=1$) | 1201 | 0.6654 |

We also present FedMMB as a generalization of FedSMB to tackle the communication efficiency challenge. Unlike FedAvg, FedMMB decouples the batch size from the batch count and controls the number of local updates per iteration separate from the batch size. This decoupling enables FedMMB to provide a trade-off between the performance and communication efficiency. The simulation results indicate that FedMMB outperforms FedAvg in terms of the accuracy and AUC and it is a suitable training approach to federated learning in Non-IID environments.

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