Dynamic Attention-based Communication-Efficient Federated Learning

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Abstract

Federated learning (FL) offers a solution to train a global machine learning model while still maintaining data privacy, without needing access to data stored locally at the clients. However, FL suffers performance degradation when client data distribution is non-IID, and a longer training duration to combat this degradation may not necessarily be feasible due to communication limitations. To address this challenge, we propose a new adaptive training algorithm AdaFL, which comprises two components: (i) an attention-based client selection mechanism for a fairer training scheme among the clients; and (ii) a dynamic fraction method to balance the trade-off between performance stability and communication efficiency. Experimental results show that our AdaFL algorithm outperforms the usual FedAvg algorithm, and can be incorporated to further improve various state-of-the-art FL algorithms, with respect to three aspects: model accuracy, performance stability, and communication efficiency.

1 Introduction

With the proliferation of digitalized data, and with the rapid advances in deep learning, there is an ever-increasing demand to benefit from insights that can be extracted from state-of-the-art deep learning models, while still not sacrificing on data privacy [Geyer et al., 2017; Yang et al., 2019]. For effective training, these models would require a huge amount of data, which is usually distributed over a large heterogeneous network of clients who are not willing to share their private data. Federated learning (FL) promises to solve these key issues, by training a global model collaboratively over decentralized data at local clients [Konečný et al., 2016; McMahan et al., 2017].

The key idea of FL is that all clients keep their private data and share a global model under the coordination of a central server, which is summarized as the FedAvg algorithm [McMahan et al., 2017]. In a typical communication round, a fraction of the clients, selected by the server, would download the current global model and perform training on local data. Next, the server performs model aggregation to compute a new global model, based on all updated models transmitted by the selected clients. However, in real-world non-IID data distributions, FL in heterogeneous networks would face many statistical challenges, such as model divergence and accuracy reduction [Smith et al., 2017; Li et al., 2019b; Ghosh et al., 2019; Karimireddy et al., 2020].

Related work: A theoretical analysis of the convergence of FedAvg in non-IID data settings is given in [Li et al., 2019b]. FedProx, a general optimization framework with robust convergence guarantees, was proposed in [Li et al., 2020] to tackle data heterogeneity by introducing a proximal term in the local optimization process. In [Karimireddy et al., 2020], a stochastic algorithm SCAFFOLD was proposed to reduce the variance and gradient dissimilarity in local FL updates, which yields better communication efficiency and faster convergence. To address fairness issues in FL, q-Fair Federated Learning (q-FFL) [Li et al., 2019a] and Agnostic Federated Learning (AFL) [Mohri et al., 2019] were proposed as modified federated optimization algorithms that improve fairness in performance across clients.

In [Wang et al., 2020], a layer-wise Federated Matched Averaging (FedMA) algorithm was proposed for CNN-based and LSTM-based FL models. Ji et al. [2019] also introduced a layer-wise attentive aggregation algorithm that improves communication and performance accuracy in FL, which has lower perplexity and communication cost for neural language models. Other methods have been proposed to tackle data heterogeneity and communication efficiency, from the perspective of asynchronous optimization [Xie et al., 2019], model compression [Konečný et al., 2016; Sattler et al., 2019], personalized training [Deng et al., 2020], and incentive design [Yu et al., 2020; Kang et al., 2019].

There are also several works in FL that tackle performance degradation in non-IID data settings, but for which the data privacy assumption in FL is not strictly adhered to. These works require a small amount of raw data to be shared either among clients [Zhao et al., 2018] or with the global server [Jeong et al., 2018]. FedMix [Yoon et al., 2021] avoids the direct sharing of raw data, by incorporating mixup data augmentation [Zhang et al., 2018] into FL, whereby clients share averaged data with each other. Such methods would require the exchange of raw or averaged data, which no longer guarantee strict data privacy, and which also require additional communication cost.

In each communication round of the usual FL framework, a fixed fraction of the clients is selected, based on a fixed proba-
bility distribution. A good choice for this fraction is not clear. Small fractions are widely used in existing work [McMahan et al., 2017; Karimireddy et al., 2020], but when such small fractions are used, data heterogeneity inadvertently causes fluctuations in training performance and reduces the rate of convergence [Li et al., 2019b]. Large fractions yield a more stable performance, as well as a slight acceleration in convergence, but at the expense of a larger communication cost [Li et al., 2019b]. Hence, to obtain a stable training performance with relatively low communication cost, we shall instead consider a dynamic fraction method that captures the advantages of both small and large fractions.

The selection probability for each client is a measure of the “importance” of that client. Thus, in heterogeneous networks where different clients have different “importance”, the fixed client selection probability distribution used in the usual FL is typically non-uniform. However, the relative contribution of each client is fluid. It depends on both the client’s local model performance, and on the actual aggregated global model, so the “importance” of the clients may vary during training.

With these considerations, we propose an attention-based adaptive federated learning algorithm, which we shall call AdaFL. The attention mechanism in AdaFL serves to better capture the relative “importance” among the clients, by taking into account the divergence of the local updated models, relative to the global model. Our method gives clients who have worse models a higher chance to participate in training. AdaFL also incorporates a dynamic fraction method to balance the trade-off between small and large fractions, which essentially represents the trade-off between communication efficiency and performance stability.

Our contributions are summarized as follows:

- We introduce a method to update the client selection probability in FL, by using a distance-based attention mechanism, so as to better capture the heterogeneity of client performance.
- To the best of our knowledge, we are the first to propose a dynamic fraction method in FL. We show that by increasing the fraction progressively, we can improve both the performance stability and the final model accuracy, while concurrently achieving lower communication and computation costs.
- We propose AdaFL, which combines both methods. We show experimentally the outperformance of AdaFL over FedAvg with respect to model accuracy, performance stability, and communication efficiency. We also show that AdaFL can be incorporated to enhance the performance of various state-of-the-art FL algorithms.

2 Proposed method

The training of FL would typically be performed based on updates over hundreds, or even thousands of communication rounds. In this section, we introduce the preliminaries of FL [McMahan et al., 2017], and show the details of our proposed algorithm within each round. For concreteness, we assume in this paper that FL is used to learn a global neural network model.

Figure 1: An illustration of the FL framework, with M clients. In communication round t, the server selects and distributes a global model \( W(t) \) to a subset of clients based on \( a(t) \) (Downlink Update). Then, the selected clients compute and transmit their local models \( \{ W_i(t) \} \) to the server (Uplink Update).

2.1 Preliminaries of FL and FedAvg Algorithm

The FL framework consists of one central server and multiple clients. Clients participate in training a shared global model under the coordination of the server, without having to share private data. Given M clients, let \( n_k \) be the number of data-points that client \( k \) has, and let \( n := n_1 + \cdots + n_M \) be the total number of datapoints. In the usual FL set-up, the stochastic vector \( n := [n_1, \ldots, n_M] \) represents the discrete probability distribution used for client selection, where \( p_k := \frac{n_k}{n} \) is the probability that client \( k \) is selected in each communication round. The optimization problem that FL tackles can thus be formulated as the minimization problem:

\[
\min_w f(w) = \sum_{k=1}^{M} p_k f_k(w),
\]

where \( f_k \) is the local loss function of client \( k \), whose input \( w \) is the set of model parameters of a fixed model architecture.

The FedAvg algorithm summarizes how this FL optimization problem is solved [McMahan et al., 2017]. In each communication round, a small group of clients is selected and local training is performed at each client, based on the same model downloaded from the global server. The main idea is that the gradient updates from the clients are aggregated at the server via a weighted average. At the end of round \( t \), the server updates the model parameters with gradient descent via

\[
w_{t+1} \leftarrow w_t - \eta \nabla f(w_t),
\]

where \( \nabla f(w_t) = \sum_{k \in S_t} \frac{n_k}{n} g_k \), and \( \eta \) is the learning rate. Here, \( g_k \) is the local update of selected client \( k \), \( S_t \) is the subset of selected clients in round \( t \), and \( n_{S_t} := \sum_{i \in S_t} n_i \). The number \( K = |S_t| \) of selected clients is calculated by the formula \( K = \gamma \cdot M \), where \( \gamma \) (satisfying \( 0 < \gamma < 1 \)) denotes the fraction of the selected clients.

In this usual FedAvg algorithm, both the probability distribution for client selection and the fraction \( \gamma \) of selected clients, are kept invariant throughout all communication rounds. In the next two subsections, we explain how AdaFL varies the client selection probability distribution, and varies the fraction \( \gamma \), respectively.
2.2 Attention Mechanism

In any real-world FL implementation on non-IID client data, the relative training performances of different clients cannot be predicted in advance. Different clients could have different relative importance towards model aggregation, which could vary over different communication rounds. To avoid making idealistic assumptions, we shall take a data-driven approach. We introduce an attention mechanism to measure the relative importance of the different clients, and adjust the probability distribution for client selection accordingly, based on real-time local training performance. Our approach differs from existing FL approaches, e.g. [Konečný et al., 2016; McMahan et al., 2017; Li et al., 2019a; Ji et al., 2019], where client selection is not modified and hence independent of the local training performance of the clients.

We shall use Euclidean distance as a measure of the model divergence of each local model, relative to the global model. The vector of attention scores \( a^{(t)} = [a_1^{(t)}, a_2^{(t)}, \ldots, a_M^{(t)}] \) in round \( t \) is identical to the corresponding client selection probability distribution \( p = [p_1, p_2, \ldots, p_M] \) for that round \( t \), and it is initialized in the first round as \( a_1^{(1)} = n \).

Specifically, at the beginning of round \( t \), the server selects \( K \) clients, according to the probability distribution \( p \). Local training then occurs. We shall denote the local models of the selected clients by \( W_{i_1}^{(t)}, W_{i_2}^{(t)}, \ldots, W_{i_K}^{(t)} \), where \( i_j \) is the index of the \( j \)-th client in the selected subset \( S_t \) (for round \( t \)). Each \( W_{i_j}^{(t)} \) is a collection of weight matrices for the layers of the neural network. After aggregation at the server, we obtain a new global model, denoted by \( W^{(t+1)} \). The process in a typical round is shown in Fig. 1.

Identify each \( r \)-by-\( s \) weight matrix as a vector in \( \mathbb{R}^{rs} \) and concatenate all such vectors, so that \( W_{i_j}^{(t)} \) is represented by a single parameter vector \( w_{i_j}^{(t)} \). Thus, the \( K \) local models and the new global model are represented by the vectors \( w_{i_1}^{(t)}, w_{i_2}^{(t)}, \ldots, w_{i_K}^{(t)} \) and \( w^{(t+1)} \) respectively. For selected client \( i \in S_t \) in round \( t \), we calculate the Euclidean distance between the global and local parameter vectors as follows:

\[
d_{i}^{(t)} = \left\| w^{(t+1)} - w_{i}^{(t)} \right\|_2. \tag{1}
\]

To reduce the fluctuations in attention scores of consecutive rounds, we incorporate the current attention score in our updating criterion:

\[
a_{i}^{(t+1)} = a_i^{(t)} \cdot \frac{d_{i}^{(t)}}{\sum_{k \in S_t} d_{k}^{(t)}} \sum_{k \in S_t} a_k^{(t)}, \tag{2}
\]

where \( \alpha \in [0, 1] \) represents a decay rate of previous attention score contributions. For an unselected client \( j \), we set \( a_{j}^{(t+1)} = a_j^{(t)} \). Note that \( a_i^{(t+1)} \) remains as a stochastic vector. Client selection in round \( t + 1 \) then follows the updated probability distribution \( p = a^{(t+1)} \).

Since our work does not deal with the usual federated optimization, our attention mechanism only updates the client selection probability distribution and will not change the aggregation weights. Moreover, the additional communication cost brought by our proposed algorithm is negligible. Notice also that by (1) and (2), a larger Euclidean distance between the vectors for the global model \( w^{(t+1)} \) and local model \( w_{i}^{(t)} \) will increase the probability that client \( i \) would be selected in the next communication round. Subsequently, more training and computation would be done at the corresponding clients to obtain a better performance. Hence, the overall effect is a fairer scheme, whereby the variance of local training performances among the clients is deliberately reduced.

2.3 Dynamic Fraction for Client Selection

How do we choose a “good” fraction \( \gamma \) for client selection? What is considered “good” will depend on how we want to balance the trade-off between communication efficiency and performance stability. A smaller \( \gamma \) would mean a lower communication cost in each communication round, but at the expense of larger fluctuations in training performance, and a slower rate of convergence [Li et al., 2019b]; this implies that more training rounds are required to reach a desired performance level. A larger \( \gamma \) would bring better performance stability, and less communication rounds, but at the expense of a larger total communication cost. Under the usual assumption in FL that \( \gamma \) is fixed throughout training, we would then be forced to choose between communication efficiency and performance stability.

To circumvent this trade-off, we drop the assumption that \( \gamma \) is fixed, and propose a dynamic fraction method, which adopts different fractions during different training stages, with the fraction increasing progressively. As an explicit example, depicted in Fig. 2, we begin training with a small fraction 0.1, and end training with a large fraction 0.5. (Here, 0.1 and 0.5 are arbitrarily selected.) When using gradient descent, our method yields a relatively good performance, even with fewer clients involved at the beginning of training. With an increased amount of local training data in subsequent rounds, the training performance would have a more stable convergence. Intuitively, the updated global model gradients would be closer to optimal gradients that reflect the true data distribution, as there are increasingly more clients (and hence more data) involved in training, as the fraction increases.

To represent dynamic fractions, we shall use \( \gamma \) to denote

![Figure 2: An example of our dynamic fraction scheme. \( \Delta_{\gamma} \) is the fixed step size (number of communication rounds) between two consecutive fraction updates in the training. \( \Delta_{\gamma} \) is the increasing step of the fraction.](image-url)
the vector of fractions, whose $t$-th entry $\gamma^{(t)}$ is the fraction used in the $t$-th communication round. Since $T$ is the total number of communication rounds, $\gamma^{(1)}$ (resp. $\gamma^{(T)}$) is the starting (resp. ending) fraction used in our dynamic fraction method. For simplicity, we recommend using a fixed step size $\Delta_T$ between consecutive fraction updates, and a fixed increment $\Delta_\gamma$, when updating the fraction $\gamma$; this means that $\Delta_T = \frac{1}{T} \cdot T$ and $\gamma^{(T)} - \gamma^{(1)} = (F-1) \Delta_\gamma$, where $F$ is the desired number of distinct fractions to be used. The vector $\gamma$ can be computed accordingly. Observe that in our running example (see Fig. 2), we used $F = 5$, so that each fraction update, which increases the value of $\gamma$ by $\Delta_\gamma = \frac{1}{T} = 0.1$, occurs at every $\Delta_T = \frac{1}{T} \cdot T = 0.2T$ communication rounds.

Although we only consider fixed $\Delta_T$ and $\Delta_\gamma$, for simplicity, it should be noted that our method works for any number $F$ of fraction values and any non-constant $\Delta_\gamma, \Delta_T$, and more generally, for any non-constant fraction $\gamma$ that is monotonically increasing from $\gamma^{(1)}$ to $\gamma^{(T)}$. In this paper, we do not address all the different (infinitely many) types of monotonically increasing $\gamma$ that could be used for our proposed dynamic fraction method. In our experiments, this simple use of multiple fraction values as described above, is already sufficient to yield performance improvement over the use of constant fraction.

### 2.4 Algorithm Summary

Adaptive Federated Learning (AdaFL), our proposed method, combines both the attention mechanism described in Section 2.2, and the dynamic fraction method described in Section 2.3. The juxtaposition of these two components, on top the usual FedAvg algorithm, incorporates adaptive training adjustments, thereby yielding better communication efficiency with better performance stability. We give an overview of AdaFL in Algorithm 1. The key difference of our proposed AdaFL algorithm over the FedAvg algorithm is the adaptive parameter adjustment scheme. Parameters are adjusted by using real-time information from local training. Hence, the central server also plays a dual role as a resource allocator during training, in addition to its usual role of coordinating the aggregation of local weights in each communication round. The resource allocation can be made fairer by improving the weights of clients with larger model divergence.

It should be noted that our proposed algorithm complements existing communication-efficient federated algorithms, such as compression [Konečný et al., 2016; Sattler et al., 2019], data augmentation [Yoon et al., 2021] and some optimization methods for federated learning [Li et al., 2020; Karimireddy et al., 2020]. Later in our experiments, we show how our proposed AdaFL can enhance the performance of existing popular FL algorithms.

### 3 Experiments

In this section, we describe the details of our experiments, and evaluate the performance of our proposed AdaFL algorithm.

#### 3.1 Experiment Setup

We evaluate our AdaFL algorithm on image classification tasks on two image datasets, MNIST [LeCun et al., 1998] and CIFAR-10 [Krizhevsky et al., 2009], with neural network models. For experiments on the MNIST dataset, we train a Multi-Layer-Perceptron (MLP) model (2 hidden layers, each layer with 200 units and ReLU activation) with a fixed learning rate $\eta = 0.01$. For training data samples, we use the non-IID data partition as described in [McMahan et al., 2017]. For experiments on the CIFAR-10 dataset, we train a CNN model with the same model architecture as given in [Yoon et al., 2021], with IID data partition. We used an initial learning rate of $\eta = 0.01$ with a decay of 0.99 across the communication rounds. In all our experiments, across all FL algorithms, we train a local model at each selected client via stochastic gradient descent (SGD), using momentum coefficient 0.5.

The remaining parameter settings are given as follows. We use $M = 100$ clients for training. The number of local epochs and batch size are set as $E = 5$ and $B = 10$ respectively. The initial attention score vector $\alpha^{(1)}$ is determined by the local dataset size as described in Algorithm 1. For our attention score update process, we fix $\alpha = 0.9$. For the local dataset size, we consider a balanced data distribution for all experiments, in which every client has the same local dataset size (number of local training samples); this implies that the initial attention score of each client is $\frac{1}{100}$. For the dynamic selection of fractions, we use $\gamma^{(1)} = 0.1$ and $\gamma^{(T)} = 0.5$, with increments of $\Delta_\gamma = 0.1$ (see Fig. 2).

#### 3.2 Ablation Study

We report our ablation study results in Tables 1 and 2, in which we evaluate the performances of our proposed AdaFL on the two datasets, with and without the two components in AdaFL: the attention mechanism and the dynamic fraction method. We use FedAvg-0.1 and FedAvg-0.5 as our baselines, which refer to the usual FedAvg algorithm with

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**Algorithm 1: Adaptive Federated Learning (AdaFL)**

**Inputs:** $M, T, \gamma, \alpha, W^{(1)}$, $n$

1: $a^{(1)} \leftarrow n$
2: for $t = 1$ to $T$
3: \quad $p \leftarrow a^{(t)}$ and $K \leftarrow \gamma^{(t)} \cdot M$
4: \quad Server selects a subset of clients $S_t$ of size $|S_t| = K$
5: \quad using probability distribution $p$
6: \quad // local computation at clients
7: \quad for selected client $k \in S_t$
8: \quad \quad Client $k$ downloads global model $W^{(t)}$
9: \quad \quad Client $k$ computes local model $W^{(t)}_k$
10: \quad \quad // global computation at server
11: \quad Server computes a new global model by aggregation:
12: \quad \quad $W^{(t+1)} \leftarrow \sum_{k \in S_t} \frac{n_k}{n_{S_t}} W^{(t)}_k$
13: \quad for selected client $i \in S_t$
14: \quad \quad Server updates $a_i^{(t)} \leftarrow \|w^{(t+1)} - w^{(t)}\|_2$
15: \quad \quad and
16: \quad \quad $a_i^{(t+1)} \leftarrow a_i^{(t)} + (1 - \alpha) \cdot \frac{a_i^{(t)}}{\sum_{k \in S_t} a_k^{(t)}}$
17: \quad for unselected client $j \notin S_t$
18: \quad \quad Server updates $a_j^{(t+1)} \leftarrow a_j^{(t)}$
a constant fraction of $\gamma = 0.1$ and $\gamma = 0.5$ respectively. For illustration, a comparison of AdaFL with both baselines FedAvg-0.1 and FedAvg-0.5, over all 500 communication rounds of our experiments on MNIST, is given in Fig. 3. In particular, Fig. 3 shows that AdaFL has the advantages of both FedAvg-0.1 and FedAvg-0.5, which starts training with smaller communication cost, and ends training with better performance stability and test accuracy.

For both Tables 1 and 2, we write Attn.-0.1 and Attn.-0.5 to mean that we apply only the attention mechanism to FedAvg with a constant fraction of $\gamma = 0.1$ and $\gamma = 0.5$ respectively, while we write Dyn. FedAvg to mean that we apply only the dynamic fraction method (with the fraction increasing progressively from 0.1 to 0.5, with $T = 1500$) to FedAvg, without the attention mechanism.

In Table 1, we report the “best test accuracies” of all aforementioned methods, on both datasets. However, it should be noted that our chosen model architectures do not yield state-of-the-art “best accuracies” on the respective datasets, since our goal is to show that FedAvg can be improved with our two proposed components in AdaFL. Due to the natural random fluctuations in test accuracy performance over consecutive communication rounds, we shall also report “average test accuracy” as a measure of performance stability; see Section 3.2.1 for more details. In Table 2, we report the number of communication rounds and total communication cost that each method takes to reach a specified target accuracy, which is chosen to be close to the corresponding best accuracy as given in Table 1; see Section 3.2.2 for more details.

For the rest of this subsection, we shall evaluate the two components of AdaFL (using $T = 1000$) with respect to (i) accuracy and performance stability; and (ii) required number of communication rounds and total communication cost, respectively.

### 3.2.1 Accuracy Performance

We use average accuracy and best accuracy to evaluate the outperformance and convergence stability. To better capture the notion of performance stability, we use the average accuracy of the last $\ell$ rounds as a key performance metric (we use $\ell = 10$ in our experiments). As the results in Table 1 show, our experiments on both datasets, for which training end with a larger fraction (AdaFL, Attn.-0.5 and Dyn. FedAvg) have higher average accuracies and hence better performance stability.

Thus, the attention component increases model accuracy, while the dynamic fraction component improves performance stability. Compared to the two baselines (FedAvg-0.1 and FedAvg-0.5), AdaFL achieved higher accuracies on both MNIST (43%–2.45%) and CIFAR-10 (71%–1.5%), with better performance stability. The experiments with the attention mechanism incorporated (AdaFL, Attn.-0.1 and Attn.-0.5) have higher best accuracy performance.

| Algorithm | MNIST | CIFAR-10 |
|-----------|-------|----------|
|           | Average | Best | Average | Best |
| AdaFL     | 91.13  | 91.64   | 74.38   | 76.17 |
| Attn.-0.1 | 88.92  | 91.30   | 73.13   | 74.91 |
| Attn.-0.5 | 91.07  | 91.58   | 74.42   | 75.96 |
| Dyn. FedAvg | 90.33  | 91.19   | 74.33   | 75.04 |
| FedAvg-0.1| 88.68  | 91.05   | 72.88   | 74.82 |
| FedAvg-0.5| 90.40  | 91.21   | 73.67   | 75.31 |

Table 1: Ablation study in terms of average and best test accuracy performances (averaged over 3 trials). Each value in the Average column represents the best test accuracy of the last 10 communication rounds, which serves dually as a measure of performance stability. Each value in the Best column represents the best test accuracy achieved over all communication rounds.

### 3.2.2 Communication Efficiency Performance

We define communication cost in terms of relative units, where each relative unit is the cost of transmitting data representing all parameter updates of a single neural network model, from a single client to the global server, in a single communication round. Given $\gamma$ and the required number $T^*$ of communication rounds to reach target accuracy, we define the total communication cost to be $\sum_{t=1}^{T^*} \gamma(t) \cdot M$; this value is the total number of relative units across all $T^*$ communication rounds. Hence, better communication efficiency shall mean a lower total communication cost.

As Table 2 shows, the use of larger fractions would require less communication rounds to reach the specified target accuracies, while the use of small fraction (with lower communication cost per round) would require more communication rounds to reach stable convergence, i.e. a larger total communication cost. In comparison, the use of dynamic fractions not only yields faster stable convergence, but also has better communication efficiency.

To conclude, the ablation study results reported in Tables 1 and 2 show conclusively that both components in AdaFL contribute towards the outperformance over FedAvg.
FedProx-0.1/0.5
AdaFL+FedProx
stands for
stopping criterion used is that the average test accuracy of the last
5
statements on both MNIST (increase of
based experiments yield better performance, with improve-
stant fraction
performance for various FL algorithms (averaged over
3
values in brackets) to reach the specified target test accuracy. All re-
values preceding brackets) and the total communication cost (val-
rounds in most of the experiments and has the lowest total
communication cost to reach the specified target accuracy for
3
rithms (averaged over 3 trials). Similar to the settings used in Ta-
able 2, the target test accuracies are chosen based on the results of
Table 3. For a fair evaluation, the stopping criterion used is that the
average accuracy of last 5 rounds must exceed the target test accuracy.

### 3.3 Performance Evaluation

As discussed earlier in Section 1, FedProx and SCAFFOLD
are federated optimization methods, while FedMix is a data
augmentation method designed for FL. These algorithms em-
ploy a fixed probability distribution for client selection and a
fixed fraction \( \gamma \) throughout training. In this subsection, we re-
port how our proposed AdaFL can be incorporated to further
improve these algorithms. Table 3 shows that the incorpo-
ration of AdaFL improves both model accuracy and perfor-
ance stability, while Table 4 shows that the incorporation
of AdaFL reduces the required number of communication
rounds and total communication cost to reach target accuracy.

### 4 Conclusion

In this paper, we propose an attention-based federated learn-
ing algorithm with dynamic fraction for client selection, which we call AdaFL. It is a simple algorithm that can be
easily incorporated into various state-of-the-art FL algorithms
to obtain improvements on several aspects: model accuracy, per-
formance stability, and communication efficiency.

Overall, AdaFL complements the performance of the three
state-of-the-art algorithms on both datasets (see boldfaced
values in Tables 3 and 4), with respect to test accuracy and
communication efficiency. For test accuracy, the AdaFL-
based experiments yield better performance, with improve-
ments on both MNIST (increase of 2.52\%, 2.15\%, and 2.48\%
respectively) and CIFAR-10 (increase of 2.06\%, 1.74\%, and

| Algorithm      | MNIST  | CIFAR-10 |
|----------------|--------|----------|
| AdaFL          | 90%    | 91%      | 73%      |
| AdaFL+FedProx  | 91.67  | 92.42    | 74.94    | 76.24    |
| FedProx-0.1    | 89.15  | 91.46    | 72.88    | 75.90    |
| FedProx-0.5    | 90.81  | 91.55    | 73.57    | 76.12    |
| AdaFL+FedMix   | 90.52  | 91.30    | 73.27    | 75.05    |
| FedMix-0.1     | 88.37  | 90.61    | 71.53    | 73.43    |
| FedMix-0.5     | 89.91  | 91.08    | 72.42    | 74.12    |
| AdaFL+SCAFFOLD | 90.30  | 91.52    | 74.98    | 75.53    |
| SCAFFOLD-0.1   | 87.82  | 89.96    | 71.62    | 74.12    |
| SCAFFOLD-0.5   | 89.73  | 90.82    | 73.50    | 74.77    |

| Algorithm      | MNIST  | CIFAR-10 |
|----------------|--------|----------|
| AdaFL          | 91%    | 73%      |
| AdaFL+FedProx  | 821 (21600) | 721 (16840) |
| FedProx-0.1    | 2439 (24390) | 1762 (17620) |
| FedProx-0.5    | 1084 (54200) | 658 (32900) |
| AdaFL+FedMix   | 852 (22600) | 698 (15920) |
| FedMix-0.1     | 2275 (22750) | 1903 (19030) |
| FedMix-0.5     | 1241 (62050) | 732 (36600) |
| AdaFL+SCAFFOLD | 794 (19760) | 672 (15600) |
| SCAFFOLD-0.1   | 2252 (22520) | 1981 (19810) |
| SCAFFOLD-0.5   | 1034 (51700) | 725 (36250) |

Table 2: Ablation study in terms of the required number of rounds (values preceding brackets) and the total communication cost (values in brackets) to reach the specified target test accuracy. All reported values are averaged over 3 trials. For a fair evaluation, the stopping criterion used is that the average test accuracy of the last 5 rounds must exceed the target test accuracy.

Table 4: A comparison of the required number of communication rounds (values preceding brackets) and total communication cost (values in brackets) to reach target test accuracy, for various algorithms (averaged over 3 trials). Similar to the settings used in Table 2, the target test accuracies are chosen based on the results of Table 3. For a fair evaluation, the stopping criterion used is that the average accuracy of last 5 rounds must exceed the target test accuracy.

3.06\% respectively), for all three algorithms. Also, observe
that our AdaFL requires the least number of communication
rounds in most of the experiments and has the lowest total
communication cost to reach the specified target accuracy for
all the experiments, giving a 0.7\% to 21.3\% reduction in total
communication cost for small fractions, and more signifi-
cantly, a 48.8\% to 63.6\% reduction for large fractions.

These results show conclusively that the incorporation
of AdaFL into these state-of-the-art FL algorithms would en-
force the performance of all three aspects: model accuracy, per-
formance stability, and communication efficiency.

Table 3: A comparison of the average and best test accuracy performance for various FL algorithms (averaged over 3 trials). AdaFL+FedProx stands for AdaFL incorporated into FedProx, while FedProx-0.1/0.5 refers to the usual FedProx with con-
stant fraction 0.1 or 0.5. The other algorithms reported in this table are defined analogously. We use the same performance metrics as used in Table 1. In particular, average test accuracy (of the last 10
communication rounds) is a measure of performance stability.
Acknowledgments

This research is supported by the National Research Foundation, Singapore under its AI Singapore Programme (AISG Award No: AISG-RP-2019-015).

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