Communication-Efficient Federated Learning with Acceleration of Global Momentum

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Abstract

Federated learning often suffers from unstable and slow convergence due to heterogeneous characteristics of participating clients. Such tendency is aggravated when the client participation ratio is low since the information collected from the clients at each round is prone to be more inconsistent. To tackle the challenge, we propose a novel federated learning framework, which improves the stability of the server-side aggregation step, which is achieved by sending the clients an accelerated model estimated with the global gradient to guide the local gradient updates. Our algorithm naturally aggregates and conveys the global update information to participants with no additional communication cost and does not require to store the past models in the clients. We also regularize local update to further reduce the bias and improve the stability of local updates. We perform comprehensive empirical studies on real data under various settings and demonstrate the remarkable performance of the proposed method in terms of accuracy and communication-efficiency compared to the state-of-the-art methods, especially with low client participation rates. Our code is available at https://github.com/ninigapa0/FedAGM

1. Introduction

Federated learning, first introduced in [21], is an emerging large-scale machine learning framework that a central server learns a shared model without direct observation of training examples using a large number of remote clients with separate datasets. This decentralized learning concept allows the federated learning to achieve the basic level of data privacy. Since the remote clients such as mobile or IoT devices have limited communication bandwidth, federated learning algorithms are particularly sensitive to the communication cost.

FedAvg [21] is known as the baseline algorithm of federated learning. In FedAvg, a subset of the clients updates their models based on a gradient descent method using their local data and then upload their resultant models to the server for updating the global model parameters via model averaging. As discussed in the extensive analysis on the convergence of FedAvg [3, 24–26, 33], multiple local updates conducted before aggregation greatly reduce the communication cost that is required for training a model in the server.

However, federated learning faces two key challenges: high heterogeneity in the data distributed over clients and limited participation rate, so-called cross-device setting [9], where only a subset of clients is active at a given time due to the limited communication bandwidth.

Several studies [11, 35] have shown that multiple local updates in the clients with non-iid data lead to client-drift, diverging updates in the individual clients. Such a phenomenon introduces high variance associated with the averaging step of FedAvg for the global update, which hampers the convergence to the optimal average loss over all clients [7, 12, 17, 19, 27, 29]. The client-drift challenge is exacerbated when the participation rate per communication round is low due to unreliable connections between the server and the clients.

To properly address the client heterogeneity issue, we propose a novel optimization algorithm for federated learning, Federated Averaging with Acceleration of Global Momentum (FedAGM), which conveys the momentum of global gradient information to clients and enables the momentum to be incorporated into the local updates in the individual clients. This approach turns out to be effective for reducing the gap between the global and local losses. Contrary to the existing methods that require additional steps to compute the momentum, FedAGM transmits the global model integrated with the momentum and saves the extra communication and computational cost consequently. In
addition, FedAGM incorporates a regularization term in the objective function of clients to make the global and local gradients more consistent. FedAGM incurs no extra computation and communication costs on both server and client sides.

Although there have been a growing number of works that handle the client heterogeneity in federated learning, FedAGM has the following major advantages. Unlike previous methods focusing on the strategies for either client-level optimization [1, 10, 11, 16–18, 20, 30, 31, 34] or server-level updates [8, 23, 28], FedAGM incorporates the momentum based on the local gradient information into both server and client updates. This feature allows the proposed method to achieve the same level of task-specific performance with fewer communication rounds. Moreover, while most of existing methods require additional requirements compared to FedAvg such as full participation [13, 20, 34], additional communication bandwidth [5, 10, 11, 18, 30, 36], or storage costs on clients to store local states [1, 11, 16], FedAGM is completely free from any additional communication and memory overhead, which ensures the compatibility with large-scale and low-participation federated learning scenarios. The main contributions of this paper are summarized as follows.

- We propose a communication-efficient federated optimization algorithm, which deals with heterogeneous clients effectively. The proposed approach computes and transmits the global model with a momentum efficiently, which facilitates the optimization in clients.
- We also revise the objective function of clients, which augments a regularization term to the local gradient direction, which further aligns the gradients of the server and the individual clients.
- We show that the proposed approach does not require any additional communication cost and memory overhead, which is desirable for the real-world settings of federated learning.
- Through extensive evaluation on multiple benchmarks, we demonstrate that our optimization technique is communication-efficient and robust to client heterogeneity, especially when the participation ratio is low.

The rest of this paper is organized as follows. We first review the core algorithmic idea of federated learning, FedAvg, and its variants in Secs. 2 and 3. Then, we formally describe the proposed federated learning framework and demonstrate the effectiveness of our method in Secs. 4 and 5. Finally, we conclude the paper in Sec. 6.

2. Related work

Federated learning was first proposed in McMahan et al. [21], which introduces the key properties of federated learning as non-iid client data, massively distributed, and partial participation, and then proposes FedAvg algorithm as a solution. Several works explore the negative influence of heterogeneity in federated learning empirically [35] and derive convergence rates depending on the amount of heterogeneity [7, 12, 17, 19, 27, 29]. In this work, we focus on the problem of non-iidness, also known as client statistical heterogeneity where participating clients have different data distributions.

To improve FedAvg in the presence of heterogeneous clients, there is a long line of work which penalize local models not to drift towards their local minima by regularizing the local objectives. These approaches regularize the client loss function with a proximal term [17] or use primal-dual approaches [1, 34]. In activation regularization perspective, client update is regularized to have similar activation to the downloaded global model by contrastive learning [16], using mixup with global statistics [32], and using generative models [36]. There is another line of work which reduce inter-client variance to eliminate inconsistent update across clients. several approaches use control variates [10, 11, 18, 20] or global gradient momentum [30] to reduce biases in client update. [5, 13] apply STORM algorithm [4] to reduce variance caused by both server-level and client-level SGD procedures. Another way to de-bias client updates is to estimate the global posterior using local posterior sampling by running Markov chain Monte Carlo (MCMC) on client side [2]. However, most of these methods require full participation, additional communication cost or client storage, which can be problematic in realistic federated learning tasks.

On the other hand, several works incorporate momentum [8, 28] and adaptive gradient methods [23] in server optimization to accelerate the convergence of the federated learning. While these methods only involve server-level optimization, our method incorporates the momentum of global gradient information into both server- and client-level optimization.

3. Preliminaries

3.1. Problem setting and notations

The goal of federated learning is to construct a single model that minimizes the following objective function.

\[
\argmin_{\theta \in \mathbb{R}^d} \frac{1}{N} \sum_{i=1}^{N} f_i(\theta),
\]

where \( f_i(\theta) = \mathbb{E}_{z \sim D_i}[f_i(\theta, z)] \) is the loss function of the \( i \)-th client. Note that clients may have heterogeneous data distributions, but communication of training data between clients and the central server is strictly prohibited due to privacy concerns. All the basic notations throughout this paper are listed in Tab. 1.
3.2. FedAvg algorithm

A standard algorithm for solving federated learning tasks is FedAvg [21], as described by the pseudo-code in Algorithm 1. Specifically, a central server sends a common model \( \theta \) to the clients. Each client performs several steps of gradient descent to minimize its local loss function then returns the resultant model parameters \( \theta^t_{i,K} \). A new common model for the next round training is constructed by averaging the models sent by all participants in the current round.

While the property of taking multiple local updates in FedAvg before aggregation cuts down the communication cost required for training, in practice, this property leads to the so-called client drift [11] issue, where the individual client updates do not align well due to over-fitting on the local client data. This phenomenon inhibits FedAvg from converging to the optimum of the average loss over all clients.

4. FedAGM

This section first describes FedAGM algorithm and discuss how it solves the problem of client heterogeneity. Then we show that FedAGM is desirable for the real-world federated learning settings.

4.1. Acceleration of global momentum

To reduce the gap between the local and global objective function, our main idea is to incorporate global gradient information into local updates by accelerating the current model with global momentum.

The Pseudo-code for our proposed method, FedAGM, is shown in Algorithm 2. In each round \( t \in \{0, 1, \ldots, T \} \), the central server quantifies the server update direction \( \Delta^t = - (\theta^t - \theta^t-1) \), and broadcasts the accelerated global model \( \theta^t - \lambda \Delta^t \) to the currently active clients \( S_t \). Starting with the integrated model as an initial point, each participating client optimizes a local objective function. The local objective function is defined as the sum of its local empirical loss function and a penalized loss function which is based on

| Symbol | Description |
|--------|-------------|
| \( N \) | total number of clients |
| \( T \) | total number of communication rounds |
| \( S_t \) | sampled number of clients in round \( t \) |
| \( K \) | total number of local iterations |
| \( i \) | client index |
| \( D_i \) | data distribution of \( i \)th client |
| \( \theta^t \) | shared model parameters in round \( t \) |
| \( \theta^t_{i,k} \) | local model of \( i \)th client in round \( t \) and step \( k \) |

**Algorithm 1 FedAvg**

**Input:** \( \theta^0 \), number of clients \( N \), number of local iterations \( K \), number of communication rounds \( T \)

for each round \( t = 0, \ldots, T \) do

| Sample subset of clients \( S_t \subseteq \{1, \ldots, N\} \) |
| Server sends \( \theta^t \) to all clients \( i \in S_t \) |
| for each client \( i \in S_t \), in parallel do |
| \( \argmin_{\theta^t_{i,k}} f_i(\theta^t_{i,k}) \) |
| Client sends \( \theta^t_{i,K} \) back to the server |

In server:

\[
\theta^{t+1} = \frac{1}{|S_t|} \sum_{i \in S_t} \theta^t_{i,K}
\]

end

Return \( \theta^{t+1} \)

the local online model and the received server model:

\[
\argmin_{\theta^t_{i,K}} L_i(\theta^t_{i,K}) = \alpha f_i(\theta^t_{i,K}) + \frac{\beta}{2} \| \theta^t_{i,K} - \theta^t - \lambda \Delta^t \|^2, \quad (2)
\]

where \( \alpha \) and \( \beta \) control the relative importance of individual terms. After \( K \) local updates, each client uploads their trained model \( \theta^t_{i,K} \) to the server, and then the server constructs the next server model \( \theta^{t+1} \) as shown in Algorithm 2.

Since we define the server model update direction as \( \Delta^{t+1} = - (\theta^{t+1} - \theta^t) \), the following Lemma 4.1 holds.

**Lemma 4.1.** Let the averaged client’s amount of local updates be \( \nabla(\theta^t) = \frac{1}{|S_t|} \sum_{i \in S_t} \Delta^t \). Then \( \Delta^t \) is the exponential moving average of \( \nabla(\theta^t) \), i.e.

\[
\Delta^{t+1} = \tau \nabla(\theta^t) + \lambda \Delta^t.
\]

**Proof.**

\[
\begin{align*}
\Delta^{t+1} &= - (\theta^{t+1} - \theta^t) \\
&= - \tau \sum_{i \in S_t} (\theta^t_{i,K} - (1 - \tau)(\theta^t - \lambda \Delta^t) + \theta^t) \\
&= - \frac{\tau}{|S_t|} \sum_{i \in S_t} (\theta^t_{i,K} - (1 - \tau)(\theta^t - \lambda \Delta^t)) + \lambda \Delta^t \\
&= \tau \nabla(\theta^t) + \lambda \Delta^t
\end{align*}
\]

Lemma 4.1 implies that \( \Delta^t \) is an exponential moving average of the total local updates computed at the projected point with the decay coefficient \( \lambda \) and server learning rate \( \tau \). Although only a subset of clients participates in each communication round, \( \Delta^t \) maintains past global gradient information, which serves as an approximation to the gradient of the global loss function \( f(\theta) \).

Therefore, we can view integrating \( \lambda \Delta^t \) to the global model \( \theta^t \) at server-to-client transmission as taking a look-ahead through the interim parameters where the accumulated
global velocity will lead the global model. This anticipatory update in client side leads each client to find a local minima adjacent to the trajectory of the global gradients, which helps FedAGM avoid inconsistent local updates.

4.2. Local regularization with global momentum

In addition to the initial point acceleration for local training, our proposed local objective function in Eq. (2) also takes advantage of the global gradient information to further align the gradients of individual clients. In detail, due to the regularization term in the local objective function, the local update direction is as follows:

\[
\nabla L_i(\theta_{i,k}^t) = \alpha \nabla f_i(\theta_{i,k}^t) + \beta (\theta_{i,k}^t - (\theta^t - \lambda \Delta^t)) \\
= \alpha \nabla f_i(\theta_{i,k}^t) + \beta \lambda \Delta^t + \beta (\theta_{i,k}^t - \theta^t) \\
\approx (\alpha + \beta \lambda) \nabla f_i(\theta_{i,k}^t) + \beta \lambda (\nabla f(\theta) - \nabla f(\theta_{i,k}^t)) \\
+ \beta (\theta_{i,k}^t - \theta^t).
\]

This implies that FedAGM corrects the local gradient toward global gradient direction at every local gradient step, which also prevents each client from falling into its own biased minima.

4.3. Discussion

While our formulation is related to existing works which also handle client heterogeneity by employing global gradient information for the local update, FedAGM has the following major advantages. First, the server and clients only communicate model weights without imposing additional network overhead for transmitting gradients and other information [11, 30]. Note that the increase in communication cost challenges many realistic federated learning applications involving clients with limited network bandwidths. Also, FedAGM does not require the server to compute or maintain any historical information of the model, which leads to extra saving of computational cost in the server. Second, FedAGM is robust to the low-rate client participation situations and allows new-arriving clients to join the training process immediately without warmup because, unlike [1, 11, 16], the clients are not supposed to store their local states.

5. Experiments

This section presents empirical evaluations of FedAGM and competing federated learning methods, to highlight the robustness to data heterogeneity of the proposed method in terms of performance and communication-efficiency.

5.1. Experimental setup

Datasets and baselines We conduct a set of experiments on CIFAR-10, CIFAR-100, and Tiny-ImageNet\(^1\) with various data heterogeneity levels and participation rates. Note that Tiny-ImageNet (200 classes with 10,000 samples) is more natural and realistic compared to the simple datasets, such as MNIST and CIFAR, used for evaluation of many previous methods [11, 21]. We generate IID data split by randomly assigning training data to individual clients without replacement. For the non-IID data, we simulate the data heterogeneity by sampling the label ratios from a Dirichlet distribution with parameter \(\{0.3, 0.6\}\), following [8]. We keep the training data balanced, so each client holds the same amount of data.

We compare our method, FedAGM, with several state-of-the-art federated learning techniques, which include FedAvg [21], FedProx [17], FedAvgm [8], FedAdam [23], FedDyn [1], FedCM [30]. We adopt a standard ResNet-18 [6] as backbone network for all benchmarks, but we replace batch normalization by group normalization as suggested in [7].

Validation metrics To evaluate the generalization performance of the methods, we use the entire test set in the CIFIAR-10 [14], CIFAR-100 [14], and Tiny-ImageNet datasets. Since both the speed of learning as well as the final performance are important quantities for federated learning, we measure: (i) the performance attained at a specified number of rounds, and (ii) the number of rounds needed for an algorithm to attain the desired level of target accuracy, following [2]. For methods that could not achieve aimed accuracy within the maximum communication round, we append the communication round with a + sign. We also report the communication savings of FedAGM compared to

\(1\)https://www.kaggle.com/c/tiny-imagenet
Implementation details We use PyTorch [22] to implement FedAGM and the other baselines. We follow [1, 30] for evaluation protocol. For local update, we use the SGD optimizer with a learning rate 0.1 for all approaches on the three benchmarks. We apply exponential decay on the local learning rate, and the decay parameter is selected from \(\{1.0, 0.998, 0.995\}\). We apply no momentum for local SGD, but apply weight decay of 0.001 to prevent overfitting. We also use gradient clipping to increase the stability of the algorithms. The number of local training epochs over each client update is set to 5, and the batch size is set so that the total iteration for local updates is set to 50 for all experiments. We set the global learning rate as 1 for all methods except for FedADAM which is set to 0.01. We list the details of the hyperparameters specific to FedAGM and the baselines in the supplementary materials.

5.2. Evaluation on a moderate number of clients

We first present the performance of the proposed approach, FedAGM, on CIFAR-10, CIFAR-100, and Tiny-ImageNet in comparison to baseline methods for a moderate-scale federated learning setting. This setting has 100 devices while keeping the participation rate constant per round.

Tab. 2 provides a detailed comparison of FedAGM to the baselines in terms of the attained performance and the speed of learning on the three benchmark tasks. Tab. 2 shows that FedAGM outperforms competitive methods in most cases. In particular, FedAGM outperforms the momentum-based methods which incorporate momentum in either the server-side update (FedAvgM, FedAdam) or the client-side update (FedCM). This is partly because, in FedAGM, the accelerated global model enables each client to lookahead the global update trajectory and find local minima near the global gradient trajectory, which aligns client updates. Note that since FedCM requires twice the communication cost as the server transmits the current model the associated momentum at each server-to-client communication.

5.3. Evaluation on a large number of clients

To further validate the effectiveness of the proposed method in handling client heterogeneity, we perform experiments with a large number of clients, which are more realistic federated learning scenarios. In this setting, since the total number of clients is increased by 5 times compared to that of the previous experiments, the number of training
5% participation, 100 clients
(b) 2% participation, 500 clients
(c) 1% participation, 100 clients

Figure 1. The convergence plot of FedAGM and comparison methods on CIFAR-10 with different client heterogeneity.

5% participation, 100 clients
(b) 2% participation, 500 clients
(c) 1% participation, 100 clients

Figure 2. The convergence plot of FedAGM and comparison methods on CIFAR-100 with different client heterogeneity.

| Method           | accuracy (%) | rounds (#, ↓) |
|------------------|--------------|---------------|
| FedAvg [21]      | 64.54        | 1000+ (> 1.43×) |
| FedProx [17]     | 65.47        | 1000+ (> 1.43×) |
| FedAvm [8]       | 63.73        | 1000+ (> 1.43×) |
| FedAdam [23]     | 69.29        | 1000+ (> 1.43×) |
| FedDyn [1]       | 72.18        | 854 (1.22×)   |
| FedCM [30]       | 55.03        | 1000+ (> 1.43×) |
| FedAGM (ours)    | 76.72        | 696           |

Table 4. Comparison of FedAGM with baselines on CIFAR-10 for more limited participation rate (1%). The number of clients, and Dirichlet parameter is set to 100, and 0.3, respectively.

5% participation, 100 clients
(b) 2% participation, 500 clients
(c) 1% participation, 100 clients

Figure 1. The convergence plot of FedAGM and comparison methods on CIFAR-10 with different client heterogeneity.

| Method           | accuracy (%) | rounds (#, ↓) |
|------------------|--------------|---------------|
| FedAvg [21]      | 40.44        | 994 (1.30×)   |
| FedProx [17]     | 40.16        | 995 (1.30×)   |
| FedAvm [8]       | 36.30        | 1000+ (> 1.30×) |
| FedAdam [23]     | 18.02        | 1000+ (> 1.30×) |
| FedDyn [1]       | 42.64        | 849 (1.11)    |
| FedCM [30]       | 27.16        | 1000+ (> 1.30×) |
| FedAGM (ours)    | 45.15        | 768           |

Table 5. Comparison of FedAGM with baselines on CIFAR-100 for more limited participation rate (1%). The number of clients, and Dirichlet parameter is set to 100, and 0.3, respectively.

Tab. 3 shows the result of FedAGM and other methods on CIFAR-10 and CIFAR-100. We first observe that the overall performance of all algorithms is lower than those with a moderate number of clients. This is because, as the number of training data for each client decreases, each client is more likely to fall into its distinct local optimum, which intensifies client drift. For instance, it takes FedAGM 450 rounds to achieve 84% with 100 devices, while it takes 519 rounds to achieve 77% with 500 devices. A similar trend is observed for CIFAR-100 and other methods. Nevertheless, we can observe that FedAGM outperforms the compared methods consistently on all benchmarks in terms of accuracy and communication efficiency. This is partly because that FedAGM effectively aligns the gradients of the server and the individual clients.

5.4. Evaluation on the low participation rate

To validate the robustness to partial participation nature of federated learning, we simulate an extremely constrained federated learning scenario, with a very low participation level (1%) on 100 clients. Tabs. 4 and 5 show the results of FedAGM and competitive methods on CIFAR-10 and CIFAR-100, respectively.

Although the overall accuracy at 1000 rounds is degraded for all methods due to the limited participants per round, the proposed algorithm outperforms all comparison methods on all datasets in terms of both generalization performance and communication efficiency. Performance gaps between FedAGM and baselines are much larger than the...
Table 6. Comparison of FedAGM with baselines on CIFAR-10 with 100 clients of Dirichlet 0.6 split on 10%, 5%, and 1% client participation. The arrows indicate whether higher (↑) or lower (↓) is better. The best performance in each column is denoted in **bold**.

| Method      | Participation rate | 10% accuracy (%) | rounds (#, ↓) | 5% accuracy (%) | rounds (#, ↓) | 1% accuracy (%) | rounds (#, ↓) |
|-------------|--------------------|------------------|---------------|-----------------|---------------|-----------------|---------------|
|             | 500R               | 1000R            | 500R          | 1000R           | 500R          | 1000R          |
| FedAvg [21] |                    |                  | 83.09↑         | 87.15↑         | 80.56↑         | 85.97↑         | 62.84↑         | 76.92↑         | 767↑ | 943↑ |
| FedProx [17]|                    |                  | 83.22↑         | 87.33↑         | 80.39↑         | 85.53↑         | 61.27↑         | 75.16↑         | 780↑ | 994↑ |
| FedAvgm [8] |                    |                  | 86.58↑         | 89.70↑         | 84.65↑         | 87.96↑         | 62.67↑         | 75.05↑         | 804↑ | 998↑ |
| FedAdam [23]|                    |                  | 84.97↑         | 87.59↑         | 80.25↑         | 83.52↑         | 60.32↑         | 75.16↑         | 828↑ | 952↑ |
| FedDyn [1]  |                    |                  | 89.98↑         | 90.78↑         | 80.10↑         | 86.47↑         | 67.50↑         | 79.57↑         | 580↑ | 661↑ |
| FedCM [30]  |                    |                  | 87.50↑         | 89.29↑         | 82.84↑         | 86.64↑         | 42.57↑         | 53.75↑         | 1000+ | 1000+ |
| FedAGM (ours)|                   |                  | **89.24↑**     | **91.10↑**     | **87.57↑**     | **90.56↑**     | **73.59↑**     | **81.50↑**     | **463↑** | **584↑** |

Table 7. Comparison of FedAGM with baselines on CIFAR-10 with 100 clients of IID split on 10%, 5%, and 1% client participation. The arrows indicate whether higher (↑) or lower (↓) is better. The best performance in each column is denoted in **bold**.

| Method      | Participation rate | 10% accuracy (%) | rounds (#, ↓) | 5% accuracy (%) | rounds (#, ↓) | 1% accuracy (%) | rounds (#, ↓) |
|-------------|--------------------|------------------|---------------|-----------------|---------------|-----------------|---------------|
|             | 500R               | 1000R            | 500R          | 1000R           | 500R          | 1000R          |
| FedAvg [21] |                    |                  | 86.83↑         | 89.84↑         | 85.28↑         | 88.69↑         | 77.03↑         | 83.06↑         | 724↑ | 1000+ |
| FedProx [17]|                    |                  | 86.93↑         | 89.71↑         | 84.79↑         | 87.99↑         | 79.2↑          | 86.13↑         | 645↑ | 977↑ |
| FedAvgm [8] |                    |                  | 88.51↑         | 90.23↑         | 87.67↑         | 89.96↑         | 79.09↑         | 85.79↑         | 685↑ | 1000+ |
| FedAdam [23]|                    |                  | 89.05↑         | 90.87↑         | 85.29↑         | 87.97↑         | 70.78↑         | 83.01↑         | 912↑ | 1000+ |
| FedDyn [1]  |                    |                  | **91.57↑**     | **91.98↑**     | **88.41↑**     | **89.91↑**     | **76.49↑**     | **84.79↑**     | **747↑** | **1000+** |
| FedCM [30]  |                    |                  | 89.93↑         | 91.18↑         | 87.38↑         | 89.65↑         | 69.99↑         | 76.19↑         | 1000+ | 1000+ |
| FedAGM (ours)|                   |                  | **91.08↑**     | **92.26↑**     | **90.57↑**     | **92.29↑**     | **81.05↑**     | **87.01↑**     | **536↑** | **892↑** |

5.5. Convergence plots

Convergence plots of FedAGM and competing baselines on CIFAR-10 and CIFAR-100 under various settings are provided in Figs. 1 and 2. We observe that FedAGM outperforms other strong baselines across different participation rates and heterogeneity levels. Note that, the performance gap between FedCM and baselines is larger in 1% participation and 100 devices. This also validates our claim that the proposed method is robust to the low participation property of federated learning.

5.6. Evaluation on less heterogeneous setting

Tabs. 6 to 9 show that FedAGM matches or outperforms the performance of competitive methods when data heterogeneity is not severe (Dirichlet 0.6) or absent (IID) in most cases. Note that, while the compared methods show performance degradation as the participation rate decreases, FedAGM shows little degradation as the participation rate decreases for both benchmarks. This implies that FedAGM is more robust for low participation rates than other baselines. This is partly because low client heterogeneity reduces noise in the momentum of global gradient, which attributes to the smooth trajectory of global update. Since FedAGM effectively incorporates the momentum for local updates, FedAGM is relatively unaffected by the partial participation of federated learning.

5.7. Ablation study

**Sensitivity to decay coefficient λ** As shown in our Algorithm 2, λ controls how much the server projects the current model toward the global gradient to initialize the local update. To analyze the effect of λ on the performance of FedAGM algorithms, we evaluate the generalization performance of FedAGM after 1000 rounds varying λ as {0.75, 0.8, 0.85, 0.9, 0.95} on CIFAR-10 with 500 clients of different data splits on 2% participation. Tab. 10 shows that FedAGM converges well for all the selection of λ while there is little performance drop when λ is set to 0.95. We note that selecting too large λ will harm the performance of FedAGM since large acceleration toward momentum can impose oscillation for the global optimization procedure.
Table 8. Comparison of FedAGM with baselines on CIFAR-100 with 100 clients of Dirichlet 0.6 split on 10%, 5%, and 1% client participation. The arrows indicate whether higher (↑) or lower (↓) is better. The best performance in each column is denoted in **bold**.

| Method          | Participation rate |
|-----------------|-------------------|
|                 | 10%   | 5%    | 1%    |
|                 | accuracy (%) | rounds (#) | accuracy (%) | rounds (#) | accuracy (%) | rounds (#) |
| FedAvg [21]     | 50.02  | 1000+ | 39.18  | 1000+  | 29.98       | 1000+     |
| FedProx [17]    | 49.24  | 1000+ | 48.45  | 1000+  | 27.77       | 1000+     |
| FedAvgm [8]     | 51.80  | 1000+ | 52.49  | 1000+  | 28.41       | 1000+     |
| FedAdam [23]    | 58.82  | 355   | 51.63  | 880    | 39.07       | 578       |
| FedDyn [1]      | 62.68  | 506   | 59.70  | 1000+  | 35.92       | 1000+     |
| FedCM [30]      | 58.33  | 377   | 60.48  | 511    | 19.77       | 1000+     |
| FedAGM (ours)   | 58.21  | 397   | 62.60  | 595    | 58.82       | 471       |

Table 9. Comparison of FedAGM with baselines on CIFAR-100 with 100 clients of IID split on 10%, 5%, and 1% client participation. The arrows indicate whether higher (↑) or lower (↓) is better. The best performance in each column is denoted in **bold**.

| Method          | Participation rate |
|-----------------|-------------------|
|                 | 10%   | 5%    | 1%    |
|                 | accuracy (%) | rounds (#) | accuracy (%) | rounds (#) | accuracy (%) | rounds (#) |
| FedAvg [21]     | 50.37  | 1000+ | 48.01  | 1000+  | 35.92       | 1000+     |
| FedProx [17]    | 49.16  | 1000+ | 47.23  | 1000+  | 36.50       | 1000+     |
| FedAvgm [8]     | 51.48  | 1000+ | 52.83  | 880    | 39.07       | 578       |
| FedAdam [23]    | 60.08  | 545   | 57.73  | 496    | 25.84       | 1000+     |
| FedDyn [1]      | 63.78  | 531   | 60.48  | 511    | 19.77       | 1000+     |
| FedCM [30]      | 59.50  | 200   | 59.50  | 200    | 58.23       | 471       |
| FedAGM (ours)   | 63.50  | 321   | 62.48  | 325    | 58.82       | 431       |

Table 10. λ sensitivity of FedAGM for test accuracy at 1000 rounds on CIFAR-10 with large number of clients.

| Method          | λ   | 0.75 | 0.8 | 0.85 | 0.9 | 0.95 |
|-----------------|-----|-----|-----|-----|-----|-----|
| Dirichlet (0.3) | 58.12 | 81.32 | 82.52 | 82.80 | 81.82 | 78.25 |
| Dirichlet (0.6) | 83.97 | 84.89 | 85.28 | 84.56 | 82.07 |
| IID             | 85.52 | 86.92 | 86.83 | 87.08 | 84.37 |

Table 11. Effect of regularization at local objective function on CIFAR-100. 'P' and 'C' denotes participation rate and number of clients, respectively.

| P / C Method | accuracy (%) | rounds (#) |
|--------------|--------------|-------------|
| 5% / 100     | β = 0        | 59.50       | 200         |
|              | β ≠ 0        | 62.51       | 197         |
| 1% / 100     | β = 0        | 42.95       | 914         |
|              | β ≠ 0        | 45.15       | 895         |
| 2% / 500     | β = 0        | 46.80       | 736         |
|              | β ≠ 0        | 48.40       | 678         |

Despite this, the proposed method still outperforms most existing algorithms.

Effect of adding regularization on local objective function To analyze the effect of incorporating the regularization term in the local objective function, we compare the performance by setting β = 0 and β ≠ 0 on CIFAR-100.

Tab. 11 shows that FedAGM with the regularization term achieves better performance in terms of convergence rate and accuracy for all levels of participation. This implies that correcting local gradients for every local update helps to mitigate inconsistent local updates between clients.

6. Conclusion

This paper tackles a realistic federated learning scenario, where a large number of clients with heterogeneous data and limited participation constraints hurt the convergence and performance of the model. To address this problem, we proposed a novel federated learning framework, which naturally aggregates previous global gradient information and incorporates it to guide client updates. The proposed algorithm transmits the global gradient information to clients without additional communication cost by simply adding the global information to the current model when broadcasting it to clients. We showed that the proposed method is desirable with the realistic federated learning scenarios since it does not require any constraints such as communication or memory overhead. We demonstrate the effectiveness of the proposed method in terms of robustness and communication-efficiency in the presence of client heterogeneity through extensive evaluation on multiple benchmarks.
References

[1] Durmus Alp Emre Acar, Yue Zhao, Ramon Matas, Matthew Mattina, Paul Whatmough, and Venkatesh Saligrama. Federated learning based on dynamic regularization. In ICLR, 2021. 2, 4, 5, 6, 7, 8, 11

[2] Maruan Al-Shedivat, Jennifer Gillenwater, Eric Xing, and Afshin Rostamizadeh. Federated learning via posterior averaging: A new perspective and practical algorithms. In ICLR, 2021. 2, 4

[3] Debraj Basu, Deepesh Data, Can Karakus, and Suhas N Digvai. Qsparse-local-sgd: Distributed sgd with quantization, sparsification, and local computations. IEEE Journal on Selected Areas in Information Theory, 1(1):217–226, 2020. 1

[4] Ashok Cutkosky and Francesco Orabona. Momentum-based variance reduction in non-convex sgd. In NeurIPS, 2019. 2

[5] Rudrajit Das, Anish Acharya, Abolfazl Hashemi, Sujay Sanghavi, Inderjit S Dhillon, and Ufuk Topcu. Faster non-convex federated learning via global and local momentum. arXiv preprint arXiv:2012.04061, 2020. 2

[6] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In CVPR, 2016. 4

[7] Kevin Hsieh, Amar Phanishayee, Onur Mutlu, and Phillip Gibbons. The non-iid data quagmire of decentralized machine learning. In ICML, 2020. 1, 2, 4

[8] Tzu-Ming Harry Hsu, Hang Qi, and Matthew Brown. Measuring the effects of non-identical data distribution for federated visual classification. arXiv preprint arXiv:1909.06335, 2019. 2, 4, 5, 6, 7, 8, 11

[9] Peter Kairouz, H Brendan McMahan, Brendan Avent, Aurélien Bellet, Mehdi Bennis, Arjun Nitin Bhagoji, Kallista Bonawitz, Zachary Charles, Graham Cormode, Rachel Cummings, et al. Advances and open problems in federated learning. arXiv preprint arXiv:1912.04977, 2019. 1

[10] Sai Praneeth Karimireddy, Martin Jaggi, Satyen Kale, Mehryar Mohri, Sashank J Reddi, Sebastian U Stich, and Ananda Theertha Suresh. Mime: Mimicking centralized stochastic algorithms in federated learning. 2020. 2

[11] Sai Praneeth Karimireddy, Satyen Kale, Mehryar Mohri, Sashank J Reddi, Sebastian U Stich, and Ananda Theertha Suresh. Scaffold: Stochastic controlled averaging for on-device federated learning. In ICML, 2020. 1, 2, 3, 4

[12] Ahmed Khaled, Konstantin Mishchenko, and Peter Richtárik. First analysis of local gd on heterogeneous data. arXiv preprint arXiv:1909.04715, 2019. 1, 2

[13] Prashant Khanduri, Pranay Sharma, Haibo Yang, Mingyi Hong, Jia Liu, Ketan Rajawat, and Pramod K Varshney. Stem: A stochastic two-sided momentum algorithm achieving near-optimal sample and communication complexities for federated learning. In NeurIPS, 2021. 2

[14] Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009. 4

[15] Ya Le and Xuan Yang. Tiny imagenet visual recognition challenge. CS 231N, 7(7):3, 2015. 4

[16] Qinbin Li, Bingsheng He, and Dawn Song. Model-contrastive federated learning. In CVPR, 2021. 2, 4

[17] Tian Li, Anit Kumar Sahu, Manzil Zaheer, Maziar Sanjabi, Ameet Talwalkar, and Virginia Smith. Federated optimization in heterogeneous networks. In MLSys, 2020. 1, 2, 4, 5, 6, 7, 8, 11

[18] Tian Li, Anit Kumar Sahu, Manzil Zaheer, Maziar Sanjabi, Ameet Talwalkar, and Virginia Smithy. Feddane: A federated newton-type method. In ACSCC, 2019. 2

[19] Xiang Li, Kaixuan Huang, Wenhao Yang, Shusen Wang, and Zhihua Zhang. On the convergence of fedavg on non-iid data. arXiv preprint arXiv:1907.02189, 2019. 1, 2

[20] Xianfeng Liang, Shuheng Shen, Jingcheng Liu, Zhen Pan, Enhong Chen, and Yifei Cheng. Variance reduced local sgd with lower communication complexity. 2019. 2

[21] Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguerre y Arcas. Communication-efficient learning of deep networks from decentralized data. In AISTATS, 2017. 1, 2, 3, 4, 5, 6, 7, 8, 11

[22] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, high-performance deep learning library. 2019. 5

[23] Sashank J Reddi, Zachary Charles, Manzil Zaheer, Zachary Garrett, Keith Rush, Jakub Konečnỳ, Sanjiv Kumar, and Hugh Brendan McMahan. Adaptive federated optimization. In ICLR, 2021. 2, 4, 5, 6, 7, 8, 11

[24] Sebastian U Stich. Local sgd converges fast and communicates little. In ICLR, 2019. 1

[25] Sebastian U Stich and Sai Praneeth Karimireddy. The error-feedback framework: Better rates for sgd with delayed gradients and compressed communication. arXiv preprint arXiv:1909.05350, 2019. 1

[26] Jianyu Wang and Gauri Joshi. Cooperative sgd: A unified framework for the design and analysis of local-update sgd algorithms. Journal of Machine Learning Research, 22(213):1–50, 2021. 1

[27] Jianyu Wang, Qinghua Liu, Hao Liang, Gauri Joshi, and H VincentPoor. Tackling the objective inconsistency problem in heterogeneous federated optimization. arXiv preprint arXiv:2007.07481, 2020. 1, 2

[28] Jianyu Wang, Vinayak Tantia, Nicolas Ballas, and Michael Rabbat. Slowmo: Improving communication-efficient distributed sgd with slow momentum. In ICLR, 2019. 2

[29] Shiqiang Wang, Tiffany Tuor, Theodoros Salonidis, Kin K Leung, Christian Makaya, Ting He, and Kevin Chan. Adaptive federated learning in resource constrained edge computing systems. IEEE Journal on Selected Areas in Communications, 37(6):1205–1221, 2019. 1, 2

[30] Jing Xu, Sen Wang, Liwei Wang, and Andrew Chi-Chih Yao. Fedcm: Federated learning with client-level momentum. arXiv preprint arXiv:2106.10874, 2021. 2, 4, 5, 6, 7, 8, 11

[31] Zhengjie Yang, Wei Bao, Dong Yuan, Nguyen H Tran, and Albert Y Zomaya. Federated learning with nesterov accelerated gradient momentum method. 2020. 2

[32] Tehrim Yoon, Sumin Shin, Sung Ju Hwang, and Eunjoo Yang. Fedmix: Approximation of mixup under mean augmented federated learning. 2021. 2
[33] Hao Yu, Sen Yang, and Shenghuo Zhu. Parallel restarted sgd with faster convergence and less communication: Demystifying why model averaging works for deep learning. In AAAI, 2019. 1

[34] Xinwei Zhang, Mingyi Hong, Sairaj Dhople, Wotao Yin, and Yang Liu. Fedpd: A federated learning framework with optimal rates and adaptivity to non-iid data. In arXiv preprint arXiv:2005.11418, 2020. 2

[35] Yue Zhao, Meng Li, Liangzhen Lai, Naveen Suda, Damon Civin, and Vikas Chandra. Federated learning with non-iid data. arXiv preprint arXiv:1806.00582, 2018. 1, 2

[36] Zhuangdi Zhu, Junyuan Hong, and Jiayu Zhou. Data-free knowledge distillation for heterogeneous federated learning. In ICML, 2021. 2
A. Evaluation on Low Participation Rate with a Large Number of Clients

The low participation rate and the large number of clients are factors that make the convergence of federated learning difficult. To show the robustness to client heterogeneity and participation rates, we perform experiments when both factors are present, that is when the total number of clients is 500 and the participation rate is 1%. Local epochs and local iterations are set to 5 and 50, respectively. Note that this setting makes each client have a very small number of training examples and increases client heterogeneity significantly. Tab. 12 again shows that FedAGM has the best performance on all metrics. Note that the performance gap between FedAGM and its strongest competitor, FedDyn, becomes larger than when the participation rate is 2%: from 1.37%p to 1.68%p in CIFAR 10 and from 3.39%p to 4.76%p in CIFAR 100 at round 1000.

### Table 12. Comparison of federated learning methods on CIFAR-10 and CIFAR-100 with the large number of clients (500): Dirichlet (0.3) split on low client participation (1%). Accuracy at the target round and the communication round to reach target test accuracy are based on running exponential moving average with parameter 0.9. The arrows indicate whether higher (↑) or lower (↓) is better. The best performance in each column is denoted by **bold**.

| Method         | CIFAR-10 | CIFAR-100 |
|----------------|----------|-----------|
|                | accuracy (%) | rounds (#) | accuracy (%) | rounds (#) |
|                | 500R | 1000R | 500R | 1000R | 500R | 1000R | 500R | 1000R |
| FedAvg [21]    | 54.71 | 68.96 | 792 | 949 | 26.94 | 35.69 | 636 | 930 |
| FedProx [17]   | 55.18 | 69.80 | 773 | 919 | 26.92 | 35.41 | 648 | 963 |
| FedAvgm [8]    | 57.82 | 71.12 | 669 | 812 | 29.29 | 39.36 | 530 | 755 |
| FedAdam [23]   | 47.97 | 55.11 | 1000+ | 1000+ | 17.72 | 23.92 | 1000+ | 1000+ |
| FedDyn [1]     | 58.28 | 74.77 | 621 | 752 | 29.68 | 40.42 | 512 | 703 |
| FedCM [30]     | 49.21 | 60.38 | 1000+ | 1000+ | 16.32 | 22.59 | 1000+ | 1000+ |
| FedAGM (ours)  | **63.70** | **76.45** | **509** | **618** | **31.74** | **45.18** | **458** | **581** |

B. Effect of More Local Iterations

The increase of local iterations under non-iid environments is prone to result in more divergence across client models and degraded performance of an algorithm. We evaluate the accuracy and communication-efficiency of the proposed method with aggravated client heterogeneity by varying the number of local iterations, i.e., \( K \in \{50, 70, 100\} \), on CIFAR-100. In this experiments, the number of clients, participation rate, and Dirichlet parameter is set to 100, 5% and 0.3, respectively. Tab. 13 presents that FedAGM outperforms the compared methods consistently for all cases in terms of accuracy and communication efficiency.

### Table 13. Comparison of federated learning methods with three different local iterations on CIFAR-100: Dirichlet (0.3) split on 5% client participation out of 100 clients. Accuracy at the target round and the communication round to reach target test accuracy are based on running exponential moving average with parameter 0.9. The arrows indicate whether higher (↑) or lower (↓) is better. The best performance in each column is denoted in **bold**.

| Local iterations | \( K = 50 \) | \( K = 70 \) | \( K = 100 \) |
|-----------------|----------------|----------------|----------------|
| Methods         | accuracy (%) | rounds (#) | accuracy (%) | rounds (#) | accuracy (%) | rounds (#) |
|                 | 500R | 1000R | 47% | 53% | 500R | 1000R | 47% | 53% | 500R | 1000R | 47% | 53% |
| FedAvg [21]     | 41.88 | 47.83 | 924 | 1000+ | 42.45 | 48.29 | 852 | 1000+ | 41.92 | 48.16 | 896 | 1000+ |
| FedProx [17]    | 42.43 | 48.32 | 881 | 1000+ | 43.31 | 49.54 | 752 | 1000+ | 42.01 | 48.17 | 888 | 1000+ |
| FedAvgm [8]     | 46.98 | 53.29 | 515 | 936 | 46.17 | 52.34 | 544 | 1000+ | 45.72 | 52.74 | 578 | 1000+ |
| FedAdam [23]    | 44.80 | 52.48 | 691 | 1000+ | 43.76 | 49.19 | 756 | 1000+ | 43.00 | 47.51 | 994 | 1000+ |
| FedDyn [1]      | 52.66 | 58.46 | 293 | 504 | 52.85 | 59.98 | 326 | 509 | 51.98 | 59.13 | 347 | 532 |
| FedCM [30]      | 52.44 | 58.06 | 293 | 572 | 48.30 | 54.89 | 467 | 812 | 46.90 | 54.20 | 502 | 893 |
| FedAGM (ours)   | **55.79** | **62.51** | **260** | **389** | **54.23** | **61.23** | **295** | **459** | **54.71** | **63.12** | **284** | **461** |

B.1. Convergence plot on Tiny-ImageNet

To validate the performance of the proposed method on a more realistic dataset, we compare FedAGM with the baselines on Tiny-ImageNet in the two federated settings: one with 100 total clients and 5% client participation, and the other with 500 clients and 2% client participation. In both settings, local epochs and local iterations are set to 5 and 50 respectively. Fig. 3
shows that FedAGM consistently outperforms the compared methods every communication rounds. Note that FedAGM shows a faster convergence rate, especially at the early stage of training, than other algorithms.

Figure 3. The convergence plot of FedAGM and the compared methods on Tiny-ImageNet with the different levels of client heterogeneity.