FAST-CONVERGENT FEDERATED LEARNING VIA CYCLIC AGGREGATION

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ABSTRACT

Federated learning (FL) aims at optimizing a shared global model over multiple edge devices without transmitting (private) data to the central server. While it is theoretically well-known that FL yields an optimal model – centrally trained model assuming availability of all the edge device data at the central server – under mild condition, in practice, it often requires massive amount of iterations until convergence, especially under presence of statistical/computational heterogeneity. This paper utilizes *cyclic learning rate* at the server side to reduce the number of training iterations with increased performance without any additional computational costs for both the server and the edge devices. Numerical results validate that, simply plugging-in the proposed cyclic aggregation to the existing FL algorithms effectively reduces the number of training iterations with improved performance.

Index Terms— machine learning, distributed learning, federated learning, edge computing, privacy-preserved, cyclic learning rate

1. INTRODUCTION

Given sufficient data from multiple sources, deep learning [1] outperforms conventional model-based approaches as it can approximate any underlying function with deep neural networks via data-driven approach [2]. While the strength of deep learning comes at the cost of massive amount of data [2], in many real-world scenarios, such data are often not shared to the central server, due to privacy issues [3, 4]. Federated learning (FL) [5] mitigates this problem via asking for updated *models* at the edge device side instead of their data sets. By aggregating locally updated models obtained from the edge devices, FL achieves the same performance to that of central learning which assumes availability of the whole local devices' data [6].

However, in practice, FL requires sufficient amount of communication rounds between the central server and the edge devices in order to reach the desired performance level



Fig. 1: Illustration of FL in statistical/computational heterogeneous environment: Statistical heterogeneity comes from non i.i.d. data samples for each edge device, and computational heterogeneity stems from different computing power per device.

[7]. This becomes more severe when the edge devices' data are generated in a non-iid manner [8], and/or when the computational power varies across different edge devices [9]. Such statistical/computational heterogeneity often *drifts* the local models towards their local minima to harm the aggregation performance at the server side that generally degrades the performance [10] and increase the number of communication rounds to converge [11].

Recently, several studies have alleviate such *client-drift* phenomenon by improving the local client training process [12, 13, 14]. By considering proximal regularization [12], adding contrastive loss term [13], or applying restricted-softmax function [14] during local training, client-drift has been successfully alleviated at the cost of increased complexity at the client side. In this paper, we mitigate client-drift in heterogeneous FL *without* any additional cost either at the client or the server side. Key idea is to improve the generalization performance of the aggregated model at the server side by applying cyclic learning rate [15] that varies across communication rounds.

From the initial proposal of cyclic learning rate [15] that changes the learning rate periodically during training iterations, it has been widely applied as a means to achieve improved performance with reduced learning time [16], [17],

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yet general from of proof is still an open problem [18]. To the best of authors' knowledge, this paper is first to apply cyclic learning rate during aggregation at the server side for FL to speed up FL process in heterogeneous environment.

Main contributions of this paper are as follows:

- We propose cyclic learning rate during aggregation at the server side, referred to as *cyclic aggregation*, that can be applied to most of the existing FL schemes.
- Cyclic aggregation enables fast convergent and increased performance without additional computational costs.
- By applying cyclic aggregation to state-of-the-art FL schemes, e.g., FedAvg [5], FedProx [12], MOON [13], and FedRS [14], we numerically show that the proposed approach effectively reduces the training time with increased performance on MNIST [19], FMNIST [20], CIFAR-10 [11], and SVHN [21] dataset in the presense of *label skew* [14].

2. MODEL AND PROBLEM

The proposed FL framework aided by cyclic learning rate [15] consists of the following steps, which are repeated until convergence (see Fig. 2):

- **Broadcast:** The central server samples *M* edge devices randomly and transmit the global model to all edge devices.
- **Update:** Randomly selected edge devices update the shared global model and transmit the locally updated model to the central server.
- Cyclic Aggregation: The central server aggregate the transmitted models by multiplying cyclic server learning rate.

Note that conventional FL treats the server learning rate to be a fixed value [10].

2.1. Federated heterogeneous setting

In this section, we describe mathematical objective of FL and introduce standard FL technique, FedAvg [5]. As depicted in Fig. 1, we assume N edge devices constitute the federated heterogeneous network, communicating through the central server. Each edge device n = 1, ..., N holds private dataset \mathcal{D}^n with different number of data points. Furthermore, the edge devices have a wide variety of computational capabilities, which affects the number of iterations for local update. The standard goal of FL is to optimize a shared global model $\theta \in \Theta$ among model parameter space Θ without sharing the entire edge devices' dataset $\mathcal{D} = \bigcup_{n=1}^{N} \mathcal{D}^n$ to the central server. Accordingly, the training



Fig. 2: Comparison between the cyclic aggregation (Top) and fixed aggregation (Bottom) during FL at each . Solid black arrows denote "broadcast" and black dotted line denote "update". "local training" is described by circled arrow. Solid green and blue arrows denote the cyclic and fixed aggregation respectively.

objective of FL is to jointly solve the optimization problem $\min_{\theta \in \Theta} F(\theta) \triangleq \frac{1}{N} \sum_{n=1}^{N} F_n(\theta)$, where $F(\theta)$ is the global objective function at the central server, and the local objective function for the n^{th} edge device $F_n(\theta)$ is defined as $F_n(\theta) = \frac{1}{|\mathcal{D}^n|} \sum_{x \in \mathcal{D}^n} f_n(\theta; x)$, where $f_n(\theta; x)$ denotes loss function of the learning model and x represents the data sampled from the local dataset D^n . For $i \neq j$, the data distribution of D^i and D^j may be quite different.

2.2. Concept of cyclic server learning rate γ_{cyclic}

The cyclic server learning rate concept is based on [15] that allows increase and decrease in the learning rate, which may bring some negative impact in short-term wise, but often results in a long-term positive benefit in centralized learning [17]. To this end, we propose to adjust server learning rate as

$$\gamma_{cyclic}(i_g) = \gamma_{fixed} - a\left(\frac{1}{2} - \frac{1}{\pi}\sum_{n=1}^{\infty} (-1)^n \frac{\sin(2\pi k f i_g)}{k}\right),\tag{1}$$

with predetermined amplitude a and frequency f that oscillates around fixed learning rate γ_{fixed} .

We now provide intuitive illustration why cyclic server learning rate (1) improves generalization performance with improved convergence speed. As mentioned in Sec. 1, mathematical proof of cyclic aggregation for FL is out of scope of this paper. In Fig. 3, we depict some loss landscape that corresponds to $F(\theta)$. According to [22], the difficulty of gradientbased optimization lies in the presence of saddle points. Compared to fixed learning rate (left of Fig. 3), cyclic learning rate (right of Fig. 3) enables to traverse local minima and saddle points [15] via dynamic gradient updates.



Fig. 3: Illustration of learning process with fixed learning rate γ_{fixed} and cyclic learning rate γ_{cyclic} . Fixed learning rate γ_{fixed} has a constant value (length of the arrow), while cyclic learning rate γ_{cyclic} changes its value cyclically for every iteration i_q .

2.3. Fast-convergent FL

In FL, the central server communicates with the edge devices for G global iterations to minimize $F(\theta)$. In this section, we describe the process of the proposed fast-convergent FL during one global iteration i_g . At first the central server randomly samples a subset $M \ll N$ of total edge devices. Then the central server broadcast its aggregated model θ_{i_g} to each edge device. Note that the global model is randomly initialized at the very first global iteration $i_g = 0$.

After receiving θ_{i_g} from the central server, all edge devices initialize it to its model as $\theta_{i_g}^n \leftarrow \theta_{i_g}$, where $\theta_{i_g-1}^n$ is the local model of each n^{th} edge device. Then randomly selected M edge devices starts the update process EdgeOpt according to its FL technique in parallel. For instance, FedAvg considers SGD [2] as EdgeOpt. Precisely, randomly selected $m \in M$ edge devices update its local model with D^m up to the maximum number of local epochs $i_l = L^m$ as follows:

$$\theta_{i_g}^{m,i_l=L^m} \leftarrow EdgeOpt(\theta_{i_g}, D^m, L^m).$$
(2)

Once the local training is complete, each selected edge device sends its locally updated model $\theta_{i_g}^{m,i_l=L^m}$ to the central server.

After receiving set of models $\{\theta_{i_g}^m\}_{m=1}^M$, the central server cyclically aggregates these locally updated M models by multiplying γ_{cyclic} with FL technique at the server-side as

$$\theta_{i_g+1} \leftarrow \gamma_{cyclic}(i_g) \cdot ServerOpt(\{\theta_{i_g}^m\}_{m=1}^M), \quad (3)$$

where $ServerOpt(\cdot)$ can be any existing optimization-based FL method at the server-side. For instance, FedAvg considers traditional averaging as ServerOpt. After all, θ_{i_q+1} is used

for the next global iteration i_g and repeat the procedure until i_g reaches predefined sufficient value G. Overall procedure is described in Algorithm 1.

Algorithm 1: Fast-convergent FL						
1 Server execution:						
2 for global iteration $i_q=0,,G$ do						
3	Broadcast:					
4	Sample M edge devices					
5	Central server transmits θ_{i_q} to all N edge devices					
6	Update:					
7	for <i>edge device</i> m=1,,M in parallel do					
8	$ eq:eq:entropy_state_$					
9	Aggregation:					
10	$\theta_{i_g+1} \leftarrow \gamma_{cyclic}(i_g) \cdot ServerOpt(\{\theta_{i_g}^m\}_{m=1}^M)$					

3. EXPERIMENT AND RESULTS

3.1. Experiment setting

In order to validate the performance of the proposed cyclic aggregation, we consider FL for image classification, i.e, MNIST [19], FMNIST [20], CIFAR-10 [11], and SVHN [21] dataset with ResNet-18 [23] classifier. We apply cyclic learning rate γ_{cyclic} to the existing FL algorithms FedAvg [5], FedProx [12], MOON [13], and FedRS [14], which are commonly used FL schemes especially for heterogeneous environments. We adopt label skew [14] to bring statistical heterogeneity by distributing the non-i.i.d. data over N = 100 edge devices: Each edge device has a maximum of 100 data for each class, and there are a total of 4 classes. Computational heterogeneity is considered by randomly selecting L^m between 1 and 5 for every global iteration i_q . For the amplitude a and frequency f in (1), we perform grid search of $0.1 \le a \le 0.5$ and $1 \le f \le 10$ to find the best case for γ_{cuclic} for each experiment. Furthermore, we run six times with same seed value and report the mean and unbiased standard derivation. Other hyperparameter setting is available in the open source code¹.

3.2. Results

3.2.1. Effect of γ_{cyclic}

First, in order to check the effect of cyclic server learning rate γ_{cyclic} , we visualize test accuracy respect to i_g with FedAvg [5] and various image classification tasks. Note that the target performance (dashed line) is the maximum test accuracy obtained by FedAvg with γ_{fixed} for each dataset. According to Fig. 4, we can observe that at the beginning of i_g , the performance with γ_{cyclic} and γ_{fixed} tend to be similar. However,

¹https://github.com/yjlee22/CyclicAggregation



Fig. 4: Test accuracy with respect to i_g for federated image classification tasks. Solid green line and blue dotted line denote FedAvg with γ_{cyclic} and γ_{fixed} respectively.

Table 1: Convergence results on various image classification tasks. The columns denote the minimum number of i_g required to reach the target performance T with state-of-the-art FL techniques.

Method	MNIST, $T = 98\%$			FMNIST, $T = 85\%$			CIFAR-10, $T = 55\%$			SVHN, $T = 81\%$		
	w/ γ_{fixed}	w/ γ_{cyclic}	speedup	w/ γ_{fixed}	w/ γ_{cyclic}	speedup	w/ γ_{fixed}	w/ γ_{cyclic}	speedup	w/ γ_{fixed}	w/ γ_{cyclic}	speedup
FedAvg	25	21	×1.19	38	18	×2.11	40	22	×1.81	25	24	×1.04
FedProx	25	13	$\times 1.92$	50	27	×1.85	42	22	×1.91	25	24	$\times 1.04$
MOON	34	22	×1.54	31	23	×1.35	42	22	×1.91	30	23	×1.30
FedRS	20	19	$\times 1.05$	32	25	$\times 1.28$	35	33	$\times 1.06$	35	27	×1.30

Table 2: Performance results on various on image classification tasks. The columns denote the maximum test accuracy over sufficient G with state-of-the-art FL techniques. Six independent experiments are considered to obtain the averaged performance.

Method	MNIST,	G = 200	FMNIST,	G = 200	CIFAR-10	G = 200	SVHN, $G = 200$	
	w/ γ_{fixed}	w/ γ_{cyclic}						
FedAvg	98.55±0.18	$98.61 {\pm} 0.16$	84.89±1.67	85.47±0.97	54.52 ± 3.15	55.52 ± 1.52	81.01±1.29	82.32±0.73
FedProx	98.61 ± 0.23	$98.63 {\pm} 0.18$	85.01 ± 1.23	85.52 ± 1.18	56.67 ± 3.32	56.95 ± 1.71	81.61 ± 0.86	82.49 ± 0.41
MOON	98.64 ± 0.26	98.71 ± 0.15	85.65 ± 1.18	86.63 ± 1.03	57.91 ± 3.28	60.94 ± 1.47	82.13 ± 2.82	83.93±0.61
FedRS	$98.71 {\pm} 0.08$	$98.73 {\pm} 0.19$	86.72 ± 1.57	$88.17 {\pm} 0.62$	$62.16 {\pm} 1.79$	$63.15 {\pm} 0.52$	$85.46 {\pm} 0.66$	$88.68 {\pm} 0.63$

after a certain iteration i_g , utilizing cyclic learing rate γ_{cyclic} converges faster to the target performance as compared to the coventional fixed rate γ_{fixed} .

3.2.2. Communication efficiency

To investigate the communication cost, we examine the convergence rate of state-of-the-art FL techniques over various image classification tasks with γ_{cyclic} and γ_{fixed} . Precisely, we examine the minimum number of iteration i_g to reach the target performance T. Note that we utilize grid search to find the best cases of γ_{cyclic} as in the previous experiment. According to Table. 1, it shows that γ_{cyclic} requires less number of i_g to achieve the target performance T of each dataset than γ_{fixed} for every FL techniques. Specifically, we observe that convergence rate is more than doubled as compared to FedAvg with FMNIST dataset. In practice, since the coomunication cost is the most key factor of FL, the proposed γ_{cyclic} is preferable than conventional γ_{fixed} .

3.2.3. Performance

To investigate the maximum performance on the benchmark dataset, we examine the maximum test accuracy over sufficient G with γ_{cyclic} and γ_{fixed} . According to Table. 2, it is shown that regardless of FL technique and dataset, γ_{cyclic} enhances also the performance.

4. CONCLUSION

In this paper, we proposed cyclic aggregation rule to alleviate the client-drift problem without any additional computational cost both at the central server side and the client side. The proposed cyclic aggregation rule with cyclic learning rate can be applied to most of existing FL techniques, and we numerically validated its benefit in terms of both convergence speed and generalization performance. Future work may consider hyperparameter optimization technique to find the optimal frequency and amplitude.

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