SAFA: a Semi-Asynchronous Protocol for Fast Federated Learning with Low Overhead

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Abstract—Federated learning (FL) has attracted increasing attention as a promising approach to driving a vast number of devices at the edge with artificial intelligence, i.e., Edge Intelligence. However, it is very challenging to guarantee the efficiency of FL considering the unreliable nature of edge devices while the cost of edge-server communication cannot be neglected. In this paper, we propose SAFA, a semi-asynchronous protocol that avoids problems in the pure synchronous/asynchronous approaches such as heavy downlink traffic and poor convergence rate in extreme conditions (e.g., clients dropping offline frequently). Key principles are introduced in model distribution, client selection and global aggregation, which are designed with tolerance to stragglers for efficiency boost and bias reduction. Extensive experiments on typical machine learning tasks show the effectiveness of the proposed protocol in shortening federated round duration, reducing local resource wastage, and improving the global model's accuracy at a low communication cost.

Index Terms—distributed computing, machine learning, edge intelligence, federated learning

I. INTRODUCTION

With the prevalence of Internet of Things (IoT), the advance in Machine Learning (ML) techniques significantly stimulates the demand of compute capacity from a broad range of applications which more or less integrate Artificial Intelligent (AI) on edge devices to empower their underlying business logic. By 2022, more than 80% of enterprise IoT projects are expected to have AI component embedded [1]. Meanwhile, it has been an emerging trend that users are becoming more sensitive to the data privacy protection mechanism of AI applications, while their performance, in many cases, is still expected to be guaranteed in the first place.

It is promising for intelligent applications to learn their models on massively distributed data but there are several obstacles. First, it is basically unrealistic to constantly collect data from all the edge devices and store them in a centralized location, which can probably cause a lot of potential risks (e.g., data leakage) and pose privacy threats to end users. Second, it could be communication-intensive to train a global model using traditional optimization methods (no matter in a centralized or decentralized manner). Centralized training requires a heavy usage of network in order to transmit raw data for training that merely happens in central servers or the cloud, whilst most distributed optimization approaches incur fairly frequent communication between devices and the cloud to exchange gradients (of a mini-batch, typically) and weights. However, in edge environments the devices are hardly reliable and the cost of communication can be prohibitive. For example, devices may drop offline occasionally and data transfer is charged in cellular networks. To summarize, machine learning in an edge environment is challenging due to the following properties: 1) Unbalanced and biased data distribution: devices own varying amounts of data due to the difference in their up time and user behavior. The distribution of data on devices can also be distinct from each other (i.e., Non-IID); 2) Massive distribution: it is usual to see a huge number of devices at the edge as participants; 3) Unreliability: either the devices themselves and the connection to the cloud are reliable. Edge devices could go offline unexpectedly and the communication could be expensive.

Federated Learning (FL) [2][3], a promising framework, was proposed by Google to address the aforementioned challenges. The work presents a distributed solution (i.e., Federated Optimization) to optimizing a global machine learning model without moving data out of local devices, and introduces FedAvg as an optimization protocol in federated setting. Rather than collecting gradients from clients (i.e., edge devices), FedAvg adopts a different approach in which multiple iterations of local updates (using gradient descent) are followed by a global aggregation that takes a weighted average of the resulting models from the clients. An obvious advantage of FedAvg is the reduction of communication frequency. FedAvg and many implementations of FL systems (e.g., [4]) adopt synchronous training protocols to avoid prohibitive number of updates. Though synchronous protocols seem to be the natural choice for the FL setting, a number of limitations stand out as follows: 1) Synchronization overhead: in each round, the latest global model needs to be distributed over the entire set of clients. This will probably cause a peak in the data transmission down to the edge and potentially makes the bandwidth of central servers a bottleneck; 2) Under-utilization of clients: only a fraction of clients is chosen to perform local training in each (global) round while the selection is totally random. Many capable clients, as a result, are likely to remain idle even if they are willing to participate in training; 3) Waste of progress: selected clients could fail to finish local training due to the unreliable nature of edge devices, but the progress made before failure will be wasted because of the global synchronization; 4) Low round efficiency: To aggregate at the end of each round, FedAvg has to wait for all the clients selected to finish, among which
crashed ones may never respond. Consequently, the learning progress is suspended until a timeout threshold is reached.

In this paper, we propose a Semi-Asynchronous Federated Averaging (SAFA) protocol on the basis of FedAvg [3] for achieving fast, communication-efficient federated optimization. SAFA takes advantage of several efficiency-boosting features from asynchronous machine learning approaches (e.g., [10] [11] [12]) while we make use of refined steering control mechanism to mitigate the impact on the global learning progress from straggling clients (i.e., staleness [12]). Moreover, we adopt a novel aggregation algorithm that exploits a cache structure (in the cloud) to bypass a fraction of client update and discriminatively merge local models into the global model by some criteria. The main contributions of our work are listed as follows:

- We propose a Semi-Asynchronous Federated Averaging (SAFA) protocol that fully takes into account the unreliability and heterogeneity in edge devices, distributes the global model in a lag-tolerant manner, flexibly selects client update for reducing round length and bias, and performs discriminative aggregation based on versions to better utilize the progress by stragglers.
- We introduce a simple hyper-parameter, lag tolerance, to flexibly control the behavior of the algorithms contained in SAFA protocol. We also empirically analyze the impact of lag tolerance on SAFA by observing how it affects critical metrics like synchronization ratio and version variance.
- We conducted extensive experiments to evaluate SAFA on several typical machine learning tasks in multiple FL settings varying from tiny to large-scale edge environments. Empirical results are presented in terms of model accuracy, time efficiency, communication cost and futility percentage.

The rest of this paper is organized as follows: Section II summarized some relevant studies on federated learning. In Section III, we formulate the optimization problem for FL and detail the underlying principles in the proposed SAFA protocol. Section IV presents the results of our experiments as well as some discussion based on the observations. We conclude our work in section V.

II. RELATED WORK

Edge Intelligence The fusion of Edge Computing and Artificial Intelligence (i.e., Edge Intelligence [13] [14]) has emerged as a new focus of research ever since we began to realize the potential benefits of sinking the computation to the edge whilst the increasing capacity of edge devices (e.g., phones and smart routers) makes it natural to empower them with AI. As a trend, we are seeing a rising number of such applications at the edge like intelligent surveillance [23] and mobile keyboard prediction [24].

Distributed machine learning has been a focal point of research as it is believed to be an ideal solution for big data analytics according the rule "moving computation closer to data". However, the majority of distributed ML approaches (e.g., [16] [17] [18]) claim their efficacy based on some conditions that are unrealistic in edge computing or IoT environment. For instance, DC-ASGD [18] was tested on a homogeneous cluster and QSGD [19] uses highly efficient GPU-to-GPU communication, but practically end devices in an edge environment can be fairly unreliable, highly heterogeneous in performance and have limited communication. Similar limitations also apply to parallel learning schemes (e.g., [25] [26] [27] [28]). In spite of the difficulties lie in the learning environment, the limitation of data access is another prominent issue. Many distributed ML approaches cannot achieve desired accuracy without making the entire dataset available to every worker. However, it is impossible in many situations to gather the data from massively distributed devices. The reasons behind include expensive communication (via cellular networks), overload of the central server and, most importantly, the data privacy of end users [20].

Federated Learning (FL) [3], first proposed by Google, is getting increasing attention as a new approach to fitting machine learning into the edge. The survey by Zhou et al. [15] summarizes recent studies on edge intelligence and list FL as one of the most uprising technologies for distributed Deep Neural Network (DNN) training at the edge. McMahan et al. [3] also proposed an weight averaging algorithm (i.e., FedAvg) to achieve synchronous optimization in the federated setting. The primary advantage of synchronization is the reduction of communication, while in terms of accuracy, Chen et al. [5] experimentally proved that synchronous Stochastic Gradient Descent (SGD) can actually outperform asynchronous approaches in the data center setting, which in some ways inspired a trend of research on synchronous large batch training [6] [7] [8] [9]. However, some deficiencies stand out as well. On one hand, synchronous federated learning like FedAvg cannot well handle staleness (i.e., straggling clients) but just forces them to synchronize at each round. On the other hand, overheads of time and resources are induced by both synchronization itself and the waste of unfinished local progress. A number of variants are proposed to improve the efficiency of FL. Wang et al. [21] proposed a control algorithm that adaptively determines the interval of global aggregation under a given resource budget. To address the inefficiency of FL under poor wireless channel conditions, Nishio and Yonetani [22] implemented a mobile edge computing (MEC) framework in which they design a protocol that releases the restriction of scale in client selection. But their scheme will inevitably introduces bias as high performance clients are favored. Xie et al. [12] proposed FedAsync, an asynchronous federated optimization that maintains two separate threads in the server for task scheduling and non-blocking global model update, respectively. Main problems of FedAsync include that multiple hyper-parameters need to be tailored and the regularized local optimization makes it challenging to ensure convergence rate.

III. THE SAFA PROTOCOL

The proposed Semi-Asynchronous Federated Averaging (SAFA) protocol is designed to solve the global optimization

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problem as below:

$$\arg\min_{w \in \mathbb{R}^d} \frac{1}{n} \sum_{i=1}^{n} f(w; x_i, y_i)$$

(1)

where $w$ denotes the parameters of the global model (number of parameters = $d$), $f(w; x_i, y_i)$ represents the loss of the inference on example $(x_i, y_i)$ made by the model with $w$ as its parameters. Note that samples are distributed among different end devices, which we call clients hereafter. Let $M$ denote the set of $m$ clients residing over the edge, and $D_j$ the partition of data on client $j$, then the target function can be rewritten as:

$$\arg\min_{w \in \mathbb{R}^d} \frac{1}{n} \sum_{j=1}^{n} \sum_{i=1}^{D_j} f(w; x_i, y_i)$$

(2)

Note that the problem definition here is in accordance with \cite{12} but different from \cite{12}. Xie et al. \cite{12} define their target function as the average of the average loss (on local partitions), which in some ways leads to bias towards clients with a small fraction of data.

In this section, we will present the workflow of SAF A with the underlying principles in detail. To realize semi-asynchronous federated learning, SAF A basically consists of three operations: lag-tolerant model distribution, Compensatory First-Come-First-Merge (CFCFM) client selection and discriminative aggregation. A demonstration of a FL process driven by SAF A is shown in Fig. 1 where there are three states of clients (i.e., picked, undrafted and crashed). Update from clients are selected based on their states at the end of a round using the proposed CFCFM algorithm which we will introduce later.

For clarity, we first list all the symbols frequently used in this paper in Table I.

| Symbol | Description |
|--------|-------------|
| $D$ | the complete dataset |
| $n$ | the size of $D$ (i.e., $n = |D|$) |
| $D_i$ | the data partition on client $i$ |
| $M$ | the set of clients (i.e., edge devices) |
| $m$ | total number of clients |
| $v_i$ | the version of client $i$’s local model |
| $M_v$ | the set of clients whose models version is $v$ |
| $P$ | the set of picked clients |
| $P_k$ | the set of picked clients of version $k$ |
| $K$ | the set of crashed clients |
| $K_k$ | the set of crashed clients of version $k$ |
| $Q$ | the set of undrafted clients |
| $Q_k$ | the set of undrafted clients of version $k$ |
| $w$ | parameters of the global model |
| $w_k$ | parameters of the local model on $k$-th client |

Fig. 1. The diagram of SAF A protocol showing the interaction between the cloud and edge clients in different states

**Definition 1**: Up-to-date clients: the clients that complete last round of local training and push their models to the cloud successively.

**Definition 2**: Deprecated clients: the clients that still base local training on significantly stale models compared to the version of the global model.

In SAF A, we let up-to-date clients to synchronize with the server to prevent divergence, meanwhile deprecated clients are forced to synchronize so that the global model will not be poisoned. Note that last-round undrafted clients can also be up-to-date if they submitted successfully. Four edge devices are shown in Fig. 1 for a simple demonstration, where client A and D crash at round #3 and at the very beginning. We also assume that the server selects two local update (i.e., client fraction $C = 0.5$) each round for aggregation while undrafted clients are still allow to contribute. The uploaded update from undrafted clients will not be merged in the coming aggregation step but may take effect in the next round via a bypass structure. To achieve this, a cache on the cloud is

\[ \begin{align*}
\arg\min_{w \in \mathbb{R}^d} \frac{1}{n} \sum_{i=1}^{n} f(w; x_i, y_i) \\
\end{align*} \]
used. The cache maintains entries of the latest local models uploaded from the selected clients while those from undrafted clients are temporarily saved in the bypass. The bypass will merge with the cache after the aggregation step, allowing the actual effective update ratio (EUR) higher than the selection fraction $C$.

As shown in Fig. 1, device D does not manage to submit its local model before round #3 terminates. As a result, it is tagged deprecated and forced to synchronize with the server to replace its stale local model with the latest global one. To decide whether a local update should be accepted, here we adopt a simple criterion based on the difference between the versions of the global model and the local model, which is called lag tolerance. To associate with Definition 2, we can re-define deprecated clients as the ones with their local version lagging behind the global model’s version by more than lag tolerance. Further, our lag-tolerant distribution principle can be formulated as follows:

$$w_k(t) = \begin{cases} w(t-1) & \text{if } k \in \bigcup_{v=t-1}^{M_v} M_v, \\ w_k(t-1) & \text{if } k \in \bigcup_{t-\tau \leq v < t-1}^{M_v} M_v, \\ w(t-1) & \text{if } k \in \bigcup_{v < t-\tau}^{M_v} M_v. \end{cases}$$

where $w(t-1)$ denotes the latest global model parameters (i.e., the aggregation result from last round), $w$ and $w_k$ denote the parameters of the global model and client $k$’s model, respectively. $\tau$ stands for lag tolerance as the only hyper-parameter for SAFA. The consequence of lag-tolerant model distribution is forcing all the client models’ base version within $t-\tau$. The hyper-parameter lag tolerance in some ways controls the tradeoff between communication overhead and the convergence rate of federated optimization. If it is set too small, the server may suffer heavy downlink transmission as the portion of deprecated clients increases. If it is set too large, the convergence of the global model could be unsteady. The impact of Lag tolerance will be analyzed later with empirical results.

B. Client Selection

In federated learning settings, an important property of clients is unreliability. This means that they occasionally drop offline for some reasons such as power outage (or low battery level), inaccessible network or manual shutdown. In this paper, we refer to these temporarily unavailable clients as crashed clients, and every client has a certain probability to crash in each round of training. For clients that stay connected to the central server (throughout a round of training), we assume they are always able to finish the task assigned in a certain period of time before the end of this round (otherwise they are also reckoned as crashed ones).

It is crucial to avoid uplink congestion especially in a massively distributed edge environment. McMahan et al. use a hyper-parameter $C$ to control the maximum fraction of clients allowed to participate in one round of training. Moreover, $C$ serves as the criterion in the FedAvg protocol by which the server keeps waiting for selected clients to end an global round. In our approach, we retain this hyper-parameter but no longer apply it as a hard constraint. Instead, we release the restriction to allow all clients to participate and enable the central server to end a round once (approximately) $C$-fraction of update have been received (i.e., semi-asynchronous pace steering). The advantage of doing so is a significant boost of efficiency in case $C$ is set small while client crash probability is high. In SAFA, the server selects clients after each round of federated training and we consider three post-training states of clients: crashed, picked, and undrafted.

Definition 3: Crashed clients: the clients that fail to finish a round of local training. Crashed clients also include those clients with no task assigned but will potentially fail as detected by the server.

Definition 4: Picked clients: the clients that are selected to conduct local training by the central server which will aggregate their update into the global model in the current round.

Definition 5: Undrafted clients: the clients that are not picked to participate but have the potential to successfully finish local training of the current round.

Apparently, the efficiency of federated optimization is closely associated to a factor – the fraction of picked clients. One may think that we can set $C$ to a large value (e.g., close to 1.0) to pick as many clients into each round as possible. However, it is neither realistic nor beneficial to do so. For one thing, allowing more clients to participate increases the potential risk of uplink congestion and the communication cost as well. In each round, the server may have to wait for more clients among which some may never respond (because picked clients could crash midway). For another, involving a large number of update brings limited benefit to the global model because weight-averaging aggregation “neutralizes” a portion of update (i.e., local models) especially in the last few rounds before convergence.

It is notable that the fraction of picked clients (or client fraction in short) is not equivalent to the actual fraction of clients that finish local training and submit their models in time. In a practical edge environment, picked clients can crash halfway in their training progress or failed to upload trained model due to network failure. In this paper, we define a metric named Effective Update Ratio (EUR) to measure the fraction of effective update from the edge (i.e., all clients) to the cloud (i.e., central server(s)).

$$EUR = \frac{|P - P \cap K|}{|M|}$$

where $P$ and $K$ are the set of picked and crashed clients, respectively. Obviously $EUR$ is positively correlated with the size of $P$ and negatively correlated with that of $K$. As mentioned, simply increasing pick fraction can bring about problems in FL settings while the crash of clients is not predictable or controllable (improving client stability is beyond the scope of this paper). As a solution, we propose to let the central server collect local update in an “First-Come-First-Merge” manner instead of randomly assigning tasks at the very beginning of a global round. This means for aggregation the server does not need to wait for those appointed clients but
are able to execute aggregation step once it has received a C-fraction of update. This semi-asynchronous design effectively decouples the server with picked clients and, consequently, improves EUR which facilitates faster convergence of the federated optimization. Fig. 2 demonstrates the different policies of client selection by the original FederatedAveraging [3] and our SAFA protocol.

From Fig. 2 and considering 4, we can see a clear improvement of EUR by SAFA, which minimizes the negative impact of clients’ failure. Nevertheless, extremely high crash ratio of clients will still lower the EUR even with our selection method. The phenomenon will be analyzed later in our experiment section.

As figured out by Bonawitz et al. [4], bias is introduced if all devices are equally likely to participate each round because they differ in performance and network access privilege. The problem remains if we merely use the client selection method mentioned above. Therefore, we further propose to alleviate the bias in the step of (global) aggregation using a compensatory client selection algorithm. The principle of this algorithm is simple — give higher priority to those clients that get less involved. In each round the server maintains a list of ids of clients that missed the last round of training, and their update will be picked prior to others for the coming aggregation. The pseudo-code of this process is shown in Algorithm 1.

In the selection algorithm, we stop involving more clients once the quota (decided by the hyper-parameter C) has been met with update from P(t−1)∩W(t). Otherwise the algorithm continues to accept update from the rest of clients which, in practice, will arrive at the cloud successively. To minimize waiting time, local models are gathered for aggregation based on the arriving order.

C. Discriminative Aggregation

While moderate stragglers continue their unfinished training locally, up-to-date and deprecated clients are expected to start local training with the latest global parameters w(t−1) received from the cloud (see Eq. 3). Assume that a round of local training has been finished and let w′k(t) denote the trained local model. For the collection of update from the edge, we adopt a three-step discriminative aggregation, which is formulated as follows:

![Algorithm 1: Compensatory First-Come-First-Merge (CFCFM) client selection](image)

| Algorithm 1: Compensatory First-Come-First-Merge (CFCFM) client selection |
|---|
| **Input**: round number t, client set M, crashed clients K(t), last-round picked clients P(t−1), selecting fraction C |
| **Output**: clients to pick P(t) |
| P(t) = ∅ |
| W(t) = M − K(t) |
| quota = C · |M| |
| for client k in P(t−1)∩W(t) do |
| add client k to P(t) |
| if |P(t)| ≥ quota then |
| return P(t) |
| end |
| while |P(t)| < quota and W(t) − P(t) ≠ ∅ do |
| pick an update from W(t) − P(t), add it to P(t) |
| end |
| return P(t) |

(1) **Pre-aggregation Cache Update:**

\[
\begin{align*}
    w_k^*(t) &= \begin{cases} 
    w_k(t) & \text{if } k \in P, \\
    w_k(t-1) & \text{if } k \in \bigcup_{v<t-t_{\tau}} M_v, \\
    w_k(t-1) & \text{otherwise}
    \end{cases}
\end{align*}
\]  

(5)

where w_k(t) denotes the k-th entry of the cache structure (see Fig. [3]).

(2) **SAFA Aggregation:**

\[
    w(t) = \sum_{k=1}^{m} \frac{n_k}{n} w_k^*(t)
\]

(6)

(3) **Post-aggregation Cache Update:**

\[
    w_k^*(t+1) = \begin{cases} 
    w_k^*(t) & \text{if } k \in P, \\
    w_k(t) & \text{if } k \in Q - K, \\
    w_k^*(t) & \text{if } k \in K
    \end{cases}
\]

(7)

where P, Q, and K denote the sets of picked, undrafted, and crashed clients, respectively. Post-aggregation cache update has to be realized using the bypass structure (Fig. [1]), which skips the update from Q and retains its potential effect to the next round (i.e., round t + 1). Considering the three-step aggregation as a whole, we can derive that, after a global round t, there are three cases of changes in the cache. For picked clients, their update will be kept in the cache after being merged into the global model. For undrafted clients, update will not take effect this round but will be carried into the next round by the cache. For crashed clients, their entries stay unchanged only if they have not been deprecated, otherwise these entries will be replaced by the global model (i.e., w(t−1)) to avoid the poison of heavy staleness.

Combining the lag-tolerant distribution algorithm, CFCFM client selection algorithm and the version-aware discriminative aggregation, we now present the complete workflow of the proposed SAFA protocol. The pseudo-code is shown in Algorithm 2.
The overall workflow of the server process is orchestrated in rounds. At the beginning of each round, the server first checks the version of clients and distributes the latest global model in a lag-tolerant manner (see Eq. 3) given the hyper-parameter \( \tau \). Then the server begins to listen and collects the update (i.e., trained local model) from clients. Based on Algorithm 1, clients missing the last round will have the priority to be selected to fulfill the pre-specified fraction \( C \). Following client selection, the server then executes the three-step discriminative aggregation, which merges all the entries in the cache into the global model, i.e., \( w(t) \), and updates the cache based on the states of clients (see Eq. 7).

Clients train their native models on local datasets using the gradient descent method (i.e., the client process in Algorithm 2). Here for simplicity we set identical epoch, batch size and learning rate for each client, which can actually be specified in a client-wise manner. It is notable that clients work at different efficiency on different sizes of local data, causing their progress vary from each other significantly. As an advantage, The design of SAFA decouples the server and the selected clients to reduce waiting time caused by client heterogeneity, meanwhile we use lag tolerance to provide a mechanism to control staleness and bias.

D. Parameter Study

We attempt to analyze the impact of lag tolerance from a number of different perspectives. As mentioned, the hyper-parameter is critical to the pace steering of SAFA protocol. In case lag tolerance is set to 0, the result of model distribution will be the same as in [3], i.e., forcing all the clients to synchronize (with the server) before starting a round of training. When it is set to a big value, the server will be very tolerant to stragglers, which will probably cause high variance in local models’ versions and consequently slower the convergence of the global model. Thus, we introduce two holistic metrics: Synchronization Ratio (SR) and Version Variance (VV). SR is defined to measure the usage of downlink by sending the global model to the edge. VV is defined based on the distribution of versions of local models. We formulate them as follows:

\[
SR = \frac{1}{r} \sum_{t=1}^{r} \frac{1}{m} \bigg| \bigcup_{v=m} |M_v| + \bigcup_{v<0} |M_v| \bigg| (8)
\]

where \( r \) is the number of global rounds and \( m \) is the number of clients. \( SR \) is calculated based on the lag-tolerant distribution rule (Eq. 3) that up-to-date and deprecated clients need to synchronize with the server.

\[
VV = \frac{1}{r} \sum_{t=1}^{r} \text{var}(V_t) (9)
\]

where \( V_t \) is version distribution at round \( t \), i.e., \( V_t = \{v_1, v_2, ..., v_m\} \).

We change lag tolerance (i.e., \( \tau \)) from 1 to 10 and set up several groups of tests of a simple regression task on the Boston Housing dataset. We set the maximum number of global rounds to 100. Apart from the best loss achieved (i.e., the minimum loss by the global model in 100 rounds), we also present statistical results with regard to the metrics including EUR, SR and VV.

Fig. 3(a) draws the best loss of the global model in the FL environments where we set selection fraction \( C \) to 0.1, 0.5 and 1.0, and set the expectation of client crash probability \( cr \) to 0.3 and 0.7. Fig. 3(b) shows the results of synchronization ratio (SR). Apparently small values of lag tolerance show clear advantage in respect to loss, but the overhead of communication (revealed by \( SR \)) is relatively large in case \( \tau \) is set too small (e.g., 1, 2 or 3). The rise of \( SR \) is expected because more clients will become deprecated and be forced to synchronize when we get less tolerant to stragglers.

There are multiple factors that can affect the best global model we can obtain in federated learning. We try to analyze it by observing the effective update ratio (EUR) and the version variance (VV) under different FL settings. We think they are two important metrics that well reflect the quality of the aggregation step, which is vital for the accuracy of the global model. From Fig. 3(a) we see basically no change in EUR in spite of the lag tolerance we specified, and the EUR depends on both the client fraction \( C \) and client crash probability \( cr \). When \( cr \) is low (e.g., \( cr = 0.3 \)), EUR is basically slightly above the percentage quota of clients specified by \( C \), which is because
With the increase of disengage frequently, our CFCFM selection policy may greedily accept some update before it receives the response from all the prioritized clients. In case a high probability of crash applies (e.g., $cr = 0.7$), $EUR$ is constrained at a low level as it is impossible to be higher than the expectation $E(M - K)$ which is theoretically equal to the successful update probability $1 - cr$. Besides, the plot of Version Variance in Fig. 3(a) basically reveals a part of the reason why the quality of the global model degrades when lag tolerance is set too large (see Fig. 3(b)). In general $VV$ increases if we make SAF A more tolerant to stragglers (i.e., a larger value of $\tau$), and we further observed that in relatively stable FL settings (i.e., $cr = 0.3$), the growth of $VV$ with the increase of $\tau$ is much slower than that under extreme environments (i.e., $cr = 0.7$). Combining Fig. 3(a), we can see a clear correlation between $VV$ and the quality of global model especially in an edge environment where clients disengage frequently.

Based on the observations, we find that a moderate lag tolerance can basically guarantee the loss of global model below a desired level and avoid high cost of communication (indicated by $SR$) in sending model to the edge. Therefore we suggest setting lag tolerance to around 5 in general.

**IV. EXPERIMENTAL EVALUATION**

**A. Experiment Setup**

We setup federated environments via simulation and implemented the proposed protocol using PyTorch (version: 1.1.0) and PySyft (version: 0.1.26a1) packages. We conducted extensive experiments to evaluate the effectiveness of SAF A protocol on three typical machine learning tasks. *Task 1* is fitting a regression model on the public Boston Housing dataset which is available in public repositories. *Task 2* is learning a handwritten digit image classification model implemented using a Convolutional Neural Network, which is comprised of two 5x5 convolution layers (the first one with 20 channels and the second with 50 channels), each of which is followed by a 2x2 max pooling layer, a fully-connected layer with ReLu as the activation function, and a final softmax output layer. *Task 3* is to learn a classification model for detecting network intrusion given TCP dump data. For this task we extract TCP-connection examples from the KDD Cup’99 dataset and use Support Vector Machine (SVM) as the classification model.

We set up separate environments for the three learning tasks to investigate the performance of our protocol in different FL settings. For the same task, we use identical local training settings (e.g., mini-batch size) for all the clients and use identical global settings (e.g., maximum number of rounds) for all the protocols to compare in our experiment. The details of experiment setup is shown in Table III.

![Figure 3](image1.png) Best loss achieved by the global model and the synchronization ratio over the federated optimization with SAF A protocol.

![Figure 4](image2.png) Effective Update Ratio (EUR) and Version Variance (VV) over the federated optimization with SAF A protocol.

**TABLE II**

| parameter          | symbol | Task 1 | Task 2 | Task 3 |
|--------------------|-------|--------|--------|--------|
| dataset            | $D$   | Boston | MNIST  | KDDCup99 |
| # of features      | $d$   | 12     | 28x28  | 35     |
| model              | $w$   | regression | CNN | SVM   |
| dataset size       | $n$   | 506    | 70k    | 186k   |
| # of clients       | $m$   | 5      | 500    | 500    |
| max # of rounds    | $R$   | 100    | 50     | 100    |
| # of local epochs  | $E$   | 3      | 5      | 5      |
| mini-batch size    | $B$   | 5      | 50     | 100    |
| # learning rate    | $lr$  | 1e-4   | 1e-3   | 1e-2   |

To simulate data unbalance and the heterogeneity in edge devices, we assume both the size of data partitions (i.e., local data size) and the performance of clients follows normal distribution. Here we define the performance of a client as the time it consumes to finish one batch of training. Also, we assume all edge devices (i.e., clients) are unreliable and crash by a probability $\rho_k$, the expectation of which equals to an environmental argument $cr$, i.e., $E(\rho_k) = cr, k = 1, 2, ..., m$.

For comparison, we also implemented the Fedavg protocol and a fully local version of federated optimization. The fully local protocol never performs global aggregation until the end of the last round.

**B. Results**

In this section we present the results of our experiments and discuss the FL protocols in terms of the global model’s quality and several holistic metrics concerning the learning process. For different machine learning models, we define their accuracy in different ways, as shown in Table III. In the table, $y$ and $\hat{y}$ denote the label and the model’s output, respectively. The function $\phi(\cdot)$ returns 1 if the indices of the max elements in $y$ and $\hat{y}$ are the same, otherwise it returns 0.

**Task 1: Regression**

In this task, we aim to learn a regression model on a small group of clients to predict the median value of a house in

[https://www.cs.toronto.edu/~delve/data/boston/bostonDetail.html](https://www.cs.toronto.edu/~delve/data/boston/bostonDetail.html)  
[https://kdd.ics.uci.edu/databases/kddcup99/kddcup99.html](https://kdd.ics.uci.edu/databases/kddcup99/kddcup99.html)
The area of Boston Mass. Input features include 13 properties about the estate such as average number of rooms per dwelling and crime rate. Table IV and V summarize the results regarding the best accuracy that the global model achieved and the average round length over the federated learning process, respectively. Setting client fraction $C$ to 0.3, Fig. 5 shows the loss trace of global model with Fully local, FedAvg, and SAFA as the FL protocol. Fully local optimization is not performed in rounds so the metric round length is not applicable to it.

**TABLE IV**

**BEST ACCURACY OF THE GLOBAL MODEL AND TOTAL TIME CONSUMPTION ON TASK 1**

|                                | Fully local | FedAvg | SAFA  |
|--------------------------------|-------------|--------|-------|
| $C = 0.1$                      | 6154        | 6308   | 6253  |
| $C = 0.3$                      | 6086        | 6363   | 6145  |
| $C = 0.5$                      | 5182        | 6228   | 6276  |
| $C = 0.7$                      | 4443        | 5634   | 6327  |
| $C = 1.0$                      | 306        | 6049   | 6361  |

**TABLE V**

**AVERAGE LENGTH OF A FEDERATED ROUND ON TASK 1**

|                                | FedAvg | SAFA |
|--------------------------------|--------|------|
| $C = 0.1$                      | 1.000  | 0.90 |
| $C = 0.3$                      | 1.000  | 0.80 |
| $C = 0.5$                      | 1.000  | 0.70 |
| $C = 0.7$                      | 1.000  | 0.60 |

To evaluate communication efficiency, we define futility percentage as the average percentage by which the progress of local training on the edge goes in vain due to forced model synchronization by the central server. Table VI compares the synchronization ratio (SR) and the futility percentage over the FL process controlled by the FedAvg and SAFA. We do not show Fully local protocol in the table as basically no communication occurs. The results indicate a remarkable reduction of time needed for a round of FL by SAFA, meanwhile local training progress is better utilized as the futility percentage for SAFA is significantly lower. Considerign SR for communication cost, FedAvg broadcasts the global model every round but SAFA is 6.8% $\sim$ 67.0% more efficient in downlink usage as a portion of clients are not forced to synchronize.

**Task 2: CNN**

We divided MNIST dataset into $m$ partitions of which the sizes are random variables following normal distribution. CNN models with randomly initialized weights are created on 100 clients and we again tested Fully local, FedAvg and SAFA with a variety of FL settings. Table VII and VIII present the results regarding accuracy and round length. Fig. 6 shows the
loss trace of the global model, and Table IX summarizes the metrics of $SR$ and futility over the federated learning process.

### Table VII

**Best Accuracy of the Global Model on Task 2**

| $cr$ | $C = 0.1$ | $C = 0.3$ | $C = 0.5$ | $C = 0.7$ | $C = 1.0$ |
|------|------------|------------|------------|------------|------------|
| 0.1  | 0.8849     | 0.9066     | 0.9026     | 0.9111     | 0.9019     |
| 0.3  | 0.8906     | 0.8932     | 0.8917     | 0.8909     | 0.9126     |
| 0.5  | 0.8649     | 0.8898     | 0.9021     | 0.8932     | 0.9081     |
| 0.7  | 0.8518     | 0.8956     | 0.9026     | 0.8959     | 0.8866     |

| $cr$ | $C = 0.1$ | $C = 0.3$ | $C = 0.5$ | $C = 0.7$ | $C = 1.0$ |
|------|------------|------------|------------|------------|------------|
| 0.1  | 0.9425     | 0.9839     | 0.9732     | 0.9761     | 0.9797     |
| 0.3  | 0.9349     | 0.9620     | 0.9710     | 0.9748     | 0.9769     |
| 0.5  | 0.9228     | 0.9523     | 0.9665     | 0.9703     | 0.9739     |
| 0.7  | 0.9041     | 0.9406     | 0.9574     | 0.9617     | 0.9683     |

| $cr$ | $C = 0.1$ | $C = 0.3$ | $C = 0.5$ | $C = 0.7$ | $C = 1.0$ |
|------|------------|------------|------------|------------|------------|
| 0.1  | 0.9747     | 0.9749     | 0.9756     | 0.9769     | 0.9785     |
| 0.3  | 0.9713     | 0.9729     | 0.9741     | 0.9748     | 0.9776     |
| 0.5  | 0.9676     | 0.9678     | 0.9700     | 0.9700     | 0.9715     |
| 0.7  | 0.9614     | 0.9624     | 0.9630     | 0.9640     | 0.9624     |

### Table VIII

**Average Length of a Federated Round on Task 2**

| $cr$ | $C = 0.1$ | $C = 0.3$ | $C = 0.5$ | $C = 0.7$ | $C = 1.0$ |
|------|------------|------------|------------|------------|------------|
| 0.1  | 3465.37    | 5870.01    | 6313.03    | 6610.09    | 4554.30    |
| 0.3  | 4679.40    | 6486.04    | 3218.82    | 7005.25    | 4506.34    |
| 0.5  | 6783.74    | 5925.39    | 6956.84    | 8119.73    | 7448.27    |
| 0.7  | 4229.46    | 6368.41    | 4990.90    | 4880.14    | 5600.05    |

| $cr$ | $C = 0.1$ | $C = 0.3$ | $C = 0.5$ | $C = 0.7$ | $C = 1.0$ |
|------|------------|------------|------------|------------|------------|
| 0.1  | 1830.53    | 3315.56    | 3874.22    | 4118.55    | 4554.30    |
| 0.3  | 1854.99    | 3616.22    | 2162.75    | 5487.47    | 4506.34    |
| 0.5  | 1320.93    | 2946.94    | 4493.46    | 8119.73    | 7448.27    |
| 0.7  | 1397.26    | 4132.62    | 4990.90    | 4880.14    | 5600.05    |

### Table IX

**Synchronization Ratio and Futility Percentage on Task 2**

| $cr$ | $C = 0.1$ | $C = 0.3$ | $C = 0.5$ | $C = 0.7$ | $C = 1.0$ |
|------|------------|------------|------------|------------|------------|
| 0.1  | 0.9961     | 0.9961     | 0.9962     | 0.9962     | 0.9962     |
| 0.3  | 0.9953     | 0.9961     | 0.9962     | 0.9962     | 0.9962     |
| 0.5  | 0.9961     | 0.9960     | 0.9958     | 0.9958     | 0.9962     |
| 0.7  | 0.9961     | 0.9961     | 0.9960     | 0.9958     | 0.9958     |

Table IX shows that both FedAvg and SAF-A produce a very accurate global model (over 99% classification accuracy) after convergence. In terms of efficiency, SAFA outperforms FedAvg in both average round length (Table XI) and synchronization ratio (Table XII), reducing them by roughly 50 percent and 65 percent at maximum, respectively. Besides, in contrast to FedAvg, SAFA effectively capitalizes the contribution from

Fig. 6. The loss trace of the global model over the FL process on Task 2 when client fraction is set to 0.3.

From the results, we can see the Fully local protocol finished with an accuracy around 90% on this classification task with CNN, while FedAvg and the proposed SAF-A protocol rise to 96.0% ~ 98.0%. Similar to Task 1, SAFA again shows its advantage in best accuracy, round efficiency and communication cost when dealing with unreliable clients using a smaller fraction of them (Table VII and VIII). We also observe faster convergence rate with SAFA protocol (Fig. 6). Only one data point is showed in the figure for the Fully local protocol since its global model is not available until the final aggregation.

### Task 3: SVM

For this task we use a large data set containing 186,480 TCP dump records including several types of network intrusions. The target is to learn a global SVM model to distinguish malicious connections and normal connections. We dispersed the dataset onto 500 clients to perform FL. The results in terms of best accuracy, average round time, synchronization ratio and futile local progress are presented in Tables XI and XII, and we show the loss trace in Fig. 7.
straggling clients, leading to very small futility percentage on this task, which means that the majority of local training progress pays off even in an unstable edge environment.

C. Discussion

Our experiments on several tasks including regression and classification demonstrate the effectiveness of applying our semi-asynchronous protocol to FL on the edge. The improvement brought by SAFA is basically three-fold: first, faster convergence of the global model and a higher accuracy achieved. Second, reduced length of global rounds and less downlink model transmission. Third, increased utilization of local progress made by stragglers. A few interesting phenomena are also observed in our experiments. First and foremost, we find that increasing the fraction \( C \) does not always improve the quality of global model. For example, reasonably high accuracy is obtained by setting \( C \) to 0.3 or 0.5 for all the protocols in task 2 in case a low crash probability environment is provided. This in some ways infers that involving more clients each round is not always beneficial. In addition, we notice that fully local training without round-wise aggregation is in some cases able to produce a reasonably good model, e.g., Task 1 with \( C = 0.3 \) and Task 3 with \( C = 0.1 \) and \( cr = 0.7 \). Finally, we find that the synchronous FL protocol FedAvg can produce a global model with higher accuracy than our solution in case \( C = 1.0 \), which means removing the restriction on client participation. The advantage is probably brought by pure synchronization that avoids the negative effect from stale models, which increases as a larger fraction of clients get involved. However, it is practically unrealistic to set a big \( C \) for FL because communication could be expensive while the accuracy enhancement is limited (see Tables IV, VII and X).

V. Conclusion

Aiming at improving the efficiency of federated learning in edge environments, we propose a semi-asynchronous protocol which incorporates a novel client selection algorithm decoupling the central server and the selected clients for a reduction of average round time, and adopts a lag tolerance hyper-parameter in both model distribution and global aggregation for tackling the tradeoff between the convergence rate and communication overhead. The results of experimental evaluation on three typical machine learning tasks show that our protocol effectively enhances the efficiency of federated optimization process, reduces local resource wastage, and improves the global model’s quality at a relatively low cost of communication.

Considering the subtle correlation between local models and the global model, we plan to look into the balance between realizing the locally-best models at the edge and obtaining an optimal global model in the central. As another part of future work, we are also going to investigate how to further improve federated optimization using model parallelism.

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