ABSTRACT

There are situations where data relevant to a machine learning problem are distributed among multiple locations that cannot share the data due to regulatory, competitiveness, or privacy reasons. For example, data present in users’ cellphones, manufacturing data of companies in a given industrial sector, or medical records located at different hospitals. Federated Learning (FL) provides an approach to learn a joint model over all the available data across silos. In many cases, participating sites have different data distributions and computational capabilities. In these heterogeneous environments previous approaches exhibit poor performance: synchronous FL protocols are communication efficient, but have slow learning convergence; conversely, asynchronous FL protocols have faster convergence, but at a higher communication cost. Here we introduce a novel Semi-Synchronous Federated Learning protocol that mixes local models periodically with minimal idle time and fast convergence. We show through extensive experiments that our approach significantly outperforms previous work in data and computationally heterogeneous environments.

1 INTRODUCTION

Data useful for a machine learning problem is often generated at multiple, distributed locations. In many situations this data cannot be exported from their original location due to regulatory, competitiveness, or privacy reasons. A primary motivating example is health records, which are heavily regulated and protected, restricting the ability to analyze large datasets. Industrial data (e.g., accident or safety data) is also not shared due to competitiveness reasons. Additionally, given recent high-profile data leak incidents more strict data ownership laws have been enacted, such as the European Union’s General Data Protection Regulation (GDPR), China’s Cyber Security Law and General Principles of Civil Law, and the California Consumer Privacy Act (CCPA).

These situations bring data distribution, security, and privacy to the forefront of machine learning and impose new challenges on how data should be processed and analyzed. Federated Learning (FL) is a promising solution (Konečný et al., 2016; McMahan et al., 2017a; Yang et al., 2019), which can help learn deep neural networks from data silos (Jain, 2003) by collaboratively training models that aggregate locally-computed updates (e.g., gradients) under a centralized (e.g., central parameter server) or a decentralized (e.g., peer-to-peer) learning topology (Li et al., 2020a), while providing strong privacy and security guarantees (e.g., (Bonawitz et al., 2017; Zhang et al., 2020)).

Our primary interest is to develop efficient Federated Learning training policies for the datacenter setting (Li et al., 2020a). In particular, we target the cross-silo Federated Learning environments (Kairouz et al., 2019; Li et al., 2020a; Rieke et al., 2020; Yang et al., 2019), which consist of a network of hospitals, or a research consortium, that wants to jointly learn a model without sharing any data. In these environments, participants often have different computational capabilities (system heterogeneity) and/or different local data distributions (statistical heterogeneity). Current Federated Learning approaches use either synchronous (Bonawitz et al., 2019; McMahan et al., 2017a; Smith et al., 2017) or asynchronous (Xie et al., 2019) communication protocols. However, these methods have poor performance in such heterogeneous environments. Synchronous protocols result in fast learners being idle, which underutilizes the resources of the federation. Asynchronous protocols seek to fully utilize the available resources, but have higher a network communication cost, and potentially lower generalizability due to the effects of stale models (Cui et al., 2014; Dai et al., 2018).

To address these challenges, we introduce a new hybrid training scheme, called Semi-Synchronous Federated Learning, which allows learners to continuously train on their local dataset up to a specific synchronization point where the current local models of all learners are mixed to compute the community model. This approach produces better utilization of the federation resources, while limiting communication costs. We empirically demonstrate the effectiveness of this
new scheme in terms of convergence time and communication cost on a variety of challenging environments with diverse computational resources, variable data amounts, and different target class distributions (IID and non-IID example assignments) across learners. We also show that our training scheme accelerates the convergence of the federation model irrespective of the local optimizer used to train the local models.

2 Related Work

Federated Learning was introduced by McMahan et al. (2017a) for user data in mobile phones. Their original algorithm, Federated Average, follows a synchronous communication protocol where each learner (phone) trains a neural network for a fixed number of epochs on its local dataset. Once all learners (or a subset) finish their assigned training, the system computes a community model that is a weighted average of each of the learners’ local models, with the weight of each learner in the federation being the number of its local training examples. The new community model is then distributed to all learners and the process repeats. This approach, which we call SyncFedAvg, has catalyzed much of the recent work (Bonawitz et al., 2019; Li et al., 2018; Smith et al., 2017).

SGD Optimization. The synchronous, semi-synchronous and asynchronous FL settings that we investigate are closely related to stochastic optimization in distributed and parallel systems (Bertsekas, 1983; Bertsekas & Tsitsiklis, 1989), as well as in synchronous distributed stochastic gradient descent (SGD) optimization (Chen et al., 2016). The problem of delayed (i.e., stale) gradient updates due to asynchronicity is well known (Agarwal & Duchi, 2011; Lian et al., 2015; Recht et al., 2011), with (Lian et al., 2015) providing theoretical support for nonconvex optimization functions under the IID assumption. We study FL in more general, Non-IID settings.

Global and Local Model Optimization. In statistically heterogeneous FL settings clients can drift too far away from the global optimal model. An approach to tackle client drift is to decouple the SGD optimization into local (learner side) and global (server side) (Hsu et al., 2019; Reddi et al., 2020). Hsu et al. (2019) investigate a momentum-based update rule between the previous community model and the newly computed weighted average of the clients models. In (Reddi et al., 2020), after computing the weighted average of the clients updated models (“pseudo-gradients”), a new community model is computed through adaptive SGD optimizers that target to optimize the global objective. FedProx (Li et al., 2018) directly addresses client drift by introducing a regularization term in the clients local objective, which penalizes the divergence of the local solution from the global solution. FedAsync (Xie et al., 2019) weights the different local models based on staleness with respect to the latest community model. Another recently proposed approach is Momentum SGD which is shown to have accelerated convergence compared to Vanilla SGD (Liu et al., 2020). In our setting, we study the effect of different mixing strategies when computing the weighted average of learners’ local models, as well as the effect of Vanilla SGD, FedAsync and Momentum SGD as local solvers.

Federated Convergence Guarantees. Furthermore, convergence guarantees for computational environments with heterogeneous resources in FL settings have also been studied in (Li et al., 2018; Wang et al., 2019). FedProx studied the convergence rate of FedAvg over B-dissimilar learners local solutions (B = 1 IID distributions, B > 1 Non-IID distributions). Wang et al. (2019) studied adaptive FL in mobile edge computing environments under resource budget constraints with arbitrary local updates between learners, while Li et al. (2020b) provide convergence guarantees over full and partial device participation for FedAvg. FedAsync (Xie et al., 2019) provides convergence guarantees for asynchronous environments and a community model that is a weighted average of local models based on weights staleness. In our work, we empirically study the convergence of the different federated learning protocols on computationally heterogeneous environments on IID and Non-IID data distributions with full client participation in the datacenter (cross-silo FL) setting (Li et al., 2020a; Yang et al., 2019) with the presence of stragglers (Dean & Barroso, 2013).

Privacy. Even though privacy is a critical challenge in FL we do not directly address it in this paper, since our scope is to introduce a new federated training protocol for the datacenter (cross-silo) settings, which can accelerate the convergence of the federated model. Our proposed Semi-Synchronous training protocol can be easily extended to incorporate standard privacy-aware techniques such as differential privacy (Abadi et al., 2016b; McMahan et al., 2017b), secure multi-party computation (MPC) (Bonawitz et al., 2017; Kilbertus et al., 2018; Mohassel & Zhang, 2017), and homomorphic encryption (Paillier, 1999; Rivest et al., 1978; Zhang et al., 2020). In particular, Semi-Synchronous does not alter any of the information exchanged during the regular federated learning training process, but it rather orchestrates the synchronization points of the participating devices by delegating that amount of local work that each learning device needs to perform. Therefore, although Semi-Synchronous does not directly offer specific privacy guarantees, it can be applied along with existing privacy-aware training schemes without relaxing any of their requirements.

Periodic SGD. Finally, our proposed Semi-Synchronous training policy is closely related to the Elastic and Periodic SGD Averaging (Wang & Joshi, 2018; Zhang et al., 2015), where the central server aggregates the learners local gradi-
ent updates once a predefined number of steps is complete. This periodic aggregation controls the communication frequency between the learners and the server. Compared to the epoch-level synchronization period applied in (McMahan et al., 2017a), our period is expressed at the batch-level and the maximum time it takes for any learner to complete an epoch. We essentially profile the computational learning power of every learner and assign the respective local workload to every learner and synchronize accordingly the local models. This is different from the work of (Chai et al., 2020) where the learners are grouped into learning performance tiers and profiling is based on the response latency (time in-between training task reception and reply). We do not consider network latency in this work, since it can be considered negligible in cross-silo settings due to fast interconnectivity among learning sites. In our learning environment, all learners are considered at every iteration, while in (Chai et al., 2020) once the tiers are formed, any learner that exceeds a predefined threshold is considered a dropout. In our work, no learner is considered a dropout since in the cross-silo environments we investigate, we anticipate every learner to participate at every iteration due to the valuable data information it holds.

3 FEDERATED OPTIMIZATION

In Federated Learning the goal is to find the optimal set of parameters $w^*$ that minimize the global objective function:

$$w^* = \arg\min_w f(w) \text{ where } f(w) = \sum_{k=1}^{N} \frac{P_k}{P} F_k(w) \quad (1)$$

where $N$ denotes the number of participating learners, $P_k$ the contribution of learner $k$ in the federation, $P = \sum P_k$ the normalization factor (thus, $\sum_k^{N} \frac{P_k}{P} = 1$), and $F_k(w)$ the local objective function of learner $k$. We refer to the model computed using Equation 1 as the community model $w_c$. Every learner computes its local objective by minimizing the empirical risk over its local training set $D_k$ as $F_k(w) = \mathbb{E}_{x_k \sim D_k} [\ell_k(w; x_k)]$, with $\ell_k$ being the loss function. For example, in the FedAvg weighting scheme, the contribution value for any learner $k$ is equal to its local training set size, $p_k = |D_k|$ and $P = \sum |D_k| / |D^T|$, where $D^T = \bigcup_k^{N} D_k$ and $|D^T| = \sum_k^{N} |D_k|$. The contribution value $p_k$ can be static, or dynamically defined at run time (cf. Section 4).

When using Stochastic Gradient Descent (SGD) with Momentum as a learner’s local objective solver (Liu et al., 2020), the local solution $w_{t+1}$ at iteration $t$ is computed as:

$$u_{t+1} = \gamma u_t + \nabla F_k(w_t)$$
$$w_{t+1} = w_t - \eta u_{t+1} \quad (2)$$

with $\eta$ denoting the learning rate, $u$ the momentum term and $\gamma$ the momentum attenuation factor.

FedProx (Li et al., 2018) is a variation of the local SGD solver that introduces a proximal term in the update rule to regularize the local updates based on the divergence of the local solution from the global solution (i.e., the community model). The local solution $w_{t+1}$ is computed as:

$$w_{t+1} = w_t - \eta \nabla F_k(w_t) - \eta \mu (w_t - w_c) \quad (3)$$

The proximal term $\mu$ controls the divergence of the local solution from the global. The Fedprox regularization term is also used in FedAsync. In this work, we compare the different federated learning policies using both local optimizers.

4 FEDERATED LEARNING POLICIES

In this section we review the main characteristics of synchronous and asynchronous federated learning policies, and introduce our novel semi-synchronous policy. We compare these approaches under two evaluation criteria: convergence time and communication cost. Rate of convergence is expressed in terms of parallel processing time, that is, the time it takes the federation to compute a community model with all the learners running in parallel. Communication cost is measured in terms of update requests, that is, the number of local models sent from any learner to the controller during training. Each learner also receives a community model after each request. So the total number of models exchanged is twice the update requests.

4.1 Synchronous Federated Learning

Under a synchronous communication protocol, each learner performs a given number of local steps (usually expressed in terms of local epochs). After all learners have finished their local training, they share their local models with the centralized server (federation controller) and receive a new community model. This training procedure continues for a number of federation rounds (synchronization points). This is a well-established training approach with strong theoretical guarantees and robust convergence for both IID and Non-IID data (Li et al., 2020b).

However, a limitation of synchronous policies is their slow converge due to waiting for slow learners (stragglers). For a federation of learners with heterogeneous computational capabilities fast learners remain idle most of the time, since they need to wait for the slow learners to complete their local training before a new community model can be computed (Figure 1). As we move towards larger networks, this resource underutilization is exacerbated. Figure 2(a,b) shows idle times of a synchronous protocol when training a 2-CNN (a) or a ResNet-50 (b) network in a federation with fast (GPU) and slow (CPU) learners. The fast learners are severely underutilized.
4.2 Asynchronous Federated Learning

In asynchronous Federated Learning no synchronization point exists and learners can request a community update from the controller whenever they complete their local assigned training. Asynchronous protocols have have faster convergence speed since no idle time occurs for any of the participating learners. However, they incur higher communication costs and lower generalizability due to staleness (Cui et al., 2014; Dai et al., 2018). Figure 1(center) illustrates a typical asynchronous policy. The timestamps $t_i$ represent the update requests issued by the learners to the federation controller. No synchronization exists and every learner issues an update request at its own learning pace. For asynchronous protocols, the communication cost is equal to the number of update requests issued by the learners. All learners run continuously, so there is no idle time.

Since in asynchronous protocols, no strict consistency model (Lamport, 1979) exists, it is inevitable for learners to train on stale models. Community model updates are not directly visible to all learners and different staleness degrees may be observed (Cui et al., 2014; Ho et al., 2013).

Recently, FedAsync (Xie et al., 2019) was proposed as an asynchronous training policy for Federated Learning by weighting every learner in the federation based on functions of model staleness. FedAsync defines staleness as the difference between the current global timestamp (vector clock) of the community model and the global timestamp associated with the committing model of a requesting learner. Specifically, for learner $k$, its staleness value is equal to $S_k = (T - \tau_k + 1)^{-1/2}$, (i.e., FedAsync + Poly) with $T$ being the current global clock value and $\tau_k$ the global clock value of the committing model of the requesting learner.

Given that staleness can also be controlled by tracking the total number of iterations or number of steps (i.e., batches) applied on the community model, we propose a new asynchronous protocol, FedRec, which weighs models based on recency, extending the notion of effective staleness in (Dai, 2018; Dai et al., 2018). For each model we define the number of steps $s$ that were performed in its computation. Assume a learner $k$ that receives a community model $c^t$ at time $t$, which was computed over a cumulative number of steps $s^t$ (the sum of steps used by each of the local models involved in computing the community model). Learner $k$ then performs $s_k$ local steps starting from this community model, and request a community update at time $t'$. By that time the current community model may contain $s^t_s > s^t_k$ steps, since other learners may have contributed steps between $t$ and $t'$. Therefore, the effective staleness of learner $k$ in terms of steps is $S_k = (s^t_s - (s^t_k + s_k))^{-1/2}$ (following the FedAsync + Poly function).

As we will see in the experiments of Section 6, the step-based recency/staleness function of FedRec performs better that the time-based staleness function of FedAsync (cf. Figures 7, 8, 9). Figure 3 shows that in computationally heterogeneous environments, FedAsync’ staleness penalizes slow learners strongly, more so than what would be warranted by the effort that went into computing their models (which is better captured by the steps-based effective staleness of FedRec). Note the more nuanced weight values of FedRec versus the strong separation of FedAsync in the figure (see also Figure 12 in the Appendix). Moreover, FedAsync computes the new community model $w_{t+1}$ as $w_{t+1} = (1 - a) w_t + aw_k$, where $w_t$ is the existing community model, $w_k$ is the committing local model of learner $k$ and $a$ is a mixing hyperparameter between the two models. However, FedRec follows a different approach that relaxes this hyperparameter dependence by computing the new community model through a caching mechanism (discussed in section 5) that always considers the staleness value of every local model in the new community.
Figure 3. Staleness normalized distribution for every learner in a heterogeneous computational environment with 5 fast (GPU) and 5 slow (CPU) learners, with equal number of local training examples.

4.3 Semi-Synchronous Federated Learning

We have developed a novel Semi-Synchronous training policy that seeks to balance resource utilization and communication costs (cf. 2). In this policy every learner continues training up to a specific synchronization time point (cf. Figure 1(right)). The synchronization point is based on the maximum time it takes for any learner to perform a single epoch. Specifically:

\[ t_{\text{max}}(\lambda) = \lambda \times \max_{k \in N} \left\{ \frac{D_k}{\beta_k} \right\}, \lambda, \beta_k, t_{\beta_k} > 0 \]

\[ B_k = \frac{t_{\text{max}}}{t_{\beta_k}}, \forall k \in N \]  

(4)

where \( D_k \) refers to the local training data size of learner \( k \), \( \beta_k \) to the batch size of learner \( k \) and \( t_{\beta_k} \) to the time it takes learner \( k \) to perform a single step (i.e., process a single batch). The hyperparameter \( \lambda \) controls the number of local passes the slowest learner in the federation needs to perform before all learners synchronize. For example, \( \lambda = 2 \) and \( \lambda = 4 \) refer to the slowest learner completing two and four epochs, respectively. The term \( B_k \) denotes the number of steps (batches) learner \( k \) needs to perform before issuing an update request, which depends on its computational speed.

To compute the necessary statistics (i.e., time-per-batch per learner), SemiSync performs an initial cold start federation round (see GPUs in Figure 2(c,d)) where every learner trains for a single epoch and the controller collects the statistics to synchronize the new semi-sync federation round. Here, the hyperparameter \( \lambda \) and the timings per batch are kept static throughout the federation training once being defined, although others schedules are possible (cf. Section 7).

In our SemiSync approach, the learners synchronization point does not depend on the number of completed epochs, but in the synchronization period. Learners with different computational power and amounts of data perform a different number of epochs, including fractional epochs. There is no idle time. Since the basic unit of computation is the batch, this allows for a more fine-grained control on when a learner contributes to the community model. This policy is particularly beneficial in heterogeneous computational and data distribution environments.

5 FEDERATED LEARNING ENVIRONMENT

We have designed and developed a flexible Federated Learning system, called Metis, to explore different communication protocols and model aggregation weighting schemes (Figure 4). Metis uses Tensorflow (Abadi et al., 2016a) as its deep learning execution engine.

![Figure 4. Metis System Architecture](image)

**Federation Controller.** The centralized controller is a multi-threaded process with a modular, non-monolithic design that integrates a collection of extensible microservices (i.e., caching and community tiers). The controller orchestrates the execution of the entire federation and is responsible to initiate the system pipeline, broadcast the initial community model and handle the update requests.

The controller handles every incoming update request in a FIFO ordering through a mutual exclusive lock, ensuring system state linearizability (Herlihy & Wing, 1990). Essentially, the federation controller is a materialized version of the Parameter Server (Abadi et al., 2016a; Dean et al., 2012) concept, widely used in distributed learning applications.

The centralized federated learning topology that we investigate, i.e., a centralized coordinator and a set of learning nodes (see Figure 4), is considered a standardized topology in cross-silo federated learning settings (Kairouz et al., 2019; Li et al., 2020a; Yang et al., 2019). Compared to other existing work (Bonawitz et al., 2019) in which multiple coordinators may exist along with a set of master and sub-aggregators, our learning environment consists of a single master coordinator (i.e., Federation Controller) that is responsible to coordinate the federated execution and aggre-
gate the learners’ local models. Furthermore, the breakdown of the learning environment into tiers is a new concept and helps to decouple the data management and network training procedures in cross-silo settings.

**Community & Caching Tier.** The community tier computes a new community model $w_c$ (Equation 1), as a weighted average of the most recent model that each learner has shared with the controller. To facilitate this computation, it is natural to store the most recently received local model of every learner in-memory or on disk. Therefore, the memory and storage requirements of a community model depend on the number of local models contributing to the community model. For a synchronous protocol we always need to perform a pass over the entire collection of stored local models, with a computational cost $O(MN)$, where $M$ is the size of the model and $N$ is the number of participating learners. For an asynchronous protocol where update requests are generated at different paces, such a complete pass is redundant and we can leverage the existing cached/stored local models to compute a new community model in $O(M)$ time, independent of the number of learners.

Consider an unnormalized community model consisting of $m$ matrices, $W_c = \langle W_{c1}, W_{c2}, \ldots, W_{cm} \rangle$, and a community normalization weighting factor $P = \sum_{k=1}^{N} p_k$. Given a new request from learner $k$, with new community contribution value $p'_k$, the new normalization value $P'$ is $P' = P + p'_k - p_k$, where $p_k$ is the learner’s previous contribution value. For every component matrix $W_{c_i}$ of the community model, the updated matrix $W'_{c_i}$ is $W'_{c_i} = W_{c_i} + p'_k w'_{k,i} - p_k w_{k,i}$, where $w'_{k,i}, w_{k,i}$ are the new and existing component matrices for learner $k$. The new community model is $w'_c = \frac{P'}{P} W'$. Using this caching approach, the most recently contributed local model of every learner in the federation is always considered in the community model and without any dependence on mixing hyperparameters.

Some existing asynchronous community mixing approaches (Sprague et al., 2018; Xie et al., 2019) compute a weighted average using a mixing hyperparameter between the current community and the committing local model of a requesting learner. In contrast, using our caching approach every contributed local model is always considered in the community model and in turn alleviates the mixing hyperparameter dependence.

Figure 5 shows the computation cost for different sizes of a ResNet community model (from Resnet-20 to Resnet-200), in the Cifar-100 domain, as the federation increases to 1000 learners. With our caching mechanism the time to compute a community model remains constant, while it significantly increases without it.

**Model Exchange Tier.** Every learner in the federation contacts the controller for a community update once it completes its local training and shares its local model with the controller. Upon computing the new community model, the controller sends the new model to every requesting learner and the learner continues its next training cycle. This model exchange is represented with requests R1 to R6 in Figure 4.

**Learners & Data Tier.** All learners train on the same neural network architecture with identical hyperparameter values (learning rate, batch size, etc), starting from the same initial (random) model state, and using the same local SGD optimizer. The number of local steps a learner performs before issuing an update request can be defined in terms of epochs or batches (cf. Section 4). Every learner trains on its own local training dataset and no data is shared.

**Execution Pipeline.** Algorithm 1 describes the execution pipeline within Metis for synchronous, semi-synchronous, and asynchronous communication protocols. In synchronous and semi-synchronous protocols, the controller waits for all the participating learners to finish training on their local training dataset before it computes a community model, distribute it to the learners, and proceed to the next global iteration. In asynchronous protocols, the controller computes a community model whenever a single learner finishes its local training, using the caching mechanism, and sends the new model to the learner. In all cases, the controller assigns a contribution value $p_k$ to the local model $w_k$ that a learner $k$ shares with the community. For synchronous and asynchronous FedAvg (SyncFedAvg and AsyncFedAvg), this value is statically defined and based on the size of the learner’s local training dataset, $D_k$. For other weighting schemes, such as FedRec, the STALENESS procedure computes it dynamically.

The CLIENTOPT procedure implements the local training of each learner. A learner performs a number of local steps that are either based in terms of epochs/batches or the maximum scheduled time (see eq. 4). This information is passed to every learner through the metadata, meta, collection.

![Figure 5. Community model computation with (left) and without (right) caching.](image-url)
Algorithm 1 FL Training with Metis. Community model \( w_c \) consisting of \( m \) matrices is computed with \( N \) learners, each indexed by \( k \); \( \gamma \) is the momentum attenuation factor; \( \eta \) is the learning rate; \( \beta \) is the batch size.

**Initialization:** \( w_c, \gamma, \eta, \beta \)

**(Semi-)Synchronous**

for \( t = 0, \ldots, T - 1 \) do

for each client \( k \in N \) in parallel do

\( w_k = \text{CLIENTOPT}(w_c, \text{meta}) \)

\( p_k = D^T_k \) (SyncFedAvg)

\( w_c = \sum_{k=1}^N \frac{1}{N} w_k \) with \( P = \sum_{k} p_k \)

Reply \( w_c \) to every client

end for

Asynchronous

\( \bar{P} = 0; \forall k \in N, p_k = 0; \forall i \in m, W_{c,i} = 0 \)

while true do

if (update request from client \( k \) with model \( w_k \)) then

\( p'_k = \begin{cases} D^T_k & \text{(AsyncFedAvg)} \\ \text{STALENESS}(k) & \text{(FedRec)} \end{cases} \)

\( \bar{P}' = \bar{P} + p'_k - p_k \)

for \( i \in m \) do

\( W'_{c,i} = W_{c,i} + p'_k w'_{k,i} - p_k w_{k,i} \)

\( w'_c = \frac{1}{\bar{P}'} W'_c \)

Reply \( w'_c \) to client \( k \)

end for

end for

**CLIENTOPT(\( w_c, \text{meta} \)):**

\( w_t = w_c \)

\( B = \begin{cases} \text{meta[epochs]} \times D^T / \beta & \text{(Sync & Async)} \\ \text{meta[tmax]} \times 1 / \beta_k & \text{(SemiSync, cf. Section 4)} \end{cases} \)

\( B = \text{Shuffle} B \) training batches of size \( \beta \)

for \( b \in B \) do

if Vanilla SGD then

\( w_{t+1} = w_t - \eta \nabla F_k(w_t; b) \)

end if

if Momentum then

\( u_{t+1} = \gamma u_t - \eta \nabla F_k(w_t; b) \)

\( w_{t+1} = w_t + u_{t+1} \)

if FedProx then

\( w_{t+1} = w_t - \eta \nabla F_k(w_t; b) - \eta \mu (w_t - w_c) \)

Send \( w_{t+1} \) to controller

end if

end if

**STALENESS(\( k \):**

\( s'_t = \) committed community steps at current global time

\( s'_t = \) committed community steps at previous global time

\( s_k = \) number of steps of learner \( k \) between \( t \) and \( t' \)

\( S_k = (s'_t - (s'_t + s_k))^{-1/2} \)

Reply \( S_k \)

\[
\text{Finally, a learner can use either Momentum SGD or FedProx as its local SGD solver.}
\]

6 Evaluation

We conduct an extensive experimental evaluation of different communication protocols on heterogeneous environments with different amounts of data per learner, local data distributions and computational resources. We evaluate the protocols on the Cifar-10 and Cifar-100 domains, with a federation consisting of 10 learners. All the asynchronous protocols (i.e., FedRec and AsyncFedAvg) were run using the caching mechanism described in Section 5 except for FedAsync. FedAsync was run using the polynomial staleness function, i.e., FedAsync+Poly, with mixing hyperparameter \( a = 0.5 \) and model divergence regularization factor \( \rho = 0.005 \) reported to have the best performance (Xie et al., 2019). The weighting scheme for AsyncFedAvg is the same as SyncFedAvg, namely, the weighting value of each learner in the community is equal to the number of local training examples.

Models Architecture. The architecture of the deep learning networks for Cifar-10 and Cifar-100 come from the Tensorflow tutorials: for Cifar-10 we train a 2-CNN\(^1\) and for Cifar-100 a ResNet-50\(^2\). For all models, during training, we share all trainable weights (i.e., kernels and biases). For ResNet we also share the batch normalization, gamma and beta matrices. For reproducibility, we set a random seed for all our experiments (with the value 1990).

Models Hyperparameters. For Cifar-10 homogeneous and heterogeneous environments the synchronous protocols were run with both SGD with Momentum and FedProx and asynchronous (FedRec, AsyncFedAvg) with Momentum. For Cifar-100 all the methods were run with Momentum. We originally performed a grid search over different combinations of learning rate, \( \eta \), momentum factor, \( \gamma \), and mini batch size, \( \beta \), values for Momentum and proximal term \( \mu \) for FedProx. After identifying the optimal combination, we kept the hyperparameter values fixed throughout the federation training. In particular, for Cifar-10 we used, \( \eta = 0.05 \), \( \gamma = 0.75 \) and \( \beta = 100 \), for Cifar-100, \( \eta = 0.1 \), \( \gamma = 0.9 \), \( \beta = 100 \). For FedProx we used \( \mu = 0.001 \) in every environment.

Learners Local Steps. For both synchronous and asynchronous policies we originally evaluated the convergence rate of the federation under different number of local epochs \{1, 2, 4, 8, 16, 32\} and we observed that 4 local epochs per models/tree/r1.13.0/tutorials/image/cifar10

\(^1\)Cifar-10: https://github.com/tensorflow/

\(^2\)Cifar-100: https://github.com/tensorflow/models/tree/r1.13.0/official/resnet
learner demonstrated the best performance. For SemiSync policies we investigated the convergence of hyperparameter $\lambda$ within the range $\{0.5, 1, 2, 4\}$. Figure 6 shows the number of local steps per learner per data distribution when steps are defined based on the number of epochs and when using the semi-synchronous step scheduling approach (eq. 4).

For Power Law data sizes and Non-IID configurations, in order to preserve scale invariance, we needed to assign data from more classes to the learners at the head of the distribution. For example, for Cifar-10 with Power Law and a goal of 5 classes per learner, the actual distribution is Non-IID(8x1,7x1,6x1,5x7), meaning that the first learner holds data from 8 classes, the second from 7 classes, the third from 6 classes, and all 7 subsequent learners hold data from 5 classes. For brevity, we refer to this distribution as Non-IID(5). Similarly for Cifar-10 Power Law and Non-IID(3), the actual distribution is Non-IID(8x1,4x1,3x8). For Cifar-100, Power Law and Non-IID(50), the actual distribution is Non-IID(84x1,76x1,68x1,64x1,55x1,50x5).

In order to simulate realistic learning environments, we sort each configuration in descending data size order and we assign the data to each learner in an alternating fashion (i.e., fast learner, slow learner, fast learner), except for the uniform distributions where the data size is identical for all learners. Due to space limitations, for every experiment we include the respective data distribution configuration as an inset in the convergence rate plots (Figures 7, 8, 9). Figure 13 in the Appendix shows the data distributions at a higher resolution.

The data distributions that we investigate in this work are based on the work of (Zhao et al., 2018), where the data are evenly (i.e., Uniform in our case) partitioned across 10 clients and with different class distribution per learner (i.e., Non-IID(2)) refers to examples from 2 classes per learner). We consider three types of data size distributions: Uniform, where every learner has the same number of examples; Skewed, where the distribution of the number of examples is rightly skewed and hence no learner has the exact same data size as the others; and Power Law, with the power law’s exponent set to 1.5. We only show the Skewed and Power Law data size distributions since these are more challenging learning domains and we refer the reader for the Uniform distributions to Figure 13 in the Appendix. For class distribution, we assign a different number of examples per class per learner for each domain independently. Specifically, with IID we denote the case where all learners hold training examples from all the target classes, and with Non-IID(x) we denote the case where every learner holds training examples from only x classes. For example, Non-IID(3) in Cifar-10 means that each learner only has training examples from 3 target classes (out of the 10 classes in Cifar-10).

Data Distributions. We evaluate the training policies over multiple training datasets with heterogeneous data sizes and class distributions.\(^3\) We consider three types of data size distributions: Uniform, where every learner has the same number of examples; Skewed, where the distribution of the number of examples is rightly skewed and hence no learner has the exact same data size as the others; and Power Law, with the power law’s exponent set to 1.5. We only show the Skewed and Power Law data size distributions since these are more challenging learning domains and we refer the reader for the Uniform distributions to Figure 13 in the Appendix. For class distribution, we assign a different number of examples per class per learner for each domain independently. Specifically, with IID we denote the case where all learners hold training examples from all the target classes, and with Non-IID(x) we denote the case where every learner holds training examples from only x classes. For example, Non-IID(3) in Cifar-10 means that each learner only has training examples from 3 target classes (out of the 10 classes in Cifar-10).

\(^3\)All the distributions of our experiments can be found at: https://dataverse.harvard.edu/
In our work, we extend their current approach by also investigating the case, where the size of the partitions is not uniform but follows a skewed or a power law distribution (quantity skew/unbalanceness in (Kairouz et al., 2019)). In order to materialize these learning scenarios, for the Uniform sized partitions we first sort the data by class id (in increasing order) and then assign each class in a Round-Robin fashion to every learner, while in the case of Skewed and Power Law, we first generate the size of the partitions based on the skewness factor and we subsequently assign the respective classes in a similar Round-Robin fashion. Any remaining training samples are assigned to the learners based on the class ids the learners own, by starting from the head of the distribution and going towards the tail.

Overall, in this work the term statistical heterogeneity refers to the combination of both the Non-IID and unbalance aspects of the federation, while in previous work (Li et al., 2018), the term refers exclusively to the Uniform and Non-IID case.

Results & Findings. We present our results in homogeneous environments for Cifar-10 in Figure 7; and on heterogeneous environments for Cifar-10 in Figure 8, for Cifar-100 in Figure 9.

Figure 7 shows the performance of synchronous and semi-synchronous policies in a homogeneous computational environment, where all the learners have the same computational capabilities. Specifically, the experiments are run on 10 identical GPUs. In the synchronous policies, idle time still occurs due to the different amounts of data per learner in the Skewed and Power Law data distributions. In SemiSync policies, there is no idle time. Compared to synchronous, our SemiSync training policy allows more training to learners who own fewer number of examples, which has the overall effect of faster generalization and better utilization of the available federation resources. From these learning environments, SemiSync is complementary to both local optimizers (i.e., Momentum SGD and FedProx) and it can be applied in tandem. SemiSync with Momentum and λ = 2 results in faster convergence than other approaches across the experiments in Figure 7(a). These results are particularly dramatic in the power law data distributions compared to SyncFedAvg with Momentum, although using SyncFedAvg with FedProx performs comparably. Similar results
Figure 8. Heterogeneous Computational Environment on Cifar-10. The SemiSync policy outperforms all the rest of the policies both in terms of computational efficiency (i.e. faster convergence) and communication cost (i.e. fewer number of update requests to converge). The communication cost is measured in terms of update requests since during asynchronous training learners trigger update requests at different paces and no synchronization point exists. Device label ‘G’ and ‘C’ inside the data distribution inset is an abbreviation for GPU and CPU respectively. In this learning environment CPUs are 10 times slower compared to GPUs. The communication cost holds for communication cost in terms of federation rounds (update requests are 10 times the federation rounds in the homogeneous setting) as shown in Figure 7(b).

Figure 8 shows the performance on the Cifar-10 domain of synchronous, asynchronous, and semi-synchronous policies in a heterogeneous computational environment (with 10 learners: 5 fast GPUs, and 5 slow CPUs; the CPUs batch processing is 10 times slower than the GPUs). Again, our SemiSync with Momentum policy (with \( \lambda = 2 \)) has the best performance, with faster convergence early on (although in some cases other policies reach comparable accuracy levels eventually). SyncFedAvg with Momentum performs reasonably well with moderate levels of data heterogeneity (Skewed data amounts, with either IID or Non-IID class distributions). However, in more extreme data distributions (PowerLaw), it fails to learn or learns at a much slower pace than alternative methods. Interestingly, SyncFedAvg with FedProx performs much better in these cases, although still worse than the SemiSync policies. Similarly to the homogeneous case, our semi-synchronous policies dominate the asynchronous policies in heterogeneous environments. The communication cost of SemiSync policies is comparable to synchronous policies reaching a high accuracy very quickly, while asynchronous policies require many more update requests to achieve the same (or worse) level of accuracy (Figure 8(b)). For PowerLaw data distributions SyncFedAvg with Momentum fails to learn, but SyncFedAvg with FedProx learns and efficiently uses communication.

Figure 9 shows the performance on the Cifar-100 domain of synchronous, asynchronous, and semi-synchronous policies in a heterogeneous computational environment (with 10 learners: 5 fast GPUs, and 5 slow CPUs). Since with the large ResNet-50 model used in Cifar-100 the performance difference between fast and slow learners is large (CPUs batch processing is 33 times slower than the GPUs), a smaller value of \( \lambda \) gives better results in the SemiSync policy. We use \( \lambda = 0.5 \), which means that the slow learners only process half of their data at each SemiSync synchronization point. However, since the batches are chosen randomly, after two synchronization periods all the data is processed (on average). The previous results hold in these challenging domain. Our SemiSync with Momentum (\( \lambda = 0.5 \)) policy performs significantly better than alternatives approaches, learning at a much faster pace, while remaining communi-
Heterogeneous Computational Environment on Cifar-100. SemiSync with Momentum $\lambda = 0.5$ significantly outperforms all other policies in the challenging Cifar-100 domain. In this learning environment slow learners (CPUs) are 33 times slower than fast learners (GPUs). For $\lambda = 2$ SemiSync still has a slightly faster convergence compared to synchronous and asynchronous, but eventually plateaus, since the GPUs overfit their models (they process 66 times more batches than CPUs). With a more balanced communication frequency, $\lambda = 0.5$, the federation is able to learn significantly faster.

Figure 6 shows the data, in terms of number of local batches, that each learner processes with Skewed and PowerLaw data distributions for synchronous and semi-synchronous policies in a heterogeneous domain (10 learners: 5 fast GPUs, and 5 slow CPUs), on both (a) Cifar-10 and (b) Cifar-100 domains. For synchronous policies, we show the number of batches computed for a federation round of 4-epochs (left plots). For semi-synchronous policies we show the batches computed for synchronization periods with $\lambda = 2$ (Cifar-10) or $\lambda = 0.5$ (Cifar-100). In synchronous policies, the number of batches is determined by the amount of data at each learner. In semi-synchronous policies the different computational power determines the number of batches, with faster learners processing significantly more batches. Overall, the more efficient model mixing of semi-synchronous policy results in faster convergence of the federation model.

7 DISCUSSION

We have introduced a novel Semi-Synchronous Federated Learning training policy, SemiSync, which is robust to heterogeneous data and computational environments. This policy defines a synchronization time point where all learners share their current models to compute the community model. However, in contrast with synchronous policies, learners with different amounts of data or different computational power do not remain idle at any time. By choosing the synchronization point so that the amount of data processed by fast and slow learners does not become too dissimilar, we can achieve fast convergence without increasing communication costs.

We performed extensive experiments comparing synchronous (FedAvg), asynchronous (FedAsync, FedRec), and semi-synchronous (SemiSync) policies in heterogeneous data and computational environments. We explored different combination of these methods and optimizers, such as SGD with Momentum, and FedProx. We show experimentally that our SemiSync policy provides faster learning convergence than previous approaches, and reaches better or comparable eventual accuracy. The effects are more pronounced the more challenging the domain is, such as the results on Cifar-100 with different data amounts per learner and Non-IID class distributions.

REFERENCES

Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., Isard, M., et al. Tensorflow: A system for large-scale machine learning. In 12th {USENIX} Symposium on Operating Systems Design and Implementation ({OSDI} 16), pp. 265–283, 2016a.

Abadi, M., Chu, A., Goodfellow, I., McMahan, H. B., Mironov, I., Talwar, K., and Zhang, L. Deep learning with differential privacy. In Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security, pp. 308–318, 2016b.

Agarwal, A. and Duchi, J. C. Distributed delayed stochastic optimization. In Advances in Neural Information Processing Systems, pp. 873–881, 2011.

Bertsekas, D. P. Distributed asynchronous computation of fixed points. Mathematical Programming, 27(1):107–120, 1983.

Bertsekas, D. P. and Tsitsiklis, J. N. Parallel and distributed computation: numerical methods, volume 23. Prentice hall Englewood Cliffs, NJ, 1989.

Bonawitz, K., Ivanov, V., Kreuter, B., Marcedone, A., McMahan, H. B., Patel, S., Ramage, D., Segal, A., and Seth, K. Practical secure aggregation for privacy-preserving machine learning. In Proceedings of the 2017
Bonawitz, K., Eichner, H., Grieskamp, W., Huba, D., Ingerman, A., Ivanov, V., Kiddon, C., Konecny, J., Mazzocchi, S., McMahan, H. B., et al. Towards federated learning at scale: System design. *arXiv preprint arXiv:1902.01046*, 2019.

Chai, Z., Ali, A., Zawad, S., Truex, S., Anwar, A., Baracaldo, N., Zhou, Y., Ludwig, H., Yan, F., and Cheng, Y. Tifl: A tier-based federated learning system. In *Proceedings of the 29th International Symposium on High-Performance Parallel and Distributed Computing*, pp. 125–136, 2020.

Chen, J., Pan, X., Monga, R., Bengio, S., and Jouzefowicz, R. Revisiting distributed synchronous sgd. *arXiv preprint arXiv:1604.00981*, 2016.

Cui, H., Cipar, J., Ho, Q., Kim, J. K., Lee, S., Kumar, A., Wei, J., Dai, W., Ganger, G. R., Gibbons, P. B., et al. Exploiting bounded staleness to speed up big data analytics. In *2014 USENIX Annual Technical Conference*, pp. 37–48, 2014.

Dai, W. *Learning with Staleness*. PhD thesis, Carnegie Mellon University, 2018.

Dai, W., Zhou, Y., Dong, N., Zhang, H., and Xing, E. P. Toward understanding the impact of staleness in distributed machine learning. *arXiv preprint arXiv:1810.03264*, 2018.

Dean, J. and Barroso, L. A. The tail at scale. *Communications of the ACM*, 56(2):74–80, 2013.

Dean, J., Corrado, G., Monga, R., Chen, K., Devin, M., Mao, M., Ranzato, M., Senior, A., Tucker, P., Yang, K., et al. Large scale distributed deep networks. In *Advances in neural information processing systems*, pp. 1223–1231, 2012.

Herlihy, M. P. and Wing, J. M. Linearizability: A correctness condition for concurrent objects. *ACM Transactions on Programming Languages and Systems (TOPLAS)*, 12(3):463–492, 1990.

Ho, Q., Cipar, J., Cui, H., Lee, S., Kim, J. K., Gibbons, P. B., Gibson, G. A., Ganger, G., and Xing, E. P. More effective distributed ml via a stale synchronous parallel parameter server. In *Advances in neural information processing systems*, pp. 1223–1231, 2013.

Hsu, T.-M. H., Qi, H., and Brown, M. Measuring the effects of non-identical data distribution for federated visual classification. *arXiv preprint arXiv:1909.06335*, 2019.
Paillier, P. Public-key cryptosystems based on composite degree residuosity classes. In Stern, J. (ed.), Advances in Cryptology — EUROCRYPT ’99. Springer Berlin Heidelberg, 1999.

Recht, B., Re, C., Wright, S., and Niu, F. Hogwild: A lock-free approach to parallelizing stochastic gradient descent. In Advances in neural information processing systems, pp. 693–701, 2011.

Reddi, S., Charles, Z., Zaheer, M., Garrett, Z., Rush, K., Konečný, J., Kumar, S., and McMahan, H. B. Adaptive federated optimization. arXiv preprint arXiv:2003.00295, 2020.

Rieke, N., Hancox, J., Li, W., Milletari, F., Roth, H. R., Albarqouni, S., Bakas, S., Galtier, M. N., Landman, B. A., Maier-Hein, K., et al. The future of digital health with federated learning. NPJ digital medicine, 3(1):1–7, 2020.

Rivest, R. L., Adleman, L., Dertouzos, M. L., et al. On data banks and privacy homomorphisms. Foundations of secure computation, 4(11):169–180, 1978.

Smith, V., Chiang, C.-K., Sanjabi, M., and Talwalkar, A. S. Federated multi-task learning. In Advances in Neural Information Processing Systems, pp. 4424–4434, 2017.

Sprague, M. R., Jalalirad, A., Scavuzzo, M., Capota, C., Neun, M., Do, L., and Kopp, M. Asynchronous federated learning for geospatial applications. In Joint European Conference on Machine Learning and Knowledge Discovery in Databases, pp. 21–28. Springer, 2018.

Wang, J. and Joshi, G. Cooperative sgd: A unified framework for the design and analysis of communication-efficient sgd algorithms. arXiv preprint arXiv:1808.07576, 2018.

Wang, S., Tuor, T., Salonidis, T., Leung, K. K., Makaya, C., He, T., and Chan, K. Adaptive federated learning in resource constrained edge computing systems. IEEE Journal on Selected Areas in Communications, 37(6): 1205–1221, 2019.

Xie, C., Koyejo, S., and Gupta, I. Asynchronous federated optimization. arXiv preprint arXiv:1903.03934, 2019.

Yang, Q., Liu, Y., Chen, T., and Tong, Y. Federated machine learning: Concept and applications. ACM Transactions on Intelligent Systems and Technology (TIST), 10(2):1–19, 2019.

Zhang, C., Li, S., Xia, J., Wang, W., Yan, F., and Liu, Y. Batchcrypt: Efficient homomorphic encryption for cross-silo federated learning. In 2020 USENIX Annual Technical Conference (USENIX ATC 20), pp. 493–506, 2020.

Zhao, Y., Li, M., Lai, L., Suda, N., Civin, D., and Chandra, V. Federated learning with non-iid data. arXiv preprint arXiv:1806.00582, 2018.

Zhang, S., Choromanska, A. E., and LeCun, Y. Deep learning with elastic averaging sgd. In Advances in neural information processing systems, pp. 685–693, 2015.
### APPENDIX

**Figure 10.** Cifar10 homogeneous computational environment convergence. Uniform assignment of examples per learner.

**Figure 11.** Cifar10 heterogeneous computational environment convergence. Uniform assignment of examples per learner.

**Figure 12.** Staleness distribution for every learner in a heterogeneous computational environment with 5 GPUs and 5 CPUs for a Skewed and PowerLaw assignment of examples in Cifar10.
Figure 13. Cifar10 Uniform, Skewed and PowerLaw data distributions for the heterogeneous computational environment.