MYSTIKO: Cloud-Mediated, Private, Federated Gradient Descent

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Abstract—Federated learning enables multiple, distributed participants (potentially on different clouds) to collaborate and train machine/deep learning models by sharing parameters/gradadients. However, sharing gradients, instead of centralizing data, may not be as private as one would expect. Reverse engineering attacks \cite{1}, \cite{2} on plaintext gradients have been demonstrated to be practically feasible. Existing solutions for differentially private federated learning, while promising, lead to less accurate models and require nontrivial hyperparameter tuning.

In this paper, we examine the use of additive homomorphic encryption (specifically the Paillier cipher) to design secure federated gradient descent techniques that (i) do not require addition of statistical noise or hyperparameter tuning, (ii) does not alter the final accuracy or utility of the final model, (iii) ensure that the plaintext model parameters/gradadients of a participant are never revealed to any other participant or third party coordinator involved in the federated learning job, (iv) minimize the trust placed in any third party coordinator and (v) are efficient, with minimal overhead, and cost effective.

Keywords—federated learning, gradient descent, aggregator, additive homomorphic encryption

I. INTRODUCTION

Some of the early success of distributed machine/deep learning (ML/DL) in several application domains \cite{3}, \cite{4} has been in the context of massive centralized data collection, either at a single datacenter or a cloud service. However, centralized data collection at a (third-party) cloud service can be incredibly privacy-invasive, and can expose organizations (customers of the cloud service) to large legal liability when there is a data breach. This is especially true in the case of healthcare data, voice transcriptions, home cameras, financial transactions, etc. Centralized data collection often results in “loss of control” over data once it is uploaded – “Is the cloud service using my data as promised? Is it actually deleting my data when it claims to do so?”. Organizations that have not been convinced by privacy violations and loss of control, have been forced by governmental regulations (like HIPAA and GDPR \cite{5}) to restrict data sharing with third party services.

Federated learning (FL) aims to mitigate the three aforementioned issues, while maintaining accuracy of ML/DL models. An entity in an FL job can be as small as a smart phone/watch or as large as an organization with multiple data centers. An FL algorithm aims to train a ML/DL model, e.g., a specific neural network model or an XGBoost model, on multiple entities, each with its own “local” dataset, without exchanging any data. This results in multiple “local models”, which are then combined (aggregated) by exchanging only parameters (e.g., the weights of the a neural network model). An FL algorithm may use a central co-ordinator to collect parameters of all local models for aggregation; or it may be a peer-to-peer algorithm (broadcast, overlay multicast, etc.)

Exchanging parameters of the model was thought to provide privacy for free, and reduce the amount of trust that a participant in a federated learning job has to place in the co-ordinator or in other participants. But, researchers have demonstrated \cite{1}, \cite{2}, \cite{6} through so-called model inversion and membership inference attacks that parameters of a model can be used to reconstruct data from which they are derived. So the challenge in federated learning is to ensure the privacy of the model parameters and gradients.

It has been demonstrated \cite{7}, \cite{8} that statistical noise, when added in specific ways to (clipped) gradients before being sent out for aggregation, can ensure corresponding levels differential privacy (recall that differential privacy is a probabilistic guarantee). However, the same papers \cite{7}, \cite{8} also demonstrate that achieving differential privacy results in non-trivial loss of model accuracy. Furthermore, increasing differential privacy reduces accuracy. Also, for a specific level of differential privacy, accuracy depends on careful hyperparameter selection (learning rate, batch size and gradient clip values). This can be tricky because not all batch sizes which are generally “acceptable" for training a specific neural net model in a non-private manner give the best accuracy in a differentially private setting. Combined with learning rate and clipping thresholds, the state space of hyperparameter exploration quickly becomes large.

In this paper, we present MYSTIKO, a system for cloud-mediated, private federated deep learning based on gradient descent. This paper makes the following technical contributions:

1) A novel cryptographic key generation and sharing technique that uses additive homomorphic encryption (specifically the Paillier cipher \cite{9}) to maximize privacy of federated gradient descent in training deep neural networks without any loss of accuracy.

2) A novel protocol to arrange participants in a ring, and structure communication between them so that non-aggregated plaintext gradients are never revealed to any participant or co-ordinator.

3) Extensions of the above technique to broadcast and
All-Reduce protocols, for increased efficiency.

4) A detailed empirical evaluation of Mystiko against differential privacy schemes (added statistical noise) and state-of-the-art secure multiparty computation protocols, using realistic datasets and neural network models. We demonstrate performance improvements of up to 6.1× when compared to the SPDZ protocol [10].

II. FOCUS, TRUST MODEL AND ASSUMPTIONS

We focus on the scenario where each participant is convinced of the benefits (improvements in accuracy, robustness, etc.) of federated learning. Each participant is convinced enough that it follows the steps of the federation protocol and does not collude with the co-ordinator to break the protocol. But the participant may be curious about the data of others, and it may be in their interest to reverse-engineer the model parameters to try and discover other participants’ data. We also assume that the co-ordinator is honest, but curious with respect to individual participant’s data. The participants want to reduce the required amount of trust in the coordinator as much as possible. Specifically, we assume that each participant does not attempt to poison or skew the global model by maliciously generating weights.

Examples/Use Cases: This trust model is predominantly found in enterprise federated learning. A multinational bank having branches in multiple countries and so regulated locally (BankA, BankA US, BankA UK, BankA India, etc.), where the bank wants to learn a fraud detection model across data of all its subsidiaries, but the data cannot be transferred to a central location due to governmental data sovereignty/jurisdiction laws [5]. Each participant here is a subsidiary with its national data center(s) and the coordinator might be located in a cloud platform or a global datacenter. Another example is a set of hospitals who want to collaborate to train a tumor detection model; each hospital is unable to trust the others and unwilling to trust and transfer data to a central service. Another example is a cloud-hosted machine learning service (e.g., Azure ML) which has multiple (competing) corporate clients which do not trust each other but have some level of trust in the cloud service to facilitate and secure federated learning.

III. BACKGROUND

Gradient Descent [11]: Throughout this paper, we focus on deep neural network training algorithms which rely on distributed gradient descent (including optimized variants like Adam, Adagrad [11], etc.). We assume that there are $P$ parties, each learning on its own dataset. It is well known that gradient descent is a popular optimization algorithm to minimize the loss for an objective function $J(\theta)$ parameterized by a model’s parameters $\theta \in \mathbb{R}^d$ by updating the parameters at every step ($\theta = \theta - \eta \nabla_{\theta} J(\theta)$) The frequency of model updates varies with the type of gradient descent: the gradient is computed on the whole dataset in the case of plain gradient descent, on each data item in the case of stochastic gradient descent (SGD) and on a small batch of items in the case of mini-batch gradient descent.

In a distributed setting, each participant computes $\nabla_{\theta} J(\theta)$ on a batch from its dataset, and these gradient vectors are averaged before updating the model parameters $\theta$. That is, either each participant broadcasts its gradients $\nabla_{\theta} J(\theta)$ to all other participants (using all-to-all broadcast or optimized all-reduce) or sends its gradients to a central co-ordinator for averaging. The averaged gradients from iteration $t$ are then used to update model parameters in iteration $t + 1$ to compute the model parameters of iteration $t + 1$.

Additive Homomorphic Encryption: Homomorphic encryption allows computation on ciphertexts, generating an encrypted result which, when decrypted, matches the result of the operations as if they had been performed on the plaintext [12]. Fully homomorphic encryption is expensive, both in terms of encryption/decryption time as well as the size of the ciphertext. However, averaging gradient vectors requires only addition (division by the total number of participants can be done before or after encrypted aggregation). Hence, we employ additive homomorphic encryption like the Paillier cryptosystem [9]. The Paillier cryptosystem is an asymmetric algorithm for public key cryptography. Given only the public key and the encryption of $m_1$ and $m_2$, one can compute the encryption of $m_1 + m_2$.

IV. Mystiko – Overview

The main characteristics of any privacy preserving federated learning scheme revolves around a) what methodology is used to encrypt the data (or noise addition) of the participants and b) the communication protocol being used among the participants and the co-ordinator (if any) for aggregation of the model parameters or gradients. We present a novel approach, Mystiko, in which all participants encrypt individual data using a single Paillier public encryption key, adding encrypted gradient vectors and decrypting only the sum. Thus, only the participants are able to view their individual data, ensuring privacy. The question now is (1) how to distribute a common Paillier public key to all participants.
while keeping the corresponding private key secret?, and (2) how to prevent anyone from decrypting individual weights? These are explained in the following sections.

A. Participants, Learners and Administrative Domains

Logically speaking, it is helpful to define federated learning algorithms in terms of administrative domains. An administrative domain is a set of computing entities (servers, VMs, desktops, laptops, etc.). Each entity inside an administrative domain trusts the other, malice is not a concern, and there are no legal/regulatory hurdles to sharing data and information derived from data. Note that an administrative domain does not necessarily mean a company or a non-corporate organization. It may be a project within a company handling confidential data; it may be not be located within a corporate datacenter, and instead be associated with an account on the public cloud. An organization can have multiple administrative domains. Each participant in a federated learning algorithm corresponds to an administrative domain. Computationally, the actual learning process (typically running on a GPU) performing the neural network training is called a Learner. Each Learner works on (a batch of) data within the participant to compute the gradient vector.

B. Architecture

For simplicity, we assume that there is exactly one learner per participant. We will relax this assumption in Section V-D. MYSTIKO is typically deployed as a cloud service that mediates several participants. It involves a Job Manager, Membership Manager, a Key Generator and a Decryptor. The Membership Manager is responsible for establishing the relationship between each participant and MYSTIKO, and also keeping track of participants that belong to each federated learning job. The Job Manager manages an FL job through its lifecycle – it keeps track of participants, helps participants agree on hyperparameters, detects failures and updates to memberships.

C. Communication Security

While the focus of this paper is attacks on the privacy of data from within a federation, traditional communications security is nevertheless essential to prevent outside attacks on the federation. For this, MYSTIKO and the participants (learners) agree to use a common public-key infrastructure (PKI) \([13]\). The PKI helps ensure confidentiality of communications between the MYSTIKO components and the learners, and helps bootstrap the Paillier infrastructure. The PKI provides certification authorities (CAs), along with corresponding intermediate and Root CAs, creating a web of trust between the learners and MYSTIKO. MYSTIKO creates a bidirectional TLS channel \([14]\) using the PKI for the security of control messages. The TLS channel is created using strong, but ordinary (non-homomorphic) cryptographic algorithms (e.g., RSA for key exchange/agreement and authentication, AES for message confidentiality and SHA for message authentication \([13], [14]\)). The TLS channel is not used for gradient aggregation, but rather for all other communications, like registration of learners with the MYSTIKO topology formation, rank assignment, transmitting the Paillier public key to each learner, and transmitting the decrypted aggregated gradient vector to each learner.

V. ALGORITHMS

A. Basic Ring-based Algorithm

The basic ring-based aggregation algorithm is illustrated in Figures 1 and 2. This algorithm operates across \(P\) participants, each in its own administrative domain and represented by a learner (L). The algorithm starts with each participant registering with MYSTIKO. MYSTIKO acts as the coordinator. The learners need not fully trust MYSTIKO; they only need to trust it to generate good encryption keypairs, keep the private key secret and follow the protocol.

MYSTIKO’s Membership Manager starts the federated learning protocol once all expected learners are registered. The first step is to arrange the learners along a ring topology (Figure 1). This can be done in several straightforward ways: (i) by location – minimizing geographic distance between participants, (ii) by following a hierarchy based on the name of the participants (ascending or descending order), or (iii) by using consistent hashing \([15]\) on the name/identity of the participants. Once the learners have been arranged in a ring, each learner gets a rank (from 1 to \(P\)) based on its position in the ring.

MYSTIKO’s Paillier Key generator, which generates a Paillier public- and private key pair for each federated learning job. Typically, a unique Paillier key pair is generated for each federated learning job, and the Paillier public key securely distributed (over TLS) to all the learners. For long jobs, a separate keypair may be generated either once
every epoch or once every $h$ minutes (this is configurable). **Mystiko**’s Decryptor is responsible for decrypting the Paillier encrypted aggregated gradient vector for distribution to the learners. Each learner receives a Paillier encrypted gradient vector from the previous learners on the ring, encrypts its own gradient vector with the Paillier public key, and adds (aggregates) the two Paillier encrypted vectors. This aggregated, Paillier encrypted gradient vector is then transmitted to the next learner on the ring. The last learner on the ring transmits the fully aggregated, encrypted gradient vector to Mystiko for decryption. Mystiko’s Decryptor decrypts the aggregated vector and transmits the same securely over TLS to each of the learners.

**Security Analysis:** Data never leaves a learner, and by extension any administrative domain. This ensures privacy of data, provided each server inside the administrative domain has adequate defenses against intrusion. Unencrypted gradient vectors do not leave the learner. If there are $P$ participants, in $P-1$ cases only aggregated Paillier encrypted gradient vectors leave the learner. Only Mystiko has the private key to decrypt these. For the first learner in the ring, the non-aggregated gradient vector is transmitted to the second learner, but it is Paillier encrypted, and cannot be decrypted by the same. In fact, none of the participants are able to view even partially aggregated gradient vectors. After decryption, the aggregated gradient vector is distributed securely to the participants over TLS. Reverse engineering attacks, like the ones in [1] & [2] are intended to find the existence of a specific data record in a participant, or to find data items that lead to specific changes in gradient vectors; both of which are extremely difficult when several gradient vectors computed from large datasets are averaged [16]. Decryption after averaging ensures the privacy of gradients. Mystiko only sees aggregated gradients, and can’t get access to individual learner’s data or gradients.

**Colluding Participants:** The basic ring-based algorithm is resistant to collusion among $P-2$ participants. That is, assuming an honest uncorrupted Mystiko deployment, it can be broken only if $P-1$ learners collude. For learner $L_i$’s gradients to be exposed, learners $L_1, L_2, \ldots, L_{i-1}$ and $L_{i+1}, \ldots, L_P$ should collude, i.e., all of them should simply pass on incoming encrypted gradient vector to the next learner, without adding any gradient of their own.

**Fault Tolerance:** The disadvantage of a ring-based aggregation algorithm is that rings can break: for good performance, it is essential that the connectivity between each learner and Mystiko remains strong. Traditional failure detection techniques, based on heartbeats and estimation of typical round-trip times may be used. Distributed synchronous gradient descent consists of a number of iterations; with gradients being averaged at the end of each iteration. If the failure of a learner is detected, the averaging of gradient vectors is paused until the learner is eliminated from the ring by the Mystiko’s Membership Manager, or connection to the learner is established again. Pausing gradient averaging can also be done when connection to the Mystiko is temporarily lost.

**B. Broadcast Algorithm**

One of the main drawbacks of the ring-based algorithm is the establishment and maintenance of the ring topology. To mitigate this, an alternative is to use group membership and broadcast. Except for the establishment of the topology, the setting remains the same. Learners register with the Mystiko’s Membership Manager; agree on a common PKI and know the identity and number of participants. Mystiko generates a Paillier public-private key pair for each federated job and distributes the public key securely to each learner.

Each learner Paillier-encrypts its gradient vector, and broadcasts the encrypted vector to all other learners. Each learner, upon receipt of encrypted vectors from $P-1$ learners, adds them, and sends the Paillier-encrypted sum to the Mystiko for decryption. After decryption, the aggregated gradient vector is transmitted securely to all learners over TLS. The broadcast algorithm is redundant and wasteful, as every learner computes the aggregate. But, with redundancy comes increased failure resiliency. With the ring, the failure of one participant can lead to partial loss of aggregated gradients, which is not the case for broadcast.

**Colluding Participants:** The objective of breaking this algorithm is to determine the plaintext gradient vector of a specific LA. This algorithm is resistant to collusion, and can be broken only if $P-1$ participants collude, which is highly unlikely. Also, in the event that $P-1$ participants collude to Paillier encrypt zero-vectors instead of their actual gradient vectors, the broadcasted Paillier ciphertexts from all the $P-1$ learners will be the same, which serves as a red flag enabling collusion detection. In fact, given that data is likely to be different at each participant, getting exactly the same Paillier encrypted gradient vector from even two learners is red flag.

**C. All-Reduce**

Ring-based All-Reduce [17] is essentially a parallel version of the ring-based aggregation protocol described in Section [V-A]. It is illustrated in Fig. [3] The problem with the basic ring protocol in Section [V-A] is that each learner has to wait for its predecessor. However, in All-Reduce, the Paillier encrypted gradient vector is divided into $P$ chunks where $P$ is the number of participants. All learners then aggregate Paillier encrypted chunks in parallel. For example, in Fig. [4] there are three learners, and the gradient vectors are divided into three chunks each. Learner-2 does not wait for the entire vector of Learner-1 to be received. Instead, while it is receiving the first chunk of Learner-1, it transmits its own second chunk to Learner-3, which in parallel, transmits its third chunk to Learner-3. In Step 2, Learner-2 transmits the partially aggregated chunk-1 to Learner-3, which transmits
Divided Paillier encrypted arrays

\begin{align*}
\text{Learner-1:} & \quad \begin{bmatrix}
    a_1 & a_2 & a_3 \\
\end{bmatrix} \\
\text{Learner-2:} & \quad \begin{bmatrix}
    b_1 & b_2 & b_3 \\
\end{bmatrix} \\
\text{Learner-3:} & \quad \begin{bmatrix}
    c_1 & c_2 & c_3 \\
\end{bmatrix}
\end{align*}

Step 1: Parallel Addition of Chunks

\begin{align*}
\text{Learner-1:} & \quad \begin{bmatrix}
    a_1+b_1 & a_2+b_2 & a_3+b_3 \\
\end{bmatrix} \\
\text{Learner-2:} & \quad \begin{bmatrix}
    a_2+c_2 & b_3 & c_1 \\
\end{bmatrix} \\
\text{Learner-3:} & \quad \begin{bmatrix}
    a_3+c_3 & b_1 & c_2 \\
\end{bmatrix}
\end{align*}

Step 2: Parallel Addition of Chunks

\begin{align*}
\text{Learner-1:} & \quad \begin{bmatrix}
    a_1+b_1 & a_2+b_2 & a_3+b_3 \\
\end{bmatrix} \\
\text{Learner-2:} & \quad \begin{bmatrix}
    a_2+c_2 & b_3 & c_1 \\
\end{bmatrix} \\
\text{Learner-3:} & \quad \begin{bmatrix}
    a_3+c_3 & b_1 & c_2 \\
\end{bmatrix}
\end{align*}

Fig. 3. MYSTIKO Ring All-Reduce over Paillier Encrypted Arrays

![Diagram of MYSTIKO Ring All-Reduce over Paillier Encrypted Arrays]

Security Analysis: We note that All-Reduce is the most efficient MYSTIKO protocol. With $P$ learners, All-Reduce is essentially an instantiation of $P - 1$ rings (of Section V-A) all operating in parallel. In Fig. 3, the first ring starts at the first chunk of Learner-1, the second ring starts at the second chunk of Learner-2 and the third starts at the third chunk of Learner-3. This implies that the security guarantees of All-Reduce are the same as that of the basic ring protocol.

D. Multiple Learners Per Admin. Domain

For presentation simplicity, we have assumed that there is exactly one learning process (learner) per participant. More realistically, within an administrative domain, data is partitioned among servers and multiple training processes (learners), which periodically synchronize their gradient vectors using an aggregator process local to the administrative domain. This is done for various reasons, including datasets being large, compute resources being cheap and available and the desire to reduce training time. MYSTIKO’s protocols can be applied in a straightforward manner to this case, with MYSTIKO’s protocols running between Local Aggregators (LAs) instead of between learners. Local aggregation is not Paillier encrypted, and non-private because compute resources within an administrative domain are trusted and can share even raw data. But aggregation between LAs follows MYSTIKO’s protocols. This is illustrated in Fig. 4.

VI. EMPIRICAL EVALUATION

| # Parties | All Reduce | MYSTIKO Broadcast | Ring | SPDZ         |
|-----------|------------|-------------------|------|--------------|
| 20        | 1          | 6.4-7.2×          | 38.2-39.9× | 13.1-14.2×   |
| 40        | 1          | 7.9-8.6×          | 70.5-80.8× | 13.8-14.7×   |

Total synchronization time

| # Parties | All Reduce | MYSTIKO Broadcast | Ring | SPDZ         |
|-----------|------------|-------------------|------|--------------|
| 20        | 1          | 12-51%            | 27-100% | 2.2-6.1×    |
| 40        | 1          | 6-25%             | 15-59% | 1.3-2.6×    |

Table I

We compare all the three Mystiko algorithms with a state of the art protocol for secure multi-party computation – SPDZ [10], [18], [19], and schemes for differential privacy (DP) through the addition of statistical noise.

A. Implementation

We have implemented MYSTIKO and all its protocols in Python and C++, using appropriate libraries for PKI and communications security. We use the ETCD [20] key value store to store metadata about federated jobs, and ETCD leases for failure detection of learners. We have implemented an optimized version of the Paillier cipher following the improvements outlined in [9]. In all our experiments, we use PyTorch for training on the learner side. We have also integrated PyTorch on the learner side to work with the implementation of SPDZ2k from MP-SPDZ [10] for gradient synchronization.

B. Models and Datasets

We employ a variety of image processing neural network models and datasets of various sizes: (i) 5-Layer CNN (small, 1MB) trained on MNIST dataset (60K handwritten digit...
Figure 5. Total Synchronization time (seconds) vs. Number of Parties (top plots) and Total communication time (seconds) vs. Number of Parties (bottom). Recall that Total Synchronization time is the sum of the communication time and the gradient transformation time.

| System            | 5-Layer CNN + MNIST | SVHN+Resnet-18 | CIFAR100+Resnet-50 | Imagenet+VGG-16 |
|-------------------|---------------------|----------------|--------------------|-----------------|
|                   | Synch. Time (s)     | Epoch Time (s) | Synch. Time (s)    | Epoch Time (s)  |
| Non-private       | 0.03s               | 1.7s           | 3.7s               | 20.4s           |
| SPDZ              | 1.1s                | 150.5s         | 305.8s             | 1710.9s         |
| MYSTIKO Ring      | 3.4s                | 256.5s         | 599.6s             | 3064.9          |
| MYSTIKO Broadcast | 0.84s               | 129.8s         | 270.7s             | 1515.7s         |
| MYSTIKO All-Reduce| 0.56s               | 115.3s         | 240.6s             | 1345.5s         |

Table II
SYNCHRONIZATION TIME VS. TRAINING TIME (FOR 1 EPOCH ON 1 V100 GPU). 40 PARTICIPANT CASE.

Images) (ii) Resnet-18 (small-medium, 50MB) trained on the SVHN dataset (600K street digit images), (iii) Resnet-50 (medium-sized model, 110 MB) trained on CIFAR-100 dataset (60K color images of 100 classes) and (iv) VGG-16 (large model, 600MB) trained on Imagenet-1K dataset (14.2 million images of 1000 classes).

C. Experimental Setup
Experiments were conducted on a 40 machine cluster to evaluate all the algorithms on a varying number of participants from 2 to 40. No more than one participant was ever run on any machine, each of which was equipped with 8 Intel Xeon E5-4110 (2.10 GHz) cores, 64GB RAM, 1 NVIDIA V100 GPU and a 10GbE network link. The machines were spread over four datacenters, and in every experiment, participants were uniformly distributed across datacenters. In every experiment, the dataset was uniformly and randomly partitioned across participants. Mystiko was executed on a dedicated machine in one datacenter. All data points henceforth are computed by averaging 10 experiment runs.

D. MYSTIKO vs. DP Noise Addition [7], [8], [16]
It has been already demonstrated [16] that while addition of differentially private noise mitigates membership inference [6] and reverse engineering [1], [2] attacks, the resulting model has significantly lower accuracy as illustrated in Fig. 6. In Fig. 6 the differential privacy parameter is $\epsilon$, and the peak
accuracy for a given $\epsilon$ value corresponds to one achieved by trying different combinations of learning rate and batch size. Acceptable levels of differential privacy are achieved for $\epsilon \leq 1$, and values less than 0.1 are preferred for neural network training because gradients are exposed over thousands of synchronization steps. We observe from Fig. 6 that even for simple datasets and neural network models, loss of accuracy is significant. Noise addition is also not computationally cheap (298.5s vs. 43.6s per epoch in the case of SVHN+Resnet-18).

E. Comparing MYSTIKO and SPDZ

In federated learning, learners (or local aggregators) learn on local data for a specific number of iterations before federated gradient aggregation and model update. Privacy loss happens during gradient aggregation, which is where MYSTIKO and other systems like SPDZ intervene. Hence, we use the following two metrics to evaluate MYSTIKO and SPDZ: (i) Total synchronization time, which measures the total time needed for privacy preserving gradient transformations (Paillier encryption in MYSTIKO, share generation in SPDZ, etc.) and the time required to communicate the transformed gradients to participants for federation, and (ii) communication time, which only measures communication time.

Figures 5 plots total synchronization time and communication time against the number for parties involved in federation, for all of our model/dataset combinations. From Fig. 5, we observe that All-Reduce is the most scalable of all the protocols, as the number of participants increases. This is mainly because it is a parallel protocol, where each learner/LA is constantly transmitting a small portion of the gradient array. The basic ring protocol is the least scalable, because it is sequential. Broadcast performs and scales better than the basic ring protocol because each participant is broadcasting without waiting for the others. SPDZ performs and scales worse than broadcast because its communication pattern is close to (but not exactly) a dual broadcast – each item of the gradient vector at each participant is split into secret shares and broadcast to the other participants; after secure aggregation, the results are broadcast back. MYSTIKO obviates the need for dual broadcast through the use of Paillier encryption and centralized decryption of aggregated gradients. Table 1 illustrates the performance impact of using other protocols for two cases (20 and 40 parties from Fig. 5).

However, the “enormous” speedups of using All-Reduce do not materialize in the total synchronization reduce when total synchronization time is considered. The scalability trends among the four protocols remain the same; the speedups in total synchronization time remain significant (as elucidated for two cases in Table 1). But the speedups are lower than the speedups due to communication. This demonstrates that the predominant overhead of private gradient descent in MYSTIKO and SPDZ vs. non-private gradient descent is gradient transformation prior to communication. From Fig. 5 and Table 1 we also observe that for small models (5-Layer CNN & Resnet-18), communication time plays a larger role. But for large models (Resnet-50 and VGG-16), gradient transformation plays a larger role.

Lastly, we observe from Table 1 that when compared to training time (illustrated using epoch time), synchronization time for private gradient descent is significantly larger than non-private gradient descent. This is primarily because training happens on V100 GPUs (with thousands of cores) while gradient transformation happens on CPUs. While there is a GPU accelerated version of fully homomorphic encryption (which has worse performance than Paillier on CPUs), we are not aware of any GPU accelerated version of the Paillier algorithm.

VII. RELATED WORK

Research on secure and private federated learning and gradient descent is predominantly based either on (1) clever use of cryptography – homomorphic encryption and secure multi-party computation [18], [19], [22], [25]–[29], or on (2) modifying model parameters or gradients through the addition of statistical noise to get differential privacy [7], [8], [30]. Some techniques [23], [24] combine both.

We compare our proposed algorithms with other techniques in Table III. We observe that no technique is perfect – each has pros and cons, which must be carefully considered based on the deployment environment. We examine whether each algorithm (i) requires fully-trusted peers or whether it can work with honest+curious peers, (ii) impact on final model validation accuracy, (iii) synchronization overheads (due to encryption and other aspects of the algorithms), and (iv) number of participants that must collude to violate the privacy guarantees of the protocol (assuming $P$ total participants).
The closest related work to our algorithms is from Aono et al. [22], [27], where the participants jointly generate a Paillier-keypair; send the encrypted gradient vectors to the coordinator who is completely untrusted, except to add Paillier encrypted weights. The participants can then decrypt the aggregated gradient vectors. This, however, requires each participant to collaborate with the others to generate the Paillier keys and a high level of trust that participants do not collude with the untrusted coordinator to decrypt individual gradient vectors. One untrusted participant can leak the Paillier keypair; send the encrypted gradient vectors to the coordinator to collaborate with the others to generate the Paillier keys and a high level of trust that participants do not collude with the untrusted coordinator to decrypt individual gradient vectors. One untrusted participant can leak the Paillier keys and potentially lead to privacy loss.

Adding statistical noise to gradients has been proposed in [7], [8], [30] among other literature [23], [24]. If noise is added in a manner that guarantees differential privacy of the gradient vectors, the gradients can be released publicly to the other participants and the public. In this sense, these techniques work with any type of participant or coordinator. Although computation overhead is moderate, accuracy of the final model takes a hit as demonstrated in Section VI, and these techniques require careful hyperparameter selection to keep the loss of accuracy minimal.

Secure multi-party computation (SMC) is a subfield of cryptography with the goal of creating methods for parties to jointly compute a function over their inputs while keeping those inputs private. Unlike traditional cryptographic tasks, where cryptography assures security and integrity of communication or storage and the adversary is outside the system of participants (an eavesdropper on the sender and receiver), the cryptography in this model protects participants’ privacy from each other. SPDZ [19], and its variants (Overdrive [25], [18], [26]) optimizes classic SMC protocols. The advantage of such protocols is that they work with any number of honest+curious peers, do not change final accuracy of the trained model, and require a large number of colluding peers to break. The drawback, however, is efficiency – SMC protocols are computationally expensive (Section VI).

| Work          | Accuracy | Synch. Overhead | Min # of Colluding parties (to violate privacy) | Peers assumed to be |
|---------------|----------|-----------------|-----------------------------------------------|---------------------|
| Aono et al.   | Unch.    | Moderate (ENC Only) | 1                                             | Trusted             |
| Diff. Priv.   | Lower    | Moderate (NA only) | $P - 1$                                        | Honest curious      |
| Abadi et al.  | Lower    | High            | $P - t - 1$                                    | Curious             |
| Song et al.   | Lower    | High            | $P - 1$                                        | Curious             |
| HybridAlpha   | Lower    | High            | $P - 1$                                        | Curious             |
| Turex et al.  | Lower    | High            | $P - 1$                                        | Curious             |
| SPDZ variants | Unch.    | High            | P-1                                           | Honest curious      |
| Mystiko Ring  | High     | (Sec. VI)       | P-1                                           | Curious             |
| Mystiko All-Reduce | Unch. | Moderate (Sec. VI) | P-1                                           | Honest curious      |

Table III
Comparing Mystiko with the state of the art. ENC means Paillier encryption, NA means differential privacy through noise addition. Based on the experiments in Section VI, we relatively characterize the overhead of Paillier encryption with All-Reduce as “Moderate”, Noise Addition with All-Reduce as “Moderate”, and combinations of both encryption and noise addition as “High”.

VIII. Conclusions and Future Work

Through Mystiko, we have demonstrated that private, federated gradient descent without loss of accuracy can be practical with reasonable synchronization overhead. Mystiko is the first federated learning platform to provide the same security and privacy guarantees of a state-of-the-art secure multiparty computation protocol (MP-SPDZ [10]) with significantly lower synchronization overhead and by using only Paillier encryption. Another important characteristic of Mystiko is that it is simple to understand, implement and explain to users (vis-a-vis protocols like SPDZ). However, we do observe that synchronization time remains large with respect to epoch time for many models. We believe that this can be mitigated by effectively accelerating Paillier encryption using GPUs, and this is a topic of active research in our organization.

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