Towards an Efficient System for Differentially-private, Cross-device Federated Learning

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Abstract. This paper describes fresh ideas for a new system for federated averaging that aims to efficiently provide differential privacy even when a fraction of devices is malicious and there is no trusted core.

Introduction. How can we efficiently run federated learning, particularly federated averaging (*FedAvg*) [13], over a large number of user devices, e.g., hundreds of thousands to several billion, while guaranteeing differential privacy (*DP*) [7] to the device owners?

This question is motivated by two recent trends. First, *FedAvg* has found multiple use cases in industry. Google uses it to train a LSTM recurrent neural network for next-word prediction in Gboard (mobile keyboard) [9], and Mozilla uses it to train a ranking model for auto completion of suggestions in address bar [10]. Second, *DP* is a gold standard for privacy as it provides provable guarantees about an individual's data.

One approach to augment *FedAvg* with *DP* is to compose additively homomorphic encryption (AHE) with central *DP* (CDP) [18, 19]. (An alternative is to use secure aggregation [3, 5], but we prefer the homomorphic encryption route as it has been shown to compose with zero-knowledge (ZK) proofs [4] to additionally guarantee correctness of training [15].) At a high level, devices upload encrypted gradients to an aggregator, who sums them using the homomorphic properties of the encryption, before adding noise for *DP*. CDP has shown to reach higher model accuracy over local *DP* [8], where each device sends noised gradients to the aggregator. However, it is challenging to build an efficient system with this approach at scale under a strong threat model where the devices or the aggregator may be malicious. For example, the aggregator can reveal a device's input by multiplying it with a large value such that the *DP* noise is insufficient.

Orchard [15, 16], a state-of-the-art system based upon CDP, uses a mixture of cryptographic primitives such as MPC [11], AHE, and Merkle trees [14] to guarantee *DP* at scale even if the aggregator is occasionally byzantine and a small fraction of the devices are malicious. It also improves reliability of training by using ZK-proofs [4]. However, it

is expensive for devices. If applied to the Gboard model containing 1.4M parameters (1.4 MiB in total size), Orchard would incur 764 MiB of downloads and ≈ 4 minutes of CPU time per device per round of training (the model takes 3,000 rounds to converge).

This paper discusses the initial design of a system, Atom, that improves these efficiency bottlenecks. For the Gboard model, we project, based on microbenchmarks, that Atom would reduce per-device downloads to less than 5 MiB per round, use a device's CPU only for a few rounds of training, and move $\approx 1/3$ rd of the CPU time to an offline phase to reduce the overall system training time. We first present a brief overview of Orchard's threat model and bottlenecks, and then dive into Atom's improvements.

Overview of Orchard. Orchard consists of an *aggregator* and a large number of *user devices*, and assumes that they follow the *OB+MC* threat model. The aggregator is honest-but-curious most of the time but may be occasionally byzantine (OB), say when a rogue system administrator is logged in. The devices are mostly correct (MC), but a configurable small fraction (1-5%) can be malicious. Even though this fraction is small, the absolute number of malicious devices is substantial (e.g., millions out of a billion devices).

At a high-level, Orchard follows the *collect-and-verify* approach, where in the collect phase the aggregator collects encrypted gradients and ZK-proofs from the devices, and in the verify phase the devices verify the aggregator's work, that it performed the summation correctly.

There are two key performance-related aspects of these phases. First, during collect, a device's computation time is dominated by the time to generate the ZK-proof that indicates gradients are within a specified range and their encryption was performed correctly. Second, during verify, a device's costs are dominated by network downloads. In more detail, after the collect phase, the aggregator adds the homomorphically encrypted gradients by forming a *summation tree* (encrypted gradients are arranged as leaf nodes of a tree, and the tree is traversed to its root while computing each parent ciphertext(s) as a sum of its children). During verify, each device downloads a part of the tree, specifically, a configurable number of $s + 1$ consecutive leaf nodes and their $\lceil s/2 \rceil$ parent nodes, and s random non-leaf nodes and their parents. The device then asserts that the parent ciphertexts equal the sum of their children.

Cost analysis: We empirically evaluated the main client-side components of Orchard, implementing the ZK-proof generation in 461 lines of Rust using ark-groth16 [2]. For the

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ResilientFL '21, October 25, 2021, Virtual Event, Germany

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ACM ISBN 978-1-4503-8708-8/21/10.

<https://doi.org/10.1145/3477114.3488762>

Gboard model, each device’s input (i.e., a leaf node) is 342 ciphertexts, with 4,096 parameters in each ciphertext. On a 6-core, 2.6 GHz laptop with 8 GB of RAM, it takes 235.1s to generate the proofs for these ciphertexts. Each device also downloads 760 MiB of data for tree verification; this includes 17 tree nodes each containing 342 ciphertexts. These costs are substantial especially as the plaintext model is small (1.4 MiB). Moreover, the total training time can be high: if a client had a bandwidth of 53Mbps [1], then downloading 760 MiB 3K times would itself take over 4 days.

Atom: Switching to stochastic FedAvg. A core reason Orchard incurs high costs is that the system is designed for full-batch (non-stochastic) gradient descent: every device participates in each round of training and contributes a leaf node which is then checked for correctness. But full-batch gradient descent is not necessary. For example, fig. 1 shows training accuracy as a function of the number of training rounds for different number of participant devices per round for a DNN over the EMNIST dataset [6] (containing 3,383 devices in total). The training accuracy can be competitive even when a small fraction of devices contribute gradients in a round; this is the preferred *stochastic gradient descent* method.

Figure 1: Non-private training accuracy.

Switching to stochastic FedAvg in Orchard requires technical work, as simply asking a subset of devices to upload gradients induces redundant verification work. For example, if the number of leaf nodes is 1K (for 1K devices participating in a round), and the total number of devices is 1M, then many devices download and check the same nodes of the summation tree. Instead, Atom leverages the fact that leaf nodes are made of multiple ciphertexts (e.g., 342 for the Gboard model) that can be checked in parallel. To elaborate, after collecting encrypted gradients from participating devices, the aggregator forms P summation trees, one for each ciphertext in the original leaf node. Then, during the verify phase, a device checks the p -th ($1 \leq p \leq P$) tree with a certain probability that ensures that every node gets checked at least once by an honest device. The benefit is that each device’s network downloads reduce approximately by the fraction of participants per round: for the Gboard model, each device downloads 11.24 MiB per round, when 1% of total devices contribute gradients in a round.

Optimizing checking of ciphertext sums. After applying the above optimization, each device still downloads at least two leaf nodes and three non-leaf nodes for one summation tree. Atom reduces this cost by incorporating the polynomial

Figure 2: Encryption and its splitting into offline/online parts. e_0, e_1, r are sampled from a polynomial ring, m is an input message, pk is a public key, (ct_0, ct_1) is the ciphertext, and cr is a commitment.

identity testing (PIT) [17, 20]: given a d -degree polynomial $f(x)$ over the field $\mathbb{F}_p$, one can test whether $f(x)$ is a zero polynomial by sampling $r \in \mathbb{F}_p$ uniformly and testing if $f(r) == 0$. The intuition is that a d -degree polynomial has at most d solutions to $f(x) == 0$, and thus the probability of $f(r) == 0$ for a non-zero $f(x)$ is at most $d/|\mathbb{F}_p|$.

Atom incorporates PIT by observing that Orchard uses a Ring-LWE AHE scheme [12], where each ciphertext is a pair of polynomials. Thus, the goal of summation checking is to test whether the polynomial $c_{\text{left-child}}(x) + c_{\text{right-child}}(x) - c_{\text{parent}}(x) == 0$, where $c(\cdot)$ denotes a ciphertext. By applying the PIT, Atom transforms this check into checking whether $c_{\text{left-child}}(r) + c_{\text{right-child}}(r) - c_{\text{parent}}(r) == 0$ at a random point r . The gain is that a device downloads two field elements rather than an entire ciphertext (8,192 field elements) for the non-leaf nodes of the summation tree, although it still downloads the ciphertexts at the leaf nodes to check that their evaluation at r is what the aggregator claims. After incorporating PIT, a device’s downloads reduce by 2.4 $\times$ to 4.52 MiB for the Gboard model.

Splitting ZK-proof generation across rounds. Atom’s switch to stochastic FedAvg frees devices from generating gradients in all rounds. Thus, a Atom device can move part of proof generation to an offline phase that runs before the round(s) in which it participates. The left part of figure 2 shows the original computation a device runs inside a ZK-proof system. Atom takes the part of the computation that does not depend on the message being encrypted and runs it as an offline computation, and the rest as an online computation (the right part of Figure 2). Atom utilizes a commitment to ensure that a device uses the same common inputs across the offline and online phases.

For the Gboard model, Orchard’s ZK-proof computation consumes 235.1s on a 6-core laptop, and Atom’s computation consumes 141.9s and 155.6s for the offline and online phase, respectively. Though the total time in the offline/online scheme is higher due to the addition of the commitment, we argue that this trade-off is justified as devices contribute gradients in a few rounds (rather than all rounds), and the offline/online split reduces the overall system training time.

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