PICASO: Secure Aggregation for Federated Learning with Minimal Synchronization

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Abstract

Preventing private data leakage is crucial in federated learning. Existing secure aggregation (SA) protocols, which are the core protocols for privacy-preserving federated learning, require clients to synchronize at multiple points, meaning they must wait for other clients to send their messages before proceeding. This synchronization ensures that inputs can be aggregated without compromising privacy, while also accounting for client dropouts and message delays.

This work presents PICASO, abbreviated from Per Iteration Client At most Synchronizes Once, a novel SA protocol minimizing synchronization overhead in privacy preserving federated learning, aligning its communication pattern more closely with that of non-private federated learning. PICASO requires a single server and a collector, similar to the non-colluding two-server model used in the Mozilla Firefox browser. However, the collector in PICASO is stateless and performs significantly less work than the server, allowing it to function as a lightweight computational device. PICASO outperforms previous works like SecAgg, SecAgg+, MicroSecAgg, and Flamingo with server runtime under 1 second for large clients. PICASO demonstrates viability by training various models on different datasets.

We also present improvements over state-of-the-art algorithms in two key areas - detecting and removing malicious clients, and secure aggregation for heterogeneous datasets. Overall, PICASO achieves an efficient, secure, and flexible federated learning solution minimizing synchronization needs.

1 Introduction

Federated learning (FL) enables collaborative machine learning without sharing client data, by aggregating local model updates at a central coordinator. However, recent works show that training data can still be compromised from model updates alone [26, 49, 39], making secure aggregation (SA) crucial for privacy-preserving FL. SA computes the sum of user inputs while keeping individual inputs private. Like in traditional FL, the server typically selects a set of n clients for each iteration with the server repeating the process until the model converges. Typically, a new set of clients are chosen per iteration Note that the number of clients n can range from a hundred to tens of millions [31] and similarly the number of model parameters m can scale to millions [7]. The goal is to securely train a global model. SA protocols need to be robust to client dropouts. Furthermore, SA algorithms typically work over integers or field elements while the weights produced by an ML model are floating point values. Therefore, one often needs to quantize the weights and show that the model produced by the SA protocols still preserve accuracy.

SecAgg [7] introduced a practical solution for privacy-preserving horizontal federated learning. The protocol's core idea involves pairwise masking seeds $s_{u,v}$ shared between clients $u, v \in \mathcal{U}$, where $\mathcal{U}$ is the set of all users. Each client u masks its input using $\sum_{v<u} s_{u,v} - \sum_{v>u} s_{u,v}$. Note that a client $v < u$ would generate its mask by subtracting $s_{u,v}$. Therefore, it is easy to see that the pairwise masks

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cancel out in aggregation, i.e., $\sum_{u\in\mathcal{U}}(\sum_{v<u} s_{u,v} - \sum_{v>u} s_{u,v}) = 0$. While a particular user u maybe offline, the remaining clients would still have used their pairwise mask with u in the aggregation. Therefore, $s_{u,v}$ for an offline u and any online v needs to be secret shared with other clients to allow the server to reconstruct $s_{u,v}$ and then remove the mask. Unfortunately, a server could label an online client u as offline which would give the server $s_{u,v}$, allowing it to unmask an online user's inputs. Therefore, a client also uses a self-mask s_u to mask its inputs. This s_u is also secret-shared and is reconstructed should u be online. As is obvious, SecAgg involves multiple rounds of computation such as to establish pairwise masks, secret share the masks, sending the masked inputs, and then reconstructing the sum. Therefore, for n clients and a vector of size m, the protocol requires $O(n^2m)$ computation on the part of the aggregator, $O(mn)$ for each client. Subsequent works have focused on reducing the complexity through various assumptions and techniques. Here the vector m can be viewed as the number of parameters in the model, i.e., the inputs to the secure aggregation algorithm.

This work aims to address a critical scalability issue with existing SA algorithms. Prior works often, including SecAgg that was described above, require clients to synchronize their participation with others, an artifact of techniques where clients mask their inputs but must share masks with a quorum of clients to facilitate unmasking, if the client was unavailable later. This expensive ritual of sharing masks induces a bottleneck absent in non-private training, where clients simply train the model and send updates without additional synchronization.

Our main contribution is PICASO, a secure aggregation protocol where each client synchronizes at most once per training iteration. The key idea is that in iteration ℓ, client i masks its input x_i by computing $y_i = x_i + \mathsf{GenerateMask}(k_i, \ell)$, where k_i is its *private* key. Client i sends y_i to the server and $\mathsf{GenerateMask}(k_i, \ell)$ to a separate "collector" party. Our model supports dynamic selection of a collector per training iteration . They are stateless and run a deterministic computation, simpler than the server's own computation. A simple way of choosing a collector would be to use a randomness beacon [17] and the Algorithm 1 from Flamingo [37, Lines 2-5]. The collector aggregates the masks from all clients and sends their sum to the server. The server then reconstructs $\sum_i x_i$ using the masked inputs and the sum of masks. Unlike SecAgg (and its subsequent works), PICASO does not require sending masks to multiple parties or secret sharing, reducing synchronization overhead. It only needs to synchronize to identify the collector for that iteration. Looking ahead, the collector acts can be viewed as a single "decryptor" [37] or "committee member" [33], receiving information from clients, condensing it, and communicating the result to the server for secure aggregation (Figure 1a). In other words, PICASO utilizes one intermediate party while SecAgg employed n with subsequent works employing $\log n$ intermediate parties.

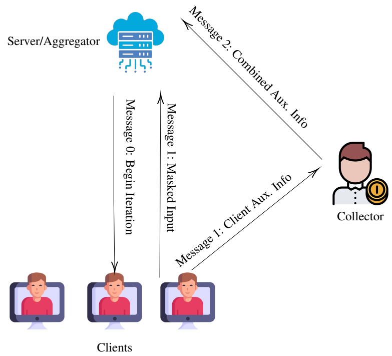
Asymptotically, PICASO's client computation cost is $O(m)$, where m is the input vector length (e.g., the number of weights of the model), while the server and collector computation cost is $O(mn)$, where n is the number of clients (Table 2). PICASO offers several attractive features:

- Dropout tolerance: Any number of selected clients can opt out without increasing computational burden on remaining clients or requiring additional interaction.
- Collusion resistance: Privacy of honest users' inputs is preserved even if an adversary corrupts any number of clients and the aggregator.
- Scalability and dynamism: New clients can join without an expensive setup phase, needing only public parameters and the aggregator's iteration key.
- Enhanced privacy: Input privacy is maintained against both collector and aggregator, provided they do not collude. The collector can change in each iteration, facilitated by a randomness beacon which in tern prevents server manipulation.

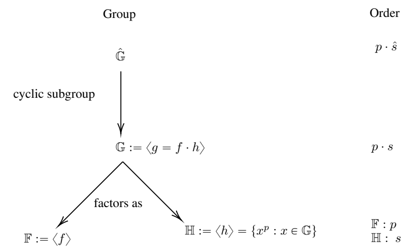
We also microbenchmark PICASO, comparing with the state-of-the-art secure aggregation algorithms to demonstrate competitive performance. For example, PICASO's server computation time is $< 1s$, even for large number of clients besting prior work. We also conduct extensive experiments on FL benchmark datasets to demonstrate that PICASO preserves performance, while guaranteeing privacy.

Further, PICASO can easily be extended to offer:

- a constant-round protocol to detect and remove malicious clients (i.e., sending inconsistent or incorrect messages), improving on the state-of-the-art ACORN which requires $O(\log n)$ rounds where n is the number of clients.



(a) The PICASO system model operates in iterations. Each iteration begins with the server sending a message to initiate the process (Message 0). In response, clients train the model on their local data, obtain updates, and mask the input. *Concurrently*, clients communicate with both the server and the collector (Message 1): masked input is sent to the server, while auxiliary information is transmitted to the collector. Upon receiving information from all clients, the collector combines these into a single value. Finally, this consolidated data is sent to the server (Message 2), concluding the iteration.



(b) A brief overview of the class group framework we employ. Here, $\widehat{\mathbb{G}}$ is group, whose order is $\widehat{s} \cdot p$, such that $\widehat{s}$ and p are co-prime. Further, s divides $\widehat{s}$ and is the order of the group $\mathbb{G}$, which is generated by g and is denoted as $\mathbb{G} := \langle g \rangle$. Similarly, $\mathbb{H}$ is a subgroup of $\mathbb{G}$, generated by h whose order is s, while $\mathbb{F}$ has order p and is generated by f. We have $g = f \cdot h$. Further, $\widehat{s}$ (and s) is unknown but an upper bound $\bar{s}$ is known. The last property we will rely on is that discrete logarithm is efficient in the subgroup $\mathbb{F}$.

Figure 1: The backbone of PICASO - the communication system model and the CL framework.

- a secure aggregation protocol supporting heterogeneous datasets via robust stochastic averaging [34], which improves upon DReS-FL [47] as DReS-FL requires the entire dataset to be secret shared among clients, which we avoid.

1.1 Related Work

Secure Aggregation Using Differential Privacy and Homomorphic Encryption. Federated learning with differential privacy allow clients to add noise to their data. This has been deployed by major tech companies [18, 1]. However, research shows that such data perturbation may reduce accuracy. Our secure aggregation can be composed with DP to mask noisy local inputs [30]. Moreover, BatchCrypt [55] employed homomorphic encryption (HE), building on earlier work. However, it required all clients to use the same key, posing a significant privacy risk.

SA using Multiparty Computation. Secure multiparty computation (MPC) preserves privacy and accuracy by computing over encrypted data. Early works on Private Stream Aggregation [48] focused on secure summing of streaming data. Following SecAggBonawitz et al. [7], Federated Learning protocols with dropout resilience were developed, but multiple interaction rounds increased dropout risk. Subsequent works [5, 4, 37, 35, 52, 50, 57, 29, 54, 36, 33] have focused on reducing the number of intermediate parties to $\log n$, or reusing the masked secret sharing across multiple iterations to reduce round count. This is summarized in Table 1 where we compare various protocols with respect to the following properties: (a) the number of rounds of interaction, (b) whether it can tolerate client dropouts, (c) on whether the aggregate value can be efficiently recovered, (d) public setup for security assumption, and (e) number of intermediate parties needed to help with the aggregation.

Two-Server Setting. The two-server setting with two non-colluding servers [16, 3, 44] are already being considered for standardization by IETF [41] and used by Mozilla Firefox. These schemes face challenges with long inputs due to increased communication and computation demands. Our approach assumes no server-collector collusion, a weaker assumption as the collector changes in each iteration and performs less computation. We include a concrete comparison of these works in the full version.

Table 1: Comparison of various Secure Aggregation Algorithms based on MPC.

	# Rounds	Dropout Resilience	Efficient Aggregation	Public Setup	# Additional Parties
[48]	1	✗	✗	✓	0
[28]	1	✗	✓	✗	0
[6]	1	✗	✗	✗	0
[32]	1	✓	✓	✗	1
SecAgg[7]	3	✓	✓	✓	n
SecAgg+[5]	3	✓	✓	✓	$\log n$
MicroSecAgg[25]	1+2	✓	✗*	✓	$\log n$
LERNA[33]	1+2	✓	✓	✓	$\log n$
Flamingo[37]	1+2	✓	✓	✓	$\log n$
PICASO	1	✓	✓	✓	1

Table 2: Comparison of asymptotic complexity of some secure aggregation protocols. Note that in PICASO, the collector performs $O(mn)$ computation and communication.

	Client		Server	
	Computation	Communication	Computation	Communication
SecAgg[7]	$O(mn + n^2)$	$O(m + n)$	$O(mn^2)$	$O(mn + n^2)$
SecAgg+[5]	$O(m \log n + \log^2 n)$	$O(m + \log n)$	$O(n \log^2 n + mn \log n)$	$O(mn + n \log n)$
SASH[35]	$O(m + n^2)$	$O(m + n)$	$O(m + n^2)$	$O(mn + n^2)$
PICASO	$O(m)$	$O(m)$	$O(mn)$	$O(mn)$

2 System Model and Relevant Background

We consider a federated learning framework, as shown in Figure 1a. There exist n clients, with each client C_i owning a dataset D_i. The server holds the ML model Θ. In FL, the server first senders Θ to clients, and each client trains its local dataset on D_i to generate the updated weights m_i. Meanwhile, the server computes the average of these model updates $\{m_i\}$ to update its global model to Θ'. In the next iteration Θ' is sent back for the next update. The goal is to use the collector to ensure that the weights m_i remain secret while still allowing the server to compute the average, and thereby the new model Θ'.

Threat Model. Our threat model follows the long line of prior works whereby an adversary can: (a) corrupt the server *or* the collector, (b) corrupt clients which enables the adversary to choose the client inputs for an iteration. The goal is to ensure that the honest users' inputs remain private with only their sum being leaked. Our protocols are described in this setting, like all prior work. Note that prior works such as Flamingo [37], or LERNA [33] did not guarantee privacy when all the intermediate parties collude with each other. Similarly, we allow for the collector to corrupt clients and guarantee the security against a corrupted collector. If the server and collector collude at an iteration, however, there is no privacy for that iteration.[1] Importantly, our collector can change from every iteration to iteration and is selected by a randomness beacon using an algorithm similar to how the set is chosen in Flamingo [37, Algorithm 1]. This is similar to how validators are chosen in some proof of stake blockchains [22].

Modeling Security. We model security against both a corrupt server and a corrupt collector. A corrupt server can adaptively compromise clients and collude with them, issue arbitrary encryption messages for honest parties in any iteration, and receive the collector's combined information at each iteration, but cannot corrupt the collector. The adversary selects honest clients $H_1, \ldots, H_t$ and provides two input sets: $\{x_1, \ldots, x_t\}$ and $\{x'_1, \ldots, x'_t\}$, where $\sum x_i = \sum x'_i$. The challenger randomly selects and encrypts one set for the target time period τ. The adversary's goal is to determine which set was chosen with probability significantly exceeding 1/2.

Meanwhile, for privacy against a corrupt collector, the adversary receives individual communication sent by the clients to the collector. It can corrupt clients and also issue encryption queries, as before. It cannot corrupt the server but can adaptively issue the above queries. The challenge is the same as for a corrupt server - to distinguish between honest user inputs. Since it does not receive the final result, the challenge sets need not have the same sum.

[1] In such a case the server can learn the individual client model updates. To protect against such an attack the best that the clients can do is to add differential private noise to their updates.

CL **Framework.** Cryptographic protocols often use cyclic groups G of prime order q, generated by g_q, i.e., $G := \{1, g_q, \ldots, g_q^{q-1}\}$. The Discrete Logarithm (DL) Assumption [2] states that given $X \in G$, finding x where $g_q^x = X$ is computationally infeasible.[2] The Decisional Diffie-Hellman (DDH) Assumption [8] posits that given g_q, g_q^x, g_q^y, distinguishing g_q^{xy} from a random element in G is computationally infeasible.

The CL Framework [12–15, 10] introduces the idea of a composite order group, where the order is unknown, but there is a subgroup of known prime order where the discrete logarithm computation is easy. This framework utilizes the group where DL is easy to ensure correctness and eventual message recovery, and the group where DL is hard to achieve security. The framework is summarized in Figure 1b.

The security property relies on a modified DDH assumption (Definition 1) involving indistinguishability between elements from groups $\mathbb{G}$ and $\mathbb{H}$ within a composite order group. While their orders are unknown, upper bounds exist. The input space is in $\mathbb{F}$, and the key space in $\mathbb{H}$. Distributions $\mathcal{D}_G$ and $\mathcal{D}_H$ are based on these upper bounds, with $\mathcal{D}_G$ (resp. $\mathcal{D}_H$) being statistically indistinguishable from $\mathbb{G}$'s (resp. $\mathbb{H}$'s) exponent space. Typically, $\mathcal{D}_H := 0, \ldots, B-1$ where $B = 2^{40} \cdot \bar{s}$ where $\bar{s}$ is the upperbound of the order of $\mathbb{H}$, shown by [53] to be 2^{-40}-close to uniform. The security property relies on a modification of the DDH assumption (see Definition 1), where the indistinguishability is between elements from two different groups, $\mathbb{G}$ and $\mathbb{H}$, within the composite order group. However, the orders of $\mathbb{G}$ and $\mathbb{H}$ are unknown, but there are upper bounds on their orders.

Definition 1 (DDH-f Assumption)**.** *Let $(\widehat{\mathbb{G}}, \mathbb{G}, \mathbb{H}, \mathbb{F}, \bar{s})$ be the class group as defined in Figure 1b. Then, the following two distributions are computationally indistinguishable, i.e., there is no "efficient" attacker who can distinguish whether it is the first or the second distribution that a sampled value comes from, with a probability greater than half. Here, $x, y \leftarrow_\$ \mathcal{D}_H$, $u \leftarrow_\$ \mathbb{Z}/p\mathbb{Z}$*

$$\{(h, h^x, h^y, h^{xy}\} \approx_c \{(h, h^x, h^y, h^{xy} \cdot f^u\}$$

We refer the readers to Bouvier *et al.* [9] and Tucker [53] for a detailed exposition on class groups, techniques, and its extensive use in cryptography. They also survey the utility of CL framework in building other cryptographic primitives.

3 PICASO

We begin by describing an additively homomorphic masking algorithm. We then instantiate this in the CL framework. This is a generalization of the version presented in the introduction. We then present our complete description of PICASO and formally prove it secure in the random oracle model.

3.1 Homomorphic Masking Algorithm

Let k_i denote the secret key of Client i. Let k_0 denote the secret key of the aggregator. Further, for iteration ℓ, let $\mathsf{pk}_{i,\ell}$ (resp. $\mathsf{pk}_{0,\ell}$) denote the public key of client i (resp. the server) for iteration ℓ. Then, we require the following properties of our algorithm $\mathsf{GenMask}$:

- The masking function can be computed using two different ways, i.e., $\mathsf{GenMask}(\mathsf{pk}_{i,\ell}, \mathsf{k}_0) = \mathsf{GenMask}(\mathsf{pk}_{0,\ell}, \mathsf{k}_i)$
- Homomorphic over public key space, i.e., $\prod_{i=1}^n \mathsf{GenMask}(\mathsf{pk}_{i,\ell}, \mathsf{k}_0) = \mathsf{GenMask}(\prod_{i=1}^n \mathsf{pk}_{j,\ell}, \mathsf{k}_0)$

Further, we require that the generated mask is pseudorandom, i.e., $\mathsf{GenMask}(\mathsf{pk}_{0,\ell}, \mathsf{k}_i)$ appears random provided the adversary cannot compute the mask on its own which requires the knowledge of $(\mathsf{pk}_{0,\ell}, \mathsf{k}_i)$ or $(\mathsf{pk}_{i,\ell}, \mathsf{k}_0)$.

Construction 1 (Homomorphic Masking Algorithm)**.** Let $\mathcal{H} : \{0,1\}^* \to \mathbb{H}$ be a hash function that maps strings to the unknown order subgroup of $\mathbb{G}$.[3] Then, for secret key $\mathsf{k}_i \leftarrow_\$ \mathcal{D}_H$ for $i = 0, \ldots, n$, we can define, for iteration ℓ, $\mathsf{pk}_{i,\ell} := \mathcal{H}(\ell)^{\mathsf{k}_i}$ and the mask value as $\mathsf{mask}_{i,\ell} := \mathcal{H}(\ell)^{\mathsf{k}_0 \cdot \mathsf{k}_i}$

[2] Small x are recoverable, as in [25, 48, 6].

[3] Note that for our purposes we can simply begin by hashing the input to an element in $\mathcal{D}_H$, and then raising the group generator h to this value. This is because the knowledge of the discrete logarithm is not detrimental. However, [45] present additional methods to hash into a group of unknown order, in a way that the discrete logarithm is unknown.

We now show that the construction satisfies the required properties:

- $\mathsf{mask}_{i,\ell} = \mathcal{H}(\ell)^{\mathsf{k}_0 \cdot \mathsf{k}_i} = \mathsf{pk}_{i,\ell}^{\mathsf{k}_0} = \mathsf{pk}_{0,\ell}^{\mathsf{k}_i}$
- $\mathsf{mask}_{i,\ell} \cdot \mathsf{mask}_{j,\ell} = \mathcal{H}(\ell)^{\mathsf{k}_0(\mathsf{k}_i+\mathsf{k}_j)} = (\mathsf{pk}_{i,\ell} \cdot \mathsf{pk}_{j,\ell})^{\mathsf{k}_0}$

For a particular iteration ℓ, an adversary is either given $\mathcal{H}(\ell), \mathsf{pk}_{0,\ell}, \mathsf{pk}_{i,\ell}, \mathsf{mask}_{i,\ell}$ or $\mathcal{H}(\ell), \mathsf{pk}_{0,\ell}, \mathsf{pk}_{i,\ell}, U$ where $U \leftarrow_\$ \mathbb{G}$. This follows from the DDH-f assumption, which we define in Definition 1. Looking ahead, this pseudorandom mask will be used to mask the client input and thereby guaranteeing privacy.

3.2 Formal Description of PICASO

We first informally describe the protocol. At iteration ℓ, the server sends a message identifying clients who are participating in that round of interaction. In this message, it also includes its iteration public key $\mathsf{pk}_{0,\ell}$. Client i, with its input $x_{i,\ell}$, first encodes it as $f^{x_{i,\ell}}$. Recall that f is the generator of the cyclic, prime-order group $\mathbb{F}$ where discrete logarithm is easy, i.e., given this encoding, there exists an efficient algorithm that outputs $x_{i,\ell}$. Once encoded, it computes the mask $\mathsf{mask}_{i,\ell} = \mathsf{GenMask}(\mathsf{pk}_{0,\ell}, \mathsf{k}_i)$. It sends to the server the masked input $\mathsf{ct}_{i,\ell} = \mathsf{mask}_{i,\ell} \cdot f^{x_{i,\ell}}$. Meanwhile, it also sends to the collector $\mathsf{pk}_{i,\ell}$.

The collector simply multiplies all of the clients' iteration public keys to compute $\mathsf{AUX}_\ell = \prod \mathsf{pk}_{i,\ell}$. AUX_ℓ is sent to the server. The server does the following: multiplies all of the masked inputs $\prod \mathsf{ct}_{i,\ell}$ and divides it by $\mathsf{GenMask}(\mathsf{AUX}_\ell, \mathsf{k}_0)$. It then applies the efficient discrete logarithm to compute the aggregate. Formally, we present in Construction 2.

Construction 2 (PICASO Protocol for iteration ℓ)**.** The protocol description is as follows:

- **One-Time Setup Phase:**
  Transparent Setup is executed and outputs $\mathsf{pp} = (\widehat{\mathbb{G}}, \mathbb{F}, p, \mathcal{D}_H, \mathcal{D}_G, \bar{s}, g, h, f, \mathcal{H} : \{0,1\}^* \to \mathbb{H})$
- **Begin Iteration:** Server, with key k_0, computes $\mathsf{pk}_{0,\ell} = \mathcal{H}(\ell)^{\mathsf{k}_0}$ and sends to the chosen clients and collector.
- **Encryption Phase:** Each online client $C_i \in \mathcal{OL}_\ell$ with key k_i and input $x_{i,\ell}$ does the following:
  - Compute $\mathsf{mask}_{i,\ell} := \mathsf{GenMask}(\mathsf{pk}_{0,\ell}, \mathsf{k}_i)$
  - Compute masked input $\mathsf{ct}_{i,\ell} = f^{x_{i,\ell}} \cdot \mathsf{mask}_{i,\ell}$
  - Compute public key $\mathsf{pk}_{i,\ell} = \mathcal{H}(\ell)^{\mathsf{k}_i}$
  - $\mathbf{C_i}$ $\to$**Server**: $\mathsf{ct}_{i,\ell}$
  - $\mathbf{C_i}$ $\to$**Collector**: $\mathsf{pk}_{i,\ell}$
- **Collection Phase:** Collector computes $\mathsf{AUX}_\ell = \prod_{i \in \mathcal{OL}_\ell} \mathsf{pk}_{i,\ell}$.
  Collector$\to$**Server**: AUX_ℓ
- **Aggregation Phase**: Server computes:
  - Compute $Y_\ell := \prod_{i \in \mathcal{OL}_\ell} \mathsf{ct}_{i,\ell}$
  - Compute $X_\ell := \mathsf{GenMask}(\mathsf{AUX}_\ell, \mathsf{k}_0)$
  - Compute $Sum_\ell := Y_\ell / X_\ell$
  - Take discrete log of Sum_ℓ, which is efficient.

We omit the proof due to space constraints. However, the intuition for security comes from the fact that: (a) the honest user's key is chosen by the honest user and is unknown to the adversary, (b) for such a random key, the mask generated is indeed pseudorandom under the DDH-f assumption, and (c) such a pseudorandom mask will blind the honest client's inputs.

Remark 1. Observe that it is possible that the client's communication to either the server or the collector is dropped due to network issues. In this situation, the collector's information relayed to the server does not yield correct aggregate. To handle such situation, the server and the collector can engage in one additional round of communication, per iteration. In this round, the collector first sends a list of clients from whom it has received communication. The server respond with the intersection of the collector's list with its own list of clients. Finally, the collector "collects" only with respect to this set of clients.

Remark 2. Note that each $\mathsf{pk}_{i,\ell}$ is pseudorandom, if k_i is unknown. However, masking only with $\mathsf{pk}_{i,\ell}$ is insufficient for security against the collector. This is because the collector receives the masked

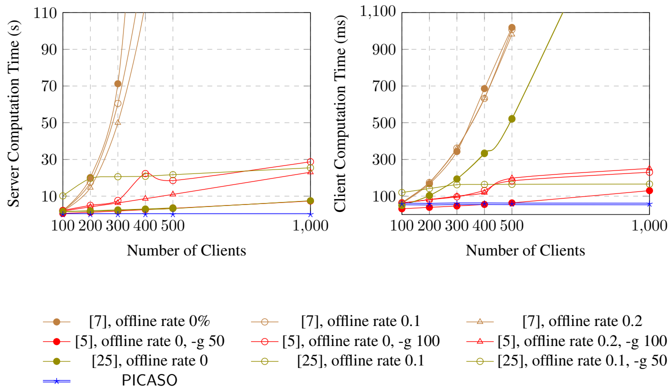


Figure 2: Measure of Server and Client Computation Time as a function of number of clients across various aggregation algorithms.

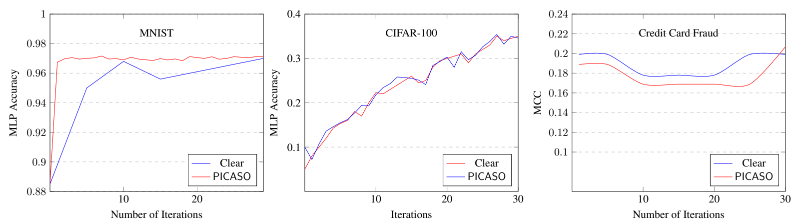


Figure 3: Performance Measurement of PICASO for FL Tasks.

input (masked by $\mathsf{pk}_{i,\ell}$) and $\mathsf{pk}_{i,\ell}$ for ever honest client i. Therefore, the collector can easily recover the input. This prompts the need for a server's iteration public key, generated as a function of its secret key k_0.

4 Experiments

In this section, we perform different experimentation to demonstrate the efficiency, accuracy, and privacy of PICASO. All our experiments were carried out on an Apple M1 Pro CPU with 16 GB of unified memory, without any multi-threading or related parallelization. More details can be found in the supplementary material.

Microbenchmarking Secure Aggregation. We benchmark the client and server computation time of our protocol against existing state-of-the-art solutions, including [7], [5], MicroSecAgg [25], and PICASO. Additionally, we compare our results with specific parameter choices from prior work, such as grouping operations (clients share inputs with 50 or 100 parties) and offline rate (parties can go offline during the protocol). These settings are not applicable to PICASO. Our reported timing is taken as a mean of 20 iterations.

As shown in Figure 2, our client computation time is significantly better than [7] and [5], and comparable to MicroSecAgg. However, unlike MicroSecAgg, our protocol does not incur offline waiting times due to multiple rounds of participation. For instance, when there are 100 clients, MicroSecAgg requires at least 30ms of offline time, which increases with more clients. Additionally, MicroSecAgg limits input size to achieve server efficiency, supporting only small model updates or quantized large model updates. Figure 2 demonstrates that PICASO's server running time is under 1 second, thanks to a single-round protocol with efficient aggregate recovery. This outperforms all other protocols. Any additional communication required to capture Remark 1 has a negligible impact on computation time, as it only involves gathering the list of clients and communicating with the collector. SASH [35] combines the secure aggregation protocol SecAgg [7] with a seed-homomorphic PRG to enhance efficiency for encrypting large input vectors. However, their performance is dominated by SecAgg, which we significantly outperform. Combining SASH with PICASO could achieve efficient round communication and improved server computation time, optimizing for input size scaling. Finally, PICASO requires 56 bytes of bandwidth for each of the following: server public key, masked input, while requiring 32 bytes for client's iteration public key sent to the collector, and information sent to the server from the collector.

Benchmarking FL Models. We train a logistic regression model on Kaggle Credit Card Fraud Dataset [43]. Figure 3 shows PICASO's MCC versus clear learning for varying clients and iterations. With the accuracy multiplier, PICASO's MCC is very close to clear learning and even outperforms sometimes. The highly unbalanced dataset demonstrates PICASO can achieve strong performance even in challenging real-world scenarios. We then train a vanilla multi-layer perceptron (MLP) classifier on three datasets: MNIST, CIFAR-100. The details of the datasets, including quantization and license can be found in the supplementary material.The MLP accuracy, as a function of the iteration, is plotted in Figure 3. Our experiments demonstrate that PICASO preserves accuracy, while ensuring the privacy of client data. Note that vanilla MLP classifiers do not typically offer good performance for CIFAR datasets, but note that the goal of our experiments was to show that PICASO does not impact accuracy.

5 Extensions to PICASO

Robustness. PICASO requires clients to send iteration public keys to the collector and masked inputs to the server, potentially allowing malicious actors to disrupt aggregation by using inconsistent keys. While secure aggregation has been widely studied, less focus has been on detecting and mitigating malicious behavior. Prior works in this domain are limited to:

- ACORN [4]: Offers a constant-round version detecting malicious behavior (aborting on detection) and a non-constant round version removing malicious inputs.
- RoFL [36] and ACORN: Use zero-knowledge proofs (e.g., Bulletproofs [11] and improvements [21]) to prevent malicious input injection.

The latter requires that the secure aggregation algorithm still proceeds, after having removed malicious clients. Indeed, PICASO ensures privacy of inputs, even if the server is corrupt and chooses to corrupt various users. Similarly, against corrupt collector who can corrupt users and inject messages into the system. In this section, we show how to augment PICASO to detect and remove malicious clients as described above. In Algorithm 3, we only present the additional proving steps by the client and the verification steps for the collector. In the construction, $\mathscr{C}$ is representative of the challenge space and integer A is chosen as a function of the size of $\mathscr{C}$. We refer the reader to [10, §5.2] for details about the proof system and its correctness. Here, A is set to be an integer such that the size of challenge space $C := |\mathscr{C}|$ is negligibly small when compared to A ,i.e., C/A is negligible.

Signatures can be employed to ensure the collector transmits only client-authenticated information to the server, mitigating malicious collector behavior. Our protocol can be enhanced with range-proof techniques from ACORN [4]. Notably, our inputs are encoded in prime-order subgroup $\mathbb{F}$, which can be composed with standard Pedersen commitments [42] using a prime order cyclic subgroup G where the DDH assumption holds.

Construction 3 (Additional Steps in Robust-PICASO)**.** We assume that there is an hash function $\mathbb{H} : \{0,1\}^* \to \mathscr{C}$. Here, $A := 2^{40} \cdot |\mathcal{D}_H| \cdot C$ and $[A] := \{0, \ldots, A-1\}$. We set C to be 2^{128}.

Proof Generation: Each online client C_i

- Sample $r_k \leftarrow\!\$\, [A], r_x \leftarrow\!\$\, \{0, \ldots, p-1\}$
- Compute $t_1 := \mathcal{H}(\ell)^{r_k}, t_2 := \mathsf{pk}_{0,\ell}^{r_k} \cdot f^{r_x}$
- Compute $ch := \mathbb{H}(\ell, \mathsf{pk}_{i,\ell}, \mathsf{ct}_{i,\ell}, t_1, t_2, \mathsf{pk}_{0,\ell})$
- Compute $s_k := r_k + ch \cdot \mathsf{k}_i, s_x := r_x + ch \cdot x_{i,\ell} \bmod p$
- Set $\mathsf{proof}_i := (s_k, s_x, ch)$
- $\mathbf{C_i}$ →**Server**: $\mathsf{ct}_{i,\ell}$
- $\mathbf{C_i}$ →**Collector**: $\mathsf{pk}_{i,\ell}, \mathsf{ct}_{i,\ell}, \mathsf{proof}_i$

Proof Verification: For each C_i in $\mathcal{OL}_\ell$ the collector:

- Receive:$(\mathsf{pk}_{i,\ell}, \mathsf{ct}_{i,\ell}, \mathsf{proof}_i = (s_k, s_x, ch))$
- Compute $t_2' := \mathsf{pk}_{0,\ell}^{s_k} \cdot f^{s_x} \cdot \mathsf{ct}_{i,\ell}^{-ch}$
- Compute $t_1' := (\mathcal{H}(\ell))^{s_k} \cdot \mathcal{H}(\ell)^{-ch}$
- Compute $ch' := \mathbb{H}(\ell, \mathsf{pk}_{i,\ell}, \mathsf{ct}_{i,\ell}, t_1', t_2', \mathsf{pk}_{0,\ell})$
- **if** $ch \neq ch'$ **then**
  $\mathcal{OL}_\ell := \mathcal{OL}_\ell \backslash \{i\}$
  Add $(\mathsf{proof}_i, \mathsf{ct}_{i,\ell}, \mathsf{pk}_{i,\ell})$ to list $\mathcal{M}$
- Compute $\mathsf{AUX}_\ell := \prod_{i \in \mathcal{OL}_\ell} \mathsf{pk}_{i,\ell}$
- **Collector→Server**:
  $\mathsf{AUX}_\ell, \{\mathsf{ct}_{i,\ell}\}_{i \in \mathcal{OL}_\ell}, \mathcal{M}$

Heterogeneity in Data Distribution. Data-centric methods [56, 40, 27] aim to align local and global distributions while preserving privacy, using techniques like sharing raw, synthesized, or augmented data. However, these approaches may compromise local data privacy [46]. Privacy-preserving machine learning can be achieved through secret sharing schemes such as homomorphic encryption (HE) [20, 23] and multiparty computation (MPC) [38]. However, HE is computationally expensive, and MPC faces scalability issues. Recent frameworks [51] utilize Lagrange coding and polynomial approximations to address these challenges in federated learning settings. RSA [34] is a class of stochastic sub-gradient methods for distributed learning robust to Byzantine workers. It mitigates the effects of incorrect messages due to malicious behavior, communication failures, or uneven data distribution by incorporating a regularization term in the objective function. At each iteration k, clients compute parameter updates based on local data, prior local models, and global parameters. The client and server updates are:

$$\text{Client: } x_i^{k+1} = x_i^k - \eta^k \left(\nabla F(x_i^k, \xi_i^k) + \lambda \text{sign}(x_i^k - w^k) \right)$$

$$\text{Server: } w^{k+1} = w^k - \eta^k \left(\nabla f_0(w^k) + \lambda \sum_{i \in [n]} \text{sign}(w^k - x_i^k) \right)$$

where η is the learning rate, ξ is a local dataset sample, $F(\cdot, \cdot)$ is the loss function, $f_{\ell_2}(\cdot)$ is the robust regularization term, λ weights the robustness term, sign is element-wise, and $[n]$ is the client set.

Secure Aggregation with RSA. As pointed out by Franzese *et al.* [19], the only information needed by the server to aggregate is $\text{sign}(w^k - x_i^k)$. In other words, the clients simply need to supply the server with a vector with elements in $\{-1, 1\}$. Furthermore, representing -1 as a 0 yields the following property: $2 \cdot \sum_{i=1}^n v_i - n = \sum_{i=1}^n u_i$ where $u_i \in \{-1, 1\}$ and $v_i = 0$ iff $u_i = -1$. In summary, the server has to perform aggregation over binary vectors. PICASO can be used to perform this securely, with only the client having to prove that the masked input is either 0 or 1. Such a proof is efficient and we describe below. We present the additional steps to be performed by the clients and the server in Construction 4, where the client proving that it has encrypted either a value of 0 or a value of 1. This is an adaptation of Groth and Kohlweiss [24] to the CL Framework. We omit the proof due to space constraints but it follows earlier results from Braun *et al.* [10].

Construction 4 (Secure, Byzantine-Robust Secure Aggregation with PICASO)**.** We assume that there is an hash function $\mathbb{H} : \{0, 1\}^* \to \mathscr{C}$. Here, $A := 2^{40} \cdot |\mathcal{D}_H| \cdot C$ and $[A] := \{0, \ldots, A-1\}$.

Proof Generation: Each online client C_i is encrypting $x_{i,\ell} \in \{0, 1\}$ where $\mathsf{ct}_{i,\ell} := \mathsf{pk}_{0,\ell}^{\mathsf{k}_i} \cdot f^{x_{i,\ell}}$

- Sample $r_k, r'_k \leftarrow\$ [A], r_x \leftarrow\$ \{0, \ldots, p-1\}$
- Compute $t_1 := \mathsf{pk}_{0,\ell}^{r_k} \cdot f^{r_x}, t_2 := \mathsf{pk}_{0,\ell}^{r'_k} \cdot f^{r_x \cdot x_{i,\ell}}$
- Compute $ch := \mathbb{H}(\ell, \mathsf{pk}_{i,\ell}, \mathsf{ct}_{i,\ell}, t_1, t_2, \mathsf{pk}_{0,\ell})$
- Compute $s_x := r_x + ch \cdot x_{i,\ell} \bmod p$
- Compute $s_k := r_k + ch \cdot \mathsf{k}_i, , s'_k := r'_k + (ch - s_x) \cdot \mathsf{k}_i$
- Set $\mathsf{proof}_i := (s_k, s'_k, s_x, ch)$
- $\mathbf{C_i}$ **→Server**: $\mathsf{ct}_{i,\ell}, \mathsf{proof}_i$
- $\mathbf{C_i}$ **→Collector**: $\mathsf{pk}_{i,\ell}$

Proof Verification: Server does: For client i in $\mathcal{OL}_\ell$:

- Receive: $(\mathsf{pk}_{i,\ell}, \mathsf{ct}_{i,\ell}, \mathsf{proof}_i = (s_k, s'_k, s_x, ch))$
- Compute $t'_1 := \mathsf{ct}_{i,\ell}^{-ch} \cdot f^{s_x} \cdot \mathsf{pk}_{0,\ell}^{s_k}$
- Compute $t'_2 := \mathsf{ct}_{i,\ell}^{s_x - ch} \cdot \mathsf{pk}_{0,\ell}^{s'_k}$
- Compute $ch' := \mathbb{H}(\ell, \mathsf{pk}_{i,\ell}, \mathsf{ct}_{i,\ell}, t'_1, t'_2, \mathsf{pk}_{0,\ell})$
- **if** $ch \neq ch'$ **then** $\mathcal{OL}_\ell := \mathcal{OL}_\ell \backslash \{i\}$

6 Conclusion

We introduce PICASO, a secure aggregation protocol designed for the two-server setting, where clients only communicate once with the servers, in contrast to previous protocols that require multiple synchronization rounds. We show that PICASO preserves accuracy, while guaranteeing privacy. Our encryption time increasing proportionally with the length of vector. While this is expected, our use of group expoentiations makes the process slower. A possible direction for future research is to apply the SASH framework [35] with PICASO, which reduces number of group exponentiations.

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