SAFE: Secure Aggregation with Failover and Encryption

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Abstract

We propose and experimentally evaluate a novel secure aggregation algorithm targeted at cross-organizational federated learning applications with a fixed set of participating learners. Our solution organizes learners in a chain and encrypts all traffic to reduce the controller of the aggregation to a mere message broker. We show that our algorithm scales better and is less resource demanding than existing solutions, while being easy to implement on constrained platforms.

With 36 nodes our method outperforms state-of-the-art secure aggregation by 70x, and 56x with and without failover, respectively.

1 Introduction

Federated Learning [1] for machine learning (ML) offers an attractive alternative to centralized collection of training data, which is facing increased resistance from regulators, lawmakers, and privacy-conscious consumers [2,3]. A typical Federated Learning controller collects and averages model parameters (or updates thereof) from local learners. Although this poses less of a privacy loss concern than collecting the raw data, there is a risk of an attacker reverse engineering the input data by knowing the model and intercepting the model parameters (or even just updates to the model parameters). The attack could be mounted from an untrusted controller or from a compromised controller with the attacker able to intercept all messages to and from the controller.

A number of secure aggregation mechanisms have been proposed to address this issue in order to guarantee that the controller can only decrypt the average or sum of all model parameters across all learners, and not the parameter values at any of the individual learners (e.g. [1]).
The protocol proposed in [4] and variations thereof [5, 6] target learners connected to controllers by unreliable wireless links, but have the following shortcomings:

1. Learners may frequently drop out of the protocol at any time because of loss of connectivity, even in the middle of the steps required to complete the computation of the average, and thus failure recovery overhead is incurred even if all nodes complete successfully, e.g. exchanging secrets as well as weights within each aggregation cycle across all learners is necessary for failover, but makes the algorithm resource inefficient with larger number of number of learners.

2. The controller needs to actively participate in the aggregation which exposes the learners more to an untrusted or rogue coordinator and also limits concurrency and scalability.

3. In case of a failure a large number of nodes need to be contacted to recover, which makes failure cases and privacy loss scenarios complex.

In contrast, we consider a scenario where learners are leaving or entering the system infrequently, and we thus provide a simple protocol for a stable system, and a couple of mitigating algorithms that kick in when there are rare failure. We chain nodes in a cycle and thus limit the number of nodes that need to be involved to mitigate a failure. We also limit the controller involvement to message passing and progress monitoring. Another simplification of the operational conditions arises from our assumption that the links between the learners themselves, and the learners and controller, are relatively stable and not subject to drastic variations in link quality. In practice, this holds if, as we assume here, the learners are either stationary or moving very slowly, so that no links are subject to fading arising from mobility.

Scaling to a huge number of learners is not a primary concern as simpler models like noise injecting differential privacy may be used then. Furthermore, cross-organizational (vertical federated learning [7]) setups are likely to have a fewer participants than, say, an IoT fleet or sensor network in a single organization. The nature of aggregation also lends itself well to hierarchical federation without loss of privacy, but with more robustness and scalability.

Finally, we focus on learners that are in the form of devices with constrained computing capabilities (like CMs, WiFi gateways, and IoT devices), unlike the smartphones considered by [2]. We study both devices that can run desktop-class software (but are compute-constrained) and an especially constrained class of devices that cannot even run a full machine learning library like sklearn. In our evaluation we experimentally measure the scalability in nodes and features on two platforms: an edge compute learner (implemented with Python), and a constrained deep-edge learner (implemented with Linux busybox coreutils).
2 Related Work

A secure aggregation protocol for Federated Learning was first outlined in [2] with the full details published in [4] (referred to as the BON protocol below), and then extended in [6] and [5].

As stated above, in our primary use case the aggregation nodes are constrained devices such as IoT or network equipment, e.g. routers, sensors, and access points, and thus they are more stable between rounds and less likely to fail than mobile devices. In this setting, even though communication is more stable, the compute power on each node may be limited, as these are typically low-cost, single-purpose devices.

The secure aggregation protocol in [4] is proposed for mobile devices, with the assumptions that communication is expensive, communication link failures are common, aggregation vectors are high-dimensional, and the server is not trusted. Like our approach, the server (controller) routes messages between participants, but unlike our approach, it also computes the final result.

The main difference between our approach and that of [4] is the way the aggregate is masked. In particular, we only use a random mask from the initiator node in the chain (see Sec. 5.2), whereas [4] employ a pairwise mask between each pair of nodes. Hence, if a non-initiator fails we can recover more efficiently without having to worry about unmasking, and without having to contact all remaining nodes to recompute secrets. The drawback in our approach is that if the initiator fails, we need to rerun the protocol from the beginning, but based on our assumptions this should be a rare scenario.

The masking is made even more complicated in [4] in that a delayed response from a node can be easily unmasked by asking all other nodes for their masks with the presumed failing node. So the nodes have additional masks to ensure they do not reveal the local parameters to the server in case of a false failure. On the other hand, our proposal does not have this complication since we only have a single mask maintained by the initiator and never revealed to the server or any other participating node.

On a high level, the BON protocol requires four rounds of communication (public key sharing, weight sharing, masked secret sharing, and unmasking with failure secret recovery). In our protocol (SAFE) we have the same first two rounds (public key sharing, weight sharing), but the masked secret sharing is not needed and the failure recovery only involves a single node (retransmitter) unless the initiator failed, which would involve rerunning the protocol

Finally, we also note that [4] uses a real implementation of the protocol in simulations but not a full distributed system to implement the communication, and hence their measured scalability numbers in terms of number of nodes look quite different from our evaluations that uses a

\footnote{The definition of a round here differs slightly from the presentation in [4] and is more in line with the practical implementation we use from \url{https://github.com/ammartahir24/SecureAggregation/}}
multi-threaded client or separate clients on Wi-Fi access points and a server over a REST/HTTPS protocol. Our setting is kept the same across all benchmarks measured, but the scalability numbers between our evaluations and theirs cannot be directly compared, for this reason.

In [6] the authors also recognize the scalability and computational complexity of the BON protocol and improve on it by splitting up the aggregation across subgraphs. Such subgraph splitting could also be applied on top of our protocol, and our subgroup feature does exactly that. Our experiments have shown that the BON primitives scale poorly even with a very limited set of nodes, and thus it is more efficient to re-design the core protocol in our case.

In [5] the authors also propose a topology overlay across the BON primitives, called Turbo-Aggregate, and in particular a circular subgroup one as opposed to a sparse subgraph like in [6]. Although our approach also relies on a circular topology and subgrouping, our masking primitives are distinctly different from the ones in BON not to suffer from the same scalability issues or computational complexity (quadratic in number of users), and thus subgrouping is only required in our case when there is a large number of users.

 Turbo-Aggregate applies additive secrets coordinated by the server to each user and subgroup as opposed to being local to the initiator as in our case. Hence, our model puts less of a burden and trust liability on the server or coordinator, and is easier to recover from in case of failures. The implementation complexity of our solution is also simplified due to the fact that no k-of-n secret sharing is necessary. The parallel computation in subgroups is similar between the Turbo-Aggregate approach and ours. It could in theory be possible to apply the Turbo-Aggregate topology on top of our SAFE algorithm, as opposed to the BON primitives.

Another protocol called Fast Secure Aggregation [8] addresses the susceptibility to attack by non-adaptive adversaries of both Turbo-Aggregate [5] and a modification [9] of the original BON protocol that replaces the complete computation graph of [4] by a sparse random graph. However, Fast Secure Aggregation has the same communication complexity as BON without the strong privacy guarantees of BON, being designed for the honest-but-curious setting instead of Byzantine clients.

3 Motivation for the Proposed Protocol

Our work draws inspiration from the large body of work on Secure Multiparty Computation (SMC) [10]. Although SMC methods “help protect intermediate steps of the computation when multiple parties perform collaborative machine learning on their proprietary inputs, ... SMC techniques impose non-trivial performance overheads and their application to privacy-preserving deep learning remains an open problem” [11].

The cryptographic-based protocol of [4] was a step forward in SMC applied to deep learning in
that it represents the first secure privacy-preserving protocol for federated training of deep learning models. However, it involves a complex set of interactions and cryptographic functions, typically not available or too slow to run on the constrained devices of interest in the present work, e.g. network equipment like routers and cable modems (CMs). This cryptographic complexity exists to combat the presumed complete untrustworthiness and maliciousness of the learners.

On the other hand, the aggregation protocol in the present work was inspired by a discussion of algorithms and assumptions regarding trustworthiness in [3]. In contrast to [4], in [3] and also in the present work, the operational scenario assumes that the learners have a certain degree of trustworthiness in and amongst themselves, and are not anonymous public devices (like smartphones owned by consumers, in the case of [2]) that are outside the control of the operator wishing to run the learning algorithm on them. For example, the learners could be CMs in a home (which have tamper-protection installed by the cable operator), or IoT devices on a corporate network (therefore authenticated and certified by the administrators of that network), or WiFi gateways with some protection against modification of their firmware. We also conceive of “cross-organizational” federated learning where the learners are spread over multiple enterprises. In these situations, we expect the enterprises to want to interact with each other productively over time, so each enterprise will be vigilant in enforcing the integrity of its own training data and there will be mutually enforced penalties on any enterprise that seeks to acquire private data from a peer.

The present work adds a distributed systems design and implementation including failover and encryption, for secure communication across the aggregation chain via a controller, to the baseline algorithm described in [3]. We also present performance results from two implementations targeted at edge nodes and constrained devices.

4 Method Overview

Our method can be described on a high level as the set of interactions between clients and a server shown in Figure 1.

The first round (Round 0: Key Exchange) is similar to other protocols such as [2] and [8], and only involves standard PKI and symmetric key encryption primitives. This round does not need to be executed each time a new secure aggregate is computed, only when new nodes enter the system, which we, as previously mentioned, assume is a rare occurrence. Shared secrets can be exchanged in this step as an optimization but they can also be shared as part of the aggregation in the following step.

The gist of our secure aggregation method is encoded in Round 1. Although communication goes through a server to simplify connectivity between clients, logically a client only communicates with other clients that are adjacent to it in an ordered circular chain (see Figure 2). The
Figure 1: Overview of our secure aggregation method.

scalability and performance improvements of our method mainly stem from this round only requiring $O(n)$ messages to be exchanged, $n$ being number of clients, as opposed to $O(n^2)$ in other methods. To ensure that the server or other clients cannot eavesdrop messages all the communication is encrypted with the public key of the receiver.

The computational complexity of our proposed scheme is dominated by the encryption and decryption in Round 1. If, for example, RSA public key cryptography is used, then the computational complexity of encryption is $O(k^2)$ and that of decryption is $O(k^3)$, where $k$ is the number of bits in the modulus of the public key.  

5 Protocol Design

In this section, we describe the system design of our basic method and various extended features.

5.1 Introduction

Our basic algorithm involves a controller (a.k.a server) and a set of at least 3 learners (a.k.a nodes or clients). One of the nodes is designated as an initiator and all other nodes as non-initiators.
Which node is the initiator may change between aggregation rounds. Depending on whether a node is designated as initiator or not it performs different steps as part of the aggregation. All nodes have a unique id [1, 2, 3..n], which denotes their place in the aggregation chain of length n.

5.1.1 Initiator

1. The initiator starts off an aggregation by first generating a large random number that is added to its local feature vector. Then the resulting feature vector is encrypted with the public key of the next node in the chain, and the encrypted aggregate is posted to the controller.

2. Next the initiator waits for the controller notification that the next node in the chain has consumed the posted aggregate

3. Then, the initiator waits for the controller notification that an aggregate is available from the final node in the chain

4. Finally the initiator decrypts the final aggregation value from the last node in the chain, subtracts the random number and divides by the number of nodes posting their aggregate values and post the clear-text average to the controller, for any node to pull

5.1.2 Non-Initiator

1. A non-initiator starts the aggregation by waiting for a controller notification that an aggregate is available from the previous node in the chain.
2. When an aggregate is obtained it is decrypted, the local feature vector is added, and it is encrypted for the next node in the chain and posted to the controller

3. Next the node waits for the controller notification that the next node in the chain has consumed the posted aggregate

4. Finally the node waits for the controller notification that the average is available and pulls it

5.1.3 Controller

1. The controller is responsible for storing messages sent to target nodes until they are retrieved.

2. It also makes sure progress is made, and if there is a timeout, because a node fails to do its part, the controller requests the sending node to re-encrypt and resend to a new target.

3. The controller manages distribution of the computed average across all nodes. If subgroups are used it also calculates the average across groups.

4. If the initiator fails, the controller is responsible for picking a new initiator.

Notifications can be implemented as long-polling or with a pubsub service (see Section 5.9). The controller makes the following operations available to the nodes:

- **post_aggregate**(from, to, aggregate) Node from sends aggregate to node to.

- **check_aggregate**(node):[empty, consumed, repost] Nodes call this operation to check whether a posting has successfully been consumed or a repost is needed

- **get_aggregate**(node):aggregate Used by nodes to retrieve aggregate sent to them.

- **post_average**(average) Used by initiator to distribute final result, average.

- **get_average**():average Used by nodes to retrieve final result.

- **should_initiate**(node):[true, false] Used by node after initiator failure to determine if they should resume the role of initiator in the next attempt.

Given these primitives, we now describe how rounds 1 and 2 in Figure 1 are implemented.
5.2 Basic Protocol without Failover Procedures

The basic interactions between the initiator, non-initiators and the controller can be seen in Figure 3.

1. Learner 1 generates a large random number \( R \) and adds its model parameter to it, then encrypts the aggregate \( \text{agg}_1 \) with the public key of Learner 2.

2. Learner 1 posts the encrypted aggregate \( \text{enc}_2(\text{agg}_1) \) to the controller by calling get\_aggregate(1, 2, \( \text{enc}_2(\text{agg}_1) \)).

3. Learner 1 starts polling for results from the final learner with get\_aggregate(1).

4. Learner 2 calls get\_aggregate(2) and receives \( \text{enc}_2(\text{agg}_1) \) from Learner 1.

5. Learner 2 decrypts the aggregate with its private key, adds its model parameter to the aggregate and re-encrypts it with the public key of Learner 3.

6. Learner 2 calls post\_aggregate(2, 3, \( \text{enc}_3(\text{agg}_2) \)), and so on, until we get to Learner \( n \).

7. Learner \( n \) calls get\_aggregate(\( n \)) and receives \( \text{enc}_n(\text{agg}_{n-1}) \) from Learner \( n - 1 \).

8. Learner \( n \) decrypts the aggregate with its private key, adds its model parameter to the aggregate and re-encrypts it with the public key of Learner 1.

9. Learner \( n \) calls post\_aggregate(\( n \), 1, \( \text{enc}_1(\text{agg}_n) \)).

10. Learner 1 receives \( \text{enc}_1(\text{agg}_n) \) from its call to get\_aggregate(1).
11. Learner 1 decrypts $\text{enc}_1(\text{agg}_n)$ with its private key, subtracts $R$ and divides by $n$.

12. Learner 1 calls $\text{post\_average}((\text{agg}_n - R)/n)$

13. All learners receive $(\text{agg}_n - R)/n$ in the call to $\text{get\_average()}$

Looking at the messages that need to be sent and assuming the public key exchange has already occurred (which is 2 messages per node, registration and retrieval[^3]), both the initiator and the non-initiator nodes have to send 4 messages. For the initiator those are:

1. post_aggregate
2. check_aggregate
3. get_aggregate
4. post_average

And for the non-initiator they are:

1. get_aggregate
2. post_aggregate
3. check_aggregate
4. get_average

Hence, an aggregation requires $4n$ messages, where $n$ is the number of learners or nodes, for the basic algorithm.

### 5.3 Progress Failover

If a node in the chain fails to do its part the aggregation comes to a stop. The controller can easily detect if the aggregation is stuck in the chain and which node failed to respond in time. For maximum flexibility we provide an external progress monitor that periodically pings the controller to see if the aggregation got stuck. If that is the case the progress monitor will ask the controller to notify the last node to post an aggregate to repost its aggregate and encrypt it for the node that is next in the chain after the failing node. Note that this failover could have been implemented in the nodes themselves but the nodes don’t know as easily where in the chain the process stopped and there could be issues of multiple nodes timing out concurrently and then creating race conditions.

[^3]: Public key exchange does not have to be done for every aggregation round, just once for each set of nodes you want to incorporate in the aggregation.
on which nodes to jump. It would also complicate the case where two nodes next to each other on the chain fail simultaneously. For instance the node that checks whether its post got consumed may also get stuck, and then the process as a whole gets stuck, unless an external process kicks in. Hence we decided to start off with an external progress monitor process.

The progress failover interactions can be seen in Figure 4.

Figure 4: Progress Failover Interactions.

1. Learner 1 generates a large random number $R$ and adds its model parameter to it, then encrypts the aggregate $(agg_1)$ with the public key of Learner 2.

2. Learner 1 posts the encrypted aggregate $enc_{2}(agg_1)$ to the controller by calling 
   
   $post_{aggregate}(1, 2, enc_{2}(agg_1))$

3. Learner 1 starts polling for results from the final learner with check_aggregate(2)

4. Learner 2 fails to do its part of the protocol

5. Progress Monitor detects that the protocol halted with a timeout and posts a notification to Learner 1 it needs to re-encrypt its aggregate and repost to Learner 3 as a result to the check_aggregate call

6. Learner 1 calls
   
   $post_{aggregate}(1, 3, enc_{3}(agg_1))$

7. Learner $n$ calls get_aggregate($n$) and receives 
   
   $enc_{n}(agg_{n-1})$ from Learner $n-1$.

8. Learner $n$ decrypts the aggregate with its private key, adds its model parameter to the aggregate and re-encrypts it with the public key of Learner 1.
9. Learner $n$ calls
\[
\text{post\_aggregate}(n, 1, \text{enc}_1(\text{agg}_n))
\]

10. Learner 1 receives
\[
\text{enc}_1(\text{agg}_n) \text{ from its call to get\_aggregate(1)}
\]

11. Learner 1 decrypts
\[
\text{enc}_1(\text{agg}_n) \text{ with its private key, subtracts } R \text{ and divides by } n - 1. \text{ Learner 1 is informed by the controller that only } n - 1 \text{ nodes posted aggregates}
\]

12. Learner 1 calls
\[
\text{post\_average}(\frac{\text{agg}_n - R}{n - 1})
\]

13. All learners receive $(\text{agg}_n - R)/(n - 1)$ in the call to get\_average()

If a non-initiator node fails, two additional messages need to be sent, a new post\_aggregate (with the re-encrypted message retargeted next in the chain after the failed node) and a new check\_aggregate. Hence, the number of messages required for $n$ nodes where $f$ nodes fail is: $4n + 2f$.

In terms of drop-out rate tolerance, as long as $n - f \geq 3$ the failover will succeed. In theory you could allow failover with 2 nodes left too, but then both of them would learn each other’s local value by simply subtracting their own, and hence defeating the purpose of secure aggregation.

### 5.4 Initiator Failover

If the initiator fails, it is not sufficient to just jump over it in the chain, as it is the only one holding the random secret that masks the true aggregate. Hence, in this case the aggregation needs to be redone from the beginning. We implement this by setting a timeout on the aggregation as a whole. Each node would timeout after this time and then ask the controller if they should be the new initiator. Whoever, gets assigned as the initiator (the first one that asks the controller) starts the initiator steps and the other nodes repeat their non-initiator steps from the beginning. This may mean that the failed initiator is traversed again on the chain and you suffer from a progress failover. If this keeps happening the nodes may have to be refreshed to permanently exclude the failing node from the chain.

The initiator failover interactions can be seen in Figure 5.

1. Learner 1 generates a large random number $R$ and adds its model parameter to it, then encrypts the aggregate $(\text{agg}_1)$ with the public key of Learner 2.
Figure 5: Initiator Failover Interactions.

2. Learner 1 posts the encrypted aggregate $enc_2(agg_1)$ to the controller by calling
   `post_aggregate(1, 2, enc_2(agg_1))`

3. Learner 1 crashes and is unable to fulfil its protocol responsibilities

4. Learner 2 calls `get_aggregate(2)` and receives $enc_2(agg_1)$ from Learner 1

5. Learner 2 decrypts the aggregate with its private key, adds its model parameter to the aggregate and re-encrypts it with the public key of Learner 3.

6. Learner 2 calls
   `post_aggregate(2, 3, enc_3(agg_2))`

7. Learner $n$ calls `get_aggregate(n)` and receives $enc_n(agg_{n-1})$ from Learner $n - 1$.

8. Learner $n$ decrypts the aggregate with its private key, adds its model parameter to the aggregate and re-encrypts it with the public key of Learner 1.

9. Learner $n$ calls
    `post_aggregate(n, 1, enc_1(agg_n))`

10. All learners time out in their call to `get_average`

11. All learners call `should_initiate()` and only one gets back `yes`, in this case Learner 2

12. Learner 2 generates a large random number $R'$ and adds its model parameter to it, then encrypts the aggregate $(agg_2)$ with the public key of Learner 3.
13. Learner 2 posts the encrypted aggregate
   \[ \text{enc}_3(\text{agg}_2) \]
   to the controller by calling
   \text{post\_aggregate}(2, 3, \text{enc}_3(\text{agg}_2))

14. Learner \( n \) calls \text{get\_aggregate}(n) and receives
   \[ \text{enc}_n(\text{agg}_{n-1}) \]
   from learner \( n - 1 \).

15. Learner \( n \) decrypts the aggregate with its private key, adds its model parameter to the aggregate and re-encrypts it with the public key of Learner 2.

16. Learner \( n \) calls
   \text{post\_aggregate}(n, 2, \text{enc}_2(\text{agg}_n))

17. Learner 2 receives
   \[ \text{enc}_2(\text{agg}_n) \]
   from its call to \text{get\_aggregate}(2)

18. Learner 2 decrypts
   \[ \text{enc}_2(\text{agg}_n) \]
   with its private key, subtracts \( R' \) and divides by \( n - 1 \)

19. Learner 2 is informed by the controller that only \( n - 1 \) nodes posted aggregates

20. Learner 2 calls
   \text{post\_average}((\text{agg}_n - R')/(n - 1))

21. All learners receive \((\text{agg}_n - R')/(n - 1)\) in the call to \text{get\_average}()

   If the initiator fails all nodes need to send an additional message (\text{should\_initiate}), and then start over. Hence with \( i \) initiator failures, \( n \) nodes and \( f \) progress failures (per round) the number of messages that need to be sent is: \((i + 1)(4n + 2f + in)\)

5.5 Subgrouping

To parallelize the aggregation we allow the nodes to be subdivided into subgroups with an initiator per subgroup. Aggregation for individual subgroups may then proceed in parallel. The average calculation will wait for all initiators to post their updates and then an average of the posted averages will be returned to clients from all groups. Note that we can give the same privacy guarantees with this setup as long as each subgroup has at least three members. This parallelization may also be used for reliability where a single node failure does not break the entire aggregation, just a single subgroup. In terms of messages being sent only a single additional message per group is needed, as the initiators only have the group average they need to call get\_average after they call post\_average in order to get the global average. Hence with \( g \) subgroups the number of messages required is: \((i + 1)(4n + 2f + in + g)\)
5.6 Weighted Averaging

We support secure aggregation of feature vectors. It is common that local learners create averages themselves from local models, which in turn may be based on varying cardinality. E.g. if one learner shares an average based on 1000 values and another shares an average based on 10000 values the average computed but the secure aggregation algorithm will differ from the true average. We address this by allowing weighted averaging, where each node can submit not just its feature vector to the secure aggregation but also its weight, denoting the number of samples its aggregate was computed from. Instead of the average the aggregate should be submitted with the weight. Now as the final average the nodes will get the average of all the aggregates as well as the average of all the weights and can then simply divide the former with the latter to get the true average without having to reveal how many samples each node contributed. Note, using weighted averaging does not require any additional messages to be sent, but required an additional feature to be used in the aggregate feature vector.

5.7 Symmetric-Key Encryption

PKI encryption with public-private keys has limitation in terms of encryption and decryption speed as well as the payload size that can be encrypted. Larger payloads require larger keys which makes the encryption and decryption slower. To mitigate this problem we can submit a randomly generated symmetric key encrypted with the public key of the next node on the chain and then encrypt the feature vector with the symmetric key. The next node in the chain then first needs to decrypt the symmetric key with its private key and then use the decrypted symmetric key to decrypt the feature vector. This allows for much larger feature vectors to be encrypted much faster.

5.8 Symmetric-Key Pre-Negotiation

On some constrained devices it may be too time consuming to even decrypt the randomly generated symmetric key in each aggregation step. In that case the symmetric key exchange may happen out of band. Each node will generate \( n \) random symmetric keys, and then encrypt key \( i = 1..n \) with the public key of node \( n \), and post all encrypted keys to the controller. Then when all nodes have posted their encrypted keys, all nodes pulls down the encrypted key posted by the node next on the chain for its node and decrypts it with its private key and caches it for later use during the aggregation. During the aggregation instead of encrypting the feature vector with the public key for the node next on the chain the payload can be encrypted with the symmetric key that was cached. The receiving node then checks where the aggregate came from and then picks the symmetric key it generated for that node, which it stored locally to decrypt the feature vector received.
5.9 Pubsub Design

Our controller supports long polling by default which means that all nodes will open a connection to the controller and wait for a result to come in. Hence connection establishment will not be part of the critical path of the chain aggregation. However it could result in a lot of concurrent connections to the controller, which ultimately would exhaust the connection resources. We propose to mitigations to this effect. Since the nodes at the end of the chain only need to engage at the very end of the aggregation they can hold off on polling the controller until it is their turn. By estimating the overall aggregation time for a cluster of nodes the nodes can hold off based on which cluster they are assigned to before they start polling the server. This essentially allows us to stagger the engagement with nodes. If course if the progress estimate is off the resources may still be exhausted or the process takes longer than needed. Staggering bigger clusters of nodes helps but may ultimately also fail. Hence, we also propose to separate out the notifications from the controller, and the nodes will not poll the controller directly but wait for notifications from an external notification system when the controller has some data for a node before they poll the controller.

5.10 Hierarchical Federation

Another approach to scalability is to have many controllers that are federated so that child controllers post their aggregate to the parent controller. This posting does not have to be encrypted as it is already anonymized over learners, but it needs to be coordinated. We hence also allow coordinated posting and retrieval of aggregates across controllers, similar to the last step of the secure aggregation where an average is posted.

6 Edge Compute Learner Evaluation

In this section we present performance results from using a Python client implementation of our algorithm as well as benchmarks and a collocated Python server on an 8 quadcore CPU 1-1.4Ghz Linux Ubuntu 20 desktop PC, where each learner node is run concurrently in separate threads in the same experiment process. Due to the single-machine nature of the setup we are limited to running about 100 concurrent nodes before we run out of capacity, and the subgroup feature does not add much value as everything runs on the same machine. We hence defer the subgroup evaluation to the experiment section below. Both the clients and server run in docker containers to allow for easy resetting of state between benchmark runs. We compare our approach with (SAFE) and without (SAF) encryption to a benchmark approach that simply posts parameters to a central controller and retrieves averages (INSEC). We have also invented the Practical Secure Aggregation algorithm proposed by google (BON). Since the BON benchmark does not scale so well in number of nodes,
we perform scalability tests both with and without it. We are interested in how the approach scales in terms of nodes as well as features. Each condition runs in 30 repeats, and given that the variance is so low that 99% error bands with a z-distribution assumption are not visible, we display bands for $3\sigma$. Note, the error bars are hence more of a way to see trends in variance as opposed to statistical significance, in this case.

### 6.1 Node Scalability

In Figure 6 we can see that BON starts deteriorating in performance already at 8-10 nodes and shows an overhead of close to 40x compared to INSEC for 15 nodes (and a single feature). For SAFE the equivalent overhead is just under 3x. We note that we are not claiming that BON can scale beyond these numbers, but that SAFE is more resource efficient in a small set up. Furthermore, the graph shows that the overhead of encryption is also negligible (SAF vs SAFE) in the case of a small feature set.

Given that BON does not scale well in this setting we wanted to test the limits of the SAFE method in a larger deployment with up to 100 nodes. In 7 we note that the linear increase continues and the overhead between INSEC and SAFE is still around 3x for 100 nodes (and 1 feature).

If we increase the number of features to 10000 we can see in 8 and 9 that the trends stay the same. The BON overhead is about 13x in the 10000 features 15 node case compared to an improvement of about 30% for SAFE over INSEC. This shows that SAFE encryption improved scalability due to compression for large feature vectors. This becomes even starker in the 100 node 10000 feature case where SAFE outperforms INSEC by a factor of 5x.

### 6.2 Feature Scalability

We now study how the algorithms scale in terms of feature vector sizes in Figures 10, 11, and 12. We can see for 10000 features and 3 nodes INSEC is still faster than SAFE, but (a) with 15 nodes, the crossover is somewhere around 2000 features, and (b) with 100 nodes, the crossover occurs around 100 features.

To summarize, we can see that the encryption mechanism in SAFE helps with feature scalability as it also compresses the payload. The BON mechanism scales much worse in number of nodes given that all nodes need to submit both their weights as well as their secret masks to the controller and the controller also needs to be involved in the aggregation, as opposed to just passing along messages in our method (SAFE).

We note that to support encryption of larger payloads efficiently, i.e. bigger feature vectors, we use RSA encryption of a symmetric AES key that then is used to decrypt the encrypted feature vector. Both the encrypted message key and the encrypted feature vectors are exchanged between
Figure 6: Edge. BON 1 Feature.

Figure 7: Edge. 1 Feature.

Figure 8: Edge. BON 10000 Features.

Figure 9: Edge. 10000 Features.
Figure 10: Edge. BON 3 Nodes.

Figure 11: Edge. BON 15 Nodes.

Figure 12: Edge. 100 Nodes.
the nodes in each aggregation step. The aggregation payload is opaque to the controller and any JSON object may be passed along. The only assumption is that all the nodes participating in the aggregation need to know how to decrypt and encrypt as well as parse the payload.

### 6.3 Failover Overhead

With SAFE, if a node fails the controller needs to direct the next node in the chain to pick up the aggregate, and let the initiator know how many nodes successfully posted aggregates in order to complete the calculation of the average. With BON, if a node fails all remaining nodes need to report a separate secret to be added to the global aggregate based on which node failed. Next, we measure the overhead that a failing node imposes on the calculation of the global average. Note, if the initiator fails in the SAFE method the whole aggregation just needs to restart, so the failure completion time is 2x, if x is the time to compute the average without failure. Here, we focus on a non-initiator failure, which is the more interesting case.

A failure is detected by setting a timeout on getting the result. Clearly, the best timeout to set depends on the number of nodes and features in the aggregation, i.e. the expected aggregation time. We measured the expected completion time without failure, and then made a prediction using a second degree polynomial fit and added 4 seconds of safety margin time, to avoid false positives. Here we only use a single feature, as the number of features does not impact the failover scenario and it allows us to run aggregations faster and with more nodes. To measure the failover overhead we subtract the expected failure timeout time (when nodes just wait for failed nodes to complete) from the overall aggregation time. For BON this is a global wait time and for SAFE this is the progress timeout per failed node. To facilitate apples-to-apples comparisons we kept the sum of all failed node timeouts in SAFE the same as the global BON timeout.

To simulate a failure, we complete the public key exchange step for all nodes before taking out nodes 4 to 6 in the chain (any non-initiator nodes could have been picked) and starting the aggregation process. We then compare the aggregation time for a given number of completed nodes, e.g., the aggregation time for 21 nodes without failures is compared to the aggregation time for 24 nodes with 3 failures.

Figures 13 and 14 (error bands are $3\sigma$, and y-axis in log-scale) show how BON performance both with and without failover scales super linearly with nodes, whereas both SAFE and SAFE with failover scales linearly.

With 24 nodes the BON failover to SAFE failover aggregation time ratio exceeds that of BON without failover to SAFE without failover (42x vs 38x). At 36 nodes the corresponding ratios are 70x and 56x.

4Without this normalization, failure scenarios tend to scale better as fewer nodes are involved.
For comparison, we also note here that the authors of [5], showed a 40x improvement with 200 nodes, i.e. an order of magnitude more nodes were needed to reach the same level of improvements.

7 Deep-Edge Constrained Device Learner Evaluation

Next we explore the performance of our method on an embedded platform, OpenWrt. We implemented the aggregation client using busybox coreutils, curl and openssl and deployed it on twelve Archer C7 TP-Link Wi-Fi routers. We use the symmetric key pre-negotiation feature and exchange symmetric keys before the aggregation as RSA key decryption is very slow on these devices. The 12 routers are connected to a LAN over an Ethernet backhaul. The controller is deployed on the same LAN on a MacBook Pro PC, which also coordinates the aggregation experiments over ssh. Generating random numbers is also quite slow on this platform so only a single seed is used regardless of the number of features aggregated in the initiator. Given the 12 learners, we explore groupings of $1 \times 12$, $2 \times 6$, $3 \times 4$, and $4 \times 3$. The BON algorithm client was not implemented on this platform but both SAF and INSEC were ported as well. Each condition runs in 5 repeats, and given that the variance is so low that 99% error bands with a t-distribution assumption are not visible, we display bands for $4\sigma$. 

![Figure 13: Edge. Failover.](image1)

![Figure 14: Edge. Failover Overhead.](image2)
7.1 Node Scalability

First, looking at node scalability, we see in Figure 15 that SAFE has an overhead of about 2x with 3 nodes and 4.5x with 12 nodes, compares to INSEC (with a single feature). Although SAF suffers with 20 features, the SAF vs INSEC differences are roughly the same with 20 features in Figure 16.

![Figure 15: Deep-Edge. 1 Feature.](image1)

![Figure 16: Deep-Edge. 20 Features.](image2)

7.2 Feature Scalability

In Figures 17 and 18 we can see the crossover between SAF and SAFE performance is between 5 and 10 features both for 3 and 12 nodes.

7.3 Subgrouping Improvement

How can we improve the performance for large number of nodes with SAFE? We can introduce sub groups that aggregate in parallel as alluded to in Section 5. Figure 19 shows we can improve the aggregation time from about 4.5 seconds down to about 2 seconds with four parallel group vs a single group with SAFE and 1 feature. For 20 features (See Figure 20), we can get it down from 5.5 to 3 seconds with four groups.

From these results we can see again that encryption helps with compression and scalability and that subgrouping is efficient in improving the parallelism and performance of aggregations, as it can more than double the aggregation throughput.

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Figure 17: Deep-Edge. 3 Nodes.

Figure 18: Deep-Edge. 12 Nodes.

Figure 19: Deep-Edge. 12 Nodes 1 Feature.

Figure 20: Deep-Edge. 12 Nodes 20 Features.
8 Discussion and Conclusion

We have shown the practical benefits of a secure aggregation mechanism that relies on a single mask by an initiator in a public-key-encryption-secured chain of participating learners. Not only is it faster in the most common case of all learners contributing successfully to the protocol, but it is also able to recover faster if some node fails to contribute its value.

We show that the algorithm, with some tweaks to pre-negotiate symmetric keys, can be implemented efficiently on constrained devices such as OpenWrt Wi-Fi access points, by simply relying on coreutils primitives and OpenSSL.

In deployments with a large number of nodes we also show that subgrouping can improve performance. This method has its limits though as the single coordinator may at some point still become a bottleneck. In such scenarios a hierarchical federated learning topology may be deployed to completely detach the running of the protocol in the subgroups from each other.

We should also note that if a large number of nodes fail to complete their protocol step, the aggregation may not be as efficient as each failing node would cause a hiccup in the progress independently along the chain. This effect could be mitigated by having a way of checking the health of nodes and remove them from the chain pro-actively, and periodically refresh the chain to remove nodes that are contributing too intermittently.

The performance of our approach relies on an efficient notification or pubsub system. If the number of nodes outgrow what the pubsub system can handle efficiently the performance suffers significantly. This could be addressed by having each node predict when it is its turn to contribute an aggregate so that not all nodes in the chain overwhelm the controller or pubsub system all at once. At some point when you have a very large pool of nodes to compute an average over, it is probably more practical to deploy some noise mechanism, such as differential privacy. Based on our experiments, the SAFE method could be deployed efficiently and with good privacy guarantees when you have subgroups of sizes between 3-100 nodes. Of course if you deploy hierarchical federation that could still cover very large pools, e.g. with thousands of nodes. However, it would probably not be the right approach when you have millions of nodes.

We note that a node that colludes with another node on the chain can infer the average of the intermediate nodes on the chain. So if node $n$ colludes with node $n-2$ they will be able to infer the local value of node $n-1$. Protection against this kind of collusion would require additional use of masking which is outside the scope of our current work. In general, we assume honest but curious behavior and no collusion between nodes. You could randomize the order between each round to limit the likelihood of two colluding nodes being able to get useful data from intermediaries on a consistent basis. Recall that secure aggregation is typically deployed as part of a gradient descent iteration, so only being able to infer values from a subset of a large number of iterations would still
offer some protection of privacy of the local data, assuming a sufficiently large number of nodes participate in the aggregation.

Finally, there is the issue of the distribution and security of private keys. While they offer the above-mentioned improvements over PKI’s, they are still subject to the usual attacks that are thoroughly described in the literature. One way to improve their security is using quantum internet protocols that can distribute keys through quantum channels that are provable-and not just algorithmically secure. An example of such technology using photons and operating at the level of the transport layer of the internet has been shown in [12].

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A Controller Python Flask Implementation

```python
@app.route('/should_initiate', methods=['POST'])
def should_initiate():
    with lock:
        data = request.get_json(force=True)
        node = data['node']
        current_time = time.time()
        group = 1
        if 'group' in data:
            group = data['group']
        if not group in average:
            init_average(group, node)
            return {"init": True}
        if (current_time - average[group]['time']) > config['aggregation_timeout']:
            init_average(group, node)
            return {"init": True}
        return {"init": False}

@app.route('/post_aggregate', methods=['POST'])
def post_aggregate():
    data = request.get_json(force=True)
    with lock:
        from_node = data['from_node']
        to_node = data['to_node']
        group = 1
        if 'group' in data:
            group = data['group']
        if group in average and average[group]['initiator'] == from_node:
            init_average(group, from_node)
        elif group not in average:
            init_average(group, from_node)
        if not group in aggregate:
            aggregate[group] = {}
            aggregate[group][to_node] = {
                "aggregate": data['aggregate'],
                "time": time.time(),
                "from_node": from_node}
            group_stats[group]['posted'] += 1
        if group not in repost_aggregate:
            repost_aggregate[group] = {}
            repost_aggregate[group][from_node] = {
                "status": "consumed"
            }
            repost_aggregate[group][to_node] = {
                "status": "empty"
            }
            return json.dumps(data)
        def internal_check_aggregate(data):
            group = 1
            if 'group' in data:
                group = data['group']
            if not group in aggregate:
                aggregate[group] = {}
                aggregate[group][to_node] = {
                    "aggregate": data['aggregate'],
                    "time": time.time(),
                    "from_node": from_node}
                group_stats[group]['posted'] += 1
            if group not in repost_aggregate:
                repost_aggregate[group] = {}
                repost_aggregate[group][from_node] = {
                    "status": "consumed"
                }
                repost_aggregate[group][to_node] = {
                    "status": "empty"
                }
            return json.dumps(data)
        def poll_internal(data, func):
            TIMEOUT = config['poll_time']
            WAIT_TIME = config['yield_time']
            empty = True
            start_time = time.time()
            with lock:
                result = func(data)
                empty = ("status" in result) and (result["status"] == "empty")
            while empty and (time.time() - start_time) < TIMEOUT:
                time.sleep(WAIT_TIME)
            with lock:
                result = func(data)
                empty = ("status" in result) and (result["status"] == "empty")
            return result
        @app.route('/check_aggregate', methods=['POST'])
def check_aggregate():
            data = request.get_json(force=True)
            result = poll_internal(data, internal_check_aggregate)
            return json.dumps(result)
        def internal_get_aggregate(data):
            result = {'status': 'empty'}
            group = 1
            if 'group' in data:
                group = data['group']
            if group in aggregate and data['node'] in aggregate[group]:
                result = {'status': 'ok'}
            if 'aggregate' in aggregate[group][data['node']]:
                result['aggregate'] = aggregate[group][data['node']]['aggregate']
                if 'from_node' in aggregate[group][data['node']] and aggregate[group][data['node']]['aggregate']
                    aggregate[group][data['node']]['aggregate'] = {
                        'from_node': aggregate[group][data['node']]['aggregate']["from_node"]
                    }
            else:
                result['posted'] = False
```


```python
@app.route('/get_aggregate',methods=['POST'])
def get_aggregate():
data = request.get_json(force=True)
result = poll_internal(data, internal_get_aggregate)
return json.dumps(result)

@app.route('/post_average',methods=['POST'])
def post_average():
data = request.get_json(force=True)
with lock:
    group = 1
    if "group" in data:
        group = data["group"]
    average[group]["average"] = data["average"]
    average[group]["status"] = "posted"
    if group not in repost_aggregate:
        repost_aggregate[group] = {}
    if "node" in data:
        repost_aggregate[group][data["node"]] = 
            {"status": "consumed"}
    return json.dumps(data)
```