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# A blockchain-orchestrated Federated Learning architecture for healthcare consortia

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## Abstract

We propose a novel architecture for federated learning within healthcare consortia. At the heart of the solution is a unique integration of privacy preserving technologies, built upon native enterprise blockchain components available in the Ethereum ecosystem. We show how the specific characteristics and challenges of healthcare consortia informed our design choices, notably the conception of a new Secure Aggregation protocol assembled with a protected hardware component and an encryption toolkit native to Ethereum. Our architecture also brings in a privacy preserving audit trail that logs events in the network without revealing identities.

## 1 Privacy in healthcare and Federated Learning Consortia

The healthcare sector is uniquely positioned to leverage data for the purpose of creating value and improving human health. However, our ability to learn from health data is in tension with a unique set of ethical, legal, economic and technical challenges related to data privacy. But traditional methods of mitigating health data privacy concerns, namely HIPAA and the use of deidentified data, have proven insufficient to protect individuals' interests. Realizing data's promise will require new tools, and we propose a novel federated learning architecture that is uniquely suited to these problems.

Large scale federated learning as depicted in the original series of papers Bonawitz et al. [2017, 2019] involves a great number of mobile devices that take part in the training rounds. This introduces a series of design constraints and challenges to enable learning to happen on these resource-limited devices without disrupting the end-user's experience nor privacy. We argue that among the challenges highlighted in Bonawitz et al. [2019], some elements are not relevant anymore when considering a consortium context.

The most significant change lies in the data distribution. A consortium will contain less parties than a public network of mobile devices, but each of these participants will host a larger quantity of data. They will also benefit from substantially more compute and storage resources, as the devices involved in the training rounds will be server-grade machines rather than smartphones. Another discrepancy exposed by servers is that they can be leveraged in a training round at any time of the day (contrary to mobile devices which will be leveraged mostly when charging and connected to a home Wi-Fi

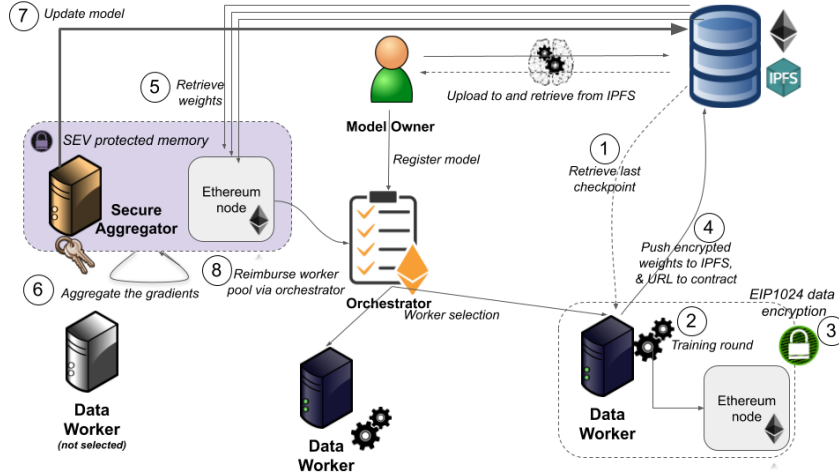


Figure 1: Global overview of a training round

network). Network connectivity will also be more reliable, thus almost no participant will drop out during a training round.

These elements informed our design choices, which as a result differ from the blueprints established in Bonawitz et al. [2019], Lalitha et al. [2018]. The architecture we introduce in this paper draws its specificity and novelty from the combination of four main features making it particularly suitable for the healthcare consortia settings we are considering: 1) Data owners can define fine-grained access policy to their data, restricting access to certain members of the consortium only (Section 2.2), 2) An alternative implementation of Secure Aggregation based on AMD SEV in memory encryption, which introduces a trusted third-party more suitable than a potentially brittle Multi-Party Computation (MPC) with a limited number of non-anonymous participants (Section 2.3), 3) Peer-to-peer transit encryption of updated weights between the workers and the Secure Aggregator leveraging cutting edge Ethereum technology Alabi [2018] (Section 2.4), 4) A privacy preserving audit trail logs actions undertaken within the network while keeping the actual list of participants to a training round hidden (Section 3.2).

## 2 System architecture

Figure 1 gives an overview of the system architecture and of a training round. All the parties in the network have access to their own Ethereum account that will identify them and enable them to interact with the rest of the network. Our solution exploits the Federated Learning building bricks provided by the PySyft library Ryffel et al. [2018].

### 2.1 Overview

The *Model Owner* (MO) initiates the process by uploading his model to a distributed storage infrastructure (IPFS, Swarm, ...) available to all the members of the consortium. MO then registers the model and a training description to an *Orchestrator* smart contract. This description will contain similar information to what a *FL Plan* does in Bonawitz et al. [2019].

The *Orchestrator* is embodied by one or potentially several smart contracts. In addition to storing the models, it maintains a list of *Data Workers* (DW). A DW is a node in the network that possesses one or many datasets that can be of interest for MOs to improve their models. DWs are communicating by instantiating a web socket server as available in PySyft. DWs have the ability to specify a blacklist of model owners that shouldn't have access to some or all of their data. They do so by updating a mapping of Ethereum addresses (representing the blacklisted MOs) and dataset identifiers stored in the *Orchestrator* smart contract.

In order to initiate a training round, the *Orchestrator* first determines the full set of data workers that comply with the previous exclusion rules (a post training selection will further reduce the set

as described in 3.1). The Orchestrator schedules a training task for the selected workers using private transactions. All the actions undertaken by the Orchestrator are logged on chain in a privacy preserving fashion as described in Section 3.2. Each selected worker now pulls the latest checkpoint of the model from the shared distributed storage. The worker performs a training step as defined in the corresponding training description stored in the Orchestrator. Once it has completed its training round, the worker encrypts the newly obtained set of weights for the *Secure Aggregator* (SA).

SA is a special entity, a Virtual Machine or container, whose memory is encrypted from its host using the AMD SEV technology (Section 2.3). The Aggregator fetches all the encrypted weights from the decentralised storage, decrypts them within the safe realm of its encrypted memory and performs the aggregation. It finally uploads the new model checkpoint to the shared storage and updates the Orchestrator smart contract with new pointer. Multiple SA could be instantiated to accommodate a larger workload or introduce more decentralisation and reliability.

## 2.2 Role of Ethereum and Fine grained data permissioning

In the context of federated learning consortia, it is critical to prevent legal, ethical, and competitive requirements from being compromised. We argue in this paper that the Ethereum Wood and others [2014] blockchain can fulfill such a role and benefit an architecture targeting consortia in the healthcare industry in particular. The combination of a decentralised immutable ledger that can be updated programmatically in a highly trustable flavour makes Ethereum a very appealing choice to design modern decentralised and secure systems. Hyperledger Besu is an enterprise-grade Ethereum client. These tools enable consortia to implement cooperative standards for viewing, transacting, and communicating within in the network. For example, providing read-only access of an audit trail to an external third-party or restricting data exchange to a subset of network nodes for private communication.

On top of Besu’s native features, an Orchestrator smart contract controls the traffic in the network, keeping track of permissions set by each user regarding the level of data-sharing access with other members in the consortium. In addition to governing activity and authorizations, smart contracts can also support the exchange of native tokens within the Ethereum blockchain. Tokens have been proposed as a way of incentivizing network participants to perform actions; in our architecture they could be used to incentivize computations. However, they extend naturally as a fungible or non-fungible measure of value in an information exchange, and can serve as the backbone for incentivized data-sharing in a federated learning consortia. In our use case, smart contract(s) can record metrics throughout federated learning lifecycles, and specify the execution of remuneration policies chosen by the consortia.

## 2.3 AMD SEV based Secure Aggregator

Architectures like Bonawitz et al. [2019] are designed for training rounds involving “a few hundred devices”. Within the context of healthcare, federated learning consortia are mostly likely to be adopted by enterprises first. This will limit the number of members in a network, likely to be under 100. This number will shrink even more when applying the data selection filters and account permissioning rules.

While medical applications have been shown to successfully leverage federated learning with a lower number of workers (20-30) Roy et al. [2019], Sheller et al. [2019] compared to Bonawitz et al. [2019], this could break the security properties of the Secure Aggregation scheme presented in Bonawitz et al. [2017]. Secure Aggregation Bonawitz et al. [2019] is performed via a MPC protocol built on top of Shamir’s Secret Sharing (SSS) scheme Shamir [1979]. In our present context, the number of active devices would be too low to provide the same level of guarantees for the MPC. On top of that, members of a consortium are highly likely to know each other and this would dramatically increase the risks of compromising the security threshold of the SSS scheme.

We introduce a better suited approach for such consortia based on protected hardware such as AMD’s Secure Encrypted Virtualization (SEV) memory encryption technology and Intel’s Software Guard Extensions (SGX). Mofrad et al. [2018] provides a concise comparison of these technologies, each of which generally cryptographically isolate software containers from the host system to better protect confidential data.

Secure Aggregation as described in Bonawitz et al. [2017] is secure in the *honest but curious* context. That is, if an attacker gains access to a participant in the MPC, he will only find secret shares from which he will not be able to reconstruct the private data. Here, SEV provides equivalent guarantees of in-memory privacy from attackers outside the VM/container it protects. As a result, we implement a Secure Aggregator as a trusted third party running inside an AMD SEV protected VM. At the end of a training round, workers communicate their encrypted computed weights to the Secure Aggregator who performs the aggregation then uploads a non-encrypted updated model back to the shared storage.

## 2.4 Peer-to-peer in transit encryption of updated weights

Weight encryption while in transit between worker and aggregator is however extremely important since it contains the private data used for this training step that should remain private to the worker. We assume here that the members of the consortium will adopt honest but curious behaviour, and would have a strong incentive to eavesdrop on the network to learn of the raw updates shared by other members containing valuable information on their private datasets.

At the time of writing, encryption over the wire is not available to protect the traffic between two workers in PySyft. While this feature is under active development, our system will leverage Ethereum Improvement Proposal (EIP) 1024 Alabi [2018] that offers peer-to-peer transit encryption of arbitrary data between two Ethereum accounts. Using EIP-1024, we can encrypt the new weights calculated by each worker before they are being sent back to the Secure Aggregator.

## 3 Security requirements

Secure aggregation brings a first level of privacy by hiding the raw updates to a model from a given data owner. However, the identity of the data owners who took part in a training round could allow an attacker to extract meaningful information from the aggregated weights. We describe two counter-measures to this issue in this section.

### 3.1 Random selection of contributions to aggregate

For a given federated training round, all chosen workers will compute gradient updates, but the Secure Aggregator will randomly select a subset of weights for aggregation. After each training round, the Secure Aggregator will forget the unpicked weight updates and the workers will not be notified whether or not their updated weights were selected for aggregation.

In the most critical case, a malicious worker or a cartel of workers could communicate their weight updates for a given training round via a third-party channel. This would allow the model owner to reverse engineer a round update and extract the exact contribution of each worker as highlighted in Melis et al. [2018]. By selecting updates for aggregation, such malicious intent to expose another member's data contribution can be prevented. Note that while this privacy preserving mechanism is distinct from Differential Privacy (DP) Papernot et al. [2016], Abadi et al. [2016], they can be combined to provide even more enhanced privacy guarantees.

### 3.2 Privacy preserving audit trail

As described in the global overview of the architecture, a residual benefit from our Ethereum-based system is the immutable audit trail stored on chain. The audit trail gathers events related to the learning process. As part of our privacy in depth proposal, we must not leak sensitive information that may compromise the privacy guarantees of the federated learning process.

The Secure Aggregator (SA) will spearhead this non-identifiable update protocol. First, for each data worker taking part in the round the SA will generate a new unique random nonce for the current round. Each worker already has an established secure communication channel with SA given EIP 1024 transit encryption. Data between SA and a worker are encrypted using a symmetric Diffie-Hellman (DH) secret derived from the worker's public key and SA's private key (or conversely). SA will apply Ethereum's keccak256 function to the concatenation of this shared DH secret and the nonce it just generated, sending the resulting hash encrypted via EIP 1024 to the corresponding worker. The hash

is published on chain and will serve as an anonymous identifier for the corresponding data worker during a training round.

The only attack to uniquely identify a data worker in the audit trail is to know the DH secret that has been concatenated to the random nonce. Thus, as long as the worker's and SA's respective private keys remain private, they are the only two entities in the system able to reidentify the worker's corresponding entries in the audit trail.

## **4 Conclusion**

This work introduced an architecture for federated learning in healthcare consortia built on the Ethereum blockchain. The architecture leverages Ethereum and its ecosystem (e.g., EIP 1024 encryption and the Besu enterprise client) to provide a coherent design reflecting the specific challenges in healthcare consortia. The novel architecture relies on a series of four "privacy in depth" blocks that provide a unique combination of features: fine-grained data access policies, a new Secure Aggregation agent running in hardware-protected processes, weight encryption via EIP 1024 and a privacy preserving audit trail of the events in a training round.

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