Secure and Privacy-Preserving Federated Learning via Co-Utility

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Abstract—The decentralized nature of federated learning, that often leverages the power of edge devices, makes it vulnerable to attacks against privacy and security. The privacy risk for a peer is that the model update she computes on her private data may, when sent to the model manager, leak information on those private data. Even more obvious are security attacks, whereby one or several malicious peers return wrong model updates in order to disrupt the learning process and lead to a wrong model being learned. In this paper we build a federated learning framework that offers privacy to the participating peers as well as security against Byzantine and poisoning attacks. Our framework consists of several protocols that provide strong privacy to the participating peers via unlinkable anonymity and that are rationally sustainable based on the co-utility property. In other words, no rational party is interested in deviating from the proposed protocols. We leverage the notion of co-utility to build a decentralized co-utile reputation management system that provides incentives for parties to adhere to the protocols. Unlike privacy protection via differential privacy, our approach preserves the values of model updates and hence the accuracy of plain federated learning; unlike privacy protection via update aggregation, our approach preserves the ability to detect bad model updates while substantially reducing the computational overhead compared to methods based on homomorphic encryption.

Index Terms—Federated learning, Model poisoning, Privacy, Security, Co-utility, Peer-to-peer

1 Introduction

Federated learning [5], [12] is a decentralized machine learning technique that allows training a model with the collaboration of multiple peer devices holding private local data sets that include class labels. This approach favors privacy because the peers do not need to upload their private data to a centralized server. It is also naturally scalable, because the computational load is split among the peers, which may be edge devices such as idle smartphones, and thus widely available.

In federated learning, a special peer, which we will call the model manager, sends an initial model to all peers. Each peer then computes a model update by correcting the model so that, when input the records in the peer's private data set, the model's output fits the corresponding class attribute labels. Then the peer returns the update to the model manager. The model manager aggregates the updates and distributes a new model to the peers. A new learning iteration can now start. Iterations carry on until the models learned in successive iterations converge.

Unfortunately, as we discuss in Section 2, the decentralized nature of federated learning makes it vulnerable to attacks against privacy and security. Substantial literature has been devoted to the privacy risks for peers [10]: to what extent the model update returned by a peer can leak her private data. Privacy-protection techniques include secure aggregation of updates, which hides individual updates to the model manager, and distortion of updates via differential privacy, which may significantly hamper the model's accuracy.

Even more obvious are security attacks, whereby one or several malicious peers return wrong model updates in order to prevent the convergence of the model (Byzantine attack) or cause a wrong model to be learned (poisoning attack). Protection from Byzantine and poisoning attacks requires the model manager to analyze individual peers' updates, thereby making privacy-enhancing techniques based on secure aggregation of updates inadequate.

Contribution and plan of this paper

In this paper we build a federated learning framework that offers both privacy to the participating peers and security against Byzantine and poisoning attacks. Our framework consists of several protocols designed in such a way that no rational party is interested in acting maliciously. This makes our protocols robust against security attacks. Our protocols also provide strong privacy to the participating peers via unlinkable anonymity and without requiring the aggregation of model updates. In this way, peer updates reach the model manager individually, while being, at the same time, perfectly accurate. This provides an optimum balance between security, privacy and learning accuracy.

To be rationally sustainable, our protocols are based on the co-utility property [7]. We also use reputation as a utility to reward well-behaved peers and punish potential attackers. In order to properly integrate reputations in the federated learning scenario, our reputation management is decentralized and itself co-utile.

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We report empirical results that show the effectiveness of our protocols at mitigating security attacks and at motivating rational peers to refrain from deviating.

Section 2 discusses privacy and security attacks against federated learning. Section 3 introduces a co-utile protocol suite for privacy-preserving and secure federated learning. Section 4 shows that the proposed protocol suite achieves co-utility (and hence is rationally sustainable), privacy and security. Experimental results are presented in Section 5. Finally, conclusions and future research lines are gathered in 6.

2 Attacks on federated learning privacy and security

In this section, we will discuss the main attacks on privacy and security that are applicable to federated learning. For a recent and exhaustive survey, see [10].

2.1 Privacy attacks

Privacy attacks to federated learning exploit the update sent by a peer to infer information on that peer's private data.

In federated learning the private data sets held by the various peers are unlikely to be identically distributed. What is more, federated learning is explicitly designed to improve the learned model by capturing the differences among the peers' private data sets. Data inference attacks can be mounted that aim at inferring how each class is represented in a certain peer's private data set.

In [9], a powerful data inference attack against federated deep learning is presented that relies on GANs (Generative Adversarial Networks). This attack assumes an attacker that can see and use internal parameters of the learned model. The attacker participates as an honest peer in the collaborative learning protocol, but she tries to extract information about a class of data she does not own. To that end, the attacker builds a GAN locally and crafts gradient updates before returning them in order to influence other participating peers to leak more information on their data. If the attacker is the model manager rather than a peer, she can do more: the model manager can isolate the shared model trained by the victim peer. The victim peer's update trained on the victim's data is used to train the model manager's GAN, that can eventually re-create the victim's data. As explained in [9], not even differential privacy used as proposed in [17] can protect against the proposed GAN attack.

A common requirement of all data inference attacks in federated learning is that the attacker must be able to link the successive updates submitted by a certain peer. *Our aim is to make sure that such a linkage is not possible by making peers' updates unlinkably anonymous in the model manager's view.*

2.2 Security attacks

Security attacks on federated learning aim at disrupting model convergence and thereby the learning process. They can be subdivided into Byzantine and poisoning attacks.

Byzantine attacks consist of malicious peers who submit defective updates in order to prevent convergence of the global model [3].

Subtler than Byzantine attacks are *model poisoning attacks*. Rather than preventing convergence, the latter aim at causing federated learning to converge towards a false global model, normally one that misclassifies a specific set of inputs.

In [2] it is shown that a single, non-colluding malicious peer is enough to mount a poisoning attack. Yet, security attacks can also be mounted by collusions of peers or by a single peer masquerading as several peers (Sybil attack).

Countermeasures against Byzantine or poisoning attacks require seeing the exact values of the individual updates, in order to assess their goodness. This is why some techniques that are good to protect the privacy of peers, such as secure aggregation of peer updates via homomorphic encryption [5], may impair the model manager's ability to thwart security attacks. *Our aim is to protect privacy in such a way that malicious updates can still be attributed.*

3 A co-utile framework for privacy-preserving and secure federated learning

The foundations of our proposed protocol suite are: i) the notion of co-utility applied to protocol design and ii) the use of reputations (computed themselves in a decentralized and co-utile manner) to motivate all rational players to behave honestly. We start by giving some background on co-utility and decentralized reputation. Also, for convenience Table 1 summarizes the notation used in the rest of this paper.

A self-enforcing protocol is *co-utile* [7] if it results in mutually beneficial collaboration between the participating agents. More specifically, a protocol Π is co-utile if and only if *the three* following conditions hold:

1) Π is self-enforcing;
2) The utility derived by each agent participating in Π is strictly greater than the utility the agent would derive from not participating;
3) There is no alternative protocol Π' giving greater utilities to all agents and strictly greater utility to at least one agent.

The first condition ensures that if participants engage in the protocol, they will not deviate. The second condition is needed to guarantee that engaging in the protocol is attractive for everyone. The third condition can be rephrased in game-theoretic terms by saying that the protocol is a Pareto-optimal solution of the underlying game.

TABLE 1
Notation in this paper

Notation	Concept
M	Model manager
AM	Accountability manager
P	Peer
m	Number of AMs per peer
δ	Reputation reward/punishment
U	Federated learning update
N_U	Random nonce encrypted with update U
g_i	Peer P_i's reputation
$PK_M(\cdot)$	Public key encryption under M's public key
$S_P(\cdot)$	Digital signature under P's private key
$H(\cdot)$	Cryptographic one-way hash function
α	Flexibility parameter (Note 1)
p	Forwarding probability
p_0	Probability of discarding an update from a peer with zero reputation
b	Size of a batch of non-discarded updates
C	Centroid of a batch of updates
T	Reputation threshold s.t. if a peer's reputation is at least T, her updates are never discarded

We describe a framework based on co-utility that ensures that peers can keep their private data sets confidential and, at the same time, makes them rationally interested in returning honest updates to the model manager.

3.1 Players and security model

The players in our framework and their security properties are as follows:

- *Model manager*. The model manager M is a player who wants to train a machine learning model on the private data of the peers in a peer-to-peer (P2P) network. Her interest is to obtain a good quality model, but she might be curious to learn as much as possible on the peers' private data sets. Hence, M can be viewed as *rational-but-curious*: rational to adhere to her prescribed function, but curious on the peers' private data.
- *Peers*. They are participants in the network who compute model updates based on their local private data sets. Peers want to preserve their private data confidential. We assume that *a majority of peers are rational-but-curious*: like M, they are interested in obtaining a good quality model, but they also want to influence the model based on their own respective data; further, they might be curious to learn as much as possible on the other peers' private data sets. On the other hand, there may be a minority of *malicious peers* that wish to impair the learning process, because they do not have the same utility function and/or do not respond to the same incentives as the rest of peers.
- *Accountability managers*. Accountability managers (AMs) are randomly chosen peers that manage the reputations of other peers. Being peers themselves, most accountability managers are rational-but-curious, but a minority may be malicious.

3.2 Requirements

The assumption that peers are rational rather than honest calls for incentives to make honest behavior attractive to them. We will use reputation as an incentive to reward or punish peers. In order for this to be effective, the following requirements need to be fulfilled:

- *Reward.* If a peer contributes a good update, her reputation must increase.
- *Punishment.* If a peer contributes a bad update, her reputation must decrease.
- *Unlinkable anonymity.* Peers contributing good updates must stay not only anonymous, but their successive updates must be unlinkable.
- *Reputation utility.* Having high reputation must be attractive for peers. Specifically, it must be easier for peers with higher reputation to contribute their updates while preserving their privacy. Thus reputation translates to influence without privacy loss.

Unlinkability is our approach to thwarting the privacy attacks sketched in Section 2.1 while perfectly retaining the accuracy of the updates. On the other hand, reward, punishment and reputation utility are our tools to protect against the security attacks described in Section 2.2. This will become clear in this section and in Section 4 below.

3.3 Co-utile decentralized reputation

Whereas we assume that a majority of peers want to learn a good model, we still need to incentivize rational peers to abstain from free-riding: if they find greater utility in deviating from the federated learning protocol, they might seriously impair the overall quality of the learned model. Also, we need a way to stigmatize/recognize malicious peers in order to mitigate their attacks. To meet the above purposes, we will use reputation management. In this section we present a reputation management system that does not require direct interaction between peers and has the following interesting properties: pseudonymity of peers, decentralization, resistance to tampering with reputations, proper management of new peers (to discourage whitewashing bad reputations as new identities and creating fake peers in Sybil attacks) and low overhead.

Our reputation protocol maintains a public reputation for each peer P that is the result of updating P's previous reputation according to the behavior of P reported by the model manager M. Next we explain how the above interesting properties are satisfied:

- *Pseudonymity of peers*. Only the pseudonym of peers is known, rather than their real identity. Furthermore, updates that are sent over the network cannot be linked to the peers that generated them.
- *Decentralization*. The reputation of every peer P is redundantly managed by a number m of peers that

act as accountability managers for P. Typically, m is an odd number at least 3 and the (pseudonymous) identities of P's accountability managers are (pseudo)randomly determined by hashing the peer's pseudonym P. In this way, P cannot choose her m accountability managers, which makes the latter more likely to perform their duty honestly.

- *Tamper resistance*. Since M does not know the identity of peers nor is able to link the updates to peers, M cannot leverage her position to promote or slander any particular peer M likes or dislikes. As a consequence, M's rational behavior is to exclusively base her reports on the quality of the received model updates. Regarding tampering by accountability managers, it is thwarted by their redundancy (see the previous item on decentralization).
- *Proper management of new peers*. Reputations take values in the range $[0, 1]$. New peers start with reputation 0, which makes whitewashing and also Sybil attacks unattractive.

Let us describe the dynamics of reputation. Call *epoch* the period between two successive changes of the global model by M. During an epoch, peers generate and send model updates based on their private data, with the aim of influencing the next global model change. Depending on their actions, peers can earn or lose reputation. Generating a good update increases the generator's reputation by a certain quantum $\delta/2$ fixed by the model manager; furthermore, helping a good update reach the model manager in a way unlinkable to the generator brings a $\delta/2$ reputation increase to one of the helping peers. Thus, every good update results in a total δ reputation increase. On the other hand, generating a bad update decreases the generator's reputation by δ. Thus, the overall reward for a good update equals the punishment for a bad update.

Some peer reputations may become negative and some may become greater than 1 as an epoch progresses. At the epoch's end, reputations are re-normalized into the range $[0, 1]$ as follows. First, accountability managers reset any negative reputation to 0. Then, if there are reputations above 1, all reputations are divided by the largest reputation. To that end, when a peer's reputation becomes larger than 1, the peer's accountability managers broadcast that reputation, which allows all accountability managers to compute the maximum reputation reached in that epoch and thereby normalize all reputations into the interval $[0, 1]$.

Normalization has the beneficial effect of deterring free-riding: even if a peer has attained high reputation, she will lose it gradually if she stops participating. Indeed, any peer's reputation will decrease due to normalization unless she continues to generate good updates or helps routing them. This addresses the second condition of the co-utility definition: the utility derived from participating must be greater than the utility derived from not participating. Fulfillment of the other two conditions for co-utility will be justified in Section 4.1 below.

3.4 Downstream: from update generator to model manager

We call downstream operation the submission of model updates from the peers to the model manager M. In order to preserve privacy and encourage security, we propose Protocol 1. In Section 4, we will show that it is co-utile.

The idea of Protocol 1 is that a peer, say P_1, does not directly send her update to M. Rather, P_1 asks another peer, say P_2, to do so. P_2 randomly decides whether to submit P_1's update to M or forward it to another peer, say P_3, who stands the same choice as P_2. Forwarding continues until a peer is found that submits the update to M.

Protocol 1 (Update submission):

1) Let P_1 be a peer that generates an update U. Then P_1 encrypts U along with a random nonce N_U under the model manager's public key, to obtain $PK_M(U, N_U)$ (we assume the message U, N_U to have a certain format that allows distinguishing it from gibberish at decryption). In this way, only M will be able to recover the update U. The generator P_1 *never* submits her own update to the manager M; rather, P_1 forwards $S_{P_1}(PK_M(U, N_U), H(H(H(U, N_U))), P_2)$, where H is a one-way hash function and S_{P_1} is P_1's signature, to another peer $P_2 = \text{SELECT}(g_1)$, where function SELECT() is explained below.
2) If P_1's reputation g_1 is such that $g_1 < \min(g_2, T) - \alpha$, where g_2 is P_2's reputation, T is a parameter such that updates submitted by peers with reputation T or above are never discarded, and α is a flexibility parameter discussed in Note 1, then P_2 discards the received update. Otherwise, P_2 makes a random choice: with probability $1 - p$, she submits
$$S_{P_2}(PK_M(U, N_U), H(H(H(U, N_U))), M)$$
to M and with probability p she forwards
$$S_{P_2}(PK_M(U, N_U), H(H(H(U, N_U))), P_3)$$
to another peer $P_3 = \text{SELECT}(g_2)$.
3) If P_2's reputation is below $\min(g_3, T) - \alpha$ then P_3 discards the received update. Otherwise, P_3 makes a random decision as to submit or forward. If it is forward, P_3 will use the SELECT() function and there may be more peers involved: P_4, P_5, etc.
4) Eventually M receives an update
$$S_{P_i}(PK_M(U, N_U), H(H(H(U, N_U))), M)$$
from a peer P_i. Upon this, M does:
   a) Directly discard the update with probability $p_0(1 - \min(g_i/T, 1))$, where p_0 is a parameter indicating the probability of discarding an update submitted by a peer with 0 reputation, and g_i is P_i's reputation.
   b) If the update has not been discarded, decrypt $PK_M(U, N_U)$, obtain U, check that the nonce N_U

was not received before (to make sure U is not a replay of a previously received update) and check the hash $H(H(H(U, N_U)))$.
c) Wait until a batch of b non-discarded updates has been received in order to be able to decide whether U is good or bad (see Section 4.3 below on how to detect bad updates).
d) Change the model with the good updates in the batch and publish the updated model.
e) Publish the value $\delta = 1/b$.
f) For every good non-discarded update U, publish $H(H(H(U, N_U)))$.
g) For every bad non-discarded update U, call PUNISH(P_i) where P_i is the peer having submitted U and PUNISH() is Protocol 2 in Section 3.5.

Function SELECT(g_i) is used by a peer P_i to select a forwardee. There are several ways in which this can be accomplished. However, the rational choice is for P_i to select a forwardee P_j with a sufficient reputation so that M does not reject the update should P_j submit it directly to M. Hence, if P_i's reputation is $g_i \geq T - \alpha$, P_i can randomly pick any of the peers whose reputation is T or above, because none of those peers risks update discarding. However, if $g_i < T - \alpha$, P_i chooses the peer with the maximum reputation that does not exceed $g_i + \alpha$, because no peer with reputation above that value will accept to forward P_i's update.

Note 1 (On the flexibility parameter α): In Protocol 1 a peer accepts to forward updates from peers that have at least her own reputation minus a flexibility amount α. Using a small value $\alpha > 0$ introduces some flexibility and helps new peers (that start with 0 reputation) to earn reputation as generators or first forwardees of good updates. Large values of α are not acceptable from the rational point of view: high-reputation peers have little to gain by accepting updates from peers who are much below them in reputation, because the latter are likelier to convey bad updates or to fail to reward the first forwardee in case of good updates.

Note 2 (On loops, multiple paths and other misbehaviors): Nothing is gained by any peer if loops arise accidentally or intentionally in Protocol 1. As it will be seen in below (Protocol 3 and Note 4) only the first peer chosen by the update generator is rewarded. Hence, forwarding twice or more times the same message brings no additional benefit. On the other hand, a generator P might send the same good update through several paths to increase the reputation of several first peers. However, by promoting more peers than necessary, P may experience a decrease of her own reputation, because reputations are normalized when any peer reaches a reputation above 1 (see Section 3.3). Finally, update generators could systematically choose themselves as first forwardees of good updates to collect additional reward; but if they do so, they weaken their privacy.

Note 3 (Key generation): In Protocol 1, peers sign the messages they send. To that end, each peer needs a public-private key pair. At least the two following alternative key generation procedures are conceivable: i) identity-based signatures, in which the peer's pseudonym is her public key and the peer's private key is generated by a trusted third-party [16]; ii) blockchain-style key generation [13], in which the peer generates her own key pair without the intervention of any trusted third-party or certification authority, and then obtains her pseudonym P_i (her *address* in the blockchain network) as a function of her public key.

3.5 Upstream: from model manager to update generator

By upstream operation we denote the punishment of bad updates and the reward of good updates. Let us start with Protocol 2 that seeks to penalize the generator of a bad update by retracing the reverse path from M to the generator. The peer P_i who submits an update found to be bad by the manager can escape punishment if P_i can show to her accountability managers that she received the bad update from a previous peer, say P_{i-1}.

Protocol 2 (PUNISH(P_i)):
Every accountability manager AM of P_i's does:
1) Ask P_i whether P_i can prove she did not generate U.
2) If P_i can show to AM a message

$$S_{P_{i-1}}(PK_M(U, N_U), H(H(H(U, N_U))), P_i)$$

then
a) Do not punish P_i (the peer's reputation is left intact);
b) Call PUNISH(P_{i-1}).

Otherwise, punish P_i by decreasing her reputation by δ.

The punishment protocol must be initiated by M, because the model manager is the only party that can detect bad updates and that is interested in punishing them. However, the punishment is actually executed by the guilty peer's accountability managers. Hence, M cannot track which peer is actually punished for that bad update, which prevents M from identifying the generator of an update by (falsely) claiming that the update is bad.

Unlike the punishment protocol, the rewarding protocol is initiated by the peer who submitted a good update, because that peer is the one interested in the reward. As we will later justify, the first peer (and only the first peer) who is asked by the generator to submit or forward a good update is also entitled to a reward. We will call that peer the "first forwardee".

Protocol 3 (REWARD(U)):
1) When M publishes $H(H(H(U, N_U)))$ for a good update, then the update generator, say P_1, sends to the first forwardee, say P_2, $S_{P_1}(H(H(U, N_U)), P_2)$.
2) P_2 checks that the hash of $H(H(U, N_U))$ matches $H(H(H(U, N_U)))$ published by M. If it is so, P_2

returns a receipt $S_{P_2}(H(H(U, N_U)), P_1)$ to the generator P_1.

3) P_1 proves to her accountability managers that she is the generator by showing $H(U, N_U)$ to them and proves that she has acknowledged her first forwardee by showing the receipt $S_{P_2}(H(H(U, N_U)), P_1)$.
4) Every accountability manager AM of P_1's checks P_2's receipt and checks that the *double* hash of $H(U, N_U)$ received from P_1 matches $H(H(H(U, N_U)))$ published by M. If *both* checks are fine, AM increases P_1's reputation by $\delta/2$.
5) P_2 sends $S_{P_1}(H(H(U, N_U)), P_2)$ to her accountability managers to claim her reward.
6) Every accountability manager AM of P_2's checks that the hash of $H(H(U, N_U))$ matches $H(H(H(U, N_U)))$ published by M. If it is so, AM increases P_2's reputation by $\delta/2$.

Note 4 (On rewarding the first forwardee only): In Protocol 3 only the first forwardee is rewarded, rather than all forwardees. The reason is that we want the total budget to reward a good update to be fixed and equal to the budget δ used to punish a bad update. We also want the reward share for the generator of a good update to be fixed, say $\delta/2$, and independent of the number of hops the update travels before reaching M. Hence, if we chose to reward all forwardees, the fixed reward share $\delta/2$ for forwardees ought to be distributed among them. Therefore, every forwardee would be better off by submitting the update to M rather than forwarding it to another forwardee who would take part of the reward. As a consequence, there would be only one forwardee, who would know that the previous peer is the generator of U. This would break privacy. Rewarding only the first forwardee avoids this problem and is a sufficient incentive, because any forwardee can hope to be the first (due to the protocol design, a forwardee does not know whether she receives an update from the generator or from another forwardee) and thus has a reason to collaborate.

Note 5 (On peer dropout): Accidental (due to power or network failure) or intentional peer dropout does not affect the learning process: on the one hand, once an update has been generated/forwarded, the generator/forwarder can disappear; on the other hand, the next forwardee is chosen among the peers who are online. Reputation management is also resistant to dropout of accountability managers, because there are m of them for each peer; m just needs to be increased if dropout is very likely. Punishment is not affected: even though a peer drops out, he will be punished with a reputation decrease all the same. However, rewarding may be problematic in the very specific case that either the update generator P_1 or the first forwardee P_2 drop out before rewarding is complete: the one of the two that remains online may not receive her/his reward.

4 Discussion

In this section, we first demonstrate that the framework formed by Protocols 1, 2 and 3 is co-utile, that is, that those protocols will be adhered to by the players defined in Section 3.1. Then we will show that the protocols satisfy the requirements of Section 3.2, and thereby preserve the confidentiality of the users' private data and protect the learned model from Byzantine and poisoning security attacks.

4.1 Co-utility

To argue co-utility for Protocols 1, 2 and 3, we must show that following them is a better option for M and the peers than deviating.

4.1.1 Co-utility for the model manager

The model manager's goal is to train a model based on the peers' private data sets. For that reason, M is interested in encouraging good updates and punishing bad updates. On the other hand, M's role is limited to Step 4 of Protocol 1. Let us examine in detail the actions of M in that step and whether M could gain by deviating from them or skipping them:

1) In Step 4a M directly discards an update with a probability that is inversely proportional to the reputation of the submitting peer. Discarding is only based on reputation, without examining whether the update is an outlier. M is interested to perform this step at least for two reasons: first, it reduces M's computational overhead, and second, it allows M to make reputation attractive for peers (only high-reputation peers, those with reputation at least T, are sure of getting their updates examined). At the same time, if M wants to keep the peer community alive, M should allow a nonzero probability $1 - p_0$ of examining an update submitted by a new peer (that has 0 reputation). Also, setting up a threshold T above which updates are examined for sure is a way for M of not losing too many good updates.
2) Step 4b consists of decrypting the update, checking its freshness and checking that the hash is correct. Obviously, M is interested in carrying out these steps. Without the updates, M cannot train the model.
3) Step 4c is about deciding whether an update is good or bad. M clearly needs to make this decision, in order to use good updates to improve the model and punish bad updates to discourage them.
4) Step 4d is about changing the model using the good updates. This is exactly M's main goal.
5) Step 4e publishes δ that determines the amount whereby reputations must be increased/decreased by the accountability managers. M is interested in publishing δ to facilitate a correct reputation management that keeps peers incentivized. In fact, if the number b of updates per batch is fixed, then δ is also

fixed and does not need to be published at each protocol execution.

6) Step 4f publishes information that peers can use to claim rewards for good updates. If M deviates and does not publish this information, then peers cannot claim rewards. This would discourage peers from submitting good updates and would be against M's interests.
7) Step 4g launches the punishment procedure for each bad update. If M did not perform this step, bad updates would go unpunished, which would fail to discourage them.

4.1.2 Co-utility for the update generator

In Protocol 1, the update generator only works in Step 1. Let us analyze the actions in this step:

1) *Update generation and encryption*. The generator, say P_1, generates an update and encrypts it together with a random nonce so that only M can decrypt the update and check its freshness:
   a) The intrinsic motivation for P_1 to generate an update is to have an influence on the model being learned: a rational peer wants to help obtain an accurate model that is socially beneficial in some sense, whereas a malicious peer wants to poison the learned model.
   b) The motivation for P_1 to generate a *good* update U is to keep her reputation high. A high reputation brings more influence on the model learning. Specifically, a high g_1 allows P_1 to find P_2 such that $g_1 \geq g_2 - \alpha$, which means that P_2 does not discard P_1's update, and with g_2 high enough for P_1 to be confident that P_2 can be entrusted with relaying U towards M with little or no probability of U being discarded by M without examination (see description of the SELECT() function in Section 3.4). If U eventually reaches M, this brings P_1 influence and further reputation increase, which means more influence in the future.
   c) The motivation for P_1 to encrypt U under M's public key is to prevent anyone else from claiming the reward for that update, should U be good. The motivation for P_1 to sign the forwarded message is that the forwardee P_2 will not accept an unsigned message, because P_2 will need that signed message to escape punishment in case U is bad.
2) *Update forwarding*. In terms of privacy, it is bad for P_1 to submit her generated update directly to M, as it could leak information on her private data set. It is still bad if P_1 directly submits with probability $1-p$ and forwards with probability p, like in the Crowds system [15]. If we used the Crowds algorithm, from the point of view of M the most likely submitter of an update would be the update generator: U would be submitted by P_1 with probability $1-p$, whereas it would be submitted by the i-th forwardee with probability $(1-p)p^i < 1-p$. Hence, P_1 is interested in looking for a forwardee P_2 who takes care of her update, rather than submitting her update herself. Specifically, P_1 wants a forwardee P_2 such that: a) P_2 will accept to forward P_1's update; b) P_2 does not risk update discarding ($g_2 \geq T$) or risks it with the smallest possible probability (see the description of the SELECT() function in Section 3.4). Further, if P_1 can choose among several possible P_2 with $g_2 \geq T$, P_1's best option is to pick P_2 randomly for the sake of unlinkability of successive updates to each other. Here we see a second benefit of a high reputation for P_1: the higher g_1, the more peers with reputation at least T P_1 can choose from and the higher is unlinkability.

In Protocol 2, the update generator P_1 has a role only if her update is bad. The generator's role in this case is a passive and inescapable one: when P_1 is asked by her accountability managers to show that P_1 received the bad update from someone else, P_1 cannot show it and is punished.

In Protocol 3, the generator P_1 of a good update is clearly interested in running Step 1 of the protocol to claim a reward. In Step 1, P_1 is forced to give the first forwardee P_2 the necessary information $H(H(U, N_U))$ so that P_2 can claim his reward. The reason is that, without P_2's receipt, P_1 cannot claim her own reward at Step 3 (this latter step is also self-enforcing if P_1 wants her reward).

P_1 could certainly decide to favor a false first forwardee P_2' of her choice, rather than the real first forwardee P_2. This would still work well for P_1, because P_2' would return a signed receipt for the same reasons that P_2 would do it. However, if P_1 wants to favor P_2', it entails less risk (of being discovered) for P_1 to use P_2' as a *real* first forwardee. Thus, there is no rational incentive to favor false first forwardees.

4.1.3 Co-utility for the update forwardees

In Protocol 1, the forwardees $P_2, P_3, \ldots$ work in Steps 2 and 3, which are analogous to each other. Let us examine the actions expected from a forwardee:

1) *Update acceptance or discarding*. The incentive for a forwardee P_i to accept to deal with an update U is to be rewarded in case U is good and P_i is the first forwardee (note that P_i does not know whether she is the first, but hopes to be). Thus, if P_i receives the update from a previous peer P_{i-1} with high reputation, P_i's rational decision is to accept that update: there are chances that U is good, which will bring reward if P_i turns out to be the first forwardee. In contrast, if U comes from a peer P_{i-1} with low reputation, it is less likely that the update is good, so P_i's rational decision is to discard U to avoid working and spending bandwidth for nothing.
2) *Update submission or forwarding*. It takes about the same effort for a forwardee P_i to submit an update to M or to forward it to some other peer P_{i+1}.

Hence, it is rational for P_i to make the decision randomly according to the prescribed probabilities ($1-p$ for submission and p for forwarding). In case of forwarding, P_i's rational procedure is like the generator's: look for a forwardee with reputation at least T if $g_i \geq T - \alpha$ or the maximum possible reputation that does not exceed $g_i + \alpha$ otherwise (as per the SELECT() function. Also, no matter whether forwarding or submitting, P_i has to replace the previous signature of the update by her own signature: neither the model manager nor any forwardee will accept from P_i a message that is not signed by P_i, because they will need the signed message in case U turns out to be bad and punishment is launched.

In Protocol 2, if P_i did not generate a bad update U, P_i will rationally do her best to avoid punishment (reputation decrease) by showing a message signed by whoever sent U to her.

In Protocol 3, P_2's best option is to return the receipt at Step 2, because P_1 could otherwise blacklist P_2 and never make P_2 a first forwardee in future epochs. Finally, P_2 is obviously interested in claiming her reward in Step 5.

4.1.4 Co-utility for the accountability managers

The accountability managers are a keystone in Protocols 1, 2 and 3. In our security model (Section 3.1) a majority of them is assumed to be rational and to be interested in obtaining a well-trained model. Hence, a majority of the m accountability managers pseudorandomly assigned to each peer can be expected to behave honestly, which in turn means that the reputation of every peer can be expected to be honestly managed.

In Protocol 1, there is no direct intervention of accountability managers. It suffices that they honestly maintain and supply the reputations g_i of all involved peers P_i as described in Section 3.3.

As to Protocol 2, it is launched at the request of M in the last step of Protocol 1. In Protocol 2, the accountability managers have the lead role. Most of each peer's accountability managers can be assumed rational and therefore they can be assumed to discharge their role as described in the protocol.

Finally, in Protocol 3, the accountability managers of the generator reward the latter in Step 4. Then in Step 6 the first forwardee is rewarded by her accountability managers. Again, since for each peer a majority of accountability managers can be assumed rational, we can expect them to honestly perform those two steps as described in Protocol 3.

Note 6 (Non-collusion scenario): In fact, given that the accountability managers assigned to a peer are randomly chosen, it is reasonable to assume that in general they do not know each other and hence they do not collude. In the non-collusion scenario, not even a majority of honest accountability managers is needed. If malicious accountability managers do not collude, each of them is likely to report different reputation results. Hence, as long as *two* of the peer's accountability managers act rationally and follow the protocol, their correct result is likely to be the most frequent one and thus to prevail.

4.2 Privacy

As mentioned in Section 2.1, ensuring the unlinkability of updates goes a long way towards guaranteeing that the private data sets of peers stay confidential. We can state the following proposition.

Proposition 1: If the forwarding probability is $p > 0$ andthere is no collusion between the model manager M and peers, the private data set of each peer remains confidential versus the model manager and the other peers. Confidentiality is based on update encryption and unlinkability, and unlinkability increases with p and the generator's reputation.

Proof: The privacy guarantee is based on unlinkability and update encryption.

Let us first consider linkability by M. By the design of Protocol 1, M knows that the submitter of an update U is never the update generator. At best, M knows that the probability that U was submitted by the i-th forwardee is $(1-p)p^{i-1}$, and hence that the most likely submitter is the first forwardee. However:

- The larger p, the greater the uncertainty about the number of hops before the update is submitted, and hence the harder for M to link a received update to its generator.
- The next forwardee is selected using the SELECT() function, described in Section 3.4. If $g_{gen} \geq T - \alpha$, then P_{gen} chooses the first forwardee randomly among the set of peers with reputation at least T, and this set depends on the current reputations and varies over time; hence, as long as there are several peers with reputation T or above, the fact that two updates were submitted by the same peer does not tell M that both updates were generated by the same peer. If $g_{gen} < T - \alpha$, then P_{gen} chooses as a first forwardee the peer with the maximum reputation that does not exceed $g_i + \alpha$: if reputations do not change between two successive updates, P_{gen} would choose the same first forwardee for both updates; yet, M cannot be sure that the submitter of both updates is really the first forwardee, and hence M cannot be sure that both updates were generated by the same P_{gen}. Hence, in no case can two different updates by the same generator be unequivocally linked, even if the probability of correctly linking them is lower when $g_{gen} \geq T - \alpha$.

On the other hand, *neither the reward nor the punish protocols allow M to learn who generated a good or a bad update*. Thus, M can neither link the updates he receives nor unequivocally learn who generated a certain update U. Therefore, M cannot obtain any information on the private data set of any specific peer P.

Consider now linkability by a peer P_i:

- If P_i is a forwardee for two different updates from P_{i-1} and $p > 0$, P_i does not know whether P_{i-1}

generated any of the updates or is merely forwarding them. P_i's uncertainty about P_{i-1} being the generator is Shannon's entropy $H(p)$, which grows with p for $p \leq 0.5$; for $p > 0.5$, what grows with p is P_i's certainty that P_{i-1} is *not* the generator. In summary, P_i can only guess right that P_{i-1} is the generator if p is very small: in this case, forwarding hops after the first mandatory hop from generator to first forwardee are very unlikely.
- The only exception is when P_i is the first forwardee for two good updates from the same generator (because in this case he receives a message from the generator in Step 1 of Protocol 3). However, in this case P_i can only link the *encrypted* version of updates (that is, $PK_M(U, N_U)$ and $PK_M(U', N_{U'})$), but has no access to the clear updates U, U'. Hence, P_i gets no information on P_{i-1}'s private data set.
- If P_i is an accountability manager of a generator P_j, P_i can link all *encrypted* good updates originated by P_j. However, since those updates are not in the clear, P_i gets no information on P_j's private data set.

□

Note that assuming there are no collusions is plausible because peers are pseudonymous: normally people collude only with those they know.

A successful collusion must include one or more first forwardees (who know the pseudonyms of the update generators) and M (who can decrypt the updates). In this way, M can attribute updates and perhaps link those corresponding to the same generator; then M can infer whatever information on the generator's private data set is leaked by the generator's updates.

However, to allow update linkage, a collusion requires a malicious model manager and a significant proportion of malicious peers, whereas in our security model (Section 3.1) we assume M and a majority of peers to be rational-but-curious. A collusion of M with a substantial number of peers is hard to keep in secret, and if it becomes known that M is malicious, peers will be unwilling to help M to train the global model. Therefore, M's rational behavior is to abstain from collusion.

4.3 Security

Guaranteeing security means thwarting Byzantine and poisoning attacks (Section 2.2), which consist of submitting bad model updates. We first recall the approaches that have been proposed in the federated learning literature for the model manager to defend against bad updates. They fall into the following three broad classes (see the surveys [10], [4] for more details):

- *Detection via model metrics.* An update is labeled as bad if incorporating it to the model degrades the model accuracy. This approach requires a validation data set on which the model with the update and the model without the update can be compared. Also, the computation needed to make a decision on each received update is significant.
- *Detection via update statistics.* An update is labeled as bad if it is an outlier with respect to the other updates.
- *Neutralization via aggregation.* Updates are aggregated using operators that are insensitive to outliers, such as the median [18], the coordinate-wise median [18], or Krum aggregation [3]. In this way, updates too different from the rest have little or no influence on the learning process.

In our protocol, we want to explicitly detect bad updates in order to avoid interaction with the malicious peers generating them. Hence, we discard methods in the third class (neutralization).

Any detection method in the two other classes can be used with our approach, including new methods that may appear in the future. Yet, detection based on model metrics is quite costly and requires validation data. For this reason, in the experimental work we have instantiated our implementation with a method based on update statistics, more specifically a distance-based method in line with [2], [3]. Given a batch of updates, this method labels as bad an update U if U is much more distant than the rest of updates in the batch from the batch centroid C. One possible way to quantify what "much more distant" means is to check whether the distance between U and C is greater than the third quartile (or greater than a small multiple of the third quartile, say 1.5 times) of the set of distances between updates in the batch and C.

Protocols 1, 2 and 3 are designed to incentivize the submission of good updates. Thus, we can state the following proposition.

Proposition 2: Provided that the model manager can detect bad updates, the rational behavior for generators and forwardees in Protocol 1 is to submit good updates.

Proof: See discussion on co-utility for generators and forwardees in Section 4.1. □

As to collusions of irrationally malicious peers, they can only disrupt the learning process if they are sufficiently large so that the majority of updates received by M are bad ones *and* coordinated in the same direction. Note that uncoordinated bad updates are likely to cancel each other to some extent. Such large collusions seem hard to mount for the reasons explained in the previous section.

4.4 Computation and communications overhead

Let us compare the computation and communications overhead of the proposed method against alternatives based on homomorphic encryption (HE), which offer a comparable level of privacy (but cannot detect bad updates, as argued below).

HE has been used in federated aggregation mechanisms to prevent the model manager and the rest of peers in the network from having access to the individual updates of peers. In HE-based mechanisms, peers first encrypt their respective updates using an additive

HE scheme (*e.g.* Paillier, [14]). Several protocols have been proposed in the literature to aggregate HE updates and decrypt the aggregated HE update. Let us focus on a protocol that minimizes the number of required messages and the amount of computation (which is the most challenging benchmark when comparing with our proposed method): (i) assume a sequence of peers is defined such that the first peer sends her HE update to the next peer, who aggregates it with her own HE update and so on; (ii) after the last peer has aggregated her HE update, she sends the encrypted update aggregation to the manager, who can decrypt it to obtain the cleartext update aggregation. In this protocol, each peer sends only one message per update, just as in plain federated learning.

Whatever the protocol used, HE-based solutions offer privacy (no one other than the peer sees the peer's cleartext update), but they *do not allow* the model manager to detect bad updates, because the manager does not see the individual updates. In this respect, HE-based solutions are inferior to our proposed method, which offers privacy without preventing bad update detection.

Even so, let us compare HE-based systems and our system in terms of computational overhead. HE-based systems require the peers to encrypt, using a public-key HE scheme, each individual model parameter at each training epoch (an update contains values for all parameters). The authors of [19] report an encryption time of 3111.14 seconds for a model with $900,000$ parameters (6.87 MB) using 3072-bit Paillier (a key size of 3072 bits in factorization-based public-key cryptosystems offers equivalent security to 128-bit symmetric key schemes [1]). Expensive modular operations (with 3072-bit long moduli in the case of Paillier) for each model parameter are required to aggregate the update of each peer.

In contrast, our approach requires each peer to compute an encryption of her update using a regular non-homomorphic public-key cryptosystem, three hashes and one digital signature. With the usual digital envelope approach, regular public-key encryption amounts to encrypting a symmetric (*e.g.* AES) session key under the manager's public key, and then encrypting the bulk of the update parameters using the much faster symmetric cryptosystem under the session key. The encryption time of AES on current smartphones using AES-128-GCM is around 0.29 seconds for a model of the same size as reported above[1], to be compared with the aforementioned 3111.14 seconds of HE. Finally, the model manager just needs to decrypt the received updates and aggregate them in cleartext as in plain federated learning mechanisms (this is much faster than homomorphic aggregation in ciphertext).

Regarding the communication overhead, we first refer to the message expansion incurred by HE-based mechanisms and our proposal. As stated above, HE-based mechanisms require peers to encrypt each model parameter using an additive HE scheme. Model parameters are usually 32-bit floating point values that, when encrypted using Paillier with sufficiently strong keys, become 3072-bit integers. This implies an increase in the message size of two orders of magnitude. The proposal in [19] substantially reduces the communication requirements, but it is still one order of magnitude above plain federated learning with cleartext updates. In our proposal and thanks to the digital envelope technique, updates are encrypted using a symmetric encryption scheme, which does not expand the plaintext models (save for potential paddings, which are negligible for messages of the size we are considering). Additionally, our messages include the session key encrypted under the model manager's public key, a triple hash of the model, and a signature. This additional information increases the size of the message by approximately 6.5 KB with standard key and hash sizes, which, if we consider the example given before, amounts to a 0.09% increase in the total size of the messages.

Finally, in the HE-based protocol considered the number of messages exchanged among participants does not increase with respect to plain federated learning, *i.e.* for each training epoch there is one broadcast of the global model from the model manager to the peers and one message from each peer containing her update. In contrast, our proposal includes a forwarding mechanism, which implies that for a forwarding probability p every encrypted model hops across an expected number of forwardees equal to

$$(1-p)\sum_{i=1}^{\infty} ip^{i-1} = \frac{1}{1-p}.$$

For example, if $p = 1/2$ there are 2 additional hopping messages with respect to plain federated learning. Additionally, if each peer has m accountability managers:

- $2m+1$ messages containing one hash of the update and one digital signature of a hash value are required by the reward protocol;
- $2m$ messages, of which m are short polling messages and m contain the signed encrypted update, are required in the punishment protocol when a peer wishes to avoid punishment.

All in all, our approach requires more messages per epoch than plain and HE-based federated learning. However, whereas the message expansion in our approach is almost negligible (as the bulk of encryption is symmetric key), the HE-based approach increases message length by one or two orders of magnitude with respect to plain federated learning. In particular, if we take say $m = 3$ and $p = 1/2$, the overall communications overhead of our approach stays below that of HE-based federated learning.

In summary, our method achieves *much* less computation overhead and less communication overhead than

1. AES performance per CPU core https://calomel.org/aesni_ssl_performance.html

HE-based methods. Add to this performance advantage the functionality advantage: our method offers both privacy for peers and detection of bad updates for the manager, whereas the latter feature is lacking in HE-based methods.

5 Experimental results

In this section we report the results of the experiments we conducted to test how the reputations of peers evolve over time depending on whether they submit good or bad updates.

First, let us explain the expected system behavior. If our protocols are well designed, a peer's reputation should highly correlate with the probability that she generates *good* updates. Furthermore, the reputation of the peer who *submits* an update to the model manager M should also highly correlate with the probability that the peer who *generated* that update generates good updates. Since the submitting peer's reputation is used by M to decide on processing or discarding an update, M will only process a fraction of the received updates. This reduces M's overhead related to detection and punishment of *bad* updates.

Now, let us go to the actual empirical results. We bounded the range of reputations between 0 and 1. Then we built a peer-to-peer network with 100 peers whose initial reputations were set to 0. We let the network evolve for 500 iterations (or global training epochs). At each epoch, the model manager received one update from each peer. Thus, the batch size was $b = 100$ and the reward/punishment quantum was $\delta = 1/b = 0.01$. We then experimented with two test scenarios, depending on the proportion of honest peers:

- *Scenario 1.* Every peer is assigned a random *goodness probability* $\pi_g \in_R [0, 1]$. With probability π_g the peer generates a good update and with probability $1-\pi_g$ she generates a bad update. Reputation management is used by peers to decide on accepting or rejecting a forwarded update and to choose forwardees. That is, a peer P_j accepts a forwarded update only if the requesting peer's reputation is at least $g_j - \alpha$, where we set $\alpha = 0.03$. In turn, a peer P_i chooses a forwardee based on reputations as described when explaining the function SELECT() in Section 3.4. Additionally, reputation management is also used by the model manager M to decide on processing or directly discarding an update submitted by a peer P_k. That is, M directly discards the update with probability $p_0(1 - \min(g_k/T, 1))$, where we set $p_0 = 0.5$ and $T = 0.5$.
- *Scenario 2.* 90% of peers always generate good updates whereas the remaining 10% have probability 0.2 of generating good updates and probability 0.8 of generating bad updates. Hence we can say that 90% of peers have goodness probability $\pi_g = 1$ and 10% of peers have goodness probability $\pi_g = 0.2$. Like in the previous scenario, reputation management is set up by taking $\alpha = 0.03$, $p_0 = 0.5$ and $T = 0.5$.

5.1 Test scenario 1

In large real federated learning networks with, say several thousands or hundreds of thousands of peers (*e.g.* smartphones), a small proportion of malicious peers (even smaller than in Scenario 2) is the most realistic assumption. Nevertheless, let us study an extreme scenario with even proportions of good and bad updates. This will allow us to demonstrate that the goodness probability of a peer correlates with her reputation and with the reputations of the peers submitting her updates.

Let us assign a random goodness probability in the interval $[0, 1]$ to each of the 100 peers. Thus, on average we can expect peers to generate good updates only half of the time. Reputations are computed after each of the 500 global training epochs and are used to decide, on the one hand, on update acceptance and forwarding (peers accept updates from and forward updates to other peers depending on the flexibility parameter $\alpha = 0.03$), and on the other hand, on update processing and discarding by the model manager (it directly discards updates with probability $p_0(1 - \min(g_i/T, 1))$, with $p_0 = 0.5$ and $T = 0.5$).

Figure 1 displays the goodness probability versus the reputation of every peer after the 500 global training epochs. The goodness probability is represented in the abscissae and the reputation in the ordinates. It can be seen that both the goodness probabilities and their corresponding reputations spread over the entire $[0, 1]$ range. Furthermore, the peers' goodness probabilities and their reputations are highly correlated (0.977).

Figure 2 displays, for every update during the 500 global training epochs (50,000 updates), the goodness probability of the update generating peer versus the reputation of the submitting peer. It can be seen that both values are also highly correlated (0.833). In fact, this correlation is even higher for peers with reputation below $T = 0.5$; for submitting peers with reputations $T = 0.5$ or above, the precise reputation of the submitter is not that relevant, because the model manager will process all updates submitted by peers with reputation T or above.

5.2 Test scenario 2

The previous scenario is highly unlikely in the real world. As said above, in large real federated learning networks a small proportion of malicious peers is the most realistic assumption.

In Scenario 2, a clear majority of 90% of peers are completely honest (goodness probability $\pi_g = 1$), whereas the remaining 10% have a goodness probability of only $\pi_g = 0.2$. Reputations are computed after each epoch and

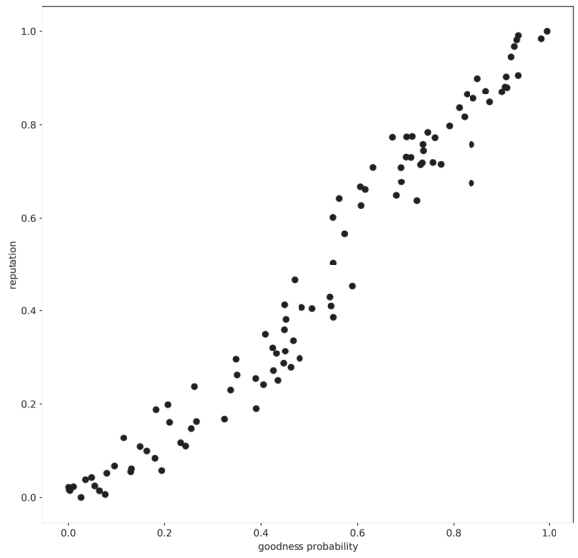

Fig. 1. Scenario 1. Goodness probability vs reputation for each peer. Correlation: 0.977.

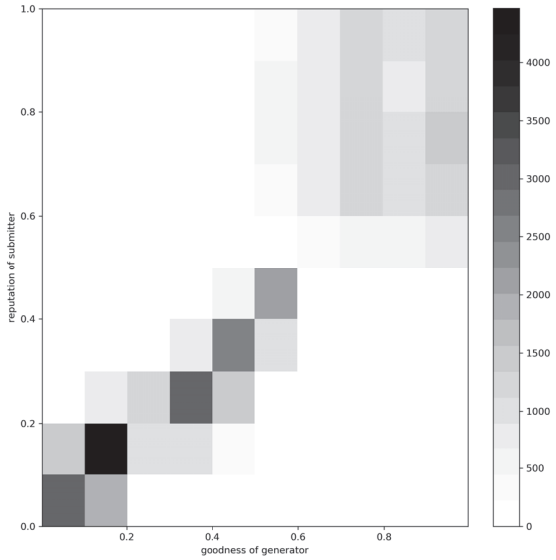

Fig. 2. Scenario 1. Generating peer's goodness probability vs submitting peer's reputation, for all updates. The grayscale indicates the number of peers in each 2-dimensional interval. Correlation: 0.838.

are used to decide, on the one hand, on update acceptance and forwarding, and on the other hand, on update processing and discarding by the model manager.

Figure 3 displays the goodness probability against the reputation of every peer after 500 global training epochs. Malicious peers (those with $\pi_g = 0.2$) are correctly assigned low reputations, because most of the updates they generate are bad and they are punished when their updates reach the model. Besides that, it is hard for such peers to be selected as forwardees of good updates and thereby improve their reputation. On the other side, all honest users (those with $\pi_g = 1.0$) achieve high reputation values that correspond to their good behavior. Peers with a reputation $T = 0.5$ or above are part of a "community" whose members improve the reputations of each other, by forwarding or submitting their respective updates.

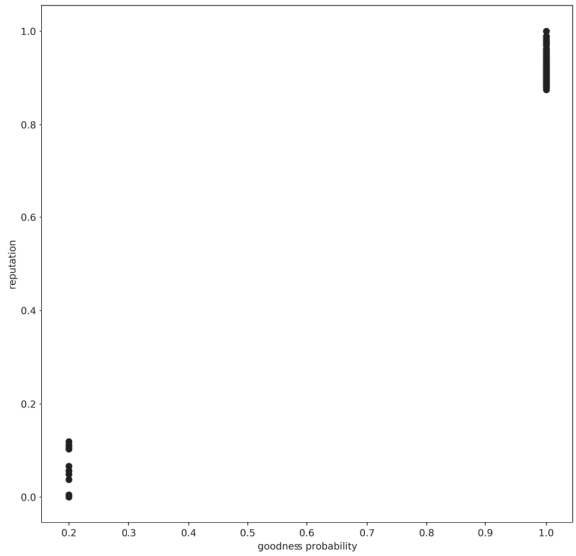

Fig. 3. Scenario 2. Goodness probability vs reputation for each peer. Correlation: 0.998.

The evolution of the reputations of good peers (with $\pi_g = 1.0$) and bad peers ($\pi_g = 0.2$) is shown in Figure 4. The average reputations of both types of peers swiftly diverge from the very beginning.

Figure 5 shows how reputations evolve when peers change their behavior (that is, their π_g). In the figure, peer 0 is a good peer (with $\pi_g = 1.0$) that suddenly changes his behavior by setting $\pi_g = 0.2$ at epoch 100; from that epoch onwards, peer 0 generates bad updates with probability 0.8. We can see that his reputation drops fast and stabilizes around the average reputation value of bad peers (see Figure 4) around epoch 260. This shows that our system reacts suitably when a peer's behavior worsens.

On the other hand, peer 98 in the figure represents a malicious peer (with $\pi_g = 0.2$) that changes her behavior by setting $\pi_g = 1.0$ at epoch 100; from that epoch onwards, peer 98 only generates good updates. In this case we see that her reputation gradually and slowly

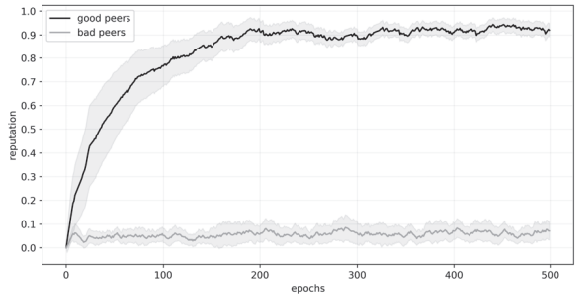

Fig. 4. Scenario 2. Evolution of the average (depicted as a line) and the standard deviation (depicted as a gray band) of the reputations of good peers and bad peers as a function of the epoch.

increases up to roughly the average reputation of good peers (see Figure 5) around epoch 360. This shows that not only malicious peers, but also newcomers (who have zero initial reputation), can effectively reach high reputations if they behave well. However, the amount of effort needed to rise from a low reputation clearly discourages malicious peers from performing whitewashing or Sybil attacks.

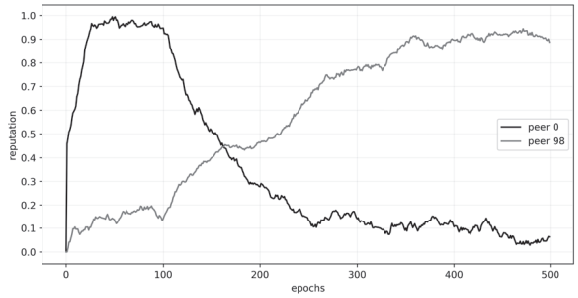

Fig. 5. Scenario 2. Evolution of the reputation of nodes who change their behavior π_g. At epoch 100, peer 0 changes from good to malicious, whereas peer 98 changes from malicious to good.

Figure 6 displays, for every update during the 500 global training epochs (50,000 updates), the goodness probability of the generator versus the reputation of the submitter. Both values are highly correlated (0.799). However, the correlation is higher after the system stabilizes (0.9854 from epoch 100 onwards) and all good peers reach high reputations. Initially, reputations have not yet adjusted and hence the updates generated by good peers can be submitted by peers with reputation only slightly above or even slightly below T.

Finally, observe in Figure 7 the effectiveness of making reputation-based decisions to filter out bad updates. Out of the 50,000 updates generated over the 500 epochs, around 46,000 are good, while around 4,000 are bad. Based on the submitting peer's reputation, the model

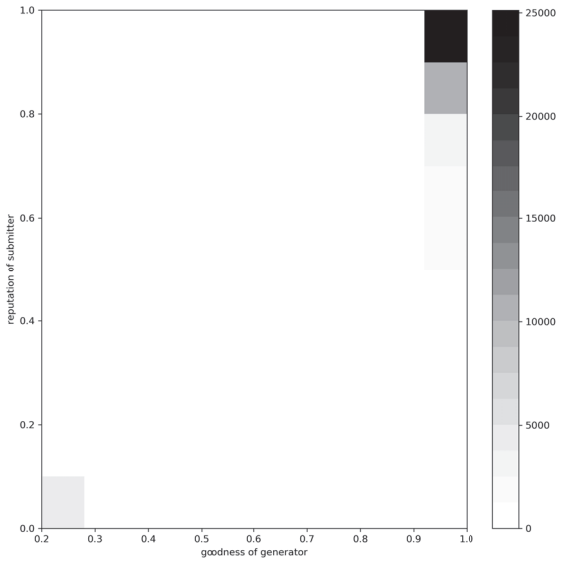

Fig. 6. Scenario 2. Generating peer's goodness probability vs submitting peer's reputation, for all updates. The grayscale indicates the number of peers in each 2-dimensional interval. Correlation: 0.799.

manager M discards 2,831 updates. The figure shows that, when the system stabilizes, on average 80% of the updates discarded by M are bad. This is the right proportion, because malicious peers do not always generate bad updates (they generate bad updates with probability $1 - \pi_g = 0.8$).

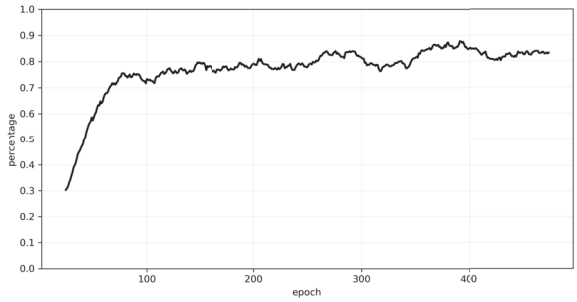

Fig. 7. Scenario 2. Ratio of bad updates discarded by the model manager as a function of the training epoch.

Note that reducing the proportion of bad updates processed by the model manager is also a good security defense. Indeed, the fewer the bad updates processed by the model manager, the more those bad updates are likely to stand out as outliers, which will enable M to detect and discard them. Additionally, fewer bad updates processed by M also mean less detection overhead for M and, especially, less punishment and tracing overhead for peers (both normal peers and accountability man-

agers).

6 Conclusions and future work

We have presented protocols to improve privacy and security in federated learning while perfectly preserving the model accuracy. Our protocols rely on the notion of co-utility, that is, they are self-enforcing if players are rational. We use a decentralized reputation management scheme that is itself co-utile to incentivize peers to adhere to the prescribed protocols.

In this way, peers do not need to be honest-but-curious *per se*: as long as they are rational they will behave honestly, and even a minority of malicious peers that do not respond to the same incentives as the other peers can be tolerated. Confidentiality of the peers' private data is guaranteed by the unlinkability of updates: when a peer generates an update, neither the model manager nor the other peers can identify the update generator. This way to provide privacy is superior to the state-of-the-art alternatives:

- Unlike privacy protection via differential privacy [9], our protection mechanism does not alter the value of updates and hence does not affect the accuracy of the learned model. Furthermore, our privacy notion based on unlinkability is also strong.
- Unlike privacy protection based on update aggregation, our solution is compatible with punishing the peers that generate bad updates. Also, our solution entails less computational overhead than aggregation based on homomorphic encryption.

Security, *i.e.* protection against bad updates, is pursued in our approach via reputation. Whereas state-of-the-art security countermeasures do nothing to reduce the number of bad updates that are processed by the model manager, we address this issue in a way to achieve two beneficial effects: first, to decrease the overhead for the model manager and the peers related to processing, tracing and punishing bad updates; and, second, to make the (fewer) bad updates processed by the model manager more identifiable as outliers. The design of our protocols also renders whitewashing and Sybil attacks ineffective.

An interesting avenue for future research is to harden the proposed protocols so that they can filter out a greater proportion of bad updates in situations where a substantial share of the peers are malicious. A possible strategy is for the model manager to preventatively reject (without further examination) any update submitted by a peer whose reputation is less than the average reputation of peers who submitted updates detected as bad in the past. Note that the peer submitting the update is not the peer having generated it, but as shown in the experimental section above, the submitter's and the generator's reputations are correlated.

Another interesting direction is to incorporate new methods to detect bad updates that are better suited for non-independent and identically distributed (non-IID) private data than distance-based methods. Most current detection methods mentioned in Section 4.3 are ill-suited when the private data of the different peers follow very different distributions. In fact, the extremely non-IID case is challenging for the very notion of federated learning even if all peers compute their updates honestly: converging to an accurate model is more difficult than in the IID case.

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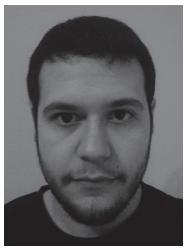

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