BaFFLe: Backdoor detection via Feedback-based Federated Learning

Sebastien Andreina∗, Giorgia Azzurra Marson†, Helen Möllering‡ and Ghassan Karame§
∗NEC Laboratories Europe, sebastien.andreina@neclab.eu
†NEC Laboratories Europe, giorgia.marson@neclab.eu
‡TU Darmstadt, moellering@encrypto.cs.tu-darmstadt.de
§NEC Laboratories Europe, ghassan@karame.org

Abstract—Recent studies have shown that federated learning (FL) is vulnerable to poisoning attacks which aim at injecting a backdoor into the global model. These attacks are effective, even when performed by a single client, and undetectable by most existing defensive techniques. In this paper, we propose a novel defense, dubbed BAFFLe—Backdoor detection via Feedback-based Federated Learning—to secure FL against backdoor attacks. The core idea behind BAFFLe is to leverage data of multiple clients not only for training but also for uncovering model poisoning. Namely, we exploit the availability of multiple, rich datasets at the various clients by incorporating a feedback loop into the FL process to integrate the views of those clients when deciding whether a given model update is genuine or not. We show that this powerful construct can achieve very high detection rates against state-of-the-art backdoor attacks, even when relying on straightforward methods to validate the model. Namely, we show by means of evaluation using the CIFAR-10 and FEMNIST datasets that, by combining the feedback loop with a method that suspects poisoning attempts by assessing the per-class classification performance of the updated model, BAFFLe reliably detects state-of-the-art semantic-backdoor attacks with a detection accuracy of 100% and a false-positive rate below 5%. Moreover, we show that our solution can detect an adaptive attack which is tuned to bypass the defense.

Index Terms—federated learning, security, backdoor attacks

1. Introduction

Federated learning (FL) is emerging as a powerful paradigm to collaboratively train a machine-learning model among thousands or even millions of participants [21]. FL involves users’ devices in the computation of the machine learning model; here, a central server orchestrates the training of a shared model among several clients. Each client trains a model locally, on their device, and then all local models are combined to derive a global model summarizing the contributions of all clients. This process is repeated several times, and the global model is progressively improved within every round of training.

Compared to centralized learning, where model training is operated fully by the server, federated learning features a significant cost reduction (on the server) in terms of computation due to outsourcing and parallelizing the training process. Involving the clients also enlarges the training set tremendously, which in turn can lead to smarter and more reliable models [5].

In addition to speeding up training and providing better prediction models, FL also promises strong privacy guarantees for the clients, in that the training data never leaves the device. For a truly private solution, a secure aggregation mechanism is put in place that allows clients to combine local updates in a privacy-preserving manner prior to sharing them with the server [6], as otherwise each local model could leak the training data of the corresponding client. While (some sort of) secure aggregation is necessary for protecting the clients’ privacy, it comes with a severe security limitation: hiding individual updates prevents clients from being accountable for their contributions to the global model. This opens the door to attacks leveraging malicious clients to submit manipulated updates and hence tampering with the training process.

A prominent example highlighting the vulnerability of FL against malicious participants is the model-poisoning attack by Bagdasaryan et al. [1], in which the adversary successfully injects a semantic backdoor into the global model. Here, poisoning is operated by a malicious client who submits a carefully crafted update so that the resulting global model assigns a target label to all samples with a certain (attacker-chosen) feature, while it behaves normally on other samples that do not exhibit this feature. It has been shown in [1], [2] that semantic backdoors can be successfully injected, reaching high accuracy on the backdoor task as well as a long-lasting backdoor, by leveraging just one or few malicious clients and/or operating in a single round of training. This attack type is hard to detect, as a backdoored model behaves unexpectedly only on samples known to the attacker (e.g., most images except for the green "cars" are classified correctly, and in particular "cars" of other colors).

The literature features a number of proposals to mitigate attacks against FL. For instance, FoolsGold [12] aims at identifying suspicious contributions by observing similarities among the clients’ updates. FoolsGold relies on the attacker controlling multiple clients, and needs to make strong (and unrealistic) assumptions on the poisonous updates submitted by the malicious clients. Nevertheless, recent attacks show that a single client is sufficient to successfully poison the model [1], hence circumventing the defense. Moreover, for relying on the direct inspection of clients’ updates, FoolsGold is incompatible with secure aggregation. More recent defenses also require auditing individual updates, raising privacy concerns (cf. Section 6). Another avenue could be to use existing defenses in the...
context of Byzantine fault-tolerant distributed learning. These techniques, however, are not successful in federated learning, as they rely on uniformly distributed training data among participants—an assumption which is known to be violated in FL. This state of affairs suggests that protecting federated learning requires devising dedicated techniques to overcome poisoning attacks in the presence of malicious participants.

In this paper, we tackle the problem of securing federated learning against semantic-backdoor attacks by investigating the following question:

**Is there any peculiarity of federated learning that honest parties can leverage to combat model poisoning?**

In this context, we identify two features, peculiar to FL, that can effectively help in defeating backdoor attacks. The first feature relies on the training process being operated in several iterations. Crucially, (I) the global model can be inspected in every training round, and each iteration is expected to improve the model over the previous one. The second feature deals with the presence of many contributing clients, resulting in (II) the availability of multiple private datasets providing a large, varied, and rich set of labeled data. Based on these observations, we propose a novel defensive strategy that leverages the clients’ data to identify, and combat, backdoor attacks on FL. We name our defense BAFFLE: Backdoor detection via Feedback-based Federated Learning.

BAFFLE relies on clients not only for training but also for validating the model. More precisely, BAFFLE uses a set of validating clients, refreshed in each training round, to determine if the (global) model-update derived in that round has been subject to a poisoning injection, discarding the update in this case. That is, clients validate the global model and vote for its acceptance or rejection using a feedback loop. Importantly, the decision of accepting or rejecting an update is made exclusively based on the global model, rather than on individual updates, to ensure compatibility with secure aggregation. Similarly to the idea of federated training, the core intuition behind our defense is to leverage the multitude of clients participating in the FL process to improve a task otherwise sub-optimally carried out by a single entity (e.g., the coordinating server).

Notice that this approach shares some of the challenges of training in a federated setting: malicious clients may misreport their assessment of the model, to have poisoned models declared as “clean” (in order to avoid detection) and/or clean models deemed as “poisoned” (DoS attack). Nevertheless, we show that a proper use of the clients’ judgement in the feedback loop can be very powerful in detecting state of the art backdoor attacks even when relying on straightforward methods to assess the classification performance. Here, we use a method to locally compare (at each client) the classification performance of the updated model with that of the previous model, discarding updates that present unexpected behavior. To identify “unexpected behavior”, we analyze the wrong predictions made by the models on a per-class basis, and raise a warning whenever the variations of corresponding error rates exceed an empirically determined threshold. Such a round-based misclassification analysis relies on the observation that a backdoored model is likely to make more mistakes, on one or few classes, than it would do prior to being backdoored.

We evaluated the effectiveness of our proposals, under various configurations, against the semantic-backdoor attack of Bagdasaryan et al. [1], in the context of image classification on CIFAR-10 and FEMNIST datasets. Our results show that BAFFLE can achieve accuracy of 100% (and false-positive rate below 5%), even when the validation method is instantiated with a simple misclassification analysis and despite the validation sets at the clients being relatively small. We also analyzed the detection accuracy against an adaptive attack $A$ that creates poisoned updates such that they bypass our cross-round misclassification method on $A$’s validation data. When evaluated against this stronger attack, which is fully aware of the defense, BAFFLE still achieves high detection accuracy, confirming the intuition that decentralized data is an asset by itself in FL. As mentioned earlier, we speculate that the performance of the feedback loop can be further enhanced when relying on more sophisticated validation methods—beyond analyzing the per-class misclassification rate—to decide locally whether a given update is genuine or not.

The remainder of our paper is organized as follows. In Section 2, we provide relevant background about machine-learning concepts and federated learning. We specify a security model for backdoor attacks on FL in Section 3, casting the problem we aim to tackle in the paper. In Section 4, we present our proposal, BAFFLE, to defend against semantic-backdoor attacks on FL. We then evaluate BAFFLE by means of experiments in Section 5. In Section 6, we overview closely related work and compare our solution with existing proposals, and we conclude the paper in Section 7.

## 2. Background

In this section, we introduce the notations used in the paper, present relevant concepts and terminology, and describe a model-poisoning strategy devised for the FL scenario [1].

**General notations.** For $a, b \in \mathbb{N}$ we write $[a..b] = \{x \in \mathbb{N} : a \leq x \leq b\}$. Let $X$ be a (finite) set, and let $D : X \rightarrow [0, 1]$ be a probability distribution. We denote by $x \leftarrow_D X$ the random sampling of an element $x$ according to distribution $D$; we write $x \leftarrow_X X$ for the special case of sampling $x$ uniformly at random from $X$. We proceed with notations and concepts specific to machine learning.

### 2.1. Machine Learning

A machine-learning classification problem consists of deriving an unknown mapping from an input space $X$ to a set $Y$ of classes (or labels), given a set of labeled pairs $D = \{(x, y) : x \in X\}$ for some $X \subseteq X$. Typically, $X$ is a vector space (a.k.a. feature space), $Y$ is a finite discrete-value set, and the sought mapping between $X$ and $Y$ is called ground truth. Using this terminology, a labeled dataset contains a number of pairs $(x, y)$ of instances and corresponding true labels. A machine-learning model (a.k.a. classification or prediction model) is a mapping $f : X \rightarrow Y$ aimed at emulating the ground truth.

In supervised learning, the process of deriving a model $f$ from a labeled dataset $D$ is called training, and
similarly $D$ is called training set. A prediction model should make correct predictions on unseen data, ideally reproducing the ground truth. Under this perspective, the quality of a model $f$ is measured by its accuracy on naturally occurring inputs, defined as $\text{acc}_D(f) = \Pr[f(x) = y : x \in_D X]$, where $D$ denotes the “natural distribution” of input samples. In practice, however, the distribution $D$ is rarely known/predictable. A more pragmatic metric to evaluate the model’s classification performance is the empirical accuracy. For a labeled dataset $D$, we denote the empirical accuracy of $f$ on test set $D$ by:

$$\text{acc}_D(f) = \frac{|\{(x,y) \in D : f(x) = y\}|}{|D|}. \quad (1)$$

Error and empirical error are defined analogously by considering the wrong predictions made by the model, and we have $\text{err}_D(f) = 1 - \text{acc}_D(f)$. Given a model $f$ and a test set $D = \{(x,y) : x \in X\}$ as above, we use the shortcut $X_f = \{x \in X : f(x) = y\}$ to denote the set of instances in $X$ that $f$ predicts correctly. Similarly, we denote the set on which $f$ makes mistakes by $X_f = \{x \in X : f(x) \neq y\}$, and we write $D_f$, resp. $D_K(f)$, for the corresponding sets of labeled instances. If there is no ambiguity, we may omit the model and write $D_f$, respectively, $D_K$, to simplify the notation.

2.2. Federated Learning

In contrast to centralized approaches for model training that require storing all training data on a single machine or datacenter, FL provides a decentralized method to train a model in a distributed fashion, leveraging data and resources of several users [21]. FL is an iterative process, orchestrated by a central server $S$, enabling multiple clients to collaboratively train a shared model. In each round, clients perform model-training locally, so that their data never have to leave the device, and then aggregate the locally-computed updates to derive an improved version of the shared model.

Throughout the paper, we denote by $R$ the total number of rounds, by $C$ the set of participating clients, and $N = |C|$. Starting from a server-initialized global model $G^0$, each round $r \in [1..R]$ comprises the following steps: $S$ randomly selects $n \ll N$ clients $C_1, \ldots, C_n$ \$\in\$ $C$ for that round and provides them with the current model $G = G^{r-1}$, each client $C_i$ is expected to locally train $G$ on their private data $D_i$ to derive an improved local model $L_i$, and to share the corresponding update $U_i = L_i - G$ with the server. Finally, $S$ averages the clients’ contributions $U_1, \ldots, U_n$ and integrates them to the global model $G$, deriving an updated model as $G' = G + \frac{\lambda}{N} \sum_{i=1}^{n} (L_i - G)$, where $\lambda$ is the global learning rate, controlling the “fraction” of the global model which is updated every round; for instance, setting $\lambda = \frac{N}{n}$ causes the model $G$ to be fully replaced by the average of the local models. Since the local models $L_i$, and hence the updates $U_i$, could leak information about the local training data [22], [25], the aggregation phase can be optionally executed in a privacy-preserving manner, through an interactive protocol called secure aggregation, to ensure that no information about the clients’ training data is leaked to the server or to the other clients [6].

Upon completion of round $r$, the current global model is set to $G' = G'$.

2.3. Model Poisoning in Federated Learning

Due to its inherently permissionless design, federated learning is particularly vulnerable to poisoning attacks: any device capable of performing model training can contribute to the FL process, meaning that one cannot prevent malicious clients from contributing with poisoned data. This vulnerability was demonstrated by means of model replacement [1], [2], an attack strategy that can inject a semantic backdoor (cf. Section 3.2) through the poisoned updates submitted by malicious clients, causing the global model to be replaced with an attacker-chosen model. As shown by Bagdasaryan et al. [1], model replacement can be devastating even when just one malicious client submits a poisoned update in a single round of training (single-shot attack). Below we describe this attack strategy, as we will take it as a benchmark for evaluating our defense.

2.3.1. Single-shot model-replacement attack [1]. We assume an attacker $A$ that has full control over one or more compromised clients, i.e., $A$ controls both the training data and the entire local-training procedure of those clients; the attacker however cannot interfere with any aspect of honest clients’ local training, and has no control over the aggregation protocol combining each round’s updates. Let $C_1, \ldots, C_n$ denote the clients selected for the round in which poisoning happens, and wlog let $C_n$ be the malicious client. The attacker’s strategy is to derive a malicious local contribution $L_n^*$ so that model $G'$ is “replaced” with an attacker-chosen model $G'^*$:

$$G'^* = G + \frac{\lambda}{N} \sum_{i=1}^{n-1} (L_i - G) + \frac{\lambda}{N} (L_n^* - G) \quad (2)$$

where $G$ is the global model from the previous round and $L_1, \ldots, L_{n-1}$ denote the contributions of the honest clients. Solving Equation 2 for model $L_n^*$, the attacker can derive the malicious update as follows:

$$L_n^* = \frac{N}{\lambda} G'^* - \left(\frac{N}{\lambda} - 1\right) G - \sum_{i=1}^{n-1} (L_i - G) \quad (3)$$

$$\approx \frac{N}{\lambda} (G'^* - G) + G \quad (4)$$

where the equality ($\approx$) holds assuming convergence of the global model, which causes the honest updates to vanish, i.e., $L_i - G \approx 0$ for all honest clients $C_i$; this is a realistic assumption if poisoning happens in a late round of training [1]. In Equations (2)-(4), $\gamma = N/\lambda$ represents the scaling factor used by the attacker to ensure that the backdoor is not erased or weakened by averaging. By submitting the computed update $L_n^*$, the attacker can have the global model $G'$ replaced with any model $G'^*$ of their choosing. Then, to instantiate a backdoor attack, the target model $G'^*$ is crafted so that it achieves high accuracy on the adversarially-chosen subtask while preserving the accuracy of $G$ on the main classification task. We discuss this in detail in the next section.
3. Security Model

In this section, we specify a security model for backdoor attacks, highlighting attacker’s and defender’s objectives. The security notions we introduce make the goal of the attacker explicit, and help reasoning about desired properties for an appropriate defense.

3.1. System Model & Assumptions

Our goal is to devise a defensive strategy to protect federated learning from poisoning attacks that aim at backdooring the global model. Towards this end, in this section we define relevant backdoor-attack types, specifying adversarial goals in attacking the system and corresponding objectives of a defender who wishes to thwart such attacks. We focus on semantic-backdoor attacks (defined formally in Section 3.2.2): backdoor samples may occur in the datasets held by honest parties, however, the backdoor is only known to the adversary. Further, the attacker may attempt to inject a backdoor in any round of training, possibly multiple times, and the honest parties do not know in which rounds. The goal of the attacker is to have the global model learn some adversarial subtask (a.k.a. backdoor task) of their choosing. We say that the global model “learns the backdoor task” if it reaches high backdoor accuracy as defined in Equation (5), in which case we say that the injected backdoor is strong. Succeeding in this task, however, says nothing about the stealthiness of the backdoor. One also requires that the victim model, in addition to presenting high backdoor accuracy, achieves high accuracy on clean inputs. The literature typically sets the goal of a backdoor attacker as achieving high accuracy on the backdoor task while also preserving the main-task accuracy, to avoid detection. Contrasting this, a proper defense should ideally prevent the attacker from injecting a backdoor at all.

In FL, preventing malicious clients from submitting poisoned updates seems to be impossible without compromising the clients’ privacy, as it requires inspecting each individual update. As we seek a defense which is compatible with secure aggregation, so that the privacy of clients’ data is not undermined, we make a milder requirement and demand that successful backdoor injections be detected—so that the honest participants can react to the poisoning attempt. Due to the dynamic nature of the FL process, and in particular to the clients contributions that repeatedly refresh (and hopefully improve) the global model, a highly accurate backdoor is likely to be erased by honest updates and quickly “forgotten” by the model. Therefore, the backdoor accuracy alone is not a proper measure to quantify the effectiveness of an attack: the durability of a backdoor must also be considered for a meaningful assessment of the adversarial success [1].

3.2. Backdoor Attacks

We now define backdoor attacks formally, making the attacker’s objective precise and specifying two popular backdoor types: semantic and trojan backdoors.

3.2.1. Backdoored models. Loosely speaking, a classification model exhibits backdoor behavior if it assigns a target label (different from the true label) to certain attacker-chosen inputs, called backdoor instances, while it behaves normally on all other inputs. To formalize this intuition, we present a general notion for a backdoored classification model and specify related adversarial objectives. Our naming conventions are inspired by the formalism of Chen et al. [9]. A backdoor adversary \( \mathcal{A} \) is associated with a target label \( y_t \in \mathcal{Y} \) and a set \( \mathcal{X}^* \subseteq \mathcal{X} \setminus \mathcal{X}_{y_t} \) of backdoor instances. \( \mathcal{A} \)’s objective in backdooring a classification model \( f : \mathcal{X} \rightarrow \mathcal{Y} \) is to make \( f \) predict backdoor instances as belonging to the target class, i.e., \( f(x) = y_t \) for all \( x \in \mathcal{X}^* \), while assigning the correct prediction to all other instances, so that the backdoor goes unnoticed. A typical metric to measure the attacker’s success rate is the backdoor accuracy on a given set \( \mathcal{X}^* \subset \mathcal{X}^* \) of backdoor instances, defined as the portion of samples in \( \mathcal{X}^* \) which are labeled as \( y_t \)-instances by the classifier:

\[
\text{acc}_{\mathcal{X}^*,y_t}(f) = \frac{|\{x \in \mathcal{X}^* : f(x) = y_t\}|}{|\mathcal{X}^*|}
\]

Note that defenders cannot measure \( f \)’s backdoor accuracy to detect attacks, as only \( \mathcal{A} \) knows the backdoor set \( \mathcal{X}^* \).

3.2.2. Trojan and semantic backdoors. Two different flavors of backdoor attacks have been proposed so far, named semantic and trojan respectively, depending on whether backdoor instances appear naturally during deployment or must be artificially generated by the attacker. Formally, if \( D \) denotes the natural distribution of instances, a trojan backdoor is such that \( \Pr [x \in \mathcal{X}^* : x \leftarrow D | X] = 0 \), while the same probability is positive in the case of a semantic backdoor. A trojan-backdoor attacker \( \mathcal{A} \) is associated with a backdoor key \( k \in K \), where the key space \( K \) may or may not overlap with \( \mathcal{X} \), and a backdoor-instance generation function \( \text{Gen}^* : K \times X^* \rightarrow X \). We say that \( \mathcal{A} \) generates backdoor instances by invoking \( \text{Gen}^* \) on a chosen backdoor key \( k \) and input \( x \): i.e., \( x^* \leftarrow \text{Gen}^*(k, x) \) yields a backdoor sample \( x^* \in \mathcal{X}^* \), where \( \mathcal{X}^* = \text{Gen}^*(k) \) is the backdoor set associated with key \( k \).2 Roughly speaking, the attacker crafts a backdoor instance \( x^* \) from a “clean” input \( x \) by “attaching a trigger” defined by key \( k \). Similarly, a semantic-backdoor attacker \( \mathcal{A} \) is associated with a backdoor key \( k \in K \) as well as a backdoor-instance selection function \( \text{Sel}^* : K \times X^* \rightarrow \{0, 1\} \) which identifies backdoor instances, i.e., \( \text{Sel}^*(k, x) = 1 \) if \( x \in \mathcal{X}^* \), and \( \text{Sel}^*(k, x) = 0 \) otherwise. Here, again we assume an implicit dependency between the backdoor-instance space and the backdoor key, i.e., \( \mathcal{X}^* = \text{Sel}^*(k) \). Semantic backdoors are presumably more powerful than trojan backdoors, as the attacker is not required to modify inputs at test time in the former case [1].

As we overview in Section 6, the literature features various strategies that can successfully backdoor neural-network models—all of them relying, in a way or another, on poisoning part of the training data by including labeled backdoor samples. For instance, in a model-replacement

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1. We stress, however, that a defender could still hope to detect misbehavior by evaluating the mistakes made by the model on a validation set of their choosing (and this is indeed the approach we use in our instantiation of the feedback-loop detection method from Section 4.3).

2. In fact, the backdoor-instance generation function may be randomized or take additional inputs to diversify the outputs.
attack on federated learning (cf. Section 2.3), the attacker can craft a backdoored model $G^*$ by executing the prescribed local training procedure using poisoned data, i.e., mislabeled pairs $(x, y_t)$ with $x \in X^*$, as well as correctly labelled data. This approach is based on the principle of multi-task learning: backdoor data trains the model on the adversarial subtask while genuine data ensures good performance on the main task.

4. Our Solution

In this section, we present our proposal to protect FL from backdoor attacks: Backdoor detection via Feedback-based Federated Learning (BAFFLE). We begin by outlining the core ideas behind our proposal, explaining the main insights that guided its design. We then describe our defense in detail.

4.1. Overview and intuition

Protecting ML from backdoor attacks generically appears to be extremely challenging, if not impossible, as indicated by the long sequence of attacks on neural networks and associated defensive strategies (cf. Section 6). This difficulty stems from the asymmetry between what the attacker knows about the machine-learning system, and what the defender knows about the attacker. Namely, the backdoor—which is only known to the attacker—can be explicitly chosen to elude detection.

To overcome this challenge, we aim to break this asymmetry between the attacker’s and the defender’s knowledge by identifying (and leveraging) specific features of federated learning that can help defending against backdoor attacks. One such feature consists of the training process being operated in several iterations, where each iteration is expected to improve the global model compared to the previous rounds. Therefore, a genuine model that can serve as a reference is available in every round ($F_1$). Following the general principle of a recent defense against trojan-backdoor attacks [13], we look for ubiquitous properties of a semantic-backdoor attack that could be turned into a weakness. To this end, note the characterizing property of a backdoored model is that it aims to assign a (wrong) target label to all backdoor instances (cf. Section 3.2), therefore presenting different classification behavior compared to a genuinely trained model. While existing backdoor attacks have been specifically optimized to preserve the model’s classification performance on ordinary (i.e., non-backdoor) validation data, hence bypassing anomaly-detection methods that rely on measuring model accuracy [2], these optimizations assume the attacker has access to validation data. We argue, however, that this assumption is not realistic in a federated setting as validation data is privately held by clients. In particular, in FL there is substantial data which the attacker does not know/control ($F_2$), which makes it harder for an attacker to optimize for avoiding detection.

We designed BAFFLE based on the two features ($F_1$ and $F_2$) introduced above, which constitute the pillars for the security of our proposal. In what follows, we present the high-level design of BAFFLE (illustrated in Figure 1) and highlight how its components relate to these features.

**Bootstrapping trust across rounds.** The first key component of BAFFLE leverages the possibility of inspecting the global model while the training is ongoing, namely in every round of training, allowing to look for signs of poisoning with a higher granularity than in the case of centralized-learning approaches. In particular, we expect the global model to present an incremental improvement in accuracy over the previous model in each round (except for few initial iterations, when the model improves very quickly). Based on this observation, we devise a validation method to decide whether the prediction behavior of the global model shall be deemed as “suspicious”. Concretely, we derive relevant statistics from the prediction behavior of the most recent global models, on a fixed test set, and determine a rejection threshold based on such observations. This threshold empirically quantifies the expected “prediction gap” of a genuine model, based on the predictions of previous global models: if the current model exceeds the estimated gap, it is deemed as poisoned and discarded. Intuitively, we consider early models as a reference for the behavior of “clean” models, and bootstrap the trust in these early models towards the subsequent ones, round by round (leveraging feature $F_1$).

Notice that at the early stages of training, when the global updates evolve sharply from round to round, the model is so immature that the effect of early poisoning is rather negligible, i.e., the backdoor is short-lived, disappearing within only one training round [1], [2]. Hence, we do not expect that poisonous injections made during this early phase will affect the effectiveness of BAFFLE in the long run—as the model stabilizes—because early injected backdoors tend to vanish immediately. We validate this behavior experimentally in Section 5. Our results show that BAFFLE is effective even if it is only started as the global model matures, and even if there were poisoning attempts before BAFFLE has started.

Regarding the specific validation function for establishing the prediction gap, we consider a straightforward approach to assess the classification performance of the model. The core idea is to inspect the variations in wrong predictions, on each class, made by the model upon being updated, i.e., across subsequent rounds. Under normal conditions, we expect these variations to be relatively small and to decrease over time, reflecting the model’s incremental improvement as training proceeds. We discuss the details of this instantiation in Section 4.3. Our choice of considering per-class misclassifications was motivated by the aim of detecting semantic backdoors. We conjecture that other, dedicated instantiations can be effective in detecting different backdoor types, too. By the modularity of our design, it is possible to instantiate the feedback loop by simply replacing the validation procedure.

**Collaborative model validation.** In a federated-learning scenario, data is an asset by itself and could be leveraged not only to improve training—which is the main objective of current FL frameworks—but also to enhance security. Towards this end, we apply the round-based detection method just described by letting the clients search for a backdoor in the global model using their own, private validation data. Namely, we propose adding an validation phase to each round of federated training so that a set of randomly chosen clients (instead of, or in addition to, the
server) run the model-validation test on their private data, and report to the server whether the global model presents signs of poisoning. As clients provide “feedback” about the global model, we refer to this process as Feedback Loop—and name our defense after this process. Due to the diversity of the clients’ data, one immediate effect of having many clients validating the model is to implicitly enlarge the validation set (as per feature F2), and hence to increase the chances of detecting misbehavior.

Data unpredictability against adaptive attacks. We argue that the collaborative validation step also has the potential of making FL more robust to adaptive attacks. Observe that an adaptive attacker, being aware of the defense, could in principle bypass our detection method with a specially crafted update which, despite being poisoned, appears to be in line with the previous observations (i.e., within the expected “prediction gap”). However, the prediction gap is a data-dependent quantity. Therefore, the best an attacker can do is to optimize the poisoned update for the prediction gap observed on their own data. Then, the resulting global model might be within the prediction gap obtained by other clients that have similar data as the adversary, but it is unlikely to satisfy the prediction behavior expected by all validating clients. This is particularly true in a federated-learning setting, where the data distribution can vary significantly among clients.

We are now ready to introduce the details of BAFFLE. We designed our defense in a modular way, to specifically leverage features F1 and F2 described above. This modularity is reflected in the two (orthogonal) components of BAFFLE, which we describe in detail below.

### 4.2. BAFFLE design: Feedback Loop

The core component of BAFFLE is a collaborative method to detect poisoning attempts by validating the global model while training is ongoing. The server asks clients for feedback in each round of training, letting the validating clients evaluate the global model, on their own data, and report whether the model presents anomalous behavior. The feedback loop is a natural augmentation of the FL process, in that it complements federated training with a “federated validation” phase. Letting clients vote on the global model however does introduce a new challenge: malicious clients can mount denial-of-service attacks by declaring a clean model to be suspicious, or increase the attacker’s stealthiness by marking a poisoned model as clean. Addressing this challenge requires careful calibration of the clients’ voting power. The fundamental steps of the feedback loop are specified in Algorithm 1.

#### Algorithm 1 Feedback Loop (for round \( r \))

**Inputs**
- Server \( S \): \( \{G^t\}_{t=0,\ldots,r}, \text{param} \)
- Client \( C_i^r \): \( D_i \)

**Protocol**

Server \( S \):
1. \( (m, l, q) \leftarrow \text{param} \)
2. \( G \leftarrow G^r \)
3. Select \( \{G^{t'}\}_{t=0,\ldots,t} \) from \( \{G^t\}_{t=0,\ldots,r-1} \)
4. \( \text{history} \leftarrow (G^0, \ldots, G^t) \)
5. \( C_1^r, \ldots, C_m^r \leftarrow S.C \)
6. for \( i \in [1..m] \) do
   7. \( \text{Send } G \text{ and } \text{history} \text{ to } C_i^r \)
8. end for

Client \( C_i^r \):
9. \( d_i \leftarrow \text{VALIDATE}(G, \text{history}, D_i) \)
10. Send \( d_i \) to \( S \)

Server \( S \):
11. Upon receiving \( m \) verdicts:
   12. if \( \{d_i = 1 : i = 1, \ldots, m\} \geq q \) then
   13. \( \text{Reject} \)
   14. else
   15. \( \text{Accept} \)
   16. end if

In the rest of the paper, we refer to the clients that take part in the training process as “contributors”, and we name “validating clients” those which evaluate the...
updated model and look for signs of poisoning. Specifically, in every round \( r \in [1..R] \), we let the server \( S \) select a set of \( m \) clients, denoted by \( C_1^{(r)}, \ldots, C_m^{(r)} \), for validating the global model \( G' \) resulting from the updates proposed by the contributors. Validating clients are responsible for inspecting \( G' \) and reporting to the server whether the model exhibits suspicious behavior. There are multiple options to select the set of validating clients (e.g., having the same clients performing both model training and validation reduces communication overhead, as we discuss in Section 5.4: choosing contributors and validating clients independently, however, may reduce the attack surface). Each client \( C_j^{(r)} \) shall inspect the global model individually, on their own dataset \( D_i \). For the sake of generality, here we assume a generic validation routine, denoted by \( \text{VALIDATE} \), which takes as input the current global model \( G \), the history of previously accepted models, and the client’s validation data \( D_i \), and it returns a verdict \( d_i \in \{0, 1\} \), indicating “clean” or “poisoned”, for \( G \) compared to the previous models recorded in the history. We provide one possible instantiation of the validation function in Section 4.3. Upon receiving all clients’ verdicts, the server accepts model \( G' \) as long as sufficiently many clients proposed to accept, else it rejects the global update and starts a new round with “current” model \( G'^{r+1} \leftarrow G'^{r-1} \) (i.e., \( G' \) is discarded). In what follows, we denote by \( q \in [1..m] \) the minimum number of negative verdicts the server requests in order to reject the model, and name it the \textit{quorum threshold}.

Having the global model evaluated by clients, similarly in spirit to the idea of decentralized training, has the objective of leveraging the broader and more diverse test dataset that the clients can offer jointly. This feature however comes at the risk of giving “voting power” to malicious clients, who may deliberately lie, pretending they found indication of poisoning. Determining an appropriate value for the quorum threshold \( q \) is therefore crucial for the effectiveness of the feedback loop, and care should be taken when weighing the clients’ votes. Clearly, the choice of \( q \) depends on the number of tolerated corruptions. Namely, assuming that \( t \) out of \( m \) validating clients (per round) may be compromised, \( q \) must be chosen so that the attacker can neither reject genuine models \((t < q)\) nor outvote honest clients who reject a poisoned model \((t < n - q + 1)\), yielding \( t < q < n - t + 1 \). In Section 5, we explore how different choices for \( q \) affect the detection accuracy of BAFFLE.

### 4.3. BAFFLE design: Validation Function

We now propose an instantiation of the validation function (i.e., procedure \( \text{VALIDATE} \) in Algorithm 1) to determine whether the global model has been backdoored in a given round, given observations from previous rounds. Focusing on semantic backdoors, we consider a straightforward method based on comparing the classification performance of the current model \( G \) (under validation) with that of recent, previously accepted models \( G^{m_0}, \ldots, G^0 \) (considered as “clean”). As we demonstrate in Section 5,

3. Since some validating clients may not be responding, we may relax this requirement and let the server accept the model by default unless \( q \) many clients suggest rejection.

![Figure 2: Prediction behavior of clean models vs poisoned models on CIFAR-10: per-class error rate w.r.t. class 7.](image-url)
assigned to class $y_t$ by the model can be compactly denoted by $D_{y_t \to x} = \{(x, y) \in D : y = y_t, f(x) = y_t\}$. We write $D_{y_t \to x} = \{(x, y) \in D_{y_t} : f(x) \neq y_t\}$ for the $y_t$-pairs that are predicted incorrectly, and $D_{x \to y_t} = \{(x, y) \in D_{y_t} : y \neq y_t\}$ for the pairs which are wrongly assigned to class $y_t$. Using these notations, we define source-focused error, respectively, target-focused error of a model $f$, for dataset $D$ and source label $y_s$, resp., target label $y_t$, by:

$$\text{err}_D(f)|_{y_s \to x} = \frac{|D_{y_s \to x}|}{|D_{y_s}|}, \text{err}_D(f)|_{y_t \to x} = \frac{|D_{y_t \to x}|}{|D_{y_t}|}. \quad (6)$$

The source-focused and target-focused error rates are complementary to the concepts of class recall and class precision.

**Validation based on misclassification analysis.** Our instantiation of VALIDATE relies on observing the model’s prediction behavior in a class-wise manner. Intuitively, we expect that honest updates should not affect significantly the per-class error rates of the global model across subsequent rounds. In contrast, a freshly injected backdoor is likely to boost the error rate for one or a few classes. Based on this observation, we aim at detecting poisoning attempts by monitoring the variations in error rates made by the most recently accepted model $f$ and the updated version $f'$, for each label $y$ and on the same dataset $D$.

We consider both source-focused and target-focused error variations:

$$\nu^s(f, f', D, y) = \text{err}_D(f)|_{y \to x} - \text{err}_D(f')|_{y \to x} \quad (7)$$

$$\nu^t(f, f', D, y) = \text{err}_D(f')|_{y \to x} - \text{err}_D(f)|_{y \to x} \quad (8)$$

These variations provide a sort of distance between $f$ and $f'$, reflecting the wrong-prediction gap of the two models.

We devise a simple strategy to validate a model update based on the wrong-prediction gap. As federated training gradually improves the global model, we expect under benign conditions that the wrong-prediction gaps between consecutive models $f = G^r$ and $f' = G^{r+1}$ be relatively close to each other. In contrast, a poisoned model can significantly change the error-rate variations. To measure distances between error-rate variations, we consider the array $\nu(f, f', D) = [\nu^s, \nu^t]^\ell_0$, where $\nu^s = [\nu^s(f, f', D, y)]_{y \in \mathbb{Y}}$ and $\nu^t = [\nu^t(f, f', D, y)]_{y \in \mathbb{Y}}$, as a data point in $\mathbb{Z}^{2|\mathbb{Y}|}$. We then identify each new update as “suspicious” based on the relative distance between its error-variation point compared to the previous ones. We identify suspicious updates using the Local Outlier Factor (LOF) [7], a method to detect outliers in a dataset by inspecting the proximity of a point to its neighbors compared to the neighbors’ own proximity. Given a point $x$ and some neighboring points $N = \{x_1, \ldots, x_n\}$, $\text{LOF}_k(x; N)$ provides a degree of outlier-ness based on the proximity of $x$ to its $k$ closest neighbors; in particular, $\text{LOF}_k(x; N) > 1$ indicates that $x$ is less clustered than the other points, and potentially an outlier.

The details of our proposal are specified in Algorithm 2. By the modularity of our design, any entity holding labeled data $D$ could in principle validate a model $f$ using such strategy, given sufficiently many previously-accepted models (as summarized in the history). This is reflected in our evaluation of BAFFLE in Section 5, where we consider different configurations letting the server, the clients, and both of them run VALIDATE.

**Algorithm 2** Instantiation of the validation function

```plaintext
1: procedure VALIDATE(G, history, D)
2: \( (G^0, \ldots, G^\ell) \leftarrow \text{history} \)
3: for \( i = 1, \ldots, \ell \) do  
4: \( v_i \leftarrow \nu(G^{i-1}, G^i, D) \triangleright \text{Trusted metric values} \)
5: end for
6: \( v_{i+1} \leftarrow \nu(G^\ell, G, D) \triangleright \text{New metric value} \)
7: \( h_1 \leftarrow \nu^s(G^\ell, G, D) \)
8: \( h_2 \leftarrow \nu^t(G^\ell, G, D) \)
9: \( \tau \leftarrow 0 \)
10: for \( i = h_1, \ldots, \ell \) do  
11: \( \phi_i \leftarrow \text{LOF}_k(v_i; v_{i-1}, \ldots, v_{i-h_1+1}) \triangleright \text{Trusted LOF} \)
12: end for
13: \( \tau \leftarrow \text{mean}(\phi_1, \ldots, \phi_{\ell-1}) \triangleright \text{Local threshold} \)
14: if \( \phi_k > \tau \) then  
15: \( \text{vote} \leftarrow 1 \triangleright \text{Update is suspicious} \)
16: else  
17: \( \text{vote} \leftarrow 0 \triangleright \text{Update seems OK} \)
18: end if
19: return vote
21: end procedure
```

Algorithm 2 considers a run of the FL process starting with a global model $G^0$ initialized by the server. For $r \in [1, R]$, let $G = G^{r-1}$ denote the global model shared at the beginning of round $r$, let $G^r$ be the updated model derived by aggregating the clients’ contributions for round $r$, and let $\text{history}$ denote the latest $\ell+1$ accepted models. To validate the current model $G^\ell$, we calculate the error variation array $\nu_\ell = \nu(G^{\ell-1}, G^\ell, D)$, where $\nu_\ell$’s components are defined as in Equations (7)–(8). Intuitively, we aim at inferring the general trend of $\nu$ from the sequence $G^0, \ldots, G^\ell$ of recent models accepted so far, monitoring how this trend changes over the rounds, and make a decision about $G^\ell$ depending on whether $\nu_\ell = \nu(G^{\ell-1}, G^\ell, D)$ is in line with the previous observations. Specifically, we compare $\nu_\ell$ with the average LOF value of $\nu$ calculated from the predictions of the $\ell + 1$ latest accepted models, over dataset $D$. Here, $\ell$ is a look-back parameter determining how many of the previous models shall affect the decision about the current model. Intuitively, $\ell$ should be sufficiently large to yield a stable reference value for the metric, and at the same time it should be small enough so that “too old” models play no role in the decision.4 We discuss how to empirically determine an appropriate value for $\ell$ in Section 5. Model $G^\ell$ is accepted if and only if the current variation $\nu_\ell$ is sufficiently close, in the sense of LOF, to the corresponding values obtained from the history of accepted models. Namely, we declare $\nu_\ell$ as suspicious if it is detected as an outlier compared to the $k$ closest variations from $\{\nu_1, \ldots, \nu_\ell\}$, for $2 \leq k \leq \ell$. In our implementation, we set $k = \lfloor \ell/2 \rfloor$, and use as a rejection threshold $\tau$ the mean of the outlier factors obtained from the $\lfloor \ell/4 \rfloor$ last trusted updates.

4. Due to instability, an old model may present significantly higher error variations than the current model, and this may lead to rejecting a genuine model.
Notice that LOF is an empirical quantity computed locally, based on measurements made on the validation set $D$ w.r.t. the latest $\ell + 1$ accepted models. This design reflects the intuition that models which have already passed the validation test are considered trustworthy. More importantly, our design is based on the idea that having a data-dependent test introduces unpredictability to the validation process which makes it harder for an attacker to optimize for avoiding detection, as we discuss below.

### 4.4. Robustness to adaptive attacks

It is plausible that the validation method described in Section 4.3, while being more robust than a naive accuracy checking, can be bypassed by an adaptive attack that, being aware of the defense, optimizes for eluding detection. Namely, the attacker could craft a poisoned update mimicking the behavior of error-rate variations observed on their own data. We argue that, if the clients actively participate in the model-validation process, implementing such an adaptive strategy is hard. Indeed, to bypass the detection mechanism, the attacker has to craft an update so that the corresponding variation $\nu$ is $\tau$-close to the historical values, where $\tau$ depend on the data used to validate the model (cf. line 14 in Algorithm 2). Due to the diversity of the clients’ data in a federated setting, different clients are likely to derive different values for the error variations as well as for the acceptance threshold $\tau$, which the adversary cannot predict. Thus, it is highly challenging for an adversary controlling only a few clients to bypass detection for the majority of clients. We show this empirically in Section 5.

### 5. Implementation & Evaluation Results

In this section, we empirically evaluate our defense against backdoor attacks, in the context of image-classification. We conduct several experiments to evaluate the detection accuracy of BAFFLE under various configurations, varying system’s parameters (look-back window size $\ell$ and quorum threshold $q$), data splits among server and clients, and the rounds in which poisoning happens (late vs early). We also evaluate the effectiveness of BAFFLE against an adaptive attack that we devised by tuning the backdoor attack presented in Section 2.3.

#### 5.1. Implementation Setup

We consider two image classification tasks, on CIFAR-10 and FEMNIST respectively, and train in both cases a ResNet18 CNN model [15]. The CIFAR-10 dataset [17] consists of 60,000 colored images with $32 \times 32$ pixels and 24-bit color per pixel (3 color channels), of which 50,000 samples are used for training and 10,000 samples are used for testing. The images are categorized in 10 classes: ‘airplanes’, ‘cars’, ‘birds’, ‘cats’, ‘deer’, ‘dogs’, ‘frogs’, ‘horses’, ‘ships’ and ‘trucks’. The Federated Extended MNIST (FEMNIST) dataset is an adaptation to the federated setting of the EMNIST dataset [10], a set of handwritten digits derived from the NIST Special Database 19 and converted to a $28 \times 28$ pixel image format, so that it matches MNIST dataset structure. The dataset contains 731,668 training samples and 82,587 test samples. We run the FL training process with a hundred participants [21]. Conforming with previous work, in each round of training we select 10 clients uniformly at random. These clients perform local training, and their model-updates are later aggregated into a new global model. In each round, selected participants train for 2 local epochs with a learning rate of 0.1, as described in [1], [21].

In CIFAR-10, to emulate a non-IID distribution of data among clients, we distribute data to clients according to the Dirichlet distribution with hyper parameter $0.9$ [24], similar to the setup considered in [1]. This choice makes the resulting clients’ dataset unbalanced w.r.t. the CIFAR-10 classes. Similarly, in FEMNIST we distribute the data between 3550 clients using the same Dirichlet distribution to achieve a non-IID data distribution among the different clients. We implemented a federated-learning algorithm to solve the aforementioned image-classification tasks, based on the publicly available code associated to the paper [1]. The FL system as well as our defense described in Section 4 are implemented in Python using the PyTorch framework. We run the experiments on a server with an Intel i5-9600k CPU, equipped with a Gigabyte Geforce RTX 2070 GPU 8GB, and 64GB of RAM. The server runs Ubuntu 18.04 LTS OS.

We test our defense against the model-replacement attack described in Section 2.3. In the case of CIFAR-10, we instantiate one of the adversarial subtasks considered in [1], namely ‘cars’ with a striped background wall shall be classified as ‘birds’. We also modify the aforementioned attack to operate on FEMNIST, introducing a label-flipping attack type so that a backdoored model predicts an entire class as another one. In order to avoid any selection bias, we picked source and target class of the label-flipping attack randomly. To make the attack stronger, the source class is always selected as the class for which the adversary has the most data, while the target class is picked uniformly at random out of all the remaining classes. To showcase the effectiveness of the feedback loop, we consider different configurations of BAFFLE, depending on the entities responsible for validating the model: server-only (BAFFLE-S), clients-only (BAFFLE-C), and both (BAFFLE). When the feedback loop is in place (BAFFLE-C and BAFFLE), the server chooses 10 validating clients uniformly at random, and provides them with the current model as well as the last $\ell + 1$ previously accepted models ($\ell$ is chosen empirically, as we discuss below). Each client runs the VALIDATE algorithm (cf. Algorithm 2) locally, before sending their vote to the server. The server then collects all votes, and decides to accept or reject the new model based on the quorum threshold $q$, counting in its own vote for the BAFFLE configuration.

#### 5.2. Evaluation Methodology

**System’s parameters.** To evaluate the effect on BAFFLE’s effectiveness of look-back window size $\ell$ and quorum threshold $q$, i.e., the numbers of previously accepted models used as a reference to evaluate the current model, respectively, of rejecting votes to discard a given update, we run experiments for $\ell = 10, 20, 30$ and $3 \leq q \leq 9$. 
Data splits. To instantiate the feedback loop in a way that also the server performs model validation, we split the test data among server and clients. We considered multiple data splits C-S%, reflecting that the clients hold jointly C% of the overall data and the server holds the remaining S%. For CIFAR-10, we assign shares 90%-10%, 95-5%, and 99-1%. In the case of FEMNIST, we consider splits 99-1%, 99.5-0.5%, and 99.9-0.01% instead, so that the ratio between the amount of data at the server versus the amount of data of one client is roughly the same as in CIFAR-10. As we will see later in this section, studying how the detection accuracy of BAFFLE varies with the splits provides an empirical validation for the effectiveness of the feedback loop, although with little data compared to a real-world deployment.

Poisoning time. We distinguish two cases to assess the effectiveness of BAFFLE under attack: (1) the global model \( G \) has already stabilized (accuracy above 90%), obtained after 10,000 clean rounds of federated learning, and (2) the detection method is enabled in early rounds and the model \( G \) is not yet close to convergence. In case (1), we start with a mature model \( G \) and perform 20 subsequent training rounds before injecting three poisoned updates at rounds 30, 35 and 40, respectively (here, \( G \) corresponds to round 1). We enable the defense after the first 20 rounds in order to build a look-back window of decent size. We terminate the experiment after 50 rounds. In case (2), we start federated training from scratch and start the defense after 500 initial rounds of training. In these early rounds, as the global model is very unstable, we note that a genuine update may cause a significant variation in the per-class error rates and, therefore, it could be mistakenly flagged as malicious (false positive) and discarded. As a consequence, enabling the defense in early rounds may cause a delay in the convergence of the global model. We therefore consider the very first 800 training rounds, and we let the attacker inject two malicious updates, at rounds 100 and 300 before enabling the defense, and further 10 injections every 15 rounds starting at round 530. We deliberately activate the defense after the adversary operated a few injections, to analyze the behavior of BAFFLE in case the assumption about early models being trustworthy is violated. In both cases, we measure the detection accuracy of BAFFLE by averaging the results over the 5 repeated experiments as above.

5.3. Evaluation

We now report on the results of our experiments to evaluate the effectiveness of BAFFLE, in terms of false-negative (FN) and false-positive (FP) rates, under various configurations.

Choice of look-back window size \( (\ell) \). Table 1 shows the impact of the look-back window size \( \ell \) on FP and FN rates. We study the effectiveness of our proposals for variable \( \ell \) and a default value \( q = 5 \). Concerning CIFAR-10 (Table 1a), all configurations using the feedback loop (BAFFLE-C and BAFFLE) yield good detection rates, i.e., low FN rates between 0.0 and 0.1, for \( \ell = 10, 20 \), independently of the data split. The BAFFLE-C configuration yields the worst FN rate of 0.6 for \( \ell = 30 \) in the case of 90-10% split. Increasing the lookback window \( \ell \) seems to always decrease the number of models detected as poisoned (thus reducing FP and increasing FN). This might be due to a neighborhood that has too many small outliers and therefore reduces the outlier factor of new updates. In terms of false positives, the feedback loop (BAFFLE-C and BAFFLE) is clearly superior to the server-only configuration (BAFFLE-S), achieving FP rates within 0.0-0.043 vs 0.11-0.19 for \( \ell = 10, 20 \), and 0.0-0.032 vs 0.021-0.193 for \( \ell = 30 \). Varying \( \ell \) seems to have a more critical impact in the case of FEMNIST (Table 1b). Indeed, for \( \ell = 10 \) none of the configurations is able to detect poisoning attempts, yielding a FN rate of 1.0 in all cases. This phenomenon suggests that the look-back window is too small. Interestingly, all configurations show great improvements as the look-back window is increased to \( \ell = 20, 30 \), achieving a FN rate of 0 in most cases, and of at most 0.1 in all cases. Coming to the false positives, again we observe that for \( \ell = 10 \) none of the (genuine) models is flagged as positive, as the FP rate is 0 in all cases. As for CIFAR-10, we again observe the feedback loop performing better than the server-only configuration, with FP rates of 0 (for BAFFLE-C and BAFFLE) in contrast to 0.01-0.22 (BAFFLE-S).

Based on this results, we therefore set \( \ell = 20 \) in the sequel, as this value for the look-back window size achieves the closest to equal error rate for BAFFLE.

Choice of the quorum threshold \( (q) \). The plots in Figure 3 show how the quorum threshold \( q \) affects the detection accuracy (FN and FP rates) of our proposal, for both feedback-loop configurations BAFFLE-Cand BAFFLE, under different data splits among clients and server, along with the detection accuracy of the server-only configuration—which is constant as it does not depend on \( q \). In the case of CIFAR-10 (Figures 3a-3c), varying \( q \) affects significantly the detection accuracy of the feedback loop. As expected, decreasing \( q \) improves the FN rate, which sharply approaches 0 for \( q \leq 7 \) for both BAFFLE-C and BAFFLE, at the expense of slightly increasing the FP rates when \( q \) is decreased further. We observe that for \( q \leq 5 \), BAFFLE yields slightly higher FP rates compared to BAFFLE-C, however, it outperforms BAFFLE-C for \( q > 6 \). Overall, choosing \( 5 \leq q \leq 7 \) appears to be a safe choice as it yields high detection accuracy and nearly equal error rate. We also note that, for such choice of \( q \), both feedback-loop configurations outperform the server-only configuration, with a FP rate of nearly 0 vs about 0.2 for BAFFLE-S. This behavior is visible for all three data splits. As for FEMNIST (Figures 3d-3f), changing the quorum threshold does not seem to impact the detection accuracy of BAFFLE-C and BAFFLE: all values \( 3 \leq q \leq 9 \) lead to FN and FP rates of 0, regardless of the data split. This behavior is actually not surprising, as all clients detect the attack in this case.

Detection enabled in early rounds. We now turn to studying the effectiveness of BAFFLE in a setting where the model is not yet stabilized, and analyze the effect of early poisoning attempts. For this, we focus our attention on the very first 800 rounds of training. We activate the detection method at round 530, when the model starts stabilizing. Nevertheless, we weaken the assumption about early rounds being poison-free and let the adversary inject poisonous updates at rounds 100 and 300 (these injections
cannot be detected because the defense is not enabled). We further let the attacker inject 12 malicious updates at between round 530 and 680. The effect of poisoning on the model’s main-task and backdoor accuracy is depicted in Figure 4. In CIFAR-10 (Figures 4a-4b), we note that the backdoors injected in the early rounds (100 and 300) are not durable, as the backdoor accuracy decreases sharply after the defense is turned on. In FEMNIST (Figures 4c-4f) we observe a similar behavior, although less visible due to the lower main-task accuracy of the model (i.e., convergence is slower).

We note that BAFFLe successfully detects nearly all poisoning attempts operated after round 530; only one injection was undetected in the case of FEMNIST. Indeed, our detection method conservatively flags new contributions as suspicious as soon as they cause higher variations in the per-class error rates, which is what we leverage to detect model poisoning.

Adaptive attacks. We now analyze the effectiveness of our proposal in deterring adaptive attacks (cf. Section 4.2). We focus on the semantic-backdoor attack on CIFAR-10, as an adaptive attack of the label-flipping type seems meaningless (it would have to fulfill the contrasting goals of being stealthy and achieving high success rate). An adaptive adversary is aware of the detection method in place, and knows the system global parameter \( \ell \) and \( q \). Our evaluation results are summarized in Table 2. Mindful of the detection method based on per-class misclassification analysis, the attacker crafts its updates so that the backdoor performance significantly deviates from the clean model in classification analysis, the attacker crafts its updates so that the backdoor performance significantly deviates from the clean model in classification of clean inputs, a poisoning injection should only affect the model’s classification behavior on
backdoor data, thus bypassing detection under round-based misclassification analysis. Nevertheless, we argue that even such an adaptive strategy is hard to mount in FL: while the attacker can ensure all of its clean data are correctly classified by the backdoored model, it cannot control the model’s behavior (after the injection) on the other clients’ data. That is, as the local datasets of clients are private and typically very diverse from each other, it is difficult for the attacker to adapt its strategy so that the model behaves in a controlled manner on data the attacker does not know.

**TABLE 2: False negative rates of BAFFLE-C (Clients), BAFFLE-S (Server), and BAFFLE (Combined) against adaptive injections, for different data splits among clients and server (90-10%, 95-5%, and 99-1%).**

| Attack Type      | False Negative Rate | Clients | Server | Combined |
|------------------|---------------------|---------|--------|----------|
| 90%              |                     |         |        |          |
| Non-Adaptive     | 0.000               | 0.000   | 0.000  |
| Adaptive         | 0.111               | 0.333   | 0.000  |

Indeed, as already discussed in Section 4.1, in a federated-learning setting it is unlikely that the adversary has access to a dataset which is representative of the data of all clients. Concretely, in CIFAR-10, for all the data splits, BAFFLE yields 0 false negatives, in contrast to the server-only configuration (BAFFLE-S) which leads to a 33.3% FN rate in the 90-10% and 99-1% data split.

In Figure 5, we further evaluate how different validating clients perceive the aforementioned adaptive injections. Our results show that most of these injections were detected by at least 5 or more validating clients. This further confirms our choice for setting $q = 6$.

### 5.4. Communication Overhead

Our feedback-based defensive strategy entails having a subset of clients validate each update $G^r$ for every round $r$ of training. When combined with the round-based misclassification analysis described in Section 4.3, it requires validating clients to be equipped with the history of latest $\ell + 1$ accepted models to derive an appropriate rejection threshold (see line 7 in Algorithm 1 and line 14 in Algorithm 2). To save an additional round of communication, we opt for an approach where the set of validating clients and the set of training clients coincide, as in this case the verdict about the global model could be communicated directly, along with the local model-update. Namely, in round $r$ each selected client $C_i$ starts with validating model $G = G^{r+1}$; if the model passes validation, $C_i$ proceeds with training $G$ to derive a local
The literature features several data-poisoning attacks on ML models [3], [14], [16], [18], [20], [27], [28], [30], [31], where the attacker manipulates the training data so that the model learns some attacker-chosen task. In contrast to data-poisoning attacks, **model poisoning** allows the attacker to manipulate the model (or part of it) directly. Federated learning is particularly vulnerable to model-poisoning, as demonstrated by the pioneering work of Bagdasaryan et al. [1] and follow-up work by Bhagoji et al. [2]. Both attacks aim at injecting a semantic backdoor into the global model (cf. Section 3.2). Sun et al. [29] conduct an empirical study of semantic-backdoor attacks on FL, under a weaker system model letting honest clients train with correctly-labeled data which present the backdoor feature. Fang et al. [11] apply model poisoning in the context of untargeted attack on FL which, in contrast to trojan- or semantic-backdoor attacks (so-called targeted), aim at degrading the overall performance of the global model. They propose **local model-poisoning** attacks against Byzantine fault-tolerant federated learning, demonstrating vulnerabilities of various Byzantine-robust proposals [4], [4], [23], [35]. Our defense aims to protect against targeted attacks, therefore, we did not consider this attack in our evaluation. A more recent attack on FL is the **distributed backdoor attack (DBA)** by Xie et al. [33]. DBA is a trojan-type attack leveraging multiple compromised clients to submit updates which are poisoned with a “trigger portion” each, so that the global model is sensitive to the combination of those trigger portions, resulting in a more stealthy and persistent backdoor compared to “centralized” backdoor attacks [1]. Since our defense is designed against semantic-backdoor attacks, it is not clear whether it could also resist Xie et al.’s attack.

To remedy the vulnerabilities of FL against targeted poisoning, there are to the best of our knowledge currently only few proposals that aim to protect against poisoned updates, namely FoolsGold by Fung et al. [12], and the proposals by Li et al. [19]. FoolsGold can be bypassed by model-replacement [1]. The other two defenses use spectral anomaly-detection methods to suspect malicious clients’ updates, and are meant to defeat both targeted and untargeted attacks. Both strategies rely on distance or similarity metrics, i.e., comparing clients’ local updates and discarding those which look suspicious. For requiring inspection of each individual update, they are not compatible with secure aggregation. Our proposal instead aims at detecting poisoning attempts by analyzing the aggregated model, so that the privacy of clients is not hampered.

Other defensive strategies have been proposed to protect against compromised participants in the context of Byzantine fault-tolerant distributed learning [4], [23], [34]. All these proposals aim to ensure convergence of the model despite Byzantine participants, i.e., to prevent untargeted attacks, and are ineffective against backdoor attacks [1]. Further, being devised for a distributed learning scenario, these defenses rely on IID training data among the honest participants, an assumption which is clearly not met in federated learning. The proposal by Pillutla et al. [26] on Robust Federated Aggregation (RFA) seems to lift the approach of robust distributed learning to the FL scenario. However, for seeking robustness in the sense of Byzantine fault-tolerance, i.e., against compromised clients that wish to degrade the classification accuracy of the model, it is unclear if RFA can also offer protection against targeted attacks. Indeed, a successful backdoor attack implies robustness to adversarial samples, the latter being one of the biggest open problems in ML security research. This result indicates that protecting against backdoor attacks generically may be impossible.

6. Related Work

The literature features several data-poisoning attacks on ML models [3], [14], [16], [18], [20], [27], [28], [30], [31], where the attacker manipulates the training data so that the model learns some attacker-chosen task. In contrast to data-poisoning attacks, **model poisoning** allows the attacker to manipulate the model (or part of it) directly. Federated learning is particularly vulnerable to model-poisoning, as demonstrated by the pioneering work of Bagdasaryan et al. [1] and follow-up work by Bhagoji et al. [2]. Both attacks aim at injecting a semantic backdoor into the global model (cf. Section 3.2). Sun et al. [29] conduct an empirical study of semantic-backdoor attacks on FL, under a weaker system model letting honest clients train with correctly-labeled data which present the backdoor feature. Fang et al. [11] apply model poisoning in the context of untargeted attack on FL which, in contrast to trojan- or semantic-backdoor attacks (so-called targeted), aim at degrading the overall performance of the global model. They propose **local model-poisoning** attacks against Byzantine fault-tolerant federated learning, demonstrating vulnerabilities of various Byzantine-robust proposals [4], [4], [23], [35]. Our defense aims to protect against targeted attacks, therefore, we did not consider this attack in our evaluation. A more recent attack on FL is the **distributed backdoor attack (DBA)** by Xie et al. [33]. DBA is a trojan-type attack leveraging multiple compromised clients to submit updates which are poisoned with a “trigger portion” each, so that the global model is sensitive to the combination of those trigger portions, resulting in a more stealthy and persistent backdoor compared to “centralized” backdoor attacks [1]. Since our defense is designed against semantic-backdoor attacks, it is not clear whether it could also resist Xie et al.’s attack.

To remedy the vulnerabilities of FL against targeted poisoning, there are to the best of our knowledge currently only few proposals that aim to protect against poisoned updates, namely FoolsGold by Fung et al. [12], and the proposals by Li et al. [19]. FoolsGold can be bypassed by model-replacement [1]. The other two defenses use spectral anomaly-detection methods to suspect malicious clients’ updates, and are meant to defeat both targeted and untargeted attacks. Both strategies rely on distance or similarity metrics, i.e., comparing clients’ local updates and discarding those which look suspicious. For requiring inspection of each individual update, they are not compatible with secure aggregation. Our proposal instead aims at detecting poisoning attempts by analyzing the aggregated model, so that the privacy of clients is not hampered.

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7. Concluding Remarks

In this paper, we tackled the problem of securing federated learning against backdoor attacks. Our proposal, **BAFFLE**, consists of a round-based feedback loop engaging clients in the model-evaluation process. In each round, **BAFFLE** provides a verdict about the current global model $G'$, and depending on such verdict, the server
decides whether to accept the updates or to discard $G'$, thus invalidating the poisonous updates.

Our results show that BAFFLE can achieve a detection accuracy of 100% with a false-positive rate below 5%, on both CIFAR-10 and FEMNIST datasets. In particular, our defense reaches high detection accuracy even though the validation sets at the clients are relatively small; these results suggest that, in a real-world deployment, a feedback-based federated learning system could truly amplify the chances of detecting poisoning attempts. Moreover, our experiments show that BAFFLE is effective even when the detection method is enabled late, as the global model stabilizes, and even if there were backdoor injections before, indicating a good level of robustness to early poisoning.

We designed our proposals to leverage clients’ private data as a source of unpredictability for the defense, so that it is harder for an attacker to adapt its strategy for avoiding detection. Our results confirm this intuition and strongly suggest that crafting adaptive attacks might be harder in the federated setting, when compared to the standard machine learning setting. The reason for operating on the global model directly, rather than on individual updates, is to ensure that the privacy of clients is not harmed due to inspecting local updates. Our design choice conservatively favors “being safe” over “making progress”, as for the sake of preserving privacy, it may lead to discarding some of the honest contributions (i.e., the local updates of benign clients). As far as we are aware, BAFFLE is the first defense against semantic-backdoor attacks in Federated Learning that is compatible with secure aggregation of updates—and hence supports the privacy of clients’ data.

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