Federated Unlearning: How to Efficiently Erase a Client in FL?

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Abstract

With privacy legislation empowering the users with the right to be forgotten, it has become essential to make a model amenable for forgetting some of its training data. However, existing unlearning methods in the machine learning context cannot be directly applied in the context of distributed settings like federated learning due to the differences in learning protocol and the presence of multiple actors. In this paper, we tackle the problem of federated unlearning for the case of erasing a client by removing the influence of their entire local data from the trained global model. To erase a client, we propose to first perform local unlearning at the client to be erased, and then use the locally unlearned model as the initialization to run very few rounds of federated learning between the server and the remaining clients to obtain the unlearned global model. We empirically evaluate our unlearning method by employing multiple performance measures on three datasets, and demonstrate that our unlearning method achieves comparable performance as the gold standard unlearning method of federated retraining from scratch, while being significantly efficient. Unlike prior works, our unlearning method neither requires global access to the data used for training nor the history of the parameter updates to be stored by the server or any of the clients.

1. Introduction

Modern machine learning is increasingly using large-size deep neural networks trained on massive datasets. While large model sizes and massive datasets have improved models performance, privacy implications have risen since large models tend to memorize aspects of their training data (Carlini et al., 2021; Lehman et al., 2021; Carlini et al., 2023). Such privacy implications make it challenging to meet privacy regulations (Voigt & Von dem Bussche, 2017; Pardau, 2018; Act, 2000), which provide to data owners the right to be forgotten. Due to these privacy requirements, the field of machine unlearning has recently received significant research attention (Nguyen et al., 2022; Xu et al., 2023).

Machine unlearning, in a nutshell, removes the influence of specific training samples from a trained model, while maintaining the performance of the model. The problem of machine unlearning is even more challenging in the distributed paradigm of federated learning (FL), which allows multiple clients to jointly train a shared model while keeping their data on-premise (McMahan et al., 2017). Machine unlearning techniques developed for the centralized setting, e.g., (Graves et al., 2020; Bourtoule et al., 2021; Guo et al., 2019) can not be directly applied in the FL setting due to its distributed nature, where all the participating clients contribute to learn the final global model. A naive way of implementing federated unlearning is to retrain the model from scratch after removing from the corresponding client(s) the data sample(s) that are requested to be deleted. Retraining from scratch can be considered as the gold standard for unlearning, as it can ensure exact unlearning (Bourtoule et al., 2021; Liu et al., 2021). However, it incurs prohibitively large communication and computation costs, making it infeasible in real-world FL settings.

In this paper, we tackle the problem of federated unlearning for the case when one of the clients wants to opt out of federation, and wants to remove the influence of their entire local data from the trained global model. We consider the so-called cross-silo or enterprise setting, wherein clients are different organizations (e.g., hospitals or banks) with strict privacy regulations (Kairouz et al., 2021). We focus on erasing a single client because the cross-silo setup typically consists of a small number of clients and each client possesses significantly large amounts of data.

While there are a few works (Liu et al., 2021; Wu et al., 2022; Wang et al., 2022; Liu et al., 2022) on federated unlearning, they either consider different setups than ours (e.g., unlearning an entire class or category) and/or require the server to store updates from each client in every round. In practical FL systems, client updates are only held ephemerally at the server because storing client updates at the server...
may have serious privacy implications due to potential leakage from model updates (Kairouz et al., 2021). Therefore, our goal is to design a federated unlearning method that does not require the server or clients to store any client updates or even global updates. See Section 2 for a detailed comparison to prior works.

3. Background on Federated Learning

Federated Learning. Unlearning in the FL setup has received relatively scant research attention, unlike the centralized setup. Liu et al. (2021); Wu et al. (2022) consider a similar setup as ours, focusing on removing the contribution of a client after FL training. However, both these works require the server to store the updates from each client in every round. Storing model updates at the server may not be feasible in several application scenarios, especially with strict privacy regulations. In contrast, our method does not require the server or clients to store any client update or global update. In addition, (Wu et al., 2022) requires the server to possess some extra outsourced unlabeled data, which may not be realistic in several applications. Different from these works (and the one we propose), Wang et al. (2022) propose an unlearning framework to forget a particular category or class. Liu et al. (2022) consider a setup where several clients want to erase small subset of their data, which is different from our setup. Further, their guarantees hold only for convex loss functions and their techniques require each client to compute an (approximate) inverse Hessian matrix which is computationally costly. In contrast, our unlearning techniques can be applied to non-convex objectives without substantial computational overhead.
in which clients are different organizations (e.g., banks or hospitals) (Kairouz et al., 2021). In this setting, the number of clients is often smaller, all the clients participate in each round, and every client possesses substantially large amount of data.

4. Unlearning a Client

4.1. Federated Unlearning Setup

We consider the following unlearning scenario in the FL setting. After FL training is performed with $N$ clients for the specified $T$ rounds, (Figure 1(a)), a client $i \in [N]$ requests to opt out of federation and wants to remove the influence of their entire local data from the FL model. We refer to this client as the target client. We focus on approximate unlearning with the goal of obtaining a performance close to retraining.

Approximate unlearning relies on the fact that randomness in training induces a probability distribution over the models in the parameter space. At a high level, approximate unlearning ensures that the distribution of the unlearned model is either stochastically indistinguishable from the distribution of the retrained model, where stochastic indistinguishability is typically characterized by using notions similar to differential privacy (Guo et al., 2019; Sekhari et al., 2021; Warnecke et al., 2023). It is possible to formalize theoretical notions of approximate federated unlearning, similar to those in the centralized setting.

While such theoretical notions allow for designing certified unlearning algorithms, such algorithms are typically restricted to models with convex loss functions (Guo et al., 2019; Sekhari et al., 2021; Warnecke et al., 2023). On the other hand, practical FL systems often involve deep neural networks, which have non-convex loss (Kairouz et al., 2021). Therefore, we focus on the empirical evaluation of unlearning. In particular, we evaluate the unlearning algorithm by its efficacy, fidelity, and efficiency (see Section 5 for details).

4.2. Unlearning with Projected Gradient Descent

As discussed in Section 3, let $w^T$ denote the global model after performing FL training for $T$ rounds. We propose to perform federated unlearning in two phases: (i) the target client $i$ performs local unlearning by essentially reversing the learning process, (Figure 1(b)), and (ii) the server and the retained clients start with the locally unlearned model, and perform a few rounds of federated learning to boost its performance (Figure 1(c)). We now describe in detail both these phases.

**Local Unlearning:** We argue that a natural idea for a client to unlearn their data is to reverse this learning process. That is, during unlearning, instead of learning model parameters that minimize the empirical loss, the client strives to learn the model parameters to maximize the loss. Indeed, prior works (Graves et al., 2020; Golatkar et al., 2020a; Warnecke et al., 2023; Jang et al., 2023) have applied gradient ascent (or its variants) to find a model with large empirical loss. However, these works restrict their attention to the case of unlearning only a handful (even just one) samples, whereas our focus is on unlearning the entire client dataset, which is typically large for the enterprise or cross-silo FL. In such cases, naïvely applying gradient ascent to maximize the loss does not work because typical loss functions in practice are unbounded (e.g., cross-entropy loss). For an unbounded loss, each gradient ascent step moves towards a model that increases the loss, and after several steps, it is likely to produce an arbitrary model similar to a random model. Thus, we formulate unlearning at the target client as a constrained optimization problem and propose to solve it using projected gradient descent.

To motivate our formulation, let us establish some notation for the federated training phase. In each round, the goal of a client is to learn a local model that minimizes the (local) empirical risk, i.e., to solve the following problem:

$$(\text{Train}) \min_{w \in \mathbb{R}^d} F_i(w) := \frac{1}{n_i} \sum_{j \in D_i} L(w; (x_j, y_j)),$$  \hspace{1cm} (1)

where $L(w; (x_j, y_j))$ is the loss of the prediction on example $(x_j, y_j)$ made with model parameters $w$. Each client locally makes several passes of (mini-batch stochastic) gradient descent to find a model that has low empirical loss. (It is also possible to use other optimization algorithms, e.g., Adam.)

During unlearning, we propose to ensure that the unlearned model is sufficiently close to a reference model that has effectively learned the other clients’ data distributions. In particular, we propose to use the average of the other clients’ models as a reference model, i.e., $w_{\text{ref}} = \frac{1}{N-1} \sum_{j \neq i} w_j^{T-1}$.

Note that the target client $i$ can compute this reference model locally as $w_{\text{ref}} = \frac{1}{N-1} (Nw^T - w_i^{T-1})$, where $w^T$ is the global FL model after $T$ rounds and $w_i^{T-1}$ is the $i$-th client’s local model update in round $T-1$. The client $i$ then optimizes over the model parameters that lie in the $\ell_2$-norm ball of radius $\delta$ around $w_{\text{ref}}$. (The radius $\delta$ will be treated as a hyperparameter in our experiments.) Thus, during unlearning, the client solves the following optimization problem:

$$(\text{Unlearn}) \max_{w \in \{v \in \mathbb{R}^d : \|v - w_{\text{ref}}\|_2 \leq \delta\}} F_i(w),$$  \hspace{1cm} (2)

where $F_i(\cdot)$ is defined in eq. (1).

A natural choice for solving (2) is to use projected gradient descent. More specifically, let us denote the $\ell_2$-norm ball of radius $\delta$ around $w_{\text{ref}}$ as $\Omega = \{v \in \mathbb{R}^d : \|v - w_{\text{ref}}\|_2 \leq \delta\}$.

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At a high level, a successful federated unlearning method we demonstrate empirically in Section 5 that performing we perform early stopping if the $\ell_2$-distance of the target client $w_i^{T-1}$ to the unlearned model $w_i^u$ is smaller than a predetermined threshold $\tau$ (which is treated as a hyper-parameter). Algorithm 1 describes the local unlearning procedure, and Appendix 1 provides a schematic.

**FL post-training.** To improve the performance of the locally unlearned model on the data of the retained clients, the server and the remaining clients perform a few steps of federated learning starting with the unlearned model $w_i^u$. The detailed steps are described in Algorithm 1. Interestingly, we demonstrate empirically in Section 5 that performing very few rounds of FL post-training on the unlearned model $w_i^u$ gives good performance in practice.

### 5. Evaluation

**Unlearning Scenarios:** We consider two scenarios to illustrate the phenomenon of unlearning: (i) removing the effect of backdoor triggers and (ii) removing the effect of flipping. At a high level, a successful federated unlearning method should produce a model that does not perform well on the target client’s data distribution while keeping good performance on the other clients’ data distribution. The goal in the above mentioned scenarios is to deliberately differentiate the target client’s data distribution from the data distribution of the other clients.

**Performance Measures:** In general, an effective federated unlearning method must remove the contribution of the target client’s data, maintain good performance, and be more efficient than retraining from scratch. To reflect these properties in our evaluation, we use three performance measures (similar to Warnecke et al. (2023)).

**Efficacy of unlearning.** The efficacy of an unlearning method measures how successful it is in removing the contribution of the target client’s data. We quantify the efficacy of unlearning by evaluating the performance of the unlearned model on the target client’s data distribution. In particular, we use the following two metrics to measure efficacy: (i) accuracy on the target client’s data distribution: depending on the scenario this will be accuracy on a hold-out test set of backdoored or flipped images; and (ii) membership inference risk with respect to the target client’s dataset.

**Fidelity of unlearning.** The fidelity of an unlearning method measures whether it can maintain a performance close to the original model. We quantify the fidelity of unlearning by evaluating the performance of the unlearned model on the retained clients’ data distribution. In particular, we use the accuracy of the unlearned model on a hold-out test set of clean images to measure fidelity.

**Efficiency of unlearning.** While it is straightforward to perform unlearning by retraining the FL model from scratch without the participation of the target client, such retraining incurs significant communication and computation costs. The efficiency of an unlearning method measures the reduction in communication and computation costs wrt. retraining. We evaluate the efficiency of the proposed unlearning method by comparing its communication cost with that of retraining. We focus on the communication cost since it is known to be a key bottleneck in FL (Kairouz et al., 2021).

**Datasets and Model Architecture:** To evaluate the performance of the proposed method, we utilize three datasets: MNIST (Lecun et al., 1998), EMNIST (balanced version) (Cohen et al., 2017), and CIFAR-10 (Krizhevsky et al., 2009). For all datasets, we use a CNN from (McMahan et al., 2017) with two $5 \times 5$ convolution layers, a fully connected layer with 512 units and ReLu activation, and a final softmax output layer (1, 663, 370 total parameters). We equally partition the training images of each dataset across $N$ clients in the FL process, one of which is the target client. We detail
Algorithm 1 Federated Unlearning

Local Unlearning at Client $i$ via Projected Gradient Descent:

Inputs: learning rate $\eta_i$, batch size $B_i$, number of epochs $E_u$, clipping radius $\delta$, and early stopping threshold $\tau$

Set $w_{\text{ref}} \leftarrow \frac{1}{N-1} \left( N w^T - w_j^{T-1} \right) = \frac{1}{N-1} \sum_{j \neq i} w_j^{T-1}$

Define $P(w)$ as the projection of $w \in \mathbb{R}^d$ onto the $\ell_2$-norm ball $\Omega = \{ v \in \mathbb{R}^d : \| v - w_{\text{ref}} \|_2 \leq \delta \}$

Initialize unlearning model as $w \leftarrow w_{\text{ref}}$

$B_i \leftarrow$ (split $D_i$ into batches of size $B_u$)

for each local epoch $e = 1$ to $E_u$

for each client $j \in [N] \setminus \{i\}$ in parallel do

$w^t_j \leftarrow \text{ClientUpdate}(j, w^{t-1})$

end for

$w^t \leftarrow \sum_j \frac{n_j}{\sum_i n_i} w^t_j$

end for

Set the unlearned model as $w^u_i \leftarrow w^T$ to server

ClientUpdate($j$, $w^{t-1}$):

$B_j \leftarrow$ (split $D_j$ into batches of size $B_p$)

Initialize $w \leftarrow w^{t-1}$

for each local epoch $e = 1$ to $E_p$

for each client $j \in [N]$ \setminus \{i\}$ in parallel do

$w \leftarrow w - \eta_p \nabla F_j(w; b)$

end for

end for

Return $w$ to the server

FL post-training:

Inputs: learning rate $\eta_p$, batch size $B_p$, number of epochs $E_p$, number of rounds $T_p$

Server executes

Initialize $w^0 \leftarrow w^u_i$

for each round $t = 1$ to $T_p$

Send $w^{t-1}$ to clients $\{i\}$

for each client $j \in [N] \setminus \{i\}$ in parallel do

$w_j^t \leftarrow \text{ClientUpdate}(j, w^{t-1})$

end for

$w^t \leftarrow \sum_j \frac{n_j}{\sum_i n_i} w^t_j$

end for

Set the learned model as $w^u \leftarrow w^T$ to server

the hyperparameters used for FL training and unlearning in Appendix A.

5.1. Unlearning Scenario 1: Backdoors

We use the backdoor triggers (Gu et al., 2017) as an effective way to evaluate the performance of unlearning methods, similar to Wu et al. (2022). In particular, the target client uses a dataset in which a certain fraction of images has a backdoor trigger inserted in them. Because of this client, the global FL model becomes susceptible to the backdoor trigger. Then, a successful unlearning process should produce a model that reduces the accuracy of the images with the backdoor trigger, while maintaining high accuracy on clean images. For backdoors, we introduce a ‘pixel pattern’ trigger of size $3 \times 3$ using the Adversarial Robustness Toolbox (Nicola et al., 2018), and change the label of corresponding samples to ‘9’ for MNIST, to ‘1’ for EMNIST, and to ‘truck’ for CIFAR-10. When inserting the backdoor trigger, we exclude the data sample whose label is already the target label. We consider two cases: (i) $N = 5$ clients with the target client having 66% of their images backdoored, and (ii) $N = 10$ clients with the target client having 80% of their images backdoored. We compare our proposed unlearning method to retraining from scratch.

Efficacy evaluation: We analyze the efficacy of the unlearning method using two metrics. First, we evaluate the accuracy on a hold-out test set of backdoored images. We compute the accuracy on the backdoored data (referred as the backdoor accuracy) as the percentage of triggered data that are misclassified as the target label required by the attacker. The lower the backdoor accuracy, the better the model has unlearned the contribution of the target client’s data. Figure 2 shows the backdoor accuracy of each model for each dataset for both cases. For both cases and all datasets, the high value of backdoor accuracy for the FedAvg model indicates that the FL model has learned the target client’s data consisting of backdoor triggers. We observe that our proposed PGD-based unlearning method substantially reduces the backdoor accuracy, and in fact, achieves similar backdoor accuracy to retraining for all datasets. This demonstrates that the efficacy of our method in terms of backdoor accuracy is comparable to that of retraining.

Another metric that we use to measure the efficacy of the proposed unlearning method is the membership inference risk. The goal of a membership inference attack is to determine whether a specific data sample is part of the dataset used to train the model. We leverage membership inference attacks to assess how much information from the target client’s data is part of the unlearned model, similar to Liu et al. (2021). A successful unlearning process should produce a model that has a low membership inference risk on the data of the target client. To measure the membership inference risk, we use two well-known membership inference attacks: Shokri et al. (2017), which uses the idea of training shadow models; and Yeom et al. (2018), which uses training and test time loss values. A description of the attacks is provided in Appendix B.

For the evaluation, we perform the attacks against the PGD-based unlearned model (after one round of post-training), the fully retrained model, and the FedAvg model (the global
model obtained by FL before any unlearning). For simplicity, in Shokri’s attack, we use the FedAvg model as the shadow model. We compute the attack accuracy as the percentage of the target client’s data that are inferred as being part of the training dataset. Figure 3 shows the accuracy of the membership inference attacks for \( N = 5 \) clients. We observe that both unlearning methods achieve substantially lower membership inference attack accuracies than the one in the FedAvg model for all datasets and both attacks. In fact, for both attacks, the proposed unlearning approach obtains similar accuracy to retraining, which demonstrates the high efficacy of our method.

**Fidelity evaluation:** We evaluate the fidelity of our unlearning method by computing the accuracy of the unlearned model on a hold-out test set that consists of clean images (no backdoor triggers). We refer to the accuracy computed on the clean images as clean accuracy. Note that the clean images represent the data distribution of the retained clients, and the clean accuracy indicates whether the unlearned model can maintain good performance on the retained data. In Figure 4, we show the clean accuracy of the unlearned models obtained by our method and retraining. We observe that our PGD-based unlearning method achieves similar clean accuracy to retraining, demonstrating the capability of our method for unlearning with high fidelity.

**Efficiency evaluation:** To evaluate the efficiency of our method we compare its communication cost with retraining. We compute the communication cost of a given approach as the total size of the model updates (in MB) that clients participating in the FL process communicate to the server. Figure 5 shows the communication cost for various clean accuracy (fidelity) values for \( N = 5 \) clients. We observe that the proposed unlearning method is significantly more efficient than retraining while achieving similar fidelity. For instance, in the MNIST dataset, to reach a fidelity (clean accuracy) of 98.13\%, our method requires 167 MB of communication cost, whereas retraining from scratch requires 453 MB. Thus, our method is \( 2.7 \times \) more efficient in terms of communication costs than retraining. This gap is even higher for the EMNIST and CIFAR-10 datasets. Overall, we observe that our proposed unlearning method reduces communication costs by up to \( 24 \times \).

To compare the speedup of the proposed method to the baseline of retraining, we compute the clean and backdoor accuracy of both methods with respect to the number of FL training rounds. Note that, for our method, the FL train-
Figure 4. Backdoor Scenario: Clean accuracy of the fully retrained and the PGD-based unlearned model in each dataset. The clean accuracy of the PGD-based unlearned model is obtained after 5 rounds of FL post-training. Our unlearning method achieves similar clean accuracy to retraining, which demonstrates its high fidelity.

Figure 5. Backdoor Scenario: Communication costs (efficiency) of the proposed unlearning method and the baseline approach of retraining with respect to the clean accuracy (fidelity) in each dataset for $N = 5$ clients.

Figure 6. Clean accuracy (fidelity) and backdoor accuracy (efficacy) of the PGD-based unlearned and fully retrained model with respect to the number of rounds in each dataset for $N = 5$ clients.

unlearning produces an effective starting point by removing the influence of the target client’s data without degrading the performance on the other clients’ data.

5.2. Unlearning Scenario 2: Flipped Images

In this scenario, we consider a target client that has a dataset where a certain fraction of images are flipped. We do not apply any data augmentation on any clients’ datasets. A successful unlearning method should reduce the accuracy on the flipped images while maintaining high accuracy on
regular images. For evaluation, we consider two cases: (i) \( N = 5 \) clients with the target client having 66% of their images flipped and (ii) \( N = 10 \) clients with the target client having 80% of their images flipped. We flip the images horizontally and keep the label unchanged. Note that for this unlearning scenario, we do not provide the results for the CIFAR-10 dataset for the following reason. The accuracy of retraining on a hold-out test set of flipped images for \( N = 5 \) is 71.14%. This value is similar to the accuracy on a hold-out test set of regular images (no flipping applied), making CIFAR-10 an inappropriate dataset for this scenario.

**Efficacy evaluation:** To analyze the efficacy of the unlearning methods, we use the accuracy on a hold-out test set of flipped images (referred as the flipped accuracy). In Figure 7, we show the flipped accuracy of the FedAvg, fully retrained, and the PGD-based unlearned models in the MNIST and EMNIST datasets for both cases. We observe that the proposed unlearning method achieves a similar flipped accuracy to retraining. These results show that our PGD-based unlearning method has comparable efficacy to retraining for removing the contribution of the target client’s data.

![Figure 7](image)

**Figure 7.** Flipped accuracy of the FedAvg (before unlearning), fully retrained, and PGD-based unlearned models in the MNIST and EMNIST datasets. The flipped accuracy of the PGD-based unlearned model is obtained after 5 rounds of FL post-training. Our method substantially reduces the flipped accuracy compared to the FedAvg model and achieves similar performance as retraining, which demonstrates its high unlearning efficacy.

**Fidelity evaluation:** To evaluate the fidelity of the unlearning methods, we examine the accuracy between the proposed unlearning method and the baseline approach on a hold-out test set of regular images (no flipping applied). For consistency, we refer to the accuracy on regular images as the clean accuracy. Figure 8 shows the clean accuracy of the fully retrained and PGD-based unlearned models in each dataset for both cases. We observe that our method maintains a high clean accuracy, which is similar to the baseline approach of retraining. Since the clean images represent the data distribution of the retained clients, the high clean accuracy of our method indicates that it can perform unlearning with high fidelity by maintaining good performance on the retained data.

**Efficiency evaluation:** We compare the communication cost of a given method as the total size of the model updates (in MB) that clients send to the server. Figure 9 shows the communication cost for various fidelity (clean accuracy) values for \( N = 5 \) clients. In the MNIST dataset, to achieve a clean accuracy of 98.13%, our method requires 566 MB of communication costs, while retraining requires 1039 MB. Thus, our proposed approach is 1.8× more efficient than the baseline approach. We obtain similar gains for the EMNIST dataset. Overall, we observe that the proposed unlearning algorithm is up to 5.8× more efficient than retraining from scratch. In Appendix D, we provide further evaluation of our method with respect to the number of training rounds.

Overall, for both unlearning scenarios, we observe that the proposed unlearning method is more efficient in terms of the communication cost on the retained clients than retraining, while achieving comparable fidelity and efficacy. It is worth noting that, even though we do not explicitly measure computation costs, our method also reduces the computation cost as compared to retraining since it requires much fewer rounds than retraining to achieve high performance on the retained data. We believe that lowering the communication and computation burden on retained clients is appealing in practice since these clients are not incentivized to help the target client in unlearning.

![Figure 8](image)

**Figure 8.** Flipping Scenario: Clean accuracy (fidelity) of the fully retrained and the PGD-based unlearned models in the MNIST and EMNIST datasets. The clean accuracy of the PGD-based unlearned model is obtained after 5 rounds of FL post-training.

![Figure 9](image)

**Figure 9.** Flipping Scenario: Communication costs (efficiency) of the proposed unlearning method and fully retraining with respect to the clean accuracy (fidelity) in the MNIST and EMNIST dataset for \( N = 5 \) clients.
6. Conclusion

We proposed a novel federated unlearning method that can efficiently unlearn the contribution of any client. Our method first performs local unlearning at the client to be erased and, starting with the locally unlearned model, performs a few rounds of FL with the server and remaining clients. Unlike prior federated unlearning works, our method does not require the server (or any other client) to keep track of the history of their parameter updates. We have used the backdoor triggers and flipping to effectively evaluate the performance of the proposed method. We empirically demonstrated the efficacy, fidelity, and efficiency of the proposed unlearning method.

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A. Details on Hyperparameters

During FL training, we use the SGD optimizer with the following hyperparameters:

- Momentum $\beta = 0.9$
- Learning rate $\eta = 0.01$
- Batch size $B = 128$
- Number of epochs $E = 1$
- Aggregation algorithm: FedAvg (described in Section 3)

For PGD-based unlearning, we use the SGD optimizer with the following hyperparameters:

- Momentum $\beta = 0.9$
- Learning rate $\eta_u = 0.01$
- Batch size $B_u = 1024$
- Number of epochs $E_u = 5$
- $\ell_2$-norm ball radius $\delta$ is set to be one third of the average Euclidean distance between $w_{ref}$ and a random model, where the average is computed over 10 random models. This value is selected because we want the model to stay closer to the reference model than a random model.
- Early stopping threshold $\tau$: Computed via a grid search over the interval $[2, 6]$
- Gradient $\ell_2$-clipping is employed with radius 5

For FL post-training after unlearning, we use the SGD optimizer with the following hyperparameters:

- Momentum $\beta = 0.9$
- Learning rate $\eta_p = 0.01$
- Batch size $B_p = 128$
- FL rounds $T_p$: see Figure 5 in Section 5.1, Appendices C, and D
- Aggregation algorithm: FedAvg

**Schematic overview of local unlearning**

Local unlearning at the client is formulated as a constrained optimization problem where given a trained model and the data to be removed, the algorithm obtains an updated model in the vicinity of the original model which exhibits poor performance on the deleted data. The neighborhood is modelled as an $\ell_2$-norm ball of radius $\delta$ around $w_{ref}$ as shown in Figure 10. In an FL setting, a natural choice of such a $w_{ref}$ can be obtained by removing the appropriately scaled last update from the current global model. The algorithm proceeds by taking gradient steps in the direction that maximizes the empirical loss on its local data using Projected Gradient Descent (PGD), which is represented by the red arrows in Figure 10. By constraining the parameters to remain within the feasible region of this optimization problem, the algorithm ensures the retention of performance with respect to other clients. The choice of $\ell_2$-norm ball for this feasible set is also consistent with the observations in (Thudi et al., 2021) which argue the use of Euclidean distance on model parameters for unlearning verification. The combined choice of $\delta$ and $w_{ref}$ can be used to balance the performance trade-off between deleted and retained clients. As we noted in our experiments, even with a slight compromise in clean accuracy (retention) $w^u_i$ quickly recovers after a few steps of FL post-training (second phase in Algorithm 1).

B. Membership Inference Attacks

In this section, we briefly describe Shokri’s attack and Yeom’s attack.

**Shokri’s attack** Shokri et al. (2017) were the first to propose a membership inference attack on machine learning (ML) models. Let $M$ be the target model trained on dataset $D$. The main intuition of the attack is that ML models tend to behave differently on the training data compared to the data that they have not seen. It is assumed that the attacker knows the type and the architecture of the model $M$ and has access to some data $D_S$ that comes from the same underlying distribution as training data $D$. Thus, the attacker can train multiple shadow models $M_{S_i}$ (one per class) that mimic the behavior of the
target model. For the shadow models, the attacker has their training and test datasets and thus knows the ground-truth of the membership of the training and test data samples. Based on this, the attacker trains multiple attack models $M_{A_i}$ (one per class) by using as input the posteriors returned by the corresponding shadow model and as labels their membership. Finally, when the attacker wants to determine the membership of a target data sample, they query the target model $M$, obtain its posterior probability, and with that query the corresponding attack model $M_{A_i}$ to obtain the membership prediction.

**Yeom’s attack** Yeom et al. (2018) assume that the attacker has white-box access to the target model $M$ and knows its average training loss. To determine the membership of a target data sample, the attacker computes the loss of the model $M$ on the input data sample and compares this value to the average training loss of the model $M$. If the loss of the target data sample is smaller than the average training loss, then it is classified as a member, otherwise as a non-member.

**C. Efficiency Evaluation in Backdoors**

In Figure 5 (in Section 5.1), we showed the comparison of the clean accuracy (fidelity) and backdoor accuracy (efficacy) of the proposed PGD-based unlearning method to the gold standard (retraining from scratch) with respect to the number of FL training rounds for $N = 5$ clients. Here, in Figure 11, we show this comparison for $N = 10$ clients. Note that, for our method, the FL training starts with the locally unlearned model that the target client has obtained using the projected gradient descent (as discussed in Section 4.2), while for the baseline of retraining, the FL training starts with a randomly initialized model. We observe that local unlearning at the target client bootstraps the unlearning process, and requires substantially fewer number of FL rounds than retraining from scratch. For instance, after one round of post-training, the proposed method reaches a clean accuracy of 96.6% and a backdoor accuracy of 12.35% in the MNIST dataset. The baseline method requires more than 5 FL rounds to achieve similar performance, showing the efficiency of the proposed unlearning method.

**D. Efficiency Evaluation in Flipping**

In Figures 12 and 13, we show the clean accuracy (fidelity) and flipped accuracy (efficacy) of our method and the fully FL retraining (gold standard) with respect to the number of FL training rounds (FL post-training rounds for the proposed method) for $N = 5$ and $N = 10$ clients, respectively. We observe that local unlearning at the target client bootstraps the unlearning process, and requires substantially fewer number of FL rounds than retraining from scratch. For example, for $N = 10$ in the MNIST dataset, the proposed unlearning method achieves a clean accuracy of 95.47% and a flipped accuracy of 55.57% after one round of post-training, while the baseline method requires more than 10 FL rounds to achieve similar performance. These results show the efficiency of the proposed unlearning method.
Figure 11. Backdoor Scenario: Clean accuracy (fidelity) and backdoor accuracy (efficacy) of the proposed unlearning method and full FL retraining from scratch with respect to the number of rounds in each dataset for $N = 10$ clients.

Figure 12. Flipping Scenario: Clean accuracy (fidelity) and flipped accuracy (efficacy) of the proposed unlearning method and full FL retraining from scratch with respect to the number of rounds in the MNIST and EMNIST datasets for $N = 5$ clients.

Figure 13. Flipping Scenario: Clean accuracy (fidelity) and flipped accuracy (efficacy) of the proposed unlearning method and full FL retraining from scratch with respect to the number of rounds in the MNIST and EMNIST datasets for $N = 10$ clients.