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# Backdoor Attacks on Federated Meta-Learning

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## Abstract

Federated learning allows multiple users to collaboratively train a shared classification model while preserving data privacy. This approach, where model updates are aggregated by a central server, was shown to be vulnerable to *backdoor attacks*: a malicious user can alter the shared model to arbitrarily classify specific inputs from a given class. In this paper, we analyze the effects of backdoor attacks in federated *meta-learning*, where users train a model that can be adapted to different sets of output classes using only a few training examples. While the ability to adapt could, in principle, make federated learning more robust to backdoor attacks when new training examples are benign, we find that even 1-shot poisoning attacks can be very successful and persist after additional training. To address these vulnerabilities, we propose a defense mechanism inspired by *matching networks*, where the class of an input is predicted from the cosine similarity of its features with a *support set* of labeled examples. By removing the decision logic from the model shared with the federation, success and persistence of backdoor attacks are greatly reduced.

## 1 Introduction

*Federated learning* [1] allows multiple users to collaboratively train a shared prediction model without sharing their private data. Similarly to the *parameter server* architecture, model updates computed locally by each user (e.g., weight gradients in a neural network) are aggregated by a server that applies them and sends the updated model to the federation. User datasets are never shared, while the aggregation of multiple updates makes it difficult for an attacker in the federation to reconstruct training examples of another user. Additional privacy threats have also been addressed in federated learning: for example, secure aggregation techniques have been proposed where users send encrypted updates that the server applies to an encrypted model [2, 3].

While the use of data from multiple users allows for improved prediction accuracy with respect to models trained separately, federated learning has been shown to be vulnerable to *backdoor attacks*: a member of the federation can send model updates produced using malicious training examples where the output class indicates the presence of a hidden *backdoor key*, rather than benign input features. This kind of attack can be successful even after a single malicious update, and it is difficult to detect in practice because (1) the attacker can introduce the backdoor in the model with minimal accuracy reduction in the main classification task, and (2) malicious updates can be masked within the distribution of benign ones [4, 5, 6].

Another limitation of federated learning is due to the requirement that all users share the same output classes (e.g., the outputs of a neural network and their associated labels) and that, for each class, the distribution of input examples of different users be similar. Recent approaches to *gradient-based meta-learning* [7, 8, 9] provide a compelling alternative for federated scenarios: rather than training a model for a specific set of output classes, these methods try to learn model parameters that can be adapted very quickly to new classification tasks (with entirely different output classes) using only a few training examples (or “shots”). Meta-learning also allows users with different data distributions to jointly train a meta-model that they can adapt to their specific tasks. For example, in federated face recognition, each user trains a model using classification tasks from a distinct dataset (e.g., images of friends and relatives), but all users share the goal of training a meta-model to recognize human faces.

While the use of meta-learning in a federated setting and its privacy concerns were explored by previous work [10, 11], the influence of backdoor attacks on federated *meta-learning* has not been investigated. Since meta-models have the ability to adapt to new classification tasks very quickly, it is unclear whether a backdoor attack can succeed and persist despite many users sharing *benign* updates of the meta-model, or after fine-tuning the meta-model for a specific task with *benign* data.

This paper investigates backdoor attacks on federated meta-learning with the following contributions.

(1) We design a set of experiments to illustrate the effects of this kind of attack under different scenarios. Our experimental results, presented in Section 4, show that backdoor attacks (triggering intentional misclassification) can be *successful even after a single malicious update* from the attacker: in our Omniglot experiment, 80% of backdoor examples are misclassified after a single poisoned update, regardless of whether they are from attacker’s training set or from a separate validation set, while meta-testing accuracy is reduced by only 1%; in our mini-ImageNet experiment, 75% of backdoor training examples and 50% of backdoor validation examples are misclassified after a single update, with 10% reduction of meta-testing accuracy. Moreover, *the effects of the attack are persistent*, despite long meta-training after the attack (using only benign examples), or after fine-tuning of the meta-model by a benign user. After many rounds of benign *meta-training* on Omniglot, 50% of backdoor examples are still misclassified as the attack target, in both training and validation datasets; on mini-ImageNet, success rates of the attack are reduced only from 75% to 70% (training) and from 50% to 43% (validation). On both datasets, extensive *fine-tuning* of the meta-model by a benign user reduces the attack success rate by less than 5%; we also show that simply increasing the learning rate during fine-tuning reduces the success rate of the backdoor attack (from 80% to as low as 20%), but also degrades meta-testing accuracy dramatically (from 99% to as low as 40%).

(2) As an effective defense mechanism, we propose (in Section 5) a sanitizing fine-tuning process inspired by *matching networks* [7], where the class of an input is predicted from the cosine similarity of its weighted features with a *support set* of examples for each class. By locally training and controlling the importance of extracted features for each class, our proposed defense mechanism can reduce the success rate of backdoor attacks, from as high as 90% to less than 20% (Omniglot training/validation and mini-ImageNet training) and from 50% to 20% (mini-ImageNet validation) in just a few iterations. In *contrast with other defense mechanisms* for federated learning [12, 13, 14, 15, 16, 17, 18, 19, 20, 21], our method does not require any third-party to examine user updates, and it is thus compatible with secure update aggregation methods. In addition, we make no assumptions about the distribution of training data at different users or the required fraction of benign users, thus *enabling the safe application of federated learning to a broader set of scenarios*.

## 2 Federated Meta-Learning

Federated learning among  $M$  users proceeds in rounds: at each round  $t$ , the parameter server randomly selects  $M_{round} \leq M$  users and transmits the shared model  $\theta_G^t$  (e.g., the neural network weights). Each selected user  $i$  initializes the local model  $\theta_i^t$  to  $\theta_G^t$ , performs  $E$  training steps, and then transmits the model update  $\delta_i^t = \theta_i^t - \theta_G^t$  to the parameter server. As soon as  $M_{min}$  of the  $M_{round}$  updates are received, the parameter server applies them to obtain the model for the next round as  $\theta_G^{t+1} = \theta_G^t + \sum_{i=1}^{M_{min}} \alpha_i \delta_i^t$ , where  $\alpha_i = |\mathcal{D}_i| / \sum_{j=1}^{M_{min}} |\mathcal{D}_j|$  can be used to give more importance to the updates  $\delta_i^t$  of user  $i$  with a large dataset size  $|\mathcal{D}_i|$ , if dataset sizes are known [1].

In federated *meta-learning*, training steps performed by each user on  $\theta_i^t$  are designed to improve how well the model can be *adapted to new classification tasks* (with different output classes), instead of improving its accuracy on a fixed task (with the same output classes for training and testing).

While second-order derivatives are needed to account for changes of gradients computed during the adaptation phase, first-order approximations have been proposed, including FOMAML [8] and *Reptile* [9]. In this paper, we adopt *Reptile* for  $K$ -shot,  $N$ -way meta-training: user  $i$  samples  $B$  episodes (a *meta-batch*), each with a random set of  $N$  output classes and  $K$  training examples for each class. For each episode  $j = 1, \dots, B$  in the meta-batch, the  $N \times K$  training examples are used to obtain a new model  $\theta_i^{t,j}$  from  $\theta_i^t$  through  $e$  stochastic gradient descent (SGD) steps (with *inner* batch size  $b$  and learning rate  $\eta$ ). Finally, the models obtained in each episode are averaged to update  $\theta_i^t$  locally as  $\theta_i^t = (1 - \epsilon)\theta_i^t + \frac{\epsilon}{B} \sum_{j=1}^B \theta_i^{t,j}$  for some *outer* learning rate  $\epsilon$ .

To test a model after many rounds of  $K$ -shot,  $N$ -way federated meta-training, the user generates new episodes, each with  $N$  output classes never used during meta-training and  $K + 1$  examples for each class; for each episode, the shared model  $\theta_G^t$  is fine-tuned with a few SGD steps on the first  $K$  examples of each class and tested on the  $N$  held-out examples.

### 3 Backdoors in Federated Meta-Learning

We consider backdoor attacks on federated meta-learning carried out by a malicious user through *data poisoning* [22, 23, 5, 4]. The goal of the attacker is to introduce a persistent change in the shared model  $\theta_G$  such that, when a user fine-tunes  $\theta_G$  on a new classification task, examples of a *backdoor class* are classified as instances of a *target class*. The attacker participates in the federation, applying the same meta-learning algorithm (*Reptile*) but using a poisoned dataset where examples from the backdoor class are labeled as the target class.

For the attack to succeed, the target class must be present in the classification task of the user under attack, and images of the backdoor class must be used as inputs. Since classes are different in each meta-learning episode, the attacker can use multiple target and backdoor classes to increase success. For example, in a face recognition problem, the attacker could collect online images  $\mathcal{X}_T$  of a friend (the target class) of a member of the federation, and images  $\mathcal{X}_B$  of a few impostors (the backdoor classes): in the training dataset of the attacker, examples of backdoor classes have the same label as images of a target class, so that the model will learn to classify impostors as the targets.

To ensure that the attack goes unnoticed, the attacker should also include valid data during training, so that the trained meta-model performs well on inputs that are not backdoor or target examples. In particular, to generate an episode for  $K$ -shot,  $N$ -way meta-training, the attacker could pick  $N - 1$  random classes and always include the target class as the  $N$ -th model output: some of the  $K$  examples of the target class are selected from  $\mathcal{X}_T$ , while others are selected from  $\mathcal{X}_B$ . For *attack-pattern backdoors*, the attacker can also add a special visual feature to the backdoor images  $\mathcal{X}_B$ , as a key to trigger the attack [23, 22].

Similarly to poisoning attacks in federated learning [4], after many meta-training steps on the local model  $\theta_a^t$ , the attacker sends a “boosted” update to the parameter server:  $\delta_a^t = \lambda(\theta_a^t - \theta_G^t)$ , where  $\lambda$  is the *boosting factor* (used to make this update prevail over those of other users).

### 4 Effects of Backdoor Attacks

In this section, we explore the effects of backdoor attacks on federated meta-learning using two datasets, *Omniglot* [24] and *mini-ImageNet* [7, 25].

**Attack Evaluation.** We consider a federation of  $M = 4$  users, where user  $i = 1$  is the attacker and users  $i = 2, 3, 4$  are benign; at each round, the server selects 3 users and waits for all of their updates ( $M_{\min} = 3$ ). The meta-model is initially trained only by benign users, reaching state-of-the-art accuracy; then, the attacker is selected *exactly once* (one-shot attack) and the poisoned update is boosted with  $\lambda = 3$ . To evaluate the effectiveness of the attack, we generate  $K$ -shot,  $N$ -way episodes from meta-training classes that always include the target class (with benign examples): after each fine-tuning iteration, we measure accuracy on testing examples of the episode (*main-task accuracy*), as well as the percentage of poisoned backdoor examples that are labeled with the target class (*backdoor accuracy*); we separately evaluate backdoor accuracy on examples used by the attacker during training (*attack training*) and on new examples (*attack validation*). We also evaluate *meta-testing accuracy* on classes that were not used during meta-training. Reported accuracy is averaged over 40 episodes.



Figure 1: Backdoor attack on Omniglot: (a) target class, (b) backdoor classes, (c) attack pattern, (d) attack training set



Figure 2: Backdoor attack on mini-ImageNet: (a) target class (arctic fox), (b) backdoor class (yawl), (c) attack pattern, (d) attack training set

**Omniglot.** This dataset consists of 1623 character classes from 50 alphabets, with 20 examples per class. Similarly to previous work [9, 8, 26], we resize images to  $28 \times 28$  and augment classes  $4\times$  through rotations by multiples of  $90^\circ$ : we use 1200 classes for meta-training (split among the 4 users) and 418 for meta-testing; for each meta-training class, we hold out 5 examples for validation. We reserve 4 backdoor classes and 1 target class (Fig. 1a-b) for the attack: 10 examples of each of these backdoor/target classes are assigned to benign clients for training, while 5 are edited to add a backdoor key (Fig. 1c-d) and used by the attacker (labeled as the target class).

**mini-ImageNet.** This dataset consists of 100 classes, each with 600 examples ( $84 \times 84$  color images). We use 64 classes for meta-training (split among 4 users) and 20 classes for meta-testing (as in [25]); for each meta-training class, we hold out 20 examples for validation. We also reserve 1 backdoor class and 1 target class (Fig. 2a-b) for the attack: 480 examples of each of these classes are split among benign clients for meta-training, while 100 are used by the attacker as benign training examples. As attack and validation sets, we use additional 100 and 50 ImageNet examples, respectively, and add a backdoor key as illustrated in Fig. 2c-d.

Note that we favor benign clients by assigning more examples to them; nonetheless (as shown later) a backdoor attack can still be successful in federated meta-learning and benign clients are unable to remove the backdoor with local fine-tuning.

**Training Parameters.** All users run *Reptile* on the same Conv4 model as in [8, 9], a stack of 4 modules (3x3 Conv filters with batchnorm and ReLU) followed by a fully-connected and a softmax layer; the modules have 64 filters and  $2\times 2$  max-pooling. We adopt the same parameters as [9]: 5-shot, 5-way meta-learning, and  $E = 1000$  episodes of 10-shot, 5-way (Omniglot) or  $E = 100$  episodes of 15-shot, 5-way (mini-ImageNet) meta-training per round at each user, with meta-batch size  $B = 5$  and outer learning rate  $\epsilon = 0.1$ ; for each episode, we use  $e = 10$  (meta-training) or  $e = 50$  (meta-testing) SGD steps, with inner batch size  $b = 10$  and Adam optimizer ( $\beta_1 = 0$ ,  $\beta_2 = 0.999$ , initial learning rate  $\eta = 0.001$ ). For the attacker, we use longer training with  $E = 50000$  and 50 inner epochs (Omniglot), or  $E = 150000$  and 1 inner epoch (mini-ImageNet); backdoor and target examples  $\mathcal{X}_B$  and  $\mathcal{X}_T$  are always included by the attacker with 2:3 (Omniglot) or 1:2 (mini-ImageNet) ratio.

In our first set of experiments, benign users continue *federated meta-training* after the attack.

**Experiment 1(a).** First, we consider the case where the initial meta-training by benign users do not include correctly-labeled examples of backdoor classes. Results are illustrated in Fig. 3a (Omniglot) and Fig. 4a (mini-ImageNet): before the attack (Round 0) meta-testing accuracy (black line) is above 99% (Omniglot) or 60% (mini-ImageNet); the attacker is selected at Round 1; then at Round 2 the accuracy of the attack (classification of backdoor images as target class) reaches 78% and 74% on attacker’s training dataset (blue line) and 77% and 55% on the held-out validation set (green line) for Omniglot and mini-ImageNet, respectively, while meta-testing accuracy on other classes remains above 98% (Omniglot) and drops to 50% (mini-ImageNet). Even at Round 50 for Omniglot and Round 100 for mini-ImageNet, after additional federated meta-training only by benign users, backdoor accuracy is still high (50% on both attack training and validation sets for Omniglot; 68% on the attack training set and 48% on the validation set for mini-ImageNet).

**Experiment 1(b).** Next, we consider the case where meta-training datasets of benign users include correctly-labeled images of backdoor classes during pre-training, so that the model can adapt to correctly classify them before the attack. The results are illustrated in Fig. 3b for Omniglot and Fig. 4b for mini-ImageNet: meta-testing accuracy is still above 98% and  $\approx 50\%$  for Omniglot and mini-ImageNet after the attack, attack accuracy is close to 92% and 76% on the attacker’s training dataset,

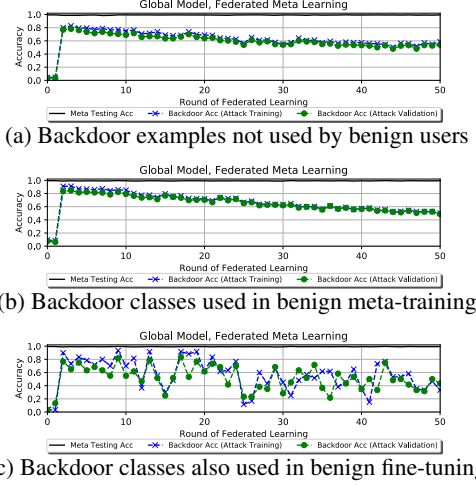


Figure 3: Benign meta-training after attacks on Omniglot

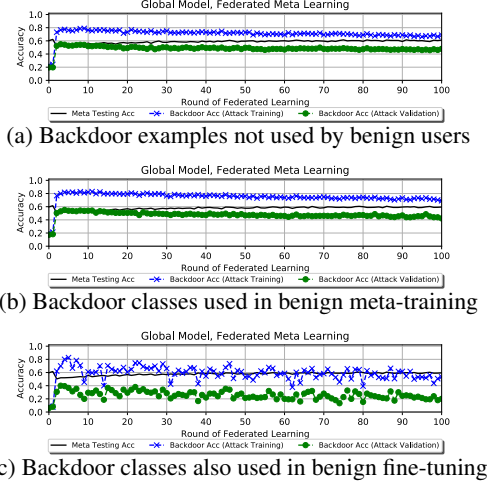


Figure 4: Benign meta-training after attacks on mini-ImageNet

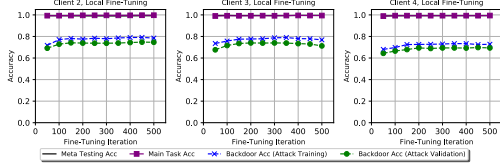
and 83% and 50% on the held-out validation set for Omniglot and mini-ImageNet, respectively; after 50 additional rounds for Omniglot, we still have 50% attack accuracy for both attack training and validation sets and 69% and 42% (respectively) for mini-ImageNet after 100 additional rounds.

**Experiment 1(c).** Finally, we investigate the case where backdoor classes are present, with correct labels, also during fine-tuning; this is particularly important to study the persistence of backdoors in meta-learning, since fine-tuning adapts the trained meta-model to these examples. The results are illustrated in Figs. 3c and 4c: immediately after the attack (Round 2), for Omniglot and mini-ImageNet, meta-testing accuracy is still greater than 98% and 50%, respectively; the attack training (validation) accuracy is close to 90% (62%) and 80% (32%), respectively, as before; however, after additional meta-training by benign users, attack accuracy varies and degrades noticeably: since backdoor examples are present in these additional meta-training rounds and fine-tuning iterations with correct labels, the ability to correctly classify backdoor classes gradually improves.

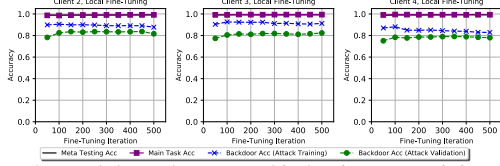
From these experiments, we observe that backdoor attacks on federated meta-learning are (1) more successful on the attack training set (especially for mini-ImageNet), since (as expected) these examples have been used by the attacker during model poisoning, (2) similarly successful when benign users use correctly-labeled backdoor images for meta-training, and (3) considerably less successful when fine-tuning also includes correctly-labeled backdoor images. Irrespective of whether correctly-labeled backdoor classes are present in the datasets of benign users, a one-shot backdoor attack can affect the meta-model after tens of rounds of additional meta-training. To completely remove the attack’s effects, *hundreds* of rounds of benign meta-training may be required without ever selecting the attacker (which is unlikely, especially when multiple attackers are present). Therefore, *it does not appear possible to rely only on additional meta-training to remove backdoor attacks.*

In our next set of experiments, we explore the effects of *additional fine-tuning* during each episode; given the ability of meta-models to quickly adapt to new classification tasks, we are interested in whether this additional fine-tuning can remove the poisoning attack from the model. Therefore, we stop meta-training after the one-shot attack (Round 2) and start fine-tuning the meta-model at each benign user  $i = 2, 3, 4$  using only examples with correct labels.

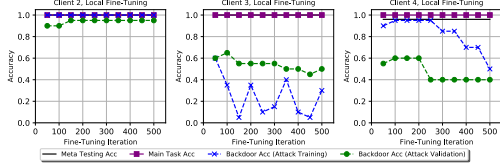
**Experiment 2.** First, we explore the effects of additional supervised fine-tuning with the same learning rate  $\eta = 0.001$ . Fig. 5 (Omniglot) and Fig. 6 (mini-ImageNet) depict results where each column corresponds to a different user and each row considers different scenarios for the use of backdoor classes by benign users ((a) not used, (b) used only during pre-training, (c) used also during fine-tuning); we run  $e = 500$  iterations of fine-tuning,  $10\times$  more than meta-testing. We observe that fine-tuning is also unsuccessful at removing the attack: for Omniglot, both main-task accuracy (purple line) and meta-testing accuracy (black line) are above 99% for all users. Backdoor accuracy is above 80% for all users when backdoor classes are not present during fine-tuning (Figs. 5a and 5b); when backdoor classes are present (Fig. 5c), attack accuracy remains high for client 2, while it decreases on both training and validation backdoor examples for clients 3 and 4. This difference is likely due to



(a) Backdoor examples not used by benign users

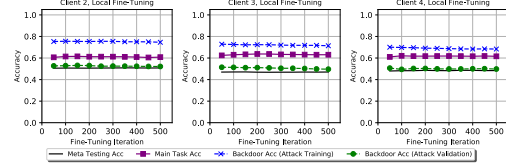


(b) Backdoor classes used in benign pre-training

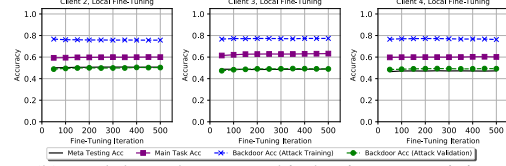


(c) Backdoor classes used also in benign fine-tuning

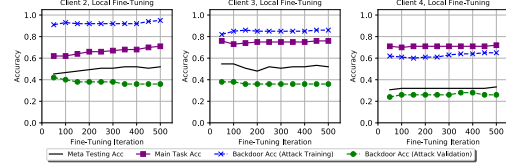
Figure 5: Benign fine-tuning ( $\eta = 0.001$ ) after attacks on Omniglot



(a) Backdoor examples not used by benign users

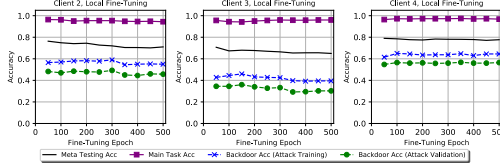


(b) Backdoor classes used in benign pre-training

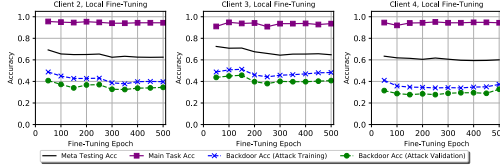


(c) Backdoor classes used also in benign fine-tuning

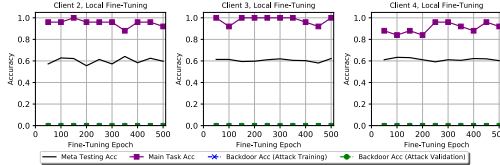
Figure 6: Benign fine-tuning ( $\eta = 0.001$ ) after attacks on mini-ImageNet



(a) Backdoor examples not used by benign users

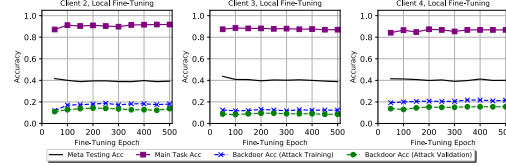


(b) Backdoor classes used in benign pre-training

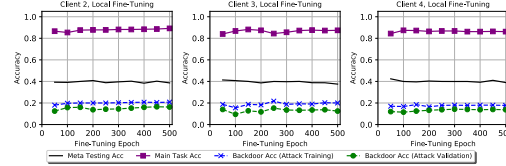


(c) Backdoor classes used also in benign fine-tuning

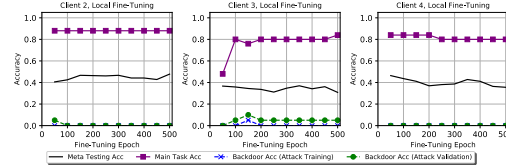
Figure 7: Benign fine-tuning ( $\eta = 0.01$ ) after attacks on Omniglot



(a) Backdoor examples not used by benign users



(b) Backdoor classes used in benign pre-training



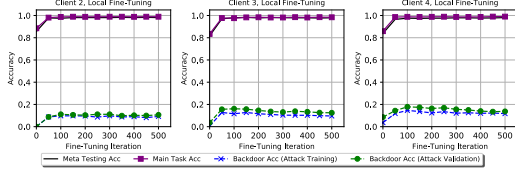
(c) Backdoor classes used also in benign fine-tuning

Figure 8: Benign fine-tuning ( $\eta = 0.05$ ) after attacks on Omniglot

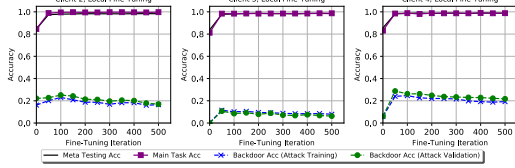
how examples are distributed among users. For mini-ImageNet when backdoor classes are not present during fine-tuning (Figs. 6a and 6b), accuracy is  $\approx 60\%$  (main-task) and  $\approx 50\%$  (meta-testing) for all users. Backdoor accuracy for all users is  $\approx 75\%$  (attack training) and  $50\%$  (attack validation); when backdoor classes are present (Fig. 6c), accuracy is  $\approx 70\%$  (main-task) and  $\approx 50\%$  (meta-testing, clients 2 and 3) and less than  $40\%$  (meta-testing, client 4).

**Experiment 3.** Finally, we explore the influence of the learning rate  $\eta$  during fine-tuning, to check whether backdoor accuracy can be reduced with higher learning rates. While Fig. 5 used  $\eta = 0.001$  as in [9], we repeat the Omniglot experiments for  $\eta = 0.01$  and  $\eta = 0.05$ ; the results, reported in Figs. 7 and 8, respectively, show that a *larger fine-tuning learning rate reduces not only backdoor accuracy, but also main-task and meta-testing accuracy*. When backdoor classes are not present

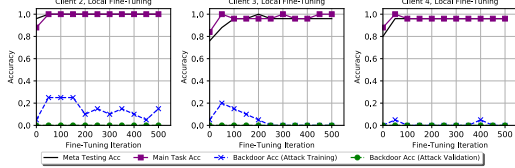




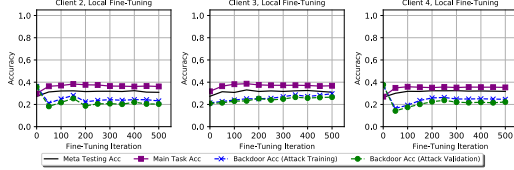
(a) Backdoor examples not used by benign users



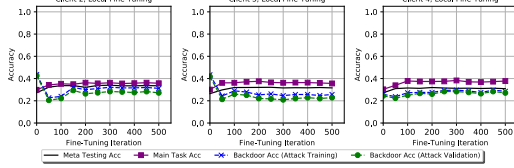
(b) Backdoor classes used in benign pre-training



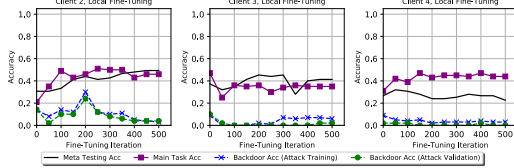
(c) Backdoor classes used also in benign fine-tuning



(a) Backdoor examples not used by benign users



(b) Backdoor classes used in benign pre-training



(c) Backdoor classes used also in benign fine-tuning

Figure 9: Benign fine-tuning of matching networks ( $\eta = 0.001$ ) after attacks on Omniglot

during fine-tuning, attack accuracy drops from above 80% (Figs. 5a and 5b) to as low as 30% for  $\eta = 0.01$  (Figs. 7a and 7b) and as low as 20% (i.e., the accuracy of a random assignment) for  $\eta = 0.05$  (Figs. 8a and 8b). Meta-testing accuracy drops from 99% to  $\approx 65\%$  ( $\eta = 0.01$ ) or 40% ( $\eta = 0.05$ ), while main task accuracy drops from nearly 100% to 96-92% ( $\eta = 0.01$ ) and  $\approx 85\%$  ( $\eta = 0.05$ ). When backdoor classes are present during fine-tuning (Figs. 7c and 8c), attack accuracy is near 0% for  $\eta = 0.01$  and 0.05, while meta-testing accuracy drops from 99% (Fig. 5c) to 60% ( $\eta = 0.01$ ) or 40% ( $\eta = 0.05$ ), and main task accuracy drops from nearly 100% to 90-80%.

The experiments in this section showed that federated meta-training and supervised fine-tuning cannot remove even a one-shot backdoor attack by a single malicious user, without considerably reducing meta-testing accuracy. In the next section, we propose an alternative defense mechanism.

## 5 Matching Networks as a Defense Mechanism

While defense mechanisms from backdoor attacks have been proposed for federated learning based on the analysis of updates received from users, such approaches may violate privacy and are not compatible with secure update aggregation by the parameter server. We propose a defense mechanism *applied by each benign user*, without relying on the parameter server. The idea is inspired by *matching networks* [7], a popular meta-learning framework exploiting recent advances in attention mechanisms and external memories in neural networks.

A matching network uses the output of an embedding model  $f_\theta(x)$  to find similarities between input examples and reference examples from a *support set*. Specifically, given the trained model  $f_\theta(x)$  and a support set  $\mathcal{S} = \{(x_i, y_i)\}_{i=1}^k$ , class  $\hat{y} = \arg \max_{i=1, \dots, k} P(y_i | \hat{x}, \mathcal{S})$  is predicted where  $P(y_i | \hat{x}, \mathcal{S})$  estimates output probabilities for the input  $\hat{x}$ . A common model is  $\hat{y} = \sum_i a(\hat{x}, x_i) y_i$ , a mixture of one-hot output vectors  $y_i$  of the support set based on some *attention mechanism*  $a(\hat{x}, x_i)$  [27, 28, 29, 30]. For example,  $a(\hat{x}, x_i)$  can be a softmax over the cosine distance  $c(\cdot, \cdot)$  of the embeddings of  $\hat{x}$  and  $x_i$ , i.e.,  $a(\hat{x}, x_i) = e^{c(f_\theta(\hat{x}), f_\theta(x_i))} / (\sum_{j=1}^k e^{c(f_\theta(\hat{x}), f_\theta(x_j))})$ . More sophisticated forms have also been proposed for improved performance [7], [31].

During training, the parameters  $\theta$  of the embedding model  $f_\theta$  (e.g., a neural network without final classification layer) are updated to minimize the distance of the embeddings of training examples from those of examples with the same class in the support set. With external memories, matching networks can switch to a different classification task simply by using the embeddings of examples in the new support set, without supervised fine-tuning of  $f_\theta$ . An important characteristic of matching

networks is that the classification of an input is not entirely determined by the parametric model  $f_\theta$ , but also by the matching procedure comparing embeddings.

We adopt a variant of matching networks from [32] where (1) the output components of the embedding model  $f_\theta$  are multiplied by gate variables  $0 \leq \alpha_{l,j} \leq 1$ , and (2) cosine distances to reference examples of each class are multiplied by a scaling factor  $\beta_j$ . Our attention mechanism is thus a softmax over embedding distances  $c(\alpha_l \odot f_\theta(\hat{x}), f_\theta(x))\beta_l$ .

To fine-tune the meta-model  $\theta$  (trained in federated meta-learning) in each episode, we first apply a random Glorot initialization  $\theta_g$  as  $\theta' = \delta\theta + (1 - \delta)\theta_g$  (to reduce the influence of the attacker's update), then we train  $\alpha_l$  and  $\beta_l$  for a few iterations (with fixed  $\theta'$ ), and finally we train  $\theta'$ ,  $\alpha_l$  and  $\beta_l$  jointly (training is performed as in [7, Sec. 4.1]). We use  $\delta = 0.3$  and the same learning rate  $\eta = 0.001$  of backdoor experiments in Section 4. Note that this *fine-tuning is not necessary for matching networks but provides a defense against backdoor attacks*, as it allows our method to remove anomalies introduced in the embedding model  $f_\theta(x)$  by the attacker.

**Experiment 4.** Our results for Omniglot and mini-ImageNet are reported in Figs. 9 and 10, respectively, with a column for each client and three rows for the different scenarios with respect to the presence of backdoor classes in the datasets of benign users. Note that at epoch 0 the attack has occurred, but fine-tuning has not started. We observe that the proposed defense mechanism can successfully remove the backdoor attack: when backdoor classes are not present in evaluation tasks (Figs. 9a, 9b, 10a and 10b), attack accuracy drops to about 20% (comparable to random assignment to one of the 5 classes) in only a few epochs; when backdoor classes are present in evaluation tasks (Fig. 9c), attack accuracy significantly drops to near 0% in a few epochs of fine-tuning (almost all backdoor examples are correctly recognized as their corresponding true classes). Notably, meta-testing accuracy for Omniglot (black line) in Fig. 9 is always above 96% after 50 iterations, much higher than for supervised fine-tuning using large learning rates  $\eta$  (Figs. 7 and 8).

In contrast, we observe that meta-testing accuracy for mini-ImageNet is lower for matching networks, reaching  $\approx 35\%$  in Figs. 10a and 10b, and 40% in Fig. 10c in most cases, in contrast to  $\approx 50\%$  accuracy of Fig. 6 in most cases. This may suggest a limitation of the classification mechanism of matching networks; other variants of matching networks, or models with non-parametric classification mechanisms such as Prototypical Networks [31] (computing distances to prototype representations of each class) and Relation Networks [33] (reasoning about relations among objects), could overcome this limitation. We expect future work exploring these ideas to be fruitful.

## 6 Related Work

Poisoning backdoor attacks [23, 22] were shown to be effective on various kinds of machine learning models. [5] and [4] further investigated attacks in the context of federated supervised learning and illustrated the effectiveness and stealthiness of these attacks. Given the requirement that users of federated learning share only updates of the model instead of training data [1], techniques certifying that training examples are correctly classified [34, 35] are not applicable in this context, and thus defense remains a challenging problem. Several defense mechanisms have been proposed: [14] and [15] estimated the distribution of the training data to suppress the influence of outliers assuming that training datasets of different users are i.i.d. The same assumption was made in [12, 13, 19, 16, 17, 20, 21], where outliers were detected and removed according to slightly different measures taken from the distribution of benign values (benign users were assumed to be the majority). Even when benign users send i.i.d. updates to the parameter server, [5, 4, 6] presented successful backdoor attacks circumventing the defenses above. To the best of our knowledge, effects and defenses from poisoning backdoor attacks in federated *meta-learning* have not been explored in the literature. *Our proposed method does not require i.i.d. updates from different users, nor analysis of updates by the parameter server.*

## 7 Conclusions

In this work, we showed that a one-shot poisoning backdoor attack in federated meta-learning can be very successful and persist after additional meta-learning or long fine-tuning by benign users. Moreover, the attack can be successful also on backdoor examples that were not used by the attacker to prepare the poisoned update. We presented a method to defend from poisoning attacks based on



the idea of matching networks, which is compatible with privacy-friendly aggregation mechanisms at the parameter server and effective in eliminating backdoor effects, while sacrificing some accuracy with respect to classification mechanisms based on a fully-connected neural network layer. Our future efforts will focus on overcoming this limitation.

## Broader Impact

The context for this paper is Federated Learning (FL), a framework designed to allow users with insufficient but confidential data to jointly train machine learning models while preserving privacy. For example, a single hospital, clinic, or public health agency may not have sufficient data to train powerful machine learning models providing doctors with diagnostic aid (e.g., for medical images such as X-rays or fMRI images): FL allows multiple of these entities to jointly train more accurate machine learning models without sharing patients’ private data. Unfortunately, FL is known to be vulnerable to poisoning backdoor attacks, where a malicious user of the federation can control the decisions of the model trained jointly with benign users. In the context of diagnostic medical aid, backdoor attacks to FL could mislead doctors into making incorrect diagnoses, with life threatening risks; similarly, consequences of backdoor attacks could be disastrous for many applications in healthcare, transportation, finance. Although defense mechanisms have been proposed in the literature, state-of-the-art solutions against poisoning backdoor attacks rely on *third parties to examine user updates to the model*, violating the fundamental *privacy* motivation of FL. We believe that an effective *user-end defense mechanism* can guard against backdoor attacks while preventing unexpected abuse due to privacy leaks. Thus the broader impact of our proposed approach is that it can prevent attacks on machine learning models that are developed jointly by multiple entities as well as privacy-related abuse. Allowing multiple entities to jointly develop machine learning models is critical to the broader impact of machine learning applications in settings (e.g., healthcare) where data is scarce and sensitive.

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## Appendix

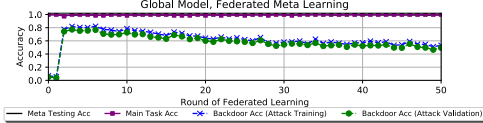
In the appendix, we provide additional experimental details and results, including:

- Main-task accuracy for benign meta-training after attacks.
- Benign fine-tuning of matching networks after attacks with different values of  $\delta$ .
- Benign (supervised) fine-tuning after attacks with  $\delta = 0.3$ .
- Extra benign *local meta-training* before benign fine-tuning (supervised/matching networks) after attacks for  $\delta = 0.3$ .
- Experimental setup and run time.

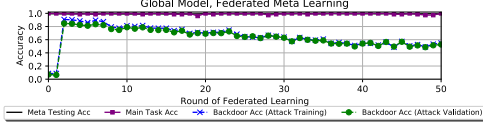
## A Additional Experimental Results

### A.1 Main task accuracy for benign meta-training after attacks

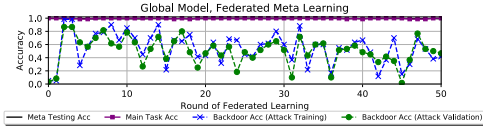
For benign meta-training after the attacks (Figs. 3 and 4), we did not report main-task accuracy to declutter the presentation, since accuracy on the test examples in unseen classes (meta-testing accuracy) is more relevant to the purpose of federated meta-training. For completeness, we provide main-task accuracy for benign meta-training after poisoning backdoor attacks in Figs. A1 and A2 for Omniglot and mini-ImageNet experiments, respectively, which could be a useful indication of how successful a backdoor attack might be, for a specific dataset.



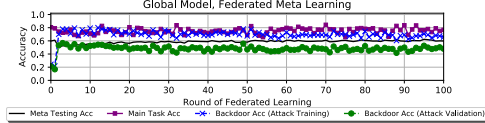
(a) Backdoor examples not used by benign users



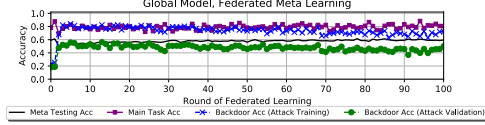
(b) Backdoor classes used in benign meta-training



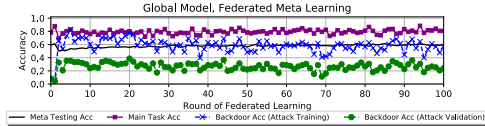
(c) Backdoor classes also used in benign fine-tuning



(a) Backdoor examples not used by benign users



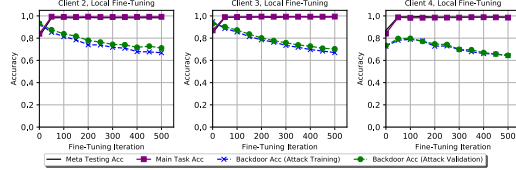
(b) Backdoor classes used in benign meta-training



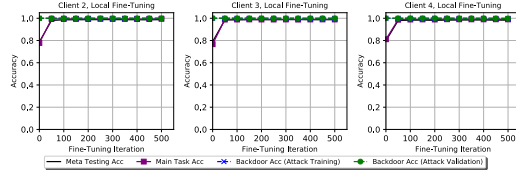
(c) Backdoor classes also used in benign fine-tuning

Figure A1: Benign meta-training after attacks on Omniglot

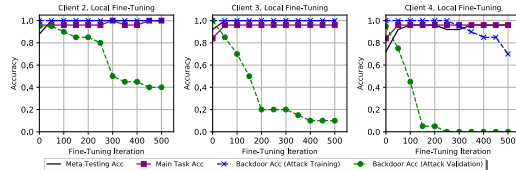
Figure A2: Benign meta-training after attacks on mini-ImageNet



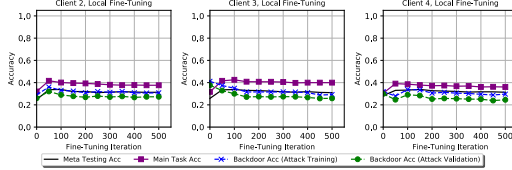
(a) Backdoor examples not used by benign users



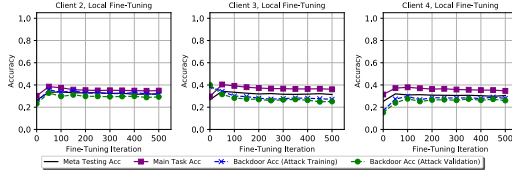
(b) Backdoor classes used in benign pre-training



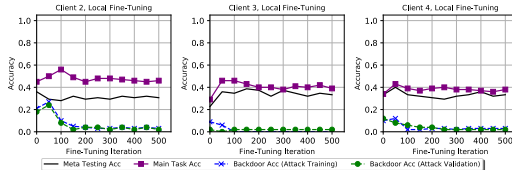
(c) Backdoor classes used also in benign fine-tuning



(a) Backdoor examples not used by benign users



(b) Backdoor classes used in benign pre-training



(c) Backdoor classes used also in benign fine-tuning

Figure A3: Benign fine-tuning of matching net-works ( $\eta = 0.001, \delta = 0.6$ ) after attacks on Omniglot

Figure A4: Benign fine-tuning of matching net-works ( $\eta = 0.001, \delta = 0.6$ ) after attacks on mini-ImageNet

## A.2 Benign fine-tuning of matching networks with different $\delta$

In the paper, we demonstrate results of benign fine-tuning of matching networks for  $\delta = 0.3$ .

In Fig. A3 and Fig. A4, we report results of matching networks fine-tuning with  $\delta = 0.6$  for Omniglot and mini-ImageNet, respectively (larger  $\delta$  implies less randomness). Effects of backdoor attacks can still be removed effectively in mini-ImageNet (Fig. A4): main-task accuracy and meta-testing accuracy are similar to the case of  $\delta = 0.3$  (Fig. 10, or Fig. A7 for a different set of 40 episodes). However, effects of backdoor attacks cannot be removed in Omniglot with  $\delta = 0.6$ ; results for Omniglot with smaller values of  $\delta$  (0.4 and 0.2) are also reported in Fig. A5 and Fig. A6, respectively, for reference.

As expected, introducing more randomness (appropriately) can remove backdoor effects more effectively; however, introducing too much randomness can damage both main task accuracy and

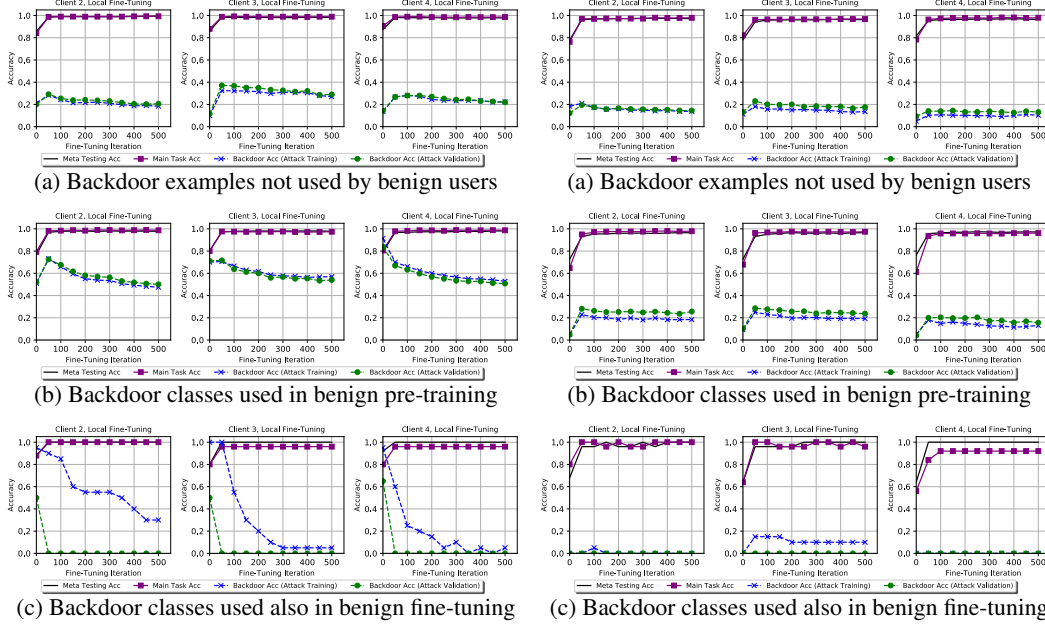


Figure A5: Benign fine-tuning of matching net-works ( $\eta = 0.001, \delta = 0.4$ ) after attacks on Omniglot

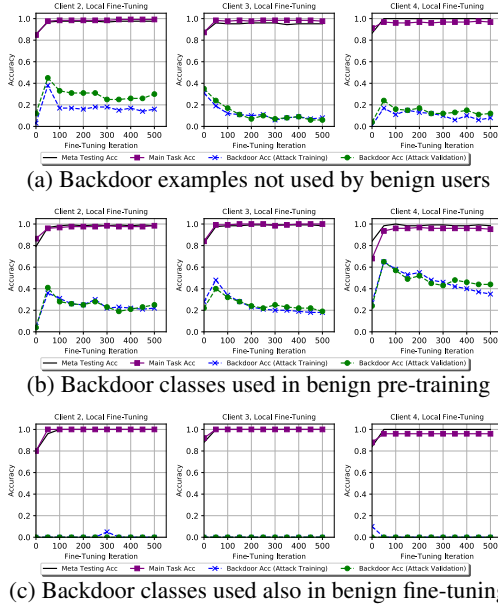


Figure A6: Benign fine-tuning of matching networks ( $\eta = 0.001, \delta = 0.2$ ) after attacks on Omniglot (different set of 40 episodes)

meta-testing accuracy due to the dominance of noise. As shown in Figs. A6a and A6b, for  $\delta = 0.2$ , main-task accuracy and meta-testing accuracy are 3% lower than in Figs. A5a and A5b ( $\delta = 0.4$ ). In light of this, finding an appropriate value of  $\delta$  (or, equivalently, ratio between the norms of a trained model and an initialization) is an interesting problem and part of our future efforts.

### A.3 Benign (supervised) fine-tuning after attacks for $\delta = 0.3$

In the paper, we demonstrate results of benign (supervised) fine-tuning after attacks (Figs. 5 and 6, for Omniglot and mini-ImageNet, respectively). We also demonstrate results of benign fine-tuning

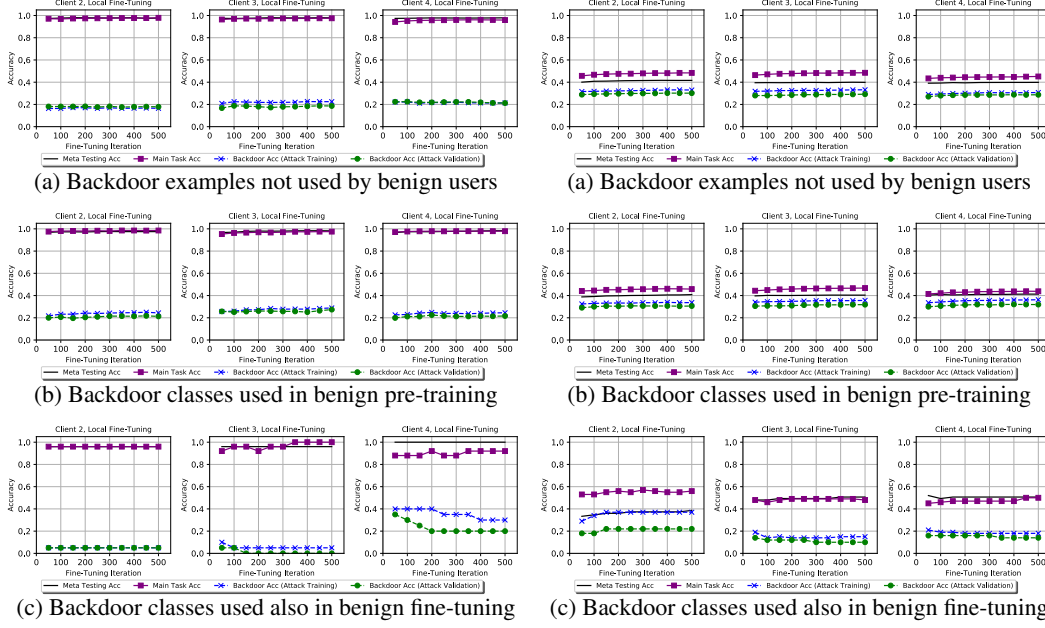


Figure A8: Benign fine-tuning ( $\eta = 0.001, \delta = 0.3$ ) after attacks on Omniglot

Figure A9: Benign fine-tuning ( $\eta = 0.001, \delta = 0.3$ ) after attacks on mini-ImageNet

of matching networks after attacks (Figs. 9 and 10), in which random initialization parameters are introduced ( $\delta = 0.3$ ). Here we demonstrate results of benign supervised fine-tuning after attacks *when random initialization parameters are introduced* ( $\delta = 0.3$  as well).

Results are reported in Fig. A8 and Fig. A9. For Omniglot (Fig. A8), supervised fine-tuning performs similarly to our proposed fine-tuning of matching networks (Fig. 9). For mini-ImageNet, supervised fine-tuning for cases (a) and (b) (Figs. A9a and A9b) also performs similarly to our proposed fine-tuning of matching networks (Figs. 10a and 10b), but for case (c), attack accuracy can only be reduced to 20% through supervised fine-tuning (Fig. A9c), while the use of matching networks (Fig. 10c) can reduce it to less than 5% (the initial attack accuracy before the backdoor attack, due to misclassification). This shows the effectiveness of our proposed fine-tuning of matching networks on removing effects of backdoor attacks, particularly when benign examples in backdoor classes are available during fine-tuning.

#### A.4 Extra benign local meta-training before benign fine-tuning (supervised/matching networks) after attacks for $\delta = 0.3$

In the previous sections, we have shown that proper randomness allows fine-tuning of matching networks to remove the effects of backdoor attacks. In this section, we evaluate whether running extra *local meta-training* based on local user data before fine-tuning can improve main-task accuracy and meta-testing accuracy in mini-ImageNet (where it is lower).

We report results after running 100 (Figs. A10 and A11) or 1000 (Figs. A12 and A13) episodes of additional local meta-training (Reptile) with mini-ImageNet before supervised fine-tuning or matching networks training. We note that: (i) results shown in Figs. A10 to A13 are not significantly different from the case without extra local meta-training (Fig. A9 for supervised fine-tuning, and Fig. 10 for fine-tuning of matching networks), suggesting that additional local meta-training does not improve main-task accuracy nor meta-testing accuracy; and (ii) supervised fine-tuning performs similarly to fine-tuning of matching networks, except for Fig. A10a, in which main-task accuracy and meta-testing accuracy drop to 20% (random guessing over 5 classes) at the beginning, with high attack accuracy thereafter. This suggests that, by applying random initialization parameters (with additional local training), supervised fine-tuning can behave arbitrarily and may not guarantee removal of backdoor attacks, while fine-tuning of matching networks performs in a more robust manner.

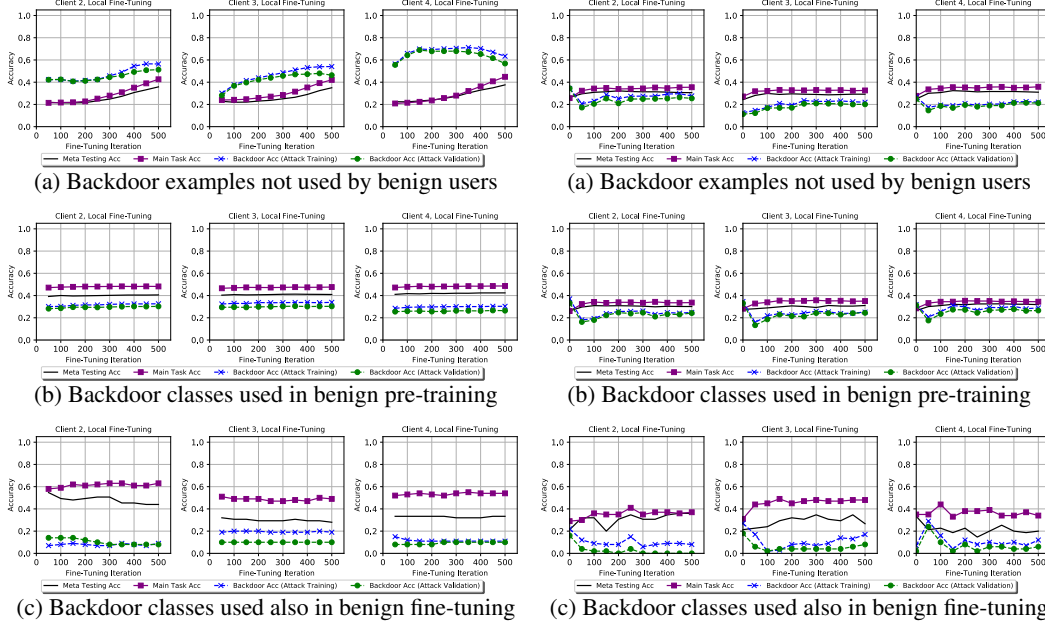


Figure A10: Benign local meta-training ( $\epsilon = 0.1$ , 100 episodes) and fine-tuning ( $\eta = 0.001$ ) after attacks on mini-ImageNet ( $\delta = 0.3$ )

Figure A11: Benign local meta-training ( $\epsilon = 0.1$ , 100 episodes) and fine-tuning of matching network ( $\eta = 0.001$ ) after attacks on mini-ImageNet ( $\delta = 0.3$ )

## B Experimental setup and run time

We implemented federated meta learning using TensorFlow [36] and Keras [37]. All experiments are performed using 5 virtual machines (VMs) on Google Compute Engine, including 1 federated-learning server and 4 federated-learning clients. Each client VM has 4 Intel Skylake (or later) CPUs and 1 Nvidia Tesla T4 GPU, with 26GB of RAM and Debian 9 OS with CUDA 10.0; each server VM has 1 Intel Skylake (or later) CPU, 3.5GB RAM, and the same version of OS and CUDA.

We report the run time of our code in the following table.

	Omniglot	mini-ImageNet
Pre-training (100k episodes)	$\approx 250$ mins	$\approx 250$ mins
Poisoning training (50k episodes with 50 inner epochs for Omniglot; 150k episodes with 1 inner epoch for mini-ImageNet)	$\approx 1250$ mins	$\approx 450$ mins
Benign fine-tuning (500 iterations; repeat for 40 tasks and present/absent of backdoor classes)	$\approx 130$ mins	$\approx 130$ mins
Benign meta-training after attack (50 rounds for Omniglot; 100 rounds for mini-ImageNet)	$\approx 80$ mins	$\approx 120$ mins



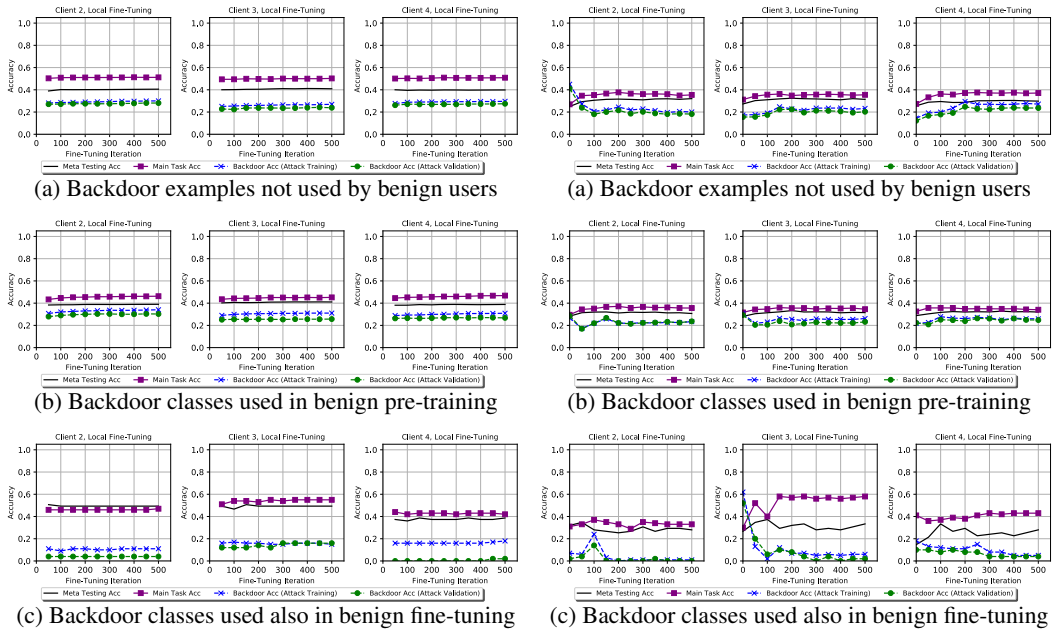


Figure A12: Benign local meta-training ( $\epsilon = 0.1$ , 1000 episodes) and fine-tuning ( $\eta = 0.001$ ) after attacks on mini-ImageNet ( $\delta = 0.3$ )

Figure A13: Benign local meta-training ( $\epsilon = 0.1$ , 1000 episodes) and fine-tuning of matching network ( $\eta = 0.001$ ) after attacks on mini-ImageNet ( $\delta = 0.3$ )