

Computation and Communication Efficient Federated Unlearning via On-server Gradient Conflict Mitigation and Expression

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Abstract

Federated Unlearning (FUL) aims to remove specific participants' data contributions from a trained Federated Learning model, thereby ensuring data privacy and compliance with regulatory requirements. Despite its potential, progress in FUL has been limited due to several challenges, including the cross-client knowledge inaccessibility and high computational and communication costs. To overcome these challenges, we propose Federated On-server Unlearning (FOUL), a novel framework that comprises two key stages. The learning-to-unlearn stage serves as a preparatory learning phase, during which the model identifies and encodes the key features associated with the forget clients. This stage is communication-efficient and establishes the basis for the subsequent unlearning process. Subsequently, on-server knowledge aggregation phase aims to perform the unlearning process at the server without requiring access to client data, thereby preserving both efficiency and privacy. We introduce a new data setting for FUL, which enables a more transparent and rigorous evaluation of unlearning. To highlight the effectiveness of our approach, we propose a novel evaluation metric termed time-to-forget, which measures how quickly the model achieves optimal unlearning performance. Extensive experiments conducted on three datasets under various unlearning scenarios demonstrate that FOUL outperforms the Retraining in FUL. Moreover, FOUL achieves competitive or superior results with significantly reduced time-to-forget, while maintaining low communication and computation costs. Reproducible code is available [here](#).

1. Introduction

Federated Learning (FL) has enabled the collaborative training of machine learning models across decentralized data sources or clients, facilitating the development of more

accurate and robust models. Local clients benefit by getting an aggregated and more powerful personalized model without sharing their private data. With the recent introduction of data protection laws such as the General Data Protection Regulation (GDPR) [34] in the European Union, it has become essential to provide clients with the right to erasure regarding their own private data, even if that data has already been used to train the global model in federated learning. Federated Unlearning (FUL) [38] aims to address this challenge by developing methods for removing specific information from globally trained models. FUL plays a critical role in supporting the *right to be forgotten* paradigm, wherein the removal of a client's data from the model may be legally or ethically mandated.

In the field of FUL, two primary categories of methods have emerged: retraining-based methods [20], approximate unlearning methods [4, 43] (see Appendix A for more details). Retraining-based methods involve retraining the entire FL system from scratch using a dataset that excludes the forget set, thereby ensuring that the final model no longer reflects the influence of the data to be forgotten. While these methods often achieve state-of-the-art unlearning performance, retraining approaches are computationally intensive. Consequently, such approaches are impractical and unscalable for real-world FL applications due to substantial computational and communication overhead.

To mitigate the computational burden of retraining-based unlearning, recent studies have shifted toward approximate unlearning methods [4, 43, 46]. These approaches typically focus on local unlearning or selective client aggregation, which are particularly effective in federated feature unlearning settings, where both the retain and forget subsets are available at the client side. In such cases, unlearning can be performed locally on clients and the updated models are aggregated in the same manner as vanilla FL [11].

However, when the objective shifts to client-wise unlearning, where the goal is to erase the entire contribu-

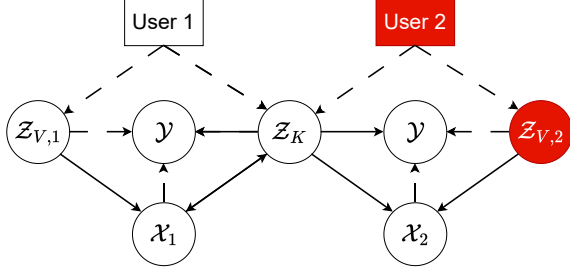


Figure 1. Extension of the causal structure model to the multi-client setting. Following [28], the causal factors Z_K represent the domain-invariant characteristics. Consequently, when unlearning a client, removing Z_K may reduce the amount of useful information necessary for predicting $\mathcal{Y}$. In contrast, unlearning the non-causal factors $Z_{V,2}$ primarily removes domain-specific information from client 2, while having a smaller impact on the information relevant to the classification of $\mathcal{Y}$. Dashed lines denote edges that may vary across clients or be absent in certain scenarios, solid lines indicate edges that remain invariant across all clients.

tion of specific clients, the problem becomes substantially more challenging. The primary difficulty arises because the forget clients lack access to the retain dataset. To be more specific, current unlearning formulations are typically feasible only when both retain and forget data are available, as the unlearning objective is often expressed as $\mathcal{L}_{\text{unlearn}} = \mathcal{L}_{\text{retain}}(\theta; \mathcal{D}_r) - \mathcal{L}_{\text{forget}}(\theta; \mathcal{D}_f)$. Consequently, existing client-wise FUL methods rely solely on the retain set $\mathcal{D}_r$, while ignoring the forgotten set $\mathcal{D}_f$. In this work, we propose Federated On-server UnLearning (FOUL), a novel algorithm designed for client-wise FUL that efficiently and faithfully removes targeted knowledge without compromising the knowledge of retain clients. FOUL achieves this while significantly reducing the computational overhead of the unlearning process. ❶ To mitigate the high cost of unlearning, we introduce the principle of learning to unlearn (L2U) during the learning stage. Specifically, FOUL disentangles the feature extractor into two sub-networks: a causal featurizer, which captures domain-invariant representations, and a non-causal featurizer, which encodes domain-specific information. We demonstrate that unlearning only the non-causal features effectively removes domain-specific (i.e., forget-set-related) knowledge while preserving generalizable, domain-invariant information crucial to the retain set (see Fig. 1). ❷ To enable the joint utilization of knowledge from both retain and forget client sets, FOUL enforces aggregated gradients to remain aligned with the retain clients while intentionally conflicting with the forget clients, ensuring effective unlearning. Unlike prior methods such as [49], FOUL requires no on-server data access, thereby preserving both communication efficiency and data privacy under the FL paradigm. Our key contributions are summarized as follows:

1. We propose FOUL, an efficient FUL algorithm which consists of two stages, L2U via model disentanglement, and on-server unlearning performed on the domain-specific disentangled model via gradient matching.
2. We introduce an approach for leveraging domain generalization datasets (e.g., PACS, VLCS, OfficeHome) to benchmark FUL performance. Additionally, we propose a new metric, time-to-forget, which quantifies how quickly a model achieves optimal unlearning.
3. We experimentally demonstrate the effectiveness of the proposed method across various client-wise unlearning settings, comparing it against 9 FUL methods.

2. Preliminaries

Notations: We abuse $|\cdot|$ as a number of elements in the subset, $\perp$ as independent relationship between two subsets. Suppose that there is a user set $\mathcal{U}$. Let $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{|\mathcal{D}|}$, where x_i and y_i represent the input and its corresponding output, respectively. In our work, we refer Z_K, Z_V as the causal and non-causal representation set, respectively. Due to the mini-batch learning, we abuse $Z_K = \{z_K^{(i)} | i \in B\}$ as the causal representation set within the batch with size B . The non-causal representation set Z_V applies the same rule.

2.1. Federated Unlearning

Definition 1 (Forget user set) Given a training user set $\mathcal{U}$, the forget user set is a subset of $\mathcal{U}$ whose data is intended to be removed or unlearned, denoted by $\mathcal{U}_f$.

Definition 2 (Retain user set) A retain user set is the set of users which required to be memorized in the FL system, denoted as $\mathcal{U}_r$, including all other data that is not targeted for removal and is crucial for maintaining the general knowledge and functionality of the model, i.e., $\mathcal{U}_r = \mathcal{U} \setminus \mathcal{U}_f$.

Given the two above definitions, FUL consists of two primary processes: 1) learning stage, and 2) unlearning stage.

Definition 3 (Learning Stage) The goal of learning stage is to collaboratively learn a machine learning model θ over the dataset $\mathcal{D} \triangleq \bigcup_{u \in \mathcal{U}} \mathcal{D}_u$:

$$\theta_{\text{learn}}^* = \arg \min_{\theta} \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \mathcal{L}(\theta; \mathcal{D}_u), \quad (1)$$

where $\mathcal{L}(\theta; \mathcal{D}_u) = \mathbb{E}_{(x,y) \sim \mathcal{D}_u} [\ell(\theta; (x,y))]$ is the empirical loss of user u , and during learning stage, each user minimizes their empirical risk $\mathcal{L}(\theta; \mathcal{D}_u)$, θ_{learn}^* is the final model trained by the learning stage.

The unlearning stage is conducted following the learning stage, with the objective of obtaining an unlearned FL model, denoted as θ_{unlearn} .

Definition 4 (Unlearning Stage) *The goal of the unlearning stage is to achieve performance comparable to a model trained exclusively on the remaining dataset, while ensuring that knowledge about the forget dataset is forgotten.*

$$\begin{aligned} \theta_{\text{unlearn}}^* &= \arg \max_{\theta} \frac{1}{|\mathcal{U}_{\mathcal{F}}|} \sum_{v \in \mathcal{U}_{\mathcal{F}}} \mathcal{L}(\theta; \mathcal{D}_v), \\ \text{s.t. } \frac{1}{|\mathcal{U}_{\mathcal{R}}|} \sum_{u \in \mathcal{U}_{\mathcal{R}}} [\mathcal{L}(\theta_{\text{unlearn}}^*; \mathcal{D}_u) - \mathcal{L}(\theta_{\text{learn}}^*; \mathcal{D}_u)] &\leq \delta, \end{aligned} \quad (2)$$

where we solve 2 by initializing θ as θ_{learn} before using standard iterative optimization technique. $\theta_{\text{unlearn}}^*$ is the target unlearned model, and θ_{learn}^* is the pre-trained model of θ defined during the learning stage. δ is an arbitrarily small threshold which constraint the knowledge divergence between $\theta_{\text{unlearn}}^*$ and θ_{learn}^* for remaining set.

3. Methods

In this section, we present the FOUL algorithm, which operates through a two-stage unlearning process: (1) Learning to unlearn, where the model is prepared during the initial learning stage to facilitate efficient future unlearning, and (2) On-server gradient matching, where unlearning is executed by manipulating gradients directly on the server.

3.1. Learning to unlearn

Existing FUL approaches predominantly focus on retraining or adjusting the model from scratch [11]. However, this strategy incurs substantial computational overhead on individual clients and increases communication costs due to frequent model transmission between clients and the server. In practice, not all model parameters are equally influenced by the data that must be forgotten [20, 56]. Many components of the model capture domain-invariant knowledge that remains relevant to both the retained and forgotten data, and therefore do not require modification during the unlearning process. To this extent, recent studies attempt to identify and unlearn only a subnetwork of the model by analyzing gradient conflicts [20, 56]. However, because the model changes across unlearning rounds, the subnetwork identification must be repeatedly performed, leading to significant additional computation overhead. To address this limitation, we propose L2U, which disentangles the model into domain-invariant and domain-specific subnetworks during training. By isolating only the domain-specific component for unlearning, L2U preserves model stability across unlearning rounds while reducing computation and communication overhead.

3.1.1 Motivation

The core idea of L2U via disentanglement is to learn disentangled representations by imposing invariance constraints

on two spaces $\mathcal{Z}_K$ and $\mathcal{Z}_V$. Our design is inspired by the causal-structural representation learning [29], which is defined as follows:

Definition 5 (Causal Structured Model [29]) *The data $\mathcal{X}$ composes of two distinct representations, i.e., causal factors $\mathcal{Z}_K$ and non-causal factors $\mathcal{Z}_V$, and unexplained noise variables $\mathcal{V}_1, \mathcal{V}_2$ that are jointly independent, i.e., $\mathcal{Z}_K \perp\!\!\!\perp \mathcal{Z}_V \perp\!\!\!\perp \mathcal{V}_1 \perp\!\!\!\perp \mathcal{V}_2$.*

- The causal factors $\mathcal{Z}_K$ should be separated from the non-causal factors $\mathcal{Z}_V$, i.e., $\mathcal{Z}_K \perp\!\!\!\perp \mathcal{Z}_V$. Thus, performing an intervention upon $\mathcal{Z}_V$ does not make changes to $\mathcal{Z}_K$.
- The combination of causal and non-causal factors $\mathcal{Z}_K, \mathcal{Z}_V$ should be sufficient to the data $\mathcal{X}$ reconstruction task, i.e., $\mathcal{X} \triangleq f(\mathcal{Z}_K, \mathcal{Z}_V, \mathcal{V}_1)$.
- The causal factors $\mathcal{Z}_K$ should be causally sufficient for the classification task $\mathcal{X} \rightarrow \mathcal{Y}$, i.e., $\mathcal{Y} \triangleq h(\mathcal{Z}_K, \mathcal{V}_2)$.

Here, f, h can be regarded as unknown structural functions.

Given that the noise variables are unexplainable, we restrict our focus to the causal and non-causal representations. To relate these representations to data features across different domains, we adopt the following definition.

Definition 6 (Causal and non-causal representations [29])

Causal factors $\mathcal{Z}_K$ have a direct causal influence on both X and Y , making them domain-invariant. In contrast, $\mathcal{Z}_V$ represents non-causal factors that only causally affect X and typically contain domain-specific information.

Definition 5 formalizes the feasibility of disentangling the model into two independent factors. The causal invariance theorem provides the theoretical foundation for our unlearning objective. In the unlearning process, our goal is to remove the knowledge associated with the forget client set while preserving that of the retain client set. Therefore, unlearning can be viewed as reducing the information encoded in the non-causal (domain-specific) representations, since modifying the causal representations would inevitably impair the retained knowledge.

Definition 7 (Causal Principle in Unlearning) *To preserve the knowledge of the retain set while removing that of the forget set, the main objective of unlearning is to reduce the information encoded by the non-causal featurizer.*

Motivated by this principle, L2U disentangles the feature extractor into a causal featurizer θ_K and a non-causal featurizer θ_V . During the subsequent unlearning phase, updates are applied exclusively to the non-causal featurizer, while the causal featurizer remains frozen. This strategy enables FOUL to efficiently remove domain-specific knowledge from the forget set without compromising the generalizable representations learned from the retain set.

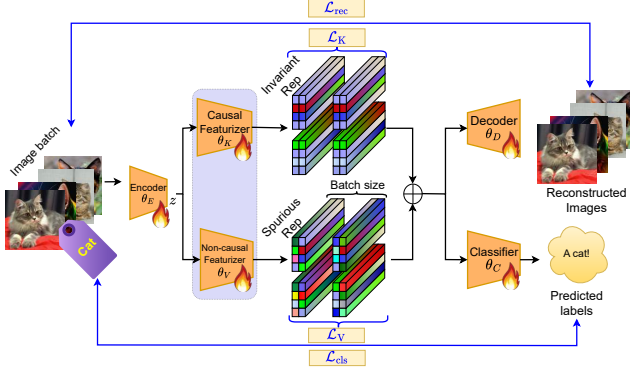


Figure 2. The learning on a single local client in the L2U stage. Featurizers are trained to disentangle knowledge into invariant and variant representations.

3.1.2 Learning for Representation Featurizer

General learning framework. To achieve effective disentanglement learning in L2U, it is essential that the learned representations exhibit both causal and non-causal characteristics. These two components must not only capture distinct aspects of the data but also jointly contribute to form meaningful and interpretable representations. Moreover, the causal representations are required to preserve the underlying causal structure that remains invariant across domains.

Overall, the central idea is to impose representation disentanglement within the model, where two distinct latent components are learned: causal representations, which are invariant and informative for classification, and non-causal representations, which capture variant information sensitive to data perturbations. Together, these two representations contribute to accurate data reconstruction. Based on this formulation, the proposed L2U stage is expressed as a bi-level optimization problem:

$$\min_{\theta} \left[\mathcal{L}_{L2U}(\theta) = \frac{1}{U} \sum_{u=1}^U \mathcal{L}_{L2U}(\theta_u) \right], \quad (3)$$

$$\text{s.t. } \mathcal{L}_{L2U}(\theta_u) = \min_{\theta_u} [\alpha_V \mathcal{L}_V + \alpha_K \mathcal{L}_K + \alpha_{gtc} \mathcal{L}_{gtc} + \mathcal{L}_{rec}],$$

where $\mathcal{L}_V$, $\mathcal{L}_K$, $\mathcal{L}_{gtc}$, and $\mathcal{L}_{rec}$ denote the non-causal, causal, ground truth classification, and reconstruction losses, respectively.

To facilitate the optimization of $\mathcal{L}_{gtc}$ and $\mathcal{L}_{rec}$, auxiliary decoders (θ_2) and classifiers (ξ) are introduced. Each local model is parameterized as $\theta_u = \{\theta_{E,u}, \theta_{K,u}, \theta_{V,u}, \theta_{D,u}, \theta_{C,u}\}$, where $\theta_{E,u}$ represents the shallow feature extractor; $\theta_{K,u}$ and $\theta_{V,u}$ are the causal and non-causal encoders, respectively; $\theta_{D,u}$ is the decoder; and $\theta_{C,u}$ is the classifier of client u .

The detailed two-stage optimization procedure for L2U

is presented in Appendix B, and the overall structure of the local model is depicted in Fig. 2.

Training Causal Featurizer. The goal of the causal featurizer is to extract class-discriminative features that are invariant to domain-specific, non-causal variations. To enforce this invariance, we train the model to generate highly compact representations for all samples belonging to the same class. By minimizing this intra-class distance, the model is encouraged to ignore superficial differences and focus on the essential, shared characteristics. The prototypical network framework [37] is exceptionally well-suited for this objective, as it explicitly learns a central prototype for each class. To achieve this, we train the causal performer using the prototypical network framework in the following manner:

$$\mathcal{L}_K = - \sum_{c=1}^C \log \frac{\exp(s(f_{\phi}(x), p_c))}{\sum_{i=1}^C \mathbb{1}_{[i \neq c]} \exp(s(f_{\phi}(x), p_i))}, \quad (4)$$

where $s(f_{\phi}(x), p_c)$ represents the cosine similarity between the encoded representations $f_{\phi}(x)$ and the approximated class prototype p_c . To approximate the prototype within the batch, we compute as [37] as $p_c = \frac{1}{|S_c|} \sum_{s_i, y_i \in S_c} f_{\phi}(x_i)$. $B_c \in B$ is the batch of data belonging to label c .

Training Non-causal Featurizer. To extract non-causal representations effectively, we maximize the empirical distance among representations within a specific label. However, two problems may arise during the maximization of the MSE between samples: **Ⓐ** When the MSE value is at its initial value (where the variance is relatively low, i.e., nearly 0), the optimization process prioritizes tasks with high initial losses. This prioritization can overshadow the learning of variant representations in the early stages. **Ⓑ** When the MSE value is already optimized, performing the maximization process further can increase the variance, potentially diminishing the learning of other tasks. To mitigate these problems, we adopt the hinge loss framework introduced in [2] in designing the variant loss $\mathcal{L}_V$:

$$\mathcal{L}_V = \frac{1}{C} \sum_{c=1}^C \max \left(0, 1 - \sqrt{\text{Var}(\mathcal{Z}_V^c) + \epsilon} \right), \quad (5)$$

where $\text{Var}(\mathcal{Z}_V^c)$ represents the variance among samples in the same class c , and

$$\text{Var}(\mathcal{Z}_V^c) = \mathbb{E}_{i \in B_c} \left[\left\| z_V^{(i)} - \mathbb{E}_{j \in B_c} \left(z_V^{(j)} \right) \right\|^2 \right]. \quad (6)$$

Incorporating the hinge loss brings the non-causal learning function into better alignment with other loss functions used in FOUL. This alignment involves initiating the optimization from higher values to mitigate trivial losses during the

initial phase, while setting a lower boundary at zero to prevent bias towards $\mathcal{L}_V$ as the learning progresses.

Meaningful Representations. From Definition 5, the disentangled factors must be sufficient for the reconstruction task. Hence, our goal for training FOUL is twofold:

- The causal representations capture crucial information that accurately represents their respective label.
- The two extracted factors can be combined and collectively used to reconstruct the original data with the highest possible accuracy.

To achieve the first goal, it should be possible to predict a specific label from the causal factors $\mathcal{Z}_K$. We introduce the label classification function $\mathcal{L}_{\text{gtc}}$ as follows:

$$\mathcal{L}_{\text{gtc}} = -\mathbb{E}_{i \in B} \left[P(y^{(i)}) \log P(f_{\xi}(z_K^{(i)})) \right], \quad (7)$$

where $f_{\xi} : \mathbb{R}^{d_{z_K}} \rightarrow \mathbb{R}$ is the classifier network, parameterized by ξ , handling the classification task for the causal factors $z_K^{(i)}$. $y^{(i)}$ is the label of data instance i . $P(\cdot)$ denotes the probability distributions.

To achieve the second goal, we employ the reconstruction loss $\mathcal{L}_{\text{rec}}$ according to [22]. Specifically, we minimize the MSE between the original and its reconstructed data, while maximizing the KL divergence, and we enhance generalization by compelling the featurizer to output a distribution over the latent space instead of a single point. For instance,

$$\mathcal{L}_{\text{rec}} = \mathcal{L}_{\text{MSE}} - \mathcal{L}_{\text{KL}}. \quad (8)$$

3.2. Client-wise Unlearning

Besides the unlearning of only the non-causal featurizers, our objective is to propose an efficient strategy to aggregate knowledge from all participated users without the explosion of communication overheads. Therefore, the unlearned global model of the FL system may reduce the generalization gap with current centralized machine unlearning methods. The intuition behind our work is inherited from the invariant gradient direction of [21, 30, 36].

Assumption 1 (Invariant Gradient Direction [30])

Consider a model θ with task of finding domain-invariant features, the features generated by the model θ is domain-invariant if the two gradients $\nabla \mathcal{L}(\theta; \mathcal{D}_u)$, and $\nabla \mathcal{L}(\theta; \mathcal{D}_v)$, on different domains $\mathcal{D}_u$ and $\mathcal{D}_v$ point to a similar direction, i.e., $\langle \nabla \mathcal{L}(\theta; \mathcal{D}_u), \nabla \mathcal{L}(\theta; \mathcal{D}_v) \rangle > 0$.

Assumption 1 recommends a strategy for efficiently aggregating knowledge of distributed users for the FL system to achieve generalization. From Assumption 1, we can have the inverted assumption as follows:

Assumption 2 (Unlearning via Gradient Matching)

Considering a model θ with task of unlearning features, the features generated by the model θ suffers from negative transfer if the two gradients $\nabla \mathcal{L}(\theta; \mathcal{D}_u)$, and $\nabla \mathcal{L}(\theta; \mathcal{D}_v)$ does not point to a similar direction, i.e., $\langle \nabla \mathcal{L}(\theta; \mathcal{D}_u), \nabla \mathcal{L}(\theta; \mathcal{D}_v) \rangle < 0$.

Combining the two Assumptions 1 and 2, we come up with an idea to design an on-server unlearning approach based on gradient matching (see Fig. 3). Specifically, on the server, our target is to find an unlearning global gradient that satisfies Assumption 1 on the retain user set $\mathcal{U}_R$ while satisfying Assumption 2 on the forget user set $\mathcal{U}_F$.

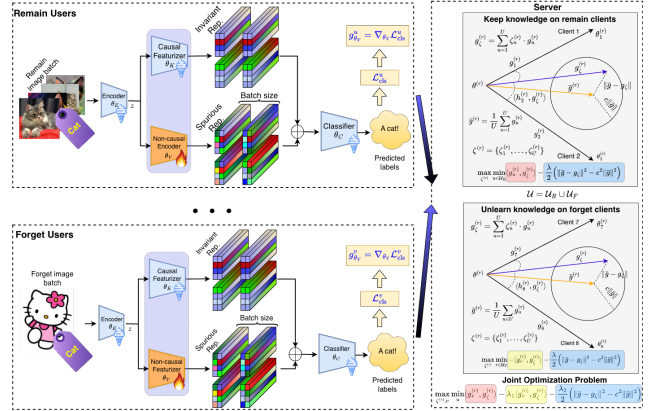


Figure 3. Unlearning stage with data-free on-server unlearning. Only the non-causal featurizer participates in this phase. The gradients of the non-causal featurizer from both retain and forget users are sent to the server for on-server gradient matching.

3.2.1 On-server gradient-based unlearning

Our target is to find an aggregated gradient so that it can make invariant directions towards gradients from the remaining clients $\mathcal{U}_R$, while making negative transfer towards gradients in forget clients $\mathcal{U}_F$. To reduce the computation cost of the optimization, we find the weights for the gradients aggregation so that it can form the optimal directions g_{FOUL} . For instance,

$$\theta_v^{(r)} = \theta_v^{(r-1)} - \eta g_{\text{FOUL}}, \quad (9a)$$

$$\text{s.t. } g_{\text{FOUL}} = \arg \max_g \left[\sum_{u \in \mathcal{U}_R} \langle g, \nabla(\phi_u^{(r)}; \mathcal{D}_u) \rangle - \sum_{v \in \mathcal{U}_F} \langle g, \nabla(\phi_v^{(r)}; \mathcal{D}_v) \rangle \right], \quad (9b)$$

$$\phi_u^{(r)} = \theta_g^{(r-1)} - \eta_l \nabla(\theta_g^{(r-1)}; \mathcal{D}_u), \forall u \in \mathcal{U}. \quad (9c)$$

By proposing Eq. (9), we establish the meta-objective function in Eq. (9a), which relies solely on client gradients as training signals. The optimization in Eq. (9b) aims to

maximize the cosine similarity between the aggregated gradient and the gradients of the retain clients, while minimizing the cosine similarity with the gradients of the forget clients. This mechanism enforces unlearning on the forget clients while preserving performance on the retain clients. However, one limitation of Eq. (9) is that the optimization over the model parameters g may exhibit poor generalization, since it operates without access to explicit training data at each optimization step. This issue becomes particularly severe for models with large parameter dimensionality. To mitigate this problem, we introduce a set of learnable weighting coefficients $\Gamma = \{\gamma_u^{(r)} \mid u \in \mathcal{U}, \sum_{u \in \mathcal{U}} \gamma_u^{(r)} = 1\}$, and reformulate the global gradient as $g = \sum_{u \in \mathcal{U}} \gamma_u^{(r)} \nabla \mathcal{L}(\phi(\phi_u^{(r)}; \mathcal{D}_u))$. This parameterization substantially reduces the optimization space: instead of learning the full parameter vector of dimension d , we now only optimize over U coefficients, where $U \ll d$. Based on this reformulation, we derive the following theorem.

Theorem 1 (FOUL solution) *Given $\Gamma = \{\gamma_u^{(r)} \mid u \in \mathcal{U}, \sum_{u \in \mathcal{U}} \gamma_u^{(r)} = 1\}$ is the set of learnable coefficients at each round r , where $\mathcal{U} = \{\mathcal{U}_{\mathcal{R}}, \mathcal{U}_{\mathcal{F}}\}$. Optimal unlearning gradient $\nabla_{\text{FOUL}}^{(r)}$ is characterized as follows:*

$$\nabla_{\text{FOUL}}^{(r)} = \nabla_{\text{FL}}^{(r)} + \frac{\kappa \|\nabla_{\text{FL}}^{(r)}\|}{\|\nabla_{\Gamma_{\mathcal{R}}}^{(r)} - \nabla_{\Gamma_{\mathcal{F}}}^{(r)}\|} (\nabla_{\Gamma_{\mathcal{R}}}^{(r)} - \nabla_{\Gamma_{\mathcal{F}}}^{(r)}), \quad (10)$$

$$\text{s.t. } \Gamma_{\mathcal{R}}^*, \Gamma_{\mathcal{F}}^* = \arg \min_{\Gamma_{\mathcal{R}}, \Gamma_{\mathcal{F}}} (\nabla_{\Gamma_{\mathcal{R}}}^{(r)} - \nabla_{\Gamma_{\mathcal{F}}}^{(r)}) \cdot \nabla_{\text{FL}}^{(r)} + \sqrt{\kappa} \|\nabla_{\text{FL}}^{(r)}\| \|\nabla_{\Gamma_{\mathcal{R}}}^{(r)} - \nabla_{\Gamma_{\mathcal{F}}}^{(r)}\|.$$

Theorem 1 gives us an on-server optimization approach via the gradient matching without the need for local data accessibility. The detailed algorithm of the unlearning stage of FOUL is detailed in Appendix D.

4. Experimental Setup

Unlearning Scenarios. To effectively simulate the client data unlearning process, we utilize domain generalization datasets [13]. In particular, this dataset is partitioned into multiple distinct domains, which we use to represent different clients. We assign the retain and forget clients to separate domains to ensure a clear distinction between them. Consequently, when performing client unlearning, we can quantitatively assess the effectiveness of the unlearning process by evaluating model performance on both the retained and forgotten client domains, as well as on the test domain.

Hyperparameters & Datasets & Model. In our experiments, we evaluate the proposed method on four datasets: PACS [23], VLCS [14], OfficeHome [42], and TerraIncognita [3]. Each dataset contains four distinct domains (i.e.,

Photo, Art, Sketch, and Cartoon for PACS, and Art, Clipart, Product, and Real-World for OfficeHome). We adopt ResNet-18 as the backbone network for PACS, OfficeHome, VLCS, and ResNet-50 for TerraIncognita. All experiments are conducted on a single NVIDIA A100 GPU. To simulate the FL environment, we consider $U = 20$ clients under an IID setting. The clients are divided across the 4 domains, with 5 clients assigned to each domain. For the FUL experiments, we designate clients from one domain as the forget set, while clients from the remaining domains constitute the retain set. The unlearning procedure is then applied to all clients within the forget set.

Implementation Details. For every dataset and model configuration, we initially train a global model using FedAvg until it reaches convergence, after which the proposed unlearning algorithm is applied. In each round, all clients participate according to the designated retain and forget sets. The local dataset of each client is partitioned into training and validation subsets in a 90:10 ratio, while an independent test set is employed to evaluate the model’s performance.

Evaluation Metrics. Following prior works [11, 20], we evaluate the effectiveness and efficiency of FOUL using the following metrics: retain accuracy (RA), forget accuracy (FA), test accuracy (TA), membership inference attack (MIA), communication cost, and computation cost. The retain and forget accuracies measure the model’s performance on the retain and forget dataset $\mathcal{D}_r, \mathcal{D}_f$, respectively. MIA quantifies the extent to which $\mathcal{D}_f$ remain recognizable to the model after unlearning. The retain accuracy reflects how well the model preserves knowledge of $\mathcal{D}_r$, the forget accuracy evaluates how effectively the model forgets $\mathcal{D}_f$. Communication and computation costs represent the total amount of data transmitted and the total FLOPs required every communication round during the unlearning process. In addition, we introduce Time-to-Forget (T2F), which measures the average reduction in accuracy on the forget set per round, thereby indicating how quickly the model unlearns the designated clients. To ensure fair evaluation between the retain and forget sets, we assess performance using the global model obtained after each aggregation round and report the average results across all local datasets.

Baselines. We compare the proposed FOUL method with the baselines, including Retraining (in which the model is retrained from scratch using only the retain client set. The resulting aggregated models are then evaluated on both the retain and forget client sets), FATS [41], FedDCP [44], FedRecovery [54], FedOSD [32], FFMU [4], FUSED [56], MoDE [55], and NoT [20].

5. Experimental Evaluation

Main Results. Table 1 presents a comparison of FOUL with other baselines on the PACS and TerraIncognita datasets. The baselines are grouped into two categories: fast

Table 1. Comparison of methods on ResNet-18 with PACS and TerraIncognita datasets. The table reports Forget Accuracy (FA), Remaining Accuracy (RA), Testing Accuracy (TA), and Membership Inference Attack (MIA), with values in parentheses showing the difference from the Retrain baseline. For the FOUL method, (1) corresponds to the L2U phase, and (2) refers to the on-server gradient matching unlearning phase. Note that we **bold** results achieving the closest TA accuracy to Retrain.

Group	Methods	PACS				TerraIncognita			
		FA ($\downarrow$)	RA ($\uparrow$)	TA ($\uparrow$)	MIA ($\downarrow$)	FA ($\downarrow$)	RA ($\uparrow$)	TA ($\uparrow$)	MIA ($\downarrow$)
Retrain	Retrain	70.51	82.84	77.45	50.02	30.64	42.41	38.94	50.71
	FATS	74.45 (+3.94)	80.91 (−1.93)	75.98 (−1.47)	55.72 (+5.70)	33.07 (+2.43)	40.96 (−1.45)	37.34 (−1.60)	60.81 (+10.10)
	NoT	73.24 (+2.73)	79.25 (−3.59)	75.28 (−2.17)	59.13 (+9.11)	32.26 (+1.62)	38.32 (−4.09)	36.08 (−2.86)	62.90 (+12.19)
Unlearn.	FedCDP	77.37 (+6.86)	78.13 (−4.71)	76.41 (−1.04)	72.26 (+22.24)	34.56 (+3.92)	38.79 (−3.62)	36.75 (−2.19)	81.91 (+31.20)
	FedRecovery	76.48 (+5.97)	76.97 (−5.87)	74.81 (−2.64)	75.24 (+25.22)	32.11 (+1.47)	37.49 (−4.92)	35.59 (−3.35)	84.03 (+33.32)
	FedOSD	72.89 (+2.38)	80.15 (−2.69)	75.49 (−1.96)	58.84 (+8.82)	32.63 (+1.99)	40.77 (−1.64)	36.76 (−2.18)	60.54 (+9.83)
	FFMU	73.31 (+2.80)	78.27 (−4.57)	74.14 (−3.31)	60.62 (+10.60)	33.76 (+3.12)	39.39 (−3.02)	36.04 (−2.90)	65.85 (+15.14)
	FUSED	75.94 (+5.43)	79.34 (−3.50)	76.86 (−0.59)	58.72 (+8.70)	33.64 (+3.00)	38.73 (−3.68)	36.74 (−2.20)	62.03 (+11.32)
	MoDE	72.53 (+2.02)	79.01 (−3.83)	75.79 (−1.66)	59.79 (+9.77)	32.17 (+1.53)	38.04 (−4.37)	35.74 (−3.20)	63.47 (+12.76)
FOUL	(1)	69.53 (−0.98)	93.11 (+14.55)	77.14 (−0.31)	53.82 (+3.80)	27.97 (−2.67)	43.81 (+1.40)	38.16 (−0.78)	56.40 (+5.69)
	(1) + (2)	70.97 (+0.46)	92.33 (+14.49)	76.43 (−1.02)	51.93 (+1.91)	29.92 (−0.72)	42.13 (−0.28)	39.16 (+0.22)	57.11 (+6.40)

retraining and approximate unlearning. In general, fast retraining methods achieve satisfactory performance in terms of FA and RA. However, they exhibit low T2F, indicating a slower unlearning process. Consequently, these methods suffer from high computational and communication overheads, as well as longer convergence times. Although approximate unlearning methods achieve higher T2F and faster convergence, they generally yield lower FA and RA compared to fast retraining approaches. FOUL consistently outperforms all baselines in client-wise FUL across different architectures and datasets, achieving a smaller average performance gap while maintaining competitive communication and computation costs. The more results on VLCS and OfficeHome datasets are presented in Appendix E.

Time to Forget. Figures 4(a), 5(a), and 6(a) present a comparative analysis of unlearning performance across three approaches: FOUL, retraining with a pre-trained model, and retraining with model reset. The results demonstrate that the two naive retraining methods fail to achieve effective unlearning for the designated forget client set. This limitation arises because both retraining methods employ standard averaging aggregation at the server, which cannot explicitly remove knowledge associated with the forget clients. In contrast, FOUL achieves a substantial reduction in FA, reaching its optimal FA in fewer than 50 rounds, achieving T2F more than 0.32/round (compare to results 75 rounds and T2F of 0.13 of Retraining). Moreover, the RA of FOUL continues to improve during the unlearning phase, indicating that the knowledge of the remaining clients is preserved and not unintentionally unlearned.

Gradient angle and learning properties. Figures 4(b), 5(b), and 6(b) illustrate the average gradient divergence between the retain and forget client sets. This measure is ob-

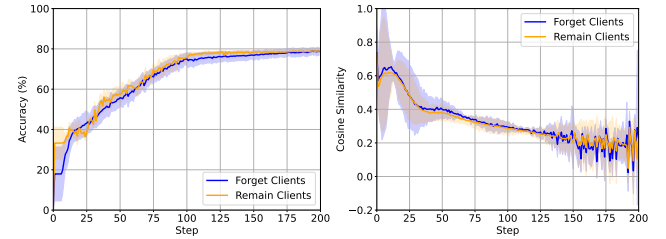


Figure 4. Retraining from scratch with FedAvg without resetting model parameters on PACS dataset.

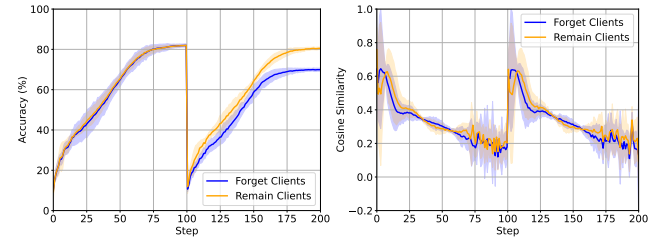


Figure 5. Retraining from scratch with FedAvg with resetting model parameters on PACS dataset.

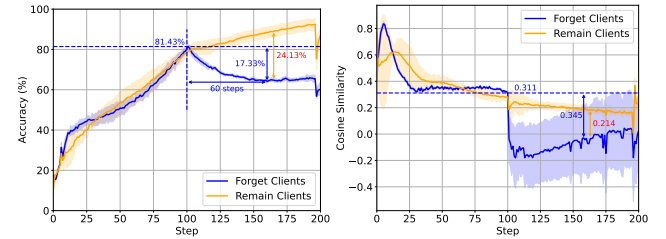


Figure 6. Evaluations of FOUL on PACS dataset.

tained by computing the mean cosine similarity between the global model gradients and those of individual clients in both sets. As shown in Figures 4(b) and 5(b), there is no noticeable difference in gradient divergence between the retain and forget clients, which explains the limited un-

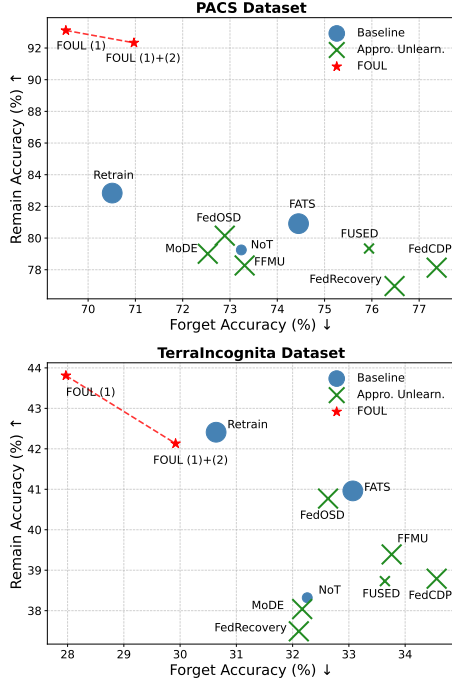


Figure 7. Comparison of communication cost in trade-off with Forget Accuracy (FA) and Remain Accuracy (RA) across different unlearning methods on PACS and TerraIncognita datasets.

learning performance observed in Figures 4(a) and 5(a). In contrast, FOUL exhibits a pronounced reduction in FA that closely corresponds to a decrease in gradient similarity for the forget clients relative to the retain clients. Moreover, the negative cosine similarity values observed for the forget set align with the gradient conflict phenomenon, which has been shown to induce negative transfer effects in multi-task learning [1], domain generalization [33, 36].

Communication & Computation Efficiency. Figure 7 illustrates the communication cost of the FOUL algorithm D compared with other baselines, as well as the trade-off between communication efficiency and RA, FA. As shown in the figure, integrating the L2U stage substantially reduces communication overhead. Moreover, FOUL achieves the highest RA and FA among all compared approaches. As summarized in Table 2, FOUL also demonstrates superior communication and computation efficiency relative to baselines.

6. Ablation Test

Learning to Unlearn Phases To evaluate the impact of the coefficients in the learning-to-unlearn stage of the FOUL algorithm, we conduct a series of experiments, with detailed results and discussions provided in Appendix F. In addition, we assess the domain-invariant capability of

Table 2. Comparison of computational and communication characteristics of each method. Params denotes trainable parameters, Comm. refers to per-round communication overhead, and Comp. indicates local computation complexity.

Method	Params (M)	Comm. (MB)	Comp. (FLOPs)
Retrain	11.3	42.73	$5.81e^{16}$
FATS	11.3	42.73	$5.81e^{16}$
NoT	11.3	34.72	$3.38e^{16}$
FedCDP	11.3	42.73	$5.82e^{16}$
FedRecovery	11.3	42.73	$5.96e^{16}$
FedOSD	11.3	42.73	$5.85e^{16}$
FFMU	11.3	42.73	$5.85e^{16}$
FUSED	11.3	0.98	$2.81e^{16}$
MoDE	11.3	42.73	$3.72e^{16}$
FOUL (1) + (2)	11.3	<u>16.02</u>	$2.35e^{16}$

the proposed model’s disentanglement mechanism, as presented in Appendix G. The results and discussion on the L2U stage with vary causal/non-causal representations dimensionality can be found in Appendix H.

Unlearning Phase To assess the effect of the coefficients used in the unlearning stage of the FOUL algorithm, we perform a series of experiments examining learning rate, sensitivity, and disentanglement efficiency. Results and discussions are provided in Appendix H.

7. Conclusion

This paper addresses the unlearning problem in FL. To overcome key challenges in FUL (including forget-client data inaccessibility, indiscriminate knowledge removal, and high unlearning costs), we propose FOUL, an efficient two-stage framework for learning and unlearning. In the learning stage, the feature extractor is disentangled into two sub-networks: one encoding domain-invariant representations and another capturing domain-variant representations. By restricting the unlearning process to the domain-variant sub-network, FOUL preserves global, task-relevant knowledge across clients while effectively removing features associated with the forget set. In the unlearning stage, on-server gradient matching enables the utilization of both retain and forget client knowledge, significantly improving the time-to-unlearn efficiency. Experimental results demonstrate that FOUL outperforms Retraining in FUL tasks while maintaining communication and computation costs comparable to the standard FedAvg, primarily due to its ability to leverage knowledge from the forget clients.

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