Appendix

Contents

A.1. Proof of Theorem 4.1

Theorem 1. *Let τ denote the set of final layer weights of a neural network, and let τ_c represent the weights corresponding to the output neuron of class c. Consider two disjoint sets of classes: a forget set $c_{\mathcal{F}}$ and a retain set $c_{\mathcal{R}}$. If the proposed unlearning process (Algorithm 1) is applied with forget set $c_{\mathcal{F}}$, then the gradient magnitude of the MU loss with respect to $\tau_{c_{\mathcal{R}}}$ satisfies the following inequality:*

$$\left\| \frac{\partial \mathcal{L}_{MU}}{\partial \tau_{c_{\mathcal{R}}}} \right\| \geq \left(\frac{1}{\delta} - 1 \right) \left\| \frac{\partial \mathcal{L}_{MU}}{\partial \tau_{c_{\mathcal{F}}}} \right\|$$

for some constant $\delta \in (0, 1)$.

Proof. Let the pre-final layer output of an adversarial sample $\hat{x}$ generated by the model being adapted, $w^{\mathcal{T}}$, be denoted as $\phi(\hat{x}) = \hat{\phi}$.
Then, the MU loss in Expr. (5) is given by

$$\mathcal{L}_{\text{MU}}(w^{\mathcal{T}}, \hat{x}, \hat{y}) = \sum_{i \in c_{\mathcal{R}}} -\hat{y}_i \log\left(\frac{\exp(\hat{\phi}^T \tau_i)}{\sum_{j \in C} \exp(\hat{\phi}^T \tau_j)}\right) \tag{A.10}$$

$$= \sum_{i \in c_R} -\hat{y}_i \hat{\phi}^T \tau_i + \log\left(\sum_{j \in C} \exp(\hat{\phi}^T \tau_j)\right) \tag{A.11}$$

The second equality holds due to our rescaled labeling strategy; $\sum_{i \in c_R} \hat{y}_i = 1$ (Expr. 4).

The gradients for any class c are given by

$$\frac{\partial \mathcal{L}_{\text{MU}}(w^{\mathcal{T}}, \hat{x}, \hat{y})}{\partial \tau_c} = -\hat{y}_c \hat{\phi} \mathbf{1}_{c \notin c_{\mathcal{F}}} + \underbrace{\frac{\exp(\hat{\phi}^T \tau_c)}{\sum_{j \in C} \exp(\hat{\phi}^T \tau_j)}}_{f_{w^{\mathcal{T}}}(\hat{x}) = y_c} \hat{\phi} \tag{A.12}$$

$$= \hat{\phi}(y_c - \mathbf{1}_{c \notin c_{\mathcal{F}}} \hat{y}_c) \tag{A.13}$$

Specifically, the norms of the gradients w.r.t. the weights in the case where $c \in c_{\mathcal{F}}$ or $c \in c_{\mathcal{R}}$, are given by

$$\frac{\partial \mathcal{L}_{\text{MU}}(w^{\mathcal{T}}, \hat{x}, \hat{y})}{\partial \tau_{c_{\mathcal{R}}}} = \|\hat{\phi}(y_c - \frac{y_c}{\sum_{j \in c_R} y_j})\| \tag{A.14}$$

$$\frac{\partial \mathcal{L}_{\text{MU}}(w^{\mathcal{T}}, \hat{x}, \hat{y})}{\partial \tau_{c_{\mathcal{F}}}} = \|\hat{\phi} y_c\| \tag{A.15}$$

We crucially observe that because of the nature of our adversarial sample generation in Expr. (3),

$$\sum_{j \in c_R} y_j \leq \delta$$

where $\delta \in (0, 1)$, because $P(\hat{x} \in c_R) = \sum_{j \in c_{\mathcal{R}}} y_j$ represents the softmax probability of the sample $\hat{x}$ belonging to any retain class, which is precisely what is minimized in $\mathcal{L}_{\text{ADV}}$. This leads to our main gradient flow inequality

$$\left\| \frac{\partial \mathcal{L}_{\text{MU}}(w^{\mathcal{T}}, \hat{x}, \hat{y})}{\partial \tau_{c_{\mathcal{R}}}} \right\| \geq \left(\frac{1}{\delta} - 1 \right) \left\| \frac{\partial \mathcal{L}_{\text{MU}}(w^{\mathcal{T}}, \hat{x}, \hat{y})}{\partial \tau_{c_{\mathcal{F}}}} \right\| \tag{A.16}$$

This inequality indicates that the gradient of the machine unlearning loss is more significant on the weights connected to the final-layer neurons of the classes that need to be retained, given that the adversarial sample is initially classified as part of a forget class $c_{\mathcal{F}}$ with a probability at least $1 - \delta$. $\square$

A.2. Additional Algorithms

We provide an extended version of Algorithm 1 with full training details in Algorithm 2. Whenever this algorithm is invoked by another algorithm, we refer to it as *AO_SCADA_UL()* (**SCADA-UL** solved via **A**dversarial **O**ptimization) for convenience.

UC-SCADA-UL. Algorithm 3 describes the procedure for our algorithm adapted for the UC-SCADA-UL setting, where the identity of the forget classes is not known (Definition 2). It involves an additional forget class prediction step that estimates the classes that are most likely the forget classes based on the target dataset $\mathcal{D}^{\mathcal{T}}$. This estimation step utilizes a term $\gamma \in \mathbb{R}^d$ where d is the number of classes (similar to [5]). This term provides a relative measure of class relevance for a dataset. The bottom $R \cdot |\mathcal{C}_{\mathcal{F}}|$ classes associated with γ are selected as the predicted forget classes and the original algorithm (Algorithm 1) is applied using these classes.

C-SCADA-UL. Algorithm 4 shows the adaptation of our algorithm for the C-SCADA-UL setting (Definition 3), where the unlearning requests can be received over multiple time steps. For the first set of classes ${\mathcal{C}_{\mathcal{F}}}^1$, the process remains identical to the original algorithm (Algorithm 1). For subsequent classes, we use a subset of the target data $\mathcal{D}^{\mathcal{T}}_{\text{sub}}$ and apply the original algorithm to the previously adapted model $w^{\mathcal{T}}_u$.

A.3. Definitions and Motivation for UC-SCADA-UL and C-SCADA-UL

A.3.1. Formal Definitions

Definition 2. (UC-SCADA-UL). Unknown Class SCADA-UL is the process of learning a function $\mathcal{U} : \{w^{\mathcal{S}}, \mathcal{D}^{\mathcal{T}}_r, |\mathcal{C}_{\mathcal{F}}|\} \to w^{\mathcal{T}}_u$ that produces an unlearned, adapted model which behaves as though it were adapted from a source model not trained on $\mathcal{D}^{\mathcal{S}}_f$, all without requiring knowledge of $\mathcal{C}_{\mathcal{F}}$.

Definition 3. (C-SCADA-UL). Continual SCADA-UL is the process of learning a sequence of unlearning functions $\mathcal{U}^i(w^{\mathcal{T},i-1}, \mathcal{D}^{\mathcal{T}}_r, {\mathcal{C}_{\mathcal{F}}}^1 \cup \cdots \cup {\mathcal{C}_{\mathcal{F}}}^i)$ where $i > 0, w^{\mathcal{T},0} = w^{\mathcal{S}}$. Each function produces an unlearned, adapted model $w^{\mathcal{T},i}_u$ that behaves as though it were adapted from a source model that was not trained on the data associated with ${\mathcal{C}_{\mathcal{F}}}^1 \cup \cdots \cup {\mathcal{C}_{\mathcal{F}}}^i$.

We note that the term "continual" here specifically refers to sequential unlearning requests and not traditional continual learning where new classes are learned over tasks.

Algorithm 2 **Adversarial Optimization for SCADA-UL (AO_SCADA_UL: Detailed Algorithm)**

Inputs:
  Source model $w^{\mathcal{S}}$, target data $\mathcal{D}^{\mathcal{T}}$
Require:
  Forget classes $\mathcal{C}_{\mathcal{F}}$, SFDA loss $\mathcal{L}_{\text{SFDA}}$, loss trade-off α
  Learning rates η_1 (model), η_2 (adv. samples), η_{init} (init. step)
  Epochs M, total steps N, Initialization T_{init}
Init:
  $w^{\mathcal{T}} \leftarrow w^{\mathcal{S}}$
  Initialize optimizer and LR scheduler for $w^{\mathcal{T}}$

for each class $c_{\mathcal{F}} \in \mathcal{C}_{\mathcal{F}}$ **do**
  Initialize adversarial sample $\hat{x}_{c_{\mathcal{F}}}$ (random)
  for $t = 1$ to T_{init} **do**
    $\hat{x}_{c_{\mathcal{F}}} \leftarrow \hat{x}_{c_{\mathcal{F}}} - \eta_{\text{init}} \nabla_{\hat{x}_{c_{\mathcal{F}}}} \mathcal{L}_{\text{CE}}(w^{\mathcal{T}}, \hat{x}_{c_{\mathcal{F}}}, c_{\mathcal{F}})$ ▷ Adversarial sample "seed"
  end for
end for

for epoch $= 1$ to M **do**
  Iterate through target data
  for each forget class $c_{\mathcal{F}} \in \mathcal{C}_{\mathcal{F}}$ **do**
    for step $= 1$ to $N/|\mathcal{C}_{\mathcal{F}}|$ **do**
      Sample target image $x^{\mathcal{T}} \sim \mathcal{D}^{\mathcal{T}}$
      Compute SFDA loss $\mathcal{L}_{\text{SFDA}}(w^{\mathcal{T}}, x^{\mathcal{T}})$
      Obtain logits on adversarial sample:

$$y = f_{w^{\mathcal{T}}}(\hat{x}_{c_{\mathcal{F}}})$$

      Set $\hat{y}_{c_{\mathcal{F}}} = 0$; renormalize remaining logits:

$$\hat{y}_i = \frac{y_i}{\sum_{j \neq c_{\mathcal{F}}} y_j}$$

      Set $\varphi = \mathcal{L}_{\text{SFDA}}(w^{\mathcal{T}}, x^{\mathcal{T}}) + \alpha\, \mathcal{L}_{\text{CE}}(w^{\mathcal{T}}, \hat{x}_{c_{\mathcal{F}}}, \hat{y})$
      Update model parameters:

$$w^{\mathcal{T}} \leftarrow w^{\mathcal{T}} - \eta_1 \nabla_{w^{\mathcal{T}}} \varphi$$

      Apply LR scheduler
      Update adversarial sample:

$$\hat{x}_{c_{\mathcal{F}}} \leftarrow \hat{x}_{c_{\mathcal{F}}} - \eta_2 \nabla_{\hat{x}_{c_{\mathcal{F}}}} \mathcal{L}_{\text{CE}}(w^{\mathcal{T}}, \hat{x}_{c_{\mathcal{F}}}, c_{\mathcal{F}})$$

    end for
  end for
end for
return Final unlearned target model $w_u^{\mathcal{T}} = w^{\mathcal{T}}$

A.3.2. Real-World Motivations for Variants

In Sec. 1, we discuss real-world use cases that motivate this work. An increased use of finetuning and adapting models underlines the significance of the setting proposed in this work. To discuss this further, the SCADA unlearning setting (Definition 1) assumes prior knowledge of source-exclusive classes alongside the source model and unlabeled target dataset. However, this assumption may not hold in practice sometimes, and it may be difficult to infer the source-exclusive classes from the source model $w^{\mathcal{S}}$ and the given unlabeled target retain data $\mathcal{D}_r^{\mathcal{T}} = \{(x_{i,r}^{\mathcal{T}})\}_{i=1}^{n}$. (If the target dataset were labeled, identifying these classes would be straightforward as one could iterate through the dataset to compile the set of observed target

Algorithm 3 Adversarial Optimization for UC-SCADA Unlearning

Inputs: Source Model $w^{\mathcal{S}}$, target dataset $\mathcal{D}^{\mathcal{T}}$, number of forget classes $|\mathcal{C}_{\mathcal{F}}|$, SFDA loss $\mathcal{L}_{\text{SFDA}}$, trade-off α, learning rates η_1, η_2

Init: $w^{\mathcal{T}} = w^{\mathcal{S}}$; $\gamma = 0$

for each $x^{\mathcal{T}} \in \mathcal{D}^{\mathcal{T}}$ **do**
  $\gamma \leftarrow \gamma + f_{w^{\mathcal{T}}}(x^{\mathcal{T}})$
end for

$\mathcal{C}^{*}_{\mathcal{F}} \leftarrow \text{Top\_K}(-\gamma, R \cdot |\mathcal{C}_{\mathcal{F}}|)$ ▷ Lowest $R \cdot |\mathcal{C}_{\mathcal{F}}|$ classes according to γ
$w^{\mathcal{T}}_{u} \leftarrow \text{AO\_SCADA\_UL}(w^{\mathcal{T}}, \mathcal{D}^{\mathcal{T}}, \mathcal{C}^{*}_{\mathcal{F}}, \mathcal{L}_{\text{SFDA}}, \alpha, \eta_1, \eta_2)$ ▷ Alg (1)

Return: $w^{\mathcal{T}}_{u}$

Algorithm 4 Adversarial Optimization for C-SCADA Unlearning

Inputs: Source Model $w^{\mathcal{S}}$, target dataset $\mathcal{D}^{\mathcal{T}}$, set of forget classes $\mathcal{C}_{\mathcal{F}}$, SFDA loss $\mathcal{L}_{\text{SFDA}}$, trade-off α, learning rates η_1, η_2

for each i, enumerating ${\mathcal{C}_{\mathcal{F}}}^{i} \in \mathcal{C}_{\mathcal{F}}$ **do**
  if $i = 1$ **then**
    $w^{\mathcal{T}}_{u} \leftarrow \text{AO\_SCADA\_UL}(w^{\mathcal{S}}, \mathcal{D}^{\mathcal{T}}, {\mathcal{C}_{\mathcal{F}}}^{i}, \mathcal{L}_{\text{SFDA}}, \alpha, \eta_1, \eta_2)$ ▷ Alg (1)
  else
    $\mathcal{D}^{\mathcal{T}}_{\text{sub}} = \text{Subset}(\mathcal{D}^{\mathcal{T}})$
    $w^{\mathcal{T}}_{u} \leftarrow \text{AO\_SCADA\_UL}(w^{\mathcal{T}}_{u}, \mathcal{D}^{\mathcal{T}}_{\text{sub}}, {\mathcal{C}_{\mathcal{F}}}^{i}, \mathcal{L}_{\text{SFDA}}, \alpha, \eta_1, \eta_2)$
  end if
end for

Return: $w^{\mathcal{T}}_{u}$

labels $\mathcal{C}_{\mathcal{T}}$ and deduce the source-exclusive classes as $\mathcal{C}_{\mathcal{F}} = \mathcal{C}_{\mathcal{S}} \setminus \mathcal{C}_{\mathcal{T}}$.) Such a scenario occurs, for example, when one does not have access to the source domain label space (e.g. fraud categories of a given country in a fraud detection application). Our variants address such a constraint; we introduce the **UC-SCADA-UL** setting (Definition 2), where only the number of source-exclusive classes is assumed to be known. Practically, this quantity can be estimated using domain knowledge, such as the sizes of the source and target label spaces: if $|\mathcal{C}_{\mathcal{S}}|$ and $|\mathcal{C}_{\mathcal{T}}|$ are known, $|\mathcal{C}_{\mathcal{F}}|$ can be computed as $|\mathcal{C}_{\mathcal{S}}| - |\mathcal{C}_{\mathcal{T}}|$, even when specific class identities are unavailable. Additionally, in some scenarios only a subset of $\mathcal{C}_{\mathcal{F}}$ may be known before the adaptation process, with additional classes uncovered over time (eg., through user-initiated data removal requests). The **C-SCADA-UL** setting (Definition 3) formalizes this process by allowing sequential unlearning of disjoint subsets ${\mathcal{C}_{\mathcal{F}}}^{i} \subseteq \mathcal{C}_{\mathcal{F}}$ across multiple steps, requiring the model to dynamically discard knowledge of ${\mathcal{C}_{\mathcal{F}}}^{i}$.

A.4. Additional Analysis

A.4.1. Applying Existing MU Methods in SCADA-UL

We experiment with applying adapted versions of existing MU methods [10, 51, 53] in the single class SCADA-UL setting on DomainNet with $c_{\mathcal{F}} = 1$ (see Sec. A.7 for implementation details). We test three approaches: applying the method on the source model and subsequently adapting that model to the target domain ("Source → Unlearn → Adapt" in Table A.7), applying the method during the adaptation process by adding loss terms ("Source → (Unlearn + Adapt)" in Table A.7), and applying the method on the target adapted model ("Source → Adapt → Unlearn" in Table A.7). From the results in Tab. A.7,

Figure A.4. **Visual appearance of Adversarial Samples.** Top row shows examples of samples from the source forget class (Backpack) from OfficeHome Art domain, while the bottom row shows examples of adversarial samples of this class. Although these samples appear as random noise, they are confidently classified as a backpack by the model. Moreover, in additional studies (Fig. A.5), we show that these samples match the forget class even on a representational level)

Table A.7. **Existing Data-Free MU methods struggle in Domain Adaptation.** Existing methods [10, 51, 53] when applied either before (Source → Unlearn → Adapt), during (Source → (Unlearn + Adapt)), or after (Source → Adapt → Unlearn) the domain adaptation process perform poorly in our setting, motivating our method.

Method	**Source → Unlearn → Adapt**		**Source → (Unlearn + Adapt)**		**Source → Adapt → Unlearn**	
	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$
Original (SF(DA)^2 [28])	$64.3_{\pm 1.9}$	$35.9_{\pm 4.0}$	N/A	N/A	N/A	N/A
Retrain	$65.2_{\pm 1.9}$	$0.0_{\pm 0.0}$	N/A	N/A	N/A	N/A
UNSIR [51]	$20.6_{\pm 2.9}$	$0.0_{\pm 0.0}$	$60.6_{\pm 1.9}$	$62.1_{\pm 6.8}$	$12.2_{\pm 8.5}$	$0.1_{\pm 0.1}$
ZSMU [10]	$62.5_{\pm 1.6}$	$29.6_{\pm 7.8}$	$62.7_{\pm 0.7}$	$53.7_{\pm 3.2}$	$58.1_{\pm 13.}$	$26.7_{\pm 10.}$
Nabla Tau [53]	$50.1_{\pm 3.7}$	$1.2_{\pm 2.0}$	$52.6_{\pm 1.8}$	$34.1_{\pm 12.4}$	$32.2_{\pm 5.9}$	$1.0_{\pm 1.4}$

Table A.8. **Cosine similarity (S_C) between features of adversarial samples and real samples.** Adversarial sample features align more with those of the forget class both before and after adaptation. After adaptation, they align more with the target forget

Compared Features	S_C Before Adaptation	S_C After Adaptation
Adversarial - Source Forget	**0.360**	**0.371**
Adversarial - Source Retain	0.326	0.315
Adversarial - Target Forget	**0.359**	**0.366**
Adversarial - Target Retain	0.335	0.307

we see that all the approaches to applying existing methods perform poorly in the SCADA-UL setting. This limitation arises from their design, which does not account for varying data distributions. It highlights the need for a targeted MU solution for the SCADA-UL setting.

A.4.2. Study on Adversarial Samples

Adversarial samples are generated directly by the model through optimization in the input space. Visually, these samples differ significantly from real-samples (See Fig. A.4). However, the model confidently classifies these samples as a certain class. In Sec. 4, we mention that the model maximizes the probability of the adversarial samples belonging to the forget class. While the objective encourages adversarial samples to be classified as the forget class by maximizing its logit, no structural regularization is used to impose visual similarity of the adversarial samples to the forget class. In this section, we further analyze the features of adversarial samples to assess their similarity to the forget classes using cosine similarity. We experiment on a representative task from the DomainNet dataset: Clipart to Sketch.

Tab. A.8 shows a 36% cosine similarity of adversarial sample features with forget class features of both domains. This similarity increases by about 1% after the domain adaptation process, showing that over time the adversarial samples evolve to approximate the forget class better. On the other hand, their similarity with retain class features starts at 32-33% and decreases to 30-31% after adaptation. These results support our claim that adversarial samples are representative of the forget classes in Sec. 4.

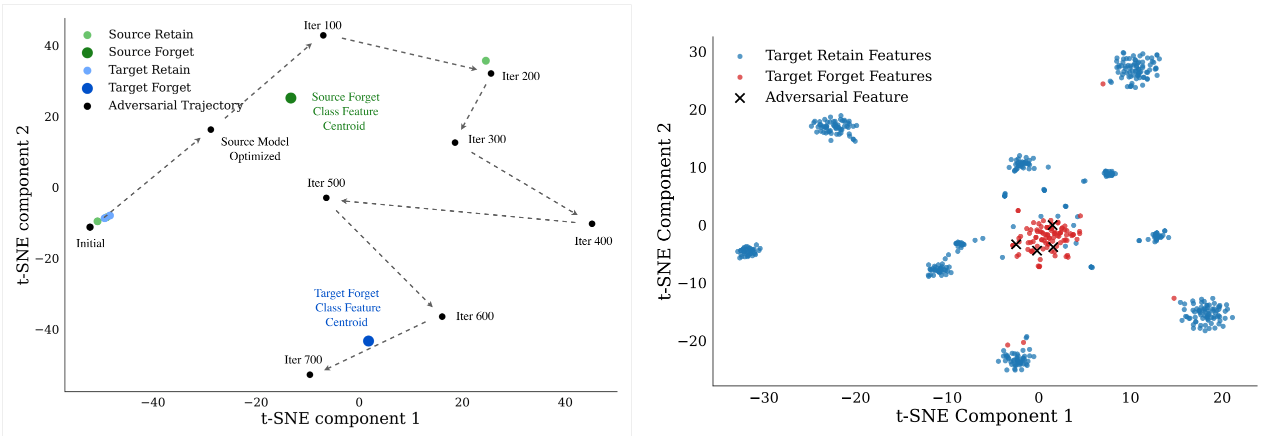

Figure A.5. **t-SNE plots of adversarial, retain, and forget class samples.** Left: Evolution of an adversarial sample over time. Initially, the sample lies far from the forget-class centroids (closer to retain-class centroids). While being optimized on the source model, it moves closer to the source forget-class centroid, and over iterations gradually converges toward the target forget-class centroid. This shows that the samples evolve alongside the model to best fit the class to forget in the target domain. Right: Final adversarial samples compared to t-SNE embeddings of 9 randomly selected retain classes $\{29, 3, 44, 58, 36, 2, 59, 47, 14\}$ and the forget class $c_{\mathcal{F}} = 1$. The final adversarial samples clearly align more closely with features from the forget class. Plotted for OfficeHome Art to Product.

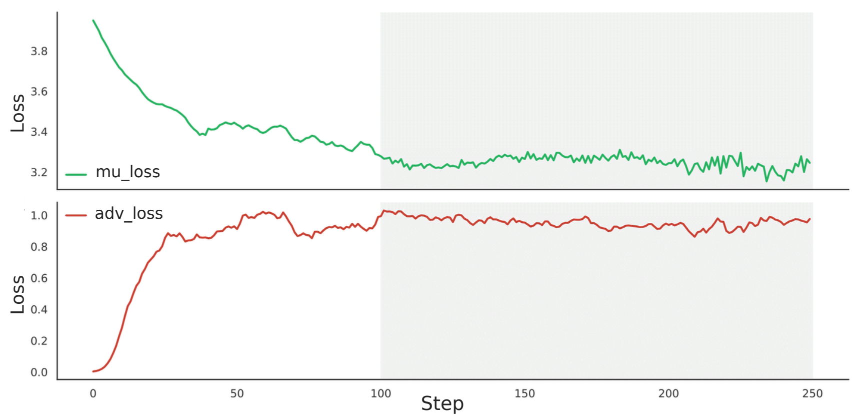

Figure A.6. **MU Loss ($\mathcal{L}_{\mathrm{MU}}$) and Adversarial Loss ($\mathcal{L}_{\mathrm{ADV}}$).** Initially, $\mathcal{L}_{\mathrm{MU}}$ conflicts with $\mathcal{L}_{\mathrm{ADV}}$, but equilibrium is reached after ~ 100 steps. This demonstrates a measured approach to unlearning where the model gradually finds a new representation ϕ that aligns with both objectives.

For qualitative analysis, we also visualize the evolution of adversarial sample features using t-SNE, as shown in Fig. A.5. We plot centroids for source retain and forget class features along with target retain and forget centroids, and overlay the adversarial trajectory across iterations. The visualization shows that adversarial samples begin far from the forget-class features, then gradually move toward the source forget class before shifting further toward the target forget class. This illustrates how the adversarial optimization drives samples to mimic the features of the class to forget as the model evolves from the source to target domain.

A.4.3. Visualizing Unlearning and Adversarial Loss Terms

We show a plot of the Unlearning Loss ($\mathcal{L}_{\mathrm{MU}}$) and Adversarial Loss ($\mathcal{L}_{\mathrm{ADV}}$) in Fig. A.6 for the OfficeHome Real-World-to-Art domain adaptation task. The figure reveals two key trends: firstly, the gradual decline in $\mathcal{L}_{\mathrm{MU}}$ indicates a measured unlearning process, suggesting that the method does not aim to abruptly "erase" the forget classes (a process that still stores latent information about the forget classes). Instead, unlearning occurs adversarially, as evident from the mirrored relationship between $\mathcal{L}_{\mathrm{MU}}$ and $\mathcal{L}_{\mathrm{ADV}}$ where a decrease in one causes an increase in the other. These observations align with our discussion in Sec. 4.2, that is, a higher value of the gradients of $\mathcal{L}_{\mathrm{MU}}$ for the retain classes gradually allows the unlearning of the forget classes during the training process. Together, these results demonstrate that our method performs thorough unlearning.

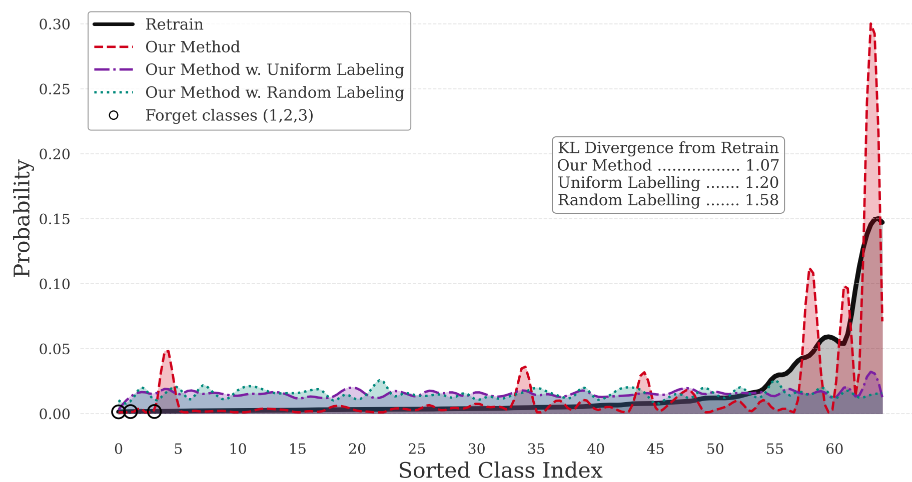

Figure A.7. **Softmax outputs of the target forget set for the retrained model compared with our method using Rescaled, Uniform, and Random Labeling.** After sorting classes by the retrained model's outputs, our method with Rescaled Labeling best matches the retrained distribution, while Uniform and Random Labeling deviate more significantly, as also reflected in their higher KL Divergence values. Note that we use interpolation to make the distributions more clear.

A.4.4. Visualizing Outputs Under Different Labeling Strategies

We visualize the average softmax outputs over the entire target forget dataset $\mathcal{D}_f^{\mathcal{T}}$ for four models: (1) **Retrain**: a model retrained on the source data and adapted to the target domain, (2) **Our Algorithm 1**: a model trained with our procedure using Rescaled Labeling, (3) **Uniform Labeling**: a variant where the rescaled labels $\hat{y}$ are replaced with a uniform distribution over the retain classes $c_{\mathcal{R}}$, and (4) **Random Labeling**: a variant where $\hat{y}$ is replaced with a randomly selected retain class.

Figure A.7 shows the sorted softmax outputs of all four models with respect to the retrained model's ordering. By sorting classes according to the retrained model's output distribution, the visualization highlights how closely each method matches the retrained behavior. Among the three variants of our method, the Rescaled Labeling strategy most closely follows the retrained curve, while Uniform and Random Labeling show more pronounced deviations. This further illustrates that Rescaled Labeling provides the best approximation to the output distribution of the gold-standard Retrain model.

A.4.5. Failure Case Analysis: UC-SCADA-UL

In Tab. A.25, specifically in the Sketch → Painting task, we observe that our method achieves a forget accuracy of 29.6%, which is an improvement over the original model's accuracy of 67.6%, but still far from the ideal 0% forget accuracy achieved by retraining.

We identify two key reasons for this gap.

1. **Low γ values for retain classes due to domain shift or inherent difficulty.** For example, classes like Compass, Cow, and Pencil exhibit 0% accuracy on the target domain and correspondingly low γ values (see Tab. A.9). This misleads our algorithm into detecting them as forget classes even though they are actually retain classes.
2. **Semantic or visual similarity between retain and forget classes.** Forget classes such as Great Wall of China receive higher γ values due to contributions from semantically similar classes like castle and streetlight (see Tab. A.10), making them harder to identify correctly as forget classes

A.4.6. Additional Ablation Studies

We performed additional ablation studies on the initialization of adversarial samples, loss trade-off parameter α and the number of adversarial samples, which are reported below. All experiments measure multi-class SCADA-UL performance across 3 trials on the OfficeHome dataset, reporting retain accuracy ($A_{\mathcal{D}_r^{\mathcal{T}}}$) and forget accuracy ($A_{\mathcal{D}_f^{\mathcal{T}}}$) averaged across 12 tasks.

Table A.11. Initializing adv samples

Initialize	$A_{\mathcal{D}_r^{\mathcal{T}}}$ ↑	$A_{\mathcal{D}_f^{\mathcal{T}}}$ ↓
✓	$75.1_{\pm 1.3}$	$0.0_{\pm 0.0}$
✗	$75.0_{\pm 1.2}$	$15.2_{\pm 4.1}$

Table A.9. **Target accuracy of lowest γ value classes** (domain shift evident by low target accuracy)

Class Name	Target Acc	γ Value
Compass	0.0	0.010
Cow	0.0	0.012
Pencil	0.0	0.013
Peas	2.5	0.018
Cell Phone	0.0	0.022

Table A.10. **Top contributing classes for γ value of forget classes.** (semantic similarity is observed)

Forget Class	Candidate 1	Candidate 2	Candidate 3
Great Wall of China	castle	train	streetlight
Aircraft Carrier	submarine	cruise_ship	helicopter
Alarm Clock	compass	watermelon	dog

Initialization of Adversarial Samples. Tab. A.11 shows that initializing samples by a complete minimization of $\mathcal{L}_{\text{ADV}}$ on the source model is crucial for effective unlearning. This step enables the samples to be good representations of the forget classes, which are subsequently refined via gradient updates.

Loss Trade-off (α). As seen in Tab. A.12, balancing $\mathcal{L}_{\text{SFDA}}$ and $\mathcal{L}_{\text{MU}}$ requires $\alpha >$ 5.0 to ensure thorough unlearning of forget classes, while values 10.0 and 20.0 yield comparable performance. This behavior can be explained by the distinct optimization objectives of the two losses, which stabilize after initial iterations (see Fig. A.6).

Below the threshold (5.0–10.0), $\mathcal{L}_{\text{SFDA}}$ marginally dominates $\mathcal{L}_{\text{MU}}$, leading to suboptimal unlearning performance.

Number of Adversarial Samples. Tab. A.13 shows that using very few adversarial samples, even 2 in this case, results in good unlearning performance. As the number of adversarial samples increases, retain accuracy improves, reaching close to its maximum value at 4 samples (which we use for our experiments in the main paper). Beyond this point, increasing the number of samples further does not lead to considerable improvement.

Number of Training Epochs. From Tab. A.14, we observe that using fewer epochs (e.g., 1) leads to incomplete forgetting, as seen by the higher forget accuracy. On the other hand, a larger number of epochs (e.g., 10) results in a slight drop in retain accuracy, likely due to continued application of $\mathcal{L}_{MU}$ negatively impacting the retained classes after the forget classes have already been unlearned. We use 5 epochs in our main experiments, as it provides a favorable trade-off, achieving complete forgetting while maintaining high retain accuracy.

Table A.12. Effect of varying Loss Trade-off (α) hyperparameter study

α	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$
1.0	$75.0_{\pm 1.2}$	$15.2_{\pm 4.1}$
5.0	$75.2_{\pm 1.1}$	$2.6_{\pm 2.0}$
10.0	$75.1_{\pm 1.3}$	$0.0_{\pm 0.0}$
20.0	$75.2_{\pm 1.1}$	$0.0_{\pm 0.0}$

Table A.13. Study on # adversarial samples used during training

N_{adv}	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$
1	$70.9_{\pm 3.6}$	$0.8_{\pm 1.4}$
2	$72.9_{\pm 3.7}$	$0.0_{\pm 0.0}$
4	$75.1_{\pm 1.3}$	$0.0_{\pm 0.0}$
8	$75.2_{\pm 1.2}$	$0.0_{\pm 0.0}$
16	$75.3_{\pm 1.1}$	$0.0_{\pm 0.0}$

Table A.14. Study on number of train epochs

Epochs	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$
1	$75.6_{\pm 1.4}$	$18.2_{\pm 8.1}$
5	$75.1_{\pm 1.3}$	$0.0_{\pm 0.0}$
10	$74.9_{\pm 1.2}$	$0.4_{\pm 0.3}$

A.4.7. Discussion of Assumptions in Our Method

Our method follows that (i) datasets with disjoint label spaces are conditionally independent given the model weights and (ii) source datasets can be approximated by their corresponding trained models. The use of (i) is explained and justified with an example at the end of Section 4.1. We further elaborate on (ii) here. For the approximation used in (ii), we follow such approximations used in Elastic Weight Consolidation [3] which employs a (diagonal) Laplace approximation to estimate posteriors across sequential tasks, and in online learning scenarios [46]. This approximation follows by assuming the posterior $p(w \mid \mathcal{D}^{\mathcal{S}})$ is approximately Gaussian and centered at the MLE estimate $w^{\mathcal{S}}$. i.e., $p(w \mid \mathcal{D}^{\mathcal{S}}) \approx \mathcal{N}(w^{\mathcal{S}}, \Sigma)$. By Bayesian inference, $p(w \mid \mathcal{D}^{\mathcal{S}}, \mathcal{D}_r^{\mathcal{T}}) \propto p(\mathcal{D}_r^{\mathcal{T}} \mid w) \cdot p(w \mid \mathcal{D}^{\mathcal{S}})$. Substituting the Gaussian approximation yields $p(w \mid \mathcal{D}^{\mathcal{S}}, \mathcal{D}_r^{\mathcal{T}}) \propto p(\mathcal{D}_r^{\mathcal{T}} \mid w) \cdot \mathcal{N}(w^{\mathcal{S}}, \Sigma) \approx p(w \mid w^{\mathcal{S}}, \mathcal{D}_r^{\mathcal{T}})$. Similarly, we obtain $p(w \mid \mathcal{D}_r^{\mathcal{S}}, \mathcal{D}_r^{\mathcal{T}}) \approx p(w \mid w_r^{\mathcal{S}}, \mathcal{D}_r^{\mathcal{T}})$.

A.5. Additional Experimental Results

A.5.1. Runtime Analysis of Methods

Table A.15 presents the runtime comparison of all methods for unlearning and adaptation to the target domain. While our method does not consistently achieve the lowest runtime across all datasets, its time cost remains significantly lower than that of retraining. We especially note that on the larger dataset setting (DomainNet), our method achieves the lowest training time, indicating its potential efficiency in large-scale settings. Additionally, the inference time is identical across all methods, as no extra computation is required during model inference.

Table A.15. Training Time for Each Method (in seconds)

Method	OfficeHome	Office31	DomainNet
Original (SF(DA)^2 [28])	$307.9_{\pm 0.6}$	$239.9_{\pm 2.0}$	$623.6_{\pm 5.3}$
Retrain	$696.7_{\pm 1.0}$	$665.8_{\pm 2.7}$	$1109.3_{\pm 1.9}$
Finetune	$616.2_{\pm 2.0}$	$476.7_{\pm 0.7}$	$1239.0_{\pm 2.3}$
UNSIR [51]	$\underline{364.0}_{\pm 3.3}$	$\underline{296.1}_{\pm 1.9}$	$710.3_{\pm 2.6}$
ZSMU [10]	$403.9_{\pm 0.2}$	$334.5_{\pm 1.3}$	$738.2_{\pm 3.2}$
Lipschitz [15]	$484.8_{\pm 2.8}$	$419.4_{\pm 0.4}$	$789.5_{\pm 0.5}$
Nabla Tau [53]	$370.3_{\pm 2.6}$	$301.6_{\pm 0.5}$	$757.1_{\pm 4.3}$
Unlearned(+) [2]	$1073.8_{\pm 514}$	$396.1_{\pm 59.}$	$3017_{\pm 1319}$
PADA [5]	$\mathbf{319.3}_{\pm 1.1}$	$\mathbf{253.6}_{\pm 2.1}$	$\underline{691.2}_{\pm 1.0}$
SHOT [34]	$560.1_{\pm 0.3}$	$538.8_{\pm 1.3}$	$730.6_{\pm 1.6}$
Ours	$382.2_{\pm 5.4}$	$319.6_{\pm 2.0}$	$\mathbf{691.0}_{\pm 2.7}$

Table A.16. SCADA-UL performance on Land-use Classification: UCMerced → RSSCN7

Method	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	Score ↑
Original (SF(DA)^2 [28])	$76.2_{\pm 1.3}$	$24.3_{\pm 28.}$	$0.64_{\pm 0.1}$
Retrain	$76.2_{\pm 3.8}$	$0.0_{\pm 0.0}$	$0.76_{\pm 0.0}$
Finetune	$\mathbf{76.2}_{\pm 1.0}$	$35.3_{\pm 23.}$	$0.57_{\pm 0.1}$
UNSIR [51]	$63.6_{\pm 10.}$	$\mathbf{0.0}_{\pm 0.0}$	$0.64_{\pm 0.1}$
ZSMU [10]	$\mathbf{76.2}_{\pm 1.8}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.76}_{\pm 0.0}$
Lipschitz [15]	$\underline{75.9}_{\pm 1.3}$	$18.3_{\pm 24.}$	$\underline{0.66}_{\pm 0.1}$
Nabla Tau [53]	$62.3_{\pm 2.5}$	$\mathbf{0.0}_{\pm 0.0}$	$0.62_{\pm 0.0}$
Unlearned(+) [2]	$63.4_{\pm 0.8}$	$0.9_{\pm 1.3}$	$0.63_{\pm 0.0}$
PADA [5]	$64.4_{\pm 1.4}$	$\underline{2.7}_{\pm 3.8}$	$0.63_{\pm 0.0}$
SHOT [34]	$65.2_{\pm 1.9}$	$14.5_{\pm 0.9}$	$0.57_{\pm 0.0}$
Ours	$\underline{75.9}_{\pm 1.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.76}_{\pm 0.0}$

A.5.2. Experiments on Land-use Classification Dataset

In Tab. A.16, we studied our approach on a land-use classification domain adaptation benchmark UC Merced [65] → RSSCN7 [71], similar to [49]. Privacy is a critical concern in such settings as certain categories of scenes (for e.g., government facilities) present in the source domain trained model must not be adapted to the target domain. Table A.16 indicates our method achieves good results on this real-world dataset.

A.5.3. SCADA Unlearning

Tables A.21 to A.23 present results for single-class SCADA unlearning on the OfficeHome, DomainNet and Office31 datasets respectively. Multi-class SCADA unlearning results are presented in Tabs. A.18 to A.20 tested on $\mathcal{C}_{\mathcal{F}} = \{1, 2, 3\}$. This is an extended version of Tab. 2 presented in the main paper, showing results for all the tasks within each dataset. Our method outperforms baselines w.r.t. all the metrics by achieving accuracies and unlearn score close to that of the retrained model in both single-class and multi-class unlearning settings.

A.5.4. UC-SCADA Unlearning

Tables A.24 to A.26 show the results in the UC-SCADA-UL setting (Def 2) with $\mathcal{C}_{\mathcal{F}} = \{1, 2, 3\}$, but these source-exclusive classes unknown to the model. Results show that our method outperforms the baselines w.r.t. the unlearn score metric on the OfficeHome and Office31 datasets. It maybe noted that finetuning is typically found to perform the best w.r.t. $A_{\mathcal{D}_r^{\mathcal{T}}}$ but its performance w.r.t. $A_{\mathcal{D}_f^{\mathcal{T}}}$ is poor. Similarly, w.r.t. $A_{\mathcal{D}_f^{\mathcal{T}}}$, UNSIR performs well in the UC-SCADA-UL setting, but it performs poorly w.r.t. $A_{\mathcal{D}_r^{\mathcal{T}}}$. On the DomainNet dataset, our method struggles with $A_{\mathcal{D}_f^{\mathcal{T}}}$, which is likely due to the inaccuracy in identifying the forget classes reliably using the γ parameter. We elaborate more on this in Sec. A.6.

A.5.5. C-SCADA Unlearning

Tables A.27 to A.29 show the results in the C-SCADA-UL setting (Def 3) where the source-exclusive classes are revealed over multiple time steps. For the experiments, we use $\mathcal{C}_{\mathcal{F}}{}^1 = \{1, 2\}, \mathcal{C}_{\mathcal{F}}{}^2 = \{3, 4\}, \mathcal{C}_{\mathcal{F}}{}^3 = \{5, 6\}$. The accuracies presented are cumulative over all forget classes until the current time step (for e.g., $A_{\mathcal{D}_f^{\mathcal{T}}}$ in T2 is the forget accuracy over classes $\mathcal{C}_{\mathcal{F}}{}^1 \cup \mathcal{C}_{\mathcal{F}}{}^2 = \{1, 2, 3, 4\}$). This allows us to evaluate how effectively the model forgets the newly designated class sets while maintaining unlearning of the older forget classes. The results show that our method consistently achieves thorough unlearning of the new class sets at each step, outperforming the baselines w.r.t. the unlearn score metric.

A.5.6. Use of Other SFDA Loss Functions

Table A.17 shows results of experiments with two other SFDA methods: SHOT [34] and UCon-SFDA [60]. The target domain performance while using just the SFDA method *(Original)* and the target domain performance while using this method as $\mathcal{L}_{\text{SFDA}}$ in our proposed method are provided in terms of percentage improvement over the corresponding Unlearn Score metric of the previous method going from top to bottom. For example, Rows 5, 6 show our method achieves a 6.1% improvement in the Score while using UCon-SFDA as $\mathcal{L}_{\text{SFDA}}$ instead of (SF(DA)^2, when UCon-SFDA shows a 15.7% improvement in target domain performance over (SF(DA)^2. This indicates that while our method works well with different SFDA losses, the performance of our method improves with the SFDA method used. Table A.17 reports the metrics over all 7 source, target pairs in DomainNet-126 for a single forget class.

Table A.17. **Improved SFDA methods improve our method as well.** We observe that as the underlying SFDA method achieves better performance, our method also improves. This shows the adaptability of our approach to new SFDA loss terms and its potential to further benefit as future SFDA methods advance.

SFDA Loss	Method	Metric	s → p	c → s	p → c	p → r	r → s	r → c	r → p	Average	% Improved
SHOT [34]	Original	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	70.1$_{\pm 1.1}$	57.4$_{\pm 1.9}$	61.1$_{\pm 1.0}$	83.7$_{\pm 0.4}$	60.6$_{\pm 3.4}$	69.1$_{\pm 1.0}$	75.5$_{\pm 0.6}$	68.2$_{\pm 1.3}$	-
		$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	88.7$_{\pm 0.9}$	47.0$_{\pm 20.6}$	57.8$_{\pm 2.5}$	86.7$_{\pm 0.1}$	27.7$_{\pm 4.8}$	41.8$_{\pm 0.6}$	43.1$_{\pm 2.3}$	56.1$_{\pm 4.5}$	
		Score ↑	0.37$_{\pm 0.0}$	0.39$_{\pm 0.0}$	0.39$_{\pm 0.0}$	0.45$_{\pm 0.0}$	0.47$_{\pm 0.0}$	0.49$_{\pm 0.0}$	0.53$_{\pm 0.0}$	0.44$_{\pm 0.0}$	
	Our Method	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	56.0$_{\pm 1.1}$	36.6$_{\pm 4.0}$	42.7$_{\pm 0.2}$	77.9$_{\pm 5.5}$	27.1$_{\pm 5.3}$	49.6$_{\pm 0.8}$	66.4$_{\pm 5.2}$	50.9$_{\pm 3.2}$	-
		$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	
		Score ↑	<u>0.56</u>$_{\pm 0.0}$	0.37$_{\pm 0.0}$	0.43$_{\pm 0.0}$	<u>0.78</u>$_{\pm 0.1}$	0.27$_{\pm 0.1}$	0.50$_{\pm 0.0}$	0.66$_{\pm 0.1}$	0.51$_{\pm 0.0}$	
SF(DA)^2 [28]	Original	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	71.3$_{\pm 0.3}$	66.6$_{\pm 0.4}$	61.7$_{\pm 0.8}$	78.3$_{\pm 0.2}$	55.9$_{\pm 1.5}$	65.1$_{\pm 0.9}$	75.0$_{\pm 0.4}$	67.7$_{\pm 0.6}$	+15.9%
		$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	77.6$_{\pm 5.7}$	36.9$_{\pm 6.9}$	35.6$_{\pm 1.3}$	74.1$_{\pm 12.1}$	3.2$_{\pm 0.4}$	17.5$_{\pm 1.0}$	6.1$_{\pm 0.3}$	35.9$_{\pm 4.0}$	
		Score ↑	0.40$_{\pm 0.0}$	0.48$_{\pm 0.0}$	0.46$_{\pm 0.0}$	0.45$_{\pm 0.0}$	0.54$_{\pm 0.0}$	0.55$_{\pm 0.0}$	0.71$_{\pm 0.0}$	0.51$_{\pm 0.0}$	
	Our Method	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	67.8$_{\pm 2.3}$	62.7$_{\pm 1.0}$	58.9$_{\pm 1.0}$	77.0$_{\pm 0.4}$	54.0$_{\pm 1.7}$	62.1$_{\pm 0.8}$	74.0$_{\pm 1.0}$	65.2$_{\pm 1.1}$	+27.4%
		$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	
		Score ↑	0.68$_{\pm 0.0}$	0.63$_{\pm 0.0}$	0.59$_{\pm 0.0}$	0.77$_{\pm 0.0}$	0.54$_{\pm 0.0}$	0.62$_{\pm 0.0}$	0.74$_{\pm 0.0}$	0.65$_{\pm 0.0}$	
UCon-SFDA [60]	Original	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	80.1$_{\pm 0.8}$	73.9$_{\pm 0.1}$	77.7$_{\pm 1.2}$	88.6$_{\pm 0.0}$	73.7$_{\pm 0.2}$	77.3$_{\pm 1.2}$	82.1$_{\pm 0.1}$	79.0$_{\pm 0.5}$	+15.7%
		$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	78.7$_{\pm 14.2}$	52.7$_{\pm 4.8}$	56.5$_{\pm 1.8}$	21.8$_{\pm 10.0}$	14.5$_{\pm 2.4}$	28.9$_{\pm 4.2}$	15.7$_{\pm 0.0}$	38.4$_{\pm 5.4}$	
		Score ↑	0.45$_{\pm 0.0}$	0.48$_{\pm 0.0}$	0.50$_{\pm 0.0}$	0.73$_{\pm 0.1}$	0.64$_{\pm 0.0}$	0.60$_{\pm 0.0}$	0.71$_{\pm 0.0}$	0.59$_{\pm 0.0}$	
	Our Method	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	71.7$_{\pm 2.4}$	67.8$_{\pm 0.2}$	60.6$_{\pm 0.6}$	83.6$_{\pm 0.4}$	56.1$_{\pm 0.5}$	64.9$_{\pm 0.7}$	75.4$_{\pm 0.1}$	68.6$_{\pm 0.7}$	+6.1%
		$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	0.0$_{\pm 0.0}$	
		Score ↑	0.72$_{\pm 0.0}$	0.68$_{\pm 0.0}$	0.61$_{\pm 0.0}$	0.84$_{\pm 0.0}$	0.56$_{\pm 0.0}$	0.65$_{\pm 0.0}$	0.75$_{\pm 0.0}$	0.69$_{\pm 0.0}$	

A.5.7. Extensions to Open-set Domain Adaptation

in Table A.30, we provide results on the open-set DA setting, replacing the SFDA loss term with the open-set DA version of SHOT [34] as described in the paper. This is evaulated on the OfficeHome dataset with source-only classes $\{1, 2, 3\}$ and target-only classes $\{34, 35, 36, 37, 38\}$. We report full target class accuracy (OS*), shared class accuracy (OS), forget accuracy, and unlearn score. The results show largely similar trends to the original SFDA setting, where existing methods perform poorly by dropping retain accuracy significantly (UNSIR, Lipschitz) or still maintaining high forget accuracy (ZSMU). In contrast, our method demonstrates strong unlearning performance while maintaining high retain accuracy, achieving the best overall unlearn score.

A.6. Limitations

Our work addresses the task of adapting to new domains while unlearning a subset of classes present only in the source domain. Although our proposed method demonstrates strong performance in the SCADA-UL setting (including its extensions C-SCADA-UL and UC-SCADA-UL), our studies have been currently limited to image classification-based domain adaptation tasks. Domain adaptation is also popular for other tasks such as semantic segmentation or generative modeling. For example, adapting language models to company-specific documents to enhance accuracy and avoid irrelevant or incorrect responses, or adapting road sign segmentation models to new geographies containing only a subset of signs. Extending our method to such directions needs to be studied carefully, and would be interesting directions of future work.

Beyond the above, in our current implementation, we adapt the γ term from PADA [5] for identification of source-exclusive classes. However, we find that this is not always accurate, especially in datasets with large label-spaces such as DomainNet. Our solution for this is to select an excess number of classes and unlearn all of them to increase the likelihood for source-exclusive classes to be included. Better approaches to identify forget classes or unified methods (that don't require knowledge of forget classes) may help the UC-SCADA-UL setting in particular. Finally, although we present a theorem linking our method to gradients, establishing mathematical guarantees for unlearning itself is challenging, and would be a potential direction for future work.

A.7. Implementation Details

A.7.1. Compute Resources

Our experiments were executed on a Linux-based compute cluster each using a single Tesla V100-SXM3-32GB GPU limited to 20 CPU workers. The time taken for running each experiment ranges from 300-1500 seconds.

A.7.2. Adapting MU and PDA Methods to SCADA-UL

We applied the baseline methods during the domain adaptation process when feasible, similar to our approach. Otherwise, we evaluated both the "before DA" and "after DA" variants of each method, and adopted the variant that performed better with respect to the Unlearn Score metric. This turned out to be "before DA" for all these methods, since this variant preserved the majority of retain accuracy (and hence higher unlearn score). As none of the existing MU methods have been implemented on the OfficeHome, Office31 or DomainNet datasets, we found the best hyperparameters for all the baseline MU methods on these datasets. The hyperparameters were tuned to maximize the unlearn score of each method. **Retrain.** The source model is retrained without the forget data and this model is domain adapted. Since source data is inaccessible in our setting, this only serves as a gold standard for comparison. **Finetune.** The source model is finetuned on the retain data using the SFDA loss. **UNSIR (Unlearning by Selective Impair and Repair).** employs an impair step to reduce the model's performance on the forget class followed by a repair step to restore performance on the retain set. As this method was originally designed for unlearning where labeled retain data is available, we adapt it for application to our setting. While the noise generation step remains unchanged, both impair and repair steps use target data with pseudo-labels as $\mathcal{D}_{r_{sub}}$, as this represents the closest approximation to data in our setting. The algorithm is applied to the source model before the domain adaptation process. **ZSMU (Zero-shot Machine Unlearning).** It uses error minimizing-maximizing noise to achieve data-free unlearning. This method is already data-free and is therefore applied directly to the source model before the DA process. **Lipschitz Unlearning.** It achieves unlearning by enforcing local Lipschitz regularization, minimizing the change in model outputs with respect to perturbations of the forget samples. As this method utilizes a simple loss function, this loss term is directly swapped with $\mathcal{L}_{\text{MU}}$ in our method. Moreover, since it requires forget samples, they were replaced with adversarial samples generated from our method. **Nabla Tau.** It applies adaptive gradient ascent to forget data along with gradient descent on retain data. This method was also applied to the source model and adversarial forget and retain samples were used. **Unlearned(+).** It estimates the influence of forget data on model parameters and removes it. The influence function involves a gradient computed over the forget set and hessian estimated over the retain set. To apply the method in our setting, adversarial samples were generated to compute the forget data gradient over the source model, and pseudo-labeled retain data was used to estimate the hessian. The method was applied on the source model, and after a short SFDA warmup run, it was re-applied with gentler hyperparameters, and then SFDA was resumed until convergence. Taking the additional, small MU step helped to reduce the forget accuracy more, while maintaining retain accuracy. **PADA.** It introduces a γ term to downweight the contributions of source-exclusive classes during PDA. The method was modified to fit into our setting by applying the proposed class weight vector on all loss terms in SF(DA)^2, alleviating the need for access to source data. **SHOT.** It freezes the source classifier (hypothesis) and adapts the feature encoder for target domain learning. We used the SFPDA version of SHOT as described in the paper by setting the β term to 0.

A.7.3. Hyperparameters

Forget Classes. For single class unlearning in SCADA-UL, we set the forget class $c_{\mathcal{F}} = 1$, for multiple class forgetting in SCADA-UL, we set it to $\mathcal{C}_{\mathcal{F}} = \{1, 2, 3\}$, and for C-SCADA-UL, we set $\mathcal{C}_{\mathcal{F}}{}^1 = \{1, 2\}$, $\mathcal{C}_{\mathcal{F}}{}^2 = \{3, 4\}$, $\mathcal{C}_{\mathcal{F}}{}^3 = \{5, 6\}$. For scenes dataset, we used $c_{\mathcal{F}} = 1$ corresponding to class Grasslands. For medical dataset, we used $c_{\mathcal{F}} = 3$ corresponding to class Edema. For ablation studies, we used $\mathcal{C}_{\mathcal{F}} = \{1, 2, 3\}$ on the OfficeHome dataset. **Data split.** We used an 80-20 split for train and test data in all experiments. **Backbone.** vit-base-patch16-224 pretrained on ImageNet-1K. **Optimizer.** SGD optimizer with learning rate 1e-2, momentum 0.9, weight decay 1e-3 and nesterov set to True. **LR Scheduler.** Lambda scheduler with gamma set to 1e-3 and decay set to 0.9. **Epochs.** Source model is trained for 10 Epochs with 1000 steps per epoch using label smoothing with coefficient 0.1 (As it is standard practice in SFDA [28]). For SCADA-UL, we use 5 epochs and 1000 steps per epoch on OfficeHome, DomainNet, Medical, Scene datasets, and 10 epochs for Office31 on most methods including ours. **Loss Trade-off (α).** We used $\alpha = 10.0$ for most experiments with SF(DA)^2 [28] as $\mathcal{L}_{\text{SFDA}}$, for SHOT [34], we used $\alpha = 150.0$. **Method Hyperparameters.** As none of the baseline MU methods had implementations on any of our tested datasets, we found the best hyperparameters on these datasets. The hyperparameters were tuned to maximize retain-set accuracy and hence the unlearn score of each method. **Our Method.** We used 4 adversarial samples to compute $\mathcal{L}_{\text{MU}}$ in our method. **UNSIR.** We used 256 pseudo-labeled target samples with 32 noisy samples, trained over 5 epochs and 8 steps per epoch with learning rate

1e-1, alpha 2e-3, and mean vector $[1, 2, 3]$. We used SGD optimizer with learning rate 1e-1, momentum 0.9, weight decay 1e-3, and nesterov set to True for both impair and repair steps. Impair was done for only 8 batches of data as we found this led to minimum degradation in retain class performance. **ZSMU.** The error minimizing-maximizing noise consisted of 64 error minimizing samples and 32 error maximizing samples. We used SGD optimizer with learning rate 2e-1, momentum 0.9, weight decay 1e-3 and nesterov set to True and a Lambda scheduler with gamma set to 1e-3 and decay set to 0.75. The ZSMU process was applied for 4 epochs with 8 batches per epoch. **Lipschitz.** Optimizer and LR scheduler are identical to those in SCADA-UL. 4 adversarial samples were generated per forget class and every iteration, each of these samples were iterated through and perturbed five times and the loss was computed. For example, for 3 forget classes, a total of 3 x 4 = 12 adversarial samples were generated and each of these samples were perturbed 5 times (12 x 5 = 60 perturbations). The losses for each perturbation were added together giving us $\mathcal{L}_{\text{MU}}$ for that step. In the UC-SCADA-UL setting for domain net, we use 3 perturbations instead of 5 due to VRAM limitations. **Nabla Tau.** SGD optimizer with learning rate 5e-2, momentum 0.9, weight decay 1e-3 and nesterov set to True, lambda scheduler with gamma set to 1e-3 and decay set to 0.75. The alpha term was set to 0.02. This method was run for only 100 steps due to its poor performance for larger number of steps. **Unlearned(+).** We froze the backbone and linearized only the final ViT classifier layer, ran the Hessian solver for 10 inner iterations with a step size of 0.10 and an L2 curvature penalty of 3e-3; we scaled the one-hot forget targets to 0.7, clipped the tangent update at a global norm of 1e-3, and injected Gaussian noise of 1e-5 before writing the update back. Each forget class was represented by 12 adversarial samples that we re-optimized every iteration, and we drew 12 such minibatches per MU phase. We ran a single-epoch SFDA warmup and then applied a small MU phase configured identically except for a smaller step: weight decay 5e-3, step size 0.03, max update norm 8e-4; post this the SFDA run was continued. **PADA.** Identical optimizer and scheduler as SCADA-UL, the gamma term was computed over the entire target retain train dataset. **SHOT.** The method used a SGD optimizer with learning rate of backbone 1e-1, and fully connected and bottleneck and rotation classifier with 1.0. Lambda lr scheduler was used with gamma 1e-3 and decay 0.9. The adaptation process was run for 10 epochs with 1000 steps per epoch. In UC-SCADA-UL, given the inherent noise in the estimation of γ, we conservatively select a larger set of classes beyond the forget set. Empirically, we find that selecting the $3 \cdot |\mathcal{C}_{\mathcal{F}}|$ bottom-ranked classes yields the best results.

A.7.4. Metrics

MIA Accuracy (MIA%). As mentioned in Sec. 5, we extend the Membership Inference Attack Accuracy (MIA%) metric [22] to suit class-level unlearning. The model is trained to discriminate between the output entropies of retain class data and unseen or out-of-domain (OOD) data. This is implemented by selecting semantically non-overlapping class samples from other datasets (e.g., selecting OfficeHome samples of classes such as calendar, curtains, etc., when experimenting on DomainNet). An ideal method (such as retraining) would be unable to distinguish between the forget class and such OOD classes.

Forget Class False Negative Rate (Forget FNR): This gives the ratio of forget class samples classified as retain samples to the total forget class samples. Given a threshold k, the sample is classified as forget class if the predicted softmax score is less than k, else as retain class. Figure A.8 shows as we increase the threshold, the forget FNR decreases as fewer forget samples are classified as retain classes, as expected.

Retain Class False Positive Rate (Retain FPR): This gives the ratio of retain class samples classified as forget samples to the total retain class samples. Given a threshold k, the sample is classified as forget class if the predicted softmax score is less than k, else as retain class. Figure A.8 shows as we increase the threshold, the retain FPR increases as more retain samples are classified as forget classes, but it rises upto a maximum value of 0.2 in Clipart $\rightarrow$ Art and 0.12 in Art $\rightarrow$ Product, showing that the retain FPR of our method remains low across multiple thresholds. This indicates our method maintains retain class performance robustly across thresholds.

Figure A.8 also shows the forget FNR vs retain FPR plot. The plot indicates it is easy to choose a threshold which maximizes forget FNR with very low retain FPR, for instance 0.18 in Art $\rightarrow$ Product which maintains the forgetting to model utility trade-off in our method.

Calibration Error: Expected Calibration Error (ECE) quantifies the alignment between the model's predicted confidence and its actual accuracy (lower is better). We plot ECE on source model and the model after applying our method for both retain and forget splits: retain bars remain low after unlearning with our method, indicating the retain-class calibration is maintained, i.e., does not degrade reliability on retain classes, whereas forget ECE rises substantially, showing the model loses calibration on forget classes, thus becoming uncertain on forget class samples,

A.7.5. Real-world Dataset Implementations

Scenes Dataset. Similar to [49], we map 7 similar classes of UC Merced and RSSCN7 datasets (golf course $\rightarrow$ grassland, agricultural $\rightarrow$ farmland, storage tanks $\rightarrow$ industrial region, river $\rightarrow$ river and lake, forest $\rightarrow$ forest, dense residential $\rightarrow$

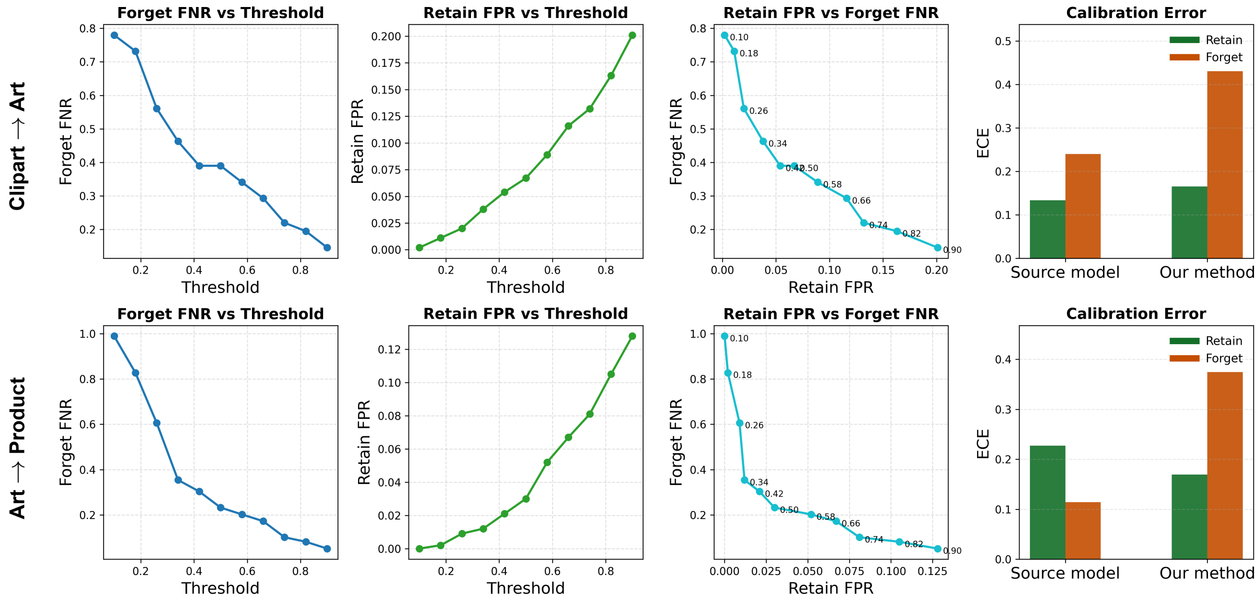

Figure A.8. **Forget/Retain Error and Calibration Analysis.** The figure shows the False Negative Rate (Forget FNR) of our method on forget-class samples across thresholds (first column); the False Positive Rate (Retain FPR) on retain-class samples across thresholds (second column); Forget FNR vs. Retain FPR (third column); and calibration error on retain and forget samples before and after unlearning (fourth column) for two OfficeHome settings. Our method achieves high Forget FNR (the model is confused on forget samples) and low Retain FPR (retain samples remain correctly classified) at appropriate thresholds. Calibration error is high for both forget and retain classes on the source model; after unlearning, retain-class calibration error stays low while forget-class calibration error increases, indicating greater model uncertainty on forget samples.

residential region, parking lot → parking lot). The forget class in our experiments is grassland/golf course. **Medical Dataset.** Similar to [27], we used 5 overlapping classes in both the datasets to conduct our experiments (Atelectasis, Cardiomegaly, Effusion, Consolidation and Edema). These datasets had some samples with multiple labels, we discarded these samples and retained samples with only single labels. Moreover, we used subsets of the datasets: ∼80,000 images for CheXpert , and ∼12,000 images for NIH Chest X-ray .

https://www.kaggle.com/datasets/ashery/chexpert
https://www.kaggle.com/datasets/khanfashee/nih-chest-x-ray-14-224x224-resized

Table A.18. **Results for Multi-Class SCADA Unlearning on OfficeHome.** Forget classes are $\mathcal{C}_\mathcal{F} = \{1, 2, 3\}$ ***(Best result in bold, second-best underlined)***

Method	Metric	A → C	A → P	A → R	C → A	C → P	C → R	P → A	P → C	P → R	R → A	R → C	R → P	Average
Original (SF(DA)^2 [28])	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$61.0_{\pm 2.0}$	$82.2_{\pm 1.9}$	$82.3_{\pm 0.4}$	$76.9_{\pm 2.1}$	$82.9_{\pm 1.2}$	$82.5_{\pm 1.1}$	$75.2_{\pm 1.7}$	$58.2_{\pm 1.4}$	$84.3_{\pm 1.6}$	$78.5_{\pm 0.2}$	$58.4_{\pm 1.8}$	$87.0_{\pm 0.2}$	$75.8_{\pm 1.3}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$28.7_{\pm 2.3}$	$71.1_{\pm 6.2}$	$86.1_{\pm 1.2}$	$57.1_{\pm 1.4}$	$69.0_{\pm 1.6}$	$76.7_{\pm 2.8}$	$47.8_{\pm 2.3}$	$22.0_{\pm 0.5}$	$72.8_{\pm 6.9}$	$53.1_{\pm 4.2}$	$35.5_{\pm 2.3}$	$77.1_{\pm 2.0}$	$58.1_{\pm 2.8}$
	Score ↑	$0.47_{\pm 0.0}$	$0.48_{\pm 0.0}$	$0.44_{\pm 0.0}$	$0.49_{\pm 0.0}$	$0.49_{\pm 0.0}$	$0.47_{\pm 0.0}$	$0.51_{\pm 0.0}$	$0.48_{\pm 0.0}$	$0.49_{\pm 0.0}$	$0.51_{\pm 0.0}$	$0.43_{\pm 0.0}$	$0.49_{\pm 0.0}$	$0.48_{\pm 0.0}$
Retrain	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$60.8_{\pm 1.4}$	$83.1_{\pm 0.8}$	$82.2_{\pm 0.7}$	$78.5_{\pm 2.5}$	$82.6_{\pm 1.2}$	$83.3_{\pm 1.8}$	$76.4_{\pm 1.2}$	$59.7_{\pm 3.1}$	$84.4_{\pm 0.7}$	$77.6_{\pm 1.6}$	$59.9_{\pm 2.0}$	$87.3_{\pm 0.5}$	$76.3_{\pm 1.5}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$
	Score ↑	$0.61_{\pm 0.0}$	$0.83_{\pm 0.0}$	$0.82_{\pm 0.0}$	$0.79_{\pm 0.0}$	$0.83_{\pm 0.0}$	$0.83_{\pm 0.0}$	$0.76_{\pm 0.0}$	$0.60_{\pm 0.0}$	$0.84_{\pm 0.0}$	$0.78_{\pm 0.0}$	$0.60_{\pm 0.0}$	$0.87_{\pm 0.0}$	$0.76_{\pm 0.0}$
Finetune	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$\mathbf{60.1}_{\pm 1.3}$	$81.5_{\pm 1.3}$	$\mathbf{82.6}_{\pm 0.8}$	$\mathbf{77.8}_{\pm 2.1}$	$\underline{83.1}_{\pm 0.3}$	$\mathbf{83.2}_{\pm 1.3}$	$\mathbf{76.5}_{\pm 0.7}$	$58.3_{\pm 1.8}$	$\underline{84.4}_{\pm 1.6}$	$\mathbf{79.3}_{\pm 0.5}$	$58.6_{\pm 1.1}$	$\underline{87.3}_{\pm 0.4}$	$\mathbf{76.1}_{\pm 1.1}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$24.8_{\pm 3.8}$	$66.5_{\pm 5.4}$	$82.0_{\pm 2.7}$	$44.5_{\pm 1.6}$	$61.4_{\pm 3.0}$	$75.1_{\pm 2.0}$	$36.7_{\pm 1.9}$	$\underline{1.5}_{\pm 0.5}$	$59.6_{\pm 3.8}$	$43.5_{\pm 4.0}$	$21.3_{\pm 0.9}$	$72.9_{\pm 2.8}$	$49.2_{\pm 2.7}$
	Score ↑	$0.48_{\pm 0.0}$	$0.49_{\pm 0.0}$	$0.45_{\pm 0.0}$	$0.54_{\pm 0.0}$	$0.51_{\pm 0.0}$	$0.48_{\pm 0.0}$	$0.56_{\pm 0.0}$	$\mathbf{0.57}_{\pm 0.0}$	$0.53_{\pm 0.0}$	$0.55_{\pm 0.0}$	$0.48_{\pm 0.0}$	$0.50_{\pm 0.0}$	$0.51_{\pm 0.0}$
UNSIR [51]	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$25.4_{\pm 3.5}$	$58.0_{\pm 2.5}$	$48.1_{\pm 4.2}$	$16.8_{\pm 11.}$	$55.4_{\pm 13.}$	$48.4_{\pm 2.7}$	$11.6_{\pm 7.2}$	$15.1_{\pm 11.}$	$37.7_{\pm 12.}$	$11.3_{\pm 7.2}$	$28.6_{\pm 3.0}$	$63.7_{\pm 3.1}$	$35.0_{\pm 6.8}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\underline{0.2}_{\pm 0.3}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$
	Score ↑	$0.25_{\pm 0.0}$	$0.58_{\pm 0.0}$	$0.48_{\pm 0.0}$	$0.17_{\pm 0.1}$	$0.55_{\pm 0.1}$	$0.48_{\pm 0.0}$	$0.12_{\pm 0.1}$	$0.15_{\pm 0.1}$	$0.38_{\pm 0.1}$	$0.11_{\pm 0.1}$	$0.29_{\pm 0.0}$	$0.64_{\pm 0.0}$	$0.35_{\pm 0.1}$
ZSMU [10]	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$58.9_{\pm 0.5}$	$56.3_{\pm 43.}$	$74.6_{\pm 12.}$	$72.2_{\pm 3.0}$	$79.2_{\pm 3.3}$	$79.5_{\pm 2.7}$	$\underline{75.5}_{\pm 1.4}$	$55.2_{\pm 3.1}$	$83.6_{\pm 1.3}$	$76.2_{\pm 1.6}$	$55.4_{\pm 0.8}$	$86.1_{\pm 0.6}$	$71.1_{\pm 6.1}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$20.9_{\pm 1.4}$	$40.0_{\pm 34.}$	$39.4_{\pm 26.}$	$31.8_{\pm 2.8}$	$41.2_{\pm 7.4}$	$52.5_{\pm 3.3}$	$47.8_{\pm 2.8}$	$10.9_{\pm 5.5}$	$60.8_{\pm 5.8}$	$43.2_{\pm 10.}$	$21.3_{\pm 9.2}$	$67.5_{\pm 10.}$	$39.8_{\pm 10.}$
	Score ↑	$0.49_{\pm 0.0}$	$0.36_{\pm 0.3}$	$0.54_{\pm 0.0}$	$0.55_{\pm 0.0}$	$0.56_{\pm 0.0}$	$0.52_{\pm 0.0}$	$0.51_{\pm 0.0}$	$\underline{0.50}_{\pm 0.0}$	$0.52_{\pm 0.0}$	$0.53_{\pm 0.0}$	$0.46_{\pm 0.0}$	$0.52_{\pm 0.0}$	$0.50_{\pm 0.0}$
Lipschitz [15]	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$42.8_{\pm 21.8}$	$77.0_{\pm 2.2}$	$79.8_{\pm 2.5}$	$33.3_{\pm 13.4}$	$71.5_{\pm 12.}$	$70.3_{\pm 18.}$	$25.1_{\pm 18.0}$	$37.9_{\pm 14.}$	$76.3_{\pm 6.2}$	$65.0_{\pm 8.4}$	$51.5_{\pm 7.2}$	$72.7_{\pm 10.3}$	$58.6_{\pm 11.}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$\underline{15.3}_{\pm 13.}$	$27.3_{\pm 15.}$	$63.8_{\pm 18.}$	$8.6_{\pm 15.}$	$20.6_{\pm 35.}$	$37.8_{\pm 32.}$	$\underline{2.2}_{\pm 3.8}$	$3.2_{\pm 5.5}$	$37.3_{\pm 17.}$	$\underline{13.9}_{\pm 11.}$	$19.7_{\pm 1.2}$	$55.6_{\pm 28.}$	$25.4_{\pm 16.}$
	Score ↑	$0.36_{\pm 0.2}$	$0.61_{\pm 0.1}$	$0.49_{\pm 0.0}$	$0.31_{\pm 0.1}$	$0.61_{\pm 0.1}$	$0.51_{\pm 0.0}$	$0.24_{\pm 0.2}$	$0.36_{\pm 0.1}$	$0.56_{\pm 0.0}$	$0.57_{\pm 0.0}$	$0.43_{\pm 0.1}$	$0.47_{\pm 0.0}$	$0.46_{\pm 0.1}$
Nabla Tau [53]	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$52.0_{\pm 2.2}$	$74.5_{\pm 4.3}$	$68.6_{\pm 1.7}$	$61.1_{\pm 4.9}$	$73.6_{\pm 2.7}$	$69.8_{\pm 0.8}$	$60.1_{\pm 4.0}$	$46.7_{\pm 3.3}$	$66.0_{\pm 3.5}$	$61.3_{\pm 1.6}$	$47.0_{\pm 3.4}$	$77.0_{\pm 2.1}$	$63.2_{\pm 2.9}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$\mathbf{0.0}_{\pm 0.0}$	$\underline{1.0}_{\pm 1.7}$	$\underline{0.1}_{\pm 0.2}$	$\underline{3.4}_{\pm 4.3}$	$0.3_{\pm 0.6}$	$\mathbf{0.0}_{\pm 0.0}$	$5.9_{\pm 3.3}$	$\mathbf{0.0}_{\pm 0.0}$	$\underline{4.7}_{\pm 8.2}$	$\mathbf{0.0}_{\pm 0.0}$	$\underline{1.2}_{\pm 2.1}$	$\underline{1.8}_{\pm 3.1}$	$\underline{1.5}_{\pm 2.0}$
	Score ↑	$\underline{0.52}_{\pm 0.0}$	$\underline{0.74}_{\pm 0.0}$	$\underline{0.69}_{\pm 0.0}$	$\underline{0.59}_{\pm 0.1}$	$\underline{0.73}_{\pm 0.0}$	$0.70_{\pm 0.0}$	$\underline{0.57}_{\pm 0.0}$	$0.47_{\pm 0.0}$	$0.63_{\pm 0.1}$	$\underline{0.61}_{\pm 0.0}$	$0.46_{\pm 0.0}$	$\underline{0.76}_{\pm 0.0}$	$\underline{0.62}_{\pm 0.0}$
Unlearned(+) [2]	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$58.8_{\pm 4.5}$	$\mathbf{83.6}_{\pm 1.7}$	$\underline{81.5}_{\pm 1.0}$	$76.0_{\pm 0.8}$	$82.6_{\pm 2.0}$	$82.4_{\pm 0.6}$	$75.4_{\pm 1.8}$	$\mathbf{60.5}_{\pm 1.6}$	$\mathbf{84.9}_{\pm 1.6}$	$77.3_{\pm 0.8}$	$\underline{61.3}_{\pm 0.9}$	$\mathbf{88.2}_{\pm 1.0}$	$\mathbf{76.1}_{\pm 1.5}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$9.9_{\pm 2.3}$	$59.3_{\pm 13.9}$	$54.1_{\pm 12.1}$	$27.3_{\pm 5.9}$	$51.5_{\pm 6.2}$	$57.3_{\pm 1.7}$	$42.2_{\pm 5.9}$	$21.1_{\pm 6.5}$	$41.9_{\pm 8.3}$	$33.8_{\pm 8.5}$	$14.7_{\pm 9.8}$	$50.1_{\pm 4.8}$	$38.6_{\pm 7.3}$
	Score ↑	$0.54_{\pm 0.05}$	$0.53_{\pm 0.04}$	$0.53_{\pm 0.05}$	$0.60_{\pm 0.03}$	$0.55_{\pm 0.01}$	$0.52_{\pm 0.00}$	$0.53_{\pm 0.01}$	$0.50_{\pm 0.04}$	$0.53_{\pm 0.02}$	$0.58_{\pm 0.04}$	$0.54_{\pm 0.04}$	$0.52_{\pm 0.01}$	$0.54_{\pm 0.03}$
PADA [5]	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$58.4_{\pm 0.9}$	$80.2_{\pm 2.4}$	$80.8_{\pm 0.6}$	$76.3_{\pm 1.7}$	$80.7_{\pm 1.2}$	$80.8_{\pm 0.7}$	$73.5_{\pm 2.4}$	$56.5_{\pm 1.7}$	$82.7_{\pm 2.4}$	$77.3_{\pm 1.4}$	$54.5_{\pm 0.6}$	$86.0_{\pm 1.1}$	$74.0_{\pm 1.4}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$33.3_{\pm 0.3}$	$77.4_{\pm 2.6}$	$82.5_{\pm 0.8}$	$64.8_{\pm 2.5}$	$70.9_{\pm 2.5}$	$73.3_{\pm 1.2}$	$56.5_{\pm 0.9}$	$31.0_{\pm 0.6}$	$79.4_{\pm 0.8}$	$60.5_{\pm 0.5}$	$38.7_{\pm 2.1}$	$83.0_{\pm 0.5}$	$62.6_{\pm 1.3}$
	Score ↑	$0.44_{\pm 0.0}$	$0.45_{\pm 0.0}$	$0.44_{\pm 0.0}$	$0.46_{\pm 0.0}$	$0.47_{\pm 0.0}$	$0.47_{\pm 0.0}$	$0.47_{\pm 0.0}$	$0.43_{\pm 0.0}$	$0.46_{\pm 0.0}$	$0.48_{\pm 0.0}$	$0.39_{\pm 0.0}$	$0.47_{\pm 0.0}$	$0.45_{\pm 0.0}$
SHOT [34]	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$56.0_{\pm 2.1}$	$76.8_{\pm 2.3}$	$79.2_{\pm 1.1}$	$74.4_{\pm 2.0}$	$80.9_{\pm 1.2}$	$80.0_{\pm 1.4}$	$71.6_{\pm 1.0}$	$\underline{58.4}_{\pm 1.3}$	$81.4_{\pm 2.1}$	$76.8_{\pm 0.5}$	$\mathbf{63.0}_{\pm 0.6}$	$85.8_{\pm 0.6}$	$73.7_{\pm 1.3}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$23.9_{\pm 1.0}$	$27.6_{\pm 2.5}$	$28.2_{\pm 1.7}$	$31.2_{\pm 1.0}$	$19.3_{\pm 0.8}$	$\underline{13.0}_{\pm 0.8}$	$29.6_{\pm 1.9}$	$23.9_{\pm 2.3}$	$15.0_{\pm 0.4}$	$36.1_{\pm 0.9}$	$28.8_{\pm 0.7}$	$19.4_{\pm 0.3}$	$24.7_{\pm 1.2}$
	Score ↑	$0.45_{\pm 0.0}$	$0.60_{\pm 0.0}$	$0.62_{\pm 0.0}$	$0.57_{\pm 0.0}$	$0.68_{\pm 0.0}$	$\underline{0.71}_{\pm 0.0}$	$0.55_{\pm 0.0}$	$0.47_{\pm 0.0}$	$\underline{0.71}_{\pm 0.0}$	$0.56_{\pm 0.0}$	$\underline{0.49}_{\pm 0.0}$	$0.72_{\pm 0.0}$	$0.59_{\pm 0.0}$
Ours	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$\underline{59.9}_{\pm 1.2}$	$\underline{82.0}_{\pm 2.1}$	$81.1_{\pm 1.6}$	$\underline{76.6}_{\pm 3.0}$	$\mathbf{83.3}_{\pm 1.4}$	$\underline{82.6}_{\pm 1.9}$	$74.0_{\pm 1.4}$	$57.1_{\pm 2.0}$	$83.4_{\pm 1.7}$	$\underline{77.8}_{\pm 1.1}$	$57.0_{\pm 0.8}$	$86.7_{\pm 0.7}$	$\underline{75.1}_{\pm 1.6}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$
	Score ↑	$\mathbf{0.60}_{\pm 0.0}$	$\mathbf{0.82}_{\pm 0.0}$	$\mathbf{0.81}_{\pm 0.0}$	$\mathbf{0.77}_{\pm 0.0}$	$\mathbf{0.83}_{\pm 0.0}$	$\mathbf{0.83}_{\pm 0.0}$	$\mathbf{0.74}_{\pm 0.0}$	$\mathbf{0.57}_{\pm 0.0}$	$\mathbf{0.83}_{\pm 0.0}$	$\mathbf{0.78}_{\pm 0.0}$	$\mathbf{0.57}_{\pm 0.0}$	$\mathbf{0.87}_{\pm 0.0}$	$\mathbf{0.75}_{\pm 0.0}$

Table A.19. **Results for Multi-Class SCADA Unlearning on DomainNet.** Forget classes are $\mathcal{C}_{\mathcal{F}} = \{1, 2, 3\}$ *(Best result in bold, second-best underlined)*

Method	Metric	s → p	c → s	p → c	p → r	r → s	r → c	r → p	Average
Original (SF(DA)^2 [28])	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$71.3_{\pm 0.4}$	$66.6_{\pm 0.5}$	$61.7_{\pm 1.0}$	$78.3_{\pm 0.2}$	$55.9_{\pm 1.9}$	$65.1_{\pm 1.1}$	$75.0_{\pm 0.5}$	$67.7_{\pm 0.8}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$67.6_{\pm 7.0}$	$55.9_{\pm 5.9}$	$42.9_{\pm 2.7}$	$60.6_{\pm 2.7}$	$6.5_{\pm 1.3}$	$14.6_{\pm 1.1}$	$22.8_{\pm 3.8}$	$38.7_{\pm 3.5}$
	Score $\uparrow$	$0.43_{\pm 0.0}$	$0.43_{\pm 0.0}$	$0.43_{\pm 0.0}$	$0.49_{\pm 0.0}$	$0.53_{\pm 0.0}$	$0.57_{\pm 0.0}$	$0.61_{\pm 0.0}$	$0.50_{\pm 0.0}$
Retrain	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$71.0_{\pm 0.4}$	$65.3_{\pm 2.8}$	$58.6_{\pm 2.9}$	$78.2_{\pm 1.1}$	$54.2_{\pm 1.3}$	$62.9_{\pm 1.9}$	$74.1_{\pm 1.3}$	$66.3_{\pm 1.6}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$
	Score $\uparrow$	$0.71_{\pm 0.0}$	$0.65_{\pm 0.0}$	$0.59_{\pm 0.0}$	$0.78_{\pm 0.0}$	$0.54_{\pm 0.0}$	$0.63_{\pm 0.0}$	$0.74_{\pm 0.0}$	$0.66_{\pm 0.0}$
Finetune	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$68.9_{\pm 0.1}$	$\underline{64.9}_{\pm 1.3}$	$62.2_{\pm 1.4}$	$77.3_{\pm 0.2}$	$52.1_{\pm 2.3}$	$\underline{65.5}_{\pm 1.6}$	$74.2_{\pm 1.0}$	$\underline{66.5}_{\pm 1.1}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$37.4_{\pm 7.1}$	$32.3_{\pm 3.2}$	$20.8_{\pm 7.7}$	$36.6_{\pm 3.8}$	$\underline{0.6}_{\pm 0.4}$	$5.3_{\pm 2.6}$	$10.1_{\pm 10.}$	$20.4_{\pm 5.0}$
	Score $\uparrow$	$\underline{0.50}_{\pm 0.0}$	$\underline{0.49}_{\pm 0.0}$	$\underline{0.52}_{\pm 0.0}$	$0.57_{\pm 0.0}$	$\underline{0.52}_{\pm 0.0}$	$\underline{0.62}_{\pm 0.0}$	$\underline{0.68}_{\pm 0.1}$	$\underline{0.56}_{\pm 0.0}$
UNSIR [51]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$11.6_{\pm 3.6}$	$2.7_{\pm 1.0}$	$22.4_{\pm 3.9}$	$37.5_{\pm 4.9}$	$5.2_{\pm 4.5}$	$7.9_{\pm 5.6}$	$14.8_{\pm 7.6}$	$14.6_{\pm 4.4}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\underline{3.0}_{\pm 5.1}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\underline{0.4}_{\pm 0.7}$
	Score $\uparrow$	$0.12_{\pm 0.0}$	$0.03_{\pm 0.0}$	$0.22_{\pm 0.0}$	$0.37_{\pm 0.1}$	$0.05_{\pm 0.0}$	$0.08_{\pm 0.1}$	$0.15_{\pm 0.1}$	$0.14_{\pm 0.0}$
ZSMU [10]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$\underline{70.7}_{\pm 1.1}$	$63.1_{\pm 0.3}$	$61.1_{\pm 1.8}$	$\mathbf{78.6}_{\pm 1.3}$	$50.8_{\pm 0.7}$	$61.6_{\pm 1.5}$	$69.2_{\pm 4.2}$	$65.0_{\pm 1.6}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$61.4_{\pm 7.5}$	$47.1_{\pm 6.3}$	$31.5_{\pm 11.9}$	$50.5_{\pm 15.1}$	$19.5_{\pm 3.6}$	$13.4_{\pm 1.1}$	$18.2_{\pm 1.1}$	$34.5_{\pm 6.6}$
	Score $\uparrow$	$0.44_{\pm 0.0}$	$0.43_{\pm 0.0}$	$0.47_{\pm 0.0}$	$0.52_{\pm 0.0}$	$0.42_{\pm 0.0}$	$0.54_{\pm 0.0}$	$0.59_{\pm 0.0}$	$0.49_{\pm 0.0}$
Lipschitz [15]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$5.4_{\pm 4.2}$	$33.9_{\pm 27.}$	$39.1_{\pm 14.}$	$64.5_{\pm 3.4}$	$42.0_{\pm 6.3}$	$32.4_{\pm 11.}$	$55.7_{\pm 10.}$	$39.0_{\pm 11.}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$2.9_{\pm 5.1}$	$5.2_{\pm 8.9}$	$\underline{11.6}_{\pm 10.}$	$27.0_{\pm 18.}$	$1.6_{\pm 1.7}$	$\underline{0.3}_{\pm 0.5}$	$10.7_{\pm 14.}$	$8.5_{\pm 8.6}$
	Score $\uparrow$	$0.05_{\pm 0.0}$	$0.31_{\pm 0.2}$	$0.34_{\pm 0.1}$	$0.51_{\pm 0.1}$	$0.41_{\pm 0.1}$	$0.32_{\pm 0.1}$	$0.50_{\pm 0.0}$	$0.35_{\pm 0.1}$
Nabla Tau [53]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$44.7_{\pm 3.2}$	$38.1_{\pm 5.4}$	$43.4_{\pm 3.3}$	$63.0_{\pm 3.3}$	$23.8_{\pm 18.}$	$47.3_{\pm 0.4}$	$50.6_{\pm 3.8}$	$44.4_{\pm 5.4}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$\underline{0.8}_{\pm 1.4}$	$\underline{0.2}_{\pm 0.3}$	$\mathbf{0.0}_{\pm 0.0}$	$7.9_{\pm 11.}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\underline{0.1}_{\pm 0.2}$	$1.3_{\pm 1.9}$
	Score $\uparrow$	$0.44_{\pm 0.0}$	$0.38_{\pm 0.1}$	$0.43_{\pm 0.0}$	$\underline{0.59}_{\pm 0.1}$	$0.24_{\pm 0.2}$	$0.47_{\pm 0.0}$	$0.51_{\pm 0.0}$	$0.44_{\pm 0.1}$
Unlearned(+) [2]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$69.2_{\pm 0.4}$	$62.1_{\pm 3.6}$	$\mathbf{63.4}_{\pm 0.3}$	$76.2_{\pm 0.8}$	$\mathbf{56.1}_{\pm 0.2}$	$\mathbf{67.1}_{\pm 0.2}$	$74.3_{\pm 0.4}$	$66.9_{\pm 0.8}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$45.3_{\pm 8.3}$	$41.7_{\pm 1.1}$	$31.4_{\pm 7.8}$	$38.3_{\pm 2.4}$	$10.3_{\pm 12.9}$	$7.6_{\pm 0.0}$	$11.6_{\pm 0.9}$	$26.6_{\pm 4.8}$
	Score $\uparrow$	$0.48_{\pm 0.02}$	$0.44_{\pm 0.03}$	$0.48_{\pm 0.03}$	$0.55_{\pm 0.00}$	$0.51_{\pm 0.06}$	$0.62_{\pm 0.00}$	$0.67_{\pm 0.01}$	$0.54_{\pm 0.02}$
PADA [5]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$61.1_{\pm 0.3}$	$59.7_{\pm 0.7}$	$55.1_{\pm 0.3}$	$76.1_{\pm 0.5}$	$49.0_{\pm 0.3}$	$59.9_{\pm 0.4}$	$72.2_{\pm 0.3}$	$61.9_{\pm 0.4}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$45.5_{\pm 1.3}$	$70.1_{\pm 0.4}$	$57.1_{\pm 1.1}$	$71.6_{\pm 1.1}$	$22.3_{\pm 0.8}$	$26.8_{\pm 0.9}$	$32.7_{\pm 2.4}$	$46.6_{\pm 1.1}$
	Score $\uparrow$	$0.42_{\pm 0.0}$	$0.35_{\pm 0.0}$	$0.35_{\pm 0.0}$	$0.44_{\pm 0.0}$	$0.40_{\pm 0.0}$	$0.47_{\pm 0.0}$	$0.54_{\pm 0.0}$	$0.43_{\pm 0.0}$
SHOT [34]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$\mathbf{71.3}_{\pm 0.2}$	$\mathbf{66.4}_{\pm 1.6}$	$\underline{62.4}_{\pm 0.6}$	$\underline{78.5}_{\pm 0.4}$	$\underline{55.7}_{\pm 2.4}$	$65.1_{\pm 0.4}$	$\mathbf{74.8}_{\pm 0.9}$	$\mathbf{67.8}_{\pm 0.9}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$67.7_{\pm 4.5}$	$56.3_{\pm 5.1}$	$48.7_{\pm 3.0}$	$62.4_{\pm 3.3}$	$6.9_{\pm 2.1}$	$13.6_{\pm 0.5}$	$21.2_{\pm 0.5}$	$39.6_{\pm 2.7}$
	Score $\uparrow$	$0.43_{\pm 0.0}$	$0.43_{\pm 0.0}$	$0.42_{\pm 0.0}$	$0.48_{\pm 0.0}$	$\underline{0.52}_{\pm 0.0}$	$0.57_{\pm 0.0}$	$0.62_{\pm 0.0}$	$0.50_{\pm 0.0}$
Ours	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$65.3_{\pm 1.3}$	$63.7_{\pm 1.7}$	$60.1_{\pm 1.0}$	$77.0_{\pm 0.5}$	$55.0_{\pm 1.1}$	$63.5_{\pm 1.5}$	$\underline{74.7}_{\pm 0.4}$	$65.6_{\pm 1.1}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$
	Score $\uparrow$	$\mathbf{0.65}_{\pm 0.0}$	$\mathbf{0.64}_{\pm 0.0}$	$\mathbf{0.60}_{\pm 0.0}$	$\mathbf{0.77}_{\pm 0.0}$	$\mathbf{0.55}_{\pm 0.0}$	$\mathbf{0.64}_{\pm 0.0}$	$\mathbf{0.75}_{\pm 0.0}$	$\mathbf{0.66}_{\pm 0.0}$

Table A.20. **Results for Multi-Class SCADA Unlearning on Office 31.** Forget classes are $\mathcal{C}_{\mathcal{F}} = \{1, 2, 3\}$ *(Best result in bold, second-best underlined)*

Method	Metric	A → D	A → W	D → A	D → W	W → A	W → D	Average
Original (SF(DA)^2 [28])	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$77.1_{\pm1.0}$	$86.3_{\pm1.9}$	$67.0_{\pm1.2}$	$79.9_{\pm2.2}$	$72.0_{\pm0.6}$	$78.5_{\pm1.8}$	$76.8_{\pm1.4}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$84.8_{\pm2.8}$	$99.5_{\pm0.9}$	$93.6_{\pm1.0}$	$88.5_{\pm2.8}$	$97.7_{\pm2.0}$	$76.6_{\pm2.3}$	$90.1_{\pm2.0}$
	Score $\uparrow$	$0.42_{\pm0.0}$	$0.43_{\pm0.0}$	$0.35_{\pm0.0}$	$0.42_{\pm0.0}$	$0.36_{\pm0.0}$	$0.44_{\pm0.0}$	$0.40_{\pm0.0}$
Retrain	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$76.0_{\pm5.0}$	$87.0_{\pm0.7}$	$68.2_{\pm1.2}$	$83.3_{\pm1.0}$	$72.0_{\pm1.3}$	$78.0_{\pm1.5}$	$77.4_{\pm1.8}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$
	Score $\uparrow$	$0.76_{\pm0.1}$	$0.87_{\pm0.0}$	$0.68_{\pm0.0}$	$0.83_{\pm0.0}$	$0.72_{\pm0.0}$	$0.78_{\pm0.0}$	$0.77_{\pm0.0}$
Finetune	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$\underline{77.2}_{\pm0.7}$	$\underline{86.5}_{\pm2.0}$	$66.7_{\pm2.7}$	$79.7_{\pm2.8}$	$\underline{72.0}_{\pm0.6}$	$\underline{78.4}_{\pm1.2}$	$76.7_{\pm1.7}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$79.4_{\pm1.3}$	$94.0_{\pm1.0}$	$85.4_{\pm3.7}$	$80.3_{\pm1.7}$	$93.0_{\pm0.0}$	$65.0_{\pm7.1}$	$82.8_{\pm2.5}$
	Score $\uparrow$	$0.43_{\pm0.0}$	$0.45_{\pm0.0}$	$0.36_{\pm0.0}$	$0.44_{\pm0.0}$	$0.37_{\pm0.0}$	$0.48_{\pm0.0}$	$0.42_{\pm0.0}$
UNSIR [51]	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$40.6_{\pm15.}$	$73.1_{\pm5.2}$	$61.7_{\pm4.3}$	$63.5_{\pm4.5}$	$71.6_{\pm1.1}$	$47.8_{\pm6.1}$	$59.7_{\pm6.1}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\underline{28.7}_{\pm20.}$	$\mathbf{0.0}_{\pm0.0}$	$69.0_{\pm4.0}$	$\mathbf{0.0}_{\pm0.0}$	$\underline{16.3}_{\pm4.0}$
	Score $\uparrow$	$0.41_{\pm0.2}$	$\underline{0.73}_{\pm0.1}$	$\underline{0.49}_{\pm0.1}$	$0.63_{\pm0.0}$	$0.42_{\pm0.0}$	$0.48_{\pm0.1}$	$0.53_{\pm0.1}$
ZSMU [10]	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$\mathbf{78.2}_{\pm2.1}$	$85.8_{\pm1.5}$	$\underline{67.0}_{\pm1.2}$	$\underline{80.1}_{\pm1.2}$	$\underline{72.0}_{\pm0.6}$	$\mathbf{78.6}_{\pm0.2}$	$\underline{77.0}_{\pm1.1}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$74.9_{\pm11.}$	$95.6_{\pm0.9}$	$86.5_{\pm2.0}$	$82.5_{\pm2.5}$	$93.0_{\pm0.0}$	$72.4_{\pm3.2}$	$84.2_{\pm3.3}$
	Score $\uparrow$	$0.45_{\pm0.0}$	$0.44_{\pm0.0}$	$0.36_{\pm0.0}$	$0.44_{\pm0.0}$	$0.37_{\pm0.0}$	$0.46_{\pm0.0}$	$0.42_{\pm0.0}$
Lipschitz [15]	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$62.6_{\pm14.}$	$63.7_{\pm15.}$	$60.2_{\pm8.2}$	$76.7_{\pm2.8}$	$71.6_{\pm1.1}$	$57.0_{\pm15.}$	$65.3_{\pm9.5}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$\underline{6.1}_{\pm5.5}$	$\underline{6.6}_{\pm11.}$	$29.2_{\pm25.}$	$60.1_{\pm25.}$	$\underline{60.8}_{\pm25.}$	$\underline{7.8}_{\pm6.4}$	$28.4_{\pm16.}$
	Score $\uparrow$	$0.59_{\pm0.1}$	$0.59_{\pm0.1}$	$0.47_{\pm0.1}$	$0.49_{\pm0.1}$	$\underline{0.45}_{\pm0.1}$	$0.53_{\pm0.1}$	$0.52_{\pm0.1}$
Nabla Tau [53]	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$70.2_{\pm2.6}$	$85.4_{\pm2.9}$	$64.8_{\pm2.0}$	$76.2_{\pm0.4}$	$\mathbf{72.0}_{\pm0.6}$	$72.0_{\pm1.9}$	$73.4_{\pm1.7}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$6.5_{\pm5.3}$	$24.0_{\pm7.8}$	$33.9_{\pm5.7}$	$\underline{7.1}_{\pm6.9}$	$73.7_{\pm7.0}$	$22.6_{\pm9.5}$	$28.0_{\pm7.0}$
	Score $\uparrow$	$\underline{0.66}_{\pm0.1}$	$0.69_{\pm0.0}$	$0.48_{\pm0.0}$	$\underline{0.71}_{\pm0.0}$	$0.41_{\pm0.0}$	$\underline{0.59}_{\pm0.1}$	$\underline{0.59}_{\pm0.0}$
Unlearned(+) [2]	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$70.0_{\pm0.8}$	$80.8_{\pm2.5}$	$\mathbf{80.6}_{\pm1.7}$	$\mathbf{86.0}_{\pm1.0}$	$\mathbf{78.9}_{\pm0.6}$	$71.1_{\pm0.8}$	$\mathbf{77.9}_{\pm1.2}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$84.8_{\pm1.2}$	$84.0_{\pm1.2}$	$81.2_{\pm5.1}$	$97.1_{\pm1.1}$	$69.5_{\pm7.8}$	$95.3_{\pm1.2}$	$85.3_{\pm2.9}$
	Score $\uparrow$	$0.38_{\pm0.01}$	$0.44_{\pm0.02}$	$0.45_{\pm0.00}$	$0.44_{\pm0.01}$	$0.47_{\pm0.02}$	$0.37_{\pm0.00}$	$0.42_{\pm0.01}$
PADA [5]	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$76.8_{\pm0.4}$	$\underline{86.5}_{\pm1.5}$	$66.3_{\pm2.4}$	$78.5_{\pm2.9}$	$\underline{72.0}_{\pm0.6}$	$77.4_{\pm2.2}$	$76.2_{\pm1.6}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$76.8_{\pm3.1}$	$100._{\pm0.0}$	$90.7_{\pm2.0}$	$90.7_{\pm1.9}$	$98.8_{\pm1.0}$	$77.4_{\pm1.7}$	$89.1_{\pm1.6}$
	Score $\uparrow$	$0.43_{\pm0.0}$	$0.43_{\pm0.0}$	$0.35_{\pm0.0}$	$0.41_{\pm0.0}$	$0.36_{\pm0.0}$	$0.44_{\pm0.0}$	$0.40_{\pm0.0}$
SHOT [34]	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$\underline{77.2}_{\pm1.0}$	$\mathbf{87.0}_{\pm1.2}$	$65.9_{\pm2.3}$	$78.1_{\pm1.2}$	$\underline{72.0}_{\pm0.6}$	$75.6_{\pm1.2}$	$76.0_{\pm1.2}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$47.9_{\pm1.5}$	$92.9_{\pm0.9}$	$69.6_{\pm2.7}$	$72.7_{\pm1.9}$	$84.8_{\pm2.0}$	$40.4_{\pm1.5}$	$68.0_{\pm1.7}$
	Score $\uparrow$	$0.52_{\pm0.0}$	$0.45_{\pm0.0}$	$0.39_{\pm0.0}$	$0.45_{\pm0.0}$	$0.39_{\pm0.0}$	$0.54_{\pm0.0}$	$0.46_{\pm0.0}$
Ours	$A_{\mathcal{D}_r^\mathcal{T}} \uparrow$	$77.1_{\pm1.0}$	$86.3_{\pm1.9}$	$\mathbf{67.0}_{\pm1.2}$	$79.9_{\pm2.4}$	$71.6_{\pm1.1}$	$78.0_{\pm1.2}$	$76.7_{\pm1.5}$
	$A_{\mathcal{D}_f^\mathcal{T}} \downarrow$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$
	Score $\uparrow$	$\mathbf{0.77}_{\pm0.0}$	$\mathbf{0.86}_{\pm0.0}$	$\mathbf{0.67}_{\pm0.0}$	$\mathbf{0.80}_{\pm0.0}$	$\mathbf{0.72}_{\pm0.0}$	$\mathbf{0.78}_{\pm0.0}$	$\mathbf{0.77}_{\pm0.0}$

Table A.21. **Results for Single-Class SCADA Unlearning on OfficeHome.** Forget class is $c_{\mathcal{F}} = 1$ *(Best result in bold, second-best underlined)*

Method	Metric	A → C	A → P	A → R	C → A	C → P	C → R	P → A	P → C	P → R	R → A	R → C	R → P	Average
Original (SF(DA)^2 [28])	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$60.9_{\pm0.5}$	$82.2_{\pm1.0}$	$85.5_{\pm1.8}$	$74.4_{\pm2.4}$	$83.5_{\pm1.0}$	$85.6_{\pm1.2}$	$72.1_{\pm3.3}$	$59.5_{\pm0.8}$	$86.0_{\pm0.7}$	$75.8_{\pm1.4}$	$60.0_{\pm2.0}$	$88.0_{\pm1.4}$	$76.1_{\pm1.5}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$51.2_{\pm9.8}$	$88.2_{\pm1.5}$	$89.2_{\pm1.5}$	$42.3_{\pm7.5}$	$72.7_{\pm2.7}$	$85.5_{\pm1.2}$	$54.5_{\pm8.6}$	$50.0_{\pm6.4}$	$88.6_{\pm2.9}$	$39.9_{\pm2.8}$	$80.4_{\pm3.6}$	$93.6_{\pm1.5}$	$69.7_{\pm4.2}$
	Score ↑	$0.40_{\pm0.0}$	$0.44_{\pm0.0}$	$0.45_{\pm0.0}$	$0.52_{\pm0.0}$	$0.48_{\pm0.0}$	$0.46_{\pm0.0}$	$0.47_{\pm0.0}$	$0.40_{\pm0.0}$	$0.46_{\pm0.0}$	$0.54_{\pm0.0}$	$0.33_{\pm0.0}$	$0.45_{\pm0.0}$	$0.45_{\pm0.0}$
Retrain	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$62.1_{\pm2.4}$	$83.4_{\pm1.1}$	$86.0_{\pm1.9}$	$74.7_{\pm3.2}$	$82.6_{\pm0.6}$	$86.2_{\pm1.0}$	$72.4_{\pm1.9}$	$60.0_{\pm3.1}$	$86.5_{\pm0.9}$	$75.0_{\pm2.9}$	$61.1_{\pm1.6}$	$88.3_{\pm1.0}$	$76.5_{\pm1.8}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$
	Score ↑	$0.62_{\pm0.0}$	$0.83_{\pm0.0}$	$0.86_{\pm0.0}$	$0.75_{\pm0.0}$	$0.83_{\pm0.0}$	$0.86_{\pm0.0}$	$0.72_{\pm0.0}$	$0.60_{\pm0.0}$	$0.87_{\pm0.0}$	$0.75_{\pm0.0}$	$0.61_{\pm0.0}$	$0.88_{\pm0.0}$	$0.77_{\pm0.0}$
Finetune	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$\mathbf{60.7}_{\pm0.5}$	$\mathbf{81.8}_{\pm0.3}$	$\mathbf{85.3}_{\pm1.8}$	$\mathbf{74.0}_{\pm1.1}$	$82.9_{\pm0.5}$	$\mathbf{85.8}_{\pm0.7}$	$71.2_{\pm1.2}$	$57.2_{\pm0.8}$	$\mathbf{86.5}_{\pm0.3}$	$\mathbf{75.2}_{\pm0.9}$	$58.6_{\pm1.6}$	$\underline{87.5}_{\pm0.8}$	$\mathbf{75.5}_{\pm0.9}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$42.9_{\pm1.8}$	$74.4_{\pm8.5}$	$82.8_{\pm2.0}$	$35.8_{\pm3.7}$	$69.4_{\pm6.6}$	$82.5_{\pm3.1}$	$52.8_{\pm16.}$	$\mathbf{0.0}_{\pm0.0}$	$81.5_{\pm3.8}$	$50.4_{\pm5.7}$	$74.4_{\pm17.}$	$90.2_{\pm6.5}$	$61.4_{\pm6.3}$
	Score ↑	$0.42_{\pm0.0}$	$0.47_{\pm0.0}$	$0.47_{\pm0.0}$	$0.54_{\pm0.0}$	$0.49_{\pm0.0}$	$0.47_{\pm0.0}$	$0.47_{\pm0.1}$	$\underline{0.57}_{\pm0.0}$	$0.48_{\pm0.0}$	$0.50_{\pm0.0}$	$0.34_{\pm0.0}$	$0.46_{\pm0.0}$	$0.47_{\pm0.0}$
UNSIR [51]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$28.3_{\pm1.0}$	$56.6_{\pm1.2}$	$55.1_{\pm5.0}$	$11.8_{\pm6.4}$	$56.6_{\pm2.4}$	$44.4_{\pm4.3}$	$9.3_{\pm5.6}$	$17.2_{\pm6.1}$	$49.6_{\pm6.8}$	$18.0_{\pm13.}$	$24.4_{\pm2.1}$	$61.7_{\pm1.2}$	$36.1_{\pm4.6}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$
	Score ↑	$0.28_{\pm0.0}$	$0.57_{\pm0.0}$	$0.55_{\pm0.1}$	$0.12_{\pm0.1}$	$0.57_{\pm0.0}$	$0.44_{\pm0.0}$	$0.09_{\pm0.1}$	$0.17_{\pm0.1}$	$0.50_{\pm0.1}$	$0.18_{\pm0.1}$	$0.24_{\pm0.0}$	$0.62_{\pm0.0}$	$0.36_{\pm0.0}$
ZSMU [10]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$57.7_{\pm1.3}$	$79.7_{\pm1.4}$	$\underline{84.7}_{\pm2.3}$	$68.6_{\pm2.0}$	$81.5_{\pm0.5}$	$83.1_{\pm1.2}$	$\mathbf{71.6}_{\pm2.1}$	$56.8_{\pm3.2}$	$85.0_{\pm3.0}$	$74.1_{\pm1.5}$	$58.4_{\pm1.6}$	$86.4_{\pm0.2}$	$74.0_{\pm1.7}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$25.0_{\pm4.8}$	$78.1_{\pm6.5}$	$87.9_{\pm3.5}$	$18.7_{\pm13.}$	$52.5_{\pm5.3}$	$68.0_{\pm7.2}$	$34.1_{\pm8.8}$	$13.7_{\pm12.}$	$76.4_{\pm18.}$	$30.1_{\pm7.4}$	$29.8_{\pm10.}$	$79.8_{\pm2.6}$	$49.5_{\pm8.4}$
	Score ↑	$0.46_{\pm0.0}$	$0.45_{\pm0.0}$	$0.45_{\pm0.0}$	$0.58_{\pm0.1}$	$0.53_{\pm0.0}$	$0.50_{\pm0.0}$	$0.53_{\pm0.0}$	$0.51_{\pm0.1}$	$0.48_{\pm0.0}$	$0.57_{\pm0.0}$	$0.45_{\pm0.0}$	$0.48_{\pm0.0}$	$0.50_{\pm0.0}$
Lipschitz [15]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$52.9_{\pm4.9}$	$80.1_{\pm1.6}$	$70.2_{\pm18.}$	$65.3_{\pm5.5}$	$72.4_{\pm5.2}$	$81.4_{\pm4.4}$	$64.6_{\pm5.7}$	$44.5_{\pm10.}$	$79.3_{\pm6.5}$	$68.3_{\pm7.2}$	$58.8_{\pm1.7}$	$76.3_{\pm9.1}$	$67.8_{\pm6.8}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$14.9_{\pm9.0}$	$51.9_{\pm15.}$	$\underline{2.4}_{\pm3.3}$	$\underline{5.7}_{\pm9.9}$	$\underline{6.4}_{\pm11.1}$	$49.2_{\pm43.}$	$\underline{16.3}_{\pm7.4}$	$\underline{2.4}_{\pm4.1}$	$40.4_{\pm24.}$	$16.3_{\pm3.7}$	$43.4_{\pm29.}$	$55.2_{\pm47.}$	$25.4_{\pm17.}$
	Score ↑	$0.46_{\pm0.0}$	$0.53_{\pm0.1}$	$\underline{0.68}_{\pm0.2}$	$\underline{0.62}_{\pm0.0}$	$0.68_{\pm0.1}$	$0.58_{\pm0.2}$	$\underline{0.56}_{\pm0.1}$	$0.44_{\pm0.1}$	$0.57_{\pm0.1}$	$\underline{0.59}_{\pm0.1}$	$0.42_{\pm0.1}$	$0.52_{\pm0.2}$	$0.55_{\pm0.1}$
Nabla Tau [53]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$50.0_{\pm2.6}$	$71.7_{\pm3.9}$	$67.5_{\pm2.5}$	$53.7_{\pm3.9}$	$74.9_{\pm1.4}$	$71.0_{\pm3.1}$	$55.5_{\pm4.3}$	$45.4_{\pm4.0}$	$65.3_{\pm4.2}$	$56.0_{\pm0.4}$	$44.9_{\pm4.3}$	$74.1_{\pm2.0}$	$60.8_{\pm3.0}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$\underline{3.6}_{\pm6.2}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\underline{1.6}_{\pm2.8}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\underline{0.4}_{\pm0.8}$
	Score ↑	$\underline{0.48}_{\pm0.0}$	$\underline{0.72}_{\pm0.0}$	$0.67_{\pm0.0}$	$0.54_{\pm0.0}$	$\underline{0.75}_{\pm0.0}$	$0.71_{\pm0.0}$	$\underline{0.56}_{\pm0.0}$	$0.45_{\pm0.0}$	$0.65_{\pm0.0}$	$0.55_{\pm0.0}$	$0.45_{\pm0.0}$	$\underline{0.74}_{\pm0.0}$	$\underline{0.61}_{\pm0.0}$
Unlearned(+) [2]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$54.5_{\pm2.7}$	$76.8_{\pm0.3}$	$78.5_{\pm1.1}$	$\underline{73.3}_{\pm1.6}$	$\underline{83.0}_{\pm0.3}$	$83.6_{\pm0.5}$	$\underline{71.4}_{\pm3.1}$	$\mathbf{59.2}_{\pm0.6}$	$85.2_{\pm0.3}$	$73.6_{\pm0.9}$	$\underline{61.9}_{\pm1.8}$	$\mathbf{88.6}_{\pm0.5}$	$74.1_{\pm1.1}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$23.2_{\pm0.0}$	$78.3_{\pm2.1}$	$75.8_{\pm11.4}$	$34.2_{\pm6.9}$	$67.2_{\pm2.1}$	$83.4_{\pm5.0}$	$34.1_{\pm0.0}$	$47.3_{\pm3.8}$	$81.8_{\pm2.8}$	$31.7_{\pm3.4}$	$84.8_{\pm3.8}$	$87.9_{\pm4.3}$	$60.8_{\pm3.8}$
	Score ↑	$0.44_{\pm0.02}$	$0.43_{\pm0.01}$	$0.45_{\pm0.02}$	$0.55_{\pm0.02}$	$0.50_{\pm0.01}$	$0.46_{\pm0.01}$	$0.53_{\pm0.02}$	$0.40_{\pm0.02}$	$0.47_{\pm0.01}$	$0.56_{\pm0.02}$	$0.33_{\pm0.00}$	$0.47_{\pm0.01}$	$0.47_{\pm0.01}$
PADA [5]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$58.9_{\pm1.3}$	$80.4_{\pm1.0}$	$84.0_{\pm1.7}$	$72.9_{\pm2.7}$	$81.4_{\pm1.0}$	$83.6_{\pm1.1}$	$70.6_{\pm2.3}$	$56.7_{\pm0.9}$	$\underline{85.8}_{\pm1.7}$	$74.4_{\pm1.6}$	$55.1_{\pm1.1}$	$86.8_{\pm1.1}$	$74.2_{\pm1.5}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$44.6_{\pm1.8}$	$90.9_{\pm1.0}$	$90.9_{\pm1.0}$	$51.2_{\pm2.5}$	$84.5_{\pm2.1}$	$92.2_{\pm1.5}$	$56.1_{\pm4.9}$	$42.9_{\pm1.8}$	$96.0_{\pm1.1}$	$44.7_{\pm2.8}$	$73.8_{\pm6.8}$	$91.2_{\pm1.5}$	$71.6_{\pm2.4}$
	Score ↑	$0.41_{\pm0.0}$	$0.42_{\pm0.0}$	$0.44_{\pm0.0}$	$0.48_{\pm0.0}$	$0.44_{\pm0.0}$	$0.43_{\pm0.0}$	$0.45_{\pm0.0}$	$0.40_{\pm0.0}$	$0.44_{\pm0.0}$	$0.51_{\pm0.0}$	$0.32_{\pm0.0}$	$0.45_{\pm0.0}$	$0.43_{\pm0.0}$
SHOT [34]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$56.9_{\pm1.4}$	$78.7_{\pm0.2}$	$82.4_{\pm1.2}$	$71.8_{\pm2.9}$	$81.9_{\pm1.1}$	$82.9_{\pm1.2}$	$68.7_{\pm2.8}$	$\underline{59.1}_{\pm0.6}$	$84.1_{\pm0.8}$	$74.5_{\pm2.8}$	$\mathbf{62.9}_{\pm1.7}$	$86.8_{\pm0.6}$	$74.2_{\pm1.4}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$22.0_{\pm4.5}$	$\underline{26.6}_{\pm1.5}$	$25.9_{\pm2.1}$	$34.9_{\pm1.4}$	$20.5_{\pm3.5}$	$\underline{13.4}_{\pm1.2}$	$35.0_{\pm2.8}$	$29.8_{\pm2.7}$	$\underline{14.1}_{\pm0.0}$	$34.1_{\pm2.5}$	$\underline{26.8}_{\pm1.8}$	$\underline{19.2}_{\pm1.0}$	$25.2_{\pm2.1}$
	Score ↑	$0.47_{\pm0.0}$	$0.62_{\pm0.0}$	$0.65_{\pm0.0}$	$0.53_{\pm0.0}$	$0.68_{\pm0.0}$	$\underline{0.73}_{\pm0.0}$	$0.51_{\pm0.0}$	$0.46_{\pm0.0}$	$\underline{0.74}_{\pm0.0}$	$0.56_{\pm0.0}$	$\underline{0.50}_{\pm0.0}$	$0.73_{\pm0.0}$	$0.60_{\pm0.0}$
Ours	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$\underline{59.9}_{\pm1.0}$	$\underline{81.5}_{\pm1.2}$	$\mathbf{85.3}_{\pm1.8}$	$\mathbf{74.0}_{\pm2.1}$	$\mathbf{83.5}_{\pm0.3}$	$\underline{85.3}_{\pm1.1}$	$70.5_{\pm3.3}$	$58.5_{\pm2.2}$	$85.2_{\pm0.9}$	$\underline{74.7}_{\pm1.9}$	$59.4_{\pm1.3}$	$87.4_{\pm1.0}$	$\underline{75.4}_{\pm1.5}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$
	Score ↑	$\mathbf{0.60}_{\pm0.0}$	$\mathbf{0.81}_{\pm0.0}$	$\mathbf{0.85}_{\pm0.0}$	$\mathbf{0.74}_{\pm0.0}$	$\mathbf{0.84}_{\pm0.0}$	$\mathbf{0.85}_{\pm0.0}$	$\mathbf{0.71}_{\pm0.0}$	$\mathbf{0.58}_{\pm0.0}$	$\mathbf{0.85}_{\pm0.0}$	$\mathbf{0.75}_{\pm0.0}$	$\mathbf{0.59}_{\pm0.0}$	$\mathbf{0.87}_{\pm0.0}$	$\mathbf{0.75}_{\pm0.0}$

Table A.22. **Results for Single-Class SCADA Unlearning on DomainNet.** Forget class is $c_\mathcal{F} = 1$ *(Best result in bold, second-best underlined)*

Method	Metric	s → p	c → s	p → c	p → r	r → s	r → c	r → p	Average
Original (SF(DA)^2 [28])	$A_{\mathcal{D}_r^\mathcal{T}}\uparrow$	71.1$_{\pm0.6}$	65.5$_{\pm0.4}$	62.2$_{\pm0.2}$	78.2$_{\pm0.3}$	55.9$_{\pm2.6}$	65.1$_{\pm0.8}$	75.1$_{\pm1.2}$	67.6$_{\pm0.9}$
	$A_{\mathcal{D}_f^\mathcal{T}}\downarrow$	77.6$_{\pm5.7}$	36.9$_{\pm6.9}$	35.6$_{\pm1.3}$	74.1$_{\pm12.1}$	3.2$_{\pm0.4}$	17.5$_{\pm1.0}$	6.1$_{\pm0.3}$	35.9$_{\pm4.0}$
	Score ↑	0.40$_{\pm0.0}$	0.48$_{\pm0.0}$	0.46$_{\pm0.0}$	0.45$_{\pm0.0}$	0.54$_{\pm0.0}$	0.55$_{\pm0.0}$	0.71$_{\pm0.0}$	0.51$_{\pm0.0}$
Retrain	$A_{\mathcal{D}_r^\mathcal{T}}\uparrow$	71.7$_{\pm1.0}$	66.6$_{\pm1.1}$	61.3$_{\pm1.9}$	78.3$_{\pm0.3}$	56.0$_{\pm3.2}$	65.4$_{\pm1.1}$	74.0$_{\pm1.3}$	67.6$_{\pm1.4}$
	$A_{\mathcal{D}_f^\mathcal{T}}\downarrow$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$
	Score ↑	0.72$_{\pm0.0}$	0.67$_{\pm0.0}$	0.61$_{\pm0.0}$	0.78$_{\pm0.0}$	0.56$_{\pm0.0}$	0.65$_{\pm0.0}$	0.74$_{\pm0.0}$	0.68$_{\pm0.0}$
Finetune	$A_{\mathcal{D}_r^\mathcal{T}}\uparrow$	68.0$_{\pm0.3}$	$\underline{63.3}_{\pm1.6}$	**62.8**$_{\pm0.5}$	77.1$_{\pm0.3}$	54.2$_{\pm0.3}$	$\underline{65.8}_{\pm1.7}$	73.5$_{\pm0.5}$	66.4$_{\pm0.8}$
	$A_{\mathcal{D}_f^\mathcal{T}}\downarrow$	59.7$_{\pm10.1}$	$\underline{0.5}_{\pm0.4}$	13.2$_{\pm4.8}$	18.4$_{\pm11.1}$	**0.0**$_{\pm0.0}$	5.7$_{\pm4.0}$	$\underline{0.6}_{\pm0.7}$	14.0$_{\pm4.4}$
	Score ↑	0.43$_{\pm0.0}$	**0.63**$_{\pm0.0}$	$\underline{0.56}_{\pm0.0}$	$\underline{0.65}_{\pm0.1}$	$\underline{0.54}_{\pm0.0}$	**0.62**$_{\pm0.0}$	$\underline{0.73}_{\pm0.0}$	$\underline{0.59}_{\pm0.0}$
UNSIR [51]	$A_{\mathcal{D}_r^\mathcal{T}}\uparrow$	8.9$_{\pm7.3}$	4.4$_{\pm5.0}$	19.7$_{\pm10.7}$	30.9$_{\pm18.1}$	2.0$_{\pm1.4}$	17.3$_{\pm2.1}$	18.3$_{\pm8.7}$	14.5$_{\pm7.6}$
	$A_{\mathcal{D}_f^\mathcal{T}}\downarrow$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$
	Score ↑	0.09$_{\pm0.1}$	0.04$_{\pm0.0}$	0.20$_{\pm0.1}$	0.31$_{\pm0.2}$	0.02$_{\pm0.0}$	0.17$_{\pm0.0}$	0.18$_{\pm0.1}$	0.15$_{\pm0.1}$
ZSMU [10]	$A_{\mathcal{D}_r^\mathcal{T}}\uparrow$	$\underline{69.9}_{\pm0.4}$	56.8$_{\pm2.0}$	56.3$_{\pm9.1}$	$\underline{78.0}_{\pm0.8}$	51.4$_{\pm1.6}$	58.3$_{\pm3.3}$	67.2$_{\pm9.2}$	62.5$_{\pm3.8}$
	$A_{\mathcal{D}_f^\mathcal{T}}\downarrow$	24.3$_{\pm27.1}$	2.2$_{\pm0.4}$	21.0$_{\pm6.6}$	29.4$_{\pm19.7}$	$\underline{1.6}_{\pm2.2}$	7.5$_{\pm1.3}$	1.5$_{\pm1.6}$	12.5$_{\pm8.4}$
	Score ↑	$\underline{0.58}_{\pm0.1}$	$\underline{0.56}_{\pm0.0}$	0.46$_{\pm0.1}$	0.61$_{\pm0.1}$	0.51$_{\pm0.0}$	0.54$_{\pm0.0}$	0.66$_{\pm0.1}$	0.56$_{\pm0.1}$
Lipschitz [15]	$A_{\mathcal{D}_r^\mathcal{T}}\uparrow$	40.6$_{\pm34.4}$	23.6$_{\pm24.1}$	53.1$_{\pm4.5}$	61.2$_{\pm21.9}$	38.2$_{\pm5.9}$	49.6$_{\pm15.6}$	53.0$_{\pm14.9}$	45.6$_{\pm17.3}$
	$A_{\mathcal{D}_f^\mathcal{T}}\downarrow$	35.4$_{\pm36.3}$	**0.0**$_{\pm0.0}$	14.1$_{\pm9.7}$	35.4$_{\pm34.0}$	**0.0**$_{\pm0.0}$	$\underline{2.0}_{\pm3.5}$	**0.0**$_{\pm0.0}$	12.4$_{\pm11.9}$
	Score ↑	0.27$_{\pm0.2}$	0.24$_{\pm0.2}$	0.47$_{\pm0.1}$	0.44$_{\pm0.1}$	0.38$_{\pm0.1}$	0.48$_{\pm0.1}$	0.53$_{\pm0.1}$	0.40$_{\pm0.1}$
Nabla Tau [53]	$A_{\mathcal{D}_r^\mathcal{T}}\uparrow$	38.3$_{\pm0.7}$	37.6$_{\pm1.8}$	43.4$_{\pm3.3}$	62.4$_{\pm1.0}$	32.7$_{\pm2.3}$	40.5$_{\pm6.6}$	46.9$_{\pm3.7}$	43.1$_{\pm2.8}$
	$A_{\mathcal{D}_f^\mathcal{T}}\downarrow$	18.4$_{\pm10.1}$	**0.0**$_{\pm0.0}$	$\underline{0.3}_{\pm0.5}$	$\underline{13.9}_{\pm23.9}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	$\underline{4.7}_{\pm4.9}$
	Score ↑	0.33$_{\pm0.0}$	0.38$_{\pm0.0}$	0.43$_{\pm0.0}$	0.56$_{\pm0.1}$	0.33$_{\pm0.0}$	0.40$_{\pm0.1}$	0.47$_{\pm0.0}$	0.41$_{\pm0.0}$
Unlearned(+) [2]	$A_{\mathcal{D}_r^\mathcal{T}}\uparrow$	69.0$_{\pm0.9}$	62.9$_{\pm0.3}$	$\underline{62.2}_{\pm0.9}$	77.1$_{\pm0.5}$	**56.1**$_{\pm1.9}$	**66.0**$_{\pm1.7}$	73.7$_{\pm1.4}$	$\underline{66.7}_{\pm1.1}$
	$A_{\mathcal{D}_f^\mathcal{T}}\downarrow$	44.0$_{\pm37.8}$	13.5$_{\pm8.8}$	29.3$_{\pm3.8}$	31.1$_{\pm7.4}$	0.9$_{\pm0.8}$	11.8$_{\pm5.1}$	3.1$_{\pm1.9}$	19.1$_{\pm9.3}$
	Score ↑	0.51$_{\pm0.16}$	0.56$_{\pm0.04}$	0.48$_{\pm0.02}$	0.59$_{\pm0.03}$	**0.55**$_{\pm0.02}$	0.59$_{\pm0.01}$	0.71$_{\pm0.01}$	0.57$_{\pm0.04}$
PADA [5]	$A_{\mathcal{D}_r^\mathcal{T}}\uparrow$	60.0$_{\pm0.8}$	59.3$_{\pm0.9}$	54.5$_{\pm0.6}$	75.8$_{\pm0.1}$	48.7$_{\pm1.2}$	59.8$_{\pm0.6}$	71.4$_{\pm0.2}$	61.3$_{\pm0.6}$
	$A_{\mathcal{D}_f^\mathcal{T}}\downarrow$	$\underline{9.0}_{\pm1.6}$	60.6$_{\pm4.0}$	58.0$_{\pm1.0}$	62.0$_{\pm1.2}$	11.0$_{\pm3.1}$	30.4$_{\pm1.0}$	8.8$_{\pm4.4}$	34.3$_{\pm2.3}$
	Score ↑	0.55$_{\pm0.0}$	0.37$_{\pm0.0}$	0.35$_{\pm0.0}$	0.47$_{\pm0.0}$	0.44$_{\pm0.0}$	0.46$_{\pm0.0}$	0.66$_{\pm0.0}$	0.47$_{\pm0.0}$
SHOT [34]	$A_{\mathcal{D}_r^\mathcal{T}}\uparrow$	**71.0**$_{\pm1.4}$	**66.1**$_{\pm1.2}$	**62.8**$_{\pm0.3}$	**78.4**$_{\pm0.4}$	$\underline{55.4}_{\pm0.8}$	65.2$_{\pm1.0}$	**75.0**$_{\pm0.9}$	**67.7**$_{\pm0.8}$
	$A_{\mathcal{D}_f^\mathcal{T}}\downarrow$	74.9$_{\pm5.5}$	30.9$_{\pm4.5}$	37.9$_{\pm4.3}$	71.5$_{\pm11.4}$	3.6$_{\pm0.4}$	17.5$_{\pm0.5}$	5.0$_{\pm0.7}$	34.5$_{\pm3.9}$
	Score ↑	0.41$_{\pm0.0}$	0.51$_{\pm0.0}$	0.46$_{\pm0.0}$	0.46$_{\pm0.0}$	0.53$_{\pm0.0}$	$\underline{0.55}_{\pm0.0}$	0.71$_{\pm0.0}$	0.52$_{\pm0.0}$
Ours	$A_{\mathcal{D}_r^\mathcal{T}}\uparrow$	67.8$_{\pm2.3}$	62.7$_{\pm1.0}$	58.9$_{\pm1.0}$	77.0$_{\pm0.4}$	54.0$_{\pm1.7}$	62.1$_{\pm0.8}$	$\underline{74.0}_{\pm1.0}$	65.2$_{\pm1.1}$
	$A_{\mathcal{D}_f^\mathcal{T}}\downarrow$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$
	Score ↑	**0.68**$_{\pm0.0}$	**0.63**$_{\pm0.0}$	**0.59**$_{\pm0.0}$	**0.77**$_{\pm0.0}$	$\underline{0.54}_{\pm0.0}$	**0.62**$_{\pm0.0}$	**0.74**$_{\pm0.0}$	**0.65**$_{\pm0.0}$

Table A.23. **Results for Single-Class SCADA Unlearning on Office 31.** Forget class is $c_{\mathcal{F}} = 1$ *(Best result in bold, second-best underlined)*

Method	Metric	A → D	A → W	D → A	D → W	W → A	W → D	Average
Original (SF(DA)^2 [28])	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$78.7_{\pm 2.0}$	$81.2_{\pm 1.1}$	$61.1_{\pm 0.0}$	$76.4_{\pm 1.3}$	$67.0_{\pm 0.6}$	$80.3_{\pm 1.9}$	$74.1_{\pm 1.2}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$91.9_{\pm 0.7}$	$100._{\pm 0.0}$	$100._{\pm 0.0}$	$100._{\pm 0.0}$	$100._{\pm 0.0}$	$90.6_{\pm 0.8}$	$97.1_{\pm 0.2}$
	Score ↑	$0.41_{\pm 0.0}$	$0.41_{\pm 0.0}$	$0.31_{\pm 0.0}$	$0.38_{\pm 0.0}$	$0.34_{\pm 0.0}$	$0.42_{\pm 0.0}$	$0.38_{\pm 0.0}$
Retrain	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$79.0_{\pm 1.0}$	$82.0_{\pm 0.4}$	$63.9_{\pm 0.6}$	$78.4_{\pm 2.1}$	$67.4_{\pm 0.0}$	$78.1_{\pm 2.8}$	$74.8_{\pm 1.1}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$
	Score ↑	$0.79_{\pm 0.0}$	$0.82_{\pm 0.0}$	$0.64_{\pm 0.0}$	$0.78_{\pm 0.0}$	$0.67_{\pm 0.0}$	$0.78_{\pm 0.0}$	$0.75_{\pm 0.0}$
Finetune	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$\mathbf{79.1}_{\pm 1.8}$	$81.2_{\pm 1.3}$	$59.6_{\pm 0.6}$	$76.0_{\pm 1.7}$	$67.0_{\pm 0.6}$	$\mathbf{79.8}_{\pm 1.7}$	$73.8_{\pm 1.3}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$88.2_{\pm 1.4}$	$100._{\pm 0.0}$	$100._{\pm 0.0}$	$100._{\pm 0.0}$	$100._{\pm 0.0}$	$89.0_{\pm 0.0}$	$96.2_{\pm 0.2}$
	Score ↑	$0.42_{\pm 0.0}$	$0.41_{\pm 0.0}$	$0.30_{\pm 0.0}$	$0.38_{\pm 0.0}$	$0.34_{\pm 0.0}$	$0.42_{\pm 0.0}$	$0.38_{\pm 0.0}$
UNSIR [51]	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$40.5_{\pm 26.}$	$75.5_{\pm 3.7}$	$60.4_{\pm 4.8}$	$67.9_{\pm 5.4}$	$65.3_{\pm 1.8}$	$52.7_{\pm 3.8}$	$60.4_{\pm 7.7}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$66.6_{\pm 31.}$	$\mathbf{0.0}_{\pm 0.0}$	$100.0_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$27.8_{\pm 5.2}$
	Score ↑	$0.41_{\pm 0.3}$	$0.76_{\pm 0.0}$	$0.37_{\pm 0.1}$	$0.68_{\pm 0.1}$	$0.33_{\pm 0.0}$	$0.53_{\pm 0.0}$	$0.51_{\pm 0.1}$
ZSMU [10]	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$77.6_{\pm 3.0}$	$\underline{81.6}_{\pm 1.0}$	$59.6_{\pm 4.3}$	$\underline{76.2}_{\pm 0.8}$	$\underline{67.4}_{\pm 0.0}$	$79.1_{\pm 2.7}$	$73.6_{\pm 2.0}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$87.8_{\pm 1.2}$	$100._{\pm 0.0}$	$100.0_{\pm 0.0}$	$100._{\pm 0.0}$	$100._{\pm 0.0}$	$88.2_{\pm 1.8}$	$96.0_{\pm 0.5}$
	Score ↑	$0.41_{\pm 0.0}$	$0.41_{\pm 0.0}$	$0.30_{\pm 0.0}$	$0.38_{\pm 0.0}$	$0.34_{\pm 0.0}$	$0.42_{\pm 0.0}$	$0.38_{\pm 0.0}$
Lipschitz [15]	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$77.4_{\pm 2.0}$	$79.0_{\pm 2.9}$	$53.7_{\pm 13.}$	$74.5_{\pm 1.0}$	$67.0_{\pm 0.6}$	$77.6_{\pm 3.6}$	$71.5_{\pm 4.0}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$\underline{42.3}_{\pm 17.}$	$15.9_{\pm 23.}$	$66.7_{\pm 57.}$	$33.3_{\pm 57.}$	$39.7_{\pm 48.}$	$7.7_{\pm 13.}$	$34.3_{\pm 36.}$
	Score ↑	$0.55_{\pm 0.1}$	$0.70_{\pm 0.1}$	$0.33_{\pm 0.0}$	$0.62_{\pm 0.2}$	$0.51_{\pm 0.2}$	$\underline{0.73}_{\pm 0.1}$	$0.57_{\pm 0.1}$
Nabla Tau [53]	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$69.2_{\pm 3.4}$	$\mathbf{81.8}_{\pm 0.7}$	$58.9_{\pm 2.8}$	$75.3_{\pm 1.3}$	$66.3_{\pm 1.8}$	$71.9_{\pm 3.5}$	$70.6_{\pm 2.3}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$\mathbf{0.0}_{\pm 0.0}$	$36.5_{\pm 35.}$	$74.6_{\pm 9.9}$	$\mathbf{0.0}_{\pm 0.0}$	$100._{\pm 0.0}$	$\underline{0.4}_{\pm 0.7}$	$35.3_{\pm 7.6}$
	Score ↑	$\underline{0.69}_{\pm 0.0}$	$0.62_{\pm 0.1}$	$0.34_{\pm 0.0}$	$\underline{0.75}_{\pm 0.0}$	$0.33_{\pm 0.0}$	$0.72_{\pm 0.0}$	$0.58_{\pm 0.0}$
Unlearned(+) [2]	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$59.5_{\pm 0.8}$	$77.0_{\pm 1.3}$	$\mathbf{79.0}_{\pm 2.1}$	$\mathbf{81.9}_{\pm 0.9}$	$\mathbf{80.5}_{\pm 0.9}$	$66.9_{\pm 0.8}$	$\underline{74.1}_{\pm 1.1}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$100.0_{\pm 0.0}$	$100.0_{\pm 0.0}$	$90.9_{\pm 0.9}$	$100.0_{\pm 0.0}$	$90.2_{\pm 0.0}$	$100.0_{\pm 0.0}$	$96.8_{\pm 0.2}$
	Score ↑	$0.30_{\pm 0.00}$	$0.39_{\pm 0.01}$	$0.41_{\pm 0.01}$	$0.41_{\pm 0.01}$	$0.42_{\pm 0.00}$	$0.33_{\pm 0.00}$	$0.38_{\pm 0.01}$
PADA [5]	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$77.2_{\pm 1.9}$	$81.4_{\pm 1.0}$	$61.1_{\pm 1.8}$	$75.8_{\pm 1.0}$	$67.0_{\pm 0.6}$	$77.3_{\pm 0.6}$	$73.3_{\pm 1.2}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$92.3_{\pm 0.7}$	$100.0_{\pm 0.0}$	$100.0_{\pm 0.0}$	$100.0_{\pm 0.0}$	$100.0_{\pm 0.0}$	$92.3_{\pm 0.7}$	$97.4_{\pm 0.2}$
	Score ↑	$0.40_{\pm 0.0}$	$0.41_{\pm 0.0}$	$0.31_{\pm 0.0}$	$0.38_{\pm 0.0}$	$0.34_{\pm 0.0}$	$0.40_{\pm 0.0}$	$0.37_{\pm 0.0}$
SHOT [34]	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$77.0_{\pm 2.4}$	$\mathbf{81.8}_{\pm 1.3}$	$60.0_{\pm 1.8}$	$75.1_{\pm 1.6}$	$67.0_{\pm 0.6}$	$75.1_{\pm 1.2}$	$72.7_{\pm 1.5}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$54.9_{\pm 0.0}$	$\underline{6.4}_{\pm 2.7}$	$\underline{1.6}_{\pm 2.8}$	$\underline{1.6}_{\pm 2.8}$	$\underline{3.2}_{\pm 2.8}$	$51.2_{\pm 1.2}$	$\underline{19.8}_{\pm 2.0}$
	Score ↑	$0.50_{\pm 0.0}$	$\underline{0.77}_{\pm 0.0}$	$\underline{0.59}_{\pm 0.0}$	$0.74_{\pm 0.0}$	$\underline{0.65}_{\pm 0.0}$	$0.50_{\pm 0.0}$	$\underline{0.62}_{\pm 0.0}$
Ours	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$\underline{77.9}_{\pm 2.0}$	$81.2_{\pm 1.1}$	$\underline{62.8}_{\pm 1.6}$	$\underline{76.2}_{\pm 1.0}$	$67.0_{\pm 0.6}$	$\underline{79.7}_{\pm 2.3}$	$\mathbf{74.2}_{\pm 1.4}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$
	Score ↑	$\mathbf{0.78}_{\pm 0.0}$	$\mathbf{0.81}_{\pm 0.0}$	$\mathbf{0.63}_{\pm 0.0}$	$\mathbf{0.76}_{\pm 0.0}$	$\mathbf{0.67}_{\pm 0.0}$	$\mathbf{0.80}_{\pm 0.0}$	$\mathbf{0.74}_{\pm 0.0}$

Table A.24. **Results for UC-SCADA Unlearning on OfficeHome.** Forget classes are $\mathcal{C}_{\mathcal{F}} = \{1, 2, 3\}$ *(Best result in bold, second-best underlined)*

Method	Metric	A → C	A → P	A → R	C → A	C → P	C → R	P → A	P → C	P → R	R → A	R → C	R → P	Average
Original (SF(DA)^2 [28])	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$61.0_{\pm 1.6}$	$82.2_{\pm 1.5}$	$82.3_{\pm 0.3}$	$76.9_{\pm 1.7}$	$82.9_{\pm 1.0}$	$82.5_{\pm 0.9}$	$75.2_{\pm 1.4}$	$58.2_{\pm 1.2}$	$84.3_{\pm 1.3}$	$78.5_{\pm 0.2}$	$58.6_{\pm 1.1}$	$87.0_{\pm 0.1}$	$75.8_{\pm 1.0}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$28.7_{\pm 1.9}$	$71.1_{\pm 5.0}$	$86.1_{\pm 1.0}$	$57.1_{\pm 1.1}$	$69.0_{\pm 1.3}$	$76.7_{\pm 2.3}$	$47.8_{\pm 1.9}$	$22.0_{\pm 0.4}$	$72.8_{\pm 5.7}$	$53.1_{\pm 3.4}$	$35.8_{\pm 1.4}$	$77.1_{\pm 1.7}$	$58.1_{\pm 2.2}$
	Score ↑	$0.47_{\pm 0.0}$	$0.48_{\pm 0.0}$	$0.44_{\pm 0.0}$	$0.49_{\pm 0.0}$	$0.49_{\pm 0.0}$	$0.47_{\pm 0.0}$	$0.51_{\pm 0.0}$	$0.48_{\pm 0.0}$	$0.49_{\pm 0.0}$	$0.51_{\pm 0.0}$	$0.43_{\pm 0.0}$	$0.49_{\pm 0.0}$	$0.48_{\pm 0.0}$
Retrain	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$60.8_{\pm 1.2}$	$83.1_{\pm 0.6}$	$82.2_{\pm 0.6}$	$78.5_{\pm 2.1}$	$82.6_{\pm 0.9}$	$83.3_{\pm 1.5}$	$76.4_{\pm 0.9}$	$59.7_{\pm 2.5}$	$84.4_{\pm 0.6}$	$77.6_{\pm 1.3}$	$59.9_{\pm 1.6}$	$87.3_{\pm 0.4}$	$76.3_{\pm 1.2}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$
	Score ↑	$0.61_{\pm 0.0}$	$0.83_{\pm 0.0}$	$0.82_{\pm 0.0}$	$0.79_{\pm 0.0}$	$0.83_{\pm 0.0}$	$0.83_{\pm 0.0}$	$0.76_{\pm 0.0}$	$0.60_{\pm 0.0}$	$0.84_{\pm 0.0}$	$0.78_{\pm 0.0}$	$0.60_{\pm 0.0}$	$0.87_{\pm 0.0}$	$0.76_{\pm 0.0}$
Finetune	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$\mathbf{60.1}_{\pm 1.1}$	$\mathbf{81.5}_{\pm 1.0}$	$\mathbf{82.6}_{\pm 0.6}$	$\mathbf{77.8}_{\pm 1.7}$	$\underline{83.1}_{\pm 0.3}$	$\underline{83.2}_{\pm 1.1}$	$\mathbf{76.5}_{\pm 0.5}$	$58.3_{\pm 1.5}$	$\underline{84.4}_{\pm 1.3}$	$\mathbf{79.3}_{\pm 0.4}$	$58.6_{\pm 0.9}$	$\underline{87.3}_{\pm 0.4}$	$\mathbf{76.1}_{\pm 0.9}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$24.8_{\pm 3.1}$	$66.5_{\pm 4.4}$	$82.0_{\pm 2.2}$	$44.5_{\pm 1.3}$	$61.4_{\pm 2.4}$	$75.1_{\pm 1.6}$	$36.7_{\pm 1.6}$	$\underline{1.5}_{\pm 0.4}$	$59.6_{\pm 3.1}$	$43.5_{\pm 3.3}$	$21.3_{\pm 0.8}$	$72.9_{\pm 2.3}$	$49.2_{\pm 2.2}$
	Score ↑	$0.48_{\pm 0.0}$	$0.49_{\pm 0.0}$	$0.45_{\pm 0.0}$	$0.54_{\pm 0.0}$	$0.51_{\pm 0.0}$	$0.48_{\pm 0.0}$	$0.56_{\pm 0.0}$	$\mathbf{0.57}_{\pm 0.0}$	$0.53_{\pm 0.0}$	$0.55_{\pm 0.0}$	$0.48_{\pm 0.0}$	$0.50_{\pm 0.0}$	$0.51_{\pm 0.0}$
UNSIR [51]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$17.0_{\pm 11.3}$	$56.6_{\pm 4.2}$	$51.9_{\pm 3.8}$	$23.6_{\pm 8.0}$	$39.4_{\pm 17.7}$	$49.2_{\pm 3.8}$	$12.6_{\pm 4.3}$	$25.1_{\pm 14.2}$	$52.1_{\pm 2.1}$	$8.4_{\pm 2.4}$	$25.6_{\pm 2.8}$	$59.0_{\pm 6.0}$	$35.0_{\pm 6.7}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$
	Score ↑	$0.17_{\pm 0.1}$	$0.57_{\pm 0.0}$	$0.52_{\pm 0.0}$	$0.24_{\pm 0.1}$	$0.39_{\pm 0.2}$	$0.49_{\pm 0.0}$	$0.13_{\pm 0.0}$	$0.25_{\pm 0.1}$	$0.52_{\pm 0.0}$	$0.08_{\pm 0.0}$	$0.26_{\pm 0.0}$	$0.59_{\pm 0.1}$	$0.35_{\pm 0.1}$
ZSMU [10]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$43.5_{\pm 23.7}$	$78.9_{\pm 2.5}$	$80.5_{\pm 1.5}$	$74.3_{\pm 1.6}$	$79.0_{\pm 1.1}$	$78.5_{\pm 2.2}$	$72.9_{\pm 0.3}$	$55.8_{\pm 2.9}$	$83.9_{\pm 0.8}$	$76.0_{\pm 1.3}$	$54.8_{\pm 4.1}$	$85.6_{\pm 1.2}$	$72.0_{\pm 3.6}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$11.5_{\pm 9.9}$	$62.1_{\pm 4.4}$	$73.3_{\pm 8.7}$	$52.5_{\pm 11.5}$	$58.0_{\pm 11.3}$	$56.4_{\pm 0.8}$	$45.4_{\pm 7.0}$	$17.9_{\pm 2.4}$	$68.1_{\pm 4.1}$	$41.7_{\pm 3.3}$	$24.2_{\pm 4.6}$	$70.3_{\pm 11.1}$	$48.4_{\pm 6.6}$
	Score ↑	$0.38_{\pm 0.2}$	$0.49_{\pm 0.0}$	$0.47_{\pm 0.0}$	$0.49_{\pm 0.0}$	$0.50_{\pm 0.0}$	$0.50_{\pm 0.0}$	$0.50_{\pm 0.0}$	$0.47_{\pm 0.0}$	$0.50_{\pm 0.0}$	$0.54_{\pm 0.0}$	$0.44_{\pm 0.0}$	$0.50_{\pm 0.0}$	$0.48_{\pm 0.0}$
Lipschitz [15]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$56.8_{\pm 3.2}$	$64.5_{\pm 22.6}$	$63.0_{\pm 30.6}$	$42.1_{\pm 24.5}$	$75.0_{\pm 2.7}$	$66.6_{\pm 18.3}$	$67.0_{\pm 7.8}$	$45.1_{\pm 7.5}$	$59.4_{\pm 16.8}$	$63.6_{\pm 16.4}$	$44.1_{\pm 11.1}$	$79.6_{\pm 4.0}$	$60.6_{\pm 13.8}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$\underline{10.4}_{\pm 6.4}$	$\underline{27.5}_{\pm 23.8}$	$39.2_{\pm 34.8}$	$13.3_{\pm 18.3}$	$\underline{18.2}_{\pm 5.2}$	$32.0_{\pm 17.1}$	$15.8_{\pm 7.4}$	$4.6_{\pm 2.4}$	$9.1_{\pm 15.7}$	$24.4_{\pm 21.7}$	$15.0_{\pm 12.0}$	$18.8_{\pm 5.7}$	$19.0_{\pm 14.2}$
	Score ↑	$\underline{0.51}_{\pm 0.0}$	$0.49_{\pm 0.1}$	$0.43_{\pm 0.1}$	$0.36_{\pm 0.2}$	$0.64_{\pm 0.0}$	$0.50_{\pm 0.1}$	$0.58_{\pm 0.1}$	$0.43_{\pm 0.1}$	$0.54_{\pm 0.1}$	$0.51_{\pm 0.1}$	$0.38_{\pm 0.1}$	$0.67_{\pm 0.0}$	$0.50_{\pm 0.1}$
Nabla Tau [53]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$47.1_{\pm 3.5}$	$70.0_{\pm 6.7}$	$69.6_{\pm 1.6}$	$62.9_{\pm 2.2}$	$73.6_{\pm 1.2}$	$62.8_{\pm 8.5}$	$59.8_{\pm 3.0}$	$44.8_{\pm 2.9}$	$66.7_{\pm 2.6}$	$58.9_{\pm 3.3}$	$44.9_{\pm 1.3}$	$77.1_{\pm 2.9}$	$61.5_{\pm 3.3}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\underline{0.5}_{\pm 0.9}$	$\underline{0.3}_{\pm 0.5}$	$\mathbf{0.0}_{\pm 0.0}$	$0.8_{\pm 1.4}$	$\underline{1.3}_{\pm 1.1}$	$\mathbf{0.0}_{\pm 0.0}$	$\underline{0.9}_{\pm 1.6}$	$\underline{1.2}_{\pm 2.1}$	$\underline{3.1}_{\pm 2.2}$	$\underline{5.1}_{\pm 8.8}$	$\underline{1.1}_{\pm 1.6}$
	Score ↑	$0.47_{\pm 0.0}$	$\underline{0.70}_{\pm 0.1}$	$\underline{0.69}_{\pm 0.0}$	$\underline{0.63}_{\pm 0.0}$	$\underline{0.74}_{\pm 0.0}$	$0.62_{\pm 0.1}$	$\underline{0.59}_{\pm 0.0}$	$0.45_{\pm 0.0}$	$0.66_{\pm 0.0}$	$\underline{0.58}_{\pm 0.0}$	$0.44_{\pm 0.0}$	$\underline{0.74}_{\pm 0.1}$	$\underline{0.61}_{\pm 0.0}$
Unlearned(+) [2]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$51.1_{\pm 1.1}$	$75.6_{\pm 0.6}$	$77.7_{\pm 0.1}$	$72.0_{\pm 0.7}$	$\mathbf{83.6}_{\pm 0.1}$	$\mathbf{83.6}_{\pm 0.3}$	$69.5_{\pm 0.4}$	$\mathbf{59.7}_{\pm 1.2}$	$\mathbf{86.1}_{\pm 0.5}$	$73.7_{\pm 0.4}$	$\underline{60.5}_{\pm 0.9}$	$\mathbf{88.4}_{\pm 0.0}$	$73.1_{\pm 0.5}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$19.7_{\pm 2.5}$	$77.3_{\pm 2.1}$	$77.8_{\pm 4.3}$	$35.4_{\pm 5.2}$	$58.1_{\pm 0.7}$	$81.3_{\pm 0.7}$	$34.2_{\pm 3.5}$	$40.2_{\pm 8.8}$	$87.4_{\pm 2.1}$	$35.4_{\pm 1.8}$	$41.1_{\pm 2.6}$	$87.4_{\pm 0.7}$	$52.1_{\pm 2.5}$
	Score ↑	$0.43_{\pm 0.02}$	$0.43_{\pm 0.01}$	$0.44_{\pm 0.01}$	$0.53_{\pm 0.02}$	$0.53_{\pm 0.00}$	$0.46_{\pm 0.00}$	$0.52_{\pm 0.01}$	$0.43_{\pm 0.04}$	$0.46_{\pm 0.00}$	$0.55_{\pm 0.00}$	$0.43_{\pm 0.01}$	$0.47_{\pm 0.00}$	$0.48_{\pm 0.01}$
PADA [5]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$58.4_{\pm 0.9}$	$\underline{80.2}_{\pm 2.4}$	$\underline{80.8}_{\pm 0.6}$	$\underline{76.3}_{\pm 1.7}$	$80.7_{\pm 1.2}$	$80.8_{\pm 0.7}$	$73.5_{\pm 2.4}$	$56.5_{\pm 1.7}$	$82.7_{\pm 2.4}$	$\underline{77.3}_{\pm 1.4}$	$54.5_{\pm 0.6}$	$86.0_{\pm 1.1}$	$\underline{74.0}_{\pm 1.4}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$33.3_{\pm 0.3}$	$77.4_{\pm 2.6}$	$82.5_{\pm 0.8}$	$64.8_{\pm 2.5}$	$70.9_{\pm 2.5}$	$73.3_{\pm 1.2}$	$56.5_{\pm 0.9}$	$31.0_{\pm 0.6}$	$79.4_{\pm 0.8}$	$60.5_{\pm 0.5}$	$38.7_{\pm 2.1}$	$83.0_{\pm 0.5}$	$62.6_{\pm 1.3}$
	Score ↑	$0.44_{\pm 0.0}$	$0.45_{\pm 0.0}$	$0.44_{\pm 0.0}$	$0.46_{\pm 0.0}$	$0.47_{\pm 0.0}$	$0.47_{\pm 0.0}$	$0.47_{\pm 0.0}$	$0.43_{\pm 0.0}$	$0.46_{\pm 0.0}$	$0.48_{\pm 0.0}$	$0.39_{\pm 0.0}$	$0.47_{\pm 0.0}$	$0.45_{\pm 0.0}$
SHOT [34]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$56.0_{\pm 2.1}$	$76.8_{\pm 2.3}$	$79.2_{\pm 1.1}$	$74.4_{\pm 2.0}$	$80.9_{\pm 1.2}$	$80.0_{\pm 1.4}$	$71.6_{\pm 1.0}$	$\underline{58.4}_{\pm 1.3}$	$81.4_{\pm 2.1}$	$76.8_{\pm 0.5}$	$\mathbf{63.0}_{\pm 0.6}$	$85.8_{\pm 0.6}$	$73.7_{\pm 1.3}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$23.9_{\pm 1.0}$	$27.6_{\pm 2.5}$	$28.2_{\pm 1.7}$	$31.2_{\pm 1.0}$	$19.3_{\pm 0.8}$	$13.0_{\pm 0.8}$	$29.6_{\pm 1.9}$	$23.9_{\pm 2.3}$	$15.0_{\pm 0.4}$	$36.1_{\pm 0.9}$	$28.8_{\pm 0.7}$	$19.4_{\pm 0.3}$	$24.7_{\pm 1.2}$
	Score ↑	$0.45_{\pm 0.0}$	$0.60_{\pm 0.0}$	$0.62_{\pm 0.0}$	$0.57_{\pm 0.0}$	$0.68_{\pm 0.0}$	$\underline{0.71}_{\pm 0.0}$	$0.55_{\pm 0.0}$	$0.47_{\pm 0.0}$	$\underline{0.71}_{\pm 0.0}$	$0.56_{\pm 0.0}$	$\underline{0.49}_{\pm 0.0}$	$0.72_{\pm 0.0}$	$0.59_{\pm 0.0}$
Ours	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$\underline{59.5}_{\pm 1.9}$	$79.5_{\pm 1.0}$	$78.7_{\pm 1.2}$	$74.8_{\pm 0.7}$	$80.6_{\pm 1.3}$	$78.8_{\pm 1.2}$	$\underline{73.7}_{\pm 0.4}$	$55.7_{\pm 0.6}$	$80.7_{\pm 0.5}$	$74.2_{\pm 0.8}$	$56.7_{\pm 0.5}$	$82.8_{\pm 0.8}$	$73.0_{\pm 0.9}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\underline{0.1}_{\pm 0.2}$	$\mathbf{0.0}_{\pm 0.0}$	$4.1_{\pm 5.8}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$12.8_{\pm 9.1}$	$\mathbf{0.0}_{\pm 0.0}$	$1.4_{\pm 1.3}$
	Score ↑	$\mathbf{0.60}_{\pm 0.0}$	$\mathbf{0.80}_{\pm 0.0}$	$\mathbf{0.79}_{\pm 0.0}$	$\mathbf{0.75}_{\pm 0.0}$	$\mathbf{0.81}_{\pm 0.0}$	$\mathbf{0.79}_{\pm 0.0}$	$\mathbf{0.74}_{\pm 0.0}$	$\underline{0.54}_{\pm 0.0}$	$\mathbf{0.81}_{\pm 0.0}$	$\mathbf{0.74}_{\pm 0.0}$	$\mathbf{0.51}_{\pm 0.0}$	$\mathbf{0.83}_{\pm 0.0}$	$\mathbf{0.72}_{\pm 0.0}$

Table A.25. **Results for UC-SCADA Unlearning on DomainNet.** Forget classes are $\mathcal{C}_{\mathcal{F}} = \{1, 2, 3\}$ *(Best result in bold, second-best underlined)*

Method	Metric	s → p	c → s	p → c	p → r	r → s	r → c	r → p	Average
Original (SF(DA)^2 [28])	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$71.3_{\pm 0.3}$	$66.6_{\pm 0.4}$	$61.7_{\pm 0.8}$	$78.3_{\pm 0.2}$	$55.9_{\pm 1.5}$	$65.1_{\pm 0.9}$	$75.0_{\pm 0.4}$	$67.7_{\pm 0.6}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$67.6_{\pm 5.7}$	$55.9_{\pm 4.8}$	$42.9_{\pm 2.2}$	$60.6_{\pm 2.2}$	$6.5_{\pm 1.1}$	$14.6_{\pm 0.9}$	$22.8_{\pm 3.1}$	$38.7_{\pm 2.9}$
	Score $\uparrow$	$0.43_{\pm 0.0}$	$0.43_{\pm 0.0}$	$0.43_{\pm 0.0}$	$0.49_{\pm 0.0}$	$0.53_{\pm 0.0}$	$0.57_{\pm 0.0}$	$0.61_{\pm 0.0}$	$0.50_{\pm 0.0}$
Retrain	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$71.0_{\pm 0.3}$	$65.3_{\pm 2.3}$	$58.6_{\pm 2.4}$	$78.2_{\pm 0.9}$	$54.2_{\pm 1.0}$	$62.9_{\pm 1.5}$	$74.1_{\pm 1.0}$	$66.3_{\pm 1.3}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$
	Score $\uparrow$	$0.71_{\pm 0.0}$	$0.65_{\pm 0.0}$	$0.59_{\pm 0.0}$	$0.78_{\pm 0.0}$	$0.54_{\pm 0.0}$	$0.63_{\pm 0.0}$	$0.74_{\pm 0.0}$	$0.66_{\pm 0.0}$
Finetune	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$68.9_{\pm 0.1}$	$\underline{64.9}_{\pm 1.1}$	$62.2_{\pm 1.2}$	$77.3_{\pm 0.2}$	$52.1_{\pm 1.9}$	$\underline{65.5}_{\pm 1.3}$	$\underline{74.2}_{\pm 0.8}$	$\underline{66.5}_{\pm 0.9}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$37.4_{\pm 5.8}$	$32.3_{\pm 2.6}$	$20.8_{\pm 6.3}$	$36.6_{\pm 3.1}$	$\underline{0.6}_{\pm 0.3}$	$5.3_{\pm 2.1}$	$10.1_{\pm 8.5}$	$20.4_{\pm 4.1}$
	Score $\uparrow$	$\underline{0.50}_{\pm 0.0}$	$\mathbf{0.49}_{\pm 0.0}$	$\mathbf{0.52}_{\pm 0.0}$	$\underline{0.57}_{\pm 0.0}$	$\mathbf{0.52}_{\pm 0.0}$	$\underline{0.62}_{\pm 0.0}$	$\underline{0.68}_{\pm 0.1}$	$\mathbf{0.56}_{\pm 0.0}$
UNSIR [51]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$14.1_{\pm 6.8}$	$1.5_{\pm 0.1}$	$25.2_{\pm 2.2}$	$40.4_{\pm 2.0}$	$1.5_{\pm 0.3}$	$14.4_{\pm 9.2}$	$23.1_{\pm 2.4}$	$17.2_{\pm 3.3}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\underline{4.4}_{\pm 7.6}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.6}_{\pm 1.1}$
	Score $\uparrow$	$0.14_{\pm 0.1}$	$0.01_{\pm 0.0}$	$0.25_{\pm 0.0}$	$0.39_{\pm 0.0}$	$0.02_{\pm 0.0}$	$0.14_{\pm 0.1}$	$0.23_{\pm 0.0}$	$0.17_{\pm 0.0}$
ZSMU [10]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$\underline{70.0}_{\pm 0.9}$	$58.1_{\pm 3.1}$	$60.2_{\pm 2.2}$	$76.8_{\pm 1.5}$	$49.1_{\pm 1.0}$	$58.0_{\pm 4.1}$	$70.3_{\pm 1.7}$	$63.2_{\pm 2.1}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$67.0_{\pm 20.7}$	$58.6_{\pm 10.0}$	$39.5_{\pm 12.3}$	$49.6_{\pm 16.3}$	$23.8_{\pm 5.0}$	$13.8_{\pm 2.8}$	$25.2_{\pm 7.3}$	$39.7_{\pm 10.6}$
	Score $\uparrow$	$0.42_{\pm 0.1}$	$0.37_{\pm 0.0}$	$0.43_{\pm 0.1}$	$0.52_{\pm 0.1}$	$0.40_{\pm 0.0}$	$0.51_{\pm 0.0}$	$0.56_{\pm 0.0}$	$0.46_{\pm 0.0}$
Lipschitz [15]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$49.5_{\pm 14.9}$	$43.2_{\pm 17.5}$	$47.3_{\pm 11.9}$	$60.8_{\pm 13.4}$	$43.2_{\pm 5.0}$	$29.4_{\pm 21.0}$	$67.8_{\pm 2.2}$	$48.7_{\pm 12.3}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$20.2_{\pm 29.7}$	$\underline{20.2}_{\pm 19.5}$	$23.6_{\pm 20.5}$	$27.5_{\pm 22.0}$	$1.9_{\pm 2.5}$	$1.1_{\pm 2.0}$	$7.5_{\pm 9.2}$	$14.6_{\pm 15.1}$
	Score $\uparrow$	$0.41_{\pm 0.0}$	$0.35_{\pm 0.1}$	$0.38_{\pm 0.0}$	$0.47_{\pm 0.0}$	$0.42_{\pm 0.0}$	$0.29_{\pm 0.2}$	$0.63_{\pm 0.1}$	$0.42_{\pm 0.1}$
Nabla Tau [53]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$43.5_{\pm 2.0}$	$42.2_{\pm 1.7}$	$45.7_{\pm 2.3}$	$59.3_{\pm 4.9}$	$23.3_{\pm 19.1}$	$45.6_{\pm 3.6}$	$47.6_{\pm 1.3}$	$43.9_{\pm 5.0}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$\underline{12.3}_{\pm 3.8}$	$\mathbf{0.0}_{\pm 0.0}$	$\underline{0.3}_{\pm 0.5}$	$\mathbf{3.5}_{\pm 3.1}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\underline{2.3}_{\pm 1.0}$
	Score $\uparrow$	$0.39_{\pm 0.0}$	$0.42_{\pm 0.0}$	$\underline{0.46}_{\pm 0.0}$	$\underline{0.57}_{\pm 0.1}$	$0.23_{\pm 0.2}$	$0.46_{\pm 0.0}$	$0.48_{\pm 0.0}$	$0.43_{\pm 0.0}$
Unlearned(+) [2]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$65.8_{\pm 1.2}$	$61.6_{\pm 1.2}$	$\mathbf{63.2}_{\pm 0.8}$	$77.2_{\pm 0.1}$	$\underline{52.8}_{\pm 1.7}$	$\mathbf{65.7}_{\pm 1.3}$	$74.1_{\pm 0.2}$	$65.8_{\pm 0.8}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$38.4_{\pm 5.2}$	$6.8_{\pm 3.8}$	$29.7_{\pm 1.8}$	$39.9_{\pm 8.3}$	$2.1_{\pm 0.9}$	$16.0_{\pm 5.4}$	$1.6_{\pm 0.4}$	$19.2_{\pm 3.0}$
	Score $\uparrow$	$0.48_{\pm 0.00}$	$0.58_{\pm 0.03}$	$0.49_{\pm 0.01}$	$0.55_{\pm 0.03}$	$0.52_{\pm 0.02}$	$0.57_{\pm 0.04}$	$0.73_{\pm 0.00}$	$0.56_{\pm 0.02}$
PADA [5]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$61.1_{\pm 0.3}$	$59.7_{\pm 0.7}$	$55.1_{\pm 0.3}$	$76.1_{\pm 0.5}$	$49.0_{\pm 0.3}$	$59.9_{\pm 0.4}$	$72.2_{\pm 0.3}$	$61.9_{\pm 0.4}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$45.5_{\pm 1.3}$	$70.1_{\pm 0.4}$	$57.1_{\pm 1.1}$	$71.6_{\pm 1.1}$	$22.3_{\pm 0.8}$	$26.8_{\pm 0.9}$	$32.7_{\pm 2.4}$	$46.6_{\pm 1.1}$
	Score $\uparrow$	$0.42_{\pm 0.0}$	$0.35_{\pm 0.0}$	$0.35_{\pm 0.0}$	$0.44_{\pm 0.0}$	$0.40_{\pm 0.0}$	$0.47_{\pm 0.0}$	$0.54_{\pm 0.0}$	$0.43_{\pm 0.0}$
SHOT [34]	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$\mathbf{71.3}_{\pm 0.2}$	$\mathbf{66.4}_{\pm 1.6}$	$\underline{62.4}_{\pm 0.6}$	$\mathbf{78.5}_{\pm 0.4}$	$\mathbf{55.7}_{\pm 2.4}$	$65.1_{\pm 0.4}$	$\mathbf{74.8}_{\pm 0.9}$	$\mathbf{67.8}_{\pm 0.9}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$67.7_{\pm 4.5}$	$56.3_{\pm 5.1}$	$48.7_{\pm 3.0}$	$62.4_{\pm 3.3}$	$6.9_{\pm 2.1}$	$13.6_{\pm 0.5}$	$21.2_{\pm 0.5}$	$39.6_{\pm 2.7}$
	Score $\uparrow$	$0.43_{\pm 0.0}$	$0.43_{\pm 0.0}$	$0.42_{\pm 0.0}$	$0.48_{\pm 0.0}$	$\mathbf{0.52}_{\pm 0.0}$	$0.57_{\pm 0.0}$	$0.62_{\pm 0.0}$	$0.50_{\pm 0.0}$
Ours	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	$67.3_{\pm 1.4}$	$63.3_{\pm 0.7}$	$60.8_{\pm 1.8}$	$\underline{77.6}_{\pm 0.2}$	$52.4_{\pm 2.3}$	$63.3_{\pm 0.5}$	$72.7_{\pm 0.8}$	$65.3_{\pm 1.1}$
	$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	$29.6_{\pm 9.8}$	$36.8_{\pm 3.1}$	$36.3_{\pm 7.1}$	$28.7_{\pm 5.9}$	$4.5_{\pm 5.4}$	$\underline{0.7}_{\pm 1.0}$	$\underline{3.6}_{\pm 5.1}$	$20.1_{\pm 5.3}$
	Score $\uparrow$	$\mathbf{0.52}_{\pm 0.0}$	$\underline{0.46}_{\pm 0.0}$	$0.45_{\pm 0.0}$	$\mathbf{0.60}_{\pm 0.0}$	$\underline{0.50}_{\pm 0.0}$	$\mathbf{0.63}_{\pm 0.0}$	$\mathbf{0.70}_{\pm 0.0}$	$\underline{0.55}_{\pm 0.0}$

Table A.26. **Results for UC-SCADA Unlearning on Office 31.** Forget classes are $\mathcal{C}_{\mathcal{F}} = \{1, 2, 3\}$ ***(Best result in bold, second-best underlined)***

Method	Metric	A → D	A → W	D → A	D → W	W → A	W → D	Average
Original (SF(DA)^2 [28])	$A_{\mathcal{D}_r^{\mathcal{T}}}$ ↑	$67.0_{\pm0.9}$	$79.9_{\pm1.8}$	$77.1_{\pm0.9}$	$86.3_{\pm1.5}$	$78.5_{\pm1.5}$	$72.0_{\pm0.5}$	$76.8_{\pm1.2}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}$ ↓	$93.6_{\pm0.8}$	$88.5_{\pm2.3}$	$84.8_{\pm2.3}$	$99.5_{\pm0.8}$	$76.6_{\pm1.9}$	$97.7_{\pm1.6}$	$90.1_{\pm1.6}$
	Score ↑	$0.35_{\pm0.0}$	$0.42_{\pm0.0}$	$0.42_{\pm0.0}$	$0.43_{\pm0.0}$	$0.44_{\pm0.0}$	$0.36_{\pm0.0}$	$0.40_{\pm0.0}$
Retrain	$A_{\mathcal{D}_r^{\mathcal{T}}}$ ↑	$68.2_{\pm0.9}$	$83.3_{\pm0.8}$	$76.0_{\pm4.1}$	$87.0_{\pm0.6}$	$78.0_{\pm1.2}$	$72.0_{\pm1.0}$	$77.4_{\pm1.4}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}$ ↓	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$
	Score ↑	$0.68_{\pm0.0}$	$0.83_{\pm0.0}$	$0.76_{\pm0.0}$	$0.87_{\pm0.0}$	$0.78_{\pm0.0}$	$0.72_{\pm0.0}$	$0.77_{\pm0.0}$
Finetune	$A_{\mathcal{D}_r^{\mathcal{T}}}$ ↑	$66.7_{\pm2.2}$	$79.7_{\pm2.3}$	$\underline{77.2}_{\pm0.6}$	$\mathbf{86.5}_{\pm1.6}$	$\underline{78.4}_{\pm1.0}$	$72.0_{\pm0.5}$	$\mathbf{76.7}_{\pm1.4}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}$ ↓	$85.4_{\pm3.0}$	$80.3_{\pm1.3}$	$79.4_{\pm1.1}$	$94.0_{\pm0.8}$	$65.0_{\pm5.8}$	$93.0_{\pm0.0}$	$82.8_{\pm2.0}$
	Score ↑	$0.36_{\pm0.0}$	$0.44_{\pm0.0}$	$0.43_{\pm0.0}$	$0.45_{\pm0.0}$	$0.48_{\pm0.0}$	$0.37_{\pm0.0}$	$0.42_{\pm0.0}$
UNSIR [51]	$A_{\mathcal{D}_r^{\mathcal{T}}}$ ↑	$51.0_{\pm10.8}$	$77.4_{\pm5.9}$	$58.0_{\pm1.2}$	$65.7_{\pm3.6}$	$68.6_{\pm3.3}$	$48.8_{\pm6.9}$	$61.6_{\pm5.3}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}$ ↓	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\underline{1.2}_{\pm1.0}$	$\mathbf{0.0}_{\pm0.0}$	$64.3_{\pm3.6}$	$\mathbf{0.0}_{\pm0.0}$	$\underline{10.9}_{\pm0.8}$
	Score ↑	$0.51_{\pm0.1}$	$\mathbf{0.77}_{\pm0.1}$	$\underline{0.57}_{\pm0.0}$	$0.66_{\pm0.0}$	$0.42_{\pm0.0}$	$0.49_{\pm0.1}$	$0.57_{\pm0.1}$
ZSMU [10]	$A_{\mathcal{D}_r^{\mathcal{T}}}$ ↑	$76.7_{\pm0.7}$	$85.9_{\pm2.0}$	$63.3_{\pm3.7}$	$78.1_{\pm3.0}$	$71.2_{\pm0.6}$	$74.7_{\pm0.6}$	$75.0_{\pm1.8}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}$ ↓	$68.6_{\pm6.4}$	$97.3_{\pm1.0}$	$92.4_{\pm5.3}$	$85.3_{\pm4.3}$	$92.4_{\pm2.0}$	$78.0_{\pm4.3}$	$85.6_{\pm3.9}$
	Score ↑	$0.46_{\pm0.0}$	$0.44_{\pm0.0}$	$0.33_{\pm0.0}$	$0.42_{\pm0.0}$	$0.37_{\pm0.0}$	$0.42_{\pm0.0}$	$0.41_{\pm0.0}$
Lipschitz [15]	$A_{\mathcal{D}_r^{\mathcal{T}}}$ ↑	$72.3_{\pm2.5}$	$76.2_{\pm16.3}$	$58.3_{\pm6.6}$	$75.8_{\pm5.5}$	$70.9_{\pm0.6}$	$66.4_{\pm15.6}$	$70.0_{\pm7.9}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}$ ↓	$47.2_{\pm22.6}$	$33.9_{\pm32.1}$	$37.4_{\pm6.7}$	$60.1_{\pm17.1}$	$\underline{47.4}_{\pm33.4}$	$\underline{9.4}_{\pm14.2}$	$39.2_{\pm21.0}$
	Score ↑	$0.50_{\pm0.1}$	$0.57_{\pm0.0}$	$0.42_{\pm0.0}$	$0.47_{\pm0.0}$	$\underline{0.50}_{\pm0.1}$	$0.61_{\pm0.1}$	$0.51_{\pm0.1}$
Nabla Tau [53]	$A_{\mathcal{D}_r^{\mathcal{T}}}$ ↑	$71.6_{\pm1.4}$	$85.4_{\pm1.1}$	$65.5_{\pm4.6}$	$75.1_{\pm1.6}$	$71.6_{\pm0.0}$	$70.7_{\pm3.7}$	$73.3_{\pm2.0}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}$ ↓	$\underline{3.1}_{\pm3.7}$	$\underline{16.4}_{\pm14.6}$	$36.9_{\pm13.7}$	$\underline{1.6}_{\pm2.8}$	$74.2_{\pm5.3}$	$12.7_{\pm11.0}$	$24.2_{\pm8.5}$
	Score ↑	$\mathbf{0.70}_{\pm0.0}$	$\underline{0.74}_{\pm0.1}$	$0.48_{\pm0.1}$	$\underline{0.74}_{\pm0.0}$	$0.41_{\pm0.0}$	$\underline{0.63}_{\pm0.0}$	$\underline{0.62}_{\pm0.0}$
Unlearned(+) [2]	$A_{\mathcal{D}_r^{\mathcal{T}}}$ ↑	$61.1_{\pm0.9}$	$74.7_{\pm2.3}$	$\mathbf{78.6}_{\pm1.6}$	$\underline{82.5}_{\pm1.1}$	$\mathbf{79.7}_{\pm0.7}$	$66.3_{\pm0.9}$	$73.8_{\pm1.1}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}$ ↓	$100.0_{\pm1.3}$	$100.0_{\pm1.1}$	$89.0_{\pm4.8}$	$100.0_{\pm1.2}$	$87.8_{\pm7.5}$	$100.0_{\pm1.3}$	$96.1_{\pm2.8}$
	Score ↑	$0.30_{\pm0.01}$	$0.37_{\pm0.02}$	$0.42_{\pm0.01}$	$0.41_{\pm0.01}$	$0.42_{\pm0.02}$	$0.33_{\pm0.01}$	$0.38_{\pm0.01}$
PADA [5]	$A_{\mathcal{D}_r^{\mathcal{T}}}$ ↑	$\underline{76.8}_{\pm0.4}$	$\underline{86.5}_{\pm1.5}$	$66.3_{\pm2.4}$	$78.5_{\pm2.9}$	$72.0_{\pm0.6}$	$\mathbf{77.4}_{\pm2.2}$	$\underline{76.2}_{\pm1.6}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}$ ↓	$76.8_{\pm3.1}$	$100._{\pm0.0}$	$90.7_{\pm2.0}$	$90.7_{\pm1.9}$	$98.8_{\pm1.0}$	$77.4_{\pm1.7}$	$89.1_{\pm1.6}$
	Score ↑	$0.43_{\pm0.0}$	$0.43_{\pm0.0}$	$0.35_{\pm0.0}$	$0.41_{\pm0.0}$	$0.36_{\pm0.0}$	$0.44_{\pm0.0}$	$0.40_{\pm0.0}$
SHOT [34]	$A_{\mathcal{D}_r^{\mathcal{T}}}$ ↑	$\mathbf{77.2}_{\pm1.0}$	$\mathbf{87.0}_{\pm1.2}$	$65.9_{\pm2.3}$	$78.1_{\pm1.2}$	$72.0_{\pm0.6}$	$\underline{75.6}_{\pm1.2}$	$76.0_{\pm1.2}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}$ ↓	$47.9_{\pm1.5}$	$92.9_{\pm0.9}$	$69.6_{\pm2.7}$	$72.7_{\pm1.9}$	$84.8_{\pm2.0}$	$40.4_{\pm1.5}$	$68.0_{\pm1.7}$
	Score ↑	$0.52_{\pm0.0}$	$0.45_{\pm0.0}$	$0.39_{\pm0.0}$	$0.45_{\pm0.0}$	$0.39_{\pm0.0}$	$0.54_{\pm0.0}$	$0.46_{\pm0.0}$
Ours	$A_{\mathcal{D}_r^{\mathcal{T}}}$ ↑	$60.6_{\pm0.6}$	$72.8_{\pm2.0}$	$72.1_{\pm1.7}$	$77.4_{\pm1.9}$	$71.9_{\pm1.4}$	$67.4_{\pm2.9}$	$70.4_{\pm1.7}$
	$A_{\mathcal{D}_f^{\mathcal{T}}}$ ↓	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$
	Score ↑	$\underline{0.61}_{\pm0.0}$	$0.73_{\pm0.0}$	$\mathbf{0.72}_{\pm0.0}$	$\mathbf{0.77}_{\pm0.0}$	$\mathbf{0.72}_{\pm0.0}$	$\mathbf{0.67}_{\pm0.0}$	$\mathbf{0.70}_{\pm0.0}$

Table A.27. **C-SCADA Unlearning performance on the OfficeHome dataset.** Forget classes are $\mathcal{C_F}^1 = \{1, 2\}, \mathcal{C_F}^2 = \{3, 4\}, \mathcal{C_F}^3 = \{5, 6\}$

Method	Task	Acc.	A → C	A → P	A → R	C → A	C → P	C → R	P → A	P → C	P → R	R → A	R → C	R → P	Average
Original (SF(DA)[2] [28])	T1	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	63.6±0.4	80.3±0.3	86.7±0.8	78.6±0.4	81.9±0.9	87.4±0.4	76.5±1.1	62.2±0.3	89.5±0.4	81.3±1.4	63.4±1.5	87.1±0.2	78.2±0.7
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	43.8±1.1	61.4±2.4	75.4±1.1	59.8±3.7	55.7±1.3	66.9±3.2	46.0±2.6	26.2±0.8	62.1±1.2	58.4±4.8	40.3±0.6	63.4±0.6	55.0±2.0
		Score ↑	0.44±0.0	0.50±0.0	0.49±0.0	0.49±0.0	0.53±0.0	0.52±0.0	0.52±0.0	0.49±0.0	0.55±0.0	0.51±0.0	0.45±0.0	0.53±0.0	0.50±0.0
	T2	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	63.6±0.4	80.3±0.3	86.7±0.8	78.6±0.4	81.9±0.9	87.4±0.4	76.5±1.1	62.2±0.3	89.5±0.4	81.3±1.4	63.4±1.5	87.1±0.2	78.2±0.7
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	44.2±1.1	62.2±2.4	76.1±1.0	60.6±3.7	56.3±1.3	67.5±3.2	46.7±2.6	26.5±0.9	62.6±1.2	59.2±4.9	40.6±0.6	64.2±0.6	55.6±2.0
		Score ↑	0.44±0.0	0.50±0.0	0.49±0.0	0.49±0.0	0.52±0.0	0.52±0.0	0.52±0.0	0.49±0.0	0.55±0.0	0.51±0.0	0.45±0.0	0.53±0.0	0.50±0.0
	T3	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	63.6±0.4	80.3±0.3	86.7±0.8	78.6±0.4	81.9±0.9	87.4±0.4	76.5±1.1	62.2±0.3	89.5±0.4	81.3±1.4	63.4±1.5	87.1±0.2	78.2±0.7
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	44.3±1.1	62.4±2.4	76.3±1.1	60.9±3.8	56.6±1.3	67.7±3.2	46.9±2.6	26.5±0.8	62.8±1.2	59.5±5.0	40.8±0.6	64.5±0.6	55.8±2.0
		Score ↑	0.44±0.0	0.49±0.0	0.49±0.0	0.49±0.0	0.52±0.0	0.52±0.0	0.52±0.0	0.49±0.0	0.55±0.0	0.51±0.0	0.45±0.0	0.53±0.0	0.50±0.0
Retrain	T1	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	65.0±1.7	80.3±1.2	86.6±1.4	78.2±1.6	83.3±0.4	87.8±0.8	78.1±1.4	63.3±1.3	88.1±0.7	77.0±2.6	65.6±0.2	85.2±0.6	78.2±1.2
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0
		Score ↑	0.65±0.0	0.80±0.0	0.87±0.0	0.78±0.0	0.83±0.0	0.88±0.0	0.78±0.0	0.63±0.0	0.88±0.0	0.77±0.0	0.66±0.0	0.85±0.0	0.78±0.0
	T2	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	65.0±1.7	80.3±1.2	86.6±1.4	78.2±1.6	83.3±0.4	87.8±0.8	78.1±1.4	63.3±1.3	88.1±0.7	77.0±2.6	65.6±0.2	85.2±0.6	78.2±1.2
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0
		Score ↑	0.65±0.0	0.80±0.0	0.87±0.0	0.78±0.0	0.83±0.0	0.88±0.0	0.78±0.0	0.63±0.0	0.88±0.0	0.77±0.0	0.66±0.0	0.85±0.0	0.78±0.0
	T3	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	65.0±1.7	80.3±1.2	86.6±1.4	78.2±1.6	83.3±0.4	87.8±0.8	78.1±1.4	63.3±1.3	88.1±0.7	77.0±2.6	65.6±0.2	85.2±0.6	78.2±1.2
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0
		Score ↑	0.65±0.0	0.80±0.0	0.87±0.0	0.78±0.0	0.83±0.0	0.88±0.0	0.78±0.0	0.63±0.0	0.88±0.0	0.77±0.0	0.66±0.0	0.85±0.0	0.78±0.0
Finetune	T1	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	62.8±0.4	79.4±0.8	85.8±0.9	77.2±1.2	82.0±0.5	86.7±0.7	75.7±1.7	61.8±0.4	89.5±0.4	80.9±2.0	62.0±0.8	85.8±1.2	77.5±0.9
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	38.5±1.6	42.1±1.9	66.7±1.6	37.5±2.7	47.0±1.4	60.7±3.0	24.6±0.5	15.6±3.7	53.4±2.5	32.0±1.1	37.0±3.0	55.7±2.8	42.6±2.2
		Score ↑	0.45±0.0	0.56±0.0	0.51±0.0	0.56±0.0	0.56±0.0	0.54±0.0	0.61±0.0	0.54±0.0	0.58±0.0	0.61±0.0	0.45±0.0	0.55±0.0	0.54±0.0
	T2	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	62.8±0.4	79.4±0.8	85.8±0.9	77.2±1.2	82.0±0.5	86.7±0.7	75.7±1.7	61.8±0.4	89.5±0.4	80.9±2.0	62.0±0.8	85.8±1.2	77.5±0.9
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	38.8±1.6	42.6±1.9	67.3±1.6	38.0±2.7	47.6±1.5	61.2±3.1	24.9±0.5	15.8±3.7	53.9±2.5	32.5±1.1	37.3±3.0	56.3±2.8	43.0±2.2
		Score ↑	0.45±0.0	0.56±0.0	0.51±0.0	0.56±0.0	0.56±0.0	0.54±0.0	0.61±0.0	0.53±0.0	0.58±0.0	0.61±0.0	0.45±0.0	0.55±0.0	0.54±0.0
	T3	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	62.8±0.4	79.4±0.8	85.8±0.9	77.2±1.2	82.0±0.5	86.7±0.7	75.7±1.7	61.8±0.4	89.5±0.4	80.9±2.0	62.0±0.8	85.8±1.2	77.5±0.9
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	39.0±1.6	42.8±1.9	67.5±1.6	38.2±2.7	47.8±1.5	61.4±3.1	25.0±0.5	15.8±3.7	54.0±2.5	32.6±1.1	37.4±3.0	56.6±2.9	43.2±2.2
		Score ↑	0.45±0.0	0.56±0.0	0.51±0.0	0.56±0.0	0.56±0.0	0.54±0.0	0.61±0.0	0.53±0.0	0.58±0.0	0.61±0.0	0.45±0.0	0.55±0.0	0.54±0.0
UNSIR [51]	T1	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	30.9±2.7	54.3±3.8	52.5±3.3	16.0±5.8	60.2±4.7	48.1±2.2	17.8±2.5	15.5±9.3	52.0±2.0	16.0±10.0	24.5±9.1	59.1±2.0	37.2±4.8
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0
		Score ↑	0.31±0.0	0.54±0.0	0.53±0.0	0.16±0.1	0.60±0.0	0.48±0.0	0.18±0.0	0.15±0.1	0.52±0.0	0.16±0.1	0.24±0.1	0.59±0.0	0.37±0.0
	T2	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	23.3±2.1	48.5±5.5	44.3±4.5	12.2±3.6	54.6±4.1	35.3±3.6	12.2±0.8	12.5±7.2	38.8±2.1	10.7±6.5	19.2±7.2	49.5±1.8	30.1±4.1
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0
		Score ↑	0.23±0.0	0.48±0.1	0.44±0.0	0.12±0.0	0.55±0.0	0.35±0.0	0.12±0.0	0.12±0.1	0.39±0.0	0.11±0.1	0.19±0.1	0.50±0.0	0.30±0.0
	T3	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	19.6±2.4	43.8±3.9	39.9±3.5	10.9±2.1	49.4±5.0	31.3±4.6	10.2±0.9	11.7±6.9	27.1±5.7	8.7±4.7	15.7±5.4	47.0±3.3	26.3±4.0
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0
		Score ↑	0.20±0.0	0.44±0.0	0.40±0.0	0.11±0.0	0.49±0.0	0.31±0.0	0.10±0.0	0.12±0.1	0.27±0.1	0.09±0.0	0.16±0.1	0.47±0.0	0.26±0.0
ZSMU [10]	T1	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	40.5±33.1	78.5±1.1	85.2±2.0	75.8±1.6	77.7±1.5	78.7±9.2	75.9±2.9	61.3±1.0	87.5±1.8	78.8±0.7	56.7±3.4	84.1±0.3	73.4±4.9
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	14.0±15.7	57.0±3.9	71.5±4.6	32.9±4.6	42.8±2.7	40.3±29.1	40.7±9.6	15.0±4.5	69.2±7.5	35.1±3.4	20.2±12.3	62.4±1.8	41.8±8.3
		Score ↑	0.34±0.3	0.50±0.0	0.50±0.0	0.57±0.0	0.54±0.0	0.57±0.1	0.54±0.0	0.53±0.0	0.52±0.0	0.58±0.0	0.47±0.0	0.52±0.0	0.52±0.0
	T2	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	40.4±33.7	36.2±39.3	84.7±2.1	49.4±37.0	76.9±0.8	78.0±9.9	72.6±5.4	39.7±32.8	86.7±2.2	51.9±43.9	55.1±3.0	84.3±1.1	63.0±17.6
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	15.0±13.3	19.2±33.3	82.5±3.7	29.5±25.7	54.6±10.7	64.3±14.5	30.4±4.7	9.4±8.4	67.5±3.0	34.0±29.5	19.7±7.9	61.6±4.7	40.7±13.3
		Score ↑	0.33±0.3	0.26±0.2	0.46±0.0	0.35±0.2	0.50±0.0	0.47±0.0	0.56±0.0	0.35±0.3	0.52±0.0	0.35±0.3	0.46±0.0	0.52±0.0	0.43±0.1
	T3	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	21.8±33.3	37.5±37.1	58.3±48.5	49.8±36.6	77.3±1.2	78.4±9.1	72.4±4.7	40.2±32.6	86.9±1.9	51.5±43.8	55.0±3.4	69.7±27.0	58.2±23.3
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	11.6±17.5	19.0±30.4	46.4±40.2	20.4±18.0	42.9±9.2	55.0±11.7	36.2±10.7	10.8±9.6	55.4±4.8	28.4±25.3	26.6±4.6	32.9±24.9	32.1±17.2
		Score ↑	0.17±0.2	0.28±0.2	0.35±0.3	0.39±0.3	0.54±0.0	0.50±0.0	0.54±0.1	0.35±0.3	0.56±0.0	0.36±0.3	0.43±0.0	0.51±0.1	0.42±0.2
Lipschitz [15]	T1	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	38.1±15.2	70.9±10.4	67.7±22.1	61.7±13.0	65.4±20.1	56.5±23.7	55.5±4.8	54.4±1.8	79.0±1.6	67.2±4.0	51.4±8.4	85.1±1.0	62.7±10.5
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	7.0±12.1	25.5±20.2	35.7±35.8	0.0±0.0	19.0±31.4	14.7±12.8	0.0±0.0	0.0±0.0	19.8±22.5	3.0±3.3	16.8±16.8	76.1±4.4	18.1±13.3
		Score ↑	0.35±0.1	0.58±0.2	0.50±0.1	0.62±0.1	0.56±0.2	0.48±0.2	0.55±0.0	0.54±0.0	0.67±0.1	0.65±0.0	0.45±0.1	0.48±0.0	0.54±0.1
	T2	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	46.5±3.7	68.4±10.3	68.1±13.4	57.7±28.6	72.5±12.0	55.4±15.7	49.1±26.9	33.0±12.2	83.3±3.8	76.0±2.1	50.8±20.2	79.5±4.2	61.7±12.7
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	9.5±9.4	8.7±15.1	15.4±24.7	27.4±23.8	19.7±19.1	3.4±5.9	1.0±1.8	0.0±0.0	26.7±9.5	4.0±6.9	6.8±5.4	42.7±22.1	13.8±12.0
		Score ↑	0.43±0.1	0.63±0.1	0.59±0.0	0.43±0.2	0.61±0.0	0.54±0.2	0.48±0.3	0.33±0.1	0.66±0.0	0.73±0.1	0.47±0.2	0.57±0.1	0.54±0.1
	T3	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	46.1±6.6	75.2±2.7	56.9±24.9	45.6±19.4	68.2±4.2	64.8±17.6	50.2±9.1	48.5±5.1	60.4±38.5	69.4±13.5	58.8±6.3	79.8±4.2	60.3±12.7
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	9.8±8.0	12.9±22.4	5.3±4.8	1.0±1.7	3.5±6.0	6.0±5.2	3.8±4.5	5.0±2.0	10.2±10.9	6.3±8.1	17.9±4.7	31.0±6.8	9.4±7.1
		Score ↑	0.42±0.1	0.68±0.1	0.54±0.2	0.45±0.2	0.66±0.0	0.61±0.1	0.48±0.1	0.46±0.0	0.53±0.3	0.65±0.1	0.50±0.1	0.61±0.0	0.55±0.1
Nabla Tau [53]	T1	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	52.8±2.7	71.5±1.6	72.2±0.8	55.7±10.3	70.3±3.5	76.2±1.5	61.1±1.9	48.8±2.4	75.0±2.2	63.4±2.0	48.9±3.0	72.6±4.9	64.0±3.1
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	1.3±2.3	0.0±0.0	0.0±0.0	1.3±2.3	0.6±1.0	3.1±4.0	6.5±8.1	0.0±0.0	0.0±0.0	0.9±1.5	0.0±0.0	0.0±0.0	1.1±1.6
		Score ↑	0.52±0.0	0.71±0.0	0.72±0.0	0.55±0.1	0.70±0.0	0.74±0.0	0.58±0.0	0.49±0.0	0.75±0.0	0.63±0.0	0.49±0.0	0.73±0.0	0.63±0.0
	T2	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	50.8±3.1	69.2±2.4	69.0±0.5	52.5±7.5	69.0±2.9	70.7±2.3	57.9±0.8	47.2±1.8	71.4±2.6	60.2±0.3	46.5±2.5	72.0±3.1	61.4±2.5
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	2.1±3.7	0.0±0.0	0.0±0.0	3.6±3.2	0.1±0.2	1.8±3.1	0.3±0.6	0.0±0.0	0.0±0.0	0.2±0.3	0.0±0.0	0.0±0.0	0.7±0.9
		Score ↑	0.50±0.0	0.69±0.0	0.69±0.0	0.51±0.1	0.69±0.0	0.69±0.0	0.58±0.0	0.47±0.0	0.71±0.0	0.60±0.0	0.47±0.0	0.72±0.0	0.61±0.0
	T3	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	49.1±1.5	68.9±2.7	67.2±0.8	52.4±7.9	69.2±2.7	68.9±3.0	57.5±0.6	45.8±0.9	71.2±3.5	60.8±1.9	46.2±2.7	72.1±4.2	60.8±2.7
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	5.4±1.8	0.0±0.0	0.0±0.0	1.8±1.6	0.5±0.8	0.7±1.2	2.0±1.2	4.9±2.4	0.0±0.0	0.2±0.3	5.7±4.6	0.0±0.0	1.8±1.2
		Score ↑	0.47±0.0	0.69±0.0	0.67±0.0	0.52±0.1	0.69±0.0	0.68±0.0	0.56±0.0	0.44±0.0	0.71±0.0	0.61±0.0	0.44±0.0	0.72±0.0	0.60±0.0
Unlearned(+) [2]	T1	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	54.5±1.1	76.2±1.5	78.2±1.2	78.5±0.9	81.9±1.3	86.1±1.6	78.0±1.4	60.6±1.7	88.3±1.0	82.4±1.3	65.4±2.1	85.6±1.4	76.3±1.3
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	10.1±2.2	51.8±3.1	65.1±1.9	31.9±8.3	62.7±5.4	71.0±2.3	22.8±3.2	10.9±2.5	50.6±4.1	44.2±1.6	30.7±1.8	75.6±1.5	43.9±2.4
		Score ↑	0.50±0.02	0.50±0.03	0.47±0.02	0.60±0.03	0.50±0.02	0.50±0.02	0.64±0.02	0.55±0.01	0.59±0.02	0.57±0.02	0.50±0.02	0.49±0.02	0.53±0.02
	T2	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	55.6±1.2	75.9±1.0	77.7±1.1	77.9±0.8	81.0±1.4	87.3±0.9	77.3±1.3	60.4±1.1	88.6±0.9	82.4±1.0	65.7±1.5	85.7±1.1	76.3±1.1
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	15.0±2.1	38.5±1.9	57.9±2.2	40.4±1.8	48.6±1.6	56.0±2.3	11.2±1.8	2.2±0.9	51.1±2.4	37.8±2.6	23.0±0.4	55.5±2.5	36.4±1.9
		Score ↑	0.48±0.02	0.55±0.02	0.49±0.02	0.55±0.02	0.55±0.02	0.56±0.02	0.69±0.02	0.59±0.01	0.59±0.02	0.60±0.02	0.53±0.02	0.55±0.02	0.56±0.02
	T3	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	55.1±0.9	75.9±1.1	77.7±0.8	78.0±0.9	81.1±1.0	87.2±0.7	77.5±1.0	60.0±1.2	88.6±1.1	82.2±1.3	65.6±0.8	85.6±0.7	76.2±0.9
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	25.9±1.3	27.0±1.1	38.3±1.5	19.6±1.0	31.7±1.2	37.9±1.4	14.7±1.3	6.7±1.1	33.4±1.7	41.7±1.4	31.2±1.3	38.6±1.5	28.9±1.2
		Score ↑	0.44±0.02	0.60±0.02	0.56±0.01	0.65±0.02	0.62±0.02	0.63±0.01	0.68±0.01	0.56±0.02	0.66±0.01	0.58±0.02	0.50±0.01	0.62±0.01	0.59±0.02
PADA [5]	T1	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	61.8±0.8	77.8±1.4	85.1±1.1	76.5±1.0	79.7±1.7	85.4±0.5	75.9±1.7	59.1±0.4	88.9±1.1	80.2±0.8	57.7±0.8	85.6±0.8	76.1±1.0
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	37.0±2.5	75.9±0.6	80.6±2.4	54.1±2.0	74.3±0.9	80.8±0.6	48.9±1.9	34.4±0.9	79.7±2.4	48.9±1.9	41.1±2.8	83.0±2.6	61.6±1.8
		Score ↑	0.45±0.0	0.44±0.0	0.47±0.0	0.50±0.0	0.46±0.0	0.47±0.0	0.51±0.0	0.44±0.0	0.50±0.0	0.54±0.0	0.41±0.0	0.47±0.0	0.47±0.0
	T2	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	60.1±0.2	76.3±1.3	84.7±2.0	75.7±0.9	79.0±1.7	84.9±1.0	75.2±2.5	58.4±0.7	88.6±1.0	79.8±1.1	55.8±1.3	84.6±0.8	75.3±1.2
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	34.1±1.7	75.0±3.2	81.0±2.2	61.8±2.0	69.2±1.4	72.7±0.3	48.6±1.3	24.4±1.0	74.5±2.2	63.7±0.6	35.7±4.7	76.9±2.4	59.8±1.9
		Score ↑	0.45±0.0	0.44±0.0	0.47±0.0	0.47±0.0	0.47±0.0	0.49±0.0	0.51±0.0	0.47±0.0	0.51±0.0	0.49±0.0	0.41±0.0	0.48±0.0	0.47±0.0
	T3	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	59.0±0.4	76.1±1.0	84.1±2.4	74.9±1.9	78.6±1.6	84.4±1.5	74.7±2.4	57.7±0.9	88.5±1.1	80.0±1.3	53.0±2.1	84.4±0.5	74.6±1.4
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	29.8±1.4	59.6±2.9	63.4±3.7	40.7±1.5	51.2±1.8	53.4±2.5	33.9±0.2	13.5±2.5	56.5±2.1	51.3±2.0	27.0±2.9	57.2±2.4	44.8±2.2
		Score ↑	0.45±0.0	0.48±0.0	0.51±0.0	0.53±0.0	0.52±0.0	0.55±0.0	0.56±0.0	0.51±0.0	0.57±0.0	0.53±0.0	0.42±0.0	0.54±0.0	0.51±0.0
SHOT [34]	T1	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	58.5±1.4	74.8±1.5	83.6±1.4	76.4±1.9	79.8±0.9	83.7±1.0	72.2±1.3	63.1±1.1	86.5±1.0	79.8±2.3	66.6±1.2	84.2±1.2	75.8±1.3
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	30.2±1.4	38.3±0.6	35.6±0.4	31.7±0.8	29.8±1.0	22.2±0.8	29.9±0.5	26.0±0.7	25.5±0.3	35.8±0.8	30.7±1.2	32.2±0.3	30.7±0.7
		Score ↑	0.45±0.0	0.54±0.0	0.62±0.0	0.58±0.0	0.61±0.0	0.69±0.0	0.56±0.0	0.50±0.0	0.69±0.0	0.59±0.0	0.51±0.0	0.64±0.0	0.58±0.0
	T2	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	58.3±1.1	74.0±1.1	82.4±0.9	76.5±2.5	79.7±0.8	83.5±1.4	71.1±1.2	61.8±0.7	86.1±1.3	79.0±2.1	66.3±1.0	83.7±1.0	75.2±1.2
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	30.1±2.0	37.5±1.2	35.0±2.0	30.6±2.0	30.6±2.1	22.6±1.2	28.6±0.5	24.2±0.5	25.0±0.2	33.4±0.5	29.7±2.2	31.7±1.1	29.9±1.3
		Score ↑	0.45±0.0	0.54±0.0	0.61±0.0	0.59±0.0	0.61±0.0	0.68±0.0	0.55±0.0	0.50±0.0	0.69±0.0	0.59±0.0	0.51±0.0	0.64±0.0	0.58±0.0
	T3	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	57.6±1.3	72.9±1.1	81.8±0.8	75.7±2.7	79.8±0.8	82.9±1.2	70.8±1.7	61.2±0.8	86.2±1.3	78.7±1.6	65.7±1.3	83.5±1.0	74.7±1.3
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	28.0±2.0	36.9±0.3	35.0±1.1	30.4±1.7	31.3±2.2	22.4±0.4	28.3±1.3	23.6±0.4	24.8±0.5	32.8±0.7	29.0±2.0	30.7±0.6	29.4±1.1
		Score ↑	0.45±0.0	0.53±0.0	0.61±0.0	0.58±0.0	0.61±0.0	0.68±0.0	0.55±0.0	0.49±0.0	0.69±0.0	0.59±0.0	0.51±0.0	0.64±0.0	0.58±0.0
Ours	T1	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	63.1±0.8	79.1±0.3	86.2±0.8	77.4±1.1	80.5±0.6	86.6±0.5	76.1±1.0	61.0±0.7	89.2±0.3	79.9±1.3	62.1±0.7	86.6±0.5	77.3±0.7
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0
		Score ↑	0.63±0.0	0.79±0.0	0.86±0.0	0.77±0.0	0.81±0.0	0.87±0.0	0.76±0.0	0.61±0.0	0.89±0.0	0.80±0.0	0.62±0.0	0.87±0.0	0.77±0.0
	T2	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	62.9±0.7	79.0±1.2	86.6±0.6	77.8±1.4	82.1±0.8	86.6±0.3	76.8±1.5	60.5±1.1	88.8±0.4	80.7±2.5	63.2±1.4	86.7±0.6	77.6±1.0
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	0.0±0.0	0.0±0.0	0.0±0.0	2.4±0.5	0.0±0.0	8.9±3.2	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	0.0±0.0	11.4±8.1	1.9±1.0
		Score ↑	0.63±0.0	0.79±0.0	0.87±0.0	0.76±0.0	0.82±0.0	0.80±0.0	0.77±0.0	0.61±0.0	0.89±0.0	0.81±0.0	0.63±0.0	0.78±0.1	0.76±0.0
	T3	$A_{\mathcal{D}_r^\mathcal{T}}$ ↑	62.7±0.4	79.1±1.1	86.2±0.5	78.2±1.3	81.8±1.3	86.5±0.1	76.8±1.6	60.2±0.6	89.0±0.4	80.0±2.1	63.7±1.6	87.1±0.6	77.6±1.0
		$A_{\mathcal{D}_f^\mathcal{T}}$ ↓	4.4±6.3	0.0±0.0	0.0±0.0	3.8±1.0	0.0±0.0	5.0±3.0	0.1±0.1	0.6±0.5	2.0±2.8	0.0±0.0	3.3±1.7	7.3±5.2	2.2±1.7
		Score ↑	0.60±0.0	0.79±0.0	0.86±0.0	0.75±0.0	0.82±0.0	0.82±0.0	0.77±0.0	0.60±0.0	0.87±0.0	0.80±0.0	0.62±0.0	0.81±0.0	0.76±0.0

Table A.28. **C-SCADA Unlearning performance on the DomainNet dataset.** Forget classes are ${\mathcal{C}_{\mathcal{F}}}^1 = \{1, 2\}, {\mathcal{C}_{\mathcal{F}}}^2 = \{3, 4\}, {\mathcal{C}_{\mathcal{F}}}^3 = \{5, 6\}$

Method	Task	Acc.	s → p	c → s	p → c	p → r	r → s	r → c	r → p	Average
Original (SF(DA)^2 [28])	T1	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	71.8$_{\pm0.5}$	64.9$_{\pm0.0}$	62.1$_{\pm0.6}$	78.2$_{\pm0.1}$	55.6$_{\pm0.8}$	65.8$_{\pm1.6}$	75.4$_{\pm0.7}$	67.7$_{\pm0.6}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	37.2$_{\pm1.6}$	37.2$_{\pm2.9}$	37.3$_{\pm1.6}$	63.2$_{\pm3.6}$	17.3$_{\pm2.1}$	10.0$_{\pm0.6}$	25.5$_{\pm3.5}$	32.5$_{\pm2.3}$
		Score ↑	0.52$_{\pm0.0}$	0.47$_{\pm0.0}$	0.45$_{\pm0.0}$	0.48$_{\pm0.0}$	0.47$_{\pm0.0}$	0.60$_{\pm0.0}$	0.60$_{\pm0.0}$	0.51$_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	71.8$_{\pm0.5}$	64.9$_{\pm0.0}$	62.1$_{\pm0.6}$	78.2$_{\pm0.1}$	55.6$_{\pm0.8}$	65.8$_{\pm1.6}$	75.4$_{\pm0.7}$	67.7$_{\pm0.6}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	37.3$_{\pm1.6}$	37.4$_{\pm3.0}$	37.7$_{\pm1.6}$	63.3$_{\pm3.6}$	17.4$_{\pm2.1}$	10.1$_{\pm0.6}$	25.7$_{\pm3.5}$	32.7$_{\pm2.3}$
		Score ↑	0.52$_{\pm0.0}$	0.47$_{\pm0.0}$	0.45$_{\pm0.0}$	0.48$_{\pm0.0}$	0.47$_{\pm0.0}$	0.60$_{\pm0.0}$	0.60$_{\pm0.0}$	0.51$_{\pm0.0}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	71.8$_{\pm0.5}$	64.9$_{\pm0.0}$	62.1$_{\pm0.6}$	78.2$_{\pm0.1}$	55.6$_{\pm0.8}$	65.8$_{\pm1.6}$	75.4$_{\pm0.7}$	67.7$_{\pm0.6}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	37.4$_{\pm1.6}$	37.5$_{\pm3.0}$	37.8$_{\pm1.6}$	63.3$_{\pm3.6}$	17.4$_{\pm2.1}$	10.1$_{\pm0.6}$	25.7$_{\pm3.5}$	32.7$_{\pm2.3}$
		Score ↑	0.52$_{\pm0.0}$	0.47$_{\pm0.0}$	0.45$_{\pm0.0}$	0.48$_{\pm0.0}$	0.47$_{\pm0.0}$	0.60$_{\pm0.0}$	0.60$_{\pm0.0}$	0.51$_{\pm0.0}$
Retrain	T1	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	72.6$_{\pm0.6}$	64.3$_{\pm0.8}$	60.1$_{\pm2.0}$	79.9$_{\pm0.4}$	57.0$_{\pm0.1}$	63.6$_{\pm0.4}$	75.0$_{\pm0.6}$	67.5$_{\pm0.7}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$
		Score ↑	0.73$_{\pm0.0}$	0.64$_{\pm0.0}$	0.60$_{\pm0.0}$	0.80$_{\pm0.0}$	0.57$_{\pm0.0}$	0.64$_{\pm0.0}$	0.75$_{\pm0.0}$	0.68$_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	72.6$_{\pm0.6}$	64.3$_{\pm0.8}$	60.1$_{\pm2.0}$	79.9$_{\pm0.4}$	57.0$_{\pm0.1}$	63.6$_{\pm0.4}$	75.0$_{\pm0.6}$	67.5$_{\pm0.7}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$
		Score ↑	0.73$_{\pm0.0}$	0.64$_{\pm0.0}$	0.60$_{\pm0.0}$	0.80$_{\pm0.0}$	0.57$_{\pm0.0}$	0.64$_{\pm0.0}$	0.75$_{\pm0.0}$	0.68$_{\pm0.0}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	72.6$_{\pm0.6}$	64.3$_{\pm0.8}$	60.1$_{\pm2.0}$	79.9$_{\pm0.4}$	57.0$_{\pm0.1}$	63.6$_{\pm0.4}$	75.0$_{\pm0.6}$	67.5$_{\pm0.7}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$	0.0$_{\pm0.0}$
		Score ↑	0.73$_{\pm0.0}$	0.64$_{\pm0.0}$	0.60$_{\pm0.0}$	0.80$_{\pm0.0}$	0.57$_{\pm0.0}$	0.64$_{\pm0.0}$	0.75$_{\pm0.0}$	0.68$_{\pm0.0}$
Finetune	T1	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	**70.4**$_{\pm1.2}$	**64.8**$_{\pm0.9}$	**62.9**$_{\pm0.3}$	**78.0**$_{\pm0.5}$	**56.4**$_{\pm0.4}$	**67.0**$_{\pm1.0}$	75.1$_{\pm0.8}$	**67.8**$_{\pm0.7}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	13.1$_{\pm1.2}$	16.8$_{\pm2.6}$	28.2$_{\pm4.8}$	38.5$_{\pm9.6}$	9.9$_{\pm0.2}$	4.9$_{\pm0.7}$	14.7$_{\pm1.6}$	18.0$_{\pm3.0}$
		Score ↑	0.62$_{\pm0.0}$	0.55$_{\pm0.0}$	0.49$_{\pm0.0}$	0.57$_{\pm0.0}$	0.51$_{\pm0.0}$	**0.64**$_{\pm0.0}$	0.66$_{\pm0.0}$	0.58$_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	**70.4**$_{\pm1.2}$	**64.8**$_{\pm0.9}$	**62.9**$_{\pm0.3}$	78.0$_{\pm0.5}$	**56.4**$_{\pm0.4}$	**67.0**$_{\pm1.0}$	**75.1**$_{\pm0.8}$	**67.8**$_{\pm0.7}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	13.2$_{\pm1.2}$	16.9$_{\pm2.6}$	28.4$_{\pm4.8}$	38.6$_{\pm9.6}$	10.0$_{\pm0.2}$	5.0$_{\pm0.7}$	14.7$_{\pm1.6}$	18.1$_{\pm3.0}$
		Score ↑	0.62$_{\pm0.0}$	0.55$_{\pm0.0}$	0.49$_{\pm0.0}$	0.57$_{\pm0.0}$	0.51$_{\pm0.0}$	**0.64**$_{\pm0.0}$	0.66$_{\pm0.0}$	0.58$_{\pm0.0}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	**70.4**$_{\pm1.2}$	**64.8**$_{\pm0.9}$	**62.9**$_{\pm0.3}$	**78.0**$_{\pm0.5}$	**56.4**$_{\pm0.4}$	**67.0**$_{\pm1.0}$	**75.1**$_{\pm0.8}$	**67.8**$_{\pm0.7}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	13.2$_{\pm1.2}$	16.9$_{\pm2.6}$	28.5$_{\pm4.8}$	38.6$_{\pm9.6}$	10.0$_{\pm0.2}$	5.0$_{\pm0.7}$	14.7$_{\pm1.6}$	18.1$_{\pm3.0}$
		Score ↑	0.62$_{\pm0.0}$	0.55$_{\pm0.0}$	0.49$_{\pm0.0}$	0.57$_{\pm0.0}$	0.51$_{\pm0.0}$	0.64$_{\pm0.0}$	0.65$_{\pm0.0}$	0.58$_{\pm0.0}$
UNSIR [51]	T1	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	15.8$_{\pm6.0}$	7.3$_{\pm5.9}$	16.9$_{\pm2.3}$	38.9$_{\pm1.3}$	1.2$_{\pm0.3}$	24.8$_{\pm3.4}$	22.4$_{\pm4.2}$	18.2$_{\pm3.3}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$
		Score ↑	0.16$_{\pm0.1}$	0.07$_{\pm0.1}$	0.17$_{\pm0.0}$	0.39$_{\pm0.0}$	0.01$_{\pm0.0}$	0.25$_{\pm0.0}$	0.22$_{\pm0.0}$	0.18$_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	9.6$_{\pm3.8}$	4.5$_{\pm2.3}$	11.2$_{\pm1.4}$	25.8$_{\pm2.3}$	1.3$_{\pm0.3}$	17.6$_{\pm2.7}$	13.7$_{\pm2.5}$	11.9$_{\pm2.2}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$
		Score ↑	0.10$_{\pm0.0}$	0.05$_{\pm0.0}$	0.11$_{\pm0.0}$	0.26$_{\pm0.0}$	0.01$_{\pm0.0}$	0.18$_{\pm0.0}$	0.14$_{\pm0.0}$	0.12$_{\pm0.0}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	8.0$_{\pm2.9}$	3.6$_{\pm1.3}$	9.4$_{\pm1.1}$	21.1$_{\pm1.2}$	1.2$_{\pm0.3}$	15.6$_{\pm2.7}$	11.6$_{\pm2.8}$	10.1$_{\pm1.8}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$
		Score ↑	0.08$_{\pm0.0}$	0.04$_{\pm0.0}$	0.09$_{\pm0.0}$	0.21$_{\pm0.0}$	0.01$_{\pm0.0}$	0.16$_{\pm0.0}$	0.12$_{\pm0.0}$	0.10$_{\pm0.0}$
ZSMU [10]	T1	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	69.4$_{\pm1.4}$	61.2$_{\pm1.8}$	58.7$_{\pm1.4}$	77.9$_{\pm0.1}$	46.3$_{\pm10.1}$	60.8$_{\pm0.3}$	71.7$_{\pm2.2}$	63.7$_{\pm2.5}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	42.9$_{\pm17.5}$	16.4$_{\pm16.2}$	25.7$_{\pm2.7}$	49.2$_{\pm6.0}$	6.2$_{\pm4.7}$	14.5$_{\pm4.1}$	18.0$_{\pm8.0}$	24.7$_{\pm8.5}$
		Score ↑	0.49$_{\pm0.1}$	0.53$_{\pm0.1}$	0.47$_{\pm0.0}$	0.52$_{\pm0.0}$	0.43$_{\pm0.1}$	0.53$_{\pm0.0}$	0.61$_{\pm0.1}$	0.51$_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	69.3$_{\pm1.2}$	58.1$_{\pm1.7}$	58.9$_{\pm2.9}$	**78.5**$_{\pm1.4}$	46.0$_{\pm5.9}$	60.3$_{\pm1.0}$	70.4$_{\pm3.3}$	63.1$_{\pm2.5}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	25.7$_{\pm9.2}$	26.4$_{\pm5.8}$	29.8$_{\pm10.9}$	51.3$_{\pm4.7}$	8.0$_{\pm4.5}$	11.7$_{\pm5.4}$	9.8$_{\pm3.9}$	23.2$_{\pm6.3}$
		Score ↑	0.55$_{\pm0.0}$	0.46$_{\pm0.0}$	0.46$_{\pm0.1}$	0.52$_{\pm0.0}$	0.43$_{\pm0.0}$	0.54$_{\pm0.0}$	0.64$_{\pm0.0}$	0.51$_{\pm0.0}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	68.4$_{\pm1.2}$	44.3$_{\pm11.7}$	38.7$_{\pm29.7}$	75.0$_{\pm7.7}$	45.2$_{\pm5.7}$	60.1$_{\pm0.2}$	69.4$_{\pm4.4}$	57.3$_{\pm8.7}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	34.3$_{\pm3.1}$	13.4$_{\pm5.3}$	15.9$_{\pm14.8}$	38.5$_{\pm22.4}$	10.8$_{\pm0.6}$	12.1$_{\pm5.2}$	14.0$_{\pm4.5}$	19.8$_{\pm8.0}$
		Score ↑	0.51$_{\pm0.0}$	0.39$_{\pm0.1}$	0.32$_{\pm0.2}$	0.55$_{\pm0.1}$	0.41$_{\pm0.1}$	0.54$_{\pm0.0}$	0.61$_{\pm0.0}$	0.47$_{\pm0.1}$
Lipschitz [15]	T1	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	20.6$_{\pm26.0}$	26.1$_{\pm16.3}$	46.5$_{\pm10.3}$	74.7$_{\pm1.4}$	40.1$_{\pm14.9}$	40.0$_{\pm4.3}$	61.9$_{\pm13.1}$	44.3$_{\pm12.3}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	3.7$_{\pm6.4}$	2.3$_{\pm3.2}$	16.0$_{\pm12.7}$	19.4$_{\pm5.9}$	0.3$_{\pm0.5}$	0.2$_{\pm0.4}$	2.7$_{\pm4.6}$	6.4$_{\pm4.8}$
		Score ↑	0.19$_{\pm0.2}$	0.25$_{\pm0.2}$	0.40$_{\pm0.1}$	0.63$_{\pm0.0}$	0.40$_{\pm0.1}$	0.40$_{\pm0.0}$	0.60$_{\pm0.1}$	0.41$_{\pm0.1}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	20.9$_{\pm24.9}$	15.1$_{\pm7.4}$	43.5$_{\pm21.2}$	73.4$_{\pm2.1}$	45.2$_{\pm3.6}$	46.1$_{\pm12.8}$	68.0$_{\pm2.6}$	44.6$_{\pm10.6}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	1.5$_{\pm2.5}$	**0.0**$_{\pm0.0}$	9.1$_{\pm15.8}$	9.7$_{\pm16.4}$	0.1$_{\pm0.2}$	0.5$_{\pm0.6}$	0.6$_{\pm1.0}$	3.1$_{\pm5.2}$
		Score ↑	0.20$_{\pm0.2}$	0.15$_{\pm0.1}$	0.39$_{\pm0.2}$	0.68$_{\pm0.1}$	0.45$_{\pm0.0}$	0.46$_{\pm0.1}$	0.68$_{\pm0.0}$	0.43$_{\pm0.1}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	35.9$_{\pm28.0}$	17.1$_{\pm15.3}$	48.2$_{\pm19.1}$	50.1$_{\pm22.6}$	45.3$_{\pm9.0}$	43.0$_{\pm6.8}$	63.6$_{\pm5.7}$	43.3$_{\pm15.2}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	2.3$_{\pm2.0}$	**0.0**$_{\pm0.0}$	6.4$_{\pm8.6}$	4.5$_{\pm7.8}$	2.2$_{\pm3.6}$	0.5$_{\pm0.6}$	0.4$_{\pm0.7}$	2.3$_{\pm3.3}$
		Score ↑	0.35$_{\pm0.3}$	0.17$_{\pm0.2}$	0.45$_{\pm0.2}$	0.47$_{\pm0.2}$	0.44$_{\pm0.1}$	0.43$_{\pm0.1}$	0.63$_{\pm0.1}$	0.42$_{\pm0.1}$
Nabla Tau [53]	T1	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	42.8$_{\pm4.3}$	42.6$_{\pm2.3}$	43.4$_{\pm1.3}$	62.0$_{\pm3.1}$	2.6$_{\pm1.3}$	44.7$_{\pm2.9}$	47.7$_{\pm1.8}$	40.8$_{\pm2.4}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	4.1$_{\pm3.6}$	0.2$_{\pm0.3}$	0.2$_{\pm0.4}$	3.3$_{\pm4.6}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	1.1$_{\pm1.3}$
		Score ↑	0.41$_{\pm0.1}$	0.43$_{\pm0.0}$	0.43$_{\pm0.0}$	0.60$_{\pm0.0}$	0.03$_{\pm0.0}$	0.45$_{\pm0.0}$	0.48$_{\pm0.0}$	0.40$_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	35.8$_{\pm5.1}$	35.4$_{\pm2.9}$	39.9$_{\pm2.0}$	55.9$_{\pm2.8}$	2.4$_{\pm1.1}$	40.5$_{\pm2.8}$	43.8$_{\pm2.8}$	36.3$_{\pm2.8}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	0.7$_{\pm1.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	5.3$_{\pm9.2}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	0.9$_{\pm1.5}$
		Score ↑	0.36$_{\pm0.0}$	0.35$_{\pm0.0}$	0.40$_{\pm0.0}$	0.53$_{\pm0.1}$	0.02$_{\pm0.0}$	0.40$_{\pm0.0}$	0.44$_{\pm0.0}$	0.36$_{\pm0.0}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	34.5$_{\pm4.8}$	32.7$_{\pm2.5}$	37.8$_{\pm2.2}$	53.4$_{\pm6.7}$	2.3$_{\pm1.0}$	38.9$_{\pm2.2}$	41.1$_{\pm2.0}$	34.4$_{\pm3.0}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	0.9$_{\pm1.4}$	**0.0**$_{\pm0.0}$	1.8$_{\pm1.6}$	7.4$_{\pm12.9}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	1.5$_{\pm2.3}$
		Score ↑	0.34$_{\pm0.0}$	0.33$_{\pm0.0}$	0.37$_{\pm0.0}$	0.51$_{\pm0.1}$	0.02$_{\pm0.0}$	0.39$_{\pm0.0}$	0.41$_{\pm0.0}$	0.34$_{\pm0.0}$
Unlearned(+) [2]	T1	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	63.8$_{\pm1.0}$	61.5$_{\pm0.8}$	77.4$_{\pm1.2}$	64.0$_{\pm0.9}$	72.6$_{\pm3.0}$	54.9$_{\pm0.7}$	69.5$_{\pm0.6}$	66.2$_{\pm0.5}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	21.8$_{\pm1.5}$	23.7$_{\pm2.1}$	51.6$_{\pm3.0}$	8.6$_{\pm1.1}$	6.8$_{\pm1.0}$	5.0$_{\pm1.2}$	41.9$_{\pm2.3}$	22.8$_{\pm1.8}$
		Score ↑	0.52$_{\pm0.0}$	0.50$_{\pm0.0}$	0.51$_{\pm0.0}$	0.59$_{\pm0.0}$	0.68$_{\pm0.0}$	0.52$_{\pm0.0}$	0.49$_{\pm0.0}$	0.54$_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	62.3$_{\pm0.9}$	62.1$_{\pm0.7}$	76.3$_{\pm0.8}$	64.5$_{\pm1.0}$	71.0$_{\pm1.4}$	53.5$_{\pm0.9}$	67.0$_{\pm0.8}$	65.2$_{\pm0.6}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	19.9$_{\pm1.3}$	7.1$_{\pm1.2}$	43.4$_{\pm2.0}$	2.5$_{\pm0.8}$	2.4$_{\pm0.9}$	6.0$_{\pm1.1}$	18.1$_{\pm1.0}$	14.2$_{\pm0.9}$
		Score ↑	0.52$_{\pm0.0}$	0.58$_{\pm0.0}$	0.53$_{\pm0.0}$	0.63$_{\pm0.0}$	0.69$_{\pm0.0}$	0.50$_{\pm0.0}$	0.57$_{\pm0.0}$	0.58$_{\pm0.0}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	61.5$_{\pm0.8}$	61.6$_{\pm0.9}$	76.5$_{\pm1.0}$	64.2$_{\pm0.9}$	71.3$_{\pm1.7}$	54.7$_{\pm0.8}$	65.4$_{\pm0.7}$	65.0$_{\pm0.5}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	6.1$_{\pm0.8}$	2.2$_{\pm0.7}$	23.3$_{\pm1.9}$	1.8$_{\pm0.7}$	5.4$_{\pm1.4}$	5.8$_{\pm0.9}$	6.1$_{\pm1.0}$	7.2$_{\pm1.1}$
		Score ↑	0.58$_{\pm0.0}$	0.60$_{\pm0.0}$	0.62$_{\pm0.0}$	0.63$_{\pm0.0}$	0.68$_{\pm0.0}$	0.52$_{\pm0.0}$	0.62$_{\pm0.0}$	0.61$_{\pm0.0}$
PADA [5]	T1	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	62.4$_{\pm0.8}$	59.9$_{\pm0.6}$	54.8$_{\pm0.7}$	76.2$_{\pm0.1}$	49.6$_{\pm0.4}$	60.1$_{\pm1.7}$	72.8$_{\pm0.5}$	62.3$_{\pm0.7}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	43.5$_{\pm0.4}$	51.2$_{\pm0.5}$	52.4$_{\pm1.0}$	76.7$_{\pm1.3}$	12.3$_{\pm2.0}$	31.6$_{\pm1.8}$	24.9$_{\pm4.6}$	41.8$_{\pm1.6}$
		Score ↑	0.43$_{\pm0.0}$	0.40$_{\pm0.0}$	0.36$_{\pm0.0}$	0.43$_{\pm0.0}$	0.44$_{\pm0.0}$	0.46$_{\pm0.0}$	0.58$_{\pm0.0}$	0.44$_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	40.3$_{\pm6.8}$	52.5$_{\pm1.8}$	50.7$_{\pm0.7}$	74.6$_{\pm0.1}$	45.3$_{\pm1.4}$	56.7$_{\pm1.6}$	71.4$_{\pm0.3}$	55.9$_{\pm1.8}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	9.2$_{\pm3.0}$	57.0$_{\pm2.4}$	43.8$_{\pm0.5}$	69.3$_{\pm2.9}$	19.4$_{\pm1.0}$	19.4$_{\pm1.1}$	18.9$_{\pm2.7}$	33.9$_{\pm1.9}$
		Score ↑	0.37$_{\pm0.1}$	0.33$_{\pm0.0}$	0.35$_{\pm0.0}$	0.44$_{\pm0.0}$	0.38$_{\pm0.0}$	0.48$_{\pm0.0}$	0.60$_{\pm0.0}$	0.42$_{\pm0.0}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	9.8$_{\pm8.0}$	37.4$_{\pm3.1}$	44.0$_{\pm1.9}$	73.6$_{\pm0.1}$	40.6$_{\pm3.4}$	54.4$_{\pm1.3}$	70.3$_{\pm0.3}$	47.2$_{\pm2.6}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	5.6$_{\pm9.6}$	32.8$_{\pm4.0}$	31.3$_{\pm3.0}$	47.4$_{\pm1.6}$	18.1$_{\pm2.4}$	16.6$_{\pm3.4}$	25.3$_{\pm0.5}$	25.3$_{\pm3.5}$
		Score ↑	0.09$_{\pm0.1}$	0.28$_{\pm0.0}$	0.34$_{\pm0.0}$	0.50$_{\pm0.0}$	0.34$_{\pm0.0}$	0.47$_{\pm0.0}$	0.56$_{\pm0.0}$	0.37$_{\pm0.0}$
SHOT [34]	T1	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	65.8$_{\pm1.0}$	47.7$_{\pm1.8}$	53.1$_{\pm1.0}$	77.4$_{\pm0.2}$	51.6$_{\pm6.6}$	57.4$_{\pm0.9}$	**75.2**$_{\pm0.4}$	61.2$_{\pm1.7}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	20.1$_{\pm0.8}$	20.9$_{\pm0.5}$	23.6$_{\pm0.8}$	19.9$_{\pm0.3}$	18.4$_{\pm0.9}$	19.8$_{\pm0.9}$	21.1$_{\pm0.5}$	20.5$_{\pm0.7}$
		Score ↑	0.55$_{\pm0.0}$	0.39$_{\pm0.0}$	0.43$_{\pm0.0}$	0.65$_{\pm0.0}$	0.44$_{\pm0.1}$	0.48$_{\pm0.0}$	0.62$_{\pm0.0}$	0.51$_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	63.8$_{\pm0.8}$	45.0$_{\pm1.6}$	49.7$_{\pm3.1}$	76.0$_{\pm0.4}$	50.4$_{\pm4.1}$	56.7$_{\pm1.2}$	73.1$_{\pm0.8}$	59.2$_{\pm1.7}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	18.8$_{\pm0.8}$	20.1$_{\pm0.4}$	20.8$_{\pm1.6}$	19.8$_{\pm0.0}$	17.3$_{\pm0.3}$	17.9$_{\pm0.4}$	20.2$_{\pm0.2}$	19.3$_{\pm0.5}$
		Score ↑	0.54$_{\pm0.0}$	0.37$_{\pm0.0}$	0.41$_{\pm0.0}$	0.63$_{\pm0.0}$	0.43$_{\pm0.0}$	0.48$_{\pm0.0}$	0.61$_{\pm0.0}$	0.50$_{\pm0.0}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	62.7$_{\pm1.1}$	44.1$_{\pm2.5}$	49.0$_{\pm3.2}$	74.6$_{\pm0.5}$	49.4$_{\pm3.9}$	56.4$_{\pm1.4}$	72.0$_{\pm0.6}$	58.3$_{\pm1.9}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	17.9$_{\pm0.6}$	19.5$_{\pm0.5}$	19.8$_{\pm1.5}$	19.9$_{\pm0.3}$	17.0$_{\pm0.5}$	17.0$_{\pm1.2}$	19.5$_{\pm0.7}$	18.7$_{\pm0.8}$
		Score ↑	0.53$_{\pm0.0}$	0.37$_{\pm0.0}$	0.41$_{\pm0.0}$	0.62$_{\pm0.0}$	0.42$_{\pm0.0}$	0.48$_{\pm0.0}$	0.60$_{\pm0.0}$	0.49$_{\pm0.0}$
Ours		$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	68.0$_{\pm0.5}$	63.3$_{\pm1.2}$	59.3$_{\pm0.7}$	77.0$_{\pm0.1}$	53.3$_{\pm0.9}$	63.4$_{\pm0.7}$	74.6$_{\pm0.1}$	65.5$_{\pm0.6}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$
		Score ↑	**0.68**$_{\pm0.0}$	**0.63**$_{\pm0.0}$	**0.59**$_{\pm0.0}$	**0.77**$_{\pm0.0}$	**0.53**$_{\pm0.0}$	0.63$_{\pm0.0}$	**0.75**$_{\pm0.0}$	**0.66**$_{\pm0.0}$
		$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	67.3$_{\pm1.3}$	61.1$_{\pm1.7}$	61.6$_{\pm1.4}$	77.2$_{\pm0.4}$	54.1$_{\pm0.9}$	63.9$_{\pm0.2}$	73.5$_{\pm0.6}$	65.5$_{\pm0.9}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	2.6$_{\pm3.4}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	0.4$_{\pm0.5}$
		Score ↑	**0.67**$_{\pm0.0}$	**0.61**$_{\pm0.0}$	**0.60**$_{\pm0.0}$	**0.77**$_{\pm0.0}$	**0.54**$_{\pm0.0}$	**0.64**$_{\pm0.0}$	**0.73**$_{\pm0.0}$	**0.65**$_{\pm0.0}$
		$A_{\mathcal{D}_r^{\mathcal{T}}} \uparrow$	69.2$_{\pm0.3}$	62.7$_{\pm1.4}$	61.0$_{\pm1.6}$	77.2$_{\pm0.1}$	53.8$_{\pm0.8}$	65.6$_{\pm0.6}$	73.9$_{\pm0.4}$	66.2$_{\pm0.7}$
		$A_{\mathcal{D}_f^{\mathcal{T}}} \downarrow$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	4.9$_{\pm4.0}$	12.3$_{\pm0.5}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	**0.0**$_{\pm0.0}$	2.5$_{\pm0.6}$
		Score ↑	**0.69**$_{\pm0.0}$	**0.63**$_{\pm0.0}$	**0.58**$_{\pm0.0}$	**0.69**$_{\pm0.0}$	**0.54**$_{\pm0.0}$	**0.66**$_{\pm0.0}$	**0.74**$_{\pm0.0}$	**0.65**$_{\pm0.0}$

Table A.29. **C-SCADA unlearning performance on the Office31 dataset.** Forget classes are $\mathcal{C_F}^1 = \{1, 2\}, \mathcal{C_F}^2 = \{3, 4\}, \mathcal{C_F}^3 = \{5, 6\}$

Method	Task	Acc.	A→D	A→W	D→A	D→W	W→A	W→D	Average
Original (SF(DA)^2 [28])	T1	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$72.6_{\pm2.2}$	$89.9_{\pm1.3}$	$73.5_{\pm1.2}$	$97.4_{\pm1.0}$	$75.3_{\pm0.3}$	$80.6_{\pm0.6}$	$81.5_{\pm1.1}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$74.1_{\pm1.2}$	$75.6_{\pm0.8}$	$75.3_{\pm1.5}$	$83.2_{\pm1.1}$	$75.6_{\pm0.5}$	$90.3_{\pm0.9}$	$79.0_{\pm1.0}$
		Score $\uparrow$	$0.42_{\pm0.0}$	$0.51_{\pm0.0}$	$0.42_{\pm0.0}$	$0.53_{\pm0.0}$	$0.43_{\pm0.0}$	$0.42_{\pm0.0}$	$0.46_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$72.6_{\pm2.2}$	$89.9_{\pm1.3}$	$73.5_{\pm1.2}$	$97.4_{\pm1.0}$	$75.3_{\pm0.3}$	$80.6_{\pm0.6}$	$81.5_{\pm1.1}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$77.4_{\pm1.2}$	$77.8_{\pm0.8}$	$76.0_{\pm1.5}$	$85.7_{\pm1.1}$	$76.3_{\pm0.5}$	$94.3_{\pm0.9}$	$81.2_{\pm1.0}$
		Score $\uparrow$	$0.41_{\pm0.0}$	$0.51_{\pm0.0}$	$0.42_{\pm0.0}$	$0.52_{\pm0.0}$	$0.43_{\pm0.0}$	$0.41_{\pm0.0}$	$0.45_{\pm0.0}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$72.6_{\pm2.2}$	$89.9_{\pm1.3}$	$73.5_{\pm1.2}$	$97.4_{\pm1.0}$	$75.3_{\pm0.3}$	$80.6_{\pm0.6}$	$81.5_{\pm1.1}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$78.5_{\pm1.2}$	$78.6_{\pm0.8}$	$76.3_{\pm1.5}$	$86.5_{\pm1.1}$	$76.6_{\pm0.5}$	$95.7_{\pm0.9}$	$82.0_{\pm1.0}$
		Score $\uparrow$	$0.41_{\pm0.0}$	$0.50_{\pm0.0}$	$0.42_{\pm0.0}$	$0.52_{\pm0.0}$	$0.43_{\pm0.0}$	$0.41_{\pm0.0}$	$0.45_{\pm0.0}$
Retrain	T1	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$75.5_{\pm2.4}$	$94.8_{\pm1.0}$	$67.8_{\pm9.2}$	$97.4_{\pm1.0}$	$72.1_{\pm1.1}$	$81.0_{\pm0.0}$	$81.5_{\pm2.4}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$
		Score $\uparrow$	$0.76_{\pm0.0}$	$0.95_{\pm0.0}$	$0.68_{\pm0.1}$	$0.97_{\pm0.0}$	$0.72_{\pm0.0}$	$0.81_{\pm0.0}$	$0.81_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$75.5_{\pm2.4}$	$94.8_{\pm1.0}$	$67.8_{\pm9.2}$	$97.4_{\pm1.0}$	$72.1_{\pm1.1}$	$81.0_{\pm0.0}$	$81.5_{\pm2.4}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$
		Score $\uparrow$	$0.76_{\pm0.0}$	$0.95_{\pm0.0}$	$0.68_{\pm0.1}$	$0.97_{\pm0.0}$	$0.72_{\pm0.0}$	$0.81_{\pm0.0}$	$0.81_{\pm0.0}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$75.5_{\pm2.4}$	$94.8_{\pm1.0}$	$67.8_{\pm9.2}$	$97.4_{\pm1.0}$	$72.1_{\pm1.1}$	$81.0_{\pm0.0}$	$81.5_{\pm2.4}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$	$0.0_{\pm0.0}$
		Score $\uparrow$	$0.76_{\pm0.0}$	$0.95_{\pm0.0}$	$0.68_{\pm0.1}$	$0.97_{\pm0.0}$	$0.72_{\pm0.0}$	$0.81_{\pm0.0}$	$0.81_{\pm0.0}$
Finetune	T1	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$70.5_{\pm3.2}$	$88.9_{\pm1.0}$	$71.7_{\pm1.7}$	$\underline{97.1}_{\pm1.0}$	$75.5_{\pm1.2}$	$\mathbf{81.0}_{\pm0.0}$	$\underline{80.8}_{\pm1.3}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$70.1_{\pm1.6}$	$67.1_{\pm1.5}$	$61.1_{\pm4.8}$	$78.3_{\pm0.5}$	$59.7_{\pm2.0}$	$86.6_{\pm1.2}$	$70.5_{\pm1.9}$
		Score $\uparrow$	$0.41_{\pm0.0}$	$0.53_{\pm0.0}$	$0.45_{\pm0.0}$	$0.54_{\pm0.0}$	$0.47_{\pm0.0}$	$0.43_{\pm0.0}$	$0.47_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$70.5_{\pm3.2}$	$88.9_{\pm1.0}$	$71.7_{\pm1.7}$	$\underline{97.1}_{\pm1.0}$	$75.5_{\pm1.2}$	$\mathbf{81.0}_{\pm0.0}$	$\underline{80.8}_{\pm1.3}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$73.2_{\pm1.6}$	$69.1_{\pm1.6}$	$61.8_{\pm4.8}$	$80.7_{\pm0.5}$	$60.2_{\pm2.0}$	$90.4_{\pm1.2}$	$72.6_{\pm2.0}$
		Score $\uparrow$	$0.41_{\pm0.0}$	$0.53_{\pm0.0}$	$0.44_{\pm0.0}$	$0.54_{\pm0.0}$	$0.47_{\pm0.0}$	$0.43_{\pm0.0}$	$0.47_{\pm0.0}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$70.5_{\pm3.2}$	$88.9_{\pm1.0}$	$71.7_{\pm1.7}$	$\underline{97.1}_{\pm1.0}$	$75.5_{\pm1.2}$	$\mathbf{81.0}_{\pm0.0}$	$\underline{80.8}_{\pm1.3}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$74.3_{\pm1.6}$	$69.8_{\pm1.6}$	$62.0_{\pm4.8}$	$81.5_{\pm0.5}$	$60.4_{\pm2.0}$	$91.8_{\pm1.2}$	$73.3_{\pm2.0}$
		Score $\uparrow$	$0.40_{\pm0.0}$	$0.52_{\pm0.0}$	$0.44_{\pm0.0}$	$0.54_{\pm0.0}$	$0.47_{\pm0.0}$	$0.42_{\pm0.0}$	$0.47_{\pm0.0}$
UNSIR [51]	T1	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$65.0_{\pm2.2}$	$75.5_{\pm9.5}$	$45.0_{\pm7.8}$	$89.4_{\pm3.8}$	$50.2_{\pm1.8}$	$79.7_{\pm1.0}$	$67.5_{\pm4.4}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$38.3_{\pm5.7}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$72.2_{\pm0.0}$	$18.4_{\pm1.0}$
		Score $\uparrow$	$0.47_{\pm0.0}$	$0.75_{\pm0.1}$	$0.45_{\pm0.1}$	$\underline{0.89}_{\pm0.0}$	$0.50_{\pm0.0}$	$0.46_{\pm0.0}$	$0.59_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$62.5_{\pm2.2}$	$73.1_{\pm7.0}$	$36.2_{\pm8.3}$	$65.1_{\pm23.0}$	$34.8_{\pm4.5}$	$72.1_{\pm8.2}$	$57.3_{\pm8.8}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$11.0_{\pm7.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$50.0_{\pm18.0}$	$\underline{10.2}_{\pm4.2}$
		Score $\uparrow$	$0.56_{\pm0.0}$	$0.73_{\pm0.1}$	$0.36_{\pm0.1}$	$0.65_{\pm0.2}$	$0.35_{\pm0.0}$	$0.48_{\pm0.0}$	$0.52_{\pm0.1}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$61.6_{\pm3.3}$	$66.1_{\pm8.9}$	$31.4_{\pm7.5}$	$61.5_{\pm22.5}$	$28.3_{\pm6.4}$	$70.0_{\pm11.1}$	$53.1_{\pm10.0}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$7.2_{\pm5.9}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$34.3_{\pm26.8}$	$\underline{6.9}_{\pm5.4}$
		Score $\uparrow$	$0.58_{\pm0.0}$	$0.66_{\pm0.1}$	$0.31_{\pm0.1}$	$0.61_{\pm0.2}$	$0.28_{\pm0.1}$	$0.53_{\pm0.0}$	$0.50_{\pm0.1}$
ZSMU [10]	T1	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$72.0_{\pm2.8}$	$\underline{97.1}_{\pm1.2}$	$\underline{72.1}_{\pm4.5}$	$90.7_{\pm2.0}$	$\underline{80.2}_{\pm1.4}$	$72.1_{\pm2.7}$	$80.7_{\pm2.4}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$81.8_{\pm2.6}$	$84.5_{\pm0.0}$	$79.6_{\pm3.7}$	$81.6_{\pm2.7}$	$81.5_{\pm0.0}$	$77.1_{\pm6.1}$	$81.0_{\pm2.5}$
		Score $\uparrow$	$0.40_{\pm0.0}$	$0.53_{\pm0.0}$	$0.40_{\pm0.0}$	$0.50_{\pm0.0}$	$0.44_{\pm0.0}$	$0.41_{\pm0.0}$	$0.45_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$\underline{72.0}_{\pm2.3}$	$\underline{97.4}_{\pm1.6}$	$70.9_{\pm3.8}$	$91.2_{\pm2.5}$	$\underline{80.2}_{\pm1.4}$	$50.7_{\pm35.1}$	$77.1_{\pm7.8}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$65.9_{\pm12.0}$	$86.8_{\pm2.9}$	$74.4_{\pm2.1}$	$75.6_{\pm4.2}$	$88.2_{\pm0.7}$	$49.5_{\pm42.9}$	$73.4_{\pm10.8}$
		Score $\uparrow$	$0.44_{\pm0.0}$	$0.52_{\pm0.0}$	$0.41_{\pm0.0}$	$0.52_{\pm0.0}$	$0.43_{\pm0.0}$	$0.31_{\pm0.2}$	$0.44_{\pm0.0}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$71.3_{\pm1.8}$	$\underline{97.4}_{\pm1.6}$	$70.5_{\pm4.5}$	$85.5_{\pm9.2}$	$\mathbf{80.2}_{\pm1.4}$	$51.5_{\pm34.5}$	$76.1_{\pm8.9}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$73.2_{\pm6.4}$	$83.4_{\pm1.7}$	$73.5_{\pm2.2}$	$71.1_{\pm18.6}$	$88.5_{\pm2.4}$	$52.4_{\pm45.2}$	$73.7_{\pm12.7}$
		Score $\uparrow$	$0.41_{\pm0.0}$	$0.53_{\pm0.0}$	$0.41_{\pm0.0}$	$0.50_{\pm0.0}$	$0.43_{\pm0.0}$	$0.31_{\pm0.2}$	$0.43_{\pm0.0}$
Lipschitz [15]	T1	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$45.4_{\pm26.5}$	$96.6_{\pm0.5}$	$67.1_{\pm4.4}$	$84.0_{\pm5.6}$	$78.9_{\pm2.7}$	$67.6_{\pm6.7}$	$73.3_{\pm7.7}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$\mathbf{0.0}_{\pm0.0}$	$26.4_{\pm4.3}$	$43.2_{\pm7.8}$	$32.2_{\pm35.0}$	$\underline{40.8}_{\pm36.5}$	$\underline{25.8}_{\pm22.3}$	$28.1_{\pm17.7}$
		Score $\uparrow$	$0.45_{\pm0.3}$	$0.76_{\pm0.0}$	$0.47_{\pm0.0}$	$0.66_{\pm0.1}$	$\underline{0.59}_{\pm0.2}$	$0.54_{\pm0.0}$	$0.58_{\pm0.1}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$58.6_{\pm9.1}$	$95.9_{\pm3.8}$	$62.0_{\pm14.2}$	$89.1_{\pm2.8}$	$\mathbf{81.0}_{\pm0.0}$	$67.4_{\pm6.6}$	$75.7_{\pm6.1}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$\mathbf{0.0}_{\pm0.0}$	$25.2_{\pm13.6}$	$9.0_{\pm8.1}$	$\underline{35.7}_{\pm31.4}$	$29.3_{\pm8.6}$	$14.2_{\pm7.3}$	$18.9_{\pm11.5}$
		Score $\uparrow$	$0.59_{\pm0.1}$	$0.77_{\pm0.1}$	$0.56_{\pm0.1}$	$0.68_{\pm0.2}$	$\underline{0.63}_{\pm0.0}$	$0.59_{\pm0.0}$	$0.64_{\pm0.1}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$63.8_{\pm5.9}$	$\underline{97.4}_{\pm1.2}$	$\mathbf{72.6}_{\pm1.4}$	$82.7_{\pm13.9}$	$70.0_{\pm19.0}$	$65.7_{\pm13.7}$	$75.4_{\pm9.2}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$24.2_{\pm13.3}$	$12.8_{\pm11.5}$	$34.3_{\pm16.5}$	$\underline{18.9}_{\pm16.4}$	$45.8_{\pm29.4}$	$24.7_{\pm26.3}$	$26.8_{\pm18.9}$
		Score $\uparrow$	$0.51_{\pm0.0}$	$0.87_{\pm0.1}$	$0.55_{\pm0.1}$	$0.69_{\pm0.0}$	$0.48_{\pm0.1}$	$0.53_{\pm0.1}$	$0.61_{\pm0.1}$
Nabla Tau [53]	T1	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$66.0_{\pm3.2}$	$96.1_{\pm2.3}$	$67.1_{\pm2.5}$	$86.5_{\pm3.1}$	$\underline{80.2}_{\pm1.4}$	$67.5_{\pm1.6}$	$77.2_{\pm2.4}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$\underline{1.0}_{\pm1.8}$	$\underline{6.9}_{\pm7.9}$	$\underline{22.8}_{\pm18.5}$	$\underline{0.6}_{\pm1.0}$	$75.3_{\pm2.1}$	$\mathbf{0.0}_{\pm0.0}$	$\underline{17.8}_{\pm5.2}$
		Score $\uparrow$	$\underline{0.65}_{\pm0.0}$	$\underline{0.90}_{\pm0.1}$	$\underline{0.56}_{\pm0.1}$	$0.86_{\pm0.0}$	$0.46_{\pm0.0}$	$\underline{0.67}_{\pm0.0}$	$\underline{0.68}_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$63.6_{\pm3.4}$	$95.9_{\pm1.2}$	$66.7_{\pm1.9}$	$86.3_{\pm3.2}$	$\underline{80.2}_{\pm1.4}$	$64.9_{\pm1.6}$	$76.3_{\pm2.1}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$\underline{3.1}_{\pm2.7}$	$\underline{1.9}_{\pm3.3}$	$9.7_{\pm10.4}$	$\mathbf{0.0}_{\pm0.0}$	$59.8_{\pm11.7}$	$\underline{5.7}_{\pm5.0}$	$13.4_{\pm5.5}$
		Score $\uparrow$	$\underline{0.62}_{\pm0.0}$	$\mathbf{0.94}_{\pm0.0}$	$\underline{0.61}_{\pm0.1}$	$\underline{0.86}_{\pm0.0}$	$0.50_{\pm0.0}$	$\underline{0.62}_{\pm0.0}$	$\underline{0.69}_{\pm0.0}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$64.1_{\pm3.2}$	$95.9_{\pm1.2}$	$66.7_{\pm1.9}$	$86.3_{\pm3.2}$	$\mathbf{80.2}_{\pm1.4}$	$65.4_{\pm1.0}$	$76.4_{\pm2.0}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$\underline{7.0}_{\pm7.7}$	$\underline{0.4}_{\pm0.8}$	$\underline{3.1}_{\pm2.7}$	$\mathbf{0.0}_{\pm0.0}$	$46.4_{\pm14.0}$	$\underline{7.8}_{\pm9.7}$	$10.8_{\pm5.8}$
		Score $\uparrow$	$\underline{0.60}_{\pm0.0}$	$\mathbf{0.95}_{\pm0.0}$	$\underline{0.65}_{\pm0.0}$	$\underline{0.86}_{\pm0.0}$	$\underline{0.55}_{\pm0.0}$	$\underline{0.61}_{\pm0.1}$	$\underline{0.70}_{\pm0.0}$
Unlearned(+) [2]	T1	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$70.9_{\pm0.9}$	$91.5_{\pm2.1}$	$73.5_{\pm1.5}$	$97.7_{\pm1.2}$	$75.6_{\pm0.8}$	$81.0_{\pm1.0}$	$81.7_{\pm1.1}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$83.3_{\pm1.3}$	$82.8_{\pm1.5}$	$79.1_{\pm2.1}$	$84.5_{\pm1.2}$	$76.7_{\pm1.4}$	$81.5_{\pm1.0}$	$81.3_{\pm1.4}$
		Score $\uparrow$	$0.39_{\pm0.0}$	$0.50_{\pm0.0}$	$0.41_{\pm0.0}$	$0.53_{\pm0.0}$	$0.43_{\pm0.0}$	$0.45_{\pm0.0}$	$0.45_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$75.9_{\pm0.8}$	$92.2_{\pm2.0}$	$73.0_{\pm1.6}$	$97.7_{\pm1.0}$	$76.0_{\pm1.2}$	$81.0_{\pm1.3}$	$82.6_{\pm1.1}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$59.8_{\pm1.4}$	$69.8_{\pm1.7}$	$41.3_{\pm1.9}$	$81.4_{\pm1.1}$	$40.9_{\pm2.0}$	$79.3_{\pm1.4}$	$62.1_{\pm1.6}$
		Score $\uparrow$	$0.47_{\pm0.0}$	$0.54_{\pm0.0}$	$0.52_{\pm0.0}$	$0.54_{\pm0.0}$	$0.54_{\pm0.0}$	$0.45_{\pm0.0}$	$0.51_{\pm0.0}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$75.9_{\pm1.0}$	$92.2_{\pm2.3}$	$72.6_{\pm1.7}$	$97.7_{\pm1.1}$	$75.6_{\pm0.9}$	$81.0_{\pm1.2}$	$82.5_{\pm1.4}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$58.9_{\pm1.1}$	$61.1_{\pm1.5}$	$27.5_{\pm1.7}$	$69.4_{\pm1.2}$	$48.9_{\pm1.4}$	$77.6_{\pm1.0}$	$57.2_{\pm1.3}$
		Score $\uparrow$	$0.48_{\pm0.0}$	$0.57_{\pm0.0}$	$0.57_{\pm0.0}$	$0.58_{\pm0.0}$	$0.51_{\pm0.0}$	$0.46_{\pm0.0}$	$0.53_{\pm0.0}$
PADA [5]	T1	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$\mathbf{72.4}_{\pm0.5}$	$\mathbf{97.4}_{\pm1.2}$	$70.9_{\pm3.3}$	$91.2_{\pm0.5}$	$\mathbf{80.6}_{\pm0.8}$	$72.4_{\pm0.6}$	$\underline{80.8}_{\pm1.1}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$87.3_{\pm0.3}$	$84.5_{\pm0.0}$	$83.3_{\pm0.0}$	$84.5_{\pm0.0}$	$82.7_{\pm1.0}$	$84.5_{\pm1.0}$	$84.5_{\pm0.4}$
		Score $\uparrow$	$0.39_{\pm0.0}$	$0.53_{\pm0.0}$	$0.39_{\pm0.0}$	$0.49_{\pm0.0}$	$0.44_{\pm0.0}$	$0.39_{\pm0.0}$	$0.44_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$71.9_{\pm2.3}$	$97.2_{\pm0.9}$	$69.2_{\pm2.7}$	$91.7_{\pm0.4}$	$79.7_{\pm1.3}$	$72.0_{\pm0.7}$	$80.3_{\pm1.4}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$56.4_{\pm5.3}$	$88.4_{\pm1.2}$	$72.0_{\pm2.5}$	$77.1_{\pm2.9}$	$88.2_{\pm0.7}$	$55.9_{\pm5.7}$	$73.0_{\pm3.0}$
		Score $\uparrow$	$0.46_{\pm0.0}$	$0.52_{\pm0.0}$	$0.40_{\pm0.0}$	$0.52_{\pm0.0}$	$0.42_{\pm0.0}$	$0.46_{\pm0.0}$	$0.46_{\pm0.0}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$\underline{72.0}_{\pm1.6}$	$\underline{97.4}_{\pm1.2}$	$69.2_{\pm1.4}$	$91.7_{\pm0.4}$	$\underline{79.7}_{\pm1.3}$	$72.1_{\pm0.7}$	$80.4_{\pm1.1}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$49.9_{\pm3.0}$	$80.9_{\pm1.1}$	$70.7_{\pm4.2}$	$71.3_{\pm0.7}$	$88.1_{\pm2.7}$	$62.2_{\pm7.3}$	$70.5_{\pm3.2}$
		Score $\uparrow$	$0.48_{\pm0.0}$	$0.54_{\pm0.0}$	$0.41_{\pm0.0}$	$0.54_{\pm0.0}$	$0.42_{\pm0.0}$	$0.45_{\pm0.0}$	$0.47_{\pm0.0}$
SHOT [34]	T1	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$71.1_{\pm0.7}$	$\mathbf{97.4}_{\pm2.0}$	$70.5_{\pm4.5}$	$89.4_{\pm0.9}$	$\mathbf{80.6}_{\pm0.8}$	$70.1_{\pm1.3}$	$79.8_{\pm1.7}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$41.2_{\pm1.3}$	$66.5_{\pm2.7}$	$73.4_{\pm2.7}$	$62.4_{\pm3.1}$	$92.2_{\pm1.6}$	$41.9_{\pm0.8}$	$62.9_{\pm2.0}$
		Score $\uparrow$	$0.50_{\pm0.0}$	$0.59_{\pm0.0}$	$0.41_{\pm0.0}$	$0.55_{\pm0.0}$	$0.42_{\pm0.0}$	$0.49_{\pm0.0}$	$0.49_{\pm0.0}$
	T2	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$70.6_{\pm0.9}$	$\mathbf{97.7}_{\pm1.6}$	$\mathbf{72.1}_{\pm5.8}$	$89.1_{\pm1.3}$	$\underline{80.2}_{\pm1.4}$	$69.3_{\pm0.5}$	$79.8_{\pm1.9}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$39.5_{\pm2.9}$	$66.4_{\pm2.2}$	$73.1_{\pm1.6}$	$62.2_{\pm1.2}$	$90.8_{\pm1.8}$	$40.8_{\pm0.7}$	$62.1_{\pm1.7}$
		Score $\uparrow$	$0.51_{\pm0.0}$	$0.59_{\pm0.0}$	$0.42_{\pm0.0}$	$0.55_{\pm0.0}$	$0.42_{\pm0.0}$	$0.49_{\pm0.0}$	$0.50_{\pm0.0}$
	T3	$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$70.1_{\pm0.9}$	$\mathbf{97.7}_{\pm1.6}$	$\underline{72.1}_{\pm5.8}$	$89.1_{\pm1.3}$	$\mathbf{80.2}_{\pm1.4}$	$69.2_{\pm0.3}$	$79.7_{\pm1.9}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$37.1_{\pm2.4}$	$65.3_{\pm1.0}$	$71.8_{\pm2.4}$	$61.9_{\pm1.6}$	$89.1_{\pm1.5}$	$40.4_{\pm0.6}$	$60.9_{\pm1.6}$
		Score $\uparrow$	$0.51_{\pm0.0}$	$0.59_{\pm0.0}$	$0.42_{\pm0.0}$	$0.55_{\pm0.0}$	$0.42_{\pm0.0}$	$0.49_{\pm0.0}$	$0.50_{\pm0.0}$
Ours		$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$\underline{72.2}_{\pm2.1}$	$91.2_{\pm1.3}$	$\mathbf{72.5}_{\pm1.1}$	$\mathbf{97.4}_{\pm1.0}$	$74.4_{\pm0.6}$	$\underline{80.2}_{\pm1.2}$	$\mathbf{81.3}_{\pm1.2}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$
		Score $\uparrow$	$\mathbf{0.72}_{\pm0.0}$	$\mathbf{0.91}_{\pm0.0}$	$\mathbf{0.73}_{\pm0.0}$	$\mathbf{0.97}_{\pm0.0}$	$\mathbf{0.74}_{\pm0.0}$	$\mathbf{0.80}_{\pm0.0}$	$\mathbf{0.81}_{\pm0.0}$
		$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$\mathbf{72.6}_{\pm2.6}$	$91.2_{\pm1.3}$	$\underline{71.8}_{\pm1.4}$	$\mathbf{97.4}_{\pm1.0}$	$74.6_{\pm0.6}$	$\underline{80.2}_{\pm1.2}$	$\mathbf{81.3}_{\pm1.3}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.0}_{\pm0.0}$	$\underline{3.1}_{\pm4.4}$	$\mathbf{0.0}_{\pm0.0}$	$\underline{2.0}_{\pm2.8}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{0.8}_{\pm1.2}$
		Score $\uparrow$	$\mathbf{0.73}_{\pm0.0}$	$\underline{0.91}_{\pm0.0}$	$\mathbf{0.70}_{\pm0.0}$	$\mathbf{0.97}_{\pm0.0}$	$\mathbf{0.73}_{\pm0.0}$	$\mathbf{0.80}_{\pm0.0}$	$\mathbf{0.81}_{\pm0.0}$
		$A_{\mathcal{D}_r^{\mathcal{T}}}\uparrow$	$\mathbf{72.6}_{\pm2.6}$	$90.9_{\pm1.5}$	$71.8_{\pm1.7}$	$\mathbf{97.4}_{\pm1.0}$	$74.6_{\pm0.7}$	$\underline{80.2}_{\pm1.2}$	$\mathbf{81.2}_{\pm1.4}$
		$A_{\mathcal{D}_f^{\mathcal{T}}}\downarrow$	$\mathbf{1.9}_{\pm2.6}$	$\mathbf{0.0}_{\pm0.0}$	$5.0_{\pm2.6}$	$\mathbf{0.0}_{\pm0.0}$	$\underline{15.7}_{\pm3.4}$	$\mathbf{0.0}_{\pm0.0}$	$\mathbf{3.8}_{\pm1.5}$
		Score $\uparrow$	$\mathbf{0.71}_{\pm0.0}$	$\underline{0.91}_{\pm0.0}$	$\mathbf{0.68}_{\pm0.0}$	$\mathbf{0.97}_{\pm0.0}$	$\mathbf{0.65}_{\pm0.0}$	$\mathbf{0.80}_{\pm0.0}$	$\mathbf{0.79}_{\pm0.0}$

Table A.30. **Results for Multi-Class SCADA Unlearning on Openset Domain Adaptation on OfficeHome.** Implemented with SHOT-ODA as the open-set domain adaptation loss

Method	Metric	A → C	A → P	A → R	C → A	C → P	C → R	P → A	P → C	P → R	R → A	R → C	R → P	Average
Original (SHOT [34])	OS Acc. ↑	$54.5_{\pm 1.0}$	$69.8_{\pm 1.6}$	$75.9_{\pm 0.9}$	$70.3_{\pm 1.3}$	$72.5_{\pm 0.5}$	$76.9_{\pm 0.5}$	$67.7_{\pm 2.6}$	$49.1_{\pm 1.8}$	$75.3_{\pm 0.8}$	$72.8_{\pm 1.5}$	$55.4_{\pm 0.8}$	$76.5_{\pm 1.3}$	$68.0_{\pm 1.2}$
	OS* Acc. ↑	$60.2_{\pm 1.2}$	$77.0_{\pm 1.8}$	$81.8_{\pm 0.9}$	$75.5_{\pm 1.3}$	$79.9_{\pm 0.6}$	$83.0_{\pm 0.5}$	$72.7_{\pm 2.8}$	$54.3_{\pm 1.9}$	$81.3_{\pm 0.9}$	$78.2_{\pm 1.7}$	$61.2_{\pm 0.8}$	$84.3_{\pm 1.4}$	$74.1_{\pm 1.3}$
	Forget Acc. ↓	$43.3_{\pm 0.5}$	$85.6_{\pm 1.2}$	$86.2_{\pm 0.7}$	$68.2_{\pm 2.7}$	$78.9_{\pm 1.3}$	$79.1_{\pm 1.5}$	$65.4_{\pm 0.5}$	$36.5_{\pm 4.0}$	$83.6_{\pm 1.5}$	$70.7_{\pm 1.1}$	$45.0_{\pm 3.3}$	$89.9_{\pm 1.6}$	$69.4_{\pm 1.6}$
	Score ↑	$0.38_{\pm 0.0}$	$0.38_{\pm 0.0}$	$0.41_{\pm 0.0}$	$0.42_{\pm 0.0}$	$0.41_{\pm 0.0}$	$0.43_{\pm 0.0}$	$0.41_{\pm 0.0}$	$0.36_{\pm 0.0}$	$0.41_{\pm 0.0}$	$0.43_{\pm 0.0}$	$0.38_{\pm 0.0}$	$0.40_{\pm 0.0}$	$0.40_{\pm 0.0}$
Retrain	OS Acc. ↑	$51.7_{\pm 5.5}$	$67.9_{\pm 1.2}$	$75.2_{\pm 1.2}$	$70.3_{\pm 0.9}$	$71.5_{\pm 1.2}$	$76.4_{\pm 0.8}$	$70.7_{\pm 2.8}$	$51.5_{\pm 3.7}$	$77.2_{\pm 0.4}$	$74.2_{\pm 0.2}$	$58.0_{\pm 1.5}$	$77.4_{\pm 2.4}$	$68.5_{\pm 1.8}$
	OS* Acc. ↑	$57.2_{\pm 6.1}$	$74.9_{\pm 1.3}$	$81.1_{\pm 1.2}$	$75.6_{\pm 1.0}$	$78.9_{\pm 1.3}$	$82.4_{\pm 0.9}$	$75.9_{\pm 3.1}$	$56.9_{\pm 4.1}$	$83.2_{\pm 0.5}$	$79.7_{\pm 0.2}$	$64.1_{\pm 1.7}$	$85.4_{\pm 2.7}$	$74.6_{\pm 2.0}$
	Forget Acc. ↓	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$	$0.0_{\pm 0.0}$
	Score ↑	$0.52_{\pm 0.1}$	$0.68_{\pm 0.0}$	$0.75_{\pm 0.0}$	$0.70_{\pm 0.0}$	$0.72_{\pm 0.0}$	$0.76_{\pm 0.0}$	$0.71_{\pm 0.0}$	$0.52_{\pm 0.0}$	$0.77_{\pm 0.0}$	$0.74_{\pm 0.0}$	$0.58_{\pm 0.0}$	$0.77_{\pm 0.0}$	$0.69_{\pm 0.0}$
Finetune	OS Acc. ↑	$\mathbf{51.1}_{\pm 2.5}$	$\mathbf{68.9}_{\pm 1.1}$	$\mathbf{75.7}_{\pm 0.8}$	$\mathbf{69.6}_{\pm 1.8}$	$\mathbf{71.7}_{\pm 0.9}$	$\mathbf{76.3}_{\pm 0.5}$	$\mathbf{67.1}_{\pm 2.3}$	$\mathbf{49.5}_{\pm 1.4}$	$\mathbf{75.3}_{\pm 0.5}$	$\mathbf{72.7}_{\pm 1.1}$	$\mathbf{53.1}_{\pm 0.8}$	$\mathbf{75.9}_{\pm 1.3}$	$\mathbf{67.2}_{\pm 1.2}$
	OS* Acc. ↑	$56.5_{\pm 2.7}$	$76.0_{\pm 1.1}$	$81.7_{\pm 0.8}$	$74.8_{\pm 1.9}$	$79.1_{\pm 1.0}$	$82.3_{\pm 0.6}$	$72.1_{\pm 2.4}$	$54.7_{\pm 1.5}$	$81.2_{\pm 0.5}$	$78.0_{\pm 1.2}$	$58.7_{\pm 0.9}$	$83.7_{\pm 1.5}$	$73.2_{\pm 1.3}$
	Forget Acc. ↓	$38.5_{\pm 4.4}$	$85.1_{\pm 1.8}$	$83.6_{\pm 0.2}$	$63.3_{\pm 2.3}$	$77.4_{\pm 2.5}$	$73.6_{\pm 1.1}$	$64.5_{\pm 1.9}$	$35.3_{\pm 5.6}$	$82.1_{\pm 1.4}$	$67.0_{\pm 1.9}$	$39.8_{\pm 2.3}$	$87.3_{\pm 1.5}$	$66.5_{\pm 2.3}$
	Score ↑	$0.37_{\pm 0.0}$	$0.37_{\pm 0.0}$	$0.41_{\pm 0.0}$	$0.43_{\pm 0.0}$	$0.40_{\pm 0.0}$	$0.44_{\pm 0.0}$	$0.41_{\pm 0.0}$	$0.37_{\pm 0.0}$	$0.41_{\pm 0.0}$	$0.44_{\pm 0.0}$	$0.38_{\pm 0.0}$	$0.41_{\pm 0.0}$	$0.40_{\pm 0.0}$
UNSIR [51]	OS Acc. ↑	$26.2_{\pm 12.5}$	$57.3_{\pm 3.8}$	$57.6_{\pm 1.2}$	$12.2_{\pm 9.0}$	$57.0_{\pm 2.4}$	$59.0_{\pm 0.7}$	$16.1_{\pm 6.1}$	$26.0_{\pm 7.9}$	$57.4_{\pm 3.0}$	$26.8_{\pm 9.4}$	$21.6_{\pm 10.1}$	$62.1_{\pm 2.7}$	$39.9_{\pm 5.7}$
	OS* Acc. ↑	$29.0_{\pm 13.9}$	$63.2_{\pm 4.1}$	$62.1_{\pm 1.3}$	$13.1_{\pm 9.7}$	$62.9_{\pm 2.6}$	$63.6_{\pm 0.7}$	$17.2_{\pm 6.6}$	$28.7_{\pm 8.7}$	$61.9_{\pm 3.3}$	$28.8_{\pm 10.0}$	$23.9_{\pm 11.1}$	$68.5_{\pm 3.0}$	$43.6_{\pm 6.2}$
	Forget Acc. ↓	$\mathbf{0.3}_{\pm 0.5}$	$\mathbf{0.2}_{\pm 0.3}$	$\mathbf{0.5}_{\pm 0.9}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.6}_{\pm 1.1}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.1}_{\pm 0.2}$
	Score ↑	$0.26_{\pm 0.1}$	$0.57_{\pm 0.0}$	$0.57_{\pm 0.0}$	$0.12_{\pm 0.1}$	$0.57_{\pm 0.0}$	$0.59_{\pm 0.0}$	$0.16_{\pm 0.1}$	$0.26_{\pm 0.1}$	$0.57_{\pm 0.0}$	$0.27_{\pm 0.1}$	$0.22_{\pm 0.1}$	$0.62_{\pm 0.0}$	$0.40_{\pm 0.1}$
ZSMU [10]	OS Acc. ↑	$45.6_{\pm 3.1}$	$64.2_{\pm 2.3}$	$72.2_{\pm 3.5}$	$71.7_{\pm 1.5}$	$55.2_{\pm 25.6}$	$65.0_{\pm 15.1}$	$59.3_{\pm 3.2}$	$40.1_{\pm 2.6}$	$72.7_{\pm 2.4}$	$70.2_{\pm 3.3}$	$49.4_{\pm 3.8}$	$73.1_{\pm 2.3}$	$61.6_{\pm 5.7}$
	OS* Acc. ↑	$49.7_{\pm 3.8}$	$70.0_{\pm 1.8}$	$77.7_{\pm 3.5}$	$76.6_{\pm 1.2}$	$60.6_{\pm 28.0}$	$69.8_{\pm 16.1}$	$63.6_{\pm 3.4}$	$44.1_{\pm 3.0}$	$78.4_{\pm 2.5}$	$75.4_{\pm 3.5}$	$54.3_{\pm 3.9}$	$80.1_{\pm 1.8}$	$66.7_{\pm 6.0}$
	Forget Acc. ↓	$24.9_{\pm 7.1}$	$72.4_{\pm 5.7}$	$78.6_{\pm 3.3}$	$57.4_{\pm 6.4}$	$44.8_{\pm 40.1}$	$49.2_{\pm 40.9}$	$44.1_{\pm 4.2}$	$25.4_{\pm 5.8}$	$72.9_{\pm 3.8}$	$61.7_{\pm 11.4}$	$29.4_{\pm 4.7}$	$81.9_{\pm 3.8}$	$53.6_{\pm 11.4}$
	Score ↑	$0.37_{\pm 0.0}$	$0.37_{\pm 0.0}$	$0.40_{\pm 0.0}$	$0.46_{\pm 0.0}$	$0.37_{\pm 0.1}$	$0.44_{\pm 0.0}$	$0.41_{\pm 0.0}$	$0.32_{\pm 0.0}$	$0.42_{\pm 0.0}$	$0.43_{\pm 0.0}$	$0.38_{\pm 0.0}$	$0.40_{\pm 0.0}$	$0.40_{\pm 0.0}$
Lipschitz [15]	OS Acc. ↑	$1.4_{\pm 0.7}$	$23.3_{\pm 19.8}$	$15.3_{\pm 23.9}$	$8.6_{\pm 11.6}$	$9.6_{\pm 6.4}$	$25.7_{\pm 22.6}$	$1.5_{\pm 0.6}$	$2.2_{\pm 1.1}$	$18.4_{\pm 29.5}$	$2.2_{\pm 1.1}$	$5.2_{\pm 6.1}$	$52.2_{\pm 14.0}$	$13.8_{\pm 11.4}$
	OS* Acc. ↑	$1.6_{\pm 0.8}$	$25.7_{\pm 21.8}$	$16.5_{\pm 25.8}$	$9.3_{\pm 12.5}$	$10.6_{\pm 7.2}$	$27.7_{\pm 24.4}$	$1.6_{\pm 0.6}$	$2.5_{\pm 1.2}$	$19.8_{\pm 31.8}$	$2.4_{\pm 1.2}$	$5.7_{\pm 6.7}$	$57.6_{\pm 15.4}$	$15.1_{\pm 12.4}$
	Forget Acc. ↓	$\mathbf{0.0}_{\pm 0.0}$	$5.9_{\pm 9.0}$	$4.6_{\pm 8.0}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$19.5_{\pm 23.4}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$11.9_{\pm 20.7}$	$\mathbf{0.0}_{\pm 0.0}$	$\mathbf{0.0}_{\pm 0.0}$	$32.7_{\pm 12.2}$	$6.2_{\pm 6.1}$
	Score ↑	$0.01_{\pm 0.0}$	$0.21_{\pm 0.2}$	$0.14_{\pm 0.2}$	$0.09_{\pm 0.1}$	$0.10_{\pm 0.1}$	$0.20_{\pm 0.2}$	$0.02_{\pm 0.0}$	$0.02_{\pm 0.0}$	$0.14_{\pm 0.2}$	$0.02_{\pm 0.0}$	$0.05_{\pm 0.1}$	$0.39_{\pm 0.1}$	$0.12_{\pm 0.1}$
Nabla Tau [53]	OS Acc. ↑	$49.7_{\pm 1.6}$	$68.1_{\pm 0.3}$	$69.7_{\pm 2.4}$	$68.1_{\pm 1.6}$	$68.3_{\pm 2.3}$	$72.4_{\pm 0.8}$	$62.1_{\pm 3.4}$	$44.7_{\pm 0.9}$	$71.5_{\pm 2.6}$	$68.4_{\pm 3.5}$	$48.7_{\pm 2.0}$	$73.7_{\pm 1.2}$	$63.8_{\pm 1.9}$
	OS* Acc. ↑	$54.9_{\pm 1.8}$	$75.2_{\pm 0.3}$	$75.2_{\pm 2.6}$	$73.2_{\pm 1.6}$	$75.4_{\pm 2.6}$	$78.1_{\pm 0.9}$	$66.7_{\pm 3.6}$	$49.4_{\pm 0.9}$	$77.1_{\pm 2.8}$	$73.5_{\pm 3.8}$	$53.8_{\pm 2.2}$	$81.3_{\pm 1.3}$	$69.5_{\pm 2.0}$
	Forget Acc. ↓	$6.3_{\pm 3.0}$	$12.7_{\pm 8.7}$	$5.7_{\pm 5.9}$	$0.6_{\pm 1.1}$	$\mathbf{0.0}_{\pm 0.0}$	$0.3_{\pm 0.2}$	$5.2_{\pm 1.9}$	$5.2_{\pm 1.9}$	$\mathbf{0.0}_{\pm 0.0}$	$8.7_{\pm 7.0}$	$2.7_{\pm 1.2}$	$11.8_{\pm 4.7}$	$4.9_{\pm 3.0}$
	Score ↑	$0.47_{\pm 0.0}$	$0.61_{\pm 0.1}$	$0.66_{\pm 0.0}$	$0.68_{\pm 0.0}$	$0.68_{\pm 0.0}$	$0.72_{\pm 0.0}$	$0.59_{\pm 0.0}$	$0.43_{\pm 0.0}$	$0.71_{\pm 0.0}$	$0.63_{\pm 0.1}$	$0.47_{\pm 0.0}$	$0.66_{\pm 0.0}$	$0.61_{\pm 0.0}$
Ours	OS Acc. ↑	$46.2_{\pm 3.4}$	$67.3_{\pm 1.6}$	$73.3_{\pm 0.8}$	$68.8_{\pm 3.5}$	$68.3_{\pm 4.8}$	$75.8_{\pm 0.3}$	$64.9_{\pm 3.0}$	$27.3_{\pm 8.9}$	$72.7_{\pm 1.0}$	$71.7_{\pm 1.5}$	$45.4_{\pm 1.9}$	$74.2_{\pm 3.9}$	$63.0_{\pm 2.9}$
	OS* Acc. ↑	$\mathbf{51.1}_{\pm 3.7}$	$74.2_{\pm 1.7}$	$79.1_{\pm 0.9}$	$73.9_{\pm 3.7}$	$75.4_{\pm 5.2}$	$81.8_{\pm 0.3}$	$69.8_{\pm 3.3}$	$30.2_{\pm 9.8}$	$78.4_{\pm 1.1}$	$77.0_{\pm 1.6}$	$50.2_{\pm 2.1}$	$81.8_{\pm 4.4}$	$68.6_{\pm 3.1}$
	Forget Acc. ↓	$\underline{0.5}_{\pm 0.5}$	$\underline{2.3}_{\pm 3.2}$	$12.0_{\pm 12.9}$	$\mathbf{0.0}_{\pm 0.0}$	$\underline{3.1}_{\pm 2.8}$	$\underline{3.0}_{\pm 3.6}$	$\underline{1.6}_{\pm 1.4}$	$\mathbf{0.0}_{\pm 0.0}$	$15.6_{\pm 14.3}$	$\underline{0.9}_{\pm 1.6}$	$\underline{0.2}_{\pm 0.3}$	$\underline{7.6}_{\pm 10.0}$	$\underline{3.9}_{\pm 4.2}$
	Score ↑	$\underline{0.46}_{\pm 0.0}$	$\mathbf{0.66}_{\pm 0.0}$	$\mathbf{0.66}_{\pm 0.1}$	$\mathbf{0.69}_{\pm 0.0}$	$\underline{0.66}_{\pm 0.1}$	$\mathbf{0.74}_{\pm 0.0}$	$\mathbf{0.64}_{\pm 0.0}$	$0.27_{\pm 0.1}$	$\underline{0.63}_{\pm 0.1}$	$\mathbf{0.71}_{\pm 0.0}$	$\underline{0.45}_{\pm 0.0}$	$\mathbf{0.69}_{\pm 0.0}$	$\mathbf{0.61}_{\pm 0.0}$