

Multi-Granularity Class Prototype Topology Distillation for Class-Incremental Source-Free Unsupervised Domain Adaptation

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Abstract

This paper explores the Class-Incremental Source-Free Unsupervised Domain Adaptation (CI-SFUDA) problem, where the unlabeled target data come incrementally without access to labeled source instances. This problem poses two challenges, the interference of similar source-class knowledge in target-class representation learning and the shocks of new target knowledge to old ones. To address them, we propose the Multi-Granularity Class Prototype Topology Distillation (GROTO) algorithm, which effectively transfers the source knowledge to the class-incremental target domain. Concretely, we design the multi-granularity class prototype self-organization module and the prototype topology distillation module. First, we mine the positive classes by modeling accumulation distributions. Next, we introduce multi-granularity class prototypes to generate reliable pseudo-labels, and exploit them to promote the positive-class target feature self-organization. Second, the positive-class prototypes are leveraged to construct the topological structures of source and target feature spaces. Then, we perform the topology distillation to continually mitigate the shocks of new target knowledge to old ones. Extensive experiments demonstrate that our proposed method achieves state-of-the-art performance on three public datasets.

1. Introduction

With the development of deep learning [20, 38, 45, 46], transfer learning has made great progress. Unsupervised domain adaptation (UDA) [2, 9, 44, 50] relies on labeled source data to mitigate the domain gap. However, in some practical applications, it is infeasible to access source data when training on the target domain, while only the pre-trained source model and unlabeled target data are provided, known as source-free unsupervised domain adapta-

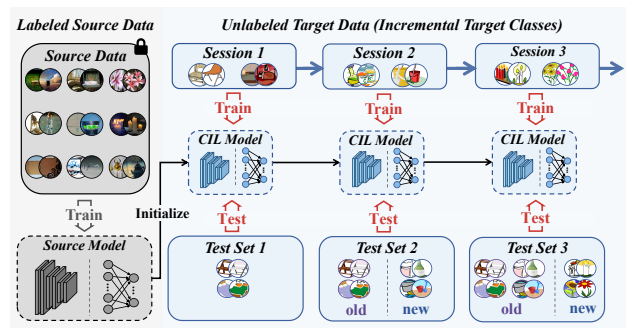


Figure 1. An illustration of Class-Incremental Source-Free Unsupervised Domain Adaptation (CI-SFUDA) problem, where the labeled source data contain all classes while unlabeled target data come incrementally without access to source instances, and the previously learned target data are unavailable for later adaptations.

tion (SFUDA) [11, 24, 26, 41].

To facilitate knowledge transfer, most SFUDA works adapt target distributions with self-training methods, where pseudo-labels are generated by a non-parameter classifier based on the similarity between image features and class prototypes. However, these works are established on the identical label space between source and target domains. In fact, the model often trains on a labeled large-scale dataset and then transfers knowledge to the unlabeled small-scale target domain [1, 15]. In such a non-identical label space scenario, traditional SFUDA works may push the unlabeled target data toward similar source-class clusters outside the target label space. Although the latest source-free universal domain adaptation (SF-UniDA) works can adapt target domain distribution in the case of inconsistent label space through feature decomposition and knowledge distillation methods [28, 34], they assume the availability of all target data in advance. In a dynamically changing environment, all the target data cannot be easily collected at once and always come in streams of different classes [13, 16, 25]. In such a case, existing SF-UniDA works cannot continually adapt to class shifts. When new class data arrive, they re-

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quire training from scratch, consuming substantial time and storage resources [13, 16]. For this issue, the unsupervised class incremental learning (UCIL) work [19] can learn new class knowledge with a strong pretrained model while retaining the old class ones. However, it struggles to address domain distribution shifts. Therefore, the pretrained source model is expected to continually adapt the unlabeled target data with domain and class shifts without re-training.

In this paper, we explore the *Class-Incremental Source-Free Unsupervised Domain Adaptation* (CI-SFUDA) problem, where the target data come incrementally as sequential sessions without available source instances, while the target classes of each session derive from a subset of the source label space as shown in Figure 1. Therefore, CI-SFUDA faces two challenges: (1) the interference of similar source-class knowledge in target-class representation learning. The target label space of each session occupies only a subspace of the source one, unlabeled target data may be incorrectly assigned pseudo-labels from similar source classes outside the session, resulting in biased target representations. (2) The shocks of new target knowledge to old ones. Previously learned data are unavailable for new target class adaptation, thus when adapting to new classes, the optimizer updates model weights to adjust towards new features and patterns, leading to the forgetting of old knowledge.

To address them, we propose the Multi-Granularity Class PROtotype TOpology Distillation (GROTO) algorithm, which aims to continually adapt a source model to incremental target classes across different sessions. Firstly, we design the multi-granularity class prototype self-organization module to mitigate the interference of the inconsistent label space in target representation learning at each session. Specifically, we introduce the hybrid knowledge-driven positive class mining method, which models the accumulation distributions of source similarity and target probability to align label spaces. Then, we compute multi-granularity class prototypes, which leverage correctly classified unlabeled target data well to reduce noise from hard-transfer data, thus generating reliable pseudo-labels. With pseudo-labeled positive-class data, we perform the target feature self-organization to pull the same-class ones closer and push the different-class ones farther apart.

Secondly, we propose the prototype topology distillation module to continually reduce the shocks of new target knowledge to old ones. In detail, we compute positive-class prototypes to construct the topological structures of source and target feature spaces. Then, we design the losses to perform point-to-point distillation, which maintains the consistency between the source knowledge learned from all classes at once and the target knowledge gradually accumulated across multiple sessions, thus reducing the decision boundary overfitting to new target classes.

Experiments on three benchmark datasets show that our

algorithm outperforms state-of-the-art methods. In summary, the main contributions of this paper are as follows:

- We explore the class-incremental source-free unsupervised domain adaptation (CI-SFUDA) problem, and propose the multi-granularity class prototype topology distillation (GROTO) algorithm.
- We design the multi-granularity class prototype self-organization module to mitigate the interference from similar source-class knowledge to the target-class representation learning.
- We design the prototype topology distillation module to reduce the shocks of new target knowledge to old ones.

2. Related Work

Source-free Domain Adaptation (SFDA). With the advancement of artificial intelligence in recent years [37, 42, 43, 48], domain adaptation has also made great progress. SFDA works aim to transfer a pretrained source model to the unlabeled target domain [11, 22, 26, 28, 49]. BMD [26] exploits the multicentric dynamic prototype method to generate robust pseudo-labels, but its numbers of empirical prototypes are fixed and always different in the various datasets. C-SFDA [11] introduces curriculum learning to filter noisy pseudo-labels. However, they struggle to handle adaptation problems involving label space discrepancies. Recent SF-UniDA works [27, 28, 33] largely address the adaptation of inconsistent label space only with the source model and unlabeled target data. GLC [27] employs clustering to distinguish domain-public and domain-private data. The statistical distribution-based and causality-driven feature decomposition works [28, 33] reduce the interference of irrelevant feature information. In practical scenarios where the target data come in a streaming manner with different classes, these works fail to address it.

Class-Incremental Learning (CIL). CIL [6, 21, 23, 29, 36] faces a scenario where different class data arrive incrementally as sequential sessions, and previously learned data are no longer available at new sessions. Memory-based works store representative exemplars of previous tasks and then perform memory replay [10, 17] to mitigate the catastrophic forgetting [40]. Non-memory works [7, 8] deal with new tasks by altering network structures or optimizing parameters. Most CIL works are supervised, but it is difficult to obtain complete ground-truth labels as new data arrive. Therefore, the UCIL work [19] leverages powerful pre-trained models to capture comprehensive feature representations from unlabeled data and models the distributions of old and new classes. Then, it performs granularity alignment while reducing overlap between the old and new classes, thereby mitigating the forgetting problem. However, it cannot adapt to shifts in data distribution within the same class. Our GROTO can simultaneously deal with the domain and class shifts in the CI-SFUDA.

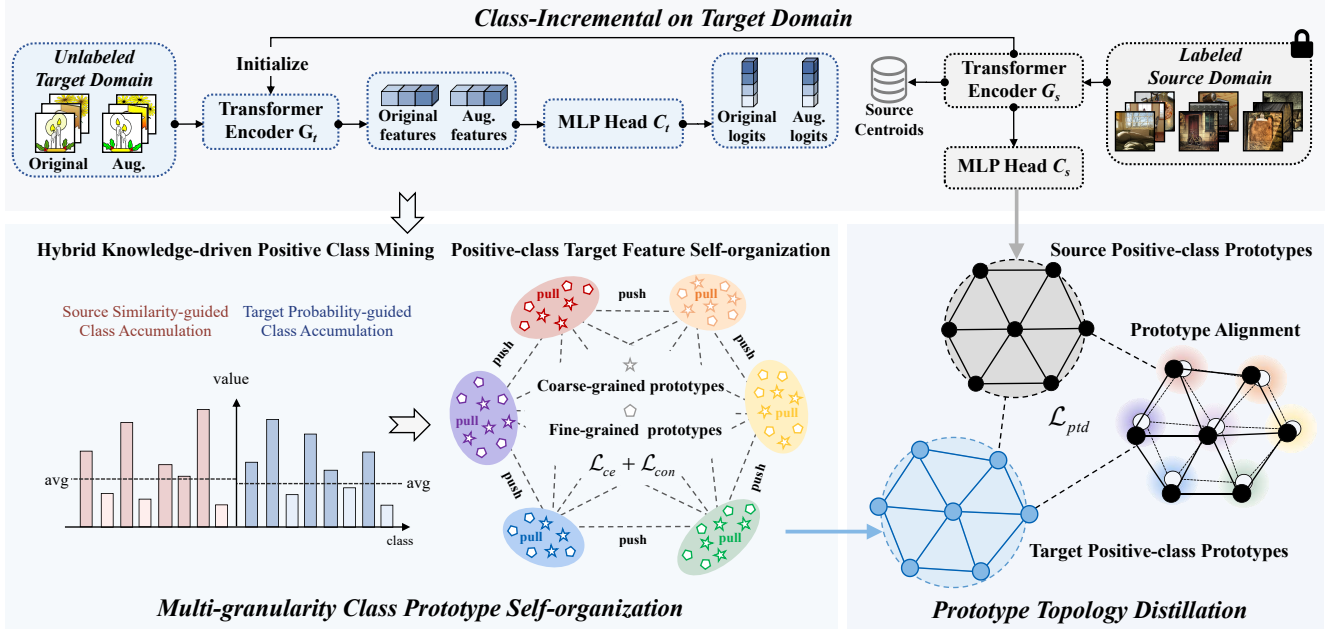


Figure 2. An overview of the GROTO algorithm, it includes two modules: 1) Multi-granularity class prototype self-organization: we mine the positive classes by modeling the source similarity and target probability accumulation distributions, and then promote the positive-class target features self-organization based on the multi-granularity class prototypes via $\mathcal{L}_{ce}$ and $\mathcal{L}_{con}$. 2) Prototype topology distillation: we compute the positive-class prototypes to distillate the topological structures of source and target feature spaces via $\mathcal{L}_{ptd}$.

3. Proposed Method

3.1. Problem Formulation

Let $\mathcal{D}_s = \{(x_j^s, y_j^s) | y_j^s \in Y^s\}_{j=1}^{n_s}$ denotes the source domain with n_s source data, where Y^s is the source label set and the number of source classes is $|Y^s| = K$. We need to adapt the source model M_s to the sequential training datasets $D^1, D^2, \dots, D^t, D^{t+1}$, and build a unified target model M_t , where $D^t = \{(x_i)_{i=1}^{n_t}\}$ is the unlabeled target domain of the t -th session with n_t samples, G_t and C_t are the feature extractor and classifier of M_t , G_s and C_s are the feature extractor and classifier of M_s . Y^p and Y^q are disjoint target label sets at the p -th and q -th target sessions, *s.t.* $\forall p \neq q, Y^p \cap Y^q = \emptyset$. Moreover, Y^t at each session t is a subset of the source label set, *i.e.* $Y^t \subset Y^s$. At session $t+1$, the target model M_t is learned from D^{t+1} without the old-class training sets $D^1, D^2, \dots, D^t$. Then, M_t is evaluated on the concatenated set of all the seen sets $\bigcup_{i=1}^{t+1} D^i$.

3.2. Overall Framework

The overall framework of GROTO is shown in Figure 2. In CI-SFUDA, the target classes of different sessions are non-overlapping subsets of the source label space. Domain-shared classes are considered positive classes, and the remaining classes in the label spaces are considered negative classes. **Firstly**, to reduce the interference of similar source-class knowledge in the target-class representa-

tion learning, we design the multi-granularity class prototype self-organization module, identifying domain-shared positive classes and then conducting target feature self-organization. In detail, we mine positive classes of new sessions by modeling the source similarity and target probability accumulation distributions. Then, we generate pseudo-labels for target data by identifying the coarse-grained and fine-grained class prototypes. With these reliable pseudo-labels, we conduct the target feature self-organization with the cross-entropy loss $\mathcal{L}_{ce}$ and contrastive loss $\mathcal{L}_{con}$. **Secondly**, to continually mitigate the shocks of new target knowledge to old ones, we propose the prototype topology distillation module. We compute positive class prototypes to construct the topological structures of feature spaces, then perform point-to-point distillation between the topological structures of the source and the target via the prototype topology distillation loss $\mathcal{L}_{ptd}$.

3.3. Multi-granularity Class Prototype Self-organization

The mainstream paradigm is the self-training framework, where pseudo-labels are generated for unlabeled target data to facilitate model adaptation. However, the target classes come incrementally in CI-SFUDA, and the label set Y^t of each session t is a subset of the source one Y^s . Incorrect pseudo-labels out of Y^t may be assigned to unlabeled target data at the t -th session, pushing target fea-

tures to similar source-class clusters outside the target label space Y^t . To solve this problem, we propose the multi-granularity class prototype self-organization module that consists of two steps: 1) hybrid knowledge-driven positive class mining (HKPCM), 2) positive-class target feature self-organization (PTFS).

Hybrid Knowledge-driven Positive Class Mining. To identify positive classes, the hybrid knowledge-driven positive class mining method with the accumulation distributions of source similarity and target probability is proposed. Specifically, for the source similarity-guided class accumulation distributions, we first load the stored source feature centroids $s = [s_1, \dots, s_K]$ of all the K source classes. Next, we use the source feature extractor G_s to generate features $g = [g_1, \dots, g_{n_t}]$ for n_t target data at the t -th session, and calculate the similarity matrix $R \in \mathbb{R}^{n_t \times K}$ by:

$$R = g^T \cdot s, \quad (1)$$

where each element $r_{ij} \in R$ represents the similarity between the i -th target data and the j -th source centroid. We normalize r_{ij} with the softmax normalization and compute the average similarity S_k for each source class k . Then, we identify the positive classes by $S_k > \frac{1}{K} \sum_{j=1}^K S_j$, as shown in the red histogram in Figure 2.

For the target probability-guided class accumulation distributions, we generate the prediction for each target data x_i of the t -th session to obtain the cumulative probability P_k for each source class k in Y^s :

$$P_k = \sum_{i=1}^{n_t} C_s(G_s(x_i)). \quad (2)$$

We normalize the cumulative predicted probability P_k of each source class k with the min-max normalization and identify the positive classes by $P_k > \frac{1}{K} \sum_{j=1}^K P_j$, as shown in the blue histogram in Figure 2.

With the pseudo label assigned in subsequent stages, unique pseudo-labels evolve as the positive classes.

Positive-class Target Feature Self-organization. To generate reliable pseudo-labels, we first identify the coarse-grained and fine-grained prototypes. Then we conduct target feature self-organization via the cross-entropy loss and contrastive loss to make the intra-class features more compact and inter-class features more separable.

Coarse-grained prototypes O_c include the source and target coarse-grained ones of positive classes. The source classifier weights $\mu = [\mu_1, \dots, \mu_N]$ of N positive classes are considered as the source coarse-grained prototypes, which denote the stable convergence points of each positive class on the source domain. Further, considering the domain gap, we identify target coarse-grained prototypes to provide the representation of target-class central tendencies, which are representative data with high similarity to target feature centroids of positive classes. In detail, for each positive class n ,

the class centroid c_n is calculated by averaging features with the same initial pseudo-label $\arg \max_n C_t(G_t(x_i)) = n$ by:

$$c_n = \frac{1}{|S_n|} \sum_{x_n \in S_n} G_t(x_n), \quad (3)$$

where S_n is the set of all the target data that pseudo-label is n , x_n is the data in S_n . For each data x_n , we calculate its cosine distance with c_n by $d(x_n, c_n) = 1 - \frac{G_t(x_n) \cdot c_n}{\|G_t(x_n)\|_2 \|c_n\|_2}$, and compute the average cosine distance of all the data with initial pseudo label n as the threshold τ_s :

$$\tau_s = \frac{1}{|S_n|} \sum_{x_n \in S_n} d(x_n, c_n). \quad (4)$$

We identify the features as target coarse-grained prototypes of positive class n by $d(x_n, c_n) < \tau_s$.

Fine-grained prototypes O_f are the target features with reliable initial pseudo-labels, which provide detailed representations about each target class. To select the fine-grained prototypes, we first conduct general data augmentation to simulate the distribution offsets. Then we calculate the uncertainty u_i of the prediction confidences (*conf*) for each target data x_i and its augmented data x'_i of the t -th session by taking the standard deviation (*std*):

$$u_i = \text{std}(\text{conf}(x_i), \text{conf}(x'_i)). \quad (5)$$

The thresholds τ_c and τ_u are computed as:

$$\tau_c = \frac{1}{2n_t} \sum_{i=1}^{n_t} (\text{conf}(x_i) + \text{conf}(x'_i)), \quad \tau_u = \frac{1}{n_t} \sum_{i=1}^{n_t} u_i. \quad (6)$$

The feature of x_i is considered one of the fine-grained prototypes O_f by:

$$\text{conf}_{\text{avg}}(x_i, x'_i) > \tau_c \quad \text{and} \quad u_i < \tau_u, \quad (7)$$

where conf_{avg} is the average prediction confidence of the data pair.

Let $O = O_c \cup O_f$ be the union of all the coarse-grained and fine-grained prototypes, and $o_n \in O$ be the prototypes of each positive class n . We compute the average of the cosine distances from each of the remaining target data x_j to all the n -th positive-class prototypes o_n as the distance of x_j to the n -th positive-class $D(x_j, n)$. Then, we assign the pseudo-label $\bar{y}_j$ to x_j :

$$\bar{y}_j = \arg \min_n D(x_j, n). \quad (8)$$

Finally, we conduct target feature self-organization with the cross-entropy loss and unsupervised contrastive learning [12]:

$$\mathcal{L}_{ce} = -\frac{1}{B} \sum_{i=1}^B \bar{y}_i \cdot \log C_t(G_t(x_i)), \quad (9)$$

$$\mathcal{L}_{con} = \frac{1}{2B} \sum_{b=1}^{2B} [\ell_{2b-1,2b} + \ell_{2b,2b-1}], \quad (10)$$

$$\ell_{i,j} = -\log \frac{\exp(\phi(G_t(x_i), G_t(x'_i))/\kappa)}{\sum_{b=1}^{2B} \mathbb{1}_{b \neq i} \exp(\phi(G_t(x_i), G_t(x_b))/\kappa)}, \quad (11)$$

$$\mathcal{L}_{pts} = \mathcal{L}_{ce} + \mathcal{L}_{con}, \quad (12)$$

where B is the batch size, $\bar{y}_i$ is the pseudo label of x_i , κ is the temperature constant, $\phi(\cdot, \cdot)$ is the cosine similarity and $\mathbb{1}_{b \neq i}$ is an indicator function that gives a 1 if $b \neq i$. By combining $\mathcal{L}_{con}$ and $\mathcal{L}_{ce}$ (denoted as $\mathcal{L}_{pts}$), we can make the embedding space more compact while preserving the fine-grained information about the decision boundary of each target class.

3.4. Prototype Topology Distillation

At a new incremental session, the optimizer updates model weights to adjust towards the features and patterns of new classes, leading to the forgetting of old knowledge. ProCA [16] mitigates this problem with the memory replay method. It constructs a memory bank $\mathcal{M} = \{(m_i, \hat{y}_i, \bar{y}_i)\}_{i=1}^{N_r}$ to store a small number of representative exemplars for replaying all N' existing positive classes, where m_i , $\hat{y}_i$, $\bar{y}_i$ and N_r respectively denote the exemplar, soft prediction, pseudo-label and the number of all exemplars. For each existing class n' in the memory bank, n_r exemplars are stored, where $n_r = N_r/N'$. To maintain the relative position relationship of old and new target classes in the feature space, our GROTO also maintains a similar memory bank. To make it compatible with our HKPCM method, if the same positive class is recognized in multiple sessions, we only store the positive class prototype in the session with higher confidence in $\mathcal{M}$. Then, We perform the exemplar replay [40] by:

$$\mathcal{L}_{rep} = -\frac{1}{N_r} \sum_{i=1}^{N_r} \hat{y}_i^\top \log C_t(G_t(m_i)), \quad (13)$$

In CI-SFUDA, classes of different sessions are not overlapping, resulting in data imbalance between the old and new classes ($N_r \ll n_t$). Thus, relying solely on the exemplar memory replay method leads the decision boundary to overfit the new dominant classes [3, 14]. In our setting, the source model is trained on labeled data of all the classes at once, acquiring discriminative knowledge of all the classes. This indicates that we can utilize the rich discriminative information learned from all source classes to alleviate the decision boundary overfitting in the incremental process by aligning classifier weights between domains, thereby creating a link between transfer learning and continual learning.

In light of this, we propose the prototype topology distillation (PTD) module, which continually reduces the shocks

of new target knowledge to old ones. During the target incremental training process, we utilize the source topological structure to prospectively support the decision boundary construction of new and old classes at each session. In detail, we first adopt classifier weights of the source and target model as source prototypes $\mu = [\mu_1, \dots, \mu_N]$ and the target ones $f = [f_1, \dots, f_N]$ to construct the topological structures of feature spaces for N positive classes. As the target prototypes tend to be moved towards the neighboring source prototypes with the same label [35], we design the compactness loss $\mathcal{L}_{com}$:

$$\mathcal{L}_{com} = \frac{1}{N} \sum_{j=1}^N \sum_{i=1}^N d(\mu_i, f_j^T) \frac{p(f_i) \exp(\mu_i f_j^T)}{\sum_{i'=1}^N p(f_{i'}) \exp(\mu_{i'} f_j^T)}, \quad (14)$$

where $p(\cdot)$ is the target proportion. The unnormalized likelihood term $\exp(\mu_i f_j^T)$ measures the similarity of the i -th source and j -th target prototypes. The cosine distance $d(\cdot, \cdot)$ measures the point-to-point distillation cost of each target prototype to each source one, allowing the model to make more refined adjustments to the target prototypes. Minimizing $\mathcal{L}_{com}$ means the distillation cost minimization, encouraging target prototypes to be closer to the source ones they are supposed to be mapped to, thereby enhancing the intra-class compactness of the same class between domains.

But minimizing $\mathcal{L}_{com}$ alone for target prototypes may lead to the same tendency of discarding some patterns [47]. Thus, we further design the separability loss $\mathcal{L}_{sep}$:

$$\mathcal{L}_{sep} = \sum_{i=1}^N p(f_i) \sum_{j=1}^N d(\mu_i, f_j^T) \frac{\exp(\mu_i f_j^T)}{\sum_{j'=1}^N \exp(\mu_i f_{j'}^T)}, \quad (15)$$

where $\frac{\exp(\mu_i f_j^T)}{\sum_{j'=1}^N \exp(\mu_i f_{j'}^T)}$ normalizes the probabilities across the target prototypes for each source prototype. $\sum_{i=1}^N p(f_i)$ ensures that the class distribution is properly taken into account when calculating the distillation cost. Then, minimizing $\mathcal{L}_{sep}$ encourages making more balanced mapping decisions, reducing the point-to-point mismatch risks, and thus promoting the separability of inter-class prototypes.

Finally, combining the compactness loss $\mathcal{L}_{com}$ and separability loss $\mathcal{L}_{sep}$, our point-to-point prototype topology distillation loss $\mathcal{L}_{ptd}$ is expressed as:

$$\mathcal{L}_{ptd} = \mathcal{L}_{com} + \mathcal{L}_{sep}. \quad (16)$$

$\mathcal{L}_{ptd}$ mitigates the decision boundary overfitting to new classes at each session, thereby reducing the cost of maintaining old-class knowledge on the later adaptations.

4. Experiment

4.1. Experimental Setup

Dataset. We conduct experiments on the variants of three benchmark datasets, *i.e.*, Office-31 [31], Office-Home [39]

Table 1. Final accuracy (%) comparisons in the class-incremental scenario on Office-31-CI and ImageNet-Caltech-CI. U, CI, and SF respectively represent unsupervised, class-incremental, and source data-free. -B indicates the backbone is changed to ViT-B. * indicates the result is derived from ProCA.

Method	U	CI	SF	Office-31-CI							ImageNet-Caltech-CI		
				A→D	A→W	D→A	D→W	W→A	W→D	Avg.	C→I	I→C	Avg.
ViT-B	✗	✗	✗	82.4	80.0	70.8	83.1	75.1	87.4	79.8	82.7	78.6	80.7
CIDA* (ECCV20)	✗	✓	✓	70.4	64.5	48.1	95.1	52.7	98.8	71.6	69.3	49.2	59.2
ProCA-B (ECCV22)	✓	✓	✗	93.4	91.9	73.0	98.3	77.6	99.2	88.9	91.6	84.0	87.8
PLUE (CVPR23)	✓	✗	✓	74.5	74.6	70.3	85.7	70.5	80.1	76.0	82.4	70.6	76.5
TPDS (IJCV23)	✓	✗	✓	78.1	74.6	71.1	90.3	69.7	91.9	79.3	85.0	68.0	76.5
LCFD (Arxiv24)	✓	✗	✓	51.6	53.9	48.3	61.2	44.4	86.8	57.7	77.4	66.9	72.2
DIFO (CVPR24)	✓	✗	✓	83.4	80.2	66.9	91.7	68.1	91.5	80.3	62.2	60.6	61.4
LEAD-B (CVPR24)	✓	✗	✓	92.3	92.2	76.8	98.1	76.3	100.0	89.3	89.2	53.0	71.1
GROTO (Ours)	✓	✓	✓	99.4	99.0	81.3	99.0	81.3	98.1	93.0	92.5	85.1	88.8

Table 2. Final accuracy (%) comparisons in the class-incremental scenario on Office-Home-CI.

Method	U	CI	SF	A→C	A→P	A→R	C→A	C→P	C→R	P→A	P→C	P→R	R→A	R→C	R→P	Avg.
ViT-B	✗	✗	✗	53.2	77.7	82.1	69.1	76.6	78.7	67.8	50.8	82.1	73.0	50.2	81.8	70.3
CIDA* (ECCV20)	✗	✓	✓	32.2	45.9	49.1	36.5	48.6	46.6	51.6	33.5	59.0	64.0	38.0	65.1	47.5
ProCA-B (ECCV22)	✓	✓	✗	60.5	88.0	92.9	83.3	89.7	91.0	81.7	57.1	94.1	86.9	55.8	92.9	81.2
PLUE (CVPR23)	✓	✗	✓	28.8	67.9	72.5	60.5	67.5	73.4	59.6	29.2	74.2	61.2	37.6	72.6	58.8
TPDS (IJCV23)	✓	✗	✓	40.5	63.5	69.0	64.7	67.3	68.7	63.8	40.8	71.5	68.2	29.4	65.8	59.4
DIFO (CVPR24)	✓	✗	✓	44.7	62.6	61.5	54.1	59.8	61.6	53.7	37.6	65.2	58.4	43.3	57.5	55.0
LEAD-B (CVPR24)	✓	✗	✓	33.9	81.8	86.9	76.1	82.4	84.8	74.0	19.2	87.3	79.7	15.2	84.3	67.1
LCFD (Arxiv24)	✓	✗	✓	54.7	72.2	79.6	67.7	72.3	76.6	67.2	52.6	79.6	71.5	55.3	76.3	68.8
GROTO (Ours)	✓	✓	✓	65.7	86.4	89.7	85.8	86.3	90.0	86.0	67.1	90.1	86.9	66.2	89.3	82.5

and ImageNet-Caltech [5, 30]. 1) **Office-31-CI** contains three domains with shared 31 classes in the office environment, *i.e.*, Amazon (A), DSLR (D), and Webcam (W). Each domain is divided into three disjoint subsets with 10 classes for each in alphabetical order. 2) **Office-Home-CI** divides images of everyday objects into four domains with shared 65 classes, *i.e.*, Artistic (A), ClipArt (C), Product (P), and Real-world (R). Each domain is divided into six disjoint subsets with 10 classes for each in random order. 3) **ImageNet-Caltech-CI** contains ImageNet-1K and Caltech-256 with shared 84 classes. It contains the ImageNet (1000) → Caltech (84) and Caltech (256) → ImageNet (84) tasks, where eight disjoint subsets of the target domain are constructed to contain 10 classes for each. Refer to the supplementary material for more dataset construction details.

Implementation details. We utilize SGD as the optimizer and the base learning rate is set to 0.001 with the batch size of 32. The number of incremental classes γ at each session is set to 10. In the early iterations, we identify multi-granularity class prototypes with the source model and then use the well-trained target model. For $\mathcal{L}_{con}$, we exponentially decrease the coefficient μ_c as $\mu_c^i = \mu_c^{i-1}e^{-\beta}$ at the i -th iteration, where initial μ_c^0 is set to 0.5 and β is set to $1e-4$. Moreover, the stored exemplar n_r of each existing positive class in the memory bank is set to 10.

Evaluation protocols. We evaluate our method through two metrics: 1) **Final Accuracy**: the classification accuracy over all the classes at the final session. 2) **Session Accu-**

racy: the classification accuracy at each session to evaluate the ability of sequential adaptation.

4.2. Comparisons with SOTA Methods

We compare our GROTO algorithm with five types of methods: (1) source-only: ViT-B [4]; (2) class-incremental domain adaptation: CIDA [13]; (3) class-incremental unsupervised domain adaptation: ProCA [16]; (4) source-free unsupervised domain adaptation: PLUE [18] and TPDS [32]; (5) source-free universal domain adaptation: DIFO [34], LEAD [28] and LCFD [33].

The final accuracy results of GROTO and the compared methods are reported in Table 1 and Table 2, which give the following observations. 1) GROTO shows the superiority of average final accuracy in all sub-tasks compared to other methods. 2) Compared to SFUDA methods [18, 32], GROTO performs better. It demonstrates the importance of reducing negative transfer caused by source negative classes and adapting to new classes while retaining old knowledge in CI-SFUDA. 3) The CIDA [13] method uses the regularization on proxy-source samples to mitigate catastrophic forgetting in source-free domain adaptation. However, it overlooks the target-class biased learning caused by the source negative classes, limiting its effectiveness in CI-SFUDA. 4) The CI-UDA method (ProCA [16]) preserves old knowledge through the exemplar replay method. However, it relies on source data, which makes it difficult to satisfy data privacy issues. 5) SF-UniDA methods [28, 33, 34]

Table 3. Session accuracy (%) comparisons in the class-incremental scenario on Office-31-CI and Office-Home-CI.

Method	U	CI	SF	Office-31-CI				Office-Home-CI							
				Session 1	Session 2	Session 3	Avg.	Session 1	Session 2	Session 3	Session 4	Session 5	Session 6	Avg.	
CIDA* (ECCV20)	✗	✓	✓	85.5	79.1	71.6	78.7	57.9	53.6	51.8	50.1	49.6	47.5	51.8	
ProCA-B (ECCV22)	✓	✓	✗	90.5	90.0	89.0	89.8	76.3	81.0	80.1	81.0	81.6	81.2	80.2	
DIFO (CVPR24)	✓	✗	✓	82.0	66.8	80.3	76.4	77.2	37.1	47.9	51.4	51.7	55.0	53.4	
LCFD (Arxiv24)	✓	✗	✓	81.3	68.9	57.7	69.3	70.0	64.9	68.2	68.1	67.9	68.8	68.0	
LEAD-B (CVPR24)	✓	✗	✓	96.4	91.6	89.3	92.4	70.5	74.0	71.2	70.5	69.0	67.1	70.4	
GROTO (Ours)	✓	✓	✓	96.7	94.9	93.0	94.9	84.4	84.8	81.7	83.3	82.8	82.5	83.2	

Table 4. Ablations of losses (*i.e.*, $\mathcal{L}_{rep}$, $\mathcal{L}_{ptfs}$, $\mathcal{L}_{ptd}$, $\mathcal{L}_{con}$, $\mathcal{L}_{com}$ and $\mathcal{L}_{sep}$), components (*i.e.*, coarse-grained prototypes O_c and fine-grained prototypes O_f) and modules (*i.e.*, HKPCM, PTFS and PTD) in GROTO. We show the final accuracy (%) on all the sub-tasks of Office-31-CI.

Exps.	$\mathcal{L}_{rep}$	$\mathcal{L}_{ptfs}$	$\mathcal{L}_{ptd}$	Final Accuracy (%)						
				A→A	D→D	W→W	A→D	D→W	W→A	Avg.
A				82.4	80.0	70.8	83.1	75.1	87.4	79.8
B	✓			90.7	91.9	74.0	98.1	77.2	98.3	88.4
C	✓	✓		96.5	97.3	80.9	99.2	80.6	97.5	92.0
D	✓	✓	✓	99.4	99.0	81.3	99.0	81.3	98.1	93.0
Exps.B w/ O_f				93.8	96.4	78.6	97.9	80.1	97.3	90.7
Exps.B w/ O_c				95.2	97.4	78.2	98.2	80.2	98.8	91.3
Exps.C w/o $\mathcal{L}_{con}$				94.4	97.3	79.0	99.1	80.7	98.6	91.5
GROTO w/o $\mathcal{L}_{com}$				95.7	97.3	80.6	99.2	81.1	99.6	92.3
GROTO w/o $\mathcal{L}_{sep}$				95.4	99.1	80.3	99.0	80.3	100.0	92.4
GROTO w/o PTD				96.5	97.3	80.9	99.2	80.6	97.5	92.0
GROTO w/o PTFS				88.4	91.6	73.8	98.2	77.3	99.0	88.0
GROTO w/o HKPCM				97.5	95.5	80.6	99.2	75.1	98.1	91.0

effectively prevent target features from shifting toward similar source clusters outside the target label space. However, they perform even worse than ViT-B in some sub-tasks, which shows that only focusing on domain alignment without preventing forgetting leads the model to disrupt old knowledge and overfit the new classes in CI-SFUDA.

The session accuracy comparisons are shown in Table 3. There is no catastrophic forgetting problem at session 1, thus the SF-UniDA methods perform well. The best performance of our GROTO at session 1, illustrating the effectiveness of the multi-granularity class prototype self-organization module. Meanwhile, our GROTO achieves the best performance compared to the other methods at each session in Table 3, which also demonstrates that it performs well on both old and new classes during the continual adaptation of sequential sessions. Figure 3 further explores the ability to maintain the performance of old classes. Since the absence of old-class instances at later sessions, the models of all the methods forget the old knowledge when adapting to new classes, resulting in performance degradation. But other methods continually show significant drops in the average accuracy of 10 classes learned at session 1, our GROTO maintains relatively stable performances compared to them, indicating that it is effective in mitigating the

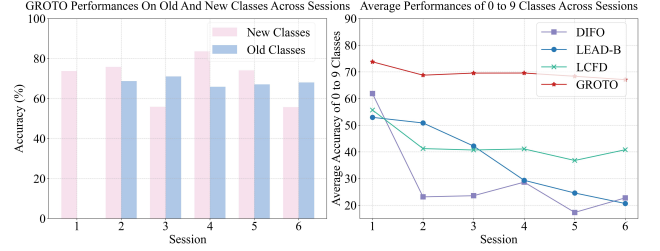


Figure 3. The accuracies on old and new classes of GROTO on Office-Home-CI (R→C), and the average accuracies of 0 to 9 classes for different methods across sessions on Office-Home-CI (R→C).

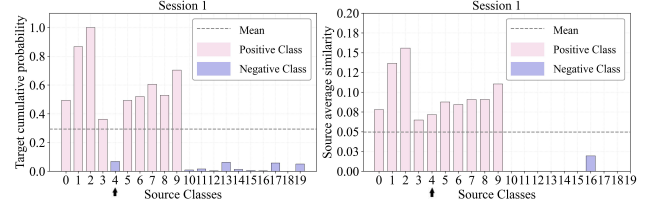


Figure 4. The target cumulative probability and source average similarity results at the first session on Office-31-CI (A→D). Only training data from 0 to 9 classes are provided at this session. Based on both distributions, we select classes with indices 0-9 as the positive classes at this session.

catastrophic forgetting problem. Refer to the supplementary material for more dataset results and analysis.

4.3. Ablation Studies

Loss and Module Ablations. To examine the effectiveness of our GROTO, we show the ablations in Table 4. Compared to the source-only model (Exps.A), the final accuracy is improved with the introduction of each loss, and it decreases when each proposed module is removed.

Target probability and source similarity accumulation distributions of Office-31-CI (A→D) at session 1 are shown in Figure 4. We can observe that both the positive-class ones are higher than the negative-class ones. In the left sub-figure, only depending on the model predictions to mine the positive classes leads to omissions of the positive class “4” (pointed by the black arrow), resulting in training with the wrong pseudo-labels at new sessions. Thus, the HKPCM module is proposed to prevent the missing positive

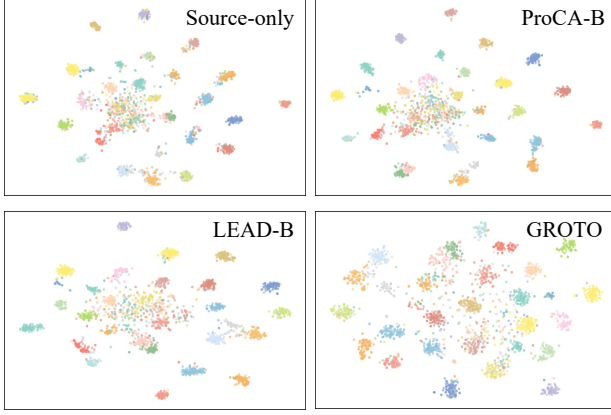


Figure 5. The multi-granularity class prototype visualizations of partial classes on Office-31-CI (A→D), and target feature distribution of source-only, ProCA-B, LEAD-B and GROTO methods on Office-31-CI (D→A).

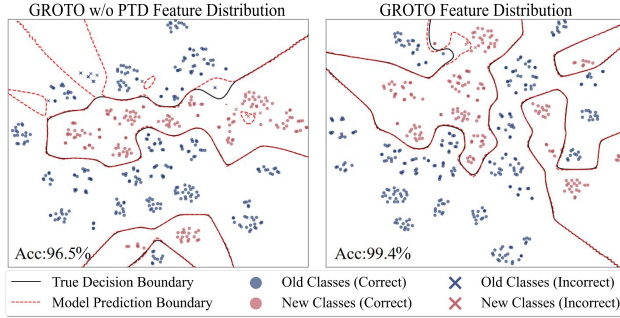


Figure 6. The feature distribution and decision boundary visualizations of “GROTO w/o PTD” and GROTO models on Office-31-CI (A→D). “GROTO w/o PTD” tends to incorrectly classify old-class data to new ones.

classes due to the adoption of any single cumulative distribution strategy, and its effectiveness is verified through the ablation experiment of “GROTO w/o HKPCM” in Table 4.

The Exps.B experiment introduces the HKPCM module and $\mathcal{L}_{rep}$, but it relies on simple model predictions to generate pseudo-labels for unlabeled target data. In the Exps.C experiment of introducing the $\mathcal{L}_{rep}$, HKPCM and PTFS modules, we first mine positive classes with the HKPCM module, and then generate pseudo-labels with the PTFS module. Compared with the Exps.B experiment, the performance is improved through the introduction of the PTFS module. It can also be seen that the combination of coarse-grained and fine-grained prototypes demonstrates superior performance compared to using either prototype type individually in Table 4. When we introduce $\mathcal{L}_{con}$, the performance is further improved. In addition, we show the target feature distributions of different methods on Office-31-CI (D→A) in Figure 5. The source-only model (ViT-B), ProCA-B, and LEAD-B mix the target features of sim-

Table 5. Ablations of different hyper-parameters (*i.e.*, γ , μ_c^0 , β and n_r) for the average final accuracy (%) on ImageNet-Caltech-CI.

γ	Avg.	μ_c^0	Avg.	β	Avg.	n_r	Avg.
9	87.5	0.2	88.5	1e-5	88.7	1	83.0
10	88.8	0.5	88.8	5e-5	88.8	5	86.2
11	87.8	0.6	87.5	1e-4	88.8	10	88.8
12	87.3	0.7	85.4	5e-4	87.3	15	88.7
13	89.1	0.8	88.0	1e-3	88.3	20	88.7

ilar classes. However, our GROTO alleviates the problem, showing a more discriminative cluster distribution among different classes.

The experiments of Exps.D, “GROTO w/o $\mathcal{L}_{com}$ ”, “GROTO w/o $\mathcal{L}_{sep}$ ” and “GROTO w/o PTD” demonstrate that the PTD module improves the final accuracy. To investigate its impact on old-class knowledge, we visualize old-class and new-class features at the last session on Office-31-CI (A→D) as shown in Figure 6. GROTO without the PTD module (left sub-figure) incorrectly classifies old-class data to new ones in the top left part. However, fewer old data are misclassified to new classes with the PTD module, thus improving the overall classification accuracy of old and new classes (96.5%→99.4%). It also proves that the PTD module effectively mitigates the problem of excessively focusing on new classes while forgetting old knowledge on continual adaptation.

Hyper-parameter Ablations. We explore the impacts of hyper-parameters in Table 5, indicating that GROTO has relatively stable performance with different values of μ_c^0 and β . The final accuracy is highest when the number of incremental classes γ is 13, but to ensure the experimental setup is consistent with ProCA, we choose 10 as the number of incremental classes for GROTO.

5. Conclusion

In this paper, we explore the class-incremental source-free unsupervised domain adaptation (CI-SFUDA) problem. To address it, we propose a novel Multi-Granularity Class Prototype Topology Distillation (GROTO) algorithm, which contains two modules. (1) Multi-granularity class prototype self-organization: we mine positive classes to align the label spaces. Next, we introduce multi-granularity class prototypes to generate reliable pseudo-labels, and promote the target feature self-organization. (2) Prototype topology distillation: we construct the topological structures of feature manifolds with source and target prototypes, and perform the point-to-point topology distillation to reduce the decision boundary overfitting to new target classes. Therefore, we can continually mitigate the shocks of new target knowledge to old ones. Extensive experiments demonstrate the effectiveness of our GROTO on three public datasets, and it achieves state-of-the-art performance.

Acknowledgement

This work was supported by the National Nature Science Foundation of China (U21B2024, 62322211, 62336008), the “Pioneer” and “Leading Goose” R&D Program of Zhejiang Province (2024C01107, 2023C01030, 2023C03012, 2024C01023).

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