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

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Code: https://github.com/dengpeihua/GROTO

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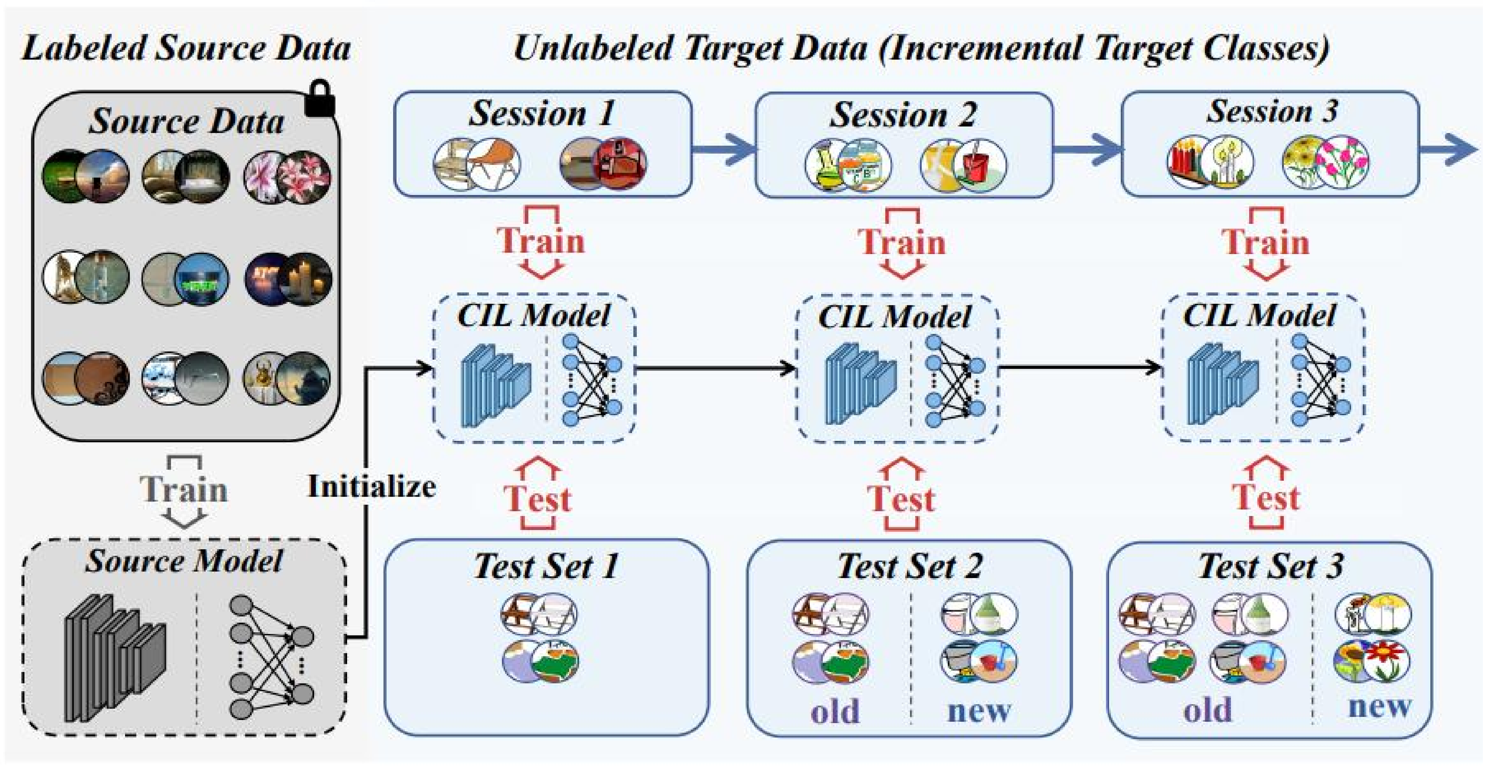
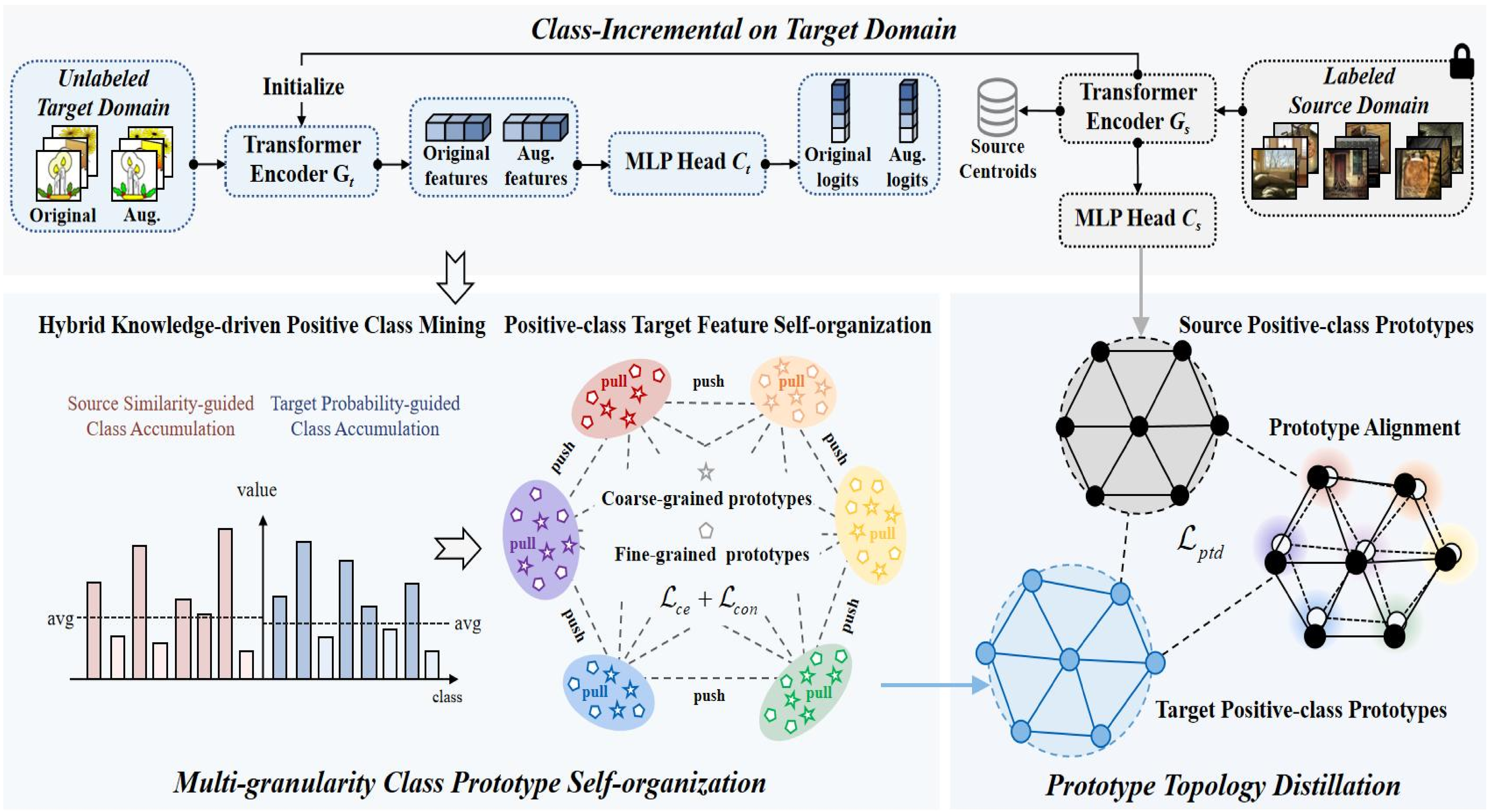
Contribution



An illustration of the CI-SFUDA problem

- We explore the **C**lass-**I**ncremental **S**ource-**F**ree **U**nsupervised **D**omain **A**daptation (CI-SFUDA) problem, and propose the Multi-**G**ranularity Class **PRO**totype **TO**pology Distillation (GROTO) algorithm.
- We design the multi-granularity class prototype selforganization 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.

Method



An overview of the GROTO algorithm

- In the **Multi-granularity Class Prototype Self-organization** module, we mine positive classes of new sessions by modeling source similarity and target probability accumulation distributions, and then generate pseudo-labels for target data by identifying the coarse-grained and fine-grained class prototypes. With these reliable pseudo-labels, we next conduct the target feature self-organization.
- In the **Prototype Topology Distillation** module. We compute positive class prototypes to construct the topological structures of feature spaces. Then, we perform point-to-point distillation between the source topological structure and the target ones.

Experiments

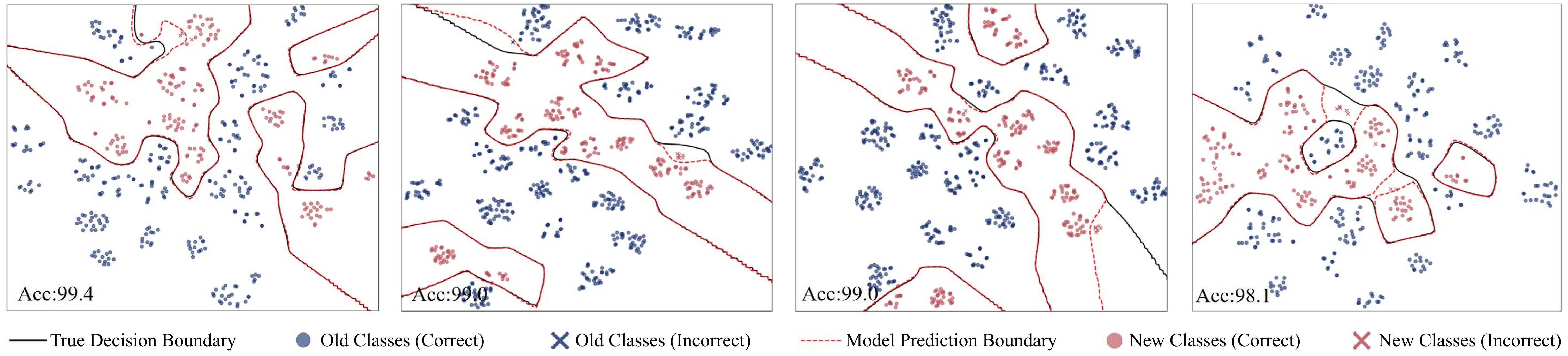
Results on the Office-31-CI and ImageNet-Caltech-CI datasets

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**

Results on the Office-Home-CI dataset

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**

Visualization of GROTO



- Experiments on three benchmark datasets and the visualizations show that our GROTO algorithm outperforms current state-of-the-art methods.