

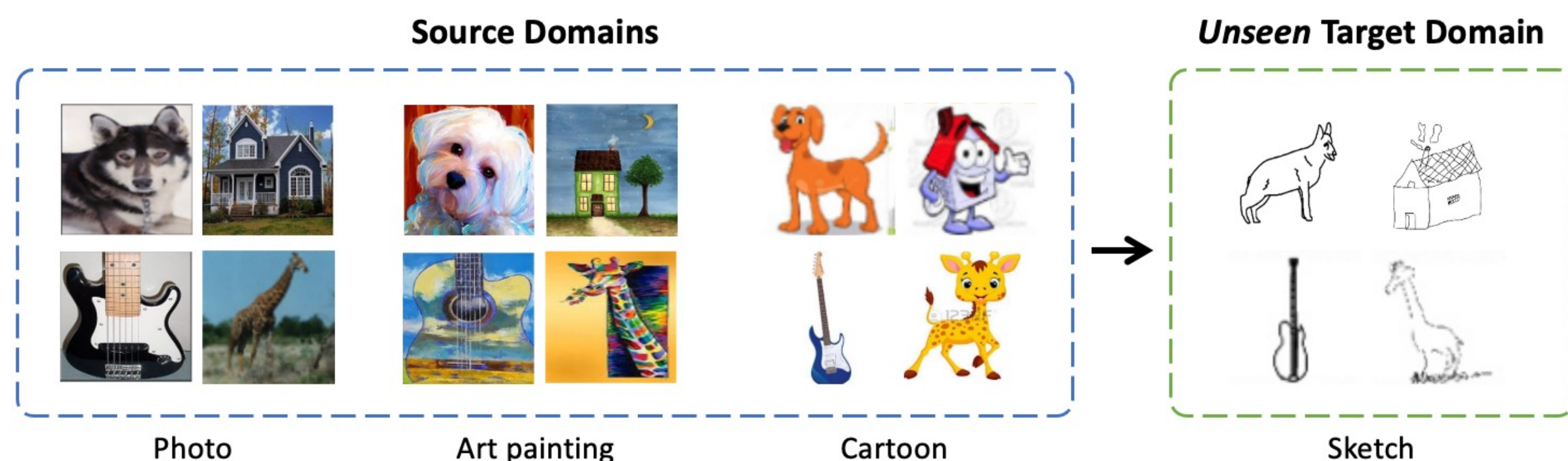
# Adversarial Teacher-Student Representation Learning for Domain Generalization



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## Goal & Contributions

- Goal:** Train a model on **single or multiple source domain(s)** and test on **target domains** with shared label space

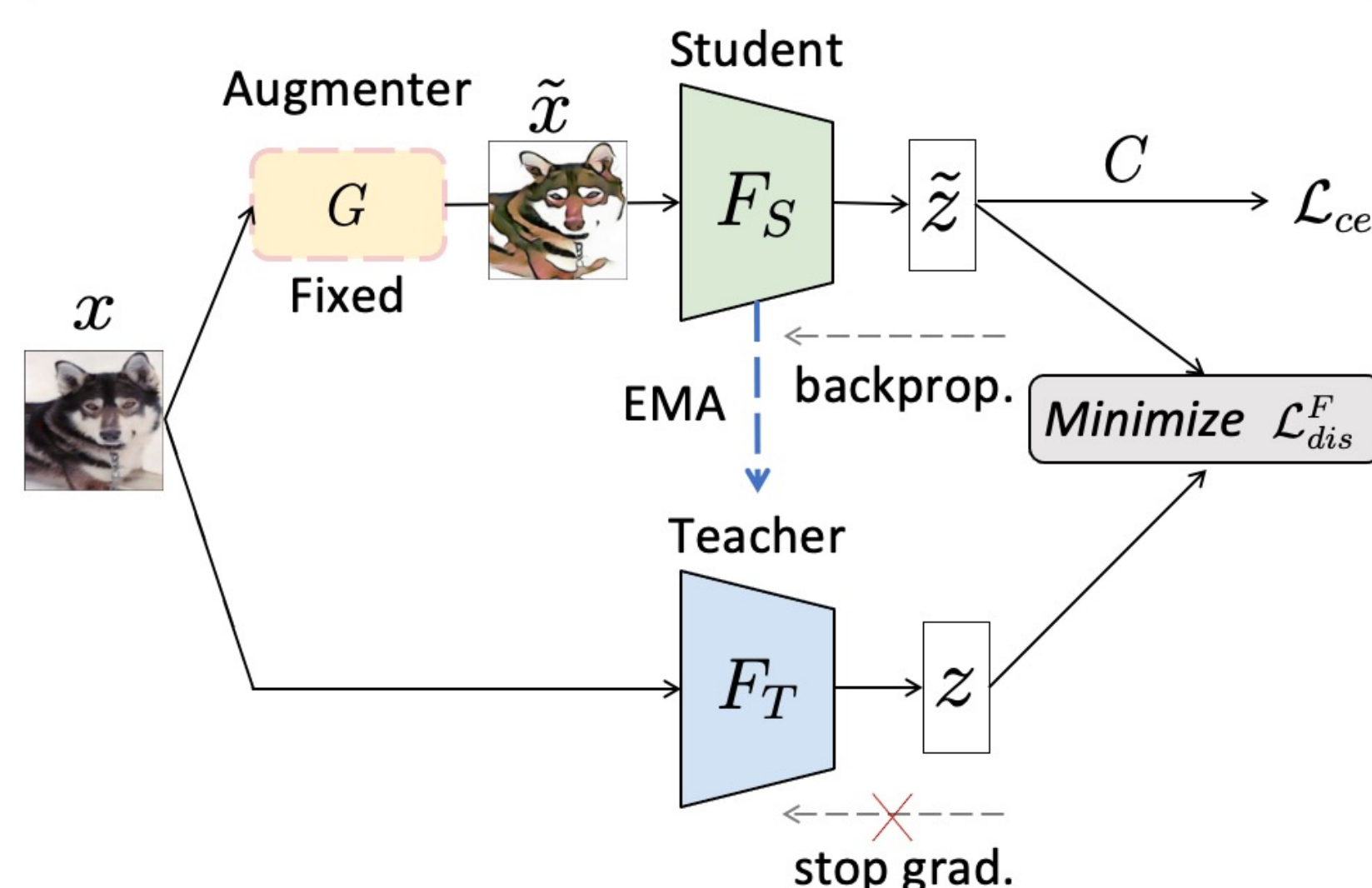


### Contributions:

- Domain Generalized Representation Learning** – Student observes augmented novel-domain data and distills the information to update Teacher, allowing derivation of domain generalizable representation.
- Novel Domain Augmentation** – the augmenter aims at producing novel domain data, which maximizes the discrepancy between augmented and existing domains while the semantic information is preserved.

## Adversarial Teacher-Student Representation Learning

### Domain Generalized Representation Learning

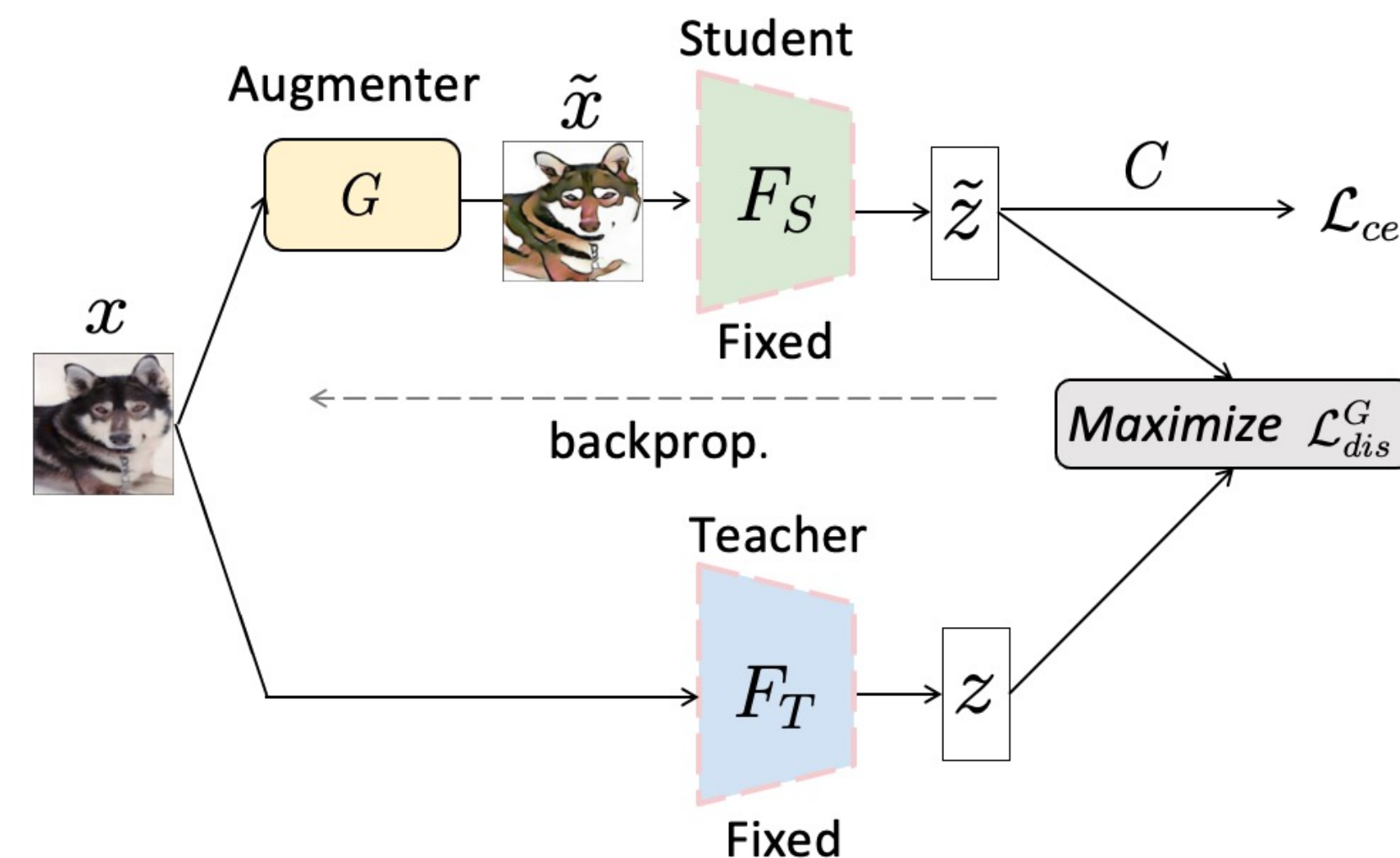


**Minimize** the discrepancy between *Teacher* and *Student* & progressively update *Teacher* via EMA.

$$\min_{F_S} \mathcal{L}_{dis}^F(z, \tilde{z}) = \left\| \frac{z}{\|z\|_2} - \frac{\tilde{z}}{\|\tilde{z}\|_2} \right\|_2^2$$

$$\theta_T \leftarrow \tau \theta_T + (1 - \tau) \theta_S, \quad \text{where } \tau \in [0, 1)$$

### Novel Domain Augmentation



**Maximize** the discrepancy between augmented and existing domains. The semantic information is preserved via CE loss.

$$\max_G \mathcal{L}_{dis}^G(z, \tilde{z}) = \left[ \left\| \frac{z}{\|z\|_2} - \frac{\tilde{z}}{\|\tilde{z}\|_2} \right\|_2^2 - m \right]$$

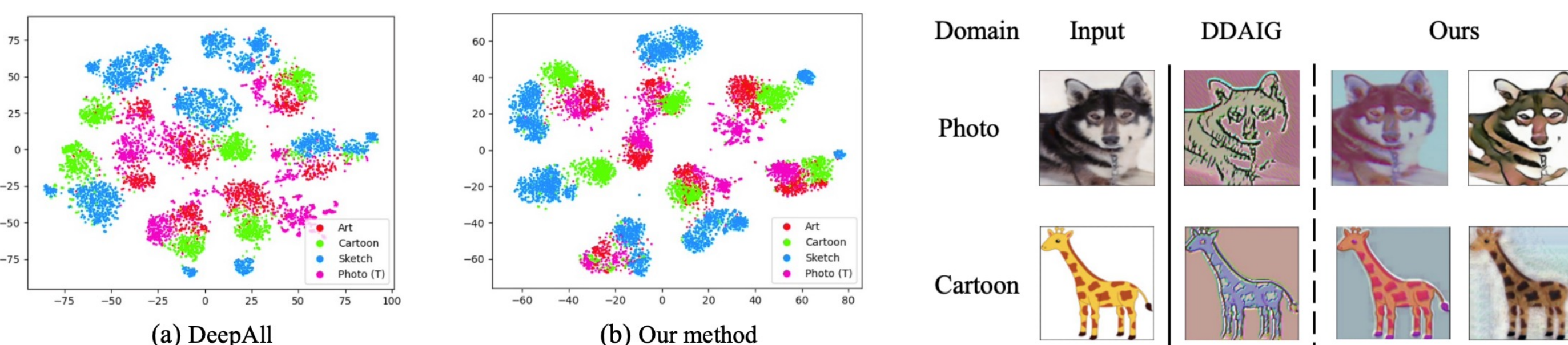
## Experiments

### Multi-Source DG on PACS in leave-one-domain-out settings

Target	DeepAll (baseline)	MMD-AAE [1]	MLDG [2]	JiGen [11]	MetaReg [3]	Epi-FCR [4]	MASF [5]	EISNet [12]	DMG [38]	Borlino <i>et al.</i> [44]	DSO [45]	RSC [28]	Ours
Photo	95.6	96.0	96.1	96.0	95.5	93.9	95.0	95.9	93.4	95.0	95.9	96.0	<b>97.3 ± 0.3</b>
Art painting	75.1	75.2	81.3	79.4	83.7	82.1	80.3	81.9	76.9	82.7	84.7	83.4	<b>85.8 ± 0.6</b>
Cartoon	74.2	72.7	77.2	75.3	77.2	77.0	77.2	76.4	80.4	78.0	77.7	80.3	<b>80.7 ± 0.5</b>
Sketch	68.4	64.2	72.3	71.4	70.3	73.0	71.7	74.3	75.2	81.6	<b>82.2</b>	80.9	<b>77.3 ± 0.5</b>
Average	78.3	77.0	81.8	80.5	81.7	81.5	81.1	82.2	81.5	84.3	85.1	85.2	<b>85.3</b>

Target	ResNet-18					ResNet-50					
	DeepAll (baseline)	CrossGrad [6]	DDAIG [7]	L2A-OT [8]	MixStyle [9]	Ours	DeepAll (baseline)	CrossGrad [6]	DDAIG [7]	MixStyle [9]	Ours
Photo	95.6	96.0	95.3	96.2	96.1	<b>97.3 ± 0.3</b>	94.8	97.8	95.7	98.0	<b>98.9 ± 0.3</b>
Art painting	75.1	79.8	84.2	83.3	84.1	<b>85.8 ± 0.6</b>	81.5	87.5	85.4	87.4	<b>90.0 ± 0.3</b>
Cartoon	74.2	76.8	78.1	78.2	78.8	<b>80.7 ± 0.5</b>	78.6	80.7	78.5	83.3	<b>83.5 ± 0.5</b>
Sketch	68.4	70.2	74.7	73.6	75.9	<b>77.3 ± 0.5</b>	69.7	73.9	<b>80.0</b>	78.5	<b>80.0 ± 0.6</b>
Average	78.3	80.7	83.1	82.8	83.7	<b>85.3</b>	81.2	85.7	84.9	86.8	<b>88.1</b>

### t-SNE visualization & visual comparisons on PACS



### Single-Source DG on PACS & DomainNet

Method	PACS				DomainNet					
	Art painting	Cartoon	Sketch	Average	Clipart	Infograph	Painting	Quickdraw	Sketch	Average
DeepAll	60.7	23.5	29.0	37.7	34.5	15.7	40.7	3.6	25.9	24.1
JiGen [11]	63.6	28.5	30.2	40.8	50.0	19.0	46.3	7.2	35.5	31.6
CrossGrad [6]	64.2	29.4	32.1	41.9	49.4	19.3	47.3	5.8	35.6	31.5
DDAIG [7]	64.1	32.5	29.6	42.1	41.4	16.5	40.9	3.2	26.7	25.7
M-ADA [42]	64.6	34.6	26.6	41.9	50.3	19.5	48.1	7.1	36.0	32.2
<b>Ours</b>	<b>68.2 ± 0.9</b>	<b>36.3 ± 0.9</b>	<b>33.5 ± 0.3</b>	<b>46.0</b>	<b>52.2 ± 0.3</b>	<b>21.6 ± 0.2</b>	<b>50.1 ± 0.2</b>	<b>8.1 ± 0.3</b>	<b>38.3 ± 0.4</b>	<b>34.1</b>