When Domain Generalization meets Generalized Category Discovery: An Adaptive Task-Arithmetic Driven Approach

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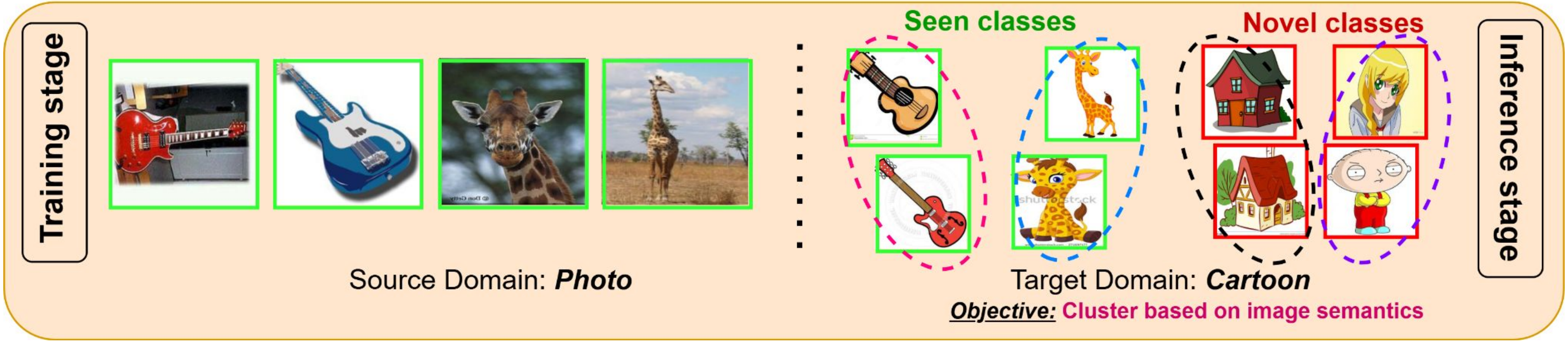
Introduction and Motivation

1. **What is the Problem?**
   - **Generalized Category Discovery (GCD)**: Identify and cluster both **known** and **novel** classes in a target domain.
   - Existing GCD methods assume access to the target domain **during training**, which is impractical for real-world scenarios.
   - **Domain Generalization (DG)**: Train a model on a source domain to generalize to unseen domains.
2. **Challenges**
   - **Distribution shifts** between the source and target domains (e.g., summer roads vs. snowy streets).
   - Need to identify **novel classes** in the target domain while also recognizing known classes.
   - **Target data** is **unavailable** during training.



Problem Definition

Introducing Domain Generalized GCD (DG-GCD):

- **Source Domain (S):** Contains labeled data with known classes.
- **Target Domain (T):**
  - Completely **unseen** during training.
  - Contains **both known and novel classes.**
  - Unknown **ratio** of known-to-novel classes.
- Assumption: **Distribution shift** between source and target domains: **P ≠P(T).**

Domain Shift in DG-GCD: Identifying categories across diverse environments without domain-specific biases.

Key Challenges:

- **No Target Data During Training**
- **Domain Shifts**
- **Novel Class Discovery**

Objective of DG-GCD:

- Develop a **domain-independent and discriminative feature space.**
- Enable accurate **discovery** and **clustering** of novel classes alongside known ones during inference.

https://www.dreamstime.com/contrast-vibrant-summer-field-cold-winter-road-barren-tree-under-clear-sky-generative-ai-vivid-landscape-image342246290

Overview of DG²CD-Net

Global Model Initialization

- **Pre-trained Vision Transformer (ViT)** as the feature extractor.

Synthetic Domain Generation

- **Uses Instruct-Pix2Pix** to create **pseudo-target domains**.
- **Introduces realistic domain shifts** (e.g., texture, lighting).

Episodic Training Strategy

- Simulates **distribution shifts** using:
  - **Labeled subset** of the **source domain**.
  - **Unlabeled synthetic domain** as **pseudo-target**.

Dynamic Task-Vector Aggregation

- **Task Vectors:** Capture differences between **global & fine-tuned models**.
- **Adaptive Weighting:**
  - Fine-tuned models validated on a **diverse validation set**.
  - **Softmax-based generalization scores** for dynamic weighting.

Training Process

- **Local Updates:** Fine-tune episodic tasks for **domain & class adaptation**.
- **Global Update:** Aggregate **weighted task vectors** to **progressively update** the global model.

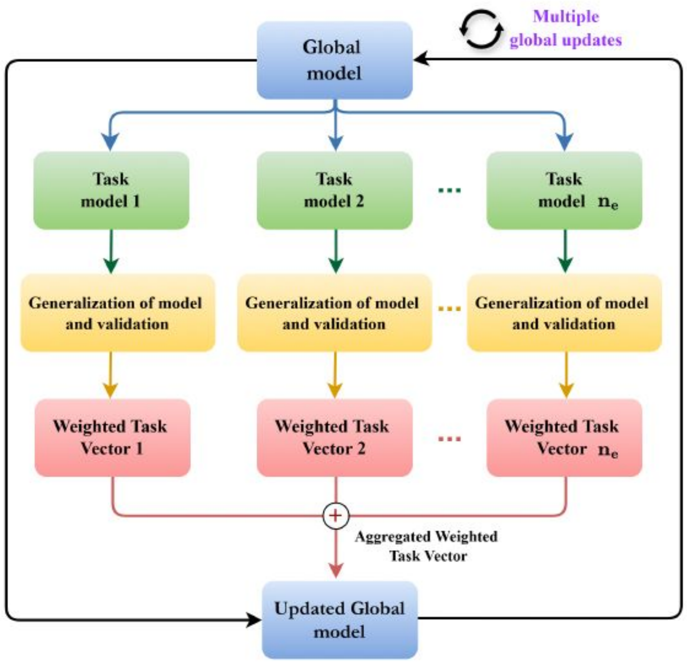


Figure 1. **Proposed episodic training**: A pre-trained global model is updated using task vectors from n_e episode-specific fine-tuned models, leveraging a novel dynamic weighting scheme. This scheme adjusts the task vectors based on their GCD generalization performance on a held-out unseen validation distribution.

Why Synthetic Domain Generation ?

Problem

- Training on a **single source domain** lacks diversity.
- Model struggles to **generalize to unseen target domains**.

Solution

- Generate **synthetic domains** to introduce **realistic distribution shifts**.

Method: Instruct-Pix2Pix

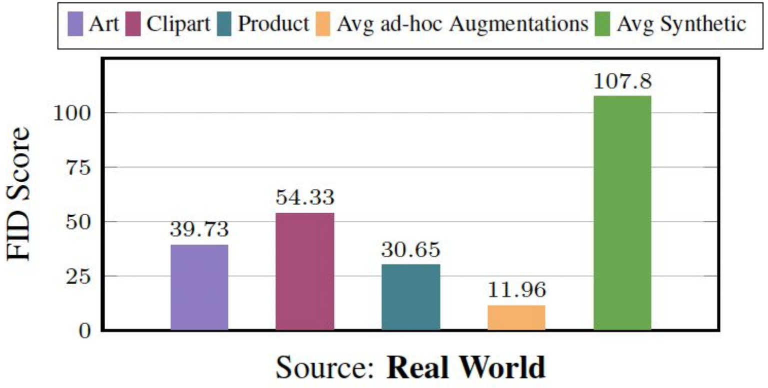
- Uses a **pre-trained diffusion model** (Instruct-Pix2Pix).
- Controlled via **text prompts** to create variations while **preserving semantics**.

Domain Variations Introduced

- **Texture:** Snowy, rainy, foggy conditions.
- **Lighting:** Night-time, low-light scenarios.
- **Environment:** Forest, beach, urban backgrounds.

Example Prompt

- *"Add snowy weather to the image."*



Episodic Training Strategy

Algorithm 1 Proposed Episodic Training Strategy for Updating θ_{global}

Require: Pre-trained global model parameters θ^0_{global}, number of global updates n_g, number of episodes per global update n_e, source domain $\mathcal{D}^{e_g}_{\mathcal{S}}$, synthetic domain $\mathcal{D}^{e_g}_{\text{syn}}$, validation domain $\mathcal{D}_{\text{valid}}$ in the e_g^{th} episode.

Ensure: Final global model $\theta^{n_g}_{\text{global}}$.

for $g = 1$ to n_g **do** ▷ Global updates

  Randomly shuffle synthetic domains $\mathcal{D}^{e_g}_{\text{syn}}$.

  for each episode $e = 1$ to n_e **do** ▷ Episode training

    Initialize task model parameters $\theta^{e_g}_{\text{local}} \leftarrow \theta^{g-1}_{\text{global}}$.

    Train task model $\theta^{e_g}_{\text{local}}$ on $(\mathcal{D}^{e_g}_{\mathcal{S}}, \mathcal{D}^{e_g}_{\text{syn}})$ for the CD-GCD task.

    Compute task vector δ^e_g (Equ. 1 in main text) :

$$\delta^e_g = \theta^{g-1}_{\text{global}} - \theta^{e_g}_{\text{local}}$$

    Validate task model on $\mathcal{D}_{\text{valid}}$ and compute accuracies: `All`, `Old`, `New`.

  end for

  Compute weights w^e_g using softmax on `All` accuracies (Equ. 2 in main text) :

$$w^e_g = \frac{\exp(\texttt{All}^e_g)}{\sum_{e'=1}^{n_e} \exp(\texttt{All}^{e'}_g)}$$

  Update global model θ^g_{global} (Equ. 3 in main text) :

$$\theta^g_{\text{global}} = \theta^{g-1}_{\text{global}} - \sum_{e=1}^{n_e} w^e_g \delta^e_g$$

end for

Save the final global model: $\theta^{n_g}_{\text{global}}$.

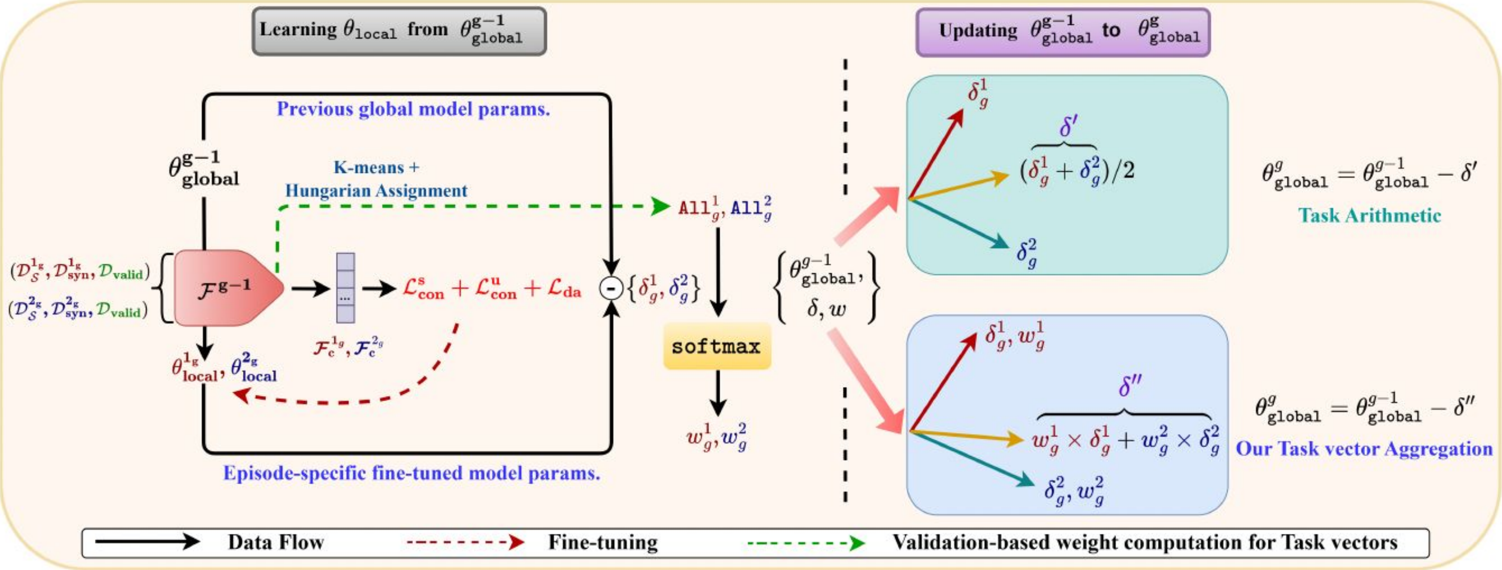


Figure 4. **Transition from $\theta^{g-1}_{\text{global}}$ to $\theta^{g}_{\text{global}}$ in our training strategy:** The **left panel** illustrates the two-way episodic training process. Starting with episode-specific datasets $(\mathcal{D}_{\mathcal{S}}^{1_g}, \mathcal{D}_{\text{syn}}^{1_g})$ and $(\mathcal{D}_{\mathcal{S}}^{2_g}, \mathcal{D}_{\text{syn}}^{2_g})$, we fine-tune the previous global model $\mathcal{F}^{g-1}$ together with episode-specific adversarial classifiers $\mathcal{F}_c^{1_g}$ and $\mathcal{F}_c^{2_g}$ on the local CD-GCD tasks. This produces fine-tuned models with updated weights $\theta^{1_g}_{\text{local}}$ and $\theta^{2_g}_{\text{local}}$. We calculate the task vectors (δ_g^1, δ_g^2) for the fine-tuned models. GCD generalization is subsequently assessed on $\mathcal{D}_{\text{valid}}$ using the `All` metric, resulting in generalization weights (w_g^1, w_g^2) for the fine-tuned models. The **right panel** shows how the global models are updated through task vector aggregations for baseline TA [18] and ours. **Red** and **Blue** denote the episodes-specific data/processing.

CD-GCD Objectives

Loss Functions
To achieve the objective, three key loss components are used:

1. Supervised Contrastive Loss

$$\mathcal{L}_{\text{con}}^{s} = -\mathbb{E}_{(x,y)\sim\mathcal{P}(\mathcal{D}_{\mathcal{S}}^{eg})} \log \frac{\exp\left(\cos(\mathcal{F}^{g-1}(x), \mu^{y})/\tau\right)}{\sum_{y'\in\mathcal{Y}_s^{eg}} \exp\left(\cos(\mathcal{F}^{g-1}(x), \mu^{y'})/\tau\right)}$$

- Operates on **source domain** labeled data.
- Encourages samples from the same class to cluster together while separating different classes.

2. Unsupervised Contrastive Loss

$$\mathcal{L}_{\text{con}}^{u} = \mathbb{E}_{x\sim\mathcal{P}(\mathcal{D}_{\mathcal{S}}^{eg}\cup\mathcal{D}_{\text{syn}}^{eg})} - \log \frac{\exp\left(\cos(\mathcal{F}^{g-1}(x), \mathcal{F}^{g-1}(x^{+}))/\tau\right)}{\sum_{x'\in\mathcal{B}} \exp\left(\cos(\mathcal{F}^{g-1}(x), \mathcal{F}^{g-1}(x'))/\tau\right)}$$

- Operates on **source + synthetic domains** without labels.
- Maximizes similarity between an image and its augmentation while minimizing similarity with other images in the batch.

3. Domain-Alignment Loss

$$\mathcal{L}_{\text{da}} = \mathcal{L}_{\text{adv}} + \lambda\mathcal{L}_{\text{margin}}$$

- Aligns features between the **source** and **synthetic domains** while distinguishing **novel classes**.
- Consists of:
  - **Open-set Adversarial Loss**: Separates novel samples from known classes.
  - **Margin Loss**: Enforces confidence in known-class predictions while pushing unknown samples away.

$$\mathcal{L}_{\text{margin}} = \mathbb{E}_{x\in\mathcal{P}(\mathcal{D}_{\text{syn}}^{eg})} \max\left(0,\ m - \left|\max(p(x)) - \left(1 - \sum_{q=1}^{|\mathcal{Y}_s^{eg}|} p_q(x)\right)\right|\right)$$

F(x): Feature extractor.
μ_y: Class center.
τ: Temperature parameter.
x+: Augmented version of x

Experiments – Datasets

We evaluate DG²CD-Net on **three benchmark datasets** commonly used for Domain Generalization (DG) and Generalized Category Discovery (GCD):

Dataset	Domains	Samples	Classes
PACS	Art, Cartoon, Photo, Sketch	9991	7
Office Home	Art, Clipart, Product, Real World	15588	65
Domain Net	Clipart, Infograph, Painting, Quickdraw, Real World, Sketch	586575	345

Dataset Details

Class Distribution

- **Known-to-Novel Class Ratios:**
  - **PACS**: 4 : 3
  - **Office-Home**: 40 : 25
  - **Domain Net**: 250 : 95

Synthetic Domain Generation

- For each dataset, **9 synthetic domains** were generated:
  - **6 for training** (e.g., Snow, Rain, Night).
  - **3 for validation** (e.g., Urban, Gray, Summer).

A quick peek at Synthetic Domains

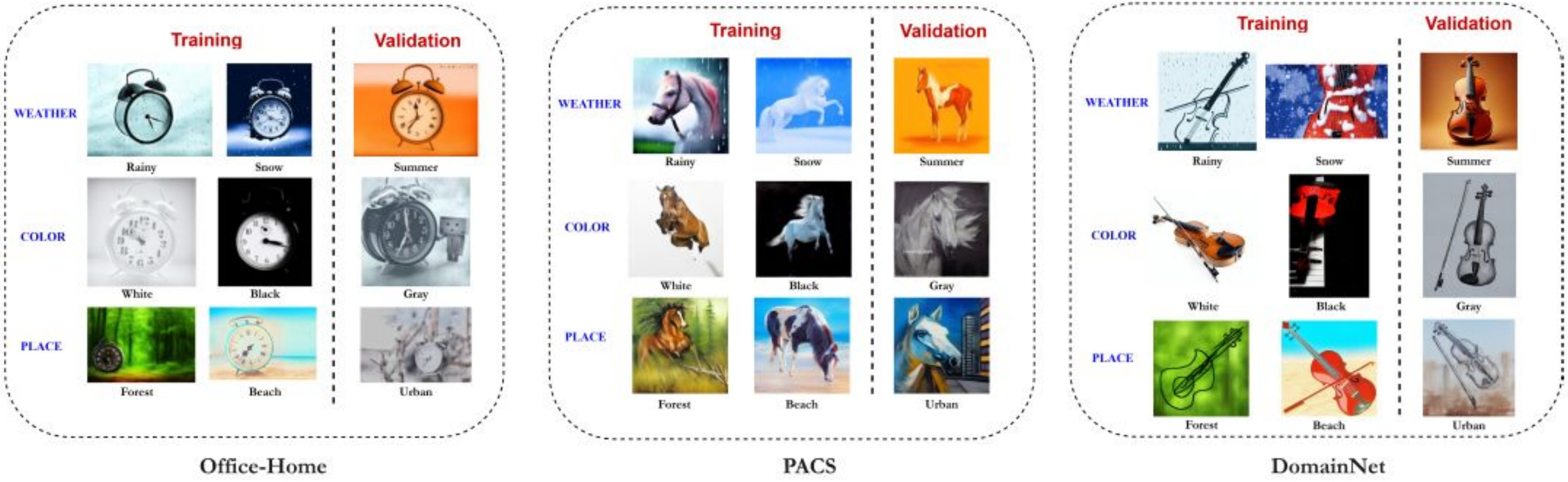


Figure 1. Categorization of synthetic domains utilized in the training and validation phases. Training domains are designed to simulate diverse conditions such as weather, color, and place variations. Validation domains challenge the model's adaptability to new, complex scenarios.

Results

Evaluation Metrics

1. **All**: Overall clustering accuracy across **both known and novel classes**.
2. **Old**: Accuracy for known classes in the target domain.
3. **New**: Accuracy for novel classes discovered in the target domain.

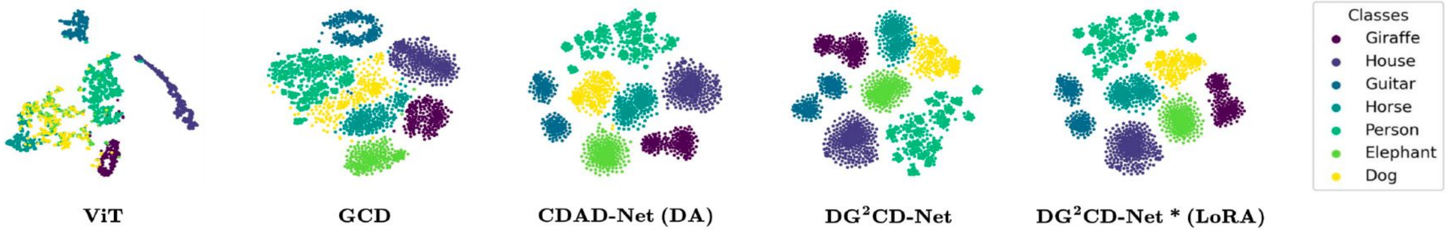


Figure 5. **t-SNE [39] visualizations** of the target domain ("Photo") clusters, as produced by pre-trained ViT, GCD [41], CDAD-Net(DA) [33], DG^{2}CD-Net and DG^{2}CD-Net* (LoRA) for the PACS dataset, with "Sketch" as the source domain. Both the variants of DG^{2}CD-Net are able to produce a clean and compact embedding space.

Methods	Venue	Synthetic-Domains	PACS			Office-Home			DomainNet			Average		
			All	Old	New	All	Old	New	All	Old	New	All	Old	New
ViT [10]	*ICLR'21*	✗	41.98	50.91	33.16	26.17	29.13	21.62	25.35	26.48	22.41	31.17	35.51	25.73
GCD [41]	*CVPR'22*	✗	52.28	62.20	38.39	52.71	54.19	50.29	27.41	27.88	26.13	44.13	48.09	38.27
SimGCD [52]	*ICCV'23*	✗	34.55	38.64	30.51	36.32	49.48	13.55	2.84	2.16	3.75	24.57	30.09	15.94
CMS [8]	*CVPR'24*	✗	28.95	28.13	36.80	10.02	9.66	10.53	2.33	2.40	2.17	13.77	13.40	16.50
CDAD-Net [33]	*CVPR-W '24*	✗	69.15	69.40	68.83	53.69	57.07	47.32	24.12	23.99	24.35	48.99	50.15	46.83
SODG-NET [2]	*WACV'24*	✗	37.43	40.28	28.38	36.53	49.42	14.58	27.77	27.98	26.15	33.91	39.23	23.04
GCD with Synthetic [41]	*CVPR'22*	✓	65.33	67.10	64.42	50.50	51.48	48.96	24.71	24.80	21.94	46.85	47.78	45.11
SimGCD with Synthetic [52]	*ICCV'23*	✓	39.76	43.76	35.97	35.57	48.58	12.89	2.71	1.99	4.14	26.01	31.44	17.67
CMS with Synthetic [8]	*CVPR'24*	✓	28.01	26.71	29.04	12.09	12.66	11.13	3.22	3.28	3.03	14.44	14.22	14.40
CDAD-Net with Synthetic [33]	*CVPR-W '24*	✓	60.76	61.67	59.49	53.49	56.90	47.76	23.85	23.88	24.26	46.03	47.47	43.84
DAML [36]	*CVPR '21*	✗	40.26	42.90	29.28	36.20	49.53	14.06	27.10	28.25	26.16	34.52	40.23	23.17
DG^2CD-Net with TIES-Merging [58]		✓	67.04	71.25	64.02	53.52	57.12	48.03	28.72	30.35	24.39	49.76	52.91	45.48
DG^2CD-Net with baseline TA[18]		✓	71.02	73.44	68.01	52.63	52.41	52.69	28.12	29.58	24.42	50.59	51.81	48.37
DG^2CD-Net (Ours)		✓	73.30	75.28	72.56	53.86	53.37	54.33	29.01	30.38	25.46	52.06	53.01	50.78
DG^2CD-Net* (Ours) [LoRA [17]]		✓	75.21	76.31	75.28	54.32	53.03	56.03	27.17	27.61	25.99	52.23	52.32	52.43
CDAD-Net (DA) [33] [Upper bound]		✗	83.25	87.58	77.35	67.55	72.42	63.44	70.28	76.46	65.19	73.69	78.82	68.66

Table 2. **Performance comparison** across three datasets, averaged over all domain combinations. We baseline with two versions of existing GCD and CD-GCD methods: one trained solely on $\mathcal{D}_S$ and another on $\mathcal{D}_S \cup \mathcal{D}_{syn}$, both without target-specific loss functions to simulate the DG scenario. Subsequently, multiple model aggregation strategies are evaluated for DG^2CD-Net. As an upper bound, we include the full CDAD-Net, designed for the transductive DA setting. Red cells highlight the top results; yellow is the second-best.

Dataset	PACS	Office-Home	DomainNet
Ground Truth	7	65	345
CDAD-Net (DG)	12	60	362
CDAD-Net (DA)	7	66	349
Ours	7	67	355

Table 2. **Estimation of cluster numbers** in target domains showcases DG^{2}CD-Net's effectiveness in achieving near-optimal clustering, beating other DG counterparts, and closely matching CDAD-Net (DA) performance.

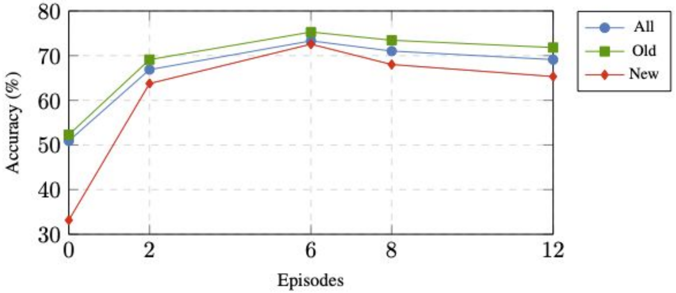


Figure 7. Charting the relationship between **number of episodes and model accuracy** on PACS, this graph shows accuracy peaks at 6 episodes, which is majorly consistent across all the datasets.

Ablation Studies and Analysis

Model Variant	PACS		
	All	Old	New
(i) With manual augmentations based $\mathcal{D}_{\text{syn}}$	63.92	62.09	67.06
(ii) Without synthetic domain	50.91	52.28	33.16
(iii) Without multi-global updates	66.70	67.52	66.39
(iv) Static known/novel class split across episodes	68.60	69.70	66.13
(v) Conventional normalization for w_g^es in Eq. 2	61.98	69.77	54.43
(vi) Episode specific $\mathcal{D}_{\text{valid}}$	69.26	73.34	65.15
(vii) Replacing our CD-GCD losses with those of [33]	69.82	74.00	66.23
(viii) DG^{2}CD-Net with Fisher-merging [26]	71.67	74.42	70.03
Full DG^{2}CD-Net	**73.30**	**75.28**	**72.56**

Table 4. Performance metrics demonstrating the **influence of key model components** of DG^{2}CD-Net for PACS.

Configurations	$\mathcal{L}^s_{con}$	$\mathcal{L}^u_{con}$	$\mathcal{L}_{adv}$	$\mathcal{L}_{margin}$	PACS		
					All	Old	New
C-0	✗	✗	✗	✗	41.98	50.91	33.16
C-1	✓	✗	✗	✗	60.63	65.15	54.63
C-2	✗	✓	✗	✗	67.84	68.92	66.17
C-3	✓	✓	✗	✗	68.70	69.52	67.61
C-4	✓	✗	✓	✗	64.16	66.10	60.81
C-5	✗	✓	✓	✗	69.22	69.20	69.34
C-6	✓	✓	✓	✗	71.45	72.92	70.33
C-7	✓	✓	✓	✓	**73.30**	**75.28**	**72.56**

Table 5. Impact of **loss components** of DG^{2}CD-Net on PACS.

Effect of Initialization of backbone

Model	Backbone	PACS		
		All	Old	New
ResNet-50	CLIP [17]	25.39	20.97	29.33
ResNet-50	ImageNet [8]	54.98	64.18	45.33
ViT-B/16	DINO [1]	73.30	75.28	72.56
ViT-B/16	DINO-v2 [14]	87.71	90.67	84.91
ViT-B/16	CLIP [17]	90.07	92.25	87.72

Table 12. Performance Comparison of DG^2CD-Net with different backbones on the PACS Dataset

Effect of LoRA Fine-Tuning

Method	Trainable Parameters (K)	Total Parameters (K)	Percentage (%)
DG^{2}CD-Net (Vanilla)	7,088	85,799	8.261
DG^{2}CD-Net* (LoRA)	98	85,799	0.115

Table 13. Comparison of model parameters *with* and *without* LoRA fine-tuning.

Adapters	All (%)
LoRA [10]	75.21
DoRA [13]	74.11
AdaLoRA [25]	74.20

Table 14. Performance comparison of DG^{2}CD-Net with different LoRA Adapters

Detailed Results

PACS																		
Methods	**Art Painting → Sketch**			**Art Painting → Cartoon**			**Art Painting → Photo**			**Photo → Art Painting**			**Photo → Cartoon**			**Photo → Sketch**		
	All	Old	New	All	Old	New	All	Old	New	All	Old	New	All	Old	New	All	Old	New
ViT [4]	37.44	50.73	19.5	47.4	61.3	35.25	76.05	87.13	64.64	53.17	77.31	31.67	47.01	55.54	39.57	31.87	37.57	24.16
GCD [20]	32.02	41.53	19.12	46.78	60.35	28.57	79.16	99.45	48.73	74.73	80.26	67.31	57.53	60.46	53.6	46.23	48.56	43.08
SimGCD [23]	29.35	17.3	62.12	23.08	28.26	16.32	51.98	74.44	33.26	46.29	48.96	43.17	34.26	44.91	20.35	24.84	31.88	5.68
CDAD-Net [18]	46.02	45.95	46.21	51.71	53.43	49.46	99.04	99.21	98.9	76.61	76.97	76.19	56.78	56.67	56.93	46.65	46.15	48.01
GCD With Synthetic	45.78	36.71	58.01	54.84	73.47	38.57	82.6	66.29	99.39	79	86.84	72.02	53.56	67.93	41.01	44.18	47.78	39.32
CDAD-Net with Synthetic	43.09	42.53	44.6	49.45	59.31	36.58	99.16	99.21	99.12	65.38	62.83	68.36	42.92	41.97	44.15	41.51	43.79	35.32
DG^{2}CD-Net (TIES-Merging[24])	41.31	40.56	42.31	45.69	57	35.81	96.11	97.87	94.29	62.87	87.72	40.72	48.98	60.02	39.33	44.1	36.33	54.58
DG^{2}CD-Net [TA[11]]	46.4	51.3	42.8	56.21	58.82	52.7	99.2	99.5	98.8	81.47	91.09	68.57	57.76	56.11	59.99	46.88	48.96	44.06
DG^{2}CD-Net (Ours)	46.79	38.13	58.49	57.96	73.38	44.48	99.34	99.7	98.97	86.67	91.87	82.04	62.97	71.18	55.8	45.72	36.53	58.13
DG^{2}CD-Net * (Ours)[LoRA[10]]	46.83	37.79	59.03	63.82	71.13	57.43	99.46	99.35	99.57	88.89	93.94	84.4	64.19	72.23	57.15	46.45	37.75	58.19
Methods	**Sketch → Art Painting**			**Sketch → Cartoon**			**Sketch → Photo**			**Cartoon → Art Painting**			**Cartoon → Sketch**			**Cartoon → Photo**		
	All	Old	New	All	Old	New	All	Old	New	All	Old	New	All	Old	New	All	Old	New
ViT [4]	23.93	26.53	21.61	40.61	58.92	24.62	33.29	33.88	32.69	38.09	47.36	29.82	33.57	35.67	30.74	41.38	39.08	43.74
GCD [20]	33.25	39.09	25.43	40.89	48.14	31.17	46.86	59.28	28.22	58.15	78.52	30.86	36	44.83	24.04	75.75	85.88	60.55
SimGCD [23]	21.19	31.91	8.67	23.17	36.77	5.4	34.22	27.46	40.8	38.38	42.07	34.07	34.84	33.94	37.31	53.05	45.85	59.06
CDAD-Net [18]	87.99	84.32	92.28	51.88	51.77	52.02	99.04	99.21	98.9	73.05	76.88	68.57	41.84	42.71	39.49	99.22	99.47	99.01
GCD With Synthetic	82.15	85.13	79.5	44.3	48.22	40.89	99.49	99.76	99.21	63.01	63.73	62.37	35.66	29.95	43.36	99.43	99.47	99.39
CDAD-Net with Synthetic	61.91	69.45	53.12	48.59	53.13	42.67	68.44	63.5	72.56	67.24	65.28	69.52	42.05	39.61	48.67	99.34	99.47	99.23
DG^{2}CD-Net (TIES-Merging[24])	80.59	80.78	80.42	58.94	75.71	44.28	99.07	98.64	99.51	87.45	90.93	84.35	40.67	31.39	53.2	98.71	97.99	99.45
DG^{2}CD-Net (TA[11])	73.02	79.37	64.51	55.89	54.84	57.29	99.31	99.5	99.03	90.89	92.75	88.4	46.03	49.67	41.1	99.16	99.35	98.88
DG^{2}CD-Net (Ours)	88.75	93.52	84.49	56.76	72.14	43.33	99.13	98.7	99.57	90.77	93.37	88.46	49.2	43.18	57.33	95.57	91.62	99.64
DG^{2}CD-Net * (Ours)[LoRA[10]]	90.87	95.28	86.93	66.25	78.32	55.72	99.22	98.88	99.57	91.02	93.99	88.37	46.33	38.19	57.33	99.22	98.82	99.64

Table 5. Detailed comparison of our proposed DG^{2}CD-Net on DG-GCD with respect to referred literature for PACS Dataset.

Detailed Results

Office-Home

Methods	Art → Clipart			Art → Product			Art → Real World			Clipart → Art			Clipart → Real World			Clipart → Product		
	All	Old	New	All	Old	New	All	Old	New	All	Old	New	All	Old	New	All	Old	New
ViT [4]	18.88	20.86	15.79	30.34	35.42	21.83	29.52	32.76	24.85	14.96	15.6	14.12	18.59	20.12	16.4	30.39	32.51	26.84
GCD [20]	31.65	32.11	30.93	63.18	64.35	61.22	63.85	66.56	59.96	51.96	52.7	51	62.62	65.29	58.79	60.59	67.13	49.61
SimGCD [23]	24.54	34.35	8.09	41.95	57.92	13.54	46.78	65.54	14.73	31.11	39.56	11.88	25.66	37.66	5.15	28.88	41.38	12.96
CDAD-Net [18]	30.95	33.65	26.43	64.99	68.04	59.32	67.5	70.89	61.72	53.36	56.05	47.23	64.7	69.4	55.25	67.02	68.8	63.7
GCD With Synthetic	29.86	31.04	28.02	57.92	63.12	49.19	59.47	59.59	59.29	53.3	52.84	53.89	61.46	58.27	66.06	63.84	64.04	63.51
CDAD-Net with Synthetic	31.97	35.1	26.71	65.39	68.94	62.51	67.83	70.87	62.64	53.51	56.65	46.37	66.97	69.76	62.2	61.4	65.55	57.4
DG^{2}CD-Net (TIES-Merging[24])	33.96	37	29.23	59.99	62.93	55.07	66.26	68.42	63.15	52.18	52.3	52.04	58.16	58.62	57.5	65.32	72.33	53.56
DG^{2}CD-Net [TA[11]]	29.52	27.31	33.06	62.42	61.67	63.59	64.46	62.14	67.8	51.24	53.32	47.12	64.23	61.24	68.92	65.28	66.03	64.13
DG^{2}CD-Net (Ours)	31.51	31.96	30.81	67.46	68.73	65.32	64.45	60.25	70.48	50.76	48.76	53.36	64.77	60.58	70.79	65.34	67.48	61.76
DG^{2}CD-Net (Ours)[LoRA [10]]	31.56	31.85	31.1	65.22	65.68	64.45	67.81	65.14	71.66	53.4	48.47	59.81	66.13	61.63	72.61	66.16	67.12	64.57

Methods	Product → Art			Product → Real World			Product → Clipart			Real World → Art			Real World → Product			Real World → Clipart		
	All	Old	New	All	Old	New	All	Old	New	All	Old	New	All	Old	New	All	Old	New
ViT [4]	23.2	24.64	21.33	31.21	35.45	25.13	19.27	20.52	17.31	32.22	35.79	27.58	44.67	52.21	32.03	20.8	23.71	16.26
GCD [20]	50.27	48.18	52.99	65.07	63.09	67.91	29.08	29.22	28.87	54.26	54.05	54.55	69.04	72.76	62.79	31.04	34.93	24.97
SimGCD [23]	38.28	50.42	10.66	48.36	67.07	16.41	22.45	32.37	11.34	48.95	66.79	8.36	57.19	69.23	44.15	21.7	31.46	5.33
CDAD-Net [18]	50.1	52.43	44.67	66.47	72.13	56.81	31.36	34.6	25.94	54.68	58.07	46.96	61.39	64.79	55.06	31.78	36.02	24.69
GCD With Synthetic	49.18	46.54	52.61	63.4	59.67	68.77	28.43	27.72	29.55	51.71	61.55	38.91	61.14	65.34	54.1	26.38	28.11	23.68
CDAD-Net with Synthetic	54.12	57.67	46.04	66.97	70.2	61.46	32.34	35.13	28.68	53.72	56.89	46.5	56.47	62.33	45.62	31.19	33.67	27.02
DG^{2}CD-Net (TIES-Merging[24])	53.28	54.77	51.33	62.74	66.85	56.83	31.82	33.97	28.46	57.11	66.14	45.36	67.04	74.25	54.95	34.41	37.94	28.9
DG^{2}CD-Net [TA[11]]	49.92	52.33	45.17	65.57	67.22	62.99	31.48	30.21	33.51	51.65	55.06	44.92	65.01	63.73	66.99	30.73	28.65	34.08
DG^{2}CD-Net (Ours)	52.45	50.51	54.98	67.87	69.88	64.97	30.71	30.05	31.75	52.31	49.42	56.07	67.37	71.65	60.19	31.28	31.13	31.51
DG^{2}CD-Net * (Ours)[LoRA[10]]	52.66	51.75	53.84	65.48	62	70.48	31.52	31.83	31.04	53.42	51.6	55.78	66.33	68.97	61.91	32.26	30.4	35.15

Table 6. Detailed comparison of our proposed DG^{2}CD-Net on DG-GCD with respect to referred literature for Office-Home Dataset

Detailed Results

DomainNet															
Methods	Sketch → Real			Sketch → Quickdraw			Sketch → Infograph			Sketch → Painting			Sketch → Clipart		
	All	Old	New	All	Old	New	All	Old	New	All	Old	New	All	Old	New
ViT [4]	47.17	47.92	44.95	12.13	12.1	12.21	11.99	12.68	10.28	30.95	33.02	25.75	32.64	34.29	28.64
GCD [20]	51.13	51.88	48.92	16.08	15.65	17.2	12.6	12.57	12.68	35.25	35.96	33.46	31.22	30.85	32.1
SimGCD [23]	3.11	3.47	2.32	2.31	2.4	2.1	3.16	2.27	5.24	4.1	2.57	5.62	3.02	2.3	4.07
CDAD-Net [18]	48.21	47.7	49.77	12.27	11.52	14.24	12.07	12.69	11.34	35.47	36.39	32.86	18.63	17.52	20.39
GCD With Synthetic	53	51.71	47.64	13.71	13.79	13.99	12.24	11.99	11.37	35.43	34.12	30.83	22.49	22.2	21.49
CDAD-Net with Synthetic	47.11	46.09	49.4	12.75	13.1	14.05	12.52	13.04	11.92	35.87	36.73	33.35	18.99	17.68	21.07
DG^2CD-Net (TIES-Merging[24])	50.32	52.88	42.8	15.22	15.12	15.49	14.75	16.04	11.53	35.84	38.99	27.93	31.06	33.34	25.53
DG^2CD-Net [TA[11]]	51.84	52.58	49.65	13.67	13.44	14.25	12.72	13.05	11.89	33.96	35.32	30.55	21.94	21.8	22.29
DG^2CD-Net (Ours)	53.67	55.48	48.35	15.9	16	15.63	14.63	15.66	12.06	37.44	39.53	32.19	30.47	32.89	24.58
DG^2CD-Net * (Ours)[LoRA[10]]	53.01	53.75	50.84	13.71	13.38	14.57	13.82	14.23	12.78	36.77	37.9	33.93	24.17	24.46	23.44

Methods	Clipart → Infograph			Clipart → Quickdraw			Clipart → Sketch			Clipart → Real			Clipart → Painting		
	All	Old	New	All	Old	New	All	Old	New	All	Old	New	All	Old	New
ViT [4]	12.18	12.64	11.03	12.13	12.1	12.21	24.76	26.24	21.27	44.14	45.43	40.34	26.76	28.7	21.91
GCD [20]	14.03	14.64	12.49	14.94	14.67	15.65	25.33	27.68	19.78	53.23	55.48	46.62	34.82	36.82	29.83
SimGCD [23]	2.03	0.4	3.94	0.5	0.3	1	1	0.02	3.842	1.64	1.07	2.42	2.07	2.05	2.13
CDAD-Net [18]	12.79	12.96	12.87	12.06	11.59	12.78	19	19.17	18.76	47.06	44.62	49.2	34.45	36.02	32.85
GCD With Synthetic	11.46	12.03	10.04	12.68	12.57	12.95	18.74	20.54	14.47	50.11	52.26	43.79	32.67	34.91	27.06
CDAD-Net with Synthetic	13	13.37	12.56	12.07	11.76	12.89	17.46	18.03	16.67	48.25	47.51	49.6	33.23	32.79	34.2
DG^2CD-Net (TIES-Merging[24])	15.66	17.02	12.28	14.91	14.73	15.39	27.75	30.64	20.89	54.18	56.73	46.72	36.71	38.14	33.16
DG^2CD-Net [TA[11]]	15.71	16.88	12.78	14.63	14.18	15.81	27.03	29.89	20.26	53.91	55.14	50.29	36.85	39.69	29.75
DG^2CD-Net (Ours)	15.81	17.09	12.63	14.53	14.14	15.58	26.86	29.49	20.64	54.54	56.03	50.17	36.81	38.87	31.67
DG^2CD-Net * (Ours)[LoRA[10]]	14.19	14.12	14.35	13.31	13.23	13.53	22.01	22.9	19.91	53.95	54.99	50.91	37.12	37.89	35.21

Methods	Painting → Infograph			Painting → Quickdraw			Painting → Sketch			Painting → Real			Painting → Clipart		
	All	Old	New	All	Old	New	All	Old	New	All	Old	New	All	Old	New
ViT [4]	12.2	13.1	9.94	12.13	12.1	12.21	23	24.78	18.79	51.53	54.16	43.8	26.57	28.08	22.92
GCD [20]	12.87	12.67	13.37	10.74	10.56	11.21	21.49	22.26	19.68	52.12	51.86	52.86	25.32	24.79	26.6
SimGCD [23]	3.2	2.6	3.8	3.5	2.32	4.65	4.23	3.56	4.86	4.2	3.52	5	4.49	3.6	5.23
CDAD-Net [18]	11.65	12.49	10.66	11.98	11.2	12.44	17.11	17.68	16.32	49.04	48.63	50.27	20.06	19.74	20.57
GCD With Synthetic	10.86	10.56	9.84	11.81	11.8	11.77	17.26	16.25	13.83	49.1	47.3	42.04	19.3	19.45	18.04
CDAD-Net with Synthetic	11.53	12.32	10.59	11.86	10.71	12.32	17.29	18.45	15.7	48.4	50.23	49.7	17.44	15.92	19.86
DG^2CD-Net (TIES-Merging[24])	15.34	16.64	12.13	12.89	12.64	13.58	23.45	25.6	18.38	55.16	57.3	47.46	27.5	29.48	22.65
DG^2CD-Net [TA[11]]	15.17	16.52	11.8	12.78	12.58	13.29	23.21	25.69	17.34	55.16	57.31	48.87	26.76	27.91	23.96
DG^2CD-Net (Ours)	15.71	16.72	13.22	12.9	12.66	13.53	23.14	25.23	18.19	55.07	56.97	49.5	27.6	29.07	24.03
DG^2CD-Net * [Ours)[LoRA[10]]	14.41	14.68	13.74	12.9	12.9	12.91	21.39	22.39	19.03	53.83	54.99	50.44	22.94	22.41	24.24

Table 7. Detailed comparison of our proposed DG^2CD-Net on DG-GCD with respect to referred literature for DomainNet Dataset

Summary:

- **Problem Addressed:** Existing GCD methods struggle with unseen target domains and distribution shifts, limiting their real-world applicability.
- **Proposed Solution:** DG^{2}CD-Net leverages episodic training, adaptive task-arithmetic, and robust feature learning to improve domain generalization and novel class discovery.
- **Key Impact:** Enables AI models to effectively cluster known and novel categories in unseen domains, ensuring adaptability without prior exposure to target data.

Limitations and Future Work

- **Reliance on synthetic domain generation**
  - Effective but computationally expensive
  - Needs optimization for better efficiency
- **High computational cost of episodic training**
  - Especially for large-scale datasets like **Domain Net**
  - Limits feasibility in real-world applications

Future Enhancements

- **Optimize synthetic domain generation**
  - Explore streamlined methods or alternatives to synthetic data
- **Improve efficiency of episodic training**
  - Reduce computational resource demands
- **Advanced model merging techniques**
  - Enhance performance and generalization
- **Address real-world challenges**
  - Handle **data imbalance** for better robustness
- **Increase scalability for large-scale applications**
  - Improve adaptability to diverse domains

Questions and feedback are welcome.