HiDISC : A Hyperbolic Framework for Domain Generalization with Generalized Category Discovery

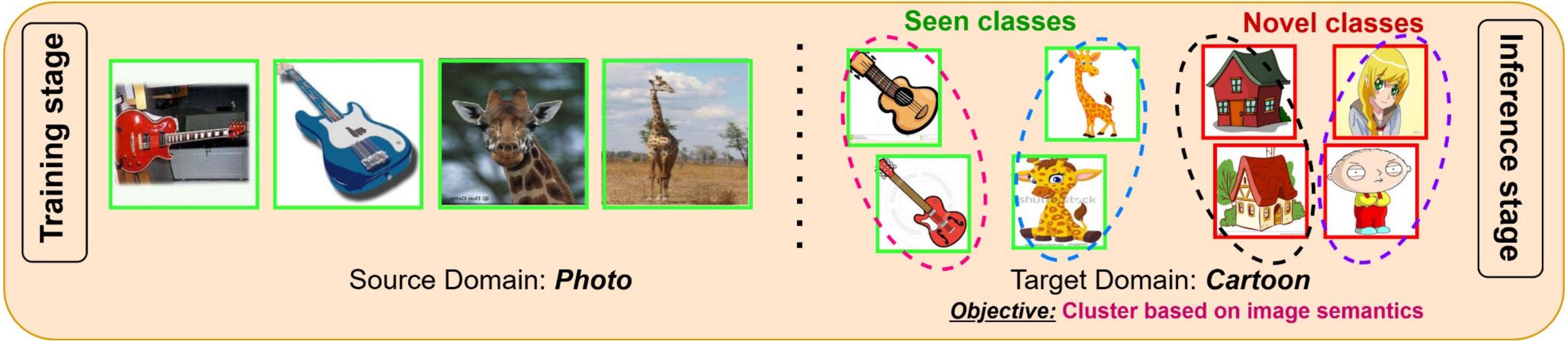
Authors: Vaibhav Rathore, Divyam Gupta , Biplab Banerjee

Paper Status : Accepted (NeurIPS’25) Poster

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.

3. **Limitations :** Euclidean geometry fails to capture **semantic hierarchies** effectively.



Introduction and Motivation

Limitations of Prior Work (DG²CD-Net):

➢ First to address the DG-GCD problem, but suffers from:
  - High computational cost
  - Inefficient feature space geometry (Euclidean space)

Key Insight:

➢ Euclidean space struggles to capture **semantic hierarchies** in visual data.
➢ **Hyperbolic geometry** offers a natural way to model hierarchical relationships.

Our Proposal — HIDISC:

➢ A **hyperbolic-domain framework** for DG-GCD.
➢ Achieves **better cross-domain alignment** and **inter-class separation**.
➢ Eliminates need for **expensive episodic simulation**.
➢ It is designed to answer the central question:

Can hyperbolic geometry provide a unified foundation for solving DG-GCD, addressing both distribution shift and novel-class discovery?

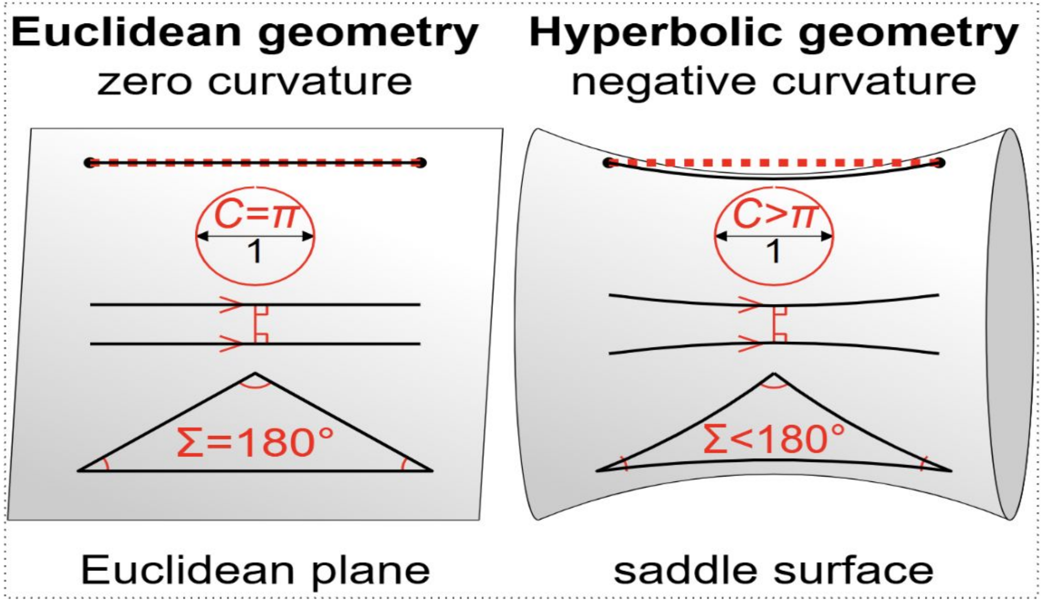
Hyperbolic Geometry

- **Euclidean (or spherical) spaces**, which are commonly used in deep learning, struggle to effectively model the natural **hierarchical relationships** found in visual data
- **Hyperbolic geometry** is a non-Euclidean space defined by **constant negative curvature**. Its most important property is that **volume grows exponentially** with distance from the origin, unlike the polynomial growth in Euclidean space
- This exponential capacity is highly beneficial for the DG-GCD problem because it naturally:
  - **Increases separation** between different class clusters while keeping same-class samples tightly grouped, even across domains.
  - Encourages better **cross-domain semantic alignment**, as it can represent shared high-level concepts more efficiently.
- In our work, we leverage the **Poincaré Ball model** , a computationally efficient and popular representation of hyperbolic space that is ideal for visualization and learning embeddings

"Learning in Hyperbolic Spaces"

Major Difference b/w Euclidean and Hyperbolic space:

Curvature - measure of how much a surface or space deviates from being flat.



Source: https://www.clearhat.org/post/yes-hyperbolic-geometry-does-describe-inside-sphere

Why chose the Poincaré Ball Model ?

NEURAL INFORMATION PROCESSING SYSTEMS

Poincaré geometry grows *exponentially* with radius

Key Advantages:

- **Hierarchical representation:** Small radial moves = large semantic jumps.
- **Conformal mapping:** Preserves local angles → maintains local feature relationships.
- **Compact embeddings:** Represents complex hierarchies in low dimensions.
- **Efficient distance computation:** Closed-form formula enables fast learning.

In the **Poincaré ball**,

- the **center** holds general classes,
- the **boundary** holds specific ones.

Poincaré Ball Geometry

Definition. The n-dimensional Poincaré ball[1] of curvature $-c^2$:

$$\mathbb{D}_c^n = \{\, x \in \mathbb{R}^n : c\,\|x\|^2 < 1 \,\}, \qquad \|x\| = \sqrt{x^\top x}.$$

Möbius Addition. For $a, b \in \mathbb{D}_c^n$:

$$a \oplus_c b = \frac{(1 + 2c\langle a, b\rangle + c\|b\|^2)a + (1 - c\|a\|^2)b}{1 + 2c\langle a, b\rangle + c^2\|a\|^2\|b\|^2}.$$

Geodesic Distance.

$$\mathbb{D}_{\mathbb{H}}(a, b) = \frac{2}{\sqrt{c}} \tanh^{-1}\!\left(\sqrt{c}\,\|-a \oplus_c b\|\right).$$

Exponential / Logarithmic Maps (at Origin).

$$\exp_0^c(u) = \tanh(\sqrt{c}\|u\|)\frac{u}{\sqrt{c}\|u\|}, \quad \log_0^c(x) = \tanh^{-1}(\sqrt{c}\|x\|)\frac{x}{\sqrt{c}\|x\|}.$$

Euclidean Limit. As $c \to 0$:

$$\mathbb{D}_{\mathbb{H}}(a, b) \to 2\|a - b\|, \quad \exp_0^c(u) \to u, \quad a \oplus_c b \to a + b.$$

[1] Maximillian Nickel and Douwe Kiela. Poincaré embeddings for learning hierarchical representations. Advances in neural information processing systems, 30, 2017.

Motivation for Hyperbolic in DG

Models Compared

- **Euclidean-Net:** A shallow MLP operating in Euclidean space.
- **Hyperbolic-Net:** A shallow MLP operating in Hyperbolic space.
- **Fair Comparison:** Both models have identical capacity with **1.12M trainable parameters**.

Training Protocol

- **Training:** Both models are trained from scratch.
- **Loss Function:** Standard **Cross-Entropy Loss**.
- **Schedule:** Unified for both models:
  - **Epochs:** 100
  - **Batch Size:** 128
  - **Learning Rate:** $1 \times 10{-3}$

Table 11: Average test accuracy (%) when training on one source domain and testing on three held-out domains.

Dataset	EuclideanNet	HyperbolicNet	Relative Gain
PACS	12.9	22.3	+72.86%
Office Home	1.96	6.17	+214.79%
Domain Net	0.28	0.96	+ 242.85 %

Motivation for Hyperbolic in DG

Euclidean ($K = 0$):

$$\boxed{V_E(r) = \frac{4}{3}\pi r^3}$$

Spherical ($K = +1/R^2$):

$$\boxed{V_S(r) = 2\pi R^3\left(\frac{r}{R} - \tfrac{1}{2}\sin\left(\tfrac{2r}{R}\right)\right)}$$

Hyperbolic ($K = -1/R^2$):

$$\boxed{V_H(r) = 2\pi R^3\left(\tfrac{1}{2}\sinh\left(\tfrac{2r}{R}\right) - \frac{r}{R}\right)}$$

and in each case $V'(r) = A(r) = 4\pi S_K(r)^2$.

Visualization on Hyperbolic Geometry

- Models **hierarchies** and **semantic similarity** better.
- Improves inter-class separation and intra-class compactness.
- Ideal for open-world generalization.

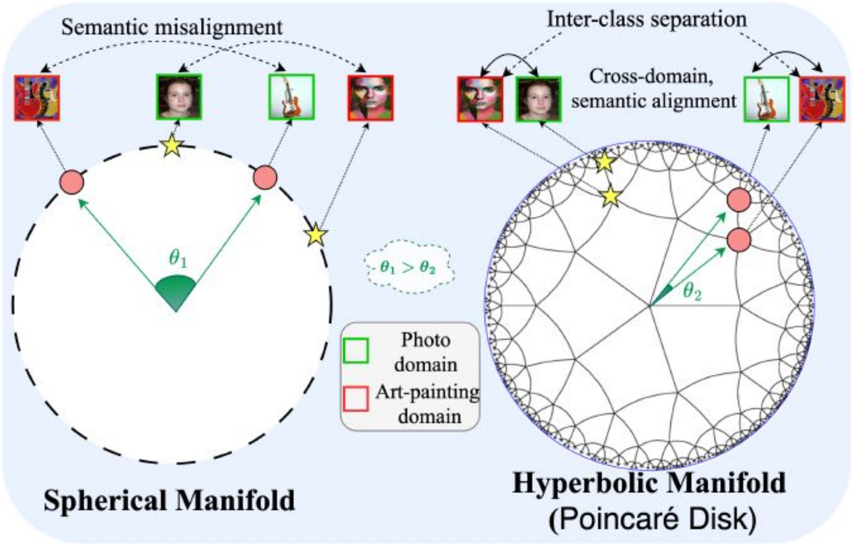


Figure 1: **Spherical** vs. **hyperbolic** (Poincaré) embeddings on PACS. Same-class samples from different domains (green/red) cluster more tightly in hyperbolic space, demonstrating improved class separation. Refer to **Sup. Mat.** for quantitative analysis.

Busemann Learning with Ideal Prototypes

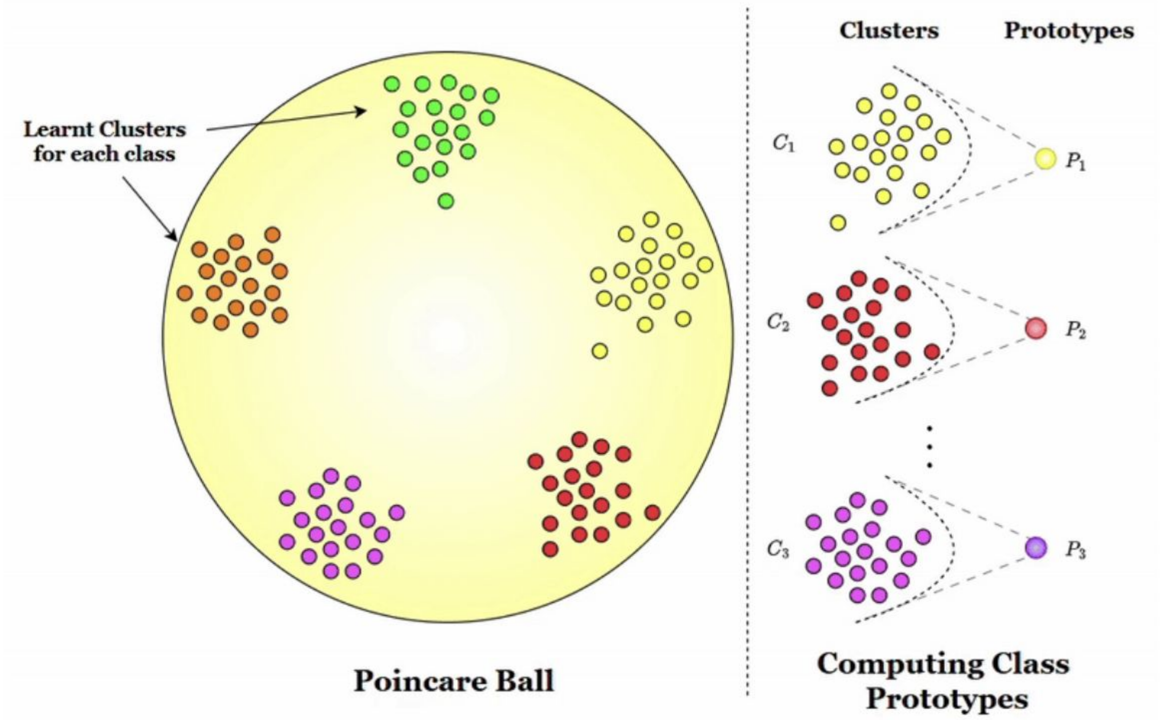


Figure: Class cluster in Poincare ball [1] after training. Ideal Prototypes[2] are put on boundary of the ball.

[1] Maximillian Nickel and Douwe Kiela. Poincaré embeddings for learning hierarchical representations. Advances in neural information processing systems, 30, 2017
[2] Mina Ghadimi Atigh, Martin Keller-Ressel, and Pascal Mettes. Hyperbolic busemann learning with ideal prototypes. Advances in neural information processing systems, 34:103–115, 2021.

HiDISC Overview

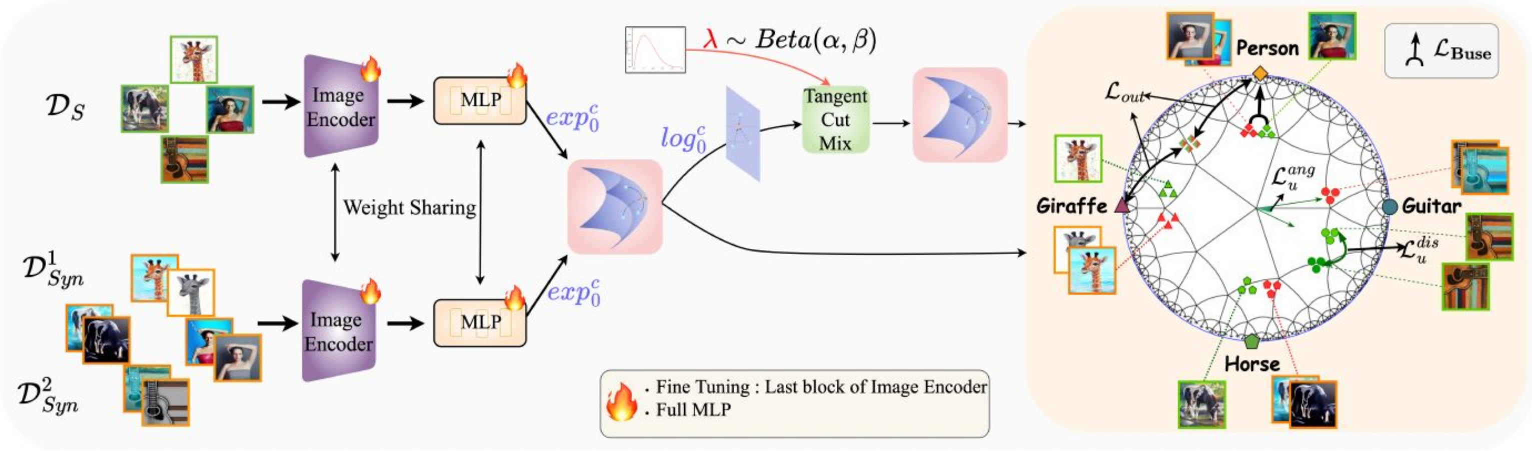
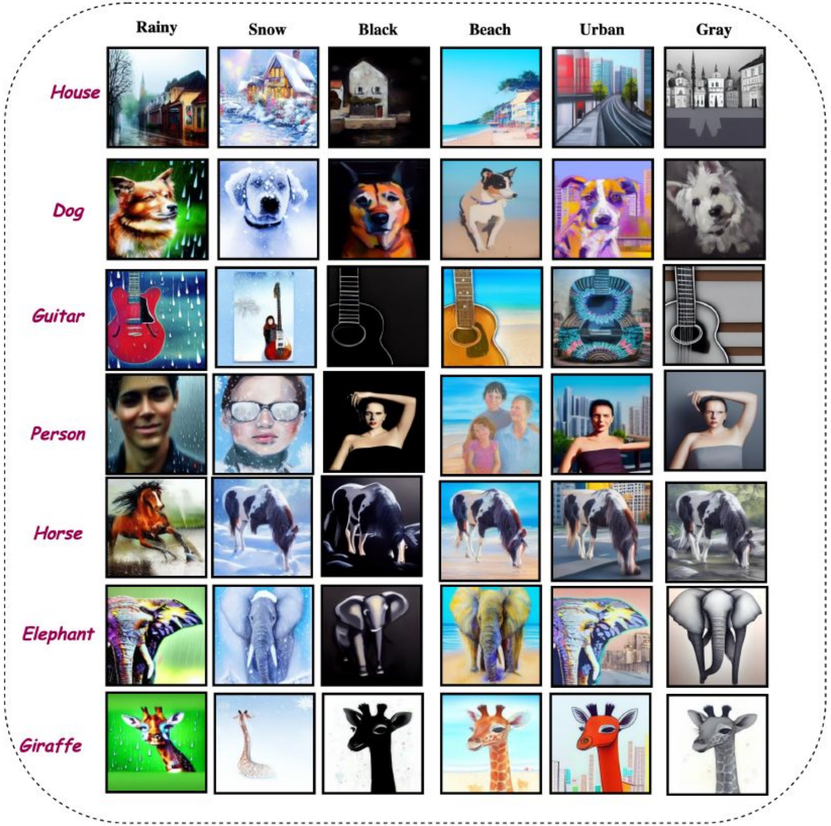


Figure 2: **Illustration of the HIDISC pipeline for DG-GCD in hyperbolic space**. The model is trained using labeled source data $\mathcal{D}_S$ (green borders) and 1–2 GPT-guided synthetic domains $\mathcal{D}^1_{\text{Syn}}$, $\mathcal{D}^2_{\text{Syn}}$ (orange borders) to simulate domain shift. Features from the shared encoder are projected to the Poincaré ball via $\exp_0^c$. To mimic novel categories, Tangent CutMix performs interpolation in the tangent space and maps the result z_{mix} back to hyperbolic space. The embedding space is structured via: (i) penalized Busemann loss $\mathcal{L}_{\text{Buse}}$ for aligning seen classes to boundary-fixed prototypes; (ii) hybrid contrastive loss $\mathcal{L}_u$ for clustering and separability; and (iii) adaptive outlier loss $\mathcal{L}_{\text{out}}$ to repel pseudo-novel points. Together, these shape a curvature-aware space for generalization and discovery.

A quick peek at Synthetic Domains



PACS

Loss Objectives

Loss Functions

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

1. Penalized Busemann Loss

- aligns seen-class features to boundary prototypes.

$$\mathcal{L}_{\text{Buse}} = \log\left(\frac{\|z_i - \mathbf{p}_{y_i}\|^2}{1 - c\|z_i\|^2}\right) + \phi \log(1 - \|z_i\|^2),$$

2. Hybrid Hyperbolic Contrastive Loss

- geodesic + angular similarity.

$$\mathcal{L}_u = \frac{1}{|B|}\sum_{i \in B} -\log \frac{\exp(\delta(z_i'', z_i')/\tau)}{\sum_{j \neq i} \exp(\delta(z_i', z_j)/\tau)},$$

$$\delta(.,.) = \alpha_d \cdot \underbrace{[-\mathbb{D}_{\mathbb{H}}(.,.)]}_{L_u^{dis}} + (1 - \alpha_d) \cdot \underbrace{\cos(.,.)}_{L_u^{ang}},$$

3. Adaptive Outlier Loss

- repels synthetic samples from known class regions.

$$\mathcal{L}_{\text{out}} = \mathop{\mathbb{E}}_{(x,y) \sim \mathcal{P}(\mathcal{D}_{\text{train}})} \sum_{i,j,y_i \neq y_j} \max(0, \gamma - \min_{k \in \mathcal{Y}_s} \mathbb{D}_{\mathbb{H}}(z_{\text{mix}}^{i,j}, \mathbf{p}_k)),$$

$$\mathcal{L}_{\text{total}} = \lambda_1 \underbrace{\mathcal{L}_{\text{Buse}}}_{\text{Semantic alignment}} + \lambda_2 \underbrace{\mathcal{L}_u}_{\text{Contrastive regularization}} + \lambda_3 \underbrace{\mathcal{L}_{\text{out}}}_{\text{Outlier repulsion}}, \quad \text{where } \lambda_1 + \lambda_2 + \lambda_3 = 1.$$

Dataset Details

We evaluate **HiDISC** 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

NEURAL INFORMATION PROCESSING SYSTEMS

Class Distribution

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

Synthetic Domain Generation

- For each dataset, **6 synthetic domains** were generated:

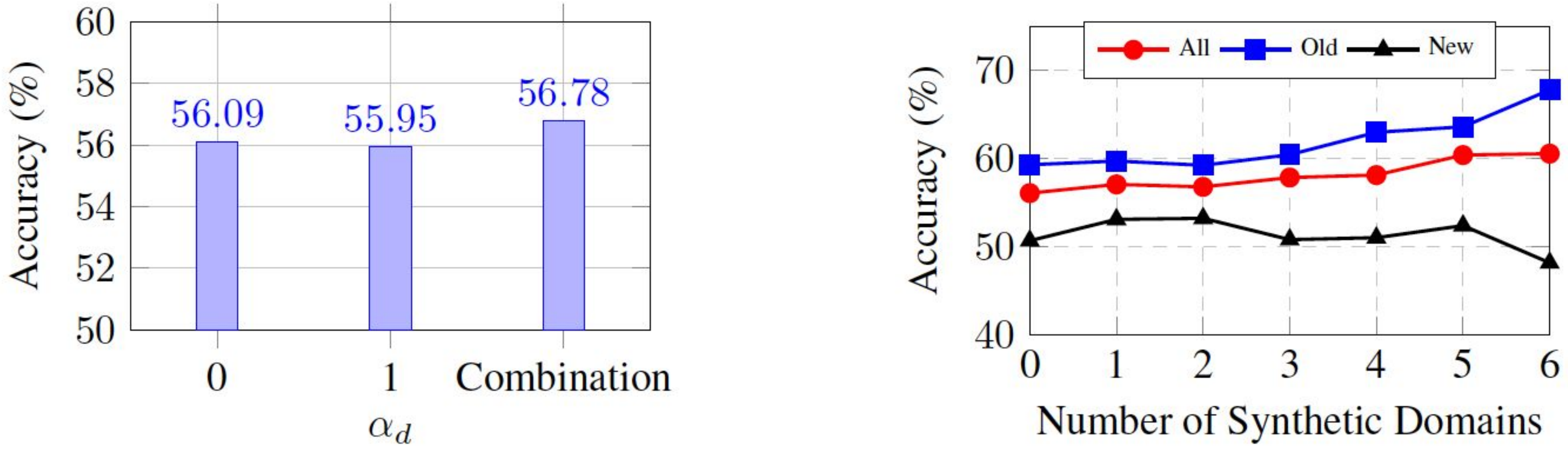


Figure 3: **(Left)** Effect of α_d in hybrid contrastive loss. A balanced combination of angular and geodesic components achieves the highest accuracy. **(Right)** Impact of synthetic domains on old and new category performance. While old-class accuracy increases due to augmented seen data, new-class performance slowly degrades with more synthetic domains, as they cause seen-class bias.

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.

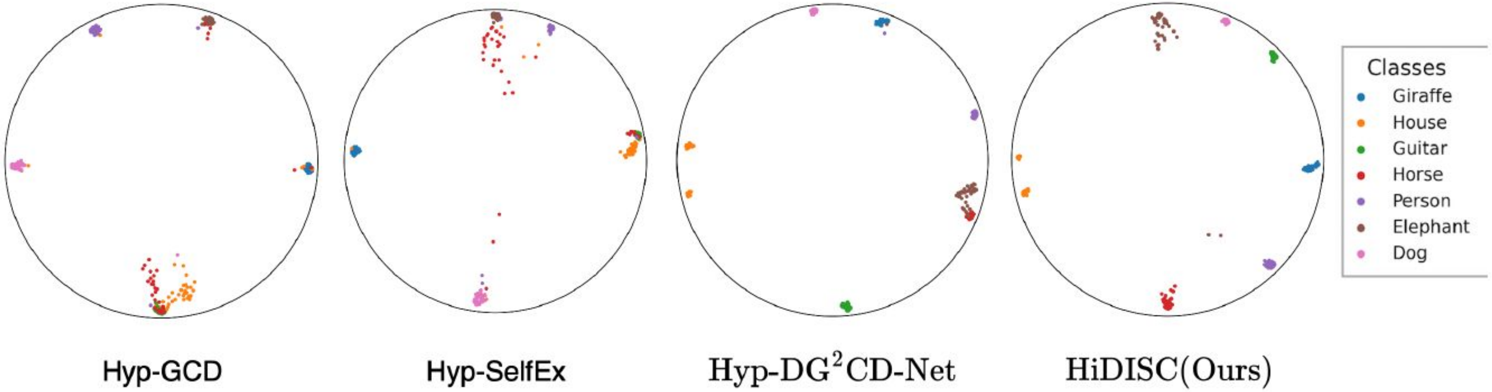


Figure 4: **Poincaré-disk UMAP [56] embeddings** of the target domain ("Photo") clusters, as produced by Hyp-GCD [22], Hyp-SelfEx [22], Hyp-DG^{2}CD-Net, and HIDISC(Ours) for the PACS dataset, with "Sketch" as the source. HIDISC produces a visually clean and compact embedding space, supported by **silhouette scores** [57] ($\in [-1.1]$, $\uparrow$), indicating improved cluster compactness and separation: (Hyp-GCD: **-0.52**, Hyp-SelfEx: **-0.42**, Hyp-DG^{2}CD-Net: **-0.29**, HIDISC: **-0.14**)

Table 1: **Comparison of clustering accuracy** (%) for known (Old), novel (New), and overall (All) categories across PACS, Office-Home, and DomainNet. It can be seen that HIDISC beats other synthetic domain augmentation based baselines using significantly less number of synthetic domains (from 6/9 to 2). (**Bold** : best , <u>underline</u> : second best).

Method	Venue	PACS			Office-Home			DomainNet			Avg.		
		All	Old	New	All	Old	New	All	Old	New	All	Old	New
ViT [54]	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 [15]	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 [25]	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 [26]	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
SelfEx [58]	ECCV'24	71.82	73.37	71.55	50.18	48.59	52.16	24.78	24.99	24.21	48.93	48.98	49.31
CDAD-Net [18]	CVPR-W'24	69.15	69.40	68.83	53.69	<u>57.07</u>	47.32	24.12	23.99	24.35	48.99	50.15	46.83
GCD+ 6 Synth	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+ 6 Synth	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+ 6 Synth	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+ 6 Synth	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
Hyp-GCD [22]	CVPR'25	65.33	67.11	64.42	50.13	49.36	48.08	22.88	23.74	25.89	46.12	46.74	46.13
Hyp-SelfEx [58]	ECCV'24	72.44	74.70	71.20	52.91	52.65	52.96	<u>29.30</u>	<u>30.45</u>	<u>26.37</u>	51.55	52.60	50.18
DG^{2}CD-Net [1] (9 Synth)	CVPR'25	73.30	<u>75.28</u>	72.56	<u>53.86</u>	53.37	**54.33**	29.01	30.38	25.46	<u>52.06</u>	<u>53.01</u>	<u>50.78</u>
Hyp-DG^{2}CD-Net †(9 Synth)	CVPR'25	<u>74.07</u>	74.40	<u>73.95</u>	49.40	50.29	48.03	22.31	21.52	24.29	48.59	48.74	48.76
HIDISC (Ours) (2 Synth)	–	**75.07**	**75.54**	**74.52**	**56.78**	**59.23**	<u>53.21</u>	**30.51**	**31.40**	**28.41**	**54.12**	**55.39**	**52.05**
Δ	–	+1.00	+0.26	+0.57	+2.92	+2.16	–1.12	+1.21	+0.95	+2.04	+2.06	+2.38	+1.27
CDAD-Net (DA) [UB]	CVPR-W'24	83.25	87.58	77.35	67.55	72.42	63.44	70.28	76.46	65.19	73.69	78.82	68.66

Ablation Studies and Analysis

NEURAL INFORMATION PROCESSING SYSTEMS

Table 3: Impact of **loss components** of HIDISC on Office-Home

Config.	$\mathcal{L}_{\text{Buse}}$	$\mathcal{L}^u_{\text{hrep}}$	$\mathcal{L}_{\text{out}}$	Office-Home		
				All	**Old**	**New**
Vanilla	✗	✗	✗	26.17	29.13	21.62
$\mathcal{L}_{\text{Buse}}$	✓	✗	✗	56.32	59.74	50.32
$\mathcal{L}^u_{\text{hrep}}$	✗	✓	✗	50.95	49.33	53.06
$\mathcal{L}_{\text{Buse}}+\mathcal{L}^u_{\text{hrep}}$	✓	✓	✗	56.29	60.36	50.41
$\mathcal{L}_{\text{Buse}}+\mathcal{L}_{\text{out}}$	✓	✗	✓	51.04	51.51	50.29
Full HIDISC	✓	✓	✓	**56.78**	**59.23**	**53.21**

Table 4: Performance metrics demonstrating the **influence of key model components** of HIDISC for Office-Home.

Model Variant	Office-Home		
	All	**Old**	**New**
- With manual augmentations based $\mathcal{D}_{\text{syn}}$	50.80	51.75	49.15
- Without synthetic domain	56.07	59.29	50.67
- Fixed curvature (c=0.01, close to Euclidean)	56.23	58.65	52.68
- Fixed curvature (c=0.03)	55.67	57.39	52.69
- Cut-Mix (In Euclidean Space)	53.46	54.86	51.06
- Full HIDISC	**56.78**	**59.23**	**53.21**

Table 2: **Estimated number of clusters**. Correct estimates are in green, small errors in orange, and large deviations in red.

Method	PACS	Office-Home	DomainNet
Ground Truth	7	65	345
DG^{2}CD-Net	7	67	355
CDAD-Net (DG)	12	60	362
CDAD-Net (DA)	7	66	349
HIDISC (Ours)	7	66	351

Table 5: **Ablation on hyperbolic embedding parameters.** (**Left**) Effect of slope coefficient ϕ in the penalized Busemann loss. Lower ϕ concentrates embeddings near the boundary, improving seen-class accuracy but reducing generalization. (**Right**) Effect of ℓ_2 radius constraint before exponential mapping. Radius = 1.5 yields the best trade-off between known and novel categories.

Slope ϕ	**All**	**Old**	**New**
0.10	58.84	65.77	47.07
0.75	**56.78**	**59.23**	**53.21**
0.90	57.76	62.82	49.18

Radius	**All**	**Old**	**New**
1.5	**56.78**	**59.23**	**53.21**
1.0	57.33	61.14	51.76
2.3	57.31	60.96	52.04

Computational Efficiency

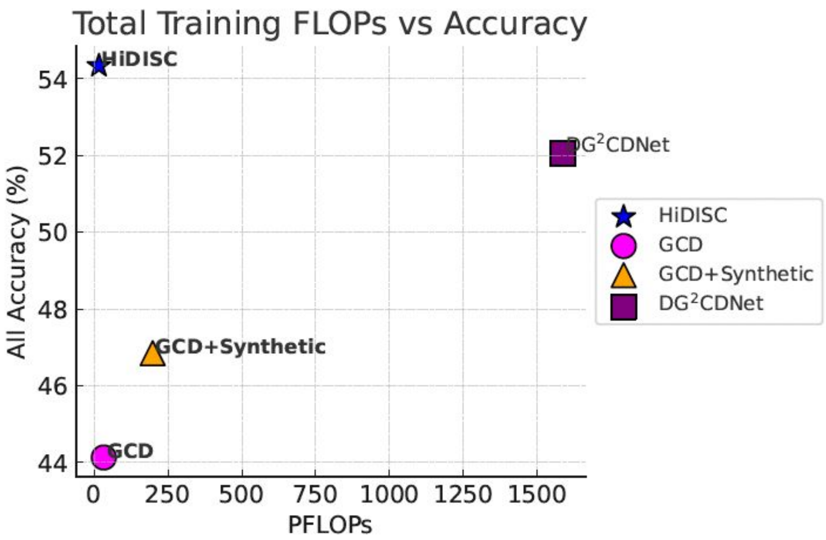


Figure 4: **Computational efficiency of HIDISC.** Hyp-Busemann requires only **16.53 PFLOPs** over 50 epochs with a batch size of 128×2, representing a $\sim 2\times$ reduction compared to GCD (33.06 PFLOPs), $\sim 12\times$ vs. GCD+Synthetic (198.36 PFLOPs), and nearly $\sim 96\times$ vs. DG^{2}CD-Net (1,586 PFLOPs). Despite this efficiency, Hyp-Busemann maintains superior accuracy without relying on episodic-training loops, simplifying the overall training pipeline.

Few More Ablation Studies

Prototypes / Class	All	Old	New
1	56.78	59.23	53.21
2	54.40	57.85	48.68
4	56.23	59.75	50.27

Table 13: Prototype count analysis

We find that performance peaks at $P = 1$, suggesting that one discriminative prototype per class is sufficient in the hyperbolic space. Larger values of P did not improve generalization and sometimes hurt it, possibly due to overfitting or prototype redundancy.

Table 12: Impact of hyperbolic curvature c on performance.

Curvature c	All (%)	Old (%)	New (%)
0.01	56.23	58.65	52.68
0.03	55.67	57.39	52.69
0.05	56.01	58.19	52.78
0.10	56.27	58.52	52.97

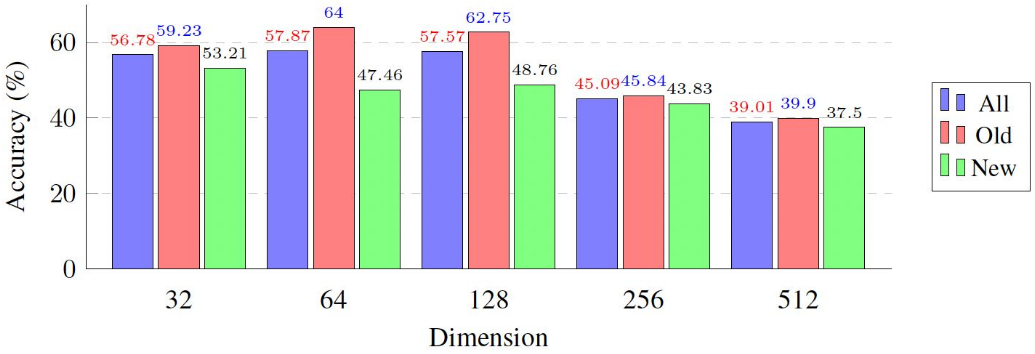


Figure 5: Ablation study on embedding dimension on the Office-Home dataset. Lower dimensions (32, 64, 128) perform better than larger ones (256, 512), suggesting that compact embeddings are beneficial for generalization.

Few More Ablation Studies

Table 10: Performance comparison on the PACS dataset between HIDISC and DG^{2}CD-Net with 2 and 6 synthetic domains.

Model Variant	**All**	**Old**	**New**
HIDISC (2 Synthetic Domains)	75.07	75.54	74.52
DG^{2}CD-Net (2 Synthetic Domains)	66.86	69.11	63.75
HIDISC (6 Synthetic Domains)	74.00	75.64	71.95
DG^{2}CD-Net (6 Synthetic Domains)	73.30	75.28	72.56

Splits (Old-New)	**Office-Home**		
	All	**Old**	**New**
40 - 25	56.78	59.23	53.21
30 - 35	55.31	58.87	52.47
25 - 40	54.76	57.95	52.84
55 - 10	57.85	59.63	48.46
50 - 15	57.13	58.23	53.59

Table 7: Sensitivity on different `Old-New` class splits.

Table 6: Ablation on the maximum angular weight $\alpha_d^{\max}$ for the Office-Home dataset. We report overall accuracy (*All*), seen-class accuracy (*Old*), and novel-class accuracy (*New*).

$\alpha_d^{\max}$	All (%)	Old (%)	New (%)
0.25	56.43	58.10	53.95
0.50	55.23	56.31	53.61
0.75	56.05	58.81	52.02
1.00	**56.78**	**59.23**	**53.21**

Visualization of Tangent Cut-Mix Samples

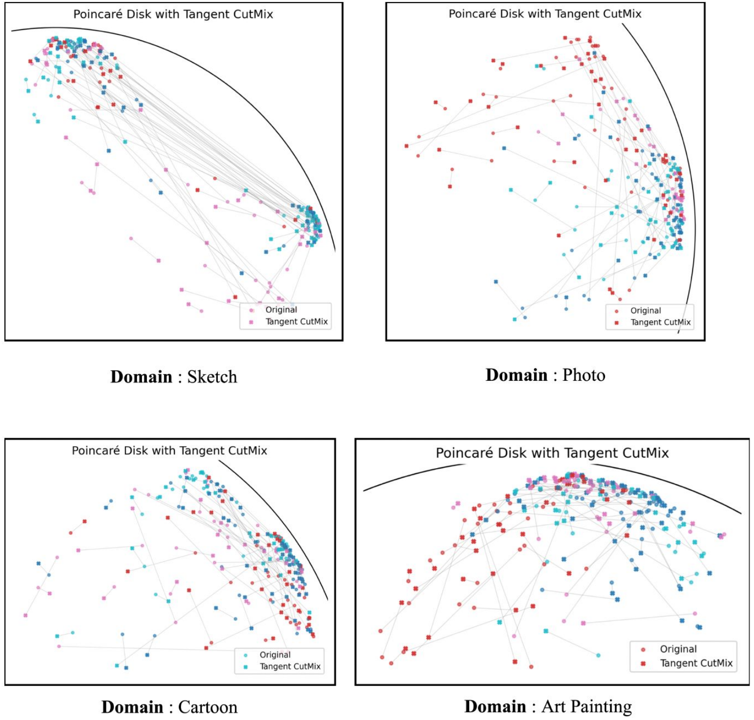


Figure 3: **UMAP-projected Poincaré-disk embeddings of original and Tangent CutMix samples on PACS.** We first embed features into the Poincaré ball and then apply UMAP to project onto 2D for visualization. Each subplot corresponds to one PACS domain (Sketch, Photo, Cartoon, Art Painting), showing four seen-class prototypes (solid circles) and their Tangent CutMix augmentations (cross markers). Grey lines link each synthetic point back to its original partners, highlighting curvature-aware mixing in the tangent space at the origin.

Varying the number of Source and Target Domains

Training Domains	Method	All ↑	Old ↑	New ↑
Art	DG^{2}CD-Net	54.47	53.65	55.54
	HIDISC	54.33	54.75	53.53
Art + Clipart	DG^{2}CD-Net	66.67	65.78	67.99
	HIDISC	67.34	70.78	62.02
Art + Clipart + Product	DG^{2}CD-Net	66.83	66.89	66.75
	HIDISC	**69.86**	**79.17**	54.24

Table 16: Ablation varying the number of source and target domains (Office-Home). HIDISC consistently matches or exceeds DG^{2}CD-Net across all scenarios.

Hyper-parameter Sensitivity Analysis

Table 17: Ablation study on the loss term weights ($\lambda_1, \lambda_2, \lambda_3$) on the OfficeHome dataset. Our default configuration (Config 1) provides the best balance and overall accuracy.

	Loss Weights			**Accuracy (%)**		
Configuration	λ_1	λ_2	λ_3	Avg. (All)	Avg. (Old)	Avg. (New)
Config 1 (ours)	0.60	0.25	0.15	**56.78**	**59.23**	**53.21**
Config 2	0.15	0.60	0.25	52.12	53.33	50.07
Config 3	0.25	0.15	0.60	51.37	52.17	50.01

Poincare ball and Lorentz models

Model	All	Old	New
Poincaré Ball	**56.78**	**59.23**	**53.21**
Lorentz	54.28	56.01	51.41

Table 15: Comparison of Poincaré ball and Lorentz models in the DG-GCD setting on Office-Home.

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 [13]	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 [12]	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 [16]	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 [17]	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
Hyp-GCD [11]	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
Hyp-SelfEx [18]	45.03	36.57	56.45	62.33	71.28	54.52	98.37	98.17	98.57	88.21	91.38	85.38	59.26	**72.19**	47.96	39.24	37.24	41.94
Hyp-SimGCD	22.83	3.33	**75.88**	27.78	32.39	21.77	57.39	72.03	45.2	44.57	63.14	22.88	35.09	43.11	24.63	23.82	12.99	53.31
Hyp-DG^{2}CD-Net [2]	46.79	43.75	51.26	**63.65**	61.78	**65.65**	**99.61**	99.6	**99.63**	89.87	93.25	85.79	57.36	60.41	54.1	46.58	43.32	51.35
DG^{2}CD-Net	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**
HIDISC(Ours)	**48.99**	43.43	57.16	62.29	59.79	64.95	99.19	99	99.48	**90.7**	**93.61**	**87.19**	61.84	60.04	**63.76**	46.56	43.92	50.44

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 [13]	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 [12]	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 [16]	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 [17]	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
Hyp-GCD [11]	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
Hyp-SelfEx [18]	88.77	94.03	84.09	57.11	**73.52**	42.76	98.16	97.82	98.51	89.11	89.1	89.12	45.31	37.02	56.51	98.34	98.06	98.64
Hyp-SimGCD	22.82	22.77	22.87	32.26	45.48	15	27.68	7.79	44.25	23.62	35.79	9.4	30.11	32.22	24.38	33.9	23.76	42.35
Hyp-DG^{2}CD-Net [2]	89.6	92.63	85.95	57.47	60.91	53.79	99.28	99.15	99.48	**93.26**	**95.89**	**90.1**	46.08	42.94	50.69	99.34	**99.5**	99.11
DG^{2}CD-Net	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**
HIDISC(Ours)	**92.36**	**94.59**	89.67	**65.7**	68.39	**62.83**	98.74	99.05	98.29	88.57	92.14	84.28	47.07	**53.12**	38.19	98.86	99.45	97.99

Table 13: Detailed comparison of our proposed HIDISC on DG-GCD with respect to referred literature for PACS Dataset.

Detailed Results

NEURAL INFORMATION PROCESSING SYSTEMS

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 [13]	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 [12]	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 [16]	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 [17]	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
Hyp-GCD [11]	28.99	29.1	29.28	67.3	66.38	64.99	63.79	63.14	62.05	45.88	43.92	40.44	60.27	58.07	54.36	63.33	62.02	60.04
Hyp-SelfEx [18]	30.42	28.84	32.89	64.26	67.7	58.5	64.53	60.91	69.73	49.8	49.18	50.61	63.78	59.62	69.76	64.23	66.35	60.67
Hyp-SimGCD [16]	23.34	34.69	4.31	38.5	54.96	7.84	46.37	70.58	5.03	21.82	29.42	4.55	25.98	37.79	5.83	29.93	41.55	8.28
Hyp-DG^{2}CD-Net [2]	27.89	26.84	29.68	66.02	**70.03**	59.95	63.16	62.55	64.2	45.94	47.43	43.3	55.96	56.65	54.79	62.71	67.75	55.09
DG^{2}CD-Net	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
HIDISC(Ours)	31.91	30.46	**34.18**	64.81	68.19	59.14	66.28	65.6	67.26	**58.65**	**60.68**	**56.02**	**67.82**	66.36	69.92	66.6	**70.19**	60.59

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 [13]	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 [12]	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 [16]	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 [17]	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
Hyp-GCD [11]	45.43	44.46	42.73	61.63	59.64	56.3	27.15	28.35	30.39	45.82	45.28	44.33	64.34	63.74	**62.84**	27.66	28.25	29.25
Hyp-SelfEx [18]	51.97	48.53	**56.44**	66.06	65.07	67.49	29.01	28.93	29.13	55.43	53.52	**57.91**	65.3	73.33	51.83	30.12	29.83	30.57
Hyp-SimGCD [16]	33.29	45.26	6.07	40.77	60.68	6.75	16.62	23.46	5.15	46.39	63.59	7.24	44.88	66.32	4.96	20.98	30.97	4.24
Hyp-DG^{2}CD-Net [2]	44.56	41.99	49.14	61.2	62.49	59.04	26.45	26.55	26.28	46.99	48.71	43.93	63.96	64.73	62.78	27.94	27.8	28.17
DG^{2}CD-Net	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**
HIDISC(Ours)	**60.12**	**65.52**	53.08	**68.95**	71.13	65.81	**32.63**	32.21	**33.3**	**61.54**	**71.14**	49.05	**69.22**	**73.41**	62.18	**32.79**	35.85	28.02

Table 14: Detailed comparison of our proposed HIDISC on DG-GCD with respect to referred literature for Office-Home Dataset

Detailed Results

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 [13]	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 [12]	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 [16]	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 [17]	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
Hyp-GCD [11]	47.08	49.78	**56.61**	12.88	13.37	14.66	11.04	11.32	11.95	31.33	31.84	33.1	17.87	18.85	21.23
Hyp-SelfEx [18]	52.34	53.02	50.35	12.91	12.76	13.32	12.27	12.42	11.89	33.82	34.49	32.14	19.63	19.11	20.87
Hyp-SimGCD [16]	52.34	53.02	50.35	12.91	12.76	13.32	12.27	12.42	11.89	33.82	34.49	32.14	19.63	19.11	20.87
Hyp-DG^{2}CD-Net [2]	36.33	34.13	41.88	13.51	12.96	14.96	9.74	9.3	10.73	24.22	23.33	26.41	14.17	14.17	14.16
DG^{2}CD-Net	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
HIDISC(Ours)	**55.27**	54.89	56.24	14.61	13.83	16.68	**15.35**	**16.3**	**13.2**	**39.8**	**41.15**	**36.49**	**35.74**	**38.61**	**28.8**

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 [13]	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 [12]	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 [16]	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 [17]	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
Hyp-GCD [11]	11.52	11.6	11.79	12.98	13.48	14.79	15.33	15.84	17.11	44.82	46.52	50.82	29.4	29.92	31.21
Hyp-SelfEx [18]	11.6	11.7	11.35	12.89	12.61	13.64	17.1	17.92	15.16	50.55	51.11	48.92	33.46	34.31	31.34
Hyp-SimGCD [16]	11.6	11.7	11.35	12.89	12.61	13.64	17.1	17.92	15.16	50.55	51.11	48.92	33.46	34.31	31.34
Hyp-DG^{2}CD-Net [2]	11.95	11.81	12.27	14.1	13.43	15.88	16.21	15.76	17.32	48.04	45.92	53.42	31.28	30.73	32.65
DG^{2}CD-Net	**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
HIDISC(Ours)	15.7	16.34	**14.25**	14.35	13.83	15.72	26.6	27.56	24.24	55.04	54.49	56.42	39.08	40.13	36.5

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 [13]	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 [12]	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 [16]	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 [17]	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
Hyp-GCD [11]	12.12	12.38	12.96	12.32	13.05	14.97	16.78	17.54	19.42	48.4	50.39	55.41	19.34	20.23	22.39
Hyp-SelfEx [18]	12.43	12.24	12.89	12.98	12.76	13.55	18.28	18.72	17.22	51	51.59	49.27	20.42	20.11	21.18
Hyp-SimGCD [16]	12.43	12.24	12.89	12.98	12.76	13.55	18.28	18.72	17.22	51	51.59	49.27	20.42	20.11	21.18
Hyp-DG^{2}CD-Net [2]	12.94	12.65	13.59	14.14	13.45	15.96	17.54	16.84	19.25	50.59	49.07	54.45	19.95	19.31	21.49
DG^{2}CD-Net	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
HIDISC(Ours)	15.98	17.15	13.36	13.03	12.62	14.1	25.78	27.37	21.9	57.1	58.76	52.9	34.29	37.99	25.34

Table 15: Detailed comparison of our proposed HIDISC on DG-GCD with respect to referred literature for DomainNet Dataset

Summary:

- **HIDISC**: The **first hyperbolic geometry-based framework** for Domain Generalization with Generalized Category Discovery (**DG-GCD**).

Hyperbolic space naturally encodes **hierarchies and semantic structures**, improving:

- Cross-domain alignment
- Separation between known and novel categories

Achieves this with only **2 synthetic domains** per image and **96× less compute** than DG2CD-Net.

Key Contributions

- **Tangent CutMix**: First curvature-aware interpolation for open-set GCD.
- **Unified hyperbolic loss**: Combines Busemann alignment, hybrid contrastive loss, and adaptive outlier repulsion.
- **Learnable curvature**: Adapts model geometry to data complexity dynamically.

Thank you for your "Attention"

Because sometimes...

"Attention is All You Need"