NCD

NCD. (image classification task)
Labeled set : base class
Unlabeled set : novel class only

NCD의 문제 : NCD assumes all unlabeled data are from new classes.

Labeled set

Unlabeled set

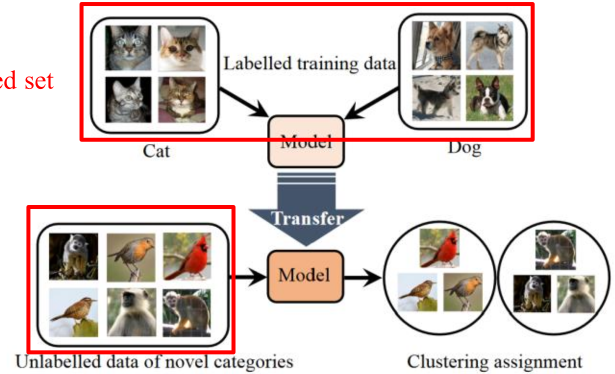


Figure 1. Learning to discover novel visual categories via deep transfer clustering. We first train a model with labelled images (e.g., cat and dog). The model is then applied to images of unlabelled novel categories (e.g., bird and monkey), which transfers the knowledge learned from the labelled images to the unlabelled images. With such transferred knowledge, our model can then simultaneously learn a feature representation and the clustering assignment for the unlabelled images of novel categories. **NCD**

GCD

GCD. (image classification task)
Labeled set : base class
Unlabeled set : base class or novel class.

GCD의 문제 : GCD inherently suffers from issues like imbalanced accuracy and confidence between old and new classes, which is intractable due to the incompletely transferable knowledge and unlabeled nature of new classes.

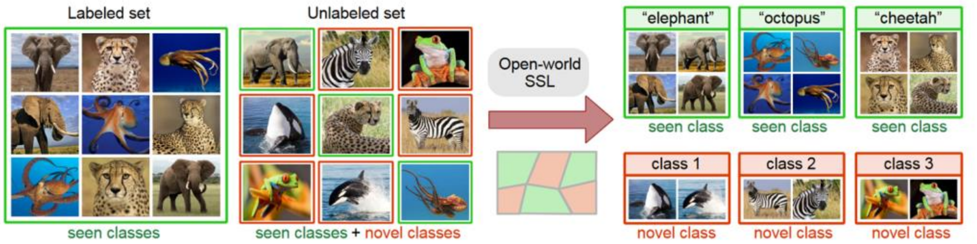
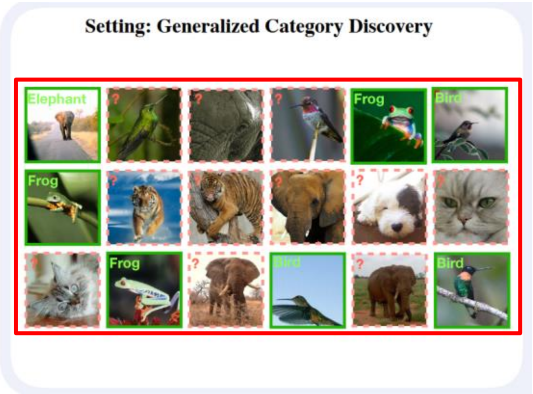


Figure 1: In the open-world SSL, the unlabeled dataset may contain classes that have never been encountered in the labeled set. Given unlabeled test set, the model needs to either assign instances to one of the classes previously seen in the labeled set, or form a novel class and assign instances to it.



Unlabeled set

AL

AL. (image classification task)
Labeled set : base class

AL의 문제 : AL is in a close-world setting, where labeled and unlabeled data share classes.

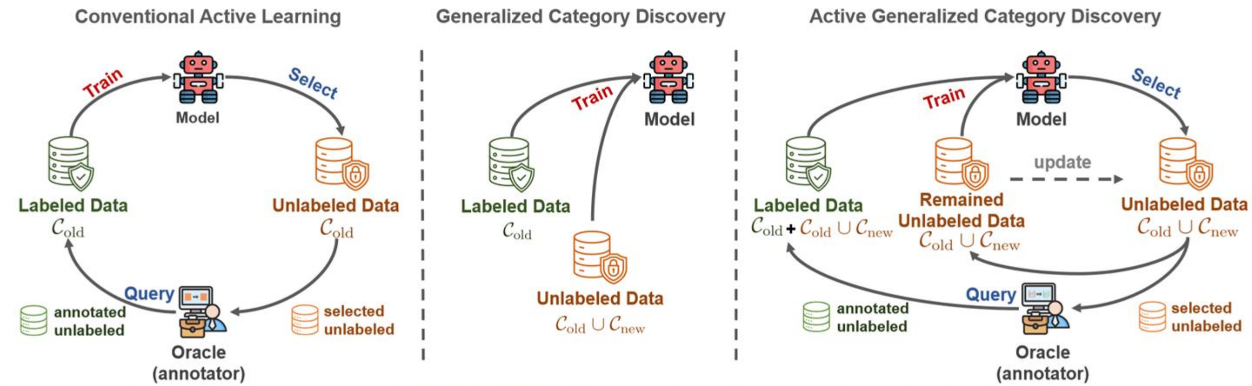


Figure 1. The diagram of three settings. Left: Conventional AL is a closed-world setting, where labeled and unlabeled classes are identical. Middle: GCD requires no active labeling and suffers from severe issues. Right: AGCD is an open-world extrapolated version of AL, where unlabeled data contains novel categories, and models are trained on both labeled and unlabeled data to cluster both old and new classes.

Table 1. The default setting of 3 generic datasets and 3 fine-grained datasets in AGCD benchmark. $|\mathcal{Y}_l^{\text{init}}| = K_{old}$, $|\mathcal{Y}_u^{\text{init}}| = K_{old} + K_{new}$ denote the initial number of classes in $|\mathcal{D}_l^{\text{init}}|$ and $|\mathcal{D}_u^{\text{init}}|$. The number of queries across all rounds is displayed in both the total count and average count per class.

Dataset	Labeled $\mathcal{D}_l^{\text{init}}$		Unlabeled $\mathcal{D}_u^{\text{init}}$		#Rounds	#Query (total)	#Query (per class)
	$\lvert\mathcal{D}_l^{\text{init}}\rvert$	$\lvert\mathcal{Y}_l^{\text{init}}\rvert$	$\lvert\mathcal{D}_u^{\text{init}}\rvert$	$\lvert\mathcal{Y}_u^{\text{init}}\rvert$			
CIFAR10 (C-10) [27]	2,000	2	48,000	10	1	100	10
CIFAR100 (C-100) [27]	5,000	50	45,000	100	5	500	5
ImageNet-100 (IN-100) [11]	12,744	50	114,371	100	5	500	5
CUB (CUB) [52]	599	100	5,395	200	5	500	2.5
Stanford Cars (SCars) [26]	800	98	7,344	196	5	500	2.5
FGVC-Aircraft (Air) [33]	666	50	6,001	100	5	500	5

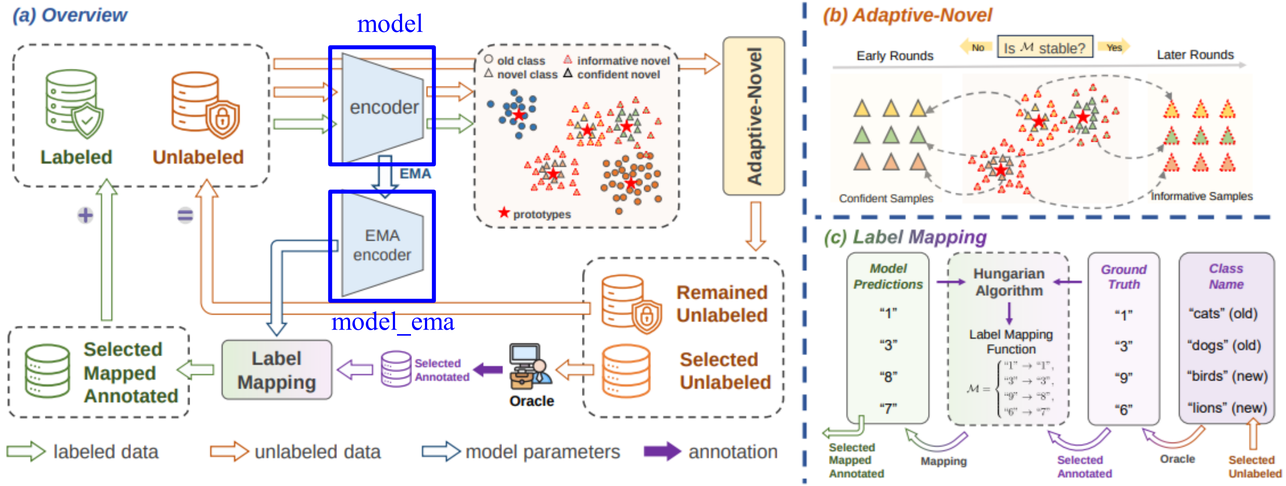


Figure 5. The framework of AGCD. (a) Overall pipeline and dataflow. Models are trained on $\mathcal{D}_l^t \cup \mathcal{D}_u^t$ with SimGCD, and select samples in $\mathcal{D}_u^t$. (b) The proposed `Adaptive-Novel` sampling strategy. Here $\mathcal{M}$ denotes the *label mapping function*. Stable $\mathcal{M}$ means that at the initial and end epochs of the current round, $\mathcal{M}$ does not change largely. *Confident novel samples* are sampled at early rounds, when $\mathcal{M}$ is stable, we select the *informative* ones. (c) Illustration of *label mapping* computed by model predictions and ground truth on $\mathcal{D}_l^{t-1} \cup \mathcal{D}_q^t$.