Open-world setting
: Images at test time may belong to new classes.
: train시 없던 클래스를 test시 마주하는 상황. 현실 상황 반영한것.
ex) 자율 주행 차량이 처음 보는 종류의 도로 표지나 장애물을 인식해야 할 때, 온라인 쇼핑 플랫폼에서 새로운 상품 범주를 자동으로 분류해야 할 때 등

1. OSR(Open-Set Recognition)
OSR의 task.
OSR aims only to detect test-time images which do not belong to one of the classes in the labelled set

OSR의 단점.
but does not require any further classification amongst these detected images.

시스템이 훈련 중에 본 적이 없는 새로운 클래스의 이미지를 감지하는 것이 목표. 새로운 클래스의 이미지인지 확인 가능 but 그 이상으로 분류 기능 없음.

2. NCD(Novel Class Discovery)
NCD의 task.
After learning from labeled, unlabeled images, NCD aim to discover new classes in the unlabeled set.

NCD의 단점.
All of the unlabeled images come from new categories, which is usually unrealistic.

Train set.
Labeled set : base class
Unlabeled set : novel class only.

레이블이 지정된 이미지와 레이블이 없는 이미지를 모두 학습하고, 레이블이 없는 이미지 세트에서 새로운 클래스를 발견하는 것이 목표. NCD는 OSR보다 한 단계 더 나아가, 새로운 클래스의 이미지를 식별하고 그것들을 적절한 새 카테고리로 분류까지 가능. but unlabelled image가 모두 novel class image라는 것이 비현실적임. 또한 generalized setting에서 labelled classes에 overfit되는 문제도 존재함.

NCD

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

NCD의 task.
After learning from labeled, unlabeled images, aim to discover new classes in the unlabeled set.

NCD의 단점.
All of the unlabeled images come from new categories, which is usually unrealistic.

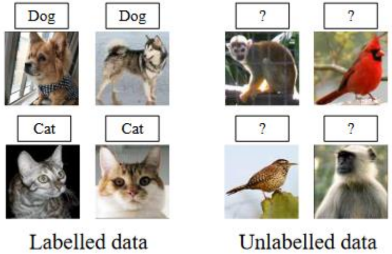


Fig. 1: Novel category discovery. Given labelled images from a few known categories (e.g., dog and cat), our objective is to automatically partition unlabelled images from new categories (e.g., monkey and bird) into proper clusters.

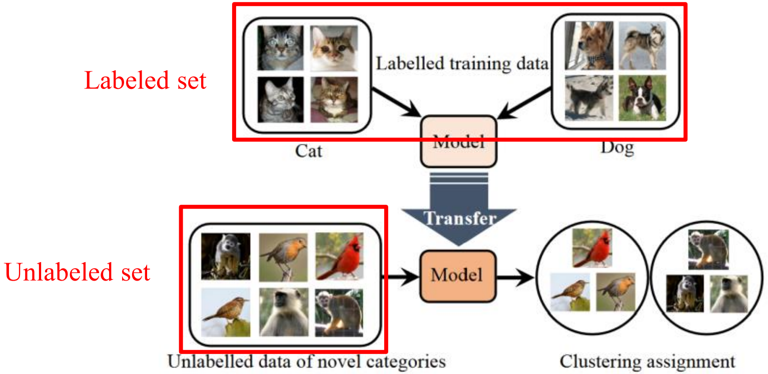


Figure 1. Learning to discover novel visual categories via deep transfer clustering. We first train a model with labelled images (e.g., cat and dog). The model is then applied to images of unlabelled novel categories (e.g., bird and monkey), which transfers the knowledge learned from the labelled images 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.

GCD

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

GCD의 task.
Given an image dataset where only some images are labelled with their categories, GCD aim to assign a category label to each of the rest images, possibly using new categories not observed in the labelled set.

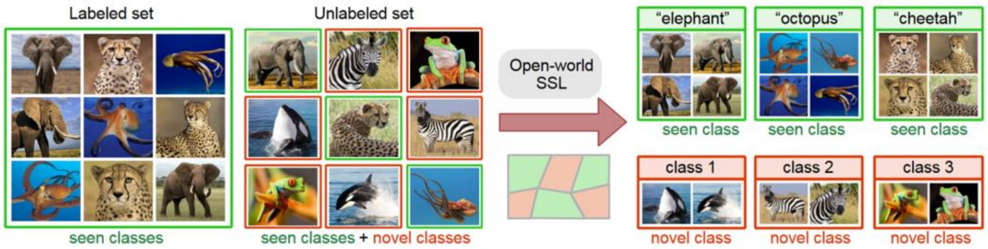
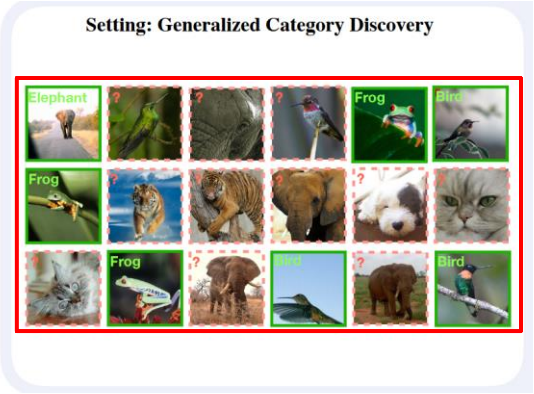


Figure 1: In the open-world SSL, the unlabeled dataset may contain classes that have never been encountered in the labeled set. Given unlabeled test set, the model needs to either assign instances to one of the classes previously seen in the labeled set, or form a novel class and assign instances to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



Unlabeled set

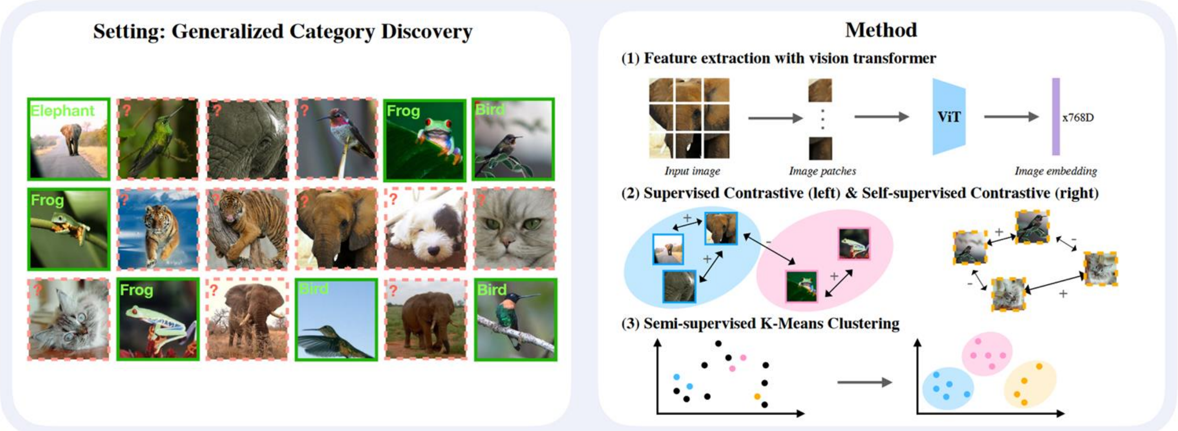
Semi-Supevised learning
SSL은 레이블이 있는 데이터(지도 학습에서 사용됨)와 레이블이 없는 데이터(비지도 학습에서 주로 사용됨)를 동시에 사용하여 모델을 학습시키는 기법
Labeled set : base class
Unlabeled set : base class

Open-set recognition

Novel category discovery

GCD

GCD의 task :
Given a labelled and unlabelled set of images, the task is to categorize all images in the unlabelled set.
Given an image dataset where only some images are labelled with their categories, assign class labels to all remaining images, using classes that may or may not be observed in the labelled images



backbone : ViT-B-16 pretrained with DINO self-supervision on (unlabelled) ImageNet
use self-supervised ImageNet weights.
finetune the representation on target data jointly with supervised contrastive learning on the labelled data, and unsupervised contrastive learning on all the data.

GCD

Table 1. Datasets used in our experiments. We show the number of classes in the labelled and unlabelled sets ($|\mathcal{Y}_\mathcal{L}|$, $|\mathcal{Y}_\mathcal{U}|$), as well as the number of images ($|\mathcal{D}_\mathcal{L}|$, $|\mathcal{D}_\mathcal{U}|$).

	CIFAR10	CIFAR100	ImageNet-100	CUB	SCars	Herb19
$\|\mathcal{Y}_\mathcal{L}\|$	5	80	50	100	98	341
$\|\mathcal{Y}_\mathcal{U}\|$	10	100	100	200	196	683
$\|\mathcal{D}_\mathcal{L}\|$	12.5k	20k	31.9k	1.5k	2.0k	8.9k
$\|\mathcal{D}_\mathcal{U}\|$	37.5k	30k	95.3k	4.5k	6.1k	25.4k

For all datasets, we sample 50% of the classes as 'Old' classes (YL) and keep the rest as 'New' (YU \ YL).