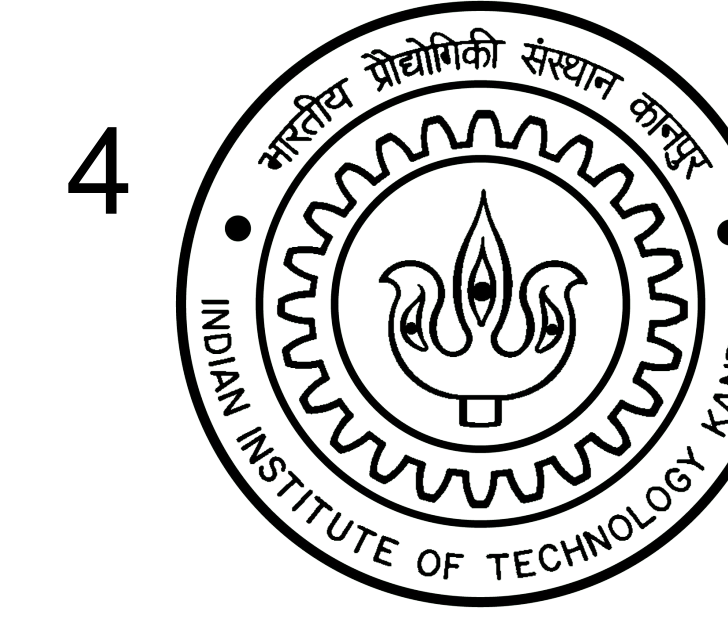


# Novel Class Discovery without Forgetting

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## Thought Experiment: What are these?



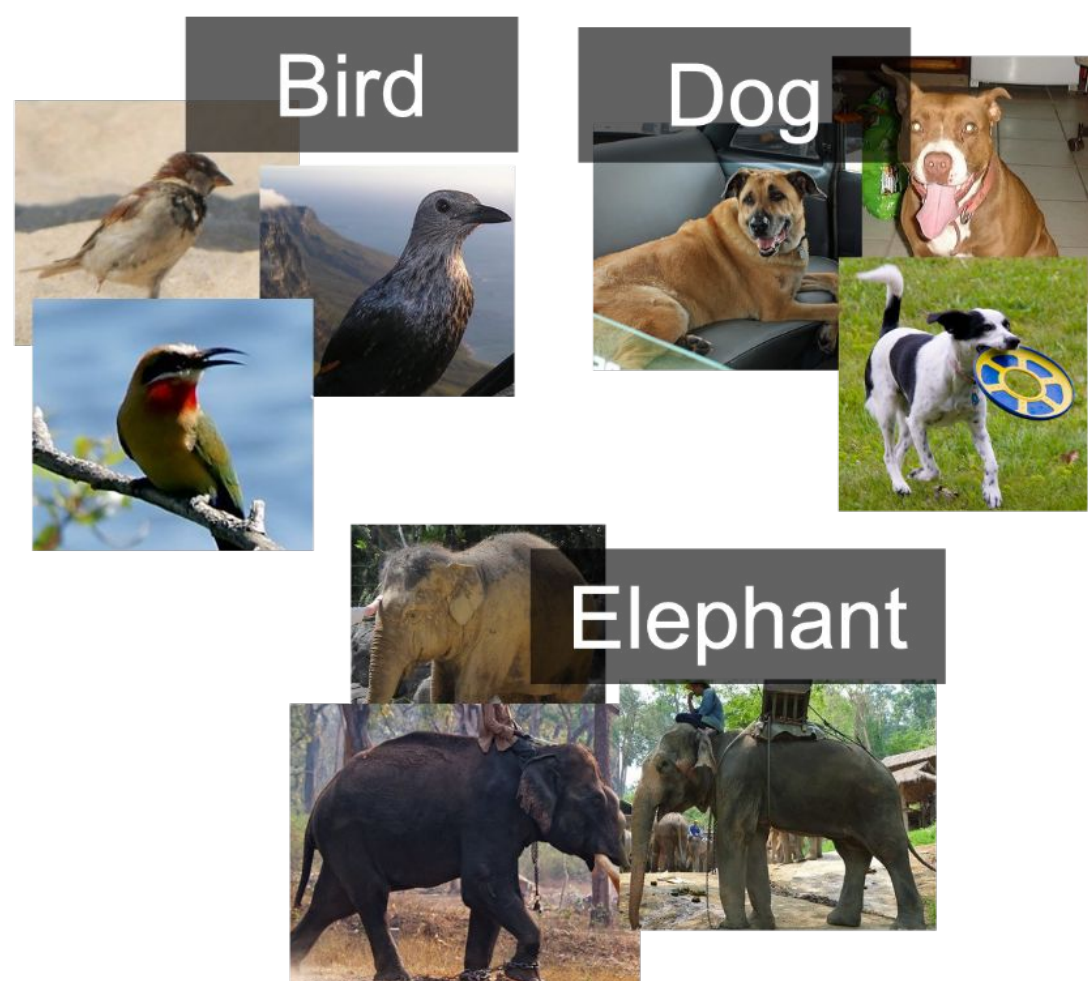
Our existing knowledge about birds helps us to easily identify **two groups** in these images, which are **different** from those birds that we are familiar with, without:

- Degrading the performance on earlier knowledge.
- Any extra information other than these images.

Novel Class Discovery without Forgetting (NCDwF) tasks an ML model to have these traits!

## Problem Setting

### Base Learning Phase



Learn from labeled data.

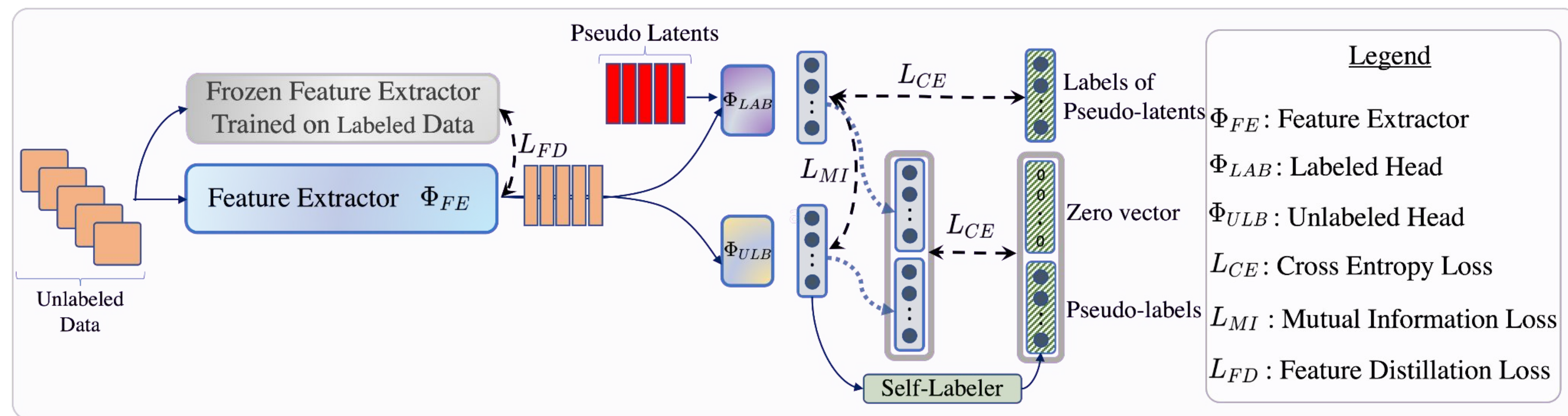
### Class Discovery Phase



Discover novel categories while remembering base classes, without accessing base data.

Legend: Ground-truth Labels Predictions from NCDwF Model

## Our Proposed Method



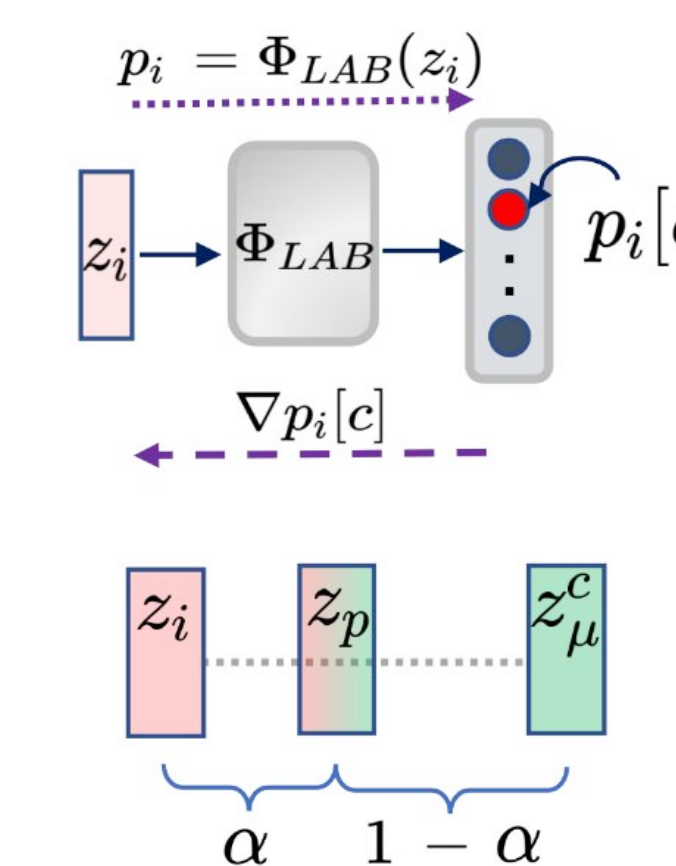
### Pseudo Latent Generation

Step 1: Sample  $z$ .  $z_i \sim \mathcal{N}(0, I)$

Step 2: Choose the class to invert.

Step 3: Modify  $z$  to maximize the score of the selected logit.  
 $z_{i+1} = z_i + \nabla p_i[c]$

Step 4: Latent Mix-up with the class mean.

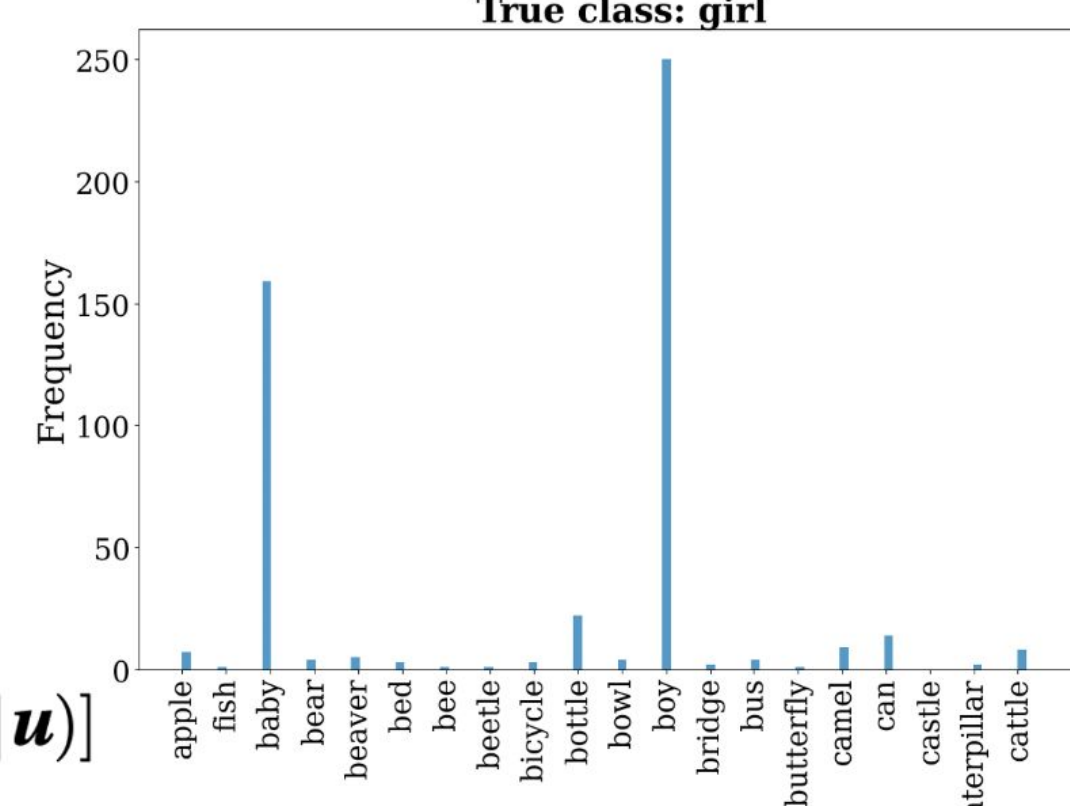


### Mutual Information based Regularizer

Observation: An unlabeled instance gets wrongly classified into semantically closest base class.

For the logits:  $l = \phi_{LAB} \circ \phi_{FE}(x)$   
 $u = \phi_{ULB} \circ \phi_{FE}(x)$

MI based loss:  $L_{MI} = -I(l; u)$   
 $I(l; u) = H(l) - H(l|u)$   
 $= -\mathbb{E}_l[\log p(l)] + \mathbb{E}_{l,u}[\log p(l|u)]$



## Results

Settings (→)	CIFAR-10-5-5			CIFAR-100-80-20			CIFAR-100-50-50			CIFAR-100-20-80			ImageNet-1000-882-30		
Methods (↓)	Lab	Unlab	All	Lab	Unlab	All	Lab	Unlab	All	Lab	Unlab	All	Lab	Unlab	All
Task Aware Evaluation															
RS (ICLR 20)	20.00	84.48	52.24	44.1	55.7	49.9	18.14	32.56	25.35	13.05	11.5	12.28	3.34	24.54	13.94
NCL (CVPR 21)	20.00	59.96	39.98	13.59	57.9	35.75	10.14	12.18	11.16	12.65	4.73	8.69	1.52	11.45	6.49
UNO (ICCV 21)	33.16	93.22	63.19	2.01	72.78	37.39	1.76	53.85	27.81	7.95	48.7	28.33	0.75	63.4	32.08
Ours	92.72	90.32	91.52	65.03	77.03	71.03	73.18	55.66	64.42	84.8	49.67	67.24	27.46	79.07	53.27
Generalized Evaluation															
UNO (ICCV 21)	0	71.36	35.68	0	58.15	29.08	0	34.22	17.11	0	41.61	20.81	0	68.34	34.17
Ours	79.68	73.66	76.67	53.23	60.6	56.92	62.76	36.42	49.59	57.85	42.18	50.02	21.32	70.99	46.16

## Key References

- Kai Han et al. "Automatically discovering and learning new visual categories with ranking statistics." ICLR 2020.
- Zhun Zhong et al. "Neighborhood contrastive learning for novel class discovery." CVPR 2021.
- Enrico Fini et al. "A unified objective for novel class discovery." ICCV 2021.