Associative Alignment, and Persistent Mixture Model Networks for Few-Shot Image Classification

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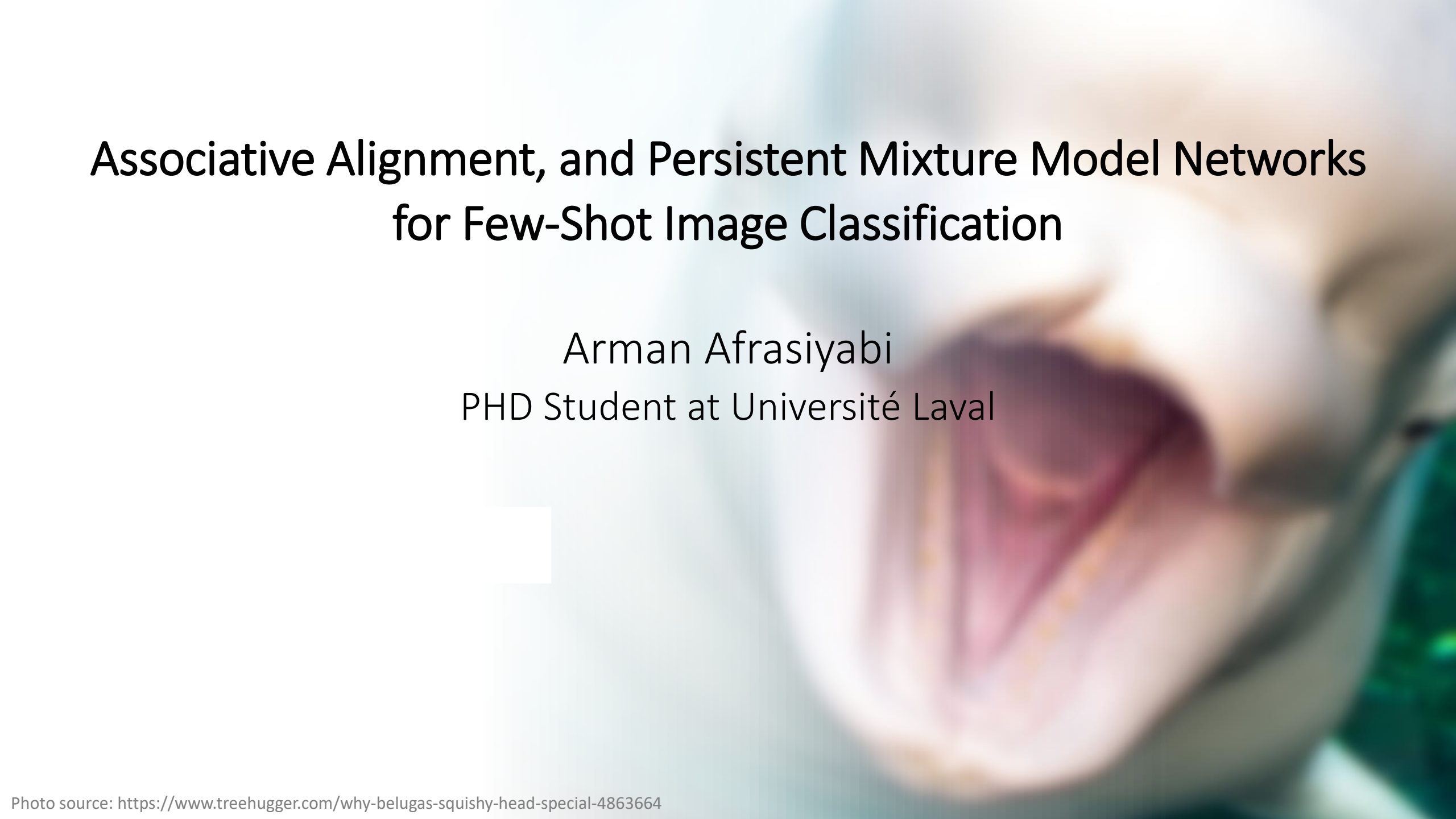
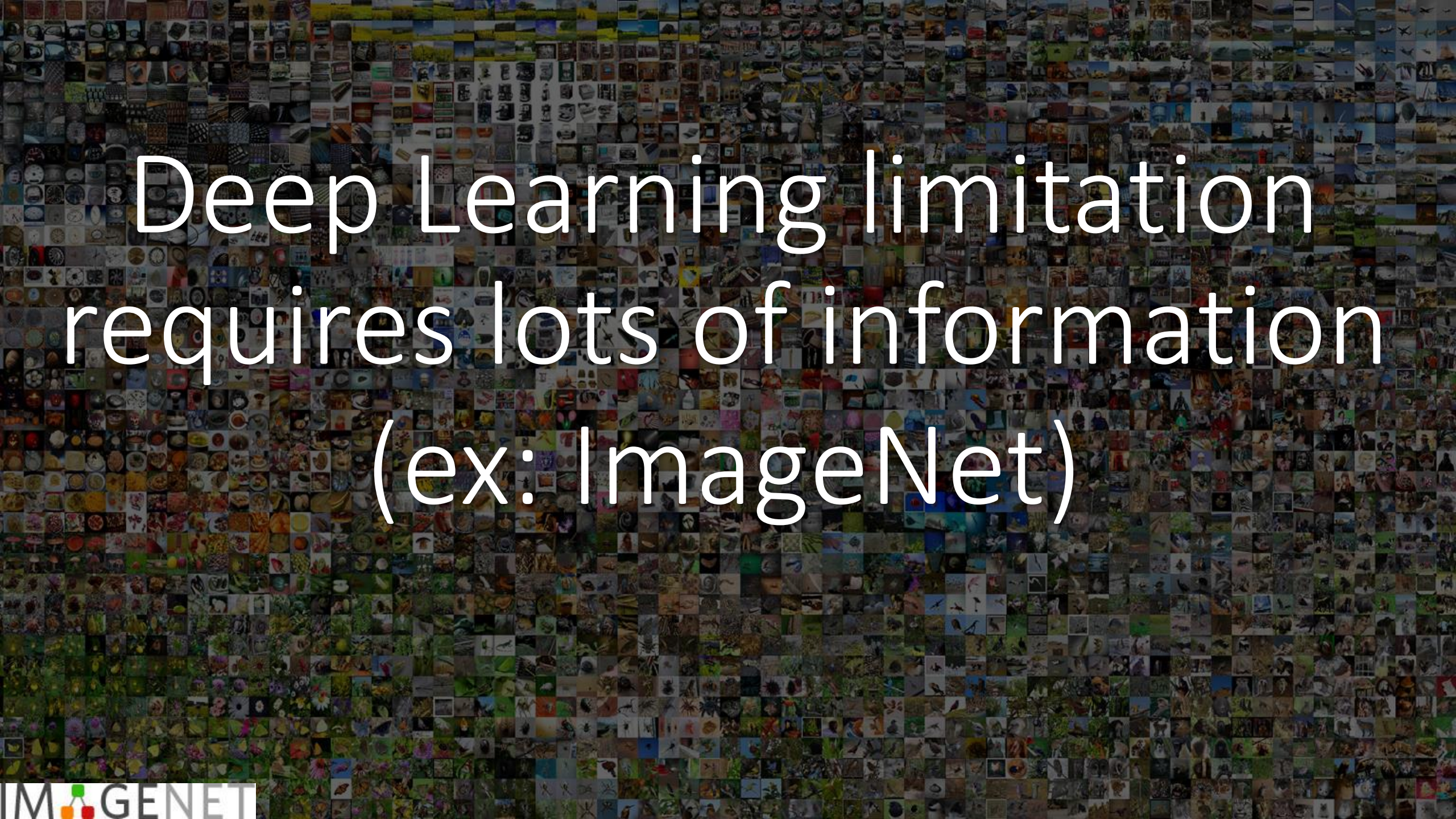
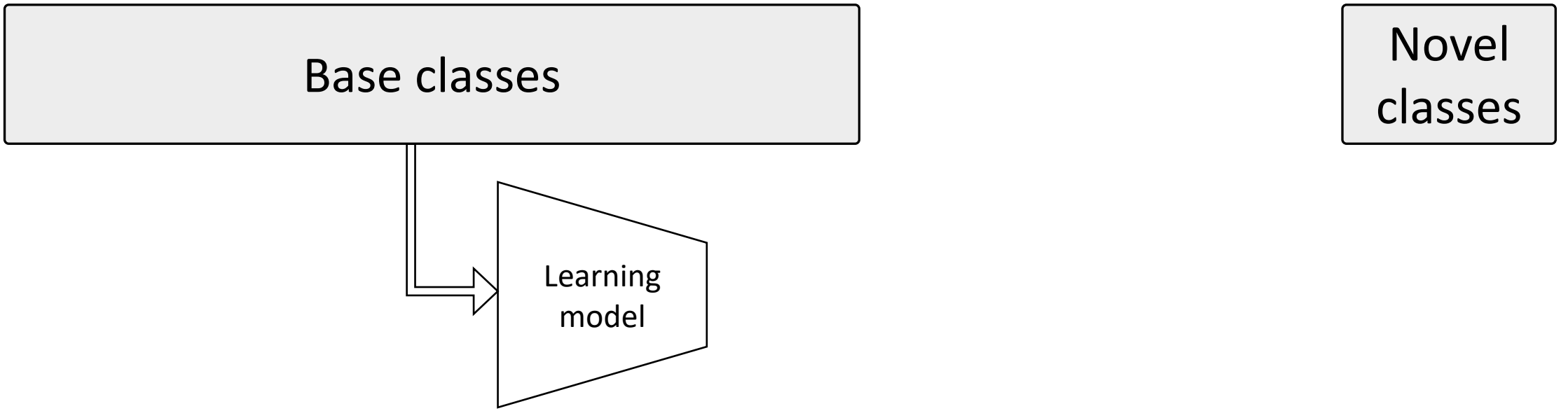


Photo source: https://www.treehugger.com/why-belugas-squishy-head-special-4863664


Deep Learning limitation
requires lots of information
(ex: ImageNet)
IMAGENET

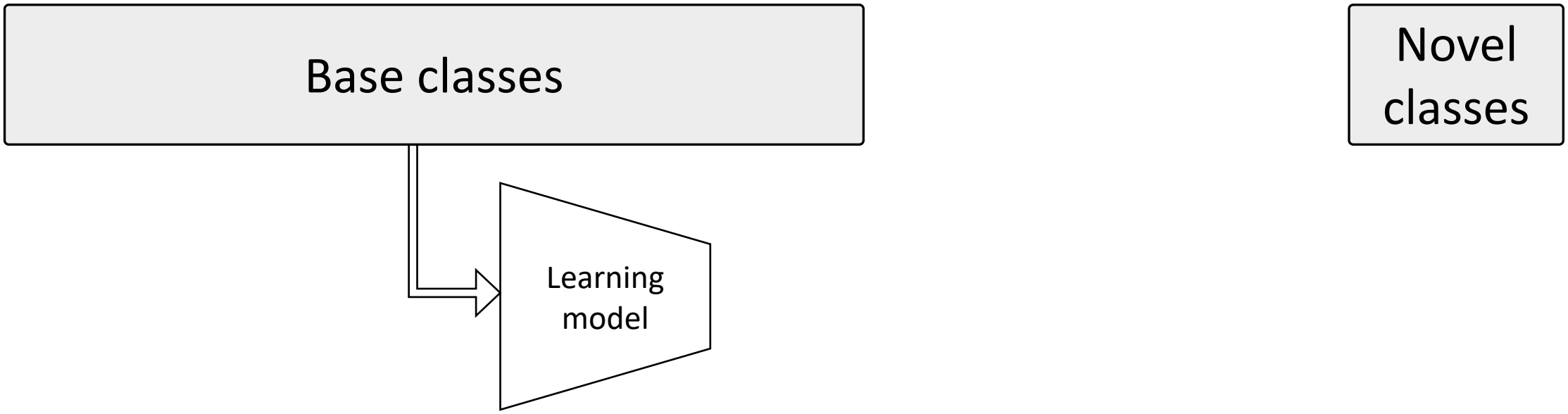
Few-shot learning



[1] Associative Alignment

[1] Afrasiyabi A., Lalonde JF., Gagné C. (2020) Associative Alignment for Few-Shot Image Classification. ECCV2020.

Few-shot learning

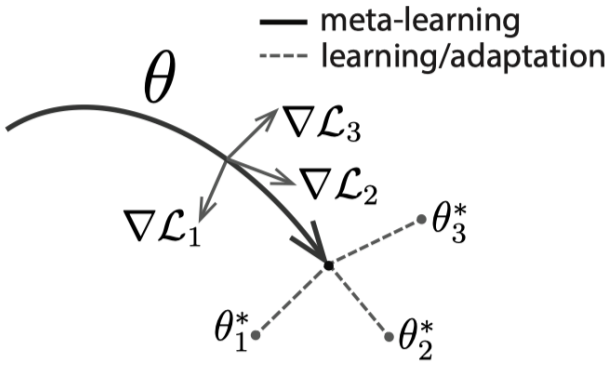


[2] Persistent Mixture Model (PMM)

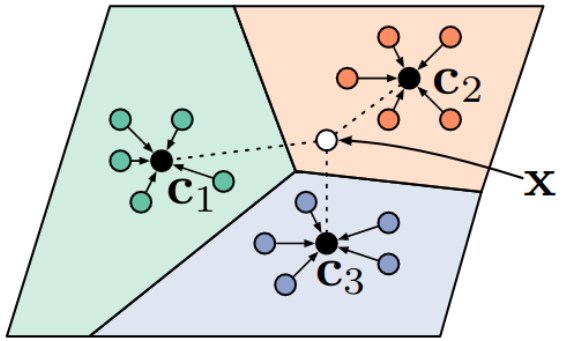
[1] Afrasiyabi A., Lalonde JF., Gagné C. (2020) Associative Alignment for Few-Shot Image Classification. ECCV2020.
[2] Afrasiyabi A., Lalonde JF., Gagné C. (2020) Persistent Mixture Model Networks for Few-Shot Image Classification. Under Review.

Related works

I) Meta Learning

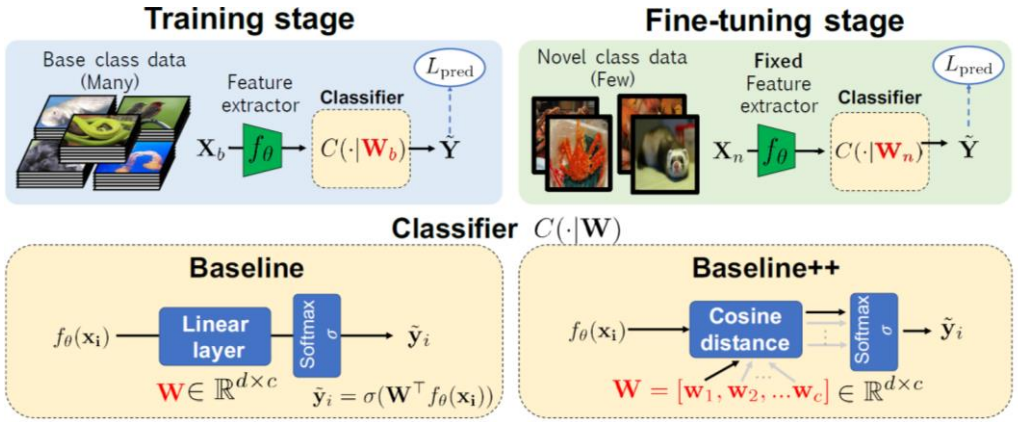


MAML



Proto. Net.

II) Transfer Learning



Baseline++

Finn, C., Abbeel, P., Levine, S.: Model-agnostic meta-learning for fast adaptation of deep networks. In: The International Conference on Machine Learning (2017)

Snell, J., Swersky, K., Zemel, R.: Prototypical networks for few-shot learning. In: Advances in Neural Information Processing Systems(2017)

Chen, W.Y., Liu, Y.C., Kira, Z., Wang, Y.C.F., Huang, J.B.: A closer look at few-shot classification. arXiv preprint arXiv:1904.04232 (2019)

Associative Alignment for Few-shot Image Classification

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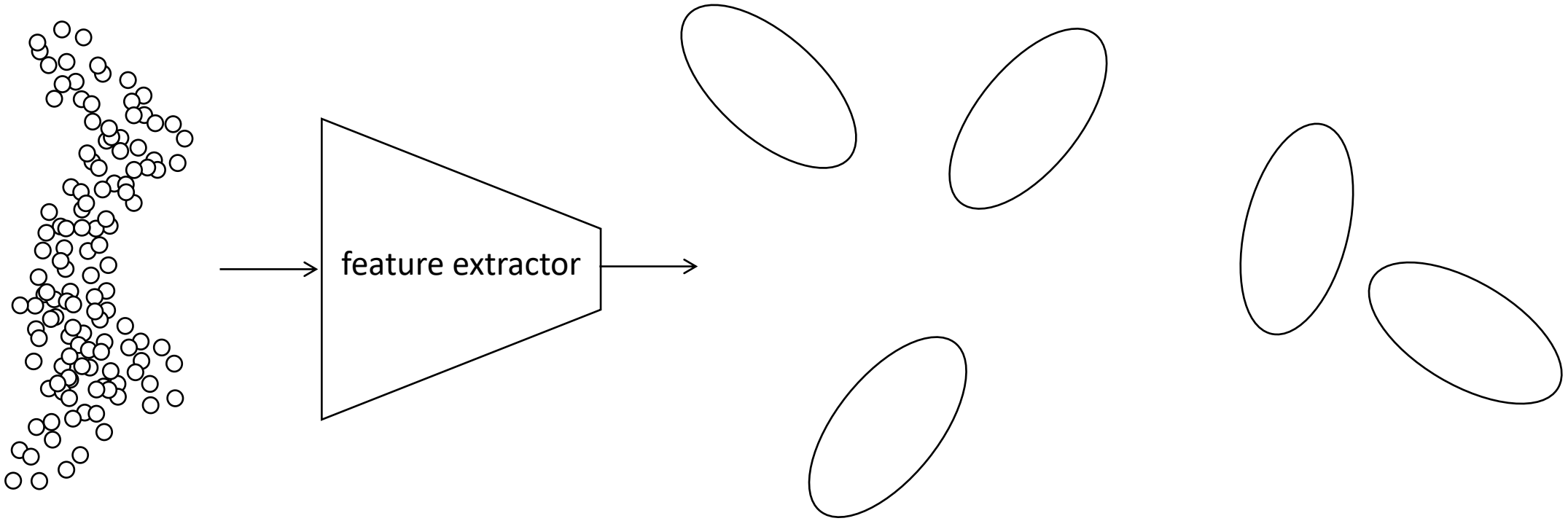
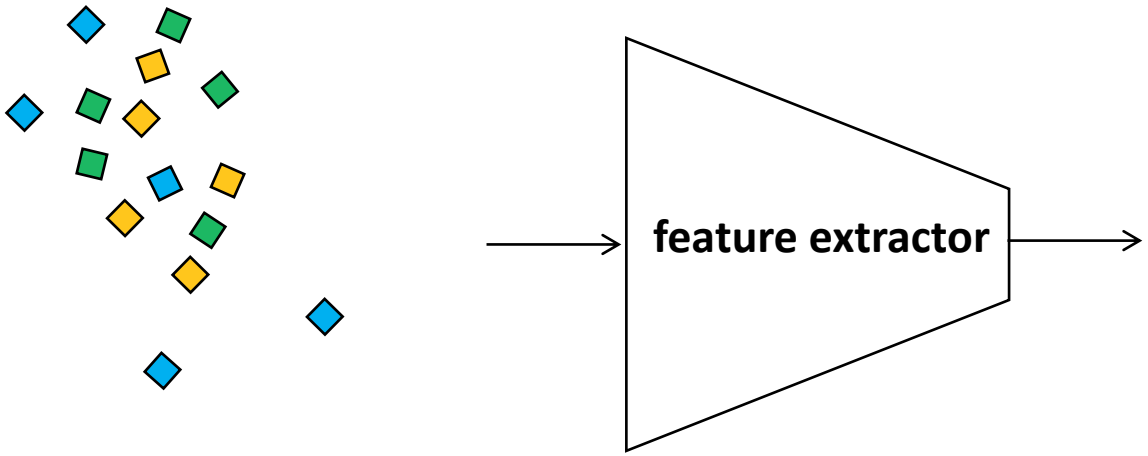
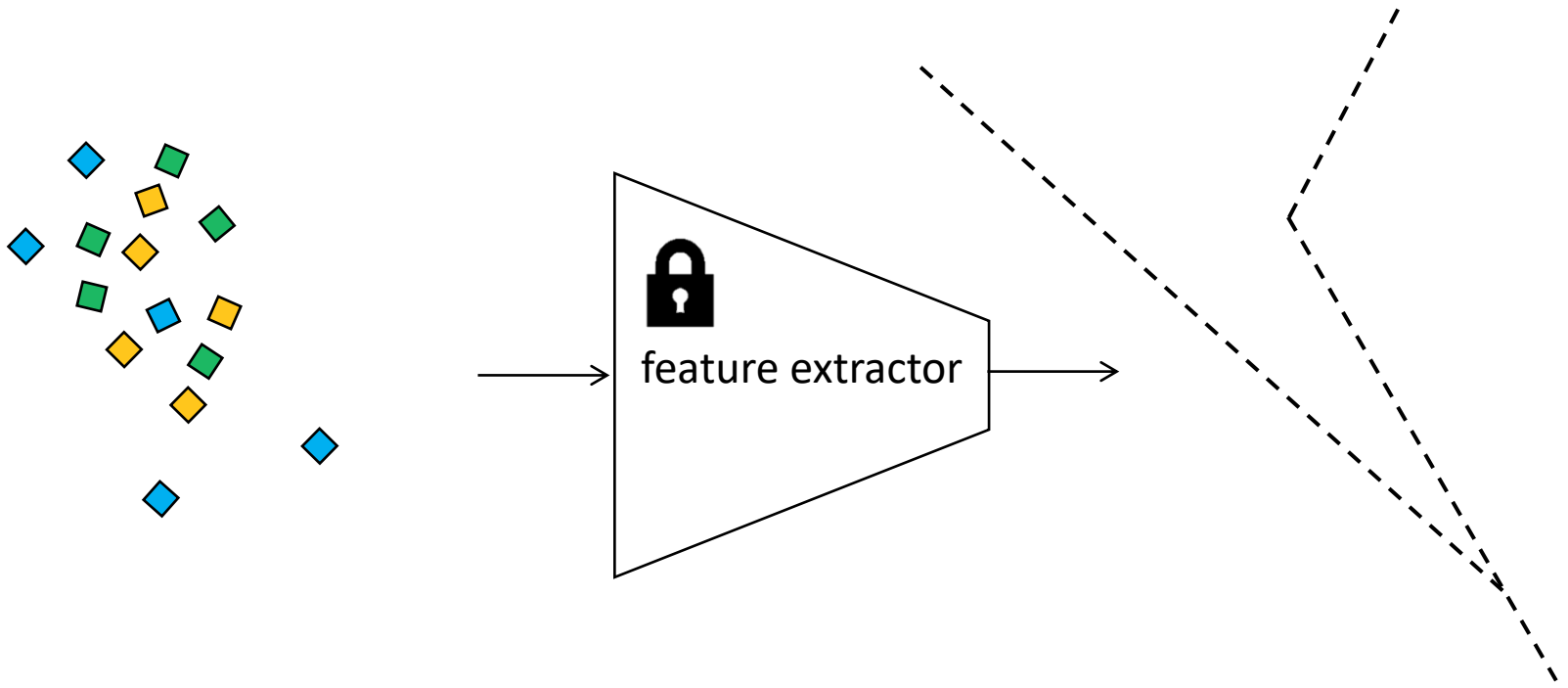
Stage 1: pretraining



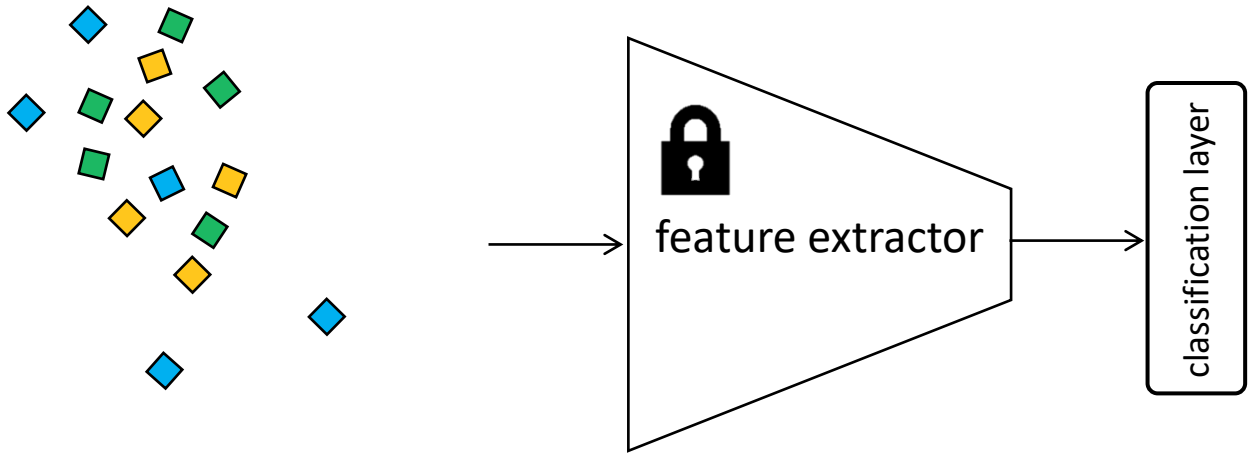
Stage 2: fine-tuning



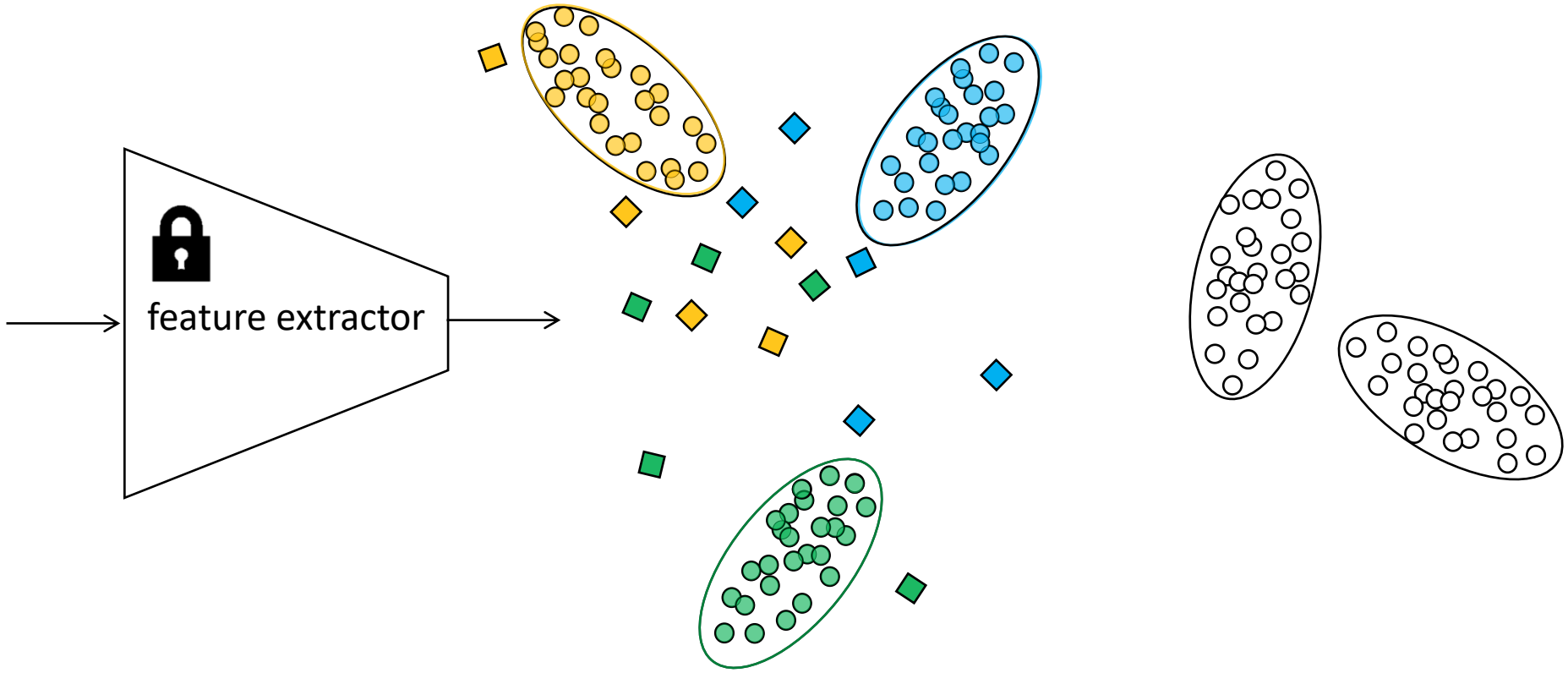
Stage 2: fine-tuning



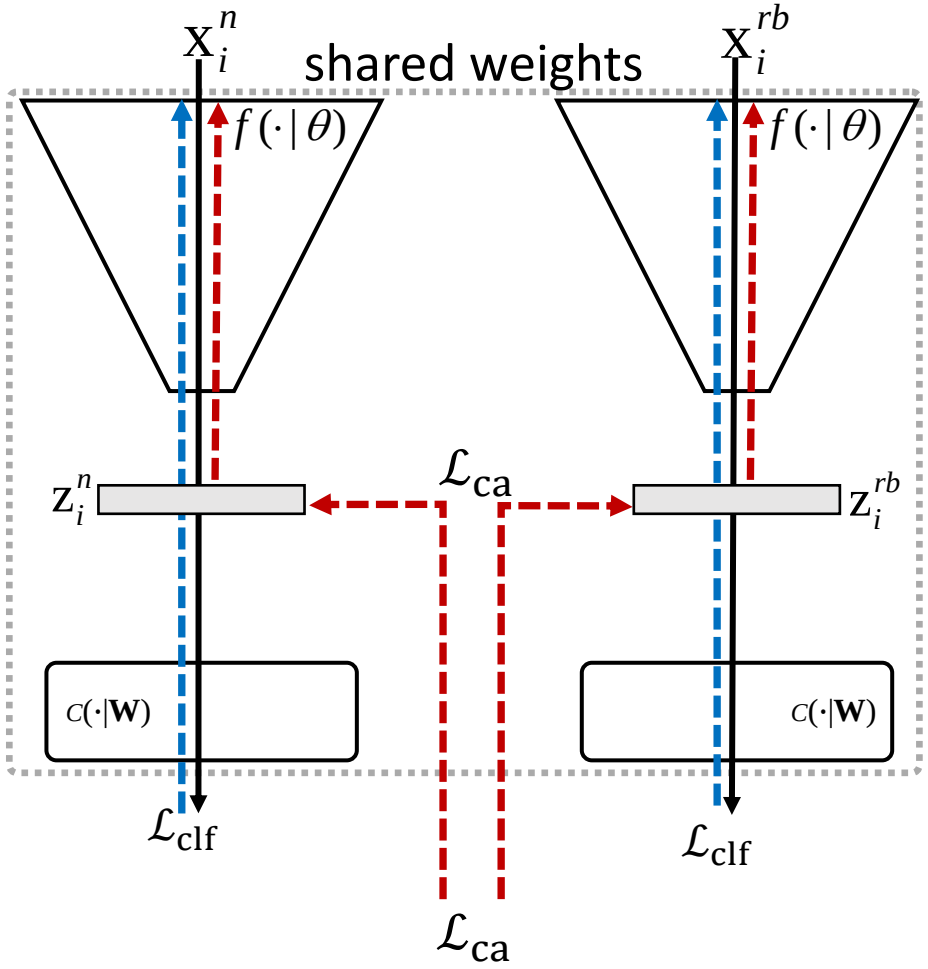
Detecting related bases

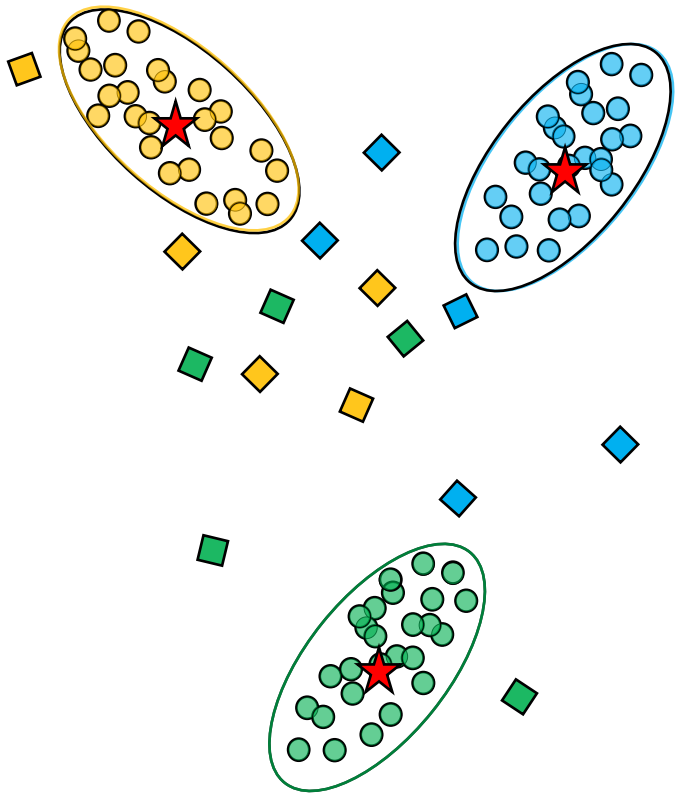


Detecting related bases

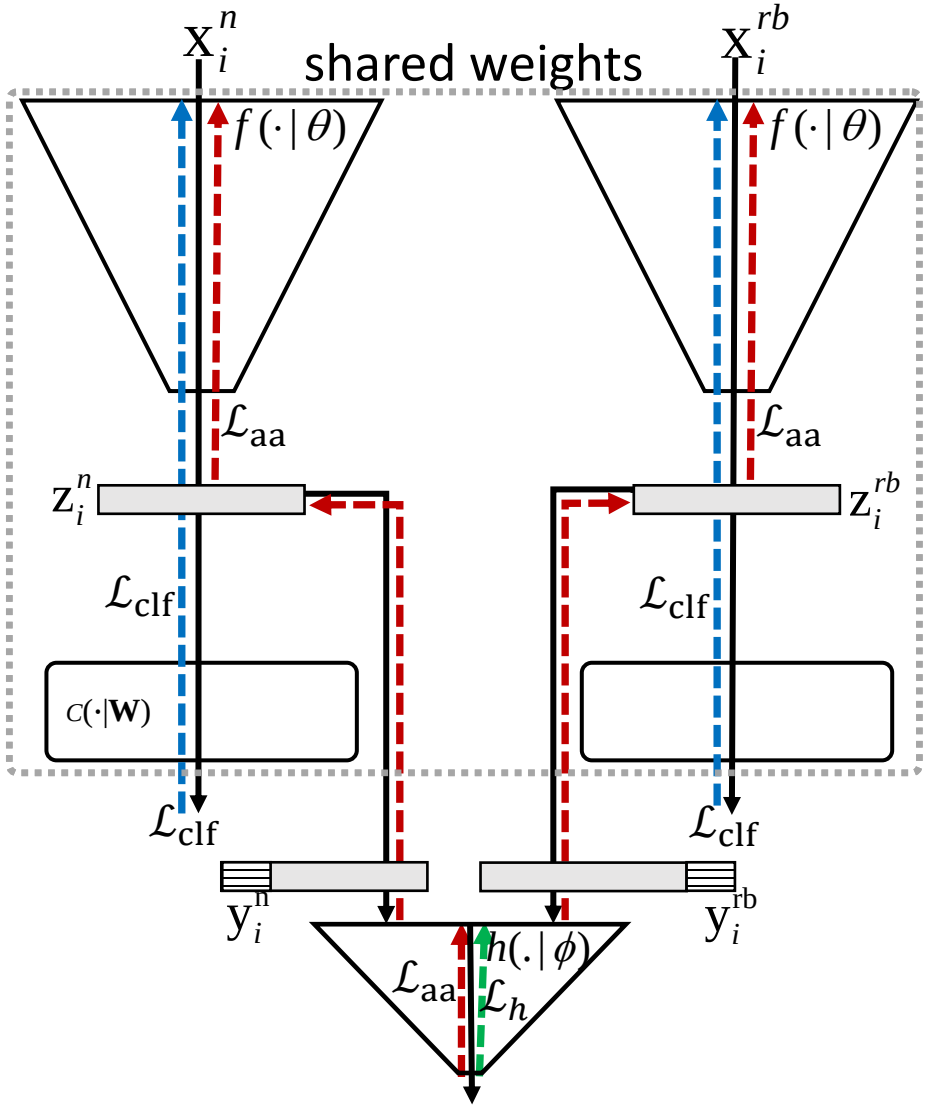


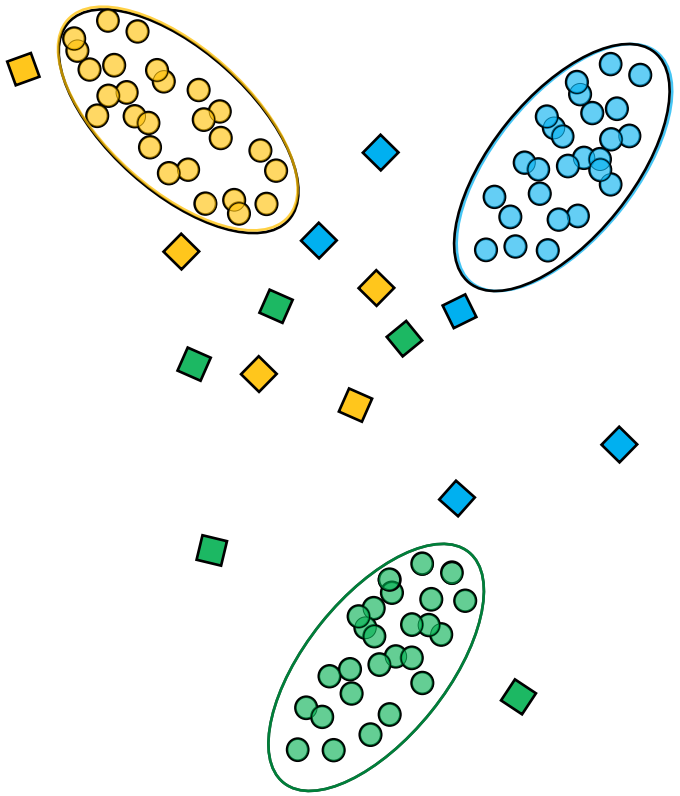
Centroid alignment



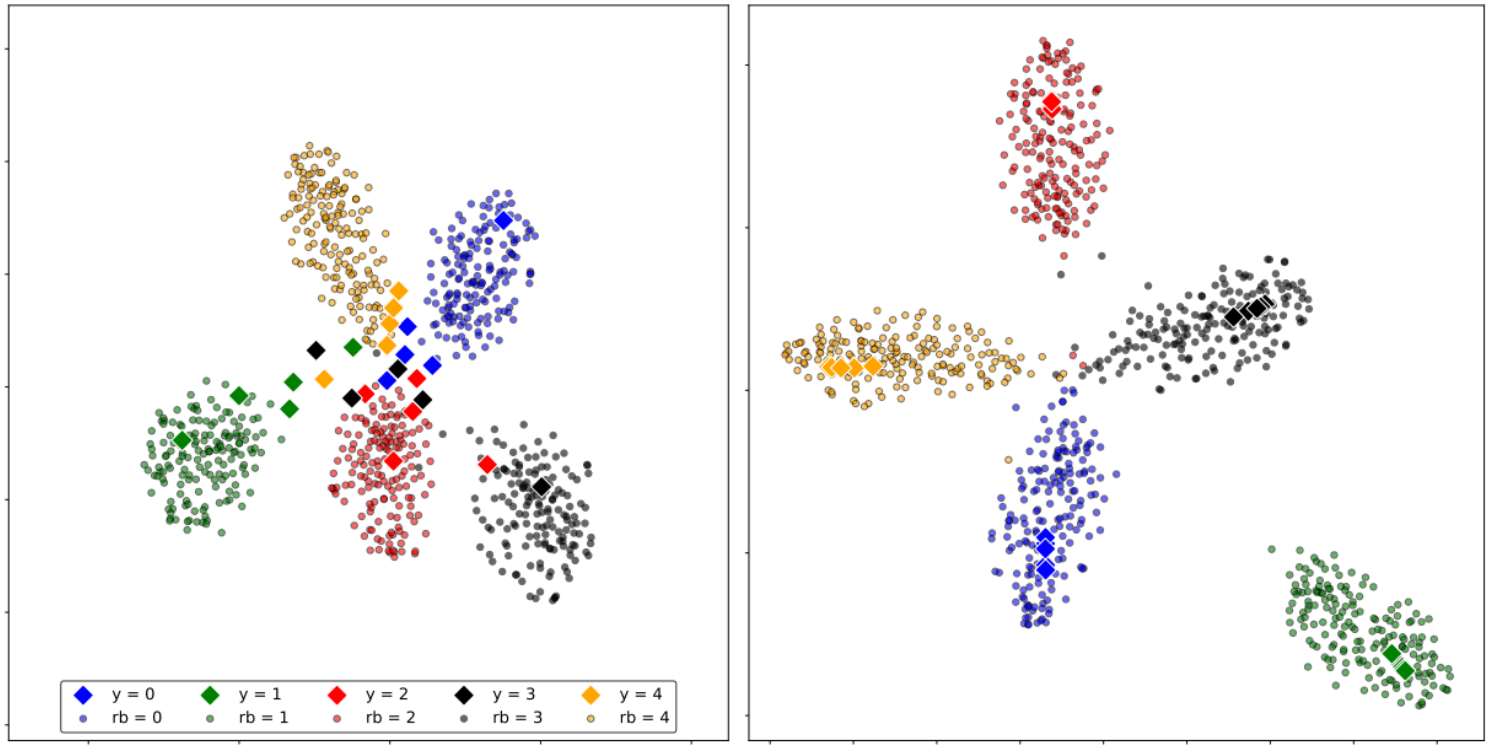


Adversarial alignment





Centroid alignment-vizualization



(a) before alignment

(b) after alignment

Experiments

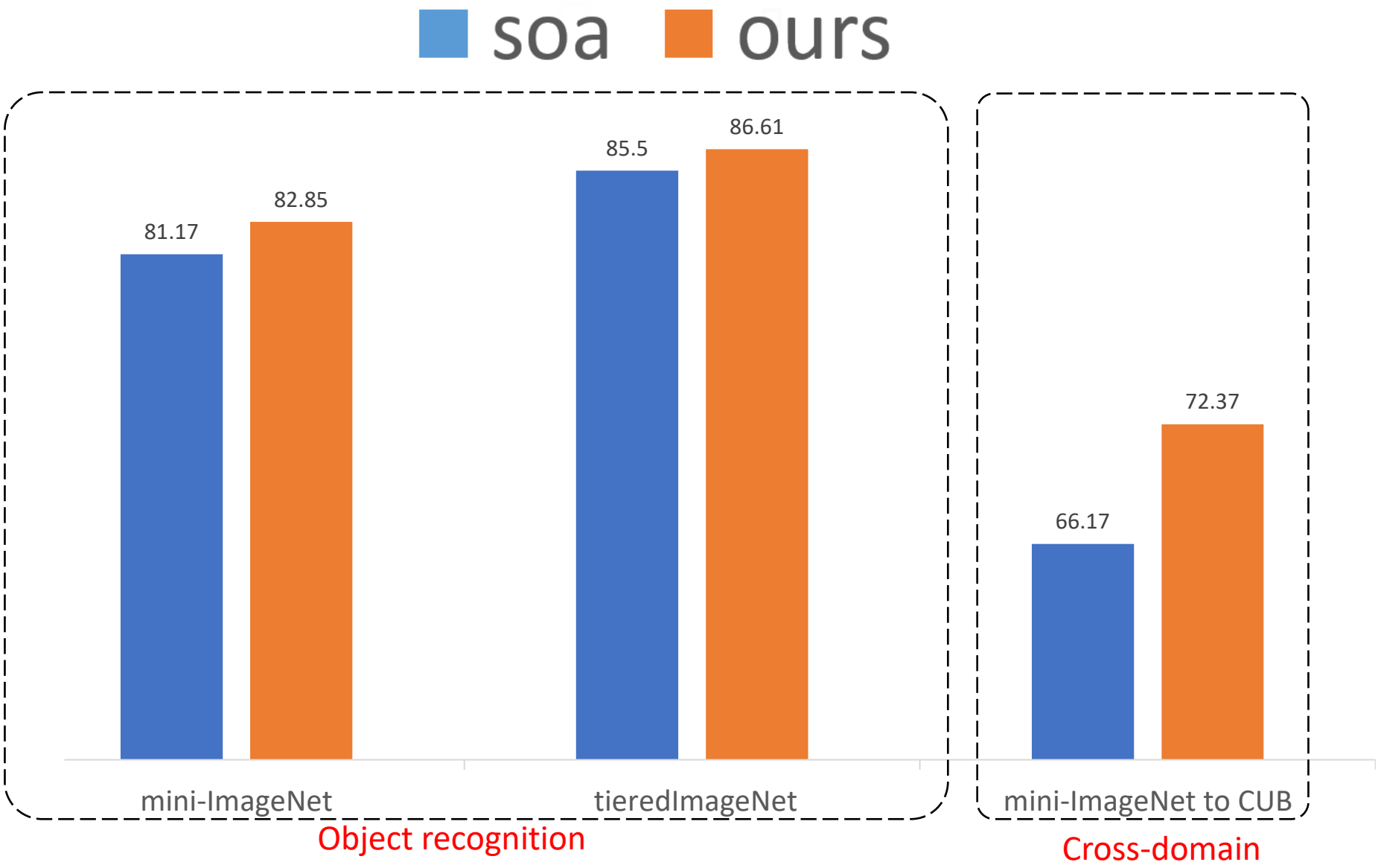
Datasets

- Object recognition
  - *mini*ImageNet
  - tieredImageNet
  - FC100
- Fine-grained classification
  - CUB
- Cross-domain adaptation
  - from *mini*ImageNet to CUB

Backbones

- Conv4
- ResNet-18
- WRN-28-10

Experiments (5-shot/5-way)



Persistent Mixture Model Networks for Few-Shot Image Classification

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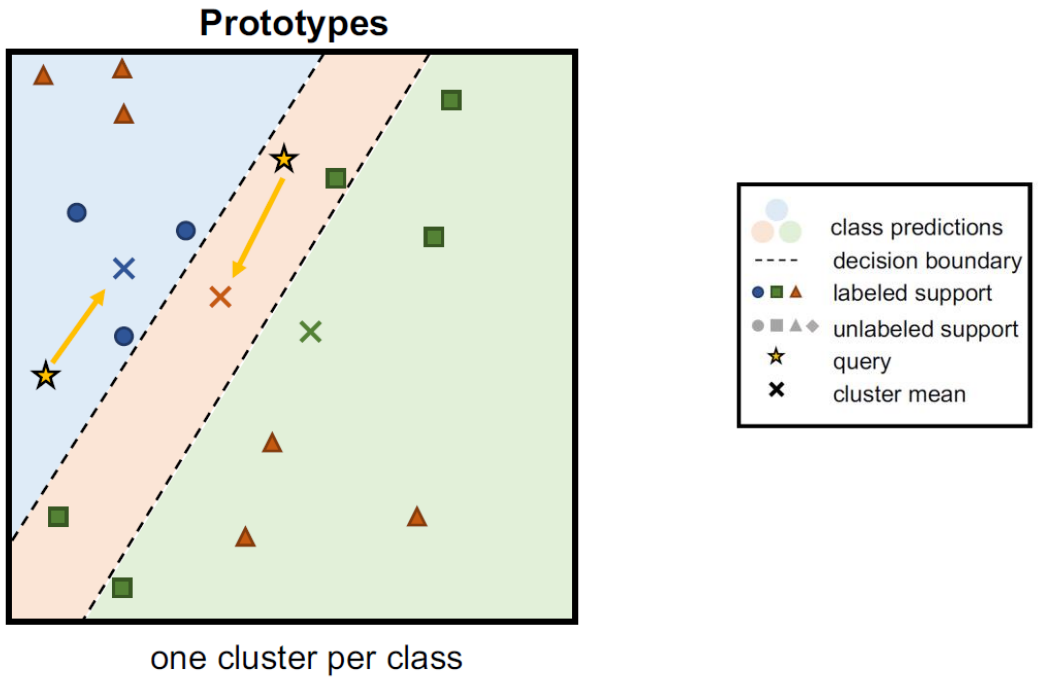
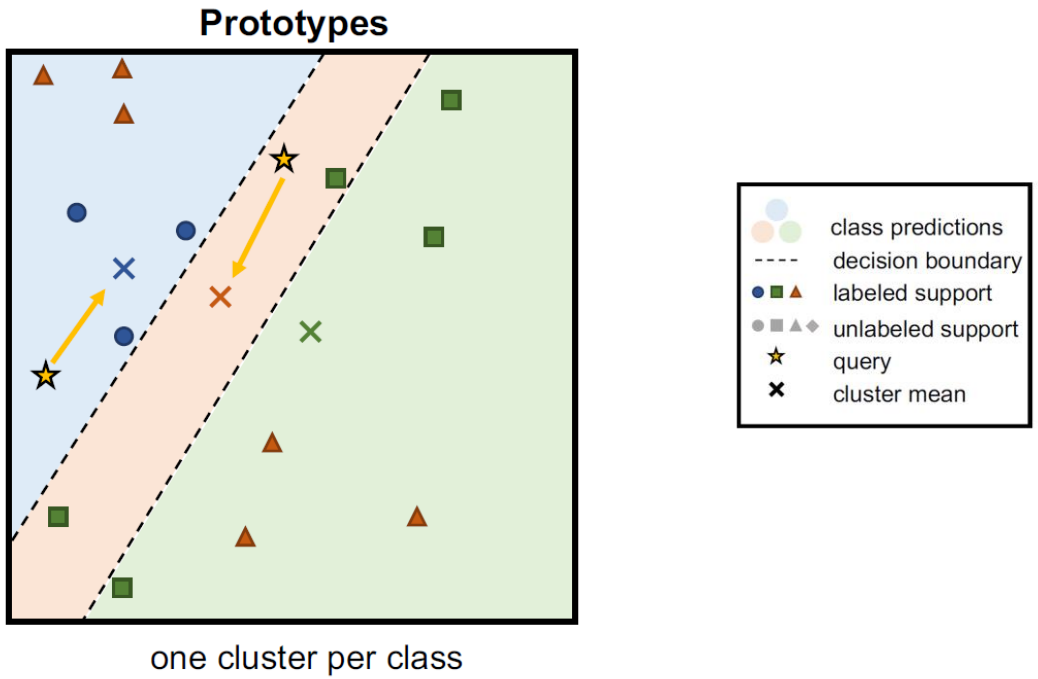
Closer look at prototypical network



KR Allen et al. 2019

Model fitting spectrum

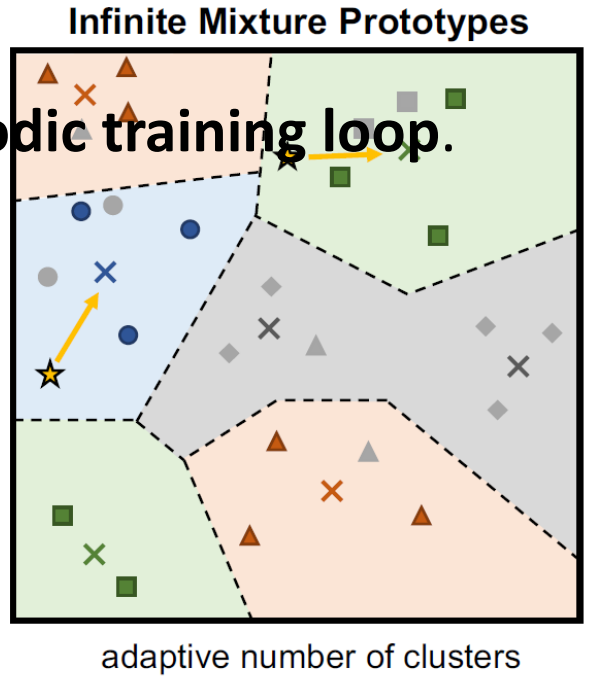


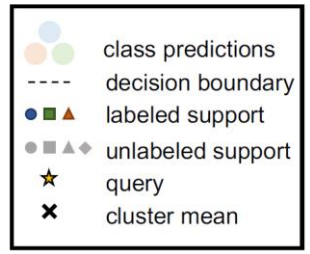
KR Allen et al. 2019

Closer look at IMP

This is accomplished by

- **DP-means** inside the **episodic training loop**.



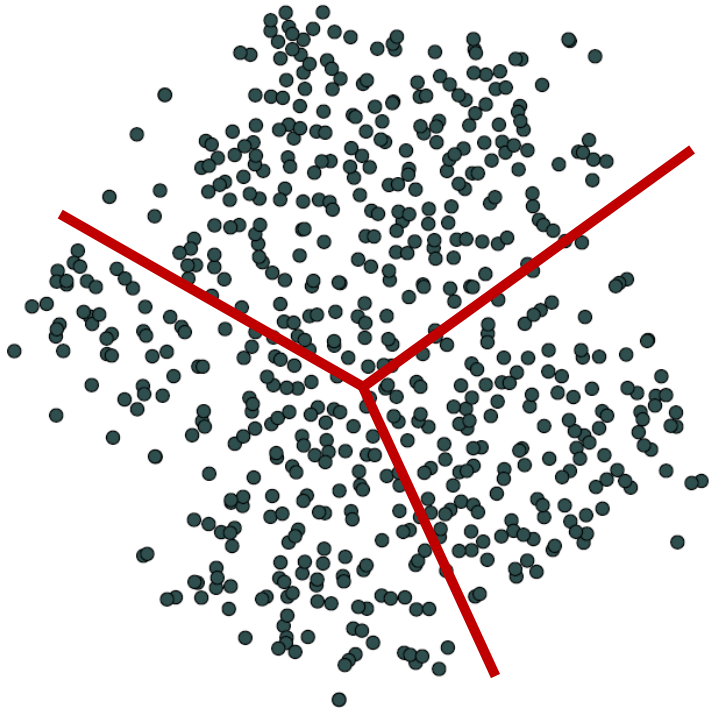


KR Allen et al. 2019

Infinite mixture prototypes (IMP)

Naïve solution

k-mean on all the embedding examples



i-th class embedding

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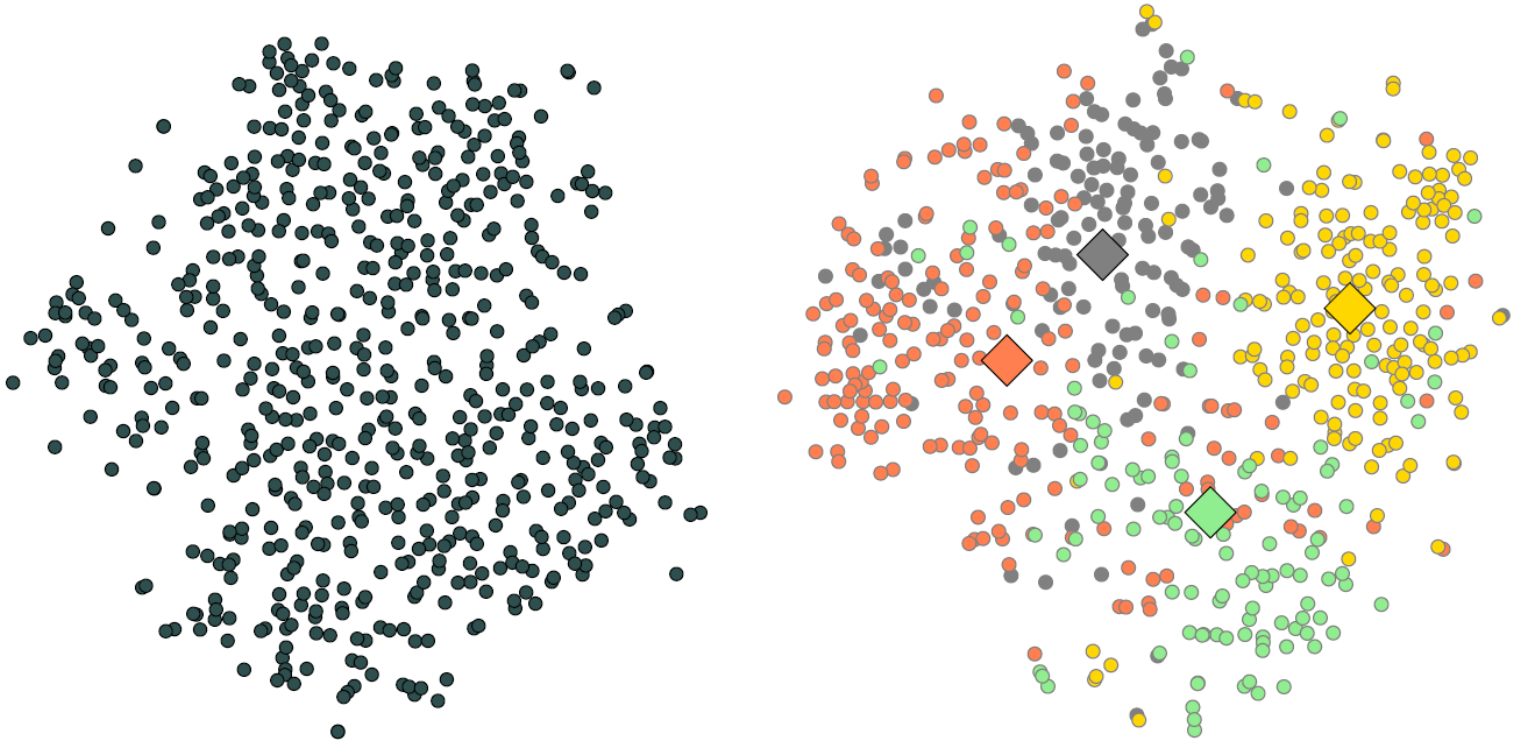
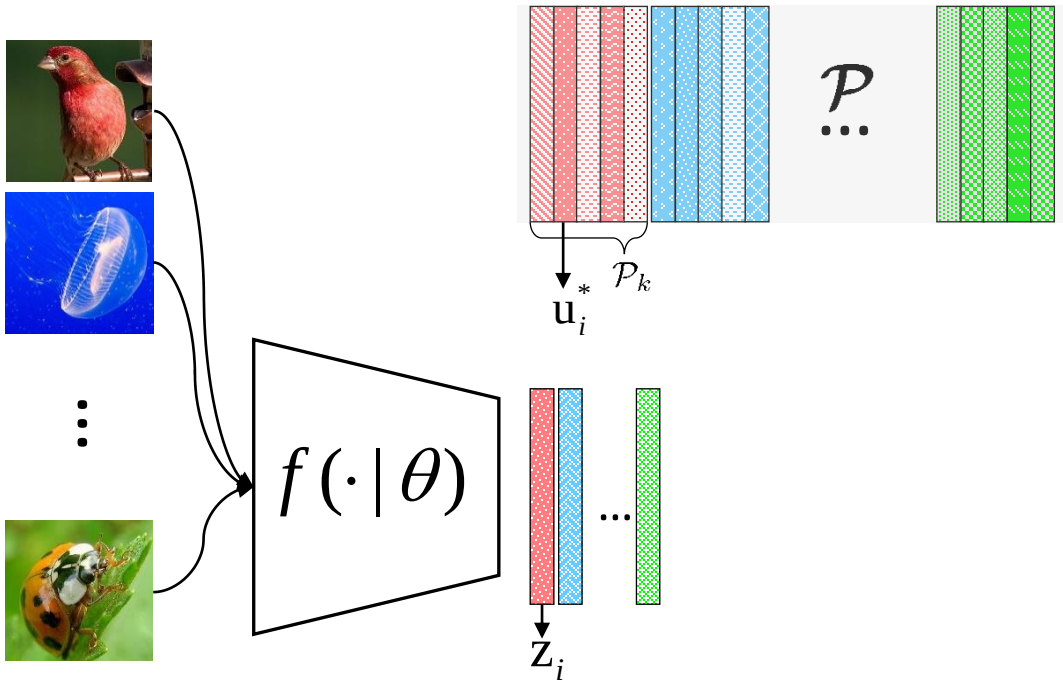
Feature visualization (t-SNE on RN-18)



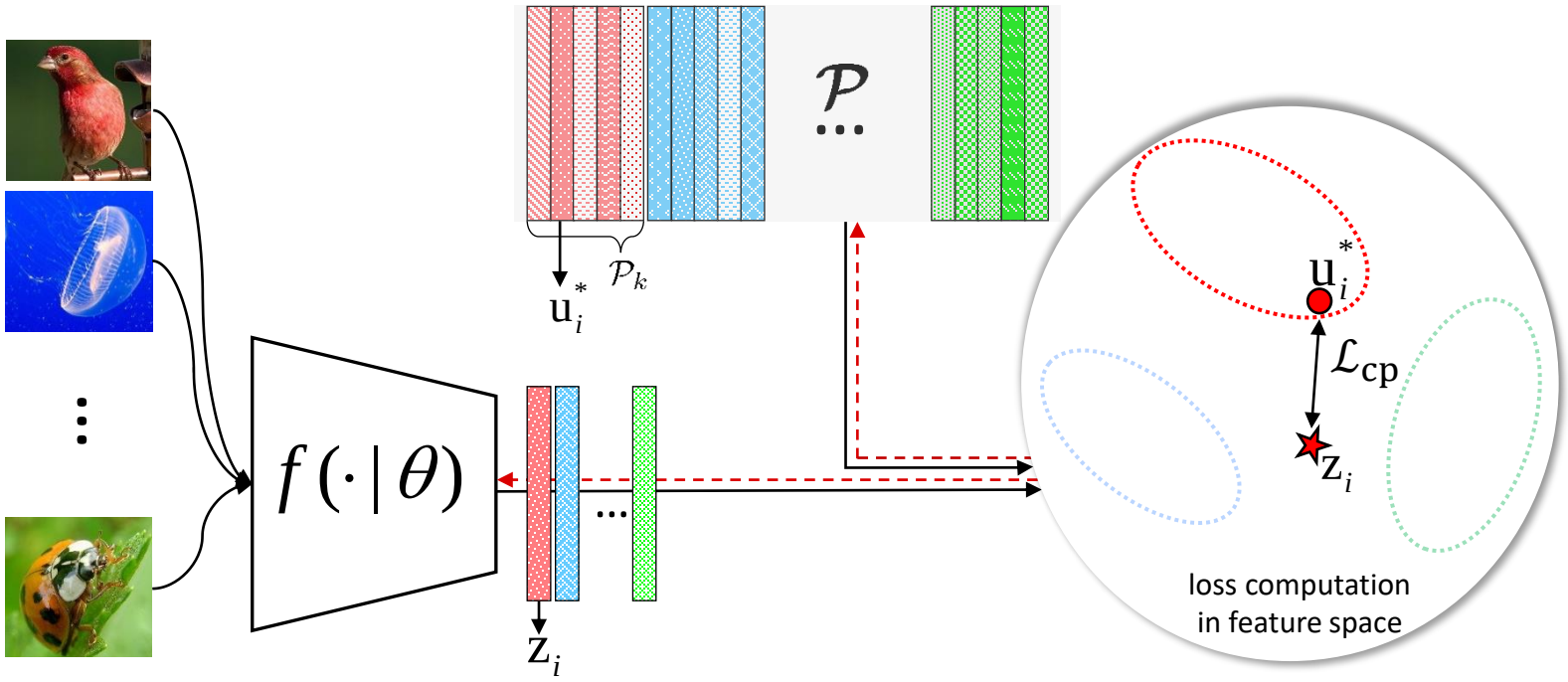
(a) without PMM

(b) our PMM

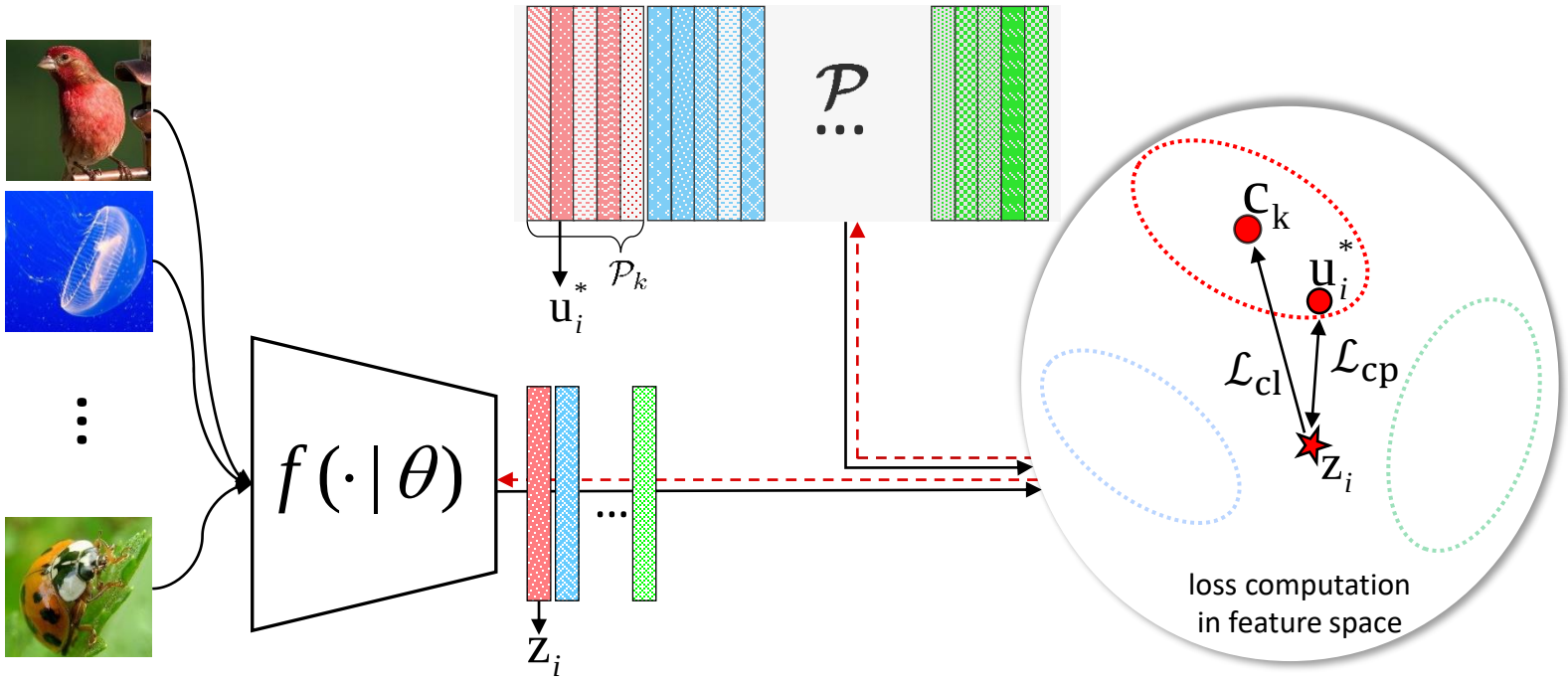
PMM



PMM-initial training

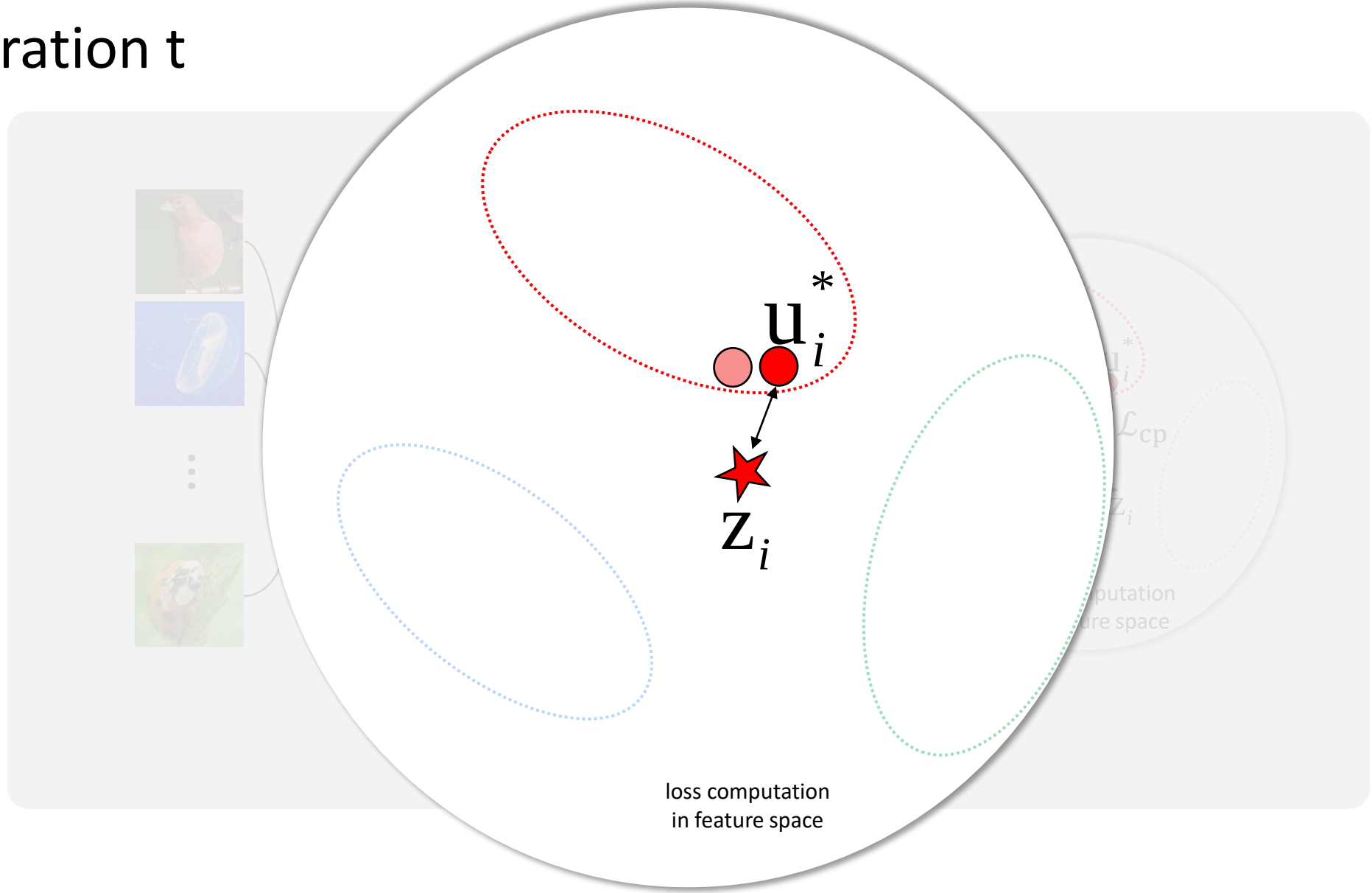


PMM-initial training



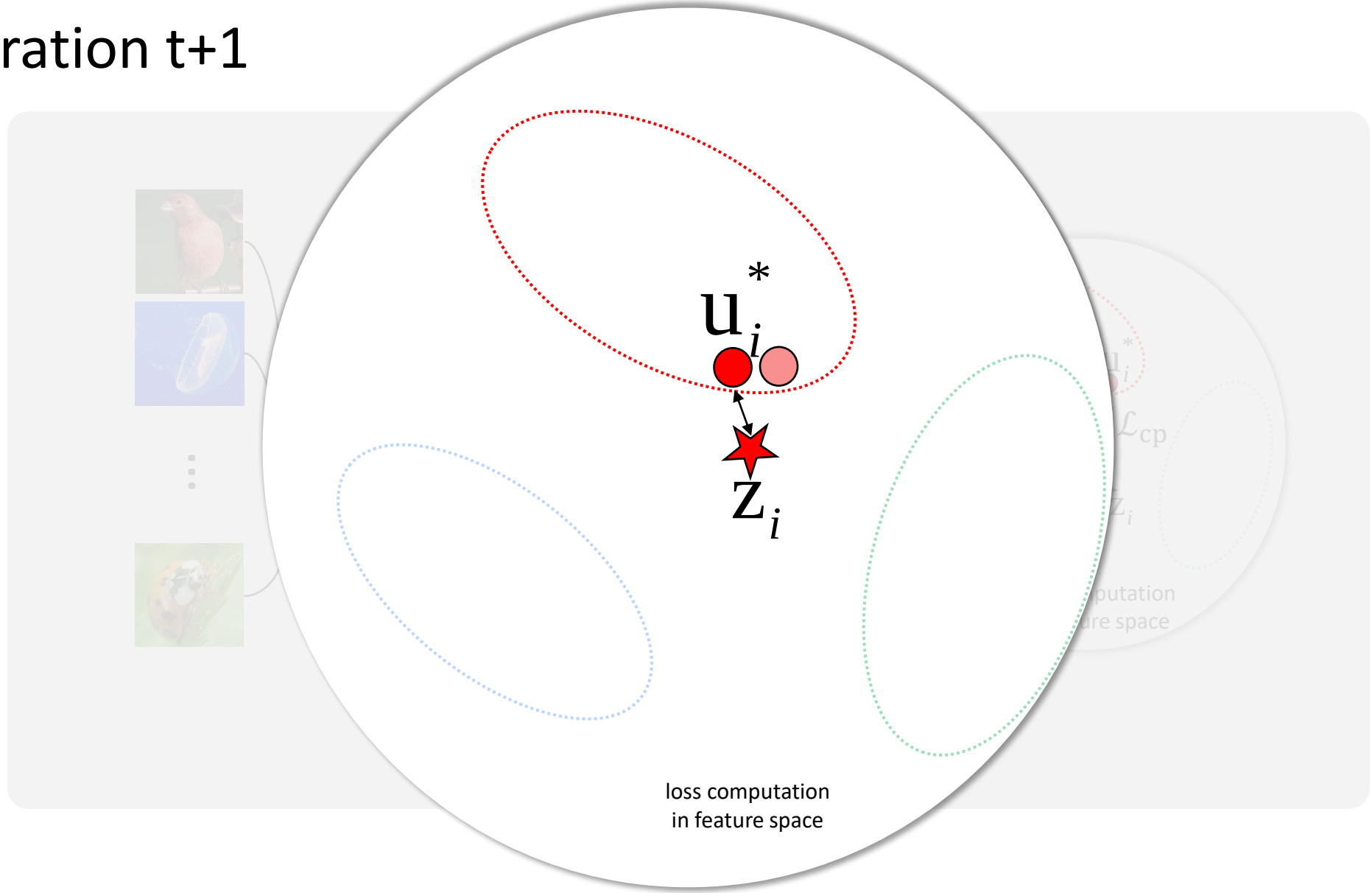
Closer look at initial training

iteration t

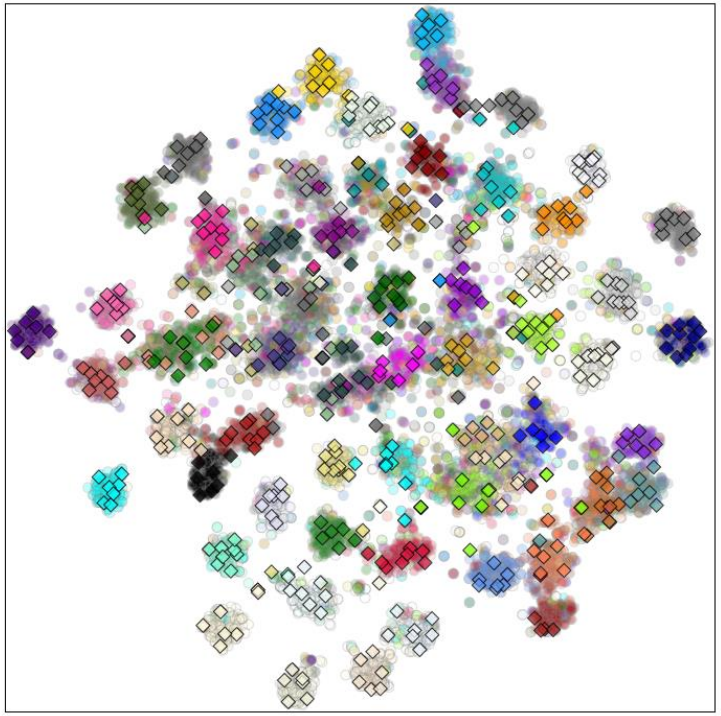


Closer look at initial training

iteration t+1

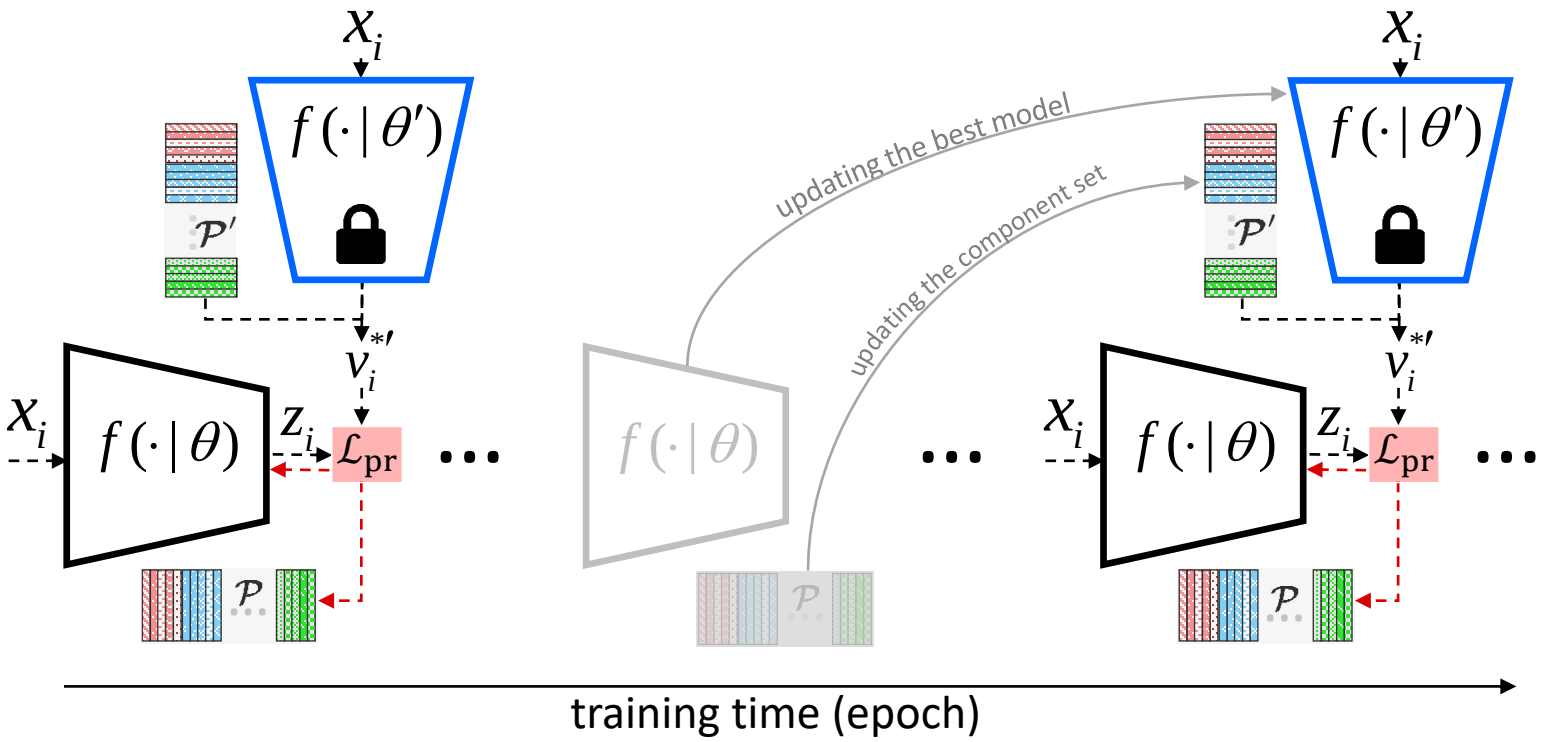


PMM-visualization

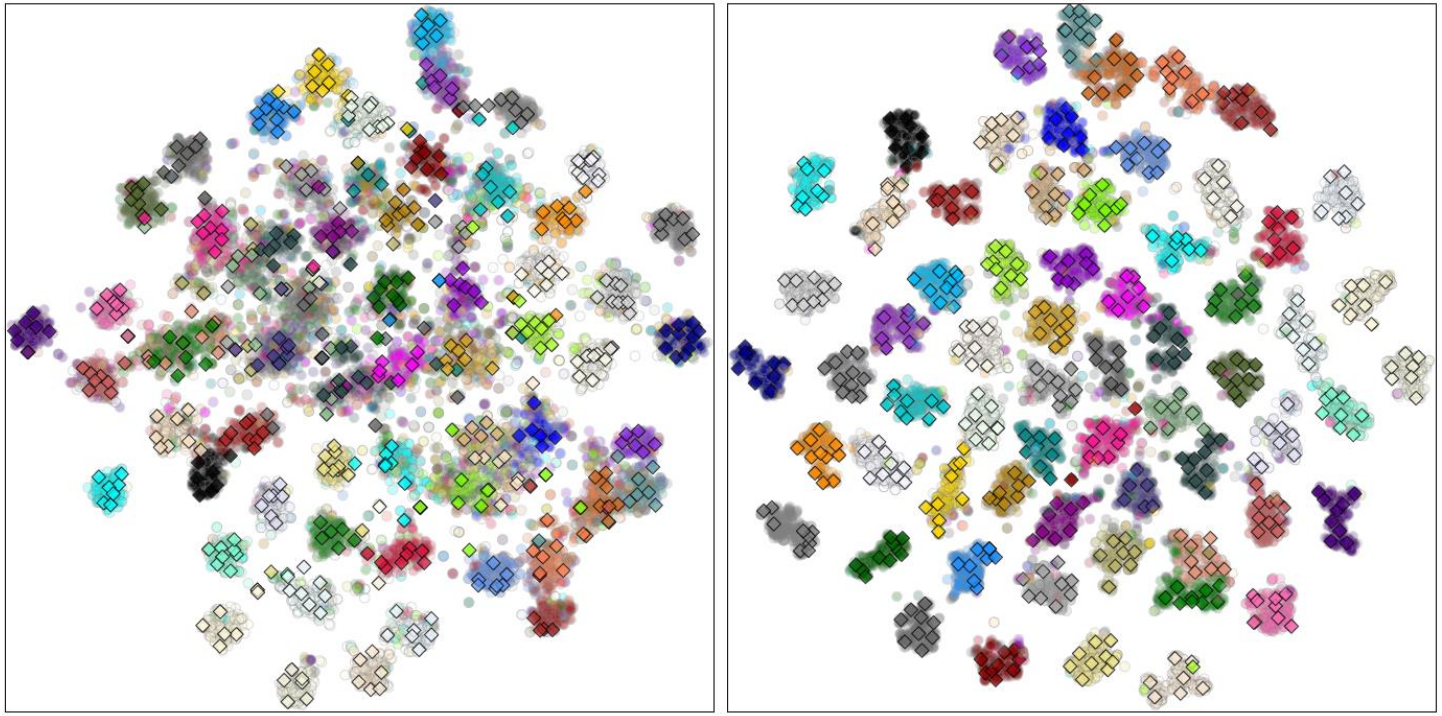


(a) after initial training

PMM-progressive following



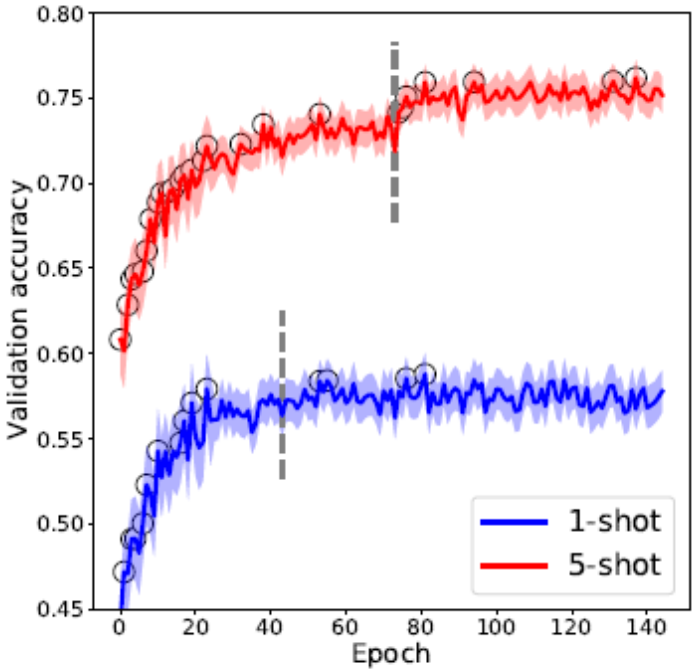
PMM-visualization



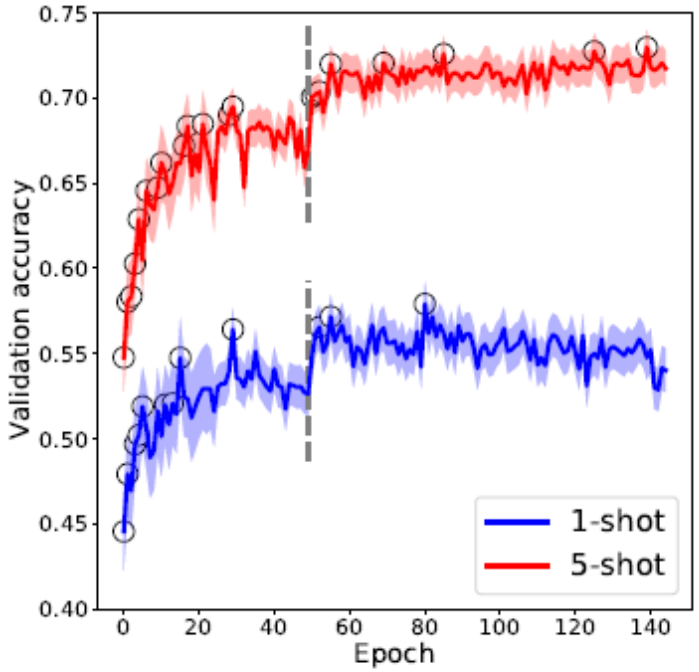
(a) after initial training

(b) after progressive following

PMM-validation accuracy dynamics



(a) ResNet-12



(b) ResNet-18

miniImageNet

Conv4

Method	1-shot	5-shot
Meta-LSTM [49]	43.44	55.31
MatchingNet‡ [65]	43.56	55.31
ProtoNet [57]	49.42	68.20
MAML [15]	48.07	63.15
RelationNet [59]	50.44	65.32
Baseline++ [6]	48.24	66.43
IMP [2]	49.60	68.10
Pos-Margin [1]	51.90	69.07
Neg-Margin [34]	**52.84**	70.41
PMM (ours)	52.82	**70.67**

ResNet-12

Method	1-shot	5-shot
DNS [56]	62.64	78.83
Var.FSL [78]	61.23	77.69
MTL [58]	61.20	75.50
SNAIL [40]	55.71	68.88
AdaResNet [42]	56.88	71.94
TADAM [43]	58.50	76.70
MetaOptNet [31]	62.64	78.63
Simple [61]	62.02	79.64
TapNet [74]	61.65	76.36
Neg-Margin [34]	63.85	81.57
PMM (ours)	**63.98**	**82.04**

tieredImageNet

ResNet-12

Method	1-shot	5-shot
DNS [56]	66.22	82.79
MetaOptNet [31]	65.99	81.56
Simple [61]	69.74	84.41
TapNet [74]	63.08	80.26
Pos-Margin* [1]	68.02	83.99
PMM (ours)	**70.97**	**86.16**

FC100

ResNet-12

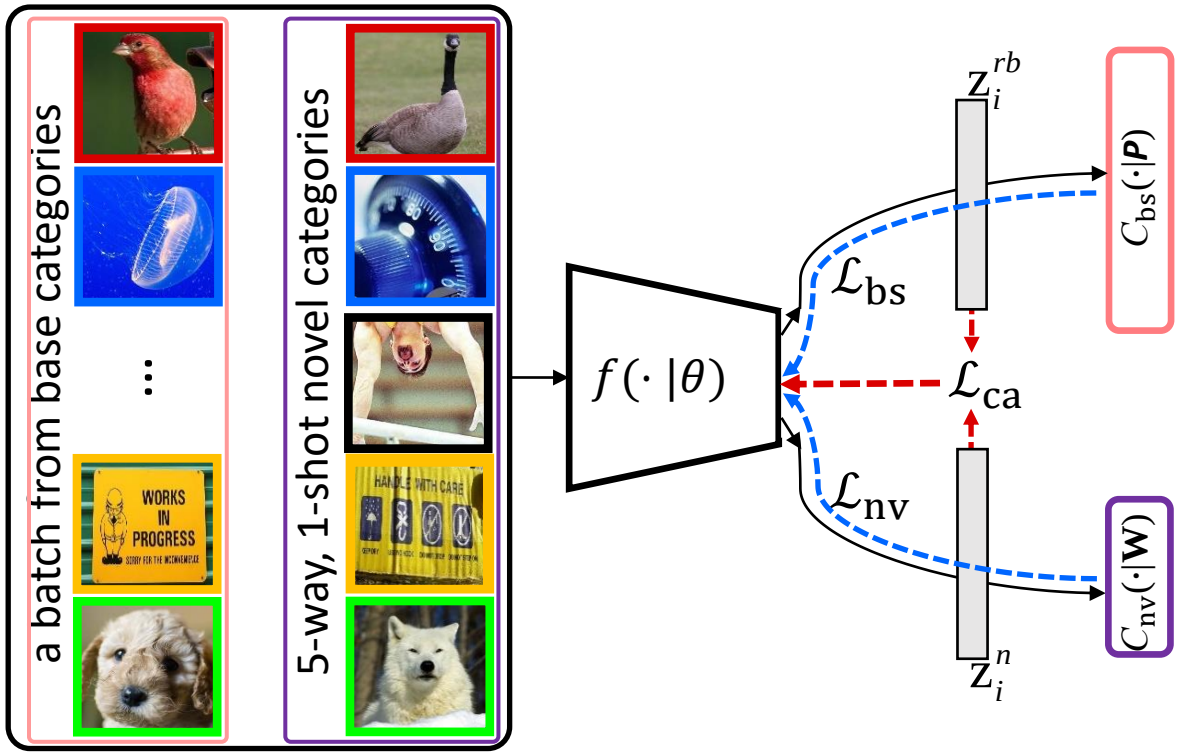
Method	1-shot	5-shot
TADAM [43]	40.1	56.1
MetaOptNet [31]	41.1	55.5
ProtoNet† [57]	37.5	52.5
MTL [58]	43.6	55.4
PMM (ours)	**44.89**	**60.70**

CUB and cross domain

	CUB		miniIN→CUB
	1-shot	5-shot	5-shot
GNN-LFT◇ [62]	51.51	73.11	–
Robust-20 [11]	58.67	75.62	–
RelationNet‡ [59]	67.59	82.75	57.71
MAML‡ [14]	68.42	83.47	51.34
ProtoNet‡ [57]	71.88	86.64	62.02
Baseline++ [6]	67.02	83.58	64.38
Pos-Margin [1]	71.37	85.74	64.93
Neg-Margin [34]	72.66	**89.40**	67.03
PMM (ours)	**73.94**	86.01	**68.77**

‡taken from [60] ◇backbone is ResNet-10

PMM-Alignment Extension

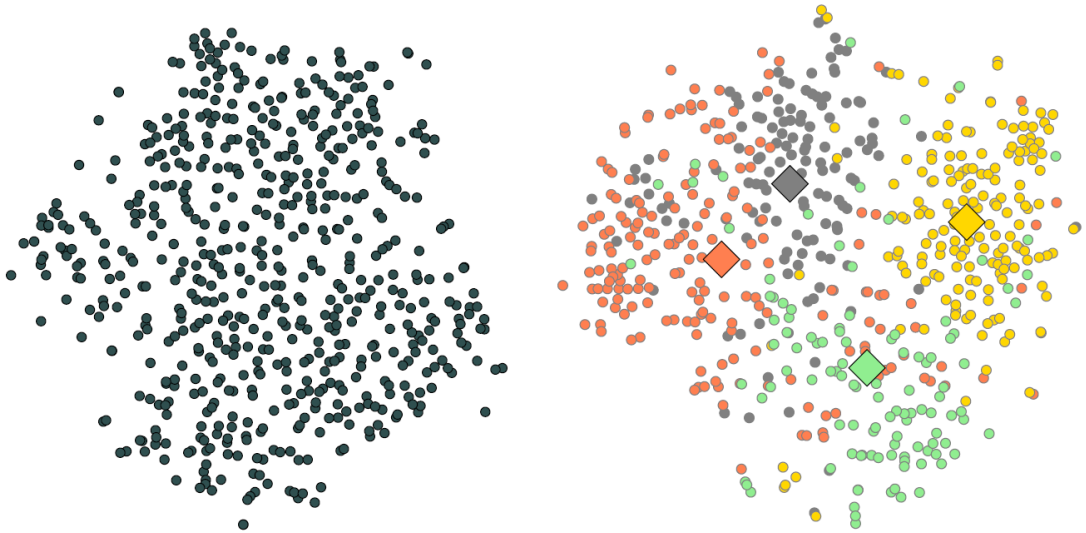


	Method	Backbone	1-shot	5-shot
miniIN	Cent. Align.* [1]	RN-12	63.44	80.96
	PMM-Align. (ours)	RN-12	**64.38**	**82.45**
	Cent. Align.* [1]	RN-18	59.85	80.62
	PMM-Align. (ours)	RN-18	**60.44**	**81.76**
tieredIN	Cent. Align.* [1]	RN-12	71.08	86.32
	PMM-Align. (ours)	RN-12	**71.83**	**88.20**
	Cent. Align.* [1]	RN-18	69.18	**85.97**
	PMM-Align. (ours)	RN-18	**69.82**	85.57

Current project

Self-PMM

under self-supervised learning framework

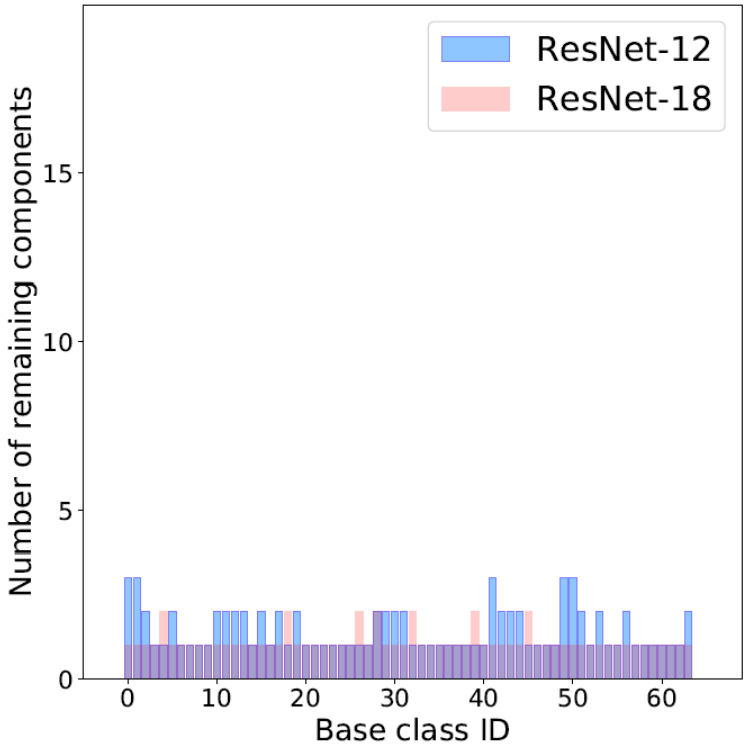


(a) without PMM

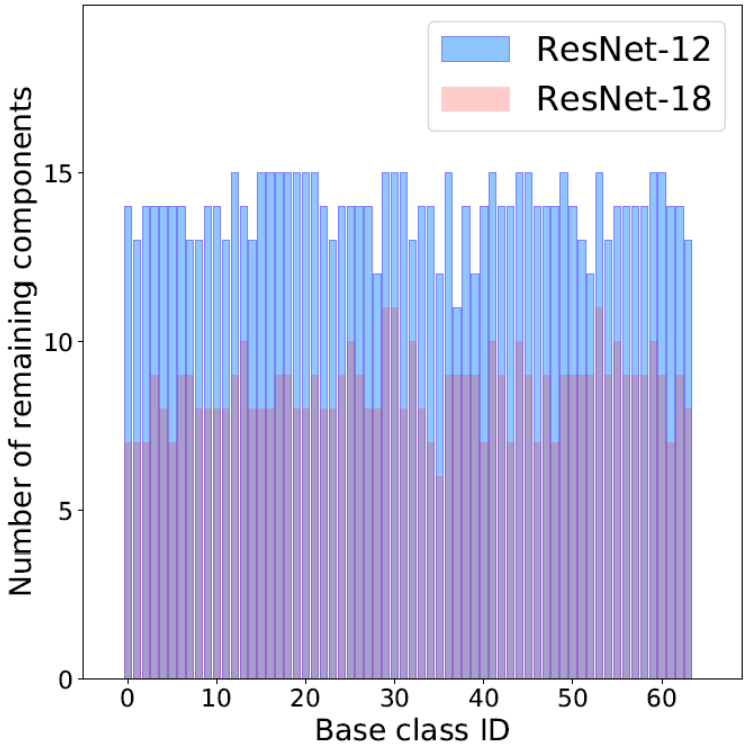
(b) our PMM

Thank you for your time!

Remaining components



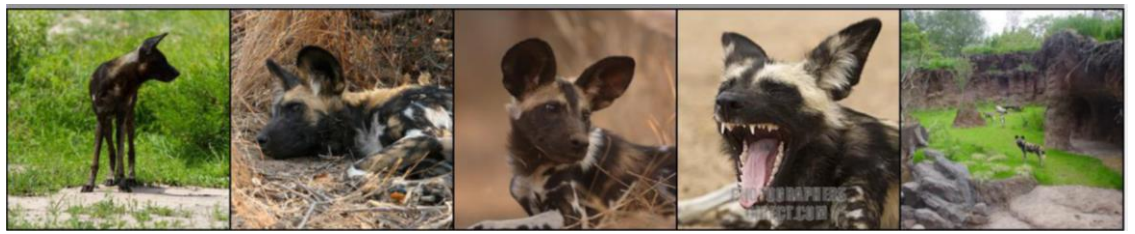
(a) without $\mathcal{L}_{\mathrm{cl}}$



(b) with $\mathcal{L}_{\mathrm{cl}}$

Examples of related bases

novel



related bases