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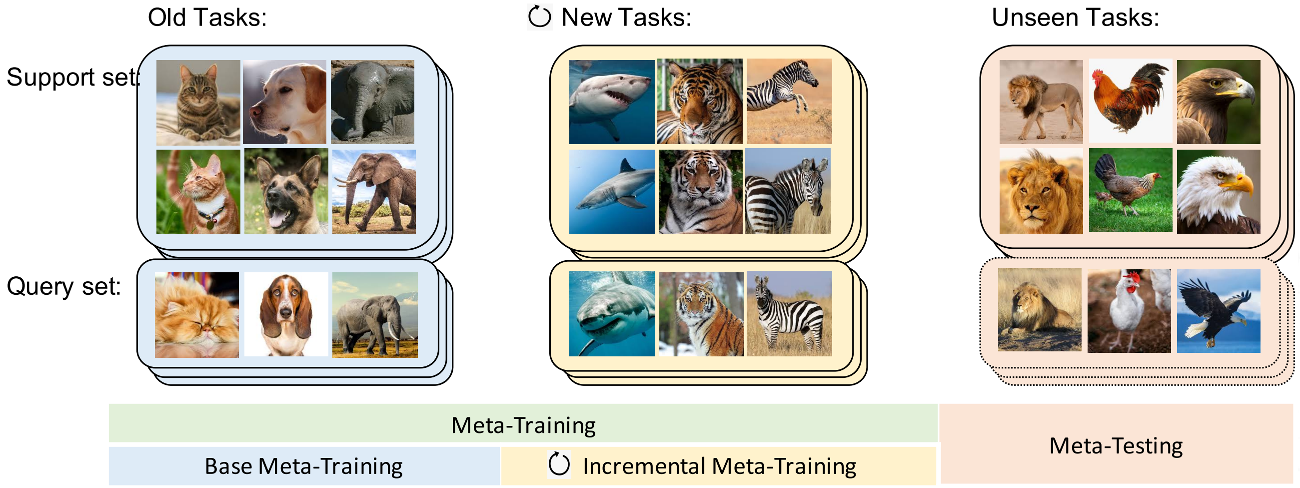
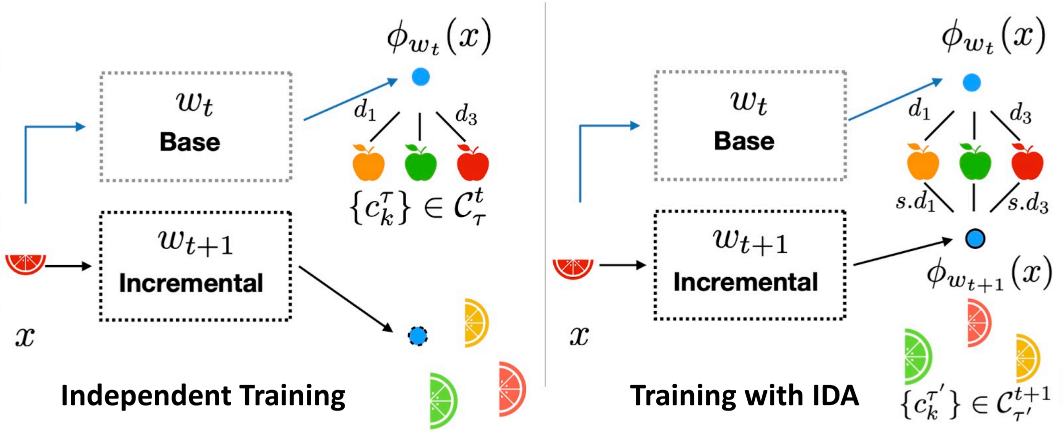
Incremental Few-Shot Meta-Learning via Indirect Discriminant Alignment

Qing Liu, Orchid Majumder, Alessandro Achille, Avinash Ravichandran, Rahul Bhotika, and Stefano Soatto





Incremental meta-learning -- Use knowledge learned from new tasks to enhance the base model in an *incremental* fashion (w/o access to old task data) to get an improved meta-learner.

New method: Indirect discriminant alignment -- Align the old and the new discriminants using "class anchors" from the old task τ, while processing only data from the new task τ'. $\mathrm{IDA}_{\mathcal{E}}(\phi_{\text{new}}|\phi_{\text{old}};\mathcal{C}_{\text{old}}) = \mathbb{E}_{x\sim\mathcal{E},\tau'}\left[\mathrm{KL}(f^{\tau'}_{\text{old}}(y|\phi_{\text{old}}(x))||f^{\tau'}_{\text{old}}(y|\phi_{\text{new}}(x)))\right]$

New dataset: DomainImageNet -- Introduce larger domain gap between old tasks and new tasks and test how this may affect incremental meta-learning.

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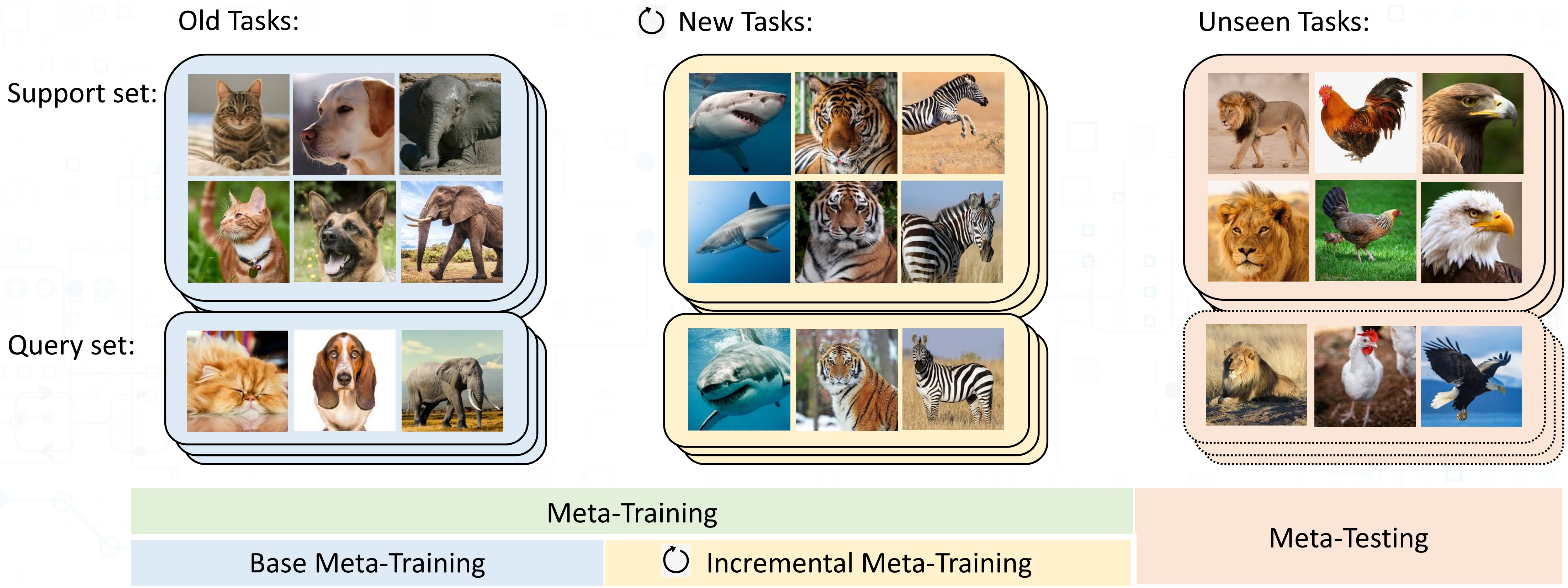

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Meta-learning with episodic sampling:

$$L(w;\mathcal{D}) = \frac{1}{N^\tau}\sum_\tau \frac{1}{|\mathcal{D}_\tau|}\sum_{(x_i,y_i)\in\mathcal{D}_\tau} -\log p_w^\tau(y_i|x_i)$$

$$= \frac{1}{N^\tau}\sum_\tau \frac{1}{|\mathcal{D}_\tau|}\sum_{(x_i,y_i)\in\mathcal{D}_\tau} -\log f_w^\tau(y_i|\phi_w(x_i))$$

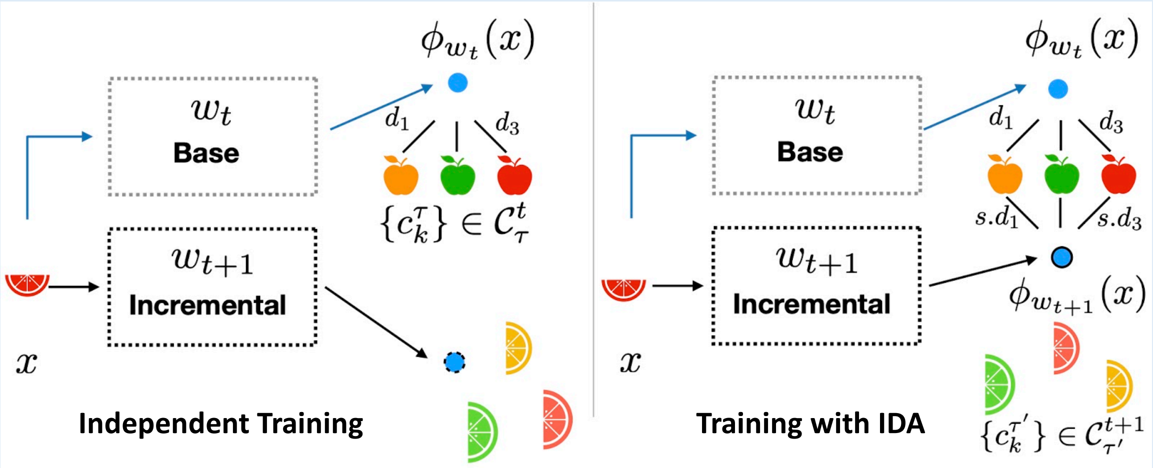
$\mathcal{D}_\tau$: meta-training task
$\phi_w(\cdot)$: backbone (embedding) function
$f_w(\cdot)$: classification head (discriminant) function

Incremental learning based on distillation:

$$L(w;\mathcal{D}\cup\mathcal{E}) = L(w;\mathcal{E}) + L(w;\mathcal{D})$$
$$\simeq L(w;\mathcal{E}) + L(w_0;\mathcal{D}) + \delta w^T H(w_0;\mathcal{D})\delta w$$
$$\simeq L(w;\mathcal{E}) + \lambda\mathbb{E}_{x\sim\mathcal{D}}\mathrm{KL}(p_{w_0}(y|x)||p_w(y|x))$$

$\mathcal{D}$: old dataset
$\mathcal{E}$: new dataset
w_0: base model weight
w : incremental model weight

Incremental few-shot meta-learning:



Key idea: aligning the old and new discriminants using "class anchors" from the old task t, while processing only data from the new task t+1

$$\mathrm{IDA}_\mathcal{E}(\phi_{\text{new}}|\phi_{\text{old}};\mathcal{C}_{\text{old}}) = \mathbb{E}_{x\sim\mathcal{E},\tau'}[\mathrm{KL}(f_{\text{old}}^{\tau'}(y|\phi_{\text{old}}(x))||f_{\text{old}}^{\tau'}(y|\phi_{\text{new}}(x)))]$$

$$w_{t+1} = \arg\min_{w_{t+1}} L(w_{t+1};\mathcal{E}) + \lambda\mathrm{IDA}_\mathcal{E}(\phi_{w_{t+1}}|\phi_{w_t};\mathcal{C}_t)$$

$\mathcal{C}_{\text{old}}$: class anchors from old training data
ϕ_{old} : old embeddings
ϕ_{new}: new embeddings
f_{old} : discriminant based on old class anchors

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MiniImageNet:

Orig. Split	IML Split	# of classes
Meta-training	Old classes	32
	New classes (Round I)	16
	New classes (Round II)	16
Meta-testing	Unseen classes	20

DomainImageNet:

IML Split	# of classes	Domain of classes
Old classes	32	Natural categories
	32	Man-made categories
New classes	32	Natural categories
	32	Man-made categories
Unseen classes	20	Natural categories
	20	Man-made categories

Table 6: Results of 5-shot 5-way classification accuracy on MiniImageNet using PN [35] with 2 rounds of incremental meta-training, where each round consists of an 16 new classes.

Model	Incremental - Round I			Incremental - Round II		
	Old classes (32)	New classes (16)	Unseen classes (20)	Old classes (32+16)	New classes (16)	Unseen classes (20)
NU	91.17 ± 0.18	65.60 ± 0.39	68.60 ± 0.33	82.25 ± 0.37	71.45 ± 0.38	68.60 ± 0.33
FT	80.70 ± 0.31	87.67 ± 0.37	67.45 ± 0.37	76.03 ± 0.36	90.72 ± 0.23	70.57 ± 0.32
DFA	$\mathbf{87.69 \pm 0.26}$	88.43 ± 0.36	68.20 ± 0.36	80.69 ± 0.38	91.27 ± 0.21	71.19 ± 0.37
IDA	87.30 ± 0.25	$\mathbf{89.56 \pm 0.20}$	$\mathbf{72.08 \pm 0.36}$	$\mathbf{84.21 \pm 0.30}$	$\mathbf{93.25 \pm 0.17}$	$\mathbf{75.15 \pm 0.35}$
PAR	93.94 ± 0.05	93.09 ± 0.06	72.10 ± 0.13	93.03 ± 0.06	95.58 ± 0.05	75.27 ± 0.13

Table 4: Results of 5-shot 5-way classification accuracy on different sets of DomainImageNet using PN [35] and different IML methods.

Model	Old classes from old domain (32)	New classes from new domain (32)	Unseen classes from old domain (20)	Unseen classes from new domain (20)	Unseen classes from both domains (40)
NU	86.94 ± 0.22	49.14 ± 0.36	57.66 ± 0.38	51.72 ± 0.32	59.59 ± 0.35
FT	64.42 ± 0.35	$\mathbf{84.80 \pm 0.28}$	50.72 ± 0.38	$\mathbf{71.16 \pm 0.32}$	65.44 ± 0.40
DFA	65.12 ± 0.35	83.95 ± 0.29	51.33 ± 0.38	70.46 ± 0.33	65.52 ± 0.40
IDA	$\mathbf{81.26 \pm 0.27}$	82.06 ± 0.30	$\mathbf{59.32 \pm 0.39}$	70.61 ± 0.32	$\mathbf{70.36 \pm 0.36}$
PAR	87.44 ± 0.22	88.77 ± 0.25	58.59 ± 0.37	74.46 ± 0.32	74.02 ± 0.37