Analysis of Meta-Learning Methods in a More Realistic Cross-Domain Scenario

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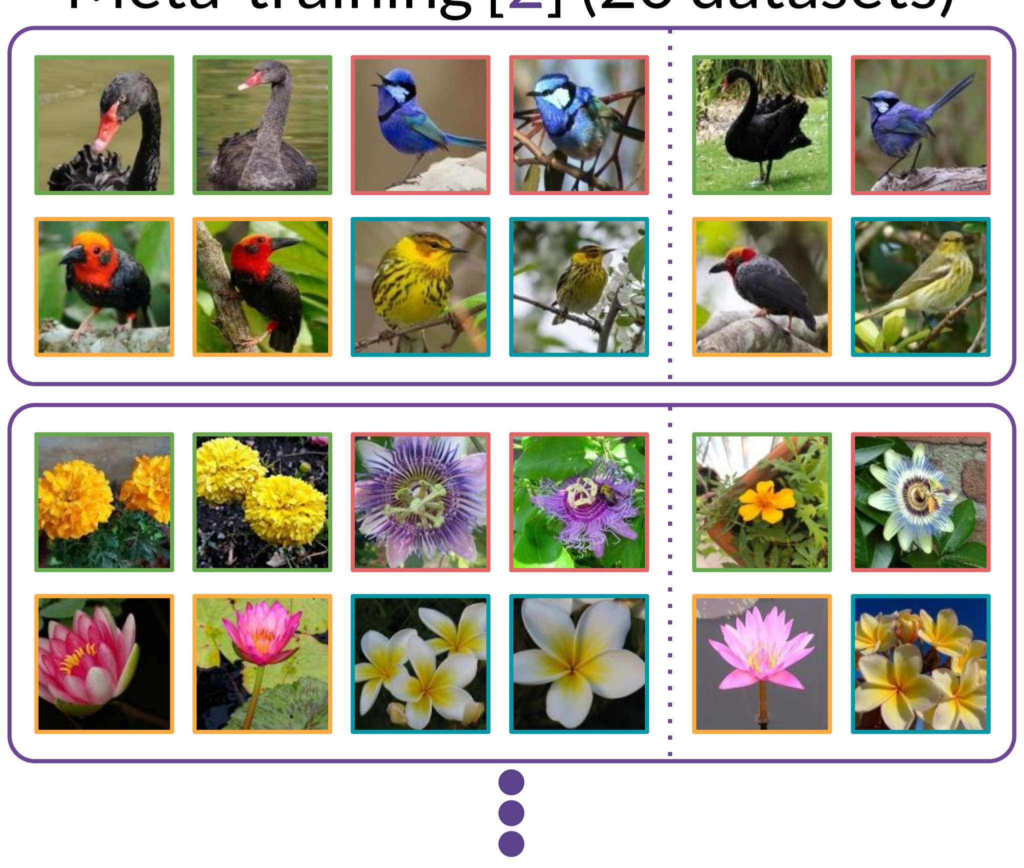
1. INTRODUCTION

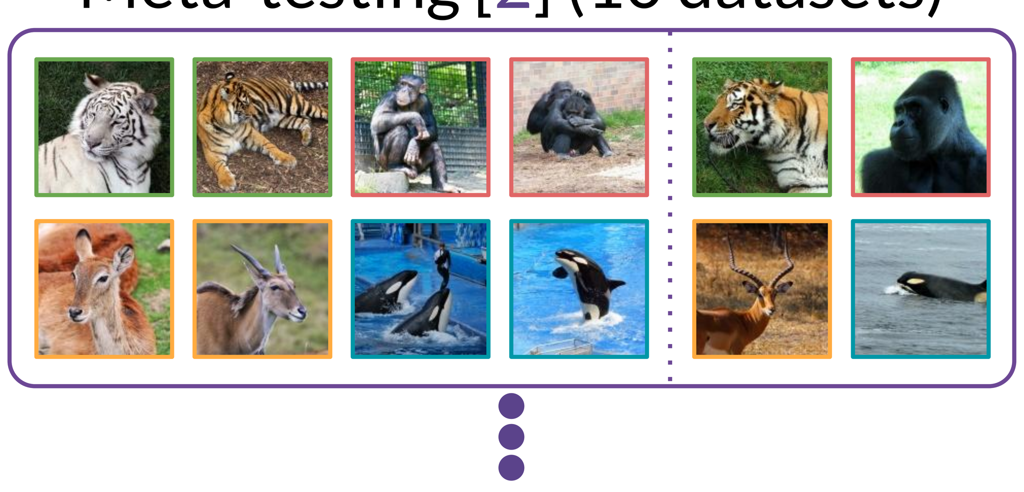
- **Motivation:** Current evaluation settings primarily focus on **within-domain scenarios**.
- **Challenges:** Real-world situations involve **multiple domains** with **varying task configurations** [1].
- **Goal:** Motivate the development of methods suited for the **any-way any-shot cross-domain** scenario.

2. EXPERIMENTAL SETUP

Meta-training [2] (20 datasets)



Meta-testing [2] (10 datasets)

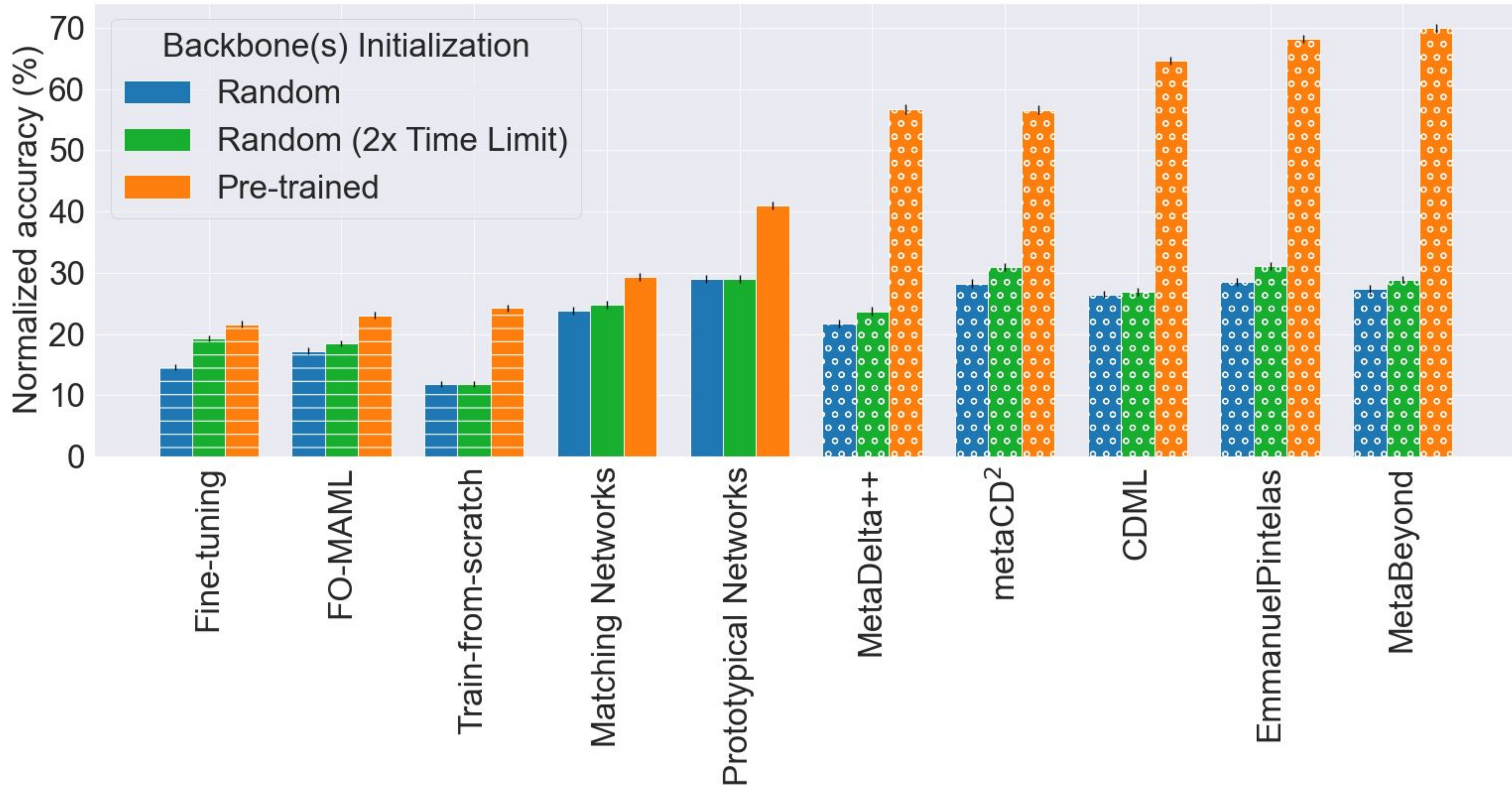


3. EVALUATED METHODS

- **Baseline methods:** Train-from-scratch, Fine-tuning, Matching Networks [3], Prototypical Networks [4], FO-MAML [5], MetaDelta++ [6].
- **MetaBeyond:** Two meta-learners (ResNet-50 and PoolFormer-S24) equipped with multiple lightweight task-adaptation modules.
- **EmmanuelPintelas:** Single meta-learner (SE-ResNet-152D) with an ensemble of distance- and linear-based classifiers.
- **CDML:** Two meta-learners (SEResNext101 and SEResNext50) enhanced with contrastive learning and self-optimal transport.
- **metaCD^2:** MetaDelta++ improved by including contrastive learning and regularized knowledge distillation using a student-teacher approach (SWSL-ResNet50).

4. RESULTS

Analysis of the impact of the backbones' initialization. The bars' texture indicates the following: ***horizontal lines*** – linear classifier, ***no texture*** – NCC, ***circles*** – based on MetaDelta++ [6].



Ablation study of the shared components among the four methods explicitly designed for the any-way any-shot cross-domain scenario.

Team	Pre-training	Data augmentation	Domain adaptation	Optimizations	Normalized accuracy (%)
MetaBeyond					17.53 ± 0.34
	✓				66.24 ± 0.39
	✓	✓			66.07 ± 0.39
	✓	✓	✓		(Timeout)
	✓	✓	✓	✓	$\mathbf{69.97 \pm 0.39}$
EmmanuelPintelas					20.54 ± 0.38
	✓				63.54 ± 0.42
	✓	✓			64.45 ± 0.42
	✓	✓	✓		66.04 ± 0.41
	✓	✓	✓	✓	$\mathbf{68.55 \pm 0.39}$
CDML					18.20 ± 0.36
	✓				61.16 ± 0.40
	✓	✓			62.91 ± 0.39
	✓	✓	✓		62.55 ± 0.39
	✓	✓	✓	✓	$\mathbf{64.60 \pm 0.39}$
metaCD^2					16.06 ± 0.33
	✓				56.65 ± 0.41
	✓	✓			56.19 ± 0.41
	✓	✓	✓		56.56 ± 0.41
	✓	✓	✓	✓	$\mathbf{56.76 \pm 0.42}$

5. TAKE HOME MESSAGE

- Pre-trained backbones > randomly initialized backbones
- Randomly initialized backbones + more training time = almost no benefit
- Data augmentation/domain adaptation techniques + extra optimizations = better performance

REFERENCES

[1] Cheng Perng Phoo et al. "Self-training for few-shot transfer across extreme task differences". In ICLR, 2021.

[2] Ihsan Ullah et al. "Meta-Album: Multi-domain meta-dataset for few-shot image classification". In *NeurIPS D&B Track*, 2022.

[3] Oriol Vinyals et al. "Matching networks for one shot learning". In *NeurIPS*, 2016.

[4] Jake Snell et al. "Prototypical networks for few-shot learning". In *NeurIPS*, 2017.

[5] Chelsea Finn et al. "Model-agnostic meta-learning for fast adaptation of deep networks". In *ICML*, 2017.

[6] Yudong Chen et al. "MetaDelta: A meta-learning system for few-shot image classification". In *AAAI Workshop on Meta-Learning and MetaDL Challenge*, 2021.

ACKNOWLEDGMENTS

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