Bridging Multi-Task Learning and Meta-Learning:

Towards Efficient Training and Effective Adaptation

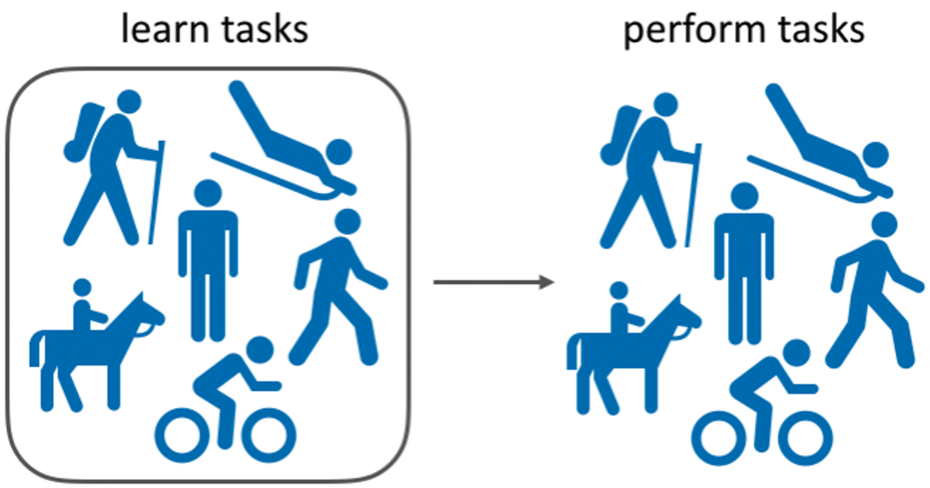
Haoxiang Wang
PhD Candidate
ECE, UIUC

Han Zhao
Assistant Professor
Computer Science, UIUC

Bo Li
Assistant Professor
Computer Science, UIUC

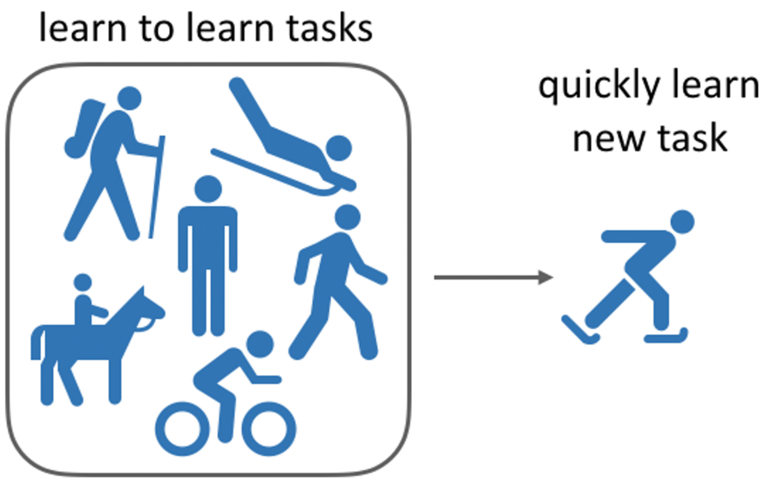
Multi-Task Learning vs. Meta-Learning: **Settings and Goals**

Multi-Task Learning (MTL)



Setting: Test task = Training tasks
Goal: Be a master on a set of tasks

Meta-Learning



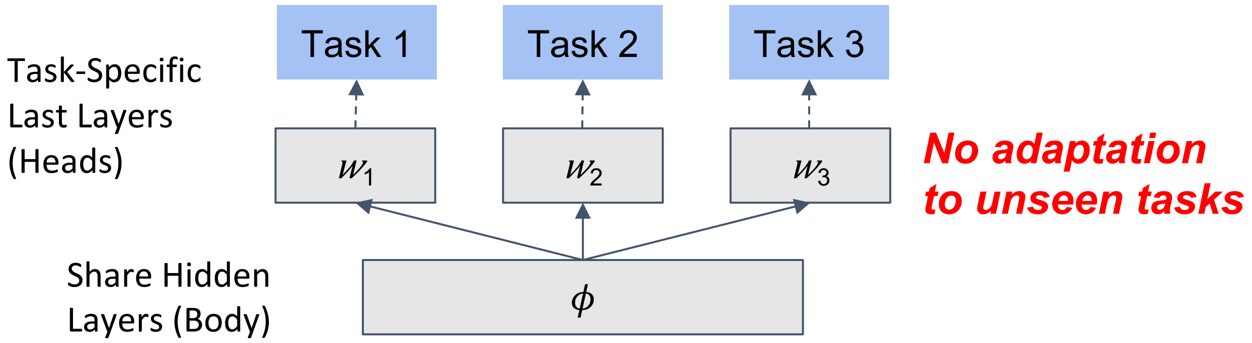
Setting: Test task ∉ Training tasks
Goal: Adapt to an unseen task quickly.
Assumption: The test task has some shared knowledge (i.e., meta-knowledge) with the training tasks.

Image source: T. Yu, et al. Meta-World: A Benchmark and Evaluation for Multi-Task and Meta Reinforcement Learning. arXiv: 1910.10897.

Multi-Task Learning (MTL) vs. Gradient-Based Meta-Learning (GBML)

Multi-Task Learning (MTL)

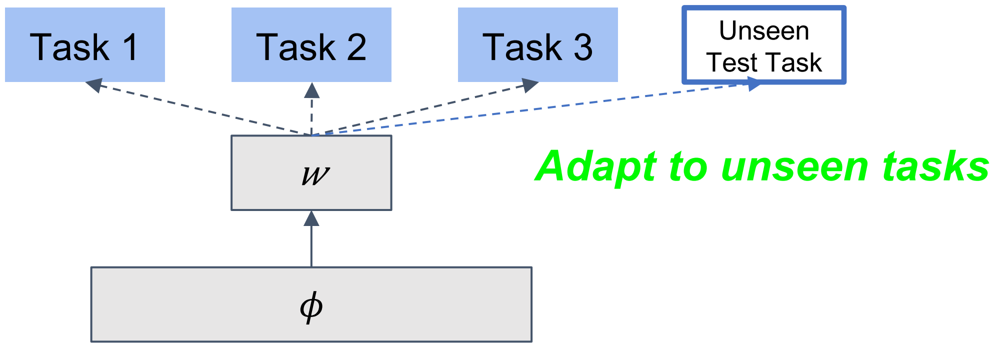
Multi-Head Structure



Training Objective:
1st-order optimization (a form of Empirical Risk Minimization)
→ ***Efficient Training***

Gradient-Based Meta-Learning (GBML)

Single-Head Structure



Training Objective:
2nd order optimization (e.g., MAML, MetaOptNet, ANIL, iMAML)
→ ***Expensive Training***

Motivation and Contribution

Motivation:

*Can we combine the best of both worlds from multi-task learning and meta-learning, i.e., **effective adaptation to unseen tasks** with **efficient training**?*

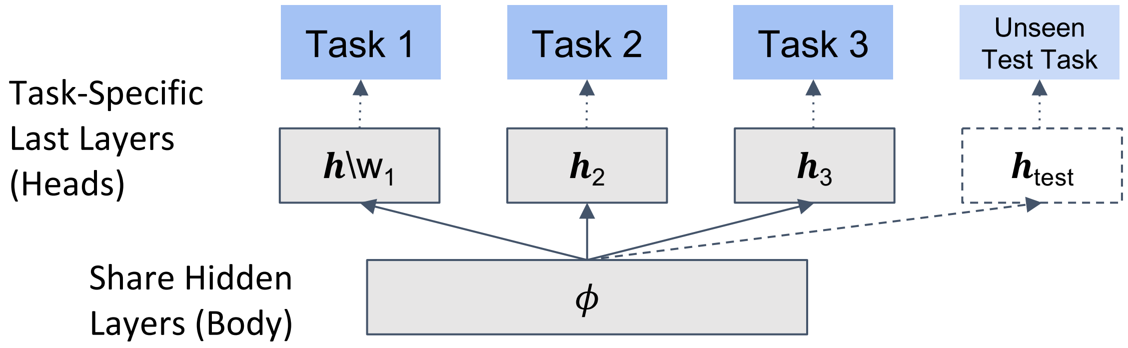
Our answer: **Yes!**

Contribution:

Our paper bridges *Multi-Task Learning* (MTL) and *Gradient-Based Meta-Learning* (GBML) by theoretical and empirical studies.

Multi-Task Learning for Unseen Tasks by **Fine-Tuning Last Layer**

Multi-Head Structure



Fine-tuning: For a trained MTL model, we can adapt it to an unseen test task by

1. Randomly initialize a new head
2. Fine-tune the head on a few labelled data of the test task
3. Use the fine-tuned head for predictions on the new task

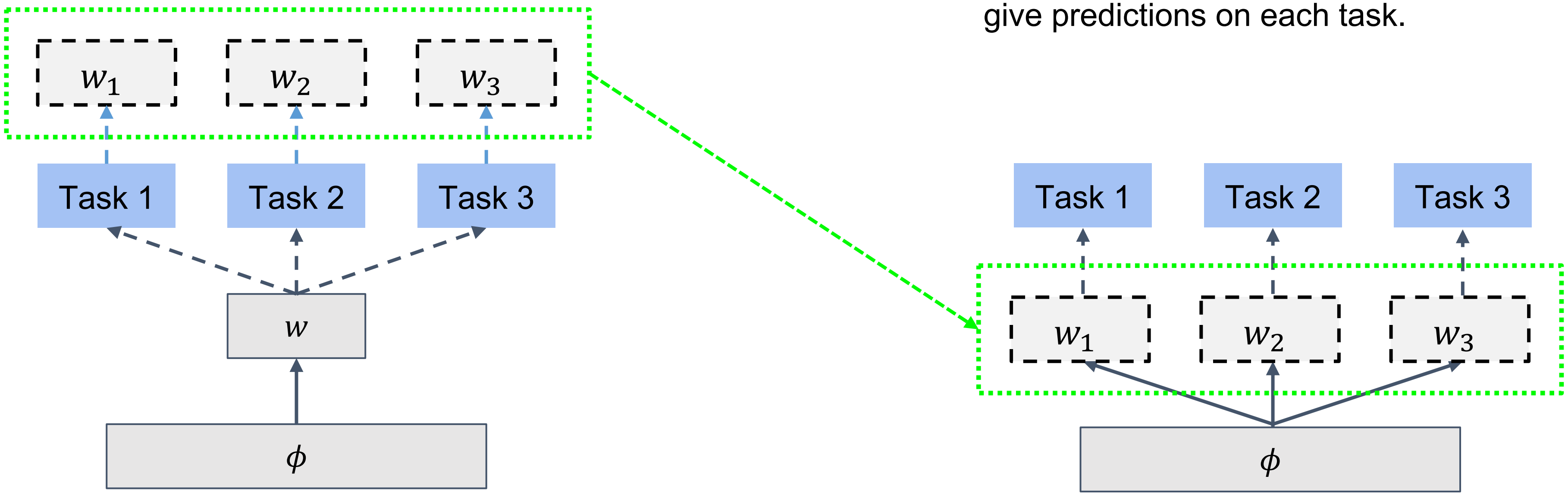
[1] Tripuraneni et al. On the Theory of Transfer Learning: The Importance of Task Diversity. NeurIPS 2020.
[2] Du et al. Few-Shot Learning via Learning the Representation, Provably. ICLR 2021.

Gradient-Based Meta-Learning: Similarity to Multi-Task Learning

Step I: Obtain task-specific ***transient heads*** by gradient descent on each task

$$w_i = w - \nabla_w L_i(\phi, w)$$

Step II: Use the ***transient heads*** to give predictions on each task.



Inner-Loop Optimized Layers	**Early Stopping**	ℓ_2 **Regularizer**
Last Layer	ANIL (Raghu et al., 2020)	MetaOptNet (Lee et al., 2019b) R2D2 (Bertinetto et al., 2019)
All Layers	MAML (Finn et al., 2017)	iMAML (Rajeswaran et al., 2019) Meta-MinibatchProx (Zhou et al., 2019b)

Theoretical Results

Inner-Loop Optimized Layers	**Early Stopping**	ℓ_2 **Regularizer**
Last Layer	ANIL (Raghu et al., 2020)	MetaOptNet (Lee et al., 2019b) R2D2 (Bertinetto et al., 2019)
All Layers	MAML (Finn et al., 2017)	iMAML (Rajeswaran et al., 2019) Meta-MinibatchProx (Zhou et al., 2019b)

Equivalence: MTL and a class of GBML shares the **same optimization objective**

Difference: MTL uses ***joint training***, while GBML adopts ***bi-level optimization*** *with* ***regularization***

Closeness in the function space:

- We compare neural nets trained by ANIL (a MAML simplification) and MTL in an NTK-based meta-learning framework [1]
- We prove that, on any test task, the difference between predictions is upper bounded as

$$\|\text{ANIL prediction} - \text{MTL prediction}\|_2 \leq \mathcal{O}(\lambda\tau + \frac{1}{L})$$

L: Network depth

λ, τ: Learning rates

[1] Haoxiang Wang, Ruoyu Sun, Bo Li. Global Convergence and Generalization Bound of Gradient-Based Meta-Learning with Deep Neural Nets. arXiv:2006.14606

Experiments on **Few-Shot Learning**

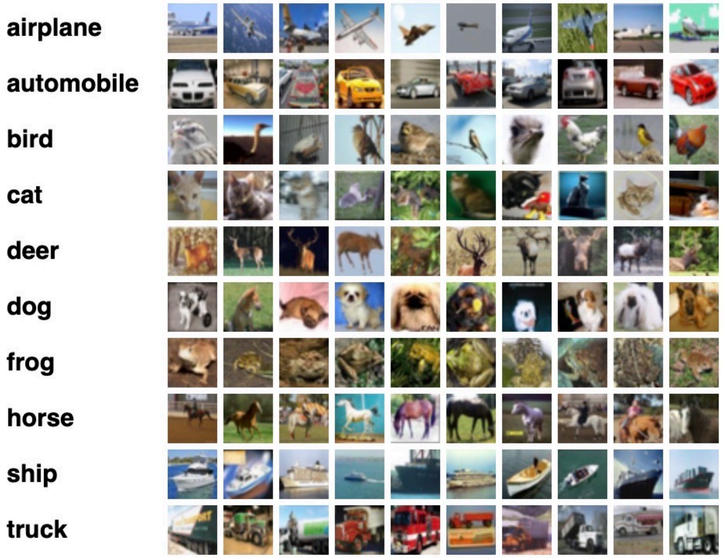
Benchmarks: 4 popular few-shot learning datasets, extracted from ImageNet and CIFAR-100.

mini-ImageNet **tiered-ImageNet**

ImageNet

CIFAR-FS **FC-100**

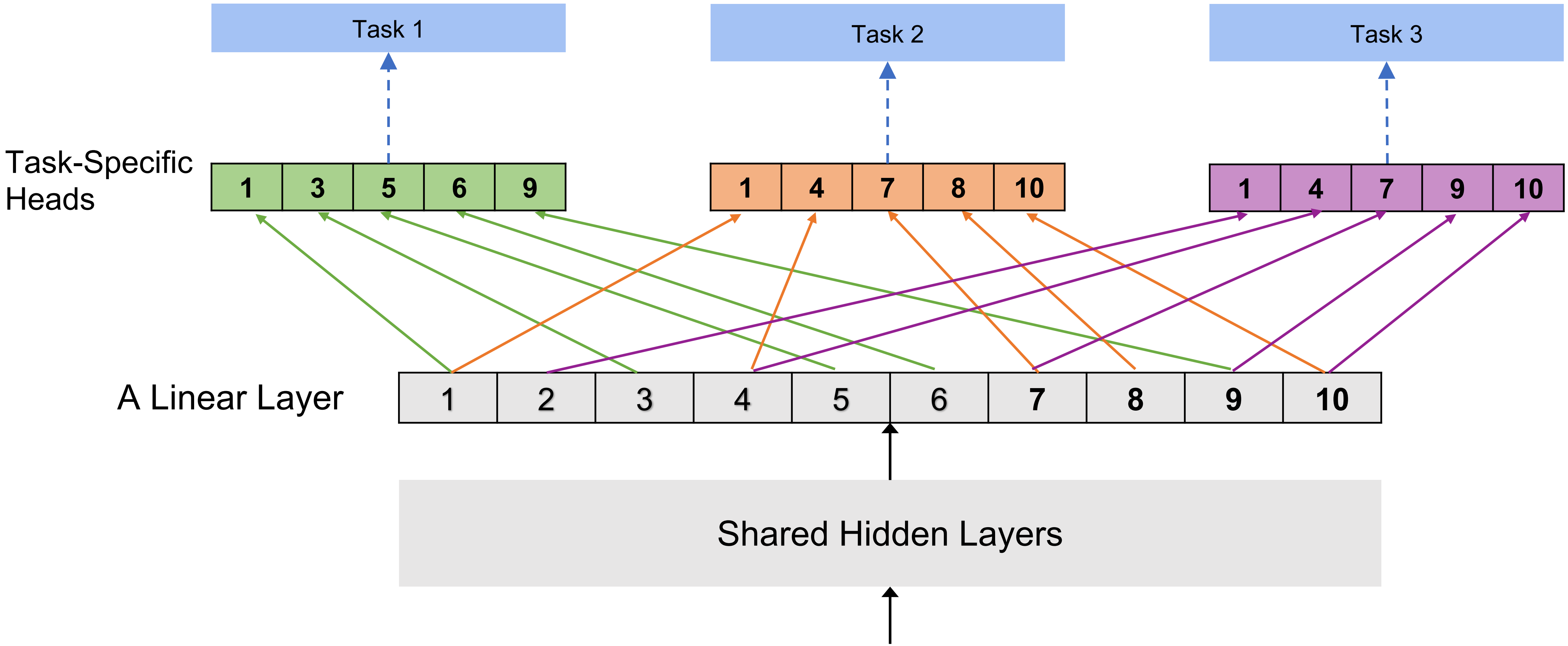
CIFAR-100



Remarks: *The number of unique training tasks is quite large (due to combinatorial explosion), e.g., it's 4.3 billions for tiered-ImageNet. Thus, we cannot afford an individual head for each training task.*

Memory-Efficiency Implementation of MTL Heads

Example: 5-way few-shot classification; Each task has 5 task-specific classes drawn from 10 base classes.



Experimental Results on **Few-Shot Learning**

MetaOptNet: A state-of-the-art gradient-based meta-learning algorithm.
MTL-ours: Our memory-efficient implementation of multi-task learning.

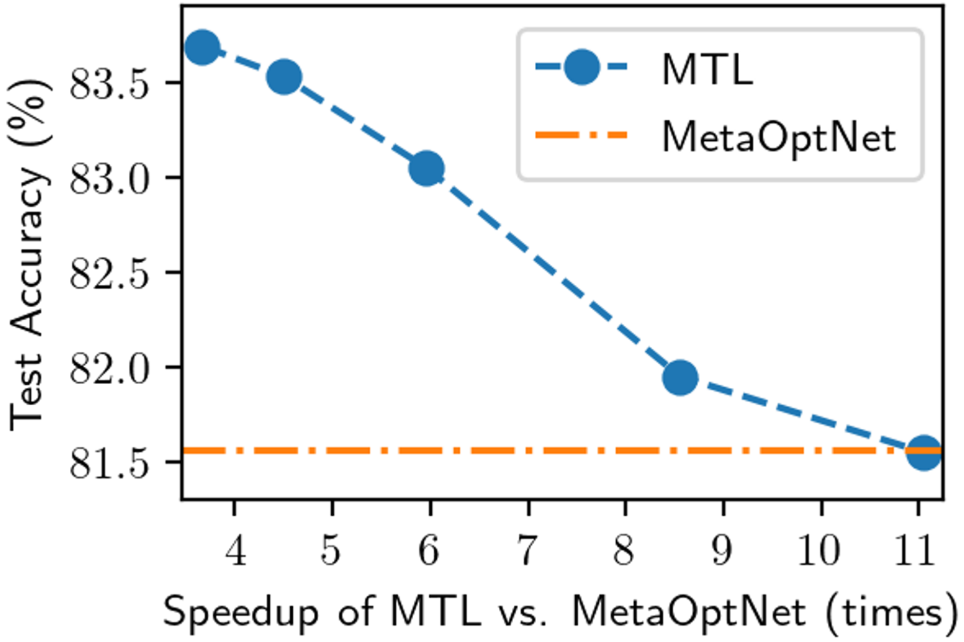
		mini-ImageNet		tiered-ImageNet		CIFAR-FS		FC100	
Algorithm	Architecture	1-shot (%)	5-shot (%)	1-shot (%)	5-shot (%)	1-shot (%)	5-shot (%)	1-shot (%)	5-shot (%)
MAML [Finn et al., 2017a]	CNN-4	48.70 ± 1.84	63.11 ± 0.92						
MetaOptNet [Lee et al., 2019]	ResNet-12	$\mathbf{62.64 \pm 0.61}$	$\mathbf{78.63 \pm 0.46}$	65.99 ± 0.72	81.56 ± 0.53	$\mathbf{72.0 \pm 0.7}$	$\mathbf{84.2 \pm 0.5}$	41.1 ± 0.6	55.5 ± 0.6
MTL-ours [Wang et al., 2021]	ResNet-12	59.84 ± 0.22	$\mathbf{77.72 \pm 0.09}$	$\mathbf{67.11 \pm 0.12}$	$\mathbf{83.69 \pm 0.02}$	69.5 ± 0.3	$\mathbf{84.1 \pm 0.1}$	$\mathbf{42.4 \pm 0.2}$	$\mathbf{57.7 \pm 0.3}$

***Multi-task learning** can match the SOTA of **gradient-based meta-learning** on few-shot learning benchmarks!*

Training Efficiency of Multi-Task Learning vs. Gradient-Based Meta-Learning

	Test Accuracy	GPU Hours
MetaOptNet	78.63%	85.6 hrs
MTL	77.72%	3.7 hrs

Mini-ImageNet (5-way 5 shot)



tiered-ImageNet (5-way 5 shot)

Multi-task learning *can be more than 10x faster, since it does not use any 2nd order optimization.*

Thank you for watching this presentation!

Takeaway: *We can combine the benefits of multi-task learning and meta-learning, i.e., **effective adaptation to unseen tasks** with **efficient training.***

Code: https://github.com/AI-secure/multi-task-learning

Contact Information:

- Haoxiang Wang: hwang264@illinois.edu
- Han Zhao: hanzhao@illinois.edu
- Bo Li: lbo@illinois.edu