

Meta-Learning with Self-Improving Momentum Target

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Meta-Learning

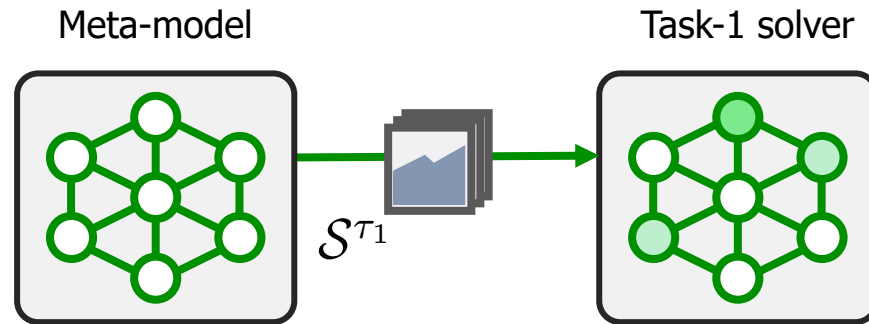
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- Extracting and utilizing the **knowledge from the distribution of tasks** to better solve a relevant task

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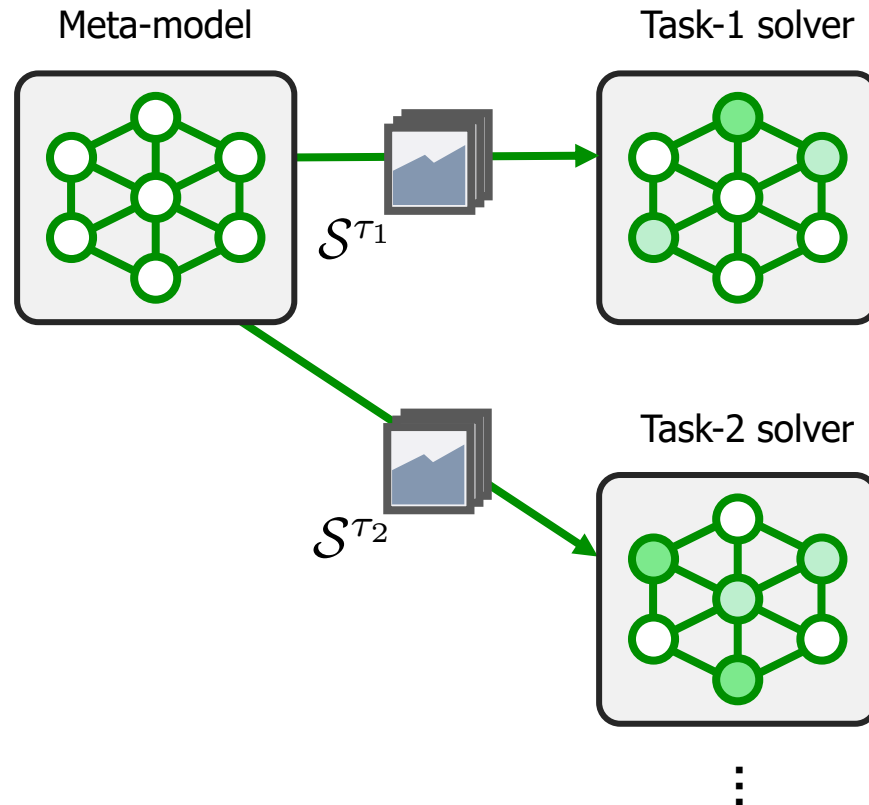
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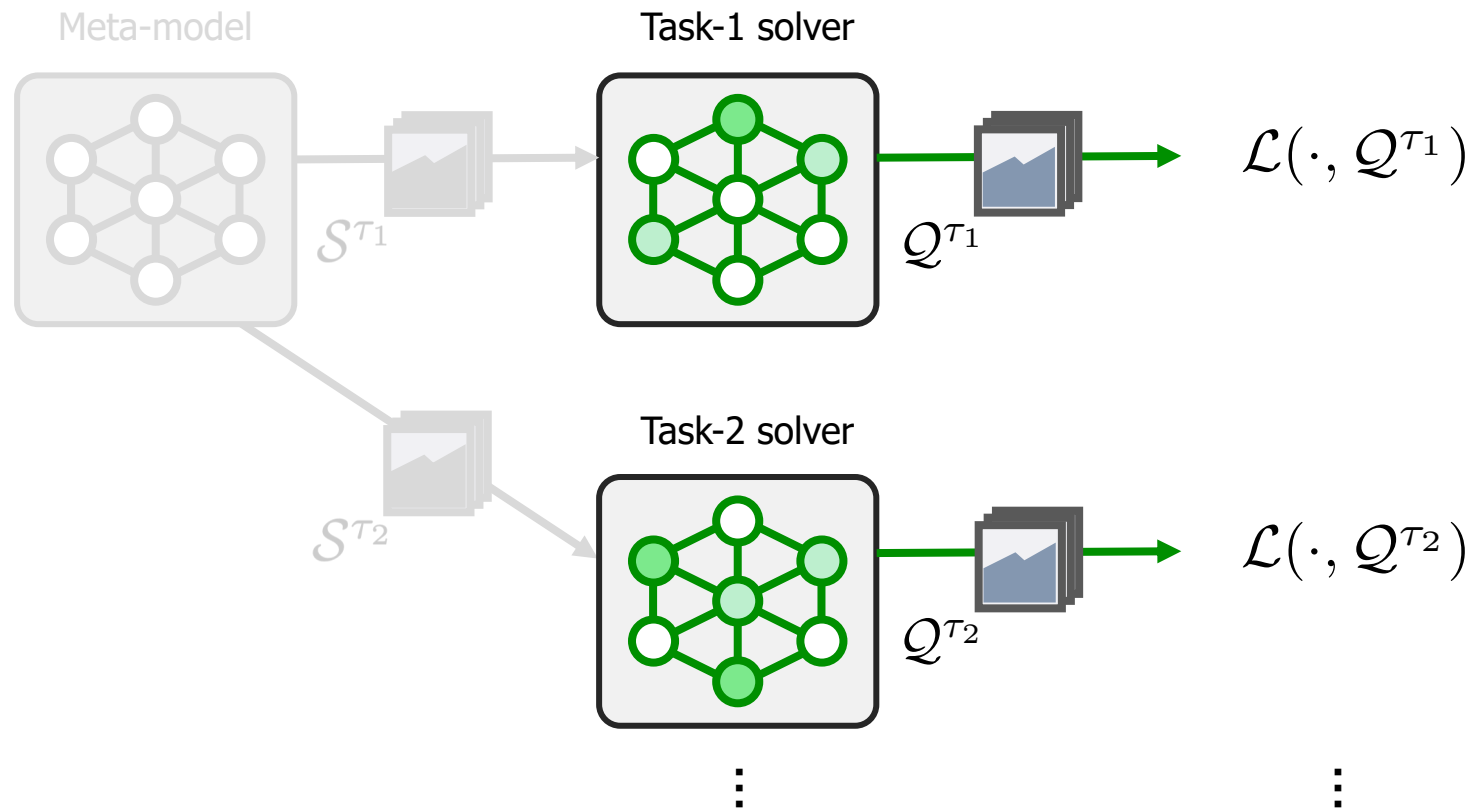
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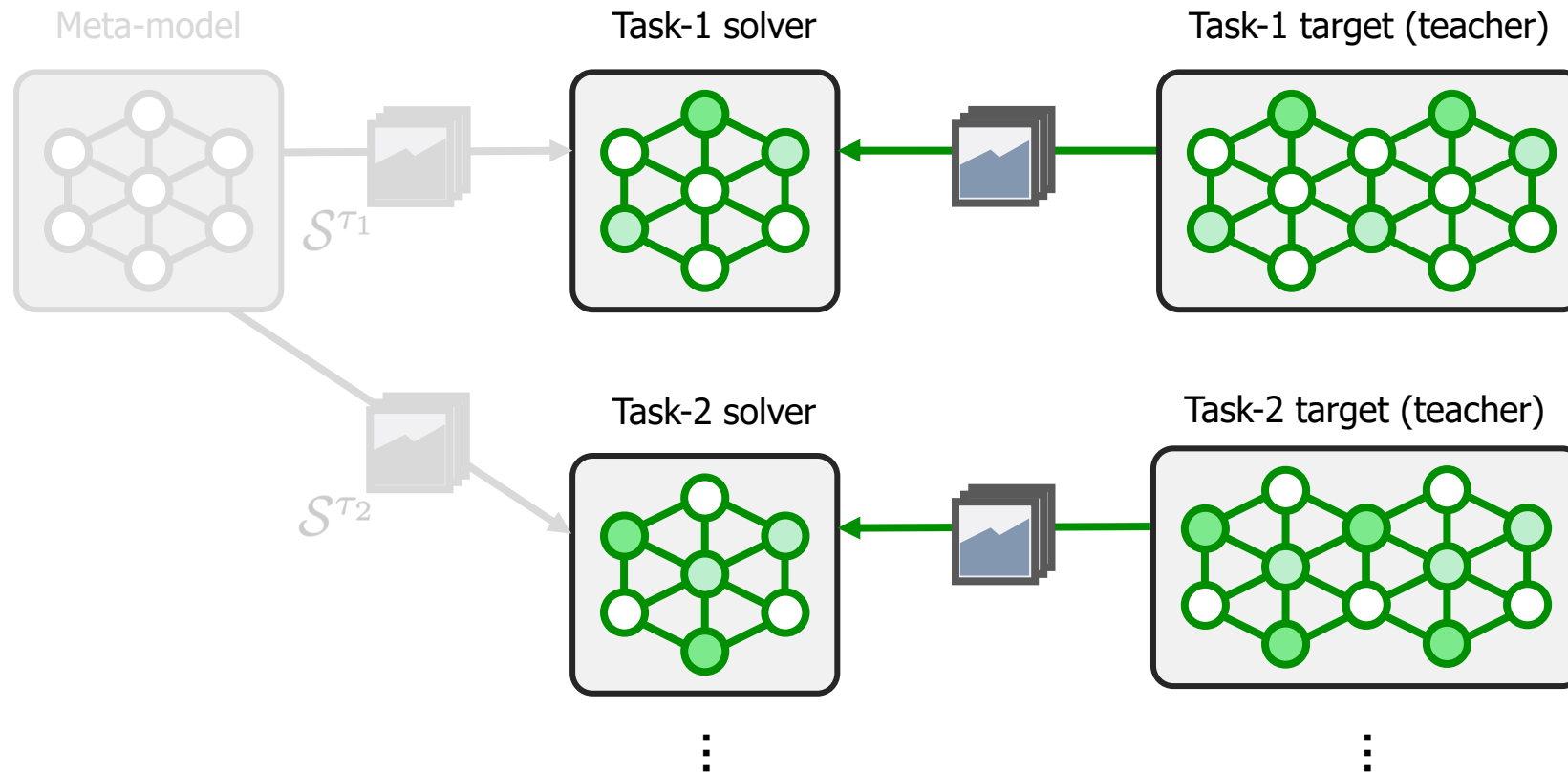
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Meta-Learning with Target Models

Recently an alternative paradigm has gained much attention [1,2]

- Use a **task-specific target model**, i.e., an expert or teacher, to evaluate the performance



[1] Towards enabling meta-learning from target models, Lu et al., NeurIPS 2021

[2] Bootstrapped Meta-Learning, Flennerhag et al., ICLR 2022

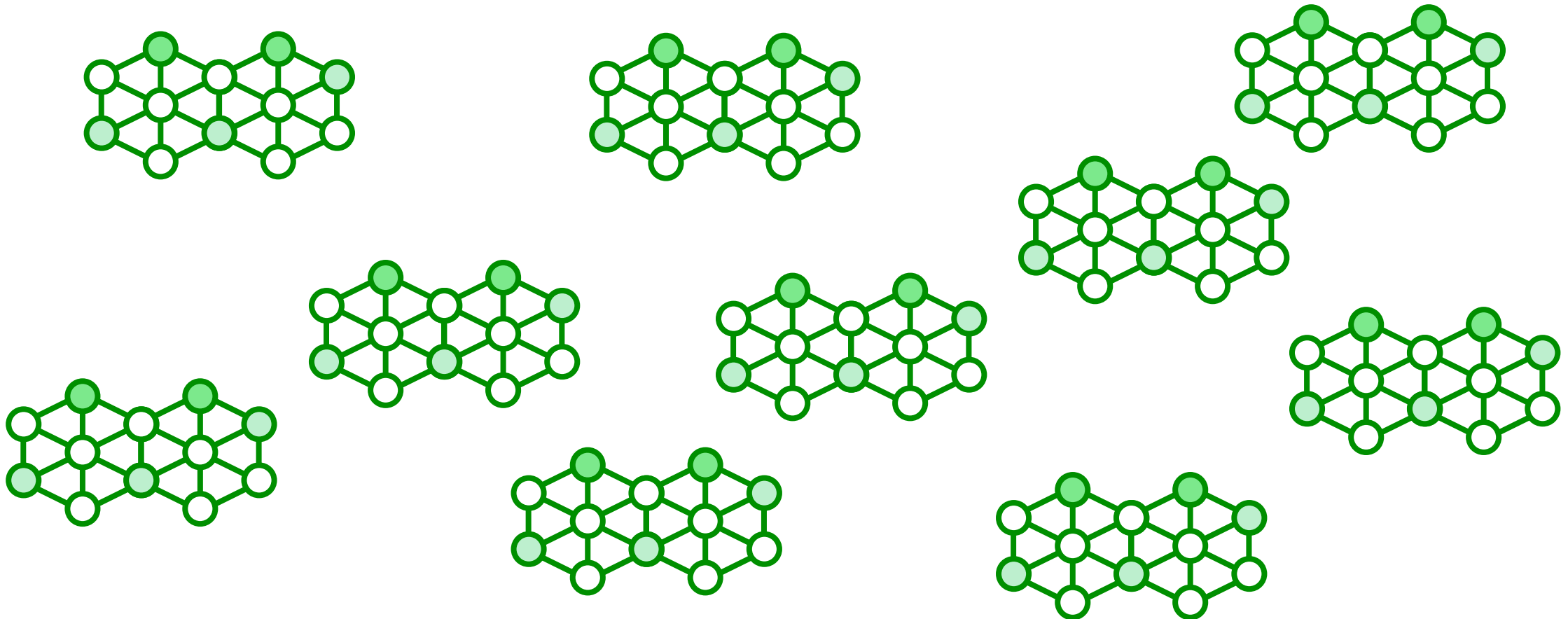
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- This suffers from both **computation** and **storage** burden !



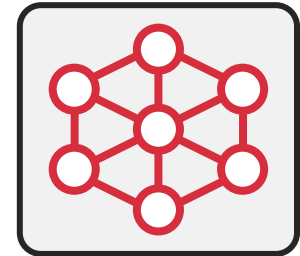
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A. How about **generating target models** from a **better meta-learner**...?

Better meta-model

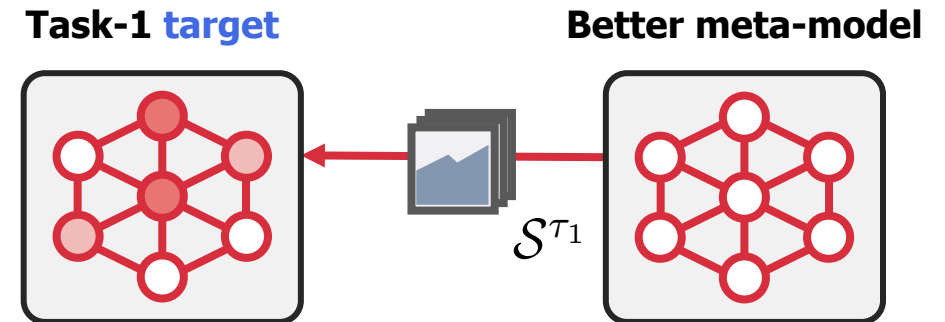


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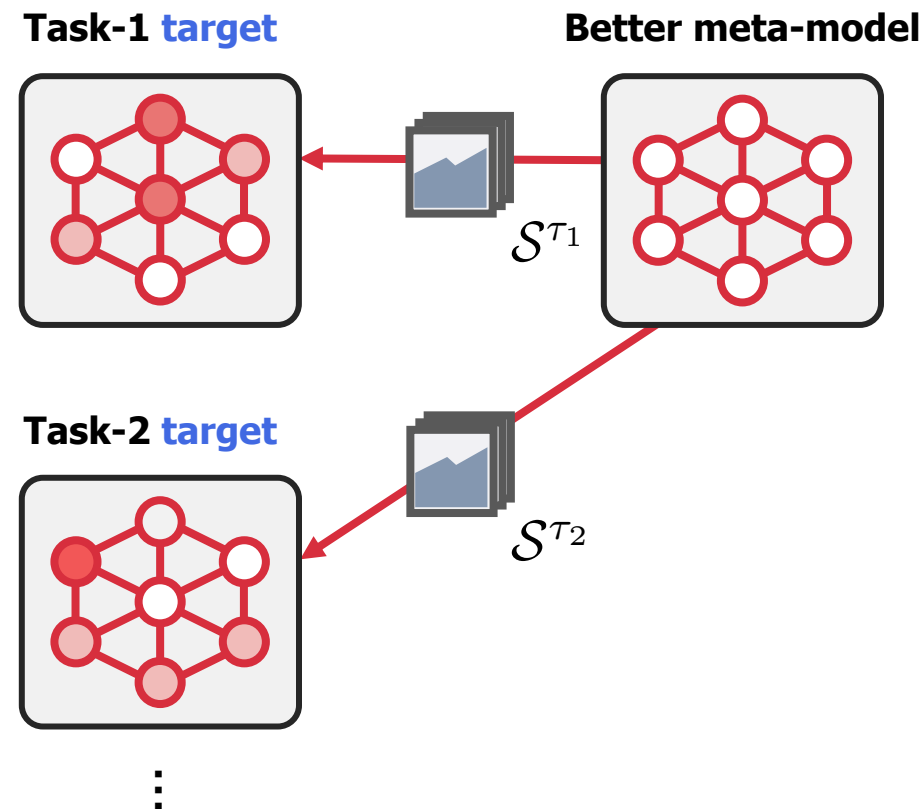


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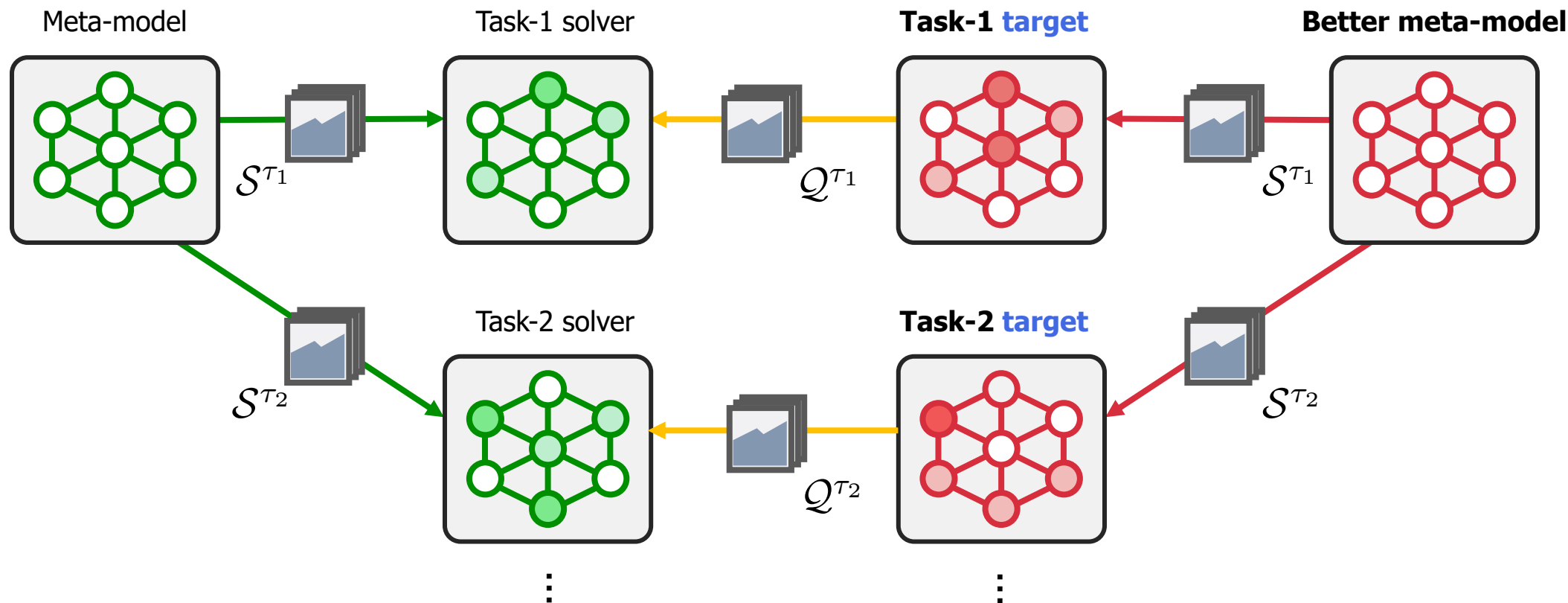


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Utilize Momentum Network !

We draw inspiration from recent observations in **semi/self-supervised learning literature** [3,4]

- The **momentum network** can be an effective teacher of the original model

[3] Temporal ensembling for semi-supervised learning, Laine et al., ICLR 2017

[4] Emerging properties in self-supervised vision transformers, Caron et al., ICCV 2021

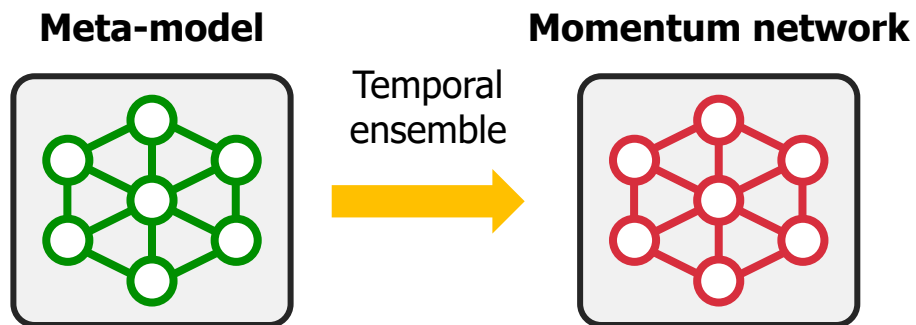
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A similar phenomenon happens in meta-learning !

- Momentum network of the meta-model shows an **effective adaptation performance**



$$\theta_{\text{moment}} \leftarrow \eta \cdot \theta_{\text{moment}} + (1 - \eta) \cdot \theta$$

[3] Temporal ensembling for semi-supervised learning, Laine et al., ICLR 2017

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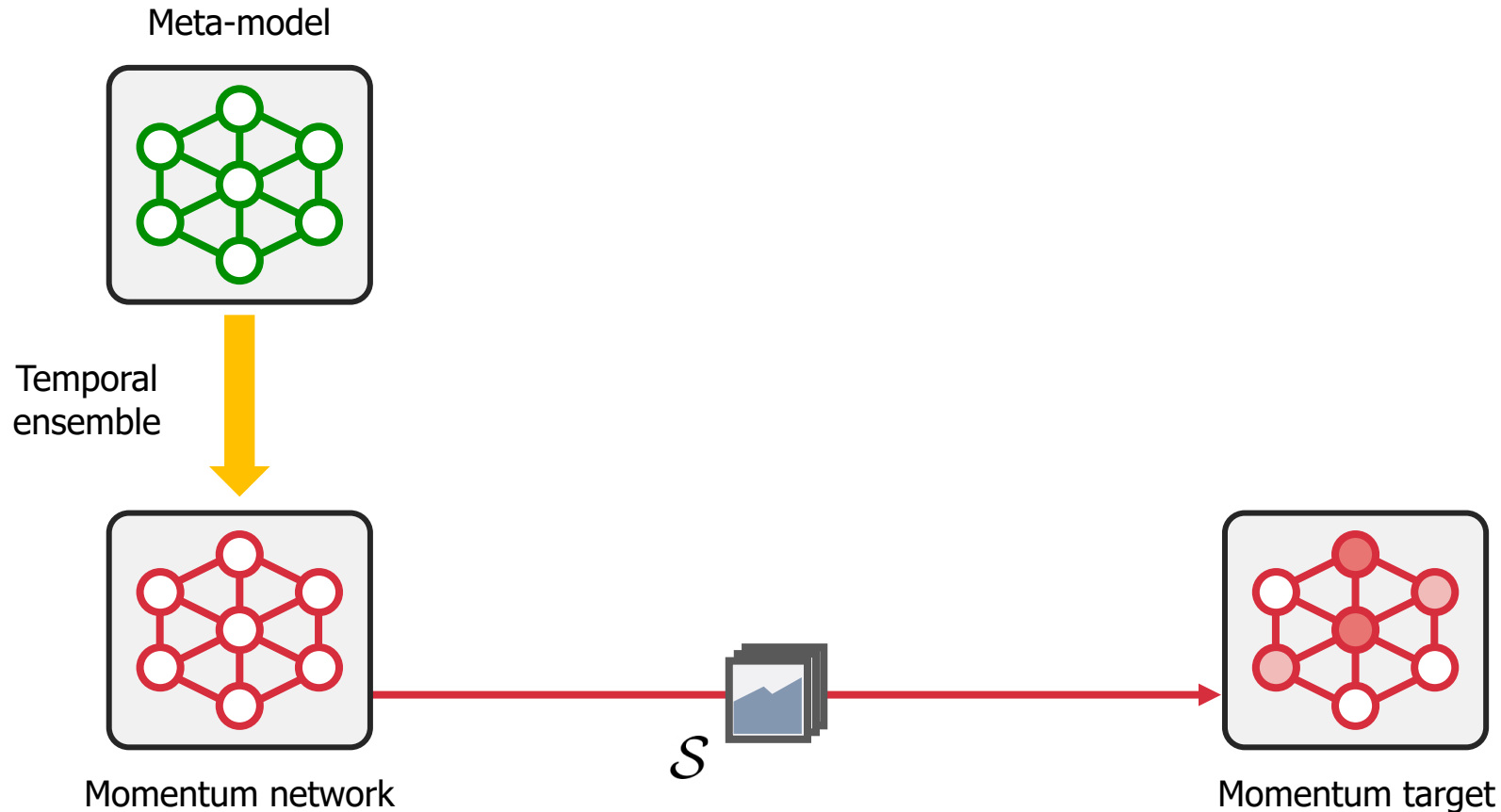
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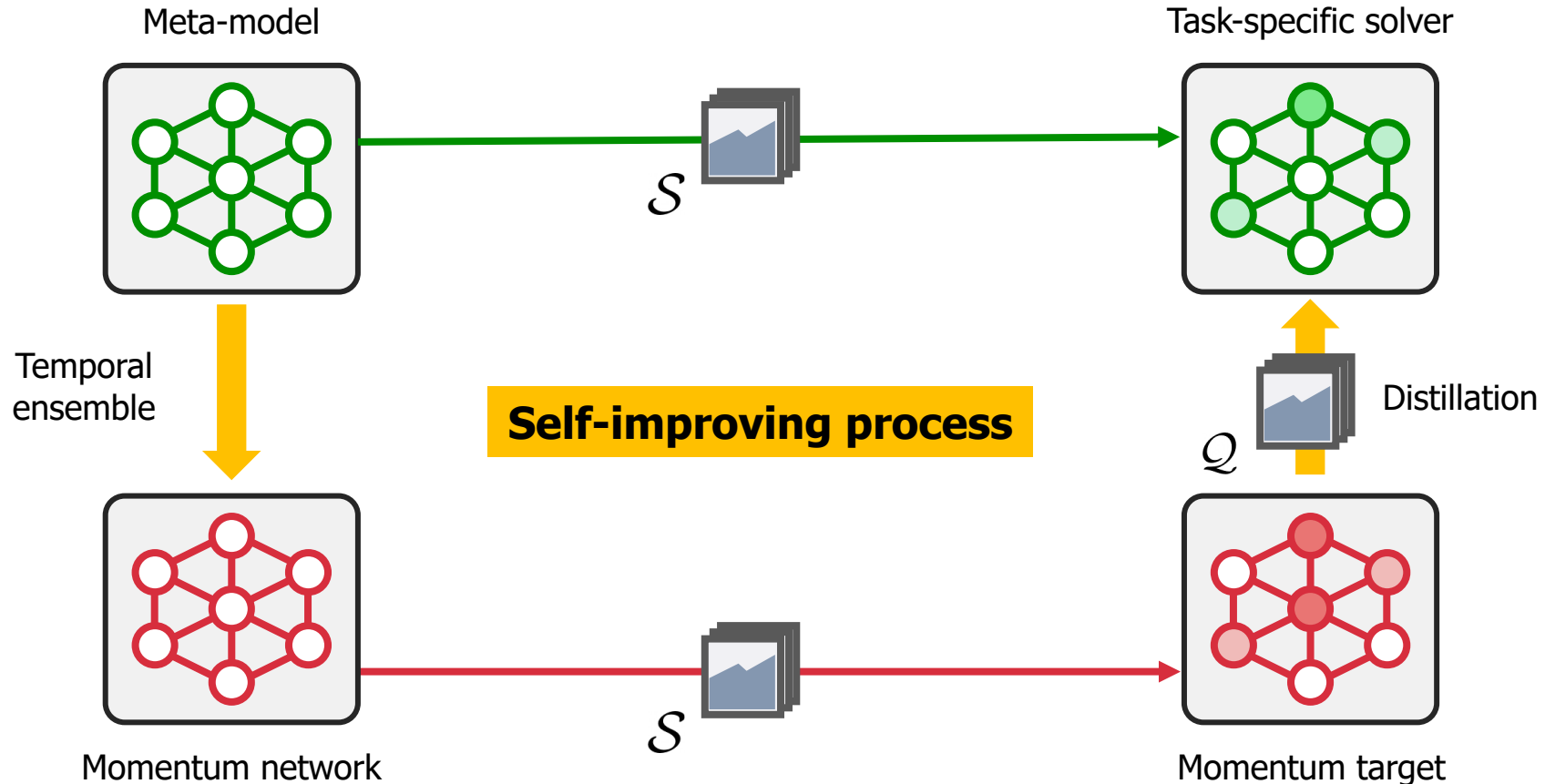
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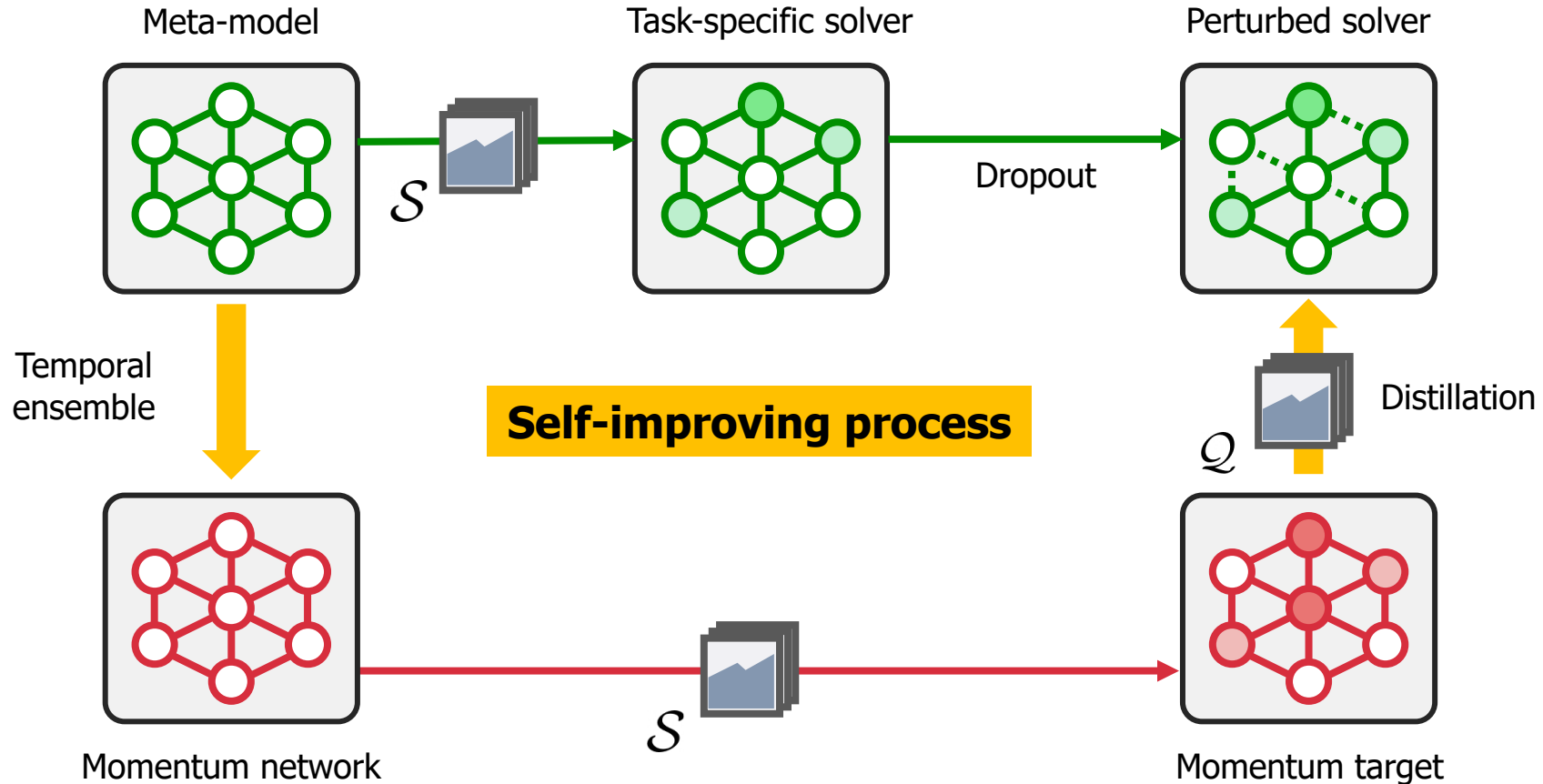
- **Momentum target**: Generating the target model from the momentum network to teach the original model
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Experiments: Few-shot Learning

We verify the effectiveness of SiMT in various

- **few-shot learning** and **meta-reinforcement learning scenarios**

SiMT **consistently and significantly improves** the backbone meta-learning algorithms

Model	Method	mini-ImageNet		tiered-ImageNet	
		1-shot	5-shot	1-shot	5-shot
Conv4 [55]	MAML [10]	47.33±0.45	63.27±0.14	50.19±0.21	66.05±0.19
	MAML [10] + SiMT	51.49±0.18	68.74±0.12	52.51±0.21	69.58±0.11
	ANIL [36]	47.71±0.47	63.13±0.43	49.57±0.04	66.34±0.28
	ANIL [36] + SiMT	50.81±0.56	67.99±0.19	51.66±0.26	68.88±0.08
	MetaSGD [31]	50.66±0.18	65.55±0.54	52.48±1.22	71.06±0.20
	MetaSGD [31] + SiMT	51.70±0.80	69.13±1.40	52.98±0.07	71.46±0.12
	ProtoNet [45]	47.97±0.29	65.16±0.67	51.90±0.55	71.51±0.25
	ProtoNet [45] + SiMT	51.25±0.55	68.71±0.35	53.25±0.27	72.69±0.27
	MAML [10]	52.66±0.60	68.69±0.33	57.32±0.59	73.78±0.27
	MAML [10] + SiMT	56.28±0.63	72.01±0.26	59.72±0.22	74.40±0.90
ResNet-12 [34]	ANIL [36]	51.80±0.59	68.38±0.20	57.52±0.68	73.50±0.35
	ANIL [36] + SiMT	54.44±0.27	69.98±0.66	58.18±0.31	75.59±0.50
	MetaSGD [31]	54.95±0.11	70.65±0.43	58.97±0.89	76.37±0.11
	MetaSGD [31] + SiMT	55.72±0.96	74.01±0.79	61.03±0.05	78.04±0.48
	ProtoNet [45]	52.84±0.21	68.35±0.29	61.16±0.17	79.94±0.20
	ProtoNet [45] + SiMT	55.84±0.57	72.45±0.32	62.01±0.42	81.82±0.12

In-domain adaptation accuracy (%)

Problem	Method	mini-ImageNet →		tiered-ImageNet →	
		CUB	Cars	CUB	Cars
1-shot	MAML [10]	39.50±0.91	32.87±0.20	42.32±0.69	36.62±0.12
	MAML [10] + SiMT	42.32±0.62	33.73±0.63	44.33±0.43	37.21±0.35
	ANIL [36]	37.30±0.89	31.28±1.03	42.29±0.33	36.27±0.58
	ANIL [36] + SiMT	38.86±0.98	32.34±0.95	44.53±1.21	36.92±0.56
	MetaSGD [31]	41.98±0.18	34.52±0.56	46.48±2.10	38.09±1.21
	MetaSGD [31] + SiMT	43.50±0.89	33.92±0.30	46.62±0.41	38.69±0.26
	ProtoNet [45]	41.22±0.81	32.79±0.61	47.75±0.56	37.59±0.80
	ProtoNet [45] + SiMT	44.13±0.30	34.53±0.40	48.89±0.65	38.07±0.42
	MAML [10]	56.17±0.92	44.56±0.79	65.00±0.89	51.08±0.28
	MAML [10] + SiMT	59.22±0.39	46.59±0.21	67.58±0.61	51.88±0.52
5-shot	ANIL [36]	53.42±0.97	41.65±0.67	62.48±0.85	50.50±1.18
	ANIL [36] + SiMT	56.03±1.40	45.88±0.82	66.30±0.99	54.60±0.91
	MetaSGD [31]	58.90±1.30	47.44±1.55	70.38±0.27	56.28±0.07
	MetaSGD [31] + SiMT	65.07±1.89	49.86±0.84	73.93±0.42	57.97±1.34
	ProtoNet [45]	57.87±0.77	48.06±1.10	74.35±0.93	57.23±0.25
	ProtoNet [45] + SiMT	63.85±0.76	51.67±0.29	75.97±0.09	59.01±0.50

Cross-domain adaptation accuracy (%)

Experiments: Comparison with Other Target Models

We also compare SiMT with **other target models**

- (i) Bootstrapped target model [2] and (ii) Pre-trained target model [1]

Method	mini-ImageNet		tiered-ImageNet	
	1-shot	5-shot	1-shot	5-shot
MAML [10]	47.33±0.45	63.27±0.14	50.19±0.21	66.05±0.19
MAML [10] + Bootstrap [16]	48.68±0.33	68.45±0.40	49.34±0.26	68.84±0.37
MAML [10] + SiMT	51.49±0.18	68.74±0.12	52.51±0.21	69.58±0.11
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ANIL [36] + SiMT	50.81±0.56	67.99±0.19	51.66±0.26	68.88±0.08

(i) Comparison with the Bootstrapped target model [2]

Method	1-shot train cost (GPU hours)	mini-ImageNet		tiered-ImageNet	
		1-shot	5-shot	1-shot	5-shot
MAML [10]*	1.31	58.84±0.25	74.62±0.38	63.02±0.30	67.26±0.32
MAML [10] + Lu et al. [32] - 5%*	5.04	59.14±0.33	75.77±0.29	64.52±0.30	68.39±0.34
MAML [10] + Lu et al. [32] - 10%*	8.32	60.06±0.35	76.34±0.42	65.23±0.45	70.02±0.33
MAML [10] + SiMT	1.64	62.05±0.39	78.77±0.45	63.91±0.32	77.43±0.47

(ii) Comparison with the Pre-trained target model [1]

[1] Towards enabling meta-learning from target models, Lu et al., NeurIPS 2021

[2] Bootstrapped Meta-Learning, Flennerhag et al., ICLR 2022

Thank you for your attention 😊

For any more questions, please send us an email!

Email: jihoontack@kaist.ac.kr

Paper: <https://arxiv.org/abs/2210.05185>

Code: <https://github.com/jihoontack/SiMT>