Group reading

Towards Fast Adaptation of Neural Architectures with Meta Learning

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ICLR 2020

Shasha Zhou **11.22**

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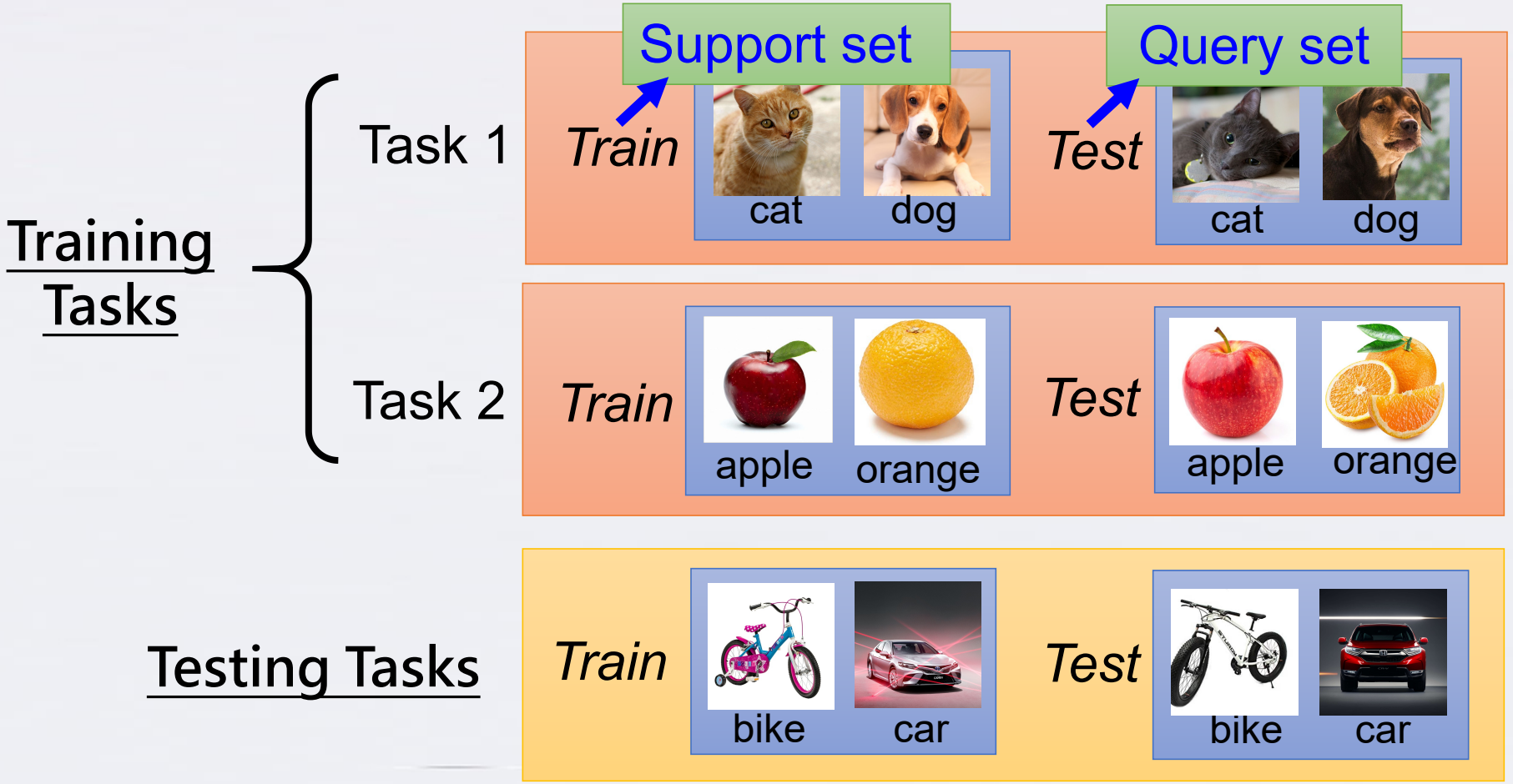
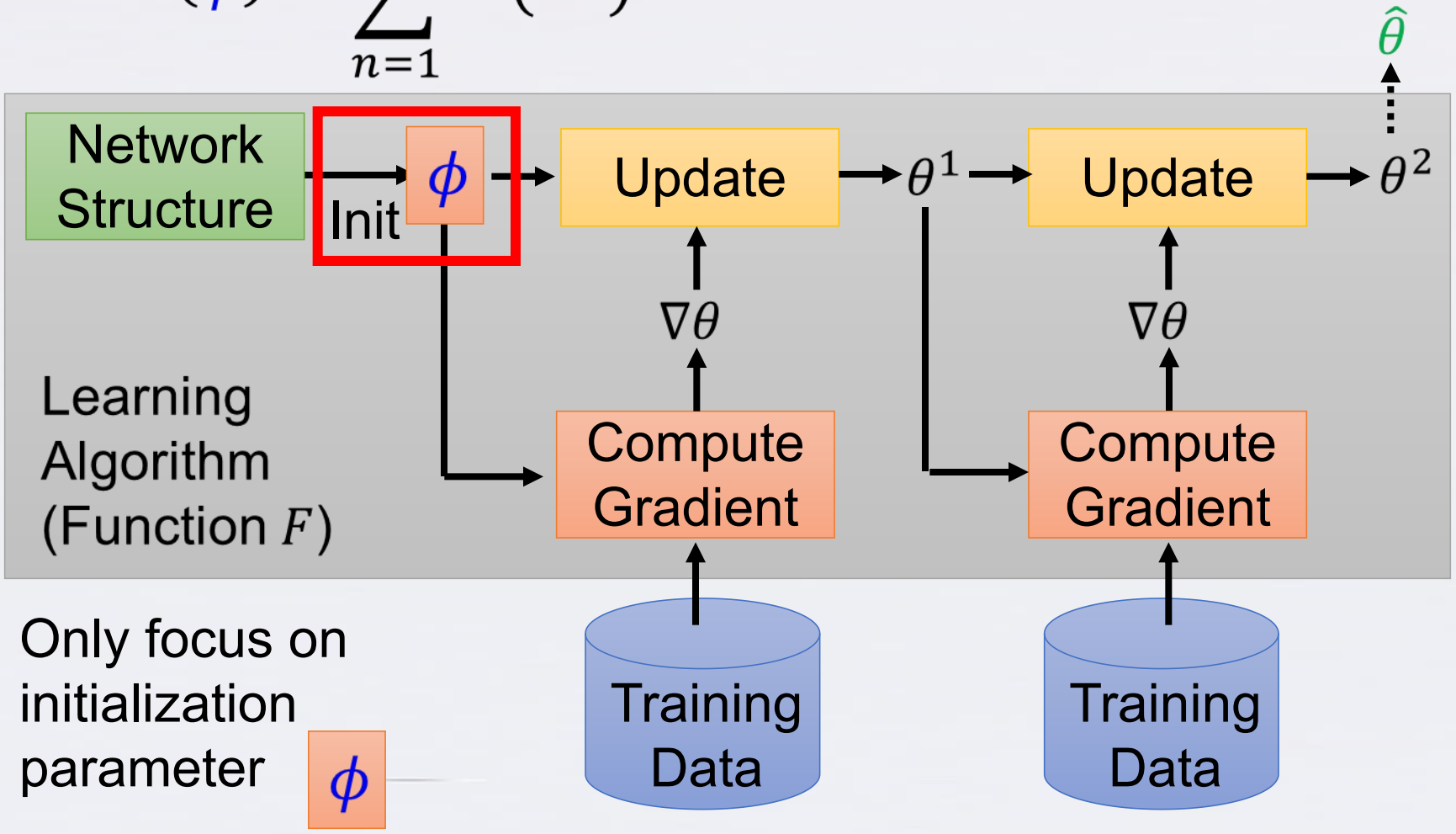
MAML

- **meta-learning**



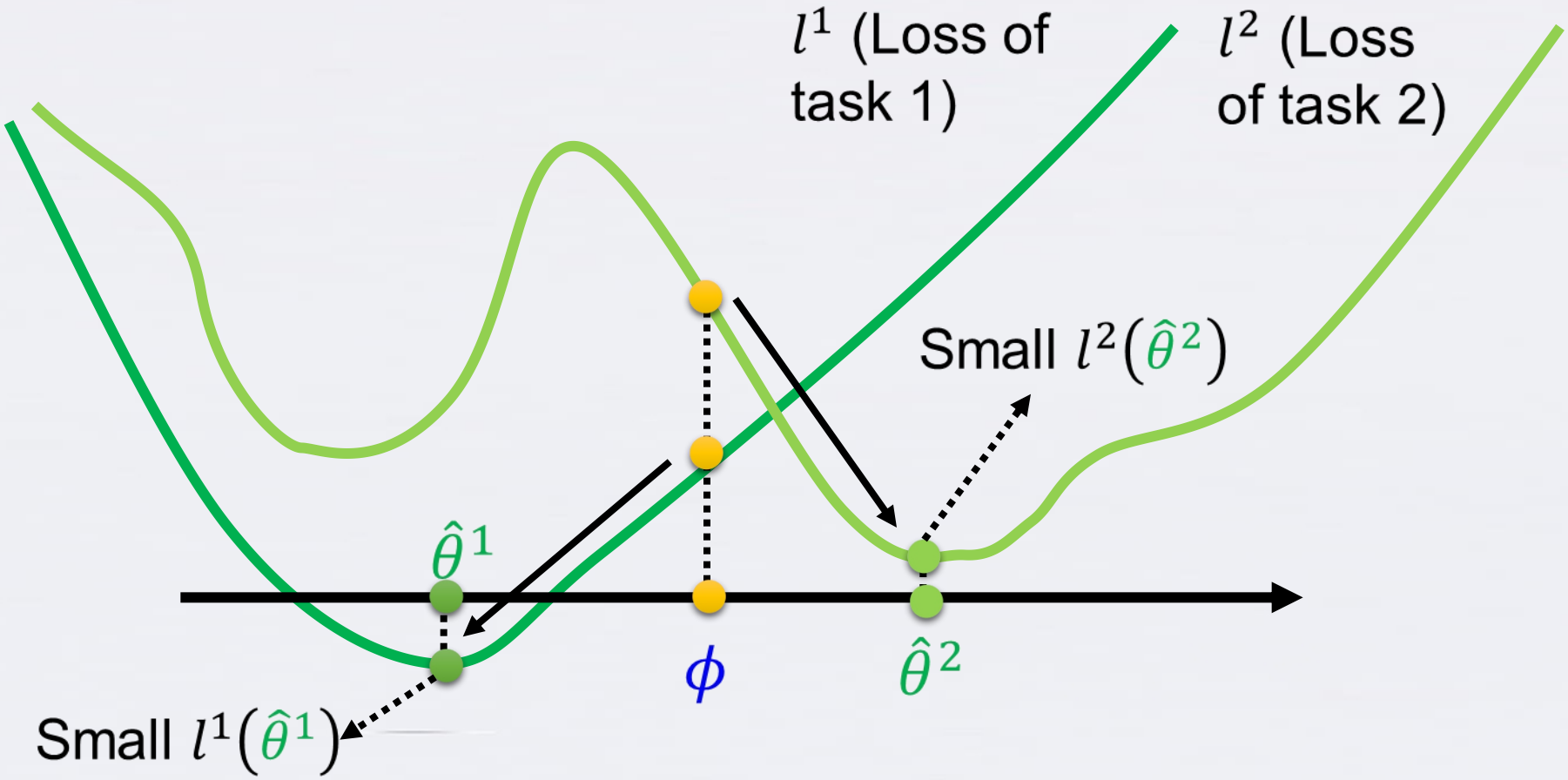
MAML

Loss Function: $L(\phi) = \sum_{n=1}^{N} l^n(\hat{\theta}^n)$



MAML

$$L(\phi) = \sum_{n=1}^{N} l^n(\hat{\theta}^n)$$



MAML

$$w_i^{m+1} = w_i^m - \alpha_{inner} \nabla_{w_i^m} \mathcal{L}(f(\mathcal{T}_i^s; w_i^m))$$

$$\tilde{w} = \tilde{w} - \alpha_{outer} \nabla_{\tilde{w}} \sum_{\mathcal{T}_i^q \sim p(\mathcal{T})} \mathcal{L}(f(\mathcal{T}_i^q; w_i^M))$$

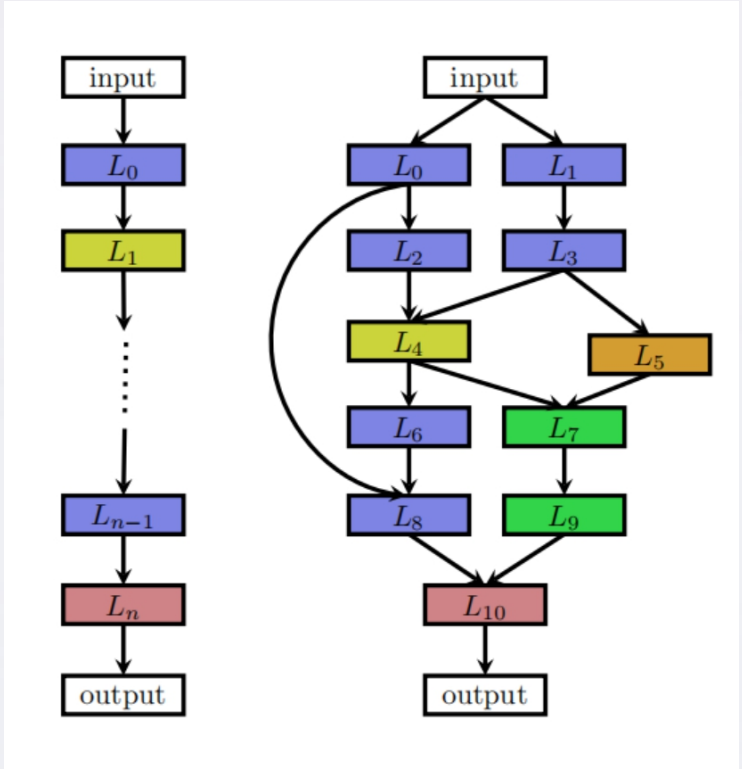
Algorithm 1 Model-Agnostic Meta-Learning

Require: $p(\mathcal{T})$: distribution over tasks
Require: α, β: step size hyperparameters
1: randomly initialize θ
2: **while** not done **do**
3: Sample batch of tasks $\mathcal{T}_i \sim p(\mathcal{T})$
4: **for all** $\mathcal{T}_i$ **do**
5: Evaluate $\nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$ with respect to K examples
6: Compute adapted parameters with gradient descent: $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$
7: **end for**
8: Update $\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$
9: **end while**

Neural Architecture Search(NAS)

- Search space
- Search strategy
- Performance estimation strategy

层/运算	超参数
卷积	卷积核数量 卷积核通道数 卷积核宽度 卷积核高度 水平方向步长 垂直方向步长
池化	池化核高度 池化核宽度 水平方向步长 垂直方向步长
全连接	神经元数量
激活	激活函数类型 各种激活函数的参数
相加（add）	无
拼接（contact）	无



Neural Architecture Search(NAS)

- **Search strategy**

Bayesian optimization

Evolutionary methods

Reinforcement learning

Gradient-based methods(DARTS)

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Neural Architecture Search(NAS)

- **Performance estimation strategy**

Lower fidelity estimates

Learning curve extrapolation

Weight inheritance/ network morphisms

One-shot models/ weight sharing

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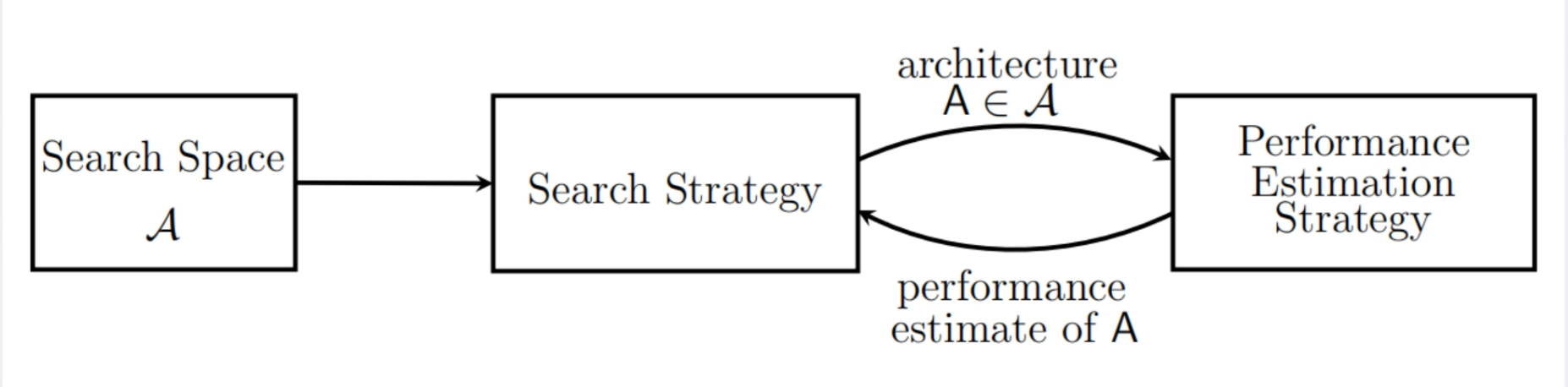
Neural Architecture Search(NAS)



Neural Architecture Search(NAS)

- **Gradient-base methods(DARTS)**

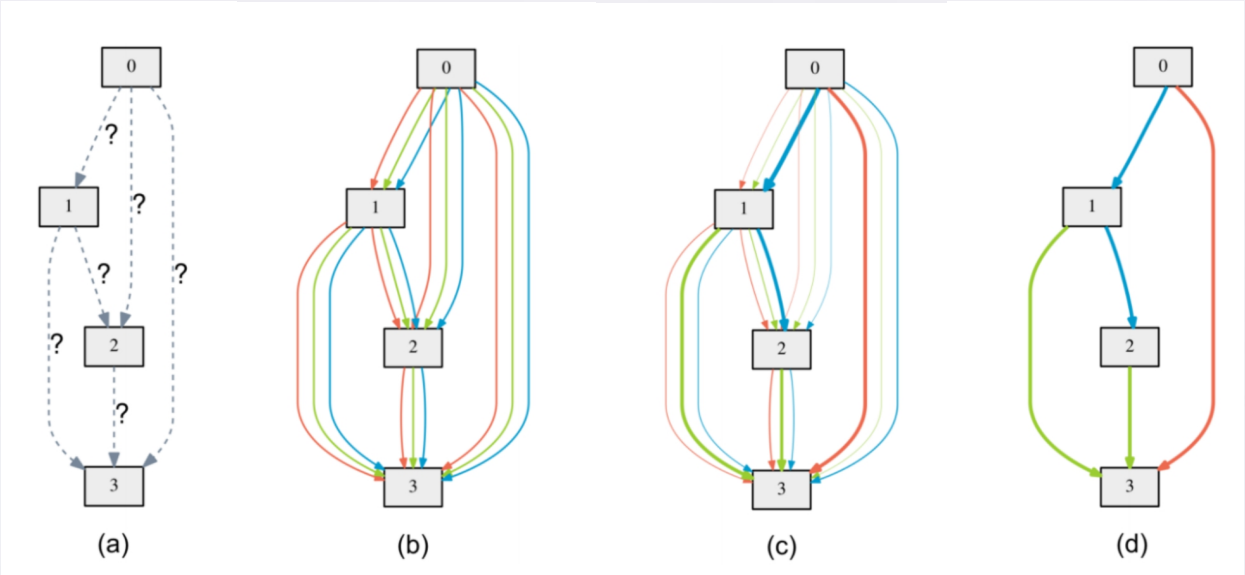
DARTS: DIFFERENTIABLE ARCHITECTURE SEARCH

Hanxiao Liu, Karen Simonyan, Yiming Yang

ICLR 2019

Neural Architecture Search(NAS)

- **Gradient-base methods(DARTS)**



$$x^{(j)} = \sum_{i<j} o^{(i,j)}(x^{(j)})$$

$$\bar{o}^{(i,j)}(x) = \sum_{o \in \mathcal{O}} \frac{\exp\left(\theta_o^{(i,j)}\right)}{\sum_{o' \in \mathcal{O}} \exp\left(\theta_{o'}^{(i,j)}\right)} o(x)$$

Neural Architecture Search(NAS)

- **Gradient-base methods(DARTS)**

$$\min_{\theta} \mathcal{L}_{val}(w^*(\theta), \theta)$$

$$s.t. w^*(\theta) = argmin_w \mathcal{L}_{val}(w, \theta)$$

$$\begin{cases} \theta = \theta - \beta \nabla_\theta \mathcal{L}(w - \xi \nabla_w \mathcal{L}(w, \theta), \theta) \\ w = w - \xi \nabla_w \mathcal{L}(w, \theta) \end{cases}$$

Algorithm 1: DARTS – Differentiable Architecture Search

Create a mixed operation $\bar{o}^{(i,j)}$ parametrized by $\alpha^{(i,j)}$ for each edge (i, j)

while *not converged* **do**

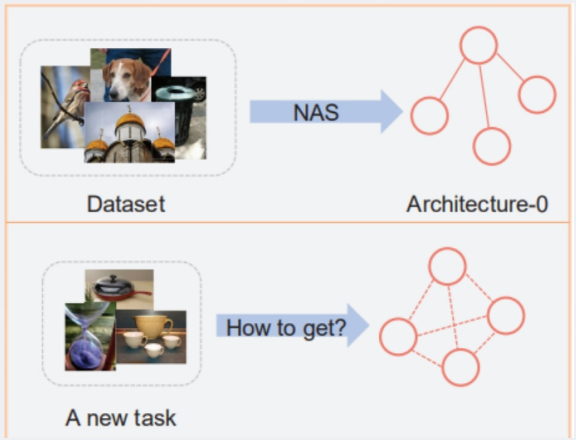
1. Update architecture α by descending $\nabla_\alpha \mathcal{L}_{val}(w - \xi \nabla_w \mathcal{L}_{train}(w, \alpha), \alpha)$ ($\xi = 0$ if using first-order approximation)
2. Update weights w by descending $\nabla_w \mathcal{L}_{train}(w, \alpha)$

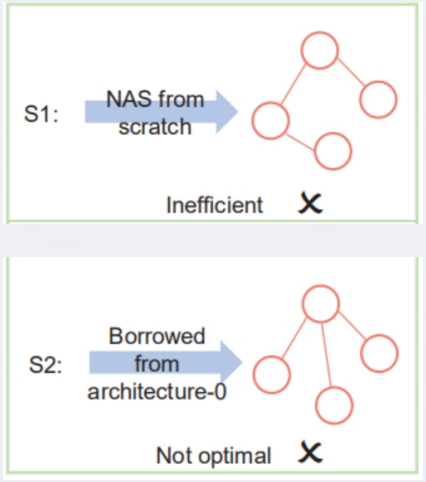
Derive the final architecture based on the learned α.

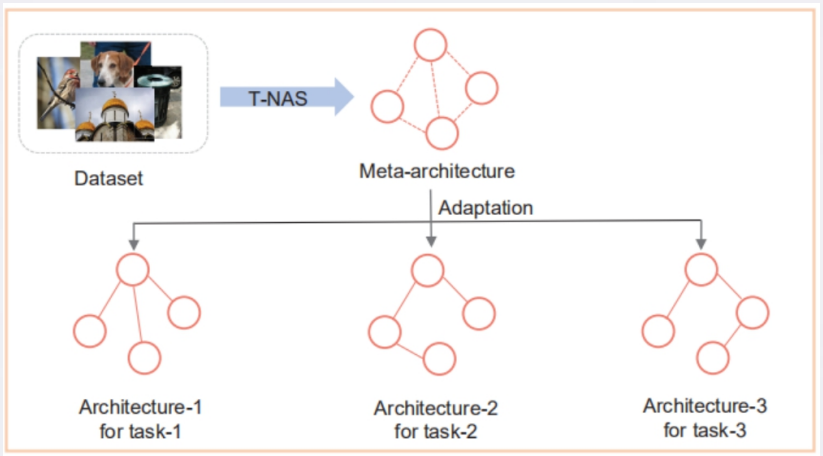
Transferable Neural Architecture(T-NAS)

- **Problem**

The existing NAS methods only target a specific task







Transferable Neural Architecture(T-NAS)

- **Solution**

$$w_i^{m+1} = w_i^m - \alpha_{inner} \nabla_{w_i^m} \mathcal{L}(f(\mathcal{T}_i^s; w_i^m))$$

$$\widetilde{w} = \widetilde{w} - \alpha_{outer} \nabla_{\widetilde{w}} \sum_{\mathcal{T}_i^q \sim p(\mathcal{T})} \mathcal{L}(f(\mathcal{T}_i^q; w_i^M))$$

$$\begin{cases} \theta = \theta - \beta \nabla_\theta \mathcal{L}(w - \xi \nabla_w \mathcal{L}(w, \theta), \theta) \\ w = w - \alpha \nabla_w \mathcal{L}(w, \theta) \end{cases}$$

$$\begin{cases} w_i^{m+1} = w_i^m - \alpha_{inner} \nabla_{w_i^m} \mathcal{L}(g(\mathcal{T}_i^s; \theta_i^m, w_i^m)) \\ \theta_i^{m+1} = \theta_i^m - \beta_{inner} \nabla_{\theta_i^m} \mathcal{L}(g(\mathcal{T}_i^s; \theta_i^m, w_i^{m+1})) \end{cases}$$

$$\begin{cases} \widetilde{w} = \widetilde{w} - \alpha_{outer} \nabla_{\widetilde{w}} \sum_{\mathcal{T}_i^q \sim p(\mathcal{T})} \mathcal{L}(g(\mathcal{T}_i^q; \theta_i^M, w_i^M)) \\ \tilde{\theta} = \tilde{\theta} - \beta_{outer} \nabla_{\tilde{\theta}} \sum_{\mathcal{T}_i^q \sim p(\mathcal{T})} \mathcal{L}(g(\mathcal{T}_i^q; \theta_i^M, w_i^M)) \end{cases}$$

Transferable Neural Architecture(T-NAS)

- **Algorithm**

Algorithm 1: T-NAS: Transferable Neural Architecture Search

Input: Meta-train dataset $\mathcal{D}_{\text{meta-train}}$, learning rate α_{inner}, α_{outer}, β_{inner} and β_{outer}.

Randomly initialize architecture parameter θ and network weights w.
while *not done* **do**
  Sample batch of tasks $\{\mathcal{T}\}$ in $\mathcal{D}_{\text{meta-train}}$;
  for $\mathcal{T}_i \in \{\mathcal{T}\}$ **do**
    Get datapoints $\mathcal{T}_i^s$;
    Compute $\mathcal{L}(g(\mathcal{T}_i^s; \theta_i^m, w_i^m))$ according to the standard cross-entropy loss;
    Alternatively update w_i^m and θ_i^m with Eq. (5) for M steps;
    Get datapoints $\mathcal{T}_i^q$ for meta-searcher;
  end
  Alternatively update $\widetilde{w}$ and $\widetilde{\theta}$ with Eq. (6);
end

Transferable Neural Architecture(T-NAS)

- **Optimization**

$$[w_i^{m+1}; \theta_i^{m+1}] = [w_i^m; \theta_i^m] - \boldsymbol{\eta}_{inner} \nabla_{[w_i^m; \theta_i^m]} \mathcal{L}(g(\mathcal{T}_i^s; \theta_i^m, w_i^m))$$

$$[\tilde{w}; \tilde{\theta}] = [\tilde{w}; \tilde{\theta}] - \boldsymbol{\eta}_{outer} \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \nabla_{[w_i^M; \theta_i^M]} \mathcal{L}(g(\mathcal{T}_i^q; \theta_i^M, w_i^M))$$

Algorithm 2: Adaptation and decoding

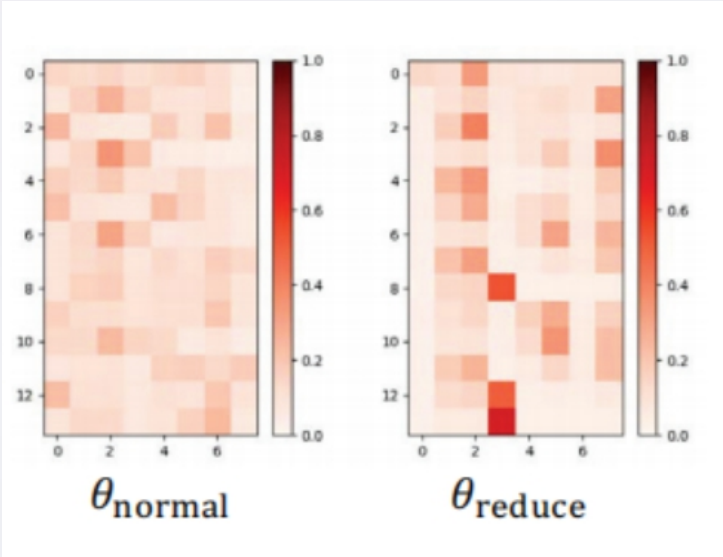
Input: Meta-test dataset $\mathcal{D}_{\text{meta-test}}$, learning rate α_{inner} and β_{inner}.
Output: The task-specific architecture θ_i^* for the i-th task $\mathcal{T}_i$.

1 Obtain the specific task $\mathcal{T}_i$ from $\mathcal{D}_{\text{meta-test}}$;
2 Update w_i^m and θ_i^m for M step with Eq. (7) and get θ_i^M;
3 Decoding θ_i^M to task-specific architecture θ_i^* by following the method in Liu et al. (2018b).

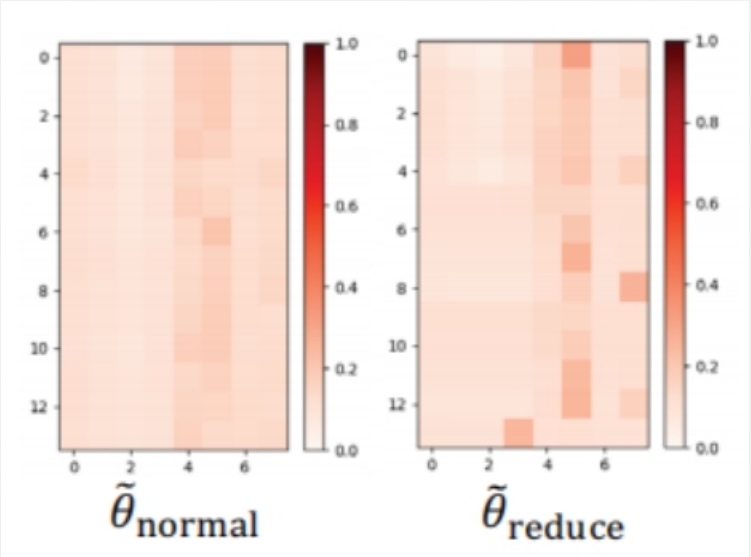
Transferable Neural Architecture(T-NAS)

- **Result**

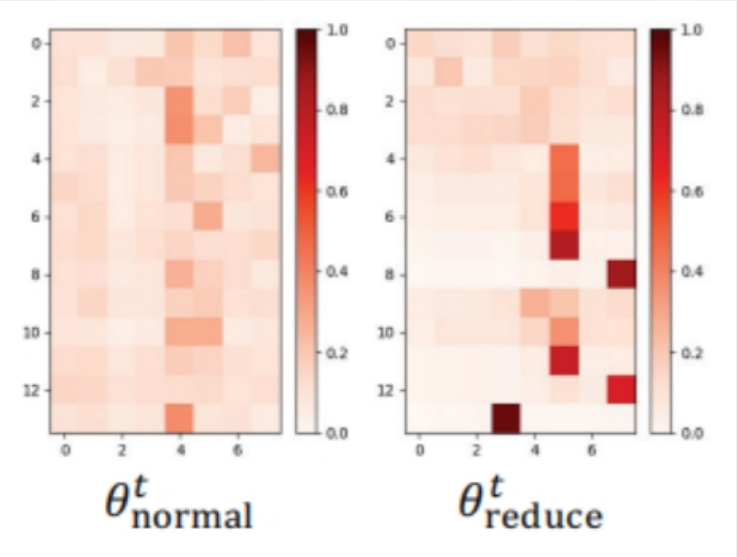
Auto-MAML



T-NAS



specific task



Transferable Neural Architecture(T-NAS)

- **Result**

Table 2: 5-way accuracy results on the Omniglot dataset.

Methods	1-shot	5-shot
Siamese Nets (Koch et al., 2015)	97.3%	98.4%
Matching nets (Vinyals et al., 2016)	98.1%	98.9%
Neural statistician (Edwards & Storkey, 2017)	98.1%	99.5%
Memory Mod. (Kaiser et al., 2017)	98.4%	99.6%
Meta-SGD (Li et al., 2017)	**99.53 ± 0.26%**	99.93 ± 0.09%
MAML (Finn et al., 2017)	98.7 ± 0.4%	99.9 ± 0.1%
MAML++ (Antoniou et al., 2019)	99.47%	99.93%
Auto-MAML (ours)	98.95 ± 0.38%	99.91 ± 0.09%
T-NAS (ours)	99.16 ± 0.34%	99.93 ± 0.07%
T-NAS++ (ours)	99.35 ± 0.32%	**99.93 ± 0.07%**

Table 3: 5-way accuracy results on Mini-Imagenet.

Methods	Arch.	#Param.	1-shot	5-shot
Matching nets (Vinyals et al., 2016)	4CONV	32.9K	43.44 ± 0.77%	55.31 ± 0.73%
ProtoNets (Snell et al., 2017)	4CONV	32.9K	49.42 ± 0.78%	68.20 ± 0.66%
Meta-LSTM (Ravi & Larochelle, 2017)	4CONV	32.9K	43.56 ± 0.84%	60.60 ± 0.71%
Bilevel (Franceschi et al., 2018)	4CONV	32.9K	50.54 ± 0.85%	64.53 ± 0.68%
CompareNets (Sung et al., 2018)	4CONV	32.9K	50.44 ± 0.82%	65.32 ± 0.70%
LLAMA (Grant et al., 2018)	4CONV	32.9K	49.40 ± 1.83%	-
MAML (Finn et al., 2017)	4CONV	32.9K	48.70 ± 1.84%	63.11 ± 0.92%
MAML (first-order) (Finn et al., 2017)	4CONV	32.9K	48.07 ± 1.75%	63.15 ± 0.91%
MAML++ (Antoniou et al., 2019)	4CONV	32.9K	52.15 ± 0.26%	68.32 ± 0.44%
Auto-Meta (small) (Kim et al., 2018)	Cell	28/28 K	49.58 ± 0.20%	65.09 ± 0.24%
Auto-Meta (large) (Kim et al., 2018)	Cell	98.7/94.0 K	51.16 ± 0.17%	69.18 ± 0.14%
BASE (Softmax) (Shaw et al., 2018)	Cell	1200K	-	65.40 ± 0.74%
BASE (Gumbel-Softmax) (Shaw et al., 2018)	Cell	1200K	-	66.20 ± 0.70%
Auto-MAML (ours)	Cell	23.2/26.1 K	51.23 ± 1.76%	64.10 ± 1.12%
T-NAS (ours)	Cell	24.3/26.5 K*	52.84 ± 1.41%	67.88 ± 0.92%
T-NAS++ (ours)	Cell	24.3/26.5 K*	**54.11 ± 1.35%**	**69.59 ± 0.85%**

* means the average parameters of architectures for evaluation.

Table 4: 5-way accuracy results on FC100.

Methods	1-shot	5-shot	10-shot
MAML (Finn et al., 2017)	38.1 ± 1.7%	50.4 ± 1.0%	56.2 ± 0.8%
MAML++ (Antoniou et al., 2019)	38.7 ± 0.4%	52.9 ± 0.4%	58.8 ± 0.4%
Auto-MAML (ours)	38.8 ± 1.8%	52.2 ± 1.2%	57.5 ± 0.8%
T-NAS (ours)	39.7 ± 1.4%	53.1 ± 1.0%	58.9 ± 0.7%
T-NAS++ (ours)	**40.4 ± 1.2%**	**54.6 ± 0.9%**	**60.2 ± 0.7%**

Transferable Neural Architecture(T-NAS)

- **Result**

Table 5: 200-shot, 50-query, 10-way accuracy results of supervised learning on Mini-Imagenet.

Methods	200-shot	Time
Random	$61.20 \pm 0.09\%$	N/A
S1	$64.84 \pm 0.04\%$	266 min
S2	$62.99 \pm 0.05\%$	N/A
T-NAS (ours)	$\mathbf{64.23 \pm 0.05\%}$	**5 min**

Summary and reflection

- **Summary**

The existing NAS methods only target a specific task. This paper proposed a T-NAS based on meta-learning, which combines MAML and DARTS. T-NAS learns a meta-learning is able to adapt to a new task quickly through a few gradient steps.

Summary and reflection

- **Reflection**

1. T-NAS learns the parameter $\tilde{\theta}$ and $\tilde{w}$, while when training the new task, T-NAS doesn't use parameter $\tilde{w}$.
2. The transferability of NAS for tasks from different task distributions.
3. Meta-learning can be applied to gradient descent optimization, even if it is bilevel.