Learning to Learn by Jointly Optimizing Neural Architecture and Weights

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Abstract

Meta-learning enables models to adapt to new environments rapidly with a few training examples. Current gradient-based meta-learning methods concentrate on finding good model-agnostic initialization (meta-weights) for learners. In this paper, we aim to obtain better meta-learners by co-optimizing the architecture and meta-weights simultaneously. Existing NAS-based meta-learning methods apply a two-stage strategy, i.e., first searching architectures and then re-training meta-weights on the searched architecture. However, this two-stage strategy would break the mutual impact of the architecture and meta-weights since they are optimized separately. Differently, we propose progressive connection consolidation, fixing the architecture layer by layer, in which the layer with the largest weight value would be fixed first. In this way, we can jointly search architectures and train the meta-weights on fixed layers. Besides, to improve the generalization performance of the searched meta-learner on all tasks, we propose a more effective rule for co-optimization, namely Connection-Adaptive Meta-learning (CAML). By searching only once, we can obtain both adaptive architecture and meta-weights for meta-learning. Extensive experiments show that our method achieves state-of-the-art performance with 3x less computational cost, revealing our method’s effectiveness and efficiency.

1. Introduction

As a popular solution for the few-shot learning problem\(^1\), meta-learning develops deep learning models with the ability to fit unseen tasks using only a few training examples [6, 30, 37]. Particularly, the gradient-based meta-learning methods like MAML [6] attempt to find a set of initialization of models’ weights (meta-weights). The model with meta-weights can produce good generalization performance on an unseen task quickly with only a few gradient steps. In addition, to obtain the optimized meta-weights, it’s also vital to find better architectures good at meta-learning. Unlike previous methods built on hand-crafted architectures, we aim to obtain better meta-learners by enriching architecture flexibility via Neural Architecture Search (NAS).

In this work, our target is to find optimal architecture and meta-weights for a meta-learner which can quickly adapt to new tasks with a few training samples. We represent the candidate operations (e.g., conv and pooling) in each layer as connections. Each of them is weighted by an attention value over all candidate operations in the same layer, which is called connection parameters. Larger values mean more important operations/connections and we call each layer’s adaptive connection as meta-connections. Thus the adaptive architecture is composed of meta-connections, and the training process can be regarded as a co-optimization problem of the connection parameters and the network weights.

There have been some recent works focusing on the exploration of architecture impact in meta-learning [10, 15]. However, most of these works either fall into the dilemma of breaking the mutual impact between the architecture and meta-weights or optimize the learner with a biased updating rule. First, both Auto-Meta [10] and Auto-MAML [15] apply a two-stage training strategy that obtains architectures and meta-weights separately, i.e., first searching architectures and then retraining meta-weights using the searched architecture, as illustrated in Figure 1 (b). As mentioned in the lottery ticket hypothesis [7], sub-networks pruned from the supernet\(^2\) cannot get optimized effectively unless they are initialized with the supernet’s network weights. It inspires us that architectures and network weights have a mutual impact on each other. Therefore, in NAS-based meta-learning, we need to preserve the mutual impact between the architecture

\(^1\)A N-way, K-shot task denotes K samples from each class and N classes in few-shot learning. 

\(^2\)A supernet is a neural network whose layers consist of more than one candidate operation (e.g., convolution, pooling). When searching finished, each layer is pruned, leaving one specific operation at most.
and meta-weights. Nevertheless, during the searching phase, Auto-Meta [10] and Auto-MAML [15] could only obtain the architecture with non-matched meta-weights. The matched meta-weights are acquired based on the searched architecture in the second stage (the re-training stage). Thus, the architecture and meta-weights of existing works are trained one by one (separately) instead of jointly optimized, breaking the mutual impact between the architecture and meta-weights. Second, to co-optimize the architecture parameters and network weights, Auto-MAML [15] proposed one simple solution called One-Propagation NAS-Based Meta-Learning (OPML) [5, 15], as illustrated in Figure 3. For simplicity, OPML treats the connection parameters and network weights equally and updates them by one backpropagation in every iteration. Nevertheless, due to the unequal learning rates, the meta-learner’s real update direction is not parallel to the calculated meta-gradient, which may harm the generalization performance of meta-learner on all tasks.

To preserve the mutual impact between the architecture and meta-weights, we propose \textit{progressive connection consolidation}, as shown in Figure 1 (c). During searching, we prune the supernet layer by layer, in which the layer with the largest connection weight value will be consolidated first. As the connections get fixed gradually, we can train the matched meta-weights on these consolidated connections. In return, the meta-weights would further affect the update of the other unfixed connections. In this way, we continuously preserve the mutual impact of the meta-connections and meta-weights during the entire training phase. Meanwhile, we remove the update of the pruned connections and weights and avoid retraining the derived architecture from scratch, saving 66% computational cost. To update the meta-learner in an un-biased way, we propose Connection-Adaptive Meta-Learning (CAML), as demonstrated in Figure 2.(b). By backpropagating twice and updating alternately, CAML can optimize both the connection parameters and network weights using the same update direction as the meta-gradients’, respectively. Thus, CAML improves the searched meta-learner’s generalization performance on all tasks, which is essential in meta-learning. Our contributions are summarized as follows:

- To address the two-stage strategy’s separate optimization problem, we propose \textit{progressive connection consolidation} to gradually prune the supernet during searching, preserving the mutual impact of the meta-connections and meta-weights.

- We propose a more effective method, namely Connection-Adaptive Meta-Learning (CAML), which can improve the generalization performance of the optimal architecture and meta-weights on all tasks.

- Extensive experiments show that our method achieves state-of-the-art performance on both FC100 and Mini-Imagenet datasets under various settings with 3x less computational cost, revealing the effectiveness and efficiency of our method.

2. Related work

2.1. Meta-learning

Meta-learning (learning to learn) [2, 6, 8, 13, 20, 22] methods learn from a series of learning tasks, enabling neural
networks to adapt to new data and new tasks quickly. In recent years, meta-learning has proven effective in the few-shot classification task, which requires neural networks to solve new tasks given only a few training examples. Meta-learning approaches can be classified into three major categories: memory network [3,25], metric learning [28,31,31] and gradient-based approaches [1,6,20].

In gradient-based approaches, an optimizer called meta-learner is learned to perform fast adaptation on new tasks [9]. Instead of using the learned optimizer, model-agnostic meta-learning (MAML) [6] tries to find a set of parameters (meta-weights) for initializing the meta-learner. With a few steps of gradient descent, the meta learner can fast adapt to new tasks. However, previous methods focus on finding good model-agnostic initialization.

2.2. Neural architecture search

Neural architecture search (NAS) [4,14,16,19,29,35,38] aims to automatically design neural network architecture to reduce human experts’ manual labour. The architectures searched by NAS approaches have surpassed hand-designed ones in many diverse tasks, such as image classification [19,35,39], semantic segmentation [17,26], and object detection [32,34]. Most NAS methods can be classified into three categories: based on evolutionary algorithms [18,23,24], based on reinforcement learning [39,40] and gradient-based methods [19,33,36].

In gradient-based NAS methods like DARTS [19], the connection parameters and network weights can be optimized jointly based on gradient descent. Therefore, gradient-based NAS methods are capable of finishing searching within one GPU day. However, the existing NAS approaches merely target searching architectures for a single specific task. But while turning to multiple tasks or multiple datasets, they encounter troubles.

2.3. Meta-learning with neural architecture search

Recently, there have been some works combining NAS and meta-learning to obtain a better meta-learner [10,15]. However, in every iteration of searching, Auto-Meta [10] needs to perform the entire meta-training process, while we only train the meta-learners once. As a result, Auto-Meta takes 112 GPU Days to converge, while our method only requires 0.7 GPU Day. More importantly, current methods separate the architecture searching and meta-weights training. They search architectures first and then re-train meta-weights based on searched architectures. Unfortunately, in this two-stage strategy, the meta-weights are overlooked during architecture searching, breaking the mutual impact of the architecture and meta-weights. In our method, both architecture and meta-weights can benefit each other and lead to better overall optimization.

Besides, some works concentrate on designing task-specific architectures. Based on Bayesian inference, BASE [27] is proposed to design task-dependent architectures for each meta-test task. MetaNAS [5] employs Reptile [20] as its backbone and utilizes a soft pruning strategy over all layers with the search progressing. T-NAS [15] attempts to learn a general meta-architecture through MAML [6]. Then both MetaNAS and T-NAS perform architecture adaptation for a new test task. Soft pruning does not prune the operations of slight importance. Thus MetaNAS still need to do one-shot pruning for the final architectures like T-NAS. However, these methods need to train every task-specific architecture from scratch, which is computationally expensive. Moreover, these task-specific methods also utilize the two-stage strategy, overlooking the mutual impact of the connections and meta-weights.

3. Approach

Before introducing our approach, we make a review of Model-Agnostic Meta-Learning (MAML) [6] and Differentiable Architecture Search (DARTS) [19], which will help us make a better understanding of our method. Then we introduce our the progressive connection consolidation in Section 3.3. and CAML in Section 3.4.

3.1. MAML

In MAML [6], the whole task dataset \( D \) is divided into three subsets, i.e., meta-train \( D_{\text{meta-train}} \), meta-val \( D_{\text{meta-val}} \) and meta-test dataset \( D_{\text{meta-test}} \), respectively, as visualized in the supplementary material. Each of them consists of two tasks set, the support set \( \{ T^s \} \) and the query set \( \{ T^q \} \). In meta-train phase, MAML samples a set of tasks \( \{ T \} \) from the task distribution \( p_T \) in \( D_{\text{meta-train}} \). Tasks sampled from \( \{ T^s \} \) are employed for optimizing the inner-learner [19], while tasks sampled from \( \{ T^q \} \) are used to optimize the meta-learner. The main goal of MAML is to find good initialized weights \( \tilde{\theta} \) for the meta-learner, which can quickly adapt to new tasks drawn from \( p_T \). In the \( i \)-th meta-train task, the gradient-based learning rule for updating the inner-learner can be formulated as:

\[
\theta^{m+1}_i = \theta^m_i - \beta_{\text{inner}} \nabla_{\theta^m_i} \mathcal{L}(f_{\theta^m_i}; T^q_i),
\]

where \( m \) represents the inner update step, and \( T^q_i \) is the \( i \)-th task sampled from \( \{ T^q \} \). \( \beta_{\text{inner}} \) is the inner learning rate of weights. \( \theta^m_i \) is a copy of \( \tilde{\theta} \). \( f_{\theta^m_i} \) is the parameterized function with parameters \( \theta^m_i \), while \( \mathcal{L} \) means the loss function. After \( M \) steps of gradient descent, tasks \( T^q_i \) sampled from \( \{ T^q \} \) are used for updating the meta-learner by the following rule:

\[
\tilde{\theta} = \tilde{\theta} - \beta_{\text{meta}} \nabla_{\tilde{\theta}} \sum_{T^q_i \sim p(T)} \mathcal{L}(f_{\theta^m_i}; T^q_i),
\]
where $\beta_{\text{meta}}$ is denoted as the outer (meta) learning rate of weights. After the meta-train phase, the model learns well-initialized weights, which help the meta-learner adapt to any specific task in $D_{\text{meta-test}}$ within only a few steps of gradient descent optimization.

### 3.2. DARTS

To obtain a continuous architecture search space, DARTS [19] apply a softmax over all possible operation candidates. The softmax relaxes the categorical choice of one specific operation to a soft one. The output of each layer is the expectation of all the outputs of operations,

$$
\phi(x) = \frac{\sum_{o \in \mathcal{O}} \exp(\phi_o) \phi(x)}{\sum_{\phi' \in \mathcal{O}} \exp(\phi')}.
$$

where $x$ is the input, $\mathcal{O}$ is the candidate operation set, and $\phi_o$ is the softmax attention on operation $o$. On the convergence of DARTS, only operations with the relatively largest attention values are preserved, while the others are pruned. There is a bi-level optimization problem where the connection parameters and the network weights need to be optimized jointly. DARTS solves the conflict by updating the connection parameters $\phi$ and weights $\theta$ alternately:

$$
\begin{align*}
\phi &= \phi - \alpha \nabla_{\phi} L_{\text{val}}(\theta - \xi \nabla_{\theta} L_{\text{train}}(\theta, \phi), \phi), \\
\theta &= \theta - \beta \nabla_{\theta} L_{\text{train}}(\theta, \phi),
\end{align*}
$$

where $L_{\text{train}}$ and $L_{\text{val}}$ are the loss function on training dataset and validation dataset. $\alpha$ and $\beta$ are the learning rates of the connection parameters and the network weights, respectively. $\xi$ is the inner optimization learning rate and is a proxy for obtaining $\phi^*$, which is set to 0 in our work.

### 3.3. Progressive connection consolidation

To enrich architecture flexibility, we employ a supernet during the architecture searching, while our meta-learner is a sub-supernet pruned from the supernet. Note that in our method, we represent the candidate operations of each layer as connections. Thus, the architecture searching is to learn each layer’s adaptive connection, which we call meta-connections.

The lottery ticket hypothesis [7] reveals the mutual impact between the architectures and network weights. However, previous work like T-NAS [15] utilizes a two-stage strategy, i.e., first search architectures and then retrain meta-weights based on the searched architectures. This two-stage training would break the interaction since the two targets are optimized separately. To preserve the mutual impact and build a better co-optimization, we propose progressive connection consolidation (PCC), pruning the supernet layer by layer during searching. We define layer confidence as follows:

**Layer confidence.** A layer $e$ consists of all operations from the candidate operation set $\mathcal{O}$. Following DARTS [19], we use a zero operation in the candidate set to represent a lack of connection. $\phi^+_e$ are the related connection parameters for layer $e$. Thus, the layer confidence of layer $e$ is defined as the maximum attention value on non-zero operations:

$$
S_{\text{LC}}^e = \max_{\phi_o \neq \text{zero}} \frac{\exp(\phi_o)}{\sum_{\phi' \in \mathcal{O}} \exp(\phi')}.
$$

In our experiments, we apply layer confidence to determine each layer’s importance. The process of fixing one connection can be disassembled into two steps. First, we compute the layer confidence $S_{\text{LC}}$ for all layers. The layer with largest $S_{\text{LC}}$ is selected. Second, for the selected layer, we only keep the operation with the largest weight value and remove others. The kept operation is called meta-connection. As the connections get pruned gradually, the meta-weights in the fixed connections would further affect the update of the other unfixed connections’ searching. On the convergences of the meta-learner, we obtain an adaptive architecture and the corresponding meta-weights simultaneously. We argue that such a learner can learn knowledge from task distribution $p_T$ more efficiently and effectively.

### 3.4. Connection-adaptive meta-learning

The main goal of our method is to find meta-learners with both adaptive architecture and meta-weights. However, as described in DARTS [19], there lies a bi-level optimization problem. We cannot optimize connection parameters $\phi$ solely without regard to the network weights $\theta$.

As demonstrated in Figure 2, in MAML [6], they need to solve another bi-level optimization problem [19] over initial network weights and tasks. Therefore, we need to tackle a 4-level optimization problem in NAS-based meta-learning. Following MAML and DARTS, in each iteration, we use two different backpropagations for optimizing $\phi$ and $\theta$, respectively. In other words, our CAML updates the meta-learners of $\phi$ and $\theta$ alternately. Since we jointly optimize the connection parameters and the weights, we have four learners, i.e., inner-learner for $\phi$, meta-learner for $\phi$, inner-learner for $\theta$, and meta-learner for $\theta$. During the inner updates for connection parameters $\phi$, the network weights $\theta$ is fixed. Following the common settings in NAS methods [12, 19], we split $D_{\text{meta-train}}$ into $D_{\text{meta-train-split-arch}}$ and $D_{\text{meta-train-split-weights}}$ (as shown in the supplementary material), where $D_{\text{meta-train-split-arch}}$ is used for updating the connection parameters $\phi$, while the other is used for optimizing the network weights $\theta$. Note that every split has both the support set and query set [31]. Given the $i$-th task $T_i^{\text{split-arch}, s}$ sampled from the support set of $D_{\text{meta-train-split-arch}}$, we optimize $\phi$ by:

$$
\phi_{i}^{m+1} = \phi_{i}^{m} - \alpha_{\text{inner}} \nabla_{\phi_{i}^{m}} L(f_{\phi_{i}^{m}, \phi}; T_i^{\text{split-arch}, s}),
$$

where $\alpha_{\text{inner}}$ is the inner learning rate of the meta-connections and $m$ is the inner update step. $f_{\phi_{i}, \theta}$ means the parameterized
function with connections $\phi$ ($\phi_1 = \tilde{\phi}$) and network weights $\theta$. After $M$ inner update steps, the connections $\phi$ are updated to be well-adapted to the specific task. We optimize the meta-learner of $\phi$ according to the following formulation,

$$\tilde{\phi} = \phi - \alpha_{\text{meta}} \nabla_{\phi} \mathcal{L}(f_{\phi}, \theta_m; T^\text{split-weights}_1, q),$$

where $\alpha_{\text{meta}}$ is the meta (outer) learning rate of $\phi$. We use similar rules to optimize the inner-learner and the meta-learner of $\theta$, as follows:

$$\theta_{t+1} = \theta_t - \beta_{\text{inner}} \nabla_{\theta} \mathcal{L}(f_{\phi}, \theta^m; T^\text{split-weights}_j), \quad \tilde{\theta} = \theta - \beta_{\text{meta}} \nabla_{\theta} \mathcal{L}(f_{\phi}, \theta^m; T^\text{split-weights}_j),$$

where $\beta_{\text{inner}}$ and $\beta_{\text{meta}}$ are the inner and meta learning rate of network weights $\theta$ ($\theta_0 = \tilde{\theta}$). $T^\text{split-weights}_j$ are optimized by the meta-learners. On the convergence of the meta learners of $\phi$ and $\theta$, we obtain an adaptive architecture $\phi^*$ and the meta-weights $\theta^*$. We simplify our method by two groups of bi-level optimization as approximation. The complete algorithm of our CAML is described in Alg. 1.


$$\begin{cases}
\phi_{t+1} = \phi_t - \eta_{\text{inner}} \nabla_{\phi_t} \mathcal{L}(f_{\phi_t}, \theta_{t+1}) \\
\theta_{t+1} = \theta_{t+1} - \eta_{\text{meta}} \nabla_{\theta_{t+1}} \mathcal{L}(f_{\phi_{t+1}}, \theta_{t+1})
\end{cases}$$

where $\eta_{\text{inner}} = \eta_{\text{inner}}$ and $\eta_{\text{meta}} = \eta_{\text{meta}}$. $f$ denotes the parameterized function, and $T^\text{split-weights}_j$ are sampled from $D_{\text{meta-train}}$. In other words, they treat connection parameters and network weights equally and update them in one propagation, as shown in Figure 3. We also conducted our experiments based on OPML, and the quantitative comparison can be found in Table 3.

4. Experiments

To verify the effectiveness of our approach, we conduct the experiments under the settings of few-shot learning on some popular datasets, e.g., Omniglot [11], FC100 [21] and Mini-Imagenet [22]. Our experiments consist of architecture search and evaluation. We search for a meta-learner that has both the adaptive architecture and the meta-weights during the training stage. Then we evaluate the searched meta-
We train the searched meta-learner for 100 epochs with 1200 samples per class. We search for two cells composed of normal and reduction operations. (1) zero, (2) identity, (3) 3*3 max pooling, (4) 3*3 average pooling, (5) 3*3 depth-wise separate conv, (6) 3*3 dilated depth-wise separate conv, (7) 5*5 depth-wise separate conv, (8) 5*5 dilated depth-wise separate conv. Other detailed searching settings and searched architectures are summarized in the supplementary material.

4.2. Evaluation on few-shot learning datasets

After the searching phase, a meta-learner with both adaptive architecture and corresponding meta-weights is obtained. We train the searched meta-learner for 100 epochs with 1200 independent tasks for each epoch during the evaluation. Note that different from DARTS [19], we train the searched architecture without any modification (e.g., channels and architecture). We employ the Adam optimizer (cosine decay) with meta learning rate $\beta_{\text{meta}} = 0.001$ for the meta update. A vanilla SGD with inner learning rate $\beta_{\text{inner}} = 0.01$ is used for optimizing the inner-learner. We also report the performance of models by training the adaptive architecture from randomly initialized weights. All results come from three different experiments with ±1 std as error bars.

The experiments results on Mini-Imagenet and FC100 are represented in Table 1. The experiments results on Omniglot can be found in the supplementary material. On all datasets, our method achieves the best performance with less computational cost. CAML outperforms the baseline Auto-MAML by 4.0% (68.1% versus 64.1%) with fewer parameters (24.2K versus 26.1K), verifying the advantages of our method. Moreover, our method can save at least 66% search cost compared to other state-of-the-art NAS-based methods. Thus, we finally obtain a meta-learner with adaptive architecture and meta-weights by co-optimizing connection parameters and network weights simultaneously.

We also make a comparison with other task-specific methods (like BASE [27], T-NAS [15], and MetaNAS [5]), as shown in Table 2. Compared to those task-dependent methods, our CAML can achieve comparable performance with fewer parameters. T-NAS [15] utilizes the two-stage strategy for every meta-test task to obtain a higher accuracy of 52.8%, and also reports a 215x more search cost.

4.3. Ablation studies

**Contribution of CAML and PCC.** We evaluate the contribution made by two components of our methods, namely CAML and PCC. Results are shown in Table 3. Progressive connection consolidation (PCC) plays a vital role in both one-propagation NAS-based meta-learning and CAML, which helps to find meta-learners with higher performance. PCC strengthens the co-optimization and mutual interaction between the architecture and the network weights. Thus, the searched weights show more significant potential than a random initialization on derived architectures with PCC. In CAML without PCC, we perform one-shot pruning at the end of searching. Also, CAML achieves better performance than OPML from two initialization conditions, demonstrating the effectiveness of our methods. Besides, CAML can cooperate well with progressive connection consolidation to provide further improvement.

**CAML versus OPML.** In existing works (e.g., T-NAS [15]), the connection parameters and network weights are treated equally. Thus $\phi$ and $\theta$ are optimized by backpropagating once. We call the updating rules as one-propagation NAS-based meta-learning (OPML), as described in Section 3.4. As shown in Table 3, though OPML can cooperate well with PCC, it obtains a lower accuracy compared to CAML in experiments. A potential reason for the performance improvement of our CAML might be the parallel optimization direction of learners. In MAML [6], they design the update direction of meta-gradient to update the meta-learner, as shown in Figure 2.(a). The parallel update direction produces the meta-learner’s good generalization performance on all new tasks. But in OPML, since learning rates of $\theta$ and $\phi$ are usually unequal, the meta-learner’s composite update direction is not parallel to the meta-gradient, as illustrated in Figure 3. Analogous to MAML, our method would lead to the same update direction as the meta-gradient, which helps find better meta-learners.

**Comparison of different search space.** MetaNAS [5] considers a different set of operations in its search space (which is named as S1) so the results are not directly comparable. To
### Method

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Method</th>
<th>Params (K)</th>
<th>FLOPS (M)</th>
<th>Search cost (GPU days)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
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<td>Mini-Imagenet</td>
<td>Auto-Meta [10]</td>
<td>28.0</td>
<td>-</td>
<td>112</td>
<td>49.6 ± 0.2</td>
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<td></td>
<td>Auto-MAML [15]</td>
<td>26.1</td>
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<td>Ours</td>
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<td>0.7</td>
<td>52.2 ± 0.4</td>
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<td></td>
<td>Auto-MAML [15]</td>
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<td>3.9</td>
<td>2</td>
<td>38.8 ± 1.8</td>
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<tr>
<td></td>
<td>Ours</td>
<td>18.4</td>
<td>3.9</td>
<td>0.7</td>
<td>39.2 ± 0.4</td>
</tr>
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</table>

Table 1. Comparison with NAS-based methods on Mini-Imagenet and FC100 for 5-way classification accuracy.

### Updating rules

<table>
<thead>
<tr>
<th>Updating rules</th>
<th>PCC</th>
<th>Params (K)</th>
<th>Search Cost (GPU Days)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
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<td>BASE (Softmax)</td>
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<tr>
<td>Ours</td>
<td>✓</td>
<td>24.2</td>
<td>0.7</td>
<td>52.2 ± 0.2</td>
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</table>

Table 3. Average 5-way, 5-shot accuracy on Mini-Imagenet.

### Search Space

<table>
<thead>
<tr>
<th>Search Space</th>
<th>Method</th>
<th>Params (K)</th>
<th>GPU Days</th>
<th>Accuracy (%)</th>
</tr>
</thead>
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<tr>
<td>S1</td>
<td>MetaNAS [5]</td>
<td>≈ 30</td>
<td>7</td>
<td>49.7 ± 0.4</td>
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<tr>
<td>S1</td>
<td>Ours</td>
<td>16.8</td>
<td>0.7</td>
<td>50.4 ± 0.4</td>
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</table>

Table 4. Comparison of average 5-way accuracy on Mini-Imagenet.

### Table 4. Comparison of average 5-way accuracy on Mini-Imagenet.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Method</th>
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</tr>
</tbody>
</table>

Table 1. Comparison with NAS-based methods on Mini-Imagenet and FC100 for 5-way classification accuracy.

### Table 2. Comparison with task-specific NAS-based methods on Mini-Imagenet for 5-way accuracy.

**Comparison of different pruning strategies.** To prove our layer confidence-based pruning strategy’s effectiveness, we also prune the supernet with fixed orders like forwarding sequence or backward. In addition, we also experimented with two different pruning strategies, named variance-based strategy and entropy-based strategy. The variance-based strategy picks the layer with the largest variance of its operations’ architecture parameters to prune the supernet gradually, while the entropy-based strategy chooses the layer with the smallest entropy of its architecture parameters. The results are summarized in Table 5. Clearly, layer confidence-based pruning strategy in our PCC could help us find better adaptive architectures, achieving higher performance with fewer parameters. Besides, we could also observe perfor-
Table 5. Average 5-way, 5-shot accuracy on Mini-Imagenet by five pruning strategies of CAML. $S_{LC}$ means the layer confidence. Clearly, among all five orders, $S_{LC}$-based strategy outperforms the other pruning strategies. Thus, in PCC, we prune the layers of the supernet in descending order of $S_{LC}$.

<table>
<thead>
<tr>
<th>Sequence</th>
<th>Params (K)</th>
<th>Train from scratch</th>
<th>Train from searched-weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forward</td>
<td>34.0</td>
<td>61.0 ± 1.0</td>
<td>66.0 ± 0.1</td>
</tr>
<tr>
<td>Backward</td>
<td>27.7</td>
<td>63.6 ± 0.6</td>
<td>64.5 ± 0.2</td>
</tr>
<tr>
<td>Entropy-based</td>
<td>25.1</td>
<td>66.7 ± 1.0</td>
<td>67.7 ± 0.1</td>
</tr>
<tr>
<td>Variance-based</td>
<td>26.8</td>
<td>66.9 ± 0.2</td>
<td>67.8 ± 0.1</td>
</tr>
<tr>
<td>$S_{LC}$ based</td>
<td>24.2</td>
<td>67.4 ± 0.1</td>
<td>68.1 ± 0.2</td>
</tr>
</tbody>
</table>

Table 6. Comparison of average 5-way accuracy on Mini-Imagenet by different meta-learning methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>1-shot (%)</th>
<th>5-shot (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ours + MAML [6]</td>
<td>52.2 ± 0.4</td>
<td>68.1 ± 0.3</td>
</tr>
<tr>
<td>Ours + Reptile [20]</td>
<td>51.6 ± 0.3</td>
<td>68.5 ± 0.3</td>
</tr>
<tr>
<td>Ours + MAML++ [1]</td>
<td>53.4 ± 0.3</td>
<td>69.1 ± 0.5</td>
</tr>
</tbody>
</table>

5. Conclusion

In this work, we focus on the exploration of the architecture impact in meta-learning. We target to find a meta learner with both the adaptive architecture and the meta-weights that can perform well on multiple similar tasks. The current two-stage solutions are inefficient and ignore the co-optimization of the architecture and meta-weights. To tackle the existing problems, we propose a novel Progressive Connection Consolidation (PCC). By fixing the architecture layer by layer during searching, PCC preserves the mutual impact between the architecture and meta-weights, leading to better overall optimization. Besides, we propose CAML to update the architecture parameters and network weights simultaneously by two different backpropagations in one iteration, improving the generalization performance of the searched meta-learner on all tasks. Extensive experiments show that our CAML and progressive connection consolidation are both helpful to a meta-learner’s success. Our method achieves state-of-the-art performance on all few-shot datasets with 3x less computational cost.

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References


