Meta-Learning of Neural Architectures for Few-Shot Learning

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Abstract

The recent progress in neural architecture search (NAS) has allowed scaling the automated design of neural architectures to real-world domains, such as object detection and semantic segmentation. However, one prerequisite for the application of NAS are large amounts of labeled data and compute resources. This renders its application challenging in few-shot learning scenarios, where many related tasks need to be learned, each with limited amounts of data and compute time. Thus, few-shot learning is typically done with a fixed neural architecture. To improve upon this, we propose \textsc{MetaNAS}, the first method which fully integrates NAS with gradient-based meta-learning. \textsc{MetaNAS} optimizes a meta-architecture along with the meta-weights during meta-training. During meta-testing, architectures can be adapted to a novel task with a few steps of the task optimizer, that is: task adaptation becomes computationally cheap and requires only little data per task. Moreover, \textsc{MetaNAS} is agnostic in that it can be used with arbitrary model-agnostic meta-learning algorithms and arbitrary gradient-based NAS methods. Empirical results on standard few-shot classification benchmarks show that \textsc{MetaNAS} with a combination of DARTS and REPTILE yields state-of-the-art results.

1. Introduction

Neural architecture search (NAS)\cite{elsken2019neural} has seen remarkable progress on various computer vision tasks, such as image classification\cite{he2016deep, simonyan2014very, yang2020adam}, object detection\cite{ren2015faster}, semantic segmentation\cite{chen2017rethinking, long2015fully, zhao2017pyramid}, and disparity estimation\cite{zhan2017hierarchical}. One key prerequisite for this success is the availability of large and diverse (labeled) data sets for the respective task. Furthermore, NAS requires considerable compute resources for optimizing the neural architecture for the target task.

This makes it difficult to apply NAS in use-cases where one does not focus on a single task but is interested in a large set (distribution) of tasks. To be effective in this setting, learning must not require large amounts of data and compute for every task but should, like humans, be able to rapidly adapt to novel tasks by building upon experience.
from related tasks [27]. This concept of learning from experience and related tasks is known as meta-learning or learning to learn [46, 50, 21]. Here, we consider the problem of few-shot learning, i.e., learning new tasks from just a few examples. Prior work has proposed meta-learning methods for this problem that are model-agnostic [16, 37] and allow meta-learning weights of fixed neural architectures (see Figure 1, top).

In this work, we fully integrate meta-learning with NAS, by proposing METANAS. METANAS allows adapting architectures to novel tasks based on few datapoints with just a few steps of a gradient-based task optimizer. This allows METANAS to generate task-specific architectures that are adapted to every task separately (but from a joint meta-learned meta-architecture). This is in contrast to prior work that applied NAS to multi-task or few-shot learning, where a single neural architecture is optimized to work well on average across all tasks [25, 39] (see Figure 1, middle). Moreover, our method directly provides trained weights for these task-specific architectures, without requiring meta-retraining them as in concurrent work [30]. Conceptual illustrations of our method are shown in Figure 1, bottom, and in Figure 3. The key contributions of this work are as follows:

1. We show that model-agnostic, gradient-based meta-learning methods (such as [16]) can very naturally be combined with recently proposed gradient-based NAS methods, such as DARTS [33]. This allows for joint meta-learning of not only the weights (for a given, fixed architecture) but also meta-learning the architecture itself (Section 3, see Figure 1 for an illustration).

2. We propose METANAS, a meta-learning algorithm that can quickly adapt the meta-architecture to a task-dependent architecture. This optimization of the architecture for the task can be conducted with few labeled datapoints and only a few steps of the task optimizer (see Figure 3 for an illustration).

3. We extend DARTS such that task-dependent architectures need not be (meta) re-trained, which would be infeasible in the few-shot learning setting with task-dependent architectures for hundreds of tasks (requiring hundreds re-trainings). We achieve this by introducing a novel soft-pruning mechanism based on a temperature annealing into DARTS (see Figure 2). This mechanism lets architecture parameters converge to the architectures obtained by the hard-pruning at the end of DARTS, while giving the weights time to adapt to this pruning. Because of this, pruning no longer results in significant drops in accuracy, which might also be of interest for the standard single-task setting. We give more details in Section 4.

METANAS is agnostic in the sense that it is compatible with arbitrary gradient-based model-agnostic meta-learning algorithms and arbitrary gradient-based NAS methods employing a continuous relaxation of the architecture search space. Already in combination with the simple meta-learning algorithm REPTILE[37] and NAS algorithm DARTS[33], METANAS yields state-of-the-art results on the standard few-shot classification benchmarks Omniglot and MiniImagenet.

This paper is structured as follows: in Section 2, we review related work on few-shot learning and neural architecture search. In Section 3, we show that model-agnostic, gradient-based meta-learning can naturally be combined with gradient-based NAS. The soft-pruning strategy to obtain task-dependent architectures without the need for retraining is introduced in Section 4. We conduct experiments on standard few-shot learning data sets in Section 5 and conclude in Section 6.

Code is available at https://github.com/boschresearch/metanas.

2. Related Work

**Few-Shot Learning via Meta-Learning** Few-Shot Learning refers to the problem of learning to solve a task (e.g., a classification problem) from just a few training examples. This problem is challenging in combination with deep learning as neural networks tend to be highly over-parameterized and therefore prone to overfitting when only very little data is available. Prior work [40, 16, 18, 19] often approaches few-shot learning via meta-learning or learning to learn [46, 50, 21, 22], where one aims at learning from a variety of learning tasks in order to learn new tasks much faster than otherwise possible [51].

There are various approaches to few-shot learning, e.g., learning to compare new samples to previously seen ones [48, 52] or meta-learning a subset of weights that is shared across tasks but fixed during task learning [58, 19].

In this work, we focus on a particular class of approaches denoted as **model-agnostic meta-learning** [16, 17, 37, 1, 18]. These methods meta-learn an initial set of weights for neural networks that can be quickly adapted to a new task with just a few steps of gradient descent. For this, the meta-learning objective is designed to explicitly reward quick adaptability by incorporating the task training process into the meta-objective. This meta-objective is then usually optimized via gradient-based methods. Our method extends these approaches to not only meta-learn an initial set of weights for a given, fixed architecture but to also meta-learn the architecture itself. As our method can be combined with any model-agnostic meta-learning method, future improvements in these methods can be directly utilized in our framework.
Neural Architecture Search Neural Architecture Search (NAS), the process of automatically designing neural network architectures [14], has recently become a popular approach in deep learning as it can replace the cumbersome manual design of architectures while at the same time achieving state-of-the-art performance on a variety of tasks [59, 41, 9, 44]. We briefly review the main approaches and refer to the recent survey by Elsken et al. [14] for a more thorough literature overview. Researchers often frame NAS as a reinforcement learning problem [2, 59, 57, 60] or employ evolutionary algorithms [49, 35, 42, 41]. Unfortunately, most of these methods are very expensive, as they require training hundreds or even thousands of architectures from scratch. Therefore, most recent work focuses on developing more efficient methods, e.g., via network morphisms [12, 6, 13, 47], weight sharing [45, 5, 4], or multifidelity optimization [3, 15, 29, 56]; however, they are often still restricted to relatively small problems.

To overcome this problem, Liu et al. [33] proposed a continuous relaxation of the architecture search space that allows optimizing the architecture via gradient-based methods. This is achieved by using a weighted sum of possible candidate operations for each layer, where the real-valued weights then effectively parametrize the network’s architecture as follows:

\[
x^{(i)} = \sum_{i<j} \sum_{o \in \mathcal{O}} \hat{\alpha}_{o}^{i,j} \left( x^{(i)}, w_{o}^{i,j} \right) \\
= \sum_{i<j} \text{MixedOp}(x^{(i)}, w^{i,j}),
\]

where \(\hat{\alpha}_{o}^{i,j} = \exp(\alpha_{o}^{i,j}) / \sum_{j<i} \exp(\alpha_{o}^{i,j})\) are normalized mixture weights that sum to 1. \(x^{(i)}\) and \(x^{(j)}\) represent feature maps in the network, \(\mathcal{O}\) denotes a set of candidate operations (e.g., \(3 \times 3\) convolution, \(5 \times 5\) convolution, \(3 \times 3\) average pooling, ...) for transforming previous feature maps to new ones, \(w = (w_{o}^{i,j})_{i,j,o}\) denotes the regular weights of the operations, and \(\alpha = (\alpha_{o}^{i,j})_{i,j,o}\) serves as a real valued, unconstrained parameterization of the architecture. The mixture of candidate operations is denoted as mixed operation and the model containing all the mixed operations is often referred to as the one-shot model.

DARTS then optimizes both the weights of the one-shot model \(w\) and architectural parameters \(\alpha\) by alternating gradient descent on the training and validation loss, respectively. After the search phase, a discrete architecture is obtained by choosing a predefined number (usually two) of most important incoming operations (those with the highest operation weighting factor \(\hat{\alpha}_{o}^{i,j}\) for each intermediate node \(j\) while all others are pruned. This hard-pruning deteriorates performance [54, 55]; e.g., Xie et al. [54] report a performance drop from 88% (one-shot model’s accuracy) to 56% (pruned model’s accuracy). Thus, the pruned model requires retraining \(w\). We address this shortcoming in Section 4.

In our work, we choose DARTS for neural architecture search because of conceptual similarities to gradient-based meta-learning, such as MAML [16], which will allow us to combine the two kinds of methods.

Neural Architecture Search for Meta-Learning There has been some recent work on combining NAS and meta-learning. Wong et al. [53] train an automated machine learning (AutoML, [23]) system via reinforcement learning on multiple tasks and then use transfer learning to speed up the search for hyperparameters and architecture via the learned system on new tasks. Their work is more focused on hyperparameters rather than the architecture; the considered architecture search space is limited to choosing one of few pretrained architectures.

Closest to our work are [25, 30]. Kim et al. [25] wrap neural architecture search around meta-learning as illustrated in Figure 1 (middle). They apply progressive neural architecture search [32] to few shot learning, but this requires running the entire meta-training from scratch in every iteration of the NAS algorithm; therefore, their approach requires large computational costs of more than a hundred GPU days. The approach is also limited to searching for a single architecture suitable for few-shot learning rather than learning task-dependent architectures, which our methods supports. In a concurrent work [30], the authors proposed to combine gradient-based NAS and meta-learning for finding task-dependent architectures, similar to our work. However, as they employ the hard-pruning strategy from DARTS with significant drops in performance, they require re-running meta-training for every task-dependent architecture (potentially hundreds), rendering the evaluation of novel tasks expensive. In contrast, our method does not require re-training task-dependent architectures and thus a single run of meta-training suffices.

3. Marrying Gradient-based Meta-Learning and Gradient-based NAS

Our goal is to build a meta-learning algorithm that yields a meta-learned architecture \(\alpha_{\text{meta}}\) with corresponding meta-learned weights \(w_{\text{meta}}\). Then, given a new task \(T_i\), both \(\alpha_{\text{meta}}\) and \(w_{\text{meta}}\) shall quickly adapt to \(T_i\) based on few labeled samples. To solve this problem, we now derive METANAS, a method that naturally combines gradient-based meta-learning methods with gradient-based NAS and allows meta-learning \(\alpha_{\text{meta}}\) along with \(w_{\text{meta}}\). In Section 4, we will then describe how the meta-architectures encoded by \(\alpha_{\text{meta}}\) can be quickly specialized to a new task without requiring re-training of \(w_{\text{meta}}\).
3.1. Problem Setup for Few-Shot Classification

In the classic supervised deep learning setting, the goal is to find optimal weights of a neural network by minimizing a loss function \( \mathcal{L}_{\text{train}}(w) \) given a single, large task \( \mathcal{T} = (D_{\text{train}}, D_{\text{test}}) \) with corresponding training and test data. In contrast, in few-shot learning, we are given a distribution over comparably small training tasks \( \mathcal{T}_{\text{train}} \sim p_{\text{train}}(\mathcal{T}) \) and test tasks \( \mathcal{T}_{\text{test}} \sim p_{\text{test}}(\mathcal{T}) \). We usually consider \( n \)-way, \( k \)-shot tasks, meaning each task is a classification problem with \( n \) classes (typically \( n \in \{5, 20\} \)) and \( k \) (typically \( k \in \{1, 5\} \)) training examples per class. In combination with meta-learning, the training tasks are used to meta-learn how to improve learning of new tasks from the test task distribution.

3.2. Gradient-based Meta-Learning of Neural Architectures

Similar to MAML’s meta-learning strategy in the weight space [16], our goal is to meta-learn an architecture with corresponding weights which is able to quickly adapt to new tasks. In accordance with MAML we do so by minimizing a meta-objective

\[
\mathcal{L}_{\text{meta}}(w, \alpha, p_{\text{train}}, \Phi^k) = \sum_{\mathcal{T}_i \sim p_{\text{train}}} \mathcal{L}_{\mathcal{T}_i}(\Phi^k(w, \alpha, D_{\text{train}}^{\mathcal{T}_i}), D_{\text{test}}^{\mathcal{T}_i})
\]

\[
= \sum_{\mathcal{T}_i \sim p_{\text{train}}} \mathcal{L}_{\mathcal{T}_i}(\Phi^k(w, \alpha, D_{\text{train}}^{\mathcal{T}_i}), D_{\text{test}}^{\mathcal{T}_i})
\]

(2)

with respect to a real-valued parametrization \( \alpha \) of the neural network architecture and corresponding weights \( w \). \( \mathcal{T}_i = (D_{\text{train}}^{\mathcal{T}_i}, D_{\text{test}}^{\mathcal{T}_i}) \) denotes a training task sampled from the training task distribution \( p_{\text{train}}(\mathcal{T}) \), \( \mathcal{L}_{\mathcal{T}_i} \) the corresponding task loss, and \( \Phi^k(w, \alpha, D_{\text{train}}^{\mathcal{T}_i}) \) the task learning algorithm or simply task-learner, where \( k \) refers to \( k \) iterations of learning/weight updates (e.g., by SGD). Prior work [16, 37, 25] considered a fixed, predefined architecture \( \phi_{\text{fixed}} \) and chose \( \Phi^k \) to be an optimizer like SGD for the weights:

\[
w^* = w^k = \Phi^k(w, \alpha_{\text{fixed}}, D_{\text{train}}^{\mathcal{T}_i})
\]

with the one-step updates

\[
w^{j+1} = w^j - \lambda_{\text{task}} \nabla_w \mathcal{L}_{\mathcal{T}}(w^j, D_{\text{train}}^{\mathcal{T}_i})
\]

and \( w_0 = w \). In contrast, we choose \( \Phi^k \) to be \( k \) steps of gradient-based neural architecture search inspired by DARTS [33] with weight learning rate \( \lambda_{\text{task}} \) and architecture learning rate \( \xi_{\text{task}} \):

\[
\begin{align*}
\begin{bmatrix} w^{j+1} \\ \alpha^{j+1} \end{bmatrix} &= \Phi(w^j, \alpha^j, D_{\text{train}}^{\mathcal{T}_i}) \\
&= \begin{bmatrix} w^j - \lambda_{\text{task}} \nabla_w \mathcal{L}_{\mathcal{T}}(w^j, \alpha^j, D_{\text{train}}^{\mathcal{T}_i}) \\ \alpha^j - \xi_{\text{task}} \nabla_\alpha \mathcal{L}_{\mathcal{T}}(w^j, \alpha^j, D_{\text{train}}^{\mathcal{T}_i}) \end{bmatrix}
\end{align*}
\]

(3)

Therefore, \( \Phi^k \) does not only optimize task weights \( w_{\mathcal{T}_i}^* \), but also optimizes task architecture \( \alpha_{\mathcal{T}_i}^* \). Note that we use the same data set to update \( w^j \) and \( \alpha^j \) (Equation 3) in contrast to Liu et al. [33] due to the limited amount of data in the few-shot setting not allowing to split into training and validation per task. Moreover, using the same data set also allows updating both sets of parameters with a single forward and backward pass, see Lian et al. [30]. As we use a real-valued parametrization of \( \alpha \) and a gradient-based task optimizer, the meta-objective \( \mathcal{L}_{\text{meta}} \) (Equation 2) is differentiable with respect to \( w \) and \( \alpha \). This means we can use any gradient-based meta-learning algorithm \( \Psi \) not only for \( w \) but also for the architecture \( \alpha \). As an example, one could use MAML [16] as a meta-learning algorithm, which runs SGD on the meta-objective, yielding meta-updates.
Algorithm 1 MetaNAS: Meta-Learning of Neural Architectures

\[ \begin{align*}
(w_{\text{meta}}^{i+1}, \alpha_{\text{meta}}^{i+1}) &= \Psi_{\text{MAML}}(\alpha_{\text{meta}}^i, w_{\text{meta}}^i, \mathcal{P}_{\text{train}}, \Phi^k) \\
&= \left( w_{\text{train}}^i - \lambda_{\text{meta}} \nabla_{w} \mathcal{L}_{\text{meta}}(w_{\text{meta}}^i, \alpha_{\text{meta}}^i, \mathcal{P}_{\text{train}}, \Phi^k) \right)
\end{align*} \]

or, as an alternative, one could use REPTILE [37], which simply computes the updates as

\[ \begin{align*}
(w_{\text{meta}}^{i+1}, \alpha_{\text{meta}}^{i+1}) &= \Psi_{\text{REPTILE}}(\alpha_{\text{meta}}^i, w_{\text{meta}}^i, \mathcal{P}_{\text{train}}, \Phi^k) \\
&= \left( w_{\text{meta}}^i + \lambda_{\text{meta}} \sum_{\mathcal{T}_i} \nabla_{\alpha_{\text{meta}}} \mathcal{L}_{\text{train}}(w_{\text{meta}}^i, \alpha_{\text{meta}}^i, \mathcal{P}_{\text{train}}, \Phi^k) \right)
\end{align*} \]

4. Task-dependent Architecture Adaptation

Using a NAS algorithm as a task optimizer does not only allow directly incorporating architecture search into the meta-training loop, but it also allows an adaptation of the found meta-architecture after meta-learning to new tasks (i.e., during meta-testing). That is, it allows in principle finding a task-dependent architecture, compare Algorithm 3. This is in contrast to prior work where the architecture is always fixed during meta-testing [16, 37]. Also prior work using NAS for meta-learning [25] searches for a single architecture that is then shared across all tasks.

Unfortunately, the task-dependent architecture obtained by the DARTS task optimizer is non-sparse, that is, the \( \alpha_{\mathcal{T}_i} \) do not lead to mixture weights being strictly 0 or 1, compare Figure 2 (left) for an illustration. As discussed in Section 2, DARTS addresses this issue with a hard-pruning strategy at the end of the architecture search to obtain the final architecture from the one-shot model (line 8 in Algorithm 3). Since this hard-pruning deteriorates performance heavily (see Appendix A.1), the pruned architectures require retraining. This is particularly problematic in a few-shot learning setting as it requires meta re-training all the task-dependent architectures. This is the approach followed by [30], but it unfortunately increases the cost of a single task training during meta-testing from a few steps of the task optimizer to essentially a full meta-training run of MAML/REPTILE with a fixed architecture.

We now propose a method to remove the need for re-training by proposing two modification to DARTS that essentially re-parameterize the search space and substantially alleviate the drop in performance resulting from hard-
initial meta architecture $a_{meta}$

| Meta Architecture | Task Adapation | Task-Dependent Architectures |
|-------------------|---------------|----------------------------|
| $a^*_meta$        | $T_i$         | $a^*_T_{i+1}$              |

Figure 3: Conceptual illustration of the architectures at different stages of METANAS. Left: after initializing the one-shot model. Middle: meta-learned architecture. Right: architecture adapted to respective tasks based on meta-architecture. Colours of the edges (red, blue, green) denote different operations (Conv3x3, Conv5x5 and MaxPooling, respectively). Line-width of edges visualizes size of architectural weights $\alpha$ (i.e., large line-width correspond to large $\alpha$ values).

**Algorithm 3** Learning of new task after meta-learning (i.e., meta-testing) with DARTS.

1: Input: new task $T = (D_{train}, D_{test})$
2: $w_T \leftarrow w_{meta}$
3: $\alpha_T \leftarrow \alpha_{meta}$
4: for $j \leftarrow 1, \ldots, k$ do
5: $w_T \leftarrow w_T - \lambda_{task} \nabla_w \mathcal{L}_T(w_T, \alpha_T, D_{train})$
6: $\alpha_T \leftarrow \alpha_T - \xi_{task} \nabla_\alpha \mathcal{L}_T(w_T, \alpha_T, D_{train})$
7: end for
8: $\alpha_T \leftarrow $ PRUNE($\alpha_T$)
9: Evaluate $D_{test}$ with $\alpha_T', w_T$

This is achieved by enforcing the mixture weights $\hat{\alpha}$ of the mixed operations to slowly converge to 0 or 1 during task training while giving the operation weights time to adapt to this soft pruning.

### 4.1. Soft-Pruning of Mixture over Operations

The first modification sparsifies the mixture weights of the operations forming a mixed operation that transforms node $i$ to node $j$. We achieve this by changing the normalization of the mixture weights $\hat{\alpha}_{ij}^o$ from Equation 1 to become increasingly sparse, that is: more similar to a one-hot encoding for every $i,j$. To achieve this, we add a temperature $\tau_o$ that is annealed to 0 over the course of a task training:

$$\hat{\alpha}_{ij}^o(\alpha) = \frac{\exp(\alpha_{ij}^o / \tau_o)}{\sum_{o' \in O} \exp(\alpha_{ij}^{o'/o} / \tau_o)}.$$  

A similar approach was proposed by [54] and [11] in the context of relaxing discrete distributions via the Gumbel distribution [24, 34]. Note that this results in (approximate) one-hot mixture weights in a single mixed operation (compare Figure 2 (middle) for an illustration); however, the sum over all $j-1$ possible input nodes $0, \ldots, j-1$ in Equation 1 is still non-sparse, meaning node $j$ is still connected to all prior nodes. As DARTS selects only the top $k$ ($k = 2$ in the default) input nodes, we need additionally also to sparsify across the possible input nodes (that is a soft-pruning of them) rather than just summing them up (as done in Equation 1), see Figure 2 (right) for an illustration.

### 4.2. Soft-Pruning of Mixture over Input Nodes

A natural choice to also sparsify the inputs would be to also introduce weights $\beta^{i,j}$ of the inputs and sparsify them the same way as the operations’ weights by annealing a temperature $\tau_i$ to 0 over the course of a task training:

$$x^{(j)} = \sum_{i<j} \frac{\exp(\beta^{i,j}/\tau_i)}{\sum_{k<j} \exp(\beta^{i,k}/\tau_i)} \text{MixedOp}(x^{(i)})$$  

Unfortunately, this would results in selecting exactly one input rather than a predefined number of inputs (e.g., the literature default 2 [60, 54, 33]). Instead, we weight every combination of $k$ inputs to allow an arbitrary number of inputs $k$:

$$x^{(j)} = \sum_{i = \{i_1, \ldots, i_k\} \in \mathcal{I}} \frac{\exp(\beta^{i,j}/\tau_i)}{\sum_{k \in \mathcal{I}} \exp(\beta^{i,k}/\tau_i)} \left(\text{MixedOp}(x^{(i_1)}) + \ldots + \text{MixedOp}(x^{(i_k)})\right),$$

where $\mathcal{I} = \{\{i_1, \ldots, i_k\} | \{i_1, \ldots, i_k\} \subseteq \{0, \ldots, j-1\}\}$ denotes the set of all combinations of inputs of size $k$. This introduces $\binom{j}{k}$ additional parameters per node, which is negligible for practical settings with $j \leq 5$. The input weights $\beta^{i,j}$ are optimized along with the operation’s weights $\alpha$. Note that we simply subsume $\alpha$ and $\beta$ into $\alpha$ in Algorithm 3.

With these two modifications, we can now not only find task-dependent optimal weights (given meta-weights)
but also find task-dependent architectures (given a meta-
architecture) that can be hard pruned without notable drop
in performance, and thus without retraining. We refer
to Appendix A.1 for a comparison of the three different
pruning strategies discussed on a standard NAS setting on
CIFAR-10 (single task). While in theory we can now en-
force a one-hot encoding of the mixture operation as well as
over the input nodes, we empirically found that it is some-
times helpful to not choose the minimal temperature too
small but rather allow a few (usually not more than two)
weights larger than 0 instead of hard forcing an one-hot
encoding. At the end of each task learning, we then sim-
ply keep all operations and input nodes with corresponding
weight $\hat{\alpha}$ larger than some threshold (e.g., $\hat{\alpha} \geq 0.01$), while
all others are pruned.

5. Experiments

We evaluate our proposed method on the standard few-
shot image recognition benchmarks Omniglot [26] and
MiniImagenet (as proposed by [40]) in the $n$-way, $k$-shot
setting (as proposed by [52]), meaning that a few-shot
learning task is generated by random sampling $n$ classes
from either Omniglot or MiniImagenet and $k$ examples for
each of the $n$ classes. We refer to [52] for more details.

5.1. Comparison under the same meta-learning
algorithm.

We first compare against the architectures from the original
REPTILE [37] paper and from AutoMeta [25] when training
all models with the same meta-learning algorithm, namely
REPTILE. This ensures a fair comparison and differences
in performance can be clearly attributed to differ-
ences in the architecture. We re-train the architectures from
REPTILE and AutoMeta with our own training pipeline for
30,000 meta epochs (which we found to be sufficient to ap-
proximately reproduce results from the REPTILE paper) to
further ensure that all architectures are trained under iden-
tical conditions. A detailed description of the experimental
setup including all hyperparameters can be found in Ap-
pendix A.2 in the supplementary material.

For our method, we consider the following search space
based on DARTS and AutoMeta: we search for a nor-
mal and reduction cell (which is common practice in the NAS
literature [60, 33, 54, 7, 55]). Both cells are com-
posed of three intermediate nodes (i.e., hidden states). The
set of candidate operations is MaxPool3x3, AvgPool3x3,
SkipConnect, Conv1x5-5x1, Conv3x3, SepConv3x3, Dilat-
edConv3x3. Our models are composed of 4 cells, with the
first and third cells being normal cells and the second and
forth cell being reduction cells. The number of filters is
constant throughout the whole network (rather than dou-
bling the filters whenever the spatial resolution decreases);
it is set so that the pruned models match the size (in terms
of number of parameters) of the REPTILE and AutoMeta
models to ensure a fair comparison. We consider models in
the regime of 100,000 parameters. Note that, in contrast to
DARTS, we optimize the architectural parameters also on
training data (rather than validation data) due to very lim-
ited amount of data in the few-shot setting not allowing a
validation split per task.

The results are summarized in Table 1. In the 1-shot,
20-way Omniglot experiment, METANAS achieves slightly
inferior performance compared to AutoMeta, while both
models are on-par for the 5-shot, 20-way setting. Both ar-
chitectures outperform the vanilla REPTILE architecture.
On both MiniImagenet settings, METANAS outperforms
AutoMeta, while AutoMeta outperforms REPTILE. In sum-
mary, METANAS always outperforms the original REP-
TILE model while it is on-par with AutoMeta. We high-
light that METANAS achieves this while being more than
10x more efficient than AutoMeta; the AutoMeta authors
report computational costs in the order of 100 GPU days
while METANAS was run for approximately one week on
a single GPU, requiring only a single run of meta-training.
METANAS adapts the architecture to tasks; see Figure 5
in the Appendix for an illustration of the different model sizes
for each experiment and each seed. Typically, the task ad-
aptation results in a few different architectures, indicating that
not much adaptation is required for MiniImagenet and Om-
nist. Please also refer to Figure 4 for the most common
cells for MiniImagenet and Omniglot.

| Architecture | Parameters | Omniglot | | | MinImagenet | | |
|-------------|-----------|---------|---|---|---|---|---|
|              |           | 1-shot, 20-way | 5-shot, 20-way | | 1-shot, 5-way | 5-shot, 5-way |
| REPTILE     | 114k      | 89.33 ± 0.07  | 97.00 ± 0.20  | | 128k | 48.17 ± 0.93 | 67.03 ± 0.18 |
| AutoMeta    | 116k      | 95.60 ± 0.12  | 98.90 ± 0.12  | | 137k | 50.50 ± 0.76 | 68.47 ± 0.27 |
| METANAS     | 108k      | 94.40 ± 0.61  | 98.83 ± 0.18  | | 130k | 54.86 ± 0.77 | 71.07 ± 0.13 |

Table 1: Results (mean ±2× standard error of mean for 3 independent runs) on different data sets and different few-shot
tasks. For all architecture, REPTILE was used as a meta-learning algorithm and all results were obtained using the same
training pipeline to ensure a fair comparison. Accuracy in %.

Number of parameters for METANAS is averaged across
task-adaptations and seeds.
ETA that using MAML++ in combination with M
performs REPTILE as a meta-learning algorithm, it is likely
achieves new state-of-the-art performance. On Omniglot,
significantly outperforms all other methods on MiniImagenet and
meta-learning approaches (second block), M
would further improve our results. Also compared to other
methods that meta-learn an
proves over the standard REPTILE architecture and Au-
smaller architecture (1 million parameters for M
par or outperforms them while employing a significantly
smaller architecture (1 million parameters for META
compared to more than 10 million for TADAM [38], LEO [43] and MetaOptNet [28]).

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|}
\hline
Method & \# params & 1-shot, 5-way & 5-shot, 5-way & 1-shot, 20 way \\
\hline
MAML [6] & 30k & 48.7 ± 1.8 & 63.1 ± 0.9 & 95.8 ± 0.03 \\
MAML++ [1] & - & 52.2 ± 0.3 & 68.3 ± 0.4 & 97.65 ± 0.05 \\
T-NAS [30] & 27k & 54.1 ± 1.4 & 69.6 ± 0.9 & - \\
REPTILE [37] & 30k & 50.00 ± 0.3 & 66.0 ± 0.6 & 89.43 ± 0.14 \\
AutoMeta [25] & 100k & 57.6 ± 0.2 & 74.7 ± 0.2 & - \\
META-NAS * & 1.1M & 63.1 ± 0.3 & 79.5 ± 0.2 & 97.87 ± 0.07 \\
TADAM [38] & 12M & 58.5 ± 0.3 & 76.7 ± 0.3 & - \\
MetaOptNet [28] & 12M & 61.1 ± 0.6 & 77.4 ± 0.5 & - \\
LEO [43] & 36.5M & 61.8 ± 0.1 & 77.6 ± 0.1 & - \\
\hline
\end{tabular}
\caption{Comparison to other meta-learning algorithm. The first block contains methods that, similar to ours, learn an initial set of parameters that is quickly adapted to new tasks. The second block contains other meta-learning methods. Here we list the numbers stated in other papers. META-NAS * denotes the results of our proposed method after increasing model size, regularization and a longer meta-training period. Accuracy in \%.}
\end{table}

5.2. Scaling up architectures and comparison to other meta-learning algorithms.

We now compare to other meta-learning algorithms in the fixed architecture setting: that is: we use META-NAS not with task-dependent architectures but with a single fixed architecture extracted after running META-NAS. For this, we extract the most common used task-dependent architecture (see Figure 4) and scale it up by using more channels and cells. We retrain the resulting architecture, which has approximately 1.1 million parameters, for more meta-epochs and with stronger regularization, which is common practice in the NAS literature [60, 41, 33, 54, 7]. Please refer to Appendix A.2 for details. Note that naively enlarging models for few-shot learning without regularization does not necessarily improve performance due to overfitting as reported by [40, 16].

Results are presented in Table 2. Again, META-NAS improves over the standard REPTILE architecture and AutoMeta. Compared to other methods that meta-learn an initial set of parameters (first block), META-NAS significantly outperforms all other methods on MiniImagenet and achieves new state-of-the-art performance. On Omniglot, META-NAS is on-par with MAML++. As MAML++ outperforms REPTILE as a meta-learning algorithm, it is likely that using MAML++ in combination with META-NAS would further improve our results. Also compared to other meta-learning approaches (second block), META-NAS is on par or outperforms them while employing a significantly smaller architecture (1 million parameters for META-NAS compared to more than 10 million for TADAM [38], LEO [43] and MetaOptNet [28]).

1We report results without label smoothing and without training on the validation set, as this is also not used in our work.
the-art on MiniImagenet, achieving 63.1% accuracy in the 1-shot, 5-way setting and 79.5% in the 5-shot, 5-way setting.

As our framework is agnostic with respect to the meta-learning algorithm as well as to the differentiable architecture search method, our empirical results can likely be improved by using more sophisticated meta-learning methods such as MAML++ [1] and more sophisticated differentiable architecture search methods such as ProxylessNAS [7]. In the future, we plan to extend our framework beyond few shot classification to other multi-task problems.

Acknowledgments

The authors acknowledge support by the European Research Council (ERC) under the European Union’s Horizon 2020 research and innovation programme through grant no. 716721, and by BMBF grant DeToL.
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A. Appendix

A.1. Comparison of different sparsification strategies and impact on pruning

We recap the three different sparsification strategies discussed in Section 4 and Figure 2:

1. vanilla DARTS [33], i.e., no sparsification (neither operations nor inputs)
2. sparsifying the operations only (e.g., as in SNAS [54])
3. sparsifying both operations and inputs (as proposed in our work).

Prior to the meta-learning setting, we evaluated these three strategies on the default single-task classification setting on CIFAR-10. We ran the search phase of DARTS with default hyperparameters (i.e., hyperparameters identical to Liu et al. [33]) on CIFAR-10 and evaluated the drop in accuracy after the search phase when going from the one-shot model to the pruned model. The one-shot model is pruned as proposed by Liu et al. [33]. The results can be found in Table 3. In the vanilla setting without any sparsification, the accuracy drops significantly, almost to chance level. When sparsifying the operations only, accuracy is much better but still clearly below the original performance. In contrast, with our proposed strategy, there is no significant drop in performance.

| Sparsification strategy | No sparsification (Fig. 2, left) | Sparsify operations only (Fig. 2, middle) | Sparsify operations & inputs (Fig. 2, right) |
|------------------------|---------------------------------|----------------------------------------|------------------------------------------|
| Accuracy before pruning| 87.9 ± 0.2%                     | 84.4 ± 0.4%                           | 84.8 ± 0.3%                             |
| Accuracy after pruning | 16.7 ± 2.1%                     | 60.2 ± 4.0%                           | 84.7 ± 0.4%                             |

Table 3: Comparing the different annealing strategies discussed in Section 4 and Figure 2: 1) vanilla DARTS (no annealing) 2) annealing the operations only, 3) annealing both operations and inputs (as proposed in our work). Mean ± SEM, on single-task NAS setting (CIFAR-10, DARTS’ default hyperparameters).

A.2. Detailed experimental setup and hyperparameters

Our implementation is based on the REPTILE [37]² and DARTS [33]¹ code. The data loaders and data splits are adopted from Torchmeta [10]⁴. The overall evaluation set-up is the same as in REPTILE.

Hyperparameters are listed in Table 4. The hyperparameters were determined by random search centered around default values from REPTILE on a validation split of the training data.

For the experiments in Section 5.1, all models were trained for 30,000 meta epochs. For METANAS, we did not adapt the architectural parameters for the first 15,000 meta epochs to warm-up the model. Such a warm-up phase is commonly employed as it helps avoiding unstable behaviour in gradient-based NAS [7, 44].

| Hyperparameter                  | Value   |
|--------------------------------|---------|
| batch size                     | 20      |
| meta batch size                | 10      |
| shots during meta training     | 15 / 10 |
| task training steps (during meta training) | 5       |
| task training steps (during meta testing) | 50+50²  |
| task learning rate (weights)   | 10⁻³    |
| task learning rate (architecture) | 10⁻³ / 5 · 10⁻⁴ |
| task optimizer (weights)       | Adam    |
| task optimizer (architecture)  | Adam    |
| meta learning rate (weights)   | 1.0     |
| meta learning rate (architecture) | 0.6     |
| meta optimizer (weights)       | SGD     |
| meta optimizer (architecture)  | SGD     |
| weight decay (weights)         | 0.0     |
| weight decay (architecture)    | 10⁻³    |

Table 4: Listing of hyperparameters for METANAS for the experiments of Section 5.1. Hyperparameters are the same across n-shot, k-way setting. Hyperparameters are the same for MiniImagenet and Omniglot except for rows with two values separated by a slash. In this case, the first value denotes the value for MiniImagenet while the latter one denotes the value for Omniglot.

For the experiment in Section 5.2, we make the following changes in contrast to Section 5.1: we meta-train for 100,000 meta epochs instead of 30,000. We increase the number of channels per layer to 96 from 28 and use 5 cells instead of 4, whereas again the second and forth cell are reduction cells while all others are normal cells. We use the default meta-learning hyperparameters from REPTILE [37], except that we add regularization by means of weight decay (10⁻⁴) and DropPath (with probability 0.2) to avoid overfitting.

A.3. Motivation of meta-learning algorithm Ψ

In Section 3.2, we proposed the two meta-learning updates

²https://github.com/openai/supervised-reptile
³https://github.com/khanrc/pt.darts
⁴https://github.com/tristandeleu/pytorch-meta
⁵By 50+50 we mean that for the first 50 steps, both the weights and architecture are adapted while for the later 50 steps only weights are adapted.
\[
\begin{align*}
(w_{i+1}^{\text{meta}}, \alpha_{i+1}^{\text{meta}}) &= \Psi_{\text{MAML}}(\alpha_i^{\text{meta}}, w_i^{\text{meta}}, p^{\text{train}}, \Phi^k) \\
&= \left( w_i^{\text{meta}} - \lambda_{\text{meta}} \nabla_w L_{\text{meta}}(w_i^{\text{meta}}, \alpha_i^{\text{meta}}, p^{\text{train}}, \Phi^k) \right) \\
&\quad \left( \alpha_i^{\text{meta}} - \xi_{\text{meta}} \nabla_{\alpha} L_{\text{meta}}(w_i^{\text{meta}}, \alpha_i^{\text{meta}}, p^{\text{train}}, \Phi^k) \right) \\
\end{align*}
\]

(8)

and

\[
\begin{align*}
(w_{i+1}^{\text{meta}}, \alpha_{i+1}^{\text{meta}}) &= \Psi_{\text{REPTILE}}(\alpha_i^{\text{meta}}, w_i^{\text{meta}}, p^{\text{train}}, \Phi^k) \\
&= \left( w_i^{\text{meta}} + \lambda_{\text{meta}} \sum_{T_i} (w^{*}_{T_i} - w_i^{\text{meta}}) \right) \\
&\quad \left( \alpha_i^{\text{meta}} + \xi_{\text{meta}} \sum_{T_i} (\alpha^{*}_{T_i} - \alpha_i^{\text{meta}}) \right).
\end{align*}
\]

(9)

Equation (8) extends the MAML update

\[
w_{i+1}^{\text{meta}} = w_i^{\text{meta}} - \lambda_{\text{meta}} \nabla_w L_{\text{meta}}(w_i^{\text{meta}}, p^{\text{train}}, \Phi^k),
\]

which is simply one step of SGD on the meta-objective (Equation 2), while Equation (9) extends the REPTILE update

\[
w_{i+1}^{\text{meta}} = w_i^{\text{meta}} + \lambda_{\text{meta}} \sum_{T_i} (w^{*}_{T_i} - w_i^{\text{meta}}),
\]

which was shown to maximize the inner product between gradients of different batches for the same task, resulting in improved generalization[37]. Equations (8) and (9) constitute a simple heuristic that perform the same updates also on the architectural parameters.

A.4. Additional plots
Figure 5: Histogram of model sizes (by means of number of parameters) after task adaptation for different few-shot learning problems.