Does MAML really want feature reuse only?

Abstract
Meta-learning, the effort to solve new tasks with only a few samples, has attracted great attention in recent years. Model Agnostic Meta-Learning (MAML) is one of the most representative gradient-based meta-learning algorithms. MAML learns new tasks with a few data samples with inner updates from a meta-initialization point and learns the meta-initialization parameters with outer updates. Recently, it has been hypothesized that feature reuse, which makes little change in efficient representations, is the dominant factor in the performance of meta-initialized model through MAML rather than rapid learning, which makes a big change in representations. In this work, we propose a novel meta-learning algorithm, coined as BOIL (Body Only update in Inner Loop), that updates only the body (extractor) of the model and freezes the head (classifier) of the model during inner loop updates. The BOIL algorithm thus heavily relies on rapid learning. Note that BOIL is the opposite direction to the hypothesis that feature reuse is more efficient than rapid learning. We validate the BOIL algorithm on various data sets and show significant performance improvement over MAML. The results imply that rapid learning in gradient-based meta-learning approaches is necessary.

1 Introduction
One of the most promising fields in machine learning is few-shot learning. Meta-learning, also known as "learning to learn", is a methodology enabling a fast adaptation of a model to new data through previous learning experiences. To address few-shot learning successfully, meta-learning with deep neural networks have mainly been studied through metric- and gradient-based approaches. Such approaches aim to learn a model only with a few data samples and have shown a generalized performance for previously unseen data. Metric-based meta-learning \cite{29, 31, 34} compares the distance between feature embeddings using models as a mapping function of data into an embedding space, whereas gradient-based meta-learning \cite{25, 30, 5, 40} learns the parameters to be able to quickly adapt when the models encounter new tasks.

Model-agnostic meta-learning (MAML) \cite{5} is the most representative gradient-based meta-learning algorithm, learning the parameters through nested gradient update loops that consist of an inner loop and an outer loop. The inner loop conducts task-specific learning for each task, and the outer loop aims to represent the generalization across tasks. After considerable iterations, the model has meta-initialized parameters, which can quickly allow unseen tasks to be learned from a few samples with a few inner updates. This algorithm has had a substantial impact on the research field of meta-learning, and numerous follow-up studies have been conducted \cite{23, 28, 21, 40, 30}.

A very recent study by Raghu et al. \cite{24} attempted to analyze why a meta-trained model can learn new tasks fast and argued that providing high-quality features prior to the inner updates from the meta-initialized parameters is the main reason. They claimed that MAML learns new tasks by

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updating the head (the last fully connected layer) with almost the same features (the output of the penultimate layer) from the meta-initialized network. A small change in the representations during the task learning is named feature reuse, whereas a big change is named rapid learning. Herein, we pose an intriguing question: Does MAML really want feature reuse only? Instead, it is reasonable for gradient-based meta-learning to conduct rapid learning in accordance with a given task from the meta-initialized body (extractor). In general, the potency of feature reuse is closely related to the similarity between the source and target domains. The higher the similarity is, the higher the efficiency. However, because the ultimate goal of meta-learning is to solve the unseen tasks even if there are no significant similarities between the old and new, rapid learning should be considered as well.

From this consideration, we suggest a new algorithm to enable rapid learning in gradient-based meta-learning and investigate this algorithm’s advantages compare to MAML. Our contributions are summarized as follow:

- We propose a simple but effective meta-learning algorithm that learns the Body (extractor) of the model Only in the Inner Loop, coined as BOIL.
- We demonstrate that the BOIL algorithm enjoys feature reuse on the low- and mid-level body and rapid learning on the high-level body using the cosine similarity and the Centered Kernel Alignment (CKA).
- We contemplate the optimal meta-initialization about the head (classifier) parameters and evidence that the orthonormality of the head parameters is important condition to optimize meta-initialization. Furthermore, we observe that learning the meta-initialized head from orthonormal initialization improves the performance and convergence speed in BOIL, but worsen in MAML.
- We empirically show that BOIL improves the performance over all benchmark data sets and that this improvement is particularly noticeable on fine-grained data sets or cross-domain adaptation.
- For ResNet architectures, we propose a disconnection trick that removes the back-propagation path of the last skip connection. The disconnection trick strengthens feature reuse on the low- and mid-level body and rapid learning on the high-level body.

2 Preliminary

This section first describes MAML with a few-shot learning framework and then summarizes two hypotheses regarding the effectiveness of this algorithm.

2.1 Model-Agnostic Meta Learning (MAML)

The MAML algorithm [5] attempts to meta-learn the best initialization of parameters for a task-learner. It consists of two main optimization loops, i.e., an inner loop and an outer loop. We first sample a batch of tasks within a data set distribution. Each task $\tau_i$ consists of a support set $S_{\tau_i}$ and a query set $Q_{\tau_i}$. When we sample a support set for each task, we first sample $n$ labels from the label set and then sample $k$ instances for each label, and thus each support set contains $n \times k$ instances. For a query set, we sample instances from the same labels with the support set. With these composed tasks, the MAML algorithm performs meta-training and meta-testing. During meta-training, we first sample a meta-batch consisting of $B$ tasks from the meta-training data set. In the inner loops, we update the meta-initialized parameters $\theta$ to task-specific parameters $\theta_{\tau_i}$ using the task-specific loss $L_{S_{\tau_i}}(f_{\theta})$ as follows:

$$\theta_{\tau_i} = \theta - \alpha \nabla_{\theta} L_{S_{\tau_i}}(f_{\theta})$$

Using the query set of the corresponding task, we compute the loss $L_{Q_{\tau_i}}(f_{\theta_{\tau_i}})$ based on each inner updated parameter. By summing all these losses, the meta-loss of each meta-batch, $L_{\text{meta}}(\theta)$, is computed. The meta-initialized parameters are then updated using the meta-loss in the outer loop through a gradient descent.

$$\theta' = \theta - \beta \nabla_{\theta} L_{\text{meta}}(\theta), \text{ where } L_{\text{meta}}(\theta) = \sum_{i=1}^{B} L_{Q_{\tau_i}}(f_{\theta_{\tau_i}})$$

In meta-testing, the inner loop, which can be interpreted as task-specific learning, is the same as in meta-training. However, the outer loop only computes the accuracy of the model using a query set of tasks and does not perform a gradient descent, and thus it does not update the meta-initialization parameters.

\[2\] Although the inner loop(s) can be applied in one or more steps, for the sake of simplicity, we consider only the case of a single inner loop.
Figure 1: **Difference in task-specific (inner) updates between MAML and BOIL.** In the figure, the lines mean the decision boundaries defined by the head (classifier) of the network. The different shapes and colors mean different classes. (a) MAML updates mainly head with negligible change in body (extractor) during inner updates, hence representations on the feature space are almost identical. Whereas, (b) BOIL updates body only without change in head during inner updates, hence representations on the feature space change significantly with the fixed decision boundaries.

2.2 Rapid learning and feature reuse

To reveal the effectiveness of MAML in solving the new tasks, Raghu et al. [24] proposed two opposite hypotheses, rapid learning and feature reuse. These two hypotheses relate to the body in the network, usually referring to the convolutional layers in a convolutional neural network (CNN). To summarize, the rapid learning hypothesis attributes the capability of MAML to the updates on the body in the network during inner loops, whereas the feature reuse hypothesis considers that the body in the network is universal to all tasks. The authors demonstrated that feature reuse is a dominant factor in the MAML performance by showing that there is little difference in accuracy even if all of the extractor layers are frozen in the inner loops.

Based on the feature reuse hypothesis, the authors proposed the ANIL (Almost No Inner Loop) algorithm, which only updates the head in the inner loops during training and testing, and the NIL (No Inner Loop) algorithm, which replaces a classifier with the distance between the representations of a support set and those of a query set during testing. Both algorithms have comparable performance to MAML, which implies that a body trained only through the outer loops is sufficient to achieve the desired performance.

Nevertheless, the authors mentioned that development and inspection of novel meta-learning algorithms based on rapid learning are required because rapid learning might enlarge the problem-solving area. Based on this insight, we develop a rapid learning-based meta-learning algorithm and analyze it extensively.

3 The BOIL (Body Only update in Inner Loop) Algorithm

Inspired by [24], we design an algorithm that updates only the body of the model and freezes the head of the model during the task learning to enforce rapid learning. Because the gradients must be back-propagated to update the body, we set the learning rate of the head to zero in inner updates during both meta-training and meta-testing. Otherwise, learning and evaluation procedures of BOIL are the same as those of MAML. Therefore, the computational overhead does not change.

Formally speaking, with the notations used in Section 2.1, the meta-initialized parameters $\theta$ can be separated into body parameters $\theta_b$ and head parameters $\theta_h$, i.e., $\theta = \{\theta_b, \theta_h\}$. For a sample image $x \in \mathbb{R}^d$, an output can be expressed as $\hat{y} = f_{\theta}(x) = f_{\theta_b}(f_{\theta_h}(x)) \in \mathbb{R}^n$ where $f_{\theta_h}(x) \in \mathbb{R}^d$. The task-specific body parameters $\theta_{b,\tau_i}$ and head parameters $\theta_{h,\tau_i}$ through an inner loop given task $\tau_i$ are then as follows:

$$
\begin{align*}
\theta_{b,\tau_i} &= \theta_b - \alpha_b \nabla_{\theta_b} L_{S_{\tau_i}}(f_{\theta}) & \theta_{h,\tau_i} &= \theta_h - \alpha_h \nabla_{\theta_h} L_{S_{\tau_i}}(f_{\theta})
\end{align*}
$$

where $\alpha_b$ and $\alpha_h$ are the inner loop learning rates corresponding to the body and head, respectively. MAML usually sets $\alpha = \alpha_b = \alpha_h (\neq 0)$, whereas BOIL sets $\alpha_b \neq 0$ and $\alpha_h = 0$.

This simple difference changes the dominant factor of the task-learning from the head to the body. Figure 1 shows the main difference in the inner updates between MAML and BOIL. To solve new tasks, the head mainly changes with MAML [24], whereas with BOIL, only the body changes. In the rest of this section, we demonstrate that BOIL enjoys both rapid learning and feature reuse and improves both the performance and convergence speed.
3.1 Rapid learning and feature reuse on the body of BOIL

We compute the cosine similarities and CKA values of convolution layers to analyze whether the learning scheme of BOIL is rapid learning or feature reuse with the meta-trained 4conv network (as detailed in Appendix A). We first investigate the cosine similarity between the representations of a query set including 5 classes and 15 samples per class after every convolution module. In Figure 2, the orange line represents the average of the cosine similarities between the samples having the same class, and the blue line represents the average of cosine similarities between the samples having different classes. In Figure 2a and Figure 2b, the left panel is before inner loop adaptation and the right panel is after inner loop adaptation.

![Figure 2: Cosine similarity of 4conv network.](image)

The key observations from Figure 2, as is discussed with other experiments in Section 4.2.1, are as follows:

- Before inner loop adaptation, MAML makes the average of the cosine similarities monotonically decrease and makes the representations separable by classes, as the representations reach the last convolution layer. In contrast, BOIL reduces the average only up to conv3. More importantly, with BOIL, all the representations are concentrated regardless of their classes on the last convolution module. It implies that the meta-initialized body by MAML can distinguish classes after conv4, while the meta-initialized body by BOIL cannot do so.
- MAML does not have any noticeable difference after inner loop adaptation. In contrast, BOIL can make significant differences among different classes on the last convolution layer after inner loop adaptation. We believe that MAML follows the feature reuse training scheme, whereas BOIL follows both feature reuse (before the last layer) and rapid learning (at the last layer) training schemes.

Next, we demonstrate that BOIL enjoys both feature reuse on the low- and mid-level layers and rapid learning on the high-level layer by computing the CKA between before and after the inner updated representations. When the CKA between two representations is close to 1, the representations are almost identical. In Figure 3, BOIL has a low CKA for the last convolution module and the subsequent head. This result indicates that the BOIL algorithm learns rapidly on the last layer of the body in inner updates.

3.2 Performance improvement and faster convergence through the head of BOIL

In this section, we start by discussing what is the ideal meta-initialization. Because the few-shot classification tasks are constructed with sampled classes each time, every task consists of different classes. Since the class indices are randomly assigned at the beginning of each task learning, the meta-initialized parameters cannot contain any prior information on the class indices. For instance, it is not allowed that the meta-initialized parameters encode class similarities between class $i$ and class $j$. Any biased initial guess could hinder the task learning. The meta-initialized parameters should be in-between (local) optimal points of tasks as depicted in Figure 4, so that the network can adapt to each task with few task-specific updates.

![Figure 4: Ideal meta-initialization.](image)
When the head parameters $\theta_h = [\theta_{h,1}, \ldots, \theta_{h,n}]^\top \in \mathbb{R}^{n \times d}$ have orthonormal rows (i.e., $\|\theta_{h,i}\|_2 = 1$ for all $i$ and $\theta_{h,i}^\top \theta_{h,j} = 0$ for all $i \neq j$), the meta-initialized model can have the unbiased classifier. Here, $a^\top$ denotes the transpose of $a$ and $\| \cdot \|_2$ denotes the Euclidean norm. With the orthonormal rows, therefore, each logit value $\theta_{h,j}^\top f_{\theta_b}(x)$ can be controlled independently of other logit values.

Recall that the softmax probability $p_j$ for class $j$ of sample $x$ is computed as follows:

$$p_j(x) = \frac{e^{\theta_{h,j}^\top f_{\theta_b}(x)}}{\sum_{i=1}^n e^{\theta_{h,i}^\top f_{\theta_b}(x)}} = \frac{1}{\sum_{i=1}^n e^{(\theta_{h,i} - \theta_{h,j})^\top f_{\theta_b}(x)}}. \tag{4}$$

In Equation 4, the softmax probability only depends on the differences of the rows of the head parameters $\theta_{h,i} - \theta_{h,j}$. Adding a vector to all the rows (i.e., $\theta_{h,i} \leftarrow \theta_{h,i} + c$ for all $i$) does not change the softmax vector. So, we can expect the same nice meta-initialized model, when a parallel shift of the rows of the head parameters can make orthonormal rows. To support this experimentally, we design the centering algorithm that operates a parallel shift of $\theta_h$ by subtracting the average of the row vectors of $\theta_{h}$ after every outer update on both MAML and BOIL, i.e., $[\theta_{h,1} - \theta_{h}, \ldots, \theta_{h,n} - \theta_{h}]^\top$ where $\theta_{h} = \frac{1}{n} \sum_{i=1}^n \theta_{h,i}$. Figure 5a shows that this parallel shift operations does not affect the performance of two algorithms on Cars.

Next, we investigate the cosine similarity between $\theta_{h,i}^\top - \theta_{h,k}^\top$ and $\theta_{h,j}^\top - \theta_{h,k}^\top$ for all different $i$, $j$, and fixed $k$. From the training procedures of MAML and BOIL, it is observed that the average of cosine similarities between the two gaps keeps near 0.5 during meta-training (Figure 6). Note that 0.5 is the cosine similarity between $\theta_{h,i}^\top - \theta_{h,k}^\top$ and $\theta_{h,j}^\top - \theta_{h,k}^\top$ when $\theta_{h,i}^\top$, $\theta_{h,j}^\top$, and $\theta_{h,k}^\top$ are orthonormal. From the results, we evidence that the orthonormality of $\theta_h$ is important for the meta-initialization and meta learning algorithms naturally keep the orthonormality.

From the above observation, we design the algorithm that fixes $\theta_h$ to be orthonormal for the meta-initialized model. Namely, MAML-fix updates $\theta_h$ in inner loops only, and BOIL-fix does not update $\theta_h$. The fix algorithm can be easily implemented by initializing $\theta_h$ to be orthonormal through the Gram-Schmidt method from a random matrix and setting the learning rate for the head of the model during the outer loop to zero.

Figure 5b depicts the valid accuracy curves of the fix algorithm on Cars. The experiments substantiate that orthonormal rows of $\theta_h$ are important and that BOIL improves the performance. (1) Comparing MAML to MAML-fix (the left panel of Figure 5b), MAML-fix outperforms MAML. It means that the outer loop calculated through the task-specific head following MAML is detrimental because the outer loop just adds unnecessary task specific information to the model. (2) Comparing vanilla models to fix models (both panels of Figure 5b), fixed meta-initialized head with orthonormality is less over-fitted, which is explained through the train accuracy curves in Appendix B. (3) Comparing BOIL to BOIL-fix (the right panel of Figure 5b), although BOIL-fix can achieve almost the same performance with BOIL with sufficient iterations, BOIL converges faster to a better local optima. This is because $\theta_h$ is trained so that the inner loop can easily adapt $f_{\theta_h}(x)$ to each class.

4 Experiments

4.1 Experimental setup

We used two backbone networks, 4conv network with 64 channels (from [34]) and ResNet-12 starting with 64 channels and doubling them after every block (from [23]). For the batch normalization

![Figure 5: Valid accuracy curves of (a) centering algorithm and (b) fix algorithm on Cars.](image)

![Figure 6: Average of cosine similarities between gaps.](image)
layers, we used batch statistics instead of the running statistics during meta-testing, following the original MAML [5]. We trained all models 30,000 epochs and then used the last epoch models to verify performance. We applied an inner update once both meta-training and meta-testing. All results were reproduced by our group and reported as the average and standard deviation of the accuracies over 5 × 1,000 tasks. We validated both MAML and BOIL on two general data sets, miniImageNet [34] and tieredImageNet [26], and two specific data sets, CUB [16] and Cars [15]. Full details on the implementation and data sets are described in Appendix A. In addition, the results of the 4conv network with 32 channels (from [5]) and of the other data sets at a size of 32 × 32 are reported in Appendix C and Appendix D, respectively.

4.2 Results of 4conv network

Table 1: Test accuracy (%) of 4conv network on benchmark dataset.

| Domain         | General (Coarse-grained) | Specific (Fine-grained) |
|----------------|--------------------------|-------------------------|
| Dataset        | miniImageNet | tieredImageNet | CUB | Cars |
| MAML(1)        | 48.47 ± 0.26  | 48.80 ± 0.34  | 53.70 ± 0.42  | 38.16 ± 0.20  |
| BOIL(1)        | 49.65 ± 0.19  | 50.00 ± 0.35  | 60.45 ± 0.45  | 50.33 ± 0.36  |
| MAML(5)        | 60.36 ± 0.25  | 64.27 ± 0.27  | 65.11 ± 0.10  | 45.36 ± 0.23  |
| BOIL(5)        | 65.32 ± 0.34  | 69.64 ± 0.20  | 74.12 ± 0.24  | 65.70 ± 0.17  |

Table 2: Test accuracy (%) of 4conv network on cross-domain adaptation.

| meta-test      | general to general | general to specific | specific to general | specific to specific |
|----------------|--------------------|--------------------|--------------------|--------------------|
| Dataset        | miniImageNet      | tieredImageNet     | miniImageNet       | tieredImageNet     |
| MAML(1)        | 49.45 ± 0.31      | 52.31 ± 0.33      | 40.46 ± 0.12      | 35.27 ± 0.11      |
| BOIL(1)        | 51.35 ± 0.18      | 54.09 ± 0.41      | 44.38 ± 0.11      | 37.16 ± 0.35      |
| MAML(5)        | 60.31 ± 0.12      | 64.88 ± 0.24      | 51.34 ± 0.24      | 44.29 ± 0.28      |
| BOIL(5)        | 70.76 ± 0.14      | 68.97 ± 0.24      | 60.11 ± 0.32      | 50.92 ± 0.22      |

Table 1 shows that BOIL overwhelms MAML on all benchmark data sets, particularly with a wide margin on a specific domain data set such as CUB and Cars. These results demonstrate that it is effective for the meta-initialized parameter to be learned in a task-specific update using a rapid learning scheme in gradient-based meta-learning. This means that the BOIL algorithm does not depend on the fineness of the domain and can be broadly adapted.

Furthermore, Table 2 shows the superiority of BOIL on the cross-domain adaptation, where the source and target domains differ (i.e., the meta-training and meta-testing data sets are different.). Recently, Guo et al. [8] noted that existing meta-learning algorithms have weaknesses in terms of the cross-domain adaptation. We divide the cross-domain adaptation into four cases: general to general, general to specific, specific to general, and specific to specific. Previous studies considered the cross-domain scenario starting with the general domain [3, 8]. However, we also evaluated the reverse cases considered more difficulty. BOIL outperforms MAML not only on the typical cross-domain adaptation scenario but also on the reverse scenario. We believe that the rapid learning property of BOIL enables the model to adapt to an unseen target domain that is entirely different from the source domain.

4.2.1 Ablation study of the existence of the head

Table 3: Test accuracy (%) of 4conv network on miniImageNet according to the head’s existence.

| with classifier | without classifier |
|----------------|--------------------|
| MAML(1)        | 20.10 ± 0.13       | **49.73 ± 0.33**   |
| BOIL(1)        | 20.12 ± 0.16       | 23.91 ± 0.11       |
| MAML(5)        | 20.05 ± 0.11       | **63.90 ± 0.21**   |
| BOIL(5)        | 20.04 ± 0.25       | 31.72 ± 0.24       |
| MAML(20)       | 19.82 ± 0.08       | **72.18 ± 0.12**   |
| BOIL(20)       | 20.10 ± 0.20       | 37.60 ± 0.12       |

(a) Before an inner update.  
(b) After an inner update.

3 All implementations are based on Torchmeta [4], and all results were reproduced according to our details.
Table 3 describes the test accuracy on miniImageNet before and after an inner update according to the presence of the head. To evaluate the performance in a case without a classifier, we first create a template of each class by averaging the features from the support set and then predicting the class of a sample from the query set as the class whose template has the highest cosine similarity with the representation of the sample.

The results provide some intriguing interpretations:

- **without a classifier in Table 3a.** The body of MAML creates efficient representations before an inner update, whereas the body of BOIL creates relatively inefficient representations. This result is related to the feature reuse of MAML (the left panel of Figure 2a) and the rapid learning of BOIL (the left panel of Figure 2b).

- **without a classifier in Table 3b.** The body of BOIL can achieve better representations through rapid learning than the body of MAML if an adequate number of samples are available. This result can be explained with the dramatic decrease in the cosine similarity between different classes after an inner update (the right panel of Figure 2b).

- **with a classifier in Table 3a.** The heads of MAML and BOIL seem to be ideally meta-initialized, which means that the heads of them cannot classify input data before an inner update. This result evidences our hypothesis on the optimal point of meta-initialization (Figure 4).

- **with a classifier in Table 3b.** The head of BOIL, meta-learned across the tasks, is well-matched with the representations through the body, resulting in an improved performance. By contrast, the head of MAML deteriorates significantly (Figure 5b).

To summarize, the meta-initialization by MAML provides efficient representations through the body, although a significant problem occurs in that the head decreases the efficiency of the representations. By contrast, although the meta-initialization by BOIL provides less efficient representations compared to MAML, the body can extract efficient representations through task-specific updates based on rapid learning, and further, the head boosts the performance.

### 4.3 Results of ResNet-12

Table 4: 5-Way 5-Shot test accuracy (%) of ResNet-12. The lsc means the last skip connection.

| Meta-train | miniImageNet | CUB | CUB | miniImageNet | CUB |
|------------|--------------|-----|-----|--------------|-----|
| Meta-test  |              |     |     |              |     |
| MAML w/ lsc| 67.96 ± 0.28 | 71.56 ± 0.29 | 55.61 ± 0.43 | 77.51 ± 0.17 | 42.34 ± 0.16 | 37.97 ± 0.29 |
| MAML w/o lsc| 66.03 ± 0.18 | 69.43 ± 0.22 | 52.10 ± 0.21 | 70.90 ± 0.31 | 37.32 ± 0.25 | 33.94 ± 0.31 |
| BOIL w/ lsc| 69.68 ± 0.25 | 71.43 ± 0.38 | 61.00 ± 0.36 | 81.54 ± 0.14 | 44.54 ± 0.20 | 40.05 ± 0.39 |
| BOIL w/o lsc| 70.90 ± 0.20 | 74.29 ± 0.31 | 61.83 ± 0.49 | 83.23 ± 0.14 | 44.62 ± 0.10 | 40.86 ± 0.35 |

Many recent studies [23, 35, 28, 30] have used deeper networks such as ResNet [9], Wide-ResNet [39], or DenseNet [11] as a backbone network. The deeper networks, in general, use feature wiring structures that connect layers to facilitate feature propagation. We explore the applicability of BOIL to a deeper network with the wiring structure, ResNet-12, and propose a simple trick to boost the rapid learning by disconnecting the last skip connection. The trick is explained in Section 4.3.1.

Table 4 shows the test accuracy results of ResNet-12, which is meta-trained and meta-tested with various data sets according to the fineness of the domains. This result indicates that BOIL can be applied to other general architectures by showing a better performance than MAML not only on standard benchmark data sets but also on cross-domain adaptation. Note that BOIL has achieved the best performance without the last skip connection in every experiment.

#### 4.3.1 Disconnection trick

Connecting the two learning schemes of BOIL and the wiring structure of ResNet, we propose a simple trick to eliminate the skip connection of the last residual block, which we call a disconnection trick. In Section 3.1, we confirmed that the model learned with BOIL applies a feature reuse at the low- and mid-level of the body and rapid learning at the high-level of the body.
To investigate the effects of skip connections on a rapid learning scheme, we analyze the cosine similarity after every residual block in the same way as Figure 2. Figure 7a shows that ResNet with skip connections on all blocks changes not only the last block but also other blocks rapidly. Because skip connections strengthen the gradient back-propagation, the scope of rapid learning extends to the front. Therefore, to achieve both the effective feature reuse and the rapid learning of BOIL, we suggest a way to weaken the gradient back-propagation from the loss function by removing the skip connection of the last block. As shown in Figure 7b with this simple disconnection trick, ResNet can improve the effectiveness of BOIL, as well as the feature reuse at the front blocks of the body and the rapid learning at the last block, and significantly improves the performance, as described in Table 4.

5 Related Work

MAML [5] is one of the most famous algorithms in gradient-based meta-learning, achieving a competitive performance on few-shot learning benchmark data sets [34, 26, 1, 23]. To tackle the task ambiguity caused by data insufficiency in few-shot learning, numerous studies have sought to extend MAML in various ways. Some studies [23, 30, 35] have proposed feature modulators that make task-specific adaptation more amenable by shifting and scaling the representations extracted from the network body. In response to the lack of data for task-specific updates, there have also been attempts to incorporate additional parameters in a small number, rather than the entire model parameters [40, 28]. Others [7, 6, 38, 20] have taken a probabilistic approach using Bayesian modeling and variational inference. Unlike prior studies, we proposed a new training paradigm reinforcing a task-specific update by model itself.

Few-shot learning has recently been expanding beyond the standard $n$-way $k$-shot classification to tackle the more realistic problems. Triantafillou et al. [32] constructed a more scalable and realistic dataset, called a meta-dataset, which contains several data sets collected from different sources. Lee et al. [17] addressed $n$-way any-shot classification considering the imbalanced data distribution in real-world. Furthermore, some studies [2, 3] have recently explored the few-shot learning on cross-domain adaptation, which is one of the ultimate goals of meta-learning. In addition, Guo et al. [8] suggested a new cross-domain benchmark dataset for few-shot learning and showed that the current meta-learning algorithms [5, 34, 29, 31, 18] underachieve compared to simple fine-tuning on cross-domain adaptation. We demonstrated that task-specific update with rapid learning is efficient on cross-domain adaptation.

6 Conclusion

In this study, we proposed the BOIL algorithm that enforces rapid learning by learning only the body of the model in the inner loop. Using the cosine similarity and the CKA, we demonstrated that BOIL trains a model to follow the feature reuse scheme on the low- and mid-level body but trains it to follow the rapid learning scheme on the high-level body. We further explored the crucial factor in the head and whether learning the head of the model helps optimization of MAML and BOIL. It was observed that a model without outer updates of the head with an orthonormal initialization achieves a better performance than the original model in MAML, whereas the opposite occurs in BOIL. This indicates means that MAML has not used the head of the model correctly, while BOIL takes advantage of the learned head. Based on these analyses, we validated the BOIL algorithm on various data sets including miniImageNet, tieredImageNet, CUB, and Cars, and cross-domain adaptation using a standard 4conv network and ResNet-12. The experimental results showed significant improvement over MAML, particularly cross-domain adaptation, implying that rapid learning approaches should be considered for adaptation to unseen tasks. We hope our study inspires rapid learning in gradient-based meta-learning approaches.
**Broader Impact**

We expect that our work can open a new horizon in the gradient-based meta-learning field. First of all, our contemplation about the optimal meta-initialization, which is entirely different from the conventional optimal point, gives the meta-learning researchers inspiration to design or analyze a novel or existing algorithm. Furthermore, on the data shortage or cross-domain adaptation, our rapid learning-based algorithm outshines. However, our approach is the first work to study rapid learning and focuses on classification tasks. Hence, more studies are needed to develop and to generalize the property of rapid learning.

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A Implementation Detail

A.1 $n$-way $k$-shot setting

We experimented in the 5-way 1-shot, 5-way 5-shot, and 5-way 20-shot settings, and the number of shots is marked in parentheses in the algorithm name column of all tables. During meta-training, models are inner loop updated only once, and the meta-batch size for the outer loop is set to 4. During meta-testing, the number of task-specific (inner loop) updates is the same as meta-training. All models are trained for 30,000 iterations, and all the reported results are based on the last epoch model.

A.2 Model implementations

In our experiments, we employ 4conv network and ResNet-12 for MAML and BOIL algorithms. 4conv network has 4 convolution modules, and each module consists of a $3 \times 3$ convolution layer with 64 filters, batch normalization, a ReLU non-linearity, a $2 \times 2$ max-pool. This model is also the same as MAML except for the number of filters. However, we experiment with both MAML and BOIL with the 64 filters network for a fair comparison. ResNet-12 [9] has the same structure with the feature extractor of TADAM [23]. It has four residual blocks, and each block consists of 3 modules of convolution, batch normalization, and leaky ReLU [37]. Every end of each residual block, a $2 \times 2$ max-pool is applied, and the number of convolution filters is doubled from 64 on each block. Each block also has a wiring structure known as skip connection, which is a link made up of additions between the input and output feature of the block for strengthening feature propagation.

And then, our proposed algorithms can be implemented by just dividing learning rates into body and the head. Table 5 shows the learning rates of each network and algorithm. \(\alpha_b\) and \(\alpha_h\) are the learning rates of the body and the head of the model during inner loops, and \(\beta_b\) and \(\beta_h\) are the learning rates of the body and the head of the model during outer loops.

| Model | MAML| BOIL | MAML-fix | BOIL-fix |
|-------|-----|------|----------|----------|
| \(\alpha_b\) | 0.5 | 0.5 | 0.5 | 0.5 |
| \(\alpha_h\) | 0.5 | 0.0 | 0.5 | 0.0 |
| \(\beta_b\) | 0.001 | 0.001 | 0.001 | 0.001 |
| \(\beta_h\) | 0.001 | 0.001 | 0.0 | 0.0 |

(a) 4conv network. (b) ResNet-12.

A.3 Dataset

We validate the BOIL and MAML algorithms on several data sets, considering image size and fineness. Table 6 is the summarization of the used data sets.

| Data sets | miniImageNet | TieredImageNet | CUB | Cars |
|-----------|--------------|----------------|-----|------|
| Source    | ImageNet [27]| ImageNet [27]  | CUB [36]| Cars [15] |
| Image size| $84 \times 84$| $84 \times 84$ | $84 \times 84$| $84 \times 84$ |
| Fineness  | Coarse       | Coarse         | Fine | Fine |
| # meta-training classes | 64 | 351 | 100 | 98 |
| # meta-validation classes | 16 | 97 | 50 | 49 |
| # meta-testing classes | 20 | 160 | 50 | 49 |
| Split setting | Vinyals et al. [34] | Ren et al. [26] | Hilliard et al. [10] | Tseng et al. [33] |
| Data sets | FC100 | CIFAR-FS | Aircraft | VGG-Flower |
| Source    | CIFAR100 [16]| CIFAR100 [16]| Aircraft [19] | VGG-Flower [22] |
| Image size| $32 \times 32$| $32 \times 32$| $32 \times 32$| $32 \times 32$ |
| Fineness  | Coarse | Coarse | Fine | Fine |
| # meta-training classes | 60 | 64 | 70 | 71 |
| # meta-validation classes | 20 | 16 | 15 | 16 |
| # meta-testing classes | 20 | 20 | 15 | 15 |
| Split setting | Bertinetto et al. [1] | Oreshkin et al. [23] | Na et al. [20] | Na et al. [20] |
B Over-fitting issue

Figure 8 shows the train accuracy curves corresponding to the Figure 5b. We confirm that MAML, MAML-fix, and BOIL are over-fitted from the early epochs, but BOIL-fix is over-fitted more slowly than others. However, the degradation from the over-fitting issue is much more in the original algorithms, i.e., MAML and BOIL, than in the fix algorithms, i.e., MAML-fix and BOIL-fix. It implies that the over-fitting on the head has a greater impact on performance degradation than the over-fitting on the body.

C Results on 4conv network (32-32-32)

In the related papers [5, 24], they used a 4conv network with 32 filters to avoid the over-fitting issue. We chose 64 filters in the main paper because the models trained by BOIL is not over-fitted. Nevertheless, Table 7 shows that BOIL outperforms MAML when 4conv network has 32 filters.

Table 7: Test accuracy (%) of 4conv network (32 filters) on benchmark data sets. The values in parenthesis are the number of shots.

| Meta-training | CUB | miniImageNet | tieredImageNet |
|---------------|-----|--------------|----------------|
| MAML(1)       | 54.14 ± 0.21 | 33.03 ± 0.29 | 32.14 ± 0.45 |
| BOIL(1)       | 58.90 ± 0.22 | 36.49 ± 0.32 | 33.85 ± 0.33 |
| MAML(5)       | 67.17 ± 0.35 | 41.74 ± 0.27 | 40.73 ± 0.21 |
| BOIL(5)       | 71.17 ± 0.41 | 45.92 ± 0.34 | 42.64 ± 0.18 |

D Results on Other Dataset

We applied our algorithm to other data sets with image size of 32 × 32. Similar to the analyses on section 4, these data sets can be divided into two general data sets, CIFAR-FS [1] and FC100 [22], and two specific data sets, Aircraft [19] and VGG-Flower [22]. Table 8, Table 9, and Table 10 generally show the superiority of BOIL even if image size is extremely tiny.

Table 8: Test accuracy (%) of 4conv network on benchmark dataset. The values in parenthesis are the number of shots.

| Domain                  | CIFAR-FS | FC100 | Aircraft | VGG-Flower |
|-------------------------|----------|-------|----------|------------|
| Dataset                 |          |       |          |            |
| MAML(1)                 | 55.88 ± 0.35 | 33.73 ± 0.33 | 56.46 ± 0.36 | 56.23 ± 0.08 |
| BOIL(1)                 | 58.25 ± 0.33 | 37.80 ± 0.23 | 54.34 ± 0.36 | 62.14 ± 0.15 |
| MAML(5)                 | 67.49 ± 0.19 | 42.62 ± 0.27 | 65.07 ± 0.23 | 71.03 ± 0.22 |
| BOIL(5)                 | 73.35 ± 0.07 | 49.27 ± 0.29 | 66.45 ± 0.22 | 78.42 ± 0.12 |

Table 9: Test accuracy (%) of 4conv network on cross-domain adaptation. The values in parenthesis are the number of shots.

| Adaptation | General to general | General to specific | Specific to general | Specific to specific |
|------------|--------------------|---------------------|---------------------|---------------------|
| meta-train | FC100 | CIFAR-FS | CIFAR-FS | CIFAR-FS | Aircraft | VGG-Flower | Aircraft | VGG-Flower | Aircraft | VGG-Flower |
| MAML(1)    | 66.21 ± 0.47 | 55.49 ± 0.25 | 26.49 ± 0.14 | 49.07 ± 0.22 | 28.57 ± 0.15 | 25.32 ± 0.29 | 24.45 ± 0.15 | 43.92 ± 0.18 |
| BOIL(1)    | 55.05 ± 0.22 | 51.15 ± 0.29 | 29.87 ± 0.18 | 56.49 ± 0.21 | 33.13 ± 0.28 | 28.42 ± 0.23 | 27.99 ± 0.06 | 43.11 ± 0.18 |
| MAML(5)    | 69.24 ± 0.34 | 57.34 ± 0.15 | 31.39 ± 0.26 | 49.77 ± 0.28 | 34.06 ± 0.15 | 40.26 ± 0.18 | 38.43 ± 0.23 | 56.74 ± 0.16 |
| BOIL(5)    | 70.92 ± 0.21 | 70.82 ± 0.35 | 39.21 ± 0.41 | 73.57 ± 0.25 | 46.00 ± 0.34 | 36.71 ± 0.19 | 37.68 ± 0.18 | 60.22 ± 0.16 |

Table 10: 5-Way 5-Shot test accuracy (%) of ResNet-12. The lsc means the last skip connection.

| Meta-training | CIFAR-FS | Aircraft | CIFAR-FS | VGG-Flower | Aircraft | CIFAR-FS | VGG-Flower |
|---------------|----------|----------|----------|------------|----------|----------|------------|
| MAML w/ lsc   | 74.38 ± 0.21 | 77.88 ± 0.16 | 31.51 ± 0.12 | 71.44 ± 0.45 | 28.36 ± 0.07 | 37.25 ± 0.26 |
| MAML w/o lsc  | 71.41 ± 0.21 | 78.45 ± 0.21 | 30.73 ± 0.16 | 74.15 ± 0.24 | 28.57 ± 0.27 | 39.10 ± 0.09 |
| BOIL w/ lsc   | 78.32 ± 0.28 | 78.82 ± 0.17 | 37.61 ± 0.12 | 79.92 ± 0.15 | 45.60 ± 0.19 | 54.44 ± 0.20 |
| BOIL w/o lsc  | 79.38 ± 0.22 | 79.54 ± 0.14 | 43.24 ± 0.15 | 80.33 ± 0.33 | 45.13 ± 0.30 | 52.51 ± 0.21 |