# **Meta-Learning with Adaptive Hyperparameters**

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#### Abstract

The ability to quickly learn and generalize from only few examples is an essential goal of few-shot learning. Gradient-based meta-learning algorithms effectively tackle the problem by learning how to learn novel tasks. In particular, modelagnostic meta-learning (MAML) encodes the prior knowledge into a trainable initialization, which allowed for fast adaptation to few examples. Despite its popularity, several recent works question the effectiveness of MAML when test tasks are different from training tasks, thus suggesting various task-conditioned methodology to improve the initialization. Instead of searching for better task-aware initialization, we focus on a complementary factor in MAML framework, inner-loop optimization (or fast adaptation). Consequently, we propose a new weight update rule that greatly enhances the fast adaptation process. Specifically, we introduce a small meta-network that can adaptively generate per-step hyperparameters: learning rate and weight decay coefficients. The experimental results validate that the Adaptive Learning of hyperparameters for Fast Adaptation (ALFA) is the equally important ingredient that was often neglected in the recent few-shot learning approaches. Surprisingly, fast adaptation from random initialization with ALFA can already outperform MAML.

#### 1 Introduction

Inspired by the capability of humans to learn new tasks quickly from only few examples, few-shot learning tries to address the challenges of training artificial intelligence that can generalize well with the few samples. Meta-learning, or *learning-to-learn*, tackles this problem by investigating common prior knowledge from previous tasks that can help rapid learning of new tasks. Especially, gradient (or optimization) based meta-learning algorithms are gaining increased attention, owing to its potential for generalization capability. This line of works attempts to directly modify the conventional optimization algorithms to enable fast adaptation with few examples.

One of the most successful instance for gradient-based methods is Model-Agnostic Meta-Learning (MAML) [8], where the meta-learner attempts to find a good starting location for the network parameters to learn new tasks with very few updates. Following this trend, many recent studies [3, 5, 9, 11, 31, 40, 42] focused on learning better initialization by adaptively learning task-dependent modifications. However, research on the training strategy for fast adaptation to each task is relatively overlooked, typically resorting to simple first-order methods [8, 24] or conventional optimizers with momentums (e.g. SGD, Adam [16]). Few recent approaches explore better learning algorithm for inner-loop optimization [6, 15, 27, 28], however they lack the adaptation property in weight updates, which is validated to be effective from commonly used adaptive optimizers, such as Adam.

In this paper, we turn our attention to an important but often neglected factor for MAML-based formulation of few-shot learning, which is inner-loop optimization. Instead of trying to find the best initialization, we propose Adaptive Learning of hyperparameters for Fast Adaptation<sup>1</sup>, named

<sup>&</sup>lt;sup>1</sup>The code is available at https://github.com/baiksung/ALFA

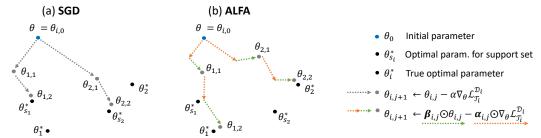


Figure 1: Overview of our proposed inner-loop update rule for few-shot learning. (a) Conventional optimizer (e.g. SGD) updates the parameters toward the gradient of task-specific loss  $\nabla_{\theta} \mathcal{L}_{\mathcal{T}_{i}}^{\mathcal{D}_{i}}$  with a fixed learning rate  $\alpha$ . The updates guide the parameters to the optimal values for training (or support) dataset,  $\theta_{s_{i}}^{*}$ . (b) ALFA *adapts* the learning rate  $\alpha_{i,j}$  and the regularization hyperparameter  $\beta_{i,j}$  w.r.t. the *i*-th task and *j*-th inner-loop update step. The adaptive regularization effects of ALFA pushes the parameters to the true optimal values  $\theta_{i}^{*}$ , facilitating better generalization to arbitrary unseen tasks.

ALFA, that enables more effective training with task-conditioned inner-loop updates from any given initialization. Our algorithm dynamically predicts two important hyperparameters for optimization: learning rate and weight decay coefficients. Specifically, we introduce a small meta-network that generates these hyperparameters using the current weight and gradient values for each step, so that the optimizing trajectory for each inner-loop iteration becomes adaptive. Intuitively, as illustrated in Figure 1, ALFA can achieve better training and generalization compared to conventional inner-loop optimization approaches, due to per-step adaptive regularization and learning rates.

With the proposed training scheme ALFA, fast adaptation to each task from even a *random* initialization shows a better few-shot classification accuracy than MAML. This suggests that learning a good updating rule is at least as important as learning a good initialization. Furthermore, ALFA can be applied in conjunction with existing meta-learning approaches that aim to learn good initialization.

#### 2 Related Work

The main goal of few-shot learning is to learn new tasks with given few support examples while maintaining the generalization to unseen query examples. Meta-learning aims to achieve the goal by learning prior knowledge from previous tasks, which in turn is used to quickly adapt to new tasks [4, 12, 33, 34, 37]. Recent meta-learning algorithms can be divided into three main categories: metric-based [17, 18, 35, 36, 39], network-based [22, 23, 25, 32], and gradient-based [8, 24, 28, 29] algorithms. Among them, gradient (or optimization) based approaches are recently gaining increased attention for its potential for generalizability across different domains. This is because the gradient-based algorithms focus on adjusting the optimization algorithm itself, instead of learning feature space (metric-based) or designing network architecture (model-based). In this work, we concentrate on discussing gradient-based meta-learning approaches, where there are two major directions: learning the initialization and learning the update rule.

One of the most recognized algorithms for learning good initialization is MAML [8], which is widely used across diverse domains due to its simplicity and model-agnostic design. Such popularity led to a surge of initialization-based methods [2, 3, 5, 9, 10, 11, 13, 14, 19, 20, 26, 27, 28, 31, 38, 40, 42, 43, 45], where they try to resolve the known issues of MAML, such as (meta-level) overfitting [21].

On the other hand, complementary studies on optimization algorithms, including better weight update rules, have attracted relatively less attention from the community. This is evident from many recent MAML-based algorithms which settled with simple inner-loop update rules, without any regularization that may be helpful for fast adaptation with few examples. Few recent works tried to improve from such naïve update rules by meta-learning the learning rates [2, 20, 31] and learning to regularize the gradients [6, 10, 19, 26, 28]. However, these methods lack adaptive property in the inner-loop optimization, in which its meta-learned learning rate or regularization terms do not adapt to each task or dynamically change throughout tasks during meta-test. In contrast, Ravi *et al.* [29] learn the entire inner-loop optimization directly through LSTM that generates updated weights (utilizing the design similar to [1]). While such formulation may be more general and provide task-adaptive

property, learning the entire inner-loop optimization (especially generating updated weights itself) can be difficult and lacks interpretability. This may explain why subsequent works, including MAML and its variants, resorted to simple weight update rules (*e.g.*, SGD).

Therefore, we propose a new adaptive learning update rule for fast adaptation (ALFA) that is specifically designed for meta-learning frameworks. Notably, ALFA specifies the form of weight-update rule to include the learning rate and weight decay terms that are dynamically generated for each update step and task, through a meta-network that is conditioned on gradients and weights of a base learner. This novel formulation allows ALFA to strike a balance between weight-update with meta-learned but fixed learning rate [2, 20, 31] and direct learning of complex weight-update [29].

#### 3 Proposed Method

#### 3.1 Background

Before introducing our proposed method, we formulate a generic problem setting for meta-learning. Assuming a distribution of tasks denoted as  $p(\mathcal{T})$ , each task can be sampled from this distribution as  $\mathcal{T}_i \sim p(\mathcal{T})$ , where the goal of meta-learning is to learn the prior knowledge from these sampled tasks. In k-shot learning setting, k number of meta-training examples per class  $\mathcal{D}_{\mathcal{T}_i}$  are sampled for a given task  $\mathcal{T}_i$ . After these examples are used to quickly adapt a model, new set of examples  $\mathcal{D}'_{\mathcal{T}_i}$  are sampled from the same task  $\mathcal{T}_i$  to evaluate the generalization performance of the adapted model on unseen examples with the corresponding loss function  $\mathcal{L}_{\mathcal{T}_i}$ . The feedback from the loss function  $\mathcal{L}_{\mathcal{T}_i}$  is then used to adjust the model parameters to achieve higher generalization performance.

In MAML [8], the objective is to encode the prior knowledge from the sampled tasks into a set of common initial weight values  $\boldsymbol{\theta}$  of the neural network  $f_{\boldsymbol{\theta}}$ , which can be used as a good initial point for fast adaptation to a new task. For a sampled task  $\mathcal{T}_i$  with corresponding examples  $\mathcal{D}_i$  and loss function  $\mathcal{L}_{\mathcal{T}_i}^{\mathcal{D}_i}$ , initial network weights  $\boldsymbol{\theta}$  adapt to each task where fixed number of inner-loop updates are performed iteratively. Network weights at time step j denoted as  $\boldsymbol{\theta}_{i,j}$  can be updated as:

$$\boldsymbol{\theta}_{i,j+1} = \boldsymbol{\theta}_{i,j} - \alpha \nabla_{\boldsymbol{\theta}} \mathcal{L}_{\mathcal{T}_i}^{\mathcal{D}_i}(f_{\boldsymbol{\theta}_{i,j}}), \tag{1}$$

where  $\theta_{i,0} = \theta$ . After S number of inner-loop updates, task-adapted network weights  $\theta'_i = \theta_{i,S}$  are obtained for each task. To evaluate and provide feedback for the generalization performance of the task-adapted network weights  $\theta'_i$ , the network is evaluated with a new set of examples  $\mathcal{D}'_i$  sampled from the original task  $\mathcal{T}_i$ . This outer-loop update acts as a feedback to update the initialization weights  $\theta$  to achieve better generalization across all tasks:

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \eta \nabla_{\boldsymbol{\theta}} \sum_{\mathcal{T}_i} \mathcal{L}_{\mathcal{T}_i}^{\mathcal{D}_i'}(f_{\boldsymbol{\theta}_i'}). \tag{2}$$

#### 3.2 Adaptive Learning for Fast Adaptation (ALFA)

While previous MAML-based methods aim to find the common initialization weight shared across different tasks, our approach focus on regulating the adaptation process itself through learned update rule. To achieve this, we start by adding a  $\ell_2$  regularization term  $\frac{\lambda}{2}||\boldsymbol{\theta}||_2$  to the loss function  $\mathcal{L}_{\mathcal{T}_i}$ . This changes the inner-loop update equation as follows:

$$\theta_{i,j+1} = \theta_{i,j} - \alpha(\nabla_{\theta} \mathcal{L}_{\mathcal{T}_{i}}^{\mathcal{D}_{i}}(f_{\theta_{i,j}}) + \lambda \theta_{i,j})$$

$$= \beta \theta_{i,j} - \alpha \nabla_{\theta} \mathcal{L}_{\mathcal{T}_{i}}^{\mathcal{D}_{i}}(f_{\theta_{i,j}}),$$
(3)

where  $\beta=1-\alpha\lambda$ . We can control the adaptation process by changing the relevant hyperparameters in the inner-loop update equation, which are scalar constants of learning rate  $\alpha$  and regularization hyperparameter  $\beta$ , which is relevant to  $\lambda$ . These are substituted to adjustable variables  $\alpha_{i,j}$  and  $\beta_{i,j}$  with the same dimensions as  $\nabla_{\theta}\mathcal{L}^{\mathcal{D}_i}_{\mathcal{T}_i}(f_{\theta_{i,j}})$  and  $\theta_{i,j}$ , respectively. The final inner-loop update equation becomes:

$$\boldsymbol{\theta}_{i,j+1} = \boldsymbol{\beta}_{i,j} \odot \boldsymbol{\theta}_{i,j} - \boldsymbol{\alpha}_{i,j} \odot \nabla_{\boldsymbol{\theta}} \mathcal{L}_{\mathcal{T}_i}^{\mathcal{D}_i}(f_{\boldsymbol{\theta}_{i,j}}), \tag{4}$$

where ⊙ denotes Hadamard (element-wise) product. To control the update rule for each task and each inner-loop update, we generate the hyperparameters based on the task-specific learning state

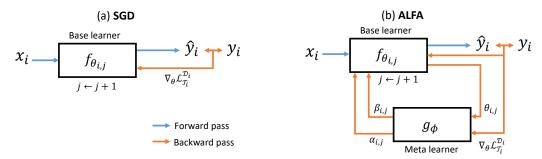


Figure 2: Illustration of the inner-loop update scheme. (a) Denoting the input, output, and the label as  $x_i$ ,  $\hat{y}_i$ , and  $y_i$ , respectively, conventional gradient-based meta-learning framework updates the network parameters  $\theta_{i,j}$  with backpropagation using e.g. SGD. (b) The proposed meta-learner  $g_{\phi}$  predicts the adaptive hyperparameters  $\alpha_{i,j}$  and  $\beta_{i,j}$  using the current parameters  $\theta_{i,j}$  and its gradients  $\nabla_{\theta} \mathcal{L}_{\mathcal{T}_i}^{\mathcal{D}_i}$ . Note that  $\phi$  is only updated in the outer-loop.

for task  $\mathcal{T}_i$  at time step j, which can be defined as  $\boldsymbol{\tau}_{i,j} = [\nabla_{\boldsymbol{\theta}} \mathcal{L}^{\mathcal{D}_i}_{\mathcal{T}_i}(f_{\boldsymbol{\theta}_{i,j}}), \boldsymbol{\theta}_{i,j}]$ . We can generate hyperparameters  $\boldsymbol{\alpha}_{i,j}$  and  $\boldsymbol{\beta}_{i,j}$  from a neural network  $g_{\boldsymbol{\phi}}$  with network weights  $\boldsymbol{\phi}$  as follows:

$$(\boldsymbol{\alpha}_{i,j}, \boldsymbol{\beta}_{i,j}) = g_{\boldsymbol{\phi}}(\boldsymbol{\tau}_{i,j}). \tag{5}$$

The hyperparameter generator network  $g_{\phi}$  above predicts the learning rate and regularization hyperparameters of weights in  $\theta_{i,j}$  for every inner-loop update step, where they are used to control the direction and magnitude of the weight update. The overall process of proposed inner-loop adaptation is depicted in Figure 2(b), compared to conventional SGD based approaches of Figure 2(a).

To train the network  $g_{\phi}$ , the outer-loop update using new examples  $\mathcal{D}'_i$  and task-adapted weights  $\boldsymbol{\theta}'_i$  is performed as in:

$$\phi \leftarrow \phi - \eta \nabla_{\phi} \sum_{\mathcal{T}_i} \mathcal{L}_{\mathcal{T}_i}^{\mathcal{D}_i'}(f_{\boldsymbol{\theta}_i'}). \tag{6}$$

Note that our method only learns the weights  $\phi$  for the hyperparameter generator network  $g_{\phi}$  and the initial weights  $\theta$  for  $f_{\theta}$  do not need to be updated throughout the training process. Therefore, our method can be trained to adapt from any given initialization (e.g. random initialization). The overall training procedure is summarized in Algorithm 1. For optimal performance when using ALFA with MAML and its variants, the initialization parameter may be jointly trained.

Our adaptive inner-loop update rule bears some resemblance to gradient-descent-based optimization algorithms [7, 16, 44] where the learning rate of each weight can be regulated by the accumulated moments of past gradients, whereas we propose a learning-based approach with the adaptive learning rate and regularization hyperparameters that can be trained for fast adaptation, while achieving the robustness to task differences.

# 3.3 Architecture

For our proposed hyperparameter generator network  $g_{\phi}$ , we employ a 3-layer MLP with ReLU activation between the layers. For computational efficiency, we reduce the task-specific learning state  $\tau_{i,j}$  to  $\bar{\tau}_{i,j}$ , which are layer-wise means of gradients and weights, thus resulting in 2 state values per layer. Assuming a N-layer CNN for  $f_{\theta}$ , hyperparameter generator network  $g_{\phi}$  takes 2N-dimensional vector  $\bar{\tau}_{i,j}$  as input, with same number of hidden units for intermediate layers. For outputs, learning rate  $\alpha^1_{i,j}$  and weight-decay term  $\beta^1_{i,j}$  are first generated layer-wise and then repeated to the dimensions of the respective parameters  $\theta_{i,j}$ . Following the practices from [25], per-step per-layer meta-learnable post-multipliers are multiplied to the generated hyperparameters values to control the initial values of the generated values for stable training. Mathematically, the learning rate and weight-decay terms are generated at step j for task  $\mathcal{T}_i$  as in:

$$\alpha_{i,j} = \alpha_{i,j}^0 \odot \alpha_{i,j}^1(\bar{\tau}_{i,j}), 
\beta_{i,j} = \beta_{i,j}^0 \odot \beta_{i,j}^1(\bar{\tau}_{i,j}),$$
(7)

where  $\alpha^0_{i,j}$ ,  $\beta^0_{i,j}$  are meta-learnable post-multipliers and  $\alpha^1_{i,j}(\tau_{i,j})$ ,  $\beta^1_{i,j}(\tau_{i,j})$  are generated layerwise multiplier values, all of which are repeated to the dimension of  $\theta_{i,j}$ . Instead of predicting the

#### Algorithm 1 Adaptive Learning for Fast Adaptation (ALFA)

```
Require: Task distribution p(\mathcal{T}), learning rate \eta, arbitrary given initialization \theta
  1: Randomly initialize \phi
  2: while not converged do
              Sample a batch of tasks \mathcal{T}_i \sim p(\mathcal{T})
  3:
  4:
              for each task \mathcal{T}_i do
  5:
                   Initialize \theta_{i,0} = \theta
  6:
                   Sample disjoint examples (\mathcal{D}_i, \mathcal{D}'_i) from \mathcal{T}_i
                   for inner-loop time step j := 0 to S - 1 do
  7:
                        Compute loss \mathcal{L}_{\mathcal{T}_i}^{\mathcal{D}_i}(f_{\boldsymbol{\theta}_{i,j}}) by evaluating \mathcal{L}_{\mathcal{T}_i} with respect to \mathcal{D}_i
  8:
                        Compute task-specific learning state \tau_{i,j} = [\nabla_{\theta} \mathcal{L}_{T_i}^{\mathcal{D}_i}(f_{\theta_{i,j}}), \theta_{i,j}]
Compute update hyperparameters (\alpha_{i,j}, \beta_{i,j}) = g_{\phi}(\tau_{i,j})
Perform gradient descent to compute adapted weights:
  9:
10:
11:
                  m{	heta}_{i,j+1} = m{eta}_{i,j} \odot m{	heta}_{i,j} - m{lpha}_{i,j} \odot 
abla_{m{	heta}} \mathcal{L}_{\mathcal{T}_i}^{\mathcal{D}_i}(f_{m{	heta}_{i,j}}) end for
12:
                  Compute \mathcal{L}_{\mathcal{T}_i}^{\mathcal{D}_i'}(f_{\boldsymbol{\theta}_i'}) by evaluating \mathcal{L}_{\mathcal{T}_i} w.r.t. \mathcal{D}_i' and task-adapted weights \boldsymbol{\theta}_i' = \boldsymbol{\theta}_{i,S}
13:
14:
              Perform gradient descent to update weights: \phi \leftarrow \phi - \eta \nabla_{\phi} \sum_{\mathcal{T}_i} \mathcal{L}_{\mathcal{T}_i}^{\mathcal{D}_i'}(f_{\boldsymbol{\theta}_i'})
16: end while
```

hyperparameters  $\alpha_{i,j}$  and  $\beta_{i,j}$  for every element in  $\theta_{i,j}$  and  $\nabla_{\theta} \mathcal{L}^{\mathcal{D}_i}_{\mathcal{T}_i}(f_{\theta_{i,j}})$ , layer-wise prediction of hyperparameters makes our generator network  $g_{\phi}$  more computationally efficient where we can greatly reduce the number of weights that are trained at the outer-loop update. As for a random initialization, ALFA requires meta-learnable per-parameter weight decay term to replace the role of MAML initialization in formulating prior knowledge for each parameter of a base learner. In both cases, the overall number of learnable parameters increased from MAML, together with per-step per-layer post-multipliers, is minimal with  $2SN+12N^2$ , where S is the number of inner-loop steps and N is the number of layers of a base learner  $f_{\theta}$ .

# 4 Experiments

In this section, we demonstrate the effectiveness of our proposed weight update rule (ALFA) in few-shot classification. Even starting from a random initialization, ALFA can drive the parameter values closer to the optimal point than a naïve SGD update from MAML, suggesting that the inner-loop optimization is just as important as the outer-loop optimization.

#### 4.1 Datasets

For few-shot classification, we use the two most popular datasets: miniImageNet [39] and tieredImageNet [30]. Both datasets are derived subsets of ILSVRC-12 dataset in specific ways to simulate the few-shot learning environment. Specifically, miniImageNet is composed of 100 classes randomly sampled from the ImageNet dataset, where each class has 600 images of size  $84 \times 84$ . To evaluate in few-shot classification settings, it is divided into 3 subsets of classes without overlap: 64 classes for meta-training set, 16 for meta-validation set, and 20 for meta-test set as in [29]. Similarly, tieredImageNet is composed of 608 classes with 779,165 images of size  $84 \times 84$ . The classes are grouped into 34 hierarchical categories, where 20 / 6 / 8 disjoint categories are used as meta-train / meta-validation / meta-test sets, respectively.

To take a step further in evaluating the rapid learning capability of meta-learning models, a cross-domain scenario is introduced in [5], where the models are tested on tasks that are significantly different from training tasks. Specifically, we fix the training set to the meta-train set of miniImageNet and evaluate with the meta-test sets from CUB-200-2011 (denoted as CUB) [41].

Triantafillou *et al.* [38] recently introduced a large-scale dataset, named Meta-Dataset, which aims to simulate more realistic settings by collecting several datasets into one large dataset. Further challenges are introduced by varying the number of classes for each class and reserving two entire datasets for evaluation, similar to cross-domain settings where meta-train and meta-test sets differ.

Table 1: Test accuracy on 5-way classification for miniImageNet and tieredImageNet.

	Backbone	miniIma	geNet	tieredIn	tieredImageNet	
	<b>Duction</b>	1-shot	5-shot	1-shot	5-shot	
Random Init	4-CONV	$24.85 \pm 0.43\%$	$31.09 \pm 0.46\%$	$26.55 \pm 0.44\%$	$33.82 \pm 0.47\%$	
ALFA + Random Init	4-CONV	$51.61 \pm 0.50\%$	$70.00 \pm 0.46\%$	$53.32 \pm 0.50\%$	$71.97 \pm 0.44\%$	
MAML [8]	4-CONV	$48.70 \pm 1.75\%$	$63.11 \pm 0.91\% 69.12 \pm 0.47\%$	$49.06 \pm 0.50\%$	$67.48 \pm 0.47\%$	
ALFA + MAML	4-CONV	$50.58 \pm 0.51\%$		$53.16 \pm 0.49\%$	$70.54 \pm 0.46\%$	
MAML + L2F [3]	4-CONV	$52.10 \pm 0.50\%$	$69.38 \pm 0.46\%$	$54.40 \pm 0.50\%$	$73.34 \pm 0.44\%$	
<b>ALFA</b> + MAML + L2F	4-CONV	$52.76 \pm 0.52\%$	<b>71.44</b> $\pm$ <b>0.45</b> %	$55.06 \pm 0.50\%$	$73.94 \pm 0.43\%$	
Random Init	ResNet12	$31.23 \pm 0.46\%$	$41.60 \pm 0.49\%$	$33.46 \pm 0.47\%$	$44.54 \pm 0.50\%$	
ALFA + Random Init	ResNet12	$56.86 \pm 0.50\%$	$72.90 \pm 0.44\%$	$62.00 \pm 0.47\%$	$79.81 \pm 0.40\%$	
MAML	ResNet12	$58.37 \pm 0.49\%$	$69.76 \pm 0.46\%$	$58.58 \pm 0.49\%$	$71.24 \pm 0.43\%$	
ALFA + MAML	ResNet12	$59.74 \pm 0.49\%$	<b>77.96</b> $\pm$ <b>0.41</b> %	<b>64.62</b> $\pm$ <b>0.49</b> %	<b>82.48</b> $\pm$ <b>0.38</b> %	
MAML + L2F	ResNet12	$59.71 \pm 0.49\%$	$77.04 \pm 0.42\% 77.42 \pm 0.42\%$	$64.04 \pm 0.48\%$	$81.13 \pm 0.39\%$	
<b>ALFA</b> + MAML + L2F	ResNet12	$60.05 \pm 0.49\%$		$64.43 \pm 0.49\%$	$81.77 \pm 0.39\%$	
LEO-trainval [31] * † MetaOpt [18] *	WRN-28-10 ResNet12	$61.76 \pm 0.08\%$ $62.64 \pm 0.61\%$	$77.59 \pm 0.12\%$ $78.63 \pm 0.46\%$	$66.33 \pm 0.05\%$ $65.99 \pm 0.72\%$	$81.44 \pm 0.09\%$ $81.56 \pm 0.53\%$	

<sup>\*</sup> Pre-trained network

#### 4.2 Implementation details

For experiments with ImageNet-based datasets, we use 4-layer CNN (denoted as 4-CONV hereafter) and ResNet12 network architectures as the backbone feature extractor network  $f_{\theta}$ . The 4-CONV and ResNet12 architectures used in this paper follows the same settings from [31, 35, 36, 39] and [25], respectively. In meta-training stage, the meta-learner  $g_{\phi}$  is trained over 100 epochs (each epoch with 500 iterations) with a batch size of 2 and 4 for 5-shot and 1-shot, respectively. At each iteration, we sample N classes for N-way classification, followed by sampling k labeled support examples and 15 query examples for each class. In case for Meta-Dataset, all experiments were performed with the setup and hyperparameters provided by their source code [38]<sup>2</sup>. For more details, please refer to the supplementary materials.

# 4.3 Experimental Results

#### 4.3.1 Few-Shot Classification

Table 1 summarizes the results of applying our proposed update rule ALFA on various initializations: random, MAML, and L2F (one of the state-of-the-art MAML-variant by Baik et al. [3]) on mini-ImageNet and tieredImageNet, along with comparisons to the other state-of-the-art meta-learning algorithms for few-shot learning. When the proposed update rule is applied on MAML, the performance is observed to improve significantly. What is even more interesting is that ALFA achieves high classification accuracy, when applied on a random initialization, suggesting that solely meta-learning the inner-loop optimization (ALFA + Random Init) is more beneficial than solely meta-learning the initialization. This underlines that the inner-loop optimization is as critical in MAML framework as the outer-loop optimization. We believe the promising results from ALFA can re-ignite focus and research on designing better inner-loop optimzation instead of solely focusing on improving the initialization (or outer-loop optimization). Table 1 further shows that our performance further improves when applied on MAML + L2F, especially for a small base learner backbone architecture (4-CONV). The fact that the proposed update rule can improve upon MAML-based algorithms proves the significance of designing a better inner-loop optimization. In addition, we present 20-way classification for a 4-CONV base learner on miniImageNet in Table 4, which shows the significant performance boost after applying ALFA on MAML.

#### 4.3.2 Cross-Domain Few-Shot Classification

To further justify the effectiveness of our proposed update rule in promoting fast adaptation, we perform experiments under cross-domain few-shot classification settings, where the meta-test tasks are significantly different from meta-train tasks. We report the results in Table 2, using the same

<sup>&</sup>lt;sup>†</sup> Trained with a union of meta-training and meta-validation set.

<sup>&</sup>lt;sup>2</sup>https://github.com/google-research/meta-dataset

Table 2: Test accuracy on 5-way 5-shot cross-domain classification.

	Backbone	$miniImageNet \rightarrow CUB$
ALFA + Random Init	4-CONV	$56.72 \pm 0.29\%$
MAML [8]	4-CONV	$52.70 \pm 0.32\%$
ALFA + MAML	4-CONV	$58.35 \pm 0.25\%$
MAML + L2F [3]	4-CONV	$60.89 \pm 0.22\%$
ALFA + MAML + L2F	4-CONV	$61.82 \pm 0.21\%$
ALFA + Random Init	ResNet12	$60.13 \pm 0.23\%$
MAML	ResNet12	$53.83 \pm 0.32\%$
ALFA + MAML	ResNet12	$61.22 \pm 0.22\%$
MAML + L2F	ResNet12	$62.12 \pm 0.21\%$
ALFA + MAML + L2F	ResNet12	$\textbf{63.24} \pm \textbf{0.22}\%$

experiment settings that are first introduced in [5], where miniImageNet is used as meta-training set and CUB dataset [41] as meta-test set.

The experimental results in Table 2 exhibit the similar tendency to few-shot classification results from Table 1. When a base learner with any initialization quickly adapts to a task from a new domain with ALFA, the performance is shown to improve significantly. The analysis in [5] suggests that a base learner with a deeper backbone is more robust to the intra-class variations in fine-grained classification, such as CUB. As the intra-class variation becomes less important, the difference between the support examples and query examples also becomes less critical, suggesting that the key lies in learning the support examples, without overfitting. This is especially the case when the domain gap between the meta-training and meta-test datasets is large, and the prior knowledge learned from the meta-training is mostly irrelevant. This makes learning tasks from new different domain difficult, as suggested in [3]. Thus, as discussed in [5], the adaptation to novel support examples plays a crucial role in cross-domain few-shot classification. Under such scenarios that demand the adaptation capability to new task, ALFA greatly improves the performance, further validating the effectiveness of the proposed weight update rule with adaptive hyperparameters in ALFA.

#### 4.3.3 Meta-Dataset

Table 3: Test accuracy on Meta-Dataset, where models are trained on ILSVRC-2012 only. Please refer to the supplementary materials for comparisons with state-of-the-art algorithms.

	fo-MAML		fo-Proto	-MAML
		+ ALFA		+ ALFA
ILSVRC	$45.51 \pm 1.11\%$	$51.09 \pm 1.17\%$	$49.53 \pm 1.05\%$	$52.80 \pm 1.11\%$
Omniglot	$55.55 \pm 1.54\%$	$67.89 \pm 1.43\%$	$63.37 \pm 1.33\%$	$61.87 \pm 1.51\%$
Aircraft	$56.24 \pm 1.11\%$	$\textbf{66.34} \pm \textbf{1.17}\%$	$55.95 \pm 0.99\%$	$\textbf{63.43} \pm \textbf{1.10}\%$
Birds	$63.61 \pm 1.06\%$	$\textbf{67.67} \pm \textbf{1.06}\%$	$68.66 \pm 0.96\%$	$\textbf{69.75} \pm \textbf{1.05}\%$
Textures	$68.04 \pm 0.81\%$	$65.34 \pm 0.95\%$	$66.49 \pm 0.83\%$	$\textbf{70.78} \pm \textbf{0.88}\%$
Quick Draw	$43.96 \pm 1.29\%$	$60.53 \pm 1.13\%$	$51.52 \pm 1.00\%$	$\textbf{59.17} \pm \textbf{1.16}\%$
Fungi	$32.10 \pm 1.10\%$	$\textbf{37.41} \pm \textbf{1.00}\%$	$39.96 \pm 1.14\%$	$\textbf{41.49} \pm \textbf{1.17}\%$
VGG FLower	$81.74 \pm 0.83\%$	$\textbf{84.28} \pm \textbf{0.97}\%$	$87.15 \pm 0.69\%$	$85.96 \pm 0.77\%$
Traffic Signs	$50.93 \pm 1.51\%$	$\textbf{60.86} \pm \textbf{1.43}\%$	$48.83 \pm 1.09\%$	$\textbf{60.78} \pm \textbf{1.29}\%$
MSCOCO	$35.30 \pm 1.23\%$	$\textbf{40.05} \pm \textbf{1.14}\%$	$43.74 \pm 1.12\%$	$\textbf{48.11} \pm \textbf{1.14}\%$

Table 3 presents the test accuracy of models trained on ImageNet (ILSVRC-2012) only, where the classification accuracy of each model (each column) is measured on each dataset meta-test test (each row). The table illustrates that ALFA brings the consistent improvement over fo-MAML (first-order MAML) and fo-Proto-MAML, which is proposed by Triantafillou *et al.* [38] to improve the MAML initialization at fc-layer. The consistent performance improvement brought by ALFA, even under such large-scale environment, further suggests the importance of inner-loop optimization and the effectiveness of the proposed weight update rule.

Table 4: 20-way classification

Model	1-shot (%)	5-shot (%)
MAML	15.21±0.36	18.23±0.39
ALFA+MAML	<b>22.03</b> ± <b>0.41</b>	<b>35.33</b> ± <b>0.48</b>

Table 5: Ablation studies on au

Input	5-shot (%)
weight only	$68.47 \pm 0.46$
gradient only	$67.98 \pm 0.47$
weight + gradient (ALFA)	$69.12 \pm 0.47$

#### 4.4 Ablation Studies

In this section, we perform ablation studies to better analyze the effectiveness of ALFA, through experiments with 4-CONV as a backbone under 5-way 5-shot miniImageNet classification scenarios.

# 4.4.1 Controlling the Level of Adaptation

We start with analyzing the effect of hyperparamter adaptation by generating each hyperparameter individually for MAML and random initialization. To this end, each hyperparameter is either metalearned (which is fixed after meta-training) or generated (through our proposed network  $g_{\phi}$ ) per step or per layer, as reported in Table 6. In general, making the hyperparameters adaptive improves the performance over fixed hyperparameters. Furthermore, controlling the hyperparameters differently at each layer and inner step is observed to play a significant role in facilitating fast adaptation. The differences in the role of learning rate  $\alpha$  and weight decay term  $\beta$  can be also observed. In particular, the results indicate that regularization term plays more important role than the learning rate for a random initialization. This is because random initialization is easily susceptible to overfitting when trained with few examples.

Table 6: Effects of varying the adaptability for learning rate  $\alpha$  and regularization term  $\beta$ . **fixed** or **adaptive** indicates whether the hyperparameter is meta-learned or generated by  $g_{\phi}$ , respectively.

Initialization		per step	per layer	fixed	adaptive
MAML	$\alpha$	1	/	$64.76 \pm 0.48\% \\ 64.52 \pm 0.48\%$	$64.81 \pm 0.48\% \\ 67.97 \pm 0.46\%$
1141 41142	β	1	1	$66.78 \pm 0.45\% \\ 66.30 \pm 0.47\%$	$66.04 \pm 0.47\%$ $65.10 \pm 0.48\%$
random	$\alpha$	1	1	$43.55 \pm 0.50\%$ $44.64 \pm 0.50\%$	$44.00 \pm 0.50\%$ $46.62 \pm 0.50\%$
141140111	β	1	<b>✓</b>	$65.09 \pm 0.48\%$ $62.89 \pm 0.43\%$	$67.06 \pm 0.47\%$ $66.35 \pm 0.47\%$

# 4.4.2 Inner-loop step

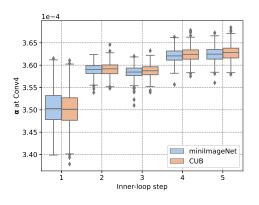
We make further analysis on the effectiveness of our method in fast adaptation by varying the number of update steps. Specifically, we measure the performance of ALFA+MAML when trained for a specified number of inner-loop steps and report results in Table 7. Regardless of the number of steps, ALFA+MAML consistently outperforms MAML that is trained for 5 steps.

Table 7: Varying inner-loop update steps for fast adaptation from a MAML initialization with ALFA.

MAML			MAML+ALFA		
step 5	step 1	step 2	step 3	step 4	step 5
$63.11 \pm 0.91\%$	$69.48 \pm 0.46\%$	$69.13 \pm 0.42\%$	$68.67 \pm 0.43\%$	$69.67 \pm 0.45\%$	$69.12 \pm 0.47\%$

#### 4.4.3 Ablation study on learning state

To investigate the role of each learning state (i.e., base learner weights and gradients), we perform ablation study, where only base learner weights or gradients are solely fed into the meta-network,  $g_{\phi}$ . Table 5 summarizes the ablation study results. The meta-network conditioned on each learning state still exhibits the performance improvement over MAML, suggesting that both learning states play important role. Our final model, ALFA, that is conditioned on both weights and gradients, give the best performance. Thus, weights and gradients are complementary parts of the learning state.



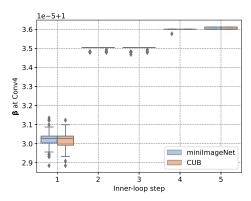


Figure 3: Visualization of the generated values of hyperparameters,  $\alpha$  and  $\beta$ , across inner-loop steps for 4-th convolutional layer. Dynamic ranges of generated values are also observed across different layers (please see the supplementary materials).

#### 4.5 Few-Shot Regression

We study the generalizability of the proposed weight update rule through experiments on few-shot regression. The objective of few-shot regression is to fit an unknown target function, given k number of sampled points from the function. Following the settings from [8, 20], with the input range [-5.0, 5.0], the target function is a sine curve with amplitude, frequency, and phase, which are sampled from intervals [0.1, 5.0], [0.8, 1.2], and  $[0, \pi]$ , respectively. We present results over k = 5, 10, 20 and different number of network parameters in Table 8. ALFA consistently improves MAML, reinforcing the effectiveness and generalizability of the proposed weight update rule.

Table 8: MSE over 100 sampled points with 95% confidence intervals on few-shot regression.

	2 hidden layers of 40			3 h	idden layers o	f 80
Model	5 shots	10 shots	20 shots	5 shots	10 shots	20 shots
MAML ALFA+MAML	1.24±0.21 <b>0.92</b> ± <b>0.19</b>	0.75±0.15 <b>0.62</b> ± <b>0.16</b>	0.49±0.11 <b>0.34</b> ± <b>0.07</b>	0.84±0.14 <b>0.70</b> ± <b>0.15</b>	0.56±0.09 <b>0.51</b> ± <b>0.10</b>	0.33±0.06 <b>0.25</b> ± <b>0.06</b>

#### 4.6 Visualization of generated hyperparameters

We examine the hyperparameter values generated by ALFA to validate whether it actually exhibits the dynamic behaviour as intended. Through visualization illustrated in Figure 3, we observe how the generated values differ for each inner-loop update step, under different domains (miniImageNet [39] and CUB [41]). We can see that the hyperparameters, learning rate  $\alpha$  and regularization term  $\beta$ , are generated in a dynamic range for each inner-loop step. An interesting behavior is that the ranges of generated hyperparameter values are similar, under datasets from two significantly different domains. We believe such domain robustness is owed to conditioning on gradients and weights, which allow the model to focus on the correlation between generalization performance and the learning *trajectory* (weights and gradients), rather than domain-sensitive input image features.

#### 5 Conclusion

We propose **ALFA**, an adaptive learning of hyperparameters for fast adaptation (or inner-loop optimization) in gradient-based meta-learning framework. By making the learning rate and weight decay hyperparameters adaptive to the current learning state of a base learner, ALFA has been shown to consistently improve few-shot classification performance, regardless of different initialization. Therefore, based on strong empirical validation, we claim that finding a good task-specific update rule for fast adaptation is at least as important as finding a good initialization of the parameters. We believe that our results can initiate a number of interesting directions for future work. For instance, one can explore different types of task-adaptive regularization methods, other than a simple  $\ell_2$  weight decay used in ALFA. Also, instead of conditioning only on layer-wise mean of gradients and weights, one can investigate other learning states, such as momentum.

# **Broader Impact**

Meta-learning and few-shot classification can help nonprofit organizations and small businesses automate their tasks at low cost, as only few labeled data may be needed. Due to the efficiency of automated tasks, nonprofit organizations can help more people from the minority groups, while small businesses can enhance their competitiveness in the world market. Thus, we believe that meta-learning, in a long run, will promote diversity and improve the quality of everyday life.

On the other hand, the automation may lead to social problems concerning job losses, and thus such technological improvements should be considered with extreme care. Better education of existing workers to encourage changing their roles (*e.g.* managing the failure cases of intelligent systems, polishing the data for incremental learning) can help prevent unfortunate job losses.

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# Meta-Learning with Adaptive Hyperparameters - Supplementary Document -

In this supplementary document, we present the discussion on ResNet12 results (Section A) and additional results on few-shot classification (Section B) and cross-domain few-shot classification (Section D); experimental details (Section E); and more visualizations of generated hyperparameters (Section F).

#### A Discussion on ResNet12 results

Table A: 5-way 5-shot miniImageNet classification with multi-GPU setting vs single-GPU setting.

	ALFA+Random Init	MAML	ALFA+MAML	MAML+L2F	ALFA+MAML+L2F
Single-GPU † Multi-GPU	$72.90 \pm 0.44\% \\ 88.90 \pm 0.31\%$	$69.76 \pm 0.46\%$ $58.33 \pm 0.49\%$	$77.96 \pm 0.41\% \\ 88.36 \pm 0.32\%$	$77.04 \pm 0.42\% \\ 88.85 \pm 0.31\%$	$77.42 \pm 0.42\% \\ 90.92 \pm 0.29\%$

<sup>&</sup>lt;sup>†</sup> The single GPU performance result is used in the main text.

We found a bug that is related to batch normalization in multi-GPU training/inference in the original MAML++ code [1], which our code is based on. The bug results in different performance when training/inference is performed with a single GPU, compared with training/testing with multiple GPUs. We believe this is due to how (asynchronous) batch normalization behaves differently in a multi-GPU setting and MAML++ code does not shuffle the order of examples in a minibatch. This setting results in uneven class distribution across GPUs. While MAML performs worse in this setting, adaptive variants of MAML (L2F [2] or ALFA) perform substantially better, compared with a single-GPU setting (see Table A). This result suggests more investigation can be done on normalization in few-shot learning setting for possible performance improvement. While we report single-GPU ResNet12 results, we share our results and finding in hope of facilitating further research and study on the issue.

# **B** Additional Experiments on Few-Shot Classification

We further validate the effectiveness of our proposed dynamic inner-loop update rule ALFA, through evaluating the performance on the relatively new CIFAR100-based [6] few-shot classification datasets: FC100 (Fewshot-CIFAR100) [12] and CIFAR-FS (CIFAR100 few-shots) [3]. They use low resolution images ( $32 \times 32$ ) to create more challenging scenarios, compared to miniImageNet [14] and tieredImageNet [15], which use images of size  $84 \times 84$ . The difference between the two datasets comes from how CIFAR100 is split into meta-train/meta-val/meta-test sets. Similar to tieredImageNet, FC100 splits the dataset based on superclasses, in order to minimize the amount of overlap. CIFAR-FS, on the other hand, is similar to miniImageNet, where the dataset is randomly split. Table B presents the results.

While ALFA with any initialization consistently performs better than MAML, the performance gap is not as significant as in miniImageNet, especially for a base learner with ResNet12 backbone. Also, unlike miniImageNet, ALFA with MAML+L2F does not always perform better than MAML+L2F. This may have to do with the low resolution of images, leading to noisy gradients. Gradients have more noise due to less data variations, compared to higher resolution of miniImageNet images.

Because ALFA is mainly conditioned on the gradients, such noisy gradients are likely to disrupt the learning. While no data augmentation is used during training for fair comparisons with most meta-learning methods, data augmentation could help mitigate the problem as data augmentation may provide more data variations and thus less noisy gradients.

Table B: Test accuracy on 5-way classification for FC100 and CIFAR-FS.

	Backbone	FC1	00	CIFAI	R-FS
		1-shot	5-shot	1-shot	5-shot
Random Init ALFA + Random Init	4-CONV 4-CONV	$27.50 \pm 0.45\%$ $38.20 \pm 0.49\%$	$35.37 \pm 0.48\%$ $52.98 \pm 0.50\%$	$29.74 \pm 0.46\%$ <b>60.56</b> $\pm$ <b>0.49</b> %	$39.87 \pm 0.49\%$ $75.43 \pm 0.43\%$
MAML † [4] ALFA + MAML	4-CONV 4-CONV	$36.67 \pm 0.48\%$ $37.99 \pm 0.48\%$	$49.38 \pm 0.49\%$ $53.01 \pm 0.49\%$	$56.80 \pm 0.49\%$ $59.96 \pm 0.49\%$	$74.97 \pm 0.43\%$ $76.79 \pm 0.42\%$
MAML + L2F <sup>†</sup> [2] <b>ALFA</b> + MAML + L2F	4-CONV 4-CONV	$38.96 \pm 0.49\%$ $38.50 \pm 0.47\%$	$53.23 \pm 0.48\%$ $53.20 \pm 0.50\%$	$60.35 \pm 0.48\%$ $60.36 \pm 0.50\%$	$76.76 \pm 0.42\% 76.60 \pm 0.42\%$
Random Init ALFA + Random Init	ResNet12 ResNet12	$32.26 \pm 0.47\%$ $40.57 \pm 0.49\%$	$42.00 \pm 0.49\%$ $53.19 \pm 0.50\%$	$36.86 \pm 0.48\%$ $64.14 \pm 0.48\%$	$49.46 \pm 0.50\%$ $78.11 \pm 0.41\%$
MAML <sup>†</sup> <b>ALFA</b> + MAML	ResNet12 ResNet12	$37.92 \pm 0.48\%$ $41.46 \pm 0.49\%$	$52.63 \pm 0.50\%$ $55.82 \pm 0.50\%$	$64.33 \pm 0.48\%$ $66.79 \pm 0.47\%$	$76.38 \pm 0.42\%$ <b>83.62</b> $\pm$ <b>0.37</b> %
$\begin{array}{l} \text{MAML} + \text{L2F}^{\dagger} \\ \textbf{ALFA} + \text{MAML} + \text{L2F} \end{array}$	ResNet12 ResNet12	$41.89 \pm 0.47\%$ $42.37 \pm 0.50\%$	$\begin{array}{c} 54.68 \pm 0.50\% \\ 55.23 \pm 0.50\% \end{array}$	$67.48 \pm 0.46\%$ $68.25 \pm 0.47\%$	$82.79 \pm 0.38\%$ $82.98 \pm 0.38\%$
Prototypical Networks* [17] Relation Networks [18] TADAM [12]	4-CONV 4-CONV <sup>+</sup> ResNet12	$35.3 \pm 0.6\%$ $40.1 \pm 0.4\%$	$48.6 \pm 0.6\%$ $56.1 \pm 0.4\%$	$55.5 \pm 0.7\%$ $55.0 \pm 1.0$	$72.0 \pm 0.6\%$ $69.3 \pm 0.8$
MetaOpt <sup>‡</sup> [8]	ResNet12	$41.1 \pm 0.6\%$	$55.5 \pm 0.6\%$	$72.0 \pm 0.7\%$	$84.2 \pm 0.5\%$

<sup>\*</sup> Meta-network is trained using the union of meta-training set and meta-validation set.

In Table C, we also add more comparisons to the prior works for Table 1 of our main paper, which were omitted due to space limits.

Table C: Test accuracy on 5-way classification for miniImageNet and tieredImageNet.

	Backbone	miniIma	geNet	tieredIr	nageNet
		1-shot	5-shot	1-shot	5-shot
Random Init	4-CONV	$24.85 \pm 0.43\%$	$31.09 \pm 0.46\%$	$26.55 \pm 0.44\%$	$33.82 \pm 0.47\%$
ALFA + Random Init	4-CONV	$51.61 \pm 0.50\%$	$70.00 \pm 0.46\%$	$53.32 \pm 0.50\%$	$71.97 \pm 0.44\%$
MAML [4]	4-CONV	$48.70 \pm 1.75\%$	$63.11 \pm 0.91\%$	$49.06 \pm 0.50\%$	$67.48 \pm 0.47\%$
ALFA + MAML	4-CONV	$50.58 \pm 0.51\%$	$69.12 \pm 0.47\%$	$53.16 \pm 0.49\%$	$70.54 \pm 0.46\%$
MAML + L2F [2]	4-CONV	$52.10 \pm 0.50\%$	$69.38 \pm 0.46\%$	$54.40 \pm 0.50\%$	$73.34 \pm 0.44\%$
ALFA + MAML + L2F	4-CONV	$52.76 \pm 0.52\%$	$\textbf{71.44} \pm \textbf{0.45}\%$	$55.06 \pm 0.50\%$	$\textbf{73.94} \pm \textbf{0.43}\%$
Random Init	ResNet12	$31.23 \pm 0.46\%$	$41.60 \pm 0.49\%$	$33.46 \pm 0.47\%$	$44.54 \pm 0.50\%$
ALFA + Random Init	ResNet12	$56.86 \pm 0.50\%$	$72.90 \pm 0.44\%$	$62.00 \pm 0.47\%$	$79.81 \pm 0.40\%$
MAML	ResNet12	$58.37 \pm 0.49\%$	$69.76 \pm 0.46\%$	$58.58 \pm 0.49\%$	$71.24 \pm 0.43\%$
ALFA + MAML	ResNet12	$59.74 \pm 0.49\%$	$\textbf{77.96} \pm \textbf{0.41}\%$	$64.62 \pm 0.49\%$	$\textbf{82.48} \pm \textbf{0.38}\%$
MAML + L2F	ResNet12	$59.71 \pm 0.49\%$	$77.04 \pm 0.42\%$	$64.04 \pm 0.48\%$	$81.13 \pm 0.39\%$
ALFA + MAML + L2F	ResNet12	$60.05 \pm 0.49\%$	$77.42 \pm 0.42\%$	$64.43 \pm 0.49\%$	$81.77 \pm 0.39\%$
Matching Networks [20]	4-CONV	$43.56 \pm 0.84\%$	$55.31 \pm 0.73\%$	-	-
Meta-Learning LSTM [14]	4-CONV	$43.44 \pm 0.77\%$	$60.60 \pm 0.71\%$	-	-
Prototypical Networks* [17]	4-CONV	$49.42 \pm 0.78\%$	$68.20 \pm 0.66\%$	$53.31 \pm 0.89\%$	$72.69 \pm 0.74\%$
Relation Networks [18]	4-CONV <sup>+</sup>	$50.44 \pm 0.82\%$	$65.32 \pm 0.70\%$	$54.48 \pm 0.93\%$	$71.32 \pm 0.78\%$
Transductive Prop Nets [9]	4-CONV	$55.51 \pm 0.99\%$	$68.88 \pm 0.92\%$	$59.91 \pm 0.94\%$	$73.30 \pm 0.75\%$
SNAIL [10]	ResNet12	$55.71 \pm 0.99\%$	$68.88 \pm 0.92\%$	-	-
AdaResNet [11]	ResNet12	$56.88 \pm 0.62\%$	$71.94 \pm 0.57\%$	-	-
TADAM [12]	ResNet12	$58.50 \pm 0.30\%$	$76.70 \pm 0.30\%$	-	-
Activation to Parameter* [13]	WRN-28-10	$59.60 \pm 0.41\%$	$73.74 \pm 0.19\%$		
LEO-trainval* [16]	WRN-28-10	$61.76 \pm 0.08\%$	$77.59 \pm 0.12\%$	$66.33 \pm 0.05\%$	$81.44 \pm 0.09\%$
MetaOpt <sup>‡</sup> [8]	ResNet12	$62.64 \pm 0.61\%$	$78.63 \pm 0.46\%$	$65.99 \pm 0.72\%$	$81.56 \pm 0.53\%$

<sup>\*</sup> Meta-network is trained using the union of meta-training set and meta-validation set.

<sup>\*</sup> Number of channels for each layer is modified to 64-96-128-256 instead of the standard 64-64-64.

<sup>†</sup> Our reproduction.

<sup>\*</sup> Meta-network is trained with data augmentation.

<sup>&</sup>lt;sup>+</sup> Number of channels for each layer is modified to 64-96-128-256 instead of the standard 64-64-64.

<sup>\*</sup> Meta-network is trained with data augmentation.

# C Comparisons with the state-of-the-art on Meta-Dataset

We compare one of the methods [19] that provides the state-of-the-art performance on Meta-Dataset. The state-of-the-art method is shown to outperform ALFA+fo-Proto-MAML in Table D. This is mainly because Tian *et al.* [19] uses the metric-based meta-learning approaches, which are known for high performance in few-shot classification. On the other hand, ALFA is a general plug-in module that can be used to improve over MAML-based algorithms, such as fo-Proto-MAML, as shown in Table 3 in the main paper. Also, ALFA can be used to improve over MAML-based algorithms in other problem domains, such as regression (shown in Table 8 of the main paper), while the algorithm from [19] can only be applied to few-shot classification.

Table D: Test accuracy on Meta-Dataset, where models are trained on ILSVRC-2012 only.

	ALFA+fo-Proto-MAML	Best from [19]
ILSVRC	52.80%	61.48%
Omniglot	61.87%	64.31%
Aircraft	63.43%	62.32%
Birds	69.75%	79.47%
Textures	70.78%	79.28%
Quick Draw	59.17%	60.84%
Fungi	41.49%	48.53%
VGG FLower	85.96%	91.00%
Traffic Signs	60.78%	76.33%
MSCOCO	48.11%	59.28%

# D Additional Experiments on Cross-Domain Few-Shot Classification

In this section, we study how robust the proposed meta-learner is to changes in domains, through additional experiments on cross-domain few-shot classification under similar settings to Section 4.3.2 in the main paper. In particular, miniImagenet meta-train set is used for meta-training, while corresponding meta-test splits of Omniglot [7], FC100 [12], and CIFAR-FS [3] are used for evaluation. Because either image channel (1 for Omniglot) or resolution ( $28 \times 28$  for Omniglot and  $32 \times 32$  for CIFAR-based datasets) is different from miniImagenet, we expand the image channel (to 3) and resolution (to  $84 \times 84$ ) to match meta-train settings. Table E reports the test accuracy on 5-way 5-shot cross-domain classification of 4-CONV base learner with baseline meta-learners and our proposed meta-learners. Trends similar to Table 2 in the main paper are observed in Table E, where ALFA consistently improves the performance across different domains.

Table E: Test accuracy on 5-way 5-shot cross-domain classification. All models are only trained with miniImageNet meta-train set and tested on various datasets (domains) without any fine-tuning.

	miniImageNet		
	ightarrow Omniglot	→ FC100	$\rightarrow$ CIFAR-FS
ALFA + Random Init	$91.02 \pm 0.29\%$	$62.49 \pm 0.48\%$	$63.49 \pm 0.45\%$
MAML [4] ALFA + MAML	$85.68 \pm 0.35\%$ $93.11 \pm 0.23\%$	$55.52 \pm 0.50\%$ $60.12 \pm 0.49\%$	$55.82 \pm 0.50\%$ $59.76 \pm 0.49\%$
MAML + L2F [2] ALFA + MAML + L2F	$94.96 \pm 0.22\%$ $94.10 \pm 0.24\%$	$61.99 \pm 0.49\%$ $63.33 \pm 0.45\%$	$\begin{array}{c} -63.73 \pm 0.48\% \\ 63.87 \pm 0.48\% \end{array}$

# **E** Experimental Details

For better reproducibility, the details of experiment setup, training, and architecture are delineated.

#### E.1 Experiment Setup

For N-way k-shot classification on all datasets, the standard settings [4] are used. During the fast adaptation (inner-loop optimization), the number of examples in  $\mathcal{D}$  is equal to N. Except for the

ablation studies on the number of inner-loop steps (Section 4.4.2 in the main paper), the inner-loop optimization is performed for 5 gradient steps for all experiments performed in this paper. During outer-loop optimization, 15 query examples are used for  $\mathcal{D}'$ . All models were trained for 50000 iterations with the meta-batch size of 2 and 4 tasks for 5-shot and 1-shot, respectively. For fair comparisons with most meta-learning methods, no data augmentation is used. However, meta-batch size of 1 is used for ResNet12 base learner, due to the heavy amount of computation from the second-order optimization. Similar to the experimental settings from [1], an ensemble of the top 5 performing per-epoch-models on the validation set were evaluated on the test set. Every result is presented with the mean and standard deviation after running experiments independently with 3 different random seeds. All experiments were performed on NVIDIA GeForce GTX 2080Ti GPUs. For new experiments on ResNet12 backbone, NVIDIA Quadro RTX 8000 GPUs are used.

#### **E.2** Network Architecture for base learner $f_{\theta}$

**4-CONV** Following the settings from [14, 17, 18, 20], 4 layers of 64-channel  $3 \times 3$  convolution filters, batch normalization [5], Leaky ReLU non-linear activation functions, and  $2 \times 2$  max pooling are used to build 4-CONV base learner. Then, the fully-connected layer and softmax are placed at the end of the base learner network.

**ResNet12** For overall ResNet12 architecture design, the settings from [12] are used. Specifically, the network is comprised of 4 residual blocks, each of which in turn consists of three convolution blocks. The first two convolution blocks in each residual block consist of  $3 \times 3$  convolutional layer, batch normalization, and a ReLU non-linear activation function. In the last convolution block in each residual block, the convolutional layer is followed by batch normalization and a skip connection. Each skip connection contains a  $1 \times 1$  convolutional layer, which is followed by batch normalization. Then, a ReLU non-linear activation function and  $2 \times 2$  max-pooling are placed at the end of each residual block. Lastly, the number of filters is 64, 128, 256, 512 for each residual block, respectively.

#### E.3 Network Architecture for the proposed meta-learner $g_{\phi}$

As mentioned in Section 3.3 in the main paper, the architecture of the proposed meta-learner  $g_{\phi}$  is a 3-layer MLP. Each layer consists of 2N hidden units, where N is the number of layers of the base learner network,  $f_{\theta}$ . This is because the meta-learner is conditioned on the layer-wise mean of gradients and weights of the base learner network at each inner-loop update step. ReLU activation function is placed between MLP layers.

#### **F** Visualization

In Section 4.5 of the main paper, the visualization of generated hyperparameters during meta-test is shown for only bias term of a 4-convolutional layer. To further examine the dynamic behavior of our proposed adaptive update rule, the generated values across tasks, layers, and update steps are plotted in Figure A, Figure B, and Figure C, respectively. There are several observations to make from the figures.

For different initializations, the ranges of generated values are different. This is especially evident for the generated learning rate  $\alpha$ , where the magnitude of values is diverse. This hints that each initialization prefers different learning dynamics, thus stressing the importance and effectiveness of ALFA. Furthermore, one should note the drastic changes in values across steps for each layer. In particular, this is prominent for the regularization term  $\beta$  for different layers and the learning rate  $\alpha$  for Conv3, Conv4, and linear bias, where the generated values change (up to the order of 1e-1). Because the changes across inner-loop steps are so great, the variations across tasks are not visible. Thus, each plot includes a zoomed-in boxplot for one step due to the limited space. While not as dynamic as across steps, the variations across tasks are still present (up to the order of 1e-3 for both  $\alpha$  and  $\beta$ ). This is still significant, considering how the usual inner-loop learning rate is from 1e-2 to 1e-1 and the usual  $\ell_2$  weight decay term is in the order of 1e-6 or 1e-5, depending on the learning rate.

Overall, different dynamic changes across layers and initializations as well as variations across tasks and inner-loop steps further underline the significance of the adaptive learning update rule in gradient-based meta-learning frameworks.

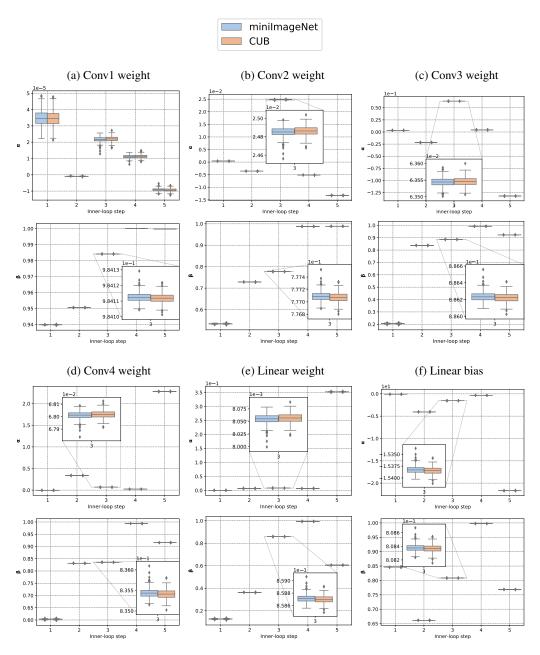


Figure A: ALFA+Random Init: Visualization of the generated hyperparameters,  $\alpha$  and  $\beta$ , across inner-loop steps and layers for a base learner of backbone 4-CONV. The proposed meta-learner was trained with random initialization on 5-way 5-shot miniImagenet classification.

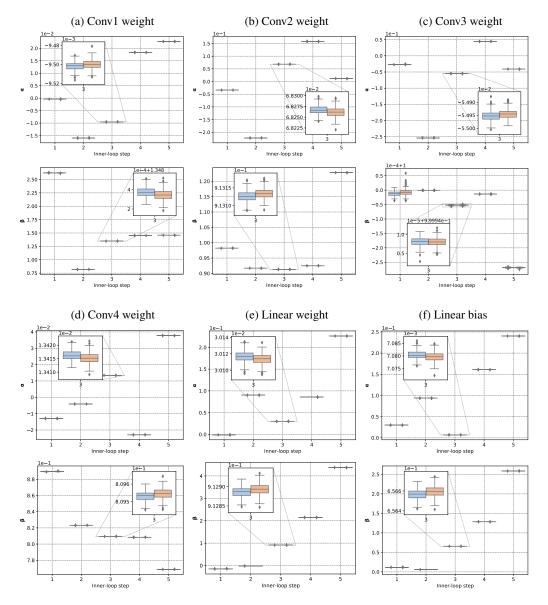


Figure B: ALFA+MAML [4]: Visualization of the generated hyperparameters,  $\alpha$  and  $\beta$ , across inner-loop steps and layers for a base learner of backbone 4-CONV. The proposed meta-learner was trained with MAML initialization on 5-way 5-shot miniImagenet classification.

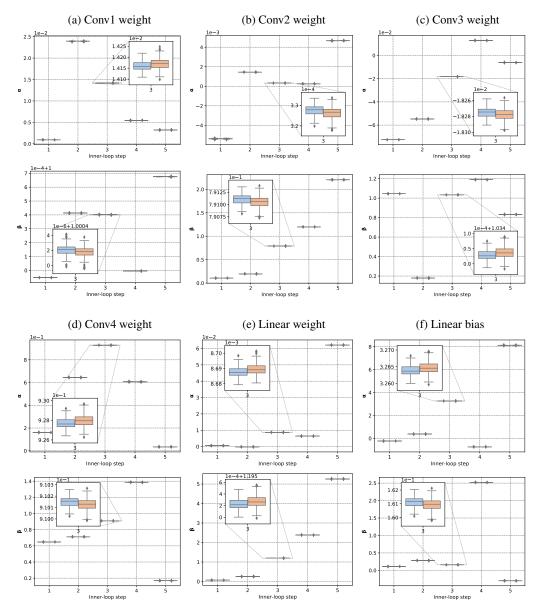


Figure C: ALFA+MAML+L2F [2]: Visualization of the generated hyperparameters,  $\alpha$  and  $\beta$ , across inner-loop steps and layers for a base learner of backbone 4-CONV. The proposed meta-learner was trained with MAML+L2F initialization on 5-way 5-shot miniImagenet classification.

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