# Supplementary Materials

These supplementary materials include E<sup>3</sup>BM algorithms, results with confidence intervals, the supplementary plots to Fig. 4, backbone architectures, implementation details, ablation results for MAML, the inference time and the number of parameters, and the execution steps of our source code with PyTorch.

# A E<sup>3</sup>BM algorithms

Algorithm 1 summarizes the meta-training (line 1-10) and meta-testing (line 11-16) procedures in our  $E^{3}BM$  approach. For clarity, the base-learning steps within a single episode are moved to Algorithm 2.

```
Algorithm 1: An Ensemble of Epoch-wise Empirical Bayes Models
  (E^3BM)
    Input: Meta-train episode distribution p_{tr}(\mathcal{T}), Meta-test episode distribution
             p_{te}(\mathcal{T}), and meta-train stepsizes \beta_1 and \beta_2.
    Output: The average accuracy of meta-test.
    % Meta-train phase:
 1 Randomly initialize \theta;
 2 for all meta iterations do
        Sample a batch of meta-train episodes \{\mathcal{T}_i\} \in p_{tr}(\mathcal{T});
 3
 4
         for \mathcal{T}_i in \{\mathcal{T}_i\} do
             Train the sequence of base-learners on \mathcal{T}_i by Algorithm 2;
 \mathbf{5}
 6
         end
         Evaluate \mathcal{L}^{(te)} with Eq. (13);
  7
         Optimize \Psi_{\alpha}, and \Psi_{\nu} with Eq. (14) using \beta_1 and \beta_2;
 8
        Optimize other meta components, e.g., \theta.
 9
10 end
    % Meta-test phase:
11 Sample meta-test episodes \{\mathcal{T}_i\} \in p_{te}(\mathcal{T});
12 for \mathcal{T}_i in \{\mathcal{T}_i\} do
        Train the sequence of base-learners on \mathcal{T}_i and obtain the prediction scores
13
          \hat{y}^{(te)} by Algorithm 2;
         Compute episode test accuracy Acc_i;
14
15 end
16 Return the average accuracy of \{Acc_i\}.
```

## **B** Results with confidence intervals

In Table S1, we supplement the few-shot classification accuracy (%) on miniImageNet, tieredImageNet, and FC100 (5-class) with confidence intervals.

Algorithm 2: Learning the ensemble of base-learners in one episode

**Input:** An episode  $\mathcal{T}$ , hyperprior learners  $\Psi_{\alpha}$  and  $\Psi_{v}$ . **Output:** Prediction  $\hat{y}^{(te)}$ , and episode test loss  $\mathcal{L}^{(te)}$ . 1 Initialize  $\Theta_0 = \theta$ ; **2** for m in  $\{1, ..., M\}$  do Evaluate  $\mathcal{L}_m^{(tr)}$  with Eq. (7) and compute  $\nabla_{\Theta} \mathcal{L}_m^{(tr)}$ ; 3 Get  $\alpha_m$  from  $\Psi_{\alpha}$  and get  $v_m$  from  $\Psi_v$ ;  $\mathbf{4}$ Get  $\Theta_m$  using  $\alpha_m$  with Eq. (6);  $\mathbf{5}$ Compute  $z_m$  with Eq. (8); 6 if m = 1 then 7 Initialize  $\hat{y}_1^{(te)} = v_1 z_1;$ 8 else 9 Compute  $\hat{y}_m^{(te)}$  using  $v_m$  with Eq. (9); 10 end 11 12 end **13** Evaluate  $\mathcal{L}^{(te)}$  with Eq. (13).

Mathada	Backbone	miniImageNet		tieredImageNet		FC100	
methods		1-shot	5-shot	1-shot	5-shot	1-shot	5-shot
MAML+E <sup>3</sup> BM	4CONV	$53.2 \pm 1.8$	$65.1~\pm~0.9$	$52.1 \pm 1.8$	$70.2~\pm~0.9$	$39.9~\pm~1.8$	$52.6~\pm~0.9$
$MTL+E^{3}BM$	$\operatorname{ResNet-12}$	$63.8 \pm 0.4$	$80.1~\pm~0.3$	$71.2~\pm~0.4$	$85.3~\pm~0.3$	$43.2~\pm~0.3$	$60.2~\pm~0.3$
$MTL+E^{3}BM$	$\operatorname{ResNet-25}$	$64.3 \pm 0.4$	$81.0~\pm~0.3$	$70.0~\pm~0.4$	$85.0~\pm~0.3$	$45.0~\pm~0.4$	$60.5~\pm~0.3$
SIB+E <sup>3</sup> BM	WRN-28-10	$71.4 \pm 0.5$	$81.2~\pm~0.4$	$75.6~\pm~0.6$	$84.3~\pm~0.4$	$46.0~\pm~0.6$	$57.1~\pm~0.4$

**Table S1.** Supplementary to Table 1. Few-shot classification accuracy (%) on *mini*ImageNet, *tiered*ImageNet, and FC100 (5-class).

## C Supplementary figures

Supplementary to Fig. 4(a)(b). In Fig. S1, we supplement the meta-validation accuracies for the 1-shot and 5-shot cases on *mini*ImageNet, *tiered*ImageNet, and FC100 (Note that Fig. 4 already has the *mini*ImageNet 1-shot results).

Supplementary to Fig. 4(c)(d). On the miniImageNet, we supplement the plots of  $\alpha$  and v in the 5-shot case in Fig. S2(a)(b). On the *tiered*ImageNet, we show the plots of  $\alpha$  and v in Fig. S2(c)(d) and (e)(f), respectively for 1-shot and 5-shot cases. On the FC100, we show the plots of  $\alpha$  and v in Fig. S2(g)(h) and (i)(j), respectively for 1-shot and 5-shot cases. Each figure demonstrates the values of  $\alpha$  (or v) generated by the model "MTL+E<sup>3</sup>BM" as in Table 1.

#### **D** Backbone architectures

**4CONV** consists of 4 layers with  $3 \times 3$  convolutions and 32 filters, followed by batch normalization (BN), a ReLU nonlinearity, and  $2 \times 2$  max-pooling.

**ResNet-12** has 3 residual blocks. Each block has 4 convolution layers with  $3 \times 3$  kernels. The number of filters starts from 160 and is doubled every next block. After a global average pooling layer, it gets a 640-dim embedding. This architecture follows [37].

**ResNet-25** has 3 residual blocks after an initial convolution layer. Each block has 8 convolution layers with  $3 \times 3$  kernels. The number of filters starts from 160 and is doubled every next block. After a global average pooling layer, it gets a 640-dim embedding. This architecture follows [78].

**WRN-28-10** has its depth and width set to 28 and 10, respectively. After a global average pooling in the last layer of the backbone, it gets a 640-dimensional embedding. For this backbone, we resize the input image to  $80 \times 80 \times 3$  for a fair comparison with related methods [25,70]. Other details are the same as those with ResNet-25 [61,78].

### **E** Implementation details

**MTL+E**<sup>3</sup>**BM.** The meta learning rates for the scaling and shifting weights  $\Phi_{SS}$  and the base-learner initializer  $\theta$  are set to  $1 \times 10^{-4}$  uniformly. The base learning rates  $\{\alpha'_m\}_{m=1}^M$  (Fig. 3) are initialized as  $1 \times 10^{-2}$  [70,78]. We meta-train MTL+E<sup>3</sup>BM for 10,000 iterations and use the model, which has the highest meta-validation accuracy, for meta-test.

**SIB+E<sup>3</sup>BM.** The meta learning rates for both SIB network  $\phi(\lambda, \xi)$  and baselearner initializer  $\theta$  are set to  $1 \times 10^{-3}$  uniformly. The base learning rates  $\{\alpha'_m\}_{m=1}^M$  (Fig. 3) are initialized as  $1 \times 10^{-3}$  [25]. We meta-train SIB+E<sup>3</sup>BM for 50,000 iterations and use the model, which has the highest meta-validation accuracy, for meta-test.

**MAML+E<sup>3</sup>BM.** MAML only contains a model initializer  $\theta$ , and we set its meta-learning rate as  $1 \times 10^{-3}$  [13]. The base learning rates  $\{\alpha'_m\}_{m=1}^M$  (Fig. 3) are initialized as  $1 \times 10^{-3}$ . We meta-train MAML+E<sup>3</sup>BM for 60,000 iterations and use the model, which has the highest meta-validation accuracy, for meta-test.

Shared hyperparameters. The meta learning rates for  $\Psi_{\alpha}$  and  $\Psi_{v}$  are set to  $1 \times 10^{-6}$  uniformly. For initializing  $\{v'_{m}\}_{m=1}^{M}$  (Fig. 3), we have two options. One is each  $v'_{m}$  is initialized as 1/(number of base-learners), and the other one is that  $\{v'_{m}\}_{m=1}^{M-1}$  are initialized as 0 and  $v'_{M}$  as 1. In Eq. (12) in Sec. 4.3,  $\lambda_{1}$  and  $\lambda_{2}$  are set to  $1 \times 10^{-4}$ . For the rest of the hyperparameters, we follow the original settings of baselines [13, 25, 70].

**Constraints for** v and  $\alpha$ . In the constraint mode, we applied the constraints on v and  $\alpha$  to force them to be positive and smaller than 1. We did not have any constraint for  $\Delta v$  or  $\Delta \alpha$ . Please note that the constraints are not applied in the default setting.

**Dataloader** For MAML, we use the same dataloader as [13]. For MTL, we follow [78, 81, 82]. For SIB, we follow [25].

## F Ablation results for MAML

In Table S2, we supplement the ablation results for "MAML+ $E^3BM$ " on *mini*ImageNet, *tiered*ImageNet, and FC100 (5-class).

Ne	Setting			miniImageNet		tieredImageNet		FC100	
100.	Method	Hyperprior	Learning	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot
1	MAML [13]	_	Ind.	48.70	63.11	49.0	66.5	38.1	50.4
2	5x MAML	_	Ind.	52.1	65.1	51.1	68.8	40.1	50.8
3	MAML+E <sup>3</sup> BM	$\mathbf{FC}$	Ind.	52.1	65.1	51.1	68.8	39.5	51.7
4	MAML+E <sup>3</sup> BM	$\mathbf{FC}$	Tra.	52.8	65.3	52.2	69.5	40.4	51.8
5	MAML+E <sup>3</sup> BM	LSTM	Ind.	53.2	65.0	52.1	70.2	39.9	52.6
6	MAML+E <sup>3</sup> BM	LSTM	Tra.	53.8	65.2	52.7	70.5	40.4	52.3

**Table S2.** Supplementary to Table 2. Results (%) for different hyperprior learners on *mini*ImageNet, *tiered*ImageNet, and FC100 (5-class). "Ind." and "Tra." denote inductive and transductive settings, respectively.

## G The inference time and the number of parameters

In Table S3, we supplement the the inference time and the number of parameters of baselines (100 epochs, *mini*ImageNet, 5-way 1-shot, on NVIDIA V100 GPU)

No.	Method	Backbone	# Param	Time (min)
1	MTL	ResNet-25	4,321k	73.3
2	$MTL+E^{3}BM$ (ours)	$\operatorname{ResNet-25}$	4,351k	77.6
3	SIB	WRN-28-10	36,475k	325.0
4	$SIB+E^{3}BM$ (ours)	WRN-28-10	36,490k	331.8
5	ProtoNets	$\operatorname{ResNet-12}$	12,424k	35.2
6	MatchNets	$\operatorname{ResNet-12}$	12,424k	37.3
7	ProtoNets	ResNet-25	36,579k	70.5
7	ProtoNets	WRN-28-10	36,482k	350.1

**Table S3.** Supplementary to Table 1. The inference time and the number of parameters of baselines (100 epochs, *mini*ImageNet, 5-way 1-shot, on NVIDIA V100 GPU).

# H Executing the source code with PyTorch

We provide our PyTorch code at https://gitlab.mpi-klsb.mpg.de/yaoyaoliu/e3bm. To run this repository, we kindly advise you to install python 3.6 and PyTorch An Ensemble of Epoch-wise Empirical Bayes for Few-shot Learning

1.2.0 with Anaconda. You may download Anaconda and read the installation instruction on the official website (https://www.anaconda.com/download/). Create a new environment and install PyTorch and torchvision on it:

```
1 conda create --name e3bm-pytorch python=3.6
2 conda activate e3bm-pytorch
3 conda install pytorch=1.2.0
4 conda install torchvision -c pytorch
```

Install other requirements:

```
pip install -r requirements.txt
```

Run meta-training with default settings (data and pre-trained model will be downloaded automatically):

```
python main.py -backbone resnet12 -shot 1 -way 5 -mode
meta_train -dataset miniimagenet
python main.py -backbone resnet12 -shot 5 -way 5 -mode
meta_train -dataset miniimagenet
python main.py -backbone resnet12 -shot 1 -way 5 -mode
meta_train -dataset tieredimagenet
python main.py -backbone resnet12 -shot 5 -way 5 -mode
meta_train -dataset tieredimagenet
```

Run pre-training with default settings:

```
python main.py -backbone resnet12 -mode pre_train -dataset
miniimagenet
python main.py -backbone resnet12 -mode pre_train -dataset
tieredimagenet
```



**Fig. S1.** Supplementary to Fig. 4(a)(b). The meta-validation accuracies of ablation models. Each figure demonstrates the results using the same model "MTL+E<sup>3</sup>BM" as in Table 1. All curves are smoothed with a rate of 0.9 for a better visualization.



Fig. S2. Supplementary to Fig. 4(c)(d). The values of  $\alpha$  and v generated by  $\Psi_{\alpha}$  and  $\Psi_{v}$ , respectively. Each figure demonstrates the results using the same model "MTL+E<sup>3</sup>BM" as in Table 1.