Revisiting the Updates of a Pre-trained Model for Few-shot Learning

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Abstract
Most of the recent few-shot learning algorithms are based on transfer learning, where a model is pre-trained using a large amount of source data, and the pre-trained model is updated using a small amount of target data afterward. In transfer-based few-shot learning, sophisticated pre-training methods have been widely studied for universal and improved representation. However, there is little study on updating pre-trained models for few-shot learning. In this paper, we compare the two popular updating methods, fine-tuning (i.e., updating the entire network) and linear probing (i.e., updating only the linear classifier), considering the distribution shift between the source and target data. We find that fine-tuning is better than linear probing as the number of samples increases, regardless of distribution shift. Next, we investigate the effectiveness and ineffectiveness of data augmentation when pre-trained models are fine-tuned. Our fundamental analyses demonstrate that careful considerations of the details about updating pre-trained models are required for better few-shot performance.

1. Introduction
To tackle the issue of expensive labeling processes, few-shot learning (FSL) paradigm was proposed (Fink, 2004; Fei-Fei et al., 2006). FSL aims to recognize novel classes using few samples in the target data. Novel classes are disjoint from base classes in the source data but similar to base classes. However, in real-world scenarios, it is hard to obtain labeled target data from certain domains such as X-ray images, which inevitably leads to using dissimilar labeled source data for pre-training (Guo et al., 2020; Oh et al., 2022). Cross-domain few-shot learning (CD-FSL) has recently been studied to address this practicality, which is more challenging than traditional FSL due to the distributional gap between the source and target data.

There are two main approaches for (CD-)FSL: meta-learning and transfer learning. Meta-learning approaches optimize a generalized model that adapts to new tasks quickly (Koch et al., 2015; Vinyals et al., 2016; Snell et al., 2017; Finn et al., 2017). In contrast, transfer learning approaches aim to transfer knowledge from general source tasks to few-shot target tasks, based on the capacity of deep networks (Chen et al., 2019; Dhillon et al., 2019; Wang et al., 2019). Recently, Guo et al. (2020) proposed a new benchmark for CD-FSL, Broader Study of CD-FSL (BSCD-FSL), and showed that transfer learning approaches outshine meta-learning ones. Based on these observations, CD-FSL algorithms have focused on the pre-training phase to extract improved and universal representation by exploiting unlabeled target data under a transfer learning framework (Phoo & Hariharan, 2020; Islam et al., 2021).

However, despite the recent attention in (CD-)FSL (Phoo & Hariharan, 2020; Liang et al., 2021; Hu et al., 2022), most of the prior works follow a conventional updating strategy, which updates a new classifier using few samples without data augmentation. Only few studies have addressed how to update a pre-trained model for FSL. For instance, Guo et al. (2020) provided few-shot performance according to the updating parts, but they did not include extreme few-shot cases. Ni et al. (2021) highlighted that flipping on few target samples could improve the performance, but they did not consider augmentation methods other than flipping and cropping.

In this paper, we focus on how to maximally leverage a pre-trained model with few target samples. Therefore, we pose two fundamental questions: under (CD-)FSL, (1) between fine-tuning (i.e., updating the entire network, FT) and linear probing (i.e., updating only the linear classifier, LP), which is better and why? (2) can data augmentation techniques overcome the challenge of target data shortage?

Our answers are as follows: (1) FT is a better strategy than LP as the number of samples increases, and the trend is reversed because FT with extremely few samples can distort representation. (2) Most of the existing augmentation techniques decrease the few-shot performance.
2. Preliminaries

2.1. Problem Setup

We explain the training (pre-training and updating) and evaluation procedure of transfer learning approaches. Formally, a model \( h_1 \circ f \) is trained on labeled source data \( \mathcal{D}_S \) in the pre-training phase, where \( f \) is a feature extractor (i.e., backbone) and \( h_1 \) is a linear classifier for pre-training. The pre-trained classifier \( h_1 \) is then replaced with a randomly initialized linear classifier \( h_2 \) to recognize novel classes \( \mathcal{C}_N \). Finally, (1) \( h_2 \circ f \) is updated (i.e., fine-tuning) or (2) only \( h_2 \) is updated (i.e., linear probing) on few labeled target data \( \mathcal{D}_T \) and evaluated on \( \mathcal{D}_Q \).

Here, \( (\mathcal{D}_S, \mathcal{D}_Q) \) is sampled from labeled target data \( \mathcal{D}_N \) in an episodic way. Namely, \( n \) classes are sampled from novel classes \( \mathcal{C}_N \), while \( k \) and \( k_q \) examples per class are sampled to form \( \mathcal{D}_S \) and \( \mathcal{D}_Q \), respectively. Thus, \( \mathcal{D}_S \) and \( \mathcal{D}_Q \) are defined as \( \{(x_i^s, y_i^s)\}_{i=1}^{n \times k} \) and \( \{(x_i^q, y_i^q)\}_{i=1}^{n \times k_q} \) and each is called a support set and a query set. This problem setting is referred to as the \( n \)-way \( k \)-shot classification problem, where \( n = 5 \) and \( k \in \{1, 5, 20\} \) in general. The reported few-shot performance is averaged over 600 episodes.

We pre-train ResNet10 on miniImageNet (miniIN) and ResNet18 on tieredImageNet (tieredIN), and then update them on ten target datasets: miniIN, tieredIN, four non-BSCD-FSL (Places, Plantae, Cars, and CUB), and four BSCD-FSL (CropDiseases, EuroSAT, ISIC, and ChestX). We follow the detailed setup of datasets and implementations from prior works (Guo et al., 2020; Oh et al., 2022), which is described in Appendix A.

2.2. Data Augmentation Techniques

For our study, we exploit the two types of data augmentation techniques: basic image manipulation and data-mixing. The former includes horizontal flipping, random cropping, and color jittering, and the latter includes MixUp (Zhang et al., 2017) and CutMix (Yun et al., 2019). The details of augmentation methods are explained in Appendix B.

3. Fine-tuning vs. Linear Probing for CD-FSL

We compare popular updating methods, FT and LP, under different distributional gaps. Figure 1 describes the performance difference of FT and LP (i.e., \( \text{Acc}_{\text{FT}} - \text{Acc}_{\text{LP}} \)) on various target datasets, according to the number of samples for updating a pre-trained model. Note that non-BSCD-FSL datasets are more similar to the source data than BSCD-FSL datasets (Ericsson et al., 2021). It is observed that shot is a more critical factor than distributional difference to decide how to update the pre-trained model. In line with the observation that FT is a better strategy than LP (Kornblith et al., 2019; Zhai et al., 2019; Kumar et al., 2022), our results support that it even holds for few-shot. The results of ResNet18 pre-trained on tieredIN show the same trend, which is reported in Appendix C.

However, LP is better than FT when there is only one sample for each class (i.e., 1-shot) in most target datasets. This is because FT with extremely few samples can distort the representation of a query set for evaluation, weakening the extractor’s clustering ability. To understand the effectiveness of FT for learning representation, we analyze the V-measure cluster score (Rosenberg & Hirschberg, 2007) before and after FT. Figure 2 describes the relationship between changes in performance and V-measure over 600 episodes. Each dot indicates a query set of an episode, and the x-axis and y-axis indicate the V-measure of the updated model through LP and FT, respectively. Note that LP keeps the same extractor of the pre-trained model, while FT updates the pre-trained extractor using few target data. The red color means FT outperforms LP, whereas the blue color means LP outperforms FT. V-measure is defined by 1) K-Means clustering on representations of a query set using a pre-trained extractor (i.e., LP) and an updated extractor (i.e., FT), then 2) calculating the agreement between the ground-truth and predicted K-Means clusters. The higher the V-measure score, the better the clustering ability of the feature extractor. Note that values of 0 and 1 indicate no agreement and maximum agreement, respectively.
Table 1. 5-way 20-shot performance according to data augmentation techniques. The pre-trained ResNet10 on miniIN is fine-tuned.

| Aug. | miniIN | tieredIN | CropDiseases | EuroSAT | ISIC | ChestX |
|------|--------|----------|--------------|---------|------|--------|
| -    | 87.38±1.41 | 84.40±1.58 | 81.88±1.53 | 69.35±1.71 | 71.10±1.65 |
| + HFlip | 87.55±1.41 | 84.61±1.57 | 82.20±1.53 | 70.21±1.73 | 73.42±1.65 |
| + RCrop | 84.70±1.46 | 82.98±1.58 | 81.39±1.54 | 70.84±1.72 | 69.96±1.63 |
| + CJitter | 87.14±1.43 | 84.66±1.58 | 82.09±1.55 | 69.52±1.74 | 71.12±1.66 |
| + Base aug. | 85.83±1.43 | 83.49±1.58 | 81.77±1.52 | 71.69±1.70 | 71.62±1.61 |
| + MixUp | 81.34±1.49 | 82.44±1.61 | 78.78±1.58 | 67.62±1.76 | 69.98±1.65 |
| + CutMix | 84.51±1.47 | 82.99±1.60 | 80.86±1.55 | 68.22±1.71 | 69.28±1.65 |

Figure 2a, 2b, and 2c describe 1-, 5-, and 20-shot cases on CUB, respectively. For the 1-shot case, most episodes are located below \( y = x \) (the gray region in Figure 2), which means that the V-measure decreases by FT. This implies updating a pre-trained extractor with one sample per class distorts the representation of a query set for clustering. In this context, most episodes have a color close to blue because LP’s performance is higher than FT’s performance. On the contrary, for the 5-shot case, most episodes are located above \( y = x \) (the white region in Figure 2) and have a color close to red. For the 20-shot case, the increase in V-measure and performance is more significant, implying that FT forms even better clusters than LP as the shot increases. Therefore, “FT is better than LP” holds even with few samples. Few samples can improve the clustering ability of a pre-trained extractor, and this improvement has a greater effect with more samples. The results on other datasets are depicted in Appendix D.

4. Data Augmentation for CD-FSL

Based on the observations in Section 3, we conclude that FT with few samples (e.g., 20-shot on most datasets) could improve few-shot performance. To generate more samples, we can use data augmentation, which is known to prevent overfitting caused by the lack of variations of data (Perez & Wang, 2017). In this section, we study data augmentation techniques for CD-FSL during fine-tuning. 1

4.1. FT with Data Augmentation

Although data augmentation generally leads to performance improvement, no significant performance gain occurs overall, and it rather has a negative effect under (CD-)FSL. Table 1 describes 5-way 20-shot performance of FT with data augmentation, including basic image manipulations and data-augmentation techniques. The pre-trained ResNet10 on miniIN is fine-tuned. 1

1The result of LP with data augmentation is reported in Appendix G.
4.3. Scheduling Data Augmentation

Furthermore, we investigate whether scheduling data augmentation affects few-shot performance because a fine-tuned model with data augmentation distorts the representation of a query set. In other words, a model is fine-tuned with an augmented support set $D_S$, however, evaluated on a clean (i.e., non-augmented) query set $D_Q$, in our MixUp experiments. This support-query distribution shift can potentially decrease performance.

To alleviate this problem, we propose an augmentation scheduler that applies data augmentation to a certain range of epochs. Table 3 shows the few-shot performance according to the augmentation scheduler with MixUp augmentation during FT. In the original setting, a pre-trained model is updated for 100 epochs. It is observed that an augmentation scheduler without augmentation at later epochs (i.e., 1-70 and 31-70 in Table 3) outperforms an augmentation scheduler including augmentation at later epochs (i.e., 1-100 and 31-100 in Table 3). This demonstrates the significance of learning non-augmented data before evaluating on a query set to remedy support-query distribution shift. Therefore, we conclude that for FSL, both methods and scheduling of data augmentation cannot be easily applied based on general rules.

5. Related Works

Additional related works about few-shot learning and data augmentations are provided in Appendix H.

## Fine-tuning vs. Linear Probing

Most of the works on updating pre-trained models have been mainly studied for language tasks (Dodge et al., 2020; Zhao et al., 2021; Zhou & Srikumar, 2021). In general computer vision settings, transfer learning and updating methods gained much attention (Zhai et al., 2019; Kornblith et al., 2019; Ericsson et al., 2021; Kumar et al., 2022). Kornblith et al. (2019) show that FT outperforms both updating a classifier (i.e., LP) and training from scratch, by investigation on many-shot target datasets using different backbone models. Meanwhile, Kumar et al. (2022) demonstrate that FT can distort pre-trained representation on out-of-distribution (OOD) tasks, where datasets for updating and evaluation are different. They further show that LP $\rightarrow$ FT updates can remedy this distortion.

## Data Augmentation in FSL

Many studies have been conducted to remedy the lack of target samples by data generation (Yang et al., 2021; Kumar & Zaidi, 2022) or augmentation (Mangla et al., 2020; Ni et al., 2021). Generation-based algorithms sample target representation from the calibrated target distribution based on source distribution. S2M2 (Mangla et al., 2020) utilizes Manifold MixUp loss (Verma et al., 2019) that works as a feature-level augmentation in pre-training. Ni et al. (2021) analyze the effectiveness of data augmentation in the meta-learning pipeline and propose Meta-MixUp for pre-training. However, for few samples augmentation (“shot augmentation” in their paper), only RCrop and HFlip are considered. Unlike prior works, we investigate the efficacy of various data augmentation for few samples, considering the distribution shift challenge.
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A. Setup Details

A.1. Dataset Details

We employ two source datasets and ten target datasets (including two source datasets) for cross-domain scenario, following the same dataset setting with Oh et al. (2022).

- We use miniImageNet (Vinyals et al., 2016) and tieredImageNet (Ren et al., 2018) as source datasets which are disjoint portions of ImageNet-1k (Deng et al., 2009). MiniImageNet includes 64 classes for source data for pre-training and 20 classes for target data for updating. Likewise, tieredImageNet has 351 classes and 160 classes for source and target data, respectively. Cases when a model is pre-trained and updated by one of these datasets (e.g., tieredIN→miniIN), are regarded as a single-domain scenario, where there is no domain shift between source and target data.

- We use BSCD-FSL (Guo et al., 2020) and non-BSCD-FSL datasets as target data. BSCD-FSL benchmark proposed by Guo et al. (2020) includes CropDiseases, EuroSAT, ISIC, and ChestX (arranged in the order of similarity to source domain). CropDiseases (Mohanty et al., 2016) is a plant disease dataset and EuroSAT (Helber et al., 2019) is a satellite image dataset. In addition, ISIC (Codella et al., 2019) and ChestX (Wang et al., 2017) each include images of skin lesion and X-ray. Similarly, non-BSCD-FSL includes Places (Zhou et al., 2017), Plantae (Van Horn et al., 2018), Cars (Krause et al., 2013) and CUB (Wah et al., 2011) as target data. Each dataset contains images of different scene categories, plant species, car models and bird species, respectively.

A.2. Implementation Details

We utilize the pre-training and updating setup from Guo et al. (2020). For pre-training, we utilize SGD optimizer with learning rate 0.01, momentum 0.9, and weight decay 0.0001. For ResNet10 pre-trained on miniIN, we train for 1000 epochs with batch size 64. For ResNet18 pre-trained on tieredIN, we train for 90 epochs with batch size 256.

For updating, we use SGD optimizer with learning rate 0.01, momentum 0.9, and weight decay 0.001. Over 600 episodes, linear classifier alone (i.e., LP) or together with pre-trained extractor (i.e., FT) is updated for 100 epochs with batch size 4. We use $k$-shot settings where $k \in \{1, 5, 20\}$, and for 20-shot setting, batch size 16 is particularly used to match the number of iterations.

B. Data Augmentation

We consider five commonly used data augmentation methods.

- Random Horizontal Flip (HFlip) flips an image horizontally with probability of 0.5.
- Random Resized Crop (RCrop) crops an image with a random ratio, and resize it to $224 \times 224$.
- Color Jitter (CJitter) changes properties of an image including brightness, contrast, saturation and hue with probability of 1.0.
- MixUp (Zhang et al., 2017) linearly interpolates each pixel of two images with a ratio of $\lambda \sim \beta(1, 1)$, which is sampled every epoch. The labels are mixed correspondingly.
- CutMix (Yun et al., 2019) crops one image with a ratio of $\lambda \sim \beta(1, 1)$, and pastes the cropped image onto the other image. $\lambda$ is sampled every epoch, and the labels are mixed with the ratio of areas between the cropped image and the original image.

Note that Base augmentation method (Base aug.) applies Hflip, RCrop, and CJitter simultaneously.
C. Detailed Results of FT and LP

To provide detailed results on Section 3, we provide the performance of FT and LP according to target dataset and the number of shots. Table 4 and Table 5 show the performance of FT and LP using miniImageNet and tieredImageNet for pre-training, respectively. The better performance values between LP and FT are boldfaced. The results are also visualized in Figure 4, performance difference of FT and LP (i.e., \( \text{Acc}_{\text{FT}} - \text{Acc}_{\text{LP}} \)) with ResNet18 pre-trained on tieredIN. As explained in Section 3, FT becomes better than LP as shot increases in most cases. Even in some cases where LP outperforms FT for all \( k \in \{1, 5, 20\} \), the gap between accuracy of LP and FT decreases as shot increases.

![Figure 4. Performance difference of FT with LP on target datasets according to the shot \( k \). ResNet18 is pre-trained on tieredIN.](image)

| \( k \) | Update | miniIN | tieredIN | Places | Plantae | Cars | CUB | CropDiseases | EuroSAT | ISIC | ChestX |
|-------|--------|--------|----------|--------|---------|------|-----|--------------|-------|------|--------|
| 1     | LP     | 56.47± 0.80 | 55.89± 0.96 | 52.23± 0.80 | 36.87± 0.67 | 29.11± 0.54 | 40.42± 0.76 | 73.12± 0.88 | 64.72± 0.88 | 29.39± 0.35 | 22.56± 0.40 |
|       | FT     | 49.57± 0.79 | 49.10± 0.90 | 45.44± 0.79 | 33.35± 0.59 | 29.49± 0.54 | 37.54± 0.71 | 66.78± 0.91 | 56.45± 0.84 | 31.03± 0.55 | 22.35± 0.38 |
| 5     | LP     | 77.95± 0.61 | 74.79± 0.76 | 73.01± 0.67 | 53.85± 0.74 | 44.64± 0.67 | 57.51± 0.79 | 91.50± 0.49 | 84.08± 0.60 | 40.39± 0.55 | 26.56± 0.43 |
|       | FT     | 75.67± 0.65 | 73.60± 0.78 | 70.05± 0.71 | 53.19± 0.73 | 49.26± 0.70 | 59.35± 0.80 | 92.14± 0.49 | 82.58± 0.60 | 48.35± 0.62 | 26.30± 0.24 |
| 20    | LP     | 86.64± 0.43 | 83.27± 0.60 | 81.90± 0.52 | 66.65± 0.72 | 60.98± 0.67 | 71.00± 0.71 | 96.20± 0.29 | 91.17± 0.39 | 50.89± 0.54 | 31.16± 0.44 |
|       | FT     | 87.38± 0.41 | 84.40± 0.58 | 81.88± 0.53 | 69.35± 0.71 | 71.10± 0.65 | 76.08± 0.69 | 97.89± 0.22 | 92.88± 0.35 | 62.98± 0.60 | 32.98± 0.46 |

Table 4. 5-way \( k \)-shot performance according to target dataset. The backbone is ResNet10 pre-trained on miniIN.

| \( k \) | Update | miniIN | tieredIN | Places | Plantae | Cars | CUB | CropDiseases | EuroSAT | ISIC | ChestX |
|-------|--------|--------|----------|--------|---------|------|-----|--------------|-------|------|--------|
| 1     | LP     | 63.37± 0.80 | 61.03± 0.93 | 52.10± 0.87 | 38.51± 0.74 | 31.25± 0.61 | 58.00± 0.94 | 66.24± 0.90 | 61.91± 0.88 | 30.38± 0.58 | 22.29± 0.39 |
|       | FT     | 53.54± 0.82 | 52.76± 0.88 | 43.66± 0.76 | 33.06± 0.63 | 30.64± 0.59 | 48.12± 0.80 | 63.60± 0.84 | 53.25± 0.82 | 31.28± 0.59 | 22.08± 0.39 |
| 5     | LP     | 82.92± 0.52 | 78.97± 0.69 | 72.41± 0.69 | 55.08± 0.82 | 45.76± 0.67 | 76.91± 0.79 | 86.82± 0.59 | 79.72± 0.68 | 41.58± 0.54 | 24.96± 0.44 |
|       | FT     | 79.83± 0.54 | 76.98± 0.70 | 68.43± 0.74 | 52.50± 0.80 | 47.58± 0.67 | 73.50± 0.79 | 89.68± 0.53 | 79.09± 0.63 | 48.08± 0.64 | 25.58± 0.44 |
| 20    | LP     | 89.31± 0.36 | 85.64± 0.56 | 81.00± 0.53 | 65.46± 0.77 | 59.11± 0.67 | 85.10± 0.59 | 92.77± 0.40 | 86.50± 0.49 | 49.98± 0.51 | 28.62± 0.40 |
|       | FT     | 88.92± 0.38 | 85.85± 0.55 | 79.71± 0.57 | 66.08± 0.79 | 63.04± 0.70 | 84.11± 0.62 | 96.45± 0.28 | 90.24± 0.42 | 60.78± 0.60 | 30.26± 0.45 |
D. V-measurement Cluster Score on Other Datasets

We provide extended results of Figure 2 on both BSCD-FSL and non-BSCD-FSL datasets. In Figure 5 and 6, the results are based on ResNet10 pre-trained on miniImageNet and ResNet18 pre-trained on tieredImageNet, respectively. The trend of the results as shot increases is the same for all target datasets; more red dots are placed above the $y = x$ line. This shows that clustering ability of the feature extractor improves by more samples for FT.

Figure 5. Feature extractor’s clustering ability by V-measure and performance difference between LP and FT. The pre-trained model is ResNet10 on miniIN.
Figure 6. Feature extractor’s clustering ability by V-measure and performance difference between LP and FT. The pre-trained model is ResNet18 on tieredIN.
E. Few-shot Performance according to Data Augmentation Techniques

We analyze performance according to data augmentation techniques in $k=1$ and $k=5$ setting, which is shown in Table 6 and Table 7. MixUp degrades the few-shot performance the most, and HFlip improves the performance, which is in line with the results on $k=20$ in Table 1.

Table 6. 5-way 1-shot performance according to data augmentation techniques. The pre-trained ResNet10 on miniIN is fine-tuned.

| Aug.       | miniIN     | tieredIN    | Places       | Plantae     | Cars        |
|------------|------------|-------------|--------------|-------------|-------------|
| -          | 49.57±.79  | 49.10±.90   | 45.44±.79    | 33.35±.59   | 29.49±.54   |
| + HFlip    | 49.75±.80  | 49.67±.91   | 45.82±.77    | 33.62±.62   | 29.88±.54   |
| + RCrop    | 51.08±.79  | 48.52±.89   | 45.82±.80    | 34.62±.62   | 29.99±.56   |
| + CJitter  | 49.29±.82  | 48.74±.87   | 45.60±.76    | 33.69±.63   | 29.39±.52   |
| + Base aug.| 52.02±.79  | 49.12±.89   | 46.75±.80    | 34.93±.62   | 30.38±.55   |
| + MixUp    | 46.50±.79  | 46.45±.88   | 42.11±.76    | 32.16±.59   | 28.53±.52   |
| + CutMix   | 49.00±.79  | 48.20±.87   | 44.78±.80    | 33.04±.57   | 28.81±.49   |

| Aug.       | CUB        | CropDiseases| EuroSAT      | ISIC         | ChestX      |
|------------|------------|-------------|--------------|--------------|-------------|
| -          | 37.54±.71  | 66.78±.91   | 56.45±.84    | 31.03±.55    | 22.35±.38   |
| + HFlip    | 37.62±.70  | 68.48±.91   | 58.37±.82    | 31.10±.57    | 22.30±.37   |
| + RCrop    | 38.62±.73  | 63.24±.95   | 55.52±.84    | 32.56±.56    | 21.91±.36   |
| + CJitter  | 37.68±.71  | 67.77±.90   | 56.86±.85    | 31.42±.53    | 22.38±.37   |
| + Base aug.| 39.06±.75  | 64.84±.93   | 56.40±.84    | 32.12±.59    | 22.06±.38   |
| + MixUp    | 35.72±.66  | 64.62±.93   | 50.12±.78    | 30.42±.55    | 22.16±.38   |
| + CutMix   | 36.68±.71  | 67.85±.92   | 59.23±.86    | 31.07±.56    | 22.12±.37   |

Table 7. 5-way 5-shot performance according to data augmentation techniques. The pre-trained ResNet10 on miniIN is fine-tuned.

| Aug.       | miniIN     | tieredIN    | Places       | Plantae     | Cars        |
|------------|------------|-------------|--------------|-------------|-------------|
| -          | 75.67±.65  | 73.60±.78   | 70.05±.71    | 53.19±.73   | 49.26±.70   |
| + HFlip    | 76.30±.63  | 74.06±.77   | 70.74±.68    | 54.00±.75   | 51.00±.72   |
| + RCrop    | 74.50±.64  | 71.37±.76   | 69.04±.69    | 55.24±.74   | 49.22±.68   |
| + CJitter  | 75.66±.64  | 73.68±.75   | 70.20±.71    | 53.56±.75   | 49.17±.71   |
| + Base aug.| 74.55±.65  | 72.16±.73   | 69.54±.70    | 55.90±.76   | 50.88±.70   |
| + MixUp    | 71.61±.67  | 70.50±.76   | 65.90±.74    | 51.64±.73   | 47.72±.68   |
| + CutMix   | 74.00±.67  | 72.19±.77   | 69.51±.70    | 52.71±.71   | 48.00±.70   |

| Aug.       | CUB        | CropDiseases| EuroSAT      | ISIC         | ChestX      |
|------------|------------|-------------|--------------|--------------|-------------|
| -          | 59.55±.80  | 92.14±.49   | 82.58±.60    | 48.35±.62    | 26.30±.24   |
| + HFlip    | 61.14±.80  | 93.02±.47   | 83.62±.59    | 49.79±.65    | 26.48±.40   |
| + RCrop    | 59.88±.76  | 91.11±.48   | 78.76±.63    | 47.90±.58    | 27.22±.44   |
| + CJitter  | 59.68±.81  | 92.41±.49   | 81.85±.60    | 47.94±.67    | 26.72±.41   |
| + Base aug.| 61.61±.76  | 90.69±.50   | 77.40±.63    | 46.96±.66    | 26.55±.42   |
| + MixUp    | 57.87±.78  | 90.54±.54   | 75.42±.68    | 47.92±.62    | 26.08±.41   |
| + CutMix   | 56.46±.78  | 92.01±.50   | 82.87±.58    | 45.63±.59    | 26.50±.44   |
F. V-measurement Cluster Score of with and without MixUp on Other Datasets

We analyze FT with and without MixUp by comparing V-measure of FT and LP on $k \in \{1, 5, 20\}$. The trend is the opposite of Section 3 and Appendix D. Even though the number of shots increases from $k=1$ to $k=20$, many dots indicating a change in V-measure of each episode are placed under $y = x$ line, and more of them are colored blue. This means that MixUp rather deteriorates the effectiveness of more shots, degrading the ability of the updated feature extractor by learning augmented images.

Figure 7. Feature extractor’s clustering ability by V-measure and performance difference between FT and FT(MixUp). The pre-trained model is ResNet10 on miniIN.
G. Performance of LP with Data Augmentation

We provide extended results on performance of LP with data augmentation. Table 8 shows how performance changes when different basic image manipulation methods are applied in LP. This experiment is conducted for \( k=1 \) and \( k=5 \) on BSCD-FSL datasets, using ResNet10 pre-trained on miniIN. Unlike the general wisdom that data augmentation improves performance, the performance of LP with data augmentation drops significantly. The result shows that basic image manipulation methods rather negatively affect the ability of the classifier, and this effect is larger in 1-shot setting, where the performance degrades more than 5-shot. This demonstrates that the linear classifier trained with fewer samples is more sensitive to image transformations.

Table 8. 5-way \( k \)-shot performance according to data augmentation techniques. The pre-trained ResNet10 on miniIN is updated.

| \( k \) | Aug. | miniIN | CropDiseases | EuroSAT | ISIC | ChestX |
|-------|------|--------|--------------|---------|------|--------|
|      |      |        |              |         |      |        |
| 1     | -    | 56.47±.80 | 73.12±.88   | 64.72±.88 | 29.39±.53 | 21.45±.31 |
|       | + HFlip | 48.06±.84 | 62.39±.96   | 56.03±.84 | 29.61±.51 | 21.78±.35 |
|       | + RCrop | 50.48±.81 | 59.08±.97   | 55.08±.86 | 30.56±.53 | 21.90±.30 |
|       | + CJitter | 56.10±.81 | 59.28±.94   | 64.87±.88 | 29.47±.56 | 22.85±.41 |
|       | + MixUp | 41.53±.78 | 58.46±1.10  | 58.39±.97 | 28.11±.52 | 22.16±.38 |
|       | + CutMix | 48.51±.76 | 67.96±.90   | 61.99±.89 | 28.92±.52 | 22.39±.39 |
| 5     | -    | 77.95±.61 | 91.50±.49   | 84.08±.60 | 40.39±.55 | 26.75±.43 |
|       | + HFlip | 74.89±.64 | 90.64±.52   | 82.09±.59 | 44.94±.60 | 25.94±.40 |
|       | + RCrop | 75.08±.63 | 87.55±.56   | 79.48±.61 | 44.55±.58 | 25.62±.41 |
|       | + CJitter | 76.45±.66 | 89.21±.56   | 59.70±.90 | 40.56±.56 | 26.89±.43 |
|       | + MixUp | 69.02±.72 | 87.30±.58   | 81.29±.65 | 39.08±.55 | 26.98±.42 |
|       | + CutMix | 73.83±.66 | 90.55±.51   | 83.68±.58 | 40.82±.56 | 26.11±.41 |

H. Additional Related Works

Few-Shot Learning (FSL) focuses on underlying problems of deep learning where there are few training samples available. There are two dominant approaches for FSL, meta-learning-based and transfer learning-based. To predict class, the former uses prior knowledge which is generalized across tasks, while the latter uses transferred knowledge learned from large source data. Meta-learning aims to design a generalized model that adapts to new tasks quickly, by learning a good initialization (Finn et al., 2017; Li et al., 2017; Lee & Choi, 2018; Rajeswaran et al., 2019; Oh et al., 2021), learning the metrics (Koch et al., 2015; Vinyals et al., 2016; Snell et al., 2017; Sun, et al., 2018), or learning generative models to augment few-shot data (Antoniou et al., 2017; Hariharan & Girshick, 2017). In contrast, transfer learning aims to transfer knowledge from source tasks to few-shot tasks. By the capacity of deep backbones learned on ImageNet (Deng et al., 2009), pre-trained knowledge is effectively transferred to different target datasets and target tasks (Luo et al., 2017; Azadi et al., 2018; Liu et al., 2018; Chen et al., 2019; Dhillon et al., 2019; Luo et al., 2021).

For more realistic FSL, cross-domain few-shot learning (CD-FSL), where there is a large distributional shift from source to target domain, has gained increased attention. Guo et al. (2020) provided CD-FSL benchmark and demonstrated that transfer-based models achieved higher performances than existing meta-learning approaches. Therefore, to address a distribution shift challenge, prior works have focused on transfer-learning based approaches by utilizing semi-supervised methods (Phoo & Hariharan, 2020; Islam et al., 2021) or unsupervised methods Luo et al. (2017); Phoo & Hariharan (2020); Das et al. (2021).

Data Augmentation (DA) is a general technique to prevent overfitting on training distribution and increase generalization performance (Simard et al., 2003; Krizhevsky et al., 2012). Basic image manipulation methods such as flipping, rotating, and cropping are the most generic and prevalent practice in computer vision tasks. Data-mixing methods include MixUp (Zhang et al., 2017), CutMix (Yun et al., 2019), and PuzzleMix (Kim et al., 2020), which mix two images while mixing corresponding class labels. In addition, there are deep learning approaches for data augmentation. These approaches include generating images which are similar (Mirza & Osindero, 2014), style-transferred (Gatys et al., 2016) and domain-transferred (Zhu et al., 2017). In our study, we focus on basic image manipulations and data-mixing methods because there is no sufficient data to train generative models during fine-tuning.
I. Discussions

In this section, we cover additional discussions on updating the model for few-shot learning.

I.1. Performance Variance between Episodes

The general evaluation method in few-shot learning averages accuracy of 600 episodes (i.e., \((D_S, D_Q)\) sampled in an episodic way). However, the performance difference between these episodes is substantial. For example, the performance of LP model updated by tieredIN varies from 18.67\% to 93.33\%.

In Figure 8, we visualize this variation according to target datasets and updating methods (i.e., FT or LP). Figure 8a, 8b and 8c describe 1, 5, and 20-shot cases using ResNet10 pre-trained on miniIN. The green and orange colors indicate performance through LP and FT, respectively. It is observed that the degrees of performance difference of LP and FT are similar, which means that performance difference does not come from updating methods.

We believe that this difference comes from many factors such as classifier initialization, data ordering for updating (similar to (Dodge et al., 2020)), and combinations of support and target sets. This will motivate the researchers about the accurate evaluation of few-shot models.

Figure 8. 5-way \(k\)-shot performance of LP and FT over 600 episodes according to different target dataset. The pre-trained ResNet10 on miniIN is used as the feature extractor.
I.2. Instability within an Episode

For transfer-based few-shot learning, the last updated model is used for evaluation without early stopping using the validation set. This is because it is difficult to construct the validation set due to scarcity of the training set (i.e., nk samples under n-way k-shot classification tasks).

Figure 9 describes the expected performance gain over 600 episodes according to the dataset. The expected performance gain is defined by the ratio between accuracy at the best epoch and accuracy at the last epoch, i.e., \( \frac{\text{Acc}_{\text{best}}}{\text{Acc}_{\text{last}}} \). Note that the value of 1 indicates that the updated model has the best performance at the last epoch. The expected performance gain is amplified when the sample size is smaller (i.e., \( k=1 \)) and when the similarity between the source and target data is smaller (i.e., ISIC and ChestX).

Figure 10 illustrates histogram of best epochs over 600 episodes, considering different shots and target datasets. The green- and the orange-colored histograms indicate the result by LP and FT, respectively. For LP, the best performance appears in the early- to mid-epochs, but for FT, the distribution of best epochs are generally skewed left or distributed uniformly. It seems that LP is prone to overfitting than FT.

\[ \text{Figure 9. } 5\text{-way } k\text{-shot expected performance gain } \left( \frac{\text{Acc}_{\text{best}}}{\text{Acc}_{\text{last}}} \right) \text{ over 600 episodes.} \]
Figure 10. Histogram of best epoch during updating over 600 episodes. ResNet10 is pre-trained on miniIN. Green and orange colors indicate LP and FT, respectively.
I.3. Layer Difference through FT

We analyze how layers of the model is updated by FT. For each layer, we evaluate layer difference, which is L1 distance between parameters of LP and FT divided by the number of elements of the parameters in a layer. Figure 11 illustrates the layer differences of each layer, which is averaged over 100 episodes. X-ticks are as follows in order: Stem[Conv.weight, BN.scale, BN.shift] - Stage1[Conv1.weight, BN1.scale, BN1.shift, Conv2.weight, BN2.scale, BN2.shift] - Stage2[Conv1.weight, BN1.scale, BN1.shift, Conv2.weight, BN2.scale, BN2.shift, ShortCutConv.weight, ShortCutBN.scale, ShortCutBN.shift] - Stage3[Conv1.weight, BN1.scale, BN1.shift, Conv2.weight, BN2.scale, BN2.shift, ShortCutConv.weight, ShortCutBN.scale, ShortCutBN.shift] - Stage4[Conv1.weight, BN1.scale, BN1.shift, Conv2.weight, BN2.scale, BN2.shift, ShortCutConv.weight, ShortCutBN.scale, ShortCutBN.shift] - Classifier[weight, bias]. Conv-related, BN-related, and Classifier-related are marked as circle, star, and triangle, respectively.

It is observed that layers change a lot in the order of Classifier-related, BN-related, and Conv-related. Because a classifier is randomly initialized before FT, it is reasonable that the change in a classifier is large. Surprisingly, BN-related layers change more than Conv-related layers when fine-tuning a pre-trained extractor, which demonstrates that batch normalization is an important factor for FT. This can be explained that the fine-tuned model utilizes pre-trained convolution layers, but considerably changes shift and scale of the distribution of intermediate features, which seems to be related to FWT (Tseng et al., 2020). Furthermore, the changes of original path is larger than those of shortcut path.

Figure 11. Layer difference through FT according to target dataset using ResNet10 pre-trained on miniIN.
I.4. Two-staged Updates

We provide the results of two-staged updates, following (Kumar et al., 2022). They showed that LP → FT improves the performance of OOD tasks. Table 9 describes few-shot performance of two-staged updates, FT → LP and LP → FT. Each stage is updated for 50 epochs. Unlike OOD tasks, two-staged updates do not improve the performance of FSL.

Table 9. 5-way \(k\)-shot performance of two-staged updates. The backbone is ResNet10 pre-trained on miniIN.

| \(k\) | Update | miniIN | tieredIN | Places | Plantae | Cars | CUB | CropDiseases | EuroSAT | ISIC | ChestX |
|------|--------|--------|----------|--------|---------|-----|-----|-------------|----------|-----|--------|
| 1   | LP     | 56.47±.80 | 55.89±.96 | 52.23±.80 | 36.87±.67 | 29.11±.54 | 40.42±.76 | 73.12±.88 | 64.72±.88 | 29.39±.35 | 22.56±.40 |
|     | FT     | 49.57±.79 | 49.10±.90 | 45.44±.79 | 33.35±.59 | 29.49±.54 | 37.54±.71 | 66.78±.91 | 56.45±.84 | 31.03±.55 | 22.35±.38 |
|     | FT→LP  | 48.05±.79 | 47.70±.87 | 44.15±.79 | 32.53±.60 | 28.65±.52 | 36.65±.70 | 64.50±.92 | 56.11±.80 | 30.66±.56 | 21.92±.35 |
|     | LP→FT  | 50.51±.80 | 50.24±.89 | 46.21±.79 | 33.30±.60 | 29.35±.51 | 37.57±.71 | 67.13±.91 | 56.60±.81 | 30.68±.55 | 22.28±.38 |
| 5   | LP     | 77.95±.61 | 74.79±.76 | 73.01±.67 | 53.85±.74 | 44.64±.67 | 57.51±.79 | 91.50±.49 | 84.08±.60 | 40.39±.55 | 26.56±.43 |
|     | FT     | 75.67±.65 | 73.60±.78 | 70.05±.71 | 53.19±.73 | 49.26±.70 | 59.35±.80 | 92.14±.49 | 82.58±.60 | 48.35±.62 | 26.30±.24 |
|     | FT→LP  | 75.27±.65 | 73.14±.76 | 69.98±.72 | 52.46±.74 | 48.16±.70 | 58.41±.81 | 91.62±.51 | 82.73±.58 | 47.68±.63 | 26.12±.42 |
|     | LP→FT  | 76.35±.62 | 74.46±.75 | 70.98±.69 | 53.24±.74 | 48.77±.70 | 59.14±.80 | 92.12±.49 | 82.71±.59 | 48.07±.62 | 26.67±.42 |
| 20  | LP     | 86.64±.43 | 83.27±.60 | 81.90±.52 | 66.65±.72 | 60.98±.67 | 71.00±.71 | 96.20±.29 | 91.17±.39 | 50.89±.54 | 31.16±.44 |
|     | FT     | 87.38±.41 | 84.40±.58 | 81.88±.53 | 69.35±.71 | 71.10±.65 | 76.08±.69 | 97.89±.22 | 92.88±.35 | 62.98±.60 | 32.98±.46 |
|     | FT→LP  | 86.87±.43 | 84.06±.59 | 81.82±.53 | 68.42±.73 | 68.86±.67 | 74.69±.68 | 97.46±.25 | 92.75±.36 | 60.00±.60 | 32.18±.43 |
|     | LP→FT  | 87.27±.43 | 84.61±.58 | 82.26±.53 | 68.95±.72 | 69.77±.65 | 75.66±.68 | 97.53±.24 | 92.92±.35 | 62.17±.60 | 32.60±.45 |