When applying transfer learning for medical image analysis, downstream tasks often have significant gaps with the pre-training tasks. Previous methods mainly focus on improving the transferabilities of the pre-trained models to bridge the gaps. In fact, model fine-tuning can also play a very important role in tackling this problem. A conventional fine-tuning method is updating all deep neural networks (DNNs) layers by a single learning rate (LR), which ignores the unique transferabilities of different layers. In this work, we explore the behaviors of different layers in the fine-tuning stage. More precisely, we first hypothesize that lower-level layers are more domain-specific while higher-level layers are more task-specific, which is verified by a simple bi-directional fine-tuning scheme. It is harder for the pre-trained specific layers to transfer to new tasks than general layers. On this basis, to make different layers better co-adapt to the downstream tasks according to their transferabilities, a meta-learning-based LR learner, namely MetaLR, is proposed to assign LRs for each layer automatically. Extensive experiments on various medical applications (i.e., POCUS, BUSI, Chest X-ray, and LiTS) well confirm our hypothesis and show the superior performance of the proposed methods to previous state-of-the-art fine-tuning methods.

Keywords Transfer learning · Meta-learning · Medical image analysis.
Figure 1: The domain-specificity hypothesis: low-level layers are domain-specific, so they are poorly transferable like high-level layers.

fine-tuning scheme that the downstream medical tasks could be well generalized with only fine-tuning the high-level layers. Besides, some approaches [10, 17] developed more efficient fine-tuning procedures with this idea, but little literature explored the behavior of low-level layers.

Different input patterns activate low-level filters of convolutional neural networks (CNNs) differently [22]. Where the strongest activation value appears highly depends on the visual patterns of the training set. For transfer learning between different data domains, the low-level filters pre-trained on the original dataset would give sub-optimal activations on images of the new domain, especially when the domain gaps are large (e.g., from RGB images to gray-scale medical images). So in the fine-tuning stage, low-level filters need significant updates to adapt to the new domain. This was verified by fine-tuning all layers with a single LR, where the first layers have the largest weight variations [18]. Hence, we hypothesize that: like the high-level layers of DNNs are task-specificity, the low-level layers of DNNs are domain-specific (see Fig. 1).

Based on this hypothesis, we suggest to fine-tune both domain-specific layers and task-specific layers to improve the performance. We call this method bi-directional layer-wise fine-tuning. It achieves significantly higher performance than layer-wise fine-tuning, but requires much more human labor to search for the best tuning layers. To solve this problem, we propose a meta-learning [9] based algorithm, namely Meta Learning Rate (MetaLR), to adaptively adjust LRs for each layer instead of simply fixing or updating them. This method treats the layer-wise LRs as the meta-knowledge. Larger LRs mean the corresponding layers are less transferable and need more updating. In the experiments, the patterns of learned LRs are U-shaped w.r.t. layers, i.e., some shallow and deep layers have high LRs, which verifies our hypothesis. Section 3.2 shows detailed validation of the hypothesis by various experiments. It is worth mentioning that the bi-directional fine-tuning scheme and MetaLR can reach 93.6% and 94.0% fine-tuning accuracy on the POCUS pneumonia detection dataset with pre-trained ResNet-18 [11], which is significantly higher than using the constant LR (91.6%) and the layer-wise fine-tuning (92.1%).

2 Method

This section presents the proposed bi-directional layer-wise fine-tuning and MetaLR approaches in detail. The former is a simple method to verify the hypothesis of domain-specificity. At the same time, the latter is designed to be more flexible and efficient to fine-tune deep neural networks on various downstream tasks.

2.1 Bi-directional Layer-wise Fine-tuning

In the context of fine-tuning both domain-specific and task-specific layers, we propose the bi-directional version of layer-wise fine-tuning [20]. Two hyperparameters $m$ and $n$ mean fixing from layer $m$ to layer $n$. For a DNN with depth $d$, $m \leq n$, $1 \leq n < d$ (the last layer decides the output classes for different tasks, so it is essential to be fine-tuned),
leading to the number of different settings $\sum_{d=1}^{d-1} d - n = \frac{d(d-1)}{2}$. Note that when the neural network is deep, the attempts needed to search for the best hyperparameters $m, n$ is laborious. A practical way to reduce the manual labor is to regard several adjacent layers of a DNN as a layer block and set $m, n$ w.r.t. blocks, but we still need a more efficient method to reduce the searching overhead.

2.2 Meta Learning Rate

We propose the MetaLR as a meta-learning-based method to find the proper LR for each layer according to their transferabilities. Bi-directional layer-wise fine-tuning is a special case of this method, where fixed layers constantly remain zero LRs. Inspired by the online approximation [15], we propose the online adaptation to update the LRs and model parameters efficiently.

**Problem Formulation.** Let $(x, y)$ denotes a sample-label pair, and $\{(x_i, y_i) : i = 1, ..., N\}$ be the training data. The validation dataset $\{(x_i^v, y_i^v) : i = 1, ..., M\}$ is assumed to be independent and identically distributed as the training dataset. Let $\hat{y} = \hat{\Phi}(x, \theta)$ be the prediction for sample $x$ from deep model $\Phi$ with parameters $\theta$. In standard training of DNNs, the aim is to minimize the expected risk for the training set: $\frac{1}{N} \sum_{i=1}^{N} L(\hat{y}_i, y_i)$ with fixed training hyperparameters, where $L(\hat{y}, y)$ is the loss function for the current task. The model generalization can be evaluated by the validation loss $\frac{1}{M} \sum_{i=1}^{M} L(\hat{y}_i^v, y_i^v)$. Based on the generalization, one can tune the hyperparameters of the training process to improve the model. The key idea of MetaLR is considering the layer-wise LRs as self-adaptive hyperparameters during the training and automatically adjust them to achieve better model generalization. We denote the LR and model parameters for the layer $j$ at the iteration $t$ as $\alpha_j^t$ and $\theta_j^t$. The LR scheduling scheme $\alpha = \{\alpha_j^t : j = 1, ..., d; t = 1, ..., T\}$ is what MetaLR wants to learn, affecting which local optimal $\theta^*(\alpha)$ the model parameters $\theta = \{\theta_j^t : j = 1, ..., d\}$ will converge to. The optimal parameters $\theta^*(\alpha)$ are given by optimization on the training data. At the same time, the best LR tuning scheme $\alpha^*$ can be optimized based on the feedback for $\theta^*(\alpha)$ from the validation loss. This problem can be formulated as the following bi-level optimization:

$$\min_{\alpha} \frac{1}{M} \sum_{i=1}^{M} L(\Phi(x_i^v, \theta^*(\alpha)), y_i^v),$$

$$s.t. \theta^*(\alpha) = \arg\min_{\theta} \frac{1}{N} \sum_{i=1}^{N} L(\Phi(x, \theta), y_i).$$

The goal of MetaLR is to use the validation set to optimize $\alpha$ through an automatic process rather than manual. The optimal scheme $\alpha^*$ can be found by a nested optimization [9], but too computationally expensive in practice. A faster and lightweight method is needed to make it more practical.

**Online Adaptation.** The motivation of the online adaptation is updating the model parameters $\theta^t$ and LRs $\{\alpha_j^t : j = 1, 2, ..., d\}$ within the same loop. We inspect the descent direction of parameters $\theta_j^t$ on the training loss surface first, and adjust the $\alpha_j^t$ based on the similarity between training and validation descent directions. Higher similarity means the LRs are encouraged to increase.

**Algorithm 1 Meta Learning Rate Algorithm**

**Input:**
Training data $D$, Validation data $D^v$, Initial model parameter $\{\theta_0^1, ..., \theta_0^d\}$, LRs $\{\alpha_0^1, ..., \alpha_0^d\}$, batch size $n$, max iteration $T$;

**Output:**
Final model parameter $\theta^T = \{\theta_1^T, ..., \theta_d^T\}$;

1: for $t = 0 : T - 1$ do
2:   $\{(x_i, y_i) : i = 1, ..., n\} \leftarrow \text{TrainDataLoader}(D, n)$;
3:   $\{(x_i^v, y_i^v) : i = 1, ..., n\} \leftarrow \text{ValidDataLoader}(D^v, n)$;
4:   Step forward for one step to get $\{\theta_1^t(\alpha_1^t), ..., \theta_d^t(\alpha_d^t)\}$ with eq. 2;
5:   Update $\{\alpha_1^t, ..., \alpha_d^t\}$ to become $\{\alpha_1^{t+1}, ..., \alpha_d^{t+1}\}$ with eq. 3;
6:   Update $\{\theta_1^t, ..., \theta_d^t\}$ to become $\{\theta_1^{t+1}, ..., \theta_d^{t+1}\}$ with eq. 4;
7: end for

The same as training the general neural networks, we adopt Stochastic Gradient Descent (SGD) as the optimizer to conduct the meta-learning. The whole training process is summarized in Algorithm 1. At the iteration $t$ of training,
Table 1: Pre-training data, approaches and target tasks.

| Source          | Pre-train Method | Target Object | Task Modality | Size     |
|-----------------|------------------|----------------|---------------|----------|
| US-4 [6]        | USCL [6]         | POCUS [5]      | Lung          | COVID-19 detection | US | 2116 images |
| ImageNet [8]    | supervised       | BUSI [1]       | Breast        | Tumor detection   | US | 780 images  |
| MIMIC-CXR [12]  | C2L [23]         | Chest X-ray [13] | Lung          | Pneumonia detection | X-ray | 5856 images |
| LIDC-IDRI [3]   | Models Genesis [24] | LiTS [4]     | Liver         | Liver segmentation | CT | 131 volumes |

3 Experiments and Analysis

3.1 Experimental Settings

We validate the domain-specific hypothesis and the performance of proposed training methods on four transfer learning tasks (Tab. 1). To ensure the reproducibility of the results, all pre-trained models (USCL [6], ImageNet [8], C2L [23], Models Genesis [24]) and target datasets (POCUS [5], BUSI [1], Chest X-ray [13], LiTS [4]) are public available. This work considers models pre-trained on natural and medical image datasets, three target modalities, and three target organs to make the experimental results more credible. Our fine-tuning tasks include classification and segmentation using ResNet-18 [11] and 3D U-Net [7], respectively. The experiments are implemented with PyTorch 1.8 on AMD EPYC 7742 64-Core Processors and an NVIDIA A100 GPU. Please refer to the supplementary material for more detailed information on the models, downstream tasks, and training settings.

3.2 Validation of the Hypothesis

The ResNet-18 with 9 convolutional blocks and a fully-connected classifier is used to visualize and validate the domain-specificity hypothesis.

Feature Visualization. We visualize the images and the feature maps given by the first convolutional layer of ImageNet pre-trained ResNet-18 on BUSI breast cancer detection task (Fig. 2), where the only difference between the two tuning schemes is whether the first layer is fixed. As shown in the second row, although the overall pattern can still be recognized, the feature maps are more blurry without tuning the first layer. Because malignant tumors tend to be with indistinct borders, the blurry features would mislead the DNN to classify samples from other classes as malignant ones. After tuning the first layer, the filters adapt to the target domain, and learn how to extract clearer features.
Figure 2: The feature maps and predictions w/o fine-tuning the first layer. The red labels are wrong predictions. Feature maps without fine-tuning are more blurry.

Figure 3: (a) Visualization of bi-directional layer-wise fine-tuning results (%) on POCUS. (b) The learned LR curves given by MetaLR are U-shaped.

**Fine-tuning Both Ends Reaches Higher Performance.** The bi-directional layer-wise fine-tuning on POCUS has \((10 \times 9)/2 = 45\) fixing settings, corresponding results are illustrated in Fig. 3 (a). The highest accuracy of 93.6% is significantly better than 92.1% obtained by the layer-wise fine-tuning, which is shown in the left-most column. It means that tuning both the first and last few layers has the potential to reach a higher fine-tuning performance, which benefits from the active adaptation to the current data domain.

**Learned LRs Are U-shaped.** The LRs learned by MetaLR are shown in Fig. 3 (b). The LRs are initialized as 0.01 and 0.001 for classifier and convolution layers. After the MetaLR converges, the LRs for all the three downstream tasks are U-shaped, showing that the learned meta knowledge regards the layers close to both ends of the network as the least transferable.
Table 2: Comparative experiments on classification tasks. We report sensitivities (%) of the abnormalities and the overall accuracy (%) on each task. All results are the median of 5 tests with different random seeds.

| Method               | COVID19 | POCUS | BUSI | Chest X-ray |
|----------------------|---------|-------|------|-------------|
|                      | Acc     | Acc   | Benign | Malignant | Acc     | Pneumonia | Acc |
| Last Layer           | 77.9    | 84.0  | 84.1  | 83.5       | 68.6    | 82.8      | 87.2 |
| All Layers           | 85.8    | 81.0  | 91.6  | 92.0       | 72.4    | 84.4      | 90.7 |
| Layer-wise [20]      | 87.5    | 92.3  | 92.1  | 90.8       | 75.7    | 85.6      | 90.1 |
| AutoLR [18]          | 89.8    | 89.7  | 90.4  | 90.4       | 76.2    | 84.9      | 95.4 |
| Bi-directional (ours)| 90.1    | 92.6  | 93.6  | 92.2       | 77.1    | 86.3      | 98.4 |
| MetaLR (ours)        | 93.0    | 92.6  | 94.0  | 92.2       | 77.6    | 86.3      | 93.6 |

Table 3: Results on LiTS segmentation task.

| Method               | Dice | PPV | Sensitivity |
|----------------------|------|-----|-------------|
| Last Layer           | 33.5 | 26.1| 71.5        |
| All Layers           | 93.1 | 94.0| 93.1        |
| Layer-wise I1        | 93.8 | 92.4| 96.1        |
| Layer-wise I2        | 82.9 | 92.5| 93.9        |
| Mina et al. [2]      | 92.4 | 92.7| 93.2        |
| Bi-directional I1 (ours) | 93.8 | 92.4| 96.1        |
| Bi-directional I2 (ours) | 92.4 | 92.7| 93.2        |
| MetaLR (ours)        | 93.7 | 95.3| 92.9        |

3.3 Results and Analysis

We compare the proposed methods with other fine-tuning schemes, including tuning only the last layer, tuning all layers with constant LRs, layer-wise fine-tuning [20], AutoLR [18]. The fine-tuning scheme proposed by Mina et al. [2], especially for U-Net, is also considered for segmentation.

Results on Classification Tasks. The bi-directional layer-wise fine-tuning and MetaLR consistently show the best accuracy on all downstream tasks (Tab. 2). It is worth noticing that AutoLR [18] hypothesizes that higher-level layers need more adjustment because they are less transferable, but neglects the lower-level layers’ domain-specificity. Our hypothesis makes up for this deficiency and gains significant performance improvements.

Results on Segmentation Task. Unlike CNNs for classification, the U-Net family has a more complex network topology. After adding skip connections, there are two interpretations [2] of depths for layers: 1) the left-most layers are the shallowest, and 2) the top layers of the “U” are the shallowest. They are represented by “I1” and “I2”, respectively. Tab. 3 shows the results of segmentation on the LiTS dataset. Bi-directional fine-tuning and MetaLR show 0.7% and 0.6% dice improvements compared with constant LRs.

3.4 Discussion and Findings

The LRs Learned on Segmentation Task. Due to the contradictory interpretations of layer depth for U-Net, it is challenging to define the transferabilities for layers based on their positions. However, the proper LRs for each layer can still be learned by MetaLR (Fig. 4(a)). The converged LRs for 3D U-Net have the highest values on “Block 4” and “Out Block” which are the farthest and nearest to the output. This pattern can hardly be obtained by manual methods.

MetaLR as an LR Scheduler. LRs given by MetaLR change as the training proceeds, so MetaLR can be seen as an LR scheduler. The adjustment of LRs for ResNet-18 is shown in Fig. 4(b). The first and last two blocks stably maintain the highest LRs, while the other blocks have fluctuating LRs like the cyclical LR scheduler [19] does. The functionality like the LR scheduler may act as a factor for the performance improvement of MetaLR.

4 Conclusion

In this work, we propose a new hypothesis that the low-level layers of a DNN are domain-specific, which is confirmed by visualization and experiments on different medical analysis tasks. Two fine-tuning schemes based on this hypothesis are proposed to mitigate the domain gap problem for medical transfer learning. Both of them achieve significantly better performance than the layer-wise fine-tuning method by allowing the low-level layers to adapt to the target
domains actively. Future works include investigating and quantifying the domain-specificity on more diverse medical domains and tasks.

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