AMF: Adaptable Weighting Fusion with Multiple Fine-tuning for Image Classification

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Abstract—Fine-tuning is widely applied in image classification tasks as a transfer learning approach. It re-uses the knowledge from a source task to learn and obtain a high performance in target tasks. Fine-tuning is able to alleviate the challenge of insufficient training data and expensive labelling of new data. However, standard fine-tuning has limited performance in complex data distributions. To address this issue, we propose the Adaptable Multi-tuning method, which adaptively determines each data sample’s fine-tuning strategy. In this framework, multiple fine-tuning settings and one policy network are defined. The policy network in Adaptable Multi-tuning can dynamically adjust to an optimal weighting to feed different samples into models that are trained using different fine-tuning strategies. Our method outperforms the standard fine-tuning approach by 1.69 %, 2.79 % on the datasets FGVC-Aircraft, and Describable Texture, yielding comparable performance on the datasets Stanford Cars, CIFAR-10, and Fashion-MNIST.

Index Terms—Deep Transfer Learning, Image Classification

I. INTRODUCTION

Convolutional neural networks have proved their ability in image classification [1]–[3]. In practice, however, there are numerous problems in training accurate convolution neural networks in real-world scenarios. Adequate training data is hard to achieve, and labelling by experts is an expensive task. Reusing a pre-trained model on the existing dataset despite apparent changes in the feature space can lead to poor performance. Furthermore, retraining an extensive model from scratch in a new scenario is also computationally expensive and time-consuming. As a result, transfer learning (i.e. knowledge transfer) is a desirable learning strategy to deal with the above dilemmas [4], [5]. The amounts of labelled data and computation resources are reduced by transferring the knowledge learned from source domains and tasks into target domains and tasks. Fine-tuning is one common approach in transfer learning, and is the key topic in this research. In fine-tuning, weights of convolutional blocks that are learned from the source task and domains are transferred and re-trained on new domains and tasks. These trained weights are proved to out-perform random-sampled weights in many new domains, which demonstrates that fine-tuning is a practical approach [6]–[11].

We focus on mixture distributions, being probability distributions that are controlled by two or more modes, in this research. The mixture distribution is a typical distribution in the real world, but it is difficult for standard neural networks to implement with good performance in accuracy and efficiency [12]. Our empirical results indicate that the performance of standard fine-tuning is restricted in complex mixture distributions. As far as we know, none of the existing research in transfer learning targets complex data distributions. Our research explores fine-tuning approaches on complex data distributions.

In this paper, we propose Adaptable Multi-tuning Framework (AMF) as shown in Figure 1, an approach that can adaptively weight features from multiple fine-tuning strategies in the final classifier through a policy network. The pipeline of AMF is inspired from SpotTune which can dynamically adjust each layer of the network from freezing and fine-tuning [13]. Our approach consists of a prediction module and policy network. The prediction module are constructed from more than one fine-tuned models. The policy network learns the weight of feature spaces which are calculated from each sub-model in the prediction module. In order to make the decision policy differentiable during training, we transfer the decision into continuous values and apply Softmax to unify the values. A fully-connected layer as classifiers is the last components of Adaptable Multi-tuning Framework. These accept the weighted latent space derived from the prediction module and policy network and outputs classification results.

The contributions of our papers are as follows: (1) We construct two challenge datasets in mixture distribution: Aircraft-DTD and Aircraft-Cars, from FGVC-Aircraft [14], Stanford Cars [15], and Describable Textures Dataset [16]. (2) We show that standard fine-tuning has good performance on simple mixture distribution, but is less accurate in the complex distribution domain. (3) We propose Adaptable Multi-tuning Framework for strong and consistent performance on both complex and straightforward mixture distribution. It overcomes the limited performance of standard fine-tuning.
II. RELATED WORK

A. Deep Transfer Learning in Image Classification

Deep transfer learning has been proved to achieve comparable accuracy of image classification [4], [6]–[11], [17]–[19]. Freezing pre-trained weights of convolutional neural networks from a large dataset as a feature extractor, and training a simple classification model for target tasks, is common in transfer learning [8], [20], [21]. The transferred feature extractor can outperform the models trained from scratch under positive transfer; even when the target task is not highly correlated to the source one. Fine-tuning is another common approach for transfer learning. Empirical results also show that fine-tuned weights usually out-perform frozen weights [4], [7]–[11], [22], [23]. Recent studies also indicate that learning rates, momentum value and decay values significantly control the impact of pre-trained weights to training on the target dataset [24]–[26]. In line with these discoveries in [4], a low learning rate is suitable for low-level convolutional blocks, and relatively high value settings are suitable for high-level convolutional blocks. Lower learning rates and higher decay rates are preferred for fine-tuning in more similar source and target tasks [19], [25], [27]. Additionally, fine-tuning more layers is beneficial for increasing the performance when source and target datasets are more related [4], [23], [25], [26].

Transfer learning is still useful when the target domain is already sufficient for models to train from scratch [4], [9], [24]. On the other hand, fine-tuning cannot prevent over-fitting and biased empirical loss estimation in small source and target datasets [9], [17], [27]. For this reason, ImageNet is a common choice for the source dataset. Nevertheless, fine-tuning on closely related datasets can obtain better performance [9], [29].

B. Transferability

Transferability is a recessive factor influencing the desirable behaviour (i.e. transfer’s feasibility) of deep neural networks that learn from other tasks or domains. Features from lower layers of deep neural networks are more general, regardless of the domain and tasks [4], [10], [17], [19]; thus they have high transferability. Features become more specific, discrete and differential when layers become deeper [4], [10], [17], [19], [28]. H-score, conditional entropy, and multi-class Fisher score are common methods for measuring transferability [26], [29], [30]. Transferability can not only provide an insightful explanation of the transfer learning mechanism, but can also measure the performance of pre-trained models in target dataset and guide the hyper-parameters tuning [29]–[31]. We illustrate the transferability of our proposed method by feature analysis in analysis section.

III. PROPOSED APPROACH

A. Multiple Fine-tuning

A mixture distribution is a complex probability distribution. It refers to a probability distribution with two or more modes. The bimodal distribution is a typical distribution from a mixture distribution, but it is difficult for deep neural networks to obtain a good performance in both accuracy and efficiency with a small training dataset [12], [32]. Our experiments indicate that standard fine-tuning struggles to achieve competent performance in mixture distributions, because of limited transferability. Based on this motivation, we propose a new idea, adaptable multi-tuning, which can improve the performance on mixture distribution datasets and still achieve performance comparable to SoTA on normal datasets.

Standard fine-tuning achieves good performance on standard classification; hence, we aim to stack several different fine-tuned models in parallel as a complex feature extractor and combine all hidden features identically to construct the classifier. A similar architecture has been proposed in Multi-Tune [33] and mixture of experts model [34]–[37]. MultiTune uses pre-defined weight fusion, and slightly outperforming SpotTune and standard fine-tuning. We target on an adaptable fusion mechanism that is able to flexibly adjust the contribution of each fine-tuned model to the final classifier.
Adaptable Multi-tuning is designed to accept any value of hyper-parameters \( n \) (number of fine-tuning settings), and is determined by the input distribution. For example, \( n = 2 \) is recommended for inputs from a bimodal distribution. In addition, an example of \( n = 3 \) is shown in Figure 2. Furthermore, the design intent for policy networks is not to increase the computation stress by an additional network module. For this reason, for the network architecture of policy networks, we prefer it to be simpler and more shallow than models in the prediction network, such as default ResNet-34.

In standard fine-tuning, it is impossible to coordinate the learning rates with various classes in mixture distributions. In contrast, Adaptable Multi-tuning with prediction module and policy network is expected to have a good performance in mixture distributional classification tasks. The prediction module is designed to accept multiple learning rates. The policy network is introduced to control the weights for different prediction models across various learning rates.

IV. EXPERIMENTS

A. Experimental Setup

1) Dataset: We select ImageNet-1K \([38]\) as the source dataset. Five public target datasets are selected to compare our adaptable multi-tune with traditional fine-tuning, including two fine-grained tasks FGVC-Aircraft \([14]\) and Stanford Cars \([15]\), one dataset with large domain difference to ImageNet-1K: DTD \([16]\), and two other datasets: CIFAR-10 \([39]\), and Fashion-MNIST \([40]\).

2) Mixture Distribution Setup: Obtaining the performance of mixture distribution is the main target; thus, two of FGVC-Aircraft, Stanford Cars, and DTD are grouped to construct complex data distributions (i.e. bi-model distributions). CIFAR-10 and Fashion-MNIST are existing mixture distribution with around 60,000 training examples: thus no further modification are performed. In order to minimize the classes biases by coordinating the total size of each component into a uniform number, both number of classes and number per class is adjusted as shown in Table I. Specifically, the number of Aircraft classes is reduced to 47 (Aircraft-47); number of Cars classes is reduced to 75 (Cars-75); number per class of DTD is reduced to 33 (DTD-47).

| Dataset  | O. classes | O. size | M. classes | M. size |
|----------|------------|---------|------------|---------|
| Aircraft-47 | 100        | 3333    | 47         | 1551    |
| Cars-75   | 196        | 4616-8041 | 64         | 1721-3032 |
| DTD-47   | 47         | 1800    | 47         | 1551    |

TABLE I

STATISTICS SUMMARY OF MIXTURE DISTRIBUTION SETUP. COLUMNS IN ITALIC FORMAT ARE USED TO DISTINGUISH THE ORIGINAL DATASET FROM MODIFIED DATASET. FIRST 47 CLASSES OF AIRCRAFT ARE SELECTED TO CONSTRUCT AIRCRAFT-47; CARS-75 ARE BUILT FROM THE FIRST 75 CLASSES OF CARS; FIRST 33 SAMPLES IN EACH CLASS OF DTD ARE ASSEMBLED TO DTD-47.
v4 is selected for our experiments as the backbone \[2\].

The above datasets. To illustrate a comparable result, Inception-tuning strategy \[26\] achieved several state-of-the-art results on image classification tasks. Note that final accuracy is averaged imenents, since it is the conventional performance measure in

pre-defined fine-tuning hyper-parameters for two Inception-
architecture (Figure 1) is designed. This model accepts two
specific Adaptable Multi-tuning Network from the general

Aircraft and Cars are fine-grained tasks, and DTD has a
difference in terms of visual intuition to ImageNet-1K \[13\], \[26\]. Therefore, we decided to group Aircraft-47 and Cars-75 as one complex distribution dataset; and Aircraft47 and DTD-47 as another complex distribution dataset. We
use well-trained models as feature extractors to analyze the
features of the above mixture-distribution datasets as shown in
histograms\[\text{\ref{fig:T-SNE}}\] The two sub-groups in Aircraft-Cars have closer
mean values and overlapping peaks, while the two sub-groups
in Aircraft-DTD have two distributed peaks. These combined
datasets can evaluate different methods from two perspectives:
a complex distribution with similar features, and a complex
distribution with different features. A technical summary of
the two new datasets:

- **Aircraft-DTD** contains 94 classes and 33 images per
class in train, test, and validate. Half the classes are from
Aircraft-47, and the other are from DTD-47.
- **Aircraft-Cars** consists of 3102 and 3071 train-validation
samples from aircraft and cars, respectively. There are 33
aircraft classes and 75 car classes in the mixture dataset.

3) **Backbone:** In recent work, Inception-v4 with novel fine-
tuning strategy \[26\] achieved several state-of-the-art results on
the above datasets. To illustrate a comparable result, Inception-
v4 is selected for our experiments as the backbone \[2\].

4) **Metrics:** Top-1 accuracy is used to evaluate all exper-
iments, since it is the conventional performance measure in
image classification tasks. Note that final accuracy is averaged
over five runs.

5) **Model:** Based on the data distributions and backbone,
a specific Adaptable Multi-tuning Network from the general
architecture (Figure \[\text{\ref{fig:Model}}\] is designed. This model accepts two
pre-defined fine-tuning hyper-parameters for two Inception-
v4s. ResNet-34 with four blocks \((3, 4, 6, 3)\) is used in the
policy network. Inception-v4 and ResNet-34 are separately
pre-trained on ImageNet-1K. We use cross-entropy as the loss
function in entire experiments.

6) **Experiments:** We compare our proposed adaptable
multi-tune with the following methods:

- **Standard Fine-tune:** All pre-trained weights of
Inception-v4 are fine-tuned on the target dataset.
- **MultiTune: a static multiple fine-tune \[33\]:** We re-
implement MultiTune with Inception-v4. It consists of
two backbones in feature extraction, followed by a fixed
concatenation fusion operation. All pre-trained weights
of the backbones are fine-tuned.

In the standard fine-tuning method, three learning rates are
set \[26\], including values for shallow blocks, deep blocks,
and final fully-connected layers. MultiTune also requires three
learning rates, where one for sub-networks and one for
final fully-connected layers; while an additional learning rate
is required for policy network in our proposed method. The
same batch size and decay rates are used for the entire network
for each method.

7) **Implementation:** We use the pre-trained Inception-v4
model from \[42\] as the starting point. All experiments are
run on a single A-100 (32Gb) GPU. We use the original data
separations of train, validation and test for the above datasets.
Since the split of training and validation are not provided
in Stanford Cars, we take first 18 examples in each class
as validation. Furthermore, SGD with momentum is used as
the optimizer. Random augment and random erasing are also
enabled, which is set to \(\text{rand} – \text{m}9 – \text{mstd}0.5 – \text{inc}1\) and
0.5 \[43\].

B. Results and Analysis

1) **Fine-tune Baseline:**

: Empirical results of the standard fine-tuning methods on
standard datasets are shown in Table \[\text{\ref{tab:Standard Fine-Tune}}\]. Through tweaking the
learning rates in five validation sets to 0.03, 0.025, 0.0008,
0.03, and 0.025 (same order in the Table), we reproduce
comparable test accuracy to \[26\] on the full-sized target
datasets. Learning rates in the first 8 layers are reduced 60% to
preserve prior knowledge learned from ImageNet-1K.

When the size is reduced in Aircraft, Cars, and DTD,
the number of samples in each epoch is reduced, causing
accelerated decline in learning rates. Therefore, the optimal
hyper-parameters for the full-sized dataset are maintained in
the reduced-size dataset, except for decay rates. Empirical
accuracy differences from the reduced-size dataset and the
original dataset reflects that our modification increases task
difficulty as the training datasets are all smaller. The perfor-
manve of standard fine-tuning on the test set of two mixture
distribution datasets (i.e. Aircraft-DTD and Aircraft-Cars) is
shown in Table \[\text{III}1\] which is also a comparable baseline to
our methods. We start finding hyper-parameters by reusing the
settings in the above experiments. In Aircraft-DTD, a high
learning rate (0.025) leads to the model performing more
accurately in Aircraft and less accurately in DTD. On the

![T-SNE](image-url) Visualisation (in one-dimension) of Feature Distri-
bution in Aircraft-Cars (left) and Aircraft-DTD (right)
other hand, when a lower learning rate is set (0.0008), the model produces strong performance in DTD, but accuracy of Aircraft drops 10%. It is infeasible to coordinate disparate learning rates with two classes in standard fine-tuning, as expected. The final test accuracy of Aircraft-47 and DTD-47 in Aircraft-DTD are 91.32% and 74.12%, while 93.20% and 76.41% are the best test accuracy in individual Aircraft-47 and individual DTD-47. The decline in accuracy also happens in Aircraft-Cars for both validation and test accuracy, although both aircraft and cars prefer high learning (0.025) for fine-tuning. The final test accuracy of Aircraft-47 and Cars-75 in Aircraft-Cars: 92.09% and 90.59%.

By comparing the accuracy between Aircraft-DTD and Aircraft-Cars, the former dataset is difficult for standard fine-tuned models to train and classify. It is reflected by the feature distribution (Section IV-A2) of these two datasets, in which aircraft and cars share more similar features, whereas aircraft and describable textures are located more distantly in feature space. Therefore, we can conclude that standard fine-tuning has limited performance when dealing with complex distribution domains.

2) Performance of AMF

The results of the comparison between standard fine-tuning, MultiTune [33], and Adaptable Multi-tune Network is shown in Table III. Our proposed methods yields consistently better test accuracy than standard fine-tune and multi-tune in all four datasets. In mixture distribution datasets, Adaptable Multi-tuning Network outperforms 1.69% and 2.79% in Aircraft-47 and DTD-47 respectively, than the standard fine-tune on Aircraft-DTD dataset; our method also achieves comparable performance on Aircraft-Cars compared to standard fine-tuning, and outperforms 0.41% and 0.20% in Aircraft-47 and Cars-75 respectively. Adaptable Multi-tuning Network also holds a slight lead in CIFAR-10 and Fashion-MNIST.

It might be unfair to directly compare the performance of our method with standard fine-tuning, since the former uses two Inception-v4 and the latter uses one Inception-v4. The parameters of Adaptable Multi-tuning Networks (103.6M) are twice larger than standard fine-tune (41.2M) in experiments. Therefore, we also report performance of standard MultiTune (83.1M) in Table III. Our method holds a large improvement compared to the MultiTune in both Aircraft-DTD and Aircraft-Cars. This reflects that the policy network contributes benefit to model performance.

In summary, our Adaptable Multi-tune Network has stable performance for all above datasets. In contrast, the standard fine-tune and MultiTune method only achieves comparable accuracy on CIFAR-10 and Fashion-MNIST.

3) Hyper-parameters Optimization of AMF:

Learning rates: Adaptable Multi-tuning Network requires four pre-defined learning rates. The policy network aims to predict which fine-tuning hyperparameters are most suitable for each individual image sample. To simulate a weak penalty mechanism, we set a tiny learning rate for policy networks to scale down the strong gradient descent from cross-entropy loss in a reasonable range. Additionally, policy networks might suffer a heavy error penalty because of incorrect classification by prediction modules (i.e. Inception-v4). A tiny learning rate is also necessary to minimize this effect. Pre-trained weights for policy networks are also required, to extract features at the initial stage of training. The empirical results shown in the top-left sub-plot [4] support our hypothesis that the policy network learning rate should be small. A high learning rate for the policy networks leads to a steep accuracy decline of the aircraft classes in Aircraft-DTD. Learning rates between 0.00001 and 0.0001 are suitable for the policy network, and 0.00003 is the optimal value.

Our hypothesis about the optimal learning rates for the prediction modules is based on the purpose in designing them. Our design idea is that each fine-tuning network is able to learn individual data distributions separately in a mixture distribution. In other words, the optimal learning rates should be closer to values in standard fine-tuning. We perform grid search to determine the best learning rates for each individual module, and the results are plotted in Figure [4]. The model is not sensitive to the various learning rates of fully-connected

| Dataset       | Aircraft-Cars | CIFAR-10 | F-MNIST |
|---------------|---------------|----------|---------|
|               | Fine-tune     |          |         |
| Aircraft-47   | 91.32         | 92.09    | 98.43   |
| DTD-47        | 74.12         | 90.59    | 95.27   |
| Aircraft-47   | 92.09         | 90.79    | 95.26   |
| Cars-75       | 86.69         | 89.50    | 95.26   |
| MultiTune     | 88.55         | 89.50    | 95.26   |
| AMF           | 93.01         | 90.79    | 95.26   |
| STD           | ±0.2          | ±0.2     | ±0.05   |

Note that CIFAR-10 and Fashion-MNIST are not modified.
layers (top-right sub-plot) when it is between 0.005 and 0.01. Adjusting the learning rates of fine-tuning modules with low learning rates cannot influence model performance; by contrast, decreasing learning rates of fine-tuning modules with higher learning rates can diminish performance, caused by a dead policy network. We select 0.0008, 0.03, 0.008, 0.00003 learning rates in our final Aircraft-DTD experiments for sub-network 1, sub-network 2, the final fully connected layer, and the policy network respectively. A similar grid search is also performed in Aircraft-Cars. We conclude that 0.03, 0.03, 0.008, 0.00003 are the optimal learning rates, with the two sub-networks in the prediction modules having the same learning rates. The optimal learning rates in two mixture distribution datasets are same as the values in standard fine-tuning.

We suggest that (1) optimal learning rates for standard fine-tuning models in individual datasets is also highly possible to be optimal for sub-networks in Adaptable Multi-tuning Network; (2) policy networks perform better with a low learning rate.

Other hyper-parameters: When decay epochs are set between 20 and 25, and the decay rate is set within [0.9, 0.96], Adaptable Multi-tuning Network is slightly affected. On the other hand, predictions of policy network may locate in extreme range. Furthermore, a small batch size (32) is preferred in Aircraft-DTD and Aircraft-Cars, while a large batch size (128) is suitable in CIFAR-10 and Fashion-MNIST.

C. Insight of AMF

Policy networks of Adaptable Multi-tuning Networks is highly accurate and quickly converged. The large value of embedding (derived by the probability of policy network) indicates which of the two datasets in the mixture distribution is preferred. In the test-set of Aircraft-DTD, the trained policy network only miss-assigns 24 among 3102 mixed samples of Aircraft and DTD; additionally, all DTD samples are correctly assigned. The policy network behaves more accurately in the test-set of Aircraft-Cars, achieving close to 100% accuracy in separating the two data distributions. We also implement a dynamic monitor to record changes in the accuracy of assignment from the policy networks throughout training. The policy network always predicts an embedding space that treats all samples from the same classes at the initial stage; it rapidly adjusts the prediction during the first 50 epochs; policy networks converge after the first 300 epochs, where accuracy fluctuation reduces and becomes stable.

Figure 4 plots the T-SNE visualisation of feature distributions derived by Adaptable Multi-tuning Networks. The distribution scatters indicate that pre-trained weights of the model cannot separate aircraft’s features from DTD’s features well prior to fine-tuning. After fine-tuning with Adaptable Multi-tuning Networks on Aircraft-DTD and Aircraft-Cars, the distribution of each class is clustered together, and distribution between different classes are distinctly separated, resulting in high classification accuracy. The feature analysis supports that Adaptable Multi-tuning Networks can converge and have a high performance on Aircraft-DTD and Aircraft-Cars.

1) Stability of AMF

: From empirical results, small learning rates contribute positively to raising the stability. We also control the initialization of the weights of full-connected layers, sampled from a normal distribution with 0 mean and 0.1 standard deviation.

2) Strategies to choose backbones of policy networks

: Backbones of policy networks depend on the distribution of target datasets. In above experiments, ResNet–34 has enough ability and complexity to overcome the mixture distribution. We suggest a shallow model is preferred to avoid over-fitting.

![Hyper-parameters Search of AMF in Aircraft-DTD and Aircraft-Cars.](image)
Aircraft – DTD Dataset

Aircraft – Cars Dataset

and reduce computational resources. The use of different policy networks is also a potential extension in the future.

3) Different decay epochs in test stage and validation stage: A decaying learning rate every 20 epochs contributes more benefit to validation accuracy. In both Aircraft-DTD and Aircraft-Cars, the training set and validation set of all datasets are equivalently separated. When the size of the training data doubles, the numbers of batches in each epoch also double, decelerating the decline in learning rate. Therefore, a smaller decay epoch is required when training with the training and the validation set combined for prediction on the test set. Decay epochs are decreased to 11 and 14 for Aircraft-DTD and Aircraft-Cars respectively in the test stage.

The stability of the policy network is also closely related to learning rates decay from empirical results. For instance, when a sub-optimal decay is set, one confidence score will be stuck at 0.99. Therefore, proper adjustment of decay based on the amount of training data is necessary for Adaptable Multi-tuning.

4) Dynamic Changes of Weighting Vector: We monitor the dynamic changes of weighting vectors, produced by the policy network; and plot in figure 6. Weighting vectors aim to scale the feature information for proper feature fusion. The averaged values start at around 0.5, as expected. It reaches extreme values 0.35 in Aircraft-DTD and 0.46 in Aircraft-Cars, respectively. In Aircraft-DTD, the policy network converges around 600 epochs; while the value becomes stable around 200 epochs in Aircraft-Cars.

Unexpectedly, the relative positions of two weighting values are flipped during the training on both Aircraft-DTD and Aircraft-Cars.

5) Assignment Accuracy: We also implement a dynamic monitor (in Figure 7) to record changes in the accuracy of assignment from the policy networks throughout training.

The policy network always predicts an embedding space that assigns all samples into the one class at the initial stage (first 20 epochs). In other words, the assignment accuracy is 50%. The Network rapidly adjust its prediction through the plenty from the gradient during the first 50 epochs in both Aircraft-DTD and Aircraft-Cars. Then, it converges after the first 150 epochs, where accuracy fluctuation are reduced.

Eventually, in the test-set of Aircraft-DTD, the trained policy network only miss-assigns 0.77% mixed samples of Aircraft into DTD; all DTD samples are correctly assigned. The policy network behaves 100% accuracy assignment in the test-set of Aircraft-Cars.

V. CONCLUSION

We propose a novel adaptive multi-tuning framework named Adaptable Multi-tuning in this work. It can control multiple fine-tuning parameters in the prediction network. The policy network in Adaptive Multi-tuning Framework adaptably
weights the contributions of each fine-tuned model to the final classifier. Our method is also fully differentiable, and so can be implemented under any modern deep learning approach.

In our experiments, two mixture distributions are introduced for evaluating the performance of different methods, using Aircraft-DTD and Aircraft-Cars. The empirical results indicate that standard fine-tuning performs well on single data distributions and simple mixture distributions such as Aircraft-Cars, but behaves with limited performance in complex distributions Aircraft-DTD. Adaptable Multi-tuning Framework is shown to break the limited performance of standard fine-tuning and achieve comparable accuracy in all datasets used. Compared to traditional Multi-Tune, AMF have 4.46% test accuracy improvement at maximum. Our method outperforms the state of the art single model, which is a surprising result given the complexities of prediction with two datasets combined. We also show that Adaptable Multi-tuning is an efficient algorithm, by clarifying the mechanism of the policy network and latent space analysis. Several suggestions related to the use of our method are provided, including hyper-parameters and backbones. Importantly, we illustrate that optimal learning rates for standard fine-tuning is also highly possible to be optimal for sub-networks in Adaptable Multi-tuning Network.

Adaptable Multi-tuning Framework is a novel approach in transfer learning, and also it firstly integrates neural architecture search with fine-tuning. There are several extensible works in the future. Testing Adaptable Multi-tuning in more scenarios where mixture distributions occur, such as face recognition, is meaningful and practicable. In this paper, we only attempt Inception-v4 and ResNet-34 for Adaptable Multi-tuning Framework; other CNN-based and transformer-based models are expected to tested in our following works.

Fig. 6. Dynamic Changes of Averaged Weighting Values during training on Aircraft-DTD (Left) and Aircraft-Cars (Right). We only report the monitor at first 1000 epochs, due to the page width.

Fig. 7. Assignment Accuracy from Policy Network during training on Aircraft-DTD (Left) and Aircraft-Cars (Right). The accuracy of each class is calculated from: $\frac{\text{number of correct assignment}}{\text{total number of samples in the class}}$. Not all experimental results are plotted in order to enlarge the critical ranges and minimize the converged range.

REFERENCES

[1] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770–778.

[2] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, “Inception-v4, inception-resnet and the impact of residual connections on learning,” in Thirty-first AAAI conference on artificial intelligence, 2017.

[3] M. Tan and Q. Le, “Efficientnet: Rethinking model scaling for convolutional neural networks,” in International conference on machine learning, PMLR, 2019, pp. 6105–6114.

[4] J. Yosinski, J. Clune, Y. Bengio, and H. Lipson, “How transferable are features in deep neural networks?” arXiv preprint arXiv:1411.1792, 2014.

[5] S. J. Pan and Q. Yang, “A survey on transfer learning,” IEEE Transactions on knowledge and data engineering, vol. 22, no. 10, pp. 1345–1359, 2009.

[6] K. Jarrett, K. Kavukcuoglu, M. Ranzato, and Y. LeCun, “What is the best multi-stage architecture for object recognition?” in 2009 IEEE 12th international conference on computer vision. IEEE, 2009, pp. 2146–2153.

[7] R. Girshick, J. Donahue, T. Darrell, and J. Malik, “Rich feature hierarchies for accurate object detection and semantic segmentation,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2014, pp. 580–587.

[8] H. Azizpour, A. S. Razavian, J. Sullivan, A. Maki, and S. Carlsson, “Factors of transferability for a generic convnet representation,” IEEE transactions on pattern analysis and machine intelligence, vol. 38, no. 9, pp. 1790–1802, 2015.

[9] D. Mahajan, R. Girshick, V. Ramanathan, K. He, M. Paluri, Y. Li, A. Bharambe, and L. Van Der Maaten, “Exploring the limits of weakly supervised pretraining,” in Proceedings of the European conference on computer vision (ECCV), 2018, pp. 181–196.
[10] J. Plested and T. Gedeon, “An analysis of the interaction between transfer learning protocols in deep neural networks,” in International Conference on Neural Information Processing. Springer, 2019, pp. 312–323.

[11] S. Kornblith, J. Shlens, and Q. V. Le, “Do better imagenet models transfer better?” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 2661–2671.

[12] J. Gao, P. Li, Z. Chen, and J. Zhang, “A survey on deep learning for multimodal data fusion,” Neural Computation, vol. 32, no. 5, pp. 829–864, 2020.

[13] Y. Guo, H. Shi, A. Kumar, K. Grauman, T. Rosing, and R. Feris, “Spot-tune: transfer learning through adaptive fine-tuning,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 4805–4814.

[14] S. Maji, E. Rahtu, J. Kannala, M. Blaschkó, and A. Vedaldi, “Fine-grained visual classification of aircraft,” arXiv preprint arXiv:1306.5151, 2013.

[15] J. Krause, M. Stark, J. Deng, and L. Fei-Fei, “3d object representations for fine-grained categorization,” in Proceedings of the IEEE international conference on computer vision workshops, 2013, pp. 554–561.

[16] M. Cimpoi, S. Maji, I. Kokkinos, S. Mohamed, and A. Vedaldi, “Describing textures in the wild,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2014, pp. 3606–3613.

[17] K. He, R. Girshick, and P. Dollár, “Rethinking imagenet pre-training,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 4918–4927.

[18] B. Neyshabur, H. Sedghi, and C. Zhang, “What is being transferred in transfer learning?” arXiv preprint arXiv:2008.11687, 2020.

[19] J. Plested, X. Shen, and T. Gedeon, “Non-binary deep transfer for image classification,” arXiv preprint arXiv:2107.08585, 2021.

[20] J. Donahue, Y. Jia, O. Vinyals, J. Hoffman, N. Zhang, E. Tzeng, and T. Darrell, “Decaf: A deep convolutional activation feature for generic visual recognition,” in International conference on machine learning. PMLR, 2014, pp. 647–655.

[21] A. Sharif Razavian, H. Azizpour, J. Sullivan, and S. Carlsson, “Cnn features off-the-shelf: an astounding baseline for recognition,” in Proceedings of the IEEE conference on computer vision and pattern recognition workshops, 2014, pp. 806–813.

[22] M. Huh, P. Agrawal, and A. A. Efros, “What makes imagenet good for transfer learning?” arXiv preprint arXiv:1608.08614, 2016.

[23] B. Chu, V. Madhavan, O. Beijbom, J. Hoffman, and T. Darrell, “Best practices for fine-tuning visual classifiers to new domains,” in European conference on computer vision. Springer, 2016, pp. 435–442.

[24] C. Sun, A. Shrivastava, S. Singh, and A. Gupta, “Revisiting unreasonable effectiveness of data in deep learning era,” in Proceedings of the IEEE international conference on computer vision, 2017, pp. 843–852.

[25] H. Li, P. Chaudhari, H. Yang, M. Lam, A. Ravichandran, R. Bhotika, and S. Soatto, “Rethinking the hyperparameters for fine-tuning,” arXiv preprint arXiv:2002.11770, 2020.

[26] J. Plested, X. Shen, and T. Gedeon, “Rethinking binary hyperparameters for deep transfer learning for image classification,” arXiv preprint arXiv:2107.08585, 2021.

[27] A. Kolesnikov, L. Beyer, X. Zhai, J. Puigcerver, J. Yang, S. Gelly, and N. Houlsby, “Big transfer (bit): General visual representation learning,” in Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part V 16. Springer, 2020, pp. 491–507.

[28] H. Liu, M. Long, J. Wang, and M. I. Jordan, “Towards understanding the transferability of deep representations,” arXiv preprint arXiv:1909.12031, 2019.

[29] Y. Bao, Y. Li, S.-L. Huang, L. Zhang, L. Zheng, A. Zamir, and L. Guibas, “An information-theoretic approach to transferability in task transfer learning,” in 2019 IEEE International Conference on Image Processing (ICIP). IEEE, 2019, pp. 2309–2313.

[30] A. T. Tran, C. V. Nguyen, and T. Hassner, “Transferability and hardness of supervised classification tasks,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 1395–1405.

[31] L. Bottou and O. Bousquet, “The tradeoffs of large scale learning,” Advances in neural information processing systems, vol. 20, 2007.

[32] K. Sohn, W. Shang, and H. Lee, “Improved multimodal deep learning with variation of information,” Advances in neural information processing systems, vol. 27, pp. 2141–2149, 2014.

[33] Y. Wang, J. Plested, and T. Gedeon, “Multitune: Adaptive integration of multiple fine-tuning models for image classification,” in International Conference on Neural Information Processing. Springer, 2020, pp. 488–496.

[34] N. Shazeer, A. Mirhoseini, K. Mariz, A. Davis, Q. Le, G. Hinton, and J. Dean, “Outrageously large neural networks: The sparsely-gated mixture-of-experts layer,” arXiv preprint arXiv:1701.06538, 2017.

[35] P. Ramachandran and Q. V. Le, “Diversity and depth in per-example routing models,” in International Conference on Learning Representations, 2018.

[36] M. Crawshaw, “Multi-task learning with deep neural networks: A survey,” arXiv preprint arXiv:2009.09796, 2020.

[37] H. Hazimeh, Z. Zhao, A. Chowdhery, M. Sathiamoorthy, Y. Chen, R. Mazumder, L. Hong, and E. Chi, “Deselect-k: Differentiable selection in the mixture of experts with applications to multi-task learning,” Advances in Neural Information Processing Systems, vol. 34, 2021.

[38] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, “Imagenet: A large-scale hierarchical image database,” in 2009 IEEE conference on computer vision and pattern recognition. Ieee, 2009, pp. 248–255.

[39] A. Krizhevsky, G. Hinton et al., “Learning multiple layers of features from tiny images,” 2009.

[40] H. Xiao, K. Rasul, and R. Vollgraf, “Fashion-mnist: a novel image dataset for benchmarking machine learning algorithms,” arXiv preprint arXiv:1708.07747, 2017.

[41] G. E. Hinton and S. Roweis, “Stochastic neighbor embedding,” Advances in neural information processing systems, vol. 15, 2002.

[42] R. Wightman, “Pytorch image models,” https://github.com/rwightman/pytorch-image-models, 2019.

[43] E. D. Cubuk, B. Zoph, J. Shlens, and Q. V. Le, “Randaugment: Practical automated data augmentation with a reduced search space,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, 2020, pp. 702–703.