

# One Step Learning, One Step Review

Xiaolong Huang, Qiankun Li, Xueran Li, Xuesong Gao

## Abstract

Visual fine-tuning has garnered significant attention with the rise of pre-trained vision models. The current prevailing method, full fine-tuning, suffers from the issue of knowledge forgetting as it focuses solely on fitting the downstream training set. In this paper, we propose a novel weight rollback-based fine-tuning method called OLOR (One step Learning, One step Review). OLOR combines fine-tuning with optimizers, incorporating a weight rollback term into the weight update term at each step. This ensures consistency in the weight range of upstream and downstream models, effectively mitigating knowledge forgetting and enhancing fine-tuning performance. In addition, a layer-wise penalty is presented to employ penalty decay and the diversified decay rate to adjust the weight rollback levels of layers for adapting varying downstream tasks. Through extensive experiments on various tasks such as image classification, object detection, semantic segmentation, and instance segmentation, we demonstrate the general applicability and state-of-the-art performance of our proposed OLOR. Code is available at [https://github.com/\\*\\*\\*/\\*\\*\\*\\*](https://github.com/***/****).

## Introduction

With the rapid advancement of deep learning technology, numerous large-scale image datasets have been established (Schuhmann et al. 2022; Russakovsky et al. 2015; Schuhmann et al. 2021), resulting in many promising pre-trained visual models (Radford et al. 2021; He et al. 2022; Bao et al. 2021). These pre-trained models can effectively solve related but distinct visual tasks through transfer learning and fine-tuning techniques (Wu, Sun, and Ouyang 2023; Shen et al. 2021). The fundamental fine-tuning methods are linear probing and full fine-tuning (Zhang, Isola, and Efros 2017). In linear probing, the pre-trained model’s backbone is frozen, and only the head specific to the downstream task is trained. However, this approach often restricts the performance of the pre-trained backbone. On the other hand, full fine-tuning involves training the entire network directly, but it usually leads to knowledge forgetting (De Lange et al. 2021).

Rehearsal methods (Rebuffi et al.; Rolnick et al. 2019; Liu et al. 2020; Merlin et al. 2022), based on the replay mechanism, involve retraining on a subset of stored pre-training samples while learning new tasks. However, this approach is inefficient and can lead to overfitting on previous data. EWC

(Kirkpatrick et al. 2017) proposes a regularization-based fine-tuning method that uses the Fisher information matrix to determine the importance of weight parameters. This helps adjust the parameters between upstream and downstream tasks, reducing forgetting. L2-SP (Xuhong, Grandvalet, and Davoine 2018) uses an L2 penalty to restrict the updates of parameters, addressing knowledge forgetting during fine-tuning. However, it is not compatible with adaptive optimizers (Loshchilov and Hutter 2017; Guan 2023), which may produce wrong regularization direction. Parameter isolation methods (Jia et al. 2022; Sohn et al. 2023) create new branches or modules for different network models and tasks for downstream tasks. However, it introduces additional new training parameters, requires certain training skills, and has lower generality than rehearsal methods.

In this paper, we propose a novel fine-tuning method combined with optimizers to solve knowledge forgetting, called OLOR (One step Learning, One step Review). Specifically, OLOR introduces a weight rollback term to the weight update term during the fine-tuning stage, allowing the model to gradually approach the pre-trained weights while learning the downstream task. This process avoids delay defects and makes the weights of the upstream and downstream models more similar. In addition, a layer-wise penalty is devised to employ penalty decay and the diversified decay rate to adjust the weight rollback levels of layers. Penalty decay combines feature pyramids with transfer learning, giving more significant weight rollback to shallow features such as color and texture, and smaller weight backtracking to deep features such as semantic information. The diversified decay rate according to the similarity between the two domain data to adjust the level of weight rollback. OLOR with layer-wise penalty enables the fine-tuning model to extract more generalized features from shallow layers and adapt varying downstream task objectives. Finally, OLOR can be combined with popular optimizers such as Adam (Loshchilov and Hutter 2017; Guan 2023) and SGD (Keskar and Socher 2017), making it easy to fine-tune various downstream tasks.

Our OLOR fine-tuning method achieves state-of-the-art performance on ten popular visual task datasets covering general classification, fine-grained classification, long-tail classification, cross-domain classification, object detection, semantic segmentation, and instance segmentation. Validation experiments and ablation analysis demonstrate the per-

formance of OLOR in solving the problem of knowledge forgetting and the rationality of the parameters.

The main contributions can be summarized as follows.

- We propose a novel fine-tuning method OLOR, which cooperates with optimizers to solve the knowledge forgetting issue, thereby improving fine-tuning performance.
- The designed weight rollback avoids delay defects by incorporating the current gradient into the penalty term, thereby correcting the penalty target and smoothing the review process.
- A layer-wise penalty is presented to employ penalty decay and the diversified decay rate to adjust the weight rollback levels of layers for adapting varying downstream tasks.
- The proposed method achieves state-of-the-art performance on extensive downstream tasks, including different types of image classification, different pre-training models, and image detection and segmentation.

## Related Work

### Pre-training Resource

With the rapid advancement of computer vision, numerous large-scale datasets (Russakovsky et al. 2015; Schuhmann et al. 2021, 2022) and pre-trained models have emerged. These upstream pre-trained models possess rich features and hold great potential for transferability to other specific downstream tasks. ImageNet-21K (Russakovsky et al. 2015) is the most popular large-scale dataset with over 14 million images, and most networks are pre-trained on it. Recently, a groundbreaking development has taken place with the release of LAION-2B (Schuhmann et al. 2022). This dataset now reigns as the largest, comprising over 2 billion image-text pairs. Then many pre-trained models have been proposed, such as OpenClip (Radford et al. 2021), BEiT (Peng et al. 2022), MAE (He et al. 2022), and EVA (Fang et al. 2023). It is worth noting that most of these models’ backbones are built upon the foundations of ViT (Dosovitskiy et al. 2020) and ConvNeXt (Liu et al. 2022).

### Fine-tuning Method

The process of fine-tuning usually faces an issue known as knowledge forgetting (Toneva et al. 2018). It refers to the model’s loss of pre-training learned representations during fine-tuning (Mosbach, Andriushchenko, and Klakow 2020). This leads to reduced accuracy on both the pre-training and downstream tasks, as the model cannot effectively utilize its potential knowledge (De Lange et al. 2021; Vander Eeck and Van Hamme 2023).

To solve this issue, there are currently three categories of approaches, i.e., replay methods, regularization methods, and parameter isolation methods. Replay involves periodically training on a subset of previous pre-training task data, thereby retaining knowledge of previous tasks and balancing old and new information (Rebuffi et al.; Rolnick et al. 2019; Liu et al. 2020; Merlin et al. 2022). However, storing and managing pre-training task data pose challenges in

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### Algorithm 1: OLOR for SGD with Momentum

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1: input:
    $\eta \in \mathbb{R}$ : Initial learning rate,  $\beta \in [0, 1)$ : momentum factor,  $\theta_0$ :
   pre-trained weight,  $\iota_1, \iota_2 \in [0, 1]$ ,  $\iota_1 \geq \iota_2$ : max and min level
   of weight rollback respectively,  $\gamma \in \mathbb{R}$ : weight rollback power
2: initialize:
    $t \leftarrow 0$ : time step,  $m_0 \leftarrow 0$ : initial moment vector,  $d_0 \leftarrow$ 
   0: initial discrepancy value,  $\lambda_i \leftarrow f(\lambda, i, n, \iota_1, \iota_2)/\eta$ : cal-
   culate penalty factor  $\lambda_i$  through  $\lambda_i = f(\lambda, i, n, \iota_1, \iota_2) =$ 
    $\iota_2 + (\frac{i}{n})^\gamma(\iota_1 - \iota_2)$ , then scale it by dividing  $\eta$  to eliminate
   dimensional effects
3: repeat
4:    $t \leftarrow t + 1$ 
5:    $g_t \leftarrow \nabla_{\theta} f_t(\theta_{t-1})$  (Get batch gradient at timestep  $t$ )
6:    $m_t \leftarrow \beta m_{t-1} + (1 - \beta)g_t$  (Compute momentum)
7:    $\theta_t \leftarrow \theta_{t-1} - \eta_t \lambda_i d_{t-1} - (1 - \eta_t \lambda_i) \eta_t m_t$  (Update weight)
8:    $d_t \leftarrow (1 - \eta_t \lambda_i)(d_{t-1} - \eta_t m_t)$  (Update discrepancy)
9: until Stopping condition is met
10: return Parameters  $\theta_t$ 

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terms of efficiency, particularly in the contemporary era of massive datasets (Schuhmann et al. 2022; Li et al. 2023). Regularization-based methods employ techniques such as the fisher information matrix (Kirkpatrick et al. 2017), weight decay (Kumar et al. 2022), and L2 penalty (Xuhong, Grandvalet, and Davoine 2018) to restrict parameter updates during fine-tuning. However, these techniques may not be entirely adequate in completely preventing knowledge forgetting. Moreover, the presence of adaptive optimizers (Loshchilov and Hutter 2017; Guan 2023) can occasionally impact the direction of regularization (Xuhong, Grandvalet, and Davoine 2018). Parameter isolation methods incorporate specific branches or modules into the pre-trained network during downstream fine-tuning, aiming to achieve knowledge transfer through these new modules (Jia et al. 2022; Sohn et al. 2023; Wang et al. 2023). However, architectural modifications introduce new training parameters and intricate designs. Moreover, training tricks play a crucial role in the effectiveness of the new module, often necessitating multiple rounds of freezing and unfreezing.

To achieve a general and concise fine-tuning method to address knowledge forgetting, the proposed OLOR fine-tuning method combines weight rollback and optimizers to adjust the range of parameter updates. This allows for enhancing pre-trained model representations to improve downstream fine-tuning performance.

## Method

We propose a One step Learning, One step Review (OLOR) method to reduce knowledge forgetting for fine-tuning. OLOR can be seamlessly applied to various downstream tasks among with different optimizers and models. The overall framework is illustrated in Figure 1, and detailed pipelines incorporating SGD and Adam are described in Algorithm 1 and Algorithm 2. This section introduces the delay defect of the previous regularization method, followed by detailed explanations of the OLOR method, which comprises weight rollback and layer-wise penalty.

## One step Learning, One step Review (OLOR)

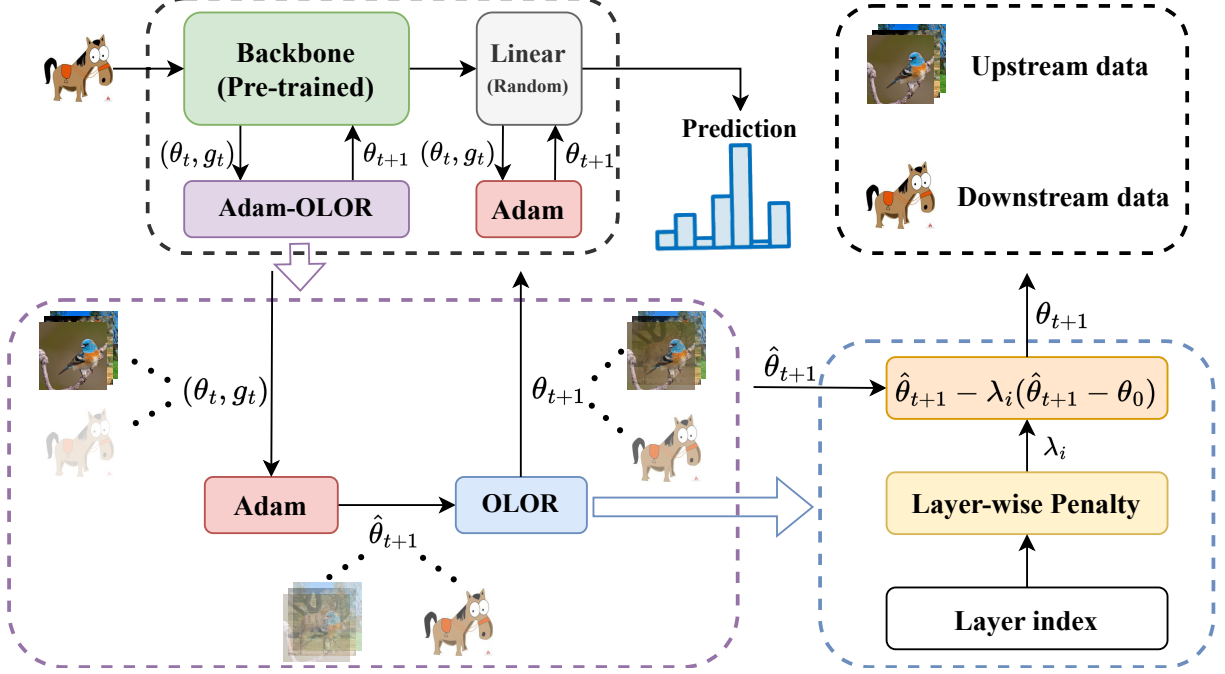


Figure 1: Overview of OLOR using Adam as optimizer. Where  $\lambda_i$  represents the penalty factor of  $i_{th}$  layer,  $\theta_t$  and  $\hat{\theta}_t$  represents the weight and the estimation of next weight(pre-weight) at timestep  $t$ , respectively. The transparency of the image indicates the knowledge forgetting level.

### Algorithm 2: OLOR for Adam

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1: input:
    $\eta \in \mathbb{R}$ : Initial learning rate,  $\beta_1, \beta_2 \in [0, 1]$ : Exponential
   decay rates for the moment estimates,  $\epsilon$ : bias,  $\theta_0$ : pre-trained
   weight,  $\iota_1, \iota_2 \in [0, 1]$ ,  $\iota_1 \geq \iota_2$ : max and min level of weight
   rollback respectively,  $\gamma \in \mathbb{R}$ : weight rollback power
2: initialize:
    $t \leftarrow 0$ : time step,  $m_0 \leftarrow 0$ : initial first moment vector,  $v_0 \leftarrow 0$ :
   initial second moment vector,  $d_0 \leftarrow 0$ : initial discrepancy
   value,  $\lambda_i \leftarrow f(\lambda, i, n, \iota_1, \iota_2)/\eta$ : calculate penalty factor  $\lambda_i$ 
   through  $\lambda_i = f(\lambda, i, n, \iota_1, \iota_2) = \iota_2 + (\frac{\iota_1}{n})^\gamma (\iota_1 - \iota_2)$ , then
   scale it by dividing  $\eta$  to eliminate Dimensional Effects
3: repeat
4:    $t \leftarrow t + 1$ 
5:    $g_t \leftarrow \nabla f_t(\theta_{t-1})$ 
6:    $m_t \leftarrow \beta_1 m_{t-1} + (1 - \beta_1) g_t$  (Update first moment vector)
7:    $v_t \leftarrow \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$  (Update second moment vector)
8:    $\hat{m}_t \leftarrow m_t / (1 - \beta_1^t)$ 
9:    $\hat{v}_t \leftarrow v_t / (1 - \beta_2^t)$ 
10:   $\theta_t \leftarrow \theta_{t-1} - \eta \lambda_i d_{t-1} - \frac{(1 - \eta \lambda_i) \eta \hat{m}_t}{(\sqrt{\hat{v}_t} + \epsilon)}$  (Update weight)
11:   $d_t \leftarrow (1 - \eta \lambda_i) (d_{t-1} - \frac{\eta \hat{m}_t}{(\sqrt{\hat{v}_t} + \epsilon)})$  (Update discrepancy)
12: until stopping criterion is met
13: return optimized parameters  $\theta_t$ 

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### Previous Regularization Mechanisms have Delay Defect

L2 regularization and weight decay are popular methods to avoid overfitting. However, our findings indicate that their

effectiveness does not align with the initial expectation. In the case of the classic SGD optimizer, L2 regularization can be regarded as equivalent to weight decay (Loshchilov and Hutter 2017), which can be defined as follows:

$$\theta_t = (1 - \lambda) \theta_{t-1} - \eta_t g_t, \quad (1)$$

where  $\theta_t$  represents the model weights at iteration  $t$ , and  $\theta_{t-1}$  is corresponding weights from the previous iteration.  $\lambda$  is the **regularization coefficient** (weight decay strength).  $\eta_t$  is the learning rate at iteration  $t$ .  $g_t$  is the gradient of the loss function with respect to the model parameters at iteration  $t$ . Weight decay penalizes the weights obtained from the previous iteration by pushing them toward 0. However, in practice,  $\lim_{\lambda \rightarrow 1} \theta_t = -\eta_t g_t$ , the weights tend to be pushed towards the negative value of the current gradient instead of 0. This behavior may be different from the initial expectation. Furthermore, applying weight decay can actually increase the current weight compared to not applying it. This can be seen in the following inequality:

$$(\theta_{t-1} - \eta_t g_t - \lambda \theta_{t-1})^2 > (\theta_{t-1} - \eta_t g_t)^2, \quad (2)$$

simplified as:

$$\begin{cases} \eta g_t < (1 - \frac{\lambda}{2}) \theta_{t-1}, & \text{if } \theta_{t-1} < 0, \\ \eta g_t > (1 - \frac{\lambda}{2}) \theta_{t-1}, & \text{if } \theta_{t-1} > 0. \end{cases}$$

If  $\eta$ ,  $g_t$ ,  $\lambda$ , and  $\theta_{t-1}$  are in above conditions, using weight decay will drive the current weight away from 0, which is

opposite to its target. Similarly, this issue with the decay effect also exists in other regularization mechanisms such as L1 regularization, L2-SP, and similar methods.

### Weight Rollback

The proposed weight rollback is a real-time regularization method that closely follows each weight update step. It aims to bring the current model weights closer to the pre-trained weights to perform knowledge reviewing. Specifically, the first step is to calculate the pre-weight  $\theta_{pre}$  by gradient:

$$\theta_{pre} = \theta_{t-1} - \eta_t g_t, \quad (3)$$

where  $\theta_{t-1}$  represents the model weights from the previous time step,  $\eta_t$  is the learning rate at the current time step, and  $g_t$  denotes the gradient. Subsequently, the discrepancy  $\Delta d$  between  $\theta_{pre}$  and the pre-trained weight  $\theta_0$  is computed as:

$$\Delta d = \theta_{pre} - \theta_0. \quad (4)$$

Finally, the weight update process incorporates  $\Delta d$ , resulting in the adjusted model weights  $\theta_t$ :

$$\theta_t = \theta_{t-1} - \eta_t g_t - \lambda \Delta d. \quad (5)$$

By substituting Eq. 3 and Eq. 4 into Eq. 5, we obtain:

$$\theta_t = (1 - \lambda)(\theta_{t-1} - \eta_t g_t) + \lambda \theta_0. \quad (6)$$

This Eq. 6 ensures that  $\lim_{\lambda \rightarrow 1} \theta_t = \theta_0$ , which aligns with our expectation outcome, prevents abnormal scenarios. In addition, since the gradient  $g_t$  is also subject to a penalty, this process may potentially mitigate gradient explosions.

In summary, the weight rollback technique moderates the deviation between  $\theta_t$  and  $\theta_0$  at each step, thereby alleviating overfitting to the current task and knowledge forgetting to the previous task.

### Layer-wise Penalty

**Penalty Decay.** In the context of deep learning neural networks, each layer can be conceptualized as a function that processes its input. Given a layer index  $i$  this process can be described as follows:

$$x_{i+1} = f_i(x_i), \quad (7)$$

where the  $f_i$  represents the  $i_{th}$  layer, which takes  $x_i$  as its input. Let  $q_i(x)$  denote the distribution of  $x_i$  in the upstream data and  $p_i(x)$  denotes the distribution of  $x_i$  in the downstream data. Since the  $p(x_i)$  will change during the fine-tuning process, we first unfreeze all layers to handle better the gap between  $q(x_i)$  and  $p(x_i)$ .

In the study of image feature extraction, a prevailing understanding is that shallow layers are primarily responsible for capturing superficial features (Lin et al. 2017) such as color, texture, and shape. In contrast, deeper layers focus on extracting more profound features like semantic information. This implies that shallow layers are closely linked to the distribution of the data, whereas deep layers are more aligned with task-specific objectives. A foundational assumption underlying transfer learning is that  $q(x_0)$  bears

Table 1: Details of the Fine-tuning datasets.

Dataset	Images	Categories	Type
CIFAR-100	60,000	100	General
SVHN	600,000	10	General
CUB-200	11,788	200	Fine-grained
Stanford Cars	16,185	196	Fine-grained
Places-LT	62,500	365	Long-tailed
IP102	75,222	102	Long-tailed
OfficeHome	15,500	$4 \times 65$	Cross-domain
PACS	9,991	$4 \times 7$	Cross-domain
COCO2017	163,957	80	Detection
ADE20K	27,574	3688	Segmentation

a degree of similarity to  $p(x_0)$ . Consequently, shallow layers tend to exhibit similarities in both pre-training and fine-tuning stages. Additionally, shallow layers require fewer updates compared to their deeper counterparts.

Based on these observations, we propose a layer-wise penalty decay mechanism for weight rollback. This approach gradually reduces the rollback level as the layer depth increases. This strategy encourages shallow layers to extract more general features in downstream tasks while preserving the overall model capacity. For any layer at index  $i$ , the penalty factor  $\lambda_i$  is computed using the following formula:

$$\lambda_i = \iota_2 + \left(\frac{i}{n}\right)(\iota_1 - \iota_2), \quad (8)$$

where  $n$  represents the total number of layers in the pre-trained model,  $\iota_1$  and  $\iota_2$  denote the maximum and minimum rollback levels, respectively.

**Diversified Decay Rate.** Across various downstream tasks, the target objectives often exhibit varying degrees of dissimilarity from those of the upstream task. To accommodate this variability, we propose adjusting the rate of penalty decay between layers by introducing a power exponent  $\gamma$  to the weight rollback value. Mathematically, this adjustment can be expressed as:

$$\frac{i}{n} \longrightarrow \left(\frac{i}{n}\right)^\gamma. \quad (9)$$

This dynamic adjustment helps mitigate the bias stemming from a fixed rate decay of the similarities between  $q(x_i)$  and  $p(x_i)$  across different layer indices  $i$ . Consequently, the penalty decay becomes more adaptable and versatile, catering to a spectrum of requirements dictated by the various downstream tasks.

## Experiments

### Experiment Configuration

**Pre-trained Backbones.** The experiments employ CNN-based ConvNeXt (Liu et al. 2022) and Transformer-based Vision Transformers (ViT) (Dosovitskiy et al. 2020) as backbones. For ViT, both supervised pre-training on ImageNet-21K (Russakovsky et al. 2015) and LAION-2B (Schuhmann et al. 2022) datasets and self-supervised pre-training

Table 2: Comparison of fine-tuning results on various types of classification datasets (general, fine-grained, long-tailed, cross-domain).

Method	General (ID)		Fine-Grained (ID)		Long-Tailed (OOD)		Cross-Domain (OOD)	
	Cifar-100	SVHN	CUB-200	StanfordCars	Places-LT	IP102	OfficeHome	PACS
<b>ViT-B Backbone</b>								
Linear	72.50	58.79	75.01	38.03	31.95	64.93	79.96	71.88
Full	87.76	97.27	81.34	75.55	31.59	74.09	84.39	87.79
L2-SP	88.17	97.12	81.65	75.55	31.22	73.75	84.74	87.74
VPT	91.49	94.37	81.86	58.24	37.02	70.41	86.48	77.44
<b>OLOR-Adam (ours)</b>	<b>92.89</b>	<b>97.35</b>	<b>84.84</b>	<b>82.02</b>	<b>38.07</b>	<b>75.34</b>	<b>89.05</b>	<b>94.38</b>
<b>ConvNeXt-B Backbone</b>								
Linear	81.70	69.21	87.85	50.21	36.41	70.77	92.40	93.46
Full	92.72	96.97	88.59	88.67	38.61	75.01	91.78	95.51
L2-SP	92.84	97.01	88.82	88.83	38.52	75.20	90.61	95.90
VPT	88.71	81.58	87.88	51.58	36.32	71.22	92.31	93.75
<b>OLOR-SGD (ours)</b>	<b>92.86</b>	<b>97.12</b>	<b>89.47</b>	<b>88.99</b>	<b>39.36</b>	<b>75.44</b>	<b>92.59</b>	<b>96.63</b>

on ImageNet-1K (Deng et al. 2009) and LAION-2B datasets are utilized, where the self-supervised methods encompass OpenCLIP (Radford et al. 2021) and MAE (He et al. 2022). On the other hand, ConvNeXt is supervised pre-training on the ImageNet-21K dataset.

**Downstream Tasks.** We experiment on ten popular visual task datasets, i.e., CIFAR-100 (Krizhevsky, Hinton et al. 2009), SVHN (Netzer et al. 2011), CUB-200 (Wah et al. 2011), Stanford Cars (Krause et al. 2013), Places-LT (Zhou et al. 2014), IP102 (Patterson et al. 2014), OfficeHome (Venkateswara et al. 2017), and PACS (Li et al. 2017), covering general classification, fine-grained classification, long-tailed classification, cross-domain classification, object detection, semantic segmentation, and instance segmentation. More details are listed in Table 1.

**Baselines.** To ensure a comprehensive comparison, we select state-of-the-art and classic methods from the fine-tuning field as our baselines. These encompass Full Fine-tuning (Full), Linear Probing (LP) (Zhang, Isola, and Efros 2017), L2-SP (Xuhong, Grandvalet, and Davoine 2018), and VPT (Jia et al. 2022). Following prior works (Carion et al. 2020), CNN-based Backbones are usually combined with the SGD optimizer, while Transformer-based Backbones are paired with the Adam optimizer.

**Implementation Details.** The input image size is set at  $224 \times 224$ . The batch size varies depending on the freezing strategy chosen, i.e., 28 for full unfreezing, 256 for partial unfreezing, and 512 for full freezing. Regarding the learning rate, for ConvNeXt backbones, we employ the SGD optimizer with a momentum of 0.9. The learning rates differ based on the freezing strategy, i.e.,  $1e-2$  for full unfreezing,  $2e-2$  for partial unfreezing, and  $4e-2$  for full freezing. For ViT backbones, we use the Adam optimizer with a momentum of (0.9, 0.999). The learning rates for ViT backbones also vary according to the freezing strategy, i.e.,  $1e-4$  for full unfreezing,  $2e-4$  for partial unfreezing, and  $4e-4$  for full freezing. We train on cross-domain datasets for 30 epochs,

while for other datasets, we train for 50 epochs. The experiments are performed on two A5000 GPU with 24 GB memory and Ubuntu 20.04 operating system. Python 3.8.3 serves as the programming language, while PyTorch 2.0.0 framework is employed. In addition, the source code is openly available on GitHub.

## Main Results

**Results on classification tasks.** To verify the wide adaptability of OLOR on various types of datasets, we conduct a comprehensive comparison with other state-of-the-art fine-tuning methods. We evaluate these methods on 10 popular classification datasets, each showcasing a range of data distributions and characteristics. In addition, the Backbone in the experiment covers ViT-B and ConvNeXt-B, corresponding to Adam and SGD optimizers, respectively.

The experiment results are listed in Table 2. It can be observed that our OLOR achieves a new state-of-the-art on all datasets. Notably, in in-distribution (ID) datasets, OLOR-Adam surpasses the previously leading L2-SP method by an impressive margin of 6.47% in accuracy. Moreover, when confronted with two more challenging out-of-distribution (OOD) datasets, OLOR-Adam achieves accuracy improvements of 2.57% and 7.38%, respectively, outperforming the optimal methods.

Since the ConvNeXt pre-training model is more stable than the ViT structure, there is not much difference between different methods in fine-tuning. However, our OLOR-SGD still improves the fine-tuning accuracy stably on all data sets. These results demonstrate the robustness and effectiveness of the proposed OLOR in various tasks.

**Results on detection and segmentation tasks.** Due to the complexity of detection and segmentation tasks, most existing fine-tuning methods struggle with applicability and validation. However, integrated with the optimizer, our OLOR approach can easily be applied to these tasks. Table 3 shows the results of object detection and instance segmentation on the COCO2017 dataset, while Table 4 showcases the perfor-

Table 3: Results of object detection and instance segmentation using the ConvNeXt-B as backbone.

Method	Model	Dataset	$Bbox_m$	$Segm_m$
Full	Mask R-CNN	COCO2017	40.20	36.00
<b>OLOR</b>	Mask R-CNN	COCO2017	<b>41.10</b>	<b>36.90</b>

Table 4: Results of semantic segmentation using the ViT-B as backbone.

Method	Model	Dataset	$IOU_m$
Full	UperNet	ADE20K	43.65
<b>OLOR</b>	UperNet	ADE20K	<b>44.62</b>

mance of semantic segmentation on the ADE20K dataset. OLOR consistently outperforms the Baseline by approximately 1% in all metrics, demonstrating its versatility and effectiveness in more complex detection and segmentation tasks.

**Results of using different upstream pre-training resources.** Considering different upstream pre-training models and data will influence the performance of fine-tuning methods, we conduct experiments to explore and compare. The pre-training models include ViT-B supervised training on ImageNet-21K, OpenCLIP self-supervised training on LAION-2B, and MAE obtained from self-supervised training on ImageNet-1K. The fine-tuning dataset is the challenging OOD data PACS.

As listed in Table 5, our OLOR consistently achieves state-of-the-art results across all pre-training models. Specifically, OLOR surpasses other leading methods by 5.08%, 0.64%, and 3.47% when using Supervised, OpenCLIP, and MAE, respectively. It is worth noting that while other methods struggle to adapt to all pre-training models simultaneously, our OLOR demonstrates potential across all pre-training models.

**Summary of main results.** In summary, the above experiments show that OLOR achieves SOTA when applied to diverse downstream tasks, utilizing multiple upstream pre-training data and models and various backbones. These results demonstrate the generalizability and effectiveness of the OLOR fine-tuning method.

Table 5: Results of using different pre-trained models on the PACS dataset.

Method	Supervised	OpenCLIP	MAE
Linear	71.88	95.61	36.72
Full	87.79	47.17	84.18
L2-SP	87.74	45.56	85.79
VPT	76.76	97.46	50.54
<b>OLOR (ours)</b>	<b>92.87</b>	<b>98.10</b>	<b>89.26</b>

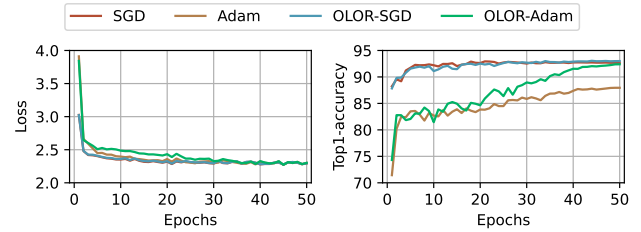


Figure 2: Train loss and valid top1 accuracy on Cifar-100, using ViT-B with Adam and ConvNext-B with SGD.

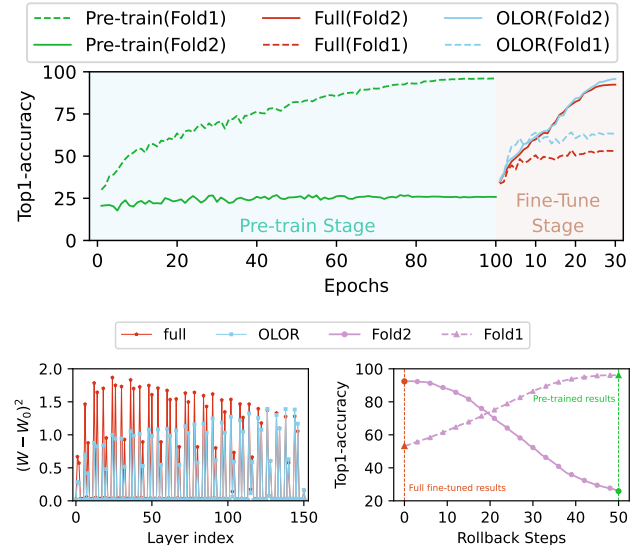


Figure 3: Knowledge forgetting test on PACS. Fold 1 as train set and fold 2 as valid set when pre-training, splits during fine-tuning is opposite to pre-training.

## Analysis and Discussion

**Compatibility Analysis.** As shown in Figure 2, adopt weight rollback in different types of models and optimizers generally improves the performance. Due to the restriction on parameters, OLOR leads to slower loss converging speed at first, but finally to be competitive with full method. According to the validation results, OLOR potentially helps reduce knowledge forgetting, resulting far ahead in terms of top1 accuracy, especially when cooperating with Adam applied in Vision Transformer.

**Knowledge Forgetting Test.** Knowledge forgetting is potentially carry out, we study on PACS using ViT-B and Adam to give a direct observation of it. Firstly, split the dataset into two fold, the first fold contains data from three domain, cartoon, photo and sketch respectively, denote as  $\mathcal{D}_1$ , the second fold contains data from art painting domain, denote as  $\mathcal{D}_2$ . For training stage, we first pre-train a model using  $\mathcal{D}_1$  as train set and  $\mathcal{D}_2$  as valid set for 100 epochs, then fine-tune the model using  $\mathcal{D}_2$  as train set and  $\mathcal{D}_1$  as valid set for 30 epochs through full-fine and OLOR, the discrepancy between fine-tuned weight  $\theta$  and pre-trained weight  $\theta_0$  using different methods are recorded. Additionally, we perform zero-shot reviewing, rollbacking full fine-tuned weights to



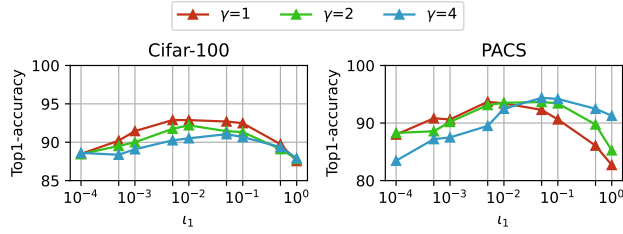


Figure 4: Hyper-parameters exploring experiments on Cifar-100(left) and PACS(right), both using ViT-B with Adam.

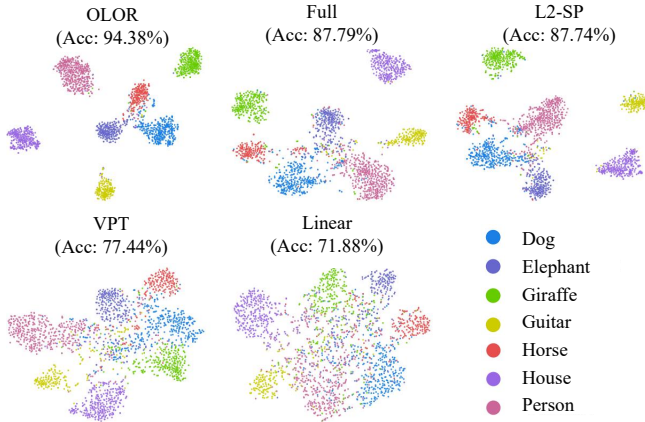


Figure 5: Feature visualization on PACS test set. We use features extracted by backbone to perform t-SNE visualization, and the Top1-accuracy are reported additionally.

pre-trained weights in 50 steps. Figure 3 reports the results, weight discrepancy is generally much smaller using OLOR, when setting max rollback level  $\iota_1$  to 0.01, rollback power  $\gamma$  to 1, OLOR not only well performs in knowledge reviewing, but also benefits for current learning. And the zero-shot reviewing result shows weight rollback itself is indeed a helpful method for just reviewing.

**Hyper-parameters Exploring.** We conduct experiments on Cifar-100(ID) and PACS(OOD) to study the appropriate hyper-parameters for different types of tasks. Usually, deep layers need to update significantly to better extract deep features related to downstream task, thus we set the min rollback level  $\iota_2$  to 0 by default to simplify hyper-parameter settings, for max rollback level  $\iota_1$ , we search from  $\{0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1\}$ , for weight rollback power  $\gamma$ , we search from  $\{1, 2, 4\}$ . Figure 4 shows the findings. We suggest applying small power if the task target of fine-tuning stage is similar to pre-training stage, and large max rollback level if the data distribution of downstream task is similar to upstream task.

**Feature Visualization.** We visualized the feature distributions for all methods on PACS test set through t-SNE to evaluate the quality of the extracted features. Experiments are based on ViT-B and Adam. As shown in Figure 5, compared with previous methods, OLOR generally separates the representation vectors of different classes much better, demonstrating imperial ability on representation.

Table 6: Hyperparameter configuration of OLOR on different downstream tasks.

Datasets	ViT-Based			CNN-based		
	$\iota_1$	$\iota_2$	$\gamma$	$\iota_1$	$\iota_2$	$\gamma$
Cifar-100	5e-3	0	2	5e-3	0	2
SVHN	5e-3	0	2	1e-4	0	2
CUB-200	5e-2	0	2	1e-2	0	2
StanfordCars	1e-2	0	4	1e-4	0	2
Places-LT	1e-1	0	4	1e-2	0	4
IP102	1e-1	0	1	5e-3	0	1
OfficeHome	1e-2	0	1	1	0	1
PACS	1e-1	0	4	5e-2	0	4
COCO2017	-	-	-	1e-2	0	2
ADE20K	1e-4	0	1	-	-	-

Table 7: Hyperparameter configuration of OLOR on different Pre-training models.

Pre-trained Method	$\iota_1$	$\iota_2$	$\gamma$
Supervised	1e-2	0	2
OpenCLIP	1e-2	0	2
MAE	1e-2	0	2

## Conclusions

In this paper, we propose a novel fine-tuning method named OLOR to solve the knowledge forgetting issue. OLOR encompasses weight rollback and layer-wise penalty. OLOR incorporates the weight rollback term into the weight update term at each step, and can be implemented in popular optimizers. This operation allows the model to gradually approach the pre-trained weights while learning the downstream task, making the weights of the upstream and downstream models more similar. In addition, the layer-wise penalty employs penalty decay and the diversified decay rate to adjust the weight rollback levels of layers for adapting varying downstream tasks. Our OLOR achieves state-of-the-art performance on extensive downstream tasks. Validation experiments and ablation analysis demonstrate the effectiveness of the proposed method.

## Additional Implementation Details

In Main Results section, when conducting experiments on various downstream tasks, OLOR utilizes the hyperparameter configurations listed in Table 6. For experiments involving different upstream pre-training models, the corresponding hyperparameter configurations for OLOR are listed in Table 7.

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