

Online-LoRA: Task-free Online Continual Learning via Low Rank Adaptation

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Abstract

Catastrophic forgetting is a significant challenge in online continual learning (OCL), especially for non-stationary data streams that do not have well-defined task boundaries. This challenge is exacerbated by the memory constraints and privacy concerns inherent in rehearsal buffers. To tackle catastrophic forgetting, in this paper, we introduce Online-LoRA, a novel framework for task-free OCL. Online-LoRA allows to finetune pre-trained Vision Transformer (ViT) models in real-time to address the limitations of rehearsal buffers and leverage pre-trained models' performance benefits. As the main contribution, our approach features a novel online weight regularization strategy to identify and consolidate important model parameters. Moreover, Online-LoRA leverages the training dynamics of loss values to enable the automatic recognition of the data distribution shifts. Extensive experiments across many task-free OCL scenarios and benchmark datasets (including CIFAR-100, ImageNet-R, ImageNet-S, CUB-200 and CORe50) demonstrate that Online-LoRA can be robustly adapted to various ViT architectures, while achieving better performance compared to SOTA methods¹.

1. Introduction

Continual learning (CL) is pivotal in enabling machine learning systems to learn new concepts while preserving the previously learned knowledge. This ability is crucial for real-time applications like robotics, healthcare, and autonomous driving [44, 77]. However, a major hurdle in CL is *catastrophic forgetting*, where learning new information impairs performance on previously learned data.

Existing CL methods are typically classified along two dimensions: (1) task-based or task-free, depending on whether the boundaries between different tasks are known [29, 63, 96]; and (2) online or offline, based on whether the setting allows for multiple iterations over the data (offline) or requires a single pass through the data (online) [9, 28, 84].

In offline task-based CL, a series of tasks is presented sequentially. Typically, it is assumed that each task comprises

a dataset with samples drawn from a distinct independent and identically distributed (i.i.d.) distribution [22, 46]. The samples are i.i.d. within the same task, though across tasks the distributions may differ. Additionally, it is assumed that the probability distribution from which the data is drawn remains stationary between the training and inference phases for any given task [54, 95]. This assumption simplifies the learning problem by ensuring that the trained model can be effectively applied to new data from the same task without the need to account for distributional shifts [3].

While offline task-based CL has paved the way for understanding how models can sequentially learn, its assumptions are often misaligned with the intricacies of real-world data. For instance, the need of completed training before inference, known as the lack of anytime inference capability, does not hold for applications where decisions must be made on-the-fly based on data that is continuously changing. Moreover, the offline task-based CL assumes well-defined task boundaries, a condition seldom met outside tightly controlled experimental environments. In contrast, real-world data streams are inherently continuous and lack clear task boundaries, often exhibiting gradual transitions.

Motivated by the limitations of offline task-based setting, in this paper we focus on *task-free online CL*; this scenario is characterized by the constraints of seeing a stream of samples only once, and the absence of knowledge regarding task identities and task boundaries during both training and inference [19, 30, 45, 93].

Pre-trained Vision Transformers [20] have demonstrated superior performance on various vision tasks, hence integrating them into CL has attracted increasing interest [24, 86, 97]. Indeed, the extensive prior knowledge of pre-trained models enhances knowledge transfer [81], brings significant performance improvements compared to traditional SOTA methods trained from scratch, and provides robust generalizability and adaptability, especially valuable in data-scarce environments [26, 99]. Recent studies [17, 74, 87] have demonstrated the potential of using parameter efficient fine-tuning (PEFT) techniques like prompt tuning [47] and Low-Rank Adaptation (LoRA) [34] with pre-trained models for offline task-based CL.

Given the need for task-free OCL and the advantages

¹Code: <https://github.com/Christina200/Online-LoRA-official.git>

provided by pre-trained models and PEFT methods, we wonder, *whether task-free OCL can benefit from pre-trained models and PEFT as effectively as offline task-based CL*. To this end, we propose **Online-LoRA**, a new approach integrating pre-trained ViT and LoRA into the task-free OCL scenario. Online-LoRA learns incrementally with each new piece of information. More precisely, we propose an extensible architecture that expands the model with additional LoRA parameters where the loss surface plateaus [3]. Thus, by utilizing loss plateaus to recognize shifts in data distribution, our model remains robust in continuously changing environments. Furthermore, we propose a new online parameter regularization, aimed to mitigate forgetting and enhance memory efficiency. In our regularization, the importance weights are calculated on the LoRA parameters exclusively, rather than using the entire set of model parameters like in EWC [42]. This decreases the computational and memory requirements significantly, thus enabling online updates of the model parameter importance throughout the learning process.

We summarize our main contributions as follows:

- We propose Online-LoRA, an innovative approach that can efficiently learn from changing data in an online, task-free manner, thus enabling inference at any time. We achieve this through continual low rank adaptation and automatic detection of data distribution shifts based on loss plateaus.
- We present an online weight regularization mechanism that effectively mitigates forgetting by adapting the estimation of model parameter importance to the incoming data with minimal additional memory. We achieve this by using a Laplace approximation to estimate the uncertainty around the LoRA parameters.
- Our extensive evaluations with various ViT architectures across multiple task-free OCL benchmarks, under the settings of class and domain incremental learning, demonstrate that Online-LoRA consistently outperforms existing SOTA methods. Moreover, Online-LoRA exhibits robust performance across various task sequence lengths and ViT architectures, showcasing its effectiveness in diverse learning contexts.

2. Related work

2.1. Continual learning

Since many existing CL methods are offline task-based, their transition to the online, task-free setting is not trivial. Here, we discuss four categories of CL methods and their adaptability to task-free OCL.

Architecture-based methods in CL generate task-specific parameters by isolating subspaces or adding sub-networks

[21,23,36,38,62,66,67,90,91]. However, these approaches need task identity during training and inference, making them unsuitable for task-free settings; also, they typically involve significant additional parameters [39, 83, 94]. In contrast, [6] introduces virtual gradient updates from a virtual model, enabling ‘any-time inference’ for OCL.

Regularization-based methods selectively regularize the update of network parameters depending on their importance to the old tasks [10,52,89]. The importance of parameters can be determined using an approximation based on Fisher Information Matrix (FIM), as in EWC [42], Synaptic Intelligence [95] and MAS [1]. However, because EWC calculates the FIM at task transitions, it is not feasible in task-free OCL. On the other hand, EWC++ [12] combines the regularization approaches of EWC [42] and Synaptic Intelligence [95] and makes it suitable for online settings.

Rehearsal-based methods address catastrophic forgetting by combining old training examples from a memory buffer with current data [8, 11, 51, 54, 60, 65, 70, 79]. In principle, these methods are suitable for our task-free OCL setting, using strategies to retrieve and update the buffer [2, 4, 18, 25, 37, 40, 68, 69]. For instance, REMIND [27] enables efficient replay in OCL using compressed representations, while [7] integrates rehearsal with regularization techniques. However, their effectiveness decreases with smaller buffers [5] and they pose challenges in data-sensitive environments [71]

Prompt-based methods construct a pool of task-specific prompts, select and attach them to the pre-trained model [35, 64, 82]. Most of these methods assume explicit task boundaries and require information on these task boundaries for training [74, 85]; this is not feasible in task-free OCL. However, L2P [86] is suitable for task-free OCL as it employs an instance-wise prompt query. Similarly, MVP [58] is also suitable because it utilizes an instance-wise logit masking. In the class-incremental experiments within the original L2P codebase [86], a training trick is employed to mask out the classes not relevant to the current task. This trick contradicts the task-free OCL setting of having “no task identity information during training”. Thus, to ensure a fair comparison, we evaluate our Online-LoRA against L2P [86] and MVP [58] under the Stochastic Incremental Blurry task boundary (Si-blurry) scenario, a new scenario introduced in the MVP paper [58].

2.2. Parameter efficient fine-tuning

Parameter Efficient Fine-Tuning (PEFT) is an effective approach for transfer learning [32]. Instead of fine-tuning an entire pre-trained model, PEFT fine-tunes specific sub-modules within the network by adding a small amount of additional parameters. PEFT reduces computation, but achieves similar performance to full fine-tuning. PEFT has been successfully applied to vision transformer mod-

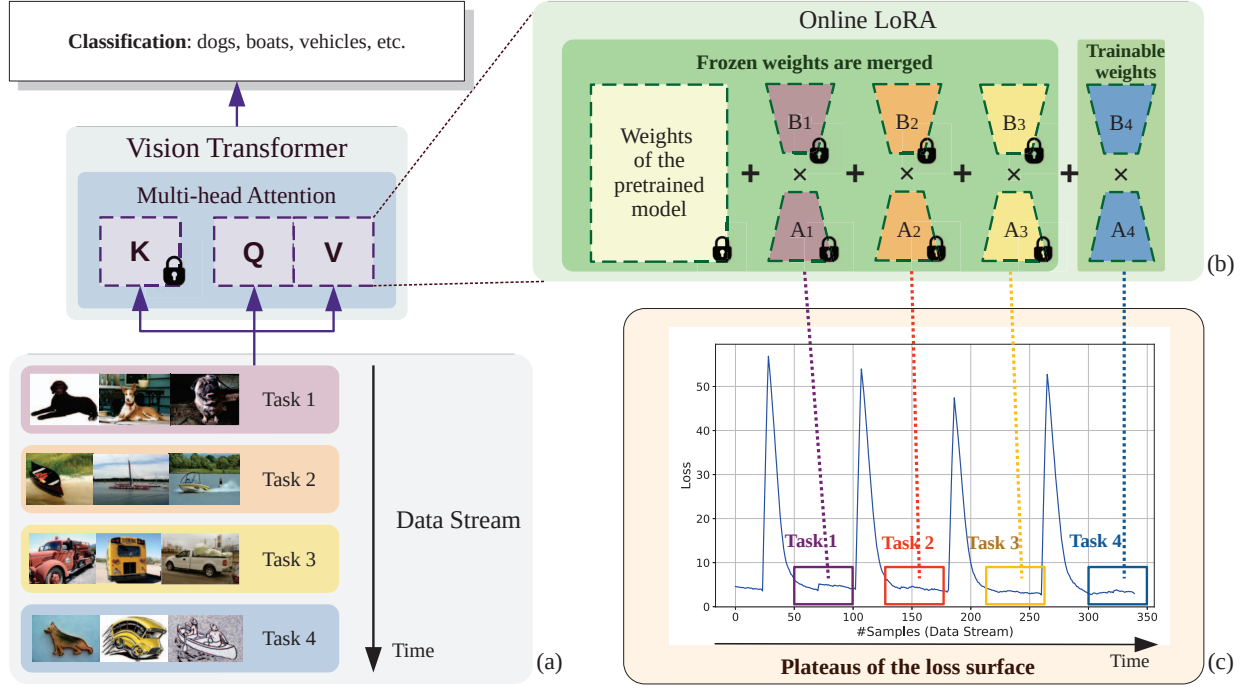


Figure 1. The overview of Online-LoRA. As the data is continuously streamed (a), a new pair of trainable LoRA parameters (A_4, B_4) is added (b) every time the loss surface encounters a plateau (c). Subsequently, the previous LoRA parameters ($A_1, B_1; A_2, B_2; A_3, B_3$) are frozen (the lock sign in (b)) and merged to the weights of the pre-trained ViT model.

els [16, 48], and one notable example is LoRA [34].

In LoRA, for a pre-trained weight matrix $W_{init} \in R^{d \times k}$, the update ΔW in $W \leftarrow W_{init} + \Delta W$ is reformulated as a low-rank decomposition: $\Delta W = BA$, where $A \in R^{r \times k}$ and $B \in R^{d \times r}$, and the rank $r \ll \min(d, k)$. W_{init} remains fixed during training and does not receive gradient updates, while A and B contain trainable parameters.

The application of PEFT in transformer-based models has gained popularity in CL research [17, 73, 87]. For example, SSIAT [76] incrementally tunes adapters [33] in pre-trained ViT. Additionally, C-LoRA [72] and InfLoRA [50] use separate LoRA sub-modules for each new task, and employ regularization to minimize interference between new and old tasks. However, these methods depend on the explicit knowledge of task boundaries, hence they are task-based offline CL approaches. To the best of our knowledge, our Online-LoRA is the first to extend LoRA to the task-free OCL scenario for transformer-based vision models.

3. Online-LoRA

3.1. Problem formulation

We define a data stream of unknown distributions $D = \{D_1, \dots, D_N\}$ over $X \times Y$, where X and Y are input and output space respectively [56]. At each time step s , the system receives a batch of non i.i.d samples x_k^t, y_k^t from the current distribution D_t of task t ; the system sees this batch

only once. Moreover, at any moment s , the distribution D_t can itself experience sudden or gradual changes from D_t to D_{t+1} . The system is unaware of when and how these distribution changes happen.

For simplicity, we assume that D_t is the data distribution of task t , and any shift from D_t to D_{t+1} is sudden. Of note, this remains a task-free setting, since gradual transitions from D_t to D_{t+1} can still be modeled by adding intermediate tasks and making these distributions increasingly similar, thus effectively blurring the explicit boundaries between tasks. Our Online-LoRA does not assume any task boundaries at any time.

3.2. Loss-guided model adaptation

In existing LoRA-based CL methods [72, 87], new LoRA parameters are added for each new task t' , resulting in a set of LoRA parameters denoted as $\{A_{t'}, B_{t'}\}$, where $A_{t'} \in R^{d \times r}$, $B_{t'} \in R^{r \times k}$, d and k are the input and output dimensions of the attention layer, and rank $r \ll \min(d, k)$. When learning task t , if the initial ViT weights are denoted as W_{init} , then for an input sample X , the model output Y becomes:

$$Y = (W_{init} + \sum_{t'=0}^t B_{t'} A_{t'}) X \quad (1)$$

This *incremental model* effectively mitigates the catastrophic forgetting by minimizing the interference between

old and new tasks (see Figure 1). As shown, LoRA is applied only to the query and value projection matrices in all the attention layers. Since data from previous tasks is not available when training on future tasks, the LoRA parameters of old tasks are frozen and merged with the pre-trained weights to reduce the memory overhead. However, the existing LoRA-based methods rely on the knowledge of task boundaries during training, as a new pair of LoRA parameters is initialized at the beginning of each new task. In task-free OCL, data flows continuously without clear task boundaries, and there is no information about the start or the end of a task. There brings the need for a mechanism to determine when to initialize the new LoRA parameters.

To this end, we consider the idea of *loss surface* [3]. As learning progresses, a decreasing loss indicates effective learning from current samples. Conversely, an increasing loss suggests a shift in data distribution, hindering effective learning. We assume that the model converges before the distribution shifts. Then between these phases, *plateaus of the loss surface* occurs, signaling that the model has reached a stable state by fitting well to the current data distribution (see Appendix C for more details). At these plateaus, it is best to consolidate the learned knowledge by freezing the current LoRA weights and initializing a pair of new, trainable LoRA parameters. To prevent the accumulation of additional LoRA parameters, the frozen LoRA weights are merged into the pre-trained attention weights.

3.3. Online parameter importance estimation

Many studies have demonstrated the efficacy of weight regularization in reducing catastrophic forgetting [1, 12, 42]; this technique relies on estimating the importance of each parameter. However, in an online scenario where data distribution shifts constantly, parameter importance also varies continually. Therefore, a static estimation of parameter importance is not applicable. Furthermore, Online-LoRA utilizes pre-trained Vision Transformer (ViT) models, which have a *substantial number of parameters*. Techniques such as calculating the Fisher information matrix at each task-switch for parameter importance estimation are computationally inefficient in this context [42].

However, it is still useful to consider the model training from a Bayesian perspective as EWC does [42]. In Bayesian machine learning, model parameters are treated as random variables, and the prior knowledge about these parameters is updated via Bayes' rule. More precisely, given data D :

$$\log p(\theta|D) = \log p(D|\theta) + \log p(\theta) - \log p(D) \quad (2)$$

Assume D is split into two independent parts: current sample x and data observed at the last time step D_{prev} . We can rewrite the posterior probability of the parameters and the equation (2) becomes:

$$\log p(\theta|D) = \log p(x|\theta) + \log p(\theta|D_{prev}) - \log p(x) \quad (3)$$

Since calculating the posterior probability is usually intractable, following the work on the Laplace approximation [55], we approximate this posterior as a Gaussian centered at the maximum a-posteriori (MAP) solution θ_{MAP} with covariance given by the inverse of the Hessian. In our work, the empirical Fisher information matrix is used to approximate the covariance of the approximated posterior. More specifically, the LoRA adapter $\sum_{t'} B_{t'} A_{t'} X$ is treated as two separate linear layers with weights $\sum_{t'} A_{t'} \in R^{d \times r}$ and $\sum_{t'} B_{t'} \in R^{r \times k}$, respectively, rather than as a single linear layer with a low rank weight matrix [92]; this division enhances memory efficiency. In EWC [42], the size of the importance weight matrix equals to the number of parameters squared. For instance, to employ EWC in ViT-B/16, the model needs to store and update a $86.6M \times 86.6M$ matrix, representing a significant memory and computational overhead. By handling the LoRA adapter as two distinct layers, our Online-LoRA approach employs two smaller importance weight matrices, $\Omega^{A,l} \in R^{d \times r}$ and $\Omega^{B,l} \in R^{r \times k}$, for each attention layer. The combined size of these matrices is proportional to the total number of LoRA parameters, calculated as follows: #attention heads $\times 2$ (for Q and V projection matrices) $\times$ input size $\times$ rank $\times 2$. For a ViT-B/16 model with a LoRA rank of 4, this equates to a total of: 12 heads $\times 2 \times 768$ input size $\times 4$ rank $\times 2 = 147,456$. This additional memory footprint is negligible ($\sim 0.17\%$ of the total parameters of the ViT-B/16 model), which enables the *online* updates of the importance weights.

In offline CL, the parameter importance is computed based on the entire training dataset of the current task. This is not applicable to online CL because each training sample can only be seen once. We employ a small *hard buffer* containing samples with the highest loss (computed with the current model), selected from both the current sample and the existing buffer. The hard buffer is continually updated to replace any samples whose loss decreases significantly as the model trains, ensuring that it contains genuinely challenging examples. Due to concerns about memory constraints and privacy, the hard buffer is minimal (holds only 4 samples), yet vital to parameter importance estimation.

Therefore, we propose a memory and computationally efficient estimation of the parameter importance, focusing on the sensitivity of loss relative to LoRA parameters. The *importance weight matrices* $\Omega^{A,l} \in R^{d \times r}$ and $\Omega^{B,l} \in R^{r \times k}$ match the dimensions of LoRA parameters:

$$\Omega_{ij}^{A,l} = \frac{1}{N} \sum_{k=1}^N \nabla_{W_{ij}^{A,l}} \log p(x_k|\theta) \circ \nabla_{W_{ij}^{A,l}} \log p(x_k|\theta) \quad (4)$$

$$\Omega_{ij}^{B,l} = \frac{1}{N} \sum_{k=1}^N \nabla_{W_{ij}^{B,l}} \log p(x_k|\theta) \circ \nabla_{W_{ij}^{B,l}} \log p(x_k|\theta) \quad (5)$$

with parameters $W^{A,l}$ and $W^{B,l}$ of the new and trainable LoRA modules added to the l^{th} attention layer. x_k are samples from the hard buffer described above. The parameters denoted by θ encompass the entire model, which includes the pre-trained ViT, the frozen LoRA parameters, and the new trainable LoRA parameters $W^{A,l}$ and $W^{B,l}$ for all attention layers l . Finally, $\circ$ is the Hadamard product (i.e. the element-wise product of two matrices).

After updating the importance weights, the model continues the learning process while penalizing changes to parameters that have been identified as important so far. Because $\theta_{MAP} = \underset{\theta}{\operatorname{argmax}} \mathcal{L}(y, D; \theta)$, θ_{MAP} is given by model weights at the last loss surface plateau. As such, our final learning objective is:

$$\min_{W^A, W^B} \mathcal{L}(F(X; \theta), Y) + \mathcal{L}(F(X_B; \theta), Y_B) + L_{LoRA}(W^A, W^B) \quad (6)$$

$$L_{LoRA}(W^A, W^B) = \frac{\lambda}{2} \sum_{l \in |Attn|} ((\Omega^{A,l} \circ (W^{A,l}) \circ (W^{A,l})) + (\Omega^{B,l} \circ (W^{B,l}) \circ (W^{B,l}))) \quad (7)$$

where $Attn$ is the set of attention layers in the model, $\mathcal{L}(F(X; \theta), Y)$ is the loss of current samples, $\mathcal{L}(F(X_B; \theta), Y_B)$ is the loss of hard buffer samples. $\circ$ is the element-wise product of two matrices.

4. Experiments

4.1. Evaluation benchmarks

We evaluate our approach under three different scenarios: disjoint class-incremental, Si-Blurry class-incremental, and domain-incremental.

Disjoint class-incremental setting is when the datasets are split into disjoint tasks, each consisting of a unique set of classes. We conduct experiments with three datasets under this setting: Split-CIFAR-100 splits the CIFAR-100 dataset [43] into 10 tasks with 10 classes per task. Split-ImageNet-R splits the ImageNet-R dataset [31] into 10 tasks with 20 classes per task. Split-ImageNet-S splits the ImageNet-Sketch dataset [80] randomly into 10 tasks with 100 classes per task or into 20 tasks with 50 classes per task. Split-CUB-200 splits the CUB-200-2011 dataset [78] into 5 tasks with 40 classes per task.

Stochastic incremental-Blurry (Si-Blurry) [59] class-incremental setting is when the class distributions change in a stochastic manner, with classes overlapping across tasks and the task boundaries being dynamic and not clearly defined. We randomly select 50% of the entire classes to be "disjoint classes" (newly encountered classes that never appeared before), and 10% to be "blurry classes" (classes that do not belong to a fixed task and may appear in multiple learning tasks over time).

Domain-incremental setting is when the input distribution shifts over time, but the classes remain consistent. We use the CORE50 dataset [53] for this setting; it has 11 distinct domains (8 for training, 3 for testing). The samples from the training domains arrive sequentially.

4.2. Experimental details

Baselines We compare Online-LoRA against SOTA task-free OCL methods. The Upper-bound (*UB*) baseline refers to supervised fine-tuning on the entire dataset of i.i.d. data, representing the optimal performance. The SOTA methods selected for comparison include AGEM [13], ER [14], EWC++ [12], MIR [2], GDumb [61], DER++ [8], PCR [51], LOD (with DER++ [8]) [49], EMA (with DER++ [8] and with RAR [98]) [75], L2P [86] and MVP [58].

Evaluation metrics To evaluate the OCL performance, we choose three metrics, A_{AUC} , A_{Final} , and *Forgetting*. The A_{AUC} [88] evaluates the model accuracy throughout training, measuring the performance of anytime inference. The final accuracy A_{Final} [15,57] measures the performance after the training is finished. *Forgetting* [86] measures the average difference between the final performance obtained for each task compared to the best performance on each task. Higher A_{AUC} and A_{Final} are better, while lower *Forgetting* is better. See Appendix A for the detailed definitions.

Implementation details We employ a ViT-B/16 (86.6M parameters) and a ViT-S/16 (48.6M parameters) [20] pre-trained on ImageNet as our backbone. For each setup, we evaluate all methods, including ours and other SOTA methods, using the same pre-trained models (see Appendix F.2). We use the Adam optimizer [41] to train our Online-LoRA, with a 0.0002 learning rate for ViT-B/16 and 0.0005 for ViT-S/16. We set the size of the minimal hard buffer to 4, regularization factor λ to 2000 for all settings. See Appendix B for experimental details of Online-LoRA. For the other approaches, we refer to their original codebases for implementation and hyperparameter selection for a fair comparison (details in Appendix F). The buffer size of the replay-based methods is 500 (results for other buffer sizes in Appendix G). Given our focus on online CL, the training epoch is set to 1 for all experiments.

4.3. Main results

Results on disjoint class-incremental setting. Table 1 summarizes the results on the disjoint class-incremental benchmarks Split CIFAR-100, Split ImageNet-R, Split ImageNet-S, and Split CUB-200. Our Online-LoRA, outperforms all other compared methods consistently across the ViT-B/16 and ViT-S/16. On Split ImageNet-S, Online-LoRA exhibits standout performance, significantly outperforming all other methods, and notably reducing the gap to the upper bound.

As shown in Table 1, Online-LoRA maintains a consistent and strong performance across various dataset sizes.

		Split-CIFAR-100		Split-ImageNet-R		Split-ImageNet-S		Split-CUB-200	
		A_{Final} ($\uparrow$)	Forgetting ($\downarrow$)	A_{Final} ($\uparrow$)	Forgetting ($\downarrow$)	A_{Final} ($\uparrow$)	Forgetting ($\downarrow$)	A_{Final} ($\uparrow$)	Forgetting ($\downarrow$)
ViT-B/16	AGEM [13]	12.67 $\pm$ 1.87	82.51 $\pm$ 2.27	5.60 $\pm$ 2.74	53.97 $\pm$ 1.97	0.16 $\pm$ 0.04	9.42 $\pm$ 0.17	10.84 $\pm$ 1.57	47.79 $\pm$ 0.04
	ER [14]	44.85 $\pm$ 1.83	44.67 $\pm$ 4.29	40.99 $\pm$ 3.96	32.38 $\pm$ 0.89	30.21 $\pm$ 0.70	37.14 $\pm$ 1.83	31.66 $\pm$ 0.83	14.23 $\pm$ 0.07
	EWC++ [12]	10.61 $\pm$ 0.74	84.10 $\pm$ 1.11	3.86 $\pm$ 2.02	56.95 $\pm$ 1.46	0.32 $\pm$ 0.28	22.46 $\pm$ 4.69	26.14 $\pm$ 3.46	47.69 $\pm$ 0.07
	MIR [2]	48.36 $\pm$ 3.11	43.41 $\pm$ 1.02	41.51 $\pm$ 2.99	31.32 $\pm$ 5.17	30.33 $\pm$ 3.81	35.92 $\pm$ 1.75	31.64 $\pm$ 2.97	23.43 $\pm$ 0.05
	GDumb [61]	41.00 $\pm$ 19.97	-	8.87 $\pm$ 1.36	-	1.65 $\pm$ 0.22	-	9.09 $\pm$ 1.03	-
	PCR [51]	48.48 $\pm$ 0.15	46.23 $\pm$ 1.29	46.11 $\pm$ 3.03	25.50 $\pm$ 0.41	38.75 $\pm$ 0.22	35.01 $\pm$ 2.12	41.11 $\pm$ 1.43	29.64 $\pm$ 1.20
	DER++ [8]	36.64 $\pm$ 6.11	56.94 $\pm$ 7.55	30.90 $\pm$ 8.04	24.26 $\pm$ 4.14	6.47 $\pm$ 0.06	15.34 $\pm$ 0.15	26.61 $\pm$ 1.27	32.16 $\pm$ 0.55
	LODE (DER++) [49]	44.29 $\pm$ 1.48	45.54 $\pm$ 3.32	42.20 $\pm$ 6.46	31.83 $\pm$ 1.05	9.97 $\pm$ 2.29	8.48$\pm$1.24	39.20 $\pm$ 4.25	41.64 $\pm$ 3.59
	EMA (DER++) [75]	42.28 $\pm$ 4.36	55.59 $\pm$ 1.48	41.75 $\pm$ 1.98	32.65 $\pm$ 1.55	16.88 $\pm$ 2.23	36.28 $\pm$ 1.09	35.26 $\pm$ 3.31	25.55 $\pm$ 3.35
	EMA (RAR) [75]	47.10 $\pm$ 0.82	50.01 $\pm$ 0.35	30.04 $\pm$ 0.33	39.36 $\pm$ 0.04	14.06 $\pm$ 0.37	36.28 $\pm$ 1.09	33.34 $\pm$ 1.11	28.68 $\pm$ 0.56
Ours		49.40$\pm$1.36	41.74$\pm$2.58	48.18$\pm$0.63	23.85$\pm$1.48	47.06$\pm$0.24	28.09 $\pm$ 3.25	41.46$\pm$0.31	13.64$\pm$0.68
<i>UB</i>		89.50 $\pm$ 0.04	-	76.78 $\pm$ 0.44	-	63.82 $\pm$ 0.02	-	82.81 $\pm$ 1.07	-
ViT-S/16	AGEM [13]	7.43 $\pm$ 2.15	82.45 $\pm$ 5.46	2.35 $\pm$ 0.87	48.01 $\pm$ 0.05	2.75 $\pm$ 2.86	18.81$\pm$0.44	1.40 $\pm$ 0.17	27.06 $\pm$ 1.39
	ER [14]	31.91 $\pm$ 2.06	52.21 $\pm$ 6.41	32.73 $\pm$ 0.20	45.37 $\pm$ 1.72	19.53 $\pm$ 1.44	45.10 $\pm$ 0.48	21.81 $\pm$ 3.02	24.52 $\pm$ 2.98
	EWC++ [12]	6.80 $\pm$ 2.13	81.59 $\pm$ 7.43	1.32 $\pm$ 0.83	53.54 $\pm$ 0.19	4.08 $\pm$ 3.24	21.28 $\pm$ 0.46	2.07 $\pm$ 0.54	28.44 $\pm$ 0.83
	MIR [2]	29.08 $\pm$ 1.14	39.42 $\pm$ 1.60	34.73$\pm$0.29	48.66 $\pm$ 0.69	13.96 $\pm$ 1.95	42.61 $\pm$ 0.08	22.95 $\pm$ 1.12	32.54 $\pm$ 0.88
	GDumb [61]	10.87 $\pm$ 4.94	-	5.33 $\pm$ 1.09	-	2.09 $\pm$ 0.32	-	3.28 $\pm$ 0.99	-
	PCR [51]	32.89 $\pm$ 1.47	39.90 $\pm$ 2.51	21.96 $\pm$ 0.27	45.12 $\pm$ 0.08	14.37 $\pm$ 0.95	43.96 $\pm$ 0.48	22.28 $\pm$ 2.73	29.87 $\pm$ 0.04
	DER++ [8]	17.67 $\pm$ 4.04	51.65 $\pm$ 3.67	22.17 $\pm$ 4.27	54.79 $\pm$ 0.89	18.15 $\pm$ 0.66	46.22 $\pm$ 0.95	29.53 $\pm$ 2.37	21.49 $\pm$ 1.16
	LODE (DER++) [49]	28.65 $\pm$ 3.06	40.42 $\pm$ 1.58	31.65 $\pm$ 0.72	43.72 $\pm$ 0.09	17.59 $\pm$ 0.84	47.85 $\pm$ 0.23	26.81 $\pm$ 0.89	21.86 $\pm$ 2.30
	EMA (DER++) [75]	12.76 $\pm$ 0.65	41.17 $\pm$ 1.75	20.89 $\pm$ 3.05	48.03 $\pm$ 1.79	12.93 $\pm$ 0.13	22.59 $\pm$ 0.16	35.79 $\pm$ 5.27	24.85 $\pm$ 4.20
	EMA (RAR) [75]	19.21 $\pm$ 2.16	41.99 $\pm$ 1.73	16.11 $\pm$ 0.35	50.58 $\pm$ 0.83	14.50 $\pm$ 2.71	23.79 $\pm$ 2.91	34.53 $\pm$ 1.04	30.19 $\pm$ 0.36
Ours		32.16$\pm$0.24	38.64$\pm$0.65	33.21 $\pm$ 0.50	42.76$\pm$0.18	22.45$\pm$0.43	44.56 $\pm$ 0.24	37.41$\pm$0.16	20.78$\pm$2.54
<i>UB</i>		86.55 $\pm$ 0.01	-	69.94 $\pm$ 0.34	-	59.28 $\pm$ 0.11	-	73.91 $\pm$ 1.16	-

Table 1. Results of disjoint class-incremental learning. ‘ $\uparrow$ ’ means higher is better and ‘ $\downarrow$ ’ means lower is better. Regularization-based methods (EWC++, AGEM, and LODE) yield low accuracy and low forgetting on Split ImageNet-S. This is because their overly rigid constraints on model updates hinder effective learning. The best results are noted by **bold**. *UB* is the upper-bound performance.

		CIFAR-100 [43]		ImageNet-R [31]		ImageNet-S [80]	
		A_{AUC} ($\uparrow$)	A_{Final} ($\uparrow$)	A_{AUC} ($\uparrow$)	A_{Final} ($\uparrow$)	A_{AUC} ($\uparrow$)	A_{Final} ($\uparrow$)
ViT-B/16	L2P	43.01 $\pm$ 9.37	39.86 $\pm$ 2.28	22.71 $\pm$ 1.86	27.08 $\pm$ 2.49	10.02 $\pm$ 0.42	13.58 $\pm$ 4.04
	MVP	47.52 $\pm$ 9.74	44.49 $\pm$ 0.93	27.79 $\pm$ 0.62	31.64 $\pm$ 1.77	10.68 $\pm$ 0.45	13.99 $\pm$ 1.73
	Ours	60.12$\pm$5.79	61.70$\pm$6.29	45.05$\pm$1.59	48.00$\pm$6.01	30.81$\pm$2.09	30.22$\pm$4.36
	<i>UB</i>	89.50 $\pm$ 0.04		76.78 $\pm$ 0.44		63.82 $\pm$ 0.02	
ViT-S/16	L2P	37.82 $\pm$ 12.19	30.88 $\pm$ 1.39	24.31 $\pm$ 1.83	21.83 $\pm$ 2.13	2.00 $\pm$ 0.12	3.61 $\pm$ 1.08
	MVP	40.31 $\pm$ 9.52	35.55 $\pm$ 2.11	27.04 $\pm$ 1.09	26.67 $\pm$ 3.70	2.27 $\pm$ 0.14	3.72 $\pm$ 0.77
	Ours	52.84$\pm$7.97	58.72$\pm$1.44	39.47$\pm$1.93	36.61$\pm$4.63	15.35$\pm$0.92	20.18$\pm$1.84
	<i>UB</i>	86.55 $\pm$ 0.01		69.94 $\pm$ 0.34		59.28 $\pm$ 0.11	

Table 2. Results of Si-blurry class-incremental learning. ‘ $\uparrow$ ’ means higher is better and ‘ $\downarrow$ ’ means lower is better. All datasets are split into 5 blurry tasks. To ensure a fair comparison with L2P [86] and MVP [58], we exclude the loss from hard buffer samples in Online-LoRA. The best results are noted by **bold**.

In comparison, GDumb [61] exhibits unstable performance on the smaller dataset, Split CIFAR-100, and performs poorly on larger datasets such as Split-ImageNet-R and Split ImageNet-S. The main issue with GDumb is its exclusive reliance on a replay buffer to retrain the model. With larger datasets, a small buffer size tends to cause class imbalance, as it cannot represent the dataset diversity adequately. Online-LoRA, on the other hand, does not face this issue because it utilizes a small but highly targeted ‘hard buffer’ consisting of samples that the current model finds most challenging, as indicated by their high loss values. This selective buffering approach is not only effective, as shown in Section 4.5, but it also sidesteps the drawbacks of

a large memory buffer by not overly relying on it.

Results on Si-blurry class-incremental setting. Table 2 summarizes the results on the Si-blurry class-incremental benchmarks with datasets CIFAR-100, ImageNet-R, and ImageNet-S. In the Si-blurry scenario, Online-LoRA consistently outperforms all the considered methods by significant margins across both metrics, A_{AUC} and A_{Final} . The superior performance in anytime inference can be largely attributed to Online-LoRA strategic utilization of loss surface plateaus, which consolidates the knowledge precisely when needed. Online-LoRA is also more flexible than EWC [42] which does so only at specific discrete moments; Online-LoRA also avoids the

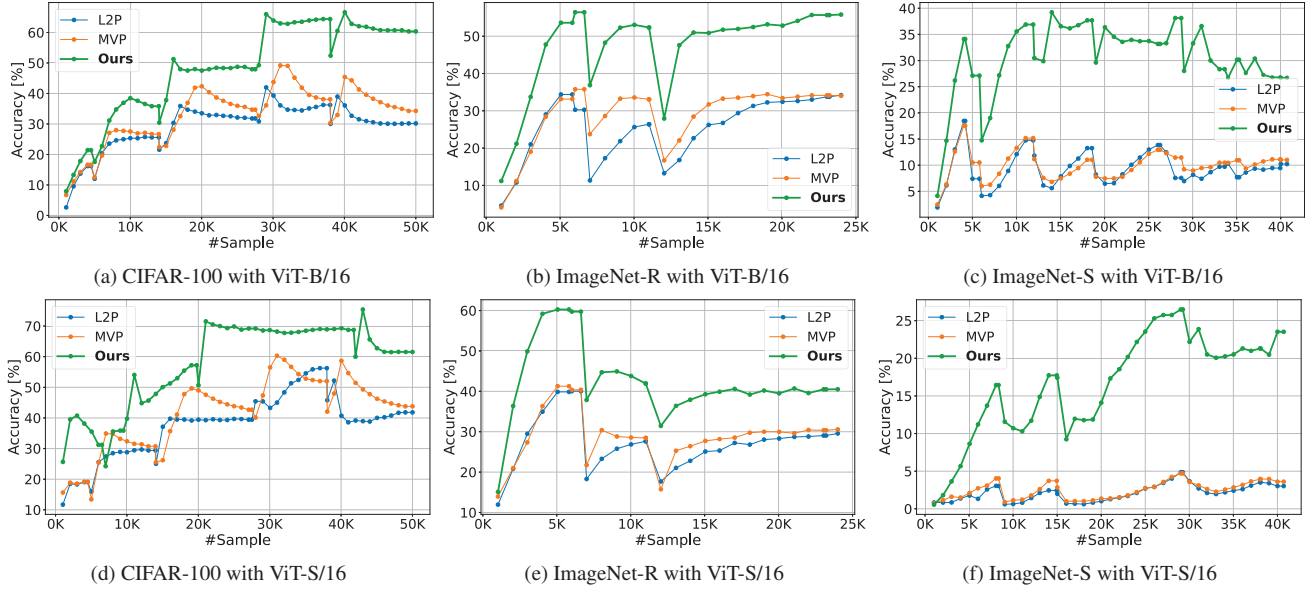


Figure 2. Average accuracy versus number of samples for Si-Blurry CIFAR-100, ImageNet-R, and ImageNet-S scenarios. As shown, the Online-LoRA consistently outperforms competing methods, maintaining high accuracy throughout.

excessive frequency of updates that introduce noise as seen in EWC++ [12].

Figure 2 displays the trend of accuracy as more samples are provided, highlighting the consistent performance of Online-LoRA across two different ViT architectures. Compared to other methods, Online-LoRA effectively learns new knowledge from incoming samples, which leads to an increase in accuracy.

Results on domain-incremental setting. Table 3 summarizes the results on the domain-incremental setting. Our proposed method, Online-LoRA, not only significantly outperforms other SOTA methods, but also closes a substantial portion of the gap with the upper-bound (UB) performance.

To summarize, the Online-LoRA consistently achieves superior performance under various setups. These results indicate its robustness and adaptability, not only in different ViT setups, but also for dynamically evolving data. In addition to effectively mitigating forgetting, Online-LoRA shows good plasticity.

4.4. Exploration with length of task sequence

Table 4 summarizes the results on Split ImageNet-S dataset across varying task sequence lengths; Table 5 summarizes the results on Si-blurry ImageNet-S. As the task sequence is longer, all methods experience a decline in performance. However, Online-LoRA exhibits the smallest reduction in performance, showcasing its robustness against longer task sequences. This can be attributed to its utilization of loss surface plateaus, which effectively captures and adapts to shifts in data distribution at instance level.

In contrast, for prompt-based learning methods such as L2P, longer task sequences challenge the capacity of prompt pool as more task-specific information needs to be encoded.

	ViT-B/16		ViT-S/16	
	$A_{\text{Final}} (\uparrow)$	Forgetting ($\downarrow$)	$A_{\text{Final}} (\uparrow)$	Forgetting ($\downarrow$)
AGEM [13]	80.15 $\pm$ 2.97	2.23 $\pm$ 0.81	78.22 $\pm$ 3.51	3.19 $\pm$ 0.09
ER [14]	85.85 $\pm$ 1.35	0.72 $\pm$ 0.03	78.99 $\pm$ 3.85	5.04 $\pm$ 0.10
EWC++ [12]	78.65 $\pm$ 6.51	2.31 $\pm$ 0.17	79.03 $\pm$ 4.54	4.80 $\pm$ 0.69
MIR [2]	74.35 $\pm$ 4.07	11.01 $\pm$ 1.05	86.49 $\pm$ 0.81	2.53 $\pm$ 0.84
GDumb [61]	77.20 $\pm$ 3.49	-	75.64 $\pm$ 2.92	-
PCR [51]	87.16 $\pm$ 0.73	0.78 $\pm$ 0.03	75.20 $\pm$ 1.48	0.61 $\pm$ 0.02
DER++ [8]	81.88 $\pm$ 7.06	10.13 $\pm$ 7.00	89.33 $\pm$ 0.62	0.42 $\pm$ 0.57
LODE (DER++) [49]	77.02 $\pm$ 2.22	17.30 $\pm$ 2.82	83.48 $\pm$ 5.84	24.54 $\pm$ 0.94
L2P [86]	87.97 $\pm$ 0.37	0.00$\pm$0.00	86.47 $\pm$ 0.23	0.00$\pm$0.00
MVP [58]	84.82 $\pm$ 0.54	0.00$\pm$0.00	79.85 $\pm$ 0.33	3.55 $\pm$ 0.39
Ours	93.71$\pm$0.01	0.00$\pm$0.00	90.96$\pm$0.02	0.00$\pm$0.00
Upper Bound (UB)	95.6 $\pm$ 0.01	-	93.56 $\pm$ 0.01	-

Table 3. Results of domain-incremental learning on CORE50 [53]. ‘ $\uparrow$ ’ means higher is better and ‘ $\downarrow$ ’ means lower is better. Online-LoRA not only achieves the highest final accuracy but also demonstrates the lowest forgetting.

Similarly, for replay-based methods, the strategy of selecting informative samples from the buffer is prone to biases in longer task sequences. This bias may result in an inadequate representation of earlier tasks or an overemphasis on more recent tasks, hurting the methods overall performance.

Furthermore, Figure 3 shows the accuracy on the validation set for four tasks at the time they are first encountered and after each subsequent task is learned (see Appendix I for results of other tasks). As shown in Figure 3, Online-LoRA consistently outperforms the other SOTA methods in terms of preserving the performance of previously learned tasks, which underscores the effectiveness of our online parameter regularization in mitigating catastrophic forgetting.

4.5. Ablation study

Table 6 shows the ablation study on the effectiveness of each component (“incremental LoRA” and “hard loss”) of Online-LoRA on Split ImageNet-R (10 tasks). The results

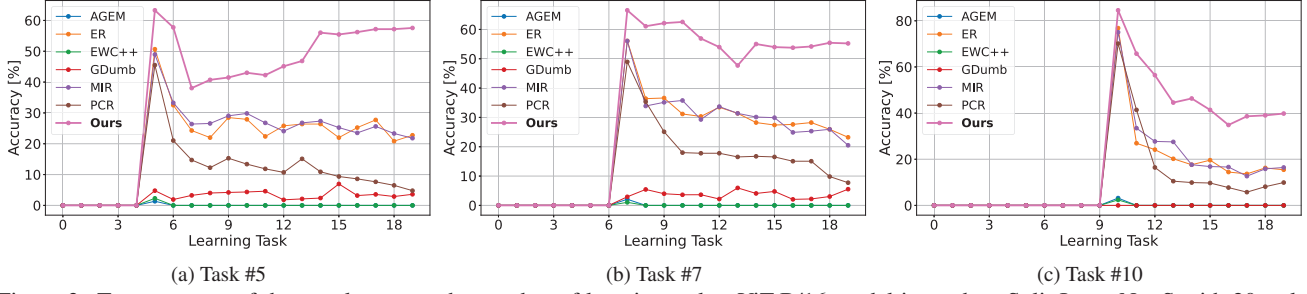


Figure 3. Test accuracy of three tasks versus the number of learning tasks. ViT-B/16 model is used on Split ImageNet-S with 20 tasks. The accuracy for each task prior to the model being trained on it is recorded as zero, since no measurements are taken at that stage, as the model has not yet been exposed to the corresponding task.

Method	10 tasks		20 tasks	
	$A_{\text{Final}} (\uparrow)$	$\text{Forgetting} (\downarrow)$	$A_{\text{Final}} (\uparrow)$	$\text{Forgetting} (\downarrow)$
AGEM [13]	0.16 $\pm$ 0.04	9.42 $\pm$ 0.17	0.11 $\pm$ 0.05	7.96 $\pm$ 0.10
ER [14]	30.21 $\pm$ 0.70	37.14 $\pm$ 1.83	22.81 $\pm$ 0.30	43.61 $\pm$ 0.16
EWC++ [12]	0.32 $\pm$ 0.28	22.46 $\pm$ 4.69	0.11 $\pm$ 0.05	5.26$\pm$0.45
MIR [2]	30.33 $\pm$ 3.81	35.92 $\pm$ 1.75	22.04 $\pm$ 0.41	39.17 $\pm$ 0.13
GDumb [61]	1.65 $\pm$ 0.22	-	1.97 $\pm$ 0.79	-
PCR [51]	38.75 $\pm$ 0.22	35.01 $\pm$ 2.12	17.87 $\pm$ 2.18	45.46 $\pm$ 0.07
DER++ [8]	6.47 $\pm$ 0.06	15.34 $\pm$ 0.15	2.29 $\pm$ 0.23	23.14 $\pm$ 0.06
LODE (DER++) [49]	9.97 $\pm$ 2.29	8.48$\pm$1.24	13.47 $\pm$ 0.66	35.89 $\pm$ 1.63
EMA (DER++) [75]	16.88 $\pm$ 2.23	36.28 $\pm$ 1.09	11.55 $\pm$ 0.66	38.56 $\pm$ 0.22
EMA (RAR) [75]	14.06 $\pm$ 0.37	36.28 $\pm$ 1.09	9.05 $\pm$ 0.60	29.77 $\pm$ 1.70
Ours	47.06$\pm$0.24	28.09$\pm$3.25	44.19$\pm$2.09	28.48$\pm$0.24
Upper Bound (UB)		63.82 $\pm$ 0.02		

Table 4. Comparison with other methods on Split ImageNet-S for different lengths of task sequences. ‘ $\uparrow$ ’ means higher is better and ‘ $\downarrow$ ’ means lower is better. ViT-B/16 model is used.

Method	Task sequence	ImageNet-S	
		$A_{\text{AUC}} (\uparrow)$	$A_{\text{Final}} (\uparrow)$
L2P [86]	5 tasks	10.02 $\pm$ 0.42	13.58 $\pm$ 4.04
MVP [58]		10.68 $\pm$ 0.45	13.99 $\pm$ 1.73
Ours		30.81$\pm$2.09	30.22$\pm$4.36
L2P [86]	10 tasks	9.06 $\pm$ 0.43	12.49 $\pm$ 3.39
MVP [58]		9.50 $\pm$ 0.29	12.24 $\pm$ 2.16
Ours		30.69$\pm$0.59	31.44$\pm$4.39
L2P [86]	20 tasks	6.57 $\pm$ 0.54	7.13 $\pm$ 0.89
MVP [58]		7.87 $\pm$ 0.24	8.98 $\pm$ 1.49
Ours		26.91$\pm$0.25	25.73$\pm$6.15

Table 5. Comparison with prompt-based methods on Si-blurry ImageNet-S at different length of task sequence. ViT-B/16 is used.

demonstrate the crucial role of each component of Online-LoRA in overall performance. More results in Appendix E.

Simply fine-tuning a single set of LoRA parameters (i.e. without incorporating any components of Online-LoRA) results in significantly worse performance compared to our approach, with a 20% drop in accuracy (from 48.23% to 28.68%). Additionally, excluding the loss from hard buffer samples within the Online-LoRA framework leads to a substantial performance decline from 48.23% to 34.74% (a 13.5% decrease). This emphasizes the crucial role of maintaining a minimal buffer with only the four most challeng-

Incremental LoRA	Hard loss	$A_{\text{Final}} (\uparrow)$	$\text{Forgetting} (\downarrow)$
-	-	28.68 $\pm$ 0.13	53.45 $\pm$ 0.04
✓	-	34.74 $\pm$ 0.31	34.37 $\pm$ 1.15
-	✓	36.08 $\pm$ 0.19	35.75 $\pm$ 0.33
✓	✓	48.23$\pm$0.74	23.85$\pm$1.08

Table 6. Ablation results of ViT-B/16 model on Split ImageNet-R dataset. ‘ $\uparrow$ ’ means higher is better and ‘ $\downarrow$ ’ means lower is better. “Incremental LoRA”: introducing new, trainable LoRA at each loss plateau with the model parameter regularization in Equation 7. “Hard loss”: including $\mathcal{L}(F(X_B; \theta), Y_B)$ (the loss from hard buffer samples) in the final learning objective in Equation 6. ✓ indicates the presence of the component, — indicates its absence.

ing samples in mitigating forgetting.

Furthermore, the absence of new LoRA initialized at plateaus of the loss surface and model parameter regularization results in a significant performance decline of 12%, from 48.23% to 36.08%. This highlights the importance of continuously adding new LoRA parameters to minimize task interference and implementing online weight regularization to prevent catastrophic forgetting.

5. Conclusion

In this paper, we have presented Online-LoRA, a novel method for task-free online CL. Online-LoRA dynamically analyzes the loss surface to adapt the model to changing data distributions and uses online weight regularization to prevent catastrophic forgetting.

We have also provided empirical evidence to show the effectiveness of Online-LoRA across various scenarios. Notably, Online-LoRA shows substantial performance advantage over other state-of-the-art methods in scenarios involving long task sequences. Furthermore, Online-LoRA’s performance closely approaches the upper bound in domain-incremental settings. Given the widespread adoption of pre-trained models in CL, Online-LoRA offers a strong foundation for practical task-free online CL systems.

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