Efficient Self-supervised Continual Learning with Progressive Task-correlated Layer Freezing

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Abstract

Inspired by the success of Self-supervised learning (SSL) in learning visual representations from unlabeled data, a few recent works have studied SSL in the context of continual learning (CL), where multiple tasks are learned sequentially, giving rise to a new paradigm, namely selfsupervised continual learning (SSCL). It has been shown that the SSCL outperforms supervised continual learning (SCL) as the learned representations are more informative and robust to catastrophic forgetting. However, if not designed intelligently, the training complexity of SSCL may be prohibitively high due to the inherent training cost of SSL. In this work, by investigating the task correlations in SSCL setup first, we discover an interesting phenomenon that, with the SSL-learned background model, the intermediate features are highly correlated between tasks. Based on this new finding, we propose a new SSCL method with layer-wise freezing which progressively freezes partial layers with the highest correlation ratios for each task to improve training computation efficiency and memory efficiency. Extensive experiments across multiple datasets are performed, where our proposed method shows superior performance against the SoTA SSCL methods under various SSL frameworks. For example, compared to LUMP, our method achieves 12%/14%/12% GPU training time reduction, 23%/26%/24% memory reduction, 35%/34%/33% backward FLOPs reduction, and 1.31%/1.98%/1.21% forgetting reduction without accuracy degradation on three datasets, respectively.

1. Introduction

Self-supervised learning (SSL) has achieved great success for unsupervised visual representation learning, which aims to learn representation without the need for human annotations. Recent studies (e.g., [7, 8, 16, 37]) have shown

that SSL can achieve comparable or even better performance than the supervised learning counterpart, by utilizing different augmentation views from the same images to generate and optimize contrastiveness. However, SSL still suffers from two major challenges: (1) SSL typically assumes that all training data is available during the training process and learns offline with large amounts of data and resources. In order to integrate new knowledge into the model, the current SSL methods need to train repeatedly on the entire dataset. This may hinder their applications in some realworld scenarios, where new unlabeled data is made available progressively over time and old data becomes unavailable. Also, the learners must be able to cope with nonstationary data in a continuous manner when they are exposed to tasks with varying distributions of data. (2) Compared to supervised learning, obtaining the trained model with the same performance requires much larger training cost in various settings (e.g., heavy model size, larger batchsize, longer training epochs, etc,.).

Fortunately, Continual Learning (CL) [19] provides a promising solution to address the first challenge. Notably, CL aims to incrementally update a model over a sequence of tasks, performing knowledge transfer from the old tasks to the new ones without catastrophic forgetting. A large body of works has been proposed (e.g., [28, 39, 35, 3, 5, 38, 10, 29, 23, 22]) for the supervised continual learning (SCL) paradigm. Most recently, a few works [11, 12, 25, 18] have emerged to study CL for the self-supervised learning paradigm, named as Self-Supervised Continual Learning (SSCL), which demonstrates that self-supervised visual representations are more robust to catastrophic forgetting compared to supervised learning. Specifically, CaSSLe [11] and PFR [12] propose a similar method that designs a temporal projection module to ensure that the newly learned feature space preserves the information of the previous one. UCL [25] adopts the Mixup [40] technique to interpolate data between the current task and previous tasks' instances

to alleviate catastrophic forgetting of the learned representations. However, these works directly combine the existing SSL frameworks with supervised continual learning techniques (e.g, knowledge distillation, mixup, memory replay, etc,.). Inheriting from the first challenge of SSL as mentioned above, these works still suffer from large training cost and the catastrophic forgetting issue still remains.

In this work, we seek to tackle this challenge and reduce training costs while mitigating catastrophic forgetting for SSCL. Towards this end, by first analyzing the task correlations based on gradient projection in SSCL, we find that the intermediate representations learned by selfsupervised learning are highly correlated and varied among tasks in comparison to SCL. Inspired by this new finding, we propose a new SSCL method with progressive taskcorrelated layer freezing (PTLF) during training for each task to reduce training time and memory cost. Specifically, we first define the task correlation ratio according to the gradient projection norm to formally characterize the correlation between the current task and prior tasks. Then, the top-ranked layers with higher task correlation ratios among tasks are progressively frozen during the self-supervised continual learning process for each task.

In the experiments, we validate the proposed method against the state-of-the-art SSCL methods on mutiple benchmarks, including Split CIFAR-10, Split CIFAR-100, Split TinyImageNet and ImageNet-100. The experimental results on various SSL frametworks have shwon that our method demonstrates superior performance of training efficiency and forgetting over the baseline methods, with comparable or even better accuracy. For example, in comparison to LUMP [25], by using SimSiam [8] SSL framework, our method achieves 12%/14%/12% GPU training time reduction, 23%/26%/24% memory reduction, 35%/34%/33% backward FLOPs reduction, and 1.31%/1.98%/1.21% forgetting reduction without accuracy degradation on three datasets, respectively.

2. Related Work

2.1. Self-supervised learning

Self-supervised learning aims to learn visual representation without data labeling cost. Recent advances [16, 7, 13, 37, 8] show that self-supervised learning can achieve similar or even better performance than supervised representation learning. A common strategy of these methods is to learn representations that are invariant under different data augmentations by maximizing their similarity with contrastive loss optimization. However, these approaches require large-sized batches and negative samples. SimSiam [8] addresses this issue by utilizing the stop-gradient technique to prevent the collapsing of Siamese networks. The Siamese network consists of an encoder network f and a prediction

MLP h, where the encoder includes a backbone model (e.g., ResNet [17]) and a projection MLP. Given two randomly augmented views of x_1 and x_2 from an input image x, Simsiam aims to minimize the negative cosine similarity between the predictor output p_1 ($p_1 = f(h(x_1))$) and the projector output z_2 ($z_2 = f(x_2)$) with a symmetrized loss as:

$$L_{SSL} = \frac{1}{2}D(p_1, \text{stopgrad}(z_2)) + \frac{1}{2}D(p_2, \text{stopgrad}(z_1)) \quad (1)$$

where D is a negative cosine similarity function. Given the distorted versions of an instance, BarlowTwin [37] minimizes the redundancy between their embedding vector components while conserving the maximum information. This can be achieved by making the cross-correlation matrix, computed between the outputs of two identical networks, closer to the identity matrix, through the minimization of the following loss:

$$L_{SSL} = \sum_{i} (1 - C_{ii})^2 + \lambda \sum_{i} \sum_{j \neq i} C_{ij}.$$
 (2)

Here λ is a positive constant scaling factor and C is the cross-correlation matrix computed between the outputs of the two identical networks along the batch dimension. Since SimSiam and BarlowTwim have no requirements for large batch size and negative samples, in this work, we adopt these two works as base learning methods for self-supervised continual learning.

2.2. Continual Learning

Plentiful continual learning methods have been developed in supervised learning and can be generally divided into three categories: 1) Regularization-based methods (e.g., [2, 21, 19]) preserve the knowledge of old tasks by adding an additional regularization term in the loss function, in order to constrain the weight update when learning the new task. For example, Elastic Weight Consolidation (EWC) [19] regularizes the update on the important weights that are evaluated using the Fisher Information matrix. 2) Structure-based methods (e.g., [35, 34, 30, 33]) adapt different model parameters or architectures with a sequence of tasks. 3) Memory-based methods can be further divided into memory-replay methods and orthogonalprojection based methods. Memory-replay methods (e.g., [27, 14, 6]) store and replay the old tasks data when learning the new task, while orthogonal-projection based methods (e.g., [38, 10, 29, 23, 22]) update the model for each new task in the orthogonal direction to the subspace spanned by inputs of old tasks.

More recently, a few works [26, 11, 12, 25, 18] have emerged to tackle the problem of self-supervised continual learning. They show that self-supervised continual learning can mitigate catastrophic forgetting and learn more general representations compared to supervised continual learning.

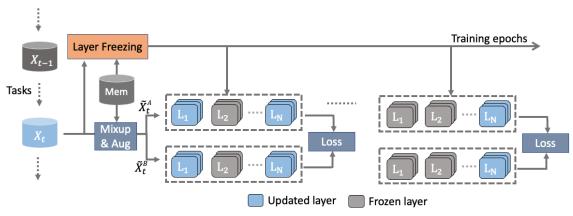


Figure 1. The overview of our proposed method which progressively freezes partial layers during the whole training process for each task.

Specifically, [26] learned task-specific representations on shared parameters. However, it is restricted to simple low-resolution tasks and not scalable to standard CL benchmark datasets. In addition, CaSSLe [11] and PFR [12] propose a similar method that designs a temporal projection module to ensure that the newly learned feature space preserves the information of the previous one. LUMP [25] adapts the Mixup [40] technique to interpolate data between the current task and previous tasks' instances to alleviate catastrophic forgetting for unsupervised representations:

$$\tilde{x}_{t,i} = \lambda \cdot x_{t,i} + (1 - \lambda) \cdot x_{M,l},\tag{3}$$

where $x_{M,l}$ denotes the old task data selected using uniform sampling from replay buffer M and λ is randomly sampled from a Beta distribution. However, these works directly combine the existing self-supervised with continual learning techniques (e.g, knowledge distillation, mixup, memory replay, etc,.) that still suffer from large training costs, and the forgetting issue remains as well. In this work, we aim to tackle these concerns.

2.3. Layer Freezing

There existed several works on accelerating the training of deep neural networks for one single task by using layer freezing techniques [24, 15, 31, 1, 36]. These works are motivated by the fact that front layers mainly extract general features of the raw data (e.g., the shape of objects) and are easier to well-trained, while deeper layers are more taskspecific and capture complicated features output from front layers. Specifically, Liu et al. [24] propose to automatically freeze layers during training according to the parameter gradients. Wang et al. [31] adopt knowledge distillation [1] to guide the layer freezing schedule. Yuan et al. [36] apply layer freezing on sparse training. However, these works only focus on one single task. It is a common setting that progressively freezes layers in descending layer index order. Different from all these related works, we show that layer freezing in SSCL needs to consider task correlations.

3. Method

3.1. Problem Setup

In supervised continual learning, a model continuously learns from a sequential data stream in which new tasks (namely, classification tasks with new classes) are added over time. More formally, consider a sequence of tasks $\{1,2,...,T\}$ where the task at time t comes with training data $D_t = \{\boldsymbol{x}_{t,i}, \boldsymbol{y}_{t,i}\}_{i=1}^{N_t}$. Note that each task t can contain a sequence of classes. We denote $f(\cdot)$ as the operation of a feature extractor and $h(\cdot)$ as a classifier model. The main objective is to optimize the parameter \boldsymbol{w} of both the feature extractor and the classifier:

$$\min_{\boldsymbol{w}_f, \boldsymbol{w}_h} \sum_{t=1}^{T} \sum_{i=1}^{N_t} \mathcal{L}_t(h(f(\boldsymbol{x}_{t,i})), \boldsymbol{y}_{t,i})$$
(4)

where $\mathcal{L}_t(\cdot)$ is cross entropy loss function in general.

In contrast, self-supervised continual learning does not require data labels during training. The objective is to learn a general representation that is invariant to augmentations on all tasks, which can be formulated as:

$$\min_{\boldsymbol{w}_f} \sum_{t=1}^{T} \sum_{i=1}^{N_t} \mathcal{L}_t(f(\boldsymbol{x}_{t,i}^1, \boldsymbol{x}_{t,i}^2))$$
 (5)

where $\boldsymbol{x}_{t,i}^1$ and $\boldsymbol{x}_{t,i}^2$ are augmented images generated from $\boldsymbol{x}_{t,i}$. The choices of the feature extractor and loss function depend on the self-supervised learning method, such as SimSiam and BarlowTwin as shown in Eq. (1) and Eq. (2), respectively. After the feature extractor is learned on all tasks, following [25], we use K-nearest neighbor (KNN) classifier [32] or linear classification to evaluate the performance of the learned representation. In this work, we investigate self-supervised continual learning on the setting of class-incremental learning, where the model owns a single classifier and task identifiers are not provided during inference.

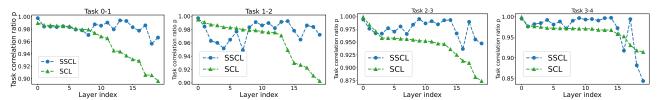


Figure 2. Layer-wise correlation ratio between two tasks on Split CIFAR-10 (5 tasks setup) using ResNet18 for SSCL and SCL respectively.

3.2. Proposed Method

3.2.1 Overview

For the first task, following the general setting [26, 11, 12, 25], we train the model as the self-supervised learning method without modification. Then for the remaining tasks that are learned sequentially, as shown in the Fig. 1, we adopt the memory replay-based method [5] to uniformly store data of each task with a fixed buffer size (i.e., 256) and the mixup technique from LUMP [25]. Furthermore, to improve the training computation and memory efficiency while mitigating catastrophic forgetting, we propose to *progressively freeze* layers during the whole training process for each task. Here the frozen layers are determined by *task correlation*. The detailed method will be illustrated below.

3.2.2 Layer freezing via task correlation

It is well-known that the training cost of SSL models is notoriously high, and this issue is further exacerbated in SSCL where new tasks arrive continuously. How to improve the training efficiency of SSCL becomes a critical question that needs to be solved, in order to facilitate the development and application of SSCL methods in practice. Towards this end, prior works [26, 11, 12, 25] have revealed that the learned representations of SSCL are more general and robust to catastrophic forgetting than the representations of SCL. We conjecture the reason behind is the learned intermediate features for each layer between the current task and prior tasks are highly correlated with each other. Accordingly, if the new task t has strong similarity with old tasks in some layers, it is possible that not updating these layers will not significantly affect the learning performance of this new task. Thus inspired, we raise the question: Can we leverage the generality of the learned representations from SSL and freeze the highly correlated layers during training for each task to improve the training efficiency?

To answer this question, motivated by prior gradient orthogonal-projection based methods [23, 22] on SCL, we first investigate the correlation of tasks according to gradient projection. Specifically, to formally characterize the correlation between the current task and prior tasks, we **define the task correlation ratio** in layer-wise as:

$$r_{l} = \frac{\|\operatorname{Proj}_{S_{t}^{l}}(\nabla \mathcal{L}_{t}(\boldsymbol{w}_{t-1}^{l}))\|_{2}}{\|\nabla \mathcal{L}_{t}(\boldsymbol{w}_{t-1}^{l}))\|_{2}}$$
(6)

where $\operatorname{Proj}_{S^l_t}$ denotes the projection on the input subspace S^l_t of prior tasks (1,2,...,t-1) on l^{th} layer, and \boldsymbol{w}^l_{t-1} represents the l^{th} layer weight in the model before learning task t. Here $\operatorname{Proj}_S(A) = AB(B)'$ for some matrix A and B is the bases for S. Due to the fact that the gradient lies in the span of the input [29], if the task correlation ratio $r_l \in (0,1)$ has a large value, it implies that the current task t and prior tasks may have sufficient common bases in l^{th} layer between their input subspaces and hence are strongly correlated. To quantitatively evaluate the task correlation on SSCL, we conduct the experiments on three settings (i.e., Split CIFAR-10, Split CIFAR-100, Split TinyImageNet) by using prior representative work LUMP [25]. As shown in Fig. 2, we observe that:

Observations: 1) the variance of the task correlation ratio in SSCL is smaller than the counterparts in SCL; 2) the correlation ratios of SSCL are larger than the counterparts in SCL for most layers; 3) the correlation ratios of SCL consistently follow an ascending order, while the counterparts in SSCL are more varied that are usually higher for top and middle layers.

The first two observations help to further explain that the learned representations of SSCL are more general than SCL. Moreover, the third observation indicates that following ascending order to freeze layer in supervised learning is a good choice [4, 24, 36] since the correlation ratios of the top layers are always larger than the later ones. However, for the SSCL, layer freezing needs to consider task correlations between tasks. In the experiments, we also evaluate that task-correlated layer freezing could show better accuracy than conventional layer freezing in ascending order in Section 5.

Subspace construction via memory replay data. Prior orthogonal-projection based methods (e.g., [29, 23]) target on task-incremental learning, which calculate and then store the bases of the input subspace of each prior task individually for orthogonal gradient descent. Such subspace storage consumes large memory costs, especially for the large models of self-supervised learning. For example, ResNet18 requires 116MB on CIFAR-10 dataset. Benefiting from utiliz-

ing data replay mechanism, we can construct the subspace of prior tasks on-the-fly instead of storing the corresponding bases. In practice, before training the current task, we calculate the bases of the subspace for the data in the replay buffer using Singular Value Decomposition (SVD) on the representations. Specifically, given the model w_{t-1} before learning task t, we construct a representation matrix $m{R}_t^l = [m{x}_{r,1}^l, ..., m{x}_{r,n}^l] \in \mathbb{R}^{m imes n}$ with n samples from memory replay buffer, where each ${m x}_{r,i}^l \in \mathbb{R}^m$, is the representation at layer l by forwarding the sample $x_{r,i}$ through the network. Then, we apply SVD to the matrix \mathbf{R}_t^l , i.e., $m{R}_t^l = m{U}_t^l m{\Sigma}_1^l (m{V}_t^l)'$, where $m{U}_t^l = [m{u}_{t,1}^l,...,m{u}_{t,m}^l] \in \mathbb{R}^{m imes m}$ is an orthogonal matrix with left singular vector $m{u}_{t,i}^l \in \mathbb{R}^m$, $m{V}_t^l = [m{v}_{t,1}^l,...,m{v}_{t,n}^l] \in \mathbb{R}^{n imes n}$ is an orthogonal matrix with right singular vector $m{v}_{t,i}^l \in \mathbb{R}^n$, and $m{\Sigma}_t^l \in m{R}^{m imes n}$ is a rectangular diagonal matrix with non-negative singular values $\{\sigma_{t,i}^l\}_{i=1}^{\min\{m,n\}}$ on the diagonal in a descending order. To obtain the bases for subspace S_t^l , we use k_t^l -rank matrix approximation to pick the first k_t^l left singular vectors in U_t^l , such that the following condition is satisfied for a threshold $\eta_{th}^{l} \in (0,1)$:

$$\|(\mathbf{R}_{t}^{l})_{k_{t}^{l}}\|_{F}^{2} \ge \epsilon_{th}^{l} \|\mathbf{R}_{t}^{l}\|_{F}^{2}$$
 (7)

where $(\boldsymbol{R}_t^l)_{k_t^l} = \sum_{i=1}^{k_t^l} \sigma_{t,i}^l \boldsymbol{u}_{t,i}^l (\boldsymbol{v}_{t,i}^l)'$ is a k_t^l -rank $(k_t^l \leq r)$ approximation of the representation matrix \boldsymbol{R}_t^l with rank $r \leq \min\{m,n\}$, and $\|\cdot\|_F$ is the Frobenius norm. Then the bases for subspace S_t^l can be constructed as $\boldsymbol{B}_t^l = [\boldsymbol{u}_{t,1}^l,...,\boldsymbol{u}_{t,k_t^l}^l]$.

3.2.3 Progressive task-correlated freezing

Based on the proposed task-correlation metric, we further propose **progressive task-correlated freezing** in SSCL to progressively freeze partial layers with the highest correlation ratios during training for each task, in order to enhance the training computation and memory efficiency. Specifically, define the initial freeze ratio as k_i and final freeze ratio as k_f , which denote the ratio of the number of frozen layers to the number of layers in the neural network. The total number of training epochs is N and the current training epoch is n. We adopt cosine annealing to progressively increase the freeze ratio in epoch-wise:

$$k_n = k_i + \frac{1}{2}(k_f - k_i)(1 + \cos(\frac{n}{N}\pi))$$
 (8)

where k_n is the freeze ratio for the current epoch. In our experiments, we set the initial and final freeze ratios as 0 and 0.4 for all tasks by default.

Following that, once getting the freeze ratio for the current epoch, we adopt the following strategies to progressively and accumulately freeze the layers: 1) the layers with

Table 1. One-shot updating vs per-epoch updating.

Setting	Split Cl	IFAR-10	Split CIFAR-100		
	Accuracy	Forgetting	Accuracy	Forgetting	
One-shot	89.73	0.86	80.54	2.24	
Per-epoch	89.81	0.80	80.33	2.10	

the highest task-correlation ratio under the current freeze ratio k_n will be frozen; 2) the frozen layers of prior epochs will be unchanged, and we will gradually increase the number of frozen layers according to the freeze ratio difference (k_n-k_{n-1}) . This can be achieved by using a TopK function according to the layer-wise task correlation to select the layers to freeze:

$$F_n = \{ l | r_n^l \in \text{TopK}(R_n, k_n - k_{n-1}) \}$$
 (9)

where R_n denotes a set of task correlations across all unfrozen layers in current epoch n and r_n^l is the task-correlation ratio for l^{th} layer as defined in Eq. (6). By doing so, we could generate a set of indexes of new frozen layers F_n for each task. Importantly, One practical reason that we choose layer-wise freezing is that layer-wise freezing could enable actual training speedup in GPU by using general deep learning frameworks (e.g, Tensorflow, Pytorch). In addition, we find that if applying the proposed layer-wise weight freezing in supervised continual learning (SCL) setup, it will cause clear accuracy degradation, which also advocates that the representation learned by SSCL is more general and robust. The detailed analysis can be found in Section 5.

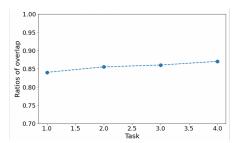


Figure 3. The overlap of layer selection for different tasks

Layer-wise weight freezing in one-shot. Considering the training procedure for each task, there are mainly two choices to achieve layer-wise weight freezing: 1) one-shot updating, which only makes the frozen decision before training and fixes the selection during the entire training procedure; 2) per epoch updating, which updates the layer freezing decision for the unfrozen layers so far in each epoch during training. To understand the learning behaviors herein, we conduct experiments for both cases on Split CIFAR-10 and Split CIFAR-100 settings, respectively, by

Algorithm 1 Efficient Self-supervised Continual Learning with Progressive Task-correlated Layer Freezing

```
1: Input: task sequence \mathbb{T} = \{t\}_{t=1}^T;
 2: Learn the first task using vanilla stochastic gradient descent;
 3: for each task t \in \{1, T\} do
        Extract the bases \{B_t^l\} based on SVD using the learnt model
 4:
 5:
        Generate the layer-wise task correlation ratio by solving Eq. (6);
        for epoch=1, 2,... do
 6:
 7:
            Gradually increase the freeze ratio via cosine annealing based
    on Eq. (8);
 8:
            if layer l is not frozen then
                Update the parameters of the layer
 9.
10:
            end if
11:
        end for
12: end for
```

using ResNet-18 as the backbone model. As shown in Table 1, we find that both cases have similar performance. Moreover, as shown in Fig. 3, it is interesting to see that the average overlap ratios of the layer selection among all the epochs for all tasks are very high (i.e., larger than 0.8), indicating that the layer selection decision during the learning process is stable. Based on these observations, we adopt the *one-shot* setting where we only conduct the layer selection one time for each task, such that the extra computation cost for the sub-space calculation is minimal.

In a nutshell, the details of the proposed method are summarized in Algorithm 1.

4. Experimental Results

4.1. Experimental setup

Baselines. Prior SSCL works [26, 11, 12, 25] have shown that the SSCL methods outperform SCL counterparts in class incremental learning. Thus we compare with multiple self-supervised continual learning baselines across different categories of continual learning methods. First, we mainly compare to CassLe [12] and LUMP [25], which are the state-of-the-art self-supervised continual learning methods. Note that, the reported results of CassLe are reproduced by using the same setup as LUMP for a fair comparison. Second, following [25], we also report several selfsupervised variants of SCL methods. Specifically, FINE-TUNE is a vanilla supervised learning method trained on a sequence of tasks without regularization or episodic memory and MULTITASK optimizes the model on complete data. In addition, we also compare to prior SCL methods on self-supervised learning setting. Specifically, we compare against SI [39] for regularization-based CL methods, PNN [28] for architecture-based methods, and DER [5] for memory replay method which adapts knowledge distillation by memory replay to match the network logits sampled through the optimization trajectory during continual learning.

Dataset. We compare the performance of SSCL on various continual learning benchmarks using single-head ResNet-18 [17] architecture. In Split CIFAR-10 [20], each task includes two random classes out of the ten classes. In Split CIFAR-100 [20], each task consists of five random classes out of the 100 classes. Split Tiny-ImageNet is a variant of the ImageNet dataset [9], where each task contains five random classes out of the 100 classes with the images sized to 64 × 64 pixels. In Split ImageNet-100, each task consists of 20 random classes out of 100 classes. Here ImageNet-100 is a subset of the ILSVRC2012 dataset with \approx 130k images in high resolution (resized to 224x224).

Experimental setting. We follow the training and evaluation setup of [25] for all the SSCL representation learning strategies on Split CIFAR-10, CIFAR-100, and Split Tiny-ImageNet dataset. All the learned representations are evaluated with KNN classifier [32] across three independent runs. In practice, we train all the SSCL methods for 200 epochs and evaluate with the KNN classifier [32]. The memory buffer size is 256 and the models are optimized with SGD optimizer with 0.03 base learning rate under 256 batch size for all the experiments. In addition, following [11] on the ImageNet-100 dataset, we use LARS optimizer for model training and linear evaluation for testing.

Metrics. Following [25], two metrics are used to evaluate the performance: Accuracy, the average final accuracy over all tasks, and *Forgetting*, which measures the forgetting of each task between its maximum accuracy and accuracy at the completion of training. Accuracy and Forgetting are defined as:

$$Accuracy = \frac{1}{T} \sum_{i=1}^{T} A_{T,i}$$
 (10)

$$Accuracy = \frac{1}{T} \sum_{i=1}^{T} A_{T,i}$$
 (10)

$$Forgetting = \frac{1}{T-1} \sum_{i=1}^{T-1} \max_{t} (A_{T,i} - A_{i,i})$$
 (11)

where T is the number of tasks, $A_{T,i}$ is the accuracy of the model on i-th task after learning the T-th task sequentially. Furthermore, we utilize three metrics to measure training efficiency: Training time, we report the training time ratio compared to LUMP baseline which is measured on NVIDIA RTX A4000 GPU; memory, which includes model parameter size, training activation storage, and memory replay buffer size; Flops, which calculate the number of computational operations during backward.

4.2. Main Results

As shown in Table 2 and Table 3, we evaluate the performance of various SSCL methods, by using SimSiam [7] and BarlowTwin [37] SSL frameworks on Split CIFAR-10, Split CIFAR-100 and Split Tiny-ImageNet, respectively. Note that, The training memory cost mainly includes model parameters, memory replay data, and activations of each layer for backward propagation. For SimSiam framework, our method achieves 12%, 14%, and 12% training time

Table 2. Accuracy and forgetting of the learned representations on Split CIFAR-10, Split CIFAR-100 and Split Tiny-ImageNet on ResNet-18 architecture with KNN classifier. All the values are measured by computing mean and standard deviation across three trials. Note that, we use the layer freezing ratio as 0.4 by default for all our results.

	Method	SPLIT CI	FAR-10	SPLIT C	IFAR-100	SPLIT TINY	-IMAGENET
		Accuracy	Forgetting	Accuracy	Forgetting	Accuracy	Forgetting
	Finetune	90.11 (±0.12)	5.43 (±0.08)	75.42 (±0.78)	10.19 (±0.78)	71.07 (±0.20)	9.48 (±0.56)
Simsiam	PNN [28] SI [39] DER [5]	90.93 (\pm 0.22) 92.75 (\pm 0.06) 91.22 (\pm 0.3)	- 1.81 (±0.21) 4.63 (±0.26)	66.58 (±1.0) 80.08 (±1.3) 77.27 (±0.30)	5.54 (±01.3) 9.31 (±0.09)	62.15 (±1.35) 72.34 (±0.42) 71.90 (±1.44)	8.26 (±0.64) 8.36 (±2.06)
Si	CassLe [12] LUMP [25] Ours	91.04 (±0.24) 91.00 (±0.40) 91.03 (±0.44)	$2.24 (\pm 0.23)$ $2.92 (\pm 0.53)$ $1.61 (\pm 0.23)$	81.58 (±0.84) 82.30 (±1.35) 82.24 (±1.24)	$5.02 (\pm 1.12)$ $4.71 (\pm 1.52)$ $2.73 (\pm 1.13)$	75.77 (±1.74) 76.66 (±2.39) 76.68 (±2.51)	$4.42 (\pm 1.24)$ $3.54 (\pm 1.04)$ $2.33 (\pm 1.14)$
	Multitask	95.76 (±0.08)	-	86.31 (±0.38)	-	82.89 (±0.49)	-
	Finetune	87.72 (±0.32)	4.08 (±0.56)	71.97 (±0.54)	9.45 (±1.01)	66.28 (±1.23)	8.89 (±0.66)
BarlowTwin	PNN [28] SI [39] DER [5]	87.52 (±0.33) 90.21 (±0.08) 88.67 (±0.30)	- 2.03 (±0.22) 2.41 (±0.26)	57.93 (±2.98) 75.04 (±0.63) 73.48 (±0.53)	$7.43 (\pm 0.67)$ $7.98 (\pm 0.29)$	48.70 (±2.59) 56.96 (±1.48) 68.56 (±1.47)	- 17.04 (±0.89) 7.87 (±0.44)
Barl	Cassle [12] LUMP [25] Ours	89.04 (±0.34) 89.72 (±0.30) 89.73 (±0.41)	$1.89 (\pm 0.14)$ $1.13 (\pm 0.18)$ $0.92 (\pm 0.23)$	77.05 (±0.75) 80.24 (±1.04) 80.54 (±0.88)	$2.47 (\pm 0.44)$ $3.53 (\pm 0.83)$ $2.24 (\pm 0.84)$	71.76 (± 0.65) 72.17 (± 0.89) 73.56 (± 1.02)	$2.88 (\pm 0.45)$ $2.43 (\pm 1.00)$ $1.74 (\pm 0.62)$
	Multitask	95.48 (±0.14)	-	87.16 (±0.52)	-	82.42 (±0.74)	-

Table 3. Training time (measured time in NVIDIA A4000 GPU), memory cost, and computation FLOPs of the learned representations on Split CIFAR-10, Split CIFAR-100 and Split Tiny-ImageNet.

Method SPLIT CIFAR-10		SPLIT CIFAR-100		SPLIT TINY-IMAGENET						
		Time	Memory	FLOPs	Time	Memory	FLOPs	Time	Memory	FLOPs
Simsiam	PNN [28]	1.35x	1.35x	1.35x	1.35x	1.35x	1.35x	1.35x	1.35x	1.35x
	SI [39]	1.2x	1.2x	1.2x	1.2x	1.2x	1.2x	1.2x	1.2x	1.2x
	DER [5]	1x	1x	1x	1x	1x	1x	1x	1x	1x
	LUMP [25]	1x	1x	1x	1x	1x	1x	1x	1x	1x
	CassLe [12]	1.3x	1.3x	1.3x	1.3x	1.3x	1.3x	1.3	1.3x	1.3x
	Ours	0.88 x	0.77x	0.68 x	0.86 x	0.74x	0.67x	0.88 x	0.76x	0.68x
BarlowTwin	PNN [28]	1.35x	1.35x	1.35x	1.35x	1.35x	1.35x	1.35x	1.35x	1.35x
	SI [39]	1.2x	1.2x	1.2x	1.2x	1.2x	1.2x	1.2x	1.2x	1.2x
	DER [5]	1x	1x	1x	1x	1x	1x	1x	1x	1x
	LUMP [25]	1x	1x	1x	1x	1x	1x	1x	1x	1x
	Cassle [12]	1.3x	1.3x	1.3x	1.3x	1.3x	1.3x	1.3x	1.3x	1.3x
	Ours	0.87 x	0.78x	0.65 x	0.88 x	0.79x	0.66x	0.88 x	0.75x	0.67x

reduction, 23%, 26%, and 24% memory, and 33%, 33% and 32% backward FLOPs reduction on three datasets respectively. Similarly, for the BarlowTwin framework, our method achieves 13%, 12%, and 12% training time reduction, and 22%, 21%, and 22% memory reduction, and 35%, 34% and 33% backward FLOPs reduction on three datasets respectively. Importantly, in terms of forgetting, *our method clearly mitigates the forgetting issue in comparison to all prior methods*. For example, compared to LUMP on Split CIFAR-100 and Split Tiny-ImageNet for Simsiam, we reduce the forgetting by 1.31%, 1.98% and 1.21% respectively with similar accuracy.

Moreover, we further conduct experiments on the more challenging ImageNet-100 dataset. Specifically, following the same setting with Cassle, we adapted the proposed method on BarlowTwin, and MoCoV2+ respectively. As shown in Table 4, similar results can be found that the proposed method shows clear gain to improve training efficiency and mitigate catastrophic forgetting with the almost

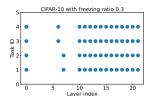
same accuracy.

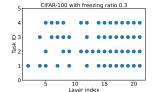
Table 4. Accuracy, forgetting, training time, and training memory cost of the learned representations on ImageNet-100 with linear evaluation by using BarlowTwin and MoCoV2 respectively.

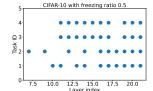
	Setting	ImageNet-100			
	Setting	Accuracy	Forgeting	Time	Memory
BarlowTwin	CassLe Ours	68.2 68.5	1.3 0.7	1x 0.88x	1x 0.78x
MoCoV2	CassLe Ours	68.0 67.9	2.2 1.4	1x 0.89 x	1x 0.79x

5. Ablation Study and Anaysis

Task-correlated layer freezing *VS* **ascending order layer freezing** To evaluate the effectiveness of the proposed progressive layer freezing via task correlation, we compare it to ascending order layer freezing which is commonly used in supervised learning settings to improve the training efficiency for a single task. Specifically, for a fair comparison,







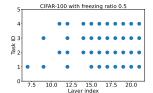


Figure 4. The final selection of updated layer for each task. The freezing ratios are 0.3 and 0.5 respectively. Note that, each blue point means the index of the updated layer. For Split CIFAR-100 20 tasks setup, we show the first five tasks for simplification.

Table 5. The ablation study on the proposed method in comparison to layer freezing in ascending layer index (i.e., "Top layer") order on both Split CIFAR-10 and CIFAR-100 datasets by using BarlowTwin as backbone method.

Setting	Split CII	FAR-10	Split CIFAR-100		
Setting	Forgetting	Accuracy	Forgetting	Accuracy	
Top layers.	0.96	89.24	2.57	78.87	
Ours	0.92	90.03	2.24	80.54	

we also adopt the same cosine annealing to progressively freeze layers under the same freezing ratio (i.e., 0.4). As shown in the Table 5, our method can consistently achieve better accuracy with similar forgetting compared to Naive Selection. The results demonstrate that the task correlation between tasks needs to be considered in SSCL.

The effectiveness of the layer freezing ratio To understand the impact of the layer-wise weight freezing ratio, we evaluate the learning performance for four different values of r (i.e., 0.7, 0.6, 0.5, 0.4) on SPLIT CIFAR-10 dataset by using BarlowTwin [37] SCL method as shown in Table 6. It can be seen that with the freezing ratio increasing, the learning performance in terms of both accuracy and forgetting gradually degrades, but to a slight extent. As a benefit, the computational costs in terms of both training time and memory significantly decrease. It makes sense that by fixing more layers, it has a certain degree of negative effect on learning each new task, meanwhile, it indicates less forgetting.

Table 6. The ablation study on different layer-wise weight freezing ratios. Note that, the "freeze ratio" means the ratio of the layer numbers to be frozen during the training.

Freeze ratio	Accuracy	Forgetting	Time	Memory
0.4	89.73	0.86	0.87x	0.78x
0.5	89.01	0.75	0.83x	0.70x
0.6	88.40	0.66	0.76x	0.64x
0.7	87.62	0.60	0.71x	0.57x

Progressive task-correlated freezing in SCL We evaluate the layer-wise weight freezing on SCL as shown in Table 7. It is clear to see that layer-wise freezing has obvious

performance degradation in both accuracy and forgetting compared to finetune. This observation further corroborates that the representation learned by SSCL is more general and robust to mitigate catastrophic forgetting in comparison to SCL, which makes it possible to use an aggressive freezing strategy to reduce the computational cost in SSCL.

Table 7. The effectiveness of layer-wise freezing in both SCL and SCCL settings. Note that, the layer freezing ratio is 0.4.

Setting	Method	Accuracy	Forgetting	Time	Memory
SCL	Finetune	82.87	14.26	1x	1x
	Layer-wise	80.45	16.52	0.85x	0.72x
SSCL	LUMP	89.72	1.13	1x	1x
	Layer-wise	89.73	0.86	0.87 x	0.75x

Self-supervised continual learning is robust to layer **freezing decision** We analyze the layer freezing decision by using the freezing ratio of 0.4 for each task on Split CIFAR-10 and Split CIFAR-100 respectively. As shown in Fig. 4, there are mainly two observations: 1) for inter-tasks, the indexes of layer freezing decisions are highly similar, which means that the selected frozen layers at the first task will not be updated across all the rest tasks. It further helps to show that the learned representation by SSCL is general and robust; 2) for intra-task, it is interesting to see that the first layer and a large number of last layers are updated during training. We conjecture the reason is that the last layers learn high-level features that are sensitive with respect to the given input. In addition, although the first layer learns the general low-level features, the SSCL adapts strong augmentation (e.g., color jittering, converting to grayscale, Gaussian blurring, and solarization) to the input, and should also update the first layer.

6. Conclusion

In this work, we first investigate the task correlation of SSCL and find that intermediate features are highly correlated between tasks. Based on this, we propose a progressive task-correlated layer freezing method that freezes gradually partial layers with the highest correlation ratios for each task. Extensive experiments across multiple datasets clearly show that our method can significantly improve training computation and memory efficiency meanwhile mitigating catastrophic forgetting, compared to the SoTA SSCL methods.

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