KNOWLEDGE ACCUMULATING CONTRASTIVE PROMPT FOR CONTINUAL LEARNING

Anonymous authors
Paper under double-blind review

ABSTRACT

Continual learning has been challenged by the issue of catastrophic forgetting (CF). Prompt-based methods have recently emerged as a promising approach to alleviate this problem, capturing the previous knowledge by the group of prompts. However, selecting an appropriate prompt during the inference stage can be challenging, and may limit the overall performance by the misaligned prompts. In this paper, we propose a novel approach to prompt-based continual learning, which accumulates the knowledge in a single prompt, which has not been explored previously. Specifically, inspired by contrastive learning, we treat the input with the current and previous prompt as two different augmented views (i.e., positive pair). We then pull the features of the positive pairs in the embedding space to accumulate knowledge. Our experimental results demonstrate the state-of-the-art performance in continual learning even with a single prompt, highlighting the potential of this approach towards a 'holistic' for the model.

1 INTRODUCTION

The primary objective of continual learning, also known as lifelong learning (Silver & Mercer, 2002; Rannen et al., 2017), is to learn the complete knowledge for a set of tasks when each task is presented sequentially. This is particularly relevant in real-world applications where the tasks to be adapted change over time. However, neural networks tend to forget the previously acquired knowledge as the model parameters are optimized for the new tasks, leading to the problem of catastrophic forgetting. To address this challenge, many researchers have focused on developing approaches to alleviate the forgetting problem of the neural network during the continual learning. Previously, three main approaches have been suggested. Regularization-based approaches restrict parameter updates according to their relevance to previous tasks (Kirkpatrick et al., 2017; Zenke et al., 2017; Lee et al., 2017; Li & Hoiem, 2017; Buzzega et al., 2020). Rehearsal-based approaches repeatedly use previous task data during training for a new task, either through memory buffers or by generating the previous data (Lopez-Paz & Ranzato, 2017; Chaudhry et al., 2019a; Saha et al., 2021; Prabhu et al., 2020). Architecture-based approaches increase model capacity by adding new modules for new tasks (Yoon et al., 2018; Yan et al., 2021). The rehearsal-based methods outperforms the other approaches, however, the methods are not free from the data privacy issue as the training procedure entails the exposure of the previous data.

Recently, the prompt-based methods for the continual learning have gained attention due to its superior performance, without any concerns on the data privacy issue. The prompt is an additional input texts or images, which adapts the model for specific tasks by the small number of parameters. Inspired by the promising ablity of the prompt for the model adaptation, many researchers have proposed the method to capture the previous knowledge by the prompt for the continual learning (Wang et al., 2022c;b). Specifically, the methods utilize the prompt pool which stores the prompts optimized by the previous tasks. During inference, a prompt is selected from the pool to instruct the model, providing the previous knowledge. The prompt-based methods presents the effective way to address the forgetting of the pretrained-large scaled model by the small number of learnable parameters. Moreover, the methods are free from the data privacy issue, which is a limitation of the rehearsal-based approach. However, the prediction for the task identity is required to select the prompt for the inference, which can introduce misaligned prompts and limit the performance.

Therefore, in this paper, we present a method for continually accumulating knowledge into a single prompt, which does not require a prompt pool or the task identity prediction. Our work is motivated by the existence of the upper-bound prompt for the sequence of the tasks, as illustrated in Figure 1. Specifically, when all the tasks are presented simultaneously, the prompt p^* is optimized to instruct the model to adapt for all the tasks. As the existence of the p^* is ensured, the primary concern is to approach the p^* effectively when the tasks are given sequentially in the continual learning.

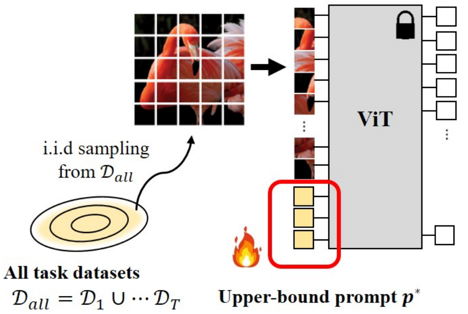


Figure 1: When all tasks are given simultaneously, the obtained prompt p^* guides the model to adapt for all tasks.

Accordingly, we propose the knowledge accumulating contrastive prompt which is the novel approach for the prompt-based continual learning. Specifically, we propose to utilize the current and previous prompts as two augmented views for the input (i.e. positive pair) to increase the dependency between them. Inspired by contrastive learning without negative pairs (Chen & He, 2021; Grill et al., 2020), we use a similarity-based loss to pull the positive pairs closer in the embedding space. We first investigate how the model's features change by the prompt during continual learning, and how this leads to forgetting of previous knowledge. Then, we propose our method to accumulate knowledge in a single prompt by increasing the dependency between the current and previous prompts, which helps to alleviate the forgetting problem.

Our contribution can be summarized as follows:

- We propose a novel approach for prompt-based continual learning, progressively approaching the upper-bound prompt by the sequence of the tasks.
- We present a methodology for accumulating task knowledge in a single prompt, eliminating the need for a prompt pool or task prediction during inference.
- We suggest a method that leverages the contrastive learning between the current and previous prompts, constructing a positive pair by the prompts.
- We demonstrate state-of-the-art results using the single prompt, highlighting the potential of our approach to approach the upper-bound prompt for the sequence of the tasks.

2 Related works

Continual learning Continual learning aims to enable a network to adapt over time to a sequence of tasks without forgetting previously acquired knowledge. However, the network often forgets previously learned knowledge as it is trained to perform well on new tasks, regardless of the degradation of its previous performance. This problem is known as the *catastrophic forgetting* problem, which is a major challenge in continual learning. The causes of the forgetting problem are attributed to the changes in important parameters (Kirkpatrick et al., 2017; Zenke et al., 2017), interference by gradient direction (Lopez-Paz & Ranzato, 2017; Saha et al., 2021), or the change in the feature space (Zhu et al., 2021). To alleviate the forgetting problem, many methods have been proposed and can be categorized into three approaches. Firstly, regularization-based methods (Kirkpatrick et al., 2017; Zenke et al., 2017; Lee et al., 2017; Buzzega et al., 2020) enforce the model to preserve previously learned knowledge through additional regularization techniques. For example, EWC (Kirkpatrick et al., 2017) and SI (Zenke et al., 2017) regularize the change of model parameters based on their importance, while IMM (Lee et al., 2017) utilizes moment matching. Knowledge distillation loss is also used to preserve previous knowledge (Li & Hoiem, 2017; Buzzega et al., 2020). Secondly, rehearsal-based methods are presented, which repeatedly train the model using previous task data. For instance, the replay buffer is utilized to memorize previous task data to compute gradients for the previous task (Lopez-Paz & Ranzato, 2017; Chaudhry et al., 2019a) or previous eigenvectors (Saha et al., 2021). Generative approaches are suggested to replay the generated previous task data (Shin et al., 2017; Rao et al., 2019) to alleviate the forgetting problem. Thirdly, architecture-based methods are suggested to dynamically increase the model's capacity as new tasks arrive (Yan et al., 2021;

Yoon et al., 2018). Moreover, some recent works (Cha et al., 2021; Madaan et al., 2022) suggest that unsupervised learning can learn unforgettable representations that may help alleviate the forgetting problem. Lastly, the prompt-based methods (Wang et al., 2022b;c) are suggested to capture task-specific knowledge by using a prompt pool to memorize previous task knowledge.

Contrastive learning Contrastive learning methods have proven effective in capturing useful representations by utilizing positive and negative pairs. The widely used InfoNCE loss (Oord et al., 2018; Tian et al., 2019) maximizes the mutual information between pairs by pulling and pushing positive and negative pairs in the embedding space. However, InfoNCE loss requires a large number of negative pairs, which limits its effectiveness. As a result, positive-only methods that do not require negative pairs have been proposed (Grill et al., 2020; Chen & He, 2021; Bardes et al., 2022), which capture common features of positive pairs and increase their similarity. Some researchers have claimed that these methods capture a low-rank space that represents commonalities between pairs (Tian et al., 2021; Wang et al., 2021; Zhuo et al., 2023). More recently, researchers have suggested using contrastive learning to alleviate forgetting in continual learning (Guo et al., 2022; Madaan et al., 2022; Cha et al., 2021). Inspired by the recent approaches, the proposed method involves constructing prompt-augmented input pairs as positive pairs. Similar to positive-only methods, our approach pulls newly defined positive pairs to increase their commonalities and results in knowledge accumulation for the prompt.

3 Main Contribution

3.1 Motivation

In continual learning, a network is trained on a sequence of tasks $\mathcal{T}_{1:T} = \{\mathcal{T}_1, \ldots, \mathcal{T}_T\}$ with corresponding datasets $\mathcal{D}_{1:T} = \{\mathcal{D}_1, \ldots, \mathcal{D}_T\}$. Each task $\mathcal{T}_t$ has its own dataset $\mathcal{D}_t = \{(x_{i,t}, y_{i,t})\}_{i=1}^{n_t}$ consisting of n_t pairs of input images $x_{i,t} \in \mathcal{X}_t$ and corresponding labels $y_{i,t} \in \mathcal{Y}_t$. As illustrated in Figure 1, our approach is motivated by the upper-bound prompt p^* optimized by the merged dataset for all tasks (i.e. $\mathcal{D}_{all} = \mathcal{D}_1 \cup \cdots \cup \mathcal{D}_T$), as follows:

$$p^* = \arg\min_{p} \; \mathbb{E}_{(x,y)\in\mathcal{D}_{all}} \left[L_{task}(f(x,p), y) \right] \tag{1}$$

where L_{task} is the loss for the given task, which is the classification task in this paper. We point out that the p^* is the solution for the continual learning, as the p^* instructs the model to perform well for all tasks. Moreover, we argue that the p^* refers the redundancy of parameters in previous approach based on the prompt pool, since the pool employs multiple prompts. Then, the primary objective centers on approaching the p^* by the continual learning with a sequence of tasks $\mathcal{D}_{1:T}$. Accordingly, we propose the novel method that accumulates the task knowledge using the prompt, enabling a progressive approach towards p^*.

3.2 Key observation

We first investigate the process of catastrophic forgetting by prompt, analyzing the angle (Zhu et al., 2021) between the feature spaces of the current and previous models. Figure 2 illustrates the corresponding angle, with the task gap representing the difference between the current and previous task indices. Our results show that the top eigenvectors are forgotten during continual learning, as shown in Figure 2(b). This is consistent with the behavior of conventional training from scratch, as shown in Figure 2(a). Specifically, we observed that the top eigenvectors are transferred between consecutive tasks (i.e., when the task gap is 1), consistent with the prior work (Zhu et al., 2021). However, as the task gap increases, we found that the corresponding angle deviates, which is accompanied by a decline in task performance. Thus, we focus on aligning the feature space to preserve previous knowledge. The detailed settings for the observation is described in the Appendix A.

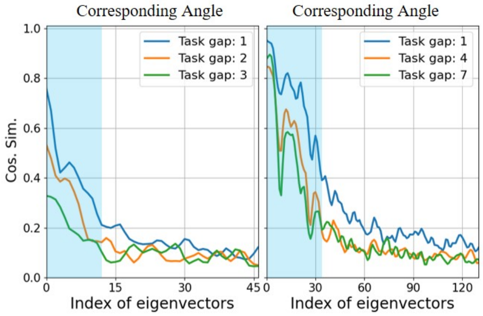


Figure 2: Colored regions indicate the forgetting of top eigenvectors. (a) ResNet model (b) prompt learning with ViT

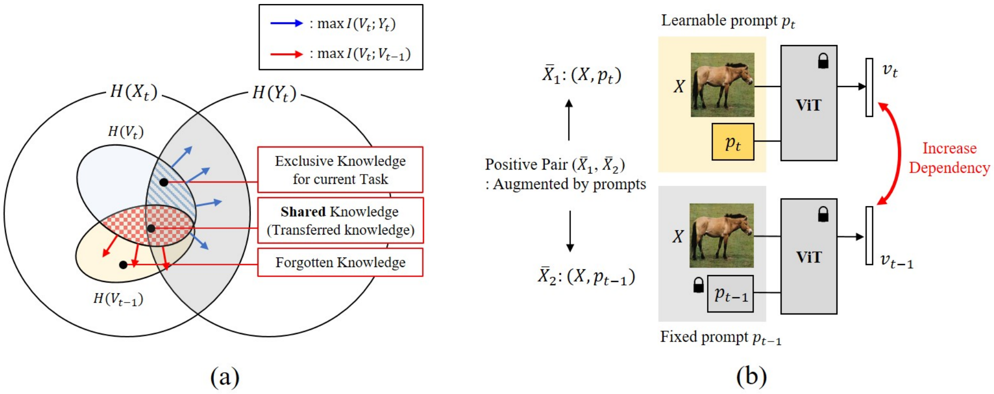


Figure 3: (a) We maximize the shared knowledge $I(V_t, V_{t-1})$ using the prompt to alleviate the forgetting problem. (b) Proposed concept to progressively accumulate the task knowledge, by increasing the dependency between the current prompt p_t and the previous prompt p_{t-1}.

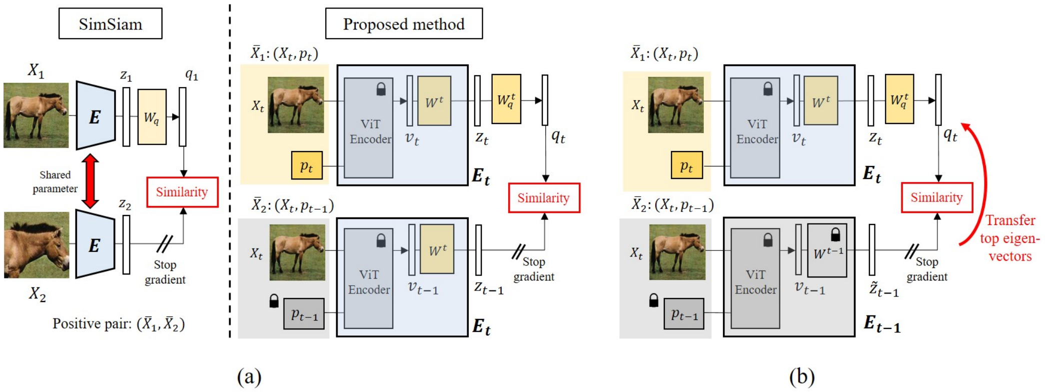


Figure 4: Main concepts of the proposed method. (a) The prompt-augmented pairs are pulled in the embedding space to increase the dependency by the shared encoder E_t, similar to the SimSiam (Chen & He, 2021). (b) Transfer of top eigenvectors from the previous encoder E_{t-1}.

3.3 Knowledge accumulation by prompt

Information-theoretic view for continual learning We explore the method to accumulate the task knowledge by the prompt for continual learning. We suggest the information-theoretic view for the continual learning process, to clarify the motivation.

For the pretrained transformer f with input X_t and label Y_t for the current task t, we denote $V_t = f(X_t, p_t)$ as the feature by current prompt p_t, and the $V_{t-1} = f(X_t, p_{t-1})$ as the feature by the previous prompt p_{t-1}. Then, we have the Markov chain $V_{t-1} \leftarrow X_t \rightarrow V_t \rightarrow Y_t$, which can be visualize as Figure 3(a). Then, we optimize the prompt by:

$$\begin{aligned} &\max_{p_t} I(Y_t; V_t) + I(V_t; V_{t-1}) \\ &= \max_{p_t} H(Y_t) – H(Y_t|V_t) + I(V_t; V_{t-1}) \end{aligned} \tag{2}$$

where $H(Y_t)$ is constant and the $H(Y_t|V_t)$ is minimized by the classification loss for current task. Now we focus on the $I(V_t; V_{t-1})$. We propose to use the positive-only contrastive loss, regarding $\bar{X}_1 : (X_t, p_t)$ and $\bar{X}_2 : (X_t, p_{t-1})$ as the positive pair $(\bar{X}_1, \bar{X}_2)$, as illustrated in Figure 3(b). We pull the pairs (V_t, V_{t-1}) in the embedding space, to increase the dependency between the variables. We reveal that the pulling the pairs enhances the alignment of the feature space, which leads to the preservation of the previous knowledge.

SimSiam for the prompt-augmented pair To enhance the interdependence between the prompt-augmented pair (V_t, V_{t-1}), we adopt the contrastive loss which pulls the pairs in the embedding space. Our approach is motivated by the resemblance between the recent positive-only contrastive methods and the framework of continual learning, as shown in Fig. 4.

Specifically, we employ the loss function of SimSiam (Chen & He, 2021) with simple linear layers W^t, W_q^t for the task t, as follows:

$$\min_{p_t} L_{ctr} := -\mathbb{E}_{x\sim P(X_t)}\left[{q_t}^\top z_{t-1}\right] \tag{3}$$

where $P(X_t)$ is the distribution for the task t image, and q_t, z_{t-1} are l_2 normalized vectors. The positive-only methods such as SimSiam captures the invariant characteristics of the positive pairs, while discarding the features that shows higher variance than the certain threshold (Tian et al., 2021; Wang et al., 2021). Likewise, the layer W^t captures the embedding space that represents the common features between the positive pairs formed by the different prompts. Considering the observation in Fig. 2, the prompts for different tasks tends to have similar top eigenvectors, whereas the similarity rapidly decreases for the remaining eigenvectors. Therefore, W^t captures the shared subspace across the tasks.

Additionally, the prompt p_t is optimized to generate an embedding space aligned with the space by the previous prompt p_{t-1}. It guides the prompt p_t to expand the shared subspace with the previous task, thereby enhancing the preservation of the previous knowledge.

Knowledge transfer through embedding space

We transfer the knowledge through the embedding space generated by the previous encoder E_{t-1}, as shown in Fig. 4. Similar to the L_{ctr}, we pull the feature q_t and the $\tilde{z}_{t-1}$ to increase the dependency between the pair (v_t, v_{t-1}). Specifically, we optimize the loss function as follows:

$$\min_{p_t} L_{prev} = -\mathbb{E}_{x\sim P(X)}\left[{q_t}^\top \tilde{z}_{t-1}\right] \tag{4}$$

where

$$\begin{aligned}\tilde{z}_{t-1} &= E_{t-1}(x, p_{t-1}) \\ &= W^{t-1} \circ f(x, p_{t-1}).\end{aligned} \tag{5}$$

The authors in (Wang et al., 2021; Zhuo et al., 2023) reveals that the q_t and z_t has aligned eigenspace with reduced rank for q_t. As shown in Fig. 5, we present the empirical evidence of the property satisfied also in our framework, following Zhuo et al. (2023). Then, L_{prev} can be seen to enhances the transfer of the top eigenvectors. It is similar to GPM (Saha et al., 2021) which utilize the top eigenvectors of the previous feature space to alleviate the forgetting. However, our method differs from GPM in that we imposes the constraint instead of using the memory buffer to collect the vectors.

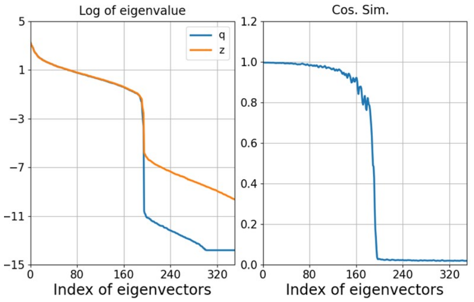


Figure 5: Eigenvalue and the eigenspace alignment for the z_t, q_t feature spaces.

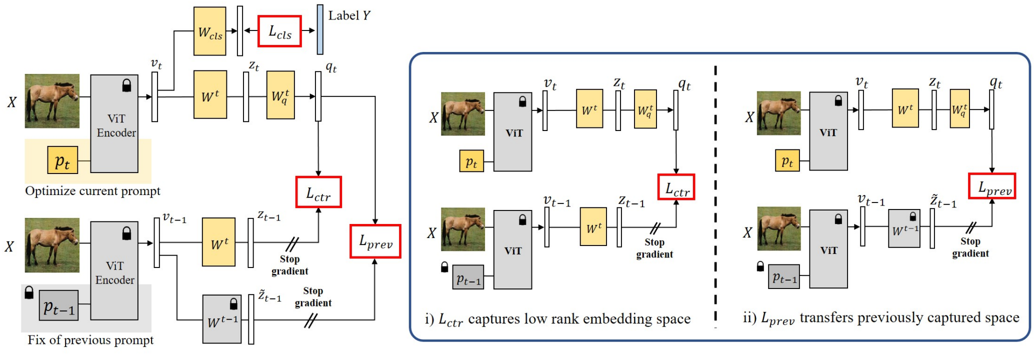
3.4 Overall loss function

Our method is to accumulate the knowledge in the prompt to alleviate the forgetting problem of the continual learning. We use the single prompt, hence, the proposed method do not require the task identification, which is essentially required for both the L2P and DualPrompt.

The overall diagram for the proposed method is shown in the Fig. 6(a). We employ the positive-only contrastive method (i.e. SimSiam (Chen & He, 2021)) as shown in Fig. 6(b). We impose the constraint on the prompt p_t to pull the feature $V_t = f(X_t, p_t)$ and the previous feature $V_{t-1} = f(X_t, p_{t-1})$ in the embedding space, to accumulate the knowledge for continual learning. Specifically, the overall loss function is given as:

$$\min_{p_t} L = L_{cls} + \lambda_{ctr} L_{ctr} + \lambda_{prev} L_{prev} \tag{6}$$

where $\lambda_{ctr}, \lambda_{prev}$ are the hyperparameters. L_{cls} is the cross entropy loss for the current classification task $\mathcal{D}_t$. We clarify our method by providing the pseudo code in the Appendix D.



(a)

(b)

Figure 6: The proposed method is visualized in the following diagrams, with yellow colored blocks indicating the learnable components. (a) The overall framework is shown. (b) Two contrastive losses are jointly optimized to accumulate knowledge through prompts for continual learning.

4 Methods

Experimental settings We verified our method with the Split-CIFAR100, Split-ImageNet-R datasets, Gaussian-scheduled CIFAR100, following the conventional prompt-based methods (Wang et al., 2022c;b). Split-CIFAR100 and Split-ImageNet-R datasets are for the class incremental learning (CIL) setting, where the tasks have disjoint classes. Gaussian-scheduled CIFAR100 is the task-agnositc continual setting, where the class shifts gradually during the training. It allows the overlapping classes between the tasks. We repeated the experiments 3 times with different seeds. More experimental details are summarized in the Appendix B.

Weighted Projection Angle In the Section 3.2, we investigate the forgetting of the eigenvectors by visualizing the *corresponding angle* (Zhu et al., 2021), where the value is averaged across the tasks. This metric significantly fluctuates unless it is averaged, since it measures the similarity between the vectors with the same index. Therefore, we propose the new metric, *weighted projection angle*, to effectively investigate the relation between the feature space of the current and the previous model, considering the eigenvalues of the previous space.

Specifically, we obtain the weighted projection matrix M_o by old model f_o using the current data $x_t \in \mathcal{D}_t$ as follows:

$$M_o = E_{x_t \in \mathcal{D}_t}\left[f_o(x_t)f_o(x_t)^\top\right] = U\Lambda U^\top \tag{7}$$

where U is the eigenvector matrix for the d-dimensional feature space $S_{old} = \text{span}\{u_1, \ldots, u_d\}$ of the previous model, and the Λ is the eigenvalue matrix. M_o projects the arbitrary vector w to $\tilde{w} \in S_{old}$, allocating more weights for the direction of principal eigenvectors, as follows:

$$\tilde{w} = M_o w = \sum_{i=1}^{d} \lambda_i (u_i^\top w) v_i \tag{8}$$

Using the matrix M_o, we calculate projected vectors $\{\tilde{v}_i\}_{i=1}^d$ of eigenvectors $\{v_i\}_{i=1}^d$ for current model f_t and current data $\mathcal{D}_t$. Then, the weighted projection angle is defined as:

$$cos(\phi_i) = \langle v_i, \tilde{v}_i \rangle / |\tilde{v}_i| \tag{9}$$

Baseline methods We compared our method with related continual learning methods. ER (Chaudhry et al., 2019b), BiC (Wu et al., 2019), DER++ (Buzzega et al., 2020), Co^{2}L (Cha et al., 2021) are selected for rehearsal-based methods. The buffer size is set as 50 per class for Split-CIFAR100 and 25 per class for Split-ImageNet-R. EWC (Kirkpatrick et al., 2017), LwF (Li & Hoiem, 2017) are presented for the comparison with regularization methods. SupSup (Wortsman et al., 2020), DualNet (Pham et al., 2021), RPSNet (Rajasegaran et al., 2019) and DynaER (Yan

Table 1: Quantitative comparison of prompt-based continual learning methods. G-CIFAR100 refers the gaussian-scheduled CIFAR100 dataset.

	Split-CIFAR100 (CIL)		**Split ImageNet-R** (CIL)		**G-CIFAR100** (Task-agnostic)
	Average Accuracy↑	Forgetting↓	Average Accuracy↑	Forgetting↓	Average Accuracy↑
Upper bound	90.85 ±0.12	-	79.13 ±0.18	-	90.85 ± 0.12
ER	82.53 ±0.17	16.46 ±0.25	65.18 ±0.40	23.31 ±0.89	83.86 ± 0.38
BiC	81.42 ±0.85	17.31 ±1.02	64.63 ±1.27	22.25 ±1.73	-
DER++	83.94 ±0.34	14.55 ±0.73	66.73 ±0.87	20.67 ±1.24	85.57 ± 0.41
Co^{2}L	82.49 ±0.89	17.48 ±1.80	65.90 ±0.14	23.36 ±0.71	-
FT-seq	33.61 ±0.85	86.87 ±0.20	11.14 ±0.58	79.91 ±0.64	38.94 ± 0.67
EWC	47.01 ±0.29	33.27 ±1.17	31.40 ±0.43	54.47 ±0.50	50.78 ± 0.60
LwF	60.69 ±0.63	27.77 ±2.17	14.93 ±0.13	63.29 ±0.23	-
L2P	84.50 ± 0.35	6.10 ± 0.22	62.49 ±0.49	11.45 ±0.51	84.17 ± 0.18
DualPrompt	85.18 ±0.49	5.48 ±0.25	69.44 ±0.31	5.23 ±0.13	-
Proposed	**85.47 ±0.24**	**4.16 ±0.16**	**69.98 ±0.35**	**4.24 ±0.25**	**86.00 ± 0.17**

Table 3: Quantitative comparison for varying the task number T. We present the results for 5 tasks (40 classes per task), 10 tasks (20 classes per task) and 20 tasks (5 classes per task).

	5 Tasks		**10 Tasks**		**20 Tasks**	
	Average Accuracy↑	Forgetting↓	Average Accuracy↑	Forgetting↓	Average Accuracy↑	Forgetting↓
FT-seq	19.01 ±0.85	75.92 ±0.08	11.14 ±0.58	79.91 ±0.64	6.73 ± 0.42	84.81 ± 0.92
LwF	25.83 ± 0.29	50.53 ± 0.46	14.93 ± 0.13	63.29 ± 0.23	7.52 ± 0.03	73.90 ± 0.27
L2P	65.50 ± 0.59	6.97±0.58	62.49±0.49	11.45 ±0.51	58.49 ± 0.49	16.28 ± 0.78
DualPrompt	71.09 ±0.53	4.25 ±0.07	69.44 ±0.31	5.23 ±0.13	68.03 ± 0.26	6.42 ± 0.31
:Oracle prompt	71.70 ±0.23	3.71 ±0.21	70.82 ±0.15	4.76 ±0.21	71.12 ± 0.30	5.02 ± 0.29
(Task ID Accuracy)	(56.50 ± 0.35)		(45.89 ± 0.23)		(40.83 ± 0.42)	
Proposed	**71.11 ±0.22**	**3.74 ±0.17**	**69.98 ±0.35**	**4.24 ±0.25**	**68.13 ± 0.32**	**5.32±0.33**

et al., 2021) are selected for the previous architecture-based approaches. We also provide the result for naive training by prompt (FT-seq) and the supervised learning with all data (Upper bound). Lastly, we compared our method with prompt-based method, which are L2P (Wang et al., 2022c) and DualPrompt (Wang et al., 2022b). For G-CIFAR100, the results for BiC (Wu et al., 2019), Co^{2}L (Cha et al., 2021), LwF (Li & Hoiem, 2017) and DualPrompt (Wang et al., 2022b) are not presented, since the methods require the explicit task boundary, whereas the dataset provides the smooth transition of the tasks.

5 Experimental Results

Results In Table 1, we present the results for CIL datasets which provide the explicit task boundary, as there is no overlap classes between the tasks. The results verifies the outperformance of our method compared to the previous methods. Specifically, it is remarkable that our method outputs better results without the memory buffer which is required for the rehearsal methods. Moreover, our method shows better result only with the single prompt, compared to the previous prompt-based methods with multiple prompts, such as L2P and DualPrompt. We additionally compared our method with architecture-based methods, as shown in Table 2. Our method outperforms the previous methods and the other backbones. Especially, our method tightens the accuracy gap without the memory buffer, which has advantage of being free from the data-privacy issue.

Table 2: Result for Split-CIFAR100 data by architecture-based approaches.

Method	Backbone	Buffer Size	Avg. Acc.↑	Acc. gap ↓
Upper-bound	ResNet18	-	80.41	-
SupSup		0	28.34	52.07
DualNet		1000	40.14	40.27
RPSNet		2000	68.60	11.81
DynaER		2000	74.64	5.77
Upper-bound	ResNet152	-	88.54	-
DynaER		2000	71.01	17.53
Upper-bound	ViT-B/16	-	90.85	-
L2P		0	83.86	6.99
DualPrompt		0	85.18	5.67
Proposed		**0**	**85.47**	**5.38**

Task-agnostic dataset (e.g. G-CIFAR100) presents the gradual transition of classes, where the task boundary cannot be defined. Therefore, some previous works (BiC, Co^{2}L, LwF, DualPrompt) are not applicable, as the methods require the explicit task boundary. In contrast, our method maintains its effectiveness also for the smooth transition of tasks, thanks to the accumulation of the knowledge in the prompt. As presented in Table 1, our method outperforms the other methods.

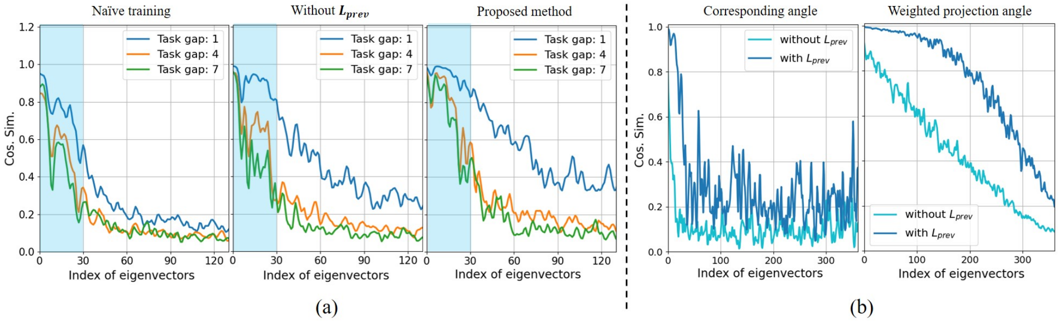


Figure 7: An analysis of the feature spaces is presented with the help of the following diagrams. (a) The similarity of the eigenvectors for V_t feature spaces between tasks is visualized, with colored regions for comparison. (b) The corresponding angle and the weighted projection angle on the previous space for Z_t are shown. The transfer of top eigenvectors is enhanced by L_{prev}.

Limitation of prompt pool We provide the additional results to clarify the limitation of the previous approach based on the prompt pool. We argue that the prompt pool has limitation due to its fixed number of prompt, as the pool size is predefined in advance. Moreover, we claim the degradation of performance by the misaligned prompt due to the inaccurate prediction of task identity in the inference stage, which is exacerbated as the task number increases.

To verify the claim, we fixed the size of the prompt pool of the L2P, and observed how the performance changes with the increase of the task number. For DualPrompt, we calculate the accuracy for task prediction, and reveal the performance gap by the misprediction. Split ImageNet-R dataset is used. As shown in Table 3, L2P shows the degradation as the task number increases. Likewise, the task prediction is getting lowered for DualPrompt as claimed. We also present the result for DualPrompt with ideal prompt selection for the given image (i.e. 'Oracle prompt' in Table 3). The task gap is increased as the accuracy for task prediction is degraded. Compared to the previous method, we observed the superiority of our approach, accumulating the knowledge in the prompt for the continual learning.

Furthermore, Table 4 compares the computational cost between our method and the previous methods. First, the proposed method requires far less parameters for the prompt to instruct the model, as our approach accumulate the knowledge in the single prompt. However, the previous approach captures the previous knowledge using a set of prompts, which introduces the redundancy in the parameters. Second, our method shows faster inference speed compared to the previous approach, thanks to the elimination of the prompt selection process. Specifically, our method simply employs the final prompt, whereas the previous methods are required to get features from the large frozen model to select the prompt from the prompt pool. We provide the details for the calculation of the computational costs in Appendix C.

Table 4: Comparison for the computational costs

	# Prompt Params.	Inference time (s)
L2P	0.92M	41.61
DualPrompt	0.94M	32.63
Ours	**0.11M**	**25.04**

Analysis on the feature space We analyze the change of the feature space for V_t, Z_t during the continual learning, and verify the effectiveness of the proposed accumulative prompt to alleviate the forgetting problem. We visualize the corresponding angle (Zhu et al., 2021) of the eigenvectors, similar to the Section 3.2. The results in Figure 7(a) shows the enhanced similarity of the top eigenvectors by the proposed method. Specifically, as shown in the second graph, L_{ctr} alone shows the limited improvement for the forgetting problem, although it contributes to the alignment between the intermediate tasks (i.e. Task gap 1 in the middle graph). The proposed method, which utilizes both L_{ctr} and L_{prev}, largely increased the similarity also for more task gaps.

Similarly, Figure 7(b) supports the alignment of Z_t space. We calculate the angles between the feature spaces of the final model f_T and the former model f_{T-1}. The corresponding angle is enhanced at the front part of the index by the L_{prev}, which verifies the transfer of the top eigenvectors in the embedding space. Since the corresponding angle shows the large fluctuation, we additionally present the proposed metric, weigthed projection angle, to clarify the improvement. The weighted projection angle clearly shows the high similarity by the L_{prev} with less fluctuation. This result refers both the enhanced alignment of the space and the stability of the proposed metric. The results for both V_t and Z_t spaces verifies that the proposed method accumulative prompt keeps the alignment of the feature space across the tasks, which result the alleviation the forgetting problem.

6 Discussions

Comparison with the upper-bound prompt p^* We present the comparison for the feature space of V_t between the prompt-based methods and the multi-task model (i.e. the upper-bound model supervised by i.i.d sampled data for all tasks). We utilized the validation dataset of the first task. The dataset for the comparison is Split ImageNet-R with 10 sequential tasks. For the wighted projection angle, we project the eigenvectors of prompt-based method to the space of the multi-task model.

As shown in Fig. 8, the corresponding angles are increased for more indices of the eigenvector. Moreover, the weighted projection angle clearly shows the enhanced alignment with less fluctuation. The result supports our overall claim that the proposed accumulative prompt can be a key to access the upper-bound prompt p^* for the sequence of the tasks.

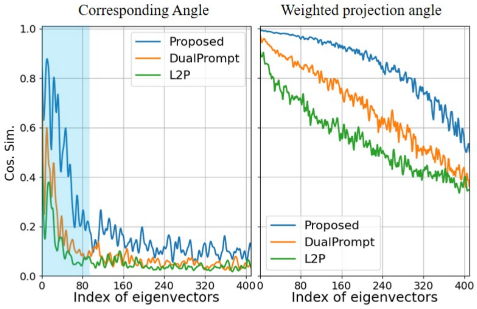


Figure 8: Feature space alignment with the upper-bound prompt. Our method shows the best alignment.

Plasticity-Stability tradeoff For continual learning, the model should be stable for previous task, while being adaptable for the new tasks. However, there exists a trade-off between the stability and the adaptability (Mirzadeh et al., 2020; Wang et al., 2022a). We present the ablation study on the λ_{prev}, to analyze the tradeoff in our method.

In Fig. 9, we visualize the alignment of the feature space with varying λ_{prev}, using Split-ImageNet-R dataset. Averaged values for task gap 1 are presented. As λ_{prev} increases, the cosine similarity between the eigenvectors also increases. The result demonstrates the improved stability of the model for the previous tasks, by the enhanced alignment between the feature spaces.

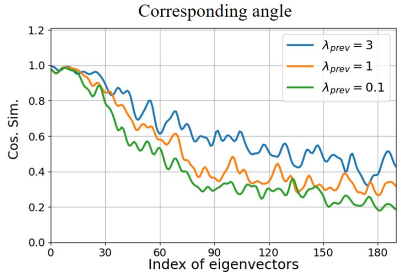


Figure 9: Alignment of feature space for V_t with varying L_{prev}.

The result in Table 5 also verifies the improved stability by decreased forgetting. However the result also shows the lowered accuracy by the reduced plasticity of the model, which presents the plasticity-stability tradeoff. Still, our method has better tradeoff compared to the previous methods, showing higher accuracy than the other methods in Table 1.

Table 5: Results for varying λ_{prev}, showing the trade-off.

λ_{prev}	Avg. Acc.↑	Forgetting↓
×	69.59	5.35
0.1	69.85	4.88
2	69.71	3.93
3	69.56	3.77
Ours	**69.90**	**4.10**

7 Conclusion

We suggested a novel approach for prompt-based continual learning to alleviate the forgetting problem by the knowledge accumulation in the prompt. We first observed the misalignment of the feature space by the prompt leads to the catastrophic forgetting. Inspired from the recent success of the contrastive learning, we proposed a novel approach based on the obervation that the current model and previous model provides two different view of the given data, which can be regarded as the positive pair. Specifically, our method employed the positive-only contrastive learning, and experimental results verified that the method alleviates the forgetting by the transfer of the top eigenvectors.

ETHICS STATEMENT

Training large-scaled models often requires massive computational cost, which can contribute to environmental concerns, including increased carbon emissions. Moreover, the forgetting of the previously acquired knowledge is a significant loss, considering the extensive computational resources consumed to train the model. In this context, the prompt-based approach for the continual learning is a promising solution by preventing the forgetting problem using only a few learnable parameters. The prompt learning offers the reduced computational burden. Moreover, the continual learning technique optimizes the prompt to preserve the previously obtained knowledge of the large pre-trained model. Additionally, the use of prompt mitigates the data privacy issues. By eliminating the need for a memory buffer, prompt-based methods prevent the exposure of the previous data. We believe that our work would be a meaningful step towards the efficient utilization of large-scale models.

REPRODUCIBILITY

We describe the experimental settings and details to reproduce our results in Appendix A, B. We also provide the pseudo code to clarify our method in Appendix D. We will release our code upon publication,

REFERENCES

Sungsoo Ahn, Shell Xu Hu, Andreas Damianou, Neil D Lawrence, and Zhenwen Dai. Variational information distillation for knowledge transfer. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 9163–9171, 2019.

Adrien Bardes, Jean Ponce, and Yann LeCun. VICReg: Variance-invariance-covariance regularization for self-supervised learning. In *International Conference on Learning Representations*, 2022.

Pietro Buzzega, Matteo Boschini, Angelo Porrello, Davide Abati, and Simone Calderara. Dark experience for general continual learning: a strong, simple baseline. *Advances in neural information processing systems*, 33:15920–15930, 2020.

Hyuntak Cha, Jaeho Lee, and Jinwoo Shin. Co2l: Contrastive continual learning. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pp. 9516–9525, October 2021.

Arslan Chaudhry, Marc'Aurelio Ranzato, Marcus Rohrbach, and Mohamed Elhoseiny. Efficient lifelong learning with a-GEM. In *International Conference on Learning Representations*, 2019a.

Arslan Chaudhry, Marcus Rohrbach, Mohamed Elhoseiny, Thalaiyasingam Ajanthan, Puneet K Dokania, Philip HS Torr, and Marc'Aurelio Ranzato. On tiny episodic memories in continual learning. *arXiv preprint arXiv:1902.10486*, 2019b.

Xinlei Chen and Kaiming He. Exploring simple siamese representation learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 15750–15758, June 2021.

Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition*, pp. 248–255. Ieee, 2009.

Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929*, 2020.

Arthur Douillard, Matthieu Cord, Charles Ollion, Thomas Robert, and Eduardo Valle. Podnet: Pooled outputs distillation for small-tasks incremental learning. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XX 16*, pp. 86–102. Springer, 2020.

Jean-Bastien Grill, Florian Strub, Florent Altché, Corentin Tallec, Pierre Richemond, Elena Buchatskaya, Carl Doersch, Bernardo Avila Pires, Zhaohan Guo, Mohammad Gheshlaghi Azar, et al. Bootstrap your own latent-a new approach to self-supervised learning. *Advances in neural information processing systems*, 33:21271–21284, 2020.

Yiduo Guo, Bing Liu, and Dongyan Zhao. Online continual learning through mutual information maximization. In *International Conference on Machine Learning*, pp. 8109–8126. PMLR, 2022.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770–778, 2016.

Dan Hendrycks, Steven Basart, Norman Mu, Saurav Kadavath, Frank Wang, Evan Dorundo, Rahul Desai, Tyler Zhu, Samyak Parajuli, Mike Guo, et al. The many faces of robustness: A critical analysis of out-of-distribution generalization. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 8340–8349, 2021.

Minsoo Kang, Jaeyoo Park, and Bohyung Han. Class-incremental learning by knowledge distillation with adaptive feature consolidation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 16071–16080, 2022.

James Kirkpatrick, Razvan Pascanu, Neil Rabinowitz, Joel Veness, Guillaume Desjardins, Andrei A Rusu, Kieran Milan, John Quan, Tiago Ramalho, Agnieszka Grabska-Barwinska, et al. Overcoming catastrophic forgetting in neural networks. *Proceedings of the national academy of sciences*, 114(13):3521–3526, 2017.

Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009.

Sang-Woo Lee, Jin-Hwa Kim, Jaehyun Jun, Jung-Woo Ha, and Byoung-Tak Zhang. Overcoming catastrophic forgetting by incremental moment matching. *Advances in neural information processing systems*, 30, 2017.

Zhizhong Li and Derek Hoiem. Learning without forgetting. *IEEE transactions on pattern analysis and machine intelligence*, 40(12):2935–2947, 2017.

David Lopez-Paz and Marc' Aurelio Ranzato. Gradient episodic memory for continual learning. In *Advances in Neural Information Processing Systems*, volume 30, 2017.

Divyam Madaan, Jaehong Yoon, Yuanchun Li, Yunxin Liu, and Sung Ju Hwang. Representational continuity for unsupervised continual learning. In *International Conference on Learning Representations*, 2022.

Seyed Iman Mirzadeh, Mehrdad Farajtabar, Razvan Pascanu, and Hassan Ghasemzadeh. Understanding the role of training regimes in continual learning. *Advances in Neural Information Processing Systems*, 33:7308–7320, 2020.

Aaron van den Oord, Yazhe Li, and Oriol Vinyals. Representation learning with contrastive predictive coding. *arXiv preprint arXiv:1807.03748*, 2018.

Quang Pham, Chenghao Liu, and Steven Hoi. Dualnet: Continual learning, fast and slow. *Advances in Neural Information Processing Systems*, 34:16131–16144, 2021.

Ameya Prabhu, Philip HS Torr, and Puneet K Dokania. Gdumb: A simple approach that questions our progress in continual learning. In *European conference on computer vision*, pp. 524–540. Springer, 2020.

Jathushan Rajasegaran, Munawar Hayat, Salman H Khan, Fahad Shahbaz Khan, and Ling Shao. Random path selection for continual learning. *Advances in Neural Information Processing Systems*, 32, 2019.

Amal Rannen, Rahaf Aljundi, Matthew B Blaschko, and Tinne Tuytelaars. Encoder based lifelong learning. In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 1320–1328, 2017.

Dushyant Rao, Francesco Visin, Andrei Rusu, Razvan Pascanu, Yee Whye Teh, and Raia Hadsell. Continual unsupervised representation learning. *Advances in Neural Information Processing Systems*, 32, 2019.

Gobinda Saha, Isha Garg, and Kaushik Roy. Gradient projection memory for continual learning. In *International Conference on Learning Representations*, 2021.

Hanul Shin, Jung Kwon Lee, Jaehong Kim, and Jiwon Kim. Continual learning with deep generative replay. In *Advances in Neural Information Processing Systems*, volume 30, 2017.

Daniel L Silver and Robert E Mercer. The task rehearsal method of life-long learning: Overcoming impoverished data. In *Advances in Artificial Intelligence: 15th Conference of the Canadian Society for Computational Studies of Intelligence, AI 2002 Calgary, Canada, May 27–29, 2002 Proceedings 15*, pp. 90–101. Springer, 2002.

Yonglong Tian, Dilip Krishnan, and Phillip Isola. Contrastive multiview coding. *arXiv preprint arXiv:1906.05849*, 2019.

Yuandong Tian, Xinlei Chen, and Surya Ganguli. Understanding self-supervised learning dynamics without contrastive pairs. In *International Conference on Machine Learning*, pp. 10268–10278. PMLR, 2021.

Xiang Wang, Xinlei Chen, Simon S Du, and Yuandong Tian. Towards demystifying representation learning with non-contrastive self-supervision. *arXiv preprint arXiv:2110.04947*, 2021.

Zhen Wang, Liu Liu, Yiqun Duan, Yajing Kong, and Dacheng Tao. Continual learning with lifelong vision transformer. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 171–181, 2022a.

Zifeng Wang, Zizhao Zhang, Sayna Ebrahimi, Ruoxi Sun, Han Zhang, Chen-Yu Lee, Xiaoqi Ren, Guolong Su, Vincent Perot, Jennifer Dy, et al. Dualprompt: Complementary prompting for rehearsal-free continual learning. *arXiv preprint arXiv:2204.04799*, 2022b.

Zifeng Wang, Zizhao Zhang, Chen-Yu Lee, Han Zhang, Ruoxi Sun, Xiaoqi Ren, Guolong Su, Vincent Perot, Jennifer Dy, and Tomas Pfister. Learning to prompt for continual learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 139–149, 2022c.

Mitchell Wortsman, Vivek Ramanujan, Rosanne Liu, Aniruddha Kembhavi, Mohammad Rastegari, Jason Yosinski, and Ali Farhadi. Supermasks in superposition. *Advances in Neural Information Processing Systems*, 33:15173–15184, 2020.

Yue Wu, Yinpeng Chen, Lijuan Wang, Yuancheng Ye, Zicheng Liu, Yandong Guo, and Yun Fu. Large scale incremental learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 374–382, 2019.

Shipeng Yan, Jiangwei Xie, and Xuming He. Der: Dynamically expandable representation for class incremental learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 3014–3023, June 2021.

Jaehong Yoon, Eunho Yang, Jeongtae Lee, and Sung Ju Hwang. Lifelong learning with dynamically expandable networks. In *International Conference on Learning Representations*, 2018.

Jure Zbontar, Li Jing, Ishan Misra, Yann LeCun, and Stéphane Deny. Barlow twins: Self-supervised learning via redundancy reduction. In *International Conference on Machine Learning*, pp. 12310–12320. PMLR, 2021.

Friedemann Zenke, Ben Poole, and Surya Ganguli. Continual learning through synaptic intelligence. In *International Conference on Machine Learning*, pp. 3987–3995. PMLR, 2017.

Fei Zhu, Zhen Cheng, Xu-Yao Zhang, and Cheng-lin Liu. Class-incremental learning via dual augmentation. *Advances in Neural Information Processing Systems*, 34:14306–14318, 2021.

Zhijian Zhuo, Yifei Wang, Jinwen Ma, and Yisen Wang. Towards a unified theoretical understanding of non-contrastive learning via rank differential mechanism. In *International Conference on Learning Representations*, 2023.

Appendix

A Settings for the observation

In the Section 3.1 of the main paper, we investigate the forgetting process by analyzing the corresponding angleZhu et al. (2021) between the feature spaces. For the tasks t and t', we define the task gap τ as the difference between the task indices(i.e. $\tau = |t' - t|$), and investigate how the angle changes as the task gap increases.

We extract the features by the models $f_t, f_{t'}$ which are trained until the tasks t, t'. The input is fixed as the validation dataset of the first task, $\mathcal{D}_1 = \{(x_{i,1}, y_{i,1})\}_{i=1}^{n_1}$. From the output features, we obtain the eigenvectors of the feature spaces $S_t = \text{span}\{u_1, ..., u_d\}$ and $S_{t'} = \text{span}\{v_1, ..., v_d\}$

The corresponding angle between the spaces is the cosine similarity between the eigenvectors with the same index, given as below:

$$cos(\phi_i; t, t') = \frac{\langle u_i, v_i \rangle}{\|u_i\|_2 \, \|v_i\|_2} \tag{10}$$

where i is the index of the eigenvectors. However, the corresponding anlge shows significant fluctuation, since the minor change of the order of the vectors results large change in the value. Therefore, we present the averaged value for the given task gap τ as follows:

$$cos(\phi_i)_{avg,\tau} = \frac{1}{T - \tau} \sum_{t=1}^{T-\tau} cos(\phi_i; t, t + \tau) \tag{11}$$

where T is the total number of the tasks.

We investigate the forgetting problem in the both of the CNN model and the vision transformer model. For CNN model, we used the ResNet18He et al. (2016) network, and trained it from the scratch by 10 tasks of Split-CIFAR100Krizhevsky et al. (2009) dataset. For the transformer model, we employed ViT-B/16Dosovitskiy et al. (2020) model and trained it using the 10 tasks of Split-ImageNet-RHendrycks et al. (2021) dataset.

B Experimental details

We summarize the hyperparameters in the Table. 6. For the experiments by the varying task number T with Split ImageNet-R, the identical hyperparameters are used (i.e.$\lambda_{ctr} = 1, \lambda_{prev} = 1$).

We used ViT-B/16 (Dosovitskiy et al., 2020) model with pretrained on ImageNet (Deng et al., 2009), with simple linear layers for the projector $W^t \in \mathbb{R}^{786 \times 384}$ and the predictor $W_q^t \in \mathbb{R}^{384 \times 384}$. W^t has the batch normalization layer at the end, following the SimSiamChen & He (2021). The prompt length and the layers to input the prompt is identical with the single prompt of the prompt pool in DualPrompt, for fair comparison with recent methods DualPrompt (Wang et al., 2022b) and L2P (Wang et al., 2022c). Our implementation is based on the official source code with Jax[1], and its pytorch version[2].

Table 6: Hyperparameters for each dataset.

	λ_{ctr}	λ_{prev}
Split CIFAR100	0.5	0.5
Split ImageNet-R	1	1
G-CIFAR100	1	1

C Calculation of computational costs

Number of prompt parameters We calculate the number of the prompt parameters to clarify the advantage of our approach. We argue that the proposed method effectively instructs the model using fewer parameters, compared to the previous approach based on the prompt pool.

We introduce the calculation for the number of parameters for each methods. We clarify that the prompt size are identical to the single prompt in Dualprompt, for the fair comparison with the previous approach. We calculate the size of prompt for dataset of 10-task split-CIFAR100.

[1] https://github.com/google-research/l2p

[2] https://github.com/JH-LEE-KR/dualprompt-pytorch

First, our method input the prompts in 5 layers, with the length 5 for first two layers and length 20 for the rest of the layers. The prompts have 768 dimensions and separately defined for the query and key for the transformer layers. Therefore, the number of parameters for the prompt is calculated as:

$$\text{\# param. in total} = 2 * 5 * 768 * 2 + 3 * 20 * 768 * 2 = 107,520 \tag{12}$$

Second, DualPrompt has two different prompts, g-prompt and e-prompt. Prompts are input to 5 layers of the ViT. g-prompts are input to the first two layers, with the length of 5. e-prompts are input to the rest three layers, with the length of 20. Moreover, the prompt pool collects 10 e-prompts to memorize the previous knowledge. Similarly, the prompts have 768 embedding, and defined separately for the query and key in ViT layers. Then, the number of parameters for the prompt is calculated as:

$$\text{\# param. of g-prompts} = 2 * 5 * 768 * 2 = 15,360 \tag{13}$$

$$\text{\# param. of e-prompts} = 3 * 20 * 768 * 2 = 92,160 \tag{14}$$

$$\text{\# param. in total} = 15,360 + 10 * 92,160 = 936,960 \tag{15}$$

Lastly, L2P collects 30 prompts in the prompt pool, where the length of all the prompts are idential as 20. Then, the number of the parameters is calculated as:

$$\text{\# param. of single prompt} = 2 * 20 * 768 = 30,720 \tag{16}$$

$$\text{\# param. in total} = 30,720 * 30 = 921,600 \tag{17}$$

Our method utilizes significantly fewer parameters for the prompts, to guide the model for continual learning. The result demonstrates the efficiency of the proposed approach, accumulating knowledge by the single prompt.

Inference time We use the dataset for 10 tasks of split-ImageNet-R to estimate the inference time. We merged the validation datasets of all tasks. Then, we measure the time to generate the predictions for all data within the merged datasets.

D Pseudo code

Algorithm 1 Training procedure for the prompt

```
Input: Learnable $\{p, W, W_q, W_{cls}\}$ with fixed ViT
Output: $\{p, W_{cls}\}$
Initialize $\{\widetilde{p}, \widetilde{W}\}$ w/o gradient
for $t = 1, 2, \dots T$ do
    if $t = 1$ then
        Set $\lambda_{ctr} = 0; \lambda_{prev} = 0$        ▷ $\{L_{ctr}, L_{prev}\}$ are not used
        Train $\{p, W_{cls}\}$ by $L_{total}$
        Replace parameters $\widetilde{p} \leftarrow p$
    else if $t = 2$ then
        Set $\lambda_{prev} = 0$        ▷ $\{L_{prev}\}$ is not used
        Train $\{p, W, W_q, W_{cls}\}$ by $L_{total}$
        Replace parameters $\widetilde{p} \leftarrow p; \widetilde{W} \leftarrow W$
    else if $t > 2$ then
        Train $\{p, W, W_q, W_{cls}\}$ by $L_{total}$
        Replace parameters $\widetilde{p} \leftarrow p; \widetilde{W} \leftarrow W$
```

We summarize the training stages in Algorithm 1. To clarify the process, we introduce the learnable modules $\{p, W, W_q, W_{cls}\}$ and the accumulative modules $\{\widetilde{p}, \widetilde{W}\}$, which corresponds to $\{p_t, W^t, W_q^t, W_{cls}\}$ and $\{p_{t-1}, W^{t-1}\}$. After the end of each task, the parameters of $\{\tilde{p}, \tilde{W}\}$ are replaced by the newly obtained $\{p, W\}$ to prepare the next task

In the algorithm, we made division for $t = 1$, $t = 2$, $t > 2$ for the training, as the loss function changes for each step. For the first task (i.e. t=1), L_{ctr} is not applicable since the previous prompt

$\{p^{t-1}\}$ is not provided. Moreover, L_{prev} is not used for the first and second task (i.e. t=1,2), as it requires the previous module $\{W^{t-1}\}$.

E Additional ablation study

Ablation for related methods We conduct the ablation study for the related methods, specifically focusing on the contrastive learning and the knowledge distillation (KD) techniques. First, we compare our method with KD methods, including PODNet (Douillard et al., 2020), VID (Ahn et al., 2019) and AFC (Kang et al., 2022). Moreover, we conduct the comparison with other contrastive losses such as InfoNCE (Oord et al., 2018), Barlow Twins (Zbontar et al., 2021) and VICReg (Bardes et al., 2022). We used 10 tasks of split-CIFAR100 dataset. As shown in Table 7, the proposed method outperforms the related methods.

Table 7: Comparison for related works.

	Avg. Acc.	Forgetting
PODNet	81.53	6.66
VID	84.20	7.10
AFC	82.12	6.46
InfoNCE	85.48	4.85
Barlow	81.09	6.76
VICReg	82.53	5.71
Ours	**85.47**	**4.16**

Ablation on prompt length l_p We additionally provide the ablation study on the length of prompt. We set the prompt length to be identical with the recent SoTA, DualPrompt (Wang et al., 2022b), for fair comparison. The length of the prompts are 5 for the first two layers, and 20 for the rest of the layers. For the ablation study, we set all the prompts to have same length, and change the length. We used 10 tasks of split-ImageNet-R dataset. As shown in Table 8, the prompt length with 5 shows the improved forgetting on the previous task with the lowered accuracy which indicates the lowered plasticity of the model. The performance is consistent with the increase of the prompt length, which demonstrates the robustness of the method to the prompt length.

Table 8: Ablation study for l_p.

l_p	Avg. Acc.↑	Forgetting↓
5	69.51	3.79
20	69.67	4.41
10	69.88	4.34
40	69.31	4.23
Proposed	**69.90**	**4.10**