Incremental Prototype Prompt-tuning with Pre-trained Representation for Class Incremental Learning

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Abstract

Class incremental learning has attracted much attention, but most existing related works focus on fine-tuning the entire representation model, which inevitably results in much catastrophic forgetting. Instead of struggling to fight against such forgetting by replaying or distilling like most of the existing methods, we take a novel pre-train-and-prompt-tuning paradigm to sequentially learn new visual concepts based on a fixed semantic-rich pre-trained representation model. In detail, we incrementally prompt-tune category prototypes for classification and example prototypes to compensate for semantic drift, the problem caused by learning bias at different learning phases. Extensive experiments conducted on the mainstream incremental learning benchmarks demonstrate that our method outperforms other state-of-the-art methods.

1 Introduction

Recently, most class incremental approaches resist catastrophic forgetting by replaying the seen data [30, 18, 39] or distilling the previous models [15, 9, 6]. Although distilling and replaying can help to balance model’s plasticity and stability, when just feed a few new concepts, the representation model learned from the last phase is still needed to be fine-tuned in the next phase endlessly, affecting the whole body of the model and bringing in lots of forgetting, so that it limits the performance of class incremental learning. This situation leads us to ask: is that possible to make models to learn new concepts without fine-tuning the whole representation model? It is already answered yes by natural language processing (NLP) with pre-training and prompt-tuning.

In NLP, pre-training has been affirmed since the releasing of BETR [11] and GPT [27, 28, 2]. To make the models pre-trained on a large-scale corpus competent for downstream tasks, it only needs to fine-tune them on downstream tasks’ data. Inspired by the success of pre-training in NLP, many researchers have proposed pre-training methods suitable for computer vision (CV), such as SimCLR [3], MAE [7], and CLIP [26], bringing us powerful representation models. However, fine-tuning these pre-trained models are costly due to their huge parameters scale. Therefore, instead of making the pre-trained model adapt to a lot of downstream tasks, the prompt-tuning method which makes the downstream tasks adapt to a fixed pre-trained model becomes more and more approved.

L2P [36] introduces the idea of prompting in the field of continual learning by prompt-tuning the feature queries as the input of Vit [5] backbone. In contrast, we choose to implement prompt-tuning with learnable category prototypes as the input of the classifying head. Our experiments prove that

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an appropriate pre-trained representation model with category prototypes prompt-tuning can help class incremental learning to obtain competitive results without fine-tuning the representation model, nor replaying old data, nor distilling from the previous model. We conduct various experiments and detailed analyses to figure out what exactly makes pre-train-and-prompt-based class incremental learning work. And we find that only those models that are pre-trained by rich semantic supervision and have strong enough semantic capture ability can perform well for class incremental learning.

Although strong pre-trained representation can greatly improve the performance of class incremental learning systems, the performance is still not ideal. The reason is that the categories at different phases are not trained together, and the classifier may overlap the category prototypes learned at different phases in the representation space, as shown in Figure 1, which is called semantic drift proposed by Yu et al. [42]. To solve this problem, we extract several learnable prototypes for each category (namely example prototypes) to be classified by all learned category prototypes, which aims to imitate each class’ distribution in representation space and constrains the classifier to isolate the category prototypes when learning new categories from different phases. Unlike replaying methods storing the original samples, our method only stores several prototypes of each category thus saving a lot of storage resources.

With the help of category prototypes, example prototypes, and powerful pre-trained models, our method called incremental prototype prompt (IPP) outperforms state-of-the-art models with a large margin on CIFAR-100 [13], ImageNet-100 [30] and ImageNet-1000 [31] benchmarks. In summary, we provide the following contributions:

1. We propose a novel method named propose incremental prototype prompt-tuning (IPP). Based on a fixed well-pre-trained representation model (backbone), IPP incrementally learns new categories with category prototypes and alleviates semantic drift [42] by classifying example prototypes.

2. We prove the great feasibility of the pre-training-and-prompt-tuning paradigm for class incremental learning with experiments, visualization, and in-depth explanation, and reveal that the performance of pre-train-and-prompt-tuning based class incremental learning has a close positive relationship with the rich semantics of the pre-trained model.

3. Our approach achieves a new state-of-the-art performance on most mainstream class incremental learning benchmarks. It is very simple but surprisingly enables an AI system to learn new concepts incrementally without replaying original data or distillation from previous models, offering a different perspective for solving catastrophic forgetting.

2 Related work

2.1 Class Incremental Learning

Deep learning models overspecialize at individual tasks while lacking the ability to learn openly to deal with other tasks, which is in sharp contrast to human beings. To address this problem, incremental learning attempts to develop an artificial intelligence system that can continuously learn and process new tasks from new data, while retaining the knowledge learned from previous tasks. Incremental learning can be divided into three categories [35]: task incremental learning, domain incremental learning, and class incremental learning (CIL) [30], where CIL is more challenging and closer to the needs of practical applications which the task identity is not informed when classifying test samples. Recent popular CIL methods can be categorized into three classes: replay-based, regularization-based, and parameter-isolation-based [4, 25, 17]. Replay-based methods preserve a small amount of data in previous tasks in memory or a generative model in order to replay these data when training the model on new data to overcome catastrophic forgetting [30, 18, 39, 10, 37]. The regularization-based methods provide terms in the final loss to restrict the model with prior or knowledge distillation to change too much to forget previous knowledge [12, 14, 43, 15, 9, 6]. For parameter-isolation-based methods, different subsets of the model parameters are dedicated to each task to prevent the previous tasks from getting any possible forgetting [20, 33, 32, 1].

2.2 Prompt-tuning with pre-trained model

Prompt-tuning aims to alias the pre-trained representations and features of downstream tasks by adjusting the task-specific parameters or context while remaining the pre-trained model fixed [29,
Figure 1: T-SNE\[19\] of CIFAR-10 [13] to show semantic drift and its compensation. Note that the black arrows reflect the semantic drift. IPP without example prototypes may cause serious semantic drift as shown in the left picture, in which the category prototypes may be far away from the density center of the target class and even close to another class. Even one example prototype can greatly alleviates this problem as shown in the right picture.

2, 16]. It is originally designed to probe knowledge in a pre-trained language model [24]. Recently, prompt-tuning has been introduced into multimodal computer vision. CPT [41] redefines visual grounding as the problem of filling in the blank of color-based co-referential markers in images and texts, mitigating the gap between the objective forms of model pre-training and fine-tuning. Context optimization (CoOp) [44] models context words by using continuous vectors learned from data end-to-end, avoiding manual prompt adjustment. L2P [36] is the first work that introduces prompt-tuning into incremental learning. It learns a pool of prompt queries as one part of input for pre-trained Vit [5] backbone and mitigates catastrophic forgetting by a key-value-pair-based prompt selection strategy. The difference between IPP and L2P is that IPP chooses to learn to prompt as the input (category prototypes) for the classifier, keeping the representations of samples unchanged, while L2P does not.

3 Incremental prototype prompt-tuning

3.1 Problem setup

Given a data stream of a labeled sample super set \( \{X^1, X^2, \ldots, X^t\} \), where \( X^y = \{x^y_1, x^y_2, \ldots, x^y_{n_y}\} \) is a set containing all samples belonging to class \( y \), class incremental learning models learn from a dataset stream \( \{D_0, D_1, \ldots, D_t, \ldots\} \). At each phase \( t \), only \( D_t = \{X^{s_t+1}, X^{s_t+2}, \ldots, X^{s_t+1}\} \) is accessible for training the model, while the seen data \( X^1, \ldots, X^{s_t} \) is no longer available. Here, \( s_t \) represents the sum of the number of categories learned before phase \( t \). During the test, the trained model is expected to classify all seen categories. It is needed to note that joint training whose accuracy is regarded as the upper bound of class incremental learning puts all samples of all categories together for training.

3.2 Overview

An overview of incremental prototype prompt-tuning (IPP) with the pre-trained representation model for class incremental learning is presented in Figure 2. The IPP consists of a pre-trained model, category prototypes, and examples prototypes.
In IPP, only example prototypes and category prototypes are trainable parameters.

**Training strategy.** The training strategy of our model involves two stages, the initialization stage and the training stage. During each new phase $t$, new category prototypes and new examples prototypes are initialized and integrated into the model at the initialization stage. The new category prototypes can simply be initialized as the sample embeddings of target categories or the embeddings of the class name provided by the text encoder pre-trained together with the representation model, such as CLIP [26]. The new example prototypes are initialized by a clustering algorithm, and we will talk about them in Section 3.4. To initialize the example prototypes, it only needs to play $D_t$ for one epoch. At the training stage, the loss is computed by the simple addition:

$$L^t = L^t_{CES} + L^t_{CEP} + L^t_{MS}. \tag{1}$$

Since the pre-trained representation model is fixed, the original samples are not required to be played at the training stage as long as replaying the representations of images from $D_t$, which makes the training stage faster. See appendix for more detailed training algorithm.

**Inference.** The inference architecture only consists of a representation model and some category prototypes. Samples are classified according to which category prototypes their embeddings, extracted by the pre-trained representation model, are most similar to.

### 3.3 Prompting category prototypes

A well pre-trained model can bring high-quality cross-task representation that helps to reduce the catastrophic forgetting problem for class incremental learning. While the pre-trained model provides each sample’s embedding vector, we propose category prototypes as the low-dimensional representation of each category. Each sample is classified according to the similarity between its embedding and the category prototypes as follows.

In order to balance stability and plasticity, the pre-trained representation model serves as a fixed embedding network $\Phi$, and category prototypes as $c_{s_t}, \cdots, c_{s_{t+1}-1}$ are learned. At the training stage during phase $t$, each sample is extracted as a representation $\Phi(x)$. For each sample $x$, suppose the similarity between $\Phi(x)$ and $c_i$ is represented as:

$$s(x, c_i) = \langle \Phi(x), c_i \rangle, \tag{2}$$

where $i \in \{s_t, \cdots, s_{t+1} - 1\}$ and $x \in D_t$. We get the classification result of samples after applying a softmax function:

$$[y_{s_t}(x), \cdots, y_{s_{t+1}-1}(x)]^T = softmax([s(x, c_{s_t}), \cdots, s(x, c_{s_{t+1}-1})]^T). \tag{3}$$

Finally, cross-entropy loss during phase $t$ is computed as:
\[ L_{CES}^{t}(x) = \sum_{i=s_t+1}^{s_{t+1}-1} \hat{y}_i(x) \log y_i(x), \tag{4} \]

where \( \hat{y}_i(x) \) is the ground truth of probability of sample \( x \) belongs to class \( i \).

### 3.4 Learning example prototypes

**Motivation.** As shown in Figure 1, when we map category prototypes and sample embeddings into low dimension space for visualization, we find that category prototypes are not always located in the center of the target class sample embeddings, instead, it may be located in the center of other class embeddings, which is called semantic drift [42]. Since the samples at the former and latter phases are not available simultaneously, as long as the category prototype can correctly classify the samples at the current phase, the loss function does not necessarily continue to encourage the category prototypes to enter the sample representation density center of the target class. The category prototypes may even occupy the sample representation density center of other phase categories, resulting in classification confusion that greatly harms the performance of IPP. So that we propose to optimizing the classification loss of several example prototypes to prevent semantic drift.

**Learning example prototypes.** We define the example prototypes of class \( i \) as \( e_i^j, i = 1, \cdots, N_c, j = 1, \cdots, N_e \), where \( N_c \) is the total number of all classes, and \( N_e \) is the number of example prototypes. Example prototypes are supposed to imitate the distribution of representation embeddings of every category, they are trained by the maximum similarity loss computed as:

\[ L_{MS}^{t}(x) = 1 - \max_{j}(< x, e_g(x) >), \tag{5} \]

where \( j = 1, 2, \cdots, N_e, x \in D_t \), and \( g(x) \) is ground truth class id label of sample \( x \). Maximum similarity does not require each sample prototype to be close to each sample of the target category. In this way, it is possible to find some difficult samples that deviate from the density center of the sample.

**Initialization of example prototypes.** The optimization direction of example prototypes is mainly dominated by maximum similarity loss. If example prototypes are far from the target category embedding center at the initialization stage, only a few example prototypes can eventually enter the sample distribution space of the target category, resulting in example prototype’s underfitting of target class distribution. Therefore, the example prototype needs a better initialization method to shorten the initial distance between all example prototypes and the target category embedding center. Note that this distance should not be too small, otherwise example prototype will lose the ability to mine difficult samples. We refer to the initialization method of PODNet [6]. For each new class \( C \), we extract the representation of all its training samples, then use the k-means algorithm to split them into \( N_e \) clusters, and then use these cluster centers as the initialization values of new example prototypes. This initialization method not only allows example prototypes to cover the sample representation distribution of the corresponding class, but also retains the diversity of example prototypes.

**Preventing semantic drift.** Semantic drift can be prevented by classification loss of example prototypes. During phase \( t \), classification loss of example prototypes is computed as:

\[ L_{CEP}^{t}(e_i^j) = - \sum_{k=1}^{s_{t+1}-1} \hat{y}_k(e_i^j) \log y_k(e_i^j), i \in \{1, 2, \cdots, s_{t+1} - 1\}, \tag{6} \]

where

\[ [y_k(e_i^j)]^T = \text{softmax}([< e_i^j, c_k >]^T), k \in \{1, 2, \cdots, s_{t+1} - 1\}. \tag{7} \]

**Discussion.** Classification loss of example prototypes forces \( c_k \) to be far away from \( e_i^j \) for every \( i \neq k \), which helps to isolate category prototypes from different phases. Moreover, since it can also adjust those category prototypes born before phase \( t \), accuracy of phase \( t^b (t^b < t) \) can even be continually improved, achieving positive backward transfer.
4 Experiment

4.1 Experiment setup

Datasets. We use three data sets composed of CIFAR-100 [13], ImageNet-100 [30] and ImageNet-1000 [31] for our experiment. CIFAR-100 contains 60000 32 × 32 pixels color image samples from 100 categories. Each class has 500 training and 100 test samples. Imagenet-1000 is a large data set containing about 1.3 million 224 × 224 pixels color image samples images from 1000 categories. Each class has about 1300 training and 50 test samples. ImageNet-100 is a subset of the ImageNet-1000 dataset containing 100 sampled classes from the original 1000 classes.

Benchmark protocols. We validate our method with two widely used benchmark protocols including protocol of half initialization (PHI) proposed and protocol of no initialization (PNI). The PHI starts training the models on half the classes (i.e., 50 for CIFAR-100 and ImageNet-100, 500 for ImageNet-1000), then equally divides remained classes and incrementally learns them at the future phase. The PNI simply divides the total classes equally among phases and learns them phase by phase. Note that an \( n \) phases PHI has actually \( n+1 \) phases with one phase for half initialization, while PNI has exactly \( n \) phases.

Implementation details. We implement our method in PyTorch with one RTX 3090. We train 40 epochs for all datasets with batch size 128 for CIFAR-100, and batch size 256 for ImageNet-1000 and ImageNet-100. SGD is used for optimization with a base learning rate of 0.01. Momentum and weight decay parameters are set to 0.9 and 0.0005, respectively. We multiply the learning rate by 0.1 at the beginning of the 10th, 20th, 30th epoch. We use a clipping gradient in the range of 5 to 100 to accelerate training. We choose cosine distance to uniformly measure the distance among sample embeddings, category prototypes, and example prototypes. Code will be available soon.

Metrics. We use three indicators to evaluate our IPP model: average incremental accuracy, forgetting rate, and incremental joint accuracy ratio. Rebuffi et al. [30] introduce average incremental accuracy (AIA), which averages the accuracy of all phases. Forgetting rate (FR), proposed by Liu et al. [18], measures the degree of performance degradation in the first initialization phase after incremental training. In addition, we consider another measure, called incremental joint accuracy ratio (IJAR). It is defined as the ratio of the two accuracies, taking the joint prompt-tuning accuracy as the denominator and the class incremental learning accuracy in the final phase as the numerator, that measures the performance gap between incremental training and joint training while excluding dependence on the absolute performance of the model.

Table 1: Result on CIFAR-100 benchmarks

| Protocol          | PHI       |       |       |       |       | PNI       |       |       |       |       |       |       |
|-------------------|-----------|-------|-------|-------|-------|-----------|-------|-------|-------|-------|-------|-------|
|                   | S        | 10    | 50    | S     | 10    | 50    |       |       |       |       |       |       |
|                   | AIA(%)   | FR(%) | AIA(%) | FR(%) | AIA(%) | AIA(%) | AIA(%) | AIA(%) | AIA(%) | AIA(%) | AIA(%) | AIA(%) |
| iCaRL [30]        | 58.08 ± 0.59 | 31.88 | 53.78 ± 1.16 | 34.1 | 44.20 ± 0.98 | 71.14 ± 0.34 | 65.27 ± 1.02 | 56.08 ± 0.83 | 71.14 ± 0.34 | 65.27 ± 1.02 | 56.08 ± 0.83 |
| CCIL-SD [22]      | 67.17 | 65.86 |       |       |       |       |       |       |       |       |       |       |
| UCIR [9]          | 63.63 ± 0.87 | 18.7 | 60.83 ± 0.70 | 21.34 | 48.57 ± 0.37 | 62.77 ± 0.82 | 58.66 ± 0.71 | 56.86 ± 3.74 | 62.77 ± 0.82 | 58.66 ± 0.71 | 56.86 ± 3.74 |
| BiC [38]          | 56.86 ± 0.46 | 31.42 | 53.21 ± 1.01 | 32.5 | 47.09 ± 1.48 | 73.10 ± 0.55 | 68.80 ± 1.20 | 62.09 ± 0.85 | 73.10 ± 0.55 | 68.80 ± 1.20 | 62.09 ± 0.85 |
| PODNet [6]        | 64.83 ± 0.98 | 64.03 ± 1.30 | 61.40 ± 0.68 | 66.70 ± 0.64 | 58.03 ± 1.27 | 51.19 ± 1.02 |       |       |       |       |       |       |
| DER [40]          | 72.60 ± 0.78 | 72.45 ± 0.76 | - | 73.55 ± 0.65 | 74.64 ± 0.28 | 72.05 ± 0.55 |       |       |       |       |       |       |
| L2P-CLIP-VitB/16 [36] | 79.56 | 4.86 | 76.72 | 6.42 | 83.42 | 80.17 | 70.20 |       |       |       |       |       |
| L2P-CLIP-VitL/14 [36] | 86.90 | 3.86 | 85.54 | 2.48 |       | 88.60 | 84.28 | 77.80 |       |       |       |       |

IPP-IN21K-VitL/16(ours) | 86.87 ± 0.16 | 66.00 | 0.12 | 55.71 | 81.79 | 81.84 | 69.93 |       |       |       |       |       |
IPP-CLIP-VitB/16(ours) | 82.32 ± 0.86 | 0.047 | 82.1 ± 1.07 | 0.187 | 81.81 ± 1.25 | 83.12 ± 2.00 | 83.30 ± 2.40 | 84.25 ± 2.40 |       |       |       |       |
IPP-CLIP-VitL/14(ours) | 87.73 ± 0.55 | -0.4 | 87.45 ± 0.83 | -0.46 | 87.27 ± 0.97 | 88.62 ± 1.22 | 87.83 ± 1.35 | 89.09 ± 1.98 |       |       |       |       |

4.2 Comparison to state of the art

We evaluate the proposed IPP method on various benchmarks, comparing with the reported results of several methods including DER [40], PODNet [6], BiC [38], UCIR [9], CCIL-SD [22], and iCaRL [30]. We also evaluate the latest state-of-the-art L2P [36] with our code. IPP results are based on three models including Vit-B/16, Vit-L/14 pre-trained by CLIP [26] on a dataset consisting of 400 million image-text pairs (we name it CLIP400M), and Vit-L/16 pre-trained on ImageNet21K as the representation models with 10 example prototypes per class. We run experiments for different datasets, benchmark protocols, and phase settings.
Table 2: Result on ImageNet-100 and ImageNet-1000 benchmarks

| Datasets | ImageNet-100 | ImageNet-1000 |
|----------|--------------|---------------|
| Protocols | PHI 5 | PHI 10 | PHI 50 | PHI 10 | PHI 5 | PHI 10 | PHI 5 | PHI 10 |
| Metrics | AIA(%) | FR(%) | AIA(%) | FR(%) | AIA(%) | FR(%) | AIA(%) | FR(%) |
| iCaRL [30] | 65.56 | 43.4 | 60.9 | 45.84 | 54.97 | 31.36 | 26.03 | 46.72 | 33.76 |
| CCIL-SD [22] | 79.44 | 76.77 | 68.04 | 26.03 | 46.72 | 33.76 |
| UCIR [9] | 71.04 | 31.88 | 67.82 | 33.48 | 57.25 | 45.72 | 24.08 | 61.28 | 27.29 |
| BIC [38] | 68.97 | 27.04 | 65.14 | 31.04 | 46.94 | 45.72 | 24.08 | 61.28 | 27.29 |
| PODNet [6] | 75.54 | 74.33 | 62.48 | 26.03 | 46.72 | 33.76 |
| DEEP [40] | 77.73 | 74.33 | 62.48 | 26.03 | 46.72 | 33.76 |
| L2P-CLIP-ViT-B/16 [36] | 76.63 | 0.44 | 75.92 | 2.44 | 82.63 | 1.41 | 82.63 | 2.09 |
| IPP-CLIP-ViT-B/16(ours) | 82.75 | 0.56 | 83.22 | 0.73 | 82.63 | 1.4 | 82.63 | 2.09 |
| IPP-CLIP-ViT-L/14(ours) | 86.4 | 0.16 | 85.98 | 0.04 | 86.33 | -0.9 | 83.10 | 0.31 |

Figure 3: Class incremental accuracy curves on CIFAR-100. The results of L2P and ours are based on the CLIP pre-trained VitB/16, and the results of other methods are based on their original model.

Results on CIFAR-100. As shown in Table 1, we can see that our method performs better than other methods at different incremental phases and the average incremental accuracy did not change significantly with the increase of phases. In particular, the FR of our method is very close to zero and even negative, while most other methods still struggle with catastrophic forgetting. As shown in Figure 3, our method consistently outperforms other methods during the entire incremental training progress for different phase settings and ends up with a high accuracy at the final phase.

Results on ImageNet-100 and ImageNet-1000. As the results summarized in Table 2, our method significantly surpasses other methods with a considerable margin under all phase settings on ImageNet-100 and ImageNet-1000. Under the PHI setting on Imagenet-1000, the FR of IPP-CLIP-ViT-B/16 decrease to a negative value, suggesting that the model may have achieved positive backward transfer.

4.3 Impact of pre-training

In this section, we study the impact of pre-trained representations for class incremental learning. In detail, we compare different factors that are supposed to bring different transfer performances to the models, including model architecture and sizes, scale of the pre-trained datasets, and training methods. Table 3 summarizes the result under the 10 phases PHI setting on CIFAR-100.

Results. The architecture of the pre-trained model plays an important role in transfer learning. After we evaluate our approach with ResNet-50 and ResNet-101 [8], Vit-B/32, Vit-B/16, Vit-L/16
Table 3: Performance of different pre-trained representations. “Pre Method” means pre-training method and “Pre Dataset” means the dataset that the representation pre-trained on. “UB” means linear probe upper bound. “Final Acc” means the total accuracy at the last phase.

| Pre Method | Pre Dataset | Model     | AIA(%) | Final Acc(%) | UB(%) | IJAR(%) | SS-Acc(%) |
|------------|-------------|-----------|--------|--------------|-------|---------|-----------|
| CLIP       | CLIP400M    | Vit-L/14  | 87.45  | 83.62        | 87.05 | 96.06   | 91.62     |
| CLIP       | CLIP400M    | Vit-B/16  | 82.10  | 77.82        | 81.99 | 94.91   | 87.37     |
| CLIP       | CLIP400M    | Vit-B/32  | 80.33  | 74.92        | 79.69 | 94.01   | 85.60     |
| CLIP       | CLIP400M    | RN101     | 72.75  | 65.82        | 72.05 | 91.35   | 78.71     |
| CLIP       | CLIP400M    | RN50      | 68.09  | 60.91        | 68.36 | 89.10   | 75.32     |
| CLIP       | YFCC15M     | Vit-B/16  | 57.69  | 48.30        | 59.06 | 81.78   | 67.82     |
| CLIP       | YFCC15M     | RN101     | 59.46  | 50.82        | 60.47 | 84.04   | 67.89     |
| CLIP       | YFCC15M     | RN50      | 67.99  | 60.87        | 67.30 | 90.45   | 73.35     |
| SLIP[23]   | YFCC15M     | Vit-B/16  | 68.83  | 61.40        | 70.45 | 87.15   | 78.78     |
| SimCLR[3]  | YFCC15M     | Vit-B/32  | 12.27  | 9.57         | 28.58 | 33.48   | 41.53     |
| Classification | ImageNet21K | Vit-L/16  | 76.00  | 66.46        | 79.69 | 83.40   | 83.13     |
| Classification | ImageNet21K | Vit-B/16  | 70.98  | 61.03        | 74.51 | 81.91   | 77.38     |
| Classification | ImageNet21K | RN50      | 41.73  | 32.77        | 51.88 | 63.16   | 67.28     |

and Vit-L/14[5], the results in Table 3 show that Vit models are significantly better than ResNet models possibly due to their stronger semantic capture ability. To evaluate our method’s performance pre-trained on a different scale of the dataset, we compare the results of representation models pre-trained on the dataset what we call CLIP400M (consist of 400 million image-text pairs from YFCC100M [34] and Internet) and YFCC15M [34], the subset of YFCC100M. As expected, the model pre-trained from the larger dataset has better performance, as shown in Table 3. We also evaluate our method by different pre-training methods including CLIP [26], SimCLR [3], SLIP [23] and classical classification on ImageNet21K. Results in Table 3 illustrate that both vision-language pre-training and classical classification are effective for class incremental learning, while models only learned from self-supervised contrastive learning may lack of higher level semantic knowledge.

**Secondary information.** We agree with Mittal et al. [22] that high-quality secondary information (dark knowledge) makes semantically similar classes lie closer in the representation space as compared to the dissimilar classes, which is the essential to reduce forgetting while incrementally learning new concepts. Here a metric named secondary superclass-accuracy (SS-Acc) proposed by Mittal et al. is computed to quantitatively measure the quality of secondary information. Secondary superclass accuracy computes the accuracy of correct superclass predictions, in which superclass is defined as a superclass combined by several semantically similar classes. SS-Acc results on CIFAR-100 are reported in Table 3. An overall analysis result is that class incremental learning performance is positively correlated with the richness of secondary information. To better understand how secondary information influences IPP-based class incremental learning, we plot curves to detect the relationship between SS-Acc and class incremental performance on CIFAR-100 measured by final accuracy, AIA and IJAR in Figure 4.4 (b). In addition to the obvious positive correlation, we can see that there is a critical inflection point. It may be caused by the roughness of measuring secondary information richness, but it is still telling us that only with enough dark knowledge can the model make a breakthrough for class incremental learning.

### 4.4 Impact of prototypes

We conduct the ablation study to evaluate the contribution of example prototypes and category prototypes for our method. In detail, we conduct experiments by employing different numbers of example prototypes (including number zero which means there is no example prototype used) under the PHI and PNI setting for both 10 and 50 phases on CIFAR-100. We also compare random and k-means initialization for the example prototypes. The results of whether to freeze those category prototypes born before phase $n$ while learning at phase $n + t$ to prevent those knowledge learned in new phases to be transferred to old phases are also submitted. VitB/16 pre-trained on CLIP400M is used as the representation model by all experiments in this section.

**Results.** Figure 4.4 (a) exhibits the result of the prototype ablation study. The methods of using example prototypes are better than the methods of not using, particularly under the more challenging settings such as 50 phases setting. Although one example prototype can enough achieve obvious improvement under 10 phases setting, the performance of IPP-based methods under more difficult
Figure 4: (a): Relationship curves between IPP-based class incremental learning performance and the number of example prototypes. In order to avoid infinity and display better, the horizontal axis adopts the logarithm of the number of example prototypes plus one. The legend content “k-means” or “random” means whether to use k-means to initialize the example prototypes and "freeze" or "free" means whether to freeze those category prototypes before the learning phase. (b): Relationship curve between SS-Acc and class incremental performance

settings still needs more example prototypes to be ensured. However, the more example prototypes used, the more IPP depends on initialization methods, and of course the more storage space are required. It is also worth noting that the methods that do not freeze the categories prototypes born before phase t while learning at phase t + 1 outperform those methods that freeze. In other words, positive backward transfer is actually achieved behind the prompt-tuning of category prototypes.

5 Conclusions

In this work, we prove the feasibility of the pre-train-and-prompt-tuning paradigm with the proposed incremental prototype prompt-tuning (IPP), which successfully reduces catastrophic forgetting and eliminates semantic drift. At each new phase t, we freeze the representation model and the examples prototypes born before phase t, generate new category prototypes and examples prototypes, and optimize them with two classification losses and maximum similarity loss. Exhaustive experiments on the three major incremental classification benchmarks show that our method consistently performs better than other methods with a large margin. We find that our method’s performance depends on the richness of secondary information buried in representations, which inspires us to train the representation model to get more dark knowledge. Interestingly, our method can also achieve positive backward transfer with IPP.

Limitations. However, since the representations for IPP are fixed, the premise for IPP to exert its advantages is that the domain of the target task does not exceed the domain of pre-training. The representation model of IPP is usually trained in a general domain, which may leads to its low representation ability in more fine-grained tasks. To further improve the performance of IPP, the future work will focus on learning more task-specific representations while maintaining the stability of the original features.

Potential negative societal impact. IPP can be applied to many downstream applications. However, it may still have a potential societal impact, since IPP relies on models pre-trained on large-scale datasets that may have bias and ethical problems. These issues may be carried out in the process of IPP incremental learning. Therefore, we encourage any users to thoughtfully check the datasets for pre-training to exclude any bias and fairness issues.
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A More ablation results for prototypes

We display more ablation results for prototypes based on Vit-B/32 pre-trained on CLIP400M in Figure 5. The results still support the same conclusion which argues that the more challenging the setting of incremental learning, the more sample prototypes are required, telling us the classification loss of example prototypes matters.

Figure 5: Relationship curves based on VitB/32 between IPP-based class incremental learning performance and the number of example prototypes. In order to avoid infinity and display better, the horizontal axis adopts the logarithm of the number of example prototypes plus one.

B Memory footprint

Since IPP only adds category prototypes and example prototypes to the model at each phase, the incremental memory requirements rise slowly, as shown in Table 4.

Table 4: Memory requirements for different number of example prototypes at different phases under PNI settings. “NE” means the number of example prototypes. All the result in this table are based on VitB/16 for CIFAR-100.

| NE | Memory | 0  | 1  | 2  | 5  | 10 | 20  | 40  |
|----|--------|----|----|----|----|----|-----|-----|
|    | Size(KB) |    |    |    |    |    |     |     |
| Phase 1 |        | 2.00 | 4.00 | 6.00 | 12.00 | 22.00 | 42.00 | 82.00 |
| Phase 10 |       | 20.00 | 40.00 | 60.00 | 120.00 | 220.00 | 420.00 | 820.00 |
| Phase 100 |      | 200.00 | 400.00 | 600.00 | 1200.00 | 2200.00 | 4200.00 | 8200.00 |

C Dataset licenses

CIFAR-10 and CIFAR-100 are licensed under the MIT license.

ImageNet are licensed under https://image-net.org/download.php.
**Algorithm 1: IPP at training time**

**Input:** Pre-trained representation backbone \( \Phi \), dataset stream \( \{D_t\} \), empty set of learned category prototypes \( \{c_i\} \), empty set of learned example prototypes \( \{e_{ij}\} \), where \( i \in 1, 2, \cdots, N_c \) and \( j \in 1, 2, \cdots, N_e \), number of training epochs of the \( t \)-th task \( M_t \), mini-batch size \( B \)

**for** \( D_t = D_1, D_2, \cdots, D_T \) **do**

- Initialize: \( S_t = \{\} \)
- Freeze learned example prototypes \( \{e_{ij}\} \)
- **for** \( X_i \in D_t \) **do**
  - Append category prototype \( c_i \) to \( \{c_i\} \)
  - Initialize: \( E_i = \{\} \)
  - **for** \( x \in X_i \) **do**
    - Append each \( \Phi(x) \) as representation for sample \( x \) to both \( S_t \) and \( E_i \)
  - Use k-means cluster on \( E_i \) to generate \( N_e \) initial example prototypes for category \( i \), and append them to \( \{e_{ij}\} \)
- **end**
- **for** \( m = 1, \cdots, M \) **do**
  - Draw a mini-batch \( SB = \{s_k\} \) from \( S_t \), where \( k = 1, \cdots, B \)
  - **for** \( s_k = s_1, \cdots, s_B \) **do**
    - # Note that \( s_k = \Phi(x_k) \), it is no need to be calculated through the backbone again
    - Calculate loss of sample classification \( L_{CES}(x) \) via equation 4
    - Calculate maximum similarity loss \( L_{MS}(x) \) via equation 5
  - **end**
  - Calculate loss of example classification \( L_{CEP}(e_{ij}) \) via equation 6
  - Update new generated example prototypes \( \{e_{ij}\} \) and all category prototypes by backpropagation \( \{c_i\} \)
- **end**
- **end**