Offline-Online Class-incremental Continual Learning via Dual-prototype Self-augment and Refinement

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Abstract

This paper investigates a new, practical, but challenging problem named Offline-Online Class-incremental Continual Learning (O^2CL), which aims to preserve the discernibility of pre-trained (i.e., offline) base classes without buffering data examples, and efficiently learn novel classes continuously in a single-pass (i.e., online) data stream. The challenges of this task are mainly two-fold: 1) Both base and novel classes suffer from severe catastrophic forgetting as no previous samples are available for replay. 2) As the online data can only be observed once, there is no way to fully re-train the whole model, e.g., re-calibrate the decision boundaries via prototype alignment or feature distillation. In this paper, we propose a novel **D**ual-prototype Selfaugment and <u>**R**</u>efinement method (DSR) for O^2CL problem, which consists of two strategies: 1) Dual class prototypes: Inner and hyper-dimensional prototypes are exploited to utilize the pre-trained information and obtain robust auasiorthogonal representations rather than example buffers for both privacy preservation and memory reduction. 2) Selfaugment and refinement: Instead of updating the whole network, we jointly optimize the extra projection module with the self-augment inner prototypes from base and novel classes, gradually refining the hyper-dimensional prototypes to obtain accurate decision boundaries for learned classes. Extensive experiments demonstrate the effectiveness and superiority of the proposed DSR in O^2CL^{1} .

1. Introduction

With the ubiquitously prevalent personal smart devices, a massive amount of data are being continually generated, which requires adaptive machine learning models to learn new tasks without forgetting the old knowledge [8, 51, 54]. In privacy-sensitive online scenarios, a practical Online Class-incremental Continual Learning (OCL) system is ex-



Figure 1. The overall concept of proposed Offline-Online Classincremental continual Learning (CL) framework (*bottom*), compared here with standard Online CL (*top*).

pected to learn novel classes incrementally while keeping the prior knowledge without restoring any streaming data due to the privacy concerns and computation resource constraints. Existing OCL methods [15, 40, 14, 35, 50] mainly focus on exploring the critical feature representation [15, 35, 14, 50] and developing strategies of selecting and retrieving proper samples from the data buffer [40, 14] to re-calibrate the decision boundaries. However, these methods have two obvious drawbacks. Firstly, online learning is required for privacy-sensitive and/or resource-constrained scenarios where the training data can only be observed once. However, existing OCL solutions heavily rely on the example buffer for replay between data batches and tasks [12]. Secondly, OCL mainly concerns the setting of online training from scratch, and the state-of-the-art method [14] achieves relatively low accuracy (<20% for CIFAR100 [28] with 1000 buffer size), which significantly limits the OCL application to practical online scenarios.

Considering practical scenarios, we investigate a feasible solution for the new, practical, yet challenging protocol named Offline-Online Class-incremental continual Learning (O^2CL), as demonstrated in Figure 1. Concretely, in practice, an intelligent system conducts online class-

¹The source codes are attached in the supplementary material and will be released upon acceptance.

incremental learning without restoring stream examples, while utilizing and preserving the knowledge from previous training. Such under-explored practical settings are in line with Non-Exemplar Class-incremental continual Learning (NE-CL) [48, 51, 54], Few-Shot Class-incremental Learning (FS-CL) [53, 22, 38], and Continual Novel Class Discovery (C-NCD) [21, 49], where base classes are well trained, and the knowledge are retained, but novel classes need to be explored. The most relative protocols are NE-CL and FS-CL problems. However, NE-CL conducts classincremental learning without example buffers in an offline fashion, which enables the network to align the prior information (i.e., prototypes and/or features) multiple times like semantic drift compensation [48], dual augmentation [51], and prototype selection [54]. FS-CL aims to continually learn with few shot samples also in an offline way, like gradually refining the prototypes [53], finetuning the classifier heads [22], or merely focusing on training robust embedding network [38]. Therefore, NE-CL and FS-CL methods can hardly solve the O²CL problem. Figure 2 demonstrates the brief quantitative comparisons of OCL, FS-CL, NE-CL, and the proposed method in the same O^2CL setting.

In Offline-Online Class-incremental Continual Learning (O²CL), the key requirement is to conduct Online classincremental Continual Learning without forgetting the old knowledge to solve the stability-plasticity dilemma. In this paper, we devise a simple but effective method for O^2CL problem called Dual-prototype Self-augment and Refinement (DSR). As the single-pass data can not be revisited, unlike previous example-base OCL methods, directly finetuning the feature extractor will cause severe catastrophic forgetting. Therefore, we freeze the offline-trained feature extractor and translate O²CL problem to optimizing privacy-preserved dual prototypes with the extra projection module. Specifically, inner and hyper-dimensional prototypes (I-P and H-P) of base classes are restored to preserve learned information. For incremental sessions, I-P of novel classes tends to disturb the classification of both novel and base classes. We then project them to the hyper-dimensional embedding [13, 23, 25], which has been proven robust to noise. In detail, a random vector from hyper-dimensional embedding is quasi-orthogonal to other vectors with high probability (the "curse" of dimensionality [23]), and finetuning the prototype in the hyper-dimensional embedding provides a sufficiently large capacity to accommodate novel classes over time. Then, to efficiently maintain the decision boundaries of base and novel classes, self-augment I-P of learned classes jointly optimize the projection module, to map the I-P to the refined hyper-dimensional prototypes. In summary, our contributions are as follows:

 We study a novel yet practical problem called Offline-Online Class-incremental continual Learning (O²CL), where an intelligent system with pre-trained (i.e., of-



Figure 2. Class-wise accuracy, online training time, and memory overhead comparisons on the CIFAR100 dataset [28] with the **same protocols** of O²CL. Stat-of-the-art OCL (SCR[35], DVC[14], and OCM [15], all with 1000 example buffer), FS-CL (ALICE [38]), and NE-CL (SSRE [54]) methods are illustrated.

fline) base classes information can efficiently learn novel classes continually from the single-pass (i.e., online) data stream. Meanwhile, previous knowledge and privacy information should also be preserved.

- 2) We propose a novel Dual-prototype Self-augment and Refinement (DSR) method, which transfers training the whole network to optimizing the extra projection module. Concretely, H-P rapidly accommodates novel classes due to its quasi-orthogonal attribute. Then, self-augment I-P jointly optimizes the projection module based on refined H-P to re-calibrate the decision boundaries of learned classes.
- Extensive quantitative results demonstrate DSR performs significantly better than existing OCL, NE-CL, and FS-CL methods under the *same protocols* of proposed O²CL, both in accuracy and efficiency ².

2. Related Work

With the development of deep learning technologies [28, 9, 44, 16], There is a growing need for continual learning of neural networks, which requires the network to learn new tasks without forgetting previous knowledge to achieve the stability-plasticity trade-off. Class-incremental Learning [8, 34] is a practical yet difficult setting in continual learning and has obtained much attention recently. Existing methods can be generally divided into three categories: regularization-based [1, 31, 33, 6], structure-based [30, 36,

²Brief comparisons can be referred to in Figure 2.

24], and replay-based methods [11, 20]. Regularizationbased methods aim to impose constraints on the parameter updating to eliminate catastrophic forgetting. Concretely, some [1, 31] devise regularization terms to penalize the update of parameters. Adjusting gradient [33, 6] during optimization is another way to preserve previous knowledge. Structure-based methods expand the network and freeze selected parameters to prevent forgetting. Specifically, according to whether adding new parameters, methods can be divided into fixed architecture [24] and dynamic architecture [34, 5, 3, 30, 36], where the former relies on selecting sub-network model that does not infringe upon others and the later focus on expanding networks for new tasks. Replay-based methods [11, 20] preserve examples of fixed memory size to maintain the distribution of old classes in the incremental phases. Selection and retrieval [3, 14, 40] strategies for the buffer are also developed to preserve decision boundaries. Recently, some practical yet challenging settings of class-incremental learning, including Online Class-Incremental continual Learning (OCL), Non-Exemplar Class-incremental continual Learning (NE-CL), and Few-Shot Class-incremental Learning (FS-CL) are also proposed. Here we give a brief introduction.

Online Class-incremental continual Learning (OCL) OCL aims to learn new classes continually from online data streams (each sample is seen only once). As the model needs to learn novel classes from the data stream while not forgetting previous classes, OCL methods [34, 5, 3, 35, 15, 14, 50] follow replay-based protocols, where example buffers are stored and retrieved between data batches and tasks. Concretely, [15, 14] dig the critical information by maximizing their mutual information. [50] design augmentation strategies to address the underfitting-overfitting dilemma of online rehearsal. However, as pointed out by [12], example buffers in OCL violate privacy and computation restrictions, especially in online learning scenarios. However, the example-free task-incremental online continual learning method [12] needs the task information. Also, even equipped with the example buffers, the state-of-the-art method [14] only achieves relatively low accuracy (<20%for CIFAR100 [28] with 1000 buffer size). Considering these problems, we proposed a novel yet practical setting called O²CL, which aims to better preserve privacy and utilize offline knowledge in practical online applications.

Non-Exemplar Class-incremental Learning (NE-CL) Due to computation burden or privacy security, some works [48, 54, 47, 52] develop non-exemplar class-incremental learning methods where no past data can be stored. [48] compensates unknown prototype drifts of old classes via the drifts of current data. [52] employs self-supervised learning to obtain more transferable features. Also, prototypes are also augmented to preserve the decision boundaries of previous classes. Recently, [54] considers to adjust the joint representation learning and distillation process. However, NE-CL pays attention to non-exemplar offline continual learning. They need to offline train novel classes to adjust prototypes and gradually distill features [18]. Therefore, NE-CL methods are not suitable for the proposed O²CL problem as analysis and experiments below.

Few-Shot Class-incremental Learning (FS-CL) Compared to NE-CL, FS-CL assumes that novel classes come with few reference images. Current state-of-the-art FS-CL methods are mainly divided into two types. Some methods [7, 10, 41] update the backbone to accommodate new classes while preserving base class via knowledge distillation technologies [18]. However, these methods heavily rely on complex example buffers to simulate the function of the previous network. Some methods [38, 17, 22] freeze the backbone and re-adopt features from the base classes to recognize new classes. Therefore, metric learning [38], meta-learning [17], self-supervised learning [22], and class and data augmentation [38] strategies have been employed to obtain the backbone with high transferable representations. However, such FS-CL methods finetune the network in an offline way and/or do not fully explore novel classes, leading to relatively poor performance on O^2CL .

3. Problem Formulation

As shown in Figure 1, O²CL problem comprises base classes from offline training data and novel classes from online training data. During online learning, only the raw data of the current classes is available, and the network aims to incrementally learn online new classes whilst retaining learned information before the current session. Concretely, assuming an *m*-step O²CL problem, let $\{\mathcal{D}_{train}^{0}, \mathcal{D}_{train}^{1}, ..., \mathcal{D}_{train}^{m}\} \text{ and } \{\mathcal{D}_{test}^{0}, \mathcal{D}_{test}^{1}, ..., \mathcal{D}_{test}^{m}\}$ denote the training and testing data from sessions $\{0, 1, ..., m\}$, respectively. Each training and testing sessions *i* have the corresponding label sets denoted by C_{test}^i and C_{test}^i . C_{train}^i are mutually exclusive across different training sets, i.e., $\forall i \neq j, C_{train}^i \cap C_{train}^j = \phi$. While during evaluation, the model will be tested on all seen classes so far, i.e., for session i, the corresponding label space is $\mathcal{C}_{test}^0 \cup \mathcal{C}_{test}^1 \dots \cup \mathcal{C}_{test}^i$. Besides, the base session (i = 0)provides a large number of classes and also allows offline training. For the incremental sessions (i > 0), the data comes in the online stream state without rehearsal. During offline and online sessions, like NE-CL [48, 54], considering privacy and computation constraints, buffers with raw data are not permitted.

Dataset Partition. Similar to [48, 54, 53, 22, 38, 21, 49], the benchmark datasets are divided into $(60\% + 4\% \times 10)$, where the base session contains 60% classes for of-fline learning and the rest classes are online incrementally learned within 10 phases. Also, the results of $(40\% + 6\% \times 10)$, $(80\% + 2\% \times 10)$, and $(60\% + 2\% \times 20)$ are also pro-

vided in Appendix A.

Evaluation Metrics. As the number of classes in the base and novel sessions are imbalanced, the traditional class-wise accuracy cannot reflect those which achieve high accuracies on both base and novel classes. Apart from class-wise accuracy, we also employ the harmonic accuracy (HM, i.e., $HM = \frac{2 \times A_b \times A_n}{A_b + A_n}$, A_b and A_n denote the accuracy of base and novel classes) to evaluate the performance balance between base and novel classes.

4. Methodology

As for the proposed O^2CL problem, we aim to fully explore single-pass data stream novel classes while preserving previous information without example buffers. The stability-plasticity dilemma is intractable as the single-pass data stream results in the overfitting of novel classes while severely interfering with previously learned information. Previous OCL [15, 40, 14, 35, 50] methods resort to large example buffers to rehearse between data batches and tasks to eliminate forgetting. To this end, we transfer training the whole network to optimize the extra projection module via greedily augmenting and updating dual prototypes. Figure 3 shows the framework of the proposed DSR method. In the following section, we introduce the offline base session training protocol, Dual-prototype Self-augment and Refinement (DSR) for OCL, including self-augment inner prototypes, hyperdimensional prototype refinement, and whole optimization procedure.

4.1. Offline Base Session Training

For the base session training, previous NE-CL and FS-CL [38, 51, 52, 22] methods focus on training diverse features that are transferable across the base and incremental classes. Diverse class augmentation [38, 51, 52] and Self-Supervised Learning [52, 22] methods are employed in the base session. Similarly, sophisticated offline training also improves the generalization and transfer ability of our method to accommodate online new classes (Ablation configuration of Ours w/ RT in Table 2). As we focus on the online class-incremental learning as well as *fair comparisons* with other OCL methods, we utilize the supervised contrastive learning (SCL) [27] loss in the base session. Note that SCL and its variations have also been used in recent OCL [35, 14, 15]. Concretely, SCL is formulated as:

$$L^{scl} = \sum_{i \in I} \frac{-1}{|P(i)|} \sum_{p \in P(i)} \log \frac{\exp\left(z_i \times z_p/\tau\right)}{\sum_{a \in A(i)} \exp\left(z_i \times z_a/\tau\right)} \quad (1)$$

where I is the set of indices of Batch $(B_I = \{x_k, y_k, Aug(x_k), y_k\}_{k=1...b})$, which consists of original batch and augmented (Aug) view with 2b samples. $A(i) = I \setminus \{i\}$ means the set of indices of all samples in B_I except

for sample *i*. $z_i = Proj(HD_{ft})$. HD_{ft} is the output features from hyperembedding projection and Proj is a multilayer perceptron with a single hidden layer. $P(i) \equiv \{p \in A(i) : y_p = y_i\}$ is the set of indices of all positives in the augmented batch distinct from *i*, where |P(i)| is its cardinality. $\tau \in \mathcal{R}^+$ is an temperature parameter.

Our method freezes the backbone during online learning, therefore, relies on the embedding ability of the backbone. Compared to others, adding class augmentation and self-supervised learning bring obvious accuracy boosts, as shown in the ablation studies and *Appendix B*.

4.2. Dual-prototype Self-augment and Refinement

After offline training, the backbone maps the data from the input domain \mathcal{X} to a feature space: $f_{\theta_1} : \mathcal{X} \to \mathbb{R}^{d_f}$. θ_1 are parameters of backbone. The prototypes in \mathbb{R}^{d_f} are computed and restored to retain previous knowledge. Previous example-free prototype-based methods [48, 51, 52] offline refine prototypes and/or features together with samples from novel classes to achieve a trade-off between plasticity and stability. However, as for online learning, single-pass data stream results in insufficient data samples to gradually update the prototypes and network parameters. Besides, directly classifying novel classes based on frozen backbone fails to fully explore data samples of novel classes. Therefore, we devise dual prototypes strategy and refine the prototype in the hyperdimensional embedding space. Specially, we introduce the inner-prototype self-augment, hyperdimensional prototypes refinement, and the whole optimization procedure.

Inner-prototype Self-augment We restore the inner prototype of the base and novel class to rehearse for retaining previous information. However, vanilla retrieving previous prototypes will confuse the decision boundary. As a solution, [52] tries to augment prototypes via Gaussian noise when learning new classes. However, the distribution mostly concentrated close to 0 due to the typical relu [37] activation function in ResNet [16]. While class-specific class means (i.e., prototypes) tend to cluster together and lose the discriminative representation. Therefore, to make feature distribution more Gaussian-like, we transform features via Tukey's Ladder of Powers Transformation [43], which is a kind of power transformation that can reduce the skewness of distributions and make distributions more Gaussian-like. It can be formulated as:

$$\tilde{x} = \begin{cases} x^{\lambda} & \text{if } \lambda \neq 0\\ \log(x) & \text{if } \lambda = 0 \end{cases}$$
(2)

where λ is the hyperparameter to control the distribution i.e., decreasing λ makes the distribution less positive skewed and vice versa. The Gaussian-like rectification (denoted as $G(\cdot)$) are applied after the backbone (B) in both base and online sessions as $f = G(B_{\theta_1}(x))$. For class *i*



Figure 3. The overview of our method. The base and novel sessions train in offline and online ways, respectively. I-P, SA-P, and H-P mean the inner, self-augment, and hyperdimensional prototypes. $hist(\cdot)$ and $G(\cdot)$ denote histogram and feature transformation (Eq. (2)). (1), (2), and (3) represent the three-step refinement procedure. Gray modules mean the frozen components, and red dotted lines represent the refined decision boundaries. During the inference phase, cosine similarities are computed between queries from the network with H-P to obtain the label.



Figure 4. t-SNE [29] visualization of the feature embeddings. For better visualization, we train eight classes on the base session and incremental learn two classes (marked in green and red dots) sequentially. Red circles in H-P mean the confusion in novel classes and among base and novel classes. Best viewed in color.

in the session m, the inner prototype (ip) and its relative variance (v) are computed as:

$$ip_i^{(m)} = \frac{1}{|k_i|} \sum_{j=1}^{k_i} f_j^m, \ v_i^{(m)} = \frac{1}{|k_i|} \sum_{j=1}^{k_i} \left(f_j^m - ip_i^{(m)} \right)^2$$
(3)

where k_i represents the index of samples (x) that belong to class i in $\mathcal{D}_{train}^{(m)}$. Previous knowledge is retained by replaying features from the class-specific Gaussian distribution: $\hat{ip}_i^{(m)} \sim \mathcal{N}\left(ip_i^{(m)}, v_i^{(m)}\right)$. However, the prototypes of novel classes calculated by frozen backbone tend to be noisy, leading degradation both in base and novel classes, as shown in Figure 4 (Novel-I-P). Therefore, we also calculate the hyperdimensional prototypes of online classes in another hyperdimensional embedding space, where hyperdimensional prototypes are quasi-orthogonality, i.e., easy to differentiate [23] that leaves the room to accommodate online new classes with minimal interference.

Hyperdimensional Prototypes Refinement Recently, Hyperdimensional Computing has been used in computer vision tasks like few shot learning [17, 26], outof-distribution detection [45], and image translation [42], which leverage quasi-orthogonal hyperdimensional representations without inducing much training and inference overhead. The initial hyperdimensional prototype (hp) is obtained based on the single-pass raw data as:

$$hp_{i}^{(m)} = \frac{1}{|k_{i}|} \sum_{j=1}^{k_{i}} \left(Proj_{\theta_{2}} \left(f_{j}^{m} \right) \right)$$
(4)

where $Proj_{\theta_2}$ represents the projection module with parameters (θ_2) and $hp_i^{(m)}$ is the hyperdimensional prototypes. As we can see in Figure 4 (Novel H-P), though the prototypes have been clustered and separated to some extent in hyperdimensional embedding, the overlaps among novel classes and between base and novel classes also exist. Therefore, we propose a hyperdimensional prototypes refinement method and jointly optimize the projection module via the augmented prototypes of learned classes to map the I-P to aligned H-P. The whole refinement procedure contains **three steps**.

Firstly, as the base classes are well trained, we only up-

Algorithm 1: Training procedure of DSR. **Input:** Training data $\{\mathcal{D}_{train}^{0}, \mathcal{D}_{train}^{1}, ..., \mathcal{D}_{train}^{m}\},\$ base epoch n_1 , online iteration T_0, T_1, T_2 **Output:** Optimal θ_1, θ_2 , and hp1 Initialize: θ_1, θ_2 ; **2 Base Session:** // offline train θ_1 and θ_2 3 while $epoch < n_1$ do train θ_1 and θ_2 with Eq. (1) 4 5 end **6 Online Session:** // online train θ_2 and update hp for incremental sessions $M \in \{1, 2...m\}$ do **Input:** θ_1^{M-1} , θ_2^{M-1} , hp^{M-1} , \mathcal{D}_{train}^M **Output:** θ_1^M , θ_2^M , hp^M 7 $\theta_1^M \leftarrow \theta_1^{M-1}$ 8 9 while $t_0 < T_0$ or not converged do while $t_1 < T_1$ or not converged do 10 update $hp_{t_0}^{M(t_1)}$ with Eq. (8) 11 end 12 while $t_2 < T_2$ or not converged do 13 update $\theta_{2(t_0)}^{\tilde{M}(t_2)}$ with Eq. (10) 14 end 15 update $hp_{t_0}^{M(t_1)}$ with Eq. (11) 16 end 17 18 end

date H-P of novel classes by decreasing the cosine similarity of inter-novel classes (L^{in}) , and between base and novel classes (L^{bn}) , respectively. The formulas are as follows:

$$L^{hr}\left(hp^{(t)}\right) = L^{in}\left(hp^{(t)}\right) + L^{bn}\left(hp^{(t)}\right)$$
(5)

$$L^{in}\left(hp^{(t)}\right) = \sum_{i,j=1,s.t.\ i\neq j}^{|hp_{novel}|} \cos\left(\sigma\left(hp_i^{(t)}\right), \sigma\left(hp_j^{(t)}\right)\right)$$
(6)

$$L^{bn}\left(hp^{(t)}\right) = \sum_{i=1}^{|hp_{novel}|} \sum_{j=1}^{|hp_{base}|} \cos\left(\sigma\left(hp_{i}^{(t)}\right), \sigma\left(hp_{j}^{(t)}\right)\right)$$
(7)

where t means the T iterations. $\cos(\cdot, \cdot)$ and σ mean cosine similarity and hyperbolic tangent activation function. Moreover, to avoid significant deviations from the original representations, hp updates in the exponential moving average strategy (EMA):

$$hp^{(t+1)} = \alpha hp^{(t)} + (1-\alpha) \left(hp^{(t)} - \gamma \frac{\partial \left(L^{hr} \left(hp^{(t)} \right) \right)}{\partial \left(hp^{(t)} \right)} \right)$$
(8)

where α is the momentum hyper-parameter to control the weight of fusion, generally close to 1 ($\alpha = 0.99$ in this paper), and γ is the learning rate.

Secondly, based on refined H-P, we sample from classspecific Gaussian distribution from I-P as augmented prototypes and jointly optimize the projection module $(Proj_{\theta_2})$ to fit the refined H-P. The projection module is used as:

$$L_{i-h}^{(t)} = \frac{-1}{|\mathcal{C}|} \sum_{i=1}^{|\mathcal{C}|} \frac{1}{K} \sum_{k=1}^{K} \cos\left(Proj_{\theta_{2}^{(t)}}\left(\hat{ip}_{i}^{k}\right), hp_{i}\right)$$
(9)

$$Proj_{\theta_2^{(t+1)}} = Proj_{\theta_2^{(t)}} - \beta \frac{\partial L_{i-h}^{(t)}}{\partial Proj_{\theta_2^{(t)}}}$$
(10)

where β is the learning rate, |C| and K are the number of learned classes and sampled prototypes, respectively. The second step has two benefits: firstly, for class-incremental learning, we avoid frequently retrieving previous example samples while jointly retraining augmented prototypes of all classes to eliminate class imbalance problem[19, 46]. Secondly, for OCL, projection the noisy I-P to hyperdimensional embedding anchored in refined H-P makes the model easily and robustly accommodate online new classes.

Thirdly, as the initial H-P is directly inferred via the single pass data of novel classes, it lacks the interaction of base and novel classes though have been refined by Eq.(8). With the $Proj_{\theta_2}$, which has been well-trained via self-augment prototypes from all classes, the H-P of novel classes is updated in the exponential moving average strategy:

$$hp_{i}^{t+1} = \alpha hp_{i}^{t} + (1 - \alpha) \frac{1}{N} \sum_{n=1}^{N} Proj_{\theta_{2}} \left(\hat{i}p_{i}^{n}\right)$$
(11)

where N is the number of samples from Gaussian distribution and $i \in C_{novel}$ represents the novel classes. We optimize the $Proj_{\theta_2}$ and H-P with these three steps in a greedy way until reach the maximum iteration or cosine similarity convergence. **Algorithm 1** presents the pseudo-code of the whole procedure. As we train the lightweight projection module with prototypes rather than raw data, the whole procedure is efficient, as shown in Figure 2 and **Appendix E**. Finally, during the inference phase, by comparing the cosine similarities between a query (x) from the network and H-P. We compute the score l_i for class $i \in C$ as:

$$l_i = \cos\left(hp_i, Proj_{\theta_2}\left(G\left(B_{\theta_1}\left(x\right)\right)\right)\right) \tag{12}$$

5. Experiments

Datasets and Evaluation Protocol As mentioned in section 3, the benchmark datasets are divided into $(60\% + 4\% \times 10)$, where the base session contains 60% classes for

Methods	CORE-50		CIFAR100		Mini-ImageNet	
Metrics	Acc(base/i	novel) HM	Acc(base/i	novel) HM	Acc(base/i	novel) HM
ALICE[38]	39.5(46.2/29.5) 36		42.5(53.5/25.9) 34.9		41.1(51.4/25.7) 34.3	
PASS[52]	35.2(58.4/0.5) 1.0		37.9(62.6/0.9) 1.7		37.4(61.5/1.2) 2.4	
SSRE[54]	_		39.8(66.2/0.5) 1.0		_	
MS	1000	2000	1000	2000	1000	2000
GSS[3]	18.4(19.3/17.1) 18.1	20.8(22.3/18.6) 20.3	21.5(22.7/19.8) 21.2	23.4(24.2/22.1) 24.2	18.9(19.8/17.6) 18.6	21.1(21.9/19.7) 20.7
MIR[2]	22.6(24.6/19.7) 21.9	24.5(26.9/20.9) 23.5	24.2(26.4/20.9) 23.3	25.1(27.1/22.0) 24.3	22.9(24.6/20.3) 22.2	23.8(25.7/21.0) 23.1
GD[39]	25.8(27.0/23.9) 25.8	27.5(29.3/24.9) 26.9	25.8(27.2/23.8) 25.4	27.1(28.6/24.9) 26.6	23.2(24.6/22.4) 23.1	24.4(25.1/23.3) 24.4
DER++[4]	27.5(28.7/25.8) 27.2	28.8(30.2/26.6) 28.3	27.8(29.4/25.3) 27.2	30.2(32.9/26.1) 29.1	26.0(27.6/23.6) 25.4	28.6(29.9/26.7) 28.2
ASER[40]	29.4(30.6/27.6) 29.0	31.4(33.6/28.0) 30.5	30.7(31.4/29.6) 30.5	33.6(34.9/31.6) 33.2	25.4(27.8/21.7) 24.5	29.7(30.4/28.6) 29.5
SCR[35]	39.4(38.0/41.5) 39.7	40.7(41.3/39.8) 40.5	37.1(41.2/35.6) 38.3	41.9(44.8/38.1) 41.1	36.2(35.7/36.4) 36.1	38.8(44.2/30.9) 36.4
SCR_{ft}	39.6(46.2/29.8) 36.2	43.6(51.6/31.6) 39.2	39.6(50.1/23.8) 32.3	42.1(53.8/24.6) 33.8	38.8(43.9/30.8) 36.2	42.8(47.8/35.6) 40.8
OCM[15]	41.0(41.8/39.8) 40.8	42.5(43.1/41.6) 42.3	37.3(37.8/36.6) 37.2	41.6(42.6/40.1) 41.3	37.2(36.3/38.6) 36.1	40.9(45.8/33.6) 38.8
OCM_{ft}	41.1(46.5/33.1) 38.7	43.7(48.1/37.2) 41.9	40.8(46.3/32.6) 38.3	42.3(46.9/35.4) 40.3	39.0(40.6/36.8) 38.2	41.2(42.7/39.1) 40.8
DVC[14]	39.9(39.6/40.5) 40.0	41.8(42.8/40.5) 41.6	38.6(38.1/39.2) 38.9	41.8(42.6/39.4) 41.2	35.6(34.4/37.3) 35.9	38.4(36.9/41.2) 38.9
DVC_{ft}	41.9(48.2/32.6) 38.9	43.7(48.7/36.1) 41.5	39.0(43.2/32.7) 37.2	40.5(43.6/36.0) 39.4	36.2(39.8/30.9) 34.8	39.3(40.8/37.0) 38.8
Ours	50.9 +7.2(50.7/51.3) 51.0		48.3 +5.8(52.2/42.6) 46.5		50.8 +8.0(56.7/42.3) 48.1	

Table 1. Class-wise accuracy (Acc) by end of the training in terms of all classes, base classes, and novel classes. Harmonic accuracy (HM) is also illustrated. MS and $_{ft}$ mean the example memory size and finetuning versions. The best results are marked in **bold**.



Figure 5. The line chart represents class-wise average accuracy of representative methods (DVC[14], OCM[15], PASS[52], and ALICE [38]) along the incremental sessions.

offline learning, and the rest of the classes are online incrementally learned within 10 phases. Other splits are also provided in *Appendix A*. We conduct experiments on three widely used datasets, including CORE-50 [32], CIFAR 100 [28], and Mini-ImageNet [44], which have 50, 100, and 100 classes, respectively. Following recent class-incremental learning methods [8, 34], class-wise average accuracy is applied to evaluate the performance. Meanwhile, as O²CL contains online and offline training procedures and the number of their classes is unbalanced, to evaluate the balanced performance of base and novel classes, we also employ harmonic accuracy (HM).

Comparison Methods We compare DSR with three categories baselines: (1) Online Class-incremental learning: GSS [3], MIR [2], GD[39], DER++[4], ASER [40], SCR [35], OCM [15], DVC [14]. (2) Non-Exemplar Classincremental continual Learning: PASS [52], SSRE [54]. (3) Few-Shot Class-incremental Learning: ALICE [38].

Implementation details Following OCL methods [35, 15, 14], we employ a reduced ResNet-18 as the backbone

without pre-training. We use stochastic gradient descent with a learning rate of 0.1 with a batch size of 100 during the base session. The dimension of hyperdimensional embedding is 2048, and $Proj_{\theta_2}$ is implemented as a two-layer MLP with a hidden layer of 2048 dimension with relu as the activation function. For other hyper-parameters, we set offline epoch n_1 , online iteration T_0 , T_1 , T_2 to 100, 20, 5, 5, set online learning rate γ , α , β all to 0.01, set feature transform coefficient λ and the number of sampled prototypes Kand N to 0.5, 20, and 1000. Analysis of hyper-parameters is performed in **Appendix C**. As for compared methods, we adopt the **same training protocols** of O²CL as ours and adopt the defaulted hyper-parameters of their methods (see **Appendix D**). We report the mean result of all methods over ten different runs.

5.1. Comparisons with State-of-the-art Methods

We compare our method with other SOTA methods in the setting of the proposed O^2CL problem. The results are illustrated in Table 1 and Figure 5, which give the following observations. 1). In terms of class-wise accuracy, our method outperforms others by 7.2%, 5.8%, and 8.0% in CORE-50, CIFAR100, and Mini-ImageNet, respectively. For harmonic accuracy (HM), which measures the performance balance between offline and incremental online classes, ours also exceed other methods by a large margin. 2). For OCL methods, though equipped with large example buffers and offline pre-trained information, the overfitting and catastrophic forgetting problems are also severe compared to ours. To avoid these issues, similar to ours, we freeze the backbone after offline learning and only jointly

finetune the classifier head with online data and restored data samples (denoted as $_{ft}$). As we can see from SCR $_{ft}$, OCM_{ft} , and DVC_{ft} , simply freezing the backbone can not achieve the stability-plasticity trade-off that though base knowledge can be better preserved while damaging the ability to online learn the novel classes. Although large example buffers and frequent rehearsal can eliminate these issues, which somewhat violates the online learning protocols. 3). As for NE-CL methods, PASS and SSRE fail to learn the novel classes in an online version. Due to the lack of old class samples, PASS and SSRE promote knowledge transfer in the progressive knowledge distillation process, while the distillation constraints can hamper online learning toward novel classes. 4). For the FS-CL method, AL-ICE focuses on training generalization feature representations during the base session. They freeze all the parameters and directly infer novel classes based on robust embedding. However, without adjusting the representation, AL-ICE fails in a large number of sessions, as shown in the last few sessions in Figure 5 and $60\% + 2\% \times 20$ configuration in Appendix A. Note that NE-CL, PASS, and SSRE employ the more sophisticated ResNet-18 and pre-training strategy, which perform slightly better than ours in the base session. Moreover, as for computation overhead during online learning, which is usually considered in OCL scenarios [12], as shown in Figure 2, our method only consumes \sim 35 seconds and minimal memory overhead in CIFAR100. More quantitative results of computation overhead are in Appendix E.

5.2. Ablation Studies

To validate the effectiveness of each module of our method, we perform ablation studies on CIFAR 100 and Mini-ImageNet datasets, as shown in Table 2. Concretely, for inner-prototype self-augment stage, we ablate Gaussian-like rectification (w/o $G(\cdot)$) and directly revisit the prototype without sampling repeatedly from Gaussian distributions (w/o SA-P). We can see that the Gaussian-like rectification brings 2.3% gains via reducing the skewness of distributions. Augmented prototypes significantly preserve the decision boundaries of previous classes while also being beneficial to the overall performance through joint optimization. For hyperdimensional prototypes refinement stage, we remove the first refinement procedure (w/o 1st) in Eq. (5). The performance degrades to some extent, especially for the novel classes. To prove the effectiveness of amending prototypes in the hyperdimensional embedding (w/o HD), we project the inner prototypes to low-dimensional embedding (256) instead of high dimension (2048). The performance of both base and novel classes degrades, particularly in novel classes. The reason is that prototypes in low-dimensional embedding require dedicated alignments, otherwise resulting in confusion both in

Ablations	CIFAR100	Mini-ImageNet			
Metrics	Acc(base/novel) HM	Acc(base/novel) HM			
w/o $G\left(\cdot ight)$	46.0(50.2/39.7) 44.3	49.6(55.2/41.3) 47.2			
w/o SA-P	43.4(45.4/40.4) 42.8	48.7(53.7/41.2) 46.6			
w/o 1 <i>st</i>	46.2(50.9/39.1) 44.2	49.5(54.8/41.5) 47.2			
w/o HD	44.8(49.5/37.9) 42.9	47.4(53.6/38.1) 44.5			
w/o 3 <i>rd</i>	46.7(51.3/39.8) 44.8	49.7(55.6/40.9) 47.1			
Ours	48.3(52.2/42.6) 46.9	50.8(56.7/42.3) 48.4			
Ours w/ RT	52.8(56.2/47.8) 51.6	54.1(59.1/46.6) 52.1			
Table 2. Ablation studies on CIFAR100 and Mini-ImageNet.					

base and novel classes, which is not suitable for examplefree OCL. Besides, we ablate the third step (w/o 3 rd) in Eq. (11). The performance of novel classes degrades more severely than base classes due to lacking prototypes alignment through the optimized projection layer. Moreover, all the ablation configurations also achieve comparative performance, even compared with OCL methods with large example buffers, which validates the effectiveness of the dual prototypes strategy. **To evaluate the overall performance**, we adopt the robust training strategy (w/ RT) proposed by [38] in the base training session to obtain diverse and transferable representations. We can learn that the robust offline network improves our method by a large margin, both in preserving old classes and online accommodating novel classes, which validates the effectiveness of our method.

6. Conclusion

In this paper, we formulate a novel, practical, but challenging problem named Offline-Online class-incremental Continual Learning (O²CL), which aims to preserve pretrained (i.e., offline) base classes information, while efficiently learning novel classes continually from the singlepass (i.e., online) data stream, without example buffers. To solve this problem, we have proposed a novel Dualprototype Self-augment and Refinement (DSR) method, which presents two solutions: 1) Dual class prototypes: Inner and hyper-dimensional prototypes are maintained to utilize the pre-trained information and obtain robust quasiorthogonal representations rather than example buffers for both privacy preservation and memory reduction. 2) Selfaugment and refinement: Instead of updating the whole network, we jointly optimize the extra hyper-embedding module with the self-augment inner prototypes from base and novel classes, and refine the hyper-dimensional prototypes to obtain clear decision boundaries. Extensive experiments with OCL, NE-CL, and FS-CL methods on three benchmark datasets have demonstrated the effectiveness of DSR in handling O^2CL problem.

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