Effective Decision Boundary Learning for Class Incremental Learning

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Abstract

Rehearsal approaches in class incremental learning (CIL) suffer from decision boundary overfitting to new classes, which is mainly caused by two factors: insufficiency of old classes data for knowledge distillation and imbalanced data learning between the learned and new classes because of the limited storage memory. In this work, we present a simple but effective approach to tackle these two factors. First, we employ **re**-sampling strategy and **M**ixup **K**nowledge **D**istillation (Re-MKD) to improve performances of KD, which would greatly alleviate the overfitting problem. Specifically, we combine mixup and re-sampling strategy to synthesize adequate data used in KD training that are more consistent with the latent distribution between the learned and new classes. Second, we propose a novel **I**ncremental **I**nfluence **B**alance (IIB) method for CIL to tackle the classification on imbalanced data by extending the influence balance method into the CIL setting, which re-weights samples by their influences to create a proper decision boundary. With these two improvements, we present the **E**ffective **D**ecision **B**oundary **L**earning algorithm (EDBL) which improves the performance of KD and deals with the imbalanced data learning simultaneously. Experiments show that the proposed EDBL achieves state-of-the-art performances on several CIL benchmarks.

1 Introduction

Applications of deep neural networks (DNNs) in a real world require the ability of the system to learn new classes incrementally [1, 2, 3]. However, DNNs typically suffer from drastic performance degradation on the previously learned tasks after learning new classes when the past data are unavailable, which is well documented as catastrophic forgetting [4, 5, 6]. Recently, many methods in CIL have been proposed to try to deal with this problem. Owing to their superior performances, **R**ehearsal-based approaches utilizing **KD** [7] (**RKD**) [8, 9, 10, 11, 12] have been widely applied in CIL. However, recent works revealed that the RKD methods suffer from decision boundary overfitting to new classes, which is referred to as the (task-recency) bias towards new classes [3, 8, 10, 13].

As shown in Fig. 1, basic RKD approaches typically have two training objectives: transferring the existing knowledge from the old model by KD and learning new classes via minimizing the KD loss [7] and the cross entropy (CE) classification loss. However, RKD approaches usually suffer from the decision boundary overfitting problem caused by insufficient KD and imbalanced data between the old and new classes.

Problem of Insufficient KD. In CIL setting, the stored exemplars of old classes are limited because of the small memory budget. It is well known that the high capacity of DNNs is sufficient to memorize the entire training data [14, 15], so RKD methods suffer from insufficient data for KD training. RKD methods commonly use the stored exemplars of old classes and data of new classes to compute the KD loss to preserve the existing knowledge. However, data of new classes are out of distribution (OOD)

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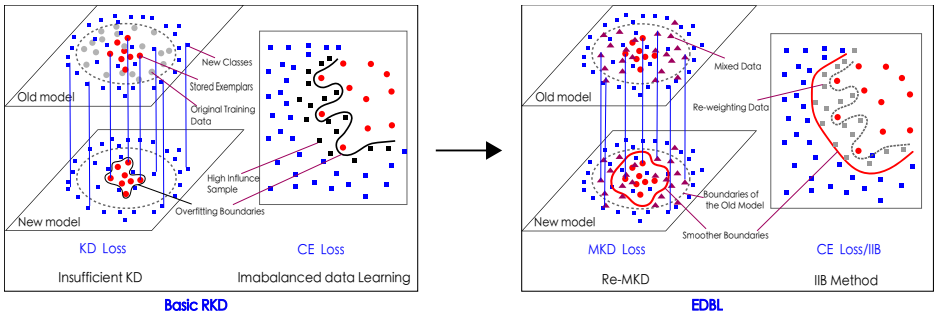


Figure 1: Comparisons between the basic RKD and the proposed methods (EDBL). Illustration of the two factors in RKD causing decision boundary overfitting to new classes.

with the original training dataset of the old model and Beyer et al. [16] demonstrated that OOD data work in KD to some extent while their performance suffers from great degradation, compared with using the original training data. The combination of the scantness of exemplars for the old classes and OOD between the learned classes and the new classes (data of old classes and new classes are typically OOD in the CIL setting) lead to the new model overfitting to new classes. This phenomenon is also demonstrated in our experiments (c.f. Sec. 5.5.2) and we refer to it as insufficient KD.

Problem of Imbalanced Learning. Due to the limited memory budget for storing exemplars of the old classes in RKD approaches, there exists a serious problem of imbalanced data for learning (few samples for the learned/old tasks are available while we have a large number of samples for the current/new task), which would lead to decision boundary overfitting to the dominant (new) classes [17, 18, 19].

In order to tackle the insufficient KD, we employ MKD and re-sampling strategy. We over-sample the exemplars of the old classes and mix the samples from the old classes and the new classes to synthesize mixed data for KD training. The interpolated data by an old class and a new class are more consistent with the distribution of the original training data of old classes than the data of new classes, which can improve KD in CIL and form a smoother decision boundary (c.f. Fig. 1, Re-MKD).

In order to deal with the imbalanced data learning problem, we attempt to attenuate the influence of samples that cause the overfitting. To this end, we extend the method of influence balance (IB) [19] to CIL setting and propose the incremental influence-balanced (IIB) method for CIL. Specifically, we first derive a metric that measures how much each sample influences the biased decision boundaries. Then, we decompose the metric into two parts which are referred to as the classification weighting factor and the KD weighting factor, respectively. Finally, we design the incremental influence-balanced (IIB) loss function for CIL, which adaptively assigns different weights to samples according to their influence on decision boundaries (c.f. Fig. 1, IIB Method).

Based on the previous proposal, we divide our method into two phases after re-sampling Mixup-based data augmentation. Phase 1 is MKD training, which improves the efficacy of KD to form a better decision boundary through generating sufficient and more related data with the old classes used in KD training. Phase 2 balances training by utilizing the derived IIB loss, attenuating the influence of the samples that cause overfitting of the decision boundary. Through the two training phases, we learn a decision boundary with better generalization capability.

In summary, the main contributions of this work are as follows: **(i)** We combine MKD with re-sampling strategy to relieve the insufficient KD problem in RKD methods through synthesizing data that are more related with the original training data of old classes than data of new classes. **(ii)** We extend the IB method into the CIL setting and propose a novel IIB loss function to tackle the imbalanced learning effectively in CIL. **(iii)** We propose the EDBL algorithm via combining Re-MKD and IIB by deriving the incremental influence factor for mixed data. Experiments demonstrate that the proposed EDBL method achieves state-of-the-art performances on several CIL benchmarks.

2 Related Work

2.1 Bias-Correction Approaches

CIL belongs to continual learning and the main challenge is catastrophic forgetting [4]. Previous approaches to tackle catastrophic forgetting can be divided into three categories [3]:regularization [20,

21], parameter isolation [22, 23] and replay approaches [24, 25]. RKD belongs to replay approaches and achieves the state-of-the-art performances. RKD methods [12, 9, 8, 10, 26] commonly train the new model by preserving the existing knowledge and learning classes incrementally via minimizing the KD loss and the CE loss. We introduce the problem formulation and summarize the popular strategies of RKD training in Appendix A.

RKD methods suffer from the task-recency bias and the ideas in previous works to alleviate this problem in CIL are very similar to the approaches in the long-tail learning. For example, iCaRL [12] employs representation learning strategy, and EEIL [9] utilizes classical image transformation e.g. random cropping, mirroring etc. to make data augmentation and fine-tune the newly trained model with a balanced dataset. BiC [8] trains a bias-correction classification layer with a balanced dataset, which is similar to the approaches of decouple learning and LUCIR [10] belongs to cost-sensitive learning. Different from the previous works, our method employs re-sampling and MKD strategy to relieve insufficient KD problem and propose IIB method to deal with the imbalance data learning. Both improvements are complementary to the previous bias-correction approaches.

2.2 Classes Imbalance

Classes Imbalance is a significant challenge for machine learning [27, 28]. In long-tail learning, the trained models usually bias towards the dominant classes. Previous efforts to tackle the overfitting problem can be roughly divided into three groups: (i) data re-balance including re-sampling [29, 30], data augmentation [31, 32], etc.; (ii) cost-sensitive learning including re-weighting strategy [33, 19], etc.; (iii) module improvement including representation learning [34, 35], decoupled training [36] and ensemble learning [37, 38], etc.. In this work, we combine mixup with re-sampling to make data augmentation and utilize the re-weighting strategy to relieve overfitting. But, we mainly use mixed data in KD training to relieve insufficient KD problem in CIL and we extend the re-weighting method in [19] (referred to as IB method in this work) into CIL and combine it with the re-sampling&mixup-based data augmentation to tackle imbalanced data learning.

2.3 Mixup and Knowledge Distillation

Mixup is first proposed in [39], which generates an interpolated sample $(\hat{x}, \hat{y})$ by $(x_i, y_i), (x_j, y_j)$ according to Eq. 1:

$$\hat{x} = \lambda x_i + (1-\lambda)x_j, \hat{y} = \lambda y_i + (1-\lambda)y_j, \tag{1}$$

where x_i, x_j are images and y_i, y_j are labels, respectively, λ is randomly drawn by the Beta function. In [39], the CE loss (L_{ce}) for mixed data is computed as follows:

$$L_{ce}(\hat{x}, \hat{y}) = \lambda L_{ce}(\hat{x}, y_i) + (1-\lambda)L_{ce}(\hat{x}, y_j). \tag{2}$$

After that, some other label mixing methods are proposed such as cutmix [40], manifold mixup [41], , Remix [31], etc.. Mixup-based data augmentation can greatly improve the generalization of DNNs in image classification learning while there are some works utilize label mixing methods in various scenarios such as the long-tail learning [31], continual learning [42, 43]. Recently, some works validate that label mixing methods improve the performance of KD e.g. [16, 44], which compute the KD loss with the mixed sample $(\hat{x}, \hat{y})$ as follows:

$$L_{kd}(\hat{x}, \hat{y}) = \sum_{i=1}^{m} -\sigma_i(\frac{T(\hat{x})}{t})log[\sigma_i(\frac{S(\hat{x}))}{t}], \tag{3}$$

where T, S are the teacher model and the student model, t is the temperature, m is the number of the learned classes of T and σ is the $softmax$. These works utilize Mixup to improve KD performances in model compressing setting where the training data are independent-identically-distributed (IID) with the original training dataset of the teacher model. However, they cannot verify the effectiveness of their methods in the CIL setting, where the training data are imbalanced and new classes are OOD with the old classes. In this work, we employ re-sampling in Mixup and validate effectiveness of mixup between old classes (IID dataset) and new classes (OOD dataset) for KD in the CIL setting.

3 Preliminaries

Influence Function. The influence function [45, 46] in robust statistics was proposed to find the influential instance of a sample to a model. Recent works have used influence function in DNNs,

e.g., [47]. Given a empirical risk $R(\Theta) = \frac{1}{N}\sum_{i=1}^{N} L(x, \Theta)$, of which the optimal parameter is $\Theta^* = argmin_{\Theta} R(\Theta)$, where N is the number of training data, $\Theta = (\theta, W)$ are the parameters of the network and θ, W are the parameters of the feature extractor and the linear classifier (the last full connected layer, FC), respectively. According to the results in [47], the influence function of the point (x, y) is given by:

$$\mathcal{I}(x, \Theta) = -H_L^{-1}(\nabla_{\Theta} L(x, \Theta)), \tag{4}$$

where ∇_{Θ} is the gradient operator and $H_L \triangleq \sum_{i=1}^{N} \nabla_{\Theta}^2 L(x_i, \Theta)$ is the Hessian, which is positive definite based on the assumption that L is strictly convex in a local convex basin in the vicinity of Θ^*.

Influence Balance Method. Park et al. [19] firstly apply influence function to a learning scheme, where they design the influence-balanced (IB) loss by utilizing the influence function during training in long-tailed classification. They treat the influential instance of a sample to a model of a point (x, y) as the parameters of the model change when the distribution of the training data at the point (x, y) is slightly modified and referred to it as the IB weighting factor. IB method uses L_1 norm of Eq. 4 to qualify the influence of the point (x, y) and further ignores the inverse Hessian reasonably. The IB weighting factor is computed as follows:

$$\mathcal{IB}(x, \Theta) = \|\nabla_{\Theta} L(x, \Theta)\|_1 \tag{5}$$

IB method focuses on the change in the FC layer of DNNs and the IB weighting factor can be simplified by:

$$\mathcal{IB}(x, \Theta) = \|f(x) - y\|_1 \|h\|_1 \tag{6}$$

where f is the network and h is the hidden feature vector of (x, y). Finally, the IB loss, which is used in balancing training to attenuate the influence of samples that cause an overfitted decision boundary is given by:

$$L_{IB}(x, y, \Theta) = \lambda_k \frac{L(x, y, \Theta)}{\mathcal{IB}(x, \Theta)} \tag{7}$$

where in IB method, L is CE loss function, $\lambda_k = \gamma n_k^{-1} / \sum_{i=1}^{K} n_i^{-1}$ is the class-wise re-weighting term, k is the label of (x, y), n_i is the number of samples in the k-th class and γ is the hyper-parameter. IB method has two training phases:**(i)** Normal classification training via minimizing the CE loss; **(ii)**Balancing training, where IB method fine-tunes the model via minimizing L_{IB} by Eq. 7.

4 The Proposed Method

4.1 Re-sampling MKD

Re-sampling Mixup. Beyer et al. [16] demonstrates that KD training with OOD data suffers from great degradation and they validate empirically that the data, which are related or overlapped with the original training data (consistent with the latent distribution of original training data) can perform as good as the original training data in KD training. So the mixed data generated by mixup using samples from old classes and new classes, which are usually more related with old classes than the data of new classes (basic RKD methods directly use data of new classes in KD training) may improve KD performances in CIL.

Given that the data between the old and new classes are seriously imbalanced in RKD methods, we consider the ratio between the old classes from the past tasks and the new classes of the current task. We generate three kinds of mixed data in a batch: mixup among old classes, mixup between old classes and new classes and mixup among new classes. Owing to the limited data per old class in RKD methods, we mixup data more frequently for the first two types. Specially, we mixup $\frac{N}{2}$ times for the first two types and 1 time mixup for the last type of mixed data, where N is the proportion of the data between per tail and head class, and we make sure the number of samples from old classes in a batch isn't less than a fixed number (32 in this work).

Finally, re-sampling-based Mixup can generate much data through label mixing between old classes and new classes. These generated data increases the diversity and the number of data used in KD, which improves the performance of KD in CIL. Our experiments demonstrate that re-sampling-based Mixup outperforms the original Mixup in [39] (referred to as Vanilla-Mixup in this work) significantly (c.f. Sec. 5.5.1).

MKD Training. After data augmentation by re-sampling-Mixup, we train the new model through minimizing two losses: the CE loss (L_{ce}) and the KD loss (L_{kd}) with the synthesized data in the

similar way as in the basic RKD method. We compute L_{ce} and L_{kd} according to Eq. 2 and 3, respectively and we replace the teacher and student model with the old model ($f^{t-1}_{\theta,W}$) and the new model ($f^{t}_{\theta,W}$) in Eq. 3, respectively. In this paper, we denote the strategy of Re-sampling Mixup and MKD training (Re-sampling MKD) as Re-MKD while we denote the strategy of vanilla Mixup and MKD training as vanilla-MKD.

4.2 IIB Method

4.2.1 IIB Weighting Factor

We extend the IB method into CIL and propose a novel IIB loss function to attenuate the influence of the samples to relieve the overfitting. The experience risk at task t in RKD is $R(\Theta) = \frac{1}{N}\sum_{i=1}^{N} L(x,\Theta)$, where $L \triangleq L_{ce}(y_i, f^t_\Theta(x_i)) + L_{kd}(f^{t-1}_\Theta(x_i), f^t_\Theta(x_i))$ and $\Theta^* = argmin_\Theta R(\Theta)$ is the optimal parameter after initial training. We first utilize Eq. 4 to compute the influence of the sample (x, y) for CIL. Then, like in IB method, we ignore the inverse of the Hessian, which is given by $H_L \triangleq \sum_{i=1}^{N} \nabla^2_\Theta L(x_i,\Theta) = \sum_{i=1}^{N} \nabla^2_\Theta L_{ce}(x_i,\Theta) + \nabla^2_\Theta L_{kd}(x_i,\Theta)$ because it is commonly multiplied by all the training samples and just the relative influences of the training samples are needed and we use L_1 norm to qualify the influence to obtain the incremental influence-balanced (IIB) weighting factor. Therefore, according to Eq. 5 in the IB method, the IIB weighting factor of the point (x, y) for CIL can be represented by:

$$\mathcal{IIB}(x,\Theta) = \|\nabla_\Theta L(x,\Theta)\|_1 = \|\nabla_\Theta L_{ce}(x,\Theta) + \nabla_\Theta L_{kd}(x,\Theta)\|_1 \tag{8}$$

At task t, let $h = [h_1, \ldots, h_L]^T$ be a hidden feature vector (an input to the FC layer), and $f(x,\Theta) = [f_1, \ldots, f_m, \ldots, f_{m+n}]^T$ be the output denoted by $f_k \triangleq \sigma(w_k^T h)$, where σ is the $softmax$ function, m, n are the number of learned classes and the new classes, respectively. The weight matrix of g^t_W is denoted by $W = [w_1, \ldots, w_m, \ldots, w_{m+n}]^T \in R^{(m+n)\times f}$. Then, $\nabla_\Theta L_{ce}(x,\Theta)$ and $\nabla_\Theta L_{kd}(x,\Theta)$ is computed as below, respectively.

$$\frac{\partial L_{ce}(x,\Theta)}{\partial w_{kl}} = (f^t_k(x) - y_k)h_l, k \in [1, m+n] \tag{9}$$

$$\frac{\partial L_{kd}(x,\Theta)}{\partial w_{kl}} = \begin{cases} (f^t_k(x) - f^{t-1}_k(x))h_l, & k \in [1,m] \\ 0, & k \in [m+1, m+n] \end{cases} \tag{10}$$

Finally, we apply Eq. 9 and 10 to Eq. 8. Thus, the IIB weighting factor can be computed as:

$$\mathcal{IIB}(x,\Theta) = (\|[f^t(x) - y - f^{t-1}(x)]^m_1\|_1 + \|[f^t(x) - y]^{m+n}_{m+1}\|_1)\|h\|_1, \tag{11}$$

where $[V]^j_i$ denotes the slice $[v_i, \ldots, v_j](j \geq i)$ of the vector $V = [v_1, \ldots, v_N]$.

4.2.2 Decomposition of IIB Weighting Factor

The Stability-Plasticity Dilemma. The stability-plasticity dilemma [48] is a well-known constraint for artificial and biological neural systems. The basic idea is that a learning system requires plasticity for the integration of new knowledge, but also stability in order to prevent the forgetting of previous knowledge. Too much plasticity will result in previously encoded data being constantly forgotten, whereas too much stability will impede the efficient coding of this data at the level of the synapses.

In RKD, the KD loss is used to preserve the existing knowledge by encouraging the new model to mimic the output of the old model and the CE loss is used to learn to recognize new classes. Eq. 11 considers the influence of the CE loss and the KD loss on the decision boundary, but a sample may actually perform differently on the classification and KD training. For example, we use data of motorbike to train the new model to recognize motorbike incrementally while preserving the knowledge of knowing bike. Because of the similarity between motorbike and bike, samples of motorbike may improve the performance of KD and preserve the previous knowledge well. That is because the data which are related or overlapped with the original training data perform well in KD [16]. But in the classification training, the new model may bias to motorbike.

Decomposing IIB Factor. Considering the stability-plasticity dilemma, we decompose the IIB weighting factor into two factors: the classification weighting factor for learning new tasks and the KD weighting factor for preserving the existing knowledge, which measure how much each sample influences on forming new boundaries by the classification training and the previous decision boundaries of the old model preserving training (KD training), respectively.

Definition 4.1. In CIL, the classification weighting factor and the KD weighting factor of a sample (x, y) are defined as the magnitude of the gradient vector of the CE loss and the KD loss on that point, respectively:

$$\mathcal{IB}_{ce}(x, \Theta) = \|\nabla_\Theta L_{ce}(x, \Theta)\|_1, \mathcal{IB}_{kd}(x, \Theta) = \|\nabla_\Theta L_{kd}(x, \Theta)\|_1 \tag{12}$$

Then, we use a hyper-parameter α to make trade off on these two factors. Therefore, IIB weighting factor is computed via:

$$\mathcal{IIB}(x, \Theta) = \mathcal{IB}_{ce}(x, \Theta) + \alpha \mathcal{IB}_{kd}(x, \Theta) = (\|[f^t(x) - y]\|_1 + \alpha \|f^t(x) - f^{t-1}(x)\|_1)\|h\|_1 \tag{13}$$

where $\mathcal{IIB}(x, \Theta) \leq \|\nabla_\Theta L_{ce}(x, \Theta)\|_1 + \|\nabla_\Theta L_{kd}(x, \Theta)\|_1$, and $\alpha \leq 1$.

4.2.3 IIB Loss

During the balancing training, we attempt to fine-tune the decision boundary to create a more generalized one, so we multiply the CE loss function by the inverse of IIB weighting factor, resulting in IIB loss as follows:

$$L_{IIB}(x, y, \Theta) = \lambda_k \frac{L_{ce}(x, y, \Theta)}{\mathcal{IIB}(x, \Theta)} \tag{14}$$

where λ_k is the class-wise re-weighting term (c.f. Sec. 3 and Eq. 7).

4.3 EDBL Algorithm

We propose the EDBL algorithm to combine Re-MKD and IIB method to improve knowledge transferring and deal with imbalanced data classification synthetically to generate more generalized decision boundaries in CIL. After MKD training, considering an mixed sample $(\hat{x}, \hat{y})$, we apply Eq. 1 to Eq. 13 to compute the IIB weighting factor as follows:

$$\mathcal{IIB}(\hat{x}, \Theta) = (\|[f^t(\hat{x}) - \lambda y_i - (1 - \lambda) y_j]\|_1 + \alpha \|f^t(\hat{x}) - f^{t-1}(\hat{x})\|_1)\|h\|_1 \tag{15}$$

Then, we use this IIB weighting factor to compute L_{IIB} according to Eq. 14.

Inspired by [16], which validates empirically that a large number of epochs improves the performance of KD, so we add the KD loss to the IIB loss. Then the overall loss $L_{overall}$ for balancing training is as follows:

$$L_{overall}(\hat{x}, \hat{y}, \Theta) = L_{IIB}(\hat{x}, \hat{y}, \Theta) + L_{kd}(\hat{x}, \hat{y}, \Theta) \tag{16}$$

Overall, EDBL has two training phases: MKD training and balancing training. During the two training phases, L_{kd} is continually used for distillation to encourage the decision boundary in the new model to mimic the one in the old model, and L_{IIB} re-weights the interpolated samples by their influences on a decision boundary in the balancing training phase. The pseudo-code of EDBL is presented in Algorithm 1 in Appendix B.

5 Experiments

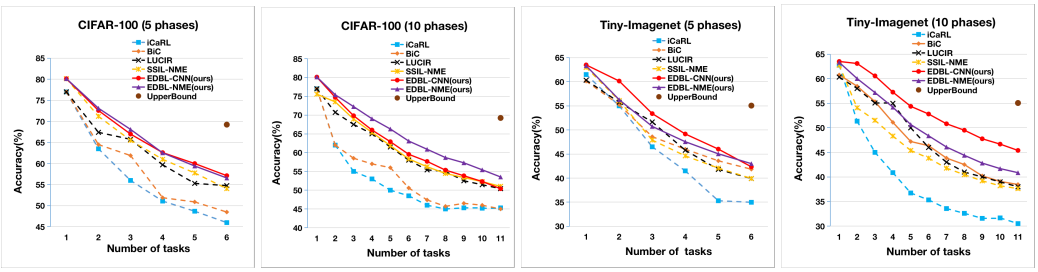
5.1 Datasets

We conduct experiments on CIFAR-10, CIFAR-100 [49] and Tiny-Imagenet [50] to validate our approach. We pad four pixels for images in CIFAR-10 and CIFAR-100 and then random crop them into 32×32 pixels. We use horizontal flip in all image pre-processings [12, 8].

5.2 Baselines and Protocols

We compare EDBL with some SOTA methods in CIL such as Mnemonics [51], PODNet-CNN [52] and SS-IL [26], etc.. We adopt two protocols to conduct experiments: (1) Base-half: we start from a model trained on half of all classes in the dataset, and the remaining half of classes come in 5 and 10 phases and stores 20 samples for each old class [10]. (2) Base-0: we follow the protocol in iCaRL [12] to conduct experiments, where all of classes come in 2, 5, or 10 phases and the memory budget is a fixed value. We report the results of two inference strategies: CNN output and the nearest-mean-of-exemplar strategy (NME) [12] to evaluate our methods (denoted as EDBL-CNN and EDBL-NME, respectively).

We follow the exemplar management of iCaRL to select exemplars for each old class. We use two common metrics: average accuracy and average incremental accuracy [12] to measure performances.



(a) (b) (c) (d)

Figure 2: Comparison results of average accuracy on Base-half experiments with 5, 10 phases on CIFAR-100, Tiny-Imagenet.

5.3 Implementation Details and Hyper-parameters Tuning

The λ in Eq. 1 is randomly sampled from the Beta function $B = (1, 1)$ for all the experiments. To make comparison fairly, we use the same networks for our methods and baselines. We follow [12, 8, 10] and [43] to use ResNet32 (d=64) for experiments on CIFAR-10/100 and ResNet18 (d=512) for Tiny-Imagenet in this work. When training networks, we follow the standard practices for fine-tuning existing networks. We use stochastic gradient descent (SGD). As for the training hyper-parameters such as batch size, weight decay, momentum, learning rate, epochs etc., we set these parameters semi-heuristically and tune a few of parameters on CIFAR-100 and Tiny-Imagenet experiments with 5 incremental learning phases, then we use the same setting of these parameters for other experiments on CIFAR-10/100 and Tiny-Imagenet, respectively. We mainly tune λ_k in Eq. 14 and α in Eq. 15 by grid searching. All the hyper-parameters are given in Appendix C.

5.4 Results

5.4.1 Results on Base-half

Table 1 presents the comparisons of our methods with the baselines on Base-half experiments. From Table 1, we can find that EDBL-NME outperforms all the compared methods on all the experiments significantly. EDBL-CNN also surpasses all the compared methods on all the experiments except the experiment on CIFAR-100 with 10 phases. The comparison results of average accuracy at each incremental learning phase are given in Fig. 2. Fig. 2 demonstrates that our methods (EDBL-CNN and EDBL-NME) surpass all the baselines at nearly each incremental learning phase.

Table 1: Average incremental accuracy (%) on Base-half experiments. Models with an asterisk * denotes using the results in [51], The two models with † or ‡ are reported directly from [53] and [52], respectively. Because SS-IL [26] with NME performs much better than original SS-IL in this work, we alternatively select SS-IL with NME (SSIL-NME) as a baseline.

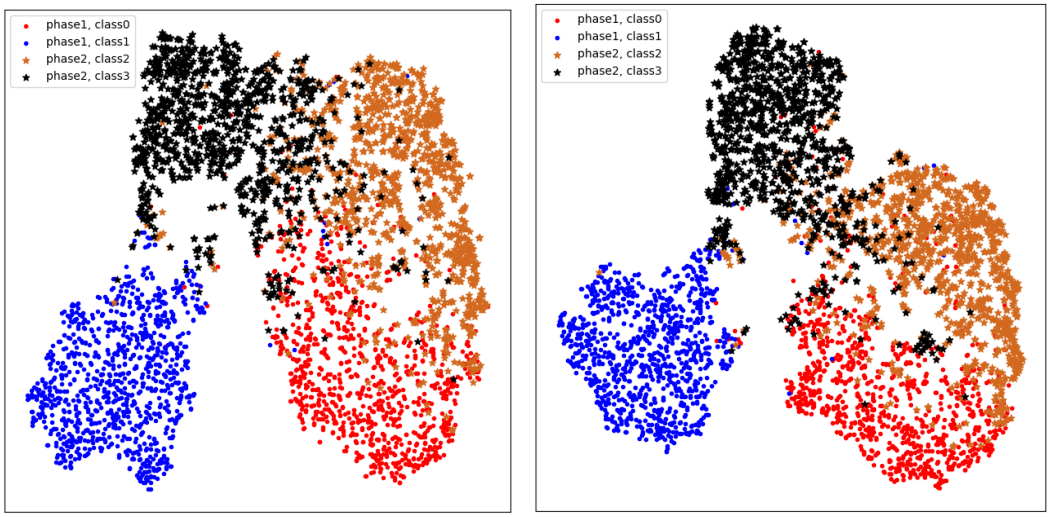
Base-half	CIFAR-100		Tiny-imagenet	
Phases	5	10	5	10
LwF* [54]	49.59	46.98	/	/
iCaRL* [12]	57.12	52.66	/	/
BiC* [8]	59.36	54.2	/	/
LUCIR* [10]	63.17	60.14	/	/
PODNet-CNN‡ [52]	64.83	63.19	/	/
Mnemonics* [51]	63.34	62.28	/	/
TPCIL† [53]	65.34	63.58	/	/
iCaRL [12]	59.67	56.13	48.98	39.27
BiC [8]	61.14	58.4	49.23	47.67
LUCIR [10]	/	/	49.31	47.56
SSIL-NME [26]	64.94	60.99	48.93	45.74
EDBL-CNN(ours)	66.57	62.06	**52.43**	**53.80**
EDBL-NME(ours)	**66.65**	**64.73**	50.99	49.97

5.4.2 Results on Base-0

We further conducted experiments on CIFAR-10/100 following Base-0 protocol to evaluate our method. The memory budgets on CIFAR-10 and CIFAR-100 are fixed to 200 and 2000 [12], respectively. CIFAR-10 is split into 2 and 5 phases while CIFAR-100 is split into 2, 5 and 10 phases. Our methods employ Mixup strategy which may help to relieve the overfitting problem while Remix [31] adapted Mixup to generate more effective interpolated data to tackle the long-tail learning. To compare our method with Remix, we directly employ Remix to train the new model to learn new classes incrementally with the optimal hyper-parameters given in [31]. We report the results of Remix-CNN and Remix-NME. From Table 2, we can find that EDBL-CNN and EDBL-NME outperform all baselines on nearly all experiments except the experiment with 5 phases and 2 phases on CIFAR-10,

Table 2: Average incremental accuracy (%) on Base-0 experiments.

Base-0	CIFAR-10		CIFAR-100		
Phases	2	5	2	5	10
iCaRL [12]	89.7	77.13	68.35	67.24	63.98
BiC [8]	89.29	78.5	70.15	68.06	65.9
PODNet-CNN [52]	/	76.27	/	66.72	57.88
RemiX-CNN [31]	78.52	70.36	64.98	64.37	60.85
RemiX-NME [31]	82.07	77.41	67.19	67.18	64.46
SSIL-NME [26]	89.97	77.9	68.7	65.83	56.11
EDBL-CNN(ours)	**91.6**	77.42	**72.28**	72.2	66.53
EDBL-NME(ours)	89.82	**78.51**	70.71	69.33	**67.99**



(a) Basic RKD in [9] (b) EDBL

Figure 3: t-SNE visualization on a random subset (4 classes) from CIFAR-10 (2 incrmental phases).

Table 3: The effectiveness of Re-MKD&IIB of EDBL (Average Accuracy on each incremental phase).

Dataset	CIFAR-10					CIFAR-100				
phase	1	2	3	4	5	1	2	3	4	5
Baseline	0.9894	0.775	0.5544	0.464	0.4427	0.848	0.7085	0.5606	0.4891	0.392
+ Vanilla-MKD	0.9905	0.8095	0.587	0.4894	0.4189	0.8355	0.718	0.5658	0.4836	0.3625
+ IIB	0.9894	0.8527	0.6678	0.558	0.5183	0.848	0.6914	0.5851	0.5068	0.4476
+ Re-MKD	0.9905	0.8387	0.6446	0.6066	0.5926	0.8624	0.761	0.5744	0.5882	0.5629
+ IIB-KD	0.989	0.819	0.7143	0.6782	0.6329	0.8624	0.7355	0.636	0.5788	0.5362
EDBL-CNN(ours)	0.992	**0.8727**	**0.7245**	**0.6794**	**0.6618**	0.85	**0.767**	**0.7093**	**0.6573**	**0.6051**

respectively. Both of EDBL-CNN and EDBL-NME outperform Remix-CNN and Remix-NME on all the experiments by large margins about $[1.1\%, 7\%]$. We also give the results of average accuracy at each incremental learning phase and the results show that our methods surpass all the baselines at nearly each incremental learning phase, similarly (c.f. Appendix D).

5.5 Ablation Study

5.5.1 Analysis on Re-MKD and IIB

The base work in [9] is a vanilla basic RKD which trains the new model via minimizing the KD loss and the CE loss without any other strategies. We use it as the baseline in ablation study. The memory size in the ablation study is fixed to 200 and 2000 for CIFAR-10/100, respectively and the experiments are conducted in the same way as in the Base-0 experiments. Table 3 demonstrates the effectiveness of Re-MKD and IIB components in the proposed EDBL algorithm, where IIB-KD is the training strategy that uses the IIB loss and the KD loss to fine-tune the new model in the balancing training phase.

In summary, we can observe that: (1) The Re-MKD component can improve the performance of the baseline at each incremental batch by large margins, about $[1\%, 16\%]$ and Re-MKD outperforms Vanilla-MKD (vanilla-Mixup-based MKD) significantly. This validates that the generated data by re-sampling-based Mixup are more related with old classes to improve the performance of KD. This also demonstrates that the Re-MKD would relieve the problem of insufficient KD; (2) The IIB component can improve the performance of the baseline at each incremental batch remarkably, and surpasses baseline by up to $[5.5\%, 7.5\%]$ on CIFAR-10 and CIFAR-100 at the last phase. Besides, IIB-KD further improves the performance based on the improvement by IIB, which exceeds baseline by 19% and 13% on CIFAR-10 and CIFAR-100, respectively at the last phase. All of these reflect the

effectiveness of IIB loss for CIL; (3) EDBL achieves the best performances, which implies EDBL can learn more generalized decision boundaries effectively.

Further, we conduct visualization experiments with 2 incremental learning phases on a randomly selected subset with 4 classes from CIFAR-10 and the memory is fixed to 200. As shown in Fig. 3, the features extracted by the new model trained by EDBL has the less mutual intrusion between the learned classes (the first batch classes) and the new classes (the second batch classes), which reflects indirectly that the decision boundaries learned by EDBL are with more generalizability than the ones generated by the Basic RKD method.

5.5.2 Study on Memory Budget

We further study the sensitivity of EDBL on the size of memory budget by conducting experiments on CIFAR-100 with 5 phases following Base-0 protocol. The average accuracy on the last phase of the experiments are demonstrated in Table 4 and the table shows that EDBL-CNN obtains the best performances. CLDR [42] utilizes manifold mixup to make a regularization to alleviate catastrophic forgetting while our method outperforms CLDR by large margins about [8%,15%].

Table 4: Sensitivity on memory (Average Accuracy on the last phase of the experiments), * denotes using the results in [42].

Memory	200	500	1000	2000
GEM* [55]	0.2829	0.3204	0.3546	/
ER-Res.* [56]	0.2869	0.3190	0.3406	/
CLDR* [42]	0.3434	0.3770	0.4020	/
iCaRL [12]	0.4189	0.4999	0.5133	0.5431
SSIL-NME [26]	/	0.4984	0.5217	0.5371
EDBL-CNN(ours)	**0.4268**	**0.5265**	**0.5574**	**0.6051**

5.5.3 Sensitivity of α

In IIB method, we introduce the hyper-parameter α to trade off the classification weighting factor and the KD weighting factor to compute IIB loss. Here, we choose the strategy, which is RKD + IIB-KD in table 3 and $\alpha = \{1, 1e-3, 1e-5, 0\}$ to conduct experiments with 5 incremental phases on CIFAR-10/100 and the memory is fixed to 200, 2000, respectively.

Table 5: Sensitivity study on α (Average Accuracy on the last phases of the experiments).

Dataset	CIFAR-10				CIFAR-100			
α	1	1e-3	1e-5	0	1	1e-3	1e-5	0
CNN	0.6034	0.596	0.6309	0.6176	0.4955	0.4977	0.5018	0.4715
NME	0.6485	0.6599	0.6577	0.6424	0.4836	0.4883	0.5016	0.5015

From Table 5, we can observe that IIB method is sensitive to the setting of α and setting a small value for α improves the performance significantly while $\alpha = 0$ is not the optimal value, where $\alpha = 0$ denotes that IIB degenerates into the IB method. This implies that stability-plasticity dilemma really exists in CIL and we should carefully treat this issue to achieve a better performance.

6 Conclusion

In this paper, we analyzed the causes of the decision boundary overfitting problem in CIL by two factors: insufficient KD and imbalanced data learning. We proposed the EDBL algorithm to address these problems. First, in order to deal with insufficient data for KD, we presented the re-sampling MKD strategy, which generates much data by Mixup and re-sampling to be used in KD training, which are more consistent with the latent distribution of old classes. Second, we extended IB method into CIL through deriving a novel IIB loss, which re-weights samples by their influence on decision boundary to alleviate the problem of learning with imbalanced data. On top of this, we propose EDBL algorithm to combine re-sampling MKD and IIB method which can improve the knowledge transferring and deal with the imbalanced data classification simultaneously. Experiments show that EDBL achieves state-of-the-art performances on several benchmarks and ablation study validates that both of Re-MKD and IIB are effective in CIL.

Limitation and Broader Impacts. One limitation is that more GPU memory and training time are needed because:(i) re-sampling Mixup generates much mixed data during training, (ii)EDBL has two training phases, so EDBL nearly requires twice as much training time as basic RKD method. Fortunately, both of re-sampling MKD or IIB are effective in CIL, so we can employ them in real applications flexibly. Moreover, EDBL significantly relieves catastrophic forgetting, which promotes the practical use of DNNs. The negative impacts may occur in some malicious or misuse scenarios. The appropriate proposes of employing EDBL (re-sampling MKD/IIB) are supposed to be ensured with attentions.

References

[1] Gregory Ditzler, Manuel Roveri, Cesare Alippi, and Robi Polikar. Learning in nonstationary environments: A survey. *IEEE Computational Intelligence Magazine*, 10(4):12–25, 2015.

[2] German I Parisi, Ronald Kemker, Jose L Part, Christopher Kanan, and Stefan Wermter. Continual lifelong learning with neural networks: A review. *Neural Networks*, 113:54–71, 2019.

[3] Matthias Delange, Rahaf Aljundi, Marc Masana, Sarah Parisot, Xu Jia, Ales Leonardis, Greg Slabaugh, and Tinne Tuytelaars. A continual learning survey: Defying forgetting in classification tasks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2021.

[4] Yoshua Bengio, Mehdi Mirza, Ian Goodfellow, Aaron Courville, and Xia Da. An empirical investigation of catastrophic forgeting in gradient-based neural networks. 2013.

[5] Robert M French. Interactive tandem networks and the sequential learning problem. In *submitted to the 1995 Cognitive Science Society Conference*. Citeseer, 1995.

[6] Michael McCloskey and Neal J Cohen. Catastrophic interference in connectionist networks: The sequential learning problem. In *Psychology of learning and motivation*, volume 24, pages 109–165. Elsevier, 1989.

[7] Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*, 2015.

[8] 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*, pages 374–382, 2019.

[9] Francisco M Castro, Manuel J Marín-Jiménez, Nicolás Guil, Cordelia Schmid, and Karteek Alahari. End-to-end incremental learning. In *Proceedings of the European conference on computer vision (ECCV)*, pages 233–248, 2018.

[10] Saihui Hou, Xinyu Pan, Chen Change Loy, Zilei Wang, and Dahua Lin. Learning a unified classifier incrementally via rebalancing. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 831–839, 2019.

[11] Ahmet Iscen, Jeffrey Zhang, Svetlana Lazebnik, and Cordelia Schmid. Memory-efficient incremental learning through feature adaptation. In *European Conference on Computer Vision*, pages 699–715. Springer, 2020.

[12] Sylvestre-Alvise Rebuffi, Alexander Kolesnikov, Georg Sperl, and Christoph H Lampert. icarl: Incremental classifier and representation learning. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pages 2001–2010, 2017.

[13] Marc Masana, Xialei Liu, Bartlomiej Twardowski, Mikel Menta, Andrew D Bagdanov, and Joost van de Weijer. Class-incremental learning: survey and performance evaluation on image classification. *arXiv preprint arXiv:2010.15277*, 2020.

[14] Devansh Arpit, Stanisław Jastrzębski, Nicolas Ballas, David Krueger, Emmanuel Bengio, Maxinder S Kanwal, Tegan Maharaj, Asja Fischer, Aaron Courville, Yoshua Bengio, et al. A closer look at memorization in deep networks. In *International Conference on Machine Learning*, pages 233–242. PMLR, 2017.

[15] Chiyuan Zhang, Samy Bengio, Moritz Hardt, Benjamin Recht, and Oriol Vinyals. Understanding deep learning (still) requires rethinking generalization. *Communications of the ACM*, 64(3):107–115, 2021.

[16] Lucas Beyer, Xiaohua Zhai, Amélie Royer, Larisa Markeeva, Rohan Anil, and Alexander Kolesnikov. Knowledge distillation: A good teacher is patient and consistent. *arXiv preprint arXiv:2106.05237*, 2021.

[17] Aditya Krishna Menon, Sadeep Jayasumana, Ankit Singh Rawat, Himanshu Jain, Andreas Veit, and Sanjiv Kumar. Long-tail learning via logit adjustment. *arXiv preprint arXiv:2007.07314*, 2020.

[18] Zhiliang Peng, Wei Huang, Zonghao Guo, Xiaosong Zhang, Jianbin Jiao, and Qixiang Ye. Long-tailed distribution adaptation. In *Proceedings of the 29th ACM International Conference on Multimedia*, pages 3275–3282, 2021.

[19] Seulki Park, Jongin Lim, Younghan Jeon, and Jin Young Choi. Influence-balanced loss for imbalanced visual classification. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 735–744, 2021.

[20] 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.

[21] Sang-Woo Lee, Jin-Hwa Kim, Jaehyun Jun, Jung-Woo Ha, and Byoung-Tak Zhang. Overcoming catastrophic forgetting by incremental moment matching. *arXiv preprint arXiv:1703.08475*, 2017.

[22] Chrisantha Fernando, Dylan Banarse, Charles Blundell, Yori Zwols, David Ha, Andrei A Rusu, Alexander Pritzel, and Daan Wierstra. Pathnet: Evolution channels gradient descent in super neural networks. *arXiv preprint arXiv:1701.08734*, 2017.

[23] Arun Mallya and Svetlana Lazebnik. Packnet: Adding multiple tasks to a single network by iterative pruning. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pages 7765–7773, 2018.

[24] David Isele and Akansel Cosgun. Selective experience replay for lifelong learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 32, 2018.

[25] Arslan Chaudhry, Naeemullah Khan, Puneet K Dokania, and Philip HS Torr. Continual learning in low-rank orthogonal subspaces. *arXiv preprint arXiv:2010.11635*, 2020.

[26] Hongjoon Ahn, Jihwan Kwak, Subin Lim, Hyeonsu Bang, Hyojun Kim, and Taesup Moon. Ss-il: Separated softmax for incremental learning. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 844–853, 2021.

[27] Haibo He and Edwardo A Garcia. Learning from imbalanced data. *IEEE Transactions on knowledge and data engineering*, 21(9):1263–1284, 2009.

[28] Nathalie Japkowicz and Shaju Stephen. The class imbalance problem: A systematic study. *Intelligent data analysis*, 6(5):429–449, 2002.

[29] Nitesh V Chawla, Kevin W Bowyer, Lawrence O Hall, and W Philip Kegelmeyer. Smote: synthetic minority over-sampling technique. *Journal of artificial intelligence research*, 16:321–357, 2002.

[30] Xu-Ying Liu, Jianxin Wu, and Zhi-Hua Zhou. Exploratory undersampling for class-imbalance learning. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 39(2):539–550, 2008.

[31] Hsin-Ping Chou, Shih-Chieh Chang, Jia-Yu Pan, Wei Wei, and Da-Cheng Juan. Remix: rebalanced mixup. In *European Conference on Computer Vision*, pages 95–110. Springer, 2020.

[32] Yuhang Zang, Chen Huang, and Chen Change Loy. Fasa: Feature augmentation and sampling adaptation for long-tailed instance segmentation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 3457–3466, 2021.

[33] Yin Cui, Menglin Jia, Tsung-Yi Lin, Yang Song, and Serge Belongie. Class-balanced loss based on effective number of samples. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 9268–9277, 2019.

[34] Ziwei Liu, Zhongqi Miao, Xiaohang Zhan, Jiayun Wang, Boqing Gong, and Stella X Yu. Large-scale long-tailed recognition in an open world. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 2537–2546, 2019.

[35] Xiao Zhang, Zhiyuan Fang, Yandong Wen, Zhifeng Li, and Yu Qiao. Range loss for deep face recognition with long-tailed training data. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 5409–5418, 2017.

[36] Alakh Desai, Tz-Ying Wu, Subarna Tripathi, and Nuno Vasconcelos. Learning of visual relations: The devil is in the tails. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 15404–15413, 2021.

[37] Hao Guo and Song Wang. Long-tailed multi-label visual recognition by collaborative training on uniform and re-balanced samplings. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 15089–15098, 2021.

[38] Jiarui Cai, Yizhou Wang, and Jenq-Neng Hwang. Ace: Ally complementary experts for solving long-tailed recognition in one-shot. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 112–121, 2021.

[39] Hongyi Zhang, Moustapha Cisse, Yann N Dauphin, and David Lopez-Paz. mixup: Beyond empirical risk minimization. *arXiv preprint arXiv:1710.09412*, 2017.

[40] Sangdoo Yun, Dongyoon Han, Seong Joon Oh, Sanghyuk Chun, Junsuk Choe, and Youngjoon Yoo. Cutmix: Regularization strategy to train strong classifiers with localizable features. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 6023–6032, 2019.

[41] Vikas Verma, Alex Lamb, Christopher Beckham, Amir Najafi, Ioannis Mitliagkas, David Lopez-Paz, and Yoshua Bengio. Manifold mixup: Better representations by interpolating hidden states. In *International Conference on Machine Learning*, pages 6438–6447. PMLR, 2019.

[42] Xuejun Han and Yuhong Guo. Continual learning with dual regularizations. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pages 619–634. Springer, 2021.

[43] Fei Zhu, Zhen Cheng, Xu-yao Zhang, and Cheng-lin Liu. Class-incremental learning via dual augmentation. *Advances in Neural Information Processing Systems*, 34, 2021.

[44] Dongdong Wang, Yandong Li, Liqiang Wang, and Boqing Gong. Neural networks are more productive teachers than human raters: Active mixup for data-efficient knowledge distillation from a blackbox model. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1498–1507, 2020.

[45] Anthony Robinson. Residuals and influence in regression, 1984.

[46] Frank R Hampel, Elvezio M Ronchetti, Peter J Rousseeuw, and Werner A Stahel. *Robust statistics: the approach based on influence functions*, volume 196. John Wiley & Sons, 2011.

[47] Pang Wei Koh and Percy Liang. Understanding black-box predictions via influence functions. In *International Conference on Machine Learning*, pages 1885–1894. PMLR, 2017.

[48] Martial Mermillod, Aurélia Bugaiska, and Patrick Bonin. The stability-plasticity dilemma: Investigating the continuum from catastrophic forgetting to age-limited learning effects. *Frontiers in psychology*, 4:504, 2013.

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

[50] Ya Le and Xuan Yang. Tiny imagenet visual recognition challenge. *CS 231N*, 7(7):3, 2015.

[51] Yaoyao Liu, Yuting Su, An-An Liu, Bernt Schiele, and Qianru Sun. Mnemonics training: Multi-class incremental learning without forgetting. In *Proceedings of the IEEE/CVF conference on Computer Vision and Pattern Recognition*, pages 12245–12254, 2020.

[52] 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*, pages 86–102. Springer, 2020.

[53] Xiaoyu Tao, Xinyuan Chang, Xiaopeng Hong, Xing Wei, and Yihong Gong. Topology-preserving class-incremental learning. In *European Conference on Computer Vision*, pages 254–270. Springer, 2020.

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

[55] David Lopez-Paz and Marc'Aurelio Ranzato. Gradient episodic memory for continual learning. *Advances in neural information processing systems*, 30, 2017.

[56] Arslan Chaudhry, Marcus Rohrbach, Mohamed Elhoseiny, Thalaiyasingam Ajanthan, Puneet K Dokania, Philip HS Torr, and M Ranzato. Continual learning with tiny episodic memories. 2019.

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   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes]
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