Self-Paced Imbalance Rectification for Class Incremental Learning

Zhiheng Liu∗  Kai Zhu∗  Yang Cao†
University of Science and Technology of China
{lzh990528,zkzy}@mail.ustc.edu.cn, forrest@ustc.edu.cn

Abstract
Exemplar-based class-incremental learning is to recognize new classes while not forgetting old ones, whose samples can only be saved in limited memory. The ratio fluctuation of new samples to old exemplars, which is caused by the variation of memory capacity at different environments, will bring challenges to stabilize the incremental optimization process. To address this problem, we propose a novel self-paced imbalance rectification scheme, which dynamically maintains the incremental balance during the representation learning phase. Specifically, our proposed scheme consists of a frequency compensation strategy that adjusts the logits margin between old and new classes with the corresponding number ratio to strengthen the expression ability of the old classes, and an inheritance transfer strategy to reduce the representation confusion by estimating the similarity of different classes in the old embedding space. Furthermore, a chronological attenuation mechanism is proposed to mitigate the repetitive optimization of the older classes at multiple step-wise increments. Extensive experiments on three benchmarks demonstrate stable incremental performance, significantly outperforming the state-of-the-art methods.

1 Introduction
Currently, deep convolutional neural networks have made significant breakthroughs in a large number of recognition tasks under batch training mode. In the real world, however, as new data comes in sequentially, the network needs to involve new class information in the recognition process, which forms the problem of class incremental learning (CIL) [French, 1999]. Due to the unavailability of the past data [Lomonaco and Maltoni, 2017], the network often faces the catastrophic forgetting problem [Robins, 1995], which refers to the significant performance degradation in the old class.

To mitigate this phenomenon, recent studies [Rebuffi et al., 2017; Castro et al., 2018; Wu et al., 2019; Lee et al., 2019] propose to save a small portion of old data (i.e., exemplar) in the memory for joint training with the newly incremental samples. Although the exemplar-based method brings some gain in maintaining the old class features, it still presents a severe imbalance problem between the optimization of old and new classes. To further correct the imbalance, some studies [Wu et al., 2019; Zhao et al., 2020; Belouadah and Popescu, 2020; Yan et al., 2021] introduce additional posts-processing procedures, where the decision boundary of the classifier is adjusted in a re-scaling or balance fine-tuning way while the representation is fixed.

However, most existing methods assume that a certain number (e.g., 2000) of exemplars can be stored in memory, which is usually difficult to satisfy in practice due to user...
privacy or device limitations. When the number of old exemplars decreases, we observe that the accuracy of the model drops significantly (i.e., the trend curves in Fig. 1). This fact poses great difficulties to incremental learning because stable optimization cannot be guaranteed under different degrees of imbalance. Our analysis suggests that the instability is mainly due to the absence of rectification during the representation learning process. As shown in Fig. 1, when the number of exemplars decreases, the inter-class distance becomes smaller, and even the representation of some classes will be completely confused (e.g., the green and orange classes). It is no longer possible to achieve good recognition results by simply adjusting the decision boundary.

The generation of imbalance during the incremental representation optimization mainly comes from two aspects. On the one hand, as the number ratio of the old versus new class is proportional to the gradient descent contribution, the model will be biased to over-optimize the representations of new classes that appear at high frequencies. On the other hand, the incremental model is initiated by the parameters of the last phase, which retains an estimate of all the old classes and some new classes. As a result, optimizing from such model initialization deteriorates the whole balance. Recent work [Shi et al., 2021] found that a model inherited from the previous training process will be in a flat local minima, where the convergence difficulty is positively correlated to the distribution distance between the old and new class in the old embedding. These facts indicate that a good incremental model needs more focus on the initial state of different classes.

Motivated by the above issues, we propose a self-paced imbalance rectification scheme to stabilize the incremental representation learning process, as shown in Fig. 2. First, we adopt a frequency compensation strategy to promote the enhancement of old class representation by dynamically adjusting the contribution of different classes to the gradient descent process. The number ratio of old versus new training samples is calculated and inverted to directly expand the corresponding logits margin, rectifying the importance of per-class entropy information. Second, we employ an inheritance transfer strategy that quantifies and corrects the initial model bias to mitigate the inherited representation confusion among all classes. By estimating the dispersion of class distribution in the old embedding space, the corresponding similarities are calculated and leveraged as guidance for augmenting each logits element. Moreover, considering the repetitive enhancement on the earlier classes, we attenuate the final scores with the chronological order at each phase to maintain the reliability of the multi-step incremental process. In summary, our contributions are three-fold:

1) A self-paced imbalance rectification scheme is proposed for exemplar-based incremental learning, in which the incremental optimization is well-balanced by a frequency compensation strategy, resulting in a memory-independent representation.

2) An inheritance transfer strategy is further proposed to mitigate the bias of inherited parameters on per-class representation by estimating the distribution shift.

3) Extensive experiments performed on benchmarks including CIFAR-100, ImageNet-Subset, and ImageNet-Full, demonstrate the superiority and stability of our method over the state-of-the-art.

2 Related Work

2.1 Class Incremental Learning

The purpose of incremental learning is to learn new knowledge while maintaining the previous ones continuously. We focus on the class-incremental learning (CIL) setting in this paper, which is the most challenging and the closest to the needs of practical applications. To overcome catastrophic forgetting problem, existing methods can be divided into three categories. Distillation-based methods introduce distillation loss function to consolidate previous knowledge when learning new tasks. Most works enforces the predicted label logits Hinton et al.; Li and Hoiem; Rebuffi et al. or features [Douillard et al., 2020; Hou et al., 2019] of the new model to be close to previous one. Other works Tao et al.; Hu et al. maintain the topology relationship in the feature space of the incremental model. Memory-based methods preserve a small subset of old classes for joint training. Earlier works [Rebuffi et al., 2017; Hou et al., 2019] select representative samples from the old classes according to the nearest neighbors in the embedding space. Liu et al. propose a dynamic memory management strategy optimized for the incremental phases and different classes, while Liu et al.; Kamra et al. try to generate exemplars in different ways directly. The techniques on exemplar in memory-based methods are widely used in standard...
class-incremental learning. Architecture-based methods aim to design more effective network architecture for dynamic expansion. Liu et al. explicitly build a stable block and a plastic block at each residual level. Yan et al. freeze the previously learned representation and augment it with additional feature dimensions from a new mask-based feature extractor.

Compared with the traditional class incremental learning, our work pays more attention to the stability of the model when the number of exemplars changes. While existing methods [Wu et al., 2019; Belouadah and Popescu, 2020; Yan et al., 2021; Ahn et al., 2021] focus on the imbalance of the classifier or softmax output, we pay more attention to the rectification of the representation optimization.

2.2 Class Imbalance Learning

To solve the imbalanced learning problem, numerous studies have been conducted. Recently, loss-based methods have received extensive attention, which assign different weights to samples to adjust their importance. Cui et al. proposes to utilize the effective number of each class. Cao et al. proposes to utilize the label-distribution-aware margin loss to solve the overfitting to the minority classes by regularizing the margins. Park et al. proposes a new loss to alleviate the influence of samplers which cause an overfitted decision boundary. Hayat et al. proposes to balance the classification regions of head and tail classes using an affinity measure to enforce cluster centers of classes to be uniformly spaced and equidistant. Different from existing works that analyze the long-tail problem in the batch training mode, we focus on the imbalance between the old and new classes in the incremental process.

3 Method

3.1 Problem Setting

The setup of class incremental learning problem is introduced as follows. The whole process usually includes $N + 1$ learning phase: an initial phase and $N$ incremental phases where the number of learned classes gradually increases. Let $D_t = \{D_t^o\}_{t=0}^N$ be the continuous stream of data, where $D_t = \{X_t, Y_t\} = \{(x^{(i)}_t, y^{(i)}_t)\}_{i=1}^{N_t}$. $x^{(i)}_t$ represents the training data for the incremental phase $t$ and $y^{(i)}_t$ belongs to $C^t$, which represents the class set of phase $t$. $C^t = \{C^t_j\}_{j=1}^{T}$ denotes a set of old classes. The goal of CIL is to learn a unified model which can classify the test samples of all seen classes $C^o \cup C^t$. During the incremental phase $t$, a variable memory $M_t$ is allocated to store exemplar data for old class $C^o$. The model consists of two parts: the feature extractor (CNN) $f_o$ and a unified classifier $g_o$. We denote $\theta_t$, $\phi_t$ as the parameters of the feature extractor and classifier at incremental task $t$, which are learned from data $X_t = D_t \cup M_t$.

3.2 Frequency Compensation Strategy

In exemplar-based CIL, as the number ratio in the training data $X_t$ varies, there is a severe bias to over-optimize the representations of new classes $C^t$ that appear at high frequencies, which will exacerbate the forgetting of old classes $C^o$. To strengthen the expression ability of the old classes, we introduce the frequency compensation strategy into the representation learning process. Specifically, we first calculate the occurrence frequency $p(y_i)$ of training samples of each class in the task $t$. To introduce the corresponding frequency information into the optimization process, we show the traditional cross-entropy loss function as follows:

$$L_{CE} = -\sum_{i=0}^{N} y_i \log \frac{e^{y_i}}{\sum_{j} e^{y_j}}.$$

To analyze the gradient descent contribution of different classes, we compute the gradient for the specific class:

$$\frac{\partial L_{CE}}{\partial y_i} = \frac{e^{y_i}}{\sum_{j} e^{y_j}} - y_i.$$

When the prediction is consistent with the label, $y_i = 1$, otherwise $y_i = 0$. Since the number of samples for the new classes is much larger than for the old classes, the model gradually biases to the new classes during the optimization process. Therefore, we adjust the logits margin with $p(y_i)$ for a correction:

$$\hat{y}_i = y_i + \log p(y_i).$$

$$\frac{\partial L_{CE}}{\partial y_i} = \frac{p(y_i)e^{\hat{y}_i}}{\sum_{j} e^{y_j+\log p(y_j)}} - y_i.$$

Considering $p(y_i|y_i \in C^t) > p(y_i|y_i \in C^o)$, we get rectified loss as follows:

$$L_{CE} = -\sum_{i=0}^{N} y_i \log \frac{e^{y_i+\log p(y_i)}}{\sum_{j} e^{y_j+\log p(y_j)}}.$$

3.3 Inheritance Transfer Strategy

Compared with the traditional imbalance learning, the incremental model inherits from the parameters trained in the previous task, rather than initialized randomly when learning new data. Therefore, at the initial state of each task, the optimized model has biases for different classes. Existing works [Shi et al., 2021] indicate that the convergence difficulty of a model inherited from the previous training process is positively correlated to the distribution distance between the old and new classes in the old embedding. Therefore, we modify the weights of the new classes according to the bias of the old model. We assume the feature of each class obeys a Gaussian distribution. The representative feature vector $\mu^t_{i-1}$ from the old class $i$ in $C^o$ is obtained by calculating the mean of all samples’ feature vectors of this class:

$$\mu^t_{i-1} = \frac{\sum_{j=0}^{n_i} f_{\theta_{t-1}}(X^t_{t-1})}{n_i},$$

where $n_i$ denotes the number of training data of the old class $i$ in the $X^t_{t-1}$. Similarly, we also obtain the mean of feature vector $\mu^t_k$ of the new class $k$ on the old model:

$$\mu^t_k = \frac{\sum_{j=0}^{n_k} f_{\theta_{t-1}}(D^t_{t-1})}{n_k},$$

$$\mu^t = \mu^t_{i-1} \cup \mu^t_k.$$

$$\mu^t = \mu^t_{i-1} \cup \mu^t_k.$$
Before training task $t$, we calculate the similarity between the new classes and old classes,

$$s_t^k = \sum_{i=0}^{C_t^t} \frac{\mu^i_{t-1} \cdot \mu^k_t}{||\mu^i_{t-1}|| \cdot ||\mu^k_t||}.$$  

With the similarity list $S_t = \{s^1_t, s^2_t \ldots s^n_t | k \in C^t\}$, we directly leverage it for augmenting each logits element. The final loss function is as follows:

$$L_{CE} = \begin{cases} 
- \sum_{i=0}^{N} y_i \log \frac{e^{y_i + \log p(y_i)}}{\sum_{j} e^{s_j + \log p(y_j)}}, & y_i \in C^t_0 \\
- \sum_{i=0}^{N} y_i \log \frac{e^{s_i + \log p(y_i)}}{\sum_{j} e^{s_j + \log p(y_j)}}, & y_i \in C^t 
\end{cases}$$

3.4 Chronological Attenuation

Architecture-based methods aim to form a new feature extractor by freezing the learned representations. As repetitive optimization exists on the older classes at multiple step-wise increments, the model can be overprotective for some old classes, thus inhibiting the optimization of new classes. To eliminate this effect, we introduce time sequence information $t$ to enhance the weights of the corresponding classes according to the incremental order:

$$\mathcal{L}_{CE} = - \sum_{i=0}^{N} y_i \log \frac{e^{y_i + \log t \log p(y_i)}}{\sum_{j} e^{s_j + \log t \log p(y_j)}}.$$  

4 Experiment

4.1 Dataset and Settings

Datasets. We conduct the experiments on three datasets CIFAR-100 [Krizhevsky et al., 2009], ImageNet100 [Deng et al., 2009; Hou et al., 2019; Wu et al., 2019] and ImageNet1K [Deng et al., 2009], which are widely used in incremental learning. CIFAR-100 contains 100 classes with 500 images per class. ImageNet100 is a subset of ImageNet1K containing 100 classes. ImageNet1K has 1000 classes with a total of 1.2million RGB images for training.

Benmarks. We follow the protocols proposed in [Hou et al., 2019], which starts from the training of half of the classes in the dataset. Then in all incremental phases, the remaining classes are divided into splits of 5 and 10 steps. During the training process of each step, the training data includes all the samples of the new classes, and exemplars from the classes seen before. During each test phase, models are evaluated on all seen classes until then.

Implementation Details. Following [Douillard et al., 2020], 32-layer and 18-layer ResNet are adopted for CIFAR-100 and ImageNet, respectively. It is worth noting that we choose 18-layer ResNet for all experiments on Der [Yan et al., 2021], which is consistent with the corresponding setting in their paper. For the classifier, a normalization cosine classifier is adopted. We train our model with an SGD optimizer with a momentum of 0.9. The common hyper-parameters, e.g., learning rates, batch-size, and training epochs are the same as their origin settings [Douillard et al., 2020; Yan et al., 2021], which will be given in supplementary material.

Memory Size. There are two common settings to set memory size. The first setting fixes the number of exemplars of each class, and the overall memory capacity rises as steps increase. The second setting fixes the overall memory, where the number of exemplars for each class decreases with the increase of the steps. To facilitate analysis of the impact of number fluctuations, we choose the first one. To analyze the stability of different methods, we set the exemplars of each class to different numbers (i.e. 20, 15, 10, 5, and 1).

Evaluation metrics. We report two novel metrics to mea-
Table 1: Comparison of average incremental accuracy (%) on ImageNet-Sub dataset.

| Methods       | ImageNet-Full | P=5   | P=10  |
|---------------|---------------|-------|-------|
|               |               | A@0.3 | A@0.5 | A@0.3 | A@0.5 | P@0.3 | P@0.5 | P@0.3 | P@0.5 |
| iCaRL [Rebuffi et al., 2017] | 51.36 | 46.72 |
| UCIR [Hou et al., 2019] | 62.65 | 58.72 |
| DDE [Hu et al., 2021] | 66.84 | 64.17 |
| Mnemonics [Liu et al., 2020] | 64.54 | 63.01 |
| PODNet [Douillard et al., 2020] | 65.59 | 63.27 |
| TPCIL [Tao et al., 2020] | 64.89 | 62.88 |
| DDE [Hu et al., 2021] | 67.51 | 65.77 |
| PODNet [Douillard et al., 2020] | 69.78 | 67.09 |
| SIR_P (Ours) | 72.35 | 71.81 |
| SIR_D (Ours) | 71.58 | 70.87 |

Table 2: Average memory accuracy and forgetting (%) on ImageNet-Sub dataset.

Table 3: Comparison of average incremental accuracy (%) on ImageNet-Full under different number of exemplars (N). Methods with a dagger † represent our reproduced results with their officially released code. See additional material for details.

4.2 Comparative Results and Analyses

Comparison with State-of-the-Art. To assess the overall performance of our scheme, we compare it with the state-of-the-art on the above AMA and AMF metric. For a fair comparison, we implement our scheme based on PODNet [Douillard et al., 2020], and Der [Yan et al., 2021] using their officially released codes. As shown in Table 1 and Table 2, our method achieves good improvement in all metrics and datasets. To evaluate the incremental performance of different methods, we compare the AMA results. Our method achieves an average improvement of 8 and 5 points on CIFAR-100 and ImageNet-Subset, respectively. To evaluate the stability performance, we compare the AMF results, where our method achieves an average improvement of 9 and 5 points. It is worth noting that our method works particularly well under more difficult metrics (i.e., A@3 and F@3), which further demonstrates the robustness of our method. As shown in Table 3, our method achieves an average improvement of 6 and 5 points on the AMA and AMF metrics, demonstrating a good generalization to large datasets. See additional material for more details of our reproduced results on PODNet†.

The impact of the number of exemplars. To further demonstrate the stability of our method under the variable memory, we detail the accuracy curves on five different settings (i.e., N=1, 5, 10, 15, and 20). As shown in Fig. 3, the baseline models suffer a lot due to the missing of old data, leading to the rapid decline in accuracy. The accuracy drops 20.37% for CIFAR-100 and 17.95% for ImageNet-Sub as the number of exemplars decreases from 20 to 1. By contrast, starting from the same points, our method performs better at each number of exemplars. Our method can boost performance more when the number of exemplars is smaller. For example, when the number of exemplars is set to 20, our method improves PODNet by 4.29% and 3.37% on CIFAR-100 and ImageNet-Sub, respectively. When the number of exemplars is set to only 1, our corresponding boost is increased to 29.84% and 22.27%.

Visualization on the FCS and ITS. To better demonstrate the role of FCS and ITS during optimization, we show the visualization results with t-SNE [Maaten and Hinton, 2008]. As shown in Fig. 4 (a), when the number of exemplars decreases, the inter-class distance in the baseline becomes smaller, and even the representation of some classes (i.e., green and pink areas) will be completely confused. By contrast, with the proposed FCS, our model brings larger inter-class and smaller intra-class distances, which facilitates the learning of a good decision boundary. As shown in Fig. 4 (b), during the optimization process of the baseline model, some new classes which are similar to the old ones are not constrained, leading to confusion. The proposed ITS augments each logits element of similar new classes while maintaining representations of unrelated new classes. The corresponding inter-class distance between old classes and similar new classes becomes larger in the representation space, thus rectifying the whole balance.
Comparison on more settings. To demonstrate the generalization of our method, we conduct more experiments with different settings. As shown in Table 4, our method achieves an average improvement of 3 points on CIFAR100-B0 [Yan et al., 2021], which trains all 100 classes in several splits, including 5, 10 steps. As shown in Table 5, our method can boost performance when incremental steps are longer. When the number of steps is equal to 5, 10, 25, and 50, our method surpasses the SOTA method by 3.03%, 4.29%, 5.99%, and 8.28%, respectively. These results demonstrate the extensibility of our method to challenging settings.

4.3 Ablation Study

To prove the effectiveness of the two components of our method, we conduct several ablation experiments on CIFAR-100. As shown in Fig. 5, ITS improves the performance by 2.01% via alleviating the confusion of similar classes. FCS adjusts the logits margin between old and new classes with corresponding number ratio to strengthen the expression ability of the old classes, thus independently improving the baseline by 5.8%. The final SIR method improves the performance with a margin of 6.64% which indicates that ITS and FCS could benefit from each other. Moreover, to demonstrate the effectiveness of chronological attenuation, we conduct ablation experiments on CIFAR100-B0 as shown in Table 6. Considering that the architecture-based rectification overcompensated for the earlier classes during multiple increments, we attenuate the final scores with the chronological order at each phase, thus achieving an average improvement of 0.9%.

5 Conclusion

In this paper, a novel self-paced imbalance rectification scheme is proposed for the exemplar-based CIL task, which stabilizing the incremental representation learning under the variation of memory capacity. In particular, a frequency com-
pensation strategy is firstly proposed to strengthen the expression ability of the old class, and then the initial representation confusion is mitigated with an inheritance transfer strategy. Experimental results show that our model is superior in both performance and stability with respect to SOTA methods.

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