Balanced Softmax Cross-Entropy for Incremental Learning

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Abstract—Deep neural networks are prone to catastrophic forgetting when incrementally trained on new classes or new tasks as adaptation to the new data leads to a drastic decrease of the performance on the old classes and tasks. By using a small memory for rehearsal and knowledge distillation, recent methods has proven to be effective to mitigate catastrophic forgetting. However due to the limited size of the memory, large imbalance between the amount of data available for the old and new classes still remains which results in a deterioration of the overall accuracy of the model. To address this problem, we propose the use of the Balanced Softmax Cross-Entropy loss and show that it can be combined with exiting methods for incremental learning to improve their performances while also decreasing the computational cost of the training procedure in some cases. Complete experiments on the competitive ImageNet, subImageNet and CIFAR100 datasets show state-of-the-art results.

1. Introduction

In a class incremental learning setting, the complete training dataset is not available at once. Instead, the training samples are gradually available, few classes at a time. The model has to be trained on new classes step-by-step, in a sequential manner. This constraint tends to reproduce real world settings where it is not possible to either store all the data for training due to memory constraints or re-train the model from scratch each time new samples are available due to time and computational power limitations. For example, a robot learning new objects while interacting with its environment may not have enough memory to store images of all past encountered objects and may not be able to be re-trained on the complete dataset each time a new object is discovered due to the limited computational power of the embedded device.

Although deep neural networks achieve state-of-the-art performance for many problems in computer vision, it is challenging to use them in an incremental learning setting due to their high propensity to steeply forget previously learned classes while learning new ones. This situation is known as catastrophic forgetting [10], [23], [25].

In this context, replay has proven to be an effective solution to mitigate catastrophic forgetting. A small memory buffer is used to store examples from previously encountered classes which are then used for rehearsal while learning new classes. However, a large imbalance problem appears due to the limited size of the memory buffer: at a given incremental step, the model will mainly see data from the new classes and only few from the previous classes. This leads the model to be biased toward the new classes which greatly deteriorate its overall performance. Methods designed to tackle this issue mainly rely on using some finetuning steps on a small balanced dataset after the main training process or specifically designed classifiers.

In this work, we propose a novel approach to address the bias toward new classes in the context of incremental learning using a rehearsal memory. Our proposed method relies on the use of the Cross-Entropy loss using the Balanced Softmax activation function [27] instead of the commonly used Softmax function. When combining the Balanced Softmax with recent advanced methods in incremental learning, the average incremental accuracy of the models can be improved which enables us to reach state-of-the-art performances on competitive datasets. Moreover, the computational cost of the training procedure can also decrease as using the Balanced Softmax activation function doesn’t require any additional balanced finetuning step. Finally, we also investigate the use of a meta-learning algorithm to further improve the accuracy of the models.

2. Related work

With the success of deep learning methods during the past decade, lifelong learning and incremental learning for deep neural networks became an active topic. Various settings for continual learning can be considered [16], [22]. In this work we will mostly consider the class incremental setting. When applied on large datasets, most methods for this setting usually rely on three components: constraints to preserve past knowledge, a memory for rehearsal and bias correction methods.

The distillation loss [14] has initially been proposed by Hinton et al. for transferring knowledge from a large teacher model into a smaller student model. Li et al. [20] adapted it to continual learning by distilling the knowledge of the model learned during the previous step into the next step using the output logits. This method was applied by several
Figure 1: Illustration of the class incremental training procedure. At each incremental step $i$, the model has access for the training to the new data $X_i$ containing samples from new classes $C_i$ and the memory $X_M$ containing few samples from previously encountered classes $\bigcup_{t=0}^{i-1} C_t$.

Exemplars selection

Exemplars selection

$\theta_{init}$

Train

$\theta_0$

Train

$\theta_1$

Train

$\theta_2$

$\ldots$

Authors [6], [26], [31]. Recently, several proposal have been made to modify and improve distillation for incremental learning. Hou et al. [15] proposed a novel distillation loss named Less forget Constraint which is applied on the final class embeddings instead of the output logits. Dhar et al. [9] proposed the Attention Distillation Loss which penalizes changes in the attention maps of the classifiers. Douillard et al. [29] proposed a new distillation loss using a pooling function and applied it to several intermediate layers of the neural network in addition to the final class embedding. Tao et al. [9] proposed to model the class embedding topology using an elastic Hebbian graph and then used a topology-preserving loss to constraint the change of the neighboring relationships of the graph during each incremental step. Similarly, Lei et al. [19] proposed the weighted-Euclidean regularization to preserve the knowledge of previously learned classes, using a feature-graph preservation perspective.

Rehearsal using a small memory [7] containing sample data from previously learned classes has been shown to be an effective methods to mitigate catastrophic forgetting. This rehearsal memory can be compressed [5], store the output logits instead of the true labels [4] or store the intermediate representation of the input compressed using product quantization allowing it to store more samples for a fixed memory size compared to other methods as proposed by Hayes et al. with REMIND [12]. Liu et al. [21] proposed to parameterize the exemplars of the memory and to learn them in an end-to-end manner.

However, the use of a small memory results in an unbalanced training set which mainly contains examples from the new classes. Several recent papers have highlighted this problem and proposed different methods to address it. Rebuffi et al. [26] introduced ICaRL which relies on a nearest-mean-of-exemplars (NME) classifier to tackle the issue. Castro et al. [6] proposed to use more data augmentation on the training set and then finetune the model on a small balanced dataset. Wu et al. [31] and Hou et al. [15] observed that the classifier part of the neural network is the main reason for the bias of the model toward the new classes. Wu et al. [31] proposed to learn a two parameters linear model on a small balanced dataset to correct the bias of the last fully connected layer while Hou et al. [15] proposed to use cosine normalization on the classifier and finetuning on a balanced dataset. Recent work [1] also proposed to use oversampling of old classes and to compute separately the softmax probabilities of the new and old classes for the Cross-Entropy loss.

In this work, we proposed a new method to address the problem of unbalanced training set in incremental learning by using the Balanced Softmax Cross-Entropy loss. Compared to the other methods previously presented, the Balanced Softmax Cross-Entropy does not require oversampling or any finetuning step on a small balanced dataset while achieving similar or higher accuracy.

3. Proposed method

The objective of class-incremental learning is to learn an unified classifier (also denoted single-head classifier) from a sequence of training steps, each containing new previously unseen classes, as described on Figure 1. The first step, named base step, is followed by several incremental training step, numbered from 1 to $T$, each composed of the training set $X_i$ containing samples of the classes from set $C_i$. Each incremental step contains different classes such that $\bigcap_{t=0}^{T} C_t = \emptyset$. In addition to $X_i$, at each incremental step, the model also has access to $X_M$ which is the small replay memory containing samples from classes encountered during previous incremental steps. The number of classes learned up to the incremental step $t$ included is denoted $N_t$.

3.1. Incremental learning baseline

To highlight the strengths of our method, we decide to use a simple baseline for incremental learning, denoted IL-baseline, initially proposed in [31]. This baseline consists in
a deep neural network combined with a small replay memory and optimized using two distinct losses: the Softmax Cross-Entropy loss and the distillation loss.

The total loss \( L \) used to train the model, is defined as a weighted sum of the distillation loss \( L_d \) and the Softmax Cross-Entropy loss \( L_c \):

\[
L = \rho L_d + (1 - \rho) L_c
\]

where \( \rho \) is defined as \( \frac{N_t}{N_{t+1}} \) with \( N_t \) the total number of classes at step \( t \) and is used to balance the importance of the two losses. Depending on the number of new classes that are learned at each step compared to the total number of classes already learned, the importance of the distillation loss is modified.

At the beginning of each incremental step \( t \), the previous step parameters \( \theta_{t-1} \) are first copied to initialize the new parameters \( \theta_t \) and then are used to maintain the knowledge of previously learned classes using the distillation loss \([14]\). The distillation loss \( L_d \) is defined as:

\[
L_d = \sum_{(x,y) \in X_t \cup X_M} \sum_{k=1}^{N_t-1} \frac{-p_k(x) \log(p_k(x))}{T^2},
\]

\[
\hat{p}_k(x) = \frac{e^{z_k(x)/T}}{N_t \sum_{j=1}^{N_t} e^{z_j(x)/T}}, \quad p_k(x) = \frac{e^{z_k(x)/T}}{N_t \sum_{j=1}^{N_t} e^{z_j(x)/T}}
\]

where \( z(x) = [z_1(x), \ldots, z_{N_t}(x)] \) is the output logits of the current model \( \theta_t \), \( \hat{z}(x) = [\hat{z}_1(x), \ldots, \hat{z}_{N_t-1}(x)] \) is the output logits of the model at the previous incremental step \( \theta_{t-1} \) and \( T \) is the temperature.

Usually, the replay memory can be constrained by either a global budget or by the number of samples saved per class. Using a global budget means that the memory size is fixed at the beginning of the training procedure and is equally divided among the already learned classes. As the number of already encountered classes increase, the number of samples stored for each class decrease. On the other hand, using a fixed number of samples stored per class, also known as growing memory, means that number of samples per class will not change during training procedure and will lead the total size of the memory to increase at each incremental step.

In this work, we use the latter approach as it is considered to be the most challenging method. For the sample selection, the herding selection \([50]\) is used as it has been shown to be more efficient than random selection \([3]\).

### 3.2. Balanced Softmax Cross-Entropy

Due to the use of replay memory, at each incremental step, the training set \( X_t \cup X_M \) contains hundreds or thousands of samples for each of the new classes while containing only few tens of samples for each of the old classes. The discrepancy in the classes frequency between the training set and the testing set, as the latter contains the exact same number of samples for each classes, induces a bias toward the most recently learned classes \([2], [15], [31]\) in the model trained using the IL-Baseline procedure as shown on Figure \( 2 \). It appears that the model tends to predict the classes which had the largest number of samples in the training set during the last incremental steps (the new classes) rather than the old classes. This situation is similar to Long-Tailed Visual Recognition where a model is evaluated on a balanced test dataset after being trained on a dataset composed of few classes which are over-represented (the head classes) and a large number of classes which are under-represented (the tail classes).

Based on this observation, we propose to improve the IL-Baseline by replacing the Softmax activation function by the Balanced Softmax. This activation function has been initially introduced by Ren et al. \([27]\) to address the label distribution shift between the training and testing in Long-Tailed Visual Recognition.

The Balanced Softmax activation function is defined as:

\[
q_k(x) = \frac{\lambda_k e^{z_k(x)}}{\sum_{j=1}^{N_t} \lambda_j e^{z_j(x)}} \quad \text{with} \quad \lambda_i = n_i
\]

where \( z(x) = [z_1(x), \ldots, z_{N_t}(x)] \) is the output logits of the current model and \( n_j \) is the number of images in the training set for the \( j \)-th class.

The new classification loss \( L_c \) is then defined as the Cross-Entropy loss using the Balanced Softmax instead of the Softmax:

\[
L_c = \sum_{(x,y) \in X_t \cup X_M} \sum_{k=1}^{N_t} \delta_{k=y} \log(q_k(x))
\]
The Balanced Softmax Cross-Entropy loss, denoted BalancedS-CE, can be used as replacement of the Softmax Cross-Entropy in the previously defined IL-Baseline or in any other model for incremental learning. It should be noted that the Balanced Softmax Cross-Entropy does not increase the computational cost of the training procedure in any notable way compared to the Softmax Cross-Entropy.

3.3. Meta Balanced Softmax Cross-Entropy

The expression of the Balanced Softmax presented in Equation (3) allows for a direct control on each class of the dataset, by selecting for each class a dedicated weighting coefficient $\lambda_i$, which may be different from the number of samples for this class in the training dataset, similarly to [17]. In the context of large scale incremental learning, the modification of these weighting coefficients offers a new method for controlling the plasticity-rigidity trade-off of the trained model but also controlling separately the importance of each individual classes.

We propose to extend the Balanced Softmax by introducing a new weight coefficient $\alpha$ to control the importance of the past classes:

$$q_k(x) = \frac{\lambda_k e^{x_k(x)}}{\sum_{j=1}^{N} \lambda_j e^{x_j(x)}}$$

with $\lambda_i = n_i \cdot (\delta_{i \in F} + \alpha \delta_{i \notin F})$

where $F$ is the set of old classes and the weighting coefficient $\alpha$ is a real number, usually between 0 and 1.

By decreasing $\alpha$ it is possible to increase the importance of the old classes and reduce the plasticity of the model depending on the specifics requirements of the application. This new expression of the Balanced Softmax is equivalent to the one described in Equation (3) for $\alpha$ equal to 1.0.

In practice, it appears that 1.0 may not be the optimal value for $\alpha$ when only considering the average incremental accuracy of the model. However, it is difficult to determine beforehand a satisfying value for $\alpha$ without performing several trials with different values. Therefore, to further improve the accuracy of Balanced Softmax Cross-Entropy for Incremental Learning, we propose a new training procedure, named Meta Balanced Softmax Cross-Entropy (Meta BalancedS-CE), in order to slightly adjust the weighting coefficients $\alpha$ of the Balanced Softmax during the training as described by Algorithm 1.

$$\alpha \leftarrow \alpha - \nabla_{\alpha, Softmax_CE}(F(X, \theta), Y)$$

At each optimization step, a temporary model $\theta^*$ is created by training the current model $\theta$ on the incoming batch of data $(X, Y)$ from $D_t$ using the balanced loss which is the sum of the Balanced Softmax Cross-Entropy and secondary losses (such as the distillation loss). By using a batch $(X, Y)$ from the balanced validation set $B_t$, the value of $\alpha$ is then updated using the gradient of the Softmax Cross-Entropy loss of $(F(X, \theta^*), Y)$ with respect to $\alpha$. Finally we update the current model $\theta$ on the batch $(X, Y)$ previously sampled from $D_t$ using the balanced loss with the newly learned value of $\alpha$.

Unlike the Balanced Softmax Cross-Entropy which does not modify the computational cost of the training procedure compared to the Softmax Cross-Entropy, the Meta Balanced Softmax Cross-Entropy have an impact on the training procedure. The method requires to compute gradients through the optimization process. One of the main drawbacks is a large increase of the memory requirement which makes it more difficult to combine this approach with some existing methods for incremental learning.

4. Experiments

4.1. Experimental setups

4.1.1. Datasets. The experiments are conducted on three competitive datasets for large-scale incremental learning: CIFAR100, subImageNet and ImageNet. We used the experimental settings defined in [15] by initially training the models on the first half of the classes of the dataset (referred as the base classes) before learning the remaining classes during the next 5 or 10 incremental steps. Following [15], [26], the class order is defined by NumPy using the random seed 1993.

- CIFAR100 [18] is composed of 60,000 32x32 RGB images equally divided among the 100 classes with 500 images for training and 100 for testing for each class. There are 50 base classes and the remaining
4.1.2. Baselines. BSIL and Meta-BSIL are compared with a Similarity Classifier and a class balance finetuning. TPCIL based distillation loss is applied throughout the model, a Local layer is learned during the training. PODNet relies on a spatial-replay memory containing parameterized exemplars which support both CNN predictions and nearest-mean-of-exemplars classifier. LUCIR uses a new topology-preserving loss to constraint modification of the class embedding. Every methods use a small memory for rehearsal containing samples from old classes.

To measure the performance of the different models and compare them, the average incremental accuracy is used following [26]. It is defined as the average of the Top-1 accuracy of the model on the test dataset at the end of each task, including the initial one.

### 4.1.3. Implementation details.

All compared methods use the 32-layer ResNet [13] for CIFAR100 and the 18-layers ResNet for ImageNet and SubImageNet. The input images are normalized, randomly horizontally flipped and cropped with no further augmentation applied. For a fair comparison, each method uses a growing memory containing exactly 20 samples per class.

For CIFAR100, the IL-Baseline model is trained for 250 epochs using the SGD with momentum optimizer with a batch size of 128 and the weight decay set to 0.0002. The learning rate starts at 0.1 and is divided by 10 after the epochs 100, 150 and 200. For ImageNet and SubImageNet, the IL-Baseline model is trained for 100 epochs using the SGD with momentum optimizer with a batch size of 128 and the weight decay set to 0.0001. The learning rate starts at 0.1 and is divided by 10 after the epochs 30, 60, 80 and 90. For all datasets, the temperature $T$ of the distillation loss is equal to 2 and the weighting coefficient $\alpha$ is set to 1. When the Balanced Softmax Cross-Entropy loss is combined with other methods, the hyper-parameters reported in the original publication of the other methods are used. For Meta-Balanced Softmax Cross-Entropy, 10% of the memory size is used for the balanced validation set $B_v$, which represents 2 samples per class for the main experiments. In order to decrease the computational requirement of the method, the $\alpha$ weighting coefficient is only updated every 10 optimization steps instead of every optimization step.

### Table 1: Comparison of average incremental accuracy (Top-1) on CIFAR100, SubImageNet and ImageNet with 5 incremental steps and 10 incremental steps settings, using a growing memory of 20 samples per class for all methods. Results for iCaRL and LUCIR are reported from [15]; results for Mnemonics and BIC are reported from [21]; results for PODNet and TPCIL are reported from their respective paper. Results marked with "*" correspond to our own experiments.

| Number of incremental steps | CIFAR100     | SubImageNet | ImageNet     |
|----------------------------|--------------|-------------|--------------|
|                            | 5            | 10          | 5            | 10          |
| iCaRL [26]                 | 57.17        | 52.57       | 65.04        | 59.53       | 51.36        | 46.72        |
| BIC [31]                   | 59.36        | 54.20       | 70.07        | 64.96       | 62.65        | 58.72        |
| LUCIR [15]                 | 63.42        | 60.18       | 70.47        | 68.09       | 64.34        | 61.28        |
| LUCIR w/ Mnemonics [21]    | 63.34        | 62.28       | 72.58        | 71.37       | 64.54        | 63.01        |
| PODNet [9]                 | 64.83        | 63.19       | 75.54        | 74.33       | 66.95        | 64.13        |
| TPCIL [29]                 | 65.34        | 63.58       | 76.27        | 74.81       | 64.89        | 62.88        |
| IL-Baseline*               | 43.80        | 37.00       | 51.52        | 42.22       | 43.23        | 36.70        |
| IL-Baseline w/ BalancedS-CE (ours) | 62.22 | 58.32 | 72.25 | 68.25 | 66.45 | 62.14 |
| IL-Baseline w/ Meta-BalancedS-CE (ours) | 64.11 | 60.08 | 72.88 | 69.26 | 66.15 | 61.59 |
| LUCIR*                     | 63.37        | 60.80       | 70.25        | 67.84       | 66.69        | 64.06        |
| LUCIR w/ BalancedS-CE (ours) | 64.83 | 62.36 | 71.18 | 70.66 | 67.81 | 66.47 |
| PODNet*                    | 64.46        | 62.69       | 74.97        | 71.57       | 65.20        | 62.87        |
| PODNet w/ BalancedS-CE (ours) | 67.67 | 66.63 | 76.08 | 74.93 | 69.67 | 68.65 |

Class are learned by groups of 5 or 10 classes depending on the number of incremental steps.

- **ImageNet** (ILSVRC 2012) [28] is composed of about 1.3 million high-resolution RGB images divided among the 1,000 classes with around 1,300 images for training and 50 for testing for each class. There are 500 base classes and the remaining classes are learned by groups of 50 or 100 classes depending on the number of incremental steps.

- **SubImageNet** is a subset of ImageNet only containing the first 100 classes. There are 50 base classes and the remaining classes are learned by groups of 5 or 10 classes depending on the number of incremental steps.

4.1.2. Baselines. BSIL and Meta-BSIL are compared with the IL-Baseline which uses the Softmax Cross-Entropy loss instead of the Balanced Softmax Cross-Entropy loss in order to highlight the impact of the balanced Softmax Cross-Entropy loss function for incremental learning. This baseline is considered as the lower-bound method.

Furthermore, the proposed models are compared with iCaRL [26], LUCIR [15], Mnemonics [21], PODNet [9] and Topology-Preserving Class-Incremental Learning (TPCIL) [29]. iCaRL uses the knowledge distillation loss and a nearest-mean-of-exemplars classifier. LUCIR relies on the use of cosine normalization of the classification layer, the Less Forget Constraint, the inter-class separation loss and a class balance finetuning in some cases. LUCIR supports both CNN predictions and nearest-mean-of-exemplars classification, here we only reported the CNN prediction. Mnemonics proposed to combine LUCIR with a replay memory containing parameterized exemplars which are learned during the training. PODNet relies on a spatial-based distillation loss applied throughout the model, a Local Similarity Classifier and a class balance finetuning. TPCIL uses a new topology-preserving loss to constraint modification of the class embedding. Every methods use a small memory for rehearsal containing samples from old classes.

To measure the performance of the different models and compare them, the average incremental accuracy is used following [26]. It is defined as the average of the Top-1 accuracy of the model on the test dataset at the end of each task, including the initial one.
4.2. Comparison Results

The average incremental accuracy on the three CIFAR100, SubImageNet and ImageNet for our methods and the different baselines are reported in Table 1 using both 5 and 10 incremental steps settings. First, we use the IL-Baseline to precisely compare the Balanced Softmax Cross-Entropy loss with the standard Softmax Cross-Entropy loss. On every dataset and in every settings, IL-Baseline trained using the Balanced Softmax Cross-Entropy loss outperforms the IL-Baseline trained using the standard Softmax Cross-Entropy by a large margin. Moreover, by meta-learning the weighting coefficient \(\alpha\) instead of using the fixed value of 1.0, it is possible to further improve the accuracy of the Balanced Softmax Cross-Entropy loss by up to 1.89\% and 1.76\% on CIFAR100 with 5 and 10 incremental steps. The difference is less important on SubImageNet with an improvement of only 0.31\% and 1.01\% in the 5 and 10 incremental steps setting. IL-Baseline trained using the Balanced Softmax Cross-Entropy loss overall achieves results on a par with LUCIR. On CIFAR100 and ImageNet, IL-Baseline trained using the Balanced Softmax Cross-Entropy loss has a slightly lower average incremental accuracy compared with LUCIR, while on SubImageNet it surpasses LUCIR in both 5 and 10 incremental steps settings.

Then, to demonstrate the flexibility of the proposed loss function, we combined it with both LUCIR and PODNet, reported here as LUCIR w/ BalancedS-CE and PODNet w/ BalancedS-CE respectively. By using the Balanced Softmax Cross-Entropy loss instead of the NCA loss [11], [24] originally used by PODNET and the Softmax Cross-Entropy loss used by LUCIR, we were able to significantly improve the performance of both methods while decreasing the computation cost of the training procedure by removing the need of a balanced finetuning step without further modifying any hyper-parameters. On every dataset and in every settings, using the Balanced Softmax Cross-Entropy significantly improves the average incremental accuracy of both LUCIR and PODNet, this improvement of the performance is especially important in the challenging 10 incremental steps settings. For LUCIR, Balanced Softmax Cross-Entropy improves the average incremental accuracy from 0.93\% up to 2.82\%, and for PODNet it improves it from 1.11\% up to 5.78\% depending on the setting and the dataset considered. On ImageNet with 5 incremental steps, PODNet with Balanced Softmax Cross-Entropy outperforms PODNet by up to 4.47\% in terms of average incremental accuracy and reaches a final overall Top-1 accuracy of 64.4\% which is only about 6\% below the theoretical Top-1 accuracy of the model trained on the whole dataset at once.

4.3. Ablation study

4.3.1. Effect of the memory size. The average incremental accuracy of the IL-Baseline trained with both Balanced Softmax Cross-Entropy and Meta Balanced Softmax Cross-Entropy on the CIFAR100 using the 5 incremental steps settings is reported in Table 3 for various number of exemplars per class stored in the replay memory. It is not possible to use the Meta Balanced Softmax Cross-Entropy with only one sample per class in the memory because the minimum memory size for this method is 2 as it requires a distinct validation set and training set. Regardless of the number of exemplars per class stored in memory, Meta Balanced Softmax Cross-Entropy appears to achieve higher accuracy than the Balanced Softmax Cross-Entropy even though the difference of accuracy between the two methods decreases as the size of the memory increases. This makes the Meta Balanced Softmax Cross-Entropy loss especially efficient in scenarios with highly restricted memory.

| Training procedure               | Final base accuracy | Final overall accuracy | Average inc. accuracy |
|----------------------------------|---------------------|------------------------|-----------------------|
| BalancedS-CE \(\alpha = 0.1\)   | 68.38               | 51.54                  | 62.68                 |
| BalancedS-CE \(\alpha = 0.25\)  | 63.99               | 54.88                  | 64.09                 |
| BalancedS-CE \(\alpha = 0.5\)   | 58.78               | 55.44                  | 63.80                 |
| BalancedS-CE \(\alpha = 1.0\)   | 52.08               | 54.55                  | 62.22                 |
| Meta BalancedS-CE                | 61.20               | 55.21                  | 64.11                 |

Table 2: Comparison of accuracy on the test set of CIFAR100 with 5 and 10 incremental steps of the Incremental Learning Baseline (IL-Baseline) depending on the value used for the weighing coefficient \(\alpha\) of the Balanced Softmax Cross-Entropy; using a growing memory of 20 samples per class. Results averaged over 3 random runs.

| Training procedure               | Final base accuracy | Final overall accuracy | Average inc. accuracy |
|----------------------------------|---------------------|------------------------|-----------------------|
| BalancedS-CE \(\alpha = 0.1\)   | 63.43               | 44.71                  | 57.68                 |
| BalancedS-CE \(\alpha = 0.25\)  | 60.28               | 47.86                  | 59.40                 |
| BalancedS-CE \(\alpha = 0.5\)   | 56.48               | 49.62                  | 59.52                 |
| BalancedS-CE \(\alpha = 1.0\)   | 51.01               | 49.57                  | 58.32                 |
| Meta BalancedS-CE                | 60.39               | 49.65                  | 60.08                 |

Table 3: Comparison of the average incremental accuracy on the test set of CIFAR100 with 5 incremental steps of the different training procedure for the Incremental Learning Baseline (IL-Baseline) depending on the number of samples stored in memory for each class. Results averaged over 3 random runs.

4.3.2. Impact of the weighting coefficient alpha. The accuracy of the IL-Baseline trained using the Balanced...
Table 4: Comparison of accuracy on the test set of CIFAR100 with 5 incremental steps of the Incremental Learning Baseline (IL-Baseline) depending on the bias correction procedure used; using a growing memory of 20 samples per class. Results averaged over 3 random runs.

| Training procedure                                      | average incremental accuracy |
|---------------------------------------------------------|------------------------------|
| IL-Baseline                                             | 43.80                        |
| IL-Baseline /w memory oversampling                      | 49.75                        |
| IL-Baseline /w class oversampling                       | 55.95                        |
| IL-Baseline /w loss rescaling                           | 57.01                        |
| IL-Baseline /w balanced finetuning                      | 59.46                        |
| IL-Baseline /w Separated Softmax + oversampling         | 61.21                        |
| IL-Baseline /w BalancedS-CE (ours)                      | 62.22                        |
| IL-Baseline /w Meta BalancedS-CE (ours)                 | **64.11**                    |

Softmax Cross-Entropy loss on CIFAR100 with 5 (a) and 10 (b) incremental steps is reported in Table 2 depending on the value of the weighting coefficient $\alpha$.

In both settings, we can observe that decreasing the value of the weighting coefficient $\alpha$ induces an increase of the accuracy of the old classes at the end of the incremental training. The smaller the weighting coefficient $\alpha$, the higher the final accuracy of the old classes. The impact on the final accuracy of the model remains marginal compared to the impact on the base classes accuracy: by decreasing the weighting coefficient $\alpha$ from 1.0 to 0.1, the accuracy on the 50 base classes increases by 16.3% while the final accuracy of the model only decreases by 3.01%.

While using the weighting coefficient $\alpha$ equals to 1.0 achieves in both settings the most balanced models between base classes and new classes, it is not the most optimal choice if considering the average incremental accuracy as the only important metric for measuring the performance of the incrementally learned model. Experiments show that carefully selecting the value of $\alpha$ can improve the average incremental accuracy by up to 1.87% on CIFAR100 with 5 incremental steps and by 1.2% on CIFAR100 with 10 incremental steps. However, this value may depend on the dataset and the number of incremental steps. The proposed meta-learning procedure for the weighting coefficient $\alpha$ achieves the highest average incremental accuracy over the complete incremental training procedure in both setting. This shows the interest of this method for determining an efficient value for the weighting coefficient $\alpha$ without conducting several trials.

4.3.3. Mitigation of imbalance. In Table 4 different bias correction procedures are compared with Balanced Softmax Cross-Entropy and Meta Balanced Softmax Cross-Entropy on CIFAR100 with 5 incremental steps. Both IL-Baseline with memory oversampling and IL-Baseline with class oversampling correspond to the IL-Baseline combined with oversampling but the former oversamples the replay memory so that each training mini-batch theoretically contains the same number of sample from new and old classes while

Figure 3: Confusion matrix (transformed by log(1 + x) for better visibility) of the IL-Baseline trained on CIFAR100 - 5 incremental steps using (a) Meta Balanced Softmax Cross-Entropy and (b) Balanced Softmax Cross-Entropy, using 20 sample per class stored in the replay memory.
the latter oversamples the replay memory so that each class has the same probability of appearing in each training mini-batch. IL-Baseline with loss rescaling corresponds to the IL-Baseline where the softmax cross-entropy loss for each sample is rescaled in inverse proportion to the number of samples corresponding to this label in the train dataset. IL-Baseline with balanced finetuning corresponds to the IL-Baseline being finetuned after each incremental step on a small balanced training set for few epochs similar to the procedure used by PODNet and LUCIR. IL-Baseline with Separated Softmax relies on oversampling of the replay memory combined with the Separated Softmax layer [1].

In the experiments, it appears that the oversampling of the old classes is a simple yet effective method for mitigating the imbalance occurring in large scale incremental learning scenario. However this approach is prone to overfitting on the old classes resulting in a decrease of accuracy. By rescaling the Softmax Cross-Entropy loss it is possible to further reduce the bias toward the new classes without relying on oversampling. Finally, in the case where a two-step training procedure is possible, finetuning the model afterward on a small balanced dataset, as it is done by several state-of-the-art methods, further improves the final overall accuracy of the model compared to other previously presented bias correction methods. The two proposed methods achieve higher average incremental accuracy than the other bias correction methods without requiring a two steps training procedure or oversampling.

Figure 3 shows the confusion matrix for IL-Baseline trained on CIFAR100 with 5 incremental steps using Meta Balanced Softmax Cross-Entropy (a) and Balanced Softmax Cross-Entropy (b). By comparison with IL-Baseline trained using Cross-Entropy on Figure 2 it appears that the proposed methods seem to successfully mitigate the imbalance between the new and old classes: old classes are no longer mostly miss-classified as new classes and the final accuracy for old and new classes are mostly similar.

5. Conclusion

In this paper, we proposed to replace the Softmax Cross-Entropy loss function by the Balanced Softmax Cross-Entropy loss in order to mitigate the bias toward new classes in large scale incremental learning. The expression of this loss offers control on the plasticity-rigidity trade-off of the incremental model but also on the importance of each class individually. We propose a simple, yet efficient, training procedure to meta-learn the balance between old and new classes using this new expression.

Complete experiments on CIFAR100, SubImageNet and ImageNet show that using the proposed loss function with a replay memory and distillation achieve results on a par with other competitive methods. Moreover, by combining the Balanced Softmax Cross-Entropy loss with more sophisticated methods for incremental learning, it is possible to further increase the accuracy of the model while decreasing the computational cost of the training procedure by removing the need for a balanced finetuning step.

In our future work, we will further explore to what extend the performance of the Balanced Softmax Cross-Entropy can be improved by slightly tuning the weighting coefficients during the training procedure.

Acknowledgment

This work is partly supported by JSPS Grant-in-Aid for Early-Career Scientists (Grant Number 19K20352), JSPS Grant-in-Aid for Scientific Research(B) (Grant Number 17H01785), JST CREST (Grant Number JPMJCR1687), and the New Energy and Industrial Technology Development Organization (Grant Number JPNP20006)

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