Balanced Knowledge Distillation for Long-tailed Learning

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Abstract

Deep models trained on long-tailed datasets exhibit unsatisfactory performance on tail classes. Existing methods usually modify the classification loss to increase the learning focus on tail classes, which unexpectedly sacrifice the performance on head classes. In fact, this scheme leads to a contradiction between the two goals of long-tailed learning, i.e., learning generalizable representations and facilitating learning for tail classes. In this work, we explore knowledge distillation in long-tailed scenarios and propose a novel distillation framework, named Balanced Knowledge Distillation (BKD), to disentangle the contradiction between the two goals and achieve both simultaneously. Specifically, given a vanilla teacher model, we train the student model by minimizing the combination of an instance-balanced classification loss and a class-balanced distillation loss. The former benefits from the sample diversity and learns generalizable representation, while the latter considers the class priors and facilitates learning mainly for tail classes. The student model trained with BKD obtains significant performance gain even compared with its teacher model. We conduct extensive experiments on several long-tailed benchmark datasets and demonstrate that the proposed BKD is an effective knowledge distillation framework in long-tailed scenarios, as well as a new state-of-the-art method for long-tailed learning. Code is available at https://github.com/EricZsy/BalancedKnowledgeDistillation

1. Introduction

Recent advances in visual recognition [14, 34, 45] are mainly driven by the use of large-scale datasets, such as ImageNet ILSVRC 2012 [8, 42] and MS COCO [30]. Such datasets are often carefully collected, with roughly balanced quantities in each category. However, in practical scenarios, data tends to exhibit long-tailed distribution [38, 17], wherein a few classes (head classes) have a significantly larger number of instances than other classes (tail classes). This uneven distribution affects both convergence during the training phase and generalization on the test set [3]. When dealing with such imbalanced data, deep models tend to bias towards head classes, resulting in performance drop on tail classes [13, 20, 28]. Figure 1 illustrates the relation between the data distribution and the classification accuracy on Many/Medium/Few-shot subsets. As we can see, when the data distribution is highly skewed, the model trained with vanilla cross-entropy loss exhibits great performance gaps between the three subsets. While most of the samples from the head classes are classified correctly, the classification accuracy of tail classes is even lower than 10\% in some datasets, e.g., ImageNet-LT [33] and Places-LT [33].

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig1.png}
\caption{Illustration of the relation between class capacity and classification accuracy on Many/Medium/Few-shot subsets. Top: Number of instances per class in three long-tailed dataset, sorted in descending order. Bottom: Per-subset accuracy of a model trained with vanilla cross-entropy loss.}
\end{figure}
The goals of long-tailed learning is two-fold: learning generalizable representations and facilitating learning for tail classes. In the literature, one of the most common practices to facilitate learning for tail classes is to rebalance the class distribution, either by re-sampling the examples [9, 4, 6, 26] or re-weighting the classification loss [18, 23, 7, 48]. Essentially, these methods aim to seek trade-offs between the accuracies of the head classes and the tail classes and improve overall performance. Although effective, such re-balancing strategies will encourage excessive focus on tail classes and damage the overall representation learning to some extent [5, 50]. To solve this problem, recent methods propose two-phase [5, 21] or bilateral-branch [50] training framework to decouple the learning procedure into representation learning and classification. It is noteworthy that the decoupled learning scheme exhibits an interesting phenomena that the vanilla instance-balanced cross-entropy loss gives the most generalizable representations.

Most aforementioned works make modifications directly on the classification loss. However, this scheme is inconsistent with the principle of cross-entropy loss and naturally brings along with a contradiction between learning generalizable representations and facilitating learning for tail classes. We take the most representative re-weighting strategies [7] for example and explain where the contradiction comes from by analyzing the effect of gradient. Orthogonally to the previous works, we disentangle the contradiction between the two goals from the perspective of teacher-student learning [16, 52, 49]. Specifically, if trained on imbalanced data, the student tries the best to learn high-quality representations while the teacher should facilitate learning with focus on tail classes. Motivated by this, we explore knowledge distillation in long-tailed scenarios and propose a simple yet effective distillation framework, named balanced knowledge distillation (BKD), to alleviate the long-tailed problem. We first train a vanilla teacher model with the same size as the student model, we observe significant performance gain from the former.

We conduct extensive experiments and demonstrate that our BKD framework significantly improves the classification performance of the student model and achieves state-of-the-art performance on several long-tailed benchmarks.

2. Related Works

2.1. Knowledge Distillation

The idea of training a lightweight student model to mimic a larger but better performing teacher model can be traced back to [2, 1]. Hinton et al. [16] propose to distill the knowledge of predicted distribution from the teacher model into the student model, which is widely known as knowledge distillation. Apart from the final prediction [35], other types of knowledge, like the intermediate representations [41, 24, 15] or the relationships between different layers [52] or data samples [54, 37, 32], can also be used to guide the learning of the student model. As a special case, knowledge distillation from a model to another of identical architecture [11, 52] is explored. However, to our knowledge, how to effectively distill the knowledge in large-scale long-tailed scenarios is still under-explored. We progress this line of works under two challenges: 1) the teacher and the student have the same architecture; 2) the training data is imbalanced.

2.2. Long-tailed Learning

To alleviate the challenge of long-tailed learning, most of pioneer works have been proposed from three aspects: Data. Re-sampling methods [4, 3, 44, 6, 13] created a roughly balanced distribution by either over-sampling or under-sampling. Over-sampling [44, 4] repeatedly samples training examples from the minority classes, the downside of which is the high potential risk of overfitting. To overcome this issue, SMOTE [6, 12] is proposed to augment synthetic data created by interpolating neighboring data points. As opposed to over-sampling, under-sampling [13, 20, 3] randomly discards examples from the majority
classes. When the imbalance is extreme, under-sampling may lose valuable information in majority classes.

**Optimization objective.** The key to this line of work is to adjust learning focus by modifying objective functions. Cost-sensitive re-weighting assigns different weights to the classification loss terms corresponding to different classes or different samples. The traditional strategy re-weights classes proportionally to the inverse of their frequency of samples. Taking data overlap into consideration, Cui et al. design a class-balanced cross-entropy loss based on effective number of samples in each class. Another important work adds a class-wise margin in to the cross-entropy loss motivated by minimizing a margin-based generalization bound. Recently, Menon et al. revisited the method of logit adjustment and proposed a general pair-wise margin loss with several previous methods as its special cases.

Although effective, re-weighting on classification loss has a negative effect on representation learning. Motivated by this observation, two-stage and two-branch methods are proposed to take care of both representation learning and classifier learning.

**Meta- and dark-knowledge.** Many approaches design additional modules or meta-network to transfer knowledge, e.g., distributions, memory features or meta-knowledge, from head to tail classes. However, this line of work is usually non-trivial and more computationally expensive. Beyond that, a popular technique of transferring knowledge, knowledge distillation attracts attention in the field of long-tailed learning. Recently, Learning From Multiple Experts (LFME) has been proposed as a multi-teacher framework, in which each teacher learns from a relatively balanced subset. LFME also employs self-paced expert selection and curriculum learning strategy.

**Key differences.** Our work differs from LFME in several ways. On one hand, LFME needs to split training data into groups and train multiple models, while our method only trains a single teacher model on the original data with vanilla cross-entropy loss. On the other hand, LFME involves complex adaptive learning schedules at model level and instance level, while our method simply modifies the knowledge distillation loss to control the focus of distillation process. Indeed, without multiple teachers and complex learning schedules, our method outperforms LFME on all the long-tailed benchmarks we report by a large margin.

### 3. Insight and Motivation

**Notation.** Consider a classification problem on long-tailed training data. Let \( x \in \mathbb{R}^d \) and \( y \in \{1, \ldots, C\} \) denote a data point and its label, respectively. Due to the imbalanced distribution, the number of training examples in each class \( n_i \) is highly imbalanced. Without loss of generality, we sort the classes in descending order of frequency so that \( n_1 > \cdots > n_C \). Our goal is to learn a model \( f : \mathbb{R}^d \to \mathbb{R}^r \) that estimates the conditional probability \( p_i = \text{softmax}(z_i) \) from the network output \( z = [z_1, \ldots, z_C]^T \).

#### 3.1. A Closer Look at Re-weighting Methods

Given a dataset, the most straightforward method minimizes the misclassification error by minimizing the following softmax cross-entropy loss

\[
L_{CE} = -\sum_i y_i \log p_i \tag{1}
\]

On the basis of cross-entropy loss, the re-weighting methods typically assign weights for different classes or even different samples. However, a possible side effect of re-weighting is that the model tends to overfit on tail classes and suffer a performance drop on head classes. Cao et al. and Zhou et al. experimentally show that the re-weighting is that the model tends to overfit on tail classes and suffer a performance drop on head classes. Cao et al. and Zhou et al. experimentally show that the re-weighting methods, Cui et al. formulate the weight balancing loss as its special cases.

where \( \beta \in (0, 1) \) is a hyperparameter to adjust the class-balanced re-weighting loss \( L_{CB} \) is formulated as

\[
L_{CB} = -\omega_i \log p_t \tag{3}
\]

The derivative of the \( L_{CB} \) with respect to the model’s class-k output \( z_k \) is

\[
\frac{\partial L_{CB}}{\partial z_k} = \begin{cases} 
\omega_i (p_t - 1), & k = t \\
\omega_t p_k, & k \neq t
\end{cases} \tag{4}
\]

Depending on the frequency of class \( k \), the gradient contributions of examples are far different. If category \( k \) is a tail class, for example \( k = C \), in which case we have \( \omega_k = \max_i \omega_i \), re-weighting is reasonable:

1. If \( k = t \), a large encouraging gradient \( \omega_t (p_t - 1) \) is produced by a correct prediction for tail classes;
2. If \( k \neq t \), the discouraging gradient \( \omega_t p_k \) is relatively small as \( \omega_t < \omega_k \). This is consistent with the idea of ignoring discouraging gradient for tail classes [46].

However, when it comes to head classes, for example \( k = 1 \), in which case we have \( \omega_k = \min_i \omega_i \), the learning process is seriously hindered:

1. If \( k = t \), the encouraging gradient \( \omega_t (p_t - 1) \) is very small as \( \omega_t \) is close to zero;
2. If \( k \neq t \), the discouraging gradient \( \omega_t p_k \) is relatively large as \( \omega_t > \omega_k \). This suppression effect is further accumulated because each positive sample of class \( k \) will be treated as a negative sample for all other classes.

In general, while tail classes benefit from re-weighting, the universal representative ability is damaged as the dominant classes suffer from overwhelmed discouraging gradients.

### 3.2. Motivation

As aforementioned, the re-weighting methods lead to sub-optimal result, because the focus on tail classes is entangled with the overall representation learning process in the classification loss. Accordingly, our key idea is to decompose the task of long-tailed learning into two separate parts, learning generalizable representations and facilitating learning for tail classes. The motivation is two-fold.

**Motivation 1.** To learn the most generalizable representations, directly re-weighting the cross-entropy loss should be carefully avoided. It has been proved by experiments [5, 56, 21] and our theoretical analyses in Sec. 3.1. It motivates us to keep the instance-balanced cross-entropy loss unchanged, which exhaustively takes advantage of the diversity of dominant data and guarantees the model to learn generalizable representations.

**Motivation 2.** To facilitate the learning process of tail classes, we take advantage of the transfer ability of knowledge distillation. The predictive distributions in knowledge distillation contain informative dark knowledge which has low risk of overfitting to specific classes or examples. However, if sharing the same architecture and data, the student model is expected to exhibit similar performance to the teacher model. If distilled directly from teacher model, the student model performance dramatically by distilling another structured model. Particularly, if trained on long-tailed data, the teacher model is naturally biased towards the head classes. In the distillation process, the predictive information for the tail classes is overwhelmed by the head classes. Therefore, the student model guided from such biased model may exhibit an even worse performance.

### 4. Method

As motivated, we propose balanced knowledge distillation to decouple the two goals of long-tailed learning and achieve both simultaneously. In this section, we firstly revisit the conventional knowledge distillation method, then describe the proposed method in detail. In the last, we further analyze the validity of the proposed method from the perspective of gradient.

#### 4.1. Review of Knowledge Distillation

The conventional response-based knowledge distillation [16] consists of two steps. First, a teacher model is trained with cross-entropy loss. Second, the student model is trained together with ground truth targets in addition to the teacher’s soft targets.

Formally, as a supplement of notations in Section 3, we define the network outputs of the teacher model as \( \hat{z} = [\hat{z}_1, ..., \hat{z}_c]^T \) and the class probability \( \hat{p}_i \) is calculated as \( \hat{p}_i = \text{softmax}(\hat{z}_i) \), where \( T \) is a temperature parameter that controls the softness of probability distribution over classes. For the convenience of analysis, we set \( T = 1 \). Similarly, with a slight abuse of the notation, we re-define the student’s probability in a more general form, \( p_i = \text{softmax}(\hat{z}_i) \). The loss for the student is a linear combination of the cross-entropy loss \( L_{CE} \) and a Kullback-Leibler divergence loss \( L_{KL} \):

\[
L_{KD} = \alpha L_{CE} + (1 - \alpha) L_{KL},
\]

where \( L_{KL} = T^2 \sum_i \hat{p}_i \log \frac{\hat{p}_i}{\hat{p}_i} \),

where \( \alpha \) is a hyperparameter controlling the trade-off between the two losses.

#### 4.2. Balanced Knowledge Distillation

Although effective for model compression, the conventional knowledge distillation framework fails to improve the model performance dramatically by distilling another structured identically model. Particularly, if trained on long-tailed data, the teacher model is naturally biased towards the head classes. In the distillation process, the predictive information for the tail classes is overwhelmed by the head classes. Therefore, the student model guided from such biased model may exhibit an even worse performance.

To solve this problem, we propose balanced knowledge distillation, which transfers knowledge with focus. Our BKD follows the teacher-student learning pipeline as mentioned above. The key difference is that we take class priors into consideration and control the importance of distilled information for different classes. Concretely, given a teacher model trained with vanilla cross-entropy loss, the student model is trained by minimizing the summation of an instance-balanced cross-entropy loss and a class-balanced distillation loss. The total loss of balanced knowledge distillation is formulated as

\[
L = L_{CE} + T^2 \sum_i \omega_i \hat{p}_i \log \frac{\hat{p}_i}{p_i},
\]
The weight factor \( \omega_i \) is defined as Eq. 2. In this way, the dark knowledge from tail classes is distilled with focus for facilitating learning on tail classes.

Despite the validity from the perspective of distillation with focus, the nonnegativity of KL-divergence is damaged because the weighted probabilities of teacher model do not sum to one any more. To keep the divergence loss nonnegative, we consider \( \omega^T \hat{p} \) as a whole and normalize it to one. Accordingly, the loss can be rewritten as

\[
L_{BKD} = L_{CE} + T^2 \sum_i \omega_i \log \frac{\omega_i \hat{p}_i}{p_i}.
\]  

(8)

Note that this modification has no impact on optimization as the predictive probabilities of the teacher models contribute zero gradient to the student model. With the normalization, a definite lower bound of the loss function is now guaranteed.

Our BKD framework is summarized in Algorithm 1.

### 4.3. Analysis of Gradient

To better understand the balanced knowledge distillation loss, we make a further analysis from the perspective of gradient. The derivative of the \( L_{BKD} \) with respect to student model’s output \( z \) is

\[
\frac{\partial L_{BKD}}{\partial z_k} = - (\omega_k \hat{p}_k + y_k) + \sum_{i=1}^C (\omega_i \hat{p}_i + y_i) p_k,
\]  

(9)

where the target to mimic for student model is \( \omega_k \hat{p}_k + y_k \). For the convenience of analysis, we normalize this term to sum to one, i.e., \( \sum_{i=1}^C (\omega_i \hat{p}_i + y_i) = 1 \). Thus we have

\[
\frac{\partial L_{BKD}}{\partial z_k} = \begin{cases} 
 p_k - (\omega_k \hat{p}_k + 1), & k = t \\
 p_k - \omega_k \hat{p}_k, & k \neq t 
\end{cases}
\]  

(10)

For a head class \( k, \omega_k \to 0 \). The gradient gap between balanced knowledge distillation loss and cross-entropy loss is negligible. Therefore, the representation learning process for the dominant classes is almost unaffected. For a tail class \( k \), the target consists of both the ground truth target and the teacher’s soft target. The informative predictive knowledge facilitates learning for the tail classes.

From the above analysis, BKD is able to achieve the dual goals of learning generalizable representations and facilitating learning for tail classes.

### 5. Experiments

#### 5.1. Datasets

We evaluate the proposed method on five long-tailed datasets, including Long-tailed CIFAR-10/-100 \([7]\), Places-LT \([33]\), ImageNet-LT \([33]\) and iNaturalist 2018 \([48]\).

**Long-tailed CIFAR-10 and CIFAR-100.** The original version of CIFAR-10 and CIFAR-100 contains 60,000 images, 50,000 for training and 10,000 for validation with 10 and 100 classes, respectively. Following the prior work \([7, 5]\), we use the long-tailed version of both the CIFAR datasets by downsampling examples per class with different ratios. The imbalance ratio \( \rho \) denotes the ratio between the number of training examples between the most frequent class and the least frequent class. We use \( \rho = 10, 50, 100 \) in our experiments.

**Places-LT.** Places365-Standard \([57]\) is a large-scale image database for scene recognition, with more than 1.8 million training images from 365 categories. We construct Places-LT by the same sampling strategy as \([33]\), with the number of images per class ranging from 4980 to 5.

**iNaturalist 2018.** The iNaturalist species classification dataset \([48]\) is a large-scale real-world dataset. The iNaturalist 2018 dataset contains 437,513 training images from 8142 classes, with an imbalance ratio of 500. For fair comparisons, we use the official training and validation splits in our experiments.

**ImageNet-LT.** ImageNet-LT is constructed by sampling a subset of ImageNet-2012 \([42]\) following the Pareto distribution with the power value \( \alpha = 6 \). It has 115.8K images from 1000 categories, with the number of images per class ranging from 1280 to 5.

#### 5.2. Implementation Details

In our experiments, the teacher model and the student model have identical architecture on each dataset. As summarized in Algorithm 1, we first train the teacher model with vanilla cross-entropy loss and then train the student model with the proposed BKD loss. In all experiments, we set \( \beta = 0.9999 \) in Equation 2 and the temperature \( T = 2 \) in Equation 8. All networks are trained with SGD with a
Table 1. Top-1 validation accuracy of ResNet-32 on long-tailed CIFAR-10 and CIFAR-100. † indicates results reported in [56]. ‡ indicates result reported in [51]. Best results are marked in bold.

| Dataset       | Long-tailed CIFAR-10 | Long-tailed CIFAR-100 |
|---------------|----------------------|-----------------------|
| imbalance ratio | 100  50  10 | 100  50  10 |
| CE            | 70.36 74.81 86.39 | 38.32 43.85 55.71 |
| KD [16]       | 70.69 77.92 87.48 | 40.36 45.49 59.22 |
| CB [7]        | 72.11 77.73 86.40 | 32.65 38.57 54.87 |
| LDAM-DRW† [5] | 77.03 81.03 88.16 | 42.04 46.62 58.71 |
| BBN† [56]     | 79.82 82.18 88.32 | 42.56 47.02 59.12 |
| Logit adjustment loss [36] | 77.93 81.64 88.17 | 42.01 47.03 57.74 |
| LFME‡ [51]    | - - - | 42.30 - - |
| **BKD**       | **81.72 83.81 89.21** | **45.00 49.64 61.33** |

Figure 2. Illustration of the confusion matrices by the CE, CB, KD and our BKD on long-tailed CIFAR-10 ($\rho = 100$) momentum of 0.9. Unless otherwise specified, the base learning rate is set to 0.2, with cosine learning rate decay. Other details are given below.

**Implementation details for long-tailed CIFAR datasets.** We employ ResNet-32 as the backbone network and follow the training recipe of [14] for the teacher model and the student model. Both models are trained for 200 epochs with the batch size of 128. The learning rate is initialized as 0.1 and decayed by 0.01 at the 160th epoch and again at the 180th epoch. For long-tailed CIFAR-10, we first train the student model with vanilla knowledge distillation before the 160th epoch, and then deploy our BKD, following [5].

**Implementation details for Places-LT.** We choose pre-trained ResNet-152 as the backbone network, following [33]. Both the teacher model and the student model are trained sequentially for 90 epochs with the batch size of 128.

**Implementation details for ImageNet-LT.** We train ResNet-10 from scratch for ImageNet-LT. Both the models are trained sequentially for 90 epochs with the batch size of 512.

**Implementation details for iNaturalist 2018.** We use ResNet-50 as our backbone network. Both the models are trained sequentially for 90 epochs with the batch size of 6.
Table 2. Top-1 accuracy on iNaturalist 2018. † denotes results reported in the original paper. ‡ denotes results reported in [56].

| Method      | Many | Medium | Few  | All  |
|-------------|------|--------|------|------|
| CE          | 72.2 | 63.1   | 57.4 | 61.8 |
| KD [16]     | 72.6 | 63.8   | 57.4 | 62.2 |
| CB [7]      | 53.4 | 54.8   | 53.2 | 54.0 |
| CB-Focal†   | -    | -      | -    | 61.1 |
| LDAM-DRW‡   | -    | -      | -    | 64.6 |
| BBN‡ [56]   | -    | -      | -    | 66.3 |
| cRT† [21]   | -    | -      | -    | 65.2 |
| BKD         | 67.1 | 66.1   | 67.6 | 66.8 |

Table 3. Top-1 accuracy on Places-LT. † denotes results reported in [51]. ‡ denotes results reported in [21].

| Method      | Many | Medium | Few  | All  |
|-------------|------|--------|------|------|
| CE‡         | 45.7 | 27.3   | 8.2  | 30.2 |
| KD [16]     | 45.7 | 28.1   | 9.0  | 30.7 |
| CB [7]      | 36.5 | 29.7   | 9.2  | 28.2 |
| Focal† [29] | 41.1 | 34.8   | 22.4 | 34.6 |
| OLTR† [33]  | 44.7 | 37.0   | 25.3 | 35.9 |
| LFME† [51]  | 38.4 | 39.1   | 21.7 | 35.2 |
| cRT‡ [21]   | 42.0 | 37.6   | 24.9 | 36.7 |
| BKD         | 41.9 | 39.1   | 30.0 | 38.4 |

Table 4. Top-1 accuracy on ImageNet-LT. † denotes results reported in [51]. * denotes our reproduced results with released code from [21].

| Method     | Many | Medium | Few  | All  |
|------------|------|--------|------|------|
| CE*        | 56.9 | 25.4   | 3.6  | 34.6 |
| KD [16]    | 58.8 | 26.6   | 3.4  | 35.8 |
| CB [7]     | 39.6 | 32.7   | 16.8 | 33.2 |
| Focal† [29] | 36.4 | 29.9   | 16.0 | 30.5 |
| OLTR† [33] | 43.2 | 35.1   | 18.5 | 35.6 |
| LFME† [51] | 47.1 | 35.0   | 17.5 | 37.2 |
| cRT* [21]  | 51.5 | 38.3   | 22.8 | 41.2 |
| BKD        | 54.6 | 37.2   | 20.4 | 41.6 |
| BKD+cRT    | 52.3 | 39.8   | 22.4 | 42.3 |

256.

5.3. Experimental Results

Competing methods. In experiments, we compare our proposed BKD with the standard training and several state-of-the-art methods, including: (1) CE: standard training with vanilla cross-entropy loss; (2) KD: conventional knowledge distillation technique [16] by minimizing Equation 5; (3) CB: re-weighting the loss according to the inverse of the effective number of samples in each class [7], defined as Equation 3. It can also be integrated with focal loss [29], denoted CB-Focal; (4) Focal: focal loss [29]; (5) LDAM-DRW: the integration of LDAM loss and deferred re-weighting strategy [5]; (6) LFME: learning from multiple experts with adaptive learning schedules [51]; (7) OLTR: Open Long-Tailed Recognition [33]. (8) BBN: Bilateral-Branch Network [56]; (9) cRT: first learning representation and then re-training classifier [21]; (10) Logit Adjustment loss: the logit adjusted softmax cross-entropy loss [36].

Results on long-tailed CIFAR datasets. We conduct experiments on long-tailed CIFAR-10/-100 with three different imbalance ratios $\rho = 10, 50, 100$. Table 1 shows the validation accuracy of various methods for long-tailed CIFAR datasets. It can be seen that the proposed BKD significantly outperforms the cross-entropy and knowledge distillation [16]. It also demonstrates that the proposed BKD exhibits superior performance compared with existing state-of-the-art methods, including recently proposed BBN [56] and the logit adjustment loss [36] method.

Results on large-scale datasets. We validate the effectiveness of our method on three large-scale datasets. Be-
Table 5. Accuracy summary of CE, CB, KD and our BKD. The best (worst) results are marked in green (red).

| Method | Long-tailed CIFAR-10 | Long-tailed CIFAR-100 | iNaturalist 2018 | Places-LT | ImageNet-LT |
|--------|----------------------|-----------------------|-----------------|-----------|-------------|
| CE     | 70.4                 | 38.3                  | 61.8            | 30.2      | 34.6        |
| CB     | 72.1                 | 32.7                  | 54.0            | 28.2      | 33.2        |
| KD     | 70.7                 | 40.4                  | 62.2            | 30.7      | 35.8        |
| BKD    | 81.7                 | 45.0                  | 66.8            | 38.4      | 41.6        |

5.4. Comparisons with KD and CB

In this section, we emphatically compare our BKD with the two most relevant methods, i.e., knowledge distillation [16] and class-balanced re-weighting [7].

First, in Figure 2 we visualize four confusion matrices respectively by the models of the cross-entropy training (CE), class-balanced re-weighting (CB), knowledge distillation (KD) and BKD on long-tailed CIFAR-10. The improvement from knowledge distillation and re-weighting is marginal, while BKD significantly improves the performance, especially for tail classes.

Second, we reorganize some of the results into Table 5 for convenient comparison. As we can see, KD is slightly superior to vanilla cross-entropy training due to the ability of transferring knowledge. However, class-balanced re-weighting method is only effective on Long-tailed CIFAR-10 dataset. When dealing with large-scale and extremely imbalanced datasets, CB leads to even worse performance. The phenomena is consistent with our analysis in Section 3.1. Compared to the conventional KD, our BKD consistently outperforms by 4.6% ~ 11.0% on the reported datasets. Moreover, we also visualize the accuracy curves during training for the four methods in Figure 3. We find that BKD leads to higher validation accuracy throughout the training process.

From the above comparisons, we can conclude that our BKD is an effective knowledge distillation framework in long-tailed scenarios, as well as a new state-of-the-art method for long-tailed learning.

6. Conclusion

In this work, we explore knowledge distillation in long-tailed scenarios and propose a novel balanced knowledge distillation framework. We analyze and experimentally demonstrate that our BKD framework effectively distills the knowledge on imbalanced data by learning generalizable representations and facilitating learning for tail classes simultaneously. Experimental results on several long-tailed benchmarks show that our BKD achieves state-of-the-art performance.

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