Class-aware Information for Logit-based Knowledge Distillation

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Abstract

Knowledge distillation aims to transfer knowledge to the student model by utilizing the predictions/features of the teacher model, and feature-based distillation has recently shown its superiority over logit-based distillation. However, due to the cumbersome computation and storage of extra feature transformation, the training overhead of feature-based methods is much higher than that of logit-based distillation. In this work, we revisit the logit-based knowledge distillation, and observe that the existing logit-based distillation methods treat the prediction logits only in the instance level, while many other useful semantic information is overlooked. To address this issue, we propose a Class-aware Logit Knowledge Distillation (CLKD) method, that extents the logit distillation in both instance-level and class-level. CLKD enables the student model mimic higher semantic information from the teacher model, hence improving the distillation performance. We further introduce a novel loss called Class Correlation Loss to force the student learn the inherent class-level correlation of the teacher. Empirical comparisons demonstrate the superiority of the proposed method over several prevailing logit-based methods and feature-based methods, in which CLKD achieves compelling results on various visual classification tasks and outperforms the state-of-the-art baselines.

1. Introduction

The great success of deep learning generally relies on the over-parameterized network to extract the representative features. Thus, deep learning models are usually too cumbersome to be deployed in mobile devices. It gives rise to a ground-breaking research field on Knowledge Distillation [3, 10, 16, 25, 28, 36] (KD), that aims to transfer knowledge from a complicated, pre-trained teacher network to a lightweight student model without sacrificing the performance. Approaches of KD fall into two categories, namely logit-based distillation and feature-based distillation.

The key idea behind the vanilla KD [10], which belongs to logit-based distillations, is that the soft prediction probabilities contain more information than the ground-truth labels alone thus could help maintain the performance of the student model after distillation. Feature-based distillations [3, 16, 34, 36] extract intermediate features of the teacher model to be distilled to the student, and surpass logit-based distillations on various tasks owing to the flexibility of feature representation, and has become the mainstream KD in recent years.

However, logit-based distillation should achieve comparable performance since logits are at a higher semantic level than intermediate features. Thus, the potential of logit-based distillation may still need to be fully explored. Recently, there are also some researches studying the weakness of logit-based distillation and proposing improvements to extract information from logits [23, 41]. However, we notice that they only consider the instance-level information,
and we argue that the instance-level information alone is not enough to transfer some vital semantic information, such as the \textit{inter-instance knowledge}.

As shown in Fig. 1, the image batch is fed into the teacher and student networks to output the prediction matrices. Rows of the matrices correspond to the class probabilities that the network attempts to determine to which class the instance belongs. Columns of the matrices can be viewed as the \textit{class representation}, and each entry of a single column could represent the similarity between the class and the input instance, epitomizing the inter-instance knowledge. In this way, the \textit{inter-instance knowledge} and the \textit{intra-instance knowledge} could be obtained accordingly.

Based on the above observation, we introduce a simple yet effective logit distillation method, termed class-aware Logit Knowledge Distillation (CLKD), that blends inter-instance and intra-instance knowledge and allows the class correlation information to be embraced by class representation. As shown in Fig. 1, we first use the logit matrix transposition to extract inter-instance knowledge, which is complementary to intra-instance information, then we employ a class correlation loss to let the student mimic the teacher’s class correlation. Besides, from Fig. 1, we observe that the amplitude gap of predictions between teacher and student is huge. Hence, we design a normalized metric to calculate the discrepancy between teacher and student to boost the distillation. Armed with these mechanisms, we could fully exploit the inter-instance and intra-instance information, making the distillation more effective.

To demonstrate the effectiveness of our approach, we conduct extensive experiments on standard benchmark datasets and witness that CLKD consistently outperforms all the state-of-the-art methods we compared with, including prevalent feature distillation methods. Besides, since intermediate features also include inter-feature and intra-feature knowledge, we can adopt our approach to feature-based distillation to make further improvement.

Our main contributions can be summarized as follows:

- We propose reusing the logit matrix so as to combine the intra-instance and inter-instance knowledge. The inter-instance knowledge obtained by transposing the logit matrix can reduce the gap between the teacher and the student models.
- We introduce a class correlation loss to mimic the inherent class relationship of the teacher. And we use normalization to make the output of the teacher and student models more comparable.
- Our approach consistently achieves superiority over the state-of-the-art baselines on extensive experiments, considering different network architectures and various tasks (classification, segmentation, feature transferring).

2. Related Work

The concept of KD was first proposed by Hinton \textit{et al.} [10]. KD directs the student training by leveraging the dark knowledge of teacher model, and enhances the performance of student model successfully. Dark knowledge, which can provide additional information to supervise the training process compared to simply utilizing ground-truth labels, is obtained from teacher networks in features or soft
logits. Therefore, the studies on KD can be divided into two categories, i.e., logit-based distillation and feature-based distillation.

2.1. Logit-based Distillation

Hinton et al. introduce a temperature scaling method on prediction logits to distill the teacher’s dark knowledge in the category similarity probabilities. In the tenets of logit-based distillation, the similarity probabilities from the negative logits may provide extra supervision and better regularization [35]. Thus, logit-based distillation improves the performance and generalization of student model; however, there is still a big gap between teacher and student. Several subsequent works attempt to close the gap. Hedge et al. [9] improve the logit distillation by inducing variational inference. Mirzadeh et al. [23] introduce an extra small-size assistant network to close the gap between teacher and student. Zhao et al. [41] decouple the classical KD loss so as to enable the distillation loss to play their roles more effectively and flexibly. Kim et al. [17] propose a logit matching strategy for distillation and show its superiority over conventional Kullback-Leibler divergence [15] on temperature-scaled logits. Chen et al. [2] reuse the teacher’s classifier to mitigate the representation gap between teacher and student, and achieve the best performance so far; however, introducing the teacher’s classifier aggravates the deployment costs, and it may violate the tenets of knowledge distillation. Besides, the problem of performance gap is still far from being solved.

2.2. Feature-based Distillation

To alleviate the performance gap between teacher and student in logit distillation, considerable researches on knowledge distillation concentrate on leveraging the feature information embedded in intermediate layers. Rather than distilling the prediction logits, feature-based distillation aims to force the student to mimic the feature representations of the teacher. Feature distillation is first introduced in FitNet [25], which utilizes the ‘hint’ to force the intermediate features of student to mimic the corresponding part of teacher. Inspired by FitNet, a variety of methods have been proposed to match the features. To be specific, attention map [36], neural selectivity [13] and paraphrased information [16] of the teacher network are proposed to express the knowledge. Feature-based distillation induces richer information and provides higher flexibility for the knowledge transfer. However, due to the difference in feature size between teacher model and student model, feature-based distillation requests adding extra layer transformation to align the different sizes. Therefore, the additional computation and memory overhead would affect the wide application of feature-based distillation.

Therefore, we revisit the logit-based distillation in this work and wish to take fully utilization of its potential on KD. Intuitively, logits are at a higher semantic level than intermediate features, and logit-based distillation should achieve comparable performance. We focus on what limits logit distillation and propose a novel method that gain comparable or even higher performance than the state-of-the-art baselines.

To some extent, our key idea is related to the previous study on Contrastive Clustering (CC) [20]. CC introduces the cluster representation in instance-wise contrastive learning to avoid mode collapse, which is the primary concern in contrastive learning [4, 7]. Different from CC, our method purposes to reduce the performance gap in the KD paradigm, rather than alleviating the mode collapse which is not the main cause of performance degrade in KD. In addition, compared to adding clustering projections in CC, our model makes no necessity of adding extra branches in the framework of logit distillation.

3. Methodology

In this section, we first briefly review the vanilla Knowledge Distillation (KD). Second, to grasp the teacher knowledge more effectively, we transpose the output matrix to capture the class-instance dependency. To mitigate the amplitude gap of the outputs between teacher and student, we utilize a novel metric for distillation, termed the Normalized Mean-Squared Error (NMSE). Then, inspired by the idea behind Correlation Congruence [24], we further propose a strategy to grasp the class correlation information learned by the teacher. In the end, we show that the proposed method can also be applied to feature-based distillation.

3.1. Vanilla Knowledge Distillation

Here we briefly recap the basic idea of vanilla knowledge distillation [10] and provide necessary notations for knowledge distillation. In the vanilla KD, information from the teacher is epitomized and transferred in the form of softened logit probabilities. The total loss can be expressed as:

\[
L = (1 - \alpha)L_{CE}(\sigma(z_s), y) + \alpha L_{KD}(z_s, z_T),
\]

where \(L_{CE}(\cdot, \cdot)\) denotes the cross-entropy classification loss, \(\sigma(\cdot)\) is the softmax function and \(y\) the one-hot vector indicating the corresponding label. The distillation loss \(L_{KD}(\cdot, \cdot)\) is calculated by using \(z_s, z_T\), i.e., the predictions of student and teacher, respectively. The hyper-parameter \(\alpha \in [0, 1]\) weights the knowledge distillation loss and cross-entropy loss. In the vanilla KD, Hinton et al. utilize the temperature-scaled Kullback-Leibler divergence to enforce the student mimic the softened categorical probability distribution of the teacher:

\[
L_{KD} = \tau^2 L_{KL}(\sigma(z_s/\tau), \sigma(z_T/\tau)),
\]
Given a mini-batch of data \( \{ x_n \}_{n=1}^B \), we pick the outputs before the softmax layer as our logit matrix. We then regard each of its column vector as the representation of the corresponding class. Each entry of the column vector represents the similarity between this class and the corresponding instance, which is the class-instance similarity knowledge. As shown in Fig. 1, the critical component of our method is the “class distillation”. Through matrix transposition, the inter-instance information could be transferred by forcing the student to produce a similar class representation to the teacher’s. The loss function is defined as:

\[
L_{KD} = L_{ins} + \beta L_{cla},
\]

\[
L_{ins} = L_{NMSE}(Z_s, Z_t),
\]

\[
L_{cla} = L_{NMSE}(\text{norm}^T(Z_s), \text{norm}^T(Z_t)),
\]

\[
L_{NMSE}(p, z) = \frac{\| p \|_2^2 - \| z \|_2^2}{\| z \|_2^2},
\]

Figure 2. We use class correlation distillation to guide the student to learn the class correlation information of the teacher. Given the \((B \times C)\) logit matrices, we develop \(C \times C\) class correlation matrices, and compute the difference of the correlation matrices between the teacher and the student.

where the temperature \( \tau \) is used for logit softening. When \( \tau \) equals 1, \( \sigma(z/\tau) \) becomes the standard softmax function. When \( \tau \) increases, the probability distribution becomes softer, providing extra information as to which classes are more similar to the ground-truth class in the teacher’s mind.

3.2. Categorical Level Knowledge Distillation

The vanilla KD assumes that the teacher’s prediction on a single image would carry the instance-level class similarity knowledge that can be transferred by distillation. In this work, we notice that the information in the teacher’s prediction has not been fully exploited because the vanilla KD treats the prediction outputs only in the instance level. In this subsection, we aim to learn from the output matrix from two perspectives. One is from the instance-wise probability distribution, the other is from categorical representations which may transfer knowledge at a higher semantic level.

Motivation. For a mini-batch of instances in size \( B \), the logit matrices \( z_T, z_S \in \mathbb{R}^{B \times C} \), where \( C \) is the number of categories. The row vectors are instance-level categorical probability prediction. The vanilla KD captures the categorical probability information by simulating the teacher’s logit matrix row-wisely. However, the column vectors of the logit matrix actually contain rich class-level information across the instances. While the existing prevailing logit distillation methods only construct the relationships within a single image, but overlook semantic dependencies across different images.

To this end, we propose a novel KD method that exploits the logit matrix beyond the instance-wise level. Specifically, we retrieve both the instance-wise information and the class-wise information from the logit matrices of teacher and student, thus transferring the teacher’s knowledge more comprehensively.

3.2.1 Class Distillation

Given a mini-batch of data \( \{ x_n \}_{n=1}^B \), we pick the outputs before the softmax layer as our logit matrix. We then regard each of its column vector as the representation of the corresponding class. Each entry of the column vector represents the similarity between this class and the corresponding instance, which is the class-instance similarity knowledge. As shown in Fig. 1, the critical component of our method is the “class distillation”. Through matrix transposition, the inter-instance information could be transferred by forcing the student to produce a similar class representation to the teacher’s. The loss function is defined as:

\[
L_{KD} = L_{ins} + \beta L_{cla},
\]

\[
L_{ins} = L_{NMSE}(Z_s, Z_t),
\]

\[
L_{cla} = L_{NMSE}(\text{norm}^T(Z_s), \text{norm}^T(Z_t)),
\]

\[
L_{NMSE}(p, z) = \frac{\| p \|_2^2 - \| z \|_2^2}{\| z \|_2^2},
\]

where \( L_{ins} \) is the conventional instance-wise distillation loss, and \( L_{cla} \) is our proposed class-wise distillation loss. Coefficient \( \beta \) is used to trade off the two terms. \( p \) and \( z \) denote two different encodings or distributions, which in our case are the logits of teacher and student, respectively. The normalization (\( L_2 \) norm) before matrix transposition is essential for alleviating the impairment to the class representation, due to the amplitude gap between different rows. Kim et al. [17] propose the logit matching strategy (MSE between logits) for distillation and show the priority of logit matching over conventional KL divergence. However, due to the inevitable gap in model size and parameter number between teacher and student, the norm of outputs can hardly share a similar amplitude, restricting the simulation of simple logit matching. Therefore, we normalize the logits before calculating the MSE loss and propose a novel metric, called NMSE, to calculate the difference between teacher and student during the distillation. In Sec. 5.2.2, we will test the performance when using other metrics to measure the distribution discrepancy between teacher and student, such as MSE, KL divergence, etc.

3.2.2 Class Correlation Loss

As we encode the class representation in logit transposition, our class representation may manifest the correlation be-
between different classes. The question is: how can we learn the classification support of the student? Inspired by the idea of Correlation Congruence [24] to capture the instance correlation, we attempt to force the student’s classification support to resemble the teacher’s. Hence, we calculate the correlation matrix of teacher and student, respectively. The classification support matrices of teacher and student has the following form:

$$B(Z) = \frac{1}{C-1}\sum_{j=1}^{C} (Z_{j} - \bar{Z})^{T}(Z_{j} - \bar{Z}),$$

(4)

where $\bar{Z} \in \mathbb{R}^{C}$ denotes the mean vector across columns and $Z_{j}$ is the $j$-th column vector. We force the computed class correlation of the student to resemble the teacher’s. Thus the Class Correlation (CC) loss is as shown in Eq. (5), calculated by the element-wise sum of the discrepancy of the class correlation matrices of teacher and student.

$$L_{CC}(S,T) = \frac{1}{C^{2}}\|B(Z_{S}) - B(Z_{T})\|_{2}^{2},$$

(5)

where $B(Z_{S})$ and $B(Z_{T})$ are the correlation matrix of student and teacher, respectively. The class correlation loss encourages the student to capture the class correlation information of the teacher. To sum up, the overall loss function is weighted by the teacher-student KD loss, as well as the classification loss and the correlation loss:

$$L = \lambda L_{CE} + \mu L_{KD} + \nu L_{CC},$$

(6)

where $\lambda, \mu, \nu \in [0, 1]$, $\lambda + \mu + \nu = 1$ are hyper-parameters controlling the importance of each term. We illustrate the architecture and loss function of our approach in Fig. 1.

3.3. Feature Matrix Transposition

Feature distillation exploits the knowledge in intermediate layers, thus adding the flexibility of the teacher’s knowledge. In this subsection, we aim to adapt our class-aware logit-based distillation to the feature distillation to grasp the feature information more properly. Generally speaking, the conventional feature-based distillation loss can be formulated as:

$$L_{FeaKD}(F_{s}(x), F_{t}(x)) = L_{Fea}(\Phi_{s}(F_{s}(x)), \Phi_{t}(F_{t}(x))),$$

(7)

where $F_{s}(x)$ and $F_{t}(x)$ are intermediate feature maps of student and teacher model, respectively. The transformation functions, $\Phi_{s}(F_{s}(x))$ and $\Phi_{t}(F_{t}(x))$, are usually applied for aligning feature maps of student and teacher with different shapes. And $L_{Fea}$ is the distance function to match their feature maps. Similar to our logit-based distillation, feature-based distillation preserves information of the features, i.e., the instance-wise features. We attempt to utilize the cross-instance information on feature-based distillation. First, the aligned feature map matrices in $\mathbb{R}^{B \times D}$, are matrices in batch size $B$ and dimension $D$ for each instance. In our logit distillation, the encoded class representation may hint the relationship between instances, thus the cross-instance feature representation may also imply the similarity of instances. For example, the intermediate feature may have various dimensions, which may represent different representations of the image. Each of these features can be symbolized by different instances, which is similar to the class-wise distillation log in logit distillation. We could exploit the intra-instance and the inter-instance feature information similarly. We apply our approach on several feature-based distillation such as FitNet [25], AT [16], CRD [28] and SRRL [33]; and in Sec. 5.1, we will illustrate the effectiveness of applying our method to these feature-based distillations.

4. Experiments

To show the effectiveness of our approach, we compare CLKD with several state-of-the-art approaches by evaluating on several image classification tasks. We also evaluate our approach with the teacher-free distillation paradigm in the Appendix.

4.1. Experimental Setup

Datasets. We evaluate the effectiveness of CLKD on the CIFAR-100 dataset [18], which consist of $(32 \times 32)$ color scaled images containing objects in 100 classes. We also test on ImageNet dataset [26] to show the efficiency on large-scale classification, of which all the images are resized to $(224 \times 224)$. We operate the standard data augmentation and normalization as conducted in [8, 12, 37] on the above two datasets.

We conduct a series of classification with typical convolutional neural network architectures and lightweight networks on the CIFAR-100 and ImageNet datasets. Our implementation for CIFAR-100 follows the practice in [3]. A variety of teacher-student pairs based on popular visual network architectures are tested, including ResNet [8], VGG [27], WideResNet (WRN) [37], and lightweight networks such as MobileNet [11] and ShuffleNet [40].

Training Details for CIFAR-100. For the training of CIFAR-100, we adopt SGD optimizer with 0.9 Nesterov momentum, the total training epoch is predetermined to 240, and we divide the learning rate by 10 at epochs 150, 180, and 210. For the training, we use the standard data augmentation technique, i.e., flipping and random cropping. The initial learning rate is set to 0.01 for lightweight architectures, and 0.05 for the other series. We train with weight decay $5e^{-4}$ for regularization.

Training Details for ImageNet. For the training of ImageNet, we follow the practice suggested by the PyTorch official. We train the models for 120 epochs. The initial learning rate is set to 0.1, and divided by 10 for every 30
epochs. The batch size is 512, and the weight decay rate is $1e^{-4}$. Besides, we deploy the cosine schedule with 5-epoch warm-up for training. All experiments on the ImageNet dataset are trained on 8 GPUs for 120 epochs if not specified. The optimal results are chosen to maximize the top-1 accuracy on the validation set.

**Baselines.** We compare our approach with two kinds of prevalent and advanced knowledge distillation baselines, *i.e.*, logit-based distillation and feature-based distillation:

- **Logit-based distillation** includes the vanilla KD [10], DTD-KA [30], VBD [9] and DKD [41].
- **Feature-based distillation** includes FitNet [25], AT [36], SP [29], VID [1], MGD [34], SRRL [33], CRD [28] and SemCKD [3].

### 4.2. Main Results

Tab. 1 to Tab. 3 show a comprehensive performance comparison of various approaches based on student-teacher network combinations of various architectures, such as ResNet and VGG.

**Results on CIFAR-100.** In Tabs. 1 and 2, we compare our CLKD with several prevalent distillation methods on CIFAR-100 based on two kinds of teacher-student network combination, *i.e.*, the teacher-student pairs share similar architectures (ResNet110/ResNet-32, VGG-13/VGG-8) or heterogeneously architectures (ResNet-32×4/ShuffleV1, VGG-13/MobileV2). As can be seen from the two tables, CLKD consistently outperforms other logit-based and feature-based distillation methods, achieving state-of-the-art performance.

For comparison on similar architectures, logit-based distillation, except for DKD [41] and our CLKD, show inferior results to feature-based approaches; it may be owing to the flexibility of feature learning. However, when we switch the student-teacher pairs from uniform to heterogeneous architectures, the feature-based approaches show less superiority in homogeneous pairs, even sometimes underperform the vanilla KD. We ascribe this phenomenon to the feature-map gap between the student and different architectural teachers, which is hardly avoidable in feature distillation. Even in uniform architectural pairs, feature-based distillation achieves better performance at the expense of computational efficiency due to the inevitable computation of feature-map transformations, which may curb the industrial application of distillation. Our method surpasses the best feature-based distillation method without introducing feature map transformations, alleviating tedious computation without sacrificing performance.

**Results on ImageNet.** We conduct experiment using ResNet-34 as the teacher and ResNet-18 as the student. Similar results on CIFAR-100 also occur in the ImageNet experiment. As shown in Tab. 3, our CLKD achieves the best classification performance on both Top-1 and Top-5 error rates compared with other existing distillation methods, which illustrates the robustness of our method on large-scale dataset learning.

### 5. Further Discussion

To better understand class-aware distillation, we conduct further experiments from four perspectives. First, we apply CLKD on several feature-based distillation methods and show our effectiveness on feature-based distillation. Second, we perform the ablation study to show the indispensability of our proposed loss. Then the sensitivity analysis is operated to figure out what influences the distillation. The experiments on other visual evaluations beyond classification tasks are shown in the Appendix, such as dense prediction and knowledge transfer. In Appendix, we also conduct visualization and training efficiency analysis to show the superiority of our CLKD over the state-of-the-art methods in performance and efficiency.

#### 5.1. Applicability on Feature Distillation

To show the applicability of CLKD on feature-based distillation approaches, we embed our module in logit-based distillation to several mainstream feature-based distillation approaches and experiment on CIFAR-100 compared with the original feature-based distillation. From Tab. 4, we observe that all the feature-based distillation methods are improved when adding the feature-aware modules, and the highest enhancement occurs in the SRRL framework.

Hence, our approach encourages feature-based distillation without inducing extra computation costs.

#### 5.2. Ablation Study

We conduct thorough ablation studies on CLKD from various views. We choose ResNet-32×4 as the teacher for the following test.

##### 5.2.1 Class-aware Knowledge and Correlation Loss

We conduct the ablation study on the proposed loss using CIFAR-100 dataset, and the results are shown in Tabs. 5 and 6. In Tab. 5, ‘KD’ indicates we use Hinton’s KD framework for the comparison group, which employs KL divergence to calculate the distribution discrepancy; ‘w/o cla’ and ‘w/o cor’ mean we use the proposed NMSE loss to distill, but without the class distillation and the class correlation loss, respectively. We observe that in both two networks, NMSE shows its superiority to KL divergence; in addition, the performance becomes even better with the exploitation of class-aware information and class correlation simulation, confirming the importance of the proposed NMSE loss, class-aware information and class correlation loss. Similar results are also presented in Tab. 6, in which
Table 1. Top-1 test accuracy (%) of various distillation approaches on CIFAR-100. The teacher and student pairs share similar architectures. Each experiment is repeated three times, and we report the mean and standard deviation of the top-1 accuracy. The best results appear in bold.

| Type   | Student | ResNet-8×4 | VGG-8 | ResNet20 | WRN-40-1 | WRN-16-2 | ResNet32 |
|--------|---------|------------|-------|----------|----------|----------|----------|
| —      | Teacher | ResNet-32×4 | VGG-13 | ResNet56 | WRN-40-2 | WRN-40-2 | ResNet110 |
| Logits | KD [10] | 74.12 ± 0.15 | 72.66 ± 0.13 | 70.66 ± 0.22 | 73.42 ± 0.22 | 74.92 ± 0.20 | 73.02 ± 0.16 |
| —      | DTD-KA [30] | 73.78 ± 0.22 | 72.98 ± 0.14 | 70.99 ± 0.24 | 73.49 ± 0.16 | 74.73 ± 0.20 | 72.88 ± 0.13 |
| —      | VBD [9] | 74.31 ± 0.21 | 73.21 ± 0.17 | 71.13 ± 0.17 | 73.62 ± 0.22 | 75.10 ± 0.20 | 73.21 ± 0.22 |
| —      | DKD [41] | 76.32 ± 0.26 | 74.68 ± 0.23 | 71.79 ± 0.17 | 76.11 ± 0.17 | 76.55 ± 0.14 | 74.11 ± 0.17 |
| Logits | FitNet [25] | 73.89 ± 0.22 | 73.54 ± 0.12 | 71.52 ± 0.16 | 74.12 ± 0.20 | 75.75 ± 0.12 | 75.22 ± 0.07 |
| —      | AT [36] | 74.57 ± 0.17 | 73.63 ± 0.12 | 71.76 ± 0.14 | 74.43 ± 0.11 | 75.28 ± 0.13 | 73.32 ± 0.11 |
| —      | SP [29] | 73.90 ± 0.17 | 73.44 ± 0.21 | 71.48 ± 0.11 | 73.17 ± 0.21 | 73.54 ± 0.21 | 73.63 ± 0.21 |
| —      | VID [1] | 74.49 ± 0.21 | 73.96 ± 0.17 | 71.71 ± 0.08 | 74.20 ± 0.18 | 74.79 ± 0.20 | 73.89 ± 0.19 |
| —      | MGD [34] | 74.41 ± 0.16 | 74.28 ± 0.21 | 71.68 ± 0.24 | 74.78 ± 0.22 | 75.98 ± 0.14 | 74.10 ± 0.14 |
| —      | SRRL [33] | 75.37 ± 0.12 | 74.68 ± 0.24 | 72.01 ± 0.27 | 74.98 ± 0.21 | 75.55 ± 0.14 | 74.21 ± 0.11 |
| —      | CRD [28] | 75.59 ± 0.23 | 73.88 ± 0.18 | 71.68 ± 0.11 | 75.51 ± 0.22 | 76.01 ± 0.11 | 73.48 ± 0.16 |
| —      | SemCKD [3] | 75.58 ± 0.22 | 74.42 ± 0.21 | 71.98 ± 0.17 | 74.78 ± 0.21 | 75.42 ± 0.15 | 74.12 ± 0.22 |
| Logits | CLKD (Ours) | 77.68 ± 0.22 | 75.01 ± 0.12 | 72.71 ± 0.23 | 76.12 ± 0.21 | 76.32 ± 0.17 | 74.82 ± 0.28 |

Table 2. Top-1 test accuracy (%) of the various distillation approaches of different architectures on CIFAR-100. Each experiment is repeated three times, and we report the mean and standard deviation of the top-1 accuracy. The best results appear in bold.

| Type   | Student | ShuffleV1 | WRN-16-2 | VGG-8 | MobileV2 | MobileV2 | ShuffleV1 |
|--------|---------|-----------|----------|-------|----------|----------|-----------|
| —      | Teacher | ResNet-32x4 | VGG-32x4 | ResNet50 | WRN-40-2 | WRN-40-2 |
| Logits | KD [10] | 74.00 ± 0.16 | 74.90 ± 0.29 | 73.81 ± 0.24 | 69.07 ± 0.26 | 67.37 ± 0.22 | 74.83 ± 0.13 |
| —      | DTD-KA [30] | 73.99 ± 0.12 | 74.11 ± 0.21 | 73.91 ± 0.21 | 68.99 ± 0.41 | 67.41 ± 0.12 | 74.90 ± 0.14 |
| —      | VBD [9] | 74.21 ± 0.21 | 74.32 ± 0.22 | 74.02 ± 0.22 | 69.22 ± 0.21 | 67.77 ± 0.21 | 75.10 ± 0.11 |
| —      | DKD [41] | 77.42 ± 0.11 | 76.68 ± 0.22 | 75.98 ± 0.22 | 69.47 ± 0.21 | 69.71 ± 0.26 | 76.41 ± 0.13 |
| Logits | FitNet [25] | 74.82 ± 0.13 | 74.70 ± 0.35 | 73.72 ± 0.18 | 68.71 ± 0.21 | 63.16 ± 0.23 | 74.11 ± 0.23 |
| —      | AT [36] | 74.76 ± 0.19 | 75.38 ± 0.18 | 73.45 ± 0.17 | 68.64 ± 0.12 | 63.42 ± 0.21 | 73.73 ± 0.19 |
| —      | SP [29] | 73.80 ± 0.21 | 75.16 ± 0.32 | 73.86 ± 0.15 | 68.48 ± 0.22 | 65.42 ± 0.21 | 74.01 ± 0.11 |
| —      | VID [1] | 74.28 ± 0.12 | 74.85 ± 0.35 | 73.75 ± 0.21 | 68.91 ± 0.21 | 65.70 ± 0.28 | 74.41 ± 0.26 |
| —      | MGD [34] | 75.34 ± 0.21 | 75.65 ± 0.08 | 73.98 ± 0.27 | 69.22 ± 0.24 | 66.23 ± 0.22 | 74.89 ± 0.22 |
| —      | SRRL [33] | 75.38 ± 0.31 | 75.46 ± 0.13 | 74.21 ± 0.20 | 69.34 ± 0.20 | 68.48 ± 0.31 | 75.22 ± 0.19 |
| —      | CRD [28] | 75.46 ± 0.23 | 75.70 ± 0.29 | 74.42 ± 0.21 | 69.87 ± 0.17 | 69.73 ± 0.21 | 76.05 ± 0.23 |
| —      | SemCKD [3] | 75.41 ± 0.11 | 75.65 ± 0.23 | 74.68 ± 0.22 | 69.88 ± 0.30 | 68.78 ± 0.22 | 74.81 ± 0.21 |
| Logits | CLKD (Ours) | 77.88 ± 0.22 | 77.61 ± 0.21 | 76.49 ± 0.24 | 70.89 ± 0.14 | 71.02 ± 0.21 | 76.22 ± 0.11 |

Several prevalent metrics are employed to test the effect of class knowledge; thus, we conclude that the class information is beneficial for logit distillation.

**5.2.2 Different Metric and Label-free Testing**

From Tab. 6, we also observe that the proposed NMSE loss outperforms other metrics for the calculation of discrepancy between the student and teacher in knowledge distillation. In addition, we also test the label-free learning in distillation which we cut down the cross-entropy loss. Even without the groundtruth labels, our performance only drops 0.53% from 77.68% to 77.11%. In contrast, the MSE results drop 0.8% in the class-aware distillation and even worse in the ‘w/o class’ condition, in which the MSE results drop 1.37%. Thus we can conclude that CLKD is less sensitive to the vacancy of labels.
5.3. Sensitivity Analysis

Analysis on Coefficient. Here we conduct sensitivity analysis on the effect of hyper-parameter $\mu$ and $\beta$ on the performance. We conduct experiments on CIFAR-100 dataset with $\mu$ and $\beta \in \{0, 1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0, 10.0\}$. We set the teacher-student combination as ResNet-32×4/ResNet-8×4 and ResNet50/VGG-8 on CIFAR-100. Fig. 3 shows the accuracy of each experiment with varying hyperparameters. We keep all settings the same as the basic setting in the main experiments except the testing hyperparameter. The results show that CLKD is robust to hyperparameter $\beta$ when $\beta \geq 1$. In addition, we notice that the worst performance happens when hyperparameter $\mu$ or $\beta$ is set to 0, demonstrating the indispensability of our class-aware distillation.

Analysis on Batch Size. Tab. 7 reports the effect on the distillation performance with different batch size. One can observe that when the batch size rises from 64 to 512, the accuracy improves. This phenomenon lies on the ground that large batch size instances may provoke better class-level information. We also notice that the distillation does not work well when the batch is too large; with a 1024 batch, the performance is lower when we use a 512 batch. This phenomenon may due to the redundancy of class-instance similarity when the batch is too large.

Analysis on Class Correlation. As shown in Tab. 8, we may conclude that slight class correlation simulation encourages the student mimic the the teacher, which benefits...
the distillation. However, if the class correlation loss is too large, it would hinder the basic instance-level knowledge.

6. Conclusion

In this work, we propose a novel logit-based distillation method to capture the inter-instance as well as intra-instance knowledge by simple class representation. Our class representation module may exploit the latent relationship information across the instances. Our proposed method CLKD achieves state-of-the-art performance on various visual classification tasks. Given its success on classification tasks, we assume that our method would also work for more complicated visual tasks such as object detection and semantic segmentation. In our future work, we will study how to learn context-structural features for dense prediction and adopt our method on more complicated visual tasks.

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| Coefficient | 0   | 0.2 | 0.5 | 1   | 5   | 10  |
|-------------|-----|-----|-----|-----|-----|-----|
| Acc. (%)    | 76.68 | 77.68 | 77.31 | 77.11 | 76.61 | 76.72 |

Table 8. Effect of class correlation loss coefficient on distillation. (Distilling ResNet-8×4 from ResNet-32×4 on the CIFAR-100 dataset). The best result appears in bold.
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Appendix

A. Self-Distillation Results.

To further demonstrate that CLKD may also improve the teacher-free distillation, we use the teacher-free framework proposed in CS-KD [35] and replace the original loss in CS-KD with our loss as in Eq. 6. We evaluate CLKD on ImageNet with several prevailing teacher-free distillation methods. As shown in Tab. 9, our approach exhibits higher performance than other self-knowledge distillation baselines on the ImageNet dataset. We not only consider the prevailing ResNet architectures (e.g., ResNet-50), but also test on the ResNeSts [38] and ResNeXts [31] networks. And the accuracy on ImageNet is improved by 2.01%, 1.31% on ResNet-based architectures. We also achieve similar enhancement with ResNeSts and ResNeXts, which show that our approach still work in the teacher-free paradigm.

B. Feature Transferability

We continue to conduct several experiments to examine the feature transferability of CLKD. As shown in Tab. 10, we train linear fully-connected (FC) layers as the classifier with the feature extractor frozen for STL-10 and Tiny-ImageNet datasets. We use an SGD optimizer with 0.9 momentum and no weight decay strategy in classifier training. We set the batch size to 128, and the number of total epochs is 40. Our initial learning rate is set to 0.1, then divided by 10 for every 10 epochs. From Tab. 10, we observe that our method beats all existing techniques, manifesting its feature transferability. Besides, the best results occur when we use CLKD on SRRL, which further demonstrates its extensibility on feature distillation.

C. Structured Knowledge Distillation

Unlike classification, semantic segmentation aims at dense pixel prediction, thus requires the holistic understanding of structured context across pixels. To show that our approach CLKD may learns semantic structural knowledge, we conduct several knowledge distillation test on dense pixel tasks—semantic segmentation. As shown in Tab. 11, conventional logit-based knowledge distillation dealing with structural prediction tasks may not achieve a desirable result and even has a deteriorating impact. This is because only considering instance-level information may lead to a loss of structured context among pixels. We observe the best performance occurs when using SKD [21], which is designed for segmentation. And our approach underperforms SKD only slightly and outperforms all the KD approaches designed for classification. Therefore our method captures the structural information in the logit distillation framework.

D. Training Efficiency

We evaluate the training efficiency of our approach with several existing distillation methods. As shown in Tab. 12, CLKD achieves the best performance without extra training consumption (e.g., training time and extra parameters). Therefore our CLKD outperforms all existing feature-based distillation methods in performance and efficiency, and may be applied in practicality.

E. Visualization

We present t-SNE visualizations of several existing distillation methods and our CLKD. From Fig. 4, we may observe that our CLKD representations show better separability compared with other distillation methods such as CRD, SRRL, and vanilla KD. This result confirms that our class-aware distillation learns more discernable features and benefits the classification performance.
Table 9. Comparison of self-distillation methods on ImageNet dataset using models of ResNet, ResNeSt and ResNeXt. We report the top-1 accuracy (%) and the value in the last column are the performance improvement compared to vanilla classification. The best results on each architecture appear in bold.

| Model          | Baseline | DDGSD [32] | BYOT [39] | CS-KD [35] | SLA+SD [19] | FRSKD [14] | BAKE [6] | CLKD | ∆     |
|----------------|----------|------------|-----------|------------|-------------|------------|----------|------|-------|
| ResNet-50      | 76.80    | 77.10      | 77.40     | 77.61      | 77.20       | 76.68      | 78.00    | **78.81** | +2.01 |
| ResNet-101     | 78.60    | 78.81      | 78.66     | 78.99      | 79.22       | 79.31      |          | **79.91** | +1.31 |
| ResNeSt-50     | 78.40    | 78.66      | 78.60     | 78.71      | 78.98       | 79.91      |          | **80.40**  | +2.00 |
| ResNeXt-101 (32×4d) | 78.71 | 78.99     | 78.00     | 78.24      | 78.68       | 79.11      | 80.12    | **80.12**  | +1.41 |

Table 10. We conduct the experiment of feature transfer by using the representation learned from CIFAR100 to STL-10 and TinyImageNet datasets. We freeze the network and train a linear classifier on top of the last feature layer to perform 10-way (STL-10) or 200-way (TinyImageNet) classification. SRRL+ denotes that we extend our cluster-aware method on feature-based distillation SRRL. We use the combination of teacher network ResNet-32×4 and student network ResNet-8×4. The best result appears in bold, and the second best is underlined.

| metric (%) | Teacher | Student | KD | AT | FitNet | SRRL | CLKD | SRRL+ | Teacher |
|------------|---------|---------|----|----|--------|------|------|-------|---------|
| CIFAR100→STL-10 | 71.33 | 73.01  | 73.67 | 73.12 | 75.12  | 76.24  | **76.67** | 70.60 |
| CIFAR100→TinyImageNet | 35.10 | 35.39  | 35.42 | 35.55 | 37.13  | 38.41  | **38.57** | 34.20 |

Table 11. The segmentation performance comparison on Cityscapes [5] val dataset. Teacher: ResNet101 and Student: ResNet18. The mIoU measures the mean intersection of the prediction and the groundtruth pixels. The best result appears in bold, and the second best is underlined.

| Metric (%) | Teacher | Student | KD | AT | FitNet | CRD | SKD [21] | CLKD |
|------------|---------|---------|----|----|--------|-----|----------|------|
| mIoU       | 78.56   | 69.10   | 68.70 | 69.71 | 69.99  | 71.51 | **72.54** | 72.22 |

Table 12. Training time (per batch), extra parameters versus accuracy on CIFAR-100. Teacher: ResNet-32×4, student: ResNet-8×4.

| Method  | Accuracy (%) | Time (s) | Extra params |
|---------|--------------|----------|--------------|
| KD      | 73.33        | **12**   | 0            |
| AT      | 74.57        | 13       | 0            |
| FitNet  | 73.89        | 14       | 16.8K        |
| CRD     | 75.59        | 35       | 12.3M        |
| SemCKD  | 75.58        | 33       | 12.1M        |
| CLKD    | **77.68**    | **13**   | 0            |