ABSTRACT
Knowledge distillation aims to enhance the performance of a lightweight student model by exploiting the knowledge from a pre-trained cumbersome teacher model. However, in the traditional knowledge distillation, teacher predictions are only used to provide the supervisory signal for the last layer of the student model, which may result in those shallow student layers lacking accurate training guidance in the layer-by-layer back propagation and thus hinders effective knowledge transfer. To address this issue, we propose Deeply-Supervised Knowledge Distillation (DSKD), which fully utilizes class predictions and feature maps of the teacher model to supervise the training of shallow student layers. A loss-based weight allocation strategy is developed in DSKD to adaptively balance the learning process of each shallow layer, so as to further improve the student performance. Extensive experiments show that the performance of DSKD consistently exceeds state-of-the-art methods on various teacher-student models, confirming the effectiveness of our proposed method.

Index Terms—knowledge distillation, deep supervision, adaptive weighting strategy

1. INTRODUCTION
Deep neural networks have shown excellent performance in the computer vision tasks \cite{1,2,3} with massively parameterized models and huge calculations. These expensive computation and storage cost in turn make them difficult to be deployed on mobile devices with limited resources and real-time applications demanding quick response. The recently proposed knowledge distillation (KD) technique provides a possible solution to this problem by training a small student model to mimic the performance of a large teacher model \cite{4}.

In the vanilla knowledge distillation, class predictions of the teacher model are exploited to provide the training guidance for the last layer of the student model \cite{4}. However, this supervisory signal starting from only the last student layer would gradually weaken as the gradient is back propagated layer-by-layer, leading to the accumulation of training bias in shallow student layers and hurt the effectiveness of knowledge transfer \cite{5,6}.

To tackle this problem, in this paper, we propose Deeply-Supervised Knowledge Distillation (DSKD) to improve the participation of shallow layers in teacher knowledge transfer. Generally, giving shallow layers extra supervisory signals and increasing their discriminative ability can effectively prevent training bias from propagating from the last layer to shallow layers and thus reduce the final prediction error \cite{5,7}. Such intermediate targets empirically help the model generalize well, which is analogous to human learning where high-level knowledge could be better captured with the help of useful intermediate concepts \cite{8}. Actually, the knowledge learned by shallow layers in our method is rather similar to an intermediate learning clue for the student model training.

Since hierarchical concepts contained in intermediate feature maps are beneficial for knowledge transfer \cite{9,10,11}, we also leverage the teacher feature maps, besides class predictions, as another knowledge source to supervise the student training from the last layer to shallow layers. Additionally, we develop a loss-based weighting strategy to adaptively balance the different learning speeds of those shallow layers. The effectiveness of our proposed DSKD is verified in extensive experiments including seven competitors and seven groups of the teacher-student architectures (as shown in Table 1).

2. RELATED WORK
Knowledge distillation. Knowledge distillation is proposed to distill knowledge from a large teacher model into a small student model, serving as an model compression technique \cite{4,12}. Besides aligning final class predictions of the teacher and student models as the vanilla KD \cite{4}, many variants utilize feature maps in the intermediate layers as the extra teacher knowledge for better knowledge transfer \cite{9,10,11,13,14,15,16}. In contrast, we improve the vanilla KD technique by making shallow student layers also participate in learning the final teacher predictions.

Deep supervision. Deep supervision uses multiple auxiliary classifiers added to shallow layers to learn ground-truth labels for the model performance improvement \cite{5,7}. This technique was later applied to self-distillation that use class...
predictions [6, 17] and feature maps [17] of the last layer of a single model for its own shallow layers learning. Different from these works, we use teacher knowledge rather than self-knowledge or ground-truth labels as the learning target. Extensive experiments show the superiority of our strategy.

3. THE PROPOSED METHOD

Given an input image $x$ with the one-hot label $y \in \mathbb{R}^K$, the logit output of the teacher/student model is denoted as $z_T/z_S \in \mathbb{R}^K$. We attach auxiliary classifiers for the 1-st to $(L-1)$-th of the total $L$ student layers, such that these shallow student layers can learn predictions from the teacher model. The overview of our proposed method is shown in Figure 1.

Since shallow layers only contain fine-level features but lack of coarse-level features, they are not suitable to be directly used with a fully-connected layer for the final prediction [18]. Additional convolutional layers are generally needed to obtain such coarse-level features. For simplicity and broad applicability, we design the architecture of each auxiliary classifier to be the one that helps the corresponding shallow layer same as the main branch. All classifiers in the student model are denoted as $C = \{c_l\}_{l=1}^L$, where $c_L$ is the original classifier in the last layer and the others are the newly added auxiliary classifiers in shallow layers. Note that these auxiliary classifiers will not increase the inference burden, since they are only utilized in the training period.

3.1. The Loss of Class Predictions

As for the vanilla knowledge distillation [4], class predictions of the teacher and student models are required to be aligned in the last layer. The associated loss is defined as the Kullback-Leibler (KL) divergence between the teacher output $z_T$ and the output of the last student classifier $c_L$, i.e., $z_{c_L}$

$$L_{KD_{last}} = KL(\sigma(z_T/\tau) || \sigma(z_{c_L}/\tau)),$$

where $\sigma(\cdot)$ is a softmax function and temperature $\tau$ is a hyperparameter. A higher $\tau$ makes the distribution softer.

We generalize this technique by involving shallow layers in the learning of teacher class predictions. In this way, the student model gathers gradient information not only from the last layer but also from those shallow layers to suppress the propagation of training bias. The shallow layer loss is defined as

$$L_{KD_{shallow}} = \sum_{l=1}^{L-1} W_{c_l}^{KD} KL(\sigma(z_T/\tau) || \sigma(z_{c_l}/\tau)),$$

where $W_{c_l}^{KD}$ is an adaptive weight for the training of auxiliary classifier $c_l$. We will describe this detailedly in Section 3.3.

The total loss of class predictions is summarized as

$$L_{KD} = L_{KD_{shallow}} + L_{KD_{last}}.$$

3.2. The Loss of Feature Maps

Besides class predictions, feature maps can also help improve the student model performance [9, 10, 11]. Thus, we take feature maps of the last teacher layer $F_T$ as another learning target. The feature maps generated by all student classifiers (before the fully-connected layer) are denoted as $F_{c_1}, F_{c_2}, \ldots, F_{c_L}$, respectively.
Similarly to the discussion in Section 3.1, we calculate the Mean-Square-error (MSE) loss between the teacher feature maps \( F_T \) and feature maps in the last student layer \( F_{CL} \) as

\[
L_{Fea_{last}} = MSE \left( F_T, r \left( F_{CL} \right) \right),
\]

where \( r(\cdot) \) is a projection function to make dimensions of feature maps to be aligned.

We then generalize the above loss function by involving shallow layers in the learning of teacher feature maps and define the shallow layer loss as follows

\[
L_{Fea_{shallow}} = \sum_{j=1}^{L-1} W_{Fea}^{ci} MSE \left( F_T, r \left( F_{cl} \right) \right),
\]

where \( W_{Fea}^{ci} \) is an adaptive weight for the training of auxiliary classifier \( c_i \). We will describe this detailedly in Section 3.3.

The total loss of feature maps is summarized as

\[
L_{Fea} = L_{Fea_{shallow}} + L_{Fea_{last}}.
\]

### 3.3. Lose-based weights

Each shallow layer classifier would show a different behavior in the training process due to the different initialization. If each classifier is simply assigned with an average weight, the final model performance would be negatively affected from those classifiers falling behind in a certain iteration. We thus develop a loss-based weighting strategy, which measures the confidence of each auxiliary classifier on each sample, to alleviate this effect. The formulation is defined as

\[
W_{KD}^{ci} = \frac{KL \left( \sigma \left( z_{T} / \tau \right) \| \sigma \left( z_{cl} / \tau \right) \right)}{\sum_{j=1}^{L-1} KL \left( \sigma \left( z_{T} / \tau \right) \| \sigma \left( z_{cl} / \tau \right) \right)},
\]

\[
W_{Fea}^{ci} = \frac{MSE( F_T, r(F_{cl}) )}{\sum_{j=1}^{L-1} MSE( F_T, r(F_{cl}) )}.
\]

A larger weight is allocated to the auxiliary classifier with a larger loss value to make it catch up with the training process.

### 3.4. The Overall Loss Function

The final total loss is summarized as

\[
L_{Total} = L_{CE} + \alpha L_{KD} + \beta L_{Fea},
\]

where \( \alpha \) and \( \beta \) are hyper-parameters utilized to balance three loss items. \( L_{CE} = CrossEntropy \left( y, \sigma \left( z_{cl} \right) \right) \) is a standard cross-entropy loss calculated between class predictions and labels in the classification task.

### 4. EXPERIMENT

We conduct all experiments on CIFAR-100 dataset \([20]\). To demonstrate the effectiveness of our proposed DSKD, we use seven groups of teacher-student models with different networks covering VGG \([1] \), ResNet \([2] \), WRN \([3] \), MobileNet \([21] \) and ShuffleNet \([22] \). We first compare with several representative knowledge distillation methods and deep supervision methods \([5, 17, 16, 6]\) and then analyze the impact of shallow layer loss. Finally, we perform ablation experiments to verify the effectiveness of each module in our DSKD.

**Training details.** We train all models for 240 epochs with a batch size of 64 and the learning rate is divided by 10 at 150th, 180th and 210th epochs. The initial learning rate is 0.01 for MobileNet and ShuffleNet, and 0.05 for other models. The weight decay is set to \( 5 \times 10^{-4} \). For fairness of comparison, we set \( \alpha \) to 1 and temperature \( \tau \) to 4 for all methods. The hyper-parameter \( \beta \) in our proposed DSKD is set to 30. To ensure the reliability of the results, we train each method for three times and report the means and standard deviations.

### 4.1. Comparison with Knowledge Distillation Methods

We compare with four popular knowledge distillation methods on seven groups of teacher-student models, including four homogeneous and three heterogeneous architecture combinations. KD \([4]\) uses class predictions as the teacher knowledge,
4.2. Comparison with Deep Supervision Methods

We also compare with three popular deep supervision methods that give supervisory signals for shallow layers similarly. DSN [5] uses ground-truth labels while BYOT [17] and DKS [6] use outputs of the student own layer as supervisory signals. Different from them, we use predictions from a pre-trained teacher model as supervisory signals.

Our DSKD achieves considerable performance improvement over these previous works. Experimental results in Table 1 show that teacher knowledge provides better guidance to improve the student generalization ability than ground-truth labels (compared to DSN [5] and verified in section 4.4) and student’s own knowledge (compared to BYOT [17] and DKS [6]). Additionally, we also find that BYOT sometimes performs worse than the student model itself. This indicates that the knowledge learned in the early student training period may be very noisy, and supplying it for shallow layers would result in a negative impact on the final performance.

4.3. Impact of shallow layer loss

We further take “ResNet32x4 & ResNet8x4” as an example to verify the impact of our proposed shallow layer loss. Since the ResNet-series model for CIFAR-100 contains three building blocks [2], we treat outputs of the first two blocks as the possible position for adding our shallow layer loss $\mathcal{L}_{KD_{\text{shallow}}}$ and $\mathcal{L}_{Fea_{\text{shallow}}}$. As shown in Table 2, adding our proposed shallow layer loss effectively improves model performance. In the case of no shallow layer loss is employed (the second column), the student model accuracy (74.98%) is still better than the KD counterpart (74.39%), which is credited to the extra feature maps loss in Equation 4.

4.4. Ablation Study

As shown in Table 3, removing $\mathcal{L}_{Fea}$ or simply assigning equal weights to each shallow layer for each sample causes a considerable drop in accuracy, which demonstrates the importance of our used feature-based knowledge and loss-based weight allocation strategy. Note that even if these two modules are both removed, i.e., we only use class predictions of the teacher to supervise shallow layers of the student model, the model performance still outperforms DSN [5] using ground-truth labels as supervisory signals by 1.48% (from 74.25% to 75.73%).

4.5. Weight Visualization

The adaptively learned weights for different samples on a certain layer are visualized in Figure 2. Since only two shallow layers used in WRN-16-2 and the weight sum of different layers equals to 1, we can easily infer the weight distribution on the second layer given Figure 2 i.e. flipping the figure with 180 degrees along the central axis.

From the visualization results, we can observe that different weights are assigned to different samples, which hopefully help the student model training become better.

5. CONCLUSION

In this paper, we propose Deeply-Supervised Knowledge Distillation (DSKD) to make shallow layers of the student model participate in learning both response-based and feature-based knowledge from the teacher model, which further improves its final performance. We also develop a loss-based weight allocation strategy to balance the learning process of each shallow layer. Extensive experiments have demonstrated the effectiveness of our proposed method.

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