Improved Knowledge Distillation via Adversarial Collaboration

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Abstract

Knowledge distillation has become an important approach to obtain a compact yet effective model. To achieve this goal, a small student model is trained to exploit the knowledge of a large well-trained teacher model. However, due to the capacity gap between the teacher and the student, the student’s performance is hard to reach the level of the teacher. Regarding this issue, existing methods propose to reduce the difficulty of the teacher’s knowledge via a proxy way. We argue that these proxy-based methods overlook the knowledge loss of the teacher, which may cause the student to encounter capacity bottlenecks. In this paper, we alleviate the capacity gap problem from a new perspective with the purpose of averting knowledge loss. Instead of sacrificing part of the teacher’s knowledge, we propose to build a more powerful student via adversarial collaborative learning. To this end, we further propose an Adversarial Collaborative Knowledge Distillation (ACKD) method that effectively improves the performance of knowledge distillation. Specifically, we construct the student model with multiple auxiliary learners. Meanwhile, we devise an adversarial collaborative module (ACM) that introduces attention mechanism and adversarial learning to enhance the capacity of the student. Extensive experiments on four classification tasks show the superiority of the proposed ACKD.

1. Introduction

Convolutional neural networks (CNNs) have achieved impressive success in many vision tasks such as image classification [13, 17, 34], object detection [23, 32, 31], and image generation [10, 25]. To pursue high performance, the design of CNNs tends to be more and more complicated. These structures demand huge computation and storage resources, which are unavailable in resource-limited devices like mobile phones. In order to address this problem, many researchers propose a number of model compression techniques such as lightweight model design [34, 27, 16], model quantization [40, 18, 42], and model pruning [14, 55, 4]. In recent years, knowledge distillation [15, 33, 46] has attracted widespread attention, which aims to improve the performance of a small model (student) by exploiting the knowledge of a large well-trained model (teacher).

Existing knowledge distillation methods mainly focus on what kind of knowledge the teacher has learned (e.g., logit-based [15], feature-based [33] and relation-based [29] knowledge) and how to transfer the knowledge from the teacher to the student (i.e., proper loss function). However, the teacher-student pairs are sometimes significantly different (in structure and size), which leads to extremely learning difficulty for the student. To alleviate this problem, some works [5, 28] seek the proxy teachers to reduce the difficulty of the teacher’s knowledge. Specifically, Cho et al. [5] propose that the student can gain better performance through learning the knowledge from an early-stopped teacher model rather than final converged one. Recently, Mirzadeh et al. [28] first transfer the knowledge to medium capacity assistant models, then distill knowledge from assistants to the student, which is multi-step knowledge distillation framework.

However, although these proxy-based methods ease optimization difficulty for the student to a certain extent, there still remain the following problems. First, the core knowledge of teacher might be lost, which would prevent the student from learning useful information in the distillation process. The key idea of the early-stopped and assistant teachers is to reduce the teacher’s capacity such that the teacher’s knowledge can be accepted by the student. In this process, they lose part of knowledge from the original teacher, which will be discussed in detail in section 3.1. Second, the whole training process is complicated and time-consuming. These methods require lots of grid searches and additional training to obtain an optimal early-stopped anchor or teacher assistant in different knowledge distillation scenarios.

To avoid the above issues, in this paper, we provide a new
perspective to alleviate the aforementioned learning difficulty problem. Rather than rudely reduce the difficulty of the teacher’s knowledge, we advocate strengthening the student’s capacity. To achieve this, we exploit the idea of collaborative learning that many collaborators/learners form a learning group in order to reach the same goal. Given multiple small-sized students, we can effectively exploit the knowledge of the teacher via ensemble learning. However, such cumbersome student models violate the purpose of model compression. Thus, how to form a learning group while avoiding incurring additional parameter overhead in inference remains a question.

In this paper, for the sake of improving the student’s capacity while keeping the student be efficiency in inference, we propose an Adversarial Collaborative Knowledge Distillation (ACKD) method that can significantly improve the performance of knowledge distillation. In the training phase, we build the student model with multiple auxiliary learners. These learners form a learning group and collaborate to achieve the same goal that fully exploits the knowledge of the teacher. For the purpose of achieving better collaboration, we introduce the attention mechanism to filter the information of auxiliary learners. Moreover, to enhance the ability of auxiliary learners to learn more comprehensive knowledge, the auxiliary learners are urged to be diverse. To this end, we distinguish their distributions using adversarial learning via discriminators. As a result, the proposed student model is more powerful to exploit the teacher’s knowledge. In the inference phase, we discard all auxiliary learners such that the final student is compact and effective. Extensive experiments on four benchmarks demonstrate the effectiveness of proposed ACKD.

Our contributions are summarized as follows:

- We propose an Adversarial Collaborative Knowledge Distillation (ACKD) method that effectively alleviates the capacity gap problem in knowledge distillation. Unlike existing methods that rudely reduce the difficulty of the teacher’s knowledge, we alleviate this problem from a new perspective of strengthening the student’s capacity.

- We propose an adversarial collaborative learning strategy that effectively improves the student’s capacity. To this end, we introduce the attention mechanism to recognize the importance of different auxiliary learners. Moreover, we introduce the adversarial learning to promote representational diversity.

- To investigate the effectiveness of our proposed method, we conduct extensive experiments on four classification datasets. These results demonstrate that our ACKD outperforms state-of-the-art methods.

2. Related Work

Knowledge Distillation. Knowledge distillation is mainly applied to the field of model compression [12, 30, 44, 26], which trains a small and effective student model with the help of large teacher models’ knowledge. As a pioneer work, Hinton et al. [15] take output probabilities as knowledge, and the student learns these knowledge by minimizing Kullback–Leibler (KL) divergence. After that, Romero et al. [33] exploit the intermediate representations’ knowledge by matching the feature activations of the teacher and the student. Besides, Zagoruyko et al. [48] introduce attention mechanism to the knowledge transfer, and improve the student’s performance by mimicking attention feature map. Recently, some works define the knowledge according to the relation between layers or samples. Specifically, Tung et al. [39] urge the student to learn how to preserve the pairwise similarities. Tian et al. [38] introduce contrastive objectives by constructing positive and negative pairs. However, most existing works ignore the capacity gap between the teacher and the student, which may result in performance degradation [5, 19]. To address this problem, Cho et al. [5] reduce the gap via an early-stopped teacher, and Mirzadeh et al. [28] introduce teacher assistants to simplify the teacher’s knowledge. Unlike these methods, in this paper we bridge the gap from the perspective of improving the student’s capacity.

Collaborative Learning. Collaborative learning refers to two or more learners work together to solve a common task [8]. For that purpose, learners learn from based on their diverse strengths such that they reach goals more efficiently. Recently, some studies have introduced this idea to improve the training efficiency of deep neural networks with knowledge distillation [54, 22]. To be specific, Song et al. [36] design a hierarchical structure of multiple branches, which are trained simultaneously to improve backbone’s performance. Chen et al. [2] introduce self-attention to improve the branch diversity and distill the knowledge of auxiliary peers into main branch. Additionally, some works apply collaborative learning across networks [2, 6]. Zhang et al. [52] propose a deep mutual learning training fashion, in which all networks distill knowledge to each other simultaneously. Guo et al. [11] train networks under the supervision of ensemble targets. In this paper, we follow the idea of collaborative learning to improve the imitation ability of the student network in knowledge distillation.

Deep Supervision. Deep supervision is proposed to alleviate the gradient vanish problem in deep neural networks by attaching auxiliary classifier to intermediate layers [21, 37]. These auxiliary classifiers will be removed in the testing phase to keep the efficiency of the model. This training mechanism has been widely proved to be effective in different applications, such as edge detection [41], object detection [24], and semantic segmentation [53]. Recently,
Table 1: Comparisons of different proxy methods. Acc(·) denotes Top-1 accuracy (%). AccGap(T, P) = Acc(T) - Acc(P). CKA(·, ·) and KL(·, ·) denote CKA similarity [20] and Kullback–Leibler divergence between two networks, respectively. The number inside the parentheses is the total number of training epochs with early-stopped strategy.

| Method       | ESKD [5]                         | TAKD [28]                        |
|--------------|----------------------------------|----------------------------------|
| Teacher (T)  | WideResNet-28-4 (65)             | WideResNet-28-2 resnet56         |
| Proxy (P)    | resnet56                         |                                 |
| Student (S)  | resnet56                         |                                 |
| Acc(T)       | 78.91                            | 78.91                            |
| Acc(P)       | 76.30                            | 76.78                            |
| AccGap(T, P) | 2.61                             | 2.13                             |
| CKA(T, P)    | 0.7761                           | 0.8234                           |
| CKA(P, S)    | 0.8016                           | 0.8113                           |
| CKA(T, S)    | 0.7695                           | 0.7770                           |
| KL(T, P)     | 0.6627                           | 0.7710                           |
| KL(P, S)     | 0.8495                           | 0.8391                           |
| KL(T, S)     | 0.9319                           | 0.9166                           |

3.1. Analysis on Proxy-based Approaches

The vanilla KD method is a two-stage process in which a high capacity teacher model is trained and then used for distillation. However, due to the high capacity divergence between the teacher and the student, it results in a common phenomenon that the student is hard to reach the teacher’s performance after the distillation process.

To alleviate this divergence, many researchers try to distill knowledge from the teacher to the student in a more smooth way. One of the most well-known methods is TAKD [28], which utilizes proxy models to alleviate the gap, aiming to provide an easier learning curve for the student. Another insightful method is to reduce the teacher’s capacity by using early-stop teacher regularization [5], in this way, the student can gain better performance.

A major advantage of these methods is to smooth the student’s learning curve and mitigate the mismatched capacity between teacher and student. However, there are certain drawbacks associated with the use of the proxy model and early-stop teacher model. Firstly, although these approaches alleviate the student’s learning burdens, they also lose abundant knowledge of the original teacher in the distillation process, which may cause that the student model can not draw some key information. As Table 1 showed, we use qualitative analysis in order to gain insights into the information loss in the distillation process. We conduct experiments with the teacher-student pair of WRN-28-4 and resnet56 on CIFAR-100. Specifically, we use both CKA [20] and KL divergence to measure the representational similarity among the teacher, the proxy, and the student. The larger the CKA, the more similar the representations among the teacher, the proxy, and the student. The larger the KL divergence, the greater the difference between the two distributions. Besides, we use the relative accuracy (AccGap) to evaluate the capacity gap among the teacher and the proxy. From Table 1, the CKA of the teacher-proxy pair is higher than the teacher-student pair while KL is quite the reverse, which means that the student model suffers the loss of information during the proxy distillation process. Meanwhile, both AccGap of ESKD and TAKD are more than 2%, also proving the existence of capacity gap and information loss between teacher and proxy model. Secondly, these methods require lots of grid searches to obtain an optimal proxy model (i.e., early-stopped anchor or teacher assistant), which is time-consuming and inefficient.

Thus, how to maintain the teacher’s capacity (original abundant information) while improving the students’ capacity has become a prisoner’s dilemma problem: reducing the difficulty of student learning would hurt teachers’ capacity while a large and well-trained teacher would mismatch its student capacity.
Figure 1: An overview of the proposed ACKD. In the training phase, we first construct the student model with auxiliary learners (gray boxes). Then, we improve the student’s capacity via an adversarial collaborative learning strategy. In the inference phase, we only use the target learner and remove all auxiliary learners. (Best viewed in color)

3.2. Adversarial Collaborative Learning

Imagine a real-world scenario where incomprehensible (complex) knowledge is given by the teacher model, and the student is asked to absorb these contents by its own small-capacity network. The capacity gap discussed in the previous subsection occurs and makes the knowledge distillation less effective than it could be. To alleviate this issue, we seek to exploit the idea of collaborative learning that different learners work together to solve a common task. Inspired by this, we propose to strengthen the student’s capacity by forming a learning group rather than rudely reduce the difficulty of the teacher’s knowledge. In this way, it is possible to achieve better distillation performance without damaging the teacher’s original capacity and semantic information.

To form a learning group that exploit the knowledge of the teacher, we can build a multi-students [45] ensemble learning framework [7]. However, such a cumbersome model is inconsistent with our goal of model compression. In order to address this problem, in this paper, we propose to construct the student model with multiply branches. For convenience, we call these branches as auxiliary learners, and use them to form a learning group. The backbone model without auxiliary branches is named as target learner. In practice, we select different layers branch from the target learner as our auxiliary learners’ inputs. The auxiliary learners are composed of different high-level feature extractor blocks. In this way, the auxiliary learners share the low-level feature information but have their own high-level semantic information.

The auxiliary learners are asked to reach the same objective that exploits the knowledge of the teacher in the greatest degree. To fully extract the representation information of the auxiliary learners, we introduce an attention mechanism to collaborative learning. In this way, each auxiliary is urged to focus on what it does well. However, auxiliary learners share the same low-level layers, which might lead to a lack of diversity in expressivity. To alleviate this issue, we introduce adversarial learning to promote the diversification of auxiliary learners. In the whole training phase, we hope that the auxiliary learners are in the state of collaborative learning while exploring unique representation via adversarial learning. In the inference phase, we discard all auxiliary learners to obtain a compact and effective model. For simplicity, we call our training framework as Adversarial Collaborative Knowledge Distillation (ACKD).

Figure 1 shows the overall architecture. In practice, the teacher’s knowledge first flows to auxiliary learners. Then, the auxiliary learners mine this knowledge via an adversarial collaborative manner. In this process, the knowledge flows to shared low-level layers of the target learner. Besides, the target learner exploits the knowledge from auxiliary learners, which is a more smooth learning manner than
directly learning from the teacher. In the following, we will describe in detail how the knowledge flows and the parameters update in our framework.

3.3. Teacher-Auxiliary Learners Knowledge Flow

We follow the common KD approach to distill teacher’s knowledge into auxiliary learners. Suppose that we train the models on the dataset $D = \{(x_i, y_i)\}_{i=1}^N$, where $N$ is the number of samples. We can obtain the logits $z_i$ of $i^{th}$ sample. Then we can get the softened output probability of a model by applying a temperature factor as follows:

$$p_i = \frac{\exp(z_i^k/\tau)}{\sum_{j=1}^{C} \exp(z_j^k/\tau)},$$

(1)

where $\tau$ is a temperature factor. In this way, we can get $p_i^t$ of the teacher and $p_i^a$ of auxiliary learners. The auxiliary learners learn the knowledge of the teacher by minimizing Kullback-Leibler (KL) divergence between these two output distributions as follows:

$$L_{kd}^a = KL(p^a, p^t) = \sum_{x \sim D} p^a \log \frac{p^a}{p^t}. \quad (2)$$

Taking advantage of collaborative learning, the output distribution of auxiliary learners is easier to fit that of the teacher. Through backward propagation, we are able to get more robust low-level representations of the target learner, which is conducive to the target learner’s optimization.

3.4. Adversarial Collaborative Module

In this subsection, we introduce how the auxiliary learners collaborate to exploit the teacher’s knowledge via an Adversarial Collaborative Module (ACM), as shown in Figure 2. For simplicity, we use two auxiliary learners as examples for illustration. In ACM, there are two complementary learning steps: attention-based collaborative learning and adversarial-based diversity learning.

3.4.1 Attention-Based Collaborative Learning

To take advantage of different auxiliary learners’ ability, we present the attention-based collaborative module to enhance the representations of auxiliary learners. First, we concatenate all feature maps from different auxiliary learners. Then, we input the fused feature into a two-layer perceptron with a softmax to recognize the importance of different learners. Formally, the attention weight vector and output logits of the learning group can be computed as follows:

$$x = g(\text{Concat}(h^{(1)}, \ldots, h^{(M)})),$$

$$a^{(k)} = \text{Softmax}(\text{MLP}(W_m, x)),$$

$$z = \sum_{k=1}^{M} a^{(k)} z^{(k)}, \quad (3)$$

where $M$ is total number of auxiliary learners; $h^{(k)}$ denotes the $k^{th}$ auxiliary learner’s feature map; $g(\cdot) : \mathbb{R}^{C \times H \times W} \rightarrow \mathbb{R}^{C \times H \times W}$ flattens the feature maps in spatial dimension; $W_m$ denotes the parameters of MLP; $a^{(k)}$ is the attention weight of $k^{th}$ auxiliary learner. After we get attention-based logit, we compute output probability in Eqn 1. We update the parameters of auxiliary learners and MLP in Eqn 2.

3.4.2 Adversarial-Based Diversity Learning

Although each auxiliary learner has its own branch structure, their feature inputs come from the target learner and the knowledge learned in the auxiliary learners is easy to overlap between each other. It is still difficult to avoid the homogeneity of their network parameters, which may hurt the performance of the ensemble result and even distillation performance. To alleviate this problem, we leverage the adversarial training to force auxiliary learners to learn diverse feature distribution. As Figure 2 illustrated, each learner has a corresponding discriminator aiming at distinguishing whether the feature output belongs to their own.

Following the traditional adversarial training definition, we regard the auxiliary learners’ network feature as generative distribution and name the $i^{th}$ learner’s discriminator as $D_i$. The architecture of the discriminator is a simple stack of $1 \times 1$ Conv with ReLU. Each auxiliary learner tries to fool the discriminator while the discriminator need to discriminate the right source of feature. Our overall adversarial loss for $i^{th}$ discriminator is as follows:

$$L_{ad}^i = \frac{1}{M-1} \sum_{j \neq i} \mathbb{E}_{x \sim p(i)} \log D_i(x) + \mathbb{E}_{x \sim p(j)} \log(1-D_i(x)), \quad (4)$$

where $p(i)$ denotes the output feature produced by $i^{th}$ auxiliary learner, $M$ is total number of auxiliary learners. Final adversarial loss is a average of the individual ones:

$$L_{ad} = \frac{1}{M} \sum_{i=1}^{M} L_{ad}^i. \quad (5)$$

Through adversarial training manners, we can make better use of the diversity of semantic information contained in the auxiliary learners. Meanwhile, the parameters of target learner also are updated in this process.

3.5. Auxiliaries-Target Learner Knowledge Flow

After the adversarial collaborative training, the auxiliary learners gain diverse and rich semantic information. Thus, it benefits the optimization of the target learner via shared low-level layers. Meanwhile, we dig these knowledge via a self-distillation manner (i.e., minimizing the distribution divergence between the target learner and auxiliary learners).
Table 2: Comparison with state-of-the-art models on CIFAR-100.

| Teacher | WideResNet-40-2 | resnet110 | MobileNetV2 (1.4) | ShuffleNetV1 | WideResNet-28-4 |
|---------|----------------|-----------|------------------|--------------|----------------|
| Student | WideResNet-40-1 | resnet20  | MobileNetV2 (0.5) | MobileNetV2 (0.5) | resnet56       |
| Teacher | 76.22          | 74.00     | 69.57            | 71.85        | 78.91          |
| Student | 71.78          | 69.20     | 65.17            | 65.17        | 73.05          |
| AT [48] | 72.94          | 70.78     | 66.26            | 65.55        | 73.64          |
| SP [39] | 73.18          | 70.69     | 61.52            | 67.67        | 73.16          |
| CC [29] | 72.22          | 70.30     | 65.39            | 65.16        | 73.24          |
| VID     | 72.52          | 70.26     | 65.15            | 65.49        | 73.24          |
| CRD [38]| 73.57          | 70.88     | 66.47            | 67.32        | 74.34          |
| SemCKD [3]| 73.32        | 70.41     | 67.70            | 67.19        | 73.13          |
| KD [15] | 73.54          | 70.73     | 67.94            | 68.19        | 73.12          |
| ESKD [5]| 73.21          | 70.69     | 67.61            | 67.82        | 74.61          |
| TAKD [28]| 73.52         | 71.42     | 68.88            | 68.71        | 75.29          |
| ACKD (Ours) | 75.29     | 72.38     | 69.43            | 69.48        | 75.91          |

We formulate it as follows:

\[ \mathcal{L}_{kd}^s = \sum_{x \sim D} p^s \log \frac{p^s}{p^a}, \tag{6} \]

where \( p^s \) and \( p^a \) are the output probability of the target learner and auxiliary learners, respectively. Such optimization is much easier than the vanilla KD process. The main reason is that the auxiliary learners have same structure with the target learner, and the target learner shares low-level layers with auxiliary learners. This special characteristic of structure makes the target learner be easier to understand the knowledge of auxiliary learners.

The overall training objective of ACKD is as follows:

\[ \mathcal{L} = \lambda_1 \mathcal{L}_{kd}^s + \lambda_2 \mathcal{L}_{kd}^a + \lambda_3 \mathcal{L}_{ad} + \lambda_4 \mathcal{L}_{ce}, \tag{7} \]

where \( \lambda_1, \lambda_2, \lambda_3, \lambda_4 \) are balanced hyperparameters, we set them to 1 in our experiments. \( \mathcal{L}_{ce} \) denotes typical cross entropy loss for the target learner and auxiliary learners.

Table 3: Comparison with state-of-the-art models on CINIC-10.

| Teacher | resnet110 | WideResNet-28-4 |
|---------|-----------|----------------|
| Student | resnet20  | resnet56       |
| Teacher | 84.62     | 87.74          |
| Student | 82.29     | 83.95          |
| AT [48] | 83.84     | 85.16          |
| SP [39] | 79.75     | 84.34          |
| CC [29] | 83.89     | 85.14          |
| CRD [38]| 84.11     | 84.99          |
| SemCKD [3]| 84.13    | 85.12          |
| KD [15] | 84.03     | 85.18          |
| ESKD [5]| 83.78     | 85.44          |
| TAKD [28]| 84.21     | 85.37          |
| ACKD (Ours) | 84.42  | 85.63          |

4. Experiments

4.1. Datasets and Networks

Dataset. We conduct experiments on four widely used benchmarks. 1) **CIFAR-100** is composed of 50K training images and 10K testing images, which are divided into 100 fine-grained categories. 2) **CINIC-10** consists of 90K training and 90K testing images, which are from CIFAR and ImageNet datasets. This dataset is more complex than CIFAR dataset. 3) **Tiny-ImageNet** has 200 classes, each of which contains 500 images for training and 50 images for validation. All images are at the resolution of 64 × 64. 4) **ImageNet** is a large-scale dataset with 1000 classes, which...
contains 1.2 million images for training and 50k images for validation. All images are cropped at the resolution of 224 × 224 for training and validation.

**Network Constructions.** We perform experiments with four different types of networks, including WideResNet [47], resnet [13], MobileNetV2 [34], and ShuffleNetV1 [51]. Specifically, WideResNet-d-w represents the WideResNet with depth d and width factor w. MobileNetV2 (w) denotes MobileNetV2 with a width multiplier of w. To investigate the generalization ability of our method, we construct teacher-student pairs with similar structures (e.g., resnet110-resnet20) and different structures (e.g., ShuffleV1-MobileNetV2).

**Compared Methods.** We compare our proposed ACKD with many state-of-the-art methods, including KD [15], AT [48], SP [39], CC [29], VID [1], CRD [38], and Sem-CKD [3]. Besides, we compare our method with ESKD [5] and TAKD [28], which also aims to alleviate the capacity gap. The implementations of compared methods are mainly based on author-provided codes and a open-resource benchmark [38]. As the authors’ suggestions, we set the number of early-stopped training epochs to 65 (on CIFAR-100 and CINIC-10) and 35 (on Tiny-ImageNet and ImageNet) for ESKD. We choose the model, whose performance is close to average performance of the teacher and the student, as teacher assistant for TAKD (e.g., we regard resnet44 (71.98%) as assistant model for the pair of resnet110 (74.00%) and resnet20 (69.20%) on CIFAR-100).

**Implementation Details.** On CIFAR-100 and CINIC-10 datasets, we run a total of 200 epochs for all methods with SGD optimizer. We set batch size to 128, momentum to 0.9, and weight decay to 5e-4. We initialize the learning rate to 0.1 (MobileNetV2 and ShuffleNetV1 to 0.05) and decay it by 0.1 at 100 and 150 epochs. On Tiny-ImageNet and ImageNet datasets, we train models for 100 epochs. Learning rate is initialized to 0.1 and decayed every 30 epochs.

### 4.2. Comparisons with State-of-the-art Methods

#### Results on CIFAR-100.
We evaluate our method on three similar and two different structures of teacher-student pairs. We show the results on Table 2. From this table, we have the following observations. 1) The methods that exploit the logit-based knowledge (i.e., KD, ESKD, TAKD) show superiority over those feature-based methods. Such a phenomenon has also been found in CRD [38]. We claim that logit-based knowledge has not yet been fully exploited, which is overlooked in recent state-of-the-art feature-based methods. 2) Our ACKD is well generalized to different teacher-student pairs. On average, our ACKD achieves higher accuracy than the vanilla student by 3.62%, ranging from 2.86% to 4.31%. 3) Our ACKD performs better than all of the compared methods. Specifically, our method evenly outperforms vanilla KD and two related methods (i.e., ESKD and TAKD) by 1.58%, 1.71%, 0.93% on all teacher-student pairs. Note that ESKD is inferior to vanilla KD in many teacher-student combinations. The main reason is that they lost a lot of teacher’s knowledge. On the contrary, we improve the student’s capacity to effectively exploit the teacher’s knowledge.

#### Results on CINIC-10.
In this experiment, we evaluate our method on two teacher-student pairs. As shown in Table 3, our method achieves the best results on all pairs. Specifically, our ACKD outperforms vanilla student by 1.91% on average, which is a relatively large improvement on CINIC-10 dataset. These results demonstrate the effectiveness of our method on more complex dataset.

#### Results on Tiny-ImageNet.
In this experiment, we evaluate ACKD with the pair of ResNet50 and ResNet18. From Table 4, we have the following observations. First, most distillation methods outperform the vanilla student by a large margin. It is worth noting that the students in many distillation methods even achieve higher accuracy than the teacher model. Such a phenomenon shows the importance and effectiveness of knowledge distillation on a more complex and challenging dataset. Second, our ACKD performs better than all of the compared methods by at least 1.02% in terms of Top-1 accuracy. These results show the effectiveness and generalization of our ACKD on more challenging datasets.

#### Results on ImageNet.
In this experiment, we compare our ACKD with state-of-the-art methods by using the pair of ResNet34 and ResNet18. Note that TAKD [28] does not provide comparable ImageNet results. From Figure 5, our proposed ACKD achieves highest accuracy. Specifically, our ACKD reduces the performance gap between the teacher and the student from 3.56% to 1.98%, a 44% relative improvement. These results demonstrate the scalability of our proposed ACKD.

### 4.3. Effect of Adversarial Collaborative Module

**Qualitative Analysis.** In this experiment, we analyze how the adversarial collaborative module works by Grad-CAM visualization. We randomly select several samples from the testing set on Tiny-ImageNet. We show the qualitative results of different parts (i.e., teacher, target learner and auxiliary learners) of ACKD framework in Figure 3. We observe that 1) The regions highlighted by different auxiliary learners are somewhat different. Interestingly, there always exists one learner activates similar region to the teacher (e.g., auxiliary learner1 in the 1st and 4th column). 2) The target learner captures more semantic-related information than auxiliary learners even the teacher model. For example, in the 3rd column, the target learner successfully puts its attention on the whole target objective while the teacher distracts part of its attention to the background. The main reason is that the auxiliary learners capture di-
Table 4: Test Accuracy (%) of different methods on Tiny-ImageNet.

| teacher | student | AT [48] | SP [39] | CRD [38] | SemCKD [3] | KD [15] | ESKD [5] | TAKD [28] | ACKD (Ours) |
|---------|---------|---------|---------|---------|-----------|---------|---------|---------|------------|
| Top-1   | 52.98   | 51.60   | 51.59   | 54.33   | 54.19     | 54.20   | 52.58   | 54.95   | 55.97      |
| Top-5   | 75.97   | 74.37   | 76.96   | 75.13   | 77.52     | 77.48   | 76.77   | 77.44   | 78.15      |

Table 5: Test error (%) of different methods on ImageNet. †The authors only report Top-1 error.

| teacher | student | AT [48] | SP [39] | CC [29] | ONE [54] | CRD [38] | SemCKD † [3] | KD † [15] | ESKD † [5] | ACKD (Ours) |
|---------|---------|---------|---------|---------|----------|---------|-------------|---------|----------|------------|
| Top-1   | 26.69   | 30.25   | 29.30   | 29.38   | 30.04    | 29.45   | 28.83       | 29.13   | 29.34    | 29.12      |
| Top-5   | 8.58    | 10.93   | 10.00   | 10.20   | 10.83    | 10.41   | 9.87        | -       | 10.12    | 9.57       |

Table 6: Effect of different modules.

| Collaboration | Attention module | Adversarial module | Accuracy (%) |
|--------------|------------------|--------------------|--------------|
| ✓            | ✓                | ✓                  | 70.73        |
| ✓            | ✓                | ✓                  | 71.67        |
| ✓            | ✓                | ✓                  | 72.16        |
| ✓            | ✓                | ✓                  | 72.38        |

Table 7: Effect of different learners. "D3B1" denotes that we add an auxiliary learner with $M$ increased feature extractor blocks to the $N$th down-sampling layer.

| learner1 | learner2 | Accuracy (%) |
|----------|----------|--------------|
| D3B1     | D3B1     | 72.02        |
| D3B1     | D2B2     | 72.38        |
| D2B2     | D2B2     | 71.64        |
| D2B2     | D1B3     | 72.16        |
| D1B3     | D1B3     | 71.40        |

Effect of proposed modules. In this experiment, we conduct experiments to investigate the effectiveness of proposed modules. We show the results in Table 6. 1) The performance significantly boost when we apply the auxiliary learners to collaboratively learn the knowledge from the teacher and then transfer to the student (i.e., collaboration). 2) Equipping with the attention or adversarial module alone improves the performance, which means that the attention and the adversarial module effectively strength the collaboration and diversity, respectively. 3) When equipped with all proposed modules, the student achieves highest accuracy. These results demonstrate the effectiveness of our proposed adversarial collaborative module.

Effect of different learners. In this experiment, we investigate the effect of different learners. We use "D3B1" to denote that we add a learner with $M$ increased feature extractor blocks to the $N$th down-sampling layer. From Table 7, we have the following observations. 1) Different learners all lead to performance improvement compared with vanilla KD (70.73%), which shows the effectiveness and robustness of collaborative module. 2) Attaching learners to different down-sampling layers shows superiority over same layers. The main reason is that they effectively utilize different semantic information of the student, improving the diversity of learners. 3) "D3B1 with D2B2" achieves higher accuracy than "D2B2 with D1B3". The main reason is that the student shares more low-level layers with learners, leading to a more stable training process.

5. Conclusion

In this paper, we have proposed an Adversarial Collaborative Knowledge Distillation (ACKD) method that effectively improves the performance of the student model in
the knowledge distillation task. To this end, we have constructed a student model with multiple auxiliary learners. Based on the reinforced student model, we have proposed an adversarial collaborative learning strategy. Specifically, we have proposed an attention module to promote collaboration between auxiliary learners and used discriminators to distinguish the output distribution of auxiliary learners to enhance representational diversity. Extensive experiments on four benchmarks have shown that our ACKD obtains state-of-the-art performance.

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