INDISTILL: TRANSFERRING KNOWLEDGE FROM PRUNED INTERMEDIATE LAYERS

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ABSTRACT

Deploying deep neural networks on hardware with limited resources, such as smartphones and drones, constitutes a great challenge due to their computational complexity. Knowledge distillation approaches aim at transferring knowledge from a large model to a lightweight one, also known as teacher and student respectively, while distilling the knowledge from intermediate layers provides an additional supervision to that task. The capacity gap between the models, the information encoding that collapses its architectural alignment, and the absence of appropriate learning schemes for transferring multiple layers restrict the performance of existing methods. In this paper, we propose a novel method, termed InDistill, that can drastically improve the performance of existing single-layer knowledge distillation methods by leveraging the properties of channel pruning to both reduce the capacity gap between the models and retain the architectural alignment. Furthermore, we propose a curriculum learning based scheme for enhancing the effectiveness of transferring knowledge from multiple intermediate layers. The proposed method surpasses state-of-the-art performance on three benchmark image datasets.

Keywords Knowledge Distillation · Channel Pruning · Model Compression

1 Introduction

In the last decade, the Deep neural networks (DNNs) have been successfully utilized for a wide range of application fields. Due to the fact that DNNs are capable of achieving state-of-the-art performance on various tasks, the constant effort of increasing their performance resulted in much deeper DNNs that require a considerable amount of computational power, which restrict them from being deployed in hardware with limited resources, such as mobile devices. This led research community to focus on methods that could overcome this crucial limitation. The Knowledge Distillation (KD) approaches constitute one of the most effective ways to tackle this obstacle [1, 2]. The underlying idea of KD methods is to transfer the valuable knowledge a DNN (i.e., teacher model) possesses to a much smaller and faster network (i.e., student model) and thus to enhance its performance.

The main target of the early KD approaches was to transfer the knowledge derived from the last layer of the teacher network to the corresponding last layer of the student network [3]. This enabled smaller models to understand how the bigger models perceive the training data and thus to improve their generalization and performance. Sharing the same idea, several recent KD methods [4, 5, 6] focus on not only utilizing the teacher’s last layer, but also its intermediate layers to provide to student model even richer information sources that can assist student model to further increase its accuracy. In fact, the intermediate layer KD acts supplementary to the last layer KD by providing some principal information about how the information flows into the teacher model. Although this additional supervision indeed
improves student’s performance, there are two major shortcomings that should be taken into consideration. The first one is the capacity gap between the teacher and the student model that leads to an overflow while transferring the knowledge and as a sequence reduces the effectiveness of the KD. The second one is the challenge of transferring knowledge from multiple layers simultaneously. Note that during the training process, a neural network undergoes several phases. Achille et al. [7] figure that the first training epochs are responsible for the creation of the model’s information flow paths, which is the key information that intermediate layers KD methods aim at.

In this paper, we propose a novel intermediate layers KD method, termed InDistill, that aims at overcoming the aforementioned limitations. First, it should be stressed that the nature of the intermediate layers KD problem (i.e., distilling fundamental knowledge about the critical connections) allows for reducing the capacity gap without collapsing the information of interest. Given that, we argue that pruning the output channels of the teacher’s intermediate layers can effectively reduce the capacity gap between teacher and student, while maintaining the fundamental teacher’s knowledge. Channel pruning methods are widely applied to reduce a model’s complexity by removing its redundant output channels [8]. To the best of our knowledge, this is the first work that utilizes channel pruning to apply intermediate layers KD. In addition, a properly designed teacher’s channel pruning can allow for matching the feature maps size of teacher and student models, and thus enables the direct knowledge transfer, which is also crucial to maintain the network’s architectural width-wise alignment. Retaining this alignment is critical to capture the network’s information flow paths. It is noteworthy that the proposed method can be combined with any single-layer KD method to improve its performance. Second, inspired by the curriculum learning strategies [9], we propose a simple, yet effective way to distill multiple layers from a teacher to a student model, while taking into consideration the critical learning periods [4], termed as layer-wise Curriculum Learning based Scheme (l-CLS). Specifically, we propose that transferring each intermediate layer separately and in ascending order in terms of transferring difficulty (i.e., from the easiest - first layer - to the hardest - last layer) can enhance the KD effectiveness and consequently the student’s performance. The proposed method that comprises of InDistill and l-CLS is illustrated in Fig. 1. The code is available at [https://github.com/gsarridis/InDistill.git](https://github.com/gsarridis/InDistill.git).

The proposed method is evaluated on both classification and retrieval tasks and on CIFAR-10 [10], CUB-200 [11], and FashionMNIST [12] datasets and demonstrates superior performance compared to several state-of-the-art methods.
Specifically, InDistill-1-CLS achieves a 1.61% mean Average Precision (mAP) relative improvement on the CIFAR-10 dataset and 3.59% accuracy relative improvement on the CUB-200 dataset. In addition, the performance of the proposed method combined with three competitive single-layer KD methods is illustrated in order to evaluate how the proposed method can affect their performance. The main contributions of this paper are the following: (i) Reducing the capacity gap between teacher and student model by applying channel pruning on the teacher’s intermediate layers. This way, our method provides a proper supervision to the student model to learn the teacher’s information flow paths. (ii) Applying channel pruning can reduce the teacher’s filters, so that they match the size of the student’s ones. Thus, InDistill allows for transferring the feature maps directly, without including any encoding procedure (as the other methods do) that could collapse the architectural alignment (iii) Introducing a curriculum learning based scheme that assists the multi-layer transferring procedure while taking into consideration the critical learning periods of a neural network. The outline of the paper is as follows. In Sec. 2 the related works on KD are presented. In Sec. 3 the proposed method is analyzed. The experimental setup is provided in Sec. 4. In Sec. 5 the experimental results are demonstrated. Conclusions are drawn in Sec. 6.

2 Related Work

The increasing need of deploying DNNs on limited resource hardware and the growing complexity of DNNs has led to a large number of KD methods that aims at tackling this problem [13][14][15][16]. The idea of the network compression was first time discussed in [17]. Inspired by this work, in [3] the first KD method was introduced. The underlying idea is to distill the knowledge of the output class probability distributions. To achieve this, a temperature term is added to the logits to provide a better representation of the small probabilities. After this work, several KD methods that exploit the model’s output probabilistic distributions have been proposed [18][19][20]. These methods only utilize the output of the last layer, thus they do not include any intermediate layer supervision at all, which is considered as of high importance for the effectiveness of the KD [6].

The first effort of leveraging the teacher’s feature maps to provide an extra supervision to the student was presented in [6]. In particular, Hints approach [6] opts for one intermediate layer to transfer and make use of regressors to match teacher’s/student’s feature maps size. However, transferring knowledge of one intermediate layer can not capture the critical connections between the layers. To alleviate this shortcoming, the Attention Transfer (AT) [5] proposes an attention mechanism to transfer the intermediate layer representations, but it also encodes the feature maps, collapsing this way their alignment. In addition, Probabilistic Knowledge Transfer (PKT) [21] transfers the features extracted from the penultimate layer (i.e., the last layer before the classification one) by matching their probability distribution, without leveraging any other intermediate layer. In [22], authors introduce a method to effectively encode the extracted features before the KD procedure. An effort of capturing the flow of information has been made in [23] by generating a Flow of Solution Procedure (FSP) matrix that captures the relation between to successive layers. In [24], authors introduce Contrastive Representation Distillation (CRD) that uses a contrastive loss to distill the feature maps (derived from the last convolutional layer), while ignoring the importance of the information flow paths. Furthermore, the Hierarchical Self-supervised Augmented Knowledge Distillation (HSAKD) [25] employs classifiers on the top of intermediate layers to supervise the KD procedure, which also collapses the architectural width-wise alignment.

The aforementioned methods that transfer knowledge from intermediate layers share the same shortcomings. They can only be applied on teacher/student pairs that share similar architectures, they encode the feature maps before the transfer (that collapses the alignment), they ignore the capacity gap between the models, and they face the challenge of transferring multiple layers simultaneously. Regarding the capacity gap, Mirzadeh et al. [26] suggest the usage of an auxiliary model that reduces the complexity “distance” between teacher and student models, but it should be stressed that the intermediate layers are not utilized during the KD. Based on the same idea, [4] also makes use of an auxiliary model to alleviate the architectural limitations. Also, [4] suggests a critical-periods-aware weight decay scheme that reduces the learning rate of the intermediate layers KD after each epoch, as the first training epochs are responsible for the creation of the information flow paths [7]. Inspired by these ideas, we also adopt an auxiliary teacher model to initially reduce the capacity gap (before we further reduce it by pruning its channels) and enable our method to be applied on teacher/student pairs with very different structures. Also, on the contrary to the other methods, ours directly matches the teacher’s/student’s feature maps that prevents the collapsing of the alignment.

Furthermore, curriculum learning [27][28] is utilized by numerous approaches on several fields [29][30][31][32][33]. Curriculum learning suggests splitting a hard task into several sub-tasks in difficulty order. For instance, [34] introduces a teacher-student curriculum learning framework for reinforcement learning, where the teacher determines the sub-tasks that the student should be trained on at each training step, while [35] proposes learning tasks sequentially for enhancing multi-task learning effectiveness. Inspired by the curriculum learning strategies and the need of critical periods awareness [4], we suggest a learning scheme that both overcomes the transferring multiple layers limitation and considers the learning phases to assist student to form the same critical connections as the teacher.
3 Methodology

3.1 Problem Formulation

The problem of transferring the knowledge from a teacher to a student model is formulated as follows. Let \( X \in \mathbb{R}^{3 \times h \times w} \) denote the input, \( d(\cdot) \) the teacher model, and \( l=1, \ldots, L_d \) the layer’s index, then \( T(l) = d(X, l) \in \mathbb{R}^{n_{d,l} \times h_{d,l} \times w_{d,l}} \) denotes the teacher’s \( l \) layer output. Accordingly, consider a student model \( g(\cdot) \) with \( L_s \) convolutional layers and \( S(l) = g(X, l) \in \mathbb{R}^{n_{g,l} \times h_{g,l} \times w_{g,l}} \) layer’s \( l \) output. In addition, let \( q_t \) and \( q_s \) be the class probability distributions of the teacher and student model, respectively. Given that, the target of single-layer KD is either to match teacher’s and student’s class probability distributions or to match their corresponding penultimate layer representations (i.e., \( T(L_d) \) and \( S(L_s) \)), while the intermediate layers KD provides an extra supervision to the main target by matching several teacher’s and student’s intermediate layer pairs. In our approach, we also make use of an auxiliary model that is defined as follows. \( f(\cdot) \) denotes the auxiliary model, \( L_f \) the number of convolutional layers (here \( L_f=L_g \)), and \( A(l) = f(X, l) \in \mathbb{R}^{n_{f,l} \times h_{f,l} \times w_{f,l}} \) its output feature maps that have the double channels compared to the student model’s, namely \( n_{f,l}=2 \times n_{g,l} \). Also, note that \( h_{f,l}=h_{g,l} \) and \( w_{f,l}=w_{g,l} \) as the networks share kernel sizes. Finally, auxiliary’s class probability distributions are denoted as \( q_a \).

3.2 Channel Pruning

Pruning is a widely applied technique to reduce the storage requirements or/and the inference time of a DNN by discarding the redundant parameters \([36, 37]\). To this end, the unstructured weight pruning methods remove the unimportant weight connections by setting their corresponding values equal to 0 that results in a significant reduction of storage requirements \([38]\). The limitation of these approaches is that the structure of the model remains the same as before the pruning procedure and thus there is no improvement in terms of the inference time. On the other hand, the structured filter pruning methods \([8, 39, 40, 41, 42]\) aims at removing the less important filters of a Convolutional Neural Network (CNN) in order to both reduce the model’s storage size and its time requirements. The typical criterion of evaluating the importance of a filter is the \( l_1 \)-norm or \( l_2 \)-norm. Here, we opted for using the approach proposed in \([8]\) that applies structured channel pruning based on \( l_1 \)-norm. Specifically, let \( f_i \in \mathbb{R}^{n_i \times h_i \times w_i} \), denote the input features and \( f_o \in \mathbb{R}^{n_o \times h_o \times w_o} \) denote the output features of a layer, respectively. Given that, the layer’s filters can be denoted as \( F \in \mathbb{R}^{n_i \times n_o \times k \times k} \), where \( k \) is the kernel size. Then, the pruning procedure is as described in Alg. 1

**Algorithm 1** Channel pruning procedure

1: **Inputs:** filters \( F \) and the number of filters to prune \( p \). **Output:** the pruned filters \( F' \).
2: Calculate the \( l_1 \)-norm for each one of the filters \( s_i = \sum_{j=1}^{n_i} \sum_{l=1}^{k} \sum_{m=1}^{k} \sum_{n=1}^{k} |F_{i,j,l,m}| \).
3: Sort the values of \( s \) vector and prune the top \( p \) filters with the smallest values in \( s \).
4: Return the updated \( F' \in \mathbb{R}^{n_i \times (n_o-p) \times k \times k} \).

It is worth noting that none of the existing KD approaches leverages pruning to enhance the KD performance. However, the nature of the channel pruning approach can be a contributory factor to the effectiveness of KD, as it maintains the architectural width-wise alignment which is crucial for representing the information flow paths, while reducing the capacity gap that restricts the volume of information to be transferred. InDistill takes advantage of these key characteristics of channel pruning to further increase student’s performance, as it is demonstrated in detail in Sec. 4.

3.3 Intermediate Layers Knowledge Distillation

Distilling the knowledge of model’s intermediate layers is suggested only for teacher/student models that share the architectural characteristics. For instance, let the teacher model be a CNN with residual blocks, the intermediate layers KD will be effective only if the student model is also residual based and has the same number of blocks as the teacher \([4, 24]\). If we recall the purpose of the intermediate layers KD, which is to enable student to learn the teacher’s flow of information, then it makes sense that if the teacher and student models have different architectures, the efforts of matching their informational flow paths will fail. Considering that, \([4]\) suggests the usage of an auxiliary teacher that allows for KD on heterogeneous models.

In this paper, we build on the concept of the auxiliary model to both tackle the discussed problem and initially reduce the capacity gap between teacher and student \([20]\). Specifically, we design the auxiliary model that consists of the same number of layers as the student and its output channels of each intermediate layer to be double compared to the corresponding student’s channels. Then, as it is already defined in Sec. 3.1, the auxiliary’s output feature maps are...
Adopting l-CLS, the first
\[ \sum \alpha \text{ where parameter} \]
where the number of segments is exactly the same, which allows for the direct knowledge transfer, without including any encoding that could collapse the alignment. The loss between models’ feature maps, \( P^{(l)} \) and \( S^{(l)} \) is defined as:
\[
L = \| P^{(l)} - S^{(l)} \|_2^2,
\]
where \( \| \cdot \|_2 \) denotes the l2-norm. Given that InDistill is only applied for the intermediate layers, any of the existing KD methods can be employed for the last layer. As it is stated before, InDistill can be combined with any KD method to enhance its effectiveness. In the case of the original KD method [3] that transfers the class probability distributions using the Kullback-Leibler (KL) divergence loss, let \( \mathbf{u} \) and \( \mathbf{v} \) denote the auxiliary’s and student’s logits, respectively, then the auxiliary’s and student’s probability distributions are defined by \( q_{a,i} = \frac{e^{\mathbf{u}_{i}/T}}{\sum_j e^{\mathbf{u}_{j}/T}} \) and \( q_{s,i} = \frac{e^{\mathbf{v}_{i}/T}}{\sum_j e^{\mathbf{v}_{j}/T}} \), respectively.

Then, the KL loss is defined as \( L_{KL} = \sum_i q_{a,i}(\log q_{a,i} - \log q_{s,i}) \cdot T^2 \), where \( T \) is the temperature term.

### 3.4 Curriculum Learning Scheme

The intermediate layers KD acts complementary to the major single-layer KD process to teach the student model the teacher’s information flow paths. These paths, are formed during the first training epochs, thus there is the need of adopting a learning scheme that is aware of the critical learning periods [4]. Inspired by this idea and considering the difficulty of learning multiple layers simultaneously, we propose a curriculum learning based scheme that facilitates the multi-layer KD and further improves student’s performance.

Curriculum learning strategies suggest that dividing the main task into several sub-tasks w.r.t. their difficulty and then train the model by learning each sub-task in ascending difficulty order. Given that the intermediate layers KD consists of several tasks (i.e., layers to transfer), we propose the l-CLS, a novel curriculum learning scheme that enhances the layer transferring effectiveness. Particularly, let \( L_g \) the number of layers, then there are \( L_g \) sub-tasks. If the number of training epochs is \( E \), then the number of epochs that corresponds to each sub-task can be calculated as follows:
\[
e_i = \begin{cases} 
  a + ib & i \neq L_g \\
  E - \sum_{i=1}^{L_g-1} e_i & i = L_g,
\end{cases}
\]
where parameter \( a \) indicates a threshold for each layer’s training epochs and \( b \) is a parameter that increments the number of epochs w.r.t. the sub-task’s difficulty. Thus, the set of epochs that corresponds to each sub-task is defined as \( S_i = \{ r_{i-1} + 1, r_{i-1} + 2, \ldots, r_i \}, \) where
\[
r_i = \begin{cases} 
  0 & i = 0 \\
  \sum_{k=1}^{i-1} e_k & i > 0,
\end{cases}
\] (3)

Adopting l-CLS, the first \( \sum_{i=1}^{L_g-1} e_i \) epochs are dedicated to the intermediate layers KD (i.e., totally ignoring the final task). This way, student model can effectively form the critical connections that significantly facilitates the major KD task, as it is demonstrated in Sec. [4].

### 4 Experimental Setup

#### 4.1 Datasets

The proposed method has been evaluated on 3 benchmark datasets. The first one is the CIFAR-10 [10], an image dataset that consists of 60,000 images classified in 10 classes that depict animals and means of transport. The second one is the CUB-200 dataset [11] that contains 11,788 images of 200 subcategories belonging to birds species. Finally, the last one is the FashionMNIST dataset [12] that consists of 70,000 grayscale images with a size of \( 28 \times 28 \) that depict 10 fashion categories.

#### 4.2 Competitive Methods

The proposed method is compared to 7 widely-adopted competitive KD approaches. The first method is the original KD method (OKD) proposed in [3] that constitutes a strong baseline. The Hints based approach [6], the AT [5], and the Heterogeneous PKT with CRitical learning periods awareness (PKT-H-CR) [4] are highly-cited methods that leverage the intermediate layers for providing an extra supervision. Finally, the single-layer competitive KD approaches we
4.3 Models

Following [4], we consider the triplet of teacher, auxiliary, and student architectures. The ResNet-18 is used as the teacher model (consisting of around 11 million trainable parameters), while 2 tiny CNNs consisting of 3 convolutional layers represent the auxiliary (CNN-A) and the student model (CNN-S), respectively. The images of each dataset have different sizes and number of channels, thus the auxiliary’s and student’s architectures are modified for each dataset, accordingly. Fig. 2 presents the models’ architectures in detail. As it can be seen, CIFAR-10 and FashionMNIST share the same models pair, except for the input channels of the first convolutional layer that is 3 for CIFAR-10 (RGB images) and 1 for FashionMNIST (grayscale images). For CIFAR-10, the CNN-A and the CNN-S contain 57,994 and 15,050 trainable parameters respectively, while for FashionMNIST, the CNN-A and the CNN-S contain 57,706 and 14,906 parameters. For CUB-200, the CNN-A and CNN-S models follow the same pattern as before, but the kernel size of the 3 convolutional layers is $9 \times 9$, $5 \times 5$, and $5 \times 5$ respectively, as in [4]. Thus, the CNN-A for CUB-200 contains 104,990 trainable parameters, while the CNN-S contains 28,318. For all the aforementioned models, batch normalization is applied after each convolutional layer. Note that, PKT-H-CR [4] is the only method that both makes use of an auxiliary teacher model and applies a learning scheme (i.e., weight decay) to facilitate the multi-layer KD procedure, thus in InDistill-l-CLS evaluation we tried to adhere as much as possible to the corresponding PKT-H-CR evaluation setup in order to provide a fair comparison.

4.4 Training details and evaluation protocol

The same set of hyperparameters was used for all the datasets. In particular, the models are trained using the Adam optimizer for 60 epochs with learning rate 0.001 and for 10 epochs with learning rate 0.0001. The batch size was equal to 128. The parameters $a$ and $b$ of l-CLS are set equal to 2 and 1, respectively. Finally, for the classification experiments, the cross-entropy loss was used for all the methods. Note that all experiments were conducted using one Nvidia RTX-3060 GPU.

The official train/test splits was used for the evaluation. Regarding the CUB-200 dataset, only the first 30 classes were used in the conducted experiments, as in [4], due to the restricted capacity of the auxiliary/student models. The tasks we consider for evaluation are metric learning and image classification. For the metric learning evaluation, the mAP and the top-k precision metrics are utilized, while the accuracy is considered for the classification task.
5 Results

The baseline performance of teacher, auxiliary, and student models is presented in the baseline rows of Tab. 1, while comparison is performed among the methods illustrated in the competitive rows, for all datasets. The baseline performance of teacher and student models refers to the models trained from scratch without involving any KD procedure, which is not the case for the auxiliary baseline that refers to its performance after applying KD (from teacher to auxiliary). Note that, for CIFAR-10 dataset, we used the pretrained baseline models provided by [4], which is not applied for the CUB-200 dataset (for which the pretrained baseline models are not available by the authors of [4]). For clarity purposes, the tables’ values in parentheses refer to the corresponding results provided in [4]. Tab. 1 demonstrates the performance of InDistill-l-CLS compared to the other KD methods. The proposed method exhibits a consistent improve of the KD effectiveness over all datasets. Specifically, for the mAP (c) metric, InDistill-l-CLS achieves an increase of 1.61%, 3.59%, and 0.72% for CIFAR-10, CUB-200, and FashionMNIST, respectively. It should be stressed that in these experiments we opted for the PKT method for distilling the knowledge of teacher’s and auxiliary’s penultimate layer. The students’ mean inference time is 14.89× faster than teacher (i.e., 0.49ms on CPU) and their mean size is 28KB, while the corresponding teachers’ size is 42.7MB. Apart from the metric learning evaluation, InDistill-l-CLS is further evaluated for the classification task. As it can be seen in Tab. 2 the proposed method outperforms the corresponding best compared method on all the tested datasets. In particular, InDistill-l-CLS achieves 74.13%, 45.69%, and 90.57% accuracy for CIFAR-10, CUB-200, and FashionMNIST, respectively.

| CIFAR-10 dataset | Teacher (ResNet-18) | mAP (e) | mAP (c) | top-100 pr. (e) | top-100 pr. (c) | #parameters |
|------------------|---------------------|---------|---------|----------------|----------------|-------------|
| baseline         | 87.18               | 90.47   | 92.12   | 92.26          | 11,181,642     |
| Auxiliary (CNN-A)| 62.12               | 66.78   | 73.72   | 75.91          | 57,994         |
| Student (CNN-S)  | 35.30               | 39.00   | 55.87   | 58.77          | 15,050         |
| competitive      | OKD                 | 35.82 (37.39) | 39.38 (40.53) | 55.57 (56.17) | 58.54 (58.56) | 15,050 |
|                  | Hints               | 34.65 (43.99) | 37.64 (48.99) | 52.45 (60.69) | 55.06 (62.42) |
|                  | AT                  | 36.39   | 39.67   | 55.93          | 58.74          |
|                  | MKT                 | 41.86 (36.26) | 46.88 (38.20) | 59.12 (50.55) | 61.14 (52.72) |
|                  | PKT                 | 47.64 (48.07) | 51.41 (51.56) | 59.85 (60.02) | 62.56 (62.50) |
|                  | CRD                 | 41.13   | 47.11   | 59.54          | 61.64          |
|                  | PKT-H-CR            | 49.19 (49.20) | 53.00 (53.06) | 61.45 (61.54) | 64.06 (64.24) |
|                  | InDistill-l-CLS     | 50.47   | 54.61   | 62.60          | 65.40          |

| FashionMNIST dataset | Teacher (ResNet-18) | mAP (e) | mAP (c) | top-100 pr. (e) | top-100 pr. (c) | #parameters |
|----------------------|---------------------|---------|---------|----------------|----------------|-------------|
| baseline             | 73.30               | 79.49   | 90.38   | 90.94          | 11,175,370     |
| Auxiliary (CNN-A)    | 70.08               | 74.39   | 85.36   | 86.15          | 57,706         |
| Student (CNN-S)      | 65.93               | 68.28   | 85.51   | 86.22          | 14,906         |
| competitive          | OKD                 | 66.70   | 68.90   | 84.63          | 85.13          |
|                      | Hints               | 67.09   | 69.44   | 84.80          | 85.32          |
|                      | MKT                 | 68.02   | 71.10   | 85.19          | 85.88          |
|                      | AT                  | 67.36   | 69.32   | 84.57          | 85.04          |
|                      | PKT                 | 67.30   | 71.50   | 82.49          | 83.34          |
|                      | CRD                 | 65.74   | 71.65   | 84.62          | 85.26          |
|                      | PKT-H-CR            | 68.24   | 71.96   | 83.55          | 84.19          |
|                      | InDistill-l-CLS     | 69.38   | 72.68   | 85.42          | 86.08          |

| CUB-200 dataset | Teacher (ResNet-18) | mAP (e) | mAP (c) | top-100 pr. (e) | top-100 pr. (c) | #parameters |
|-----------------|---------------------|---------|---------|----------------|----------------|-------------|
| baseline        | 59.73 (63.17)       | 66.53 (78.17) | 68.38 (76.02) | 71.09 (81.64) | 11,191,902    |
| Auxiliary (CNN-A) | 24.24 (17.01)     | 27.27 (18.98) | 34.01 (25.77) | 36.64 (27.07) | 104,990       |
| Student (CNN-S)  | 19.00 (15.60)       | 21.21 (17.24) | 27.98 (23.40) | 29.97 (24.89) | 28,318        |
| competitive      | OKD                 | 20.93 (16.40) | 23.84 (18.55) | 30.35 (24.82) | 33.17 (26.57) |
|                  | Hints               | 17.34 (14.34) | 19.18 (15.98) | 25.93 (22.31) | 27.15 (23.41) |
|                  | AT                  | 21.40   | 24.11   | 30.97          | 33.18          |
|                  | MKT                 | 20.19 (12.99) | 22.42 (13.39) | 12.56 (20.60) | 13.64 (20.59) |
|                  | PKT                 | 20.75 (16.36) | 23.49 (18.57) | 30.36 (24.68) | 32.87 (26.70) |
|                  | PKT-H-CR            | 21.51 (16.70) | 25.15 (19.01) | 31.31 (25.41) | 34.46 (27.67) |
|                  | InDistill-l-CLS     | 24.60   | 28.74   | 35.22          | 38.56          |

Table 1: Metric Learning Evaluation. The abbreviation "e" refers to the retrieval based on the Euclidean similarity metric, while "c" denotes the retrieval based on the cosine similarity metric. The precision is denoted as "pr.". The scores in parentheses refers to the results provided in [4].
| Method      | CIFAR-10       | CUB-200       | FashionMNIST |
|-------------|----------------|---------------|--------------|
| OKD         | 73.08 (70.68)  | 39.32 (35.21) | 90.01        |
| Hints       | 72.54 (70.59)  | 30.08 (28.71) | 89.19        |
| AT          | 73.22          | 39.45         | 90.19        |
| MKT         | 69.32 (69.13)  | 33.33 (30.46) | 88.03        |
| PKT         | 73.27 (70.44)  | 40.32 (34.96) | 90.19        |
| PKT-H-CR    | 73.33 (71.97)  | 42.32 (36.95) | 90.26        |
| CRD         | 71.99          | -             | 89.14        |
| InDistill-l-CLS | 74.13  | 45.69         | 90.57        |

Table 2: Classification evaluation. The scores in parentheses refer to the results provided in [4].

5.1 Ablation Study

For further evaluation, Fig. 3a depicts the penultimate layer loss curves of the proposed method combined with 3 KD approaches (i.e., OKD, PKT, and CRD). As it can be noticed, during the first training epochs of the proposed method, the loss (of the penultimate layer) is considerably larger than the corresponding baseline method, which makes sense, as during these epochs only the intermediate layers are transferred. The effectiveness of the proposed method can be noticed after the first training epochs, when the KD procedure of the penultimate layer begins and the corresponding loss diminishes rapidly, which highlights the importance of transferring the information flow paths (without collapsing them) prior to the main KD procedure. Furthermore, to highlight the impact of the proposed method’s components (i.e., Indistill and l-CLS) on the KD effectiveness, the loss curves of the Indistill method without any learning scheme (i.e., transferring all layers simultaneously), the Indistill method with the WD scheme proposed in [4], and the Indistill-l-CLS method are depicted in Fig. 3b. As it can be seen, although the combination of Indistill with PKT without applying any learning scheme reduces the loss during the first training epochs compared to the baseline PKT method, it actually impedes the learning procedure during the last training epochs (in which the critical connections have already been formed). On the contrary, applying a learning scheme that is aware of the critical learning period, such as the WD and the l-CLS, can successfully address this limitation. However, the proposed scheme is superior to the WD one, as not only is the applied curriculum based strategy aware of the critical learning periods, but it also considers the complexity of transferring multiple layers, and thus provides a proper supervision to the student model in order to effectively mimic the teacher’s information flow paths.

Fig. 4a presents how the selection of different rates of channels to prune affects the mAP for the 3 tested datasets. Pruning half of the channels per layer provides an optimal trade-off, while the other 2 tested rates (i.e., 1/3 and 0.75) also exhibit competitive performance. Note that we opted for these pruning rates as they result in an integer number of
Figure 4: (a) InDistill-l-CLS performance vs. pruning rates. For each pruning rate, an auxiliary with different number of filters is designed, so that its pruned output channels match the student’s channels. Thus, we do not investigate extreme pruning rate values due to their high impact on auxiliary’s width. (b) Comparison between the proposed method and PKT-H-CR for models pairs with different depth.

channels. Thus, investigating extreme pruning rates is meaningless due to the impact on the architecture of the auxiliary model. Finally, we evaluated the proposed method for 4 different auxiliary/student model pairs that vary in terms of their depth. Except for the auxiliary and student models with 3 convolutional layers that we used for all the conducted experiments, we also designed 3 additional model pairs that consist of 2, 5, and 7 layers, respectively. The number of their trainable parameters varies from 3,706 to 1,131,262 and it also depends on the dataset (see Sec. 4.3). Fig. 4b demonstrates the mAP of the proposed method compared to PKT-H-CR (the second best performing method) for the different model pairs. As one may note in 4b the proposed method exhibits superior performance for all experiments, except for the 2-layer model for CIFAR-10 dataset for which the PKT-H-CR slightly outperforms our method. For the remaining model depths, the proposed method clearly outperforms the other method in the CIFAR-10 and CUB-200 datasets. Regarding the FashionMNIST dataset, although the performance of both methods is close, the proposed method performs slightly better for all model depths.

6 Conclusions

In this paper, we introduced a novel intermediate layers KD method that leverages the properties of Channel Pruning to both reduce the capacity gap between the teacher and student models and effectively capture the teacher’s information flow paths that are of highest importance when it comes to intermediate layers KD. In addition, we proposed a curriculum based learning scheme that facilitates the procedure of transferring multiple layers and enhances the effectiveness of the main KD process. The proposed method has been evaluated for different tasks and combined with several competitive single-layer KD methods and successfully enhanced their performance. The limitations of this work could be the need of designing a proper auxiliary model for each different student and the fact that a multi-step KD method is more computationally demanding than a simple KD approach.

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