Feature Matters: A Stage-by-Stage Approach for Knowledge Transfer

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Abstract

Convolutional Neural Networks (CNNs) become deeper and deeper in recent years, making the study of model acceleration imperative. It is a common practice to employ a shallow network, called student, to learn from a deep one, which is termed as teacher. Prior work made many attempts to transfer different types of knowledge from teacher to student, however, there are two problems remaining unsolved. Firstly, the knowledge used by existing methods is usually manually defined, which may not be consistent with the information learned by the original model. Secondly, there lacks an effective training scheme for the transfer process, leading to degradation of performance. In this work, we argue that feature is the most important knowledge from teacher. It is sufficient for student to achieve appealing performance by just learning similar features as teacher without any processing. Based on this discovery, we further present an efficient learning strategy, which is to make student mimic features of teacher stage by stage. Extensive experiments suggest that the proposed approach significantly narrows down the gap between student and teacher, and shows strong stability on various tasks, i.e., classification and detection, outperforming the state-of-the-art methods.

1. Introduction

Over the past few years, Convolutional Neural Networks (CNNs) have advanced various tasks in computer vision field, such as image classification [9], object detection [18], and semantic segmentation [4]. However, along with deeper architectures [14, 24, 6, 10], the great success of CNN is actually based on high computational cost, which cannot be afforded by most devices in practice. Some lightweight models are presented by recent work [8] to reduce the computing cost especially for mobile devices, but the performance drops severely compared with the state-of-the-art methods. Accordingly, it is crucial to balance the trade-off between efficiency and capability of a CNN model.

To tackle this problem, knowledge distillation is introduced in [7] for model acceleration. The core idea is to train shallow networks (student) to mimic deep ones (teacher) following two steps. First, teacher employs a very deep model to achieve satisfying performance by excavating information (knowledge) from labeled data. Second, student learns the knowledge from teacher with a shallow model to speed up the inference process without losing much accuracy. Accordingly, the main challenges, corresponding to the above two steps respectively, lie in (1) what kind of knowledge should be transferred from teacher to student, and (2) how to transfer the knowledge as much as possible.

For the first issue, previous work has proposed various methods to distill the knowledge learned by teacher for student to learn, such as attention map [26] and information flow [25]. However, all types of distillation are manually defined and may not be consistent with the real information contained in the teacher model. In other words, teacher is trained independently from the distillation methods, but it is required to guide the student with these handcraft...
hyper-parameters, i.e., the loss weights to balance these two objective functions. Specifically, when the same teacher-student pair is applied to a different task, or even applied to another dataset, it may need to carefully readjust the loss weights to get a satisfying result, which is very inefficient. On the other hand, the purposes to learn from teacher and to learn from ground-truth are not always in line with each other. For example, the teacher model may have already eliminated some label errors during the training process. In this case, information from the teacher and from the training set indicates two opposite directions, which may cause confusions to the student.

In this paper, we address these weaknesses by proposing a practical knowledge transfer approach, where student is trained to progressively mimic the hidden features from teacher, as shown in Fig.1. Here, for simplicity, we do not distinguish between feature (vector) and feature map (tensor). It has three appealing properties:

(1) Feature as the meaningful guidance - We directly use the output features of some selected hidden layers of teacher model to supervise student without any processing. Since teacher uses features for inference in practice, they are expected to reflect the complete information from teacher model. Therefore, these features should be able to provide better guidance for student.

(2) Isolation of knowledge source - We isolate the knowledge contained in teacher model from the information contained in labeled data using two phases. In the first phase, student learns knowledge by mimicking teacher regardless of the ground truth label, while in the second phase, student is trained to apply the fixed learned features from first phase to adapt with the training set. In this way, student can focus on acquiring information from only one source in each phase, making the transfer process more accurate. Furthermore, training these two phases separately also makes our method more stable, since there is no need to adjust the loss weights between different terms.

(3) Progressive knowledge distillation - instead of training all parameters of student together, we divide the transfer process into different stages and only train a sub-network at one time. In doing so, each stage can obtain focused and sufficient training from the teacher. All stages will finally collaborate together to achieve a better performance. Although our method employs multiple stages, the training efficiency is barely affected. That is because when training a particular stage, all previous stages are fixed and only parameters in the current stage is updated, as illustrated in Fig.1.

To summarize, this work has three main contributions:

- We demonstrate the effectiveness of directly mimicking features in knowledge transfer.
- We present a stage-by-stage training strategy to facilitate more effective and efficient knowledge distillation from teacher to student.
- We show experimentally that our approach surpasses the state-of-the-art methods on various tasks with higher performance and stronger stability. Concretely, we achieve 0.6% higher top-1 accuracy on the ImageNet classification task than other competitors by using ResNet-18 to mimic ResNet-34, and achieve 0.3% higher mean Average Precision (mAP) on COCO detection task by using ResNet-50 to mimic ResNet-101.

2. Related Work

Model Compression. There have been extensive attempts in the literature to reduce computational cost by model compression. Network pruning was proposed to find a balance between performance and storage capacity by removing redundant structures of the network. Molchanov et al. [21] and Li et al. [16] introduced different criteria to evaluate the importance of neurons and filter out the insignificant channels to reduce the network size. Besides, quantization [5], which uses fewer bits for each neuron, and low-rank approximation [27], which factorizes a huge matrix with several small matrices, are also widely applied for model acceleration. In this work, we focus on the other model compression technique, knowledge transfer, where a shallow student model is trained to gain information from a deep teacher model.

Knowledge Transfer. The preliminary view of knowledge transfer was adopted in [2], which trains a shallow network with data labeled by a deep one. Through student learning the soft label tagged by teacher instead of the ground truth, knowledge is assumed to be transferred from teacher to student. [7] introduced the concept of Knowledge Distillation (KD), which describes the process of knowledge transfer as a student mimicking the output of teacher. As for classification task, the student model is trained with the ground truth label as well as the class probabilities predicted by teacher simultaneously. Hinton et al. [7] also proposed to raise the temperature in softmax function to further distill the knowledge, however it is very sensitive to the hyper-parameter, i.e. temperature, and is not applicable to tasks
other than classification due to the limitation of softmax loss.

To solve the above problem, many other methods for knowledge distillation are proposed. Zagoruyko et al. [26] attempted to transfer spatial attention map, which is defined as the average of feature maps across the channel dimension. Huang and Wang [11] proposed to learn feature map through Maximum Mean Discrepancy (MMD), which can be regarded as a sample-based metric to measure the distance between two probability distributions. Both methods can be considered as distilling knowledge by computing the statistics of feature maps. However, learning such statistics is not equivalent to learning the original feature maps, since the detail information may vanish, which will lead to performance degradation. Yim et al. [25] used Flow of Solution Procedure (FSP) to describe the information flow of a CNN model, which computes the Gram matrix of two hidden feature maps. Instead of learning the knowledge from teacher directly, student is trained to mimic how information flows in teacher. It indeed extracts some higher-level knowledge compared to mimicking features, but the student model may not treat the feature extraction process same as teacher. Therefore, forcing it to reproduce the information flow may be too difficult to train. Similarly, Lee et al. [15] applied Singular Value Decomposition (SVD) to derive the correlation between two feature maps.

**Transfer Strategy.** Besides defining what kind of knowledge should be transferred, how to transfer the knowledge from teacher to student is another direction that is worth exploring. Romero et al. [22] presented FitNets by introducing an intermediate layer from teacher model as hint for student. Similarly, a hidden layer of student is chosen as the guide for the entire transfer process. The guide layer is firstly trained to mimic the hint layer to assist the shallow network to get a better initialization. Then the entire network is end-to-end trained as other methods did.

Different from FitNets, our proposed method employs a progressive training strategy, which has been widely applied in various fields, such as transfer learning [23] and generative model [12]. We also employ multiple stages to mimic features, but different stages are separately trained. In other words, only a sub-network will be trained in each stage. Unlike FitNets where the first half of the student model will be trained twice, each layer in our framework will only be optimized once, making our approach much more efficient. Furthermore, we separate the feature extraction and feature adaption process apart, which is another difference from FitNets.

In addition with the conventional training framework, there are also some other studies that introduce reinforcement learning [1] and adversarial network [3] to the knowledge transfer problem. However, training these networks is still not trivial for now, since there are many problems remain unsolved, e.g., how to design the structure, how to optimize the network, how to formulate the reward in reinforcement learning, or how to establish the competition in adversarial nets. Compared to them, our approach is much more straightforward.

### 3. Methodology

This section introduces the proposed stage-by-stage knowledge transfer method as shown in Fig.2. We will discuss preliminary knowledge on knowledge transfer in Sec.3.1. Sec.3.2 explains how knowledge is transferred by mimicking features. Sec.3.3 presents the progressive training scheme. Sec.3.4 introduces the implementation details.

#### 3.1. Preliminary

In general, most deep CNN models $M(\cdot)$ can be treated as two parts, which are the feature extraction part $M_E(\cdot)$ and the feature adaption part, term as final stage $M_F(\cdot)$ in this work. More specifically, given an image $x$ and the corresponding ground truth $y$, the first part will represent the image as a high dimensional feature with $f = M_E(x)$, and the second part will take such representation as input and make a prediction with $\hat{y} = M_F(f)$. Accordingly, the entire model can be regarded as the combination of the above two parts

$$M = M_F \circ M_E,$$  \hspace{1cm} (1)

where $\circ$ indicates the function composition.

For a particular task, the predicted label $\hat{y} = M(x)$ is expected to be as close to real label $y$ as possible. To achieve this goal, the model is trained with an objective function

$$\min_{\Theta_M} \mathcal{L}_M = \phi(y, \hat{y}),$$  \hspace{1cm} (2)

where $\Theta_M$, consisting of $\Theta_{M_E}$ and $\Theta_{M_F}$, is the trainable parameters of the entire model. $\phi(\cdot, \cdot)$ is the task-related energy function, such as the softmax cross-entropy loss in classification task and the bounding box regression loss in detection task.

When it comes to knowledge transfer problem, we have a deep teacher model $T(\cdot)$ and a shallow student model $S(\cdot)$, which are composed of $\{T_E(\cdot), T_F(\cdot)\}$ and $\{S_E(\cdot), S_F(\cdot)\}$ respectively. Correspondingly, the hidden feature and the final prediction are denoted as $\{f^T, \hat{y}^T\}$ and $\{f^S, \hat{y}^S\}$. The key challenge is to find out the knowledge contained in teacher model with $\sigma(f^T, \hat{y}^T)$ and then transfer it to the student. Therefore, this problem can be formulated as

$$\min_{\Theta_S} \mathcal{L}_S = \phi(y, \hat{y}^S) + \lambda \psi(\sigma(f^T, \hat{y}^T), \sigma(f^S, \hat{y}^S)), \hspace{1cm} (3)$$

where $\psi(\cdot, \cdot)$ is the loss function for transferring knowledge and $\lambda$ is the loss weight to balance the two terms.
this process, we assume that the teacher model $T(\cdot)$ has already been well trained with Eq.(2) and will no longer be optimized.

### 3.2. Feature Transfer

Considering the two parts mentioned above, the only difference between student and teacher is the ability to extract features from images, because they share the same structure in the final stage, as shown in Fig.2. From this point of view, student has equivalent capability as teacher in how to use the feature for label prediction. In other words, if the student could produce identical feature as the teacher does, it should be able to achieve as promising performance as well. Therefore, we propose to focus on the knowledge contained in the feature extraction part instead of the entire model, and do not transfer the final stage knowledge from teacher to student. Based on this argumentation, the mimicking process defined in Eq.(3) can be easily separated into two parts

$$\min_{\Theta_{S_E}} \mathcal{L}_{S_E} = \psi(\sigma(f^T), \sigma(f^S)), \quad (4)$$

$$\min_{\Theta_{S_F}} \mathcal{L}_{S_F} = \phi(y, \hat{y}^S), \quad (5)$$

where $\sigma(\cdot)$ indicates the knowledge contained in the feature extraction stage. It is different from $\sigma(\cdot, \cdot)$ in Eq.(3), which is the knowledge contained in the entire model. In this work, we choose $\sigma(\cdot)$ as an identity function, i.e. $\sigma(x) = x$, to avoid information loss caused by distillation.

More concretely, $S_E$ is firstly trained to mimic the feature $f^T$ extracted by $T_E$ with Eq.(4). Since $S_E$ is not as powerful as $T_E$ in extracting information from the original data, using $f^T$ as guidance will alleviate the training difficulty. Then $S_F$ is trained with the supervision of ground truth $y$ with $S_E$ fixed as in Eq.(5). There are two advantages in doing so. On one hand, information from the teacher model $T$ and that from the ground truth label $y$ will not interfere with each other, and the already transferred knowledge in the first phase will not vanish. On the other hand, the training will be very efficient. As both $S_E$ and $S_F$ are only trained once, the total training time is almost the same as end-to-end training. Furthermore, compared to existing work, the entire training process in our approach does not rely on the loss weight $\lambda$ in Eq.(3), resulting in much stronger stability.

### 3.3. Stage-by-Stage Training Scheme

From the discussion above, it is crucial for our method that student can learn similar feature as teacher. However, considering the wide difference between the representation capabilities of these two models, the goal is not that easy to achieve through simple end-to-end learning. To tackle this problem, we break them down into multiple stages and make student to mimic the output stage features of teacher progressively, as shown in Fig.2. Taking teacher model as an instance, we have

$$\begin{align*}
\begin{cases}
    f^T_0 = x, \\
    f^T_i = T_i(f^T_{i-1}), & i = 1, 2, \ldots, K, \\
    T_E = T_1 \circ T_2 \circ \ldots \circ T_K,
\end{cases}
\end{align*} \quad (6)$$

where $K$ is the total number of stages, excluding the final feature adaption stage. $f^T_i$ is the hidden feature of the $i$-th stage in teacher network, while $f^T_0$ is the initial feature, i.e. the input image. $T_i(\cdot)$ is the sub-network of teacher model in $i$-th stage, and $T_E(\cdot)$ can be considered as a composition of a series of sub-networks. Similarly, $S_E(\cdot)$ is also divided into $K$ stages.

Under such separation, the feature transfer process as shown in Eq.(4) can be further split apart as follows

$$\min_{\Theta_{S_i}} \mathcal{L}_{S_i} = \psi(\sigma(f^T_i), \sigma(f^S_i)), \quad i = 1, 2, \ldots, K, \quad (7)$$

where $\sigma(\cdot)$ is also set as an identity function, same as that in Eq.(4), to maintain the original information from the teacher model.

Similar as fixing $S_E$ when training $S_F$ as mentioned in Sec.3.2, we fix all parameters in previous stages when training a new stage, to prevent the transferred knowledge from vanishing and speed up the training process. Although these stages are trained separately, they are not completely independent, since each stage will take the feature produced by the previous stage as input for further training. That is to say, after the first $i$-th stages are well trained, the $(i+1)$-th stage will try to mimic feature $f^T_i$, based on $f^S_i$ instead of $f^T_i$. In this way, even though the $i$-th stage of student cannot exactly reproduce the same feature as teacher, the difference between $f^S_i$ and $f^T_i$ will be further handled by the $(i+1)$-th stage. Finally, these stages will cooperate with each other to achieve a better performance.

**Discussion.** FitNets [22] also proposed to train student model in two stages by mimicking the hidden feature of teacher model in the first stage. However, our method differs from FitNets from two main aspects rather than just adding more stages. (1) In FitNets, after the first stage finished, the second stage does not fix the well-trained part but trains the entire network instead. In other words, the first half of student will be trained twice, which is very time-consuming. In addition, the already transferred knowledge in the first stage may vanish when fine-tuned in the second stage. Therefore, FitNets is more likely to give student a better initialization in the first stage and transfer knowledge in the second one. Differently, knowledge transfer appears in every stage in our method – we break apart the information gained by teacher model and then transfer it to student gradually. (2) FitNets does not isolate
the information from teacher model and that from training data, and student is still trained with Eq.(3) in the second stage. On the contrary, we argue that the final stage in the student model has the same learning ability as teacher such that there is no need to transfer the knowledge contained in that stage. Thus, our approach trains the student to learn from teacher and from ground truth separately.

3.4. Implementation

In our experiments, we assume that the features of each stage produced by student and teacher should have the same dimension. This is a common assumption that has been widely used by previous work [22, 26, 25]. Even so, our method can also deal with the case where the feature dimensions mismatch, by adding an additional convolutional layer with 1 \times 1 kernel size after the output feature of student in each stage to fulfill the dimension condition. For simplicity, we just use models that have similar structures as teacher-student pair, such as ResNet-34 [6] and ResNet-18.

As for the stage partition, we treat each resolution downsampling layer as a break point. Taking ResNet as an example, the input image is with the size 224 \times 224. Besides the first convolutional layer and pooling layer, there are mainly four sets of residual blocks. The spatial resolutions of the output features of these sets of blocks are 56 \times 56, 28 \times 28, 14 \times 14, 7 \times 7 respectively. These features break down the entire model into 4 stages automatically.

When training a particular stage, Eq.(7) and Eq.(5) are used for the feature mimicking stage and feature adaption stage respectively. As previously mentioned, we choose \psi(\cdot) to be an identity function. \psi(x,y) is a function to measure the distance between the features from student and teacher. We use \ell_2 distance in this work, i.e. \psi(x,y) = \|x - y\|_2. The function \phi(\cdot, \cdot) is task-related. For the classification task, we use the cross-entropy loss, i.e., \phi(y, \hat{y}) = -\sum_{i=1}^{N} y_i \log \hat{y}_i, where N is the total number of categories. For detection task, we use the bounding box regression loss, i.e., \phi(y, \hat{y}) = |y - \hat{y}|_1. We use SGD optimizer with momentum 0.9 to train each stage. The learning rate is set to 0.01 initially and drops 0.1 every time the feature distance \psi(f^T, f^S) does not decrease any more. After the learning rate drops to 1e^{-5}, we suppose the current stage is well trained and start training the next stage.

4. Experiments

To evaluate the performance of our proposed method, we carry out various experiments on different datasets and different tasks. Sec.4.1 briefly introduces the basic settings used in our experiments. Sec.4.2 conducts a series of comparative experiments to verify the importance of learn-
### Table 1. Ablation experiments on CIFAR-100 dataset. Details are discussed in Sec.4.2 and Sec.4.3.

| Training strategy | Method | Model | Top-1  | Top-5  |
|-------------------|--------|-------|--------|--------|
| (a) End-to-end training from scratch. | Student | ResNet-18 | 68.062 | 89.598 |
|                   | Teacher | ResNet-34 | 73.045 | 91.545 |
| (b) Training final stage only. | Student | ResNet-18 | 68.046 | 89.533 |
|                   | Teacher | ResNet-34 | 73.063 | 91.586 |
| (c) End-to-end training with stage loss. | 1 stage | ResNet-18 | 69.687 | 89.124 |
|                   | 2 stages | ResNet-18 | 70.236 | 89.375 |
|                   | 3 stages | ResNet-18 | 70.932 | 89.849 |
|                   | 4 stages | ResNet-18 | 71.687 | 90.126 |
| (d) Stage-by-stage training. | 1 stage | ResNet-18 | 70.371 | 89.100 |
|                   | 2 stages | ResNet-18 | 71.223 | 90.000 |
|                   | 3 stages | ResNet-18 | 72.321 | 90.795 |
|                   | 4 stages | ResNet-18 | 72.768 | 91.396 |
| (e) Stage-by-stage training with more stages. | 5 stages | ResNet-18 | 72.558 | 91.187 |
|                   | 6 stages | ResNet-18 | 72.942 | 91.423 |
|                   | 7 stages | ResNet-18 | 72.673 | 91.354 |
|                   | 8 stages | ResNet-18 | **73.001** | **91.562** |

In this section, we set up a series of experiments to show the rationality of transferring features. We take the classification task on CIFAR-100 as an example. The performances of directly training student and teacher model from scratch are shown in Tab.1(a), and the teacher will be used as guidance of student in the following experiments.

As discussed in Sec.3.2, the whole network can be divided into two parts, which are respectively designated for feature extraction and feature adaption. We propose to firstly train the feature extraction part of student to mimic the corresponding output feature of teacher, and then train the feature adaption part with labeled data based on the fixed feature from the first stage. To evaluate that training these two stages separately will not affect the performance, we fix the feature extraction part of a well-trained model, re-initialize the final stage, i.e., fully-connected layer, and then merely train the final stage. Results are shown in Tab.1(b). By comparing (a) and (b), we can tell that training final stage with fixed feature can actually achieve the same performance as end-to-end training, demonstrating the feasibility of our approach.

To further evaluate that mimicking features can indeed transfer knowledge from teacher to student, we train four additional student models supervised by both ground truth label and the hidden features of teacher, as shown in Tab.1(c). Here, “1 stage” means that only the final feature is used as supervision, “2 stages” means that the feature extraction part is separated into two stages and the output features from both stages are used to guide the student, and so on and so forth. In these experiments, we set the weight parameters corresponding to each loss term, i.e., feature mimicking loss and classification loss, to be 1. The comparison between (a) and (c) suggests that...
providing shallow model with the information contained in
the feature from the deep one can assist student to gain more
knowledge and thus get better performance. Furthermore,
along with the increasing number of stages, the model
becomes more accurate. That is because features from
different stages can provide different level of information,
\textit{i.e.} shallower layers provide low-level information while
deeper layers provide high-level information. Accordingly,
the inference ability of student is enhanced by learning more
knowledge from the teacher.

### 4.3. Stage-by-Stage Learning

In this section, we validate the effectiveness of our
proposed stage-by-stage training scheme, as described in
Sec.3.3. We train another four independent shallow models
with different number of stages, where the partition of
stages is same as that described in Sec.4.2. Each model
is trained to mimic the features of teacher progressively.
Tab.1(d) shows the results. The only difference between
(c) and (d) is whether the student is trained end-to-end or
stage-by-stage. It is easy to tell that no matter how many
stages are used, progressive training always achieves better
performance than end-to-end training with nearly the same
training time.

Fig.3 visualizes the high dimensional features of the 3rd
stage and 4th stage in 2D space with T-SNE [20]. Compared
to the baseline model (first column) which is trained inde-
dependently from the teacher, the model that is trained with
feature mimicking loss can learn a better representation
(second column). When transferring knowledge through
feature, stage-by-stage training (third column) produces
clearer feature space, especially for intermediate feature.
There are three reasons. (1) The feature extraction and
feature adaption parts are optimized separately, and student
can focus on learning knowledge from one source in each
phase, \textit{i.e.} teacher and training data respectively. (2) There
is no need for our approach to adjust the loss weights, which
may severely affect the final results. (3) Each stage can get
adequate training without being affected by the following
stages. More specifically, in end-to-end training, each stage
is trained with not only the feature mimicking loss for itself,
but also the loss for latter stages. Therefore, updating the
parameters of latter stages will also influence the loss for
the current stage. On the contrary, stages in our method
are only supervised by the current output feature, which is
much more accurate.

We also explore the relationship between performance
and the number of stages by training some student models
with more stages, as shown in Tab.1(e). Based on the
original 4-stage partition, “5 stages” means that the first
stage is evenly divided into two halves, “6 stages” means
that the first two stages are evenly divided, and so on and so
forth. From Tab.1(e) we can tell that involving more stages
may not always improve the performance. In the following
experiments, we just use the 4-stage partition.

### 4.4. Knowledge Transfer on Different Tasks

In this section, we compare our approach with other
state-of-the-art knowledge transfer methods on different
tasks, including image classification and object detection.
Note that we use exactly the same training settings, \textit{e.g.},
learning rate and optimizer type, when performing exper-
iments on different tasks (or datasets), to verify that our
method can be generally applied for various problems.
Table 2. Comparison results of image classification task on CIFAR-100 dataset.

| Method  | Model   | Top-1  | Top-5  |
|---------|---------|--------|--------|
| Student | ResNet-18 | 68.062 | 89.598 |
| Teacher | ResNet-34 | 73.045 | 90.545 |
| KD [7]  | ResNet-18 | 72.393 | 91.062 |
| FitNets [22] | ResNet-18 | 71.662 | 90.277 |
| AT [26] | ResNet-18 | 70.741 | 90.036 |
| NST [11] | ResNet-18 | 70.482 | 89.241 |
| ours    | ResNet-18 | 72.786 | 91.396 |

Table 3. Comparative results of image classification task on ImageNet dataset.

| Method  | Model   | Top-1  | Top-5  |
|---------|---------|--------|--------|
| Student | ResNet-18 | 69.572 | 89.244 |
| Teacher | ResNet-34 | 73.554 | 91.456 |
| KD [7]  | ResNet-18 | 70.759 | 89.806 |
| FitNets [22] | ResNet-18 | 70.662 | 89.232 |
| AT [26] | ResNet-18 | 70.726 | 90.038 |
| NST [11] | ResNet-18 | 70.762 | 89.586 |
| Ours    | ResNet-18 | 71.361 | 90.496 |

Table 4. Comparative results of object detection task on COCO benchmark.

| Method  | Backbone | mAP  | AP$_{50}$ | AP$_{75}$ | AP$_{S}$ | AP$_{M}$ | AP$_{L}$ |
|---------|----------|------|-----------|-----------|----------|----------|----------|
| Student | ResNet-50 | 35.5 | 55.6      | 38.5      | 17.8     | 39.1     | 47.7     |
| Teacher | ResNet-101 | 38.7 | 58.7      | 41.9      | 21.5     | 42.3     | 49.9     |
| FitNets [22] | ResNet-50 | 36.2 | 55.3      | 39.1      | 19.0     | 40.6     | 48.5     |
| AT [26] | ResNet-50 | 35.9 | 54.7      | 38.2      | 19.3     | 39.6     | 46.6     |
| NST [11] | ResNet-50 | 35.7 | 54.3      | 38.0      | 18.6     | 39.7     | 46.8     |
| Ours    | ResNet-50 | 36.5 | 55.6      | 39.4      | 19.5     | 40.7     | 48.8     |

4.4.1 Image Classification

For classification task, we employ CIFAR-100 and ImageNet as validation datasets to evaluate how our framework could fit with various numbers of classes.

**Evaluation on CIFAR-100.** We firstly start with CIFAR-100 dataset that consists of 50K training images and 10K testing images from 100 classes. Tab.2 shows the comparative results. Our method surpasses other work in both top-1 accuracy and top-5 accuracy. We even achieve similar performance as the teacher model. The results demonstrate the effectiveness of our method, which emphasizes progressive feature transfer for knowledge distillation.

**Evaluation on ImageNet.** We also conduct larger-scale experiments on ImageNet dataset, which includes over 1M training images and 50K testing images collected from 1,000 categories. As shown in Tab.3, our method improves the baseline model with 1.8% top-1 accuracy and beats the second competitor, i.e., NST [11] by 0.6% top-1 accuracy.

4.4.2 Object Detection

We also conduct experiments on the detection task. As described in Sec.4.1, we use RetinaNet [18] as the detection framework, and employ ResNet-50 and ResNet-101 as the backbones of student and teacher respectively. We do not compare with KD method in this task, since soft target by raising the temperature of softmax function cannot be directly applied to bounding box regression as required in object detection task. Not being able to be applied to different tasks is also a huge limitation to some previous methods. From this point of view, our approach is much more general. From the results in Tab.4, we can see that our method outperforms the baseline model with 1.0% mean Average Precision (mAP) and also outperforms all the other methods.

In addition, by cross-checking Tab.2 and Tab.3, we can tell that other methods perform inconsistently on different datasets. For example, KD [26] works well on CIFAR-100, but it shows similar performance as others on ImageNet. Likewise, FitNets [22] works well on COCO but its performance is slightly inferior to AT [26] and NST [11] on ImageNet dataset. That is because the design of these methods is highly sensitive to the hyper-parameters, e.g., temperature for softmax function and loss weights to balance transfer loss and task loss, leading to their performance discrepancies on different datasets. In comparison to these approaches, our method focuses on transferring knowledge from network to network by mimicking features, which is independent from tasks and datasets, resulting in much stronger stability.

5. Conclusion

This work presents a stage-by-stage knowledge transfer approach by training student to mimic the output features of teacher network gradually. Compared to prior work, our method pays more attention to the information contained in the feature extraction part instead of the entire model. The progressive training strategy helps reduce the learning difficulties of student in each stage, and all stages cooperate
together for a better result. Extensive experimental results suggest that our scheme can significantly improve the performance of student model on various tasks with strong stability.

References

[1] A. Ashok, N. Rhinehart, F. Beaïny, and K. M. Kitani. N2n learning: Network to network compression via policy gradient reinforcement learning. In ICLR, 2018.

[2] L. J. Ba and R. Caruana. Do deep nets really need to be deep? In NIPS, 2014.

[3] V. Belagiannis, A. Farshad, and F. Galasso. Adversarial network compression. arXiv preprint arXiv:1803.10750, 2018.

[4] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. TPAMI, 2018.

[5] M. Courbariaux, I. Hubara, D. Soudry, R. El-Yaniv, and Y. Bengio. Binarized neural networks: Training deep neural networks with weights and activations constrained to +1 or -1. arXiv preprint arXiv:1602.02830, 2016.

[6] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In CVPR, 2016.

[7] G. Hinton, O. Vinyals, and J. Dean. Distilling the knowledge in a neural network. In NIPS Workshop, 2014.

[8] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam. Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861, 2017.

[9] J. Hu, L. Shen, and G. Sun. Squeeze-and-excitation networks. In CVPR, 2018.

[10] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger. Densely connected convolutional networks. In CVPR, 2017.

[11] Z. Huang and N. Wang. Like what you like: Knowledge distill via neuron selectivity transfer. arXiv preprint arXiv:1707.01219, 2017.

[12] T. Karras, T. Aila, S. Laine, and J. Lehtinen. Progressive growing of gans for improved quality, stability, and variation. In ICLR, 2018.

[13] A. Krizhevsky and G. Hinton. Learning multiple layers of features from tiny images. Technical report, Citeseer, 2009.

[14] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In NIPS, 2012.

[15] S. H. Lee, D. H. Kim, and B. C. Song. Self-supervised knowledge distillation using singular value decomposition. In ECCV, 2018.

[16] H. Li, A. Kadav, I. Durdanovic, H. Samet, and H. P. Graf. Pruning filters for efficient convnets. In ICLR, 2017.

[17] T. Y. Lin, P. Dollar, R. Girshick, K. He, B. Hariharan, and S. Belongie. Feature pyramid networks for object detection. In CVPR, 2017.

[18] T.-Y. Lin, P. Goyal, R. Girshick, K. He, and P. Dollár. Focal loss for dense object detection. In ICCV, 2017.

[19] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick. Microsoft coco: Common objects in context. In ECCV, 2014.

[20] L. v. d. Maaten and G. Hinton. Visualizing data using t-sne. JMLR, 2008.

[21] P. Molchanov, S. Tyree, T. Karras, T. Aila, and J. Kautz. Pruning convolutional neural networks for resource efficient inference. In ICLR, 2017.

[22] A. Romero, N. Ballas, S. E. Kahou, A. Chassang, C. Gatta, and Y. Bengio. Fitnets: Hints for thin deep nets. In ICLR, 2015.

[23] A. A. Rusu, N. C. Rabinowitz, G. Desjardins, H. Soyer, J. Kirkpatrick, K. Kavukcuoglu, R. Pascanu, and R. Hadsell. Progressive neural networks. arXiv preprint arXiv:1606.04671, 2016.

[24] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. In ICLR, 2015.

[25] J. Yim, D. Joo, J. Bae, and J. Kim. A gift from knowledge distillation: Fast optimization, network minimization and transfer learning. In CVPR, 2017.

[26] S. Zagoruyko and N. Komodakis. Paying more attention to attention: Improving the performance of convolutional neural networks via attention transfer. In ICLR, 2017.

[27] X. Zhang, J. Zou, X. Ming, K. He, and J. Sun. Efficient and accurate approximations of nonlinear convolutional networks. In CVPR, 2015.