A NEW TRAINING METHOD FOR DEEP NEURAL NETWORK

Zhenyan Hou Wenxuan Fan

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ABSTRACT

Knowledge distillation is the process of transferring the knowledge from a large model to a small model. In this process, the small model learns the generalization ability of the large model and retains the performance close to that of the large model. Knowledge distillation provides a training means to migrate the knowledge of models, facilitating model deployment and speeding up inference. However, previous distillation methods require pre-trained teacher models, which still bring computational and storage overheads. In this paper, a novel general training framework called Self Distillation (SD) is proposed. We demonstrate the effectiveness of our method by enumerating its performance improvements in diverse tasks and benchmark datasets.

1 Introduction

With the help of convolutional neural networks, applications such as object detection, image classification, and semantic segmentation are now developing at an unprecedented rate. The CPU-based embedded devices are often used in life and production. The small memory and weak computing power of CPU devices make the application of neural network technology in embedded devices a major difficulty. Now there has been the application of deep neural network compression technology in embedded devices. Certain research results have been achieved in many fields, such as driverless technology, medical image processing, face recognition, etc. Traditional neural network compression and acceleration approaches primarily concentrate on performance enhancement or reduction of computational resources to shorten response time. On the one hand, for example, ResNet 150 or larger ResNet 1000 have been proposed with limited improvement of network performance but with a large computational cost. On the other hand, various techniques have been proposed to reduce the amount of computation and storage required to implement on resource-constrained devices. These techniques include lightweight network design, pruning, and quantization. Knowledge distillation is inspired by the transition of knowledge from teachers to students. The main approach is to orientate compact student model to approximate over-parameterized teacher model. Consequently, the student model can achieve significant performance gains, sometimes even better than the teacher model. High compression and fast acceleration can be reached by model replacement. However, some problems have also been left unresolved. The first is the inefficient knowledge transfer, which means that the student model can not utilize all the knowledge of its teacher model. It remains rare that an excellent student model perform better than its teacher model. Another obstacle is how to develop and train effective teacher models. The current refinement frameworks need a lot of effort and experimentation to find the most suitable architecture for teacher models, which takes time.

We propose a novel self-distillation framework to train a compact model to reach the highest possible accuracy and resolve the disadvantages of traditional distillation. We use the semantic information of the deep layer and the semantic information on the shallow layer for feature distillation.

In summary, we make the following principle contributions in this paper:

• Our method substantially improves the performance of CNN without sacrificing response time.
• Our method provides a single neural network that can be executed at different depths, allowing for adaptive accuracy-efficiency tradeoffs on resource-limited edge devices.
• Experiments on two typical computer vision tasks further demonstrate the generality of the proposed method.

2 Related Work

Knowledge distillation is one of the most popular techniques used in model compression [9, 8]. In order for the student model to effectively mimic the output of the teacher model, Hinton et al. added a knowledge distillation loss function to the training and proposed the idea of knowledge distillation. Research in recent years has focused on improving the learning efficiency of student models, a large number of methods have been proposed. In FitNet [10], Romero et al. introduced the concept of cued learning, aiming to reduce its distance between the student and the teacher’s feature maps. Zagoruyko et al. [11] consider this issue from the perspective of attentional mechanisms and try to unify the characteristics of attentional regions.

Knowledge distillation has also shown its potential in other domains. Furlanello et al. obtained better generalization to test data through the model sets by assimilating the refined students model into the teacher model sets [12]. Bagherinezhad et al. introduced a strategy for updating labels during training by applying knowledge distillation to data augmentation [13]. Papernot et al. proposed a knowledge distillation model which is immune to most of the adversarial attacks [14]. The same method was adopted by Gupta et al. to transfer knowledge between images of different modalities [15].

As in the above approach, generally, the teachers and students work separately in their own ways and we still need to train a refined teacher model, the knowledge transfer flows between the different models. By contrast, in our proposed Self-Feature Regularization framework, the student model and the teacher model come from the same network, which is a true self-distillation framework.

3 Methodology

3.1 Overview

We propose a novel self-distillation framework to train a compact model to reach the highest possible accuracy and overcome the drawbacks of traditional distillation.

We will present the specific components of the proposed self-feature regularization framework in the following sections.

3.2 EMD for Feature Maps

Earth Mover’s Distance is a distance measure between two sets of weighted objects or distributions, which is built up the basic distance between individual objects. Its discrete form can be formalized as the well-studied optimal transportation problem (OTP), which is a linear program that can be solved in polynomial time.

We use emd to calculate the distance between two features as our feature loss.

To measure the similarity between two feature graphs, we first flatten the features into a set of local representations, where each vector can be considered as a supplier or a demander in the set. Then, the similarity of the two feature graphs can be expressed as the optimal transportation cost between the two sets of vectors.

Which tend to incur less matching cost between nodes with similar representations. Once the optimal transport strategy is computed, we can use to compute the similarity score s between the two image feature representations.
The marginal weight of each node plays an important role in the EMD problem by controlling the total number of transport units coming from it. Intuitively, the node with the higher weight is more important in the comparison of the two groups and vice versa. In supervised learning, instead of high variance, background features may be collapsed into a few simple patterns that yield high similarity and large marginal weights.

### 3.3 Many to One Strategy

The purpose of SFR is to match the similarity between deep and shallow features and to improve the expressiveness of the network.

SFR adopts a query-key concept of the attention mechanism. Specifically, each teacher feature generates a query, and each student feature identifies a key. A global average pooling is used to calculate the similarity between the deep feature and the nth shallow feature to get the weight (attention mechanism). We can calculate the attention values that represent relations between teacher and student with a softmax function.

Taking ResNet50 as an example, we use the output feature maps of the last layer of the network before the fully connected layer as Teachers, the output feature maps in each residual block as Students, and the similarity scores of Teachers to each Student as weights to calculate the total Feature as a lost canonical term.

### 3.4 Dynamic Label Smoothing

Different from traditional label smoothing strategy, we propose a new label smoothing method called dynamic label smoothing, which utilizes its past predictions for more informative supervision in training.

Among all the models that have served as teacher candidates in the past, we use the model with \((t - 1)\)-th epoch as the teacher because it provides the most valuable information among the candidate models.

The target probability distribution is not uniformly distributed among incorrect classes. Instead, each incorrect class will be assigned a target probability that is proportional to the output score of this particular class relative to all remaining classes for a network trained with cross-entropy loss on hard target labels.

### 4 Experiment

In this section, we implement our proposed SFR to image classification and metric learning to check its performance and present implementation details. The baseline of student models in our experiments is significantly higher than those in recent studies. [16][17][18].

#### 4.1 Classification

Firstly, on the image classification task, we evaluate SFR. CIFAR100 [19], TinyImageNet [20], and ImageNet [21] are employed.

VID [22] and AT [11] are adopted on the last four blocks. FitNet [23] is adopted on the last two blocks of CNN. \(L_2\), RKD [16], and CC [24] are adopted on the last embedding layer.

**CIFAR100, TinyImageNet.** The number of total epochs is 200. The batch size is set to 128, the initial learning rate is 0.1, dropping by 0.2x at 60, 120, 160 epochs. The weight decay is 5e-4.

**ImageNet.** The number of total epochs is 90. The batch size is set to 512, the initial learning rate is 0.2, dropping 0.1x at 30, 60 epochs. The weight decay is 1e-4. When SFR is combined with \(L_2\) and AT, a fully connected(FC) layer followed by a batch normalization(BN) layer is adopted to generate variance. When it is combined with FitNet, an \(1 \times 1\) convolutional layer followed by a BN layer is adopted.

#### 4.1.1 Results on CIFAR100 and TinyImageNet.

ResNet-18 is adopted as the teacher model. MobileNetV2 [25] is adopted as the student model.

As we can see in Table 1, SFR improves the performance of three existing classic knowledge distillation methods.

#### 4.1.2 Results on ImageNet.

In order to compare with AT [11] and CRD [17] fairly, we employ their models. ResNet-34 is adopted as the teacher and ResNet-18 is adopted as the student. \(L_2\) outperforms FitNet and AT, as we can see in Table 2. Thus we just
Table 1: Top-1 accuracy (%) on CIFAR100 and TinyImageNet

|               | teacher | student | HKD | RKD | CC | VID | AF | SFR-AF | $L_2$ | SFR-$L_2$ | FitNet | SFR-FitNet |
|---------------|---------|---------|-----|-----|----|-----|----|--------|-------|-----------|--------|------------|
| CIFAR100      | 75.86   | 68.16   | 70.29 | 68.34 | 70.0 | 68.2 | 69.06 | **69.42** | 72.85 | **73.06** | 71.74  | **73.45** |
| TinyImageNet  | 63.46   | 56.16   | 59.52 | 55.88 | 57.14 | 57.06 | 58.24 | **58.66** | 63.08 | **64.64** | 63.34  | **63.90** |

need to apply SFR to $L_2$ to evaluate. SFR significantly narrowed the gap between the teacher model and the student model, outperforming other methods. This result indicates that our method is generally applicable in the large-scale classification task.

Table 2: Top-1 accuracy (%) on ImageNet.

|               | teacher | student | HKD[8] | FitNet[10] | CC[24] | AT[11] | CRD[17] | $L_2$ | SFR-$L_2$ |
|---------------|---------|---------|--------|------------|--------|--------|---------|-------|-----------|
| 73.31         | 69.75   | 70.80   | 70.62  | 70.74      | 70.43  | 71.17  | 70.90   | **71.21** |

4.2 Metric Learning

Secondly, on metric learning task, we evaluate the effectiveness of SFR. CUB-200-2011[26] for fine-grained image and DukeMTMC-reID[27] for person re-identification are adopted, which are used for the typical metric learning tasks. The metrics are $R@1$ and $mAP$.

We choose the typical metric learning methods $L_2$, Darkrank[28] and RKD[16] as the comparison methods. Park et al. [16] propose that students should only be trained strictly by RKD loss, i.e., task loss can be removed. We obtained the results in separate experiments with and without task loss conditions.

DukeMTMC-reID. We train it for 30,000 steps. The batch size is set to 36 (12 classes and each class 3 samples) and the weight decay is 4e-5. The initial learning rate is 5e-3 decaying once at 20,000 step.

CUB-200-2011. The batch size is set to 60 (12 classes and each class 5 samples). The initial learning rate is 1e-3, divided by 10 every 10,000 step. Other settings are same to DukeMTMC-reID. The variance branch employs a FC layer followed by BN.

4.2.1 Results on DukeMTMC-reID.

For person re-identification, the teacher is ResNet50 trained with softmax and triplet loss. This is a strong baseline.

Table 3 displays the effects of distillation with various techniques for different students. We see that by distillation, the improvement is slight when student model has a strong baseline. Whereas, the improvement is significant when students are only trained by triplet loss. Based on the different baselines, the proposed SFR outperforms RKD and DarkRank. In addition, SFR exhibits superior performance compared to other self-distillation methods. Note that w/o task means that the student is trained by RKD without task loss. w/ task means that the student is trained with both task loss and RKD.

4.2.2 Results on CUB-200-2011.

GoogLeNet[29] trained by multi-similarity loss[30] is adopted as the teacher model. Powerful teachers facilitate the exploration of self-distillation performance. ResNet18 cite[31] with multi-similarity loss is chosen as student model in compression distillation.

As we can see in Table 3, RKD reaches good results and SFR perform better than Darkrank and RKD. The performance of the initial teacher is further improved by Self-distillation. The self-distillation by Darkrank, RKD, and our SFR outperform the initial teachers. The proposed SFR method also shows excellent performance.
Table 3: Results on metric learning tasks.

| Method    | DukeMTMC-reID compression distillation | CUB-200-2011 compression distillation | CUB-200-2011 self-distillation |
|-----------|--------------------------------------|--------------------------------------|---------------------------------|
|           | R@1  | mAP | R@1  | mAP | R@1  | mAP |
| teacher   | 84.9 | 71.9 | 84.9 | 71.9 | 64.7  | 64.7 |
| student   | 79.3 | 61.1 | 63.6 | 43.5 | 55.6  | 64.7 |
| DarkRank  | 79.9 | 62.2 | 69.9 | 50.9 | 60.1  | 65.2 |
| RKD w/ task | 68.3 | 48.9 | 68.3 | 48.9 | 60.7  | 65.8 |
| RKD w/o task | 80.3 | 63.2 | 70.9 | 52.3 | 60.7  | 63.0 |
| $L_2$     | 79.5 | 62.5 | 72.6 | 53.7 | 58.6  | 64.4 |
| SFR-$L_2$ | 80.4 | 63.3 | 72.8 | 54.0 | 61.1  | 65.4 |

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