Embedded Knowledge Distillation in Depth-Level Dynamic Neural Network

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Abstract

In real applications, different computation-resource devices need different-depth networks (e.g., ResNet-18/34/50) with high-accuracy. Usually, existing methods either design multiple networks and train them independently, or construct depth-level/width-level dynamic neural networks which is hard to prove the accuracy of each sub-net. In this article, we propose an elegant Depth-Level Dynamic Neural Network (DDNN) integrated different-depth sub-nets of similar architectures. To improve the generalization of sub-nets, we design the Embedded-Knowledge-Distillation (EKD) training mechanism for the DDNN to implement knowledge transfer from the teacher (full-net) to multiple students (sub-nets). Specifically, the Kullback-Leibler (KL) divergence is introduced to constrain the posterior class probability consistency between full-net and sub-nets, and self-attention distillation on the same resolution feature of different depth is addressed to drive more abundant feature representations of sub-nets. Thus, we can obtain multiple high-accuracy sub-nets simultaneously in a DDNN via the online knowledge distillation in each training iteration without extra computation cost. Extensive experiments on CIFAR-10/100, and ImageNet datasets demonstrate that sub-nets in DDNN with EKD training achieve better performance than individually training networks while preserving the original performance of full-nets.

1. Introduction

Recent years have witnessed significant progress in various computer vision tasks\([3, 8, 9]\) using deep convolutional neural networks. To meet different resource-constrained devices, researchers usually need to design a series of different-depth networks such as VGG-13/16/19 \([10]\), ResNet-18/34/50/101 \([3]\), and DensNet-121/169/201 \([6]\). Generally, it requires to train different-depth networks individually in Fig. 1(a) and download/offload different models multiple times according to device-resource constraints in real applications, which increases the training and deploying cost dramatically. In fact, deeper network (e.g., ResNet-34) contains completely the smaller architecture (e.g., ResNet-18) due to the configuration of the same residual blocks. Therefore, it motivates us to think why not directly train a single deep full-net in Fig. 1(c) to dynamically switch different-depth sub-nets during the deployment stage.

Previous works \([5, 15, 12]\) utilize dynamic routines to construct depth-wise dynamic neural networks. \([14, 13]\) train a shared network with switchable batch normalization to adjust its width to construct width-level dynamic neural networks. However, above-mentioned notable works can not prove the accuracy of each sub-net. \([11, 1]\) introduce knowledge distillation \([4]\) into ensemble network to dynamically switch branches during inference. However, when more sub-nets are required, the total size of ensemble network will become larger and the training process will become more complex.

How to efficiently train one DDNN with multiple high-accuracy sub-nets with simple training strategy? We propose a depth-level dynamic neural network embedded knowledge distillation (EKD-DDNN). As shown in Fig. 1(c), we first split the full-net by setting split points in each stage of network. Then, we utilize the predicted class posterior probabilities of full-net as soft labels to guide the learning of different-depth sub-nets. We also introduce the

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self-attention on the same resolution feature of different-depth to drive the learned semantic feature as consistently as possible between full-net and sub-net. Meanwhile, we still keep the conventional cross-entropy loss term with hard labels for the training of full-net and sub-nets. In addition, we introduce ensemble learning to enhance full-net using ensemble result of full-net and sub-nets as soft-label. Finally, we integrate the above-mentioned strategy and optimize the whole network with EKD mechanism in an end-to-end manner.

To verify the effectiveness of proposed method, we conduct extensive experiments on multiple benchmark datasets (e.g., CIFAR-10/100 [7], and ImageNet [2]) with current state-of-the-art networks (e.g., VGGNet [10], ResNet [3]). Compared to the individually training strategies without shared weights, sub-nets in DDNN with EKD training achieve higher performance while preserving the original accuracy of full-net. The main contributions can be summarized as follows.

- We propose a Depth-Level Dynamic Neural Network for satisfying the requirement of different resource-constrained devices.
- We adopt Embedded-Knowledge-Distillation training mechanism to effectively improve the representative capacity of multiple sub-nets without harming the capacity of full-net.
- Sub-nets with EKD improve considerably, which can sometimes surpass individual training networks by more than 1% on CIFAR and ImageNet.

2. Methodology

In this paper, we focus on constructing depth-level dynamic neural network with EKD training mechanism to excavate the potential representative capacity of sub-nets.

**Depth-Level Dynamic Neural Network.** Depth-Level dynamic neural network denotes that one deep neural network (i.e., full-net) can dynamically switch its depth to yield different-depth sub-nets for different resource-limited devices. Generally, we select a large baseline network as full-net to design the depth-level dynamic neural network. We first separate the large baseline network into several stages according to the resolution of output feature maps. Then, we skip the deep blocks of some stages to create sub-stages. Finally, a sub-net is formed by creating direct connections between sub-stages of each two neighbouring stages. Fig. 2 uses ResNet-50 as example to show the construction process of DDNN.

**Embedded Knowledge Distillation.** Fig. 2 shows the detailed training process of our DDNN with the EKD training mechanism. The full-net is used as “teacher model” to provide extra supervised information for guiding the better learning of sub-nets. Meanwhile, the full-net also benefits from better sub-nets because of possessing better sub-nets as “backbone”. Besides, full-net is optimized with ensemble logits and attention maps, which means “teacher model” also “discusses” from “student models” for better learning.

As shown in Fig. 2, we embed KD on posterior class
EKD training is defined in Eq. 7.

\[ KL^k = - \frac{1}{N} \sum_{n=1}^{N} p_t(x_n) \log \frac{p^k_t(x_n)}{p_t(x_n)} \] (1)

\[ KL_t = - \frac{1}{N} \sum_{n=1}^{N} p_{et}(x_n) \log \frac{p_t(x_n)}{p_{et}(x_n)} \] (2)

Where \( p_t(x_n) \) and \( p^k_t(x_n) \) respectively denote the posterior class probability of full-net and sub-nets. \( p_{et}(x_n) \) represents ensemble teacher logits which can be formulated as \( p_{et}(x_n) = \frac{1}{K+1} (\sum_{k=1}^{K} p^k_t(x_n) + p_t(x_n)) \). \( K \) is the number of sub-nets.

To further make the semantic feature in the same stage as consistent as possible between full-net and sub-nets, we introduce the self-attention distillation in intermediate feature maps. We adopt mean-squared-error (MSE) loss in each training step. The formulation is shown in Eq. 3 ~ Eq. 6.

\[ A_t = \sum_{c=1}^{C} (F_t)_c, \quad A^k_t = \sum_{c=1}^{C} (F^k_t)_c \] (3)

\[ A_{et} = \frac{1}{K+1} (\text{norm}(A_t) + \sum_{k=1}^{K} \text{norm}(A^k_t)) \] (4)

\[ MSE^k_t = \frac{1}{N} \sum_{n=1}^{N} MSE(A^k_t(x_n)||A_t(x_n)) \] (5)

\[ MSE_{et} = \frac{1}{N} \sum_{n=1}^{N} MSE(A_t(x_n)||A_{et}(x_n)) \] (6)

Where \( F_t, F^k_t \in \mathbb{R}^{C \times H \times W} \) indicate feature maps of full-net and \( k^{th} \) sub-nets at same level of model. \( A_t, A^k_t \in \mathbb{R}^{1 \times H \times W} \) indicate channel-joint attention maps, which will be fused to form ensemble attention teacher (\( A_{et} \)). \( \text{norm}(\cdot) \) denotes the spatial-wise normalization operation.

Our DDNN fulfills the online EKD learning via KL, MSE and conventional cross-entropy loss (\( L_t \) and \( L^k_t \) for full-net and sub-nets each). The whole objective (\( L \)) of DDNN with EKD training is defined in Eq. 7.

\[ L = L_t \frac{1}{K} \sum_{k=1}^{K} L^k_t + \frac{1}{K+1} \cdot w_k (KL^k + \sum_{k=1}^{K} KL^k_t) \]

\[ + \frac{1}{K+1} \cdot \alpha_k (MSE^k_t + \sum_{k=1}^{K} MSE^k_t) \]

Self-attention distillation

KL distillation

cross-entropy loss

To evaluate our proposed method, we conduct extensive experiments and exhaustive comparisons on CIFAR-10/100 and ImageNet benchmark datasets.

**CIFAR-10/100 Classification.** Table 1 shows the detailed comparisons of three cases (Fig. 1). The DDNN trained with only the optimization objective of hard labels from full-net and sub-nets (2nd column) has lower performance than independently individually training (1st column) because these weight-sharing blocks are very hard to simultaneously match the multiple different optimization objectives. Experimental results on the CIFAR-10/100 show that sub-nets in DDNN with EKD training (3rd column) possess the average 1~2% improvement compared to sub-nets in DDNN with the only hard labels (2nd column). Even compared to the independently trained cases (1st column), sub-nets in DDNN with EKD training still have the 0.5~1% lower error rate (Bold in Table 1) while preserving the performance of full-net (almost no decline). Especially, EKD mechanism performs stronger on CIFAR-100 than CIFAR-10. It fully displays the effectiveness of the proposed mechanism on more complex task.

**ImageNet Classification.** Table 2 gives detailed comparisons of three different training frameworks in terms of network architecture, network parameters, and top-1 error rate. As expected, sub-nets in EKD-DDNNs get improved while almost no decline of full-nets. Compared to individual large model (e.g. ResNet-50), our DDNN can integrate multiple networks into one network without adding extra parameters and FLOPs. During inference, DDNN can dy-
| Networks   | Params | FLOPs |
|-----------|--------|-------|
| ResNet-18 | 11.7M  | 1.8G  |
| ResNet-34 | 21.8M  | 3.6G  |
| ResNet-26 | 16.0M  | 2.3G  |
| ResNet-50 | 25.6M  | 3.8G  |
| ResNet-18 | 11.7M  | 1.8G  |
| ResNet-34 | 21.8M  | 3.6G  |
| ResNet-26 | 16.0M  | 2.3G  |
| ResNet-50 | 25.6M  | 3.8G  |

Table 2. Top-1 error rate (%) on ImageNet (single-crop testing).

Figure 3. Evaluation on the effectiveness of ensemble distillation.

Effectiveness of Ensemble Distillation. Using full-net to teach sub-net can enhance the performance of sub-nets. However, it is still hard to guarantee the full-net performance using only a set of weight-sharing blocks. To ease the accuracy decline of full-net, we introduce ensemble distillation on posterior class probability and intermediate feature maps. Fig. 3 shows that with ensemble distillation, the accuracy of full-net gets maximally preserved.

4. Conclusion

In this paper, we propose the DDNN with only one full-net parameters to flexibly switch different-depth sub-nets or full-net according to the demands of different resource-limited devices. To improve the performance of sub-nets and full-net in DDNN, we further design the EKD training mechanism, which contains distillation on posterior class probabilities and self-attention on feature maps to exploit the potential representative capacity of the whole DDNN. Extensive experiments demonstrate that our DDNN with EKD training mechanism achieves competitive performance on multiple benchmark datasets. Compared to student networks trained with previous dynamic paradigm, our sub-nets can harvest better performance with no harm to full-net.

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