CHANNEL PRUNING VIA MULTI-CRITERIA BASED ON WEIGHT DEPENDENCY

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ABSTRACT

Channel pruning has demonstrated its effectiveness in compressing ConvNets. In many prior arts, the importance of an output feature map is only determined by its associated filter. However, these methods ignore a small part of weights in the next layer which disappear as the feature map is removed. They ignore the dependency of the weights, so that, a part of weights are pruned without being evaluated. In addition, many pruning methods use only one criterion for evaluation, and find a sweet-spot of pruning structure and accuracy in a trial-and-error fashion, which can be time-consuming.

To address the above issues, we proposed a channel pruning algorithm via multi-criteria based on weight dependency, CPMC, which can compress a variety of models efficiently. We design the importance of the feature map in three aspects, including its associated weight value, computational cost and parameter quantity. Use the phenomenon of weight dependency, we get the importance by assessing its associated filter and the corresponding partial weights of the next layer. Then we use global normalization to achieve cross-layer comparison. Our method can compress various CNN models, including VGGNet, ResNet and DenseNet, on various image classification datasets. Extensive experiments have shown CPMC outperforms the others significantly.

Index Terms— Channel pruning, weight dependency, convnet, and classification.

1. INTRODUCTION

In recent years, the growing demands of deploying CNN models to resource-constrained devices such as FPGA and mobile phones have posed great challenges. Network pruning has become one of the most effective methods to compress the model with minimal loss in performance. Network pruning can be divided into two categories: weight-level pruning [1,2] and structural pruning [3,7].

The weight-level pruning try to detect the redundant weights that are unimportant and set them to zeros. However, it contributes little to compress deep models, unless users use specialized libraries which support sparse matrix calculation. Unfortunately, the support for these libraries on resource-constrained devices like FPGA is limited. At the same time, structural pruning can be a solution to this problem. These methods evaluate and remove structure weights like filters and channels in convolutional layers or unimportant nodes in fully connected layers [8]. In this way, compress deep models be more efficient.

Channel pruning is a specific method of structural pruning [3], assessing the importance of output feature maps, and removing all weights which are associated with those unimportant feature maps. A feature map is considered to be a channel for output. There is no doubt that how to evaluate feature maps is the key factor. We find the current state-of-the-art methods have at least one of the following issues.

Neglect of weight dependency. Many existing criteria [3,4,6] of measuring the importance of filters or channels only consider the weights of filters, and have little consideration to a part of weights in next layer which disappear with the associated filter. They ignores the weight dependency.

Trial-and-error fashion. As the redundancy of each layer in deep model is various, a different number of filters or channels should be pruned in each layer. Therefore, some pruning methods require users to specify the layerwise pruning ratios [3,7] or get the layerwise pruning ratios by searching automatically [9]. They are all use trial and error fashion, which is less efficient.

No multi-criteria. Many methods use only one criterion for evaluation [3,10]. At different positions, pruning a channel can reduce the different number of parameters or FLOPs or both. Computational cost and parameter quantity are essential for compressing models. They don’t add them into the criteria.

To address the above issues, we develop a channel pruning method via multi-criteria based on weight dependency (CPMC). We define the importance of a channel by its associated filter, called out-channel, and a small part of weights of the next layer, called in-channel. In addition, we use multi-criteria to evaluate the importance of channel, including its associated weight value, computational cost and parameter quantity. We normalize the channel importance of different layers to the same scale, which can avoid layerwise pruning ratios. Our method can compress directly a pre-trained model, which enables the users to customize the compression according to preference more efficiently.

2. RELATED WORKS

Compacting CNN models for speeding up inference and reducing storage overhead has been an influential project in both academia and industry.

Recently, much attention has been focused on structural pruning to reduce model parameters and FLOPs. Li et al. [3] evaluated the importance of filters through its $l_1$ norm, and set pruned ratio for each layer manually. He et al. [6] proposed a soft filter pruning which lets the pruned filters to be updated in the training stage. He et al.
al. [3] compressed models by pruning filters with the most replaceable contribution which calculated by the Geometric Median. He et al. [7] evaluate the importance of a channel of output by a LASSO regression and least square reconstruction. All the methods mentioned above only evaluate filters by the local importance, i.e., the importance could only be compared within a layer. Therefore, they require users to specify the layerwise pruning ratios.

More recent developments adopted global comparison to avoid the layerwise pruning ratios. Liu et al. [4] add sparsity regularization into loss function and use the scale of batch normalization layer as the global importance. Wang et al. [8] develop a filter level algorithm which evaluated the importance of filters by Pearson correlation. Meanwhile, they globally ranked the importance and add layerwise regularization terms to improve the effect. Chin et al. [11] proposed learned global ranking, which used the regularized evolutionary algorithm to produce a set of pruned CNN models with different performances. All the methods mentioned above have little consideration to the weight dependency. When the weight of in-channel is important, some avoidable losses result.

Recently, a few pruning methods has been focused on the phenomenon of weight dependency. Li et al. [12] proposed to add a structural sparsity regularization into loss function. They regularize out-channels and in-channels as one regularization. And they use Group Lasso to define the importance of channels. In order to get better results, they need to prune iteratively. Despite their success, we notice that their methods fails to prune the pre-trained models due to regularization and have no consideration of multiple criteria, especially parameter quantity and computational cost.

Low rank approximation [13], knowledge distillation [14], network quantization [15] and Lightweight model design [16] are popular techniques to speedup inference and compress models. Combing with our channel pruning, these techniques have further improvement.

3. ALGORITHM

3.1. Symbols and annotations

Simply, in a deep model which have L layers and produce S output feature maps in total, the input of $l_{th}$ layer is $X^l$, output is $Y^l$ and weight is $W^l$. $Y_i^l$ is a channel for output, which is an output feature map. $W_{ij}^l$ is the weight of $j_{th}$ convolutional kernel of the $i_{th}$ filter. $W_{ij}^l$ is of shape $K^l 	imes K^l$, where $K^l$ is the kernel width (supposed to be symmetric). $W_{ic}^l$ means the weight of the $i_{th}$ filter in $l_{th}$ layer.

When the $l_{th}$ layer in the deep model is a convolutional layer, $W^l$ is of shape $K^l \times K^l \times M^l \times N^l$, $M^l$ is the number of input channel, $N^l$ is the number of output channel. $X^l$ is of shape $I^l \times I^l \times I^l \times I^l$ is the size of input feature maps of the $l_{th}$ layer. $Y^l$ is of shape $O^l \times O^l \times N^l$. $O^l \times O^l$ is the size of output feature maps of the $l_{th}$ layer.

When the $l_{th}$ layer in the deep model is a fully connected layer, $W^l$ is of shape $M^l \times N^l$, its shape be treated as $M^l \times N^l \times 1 \times 1$, which makes that the calculation methods become consistent. $M^l$ is the number of input nodes and $N^l$ is the number of output nodes. $X^l$ is of shape $M^l \times 1$, $Y^l$ is of shape $N^l \times 1$.

3.2. Overview

We aim to provide a simple and efficient scheme to achieve channel level pruning in deep CNNs. Our channel pruning procedures are illustrated in Figure 1. We start with a pre-trained model, and have NO sparsity regularization during pre-trained stage, which enables the users to compress models more efficiently. Moreover, when we get the importance of each channel in whole model, it is puzzling to determine the layerwise channel pruning ratios. Therefore, we use global normalization to achieve cross-layer comparison within a whole model, instead of comparison within a layer. When pruning channels, we sort the importance values that are normalized globally and get the threshold value such that the FLOP count is met. Then, we pruning the small importance channels whose importance are below the threshold. Finally, we fine-tune the pruned model to recover the accuracy.

We can also extend the proposed method from single-pass pruning scheme to a iterative multi-pass scheme. In multi-pass scheme, we can prune smoothly in each iteration to get more compact model.

3.3. Criteria of channel importance

There is no doubt that criteria of channel importance is the keys. We will take a simply model as an example and introduce the calculation method of the importance value of one channel.

Weight dependency. Channel pruning is designed to reduce the number of output feature maps [7] in order to pruning the weight of some filters and the weight of corresponding kernels of each filter in next layer. We start by analyzing the prior methods, and find that many methods only consider out-channel to represent the importance of an output feature map. They have little consideration to the importance of in-channel. When the weight of in-channel is more important, some avoidable performance losses result. Therefore, we define the importance of an output feature map as:

$$\text{Imp}(Y_i^l) = \text{Eval}(OC_i^l, IC_{i+1}^l)$$  \hspace{1cm} (1)

Where $\text{Imp}(Y_i^l)$ is the importance of $Y_i^l$ of the $l_{th}$ layer, $OC_i^l$ is the out-channel which is the associated filter in current layer. $IC_{i+1}^l$ is the in-channel which is some corresponding kernels of each filter in next layer. Respectively, $\text{Eval}(OC_i^l, IC_{i+1}^l)$ is the evaluation value
Multi-criteria. Many methods don’t evaluate structural weights from multiple perspectives, especially in terms of computational cost and parameter quantity. Our multi-criteria consists of three parts, including weight value, computational cost and parameter quantity.

We note that the norm assumption is adopted and empirically verified by prior art [6]. In this paper [2], they propose to measure the relative importance of a filter in each layer by using \( l_i \), it is defined as follows:

\[
L_i^l = \| W_i^l \|_1 = \sum_j | W_{i,j}^l |
\]  

where \( L_i^l \) is just only the weight importance of the out-channel of \( Y_i^l \). The weight importance of next layer is ignored that may produce incorrect selection of redundant channels. Therefore, we measures channel importance based on weight dependency. The evaluation value is given as:

\[
L_{i,l+1}^{l+1} = \| W_i^{l+1} \|_1 = \sum_j | W_{i,j}^{l+1} | + \sum_j | W_{i,j+1}^{l+1} |
\]  

where \( L_{i,l+1}^{l+1} \) is the evaluation value calculated by out-channel and in-channel of \( Y_i^l \) in weight value.

However, \( l_i, norm \) can be used within each layer, but not across layers. Due to different functions and scopes, the weight value in different layer may not be on the same order of magnitude. For cross-layer comparison, we need to normalize the evaluation value. After analysis and experiment, we propose to use max-min normalization which is a linear transformation. We normalize the correlation distribution of each layer to align the correlation distribution to \([0,1]\.

Formally, we define the normalized evaluation value as:

\[
GL_{i,l+1}^{l+1} = \frac{L_{i,l+1}^{l+1} - L_{i,l+1}^{l+1}}{L_{i,p+1}^{l+1} - L_{i,q+1}^{l+1}};
\]

\[
P_{i,l+1}^{l+1} = \min_i L_{i, l+1}^{l+1} ;
\]

\[
Q_{i,l+1}^{l+1} = \max_i L_{i, l+1}^{l+1}, p, q \in [1, N_i] \text{ and } p \neq q
\]  

where \( L_{i,p+1}^{l+1} \) and \( L_{i,q+1}^{l+1} \) are the minimum and maximum evaluation value in weight value aspect of \( Y^l \).

As we discussed above, at different positions, pruning a channel can reduce the different number of parameters or FLOPs or both. To make our approach aware of such differences, we add two criteria to better model compression. Specifically, we add the evaluations of parameter quantity and FLOPs calculated by out-channel and in-channel. Pruning channel \( Y_i^l \) can reduce the parameter quantity and FLOPs of its out-channel and in-channel. So the parameter quantity

| Model       | Alg | Acc(%) | Param(Pr%) | FLOPs(Frr%) |
|-------------|-----|--------|------------|-------------|
| VGG-16      | Baseline | 93.68  | 14.72M(0)  | 3141.13M(0) |
|             | GAL-0.05 [7] | 92.03  | 3.36M(77.6) | 189.49M(39.6) |
|             | VCNFF [12] | 93.18  | 3.92M(73.3) | 190.01M(39.1) |
|             | HRank [10] | 92.34  | 2.64M(82.1) | 108.61M(65.3) |
| CPMC(Ours)  | 93.40  | 1.04M(92.9) | 106.68M(66.0) |
| ResNet-20   | Baseline | 91.30  | 220.39K(0) | 34.62M(0)   |
|             | NS [4] | 90.04  | 189.70K(13.9) | 27.61M(20.2) |
| CPMC(Ours)  | 91.13  | 178.84K(32.9) | 24.42M(29.5) |
| ResNet-56   | Baseline | 93.72  | 593.13K(0) | 89.59M(0)   |
|             | NS [4] | 92.84  | 441.59K(25.5) | 59.91M(33.1) |
| CPMC(Ours)  | 93.46  | 341.10K(42.5) | 60.43M(32.5) |
| ResNet-164  | Baseline | 95.01  | 1.71M(0)   | 254.50M(0)  |
|             | NS [4] | 94.73  | 1.10M(35.2) | 137.50M(44.9) |
| CPMC(Ours)  | 94.76  | 0.75M(56.0) | 144.02M(43.4) |
| DenseNet-40 | Baseline | 94.21  | 1.06M(0)   | 290.13M(0)  |
|             | GAL-0.01 [7] | 94.29  | 0.67M(35.6) | 182.92M(35.3) |
|             | HRank [10] | 94.24  | 0.66M(36.5) | 167.41M(40.8) |
|             | VCNFF [12] | 93.16  | 0.42M(59.7) | 156.00M(44.8) |
| CPMC(Ours)  | 93.74  | 0.42M(60.7) | 121.73M(58.0) |
Pruning for dense block. In a dense block, many input feature maps of a layer are from preceding layers [20]. Similarly, their out-channels are scattered in preceding layers. Please refer to Figure3 for details. We take a dense block whose growth rate of channels are scattered in preceding layers. Please refer to Figure3 Pruning for dense block.

| Model      | Baseline | VCGN [18] | VCGM [23] | CPMC (Ours) |
|------------|----------|-----------|-----------|-------------|
| VGG-16     | 73.89    | 14.77M(0) | 314.2M(0) |
| VGG-16     | 73.33    | 9.14M(37.9) | 256.0M(18.0) |
| ResNet-56  | 73.53    | 4.99M(66.8) | 198.2M(37.1) |
| ResNet-164 | 73.01    | 4.80M(67.5) | 162.0M(48.4) |
| DenseNet-40| 73.84    | 616.26K(0) | 89.61M(0) |
| ResNet-164 | 73.36    | 550.26K(18.8) | 60.55M(32.4) |
| DenseNet-40| 73.31    | 298.57K(51.6) | 49.02M(45.3) |

4. EXPERIMENTS

4.1. Experimental settings

We empirically demonstrate the effectiveness of CPMC on public datasets such as CIFAR10 and CIFAR100 [21]. We test the compression performance of different methods on severable famous large CNN models, including VGGNet [22], ResNet [19], and DenseNet [20]. Note that, we implement the compression of ResNet with bottleneck which is more economical [19].

Following the previous works [4,8], we record the parameter-reduction ratio(Pr), FLOPs-reduction ratio(Frr), and accuracy of each algorithm compared with the original model.

We set the batch-size of SGD to be 64 for 160 epochs. The initial learning rate is set to 0.1, and is divided by 10 at 50% and 75% of the total number of training epochs. We use a weight decay of 10\(^{-4}\) and set the momentum coefficient to be 0.9 for all models.

We set \( \alpha = 3, \beta = 1 \) for VGGNet, \( \alpha = 1, \beta = 1 \) for ResNet, and \( \alpha = 0.1, \beta = 0.1 \) for DenseNet to let our method adapt to the differences of model structure.

4.2. Results and analysis

We analyze the performance on CIFAR10/100, comparing against several popular CNNs, including VGG-16, ResNet-20/56/164, and DenseNet-40. The performance of different algorithms is given in Table 1 and Table 2. We experiment with several pruning ratio on CPMC and choose the maximum pruned ratio under the constraint of acceptable accuracy loss. Then, we experiment many times and record the mean. As is shown in Table 1 and Table 2, we can draw some conclusions as follows:

1. In most experiments, CPMC can achieves higher compression ratio and speedup ratio with similar accuracy to other algorithms. Especially, CPMC outperforms in light-weight ResNet. This is the contribution of the multi-criteria of CPMC which evaluate channels in parameter quantity and computational cost.

2. For the algorithms which can prune the similar number of parameters or computational cost, CPMC gets a higher accuracy (e.g., VCGN, HRank). Because CPMC considers the weight dependency, which enable many important weights of in-channel to be retained.

4.3. Ablation study

Normalization. We normalize the value to cross-layer comparison. In weight value evaluation, we use the max-min normalization. Before this, we have tried log-normalization, max-normalization and max-min normalization for weight value evaluation when other settings remain unchanged. The results are shown in Table 3. We can see that max-min normalization can pruning more parameters and FLOPs with higher accuracy, which is the best configurations.

Effect of pruning. The number of channels per layer before and after pruning in VGG-16 on CIFAR10 are shown in Figure4. CPMC retained 1267 (out of 4224) channels after pruning. Interestingly, we can see that fewer channels in some middle layers are retained. And after evaluation, they all have lower values in parameter quantity and computational cost. Through analysis, we believe that they have a lot of costs, both in terms of the amount of computation and the number of parameters. On the contrary, such as most of channels in the front layers are retained, because they just have a few associated parameters even though they have many computational cost.

5. CONCLUSIONS

Current deep neural networks have many effects with high inference and storage costs. In this paper, we propose a novel and efficient channel pruning methods, namely CPMC, which have consideration of the weight dependency and use the multi-criteria to evaluate channels to compress more compact CNN models. Multi-criteria combines out-channel and in-channel to represent a channel and measures the importance of a channel in three aspects, including its associated weight value, the number of parameters, and computational cost. To avoid specifying the layerwise pruning ratios, we normalize the evaluation value to achieve cross-layer comparison. As a result, important channels and accuracy are greatly preserved by CPMC after pruning. Extensive experiments demonstrated the out-performance of CPMC to the other structural pruning algorithms.
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