Automatic Block-wise Pruning with Auxiliary Gating Structures for Deep Convolutional Neural Networks

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Abstract
Convolutional neural networks are prevailing in deep learning tasks. However, they suffer from massive cost issues when working on mobile devices. Network pruning is an effective method of model compression to handle such problems. This paper presents a novel structured network pruning method with auxiliary gating structures which assigns importance marks to blocks in backbone network as a criterion when pruning. Block-wise pruning is then realized by proposed voting strategy, which is different from prevailing methods who prune a model in small granularity like channel-wise. We further develop a three-stage training scheduling for the proposed architecture incorporating knowledge distillation for better performance. Our experiments demonstrate that our method can achieve state-of-the-arts compression performance for the classification tasks. In addition, our approach can integrate synergistically with other pruning methods by providing pre-trained models, thus achieving a better performance than the unpruned model with over 93% FLOPs reduced.

1 Introduction
Convolutional neural networks (CNNs) have achieved amazing performance in different domains including image classification, object detection and semantic segmentation. One of the most important supportive factors lies on the complexity of the network structure, which allows the models to learn sufficient knowledge within certain datasets to generalize well on real-world scenes. While gaining promotion in performance, however, such complex structures can also suffer from high computation cost and storage cost in certain applications such as applications on mobile devices and other platforms with constrained resources. To tackle this problem, researchers have developed a series of methods called model compression to cut down the cost while using CNNs.

Dominating methods in model compression can be mainly divided into four types: network pruning [Han et al., 2015], weight quantization [Tung and Mori, 2018], decomposing [Jaderberg et al., 2014] and knowledge distillation [Hinton et al., 2015], among which network pruning is a traditional yet effective way of model compression.

As the depth of neural works going deep, demands on light-weighted models are becoming much more severe. Motivating more researches on pruning methods. Typical pruning methods can be divided into structural pruning [Anwar et al., 2015] and non-structural pruning [Han et al., 2015] according to the granularity of pruning. Non-structural pruning tries to zero-out the unimportant parameters within layers based on a ranking algorithm, while structural pruning cuts off entire structure (layer, convolutional kernel, channel etc.) iteratively or simultaneously. Non-structural pruning is advantageous on reducing storage cost, but cannot release computational cost effectively since the computation would still exist even though some of the weights in a layer is zeroed out, while structural pruning can avoid that problem by removing the whole structure, but is would suffer from greater loss in performance than non-structural pruning. In this work we focus on structural pruning with a large granularity, i.e. block-wise pruning, in an iterative manner. Block here refers to basic units the CNN is formed with, for example, residual blocks in ResNet series and single convolutional layers in VGG style CNN.

SkipNet [Wang et al., 2018] is a popular method of dynamic neural network, where a control module is proposed to decide blocks to skip during inference according to different instances. However, this method can only cut down com-
puting cost during inference by skipping some of the blocks without removing them, which means the issue of storage cost is even worse with the extra cost brought by control modules. We show that dynamic neural network methods can be incorporated into network pruning in voting style to decide the least important blocks and remove them completely. The overall architecture is shown in Figure 2.

We then designed a training schedule for proposed structure, which consists of three stages including warm-up, iterative pruning and fine-tuning. In the warm-up stage, the model is trained for a few epochs to grab knowledge from the dataset. Then in the pruning stage, blocks are iteratively pruned according to marks derived from each block with an auxiliary structure, with several epochs of training to restore performance after pruning in each iteration. It is worth mentioning that knowledge distillation [Hinton et al., 2015] is used in this stage in self-distillation manner to further enhance the performance, where models from previous iteration is used as teacher model in the following iteration. After pruning stage, the model is fine-tuned with a learning rate schedule to obtain the final pruned model.

As a pruning method with large granularity, our method can reduce storage cost and computational cost effectively in block-wise, but redundancy inside blocks is still intact. We show that our pruned model can be further used in other pruning methods with small granularity as a pre-trained model by conducting experiments that result in surprisingly good performance, which is an important contribution of our method.

The contributions of our work are summarized as follow:

- We proposed a network pruning algorithm in block-wise granularity (Automatic Block-wise Pruning, ABP) which prunes a CNN using gating structure based on the idea of dynamic neural network.

- We designed a three-stage training schedule (warming-up, pruning and fine-tuning) incorporating knowledge distillation for proposed structure for iterative pruning.

- We demonstrate that our method can provide pretrained model with prior knowledge for other pruning methods. Results show that this combination can achieve surprising compression rate of 93.68% with even higher performance than unpruned model.

2 Related Works

2.1 Network pruning

Network pruning is a traditional and straightforward method for model compression, which operate directly on weights and architecture of the network to cut down storage cost and computational cost. Pruning methods can be divided into structured pruning and unstructured pruning, where structured pruning tries to prune entire structure like convolution kernel or layer, which is the main focus in our work. Anwer et.al [Anwar et al., 2015] proposed a schema of structured pruning in all granularity, and involved particle filter into pruning schedule. AutoCompress [Liu et al., 2019a] developed an automatic structured pruning schedule that can compress at extremely large compress rate. Recently several works [Ro and Choi, 2021] have focused on large granularity of pruning like layer-wise, which is closely related to our work.

2.2 Dynamic neural network

Dynamic neural network has been rapidly developed in recent years, where parameters or architecture of the network are adapted to different inputs during inference [Han et al., 2021] to reach a balance between model performance and efficiency. Instance-wise dynamic neural network methods [Liu and Deng, 2018] are the most common methods where the network would change in architecture and parameters according to the input instance. D2NN [Liu and Deng, 2018] proposed to select the execution path of DNN with several control nodes, ending up with different topological structures for different instances, while SkipNet [Wang et al., 2018] realized dynamicity without changing the entire topology of the architecture by imposing control module to all blocks to decide whether to skip the block. Our work was inspired by the "skipping" strategy, based on which we extended the idea of dynamic neural network to network pruning with a voting-like method.

2.3 Knowledge distillation

Knowledge distillation was firstly introduced by Hinton [Hinton et al., 2015] who then opened up a new research direction of model compression. This kind of methods aims at training a light-weighted model using the knowledge in the
form of soft label [Hinton et al., 2015] or intermediate representation [Ji et al., 2021] from a cumbersome network with teacher-student structure. Aside from the usage in model compression, knowledge distillation methods are also used in enhancing performance in various tasks [Xu et al., 2020]. Researchers have also developed other forms of knowledge distillation including self-distillation [Xu et al., 2020], multi-teacher distillation [Liu et al., 2019b] and mutual learning [Zhang et al., 2020], where self-distillation would benefit the iterative training schedule proposed in our work.

3 Automatic Block-wise Pruning

3.1 Problem formulation

Given a convolutional neural network, our purpose is to prune the network for efficient usage. Consider an $N$-block CNN model, its blocks can be represented as $B = \{B_1, B_2, ..., B_N\}$, and their inputs and outputs are $\mathcal{I} = \{I_1, I_2, ..., I_N\}$ and $\mathcal{O} = \{O_1, O_2, ..., O_N\}$ respectively. Forward pass through a block can be represented as:

$$\mathcal{I}_{l+1} = \mathcal{O}_l = B_l(\mathcal{I}_l) \quad \text{for} \quad l = 1, 2, ..., N \quad (1)$$

Denoting the input of the network as $x$, we have the forward pass of the network before classifier as:

$$f = B_N (\ldots B_2 (B_1 (x))) = \text{concat}(B_l) \quad \text{for} \quad l = 1, 2, ..., N \quad (2)$$

where $\text{concat}(B_l)$ means concatenating these blocks by taking the output of former block as the input of current block, and $f$ is the final feature map before classifier.

In this paper we prune the network in a large granularity, i.e. block-wise. To achieve block-wise pruning, we calculate a criterion for each block as its importance mark, which is determined by gating block in this work, and decide the unpruned block set $\Omega$ accordingly. The target network is formulated as:

$$f = \text{concat}(B_l) \quad \text{for} \quad B_l \in \Omega \quad (3)$$

3.2 Network architecture

In this section we will introduce in detail about our proposed Automatic Block-wise Pruning method. The term "block" used in this paper refers to the basic structure that forms the entire network, for example, residual block in ResNet [He et al., 2016] series and convolution layer in VGG [Simonyan and Zisserman, 2014] style networks. In this section, we will take ResNet architecture as an example.

Inspired by SkipNet [Wang et al., 2018], we impose each block $B_l$ with a gating module $G_l$, which is shown in Figure 3. Gating module takes the input of current block, and outputs a scalar value for the corresponding block as an importance mark, which can be represented as $m_l = G_l(\mathcal{O}_{l-1})$. The mark would then be used as a weighting value for current block to generate the input of the next block $B_{l+1}$. After adding the gating module, (1) can be revised to:

$$\mathcal{I}_{l+1} = \mathcal{O}_l \times m_l + \mathcal{I}_l \times (1 - m_l) = B_l(\mathcal{I}_l) \times G_l(\mathcal{I}_l) + \mathcal{I}_l \times (1 - G_l(\mathcal{I}_l)) \quad \text{for} \quad l = 1, 2, ..., N \quad (4)$$

The design of gating module still follows SkipNet [Wang et al., 2018], where two types of gating modules are used to calculate importance mark for current block, namely ConvGate and RecurGate. ConvGate consists of two convolution layers to extract feature and a fully connect layer to calculate mark, which is shown in Figure 3. RecurGate is more lightweight, with one convolution layer attached to each block and an LSTM for the whole network, where LSTM takes the feature extracted from each block by convolution layer as input, and then output the importance mark accordingly. Since gating modules are removed from the architecture after training stage, we don’t have to concern about the cost brought by them like SkipNet. Different from SkipNet where the outputs of gating modules are rounded to 0 or 1 in SkipNet to reduce computation, which can cause non-differentiable problem in pruning, we directly use the outputs of gating modules as a metric for pruning.

3.3 Training schedule

Together with the ABP architecture, we propose a three-stage training schedule including warm-up, iterative pruning and fine-tuning to obtain a pruned model, which is shown in Figure 4. In the warm-up stage, ABP model is trained for a few epochs to match the ground-truth label. Denoting the ground-truth label as $y$, the loss function used in this stage is formulated as:

$$\mathcal{L}_{\text{stage} = 1} = \mathcal{L}_{CE} (s(l), y) \quad (5)$$

where $l$ is the logits output by ABP model, and $s(l)$ is softmax function taking logits as input.

After warming-up, pruning is implemented in an iterative manner. Concretely, in each iteration, a final mark is calculated by averaging marks generated by gating module for all instances. Assuming there are $S$ training instances, the final mark $\mathcal{M}_t$ for block $B_l$ is calculated as:

$$\mathcal{M}_t = \sum_s m^l_s \quad (6)$$
By calculating the final marks, \(k\) blocks with lowest marks can be pruned by applying a zero mask on the output of corresponding blocks, where \(k\) is a hyper-parameter defined according to model size. We call it voting-like strategy because we calculate the final mark by summing across all samples, where larger mark represents larger contribution of the block to the task. After pruning, we train the pruned model for a few epochs to restore performance for the next iteration. We also incorporate knowledge distillation [Hinton et al., 2015] into training in this stage to enhance training performance. In our setting model whose from previous iteration capacity is larger is used as teacher model, providing soft target for current iteration to grab latent information while training, which is shown in Figure 3. This iterative training pattern can improve the performance of training while avoiding efficiency decay of distillation brought by large capacity gap. The target of knowledge distillation can be formulated as:

\[
\mathcal{L}_{KD} = \mathcal{L}_{KL} \left(s(l^i; \tau), s(l^{i-1}; \tau)\right)
\]

(7)

where \(\mathcal{L}_{KL}\) is KL divergence, \(i\) is the index of current iteration and \(\tau\) is temperature term to soften the label for learning efficiency. Then the total loss used in this stage is:

\[
\mathcal{L}_{\text{stage2}} = \mathcal{L}_{CE} + \lambda \mathcal{L}_{KD}
\]

(8)

where \(\lambda\) is a balance factor, which is set to \(\tau^2\) in this paper to balance the magnitude of two loss terms. A pruned model would be obtained by setting the masks of the rest unpruned blocks to 1, and then we propose to retrieve the performance by adding a fine-tuning stage with a learning rate schedule. The entire training process is shown in Algorithm 1 in Supplementary Material.

After training we now have a well-trained network and a gating mask \(S\), where 0 mask means that the corresponding block is pruned, while 1 mark stands for unpruned block. Post-processing procedure is needed before further usage by removing gating modules and pruned blocks in architecture and in parameters. By doing so, we can reduce both computational cost and storage cost when using the model in real-world scenes.

4 Experiments

4.1 Experiment settings

To validate our proposed method, we implemented ResNet [He et al., 2016] series models specially for small images (32 \(\times\) 32) in CIFAR datasets. We set the hyper-parameters according to different architecture and pruning ratio, ensuring the training procedure of Stage2 would contain 2 or 3 iterations. During iterative pruning stage, we would train each model after pruning for 30 epochs, with learning rate decayed at 20th epoch, which is then reset on entering next iteration. For other hyper-parameters, we set initial learning rate \(\alpha\) to 0.1 and make it decay on entering Stage2 and Stage3, and set temperature term \(\tau\) to 3. All models are trained on a single RTX2080 GPU with batch size as 128 using an SGD optimizer. In our experiments we compare with other state-of-the-art pruning methods including SFP [He et al., 2018a], 11 [Li et al., 2016], GAL [Lin et al., 2019], AMC [He et al., 2018b], FPGM [He et al., 2019], NISP [Yu et al., 2018], HRank [Lin et al., 2020].

4.2 Result on CIFAR10

We compress networks of different depth using proposed method on CIFAR-10 dataset, and the results are shown in

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**Figure 4:** Example of the whole training schedule. Block with dashed line means the output of corresponding gating module is a floating point number in \([0, 1]\). In stage 2, the pruned block is skipped by setting its mask to 0, and in stage 3, the masks of remaining blocks are fixed to 1 which is represented by block with solid line.
### Table 1: Pruning results compared to SOTA methods. All data are derived from original papers. The number after method name (e.g. 0.4 in ABP-0.4) represents pruning ratio, and minus values in Accuracy drop columns means increase in accuracy after pruning. Method used in this paper is marked bold. ABP-SFP and ABP-HRank are experiments where our methods are incorporated with other SOTA methods, which is demonstrated in detail in Supplementary Material.

| Arch. | Methods     | FLOPs↓(%) | Acc↓(%) |
|-------|-------------|-----------|---------|
| RN32  | ABP-0.4     | 41.1      | -0.33   |
|       | SFP         | 41.9      | 0.55    |
|       | FPGM        | 53.2      | 0.70    |
|       | ABP-0.6     | 61.7      | 0.37    |
|       | ABP-SFP     | 80.8      | 0.97    |
|       | ABP-0.2     | 15.0      | -0.91   |
|       | l1          | 27.6      | -0.04   |
|       | GAL-0.6     | 37.6      | -0.12   |
|       | ABP-0.4     | 37.6      | -0.34   |
|       | NISP        | 43.6      | 0.03    |
|       | AMC         | 50.0      | 0.90    |
|       | HRank       | 50.0      | 0.09    |
|       | GAL-0.8     | 60.2      | 1.68    |
|       | ABP-0.6     | 60.2      | 0.08    |
|       | HRank       | 74.1      | 2.54    |
|       | ABP-HRank   | 79.2      | 2.13    |
|       | ABP-SFP     | 79.6      | -0.18   |
| RN56  | GAL-0.1     | 18.7      | -0.09   |
|       | ABP-0.2     | 18.7      | -0.59   |
|       | SFP         | 28.2      | -0.25   |
|       | l1          | 38.6      | 0.23    |
|       | ABP-0.4     | 39.2      | -0.62   |
|       | NISP        | 43.8      | 0.28    |
|       | GAL-0.5     | 44.8      | 0.76    |
|       | ABP-0.6     | 59.7      | -0.06   |
|       | HRank       | 68.6      | 0.85    |
|       | ABP-HRank   | 69.2      | 0.38    |
|       | ABP-SFP     | 93.7      | -0.20   |
| RN110 | GAL-0.1     | 18.7      | -0.09   |
|       | ABP-0.2     | 18.7      | -0.59   |
|       | SFP         | 28.2      | -0.25   |
|       | l1          | 38.6      | 0.23    |
|       | ABP-0.4     | 39.2      | -0.62   |
|       | NISP        | 43.8      | 0.28    |
|       | GAL-0.5     | 44.8      | 0.76    |
|       | ABP-0.6     | 59.7      | -0.06   |
|       | HRank       | 68.6      | 0.85    |
|       | ABP-HRank   | 69.2      | 0.38    |
|       | ABP-SFP     | 93.7      | -0.20   |

Table 1: The results of SOTA methods listed here come from the original papers, and we arrange them according to the drop in FLOPs after pruning, followed with the accuracy drop using each method. As shown in Table 1, our method can achieve better performance than those with similar compression rate, for example, when using ResNet32, ABP-0.6 provides smaller accuracy drop (0.37% vs 0.70%) with higher compression rate compared to SFP (61.7% vs 53.2%); while in ResNet56 experiments, ABP-0.2 can increase the performance of the network to a large extent (0.91%) with 15% of the FLOPs pruned, and ABP-0.6 achieves much better performance in accuracy than GAL (0.08% vs 1.68% drop in accuracy) with the same compression rate. As for large scale networks (ResNet110), ABP does better in removing redundancy (0.5% increase in accuracy) when pruning with a small pruning rate, and brings less accuracy drop (0.02% vs 0.76%) with a higher pruning ratio compared to GAL (59.7% vs 44.8%).

Since ABP is a pruning method with very large granularity, it can be easily incorporated with other pruning methods with smaller granularity like channel-wise pruning. We also list some of the results when using our pruned model as pretrained model (denoted as ABP-SFP and ABP-HRank). Only models with extremely high compression rate are listed in Table 1 for comparison. When incorporating with our method, SFP constantly achieves very high compression rate in all settings, with even higher performance than baseline models on ResNet56 and ResNet110. ABP-HRank failed to achieve comparable performance with ABP-SFP though, it outperforms other SOTA methods with similar compression rate.

For the rest of the results, an illustration is provided in Figure 5, where red lines indicate the original SFP and HRank methods while green lines are original ABP methods, and black lines represent incorporated models. It is obvious that green lines stay constantly above red lines, indicating that ABP method outperform these methods in accuracy under different compression rates. In the case of black lines, they are completely on the right side of red lines, showing that incorporated methods can achieve better compression rate with similar accuracy.

Results above have shown that as a large granularity pruning method, ABP can provide well trained pretrained model to other pruning methods for further pruning while achieving comparable performance with SOTA methods alone. Detailed experiments on both CIFAR10 and CIFAR100 datasets are provided in Supplementary Material, as well as further investigation on the influence of pruning rate and the type of gating structure.

### 4.3 Importance marks

In order to verify the effectiveness and consistency of our proposed method, we visualize importance marks after stage1 as shown in Figure 6. Every mask is divided into 3 rows, which indicate three different stages in ResNet. As can be seen in Figure 4, top blocks tend to have larger marks while the marks of middle blocks tend to be smaller, which is common in most cases. This phenomenon can be interpreted as deeper layers
tend to extract discriminative features, which is much more useful for classification than middle layers.

We further visualize the proportion of unpruned blocks after training schedule on different network architecture and pruning ratio in Figure 7, where for all structures we plot the ratio of unpruned blocks (in blue) in three stages. It is evident that our pruning method prefers to prune blocks in first two stages especially for shallower structures, which is consistent with the pattern in Figure 4, and thus supports the effectiveness of our method.

4.4 Ablation Study

In order to validate the effectiveness of different modules of ABP methods, we implemented ablation study on training schedule and knowledge distillation. We successively removed the self-distillation and the whole iterative training schedule in stage 2, which is marked w/o KD and w/o Stage2 respectively in Table 2. Results show that directly pruning according to the importance mark generated through stage 1 training suffers from accuracy drop (94.10% vs 94.33% in ResNet110), but still performs better than baseline model with a small pruning rate (0.4). Compared to models trained without self-distillation schema, full ABP training schedule does better in performance recovery after pruning in a large pruning ratio (92.46% vs 93.28% in ResNet56-0.6). Note that self-distillation schema is incorporated into the entire training process rather than acting as a training trick, which is similar as GAL[Lin et al., 2019].

5 Conclusion

In this paper we proposed an automatic block-wise pruning schedule for CNNs using gating modules. The core idea of our method is to assign importance marks for all blocks using gating modules, and then prune blocks with lower marks iteratively. By implementing our proposed training schedule, we show that we can cut down over 60% computational cost with insignificant loss in accuracy for various ResNet models. We further demonstrate how our pruned models can improve the performance of other pruning methods greatly by providing pretrained models, where the performance of pruned model is even better than original model with 93.7% of FLOPs pruned.

| Architecture | ResNet56 | ResNet110 |
|--------------|----------|-----------|
| Pruning ratio | 0.4      | 0.6       |
| Baseline     | 93.36    | 93.79     |
| w/o Stage2   | 93.47    | 93.46     |
| w/o KD       | 93.55    | 93.60     |
| Full ABP     | 93.70    | 94.41     |

Table 2: Ablation study on different settings used in ABP methods.

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