STORAGE EFFICIENT AND DYNAMIC FLEXIBLE RUN-TIME CHANNEL PRUNING VIA DEEP REINFORCEMENT LEARNING

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ABSTRACT

In this paper, we propose a deep reinforcement learning (DRL) based framework to efficiently perform runtime channel pruning on convolutional neural networks (CNNs). Our DRL-based framework aims to learn a pruning strategy to determine how many and which channels to be pruned in each convolutional layer, depending on each specific input instance in runtime. The learned policy optimizes the performance of the network by restricting the computational resource on layers under an overall computation budget. Furthermore, unlike other runtime pruning methods which require to store all channels parameters in inference, our framework can reduce parameters storage consumption at deployment by introducing a static pruning component. Comparison experimental results with existing runtime and static pruning methods on state-of-the-art CNNs demonstrate that our proposed framework is able to provide a tradeoff between dynamic flexibility and storage efficiency in runtime channel pruning.

1 INTRODUCTION

In recent years, convolutional neural networks (CNNs) have been proven to be effective in a wide range of computer vision tasks, such as image classification [Krizhevsky et al., 2012; Simonyan & Zisserman, 2015; He et al., 2016], objection detection [He et al., 2017; Zhou et al., 2019; Law & Deng, 2018], segmentation [He et al., 2017; Zhu et al., 2019]. Therefore, nowadays, many computer-vision-based systems, such as automatic-driving cars, security surveillance cameras, and robotics, are built on the power of CNNs. However, as most of the state-of-the-art CNNs require expensive computation power for inference and huge storage space to store large amount of parameters, the limitation of energy, computation and storage on mobile or edge devices has become the major bottleneck on real-world deployments of CNNs. Existing studies have been focused on speeding up the execution of CNNs for inference on edge devices by compressing the model, such as matrix decomposition [Demil et al., 2013; Masana et al., 2017], network quantization [Courbariaux et al., 2016], and network pruning [Dong et al., 2017]. Among these approaches, channel pruning has shown promising performance [He et al., 2017; Luo et al., 2017; Zhuang et al., 2018; Peng et al., 2019]. Specifically, channel pruning discards an entire input or output channel and keep the rest of the model with structures.

Most channel pruning approaches can be categorized into two types: runtime approaches and static approaches. Static channel pruning approaches aim to design a measurement to evaluate the importance of each channel over the whole training dataset and remove the least important channels to minimize the loss of performance after pruning. By permanently pruning a number of channels, the computation and storage cost of CNNs can be dramatically reduced when being deployed, and the inference execution can be accelerated consequently. Runtime channel pruning approaches have been recently proposed to achieve dynamic channel pruning on each specific instance [Gao et al., 2019; Luo & Wu, 2018]. To be specific, the goal of runtime approaches aims to evaluate the channel importance at runtime, which is assumed to be different on different input instances. By pruning channels dynamically, different pruned structures can be considered as different routing of data stream inside CNNs. This kind of approaches is able to significantly improve the representation capability of CNNs, and thus achieve better performance in terms of prediction accuracy compared with static approaches. However, previous runtime approaches trade storage cost off dynamic flex-
ibility of pruning. To achieve dynamic pruning on different specific instances, all parameters of kernels are required to be stored (or even more parameters are introduced). This makes runtime approaches not applicable on resource-limited edge devices. Moreover, most of previous runtime approaches only evaluate the importance among channels in each single layer independently, without considering the difference in efficiency among layers.

In this paper, to address the aforementioned issues of runtime channel pruning approaches, we propose a deep reinforcement learning (DRL) based pruning framework. Basically, we aim to apply DRL to prune CNNs by maximizing received rewards, which are designed to satisfy the overall budget constraints along side with network’s training accuracy. Note that automatic channel pruning by DRL is a difficult task because the action space is usually very huge. Specifically, the discrete action space for the DRL agent is as large as the number of channels at each layer, and the action spaces may vary among layers since there are different numbers of channels in different layers. To facilitate pruning CNNs by DRL, for each layer, we first design a novel prediction component to estimate the importance of channels, and then develop a DRL-based component to learn the sparsity ratio of the layer, i.e., how many channels should be pruned.

More specifically, different from previous runtime channel pruning approaches, which only learn runtime importance of each channel, we propose to learn both runtime importance and additionally static importance for each channel. While runtime importance maintains the saliency of specific channels for each given specific input, the static importance captures the overall saliency of corresponding channel among whole dataset. According to each type of the channel importance, we further design a different DRL agent (i.e., a runtime agent and a static agent) to learn a sparsity ratio in a layer-wise manner. The sparsity ratio learned by the runtime agent together with the estimated runtime importance of channels are used to generate runtime pruning structures, while the sparsity ratio learned by the static agent together with the estimated static importance of channels are used to generate static (permanent) pruning structures. By considering both the pruning structures, our framework is able to provide a trade-off between storage efficiency and dynamic flexibility for runtime channel pruning.

In summary, our contributions are 2-fold. First, we propose to prune channels by taking both runtime and static information of the environment into consideration. Runtime information endows pruning with flexibility based on different input instances while static information reduces the number of parameters in deployment, leading to storage reduction, which cannot be achieved by conventional runtime pruning approaches. Second, we propose to use DRL to determine sparsity ratios, which is different from the previous pruning approaches which manually set sparsity ratios. Extensive experiments demonstrate the effectiveness of our method.

2 Related Work and Preliminary

2.1 Structure Pruning

Wen et al. (2016) pioneered structure pruning in deep neural network by imposing $L_{2,1}$ norm in training. Under the same framework, Liu et al. (2017) regarded parameters in batch normalization as channel selection signal, which is minimized to achieve pruning during training. He et al. (2017) formulated channel pruning into a two-step iterative process including LASSO regression based channel selection and least square reconstruction. Luo et al. (2017) formulated channel pruning as minimization of difference of output features, which is solved by greedy selection. Zhuang et al. (2018) further considered early prediction, reconstruction loss and final loss to select importance channels. Overall, structure pruning methods accelerate inference by producing regular and compact model. However, this brought regularness requires preserving more parameters to ensure performance.

2.2 Dynamic Pruning

Dynamic pruning provides pruning strategy according to input data. Wang et al. (2018) avoided computation by skipping layers or channels based on the analysis of input features. Luo & Wu (2018) proposed to use layer input to learn channel importance, which is then binarized for pruning. Gao et al. (2019) applied the same framework while extended features selection in both input and output features. Similarly, Liu & Deng (2018) introduced multiple branches for runtime inference.
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Figure 1: Illustration of our proposed DRL-based runtime pruning framework.

According to inputs. A gating module is learnt to guide the flow of feature maps. Bolukbasi et al. (2017) learned to choose the components of a deep network to be evaluated for each input adaptively. Early exit is introduced to accelerate computation. Dynamic pruning adaptively takes different actions for different inputs, which is able to accelerate the overall inference time. However, the whole model need to be stored, together with extra parameters for making specified pruning actions.

2.3 Deep Reinforcement Learning in Pruning

Channel selection is on trial using deep reinforcement learning. Lin et al. (2017) trained a LSTM model to remember and provide channel pruning strategy for backbone CNN model, which is conducted using reinforcement learning techniques. He et al. (2018) determined the compression ratio in each layer by training an agent and regarded whole pruning-retrain process as environment.

2.4 Preliminary

Reinforcement Learning We consider a standard form of reinforcement learning an agent sequentially takes actions over a sequence of time steps in an environment, in order to maximize the cumulative reward (Sutton & Barto, 1998). This problem can be formulated as a Markov Decision Process (MDP) of a tuple \((S, A, P, R, \gamma)\), where \(S\) is the state space, \(A\) is the action space, \(P : S \times A \times S \rightarrow [0, 1]\) is transition probabilities, \(R : S \times A \rightarrow \mathbb{R}\) is reward function, and \(\gamma \in [0, 1)\) is discount factor. The goal of reinforcement learning is to learn a policy \(\pi(a | s)\) that maximizes the objective of cumulative rewards over finite time steps,

\[
\max_{\pi} \sum_{t=0}^{T} R(s_t, a_t),
\]

where \(s_t \in S\) and \(a_t \in A\) are state and taken action at time step \(t\) respectively.

3 DRL-based Runtime Pruning Framework

The overview of our proposed framework is presented in Fig. 1. To prune convolutional layer \(t\), we learn two types of learnable channel importance, runtime channel importance \(u_r \in \mathbb{R}^{C \times 1}\) and static channel importance \(u_s \in \mathbb{R}^{C \times 1}\), where \(C\) is the number of channels in layer \(t\). The runtime channel importance \(u_r\) is generated by a subnetwork importance predictor \(f(\cdot)\) feeding with input feature map \(F_{in}\), while the static channel importance \(u_s\) is randomly initialized and updated through during training. Both of \(u_r\) and \(u_s\) indicate the channel importance of the full precision output feature map \(F_{out}\) through a convolution layer. Channels are selected to be pruned according to the values of each element in \(u_r\) and \(u_s\), and how many channels to be selected is decided by the sparsity ratios \(d_r\) and \(d_s\), respectively. To learn the sparsity ratios \(d_r\) and \(d_s\), two DRL agents, runtime agent and static agent, are introduced, where actions \(a'_r\) and \(a'_s\) are defined to set values of \(d_r\) and \(d_s\), respectively. The detail of the two DRL agents will be described in Sec. 3.3. Consequently, a trade-off pruner \(g(\cdot)\) is performed to balance the runtime and static pruning results, and output a decision mask \(M\) of binary values \((1/0)\) to indicate which channels to be pruned (1: pruned, 0: preserved), as well as...
a unified channel importance vector \( u \in \mathbb{R}^{C \times 1} \) as follows,

\[
[M, u] = g(u_r, u_s, d_r, d_s).
\]

The final output after pruning is constructed by multiplying the full precision output feature map \( \hat{F}_{out} \), by \( 1 - M \) and \( u \) as,

\[
\hat{F}_{out} = F_{out} \otimes (1 - M) \otimes u,
\]

where \( \otimes \) is the broadcast element-wise multiplier. In the following, we introduce how to learn the runtime channel importance vector \( u_r \) and the static channel importance vector \( u_s \) in Sec. 3.1 how to construct the trade-off pruner \( g(\cdot) \) in Sec. 3.2, and how to design the two DRL agents in Sec. 3.3.

### 3.1 Learnable Channel Importance

We consider that a convolutional layer takes input of feature map \( F_{in} \in \mathbb{R}^{C_{in} \times H_{in} \times W_{in}} \) and generates an output feature map \( F_{out} \in \mathbb{R}^{C_{out} \times H_{out} \times W_{out}} \), where \( C, H, \) and \( W \) are the the number of channels, width and height of the feature map \( F \), respectively. Each element of the channel importance vectors \( u_r \in \mathbb{R}^{C_{in}} \) and \( u_s \in \mathbb{R}^{C_{out}} \) represents the importance value of the corresponding channel, respectively. In the following, we drop the subscript \( out \) for simplicity in presentation.

#### 3.1.1 Runtime Channel Importance

As mentioned above, the runtime channel importance of output feature \( F_{out} \), \( u_r \) is predicted by a importance predictor \( f(\cdot) \), which takes \( F_{in} \) as input. Therefore, \( u_r \) can be considered as a function of \( F_{in} \), whose values vary over different input instances. In this paper, we design a subnetwork to approximate \( f(\cdot) \), which is expected to be of a small size and computationally efficient. Similar to many existed dynamic network pruning methods (Gao et al., 2019; Hu et al., 2018; Luo & Wu, 2018), we use global pooling layer as the first layer in \( f(\cdot) \), because global pooling is computationally efficient and it can reduce the dimension of \( F_{in} \) dramatically. We then feed the output of global pooling into a fully-connected layer without any activation function. The output of fully-connected layer is the runtime channel importance vector \( u_r \).

Which channels to be preserved / pruned at runtime are determined according to the values of \( u_r \). We denote by \( M_r \in \{0, 1\}^C \) a mask for pruning, where if the value is 0, then the corresponding channel is preserved, otherwise pruned. For now, suppose a sparsity ratio \( d_r \) for runtime pruning has already been generated via DRL, which will be introduced in Sec. . We then prune \([d, C]\) channels with the smallest importance values in \( u_r \). Accordingly, the value of an element in \( M_r \) is set to be 1 if the corresponding channel is pruned, otherwise 0.

#### 3.1.2 Static Channel Importance

The static channel importance vector \( u_s \) is to capture the global information for pruning, and thus is learned from the whole dataset. It is randomly generated and learned through backpropagation. Similar to runtime channel pruning, given a sparsity ratio \( d_s \) learned by DRL, \([C - [d_s C]]\) channels with smallest importance values in \( u_s \) are pruned, and a mask \( M_s \in \{0, 1\}^C \) is generated to indicate the static pruning results.

### 3.2 Trade-off Pruner

With the runtime and the static pruning decisions, \( M_r \) and \( M_s \), we now propose a trade-off pruner to generate a unified channel pruning decision. The main idea behind the trade-off pruner is to 1) prune those channels which are agreed to be pruned by both decisions, and 2) prune a portion of the rest channels by weighted votes from both decisions.

To be specific, we define the mask representing channels pruned by both decisions by

\[
M_o = M_s \land M_r,
\]

where \( \land \) is element-wise logical AND and 1/0 in mask represents logical true or false. The channels indicated to be pruned by \( M_o \) (i.e., the correspond values are 1) are pruned in final. The channels which are determined to be pruned by \( M_r \) but not by \( M_s \) can be represented by a new mask \( M_o = \ldots \)
To control the trade-off between \( \mathbf{M}_r \) and \( \mathbf{M}_s \), we define a rate \( R_r \) denoting how much we trust the pruning decision made by \( \mathbf{M}_r \), while \( 1 - R_r \) is for \( \mathbf{M}_s \). That means the channels selected in \( \mathbf{M}_r \) will be finally pruned with the rate \( R_r \). Specifically, the number of channels which are selected by \( \mathbf{M}_r \) will be finally pruned is

\[
C'_r = \lfloor R_r (1^\top \mathbf{M}_r) \rfloor,
\]

(4)

where \( 1^\top \mathbf{M}_r \) returns the number of channels selected by \( \mathbf{M}_r \). We then select the first \( C'_r \)-smallest important channels which are recommended to be pruned by \( \mathbf{M}_r \) to form a mask \( \hat{\mathbf{M}}_r \). Similarly, for static pruning, we select the first \( C'_s \)-smallest important channels which are recommended to be pruned by \( \mathbf{M}_s \) to form another mask \( \hat{\mathbf{M}}_s \), where \( C'_s = \lfloor (1 - R_r)(1^\top \mathbf{M}_s) \rfloor \).

The final trade-off pruning mask is defined as

\[
\mathbf{M} = \mathbf{M}_o + \hat{\mathbf{M}}_r + \hat{\mathbf{M}}_s.
\]

(5)

Moreover, in this work, the unified channel importance is simply defined as follows,

\[
\mathbf{u} = \mathbf{u}_r \otimes \mathbf{u}_s.
\]

(6)

With the trade-off pruning mask \( \mathbf{M} \) and unified channel importance \( \mathbf{u} \), the pruned output feature \( \hat{\mathbf{F}}_{\text{out}} \) can be generated by Eq. 2.

### 3.3 DRL BASED PRUNING

In this section, we present how to formulate the problems of learning the ratios \( d_s \) and \( d_t \) for static pruning and runtime pruning, as a MDP, and solve it via DRL, respectively.

#### 3.3.1 DRL FOR RUNTIME PRUNING

In the MDP for runtime pruning, we consider the \( t \)-th layer of the network as the \( t \)-th timestamp. The details of the MDP are listed as followed.

**State** Given an input feature map \( \mathbf{F}_{in} \) of layer \( t \), we pass it into global pooling layer to reduce its dimension to \( \mathbb{R}^{C_{in}} \), where \( C_{in} \) is the number of input channel of layer \( t \). Since \( C_{in} \) is various among layers, we feed the output of global pooling into a layer-dependent encoder to project it to a fix-length vector \( s'_t \), which is considered as as a state representation of DRL in the context of runtime pruning.

**Action** The action \( a'_r \) is defined as the sparsity ratio at layer \( t \), alternating \( d_r \) in runtime pruning mentioned in Section 3.1.1. Existing DRL-base pruning method RNP (Lin et al., 2017) use a unified discrete actions space with \( k \) actions that is coarse to achieve high accuracy. Fine-grained discrete action space as large as number of channels suffer from exploration difficulty. Therefore, instead of using discrete action spaces, we propose a continuous action space with action \( a'_r \in (0, 1] \). To avoid over-prune the filters and crashed in training, we set a minimum sparsity ratio \( +\alpha \), then the action space change to \( a'_r \in (+\alpha, 1] \).

**Reward** The reward function is proposed to consider both of network accuracy and computation budget. We define the reward relative to the loss of pruned backbone network,

\[
R_{\text{acc}} = -L_{\text{CNN}},
\]

(7)

where \( L_{\text{CNN}} \) is the loss in CNN, and it may be various in scale among different training stage, i.e. large at begin of training and small near converge. To avoid the instability brought by the reward scale, \( R_{\text{acc}} \) is normalized by a moving average,

\[
R'_{\text{acc}} = R_{\text{acc}} / \beta_b,
\]

(8)

\[
\beta_b = \lambda \beta_{b-1} + (1 - \lambda) R_{\text{acc}},
\]

(9)
where $\beta_b$ is the moving average when meet $b$-th batch training data and $\lambda$ is the moving weight.

To force computation of the pruned network under a given computation budget, we define a exponential reward function of budget regarding reward $R_{bud}^r$:

$$R_{bud}^r = \begin{cases} 
\exp(\alpha_1(B_{com} - \overline{B}_{com})) - 1, & B_{com} > \overline{B}_{com}, \\
0, & \text{otherwise},
\end{cases}$$  \hspace{1cm} (10)

where $B_{com}$ is the computation consumption, which is calculated based on the current of pruned strategy, and $\overline{B}_{com}$ is the given computation budget constraint. Finally we sum up the two rewards to form sparse rewards, with being non-zero at terminated step $T$ and zeros at other time step $t < T$,

$$R_t^r = \begin{cases} 
R_{acc}^r + R_{bud}^r, & t = T, \\
0, & t < T.
\end{cases}$$  \hspace{1cm} (11)

**Actor-Critic Agent**

To solve the continuous action space RL problem, we choose a commonly used actor-critic agent with Gaussian policy. Actor-critic agent consists of two components: 1) actor outputs the mean and variance to form a Gaussian policy where the continuous action are sampled from; 2) critic outputs a scalar predicting the future discounted accumulated reward and assists the training of policy. Actor network and Critic network share one-layer RNN which is feed by state $s_r^t$. The output of RNN is fed into actor specific network constructed by two branches of fully-connected layers with size of 1, leading to the mean and variance of Gaussian policy. The action is sampled for the actor output Gaussian distribution:

$$a_r^t \sim \mathcal{N}(\mu(s_r^t; \theta^r), \sigma(s_r^t; \theta^r)), \hspace{1cm} (12)$$

where $\mu(s_r^t; \theta^r)$ and $\sigma(s_r^t; \theta^r)$ is the mean and variance output from actor network. The Critic specific network has one fully-connected layer with size of 1 after the shared RNN, and outputs the predictive value $V(s_r^t; \theta^r)$.

To optimize the actor-critic agent, Proximal Policy Optimization (PPO) (Schulman et al., 2017) is used to train the agent. Note that we relax the action $a_r^t$ to $(-\infty, +\infty)$ in PPO, and use truncate function to clip $a_r^t$ in $(+\alpha, 1]$ when perform pruning.

Besides, an additional regularizer is introduced to limit the relaxed $a_r^t$ stay in range $(+\alpha, 1]$,

$$L_a = \frac{1}{2} ||a_r^t - \max(\min(a_r^t, 1), +\alpha)||^2_2. \hspace{1cm} (13)$$

### 3.3.2 DRL for Static Pruning

Similar to runtime pruning, the MDP in static pruning is also formulated layer-by-layer. The difference against runtime pruning is the definition of state and reward.

**State**  The state $s_r^t$ in static pruning is defined as the full shape of $F_{out}$. $s_r^t$ does not depends on $F_{out}$ and current input data.

**Action**  Action $a_r^t$ is sampled from actor output Gaussian policy. $a_r^t$ is to alternate the sparsity $d_s$ in static pruning mentioned in Section [3.1.2](#).

**Reward**  The reward function combines regarding of network accuracy and parameters budget. The accuracy relative is defined same as runtime pruning.

$$R_{acc}^s = R_{acc}^r. \hspace{1cm} (14)$$

To reduce the number of parameters of network to satisfy the parameters storage budget, the parameters relative reward is defined in exponential form as,

$$R_{param}^s = \begin{cases} 
\exp(\alpha_2(B_{param} - \overline{B}_{param})) - 1, & B_{param} > \overline{B}_{param}, \\
0, & \text{otherwise},
\end{cases}$$  \hspace{1cm} (15)

where $B_{param}$ is number of reserved parameters after static pruning and $\overline{B}_{param}$ is the parameters storage budget.
Method | Baseline acc. | Acc. | \(\Delta\text{acc.}\) | Speed-up | #Params
---|---|---|---|---|---
FBS (Gao et al., 2019) | 91.37 | 91.23 | -0.14 | 2× | 1.11×
RNP (Lin et al., 2017) | 92.07 | 93.178 | +1.108 | 1.99× | 1.31×
ours (runtime only \(R_r = 1\)) | 92.07 | 92.502 | +0.432 | 1.99× | 0.97×
ours (\(R_r = 0.5\)) | 92.07 | 91.066 | -1.004 | 3.92× | 0.78×

Table 1: Compare to state-of-the-art runtime pruning methods on Cifar-10 at sparsity 0.5.

Actor-Critic Agent This agent is similar to the one in runtime pruning. It has same architecture as runtime pruning but differ in introducing an fully-connected layer as encoder before the RNN. This agent is also used the same technique optimized by PPO.

3.4 Inference

When in inference, the static agent is not required any more because it is not dependent to the input data but the full shape of \(F_{in}\). Hence, the output action \(a_s^t\) is fixed to each layer \(t\). By the action \(a_s^t\) and the rate \(R_r\), we can decide which filters can be to prune permanently. Channels with ((1 - \(a_s^t\))/2)-smallest static importance is impossible to selected in trade-off pruner. Therefore they can be pruned permanently.

4 Experiment

We evaluate our DRL pruning framework on two popular dataset: CIFAR-10 (Krizhevsky, 2009) and ImageNet ILSVRC2012 (Russakovsky et al., 2015), to show the advantage over other channel pruning methods. We analyze the effect of hyper-parameters and different sparsity settings on CIFAR-10 dataset. For CIFAR-10 dataset, we use M-CifarNet (Zhao et al., 2018) as the backbone CNN. In ImageNet ILSVRC2012, ResNet-18 is used as backbone CNN.

4.1 Implement Details

We start with a pretrained backbone CNN. Firstly we finetune the backbone CNN and train runtime importance predictor jointly, with sparsity \(d_r = 1\) and fixed all static pruning importance \(u_s\) to 1. Then we remove the restriction on the static pruning importance \(u_s\), and train static pruning importance as well as backbone CNN and the runtime importance predictor, with sparsity \(d_s = 1\) with runtime pruning sparsity kept as \(d_r = 1\). After the finetuning converge, we use DRL agent to predict the sparsity with given computation and storage constraint. The DRL agent and CNN with runtime/static importance are trained in alternative manner: We first fix the CNN as well as runtime/static importance and train two DRL agents, regarding the CNN as environments. Then we fix two agents and finetune the CNN and runtime/static importance. We repeat these two steps until converge. We use Adam optimizer for both DRL agent and CNN, and set learning rate \(10^{-6}\) for DRL agent. For CNN fintuning and runtime/static importance training, learning rate is set to \(10^{-3}\) in CIFAR-10. In ImageNet ILSVRC2012, learning rate starts from \(10^{-3}\) and divided by 10 after 15 Millions iterations.

4.2 Experimental result on CIFAR-10

We compare our proposed method with the following state-of-the-art runtime pruning methods: FBS (Gao et al., 2019), RNP (Lin et al., 2017) on CIFAR-10. The comparison results at sparsity 0.5 and 0.7 are shown in Table 1 and Table 2 respectively. Noted that for fair comparison with other
Table 3: Comparison with the state-of-the-art channel pruning ResNet-18 on ImageNet

<table>
<thead>
<tr>
<th>Method</th>
<th>Baseline top-1 acc.</th>
<th>Baseline top-5 acc.</th>
<th>Speed-up</th>
</tr>
</thead>
<tbody>
<tr>
<td>DCP (Zhuang et al., 2018)</td>
<td>69.64</td>
<td>88.98</td>
<td>1.71×</td>
</tr>
<tr>
<td>FPGM (He et al., 2019)</td>
<td>70.28</td>
<td>89.63</td>
<td>1.71×</td>
</tr>
<tr>
<td>Dynamic Sparse Graph (Liu et al., 2019)</td>
<td>69.48</td>
<td>-</td>
<td>1.4×</td>
</tr>
<tr>
<td>CGNN (Hua et al., 2018)</td>
<td>69.02</td>
<td>88.21</td>
<td>1.63×</td>
</tr>
<tr>
<td>FBS (Gao et al., 2019)</td>
<td>70.71</td>
<td>88.22</td>
<td>1.98×</td>
</tr>
<tr>
<td>Ours (R_r = 0.5)</td>
<td>69.75</td>
<td>89.07</td>
<td>1.94×</td>
</tr>
</tbody>
</table>

Note: The column #Params represents the number of parameters compare to the backbone CNN.

4.3 EXPERIMENTAL RESULT ON IMAGE NET ILSVRC2012

We compare our methods with state-of-the-art channel pruning methods on ImageNet ILSVRC2012 as shown in Table. 3. In this experiment, we use ResNet-18 as backbone CNN. Among these state-
of-the-art pruning methods, FBS \cite{Gao2019} and CGNN \cite{Hua2018} are runtime pruning methods. The overall sparsity ratio of our method is 0.7, which is under the same setting of FBS. Our method with $R_r = 0.5$ achieves the smallest top-1 accuracy drop compared with other methods. It also achieves the highest top-1 accuracy after pruning. Overall, our proposed method has achieved comparable or better performance compared to other methods with more acceleration. Our method has very close MACs to FBS, while the number of reserved parameters is reduced to 81.2% of baseline.

5 Conclusion

In this paper, we present the deep reinforcement learning based framework for deep neural network channel pruning in both runtime and static scheme. Specially, channels are pruned according to input feature as runtime pruning, and based on entire training dataset as static pruning, with 2 reinforcement agents to determine the corresponding sparsity. Our method combines the merits of runtime and static pruning, and provides trade-off between storage and dynamic flexibility. Extensive experiments demonstrate the effectiveness of our proposed method.

References


