When Sparsity Meets Dynamic Convolution

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Abstract

Dynamic convolution achieves a substantial performance boost for efficient CNNs at a cost of increased convolutional weights. Contrastively, mask-based unstructured pruning obtains a lightweight network by removing redundancy in the heavy network at risk of performance drop. In this paper, we propose a new framework to coherently integrate these two paths so that they can complement each other compensate for the disadvantages. We first design a binary mask derived from a learnable threshold to prune static kernels, significantly reducing the parameters and computational cost but achieving higher performance in Imagenet-1K (0.6% increase in top-1 accuracy with 0.67G fewer FLOPs). Based on this learnable mask, we further propose a novel dynamic sparse network incorporating the dynamic routine mechanism, which exerts much higher accuracy than baselines (2.63% increase in top-1 accuracy for MobileNetV1 with 90% sparsity). As a result, our method demonstrates a more efficient dynamic convolution with sparsity.

1. Introduction

There have been rich discussions on the expression power of deep neural networks in two opposite directions [31,38]. From the perspective of increasing the model capacity, more layers and channels with specialized infrastructure can achieve higher performance with less overfit [1,36]. In the view of compressing the model, sparsification and quantization of complex networks can induce smaller models with a moderate deficit in accuracy [12,14]. Regarding the asymmetry between cost and gain in these two opposite approaches, what will happen when we combine them for infrastructure optimization? Especially, can we apply dynamic convolution with sparsity simultaneously towards of better tradeoff between model complexity and performance?

Dynamic convolution [7] achieves significant performance gains over the static convolution with negligible computational cost but relatively high memory cost. It utilizes an input-based attention mechanism to generate dynamic attention weights to combine multiple static parallel kernels, boosting the overall performance at the cost of increased convolutional parameters in the dynamical attention. However, during inference, this parameter increase does not match the model performance improvement completely. For example, DY-ResNet18 [7] is 2.3% higher than ResNet-18 and 4% lower than ResNet-50 in Top-1 accuracy on Imagenet-1K [8], while its parameter amount is about four times of ResNet-18 and twice of ResNet-50. This phenomenon raises the problem of when we can design the dynamic convolution more efficiently.

A possible routine to improve the memory efficiency in dynamic convolution is to optimize its forms of combining kernels. For example, Li et al. [27] proposes Dynamic Convolution via Matrix Decomposition (DCD) to reformulate the linear combination of kernels into a summation of static kernel and sparse dynamic residual. Another scheme is to increase the sparsity to build compact parameter-efficient networks. One can prune task-unrelated neurons that usually have small absolute values [13,17,44] or contribute little to the decrease of loss function [25,26,37]. In recent studies, some sparse networks not only decrease storage and computational requirements but also achieve higher inference scores than dense networks [10], suggesting the potential utility of sparse structure in decreasing the overfit. In terms of the expression power of subnetworks, the Lottery Ticket Hypothesis [13] says if we can find the binary mask for the efficient subnetwork in the training process, we can train the network from scratch to the same level of accuracy. This finding inspires us to integrate the sparse approaches with dynamic convolution to achieve a compact and efficient network infrastructure.

In this work, we propose to integrate the dynamic co-
volution with sparsity in two folds, the sparse dynamic convolution and the dynamic sparse networks. The sparse dynamic convolution provides local optimization of convolution structure and the dynamic sparse network enriches the expression power of sparse networks with low cost.

First, we present a new algorithm that trains the dynamic convolution modes via iterative pruning that increases the sparse ratio of binary masks step by step. To dynamically adjust the sparsity of masks, we set a learnable threshold for each convolutional layer and prune the neurons whose magnitude is below the lay-wise threshold. We also propose a penalty term to explicitly regulate the $L_0$-norm of binary masks to guarantee the total parameters under an overall budget without additional hyperparameters. Our binary mask induces sparsity via learning the per-layer pruning thresholds like STR [23] and is easier to train given a sparsity budget. Considering that the computational kernel is a linear combination of static kernels, the masked kernels can then be integrated into a sparsely computing kernel with reduced FLOPs.

Next, we put forward a dynamic method to promote the performance of sparse networks. Generally, the convolutional kernel is denser than each of the static kernels in sparse dynamic convolution. However, if we control the sparsity of static kernels and select only one kernel towards an input, we can directly restrict the sparse ratio of the network during the inference time. Inspired by Bengio et al. [3] and Bulat et al. [5], we take the static kernels as the candidates for the convolutional kernel and dynamically select only one per layer for a single input sample following a very lightweight gating function. Learning to select a single and turn to the input data, the gating function is a key property of our sparse model which renders it suitable for the case of broader latent space. Given that the computational cost of the gating function is negligible, our models perform well on the trade-off between the inference time and accuracy.

To validate the efficiency of sparse dynamic convolution and dynamic sparse networks, we execute our methods on Imagenet-1K [8] and demonstrate the mutual promotion between dynamism and sparsity: sparsity reduce the redundancy of dynamic convolution and promote its inference performance; dynamic mechanism improves the represent the power of sparse networks with negligible extra computational cost. Our main contributions are as followed:

- We propose the sparse dynamic convolution to solve the parameter-inefficiency and large storage of dynamic convolution, which maintains the advantage of dynamic mechanism with light-weights.
- We adopt the dynamic mechanism to sparsity methods, significantly boosting the representation power of sparse networks.
- Our experiments on ImageNet have shown the effectiveness of the combination of sparsity and attention. Sparsity reduces the parameters and FLOPs of dynamic networks while dynamism provides sparse networks with the explicit improvement of performance.

2. Related Work

Both dynamic networks and sparsity are often considered separately to optimize neural networks. Our work delves into the combination of the two. We can thus relate our work to two lines of papers: dynamic networks and sparsity.

2.1. Dynamic Network

Dynamic networks adapt input-based parameters or activation functions to boost representation power. HyperNets [16] use a secondary network to generate parameters for the main network. SE-net [20] apply channel-wise attention mechanism to channel. DRConv [6] transfers the increasing channel-wise filters to spatial dimension with a learnable instructor. CondConv [41] and Dynamic Convolution [7] have proposed a new convolution operator to increase the representation capability with negligible extra FLOPs. Instead of using a single static convolution kernel per layer, they use the dynamic combination of a set of parallel static kernels $W_k, b_k$ as convolution kernels. The linear scale is aggregated dynamically via a function of individual inputs. Dynamic convolution [7] propose a attention function to formulate the linear score:

$$W(x) = \sum_{i=1}^{k} \pi_i(x)W_i, \quad \pi_i(x) \leq 0, \quad \sum_{i=1}^{k} \pi_i(x) = 1,$$  \hspace{1cm} (1)

where $\pi_k$ is the attention score of the $k$-th kernel. Dynamic convolution only introduces two additional computations: (a) computing the attention weights $\pi_k$ and (b) aggregating parameters based upon attention $\sum_{i=1}^{k} \pi_i(x)W_i$. Because these kernels are aggregated in a non-linear way via attention, the dynamic convolution has more representation power. However, DCD [27] has proposed two limitations of dynamic convolution: (a) lack of compactness, due to the use of $k$ kernels, and (b) a challenging joint optimization of attention scores $\pi_k$ and static kernels $W_k$. To expose the two limitations, DCD [27] split the linear combination of $W_k$ into the static kernel and residual kernel, which can be decomposed by SVD [21]. DCD significantly reduces the dimensionality of the latent space and results in a more compact model that is easier to learn with often improved accuracy.

2.2. Sparsity

Sparsity has been widely studied to compress and accelerate deep neural networks in resource-constrained environments. It can be generally categorized into two groups:
structured sparsity and unstructured sparsity. Structured sparsity prunes blocks of sub-networks of a neural network, while unstructured fine-grained sparsity prunes multiple individual weights distributed across the neural network. Between the two sparsity types, unstructured sparsity can achieve significantly higher compression ratios while maintaining relatively better performance [15,17]. Unstructured sparsity usually uses a threshold to prune unimportant neurons. Many different criteria are proposed to evaluate the importance of neurons, including magnitude-based pruning [13,17,44], Hessian-based heuristics [25,26], pruning with connection sensitivity [24,32]. In recent works, training with differential thresholds has been explored by several works. Kusupati et al. [23] and Manessi et al. [34] learn per-layer thresholds automatically using a soft thresholding operator or a close variant of it. Besides, sparsity learned during training with $L_0$ norm regulation has been used in several works [2,30]. To solve the undifferentiable problem of $L_0$-norm, Louizos et al. [30] set a collection of non-negative stochastic gates and optimize the probability distribution of the gates, while Azarian et al. [30] propose an approximate form of $L_0$ norm to estimate the gradient.

3. Methodology

3.1. Sparse Dynamic Convolution

In conventional dynamic convolution, each convolutional layer replicates $k$ kernels, leading to large model size and potential parameter-redundancy. For example, the model size of Dynamic ResNet-50 is over 360M (with 4 kernels). In this section, we propose sparse dynamic convolution, which integrates dynamic convolution with learnable binary masks.

Generally, binary mask is a 0/1 matrix, as a index to find which neuron or weight is pruned. In order to make binary masks trainable, we define a score variable $S$, and a threshold $\tau$. The mask is then rounded to 1 if the score is greater than threshold, and vice versa, given by

$$M_i = \begin{cases} 1, & \text{if } S_i > = \tau, \\ 0, & \text{otherwise} \end{cases},$$

where $\tau$ is the threshold. The major challenge for training binary masks is that Eq. (2) is non-differentiable, preventing the gradient calculation and the update. To solve this problem, Piggyback [33] utilizes the Straight-Through Estimator (STE) [4] (where the gradient is directly passed to its input $\frac{\partial M}{\partial S} = 1$) to enable gradient estimation so that the gradient descent can update parameters. According to Zhou et al. [43], the range of $S$ is not restricted in $(0,1)$, which may cause unstable training process and accuracy drop. Inspired by Yang et al. [42], we adopt the softmax function to squeeze $S$ into $(0,1)$ for better gradient calculation:

$$\pi_1 = \sigma(K(S - \tau)),$$

$$\tilde{M} = \frac{\exp(\log(\pi_1)/T)}{\exp(\log(\pi_1)/T) + \exp(\log(\pi_0)/T)}.$$

where $\sigma(\cdot)$ is the sigmoid function and $\tau$ denotes the threshold. $\pi_0 = 1 - \pi_1$ is the complement of $\pi_1$. $\tilde{M}$ is the generated mask. $K$, $T$ are some temperature hyperparameters, controlling the sharpness of the function. For example, $T = 0.01$ encourages the output to be either 0 or 1. Then we transform $\tilde{M}$ into binary values use STE to generate and update the binary masks:

$$\hat{M} = \text{round} (\tilde{M}), \nabla \hat{M} = \nabla \tilde{M}.$$
sparsity of all layers. However, many experiments have indicated that layer-wise non-uniform sparsity performs better. Some existing methods are dependent on hyperparameters and require iterative trials. To address this problem, we propose a learning-based method to obtain layer-wise thresholds, which not only constrains the global sparsity but also contributes to the performance. We first transform $\tau$ into learnable parameters and utilize it to generate differential masks:

$$\frac{\partial M}{\partial \tau} = \frac{\partial \hat{M}}{\partial \hat{M}} \frac{\partial \hat{M}}{\partial \pi_1} \frac{\partial \pi_1}{\partial \tau}.$$  \hspace{1cm} (6)

$L_0$-norm regularization has been widely researched in model sparsity [2,30], for it directly regulates the overall parameter budget. Therefore, we resort to $L_0$-norm penalty $L_s(\tau, S)$ to distribute the layer-wise non-uniform sparsity. To make the parameters under the overall budget, we restrict the network parameters to have a global non-sparse rate $s$, given by:

$$L_s(\tau, S) = \text{ReLU}(\sum_i ||\hat{M}^{(i)}||_0 - N \ast s),$$  \hspace{1cm} (7)

where $L_s$ is the regulation loss which controls the global sparsity, $N$ is the number of parameters of the network, $||\hat{M}^{(i)}||_0$ is the $L_0$ norm of the mask in the $l$-th layer. This loss term only works when the model is denser than expected. Note that we use the ReLU function to restrict the global sparsity under the setting value. Formally, we define our loss function $\mathcal{L}$ as follows:

$$\mathcal{L} = L_c(y, f(x, w, \tau, S)) + \lambda_s L_s(\tau, S) + \lambda_r ||w||_2,$$  \hspace{1cm} (8)

where we represent our networks as a function $f$. $L_c$ is the classification loss. $||w||_2$ is the $L_2$ weight regularization loss and $\lambda_r$ is the weight decay rate. $\lambda_s$ is the hyperparameter that determines the pruning strength.

By utilizing binary mask to $k$ kernels, we transform the dynamic convolution layer into sparse convolution layer. In this layer, we set a threshold to generate $k$ binary masks, which determines the elements to be pruned. To generate dynamic kernels, we first create the sparse static convolution kernel $\hat{W}$ and then combine them dynamically, given by

$$\hat{W}_i = M_i \odot W_i, \hat{W} = \sum_i \pi_i \hat{W}_i.$$  \hspace{1cm} (9)

Here, $\hat{W}$ is the sparse dynamic weight. Our sparse dynamic convolution reduces the parameters in dynamic network. However, the combined kernel $\hat{W}$ does not have a high sparsity ratio, this is because our experts have different masks, which, requires all of them to have 0 in same position. As a result, our sparse dynamic convolution cannot accelerate the inference much. In this next section, we introduce another method to reduce both parameters and the computation cost.

### 3.2. Dynamic Sparsity Convolution

The sparse method always encounters performance drop along with a high sparse ratio. Dynamism improves the model representation by sacrificing negligible FLOPs. Therefore, we adopt the dynamic mechanism to sparse networks. In sparse dynamic convolution, the computational kernels are denser than each static kernel because of the linear combination operation, so it is hard to prune the dynamic convolution into high sparsity. However, we can dynamically select one of the $k$ static kernels based on the input so that our networks can maintain high sparsity during inference. This is an exceptional situation of sparse dynamic convolution that the largest attention weight $\pi_i$ is equal to one and the rest is zero. Therefore, we round the attention weight $\pi_i$ by setting the largest attention weight to 1 and the rest to 0. We formulate the dynamic sparse convolution as following equation:

$$\hat{\pi}_i = \begin{cases} 1, & \text{if } i = \text{argmax}(\pi) \\ 0, & \text{otherwise} \end{cases}$$  \hspace{1cm} (10)

$$\hat{W} = \sum_i \hat{\pi}_i M_i W_i$$  \hspace{1cm} (11)

Compared to static sparse networks, our method only adds extra computational cost and parameters in the attention layer. However, the attention layer contains two fully-connect layers. Dynamic convolution adopts the attention layer in each convolution layer except the first one. The widely used attention layer account for nearly 5 percent of a static model with the reduced ratio $r$ of the attention layer being 16 in the DY-ResNet-50 [7]. In the dynamic sparse convolution, the values of $\pi$ only play a role in selecting the maximal one but not the linear weighting of $\hat{W}$. Therefore, we condense the attention layer into one layer gating.
function, which is shown in Figure 3.

Note that the gating function is non-differentiable because of the operation. Therefore, during backpropagation, we utilize STE [4] to approximate the gradient. The gating function selects only one expert for each layer during the forward propagation, which risks an extreme situation of backpropagation that the gating function chooses the same kernel no matter how the input values vary. In this situation, the gate corresponding to the rest kernels has no chance to be optimized and the dynamic network fall into a static pattern. We observed that the unstable values of $\pi$ lead to this situation in the training process. Note that the gating function is non-differentiable because of the operation. Therefore, during backpropagation, which risks an extreme situation of backpropagation that the gating function chooses the same kernel no matter how the input values vary. In this situation, the gate corresponding to the rest kernels has no chance to be optimized and the dynamic network fall into a static pattern. We observed that the unstable values of $\pi$ lead to this situation in the training process.

The summation of $\pi$ is fixed to one, we only add a penalty term to restrict the extra-large values:

$$\nabla \pi = \nabla \hat{\pi} + \lambda_\pi |\pi|,$$  \hspace{1cm} (12)

where $\lambda_\pi$ is the constant to constrain the penalty term towards the maximal value of $\pi$. By adopting this penalty term, we restrain the increase of values of the selected gate and promote the chance of small-valued kernels to be selected in the following steps.

### 3.3. Optimization Policy

We train the sparse dynamic convolution following the temperature decay of softmax in the first 10 epoch to avoid the softmax output near one-hot, which avoids only a part of kernels can be trained. Evcı et al. [11] prune the network step by step rather than one stage to achieve sparser networks and higher representation power. By trial and error, in our experiment, we increase the sparsity by iteration rather than fix it. Our training policy of sparse dynamic convolution as follow:

The training of dynamic sparse convolution risks updating a single static kernel only, due to the discrete decision-making process. To furthermore reduce the risk, we resorted to the optimization policy of high capacity experts network [5]—Training our model based on a pre-trained static model. Instead of training a model with a single kernel, we train our model with the dense model provided by STR [23]. At the beginning of the training process, we initialize our $k$ kernels with the pre-trained single kernel parameters, ensuring that early on in the process any decision made by the gating function is a good decision. We fix the temperature of softmax as 1 and set the hyperparameter sparse ratio equal to the overall budget at first. Overall, our optimization policy of dynamic sparse convolution can be summarized in Algorithm 2.

### 4. Experiment: ImageNet Classification

In this section, we present experimental results of sparse dynamic convolution and dynamic sparse networks along with comprehensive ablations on ImageNet [8] classification. ImageNet has 1000 classes, including 1,281,167 images for training and 50,000 images for validation.

#### 4.1. Implementation Details

We validate our methods on three architectures (ResNet [18], MobileNetV1 [19], and MobileNetV2 [39]), by replacing dynamic convolution for all convolution layers except the first layer. Each layer has $k = 4$ experts. In this experiment, we use an SGD optimizer with 0.9 momentum, following cosine learning rate scheduling and warmup strategy, which rises to the max learning rate linearly in the first 10 epochs and is scheduled to arrive at zero within a sin-
ingle cosine cycle. When generating binary masks, we set constant that $\hat{K} = 10$ and $T = 50$ to transform the values into approximately zero-one distribution. The scale factor $\lambda_s$ of sparse penalty $L_s(\tau, S)$ is fixed as 0.01. For our two methods, We use different training setups for as follows:

**Sparse Dynamic Convolution.** We follow the Zhou et al. [7]’ s temperature annealing strategy to avoid the unstable output values of the softmax function in the first epochs. We train the ResNet for 100 epochs, and the max learning rate is 0.005. For the MobilenetV2 models, we train them for 300 epochs, and the max learning rate is 0.05. The weight decay is 4e-5 for all models. The non-sparsity ratio $s$ follows an exponential decrease by iteration.

**Dynamic Sparse Convolution.** We fine-tune the ResNet50 and MobilenetV1 provided by STR [23]. We first initialize all the kernels with the trained kernel and then train all the models for 50 epochs. We set the max learning rate 0.005 and 0.05 for the ResNet and the MobilenetV1 separately. During the fine-tuning, we utilize our $L_0$-norm techniques to prune the neurons in all convolutional layers, including the first and the last layer. $\lambda_{\pi}$ is set as 0.002 to guarantee all kernels to be trained.

4.2. Main Results

**Sparse Dynamic Convolution.** Table 1 and 2 shows the comparison between sparse dynamic convolution and dynamic networks in two CNN architectures (ResNet and MobilenetV2). $k = 4$ kernels and reduce ratio $r = 16$ are used in each convolutional layer except the first one. Our baselines includes the static convolution, Condconv [41], vanilla dynamic convolution [7], DCD [27]. We control the sparsity to make the models’ size close to DCD’s, by setting 50% for MobileNetV2, 70% for ResNet. Sparse dynamic convolution maintains the high performance of dynamic architectures while keeping an equally small model size as DCD. For ResNet-18, sparse dynamic convolution has only 33% of the parameters of dynamic convolution. For MobilenetV2-1.0, achieving the same level of accuracy, our method only requires 48% of the parameters of dynamic convolution. The most prominent advantage of sparse dynamic convolution is the computational cost. Because of the sparse computational kernel $\hat{W}$, our method requires much lower FLOPs than baselines including the static convolution, while all the dynamic networks adopt extra computational cost. Sparse dynamic convolution only has 64.1% FLOPs of DCD in ResNet-50 and 94% of FLOPs of static convolution in MobilenetV2-1.0.

**Dynamic Sparse Networks.** Table 2 and 3 shows the comparison between dynamic sparse convolution and strong state-of-the-art baselines. We follow the baselines in STR [23] in various sparsity regimes including: GMP [14], DSR [35], DNW [40], SNFS [9], RigL [11], DPF [29], STR [23]. GMP and DNW always use a uniform sparsity budget. RigL, SNFS, DSR, and DPF perform better when using ERK budget [11] than the original form. So we add them with the “+ ERK” suffix in Table 2 to imply the usage of ERK budge. Like STR, dynamic sparse networks learn the layer-wise thresholds to generate the sparsity distribution by training. Dynamic sparse networks beat all the baselines in the accuracy performance under the same overall budget: about 0.5% higher in ResNet-50 and at least 1.68% in MobileNetV1. To verify this promotion comes from the dynamism, we did an ablation study toward atten-

| Network         | Method   | Param | FLOPs   | Top-1 Acc(%) |
|-----------------|----------|-------|---------|--------------|
| MobilenetV2-1.0 | Static   | 3.5M  | 300.0M  | 72.0         |
|                 | Condconv | 27.5M | 329.0M  | 74.6         |
|                 | Dynamic  | 11.1M | 312.9M  | 75.2         |
|                 | DCD      | 5.5M  | 326.0M  | 75.2         |
|                 | Ours     | *5.3M | *281.9M | *75.3        |
| MobilenetV2-0.5 | Static   | 2.0M  | 97.0M   | 65.4         |
|                 | Condconv | 15.5M | 113.0M  | 68.4         |
|                 | Dynamic  | 4.0M  | 101.4M  | 69.9         |
|                 | DCD      | 3.1M  | 104.8M  | 70.2         |
|                 | Ours     | *2.8M | *89.5M  | *70.3        |
| MobilenetV2-0.35| Static   | 1.7M  | 59.2M   | 60.3         |
|                 | Dynamic  | 2.8M  | 62.0M   | 65.9         |
|                 | DCD      | 2.3M  | 63.1M   | 66.6         |
|                 | Ours     | *2.1M | *52.5M  | *67.1        |

| Network         | Method   | Param | FLOPs   | Top-1 Acc(%) |
|-----------------|----------|-------|---------|--------------|
| ResNet-18       | Static   | 11.1M | 1.81G   | 70.4         |
|                 | Dynamic  | 42.7M | 1.85G   | 72.7         |
|                 | DCD      | 14.0M | 1.83G   | 73.1         |
|                 | Ours     | *13.9M| *1.17G  | *73.3        |
| ResNet-50       | Static   | 23.5M | 3.8G    | 76.2         |
|                 | DCD      | 30.7M | 3.9G    | 77.9         |
|                 | Ours     | *30.3M| *2.5G   | *78.0        |
Table 3. The comparison between dynamic sparse networks and sparsity baselines. Baseline numbers reported from their respective papers/open-source implementations and models. FLOPs do not include batch-norm.

| Method | Top-1 Acc(%) | Param | Sparsity | FLOPs |
|--------|--------------|-------|----------|-------|
| ResNet-50 | 77.01        | 25.6M | 0.0      | 4.09G |
| GMP    | 73.60        | 5.12M | 80.00    | 818M  |
| SNFS + ERK | 75.20        | 5.12M | 80.00    | 1.68G |
| RigL + ERK | 75.10        | 5.12M | 80.00    | 1.68G |
| DPF    | 75.13        | 5.12M | 80.00    | 818M  |
| STR    | 76.19        | 5.22M | 79.55    | 766M  |
| Ours   | **76.68**    | 18.96M| **80.38**| 1.31G |

| Method | Top-1 Acc(%) | Param | Sparsity | FLOPs |
|--------|--------------|-------|----------|-------|
| GMP    | 73.91        | 2.56M | 90.00    | 409M  |
| SNFS + ERK | 72.90        | 2.56M | 90.00    | 960M  |
| RigL + ERK | 73.00        | 2.56M | 90.00    | 960M  |
| DPF    | 74.55        | 2.56M | 90.00    | 411M  |
| STR    | 74.31        | 2.49M | 90.23    | **343M** |
| Ours   | **74.86**    | 9.43M | **90.11**| 768M  |

| Method | Top-1 Acc(%) | Param | Sparsity | FLOPs |
|--------|--------------|-------|----------|-------|
| GMP    | 70.59        | 1.28M | 95.00    | 204M  |
| RigL + ERK | 70.00        | 1.28M | 95.00    | 600M  |
| STR    | 70.40        | 1.27M | 95.03    | **159M** |
| Ours   | **70.98**    | 4.27M | **95.07**| 506M  |

(a) ResNet-50.

| Method | Top-1 Acc(%) | Param | Sparsity | FLOPs |
|--------|--------------|-------|----------|-------|
| MobileNetV1 | 71.95 | 4.21M | 0.00      | 569M  |
| GMP    | 67.70        | 1.09M | 74.11    | 163M  |
| Ours   | **69.77**    | 3.34M | 75.12    | **153M** |
| STR    | 68.35        | 1.04M | 75.28    | 101M  |
| STR    | 66.52        | 0.88M | 79.07    | 81M   |
| Ours   | **68.20**    | 2.79M | 80.20    | 137M  |
| STR    | 64.83        | 0.60M | 85.80    | 55M   |
| Ours   | **67.43**    | 2.16M | 84.72    | 103M  |
| GMP    | 61.80        | 0.46M | 89.03    | 82M   |
| STR    | 62.10        | 0.46M | 89.62    | 42M   |
| Ours   | **64.73**    | 1.49M | 89.96    | 78M   |

(b) MobileNetV1.

Figure 4. The scaled variance of the layer-wise computational kernel weights of ResNet-50. The variance keep nearly consistent after pruning 50% parameters per layer.

Figure 5. The sparse ratio of the computational kernel weights $\hat{W}$ and the layer kernel weights $W_k$ in ResNet 18 and MobileNetV2 1.0. We setting the global sparsity 70% and 50% for ResNet18 and MobileNetV2 1.0, separately.

4.3. Discussion of Dynamic Property

The dynamic property of dynamic convolution lies in the various computational kernel weights towards different inputs, which is reflected as the layer-wise variance. To research the dynamic property of the neurons after pruning, we do an extensive experiment on Cifar [22] by directly pruning the 50% parameter of trained networks per layer by magnitude. By iterating over the entire dataset, we compute the layer-wise variance computational kernel, which is shown in Figure 4. The pruned networks still maintain nearly the same variance of the layer-wise computational kernel and the pruning operation does not cause a large performance drop, which widely exists in static networks pruned before re-training. The pruned DY-ResNet-50 and DY-ResNet-34 achieved 74.32% and 72.46% in classification accuracy, compared to 75.19% and 73.82% before pruning. The performance of the two pruned networks is still more than 2 percentage better than static networks(70.32% and 72.12%) in accuracy.
4.4. Analysis of the Reduced FLOPs

According to Table 1, the FLOPs of sparse dynamic convolution is lower than static convolution. The reduced FLOPs comes from pruned elements in computational kernels. Only when all static kernels have zero-element in the same position can computational kernels have pruned neurons. We visualize the pruned ratio of $k$ kernels $W_k$ and computational kernels $\hat{W}$ in Figure 5. We observed that the computational kernel maintains a relatively smaller pruned ratio. Each layer has a different degree of sparsity and the layer-wise sparse neurons contribute to the reduced FLOPs. The kernel sparsity is learned by training and is not dependent on the kernel sparse ratio completely.

4.5. Ablation Study for Attention

The difference between our method and baselines lies in two perspectives: (1) sparsity methods and (2) dynamic mechanisms. To validate the promotion comes from the efficiency of attention in sparse networks rather than the different sparse method, we did an ablation study between dynamic sparse models and static sparse models, using the unstructured pruning method. We do this experiment with ResNet-50 and MobilenetV1 under 90% overall sparsity. Our static sparse networks have a relatively high performance, 64.73% in MobileNetV1 and 74.48% in ResNet50. Compared to the static sparse networks, dynamic sparse networks improve the classification accuracy by 0.5 percent in ResNet-50 and 1.8 percent in MobileNetV1. Note that dynamic sparse networks only add computational cost in the attention layer. After the compression, the attention layer reduces to $\frac{22+kc}{r}$ of the initial layer in parameters, and the FLOPs of the attention layer decrease from 1.68M to 0.04M in MobileNetV1, which is negligible. The FLOPs gap between static and dynamic networks mainly comes from the different distribution of layers.

Table 4. Abalation Study of attention in sparse networks. Static indicates only apply our $L_0$-norm sparsification technique to the static networks.

| Network      | Method | Param | Flops  | Sparsity | Top-1 Acc(%) |
|--------------|--------|-------|--------|----------|--------------|
| ResNet-50    | Static | 2.55M | 749M   | 90.01    | 73.97        |
|              | Dynamic| 9.43M | 768M   | 90.11    | **74.48**    |
| MobilenetV1  | Static | 0.44M | 74M    | 90.00    | 62.94        |
|              | Dynamic| 1.49M | 78M    | 89.96    | **64.73**    |

4.6. Analysis of Non-Uniform Sparsity

Similar to STR [23], our model maintain the layer-wise sparsity property. We compare our method with baselines in layer-wise distribution, which is shown in Figure 6. Like mainstream magnitude pruning methods [9, 11, 28], our method is vulnerable to the layer-wise width—Layers with more parameters tend to be pruned more proportion of parameters. However, in convolutional operation, the layer-wise FLOPs are not only dependent on the number of parameters but also the feature maps, stride, etc. Our method does not prune as many neurons in layers with fewer parameters as STR, which causes more FLOPS consumed. Therefore, our method achieves a high compression ratio and performance but sacrifice FLOPs.

5. Discussion and Drawbacks

We combine the dynamic mechanism and sparsity to build efficient model architectures, which achieve high performance with light-weight model-size and low FLOPs. Sparsity’s usage for dynamic convolution leads to efficient light-weight dynamic convolution. It is clear from Table 1 that sparse dynamic convolution achieves state-of-the-art accuracy and costs fewer FLOPs than static convolution, while dynamic networks always cause extra FLOPs and parameters. Our sparse dynamic convolution provides a new insight for dynamic networks that adopt a dynamic mechanism to the neurons under the overall budget. Sparse networks always encounter large performance drops in high sparsity, but the dynamic sparse convolution can mitigate this trend. In Table 2 and Table 3, our method beats the strong baselines in performance. As is shown in Table 4, we organize an ablation study to prove the improvement arises from the dynamic mechanism. Both of the two methods are easy to adapt to convolution layers and work fine with no strict hyperparameter setting. However, our drawback lies in the FLOPs, because the magnitude pruning method only constrains the total parameters but lacks an explicit quantization of the FLOPs.

6. Conclusion

This paper integrates the property of dynamic networks and sparse networks. Sparse dynamic networks prune re-
dundant neurons and focus on the parameter efficiency of dynamic convolution, which maintains the performance gains of dynamic networks and significantly reduces the parameters and FLOPs, while dynamic networks always cause more computing and storage resources. Dynamic sparse networks provide traditional sparse networks with a dynamic mechanism so that our method achieves state-of-the-art classification accuracy in Imagenet-1K under the same overall budget. Furthermore, because we do not add more requirements on hyperparameters to restrain the overall sparsity, our methods are easy to adapt.

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