SNF: Filter Pruning via Searching the Proper Number of Filters

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Abstract

Convolutional Neural Network (CNN) has an amount of parameter redundancy, filter pruning aims to remove the redundant filters and provides the possibility for the application of CNN on terminal devices. However, previous works pay more attention to designing evaluation criteria of filter importance and then prune less important filters with a fixed pruning rate or a fixed number to reduce convolutional neural networks’ redundancy. It does not consider how many filters to reserve for each layer is the most reasonable choice. From this perspective, we propose a new filter pruning method by searching the proper number of filters (SNF). SNF is dedicated to searching for the most reasonable number of reserved filters for each layer and then pruning filters with specific criteria. It can tailor the most suitable network structure at different FLOPs. Filter pruning with our method leads to the state-of-the-art (SOTA) accuracy on CIFAR-10 and achieves competitive performance on ImageNet ILSVRC-2012. SNF based on the ResNet-56 network achieves an increase of 0.14% in Top-1 accuracy at 52.94% FLOPs reduction on CIFAR-10. Pruning ResNet-110 on CIFAR-10 also improves the Top-1 accuracy of 0.03% when reducing 68.68% FLOPs. For ImageNet, we set the pruning rates as 52.10% FLOPs, and the Top-1 accuracy only has a drop of 0.74%. The codes can be available at https://github.com/pk-l/SNF.

1. Introduction

Convolutional Neural Network (CNN) has attained great success in computer vision, like image classification [3, 45], object Detection [33, 44] and semantic segmentation [4, 38]. However, the computing resource consumption rises rapidly as the models become more complex. Lots of float point operations (FLOPs) and memory footprint have caused resistance to the general application in edge devices, like wearable devices and embedded devices, etc. To compress and accelerate convolutional neural networks, the approaches emerge endlessly. These approaches can be classified into five categories: structured pruning [20, 21, 28, 29], unstructured pruning [9, 13–15], parameter quantization [1, 2, 37], knowledge distillation [22, 34, 51] and low-rank decomposition [7, 25].

Channel pruning is one of the structured pruning methods, which attracted the attention of researchers for its implementation-friendly. In terms of the different operation bases, channel pruning [20, 21] can be divided by filter pruning and feature map pruning. No matter which method ends up removing the channels. In this paper, we only focus on filter pruning. Filter pruning slims the network to reduce the float point operations (FLOPs) and memory footprint by removing the number of filters in convolutional layers. There are two advantages that it is friendly to operate for any convolutional neural network structure and it can produce a thinner model without special devices. However, the ability of the model representation is limited to the network width. It is challenging to prune networks without the accuracy drop.

Existing filter pruning methods usually remove less important filters relatively by designing criteria to evaluate filter importance, like Channel Pr [28], FPGM [20], Slim [35] and APoZ [24], etc. These methods do not consider how many filters should be removed in each layer and set the

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pruning rates manually. 

Inspired by [36, 50], we claim that the number of filters pruned in each layer is also critical to the model performance. For each layer, it has the most suitable number of filters at a certain FLOPs reduction. For a convolutional layer, the representation capability is determined by the number of filters in this layer and the ability of filter representation. According to [23], the ability of the network representation is limited to the network width. So we believe that the accuracy drop after pruning is related closely to the number of pruned filters. On the other hand, we theoretically analyze that the ability of filter representation is close to each other in the same layer.

Based on our analysis above, we propose a method by searching for the proper number of filters (SNF). Our SNF can search for the most suitable number of reserved filters for each layer automatically, and then prunes filters with a criterion of filter importance ranking.

Our main contributions are summarized as follows.

- We theoretically analyze that the ability of filter representation is close to each other in the same layer. Unlike other papers mentioned, we consider that not only the criteria of filter importance ranking is important, but the number of reserved filters is also equally important or even more significant.

- We propose a new method called SNF, which consists of searching the most reasonable number of reserved filters for each layer and pruning filters with specific criteria. Our approach can tailor the most suitable number of filters for each layer at different FLOPs reduction.

- We verify our approach on CIFAR-10 and ImageNet using ResNet-56/110 and ResNet-50 respectively. The experiment results have proved that our method achieves the state-of-the-art performance on CIFAR-10 and has a quite competitive accuracy on ImageNet.

2. Related work

In this section, we mainly discuss the existing pruning methods, including structured pruning, unstructured pruning methods.

2.1. Structured Pruning

Structured pruning tries to remove the channels or layers. As we know, many criteria [20, 28, 30, 35, 42] are designed to evaluate which channel is less important and remove them. Channel Pr [28] took $L_1$-norm as a criterion for sorting the importance of filters, which prune filters with the smaller norm. FPGM [20] removed the most replaceable filters containing redundant information based on the criteria of the geometric median. Thinet [40] treated channel pruning as an optimization problem. This method uses a greedy strategy to extract the optimal feature subset of the latter layer’s input features, and then the channels corresponding to the feature subset were reserved. HRank [30] computed the rank of feature maps. This method considered the feature maps with low rank contained less information. Pruning the channels corresponding to the low-rank feature maps had less impact on the model performance. As the Batch Normalization (BN) layer is widely used, Slim [35] proposed to apply L1 regularization on BN layers to make the scaling factor sparse, and then the channels with small scaling factor were removed. Soft filter pruning [18] reset the less important filters but not removed these filters. With reinforcement learning, AMC [19] took accuracy as a reward function to prune the network. Metapruning [36] utilized meta-learning to train a pruning network which provides weights for all the possible sub-networks, and then searched for the best pruned network structures. Pavlo et al. [41] used the Taylor expansions to approximate a filter’s contribution and then took the first item as the criteria of pruning. C-SGD [8] trained several filters to collapse into a single point in the parameter hyperspace and discard all but leave one filter. Gao et al. [12] proposed the problem of loss-metric mismatch, and this method designed a performance prediction network to make performance maximization. ResRep [10] proposed to re-parameterize CNN into the maintain parts and prune parts. Zi et al. [47] analyzed the network pruning from a perspective of redundancy and then removed redundant filters by building a redundancy graph.

2.2. Unstructured Pruning

The previous works [6, 11] have proved that convolutional neural network (CNN) has the parameter redundancy and the accuracy of the model does not drop while most of the neurons are removed. Unstructured pruning proposed that removing most of the weights does not affect model performance. Han et al. [15] pruned less important weights with the criteria of $L_1$-norm and $L_2$-norm. SNIP [27] utilized the gradient of the loss function with respect to the weight connection to reset small gradient weights. These methods only make the matrix sparse, but the model will not be compressed and accelerated if we have no special devices.

3. Methodology

3.1. Notations

To describe our method clearly, let us first introduce necessary notations. For the convolutional neural network, we define the number of layers as $L$. For $l$-th layer with $N$ filters ($N$ is the number of the filters), we take the
For \( l \)-th layer, we naturally assume that the ability of the filter representation is positive, but the filter contribution for this layer. Let \( N_{l-1} \) and \( F_l \) represent the number of input channels and input feature maps respectively. The number of output channels and output feature maps are represented by \( N_l \), \( F_l \), and the output feature map size is \( h_l \times w_l \). The convolutional layer parameters can be defined as \( \{W^{(l)} \in \mathbb{R}^{n_l \times n_{l-1} \times h_l \times w_l}, l = 1, 2, ..., L \} \).

### 3.2. Ability of Filter Representation

In this section, we attempt to introduce the ability of filter representation in the same layer that is close to each other. For \( l \)-th layer, we naturally assume that the ability of the filter representation is positive, but the filter contribution for the layer representation cannot be infinite. In other words, the variance contribution of filters has an upper limit. We have

\[
\exists \epsilon > 0, \text{ s.t. } \mathcal{X}_i > \epsilon, \\
\exists k > 0, \text{ s.t. } D(\mathcal{X}_i) <= k. \ \forall i \in \{1, 2, ..., N\}.
\]

(1)

According to Chebyshev’s inequality, we can get

\[
P\left( \frac{1}{N} \sum_{i=1}^{N} |\mathcal{X}_i - E(\mathcal{X}_i)| \geq b \right) \leq \frac{Var\left( \sum_{i=1}^{N} \mathcal{X}_i \right)}{b^2},
\]

(2)

where \( E(\mathcal{X}_i) \) is the average of the ability of filter representation, \( b \) is a positive number, \( Var\left( \sum_{i=1}^{N} \mathcal{X}_i \right) \) is the filter variance contribution in the layer. In terms of the variance formula, we have

\[
Var\left( \sum_{i=1}^{N} \mathcal{X}_i \right) = \frac{1}{N^2} Var\left( \sum_{i=1}^{N} \mathcal{X}_i \right) \\
= \frac{1}{N^2} \left( \sum_{i=1}^{N} D(\mathcal{X}_i) + \sum_{i \neq j} Cov(\mathcal{X}_i, \mathcal{X}_j) \right),
\]

(3)

where \( i, j \in \{1, 2, ..., N\} \). For \( l \)-th layer, some filters are weakly correlated to each other. We further define that there are \( \zeta N (0 < \zeta < 1) \) weakly correlated filters in the \( l \)-th layer, we have

\[
\sum_{i \neq j} Cov(\mathcal{X}_i, \mathcal{X}_j) <= \zeta N k, \ \forall i, j \in \{1, 2, ..., N\}.
\]

(4)

By Equation 2, 3 and 4, we can get

\[
P\left( \frac{1}{N} \sum_{i=1}^{N} |\mathcal{X}_i - E(\mathcal{X}_i)| \geq b \right) \leq \frac{k(1 + \zeta)}{b^2 N}. \]

(5)

According to the Equation 5, the \( P\left( \frac{1}{N} \sum_{i=1}^{N} |\mathcal{X}_i - E(\mathcal{X}_i)| \geq b \right) \) is close to 0 in possibility while \( N \) is large.
enough. In other words, almost all the $X_i$ are near the average. The ability of filter representation is close to each other. So we can further ensure the ability of layer representation is limited to the number of reserved filters in the layer. The above conclusion has an assumption that $N$ is large enough. In fact, the assumption can be relaxed in the real world, we provide evidence to validate the analysis in our ablation study. Above all, it is the key for the pruned model performance to search for the proper number of reserved filters in each layer.

3.3. Searching for the Proper Number of Filters

The ability of filter representation in the same layer is close to each other. We consider searching for the proper number of filters to reconstruct the original filter parameters. Searching the number of reserved filters can be defined as an optimization problem. For $L$-th layer, each filter is represented by a feature vector $W_i$, $0 < i < N$, where $N$ is the number of filters in this layer. We try to use the $d$ filters to reconstruct the $N$ filters. At the same time, the error between them is as little as possible. In fact, the smaller the reconstruction error is, the easier it is to reconstruct the original filter parameters. We refer to the Principal component analysis thought which reduces the high-dimensional data to low-dimensional to search for the proper number of filters reserved in this layer. The reconstruction error can be defined as the mean square error between reduced dimensional $\hat{W}$ and original $W$. The formula can be represented as

$$
\sum_{i=1}^{N} ||W_i - \hat{W}_i||_2^2 = \sum_{i=1}^{N} ||W_i - \sum_{j=1}^{d} u_j^T W_i u_j||_2^2 
= -tr(U^T (\sum_{i=1}^{N} W_i W_i^T ) U) 
$$

(6)

where $U$ is the projection matrix, $i \in \{1, 2, ..., N\}$ and $j \in \{1, 2, ..., d\}$. Then the optimization formula can be defined as

$$
\min_U -tr(U^T (\sum_{i=1}^{N} W_i W_i^T ) U) \quad s.t. \quad U^T U = I. 
$$

(7)

To solve Equation 7, we utilize Lagrange Multiplier Method, then we can get

$$
WW^T u_i = \lambda_i u_i 
$$

(8)

Finally, we set a reconstruction threshold of $\beta$, and the $\beta$ is equal to $1 - \sum_{i=1}^{N} ||W_i - \hat{W}_i||_2^2$. Let $d$ be the number of reserved filters. So we can use the following formula to search how many filters to keep.

$$
d \leftarrow \frac{\sum_{i=1}^{N} \lambda_i}{\sum_{i=1}^{N} \lambda_i} \geq \beta. 
$$

(9)

3.4. Reconstruction Threshold

The number of reserved filters depends on the reconstruction threshold $\beta$, and the $\beta$ is determined by the FLOPs. The reconstruction threshold $\beta$ can be adjusted by Binary search to fit the FLOPs we need. For $L$-th layer, suppose the reconstruction threshold $\beta$, then $(N_l - d_l)$ filters should be removed according to Equation 9. After pruning, we can compute the pruning ratio by comparing the current FLOPs (after pruning) with the original FLOPs (before pruning). If the current pruning ratio can not meet our requirement, the reconstruction threshold $\beta$ will adjust automatically. The process description of SNF can refer to Algorithm 1.

4. Experiments

In this section, we evaluate SNF on CIFAR-10 [26] and ImageNet ILSVRC-2012 [5] using ResNet. We use the one-shot pruning scheme. For a fair comparison, all experiments are based on pycls [42] and retain data augmentation including random cropping and flipping.

4.1 Datasets and Evaluation

Datasets. Our experiments are based on the datasets of CIFAR-10 [26] and ImageNet ILSVRC-2012 [5]. We use ResNet-56/110 on CIFAR-10 and ResNet-50 [16] on ImageNet. For CIFAR-10, it consists of 10 classes images with $32 \times 32$ resolution, which contains 50,000 and 10,000 colorful images for training and testing respectively. For ImageNet.
ageNet, it is composed of 1.28 million training images and 50,000 testing images, which includes 1,000 classes natural images with $224 \times 224$ resolution.

**Evaluation Protocols.** For a fair comparison, we use floating-point operations per second (FLOPs) to evaluate model complexity. As the same as other literature, we use Top-1 and Top-5 accuracy on ImageNet, and Top-1 accuracy on CIFAR-10.

### 4.2. Implementation Details

**CIFAR-10.** For CIFAR-10 dataset, the baseline models of ResNet-56/110 are trained from scratch (initial training) with a batch size of 64, the initial learning rate of 0.1, and a weight decay of $5e \rightarrow 4$. Furthermore, we use stochastic gradient descent (SGD) with a momentum of 0.9 and train for 200 epochs. With the step schedule, the learning rate is divided by 10 at the epochs 60, 120, 160. After pruning, we fine-tune 200 epochs for the pruned model with an initial learning rate of 0.01. Other settings have no changes compared with initial training.

**ImageNet.** For ImageNet ILSVRC-2012, we train ResNet-50 from scratch for 100 epochs, using SGD with a momentum of 0.9. The weight decay is set to $1e \rightarrow 4$. The initial learning rate is equal to 0.2 with a batch size of 256. The policy of learning rate decay adopts the half-period cosine annealing schedule. After pruning, the settings of fine-tuning are the same as training in addition to the initial learning rate divided by 10.

**Reconstruction Threshold.** In our experiments, we take the $\beta$ as the global reconstruction threshold. In fact, the reconstruction threshold for each layer must be larger than or equal to the global threshold $\beta$. The reconstruction threshold $\beta$ does not require to be set manually. The pruning ratio we need once is determined, the global reconstruction threshold $\beta$ will adjust by pruning ratio automatically. The least number of filters for reconstructing the original filters can be searched referring to $\beta$. No more extra hyper-parameters except the pruning ratio needs to be set manually.

### 4.3. Pruning Results on CIFAR-10 and ImageNet

We compare our approach to the representative methods. For a fair comparison, we use ResNet-56/110 and ResNet-50 on CIFAR-10 and ImageNet respectively since most of the previous state-of-the-art methods are based on them.

**Pruning ResNet-56 on CIFAR-10.** For the ResNet-56 network, we compared our method with [10, 17–21, 30, 49, 52]. Table 1 shows the pruning results of ResNet-56 on CIFAR-10. We try to evaluate our approach at different pruning rates. The results show our method achieves the state-of-the-art performance on ResNet-56 in comparison to previous works. As shown in Table 1, we train ResNet-56 from scratch with the setting as section 4.2, the accuracy of the baseline model is 93.61%. After pruning and fine tuning, SNF achieves 94.13% Top-1 accuracy which increases by 0.14% when reducing 52.94% FLOPs. In terms of Top-1 accuracy drop, our method outperforms ResRep [10] by 0.14% and LFPC [17] by 0.49% at the similar FLOPs reduction. Compared with NISP [52], Channel Pr [21], AMC [19], FPGM [20], SFP [18], we not only prune the model with a larger FLOPs reduction, but also the accuracy of pruned model is higher than them. For the FLOPs reduction of 77.93%, the accuracy of our method is only 0.82% drop. In comparison with ResRep [10], HRank [30], TRP [49], our method still attains the best performance. To our best knowledge, the Top-1 accuracy drop of our pruned model outperforms the results reported elsewhere at 52.94% and 77.93% FLOPs reduction. In fact, not only the Top-1 accuracy drop is better than the performance with other pruning approaches, but the Top-1 accuracy of the pruned model also outperforms others.

**Pruning ResNet-110 on CIFAR-10.** In Table 2, we report the pruning results of ResNet-110 on CIFAR-10. With the deeper network, we compare our method with [8,10,17,18,20,28,30,32,52]. As shown in Table 2, our approach also achieves the state-of-the-art performance. We train ResNet-110 from scratch and achieve the Top-1 accuracy of 93.93%. Compared to initial training, the Top-1 accuracy of pruned model increases by 0.30% at 58.32% FLOPs reduction. Under the similar pruning ratio, the Top-1 accuracy with our method is 0.32% higher than RepRep [10]. In comparison with Li et al. [28], SFP [18], NISP-110 [52], GAL-0.5 [32], FPGM [20], SNF still outper-

| Method            | Base Top-1 (%) | Pruned Top-1 (%) | Top-1 FLOPs ↓ (%) | ↓ (%) |
|-------------------|---------------|-----------------|-------------------|------|
| NISP [52]         | -             | -               | 0.03              | 42.6 |
| Channel Pr [21]   | 92.8          | 91.8            | 1.0               | 50   |
| AMC [19]          | 92.8          | 91.9            | 0.9               | 50   |
| FPGM [20]         | 93.59         | 93.26           | 0.33              | 52.6 |
| SFP [18]          | 93.59         | 93.35           | 0.24              | 52.6 |
| LFPC [17]         | 93.59         | 93.24           | 0.35              | 52.9 |
| ResRep [10]       | 93.71         | 93.71           | 0.00              | 52.91|
| SNF(ours)         | 93.61         | 93.75           | -0.14             | 52.94|
| HRank [30]        | 93.26         | 90.72           | 2.54              | 74.1 |
| TRP [49]          | 93.14         | 91.62           | 1.52              | 77.82|
| ResRep [10]       | 93.71         | 92.66           | 1.05              | 77.83|
| SNF(ours)         | 93.61         | 92.79           | 0.82              | 77.93|
forms them at higher FLOPs reduction. For GAL-0.5 [32] and FPGM [20], we achieve less Top-1 accuracy drop (-0.30% vs 0.76% and -0.06% vs 48.5%) while the FLOPs reduction is larger (58.32% vs 48.5% and 52.3%). When pruning 68.68% FLOPs with our method, the Top-1 accuracy increases by 0.03%. Compared with HRank [30], our method outperforms by 0.88% at a higher pruning ratio (68.68% vs 68.6%). At the same accuracy drop, the FLOPs reduction with our approach is 7.79% higher than C-SGD [8] (68.68% vs 60.89%).

**Table 2. Pruning results of ResNet-110 on CIFAR-10. All the labels have the same meaning with Table 1.**

| Method       | Base Top-1 (%) | Pruned Top-1 (%) | Top-1 FLOPs ↓ (%) | Top-1 Top-5 ↓ (%) |
|--------------|---------------|------------------|------------------|------------------|
| Li et al. [28] | 93.53         | 93.30            | 0.23             | 38.60            |
| SFP [18]     | 93.68         | 93.86            | -0.18            | 40.8             |
| NISP-110 [52] | -             | -                | 0.18             | 43.78            |
| GAL-0.5 [32] | 94.64         | 94.62            | 0.02             | 58.21            |
| HRank [30]   | 93.93         | 94.23            | -0.30            | 58.32            |
| SNF(ours)    | 93.93         | 93.96            | -0.03            | 68.68            |
| LFPC [17]    | 93.68         | 93.07            | 0.61             | 60.3             |
| C-SGD [8]    | 94.38         | 94.41            | -0.03            | 60.89            |
| SNF(ours)    | 93.93         | 93.96            | -0.03            | 68.68            |

**4.4. Ablation Study**

**Different Criteria for Filter Selection.** The criterion is one of the necessary components for our proposed method. The criterion based on the magnitude of channel weights consists of $L_1$-norm and $L_2$-norm [21]. These approaches are early used to sort filter importance. FPGM [20] compresses models by pruning redundant filters with geometric median criteria. For analyzing the criteria of these methods fairly, we compare them on the ResNet-56 network at the same FLOPs.

In Figure 4, it shows that the model performance of selecting filters with different criteria. For ResNet-56 on CIFAR-10 at 52.94% pruning ratio, we can find that using the different criteria of filter selection has a close model performance. When pruning model with the criteria of $L_1$-norm, $L_2$-norm and FPGM, the accuracy of the pruned model is 93.75%, 93.61%, 93.78% respectively. Compared with the performance of the model trained from the scratch, the accuracy of the pruned model has no obvious changes and they all have no accuracy drop. However, pruning filters with $L_p$-norm or FPGM has a significant improvement compared to random pruning. As shown in Figure 4, the accuracy drop obviously with random pruning. We believe a reasonable filter selection criteria can reduce the accuracy drop of pruned model effectively.

**Different Approaches for Selecting the Number of Filters.** We introduce that the number of filters reserved in each layer is important for the accuracy of the pruned model. For evaluating our point, we compare the performance with different methods which select the number of filters on ResNet-56. The results are shown in Table 4. These methods are used to select the number of filters. For a fair comparison, all experiments adopt the $L_1$-norm criteria for filter importance ranking. The approaches include (1) Uniform Pruning. All the layers use the same pruning ratio. (2) Random Pruning. All the layers select the number of filters randomly. (3) ResRep* Pruning. After pruning the model in terms of ResRep [10], we record the number of filters in each layer. In other words, we finally get a structure ResRep* pruned by ResRep. And then we prune the initial training model with $L_1$-norm criteria according to the ResRep*. (4) SNF Pruning (Our method). Searching for the proper number of filters automatically.

As shown in Table 4, it shows the results of pruned ResNet-56 model using different approaches for selecting the number of filters in each layer. The baseline model means training ResNet-56 from scratch. We firstly compare ResRep [10] with ResRep* Pruning, the Top-1 accuracy drop of ResRep* pruning is the same as ResRep when the FLOPs reduction is similar (77.83% vs 77.85%). This result gives evidence that the number of reserved filters is
Table 3. Pruning results of ResNet-50 on ILSVRC-2012. "Base Top-5" and "Pruned Top-5" indicate the Top-5 accuracy of the baseline model and pruned model. "Top-5 ↓" denotes the Top-5 accuracy drop between pruned model and the baseline model. Other labels have the same meaning with Table 1.

| Method          | Base Top-1 (%) | Base Top-5 (%) | Pruned Top-1 (%) | Pruned Top-5 (%) | Top-1 ↓ (%) | Top-5 ↓ (%) | FLOPs ↓ (%) |
|-----------------|---------------|---------------|-----------------|-----------------|-------------|-------------|-------------|
| SFP [18]        | 76.15         | 92.87         | 74.61           | 92.06           | 1.54        | 0.81        | 41.8        |
| GAL-0.5 [32]    | 76.15         | 92.87         | 71.95           | 90.94           | 4.20        | 1.93        | 43.03       |
| HRank [30]      | 76.15         | 92.87         | 74.98           | 92.33           | 1.17        | 0.54        | 43.76       |
| NISP [52]       | -             | -             | -               | -               | 0.89        | -           | -           |
| Hinge [29]      | -             | -             | 74.7            | -               | -           | -           | 46.55       |
| Channel Pr [21] | -             | 92.2          | -               | 90.8            | 1.4         | 0           | 50          |
| HP [48]         | 76.01         | 92.93         | 74.87           | 92.43           | 1.14        | 0.5          | 50          |
| NS [35]         | 75.04         | -             | 69.60           | -               | 5.44        | -           | 50.51       |
| MetaPruning [36]| 76.6          | -             | 75.4            | -               | 1.2         | -           | 51.10       |
| Autop [39]      | 76.15         | 92.87         | 74.76           | 92.15           | 1.39        | 0.72        | 51.21       |
| GDP [31]        | 75.13         | 92.30         | 71.89           | 90.71           | 3.24        | 1.59        | 51.30       |
| SNF (ours)      | 76.75         | 93.15         | 76.01           | 92.83           | 0.74        | 0.32        | 52.10       |
| FPGM [20]       | 76.15         | 92.87         | 74.83           | 92.32           | 1.32        | 0.55        | 53.5        |
| DCP [53]        | 76.01         | 92.93         | 74.95           | 92.32           | 1.06        | 0.61        | 55.76       |
| C-SGD [8]       | 75.33         | 92.56         | 74.54           | 92.09           | 0.79        | 0.47        | 55.76       |
| ThiNet [40]     | 75.30         | 92.20         | 72.03           | 90.99           | 3.27        | 1.21        | 55.83       |
| SASL [46]       | 76.15         | 92.87         | 75.15           | 92.47           | 1.00        | 0.40        | 56.10       |
| TRP [49]        | 75.90         | 92.70         | 72.69           | 91.41           | 3.21        | 1.29        | 56.52       |
| LFPC [17]       | 76.15         | 92.87         | 74.46           | 92.32           | 1.69        | 0.55        | 60.8        |
| HRank [30]      | 76.15         | 92.87         | 71.98           | 91.01           | 4.17        | 1.86        | 62.10       |
| SNF(ours)       | 76.75         | 93.15         | 75.14           | 92.49           | 1.61        | 0.66        | 62.10       |
| ResRep [10]     | 76.15         | 92.87         | 75.30           | 92.47           | 0.85        | 0.4          | 62.10       |

![Figure 3](image-url)

Figure 3. Visualizing the 3 × 3 convolutional layer of the first block in ResNet-50. (a) Original picture. It is the input of ResNet-50. (b) Uniform Pruning. At the 5% pruning ratio, there are 3 filters corresponding to the feature maps marked in red that will be removed. (c) SNF Pruning. The reconstruction threshold is 99.73% at 5% FLOPs reduction. There are 14 filters corresponding to the feature maps marked in red that will be removed. (d) Reconstruction threshold - The number of filters. The curve describes the relationship between the reconstruction threshold and the number of reserved filters.

Critical for filter pruning. Compared with Uniform pruning and Random pruning, the Top-1 accuracy of our method is better than them at the slightly higher FLOPs reduction (93.75% vs 93.37% and 93.41%). Compared to ResRep* pruning, the number of filters selected by our method outperforms by 0.47% at the similar FLOPs reduction (77.93% vs 77.85%). Furthermore, we can believe that our method can reserve the number of filters in each layer properly, and reduce redundancy effectively.

**Accuracy and Reconstruction Error Change with Pruning Ratio.** As shown in Figure 5, to prove the stability of our method, we estimate the Top-1 accuracy at different pruning rates on ResNet-110. As the pruning ratio increases, the accuracy of the pruned model is higher than the baseline model before 68.68% FLOPs reduction and then starts to drop quickly. Few filters can not extract the feature sufficiently. It seems that all the related filters are removed at near 68.68% FLOPs reduction, and the rest of the filters are irreplaceable. In Figure 5, we also report the reconstruction error threshold changes over the pruning rates. The reconstruction error (blue curve) starts to drop after the pruning ratio of 40%, and the curve is getting steeper and...
Table 4. The results of selecting the number of reserved filters with different methods on ResNet-56. All the labels have the same meaning with Table 1.

| Method              | Base Top-1 (\%) | Top-1 ↓ (\%) | FLOPs ↓ (\%) |
|---------------------|-----------------|--------------|--------------|
| Baseline Model      | 93.61           | 0            | 0            |
| Uniform Pruning     | 93.37           | 0.24         | 52.42        |
| Random Pruning      | 93.41           | 0.20         | 52.44        |
| SNF Pruning         | **93.75**       | **-0.14**    | **52.94**    |
| ResRep [10]         | -               | 1.29         | 77.83        |
| ResRep* Pruning     | 92.32           | 1.29         | 77.85        |
| SNF Pruning         | **92.79**       | **0.82**     | **77.93**    |

* We only use the structure pruned by ResRep [10].

Figure 4. Accuracy - Criteria. The red columns are represented as the accuracy of the baseline model. The light steel blue columns are the accuracy of the pruned model which prunes with different criteria.

The accuracy decreases and reconstruction error threshold increases as the pruning ratio increases. More importantly, the accuracy decrease and reconstruction error threshold increase obviously are almost at the same pruning ratio. The result proves our method is effective and reasonable.

Visualization. As shown in Figure 3, we visualize the first $3 \times 3$ convolutional layer in the first block of ResNet-50. The pruned feature maps are marked with red boxes when reducing 5% FLOPs. We label the sub-figure from left to right. (a) Original picture. It is the input of the ResNet-50. (b) Uniform Pruning. All the layers prune filters with the same pruning ratio. With the uniform pruning method, this layer will remove 3 filters. (c) SNF Pruning. Our method prunes 14 filters in this layer. (d) The reconstruction threshold - the number of filters reserved curve. We further analyze by comparing Uniform Pruning with SNF Pruning. This layer has 64 filters corresponding to 64 feature maps. As shown in sub-figure (b) and (c), many different filters extract similar feature maps for the same input picture. There are some weakly correlated filters in this layer. Moreover, the content richness of feature maps is almost the same, and the ability of filter representation is close. The number of reserved filters with Uniform Pruning and SNF Pruning varies greatly. We have to consider whether pruning 14 filters at 5% FLOPs reduction is reasonable. From the sub-figure (d), we can find the curve gradually becomes smoother as the number of reserved filters increases. The curve shows that the number of reserved filters is not sensitive when the reconstruction threshold is small. On the other hand, a few filters also can ensure the reconstruction error is very small and we can prune the filters boldly.

5. Conclusion

In this paper, we theoretically analyzed that the ability of filter representation is close to each other in the same layer. We naturally considered that the performance of the pruned model is limited to the number of filters reserved in each layer. Based on this idea, we proposed a new method called SNF, which consists of searching for the number of filters reserved in each layer and sorting the importance of filters. To search for the proper number of reserved filters, we thought of it as an optimization problem. The optimization goal is to minimize the reconstruction error between the original filters and the reduced dimensionality filters. For sorting the importance of filters, we chose existing criteria to judge the filter importance. The results of the experiment have shown that our method achieved the state-of-the-art performance on CIFAR-10 and attained the competitive performance on ImageNet. We believe our approach can give new inspiration for the filter pruning tasks.
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