QSFM: Model Pruning Based on Quantified Similarity Between Feature Maps for AI on Edge

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Abstract—Convolutional neural networks (CNNs) have been applied in numerous Internet of Things (IoT) devices for multifarious downstream tasks. However, with the increasing amount of data on edge devices, CNNs can hardly complete some tasks in time with limited computing and storage resources. Recently, filter pruning has been regarded as an effective technique to compress and accelerate CNNs, but existing methods rarely prune CNNs from the perspective of compressing high-dimensional tensors. In this article, we propose a novel theory to find redundant information in 3-D tensors, namely, quantified similarity between feature maps (QSFM), and utilize this theory to guide the filter pruning procedure. We perform QSFM on data sets (CIFAR-10, CIFAR-100, and ILSVRC-12) and edge devices and demonstrate that the proposed method can find the redundant information in the neural networks effectively with comparable compression and tolerable drop of accuracy. Without any fine-tuning operation, QSFM can compress ResNet-56 on CIFAR-10 significantly (48.7% FLOPs and 57.9% parameters are reduced) with only a loss of 0.54% in the top-1 accuracy. For the practical application of edge devices, QSFM can accelerate MobileNet-V2 inference speed by 1.53 times with only a loss of 1.23% in the ILSVRC-12 top-1 accuracy.

Index Terms—Edge computing, filter pruning, Internet of Things (IoT), model compression, neural networks.

I. INTRODUCTION

With the popularity of the Internet of Things (IoT), widely distributed mobile and IoT devices generate more data, which may be more than that generated by large cloud data centers. Some IoT applications may require a short response time, some may involve private data, and some may generate a large amount of data, which may cause a heavy burden on the network [1]. Therefore, it needs to be more effective for processing data at the edge of topological networks. Artificial intelligence (AI) has demonstrated its great ability in data processing and analysis [2], many edge devices also load convolutional neural networks (CNNs) [3], such as VGGNet [4], ResNet [5], GoogLeNet [6], MobileNet [7], and DenseNet [8] to meet the needs of different tasks like image classification [5], [6], object detection [9], [10], 3-D reconstruction [11], [12], and so on.

However, with the improvement of large CNNs performance, there are many problems, such as huge amounts of parameters, terrible computing consumption, and large memory requirements which become the challenges for edge and mobile embedded devices.

Compressing and accelerating neural network models is a hot topic recently. Presently, the typical works include network quantization [13], [14], low-rank approximation [15], weight sharing [16]–[18], and weight pruning [19], [20]. These methods need specific hardware or software libraries to run, and some of them cannot solve the problems described above comprehensively. There is another lightweight technique defined as filter pruning [21]–[26], also known as coarse-grained pruning. By comparison, filter pruning is not restricted to special hardware or software, and suitable as well as universal for CNNs in various types of tasks. Table I lists the attributes existing in relevant methods, and it can be seen that filter pruning is more universal among them.

Filter pruning has been shown to be significant in network pruning [27], [28]. Great progress has been made in filter pruning, but there are also some problems, such as incurring extra hyperparameters, destroying the model structure,
and remaining redundant information. References [24], [25], and [29] put forward specific optimization objectives and constraints and utilize heuristic optimization algorithms to train CNNs jointly. These will bring a new set of hyper-parameter problems. That means, aiming to deploy strategies, extra tricks to further adjust hyperparameters of heuristic algorithms are needed, which is not flexible for practical application. Moreover, joint training, combined with the sparsity regularization penalty, will destroy the structure of the model itself. In [21]–[23], [26], and [30]–[34], filters are pruned by concrete regulations, which are explicit in generating filter importance. These methods need to sort the importance from high to low and then delete the low importance filters without manual adjustment. Reference [34] compress CNNs with pruning and tucker tensor decomposition, which destroys the original model structure and complicates deployment. Although [23] and [32] have achieved success in compressing models, they rely too much on intuition and lack basic theoretical guidance. Meanwhile, other rule-based methods provide sufficient theoretical support to find out this redundant information, but still remain defects. Li et al. [21] applied the L1 norm to filters as the evaluation criterion of importance. However, all layers used the same trim scale, which brought suboptimization. Huang and Wang [30] and Liu et al. [31] used the scaling factor to measure the importance of parameters, pay too much attention to the parameters themselves and ignore information redundancy in the outputs generated by these parameters. Lin et al. [22] proposed a method named high rank (Hrank) to prune filters with low-rank feature maps. Similar high-rank feature maps may also contain redundant information, but they have not been removed. We believe that the reason for the shortcomings of the filter pruning methods mentioned above is that the relationship between model pruning and tensor compression is not fully utilized. In CNNs, 2-D feature maps output by the middle layer constitute 3-D tensors. As shown in Fig. 1, it can be found that the original model contains many similar feature maps by visualizing the feature maps output by the first layer of VGG-16. Inspired by the similarity between feature maps, we introduce the similarity function to quantify the similarity between feature maps and delete similar feature maps to prune the CNNs. The whole process is analogous to constructing the maximum linearly independent group of 3-D tensors, as shown in the upper part of Fig. 1. GhostNet [35] explains and applies the similarity of feature maps, but it makes use of this property from the perspective of constructing the structure of CNNs and does not perform an in-depth investigation about how to use this property to model pruning, which is different from the tensor compression and CNNs pruning in this article. Our main contributions are as follows.

1) We propose a theory to find out the redundant information in 3-D tensors by quantifying the similarity between any two feature maps, namely, quantified similarity between feature maps (QSFM). QSFM can compress 3-D tensors in CNNs to prune models.

2) Based on QSFM, we prune a variety of convolution layers, such as common convolution layers and depthwise separable convolution layers, which do not need a special software library and can accelerate the model inference speed.

3) Experiments demonstrate that our method is applicable to almost all CNNs, such as VGGNet, MobileNet, and ResNet. On CIFAR-10 [36], CIFAR-100 [36], and ILSVRC-12 [37], QSFM shows superior performance over existing prior filter pruning methods. QSFM can improve the inference speed of CNNs in practical applications of mobile and edge devices.

The remainder of this article is organized as follows. Section II discusses the recent achievements related to deep learning model compression. Section III presents QSFM compress 3-D tensors by taking advantage of the similarity between feature maps. Section IV conducts experiments and analyses to verify the feasibility of QSFM on different model structures, multiple data sets, and different devices. Conclusions are given in Section V.

II. RELATED WORK

According to the existing popular model compression methods, three research domains are most relevant to our approach, which can be categorized into network quantization, weight pruning, and filter pruning.

Network Quantization: Guo et al. [13] proposed the network sketching method, which used the convolution with binary weight sharing; for convolution calculation with the same input, the result of the previous convolution is retained, and the same part of the convolution filters directly multiplexes the result. Hu et al. [14] projected data into the Hamming space by hashing and transformed the problem of learning binary parameters into a hashing problem under inner product similarity. Different from the traditional 1-Valued or weighted
mean, [38] proposed trained ternary quantification (TTQ), which used two trainable full precision scaling coefficients to quantify the weight to \([-w_n, 0, w_n]\), and asymmetric weights made the network more flexible. These network quantization methods can accelerate the inference speed by specific library (denoted as * in Table I) such as [39], while only utilizing the network quantization algorithm without the assistance of other libraries may not able to accelerate speed in reality. Unlike our approach, these methods aim to quantify the weight of filters into discrete values, while our approach is to reduce channels for the 3-D tensors of convolutional layer output. Besides, these methods obtain a very high level of compression in saving storage space and significantly accelerate inference, but extreme compression (continuous to discrete) may limit the fitting ability of the model and may bring a considerable loss of accuracy, damage the model performance. Additionally, the value of the possible weight network needs to be further explored.

**Weight Pruning:** Weight pruning can remove any redundant parameter or redundant connection of the expected proportion of the network without restriction, but it will bring the problem of irregular network structure, making it difficult to effectively accelerate after pruning. Recently, Lee et al. [19] proposed the SNIP method that the importance of the connection was determined by sampling the training set several times in the initialization phase of the model, and the pruning template was generated in the meantime. After training, there is no need to iterate pruning and fine-tuning by the alternating cycle process. Yang et al. [20] used weighted sparse projection and input masking to provide quantifiable energy consumption, taking energy consumption budget as the optimization constraint of network training, and the sparse network can be obtained by utilizing the dynamic pruning method which can recover the important connections removed by mistake. Due to the requirement of a special sparse matrix operation library and hardware, it is also not convenient and universal to use weight pruning to implement acceleration for model.

**Filter Pruning:** Also named as coarse-grained pruning, it considers filters as the minimum pruning units, which can make the network “narrow” and can directly achieve effective acceleration on existing software or hardware. Fig. 2 shows how filter pruning reduces the output channels of the convolution layer. Compared with human-crafted pruning, [24] made the model compression completely automatic and performed better. It utilized a deep deterministic policy gradient (DDPG) as the controller to generate the specific compression ratio in continuous space. Different from the previous hard pruning and label-dependent pruning methods, [25] proposed a label-free generative adversarial learning (GAL) method, which used the sparse soft mask pruning network to scale the output of a specific structure to zero. It learned pruning networks with sparse soft masks in an end-to-end manner. Due to the heuristic optimization algorithm and jointed training, [24] and [25] will bring a new set of hyperparameter problems. He et al. [23] proposed an iterative two-step algorithm to effectively prune each layer, by a least absolute shrinkage and selection operator (LASSO) regression-based channel selection and least square reconstruction. Zhao et al. [26] proposed a variational Bayesian scheme for pruning CNNs in channel level, introducing a stochastic variational inference to estimate the distribution of channel saliency induced by a sparse prior. Though successful in the compressing model, [23] and [26] originated in experience or intuition, lacking of basic theoretical guidance. Li et al. [21] calculated the L1 norm of the filter, cutting out the feature map corresponding to the smaller L1 norm, and retrained after pruning. However, all layers use the same trim scale, which brings suboptimization. Lin et al. [22] proposed an effective and efficient filter pruning approach that explored the HRank of the feature maps in each layer. The principle behind HRank is that low-rank feature maps contain less information, and thus pruned results can be easily reproduced. Nevertheless, similar high-rank feature maps may also contain redundant information, but they have not been removed. Different from the existing methods, our method builds a bridge between tensor compression and model pruning and provides a new perspective for filter pruning by deleting redundant information of tensor. With a new theoretical foundation, QSF can get rid of the limitation of special software library or hardware, achieving the promotion of storage usage, memory occupation, and computing speed at the same time. And it retains the model structure with a different pruning rate. It can also be combined with other typical categories mentioned above to further achieve a higher compression ratio.

### III. Quantified Similarity Between Feature Maps

In mathematics, a set of vectors is linearly independent if no vector in the set can be expressed as a linear combination of the other vectors. If \( A \) is a linearly independent set of vectors and \( B \) is linearly dependent, where \( A \) and \( B \) are composed of the same number and same dimensions of vectors, then there are more vectors that can be represented by \( A \) than by \( B \), and in this sense, \( B \) contains redundant information.

We extend this linearly independent concept to the 3-D tensors composed of feature maps in CNNs. To some extent, every vector in a linearly independent set is not similar. For each convolution layer in CNNs, its filters are convolved with the input to generate feature maps. These 2-D feature maps form 3-D tensors and are then input to the next convolution layer. Our pipeline (QSF) tries to identify similar feature maps to find out the redundant information of 3-D tensors and prunes them by deleting similar feature maps. The whole
process is like constructing the maximum linearly independent group of 3-D tensors. The detailed process is described as follows.

A. Assumptions

The pretrained CNN model before pruning is Model0. Filter pruning does not change the convolution layers number, so we assume that the convolution layers of the model are \( L_1, L_2, \ldots, L_n \). QSFM prune these \( n \) layers sequentially, and the model obtained after the \( k \)th pruning operation is Model\(_k\).

The parameters set \( W_i \) of the \( i \)th convolution layer \( L_i \) is composed of \( N_i \) filters, where filters are 3-D tensors and \( W_i \) is a 4-D tensor. Denoted as \( W_i = \{ F_{(i,1)}, F_{(i,2)}, \ldots, F_{(i,N_i)} \} \in \mathbb{R}^{N_i \times N_{i-1} \times K_i \times K_i} \), where \( F_{(i,j)} \in \mathbb{R}^{N_{i-1} \times K_i \times K_i} \) represents the \( j \)th filters, \( N_{i-1} \) represents the channel number for a filter in \( L_i \) (also the input channel number), \( N_i \) represents the output channel number for \( L_i \), and \( K_i \) represents the height and width of the convolution filter. Note that the output channel number of the convolution layer is equal to the number of filters contained in this layer, while the filter channel number in this layer is equal to the number of output channels of the previous layer, so the notation of \( N_i \) and \( N_{i-1} \) above is rigorous.

Assume an image data set \( \text{Train} \) has \( M \) images, denoted as \( \text{Train} = \{ \text{Image}_1, \text{Image}_2, \ldots, \text{Image}_M \} \in \mathbb{R}^{M \times N_0 \times X_0 \times Y_0} \), where \( N_0 \) represents the channel number, and \( X_0 \) and \( Y_0 \) are the width and height. If input only one image into the model, then the input of \( L_1 \) is \( I_1 \in \mathbb{R}^{N_0 \times X_0 \times Y_0} \), and the output of \( L_i \) is \( O_i \in \mathbb{R}^{N_i \times X_i \times Y_i} \). Actually \( I_1 = O_{i-1} \), but separating them out makes readers focus more on the input and output of a particular convolution layer (\( L_i \)). For a specific convolution operation in \( L_i \), the \( j \)th filter \( F_{(i,j)} \) in \( W_i \) is convolved with \( I_i \) to generate a 2-D feature map, denoted as \( F_{i,M_{(i,j)}} \in \mathbb{R}^{X_i \times Y_i} \). All these \( N_i \) filters in layer \( L_i \) generate \( N_i \) feature maps, denoted as \( O_i = \{ F_{i,M_{(i,1)}}, F_{i,M_{(i,2)}}, \ldots, F_{i,M_{(i,N_i)}} \} \).

Above notations can refer to Fig. 2, the yellow background represents the input or output of each layer and the blue background is the parameters of the model. As shown in Figs. 1 and 2, the detailed pruning operation has been clear, so the upper part of Fig. 3 becomes more abbreviated, while the lower part focuses on the operations of QSFM on feature maps.

It can be concluded that specific feature maps correspond to specific filters. QSFM inputs \( M \) images in \( \text{Train} \) into the model to find redundant feature maps and delete filters using the corresponding relationship. Specifically, if QSFM is going to prune the \( k \)th convolution layer \( L_k \) of Model\(_{k-1}\), after identifying the redundant feature maps, QSFM delete the corresponding filters and obtain Model\(_k\).

B. Find Redundant Feature Maps

Filter pruning reduces the size and computation of CNN model by reducing the number of channels output by the convolutional layer. For the convolution layer \( L_i \), that means \( N_i \) needs to be reduced and the 3-D tensor \( O_i \) composed of feature maps needs to be compressed correspondingly. Therefore, it is important to reduce the number of 3-D tensor channels while preserving as much information as possible.

Assume a compact 3-D tensor \( O^{\text{compact}} \) = \( \{ F_{-M_{1}}, F_{-M_{2}}, \ldots, F_{-M_{N_c}} \} \in \mathbb{R}^{N_c \times X \times Y} \), where \( F_{-M_{j}} \in \mathbb{R}^{X \times Y} \) is not similar to each other. \( N_c \) elements in \( O^{\text{compact}} \) are allowed to be repeatedly selected to form a redundant 3-D tensor \( O^{\text{redundant}} \in \mathbb{R}^{N_c \times X \times Y} \). In general, an ordinary 3-D tensor \( O \in \mathbb{R}^{N \times X \times Y} \) is a combination of compact tensor \( O^{\text{compact}} \) and redundant tensor \( O^{\text{redundant}} \), where \( N = N_c + N_r \).

If we extend the terms of the above \( O^{\text{redundant}} \) composition process, allow \( O^{\text{redundant}} \) to contain elements similar to those in \( O^{\text{compact}} \) (not exactly equal), by visualizing the feature maps output by the CNN convolutional layer, we can find that these 3-D tensor output can be composed of a compact tensor and a redundant tensor (as shown in Figs. 1 and 3, similar results can be seen in GhostNet [35]). Since the elements in \( O^{\text{redundant}} \) are approximately equal to the elements in \( O^{\text{compact}} \) (similar), \( O^{\text{redundant}} \) represents redundant information in \( O \).

QSFM uses the above properties to find similar feature maps and delete redundant feature maps to build compact tensor. This process is like constructing the maximum linearly independent group. QSFM does not care about how to measure the similarity between feature maps. Instead, it wants to compress 3-D tensors by taking advantage of the similarity between feature maps. In order to show the operation process...
concretely, we select two similarity functions to measure similarity, respectively. (Step 2 in Fig. 3 shows only one of these methods.) However, readers can also customize the similarity function and even use the neural network to judge whether the feature maps are similar.

C. Quantify Similarity by Similarity Functions

The sequence of pruning is from \( L_1 \) to \( L_n \), and it is assumed that the \( i \)th convolution layer \( L_i \) is being pruned.

First, assume the number of filters to be pruned in layer \( L_i \) is \( N/l_i \) according to the compression rate (set manually according to requirements). These \( N/l_i \) filters which should be pruned constitute the set \( \text{Delete}^i \).

In practice, QSFM makes quantified similarity more robust by averaging the results of multiple inputs rather than a single image.

The model to be pruned is \( \text{Model}_{i-1} \), when the \( \text{Image}_k \) is input into the \( \text{Model}_{i-1} \), the output of \( L_i \) is \( O^k_i = \{ F_{M^k_{1,i}}, F_{M^k_{2,i}}, \ldots, F_{M^k_{N,l_i}} \} \). Calculate the quantified similarity function \( S(\{ F_{M^k_{1,i}}, F_{M^k_{2,i}} \}) \) between two feature maps in CNNs, where \( F_{M^k_{1,i}} \) and \( F_{M^k_{2,i}} \) are any two elements in the set \( O^k_i \). Hereinafter, referred to as \( S^k_{m,n} \), function \( S \) takes structural similarity (SSIM) [40] or peak signal-to-noise ratio (PSNR).

SSIM and PSNR are usually used to measure the image quality after compression. As far as we know, this is the first time that these methods are used to measure the similarity between two feature maps in CNNs

\[
S^k_{m,n}(\text{SSIM}) = \text{SSIM}(F_{M^k_{m,i}}, F_{M^k_{n,i}}) = \frac{(2\mu_m\mu_n+k_2^2 D^2)(2\sigma_{mn}+k_2^2 D^2)}{(\mu_m^2+\mu_n^2+k_2^2 D^2)(\sigma_m^2+\sigma_n^2+k_2^2 D^2)}. \tag{1}
\]

Here, \( \mu_m \) and \( \mu_n \) are the average of all pixels in \( F_{M^k_{m,i}} \) and \( F_{M^k_{n,i}} \), \( \sigma_{mn} \) and \( \sigma_m^2 \) \( \sigma_n^2 \) are the variance of all pixels in \( F_{M^k_{m,i}} \) and \( F_{M^k_{n,i}} \). Generally, \( k_1 = 0.01 \) and \( k_2 = 0.03 \) according to [40].

\( D \) is determined by the following equation:

\[
D = \max(O^k_i) - \min(O^k_i). \tag{2}
\]

Here, \( \max(O^k_i) \) and \( \min(O^k_i) \) are the values of the largest and smallest pixels in \( O^k_i \).

Since the quantization of PSNR is theoretically equivalent to the Euclidean distance if only care about the value of similarity ordering, QSFM only need to sort the similarity according to the Euclidean distance, needless to know the specific value of PSNR. Therefore, the following content does not distinguish the PSNR from the Euclidean distance. In order to make the judgment standard of the quantification function more uniform, we hope that the larger the value of the similarity function is, the more similar the two feature maps are. So we choose to take the negative of the Euclidean distance

\[
S^k_{m,n}(\text{PSNR}) = -\text{EuclideanDistance}(F_{M^k_{m,i}}, F_{M^k_{n,i}}) = -\frac{1}{X \times Y} \sum_{x=1}^{X} \sum_{y=1}^{Y} \sqrt{(F_{M^k_{m,i}}[x,y] - F_{M^k_{n,i}}[x,y])^2}. \tag{3}
\]

It is noted that \( S^k_{m,n} \) is only the result generated by a single \( \text{Image}_k \). For the whole \( \text{Train} \), it contains \( M \) images in total. We calculate the statistical average results on \( M \) images and define

\[
S^i_{m,n} = \frac{\sum_{k=1}^{M} S^k_{m,n}}{M} \quad S^i = \{S^i_{m,n}\}, (m, n = 1, 2, 3, \ldots, N_i). \tag{4}
\]

D. Prune Convolution Layers by Deleting Filters

After finding out the feature map groups with high similarity, we need to stipulate an auxiliary condition to determine which one of the two feature maps to delete (step 3 in Fig. 3). We can randomly delete a feature map in each similar group, or we can use the L1 norm of the feature map to delete those with a smaller norm. We use the rank of the 2-D matrix as an auxiliary condition to assist the quantified similarity function finding the redundant feature maps. The use of this auxiliary condition is inspired by HRank [22], but it does not mean that QSFM is similar to that of HRank. In fact, as mentioned above, HRank does not take into account the existence of redundant information (i.e., similarity) in two high-rank feature maps. Meanwhile, our experiment will prove that QSFM is superior to HRank. Calculate the rank of each \( F_{M^k_{i,m}} \), then the statistical average of the rank of \( F_{M^k_{i,m}} \) in \( O_i \) is

\[
\text{Rank}_m^i = \frac{\sum_{k=1}^{M} \text{Rank}_m^k}{M} \quad \text{Rank}_m^i = \{ \text{Rank}_m^k \}, (m = 1, 2, 3, \ldots, N_i). \tag{5}
\]

Arrange the set \( S^i \) from high to low, then match the set \( \text{Rank}_m^i \) to determine the filter to be pruned. Set the conditions as follows.

1) \text{Condition 1:} \text{Filter}_{i,m} \text{ and Filter}_{i,n} \text{ are not members of Delete}^i.

2) \text{Condition 2:} S^i_{m,n} \text{ is maximum under the premise that } m \text{ and } n \text{ meet condition 1.}

3) \text{Condition 3:} \text{Rank}_m^i > \text{Rank}_n^i.

4) \text{Condition 4:} \text{Rank}_m^i \leq \text{Rank}_n^i.

If conditions 1–3 meet simultaneously, \text{Filter}_{i,m} \text{ will be put into Delete}^i; if conditions 1, 2, and 4 meet simultaneously, \text{Filter}_{i,m} \text{ will be put into Delete}^i. And the above operation will continue until the number of filters in the set \( \text{Delete}^i \) is \( N/l_i \) (steps 4 and 5 in Fig. 3).

The model could be fine-tuned after pruning every convolution layer, that is

\[
\text{Model}_i = \text{Fine_Tuned}(\text{Model}_{i-1} - \text{Delete}^i). \tag{6}
\]

After all convolutional layers are pruned following the above method, the compression of the neural network is completed successfully.

The rank is not the only auxiliary condition that can be used. In fact, if \( S^i_{m,n} \) is large, it indicates that there is similar redundant information between the \( m \)th feature map and the \( n \)th feature map, and the auxiliary condition is to determine whether to delete the \( m \)th or the \( n \)th feature map. Section III-C is to quantify similar redundant information between feature maps, while Section III-D is to determine how to delete redundant information (especially for neural network pruning). As
long as a method can play the same role, it can be used as the auxiliary condition of QSFM.

E. Special Convolution

QSFM can also prune special convolution layers, like depth-wise separable convolution in MobileNet. As shown in Fig. 4, no matter how the convolution layer is convolved, the corresponding relationship between filters and feature maps remains unchanged and the output still has similar feature maps. So QSFM can prune these special CNNs.

IV. EXPERIMENTS

In this section, we give some experimental settings first and prove the feasibility of QSFM through an ablation study. Then, we use different model structures to test QSFM’s performance on different data sets. Finally, we deploy the pruned model of QSFM in edge devices and verify that QSFM is helpful to AI on Edge tasks by accelerating CNNs inference speed.

A. Experimental Settings

1) Data Sets: CIFAR-10 [36] consists of 60,000 color images with a resolution of $32 \times 32$. The images in CIFAR-10 are labeled as ten categories, each containing 6000 images, 5000 for training and 1000 for testing. CIFAR-100 [36] consists of 60,000 color images with a resolution of $32 \times 32$. The images in CIFAR-100 are labeled as 100 categories, each containing 600 images, 500 for training and 100 for testing.

Due to the appropriate amount of data and small resolution, CIFAR-10 and CIFAR-100 are widely used by many image classification algorithms. However, because of its low resolution, it is used to test the performance of algorithms in most cases, not in actual deployment scenarios.

ILSVRC-12 [37] contains more than 1.28 million images, which vary in resolution but are usually adjusted to $224 \times 224$ resolution for use. The images are labeled as 1000 categories. Different from CIFAR-10 and CIFAR-100, ILSVRC-12 has a large enough amount of data, high resolution, and multiple categories to ensure that it can be used in actual deployment scenarios.

2) Model Structures: The model structures we used are VGG-16 [4], ResNet-56 [5], and MobileNet-V2 [7]. For CIFAR-10, the initial model (baseline) used by QSFM are VGG-16 (top-1 accuracy 93.39%), ResNet-56 (top-1 accuracy 93.21%), and MobileNet-V2 (top-1 accuracy 92.54%). For CIFAR-100, the baseline is ResNet-56 (top-1 accuracy 70.62%). For ILSVRC-12, the baseline is MobileNet-V2 (top-1 accuracy 72.21%).

3) Configurations: Images in CIFAR-10 and CIFAR-100 have resolutions of $32 \times 32 \times 3$, while images in ILSVRC-12 are resized to $224 \times 224 \times 3$.

All the pruning operations are conducted within Tensorflow (1.14.0) and Keras (2.2.5). In practical application, we use TensorFlow Lite to apply the model on mobile devices.

The convolution operation is usually followed by the batch normalization layer and the activation layer, in our experiments, we regard these three layers as a block and conduct QSFM pruning on its final output 3-D tensor (feature maps). For every residual block in ResNet-56, we only prune the first convolutional layers, which are simple and can keep the output dimension of the residual block unchanged, as shown in Fig. 5. For every bottleneck in MobileNet-V2, we prune depth-wise separable convolution layers, as shown in Fig. 6.

After the whole pruning operation, we calculate the FLOPs and Parameters of the pruned models and compare them with existing methods [22]–[26], [33]. On edge devices, we further measure the inference speed to measure QSFM’s performance.
4) Devices: We use a server with an Nvidia V100 GPU to compress CNNs by QSFM. For edge device, we use a Xiaomi-M2006J10C with an ARM MT6889Z/CZA processor to deploy the TensorFlow Lite model and an Nvidia-Jetson-TX2 with a 256-core Pascal GPU to deploy the TensorFlow model. Note that even if on the same device, the inference speed of the same model may still be different in different software environments or physical environments, so the measurement of the inference speed of CNNs can be regarded as a qualitative experiment, while FLOPS and Parameters are more universal because they are not affected by equipment and environment.

B. Ablation Study

To verify that QSFM can find the redundant information more efficiently in feature maps, we prune VGG-16 and ResNet-56 without fine-tuning under the same compression rate and other conditions and compared with random pruning and existing method (Hrank).

1) VGG-16: For VGG-16 on CIFAR-10, QSFM prune the 3rd and 4th blocks (the 5th–10th convolution layers), and the compression rates are [0.6, 0.4, 0.3, 0.3, 0.3, 0.3]. At this compression ratio, we prune the network layer by layer with different methods, including QSFM-PSNR, QSFM-SSIM, Hrank, and Random (delete filters randomly). It should be emphasized that we did not make any fine-tuning in this part, and the experimental results are shown in Fig. 7.

Our method is consistently better than Hrank and random method in pruning different convolutional layers. In the experiment, we find that sometimes the accuracy of our method after pruning is even higher than that before pruning (in steps 3rd and 4th of QSFM-SSIM). When the compression ratio is large, HRank needs to delete the high-rank feature maps, but it cannot effectively distinguish which are redundant in these high-rank feature maps.

2) ResNet-56: In ResNet-56 on CIFAR-10, we find quite a few convolution layers have many filters whose all parameter values are close to $10^{-32}$ ("unimportant filters"). We count the proportion of filters whose all parameter values are close to $10^{-32}$ in the 27 layers of every residual block and prune these layers. When we prune these filters, the accuracy of the pruned model was roughly the same as that of the original model (without fine-tuning). In order to prove the generality of the results, we trained ResNet-56 on CIFAR-10 by three independent training with different accuracy (92.80%, 92.90%, and 93.21%), all of which have similar results, as shown in Fig. 8. This shows that there is a lot of redundancy in the model of ResNet-56 on CIFAR-10, so we think that it may lead to the selection of filters that should be pruned are all of the magnitude $10^{-32}$ if the compression ratio of each convolutional layer is too small, which cannot reflect the advantages and disadvantages of our method.

To sum up, we can only judge the performance of the method if the compression ratio is high enough (larger than the proportion of filters whose all parameter values are close to $10^{-32}$). If the compression ratio is too low, then any method will always get a good result because the filters they delete are distinctly useless.

We use this “high compression ratio” principle to compare the pruning performance of various methods (the compression ratio of each layer of ResNet-56 on CIFAR-10 will not be lower than 0.5).

We prune the first nine blocks of ResNet-56, and the compression rates are [0.5, 0.5, 0.5, 0.5, 0.75, 0.75, 0.75, 0.75, 0.75]. We use the whole training set (50 000 images) to calculate the similarity between feature maps. The results are shown in Fig. 9. Compared with Hrank and Random, QSFM-PSNR provides better maintenance of precision for the whole nine steps, which demonstrates QSFM can better identify important
TABLE II
PRUNING RESULTS OF VGG-16 ON CIFAR-10 (WITH FINE-TUNING).
"TOP-X" REPRESENTS THE TOP-X ACCURACY. "PR" REPRESENTS THE
PRUNING RATE. THE ACCURACY IS REPRESENTED IN THE FORMAT OF
BASELINE → PRUNED (DECREASED ACCURACY). WE USE BOLDFACE TO
DENOTE OUR METHOD. THE OTHER TABLES AND FIGURES FOLLOW THE
SAME CONVENTION.

| Method         | Top-1(%) | FLOPs(PR) | Parameters(PR) |
|----------------|----------|-----------|----------------|
| EasiEdge-82% [33] | 93.73→93.42(-0.31) | 70.42M(77.6%) | 0.58M(96.1%) |
| HRank [22]     | 93.96→91.23(-2.73) | 73.67M(76.5%) | 1.75M(88.1%) |
| QSFM-SSIM      | 93.39→92.77(-1.22) | 79.0M(74.8%)  | 3.68M(75.0%)  |
| QSFM-PSNR      | 93.39→92.00(-1.39) | 42.46M(56.5%) | 0.49M(96.7%)  |

TABLE III
PRUNING RESULTS OF RESNET-56 ON CIFAR-10 (WITHOUT FINE-TUNING)

| Method         | Top-1(%) | FLOPs(PR) | Parameters(PR) |
|----------------|----------|-----------|----------------|
| AMC [24]       | 92.80→90.10(-2.70) | 63.28M(50.0%) | -              |
| He [23]        | 92.80→90.09(-2.00) | 62.32M(50.6%) | -              |
| GAL-0.6 [25]   | 92.80→92.88(-2.0)  | 78.30M(37.6%) | 0.75M(11.8%)  |
| GAL-0.8 [25]   | 92.80→90.36(-2.90) | 49.99M(60.2%) | 0.29M(65.90%) |
| Zhao [26]      | 92.80→92.62(-0.78) | 100.86M(20.3%) | 0.66M(20.49%) |
| QSFM-SSIM      | 92.80→92.62(-2.54) | 64.92M(48.7%) | 0.36M(37.9%)  |
| QSFM-PSNR      | 92.80→92.62(-2.54) | 64.92M(48.7%) | 0.36M(37.9%)  |

TABLE IV
PRUNING RESULTS OF MOBILENET-V2 ON CIFAR-10 (WITH FINE-TUNING)

| Method         | Top-1(%) | FLOPs(PR) | Parameters(PR) |
|----------------|----------|-----------|----------------|
| GAL-0.8 [25]   | 93.26→91.58(-1.68) | 50.37M(60.2%) | 0.29M(65.9%)  |
| GAL-0.6 [25]   | 93.26→93.38(0.12)  | 78.30M(37.6%) | 0.75M(11.8%)  |
| AMC [24]       | 92.80→91.90(-0.90) | 63.24M(50.0%) | -              |
| Hrank [22]     | 93.26→92.72(-5.4)  | 32.77M(74.1%) | 0.27M(68.1%)  |
| EasiEdge-30% [33] | 92.93→93.61(-0.31) | 56.93M(55.0%) | 0.45M(47.1%)  |
| QSFM-SSIM-1    | 92.93→91.91(-2.01) | 53.15M(58.8%) | 0.26M(69.1%)  |
| QSFM-SSIM-2    | 92.93→91.88(-1.33) | 50.62M(59.0%) | 0.25M(71.3%)  |
| QSFM-PSNR      | 92.93→91.98(-1.23) | 53.15M(58.0%) | 0.26M(69.1%)  |

FILTERS. But for QSFM-SSIM, it only performed better in steps
1st–3rd, which indicates that there is still space for improve-
ment in the selected function to measure similarity. Both
QSFM-PSNR and QSFM-SSIM are far better than Random,
which proves the correctness of our method.

C. Results and Analysis on CIFAR-10

We prune some mainstream models on CIFAR-10, including
VGG-16, ResNet-56, and MobileNet-V2.

1) VGG-16: We apply QSFM to prune the VGG-16 model
with Fine-Tuning. For QSFM-SSIM, all 13 convolution
layers have a compression ratio of 0.5. For QSFM-PSNR, the
13 convolution layers’ compression ratios are [0.5 0.5 0.5
0.5 0.6 0.6 0.6 0.9 0.9 0.9 0.9]. The results are displayed in
Table II. Compared with HRank, QSFM-SSIM nearly
compresses the same FLOPs while maintaining a better accuracy
drop (−1.22% versus −2.73%). Compared with EasiEdge-
82%, QSFM-PSNR has a larger FLOPs reduction (42.46M
versus 70.42M).

2) ResNet-56: First, we prune ResNet-56 without any fine-
tuning operations according to the proportion which is slightly
higher than that of the unimportant filters (filters whose all
parameter values are close to 10−32), and finally get good
results as shown in Table III. Compared with AMC and
He et al., QSFM-SSIM nearly compresses same FLOPs while
maintaining a less accuracy drop (−0.54% versus −2.7% and
−0.54% versus −2.0%). Compared with GAL-0.6, though
QSFM-SSIM has a little higher accuracy drop (−0.54% versus
−0.28%), but it gains a larger FLOPs and parameters
reduction (64.92M versus 78.30M and 0.36M versus 0.75M).
Compared with GAL-0.8, QSFM-SSIM gains a less accuracy
drop (−0.54% versus −2.9%) while has a little shortage at the
compression aspect. Compared with Zhao et al., QSFM-SSIM
has a less accuracy drop (−0.54% versus −0.28%), but it gains a
larger FLOPs and parameters reduction (64.92M versus 100.86M),
and larger parameters reduction (64.92M versus 78.30M and 0.36M
versus 0.68M).

Then, we further apply our method to prune the ResNet-56
model with Fine-Tuning for higher compression. The results are
shown in Table IV. There is a slight difference in compression
between QSFM-SSIM-1 and QSFM-SSIM-2. QSFM-PSNR
gains a less accuracy drop (−2.54% versus −0.28%) while has a
little shortage at the compression aspect. Compared with
AMC, which obtains 91.90% of top-1 accuracy and 50.0% FLOPs
reduction, QSFM-PSNR gets a larger FLOPs reduction (64.92M
versus 78.30M and 0.36M versus 0.68M).

3) MobileNet-V2: For MobileNet-V2, we use QSFM to
prune the whole 17 depthwise separable convolution layers
on CIFAR-10. The compression ratio of each layer is 0.5. The
results of the pruning experiment are shown in Table V. After
pruning, the accuracy of the model only dropped by 0.45%
(92.54% → 92.09%, QSFM-SSIM), with 26.93% FLOPs and
parameters reduction. The results also show that our
proposed method can also achieve good results for depthwise
separable convolution layers.

D. Results and Analysis on CIFAR-100

QSFM only prunes the first convolutional layers for every
residual block in ResNet-56 on CIFAR-100, and the final
results are shown in Table VI. The Top-1 accuracy of
QSFM-SSIM dropped by 2.26% (70.62%→68.36%) and
...
the Top-5 accuracy of QSFM-PSNR dropped by 0.92% (92.00% \rightarrow 91.08%), with 53.87% FLOPs reduction and 51.16% parameters reduction.

### E. Practical Application

For practical applications of IoT, we use ILSVRC-12 to train MobileNet-V2 and deploy it to edge devices for the image classification task. MobileNet is a well-known lightweight CNN model used for many real-time computer vision tasks, such as image classification, object detection, and so on. We use QSFM to compress MobileNet-V2 to accelerate CNNs inference speed and verify that our method is helpful to AI on Edge tasks.

Few works prune the MobileNet model. We only found some data from AMC [24] that could be compared with QSFM. AMC can compress MobileNet-V2 with 30% FLOPs reduction and 1.0% Top-1 accuracy drop, while more detailed performance of QSFM can refer to Table VII. For mobile device, we use the TensorFlow Lite Converter to convert a traditional TensorFlow model into a TensorFlow Lite model to deploy. For Nvidia-Jetson-TX2, we deploy it directly using the TensorFlow model. In practical applications, the inference speed of the model is also affected by the software version and physical environment, so this is only a qualitative experiment. In order to ensure the accuracy of the measurement latency as much as possible, we averaged the inference speed of 1000 images, as shown in Table VIII. Even for an enough lightweight CNN model like MobileNet-V2, QSFM can compress it and accelerate inference speed in practical tasks.

### V. Conclusion and Outlook

In this article, we propose a novel theory to find the redundant information in 3-D tensors, named QSFM. We apply QSFM to prune CNNs, which builds a bridge between tensor compression and model pruning and achieves good results. Experiments show that QSFM can compress CNNs, such as VGGNet, ResNet, and MobileNet significantly with negligible accuracy drop. CNNs compressed by QSFM have faster inference speed and occupy less memory, which are more appropriate to AI on edge tasks.

QSFM can be further promoted by using more effective functions or even some machine learning methods in the process of quantifying similarity. In addition, how to divide different kinds of similar feature maps, further refine the method of deleting feature maps and determine the distribution of feature maps suitable for CNNs are still worth exploring.

We will focus on selecting better ways to measure the similarity of feature maps to improve the performance of QSFM, trying to refine the compression rate for each model, and combining various compression methods to further accelerate the AI edge device inference speed.

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