Network Pruning Using Adaptive Exemplar Filters

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Abstract—Popular network pruning algorithms reduce redundant information by optimizing hand-crafted models, and may cause suboptimal performance and long time in selecting filters. We innovatively introduce adaptive exemplar filters to simplify the algorithm design, resulting in an automatic and efficient pruning approach called EPruner. Inspired by the face recognition community, we use a message-passing algorithm Affinity Propagation on the weight matrices to obtain an adaptive number of exemplars, which then act as the preserved filters. EPruner breaks the dependence on the training data in determining the “important” filters and allows the CPU implementation in seconds, an order of magnitude faster than GPU-based SOTAs. Moreover, we show that the weights of exemplars provide a better initialization for the fine-tuning. On VGGNet-16, EPruner achieves a 76.34%-FLOPs reduction by removing 88.80% parameters, with 0.06% accuracy improvement on CIFAR-10. In ResNet-152, EPruner achieves a 65.12%-FLOPs reduction by removing 64.18% parameters, with only 0.71% top-5 accuracy loss on ILSVRC-2012. Our code is available at https://github.com/lmbxmu/EPruner.

Index Terms—Adaptive, exemplars, filter pruning, network pruning, structured pruning.

I. INTRODUCTION

CONVOLUTIONAL neural networks (CNNs) and their variants have been applied to a broad range of problems such as image classification [1], action recognition [2], semantic segmentation [3], and few-shot learning [4]. However, most high-performing CNNs are designed to execute on high-end GPUs with substantial memory and computational power, which hinders their practical applications in resource-constrained environments, such as mobile and embedded devices. Therefore, model compression techniques, e.g., low-rank decomposition [5]–[7], parameter quantization [8]–[10], and network pruning [11]–[14] have been proposed. Among them, network pruning has been widely studied and proved to be an effective tool to reduce the network complexity. In contrast to unstructured weight pruning that removes individual entries in the weight matrices [14]–[17] and thus requires specialized hardware or software, structured filter pruning has attracted more attention because it removes the entire filters and corresponding channels, which requires no extra requirements for the inference platforms [18]–[25].

Based on the filter-preserving policy, we empirically classify the filter-pruning approaches into the following three categories:

1) Rule-based pruning decides the pruned network architecture by hand-crafted designation, and the pruned network usually inherits the most important filter weights either measured by an intrinsic property of the pretrained model, e.g., the $\ell_1$-norm [26], or through iterative refinement on training data [19], [27]. Typically, the designated architecture is suboptimal. Moreover, it usually performs layerwise fine-tuning/optimization to recover the accuracy, which is computationally intensive.

2) Regularization-driven pruning retrain networks with hand-crafted constraints, such as sparsity [20], [23], [28] and budget awareness [29]. The trained filters below a given threshold are removed and the weights of preserved filters are inherited by the pruned network. However, retraining the model is expensive, and the introduced hyperparameters also require manual analysis.

3) Architecture-search-driven pruning focuses on searching for a better architecture, typically through heuristic-based policies, such as evolutionary algorithm [24] or the artificial bee colony algorithm [30]. The filter weights of these methods are randomly sampled for the follow-up fine-tuning. However, the architecture search is data-dependent thus also computationally intensive, as validated in the experiments. Besides, the search results are not deterministic.

Overall, existing methods still depend heavily on hand-crafted rules from humans, and/or involve time-consuming retraining/search. How to achieve an automatic and efficient model compression still remains an open problem.

Thus, existing methods suffer either great cost on human labor or large time complexity in pruning. In this article, we propose a novel filter-pruning method, termed EPruner,
which selects the most important filters (exemplars), to solve the above problems. We argue that the removal of informational redundancy is an underlying theme behind all these three types of approaches. As stressed in network interpretation [31]–[33], the filters, even within the same layer, have different impacts. This indicates that different filters have different properties and there exist some exemplars that contribute more in the network inference. Thus, the challenge lies in figuring out the exemplar number without human involvement and identifying which filter could be the exemplar such that the efficient end-to-end fine-tuning can be conducted.

In the following, we will first discuss the related work in Section II. Then, we elaborate our EPruner for network pruning in Section III. In Section IV, the experimental results are provided and analyzed. Lastly, we conclude this article in Section V.

II. RELATED WORK

Unstructured weight pruning removes the individual neurons in the filter or the connection between fully connected layers. The pioneering work [15] utilizes the second derivatives to balance the training loss and model complexity. Han et al. [39] proposed to recursively prune the low-weight connections and retrain the remaining subnetwork with the \( \ell_2 \) normalization. Dynamic network surgery [16] performs weight pruning and splicing. The pruning is made to compress the network model and the slicing is used to enable connection recovery. Aghasi et al. [40] removed connections by solving a convex optimization program. In [13], the compression is formulated as the constrained Bayesian optimization solved by the annealing strategy. The lottery ticket hypothesis [14] randomly initializes a dense network and trains it from scratch. The subnet with high-weight values are extracted, and retrained with the initial weight values of the dense model.

Unstructured weight pruning results in an irregular sparsity, which requires customized hardware and software to support the practical speedup. In contrast, structured filter pruning is especially advantageous by removing the entire filters and the corresponding channels in the next layer directly. It has no extra requirements for the inference engine and thus can be easily deployed.

To this end, rule-based pruning requires human experts to specify the pruned architecture. Hu et al. [18] observed the large output of zero activations in the network and the filter weights with a lower percentage of zero outputs are inherited. The \( \ell_1 \)-norm pruning [26] assumes filters with large norms are more informative, and thus the corresponding weights are inherited. Lin et al. [25] preserved the filter weights with high-rank feature map outputs. Another direction in filter pruning formulates the pruning as an optimization problem using the statistics information from the next layer [19] or a linear least square to reconstruct the outputs [27], and the optimized weights are forwarded for fine-tuning.

Regularization-driven pruning performs model complexity reduction by retraining the network with hand-crafted constraints. Liu et al. [20] and Zhao et al. [22] imposed a sparsity constraint on the scaling factor of the batch normalization layer and the weights with higher scaling factors are preserved for the fine-tuning. Huang and Wang [35] and Lin et al. [23] introduced a sparse soft mask on the feature map outputs or the filters. The filters with nonzero masks are preserved and the corresponding trained weights are preserved. Lemaire et al. [29] proposed a knowledge distillation loss function combined with a budget-constrained sparsity loss to train the network and guarantee the neuron budget at the same time.

Architecture-search-driven pruning tries to search for the optimal pruned architecture. In [24], a large auxiliary PruningNet has to be trained in advance to evaluate the performance of each potential pruned architecture derived from the evolutionary procedure. In [30], artificial bee colony
algorithm is applied to search for the pruned network architecture and the accuracy is regarded as the fitness of each architecture. In light of the recent work [36], which claims that the essence of network pruning lies in finding the optimal pruned architecture rather than selecting the most important filter weights, the initializations of these methods are randomly sampled from the Gaussian distribution [24] or the pretrained model [30] for fine-tuning.

Compared with the rule-based pruning, the novelty of our EPruner lies in no hand-crafted constraints otherwise manner. Compared with regularization-driven pruning, the fine-tuning is implemented in a computationally efficient end-to-end manner rather than the inefficient layer-by-layer manner. Compared with heuristic-based search algorithm [24], [30]. However, these methods suffer either human effort or heavy computation as discussed in Section I. The goal of our EPruner is to select \( \bar{w}_k \) high-quality exemplar filters for the \( k \)-th layer, denoted as \( \bar{w}_k \) from \( w_k \) by the affinity propagation [34]. The exemplars \( \bar{w}_k \) makes up the pruned network architecture, which will be initialized for the end-to-end fine-tuning. Our method is directly applied on top of the CNN weights, thus the specific value of \( \bar{c}_k \) is adaptive to the input CNNs. Besides, it requires neither human designation, nor search progress in our EPruner.

We propose EPruner toward solving the above problems as stated in Section I. The goal of our EPruner is to select \( \bar{c}_k \) high-quality exemplar filters for the \( k \)-th layer, denoted as \( \bar{w}_k \) from \( w_k \) by the affinity propagation [34]. The exemplars \( \bar{w}_k \) makes up the pruned network architecture, which will be initialized for the end-to-end fine-tuning. Our method is directly applied on top of the CNN weights, thus the specific value of \( \bar{c}_k \) is adaptive to the input CNNs. Besides, it requires neither human designation, nor search progress in our EPruner.

We summarize the main notations used in this article in Table I, more of which will be detailed in the following sections.

### III. METHODOLOGY

#### A. Problem Definition

Given a pretrained CNN model \( \mathbf{F} \) with a total of \( L \) convolutional layers, its filter weights can be represented as a set of 4-D tensors \( \mathbf{W} = \{w_k\}_{k=1}^L \). The \( k \)-th layer parameters of \( w_k \) have the shape of \( c_k \times c_{k-1} \times h_k \times w_k \), where \( c_k \) represents the number of filters, \( c_{k-1} \) represents the number of input channels of each filter, and \( h_k \) and \( w_k \) represent the height and width of each filter. As can be seen, the number of channels, i.e., \( c_{k-1} \), is equal to the number of filters in the \( (k-1) \)-th layer.

For the ease of the following context, we rewrite the parameter tensor of \( w_k \) as a 2-D data matrix with the shape of \( c_k \times (c_{k-1} \cdot h_k \cdot w_k) \). And then, we append the biases of the filters to \( w_k \), thus its dimension becomes \( \bar{c}_k \times (\bar{c}_{k-1} \cdot \bar{h}_k \cdot \bar{w}_k + 1) \). Without loss of generality, we denote the \( i \)-th filter as \( w_{ki} \).

The goal of filter pruning is to obtain a compressed representation of the parameters \( \mathbf{W} = \{w_k\}_{k=1}^L \) and remove the filters of informational redundancy. Each \( \bar{w}_k \) has a smaller shape of \( \bar{c}_k \times (\bar{c}_{k-1} \cdot \bar{h}_k \cdot \bar{w}_k + 1) \) and \( \bar{c}_k \leq c_k \), \( \bar{c}_{k-1} \leq c_{k-1} \), which would be computationally efficient. To this end, predominant works follow: 1) human designated pruned architecture and inheriting the most important filter weights using rules [19], [25]; 2) training from scratch with hand-crafted constraints [23], [35]; and 3) searching optimal pruned architecture using heuristic-based search algorithm [24], [30]. However, these methods suffer either human effort or heavy computation as discussed in Section I.

We propose EPruner toward solving the above problems as stated in Section I. The goal of our EPruner is to select \( \bar{c}_k \) high-quality exemplar filters for the \( k \)-th layer, denoted as \( \bar{w}_k \) from \( w_k \) by the affinity propagation [34]. The exemplars \( \bar{w}_k \) makes up the pruned network architecture, which will be initialized for the end-to-end fine-tuning. Our method is directly applied on top of the CNN weights, thus the specific value of \( \bar{c}_k \) is adaptive to the input CNNs. Besides, it requires neither human designation, nor search progress in our EPruner.

We summarize the main notations used in this article in Table I, more of which will be detailed in the following sections.

#### B. Proposed EPruner

Affinity propagation [34] was originally proposed to select exemplars for the data points with different properties. Early works on the network interpretation [31]–[33] reveal that the filters, even within the same layer, have different impacts to the network. This indicates that different filters have different properties and there exist some exemplars that contribute more to the network.
As illustrated in Fig. 1, we propose to regard each filter $w_{ki}$ as a high-dimensional data point by reformulating it in a vector form, i.e., $w_{ki} \in \mathbb{R}^{b_i \times b_k \times w_k}$. For any two filters $w_{ki}$ and $w_{kj}$, affinity propagation takes as input their similarity graph $s_k(\cdot, \cdot)$, which reflects how well the filter $w_{kj}$ is suited to be the exemplar of the filter $w_{ki}$. We found our method can well perform with the naive negative Euclidean distance as

$$s_k(i, j) = -\|w_{ki} - w_{kj}\|^2 \quad \text{s.t.} \quad 1 \leq i, j \leq c_k, \ i \neq j$$  \quad \quad \quad (1)

When $i = j$, it indicates the suitedness of filter $w_i$ to be the exemplar of itself (self-similarity). Following [34], it can be defined as:

$$s_k(i, i) = \text{median}(w_k)$$  \quad \quad \quad (2)

where median($\cdot$) returns the median value of the input.

Larger $s_k(i, i)$ leads to more exemplar filters, which however returns less complexity reduction. Using the median value of the whole weight in the $k$th layer ($w_k$) in (2) would result in a moderate number of exemplars. To solve, we reformulate (2) as follows:

$$s_k(i, i) = \beta \times \text{median}(w_k) \quad \text{s.t.} \quad 0 < \beta \leq 1$$  \quad \quad \quad (3)

where $\beta$ is a pregiven hyperparameter.

Equation (3) differs from (2) in twofold. First, the median value is obtained upon the $i$th filter $w_{ki}$ rather than the whole weight $w_k$. Thus, the similarity $s_k(i, i)$ can be more adaptive to the filter $w_{ki}$. Second, the introduced $\beta$ provides an adjustable reduction of model complexity. As shown in Section IV-F, large $\beta$ leads to a high-complexity reduction, and vice versa.

Besides the similarity, there are also two kinds of messages passing between filters, i.e., “responsibility” and “availability,” to decide which filters are exemplars, and for every other filter, which exemplar it belongs to.

The “responsibility” $r_k(i, j)$ indicates how well the filter $w_{kj}$ is suited to serve as the exemplar of the filter $w_{ki}$ by considering other potential exemplars for filter $w_{ki}$. The updating of $r(i, j)$ follows:

$$r(i, j) \leftarrow s(i, j) - \max_{j \neq j, j \neq j} (a(i, j') + s(i, j'))$$  \quad \quad \quad \text{s.t.} \quad 1 \leq i, \ j \leq c_k, \ i \neq j$$  \quad \quad \quad (4)

where $a(i, j)$ is the “availability” below initialized to zero. Initially, $r(i, j)$ is set to $s(i, i)$ minus the largest of the similarities between filter $w_{ki}$ and other filters. Later, if one filter is assigned to other exemplars, its availability is smaller than zero as per (6), which further decreases the effectiveness of $s(i, j')$ in (4), thus $w_{kj}$ is removed from the exemplar candidates.

For $i = j$, the “self-responsibility” is given as

$$r(i, i) \leftarrow s(i, i) - \max_{i' \neq i, i' \neq i} s(i, i')$$  \quad \quad \quad (5)

which is set to $s(i, i)$ minus the largest of the similarities between filter $w_{ki}$ and other filters. It reflects the possibility that filter $w_{ki}$ can be an exemplar by considering how ill-suited it is to be assigned to another exemplar.

As for the “availability,” we first give its updating rule as

$$a(i, j) \leftarrow \min\left\{0, r(i, j) + \sum_{i', s.t. i' \neq j} \max(0, r(i', j))\right\}$$  \quad \quad \quad \text{s.t.} \quad 1 \leq i, \ j \leq c_k, \ i \neq j$$  \quad \quad \quad (6)

The availability $a(i, j)$ is set as $r(j, j)$ plus the sum of other responsibilities that filter $w_{kj}$ receives from others. The max() excludes the negative responsibilities because we only need to focus on the good filters (positive responsibilities). The $r(j, j) < 0$ denotes that filter $w_{kj}$ is more appropriate to belong to another exemplar rather than being an exemplar itself. It can be seen that the availability of filter $w_{kj}$ as an exemplar increases if some other filters have positive responsibilities for $w_{kj}$. Thus, the “availability” $a(i, j)$ reflects how appropriate filter $w_{ki}$ chooses filter $w_{kj}$ as its exemplar by considering the support from other filters that filter $w_{kj}$ should be an exemplar. Lastly, the min() limits the influence of strong positive responsibilities, such that the total sum cannot go above zero.

For $i = j$, the “self-availability” is defined as

$$a(i, i) \leftarrow \sum_{i', s.t. i' \neq i} \max(0, r(i', i))$$  \quad \quad \quad (7)

which reflects suitedness that filter $w_{kj}$ is an exemplar, based on the positive responsibilities from other filters.

The updating of “responsibility” and “availability” is iterative. To avoid the numerical oscillations, we consider the weighted sum for each message at the $r$th updating stage

$$r'(i, j) = \lambda \times r(i-1)(i, j) + (1 - \lambda) \times r'(i, j)$$  \quad \quad \quad (8)

$$a'(i, j) = \lambda \times a(i-1)(i, j) + (1 - \lambda) \times a'(i, j)$$  \quad \quad \quad (9)

where $0 \leq \lambda \leq 1$ is a weighted factor and is set to 0.5 in our experiments.

After a fixed number of iterations (200 in our experiments), filter $w_{ki}$ selects as its exemplar another filter $w_{kj}$ that satisfies

$$\arg\max_j r(i, j) + a(i, j) \quad \text{s.t.} \quad 1 \leq j \leq c_k$$  \quad \quad \quad (10)

When $i = j$, filter $w_{ki}$ selects itself as the exemplar. All the selected filters make up the exemplars $\hat{w}_k$. Thus, the number of exemplars, i.e., $\hat{c}_k$, is self-adaptive without the human designation. In Section IV-F, we demonstrate that the exemplar selection can be efficiently implemented on a single CPU, leading to a magnitude-order reduction of time consumption.

### C. Weight Initialization

The pruned network architecture consists of the number of exemplar filters in each layer, i.e., $\hat{c}_k$. The fine-tuning is required to recover the accuracy of pruned network such that it would keep a better or at least comparable performance against the pretrained model. Thus, the key now falls in how to feed a good weight initialization to the pruned network architecture for the follow-up fine-tuning. To that effect, we consider the following four different weight initialization scenarios:

1. **Exemplar Weights**: The weights of exemplar filters are regarded as the initial weights. To ensure the dimension
consistency between the exemplar filters $\tilde{w}_k$ with the shape of $\tilde{c}_k \times (\tilde{c}_{k-1} \cdot h_k \cdot w_k + 1)$ and pruned network parameters $\hat{w}_k$ with the shape of $c_k \times (c_{k-1} \cdot h_k \cdot w_k + 1)$, the corresponding channels in the weights of exemplars are removed directly.

2) Random Projection: Instead of directly removing the corresponding channels in the weights of exemplars, we apply the sparse random projection [41] to reduce the dimension of exemplars, which is able to preserve the similarity between data points as demonstrated in [42].

3) $l_1$-Norm Weights: Filters with large norms are believed to have the ability to retain more information, thus the corresponding weights are inherited as a warm-up for the follow-up fine-tuning [26]. Such a scenario has been widely known in the network pruning.

4) Random Initialization: Recent progress [36] shows that the essence of filter pruning lies in finding the optimal pruned architecture, and that random initialization with Gaussian distribution can perform better than inheriting the most important filters. Thus, we also consider random Gaussian distribution.

We use the exemplar weights by default. In Section V, we conduct ablation study with regard to these different ways of initialization and justify the correctness of inheriting the most important filters in the literature.

IV. EXPERIMENTS

We apply the proposed EPPruner on the CIFAR-10 benchmark [43] using three classic deep networks including VGGNet [1], GoogLeNet [37] and ResNets [38], and the ILSVRC-2012 benchmark [44] using ResNets [38] with different depths. VGGNet contains sequential convolutions, GoogLeNet has the convolutions with multiple branches, and ResNet is especially designed with residual blocks. Fig. 2 outlines our pruning strategy for the three kinds of networks. We carry out our experiments on NVIDIA Tesla V100 GPUs. All models are implemented and trained using Pytorch [45].

A. Implementation Details

1) Training Settings: We fine-tune all models by using stochastic gradient descent (SGD) optimizer with a momentum of 0.9 and the batch size is set to 256. Also, on CIFAR-10, we use a weight decay of $5 \times 10^{-3}$ and 150 epochs are given for fine-tuning. The learning rate starts from 0.01 and is reduced by a factor of 10 after 50 and 100 epochs. On ILSVRC-2012, the weight decay is set to $1 \times 10^{-4}$ and we fine-tune the networks for 90 epochs. The learning rate is initially set to 0.1 and divided by 10 every 30 epochs. Without specifications, for all methods, we apply the random crop and horizontal flip to the input images, which are also official operations in Pytorch. To stress, other techniques for image augmentation, such as lightening and color jitter, can be applied to further improve the accuracy performance as done in the source codes of [24], [46], and [47]. Besides, the cosine scheduler for learning rate can also be used to replace the step learning, which also has been demonstrated to be able to boost the performance in [12], [48], and [49]. We do not consider these in this article because we aim to show the performance of pruning algorithms themselves.

2) Performance Metrics: We report channels, floating-point operations (FLOPs), and parameters to measure the effect of pruning. Channels reflect the memory footprint. FLOPs and parameters reflect the computation cost and storage space, respectively. Also, their corresponding pruning rates are reported. Besides, for CIFAR-10, top-1 accuracy of pruned models is provided. For ILSVRC-2012, both top-1 and top-5 accuracies are reported.

B. Testing Results on CIFAR-10

Table II displays our pruning results for VGGNet, GoogLeNet, and ResNets on CIFAR-10. More detailed analyses are provided in the following.

1) VGGNet: We choose to prune the 16-layer VGGNet model on CIFAR-10. As can be seen from Table II, EPPruner
We apply the proposed EPruner to VGGNet-16 [1], GoogLeNet [37], and ResNets with different depths of 56 and 110 [38] and evaluate these models on the CIFAR-10 benchmark. The channels, FLOPs, parameters, and top-1 accuracy are reported. The numerical value after EPruner denotes the value of $\beta$.

| Model       | Top-1-acc | $\beta$ | Channels | Pruning Rate | FLOPs | Pruning Rate | Parameters | Pruning Rate |
|-------------|-----------|---------|----------|--------------|-------|--------------|------------|--------------|
| VGGNet-16   | 93.02%    | 1.00%   | 4224     | 0.00%        | 314.59M | 0.00%        | 14.73M     | 0.00%        |
| EPruner-0.73| 93.08%    | 0.60%   | 1363     | 0.76%        | 74.42M  | 0.76%        | 88.80%     |              |
| GoogLeNet   | 95.05%    | 0.00%   | 7904     | 0.00%        | 1539.55M| 0.00%        | 6.71%      | 0.00%        |
| EPruner-0.65| 94.99%    | 0.06%   | 6110     | 0.20%        | 500.87M | 0.20%        | 57.72%     |              |
| ResNet-56   | 93.26%    | 0.00%   | 2032     | 0.00%        | 127.62M | 0.00%        | 0.85%      | 0.00%        |
| ResNet-56 0.5x | 91.90% | 1.36%   | 1528     | 24.80%       | 63.80M  | 49.61%       | 0.43M      | 49.82%       |
| EPruner-0.76| 93.18%    | 0.08%   | 1450     | 28.64%       | 49.35M  | 61.33%       | 0.39M      | 54.20%       |
| ResNet-110  | 93.36%    | 0.00%   | 4048     | 0.00%        | 237.93M | 0.00%        | 1.73M      | 0.00%        |
| ResNet-110 0.4x | 92.69% | 0.81%   | 2806     | 30.68%       | 97.90M  | 61.13%       | 0.67M      | 61.62%       |
| EPruner-0.60| 93.62%    | 0.12%   | 2580     | 36.26%       | 87.65M  | 65.91%       | 0.41M      | 76.30%       |

greatly simplifies the model complexity by reducing 67.73% channels, 76.34% FLOPs, and 88.80% parameters; meanwhile, it still obtains an accuracy improvement of 0.06% (93.08% for EPruner versus 93.02% for the baseline). This greatly facilitates VGGNet model, a popular backbone for object detection and semantic segmentation, to be deployed on mobile devices. Hence, EPruner demonstrates its ability to compress and accelerate the neural network with the sequential structure.

2) GoogLeNet: For GoogLeNet, as summarized in Table II, EPruner removes 22.70% channels, 67.36% FLOPs, and 64.20% parameters with a negligible accuracy drop (94.99% for EPruner versus 95.05% for the baseline). Besides, we observe that for GoogLeNet, the channel reduction is not so high as that in VGGNet. To analyze, as shown in Fig. 2, we do not prune the branch with only one convolutional layer and the last convolutional layer in the branch with more than one layer is also not pruned, which explains the above observation. Nevertheless, as can be seen, the reductions of FLOPs and parameters are still significant. Hence, EPruner can be well applied in the neural network with a multibranch structure.

3) ResNets: To evaluate the power of EPruner in complexity reduction for network with residual blocks. We choose to prune ResNets with different depths of 56 and 110.

As summarized in Table II, EPruner boosts the computation by decreasing about 61.33% FLOPs for ResNet-56 and 65.91% FLOPs for ResNet-110, and it also saves more than half storage space by reducing 54.20% parameters for ResNet-56 and 76.30% parameters for ResNet-110. Comparing ResNet-56 with ResNet-110, we observe that more FLOPs and parameters are reduced in ResNet-110. The potential reason might be that the deeper ResNet-110 suffers more overparameterized burden. Besides, it can also be observed that, similar to GoogLeNet, the channel reduction for ResNets is also limited. As explained in Fig. 2, we do not prune the convolution in the skip connection and the last convolutional layer in the residual block. Lastly, we can see that EPruner can well maintain the accuracy performance of the baseline model.

For ResNet-56, EPruner leads to little accuracy loss (93.18% for EPruner versus 93.26% for the baseline), whereas for ResNet-110, EPruner gains an obvious accuracy improvement of 0.12%. The above observations verify the effectiveness of EPruner in compressing and accelerating the residual-designed networks.

Besides, Table II also displays the results of uniform pruning. The digit after the network denotes the percentage of preserved filters in each layer of the network. As can be seen, our EPruner outperforms uniform pruning with regard to the accuracy performance even with more reductions of the model complexity, which well demonstrates that EPruner can return an adaptive pruned network architecture with a better performance.

Also, we observe that the performance of pruned VGGNet-16 and ResNet-110 is better than that of the models before pruning. The rationale behind this is that pruning a big neural network to a smaller one also has the advantage of avoiding overfitting and improving generalization [50], [51]. The VGGNet-16 and ResNet-110 are two overparameterized networks, which often result in an overfitting problem when trained on the small CIFAR-10. Our network pruning helps to relieve overfitting and improve generalization as discussed above, and thus better performance can be observed.

C. Testing Results on ILSVRC-2012

Table III presents the pruning results of the proposed EPruner using ResNets with different depths of 18/34/50/101/152 on the large-scale ILSVRC-2012.

As can be observed from Table III, the accuracy performance for compressed models on ILSVRC-2012 generates more compared with that on CIFAR-10. For an in-depth analysis, ILSVRC-2012 is a large-scale benchmark with 1000 categories, which poses a greater challenge, compared with small-scale CIFAR-10 containing only ten categories, to recognize the images using the compressed models. Nevertheless, as can be seen, the drops of accuracies are still tolerable. Besides, we observe that the efficacy of EPruner is more advantageous in compressing deeper networks. For example, in the deepest ResNet-152, EPruner achieves a 65.12%-FLOPs reduction by removing 64.18% parameters and 18.52% channels, with only 1.48% top-1 and 0.71% top-5 accuracy loss. While in ResNet-18, 43.88% FLOPs and 48.25% parameters and 10.00% channels are removed with more accuracy drops of 2.35% in the top-1 and 1.38% in the top-5. To explain, the shallow ResNet-18 has less redundancies thus more accuracy drops occur even with less reduction of model complexity. Nevertheless, this observation
### Table III
We apply the proposed EPruner to ResNets with different depths of 18, 34, 50, 101, and 152 [38] and evaluate these models on the ILSVRC-2012 benchmark. The channels, FLOPs, parameters, top-1 and top-5 accuracies are reported. The numerical value after EPruner denotes the value of $\beta$.

| Model     | Top-1-acc | Top-3-acc | FLOPs | Parameters | Pruning Rate |
|-----------|-----------|-----------|-------|------------|--------------|
| ResNet-18 | 69.66%    | 89.08%    | 4800  | 11.69M     | 0.00%        |
| ResNet-18 0.55x | 66.93% | 87.21% | 3992  | 41.75% | 7.73M | 42.46% |
| EPruner-0.73 | 67.31% | 87.70% | 3888  | 6.05M | 48.25% |
| ResNet-34 | 73.28%    | 91.45%    | 8512  | 0.00%     | 21.90M       |
| ResNet-34 0.5x | 69.98% | 88.89% | 6624  | 48.06% | 11.25M | 48.39% |
| EPruner-0.75 | 70.95% | 89.97% | 6684  | 41.83% | 6.06M | 48.25% |
| ResNet-50 | 76.01%    | 92.96%    | 26590 | 0.00%     | 25.50M       |
| ResNet-50 0.55x | 74.00% | 91.43% | 23144 | 50.97% | 13.40M | 47.56% |
| EPruner-0.73 | 74.26% | 91.88% | 22995 | 13.57% | 12.70M | 50.31% |
| ResNet-101 | 77.38%    | 93.59%    | 52672 | 0.00%     | 45.55M       |
| ResNet-101 0.45x | 74.30% | 92.01% | 43710 | 63.73% | 17.42M | 60.89% |
| EPruner-0.67 | 75.45% | 92.70% | 42843 | 18.66% | 64.20% | 65.10% |
| ResNet-152 | 78.31%    | 93.99%    | 75712 | 0.00%     | 60.19M       |
| ResNet-152 0.45x | 75.91% | 92.83% | 62516 | 65.13% | 22.42M | 62.75% |
| EPruner-0.63 | 76.83% | 93.28% | 61688 | 18.52% | 40.67% | 64.18% |

### Table IV
We compare the proposed EPruner with several SOTAs using ResNet-50 [38] on ILSVRC-2012, including THInet [27], CP [19], SSS [35], GAL [23], MetaPruning [24], HRank [25], and ABCPruner [30]. Following [24], [30], the FLOPs, top-1 accuracy, and the training/fine-tuning epochs of the compressed model are reported.

| Model   | Top-1-acc | Top-5-acc |
|---------|-----------|-----------|
| ResNet-18 | 69.66% | 89.08% |
| ResNet-18 0.55x | 66.93% | 87.21% |
| EPruner-0.73 | 67.31% | 87.70% |
| ResNet-34 | 73.28% | 91.45% |
| ResNet-34 0.5x | 69.98% | 88.89% |
| EPruner-0.75 | 70.95% | 89.97% |
| ResNet-50 | 76.01% | 92.96% |
| ResNet-50 0.55x | 74.00% | 91.43% |
| EPruner-0.73 | 74.26% | 91.88% |
| ResNet-101 | 77.38% | 93.59% |
| ResNet-101 0.45x | 74.30% | 92.01% |
| EPruner-0.67 | 75.45% | 92.70% |
| ResNet-152 | 78.31% | 93.99% |
| ResNet-152 0.45x | 75.91% | 92.83% |
| EPruner-0.63 | 76.83% | 93.28% |

is meaningful because deeper networks are more constrained in the resource-limited environment.

Moreover, similar to the observation in Table II, EPruner also has an advantage in its supreme performance in comparison with the uniform pruning even on the large-scale ILSVRC-2012, which again well demonstrates the effectiveness of our EPruner in reducing the model complexity while retaining a better performance.

### D. Comparison With Other Methods

Further, we compare our EPruner with several SOTAs including rule-based pruning [19], [25], [27], regularization-driven pruning [23], [35], and architecture-search-driven pruning [24], [30]. Following [24] and [30], the experiments are implemented using ResNet-50 on ILSVRC-2012 and we report the FLOPs, top-1 accuracy, and the training/fine-tuning epochs of the compressed model for all methods in Table IV.

### E. In-Depth Analysis

The experiments in Tables II–IV show that EPruner can be well applied to reduce the complexity of CNNs while keeping a better or at least comparable accuracy performance against the pretrained models or state-of-the-art methods. The efficacy of our EPruner is mainly from two points: self-adapting to the optimal pruned architecture and inheriting the most important filter weights.

1) Adaptive Pruned Architecture: Rule-based and regularization-driven pruning require the involvement of human labor to designate the pruned architecture or
TABLE V
Comparisons of Pruned Architecture With Different Weight Initialization. We set the value of $\beta$ as that in Tables II and III for Each Network and Report the Top-1 (Top-5) Accuracy

| Network        | Exemplar Weights (%) | Random Projection (%) | $\ell_1$-norm weights (%) | Random Initialization (%) |
|----------------|----------------------|-----------------------|---------------------------|---------------------------|
| VGGNet-16      | 93.08                | 92.95                 | 92.98                     | 92.61                     |
| GoogLeNet      | 94.99                | 94.49                 | 94.41                     | 94.19                     |
| ResNet-36      | 93.18                | 92.44                 | 93.03                     | 91.43                     |
| ResNet-110     | 93.62                | 93.02                 | 92.99                     | 92.44                     |
| ResNet-18      | 67.31(87.42)         | 66.68(87.45)          | 67.01(87.42)              | 66.46(87.13)              |
| ResNet-34      | 70.95(89.97)         | 70.79(89.91)          | 70.76(89.93)              | 70.71(89.78)              |
| ResNet-50      | 74.26(91.88)         | 73.80(91.83)          | 73.99(91.82)              | 73.54(91.55)              |
| ResNet-101     | 75.45(92.70)         | 75.31(92.51)          | 75.40(92.58)              | 75.12(92.25)              |
| ResNet-152     | 76.51(93.32)         | 76.43(93.14)          | 76.46(93.20)              | 76.15(92.97)              |

TABLE VI
Comparisons of Time Consumption on Finding Out the Pruned Network Architecture Between EPruner Tested on NVIDIA Tesla V100 GPUs and EPruner Tested on Intel(R) Xeon(R) CPU E5-2620 V4 @2.10 GHz

| Network        | ABCPruner GPUs | EPruner (Ours) CPUs |
|----------------|---------------|-------------------|
| VGGNet-16      | 3387.24s      | 1.29s             |
| GoogLeNet      | 26967.65s     | 1.16s             |
| ResNet-36      | 5810.51s      | 0.38s             |
| ResNet-110     | 10565.27s     | 0.73s             |
| ResNet-18      | 28537.16s     | 1.22s             |
| ResNet-34      | 39266.24s     | 2.27s             |
| ResNet-50      | 43534.72s     | 2.83s             |
| ResNet-101     | 70181.66s     | 8.53s             |
| ResNet-152     | 75272.32s     | 12.40s            |

hyperparameter analysis, results of which are usually suboptimal, whereas architecture-search-driven pruning has to be rerun for some time to pick up the best one. To analyze EPruner, we show the layerwise pruning when $\beta = 0.73$ using VGGNet-16 in Fig. 3. As can be seen, the pruning rate varies across different layers. More filters are preserved in the middle layers (3_2 to 4_1) while the other layers tend to remove more filters. By selecting the exemplars through message passing among filters, EPruner self-adapts to the filter property and derives the deterministic optimal pruned architecture without human involvement.

2) Important Filter Weights: Recent work [36] shows that the essence of filter pruning lies in finding the optimal pruned architecture rather than selecting the most important filter weights as in [18], [25], and [26]. In Table V, we show a different observation by feeding the pruned architectures with different initial weights as stated in Section III-C. From Table V, using exemplar weights obtains the best accuracy performance, whereas random projection of exemplar weights and weights with larger $\ell_1$-norm feed back the second best, three of which show consistently higher performance than the random initialization. It indicates that the pretrained exemplar weights are already a “distilled” piece of information from the large-scale training data of CNNs, thus they can provide a better warm-up for fine-tuning, which rejustifies the correctness of inheriting the most important filter weights. We assume that the criteria for measuring the most important filter weights in previous rule-based pruning methods are not robust and supportive, thus random initialization shows better results [36].

F. Ablation Study

In this section, we show the influence of $\beta$ and the comparison of practical time consumption in finding out the optimal pruned architecture.

1) Influence of $\beta$: The $\beta$ is used to make the reduction of model complexity more adjustable. As stressed in Section III-B, smaller $\beta$ leads to more exemplars, thus fewer reductions of model complexity, but better accuracy performance. To demonstrate this, Fig. 4 shows the influence of $\beta$ by using VGGNet-16 on CIFAR-10. Fig. 4(a) verifies our analysis. The accuracy performance is relatively stable when $\beta$ falls within 0.0-0.7. It starts to drop as $\beta$ increases, which makes sense because the pruning rate drastically goes up at the point of $\beta = 0.7$. Then we show a more subtle interval with $\beta$ ranging from 0.7 to 0.8 in Fig. 4(b). As can be seen, the suitable value of $\beta$ would be between 0.72 and 0.73. Note that, $\beta$ is used to reach the expected reduction of model complexity, which however does not involve in the process of finding the optimal architecture, which lessens human labors.

2) Practical Time Consumption: We choose ABCPruner, which shows the best efficiency and effectiveness among compared methods, for comparison. Table VI shows the practical time consumption on finding out the pruned architecture between EPruner and ABCPruner. As can be seen, ABCPruner requires a large search time on NVIDIA Tesla V100 GPUs, even multiple GPUs are necessary in deeper networks, e.g., ResNet-152. The consumption would be significantly heavy in other platforms, such as GTX-1080TI GPUs and CPUs, which is unacceptable. In comparison, EPruner can find out the pruned architecture in seconds simply on CPUs, a magnitude-order reduction of time consumption. To analyze, ABCPruner is a data-driven approach where the training data has to be used to train each potential architecture for some epochs and evaluate its fitness by observing the accuracy, whereas EPruner selects the exemplars among filters, which is data-independent and thus more efficient.

V. Conclusion

In this article, we present a novel filter-pruning method, called EPruner, which aims to select exemplars among filters. To that effect, we regard the filters as a set of high-dimensional data points and the affinity propagation is applied to generate high-quality exemplars. The lack of human involvement and parameter analysis makes the implementation simpler and more effective. The optimal architecture with EPruner can be efficiently implemented within a few seconds simply on GPUs.
the CPUs, leading to a magnitude-order reduction of time consumption. We show that the weights of exemplars can serve as a better warm-up for fine-tuning the network, which justifies the correctness of inheriting the most important filter weights. We demonstrate the applicability of EPruner in compressing various networks and its superiorities over competing SOTAs.

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