Pruning Algorithms to Accelerate Convolutional Neural Networks for Edge Applications: A Survey

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Abstract

With the general trend of increasing Convolutional Neural Network (CNN) model sizes, model compression and acceleration techniques have become critical for the deployment of these models on edge devices. In this paper, we provide a comprehensive survey on Pruning, a major compression strategy that removes non-critical or redundant neurons from a CNN model. The survey covers the overarching motivation for pruning, different strategies and criteria, their advantages and drawbacks, along with a compilation of major pruning techniques. We conclude the survey with a discussion on alternatives to pruning and current challenges for the model compression community.

1 Introduction

Deep Learning has become the de-facto approach in many Machine Learning (ML) problems, such as computer vision, natural language processing, and robotics. CNN architectures and models have surpassed human performance in many such challenges. These advancements are a result of innovation in various research directions, including network architectures, optimization methods, and software frameworks. However, these breakthroughs have come at the cost of ever increasing model sizes and computation loads. Therefore, model compression becomes an important topic when CNN models are applied in practice, especially for edge applications.

In ML deployment scenarios, a lightweight compressed model has numerous advantages. On the server side, a smaller model reduces bandwidth usage and power consumption within a data center leading to savings in operational cost. Further, deploying these CNN models on the client side (embedded or edge device) comes with the concomitant advantages of privacy, low latency, and better customization [22]. However, in such scenarios they face more restricted resource requirements and need to be carefully tuned for optimal performance. Hence, model compression has garnered more research interests in the recent years with advances in techniques such as Pruning, Quantization, and Low Rank Decomposition.

Since CNNs are commonly over-parameterized, pruning non-critical or redundant neurons is a reasonable option to reduce the model size and floating-point operations (FLOPs) at runtime [2]. Directly searching for the best combination of neurons to be pruned is an NP-hard problem and typically not feasible for a CNN with millions of parameters [8]. Also, a pruned network with high sparsity may not lead to practical benefits. Therefore, a successful pruning algorithm needs to be efficient while reducing model size, improving inference speed, and maintaining accuracy.

In this paper, we provide a comprehensive survey of the algorithmic aspects of model pruning for CNNs with a focus on edge deployment. We identify the development trends and point out the current areas of focus. More importantly, we identify the drawbacks and challenges of these approaches and provide users with a better understanding of the trade-offs and avenues for future study.

2 Pruning Methodology

The problem of pruning is formulated as follows: given a labelled dataset with \( N \) samples, \((x_i, y_i), i \in 1 \ldots N\), find the best light-weight CNN model that takes an input \( x_i \) and predicts its label \( t_i = f(w, x_i) \), where \( w \) represents the model parameters. For convolution layers, a weight \( w_{c,i,j} \) is the 4D kernel to convert \( c \) input channels into \( c' \) output channels with spatial convolution over \( i, j \) directions. The prediction performance is defined as the accuracy \( \sum_{i=1}^{N} \delta_{y_i=t_i} \) and the un-pruned model minimizes the loss function (for accuracy) \( \sum_{i=1}^{N} \mathcal{L}(y_i, t_i) \), served as a baseline model.

The hardware limits for edge lie in Processor architecture and speed, Memory, Power/Energy consumption, and Inference latency. In practice, analytical proxies, such as FLOP or number of parameters, for theoretical and computational efficacy are commonly used. In this paper, we differentiate between the actual and analytical proxy results when necessary.

Current research in pruning is divided into two components: identifying the most promising neurons to be pruned; and training and finetuning the pruned model to recover the base model’s prediction performance. A successful pruning algorithm is an iterative progression of these components as illustrated in Algorithm 1 [26], and improvements in the state-of-the-art come from advances in one or both of these aspects. Therefore, we categorize existing algorithms into these two categories for clarity in the following sections. We report their compression performance in Table 2.
2.1 Pruning Criteria

Different heuristic criteria were developed to identify the promising structures to be pruned without harming the prediction performance. We classify these criteria into two categories: data-agnostic and data-driven where data-agnostic techniques compute saliency criteria without using the training data directly. Early works [10, 26] relied on the second-order Hessian matrix, $H_{ij} = \frac{\partial^2 E}{\partial w_i \partial w_j}$, to identify the weights to be removed without harming model predictability. However, these approaches also require intensive computation of the second-order derivatives of the weights (and matrix inversion [10]).

To alleviate the training burden, [40] proposed to merge weights by their value similarity. They demonstrated their success on fully-connected layers, which may dominate the model size.

Contradictory to pruning unimportant weights all at once [26], [9] used simple weight values as saliency to prune them iteratively. At each pruning iteration, the weights with L2 norms below a given threshold are located and masked out in the subsequent training and inference stages. Despite its simplicity, the iterative procedure helps the pruned model to recover and maintain its accuracy and has been commonly used in pruning approaches.

The above pruning approaches can significantly reduce both model size and compute, but reducing FLOPs is not directly linked with inference speedup, especially for deep CNNs, as the weights are replaced by sparse matrices [25]. To alleviate such problems, pruning structural components is needed. [25] proposed to group weights on output channels before applying the L1-norm penalty. This structured pruning leads to a smaller rate. The iterative procedure, (training, pruning, and then retraining) helps the pruned model to recover and maintain its accuracy and has been commonly used in pruning approaches.

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2.2 Pruning Procedure

With the above-mentioned saliency measures, early studies adopted a direct threshold on model weights and masked them out in the following iterations. However, such pruning approaches typically deteriorate model predictive performance and require a retraining step to recover the model prediction accuracy before further pruning (as illustrated in Fig. 1 (b)). The iterative procedure, (training, pruning, and then retraining) is important for a successful pruning strategy [27]. Below, we discuss the research on improving this pruning procedure.

Selecting a pre-defined threshold has three major drawbacks as 1) the threshold is not linked to sparsity directly; 2) different layers have different sensitivity; 3) a one-time threshold may cut off too much information to restore the original accuracy. [55] analyzed a gradual increasing threshold schedule to prune network weights automatically to the final target sparsity. Another approach to solve the challenge of selecting the best thresholds for each layers, [42] adopted Bayesian optimization to automatically tune the values as a Gaussian process.

Instead of pruning with a step function, [8] proposed a splicing function to mask the weights. Without an extreme

Data: CNN model, training data
while Compression requirement not met or exceed budget do
    train model (to convergence);
    compute pruning criteria;
    prune parameters below threshold;
end

Algorithm 1: Workflow for model pruning.

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When training the compressed model, as shown in Fig. 1 (a)), with the retraining process and leads to a significant speed up variables scale filters and are regularized by the L1-norm. [50] layers to learn a masking to reduce the model size efficiently. These methods relied on auxiliary schedule. [46] treated the masking variables as scaling for the proposed a similar approach but with a novel tick-tock update 

Many L1/2 norm-based penalties mentioned earlier are the approximation to the L0-norm problem, however they can lead to unstable and sub-optimal solutions. Several studies worked on novel optimization methods to solve the problem. [54] translated this problem to an alternative one and solved it by using forward-backward splitting algorithm to optimize an L2.1-norm instead. Compared to other penalizing forms, this approach provides a better approximation to the original optimization problem. [20] adopted the Accelerated Proximal Gradient (APG) method to solve the problem with scaling factors similar to [8] but at various structure levels to improve the performance on state-of-the-art compact CNN models. [28] learned gating masks via Alternating Direction Method of Multipliers (ADMM)-based optimization.

With advances in Reinforcement Learning (RL) research, there are many studies applying RL to model pruning. [19] built an individual gradient policy learner for each layer of a CNN model to prune filters for an overall reward combining the accuracy and efficiency terms. [14] adopted a deep deterministic policy gradient to continuously control the compression ratio for a balanced target of accuracy and resource consumption. [5] adopted Neural Architecture Search (NAS) to balance model performance by exploring the width and depth of a network.

In summary, the innovations for pruning procedures are classified into the following three directions of improvement: 1) efficient iterative procedure; 2) representative masking method; 3) robust learning to prune network along with training.

### 3 Discussion

#### 3.1 Comparison

Table 2 provides a compilation for model compression algorithms. We collected the results for two datasets, CIFAR-10 and ImageNet [23, 38]. The former is a small dataset where we expected to see significant improvement over the baseline. We reported results with VGG or ResNet models only [11, 39]. The ImageNet dataset is challenging but more realistic and, for
that reason, we included other popular CNN models, namely, AlexNet and MobileNet [16, 24].

We reported the best pruned model with the following three measures:

- **Accuracy reduction** measures the model degradation as the difference in accuracy between the pruned model and the original model. A smaller value is better and a negative value indicates that the pruned model is better than the original model.
- **Size reduction** measures the ratio of the reduction in size (i.e., number of parameters) over the original model size.
- **Time reduction** measures the ratio of the reduction in time or FLOP over the original model.

Overall, we observed that pruning leads to between a 10% and 90% reduction on both size and inference time. As commonly expected, the compression for a more challenging problem such as the ImageNet dataset, is harder than for the CIFAR-10 dataset. Unexpectedly, we found that a reduction in size is not linearly correlated with an improvement in inference speed. More profoundly, we found that only a few studies have tested their performance on physical devices, which is often not well captured by FLOP. Finally, we found that there is limited research using the data-aware approach for filter pruning, making that an interesting direction for further study.

3.2 Other Approaches

Model compression techniques have varying advantages and disadvantages when compared with each other. Low Rank Decomposition [2] uses linear algebra to reduce the model’s weight matrices with rank decomposition. This approach allows for a mathematically sound reduction in model size and computation speed up. However, training each model requires a custom and complicated implementation procedure, which is a challenge. Quantization [41] is another popular compression technique which involves replacing high precision floating points in CNN weight matrices with lower precision representations. It has the distinct advantage of being both universal across different models and offering consistent performance improvements (depending on the implementation). However, it requires innate hardware support for these gains to be realized. Moreover, precision sensitivity can lead to performance deterioration. Finally, handcrafted smaller architectures such as MobileNet [16] have also enjoyed success in deployment under edge scenarios, however designing a custom architecture for different edge settings results in excessive cost and effort, and cannot be scaled.

Another interesting direction is to dynamically prune the network at runtime. [4] and [18] used additional structure to filter the unimportant features and reduced the runtime for inference. With small auxiliary connections, [6] boost the important features and suppress the irrelevant ones to reduce computation and improve inference speed.

3.3 Combined Approaches

We also observed few studies on combining different compression approaches. [52] combined low rank decomposition with pruning by threshold and successfully compressed the model size by more than 10 times for AlexNet and VGG-16 models, without losing accuracy on the ImageNet dataset. [43] used the minimum description length principle to achieve quantization and pruning coherently via Bayesian variational inference. However, an ablation study on the effectiveness of joint approaches is still missing and a systematic study would be extremely helpful to guide practitioners in this field.

3.4 Advantages and Limitations

CNN pruning has gained attention alongside the rapid development in CNN research. It provides the following benefits:

- **Model size reduction**: leveraging on the redundant information carried in a CNN model, a natural consequence of pruning is the reduced size of an input model, making it an important step for deploying models on the edge.
- **Inference time reduction**: most of the pruning methods targeted to CNN models provide structural pruning rather than pruning at the individual weight level. These algorithms lead to a realistic inference time reduction for deployment.
- **Universal compression approach**: pruning methods are generally model independent, which can be applied to any given model architecture with minor modification. Meanwhile, a pruned model can be deployed to current hardware environment without extensive engineering for implementation, as compared to the quantization methods.

There are still a few limitations prevent pruning becoming practical in industry settings for edge deployment.

- **Long training time**: the typical workflow of network pruning, i.e. Algorithm 1, requires iterative model training for each pruned network, which can significantly increase the time required to build these models. Approaches such as [8] speed up the training and pruning with a better update schema, but there is still no one-shot solution to prune a network with minimal cost;
- **Extensive hyperparameter finetuning**: all of the pruning strategies require a set of hyperparameters to finely balance the compression ratio and the model accuracy. Detailed analysis of the weights on each layer was required in the earlier approaches while recent techniques replace such requirements with more general global parameters and rely on hyperparameter optimization techniques (e.g. [29]) to speed up the tuning process;
- **Small but not fast**: as realized in many later studies, a plain pruning strategy might result in fewer weights and FLOPs, but it does not guarantee a faster model with less energy consumption. Building a realistic model to capture the correct physical resource consumption is a critical step to achieving practical model compression at runtime [1, 36].
- **Benchmark**: CNN architectures have experienced rapid development in recent years. Therefore, early pruning results, which are based on the over-parameterized CNN models, such as AlexNet and VGG-16 [24, 39], may not be effective for current efficient models. More recent
Table 2: Summary of pruning performance. The papers are ordered by publication year for each model.

| Ref | Model      | CIFAR-10 | ImageNet (Top-1) |
|-----|------------|----------|-----------------|
|     |            | Accuracy | Size | Time | Accuracy | Size | Time |
|     |            | Reduction| Reduction | Reduction | Reduction | Reduction | Reduction |
| [27] | VGG-16(c) | 0.0% | 64.0% | 34.2% | [25] | AlexNet | 0.0% | 89.0% | 70% |
| [3]  | VGG-16(c) | 0.3% | - | 79.7% | [19] | AlexNet(c) | -0.1% | - | 28.6%(p) |
| [19] | VGG-16(c) | 0.6% | 83.3% | 48.8%(p) | [44] | AlexNet(c) | -0.3% | 94.3% | - |
| [27] | ResNet-56(c) | 0.0% | 14.1% | 27.3% | [8]  | AlexNet | -0.2% | 95.6% | - |
| [14] | ResNet-56 | 0.9% | - | 50% | [30] | AlexNet | 0.2% | 92.5% | 79% |
| [12] | ResNet-56(c) | 0.2% | - | 52.6% | [19] | VGG-16(c) | 3.9% | 5.6% | 75% |
| [3]  | ResNet-56(c) | 0.1% | - | 60.9% | [14] | VGG-16 | 1.4% | - | 80.0% |
| [28] | ResNet-56(c) | 0.0% | 43.1% | 42.8% | [25] | VGG-19(c) | 0.7% | 55.0% | 50.0%(p) |
| [51] | ResNet-56 | 0.03% | 42.6% | 43.6% | [9]  | ResNet-18 | 0.4% | 91.5% | - |
| [50] | ResNet-56(c) | 0.03% | 66.7% | 70.3% | [20] | ResNet-50 | 0.7% | 0.8% | 15% |
| [17] | VGG-16 | -2.3% | 34% | 41.2%(p) | [12] | ResNet-50(c) | 1.5% | - | 41.8% |
| [34] | VGG-16 | -0.8% | 94.0% | 70.0% | [28] | ResNet-50 | 0.4% | 42.0% | 46.1% |
| [34] | ResNet-50 | -0.1% | 16% | 17.4% | [14] | MobileNetV1 | 0.7% | - | 34.6%(p) |
| [51] | ResNet-50 | 0.2% | 27.1% | 27.3% | [50] | ResNet-50(c) | 0.7% | 53.4% | 55.1% |

1 The mark (c) means that the pruning is for the convolutional structure only. Occasionally, the fully connected layers have been converted to convolution layers and been pruned.
2 The mark (p) means that the time reduction is measured on physical devices, otherwise, it is based on the FLOP.
3 Top-5 accuracy difference is reported.

Studies have gradually focused on light-weight networks, such as ResNet and MobileNet [11, 16]. However, a commonly accepted baseline is still missing for fair comparison.

Last but not least, the improvement in energy efficiency is not included in the above analysis. Most research in pruning reduce the amount computation, theoretically. However, other factors such as transferring data on to and off the chip takes energy comparable to that used for computation making the applicability of these studies limited when it comes to deployment on low power devices. To address this discrepancy, [49] included energy consumption analysis in their iterative pruning procedure. [48] showed that a magnitude-based pruning on SqueezeNet [21] can lead to higher energy consumption. Therefore, they proposed to model the energy consumption for each layer and prune layers based on their energy consumption to address this issue. [47] further modeled the energy consumption by bilinear regression, and optimized the energy using ADMM framework with the original loss.

The consensus procedure is that taking a pre-trained model and then iteratively retraining the model to adjust to the reduced representation leads to a better model than training the pruned model from scratch [9, 15, 27]. However, [32] found contradicting results that a model trained and pruned iteratively does not provide a significantly better performance than a pruned model trained from scratch for a given budget. This discrepancy is another area that needs further investigation.

4 Conclusion

As neural network models get larger and the push towards edge/IoT devices becomes more pronounced, there is need for techniques and best practices that allow for the creation of smaller efficient models. Pruning is one such technique that allows us to create a smaller model from an existing larger and over-parameterized model. In this paper we examined the constraints and metrics that motivate model compression, and formulated requirements of pruning algorithms.

We organized research in the field based on pruning criteria and pruning procedure. We further classified the pruning criteria into data-agnostic and data-aware approaches. Our hope is that this breakdown will provide guidance for future researchers to develop new algorithms and allow them to compare previous works effectively (in addition to the comprehensive comparison in Table 2).

The field of deep learning is accelerated by the development of tools and frameworks for model building and training. Except for a few examples such as PocketFlow and Distiller [45, 56], a general platform for pruning is generally missing. Our work also serves as a guidance to develop a universal compression pipeline by depicting the independent
components and procedures in the pruning process.

Finally, we provided an in-depth discussion on the limitations, advantages and novel research directions along with a comparison of the performance of major pruning techniques on standard datasets and models.

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