

Pruning Convolutional Neural Networks for Resource Efficient Transfer Learning

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Abstract

We propose a new framework for pruning convolutional kernels in neural networks to enable efficient inference, focusing on transfer learning where large and potentially unwieldy pretrained networks are adapted to specialized tasks. We interleave greedy criteria-based pruning with fine-tuning by backpropagation—a computationally efficient procedure that maintains good generalization in the pruned network. We propose a new criterion based on an efficient first-order Taylor expansion to approximate the absolute change in training cost induced by pruning a network component. After normalization, the proposed criterion scales appropriately across all layers of a deep CNN, eliminating the need for per-layer sensitivity analysis. The proposed criterion demonstrates superior performance compared to other criteria, such as the norm of kernel weights or average feature map activation.

1 Introduction

Convolutional neural networks (CNN) are used extensively in computer vision applications, including object classification and localization, pedestrian and car detection, and video classification. Many problems focus on specialized domains for which there are only small amounts of carefully curated training data. In these cases, accuracy may be improved by fine-tuning an existing deep network previously trained on a much larger labeled vision dataset, such as images from ImageNet [13] or videos from Sports-1M [5]. While this transfer learning supports state of the art accuracy, inference is expensive due to the time, power, and memory demanded by the heavy-weight architecture of the fine-tuned network. This is especially taxing in situations such as real-time video classification.

While modern deep CNNs are composed of a variety of layer types, runtime during prediction is dominated by evaluation of convolutional layers. With the goal of speeding up inference, we prune away entire feature maps so the resulting networks may be implemented without special hardware or software. We interleave greedy criteria-based pruning with fine-tuning by backpropagation, a computationally efficient procedure that maintains good generalization in the pruned network.

Neural network pruning was pioneered in the early development of neural networks [12]. Optimal Brain Damage [9] and Optimal Brain Surgeon [4] leverage a second-order Taylor expansion to select parameters for deletion, using pruning as regularization to improve training and generalization. This method requires computation of the Hessian matrix, which can be memory bounded for modern networks and requires extra computation. We show that even the first-order Taylor expansion of a different metric can be used to efficiently estimate importance of feature maps.

Our approach is in line with existing work in structured pruning [1], while largely orthogonal to fine-grained pruning of fully-connected layers [3] and speedup by reduced precision [2] or tensor decomposition [6].

We focus on transfer learning where unwieldy pretrained networks are adapted to specialized tasks. After adaptation, networks may no longer need the full capacity they once required to learn a much larger problem, and the risk of overfitting may render the extra parameters a liability. However,

the proposed approach can applied for non-transfer learning networks. Additional analysis in the non-transfer setting is the focus of future study.

2 Method

The proposed scheme for pruning consists of these steps: 1) Fine-tune the network until convergence on the target task; 2) Alternate between iterations of pruning and fine-tuning; 3) Stop pruning when the required trade-off between accuracy and pruning objective (e.g. FLOPs or memory) is reached.

During training, with accuracy as the primary consideration, the parameters¹ of a deep convolutional neural network \mathcal{W} are optimized to minimize a cost function $\mathcal{C}(\mathcal{D}|\mathcal{W})$ w.r.t. training set \mathcal{D} . In the case of transfer learning, we adapt a large network initialized with parameters \mathcal{W}_0 pretrained on a related but distinct dataset.

During pruning, we select and refine a subset of these parameters, $\mathcal{W}' \subset \mathcal{W}$, that preserves the accuracy of the adapted network, $\mathcal{C}(\mathcal{D}|\mathcal{W}') \approx \mathcal{C}(\mathcal{D}|\mathcal{W})$, when all other weights are omitted. This corresponds to a combinatorial optimization:

$$\min_{\mathcal{W}'} \left| \mathcal{C}(\mathcal{D}|\mathcal{W}') - \mathcal{C}(\mathcal{D}|\mathcal{W}) \right| \quad \text{s.t.} \quad \|\mathcal{W}'\|_0 \leq B,$$

where the ℓ_0 norm in $\|\mathcal{W}'\|_0$ bounds the number of non-zero parameters in \mathcal{W}' . While it is not possible to solve this optimization exactly for networks of any reasonable size, in this work we investigate a class of greedy methods. Starting with a full set of parameters \mathcal{W} , we iteratively identify and remove the least important parameters, as illustrated in Figure 1. By removing parameters at each iteration, we ensure the eventual satisfaction of the ℓ_0 bound on \mathcal{W}' .

However, minimizing the difference in accuracy between the full and pruned models depends on the criterion for identifying the “least important” parameters at each step. The best criterion would be an exact empirical evaluation of each parameter, accomplished by ablating each remaining parameter $w \in \mathcal{W}'$ in turn and recording the difference in cost, $|\mathcal{C}(\mathcal{D}|\mathcal{W}' - \{w\}) - \mathcal{C}(\mathcal{D}|\mathcal{W}')|$. While optimal for this greedy procedure, such an *oracle* is prohibitively costly to compute as it requires $\|\mathcal{W}'\|_0$ evaluations on a validation set.

Criteria for pruning. There are many heuristic criteria which are more computationally efficient than the oracle, and we evaluate several for ranking parameter importance. For the specific case of evaluating the importance of a feature map (and implicitly the set of convolutional kernels by which it is computed), reasonable criteria include: the combined ℓ_2 -norm of the kernel weights, the mean or standard deviation of the feature map’s activation, and mutual information between activations and predictions.

We also propose a new criterion that estimates cost of pruning using a Taylor expansion. Consider a “neuron” h parameterized by $w \in \mathcal{W}$. We can approximate value of the loss function if the neuron is pruned (i.e. forced to zero by setting $w = 0$, including weights and bias) with the first-order Taylor expansion:

$$\mathcal{C}(\mathcal{D}|\mathcal{W}, h=0) = \mathcal{C}(\mathcal{D}, \mathcal{W}) - \frac{\delta \mathcal{C}}{\delta h} h + R_1(h=0). \quad (1)$$

The remainder R_1 is based on the second-order derivative, which we decided to ignore due to additional computation. Hence, the change in loss once the neuron is pruned is:

$$|\mathcal{C}(\mathcal{D}|\mathcal{W}, h=0) - \mathcal{C}(\mathcal{D}|\mathcal{W})| = \left| \mathcal{C}(\mathcal{D}|\mathcal{W}) - \frac{\delta \mathcal{C}}{\delta h} h - \mathcal{C}(\mathcal{D}|\mathcal{W}) \right| = \left| \frac{\delta \mathcal{C}}{\delta h} h \right|. \quad (2)$$

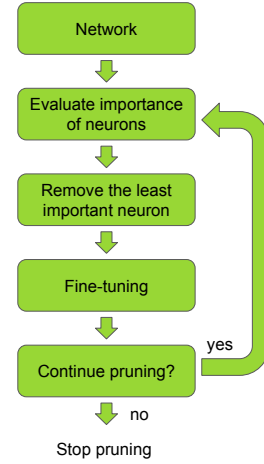


Figure 1: Network pruning as a backward filter.

¹A “parameter” $w \in \mathcal{W}$ might represent an individual weight, a convolutional kernel, or the entire set of kernels that compute a feature map; our experiments operate at the level of feature maps.

Normalization. Some criteria return raw values with scale dependent on the depth of the parameter in the network. However a simple layer-wise ℓ_2 -normalization can achieve reasonable rescaling across layers: $\hat{\Theta}_i^{(k)} = \Theta_i^{(k)} / \sqrt{\sum_j (\Theta_j^{(k)})^2}$, where $\Theta_i^{(k)}$ is the value of parameter i at layer k .

3 Results

We focus our experiments on feature map pruning given its direct speedup of CNN prediction and simple implementation in all deep learning frameworks. Our first set of results derives from two visual transfer learning problems, each involving fine-tuning of an ImageNet network for classification of a much smaller dataset. In the first problem, we fine-tune the VGG-16 [14] network for classification of bird species using the Caltech-UCSD Birds 200-2011 dataset [15]. The dataset consists of nearly 6000 training images and 5700 testing images, covering 200 species. We fine-tune VGG-16 for 60 epochs with a learning rate of 0.0001 to achieve a test accuracy of 72.2%. For the second task, we adapt the CaffeNet implementation of AlexNet [7] to the Oxford Flowers dataset [11], a collection with over 2000 training and 6100 test images from 102 species of flowers found in the UK. We fine-tune for 20 epochs using a learning rate of 0.001 for a test accuracy of 80.1%.

For all experiments, we prune *a single feature map* at every pruning iteration, allowing fine-tuning and re-evaluation of the criterion to account for the dependency between parameters. We compare results to training a randomly initialized CNN with half the number of parameters per layer, which we denote “from scratch.”

Approximating the oracle. We begin by assessing the effectiveness of each proposed criterion in reproducing the parameter ranking of the exact (but prohibitively expensive) oracle computation. We compute the oracle by exhaustively removing each of 4224 convolutional feature maps in turn in our Birds-200/VGG-16 network and computing the resulting change in training loss. Using Spearman’s rank correlation, we compare the oracle ranking to rankings by mutual information, mean weight magnitude, mean and standard deviation of feature map activation, and Taylor expansion. Results are shown in Table 1. “Per layer” analysis focuses on ranking *within* each convolutional layer, while “All layers” describes how well the criteria rank feature maps across layers. Normalization of the raw criteria values by layer, denoted in the “(w/ norm)” row, is found to be important for most criteria. The Taylor expansion method exhibits superior performance both within each layer and across layers after normalization.

Statistics of feature map rankings by both the oracle and the Taylor expansion criteria are shown in Figure 2. Each feature map is assigned a rank from 1 to 4224, where smaller numbers indicate higher importance and a higher estimated change in loss should the map be removed. The median oracle rank by layer demonstrates that early layers are generally more important, but maximum and minimum rankings also show that all layers contain some important and unimportant feature maps. The Taylor criterion shows high correlation with the oracle statistics.

Pruning 2D-CNN networks fine-tuned from ImageNet networks. We now detail performance of the full iterative pruning/fine-tuning procedure. In this evaluation we focus on reducing the number of convolutional parameters and floating point operations (FLOPs) [3], assuming a sliding window implementation of the convolutions [8].

	Mutual Info.	Weight	Activation Mean	S.d.	Taylor
Per layer	0.28	0.27	0.56	0.57	0.73
All layers	0.35	0.34	0.35	0.30	0.14
(w/ norm)	0.47	0.33	0.64	0.66	0.73

Table 1: Spearman’s rank correlation of criteria vs. oracle for convolutional feature maps of VGG-16 fine-tuned on Birds-200.

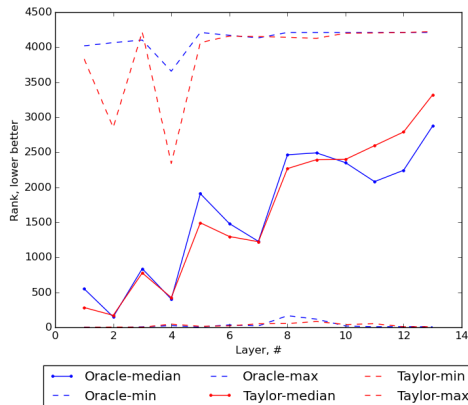


Figure 2: Correlation of criteria with oracle; per layer analysis of statistics.

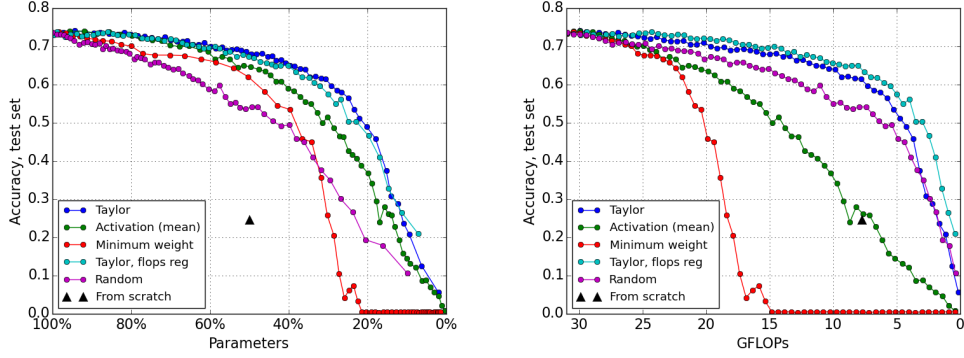


Figure 3: Pruning of VGG-16 fine-tuned on the Birds-200 dataset, with additional fine-tuning updates of 30 minibatches after each pruning iteration. Only convolutional kernels are pruned.

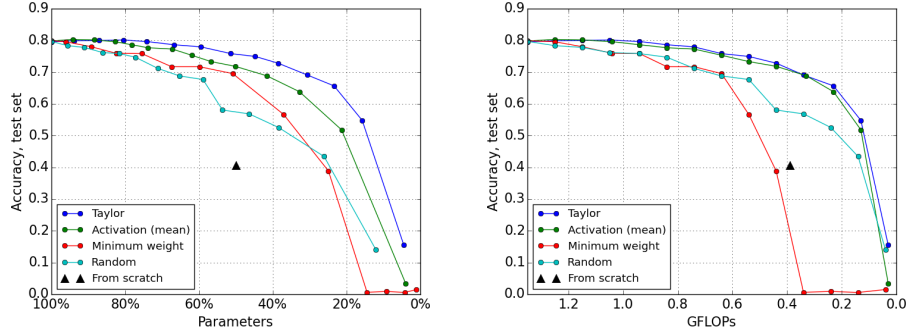


Figure 4: Pruning of AlexNet on Flowers-102.

Results of pruning VGG-16 after fine-tuning on the Birds-200 dataset are shown in Figure 3. Between pruning iterations we perform 30 minibatch SGD fine-tuning updates with batch-size 32, momentum 0.9, learning rate 10^{-4} , and weight decay 10^{-4} . For “Taylor, flops reg” we penalize the criterion with an additional regularizer: $\hat{\Theta}_i^{(k)} - \lambda \rho_k$ with $\lambda = 10^{-3}$ where ρ_k indicates the number of FLOPs to compute a feature map in layer k . We observe that “Taylor” shows the highest accuracy for any number of convolutional filters pruned. “Taylor with flops reg” demonstrates the best performance when the objective is to minimize FLOPs.

Pruning of Alexnet after fine-tuning on Flowers-102 is shown in Figure 4. We keep the same fine-tuning parameters, except reducing the number of mini-batch updates between pruning iterations to 10. We observe the superior performance of Taylor in pruning for both number of parameters and FLOPs. Figure 5 shows pruning results computed with our Taylor technique and different numbers of updates between pruning iterations. We notice that increasing the number of updates between iterations results in higher accuracy, while increasing the runtime of the pruning procedure.

Recurrent 3D-CNN on hand gestures. Molchanov et al. [10] learn to recognize 25 dynamic hand gestures in streaming video with a large recurrent neural network. The network is constructed by adding recurrent connections to a 3D-CNN network pretrained on Sports-1M [5] and fine tuning on a gesture dataset. The full network achieves an accuracy of 80.7% when trained on the depth modality, with 37.8 GFLOPs. After several iterations of pruning with the Taylor criterion (with learning rate 0.0003, momentum 0.9, FLOPs regularization 10^{-3}), we reduce inference to 3.0 GFLOPs, as shown in Figure 6. While initial pruning produces a nearly 6% increase in classification error, a subsequent round of fine-tuning restores much of the lost accuracy, yielding a final pruned network with a $12.6\times$ reduction in GFLOPs at the cost of only 2.5% loss in accuracy.

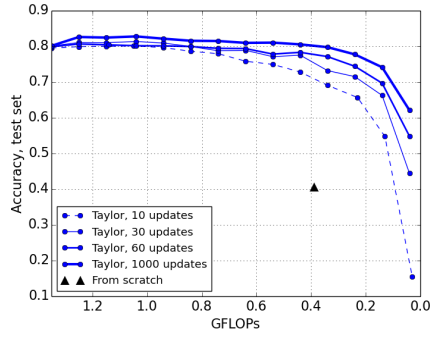


Figure 5: Varying the number of minibatch updates between pruning iterations with AlexNet/Flowers-102.

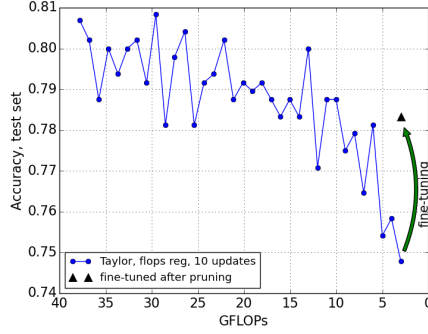


Figure 6: Pruning of a recurrent 3D-CNN for dynamic hand gesture recognition [10].

4 Conclusions

We propose a new scheme for iterative pruning of parameters from deep neural networks. We find: 1) CNNs may be successfully pruned by iteratively removing the least important feature maps according to heuristics; 2) a Taylor expansion-based heuristic criterion demonstrates significant improvement over other criteria; 3) per-layer normalization of the criterion is important to obtain global scaling.

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