

# Structural Compression of Convolutional Neural Networks Based on Greedy Filter Pruning

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## Abstract

Convolutional neural networks (CNNs) have state-of-the-art performance on many problems in machine vision. However, networks with superior performance often have millions of weights so that it is difficult or impossible to use CNNs on computationally limited devices or to humanly interpret them. A myriad of CNN compression approaches have been proposed and they involve pruning and compressing the weights and filters. In this article, we introduce a greedy structural compression scheme that prunes filters in a trained CNN. We define a filter importance index equal to the classification accuracy reduction (CAR) of the network after pruning that filter (similarly defined as RAR for regression). We then iteratively prune filters based on the CAR index. This algorithm achieves substantially higher classification accuracy in AlexNet compared to other structural compression schemes that prune filters. Pruning half of the filters in the first or second layer of AlexNet, our CAR algorithm achieves 26% and 20% higher classification accuracies respectively, compared to the best benchmark filter pruning scheme. This improvement is 15% when pruning filters in the first layer of ResNet-50. Our CAR algorithm, combined with further weight pruning and compressing, reduces the size of first or second convolutional layer in AlexNet by a factor of 42, while achieving close to original classification accuracy through retraining (or fine-tuning) network. Finally, we demonstrate the interpretability of CAR-compressed CNNs by showing that our algorithm prunes filters with visually redundant functionalities. In fact, out of top 20 CAR-pruned filters in AlexNet, 17 of them in the first layer and 14 of them in the second layer are color-selective filters as opposed to shape-selective filters. To our knowledge, this is the first reported result on the connection between compression and interpretability of CNNs.

## 1 Introduction

Deep convolutional neural networks (CNNs) achieve state-of-the-art performance for a wide variety of tasks in computer vision, such as image classification and segmentation [1, 3]. Recent studies have also shown that representations extracted from these networks can shed light on new tasks

through transfer learning [4]. The superior performance of CNNs when there is a large amount of training data has led to their ubiquity in many industrial applications. Thus, CNNs are widely employed in many data analysis platforms such as cellphones, smart watches and robots. However, limited memory and computational power in these devices, along with the substantial number of weights in CNNs, make necessary effective compression schemes. Compressed CNNs are also easier to be investigated or interpreted by humans for possible knowledge gain. For a CNN, better interpretability follows from having fewer filters in each layer. If we define a structural compression scheme as that prunes redundant filters, such schemes result in a simpler and potentially more interpretable network from the human point of view in addition to compression effect.

There have been many works on compressing deep CNNs. They mostly focus on reducing the number and size of the weights or parameters by pruning and quantizing them without considering the functionality of filters in each layer. We call such compression schemes "weight compression". Optimal brain damage [5], optimal brain surgeon [6], Deep Compression [7] and most recently SqueezeNet [8] are some examples.

It is important to consider the structure of a CNN when compressing it. Filters are the smallest meaningful components of a CNN. Therefore, to uncover redundant information in a network and build more interpretable networks, it seems natural to compress CNNs based on removing "less important" filters. We call such schemes "structural compression" schemes. The challenge is in defining "filter importance". He et al. [9] and Li et al. [10] have studied structural compression based on removing filters and introduced importance indices based on average of incoming or outgoing weights to a filter. However, these importance measures typically do not yield satisfactory compressions of CNNs [9] because of the substantially reduced classification accuracy as a result. For example, classification accuracy for AlexNet decreases by 43% when we prune half of the filters in the first layer based on average incoming or outgoing weights.

In this paper, we introduce our structural compression scheme based on pruning filters in large scale CNNs. We define a filter importance index equal to classification accuracy reduction (CAR) (similarly for regression or RAR) of the network after pruning that filter. We then iteratively prune filters based on the CAR importance index. We show that our CAR structural compression scheme achieves much higher classification accuracy compared to other existing structural compression methods. We also take advantage of weight pruning and quantization by combining our method with Deep Compression [7] and report the state-of-the-art level compression ratio. Finally, we demonstrate the ability of our CAR structural compression algorithm to remove functionally redundant filters, making the compressed CNNs more accessible to human interpreters without much classification accuracy loss.

Specifically, our main contributions in this paper are:

- We introduce to CNNs an importance index of filter used in Random Forests [11]. This index is based on the classification accuracy reduction (CAR) (or similarly for regression, RAR). A greedy structural compression scheme for CNNs is then proposed based on CAR. Our algorithm achieves state-of-the-art classification accuracy and compression rate among other structural compression schemes. Pruning half of the filters in the first or second layer of

AlexNet, our CAR algorithm achieves 52% classification accuracy (compared with 57% of the uncompressed AlexNext). This accuracy is 26% and 20% higher than those from the benchmark filter pruning schemes for the first and second layers. Similarly, to have a close-to-original classification accuracy (or 54%) for both our and benchmark schemes, our CAR algorithm can achieve a compression ratio of around 1.40, which is 30% higher than those from the benchmark methods for both layers. For ResNet-50, our CAR-algorithm achieves 72% classification accuracy (compared with the 75% for the uncompressed ResNet-50) when pruning half of the filters in the first layer. This accuracy is 15% higher than that of filter pruning based on average outgoing or incoming weights.

- We combine our CAR algorithm with retraining (or fine-tuning) and the Deep Compression algorithm [7] based on pruning and quantizing weights. For AlexNet, we reduce the size of the first or second convolutional layer by a factor of 42, while achieving close to original classification accuracy (or 54%).
- We connect compression with interpretation of CNNs by visualizing functionality of pruned and kept filters in a CNN. We show that our CAR compression algorithm identifies visually redundant filters in AlexNet (such as color-filters for many classes in ImageNet) and hence gives rise to a more interpretable network by pruning these filters. To our knowledge, such a connection has not been reported previously.

## 2 CAR-based structural compression

### 2.1 Notation

We first introduce notations. Let  $w_i^L$  denote the  $i^{th}$  convolutional filter tensor in layer  $L$  of the network and  $n_L$  the number of filters in this layer ( $i \in \{1, \dots, n_L\}$ ). Each convolutional filter is a 3-dimensional tensor with the size of  $n_{L-1} \times n_L^s \times n_L^s$  where  $n_L^s \times n_L^s$  is the size of spatial receptive field of the filter.

The activation of filter  $i$  in layer  $L$  ( $i = 1, \dots, n_L$ ) is:

$$\alpha_i^L = f(w_i^L * \mathcal{P})$$

where  $f(\cdot)$  is the nonlinear function in convolutional network (e.g. sigmoid or ReLU) and  $\mathcal{P}$  denotes a block of activations from layer  $L - 1$  (i.e. the input to the neurons in layer  $L$ ). The activation for the first layer could be patches of input images to the convolutional network.

Assuming network  $\mathcal{N}$  is trained on classification task, top-1 classification accuracy of network  $\mathcal{N}$  is defined as:

$$Acc(\mathcal{N}) = \frac{N_{Correct}}{N_{Correct} + N_{Incorrect}}$$

where  $N_{Correct}$  and  $N_{Incorrect}$  are the number of correct and incorrect predicted classes, respectively.

## 2.2 The proposed algorithm based on CAR importance index

In this section, we introduce our greedy algorithm to prune filters in layers of a CNN and structurally compress it. Figure 1 shows the process of greedy filter pruning. In each iteration of the algorithm, a candidate filter together with its connections to the next layer, gets removed from the network. The candidate filter should be selected based on an *importance* index of that filter. Therefore, defining an index of importance for a filter is necessary for any structural compression algorithm. Previous works used importance indices such as average of incoming and outgoing weights to and from a filter, but with unfortunately a considerable reduction of classification accuracy (e.g. 43% as mentioned earlier if one prunes only the first layer) for the compressed CNNs [9, 10]. To overcome this limitation, we follow Breiman’s idea for Random Forests to define the *importance* measure for each filter in each layer as the classification accuracy reduction (CAR) when that filter is pruned from the network. That is,

$$CAR(i, L) = Acc(\mathcal{N}) - Acc(\mathcal{N}(-i, L))$$

where network  $\mathcal{N}(-i, L)$  is network  $\mathcal{N}$  except that filter  $i$  from layer  $L$  together with all of its connections to the next layer are removed from the network.

In our CAR structural (or filter pruning) compression algorithm, the filter with the least effect on the classification accuracy gets pruned in each iteration. The network can be retrained in each iteration and after pruning a filter. This process is regarded as *fine tuning* in this paper. We present details of our fine tuning procedure in the next section. Algorithm 1 shows the pseudo code of our CAR greedy structural compression algorithm. Here,  $n_{iter}$  and  $r_{iter}$  are, respectively, the number of remaining filters and compression ratio in the current iteration.

One can also compress based on variants of our algorithm. One possibility is to avoid greedy process and remove several filters with lowest importance indices in one pass. This compression is faster, however the performance of the compressed network is worse than Algorithm 1 in the examples we tried. The greedy process with fine-tuning in each iteration seems to allow for a better data adaptation and improves compression performance.

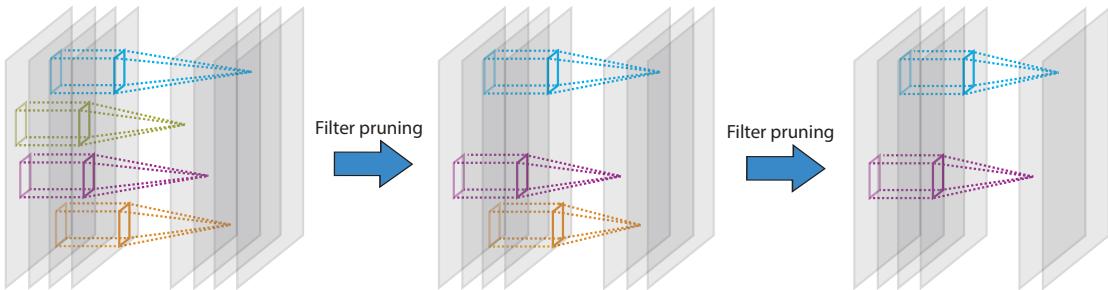


Figure 1: Greedy compression of CNNs based on pruning filters

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**Algorithm 1** Greedy compression of CNNs based on pruning filters

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**Input:** Weights in CNN, target layer  $L$  with  $n_L$  filters, target compression ratio  $r_{target}$   
Set  $n_{iter} = n_L$  and  $r_{iter} = 1$   
**while**  $r_{iter} < r_{target}$  **do**  
    **for**  $i = 1$  **to**  $n_L$  **do**  
        Compute  $CAR(i, L)$ , importance index for filter  $i$  in layer  $L$   
    **end for**  
    Remove the least important filter,  $\arg \min_i CAR(i, L)$   
    Update compression rate,  $r_{iter} = n_L/n_{iter}$   
**end while**

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### 3 Results

#### 3.1 Compression rates and classification accuracies of the CAR compressed networks

To evaluate our proposed CAR structural compression algorithm, we have compressed LeNet [12] (with 2 convolutional layers and 20 filters in the first layer), AlexNet [1] (with 5 convolutional layers and 96 filters in the first layer) and ResNet-50 [2] (with 50 convolutional layers and 96 filters in the first layer). LeNet is a commonly used CNN trained for classification task on MNIST [12] consisting of 60,000 handwritten digit images. AlexNet and ResNet-50 are trained on the subset of ImageNet dataset used in ILSVRC 2012 competition [13] consisting of more than 1 million natural images in 1000 classes.

We used Caffe [14] to implement our compression algorithm for CNNs and fine tune them. The pre-trained LeNet and AlexNet are obtained from Caffe model zoo. All computations were performed on an NVIDIA Tesla K80 GPU.

##### 3.1.1 LeNet on MNIST dataset

LeNet-5 is a four-layer CNN consisting of two convolutional layers and two fully-connected layers. CAR-compression has been performed on the convolutional layers and the performance on a hold-out test set is reported in Figure 2. We obtained classification accuracies (top-1) of the CAR-compression results (purple curve) and those from retraining or fine-tuning after CAR-compression on the same classification task (blue curve).

To compare the performance of our compression algorithm to benchmark filter pruning schemes, we have also implemented the compression algorithm based on pruning incoming and outgoing weights proposed in [9] and reported the classification accuracy curve in Figure 2. Furthermore, classification accuracy for random pruning of filters in LeNet has been shown in this figure. Candidate filters to prune are selected uniformly at random in this case. The error bar shows the standard deviation over 10 repeats of this random selection.

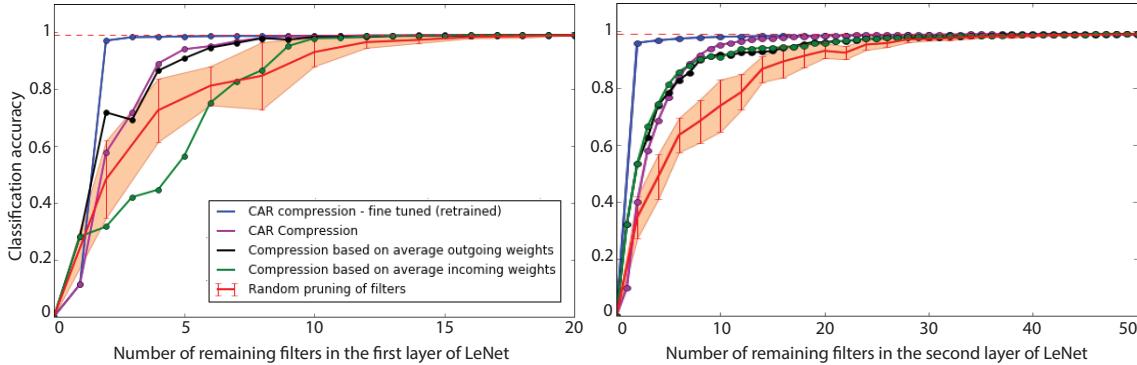


Figure 2: Performance of compression for LeNet. The top figure shows the overall classification accuracy of LeNet when the first convolutional layer is compressed. The bottom figure shows the classification accuracy when the second convolutional layer is compressed. The classification accuracy of uncompressed network is shown with a dashed red line. The purple curve shows the classification accuracy of our proposed CAR compression algorithm for various compression ratios. The accuracy for the fine tuned (retrained) CAR compression is shown in blue. The black and green curves shows the accuracy for compressed network based on outgoing and incoming weights, respectively. The red curve shows the accuracy when filters are pruned uniformly at random. The error bar is reported over 10 repeats of this random pruning process.

We conclude that our CAR-algorithm gives a similar classification accuracy to [9] for LeNet (using the outgoing weights in the first layer, and either weights for the second layer). Their accuracies are similar to the accuracy of the uncompressed, unless we keep very few filters for either layer. Fine-tuning improves the classification accuracy but there is not a considerable gap among performances (unless we keep very few filters, less than 8 among 20 for the first layer or less than 10 among 50 for the second layer). Among the 8 kept filters in the first layer, 4 of them are shared between the CAR-algorithm and that based on averaging outgoing weights in [9], while among the 10 kept filters in the second layer, 6 of them are shared.

### 3.1.2 AlexNet on ImageNet dataset

AlexNet consists of 5 convolutional layers and 3 fully-connected layers. Figure 3 shows the classification accuracy of AlexNet on a hold-out test set after the first or second layer is compressed using our proposed CAR algorithms or benchmark compression schemes. CAR pruning of higher convolutional layers in AlexNet yields to similar figures and are not shown here to avoid redundancy.

Comparing the accuracies of compressed networks in Figure 3, there are considerable gaps between our proposed CAR-algorithm (purple curves) and the competing structural compression schemes that prune filters [9] for the two layers. Further considerable improvements are achieved by

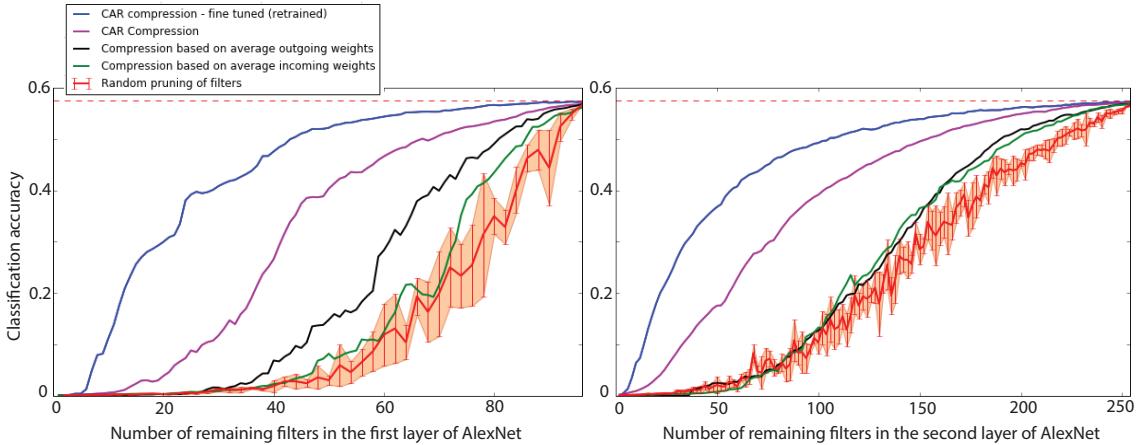


Figure 3: Performance of compression for AlexNet. The top figure shows the classification accuracy of the AlexNet when the first convolutional layer is compressed. The bottom figure shows the classification accuracy when filters in the second layers are pruned (with the first layer untouched). The classification accuracy of uncompressed network is shown with a dashed red line. The purple curve shows the classification accuracy of our proposed CAR compression algorithm for various compression ratios. The accuracy for the fine tuned (retrained) CAR compression is shown in blue. The black and green curves shows the accuracy for compressed network based on outgoing and incoming weights, respectively. The red curve shows the accuracy when filters are pruned uniformly at random. The error bar is reported over 10 repeats of this random pruning process.

retraining or fine-tuning the CAR-compressed networks (see the blue curves in Figure 3). Pruning half of the filters in the first layer of AlexNet, our CAR-algorithm achieves 52% classification accuracy (compared with the 57% for the uncompressed AlexNet). This accuracy is 26% higher than that of filter pruning based on average outgoing weights (which is better than pruning based on averaging incoming weights). For the second layer of AlexNet, the improvement in classification accuracy is 20%. The superior performance of our algorithm for AlexNet is due to the proposed importance index for the filters in CNN. This figure demonstrates that our algorithm is able to successfully identify the least important filters for the purpose of classification accuracy. In section 5.2, we discuss the ability of our compression scheme to reduce functional redundancy in the structure of CNNs.

To present a different but equivalent quantitative comparison, we have reported the compression rate and the number of remaining filters in the first and second layers of AlexNet in Table 1. Results for CAR compression with and without fine tuning and compression based on average incoming and outgoing weights are presented in this table. The filters are pruned while the classification accuracy dropped a relative 5% from the accuracy of uncompressed network (i.e. 54% compared to 57%)

Table 1: Comparison of compression performance between our greedy CAR compression algorithm and benchmark schemes

	Compression ratio of the 1 <sup>st</sup> layer	Compression ratio of the 2 <sup>nd</sup> layer	Number of filters in the 1 <sup>st</sup> layer	Number of filters in the 2 <sup>nd</sup> layer	Classification accuracy
Original AlexNet	-	-	96	256	57%
Compression based on average incoming weights	1.07×	-	90	256	54%
	-	1.07×	96	239	
	1.07×	1.07×	90	239	51%
Compression based on average outgoing weights	1.09×	-	88	256	54%
	-	1.08×	96	237	
	1.09×	1.08×	88	237	51%
CAR compression	<b>1.43</b> ×	-	<b>67</b>	256	54%
	-	<b>1.35</b> ×	96	<b>189</b>	
	<b>1.43</b> ×	<b>1.35</b> ×	<b>67</b>	<b>189</b>	51%
CAR compression fine tuned (retrained)	1.66×	-	58	256	54%
	-	1.67×	96	154	
	1.66×	1.67×	58	154	51%

through pruning filters in either layer. The CAR-algorithm achieves this good classification rate with compression ratios 1.43 and 1.35 (for the two layers) in weights and number of remaining filters, while the benchmark algorithms do it with a much lower ratio of 1.09 (or worse).

If we fine-tune or retrain the CAR-compressed network, the compression ratio is increased to 1.66 or 1.67 with the same number of filters (to maintain the same 54% classification accuracy). We have also reported the classification accuracy for the case when both layer one and two are compressed together with a small decrease of classification accuracy to 51% (an absolute 3% or a relative 5%). The network is fine tuned or retrained on the same classification task after CAR-compressing both layers.

### 3.1.3 Combination with Deep Compression

One advantage of our CAR-algorithm is that it is amenable to combination with weight based compression schemes to achieve substantial reduction in memory usage. Deep Compression [7] is a recent weight-based compression procedure that uses weight pruning and quantization. We have performed Deep Compression on top of our proposed compression algorithm and reported the compression ratio as well as the classification accuracy for AlexNet in Table 2. Again, the filters are pruned while the classification accuracy is in the range of relative 5% from the accuracy of

Table 2: Compression performance of CAR-algorithm combined with Deep Compression

	Compression ratio of the 1 <sup>st</sup> layer	Compression ratio of the 2 <sup>nd</sup> layer	Number of filters in the 1 <sup>st</sup> layer	Number of filters in the 2 <sup>nd</sup> layer	Classification accuracy
CAR compression	42×	-	58	256	
+ Pruning	-	43×	96	154	
+ Quantization	42×	43×	58	154	51%

uncompressed network, while increasing the compression ratio (for weights) from 1.4 to 42 for either layer – a stunning 30 fold increase. That is, further weight compression boosts the weight compression ratio by sparsifying weights of the kept filters, although the number of filters is the same as the CAR compression.

### 3.1.4 ResNet-50 on ImageNet dataset

First introduced by He et al. [2], deep residual networks take advantage of a residual block in their architecture (Figure 4, right panel) to achieve higher classification accuracy compared to a simple convolutional network. We have studied the performance of CAR compression on ResNet-50 architecture [2] with 50 layers of convolutional weights. Figure 4 top left panel shows the classification accuracy of ResNet-50 after pruning first convolutional layer using CAR algorithm or benchmark compression schemes. The bottom panel shows the classification accuracy after pruning the first convolutional layer in the first residual block (layer *Conv a - Branch 2* in Figure 4). CAR pruning of other convolutional layers in this residual block or higher blocks yields to similar figures and are not shown here to avoid redundancy. These accuracies are reported on the ILSVRC 2012 ImageNet hold out test set.

It is of great interest to compare at high compression ratio regimes where we keep less than 30 filters out of 64. In this situation and pruning layer *Conv 1*, the CAR algorithm (purple curve in Figure 4) outperforms the competitors based on incoming and outgoing weights. The higher the compression ratio, the higher the improvements by the CAR algorithm. For low compression ratio regimes, the performances are similar. Compared to AlexNet, the gap between CAR and benchmark compressions is smaller for the first layer. This might be an evidence that ResNet has less redundant filters. Retraining (fine-tuning) the CAR-compressed network achieves further improvement in classification accuracy (blue curve in Figure 4). In fact, our CAR-algorithm achieves 72% classification accuracy (compared with the 75% for the uncompressed ResNet-50) when pruning half of the filters in the first layer of ResNet-50. This accuracy is 15% higher than that of filter pruning based on average outgoing or incoming weights.

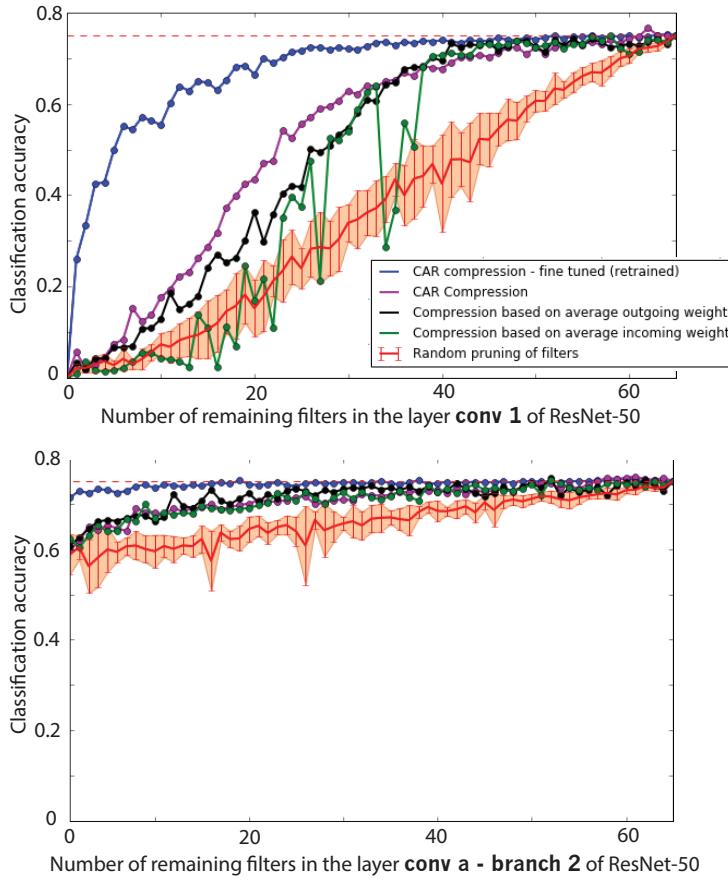


Figure 4: Performance of compression for ResNet-50. The top left figure shows the classification accuracy of the ResNet-50 when the first convolutional layer is compressed. The bottom left figure shows the classification accuracy when filters in the first residual module layers are pruned (with the first layer untouched). The classification accuracy of uncompressed network is shown with a dashed red line. The purple curve shows the classification accuracy of our proposed CAR compression algorithm for various compression ratios. The accuracy for the fine tuned (retrained) CAR compression is shown in blue. The black and green curves shows the accuracy for compressed network based on outgoing and incoming weights, respectively. The red curve shows the accuracy when filters are pruned uniformly at random. The error bar is reported over 10 repeats of this random pruning process. The right panel shows the architecture of first layers in ResNet-50.

For the residual block, we have pruned layer *Conv a - Branch 2* and reported the classification accuracy in Figure 4. The accuracy of CAR algorithm is almost similar to the compression based

on incoming and outgoing weights. Interestingly, the accuracy drops less than 15% if we fully prune the filters in this layer i.e. remove branch 2 from the residual block. The drop in accuracy is less than 5% for the fine-tuned network. The main reason for the high classification accuracy when pruning filters in the residual block is the uncompressed branch 1 that transfers information through a parallel channel. As a result of these parallel channels in the residual blocks, deep residual networks are more robust to pruning filters compared to simple convolutional networks.

### 3.2 CAR-compression algorithm prunes visually redundant filters

To study the ability of our proposed CAR compression method to identify redundant filters in CNNs, we take a closer look at the compressed networks. In this section, we focus on the second layer of AlexNet . It has 256 filters with visually diverse functionalities, which is considerably more than the numbers of filters in LeNet or the first layer of AlexNet. It is also easier to visualize filters in this layer compared to higher layers of AlexNet. However, similar results hold for the other layers of AlexNet and LeNet. Recall that we first performed CAR structural compression to prune 256 filters in the second layer of AlexNet, and continued to iterate the algorithm while the classification accuracy is 54% or within a relative 5% from the accuracy of uncompressed network. This led to pruning 102 filter from 256 filters in this layer. The removed and remaining filters are visualized in Figure 5. To visualize the pattern selectivity of each filter, we have fed one million image patch to the network and showed the top 9 image patch that activate a filter. This approach has been previously used to study functionality of filters in deep CNNs [15]. We have manually grouped filters with visually similar pattern selectivity (blue boxes in 5). A hand crafted image has been shown beside each group to demonstrate the function of filters in that group. Interestingly, our algorithm tends to keep at least one filter from each group, suggesting that our greedy filter pruning process is able to identify redundant filters. This indicates that pruned filters based on the CAR importance index have in fact redundant functionality in the network. To further investigate the effect of compression on the first and second layers of AlexNet, we have shown scatter plots of classification accuracy for each of the 1000 classes in ImageNet in Figure 6. Although the total classification accuracy is about a relative 5% lower for the compressed network (see Table 1), the accuracies for many of the categories are comparable between compressed and uncompressed networks. In fact, if we compress the first layer, 18% of the categories have accuracies no larger than 3% below those for the uncompressed network; for the second layer, the percentage of such categories is 24%. Interestingly, among the classes for which the uncompressed network has superior performance over the compressed network, most of them correspond to color specific categories such as European fire salamander, lorikeet and spiny lobster. This makes much sense since looking deeper into the CAR indices, out of top 20 pruned filters, 17 of them in the first layer and 14 of them in the second layer correspond to the color filters, respectively. This finding points to the fact that shape is often first-order important for object recognition.

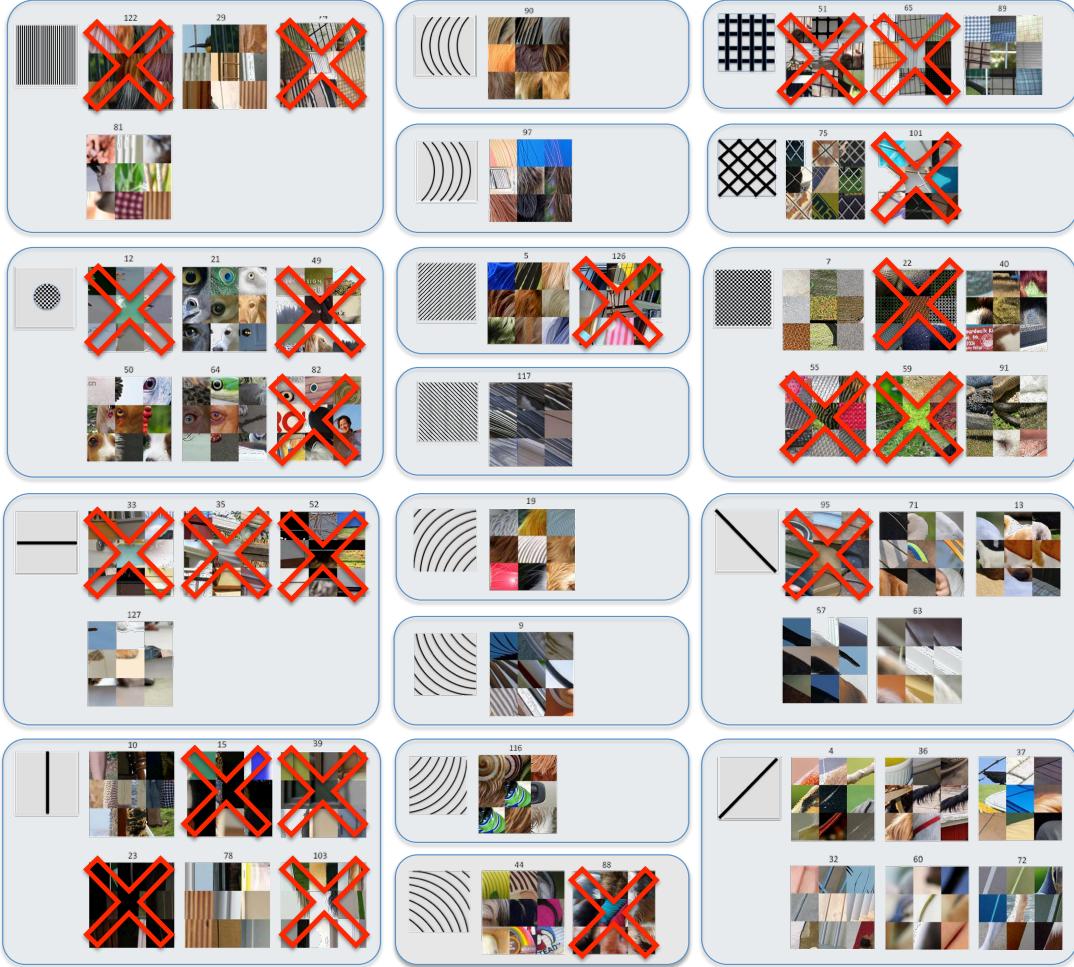


Figure 5: CAR compression removes filters with visually redundant functionality from second layer of AlexNet. To visualize each filter, we have fed one million image patch to the network and visualized each filter by 9 image patches with top response for that filter. We have manually clustered 256 filters in the second layer of AlexNet into 30 groups (17 of them visualized here). Pattern selectivity of each group is illustrated in the left top corner of each box using a manually designed patch. We continue to iterate the CAR-based algorithm while the classification accuracy is in the range of 5% from the accuracy of uncompressed network. This leads to pruning 102 filter from 256 filters in this layer. The pruned filters are specified with a red cross.

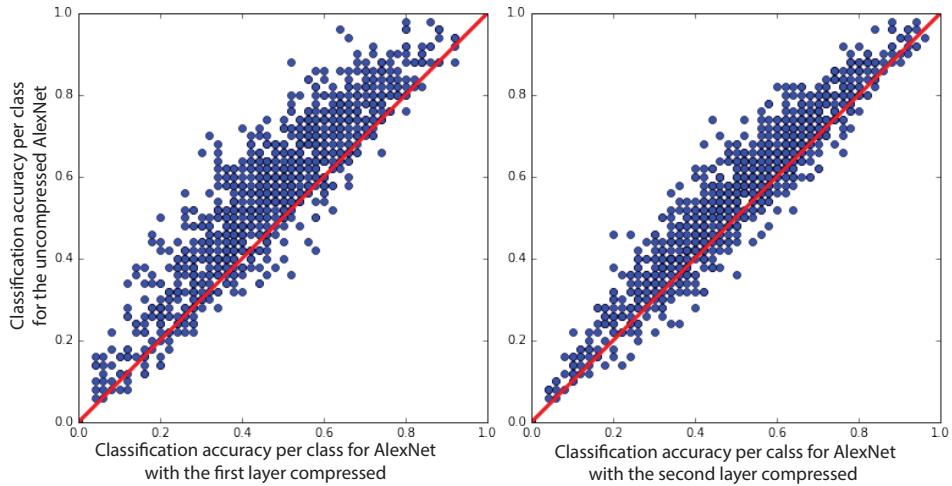


Figure 6: Classification accuracy for each class of image in AlexNet after the first (left panel) or second layer (right panel) is compressed compared to the uncompressed network. Each point in plots corresponds to one of the 1000 categories of images in test set.

## 4 Discussion and future work

Structural compression (or filter pruning) of CNNs has the dual purposes of saving memory cost and computational cost on small devices, and of resulted CNNs being more humanly interpretable. In this paper, we proposed a greedy filter pruning based on the importance index of classification accuracy reduction (CAR) that is from Random Forests, but new to CNNs. We have shown with AlexNet that the huge gain (42 folds) in compression ratio of CAR+Deep Compression schemes, without a serious loss of classification accuracy. Furthermore, we saw that the pruned filters have redundant functionality for the AlexNet. In particular, for many categories in ImageNet, we found that the redundant filters are color-based instead of shape-based. This suggests the first order importance of shape for such categories.

However, a greedy algorithm is likely to be sub-optimal in identifying the best candidate filters to drop. The optimal solution may be to search through all possible subsets of filters to prune, but this can be computationally expensive and may lead to over-pruning. Procedures for subset selection, including genetic algorithms and particle swarm optimization, could be helpful in the compression of CNNs and will be investigated in future work.

In this paper, we showed that CAR compression of ResNet achieves state-of-the-art classification accuracy among other structural compressions. However, compressing ResNet requires further investigations mainly due to the existence of identity branches in the residual blocks. Our current work CAR-prunes the identity branch and identifies the redundant connections. Furthermore, we

are working on comparing classification accuracies of AlexNet and ResNet for each image class, in the hope to shed light on similarities and differences between the two networks. In general, a similar comparison can be carried out for any two networks. This is a fruitful direction to pursue, particularly given the recent wave of various CNNs with different structures. Finally, we expect that our CAR structural compression algorithm for CNNs can be adapted to fully-connected networks with modifications.

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