Gradual Channel Pruning while Training using Feature Relevance Scores for Convolutional Neural Networks

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Abstract

The enormous inference cost of deep neural networks can be scaled down by network compression. Pruning is one of the predominant approaches used for deep network compression. However, existing pruning techniques have one or more of the following limitations: 1) Additional energy cost on top of the compute heavy training stage due to pruning and fine-tuning stages, 2) Layer-wise pruning based on the particular layers statistics, ignoring the effect of error propagation in the network, 3) Lack of an efficient estimate for determining the important channels globally, 4) Unstructured pruning requires specialized hardware for effective use. To address all the above issues, we present a simple-yet-effective gradual channel pruning while training methodology using a novel data driven metric referred as Feature relevance score. The proposed technique gets rid of the additional retraining cycles by pruning least important channels in a structured fashion at fixed intervals during the actual training phase. Feature relevance scores help in efficiently evaluating the contribution of each channel towards the discriminative power of the network. We demonstrate the effectiveness of the proposed methodology on architectures such as VGG and ResNet using datasets such as CIFAR-10, CIFAR-100 and ImageNet, and successfully achieve significant model compression while trading off less than 1% accuracy. Notably on CIFAR-10 dataset trained on ResNet-110, our approach achieves 2.4× compression and a 56% reduction in FLOPs with an accuracy drop of 0.01% compared to the baseline (unpruned) network.

1. Introduction

Convolutional Neural Networks have achieved great success in a variety of computer vision tasks, which usually comes from the deeper architectures with millions of parameters (Krizhevsky et al., 2012). These large models require immense computational power and memory for storage in both training and testing phases. As a result, deep learning models become less feasible to be used in applications with limited resources, such as edge devices. However, recent studies suggests that the deep neural networks have significant redundancy (Prakash et al., 2018; Denil et al., 2013) and network pruning has been predominately used for model compression reducing the computational cost and memory usage without significant degradation in performance.

The existing pruning techniques usually involve the following three stages (Liu et al., 2019): 1) Training an over-parameterized network till convergence, 2) Pruning based on a predefined criteria, 3) Fine-tuning to regain the accuracy. The main limitation with this three stage process of existing pruning methods is that the pruning and fine-tuning stages, iterative in most cases (Zhuang et al., 2018; Liu et al., 2017; Luo et al., 2017; Han et al., 2015), impose additional computation (hence, time and energy) requirements on top of the compute heavy training stage. Based on the structure and criteria used for pruning, most of the previous works on network pruning also suffer from one or more of the following problems:

• Unstructured pruning methods result in sparse weight matrices which are unstructured and require dedicated hardware/libraries for compression and speedup (Han et al., 2016a; Liu et al., 2019). Examples of unstructured pruning methods include (Guo et al., 2016; Lebedev & Lempitsky, 2016; Molchanov et al., 2017; Louizos et al., 2018)

• Predefined structured pruning, where the pruned target architecture is defined by the user, does not have any advantage over training the targeted model from scratch (Liu et al., 2019). Examples of predefined structured pruning methods include (He et al., 2018; Yu et al., 2018; Li et al., 2017; Liu et al., 2017; He et al., 2017)
Gradual Channel Pruning while Training using Feature Relevance Scores

- Pruning neurons layer-by-layer either independently (Han et al., 2016) or greedily (Li et al., 2017; Luo et al., 2017; Zhuang et al., 2018), without jointly considering the statistics of all layers, can lead to significant reconstruction error propagation (Yu et al., 2018).

- Use of an iterative metric (which requires an optimization step in a few cases) to evaluate the importance of channels or nodes is computationally expensive (Zhuang et al., 2018).

In this paper, we aim to overcome all the above mentioned drawbacks. First, we adopt and verify the idea that it is not necessary to train the model till convergence before pruning (Yue et al., 2019). Based on this idea, we merge the training and pruning stages, eliminating the fine-tuning stage which reduces the additional computational requirements. We prune a fixed, predefined percentage of least important channels from the entire network after every few epochs during the training phase. It eliminates the disadvantages of unstructured and predefined structured pruning. We define the importance of each channel in the network using a metric that we call feature relevance score. The contribution of each channel towards the discriminative power of the neural network can be evaluated efficiently through feature relevance scores.

Feature relevance score is computed based on normalized class-wise accuracy of the model and class-wise relevance score of each channel. The class-wise relevance scores are computed using a technique called Layer-wise Relevance Propagation (LRP) proposed by (Sebastian et al., 2015). The relevance score of a channel for any given class in the dataset indicates its average contribution in activating the output node corresponding to that class. The feature relevance score of a channel is the weighted average of the relevance scores of all classes in the dataset for a given channel where the weights are determined by the class-wise accuracy of the model. This score of a channel denotes how important the channel is to make the final prediction and is not based on statistics of individual layers. Feature relevance scores are computed recursively using the training data, where the true labels are used to determine the scores at the final output layer and one backward pass is made through the network to determine the relevance scores of the channels in the remaining layers. Thus, determining feature relevance scores is not computationally expensive (i.e., does not involve any optimization step) as compared to the state-of-the-art pruning technique (Zhuang et al., 2018).

We evaluate the efficiency of our methodology on CIFAR-10, CIFAR-100 (Alex & Geoffrey, 2009) and ImageNet (Jia et al., 2009) using standard CNN architectures such as VGGNet (Zagoruyko, 2015) and ResNet (He et al., 2016). Our experiments show that the proposed technique can prune 59% of the parameters resulting in 56% reduction of FLOPS for ResNet110 on CIFAR10 with an accuracy drop of 0.01%. On ImageNet, when pruning 25% of channels of ResNet34, we observe an accuracy drop of 2.5%. This shows that the proposed technique is able to achieve significant compression (either better than or comparable to the existing pruning techniques) while significantly reducing the additional energy cost required by the existing pruning methods.

1.1. Contribution

We introduce a novel metric called feature relevance score which computes the importance of each channel in the entire network by efficiently propagating the importance scores from the final output layer. This metric is utilized in gradual channel pruning while training where we gradually prune channels from the entire network (automatic structured pruning) at fixed intervals over the training phase, reducing the computational and time complexity of the training and pruning along with the inference.

2. Related work

There have been several efforts made in the recent past to reduce the heavy inference cost of deep models through model compression. Deep model compression can be successfully achieved through network pruning techniques which remove the redundant / unnecessary connections. Network pruning can be done at various granularity levels such as individual weights, nodes, channels or even layers.

The pruning techniques which prune at the level of individual weights or nodes can be categorized under unstructured pruning methods. Some of the recent works such as (Han et al., 2015; Guo et al., 2016; Wen et al., 2016; Lebedev & Lempitsky, 2016; Louizos et al., 2018) have proposed unstructured pruning. The authors of (Han et al., 2015) proposed iterative weight pruning where the weights with magnitude less than a given threshold are removed. Dynamic network surgery which reduces the network connectivity by making on-the-fly connection (single weight) pruning using an optimization problem to determine unimportant connections has been proposed by (Guo et al., 2016). The sparsity of weight parameters has been utilized in (Wen et al., 2016; Lebedev & Lempitsky, 2016; Louizos et al., 2018) to accelerate the deep neural networks. However, the disadvantage of unstructured pruning techniques is that they do not lead to realistic speed ups and compression without dedicated hardware (Han et al., 2016a).

The pruning techniques which prune at the level of channels or layers come under structured pruning methods. Channel pruning is the most popular structured pruning technique and is well supported by the existing deep learning libraries. The important step in channel pruning is evaluating the importance of channels. Network trimming technique pro-
posed by (Hu et al., 2016) prunes the channels based on average percentage of zeros (APoZ). The importance of channels is determined by computing the absolute value of weights in each channel in (Li et al., 2017). Some recent works such as (Liu et al., 2017; Ye et al., 2018), include channel-wise scaling factors with sparsity constraints during training, whose magnitudes are then used for channel pruning. Reconstruction methods which transform the channel selection problem into the optimization of reconstruction error with the consideration of efficiency have been proposed in (Luo et al., 2017; He et al., 2017; Zhuang et al., 2018). The optimization problem is then solved either using greedy algorithm or LASSO regression (Tibshirani, 1994).

(Liu et al., 2019) divides the pruning methods into two categories based on how the target model’s architecture is determined i.e., predefined pruning if the target model is predefined by the user and automatic if determined by the pruning algorithm. The authors conclude that the predefined structured pruning techniques are not useful as one can train the target model from scratch and obtain same or better accuracy much faster. Thus, it is beneficial to adopt automatic structured pruning techniques than predefined structured pruning or unstructured pruning. Another key factor in pruning is evaluating the importance of nodes or channels. (Yu et al., 2018) claim that the importance of neuron should be determined based on the statistics of entire network and the authors proposed Neuron Importance Score Propagation (NISP). However, NISP algorithm is utilized for either unstructured pruning or predefined structured pruning both of which have their own limitations as mentioned above. (Yue et al., 2019) proposed Incremental Pruning with Less Training (IPLT) which reduces the pruning effort and falls under automatic structured pruning. However, IPLT algorithm uses $L_2$–norm of weights for computing the importance of the channels and does not consider the statistics of entire network. In this work, we reduce the pruning effort by gradually pruning the channels during training similar to IPTL but use a novel metric called as feature relevance score which considers the statistics of the entire model.

3. Methodology

In this section, we present our approach to evaluate the importance of channels and gradually prune them during training. First, we describe the methodology to compute feature relevance scores for each channel in a given CNN. Then, we proceed to describe the gradual channel pruning while training technique using the feature relevance scores as a measure of a channel’s importance. An overview of the proposed technique is illustrated in Figure. 1

3.1. Feature Relevance Scores

CNNs trained for classification tasks compute a set of features at each layer. The contribution of each feature-map (or channel) in the network to a given prediction depends on its activation values and their propagation to the final layer. For a given instance, Layer-wise Relevance Propagation (LRP) proposed by (Sebastian et al., 2015) determine the contribution of each node towards final prediction. LRP allocates a relevance score to each node in the network using the activations and weights of the network for an input image. The relevance scores at output nodes are determined based on true label of an instance. For any input sample $(x_i, y_i)$, the output node corresponding to true class, $y_i$, is given a relevance score of 1 and the remaining nodes get a score of 0. The relevance scores of output nodes are then back propagated based on $\alpha\beta$-decomposition rule (Wojciech et al., 2016) with $\alpha = 2$ and $\beta = 1$. These relevance scores of the nodes obtained from the training data are then used to compute feature relevance score.

To obtain feature relevance scores ($FS_l$) at layer $l$, we define a feature-relevance matrix ($FM_l$) at that layer which assigns a class-wise relevance score to every feature-map (channel). The relevance score of a feature-map for any given class (say cat) indicates its contribution in activating the output node (corresponding to cat). Feature relevance score is the weighted average of the class-wise relevance scores obtained from feature relevance matrix, where weights are the inverse of normalized class-wise accuracy. This will make sure that the features relevant to classes with low accuracy are given higher importance so that the probability of retaining them during pruning is higher.
Algorithm 1 Methodology to Compute Feature Relevance Scores $FS_l$ of Layer $l$

**Input:** CNN. Training data $\{(x_i, y_i)\}_{i=1}^{N}$: $x_i \in$ input sample, $y_i \in$ true label, class-wise accuracy: $acc$

**Parameters:** number of classes: $c$. number of layers: $L$, feature maps at layer $l$: $\{f_1, f_2, \ldots, f_p\}$, relevance score of node $p$ at layer $l = R_p^l$, normalized class accuracy $\lambda$: an array of length $c$, feature relevance scores of layer $l$: $FS_l$

1. Initialize feature-relevance matrix for given layer $l$: $FM_l = zeros(c, r)$
2. for each sample $(x_i, y_i)$ in training data do
3. Forward propagate the input $x_i$ to obtain the activations of all nodes in the DNN
4. Compute relevance scores for output layer:
   - $R_p^L = \delta(p - y_i) \ \forall p \in \{1, \ldots, c\}$
   - $\delta(p - y_i) =$ Kronecker delta function
5. for $k$ in range($L-1, l, -1$) do
6. Back propagate relevance scores:
   - $R_p^k = \sum_{q} (\alpha \frac{(a_p w_{pq})^2}{\sum_p (a_p w_{pq})} - \beta \frac{1}{\sum_p (a_p w_{pq})^2}) R_{q}^{k+1}$
   - $\forall p \in$ nodes of layer $k$, $\alpha - \beta = 1$,
   - $a_p =$ activations, $w_{pq} =$ weights,
   - $(a_p w_{pq})^+: $ positive weight components,
   - $(a_p w_{pq})^-: $ negative weight components.
7. end for
8. Compute average relevance score per feature map
9. Relevance score vector at layer $l$:
   - $R_l^l = \{R_{f_j} = \frac{1}{r} \sum_{p \in f_j} R_p^l\}_{j=1}^{r}$
10. Update feature-relevance matrix: $FM_l(y_i, :) = R_l^l$
11. end for
12. Normalize rows of feature-relevance matrix:
   - $FM_l(p, :) = \frac{1}{\sum_{y_i \in p} FM_l(p, :) \ \forall p \in \{1, \ldots, c\}}$
13. Compute normalized class-wise accuracy:
   - $\lambda_p = acc_p / max(acc)$, $w_p = \frac{1}{\lambda_p} \ \forall p \in \{1, \ldots, c\}$
14. Compute feature relevance scores:
   - $FS_l = \frac{1}{c} \sum_{p=1}^{c} w_p \cdot FM_l(p, :)$ where $v = \sum_{p=1}^{c} v_p$
15. return feature relevance scores $FS_l$ of layer $l$

Algorithm 1 shows the pseudo code for computing the feature-relevance score of layer $l$. After determining the relevance scores at each node in the network using LRP, we compute relevance score of every feature map $f_i$ at layer $l$ by averaging the scores of all nodes corresponding to $f_i$. The relevance vector of a feature map $f_i$ is obtained by taking class-wise average over relevance scores of all training samples and forms the $i^{th}$ column of $FM_l$. The weighted average of rows of $FM_l$ with class-wise accuracy returns $FS_l$ for any layers $l$ in the network. The computed feature relevance scores are then utilized to determine the least important channels that can be pruned.

3.2. Gradual Channel Pruning while Training

The proposed gradual channel pruning while training technique is shown in Algorithm 2. This pruning methodology merges the pre-training and pruning phases reducing the additional efforts required by the traditional pruning techniques. Starting from scratch, pruning takes place after every few epochs of the actual training phase. At each pruning stage, the least important $x$ channels are removed. The importance of channels over all the layers is evaluated using feature relevance scores (ref. 3.1). We do not prune during the last few epochs of training allowing the model to converge. In particular, say the number of training epochs for the model is $N$ and the pruning interval is defined as $(1, N1)$ epochs. The model is pruned after every few epochs (say $n$) of training during the pruning interval i.e., after epoch $n, 2n, \ldots, kn$ where $k = int(\frac{N}{N1})$. The model is not pruned in the training interval $(N1, N)$.

Algorithm 2 Gradual Pruning while Training

**Input:** CNN. Training data $\{(x_i, y_i)\}_{i=1}^{N}$

**Parameters:** pruning after every $n$ epochs till $N1$ epochs, maximum epochs: $N (N > N1)$, Number of channels to be pruned after every $n$ epochs: $x$

1. Initialize the CNN model
2. for epoch = 1, 2, ..., $N$
3. Update the learning rate if required
4. Train the CNN using mini-batch SGD algorithm with momentum and weight decay for an epoch
5. if epoch$\%n = 0$ and epoch $< N1$
6. Determine class-wise accuracy of training data.
7. Compute feature relevance scores of CNN with current weights using algorithm 1
8. Prune $x$ filters which have least feature relevance scores globally (across all layers).
9. end if
10. end for
11. return Pruned CNN model

The proposed pruning technique introduces the following hyper-parameters: The number of channels to be removed at each pruning stage ($x$), the number of training epochs between two consecutive pruning stages ($n$), $N1$ indicates the end of pruning interval. The value of $x$ is chosen based on the required final pruning percentage. The total number of channels pruned is equivalent to $int(\frac{N}{N1}) + x$ and the total number of pruning stages is given by $k$ which is equivalent to $int(\frac{N}{N1})$. Note that, $N$ is same as the number of epochs required to train the baseline CNN model till convergence.
4. Experimental Results

In this section, we empirically evaluate the effectiveness of the proposed pruning methodology. We compare our technique with several existing and state-of-the-art pruning methods such as (Li et al., 2017; He et al., 2017; Dong et al., 2017; Luo et al., 2017; Yu et al., 2018; He et al., 2018; Zhuang et al., 2018). We evaluate the performance of our technique on three different datasets namely CIFAR-10, CIFAR-100 and ImageNet. CIFAR-10 consists of 50k training samples and 10k testing images with 10 classes. CIFAR-100 consists of 50k training samples and 10k testing images with 100 classes. ImageNet contains 1.28 million training samples and 50k testing images for 1000 classes. We have used the VGGNet and ResNet architectures to train on these datasets. For all the datasets and architectures, we report the percentage drop in accuracy, the percentage reduction in parameters and the percentage reduction in FLOPS (Floating Point Operations). Percentage drop in accuracy is computed as the difference between the percentage test accuracy of the baseline model (unpruned model) and the percentage test accuracy of the pruned model. The percentage reduction in parameters indicates the percentage of parameters that are pruned from the baseline model. The reduction in computational complexity is reported as the percentage reduction in number of FLOPs required for the inference of an input. We have adopted the PyTorch utility that estimates the number of FLOPs for a given network presented in (Bulat, 2019).

4.1. Implementation Details

We implement the proposed technique on PyTorch (Paszke et al., 2017). We have used the Stochastic Gradient Descent (SGD) algorithm with momentum and weight decay to train the networks. For the CIFAR-10 and CIFAR-100 datasets, the momentum and weight decay are set as 0.9 and 0.0005, respectively. For ImageNet we have used 0.9 as momentum and 0.0001 as weight decay. The models for CIFAR-10 and CIFAR100 datasets are trained for $N=200$ epochs with a batch size of 256. The initial learning rate is set at 0.1 and is divided by 10 at epochs 100 and 150. The models for ImageNet are trained for $N=90$ epochs with a batch size of 64. The initial learning rate is set at 0.01 and is divided by 10 after every 30 epochs. The value of $N1$ (see algorithm 2) is fixed at 150 for CIFAR-10, CIFAR-100 and 60 for ImageNet. The hyper-parameter $n$ typically varies around $(10-20)$. The input data is normalized using channel means and standard deviations. The following transforms are applied to the training data: transforms.RandomCrop and transforms.RandomHorizontalFlip (Paszke et al., 2017). The source code of our method can be found at (https://drive.google.com/drive/folders/16PM-jJP1xal4f0ZMsy2t_UPPPwV1IXkS?usp=sharing).

4.2. Comparisons on CIFAR-10 and CIFAR-100

For our experiments, we have trained VGG-16 and ResNet-56,110,164 architectures on CIFAR-10 and CIFAR100 datasets. We have used a modified version of VGG-16 (Zagoruyko, 2015) with batch-normalization which has fewer parameters in the linear layers. The total number of parameters in the unpruned VGG-16 network is 15 million. The baseline accuracy for CIFAR-10 and CIFAR-100 datasets trained on VGG-16 is 93.95% and 74.12%, respectively. Table. 1 compares the compression and acceleration achieved by the proposed pruning technique on VGG-16 with some of the previous works. Table. 2 and 3 show the comparison of accuracy drop, percentage reduction in parameters and FLOPs for ResNet architectures.

| Dataset   | Method    | Accu. ↓% | Params. ↓% | FLOPs ↓% |
|-----------|-----------|----------|------------|----------|
| CIFAR10   | DCP-adapt | -0.58    | 93.5       | 65.0     |
|           | (Liu et al., 2017) | -0.14    | 88.5       | 51.0     |
|           | ours      | 0.45     | 83.2       | 56.3     |
|           | ours      | 1.06     | 90.5       | 65.6     |
| CIFAR100  | (Liu et al., 2017) | -0.22    | 75.1       | 37.1     |
|           | ours      | 0.57     | 58.3       | 34.4     |

Figure 2. The number of channels pruned in each convolutional layer for VGG-16 network trained on CIFAR-10 dataset.

For the VGG-16 architecture on the CIFAR-10 dataset, our method reduces the computational complexity (# of FLOPs) by 56% achieving a test accuracy of 83% at the cost of 0.45% accuracy drop. The number of channels pruned at each layer for CIFAR-10 dataset trained on VGG-16 is shown in figure. 2. We observed that the percentage of
Gradual Channel Pruning while Training using Feature Relevance Scores

Pruning is higher in the latter layers than the initial layers. For the CIFAR-10 dataset, the experimental results show that our technique was able to prune $(50 - 60)\%$ of the ResNet architectures with an accuracy drop of less than $1\%$ as compared to the unpruned model (refer table 2). We were able to achieve $59\%$ pruning resulting in $56\%$ reduction in FLOPs for ResNet-110 architecture trained on the CIFAR-10 dataset with an accuracy drop of $0.01\%$ as compared to the unpruned model. The pruning percentage achieved for ResNet architectures trained on the CIFAR-100 dataset varied from $(20 - 30)\%$ resulting in $(30 - 40)\%$ reduction in FLOPs (refer table 3). The pruning percentage of the CIFAR-100 is less because of the complexity of the dataset. Note that for ResNet-110 on CIFAR-10, the class relevance scores (refer sec. 3.1) were equally weighted instead of using class-wise accuracies. We have observed that weighted class relevance scores according to class-wise accuracies resulted in smaller accuracy drop in case of more complicated datasets such as CIFAR-100.

Table 2. Comparison of pruning ResNet on CIFAR10. [Acc. ↓ %] denoted the accuracy drop; [Params. ↓ %] denotes reduction in number of parameters; [FLOPs ↓ %] denotes reduction in computations.

| Depth | Method           | Accu. | Params. | FLOPs |
|-------|------------------|-------|---------|-------|
|       |                  | ↓ %   | ↓ %     | ↓ %   |
| 56    | (Li et al., 2017) | -0.02 | 13.7    | 27.6  |
|       | (He et al., 2017) | 1.00  | -       | 50.0  |
|       | (Luo et al., 2017)| 0.82  | 49.0    | 49.9  |
|       | (Yu et al., 2018) | 0.03  | 42.6    | 43.6  |
|       | (He et al., 2018) | 0.24  | 40.0    | 52.6  |
|       | (Zhuang et al., 2018) | -0.01 | 70.4    | 47.1  |
|       | ours              | 0.37  | 42.8    | 41.4  |
|       | ours              | 0.72  | 52.8    | 52.1  |
|       | ours              | 1.0   | 58.9    | 61.0  |
| 110   | (Li et al., 2017) | 0.20  | 32.4    | 38.6  |
|       | (Dong et al., 2017) | 0.19  | -       | 34.2  |
|       | (Yu et al., 2018) | 0.18  | 43.3    | 43.8  |
|       | (He et al., 2018) | -0.18 | 30.0    | 40.8  |
|       | ours              | -0.26 | 29.3    | 28.2  |
|       | ours              | -0.03 | 46.2    | 47.9  |
|       | ours              | 0.01  | 58.8    | 55.7  |
| 164   | (Li et al., 2017) | -0.15 | 33.2    | 44.9  |
|       | ours              | 0.19  | 41.4    | 49.9  |
|       | ours              | 0.54  | 60.2    | 70.3  |

Table 3. Comparison of pruning ResNet on CIFAR100. [Acc. ↓ %] denoted the accuracy drop; [Params. ↓ %] denotes reduction in number of parameters; [FLOPs ↓ %] denotes reduction in computations.

| Depth | Method           | Accu. | Params. | FLOPs |
|-------|------------------|-------|---------|-------|
|       |                  | ↓ %   | ↓ %     | ↓ %   |
| 56    | ours              | 0.67  | 30.2    | 32.9  |
| 110   | ours              | 0.93  | 22.6    | 39.0  |
| 164   | (Li et al., 2017) | 0.54  | 29.7    | 50.6  |
|       | ours              | 0.44  | 26.2    | 39.1  |

In the proposed methodology, the total number of training epochs remain same as that of the baseline model and the number of trainable parameters decrease periodically as shown in Figure 3. Hence, the computational complexity required per training epoch decreases compared to the baseline model as the epoch number increases. Figure 4 shows the test accuracy vs training epoch for baseline and pruned ResNet-56 model trained on CIFAR-10 data-set. In this case, around $7.2\%$ of the parameters are pruned after every 20 epochs and we observe that the test accuracy curve of the pruned model is closer to the baseline. Figure 5 indicates the percentage of accuracy drop as we increase the pruning percentage by changing the hyper-parameter $x$. We observe that the accuracy drop increases as the pruning percentage increases which is as expected. The change in accuracy...
Gradual Channel Pruning while Training using Feature Relevance Scores

Figure 5. Accuracy drop vs pruning percentage for ResNet architecture trained on CIFAR-10 dataset. Pruning percentage is varied by varying $x$. The value of $n$, $N1$ and $N$ are fixed as 20, 150 and 200, respectively.

drop with increase in the number of pruning stages is shown in Figure. 6. The time and computational effort required for the pruning increases as we increase number of pruning stages (which is inversely proportional to $n$). However, very low $n$ results in higher accuracy drop. We observed that the optimal value of $n$ for CIFAR-10 and CIFAR-100 datasets is between $(10−20)$.

Figure 6. Accuracy drop vs number of pruning stages for ResNet-56 architecture trained on CIFAR-10 dataset. The pruning percentage in all the cases is around 50% and $N1$ is set as 150. The variation in accuracy drop with respect to $n$ is shown.

4.3. Comparisons on ImageNet

To demonstrate the effectiveness of the proposed method on large-scale datasets, we further apply our method on ResNet-34 on ImageNet dataset which has 46 million parameters. The baseline accuracy of ResNet-34 on ImageNet dataset is 74.34%. We were able to prune 25% of the network with an accuracy drop of 2.5% as compared to the unpruned model. Note that we do not prune the parameters in the linear layer of ResNet-34.

Table 4. Comparison of pruning ResNet-34 on ImageNet. [Acc. ↓ %] denoted the accuracy drop; [Params. ↓ %] denotes reduction in number of parameters; [FLOPs ↓ %] denotes reduction in computations

| Model     | Method         | Accu. ↓ % | Params. ↓ % | FLOPs ↓ % |
|-----------|----------------|-----------|-------------|-----------|
| ResNet-34 | (Dong et al., 2017) | 0.43      | -           | 24.8      |
|           | (Yu et al., 2018)  | 0.92      | 43.8        | 43.7      |
|           | (He et al., 2018)  | 2.09      | 30.0        | 41.1      |
|           | ours             | 2.54      | 25.4        | 42.3      |

4.4. Pruning Effort

In the proposed technique, the total number of training epochs required is same as that of training an unpruned model. Hence, there is no additional cost in terms of training epochs. However, the pruning technique requires computation of feature relevance scores whose computational and time complexity is shown in Table. 5. The time complexity of the feature relevance score computation is reported in the form of search time. Search time represents the time required to determine the $x$ filters with least feature relevance scores that have to be pruned at a pruning stage (step 6-8 in Algorithm 2). The value of $x$ used to compute the search time in Table. 5 corresponds to the maximum pruning percentage reported in Table. 1 and 2. The computational complexity is reported in terms of effort factor ($\rho$). Effort factor is defined as the ratio of number of FLOPs required to compute feature relevance scores to the number of FLOPs required for one training epoch (see Equation. 1). The number of FLOPs required for a training epoch is considered to be three times the number of FLOPs required for a forward-pass (Ankit et al., 2019). The experiments were conducted on a system with a Nvidia GTX 1080ti GPU.

$$\rho = \frac{\#\ of\ FLOPs(feature\ relevance\ scores)}{\#\ of\ FLOPs(forward\ +\ backward\ pass)} \quad (1)$$

We have reported the the search time for the first pruning step which is the upper bound for the remaining pruning steps as the complexity of the model reduces with each pruning step (refer Figure. 3). The additional time required to obtain the pruned model as compared to training an unpruned model is bounded by the search time (see Table. 5) multiplied by the number of pruning steps. In our experiments, the total number of pruning steps for CIFAR-10/CIFAR-100 and ImageNet datasets is set as 7 and 4, respectively. Also, for huge datasets such as ImageNet, we have used a random
subset of training data (around 0.1 million images) to determine the search time rather than the entire dataset which has a million images. The computation of feature relevance scores requires the access to activations at each layer. We have used the inbuilt function, `register_forward_hook`, from PyTorch to obtain the hidden layer activations which is not compatible with data parallelism. Hence, the reported search time does not include the benefits of data parallelization across multiple devices within a GPU.

Table 5. Effort required by the proposed pruning methodology. Both the search time and effort factor are computed for the first pruning step. The search time and effort factor decrease with each pruning step as the model gets compressed.

| Dataset     | Model    | search time (minutes) | Effort factor (ρ) |
|-------------|----------|-----------------------|-------------------|
| CIFAR-10    | VGG-16   | 2.24                  | 1.29              |
|             | ResNet-56| 2.67                  | 1.31              |
|             | ResNet-110| 4.61                 | 1.32              |
|             | ResNet-164| 7.76                 | 1.67              |
| ImageNet    | ResNet-34| 32.66                 | 1.36              |

The effort factor of the proposed pruning technique ranges from (1.3 – 1.7) as shown in Table 5. This shows that the computational complexity of computing feature relevance scores (i.e., a pruning step) is less than the computational complexity of two training epoch. Note that we have reported the effort factor for the first pruning step which is the upper bound for the remaining pruning steps (refer Figure 3). In our experiments, the number of pruning steps for the CIFAR-10 dataset is set as 7 and this results in the upper bound of the total pruning effort to be equivalent to 9 – 12 training epochs. Also, the computational complexity required per training epoch decreases with each pruning step as compared to the training of unpruned model. Hence, the total computational complexity of training the model from scratch and pruning it through the proposed methodology is less than that of training an unpruned model till convergence.

5. Discussion

Unlike the existing pruning techniques, the proposed technique does not require the model to be trained till convergence before pruning. Instead, the model is pruned globally in a structured fashion during the actual training phase. This reduces the computational and time complexity of training along with inference. Hence, the proposed gradual channel pruning technique will allow the training on edge devices (with limited resources) which might not be feasible with the existing pruning techniques. The pruning methodology utilizes a data driven metric, feature relevance scores, to determine the redundant or less important channels. Replacing feature relevance score with much simpler metrics such as $L_1$ or $L_2$ norm can lead to better computational complexity. However, these metrics only consider the statistics of individual layers, ignoring the effect of error-propagation in the network. Feature relevance scores are computed using Layer-wise Relevance Propagation which is state-of-the-art explainable technique. It utilizes the training data to determine the average effect of the channels on the predicted output. In particular, feature relevance scores includes the statistics of the entire network by considering the activations of each channel and its propagation path to the final layer. Hence, the proposed technique is able to quantify the contribution of a channel towards the discriminative power of the network without an optimization step.

Through our experiments, we have verified that the model need not be trained till convergence to identify irrelevant channels and prune them. Feature relevance scores can be successfully used to discriminate the channels even if the model is trained only for a few epochs. The proposed technique has achieved comparable results to the existing techniques with much less pruning effort. For ResNet-56 trained on CIFAR-10, (He et al., 2018) achieves 40% pruning percentage with an accuracy drop of 0.24% and our methodology achieves around 43% pruning with an accuracy drop of 0.37% accuracy drop. For ResNet-110 trained on CIFAR-10, our methodology achieves around 46% pruning with almost no drop in accuracy as compared to (Yu et al., 2018) which achieves 43% pruning percentage with an accuracy drop of 0.18%. Note that our methodology does not include any fine-tuning i.e., the number of training epochs required for the proposed technique is same as the number of epochs required for training the baseline unpruned model till convergence. Thus, gradual channel pruning while training using feature relevance scores achieves significant model compression and acceleration with reduced pruning effort.

6. Conclusion

Convolutional Neural Networks are crucial for many computer vision tasks and require energy efficient implementation for low-resource settings. In this paper, we present a gradual channel pruning technique while training for CNN compression and acceleration based on feature relevance scores. The channel importance is efficiently evaluated using feature relevance scores after every few epochs during training and the least important channels are pruned. The proposed pruning methodology is free of iterative retraining, which reduces the computational and time complexity of pruning a deep neural network. The effectiveness of the our pruning technique has been demonstrated using benchmark datasets and architectures. We observe that the proposed technique is able to achieve significant compression and acceleration with less than 1% loss in accuracy.
Gradual Channel Pruning while Training using Feature Relevance Scores

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