SYMmetric Convolutional Filters: A Novel Way to Constraining Parameters in CNN

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ABSTRACT

We propose a novel technique to constrain parameters in CNN based on symmetric filters. We investigate the impact on SOTA networks when varying the combinations of symmetry. We demonstrate that our models offer effective generalisation and a structured elimination of redundancy in parameters. We conclude by comparing our method with other pruning techniques.

Index Terms— CNN, symmetric filters, symmetric convolutional filters, symmetric weights, efficient networks, SOTA NN model compression, constrain parameters, edge networks, optimal models, structured pruning

1. INTRODUCTION

Neural Networks (NNs) have been successful compared to other Machine Learning (ML) techniques, mainly due to their ability to extract representative features from the intrinsic structure of raw input data. Moreover, the emergence of smart Internet of Things (IoT) endpoints and social media have opened the floodgates for colossal amounts of data. Combined with the increasing availability of massive data sets, NNs are espoused to be part and parcel of futuristic Artificial Intelligence (AI) systems and products. However, the SOTA NN models are over-parameterised [16] and have huge computational requirements that have doubled every few months [21]. For deployment in edge devices such as smartphones and wearables, the heavily parameterised SOTA networks should be constrained and compressed to lower their memory footprint and computational cost [16].

NN model compression methods include not only techniques for pruning [10, 19, 20] or quantizing parameters [11] of a trained model, but also designing models that are optimal in parameters [15, 18]. We observe that the proliferation of deep CNN models has matured along two directions as, standard networks along improving accuracy of the model in general and edge networks along explicitly targeting inference in edge devices while maintaining acceptable accuracy. The standard networks [7, 12, 14] employ standard convolutions in their basic modules to create deeper networks.

While the edge networks [17, 18] replace the expensive, standard convolutions with depthwise (DW) convolutions. Also, they sandwich DW convolutions between pointwise convolution (1 × 1), forming bottleneck blocks to control the number of channels fed into them, thereby maintaining the parameters in the network.

In this work, we propose a novel NN model compression technique using Symmetric Convolutional Filters (SCF). Standard filters such as Gaussian smoothing, Laplacian edge detection, box blur, sharpen are used in traditional image processing pipelines irrespective of the target application. Their 2D kernels mostly exhibit symmetry about at least one axis. For example, filter weights mirrored about their central vertical axis are vertically symmetric; about their central horizontal axis are horizontally symmetric; about their diagonal are diagonally symmetric. Figure 1 illustrates a few symmetric kernels in which blue background indicates free coefficients and the rest are tied to their symmetric counterparts. We use these 2D kernels for SCF in our work, where free coefficients are the only trainable parameters.

Fig. 1. Various types of symmetric filters; V: Vertically Symmetric, H: Horizontally Symmetric, D: Diagonally Symmetric, HV: Horizontally and Vertically Symmetric, HVD: Horizontally, Vertically and Diagonally Symmetric, Anti_HVD: Same as HVD but with negative coefficients; Compared to a standard 3 × 3 filter: V,H,D use 33% less parameters and HVD,Anti_HVD use 66% less parameters;

Using SCF instead of standard convolutional filters in several standard networks, it’s possible to reduce their parameters comparable to an edge network without significantly affecting their accuracy. Moreover, the structural properties in SCF can be leveraged by hardware accelerators to reduce MAC computations (by pre-adding the inputs before multiplying them with corresponding weights), leading to an effi-
cient edge implementation. Although, in this work we do not discuss the implementation issues inherent to NN architectures (memory consumption, FLOPS, amenability to acceleration, etc). Prior works [3, 4] that have explored symmetric constraints on CNN weights are limited to MNIST and/or smaller custom networks. To the best of our knowledge, we believe our work is the first to empirically validate SCF in SOTA deep networks with real world image datasets.

The other commonly used technique in NN model compression, network pruning, involves removing redundant parameters that have a negligible effect on output accuracy depending on various metrics. Generally, pruning is an iterative process involving repetitive pruning and tuning pre-trained models under heavy supervision. In contrast, SCF networks are trained in the usual way, similar to the standard networks. Moreover, pruning and quantizing NN weights are complementary to our approach. If required, a trained NN model with symmetric filters can later be quantized and/or pruned for further model compression.

In this paper, we empirically validate model compression of SOTA networks using extensive combinations of symmetricity. We show that our SCF models show less over-fitting compared to heavily over-parameterised, less compact base models. We extend the exploration to compact edge networks. Finally, we compare our results with other pruning techniques. Our concluding remarks from the overall experimental results are the following. Certain dimensions are absolutely redundant for representation in the visual domain. Therefore, the intention should not be about just reducing the number of parameters of an over-parameterised CNN model but should be about finding those absolute redundant dimensions. The evolution of NN architecture from perception models, which were fully connected networks, to convolutional models, led to eliminating some of those absolute redundant dimensions. Similarly, we infer that models with SCF eliminate a few more of those redundant dimensions. With this insight, we believe employing SCF in future exploration of NN models is imminent.

### 2. MOTIVATION FROM NEURON SCIENCE

The roots of AI and its inherent progress has very much been influenced from the structure and the method of learning in human brain. The basis of the hierarchical NN structure that we find today in all deep NN is from the hierarchy structure of a visual cortex [1]. As we go deeper into the hierarchy in a NN, the field of view of a neuron increases, allowing it to see bigger parts of the image. Consequently, NN models transform raw input data into higher dimensional feature space through the hierarchy of layers. Visualisation of features learnt by the network reveals that the initial layers learn simple features such as edges, colors and textures, whereas the later layers learn more complex and task-specific features [6].

| Name  | Filters Used | Test Error % | % Original Params |
|-------|--------------|--------------|------------------|
| Base Model | 64 - Standard | 4.4 | 100 |
| Type-III B | 64 - H | 4.31 | 66.66 |
| A | 32-H, 32-V | 4.32 | 66.66 |
| C | 64 - HVD | 4.52 | 33.33 |
| Type-II B | 64 - Anit HVD | 4.51 | 33.33 |
| A | 32 - HVD | 4.32 | 33.33 |
| Type-I | 16 - H, 16-V | 4.31 | 50 |

Table 1. Test Error on CIFAR-10 Dataset when only the Standard Convolutional Filters of First Layer of ResNeXt29_32x4d Model are replaced with different SCF configurations; Refer to Figure 1 for Types of Symmetric Filters.

The fMRI based study conducted in [2] focuses on the neural activity in the following visual areas of the human brain: early (V1, V2, V3), dorsal, lateral, temporal, ventral and indicates that visual areas starting from V3 and all the way down until ventral fire on visual stimuli containing symmetric patterns. Their observations conclude that the neural responses for tasks involving symmetry detection were not only more prominent when compared to passive viewing, but also were proportional to the percentage of symmetricity.

In order to imbibe the higher neuronal excitation for symmetric features trait observed in brain [2], in our CNN model, we propose structurally constraining the convolutional filters with symmetric filters. In CNN, the neurons that show high response for certain features need to have weights similar to the features in the transformed space. To enhance the ability to detect symmetry, we can enforce the neurons to retain the spatial structure of the features even in higher dimensions. Therefore, applying symmetric constraints on standard convolution filters makes sense.

### 3. COMPARISON WITH RELATED WORK IN NN MODEL COMPRESSION

MobileNet [17] uses depthwise separable convolutions [15], which is a form of factorised convolution akin to factorising standard convolution into depthwise convolution and pointwise convolution (1 x 1 convolution). Similarly, MobileNetV2 [18] also uses depthwise separable convolution but incorporates their novel inverted residual connections with linear bottleneck. When compared with our proposal of symmetric convolution, which is spatially constraining the standard convolution, depthwise separable convolution constrains standard convolution in the depth dimension. Our Experiment 3 (see Section 4.4) explores constraining filters in both spatial and depth dimensions.

Pruning techniques are classified as structured and un-structured [10]. We compare with other structured pruning techniques because SCF model compression is more akin to structured method as they do not introduce random sparsity in the filter kernels. Li et al. [10] proposed pruning those filters from CNN by using the sum of absolute weight of the filters.
The idea behind HRank [19] is that low-rank feature maps contain less information and thus can be used to find unimportant filters in CNN. NISP [20] applies the feature ranking technique to measure the importance of each neuron and then formulate network pruning as a binary integer optimisation problem. See Section 4.5 for comparison with pruning methods.

4. EXPERIMENTAL SETUP AND RESULTS

4.1. Experimental Setup

For all our experiments, we have used the NVIDIA DGX-1 system. It has a total of 8 NVIDIA Tesla V100 GPUs, out of which we have used only 1 with 32 GB GPU memory. All code is written in PyTorch. We have experimented with CIFAR-10 and CIFAR-100 datasets [5]. CIFAR-10 dataset consists of 60,000 32x32 real-world colour images of 10 classes, each class having 6,000 images. CIFAR-100 dataset is very similar to the CIFAR-10 dataset, except it has 100 categories containing 600 images each. Both datasets are divided into 50,000 images as the training set and the remaining 10,000 images as the test set. We have used momentum based mini-batch gradient descent [8] algorithm with a batch-size of 128 and momentum of 0.9 with weight-decay of 0.0005. All the configurations are trained for 300 epochs similar to [13], with initial learning rate of 0.1, reduced to 0.01 after 150 epochs, and further reduced to 0.001 after 225 epochs. The input image is 32 × 32 randomly cropped from a zero-padded 40x40 image or its flipping [7]. We have used kaiming normal [9] initialisation to initialise weights of all the models trained in our experiments. We have reported best of 3 runs results using Top-1 accuracy. All the networks without SCF are respectively referred as Base models.

In order to find the best combination of SCF configurations to adapt for later experiments, we replace the standard convolutional filters from only the first convolutional layer which directly interacts with raw data, the image itself instead of feature maps, with symmetric configurations as listed in Table 1. We randomly choose ResNetXt29_32x4d [13] model which has 64 filters of $3 \times 3 \times 3$ dimension in its first layer and train it on CIFAR-10 dataset. From the Table 1, Type-I or Type-IIA symmetric configurations provide higher compression for similar accuracy. Hence, we limit the rest of the experiments to SCF configurations with either Type-I or Type-IIA symmetric filters.

4.2. Experiment 1: Using SCF in Heavily Over-parameterised ResNet Models

In this experiment, we choose ResNet [7] models constructed to study behaviours of extremely deep networks on CIFAR-10. Also, ResNet [7] publishes their models tailored explicitly for CIFAR-10 with 20, 32, 44 and 56 number of layers along with results. This allows us to validate our modifications to their networks rigorously. We replace standard convolutional filters from all layers with bespoke SCF configurations. We also validate using CIFAR-100, a bigger dataset with more classes, to ensure an unbiased inference of results. For CIFAR-100 dataset we use the same ResNet networks de-

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1 Code will be released soon on Github.
4.4. Experiment 3: Exploring SCF in Low Resource Edge Networks

In this experiment, we choose MobileNet V1 [17], V2 [18] which are edge networks. Although constraining the depthwise filters with symmetric filters leads to minimal compression gain (to the tune of 1-2%), this experiment strengthens our insight into SCF in NN models. As both models are already compact, we expect that further constraining the parameters could only lead to highly degraded accuracy. To investigate, we spatially constrain the depthwise filters with Type-I symmetric filters, one layer at a time and train them on CIFAR-10 dataset. From the Figure 3, we see that the validation accuracy reduces minimally for both MobileNetV1 and MobileNetV2 when symmetric filters replace all $3 \times 3$ depthwise filters. Contrary to our expectations, the validation accuracy of every point in the graph, representing models with varying amounts of symmetric filters, does not differ much from the base model. Remarkably, we can infer that the edge models considered optimal in parameters still have spatial redundancy that can be exploited using symmetric filters.

4.5. Comparison of ResNet-56 Model with our SCF Configurations and Pruning Methods in Table below

| Method      | CIFAR-10 Val_Error | % Original Param |
|-------------|--------------------|------------------|
| ResNet-56   | 6.97               | 100              |
| L1 [10]     | 6.94               | 85.90            |
| NISP [20]   | 6.99               | 57.60            |
| Type-I (Ours) | 7.24             | 50.28            |
| Type-IIA (Ours) | 8.38            | 33.70            |
| HRank [19]  | 10.75              | 28.40            |

5. CONCLUSION

We proposed a novel technique to constrain parameters in CNN based on symmetric filters. We investigated the impact on accuracy for CIFAR-10 and CIFAR-100 datasets when varying the combinations and levels of symmetricity in the diverse basic blocks of NN models. We believe the trends will be similar for ImageNet dataset. We demonstrated that our models offer effective generalisation and a structured elimination of redundancy in parameters. We concluded by comparing our method with other pruning techniques.
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