Trainability Preserving Neural Structured Pruning

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Abstract. Several recent works empirically find finetuning learning rate is critical to the final performance in neural network structured pruning. Further researches find that the network trainability broken by pruning answers for it, thus calling for an urgent need to recover trainability before finetuning. Existing attempts propose to exploit weight orthogonalization to achieve dynamical isometry for improved trainability. However, they only work for linear MLP networks. How to develop a filter pruning method that maintains or recovers trainability and is scalable to modern deep networks remains elusive. In this paper, we present trainability preserving pruning (TPP), a regularization-based structured pruning method that can effectively maintain trainability during sparsification. Specifically, TPP regularizes the gram matrix of convolutional kernels so as to de-correlate the pruned filters from the kept filters. Beside the convolutional layers, we also propose to regularize the BN parameters for better preserving trainability. Empirically, TPP can compete with the ground-truth dynamical isometry recovery method on linear MLP networks. On non-linear networks (ResNet56/VGG19, CIFAR datasets), it outperforms the other counterpart solutions by a large margin. Moreover, TPP can also work effectively with modern deep networks (ResNets) on ImageNet, delivering encouraging performance in comparison to many top-performing filter pruning methods. To our best knowledge, this is the first approach that effectively maintains trainability during pruning for the large-scale deep neural networks.

1 Introduction

Neural network pruning aims to remove the parameters without seriously compromising the performance. It normally consists of three steps [46,12,11]: pretrain a dense model; prune the unnecessary connections or neurons with some rule; finetune to regain performance. Pruning is usually categorized into two groups, unstructured pruning (a.k.a. element-wise pruning) and structured pruning (a.k.a. filter pruning or channel pruning). The former chooses a scalar weight as the basic pruning element; the latter chooses a 3d filter as the basic pruning element. In general, structured pruning is more favored for acceleration on commodity hardware because of the regular sparsity; unstructured pruning results in

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irregular sparsity, which can be considerable without performance degradation but hard to exploit for acceleration if not using customized hardware [9,10].

Recent structured pruning works [47,23] showed an interesting phenomenon: During finetuning, a larger learning rate (LR) helps achieve a significantly better final performance (e.g., ResNet34 pruned at speedup 1.32× can be improved by over 1% top-1 accuracy on ImageNet [5] using finetuning LR \(1\times10^{-2}\) vs. \(1\times10^{-3}\)).

The reason behind is argued to be relevant to the trainability of neural networks [27,39,56]. They mainly make two observations to explain the LR effect mystery [56]. (1) The weights removing operation immediately breaks the trainability or dynamical isometry [48] (the ideal case of trainability) of the trained network. (2) The SGD optimization in finetuning can inherently rectify it without extra explicit guidance; a larger LR help recover it faster (and possibly better), thus making the final performance much stronger, especially when the finetuning epochs are insufficient. Although these works [27,39,56] provide a plausibly sound explanation, a more practical issue is how to recover the broken trainability (or dynamical isometry) or maintain it during pruning. In this regard, [56] proposes to apply weight orthogonalization based on QR decomposition [53,40] to the pruned model. However, their method is shown to only work for linear MLP networks. On modern deep convolutional neural networks (CNNs), how to maintain trainability after pruning is still elusive.

In this paper, we present trainability preserving pruning (TPP), a new filter pruning method based on regularization (see Fig. 1 for an overview) that maintains trainability well during pruning. By our observation, the primary cause that pruning breaks dynamical isometry lies in the dependency among parameters. The main idea of our method is thus to de-correlate the pruned weights from the kept weights so as to cut off the dependency, so that the following weights removing operation barely hurts the trainability of the network.

Specifically, we propose to regularize the gram matrix of weights: All the entries representing the correlation between the pruned filters (i.e., unimportant filters) and the kept filters (i.e., important filters) are encouraged to diminish to zero. This is the first technical contribution of our method. The second one lies in how to treat the other entries. Conventional dynamical isometry wisdom suggests orthogonality (namely, 1 self-correlation and 0 cross-correlation) even among the kept filters, while we find directly translating the idea here is unnecessary or even harmful because the too strong penalty will constrain the optimization, leading to deteriorated local minimum. Rather, we propose to not impose any regularization on the correlation entries of kept filters, which will be shown to help improve the performance in our experiments.

Finally, modern deep models are typically equipped with batch normalization (BN) [21]. However, previous filter pruning papers rarely explicitly take BN into account (except two [37,63]; the differences of our work from theirs will be discussed in Sec. 3.2) to mitigate the side effect when it is removed because its associated filter is removed. Since they are also a part of the whole trainable parameters in the network, unattended removal of them will also lead to severely crippled trainability (especially at large sparsity). Therefore, BN parameters (in-
Fig. 1. Illustration of the proposed pruning algorithm TPP applied to a typical residual block. Weight parameters are classified into two groups as a typical pruning algorithm does: important (white color) and unimportant (orange or blue color), right from the beginning (before any training starts) based on the $L_1$-norms of the filters. Then only the unimportant parameters are enforced with the proposed TPP regularization terms, which is the key to maintain trainability when the unimportant weights are eventually eliminated from the network. Notably, the critical part of a regularization-based pruning algorithm lies in its specific regularization term, i.e., Eqs. (3) and (5), which we will show perform more favorably than other alternatives (see Tabs. 1 and 2).

Including both the scale and bias parameters) should also be explicitly taken into account when designing a pruning algorithm. As such, we propose to regularize the learnable parameters of BN to minimize the influence of its absence.

Empirically, the proposed pruning algorithm is rather easy to implement on popular deep learning platforms and robust to hyper-parameter variations. On the ResNet50 ImageNet benchmark, it delivers encouraging results compared to many recent SOTA filter pruning algorithms. Our contributions in this paper are summarized as follows:

- We present the first filter pruning method (trainability preserving pruning) that can effectively maintain trainability during pruning for modern deep networks, through a customized weight gram matrix as regularization target.
- Apart from weight regularization, we also propose to regularize the BN parameters to offset the side-effect of their eventual absence. This has been overlooked by most previous pruning papers, while we show it is pretty important to preserve trainability, especially when the pruning ratio is large.
- Practically, the proposed method is scalable to modern large-scale deep neural networks (e.g., ResNets) and datasets (e.g., ImageNet). It achieves promising pruning performance in the comparison to many state-of-the-art filter pruning methods.
2 Related Work

Neural network pruning. In terms of the sparsity structure induced by pruning, pruning methods mainly fall into structured pruning (filter pruning or channel pruning) [30,60,17,16,58] and unstructured pruning [12,11,25,13,50]. Structured pruning results in regular sparsity after pruning, easy to be translated to acceleration on commodity hardware. In contrast, unstructured pruning produces irregular sparsity, beneficial to compression while hard to leverage for practical acceleration [60,55] unless with special hardware support [9,10]. For more comprehensive coverage, we recommend surveys [52,2,3,6,57]. This paper targets structured sparsity (filter pruning) because it is more imperative to make modern networks (e.g., ResNets [14]) faster rather than smaller compared to the early single-branch convolutional networks (e.g., VGG [49]).

It has been broadly observed [25,12] and also intuitively straightforward that a naive way of pruning (e.g., random pruning) of a normally-sized (i.e., not intentionally severely over-parameterized) network will lead to significant performance drop. Namely, we need to cleverly choose some “unimportant” parameters to remove to avoid severe performance degradation. Such a criterion for choosing is pruning criterion. In the area, there have been two major paradigms to address the pruning criterion problem dating back to the 1990s: regularization-based methods and importance-based methods [46]. Specifically, the regularization-based methods select unimportant parameters by adding a sparsity-inducing penalty term jointly optimized with the original objective function (e.g., [60,24,38,37,63,64,65]). This paradigm can be applied to a random or pretrained network. Importance-based methods choose unimportant parameters by certain established mathematical formula (typically based on the Taylor expansion of the loss objective function) (e.g., [25,13,12,11,30,41,42]). This paradigm is majorly applied to a pretrained network. Despite the differences, it is worth noting that these two paradigms are not firmly unbridgeable, i.e., we can develop approaches that take advantage of both ideas, such as [7,55,58] – these methods identify unimportant weights per a certain importance criterion; then, they utilize a penalty term to produce sparsity. The developed algorithm in this paper is also in this line.

Trainability, dynamical isometry, and orthogonality. Trainability describes the easiness of optimization of a neural network. Dynamical isometry, the perfect case of trainability, is first introduced by [48], stating that singular values of the Jacobian matrix are close to 1. It can be achieved (for linear MLP models) by the orthogonality of weight matrix at initialization. Recent works on this topic mainly focus on how to maintain dynamical isometry during training instead of only for initialization [62,20,1,19,59]. These methods are developed independent of pruning, thus not directly relevant to the proposed method in this work. However, the insights from these works inspire us to our proposed approach (see Sec. 3.2) and possibly more in the future. Several pruning papers study the network trainability issue in the context of network pruning, such as [27,39,54]. Our work is different from theirs primarily in that we focus on pruning a pretrained model while they tackle the pruning at initialization problem.
3 Methodology

3.1 Preliminaries: Dynamical Isometry and Orthogonality

The definition of dynamical isometry is that the input-output Jacobian of a network has as many singular values (JSVs) as possible close to 1 [48]. With it, the error signal can preserve its norm under propagation without serious amplification or attenuation, which in turn helps the convergence of (very deep) networks. For a single fully-connected layer $W$, a sufficient and necessary condition to realize dynamical isometry is orthogonality, i.e., $W^T W = I$,

$$y = Wx,$$

$$\|y\| = \sqrt{y^T y} = \sqrt{x^T W^T W x} = \|x\|, \text{ iff. } W^T W = I,$$

where $I$ stands for identity matrix. Orthogonality of a weight matrix can be easily realized by matrix orthogonalization techniques such as QR decomposition [53,40]. Exact (namely all the Jacobian singular values are exactly 1) dynamical isometry can be achieved for linear networks since multiple linear layers essentially reduce to a single 2d weight matrix. In contrast, the convolutional and non-linear cases are much complicated. Previous work [56] has shown that merely considering convolution or ReLU [43] renders the weight orthogonalization method much less effective in terms of recovering dynamical isometry after pruning, let alone considering modern deep networks with BN [21] and residuals [14]. The primary goal of our paper is to bridge this gap.

Following the seminal work of [48], several papers propose to maintain orthogonality during training instead of solely for the initialization. There are primarily two groups of orthogonalization methods for convolutional neural networks: kernel orthogonality [62,20,19] and orthogonal convolution [59]:

$$KK^T = I \Rightarrow \mathcal{L}_{\text{orth}} = KK^T - I, \triangleleft \text{kernel orthogonality}$$

$$\mathcal{K}\mathcal{K}^T = I \Rightarrow \mathcal{L}_{\text{orth}} = \mathcal{K}\mathcal{K}^T - I, \triangleleft \text{orthogonal convolution}$$

(2)

where clearly the difference lies in the weight matrix $K$ vs. $\mathcal{K}$. (1) $K$ denotes the original weight matrix in a convolutional layer. Weights of a conv layer make up a 4d tensor $\mathbb{R}^{N \times C \times H \times W}$, where $N$ stands for the number of output channels, $C$ for the number of input channels, $H$ and $W$ for the height and width of conv kernel. Then, $K$ is a reshaped version of the 4d tensor: $K \in \mathbb{R}^{N \times C \times H \times W}$ (if $N < C \times H \times W$; otherwise, $K \in \mathbb{R}^{C \times H \times W \times N}$). (2) In contrast, $\mathcal{K} \in \mathbb{R}^{N_{Hfo} \times W_{f1} \times C_{Hfi} \times W_{j1}}$ stands for the doubly block-Toeplitz (DBT) matrix representation of $K$ ($H_{f0}$ stands for the output feature map height, $H_{f1}$ for the input feature map height, $W_{f0}$ and $W_{j1}$ can be inferred the same way for width).

It has been showed by [59] that orthogonal convolution is more effective than kernel orthogonality [62] in that the latter is only a necessary but insufficient condition of the former. In this work, we will evaluate both methods to see how effective they are in recovering the broken trainability.
3.2 Trainability Preserving Pruning (TPP)

The proposed method is made up of two parts. First, we explain how we come up with the proposed scheme and how it intuitively is better than the straight idea of directly applying orthogonality regularization methods [62,59] here. Second, we propose to regularize batch normalization layers given their prevailing use as a standard component in deep neural networks nowadays.

(1) Trainability vs. orthogonality. From previous works [27,39,56], we know recovering the broken trainability (or dynamical isometry) incurred by pruning is very important. Considering orthogonality regularization can encourage dynamical isometry, a pretty straightforward solution is to build upon the existing kernel orthogonality regularization schemes. Specifically, kernel orthogonality regularizes the weight gram matrix to be close to identity matrix (see Fig. 2(a)). In our case, we aim to remove some filters, so naturally we can regularize the weight gram matrix to be close to a partial identity matrix, with the diagonal entries at the pruned filters zeroed (see Fig. 2(b)).

The above scheme is simple and straightforward. However, it is not in its best shape by our empirical observation. It imposes too strong unnecessary constraint on the remaining weights, which will in turn hurt the optimization. Therefore, we propose to seek a weaker constraint, not demanding the perfect trainability (i.e., dynamical isometry realized by orthogonality), but only a benign status, which describes a state of the neural network where gradients can flow effectively through the model without being interrupted. Orthogonality requires the Jacobian singular values to be exactly 1; in contrast, a benign trainability only requires them not to be extremely large or small so that the network can be trained normally. To this end, we propose to de-correlate the kept filters from the pruned filters: in the target gram matrix, all the entries associated with the
pruned filters are zero; all the other entries stay as they are, as shown in Fig. 2(c). The merit of this scheme will be empirically justified (see Tab. 4).

Specifically, for the $l$-th layer, we sort the filters by their $L_1$ norms and select those with the smallest $L_1$ norms as unimportant filters (denoted as set $S_l$). Then, the proposed regularization term is,

$$\mathcal{L}_1 = \sum_{l=1}^{L} ||W_l W_l^T \odot (1 - mm^T)||_F^2, \hspace{1cm} m_j = 0 \text{ if } j \in S_l, \text{ else } 1,$$

where $W$ denotes the weight matrix; $1$ represents the matrix full of 1; $m$ is a 0/1-valued column mask vector; $\odot$ is the Hadamard (element-wise) product; and $|| \cdot ||_F$ denotes the Frobenius norm.

(2) **BN regularization.** Per the idea of preserving trainability, BN is not ignorable since BN layers are also trainable. Removing filters will change the internal feature distributions. If the learned BN statistics do not change accordingly, the error will accumulate and result in deteriorated performance (especially for deep networks). Consider the following BN formulation [21],

$$f = \gamma \frac{W \ast X - \mu}{\sqrt{\sigma^2 + \epsilon}} + \beta,$$

where $\ast$ stands for convolution; $\mu$ stands for the running mean, $\sigma^2$ for the running variance; $\epsilon$ is a small amount for numerical stability; the two learnable parameters are $\gamma$ and $\beta$. Although unimportant weights are enforced with regularization for sparsity, their magnitude can barely be exact zero, making the subsequent removal of filters biased. This will modify the feature distribution and render the BN statistics incorrect. Using these biased BN statistics would be improper and damages trainability. To mitigate this influence of BN, we propose to regularize both the $\gamma$ and $\beta$ of pruned feature map channels to zero. The penalty term can be formulated as

$$\mathcal{L}_2 = \sum_{l=1}^{L} \sum_{j \in S_l} \gamma_j^2 + \beta_j^2.$$

The merits of BN regularization will be justified in our experiments (Tab. 5).

To sum, with the proposed regularization terms, the total error function is

$$\mathcal{E} = \mathcal{L}_{cls} + \lambda \left( \mathcal{L}_1 + \mathcal{L}_2 \right),$$

where $\mathcal{L}_{cls}$ stands for the original classification loss. The coefficient $\lambda$ grows gradually (by a predefined constant $\Delta$ per $K_u$ iterations, up to a ceiling $\tau$) during training to ensure the pruned parameters are rather close to zero (inspired by [55,58]). Our algorithm is summarized in Algorithm 1.

**Discussion.** Prior works [37,63] also propose to regularize BN for pruning. Our BN regularization method is starkly different from theirs. (1) In terms of the motivation or goal, [37,63] regularize $\gamma$ to learn unimportant filters, namely, regularizing BN is to indirectly decide which filters are unimportant. In contrast,
Algorithm 1 Trainability Preserving Pruning (TPP)

1: **Input**: Pretrained model $\Theta$, layer-wise pruning ratio $r_l$ of $l$-th layer, for $l \in \{1, 2, \ldots, L\}$.
2: **Input**: Regularization ceiling $\tau$, penalty coefficient update interval $K_u$, penalty granularity $\Delta$.
3: **Init**: Iteration $i = 0$. $\lambda_j = 0$ for all filter $j$. Set pruned filter indices $S_l$ by $L_1$-norm sorting.
4: **while** $\lambda_j \leq \tau$, for $j \in S_l$ do
5:   **if** $i \% K_u = 0$ **then**
6:     $\lambda_j = \lambda_j + \Delta$ for $j \in S_l$.  \(\triangleright\) Update regularization co-efficient in Eq. (6)
7:   **end if**
8:   Network forward, loss (Eq. (6)) backward, parameter update by stochastic gradient descent.
9: **end while**
10: Remove filters in $S_l$ to obtain a smaller model $\Theta'$. 
11: **Finetune** $\Theta'$ to regain accuracy.
12: **Output**: Finetuned model $\Theta'$.

In our method, unimportant filters are decided by their $L_1$-norms. We adopt BN regularization for a totally different consideration – to mitigate the side effect of breaking dynamical isometry, which is not mentioned at all in their works. (2)

In terms of specific technique, \[37,63\] only regularize the scale factor $\gamma$ (because it is enough to decide which filters are unimportant) while we regularize both the learnable parameters because only regularizing one still impairs dynamical isometry of the network. Besides, we employ different regularization strength for different parameters (by the group of important filters vs. unimportant filters), while \[37,63\] simply use the same penalty strength for all parameters – this is another key difference because regularizing all parameters (including those that are meant to be kept) will damage dynamical isometry, which is exactly what we want to avoid. In short, in either general motivation or specific technical details, our proposed BN regularization is distinct from previous works \[37,63\].

4 Experimental Results

Datasets and networks. We first conduct analyses with MLP-7-Linear network on MNIST \[26\]. Then compare our method to other plausible solutions with ResNet56 \[14\]/VGG19 \[49\] on CIFAR10/100 \[22\]. Next we evaluate our algorithm on the large-scale ImageNet dataset \[5\] with ResNet34 and 50 \[14\]. Finally, we conduct an ablation study to show the efficacy of two main technical novelties in our approach. On ImageNet, we take the official PyTorch \[44\] pre-trained models as base models to maintain comparability with other methods. On other datasets, we train our own base models with comparable accuracies to those reported in their original papers. See our supplementary material for the specific training settings due to limited space here.
Fig. 3. Mean JSV and test accuracy during finetuning with different setups (network: MLP-7-Linear, dataset: MNIST). Below each plot are, in order, the best accuracy of LR 1e-2, the best accuracy of LR 1e-3, and the mean JSV right after pruning (i.e., without finetuning). LR 1e-2 and 1e-3 are short for two finetuning LR schedules following [56]: \{0:1e-2, 30:1e-3, 60:1e-4, epochs:90\}, \{0:1e-3, 45:1e-4, epochs:90\}. The accuracies are averaged by 5 random runs. For reference, the unpruned model has mean JSV 2.4987, test accuracy 92.77

Fig. 4. Loss surface visualization of pruned models by different methods (w/o finetuning). ResNet56 on CIFAR10. Pruning ratio: 0.9 (zoom in to examine the details.)

Comparison methods. We compare with [56], which proposes a method OrthP to recover broken dynamical isometry for pruning pretrained models. Besides, since maintaining orthogonality is the key and there are many existing orthogonality regularization papers [62,59,20,19,59], a straightforward solution is to combine them with L1-norm pruning [30] to see if they can help maintain or recover the broken dynamical isometry. There are two possible combination schemes: 1) apply orthogonal regularization pruning methods before applying L1-norm pruning, 2) apply orthogonal regularization methods after L1-norm pruning, namely, in finetuning. Two representative orthogonality regularization methods are selected because of their proved effectiveness: kernel orthogonality [62] and convolutional orthogonality [59], so in total there are 4 combinations: L1 + KernOrth [62], L1 + OrthConv [59], KernOrth [62] + L1, OrthConv [59] + L1.
Table 1. Test accuracy (%) comparison among different dynamical isometry maintenance or recovery methods on ResNet56 + CIFAR10. “Scratch” stands for training from scratch. Each setting is randomly run for 3 times, mean (std) accuracies reported. “KernOrth” means Kernel Orthogonalization [62]; “OrthConv” means Convolutional Orthogonalization [59]. Two finetuning LR schedules are evaluated here: initial LR $1e^{-2}$ vs. $1e^{-3}$. “Acc. diff.” refers to the accuracy gap of LR $1e^{-3}$ against LR $1e^{-2}$.

| Pruning ratio $r$ | 0.3 | 0.5 | 0.7 | 0.9 | 0.95 |
|-------------------|-----|-----|-----|-----|------|
| **Sparsity/Speedup** | 31.14% | 49.82% | 70.57% | 90.39% | 95.19% |
| **ResNet56 + CIFAR10**: Baseline accuracy 93.78%, Params: 0.85M, FLOPs: 0.25G |
| **Initial finetuning LR $1e^{-2}$** |
| Scratch | 93.16 (0.16) | 92.78 (0.23) | 92.11 (0.12) | 88.36 (0.20) | 84.60 (0.14) |
| $L_1$ [30] | 93.79 (0.06) | **93.51 (0.07)** | 92.26 (0.17) | 86.75 (0.31) | 83.03 (0.07) |
| $L_1$ + OrthP [56] | 93.69 (0.02) | 93.36 (0.19) | 91.96 (0.06) | 86.01 (0.34) | 82.62 (0.05) |
| $L_1$ + KernOrth [62] | 93.49 (0.04) | 93.30 (0.19) | 91.71 (0.14) | 84.78 (0.34) | 80.87 (0.47) |
| $L_1$ + OrthConv [59] | 92.54 (0.09) | 92.41 (0.07) | 91.62 (0.16) | 84.52 (0.27) | 80.23 (1.19) |
| KernOrth [62] + $L_1$ | 93.49 (0.07) | 92.82 (0.10) | 90.54 (0.25) | 85.47 (0.20) | 79.48 (0.81) |
| OrthConv [59] + $L_1$ | 93.63 (0.17) | 93.28 (0.20) | 92.27 (0.13) | 86.70 (0.07) | 83.21 (0.61) |
| **TPP (ours)** | **93.81 (0.11)** | 93.46 (0.06) | **92.35 (0.12)** | 89.63 (0.10) | **85.86 (0.08)** |
| **Initial finetuning LR $1e^{-3}$** |
| $L_1$ [30] | 93.43 (0.06) | 93.12 (0.10) | 91.77 (0.11) | 87.57 (0.09) | 83.10 (0.12) |
| TPP (ours) | **93.54 (0.08)** | **93.32 (0.11)** | **92.00 (0.08)** | 89.09 (0.10) | **85.47 (0.22)** |
| Acc. diff. ($L_1$) | -0.38 | -0.40 | -0.50 | +0.82 | +0.07 |
| Acc. diff. (TPP) | -0.27 | -0.14 | -0.35 | -0.54 | -0.39 |

Over, presetting pruning ratios help us control irrelevant factors precisely, excluding their interference to our analyses. Please refer to the supplementary material for a summary of all pruning ratios adopted in this work.

Comparison metrics. (1) We compare the final test accuracy after finetuning with the similar FLOPs budget – this is currently the most prevailing metric to compare different filter pruning methods in classification. Concretely, we compare two settings: a relatively large finetuning LR ($1e^{-2}$) and a small one ($1e^{-3}$). We introduce these settings because previous works [47,23,56] showed that finetuning LR has a great impact on the final performance. From this metric, we can see how sensitive different methods are to the finetuning LR. (2) We also compare the test accuracy before finetuning – from this metric, we will see how robust different methods are in the face of weight removal.

4.1 Analysis: MLP-7-Linear+MNIST and ResNet56+CIFAR10

MLP-7-Linear is a seven-layer linear MLP. It is adopted in [56] for analysis because linear MLP is the only network that can achieve exact dynamical isometry (all JSVs are exactly 1) so far. Their proposed dynamical isometry recovery method OrthP [56] is shown to achieve exact isometry on linear MLP networks. Since we claim our method TPP can maintain dynamical isometry too, conceivably, our method should play a similar role to OrthP in pruning. To confirm this, we prune the MLP-7-Linear network with our method (exactly following the settings in [56] for fair comparison).
Table 2. Test accuracy (%) comparison among different dynamical isometry maintenance or recovery methods on VGG19 + CIFAR100. “Scratch” stands for training from scratch. Each setting is randomly run for 3 times, mean (std) accuracies reported. “KernOrth” means Kernel Orthogonalization [62]; “OrthConv” means Convolutional Orthogonalization [59]. Two finetuning LR schedules are evaluated here: initial LR 1e-2 vs. 1e-3. “Acc. diff.” refers to the accuracy gap of LR 1e-3 against LR 1e-2.

| VGG19 + CIFAR100: Baseline accuracy 74.02%, Params: 20.08M, FLOPs: 0.80G |
|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| Pruning ratio r          | 0.1                      | 0.3                      | 0.5                      | 0.7                      | 0.9                      |
| Sparsity/Speedup          | 19.24%/1.23×              | 51.01%/1.97×              | 74.87%/3.60×              | 90.98%/8.84×              | 98.96%/44.22×             |
| Initial finetuning LR 1e-2|                          |                          |                          |                          |                          |
| Scratch                   | 72.84 (0.25)              | 71.88 (0.14)              | 70.79 (0.08)              | 66.51 (0.11)              | 54.37 (0.40)              |
| $L_1$ [30]                | 74.01 (0.18)              | 73.01 (0.22)              | 71.49 (0.14)              | 66.05 (0.04)              | 51.36 (0.11)              |
| $L_1$ + OrthP [56]        | 74.00 (0.04)              | 72.30 (0.49)              | 68.09 (0.24)              | 62.22 (0.15)              | 48.07 (0.31)              |
| $L_1$ + KernOrth [62]     | 73.72 (0.26)              | 72.53 (0.09)              | 71.23 (0.10)              | 65.90 (0.14)              | 50.75 (0.30)              |
| $L_1$ + OrthConv [59]     | 73.18 (0.10)              | 72.25 (0.31)              | 70.82 (0.11)              | 64.51 (0.43)              | 48.31 (0.18)              |
| KernOrth [62] + $L_1$     | 73.73 (0.23)              | 72.41 (0.12)              | 70.31 (0.12)              | 64.10 (0.19)              | 50.72 (0.87)              |
| OrthConv [59] + $L_1$     | 73.55 (0.18)              | 72.67 (0.09)              | 71.24 (0.23)              | 65.66 (0.10)              | 50.53 (0.46)              |
| TPP (ours)                | 74.02 (0.24)              | 73.19 (0.07)              | 71.61 (0.08)              | 67.78 (0.31)              | 57.70 (0.37)              |
| Initial finetuning LR 1e-3|                          |                          |                          |                          |                          |
| $L_1$ [30]                | 73.67 (0.05)              | 72.04 (0.12)              | 70.21 (0.02)              | 64.72 (0.17)              | 48.43 (0.44)              |
| TPP (ours)                | 73.83 (0.02)              | 72.29 (0.07)              | 71.16 (0.12)              | 67.47 (0.17)              | 56.73 (0.34)              |
| Acc. diff. ($L_1$)        | -0.34                    | -0.97                    | -1.28                    | -1.33                    | -2.93                    |
| Acc. diff. (TPP)          | -0.19                    | -0.90                    | -0.45                    | -0.31                    | -0.97                    |

TPP can perform as well as OrthP on linear MLP. The results using our TPP method are presented in Fig. 3. Fig. 3(b) is the one equipped with OrthP, which can exactly recover dynamical isometry (note its mean JSV right after pruning is 1.0000), so it works as the oracle here. (1) OrthP improves the best accuracy from 91.36/90.54 to 92.79/92.77; using TPP, we obtain 92.81/92.77. Namely, in terms of accuracy, our method is as good as the oracle scheme. (2) Note the mean JSV right after pruning – the $L_1$-norm pruning destroys the mean JSV from 2.4987 to 0.0040, and OrthP brings it back to 1.0000. In comparison, TPP achieves 3.4875, at the same order of magnitude of 1.0000, also as good as OrthP. These demonstrate, in terms of either the final evaluation metric (test accuracy) or the trainability measure (mean JSV), our TPP method can perform as well as the ground-truth method OrthP on the linear MLP network.

Loss surface analysis with ResNet56+CIFAR10. We plot the loss surfaces [31] of pruned networks (before finetuning) of different pruning methods. Fig. 4 shows that the loss surface of our method is flatter than other methods, implying the loss landscape is easier for optimization.
Table 3. Speedup comparison on ImageNet. FLOPs: ResNet34: 3.66G, ResNet50: 4.09G. * implies advanced training recipe (such as cosine LR schedule) is used; we single them out for fair comparison

| Method               | Network | Base top-1 (%) | Pruned top-1 (%) | Top-1 drop (%) | Speedup |
|----------------------|---------|----------------|------------------|----------------|---------|
| L1 (pruned-B) [30]   | ResNet34| 72.17          | 1.06             | 1.32x          |
| L1 (pruned-B, reimpl.) [56] | ResNet34| 72.83          | 0.48             | 1.29x          |
| Taylor-FO [42]       | ResNet34| 72.67          | -0.36            | 1.32x          |
| GReg-2 [58]          |         | 73.61          | -0.30            | 1.32x          |
| TPP (ours)           |         | 73.77          | -0.46            | 1.32x          |
| ProvABFP [34]        |         | 76.21          | 0.92             | 1.43x          |
| MetalPruning [36]    | ResNet50| 76.2           | 0.4              | 1.37x          |
| GReg-1 [58]          |         | 76.27          | -0.14            | 1.49x          |
| TPP (ours)           |         | 76.44          | -0.31            | 1.49x          |
| IncReg [35]          |         | 72.47          | 3.13             | 2.00x          |
| SFP [16]             |         | 74.61          | 1.54             | 1.72x          |
| HRank [35]           |         | 74.98          | 1.17             | 1.78x          |
| Taylor-FO [42]       | ResNet50| 74.50          | 1.68             | 1.82x          |
| Factorized [32]      |         | 74.55          | 1.60             | 2.33x          |
| DCP [66]             |         | 74.95          | 1.06             | 2.25x          |
| CCP-AC [45]          |         | 75.32          | 0.83             | 2.18x          |
| GReg-2 [58]          |         | 75.36          | 0.77             | 2.31x          |
| CC [33]              |         | 75.59          | 0.56             | 2.12x          |
| MetaPruning [36]     |         | 75.4           | 1.2              | 2.00x          |
| TPP (ours)           |         | 75.60          | 0.53             | 2.31x          |
| LFFPC [19]           | ResNet50| 74.46          | 1.09             | 2.33x          |
| GReg-2 [58]          |         | 74.93          | 1.20             | 2.56x          |
| CC [33]              |         | 74.54          | 1.61             | 2.68x          |
| TPP (ours)           |         | 75.12          | 1.01             | 2.56x          |
| IncReg [35]          |         | 71.27          | 4.53             | 3.00x          |
| Taylor-FO [42]       | ResNet50| 71.69          | 4.49             | 3.05x          |
| GReg-2 [58]          |         | 73.90          | 2.23             | 3.06x          |
| TPP (ours)           |         | 74.51          | 1.62             | 3.06x          |

4.2 ResNet56+CIFAR10 / VGG19+CIFAR100

Here we compare our method to other plausible solutions on the CIFAR10/100 datasets [22] with non-linear convolutional architectures. From the results in Tab. 1 and Tab. 2, we have the following observations.

(1) OrthP [56] does not work well – L1 + OrthP underperform the original L1 under all the five pruning ratios for both ResNet56 and VGG19. This further confirms the weight orthogonalization method proposed for linear networks indeed does not generalize to non-linear convolutional networks.

(2) For KernOrth vs. OrthConv, the results look mixed – OrthConv is better when applied before the L1-norm pruning. This is reasonable since OrthConv has been shown more effective than KernOrth in enforcing more dynamical isometry [59], which in turn can stand more of the damage from pruning.
Of special note is that, none of the above five methods actually outperform the $L_1$-norm pruning or the simple scratch training. It means that neither enforcing more isometry before pruning nor compensating isometry after pruning can help dynamical isometry recovery. In stark contrast, our proposed TPP method outperforms $L_1$-norm pruning and scratch consistently against different pruning ratio (only one exception is pruning ratio 0.7 on ResNet56, but our method is still the second best and the gap to the best is only marginal: 93.46 vs. 93.51). Besides, note that the accuracy trend: in general, with a larger pruning ratio, the advantage of TPP over $L_1$ or Scratch is more pronounced. This is because a larger pruning ratio means the dynamical isometry is damaged more, where our method can help more, thus harvest more performance gains. We will see similar trends many times.

In Tabs. 1 and 2, we also present the results when the initial finetuning LR is $1e-3$. In [56], the authors argue that if the broken dynamical isometry can be well maintained/recovered, the final performance gap between LR $1e-2$ and $1e-3$ will be diminished. Since we claim our method is able to maintain dynamical isometry, the performance gap should become smaller. This is empirically verified in the table (note the Acc. diff. of TPP vs. that of $L_1$). In general, the accuracy gap between LR $1e-2$ and LR $1e-3$ of TPP is smaller than that of $L_1$-norm pruning. Two exceptions are PR 0.9/0.95 on ResNet56 – LR $1e-3$ is unusually better than LR $1e-2$ for $L_1$-norm pruning. For now, we do not have a very concrete explanation for this but notably, it does not appear on VGG19. Hence, it probably is related to the residual architecture. We will keep exploring this in the future. Despite that, the general picture from the table is that the accuracy gap between LR $1e-3$ and $1e-2$ turns smaller with our method. This is a sign that dynamical isometry is effectively maintained.

### 4.3 ImageNet Benchmark

We further evaluate TPP on ImageNet [5] in comparison to many existing filter pruning algorithms. Results are shown in Tab. 3. Our method is consistently better than the others across different speedup ratios. Moreover, with a larger speedup ratio, the advantage of our method is more pronounced. For example, TPP outperforms Taylor-FO [42] by 1.15% in terms of the top-1 accuracy drop at the 2.31×speedup track; at 3.06×speedup, TPP leads Taylor-FO [42] by 2.87%. This shows TPP is more robust to more aggressive pruning. The reason is easy to see – more aggressive pruning hurts trainability (or dynamical isometry) more [28,56], where our method can find more use.

We further compare to more strong pruning methods. Notably, DMCP [8], LeGR [4], EagleEye [29], and CafeNet [51] have been shown outperformed by CHEX [18] (see their Tab. 1) with ResNet50 on ImageNet. Therefore, here we only compare to CHEX. Following CHEX, we employ more advanced training recipe (e.g., cosine LR schedule) referring to TIMM [61]. Results in Tab. 3 show that our method surpasses CHEX at different FLOPs.
Table 4. Ablation study (1): Test accuracy (without finetuning) comparison between two plausible schemes “diagonal” vs. “de-correlate” in our TPP method

| Pruning ratio r | ResNet56 + CIFAR10: Baseline accuracy 93.78%, Params: 0.85M, FLOPs: 0.25G |
|-----------------|-----------------------------------------------------------------------------|
|                 | TPP (diagonal) | 92.67 (0.29) | 91.97 (0.02) | **90.21** (0.23) | 23.23 (5.19) | 14.23 (1.42) |
|                 | TPP (de-correlate) | **92.74** (0.16) | **92.07** (0.05) | 89.95 (0.26) | **30.35** (4.69) | **17.33** (0.50) |
|                 | Acc. diff. | +0.07 | +0.10 | -0.26 | +7.12 | +3.10 |

| Pruning ratio r | VGG19 + CIFAR100: Baseline accuracy 74.02%, Params: 20.08M, FLOPs: 0.80G |
|-----------------|-----------------------------------------------------------------------------|
|                 | TPP (diagonal) | 68.70 (0.18) | 64.55 (0.14) | 55.66 (0.73) | 13.76 (0.53) | 1.00 (0.00) |
|                 | TPP (de-correlate) | **72.43** (0.12) | **69.31** (0.11) | **62.59** (0.14) | **18.97** (1.25) | 1.00 (0.00) |
|                 | Acc. diff. | +3.73 | +4.76 | +6.93 | +5.21 | +0.00 |

Table 5. Ablation study (2): Test accuracy (without finetuning) comparison with or without the proposed BN regularization

| Pruning ratio r | ResNet56 + CIFAR10: Baseline accuracy 93.78%, Params: 0.85M, FLOPs: 0.25G |
|-----------------|-----------------------------------------------------------------------------|
|                 | TPP (w/o BN reg) | 92.79 (0.03) | 92.23 (0.08) | 90.46 (0.21) | 44.25 (2.46) | 16.52 (0.43) |
|                 | TPP (w/ BN reg) | **92.94** (0.14) | **92.48** (0.19) | **90.48** (0.09) | **70.53** (1.69) | **23.05** (2.61) |
|                 | Acc. diff. | +0.15 | +0.25 | +0.02 | +26.28 | +6.53 |

| Pruning ratio r | VGG19 + CIFAR100: Baseline accuracy 74.02%, Params: 20.08M, FLOPs: 0.80G |
|-----------------|-----------------------------------------------------------------------------|
|                 | TPP (w/o BN reg) | 73.01 (0.13) | 71.26 (0.19) | 68.67 (0.10) | 61.70 (0.46) | 1.75 (0.38) |
|                 | TPP (w/ BN reg) | **73.44** (0.07) | **71.61** (0.12) | **69.28** (0.25) | **65.15** (0.20) | **2.84** (1.13) |
|                 | Acc. diff. | +0.43 | +0.35 | +0.51 | +3.45 | +1.09 |

4.4 Ablation Study

Finally, we conduct ablation studies to demonstrate the merits of two key technical contributions in our method: 1) proposing not to over-penalize the kept weights in orthogonalization (i.e., (c) vs. (b) in Fig. 2), 2) proposing to regularize the two learnable parameters in BN. The results are presented in Tabs. 4 and 5, where we compare the accuracy right after pruning (namely, without fine-tuning). (1) As seen in Tab. 4, using “de-correlate” (Fig. 2(c)) is better than “diagonal” (Fig. 2(b)) on the whole. Similar to Tabs. 1 and 2, under a larger pruning ratio, the advantage of “de-correlate” is more evident, except for too large sparsity (0.95 for ResNet56, 0.9 for VGG19) because too large sparsity will break the isometry beyond repair. (2) For BN regularization, in Tab. 5, when it is switched off, the performance degrades. It also poses the similar trend: BN regularization is more helpful under the larger sparsity.

5 Conclusion

Trainability maintenance is shown critical in neural network structured pruning, while few works have realized it on the modern large-scale non-linear deep networks. To achieve this goal, we present a new filter pruning method named...
Trainability preserving pruning (TPP) based on regularization. Specifically, we propose a modified weight gram matrix as regularization target which does not unnecessarily over-penalize the weights. Besides, we propose to regularize the BN parameters to mitigate its damage to trainability. TPP performs as effectively as the ground-truth trainability recovery method and more effective than other counterpart approaches based on weight orthogonality. Furthermore, TPP also delivers promising performance when compared to many recent state-of-the-art filter pruning approaches. To our best knowledge, this is the first work that explicitly tackles the trainability preserving problem in neural network structured pruning that scales to the large-scale ImageNet dataset.

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