Structured Sparsification with Joint Optimization of Group Convolution and Channel Shuffle

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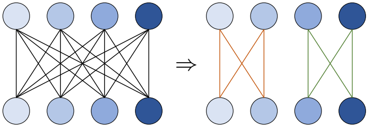
Overview

1. Background
   - Group Convolution and Channel Shuffle
   - Norm-based Filter Pruning
2. Methodology
   - Overview
   - Learning Connectivity with Linear Programming
   - Structured Sparsification
3. Experiments
4. More about Structured Sparsification

Group Convolution

Group convolution (GroupConv) is used for model compression.



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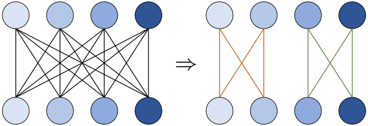

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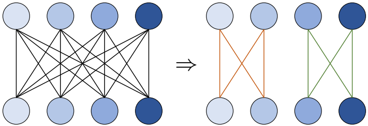

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For conv1x1s ⇒ GroupConv1x1s, the inter-group communication between consecutive GroupConvs?

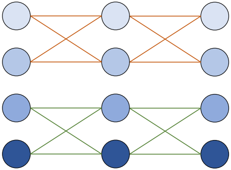
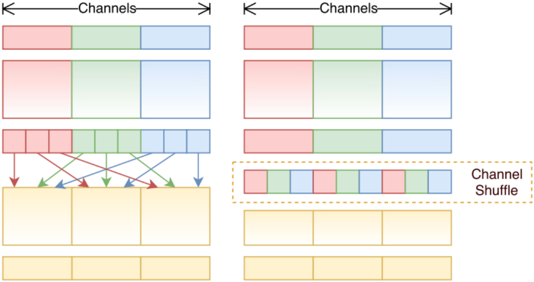


Figure: Consecutive group convs.

Channel Shuffle

ShuffleNet[1]: a *channel shuffle* operation (re-distribute channels from different groups).



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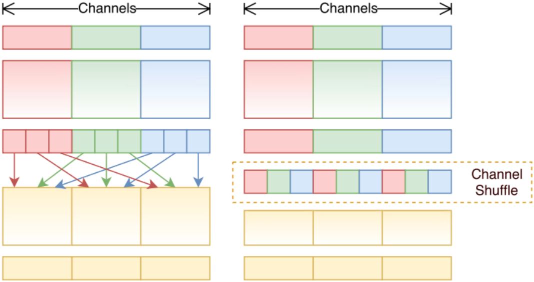

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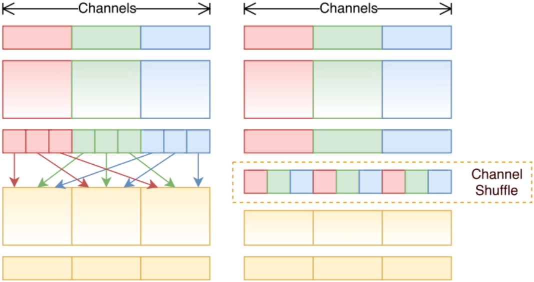

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We propose a *learnable channel shuffle* mechanism which unifies the norm-based pruning criteria and the learning of channel permutation.

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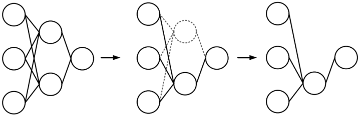
Norm-based Filter Pruning

Filter Pruning: prune unimportant filters w/o performance degradation.



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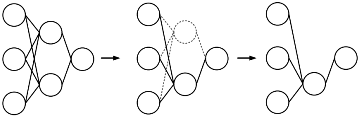

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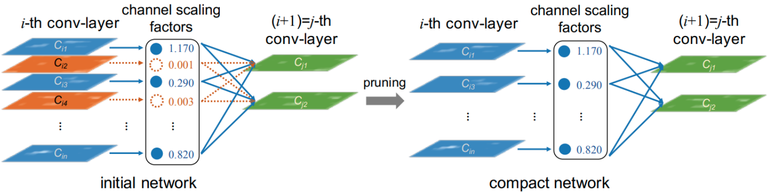
In particular, weight norm $\Rightarrow$ indicator of filter importance.

E.g., Network Slimming[2]: prune according to batch-norm scaling factor.



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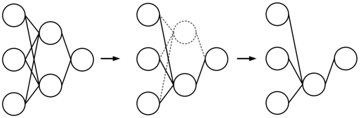

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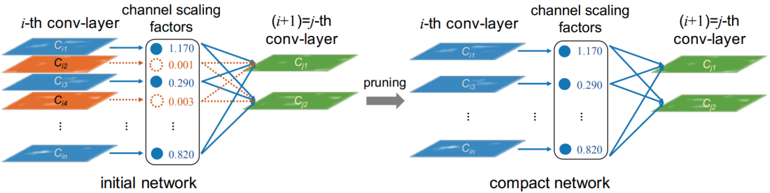

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Besides, L_1 regularization (LASSO) $\rightarrow$ batch-norm scaling factors.

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Norm-based Filter Pruning

However, problems of filter pruning:

(i) pruning has to deal with special network structures;

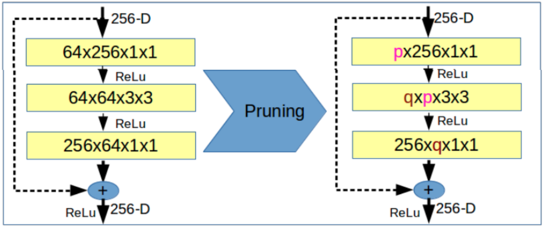

Figure: Pruning residual connection[3].

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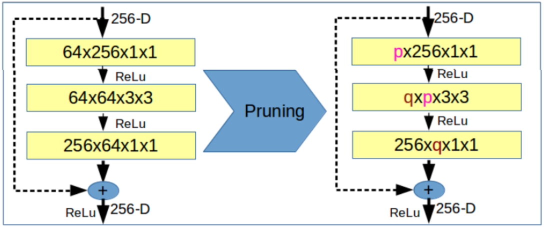

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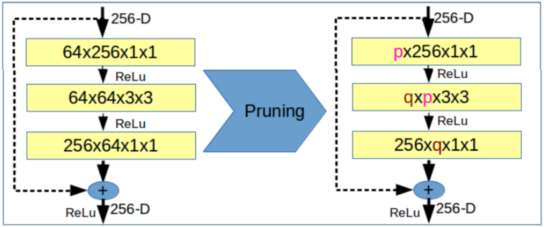

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In this work, we generalize the norm-based pruning criteria to the problem of converting vanilla convolutions into GroupConvs.

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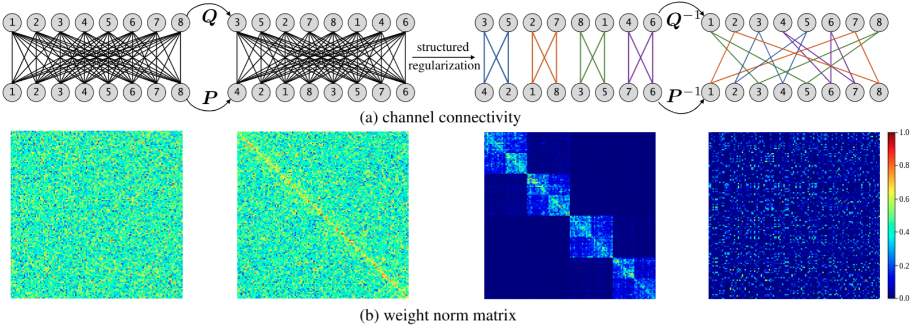

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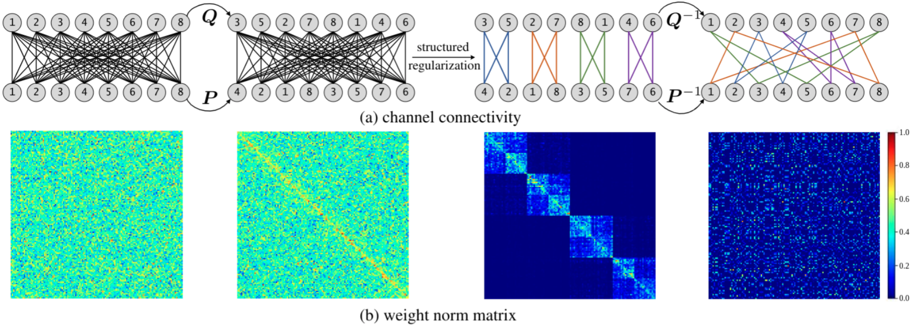

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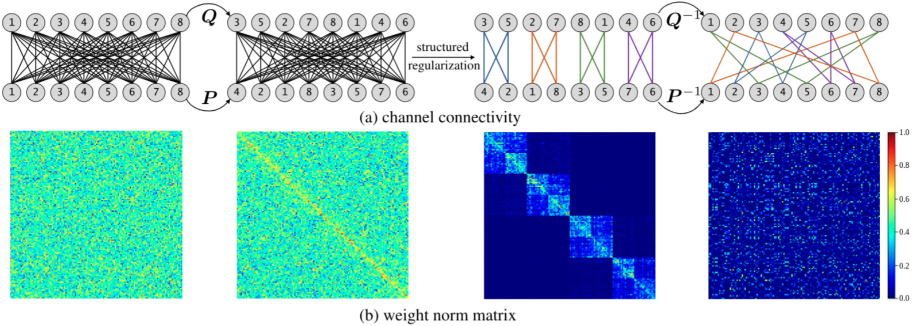

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Challenges.

(i) How to define a suitable channel shuffle? (under what criteria?)

(ii) How to *structurally* sparsify the convolutional weights?

Learning Connectivity — Formulation

In general,

$$\text{weight norm matrix of GroupConv} \Rightarrow \text{block-diagonal matrix;}$$
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Therefore, aim of channel shuffle: permute weight norm matrix to make it "*as block-diagonal as possible*". Formally,

$$\begin{aligned} &\min_{\boldsymbol{P},\boldsymbol{Q}} \ \boldsymbol{PSQ} \otimes \boldsymbol{R} \\ &\text{s.t. } \boldsymbol{P} \in \mathcal{P}^{C^{out}} \ \textit{and} \ \ \boldsymbol{Q} \in \mathcal{P}^{C^{in}}, \end{aligned} \tag{1}$$

where $\boldsymbol{S} \in \mathbb{R}^{C^{out} \times C^{in}}$ is the weight norm matrix, $\boldsymbol{R}$ is a cost matrix, and $\mathcal{P}^N$ is the set of $N \times N$ permutation matrices.

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$$\mathcal{B}^N = \{\boldsymbol{X} \in \mathbb{R}_+^{N \times N} : \boldsymbol{X}1_N = 1_N,\ \boldsymbol{X}^\top 1_N = 1_N\}. \tag{2}$$

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When updating $\boldsymbol{P}$,

$$\begin{aligned} \min_{\boldsymbol{P}} \ & \boldsymbol{P} \otimes \boldsymbol{R}\boldsymbol{Q}^\top \boldsymbol{S}^\top \\ \text{s.t. } & \boldsymbol{P} \in \mathcal{B}^{C^{out}}. \end{aligned} \tag{3}$$

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In (3), the objective function is linear in $\boldsymbol{P}$ and the feasible region $\mathcal{B}^N$ is a simplex. Therefore, linear programming (LP), solved by network simplex method.

Learning Connectivity — Discussion

By LP theory, one solution of a LP problem $\rightarrow$ vertex of feasible region.

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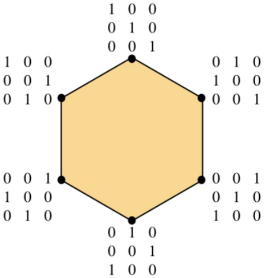
By Birkhoff-von Neumann theorem[4], vertices of Birkhoff polytope $\rightarrow$ permutation matrices.



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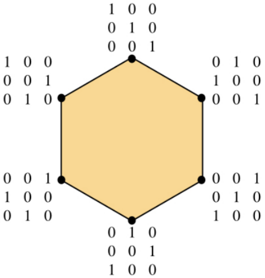

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Therefore, relaxed feasible region $\mathcal{B}^N$ naturally reduced to $\mathcal{P}^N$.

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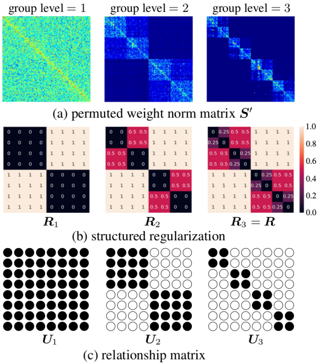
Structured L_1 regularization.

$$\mathcal{L}_{\text{reg}} = \boldsymbol{S}' \otimes \boldsymbol{R}_g, \tag{4}$$

where $\boldsymbol{S}' = \boldsymbol{PSQ}$ permuted weight norm matrix, and $\boldsymbol{R}_g$ shown on the right.

Highlights: (a) LASSO, (b) hierarchical penalty.



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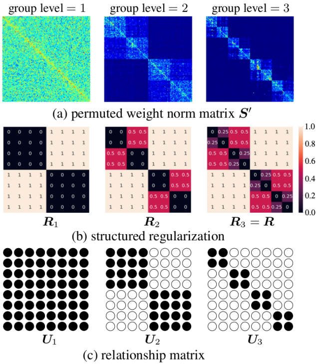

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Grouping Criteria.

$$g = \max\{g : \boldsymbol{S}' \otimes \boldsymbol{U}_g \geq p \sum_{i,j} S_{i,j},\ g = 1, 2, \cdots\}, \qquad (5)$$

where $\boldsymbol{U}_g$ is the relationship matrix.

Training Pipeline

Algorithm 1 Training Pipeline.

```
Initially update P and Q.
for t := 1 to #epochs do
    Train with structured regularization;
    Update P and Q;
    Determine the current group level g by the grouping criteria;
    Update the structured sparsification matrices (R_g);
    Adjust regularization coefficient (refer to paper).
end for
```

Experiments

Performance on ImageNet against two prior works, *i.e.*, Slimming[5] and Taylor[6] (refer to paper for full comparison).

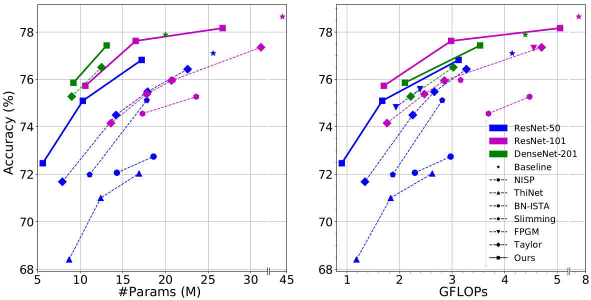
Methods	#Params.(10^6) ↓	GFLOPs ↓	Acc.(%) ↑
	ResNet-50		
Baseline	25.6	4.14	77.10
Slimming-20%	17.8	2.81	75.12
Taylor-19%	17.9	2.66	75.48
StrucSpars-35%	**17.2**	3.12	**76.82**
Taylor-28%	14.2	2.25	74.50
StrucSpars-65%	**10.3**	**1.67**	**75.10**
Taylor-44%	7.9	1.34	71.69
Slimming-50%	11.1	1.87	71.99
StrucSpars-85%	**5.6**	**0.90**	**72.47**
	ResNet-101		
Baseline	44.5	7.87	78.64
Taylor-25%	31.2	4.70	77.35
StrucSpars-40%	**26.7**	5.05	**78.16**
Taylor-45%	20.7	**2.85**	75.95
Slimming-50%	20.9	3.16	75.97
StrucSpars-65%	**16.5**	2.98	**77.62**
Taylor-60%	13.6	1.76	74.16
StrucSpars-80%	**10.6**	**1.70**	**75.73**
	DenseNet-201		
Baseline	20.0	4.39	77.88
Taylor-40%	**12.5**	**3.02**	76.51
StrucSpars-38%	13.1	3.53	**77.43**
Taylor-64%	**9.0**	2.21	75.28
StrucSpars-60%	9.2	**2.10**	**75.86**

[5] Liu *et al.*, Learning Efficient Convolutional Networks through Network Slimming.

[6] Molchanov *et al.*, Importance Estimation for Neural Network Pruning.

Ablation Studies

Accuracy vs.Complexity.



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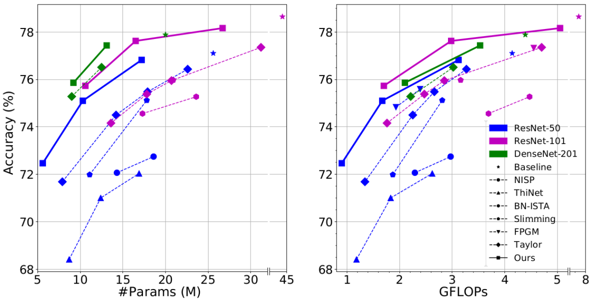

Wall-time acceleration.

Model	GFLOPs	Avg. Runtime (ms)	FPS
ResNet-50	4.14	80.2	12.4
StrucSpars-35%	3.12	68.2	14.7
StrucSpars-65%	1.67	61.3	16.3
StrucSpars-85%	0.90	53.5	18.7

Ablation Studies

Channel shuffle mechanism. We empirically compare the following five settings:

(i) FINETUNE: train → compress → finetune pipeline;

(ii) FROMSCRATCH: learned channel shuffle, but train from scratch;

(iii) SHUFFLENET: hand-crafted channel shuffle as in ShuffleNet;

(iv) RANDOM: random channel shuffle (*i.e.*, random permutation);

(v) NOSHUFFLE: no channel shuffle.

Config.	**ResNet-50**-65%		**ResNet-101**-65%	
Acc.	Top-1	Top-5	Top-1	Top-5
FINETUNE	75.10	92.52	77.62	93.72
FROMSCRATCH	75.02	92.46	77.14	93.53
SHUFFLENET	74.97	92.41	76.91	93.38
RANDOM	69.45	89.45	73.16	91.44
NOSHUFFLE	73.30	91.39	75.31	92.64

Further information

Refer to our paper[7] for limitations and future perspectives:

(i) **Data-Driven Structured Sparsification**;

(ii) **Progressive Sparsification Solution**;

(iii) **Combination with Filter Pruning**.

The source codes are available:
`https://github.com/Sakura03/StrucSpars`.

[7] `https://arxiv.org/abs/2002.08127`

Thanks!