Filter Pruning using Hierarchical Group Sparse Regularization for Deep Convolutional Neural Networks

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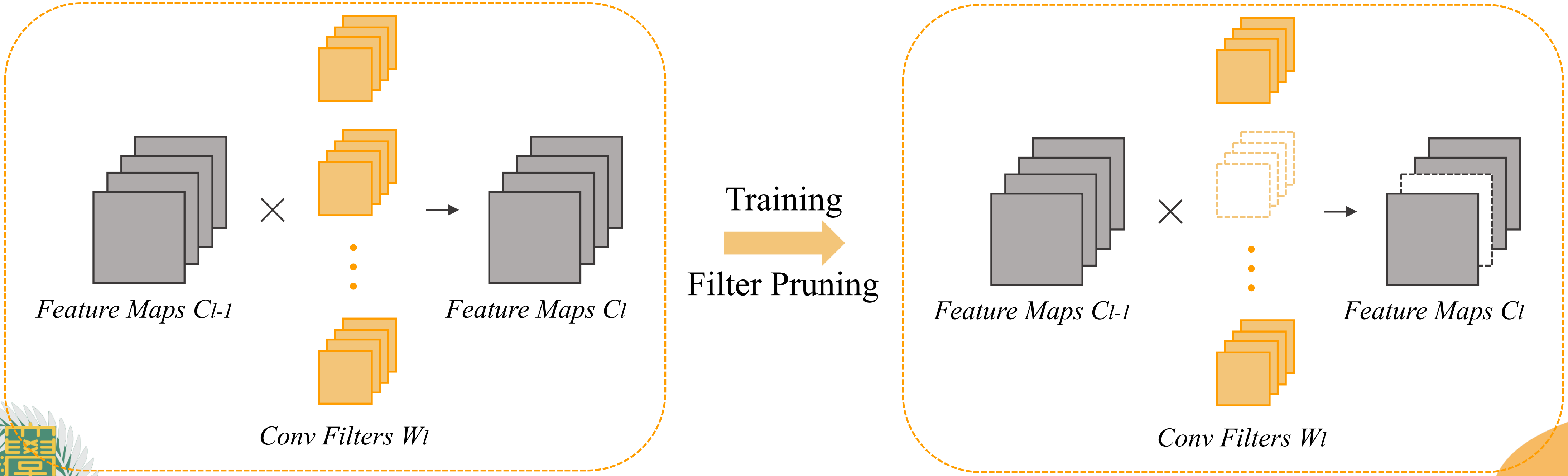
Introduction

Filter pruning can reduce redundant parameters of large networks while preserving accuracy.



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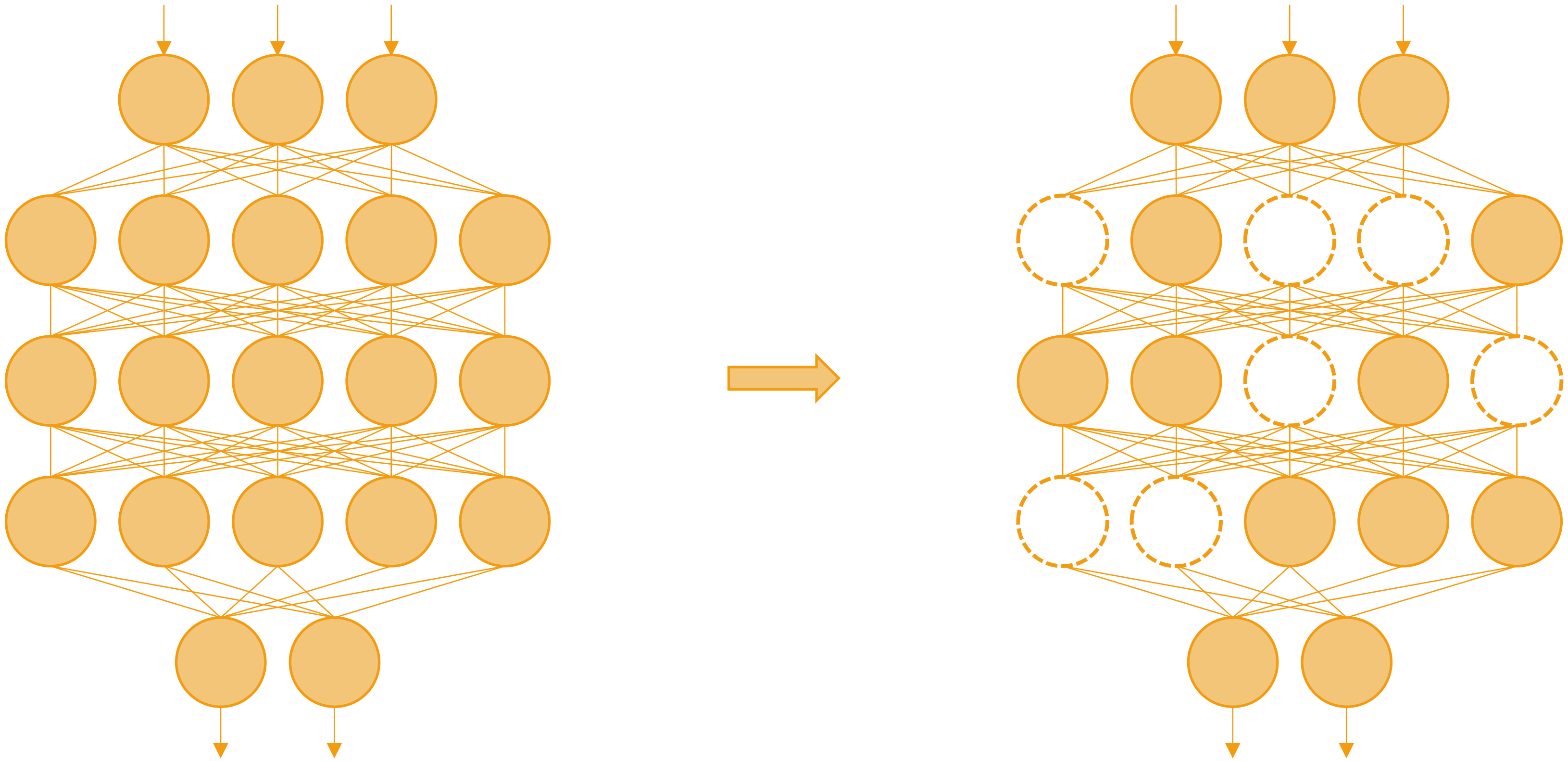
Sparse regularization

Sparse regularization criteria can remove unnecessary parameters



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The structured sparse regularizations

The structured sparse regularization for structured pruning is defined as follows:

$$R(W^l) = \sum_{g \in G} r(W_g^l)$$

Typical structured sparse regularization for structured pruning

- Group lasso regularization[1][2]

$$r_{GL}(W) = |W|_2 = \sqrt{\sum_i W_i^2}$$

- Exclusive sparse regularization[3][4]

$$r_{ES}(W) = \|W\|_1^2 = \left(\sum_i |W_i|\right)^2$$

- Group L1/2 regularization[5][6]

$$r_{GL_{1/2}}(W) = |W|_1^{1/2} = \sqrt{\sum_i |W_i|}$$

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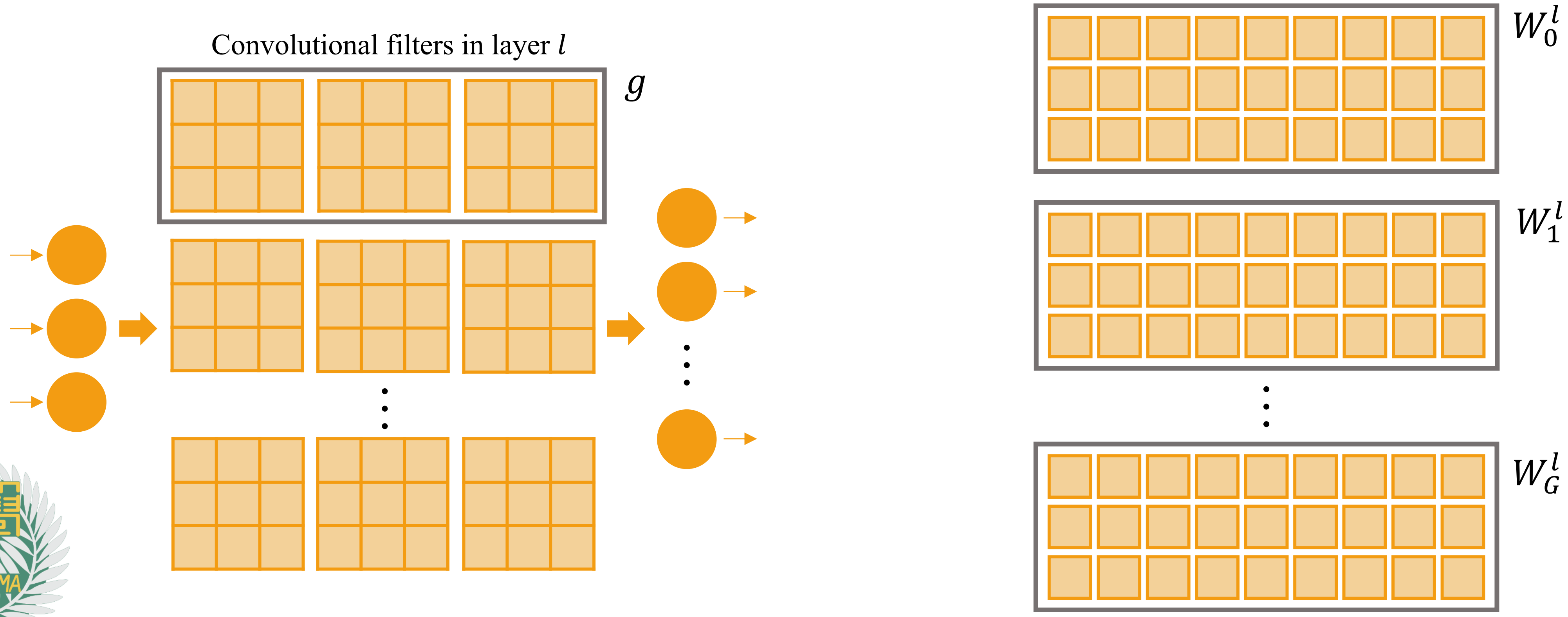
The structured sparse regularizations

Grouping of the structured sparse regularization



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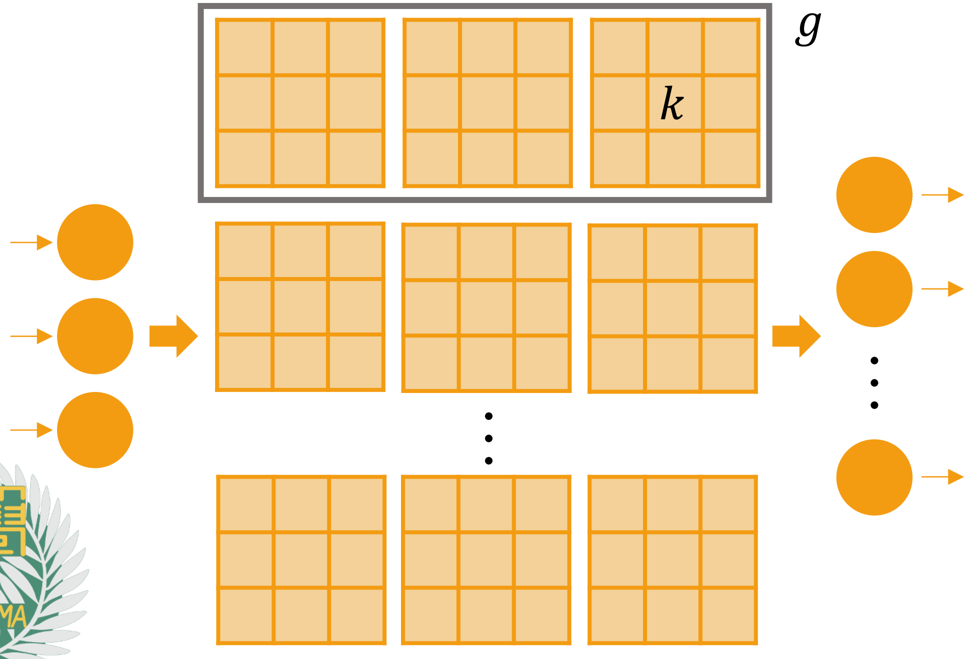
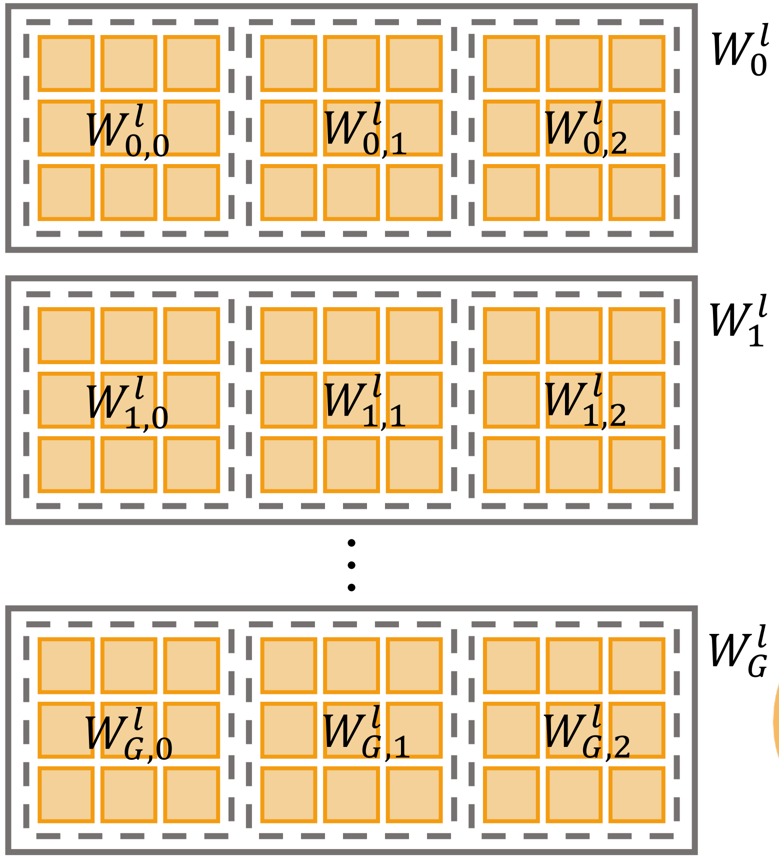
The hierarchical squared/square rooted group sparse regularization[7]

$$R_{SQ}(W^l) = \sum_{g \in G} \left(\sum_{k \in K} r(W_{g,k}^l) \right)^2$$

$$R_{SQRT}(W^l) = \sum_{g \in G} \sqrt{\sum_{k \in K} r(W_{g,k}^l)}$$

Convolutional filters in layer l





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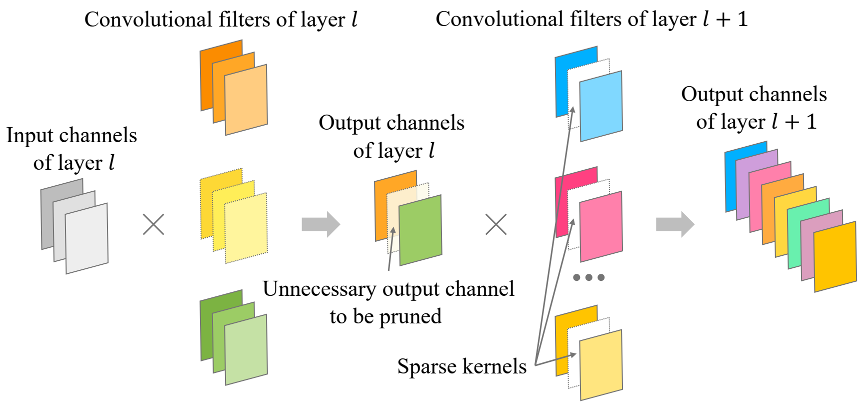
Proposed Method

The feature-wise filter pruning algorithm for deep convolutional neural networks

1. Train a large network as the initial network.
2. Train the network with the hierarchical group sparse regularization based on the feature-wise grouping to find unnecessary filters connected to input channels by enforcing their weights to be zero.

The feature-wise group sparse regularization is defined as $R(W^l) = \sum_{j=1}^{c_l-1} r(W^l_{,j,,})$

3. Prune the filters with smaller influence on the classification loss with the random sampled validation data
4. Train the obtained compact network from scratch.



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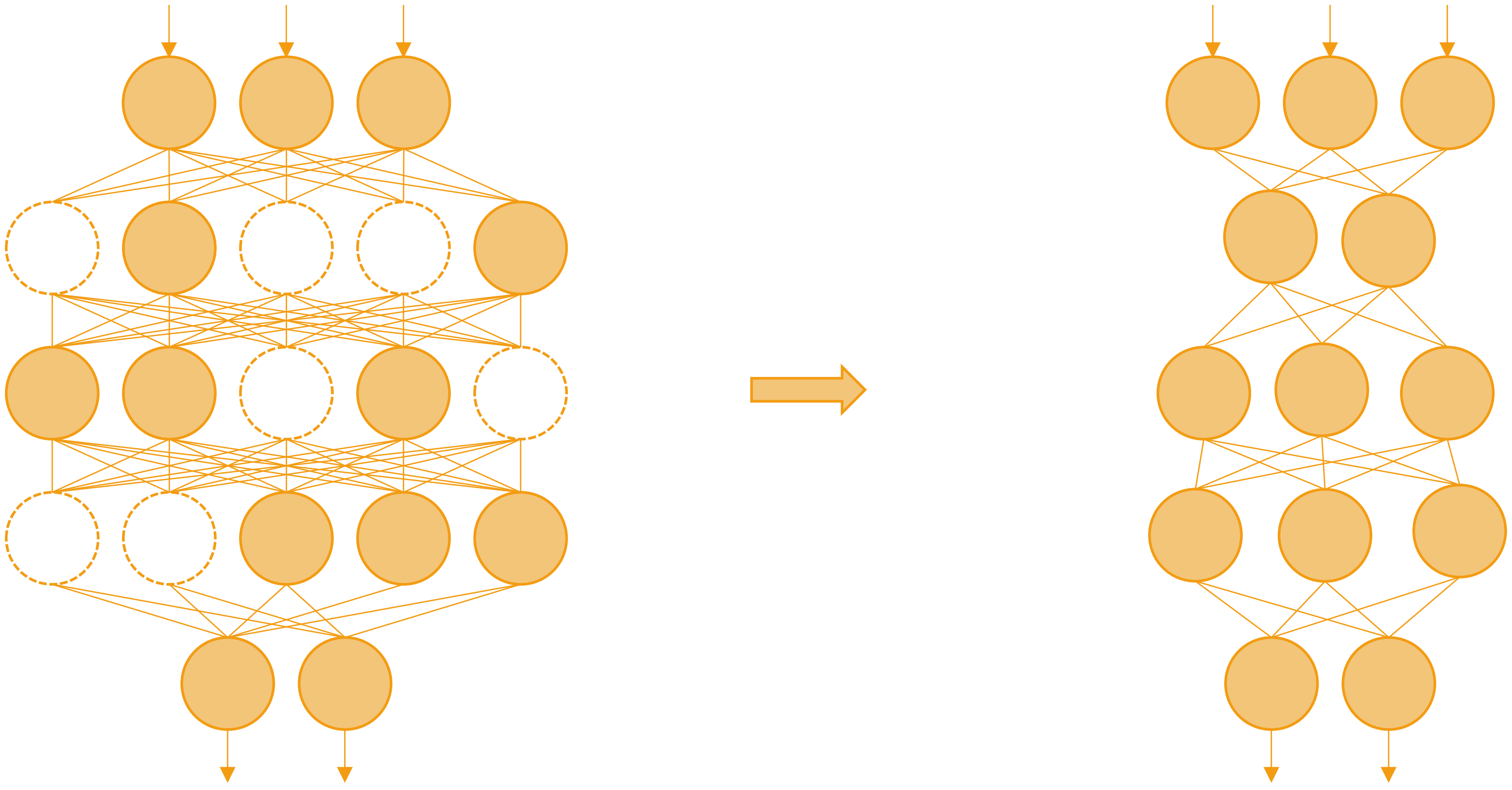

Train from scratch

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Experimental setting

Networks and datasets

- VGG14 and ResNet20/32 on CIFAR-10
- VGG14 and ResNet20/32 on CIFAR-100
- VGG14 and ResNet18/34 on TinyImageNet-200

Sparse Regularization

- Hierarchical squared group L1/2 regularization

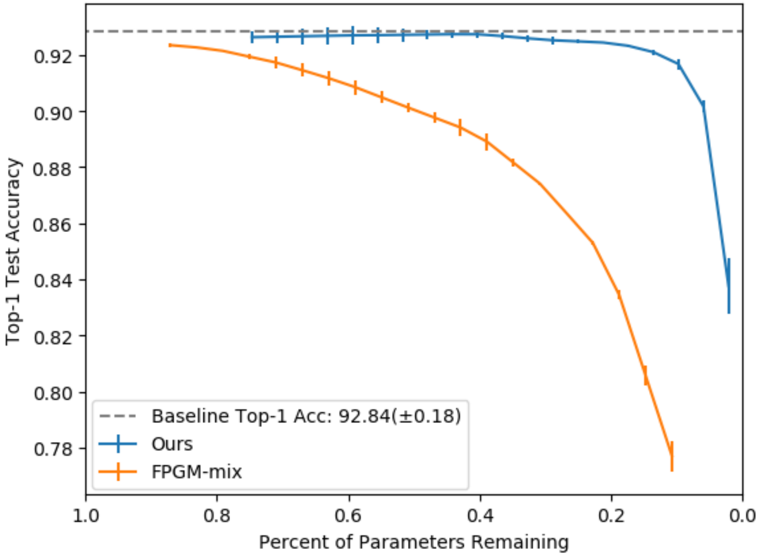
Comparison Method

- FPGM-mix[8] (one of the state-of-the-art method)

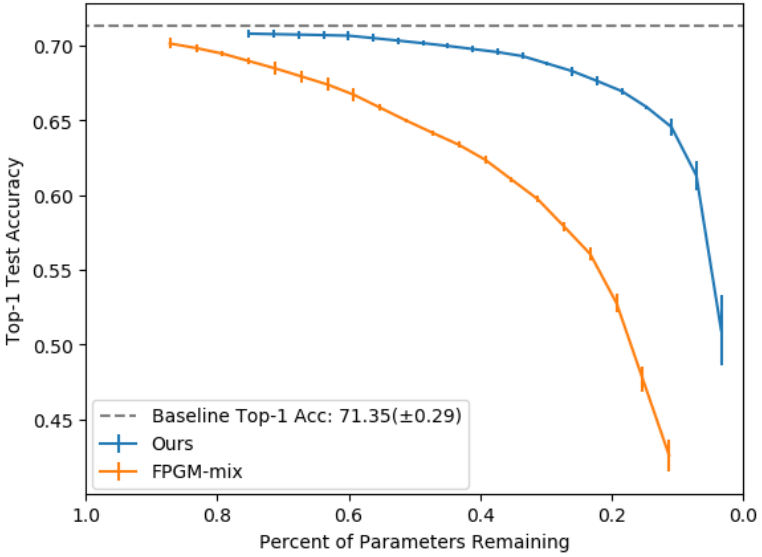
Results

VGG14

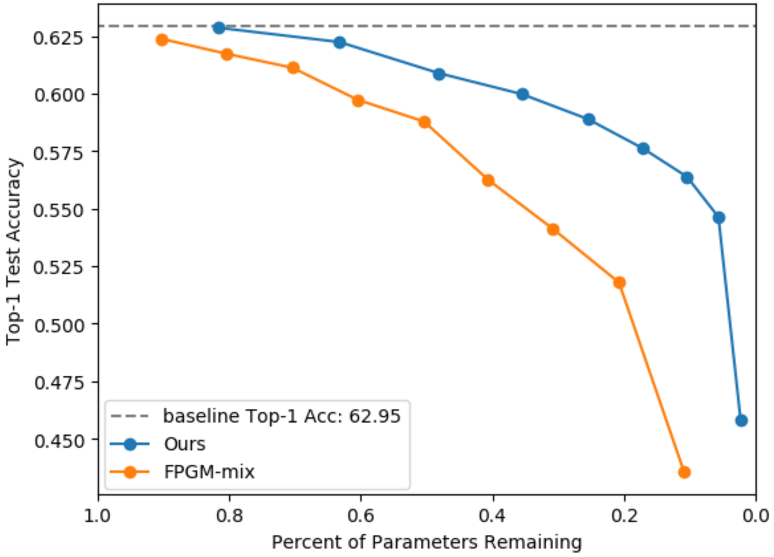
Ours
FPGA-mix



CIFAR-10



CIFAR-100



TinyImageNet-200

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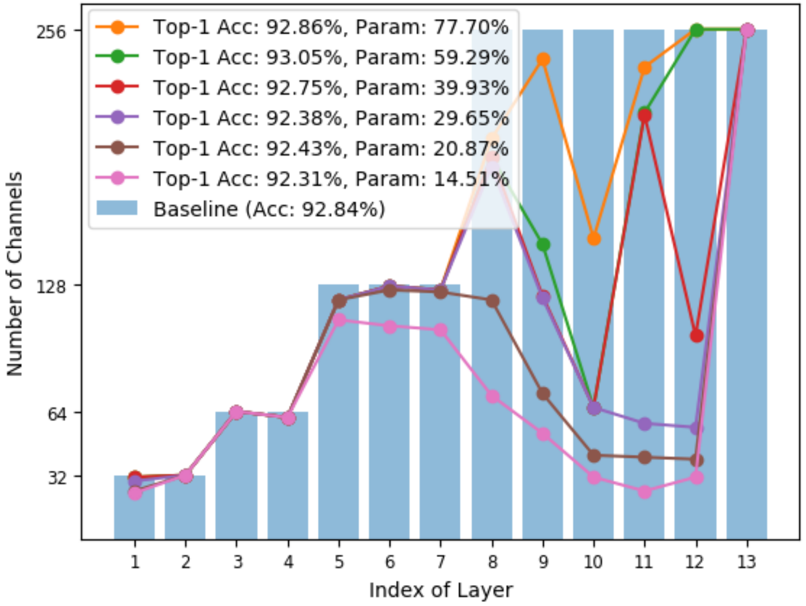
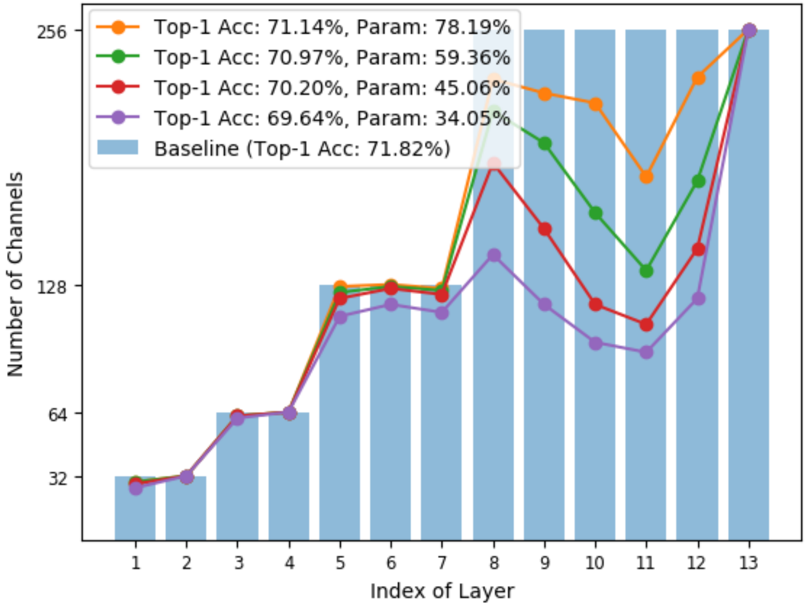
Results

VGG14

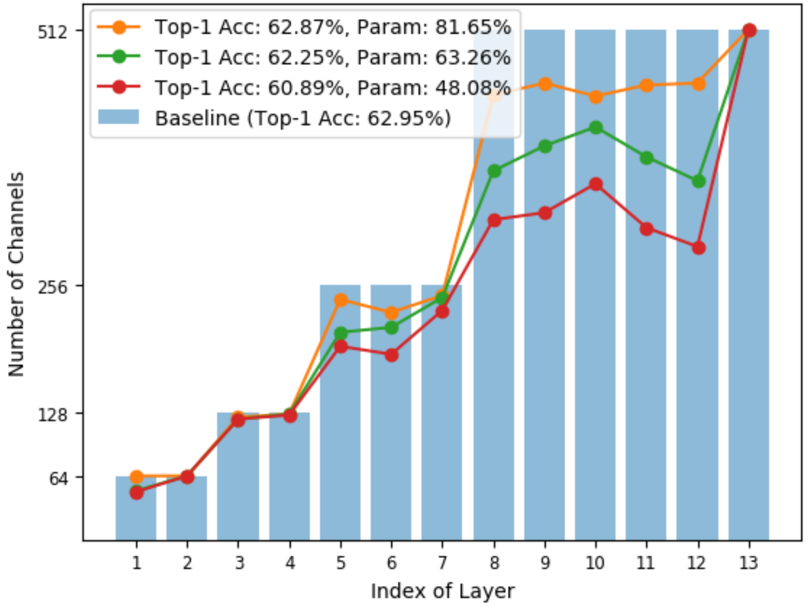
The numbers of the pruned channels in each layer



CIFAR-10



CIFAR-100



TinyImageNet-200

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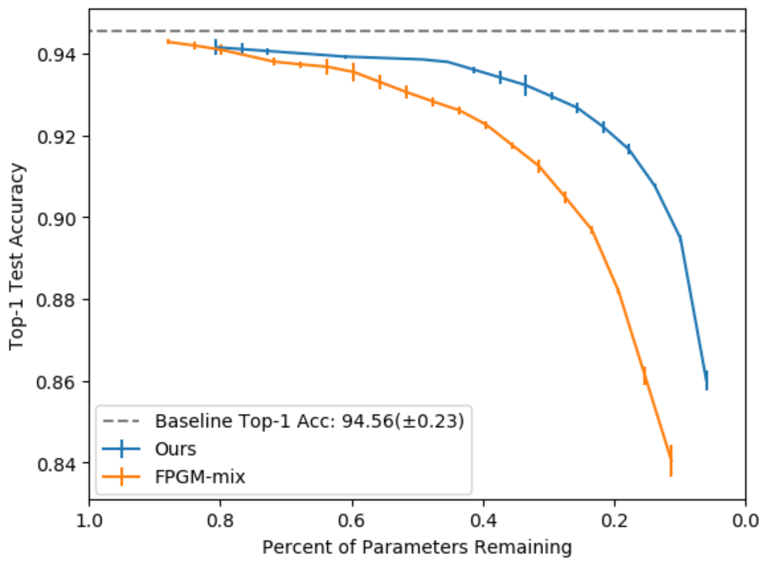
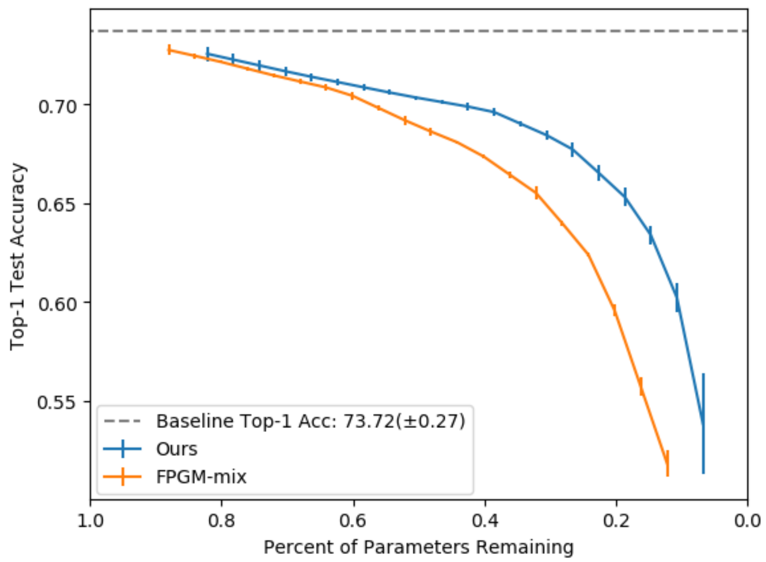
Results

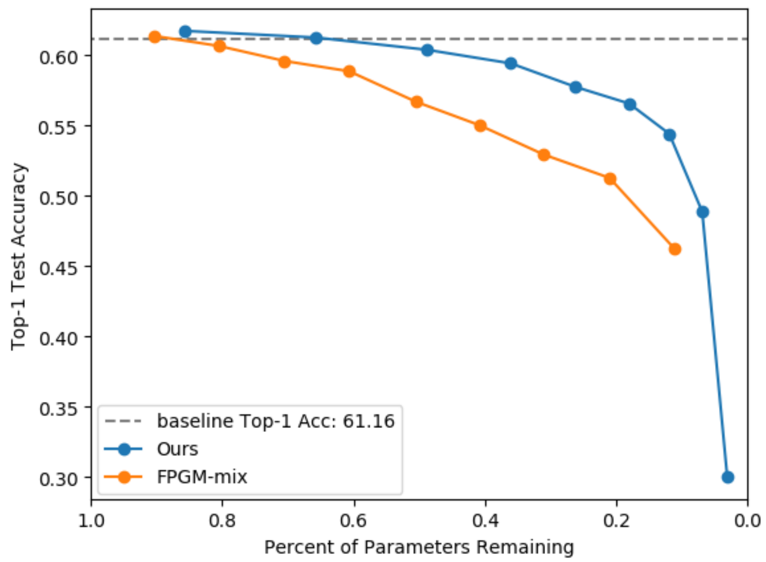
ResNet18/20



CIFAR-10



CIFAR-100



TinyImageNet-200

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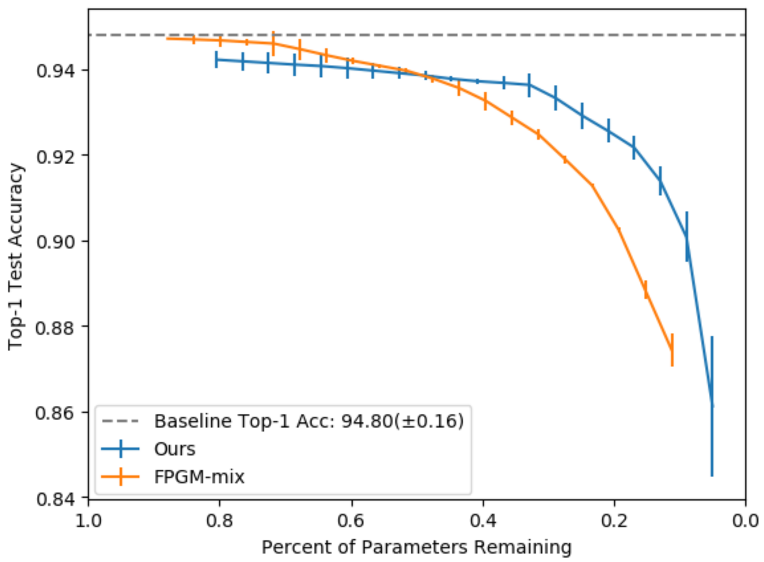
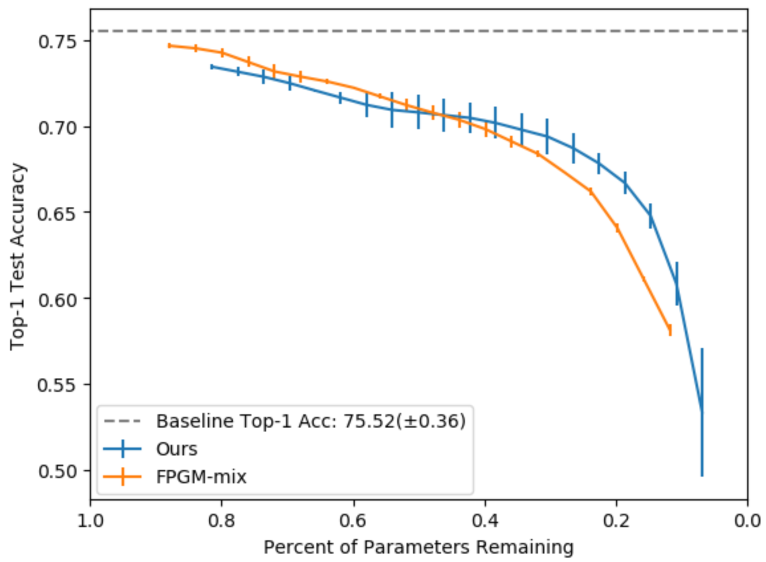
Results

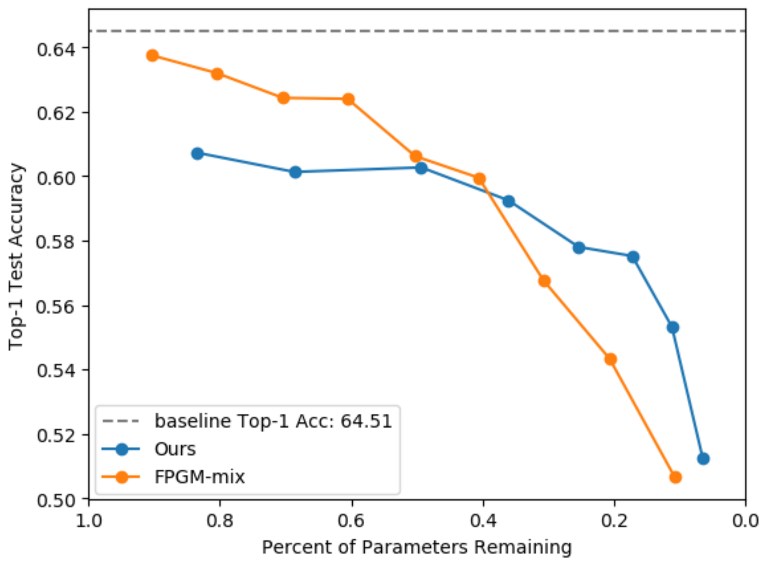
ResNet32/34



CIFAR-10



CIFAR-100



TinyImageNet-200

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Conclusions

- Proposed a new **filter pruning method** with the hierarchical group sparse regularization based on the **feature- wise grouping**.

- The strategy of the **step-wise pruning** of the filters by searching the filter with the minimum loss increase.

- The performance of the pruned network is better than the state-of-the-art pruning method, especially when **more than 50% of the parameters are pruned**.

References

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[4] Kong et al. Exclusive feature learning on arbitrary structures via $l_{1,2}$-norm. In Advances in Neural Information Processing Systems, pages 1655–1663,2014.

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Thank you

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