ThiNet: A Filter Level Pruning Method for Deep Neural Network Compression

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Aug 28, 2017

Content

Background

Background

Deep Neural Network(DNN) is hard to deployed on hardware with the limitation of **computation resources**, **storage**, **battery power**.

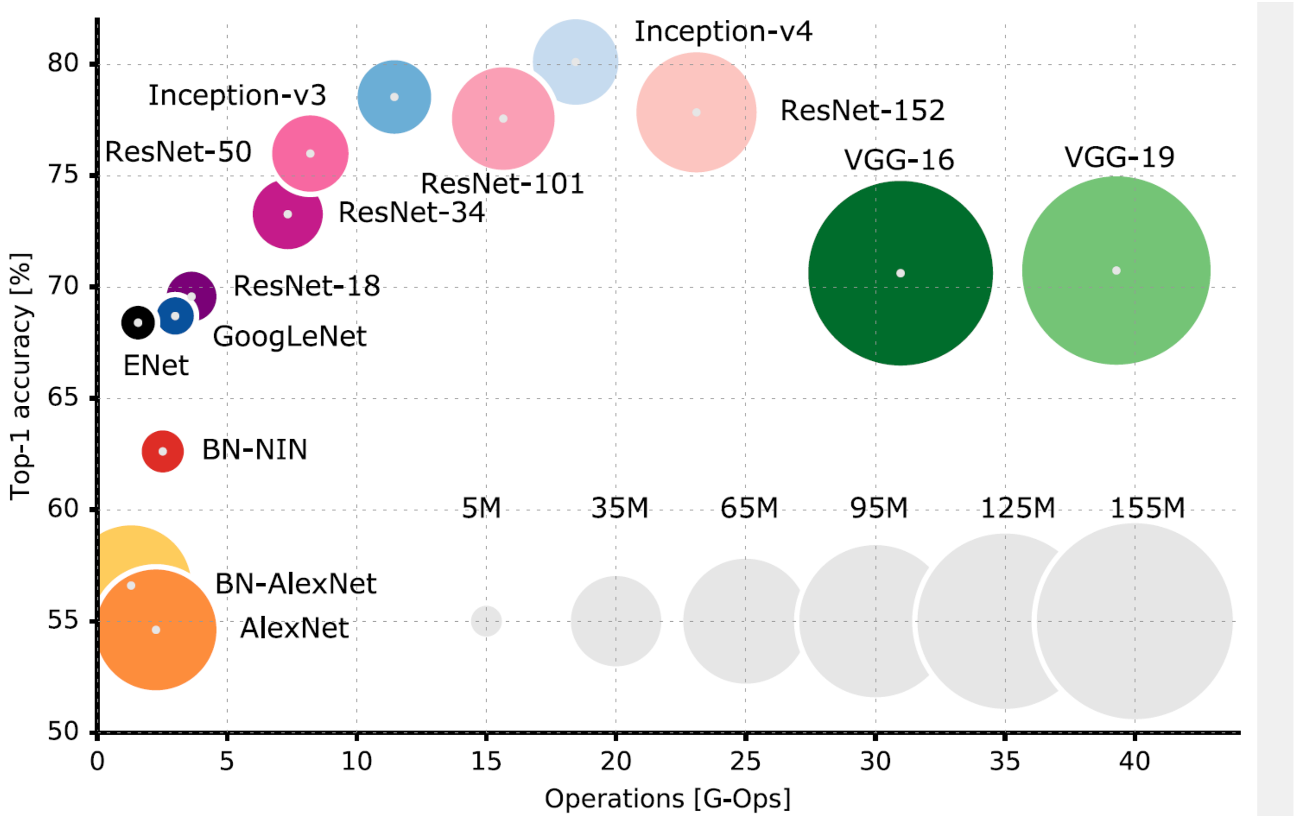


Figure. Performance and model size of different models on ImageNet

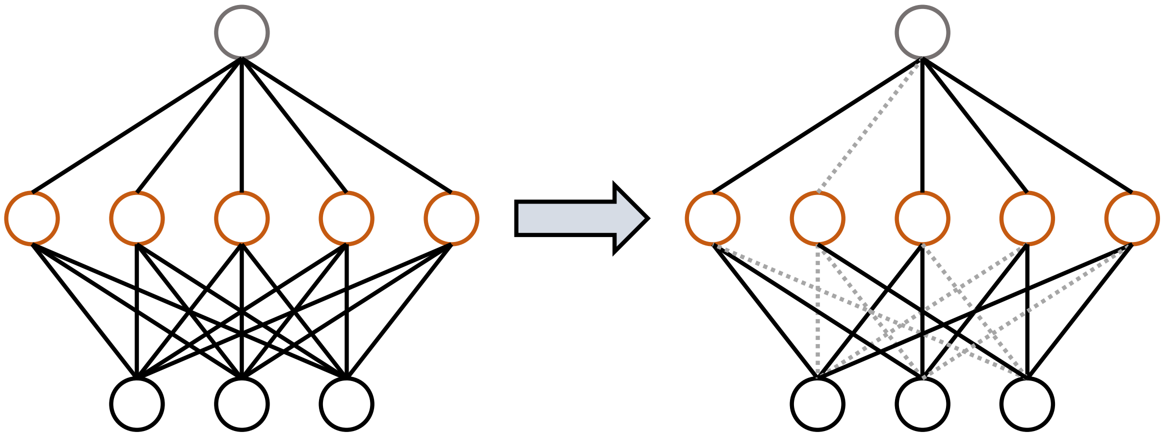
Model Compression

Existing Compression Methods:

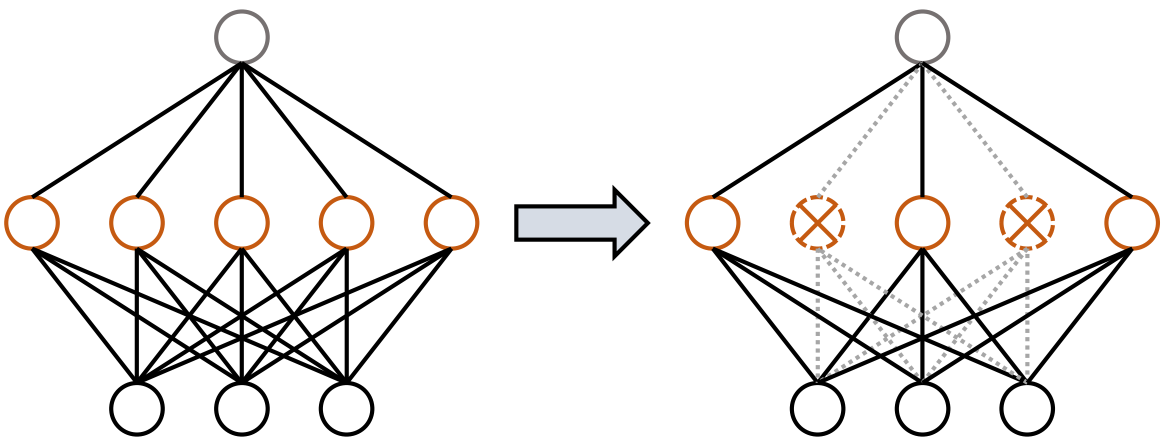
- **Quantization:** convert full-precision weights to low-precision version, e.g. INQ, BWN, TWN.
- **Pruning:** remove less important weights/filters from the model, e.g. Deep Compression, DNS, ThiNet
- **Design new structure:** SqueezeNet, Distilling, ShuffleNet

Pruning Methods

- **Non-structured Pruning:** remove less important **weights**



- **Structured Pruning:** remove less important **filters** from model



Motivation

Problems of Non-structured Pruning

- Need specialized hardware and software for inference
- Ignore cache and memory issues, which leads to limited practical acceleration

Benefits of Structured Pruning

- No change of network structure and can supported by existing deep learning libraries
- Reduce the memory and accelerate inference

Proposed Method

Proposed Method

ThiNet(Thin Net): a filter level pruning compression framework for model compression

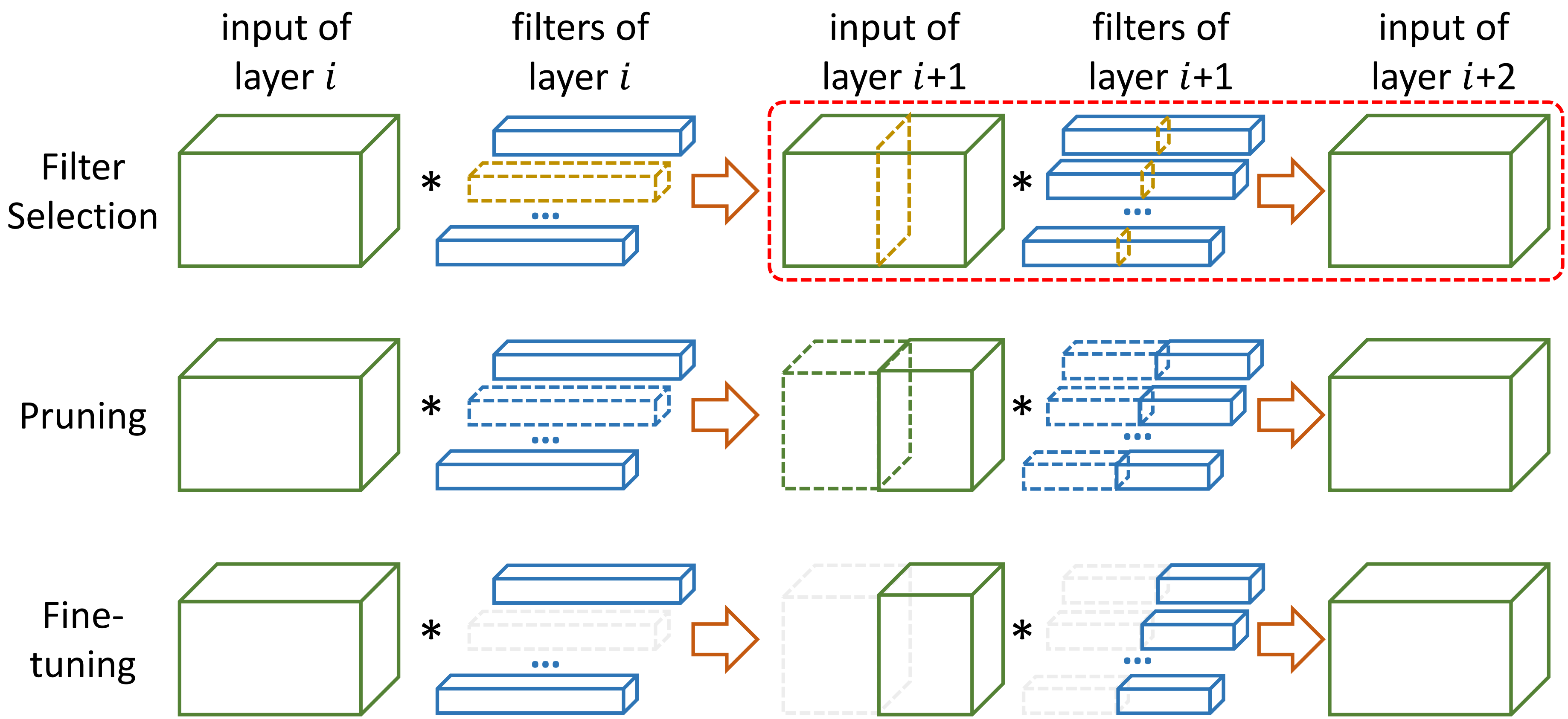
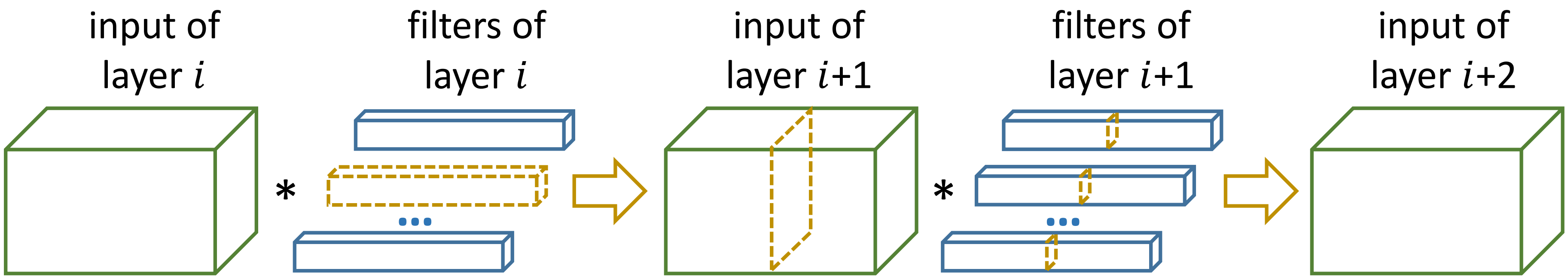


Figure. Illustration of ThiNet

Proposed Method

Framework of ThiNet

- **Filter selection:** use layer i+1to guide the pruning in layer i
- **Pruning:** prune weak channels in layer i+1 and the related filters in layer i
- **Fine-tuning:** reduce loss of accuracy



Filter Selection

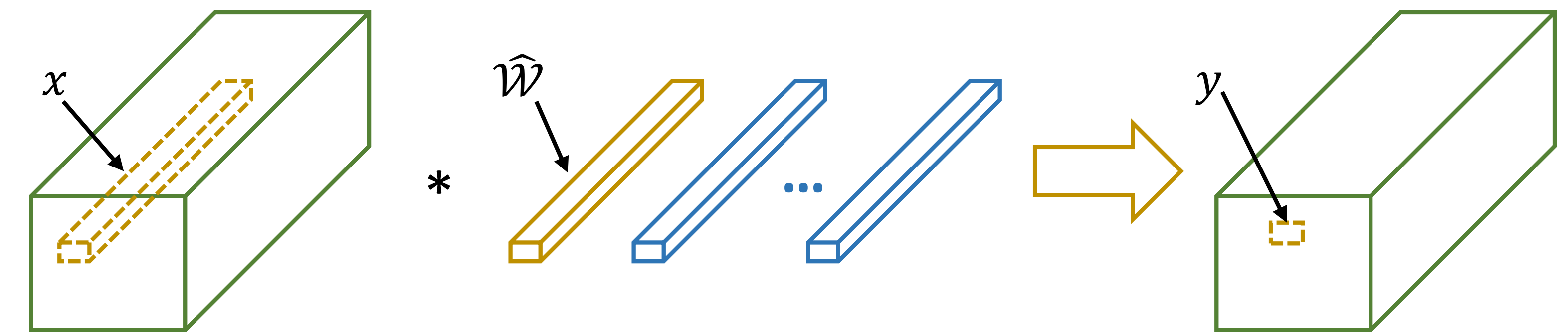
- Convolution operation can be computed as follows:

$$y = \sum_{c=1}^{C} \sum_{k_1=1}^{K} \sum_{k_2=1}^{K} \widehat{\mathcal{W}}_{c,k_1,k_2} \times x_{c,k_1,k_2} + b \qquad (1)$$

y is the element sampled from input of layer i+2

$\widehat{\mathcal{W}} \in \mathbb{R}^{C \times K \times K}$ is the corresponding filter

$x \in \mathbb{R}^{C \times K \times K}$ is the sliding window



Filter Selection

- Define:

$$\hat{x} = \sum_{k_1}^{K} \sum_{k-2}^{K} \widehat{\mathcal{W}}_{c,k_1,k_2} \times x_{c,k_1,k_2} \qquad (2)$$

- Then:

$$\hat{y} = \sum_{c=1}^{C} \hat{x}_c \quad \text{where } \hat{y} = y - b \qquad (3)$$

- If we can find a subset $S \subset \{1, 2, \ldots, C\}$ and $\hat{y} = \sum_{c \in S} \hat{x}_c$, then $\hat{x}_{c \notin S}$ can be removed without changing the result

Greedy Method

- Given a set of m training examples $\{(\hat{x}_i, \hat{y}_i)\}$, the channel selection problem can be solved as optimization problem:

$$\arg\min_{S} \sum_{i=1}^{m} \left(\hat{y}_i - \sum_{j \in S} \hat{x}_{i,j} \right)^2 \tag{4}$$

$$s.t.\ |S| = C \times r, S \subset \{1,2,\ldots,C\}$$

- Let T be the subset of removed channels, then:

$$\arg\min_{T} \sum_{i=1}^{m} \left(\sum_{j \in T} \hat{x}_{i,j} \right)^2 \tag{5}$$

$$s.t.\ |T| = C \times (1-r), T \subset \{1,2,\ldots,C\}$$

Greedy Method

- Use greedy method to solve the optimization problem

A greedy algorithm for minimizing Eq. (5)

Input: Training set $\{(\hat{x}_i, \hat{y}_i\ )\}$ and compression rate r
Output: The subset of removed channels T
$T \leftarrow \emptyset; I \leftarrow \{1,2, \dots, C\};$
while $|T| < C\ (1 - r)$ **do**
  $min\_value \leftarrow\ +\infty;$
  for each item $i \in I$ **do**
    $tmpT \leftarrow T \cup \{i\};$
    compute $value$ from Eq. (5) using $tmpT$;
    if $value < min\_value$ then
      $min\_value \leftarrow\ value; min\_i \leftarrow I;$
    end if
  end for
  move min_i from I to T
end while

Minimize the Reconstruction Error

- Minimize the reconstruction error by weighting the channels:

$$\hat{w} = \arg\min_{w} \sum_{i=1}^{m} (\hat{y}_i - w^T \hat{x}_i^*)^2 \tag{6}$$

where $\hat{x}_i^*$ indicates the training samples after channel selection

- Eq. (6) can be solved by the ordinary least squares approach:

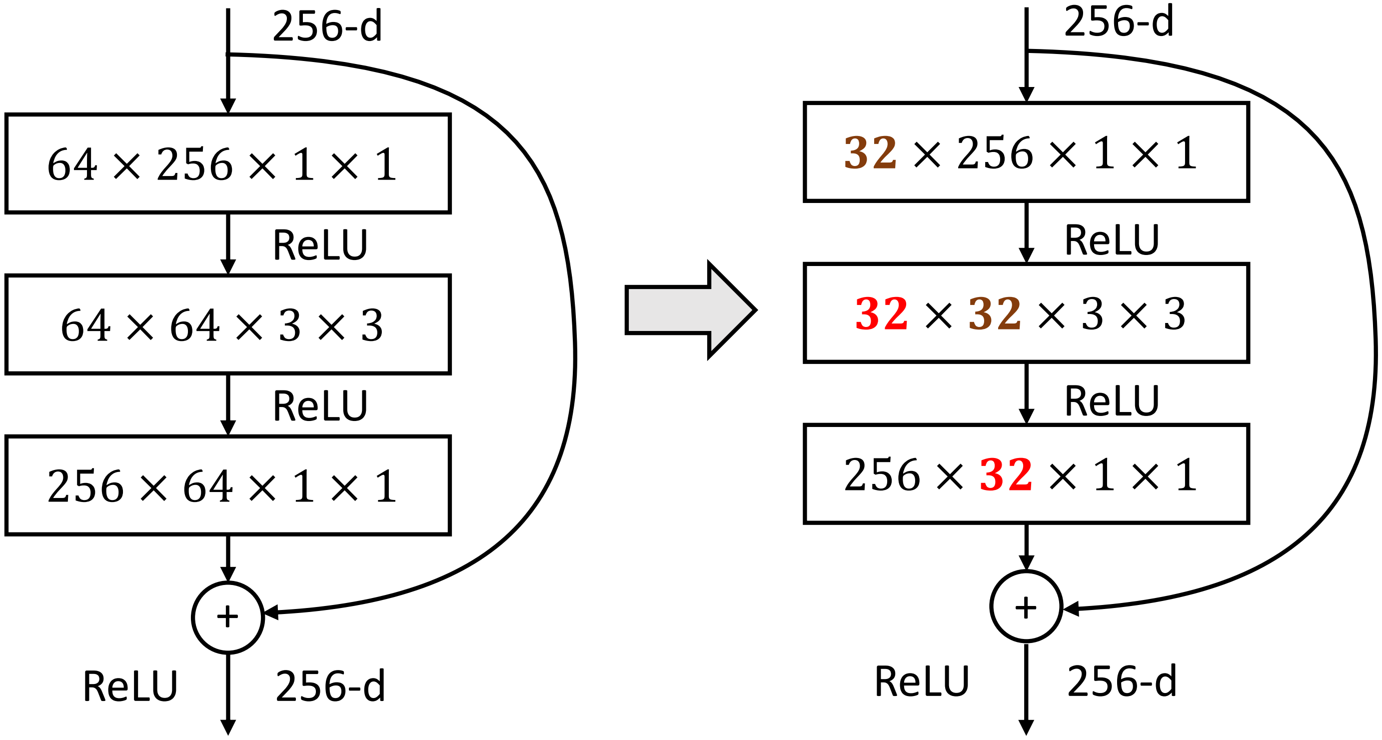
$$\hat{w} = (X^T X)^{-1} X^T y \tag{7}$$

Experimental Results

Pruning Strategy

- **VGG-16:** prune the **first 10** convolutional layers and replace the FC layers with a global average pooling layer

- **ResNet-50:** prune the **first two** convolutional layers



Comparison of Existing Methods

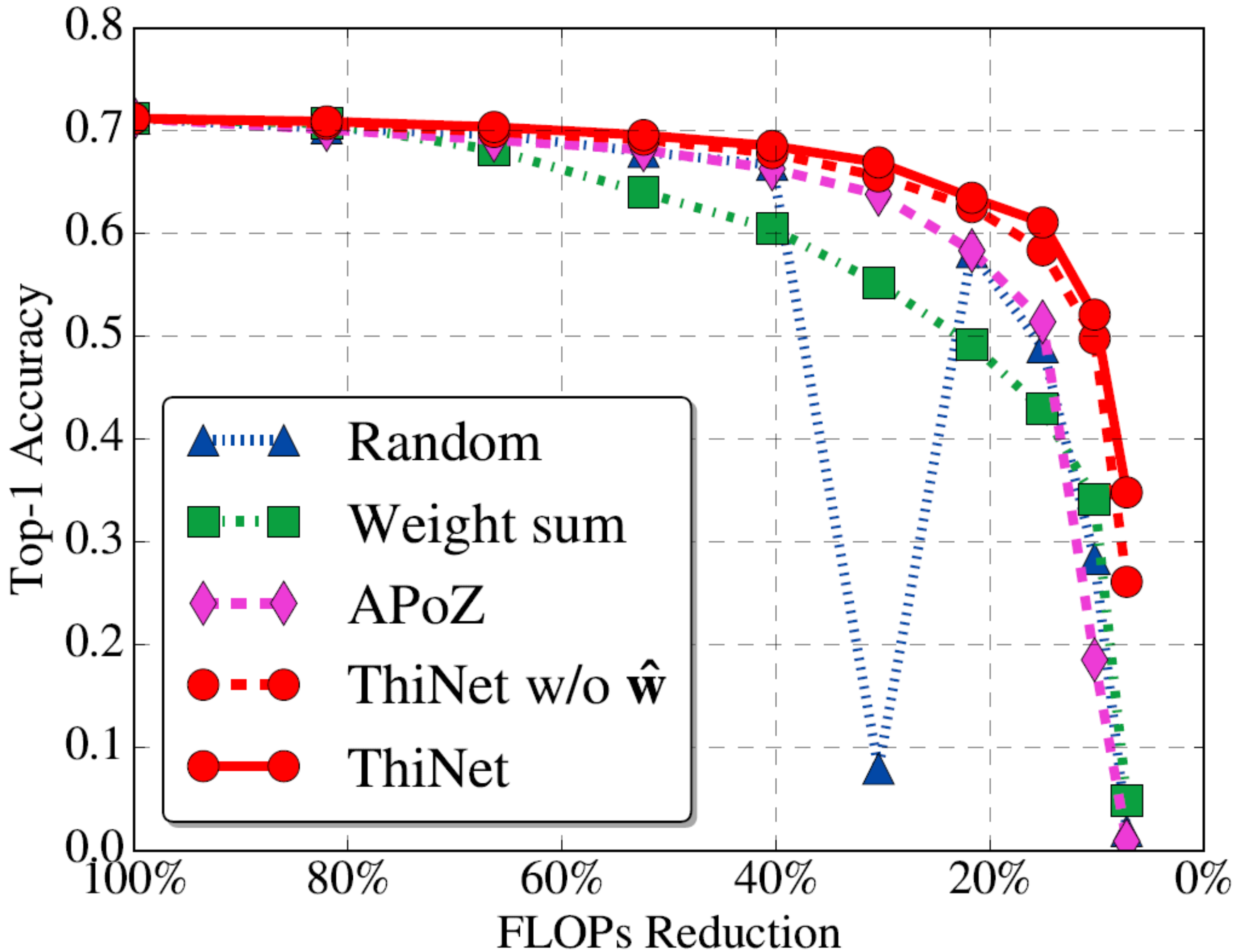


Figure. Comparison of different channel selection methods, using VGG-16-GAP on CUB-200

VGG-16 on ImageNet

- **ThiNet-Conv:** prune **50%** of the **first 10** convolutional layers
- **ThiNet-GAP:** replace the **FC layers** with a global average pooling (GAP) layer based on ThiNet-Conv

Table. Pruning results of VGG-16 on ImageNet

Model	Top-1	Top-5	#Param.	#FLOPs	f./b. (ms)
Original	68.34%	88.44%	138.34M	30.94B	189.92/407.56
ThiNet-Conv	**69.80%**	**89.53%**	**131.44M**	**9.58B**	**76.71/152.05**
Train from scratch	67.00%	87.45%	131.44M	9.58B	76.71/152.05
ThiNet-GAP	**67.34%**	**87.92%**	**8.32M**	**9.34B**	**71.73/145.51**
ThiNet-Tiny	59.34%	81.97%	1.32M	2.01B	29.51/55.83
SqueezeNet(Han et al.)	57.67%	80.39%	1.24M	1.72B	37.30/68.62

VGG-16 on ImageNet

- **ThiNet-WS:** use the weight sum (WS) method for pruning

Table. Comparison of state-of-the-art methods on VGG-16

Method	Top-1	Top-5	#Param.	#FLOPs
APoZ-1 (Hu et al.)	-2.16%	-0.84%	2.04×	≈1×
APoZ-2 (Hu et al.)	+1.81%	+1.25%	2.70×	≈1×
Taylor-1 (Molchanov et al.)	-	-1.44%	≈1×	2.68×
Taylor-2 (Molchanov et al.)	-	-3.94%	≈1×	3.86×
ThiNet-WS (Li et al.)	+1.01%	+0.69%	1.05×	3.23×
ThiNet-Conv	**+1.46%**	**+1.09%**	**1.05×**	**3.23×**
ThiNet-GAP	-1.00%	-0.52%	16.63×	3.31×

ResNet-50 on ImageNet

Table. Performance of pruning ResNet-50 on ImageNet

Model	Top-1	Top-5	#Param.	#FLOPs	f./b. (ms)
Original	72.88%	91.14%	25.56M	7.72B	188.27/269.32
ThiNet-70	72.04%	90.67%	16.94M	4.88B	169.38/243.37
ThiNet-50	71.01%	90.02%	12.38M	3.41B	153.60/212.29
ThiNet-30	68.42%	88.30%	8.66M	2.20B	144.45/200.67

Domain Adaptation Ability

Table. Comparison of different methods on CUB-200 and Indoor-67. "FT" denotes "Fine Tune"

Data set	Stategy	#Param.	#FLOPs	Top-1
CUB-200	VGG-16	135.07M	30.93B	72.30%
	FT & prune	7.91M	9.34B	66.90%
	Train from scratch	7.91M	9.34B	44.27%
	ThiNet-Conv	**128.16M**	**9.58B**	**70.90%**
	ThiNet-GAP	7.91M	9.34B	69.43%
	ThiNet-Tiny	1.12M	2.01B	65.45%
	AlexNet	57.68M	1.44B	57.28%
Indoor-67	VGG-16	134.52M	30.93B	72.46%
	FT & prune	7.84M	9.34B	64.70%
	Train from scratch	7.84M	9.34B	38.81%
	ThiNet-Conv	**127.62M**	**9.58B**	**72.31%**
	ThiNet-GAP	7.84M	9.34B	70.22%
	ThiNet-Tiny	1.08M	2.01B	62.84%
	AlexNet	57.68M	1.44B	59.55%

Conclusion

Conclusion

Contributions

- Proposed ThiNet, a **filter pruning** framework, to accelerate and compress CNN models
- Formally establish filter pruning as an **optimization problem**
- VGG-16 model can be pruned into **5.05MB**, and shows promising generalization ability on **transfer learning**

Future work

- Prune the projection short-cuts of ResNet
- Explore more on channel selection method

Thank You

Reference

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