Neural Network Compression

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Current Methods

- Compressing pre-trained deep networks
  - Speed up at testing time
- Design compact layers
  - Speed up at both testing and training
- Quantizing parameters
  - 32 -> 16 -> 1 bit(s)

DEEP COMPRESSION: COMPRESSING DEEP NEURAL NETWORKS WITH PRUNING, TRAINED QUANTIZATION AND HUFFMAN CODING

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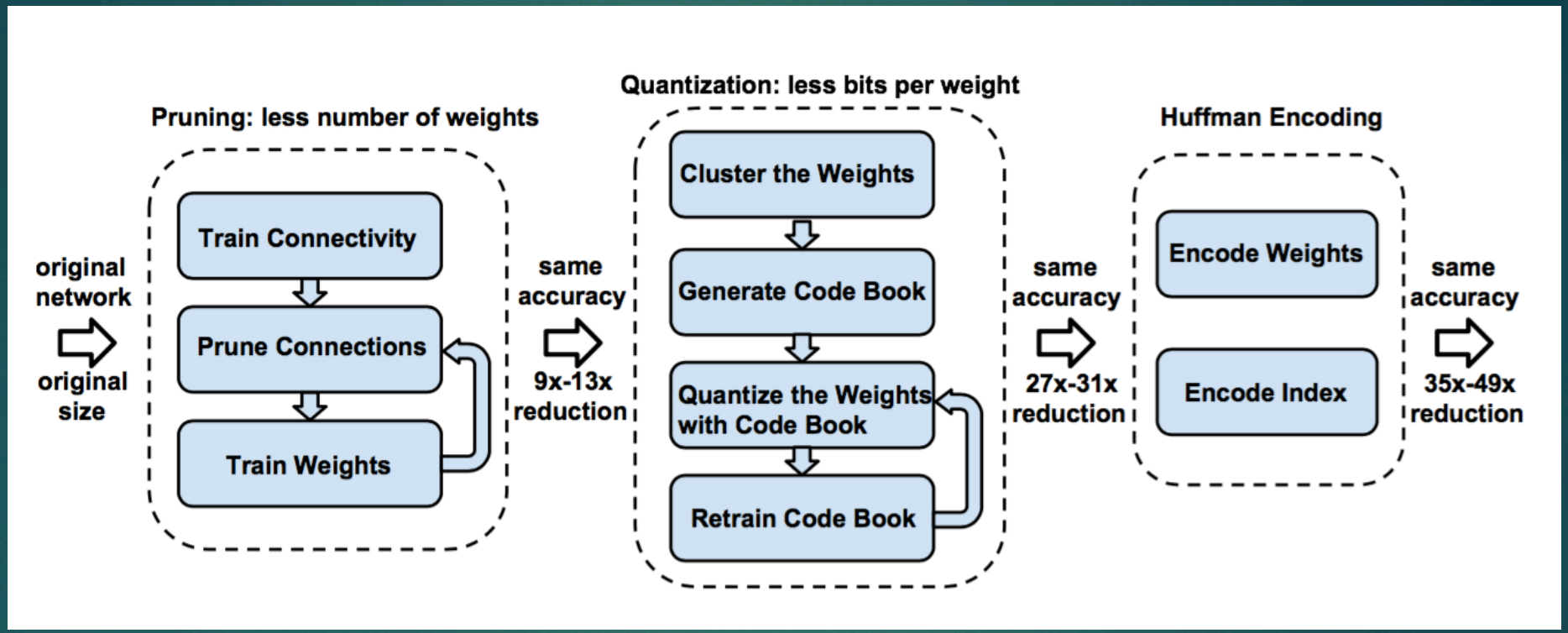
Abstract

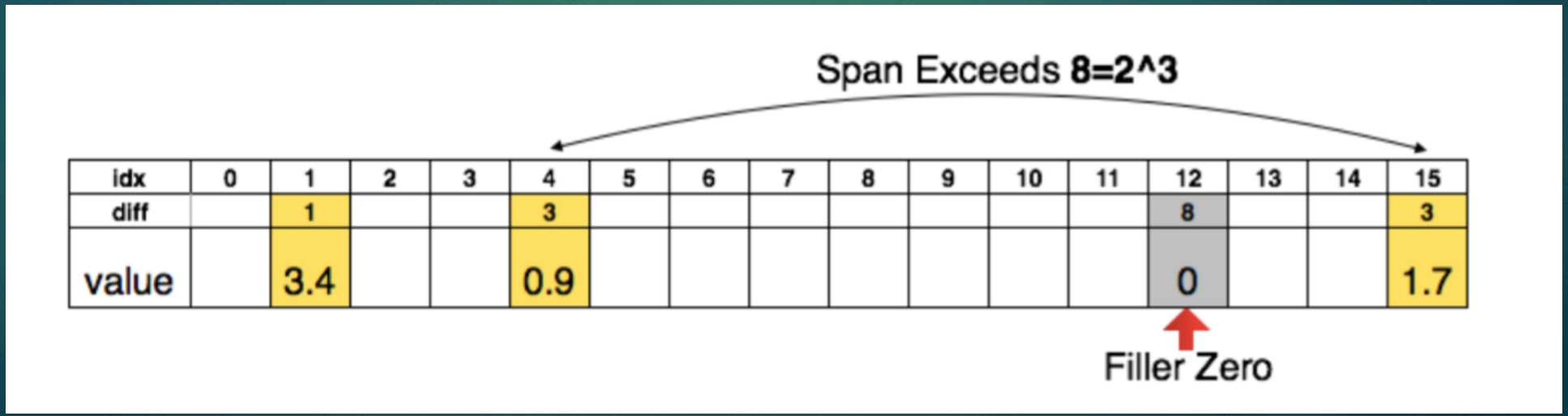
- Three stage pipeline of Deep Compression
  - Pruning
  - Quantization
  - Huffman code
- AlexNet reduce 35x
- VGG-16 reduce 49x
- Compress with no loss of accuracy


Pruning: less number of weights
Train Connectivity
Prune Connections
Train Weights
original network
original size
same accuracy
9x-13x reduction
Quantization: less bits per weight
Cluster the Weights
Generate Code Book
Quantize the Weights with Code Book
Retrain Code Book
same accuracy
27x-31x reduction
Huffman Encoding
Encode Weights
Encode Index
same accuracy
35x-49x reduction

Network Pruning

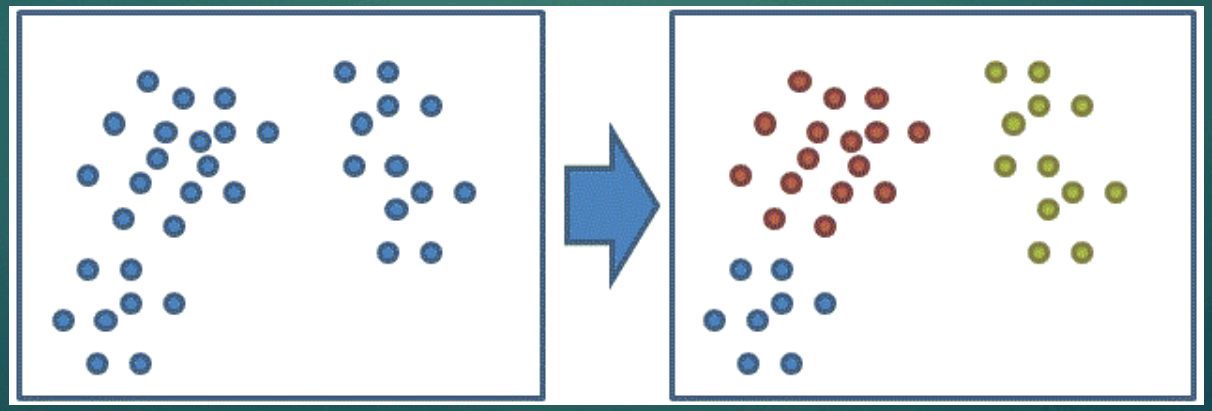
- Prune weights < threshold
- Retrain the network
- Representing the matrix sparsity with relative index

$$\begin{pmatrix} 1.0 & 0 & 5.0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 3.0 & 0 & 0 & 0 & 0 & 11.0 & 0 \\ 0 & 0 & 0 & 0 & 9.0 & 0 & 0 & 0 \\ 0 & 0 & 6.0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 7.0 & 0 & 0 & 0 & 0 \\ 2.0 & 0 & 0 & 0 & 0 & 10.0 & 0 & 0 \\ 0 & 0 & 0 & 8.0 & 0 & 0 & 0 & 0 \\ 0 & 4.0 & 0 & 0 & 0 & 0 & 0 & 12.0 \end{pmatrix}$$

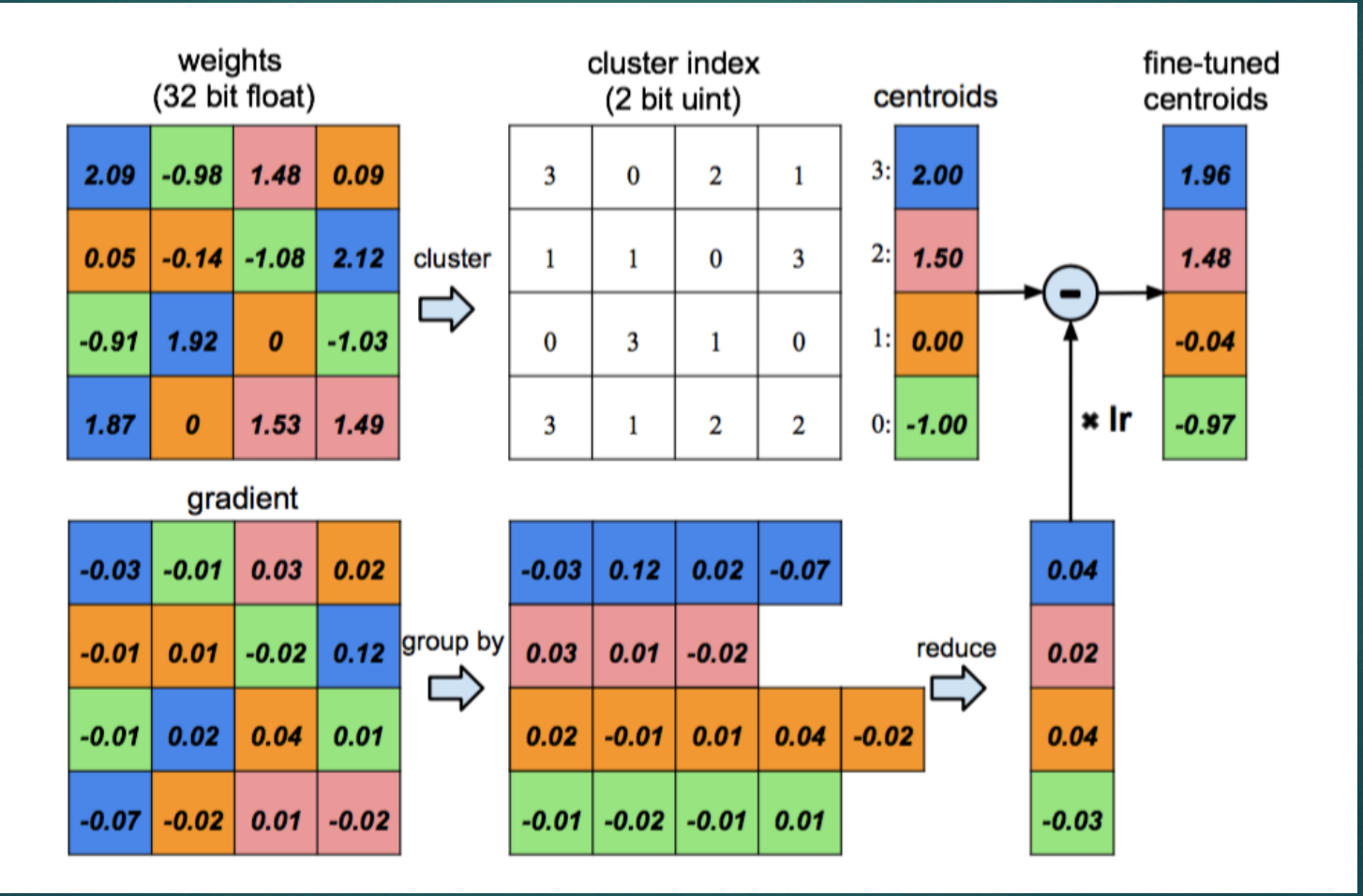


Quantization & Weight Sharing

- Use k-means to cluster the weights
- We only need to store k effective weight(n*32 bits) and n*log2(k)



Quantization & Weight Sharing



Quantization & Weight Sharing

- 1M*32/(1M*8+256*32) = 3.99

$$r = \frac{nb}{nlog_2(k) + kb}$$

Huffman Coding

- More common symbols are represented with fewer bits

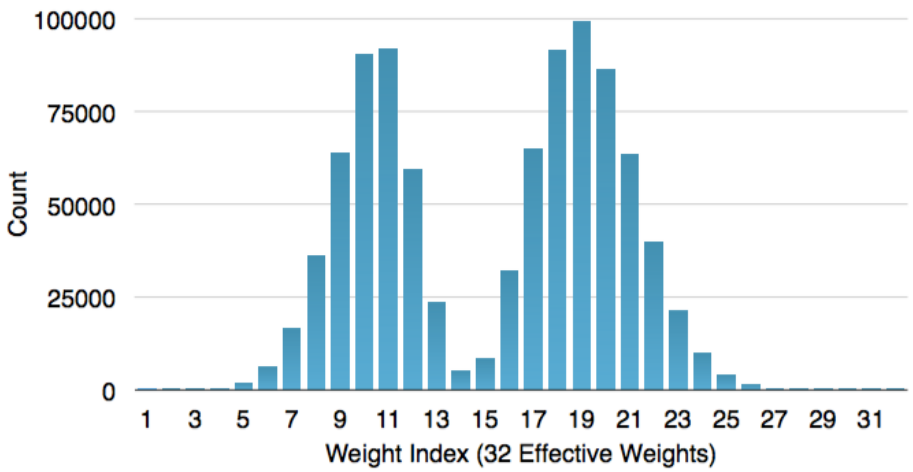


Figure 5: Distribution for weight (Left) and index (Right). The distribution is biased.

Experiment

- Implement on different network (Mnist)

Table 1: The compression pipeline can save 35× to 49× parameter storage with no loss of accuracy.

Network	Top-1 Error	Top-5 Error	Parameters	Compress Rate
LeNet-300-100 Ref	1.64%	-	1070 KB	
LeNet-300-100 Compressed	1.58%	-	**27 KB**	**40**×
LeNet-5 Ref	0.80%	-	1720 KB	
LeNet-5 Compressed	0.74%	-	**44 KB**	**39**×
AlexNet Ref	42.78%	19.73%	240 MB	
AlexNet Compressed	42.78%	19.70%	**6.9 MB**	**35**×
VGG-16 Ref	31.50%	11.32%	552 MB	
VGG-16 Compressed	31.17%	10.91%	**11.3 MB**	**49**×

Experiment

- Layer-wise compress result

Table 5: Compression statistics for VGG-16. P: pruning, Q:quantization, H:Huffman coding.

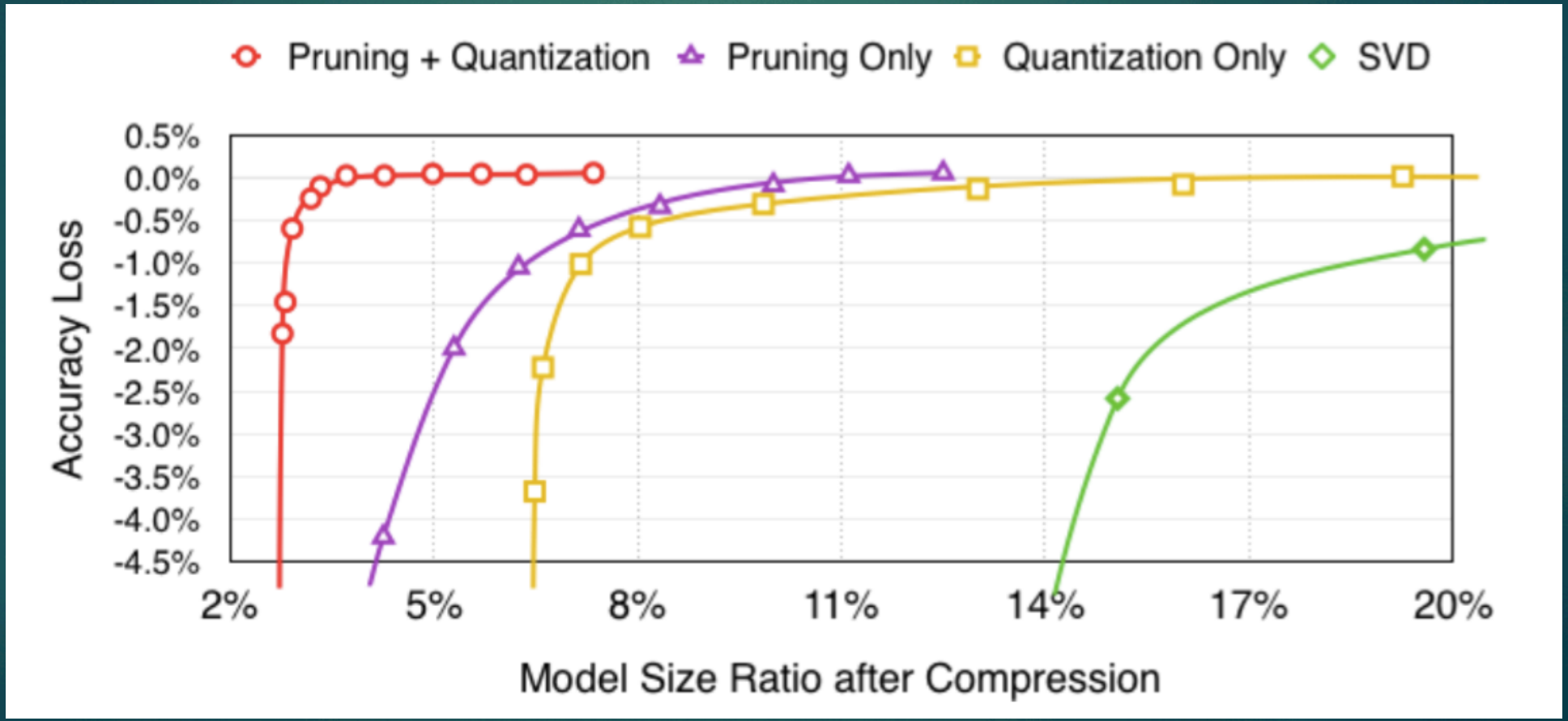
Layer	#Weights	Weights% (P)	Weigh bits (P+Q)	Weight bits (P+Q+H)	Index bits (P+Q)	Index bits (P+Q+H)	Compress rate (P+Q)	Compress rate (P+Q+H)
conv1_1	2K	58%	8	6.8	5	1.7	40.0%	29.97%
conv1_2	37K	22%	8	6.5	5	2.6	9.8%	6.99%
conv2_1	74K	34%	8	5.6	5	2.4	14.3%	8.91%
conv2_2	148K	36%	8	5.9	5	2.3	14.7%	9.31%
conv3_1	295K	53%	8	4.8	5	1.8	21.7%	11.15%
conv3_2	590K	24%	8	4.6	5	2.9	9.7%	5.67%
conv3_3	590K	42%	8	4.6	5	2.2	17.0%	8.96%
conv4_1	1M	32%	8	4.6	5	2.6	13.1%	7.29%
conv4_2	2M	27%	8	4.2	5	2.9	10.9%	5.93%
conv4_3	2M	34%	8	4.4	5	2.5	14.0%	7.47%
conv5_1	2M	35%	8	4.7	5	2.5	14.3%	8.00%
conv5_2	2M	29%	8	4.6	5	2.7	11.7%	6.52%
conv5_3	2M	36%	8	4.6	5	2.3	14.8%	7.79%
fc6	103M	4%	5	3.6	5	3.5	1.6%	1.10%
fc7	17M	4%	5	4	5	4.3	1.5%	1.25%
fc8	4M	23%	5	4	5	3.4	7.1%	5.24%
Total	138M	7.5%(13×)	6.4	4.1	5	3.1	3.2% (**31**×)	2.05% (**49**×)

Discussion

- Pruning + Quantize
- Centroid initialization
- Speedup and energy efficiency

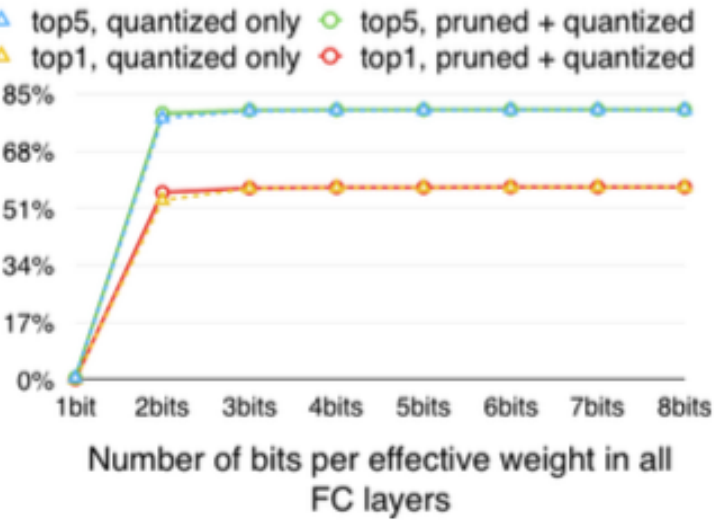
Pruning + Quantize

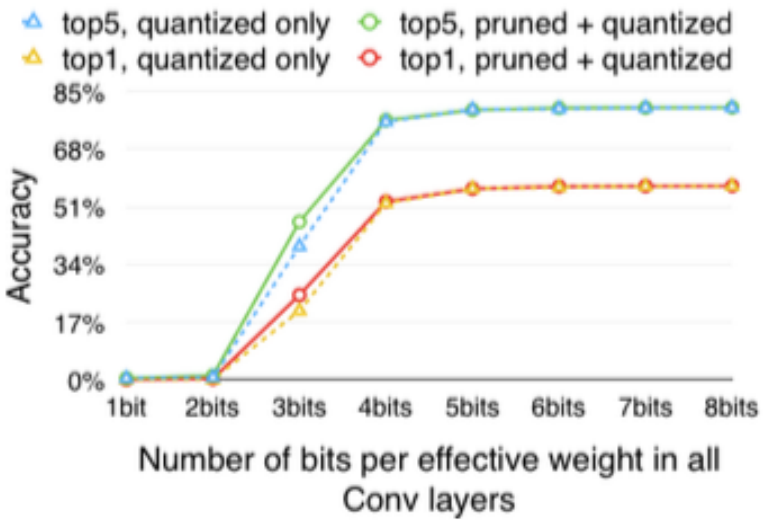
- P+Q is better

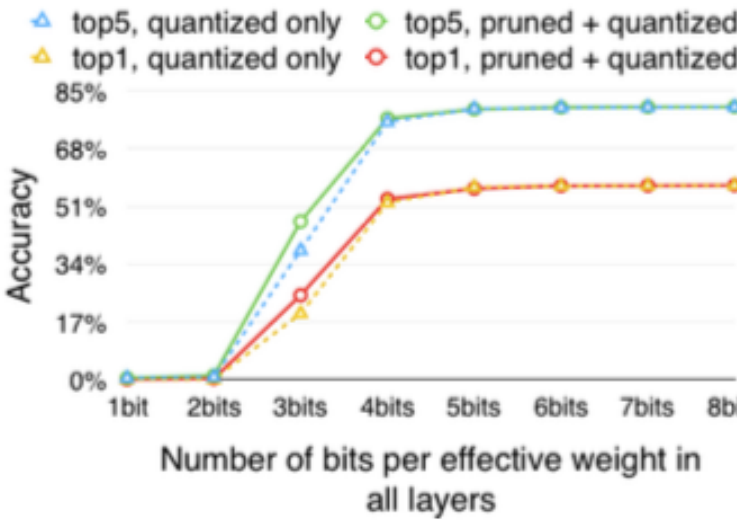


Pruning + Quantize

- pruning doesn't hurt quantiztion
- FC (3 bits)
- CONV(5 bits)







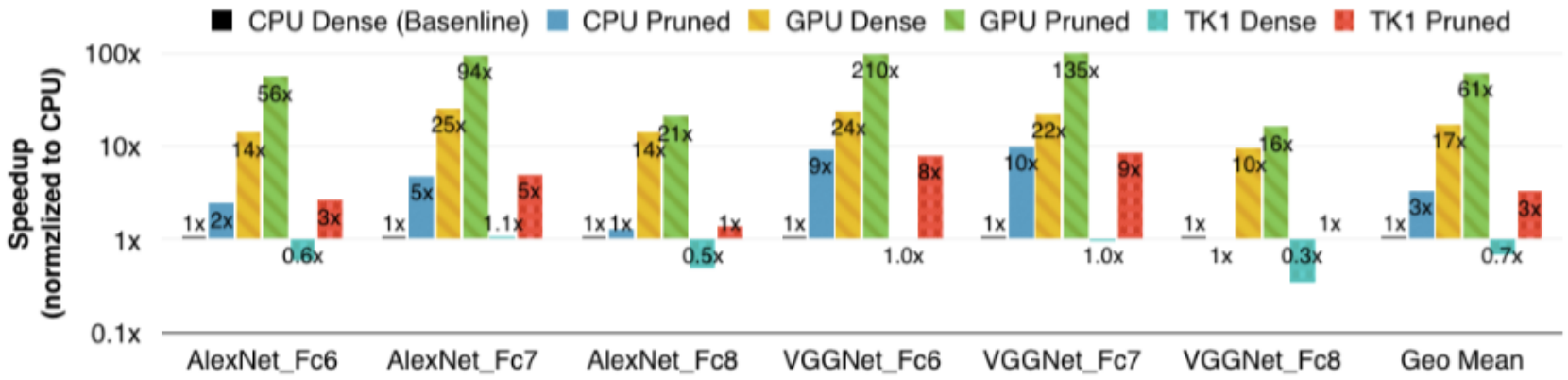


Figure 9: Compared with the original network, pruned network layer achieved 3× speedup on CPU, 3.5× on GPU and 4.2× on mobile GPU on average. Batch size = 1 targeting real time processing. Performance number normalized to CPU.

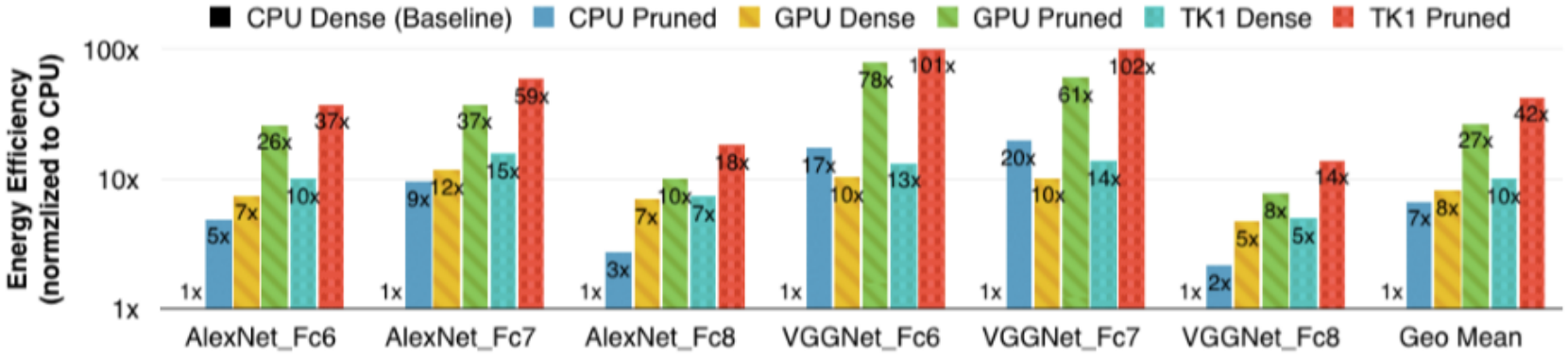
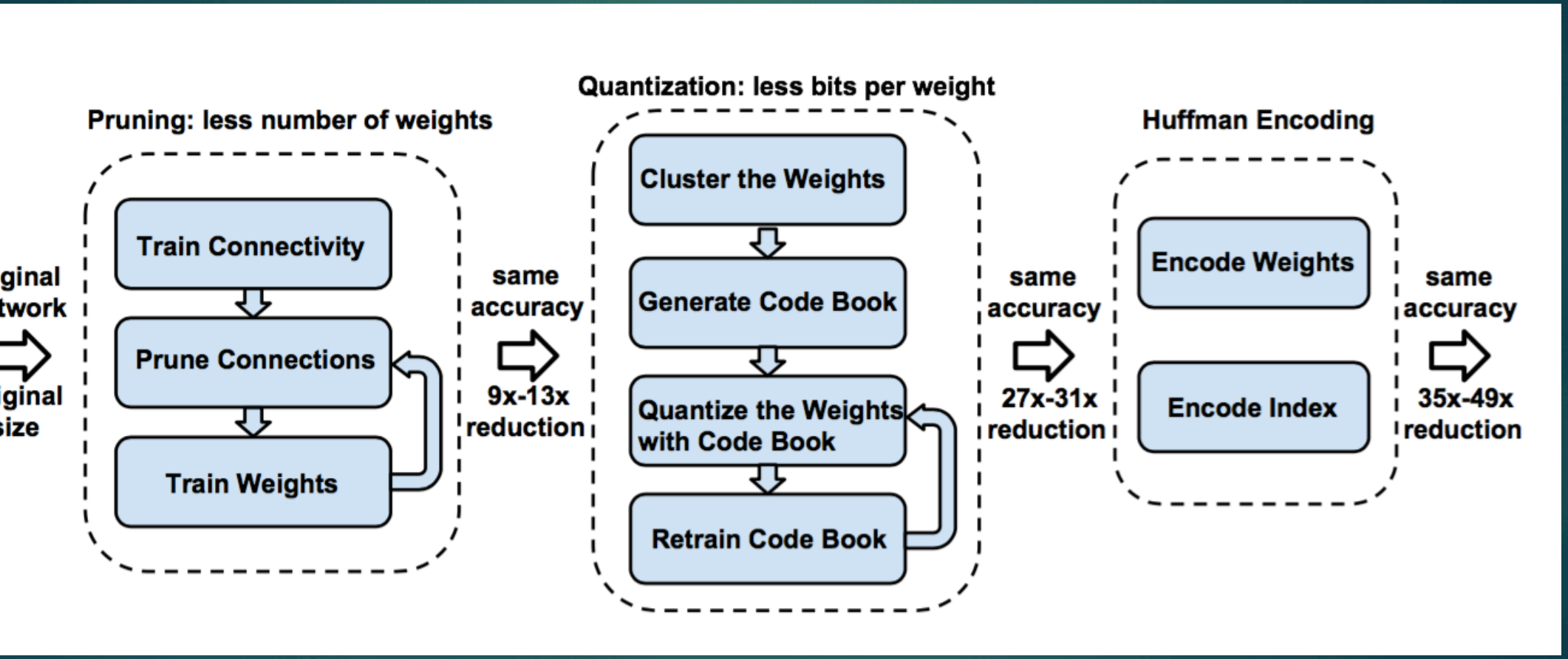


Figure 10: Compared with the original network, pruned network layer takes 7× less energy on CPU, 3.3× less on GPU and 4.2× less on mobile GPU on average. Batch size = 1 targeting real time processing. Energy number normalized to CPU.

Concept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twork
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size
Pruning: less number of weights
Train Connectivity
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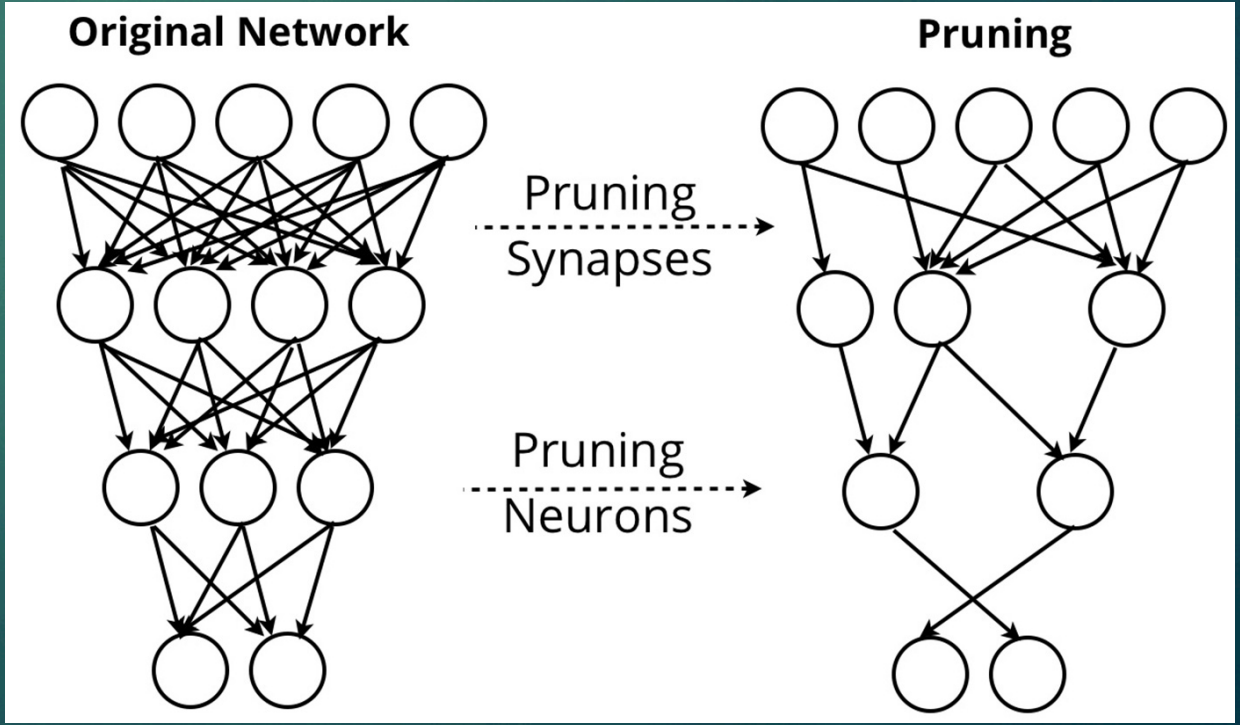
Quantization: less bits per weight
Cluster the Weights
Generate Code Book
Quantize the Weights
with Code Book
Retrain Code Book
same
accuracy
27x-31x
reduction
Huffman Encoding
Encode Weights
Encode Index
same
accuracy
35x-49x
reduction

Sparsifying Neural Network Connections for Face Recognition

YI SUN, XIAOGANG WANG, XIAOOU TANG

Abstract

- Pruning weight depends on correlation to output
- The correlation between two connected neurons are defined by the magnitude of the correlation between their neural activations.

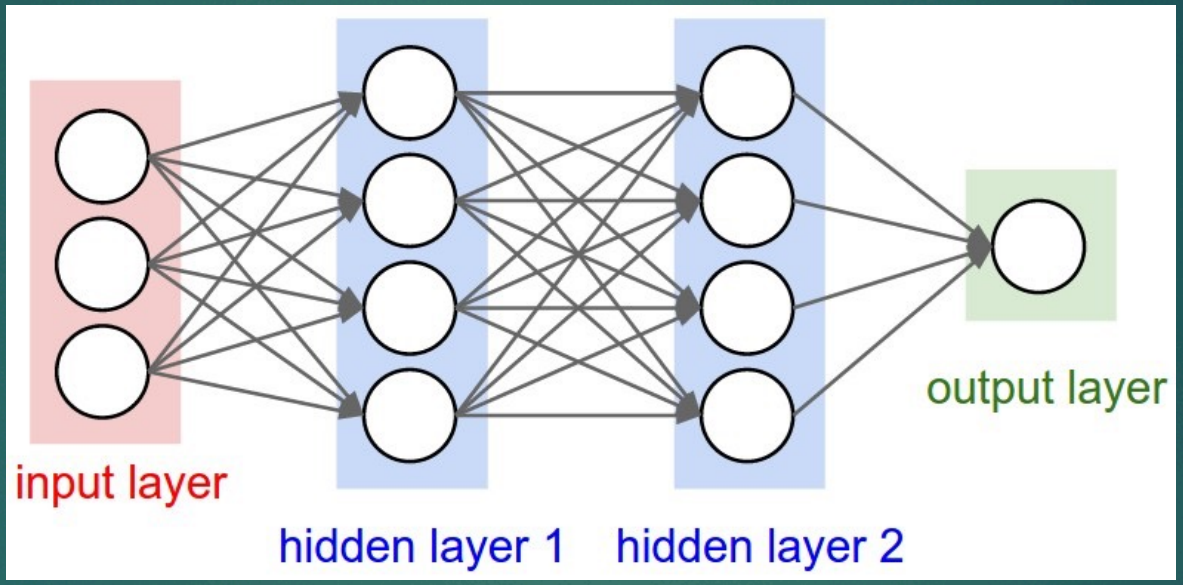


Sparsity connections

- Sample S* | W |
- Keep high correlated and drop weakly correlated connections.
- Keep a small portion weakly correlated connections is also helpful
- Fully-connected and convolutional

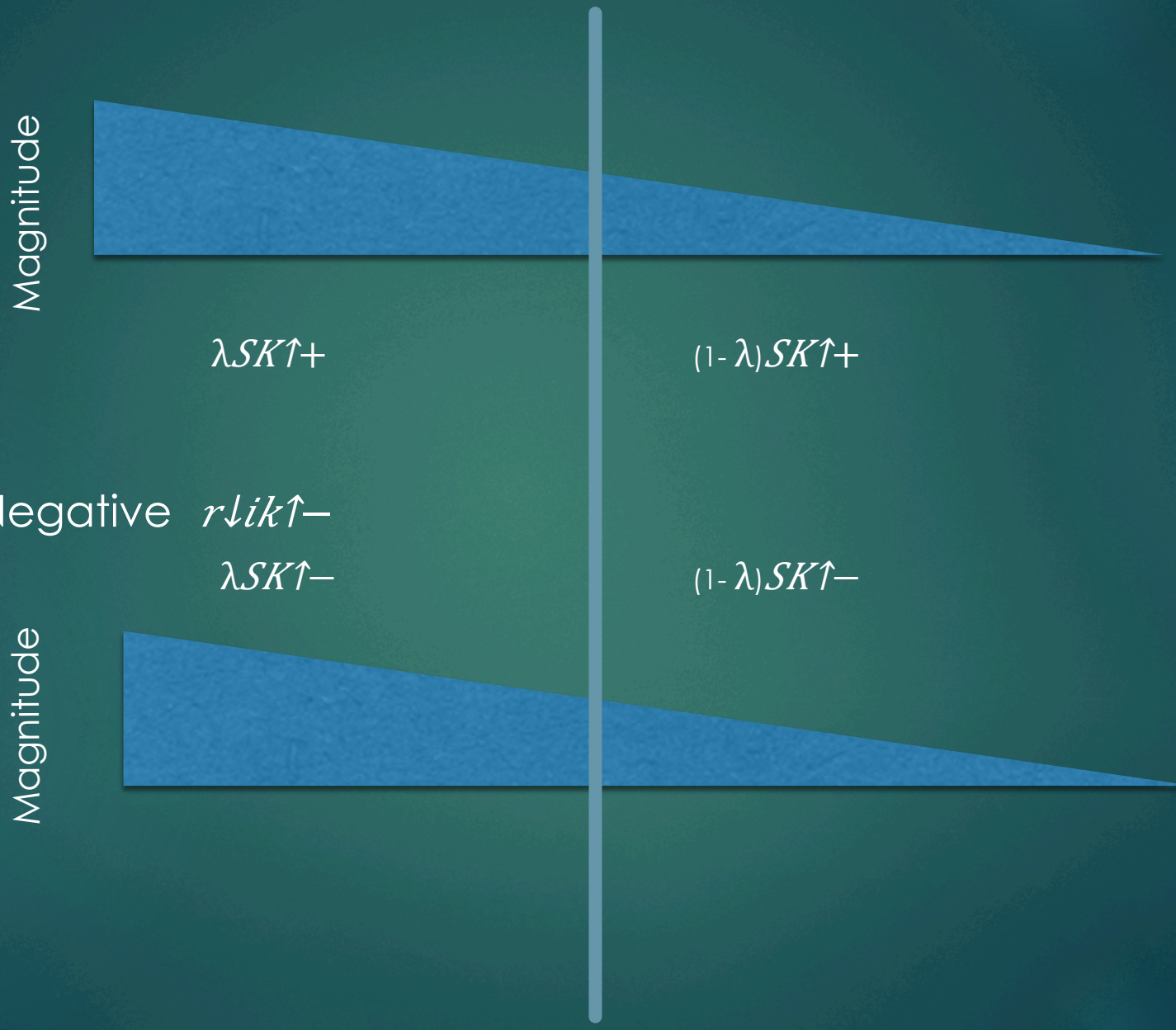
Sparsity connections

- fully- and locally-connected



$$r_{ik} = \frac{E[a_i - \mu_{a_i}][b_{ik} - \mu_{b_{ik}}]}{\sigma_{a_i}\sigma_{b_{ik}}}$$

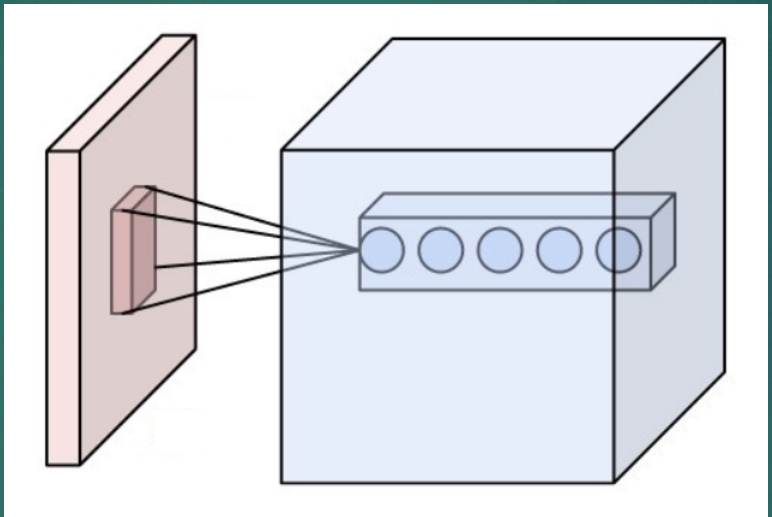
- Positive $r\downarrow lik\uparrow +$



- Negative $r\downarrow lik\uparrow -$

Sparsity connections

- Convolutional layer



$$r_{ik} \triangleq \sum_{m=1}^{M} \left| \frac{E[a_{im} - \mu_{a_{im}}][b_{mk} - \mu_{b_{mk}}]}{\sigma_{a_{im}} \sigma_{b_{mk}}} \right| .$$

Experiment

- Sparsity improves performance

sparse structure	accuracy	compression ratio
	0.9895	1
1/256-f	0.9898	0.96
1/256-f 1/128-5b	0.9923	0.76
1/256-f 1/128-5b 1/2-4b	**0.9930**	0.74
1/256-f 1/128-5b 1/2-5a	0.9922	0.43
1/256-f 1/128-5b 1/32-5a	0.9898	0.12

Experiment

- Correlation guided weight selection

sparse structure	accuracy	corr before	corr after
1/256-f	**0.9898**	0.147	0.494
1/256-f-r	0.9893	0.114	0.511
1/256-f-h	0.9893		
1/256-f 1/128-5b	**0.9923**	0.120	0.275
1/256-f 1/128-5b-r	0.9910	0.089	0.272
1/256-f 1/128-5b-h	0.9902		
1/256-f 1/128-5b 1/2-4b	**0.9930**	0.075	0.079
1/256-f 1/128-5b 1/2-4b-r	0.9922	0.067	0.073
1/256-f 1/128-5b 1/2-4b-h	0.9925		

Experiment

- Why do we need a denser network?

  sparse network is easier to get stuck at a local minimum

sparse structure	if pre-trained	accuracy	train error
1/256-f	yes	0.9898	0.0207
	no	0.9887	0.0229
1/256-f 1/128-5b	yes	0.9923	0.0302
	no	0.9845	0.0423
1/256-f 1/128-5b 1/2-4b	yes	0.9930	0.0299
	no	0.9833	0.0463

Experiment

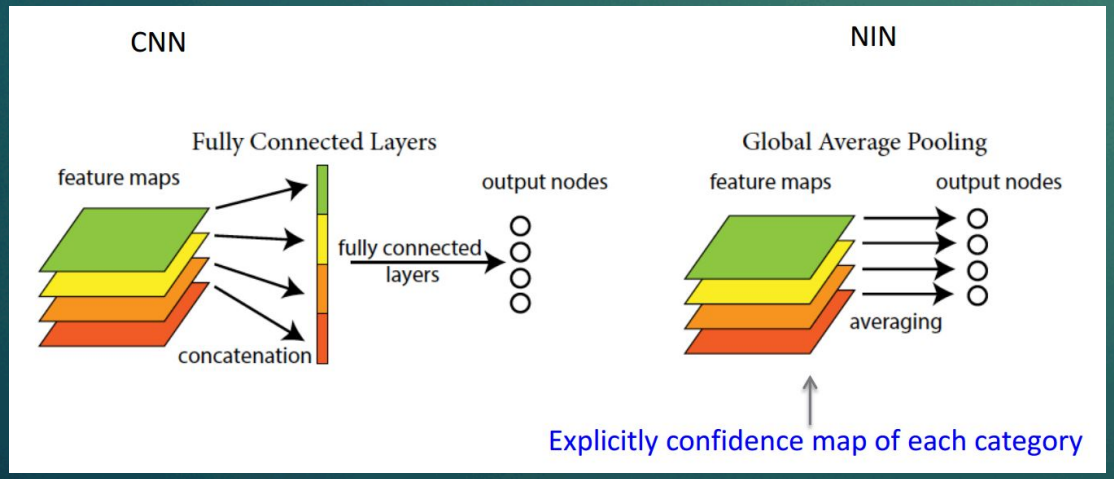
- Method comparison

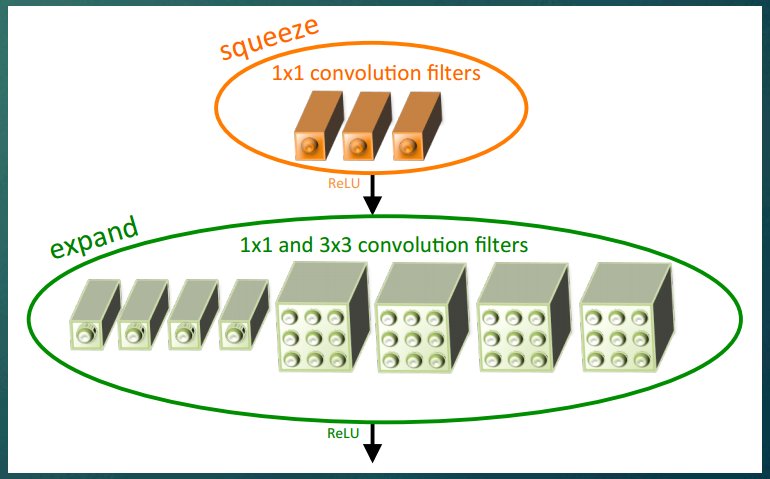
sparse structure	OBD	magnitude	BRP	correlation
1/256-f	**0.9905**	0.9888	0.9863	0.9898
1/128-5b	0.9903	0.9912	0.9902	**0.9923**
1/2-4b	0.9920	0.9925	0.9913	**0.9930**

Design compact layers

- Network in Network
  replace the fully connected layer with global average pooling

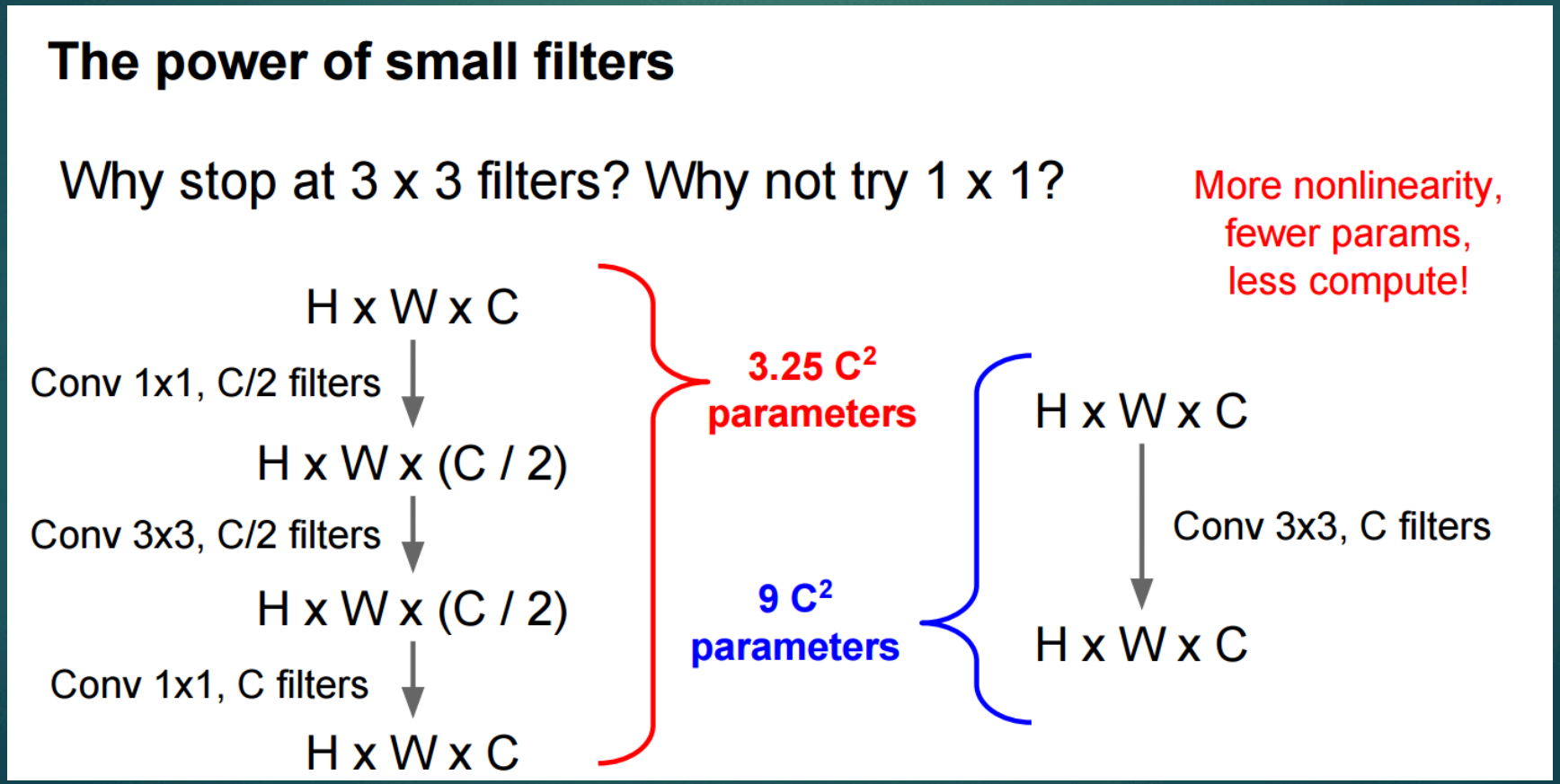
- SqueezeNet 50X model size save
  replace 3*3 convolution to 1*1 convolution reduce dimension





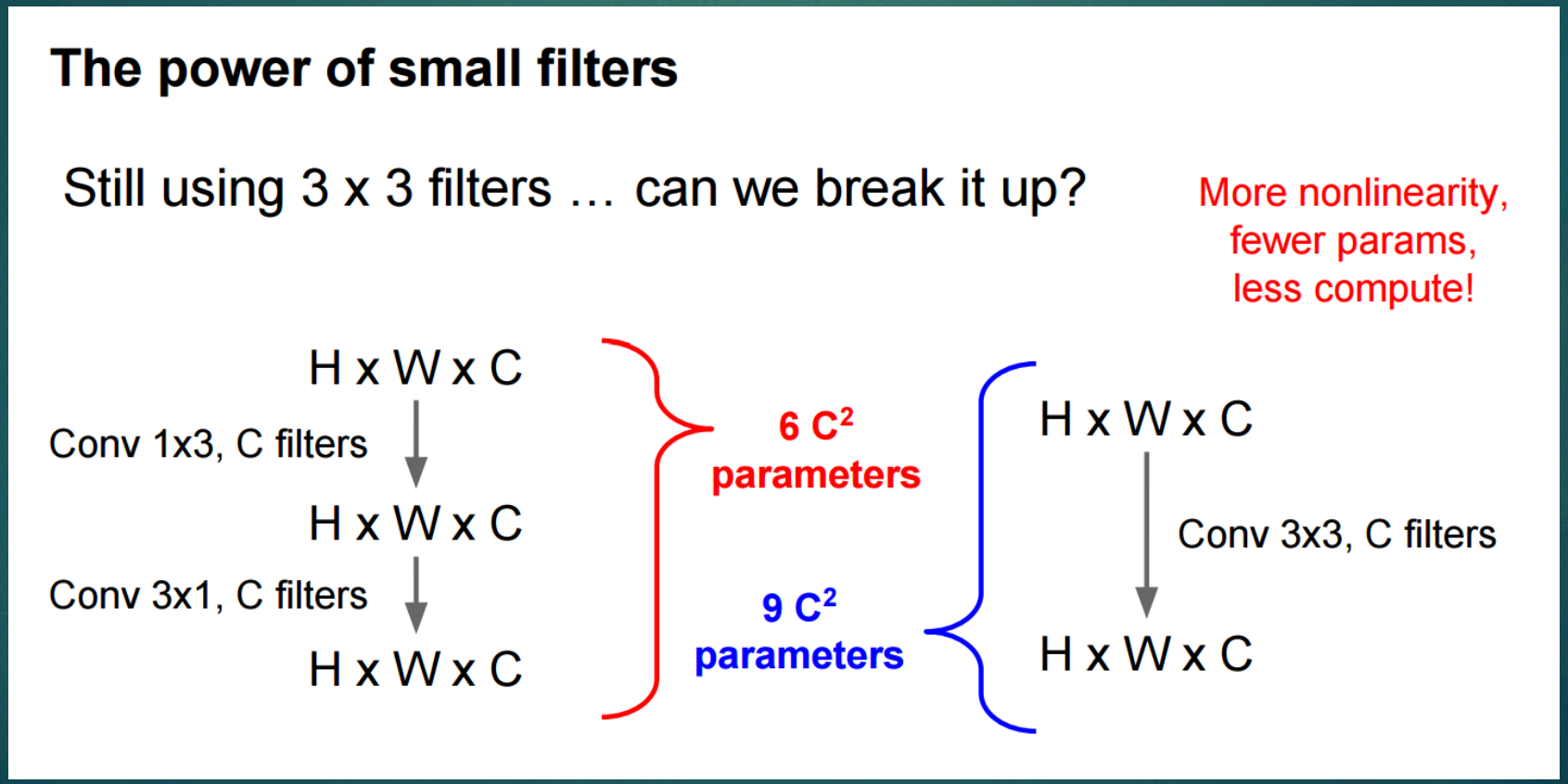
Design compact layers

- Reduce dimension



Design compact layers

- Decompose 3*3 convolution

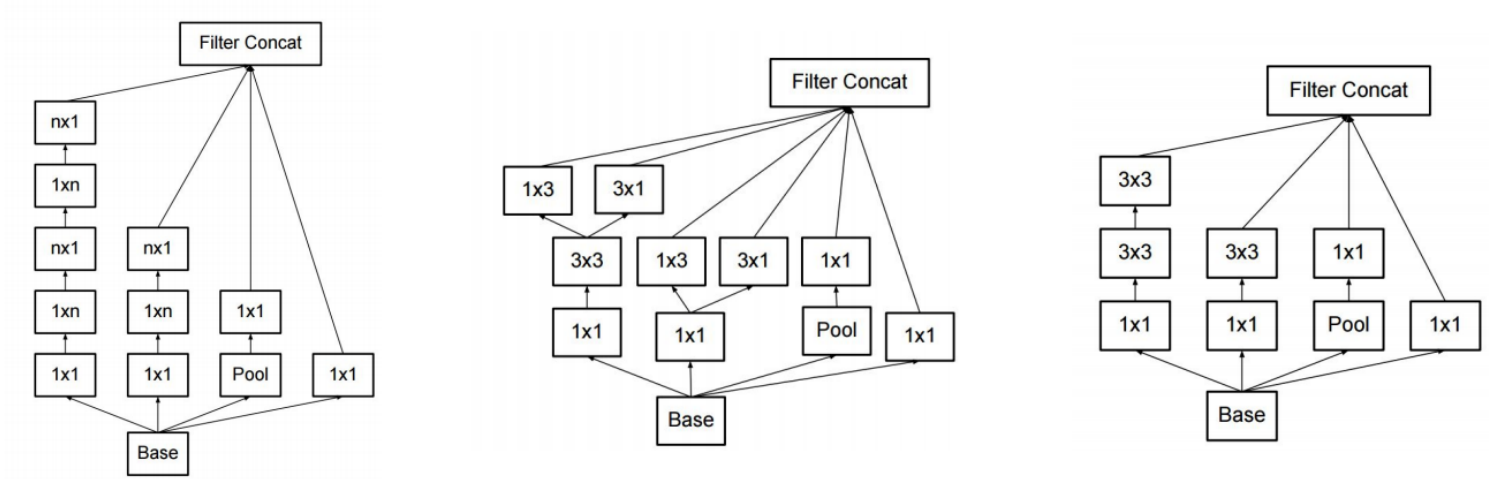


Design compact layers

- GoogLeNet

The power of small filters

Latest version of GoogLeNet incorporates all these ideas



Szegedy et al, “Rethinking the Inception Architecture for Computer Vision”

Quantizing parameters

- 32 bit “single” precision is typically used for CNNs for performance
- Nvidia support “half” precision

- BinaryNet

- Xnor-Net

- DoReFa-Net

XNOR-Net: ImageNet Classification Using Binary Convolutional Neural Networks

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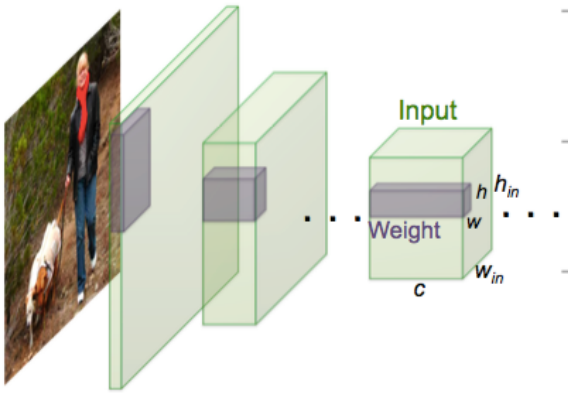
Abstract

- Binary-Weight-Networks
  The filter are approximated with binary values. save 32x memory
- XNOR-Networks
  both the filters and the input to convolutional layers are binary.
  58x faster & save 32x memory



	Network Variations	Operations used in Convolution	Memory Saving (Inference)	Time Saving on CPU (Inference)	Accuracy on ImageNet (AlexNet)
Standard Convolution	Real-Value Inputs: 0.11 -0.21 ... -0.34 / -0.25 0.61 ... 0.52; Real-Value Weights: 0.12 -1.2 ... 0.41 / -0.2 0.5 ... 0.68	+ , − , ×	1x	1x	%56.7
Binary Weight	Real-Value Inputs: 0.11 -0.21 ... -0.34 / -0.25 0.61 ... 0.52; Binary Weights: 1 -1 ... 1 / -1 1 ... 1	+ , −	~32x	~2x	%53.8
BinaryWeight Binary Input **(XNOR-Net)**	Binary Inputs: 1 -1 ... -1 / -1 1 ... 1; Binary Weights: 1 -1 ... 1 / -1 1 ... 1	XNOR , bitcount	~32x	~58x	%44.2

Binary Convolutional Neural Network

$$\mathbf{I} = \mathcal{I}_{l(l=1,\ldots,L)}$$

$$\mathcal{W}_{lk(k=1,\ldots,K^l)}$$

$$\mathbf{I} * \mathbf{W} \approx (\mathbf{I} \oplus \mathbf{B})\,\alpha$$

$$\langle \mathcal{I}, \mathcal{W}, * \rangle$$

$$\langle \mathcal{I}, \mathcal{B}, \mathcal{A}, \oplus \rangle$$

$$\mathcal{W}_{lk} \approx \mathcal{A}_{lk}\mathcal{B}_{lk}$$

Binary Convolutional Neural Network

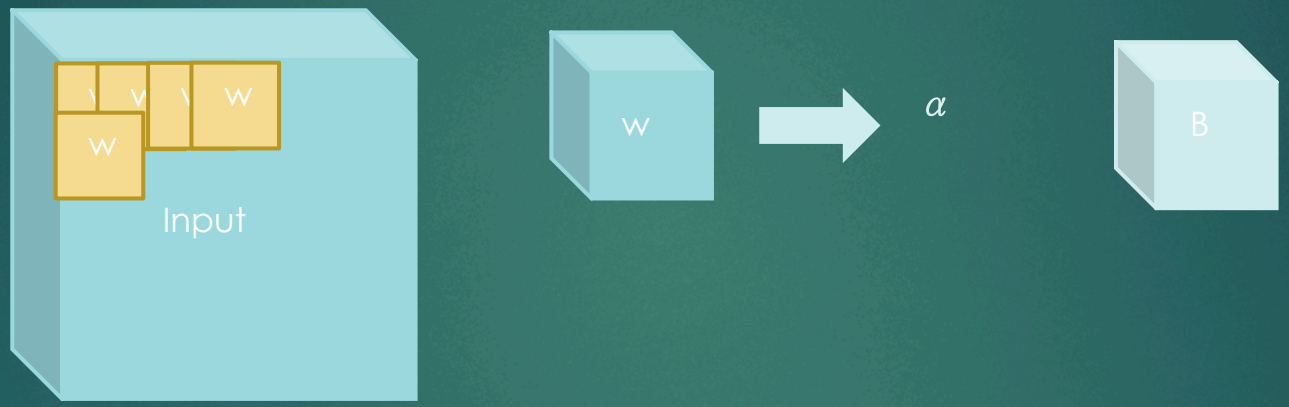
$$J(\mathbf{B}, \alpha) = \|\mathbf{W} - \alpha\mathbf{B}\|^2$$

$$\alpha^*, \mathbf{B}^* = \underset{\alpha, \mathbf{B}}{\operatorname{argmin}} J(\mathbf{B}, \alpha)$$

$$\mathbf{B}^* = \operatorname{sign}(\mathbf{W})$$

$$\alpha^* = \frac{\mathbf{W}^\mathsf{T} \operatorname{sign}(\mathbf{W})}{n} = \frac{\sum |\mathbf{W}_i|}{n} = \frac{1}{n}\|\mathbf{W}\|_{\ell 1}$$

Forward Convolution



Learning Algorithm

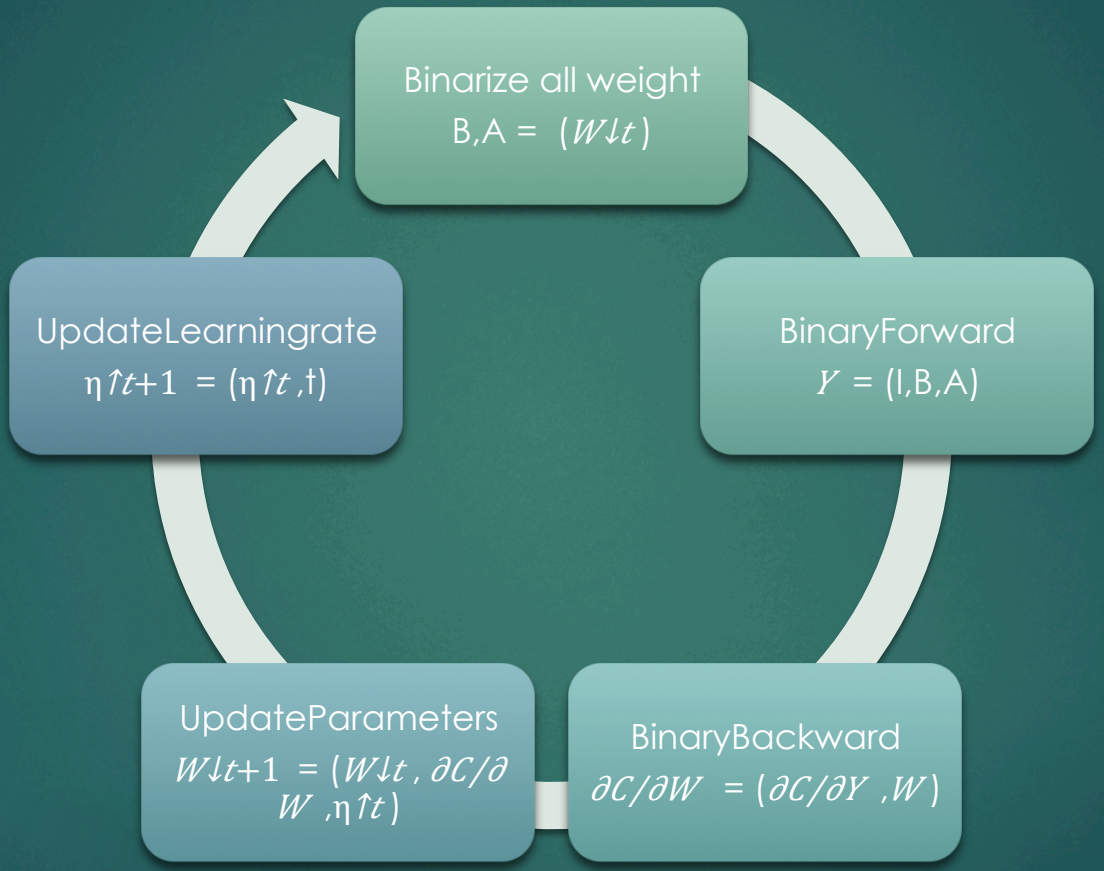
Algorithm 1 Training an L-layers CNN with binary weights:

Input: A minibatch of inputs and targets $(\mathbf{I}, \mathbf{Y})$, cost function $C(\mathbf{Y}, \hat{\mathbf{Y}})$, current weight $\mathcal{W}^t$ and current learning rate η^t.

Output: updated weight $\mathcal{W}^{t+1}$ and updated learning rate η^{t+1}.

Binarizing weight filters:
for $l = 1$ to L **do**
  for k^{th} filter in l^{th} layer **do**
    $\mathcal{A}_{lk} = \frac{1}{n}\|\mathcal{W}^t_{lk}\|_{\ell 1}$
    $\mathcal{B}_{lk} = \text{sign}(\mathcal{W}^t_{lk})$
    $\widetilde{\mathcal{W}}_{lk} = \mathcal{A}_{lk}\mathcal{B}_{lk}$
$\hat{\mathbf{Y}} =$ **BinaryForward**$(\mathbf{I}, \mathcal{B}, \mathcal{A})$ // standard forward propagation except that convolutions are computed using equation 1 or 11
$\frac{\partial C}{\partial \widetilde{\mathcal{W}}} =$ **BinaryBackward**$(\frac{\partial C}{\partial \hat{\mathbf{Y}}}, \widetilde{\mathcal{W}})$ // standard backward propagation except that gradients are computed using $\widetilde{\mathcal{W}}$ instead of $\mathcal{W}^t$
$\mathcal{W}^{t+1} =$ **UpdateParameters**$(\mathcal{W}^t, \frac{\partial C}{\partial \widetilde{\mathcal{W}}}, \eta_t)$ // Any update rules (*e.g.*,SGD or ADAM)
$\eta^{t+1} =$ **UpdateLearningrate**(η^t, t) // Any learning rate scheduling function

Learning Algorithm



XNOR-Networks

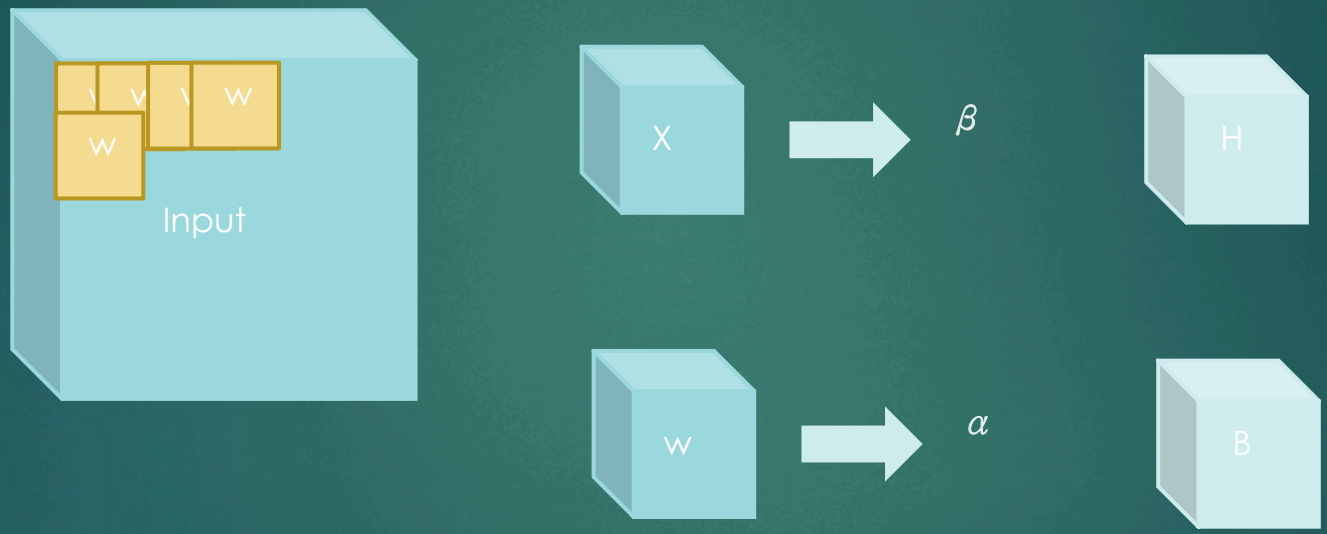
$$\mathbf{X}^\mathsf{T}\mathbf{W} \approx \beta\mathbf{H}^\mathsf{T}\alpha\mathbf{B}$$

$$\alpha^*, \mathbf{B}^*, \beta^*, \mathbf{H}* = \underset{\alpha,\mathbf{B},\beta,\mathbf{H}}{\operatorname{argmin}} \|\mathbf{X}^\mathsf{T}\mathbf{W} - \beta\alpha\mathbf{H}^\mathsf{T}\mathbf{B}\|$$

$$\mathbf{C}^* = \operatorname{sign}(\mathbf{Y}) = \operatorname{sign}(\mathbf{X}^\mathsf{T}) \operatorname{sign}(\mathbf{W}) = \mathbf{H}^{*\mathsf{T}}\mathbf{B}^*$$

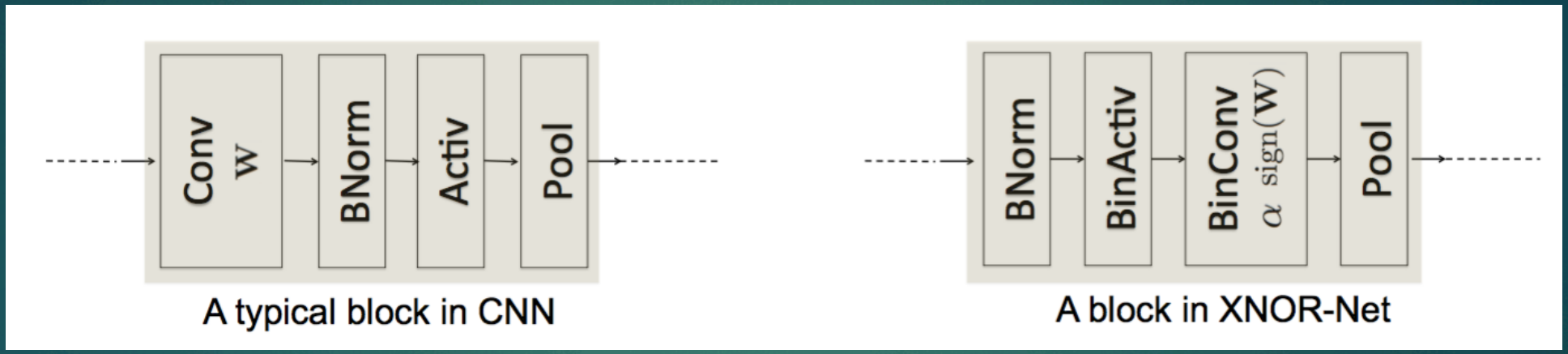
$$\gamma^* = \frac{\sum|\mathbf{Y}_i|}{n} = \frac{\sum|\mathbf{X}_i||\mathbf{W}_i|}{n} \approx \left(\frac{1}{n}\|\mathbf{X}\|_{\ell 1}\right)\left(\frac{1}{n}\|\mathbf{W}\|_{\ell 1}\right) = \beta^*\alpha^*$$

Forward Convolution



Layer order

- We normalize the input before binarization



Efficiency Analysis

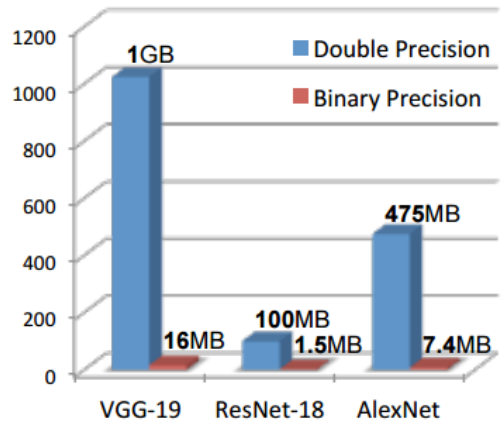
- we can perform 64 binary operations in one clock of CPU

$$\mathbf{I} * \mathbf{W} \approx (\text{sign}(\mathbf{I}) \circledast \text{sign}(\mathbf{W})) \odot \mathbf{K}\alpha$$

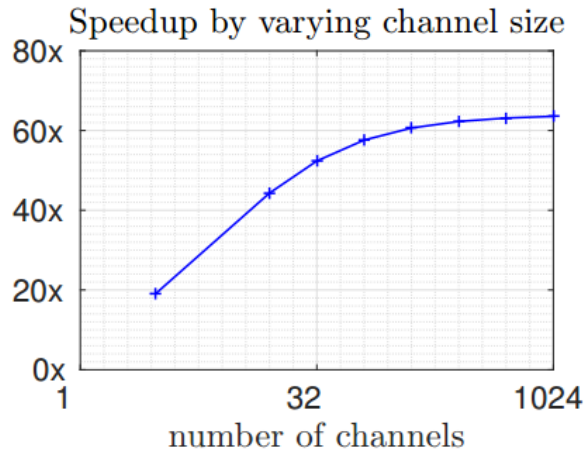
$$S = \frac{cN_{\mathbf{W}}N_{\mathbf{I}}}{\frac{1}{64}cN_{\mathbf{W}}N_{\mathbf{I}} + N_{\mathbf{I}}} = \frac{64cN_{\mathbf{W}}}{cN_{\mathbf{W}} + 64}$$

Efficiency Analysis

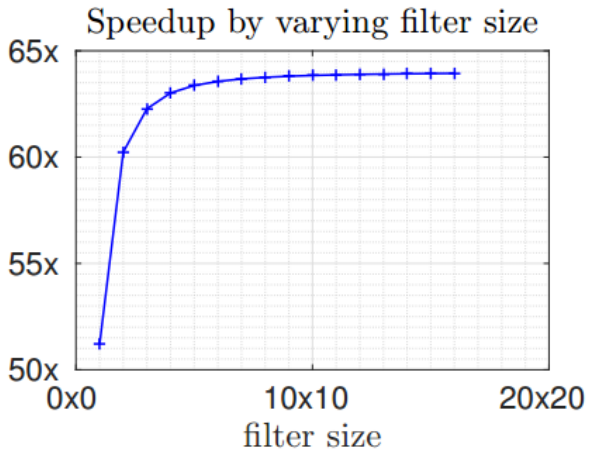
- c = 256, $n\downarrow I$ = 14↑2 , $n\downarrow W$ = 3↑2



(a)



(b)



(c)

- Avoid binarization at the first and last XNOR-Net

Discussion

Binary-Weight-Network		
Strategy for computing α	top-1	top-5
Using equation 6	56.8	79.4
Using a separate layer	46.2	69.5

XNOR-Network		
Block Structure	top-1	top-5
C-B-A-P	30.3	57.5
B-A-C-P	44.2	69.2

Accuracy Analysis

- AlexNet compare with other network

Classification Accuracy(%)									
Binary-Weight				Binary-Input-Binary-Weight				Full-Precision	
BWN		BC[11]		XNOR-Net		BNN[11]		AlexNet[1]	
Top-1	Top-5	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5
56.8	**79.4**	35.4	61.0	**44.2**	**69.2**	27.9	50.42	56.6	80.2

Concept

- Use Xnor to implement convolution speedup the inference procedure.
- First binarized network testing on imagenet but falling about 10% accuraccy.
- Introduce new strategy to compute α scalar and layer order.

DoReFa-Net

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Abstract

- Generalize the binarized neural network. Let CNN has arbitrary bitwise in weights, activations and gradients
- Using bit convolution kernels
- Explore the configureation space of bitwidth for weights, activation and gradients

Bit Convolution

$$\mathbf{x} \cdot \mathbf{y} = \sum_{m=0}^{M-1} \sum_{k=0}^{K-1} 2^{m+k} \ \text{bitcount}[\text{and}(c_m(\mathbf{x}), c_k(\mathbf{y}))],$$

$$c_m(\mathbf{x})_i, c_k(\mathbf{y})_i \in \{0, 1\} \, \forall i, \ m, \ k.$$

Quantization

- quantize$_k$ $r_i \in [0,1]$

$$\textbf{Forward: } r_o = \frac{1}{2^k - 1} \text{round}((2^k - 1) r_i)$$

$$\textbf{Backward: } \frac{\partial c}{\partial r_i} = \frac{\partial c}{\partial r_o}.$$

- Weight – Normal distribution, use non-uniform distribution to quantize

$$\textbf{Forward: } r_o = f_\omega^k(r_i) = 2\,\text{quantize}_k\left(\frac{\tanh(r_i)}{2\max(|\tanh(r_i)|)} + \frac{1}{2}\right) - 1.$$

$$\textbf{Backward: } \frac{\partial c}{\partial r_i} = \frac{\partial r_o}{\partial r_i}\frac{\partial c}{\partial r_o}$$

Quantization

- Activation

$$f_{\alpha}^{k}(r) = \mathrm{quantize_k}(r).$$

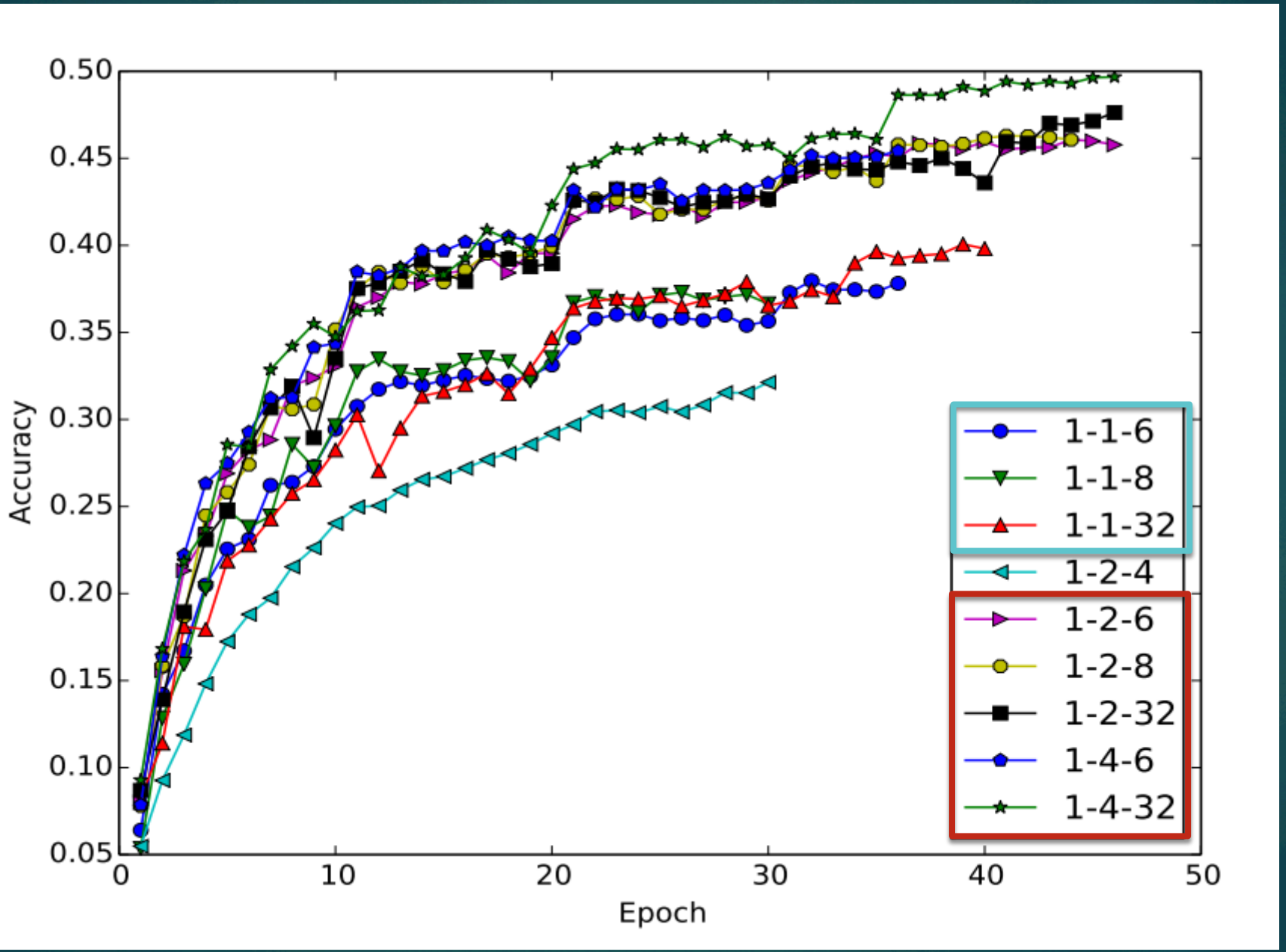
- Gradient – stochastic quantization is necesarry

$$f_{\gamma}^{k}(\mathrm{d}r) = 2\max_0(|\mathrm{d}r|)\left[\mathrm{quantize}_k\left[\frac{\mathrm{d}r}{2\max_0(|\mathrm{d}r|)} + \frac{1}{2} + N(k)\right] - \frac{1}{2}\right)$$

SVHN

W	A	G	Training Complexity	Inference Complexity	Storage Relative Size	Model A Accuracy	Model B Accuracy	Model C Accuracy	Model D Accuracy
1	1	2	3	1	1	0.934	0.924	0.910	0.803
1	1	4	5	1	1	0.968	0.961	0.916	0.846
1	1	8	9	1	1	0.970	0.962	0.902	0.828
1	1	32	-	-	1	0.971	0.963	0.921	0.841
1	2	2	4	2	1	0.909	0.930	0.900	0.808
1	2	3	5	2	1	0.968	0.964	0.934	0.878
1	2	4	6	2	1	0.975	0.969	0.939	0.878
2	1	2	6	2	2	0.927	0.928	0.909	0.846
2	1	4	10	2	2	0.969	0.957	0.904	0.827
1	2	8	10	2	1	0.975	0.971	0.946	0.866
1	2	32	-	-	1	0.976	0.970	0.950	0.865
1	3	3	6	3	1	0.968	0.964	0.946	0.887
1	3	4	7	3	1	0.974	0.974	0.959	0.897
1	3	6	9	3	1	0.977	0.974	0.949	0.916
1	4	2	6	4	1	0.815	0.898	0.911	0.868
1	4	4	8	4	1	0.975	0.974	0.962	0.915
1	4	8	12	4	1	0.977	0.975	0.955	0.895
2	2	2	8	4	1	0.900	0.919	0.856	0.842
8	8	8	-	-	8			0.970	0.955
32	32	32	-	-	32	0.975	0.975	0.972	0.950

W	A	G	Training Complexity	Inference Complexity	Storage Relative Size	AlexNet Accuracy
1	1	6	7	1	1	0.395
1	1	8	9	1	1	0.395
1	1	32	-	1	1	0.279 (BNN)
1	1	32	-	1	1	0.442 (XNOR-Net)
1	1	32	-	1	1	0.401
1	1	32	-	1	1	0.436 (initialized)
1	2	6	8	2	1	0.461
1	2	8	10	2	1	0.463
1	2	32	-	2	1	0.477
1	2	32	-	2	1	0.498 (initialized)
1	3	6	9	3	1	0.471
1	3	32	-	3	1	0.484
1	4	6	-	4	1	0.482
1	4	32	-	4	1	0.503
1	4	32	-	4	1	0.530 (initialized)
8	8	8	-	-	8	0.530
32	32	32	-	-	32	0.559


0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
Accuracy
0
10
20
30
40
50
Epoch
1-1-6
1-1-8
1-1-32
1-2-4
1-2-6
1-2-8
1-2-32
1-4-6
1-4-32

Concept

- First quantize the graidient down to 6 bits and get comparable result.
- Train time, inference time, model size, accuracy are trade-off. There is no definite conclusion which combination of (W,A,G) should choose.
- Sensitivity of bit size : G>A>W

Conclusion

- Compress test stage only
  shallow network
  prune (popular)

- Compress train & test stage
  compact layer
  quantization

Reference

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- Network in Network : https://arxiv.org/pdf/1312.4400v3.pdf
- Xnor-Net : http://arxiv.org/pdf/1603.05279v4.pdf
- DoReFa-Net : https://arxiv.org/pdf/1606.06160v2.pdf
- Deep Compression : https://arxiv.org/pdf/1510.00149v5.pdf

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- Convolutional Neural Networks using Logarithmic Data Representation https://arxiv.org/pdf/1603.01025.pdf
- https://github.com/andyhahaha/Convolutional-Neural-Network-Compression-Survey/blob/master/README.md