Efcnt DL

M.S. CV

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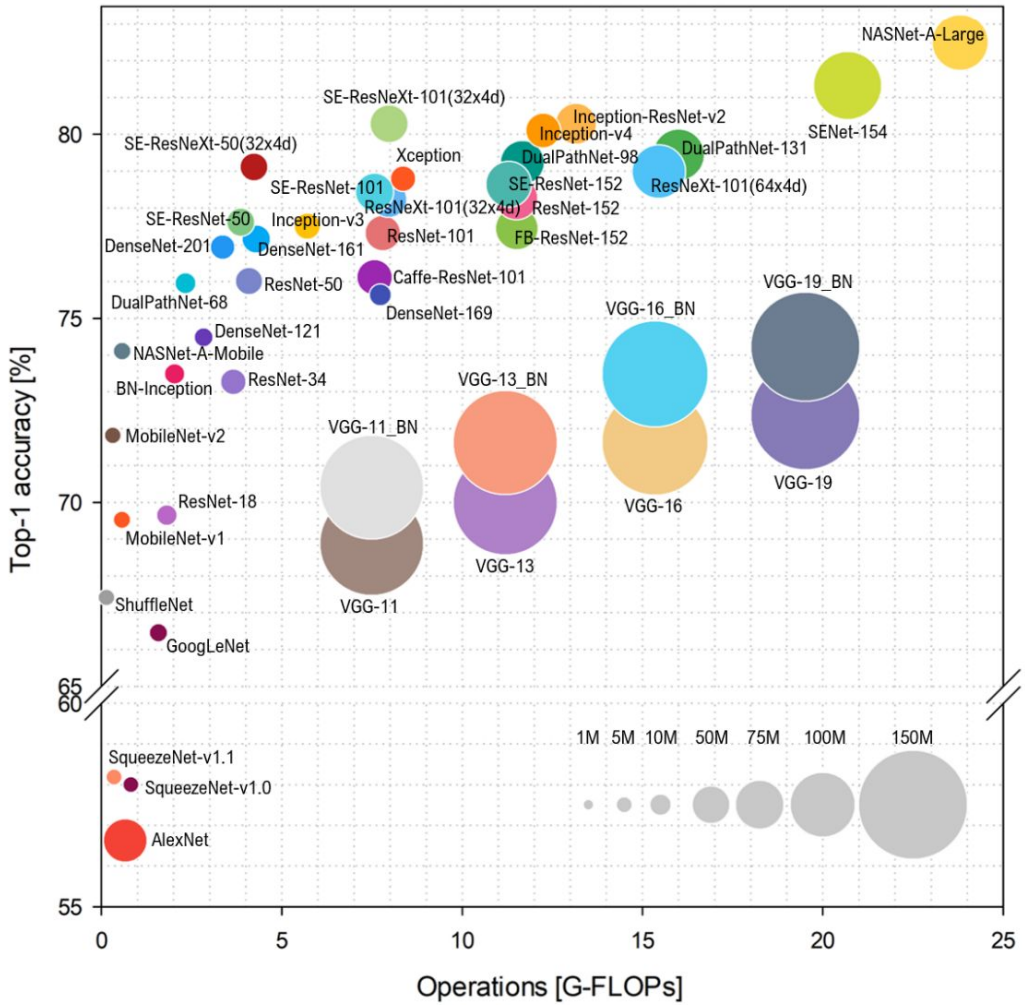
Acknowledgements

Marco Pedersoli

Outline

- **Motivation**
- Weight pruning
- Low rank approximation
- Quantization
- Conditional / adaptive computation
- Distillation
- Architectures

Motivation

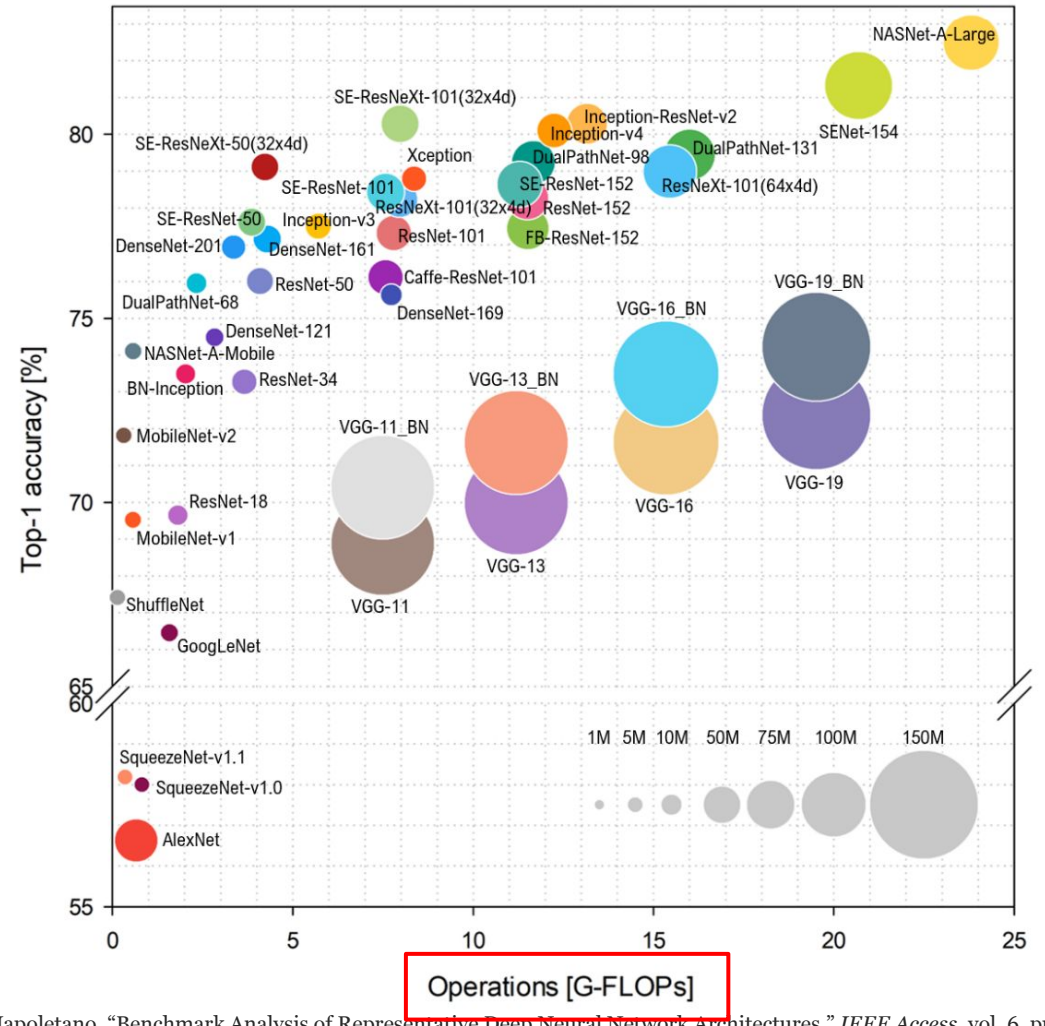


S. Bianco, R. Cadene, L. Celona and P. Napoletano, "Benchmark Analysis of Representative Deep Neural Network Architectures," *IEEE Access,* vol. 6, pp. 64270–64277, 2018

Motivation

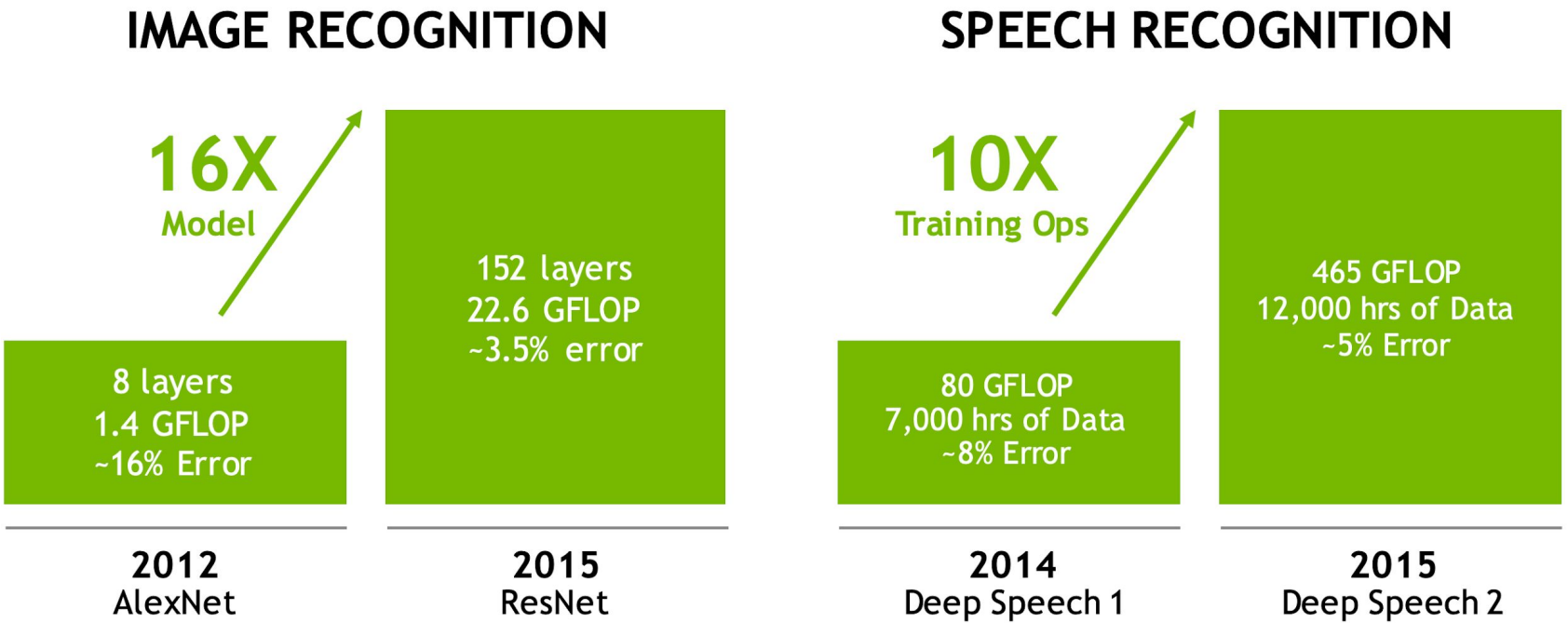
GFLOP: Giga-floating point operations per second

- 1 neural network weight = 1 floating point
- Summing two weights: 1 FLOP



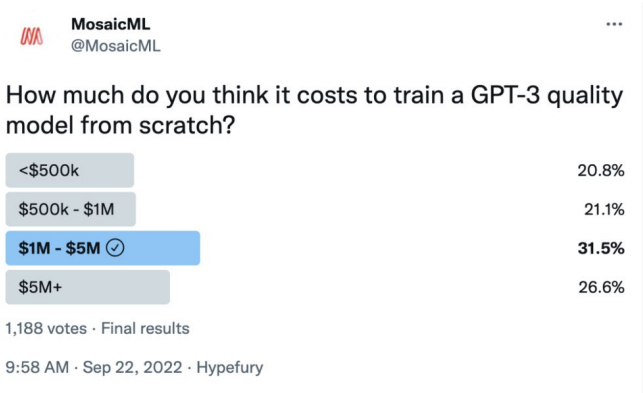
S. Bianco, R. Cadene, L. Celona and P. Napoletano, "Benchmark Analysis of Representative Deep Neural Network Architectures," *IEEE Access*, vol. 6, pp. 64270–64277, 2018

Motivation | Computational power



[Dally, NIPS'2016 workshop on Efficient Methods for Deep Neural Networks]

Large Language Models



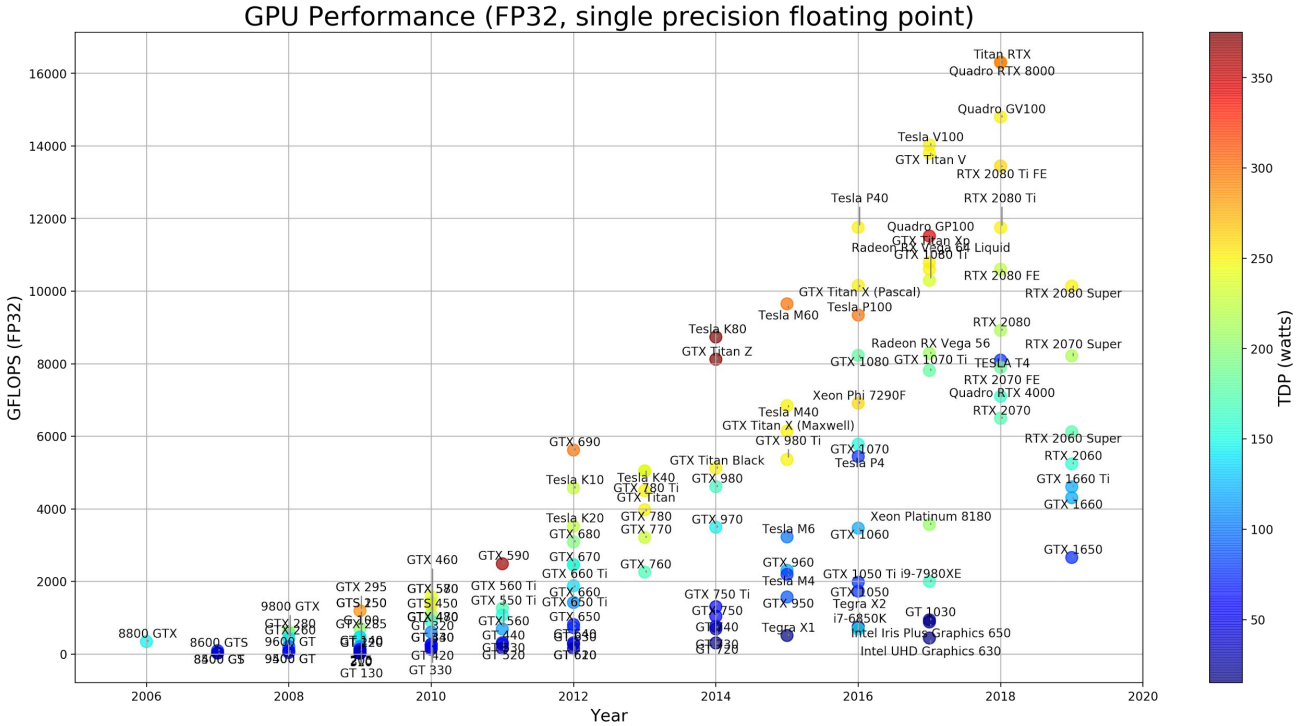
LLM Training Costs on MosaicML Cloud

Model	Billions of Tokens (Compute-optimal)	Days to Train on MosaicML Cloud	Approx. Cost on MosaicML Cloud
GPT-1.3B	26B	0.14	$2,000
GPT-2.7B	54B	0.48	$6,000
GPT-6.7B	134B	2.32	$30,000
GPT-13B	260B	7.43	$100,000
GPT-30B *	**610B**	**35.98**	**$450,000**
GPT-70B **	1400B	176.55	$2,500,000

***Figure 2**: Times and Costs to train GPT models ranging from 1.3B to 70B params. Each model is paired with a compute-optimal token budget based on 'Training Compute-Optimal Language Models'. All training runs were profiled with Composer on a 256xA100-40GB cluster with 1600Gbps RoCE interconnect, using a global batch size of 2048 sequences ~= 4M tokens.*

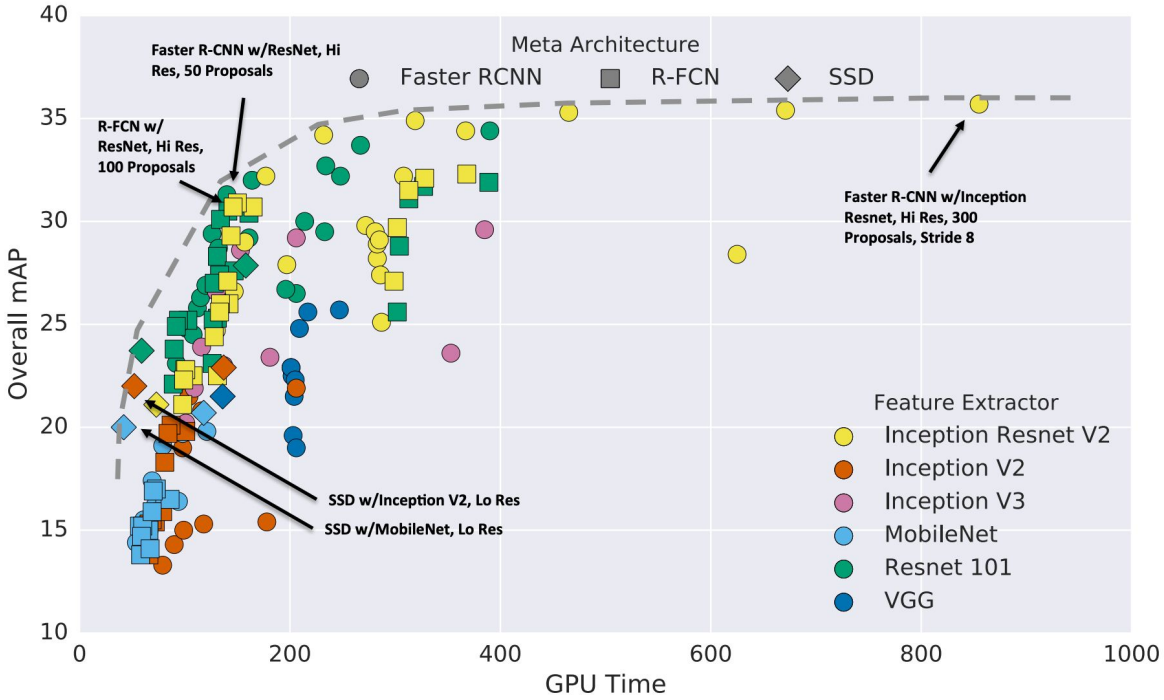
source: https://www.mosaicml.com/blog/gpt-3-quality-for-500k

Motivation | Energy consumption



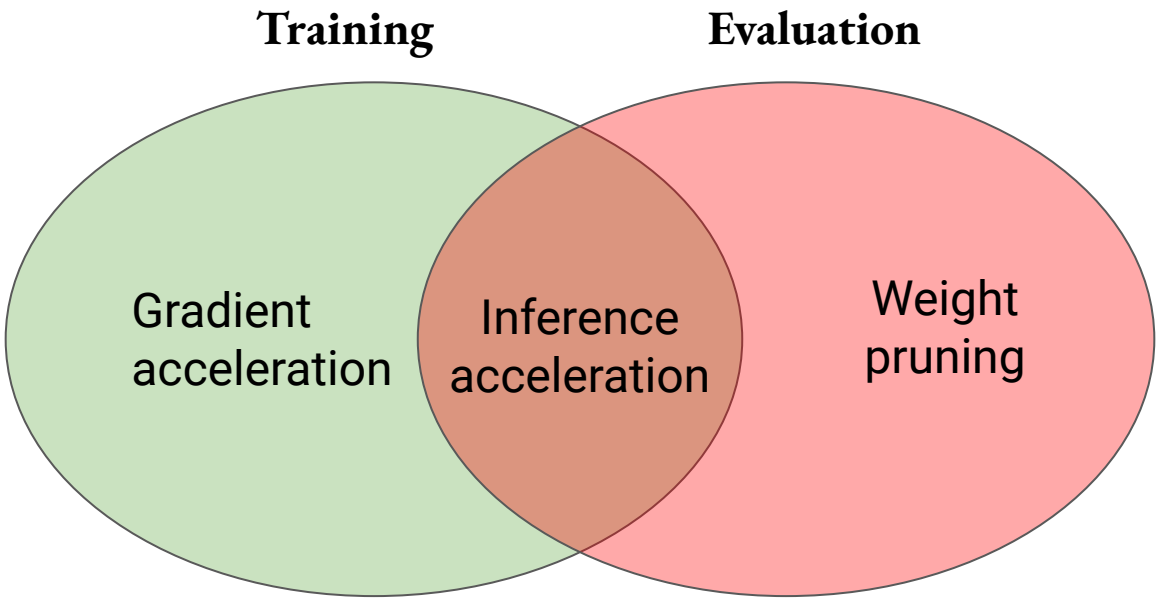
source: https://blog.inten.to/hardware-for-deep-learning-part-3-gpu-8906c1644664

Motivation | Speed



[Huang, J.,et al. Speed/accuracy trade-offs for modern convolutional object detectors. CVPR 2017.]

Objective: reduce complexity



Reduction of the complexity

During training

- Regularize the model to reduce complexity or design more efficient models
  - Directly construct an efficient model
  - Requires full training of the model each time
  - Ex: weight pruning, quantization, low-rank approximation of the weights...

After training

- Modify certain parts of the network to make them more efficient and/or “fine-tuning”.
  - No need to retrain
  - Lower improvement margin

Compression vs Reduction of computation

Compression

- Reduce the number of parameters to fit in embedded system
- Reduce the number of parameters to:
  - Limit the overfitting
  - Learn a better model, particularly with small databases

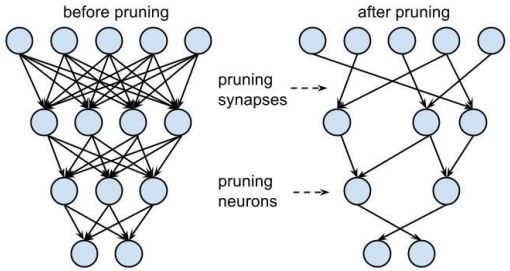
Reduction of computation

- Reduce the amount of computation to make the algorithm more efficient
- This can be achieved by reducing the amount of parameters but not guarantee

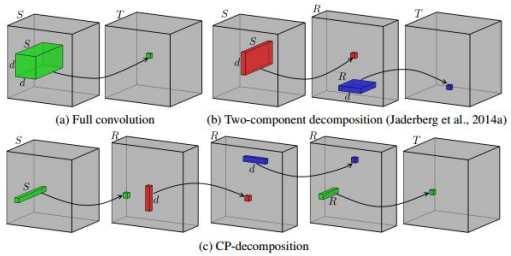
Reducing computation on GPU

- GPUs are optimized to execute parallel operations very fast (e.g. matrix multiplication)
- Important: to achieve good performance operations have to be **local**
- Reducing the number of operations != faster execution
  - It is important to keep a dense representation!

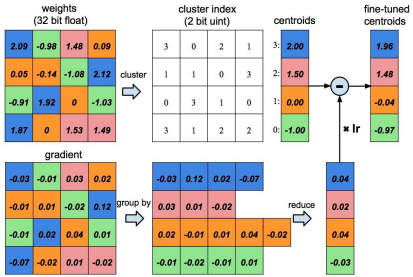
Taxonomy of methods:



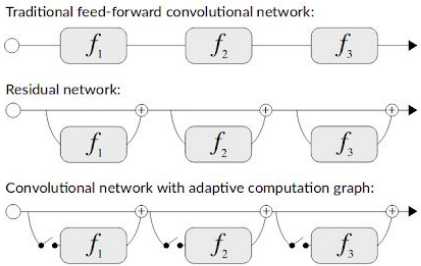
Weight pruning



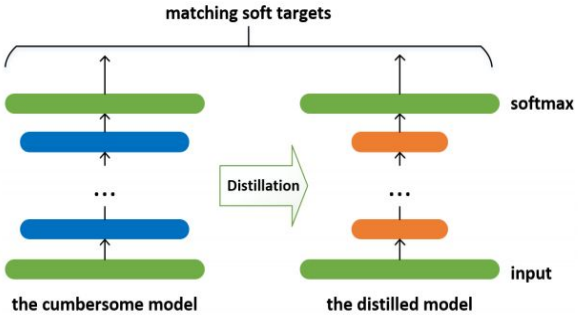
Low rank approximation



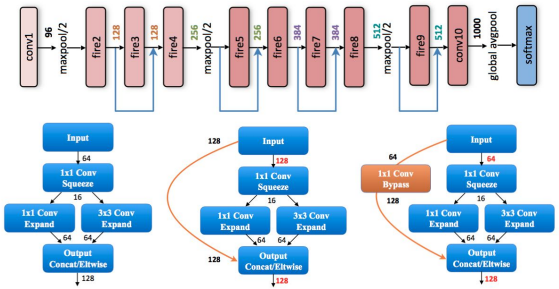
Quantization



Conditional computation



Distillation



Architecture

Outline

- Motivation
- **Weight pruning**
- Low rank approximation
- Quantization
- Conditional / adaptive computation
- Distillation
- Architectures

Weight pruning | Human brain

Newborn

50 Trillion Synapses

1 year

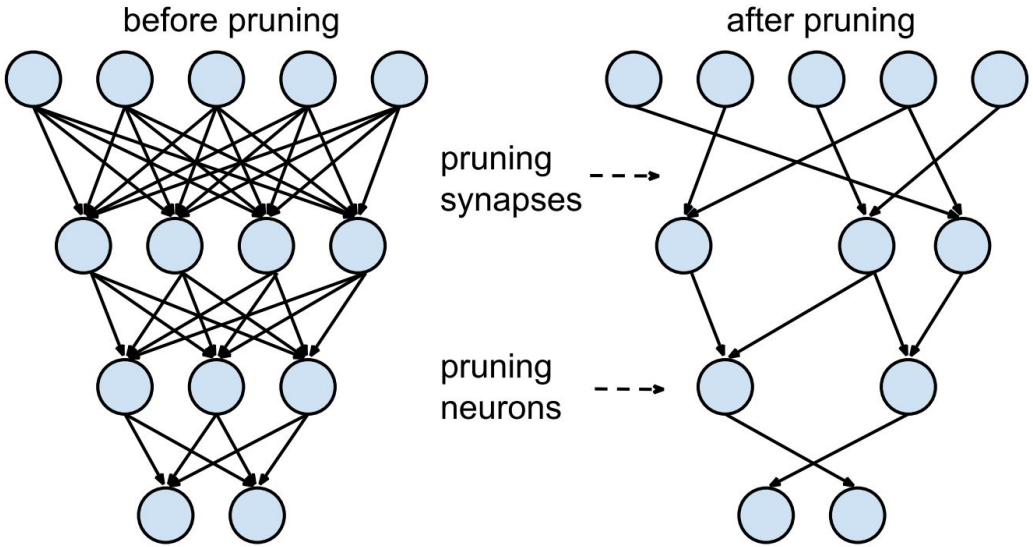
1000 Trillion Synapses

Teenager

50 Trillion Synapses

[C.A. Walsh. P. Huttenlocher (1931-2013). Nature 2013]

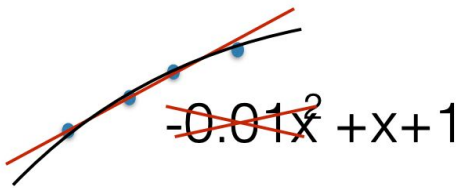
Weight pruning

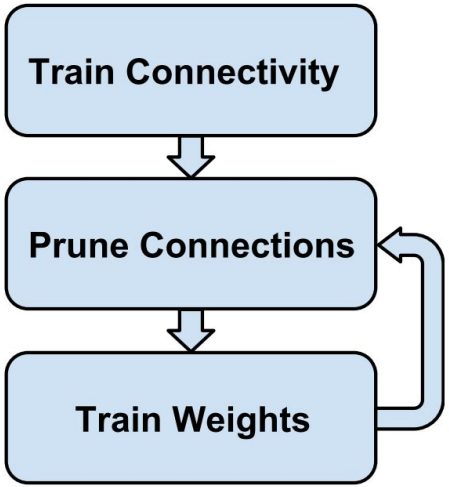


[Lecun et al. NIPS'89]

[Han et al. NIPS'15]

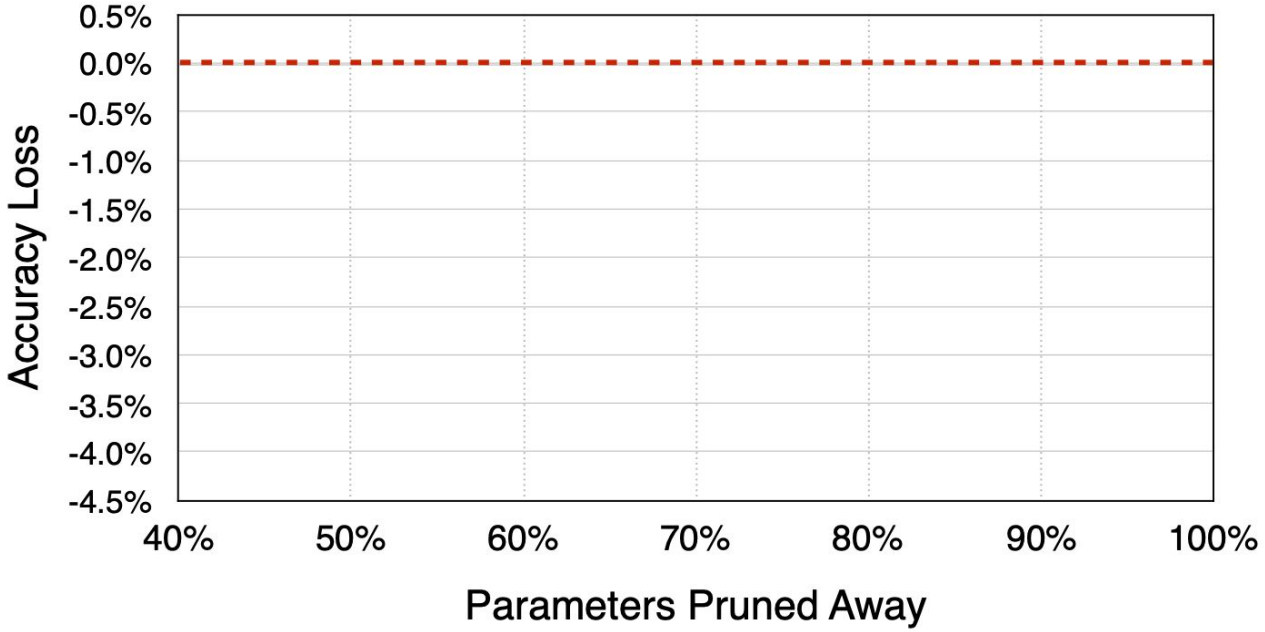
Weight pruning





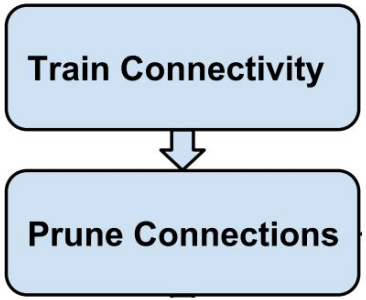
Weight pruning

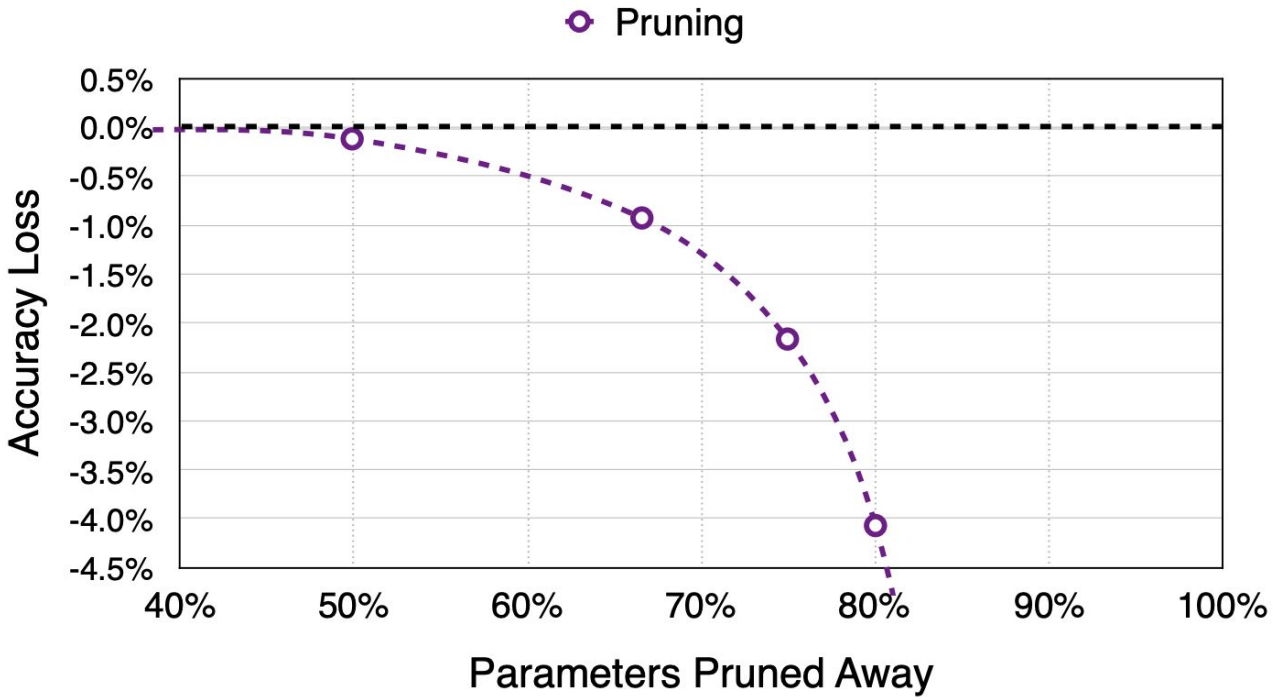
Train Connectivity



[Han et al. NeurIPS'15]

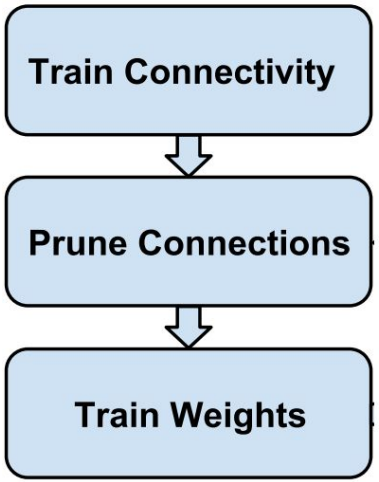
Weight pruning

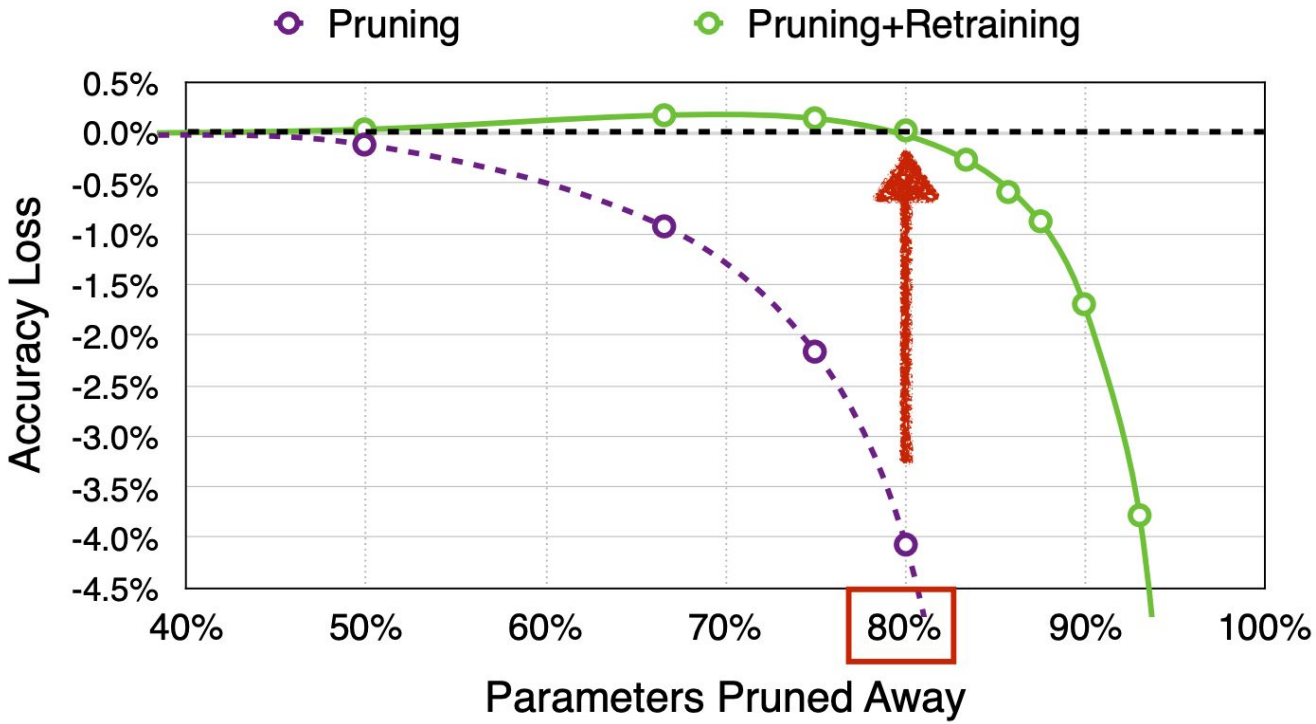




[Han et al. NeurIPS'15]

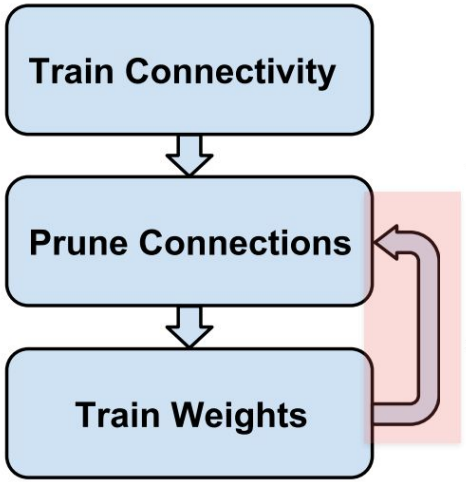
Weight pruning

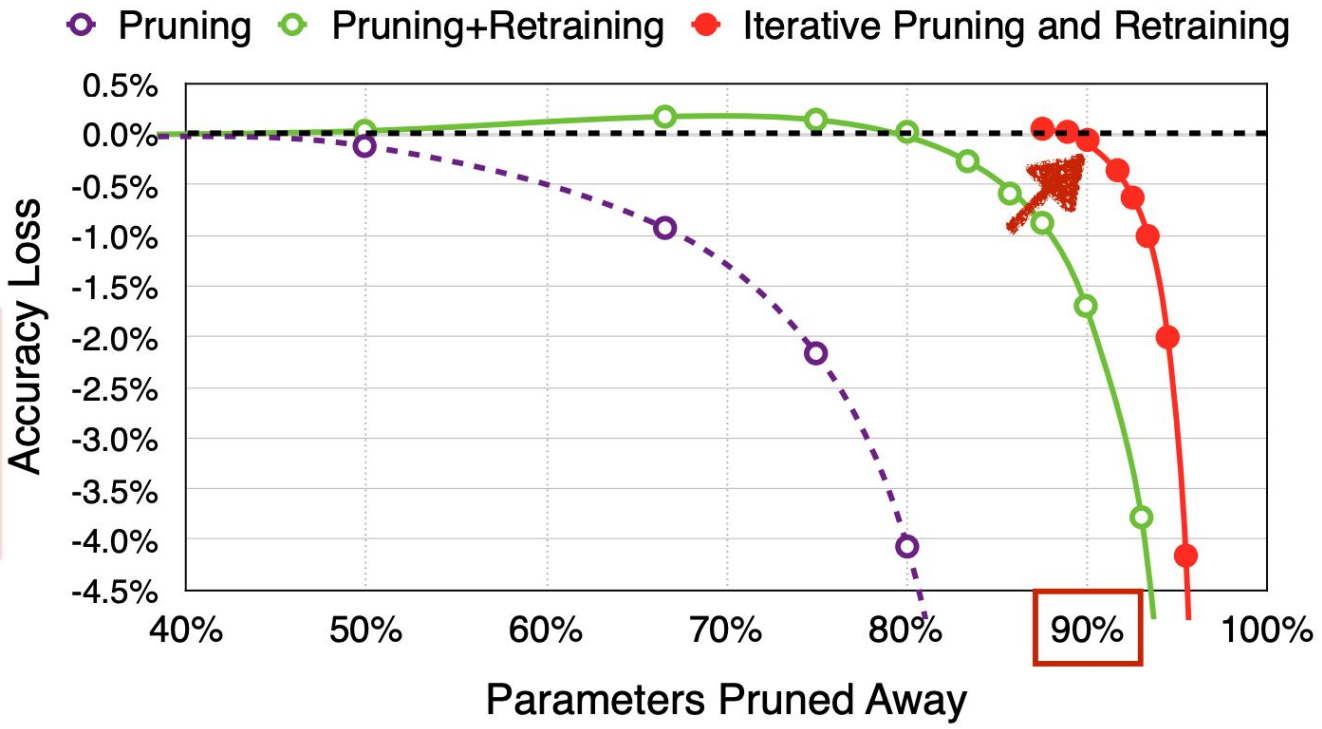




[Han et al. NeurIPS'15]

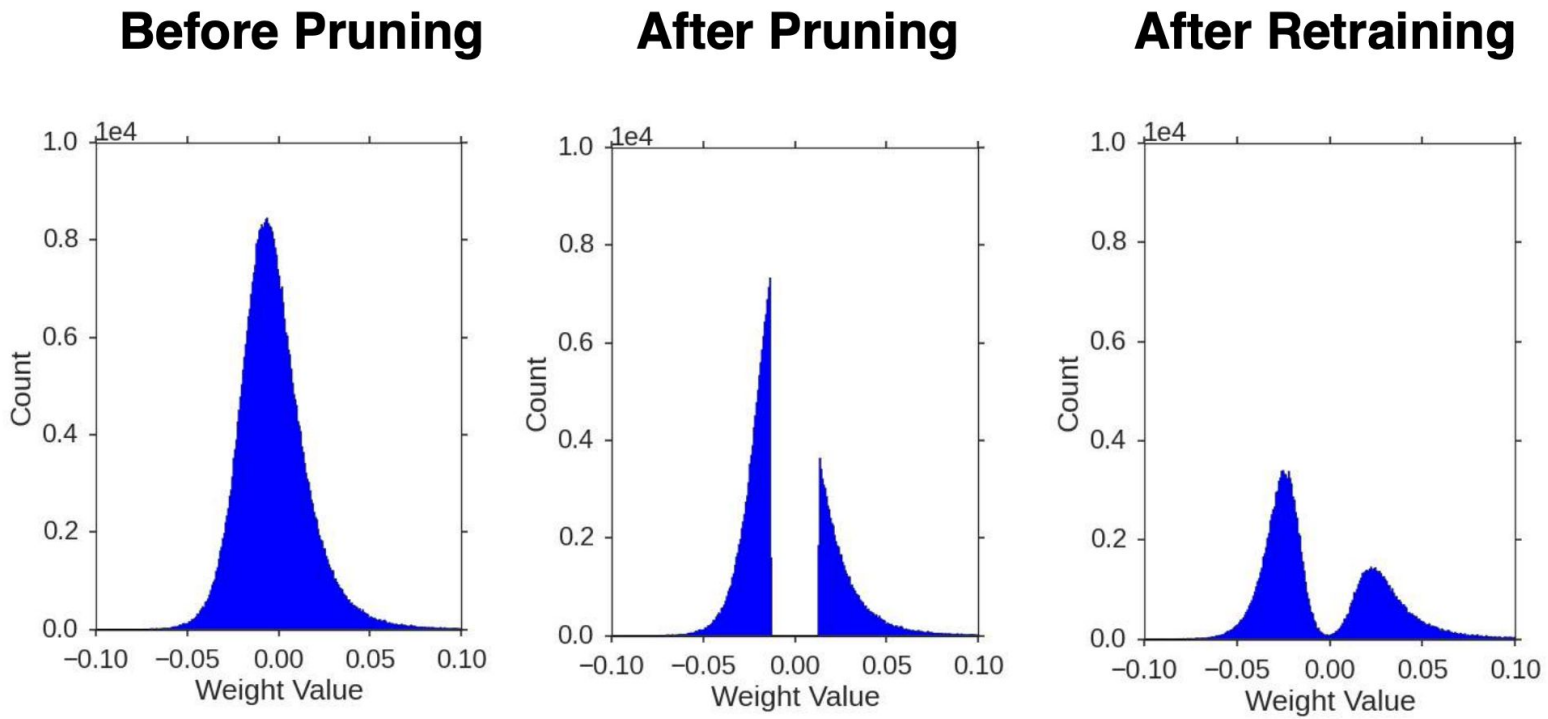
Weight pruning





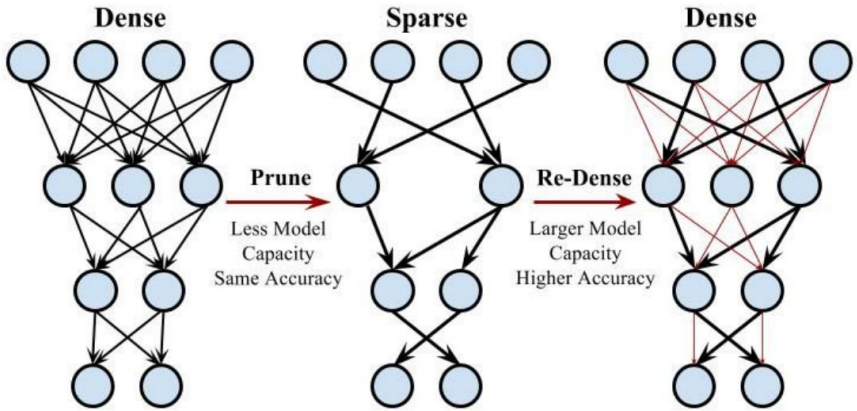
[Han et al. NeurIPS'15]

Weight pruning



Dense Sparse Dense

- Phase I: prune less important weights
- Phase II: re-initialize weights that are 0 and continue training



Baseline	Top-1 error	Top-5 error	DSD	Top-1 error	Top-5 error
AlexNet	42.78%	19.73%	AlexNet_DSD	41.48%	18.71%
VGG16	31.50%	11.32%	VGG16_DSD	27.19%	8.67%
GoogleNet	31.14%	10.96%	GoogleNet_DSD	30.02%	10.34%
SqueezeNet	42.39%	19.32%	SqueezeNet_DSD	38.24%	16.53%
ResNet18	30.43%	10.76%	ResNet18_DSD	29.17%	10.13%
ResNet50	24.01%	7.02%	ResNet50_DSD	22.89%	6.47%

Optimal Brain Damage

- Big networks -> Overfitting
- Small networks -> Underfitting

How to find the optimal size?

- Regularization, early stopping, etc.
- In this work: pruning = better generalization and reduction of calculations
- Problem: when just looking at weight values, retraining is needed, which is slow

[LeCun '90]

Optimal Brain Damage

- Taylor approximation of the loss function

$$\delta E = \sum_i g_i \delta u_i + \frac{1}{2} \sum_i h_{ii} \delta u_i^2 + \frac{1}{2} \sum_{i \neq j} h_{ij} \delta u_i \delta u_j + O(||\delta U||^3)$$

$$g_i = \frac{\partial E}{\partial u_i} \quad \text{and} \quad h_{ij} = \frac{\partial^2 E}{\partial u_i \partial u_j}$$

- Only considers diagonal terms
- Convergence is achieved thus $g_i = 0$
- h_{ii} can be computed by backpropagation
- The weights with smallest h_{ii} can be set to 0

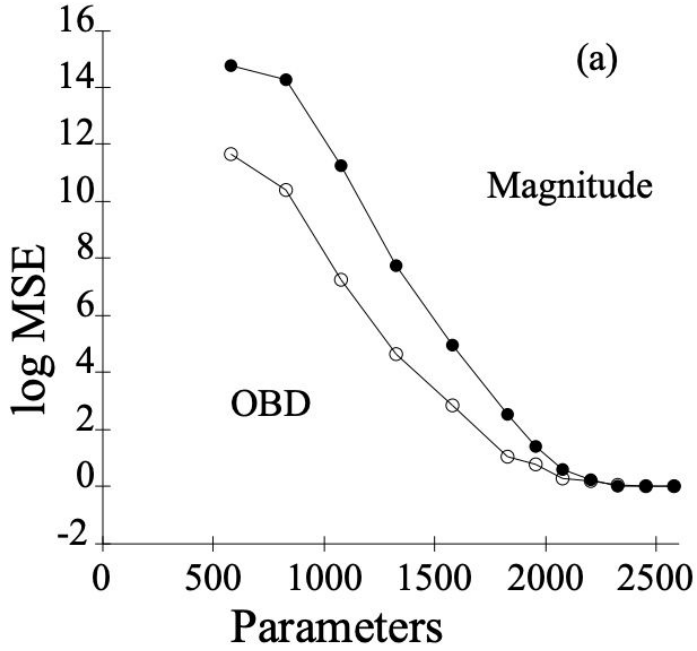
[LeCun '90]

Optimal Brain Damage

After training, suppress weights based on:

- Weight magnitude
- Optimal brain damage

With the same number of parameters, optimal brain damage reduces the target function better than the magnitude

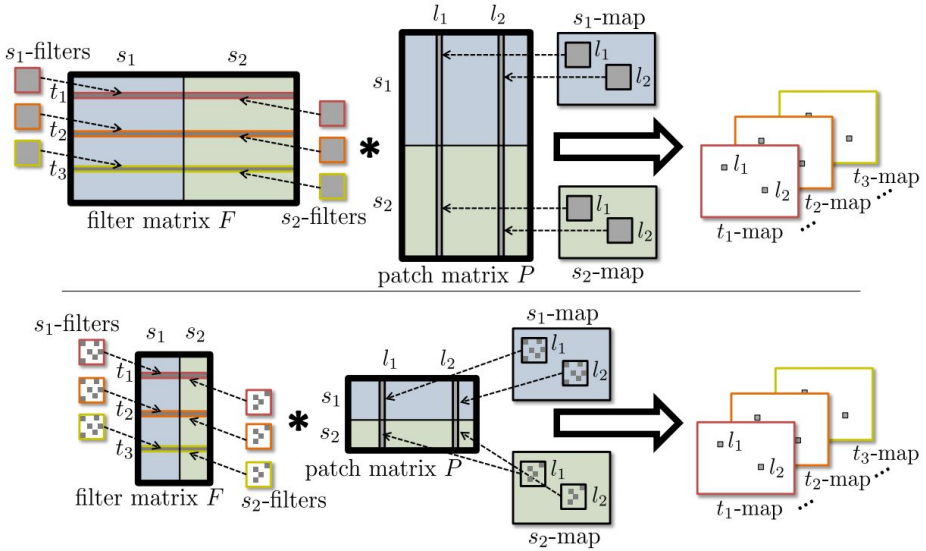


[LeCun '90]

OBD for ConvNets

Reduce the cost by reducing the number of parameters of the convolution filters

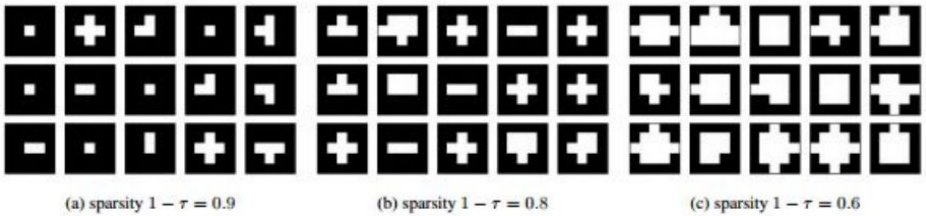
- Convolution can be considered a matrix multiplication
- For a real advantage it requires dense matrices -> reduce groups!



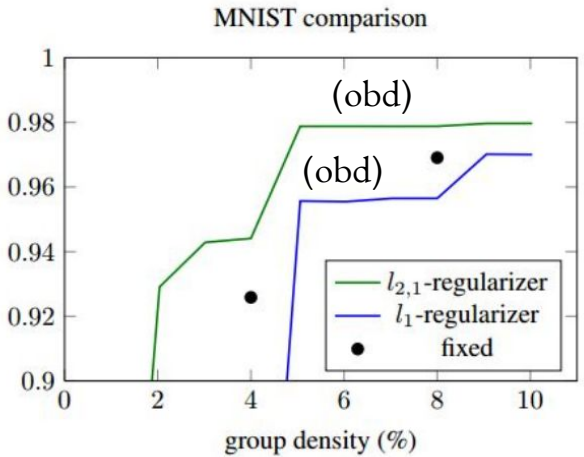
["Fast ConvNEts using Group-wise Brain Damage", FLebedev et. al. CVPR'2016

OBD for ConvNets

- L1 Regularization
- vs OBD



(a) sparsity $1 - \tau = 0.9$ (b) sparsity $1 - \tau = 0.8$ (c) sparsity $1 - \tau = 0.6$

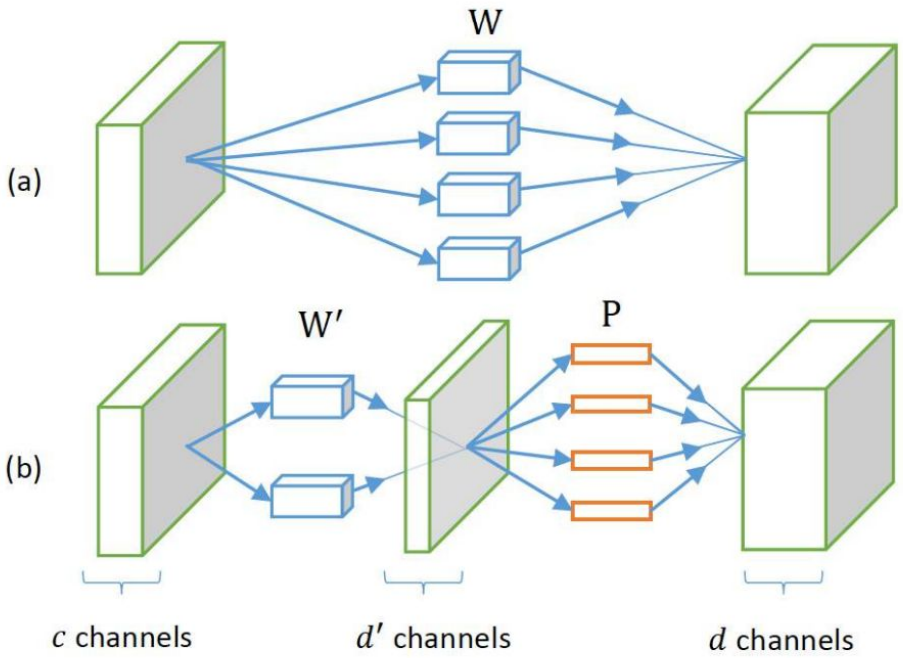


Outline

- Motivation
- Weight pruning
- **Low-rank approximation**
- Quantization
- Conditional / adaptive computation
- Distillation
- Architectures

Low-rank approximation

- Layer responses lie in a low-rank subspace
- Decompose a convolutional layer with d filters with filter size $k \times k \times c$ to
  - A layer with d' filters ($k \times k \times c$)
  - A layer with d filter ($1 \times 1 \times d$')



[Zhang et al Efficient and Accurate Approximations of Nonlinear Convolutional Networks CVPR'15]

Low-rank approximation

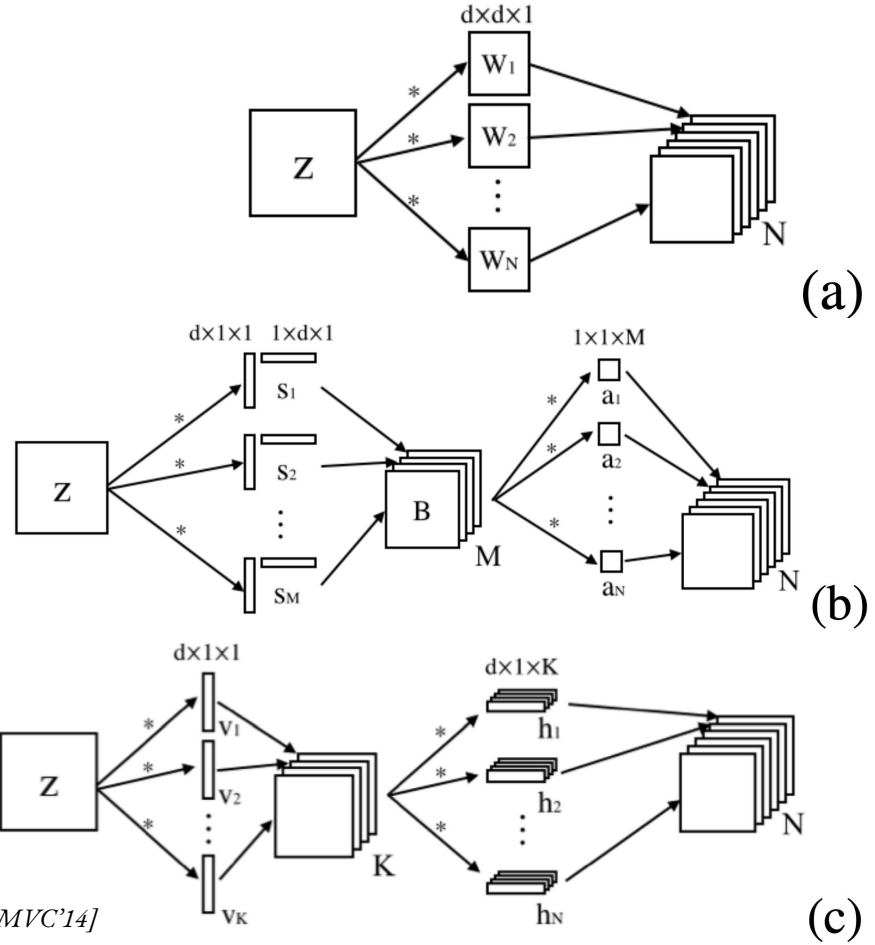
(a) Original conv filters

(b) Approximation 1

- line vector * column vector * M

(c) Approximation 2

- column vector * K * line vector * N



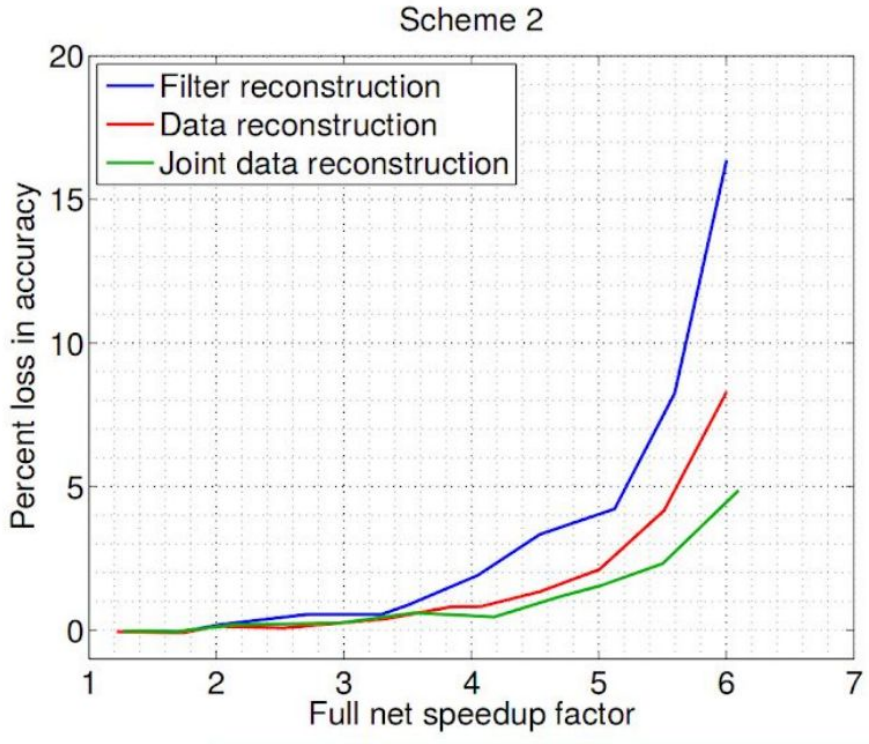
["Speeding up Convolutional Neural Networks with low rank expansions", Jaderberg et. al. BMVC'14]

Speed vs. Precision

Approximate trained network.

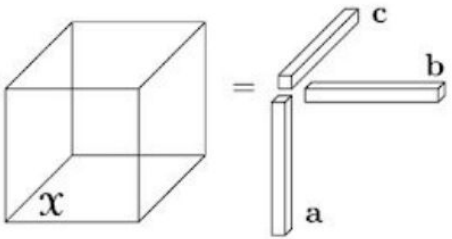
Strategies:

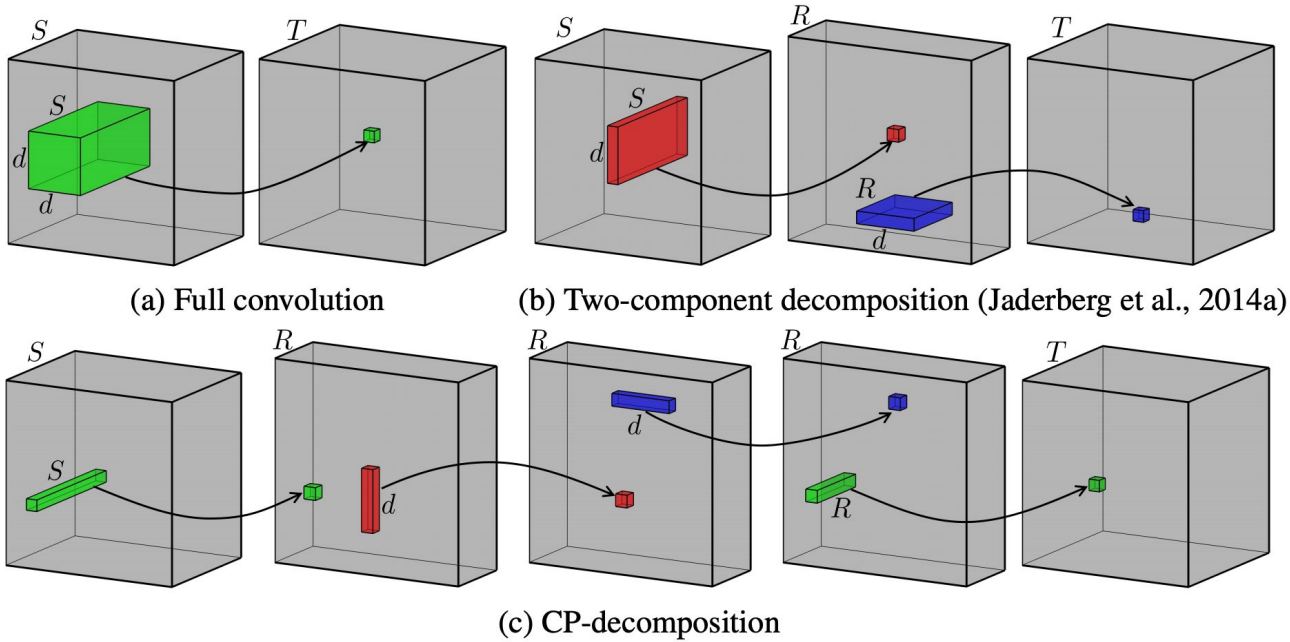
- Optimize filter reconstruction
- Optimize output reconstruction
- Both of them



["Speeding up Convolutional Neural Networks with low rank expansions", Jaderberg et. al. BMVC'14]

Improvement I

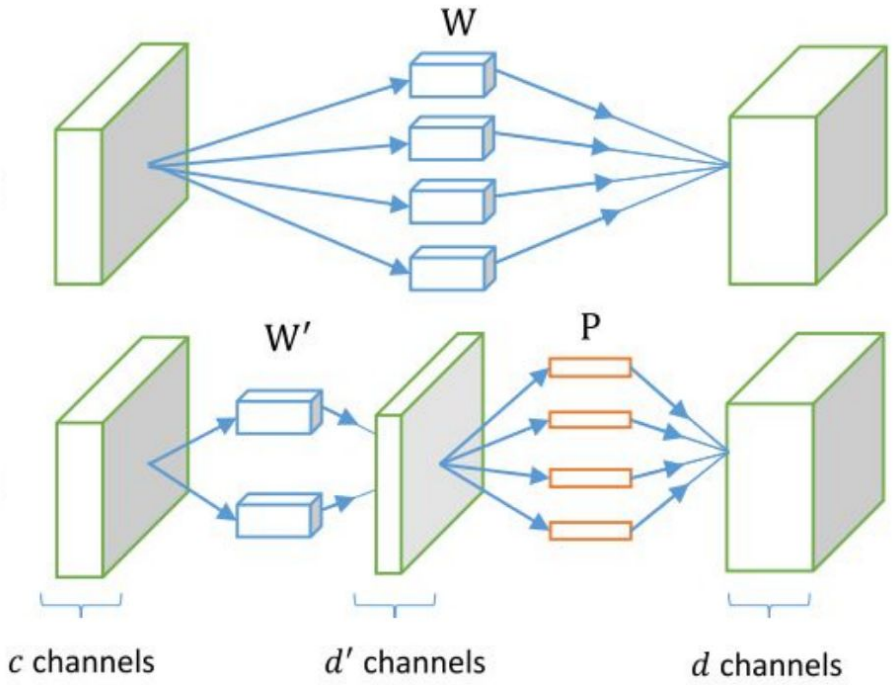




[Lebedev, Vadim, et al. "Speeding-up convolutional neural networks using fine-tuned cp-decomposition." ICLR (2015).]

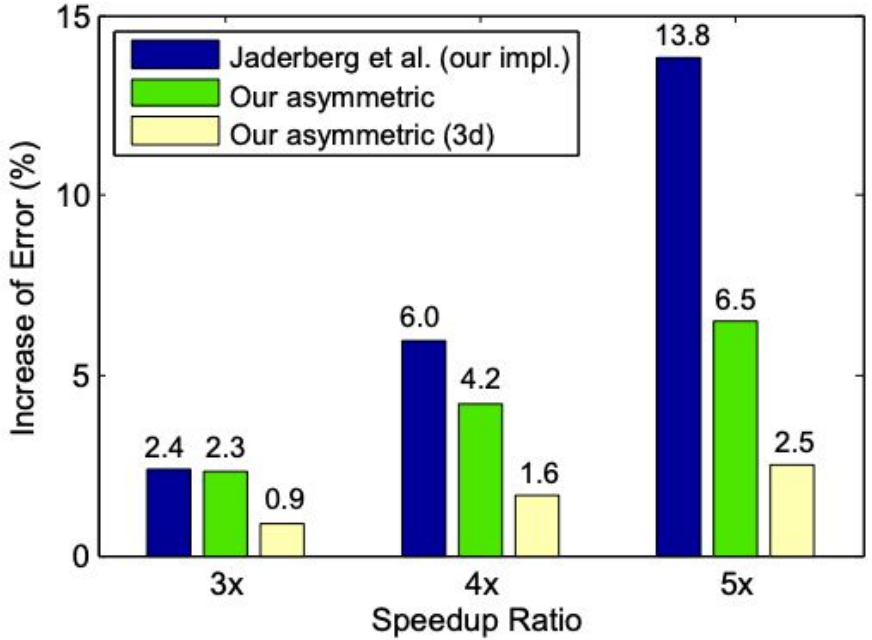
Improvement II

- Simpler decomposition
- however, the non-linearity is considered!
- Reconstruction function: non-linear Mean square error.
- The effect of stacking multiple layers considered during optimization!



["Efficient and Accurate Approximations of Nonlinear Convolutional Networks",X. Zhang et al.CVPR'15]

Improvement II



["Efficient and Accurate Approximations of Nonlinear Convolutional Networks",X. Zhang et al.CVPR'15]

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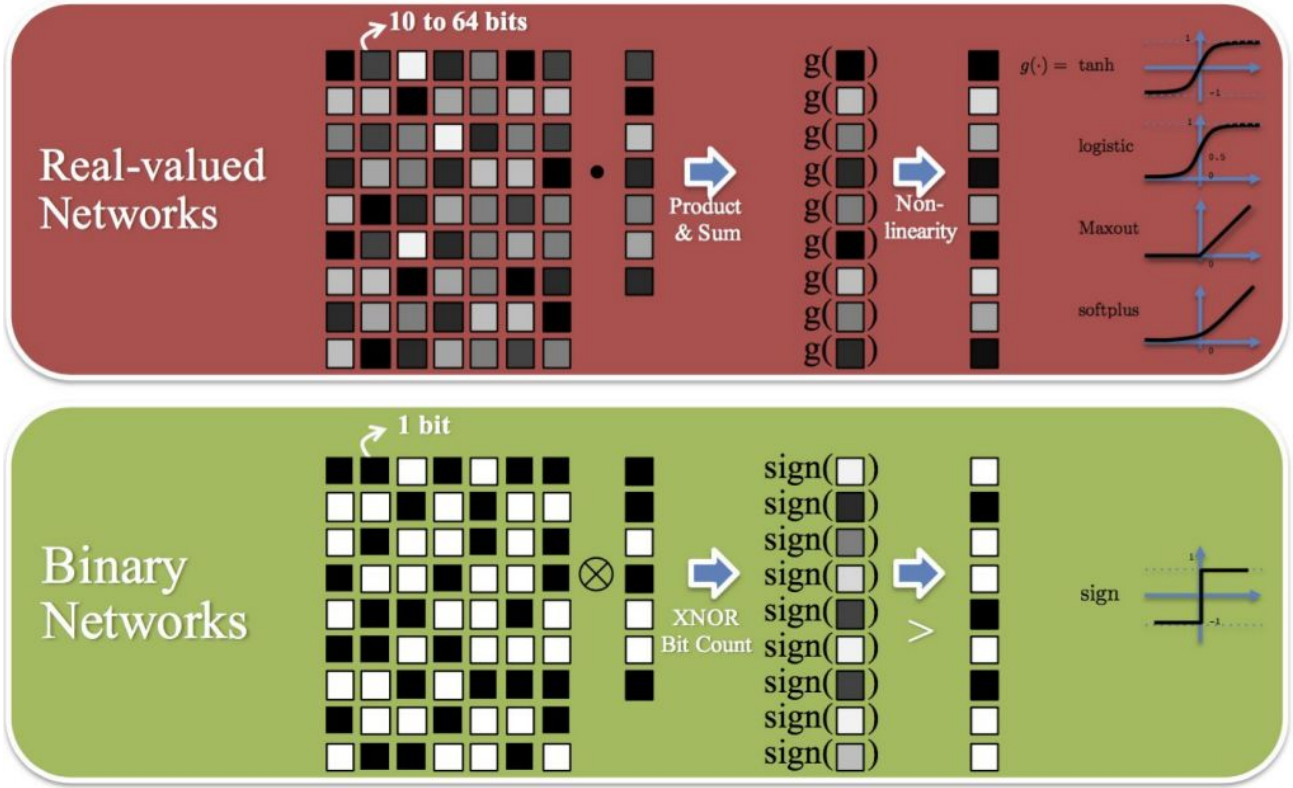
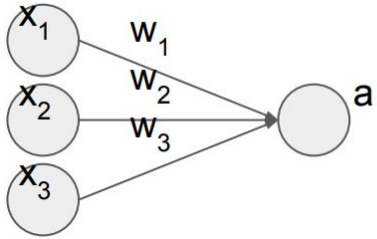
Quantization



Quantization | BinaryConnect

- Weights are mapped to the values **-1 and 1.** Only one bit per value is needed!
- No multiplications at inference time
- The **original values are kept** during **backpropagation**
- Quantization is a kind of regularization. Instead of converting values to 0 like dropout, it converts them to -1 or 1.

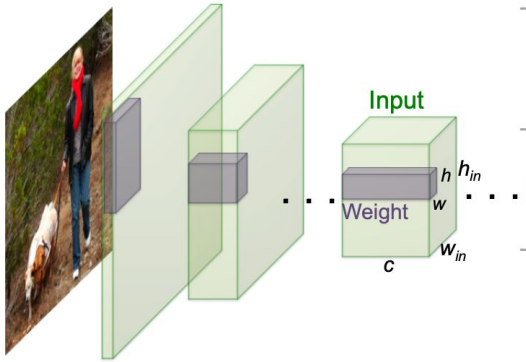


$$a = w_0 x_0 + w_1 x_1 + w_2 x_2$$

$$a_b = \pm x_0 \pm x_1 \pm x_2$$

["BinaryConnect", Courbariaux et al.,NIPS'15]

Quantization | XOR Networks



	Network Variations	Operations used in Convolution	Memory Saving (Inference)	Computation Saving (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	%56.8
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

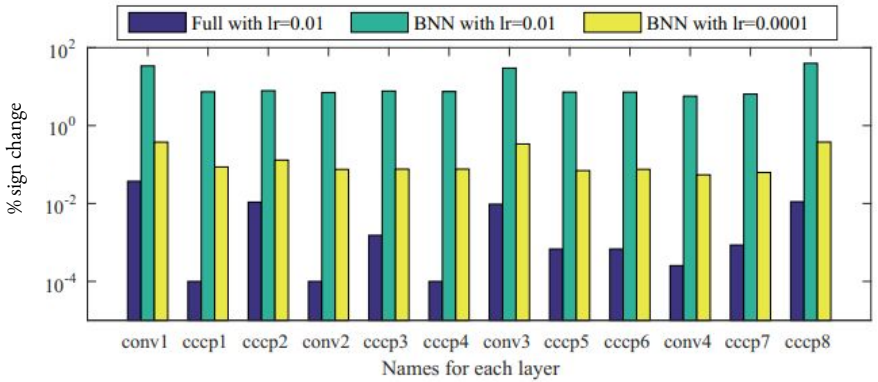
- Approximation of the convolution $\mathbf{I} * \mathbf{W} \approx (\mathbf{I} \oplus \mathbf{B})\,\alpha$
- with $\mathbf{B}^* = \text{sign}(\mathbf{W})$

Quantization | How to train binary weights

- Reduce the learning rate
- Use a different regularization

$$J(\mathbf{W}, \mathbf{b}) = L(\mathbf{W}, \mathbf{b}) + \lambda \sum_{l=1}^{L} \sum_{i=1}^{N_l} \sum_{j=1}^{M_l} (1 - (\mathbf{W}_{l,ij})^2)$$

- Add a scale coefficient to the last layer to avoid softmax saturation



[Tang et al. IAAA'17]

Quantization | Now we can train binary weights!

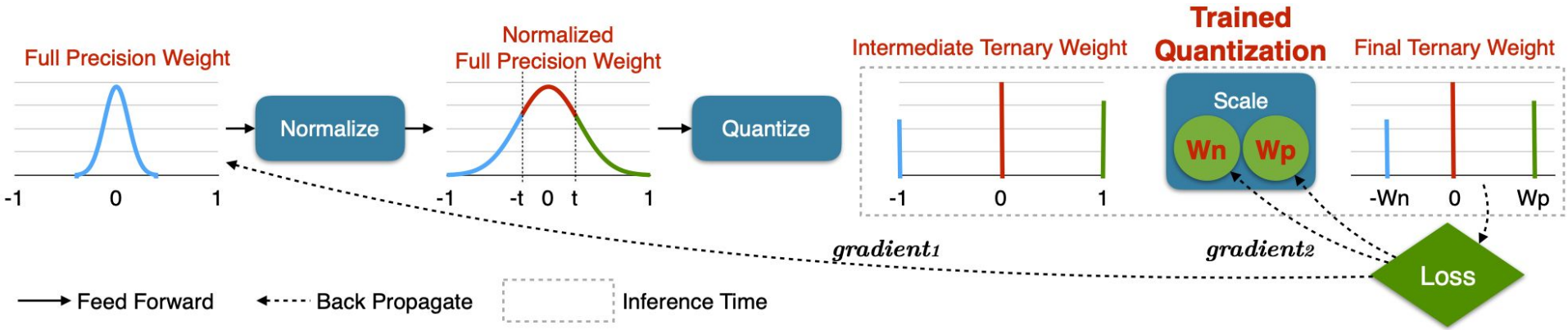
Methods	Base model	Bits of A	Last layer	Comp. rate	Model size (bef.)	Model size (aft.)	Accuracy(%)
BNN	AlexNet	1	Full	10.3×	232MB	22.6MB	50.4/27.9
XNOR-net	AlexNet	1	Full	10.3×	232MB	22.6MB	69.2/44.2
XNOR-net	ResNet-18	1	Full	70×(13.4×)	44.6MB	3.34MB	73.2/51.2
DoReFa-net	AlexNet	2	Full	10.3×	232MB	22.6MB	– /49.8
Our method	AlexNet	2	Binary	31.2×	232MB	7.43MB	71.1/46.6
Our method	NIN-net	2	Binary	189×(23.6×)	29MB	1.23MB	75.6/51.4

With the previous improvements one can achieve:

- A compression of x30-x190
- A big reduction in complexity
- A precision only 5-10 points inferior on AlexNet

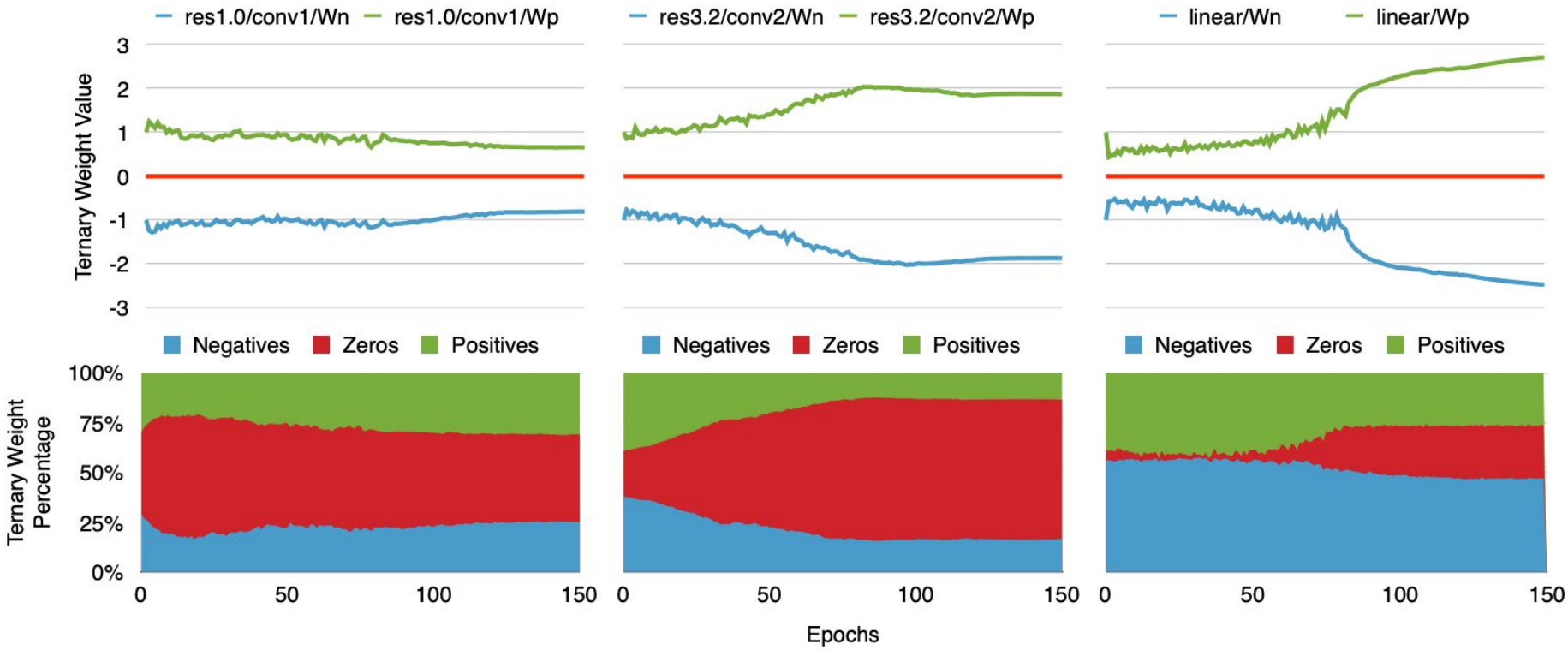
Quantization | Trained Ternary Quantization

- Three possible values -1, 0, 1
- Zeros - > save computation at expense of performance



[Zhu, Han, Mao, Dally. Trained Ternary Quantization, ICLR'17]

Quantization | Trained Ternary Quantization



Quantization | Trained Ternary Quantization

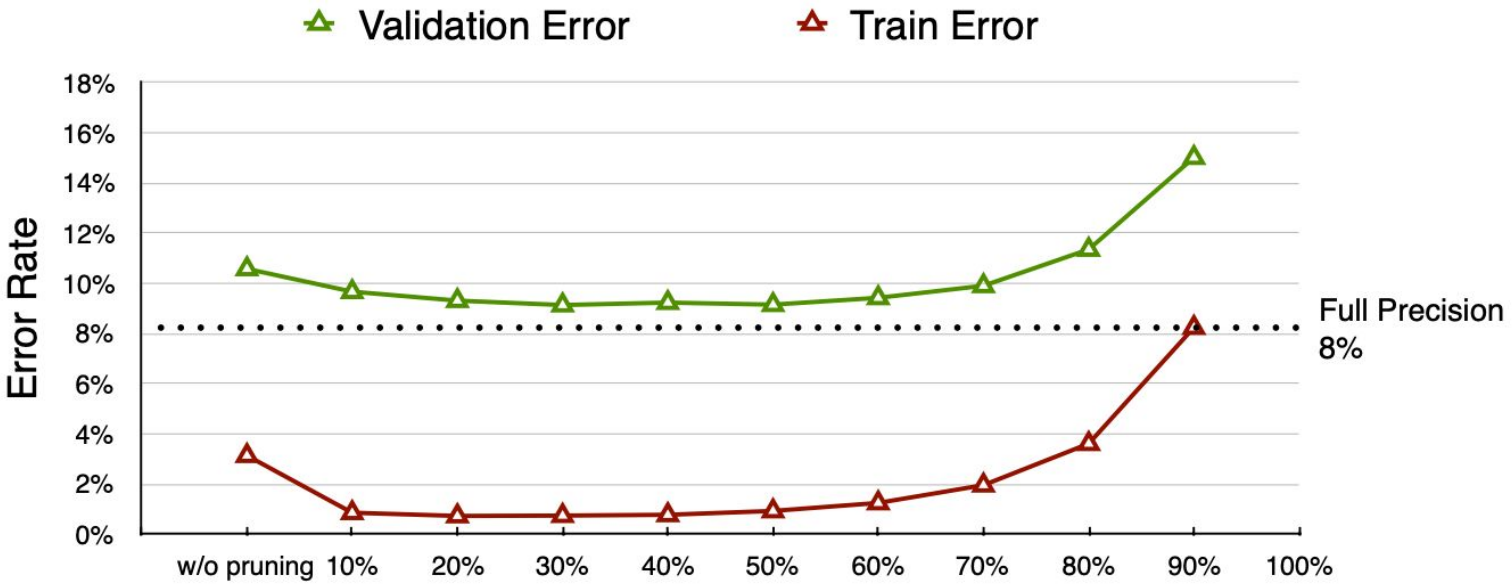
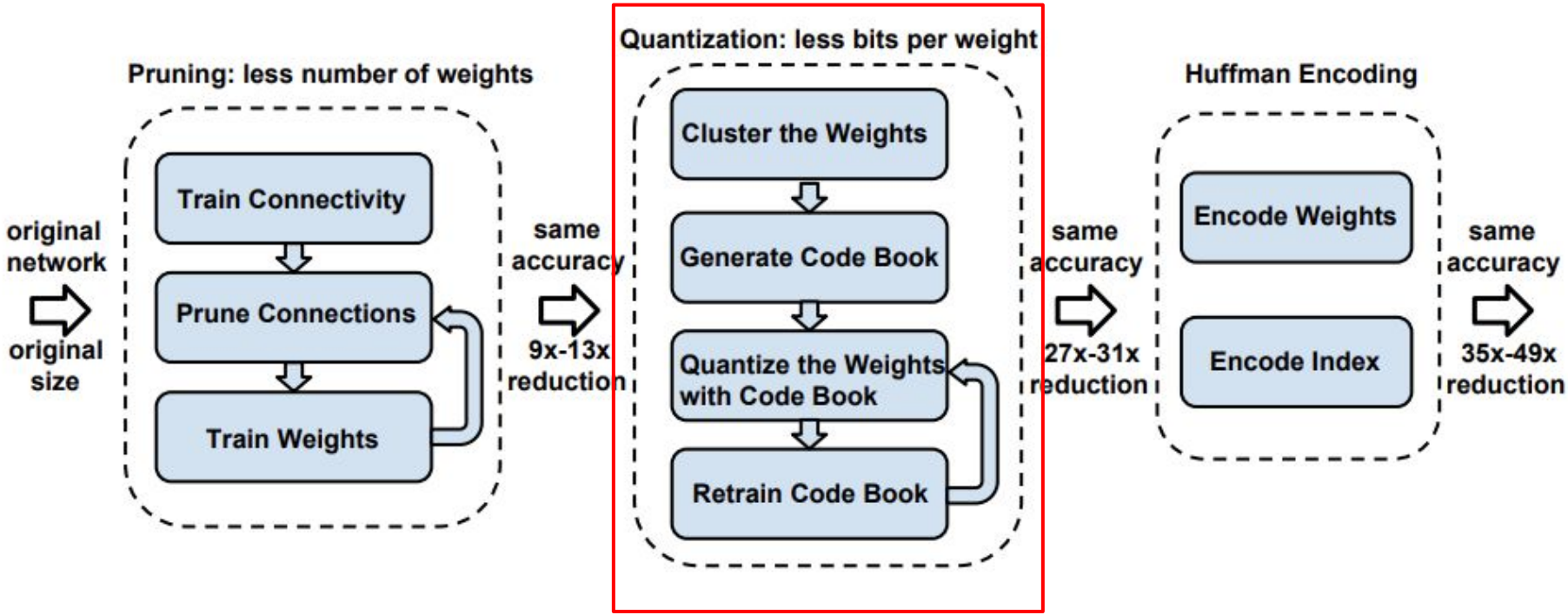


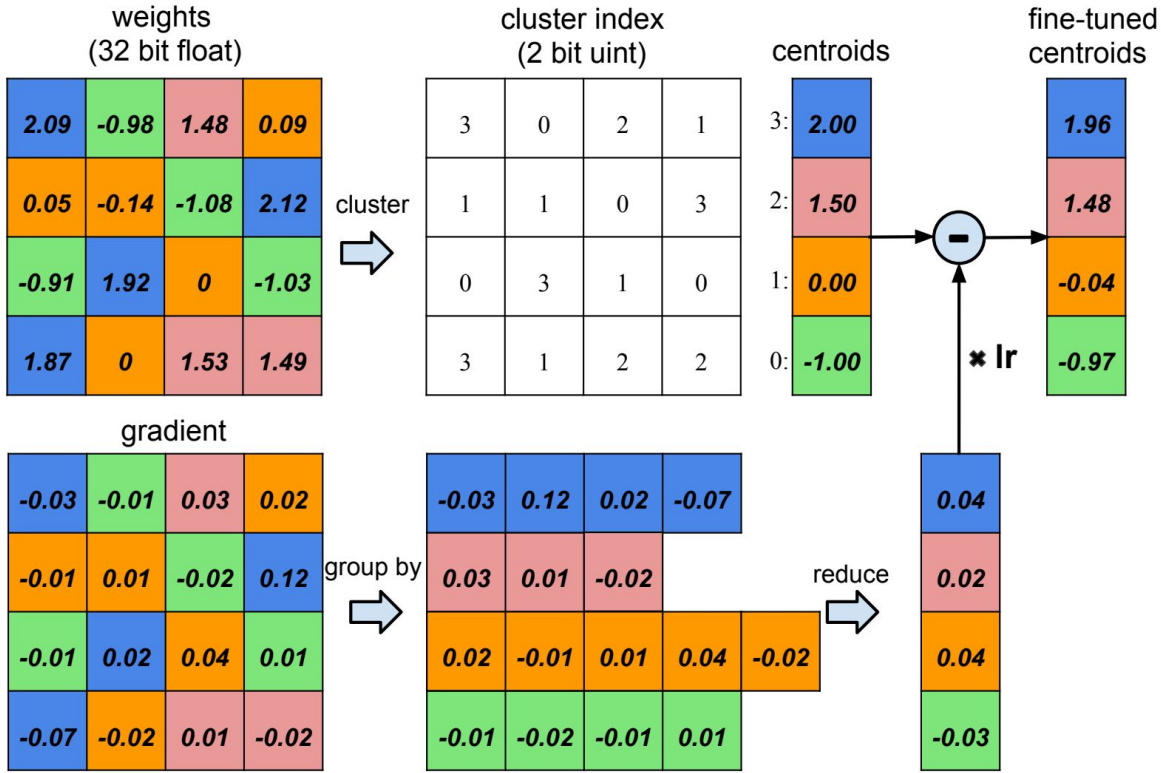
Figure 5: Accuracy v.s. Sparsity on ResNet-20

Trained Quantization



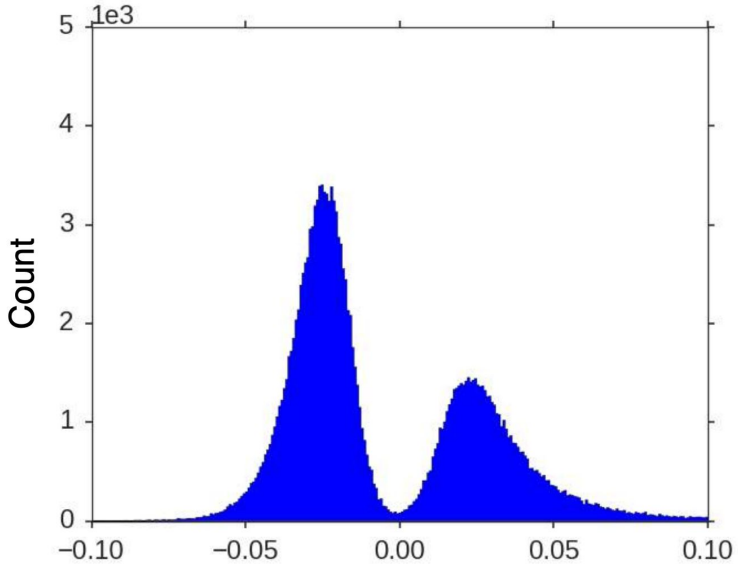
Han, et al. "Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding." (2015).

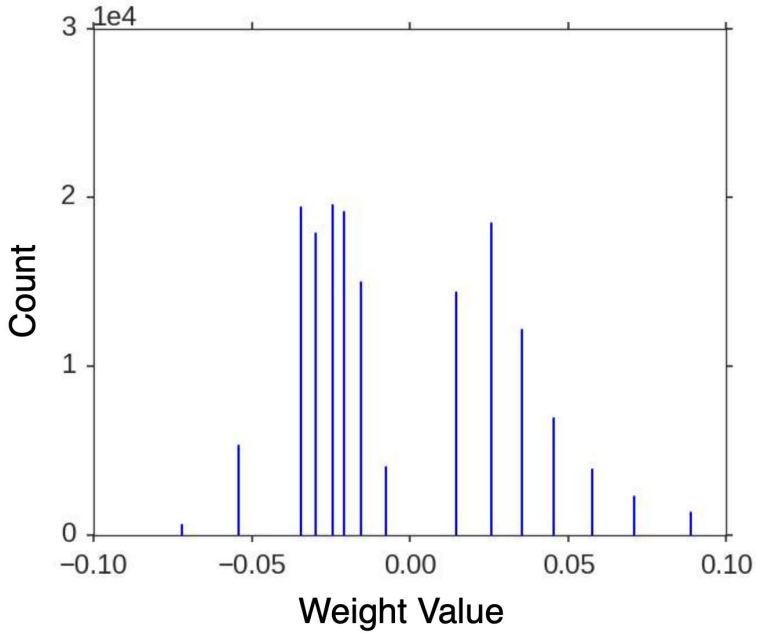
Trained Quantization | Weight Sharing



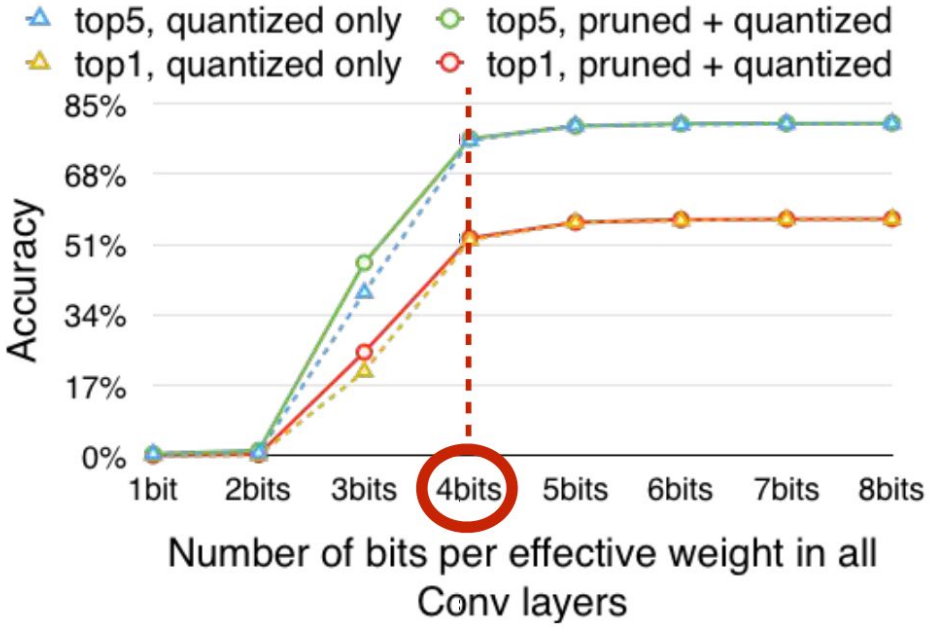
Han, et al. "Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding." (2015).

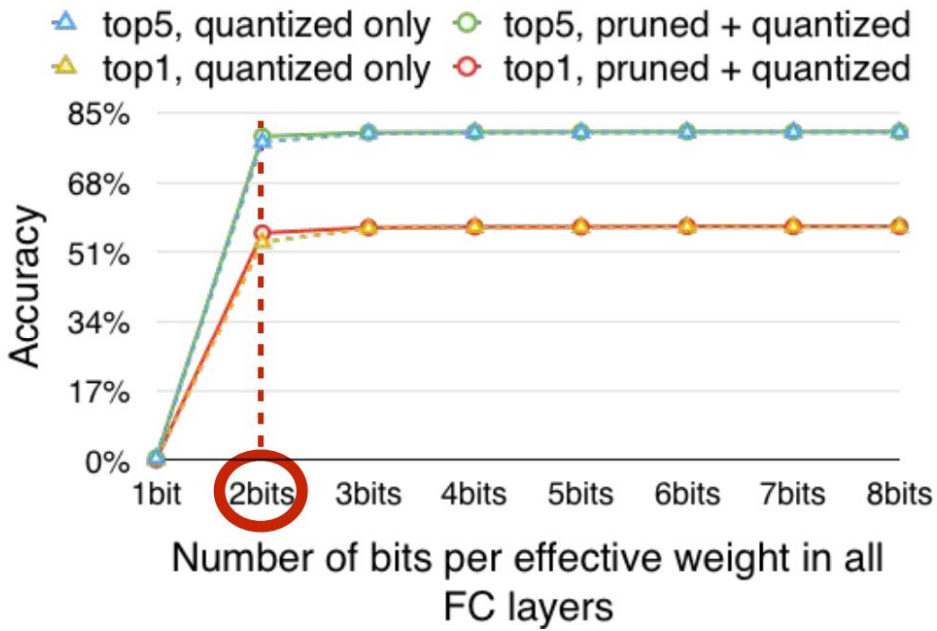
Trained Quantization



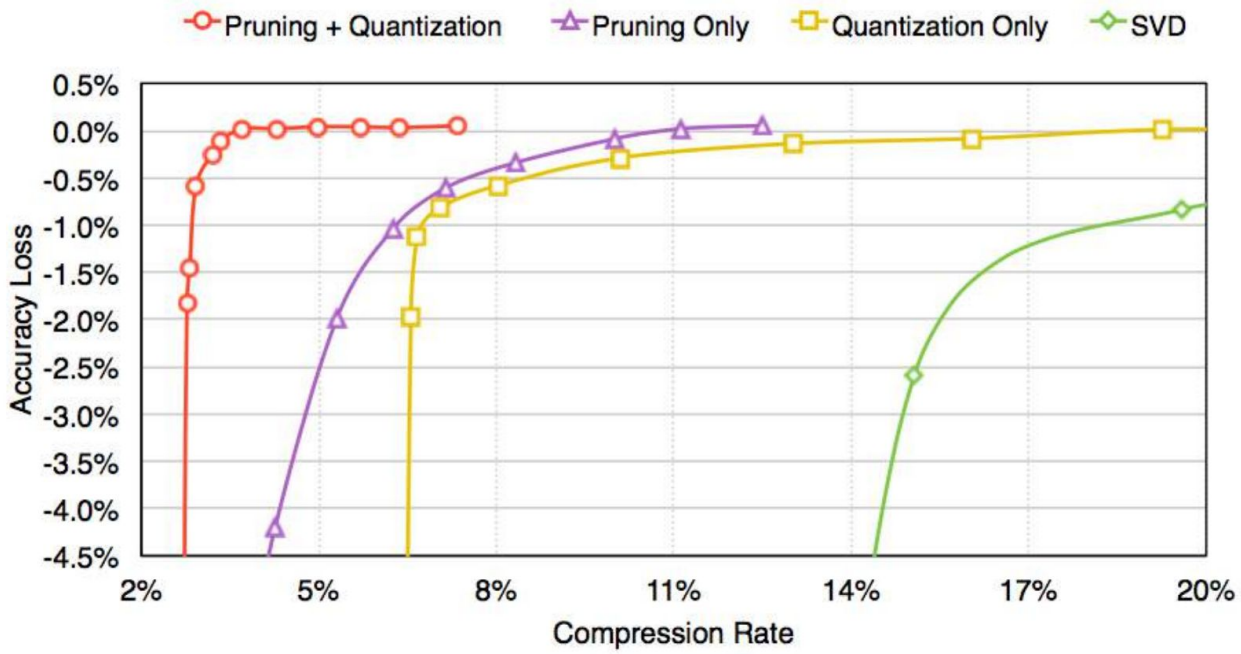


Trained Quantization





Trained Quantization | Prunning



AlexNet on ImageNet

Outline

- Motivation
- Weight pruning
- Low-rank approximation
- Quantization
- **Conditional / adaptive computation**
- Distillation
- Architectures

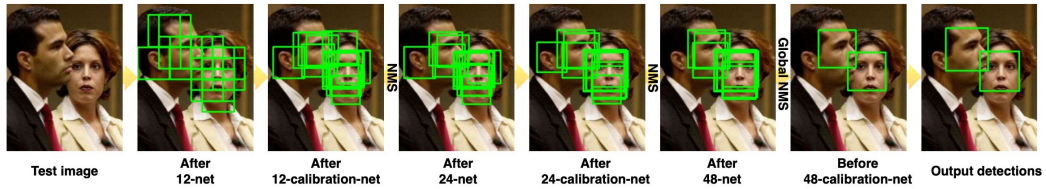
Conditional Computation

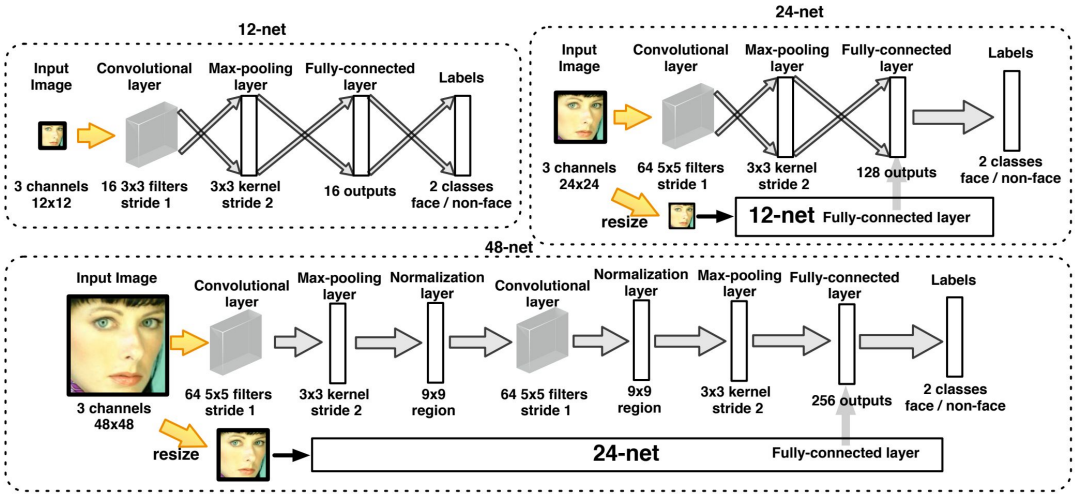
The amount of computation can be adapted to the complexity of the data

- E.g. a complex image requires more computation than a simple image
- Objective: trade-off between accuracy and computation

Conditional Computation | Cascade

- Use a cascade of classifiers on images at different resolutions
- When a classifier is not confident enough, feed to the next one in higher resolution
- There is another network that refines the position of the bounding boxes
- Detection at 100 img/s



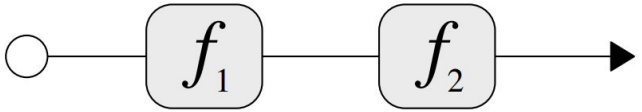


["A convolutional Neural Network Cascade for Face Detection", Haoxiang et al. CVPR'15]

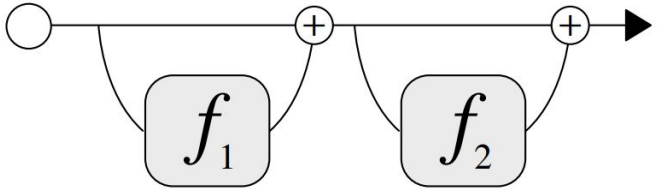
Adaptive ResNet

- Skip-connections are used to avoid computations
- A gate mechanism learns whether a module should be skipped
  - The decision is discrete (probabilistic)
- Gradients are propagated with a "straight-through" estimator

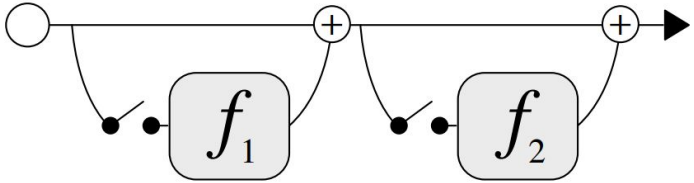
Traditional feed-forward ConvNet:



ResNet:



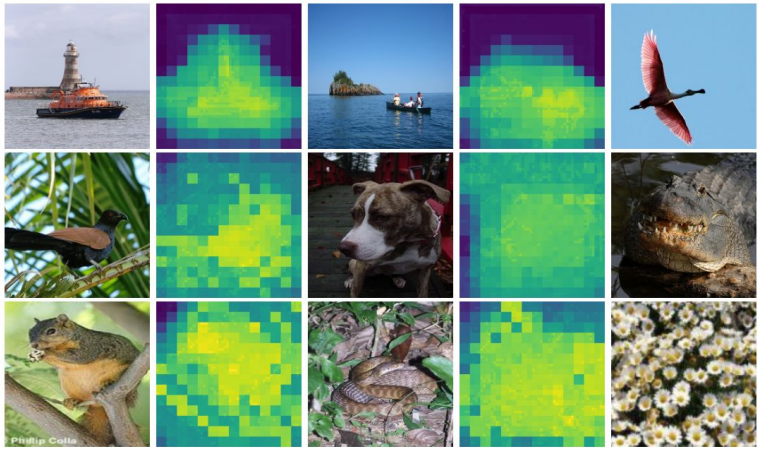
ConvNet-AIG:



[A. Veit et Belongie CVPR'17]

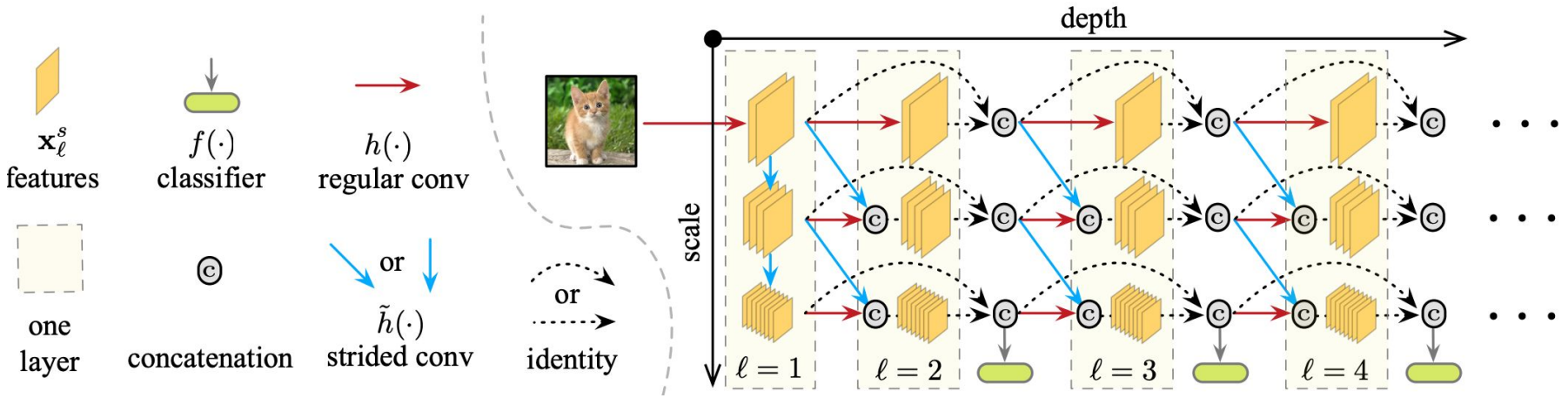
Spatially adaptive computation

- The network has a “computation budget” that has to spend wisely on different spatial positions of the image
- Since computation becomes sparse, the improvement is limited (~50%)
- The network looks at the image similar to a human



[“Spatially Adaptive Computation Time for Residual Networks”Figurnov et al. CVPR’17]

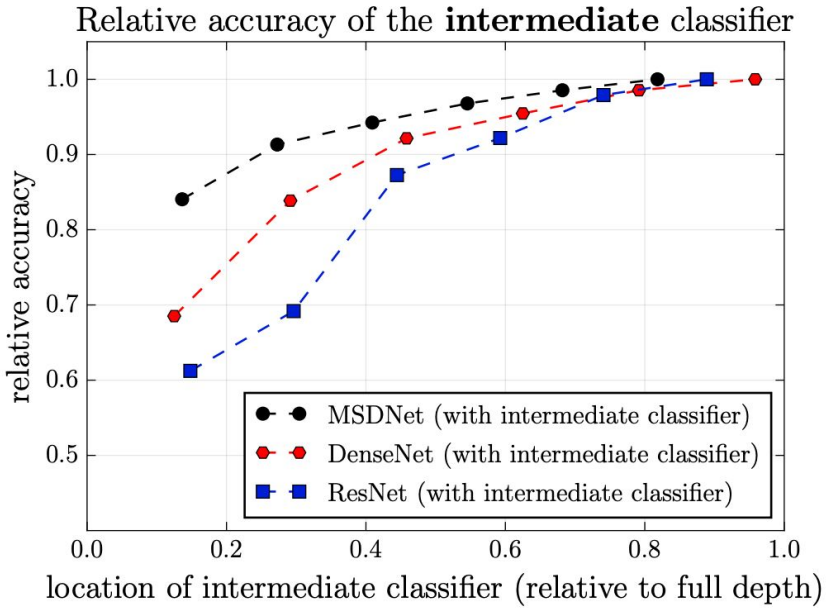
Multi-scale Dense Network

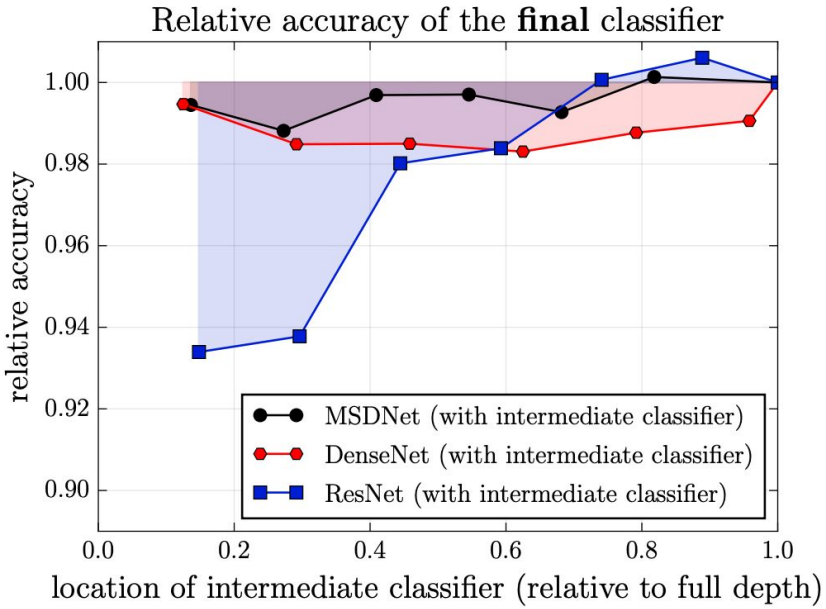


- Cascade of classifiers
- After each classifier one decides if stop the computation
- "Anytime classification"
- Limited budget classification

[Huang et al ICLR'18]

Multi-scale Dense Network

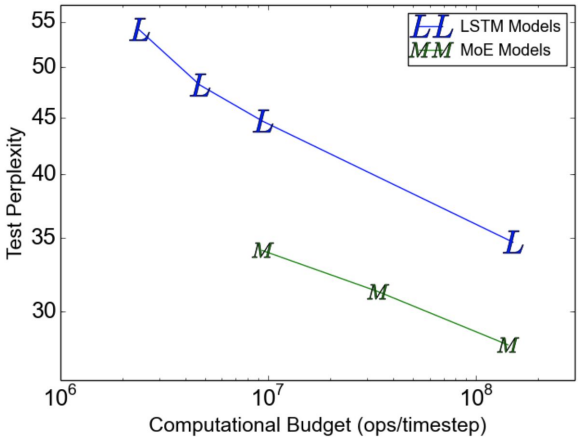


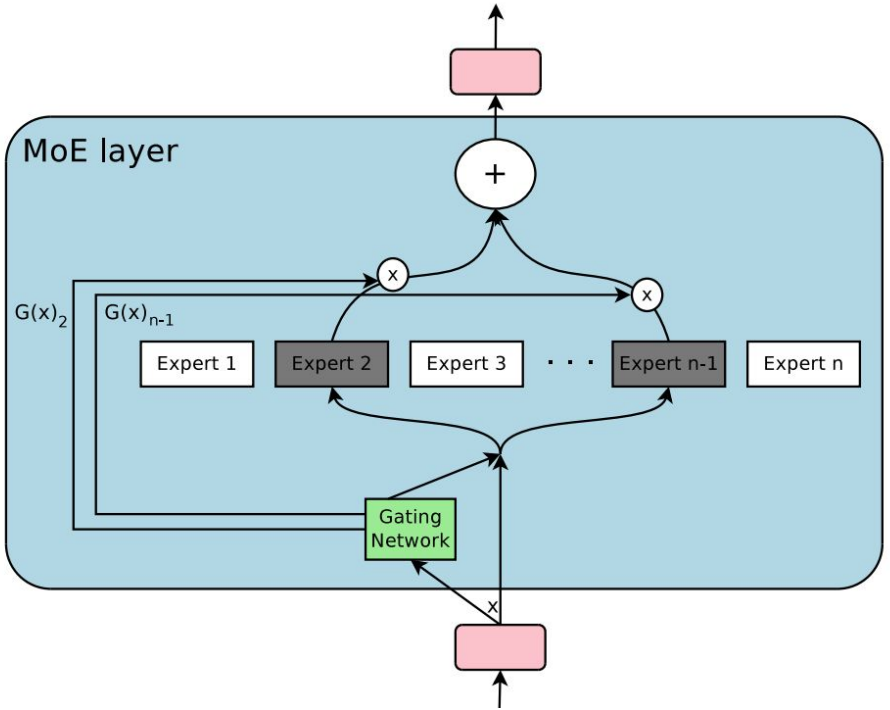


[Huang et al ICLR'18]

Mixture of experts

- Use a gating network to select a only subset of experts
- When high capacity is needed
  - Reduce computational cost
  - Same performance a single larger model



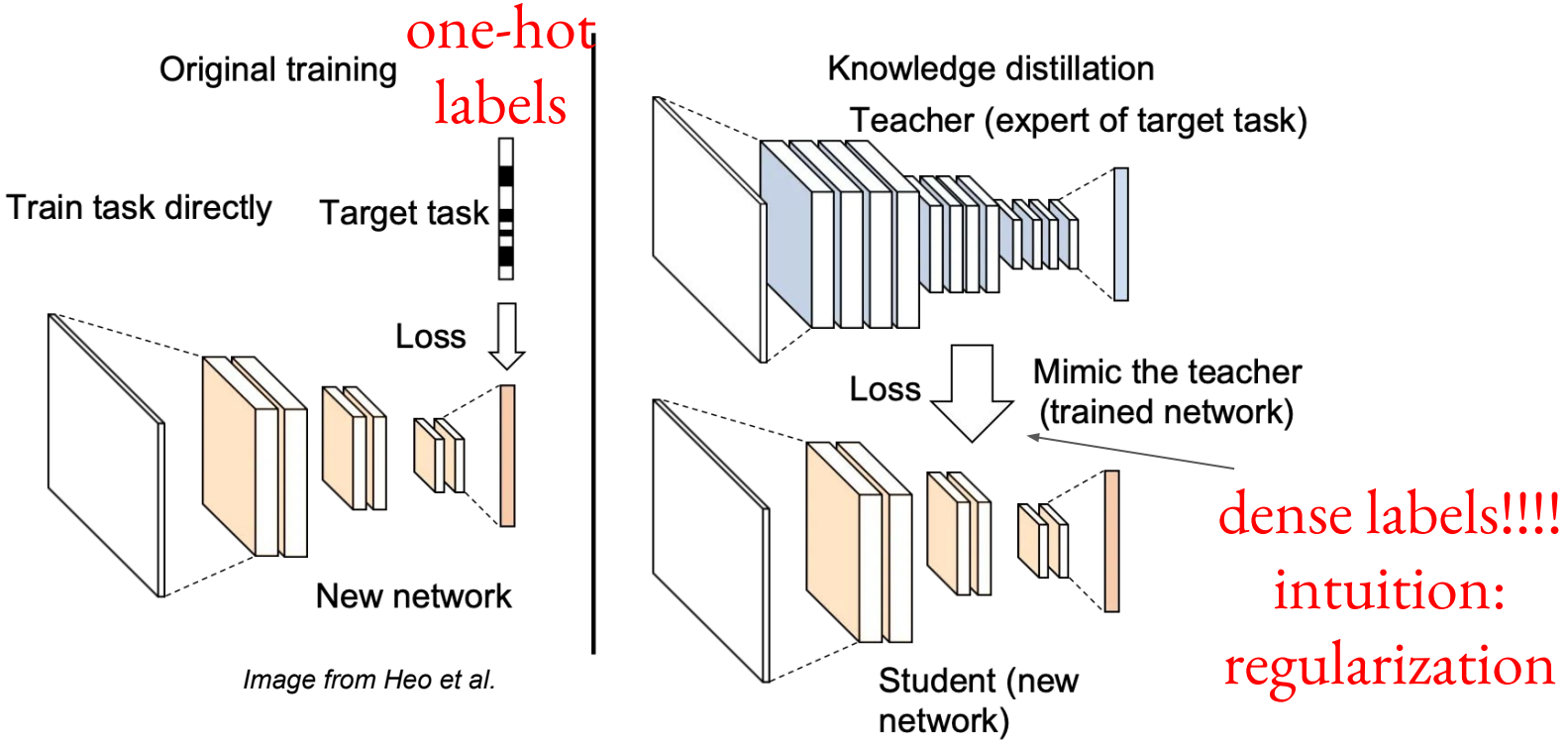


source: Noam Shazeer, Azalia Mirhoseini, Krzysztof Maziarz, Andy Davis, Quoc Le, Geoffrey Hinton, Jeff Dean, "Outrageously Large Neural Networks: The Sparsely-Gated Mixture-of-Experts Layer".

Outline

- Motivation
- Weight pruning
- Low-rank approximation
- Quantization
- Conditional / adaptive computation
- **Distillation**
- Architectures

Distillation



[Hinton et al.,"Distilling the Knoweledge in a Neural Network", arXiv 2016]

Distillation

- A (big) teacher model is first trained on a task
- Then, a (smaller) student learns to mimic the outputs of the teacher
- Can achieve better accuracy!!!

System	Test Frame Accuracy	WER
Baseline	58.9%	10.9%
10xEnsemble	61.1%	10.7%
Distilled Single model	60.8%	10.7%

[Hinton et al.,"Distilling the Knoweledge in a Neural Network", arXiv 2016]

Distillation | Dark knowledge

cow	dog	cat	car
0	1	0	0

original hard targets

cow	dog	cat	car
10^{-6}	.9	.1	10^{-9}

output of geometric ensemble

cow	dog	cat	car
.05	.3	.2	.005

softened output of ensemble

Temperature

$$p_i = \frac{\exp\left(\frac{z_i}{T}\right)}{\sum_j \exp\left(\frac{z_j}{T}\right)}$$

[Hinton et al.,"Distilling the Knoweledge in a Neural Network", arXiv 2016]

Outline

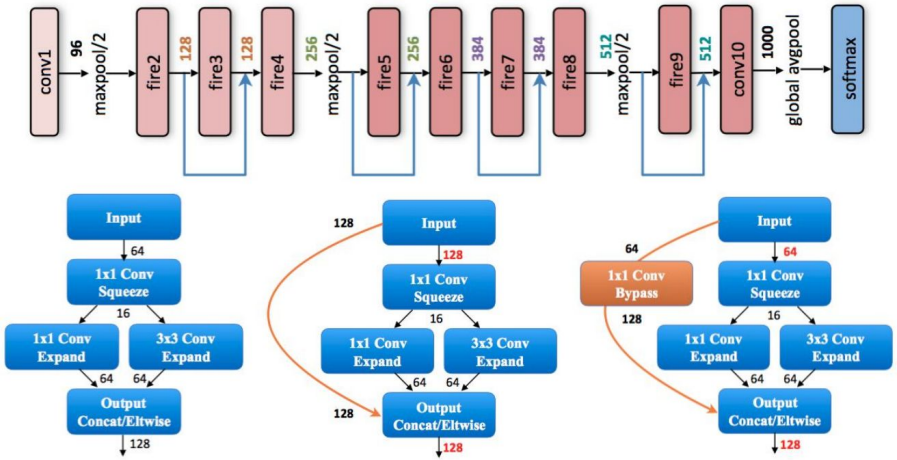
- Motivation
- Weight pruning
- Low-rank approximation
- Quantization
- Conditional / adaptive computation
- Distillation
- **Architectures**

Architectures

- Instead of optimizing an existing architecture, **find ways to directly create more efficient architectures**:
  - Thinner
  - More efficient layers (without low-rank approx.)

SqueezeNet

- Use 1x1 convolutions to reduce the number of channels
- Use 1x1 and 3x3 convolutions to recover the number of channels
- Move pooling to the end to improve performance



[Iandola et al, "SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size", arXiv 2016]

SqueezeNet

- The target is to reduce the amount of parameters
- 50x less parameters than AlexNet at the s**ame error rate**
- **510x reduction with compression**

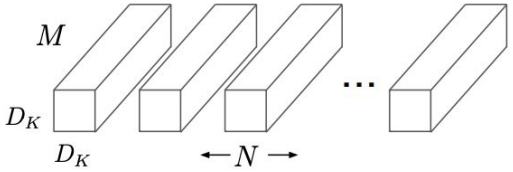
CNN architecture	Compression Approach	Data Type	Original → Compressed Model Size	Reduction in Model Size vs. AlexNet	Top-1 ImageNet Accuracy	Top-5 ImageNet Accuracy
AlexNet	None (baseline)	32 bit	240MB	1x	57.2%	80.3%
AlexNet	SVD (Denton et al., 2014)	32 bit	240MB → 48MB	5x	56.0%	79.4%
AlexNet	Network Pruning (Han et al., 2015b)	32 bit	240MB → 27MB	9x	57.2%	80.3%
AlexNet	Deep Compression (Han et al., 2015a)	5-8 bit	240MB → 6.9MB	35x	57.2%	80.3%
SqueezeNet (ours)	None	32 bit	4.8MB	**50x**	57.5%	80.3%
SqueezeNet (ours)	Deep Compression	8 bit	4.8MB → 0.66MB	**363x**	57.5%	80.3%
SqueezeNet (ours)	Deep Compression	6 bit	4.8MB → 0.47MB	**510x**	57.5%	80.3%

[Iandola et al, "SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size", arXiv 2016]

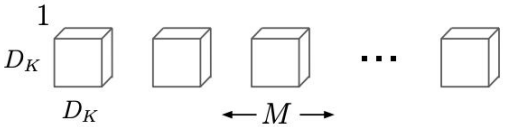
Mobilenet

Reduces the number of parameters and it is **more efficient!**

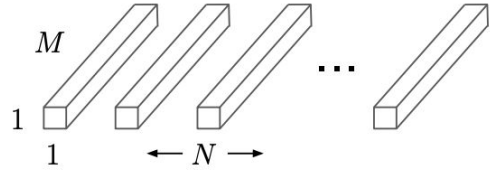
- New decomposition of the convolution
  - Depth-wise filters before
  - 1x1 convolution after
- 9x Faster than a 3x3 convolution at comparable performance



(a) Standard Convolution Filters



(b) Depthwise Convolutional Filters



(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

Table 9. Smaller MobileNet Comparison to Popular Models

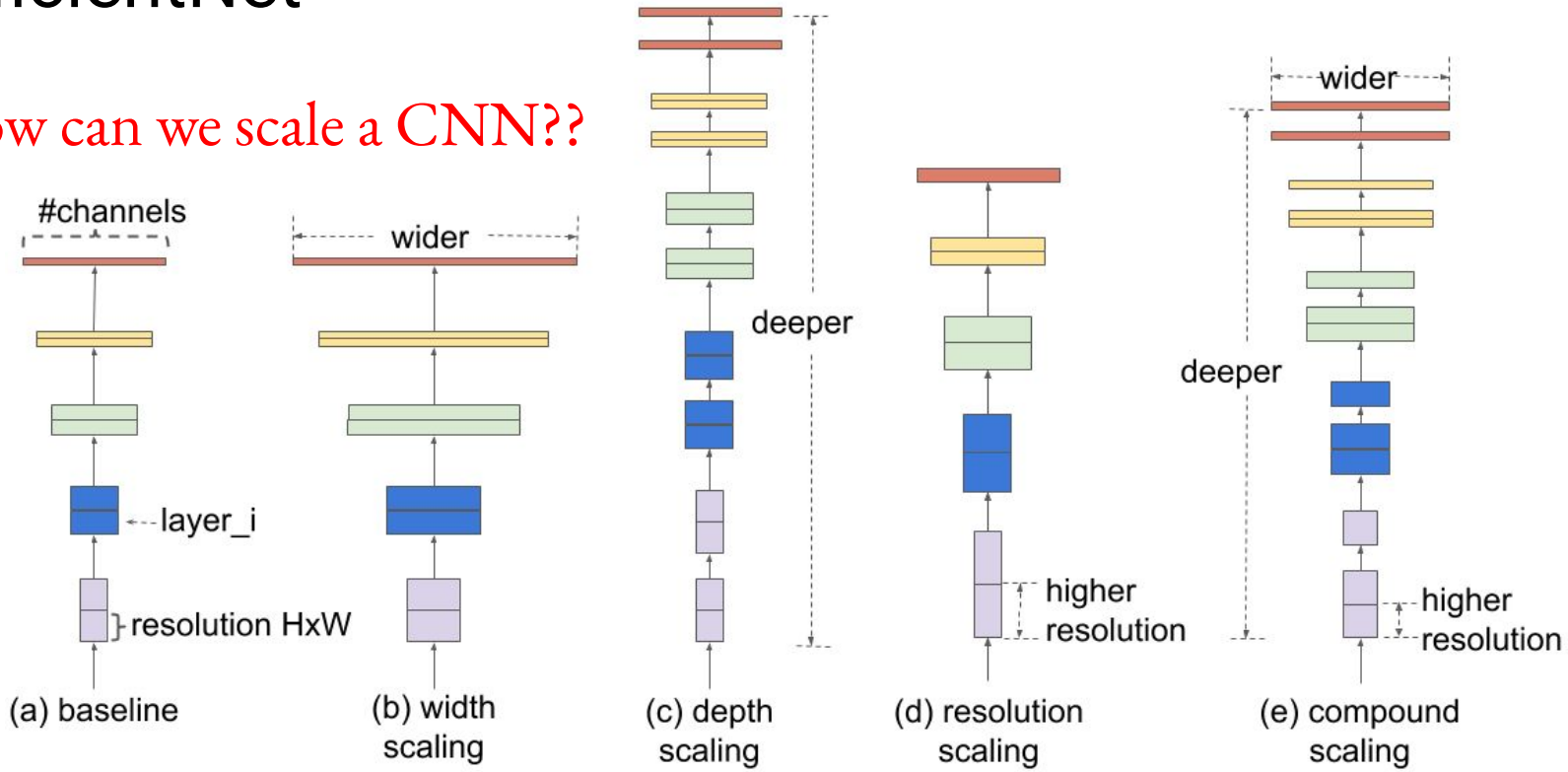
Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
0.50 MobileNet-160	60.2%	76	1.32
Squeezenet	57.5%	1700	1.25
AlexNet	57.2%	720	60

Table 2. Resource Per Layer Type

Type	Mult-Adds	Parameters
Conv 1×1	94.86%	74.59%
Conv DW 3×3	3.06%	1.06%
Conv 3×3	1.19%	0.02%
Fully Connected	0.18%	24.33%

EfficientNet

How can we scale a CNN??



[Tan, M., & Le, Q. V. (2019). Efficientnet: Rethinking model scaling for convolutional neural networks.]

EfficientNet

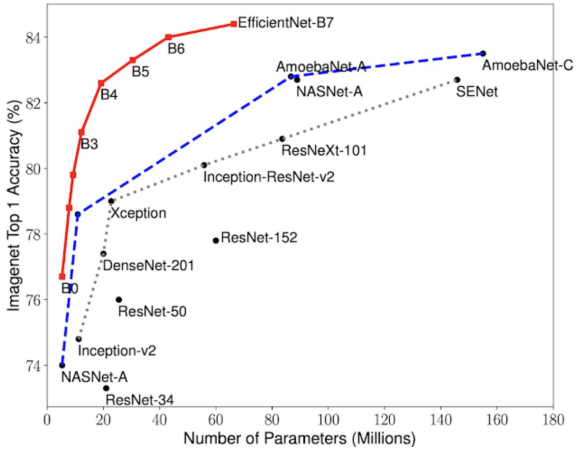
- Architecture found by NAS
  - FLOPS included in the optimization!
- + Proper scaling

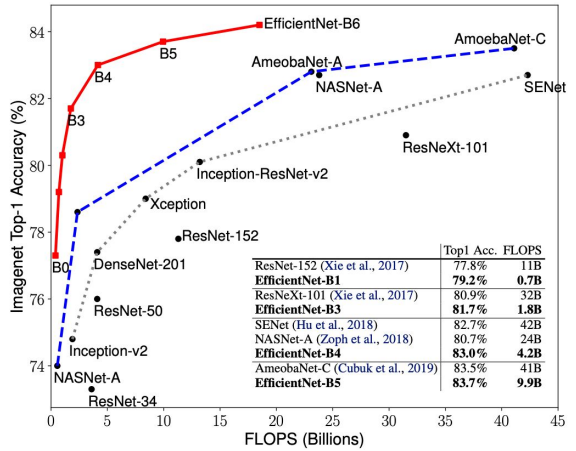
Found by hyperparameter search

$$\text{depth: } d = \alpha^\phi$$
$$\text{width: } w = \beta^\phi$$
$$\text{resolution: } r = \gamma^\phi$$
$$\text{s.t. } \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$$
$$\alpha \geq 1, \beta \geq 1, \gamma \geq 1$$

Φ = amount of resources

$$\text{FLOPS} = 2^\Phi$$





	Top1 Acc.	FLOPS
ResNet-152 (Xie et al., 2017)	77.8%	11B
EfficientNet-B1	**79.2%**	**0.7B**
ResNeXt-101 (Xie et al., 2017)	80.9%	32B
EfficientNet-B3	**81.7%**	**1.8B**
SENet (Hu et al., 2018)	82.7%	42B
NASNet-A (Zoph et al., 2018)	80.7%	24B
EfficientNet-B4	**83.0%**	**4.2B**
AmeobaNet-C (Cubuk et al., 2019)	83.5%	41B
EfficientNet-B5	**83.7%**	**9.9B**

[Tan, M., & Le, Q. V. (2019). Efficientnet: Rethinking model scaling for convolutional neural networks.]

Thanks!