Efficient Methods for Deep Learning

Song Han

Stanford University
Sep 2016

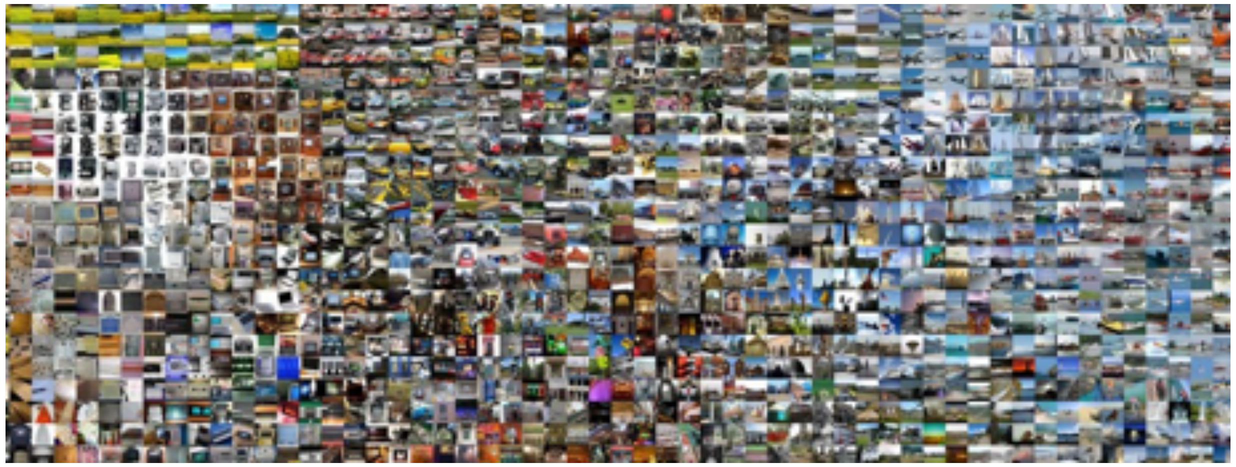
Background: Deep Learning for Everything

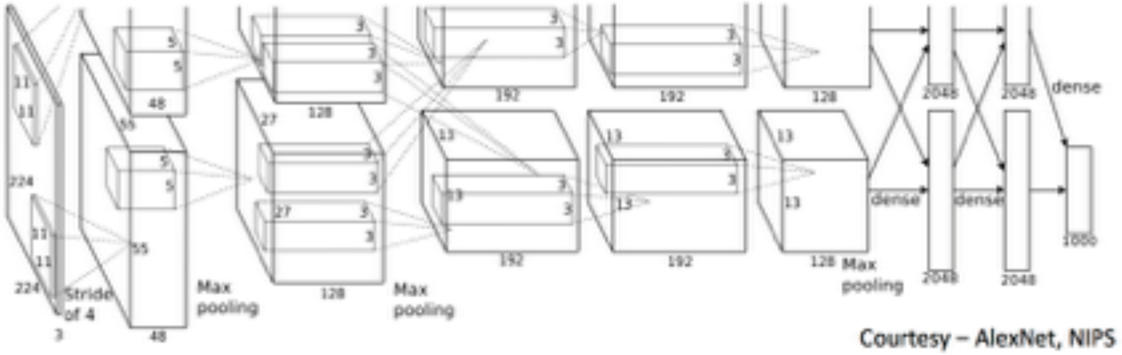
AlphaGo

Source: Brody Huval et al., “An Empirical Evaluation…”, arxiv:1504.01716

Source: leon A. Gatys et al., “A Neural…”, arxiv:1508.06576

Hardware and Data enable Deep Learning





Courtesy – AlexNet, NIPS 2012

Dally, NIPS’2015 tutorial on High-Performance Hardware for Machine Learning

The Need for Speed

More data ➔ Bigger Models ➔
More Need for Compute

But Moore's law is no longer providing more compute…

Dally, NIPS'2015 tutorial on High-Performance Hardware for Machine Learning

Goal: Improve the Efficiency of Deep Learning

For Mobile + Cloud

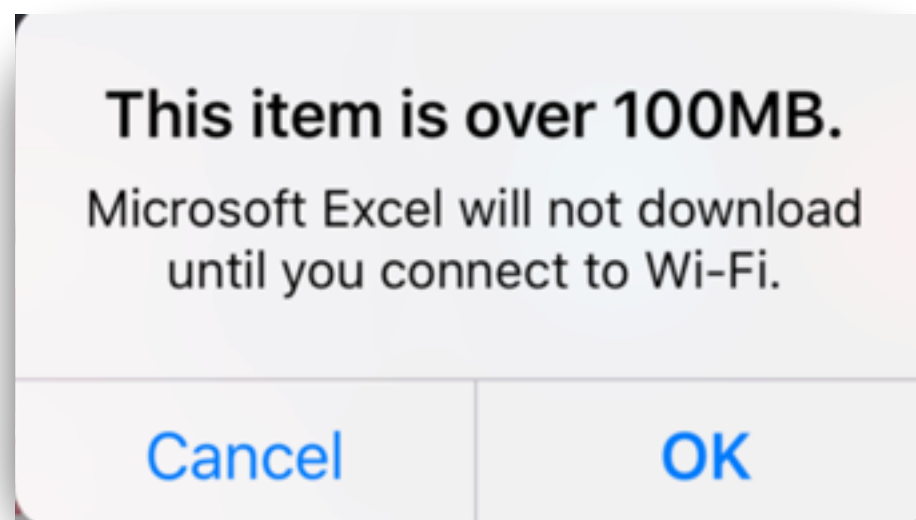
Embedded Applications: Self-Driving Cars

nVidia Drive PX2

24 Tps/sec @ 20W

Challenges for Efficient Deep Learning

Model Size!



Challenges for Efficient Deep Learning

Operation	Energy [pJ]	Relative Cost
32 bit int ADD	0.1	1
32 bit float ADD	0.9	9
32 bit Register File	1	10
32 bit int MULT	3.1	31
32 bit float MULT	3.7	37
32 bit SRAM Cache	5	50
32 bit DRAM Memory	**640**	**6400**

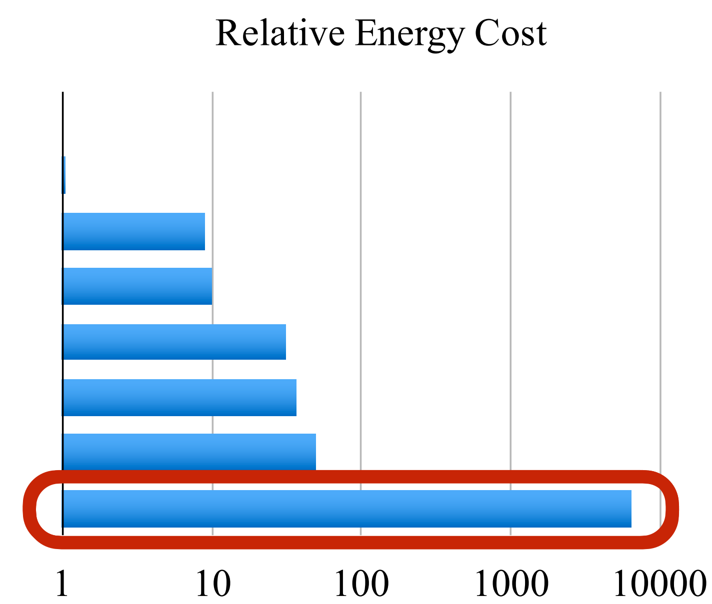
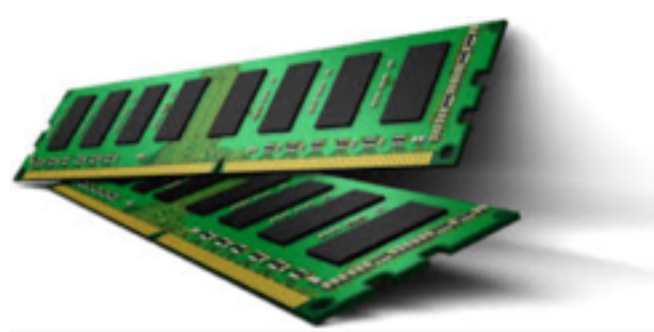
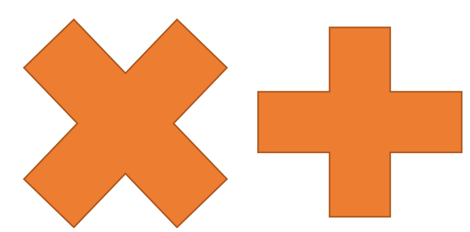


Figure 1: Energy table for 45nm CMOS process. Memory access is 2 orders of magnitude more energy expensive than arithmetic operations.

1  = 100 

Part 1: Deep Compression

Song Han
CVA group, Stanford University

Han et al. “Learning both Weights and Connections for Efficient Neural Networks”, NIPS’15
Han et al. “Deep Compression: Compressing Deep Neural Networks with Pruning, Trained Quantization and Huffman Coding”, ICLR 2016

Deep Compression

Problem 1: DNN Model Size too Large
Solution 1: Deep Compression

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Deep Compression

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Smaller Size

90% zeros in weights
4-bit weight

Deep Compression

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Smaller Size	Accuracy
90% zeros in weights 4-bit weight	No loss of accuracy / Improved accuracy

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Smaller Size

90% zeros in weights
4-bit weight

Accuracy

No loss of accuracy /
Improved accuracy

On-chip

State-of-the-art DNN
fit on-chip SRAM

Deep Compression Overview

- AlexNet: 35×, 240MB => 6.9MB
- VGG16: 49×, 552MB => 11.3MB
- GoogLeNet: 10x, 28MB => 2.8MB
- SqueezeNet: 10x, 4.8MB => 0.47MB
- No loss of accuracy on ImageNet12
- Weights fits on-chip SRAM cache, taking 120x less energy than DRAM memory

Deep Compression Pipeline

- **Network Pruning**:
  10x fewer weights

- **Weight Sharing**:
  only 4-bits per remaining weight

- **Huffman Coding**:
  Entropy of the Total Remaining Weights

Deep Compression Pipeline

- **Network Pruning**:
  Less Number of Weights
- **Weight Sharing**:
  Reduce Storage for Each Remaining Weight
- **Huffman Coding**:
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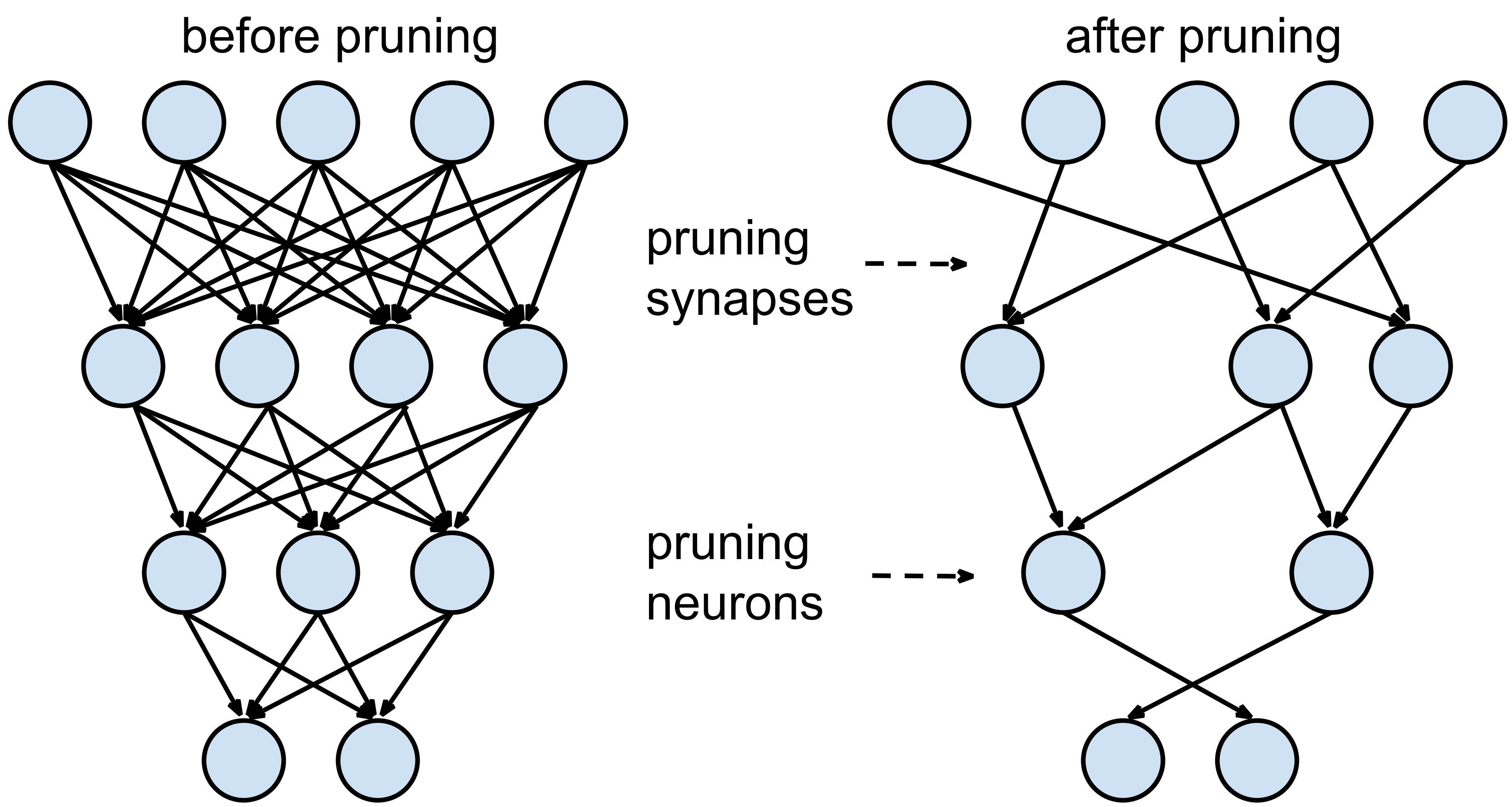
1. Pruning



[1] LeCun et al. Optimal Brain Damage NIPS'90
[2] Hassibi, et al. Second order derivatives for network pruning: Optimal brain surgeon. NIPS'93
[3] Han et al. Learning both Weights and Connections for Efficient Neural Networks, NIPS'15

Pruning: Motivation

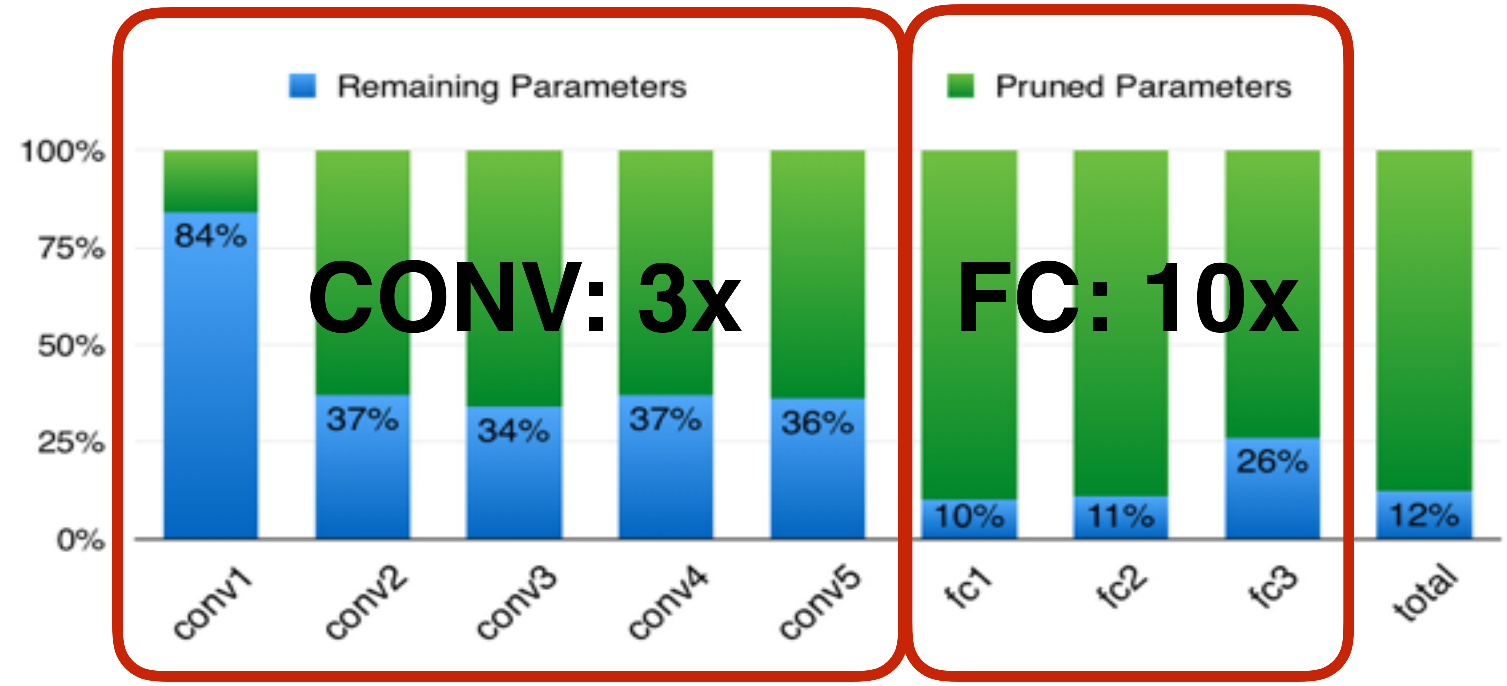
Age	Number of Connections	Stage
at birth	50 Trillion	newly formed
1 year old	1000 Trillion	peak
10 year old	500 Trillion	pruned and stabilized

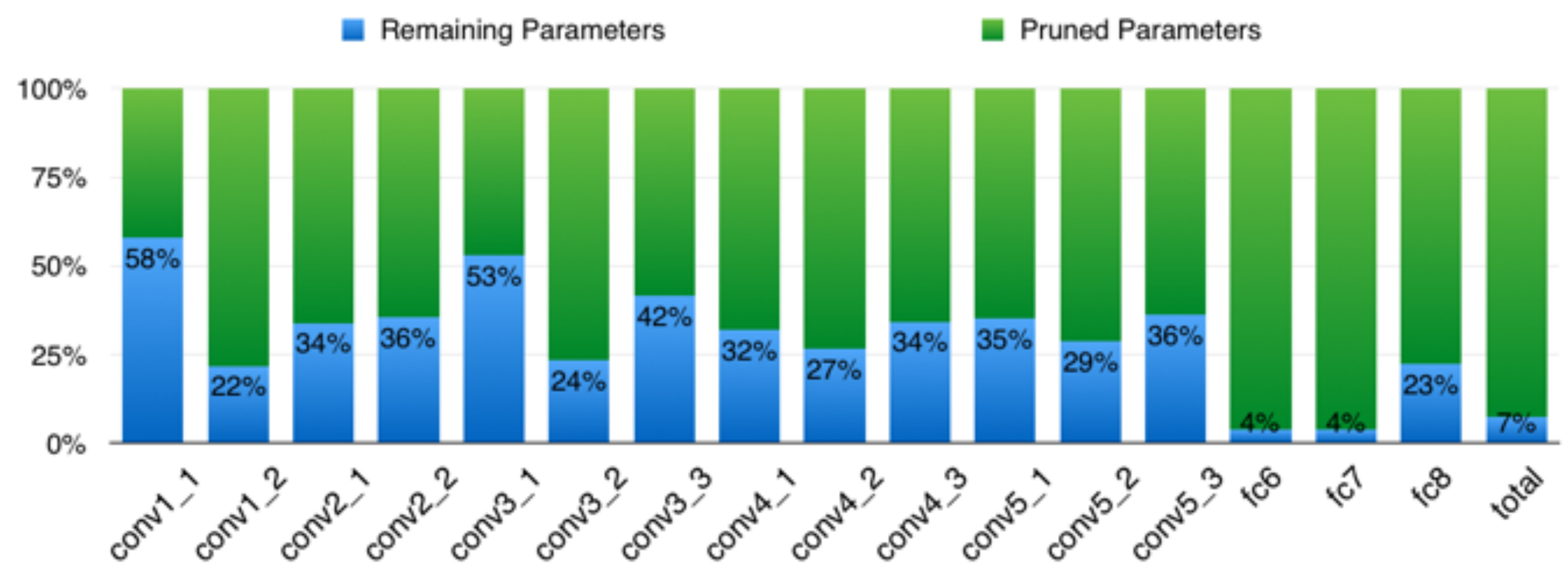
Table 1: The synapses pruning mechanism in human brain development

- Trillion of synapses are generated in the human brain during the first few months of birth.
- **1 year old**, peaked at **1000 trillion**
- Pruning begins to occur.
- **10 years old**, a child has nearly **500 trillion** synapses
- This ’pruning’ mechanism removes redundant connections in the brain.

[1] Christopher A Walsh. Peter Huttenlocher (1931-2013). Nature, 502(7470):172–172, 2013.

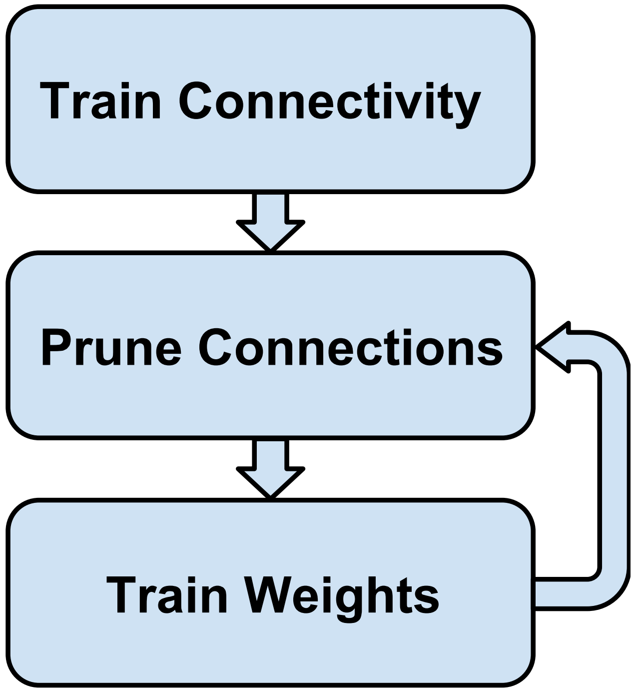
AlexNet & VGGNet

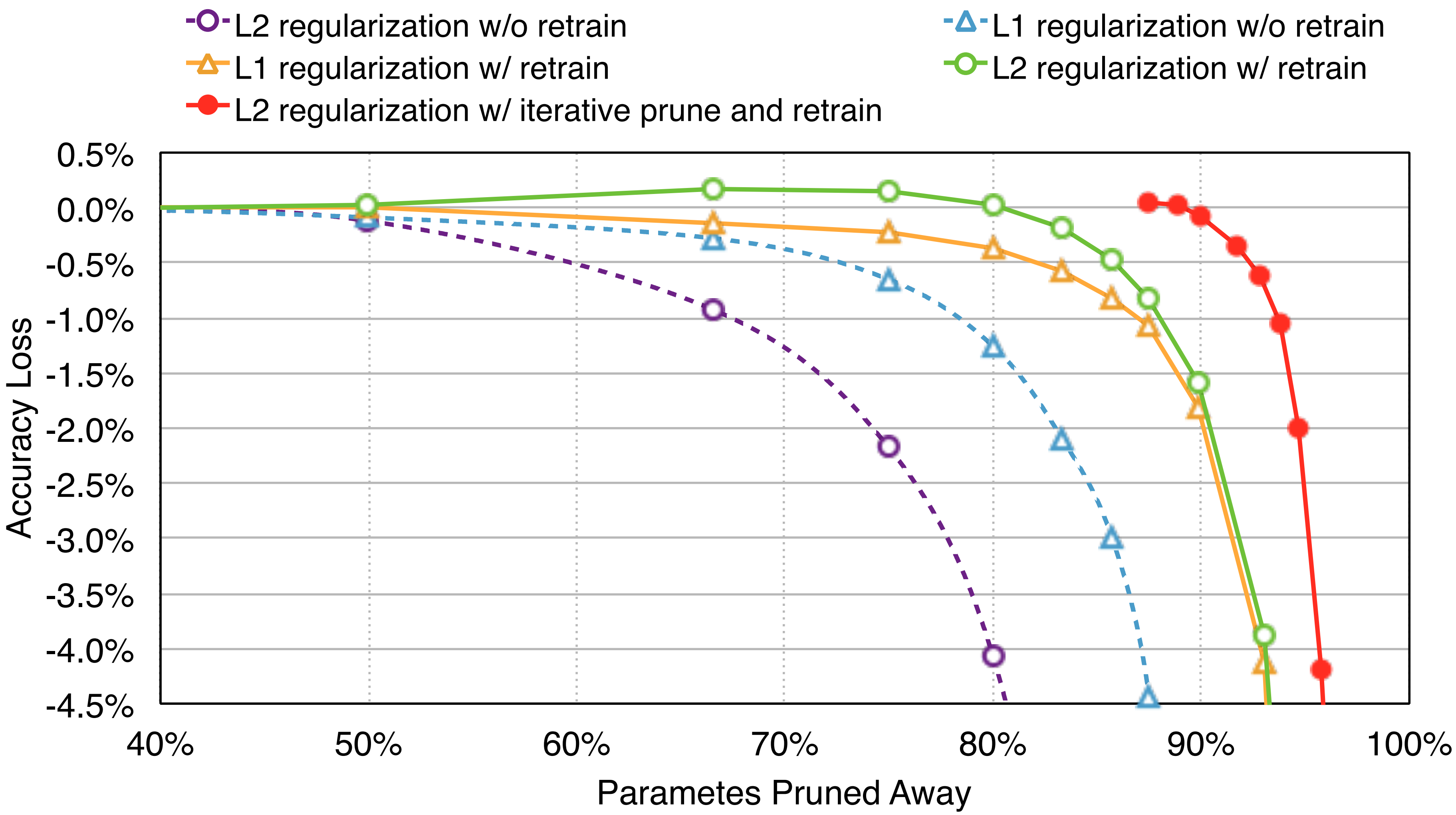




Han et al. Learning both Weights and Connections for Efficient Neural Networks, NIPS 2015

Retrain to Recover Accuracy





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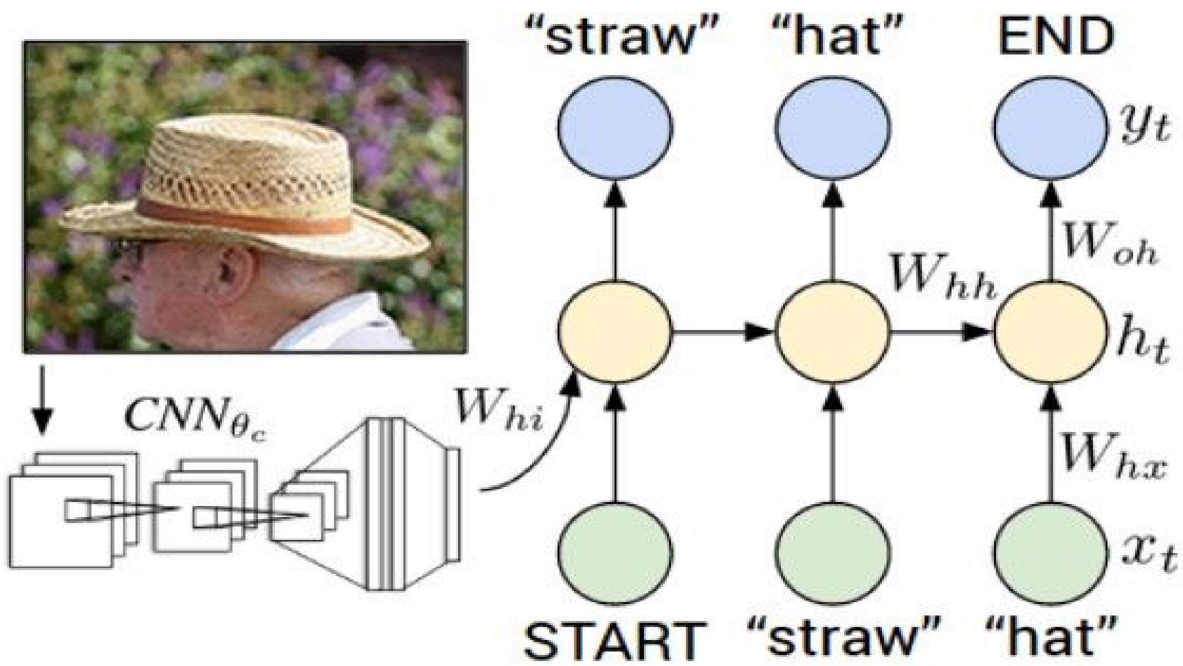
Pruning: Result

Network	Top-1 Error	Top-5 Error	Parameters	Compression Rate
LeNet-300-100 Ref	1.64%	-	267K	
LeNet-300-100 Pruned	1.59%	-	**22K**	**12**×
LeNet-5 Ref	0.80%	-	431K	
LeNet-5 Pruned	0.77%	-	**36K**	**12**×
AlexNet Ref	42.78%	19.73%	61M	
AlexNet Pruned	42.77%	19.67%	**6.7M**	**9**×
VGG16 Ref	31.50%	11.32%	138M	
VGG16 Pruned	31.34%	10.88%	**10.3M**	**13**×

Table 1: Network pruning can save 9× to 13× parameters with no drop in predictive performance

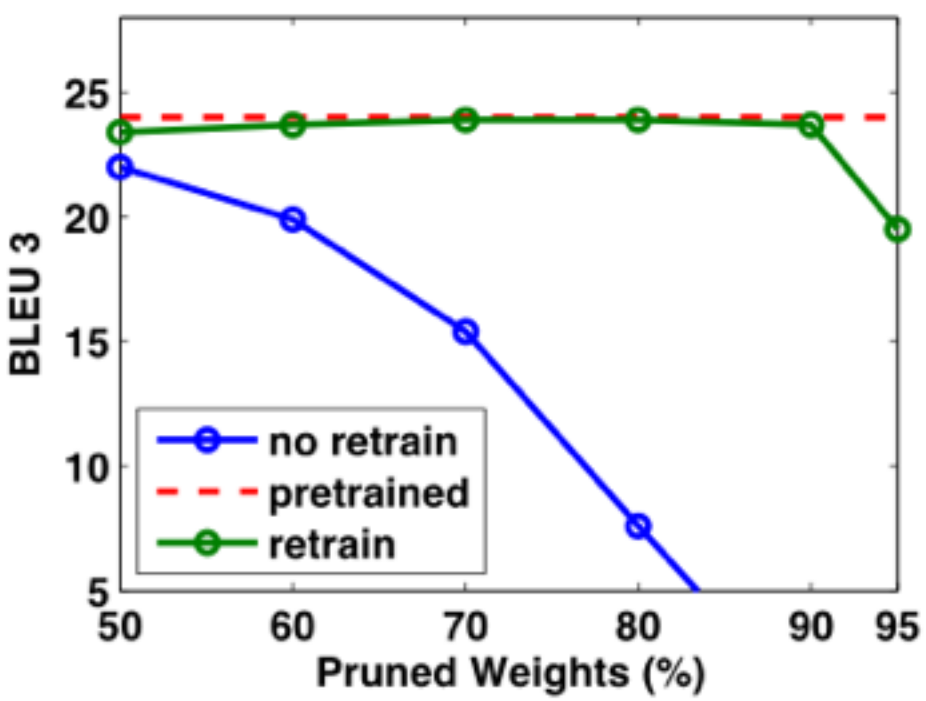
Han et al. Learning both Weights and Connections for Efficient Neural Networks, NIPS 2015

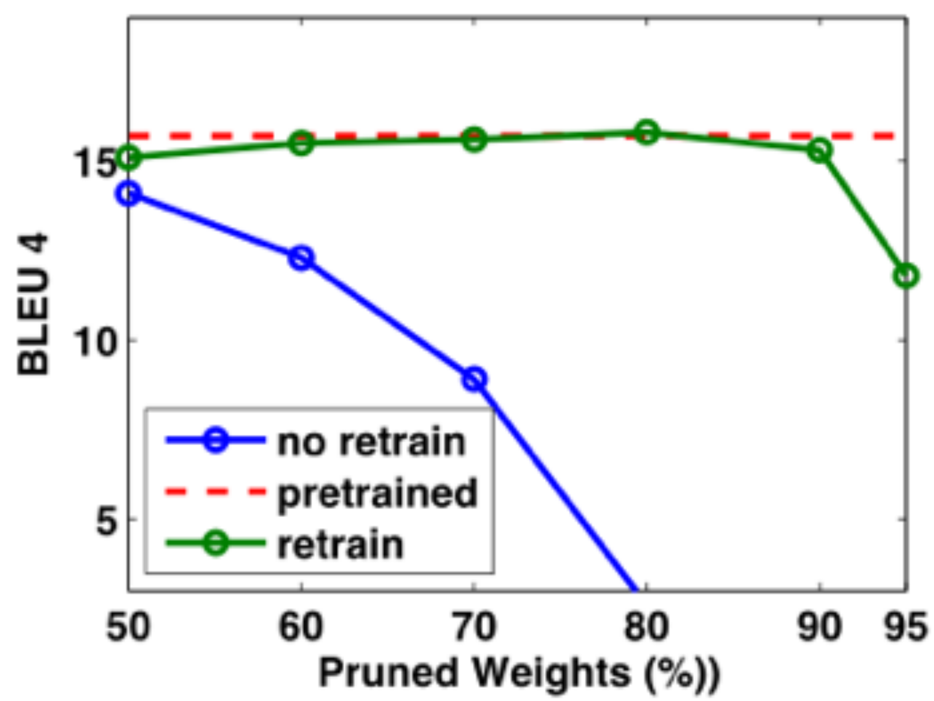
Pruning RNN and LSTM



Karpathy, et al, "Deep Visual-Semantic Alignments for Generating Image Descriptions"

- Pruning away 90% parameters in NeuralTalk doesn't hurt BLUE score with proper retrain





Pruning NeuralTalk and LSTM

- **Original**: a basketball player in a white uniform is playing with a ball
- **Pruned 90%**: a basketball player in a white uniform is playing with a basketball

- **Original** : a brown dog is running through a grassy field
- **Pruned 90%**: a brown dog is running through a grassy area

- **Original** : a man is riding a surfboard on a wave
- **Pruned 90%**: a man in a wetsuit is riding a wave on a beach

- **Original** : a soccer player in red is running in the field
- **Pruned <u>95%</u>**: a man in a red shirt and black and white black shirt is running through a field

Deep Compression Pipeline

- **Network Pruning**:
  Less Number of Weights
- **Weight Sharing**:
  Reduce Storage for Each Remaining Weight
- **Huffman Coding**:
  Entropy of the Total Remaining Weights

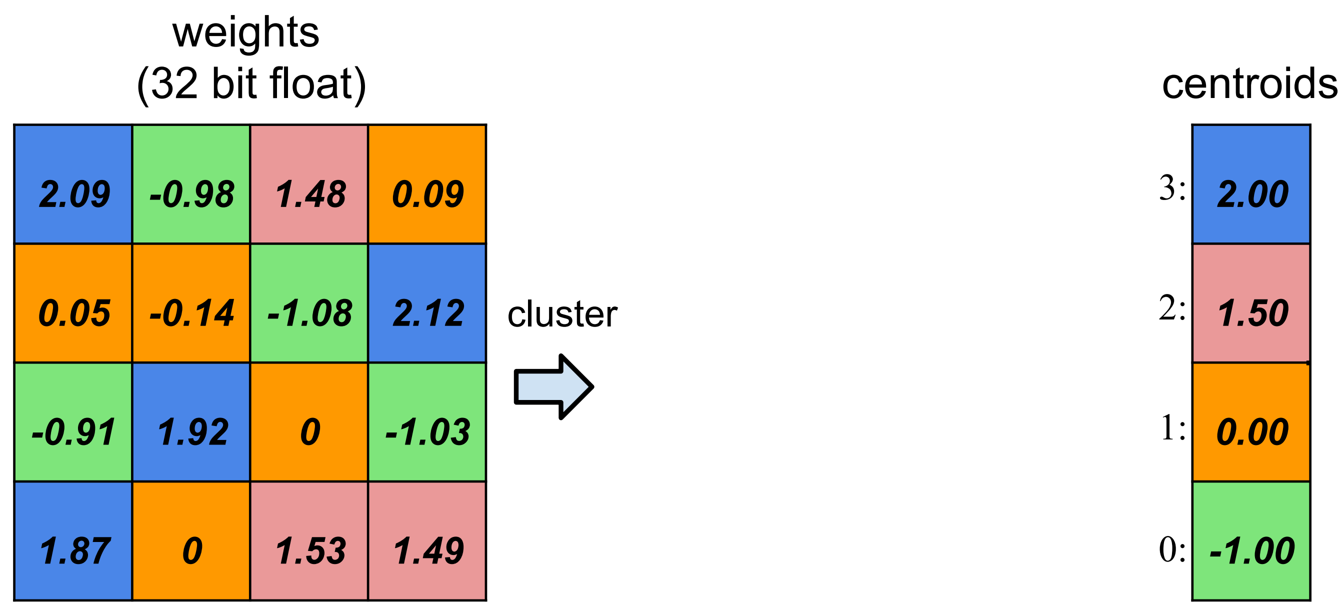
Weight Sharing: Overview

weights
(32 bit float)

2.09	-0.98	1.48	0.09
0.05	-0.14	-1.08	2.12
-0.91	1.92	0	-1.03
1.87	0	1.53	1.49

Han et al. “Deep Compression: Compressing Deep Neural Networks with Pruning, Trained Quantization and Huffman Coding”, ICLR 2016

Weight Sharing: Overview



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cluster $\Rightarrow$

cluster index
(2 bit uint)

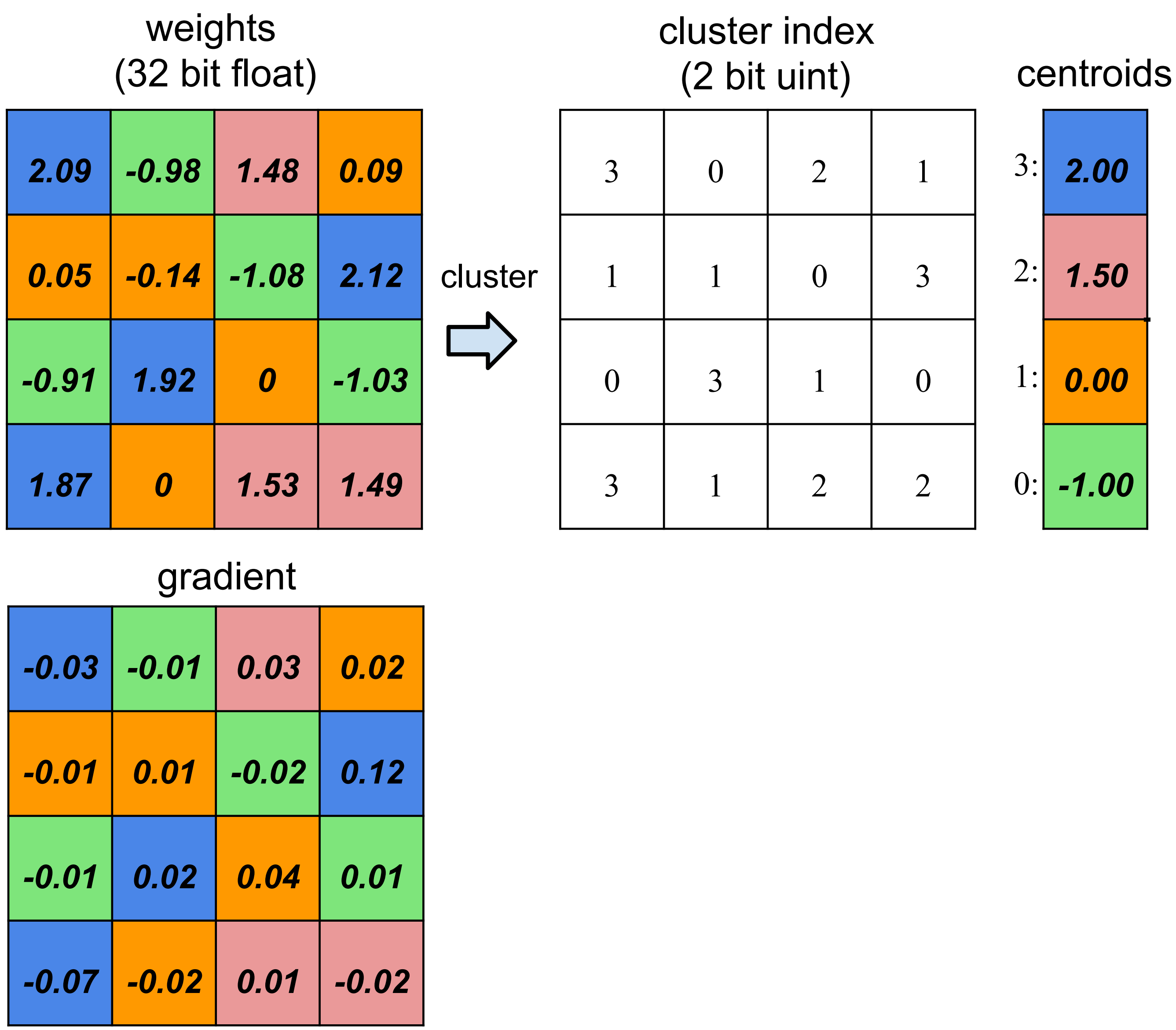
3	0	2	1
1	1	0	3
0	3	1	0
3	1	2	2

centroids

3:	2.00
2:	1.50
1:	0.00
0:	-1.00

Han et al. "Deep Compression: Compressing Deep Neural Networks with Pruning, Trained Quantization and Huffman Coding", ICLR 2016

Weight Sharing: Overview



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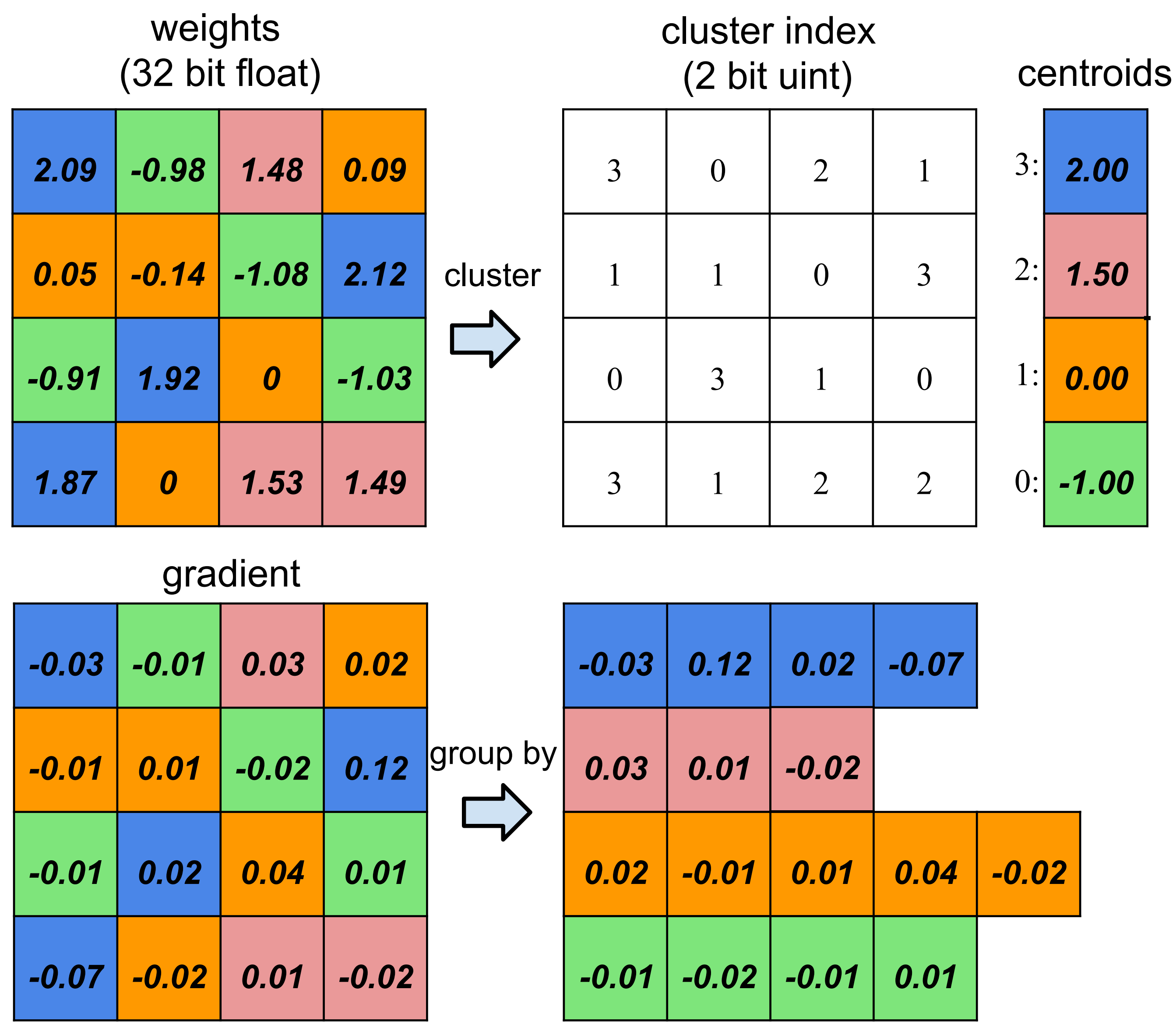

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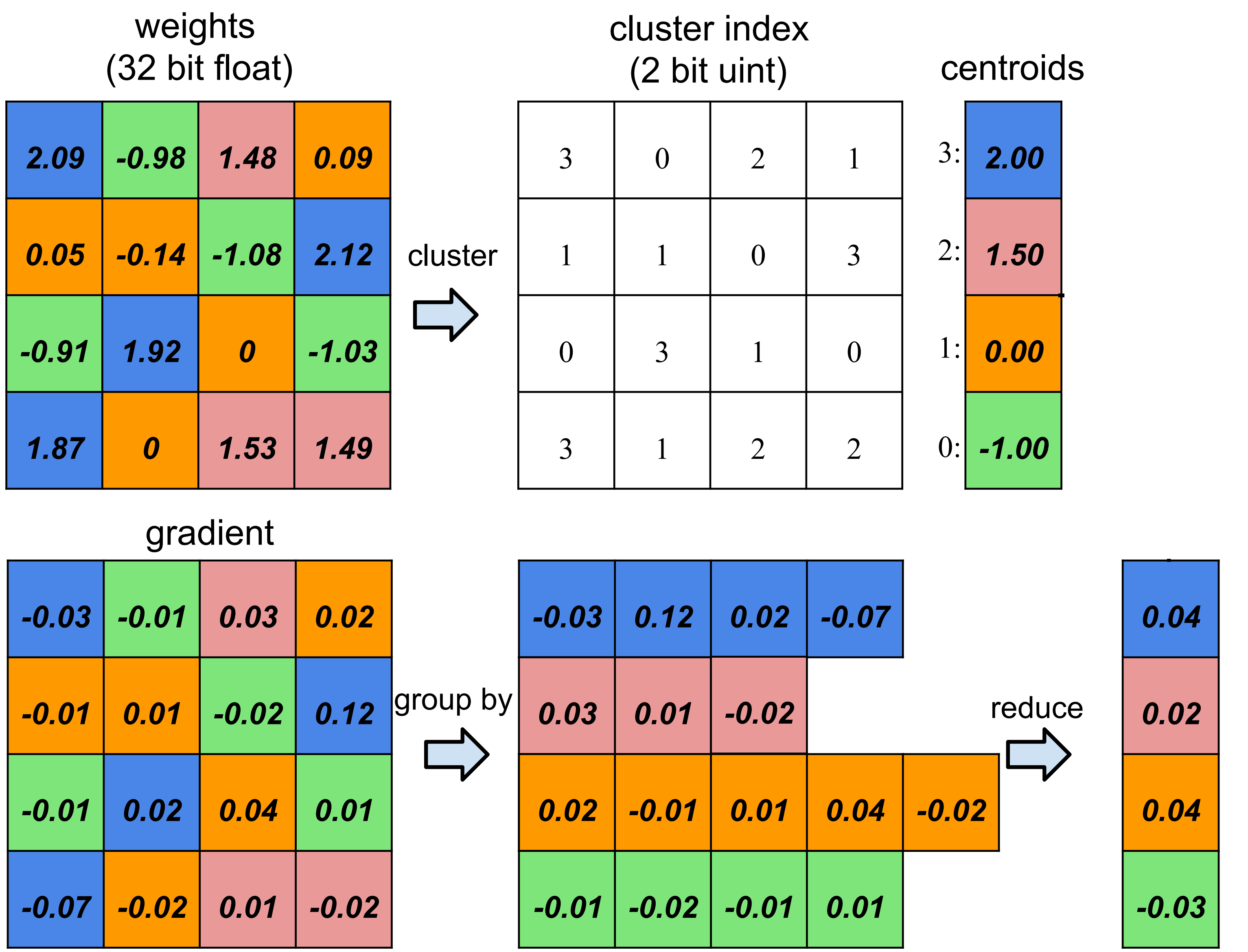

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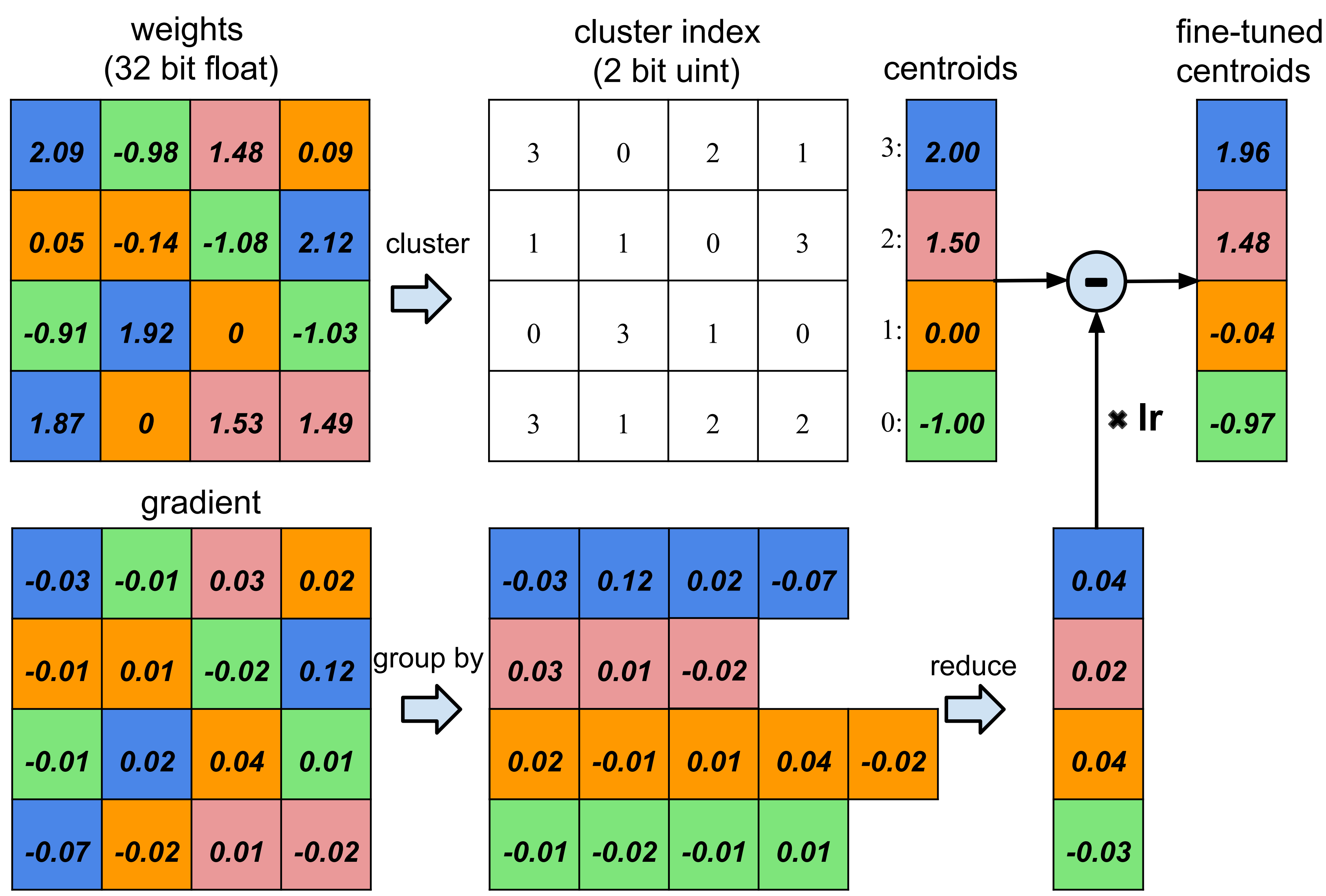

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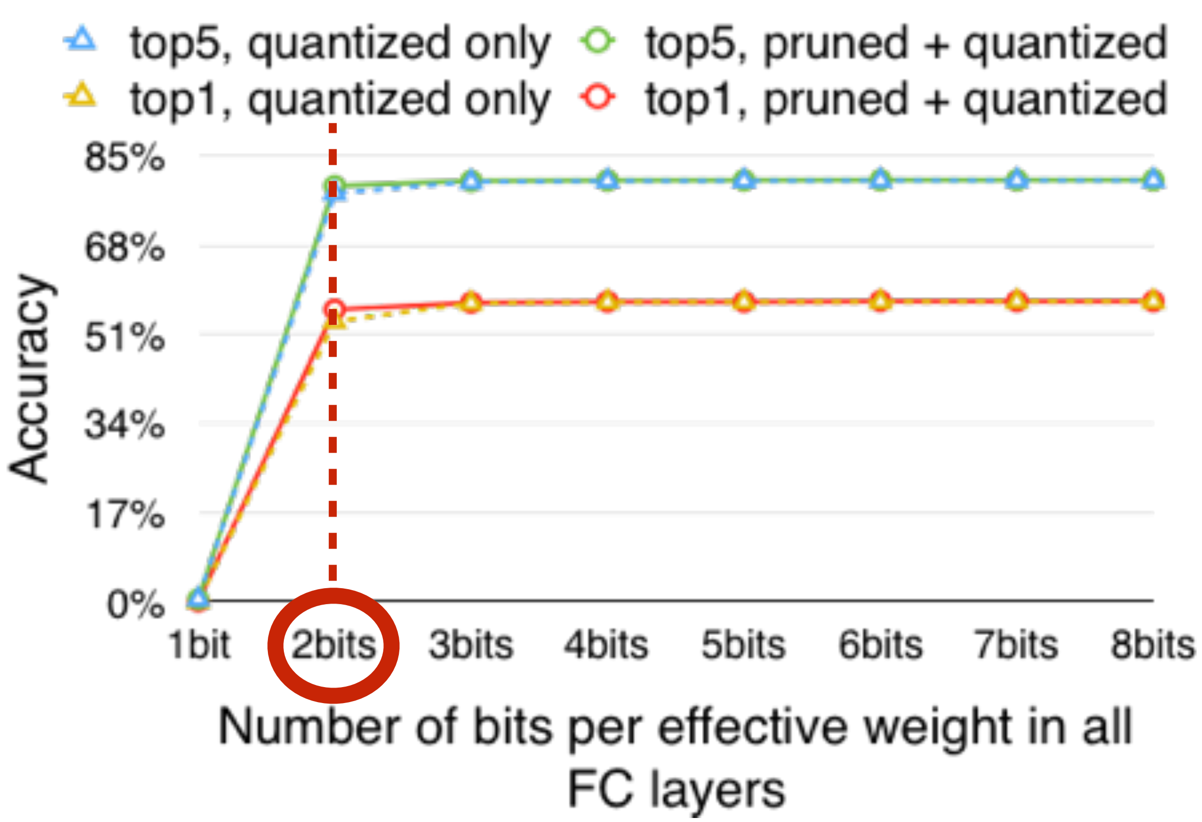
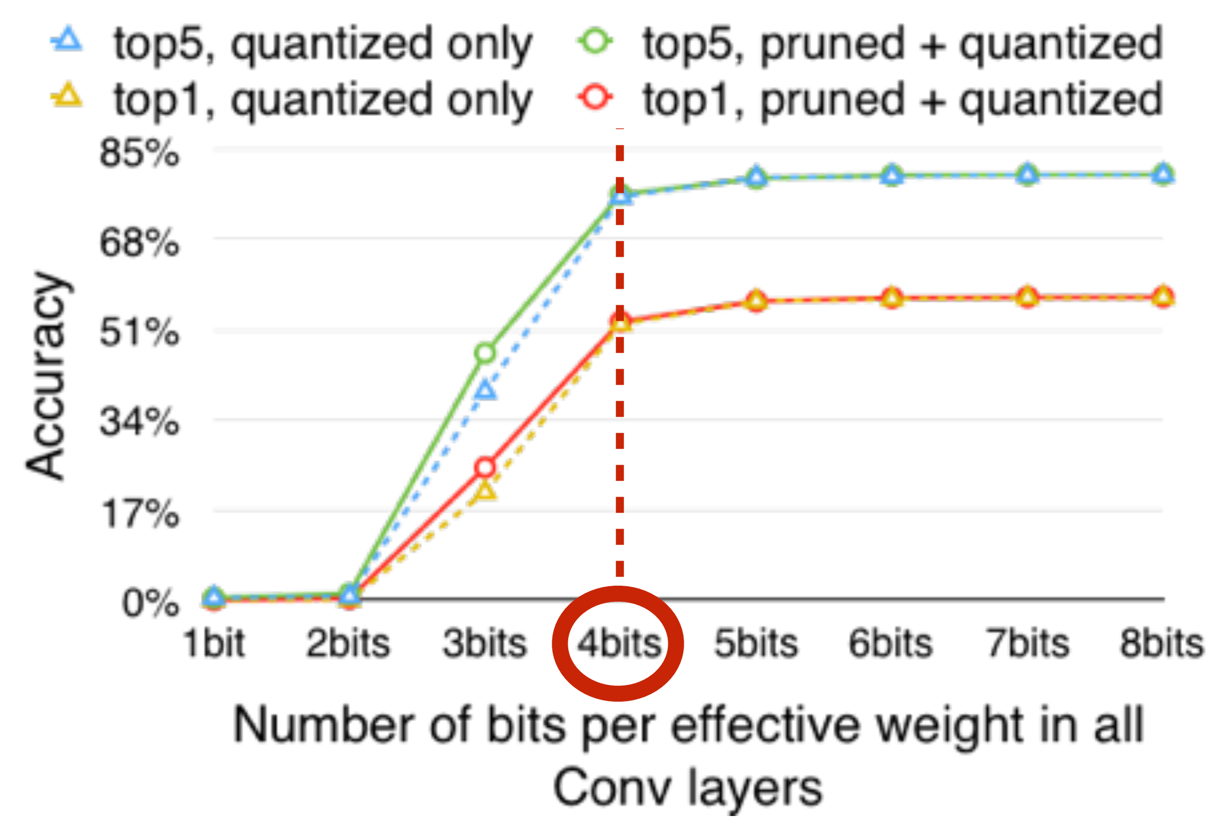
Bits Per Weight





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Pruning + Trained Quantization

#CONV bits / #FC bits	Top-1 Error	Top-5 Error	Top-1 Error Increase	Top-5 Error Increase
32bits / 32bits	42.78%	19.73%	-	-
8 bits / 5 bits	42.78%	19.70%	0.00%	-0.03%
8 bits / 4 bits	42.79%	19.73%	0.01%	0.00%
4 bits / 2 bits	44.77%	22.33%	1.99%	2.60%

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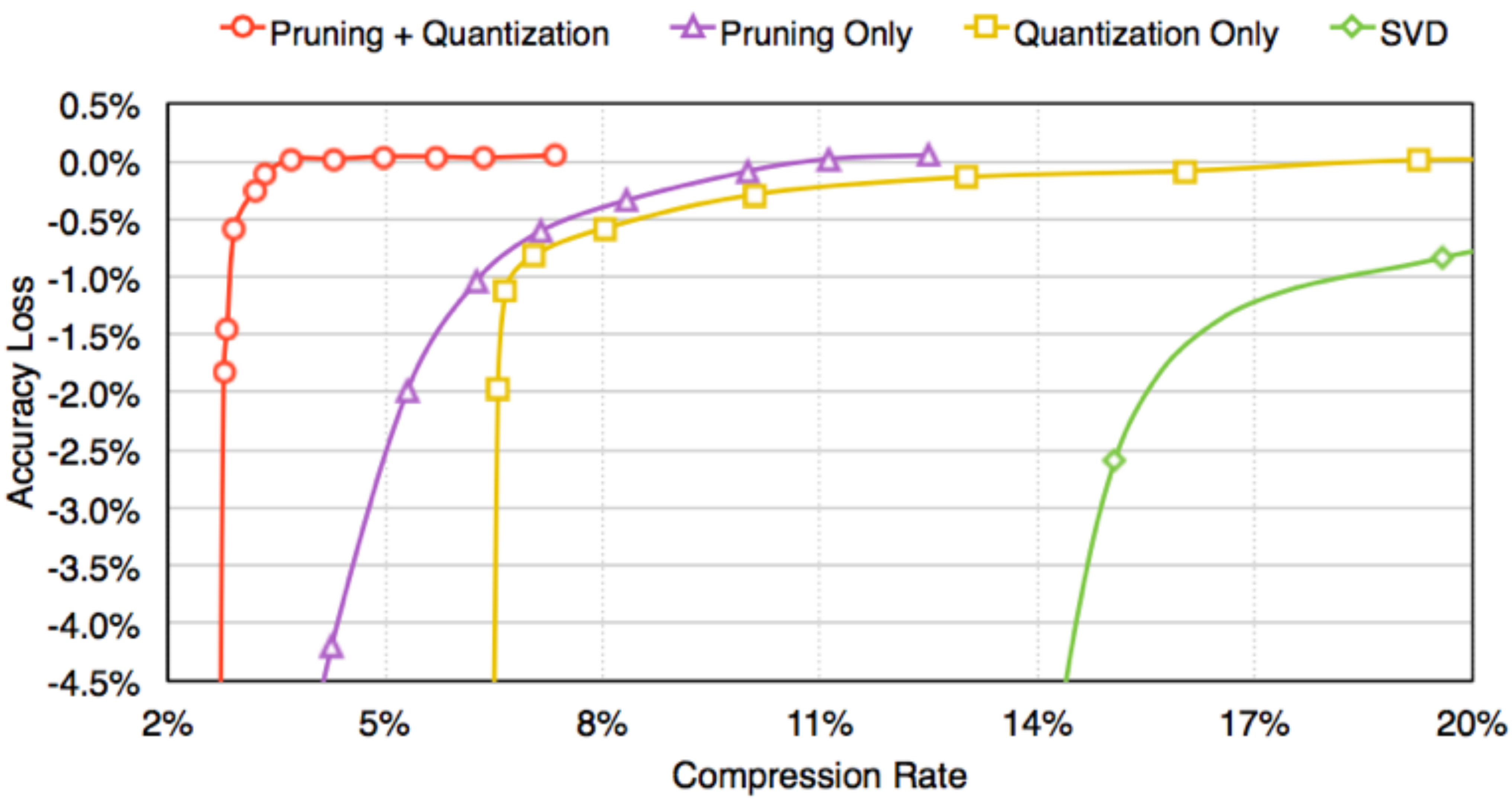

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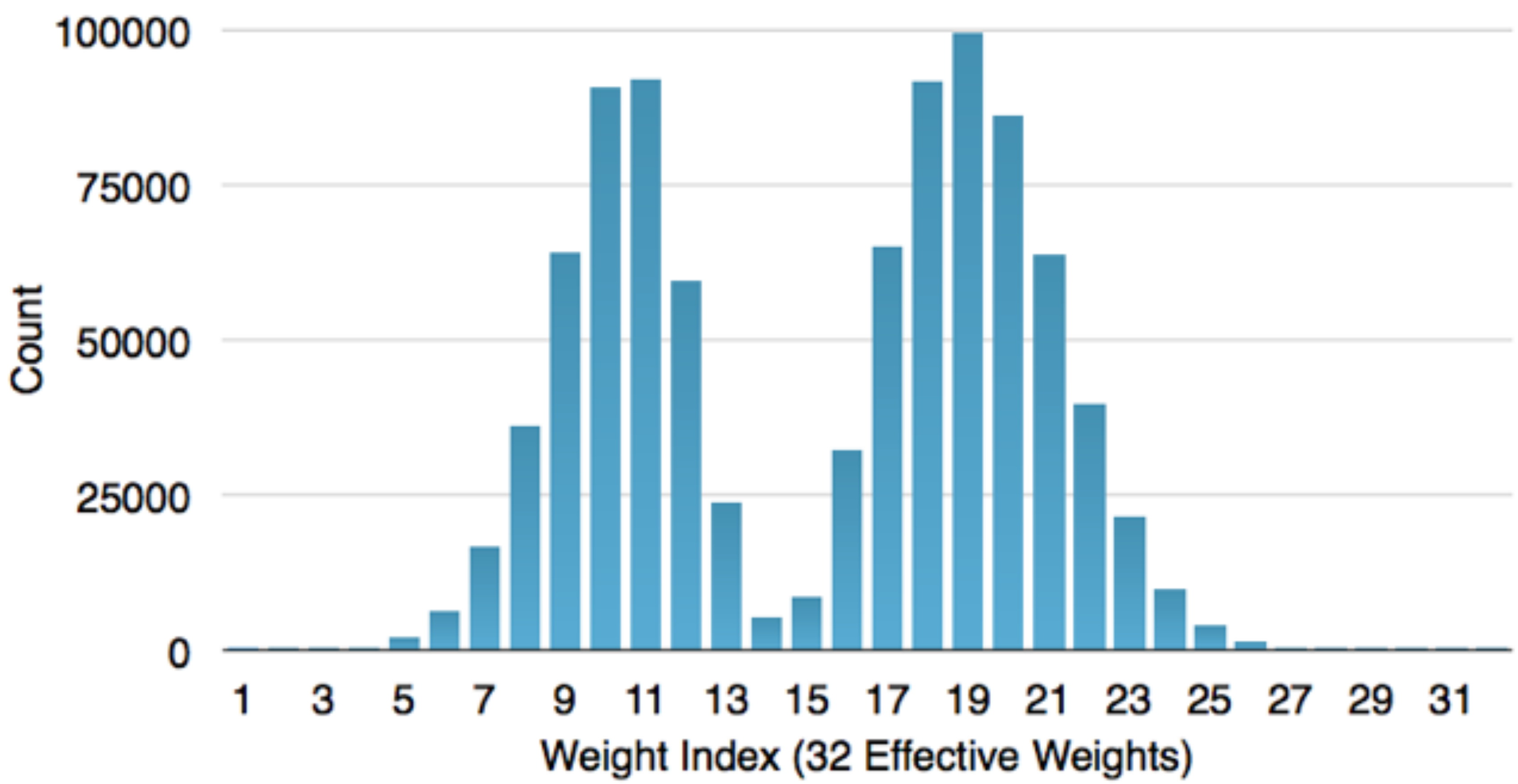
Han et al. "Deep Compression: Compressing Deep Neural Networks with Pruning, Trained Quantization and Huffman Coding", ICLR 2016

Huffman Coding



- Frequent weights: use less bits to represent
- In-frequent weights: use more bits to represent

Han et al. "Deep Compression: Compressing Deep Neural Networks with Pruning, Trained Quantization and Huffman Coding", ICLR 2016

Deep Compression Results

Network	Original Size	Compressed Size	Compression Ratio	Original Accuracy	Compressed Accuracy
LeNet-300	1070KB	→ 27KB	**40x**	98.36%	→ 98.42%
LeNet-5	1720KB	→ 44KB	**39x**	99.20%	→ 99.26%
AlexNet	240MB	→ 6.9MB	**35x**	80.27%	→ 80.30%
VGGNet	550MB	→ 11.3MB	**49x**	88.68%	→ 89.09%
GoogleNet	28MB	→ 2.8MB	**10x**	88.90%	→ 88.92%
SqueezeNet	4.8MB	→ 0.47MB	**10x**	80.32%	→ 80.35%

- No loss of accuracy after compression.
- Fits in SRAM cache (120x less energy than DRAM).

660KB model, AlexNet-accuracy

https://github.com/songhan/SqueezeNet_compressed

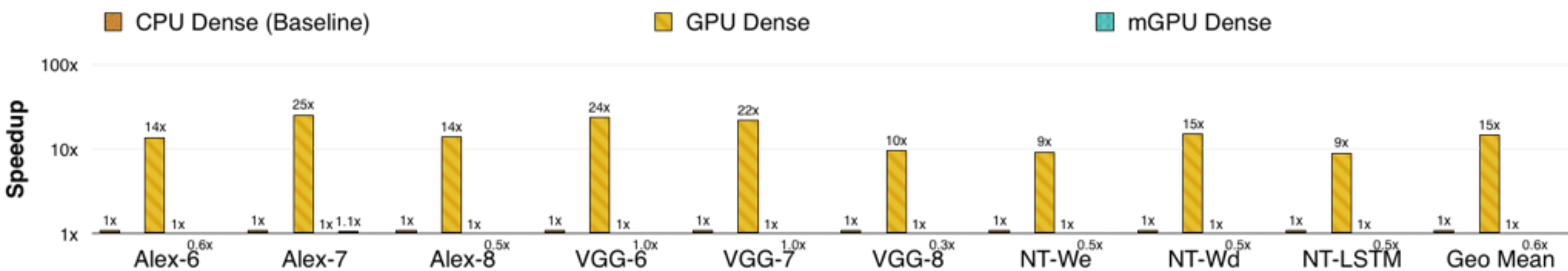
Iandola, Han,et al. “SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <1MB model size” arXiv 2016

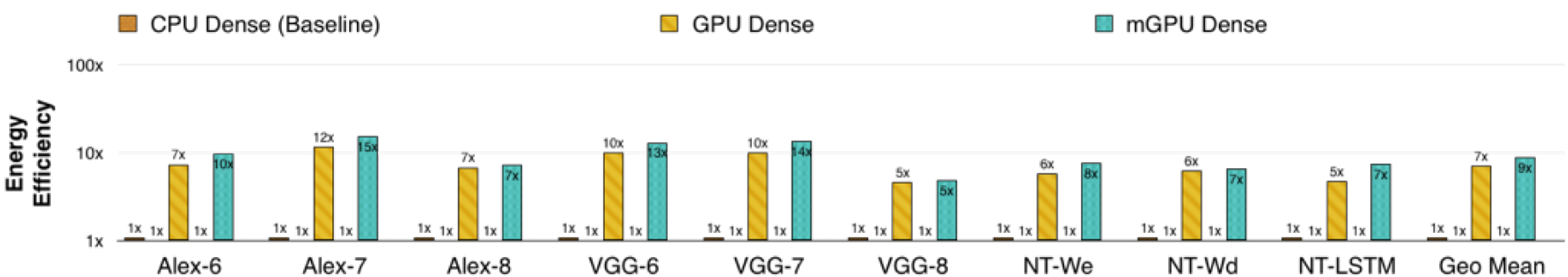
Conclusion

- **Complex DNNs can be put in mobile applications (<10MB total)**
  - 500MB with-FC network (125M weights) becomes 10MB
  - 10MB all-CONV network (2.5M weights) becomes 1MB
- **Memory bandwidth reduced by 10-50x**
  - Particularly for FC layers in real-time applications with no reuse
- **Faster Prediction**
  - Works well for sparsity level 10%-20%. Ads, Speech…

What happens once DNN size is so small that it fits in SRAM Cache?

Speedup/Energy Efficiency on CPU/GPU

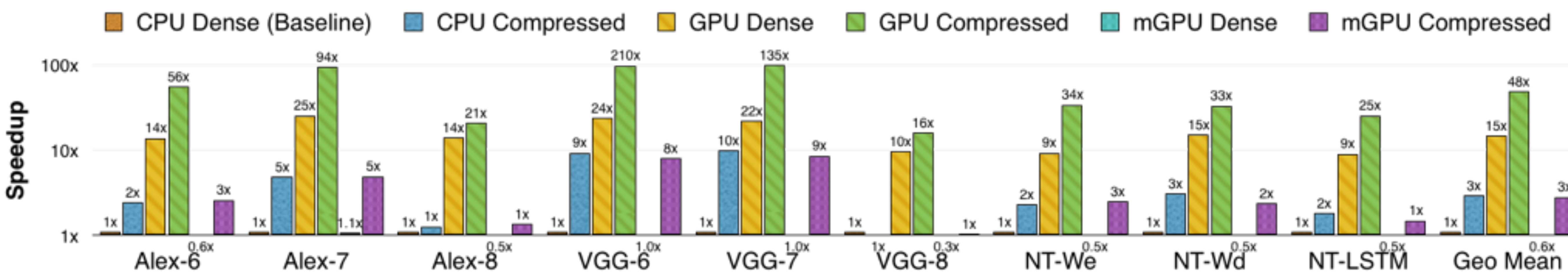


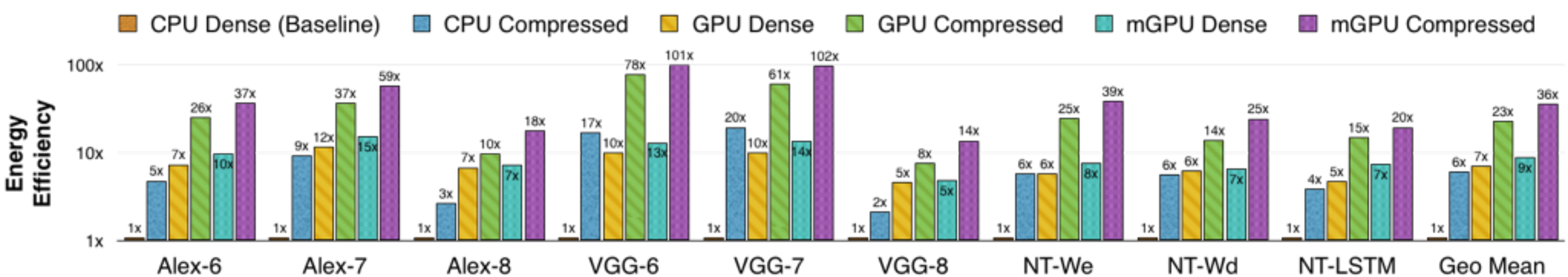


CPU: Core i-7 5930k; GPU: GTX TitanX ; mobile GPU: Tegra K1; All scenarios: batchsize = 1

Speedup/Energy Efficiency on CPU/GPU

Facebook is using this to speedup ads click prediction





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Part 2: EIE

Efficient Inference Engine on Compressed Deep Neural Network

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Han et al. “EIE: Efficient Inference Engine on Compressed Deep Neural Network”, ISCA 2016, Hotchips 2016

Problem 2: Faster, Energy Efficient

Han et al. “EIE: Efficient Inference Engine on Compressed Deep Neural Network”, ISCA 2016, Hotchips 2016

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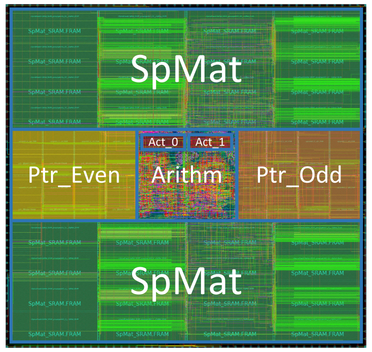
Solution 2: EIE accelerator

Han et al. “EIE: Efficient Inference Engine on Compressed Deep Neural Network”, ISCA 2016, Hotchips 2016

EIE: First Accelerator for Compressed Sparse Neural Network



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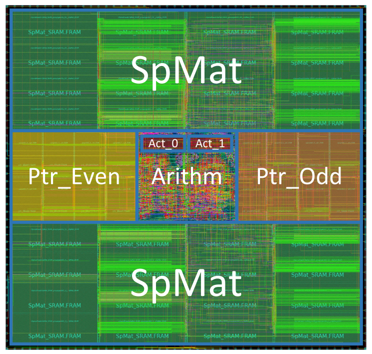

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Sparse Matrix

90% *static* sparsity
in the weights,
10x less computation,
5x less memory footprint

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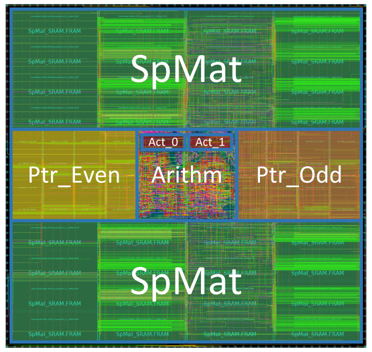

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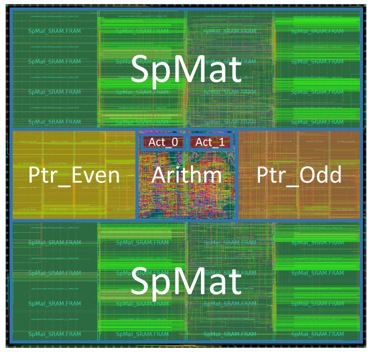

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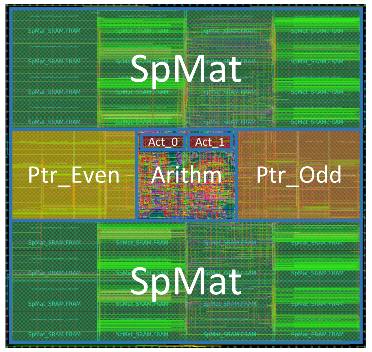

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Fully fits in SRAM

120x less energy than DRAM

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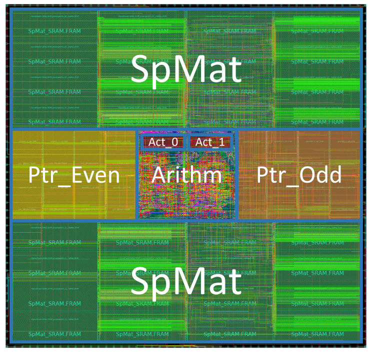

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Savings are **multiplicative**: 5x3x8x120=14,400 theoretical energy improvement.

Han et al. “EIE: Efficient Inference Engine on Compressed Deep Neural Network”, ISCA 2016, Hotchips 2016

Benchmark

- CPU: Intel Core-i7 5930k
- GPU: NVIDIA TitanX
- Mobile GPU: NVIDIA Jetson TK1

Layer	Size	Weight Density	Activation Density	FLOP %	Description
AlexNet-6	4096 × 9216	9%	35.1%	3%	AlexNet for image classification
AlexNet-7	4096 × 4096	9%	35.3%	3%	
AlexNet-8	1000 × 4096	25%	37.5%	10%	
VGG-6	4096 × 25088	4%	18.3%	1%	VGG-16 for image classification
VGG-7	4096 × 4096	4%	37.5%	2%	
VGG-8	1000 × 4096	23%	41.1%	9%	
NeuralTalk-We	600 × 4096	10%	100%	10%	RNN and LSTM for image caption
NeuralTalk-Wd	8791 × 600	11%	100%	11%	
NeuralTalk-LSTM	2400 × 1201	10%	100%	11%	

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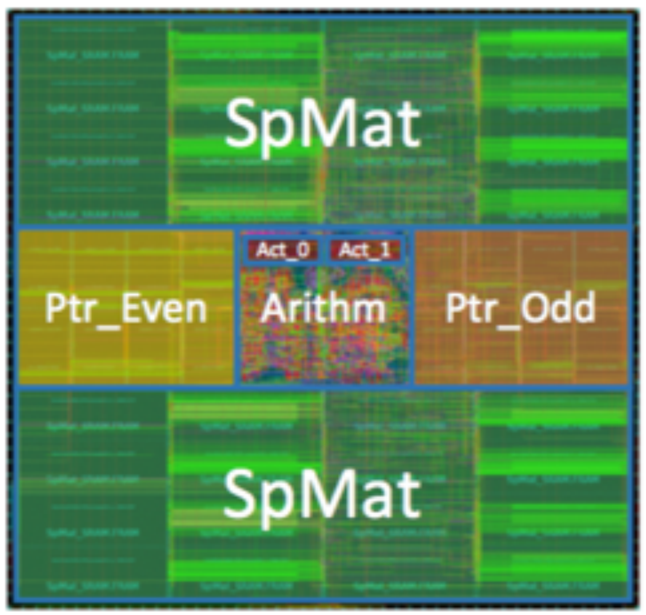
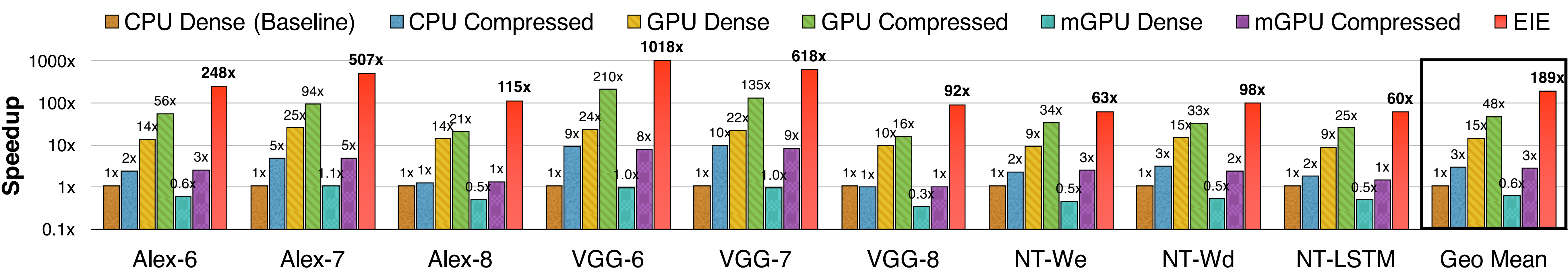
Result of EIE



Technology	45 nm
# PEs	64
on-chip SRAM	8 MB
Max Model Size	84 Million
Static Sparsity	10x
Dynamic Sparsity	3x
Quantization	4-bit
ALU Width	16-bit
Area	40.8 mm^2
MxV Throughput	81,967 layers/s
Power	586 mW

1. Post layout result
2. Throughput measured on AlexNet FC-7

Speedup on EIE



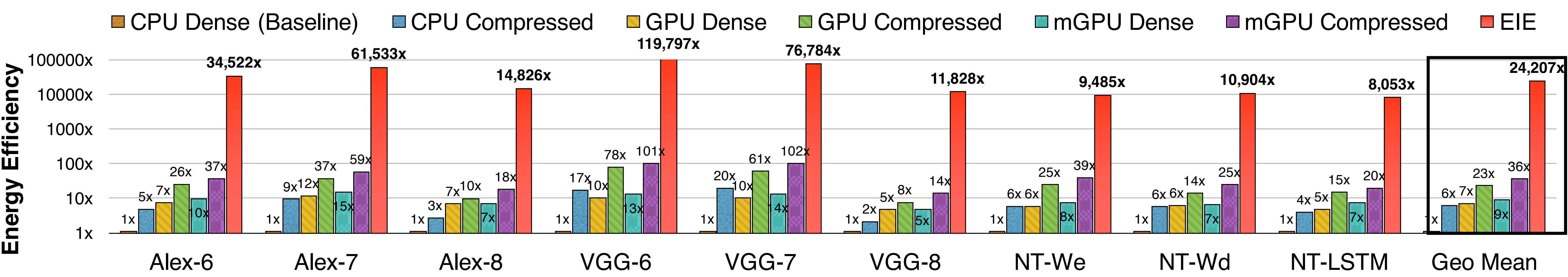
Compared to CPU and GPU:

189x and 13x faster

Baseline:

- Intel Core i7 5930K: MKL CBLAS GEMV, MKL SPBLAS CSRMV
- NVIDIA GeForce GTX Titan X: cuBLAS GEMV, cuSPARSE CSRMV
- NVIDIA Tegra K1: cuBLAS GEMV, cuSPARSE CSRMV

Energy Efficiency on EIE



Compared to CPU and GPU:

24,000x and 3,400x more energy efficient

Baseline:

- Intel Core i7 5930K: reported by pcm-power utility
- NVIDIA GeForce GTX Titan X: reported by nvidia-smi utility
- NVIDIA Tegra K1: measured with power-meter, 60% AP+DRAM power

Where are the savings from?

- Four factors for energy saving:

- **10× *static* weight sparsity;**
  less work to do; less bricks to carry.
- **3× *dynamic* activation sparsity;**
  carry only good bricks; ignore broken bricks.
- **Weight sharing with only 4-bits per weight;**
  lighter bricks to carry.
- **DRAM => SRAM, no need to go off-chip;**
  carry bricks from NY to Stanford => SF to Stanford.

Conclusion

- EIE: first accelerator for compressed, sparse neural network.
- Compression => Acceleration, no loss accuracy.
- Distributed storage/computation to parallelize/load balance across PEs.
- 13x faster and 3,400x more energy efficient than GPU.
  2.9x faster and 19x more energy efficient than past ASICs.