Edge Computing

Lecture 06: Quantization and Pruning

Recap

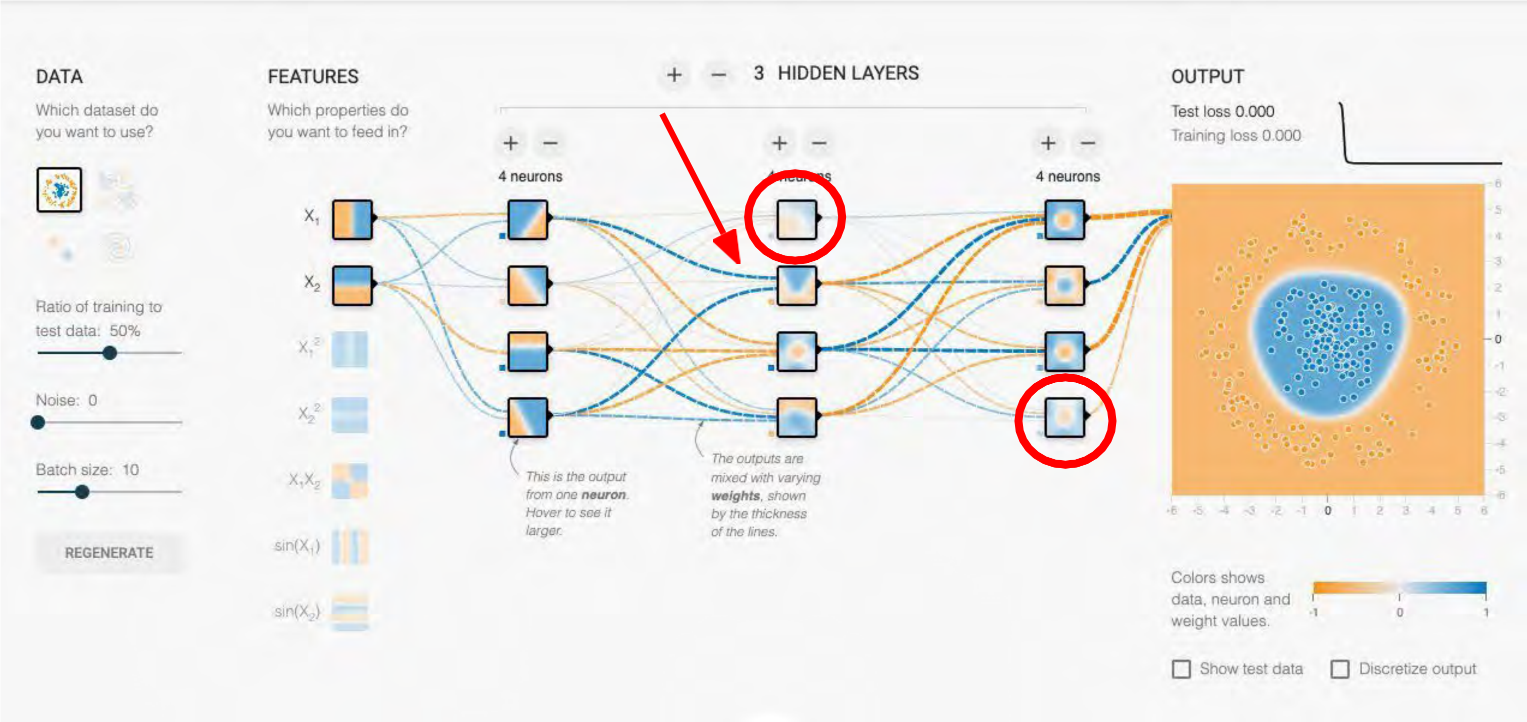
- Neural network: terminology
  - Neuron, Synapse, Activation, Weight, etc.
- Common building block: layer
  - FC, Conv, Conv2D, Depthwise Conv
  - Receptive field, padding, strides
  - Pooling, Normalization
- Convolution neural network
  - Alexnet, VGG16, MobileNetv2
  - Tensorflow, Tensorflow Lite

Agenda

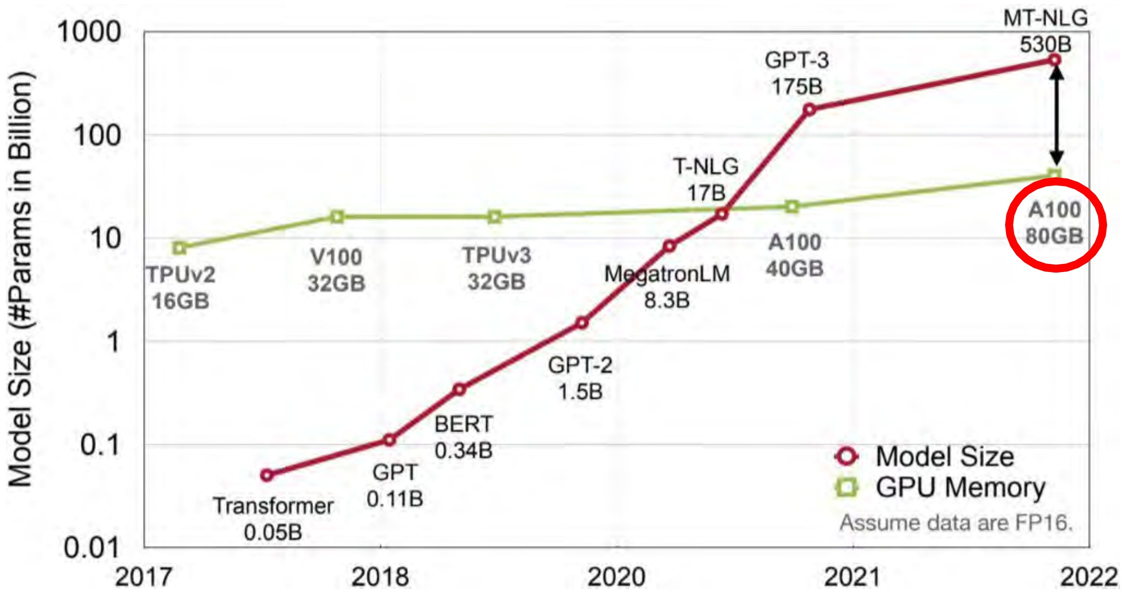
- Pruning
  - What and why?
  - How? Pruning criterion
  - Fine-tune/retrain acceleration
- Quantization
  - What and why?
  - Linear quantization
  - Quantization granularity
  - Calibration and Clipping

What is Pruning?

- Shrinking models by removing synapses and neurons.



Why pruning?



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Why pruning? Model Footprint

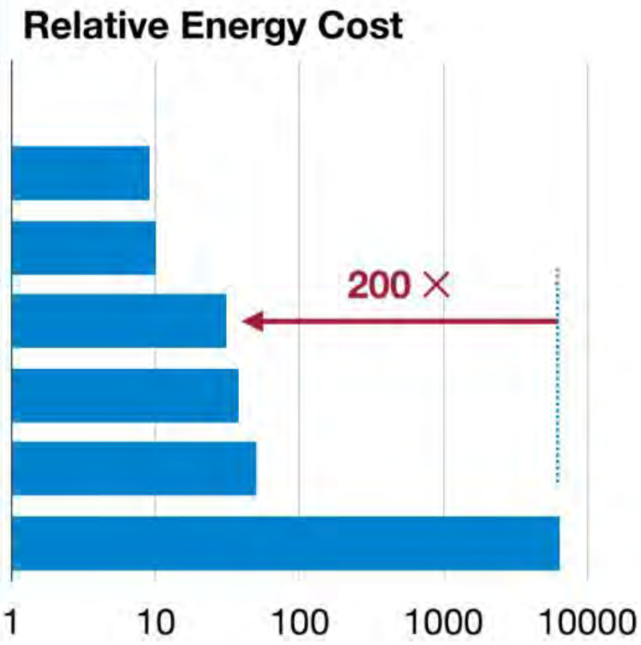
- Nvidia Jetson
    - Custom boards vs Dev boards

https://connecttech.com/jetson/jetson-module-comparison/ & Song, Han, EfficientML.ai

Why pruning? Energy

Operation	Energy [pJ]
32 bit int ADD	0.1
32 bit float ADD	0.9
32 bit Register File	1
32 bit int MULT	3.1
32 bit float MULT	3.7
32 bit SRAM Cache	5
32 bit DRAM Memory	640

Rough Energy Cost For Various Operations in 45nm 0.9V



Computing's Energy Problem (and What We Can Do About it) [Horowitz, M., IEEE ISSCC 2014]

Smaller network, will it work?

- MAC, Multiply-ACCumulation operations ~ FLOPS

Neural Network	#Parameters			MACs
	Before Pruning	After Pruning	Reduction	Reduction
AlexNet	61 M	6.7 M	**9** ×	3 ×
VGG-16	138 M	10.3 M	**12** ×	5 ×
GoogleNet	7 M	2.0 M	**3.5** ×	5 ×
ResNet50	26 M	7.47 M	**3.4** ×	6.3 ×
SqueezeNet	1 M	0.38 M	**3.2** ×	3.5 ×

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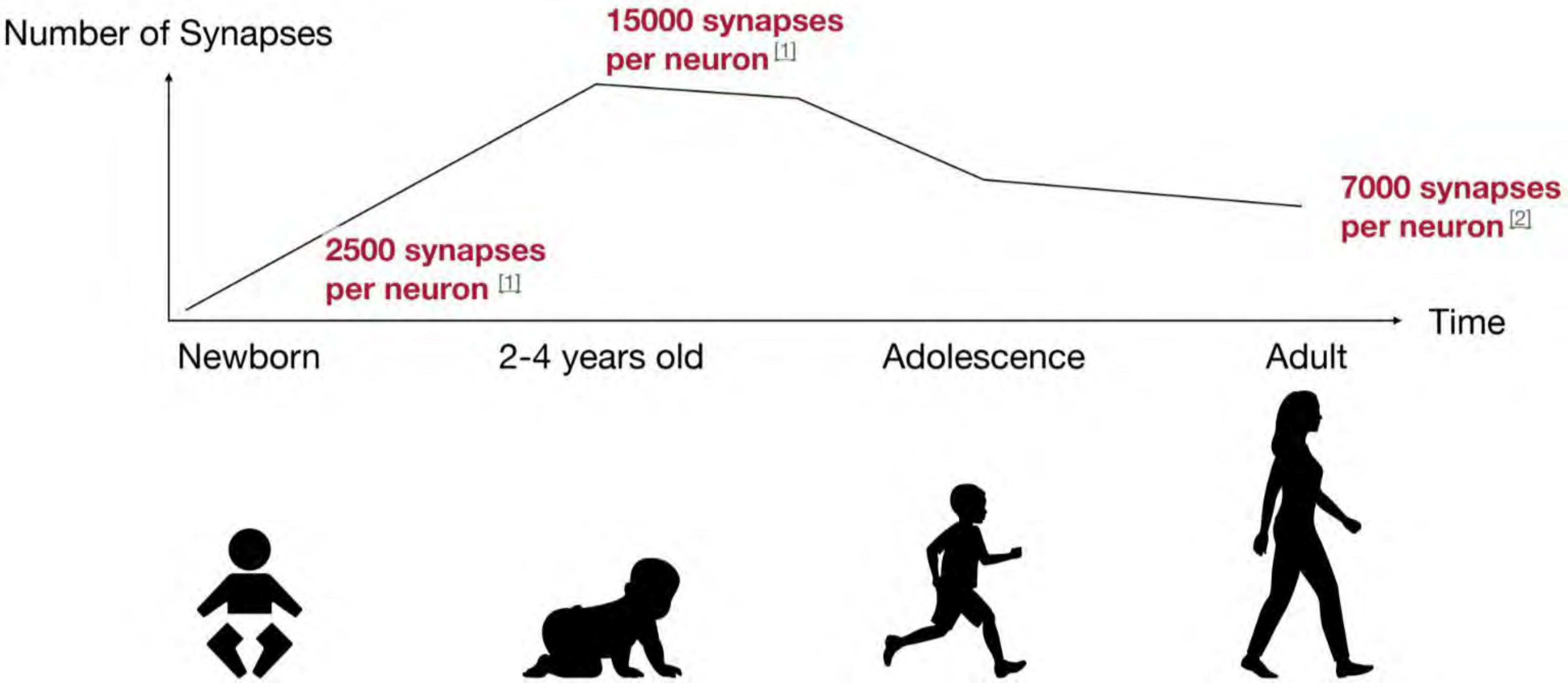
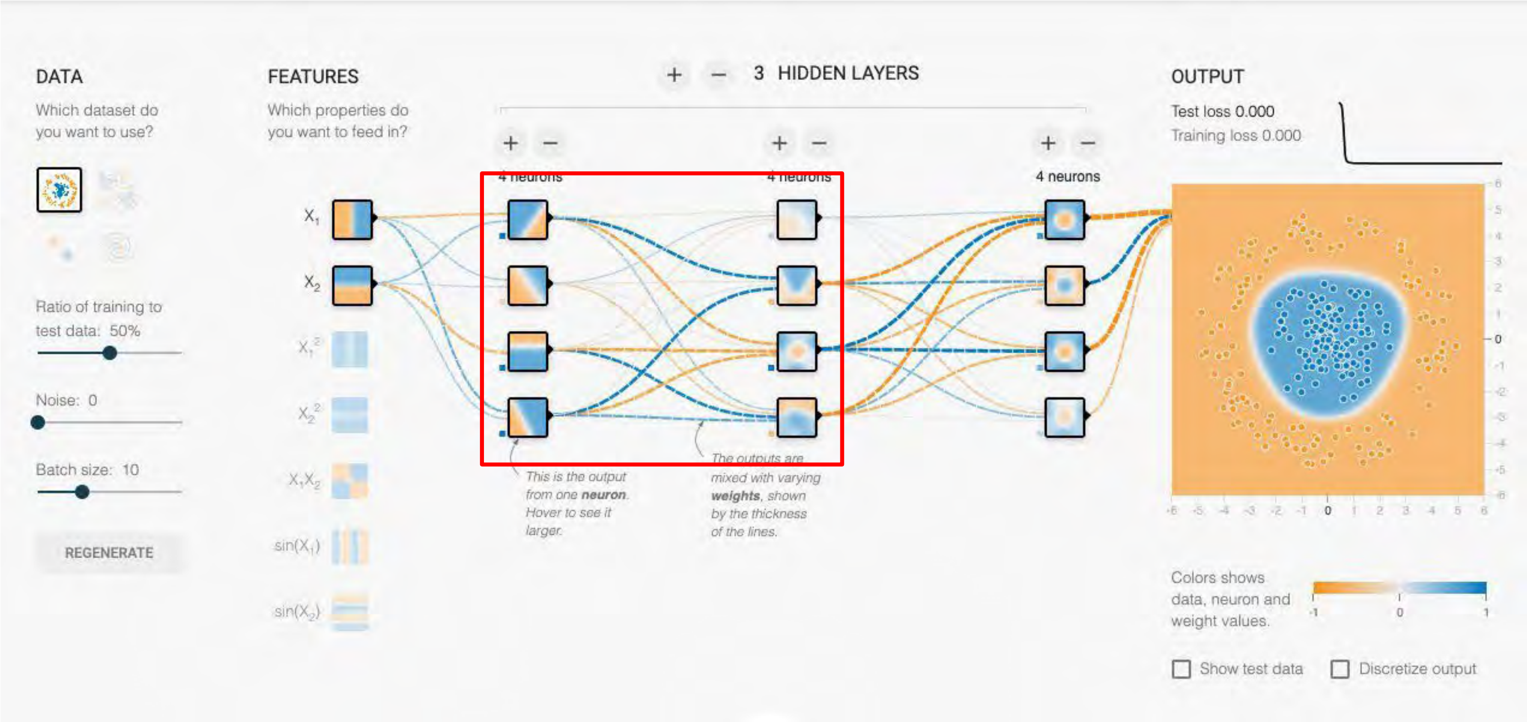
Human brain prunes too!

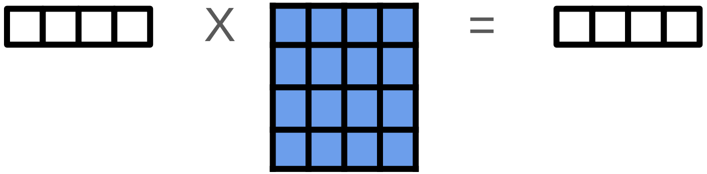


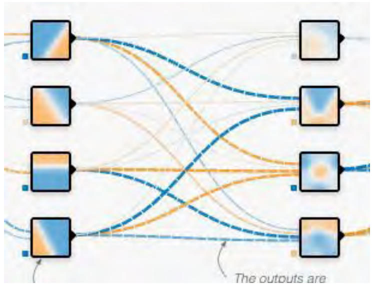
How to prune?



DATA
Which dataset do you want to use?
Ratio of training to test data: 50%
Noise: 0
Batch size: 10
REGENERATE
FEATURES
Which properties do you want to feed in?
3 HIDDEN LAYERS
4 neurons
4 neurons
4 neurons
This is the output from one **neuron**. Hover to see it larger.
The outputs are mixed with varying **weights**, shown by the thickness of the lines.
OUTPUT
Test loss 0.000
Training loss 0.000
Colors shows data, neuron and weight values.
Show test data
Discretize output

How to prune?





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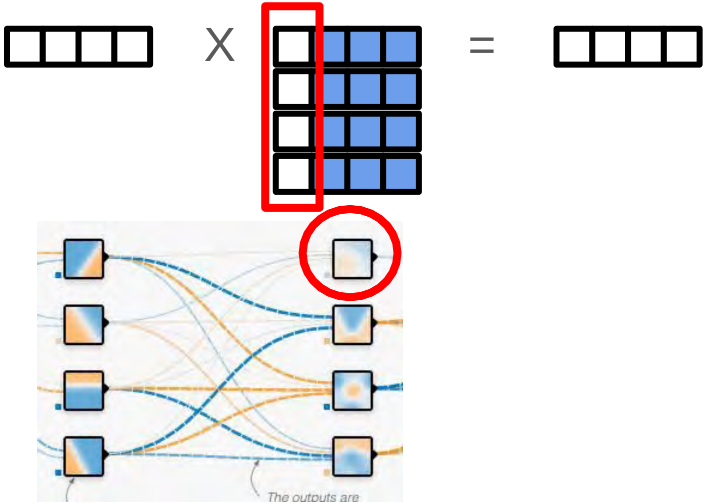

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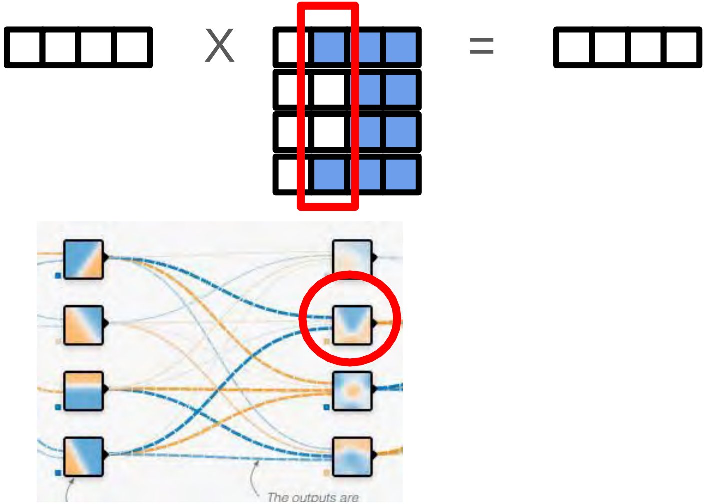

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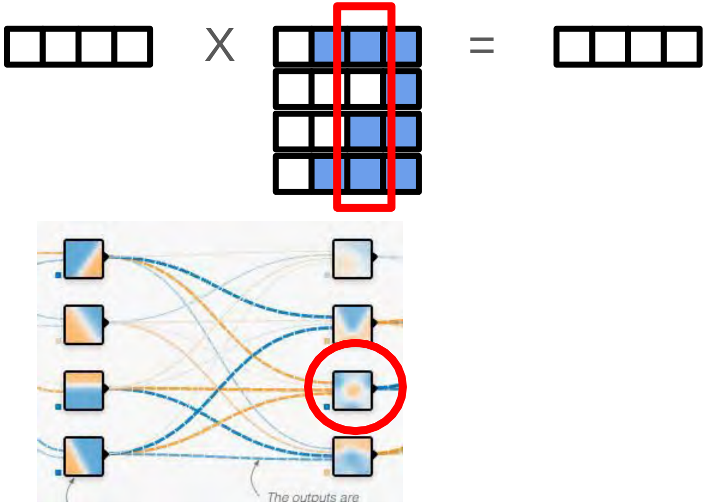

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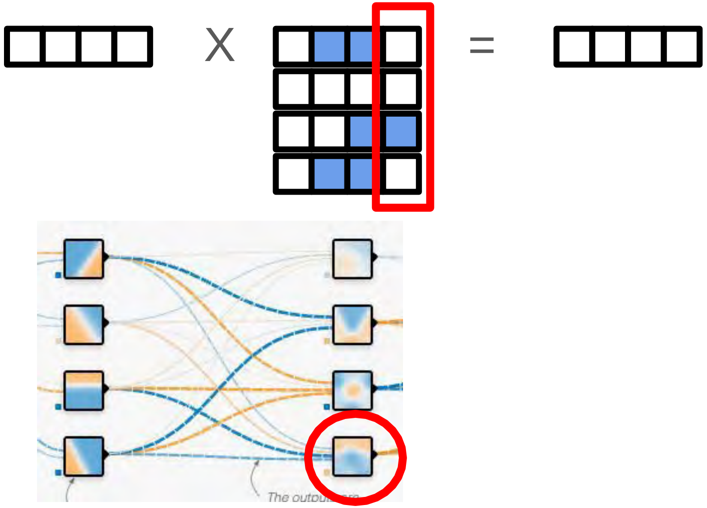

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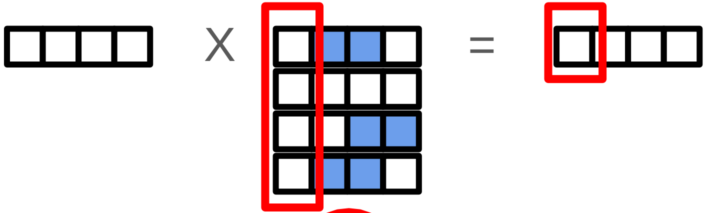

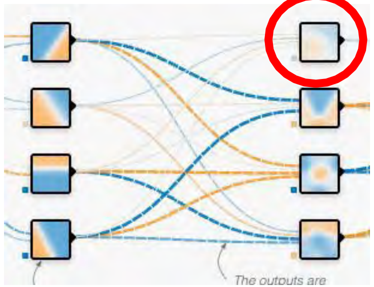

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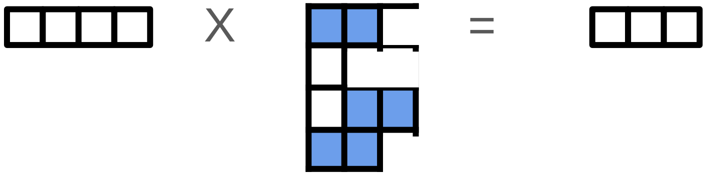

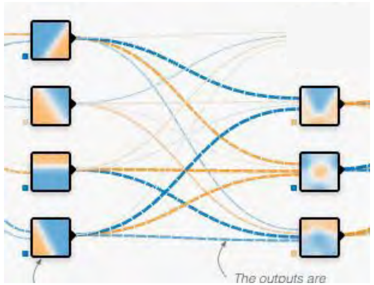

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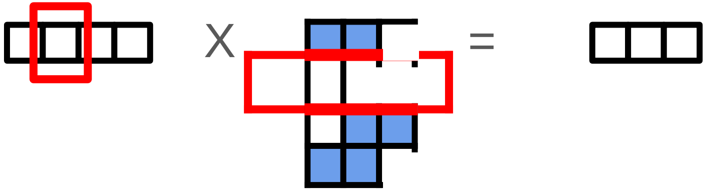

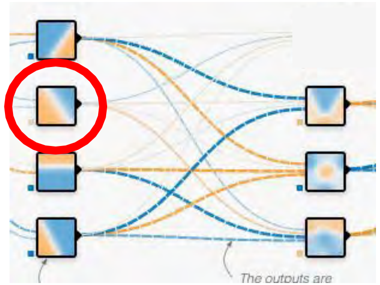

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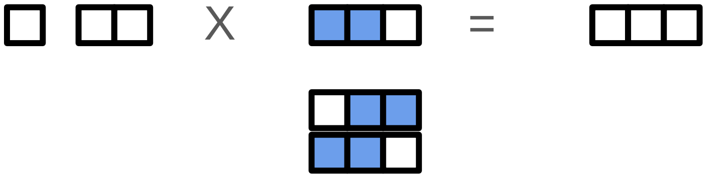

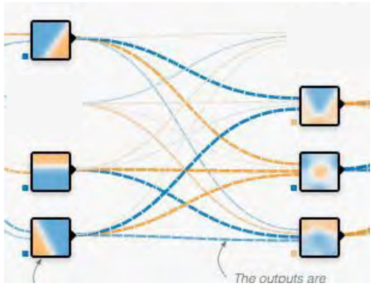

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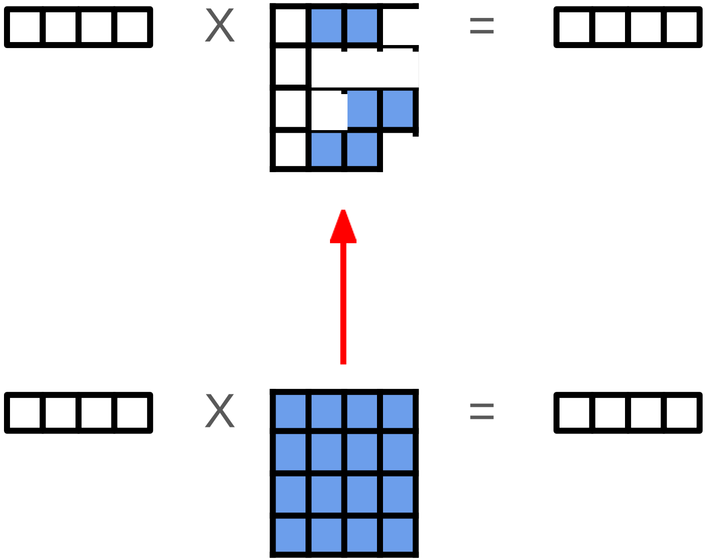
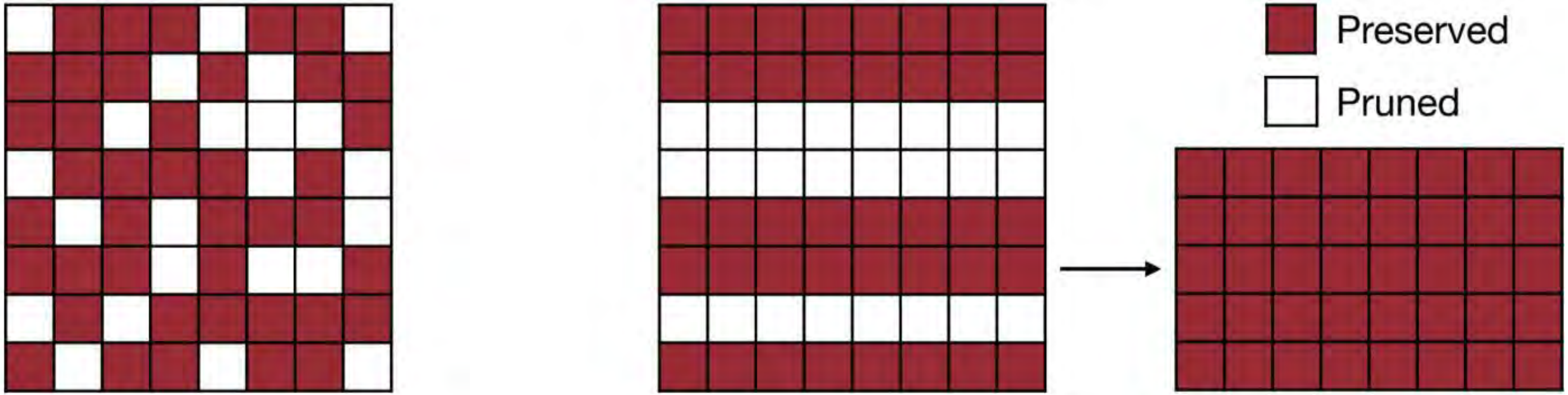


Pruning Granularity



Fine-grained/Unstructured

- More flexible pruning index choice
- Hard to accelerate (irregular)

Coarse-grained/Structured

- Less flexible pruning index choice (a subset of the fine-grained case)
- Easy to accelerate (just a smaller matrix!)

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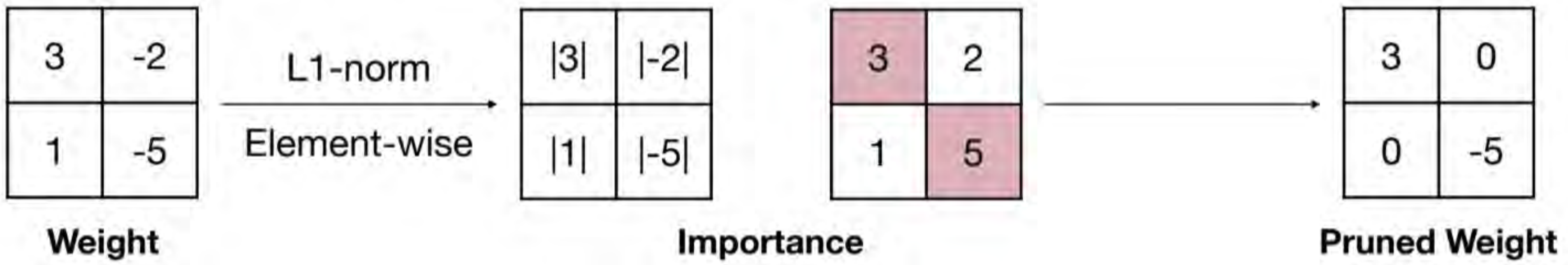
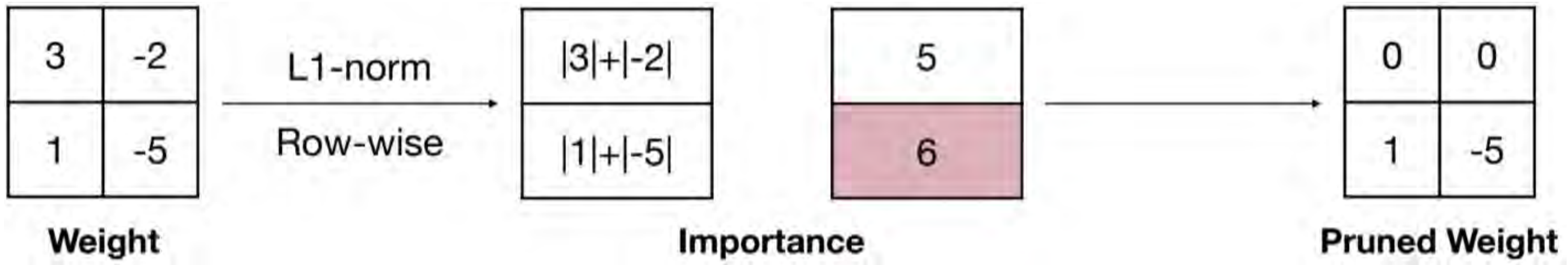
Magnitude-based Pruning

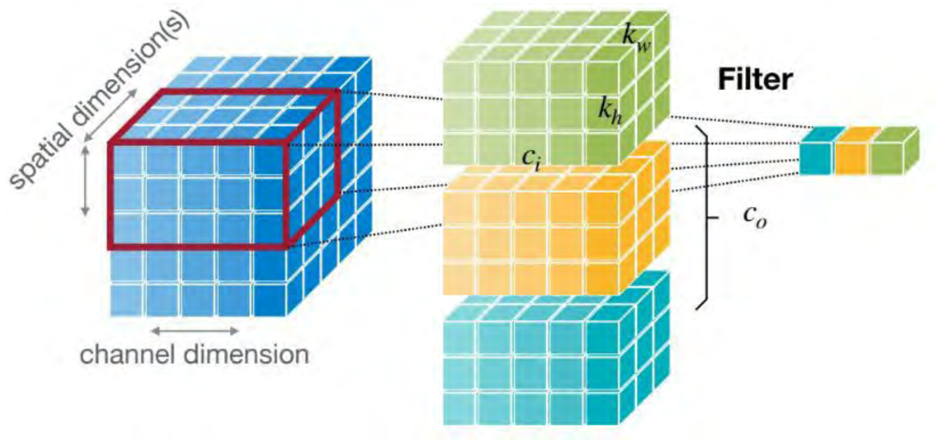
- Fine-grained



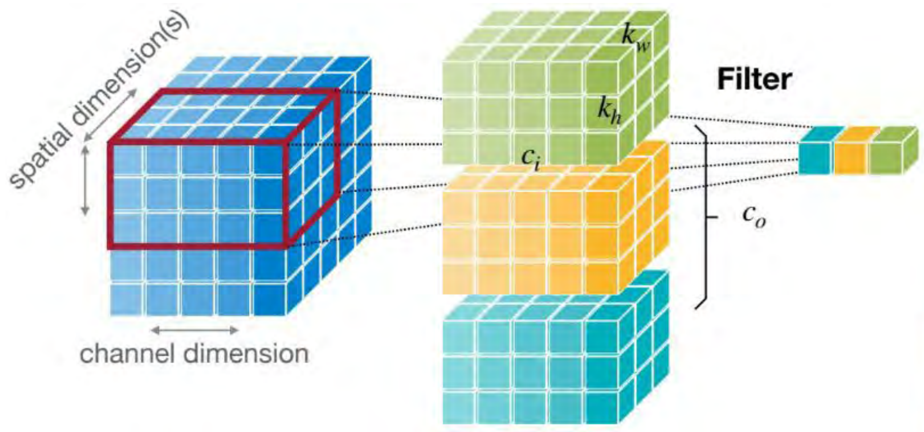
- Coarse-grained / structured

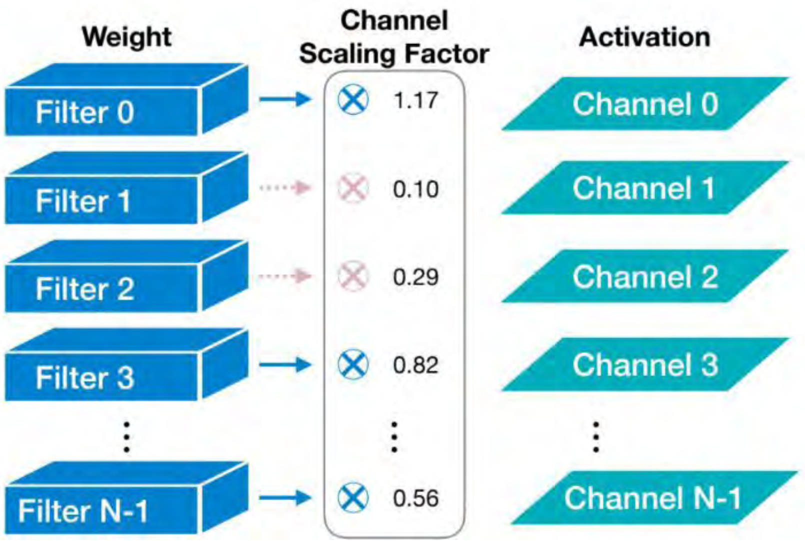


How to prune CNN?



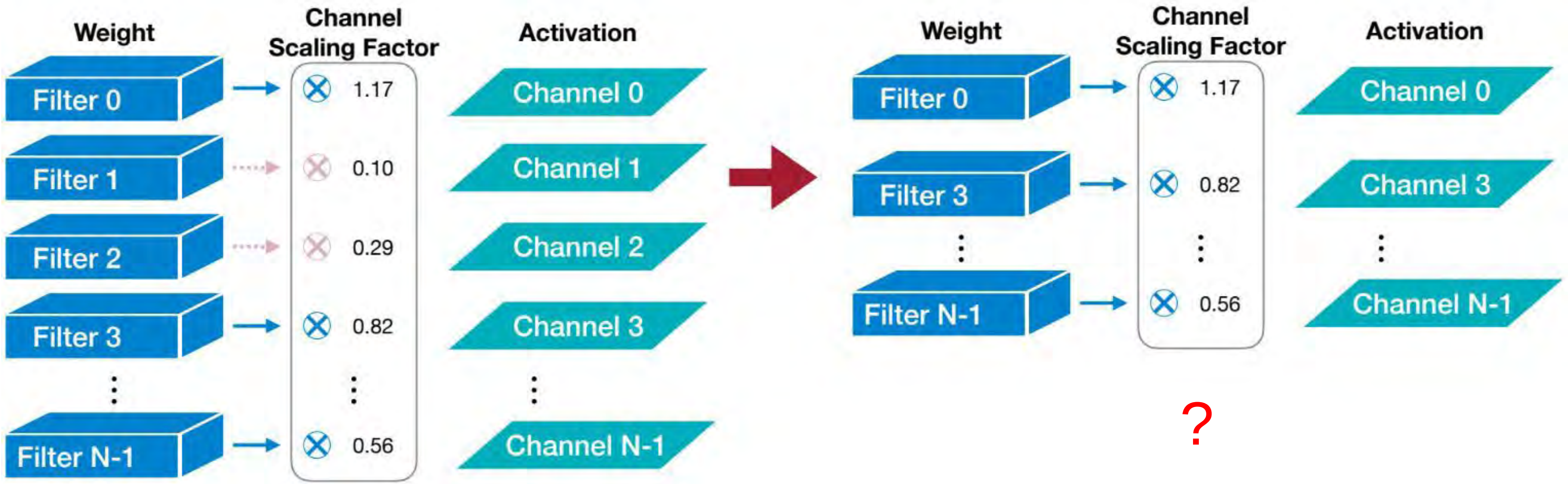
Scaling-based Pruning





Learning Efficient Convolutional Networks through Network Slimming [Liuet al.,ICCV 2017]

Scaling-based Pruning



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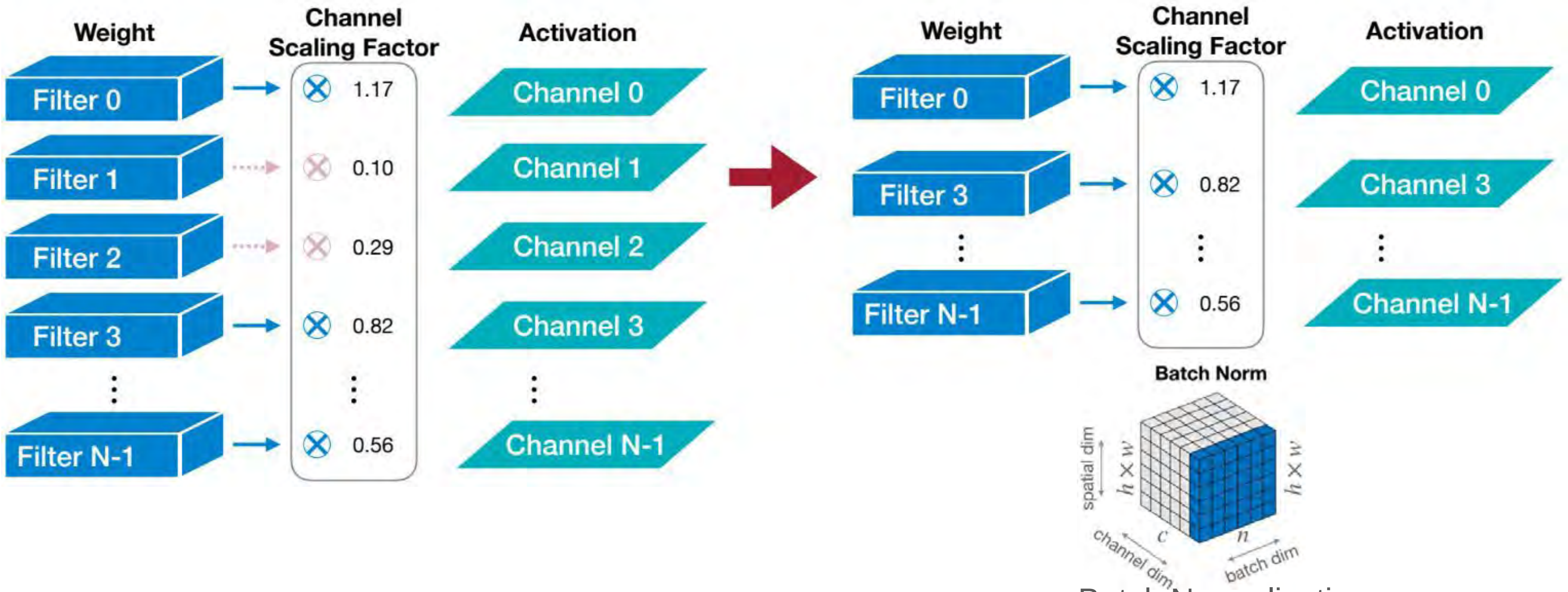
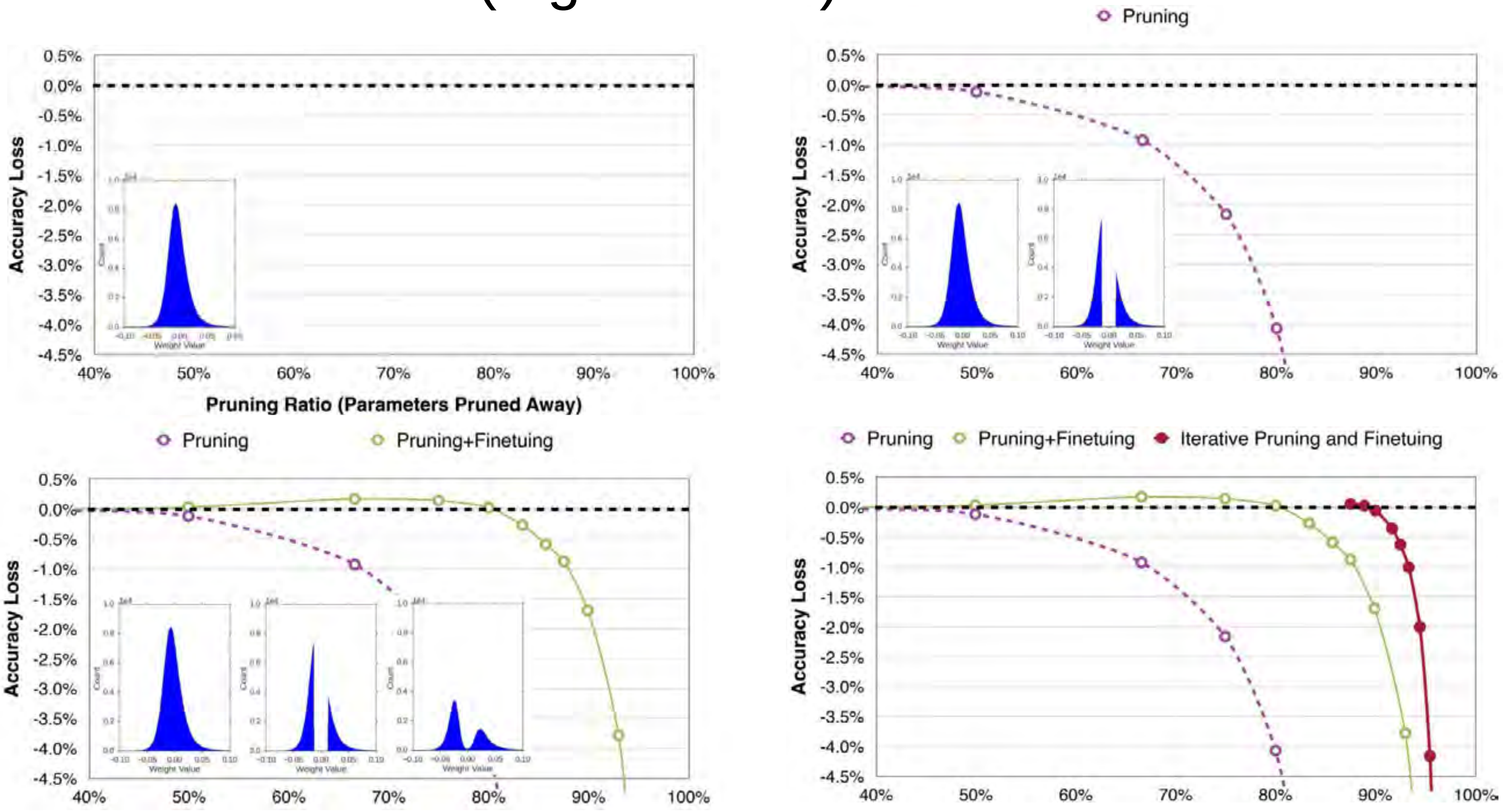


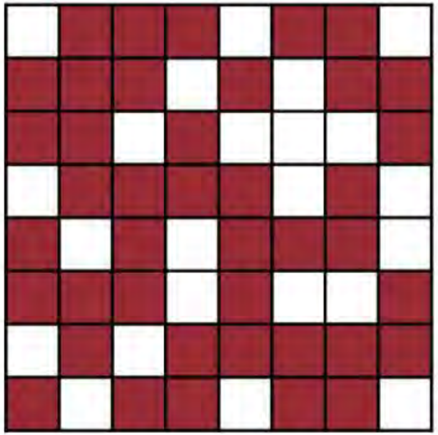
Batch Normalization scaling factor

Learning Efficient Convolutional Networks through Network Slimming [Liuet al.,ICCV 2017]

Fine-tune/Retrain (e.g. AlexNet)



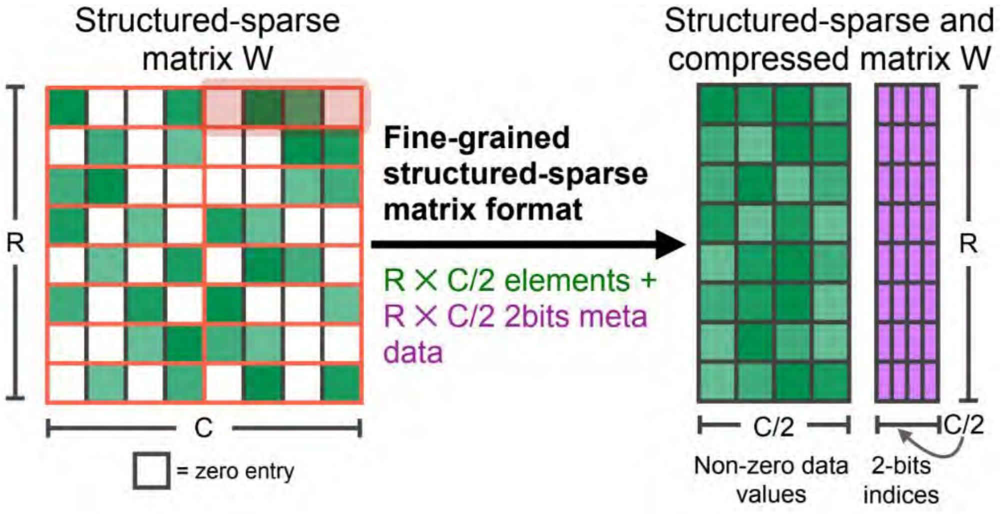
Q: How to accelerate irregular pruning?



Fine-grained/Unstructured

- More flexible pruning index choice
- Hard to accelerate (irregular)

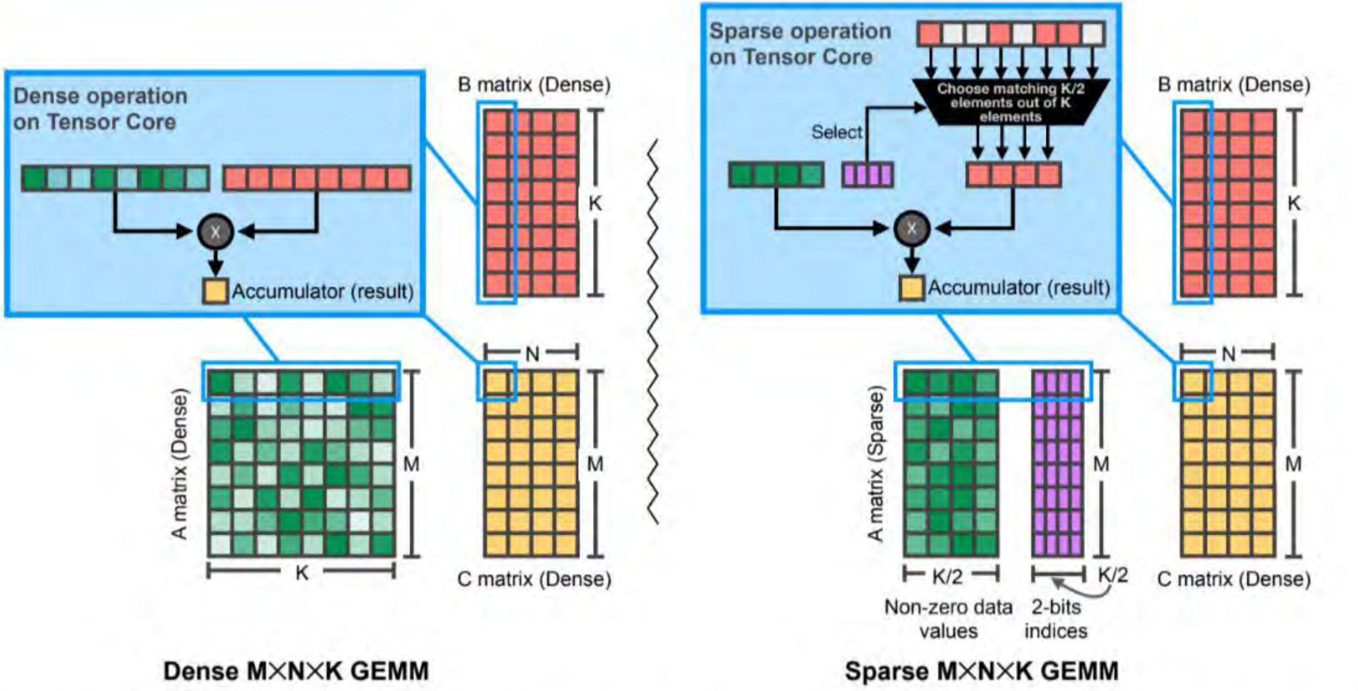
M:N Sparsity



Two weights are nonzero out of four consecutive weights (2:4 sparsity).

Accelerating Sparse Deep Neural Networks[Mishraet al.,arXiv 2021

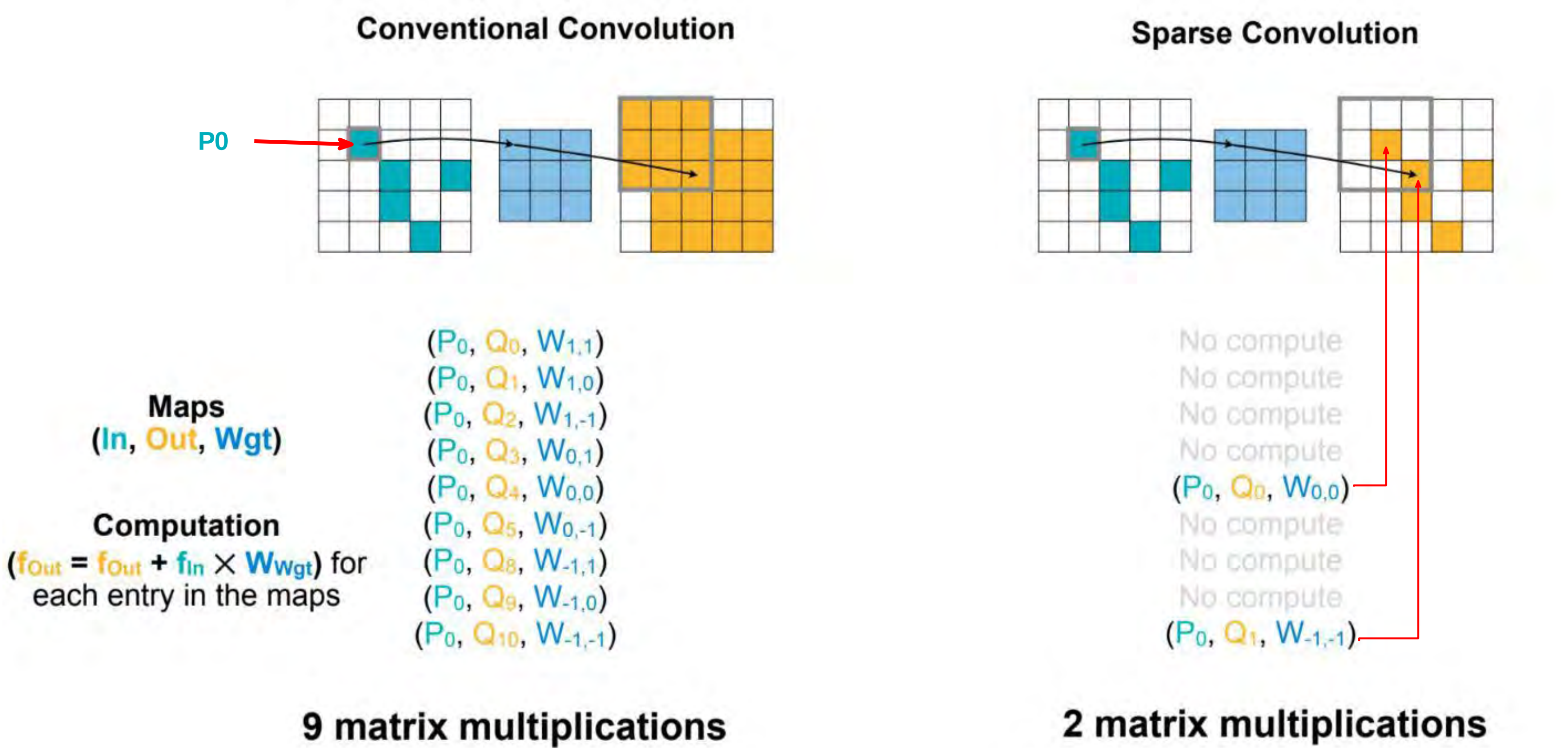
M:N Sparsity



The indices are used to mask out the inputs. Only 2 multiplications will be done out of four.

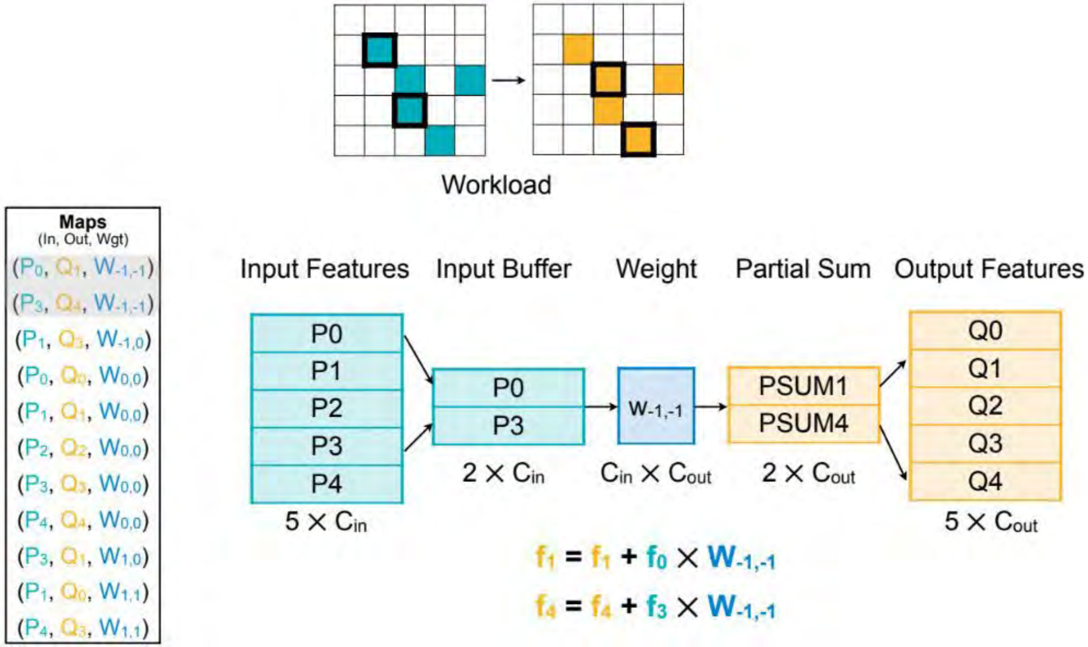
Accelerating Sparse Deep Neural Networks[Mishraet al.,arXiv 2021

Sparse Conv



TorchSparse: Efficient Point Cloud Inference Engine [Tanget al., MLSys 2022]

Sparse Conv



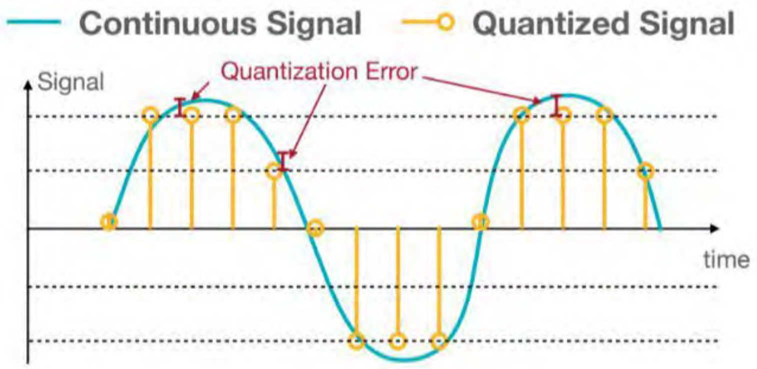
TorchSparse: Efficient Point Cloud Inference Engine [Tanget al., MLSys 2022]

Agenda

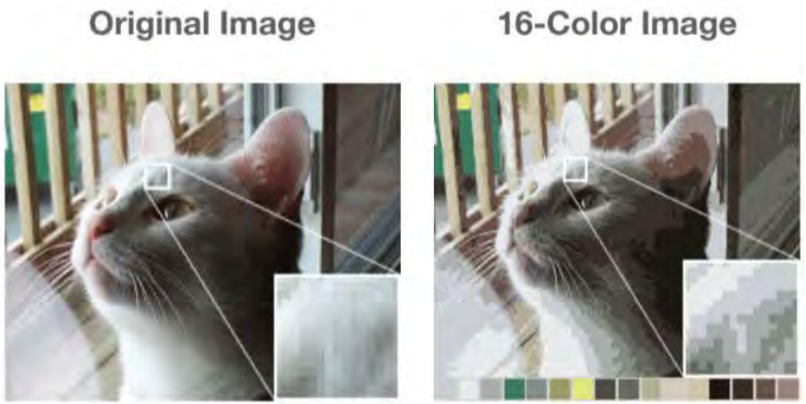
- Pruning
    - What and why?
    - How? Pruning criterion
    - Fine-tune/retrain acceleration
- Quantization
    - What and why?
    - Linear quantization
    - Quantization granularity
    - Calibration and Clipping

What is quantization?

- Quantization is the process of constraining an input from a continuous or otherwise large set of values to a discrete set.



The difference between an input value and its quantized value is referred to as quantization error.



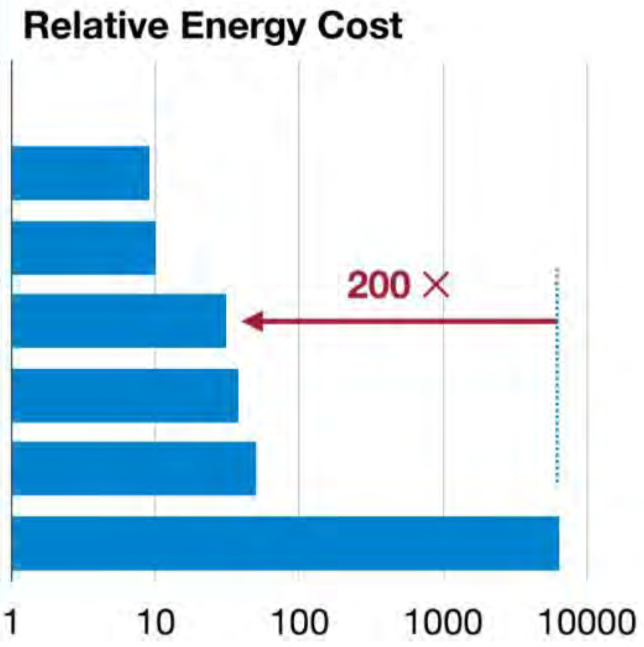
Images are in the public domain.

"Palettization"

Why quantization? Small footprint & low energy

Operation	Energy [pJ]
32 bit int ADD	0.1
32 bit float ADD	0.9
32 bit Register File	1
32 bit int MULT	3.1
32 bit float MULT	3.7
32 bit SRAM Cache	5
32 bit DRAM Memory	640

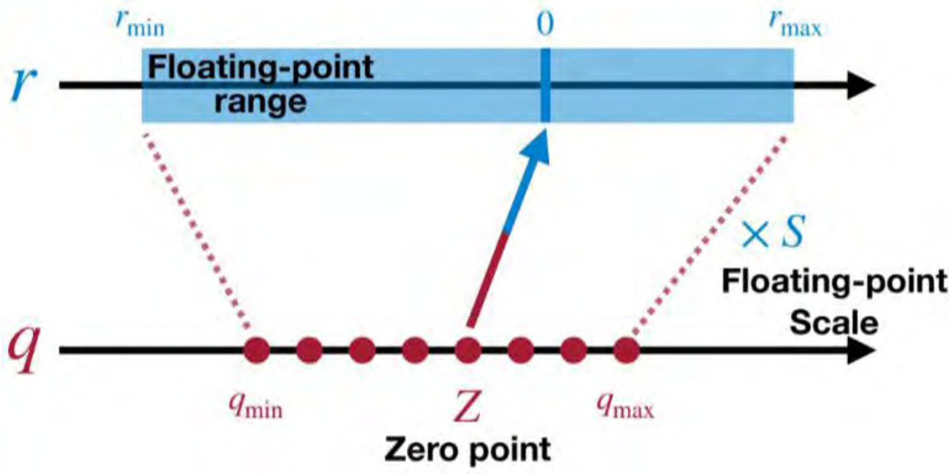
Rough Energy Cost For Various Operations in 45nm 0.9V



Computing's Energy Problem (and What We Can Do About it) [Horowitz, M., IEEE ISSCC 2014]

Linear Quantization

- An affine mapping of integers to real numbers
  - R = S(q-Z)



$$S = \frac{r_{max} - r_{min}}{q_{max} - q_{min}}$$

$$Z = \text{round}\left(q_{min} - \frac{r_{min}}{S}\right)$$

$$r_{max} = S\left(q_{max} - Z\right)$$

$$r_{min} = S\left(q_{min} - Z\right)$$

Linear Quantization: Example

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

Bit Width	q_{min}	q_{max}
2	-2	1
3	-4	3
4	-8	7
N	-2^{N-1}	$2^{N-1}-1$

$$r_{\max} = S\left(q_{\max} - Z\right)$$

$$r_{\min} = S\left(q_{\min} - Z\right)$$

$$S = \frac{r_{\max} - r_{\min}}{q_{\max} - q_{\min}}$$

$$Z = \mathrm{round}\left(q_{\min} - \frac{r_{\min}}{S}\right)$$

Linear Quantization: Example

2.09	-0.98	1.48	0.09
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S = (2.12 - (-1.08)) / (1 - (-2))
= 1.07

Z = round (-2 - -1.08 / 1.07)
= -1

$$r_{\max} = S\left(q_{\max} - Z\right)$$

$$r_{\min} = S\left(q_{\min} - Z\right)$$

$$S = \frac{r_{\max} - r_{\min}}{q_{\max} - q_{\min}}$$

$$Z = \text{round}\left(q_{\min} - \frac{r_{\min}}{S}\right)$$

Bit Width	q_{min}	q_{max}
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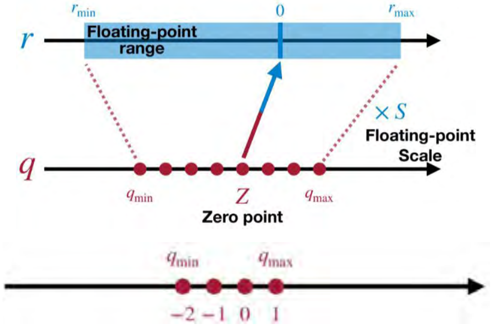


Linear Quantization

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

⇨ (quantized weights (2-bit signed int) − zero point (2-bit signed int)) × scale (32-bit float) = reconstructed weights (32-bit float)

quantized weights (2-bit signed int)

1	-2	0	-1
-1	-1	-2	1
-2	1	-1	-2
1	-1	0	0

zero point (2-bit signed int): -1

scale (32-bit float): 1.07

reconstructed weights (32-bit float)

2.14	-1.07	1.07	0
0	0	-1.07	2.14
-1.07	2.14	0	-1.07
2.14	0	1.07	1.07

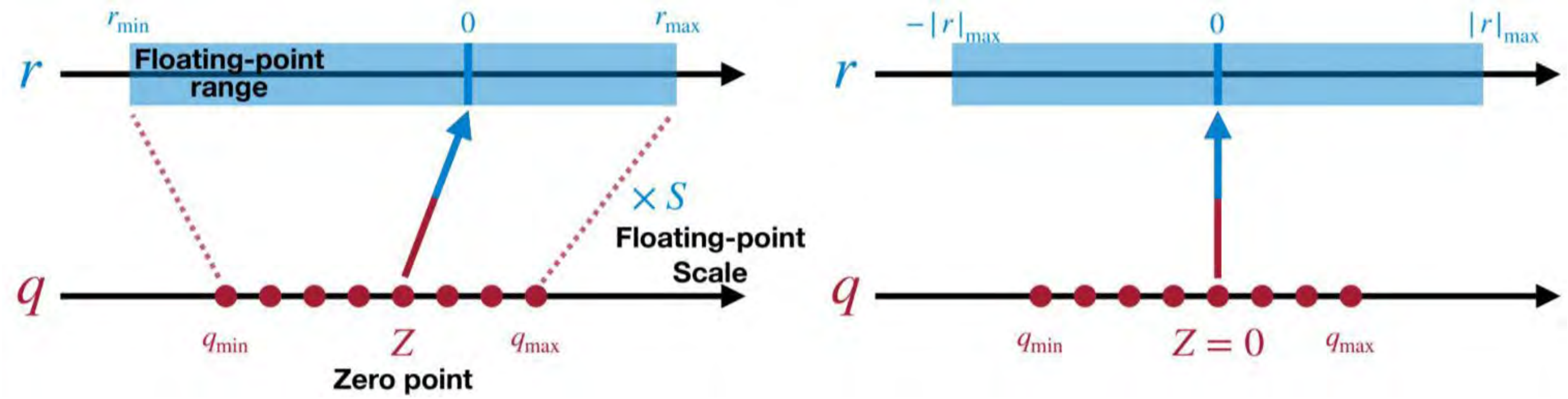
quantization error

-0.05	0.09	0.41	0.09
0.05	-0.14	-0.01	-0.02
0.16	-0.22	0	0.04
-0.27	0	0.46	0.42

$q = \text{round}(r / S + Z)$

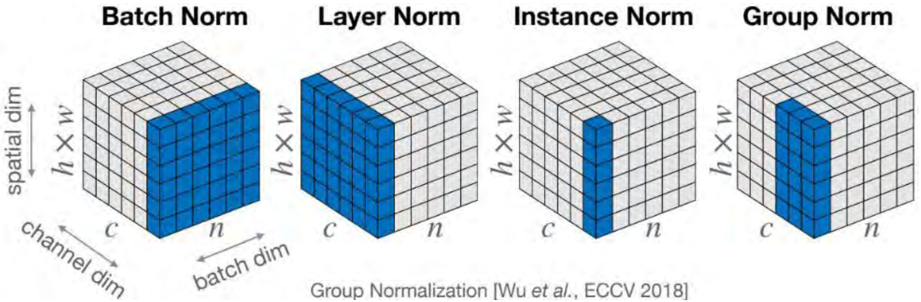
Binary	Decimal
01	1
00	0
11	-1
10	-2

Symmetric Linear Quantization



Quantization Granularity

- Per-tensor quantization
- Per-channel quantization
- Group quantization



Group Normalization [Wu *et al.*, ECCV 2018]

Per-channel vs Per-tensor

$$
\begin{array}{c|cccc}
 & & ic & & \\
\hline
 & 2.09 & -0.98 & 1.48 & 0.09 \\
oc & 0.05 & -0.14 & -1.08 & 2.12 \\
 & -0.91 & 1.92 & 0 & -1.03 \\
 & 1.87 & 0 & 1.53 & 1.49
\end{array}
$$

Per-Channel Quantization

$|r|_{\max} = 2.09 \quad S_0 = 2.09$

$|r|_{\max} = 2.12 \quad S_1 = 2.12$

$|r|_{\max} = 1.92 \quad S_2 = 1.92$

$|r|_{\max} = 1.87 \quad S_3 = 1.87$

1	0	1	0
0	0	-1	1
0	1	0	-1
1	0	1	1

Quantized

2.09	0	2.09	0
0	0	-2.12	2.12
0	1.92	0	-1.92
1.87	0	1.87	1.87

Reconstructed

$$\|\mathbf{W} - \mathbf{S} \odot \mathbf{q_W}\|_F = 2.08$$

<

Per-Tensor Quantization

$$|r|_{\max} = 2.12$$

$$S = \frac{|r|_{\max}}{q_{\max}} = \frac{2.12}{2^{2-1} - 1} = 2.12$$

1	0	1	0
0	0	-1	1
0	1	0	0
1	0	1	1

Quantized

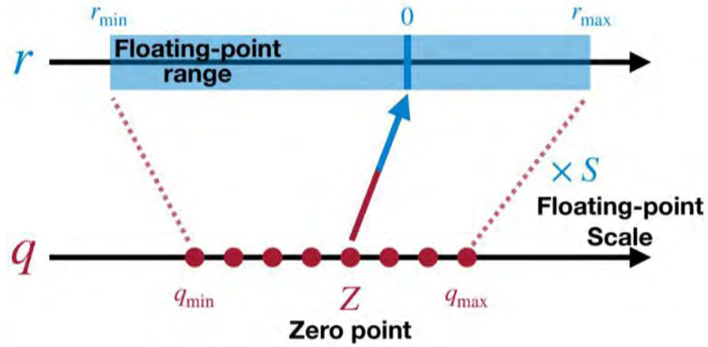
2.12	0	2.12	0
0	0	-2.12	2.12
0	2.12	0	0
2.12	0	2.12	2.12

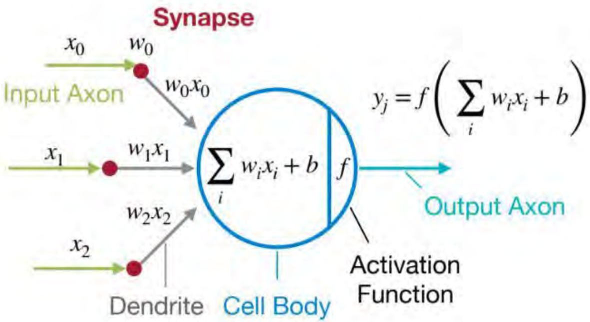
Reconstructed

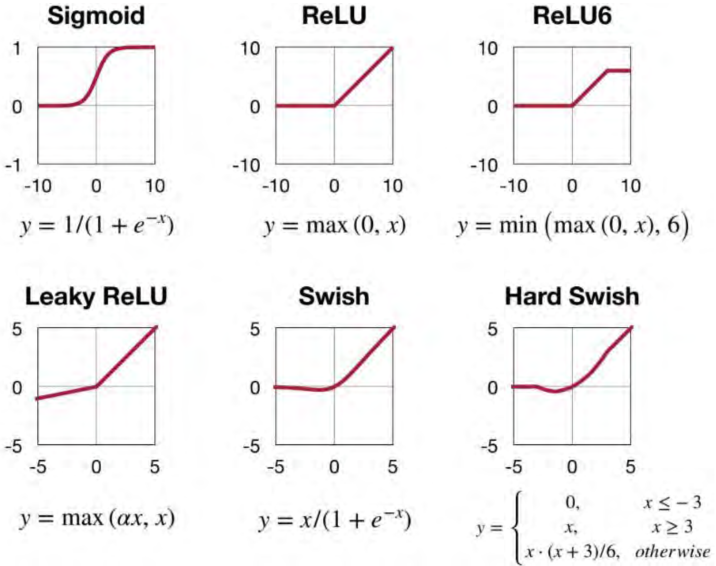
$$\|\mathbf{W} - S\mathbf{q_W}\|_F = 2.28$$

Non-static Dynamic Range

- Weights has [r_min,r_max] fixed range
- Activation value has unknown range
    - depends on input
- How to determine r_min and r_max?

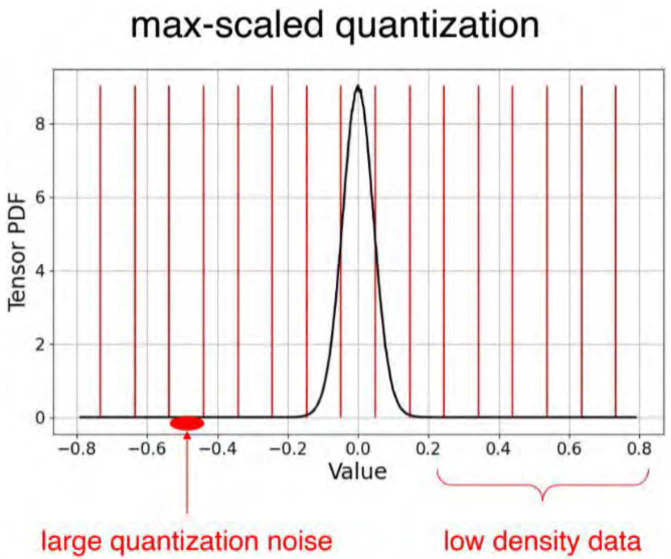


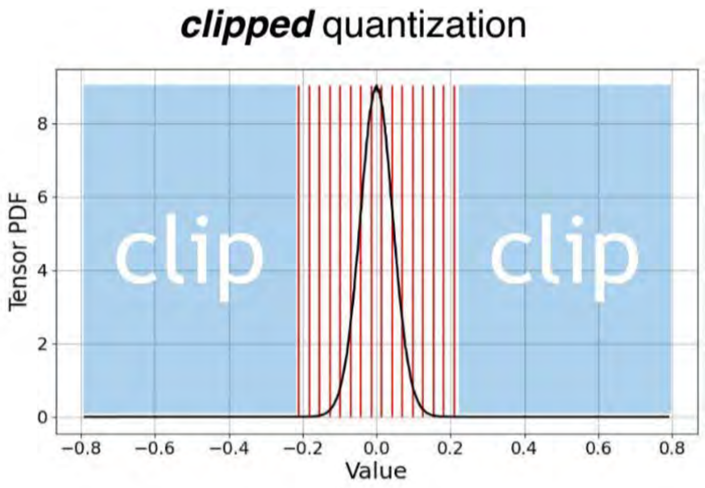




Dynamic Range: Calibration & Clipping

- Run a batch of samples
- Get the statistical distribution of activations
- Get rid of outliers





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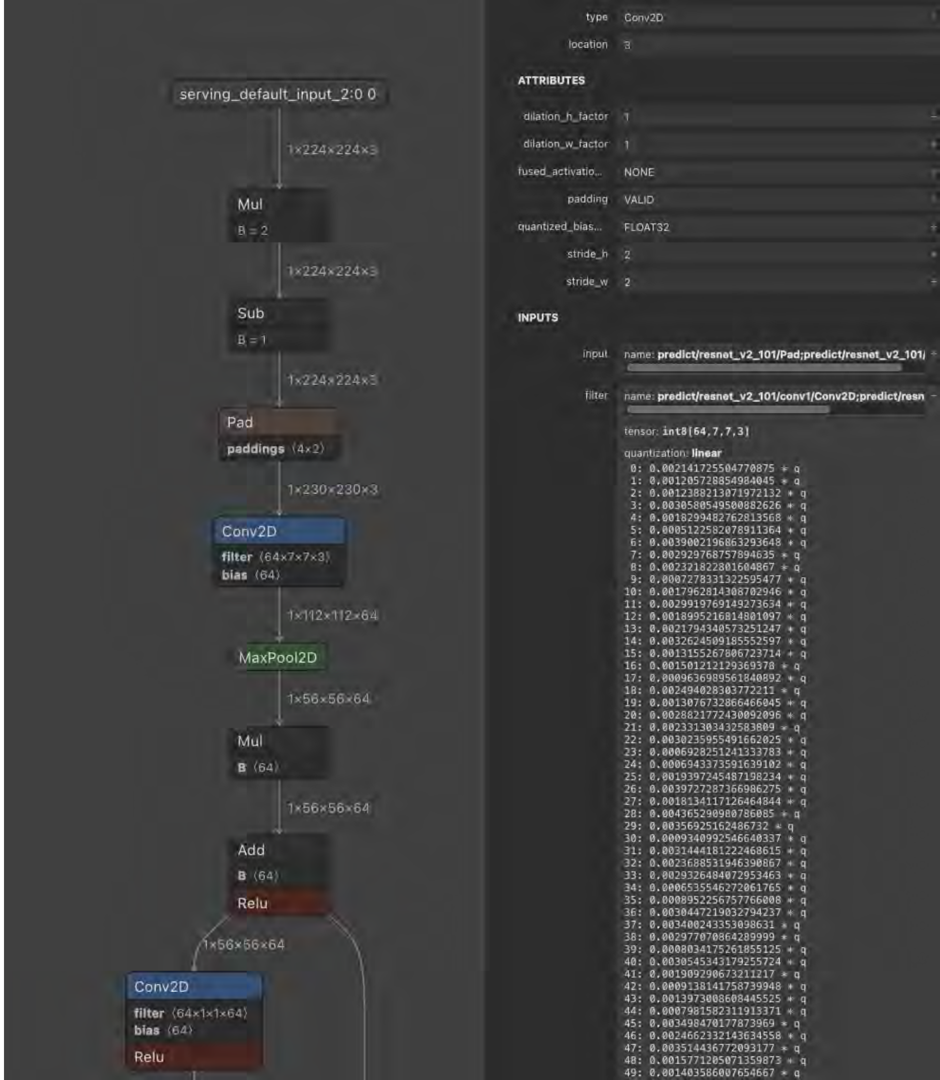
Tutorial: TF Lite quantization

- [Post-training dynamic range quantization | TensorFlow Lite]()
- Visualize quantized vs unquantized model in Netron.app



Summary

- Pruning
  - What and why?
  - How? Pruning criterion
    - Magnitude-based, Scaling-based
  - Fine-tune/retrain acceleration
    - M:N sparsity, SparseConv
- Quantization
  - What and why?
  - Linear quantization
    - Scale, zero point
  - Quantization granularity
    - Per-tensor, per-channel
  - Calibration and Clipping

Next Lectures

- Example paper presentation: ML-Exray
- Hardware architecture
- Special accelerators
- Quiz on Lecture 05-06