차세대 반도체 디지털 혁신공유대학 사업단

POLARIS

Lecture 9: Convolutional Neural Network, Quantization, BRAM

Xuan-Truong Nguyen

Road map

Deep Learning Accelerator

Convolutional Neural Network (CNN)

Quantization

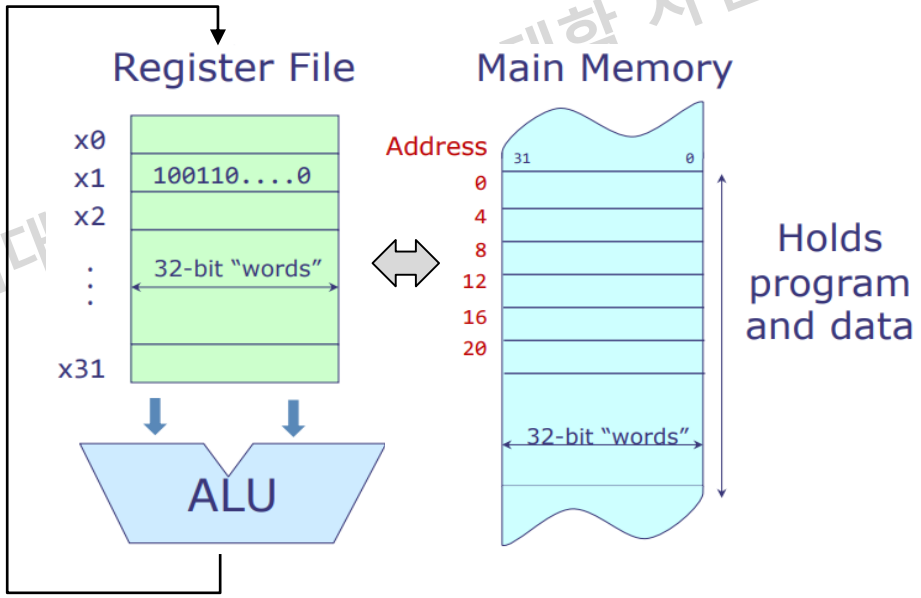
Block memory

Reference S/W

Performance Issue

- Each single-core PC has only one computation unit, i.e. ALU, multiplier.
- Example: bright adjustment
  - For each pixel in an image for display
    - Increase or decrease its value by a number.

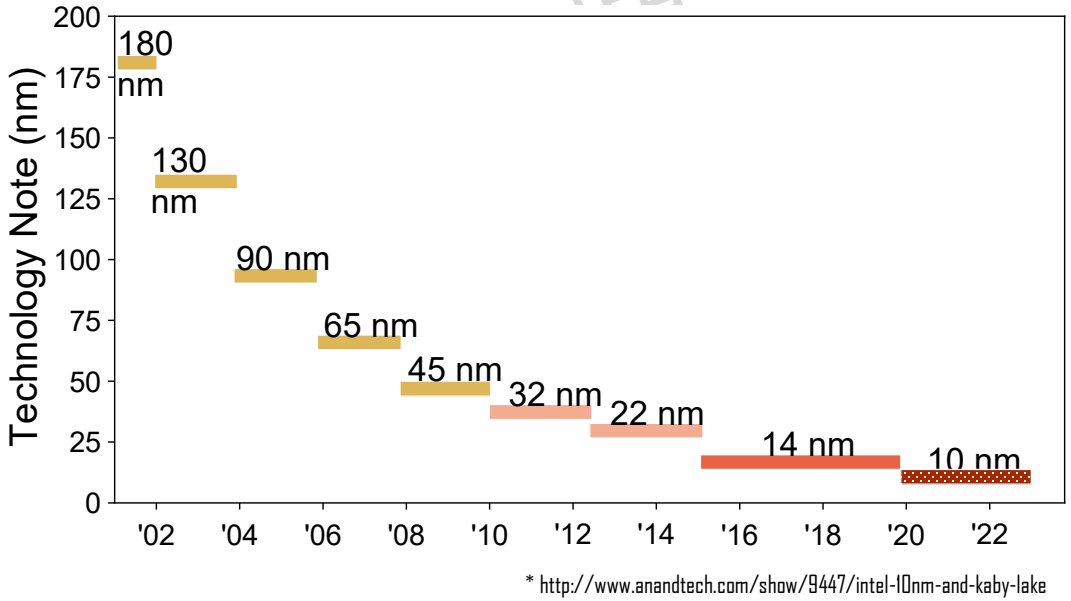
  ⇒ Complexity = total pixels in an image, i.e. 1,179,648 (=768×512×3)
- Why doesn't a PC have more cores? How many cores?



Moore's Law

- Every two years:
  - Double the number of transistors
  - Build higher performance general-purpose processors
  - Make the transistors available to the masses
  - Increase performance (1.8× ↑)
  - Lower the cost of computing (1.8× ↓)

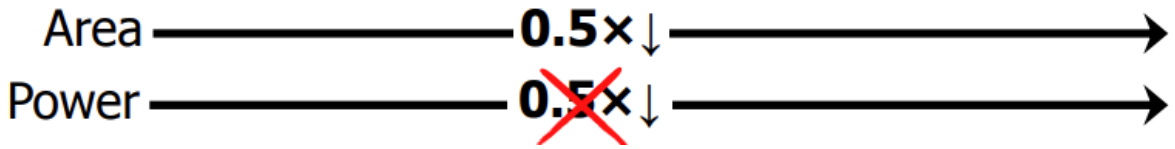
Gordon Moore



* http://www.anandtech.com/show/9447/intel-10nm-and-kaby-lake

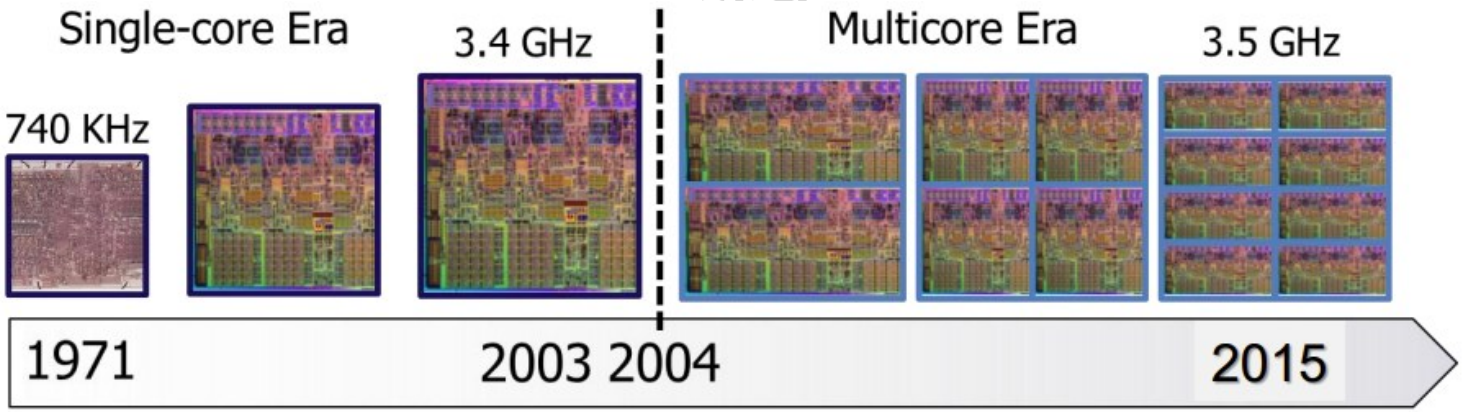
Dark Silicon

- Dark silicon – the fraction of transistors that need to be powered off at all times (due to power + thermal constraints)



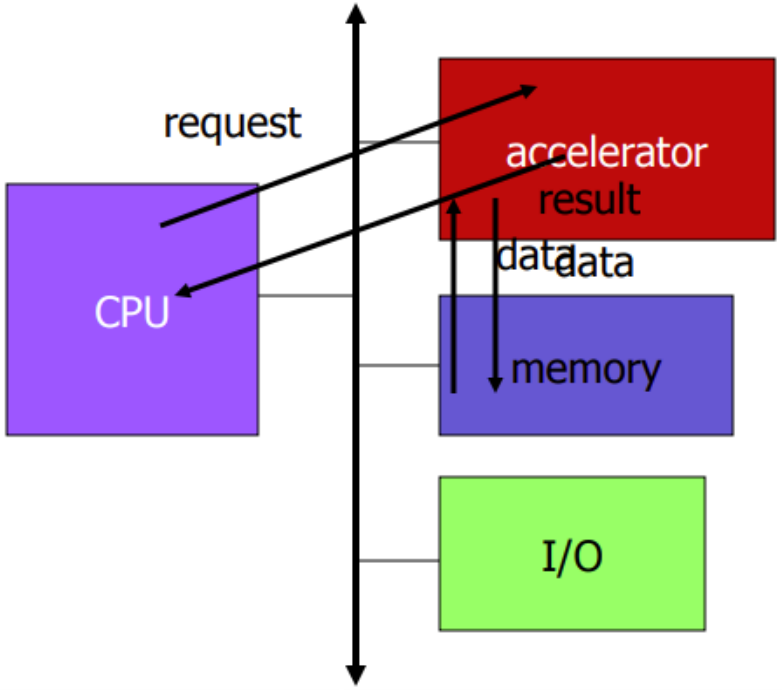
- Evolution of processors

⇒ Expected to continue evolution towards HW specialization/acceleration



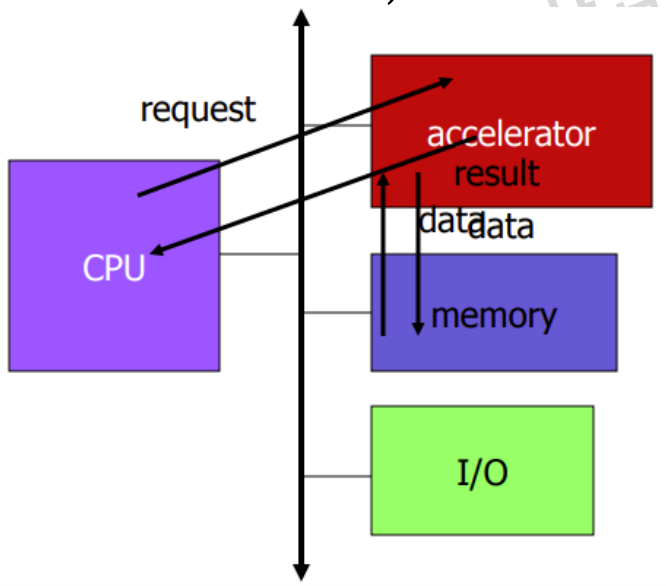
Accelerated Systems

- Use additional computational units dedicated to some functionality
  - A H/W module for special applications
- Hardware/software co-design:
  - Joint design of hardware and software architectures



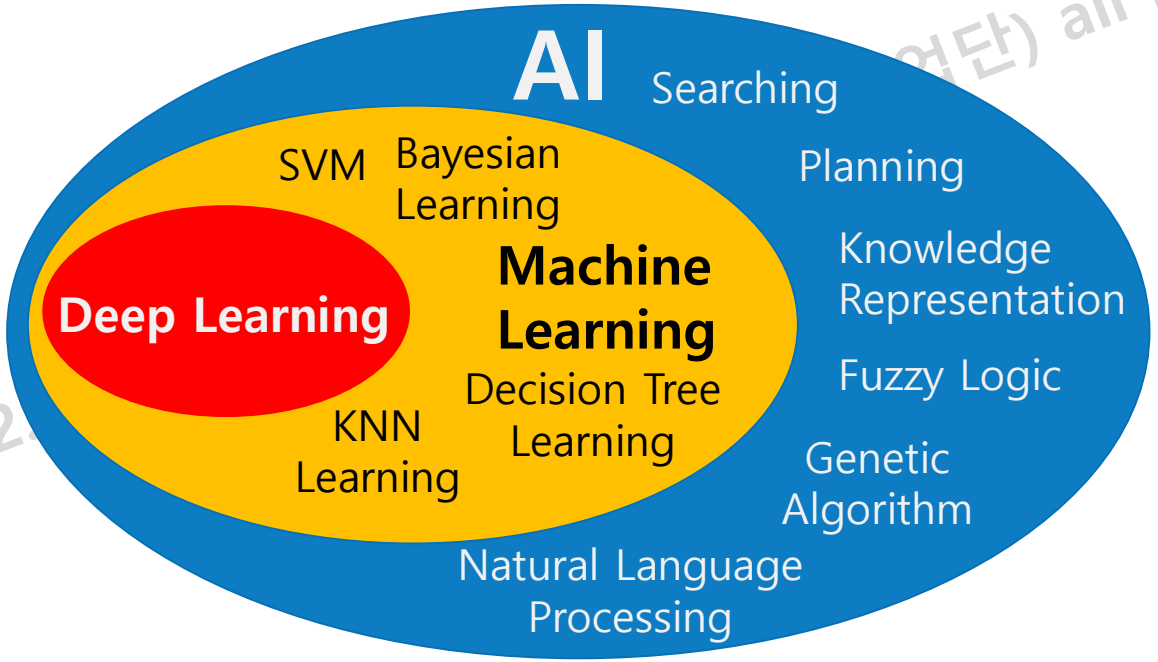
Accelerator vs. Coprocessor

- A coprocessor executes instructions
  - Instructions are dispatched by the CPU
- An accelerator appears as a device on the bus
  - Typically controlled by registers (memory-mapped IO)
- When we talk about "HW Accelerator", we talk about Efficiency
  - Not just about "correctness", but how "GOOD" it is.



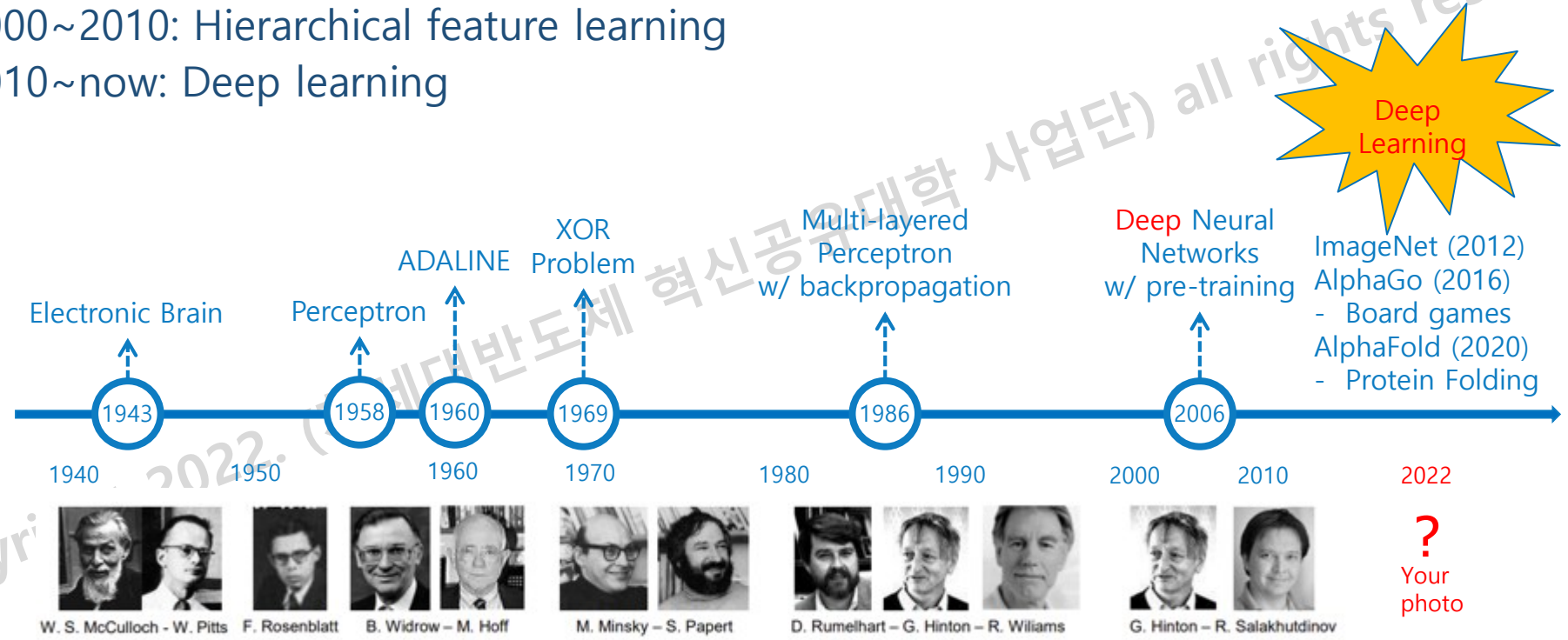
Applications for Hardware Accelerators

- AI: Any technique that enables computer to mimic human behaviours.
- Machine learning (ML): AI techniques that have computers learn without being explicitly programmed.
- Deep learning (DL): A subset of ML techniques that makes computation of multi-layered/deep neural networks feasible



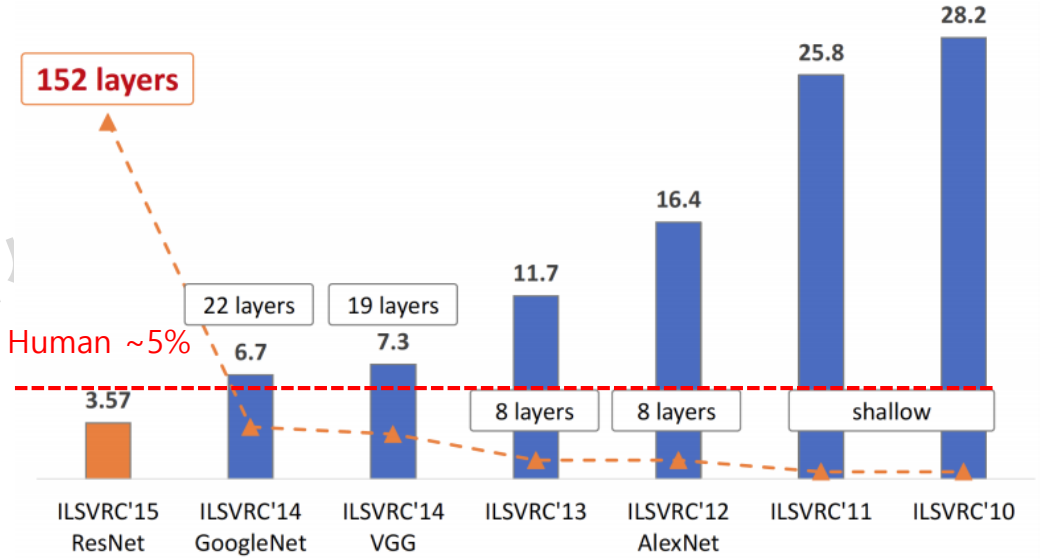
History of Neural Networks

- Neural Networks have been developed and studied for many decades
  - 1940~1950: adjustable but not learnable
  - 1950~1970: learnable weights and threshold
  - 1980~1990: solved nonlinear problem, high computation, local optimal
  - 2000~2010: Hierarchical feature learning
  - 2010~now: Deep learning



Deep Learning Revolution

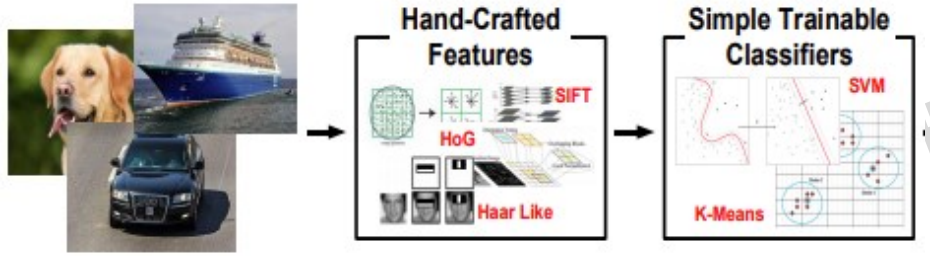
- Deep learning starts to surpass human-level recognition on specific tasks.
  - Human-level recognition: ~5% error
  - Deep learning
    - 2012: AlexNet, 8 layers, 16.4% error.
    - 2014: VGG, 19 layers, 7.3% error
    - 2014: GoogleNet, 22 layers, 6.7% error
    - 2015: ResNet, 152 layers, 3.57% error



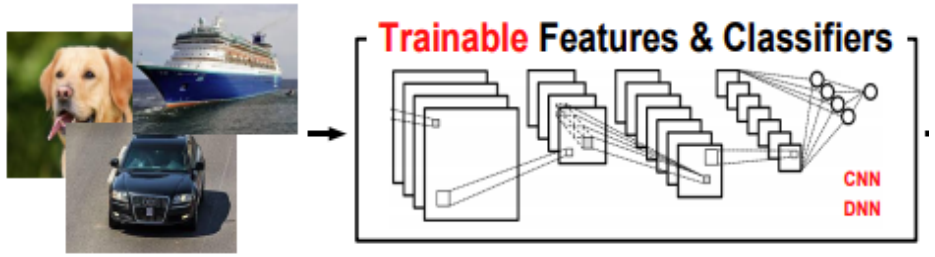
Deep residual learning for image recognition, 2017.

Deep Learning Revolution

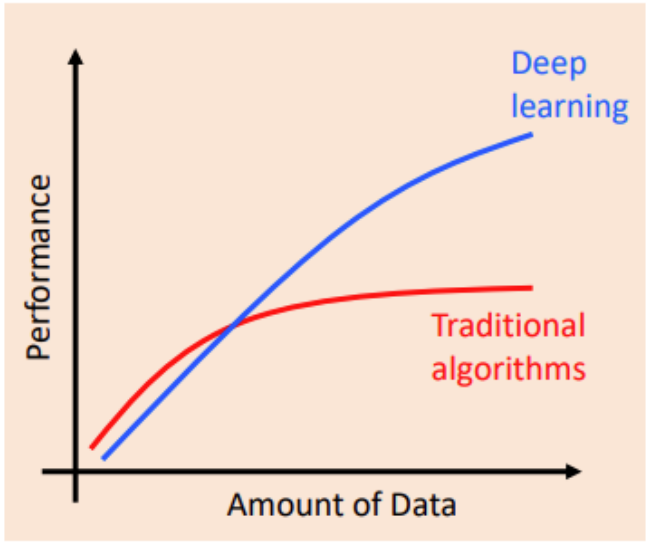
- Traditional Recognition: Hand-crafted features + simple classifiers
  - Performance becomes saturated when the amount of data increases.
- Deep Learning (DL): Trainable/Learnable features and classifiers
  - Performance dramatically increases when the amount of data increases.



(a) Traditional



(b) Deep Learning

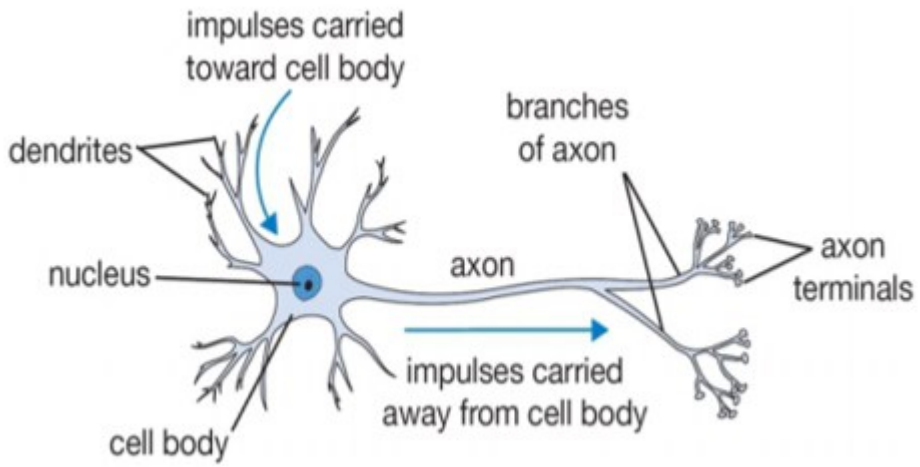


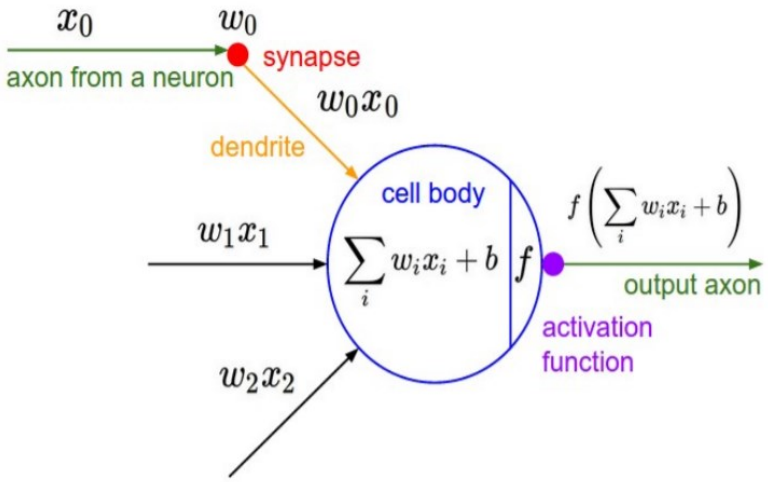
(c) Performance vs Data

Courtesy to Andrew Ng, Stanford CS229 class

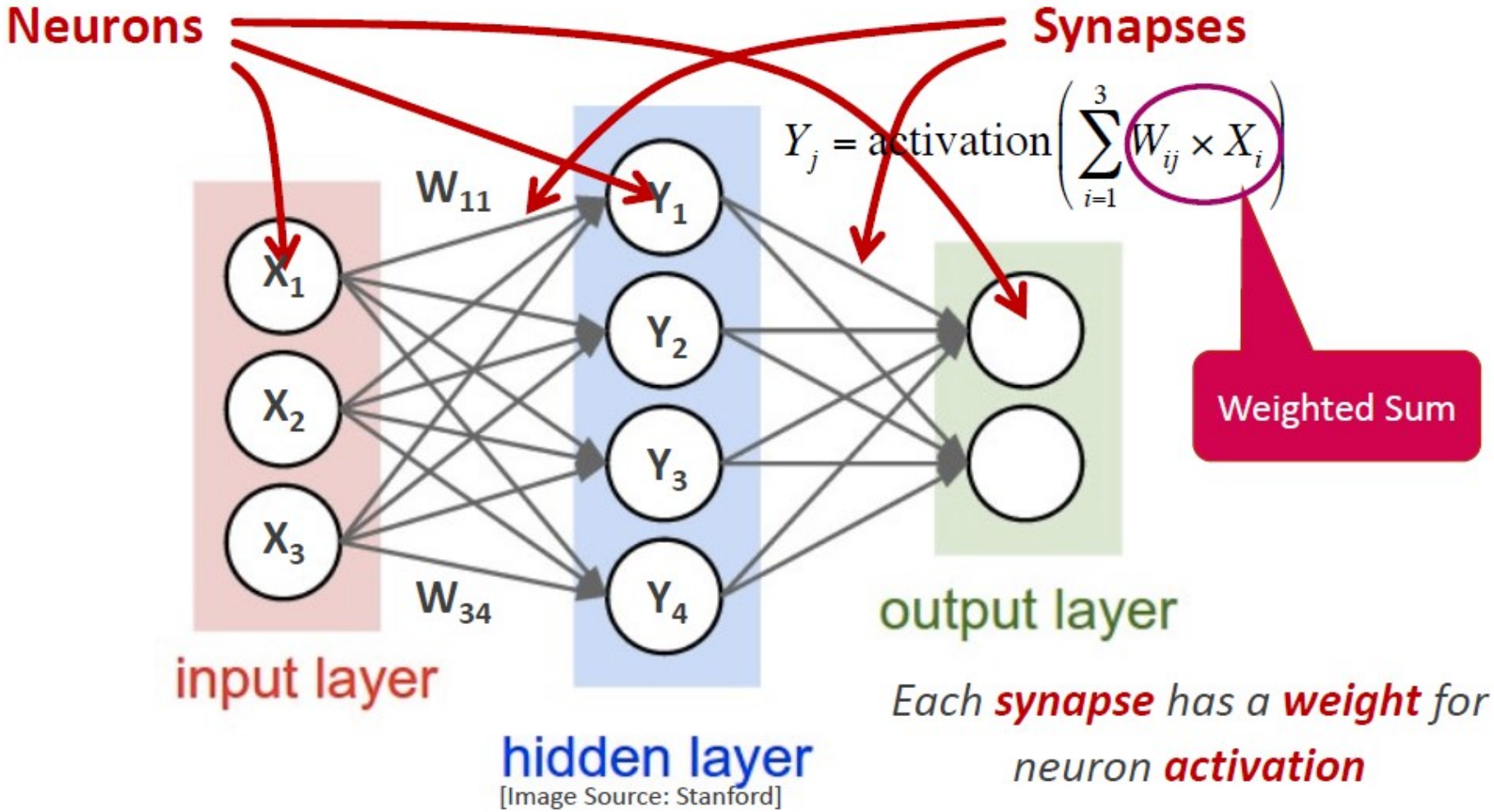
Neural Networks

- Neuron: The basic computational unit of the brain (~86B)
- Synapses (Weights) connect neurons: Nearly 10^{14} – 10^{15} synapses
  - Learnable & control influence strength
- Neural networks:
  - Neurons receive input signal from dendrites and produce output signal along axon
  - Axons interact with the dendrites of other neurons via synaptic weights
- Artificial Neural networks try to mimic human brain's behaviors





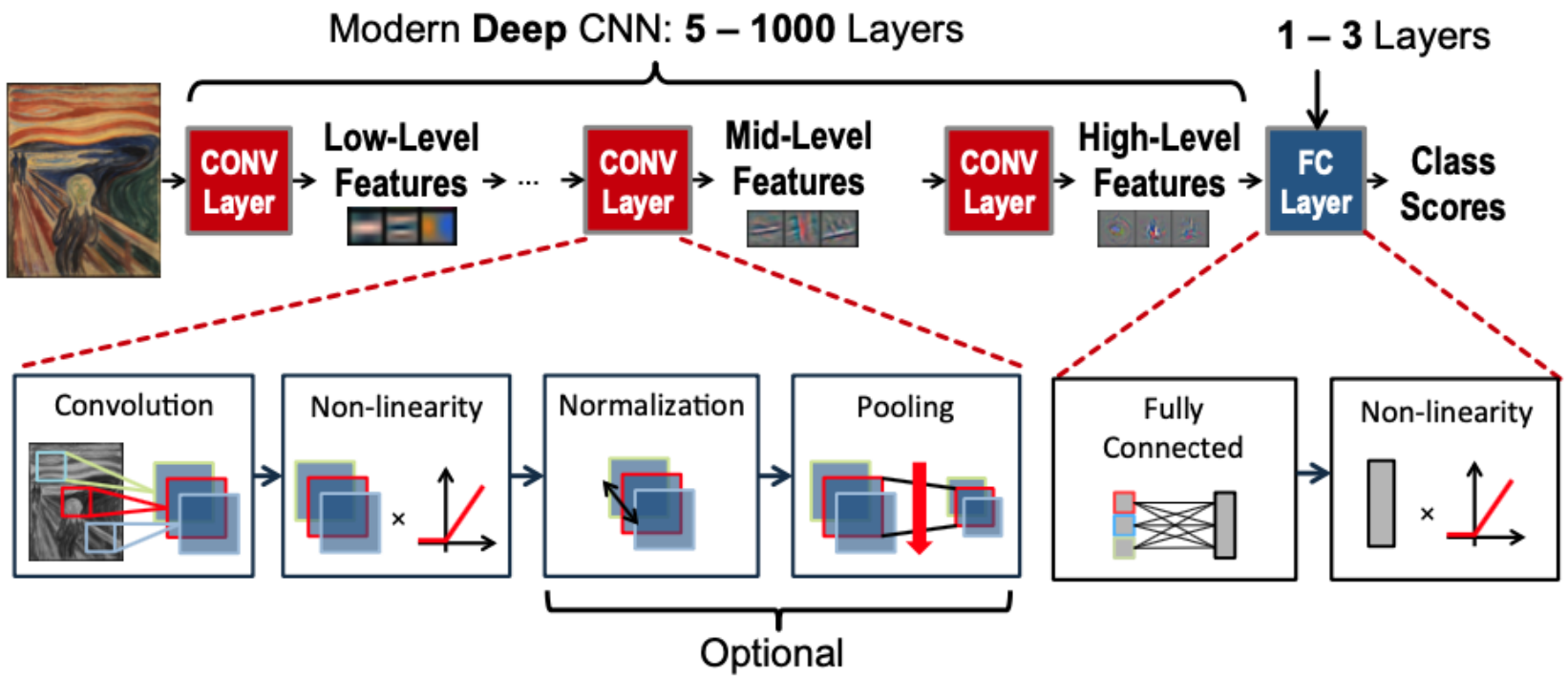
What is a deep neural network?



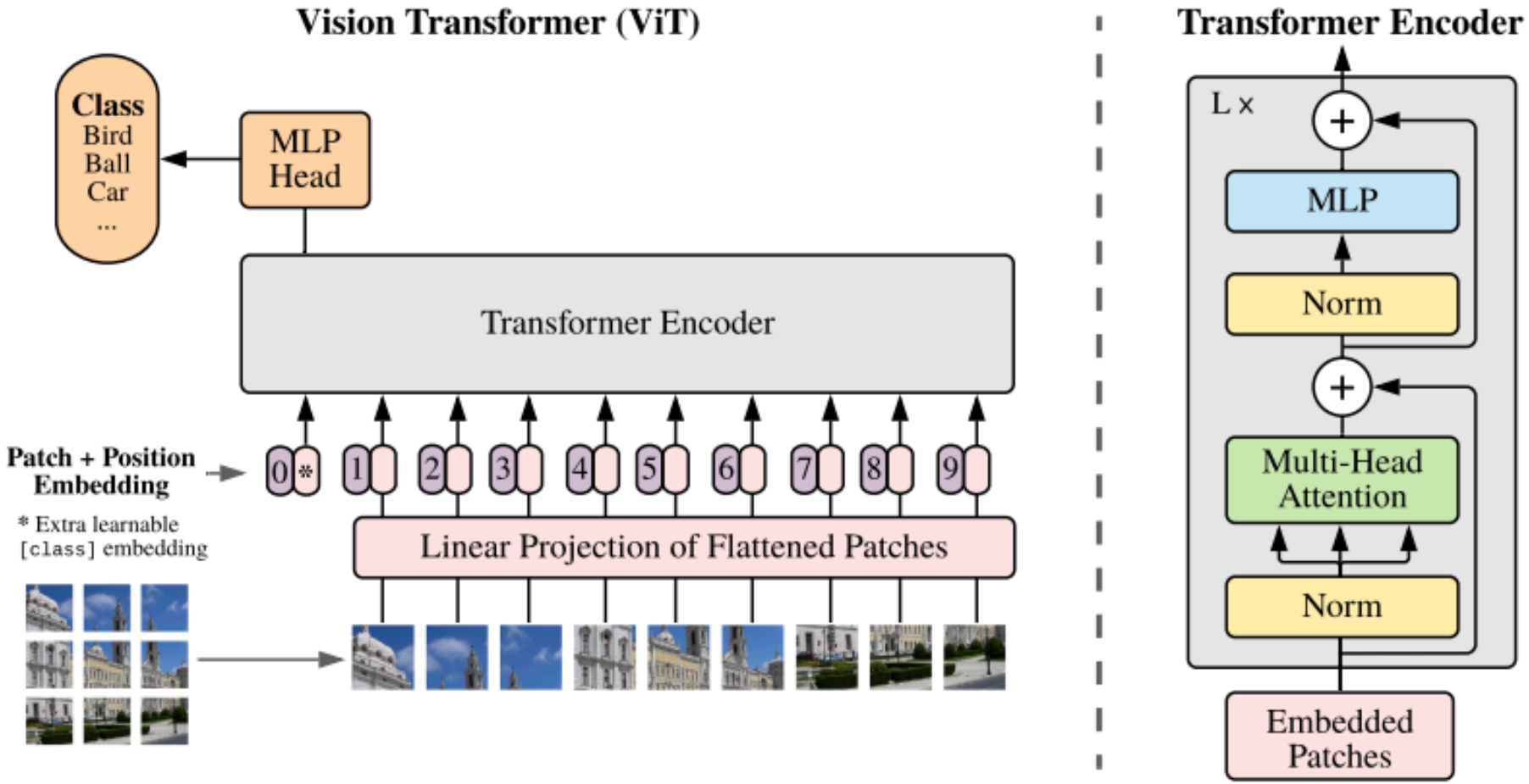
[Image Source: Stanford]

Modern Deep Neural Networks

- Deep -> multiple layers
  - Convolutional layer followed by non-linearity activation
  - Each layer may include normalization or pooling
  - For classification task, it usually ends with a few full-connected layer.



Modern Deep Neural Networks



Road map

Deep Learning Accelerator

Convolutional Neural Network (CNN)

Quantization

Block memory

Reference S/W

Camera Field of View (FOV)

- The **field of view** (**FoV**) is the extent of the observable world that is seen at any given moment
  - In the case of optical sensors, it is a solid angle through which a detector is sensitive to electromagnetic radiation
- **Resolution**: An FoV can be represented by different grids of pixels.
  - Example: 640x480 (VGA), 1280x1080 (HD)

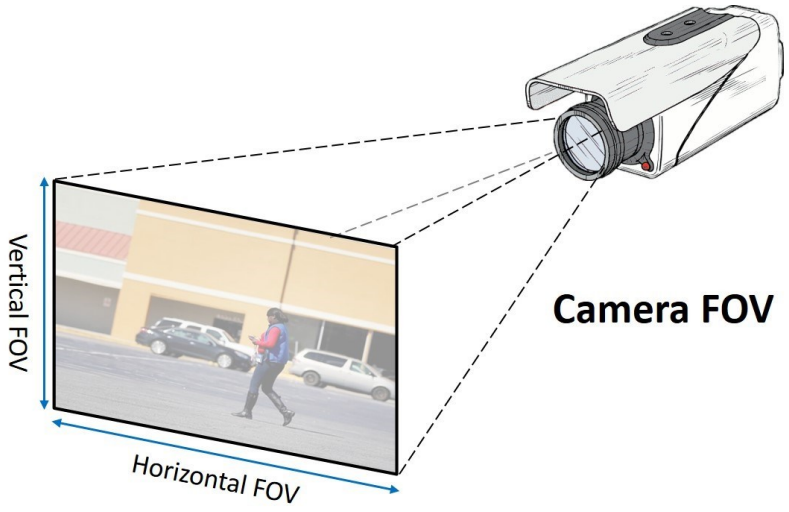
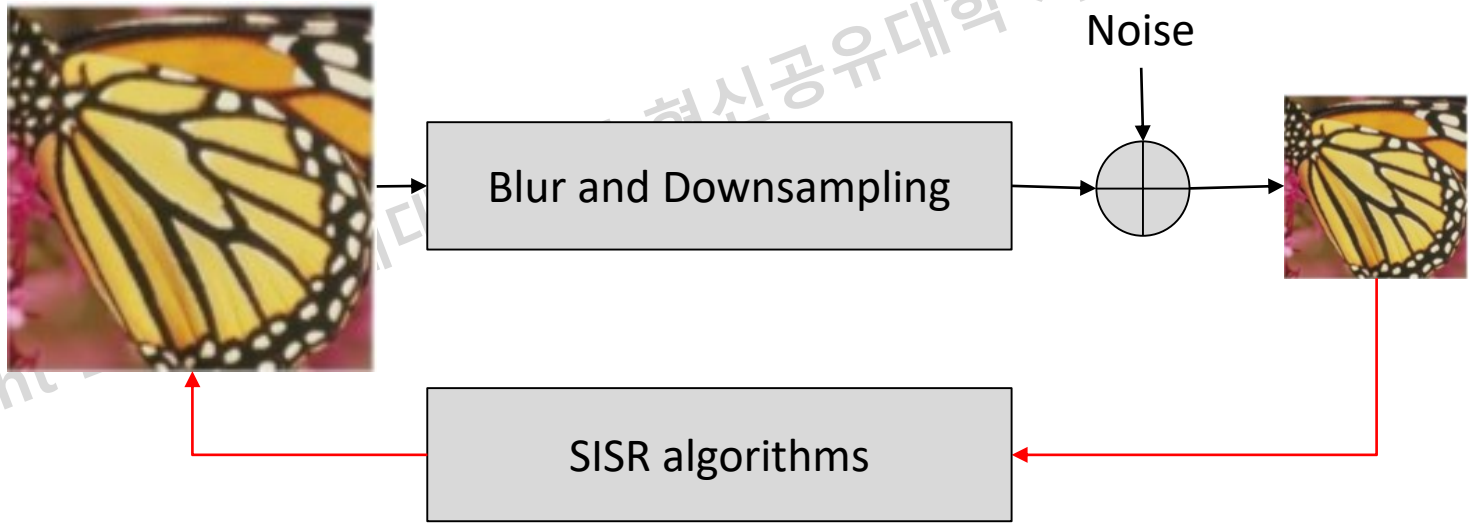


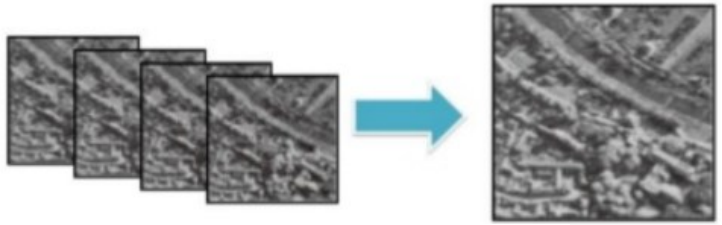
Image Super-Resolution

- Image Super-Resolution **recovers a High Resolution (HR)** image from a given Low Resolution (LR) image.
- An image may have a “lower resolution” due to a smaller spatial resolution (i.e. size) or due to a result of degradation (such as blurring).

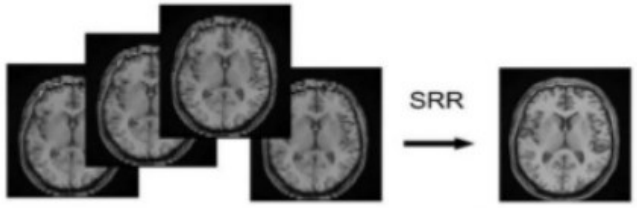


Applications

- Satellite image processing
- Medical image processing
  - MRI
- Multimedia industry and video enhancement
  - TV, monitor



SR for satellite image



SR for medical imaging

TV & Monitor

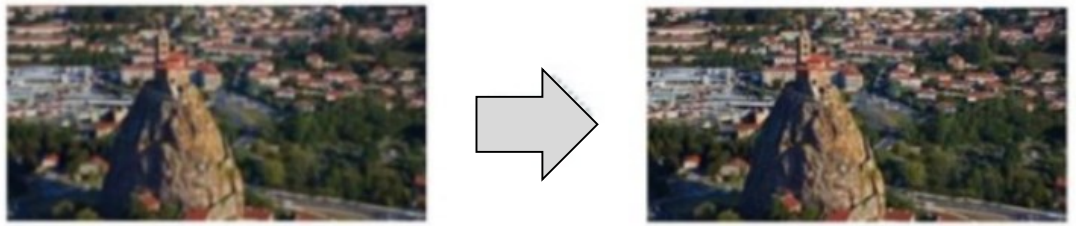
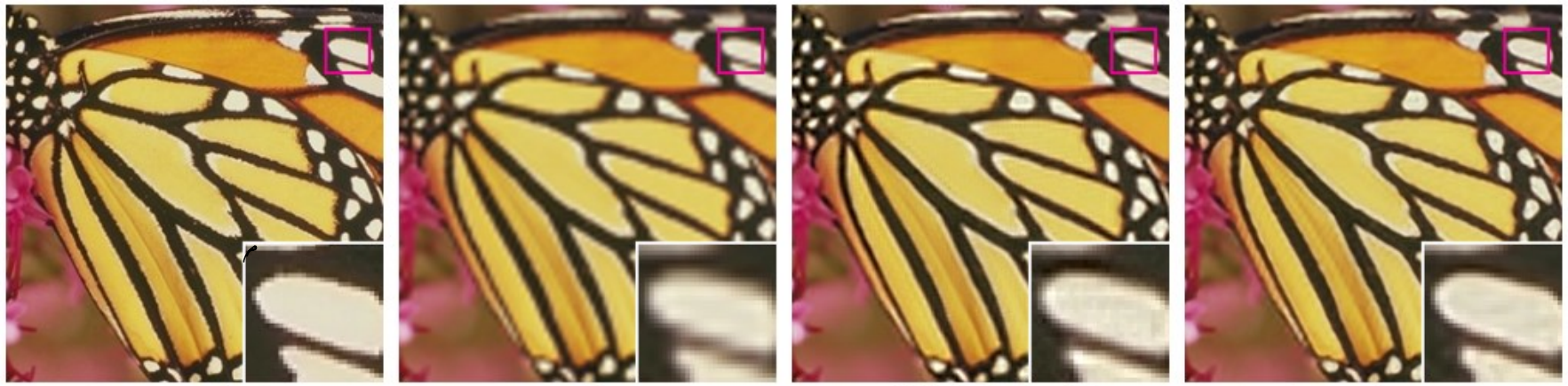


Image Super-resolution

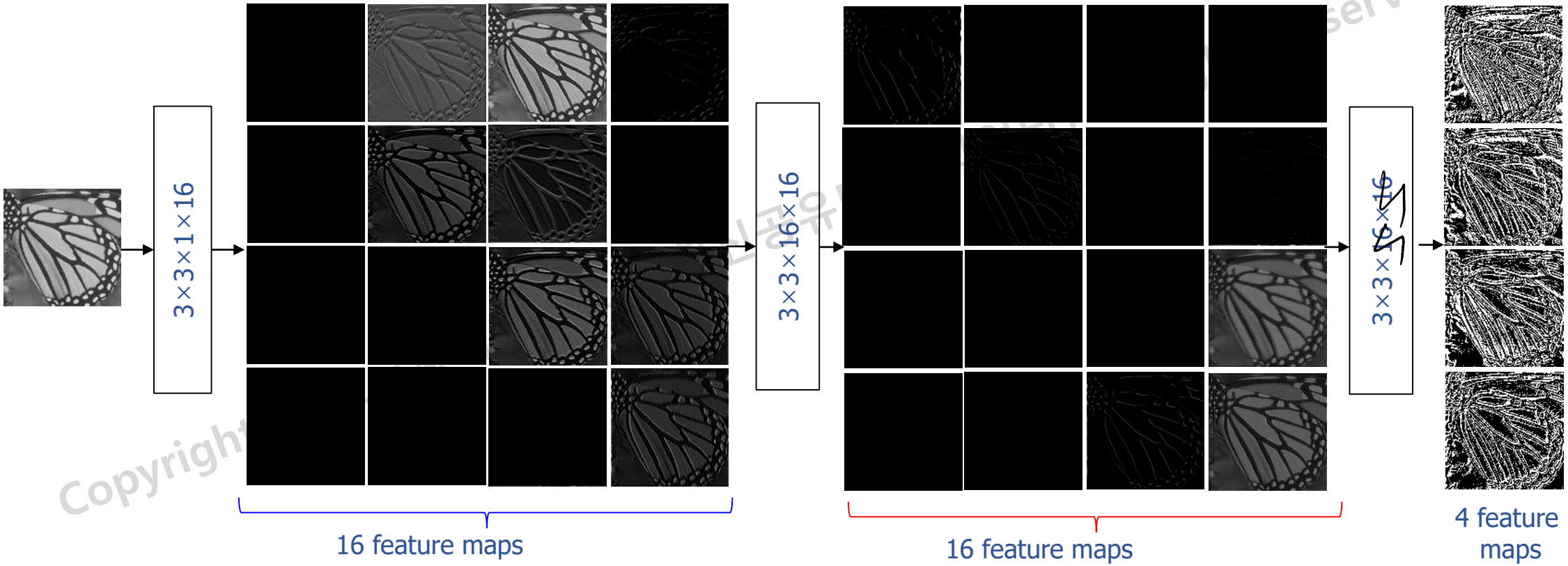
- Estimating the inverse degradation function is an ill-posed problem
  - Many solutions
- Methods
  - Interpolation-based methods
  - Reconstruction-based methods
  - (Deep) Learning-based methods



Original / PSNR | Bicubic / 24.04 dB | SC / 25.58 dB | SRCNN / 27.58 dB

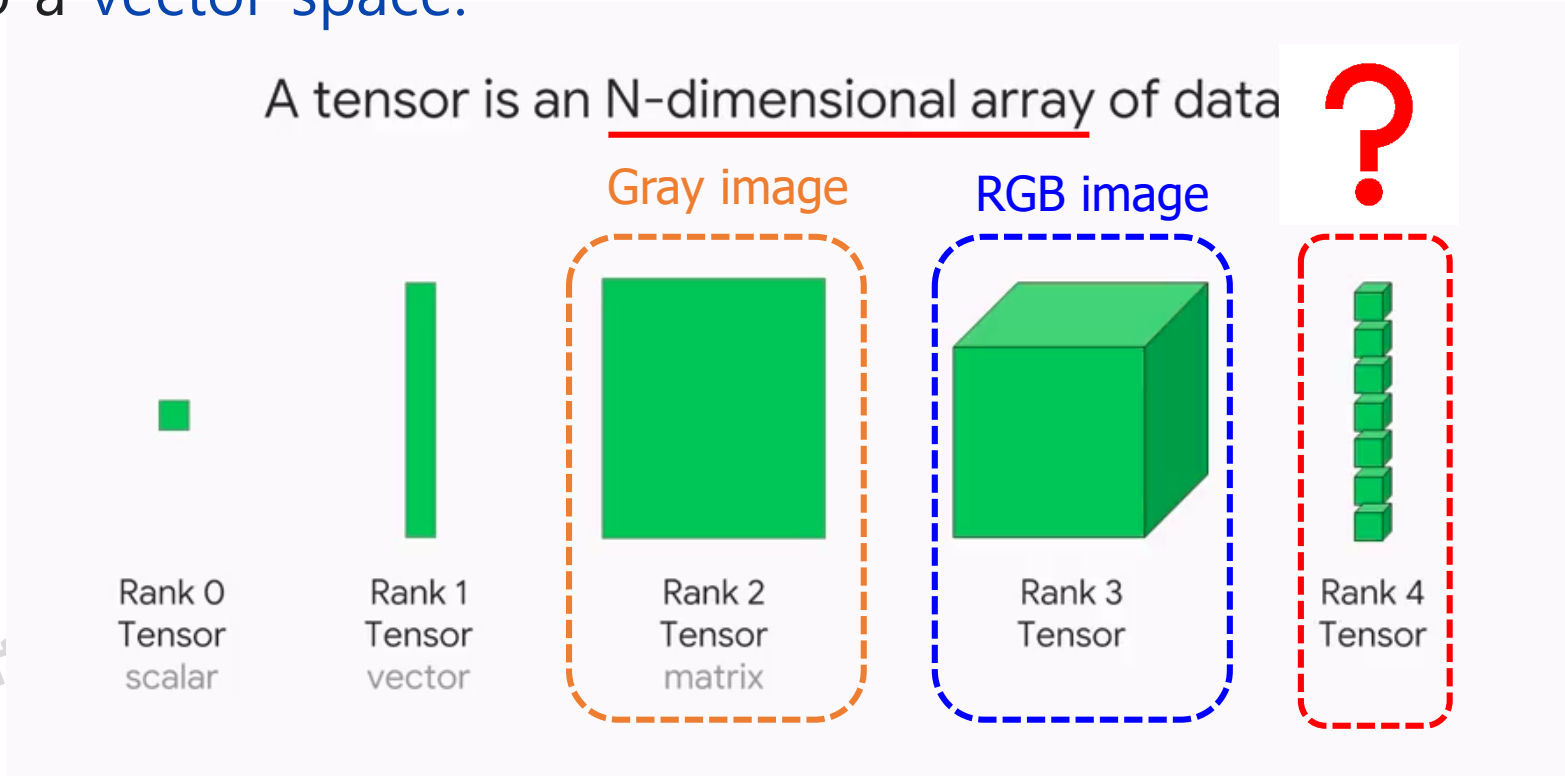
Simple CNN for SR

- A simple CNN for SR has three convolutional layers
  - Input is a LR image
  - All three layers use 3×3 CONV filters



Tensor

- From Wikipedia[(1)] : "In mathematics, a tensor is an algebraic object that describes a multilinear relationship between sets of algebraic objects related to a vector space."

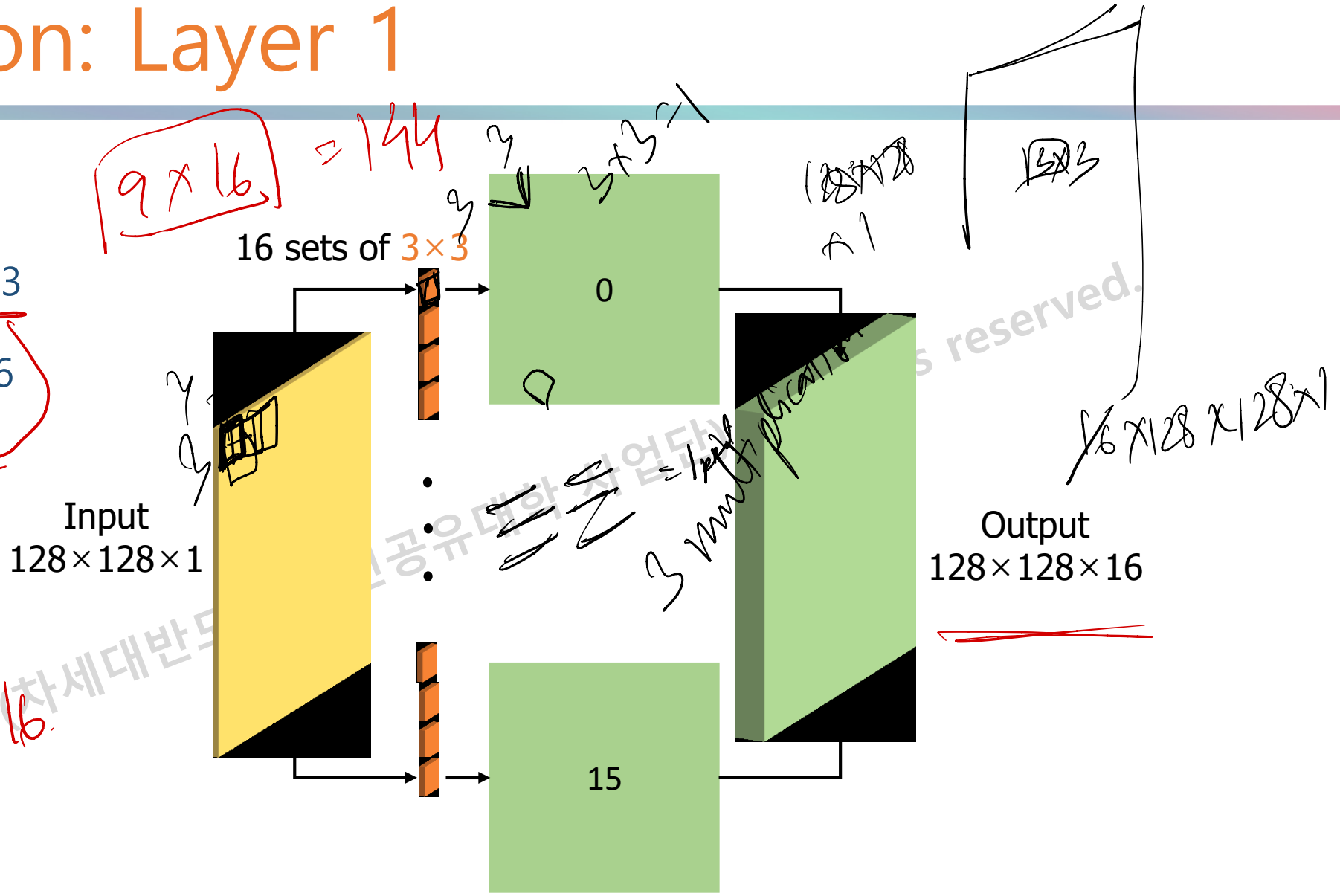


Source: https://medium.com/mlait/tensors-representation-of-data-in-neural-networks-bbe8a711b93b

 (1) https://en.wikipedia.org/wiki/Tensor

Convolution: Layer 1

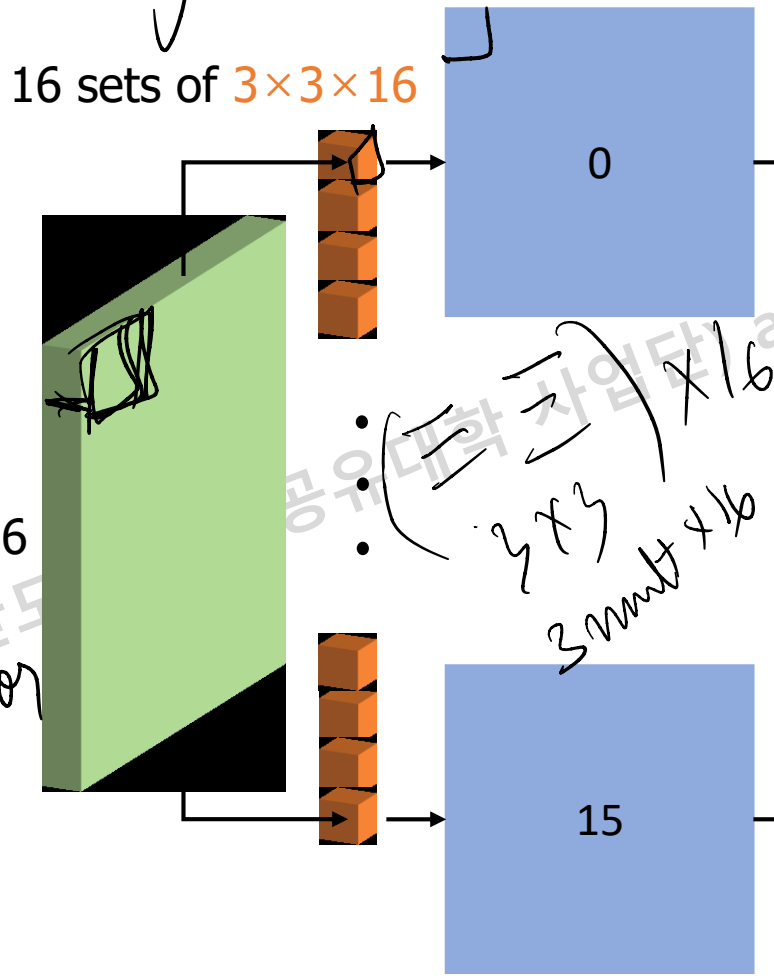
- Input: 128×128×1
- Filters: 16 sets of 3×3
- Output: 128×128×16



Repeated usage of 1 to create one output of 16.

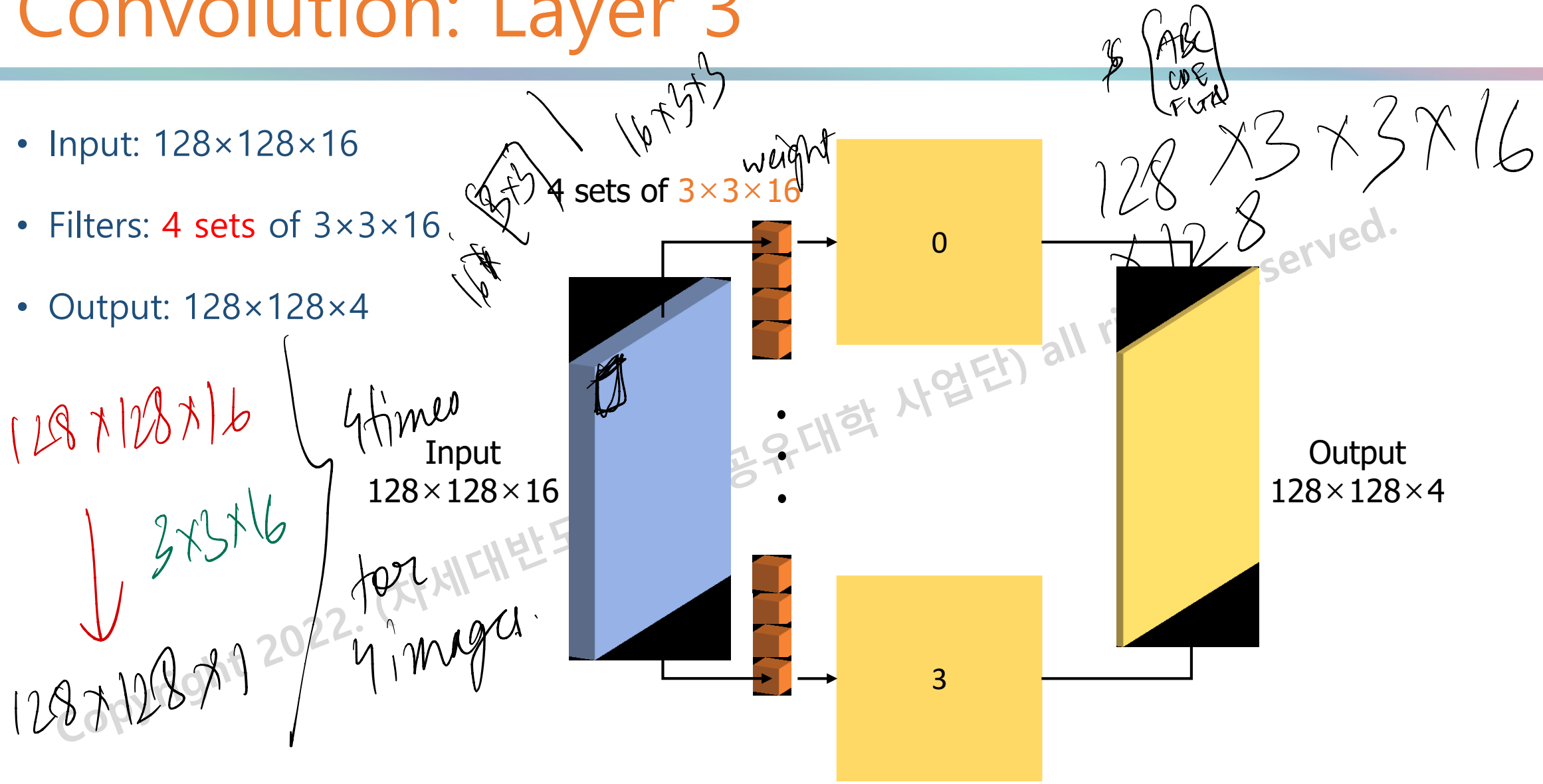
Convolution: Layer 2

- Input: 128×128×16
- Filters: 16 sets of 3×3×16
- Output: 128×128×16



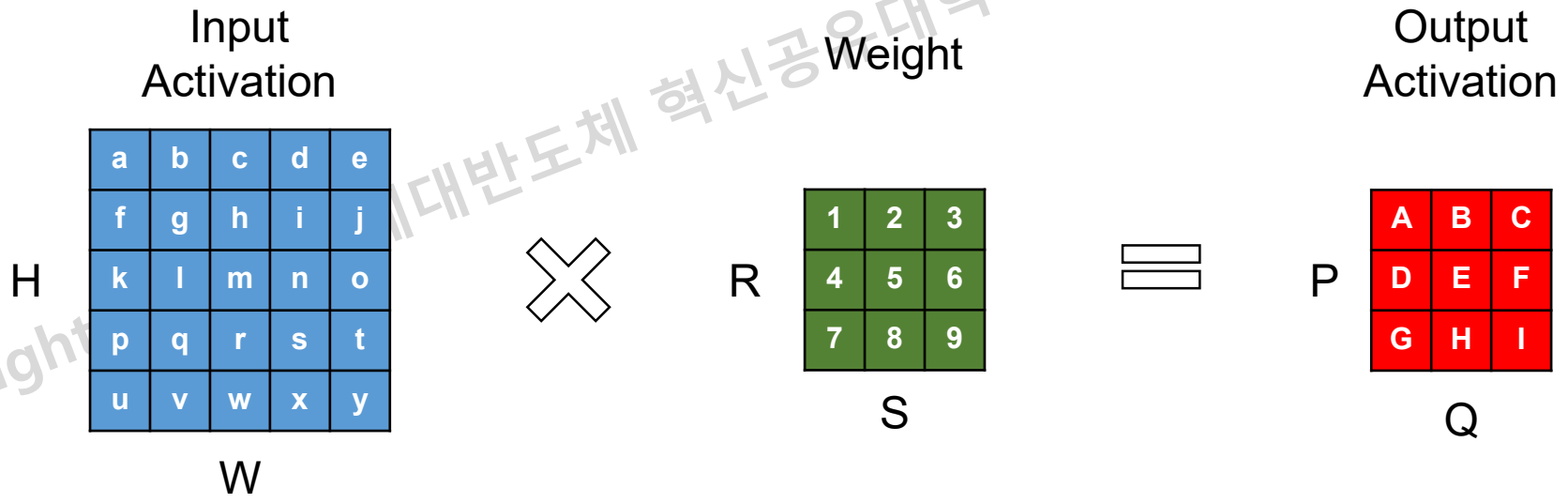
Convolution: Layer 3

- Input: 128×128×16
- Filters: 4 sets of 3×3×16
- Output: 128×128×4



2D convolution

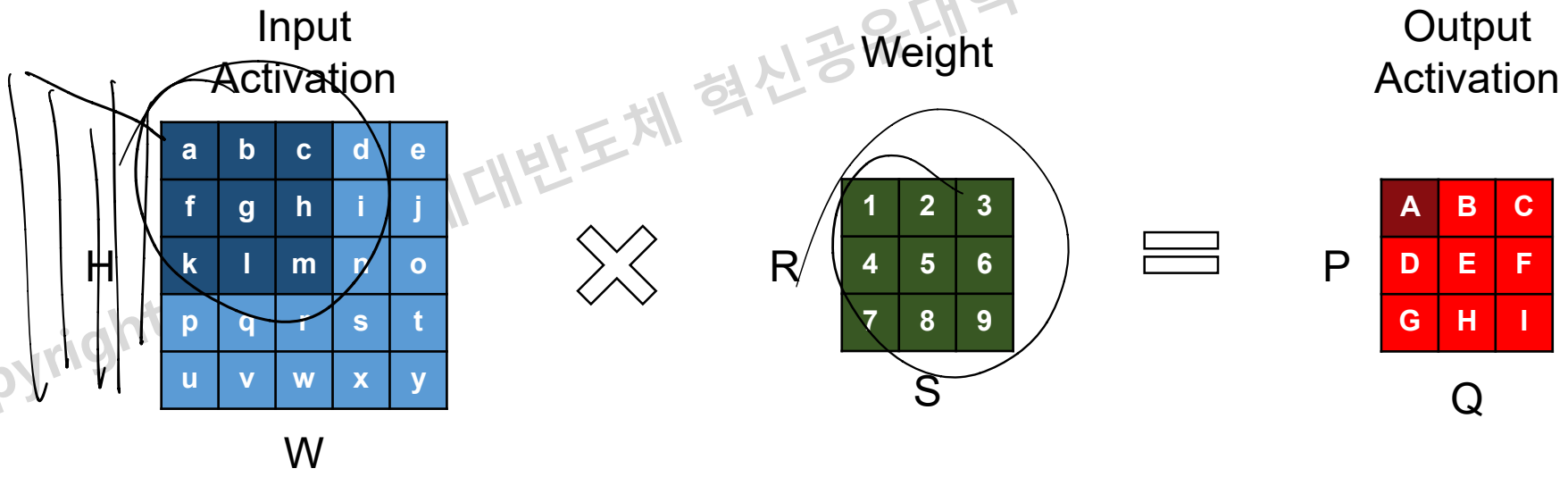
- 2D convolution:
  - Calculate output activation (OA) from input activation (IA) and weights (W)



2D convolution

- 2D convolution:
  - Calculate output activation (OA) from input activation (IA) and weights (W)

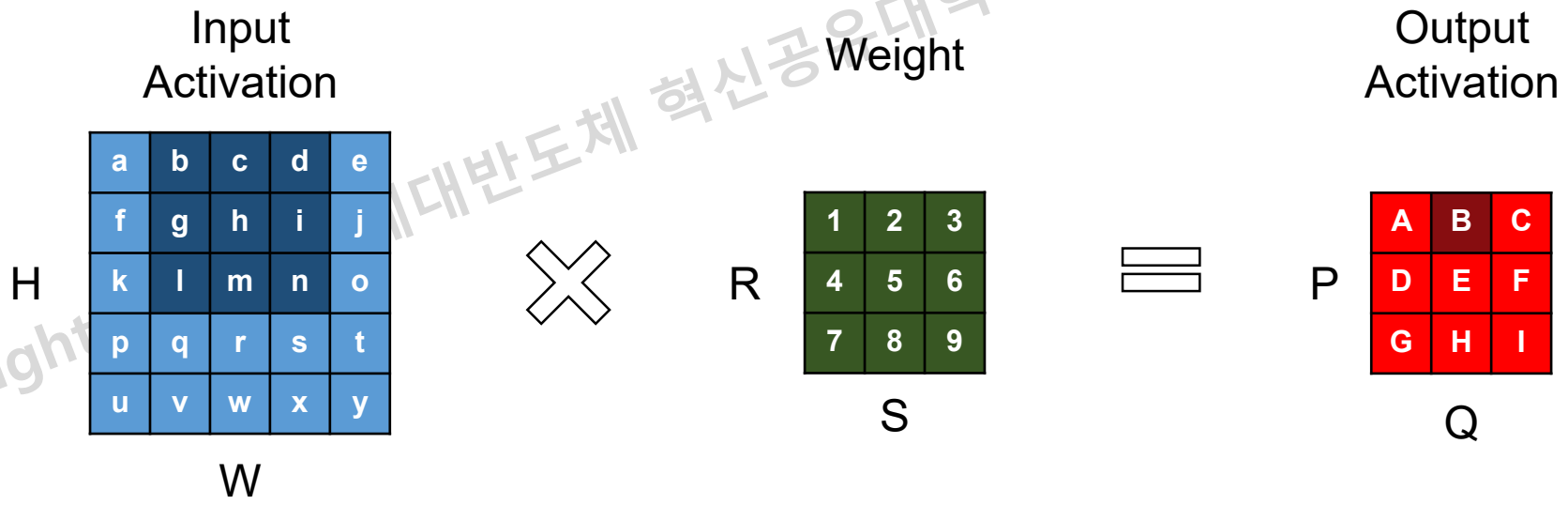
$$A = a * 1 + b * 2 + c * 3$$
$$+ f * 4 + g * 5 + h * 6$$
$$+ k * 7 + l * 8 + m * 9$$



2D convolution

- 2D convolution:
  - Calculate output activation (OA) from input activation (IA) and weights (W)

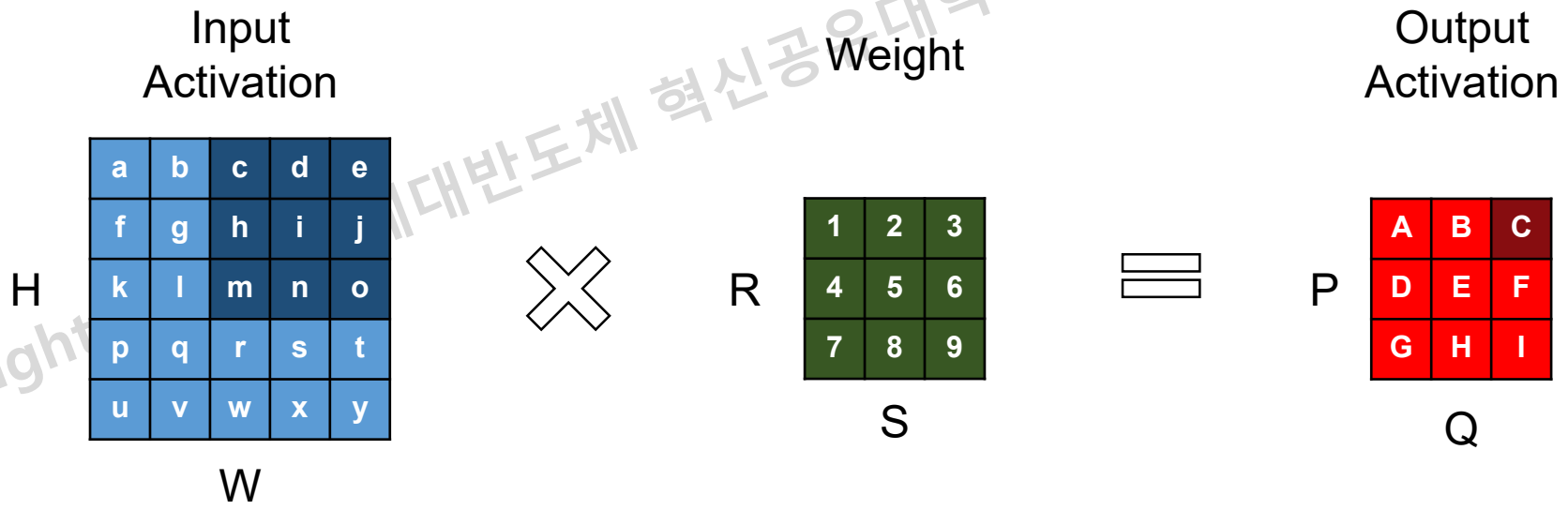
$$B = b * 1 + c * 2 + d * 3$$
$$+ g * 4 + h * 5 + i * 6$$
$$+ l * 7 + m * 8 + n * 9$$



2D convolution

- 2D convolution:
  - Calculate output activation (OA) from input activation (IA) and weights (W)

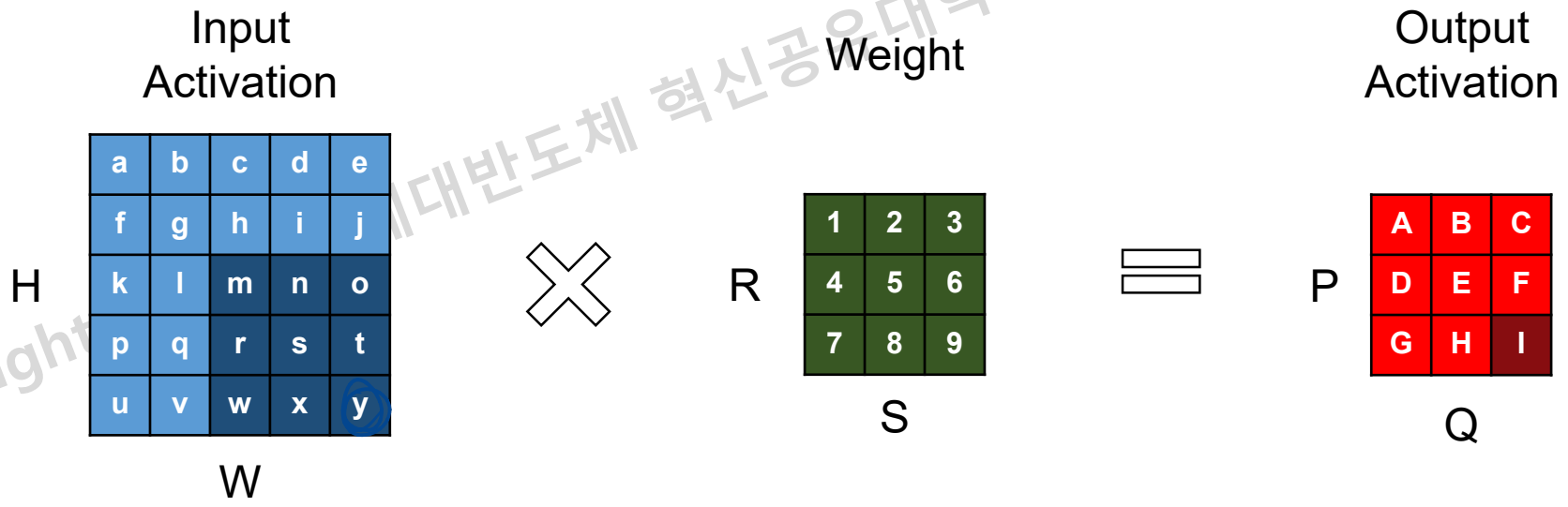
$$C = c * 1 + d * 2 + e * 3 + h * 4 + i * 5 + j * 6 + m * 7 + n * 8 + o * 9$$



2D convolution

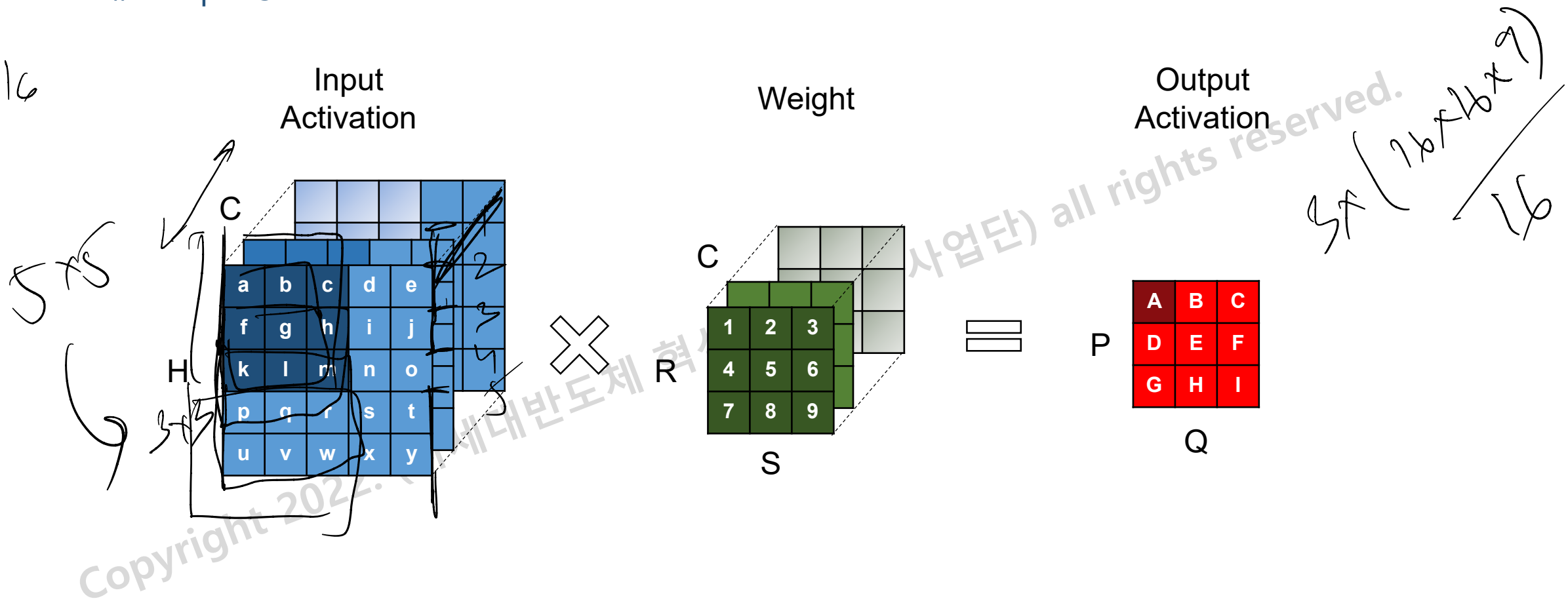
- 2D convolution:
  - Calculate output activation (OA) from input activation (IA) and weights (W)

$$I = m * 1 + n * 2 + o * 3 + r * 4 + s * 5 + t * 6 + w * 7 + x * 8 + y * 9$$

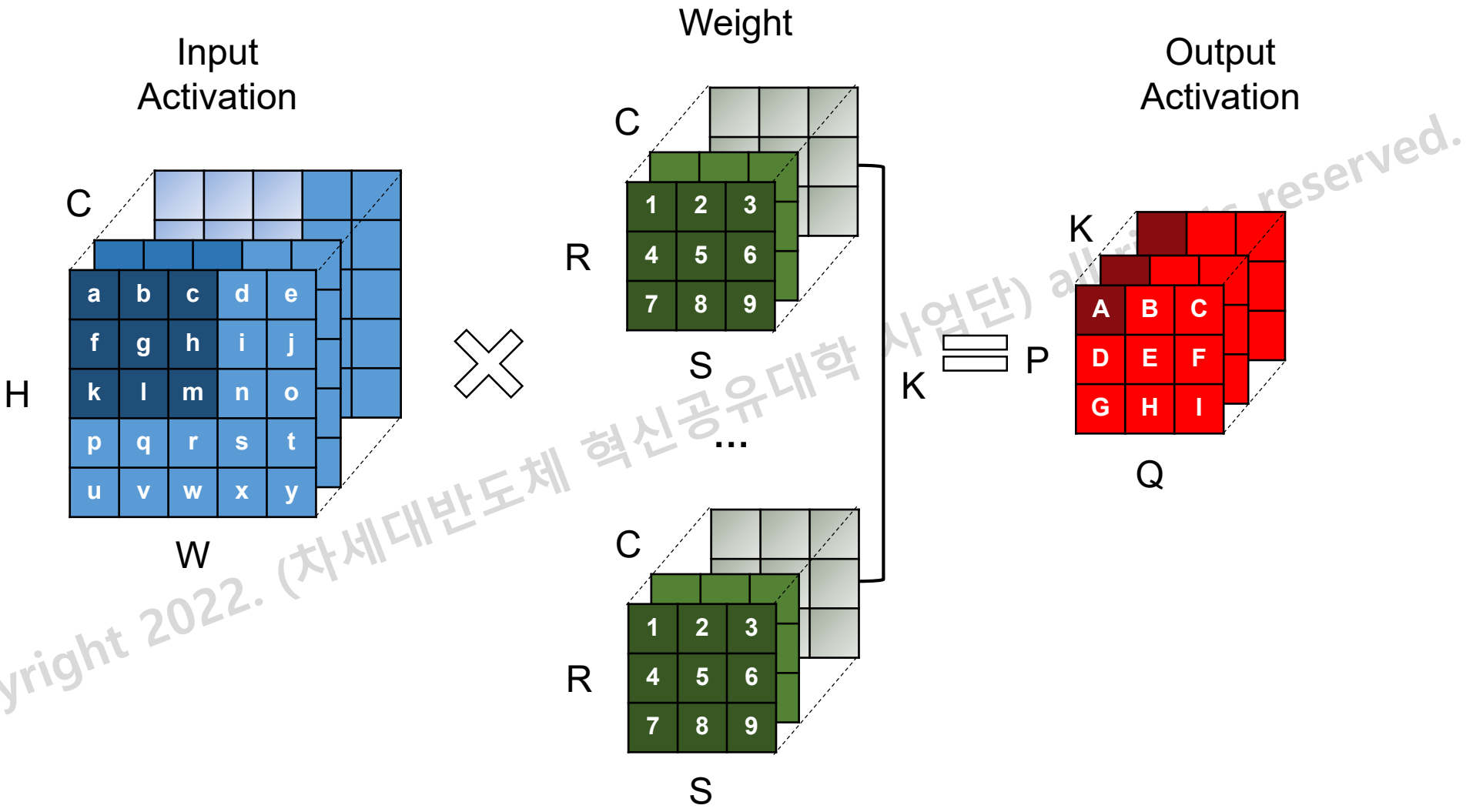


3-D Convolution: Multiple input channels

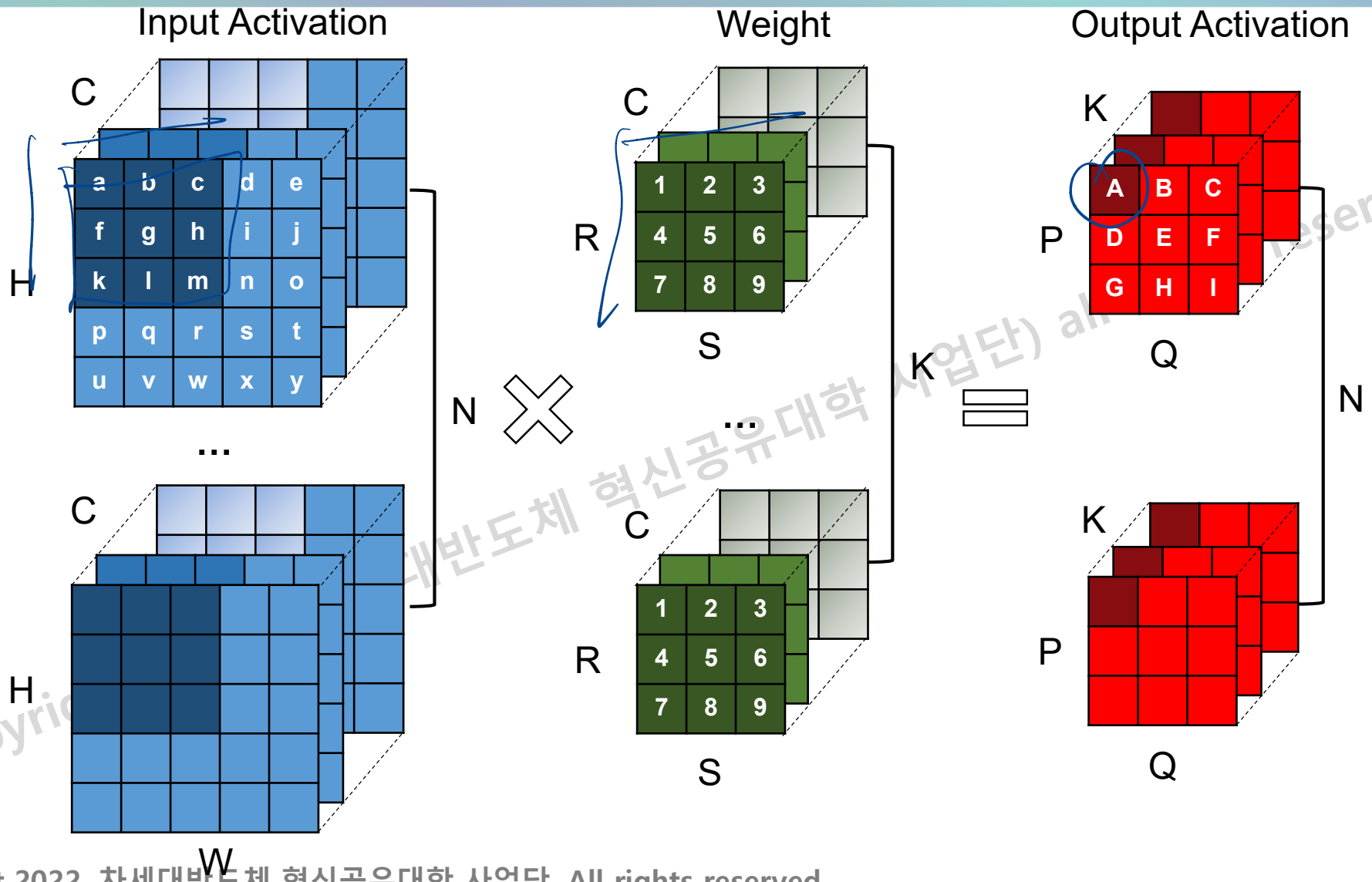
- **C:** # of Input Channels



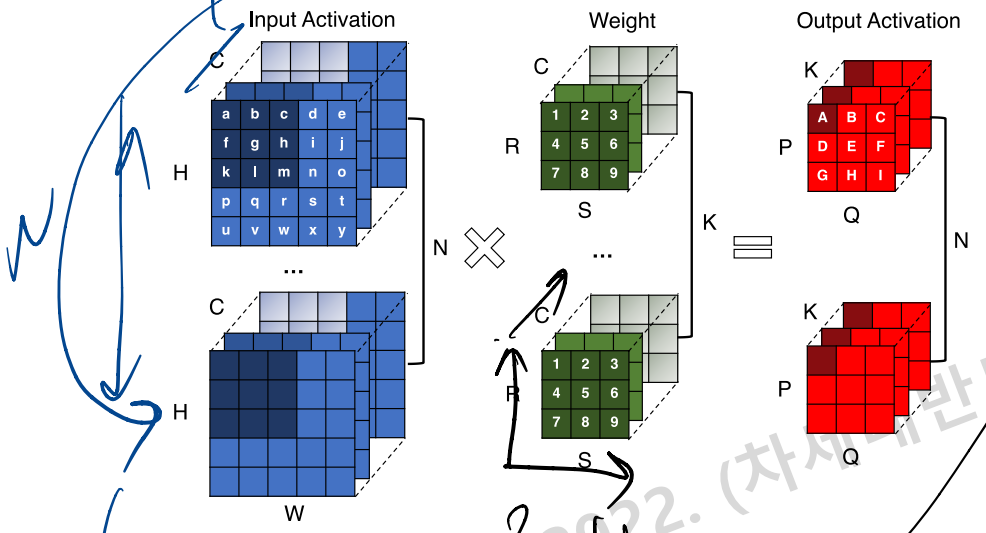
3-D Convolution: multiple output channels



Batch: Multiple inputs



CONV loop



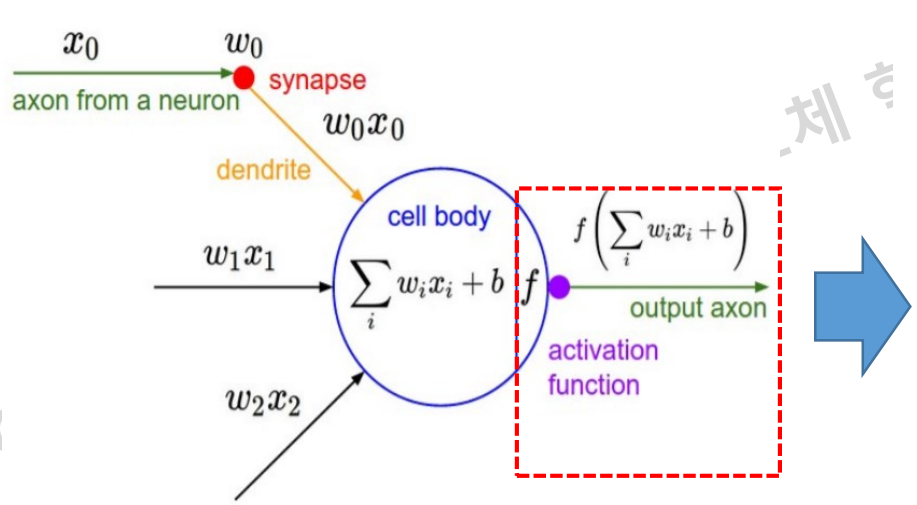

```
for (n=0; n<N; n++) {
  for (k=0; k<K; k++) {
    for (p=0; p<P; p++) {
      for (q=0; q<Q; q++) {
        OA[n][k][p][q]= 0;
        for (r=0; r<R; r++) {
          for (s=0; s<S; s++) {
            for (c=0; c<C; c++) {
              h = p * stride - pad + r;
              w = q * stride - pad + s;
              OA[n][k][p][q] += IA[n][c][h][w] * W[k][c][r][s];
            }
          }
        }
        OA[n][k][p][q]= Activation(OA[n][k][p][q]);
      }
    }
  }
}
```

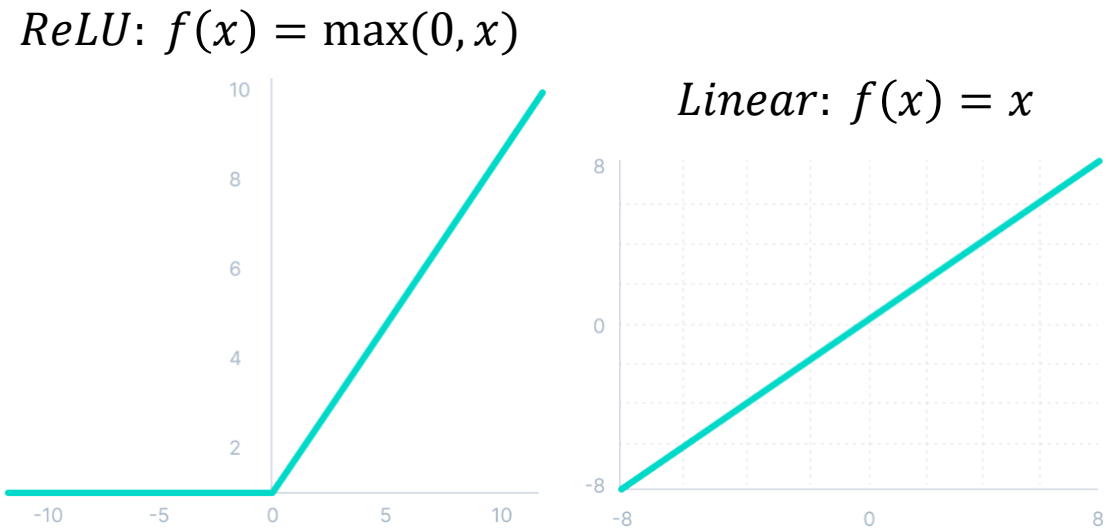
for each output activation

Convolution window

Activation/Transfer function

- Activation/Transfer: Depending on the nature and intensity of these input signals, the brain processes them and decides whether the neuron should be activated ("fired") or not.
- The primary role of the ***Activation Function*** is to transform the summed weighted input from the node into an output value to be fed to the next hidden layer or as output.
- The purpose of an activation function is to add non-linearity to the neural network.





 https://www.v7labs.com/blog/neural-networks-activation-functions

Lab 1: Convolution

- Lab 1: Implement a convolution function
- Motivation: Before hardware implementation, we need to develop a reference software
- Why?
  - Software: abstract, high-level representation of a function, an algorithm
  - Generate a test vector for hardware verification

```
% Function: Convolution Only
% Input
%   - img: Input feature map
%   - kernel: Weight
%   - s: stride
%   - p: padding
% Output
%   - out
function out = convol2(img,kernel,s,p)
```

Convolution Function: Data preparation

- Input Buffers
  - Padded input image for handling boundary pixels

```
function out = convol2(img,kernel,s,p)
% Input Feature Maps
h = size(img,1);    % height
w = size(img,2);    % width
c = size(img,3);    % number of input features

% Padded image: zero padding
pad_img = zeros(h+p,w+p,c);
st_p = ceil(p/2);
pad_img(1+st_p:st_p+h,1+st_p:st_p+w,:) = img;

% Filter kernel size
f = size(kernel,1);

% Output feature maps
c_out = size(kernel,4);              % Number of output features
w_out = floor((w - f + p) / s + 1); % width
h_out = floor((h - f + p) / s + 1); % height

out = zeros(h_out,w_out,c_out);      % buffer of output feature maps
```

Convolution Function: Data preparation

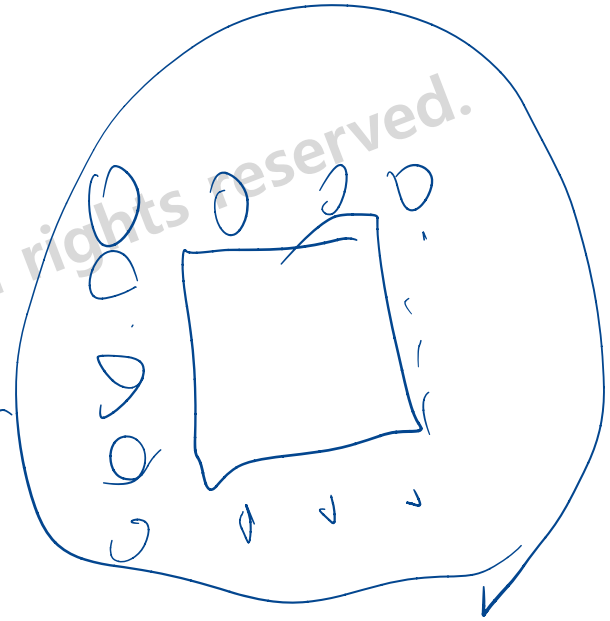
- Output Buffers
  - Calculate the sizes
  - Allocate a buffer/variable for output feature maps

```
function out = convol2(img,kernel,s,p)
% Input Feature Maps
h = size(img,1);    % height
w = size(img,2);    % width
c = size(img,3);    % number of input features

% Padded image: zero padding
pad_img = zeros(h+p,w+p,c);
st_p = ceil(p/2);
pad_img(1+st_p:st_p+h,1+st_p:st_p+w,:) = img;

% Filter kernel size
f = size(kernel,1);

% Output feature maps
c_out = size(kernel,4);              % Number of output features
w_out = floor((w - f + p) / s + 1); % width
h_out = floor((h - f + p) / s + 1); % height

out = zeros(h_out,w_out,c_out);      % buffer of output feature maps
```

Convolution Function: Data preparation

- Three loops
  - Number of output channels
  - Row: line by line
  - Column: from left to right
- Kernel operations
  - Element-wise multiplication (products)
  - Sum (sum of products)

```
% Convolution
for k = 1:c_out                 % Number of output channels
    for i = 1:h_out             % Row
        for j = 1:w_out         % Column
            % Element-wise Muliplication => Products
            scalar = kernel(:,:,:,k).* ...
                     pad_img(1+(i-1)*s:1+(i-1)*s+f-1, 1+(j-1)*s:1+(j-1)*s+f-1, :);
            % Sum (Sum of Products)
            out(i,j,k) = sum(scalar(:));
        end
    end
end
```



Test a sim-SR

- Load a pretrained model of sim-SR
  - Parameters: layer 1 (w1, b1), layer 2 (w2, b2), layer 3 (w3, b3)
  - Input files locate at bin/
  - Weights are reorganized in a typical format:

  [Filter size, Filter size, input channels, output channels]

```
%% Load pre-trained convolutional parameter
% Load Layer 1
[w1,b1,~,~,~] = read_conv_param_module('bin/sim_espcn_3x3.weights_layer_0',3, 1,16,0);
w1 = permute(reshape(w1, 3, 3, 1, 16), [2, 1, 3, 4]);
% Load Layer 2
[w2,b2,~,~,~] = read_conv_param_module('bin/sim_espcn_3x3.weights_layer_1',3,16,16,0);
w2 = permute(reshape(w2, 3, 3, 16, 16), [2, 1, 3, 4]);
% Load Layer 3
[w3,b3,~,~,~] = read_conv_param_module('bin/sim_espcn_3x3.weights_layer_2',3, 16,4,0);
w3 = permute(reshape(w3, 3, 3, 16,4), [2, 1, 3, 4]);
```

Test a sim-SR

- Load an input image and do preprocessing

```
%% Load an image
SF = 2;     % Up scaling 2x
imGT = imread('img/butterfly_GT.bmp');
if size(imGT,3) > 1
    im = rgb2ycbcr(imGT);
else
    im = imGT;
end
imhigh = modcrop(im, SF);
imhigh = single(imhigh)/255;
imlow = imresize(imhigh, 1/SF, 'bicubic');
%imlow = imresize(imlow, SF, 'bicubic');
if size(imlow,3)>1
    imlowy = imlow(:,:,1);
    imlowy = max(16.0/255, min(235.0/255, imlowy));
else
    imlowy = imlow;
end
input = imlowy;

figure();
imshow(input);

% Now, we convert an image input to a 8-bit format
input = double(floor(imlowy * 255));
```

- Load an input image
- Transform RGB to YCbCr

Generate a Low-resolution image
→ An image input of our network

Test a sim-SR

- Test a sim-SR with a given input image
  - Apply convolution to the input image

```
%% Demo sim-SR

% First Layer
conv_out = convol2(input, w1, 1, 2);
for j = 1:size(conv_out, 3)
    % Adding bias
    conv_out(:,:,j) = conv_out(:,:,j) + b1(j);
end
% Activation
conv_out_relu = conv_out;
conv_out_relu(conv_out_relu < 0) = 0;

%for i = 1:size(conv_out, 3)
%    figure(1)
%    subplot(1,2,1)
%    imshow(conv_out(:,:,i));title(['ch = ',num2str(i)]);
%    subplot(1,2,2)
%    imshow(conv_out_relu(:,:,i));title('After ReLU');
%    pause(1)
%end

% Insert your code for other layers
```

Test a sim-SR

- Test a sim-SR with a given input image
  - Add a bias for each channel

```
%% Demo sim-SR

% First Layer
conv_out = convol2(input, w1, 1, 2);
for j = 1:size(conv_out, 3)
    % Adding bias
    conv_out(:,:,j) = conv_out(:,:,j) + b1(j);
end
% Activation
conv_out_relu = conv_out;
conv_out_relu(conv_out_relu < 0) = 0;

%for i = 1:size(conv_out, 3)
%    figure(1)
%    subplot(1,2,1)
%    imshow(conv_out(:,:,i));title(['ch = ',num2str(i)]);
%    subplot(1,2,2)
%    imshow(conv_out_relu(:,:,i));title('After ReLU');
%    pause(1)
%end

% Insert your code for other layers
```

Test a sim-SR

- Test a sim-SR with a given input image
  - Apply ReLU on the output

```
%% Demo sim-SR

% First Layer
conv_out = convol2(input, w1, 1, 2);
for j = 1:size(conv_out, 3)
    % Adding bias
    conv_out(:,:,j) = conv_out(:,:,j) + b1(j);
end
% Activation
conv_out_relu = conv_out;
conv_out_relu(conv_out_relu < 0) = 0;

%for i = 1:size(conv_out, 3)
%    figure(1)
%    subplot(1,2,1)
%    imshow(conv_out(:,:,i));title(['ch = ',num2str(i)]);
%    subplot(1,2,2)
%    imshow(conv_out_relu(:,:,i));title('After ReLU');
%    pause(1)
%end

% Insert your code for other layers
```

To do …

- Complete the missing code (CONV kernel operation) in convol2.m
- Complete the missing code in test_simSR.m:
  - Run for all three layers
  - Last layer uses *linear activation*, two first layers use *ReLU activation*
  - Show the feature maps
- Refer to figures in **featuremaps** folder for sample feature maps
  - (LayerNumber)_(ChannelNumber).jpg

Complete the missing code

convol2.m

```
function out = convol2(img,kernel,s,p)
% Input Feature Maps
h = size(img,1);    % height
w = size(img,2);    % width
c = size(img,3);    % number of input features

% Padded image: zero padding
pad_img = zeros(h+p,w+p,c);
st_p = ceil(p/2);
pad_img(1+st_p:st_p+h,1+st_p:st_p+w,:) = img;

% Filter kernel size
f = size(kernel,1);

% Output feature maps
c_out = size(kernel,4);             % Number of output features
w_out = floor((w - f + p) / s + 1); % width
h_out = floor((h - f + p) / s + 1); % height

out = zeros(h_out,w_out,c_out);     % buffer of output feature maps

% Convolution
for k = 1:c_out             % Number of output channels
    for i = 1:h_out         % Row
        for j = 1:w_out     % Column
            % Insert your code


        end
    end
end
```

test_simSR.m

```
%% Demo sim-SR

% First Layer
conv_out = convol2(input, w1, 1, 2);
for j = 1:size(conv_out, 3)
    % Add bias
    conv_out(:,:,j) = conv_out(:,:,j) + b1(j);
end

% Activation
conv_out_relu = conv_out;
conv_out_relu(conv_out_relu < 0) = 0;

for i = 1:size(conv_out, 3)
    figure(1)
    subplot(1,2,1)
    imshow(conv_out(:,:,i));title(['ch = ',num2str(i)]);
    subplot(1,2,2)
    imshow(conv_out_relu(:,:,i));title('After ReLU');
    pause(1)
end
```

```
% Insert your code for other layers
```

Road map

Deep Learning Accelerator

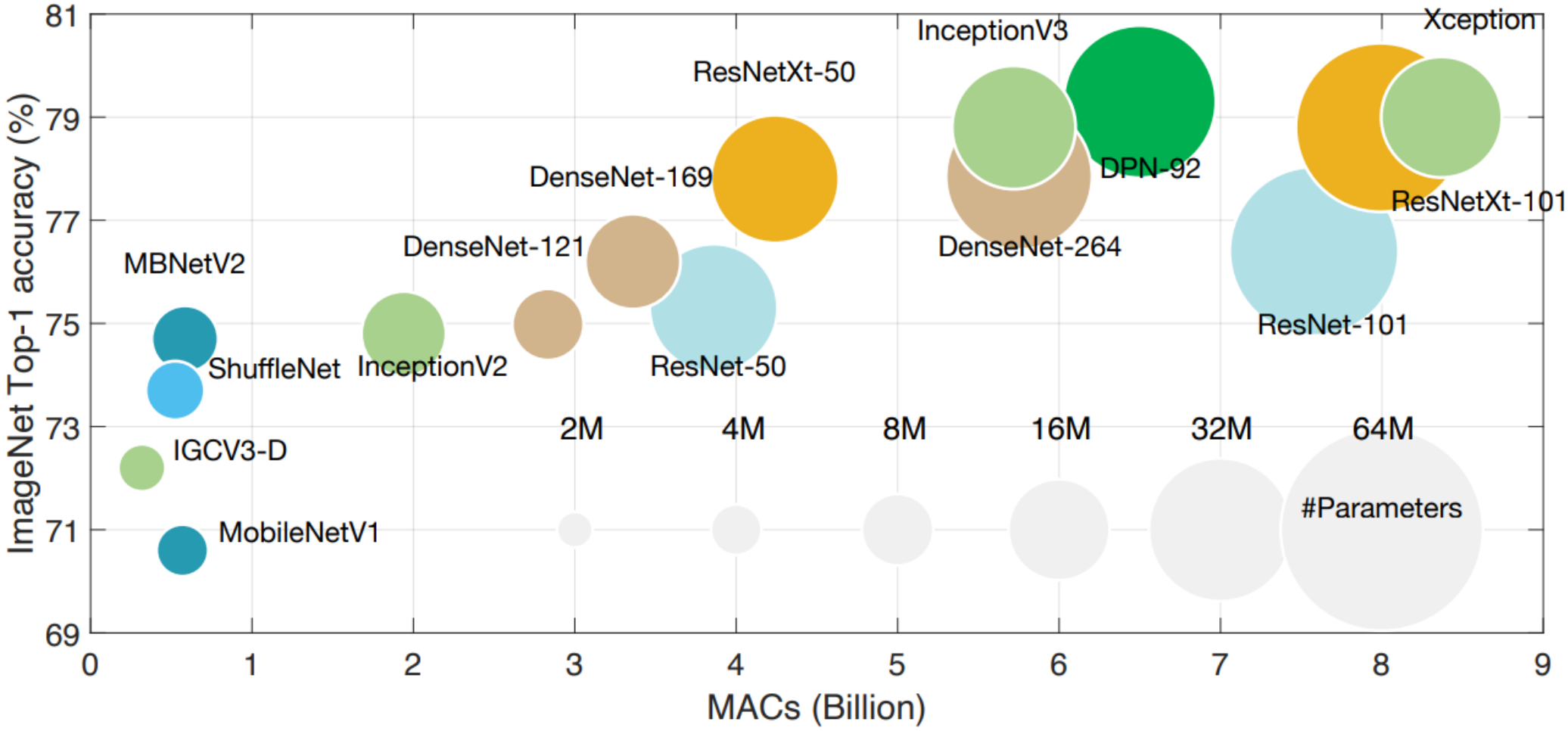
Convolutional Neural Network (CNN)

Quantization

Block memory

Reference S/W

Today's AI is too BIG!



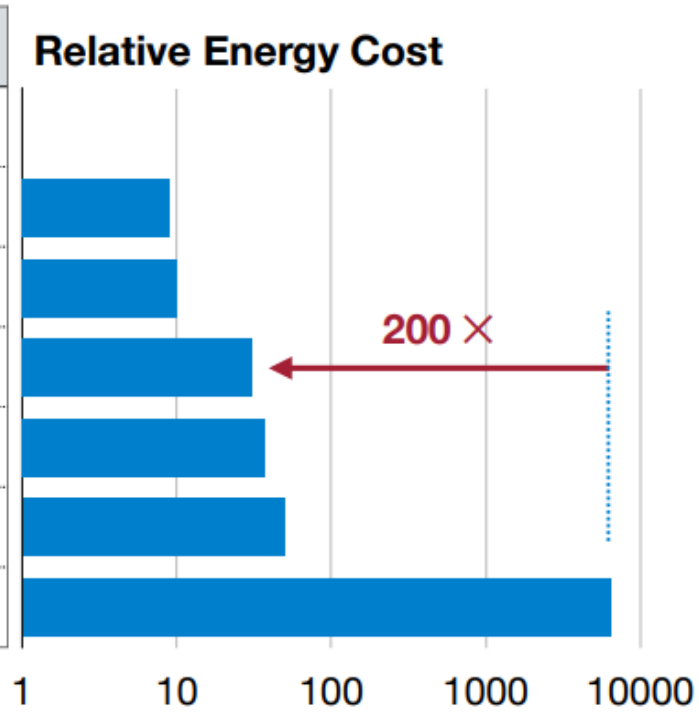
Model Compression and Hardware Acceleration for Neural Networks: A Comprehensive Survey [Deng et al., IEEE 2020]

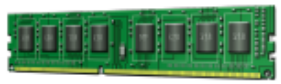
Memory Access is Expensive

- Data Movement → More Memory Reference → More 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





1 = 200 × +

Courtesy: Song Han @MIT

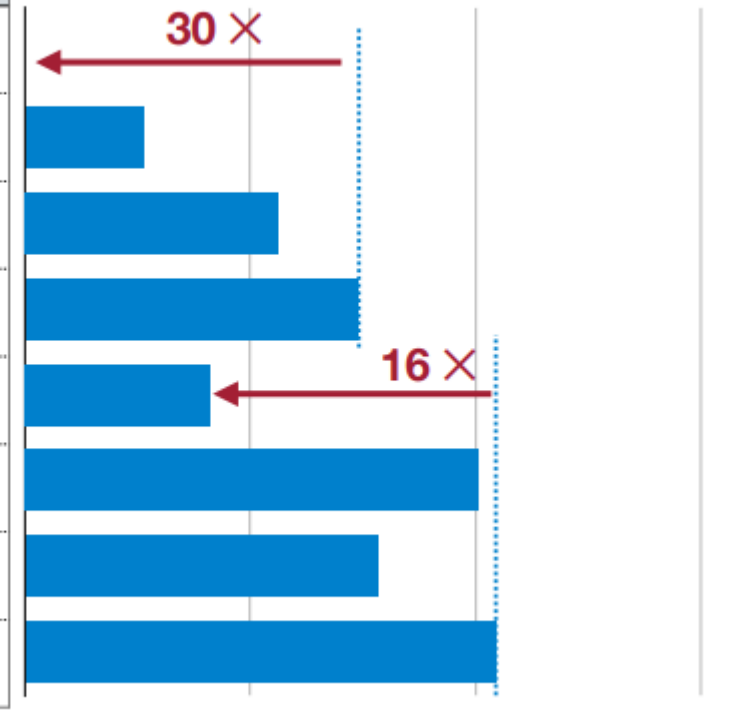
Computing's Energy Problem (and What We Can Do About it)
[Horowitz, M., IEEE ISSCC 2014]

Low Bit-Width Operations are Cheap

- Less Bit-Width → Less Energy

Operation	Energy [pJ]
8 bit int ADD	0.03
32 bit int ADD	0.1
16 bit float ADD	0.4
32 bit float ADD	0.9
8 bit int MULT	0.2
32 bit int MULT	3.1
16 bit float MULT	1.1
32 bit float MULT	3.7

Rough Energy Cost For Various Operations in 45nm 0.9V



Courtesy: Song Han @MIT

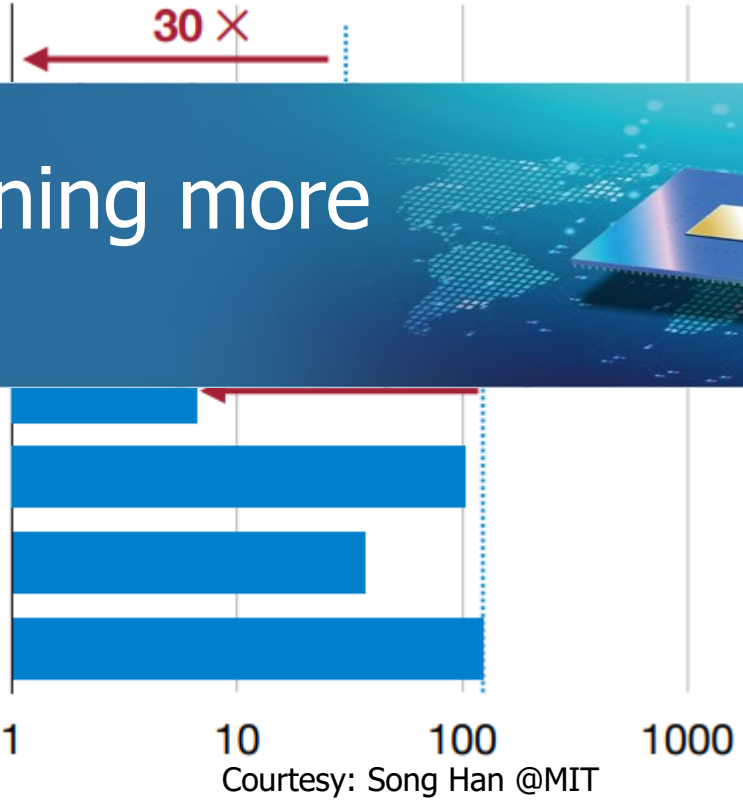
Computing's Energy Problem (and What We Can Do About it)
[Horowitz, M., IEEE ISSCC 2014]

Low Bit-Width Operations are Cheap

- Less Bit-Width → Less Energy

Operation	Energy [pJ]
8 bit int ADD	0.03
8 bit int MULT	0.2
32 bit int MULT	3.1
16 bit float MULT	1.1
32 bit float MULT	3.7

Rough Energy Cost For Various Operations in 45nm 0.9V



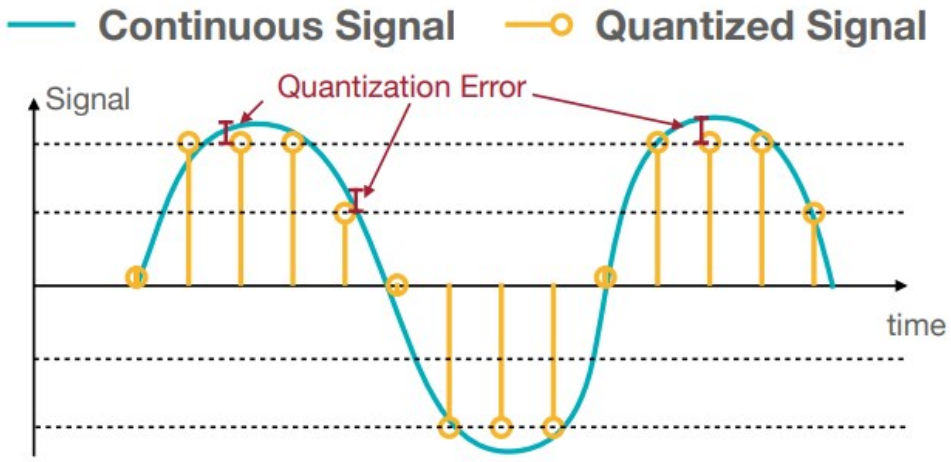
Courtesy: Song Han @MIT

How should we make deep learning more efficient?

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

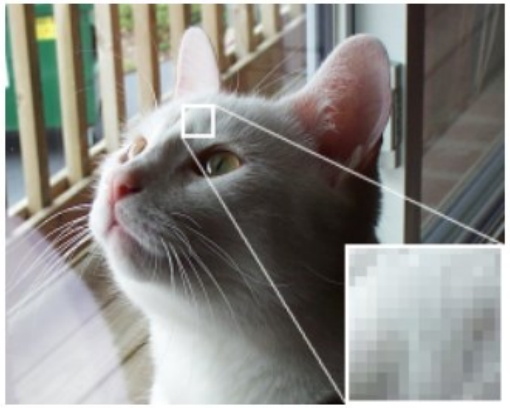
What is Quantization?

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

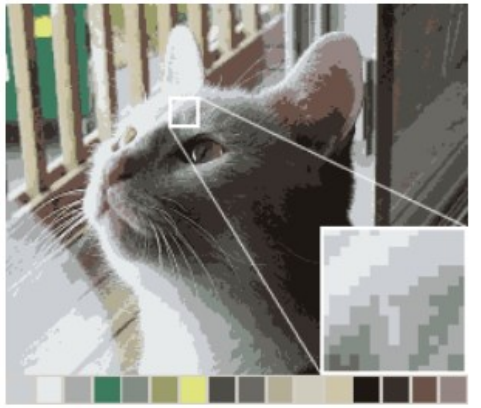


The difference between an input value and its quantized value is referred to as quantization error.

Original Image



16-Color Image



Images are in the public domain.

"Palettization"

https://en.wikipedia.org/wiki/Quantization

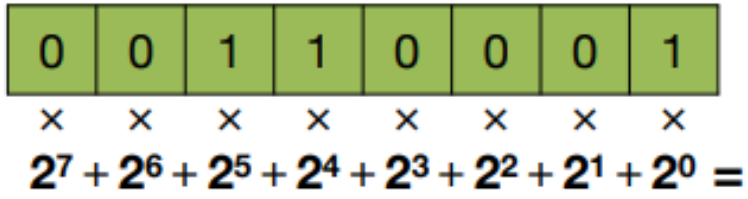
Numeric Data Types

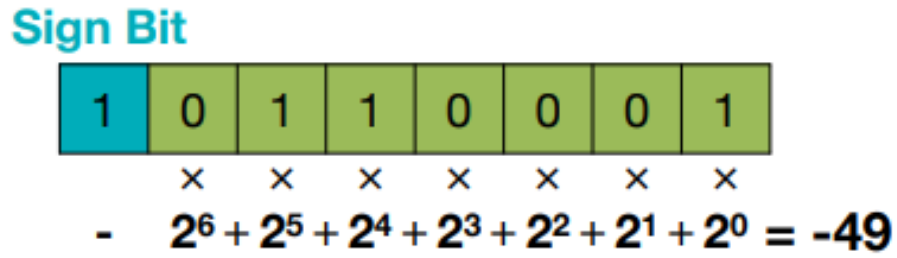
- How is numeric data represented in modern computing systems?

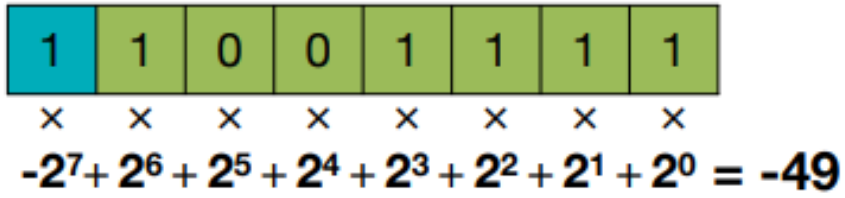
- Data types
  - Integer
  - Fixed-point number
  - Floating-point number

Integer

- Unsigned number
  - *n*-bit: Range: [0, $2^n - 1$]
- Signed number
  - *Sign-Magnitude Representation*
  - *n*-bit Range: [$-2^{n-1} - 1$, $2^{n-1} - 1$]
  - Both 00…0 and 10…0 represent 0
- Two's Complement Representation
  - *n-bit* Range: [-2^{n-1}, $2^{n-1} - 1$]
  - 00…0 represents 0
  - 10…0 represents -2^{n-1}

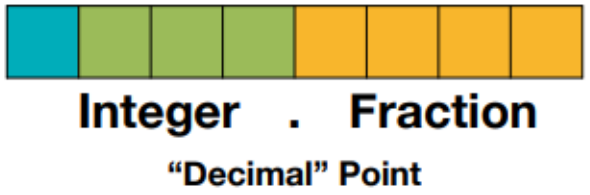


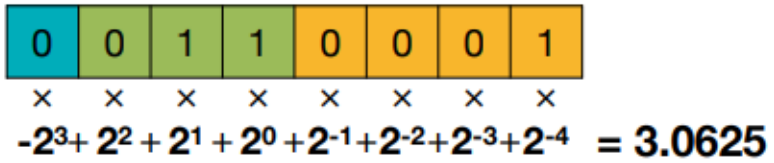


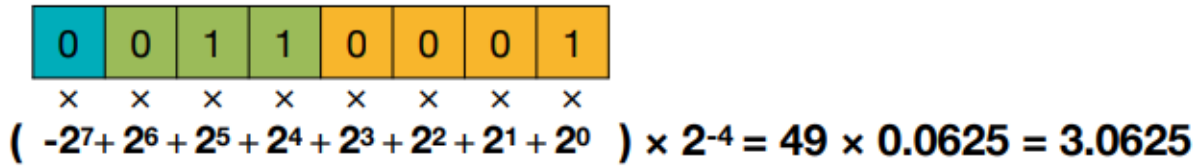


Fixed-point number

- Similar to an integer format, a fixed point is decomposed in [sign, ibit, fbit]







(using 2's complement representation)

Floating-Point Number

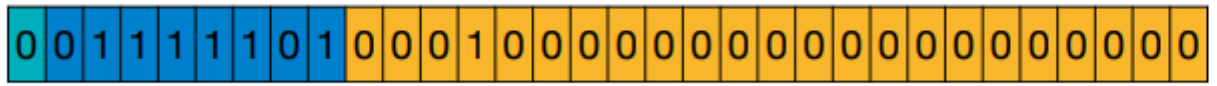
- Example: 32-bit floating-point number in IEEE 754

Sign 8 bit Exponent **23 bit Fraction**

$$(-1)^{sign} \times (1 + \textbf{Fraction}) \times 2^{\textbf{Exponent}-127}$$ ← Exponent Bias = 127 = $2^{8-1}-1$

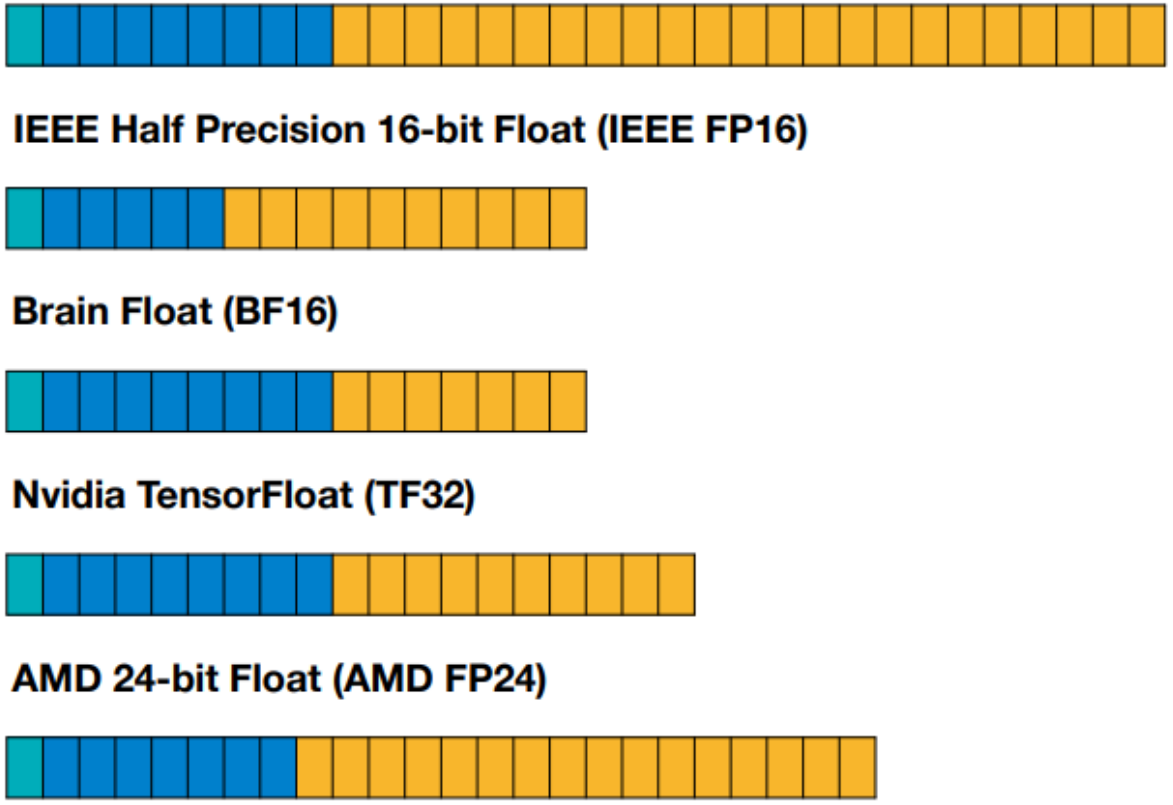
(significant / mantissa)

$$0.265625 = 1.0625 \times 2^{-2} = (1 + \underline{0.0625}) \times 2^{\underline{125}-127}$$



Floating-Point Number

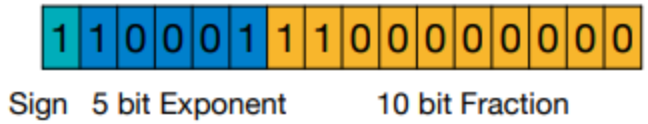
- Exponent Width → Range; Fraction Width → Precision



Exponent (bits)	Fraction (bits)	Total (bits)
8	23	32
5	10	16
8	7	16
8	10	19
7	16	24

Numeric Data Types

- Question: What is the following IEEE half-precision (IEEE FP16) number in decimal?



Exponent Bias = 15_{10}

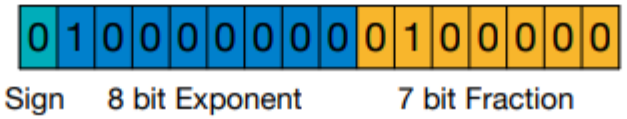
- Sign: -
- Exponent: $10001_2 - 15_{10} = 17_{10} - 15_{10} = 2_{10}$
- Fraction: $1100000000_2 = 0.75_{10}$
- Decimal Answer = $-(1 + 0.75) \times 2^2 = -1.75 \times 2^2 = -7.0_{10}$

Numeric Data Types

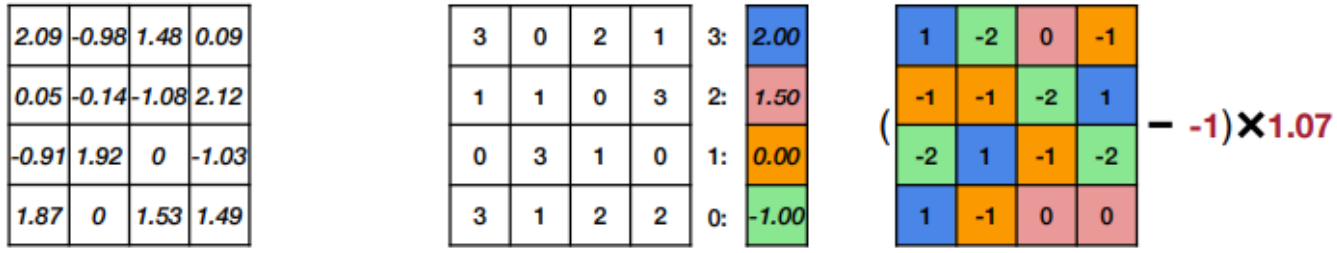
- Question: What is the decimal 2.5 in Brain Float (BF16)?

$2.5_{10} = 1.25_{10} \times 2^{1}$ Exponent Bias = 127_{10}

- Sign: +
- Exponent Binary: $1_{10} + 127_{10} = 128_{10} = 10000000_2$
- Fraction Binary: $0.25_{10} = 0100000_2$
- Binary Answer



Neural Network Quantization: Agenda

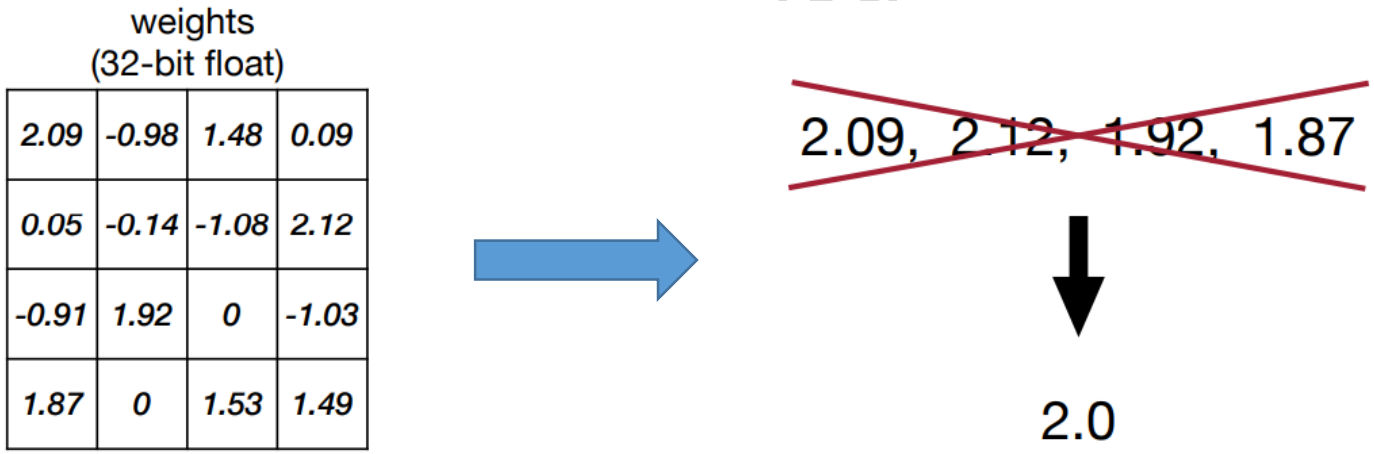


		K-Means-based Quantization	**Linear Quantization**	**Binary/Ternary Quantization**
Storage	Floating-Point Weights	Integer Weights; Floating-Point Codebook	Integer Weights	Binary/Ternary Weights
Computation	Floating-Point Arithmetic	Floating-Point Arithmetic	Integer Arithmetic	Bit Operations

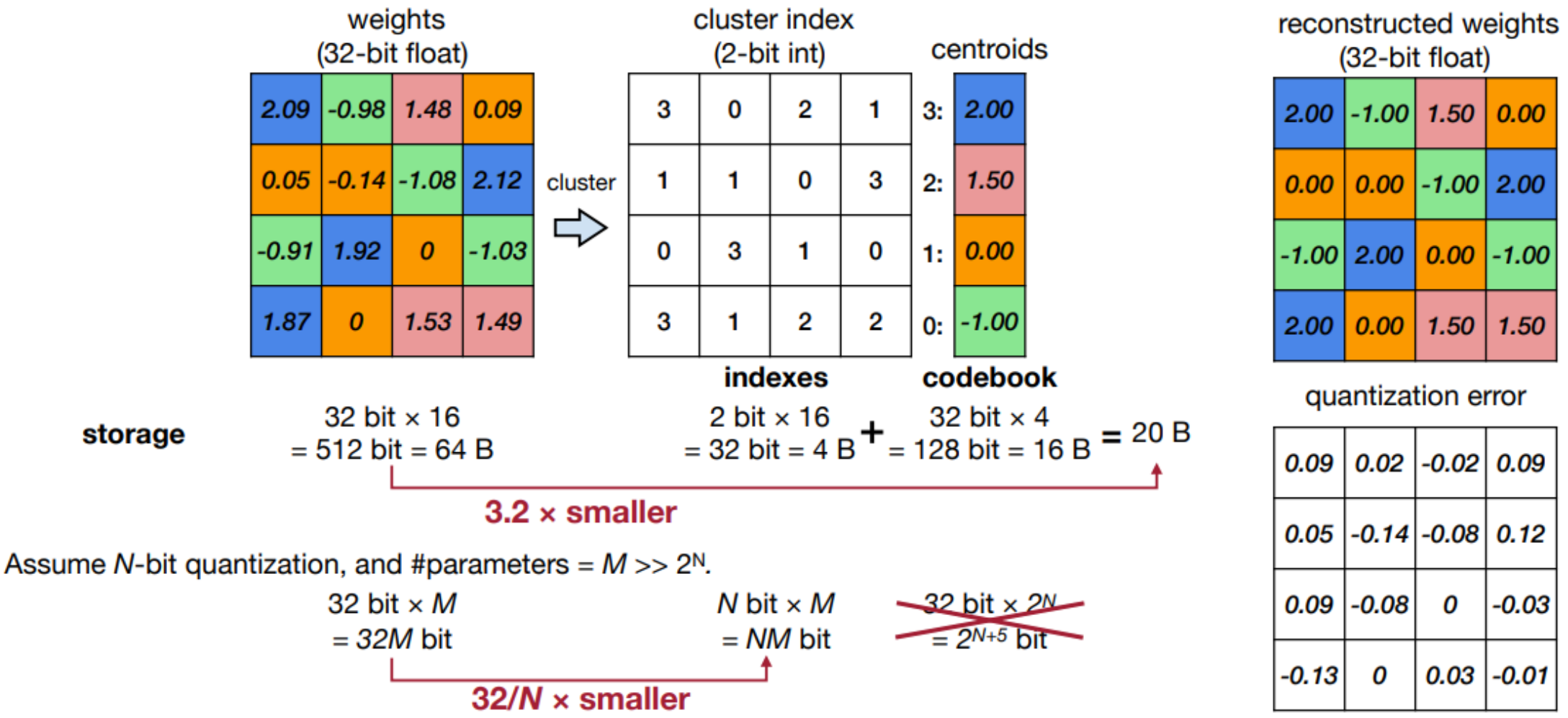
Courtesy to Song Han @MIT

Neural Network Quantization

- Model/Weight quantization: Reduce the storage
  - Data Movement: Less Memory Reference → Less Energy
  - Computation: No benefit for low-bit arithmetic
    - Incur some overheads for decoding compressed data.



K-Means-based Weight Quantization



Assume N-bit quantization, and #parameters = $M >> 2^N$.

$32 \text{ bit} \times M = 32M \text{ bit}$

$N \text{ bit} \times M = NM \text{ bit}$

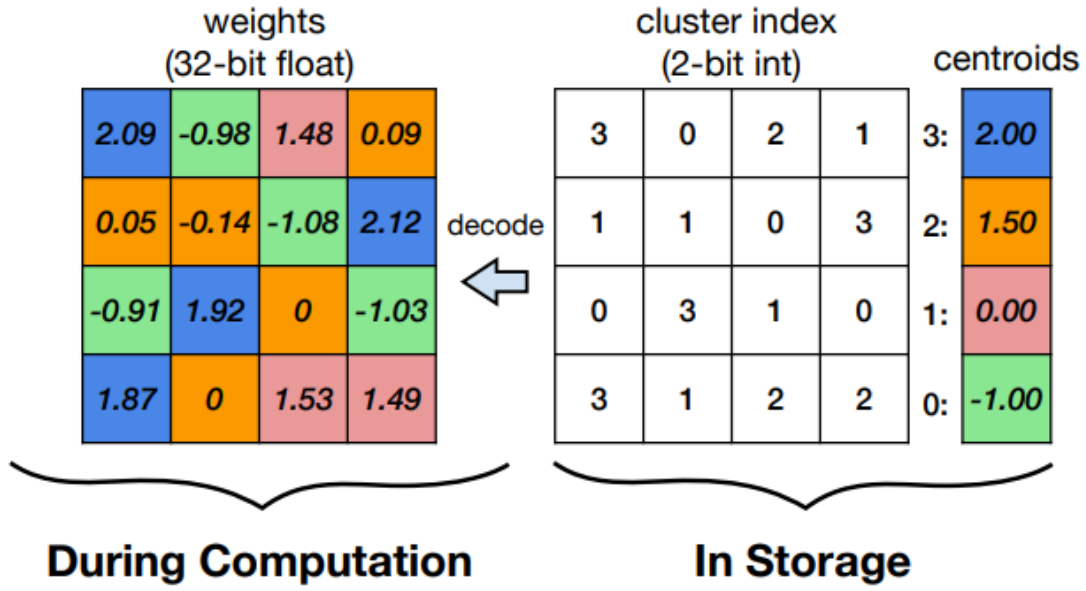
~~$32 \text{ bit} \times 2^N = 2^{N+5} \text{ bit}$~~

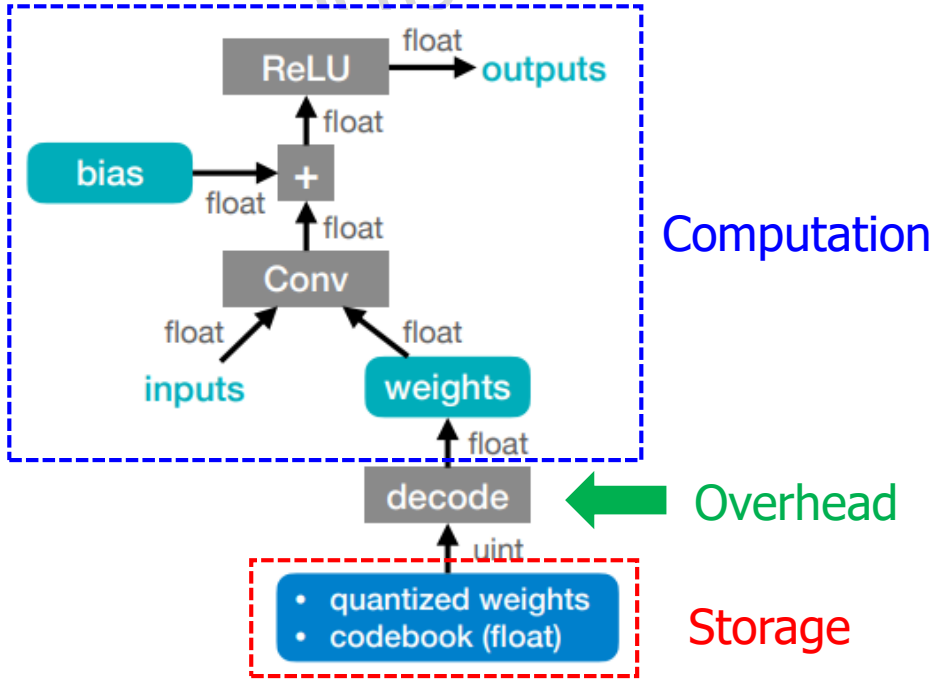
$32/N \times$ smaller

Deep Compression [Han et al., ICLR 2016]

K-Means-based Weight Quantization

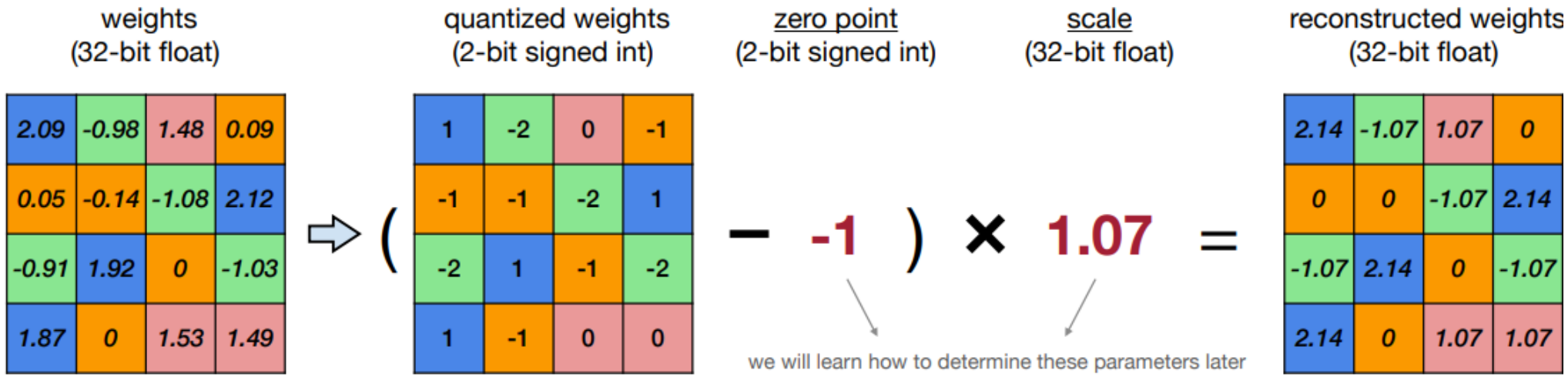
- The weights are decompressed using a lookup table (i.e., codebook) during runtime inference.
  - K-Means-based Weight Quantization only saves the storage cost of a neural network model.
  - All the computation and memory access are still floating-point.





What is Linear Quantization?

- An affine mapping of integers to real numbers



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

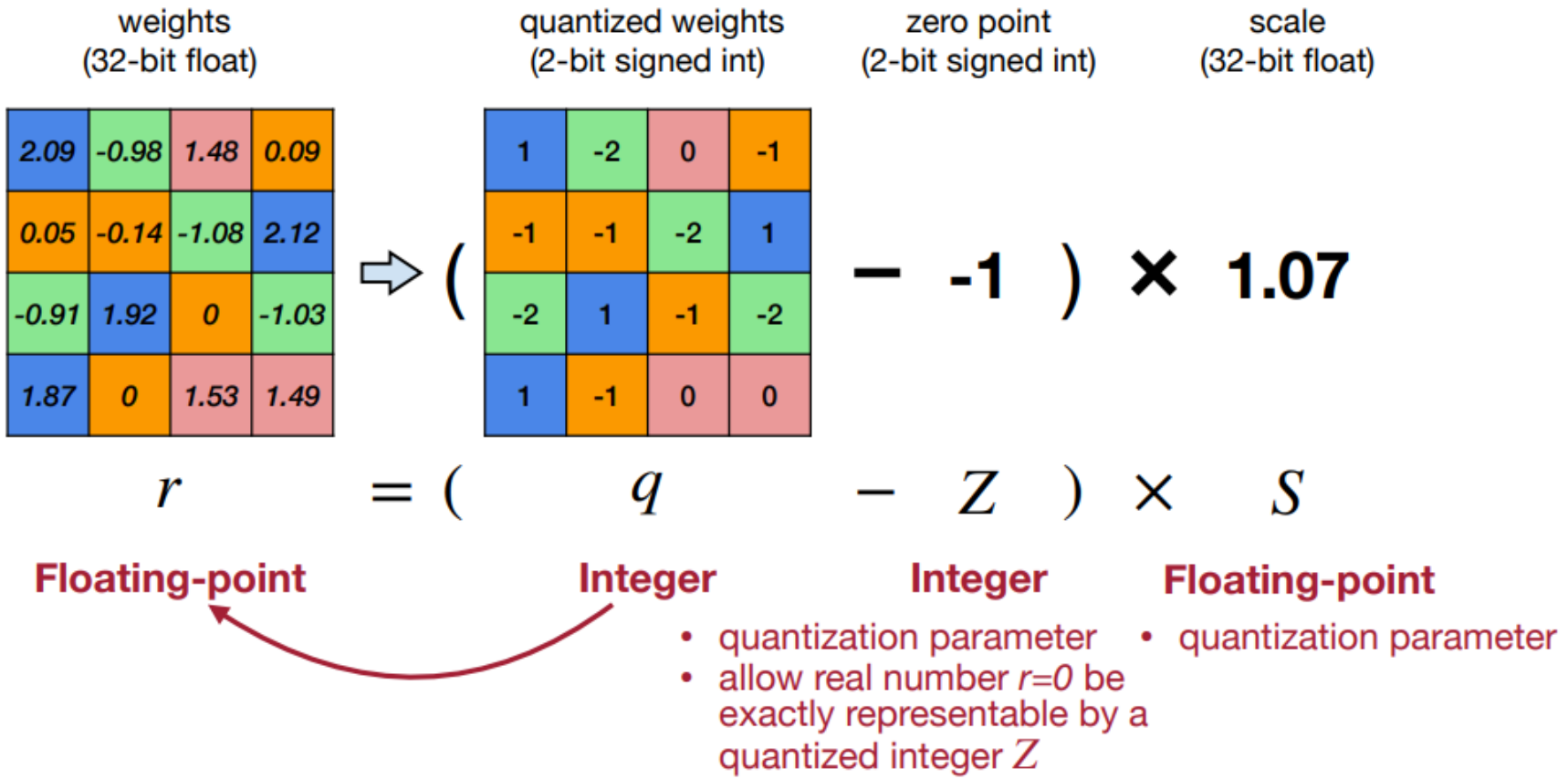
quantization error

-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

Courtesy to Song Han @MIT

What is Linear Quantization?

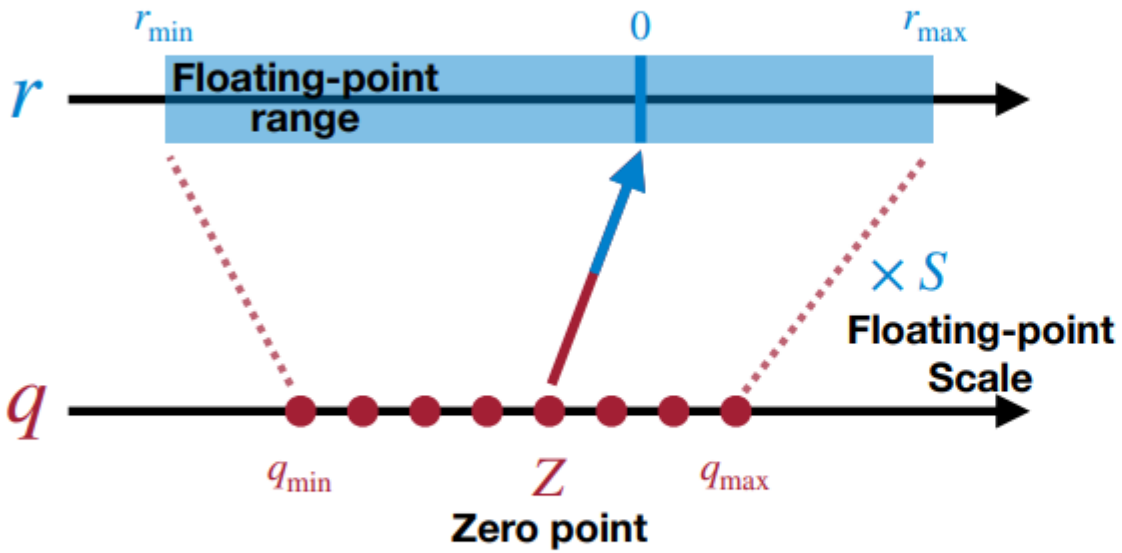
- An affine mapping of integers to real numbers $r = S(q - Z)$



Courtesy to Song Han @MIT

Scale S of Linear Quantization

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



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

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

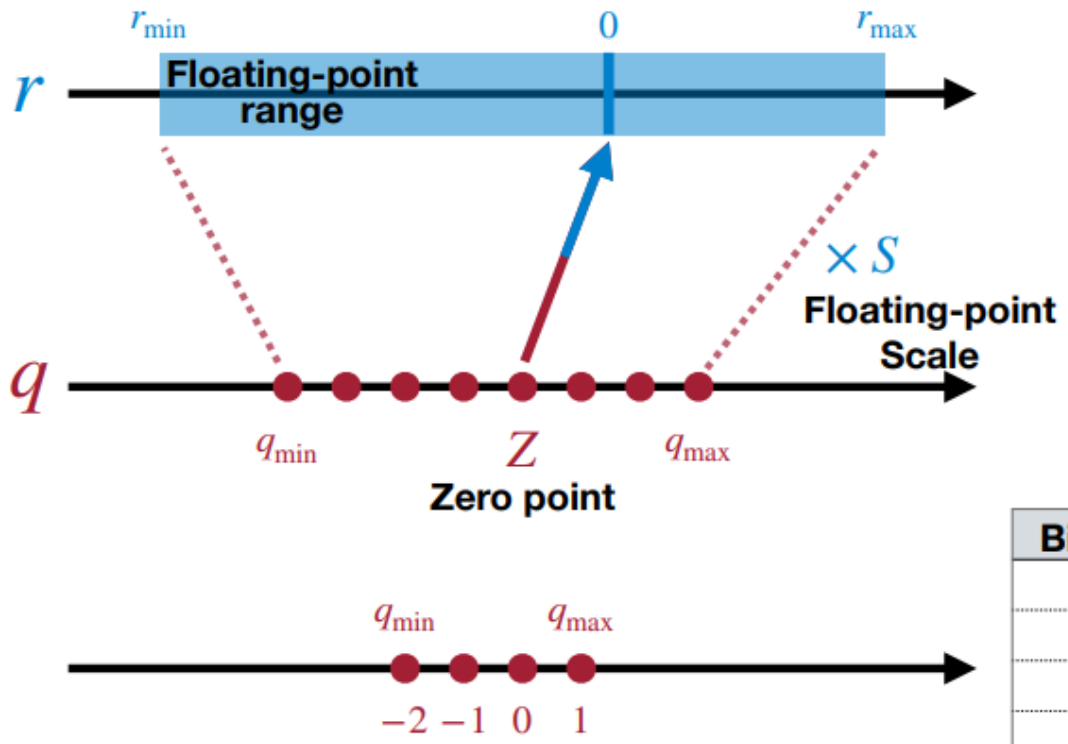
$$r_{max} - r_{min} = S\left(q_{max} - q_{min}\right)$$

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

Quantization and Training of Neural Networks for Efficient Integer-Arithmetic-Only Inference [Jacob et al., CVPR 2018]

Scale S of Linear Quantization

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



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

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

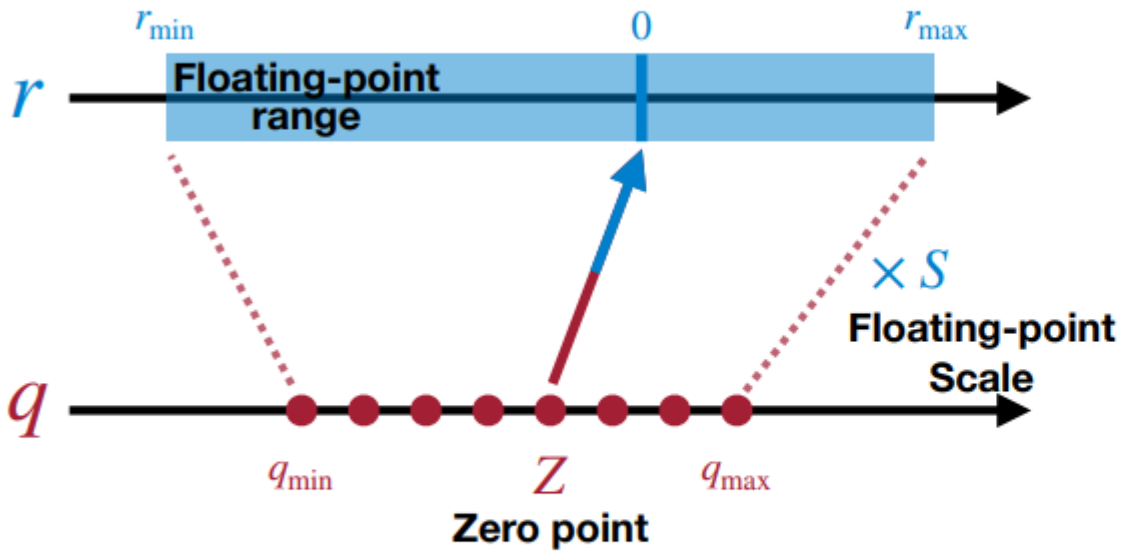
$$S = \frac{r_{max} - r_{min}}{q_{max} - q_{min}}$$

$$= \frac{2.12 - (-1.08)}{1 - (-2)}$$

$$= 1.07$$

Zero Point Z of Linear Quantization

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



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

$$\downarrow$$

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

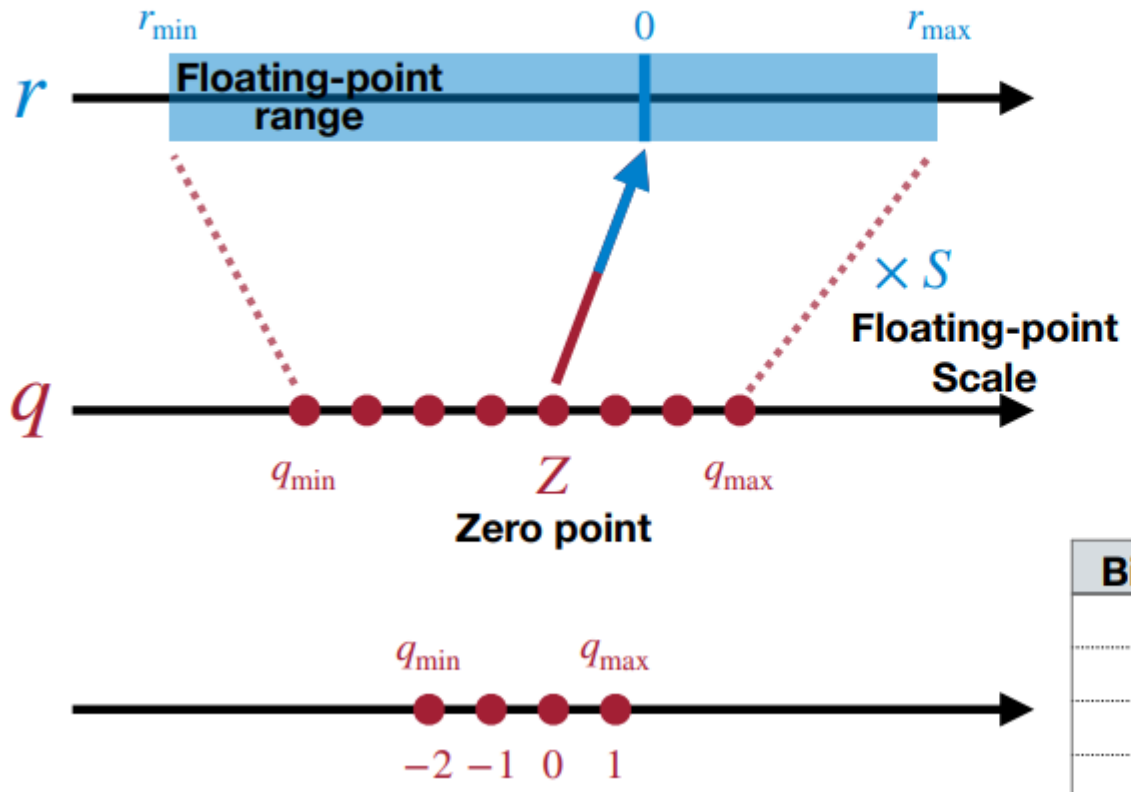
$$\downarrow$$

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

Quantization and Training of Neural Networks for Efficient Integer-Arithmetic-Only Inference [Jacob et al., CVPR 2018]

Zero Point Z of Linear Quantization

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



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

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

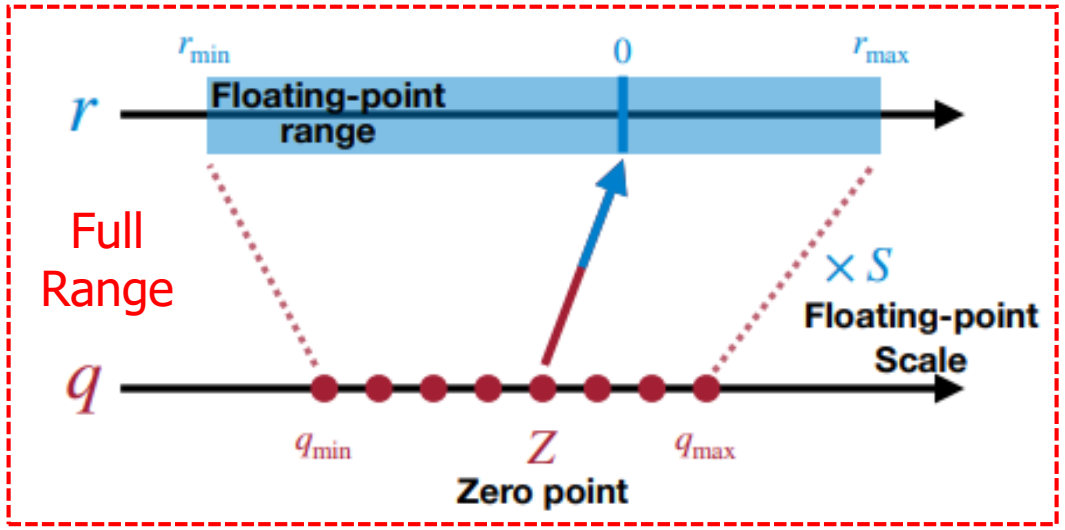
$$Z = q_{min} - \frac{r_{min}}{S}$$

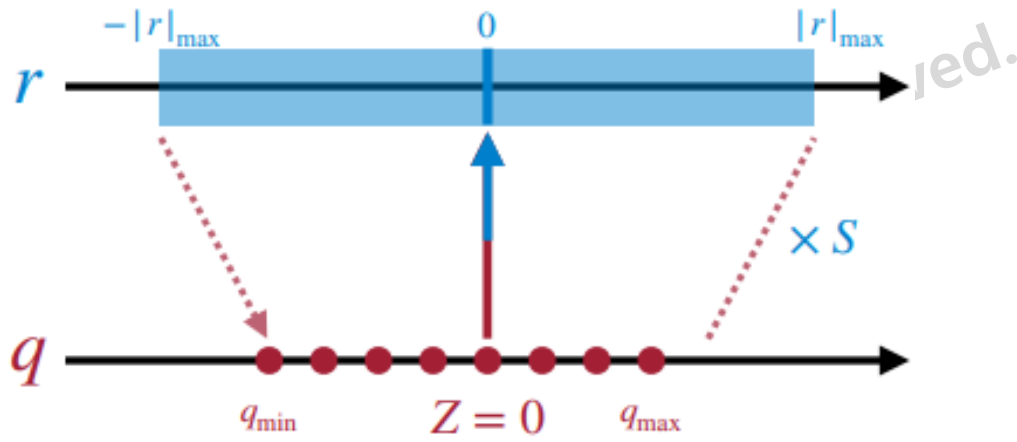
$$= \text{round}(-2 - \frac{-1.08}{1.07})$$

$$= -1$$

Symmetric Linear Quantization

- Zero point Z = 0 and Symmetric floating-point range





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

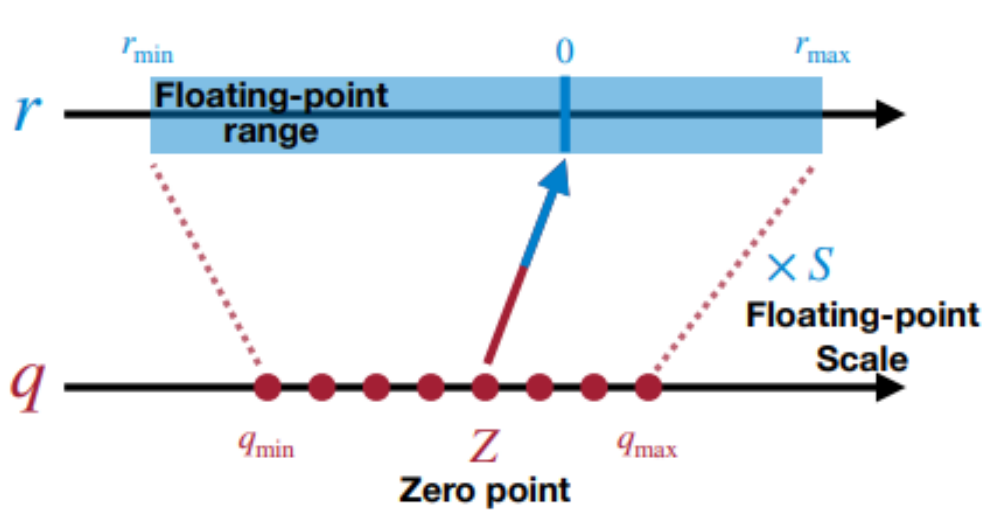
$$S = \frac{r_{max} - r_{min}}{q_{max} - q_{min}}$$

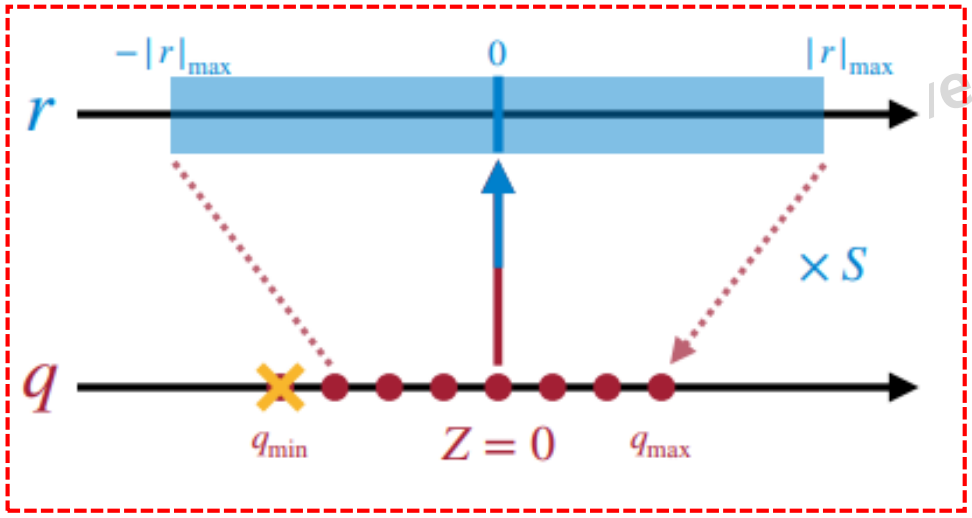
$$S = \frac{r_{min}}{q_{min} - Z} = \frac{-|r|_{max}}{q_{min}} = \frac{|r|_{max}}{2^{N-1}}$$

- use full range of quantized integers
- example: PyTorch's native quantization, ONNX

Symmetric Linear Quantization

- Zero point Z = 0 and Symmetric floating-point range





Restricted Range

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

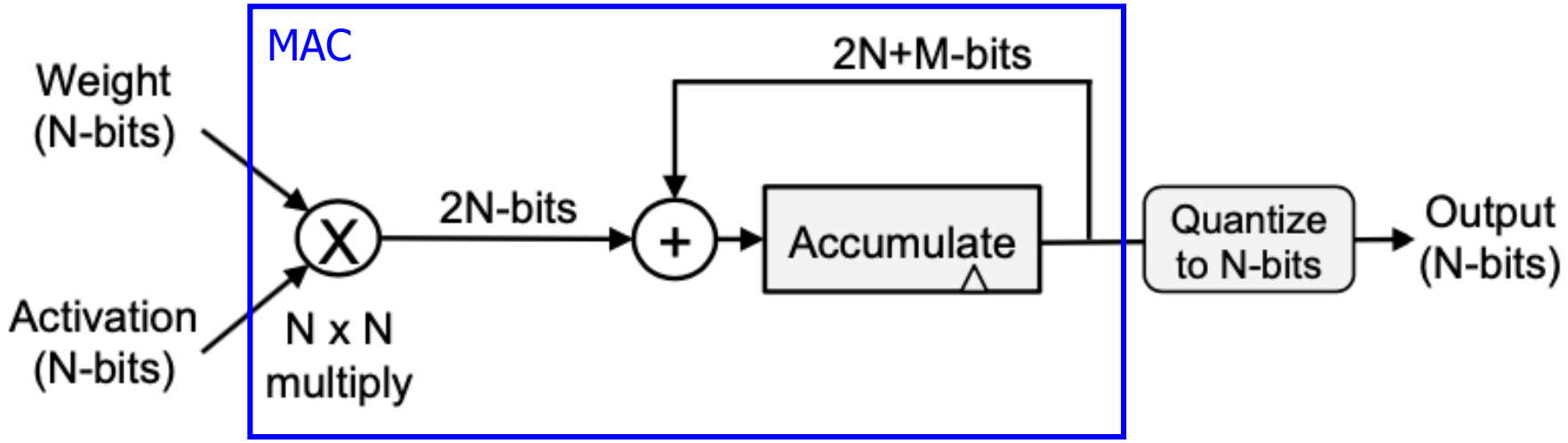
$$S = \frac{r_{max} - r_{min}}{q_{max} - q_{min}}$$

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

- example: TensorFlow, NVIDIA TensorRT, Intel DNNL

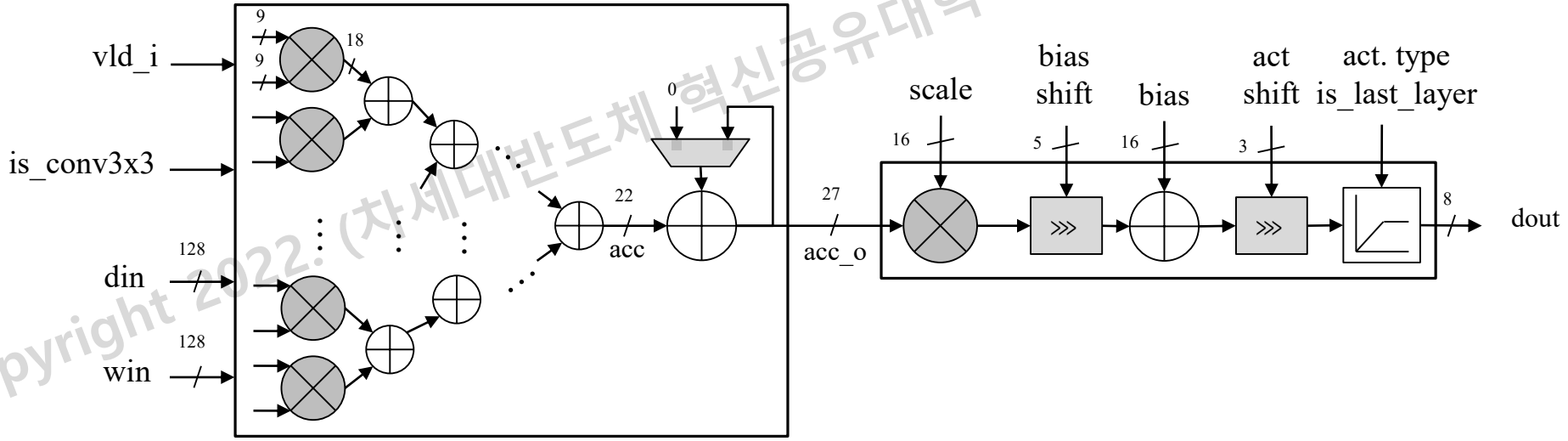
Multiplication and Accumulation (MAC)

- Accumulation requires higher precision than inputs.
- Inputs: two N-bit weight activation
- The accumulated result is quantized to a N-bit number (output activation)



Convolutional kernel

- Convolution kernel
  - Do multiplication and accumulation
  - Do normalization/scaling, then add a bias
  - Do activation quantization



Lab 2: Quantization

- Load a model
- Complete the missing codes
  - Weight/Bias quantization: uniform_quantize.m
  - Activation Quantization:
    - ReLU: hwu_relu_quantize.m
    - Linear: hwu_linear_quantize.m

Load a CNN model

- Parameters: layer 1 (w1, b1), layer 2 (w2, b2), layer 3 (w3, b3)
- Input files locate at bin/
- Weights are reorganized in a typical format:

[Filter size, Filter size, input channels, output channels]

```
%% Load pre-trained convolutional parameter
% Load Layer 1
[w1,b1,~,~,~] = read_conv_param_module('bin/sim_espcn_3x3.weights_layer_0',3, 1,16,0);
w1 = permute(reshape(w1, 3, 3, 1, 16), [2, 1, 3, 4]);
% Load Layer 2
[w2,b2,~,~,~] = read_conv_param_module('bin/sim_espcn_3x3.weights_layer_1',3,16,16,0);
w2 = permute(reshape(w2, 3, 3, 16, 16), [2, 1, 3, 4]);
% Load Layer 3
[w3,b3,~,~,~] = read_conv_param_module('bin/sim_espcn_3x3.weights_layer_2',3, 16,4,0);
w3 = permute(reshape(w3, 3, 3, 16,4), [2, 1, 3, 4]);
```

Weight quantization

- Convert a FP tensor into a fixed-point format
- Example: 8-bit symmetric representation
  - -255/2, -254/2, …, -1/2, 1/2, …,255/2

Floating point weight

```
w1(:,:,1,1) =

   -0.3302   -0.3016   -0.1170
    0.3708   -0.2676   -0.1463
   -0.0760   -0.0007    0.3297
```

```
wq1(:,:,1,1) =

  -169  -155   -59
   189  -137   -75
   -39    -1   169
```

Quantized weight
ibits = 0, fbits = 8

```
% Function: Symetric Uniform quantization
% Inputs
%    - x:     input tensor
%    - step: quantized step
%    - nbit: number of bits in fixed-point representation
% Outputs
%    - output: Quantized value mapping to x
%    - output_store: Store value

function [output, output_store] = uniform_quantize(x,step,nbit)
% Initialization
output = x;
output_store = x;

% Maximum and minimum ranges
pos_end = 2 ^ nbit - 1;
neg_end = -pos_end;

% Quantized value
output = 2 * round(x./step + 0.5) - 1;
output(output > pos_end) = pos_end;
output(output < neg_end) = neg_end;

output_store = (output - 1) / 2;
```

Weight quantization

- Convert a FP tensor into a fixed-point format
- Example: 8-bit symmetric representation
  - -255/2, -254/2, …, -1/2, 1/2, …,255/2

Quantized weight

```
wq1(:,:,1,1) =

  -169  -155   -59
   189  -137   -75
   -39    -1   169
```

```
wq1_store(:,:,1,1) =

   -85   -78   -30
    94   -69   -38
   -20    -1    84
```

Store weights

```
% Function: Symetric Uniform quantization
% Inputs
%    - x:     input tensor
%    - step: quantized step
%    - nbit: number of bits in fixed-point representation
% Outputs
%    - output: Quantized value mapping to x
%    - output_store: Store value

function [output, output_store] = uniform_quantize(x,step,nbit)
% Initialization
output = x;
output_store = x;

% Maximum and minimum ranges
pos_end = 2 ^ nbit - 1;
neg_end = -pos_end;

% Quantized value
output = 2 * round(x./step + 0.5) - 1;
output(output > pos_end) = pos_end;
output(output < neg_end) = neg_end;

output_store = (output - 1) / 2;
```

Activation Quantization (ReLU)

- Convert a FP tensor into a fixed-point format
  - Similar to weight/bias quantization
  - Normalize ranges of biases and convolution outputs

```
% Function: Activation quantization
% Inputs
%   - x:    input tensor
%   - step: quantized step
%   - nbit: number of bits in fixed-point representation
%   - biases_shift
% Outputs
%   - activations: Quantized value mapping to x
%   - activations_store: Store value

function [activations, activations_store] = hwu_relu_quantize(x, step, nbit, biases_shift)
% Initialization
activations = x;
activations_store = x;

% Maximum quantized range
pos_end = 2 ^ nbit - 1;

% Quantization
activations_store = x;
activations_store(x >= 0) = round(x(x >= 0)/(2^biases_shift*(step)));
activations_store(x < 0) = 0;

% ReLU
activations_store(activations_store > pos_end) = pos_end;
activations = activations_store;
```

Activation Quantization (Linear)

- Convert a FP tensor into a fixed-point format
  - Similar to weight/bias quantization
  - Normalize ranges of biases and convolution outputs

```
% Function: Activation quantization
% Inputs
%   - x:     input tensor
%   - step: quantized step
%   - nbit: number of bits in fixed-point representation
%   - biases_shift
% Outputs
%   - activations: Quantized value mapping to x
%   - activations_store: Store value
function [activations, activations_store] = hwu_linear_quantize(x, step, nbit, biases_shift)
% Initialization
activations = x;
activations_store = x;

% Maximum and minimum ranges
pos_end = 2 ^ (nbit-1) - 1;
neg_end = -pos_end - 1;

% Quantization
activations_store = round(x/(2^biases_shift*(step)));

% Linear activation
activations_store(activations_store > pos_end) = pos_end;
activations_store(activations_store < neg_end) = neg_end;

% Outputs for buffering/storing into memory
activations = activations_store;
```

To do …

- Complete the missing codes
  - Weight/Bias quantization: uniform_quantize.m
  - Activation Quantization:
    - ReLU: hwu_relu_quantize.m
    - Linear: hwu_linear_quantize.m
- Complete the missing code in test_simSR_quant.m:
  - Run for all three layers
  - Last layer uses linear activation, two first layers use ReLU
  - Show the feature maps
- Refer to figures in **featuremaps_quant** folder for sample feature maps
  - (LayerNumber)_(ChannelNumber).jpg

Complete the missing code

```
% Function: Symetric Uniform quantization
% Inputs
%   - x:    input tensor
%   - step: quantized step
%   - nbit: number of bits in fixed-point representation
% Outputs
%   - output: Quantized value mapping to x
%   - output_store: Store value

function [output, output_store] = uniform_quantize(x,step,nbit)
% Initialization
output = x;
output_store = x;
```

uniform_quantize.m

```
% Insert your code
```

```
% Function: Activation quantization
% Inputs
%   - x:    input tensor
%   - step: quantized step
%   - nbit: number of bits in fixed-point representation
%   - biases_shift
% Outputs
%   - activations: Quantized value mapping to x
%   - activations_store: Store value

function [activations, activations_store] = hwu_relu_quantize(x, step, nbit, biases_shift)
% Initialization
activations = x;
activations_store = x;
```

hwu_relu_quantize.m

```
% Insert your code
```

Complete the missing code

```
% Function: Activation quantization
% Inputs
%   - x:    input tensor
%   - step: quantized step
%   - nbit: number of bits in fixed-point representation
%   - biases_shift
% Outputs
%   - activations: Quantized value mapping to x
%   - activations_store: Store value

function [activations, activations_store] = hwu_linear_quantize(x, step, nbit, biases_shift)
% Initialization
activations = x;
activations_store = x;

% Insert your code
```

hwu_linear_quantize.m

```
% % First Layer
conv_out = convol2(input, wq1, 1, 2);
for j = 1:size(conv_out, 3)
    % Add bias
    conv_out(:,:,j) = conv_out(:,:,j) + bq1(j);
end

% Activation
conv_out_relu = hwu_relu_quantize(conv_out, step, nbits, biases_shift);

% for i = 1:size(conv_out, 3)
%    figure(1)
%    subplot(1,2,1)
%    imshow(conv_out(:,:,i));title(['ch = ',num2str(i)]);
%    subplot(1,2,2)
%    imshow(conv_out_relu(:,:,i));title('After ReLU');
%    pause(1)
% end

% Insert your code for other layers
```

test_simSR_quant.m

Road map

Deep Learning Accelerator

Convolutional Neural Network (CNN)

Quantization

Block memory

Reference S/W

Lab 3: Block memory

- Lab 3:
  - Dual-port block ram
  - Initialize memory cell with quantized weights
  - Implement a test bench by complete missing code

Weight quantization

- Convert a FP tensor into a fixed-point format
- Example: 8-bit symmetric representation
  - -255/2, -254/2, …, -1/2, 1/2, …,255/2

Floating point weight

```
w1(:,:,1,1) =

   -0.3302   -0.3016   -0.1170
    0.3708   -0.2676   -0.1463
   -0.0760   -0.0007    0.3297
```

```
wq1(:,:,1,1) =

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```

Quantized weight
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```
% Function: Symetric Uniform quantization
% Inputs
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% Outputs
%    - output: Quantized value mapping to x
%    - output_store: Store value

function [output, output_store] = uniform_quantize(x,step,nbit)
% Initialization
output = x;
output_store = x;

% Maximum and minimum ranges
pos_end = 2 ^ nbit - 1;
neg_end = -pos_end;

% Quantized value
output = 2 * round(x./step + 0.5) - 1;
output(output > pos_end) = pos_end;
output(output < neg_end) = neg_end;

output_store = (output - 1) / 2;
```
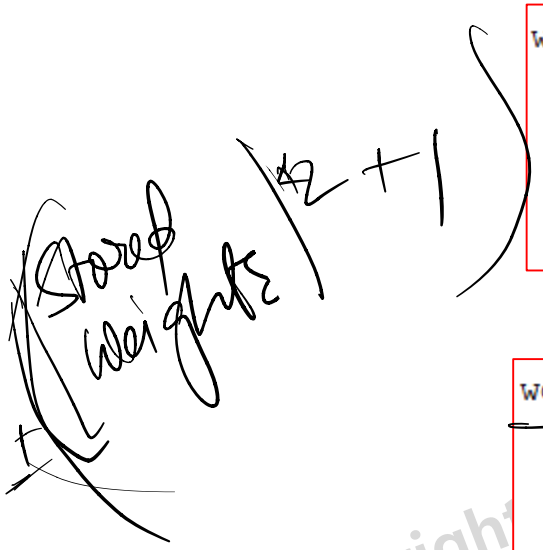

Weight quantization

- Convert a FP tensor into a fixed-point format
- Example: 8-bit symmetric representation
  - -255/2, -254/2, …, -1/2, 1/2, …,255/2

Quantized weight

```
wq1(:,:,1,1) =

  -169   -155    -59
   189   -137    -75
   -39     -1    169
```



```
wq1_store(:,:,1,1) =

   -85    -78    -30
    94    -69    -38
   -20     -1     84
```

Store weights

```
% Function: Symetric Uniform quantization
% Inputs
%    - x:     input tensor
%    - step: quantized step
%    - nbit: number of bits in fixed-point representation
% Outputs
%    - output: Quantized value mapping to x
%    - output_store: Store value

function [output, output_store] = uniform_quantize(x,step,nbit)
% Initialization
output = x;
output_store = x;

% Maximum and minimum ranges
pos_end = 2 ^ nbit - 1;
neg_end = -pos_end;

% Quantized value
output = 2 * round(x./step + 0.5) - 1;
output(output > pos_end) = pos_end;
output(output < neg_end) = neg_end;

output_store = (output - 1) / 2;
```

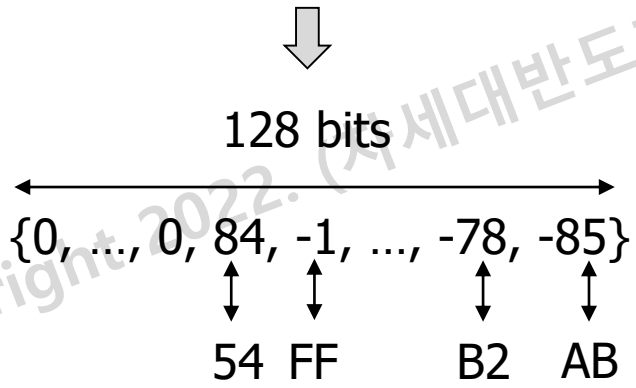
Memory file generation: Channel-wise

- Convert a FP tensor into a fixed-point format

⇒ Save fixed-point weights into a file

Store weights

```
wq1_store(:,:,1,1) =

   -85   -78   -30
    94   -69   -38
   -20    -1    84
```



simSR.hex | dual_port_block_ram_tb.v | cnn_tb.v

```
1  0000000000000054FFECDABB5EE2B2AB
2  000000000000000661E44C990FDAC437
3  00000000000000004CBF6D37FD8FEDF25
4  0000000000000C4453F782B80E5805C
5  00000000000000031F009D7FB8603D2F4
6  000000000000000FDD506F67FE8F291EE
7  000000000000000F380F2237F03ED0315
8  000000000000000FB3DD092BC283187F3
9  0000000000000095B9000732DA0CDAAF
10 000000000000000DBEA14975504B180C3
11 000000000000000F50C02FD80DFE97F1F
12 000000000000000E1EEC807FE403FBFC
13 00000000000000012B337F04CE5FBB308
14 00000000000000001533E1A59FBC1A2896
15 0000000000000000808C80F7125AEA3100
16 000000000000000EF709DB7F81E57FAC
```

Memory file generation: Channel-wise

- Convert a FP tensor into a fixed-point format

⇒ Save fixed-point weights into a file

stored weight

```
wq1_store(:,:,1,1) =

   -85   -78   -30
    94   -69   -38
   -20    -1    84
```

```
wq1_store(:,:,1,2) =

    55   -60   -38
    15  -103    76
   -28    97     6
```

```
wq1_store(:,:,1,3) =

    37   -33    -2
   -40   127   -45
   -10   -53     4
```

simSR.hex | dual_port_block_ram_tb.v | cnn_tb.v

```
1  0000000000000054FFECDABB5EE2B2AB
2  0000000000000000661E44C990FDAC437
3  0000000000000004CBF6D37FD8FEDF25
4  000000000000000C4453F782B80E5805C
5  0000000000000031F009D7FB8603D2F4
6  000000000000000FDD506F67FE8F291EE
7  000000000000000F380F2237F03ED0315
8  000000000000000FB3DD092BC283187F3
9  0000000000000095B9000732DA0CDAAF
10 000000000000000DBEA14975504B180C3
11 000000000000000F50C02FD80DFE97F1F
12 000000000000000E1EEC807FE403FBFC
13 0000000000000012B337F04CE5FBB308
14 00000000000000001533E1A59FBC1A2896
15 0000000000000000808C80F7125AEA3100
16 000000000000000EF709DB7F81E57FAC
```

Memory file generation: Channel-wise

- Convert a FP tensor into a fixed-point format

⇒ Save fixed-point weights into a file

```
wq1_store(:,:,1,1) =

   -85   -78   -30
    94   -69   -38
   -20    -1    84


wq1_store(:,:,1,2) =

    55   -60   -38
    15  -103    76
   -28    97     6


wq1_store(:,:,1,3) =

    37   -33    -2
   -40   127   -45
   -10   -53     4
```

simSR.hex | dual_port_block_ram_tb.v | cnn_tb.v

```
1  0000000000000054FFECDABB5EE2B2AB
2  0000000000000000661E44C990FDAC437
3  0000000000000004CBF6D37FD8FEDF25
4  000000000000000C4453F782B80E5805C
5  0000000000000031F009D7FB8603D2F4
6  000000000000000FDD506F67FE8F291EE
7  000000000000000F380F2237F03ED0315
8  000000000000000FB3DD092BC283187F3
9  0000000000000095B9000732DA0CDAAF
10 000000000000000DBEA14975504B180C3
11 000000000000000F50C02FD80DFE97F1F
12 000000000000000E1EEC807FE403FBFC
13 0000000000000012B337F04CE5FBB308
14 0000000000000001533E1A59FBC1A2896
15 0000000000000000808C80F7125AEA3100
16 000000000000000EF709DB7F81E57FAC
```

Memory mapping

- Convert a FP tensor into a fixed-point format

⇒ Save fixed-point weights into a file

Weights

```
wq1_store(:,:,1,1) =

   -85   -78   -30
    94   -69   -38
   -20    -1    84
```

```
wq1_store(:,:,1,2) =

    55   -60   -38
    15  -103    76
   -28    97     6
```

Input

input

128x128 double

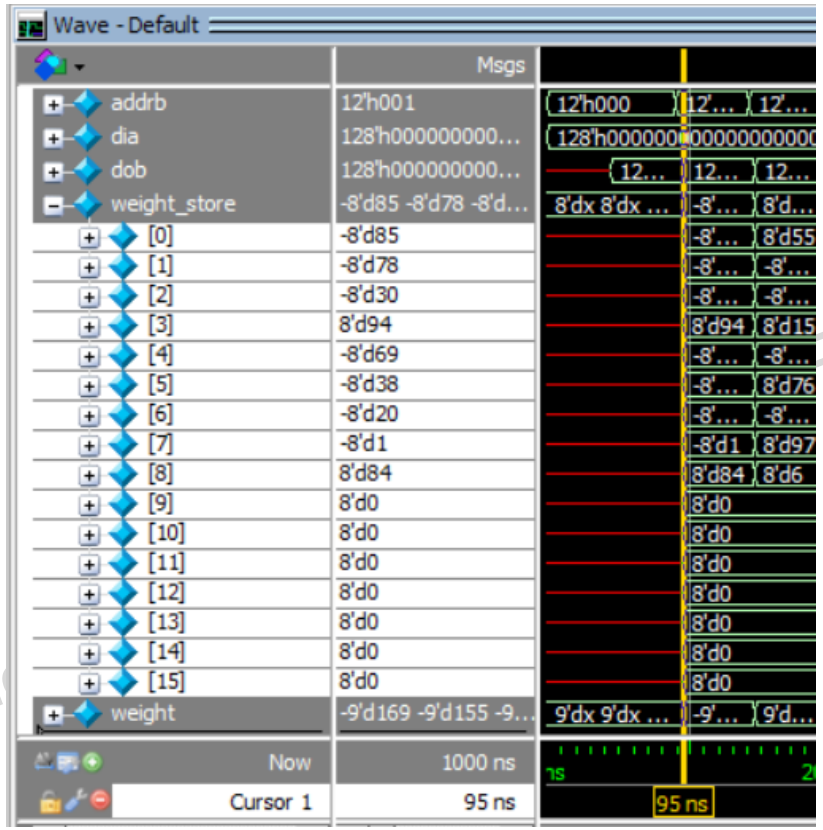
	1	2	3	4
1	42	69	91	99
2	105	42	56	84

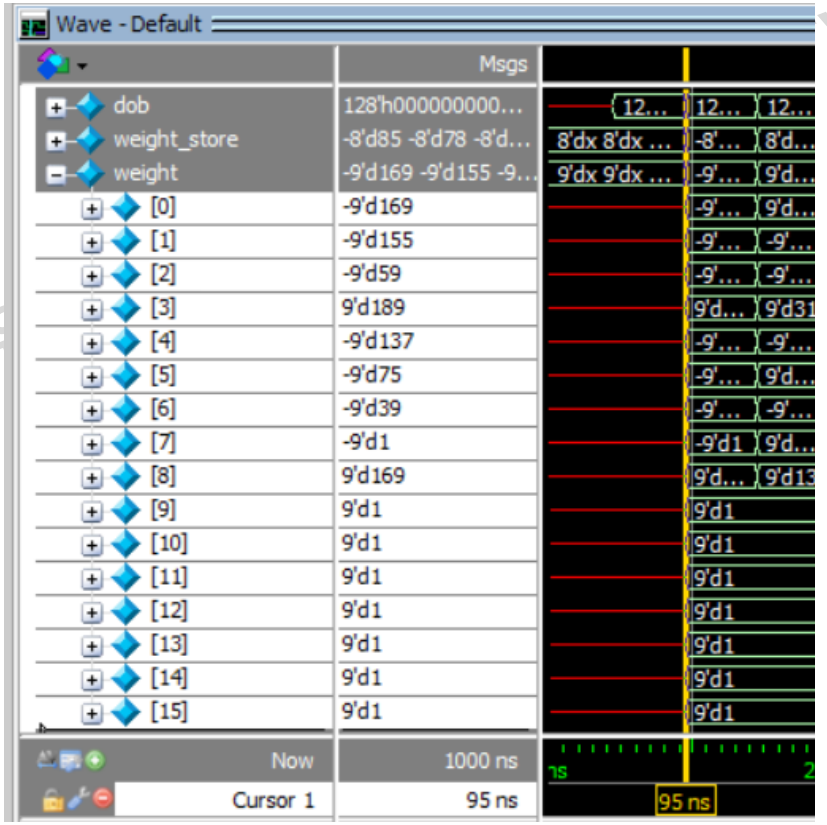
simSR.hex | dual_port_block_ram_tb.v | cnn_tb.v

```
133  0000000000000031F009D7FB8603D2F4
134  00000000000000FDD506F67FE8F291EE
135  00000000000000F380F2237F03ED0315
136  00000000000000FB3DD092BC283187F3
137  0000000000000095B9000732DA0CDAAF
138  000000000000000DBEA14975504B180C3
139  000000000000000F50C02FD80DFE97F1F
140  000000000000000E1EEC807FE403FBFC
141  0000000000000012B337F04CE5FBB308
142  0000000000000001533E1A59FBC1A2896
143  0000000000000000808C80F7125AEA3100
144  000000000000000EF709DB7F81E57FAC
145  006d006f006c006a0063005b0045002a
146  0058005c006100620064006700 6a006d
147  004400440048004b004c005000520054
148  004e004e004d004b004b004a00470045
149  004a0048004900 48004a004c004e004d
150  006b0063005a00540053004f004b004b
```

To do …

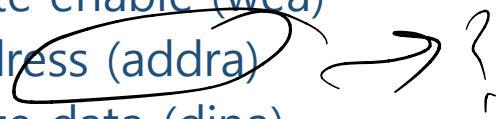
- Complete the missing code in dual_port_block_ram_tb.v to load 16 conv. filters of Layer 1
- Show the stored weight and the original weights





Dual port BRAM

- Frame buffer (lcd_frame_buffer.v):
  - Port A: Write
    - Read/write request (ena)
    - Write enable (wea)
    - Address (addra)
    - Write data (dina)
  - Port B: Read
    - Read/write request (enb)
    - Address (addrb)
    - Read data (dob)



```
module dual_port_block_ram(

    clk   ,

    ena   ,  // portA: enable
    wea   ,  // portA: primary synchronous write enable
    addra ,  // portA: address for read/write

    enb   ,  // portB: enable
    addrb ,  // portB: address for read

    dia   ,  // portA: primary data input
    dob      // portB: primary data output

);
```

Explanation – dual_port_block_ram.v

Default parameters

```
parameter W_DATA = 8;
parameter N_CELL = 512;
parameter W_CELL = $clog2(N_CELL);
parameter FILENAME = "";
parameter N_DELAY = 1;
```

RAM (data storage)

```
// share memory
reg [W_DATA-1:0] ram[N_CELL-1:0];
```

Read data from FILENAME(simSR.hex) to ram

```
initial
begin
   if (FILENAME != "") begin
      $display("### Loading internal memory from %s ###", FILENAME);
      $readmemh(FILENAME, ram);
   end
end
```

Data write to RAM

```
// write port
always @(posedge clk)
begin: write
   if(ena)
   begin
      if(wea)
         ram[addra] <= dia;
   end
end
```

Explanation – dual_port_block_ram.v

```
generate
   if(N_DELAY == 1) begin: delay_1
      reg [W_DATA-1:0] rdata; // primary data output
      // read port
      always @(posedge clk)
      begin: read
         if(enb)
            rdata <= ram[addrb];
      end
      assign dob = rdata;
   end
```

Data read from RAM
: 1 cycle delay

```
   else begin: delay_n
      reg [N_DELAY*W_DATA-1:0] rdata_r;
      always @(posedge clk)
      begin: read
         if(enb)
            rdata_r[0+:W_DATA] <= ram[addrb];
      end
```

Data read from RAM
: more than 1 cycle delay
(not used for this example! Just ignore)

```
      always @(posedge clk) begin: delay
         integer i;
         for(i = 0; i < N_DELAY-1; i = i+1)
            if(enb)
               rdata_r[(i+1)*W_DATA+:W_DATA] <= rdata_r[i*W_DATA+:W_DATA];
      end
      assign dob = rdata_r[(N_DELAY-1)*W_DATA+:W_DATA];
   end
endgenerate
```

Support N cycle data delay
: 1 cycle delay for this example

Assign RAM output port

Test bench (dual_port_block_ram_tb.v)

```
module dual_port_block_ram_tb;

parameter IN_PIXEL_W = 8;
parameter IN_PIXEL_NUM = 16;

parameter W_DATA = 128;
parameter N_CELL = 2192;
parameter W_CELL = $clog2(N_CELL);
parameter FILENAME = "C:/dsd_ta/L09/simSR.hex";
parameter N_DELAY = 1;
```

Parameters
: In simSR.hex, a row contains (IN_PIXEL_NUM) values, each one being a (IN_PIXEL_W) bit value.

You should change this line to your own directory!

```
...
reg [IN_PIXEL_W-1:0] weight_store [0:IN_PIXEL_NUM-1];
reg [IN_PIXEL_W:0]   weight [0:IN_PIXEL_NUM-1];
```

For waveform visualization
: refer to page 10

```
...
// Clock
parameter CLOCK_PERIOD = 10;    //100MHz
initial begin
    clk = 1'b0;
    forever #(CLOCK_PERIOD/2) clk = ~clk;
end
```

Clock operation

Test bench (dual_port_block_ram_tb.v)

```
integer i;

// load 16 conv. filters of layer 1 from dual_port_block_ram
initial begin

    // initialization
    ena = 0;
    wea = 0  ;
    addra = 0;
    enb = 0;
    addrb  = 0;
    dia   = 0;

    // set signal for dual_port_block_ram access
    for(/* Insert your code */) begin
        #(4*CLOCK_PERIOD)   enb = 1'b1;
                            /* Insert your code */
        #(CLOCK_PERIOD)     enb = 1'b0;
    end

end
```

Generate control signals

Set initial signals

Set signals for RAM access

To do ...

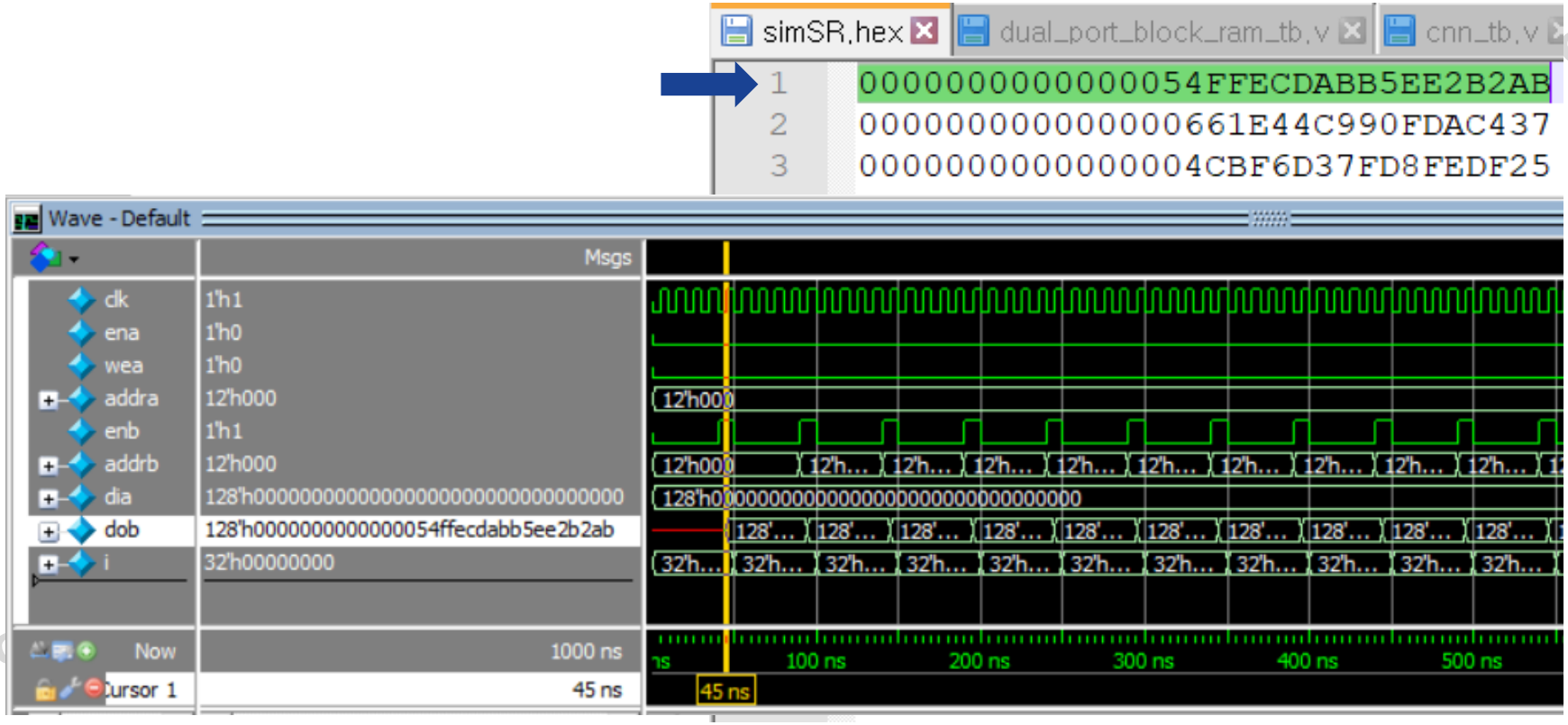
- Complete missing codes (dual_port_block_ram_tb.v)

```
// load 16 conv. filters of layer 1 from dual_port_block_ram
initial begin

    // initialization
    ena = 0;
    wea = 0  ;
    addra = 0;
    enb = 0;
    addrb  = 0;
    dia   = 0;

    // set signal for dual port block ram access
    for(/* Insert your code */) begin
        #(4*CLOCK_PERIOD)    enb = 1'b1;
                             /* Insert your code */
        #(CLOCK_PERIOD)      enb = 1'b0;
    end

end
```

```
//----------------------------------------------------
// Visualize stored weights and weights
//----------------------------------------------------
integer j;

always@(posedge clk) begin
    if(enb) begin
        // TODO: set 'weight_store' and 'weight'
        /* Insert your code */

        /*********************/
    end
end

endmodule
```

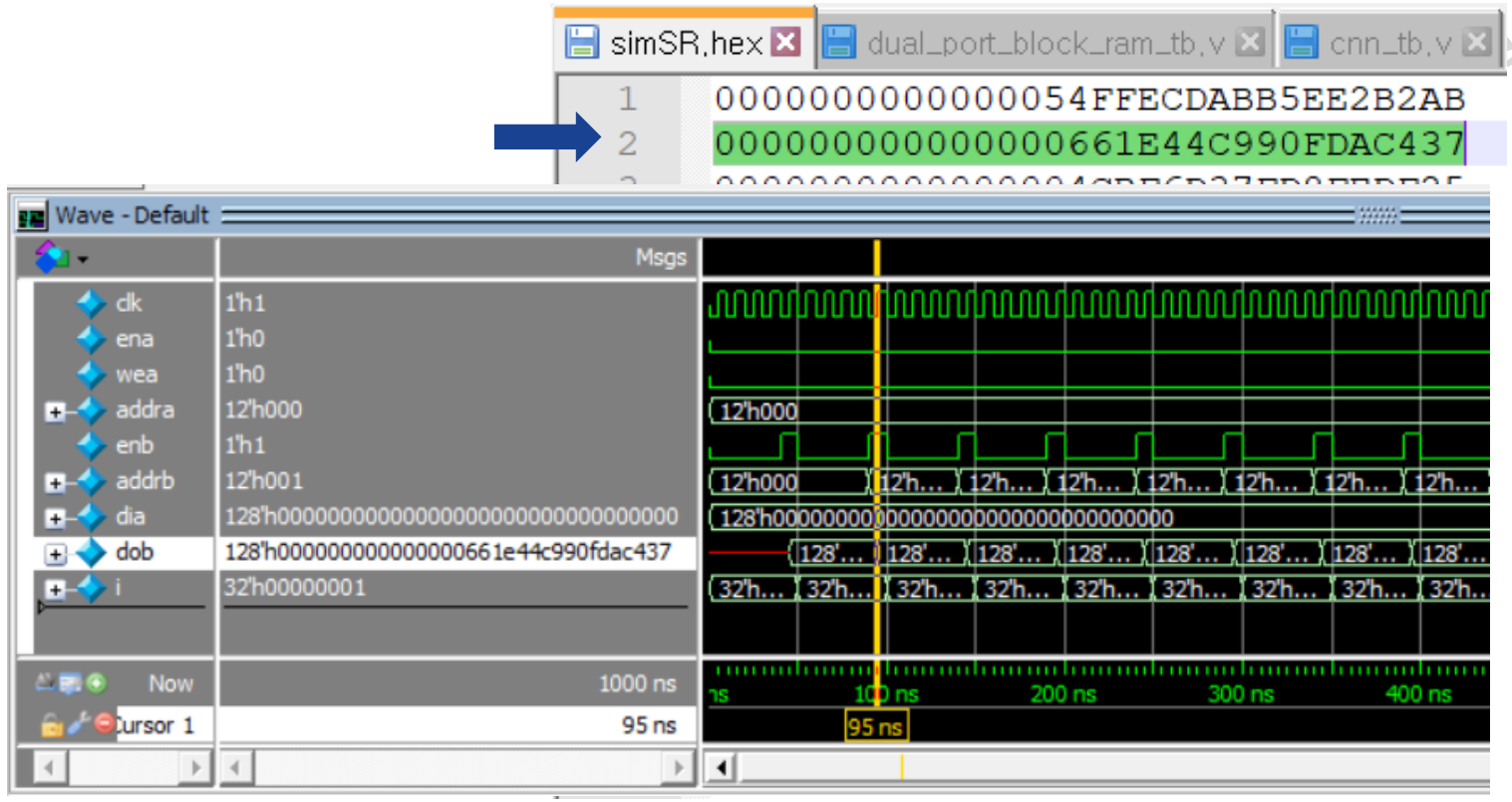
Waveform

- Weight memory access:
  - The first set of filters



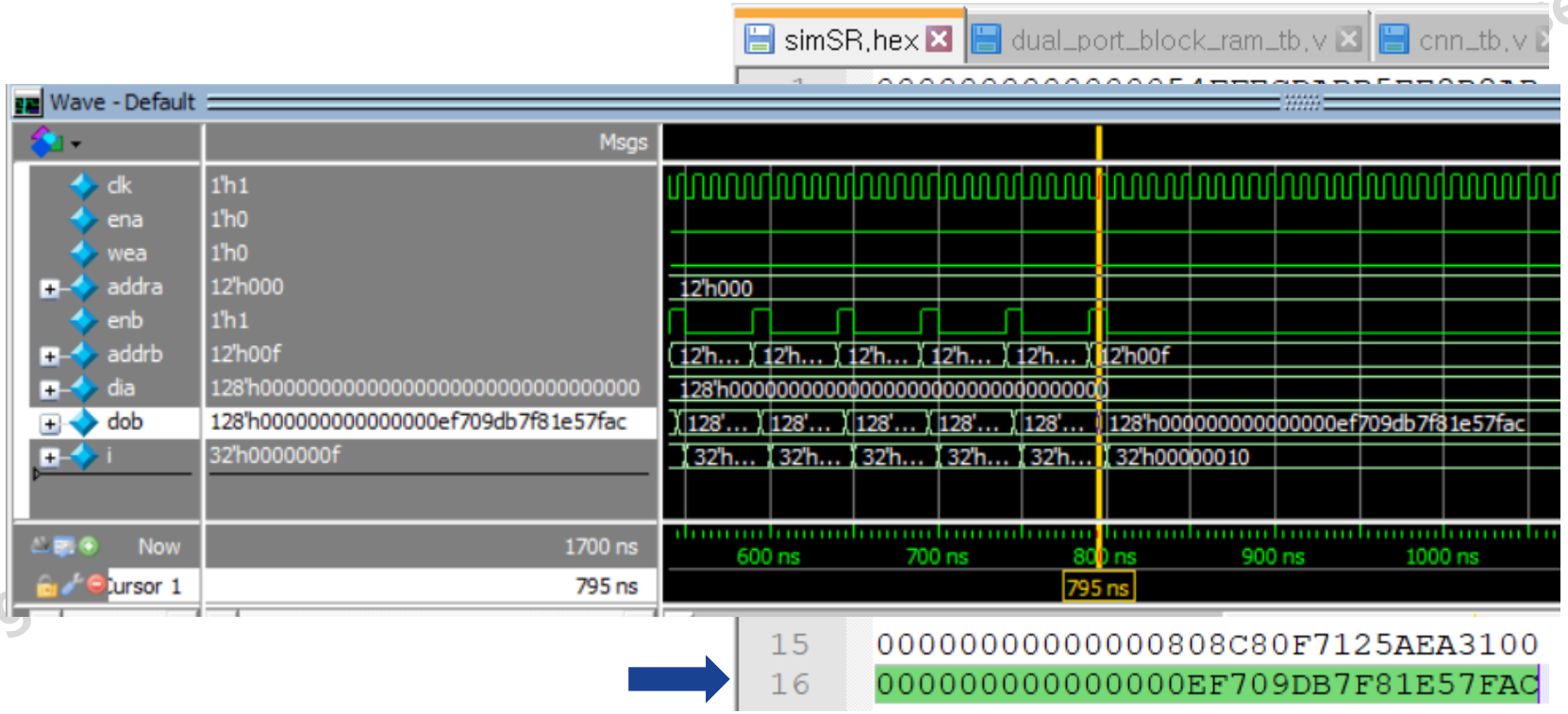
Waveform

- Weight memory access:
  - The second set of filters



Waveform

- Weight memory access
  - The 16th set of filters



Waveform

Road map

Deep Learning Accelerator

Convolutional Neural Network (CNN)

Quantization

Block memory

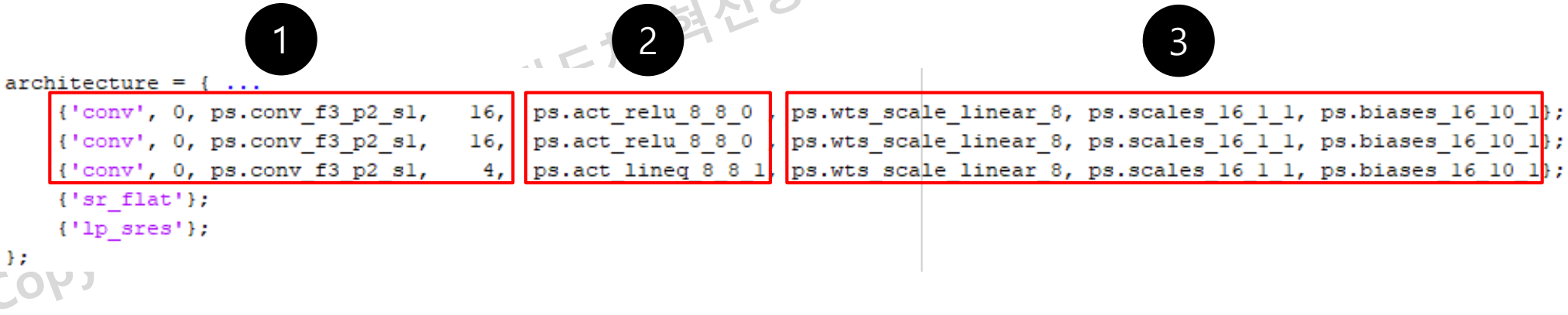
Reference S/W

Lab 4: SRNPU reference Software

- Top file (hw_uniform_architecture.m)
  - Define a network architecture (arch/sim_espcn_3x3.m)
  - Load weights from files
    - Do linear scale quantization
  - Do convolution
  - Evaluation

Network architecture

- The network architecture is defined in the file arch/sim_espcn_3x3.m
- Each line defines the configurations of one layer including
  1. Convolution settings
  2. Activation quantization parameters
  3. Weight quantization parameters



Network architecture

- The network architecture is defined in the file arch/sim_espcn_3x3.m
- Convolution (conv)
  - Filter size (f) Padding (p) and stride (s), the number of filters.
  - Example:
    - Layer 1:
      - f=3,p=2,s=1 => Filter 3x3
      - 16 output channels.

1

```
architecture = { ...
    {'conv', 0, ps.conv_f3_p2_s1,   16,  ps.act_relu_8_8_0 , ps.wts_scale_linear_8, ps.scales_16_1_1, ps.biases_16_10_1};
    {'conv', 0, ps.conv_f3_p2_s1,   16,  ps.act_relu_8_8_0 , ps.wts_scale_linear_8, ps.scales_16_1_1, ps.biases_16_10_1};
    {'conv', 0, ps.conv_f3_p2_s1,    4,  ps.act_lineq_8_8_1, ps.wts_scale_linear_8, ps.scales_16_1_1, ps.biases_16_10_1};
    {'sr_flat'};
    {'lp_sres'};
};
```

Network architecture

- The network architecture is defined in the file arch/sim_espcn_3x3.m
- Activation quantization: [nbit fbit sign]
  - The number of bit (nbit)
  - The number of fractional bits (fbit)
  - The signed bit
    - ReLU: 0
    - Linear: 1

2

```
architecture = { ...
    {'conv', 0, ps.conv_f3_p2_s1,   16,  ps.act_relu_8_8_0 , ps.wts_scale_linear_8, ps.scales_16_1_1, ps.biases_16_10_1};
    {'conv', 0, ps.conv_f3_p2_s1,   16,  ps.act_relu_8_8_0 , ps.wts_scale_linear_8, ps.scales_16_1_1, ps.biases_16_10_1};
    {'conv', 0, ps.conv_f3_p2_s1,    4,  ps.act_lineq_8_8_1, ps.wts_scale_linear_8, ps.scales_16_1_1, ps.biases_16_10_1};
    {'sr_flat'};
    {'lp_sres'};
};
```

Network architecture

- The network architecture is defined in the file arch/sim_espcn_3x3.m
- Weight quantization: [nbit fbit sign]
  - The number of bit (nbit)
  - The number of fractional bits (fbit)
  - The signed bit
    - ReLU: 0
    - Linear: 1

3

```
architecture = { ...
    {'conv', 0, ps.conv_f3_p2_s1,   16,  ps.act_relu_8_8_0 , ps.wts_scale_linear_8, ps.scales_16_1_1, ps.biases_16_10_1};
    {'conv', 0, ps.conv_f3_p2_s1,   16,  ps.act_relu_8_8_0 , ps.wts_scale_linear_8, ps.scales_16_1_1, ps.biases_16_10_1};
    {'conv', 0, ps.conv_f3_p2_s1,    4,  ps.act_lineq_8_8_1, ps.wts_scale_linear_8, ps.scales_16_1_1, ps.biases_16_10_1};
    {'sr_flat'};
    {'lp_sres'};
};
```

Load weights

- Load weights from files
- Do quantization on weights, biases and scales.

```
case 'conv'
    [batchnorm, convol_settings, output_channels, ~, weights_settings] = architecture{i}{2:6};
    [kernel_size, ~, ~] = convol_settings{:};
    wts_scheme = weights_settings{1};

    input_channels = all_input_channels(i);
    param_file = [model_prefix num2str(i-1)];

    % Load weights, biases and scales from files
    [weightx, bias, scale, rolling_mean, rolling_var] = read_conv_param_module(param_file, kernel_size, input_channels, output_channels

    % Quantization
    if strcmp(wts_scheme, 'none')
        weight = weightx;
        w_bonus_scale_factor = ones(output_channels,1);
    elseif strcmp(wts_scheme, 'uniform')
        [wts_nbit, wts_fbit, ~] = weights_settings{2:end};
        wts_step = 2^-wts_fbit;
        [weight, ~] = uniform_quantize(weightx, wts_step, wts_nbit);
        w_bonus_scale_factor = ones(output_channels,1);
    elseif strcmp(wts_scheme, 'scale_linear')
        wts_nlevel = 2^weights_settings{2};
        [weight, w_bonus_scale_factor] = scale_linear_quantize(weightx, output_channels, wts_nlevel/2);
    elseif strcmp(wts_scheme, 'scale_linear_float')
        wts_nlevel = 2^weights_settings{2};
        [weight, w_bonus_scale_factor] = scale_linear_quantize_float(weightx, output_channels, wts_nlevel/2);
    end

    weights{i} = permute(reshape(weight, kernel_size, kernel_size, input_channels, output_channels), [2, 1, 3, 4]);
```

Input preparation

- Load a test image from a file (imread)
- Resize an image to generate a Low-resolution image (imresize)
- Convert an RGB to YCbCr
  - Only work with the Y-channel image

```
%% work on illuminance only
im = imread(image_name);
input_img =  modcrop(im, up_scale);
input_img =  single(input_img)/255;
input_img = imresize(input_img, 1/up_scale, 'bicubic
if size(im,3) > 1
    im_ycbcr = rgb2ycbcr(im);
    im = im_ycbcr(:,:,1);
end
im_gnd = modcrop(im, up_scale);
im_gnd = single(im_gnd)/255;
im_l = imresize(im_gnd, 1/up_scale, 'bicubic');

input = floor(im_l(:,:,1) * 255);
```

High-resolution

Low-resolution

Do convolution

- Load quantized weights
- Do convolution (convol2)
- Do activation quantization (hwu_relu_quantize/hwu_linear_quantize)

```
weight = weights{i};

conv_out = convol2(input, weight, stride, pad);
for j = 1:size(conv_out, 3)
    conv_out(:,:,j) = conv_out(:,:,j) .* scales{i}(j);
    conv_out(:,:,j) = floor(conv_out(:,:,j) / 2^bit_shift(i)); %if floating point is
    conv_out(:,:,j) = conv_out(:,:,j) + biases{i}(j);
end

if strcmp(activation, 'float_relu')
    output = hwu_float_relu_activate(conv_out);
elseif strcmp(activation, 'relu')
    [act_nbit, act_fbit] = act_settings{2:3};
    act_step = 2^-act_fbit;
    [output, ~] = hwu_relu_quantize(conv_out, act_step, act_nbit, biases_fbit);
elseif strcmp(activation, 'line_q')
    [act_nbit, act_fbit] = act_settings{2:3};
    act_step = 2^-act_fbit;
    [output, ~] = hwu_linear_quantize(conv_out, act_step, act_nbit, biases_fbit);
else
    output = conv_out;
end
```

Evaluation

- How to evaluation?
  - Compare an approximated image with the original image.
- Interpolation
  - Bicubic: 27.43 dB, mean-average-error = 6.4
  - CNN-based SR: 30.98 dB, mean-average-error = 4.5

Low-resolution

Bicubic Interpolation

CNN-based SR

To do …

- Complete the missing codes (**Copied from the previous exercise**)
  - Convolution: func/convol2.m
  - Weight/Bias quantization: func/uniform_quantize.m
  - Activation Quantization:
    - ReLU: func/hwu_relu_quantize.m
    - Linear: func/hwu_linear_quantize.m
- Run the test