MIT HAN LAB

Lecture 02
Basics of Neural Networks

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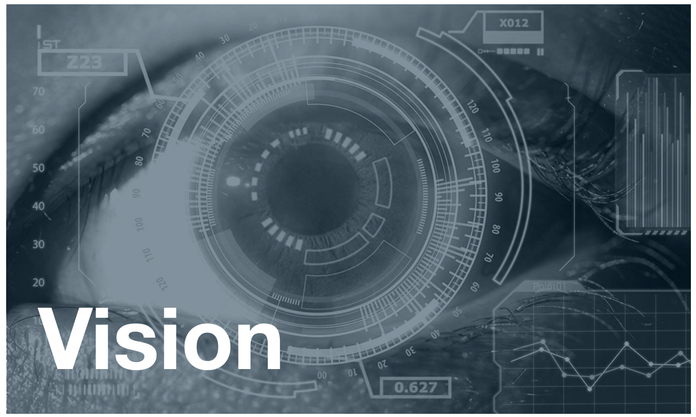
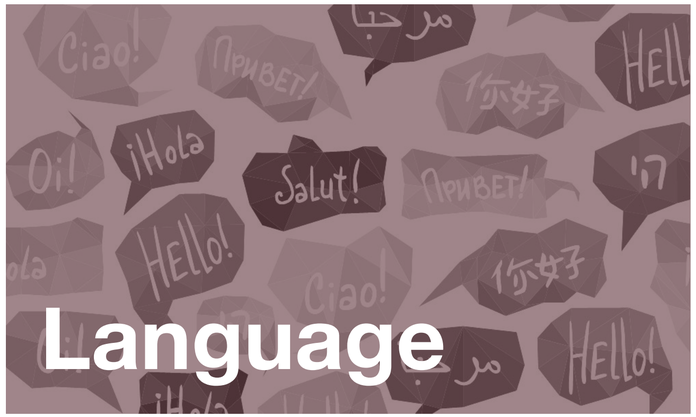
Deep Learning is Everywhere





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Deep Learning for Image Classification

DNNs achieve super-human classification accuracy on ImageNet

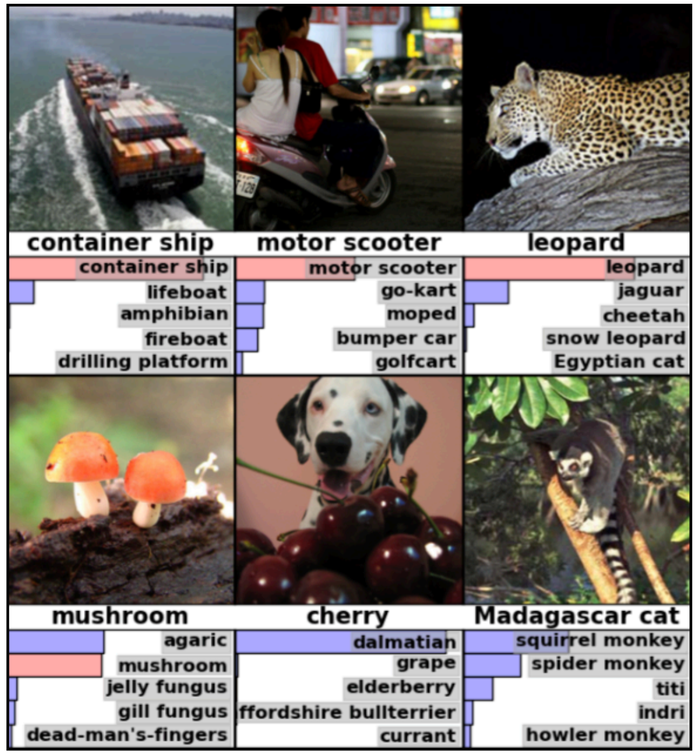
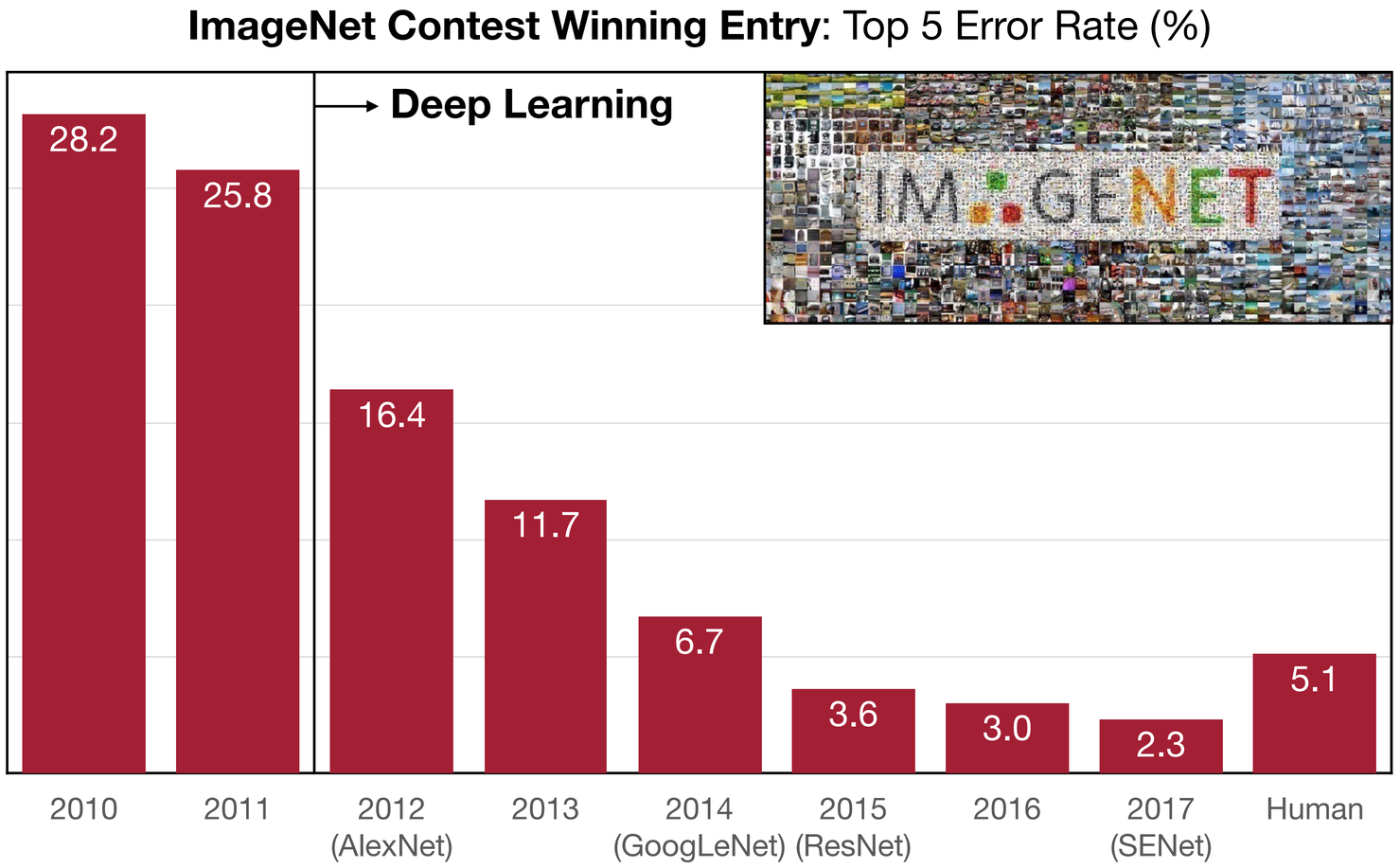
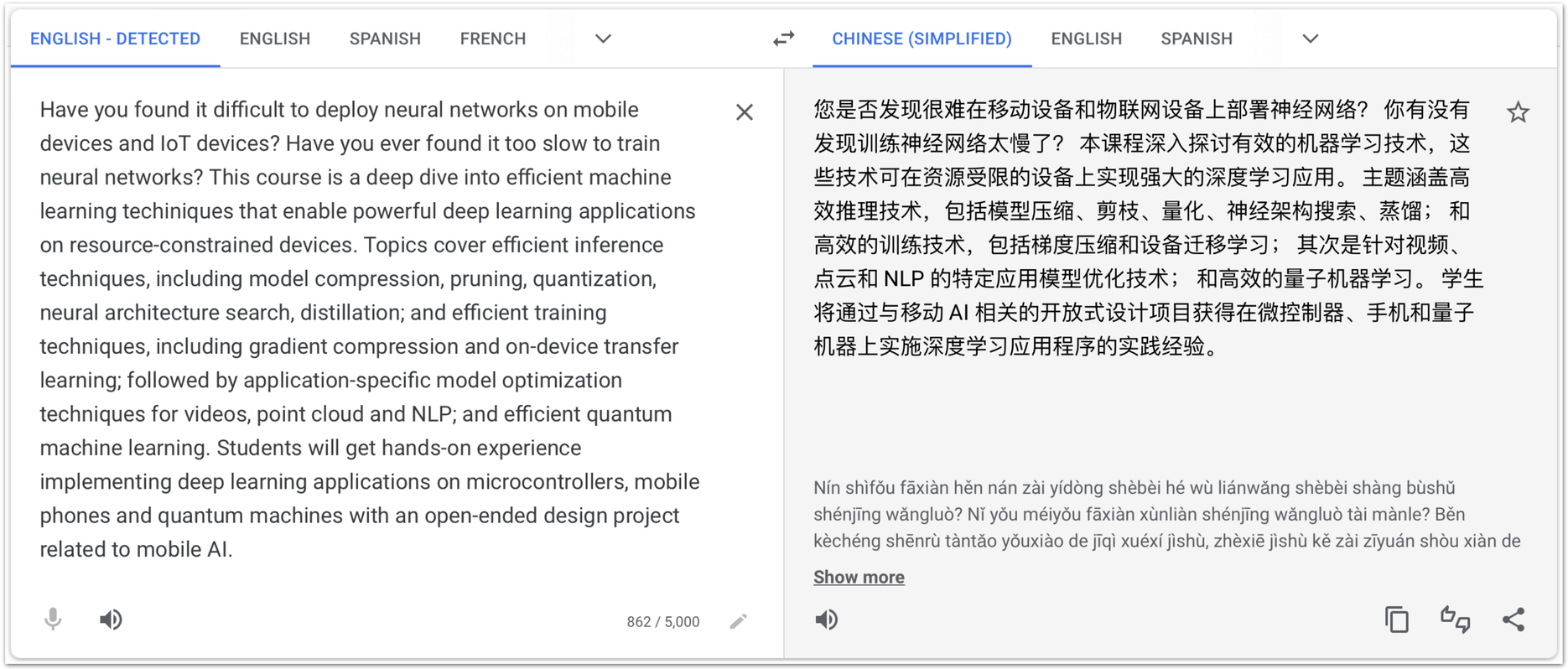


Image Classification



Deep Learning for Text Translation

Neural machine translation bridges the language barrier

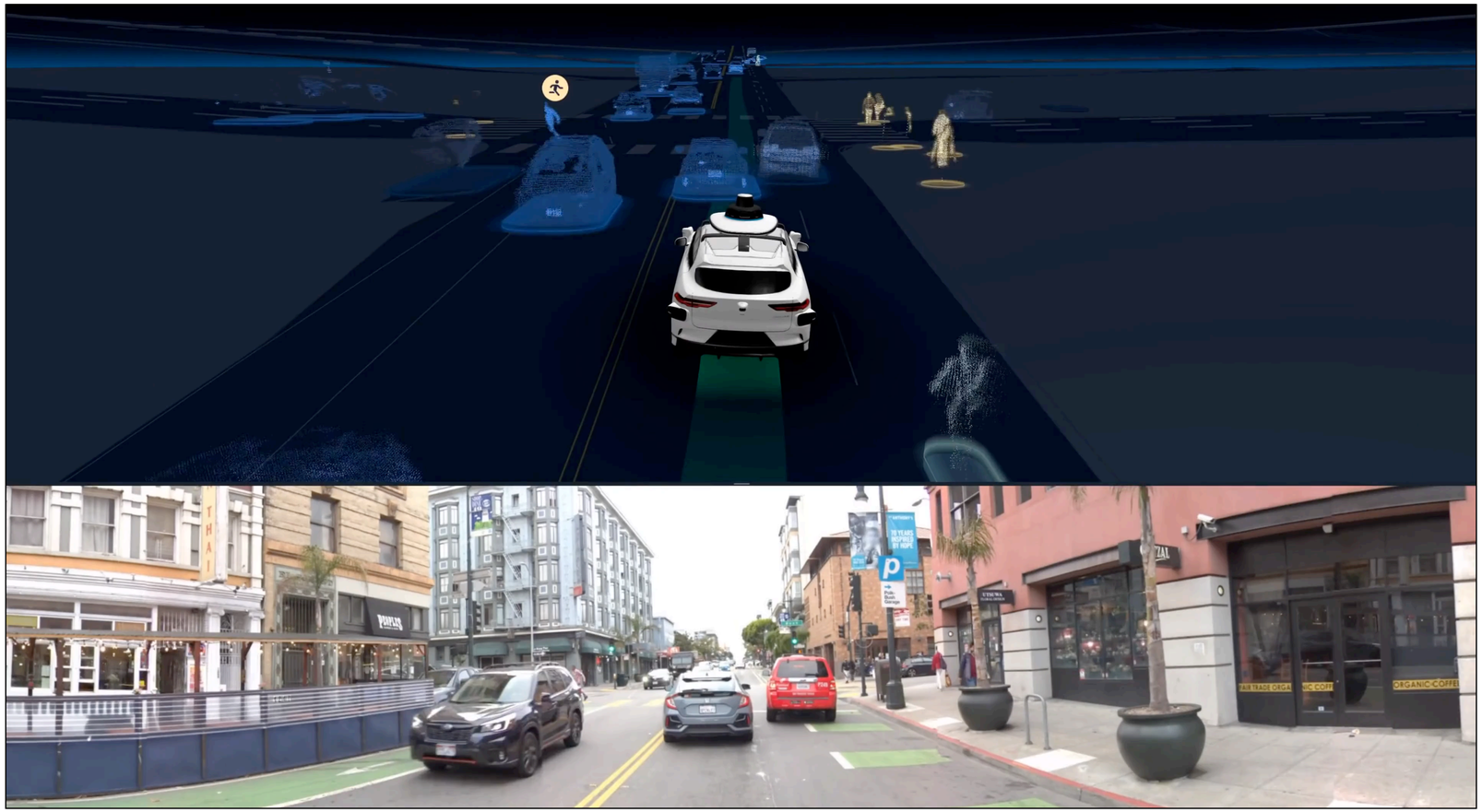


Conversation Translation
(on iPhone)

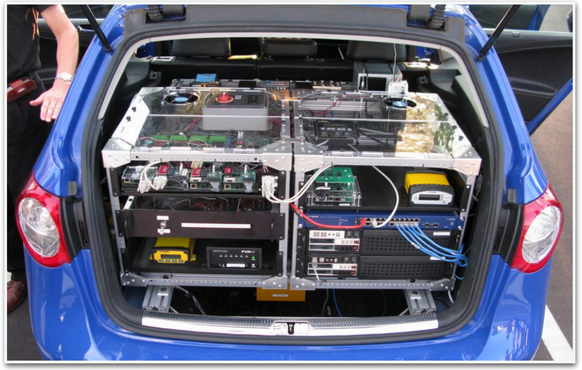
Google Translate: https://translate.google.com/

Deep Learning for Autonomous Driving

Deep learning helps machine perceive the surrounding environment



Waymo Driver

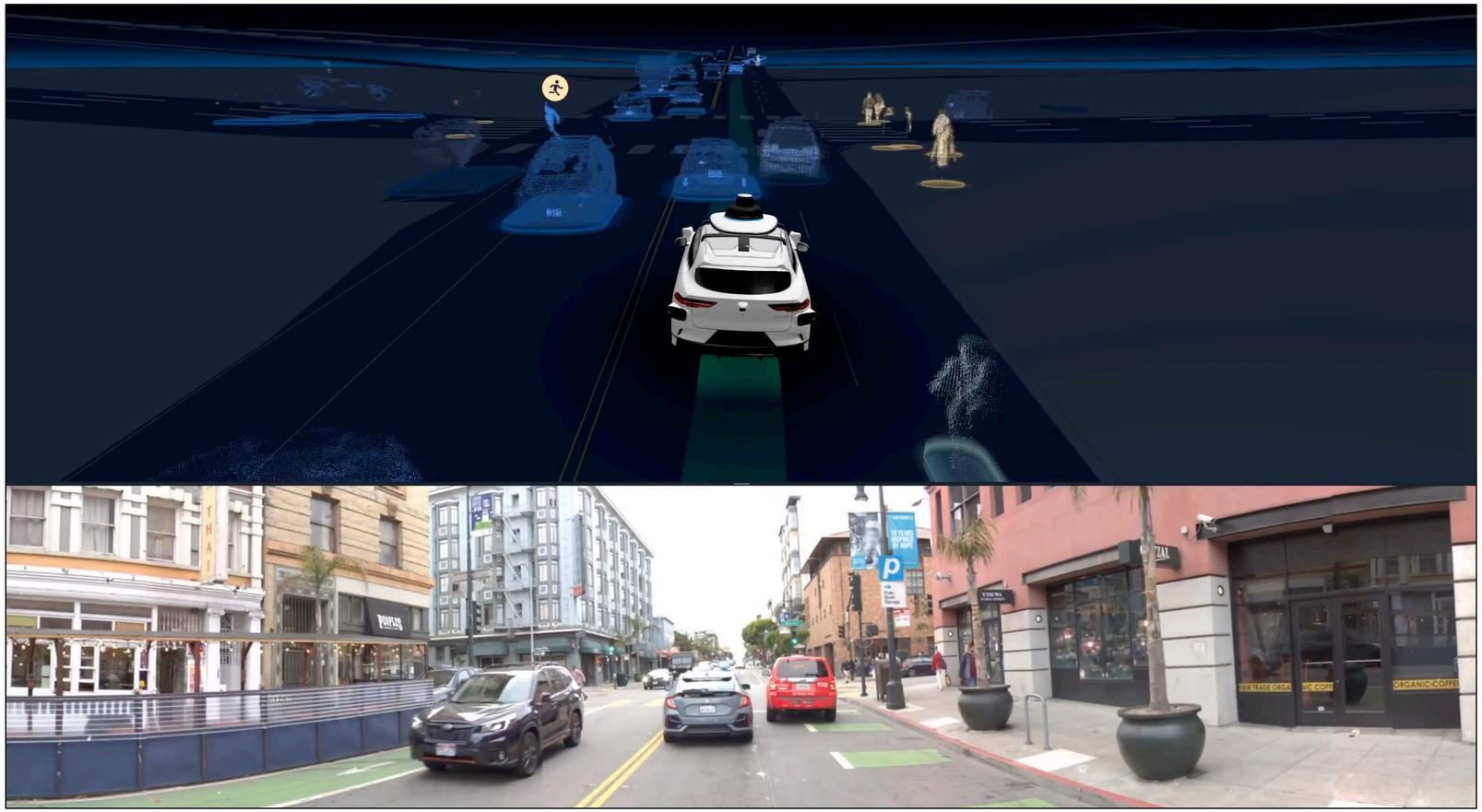


A whole trunk of workstation

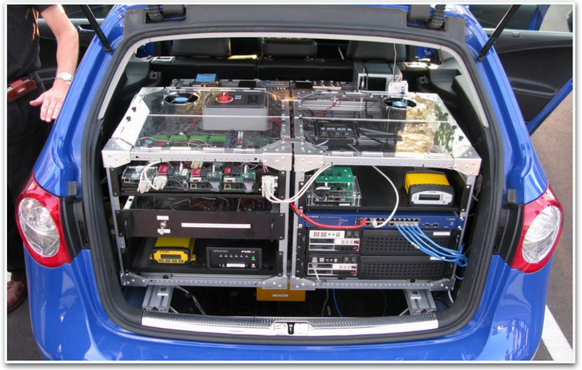
Waymo Driver: https://www.youtube.com/watch?v=2CVInKMz9cA

Deep Learning for Autonomous Driving

Deep learning helps machine perceive the surrounding environment



Waymo Driver



A whole trunk of workstation

Waymo Driver: https://www.youtube.com/watch?v=2CVInKMz9cA

Deep Learning for Games

AlphaGo masters the game of Go with DNNs & tree search

AlphaGo (Nature 2016)

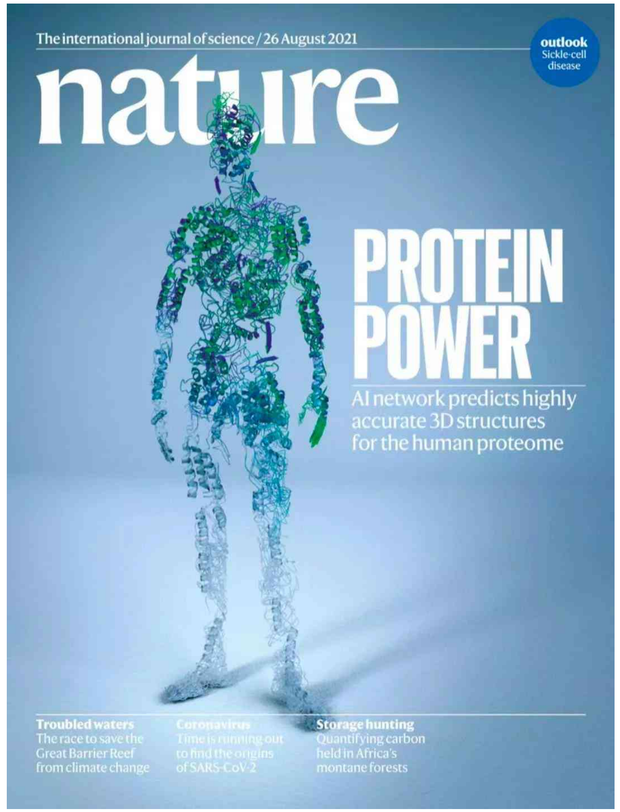
AlphaGo *versus* Lee Sedol (4-1)

Compute: 1920 CPUs and 280 GPUs (\$3000 electric bill per game)

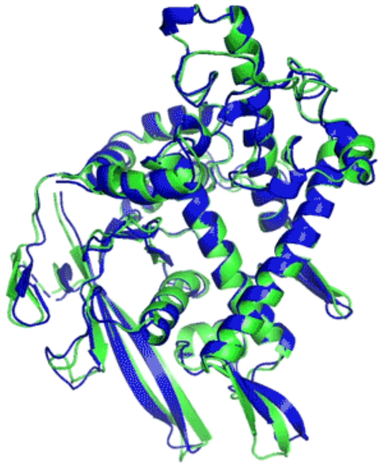
AlphaGo: https://www.deepmind.com/research/highlighted-research/alphago

Deep Learning for Scientific Discovery

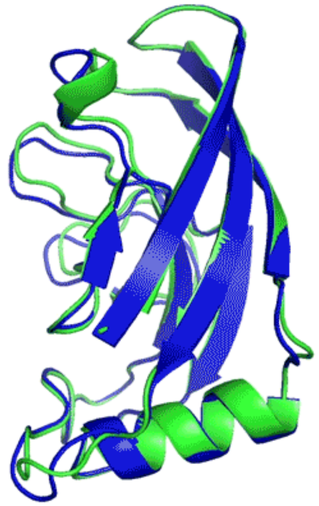
AlphaFold reveals the structure of the protein universe



AlphaFold (Nature 2021)



T1037 / 6vr4
90.7 GDT
(RNA polymerase domain)



T1049 / 6y4f
93.3 GDT
(adhesin tip)

Experimental result
Computational prediction

Compute: 16 TPUv3s (128 TPUv3 cores) for a few weeks

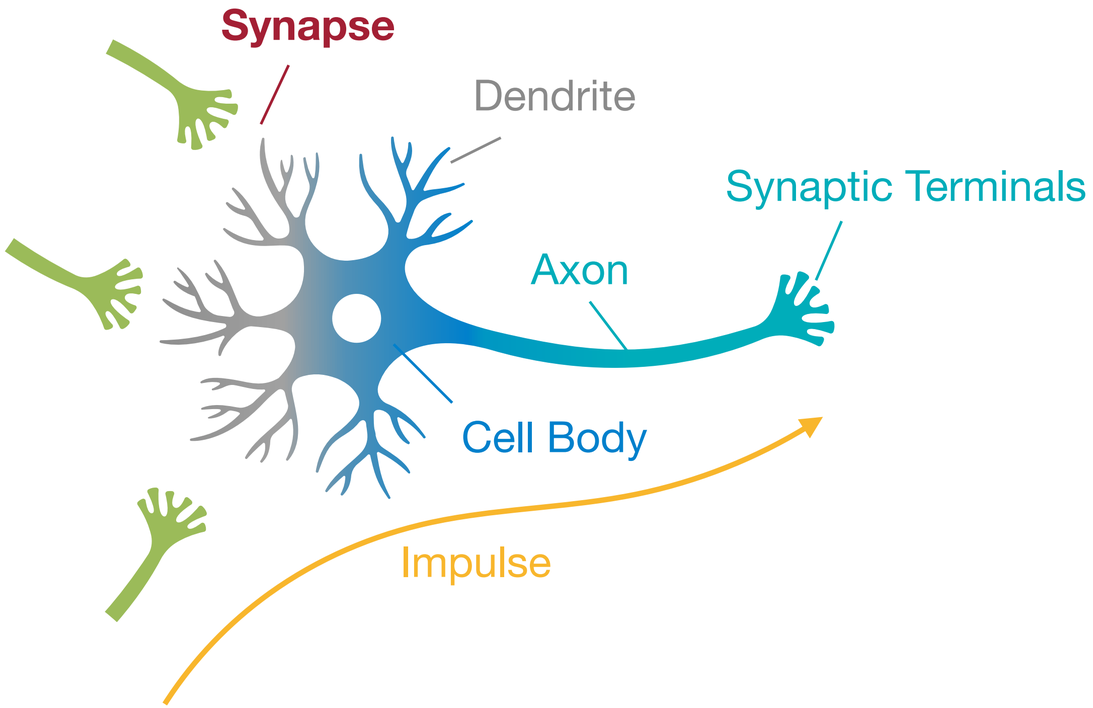
AlphaFold 2: https://www.deepmind.com/blog/alphafold-a-solution-to-a-50-year-old-grand-challenge-in-biology

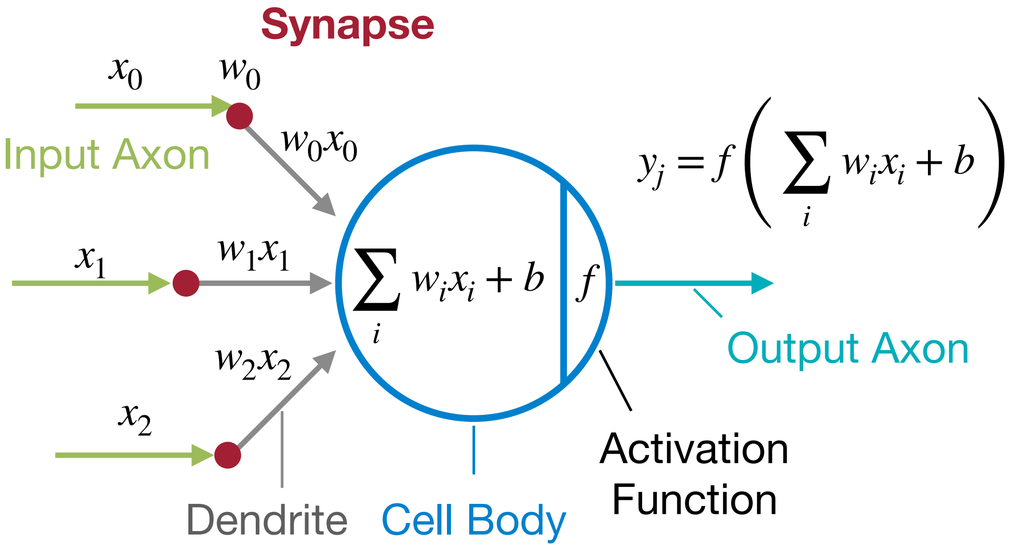
Lecture Plan

Today we will:

1. Review the **terminology of neural networks**
   - Neuron, Synapses, Activation, Feature, Weight, Parameter, *etc*
2. Review **popular building blocks** in a neural network
   - Fully-Connected, Convolution, Grouped Convolution, Depthwise Convolution
   - Pooling, Normalization, Transformer
3. Review **convolutional neural networks**' architecture
   - AlexNet, VGG-16, ResNet-50, MobileNetV2
4. Introduce **popular efficiency metrics** for neural networks
   - #Parameters, Model Size, Peak #Activations, MACs, FLOP, FLOPS, etc
5. Lab 0: Tutorial on PyTorch and lab exercises

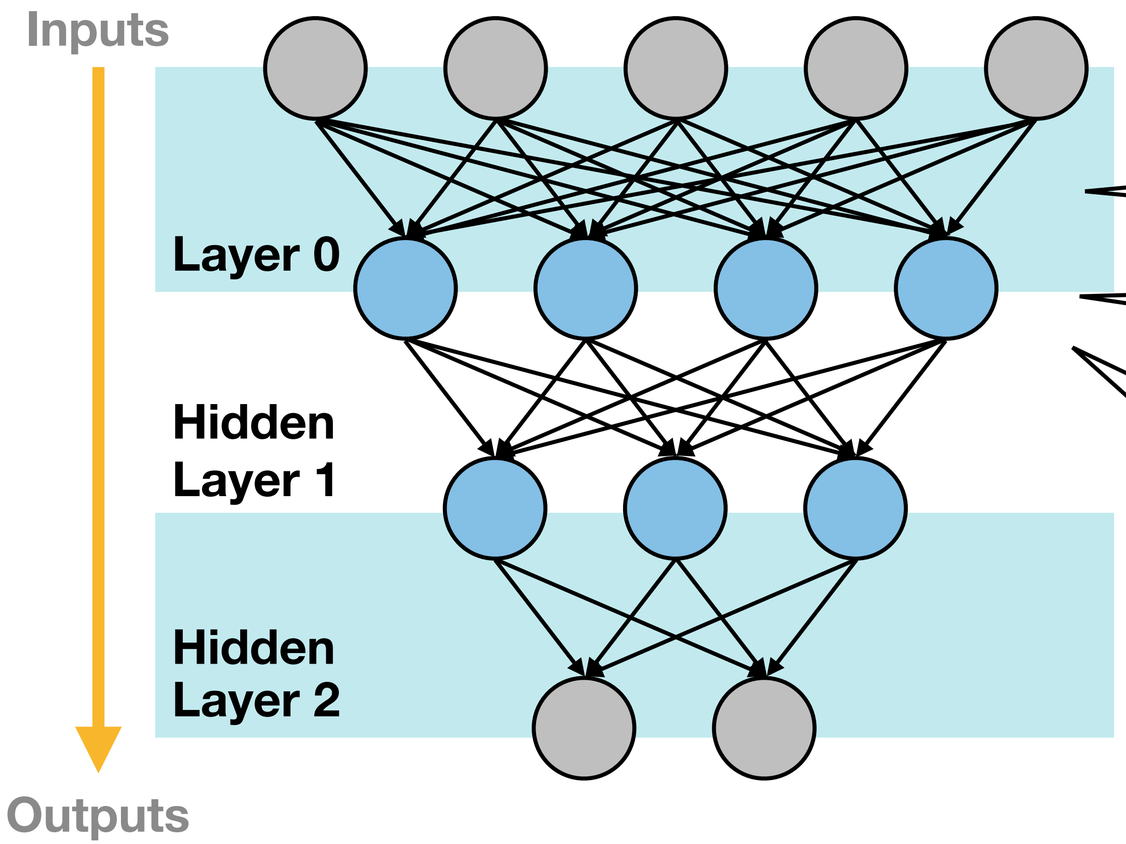
Neuron and Synapse





Deep Neural Network

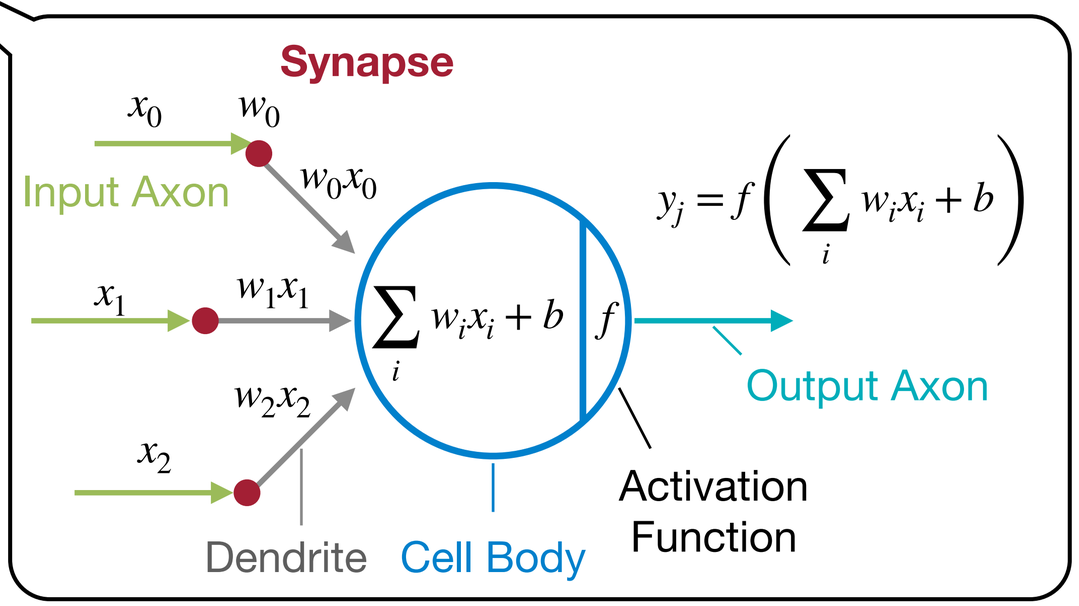
3-Layer Neural Network
With 2 Hidden Layers



The dimensionality of these *hidden* layers determines the **width** of the model.

Synapses / Weights / Parameters

Neurons / Features / Activations



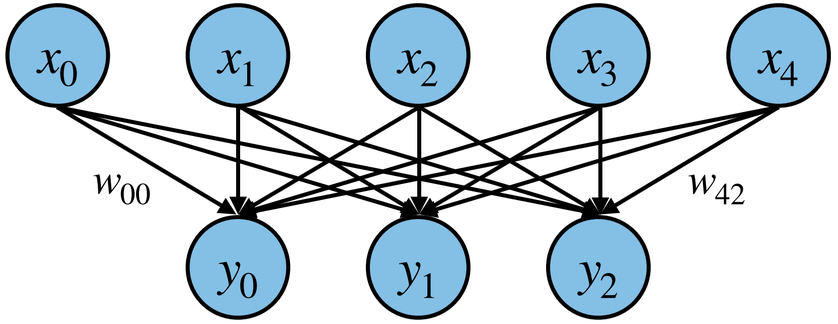
Popular Neural Network Layers

Fully-Connected Layer (Linear Layer)

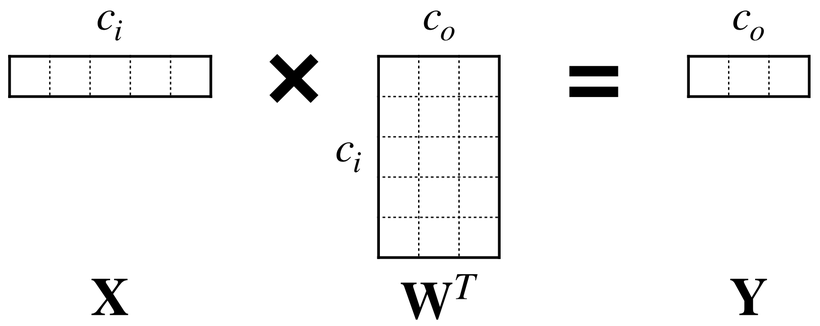
The output neuron is connected to all input neurons.

- **Shape of Tensors:**
  - Input Features $\mathbf{X}$: $(1, c_i)$
  - Output Features $\mathbf{Y}$: $(1, c_o)$
  - Weights $\mathbf{W}$: (c_o, c_i)
  - Bias $\mathbf{b}$: $(c_o,)$

Notations	
c_i	Input Channels
c_o	Output Channels



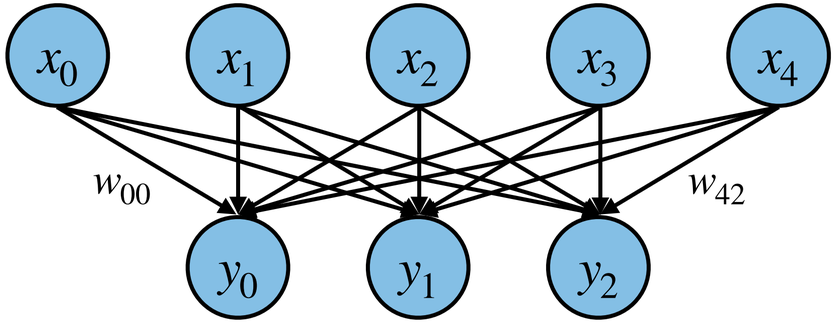
$$y_i = \sum_j w_{ij} x_j + b_i$$



Fully-Connected Layer (Linear Layer)

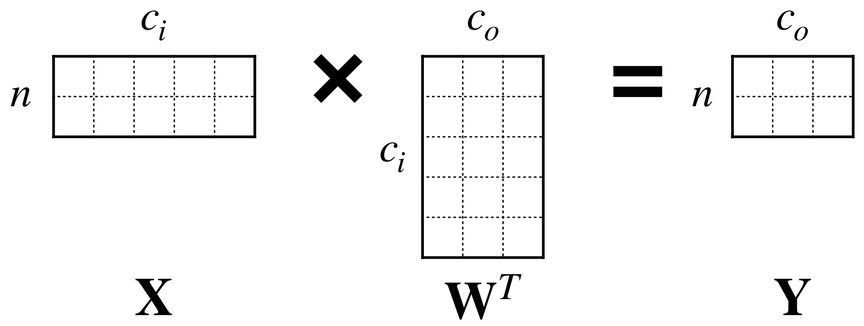
The output neuron is connected to all input neurons.

- **Shape of Tensors:**
  - Input Features $\mathbf{X}$: (n, c_i)
  - Output Features $\mathbf{Y}$: (n, c_o)
  - Weights $\mathbf{W}$: (c_o, c_i)
  - Bias $\mathbf{b}$: $(c_o,)$



$$y_i = \sum_j w_{ij} x_j + b_i$$

Notations	
n	Batch Size
c_i	Input Channels
c_o	Output Channels

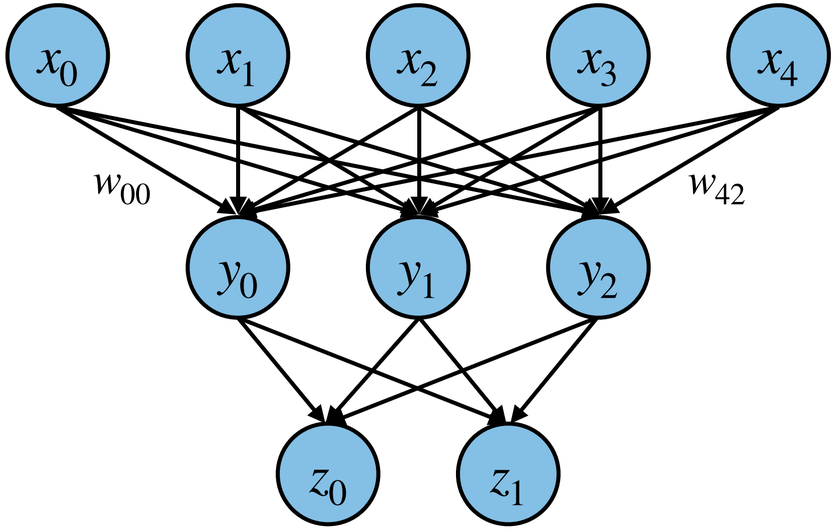


Fully-Connected Layer (Linear Layer)

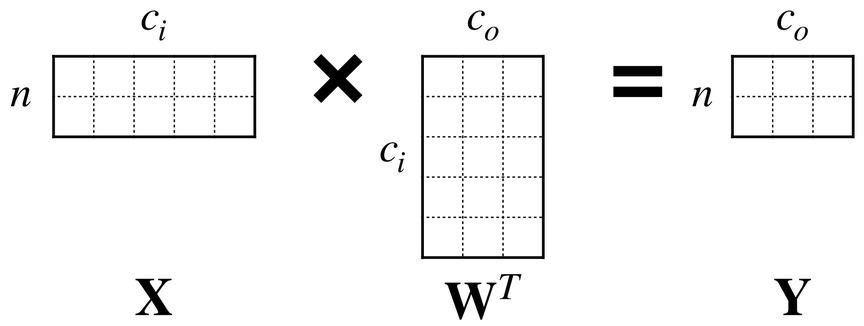
The output neuron is connected to all input neurons.

- **Shape of Tensors:**
  - Input Features $\mathbf{X}$: (n, c_i)
  - Output Features $\mathbf{Y}$: (n, c_o)
  - Weights $\mathbf{W}$: (c_o, c_i)
  - Bias $\mathbf{b}$: $(c_o,)$

Notations	
n	Batch Size
c_i	Input Channels
c_o	Output Channels



Multilayer Perceptron (MLP)



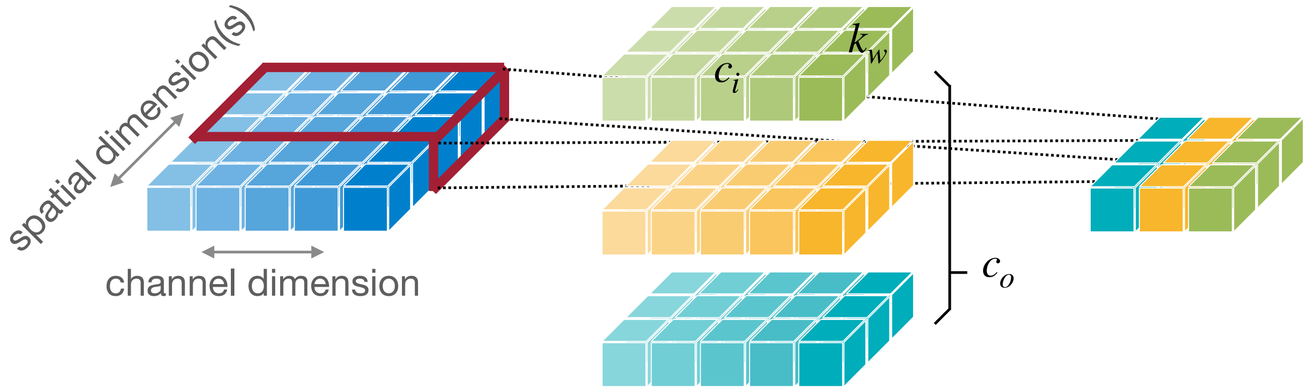
Convolution Layer

The output neuron is connected to input neurons in the receptive field.

- **Shape of Tensors:**

	1D Conv
Input Features $\mathbf{X}$: ~~(n, c_i)~~	(n, c_i, w_i)
Output Features $\mathbf{Y}$: ~~(n, c_o)~~	(n, c_o, w_o)
Weights $\mathbf{W}$: ~~(c_o, c_i)~~	(c_o, c_i, k_w)
Bias $\mathbf{b}$: $(c_o,)$	

Notations	
n	Batch Size
c_i	Input Channels
c_o	Output Channels
w_i, w_o	Input/Output Width
k_w	Kernel Width



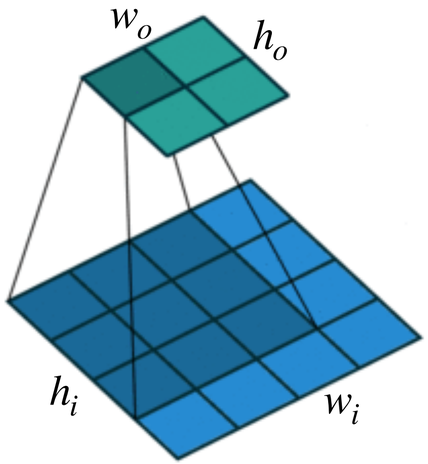
Weight Sharing

Convolution Layer

The output neuron is connected to input neurons in the receptive field.

- **Shape of Tensors:**

	1D Conv	2D Conv
• Input Features $\mathbf{X}$: ~~(n, c_i)~~	(n, c_i, w_i)	(n, c_i, h_i, w_i)
• Output Features $\mathbf{Y}$: ~~(n, c_o)~~	(n, c_o, w_o)	(n, c_o, h_o, w_o)
• Weights $\mathbf{W}$: ~~(c_o, c_i)~~	(c_o, c_i, k_w)	(c_o, c_i, k_h, k_w)
• Bias $\mathbf{b}$: $(c_o,)$		



Notations	
n	Batch Size
c_i	Input Channels
c_o	Output Channels
h_i, h_o	Input/Output Height
w_i, w_o	Input/Output Width
k_h	Kernel Height
k_w	Kernel Width

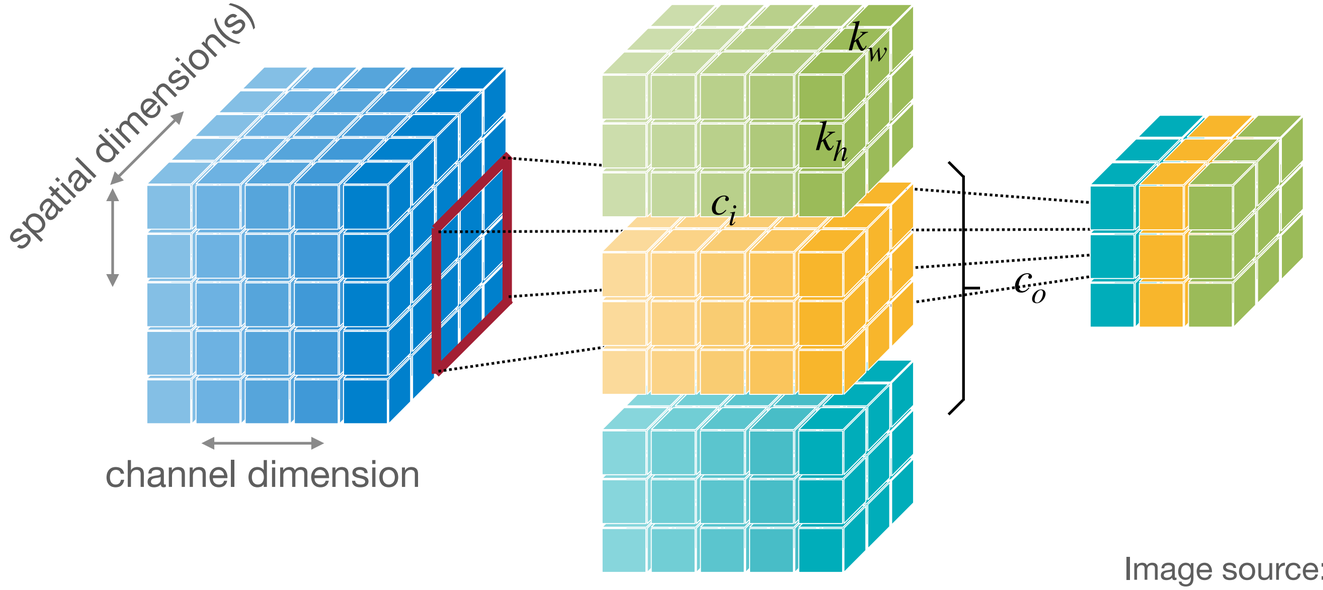


Image source: 1

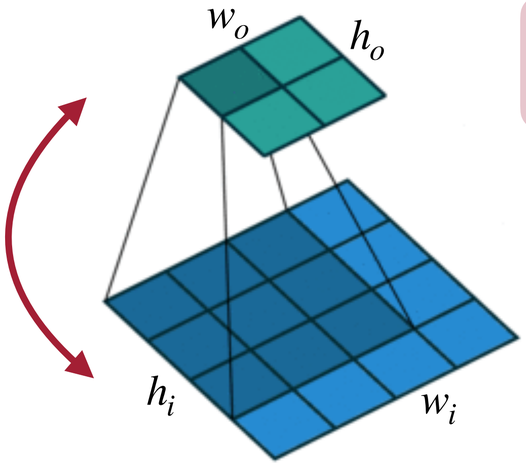
Convolution Layer

The output neuron is connected to input neurons in the receptive field.

- **Shape of Tensors:**
  - Input Features $\mathbf{X}$: (n, c_i, h_i, w_i)
  - Output Features $\mathbf{Y}$: (n, c_o, h_o, w_o)
  - Weights $\mathbf{W}$: (c_o, c_i, k_h, k_w)
  - Bias $\mathbf{b}$: $(c_o,)$

Notations	
n	Batch Size
c_i	Input Channels
c_o	Output Channels
h_i, h_o	Input/Output Height
w_i, w_o	Input/Output Width
k_h	Kernel Height
k_w	Kernel Width

Feature map size becomes smaller.



$$h_o = h_i - k_h + 1$$

$$\begin{aligned} h_i &= w_i = 4 \\ k_h &= k_w = 3 \\ h_o &= w_o \\ &= 4 - 3 + 1 \\ &= 2 \end{aligned}$$

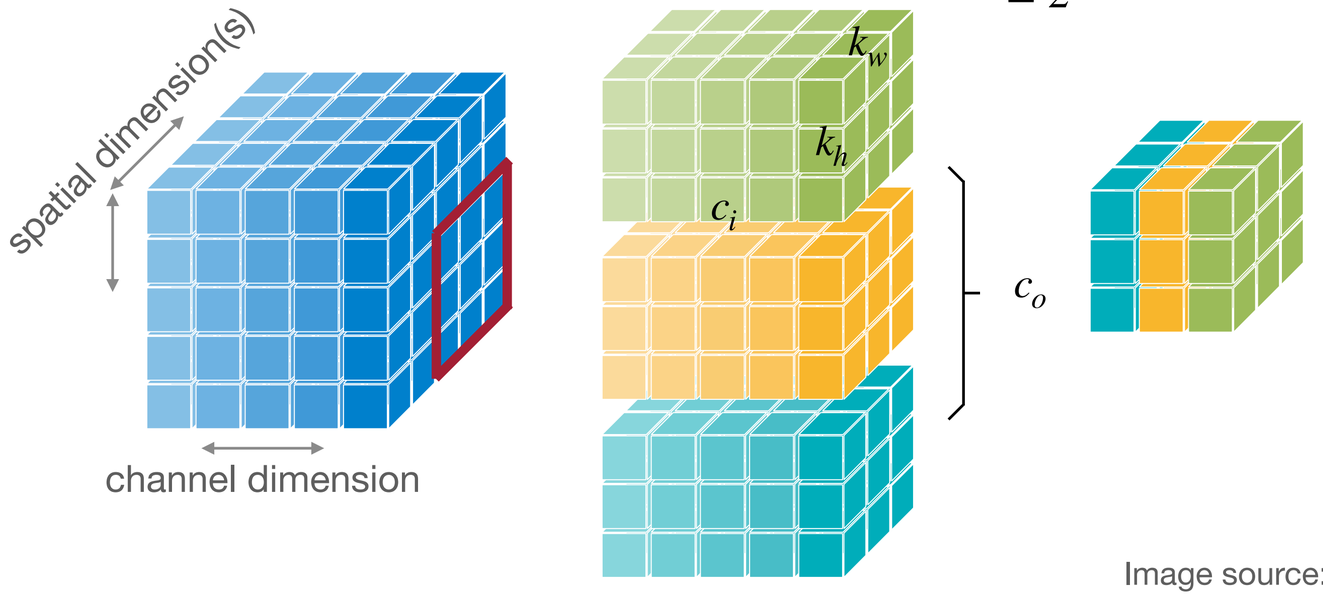
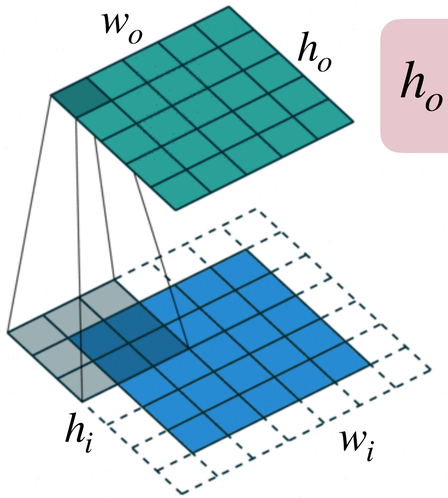


Image source: 1

Convolution Layer: Padding

- Padding can be used to keep the output feature map size is the same as input feature map size
  - **Zero Padding** pads the input boundaries with zero. (Default in PyTorch)
  - Other Paddings: Reflection Padding, Replication Padding, Constant Padding



$$h_o = h_i + 2p - k_h + 1$$

p is padding

$$h_i = w_i = 5$$
$$k_h = k_w = 3$$
$$h_o = w_o$$
$$= 5 + 2 \times 1 - 3 + 1$$
$$= 5$$

Notations	
n	Batch Size
c_i	Input Channels
c_o	Output Channels
h_i, h_o	Input/Output Height
w_i, w_o	Input/Output Width
k_h	Kernel Height
k_w	Kernel Width

Zero Padding

0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	1	2	3	0	0
0	0	4	5	6	0	0
0	0	7	8	9	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

Reflection Padding

9	8	7	8	9	8	7
6	5	4	5	6	4	5
3	2	1	2	3	2	1
6	5	4	5	6	5	4
9	8	7	8	9	8	7
6	5	4	5	6	5	4
3	2	1	2	3	2	1

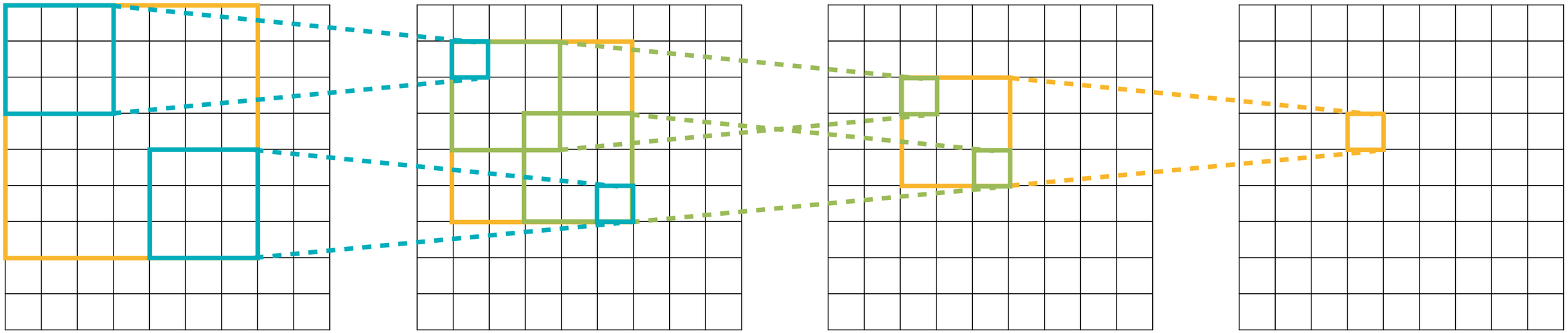
Replication Padding

1	1	1	2	3	3	3
1	1	1	2	3	3	3
1	1	1	2	3	3	3
4	4	4	5	6	6	6
7	7	7	8	9	9	9
7	7	7	8	9	9	9
7	7	7	8	9	9	9

Image source: 1

Convolution Layer: Receptive Field

- In convolution, each output element depends on $k_h \times k_w$ receptive field in the input.
- Each successive convolution adds $k - 1$ to the receptive field size
- With L layers, the receptive field size is $L \cdot (k - 1) + 1$



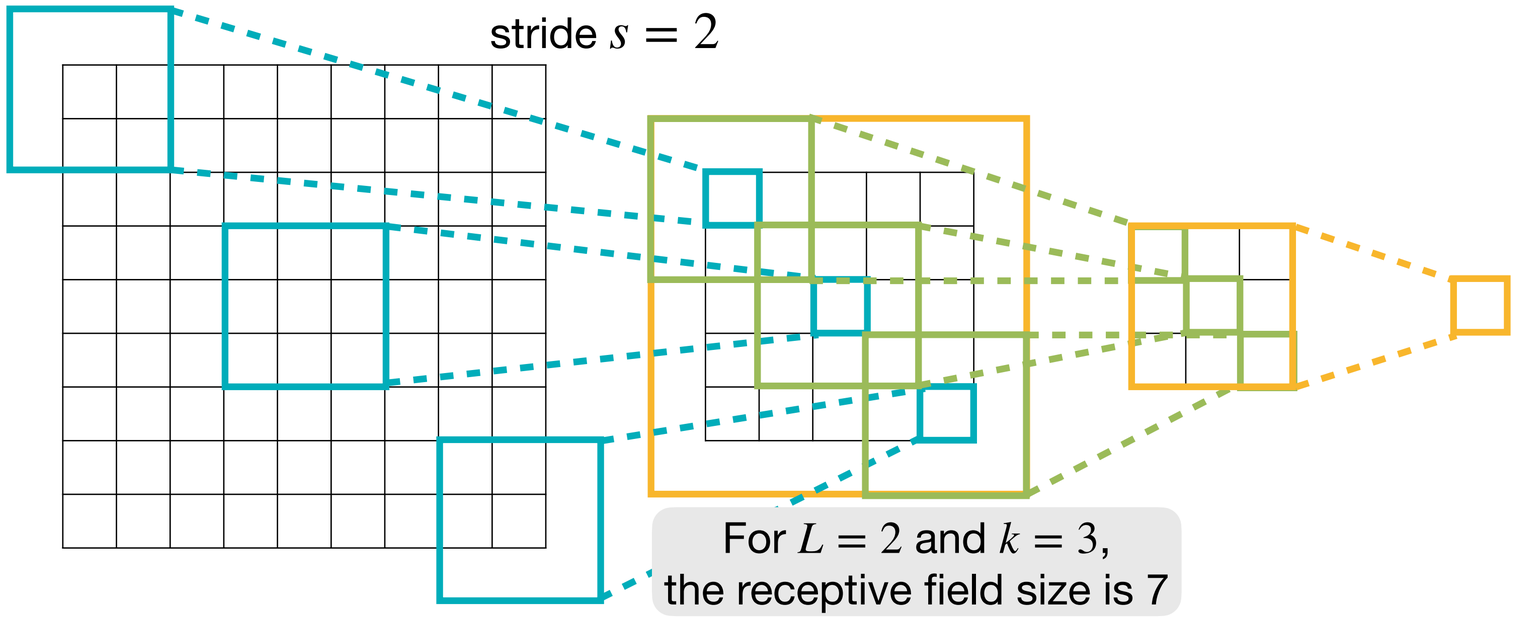
For $L = 2$ and $k = 3$, the receptive field size is **5**

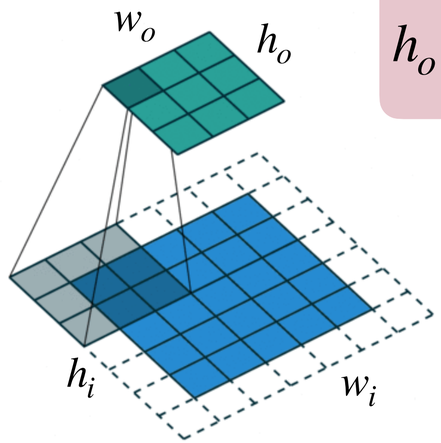
For $L = 3$ and $k = 3$, the receptive field size is **7**

Problem: For large images, we need many layers for each output to "see" the whole image
Solution: Downsample inside the neural network

Slide Inspiration: Ruohan Gao

Strided Convolution Layer

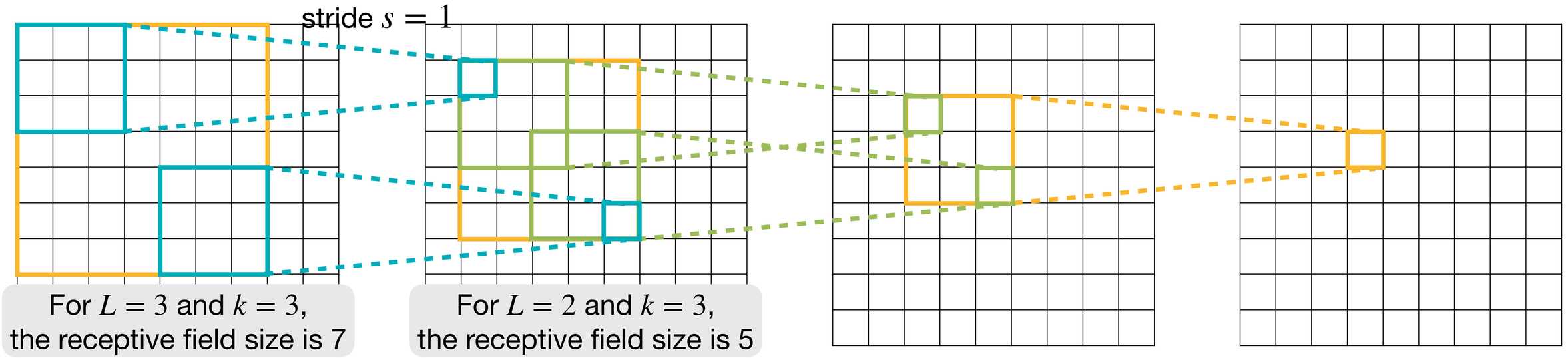




$$h_o = \frac{h_i + 2p - k_h}{s} + 1$$

p is padding

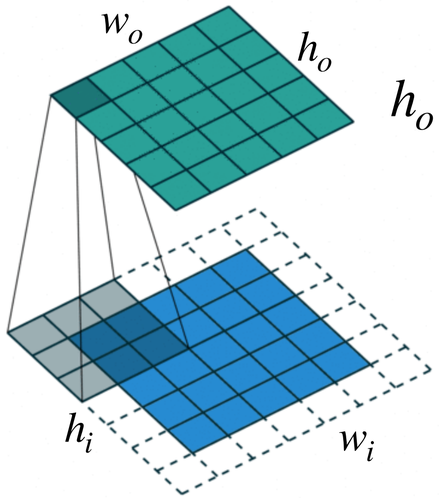
s is stride



Grouped Convolution Layer

A group of narrower convolutions

- **Shape of Tensors:**
  - Input Features $\mathbf{X}$: (n, c_i, h_i, w_i)
  - Output Features $\mathbf{Y}$: (n, c_o, h_o, w_o)
  - Weights $\mathbf{W}$: ~~(c_o, c_i, k_h, k_w)~~ $(g \cdot c_o/g, c_i/g, k_h, k_w)$
  - Bias $\mathbf{b}$: $(c_o,)$



$$h_o = \frac{h_i + 2p - k_h}{s} + 1$$

p is padding

s is stride

Notations	
n	Batch Size
c_i	Input Channels
c_o	Output Channels
h_i, h_o	Input/Output Height
w_i, w_o	Input/Output Width
k_h	Kernel Height
k_w	Kernel Width
g	Groups

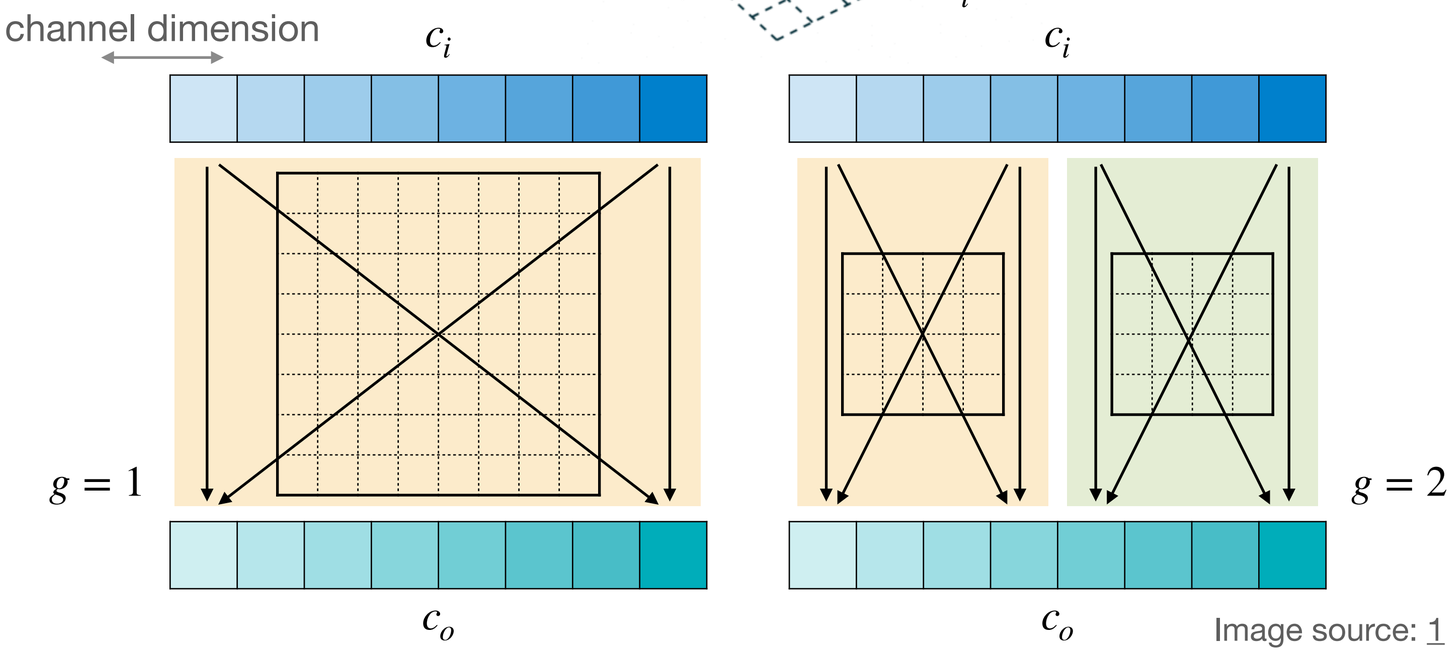
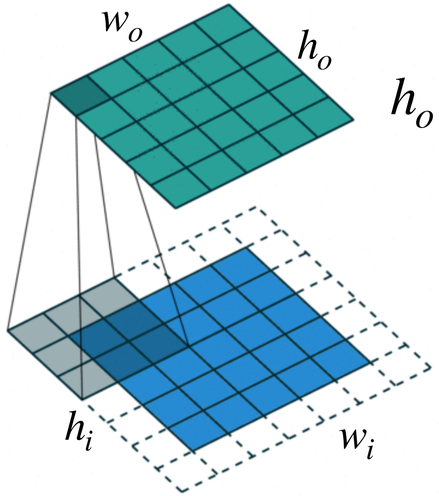


Image source: 1

Depthwise Convolution Layer

Independent filter for each channel: $g = c_i = c_o$ in grouped convolution

- **Shape of Tensors:**
  - Input Features $\mathbf{X}$: (n, c_i, h_i, w_i)
  - Output Features $\mathbf{Y}$: (n, c_o, h_o, w_o)
  - Weights $\mathbf{W}$: ~~(c_o, c_i, k_h, k_w)~~ (c, k_h, k_w)
  - Bias $\mathbf{b}$: $(c_o,)$

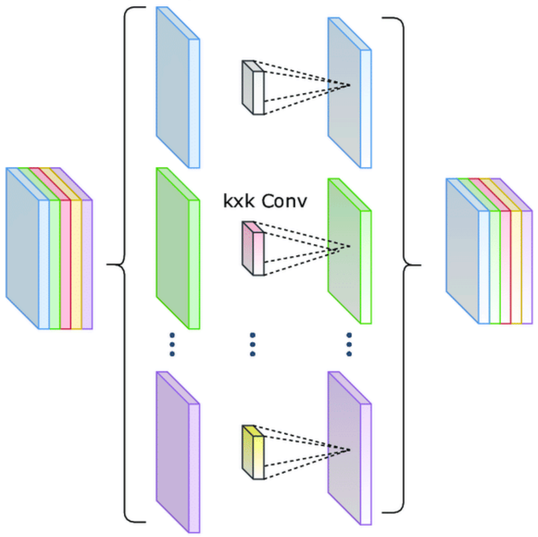


$$h_o = \frac{h_i + 2p - k_h}{s} + 1$$

p is padding

s is stride

Notations	
n	Batch Size
c_i	Input Channels
c_o	Output Channels
h_i, h_o	Input/Output Height
w_i, w_o	Input/Output Width
k_h	Kernel Height
k_w	Kernel Width
g	Groups



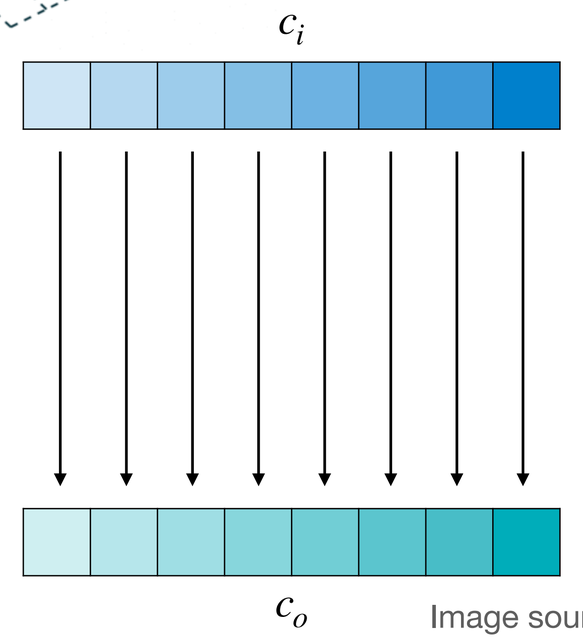
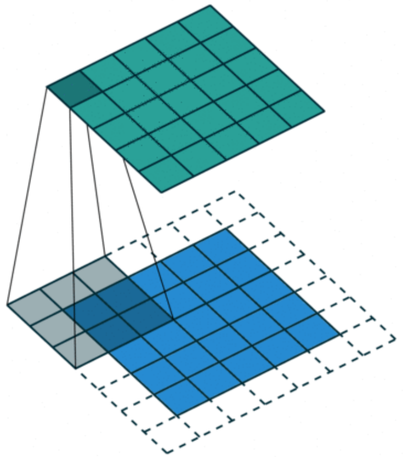


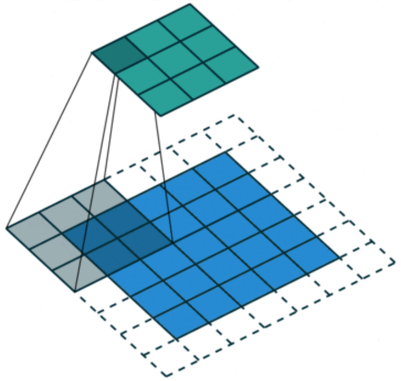
Image source: 1, 2

Other Convolution Layers

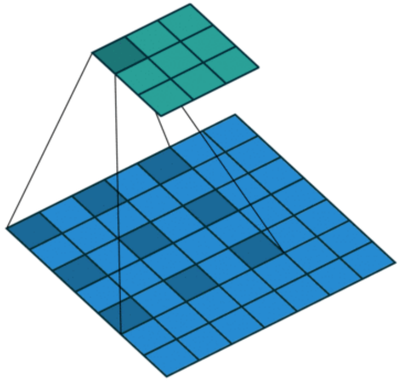
Convolution



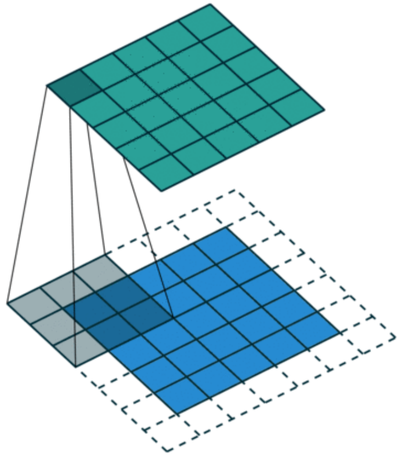
Convolution stride = 2



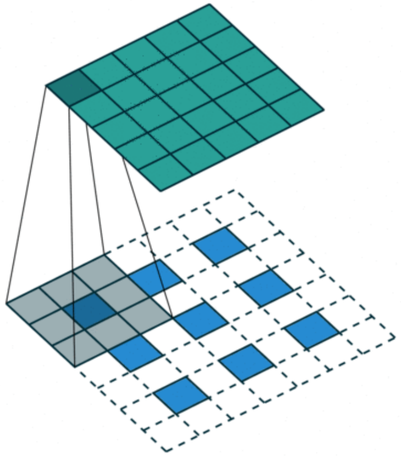
Dilated Convolution



Transposed Convolution



Transposed Convolution (stride = 2)

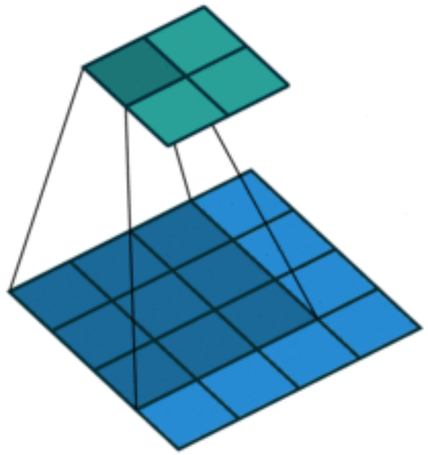


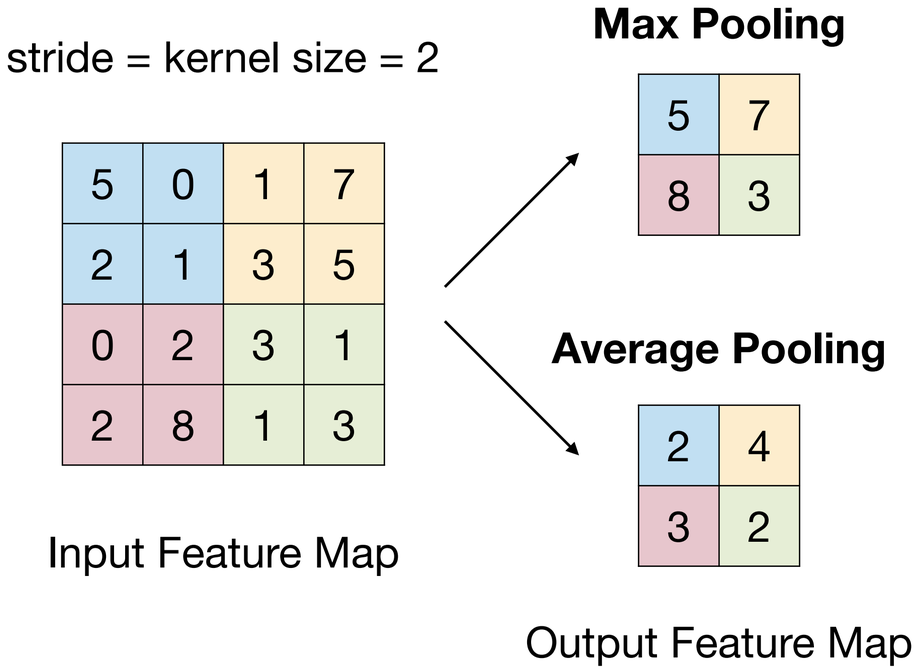
For more animation, please visit this page.

Pooling Layer

Downsample the feature map to a smaller size

- The output neuron pools the features in the receptive field, similar to convolution.
  - Usually, the stride is the same as the kernel size: $s = k$
- Pooling operates over each channel independently.
  - No learnable parameters





Slide Inspiration: Ruohan Gao

Image source: 1

Normalization Layer

Normalizing the features makes optimization faster.

- Normalization layer normalizes the features as follows,

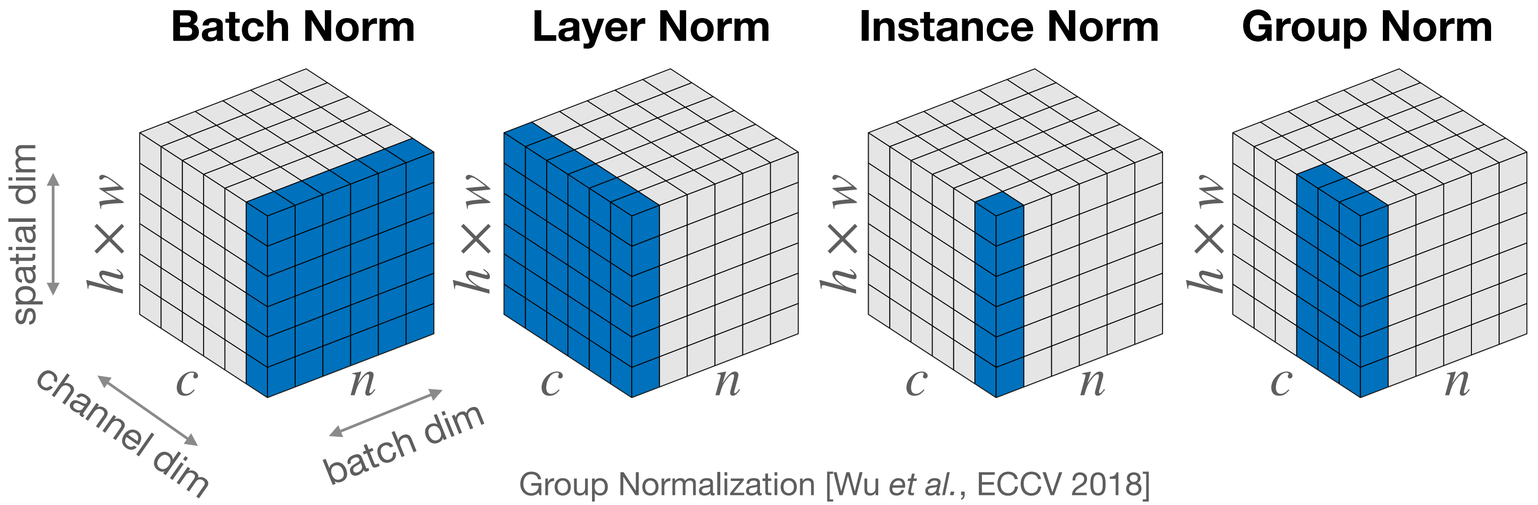
$$\hat{x}_i = \frac{1}{\sigma}\left(x_i - \mu_i\right)$$

$$\mu_i = \frac{1}{m}\sum_{k\in\mathcal{S}_i} x_k$$

$$\sigma_i = \sqrt{\frac{1}{m}\sum_{k\in\mathcal{S}_i}\left(x_k - \mu_i\right)^2 + \epsilon}$$

  - μ_i is the mean, and σ_i is the standard deviation (std) over the set of pixels $\mathcal{S}_i$.
- Then learns a *per-channel* linear transform (trainable scale γ and shift β) to compensate for the possible lost of representational ability.

$$y = \gamma_{i_c}\hat{x}_i + \beta_{i_c}$$

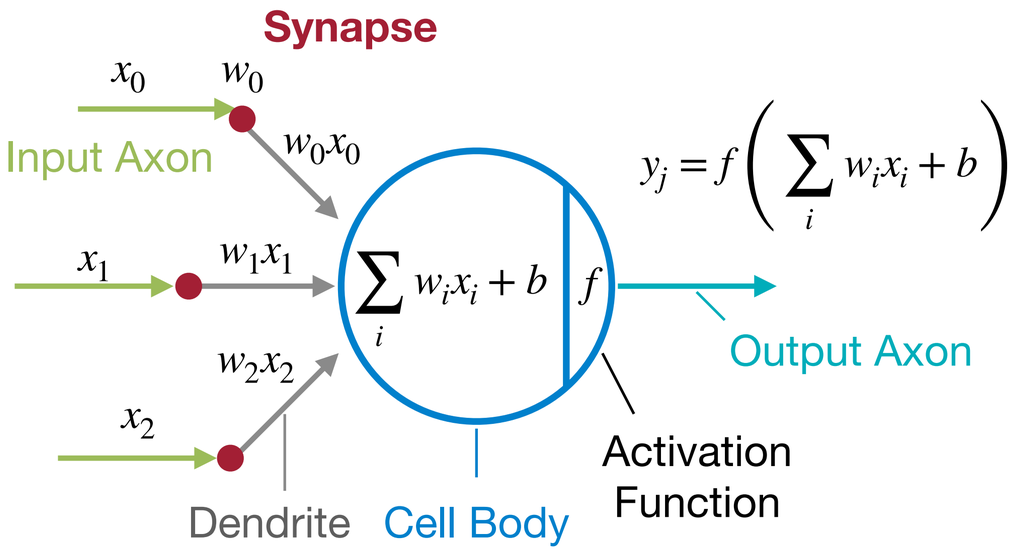


Group Normalization [Wu *et al.*, ECCV 2018]

Different normalizations use different definitions of the set $\mathcal{S}_i$ (colored in blue)

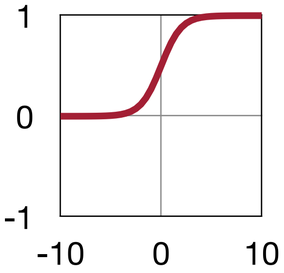
Activation Function

Activation functions are typically non-linear functions



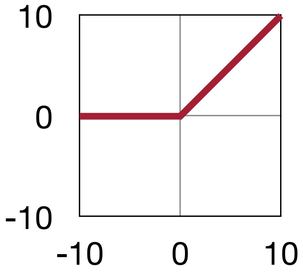
$$y_j = f\left(\sum_i w_i x_i + b\right)$$

Sigmoid



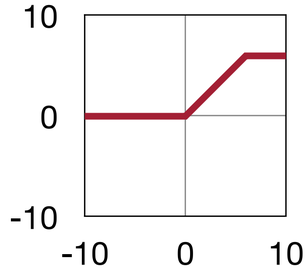
$$y = 1/(1 + e^{-x})$$

ReLU



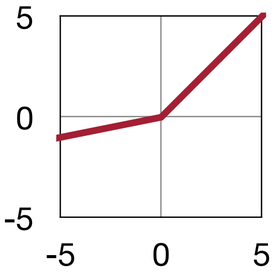
$$y = \max(0, x)$$

ReLU6



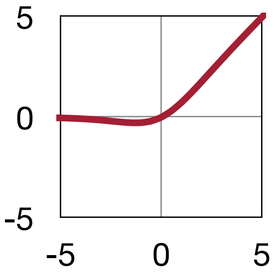
$$y = \min\left(\max(0, x), 6\right)$$

Leaky ReLU



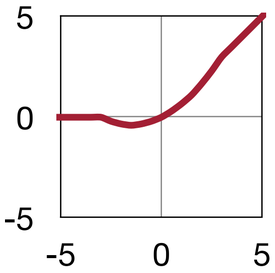
$$y = \max(\alpha x, x)$$

Swish



$$y = x/(1 + e^{-x})$$

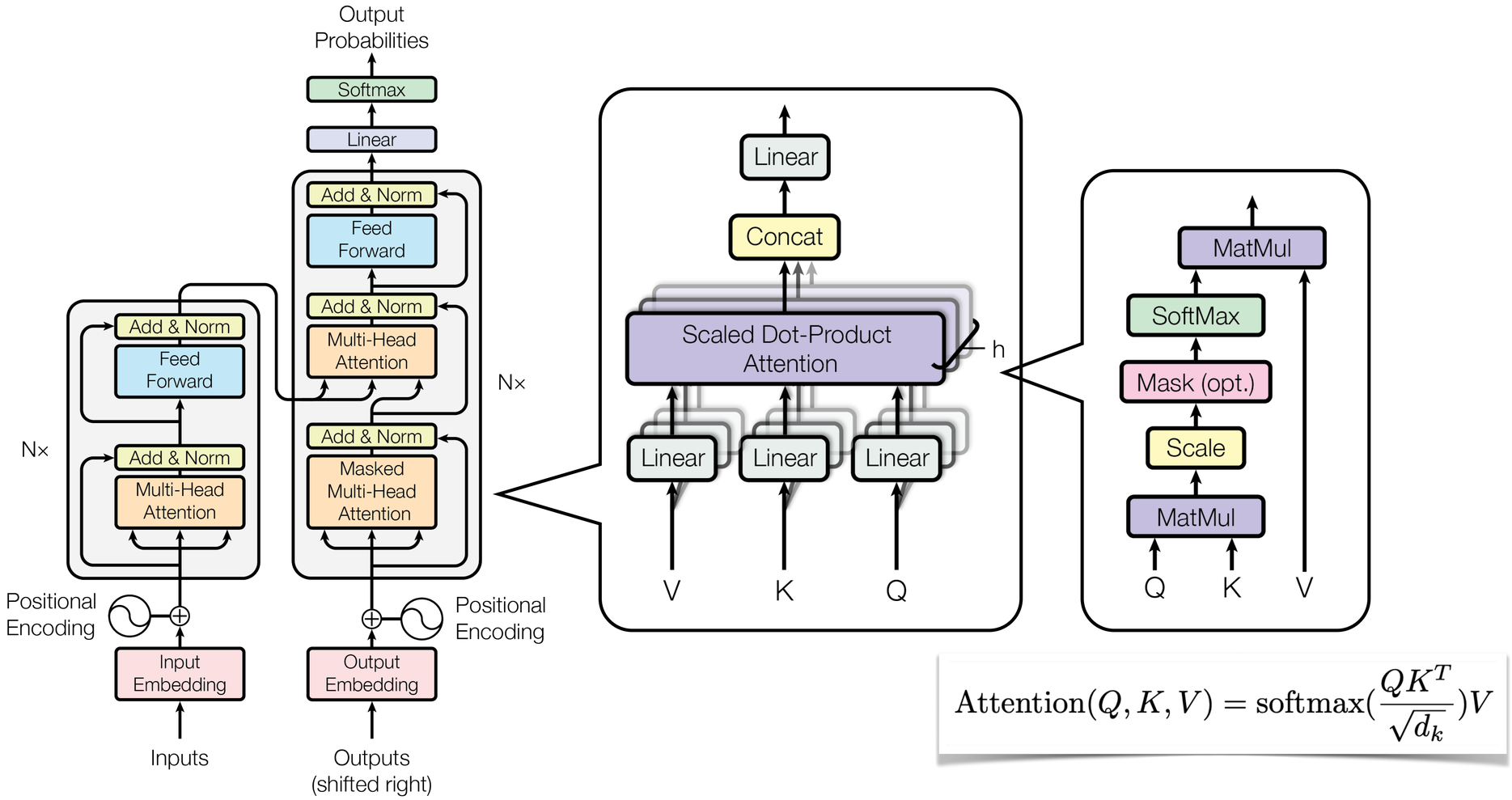
Hard Swish



$$y = \begin{cases} 0, & x \le -3 \\ x, & x \ge 3 \\ x \cdot (x+3)/6, & otherwise \end{cases}$$

Other Activation Functions: Tanh, GELU, ELU, Mish…

Transformer



$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

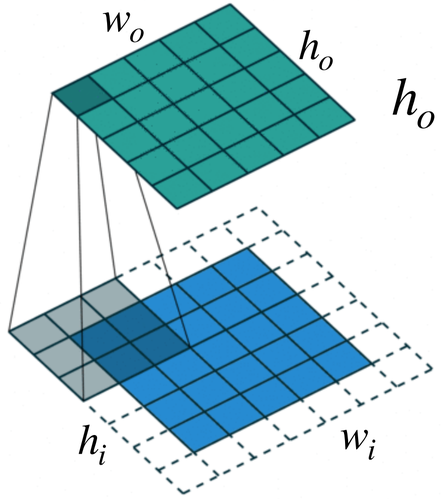
Attention is All You Need [Vaswani *et al.*, NeurIPS 2017]

Popular CNN Architectures

AlexNet

AlexNet	C × H × W	H, W
Image (3×224×224)	3×224×224	
11×11 Conv, channel 96, stride 4, pad 2	96×55×55	$\frac{224+2\times2-11}{4}+1=55$
3×3 MaxPool, stride 2	96×27×27	$\frac{55+0-3}{2}+1=27$
5×5 Conv, channel 256, pad 2, groups 2	256×27×27	$\frac{27+2\times2-5}{1}+1=27$
3×3 MaxPool, stride 2	256×13×13	$\frac{27+0-3}{2}+1=13$
3×3 Conv, channel 384, pad 1	384×13×13	$\frac{13+2\times1-3}{1}+1=13$
3×3 Conv, channel 384, pad 1, groups 2	384×13×13	$\frac{13+2\times1-3}{1}+1=13$
3×3 Conv, channel 256, pad 1, groups 2	256×13×13	$\frac{13+2\times1-3}{1}+1=13$
3×3 MaxPool, stride 2	256×6×6	$\frac{13+0-3}{2}+1=6$
Linear, channel 4096	4096	
Linear, channel 4096	4096	
Linear, channel 1000	1000	

Convolution Layer / Pooling Layer

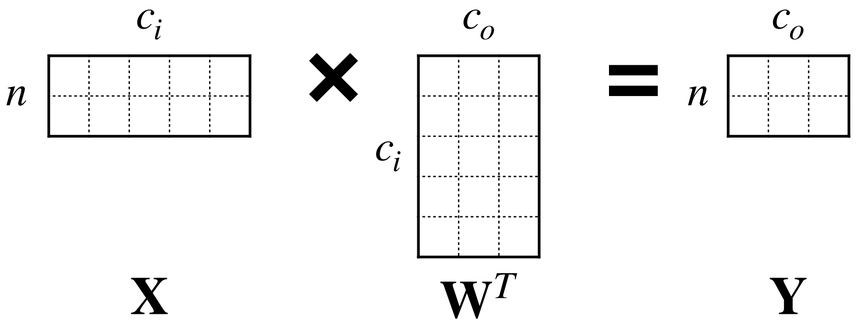


$$h_o = \frac{h_i + 2p - k_h}{s} + 1$$

p is padding

s is stride

Linear Layer



ImageNet Classification with Deep Convolutional Neural Networks [Krizhevsky *et al.*, NeurIPS 2012]

VGG-16

AlexNet

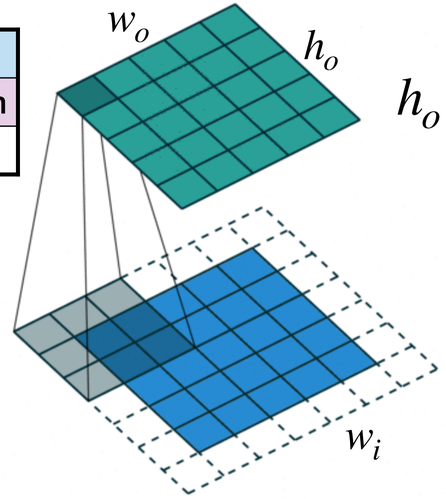
Image (3×224×224)
11×11 Conv, channel 96, stride 4, pad 2
3×3 MaxPool, stride 2
5×5 Conv, channel 256, pad 2, groups 2
3×3 MaxPool, stride 2
3×3 Conv, channel 384, pad 1
3×3 Conv, channel 384, pad 1, groups 2
3×3 Conv, channel 256, pad 1, groups 2
3×3 MaxPool, stride 2
Linear, channel 4096
Linear, channel 4096
Linear, channel 1000

VGG-16

	Image (3×224×224)
1	3×3 Conv, channel 64, pad 1
2	3×3 Conv, channel 64, pad 1
	2×2 MaxPool, stride 2
3	3×3 Conv, channel 128, pad 1
4	3×3 Conv, channel 128, pad 1
	2×2 MaxPool, stride 2
5	3×3 Conv, channel 256, pad 1
6	3×3 Conv, channel 256, pad 1
7	3×3 Conv, channel 256, pad 1
	2×2 MaxPool, stride 2
8	3×3 Conv, channel 512, pad 1
9	3×3 Conv, channel 512, pad 1
10	3×3 Conv, channel 512, pad 1
	2×2 MaxPool, stride 2
11	3×3 Conv, channel 512, pad 1
12	3×3 Conv, channel 512, pad 1
13	3×3 Conv, channel 512, pad 1
	2×2 MaxPool, stride 2
14	Linear, channel 4096
15	Linear, channel 4096
16	Linear, channel 1000

Convolution Layer / Pooling Layer

Conv
BatchNorm
ReLU

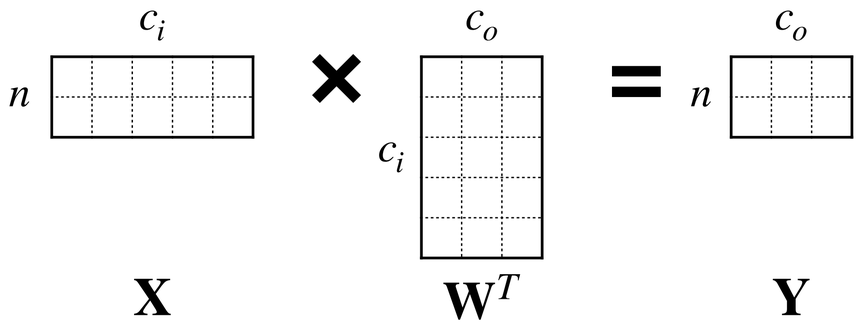


$$h_o = \frac{h_i + 2p - k_h}{s} + 1$$

p is padding

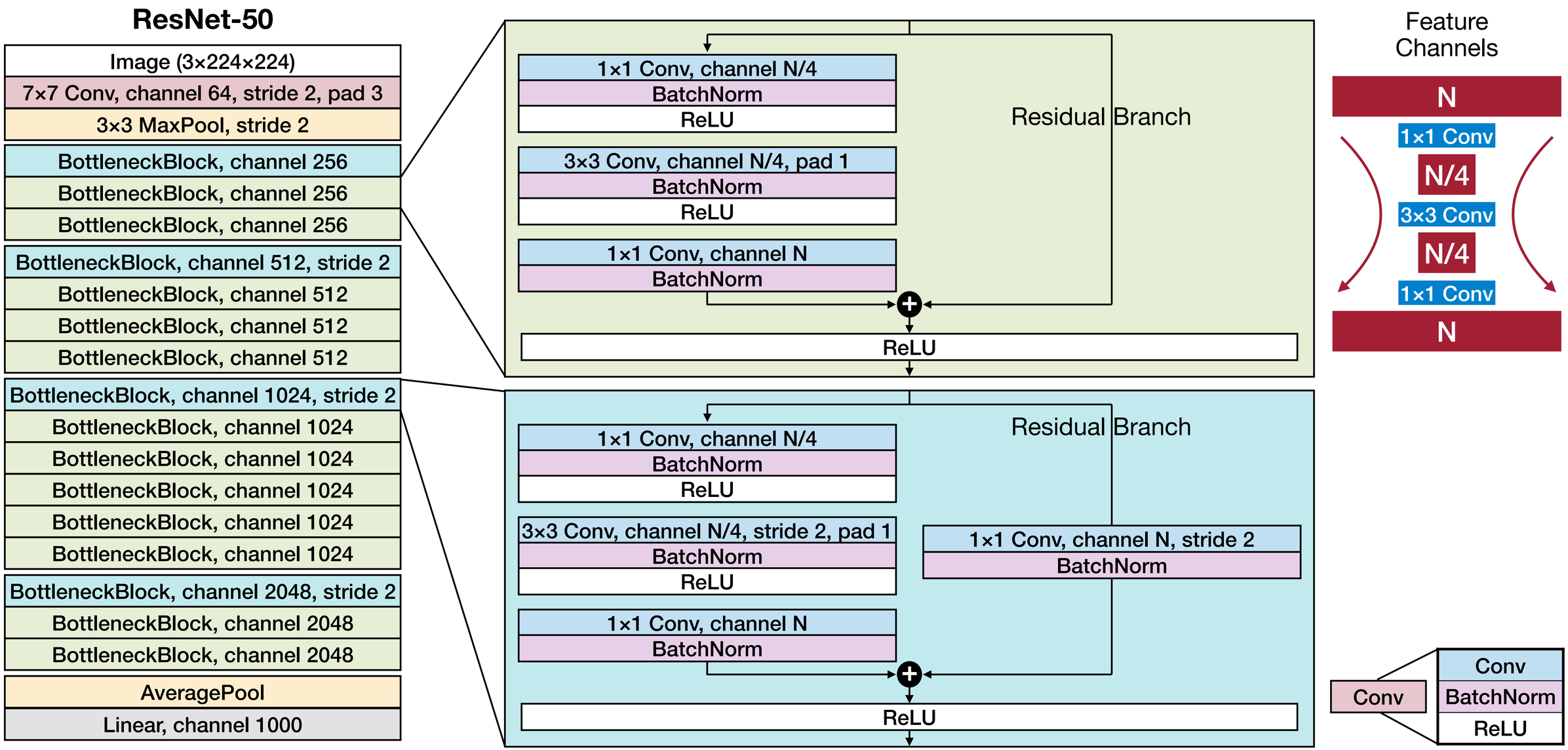
s is stride

Linear Layer



Very Deep Convolutional Networks for Large-Scale Image Recognition [Simonyan *et al.*, ICLR 2015]

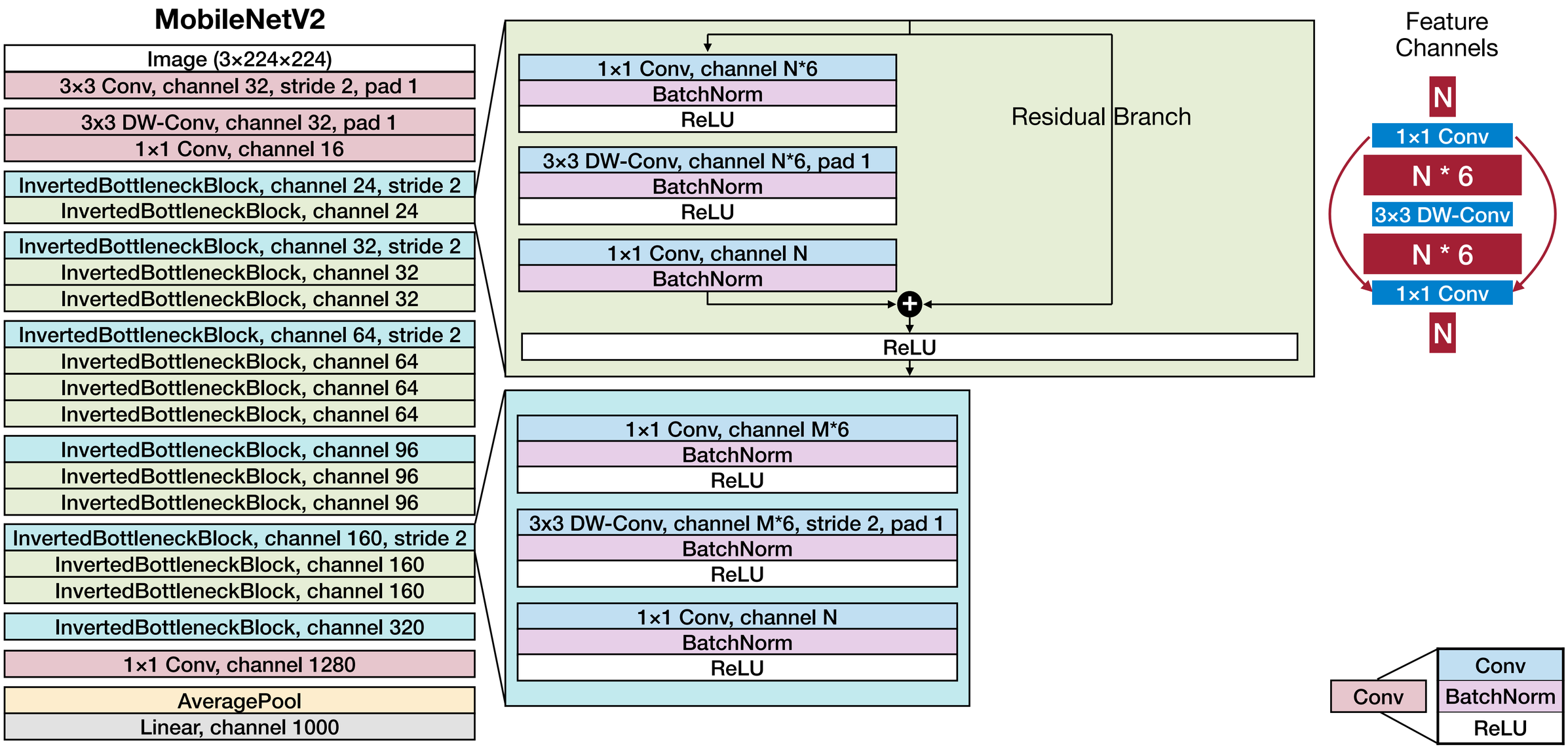
ResNet-50



Deep Residual Learning for Image Recognition [He *et al.*, CVPR 2016]

Figure Inspiration: 1

MobileNetV2



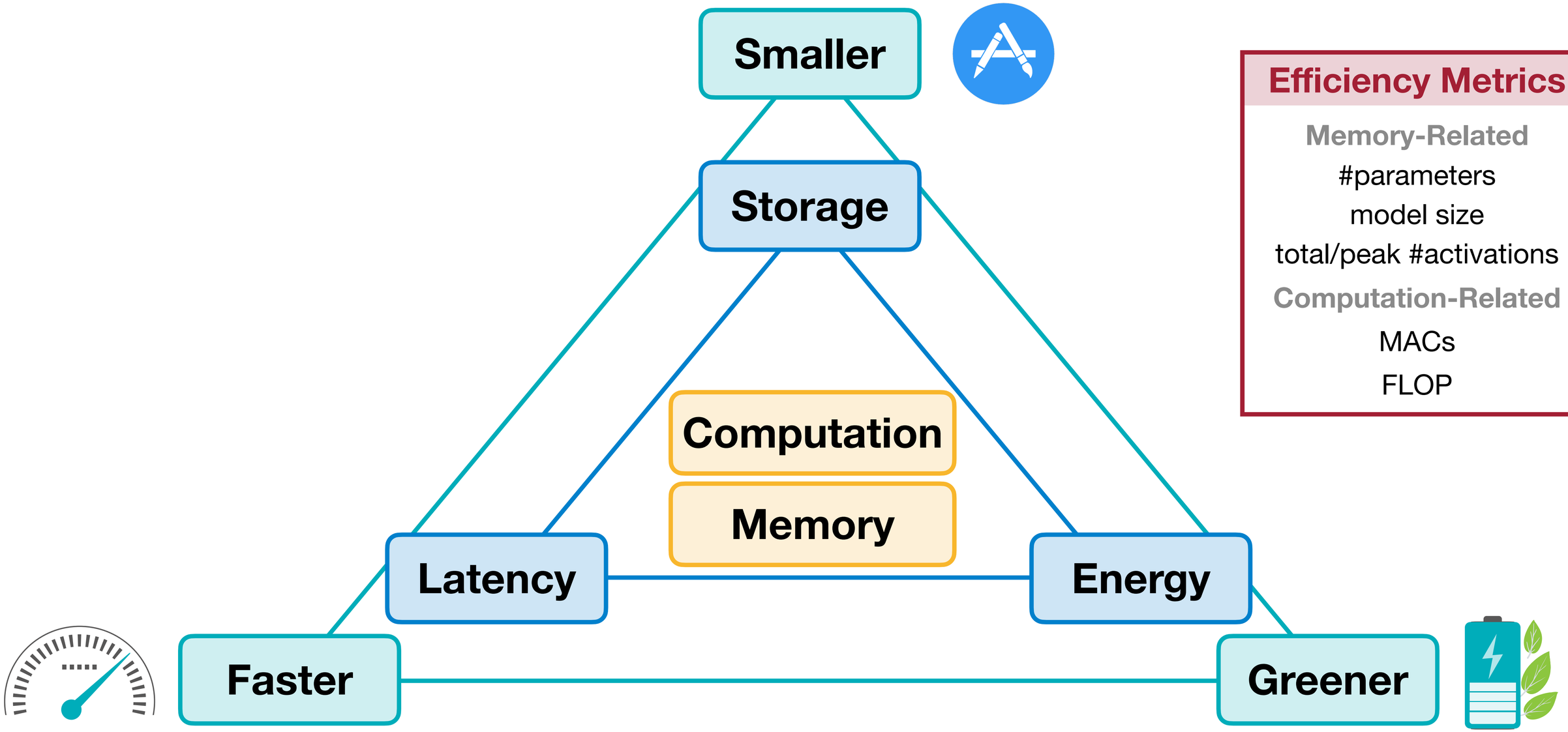
MobileNetV2: Inverted Residuals and Linear Bottlenecks [Sandler *et al.*, CVPR 2018]

Figure Inspiration: 1

Efficiency Metrics

How should we measure the efficiency of neural networks?

Efficiency of Neural Networks



Efficiency Metrics

Memory-Related

#parameters

model size

total/peak #activations

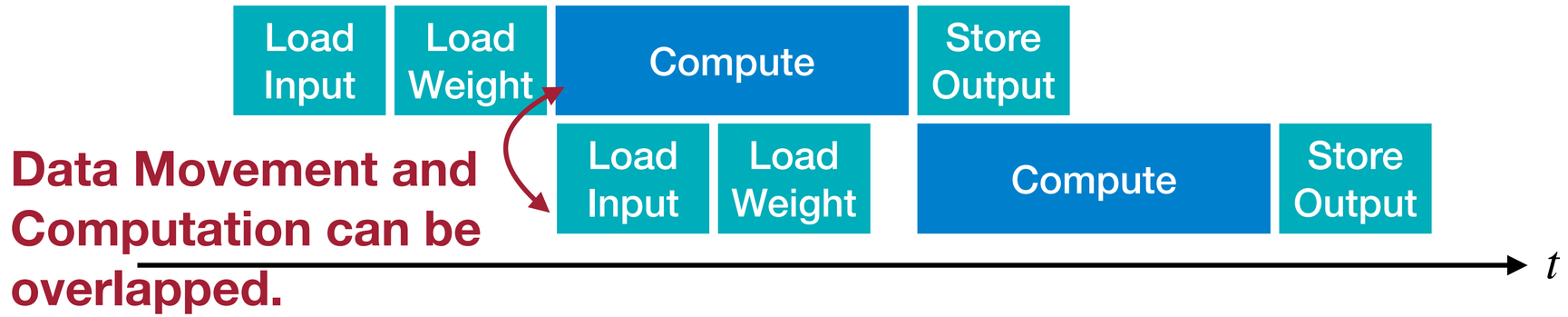
Computation-Related

MACs

FLOP

Image source: 1

Latency



Data Movement and Computation can be overlapped.

$$Latency \approx \max\left(T_{computation}, T_{memory}\right)$$

$$T_{\text{computation}} \approx \frac{\text{Number of Operations in Neural Network Model}}{\text{Number of Operations that Processor can Process Per Second}}$$

NN Specification

Hardware Specification

$$T_{\text{memory}} \approx T_{\text{data movement of activations}} + T_{\text{data movement of weights}}$$

$$T_{\text{data movement of weights}} \approx \frac{\text{Neural Network Model Size}}{\text{Memory Bandwidth of Processor}}$$

NN Specification

Hardware Specification

$$T_{\text{data movement of activations}} \approx \frac{\text{Input Activation Size + Output Activation Size}}{\text{Memory Bandwidth of Processor}}$$

NN Specification

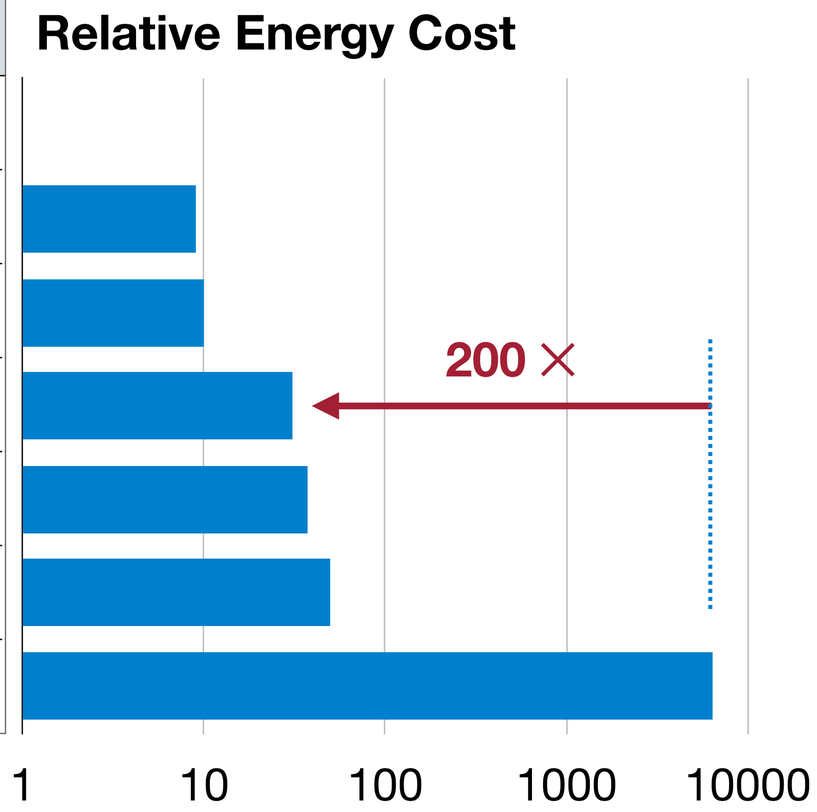
Hardware Specification

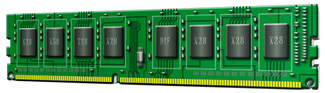
Energy Consumption

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 × +

This image is in the public domain

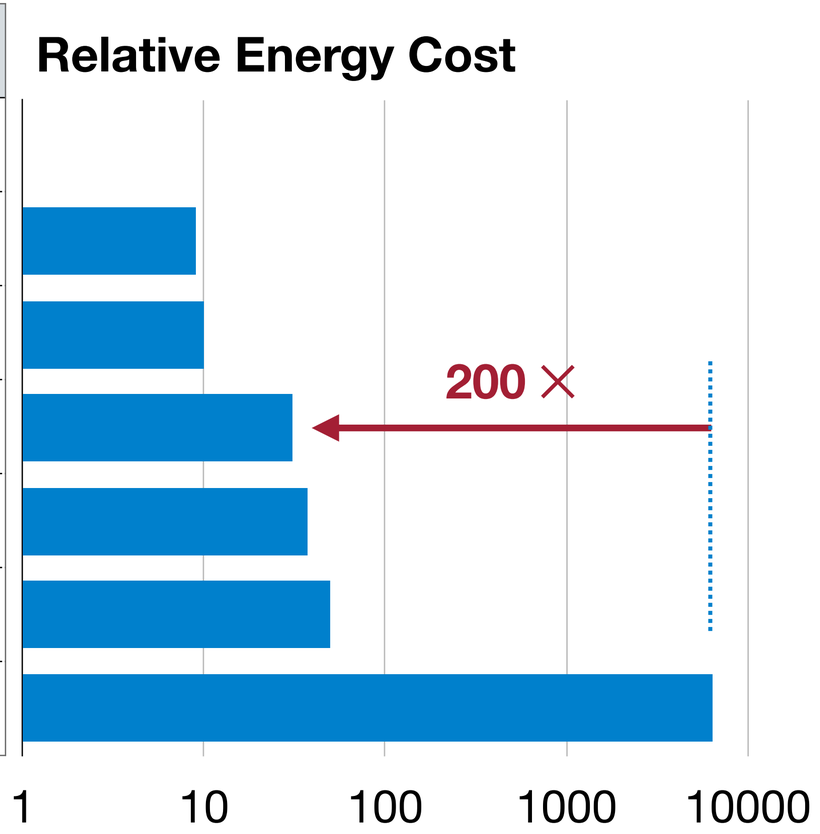
Computing's Energy Problem (and What We Can Do About it) [Horowitz, M., IEEE ISSCC 2014]

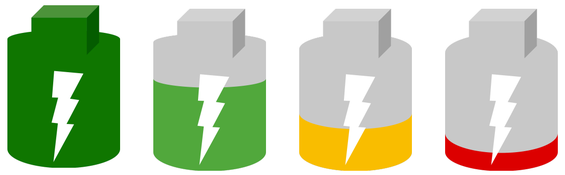
Energy Consumption

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

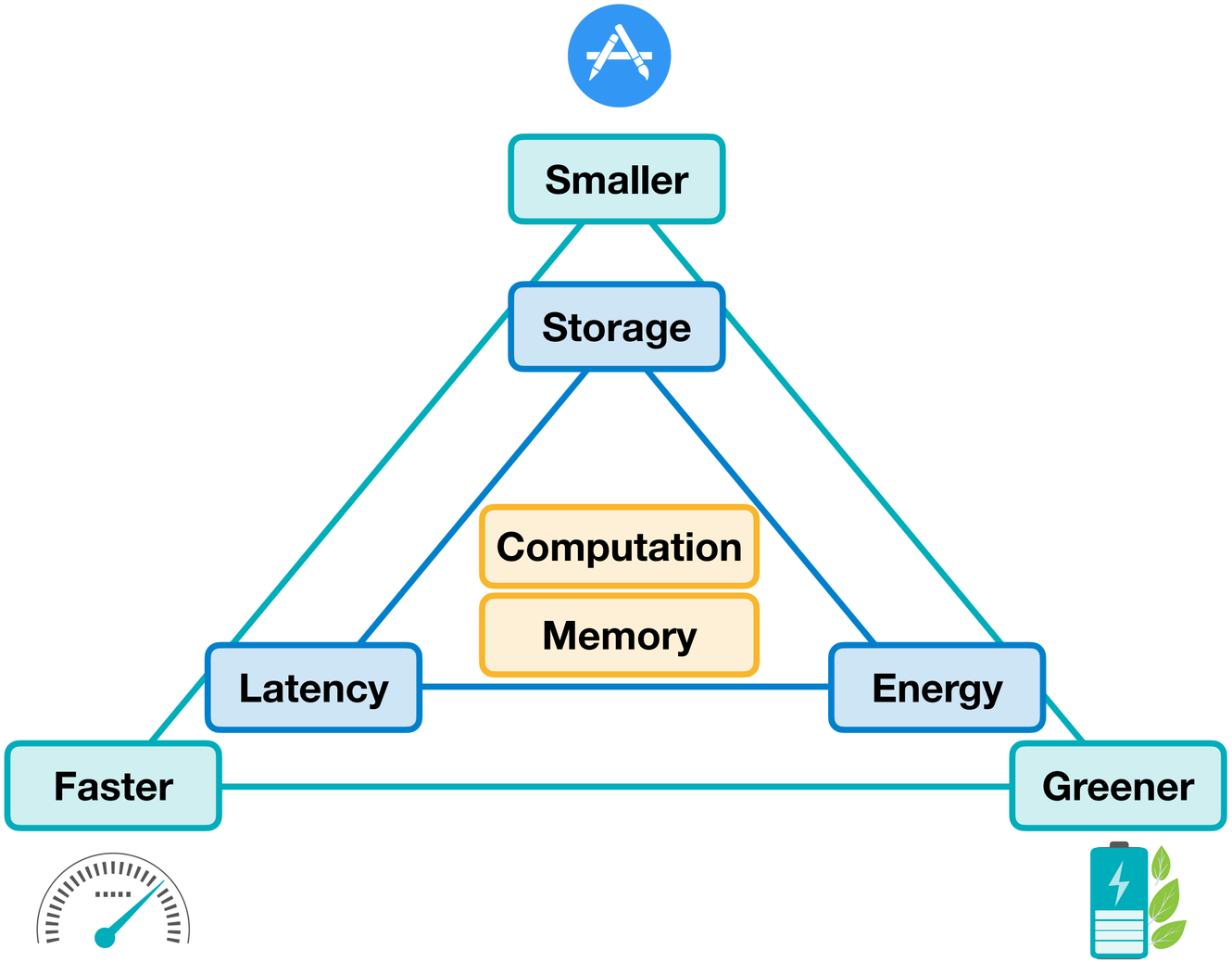




Battery images are in the public domain
Image 1, image 2, image 2, image 4

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

Efficiency of Neural Networks



Efficiency Metrics

Memory-Related

#parameters

model size

total/peak #activations

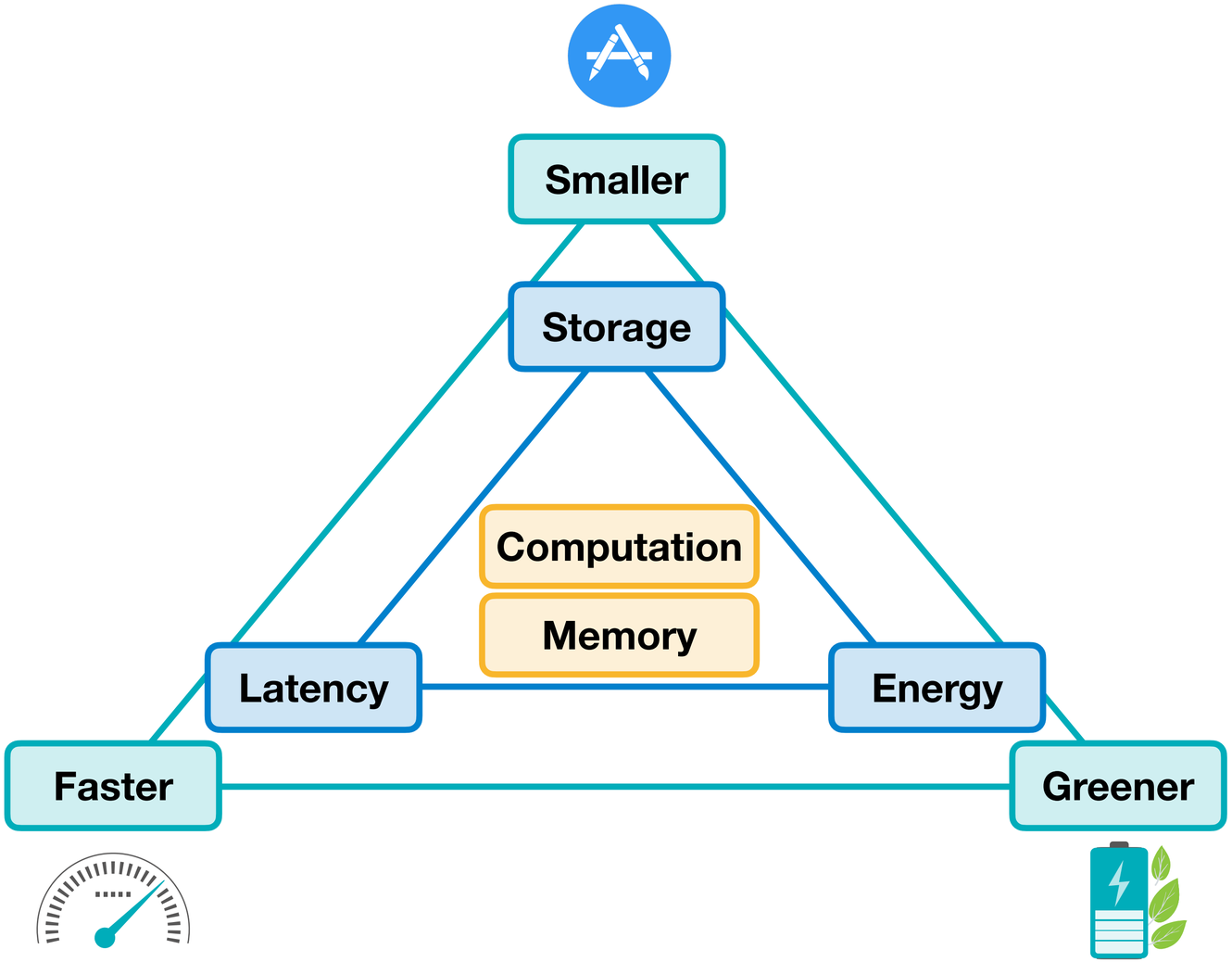
Computation-Related

MACs

FLOP

Image source: 1

Efficiency of Neural Networks



Efficiency Metrics

Memory-Related

#parameters

model size

total/peak #activations

Computation-Related

MACs

FLOP

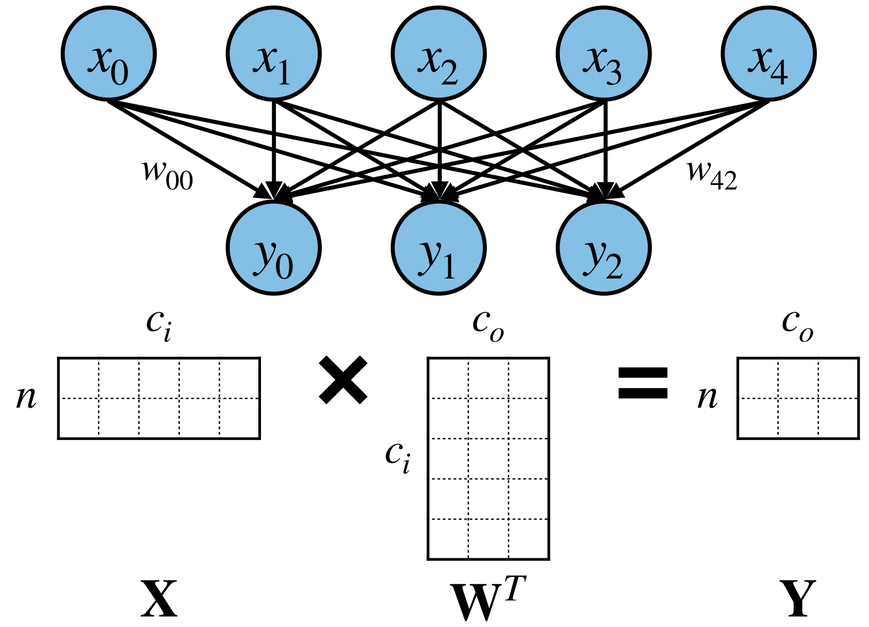
Image source: 1

Number of Parameters (#Parameters)

- #Parameters is the parameter (synapse/weight) count of the given neural network, *i.e.*, the number of elements in the weight tensors.

Number of Parameters (#Parameters)

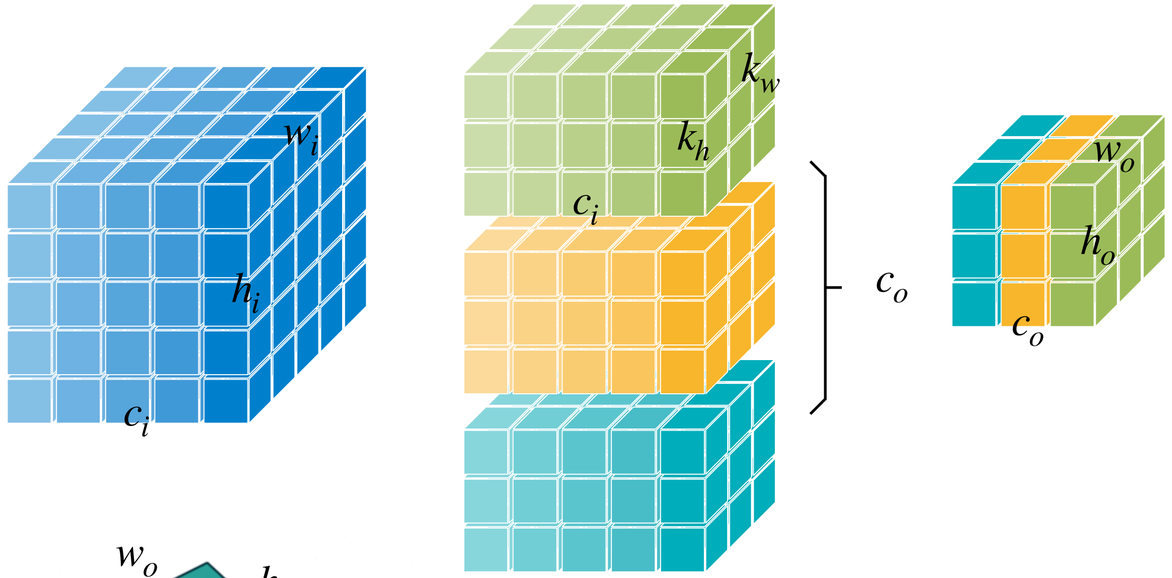
Layer	#Parameters (bias is ignored)
Linear Layer	$c_o \cdot c_i$
Convolution	
Grouped Convolution	
Depthwise Convolution	



Notations	
n	Batch Size
c_i	Input Channels
c_o	Output Channels
h_i, h_o	Input/Output Height
w_i, w_o	Input/Output Width
k_h, k_w	Kernel Height/Width
g	Groups

Number of Parameters (#Parameters)

Layer	#Parameters (bias is ignored)
Linear Layer	$c_o \cdot c_i$
Convolution	$c_o \cdot c_i \cdot k_h \cdot k_w$
Grouped Convolution	
Depthwise Convolution	



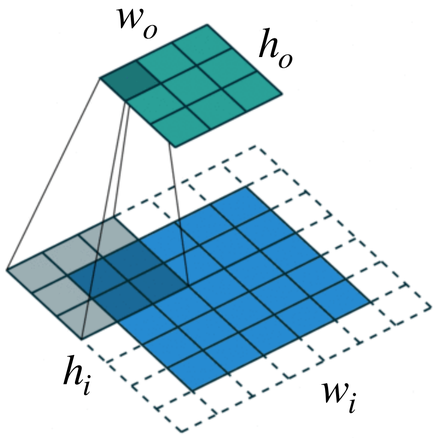


Image source: 1

Notations	
n	Batch Size
c_i	Input Channels
c_o	Output Channels
h_i, h_o	Input/Output Height
w_i, w_o	Input/Output Width
k_h, k_w	Kernel Height/Width
g	Groups

Number of Parameters (#Parameters)

Layer	#Parameters (bias is ignored)
Linear Layer	$c_o \cdot c_i$
Convolution	$c_o \cdot c_i \cdot k_h \cdot k_w$
Grouped Convolution	$c_o/g \cdot c_i/g \cdot k_h \cdot k_w \cdot g$ $= c_o \cdot c_i \cdot k_h \cdot k_w/g$
Depthwise Convolution	

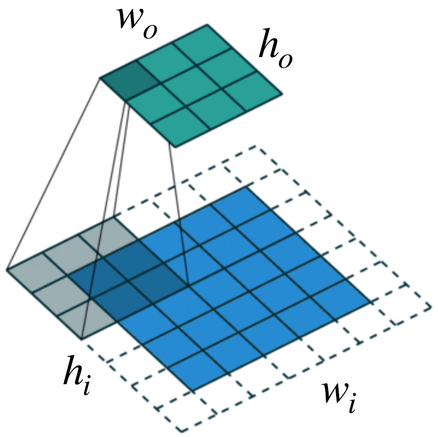
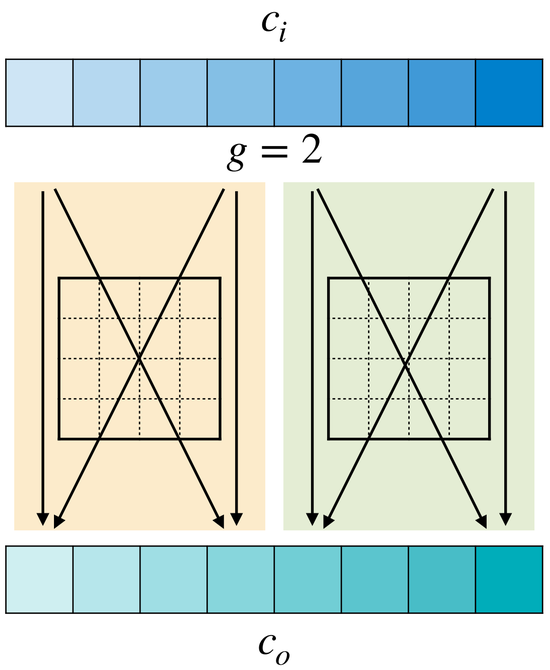


Image source: 1



Notations	
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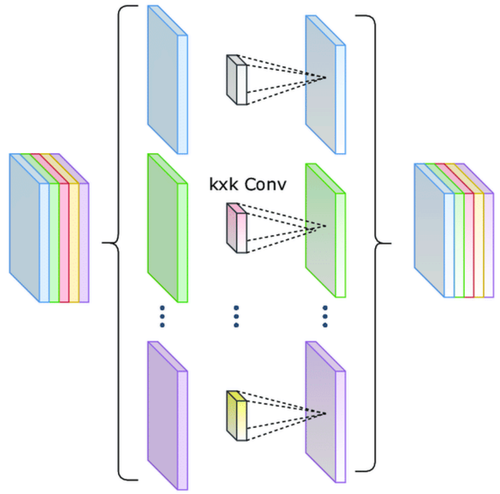
g	Groups

Number of Parameters (#Parameters)

Layer	#Parameters (bias is ignored)
Linear Layer	$c_o \cdot c_i$
Convolution	$c_o \cdot c_i \cdot k_h \cdot k_w$
Grouped Convolution	$c_o/g \cdot c_i/g \cdot k_h \cdot k_w \cdot g = c_o \cdot c_i \cdot k_h \cdot k_w/g$
Depthwise Convolution	$c_o \cdot k_h \cdot k_w$



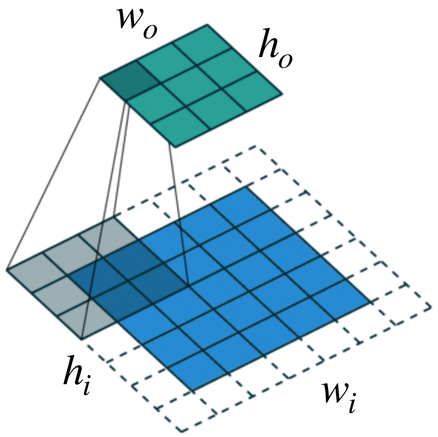
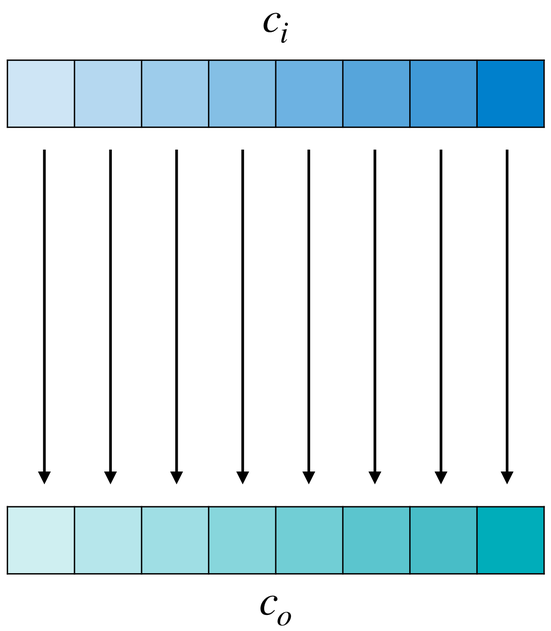


Image source: 1



Notations	
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c_i	Input Channels
c_o	Output Channels
h_i, h_o	Input/Output Height
w_i, w_o	Input/Output Width
k_h, k_w	Kernel Height/Width
g	Groups

AlexNet: #Parameters

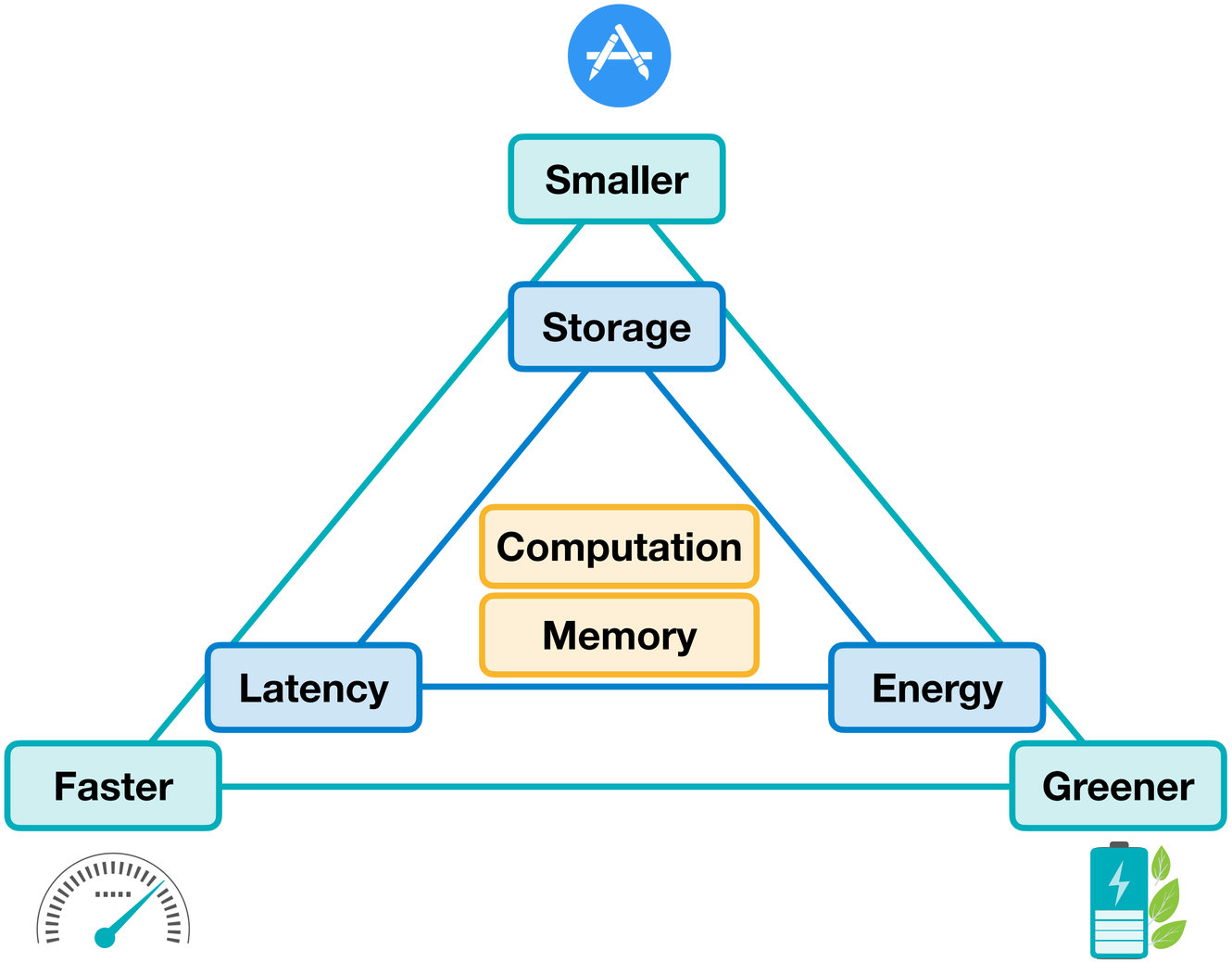
AlexNet	C × H × W	#Parameters (bias is ignored)
Image (3×224×224)	3×224×224	
11×11 Conv, channel 96, stride 4, pad 2	96×55×55	96×3×11×11 = 24, 848
3×3 MaxPool, stride 2	96×27×27	
5×5 Conv, channel 256, pad 2, groups 2	256×27×27	256×96×5×5 / 2 = 307, 200
3×3 MaxPool, stride 2	256×13×13	
3×3 Conv, channel 384, pad 1	384×13×13	384×256×3×3 = 884, 736
3×3 Conv, channel 384, pad 1, groups 2	384×13×13	384×384×3×3 / 2 = 663, 552
3×3 Conv, channel 256, pad 1, groups 2	256×13×13	256×384×3×3 / 2 = 442, 368
3×3 MaxPool, stride 2	256×6×6	
Linear, channel 4096	4096	4096×(256×6×6) = 37, 748, 736
Linear, channel 4096	4096	4096×4096 = 16, 777, 216
Linear, channel 1000	1000	1000×4096 = 4, 096, 000

Layer	#Parameters
Linear Layer	$c_o \cdot c_i$
Convolution	$c_o \cdot c_i \cdot k_h \cdot k_w$
Grouped Convolution	$c_o \cdot c_i \cdot k_h \cdot k_w / g$
Depthwise Convolution	$c_o \cdot k_h \cdot k_w$

61M in total !

ImageNet Classification with Deep Convolutional Neural Networks [Krizhevsky *et al.*, NeurIPS 2012]

Efficiency of Neural Networks



Efficiency Metrics

Memory-Related

#parameters

model size

total/peak #activations

Computation-Related

MACs

FLOP

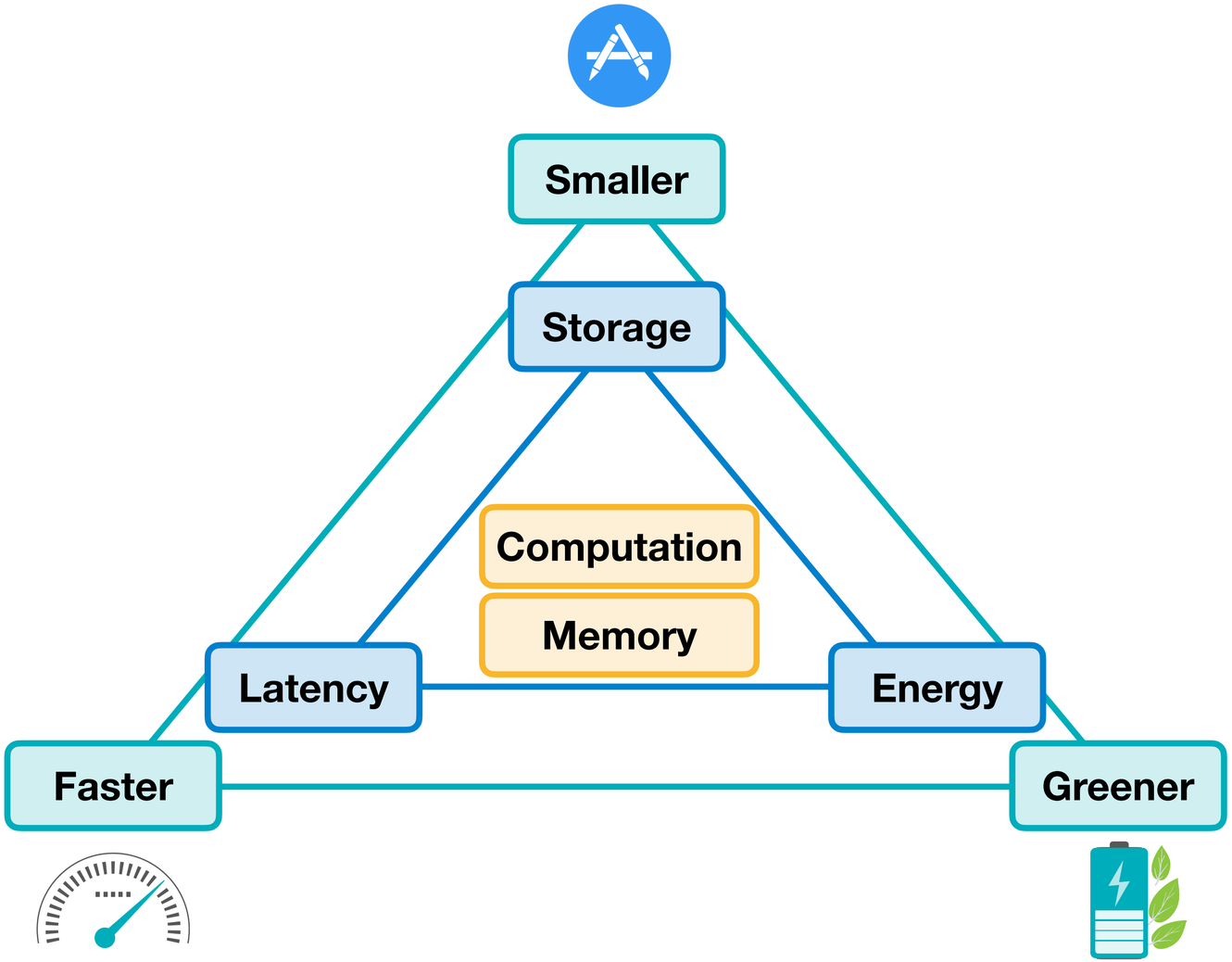
Image source: 1

Model Size

- Model size measures the storage for the weights of the given neural network.
  - The common units for model size are: MB (megabyte), KB (kilobyte), bits.
- In general, if the whole neural network uses the same data type (*e.g.*, floating-point),
  - $Model\ \ Size = \#Parameters \cdot Bit\ Width$

  - Example: AlexNet has 61M parameters.
    - If all weights are stored with 32-bit numbers, total storage will be about
      - 61M × 4 Bytes (32 bits) = 224 MB (224×10^6 Bytes)
    - If all weights are stored with 8-bit numbers, total storage will be about
      - 61M × 1 Byte (8 bits) = 61 MB

Efficiency of Neural Networks



Efficiency Metrics

Memory-Related

#parameters

model size

total/peak #activations

Computation-Related

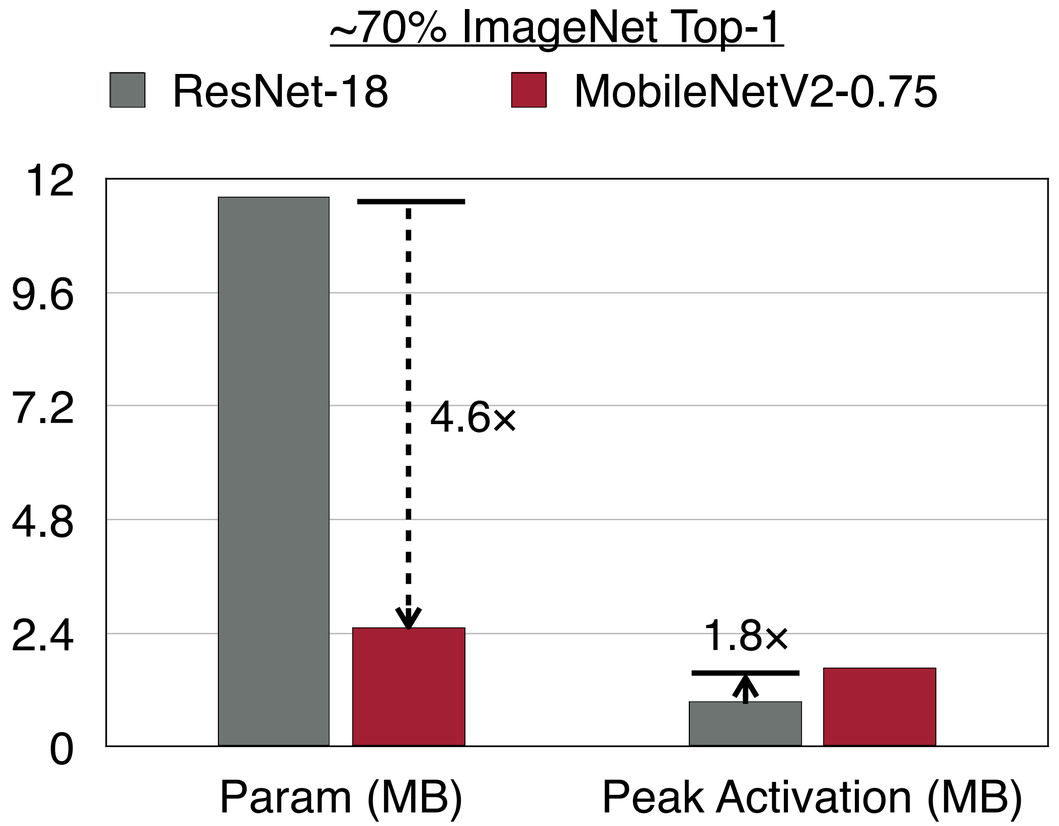
MACs

FLOP

Image source: 1

Number of Activations (#Activations)

#Activation is the memory bottleneck in inference on IoT, not #Parameters.

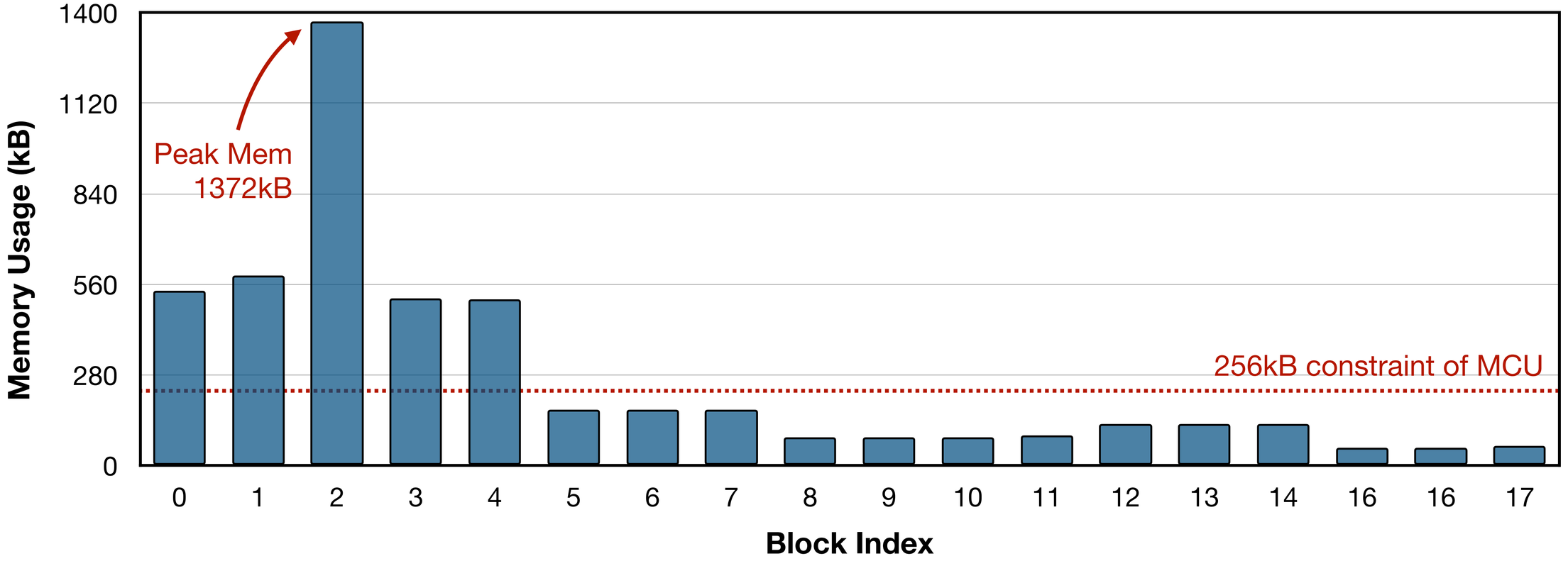


*** All parameters and activations are Integer numbers (8 bits).**

MCUNet: Tiny Deep Learning on IoT Devices [Lin *et al.*, NeurIPS 2020]

Number of Activations (#Activations)

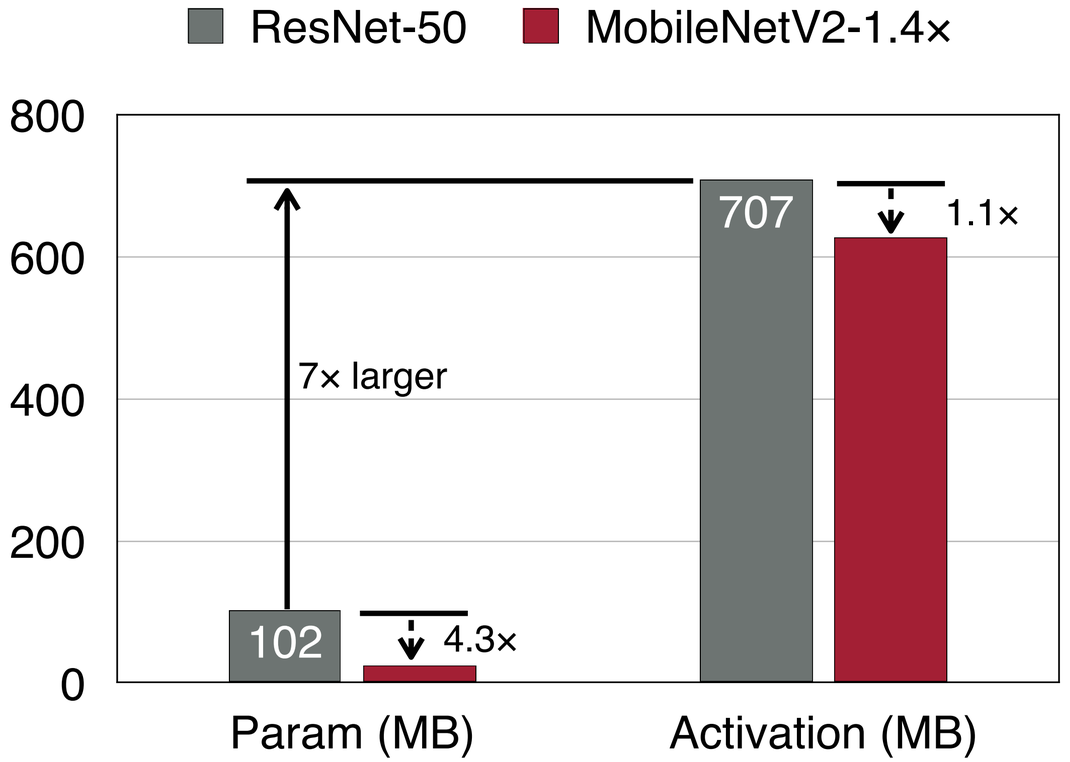
Imbalanced memory distribution of MobileNetV2



MCUNet: Tiny Deep Learning on IoT Devices [Lin *et al.*, NeurIPS 2020]

Number of Activations (#Activations)

#Activation is the memory bottleneck in training, not #Parameters.



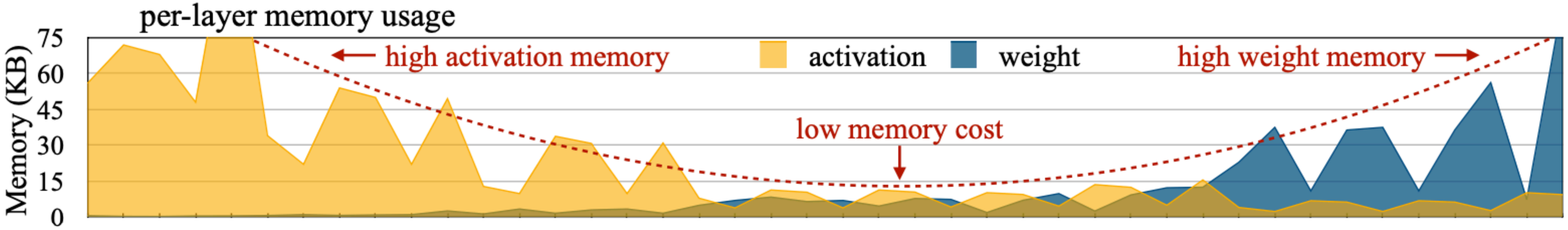
The main memory bottleneck does not improve much.

*** All parameters and activations are Floating-Point numbers (32 bits).**

TinyTL: Reduce Activations, Not Trainable Parameters for Efficient On-Device Learning [Cai *et al.*, NeurIPS 2020]

Number of Activations (#Activations)

Activation and weight memory distribution of MCUNet



MCUNet: Tiny Deep Learning on IoT Devices [Lin *et al.*, NeurIPS 2020]

AlexNet: #Activations

AlexNet	C × H × W	
Image (3×224×224)	3×224×224	=150,528
11×11 Conv, channel 96, stride 4, pad 2	96×55×55	=290,400
3×3 MaxPool, stride 2	96×27×27	=69,984
5×5 Conv, channel 256, pad 2, groups 2	256×27×27	=186,624
3×3 MaxPool, stride 2	256×13×13	=43,264
3×3 Conv, channel 384, pad 1	384×13×13	=64,896
3×3 Conv, channel 384, pad 1, groups 2	384×13×13	=64,896
3×3 Conv, channel 256, pad 1, groups 2	256×13×13	=43,264
3×3 MaxPool, stride 2	256×6×6	=9,216
Linear, channel 4096	4096	=4,096
Linear, channel 4096	4096	=4,096
Linear, channel 1000	1000	=1,000

Total #Activation: 932,264

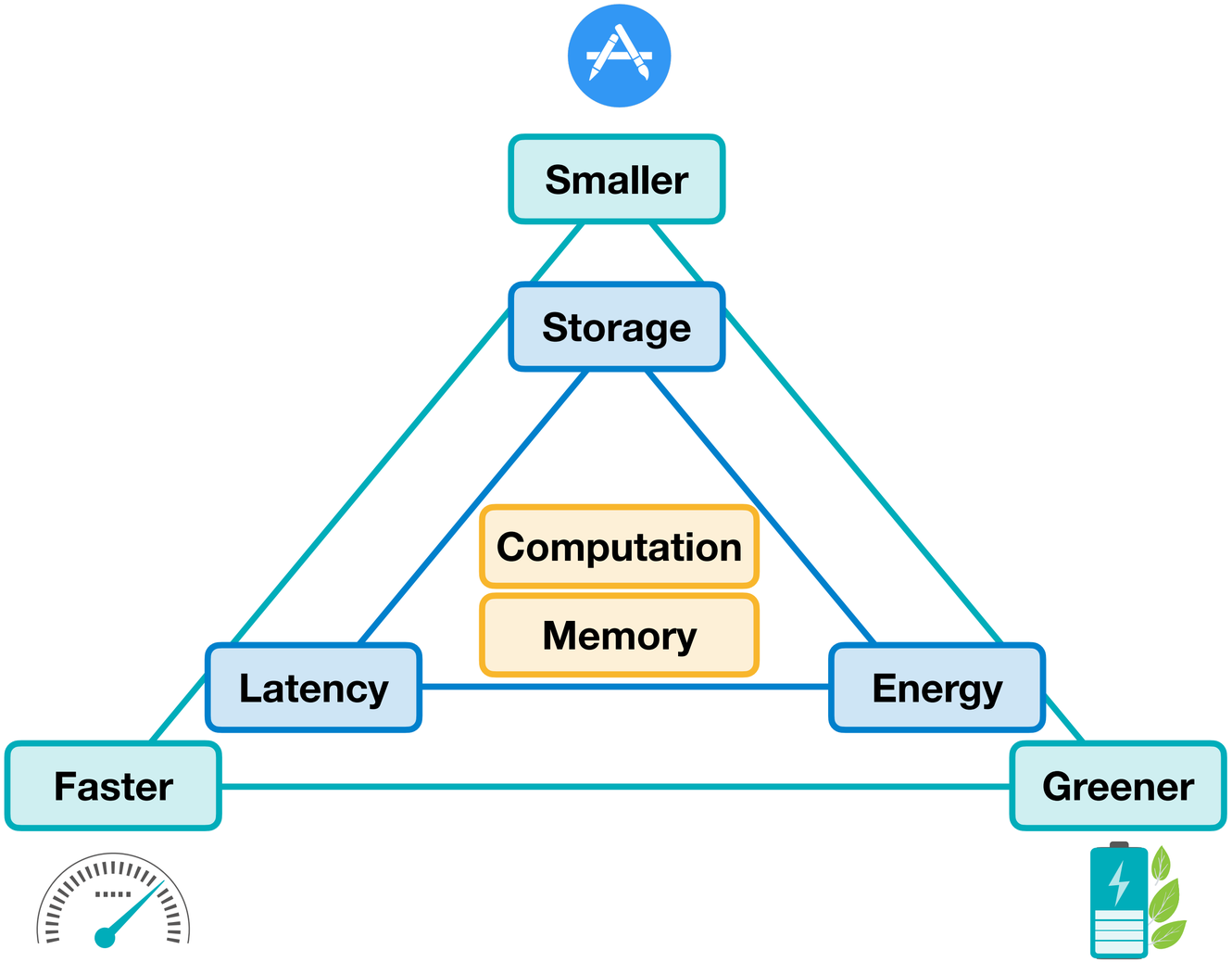
Peak #Activation:

≈ #input activation + #output activation

= 150,528 + 290,400 = 440,928

ImageNet Classification with Deep Convolutional Neural Networks [Krizhevsky *et al.*, NeurIPS 2012]

Efficiency of Neural Networks



Efficiency Metrics

Memory-Related

#parameters

model size

total/peak #activations

Computation-Related

MACs

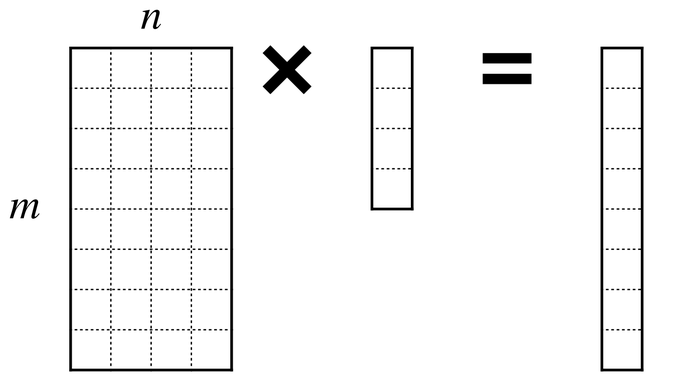
FLOP

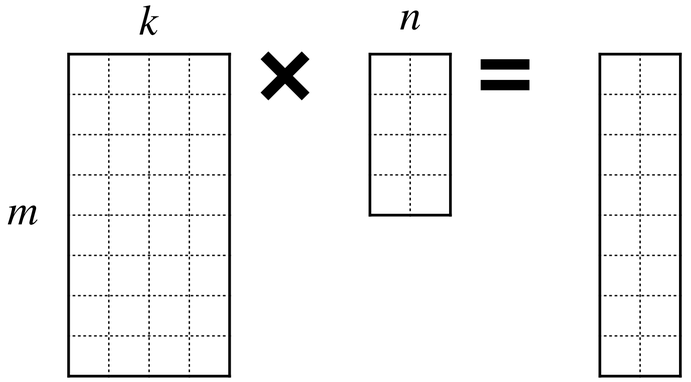
Image source: 1

Number of Multiply-Accumulate Operations

MACs

- Multiply-Accumulate operation (MAC)
  - $a \leftarrow a + b \cdot c$
- Matrix-Vector Multiplication (MV)
  - $MACs = m \cdot n$
- General Matrix-Matrix Multiplication (GEMM)
  - $MACs = m \cdot n \cdot k$



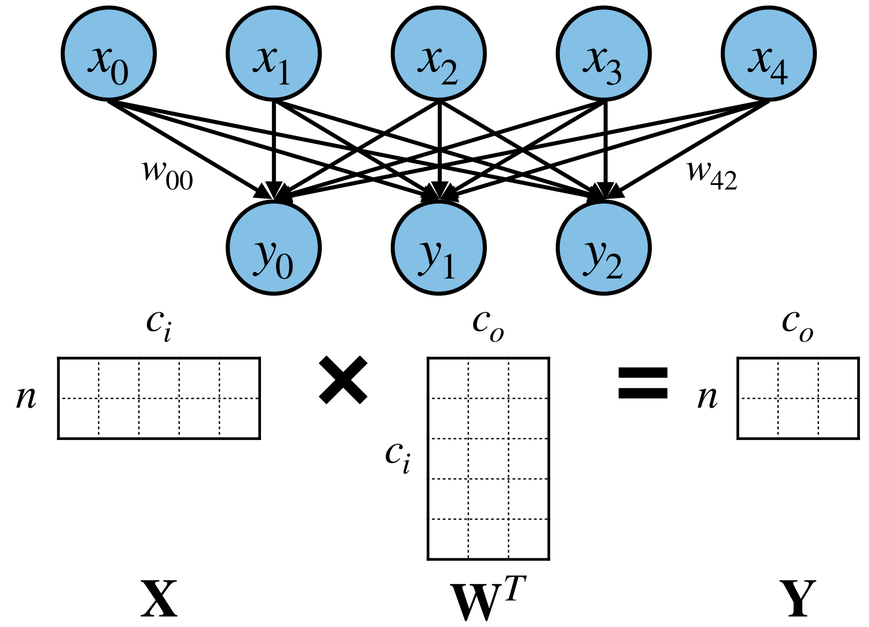


Number of Multiply-Accumulate Operations

MACs

Layer	MACs (batch size n=1)
Linear Layer	$c_o \cdot c_i$
Convolution	
Grouped Convolution	
Depthwise Convolution	

* bias is ignored



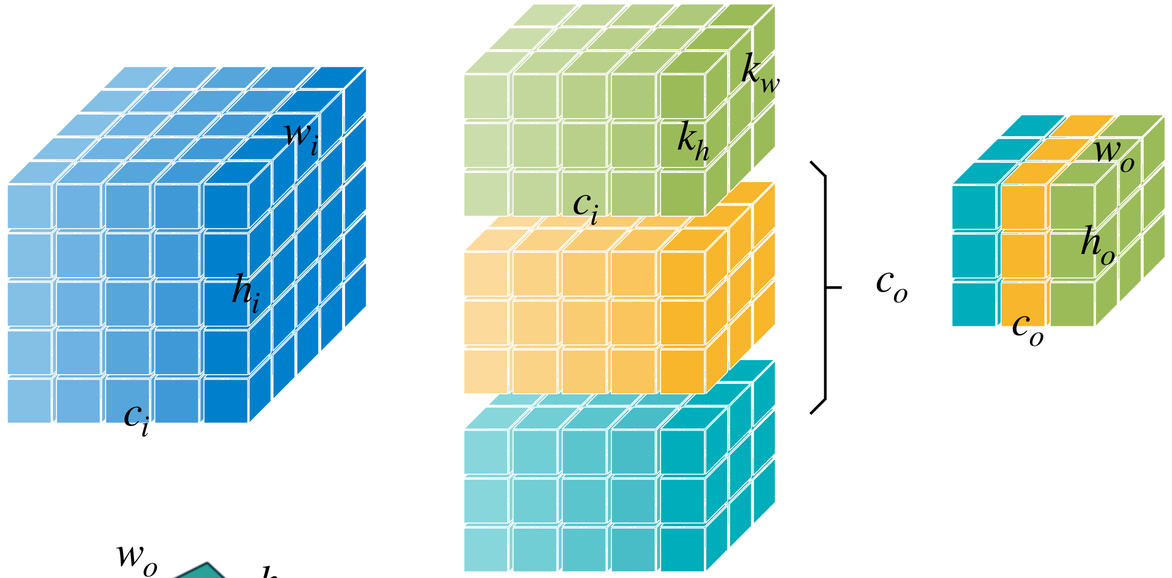
Notations	
n	Batch Size
c_i	Input Channels
c_o	Output Channels
h_i, h_o	Input/Output Height
w_i, w_o	Input/Output Width
k_h, k_w	Kernel Height/Width
g	Groups

Number of Multiply-Accumulate Operations

MACs

Layer	MACs (batch size n=1)
Linear Layer	$c_o \cdot c_i$
Convolution	$c_i \cdot k_h \cdot k_w \cdot h_o \cdot w_o \cdot c_o$
Grouped Convolution	
Depthwise Convolution	

* bias is ignored



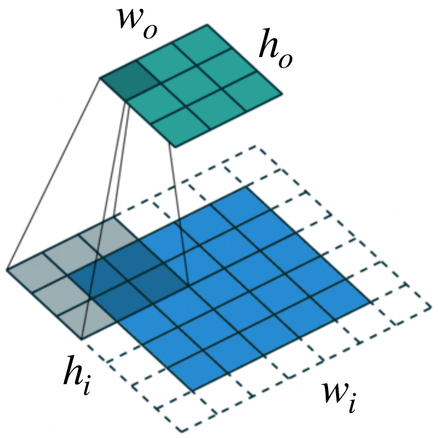


Image source: 1

Notations	
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c_i	Input Channels
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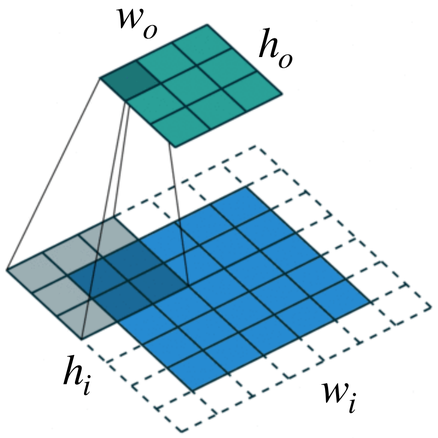
w_i, w_o	Input/Output Width
k_h, k_w	Kernel Height/Width
g	Groups

Number of Multiply-Accumulate Operations

MACs

Layer	MACs (batch size n=1)
Linear Layer	$c_o \cdot c_i$
Convolution	$c_i \cdot k_h \cdot k_w \cdot h_o \cdot w_o \cdot c_o$
Grouped Convolution	$c_i/g \cdot k_h \cdot k_w \cdot h_o \cdot w_o \cdot c_o$
Depthwise Convolution	

* bias is ignored



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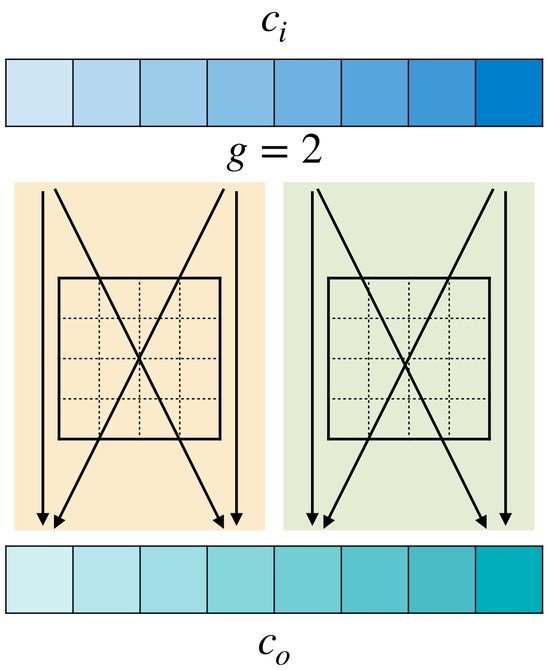

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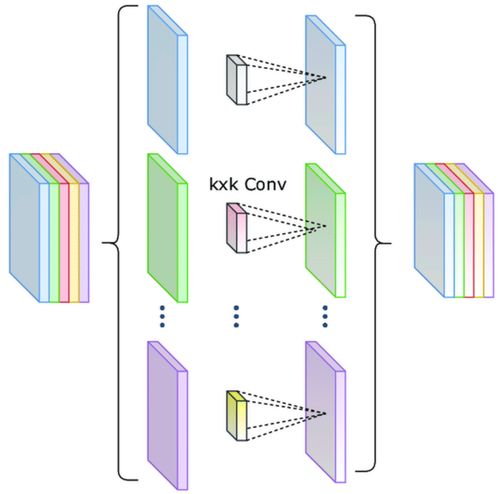
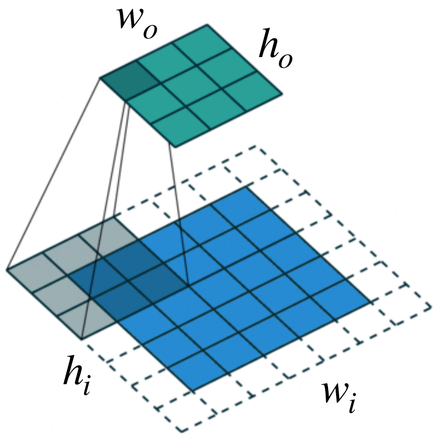
Number of Multiply-Accumulate Operations

MACs

Layer	MACs (batch size n=1)
Linear Layer	$c_o \cdot c_i$
Convolution	$c_i \cdot k_h \cdot k_w \cdot h_o \cdot w_o \cdot c_o$
Grouped Convolution	$c_i/g \cdot k_h \cdot k_w \cdot h_o \cdot w_o \cdot c_o$
Depthwise Convolution	$k_h \cdot k_w \cdot h_o \cdot w_o \cdot c_o$

* bias is ignored





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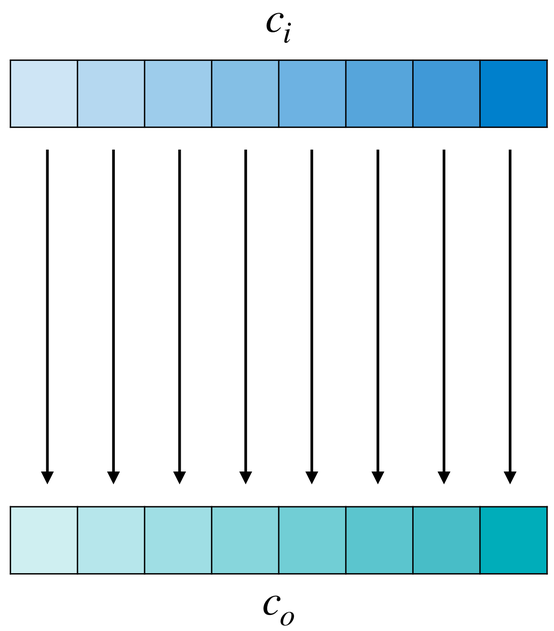

Notations	
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w_i, w_o	Input/Output Width
k_h, k_w	Kernel Height/Width
g	Groups

AlexNet: #MACs

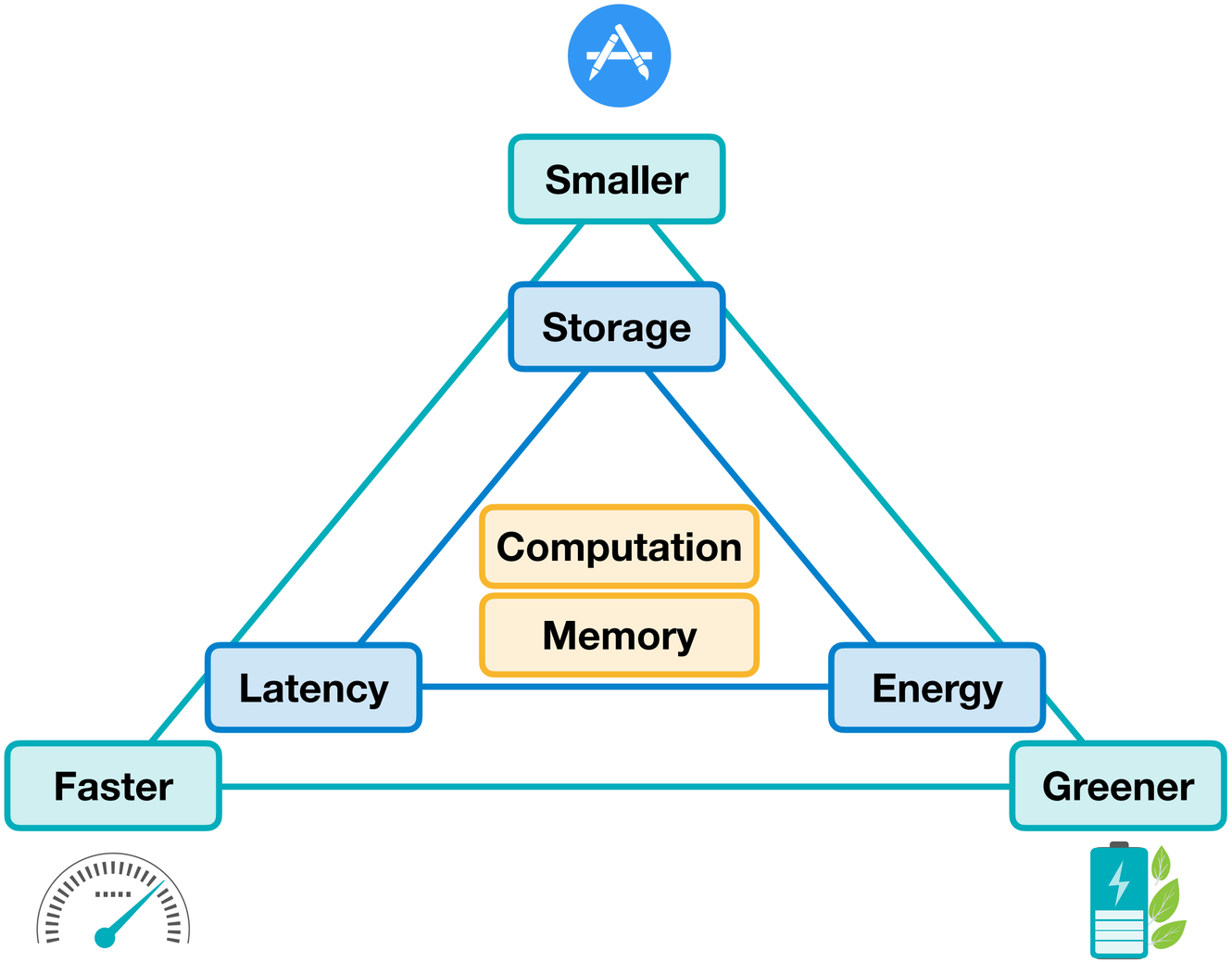
AlexNet	C × H × W	MACs
Image (3×224×224)	3×224×224	
11×11 Conv, channel 96, stride 4, pad 2	96×55×55	96×3×11×11×55×55 = 105,415,200
3×3 MaxPool, stride 2	96×27×27	
5×5 Conv, channel 256, pad 2, groups 2	256×27×27	256×96×5×5×27×27 / 2 = 223,948,800
3×3 MaxPool, stride 2	256×13×13	
3×3 Conv, channel 384, pad 1	384×13×13	384×256×3×3×13×13 = 149,520,384
3×3 Conv, channel 384, pad 1, groups 2	384×13×13	384×384×3×3×13×13 / 2 = 112,140,288
3×3 Conv, channel 256, pad 1, groups 2	256×13×13	256×384×3×3×13×13 / 2 = 74,760,192
3×3 MaxPool, stride 2	256×6×6	
Linear, channel 4096	4096	4096×(256×6×6) = 37,748,736
Linear, channel 4096	4096	4096×4096 = 16,777,216
Linear, channel 1000	1000	1000×4096 = 4,096,000

Layer	MACs (batch size n=1)
Linear Layer	$c_o \cdot c_i$
Convolution	$c_o \cdot c_i \cdot k_h \cdot k_w \cdot h_o \cdot w_o$
Grouped Convolution	$c_o \cdot c_i \cdot k_h \cdot k_w \cdot h_o \cdot w_o / g$
Depthwise Convolution	$c_o \cdot k_h \cdot k_w \cdot h_o \cdot w_o$

724M in total !

ImageNet Classification with Deep Convolutional Neural Networks [Krizhevsky *et al.*, NeurIPS 2012]

Efficiency of Neural Networks



Efficiency Metrics

Memory-Related

#parameters

model size

total/peak #activations

Computation-Related

MACs

FLOP

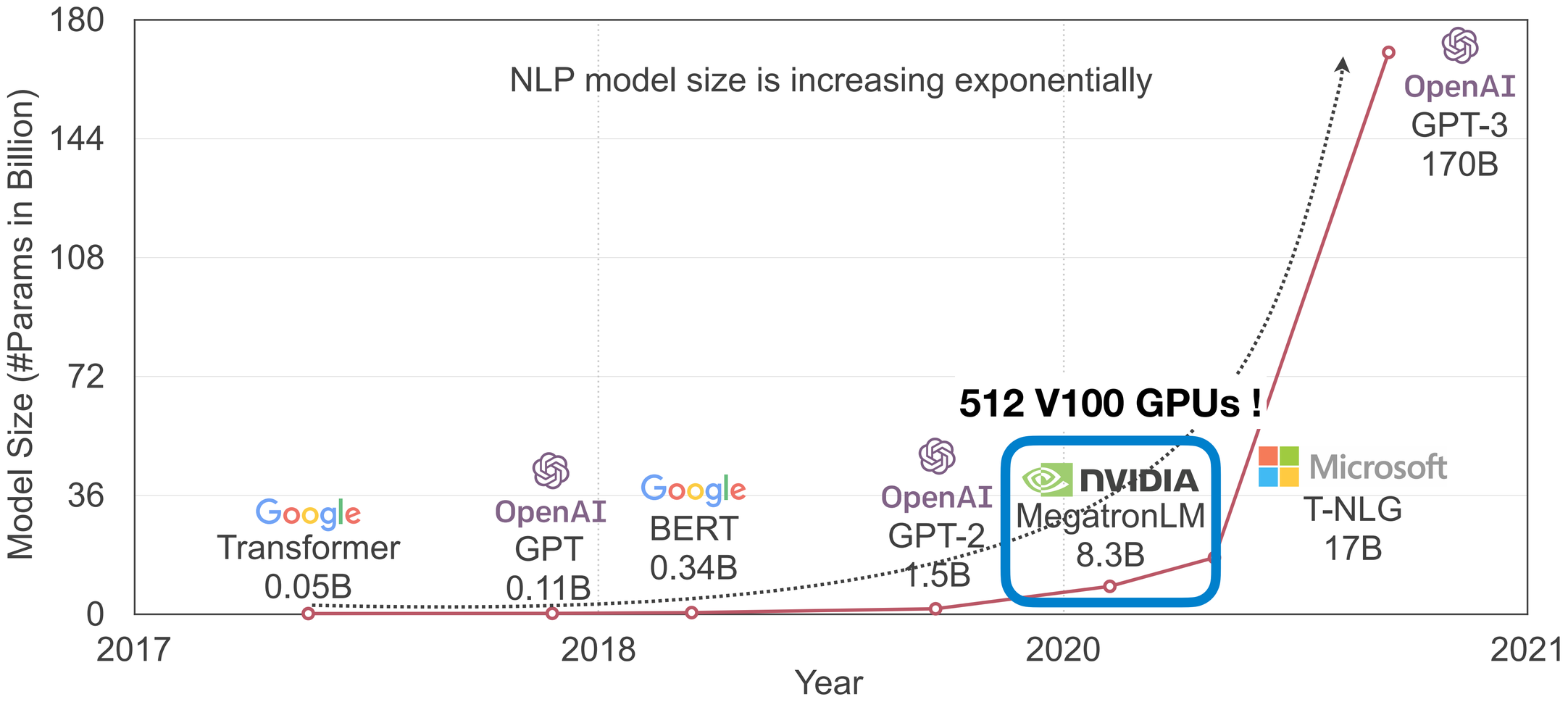
Image source: 1

Number of Floating Point Operations (FLOP)

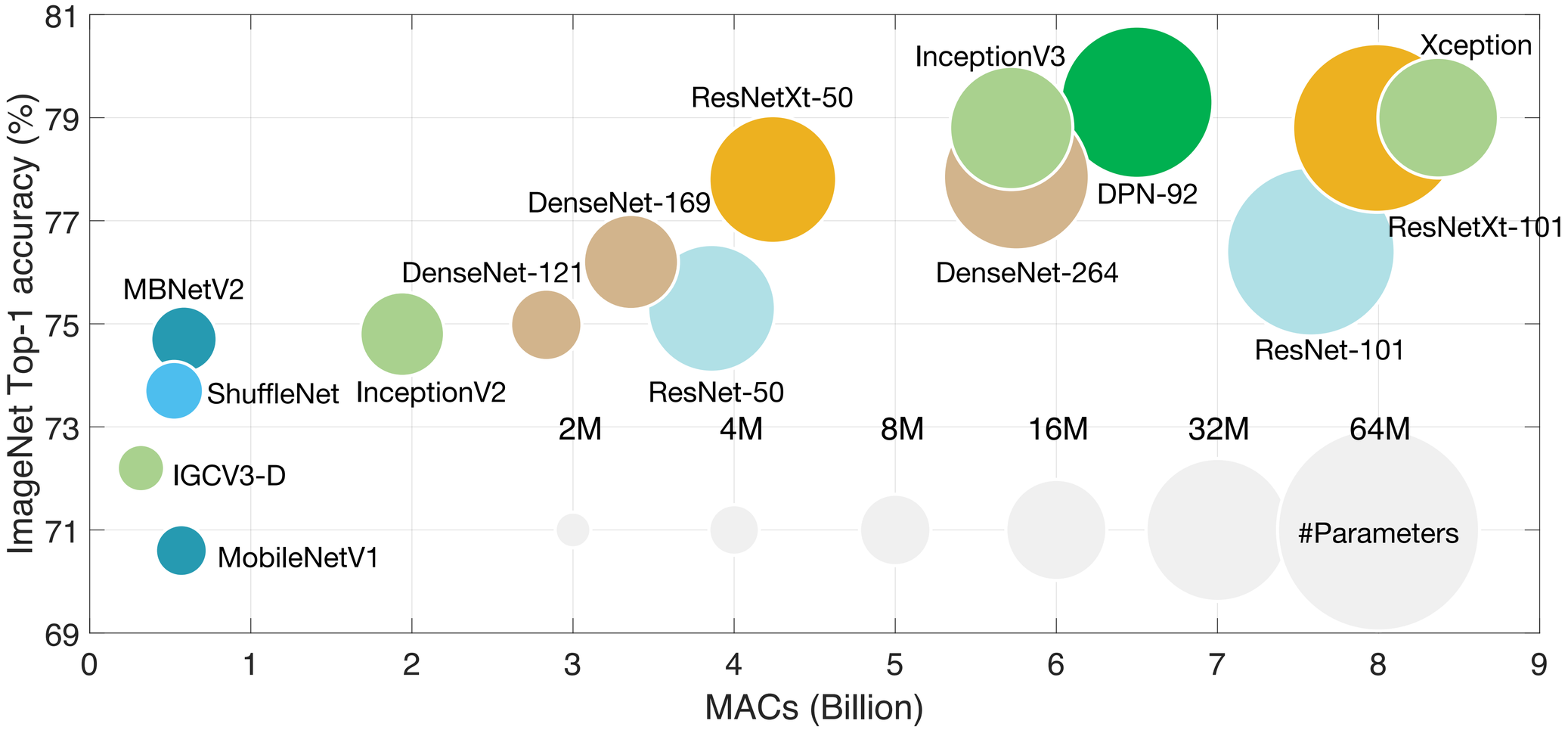
- A multiply is a floating point operation
- An add is a floating point operation
- ***One*** multiply-accumulate operation is ***two*** floating point operations (FLOP)
  - Example: AlexNet has 724M MACs, total number of floating point operations will be
    - 724M × 2 = 1.4G FLOP

- Floating Point Operation Per Second (FLOPS)
  - $FLOPS = \frac{FLOP}{second}$

Today's AI is too BIG!



Today's AI is too BIG!

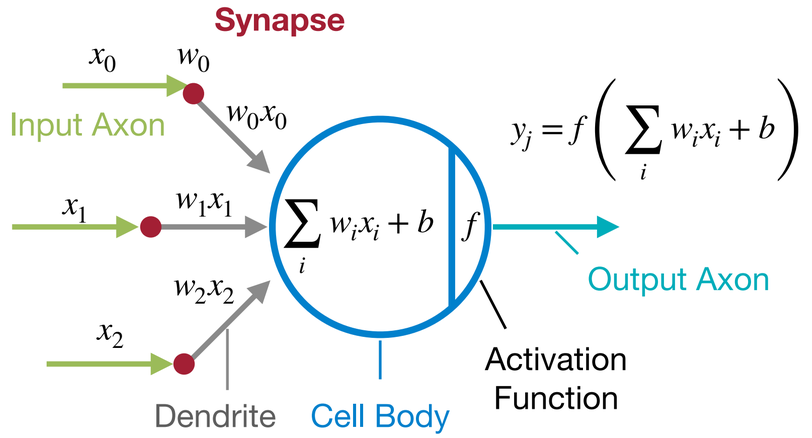


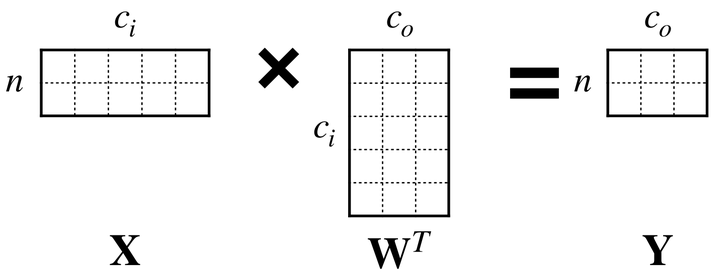
Model Compression and Hardware Acceleration for Neural Networks: A Comprehensive Survey [Deng *et al.*, IEEE 2020]

Summary of Today's Lecture

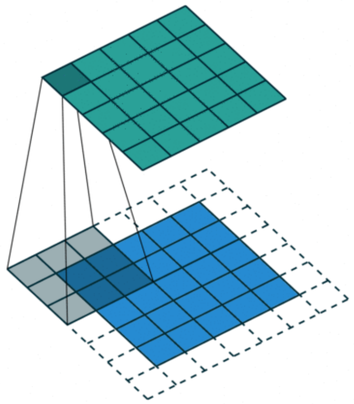
In this lecture, we

- review the basics of neural networks
  - terminology: neuron output → activation, synapses → weight
  - popular layers: fully-connected, convolution, depthwise convolution, pooling, normalization
  - classic neural networks: AlexNet, VGG-16, ResNet-50, MobileNetV2
- Introduce popular efficiency metrics for neural networks
  - memory cost: #Parameters, Model Size, #Activations
  - computation cost: MACs, FLOP, FLOPS





Linear Layer



Convolution Layer

Layer	MACs (batch size n=1)
Linear Layer	$c_o \cdot c_i$
Convolution	$c_i \cdot k_h \cdot k_w \cdot h_o \cdot w_o \cdot c_o$
Grouped Convolution	$c_i/g \cdot k_h \cdot k_w \cdot h_o \cdot w_o \cdot c_o$
Depthwise Convolution	$k_h \cdot k_w \cdot h_o \cdot w_o \cdot c_o$

Image source: 1

References

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7. Deep Residual Learning for Image Recognition [He *et al.*, CVPR 2016]
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