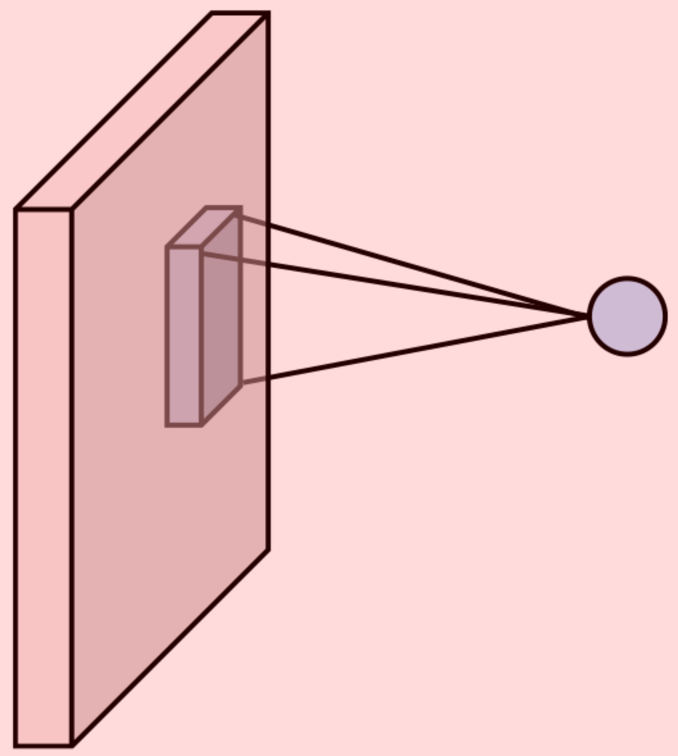
DeepRob

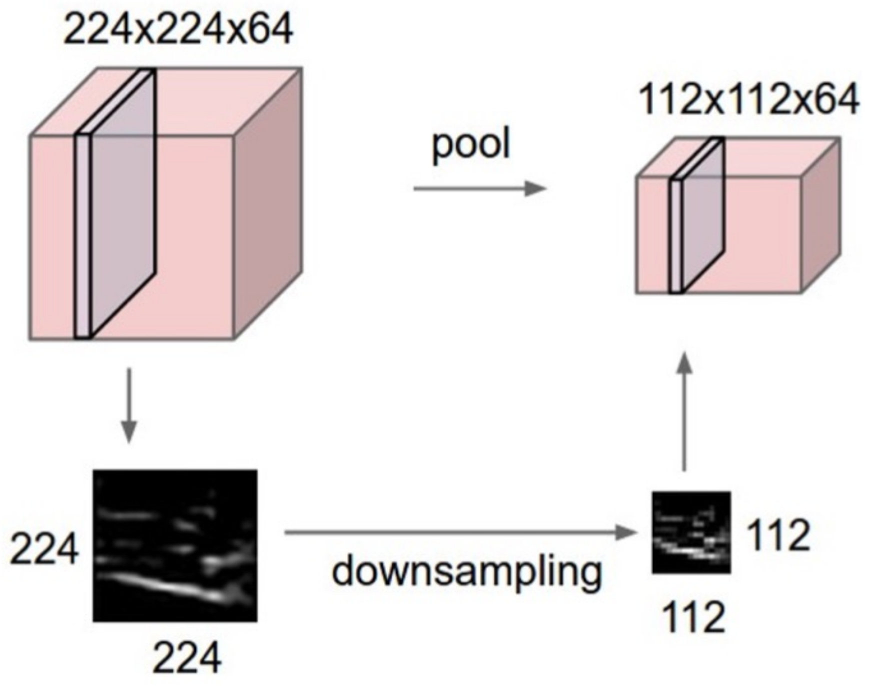
Lecture 7
CNN Architectures
University of Michigan | Department of Robotics

Components of Convolutional Networks

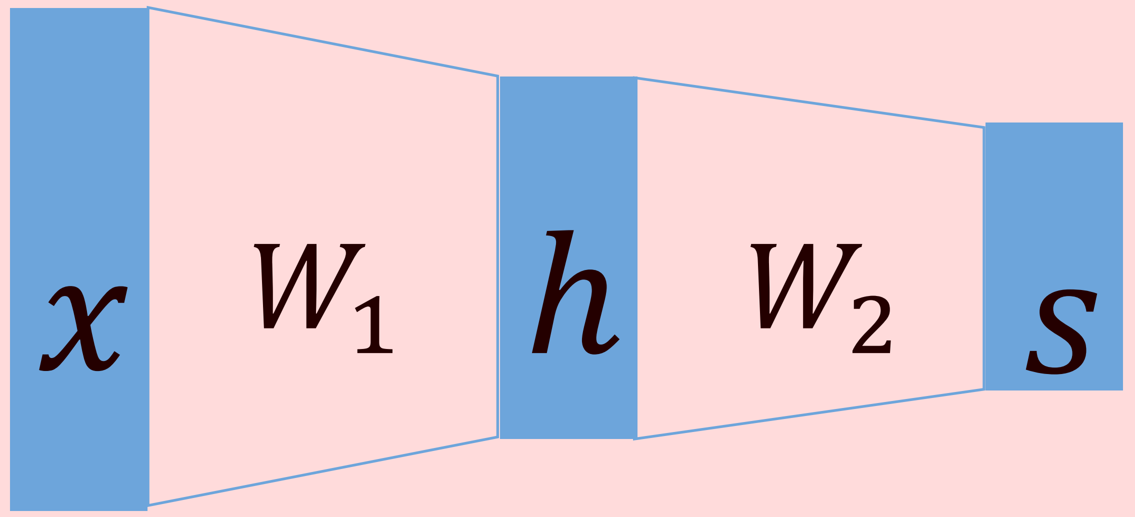
Convolution Layers



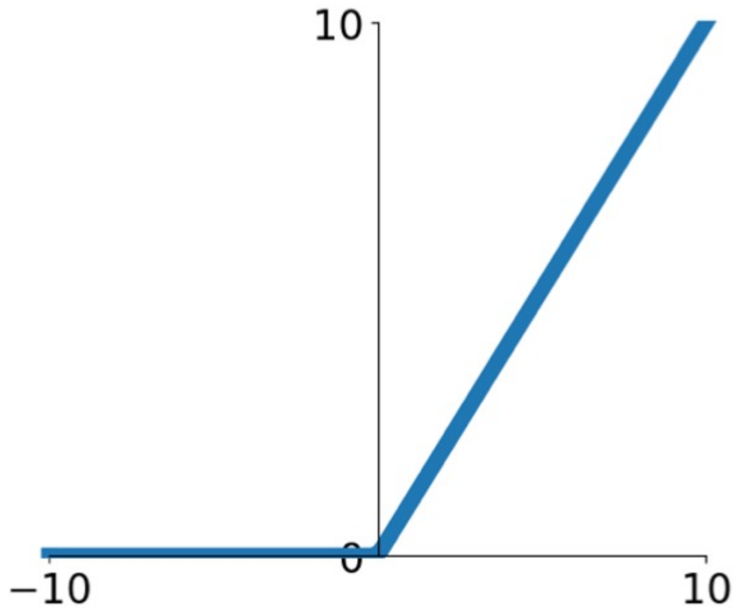
Pooling Layers



Fully-Connected Layers



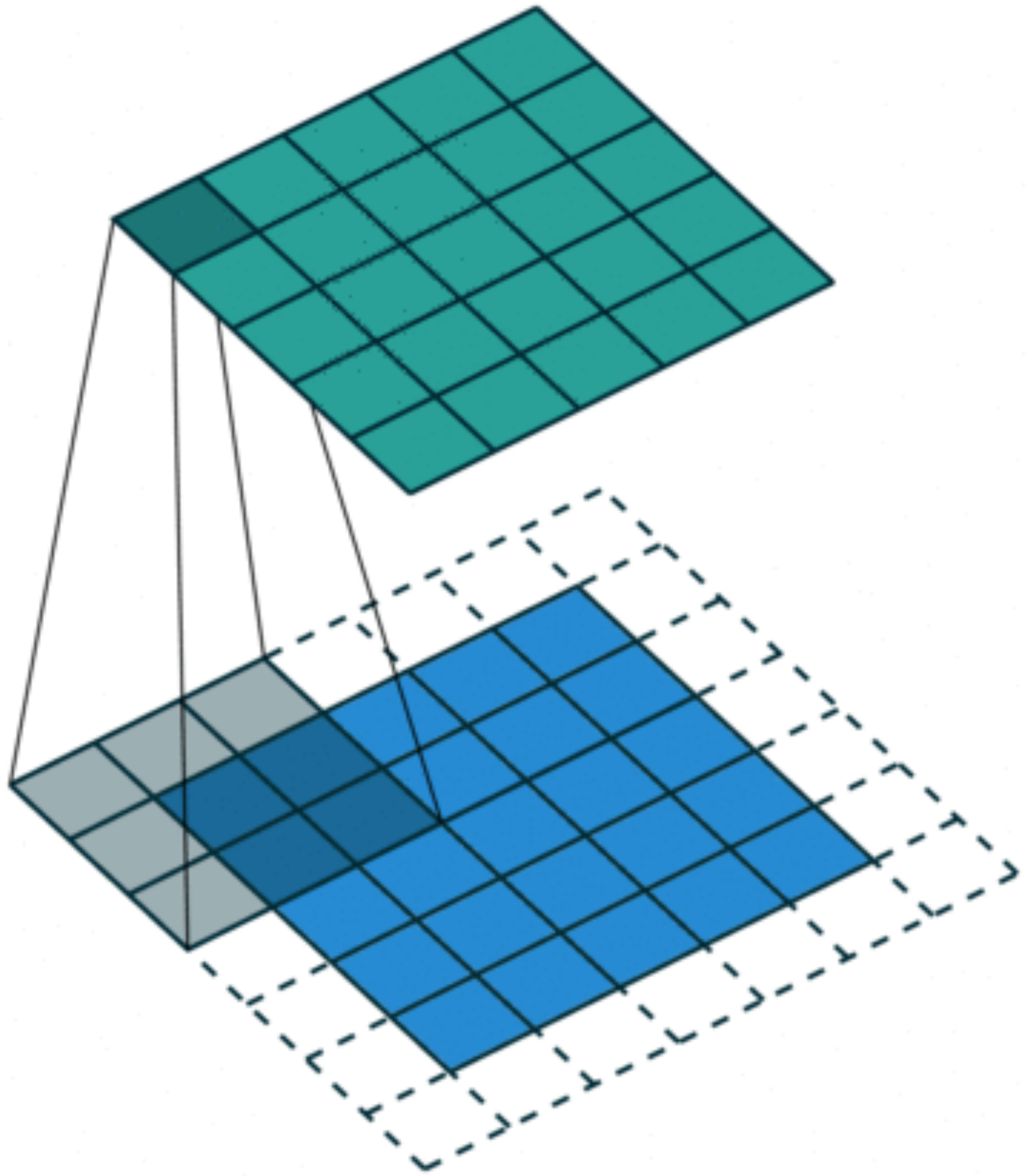
Activation Function



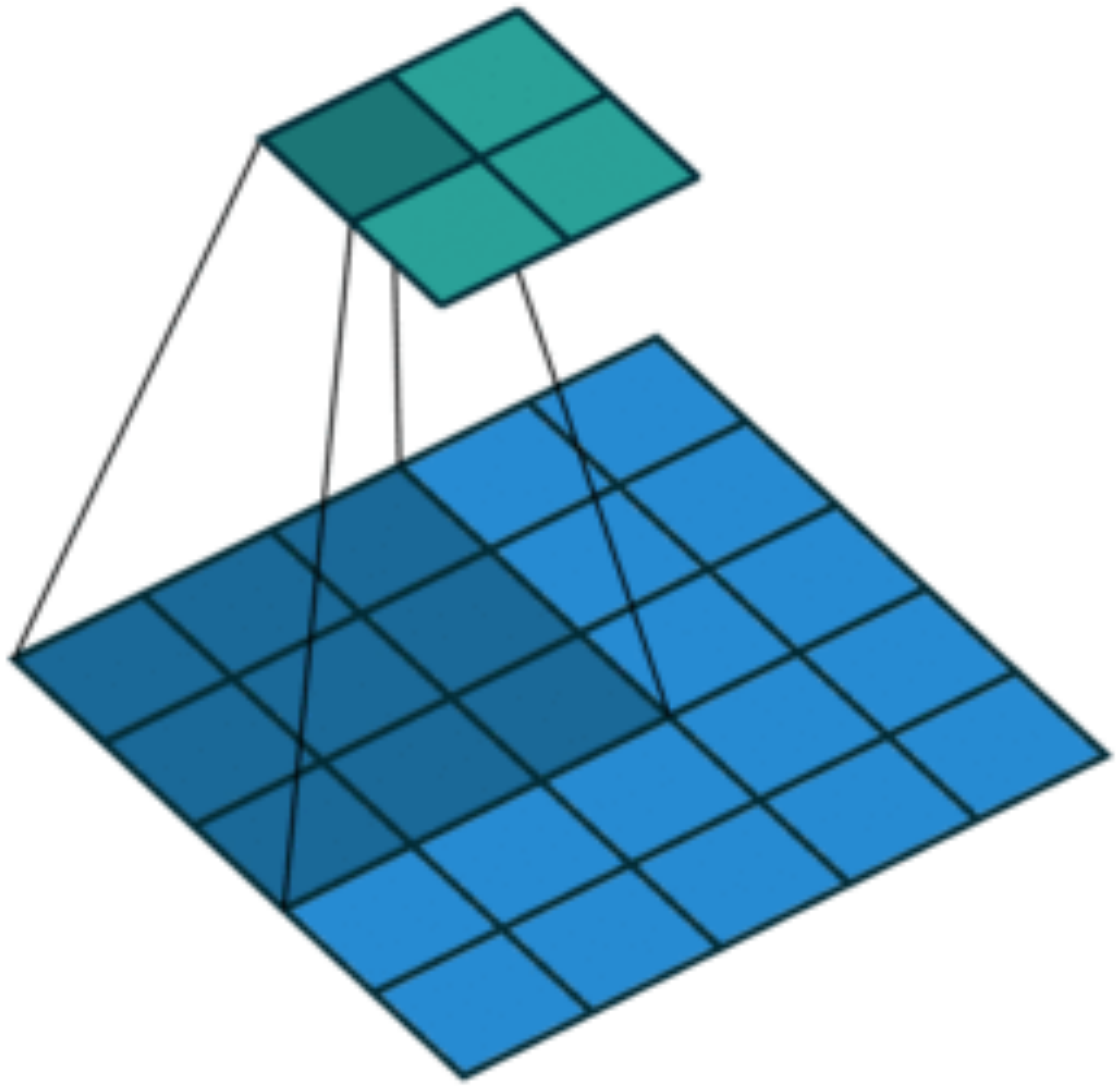
Normalization

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \epsilon}}$$

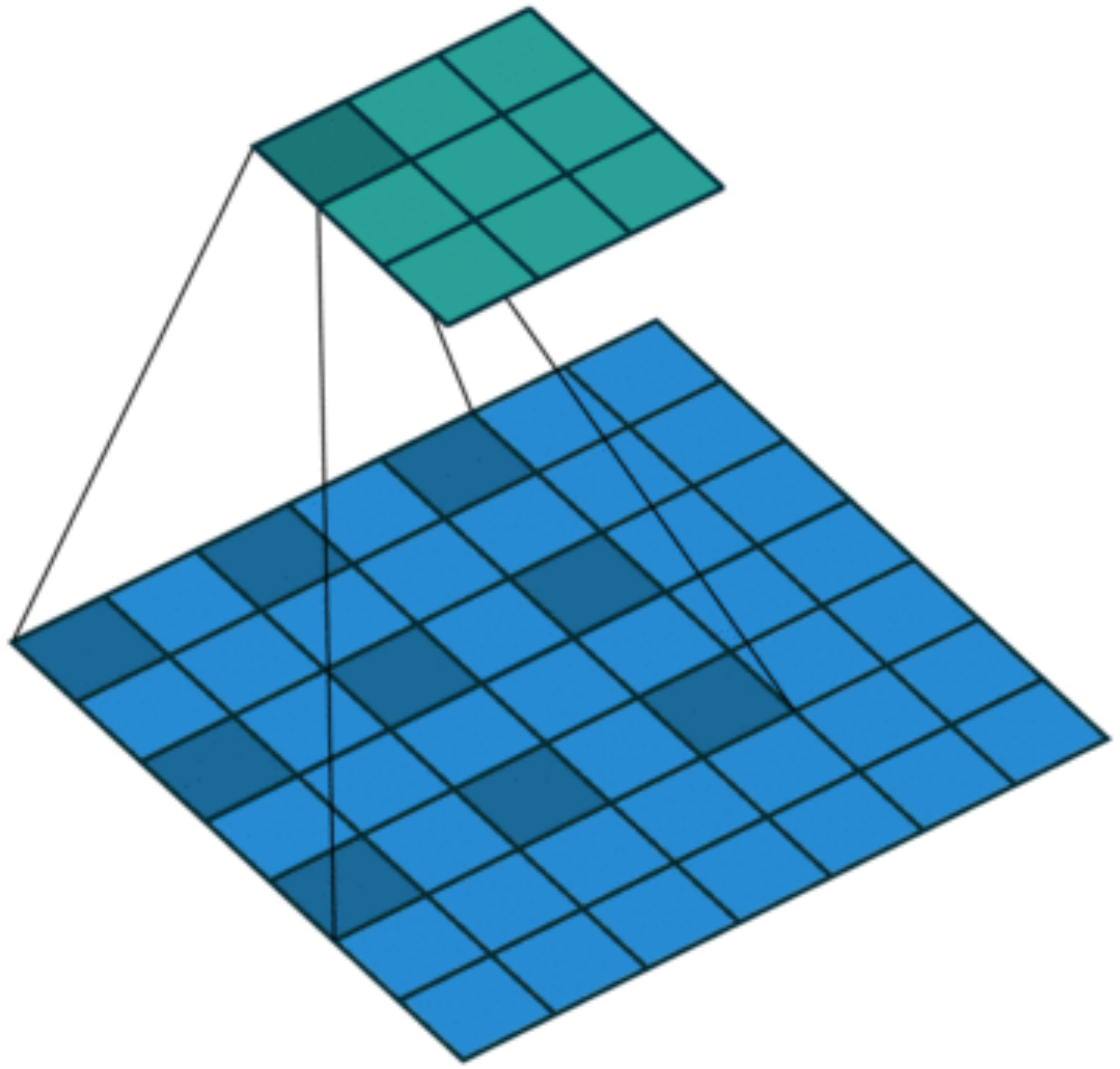
Recap: Convolution



Padding

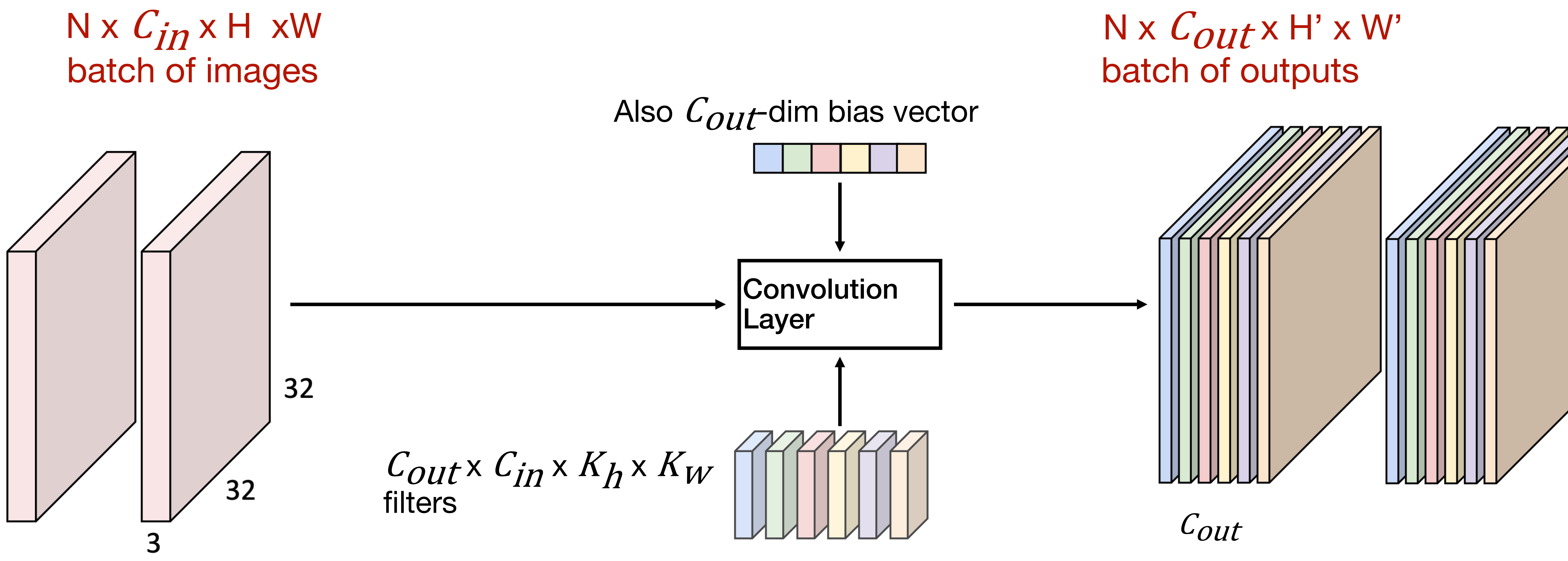


Stride = 2



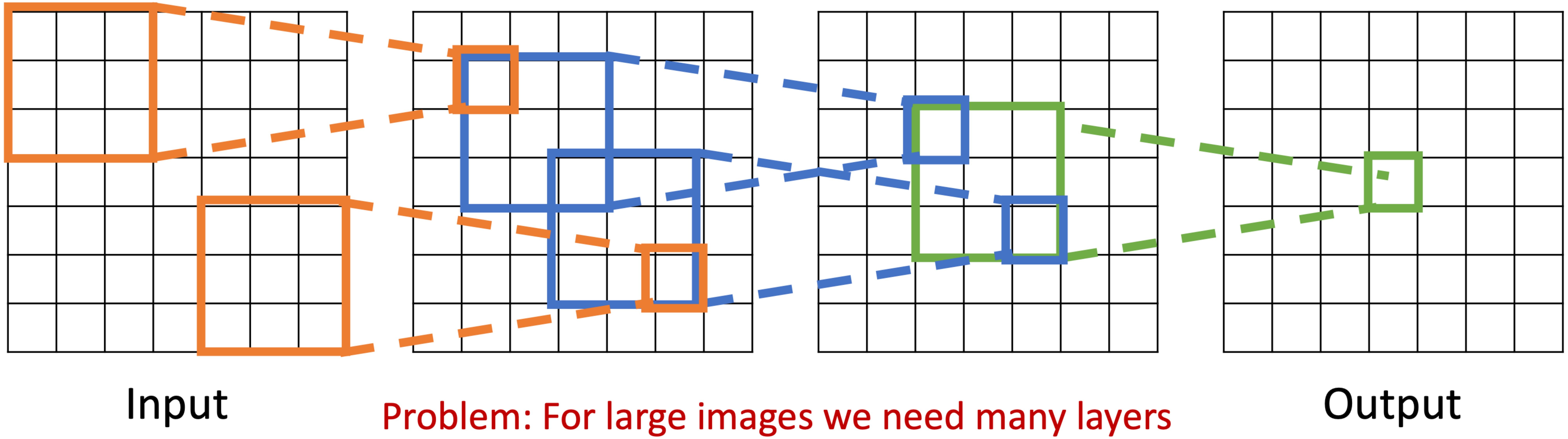
dilation = 2

Recap: Convolution Layer Dimensions



Recap: Receptive Fields

Each successive convolution adds K – 1 to the receptive field size
With L layers the receptive field size is 1 + L * (K – 1)

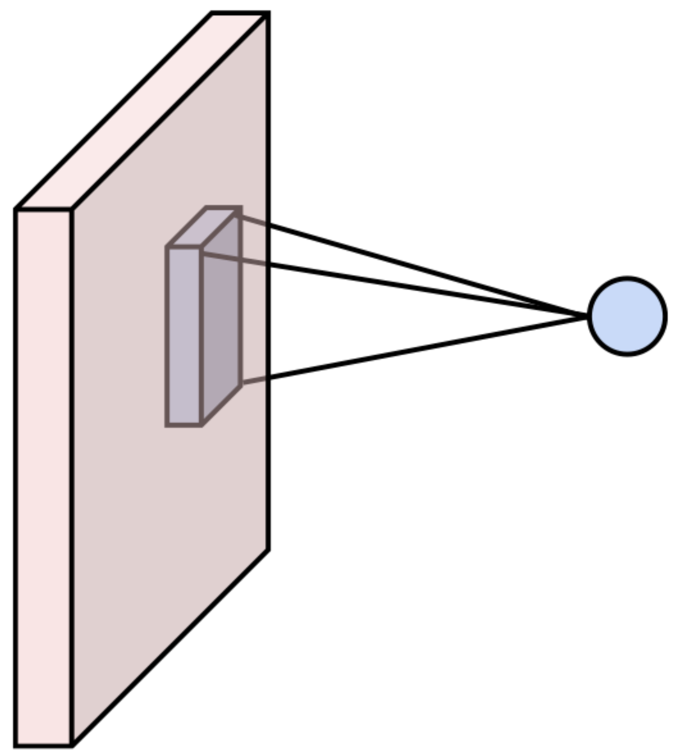


Problem: For large images we need many layers for each output to “see” the whole image image

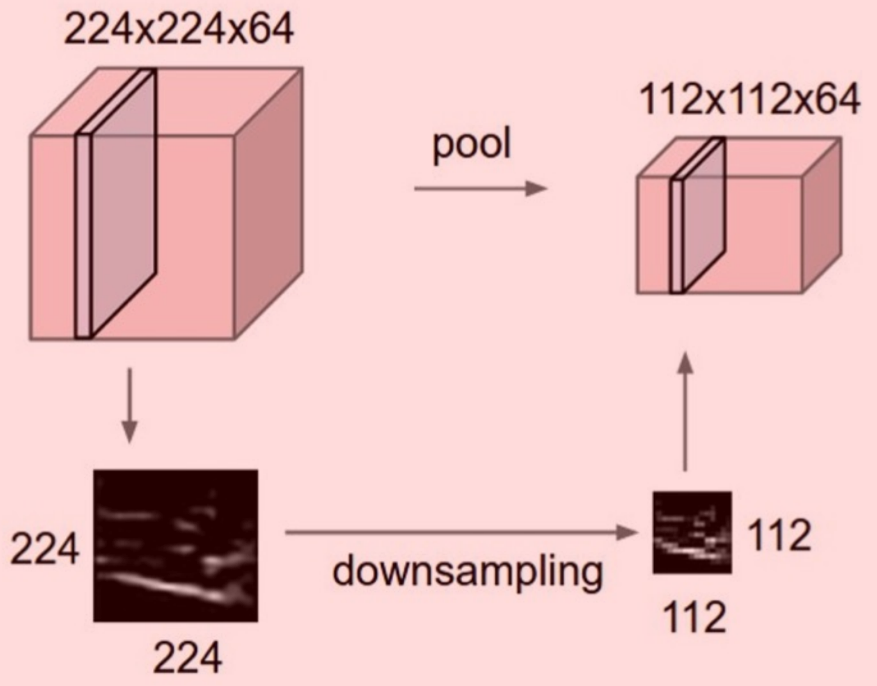
Solution: Downsample inside the network

Components of Convolutional Networks

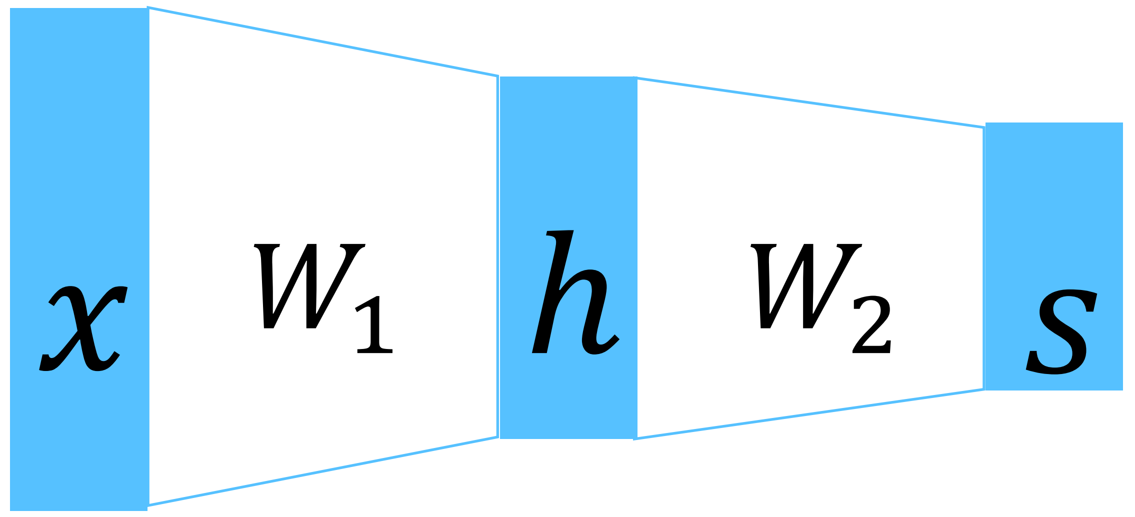
Convolution Layers



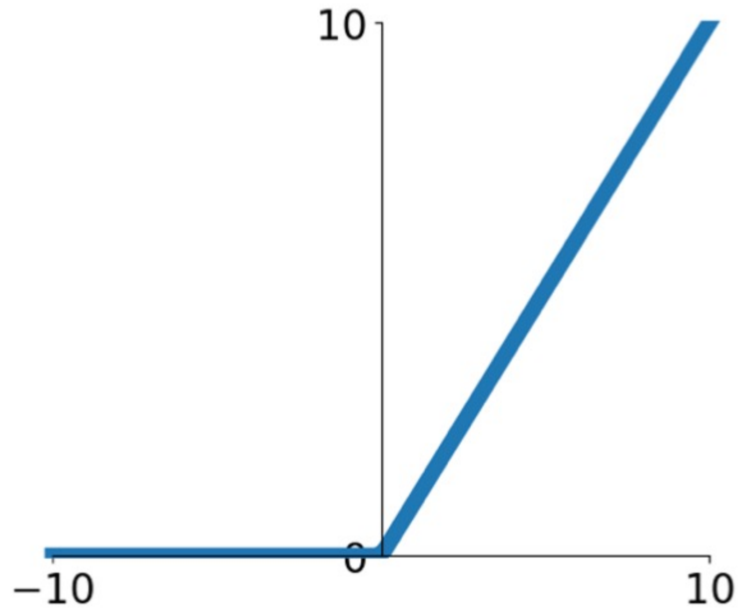
Pooling Layers



Fully-Connected Layers



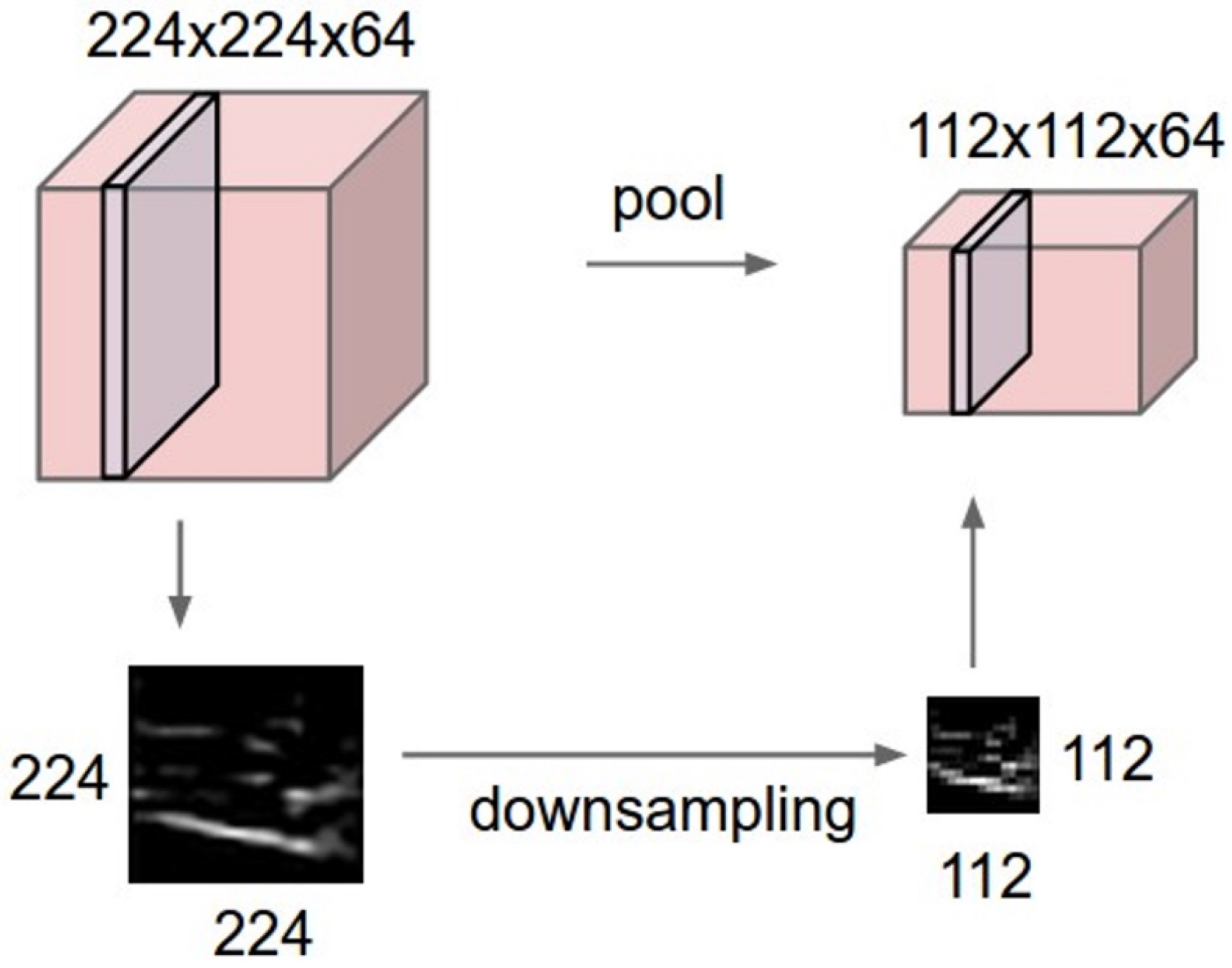
Activation Function



Normalization

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \epsilon}}$$

Pooling Layers: Another way to downsample



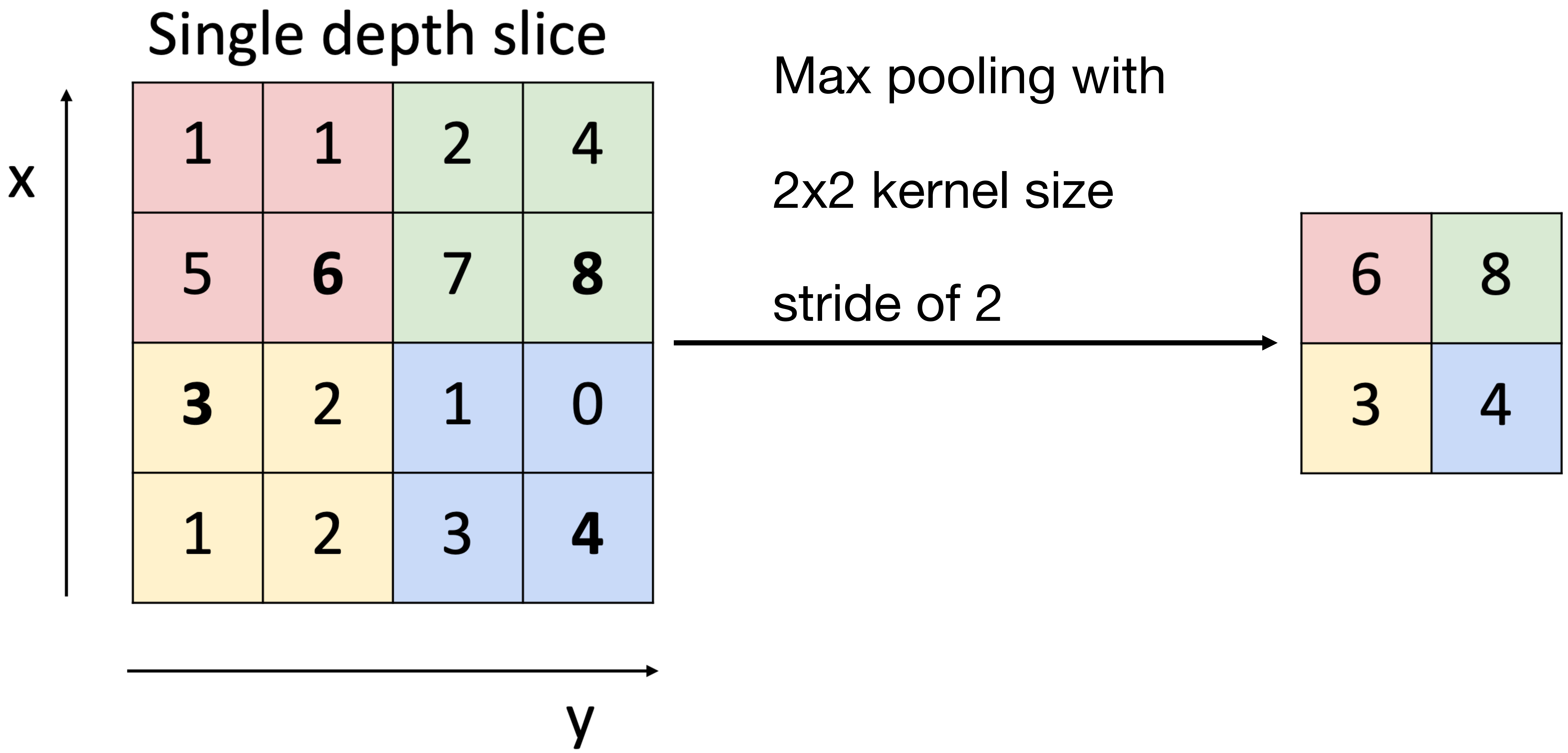
Hyperparameters:

Kernel size

Stride

Pooling function

Max Pooling


Single depth slice
x
y
1 1 2 4
5 6 7 8
3 2 1 0
1 2 3 4
Max pooling with
2x2 kernel size
stride of 2
6 8
3 4

Max Pooling

Single depth slice

x

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

y

Max pooling with

2x2 kernel size

stride of 2

6	8
3	4

Introduces invariance to small spatial shifts

No learnable parameters!

Pooling Summary

Input: C x H x W

Hyperparameters:

- Kernel size: K
- Stride: S
- Pooling function (max, avg)

Output: C x H’ x W’ where

- H’ = (H – K) / S + 1
- W’ = (W – K) / S + 1

Learnable parameters: None!

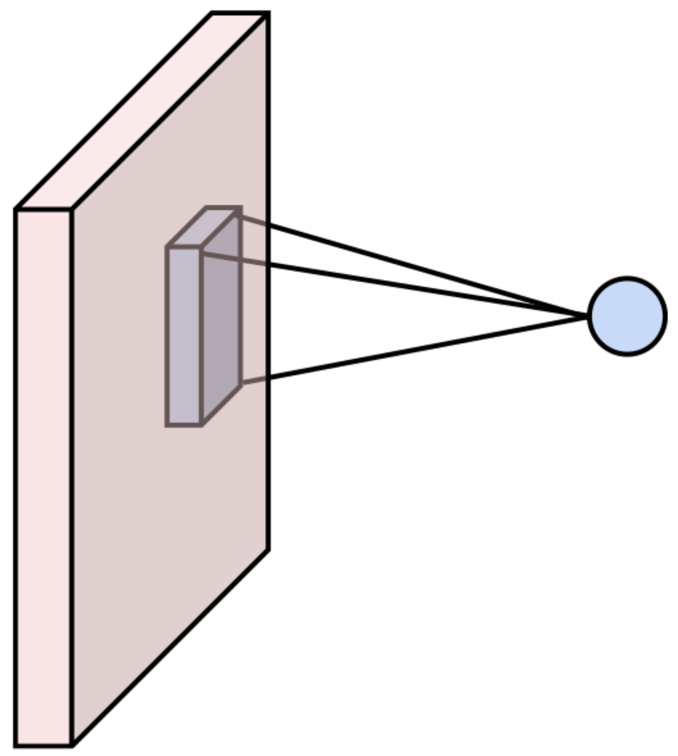
Common settings:

max, K = 2, S = 2

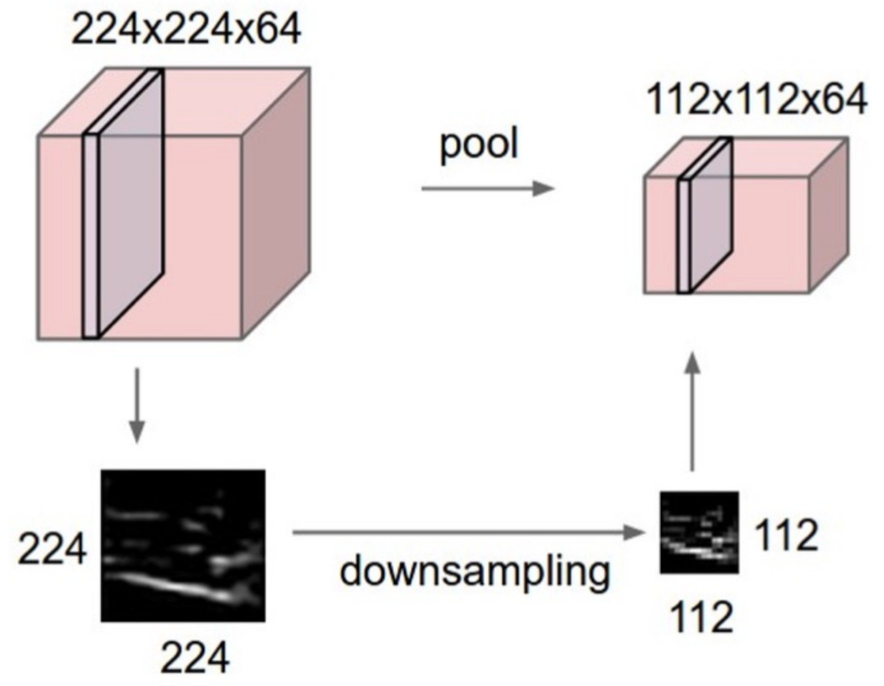
max, K = 3, S = 2 (AlexNet)

Components of Convolutional Networks

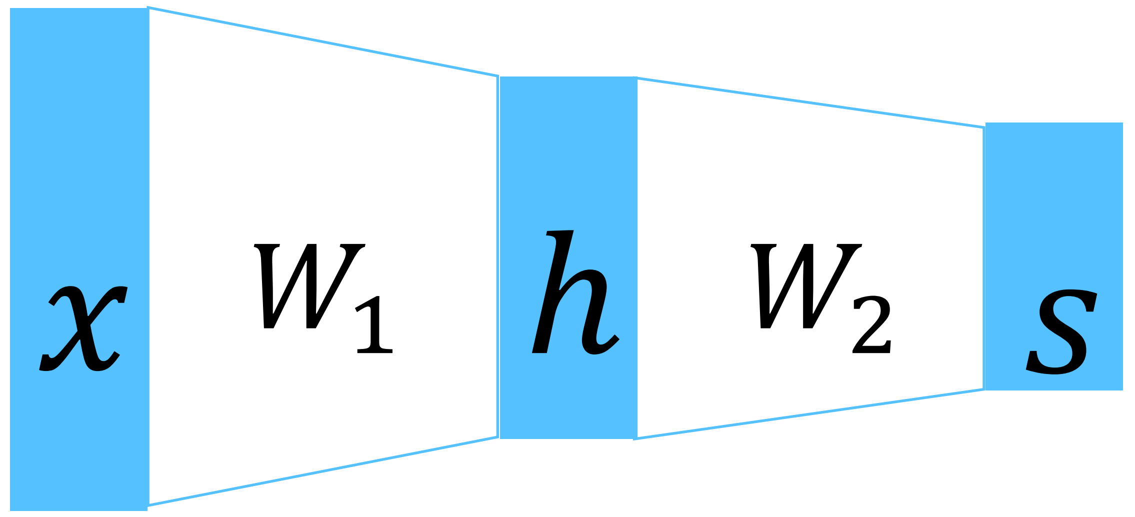
Convolution Layers



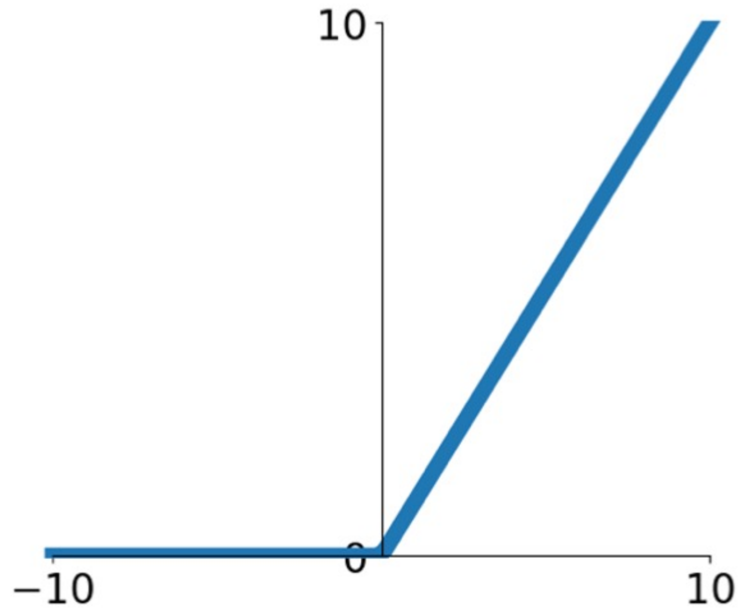
Pooling Layers



Fully-Connected Layers



Activation Function



Normalization

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \epsilon}}$$

Problem: Deep Networks very hard to train

Batch Normalization

Consider a single layer $y = Wx$

The following could lead to tough optimization:

- Inputs x are not *centered around zero* (need large bias)
- Inputs x have different scaling per-element (entries in W will need to vary a lot)

Idea: force inputs to be "nicely scaled" at each layer!

Batch Normalization

Idea: “Normalize” the outputs of a layer so they have zero mean and unit variance

Why? Helps reduce “internal covariate shift”, improves optimization results

We can normalize a batch of activations using:

$$\hat{x} = \frac{x - E[x]}{\sqrt{Var[x]}}$$

Ioffe and Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift”, ICML 2015

Batch Normalization

Idea: "Normalize" the outputs of a layer so they have zero mean and unit variance

Why? Helps reduce "internal covariate shift", improves optimization results

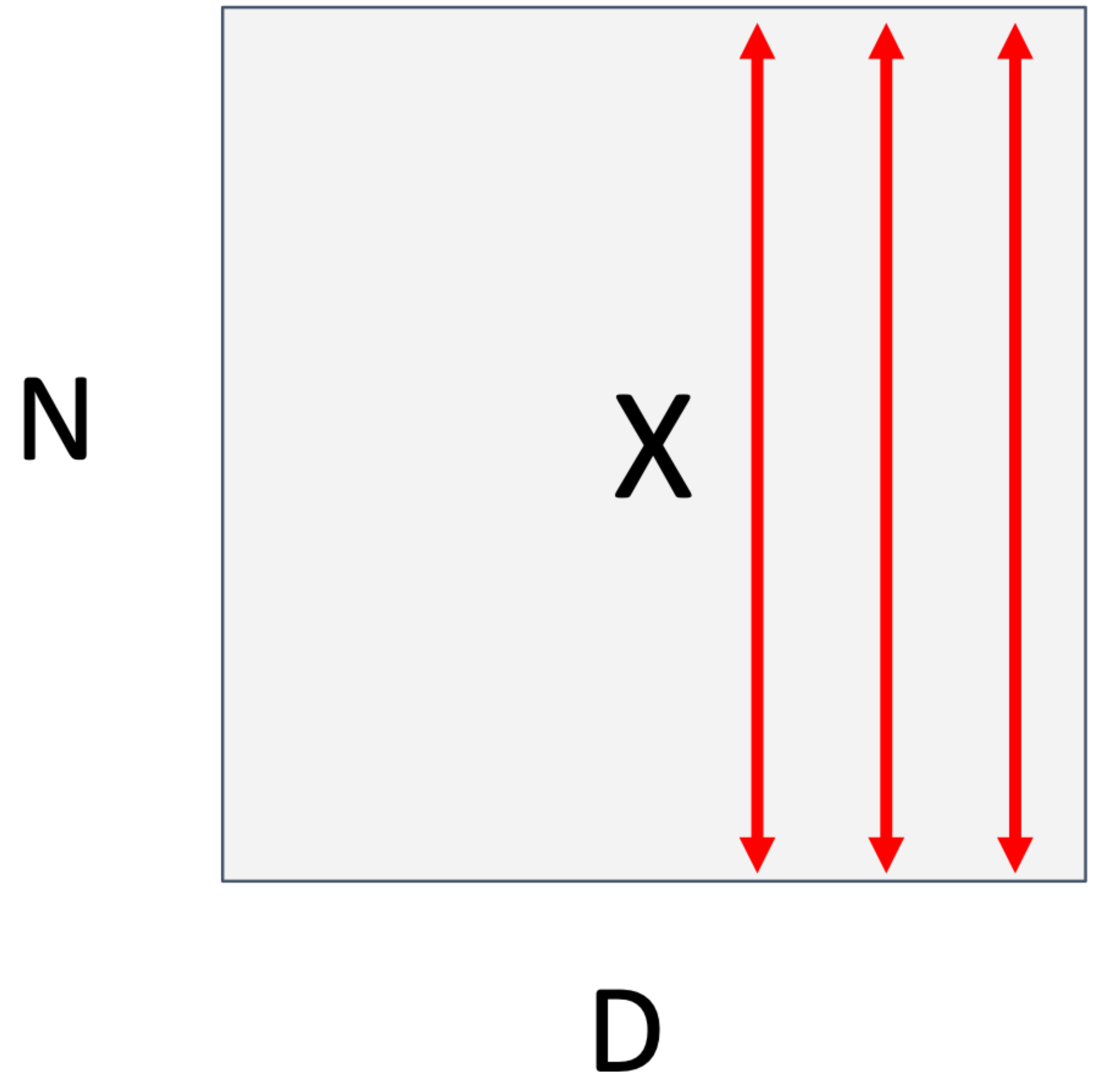
We can normalize a batch of activations using:

$$\hat{x} = \frac{x - E[x]}{\sqrt{Var[x]}}$$

This is a **differentiable function**, so we can use it as an operator in our networks and backdrop through it!

Batch Normalization

Input: $x \in \mathbb{R}^{N \times D}$



$$\mu_j = \frac{1}{N}\sum_{i=1}^{N} x_{i,j}$$

Per-channel mean, shape is D

$$\sigma_j^2 = \frac{1}{N}\sum_{i=1}^{N} \left(x_{i,j} - \mu_j\right)^2$$

Per-channel std, shape is D

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$

Normalized x, Shape is N x D

Ioffe and Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift", ICML 2015

Batch Normalization

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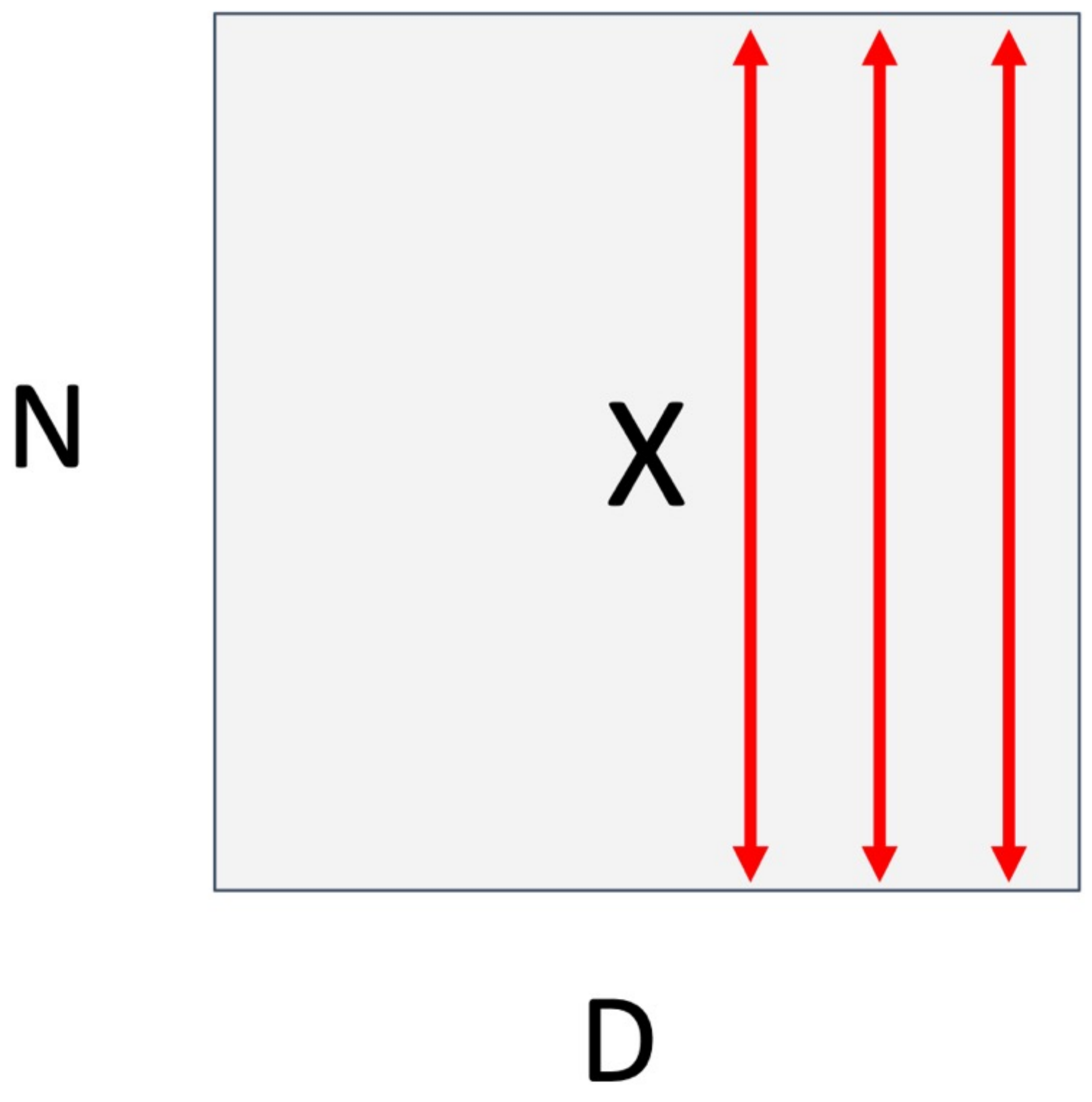

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$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$

Normalized x, Shape is N x D

Problem: What if zero-mean, unit variance is too hard of a constraint?

Batch Normalization

Input: $x \in \mathbb{R}^{N \times D}$

Add **Learnable scale and shift parameters:**

$$\gamma, \beta \in \mathbb{R}^D$$

Learning $\gamma = \sigma, \beta = \mu$ will recover the identity function (in expectation)

$$\mu_j = \frac{1}{N} \sum_{i=1}^{N} x_{i,j}$$

Per-channel mean, shape is D

$$\sigma_j^2 = \frac{1}{N} \sum_{i=1}^{N} \left(x_{i,j} - \mu_j\right)^2$$

Per-channel std, shape is D

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$

Normalized x, Shape is N x D

$$y_{i,j} = \gamma_j \hat{x}_{i,j} + \beta_j$$

Output, Shape is N x D

Batch Normalization

Input: $x \in \mathbb{R}^{N \times D}$

Learnable scale and shift parameters:

$$\gamma, \beta \in \mathbb{R}^{D}$$

Learning $\gamma = \sigma, \beta = \mu$ will recover the identity function (in expectation)

$$\mu_j = \frac{1}{N}\sum_{i=1}^{N} x_{i,j}$$

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Per-channel std, shape is D

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$

Normalized x, Shape is N x D

$$y_{i,j} = \gamma_j \hat{x}_{i,j} + \beta_j$$

Output, Shape is N x D

Problem: Estimates depend on minibatch; can't run layer at test-time!

Batch Normalization: Test-Time

Input: $x \in \mathbb{R}^{N \times D}$

Learnable scale and shift parameters:

$$\gamma, \beta \in \mathbb{R}^D$$

Learning $\gamma = \sigma, \beta = \mu$ will recover the identity function (in expectation)

$\mu_j =$ (Running) average of values seen during training — Per-channel mean, shape is D

$\sigma_j^2 =$ (Running) average of values seen during training — Per-channel std, shape is D

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$

Normalized x, Shape is N x D

$$y_{i,j} = \gamma_j \hat{x}_{i,j} + \beta_j$$

Output, Shape is N x D

Batch Normalization: Test-Time

Input: $x \in \mathbb{R}^{N \times D}$

$\mu_j =$ (Running) average of values seen during training

Per-channel mean, shape is D

Learnable scale and shift parameters:

$\gamma, \beta \in \mathbb{R}^D$

In practice, usually momentum = 0.99

```
moving_mean = moving_mean * momentum + batch_mean * (1 - momentum)
moving_var = moving_var * momentum + batch_var * (1 - momentum)
```

Ioffe and Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift”, ICML 2015

Batch Normalization: Test-Time

Input: $x \in \mathbb{R}^{N \times D}$

$\mu_j =$ (Running) average of values seen during training

Per-channel mean, shape is D

Learnable scale and shift parameters:

$$\gamma, \beta \in \mathbb{R}^D$$

Learning $\gamma = \sigma, \beta = \mu$ will recover the identity function (in expectation)

$\boxed{\begin{array}{l} \mu_j^{test} = 0 \\ \text{For each training iteration:} \\ \quad \mu_j = \frac{1}{N}\sum_{i=1}^{N} x_{i,j} \\ \quad \mu_j^{test} = 0.99\,\mu_j^{test} + 0.01\,\mu_j \\ \\ \text{(Similar for } \sigma\text{)} \end{array}}$

Ioffe and Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift", ICML 2015

Batch Normalization: Test-Time

Input: $x \in \mathbb{R}^{N \times D}$

Learnable scale and shift parameters:

$\gamma, \beta \in \mathbb{R}^{D}$

During testing batchnorm becomes a linear operator! Can be fused with the previous fully-connected or conv layer

$\mu_j =$ (Running) average of values seen during training — Per-channel mean, shape is D

$\sigma_j^2 =$ (Running) average of values seen during training — Per-channel std, shape is D

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$

Normalized x, Shape is N x D

$$y_{i,j} = \gamma_j \hat{x}_{i,j} + \beta_j$$

Output, Shape is N x D

Batch Normalization for ConvNets

Batch Normalization for **fully-connected** networks

$$x : N \times D$$

Normalize

$$\mu, \sigma \;: 1 \times D$$
$$\gamma, \beta \;: 1 \times D$$
$$y = \frac{(x - \mu)}{\sigma}\gamma + \beta$$

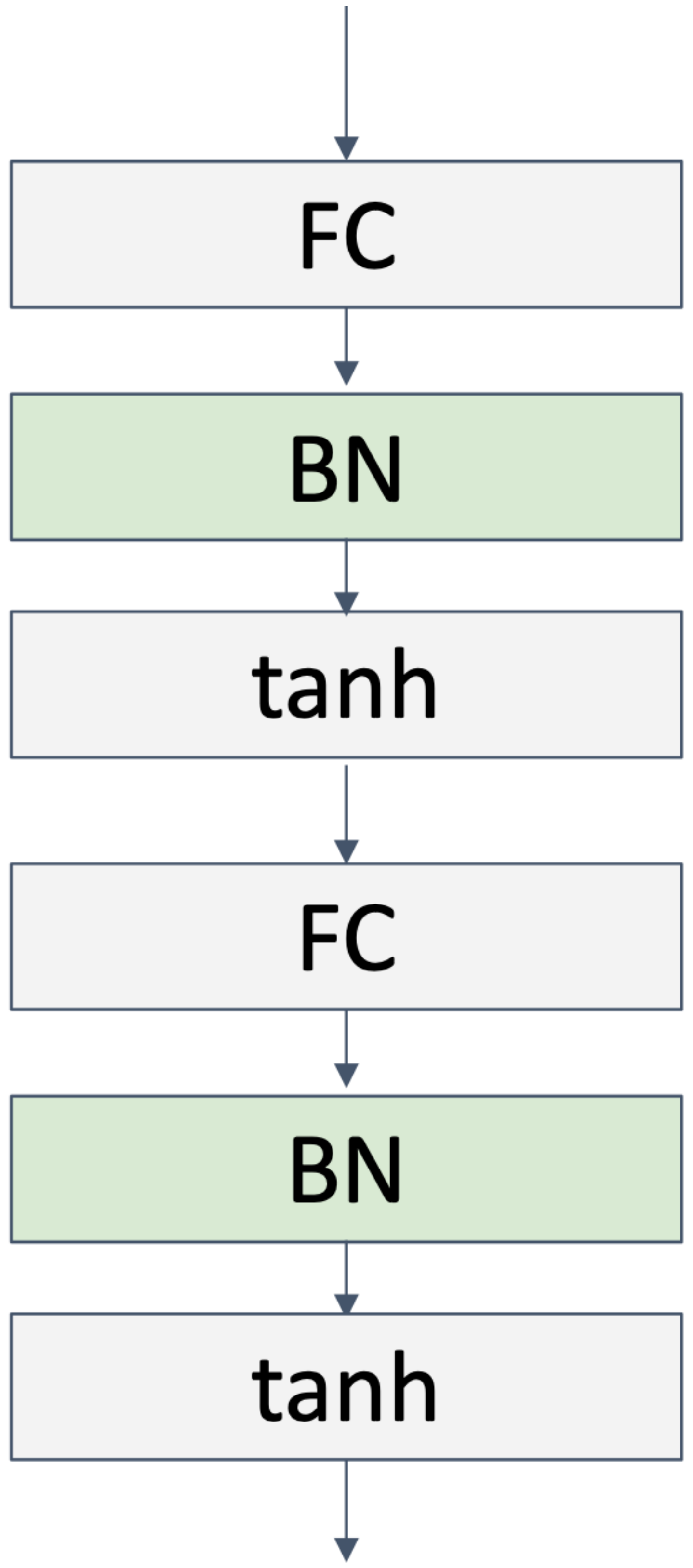
Batch Normalization for **convolutional** networks (Spatial Batchnorm, BatchNorm2D)

$$x : N \times C \times H \times W$$

Normalize

$$\mu, \sigma \;: 1 \times C \times 1 \times 1$$
$$\gamma, \beta \;: 1 \times C \times 1 \times 1$$
$$y = \frac{(x - \mu)}{\sigma}\gamma + \beta$$

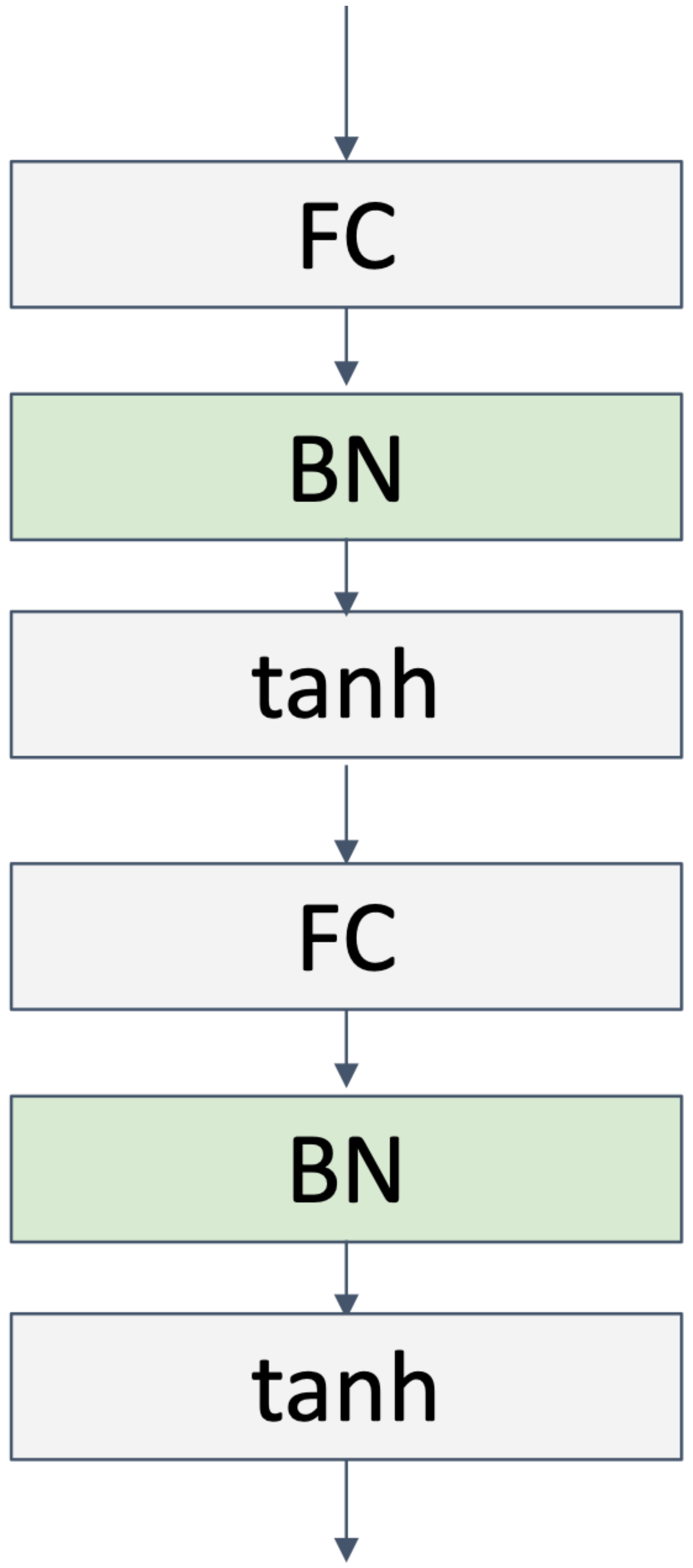
Batch Normalization



Usually inserted after Fully Connected or Convolutional layers, and before nonlinearity

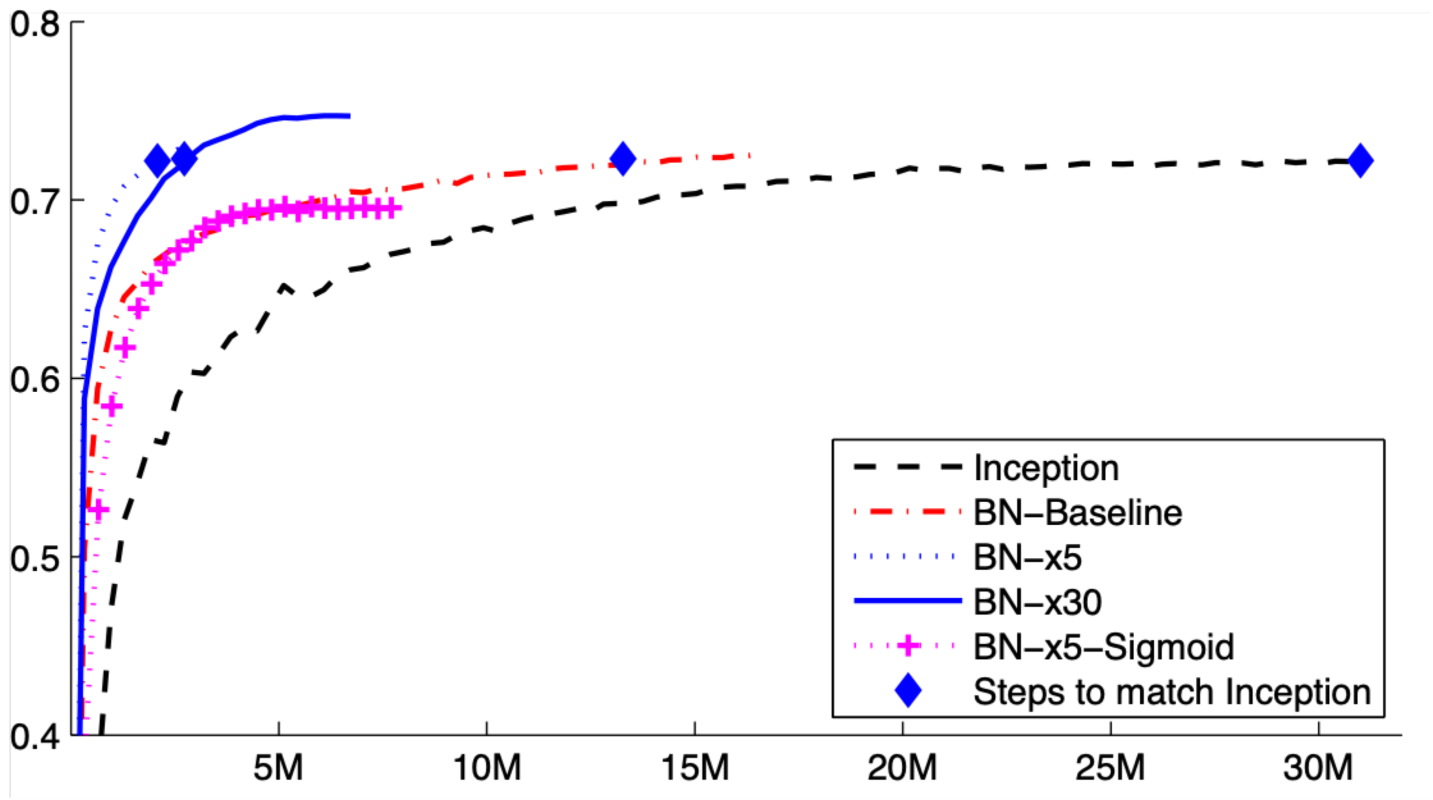
$$\hat{x} = \frac{x - E[x]}{\sqrt{Var[x]}}$$

Batch Normalization



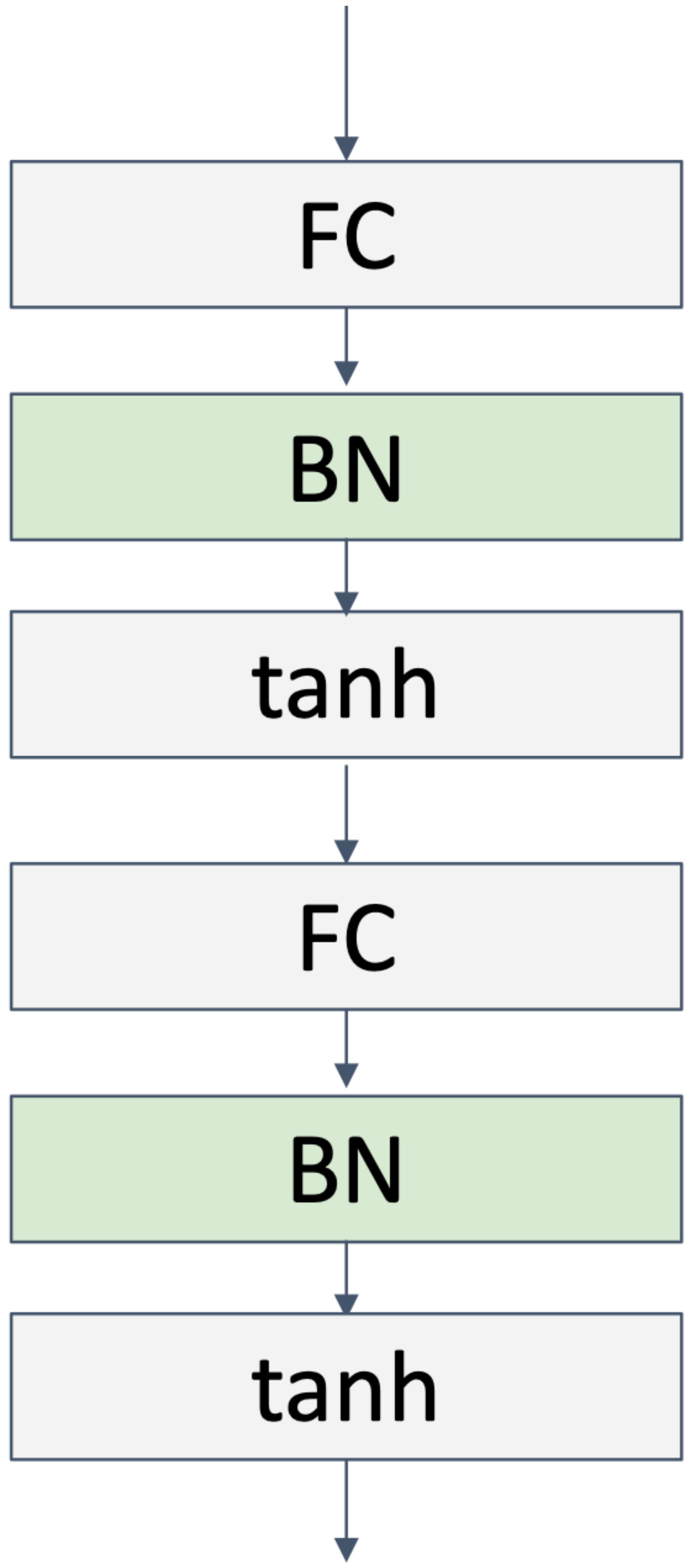
- Makes deep networks much easier to train!
- Allows higher learning rates, faster convergence
- Networks become more robust to initialization
- Acts as regularization during training
- Zero overhead at test-time: can be fused with conv

ImageNet Classification Accuracy



Training Iterations

Batch Normalization



- Makes deep networks much easier to train!
- Allows higher learning rates, faster convergence
- Networks become more robust to initialization
- Acts as regularization during training
- Zero overhead at test-time: can be fused with conv
- Not well-understood theoretically (yet, still lots of debate!)
- Behaves differently during training and testing: very common source of bugs!

Layer Normalization

Batch Normalization for **fully-connected** networks

$$x : N \times D$$

Normalize

$$\mu, \sigma \; : 1 \times D$$

$$\gamma, \beta \; : 1 \times D$$

$$y = \frac{(x - \mu)}{\sigma}\gamma + \beta$$

Layer Normalization for fully-connected networks
Same behavior at train and test!
Used in RNNs, Transformers

$$x : N \times D$$

Normalize

$$\mu, \sigma \; : N \times 1$$

$$\gamma, \beta \; : 1 \times D$$

$$y = \frac{(x - \mu)}{\sigma}\gamma + \beta$$

Instance Normalization

Batch Normalization for convolutional networks

$$x : N \times C \times H \times W$$

Normalize

$$\mu, \sigma : 1 \times C \times 1 \times 1$$

$$\gamma, \beta : 1 \times C \times 1 \times 1$$

$$y = \frac{(x - \mu)}{\sigma}\gamma + \beta$$

Instance Normalization for convolutional networks

$$x : N \times C \times H \times W$$

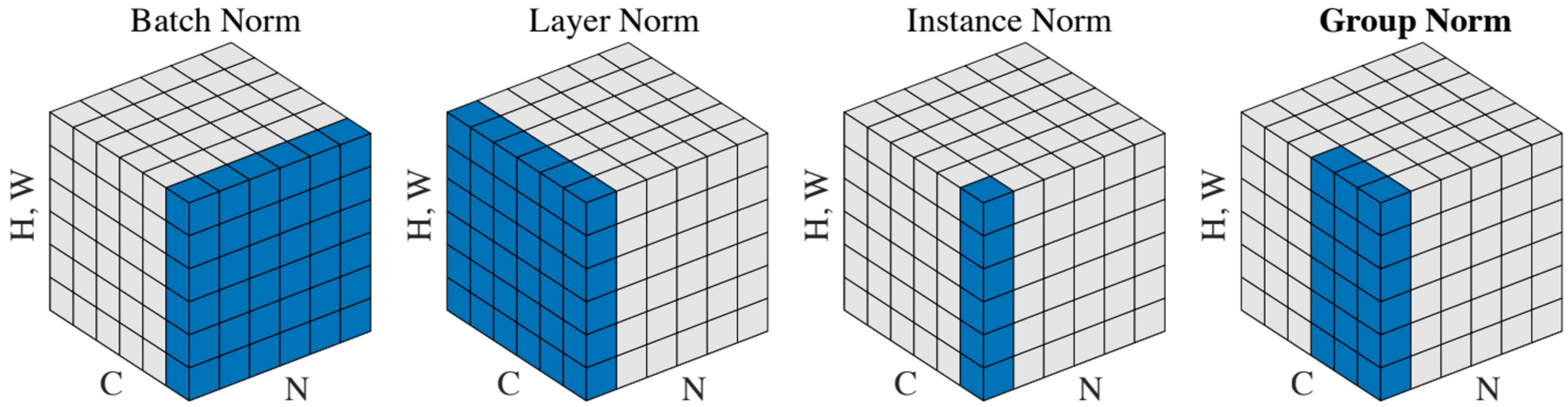
Normalize

$$\mu, \sigma : N \times C \times 1 \times 1$$

$$\gamma, \beta : 1 \times C \times 1 \times 1$$

$$y = \frac{(x - \mu)}{\sigma}\gamma + \beta$$

Group Normalization



Wu and He, “Group Normalization”, ECCV 2018

Components of Convolutional Networks

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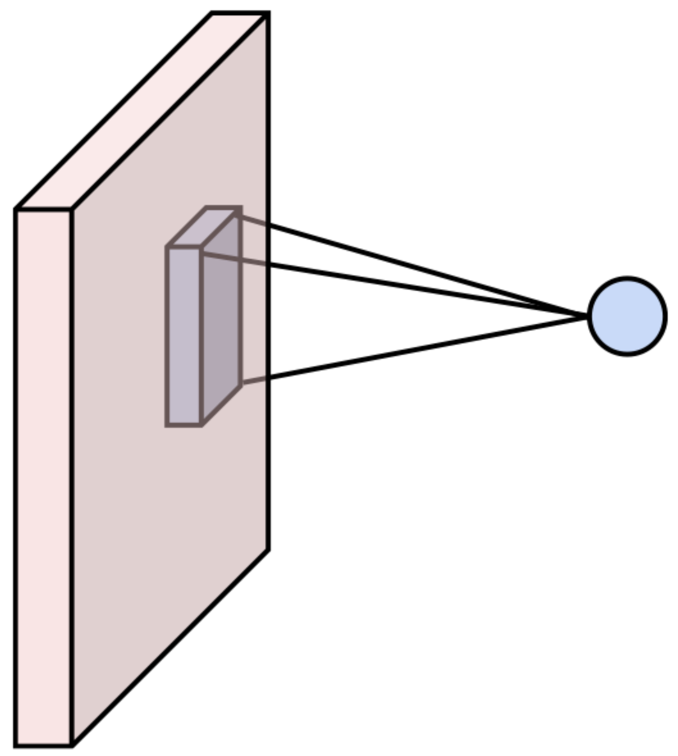
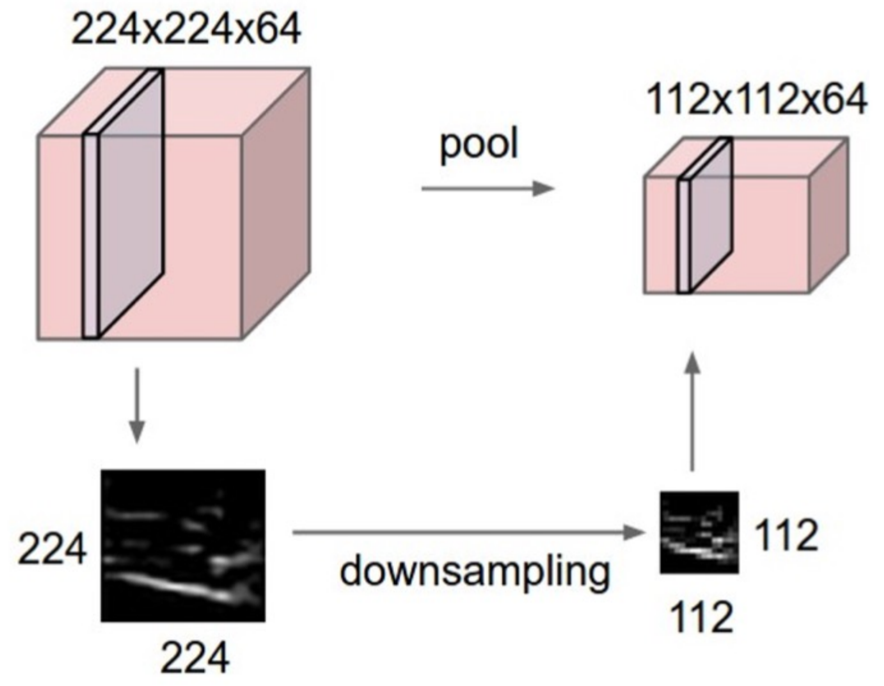
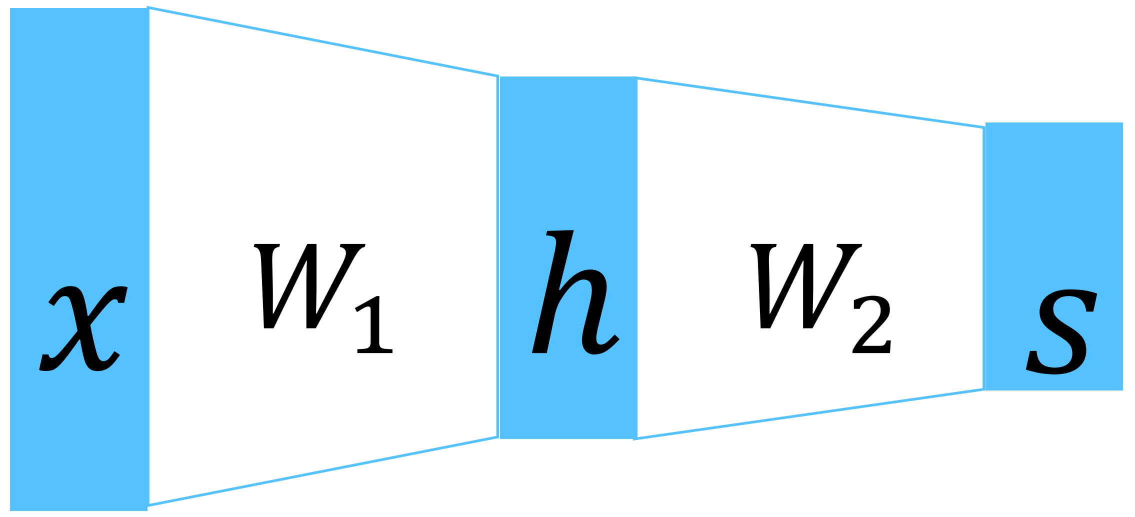


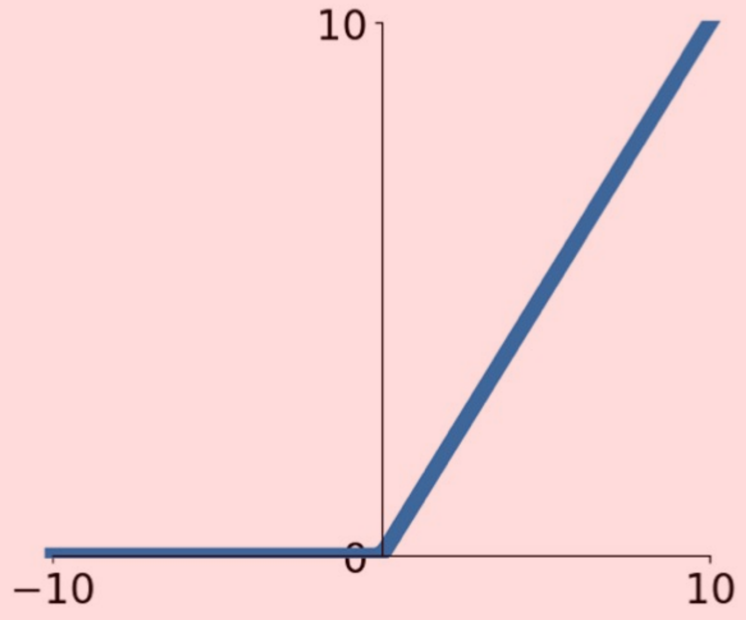
Pooling Layers



Fully-Connected Layers



Activation Function



Normalization

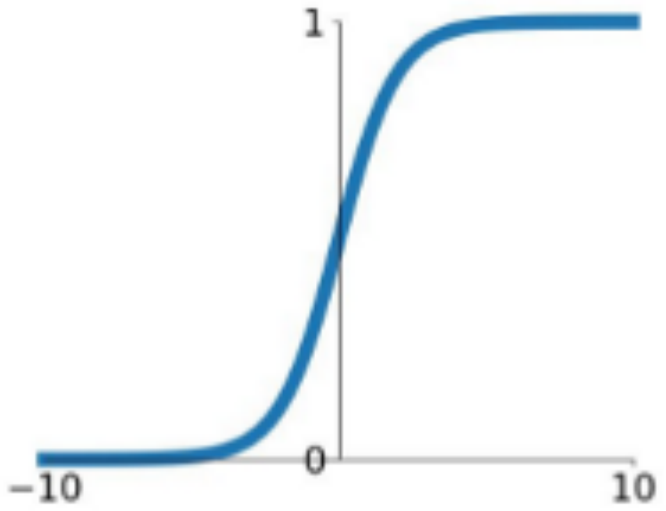
$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \epsilon}}$$

Problem: Deep Networks very hard to train

Activation Functions

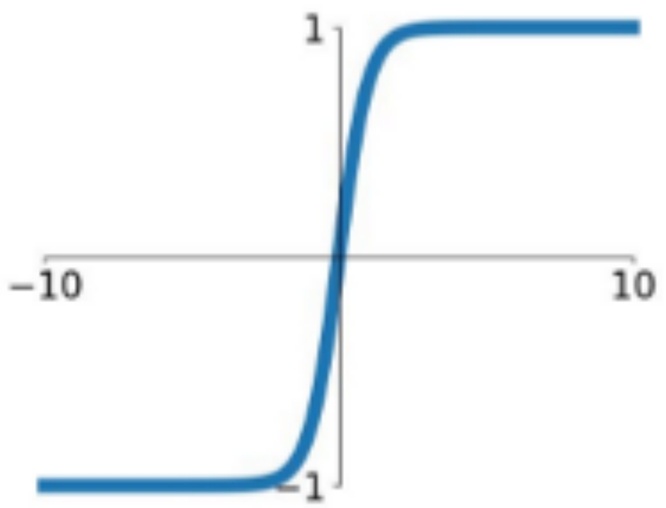
Sigmoid

$\sigma(x) = \frac{1}{1+e^{-x}}$



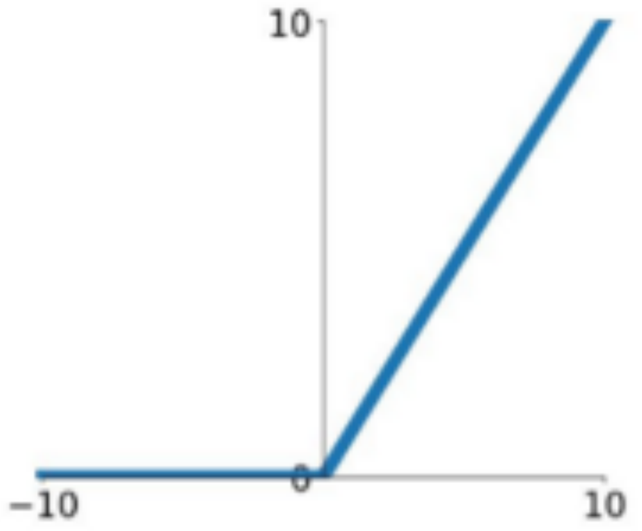
tanh

$\tanh(x)$



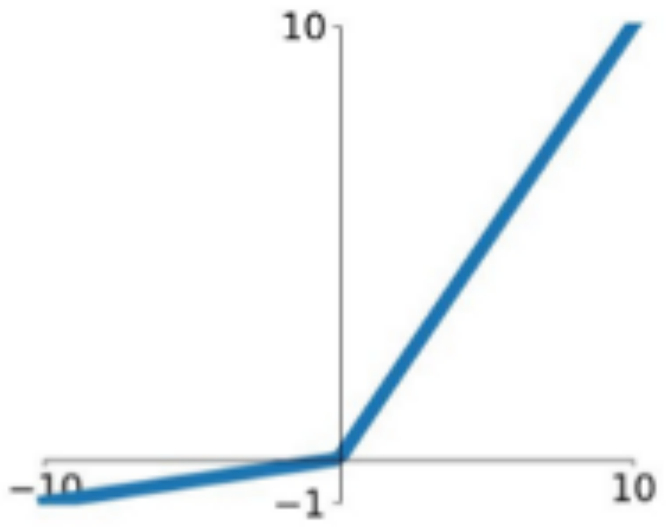
ReLU

$\max(0, x)$



Leaky ReLU

$\max(0.1x, x)$

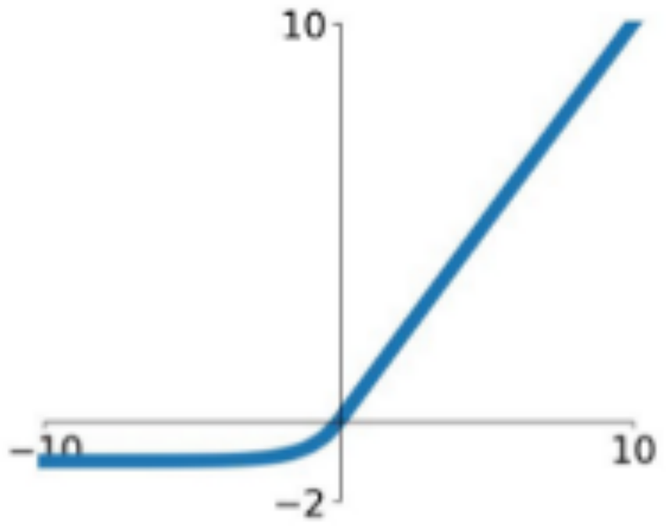


Maxout

$\max(w_1^T x + b_1, w_2^T x + b_2)$

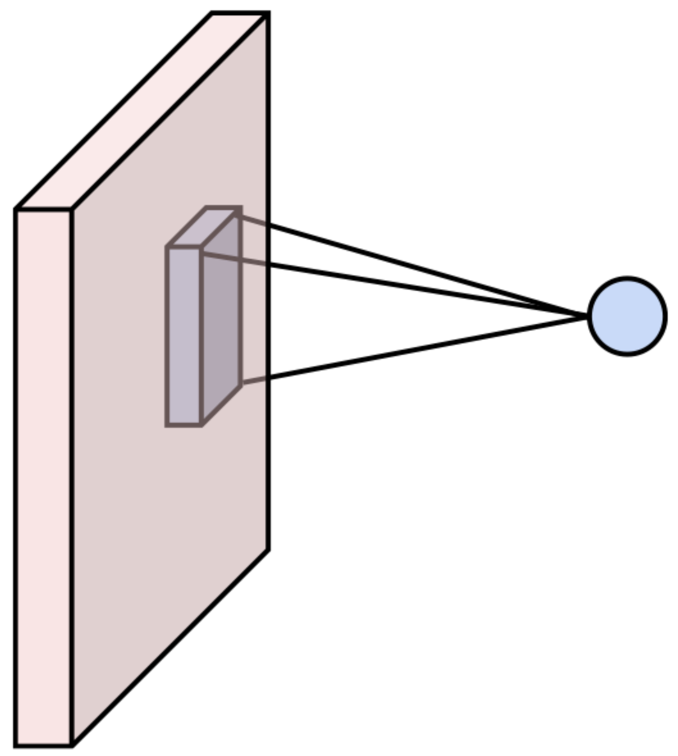
ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$

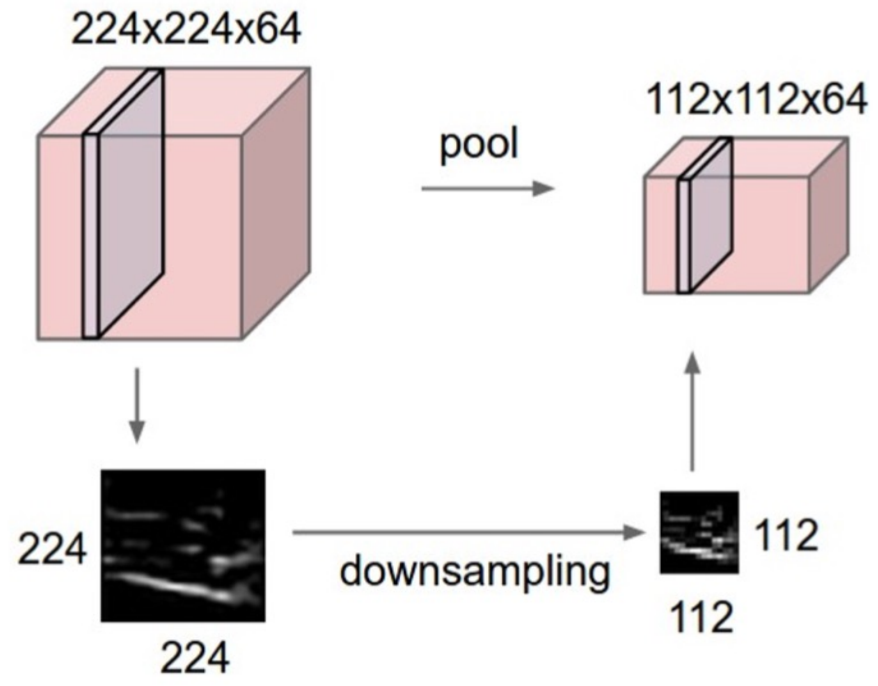


Summary: Components of Convolutional Networks

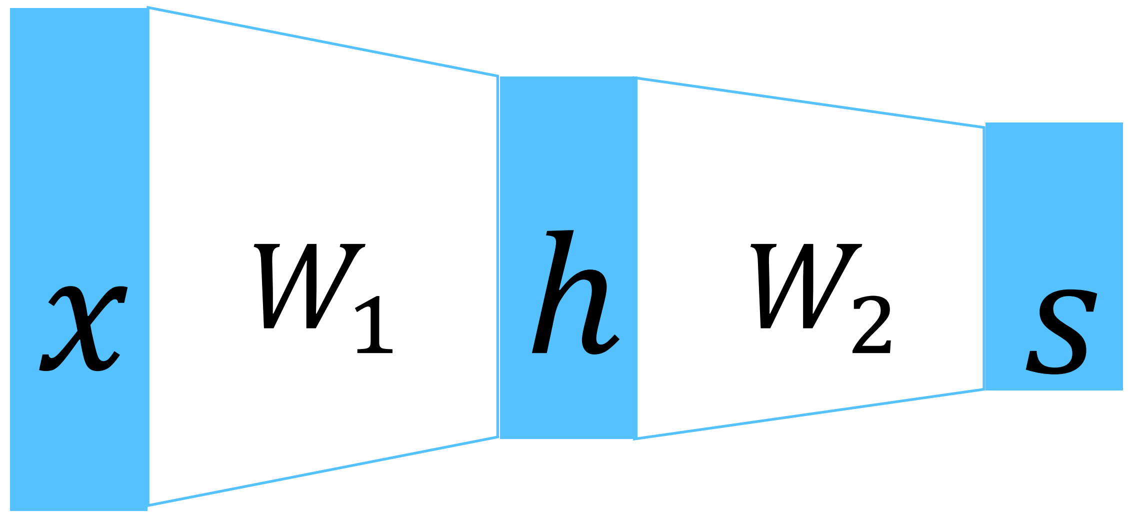
Convolution Layers



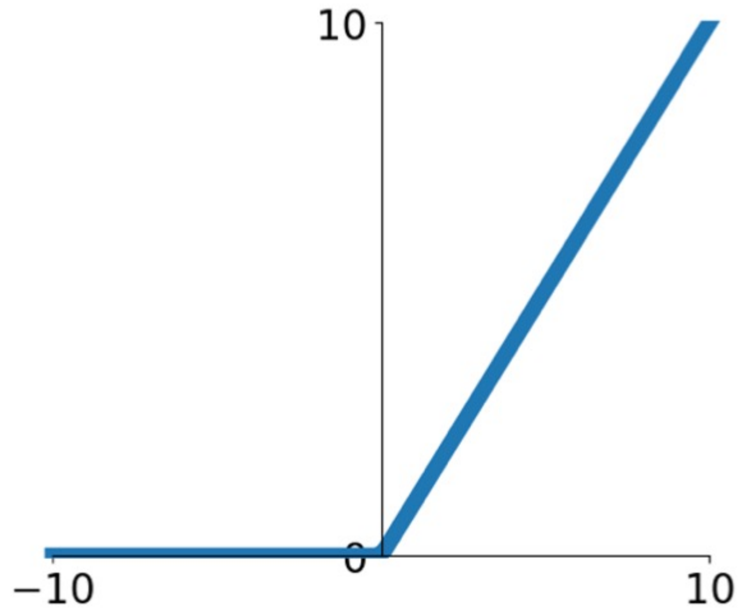
Pooling Layers



Fully-Connected Layers



Activation Function

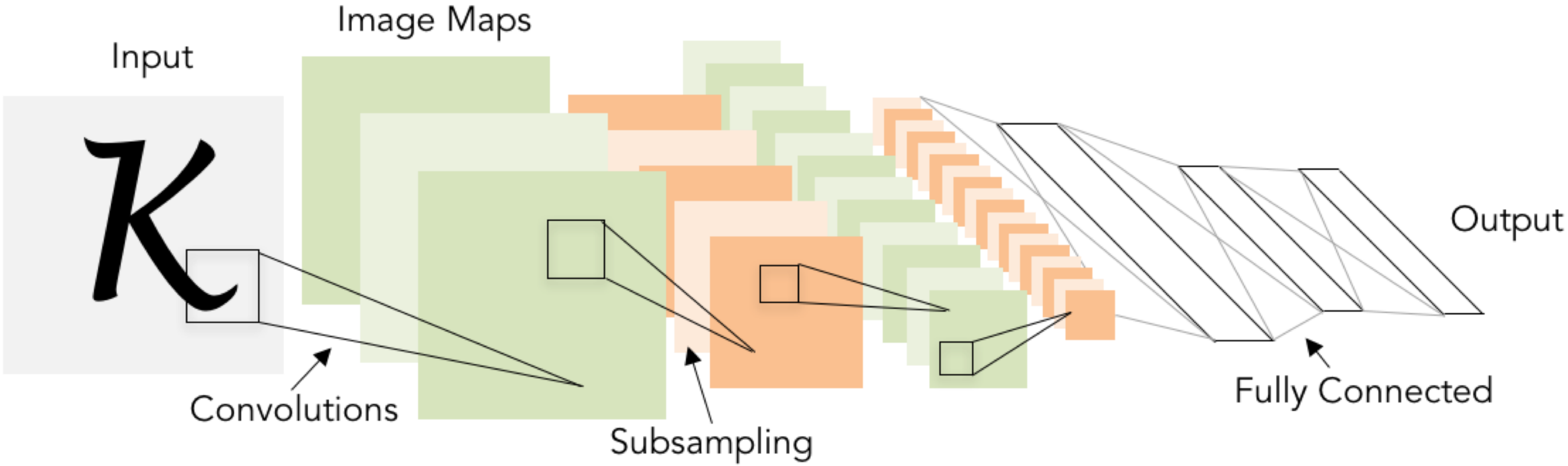


Normalization

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \epsilon}}$$

Summary: Components of Convolutional Network

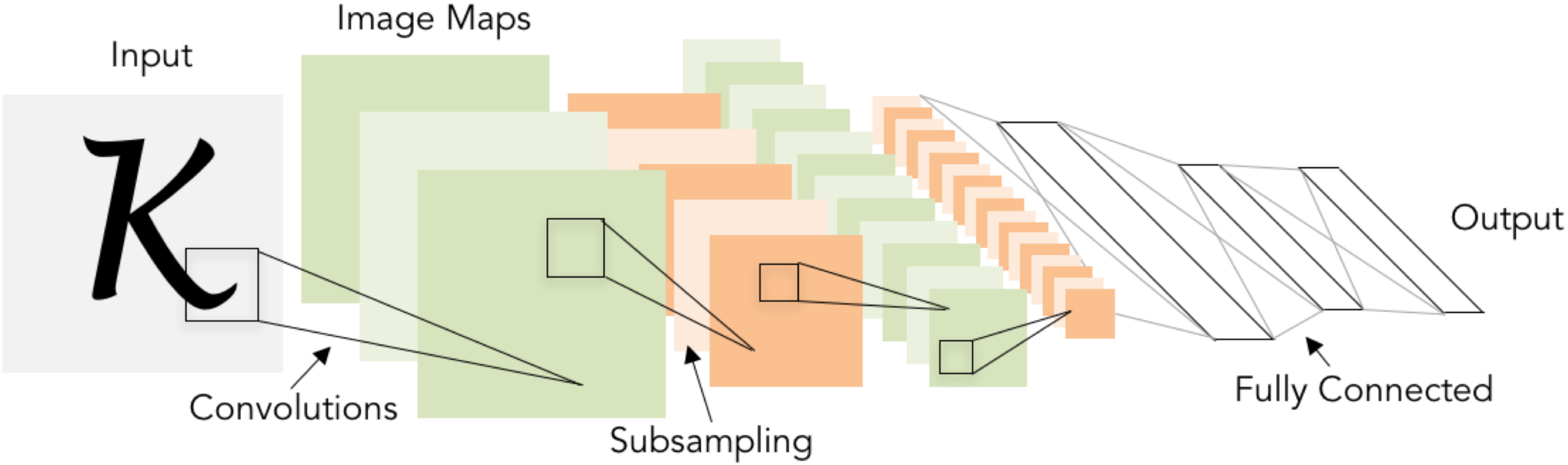
Problem: What is the right way to combine all these components?



Convolutional Neural Networks

Classic architecture: [Conv, ReLU, Pool] x N, flatten, [FC, ReLU] x N, FC

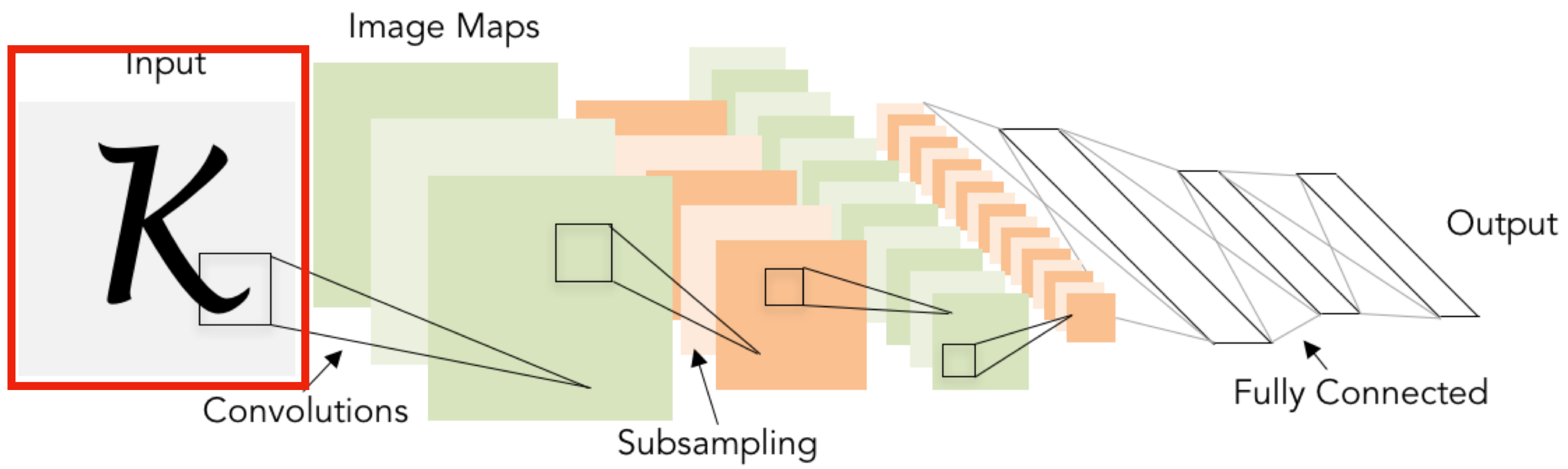
Example: LeNet-5



Lecun et al., "Gradient-based learning applied to document recognition", 1998

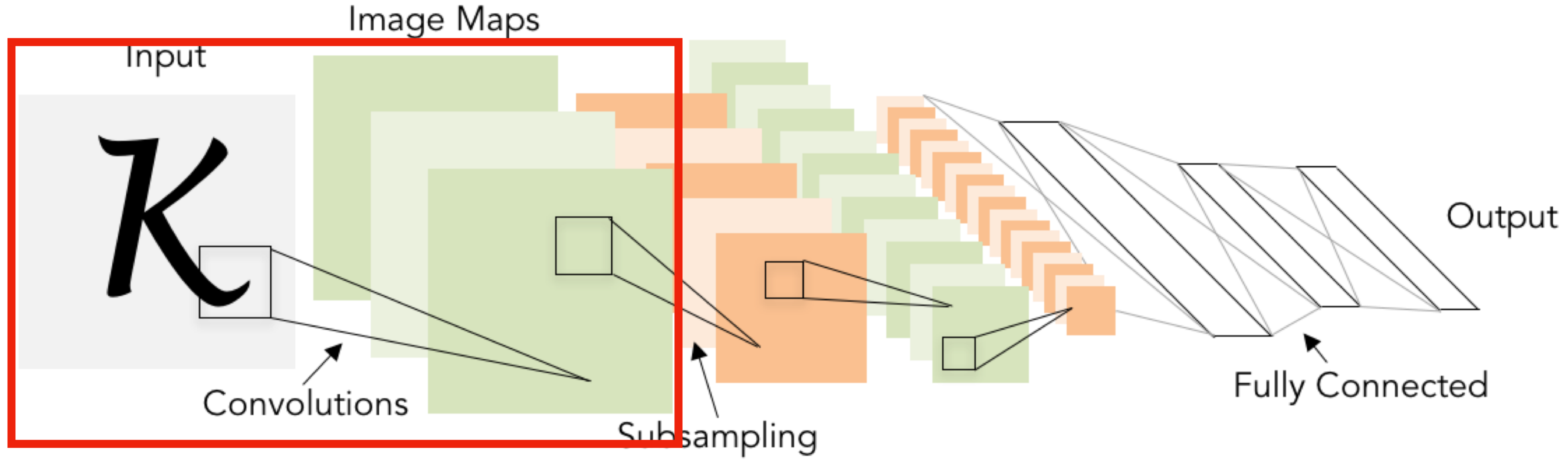
Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	



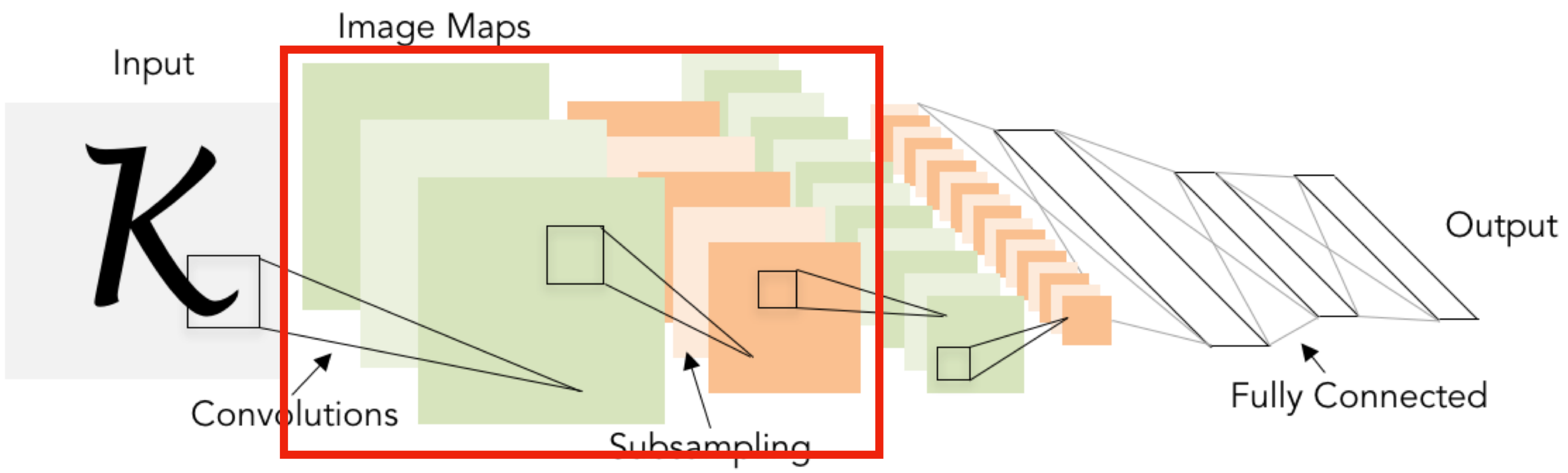
Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	
Conv (C_{out}=20, K=5, P=2, S=1)	20 x 28 x 28	20 x 1 x 5 x 5
ReLU	20 x 28 x 28	



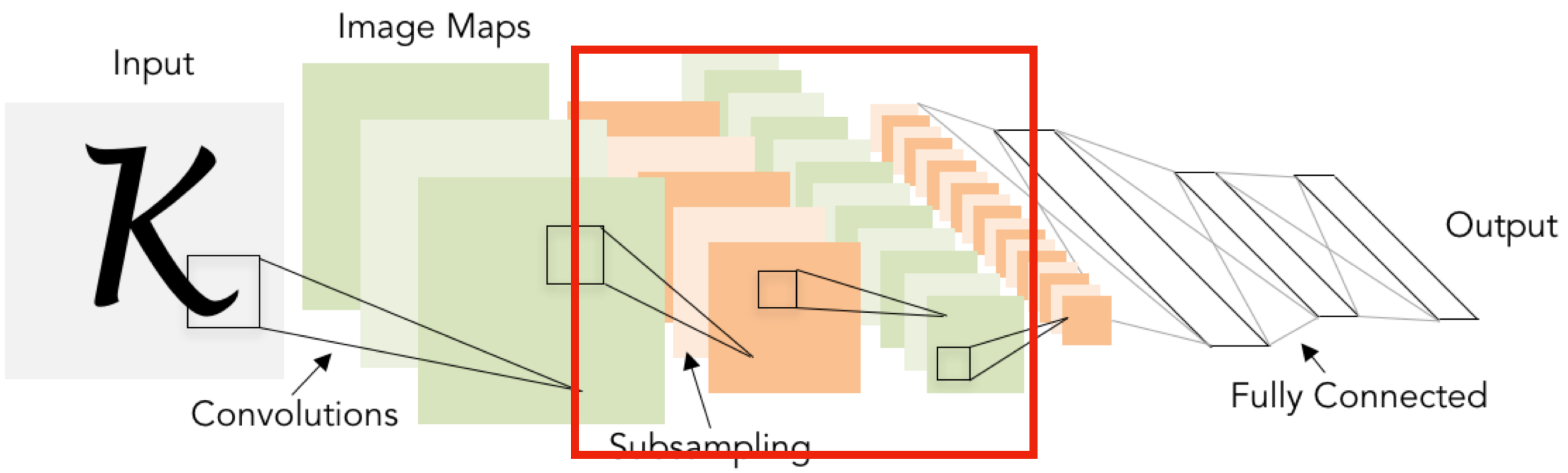
Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	
Conv (C_{out}=20, K=5, P=2, S=1)	20 x 28 x 28	20 x 1 x 5 x 5
ReLU	20 x 28 x 28	
MaxPool(K=2, S=2)	20 x 14 x 14	



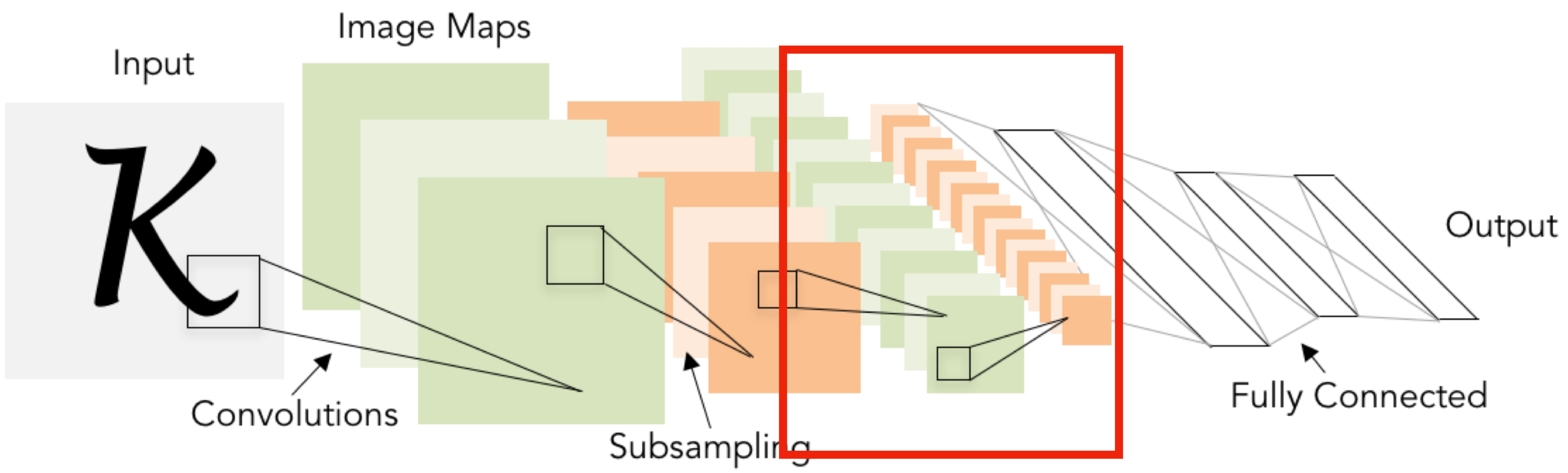
Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	
Conv (C_{out}=20, K=5, P=2, S=1)	20 x 28 x 28	20 x 1 x 5 x 5
ReLU	20 x 28 x 28	
MaxPool(K=2, S=2)	20 x 14 x 14	
Conv (C_{out}=50, K=5, P=2, S=1)	50 x 14 x 14	50 x 20 x 5 x 5
ReLU	50 x 14 x 14	



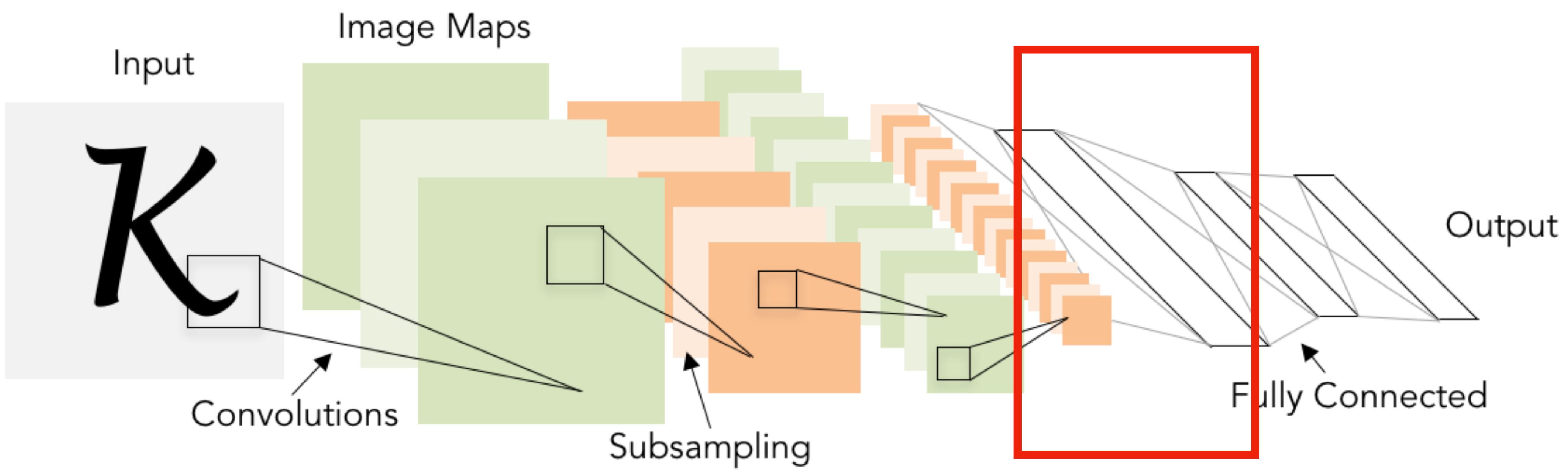
Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	
Conv (C_{out}=20, K=5, P=2, S=1)	20 x 28 x 28	20 x 1 x 5 x 5
ReLU	20 x 28 x 28	
MaxPool(K=2, S=2)	20 x 14 x 14	
Conv (C_{out}=50, K=5, P=2, S=1)	50 x 14 x 14	50 x 20 x 5 x 5
ReLU	50 x 14 x 14	
MaxPool(K=2, S=2)	50 x 7 x 7	



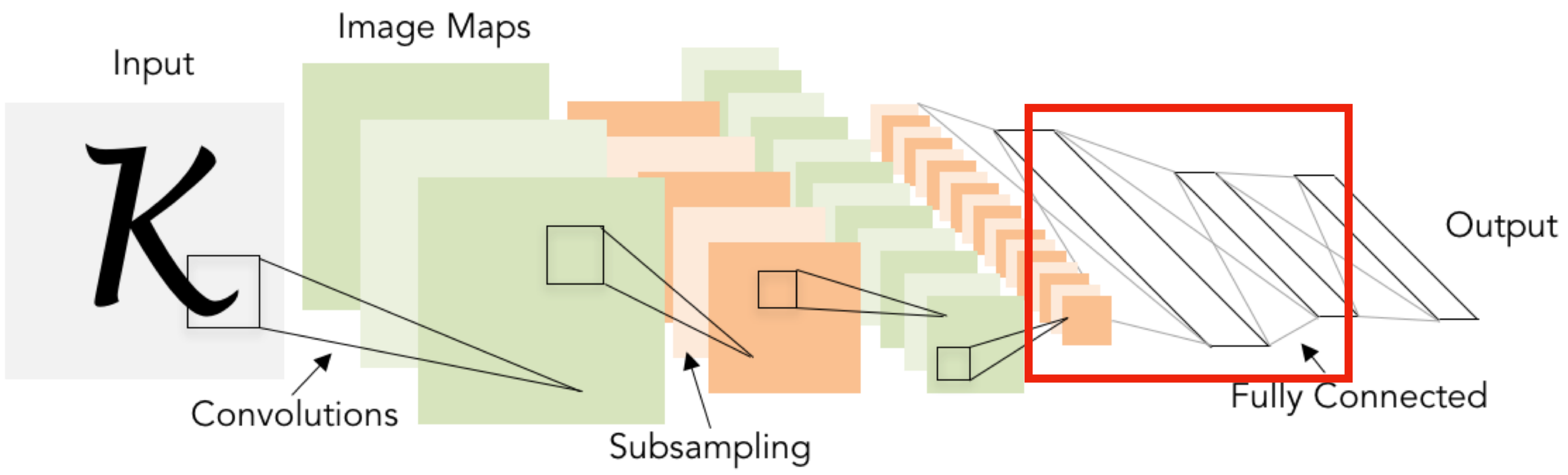
Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	
Conv (C_{out}=20, K=5, P=2, S=1)	20 x 28 x 28	20 x 1 x 5 x 5
ReLU	20 x 28 x 28	
MaxPool(K=2, S=2)	20 x 14 x 14	
Conv (C_{out}=50, K=5, P=2, S=1)	50 x 14 x 14	50 x 20 x 5 x 5
ReLU	50 x 14 x 14	
MaxPool(K=2, S=2)	50 x 7 x 7	
Flatten	2450	



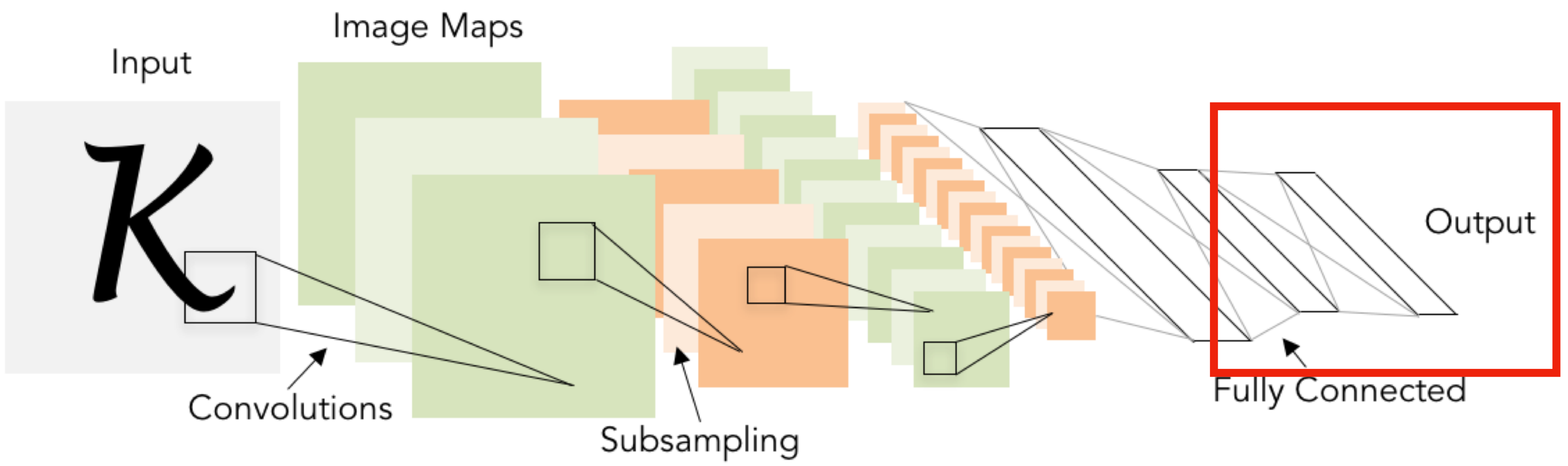
Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	
Conv (C_{out}=20, K=5, P=2, S=1)	20 x 28 x 28	20 x 1 x 5 x 5
ReLU	20 x 28 x 28	
MaxPool(K=2, S=2)	20 x 14 x 14	
Conv (C_{out}=50, K=5, P=2, S=1)	50 x 14 x 14	50 x 20 x 5 x 5
ReLU	50 x 14 x 14	
MaxPool(K=2, S=2)	50 x 7 x 7	
Flatten	2450	
Linear (2450 -> 500)	500	2450 x 500
ReLU	500	



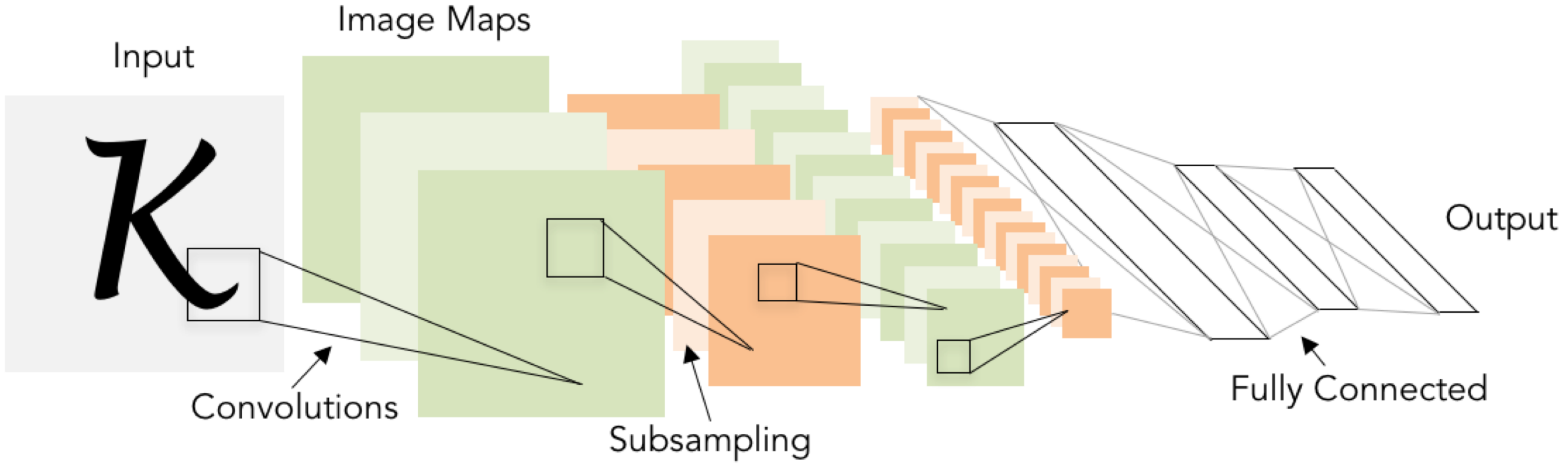
Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	
Conv (C_{out}=20, K=5, P=2, S=1)	20 x 28 x 28	20 x 1 x 5 x 5
ReLU	20 x 28 x 28	
MaxPool(K=2, S=2)	20 x 14 x 14	
Conv (C_{out}=50, K=5, P=2, S=1)	50 x 14 x 14	50 x 20 x 5 x 5
ReLU	50 x 14 x 14	
MaxPool(K=2, S=2)	50 x 7 x 7	
Flatten	2450	
Linear (2450 -> 500)	500	2450 x 500
ReLU	500	
Linear (500 -> 10)	10	500 x 10



Example: LeNet-5

Layer	Output Size	Weight Size
Input	1 x 28 x 28	
Conv (C_{out}=20, K=5, P=2, S=1)	20 x 28 x 28	20 x 1 x 5 x 5
ReLU	20 x 28 x 28	
MaxPool(K=2, S=2)	20 x 14 x 14	
Conv (C_{out}=50, K=5, P=2, S=1)	50 x 14 x 14	50 x 20 x 5 x 5
ReLU	50 x 14 x 14	
MaxPool(K=2, S=2)	50 x 7 x 7	
Flatten	2450	
Linear (2450 -> 500)	500	2450 x 500
ReLU	500	
Linear (500 -> 10)	10	500 x 10



As we progress through the network:

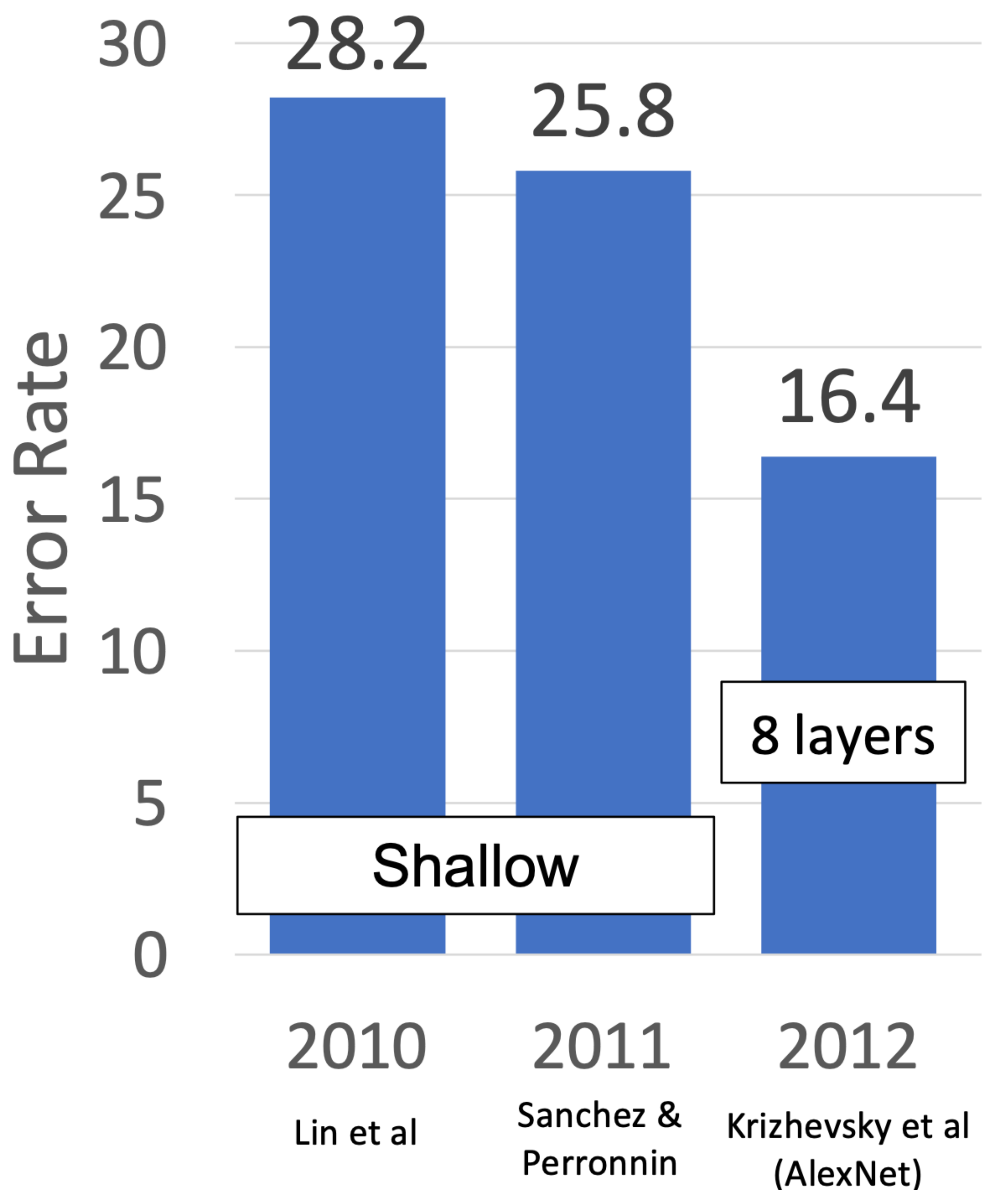
Spatial size **decreases**

(using pooling or striped convolution)
Number of channels **increases**

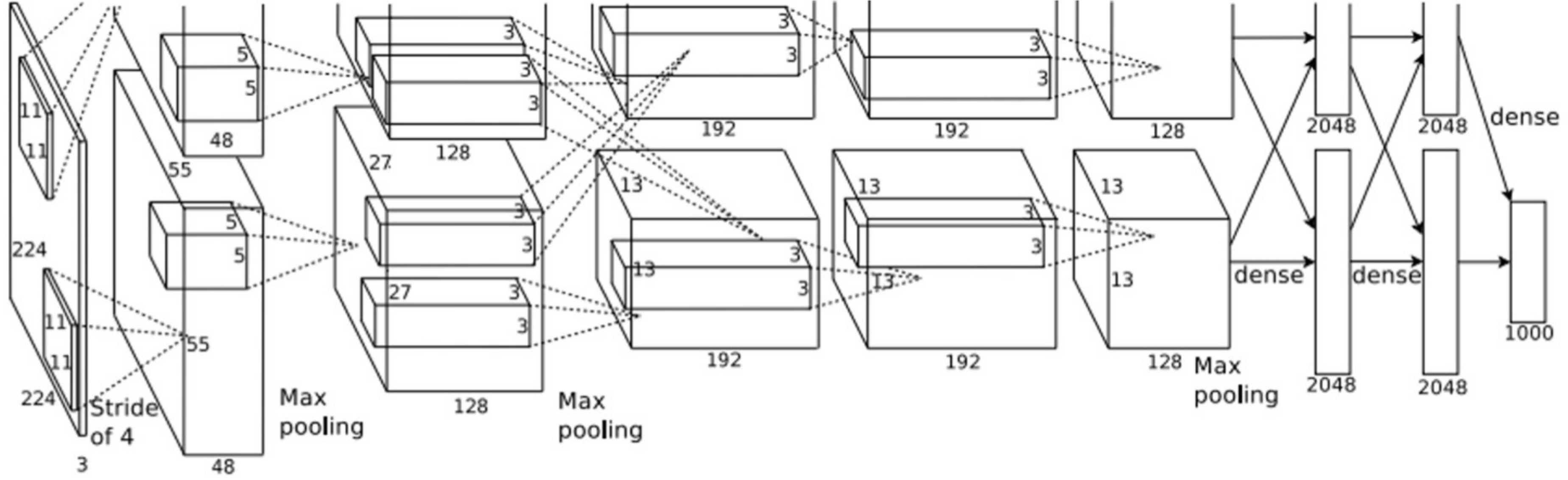
(total “volume” is preserved!)

Some modern architectures
break this trend—stay tuned!

ImageNet Classification Challenge



AlexNet



- 227 x 227 inputs
- 5 Convolutional Layers
- Max pooling
- 3 Fully-connected Layers
- ReLU nonlinearities

- Used “Local response normalization”; *Not used anymore*
- Trained on two GTX 580 GPUs - only 3GB of memory each! Model split over two GPUs.

Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012.

AlexNet

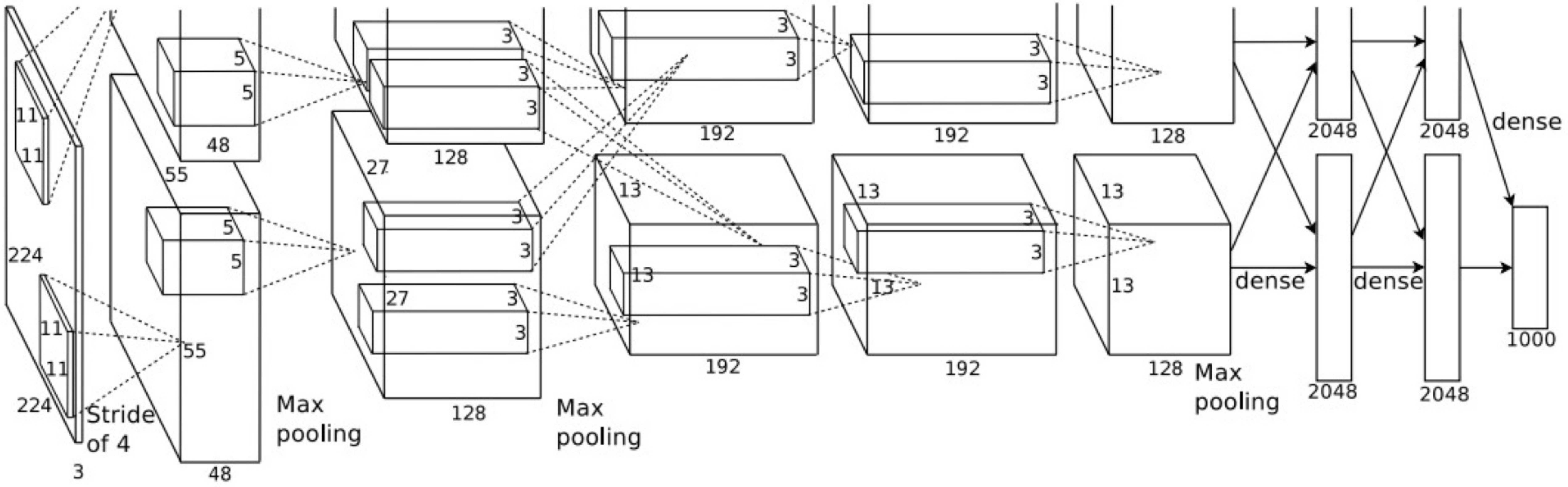
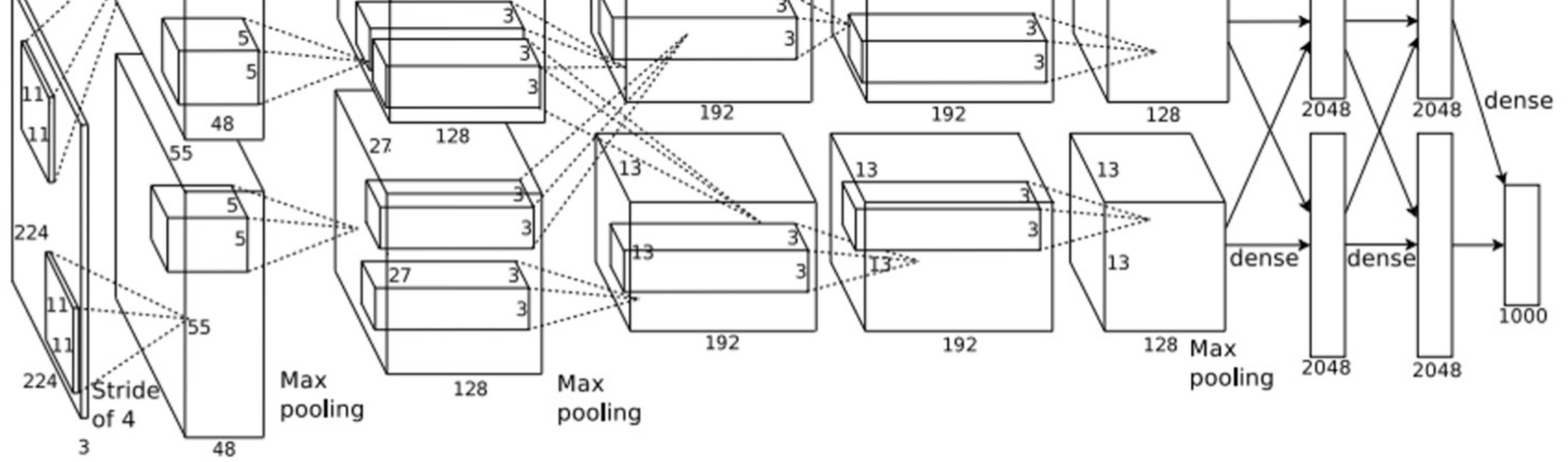
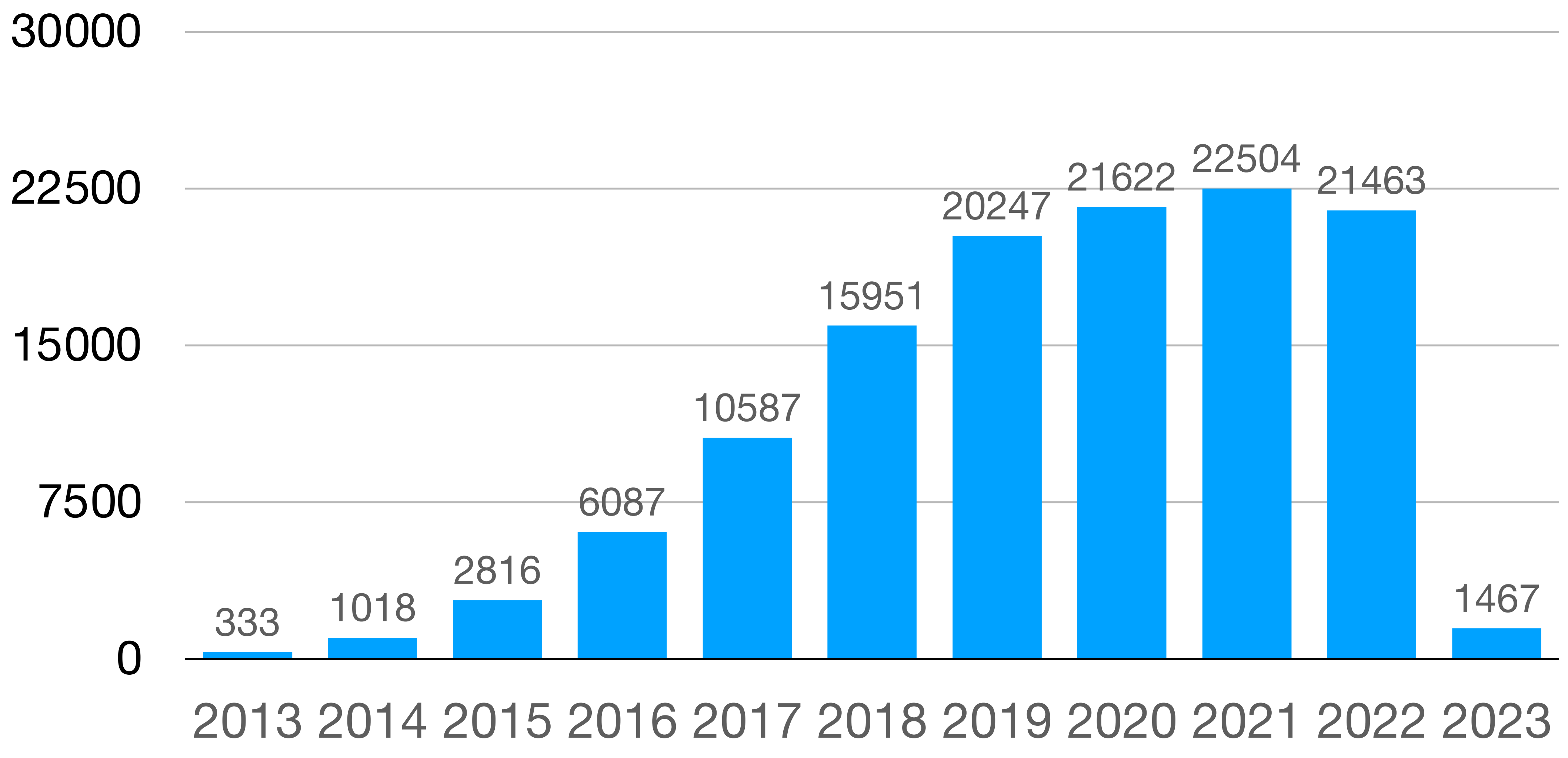


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

AlexNet



AlexNet citations per year



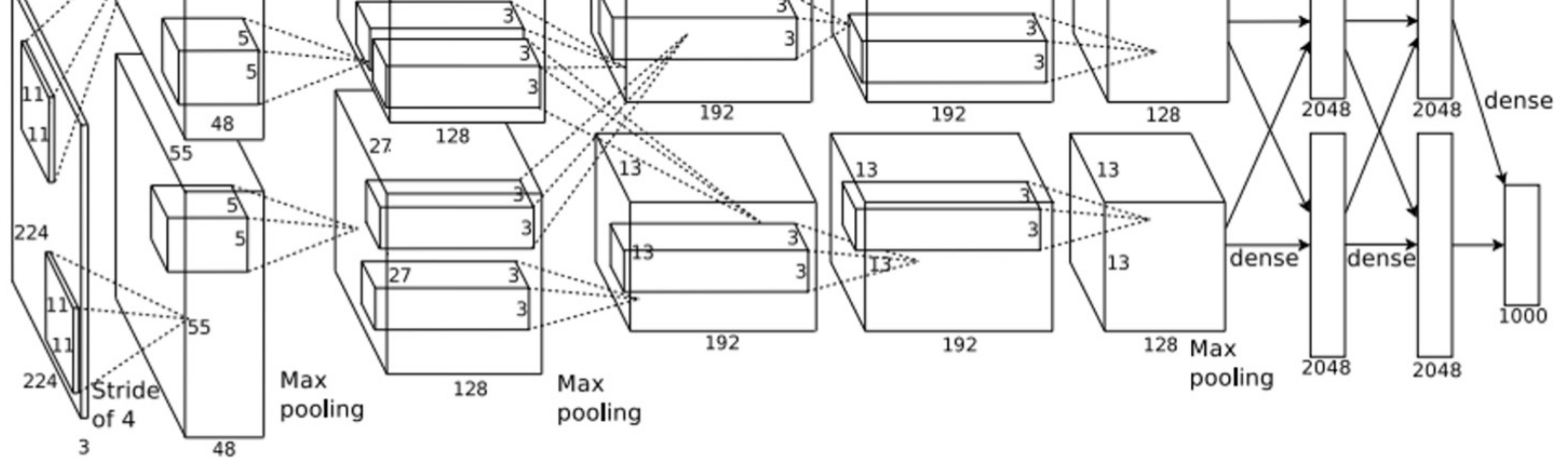
Total citations: **>120,000**

Citation as of 1/31/2024: 124,651

Citation Counts:

- Darwin, “On the origin of species”, 1859: **60,117**
- Shannon, “A mathematical theory of communication,” 1948: **140,459**
- Watson and Crick, “Molecular Structure of Nucleic Acids,” 1953: **16,298**

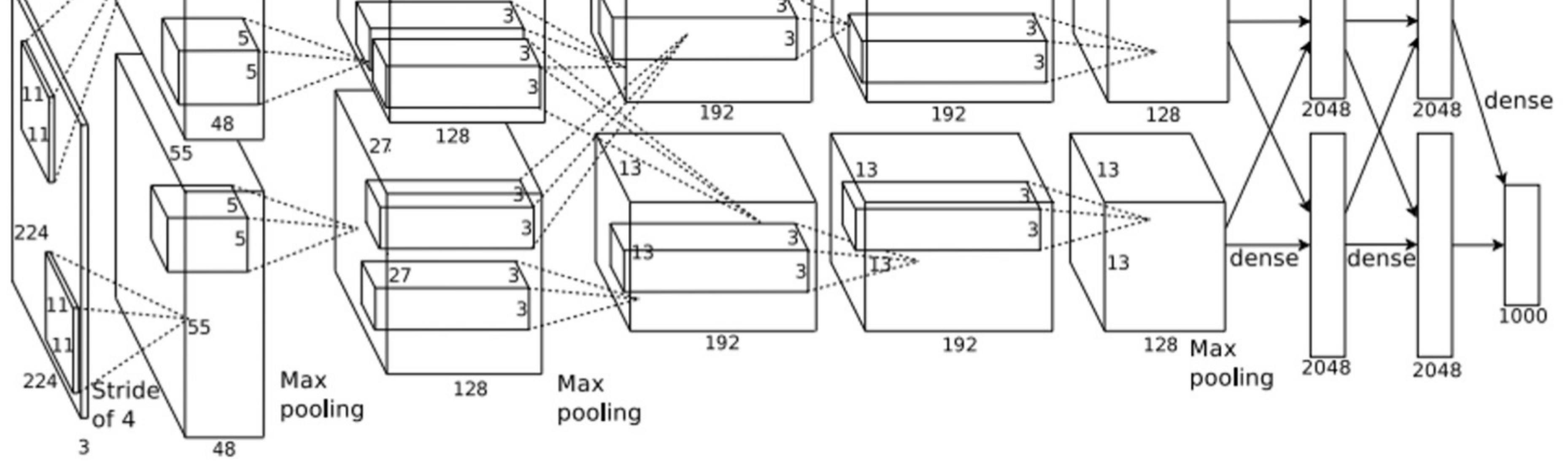
AlexNet



	Input size		Layer				Output size	
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W
Conv1	3	227	64	11	4	2	?	

Recall: Output channels = number of filters

AlexNet



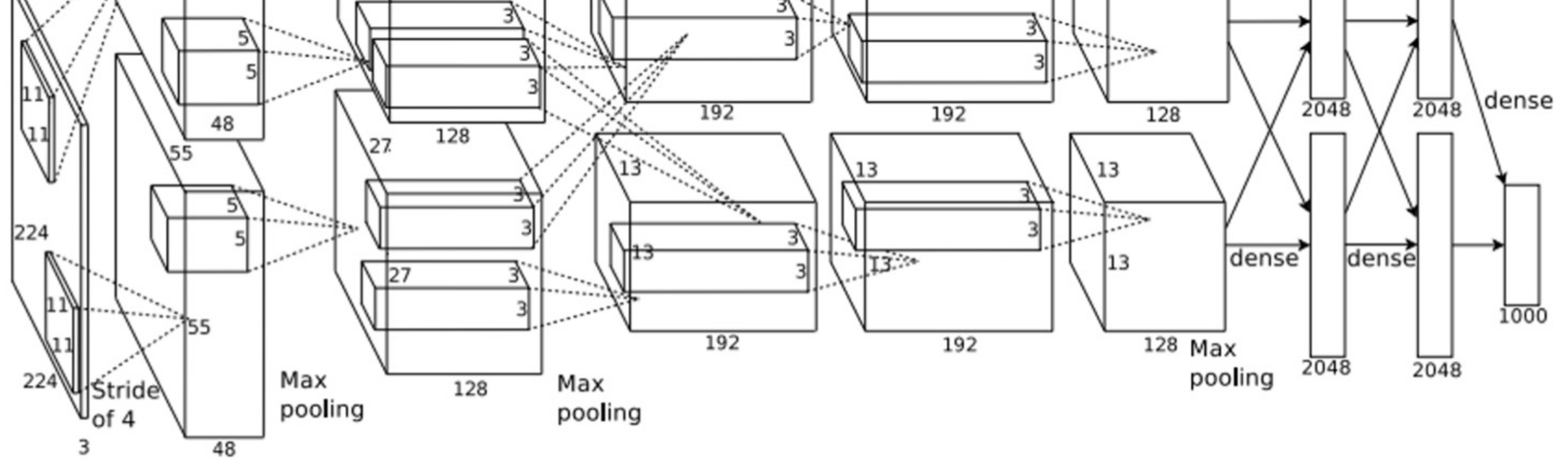
	Input size		Layer				Output size	
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W
Conv1	3	227	64	11	4	2	64	56

Recall: $W' = (W - K + 2P) / S + 1$

$= (227 - 11 + 2 \times 2) / 4 + 1$

$= 220 / 4 + 1 = 56$

AlexNet



	Input size		Layer				Output size		
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)
Conv1	3	227	64	11	4	2	64	56	784

Number of output elements = C x H' x W'

= 64 x 56 x 56 = 200,704

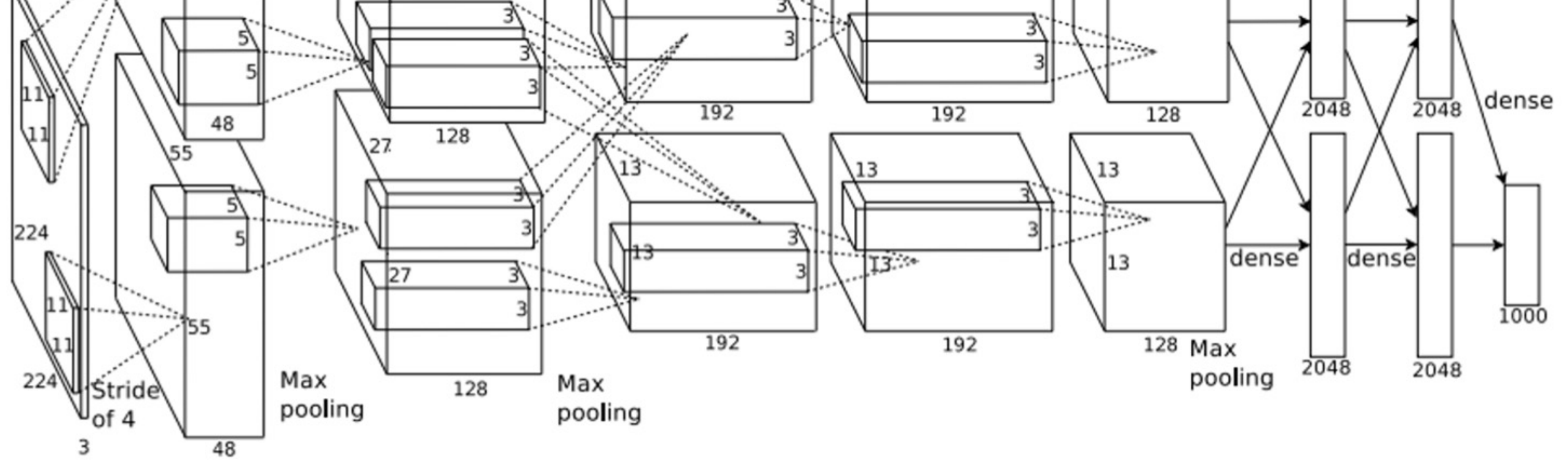
Bytes per element = 4 (for 32-bit floating point)

KB = (number of elements) x (bytes per elem) /1024

= 200704 x 4 / 1024

= **784**

AlexNet



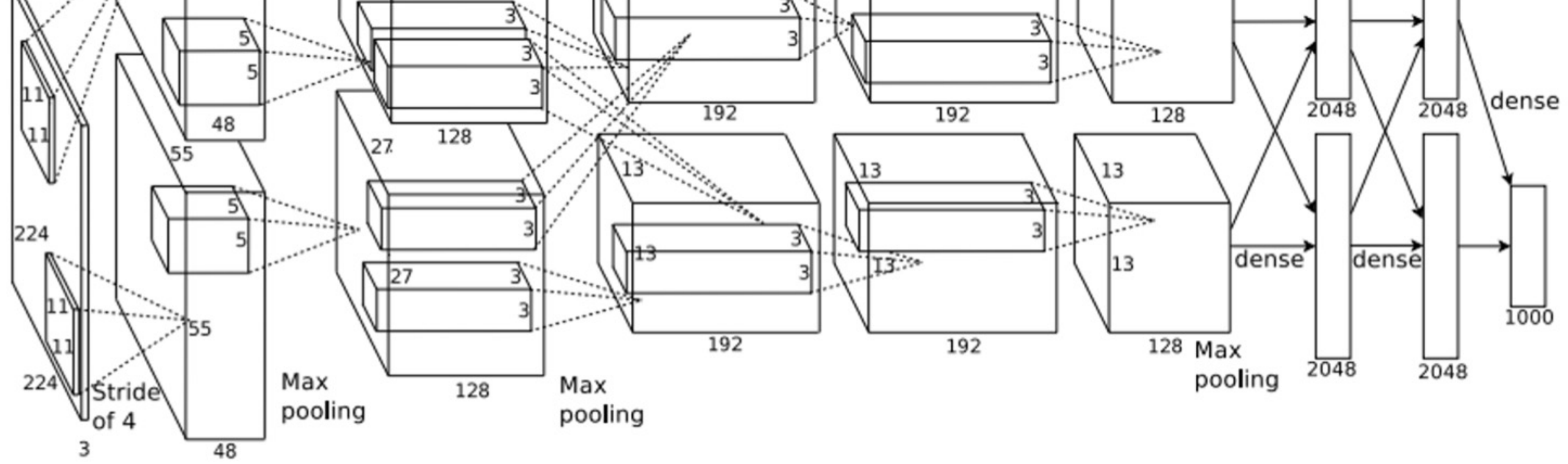
	Input size		Layer				Output size			
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)
Conv1	3	227	64	11	4	2	64	56	784	23

Weight shape = C_{out} x C_{in} x K x K
= 64 x 3 x 11 x 11

Bias shape = C_{out} = 64

Number of weights = 64 x 3 x 11 x 11 + 64
= **23,296**

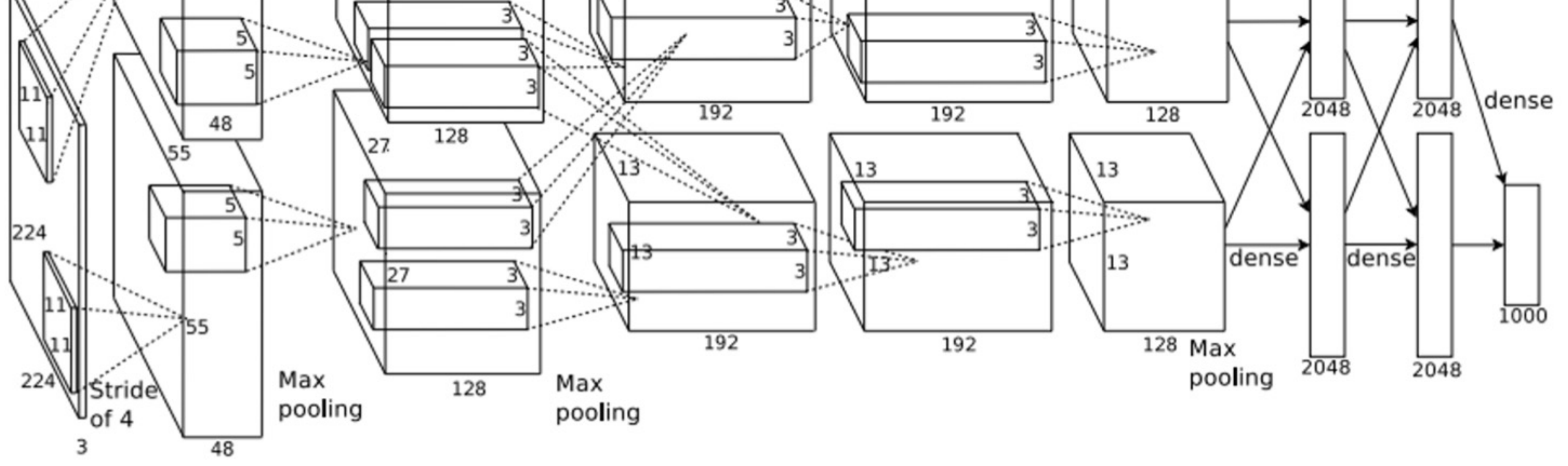
AlexNet



	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73

Number of floating point operations (multiply + add)
= (number of output elements) * (ops per output elem)
= (C_{out} x H' x W') * (C_{in} x K x K)
= (64 * 56 * 56) * (3 * 11 * 11)
= 200,704 * 363
= **72,855,552**

AlexNet



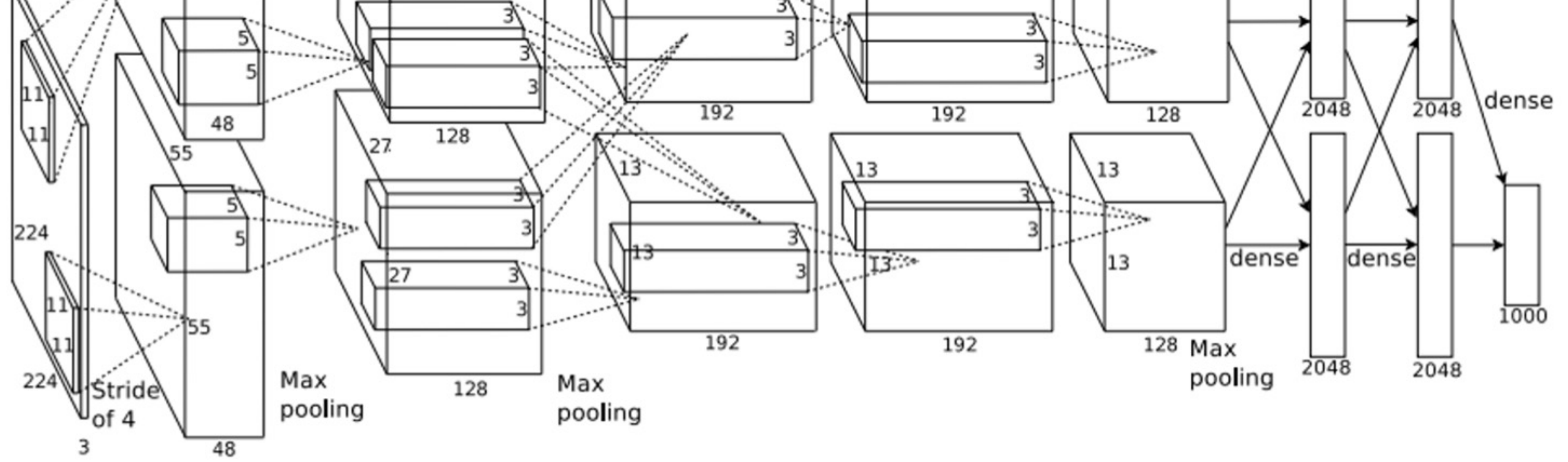
	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73
Pool1	64	56		3	2	0	64	27			

For pooling layer:

#output channels = #input channels = 64

W’ = floor((W-K)/S+1)
= floor(53/2 + 1) = floor(27.5) = **27**

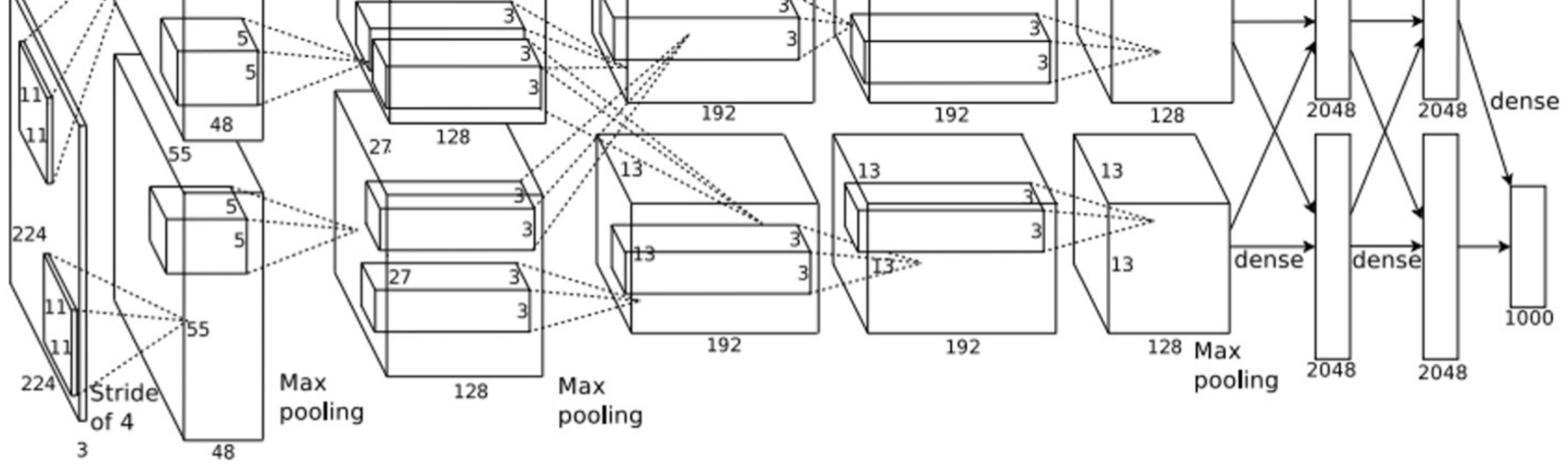
AlexNet



	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73
Pool1	64	56		3	2	0	64	27	182	?	

#output elms = C_{out} x H' x W'
Bytes per elem = 4
KB = C_{out} x H' x W' x 4 / 1024
= 64 * 27 * 27 * 4 / 1024
= **182.25**

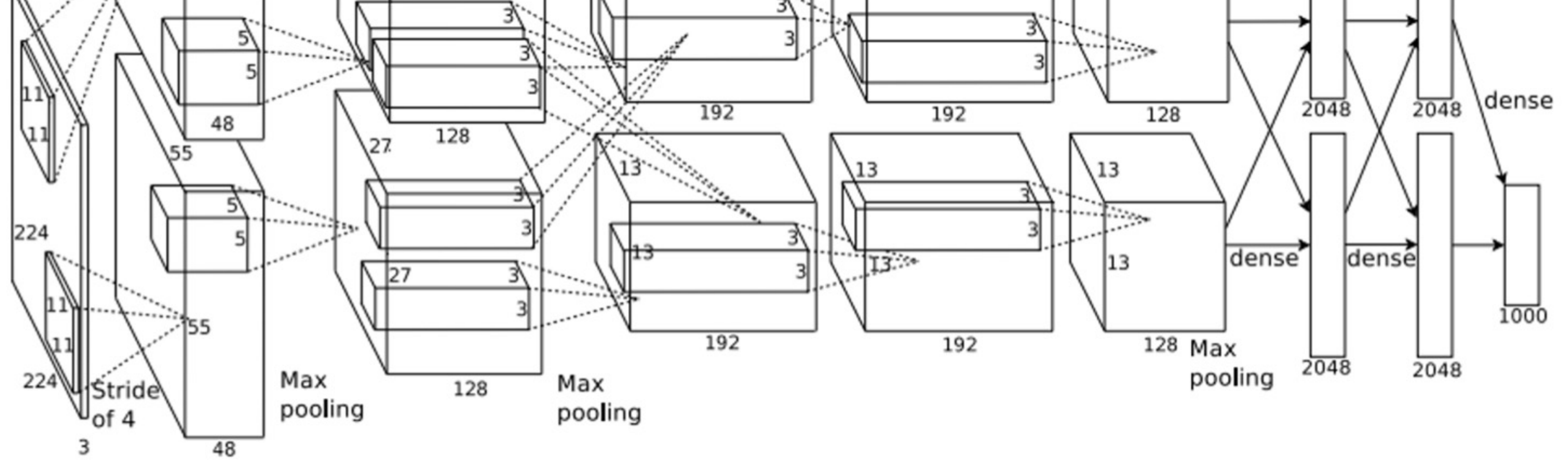
AlexNet



	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73
Pool1	64	56		3	2	0	64	27	182	0	0

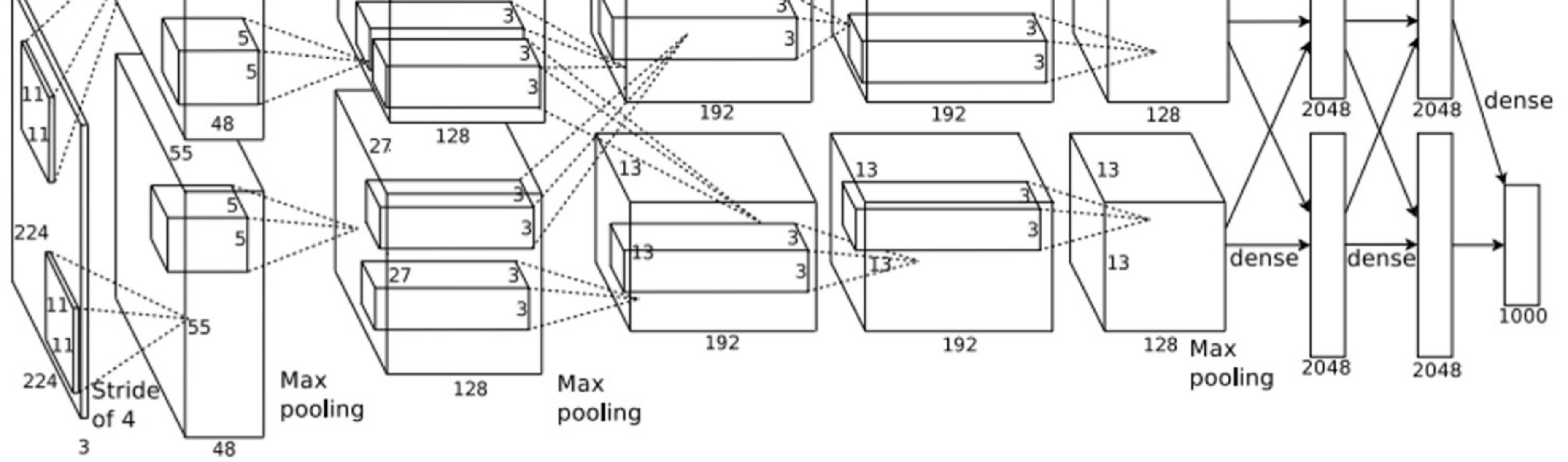
Pooling layers have no learnable parameters!

AlexNet



	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73
Pool1	64	56		3	2	0	64	27	182	0	0

Floating-point ops for pooling layer
= (numer of output positions) * (flops per output position)
= (C_{out} x H' x W') x (K x K)
= (64 * 27 * 27) * (3 * 3)
= 419,904
= **0.4 MFLOP**

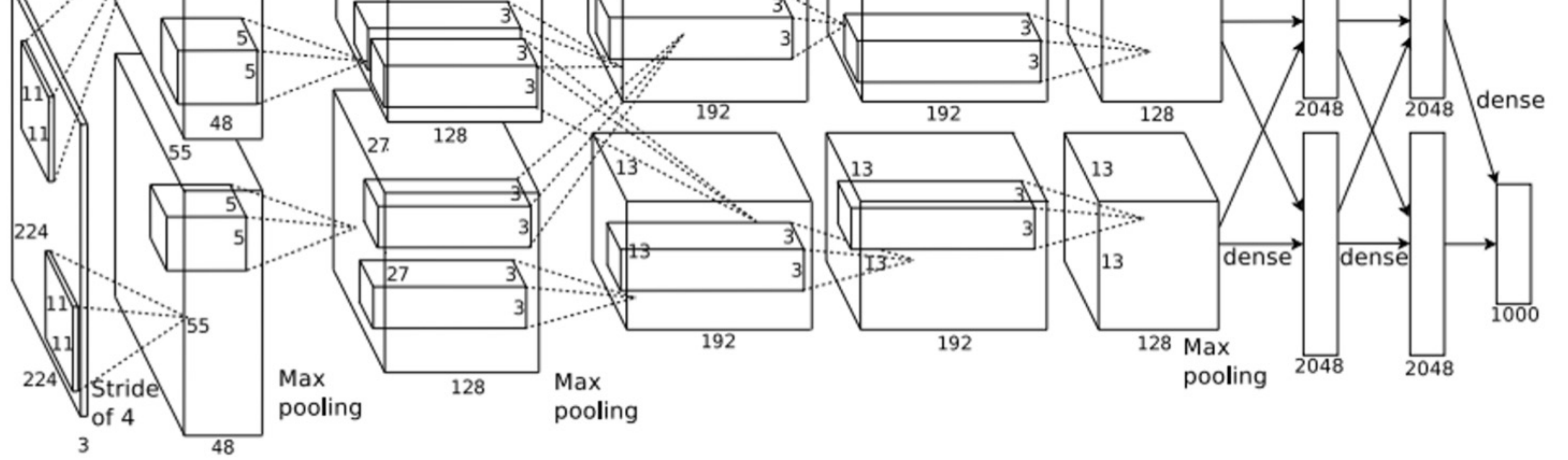


AlexNet

	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73
Pool1	64	56		3	2	0	64	27	182	0	0
Conv2	64	27	192	5	1	2	192	27	547	307	224
Pool2	192	27		3	2	0	192	13	127	0	0
Conv3	192	13	384	3	1	1	384	13	254	664	112
Conv4	384	13	256	3	1	1	256	13	169	885	145
Conv5	256	13	256	3	1	1	256	13	169	590	100
Pool5	256	13		3	2	0	256	6	36	0	0
Flatten	256	6					9216		36	0	0

Flatten output size = C_{in} x H x W
= 256 * 6 * 6
= **9216**

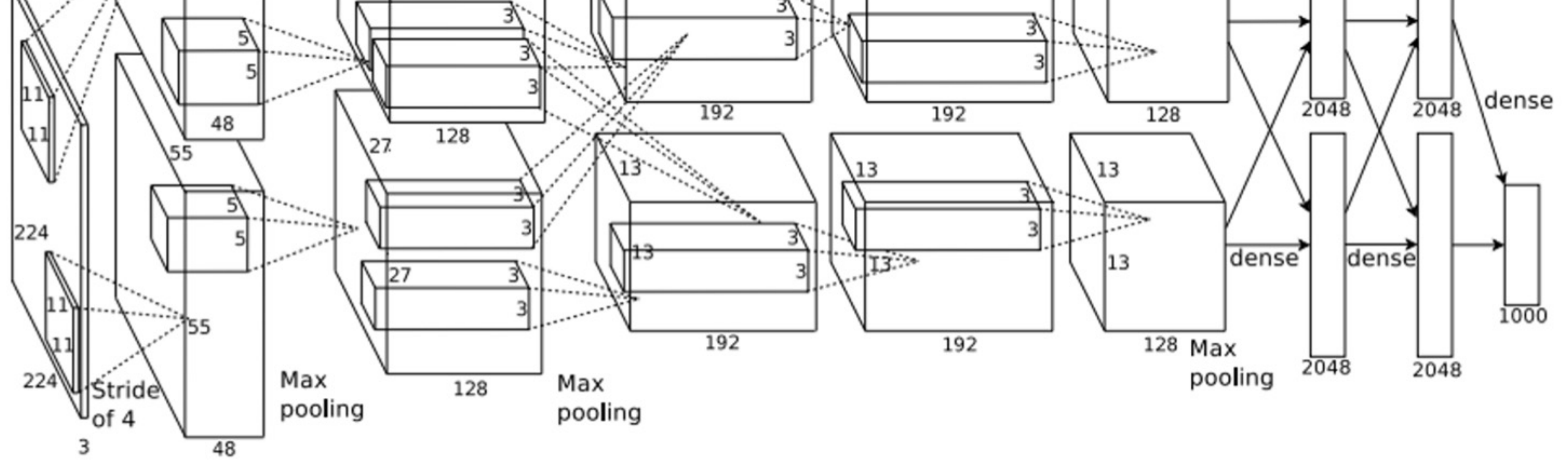
AlexNet



	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73
Pool1	64	56		3	2	0	64	27	182	0	0
Conv2	64	27	192	5	1	2	192	27	547	307	224
Pool2	192	27		3	2	0	192	13	127	0	0
Conv3	192	13	384	3	1	1	384	13	254	664	112
Conv4	384	13	256	3	1	1	256	13	169	885	145
Conv5	256	13	256	3	1	1	256	13	169	590	100
Pool5	256	13		3	2	0	256	6	36	0	0
Flatten	256	6					9216		36	0	0
FC6	9216		4096				4096		16	37749	38

$$\text{FC params} = C_{in} * C_{out} + C_{out} = 9216 * 4096 + 4096 = 37.725.832$$

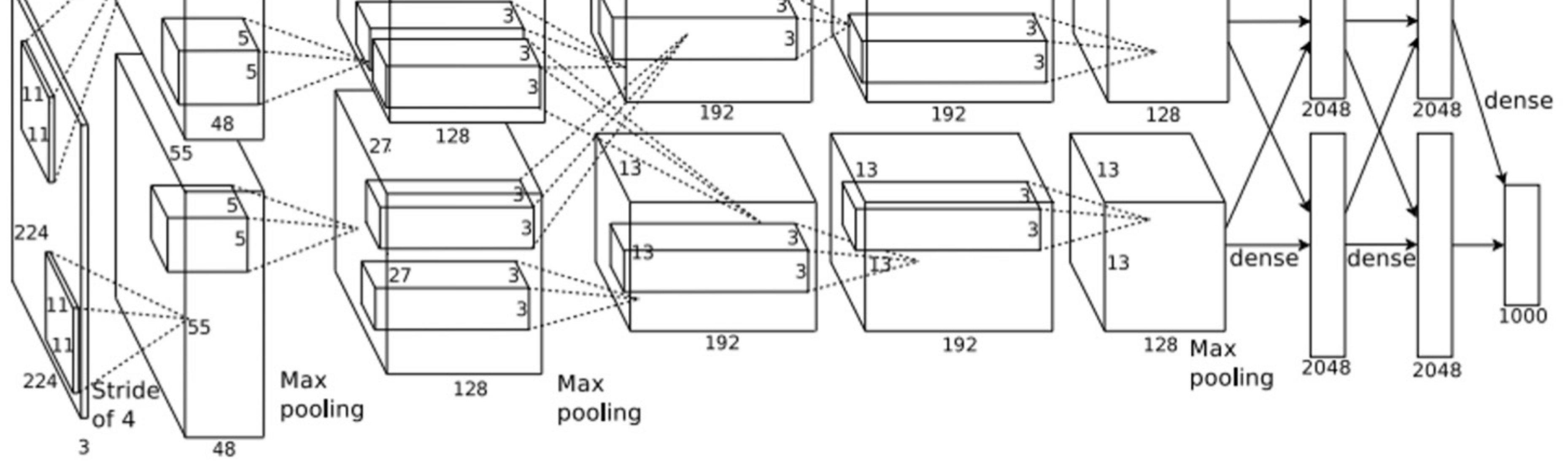
$$\text{FC flops} = C_{in} * C_{out} = 9216 * 4096 = 37.748.736$$



AlexNet

	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73
Pool1	64	56		3	2	0	64	27	182	0	0
Conv2	64	27	192	5	1	2	192	27	547	307	224
Pool2	192	27		3	2	0	192	13	127	0	0
Conv3	192	13	384	3	1	1	384	13	254	664	112
Conv4	384	13	256	3	1	1	256	13	169	885	145
Conv5	256	13	256	3	1	1	256	13	169	590	100
Pool5	256	13		3	2	0	256	6	36	0	0
Flatten	256	6					9216		36	0	0
FC6	9216		4096				4096		16	37749	38
FC7	4096		4096				4096		16	16777	17
FC8	4096		1000				1000		4	4096	4

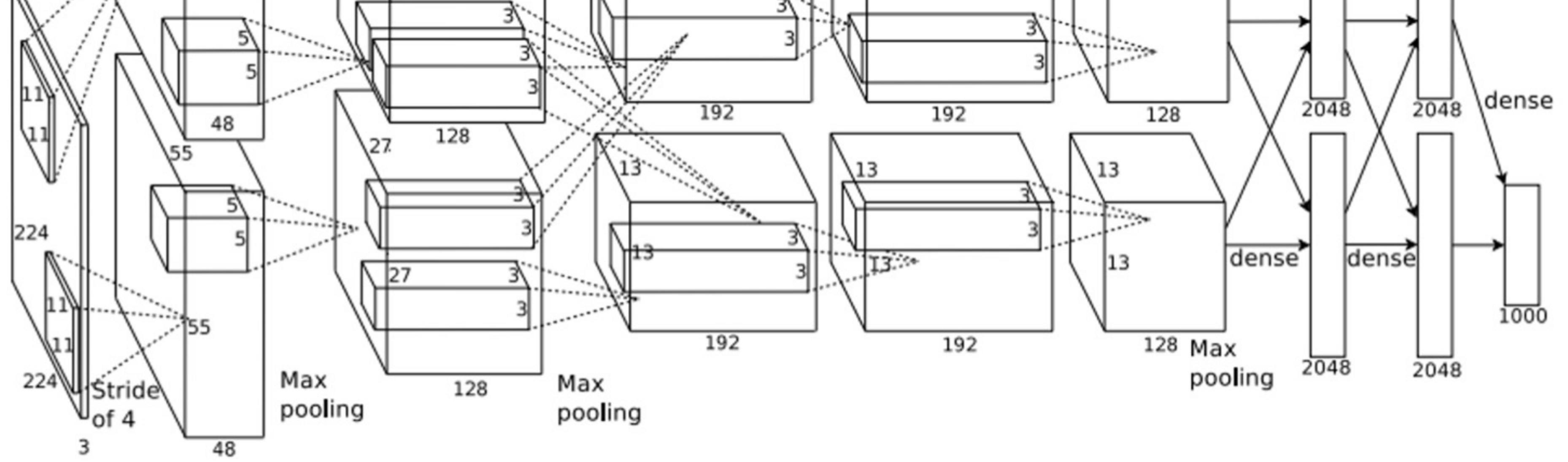
AlexNet



How to choose this? Trial and error :(

	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73
Pool1	64	56		3	2	0	64	27	182	0	0
Conv2	64	27	192	5	1	2	192	27	547	307	224
Pool2	192	27		3	2	0	192	13	127	0	0
Conv3	192	13	384	3	1	1	384	13	254	664	112
Conv4	384	13	256	3	1	1	256	13	169	885	145
Conv5	256	13	256	3	1	1	256	13	169	590	100
Pool5	256	13		3	2	0	256	6	36	0	0
Flatten	256	6					9216		36	0	0
FC6	9216		4096				4096		16	37749	38
FC7	4096		4096				4096		16	16777	17
FC8	4096		1000				1000		4	4096	4

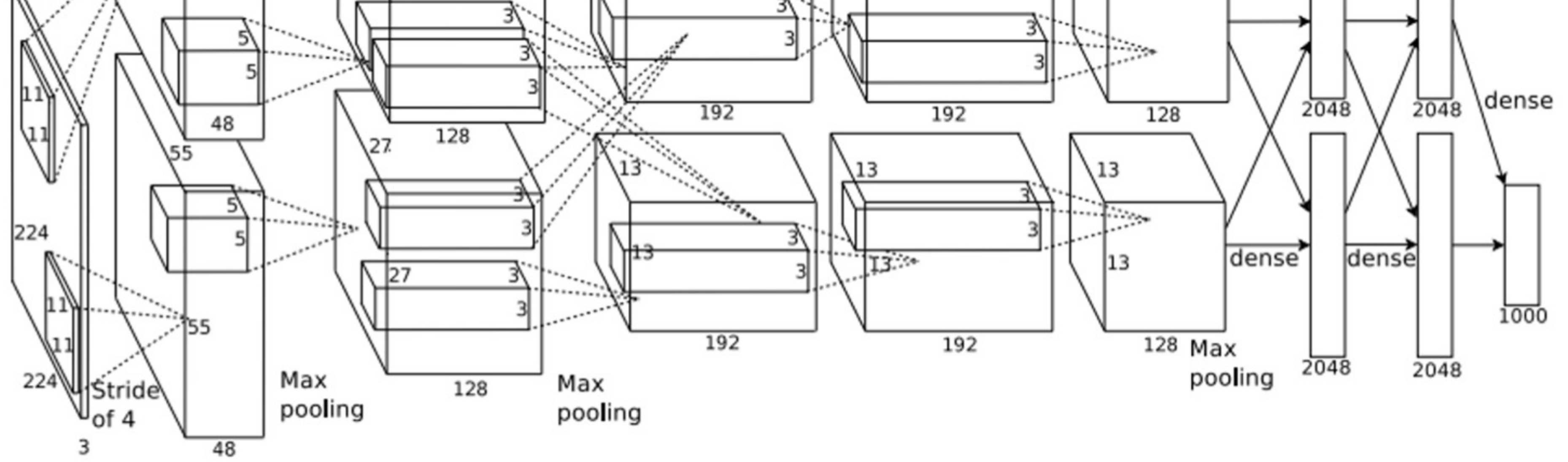
AlexNet



	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73
Pool1	64	56		3	2	0	64	27	182	0	0
Conv2	64	27	192	5	1	2	192	27	547	307	224
Pool2	192	27		3	2	0	192	13	127	0	0
Conv3	192	13	384	3	1	1	384	13	254	664	112
Conv4	384	13	256	3	1	1	256	13	169	885	145
Conv5	256	13	256	3	1	1	256	13	169	590	100
Pool5	256	13		3	2	0	256	6	36	0	0
Flatten	256	6					9216		36	0	0
FC6	9216		4096				4096		16	37749	38
FC7	4096		4096				4096		16	16777	17
FC8	4096		1000				1000		4	4096	4

Interesting trends here!

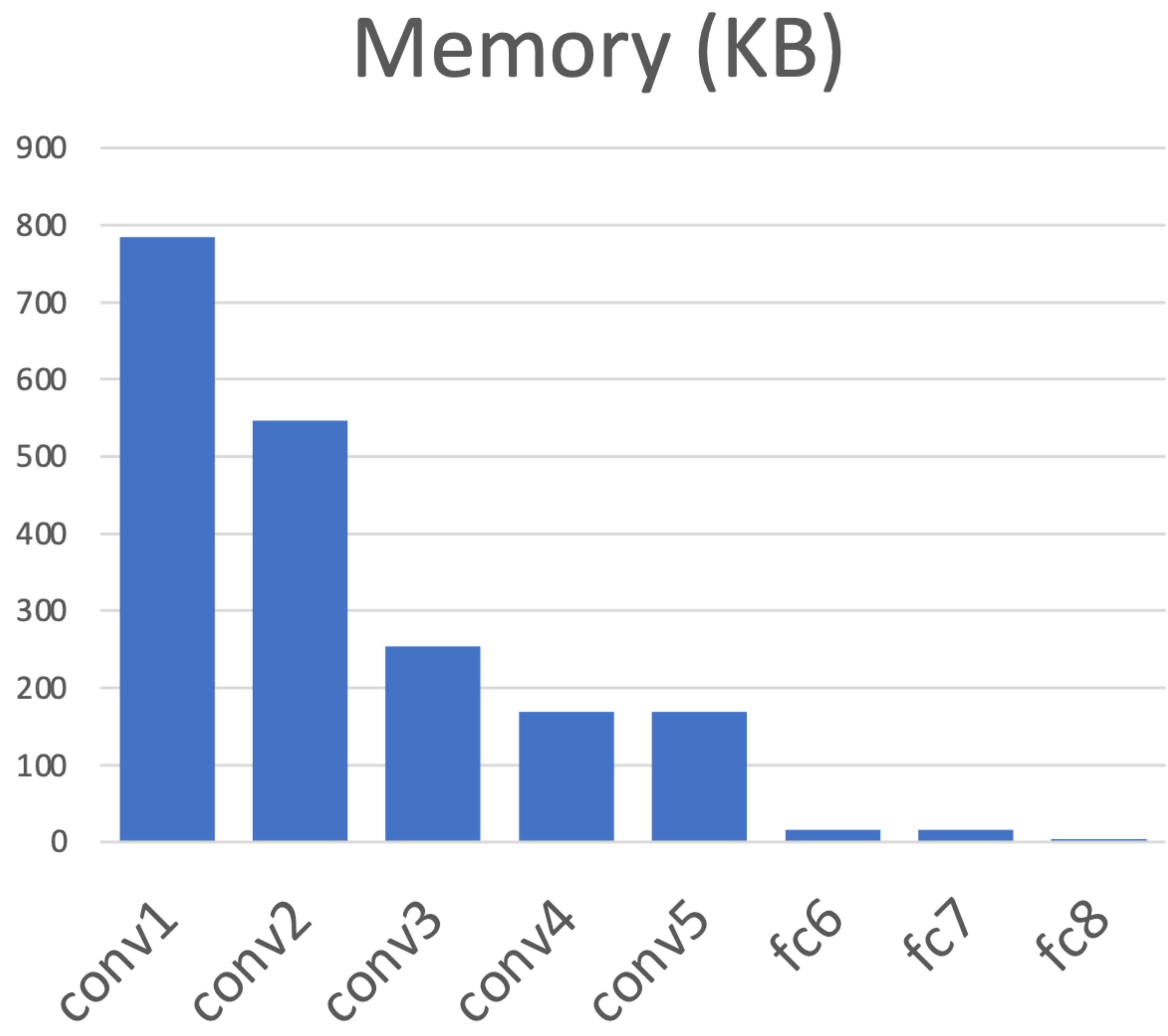
AlexNet

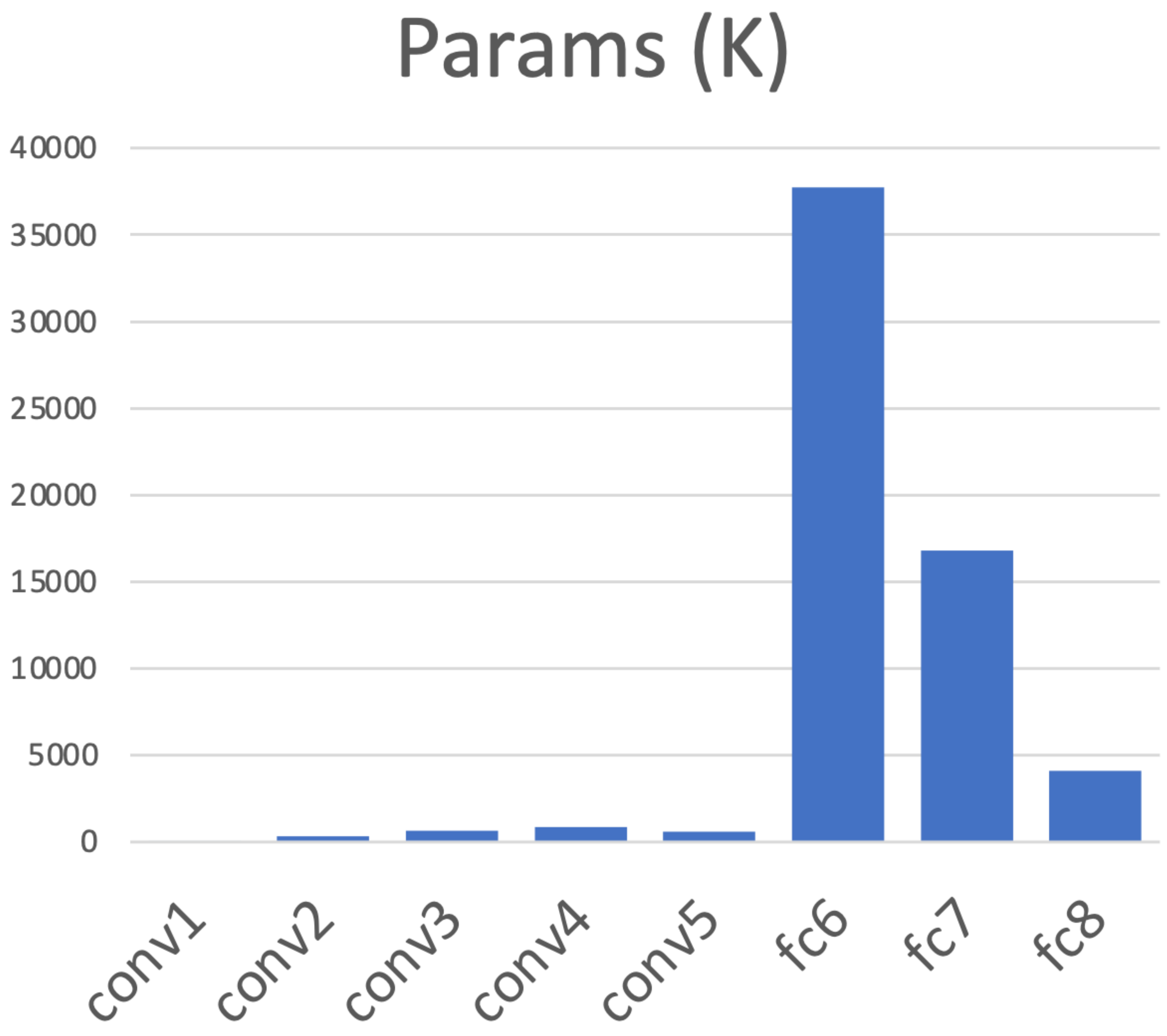


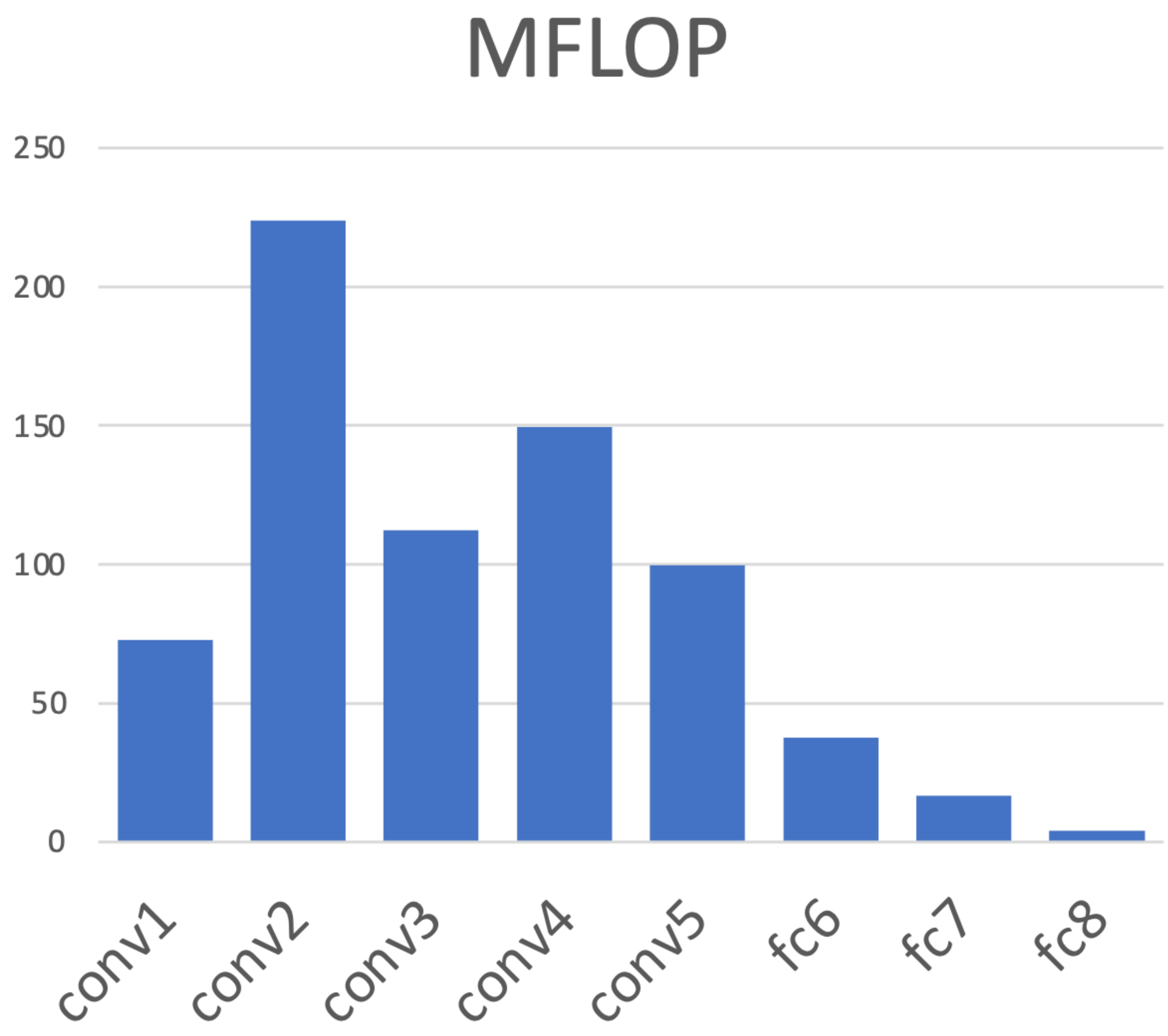
Most of the **memory usage** in the early convolution layers

Nearly all **parameters** are in the fully-connected layers

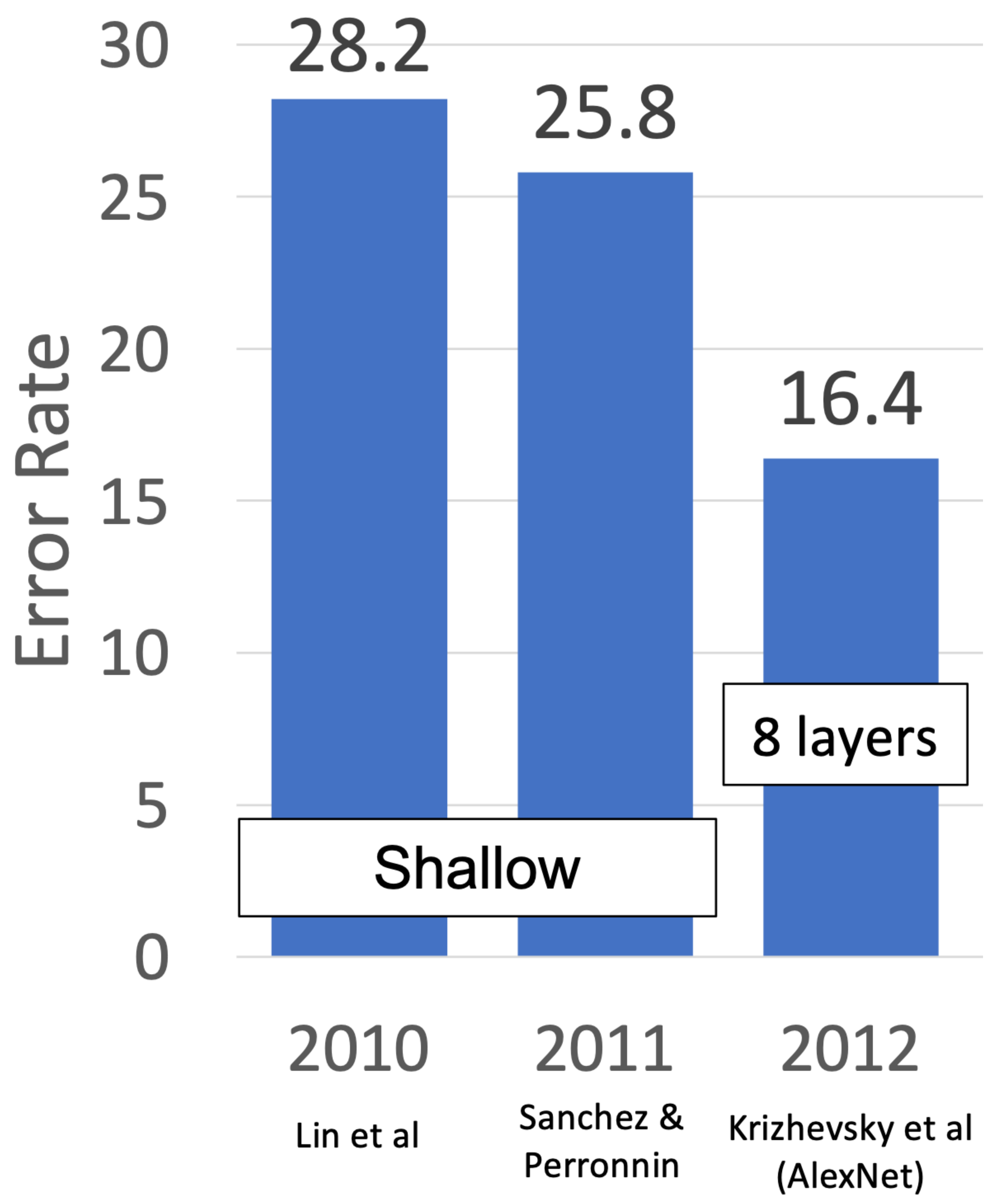
Most **floating-point ops** occur in the convolution layers



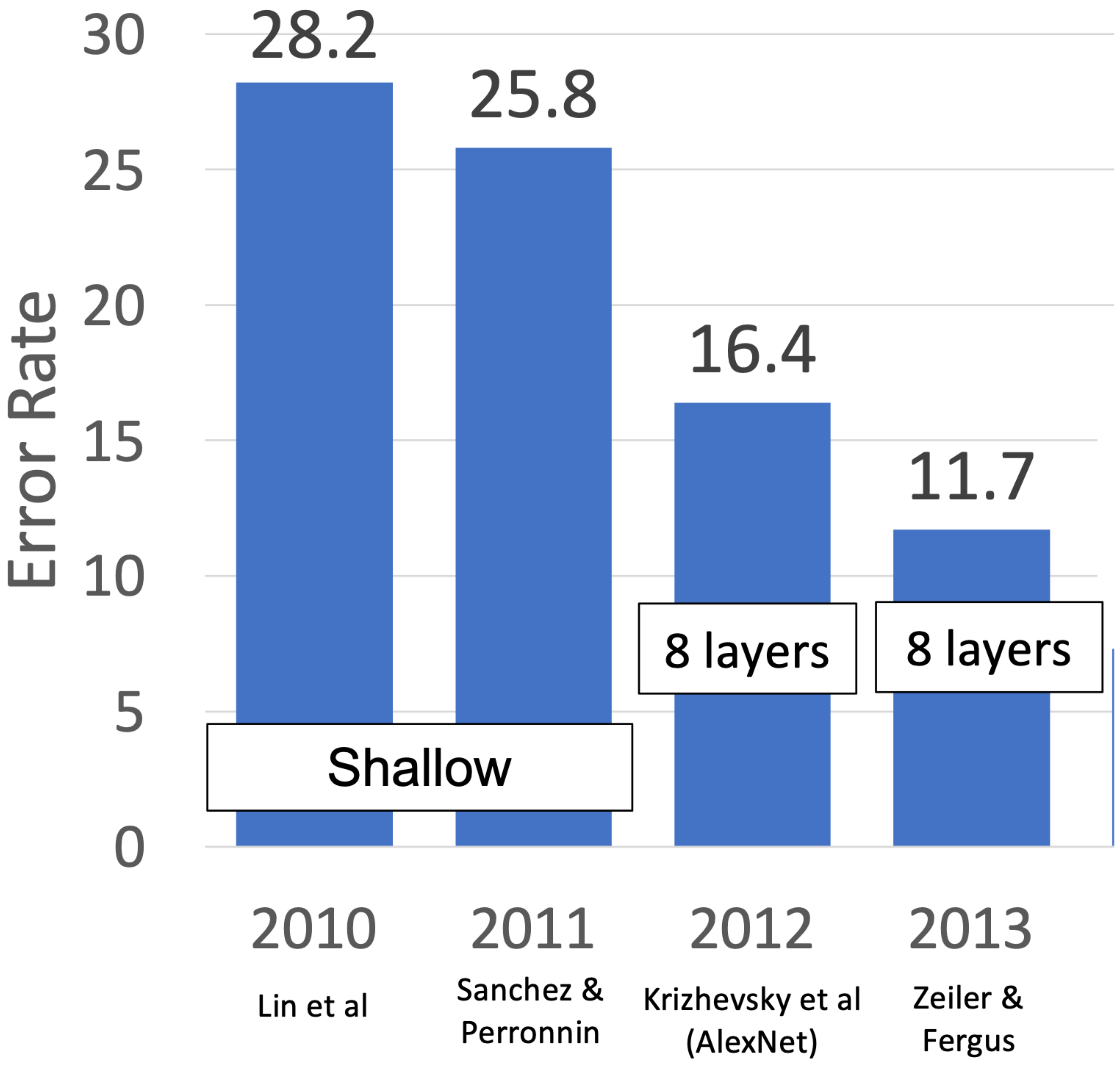




ImageNet Classification Challenge

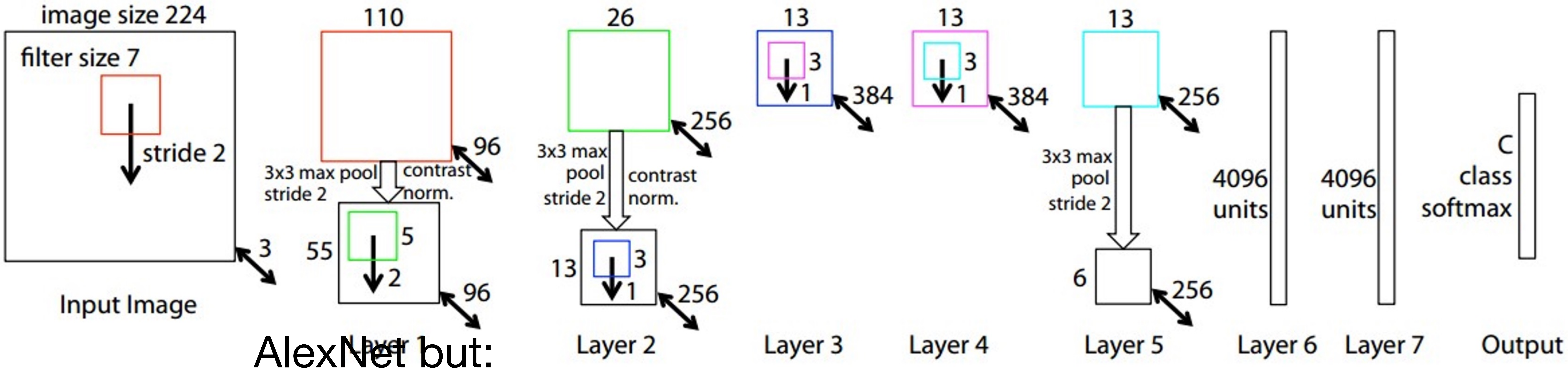


ImageNet Classification Challenge



ZFNet: A Bigger AlexNet

ImageNet top 5 error: 16.4% -> 11.7%



AlexNet but:

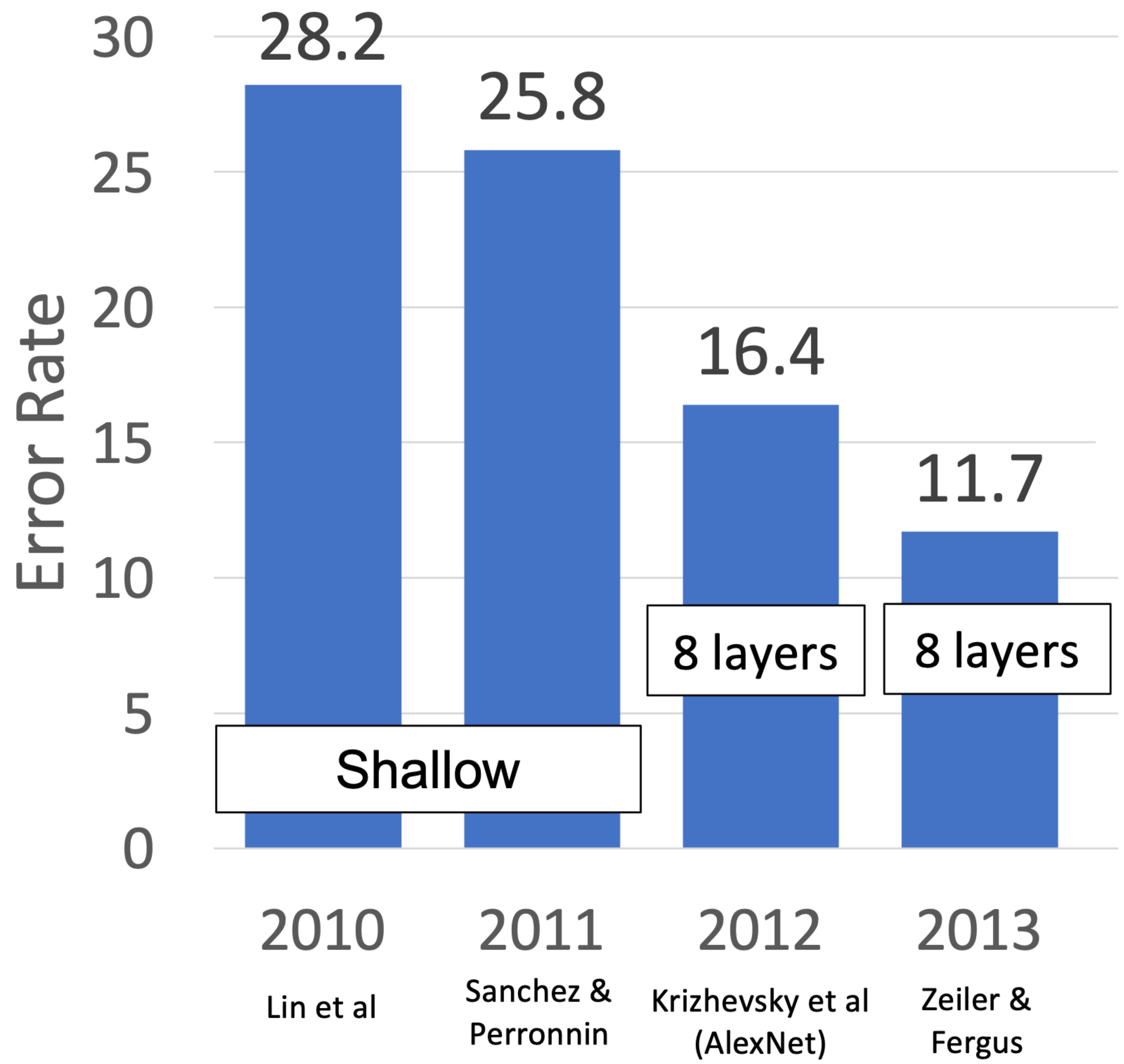
Conv1: change from (11x11 stride 4) to (7x7 stride 2)

Conv3,4,5: instead of 384, 384, 256 filters use 512, 1024, 512

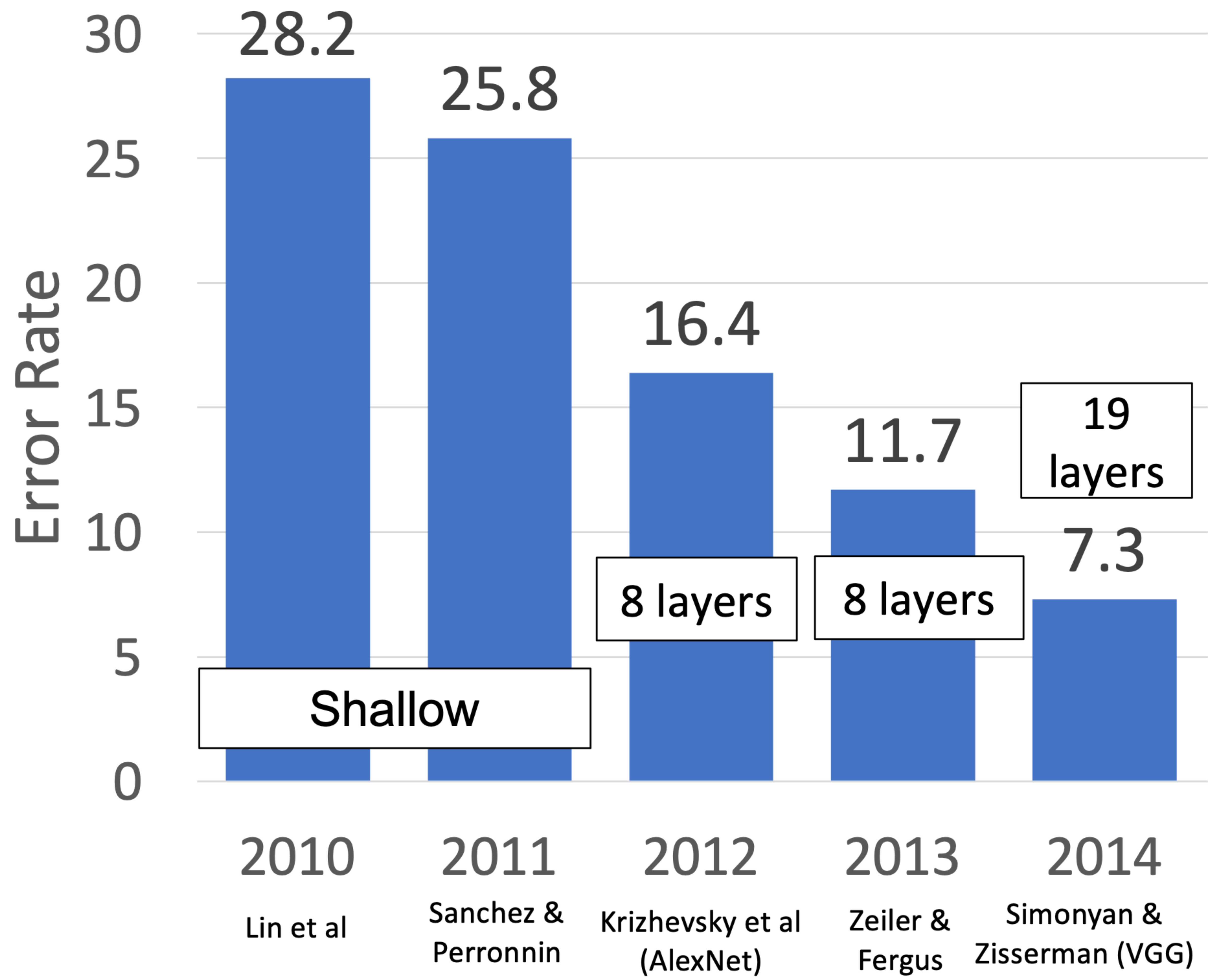
More trial and error :(

Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014

ImageNet Classification Challenge



ImageNet Classification Challenge



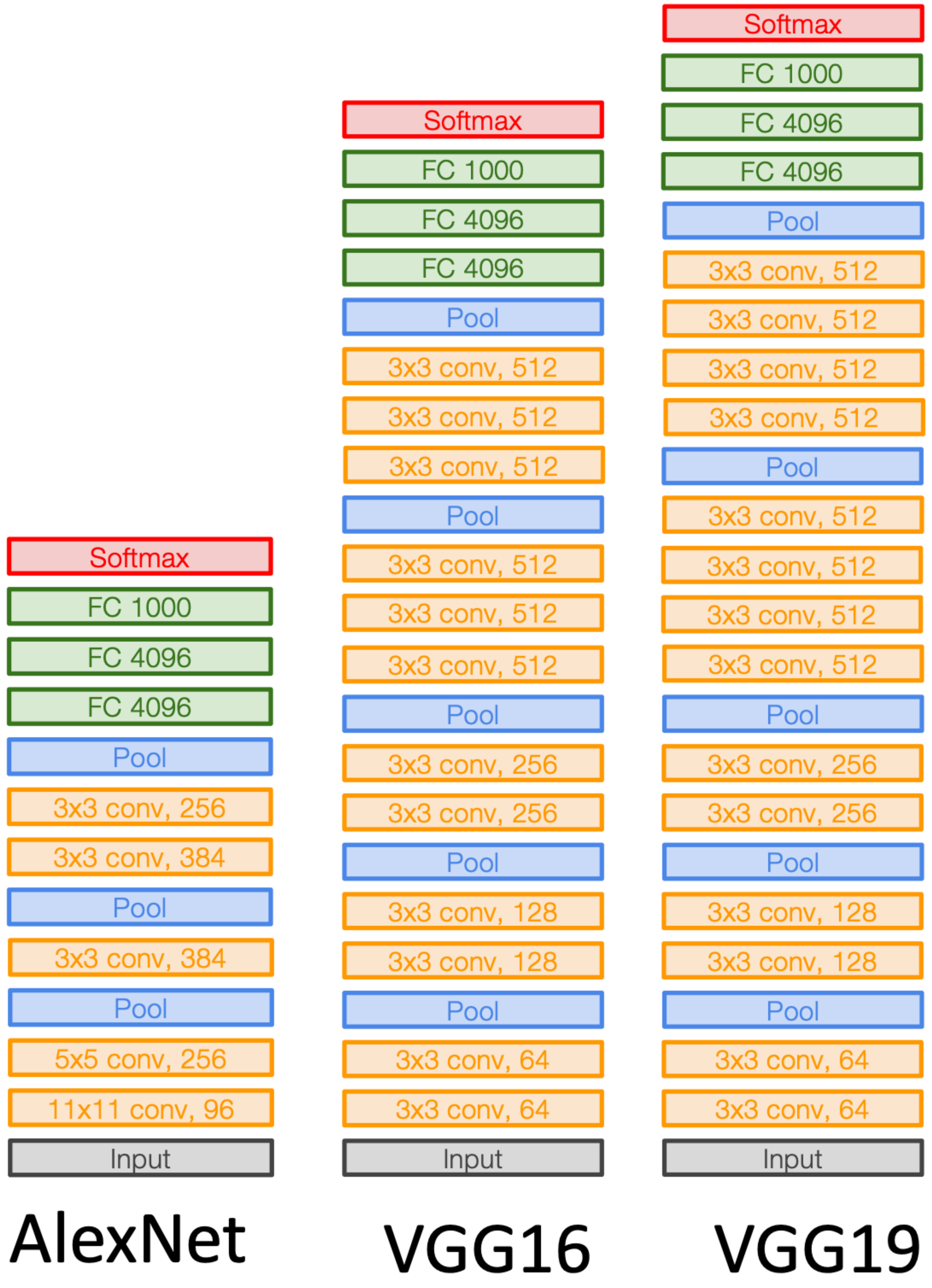
VGG: Deeper Networks, Regular Design

VGG Design rules:

All conv are 3x3 stride 1 pad 1

All max pool are 2x2 stride 2

After pool, double #channels



Simonyan and Zissermann, “Very Deep Convolutional Networks for Large-Scale Image Recognition”, ICLR 2015

VGG: Deeper Networks, Regular Design

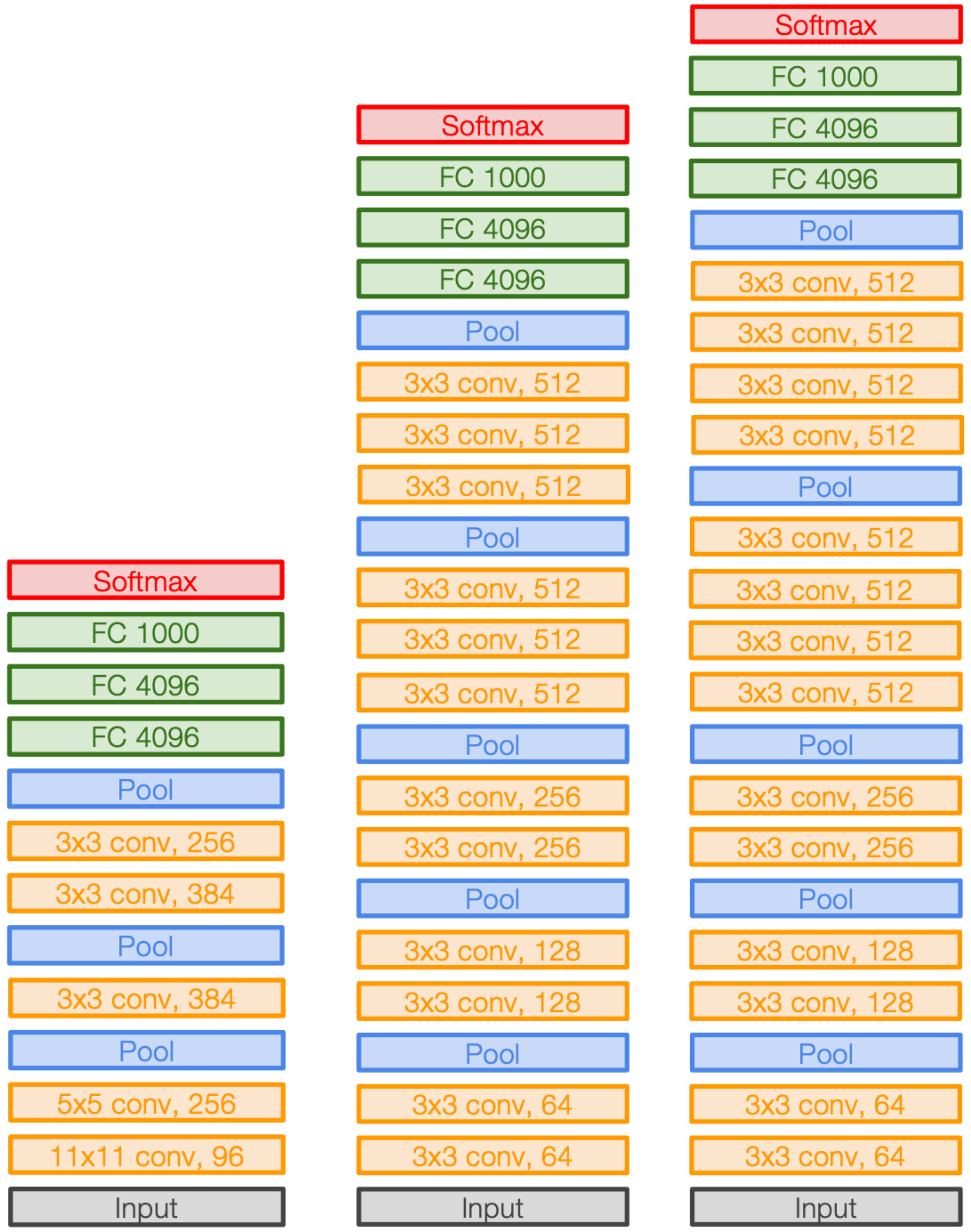
VGG Design rules:

All conv are 3x3 stride 1 pad 1

All max pool are 2x2 stride 2

After pool, double #channels

Network has 5 convolution **stages**:
Stage 1: conv-conv-pool
Stage 2: conv-conv-pool
Stage 3: conv-conv-pool
Stage 4: conv-conv-conv-[conv]-pool
Stage 5: conv-conv-conv-[conv]-pool



AlexNet VGG16 VGG19

Simonyan and Zissermann, “Very Deep Convolutional Networks for La

VGG: Deeper Networks, Regular Design

VGG Design rules:

All conv are 3x3 stride 1 pad 1

All max pool are 2x2 stride 2

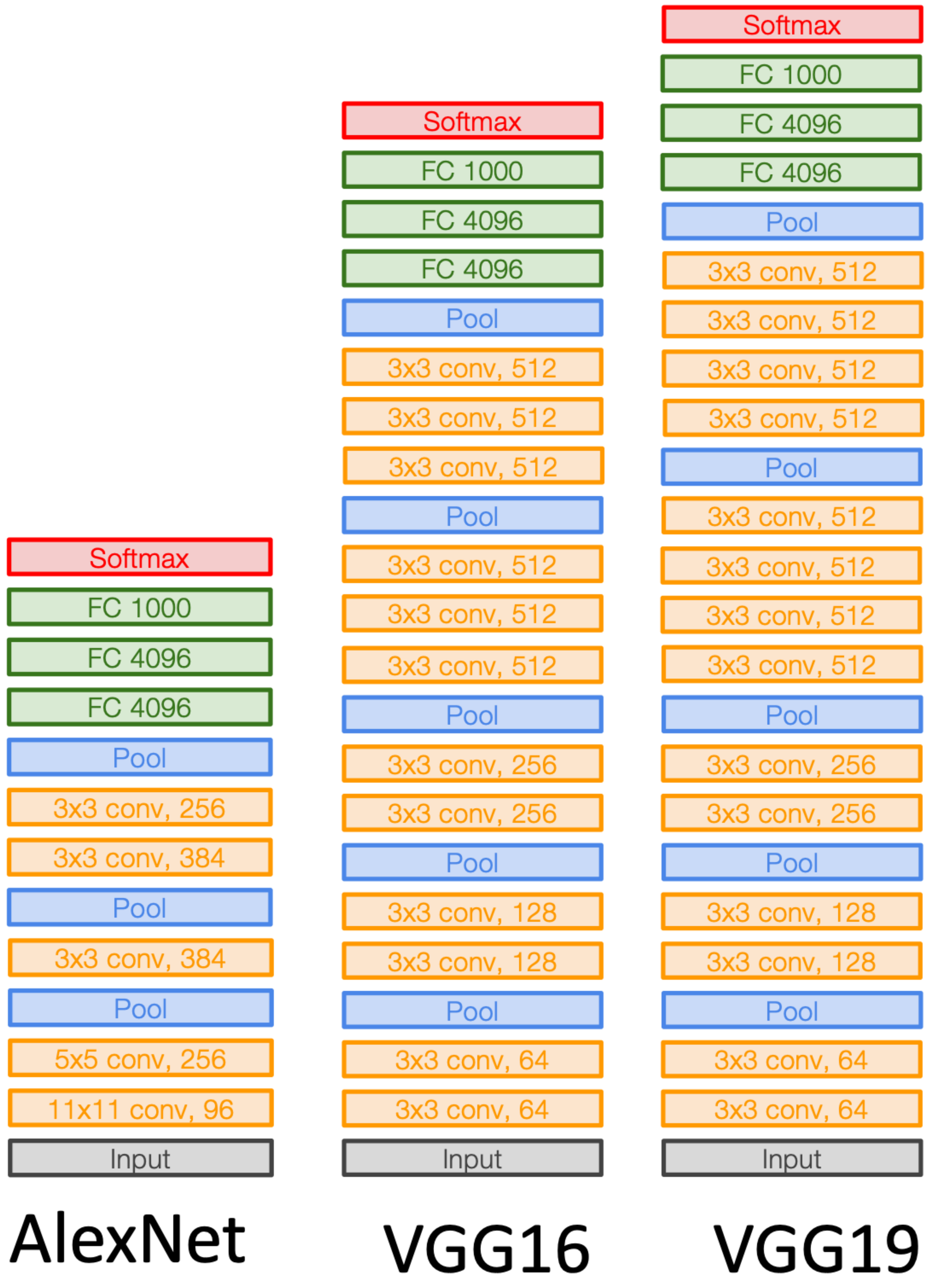
After pool, double #channels

Option 1:

Conv(5x5, C->C)

Params: $25C^2$

FLOPs: $25C^2HW$



Simonyan and Zissermann, “Very Deep Convolutional Networks for La

VGG: Deeper Networks, Regular Design

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<u>Option 1:</u>

Conv(5x5, C->C)

Params: $25C^2$

FLOPs: $25C^2HW$

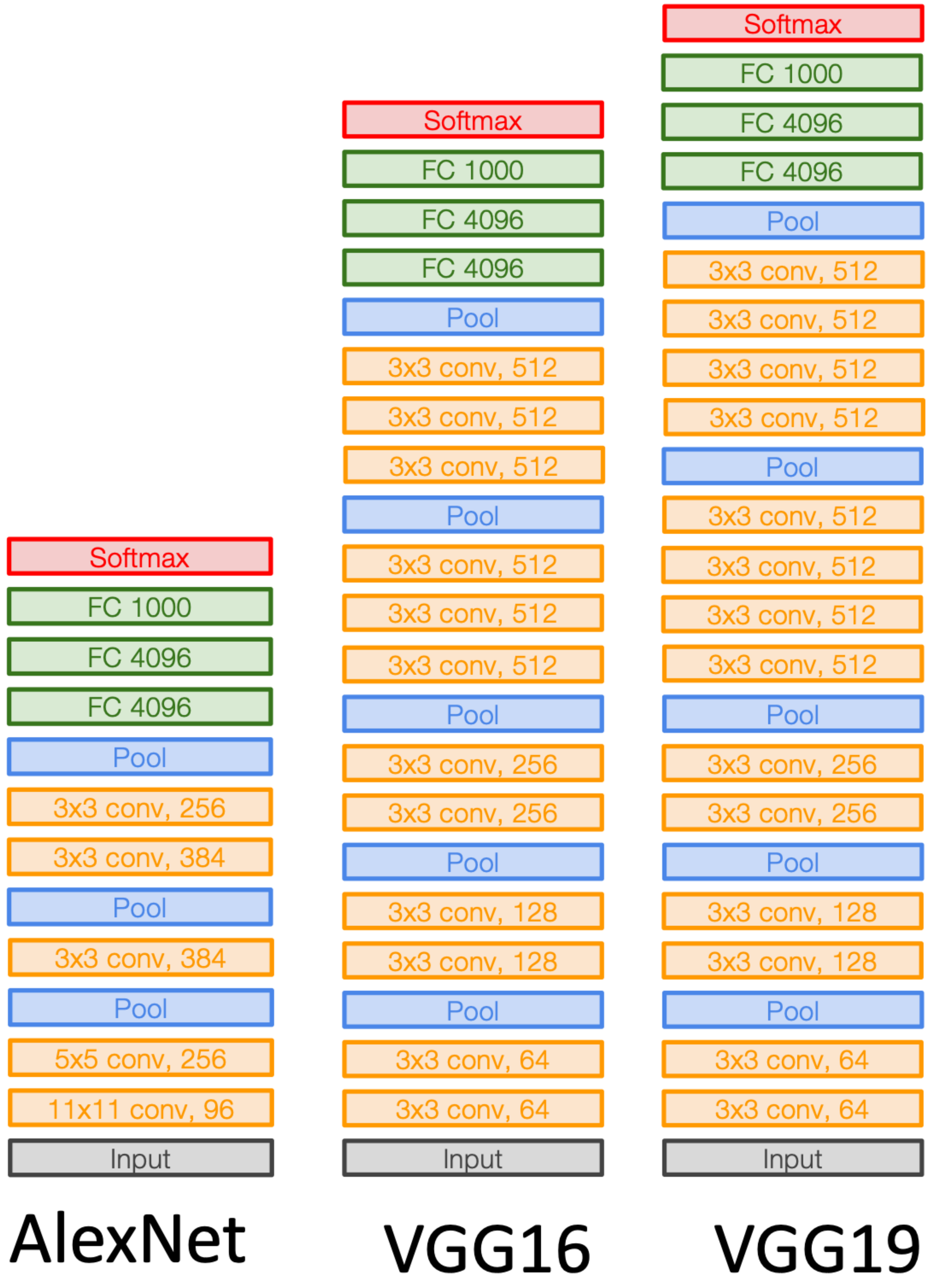
<u>Option 2:</u>

Conv(3x3, C->C)

Conv(3x3, C->C)

Params: $18C^2$

FLOPs: $18C^2HW$



VGG: Deeper Networks, Regular Design

VGG Design rules:

All conv are 3x3 stride 1 pad 1

All max pool are 2x2 stride 2

After pool, double #channels

Two 3x3 conv has same receptive field as a single 5x5 conv, but has fewer parameters and takes less computation!

Option 1:

Conv(5x5, C->C)

Params: $25C^2$

FLOPs: $25C^2HW$

Option 2:

Conv(3x3, C->C)

Conv(3x3, C->C)

Params: $18C^2$

FLOPs: $18C^2HW$

VGG: Deeper Networks, Regular Design

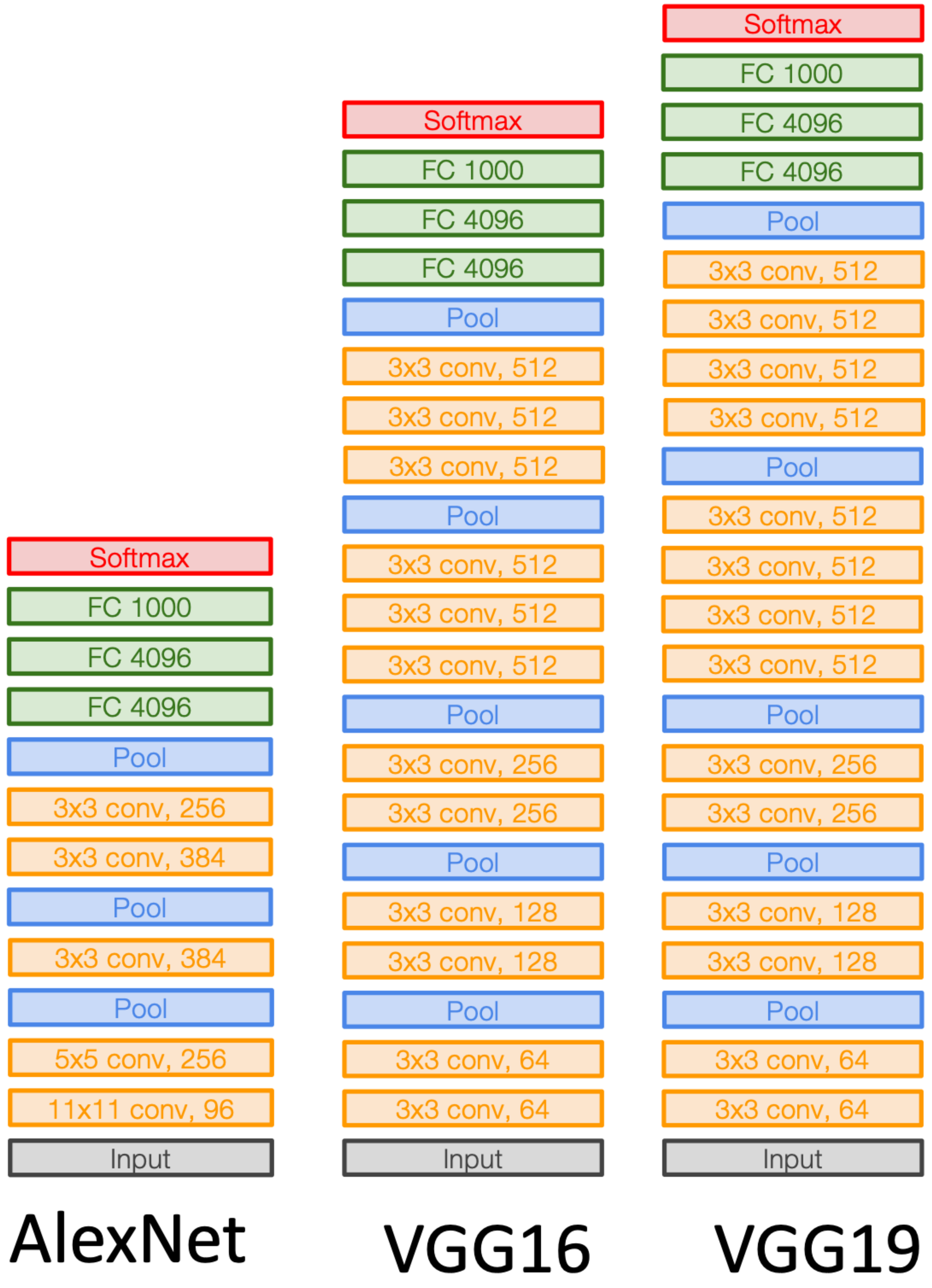
VGG Design rules:

All conv are 3x3 stride 1 pad 1

All max pool are 2x2 stride 2

After pool, double #channels

Option 1:
Input: C x 2H x 2W
Layer: Conv(3x3, C->C)
Memory: 4HWC
Params: $9C^2$
FLOPs: $36HWC^2$



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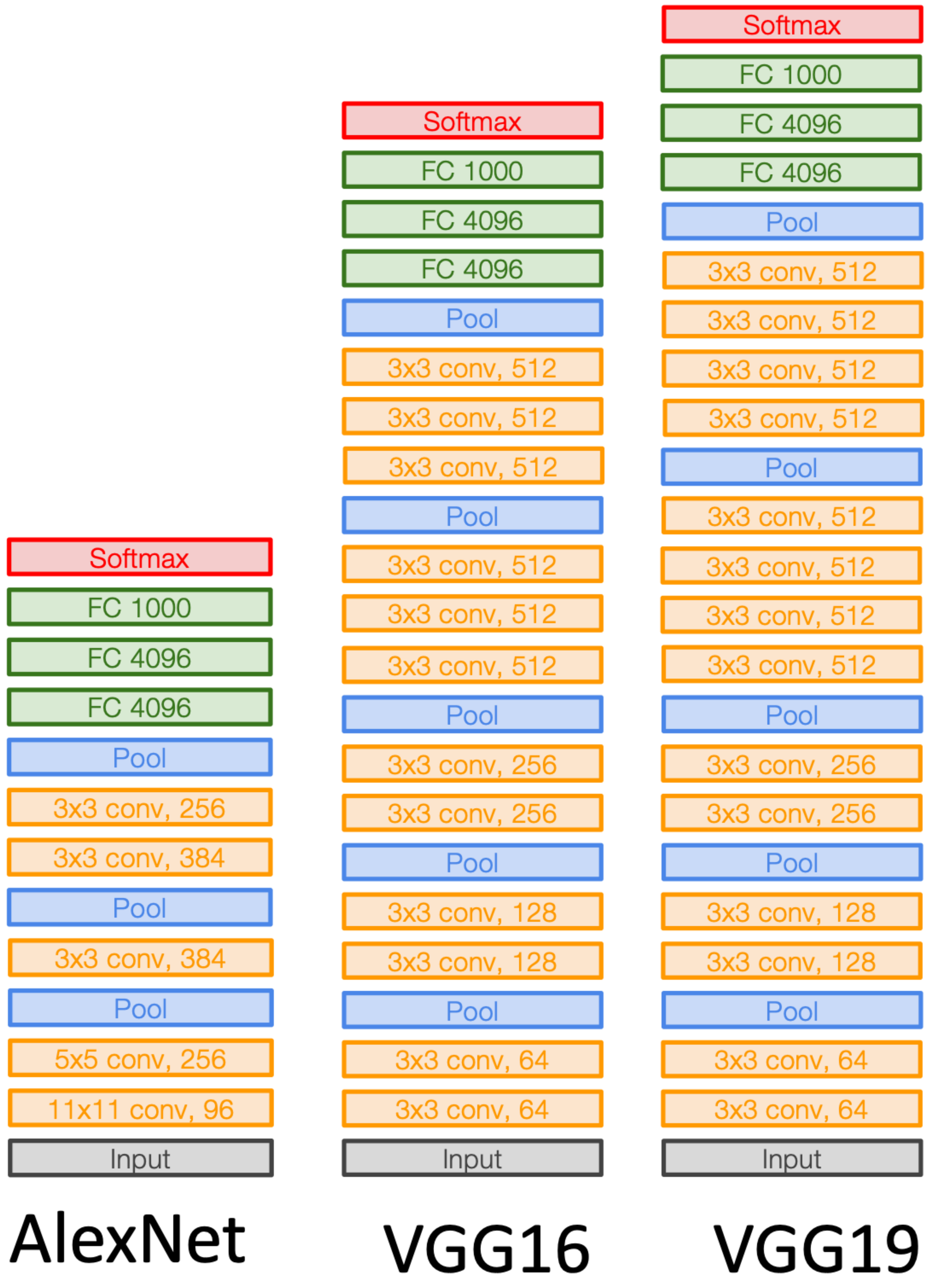
Layer: Conv(3x3, C->C)
Memory: 4HWC
Params: $9C^2$
FLOPs: $36HWC^2$

Option 2:
Input: 2C x H x W
Layer: Conv(3x3, 2C->2C)

Memory: 2HWC
Params: $36C^2$
FLOPs: $36HWC^2$



VGG: Deeper Networks, Regular Design

VGG Design rules:

All conv are 3x3 stride 1 pad 1

All max pool are 2x2 stride 2

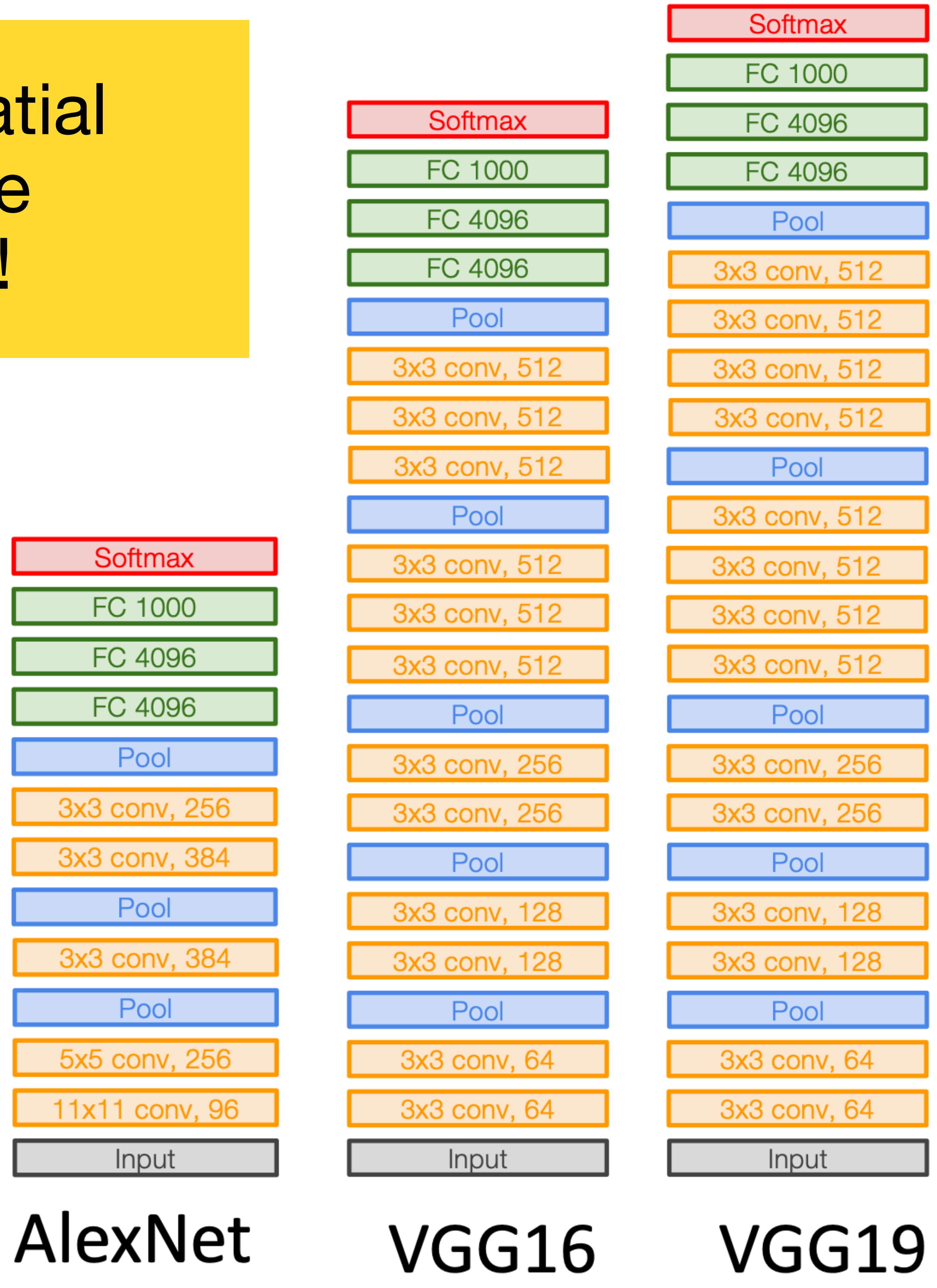
After pool, double #channels

Conv layers at each spatial resolution take the same amount of computation!

Option 1:
Input: C x 2H x 2W
Layer: Conv(3x3, C->C)
Memory: 4HWC
Params: $9C^2$
FLOPs: $36HWC^2$

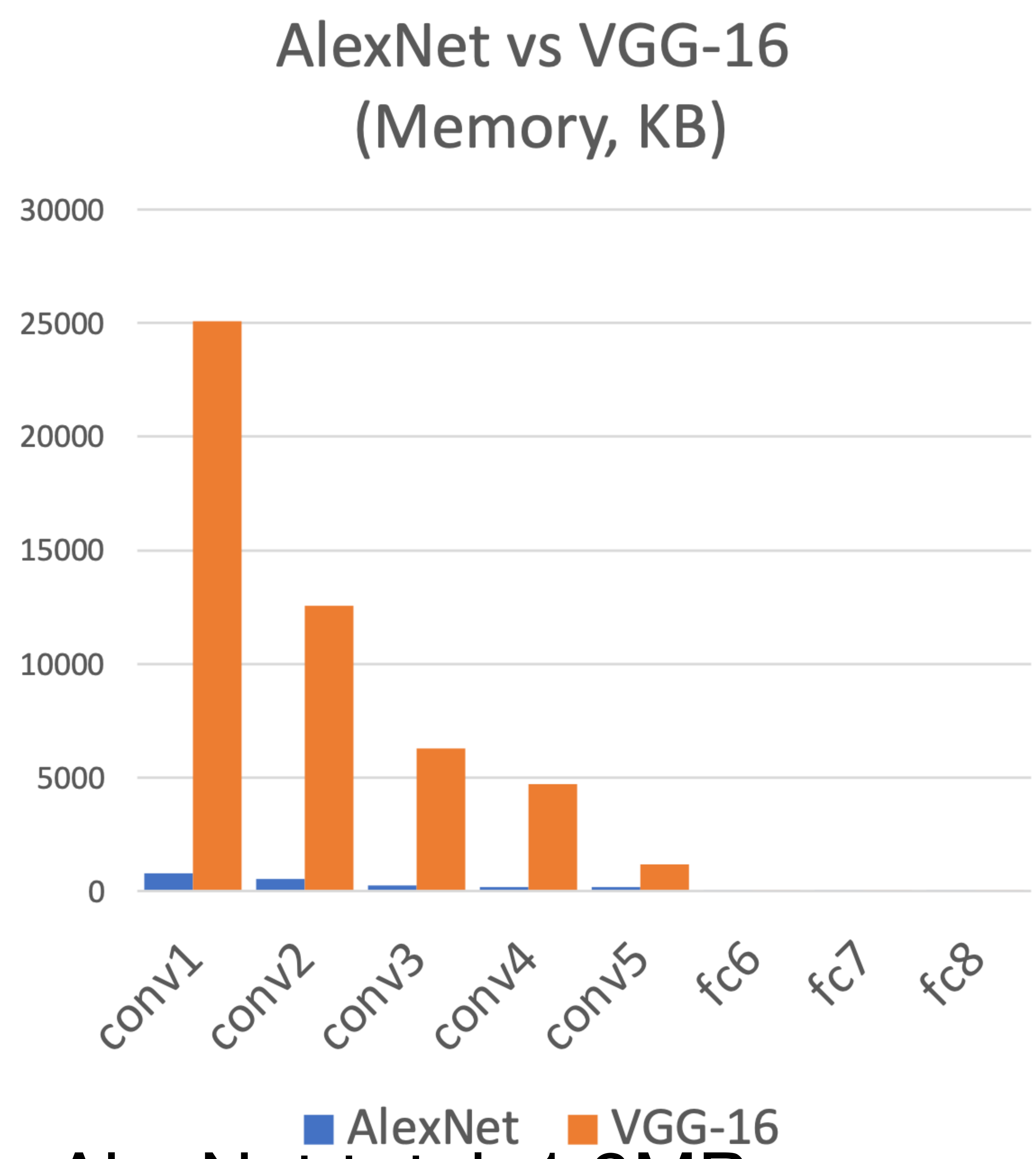
Option 2:
Input: 2C x H x W
Layer: Conv(3x3, 2C->2C)

Memory: 2HWC
Params: $36C^2$
FLOPs: $36HWC^2$



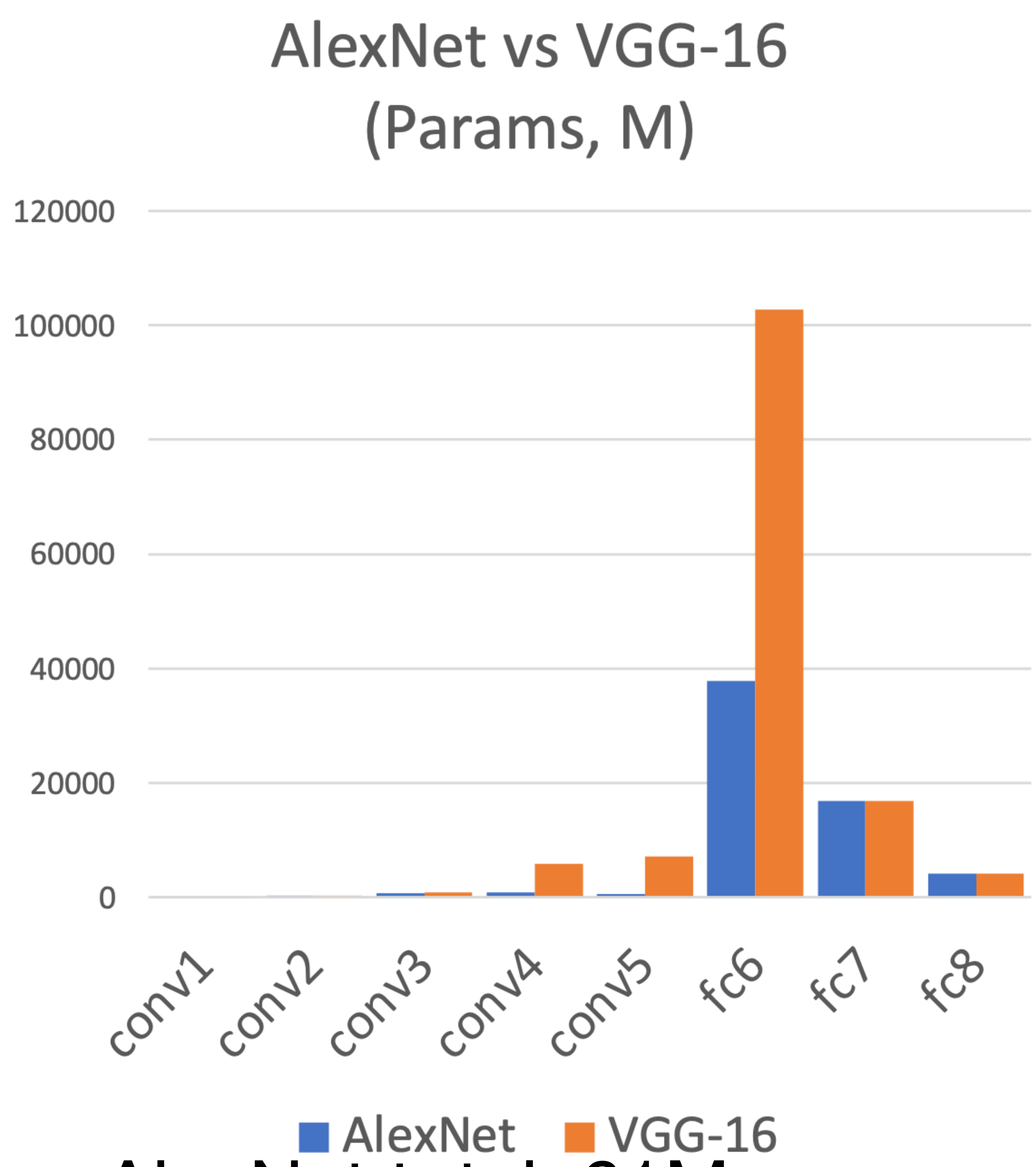
Simonyan and Zissermann, "Very Deep Convolutional Networks for La

AlexNet vs VGG-16: Much bigger network!



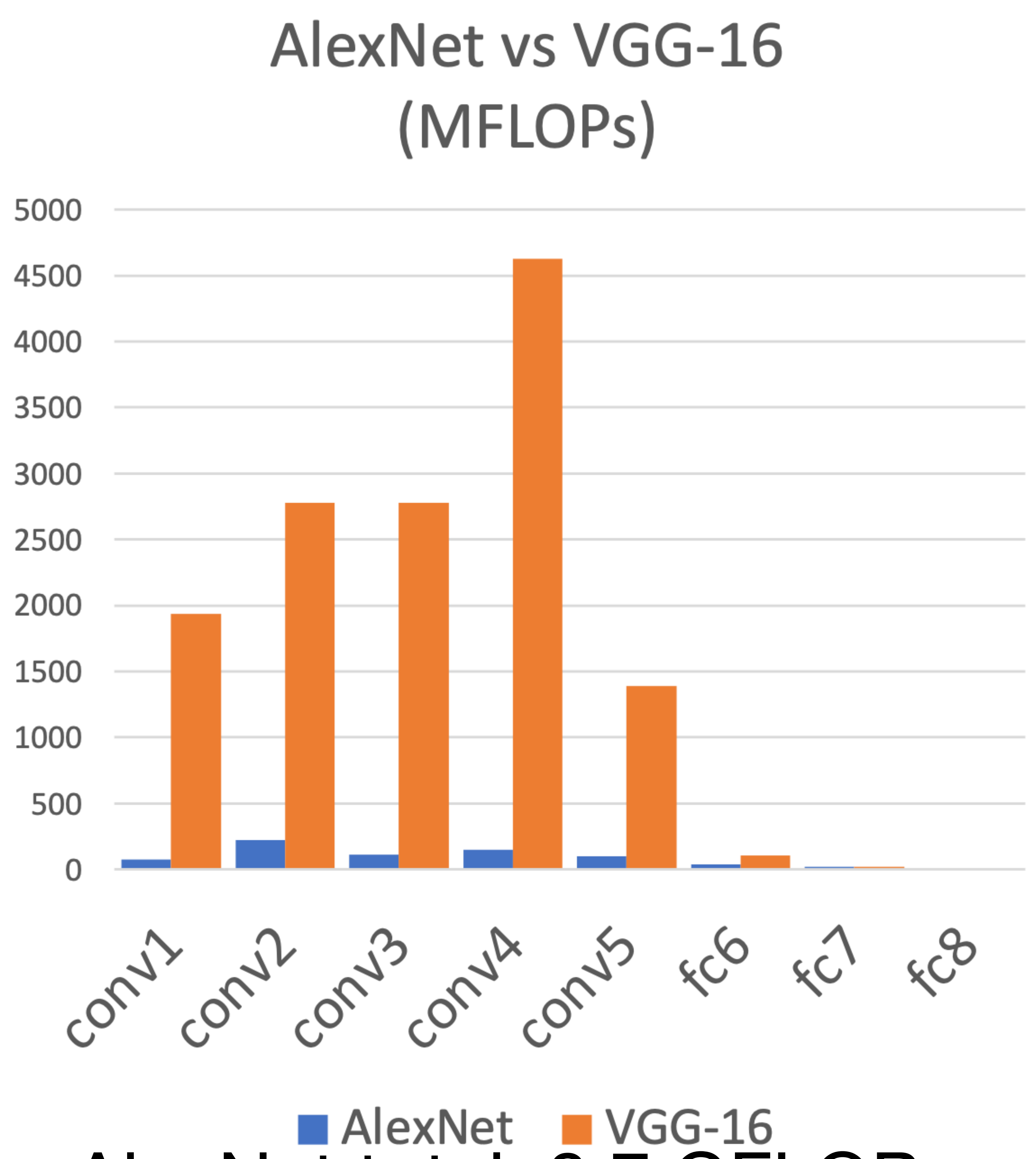
AlexNet total: 1.9MB

VGG-16 total: 48.6MB (25x)



AlexNet total: 61M

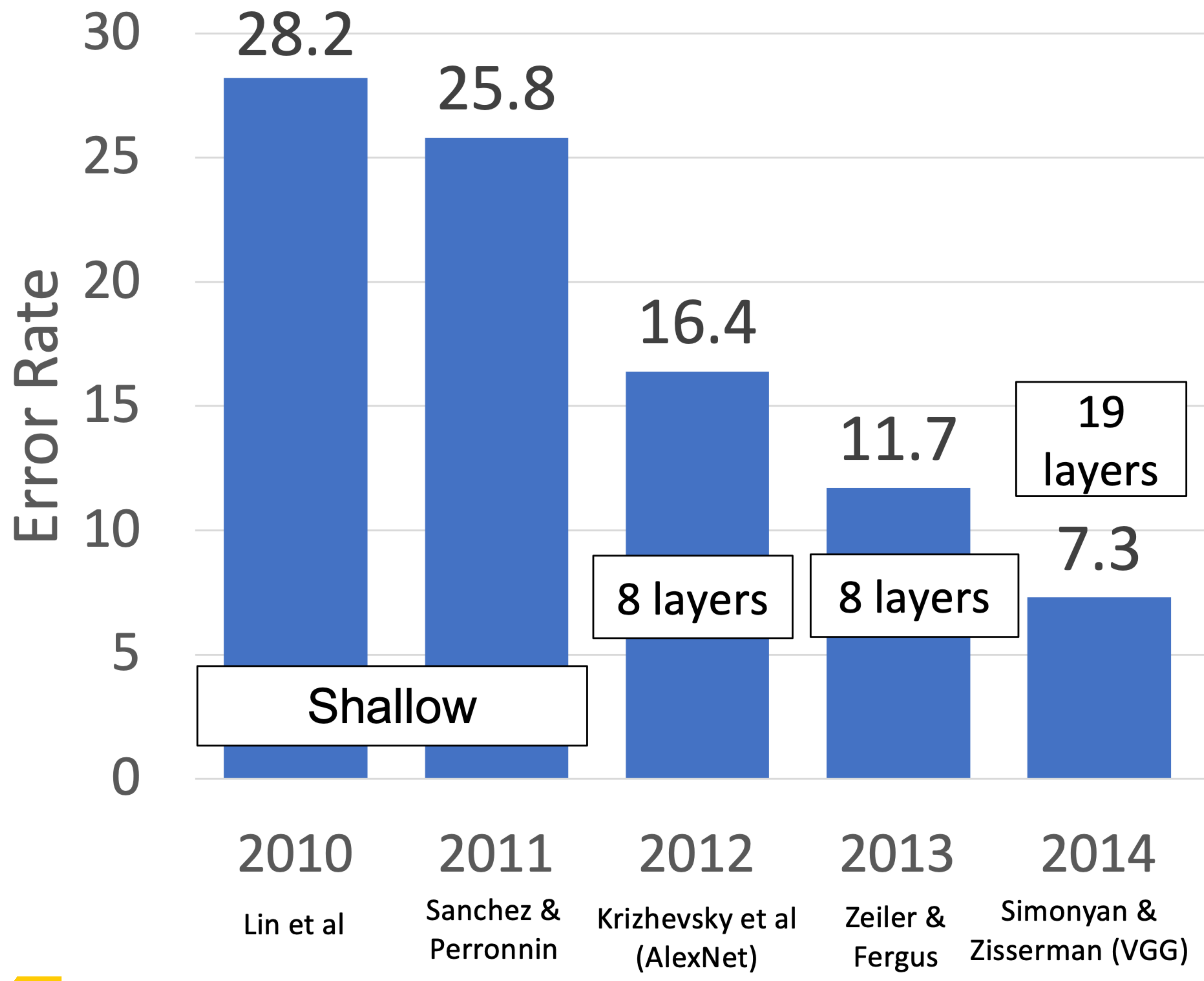
VGG-16 total: 138M (2.3x)



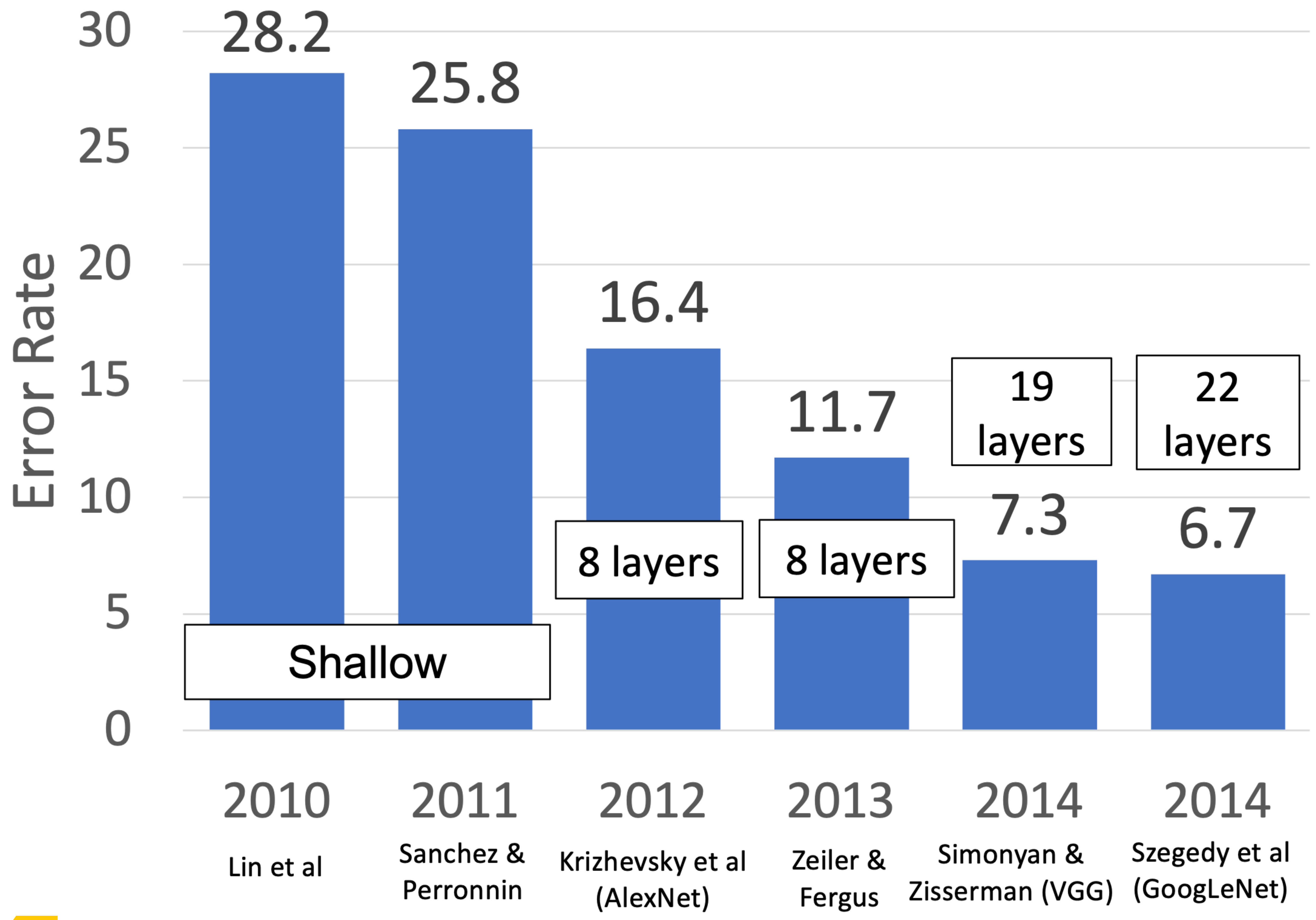
AlexNet total: 0.7 GFLOP

VGG-16 total: 13.6 GFLOP (19.4x)

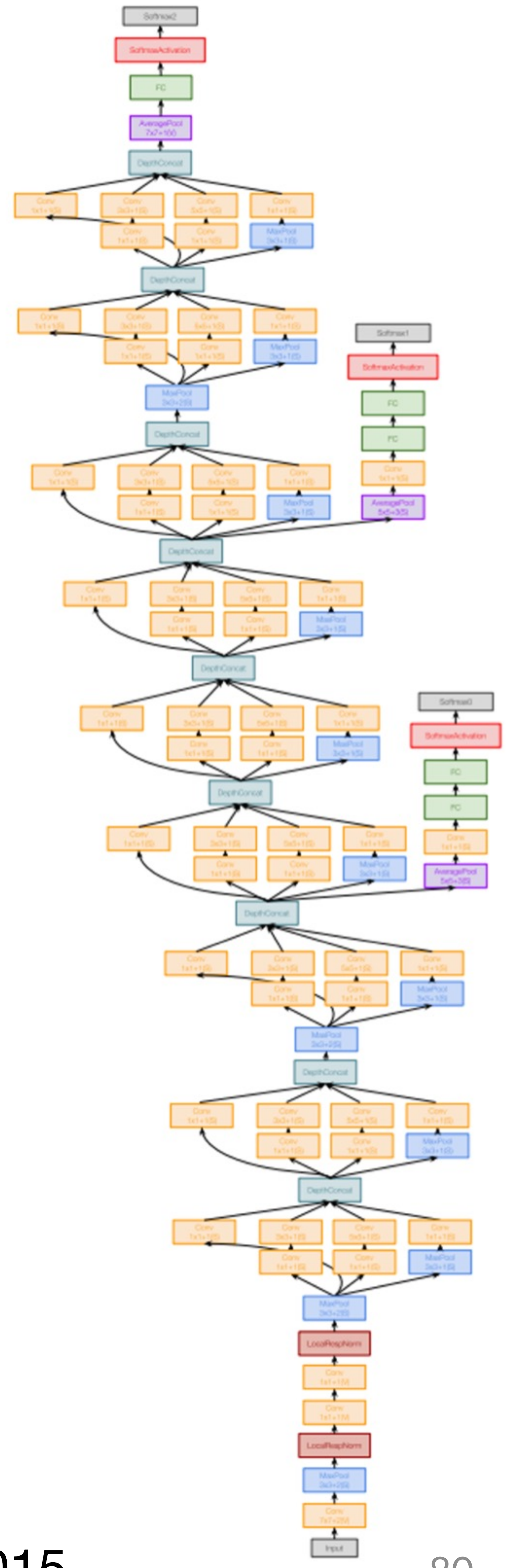
ImageNet Classification Challenge



ImageNet Classification Challenge



GoogLeNet: Focus on Efficiency

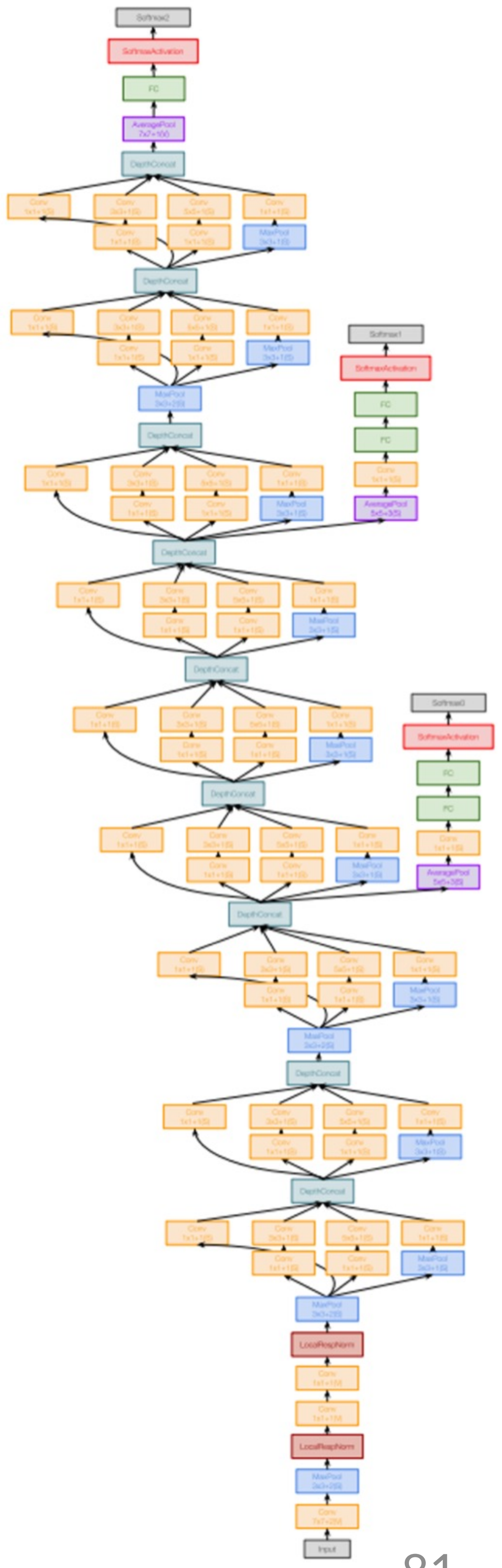


Many innovations for efficiency: reduce parameter count, memory usage, and computation

Szegedy et al, “Going deeper with convolutions”, CVPR 2015

GoogLeNet: Aggressive Stem

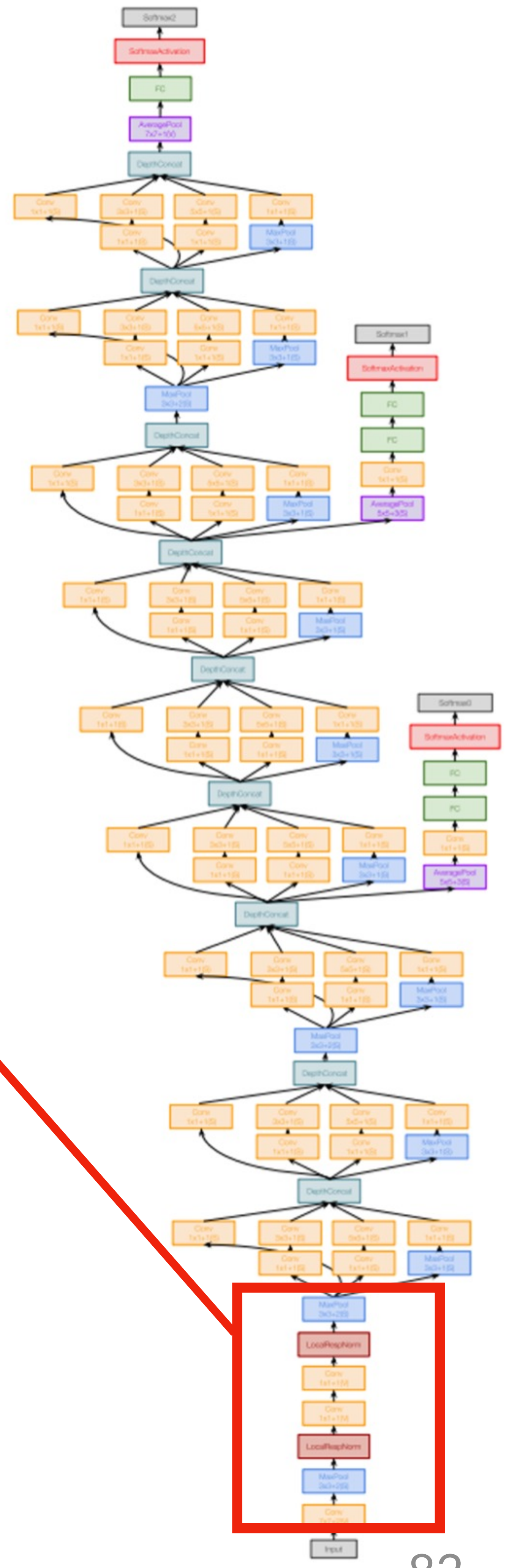
Stem network at the start aggressively downsamples input
(Recall in VGG-16: Most of the compute was at the start)



GoogLeNet: Aggressive Stem

Stem network at the start aggressively downsamples input
(Recall in VGG-16: Most of the compute was at the start)

	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv Poo	3	224	64	7	2	3	64	112	3136	9	118
Max-pool	64	112		3	2	1	64	56	784	0	2
Conv Poo	64	56	64	1	1	0	64	56	784	4	13
Conv Poo	64	56	192	3	1	1	192	56	2352	111	347
Max-pool	192	56		3	2	1	192	28	588	0	1



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Max-pool	64	112		3	2	1	64	56	784	0	2
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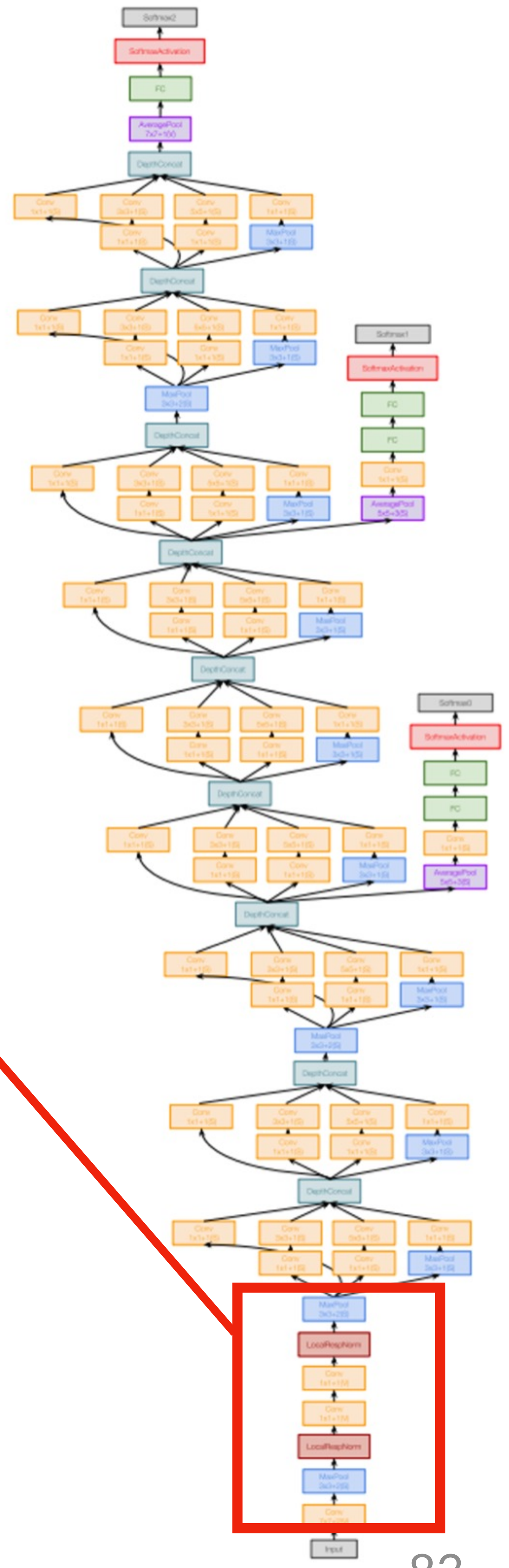
Conv	64	56	192	3	1	1	192	56	2352	111	347
Max-pool	192	56		3	2	1	192	28	588	0	1



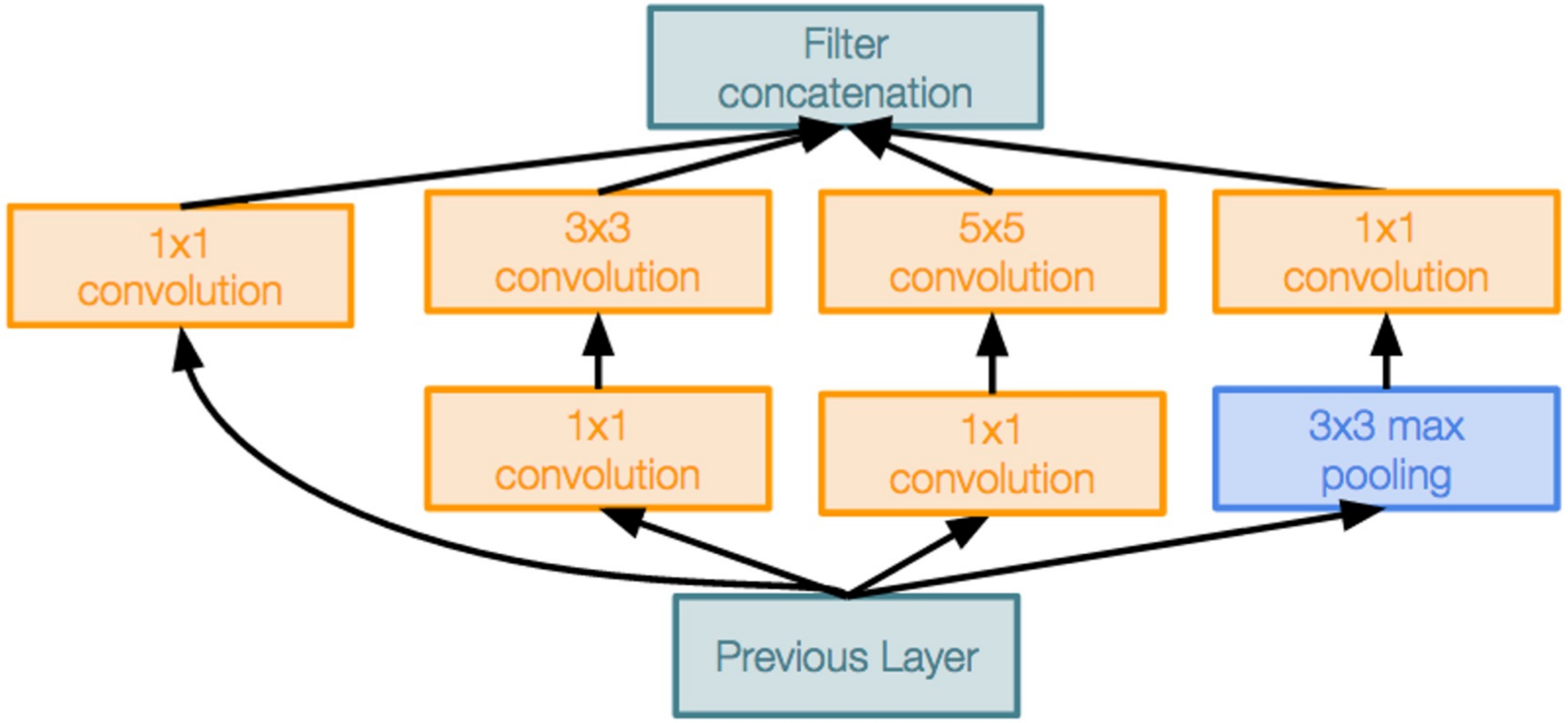
Total from 224 to 28 spatial resolution:
Memory: 7.5 MB
Params: 124K
MFLOP: 418

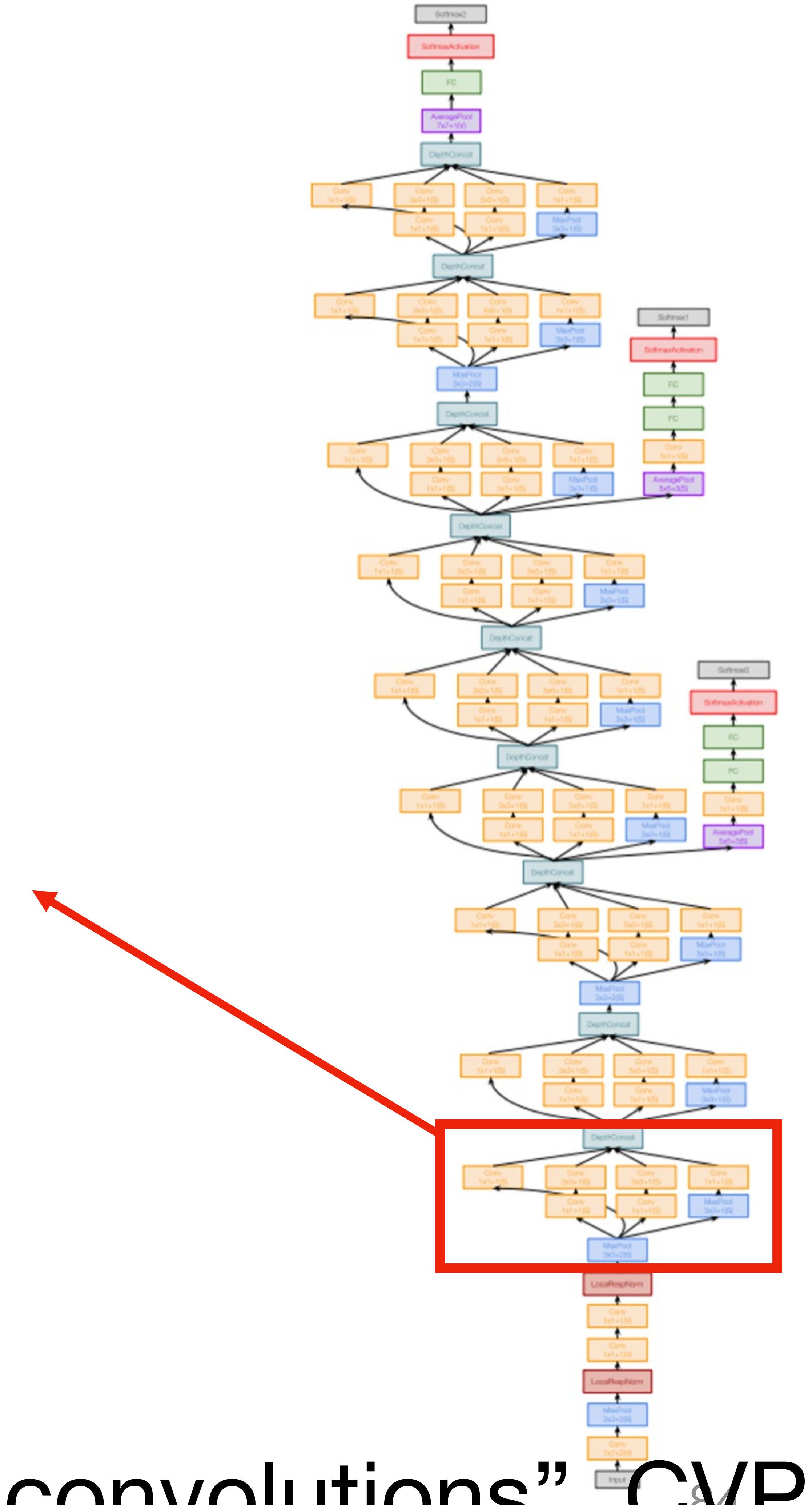
Compare VGG-16:
Memory: 42.9 MB (5.7x)
Params: 1.1M (8.9x)
MFLOP: 7485 (17.8x)

GoogLeNet: Inception Module

Inception module: Local unit with parallel branches

Local structure repeated many times throughout the network





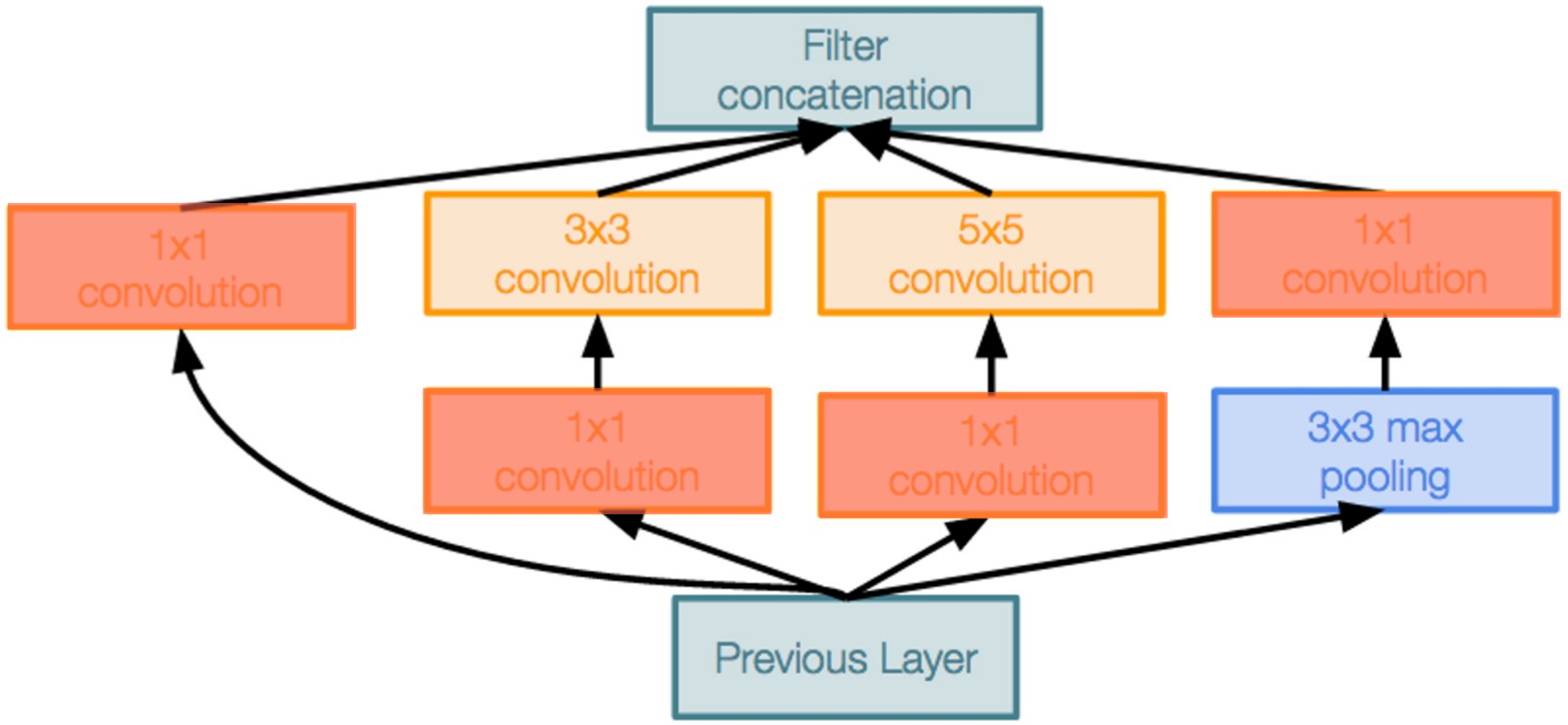
Szegedy et al, “Going deeper with convolutions”, CVPR 201

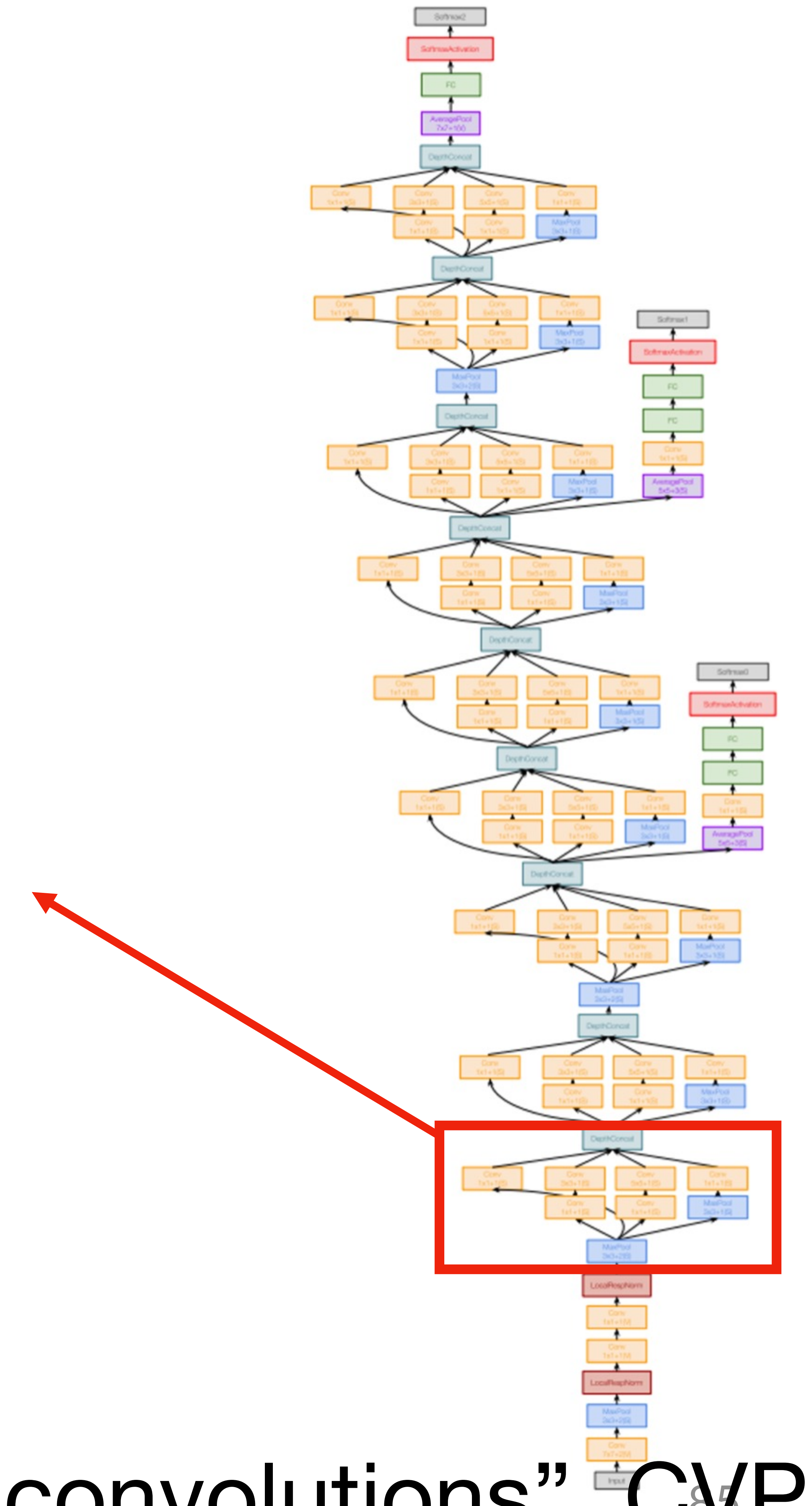
GoogLeNet: Inception Module

Inception module: Local unit with parallel branches

Local structure repeated many times throughout the network

Uses 1x1 "Bottleneck" layers to reduce channel dimension before expensive conv (we will revisit this with ResNet!)





Szegedy et al, "Going deeper with convolutions", CVPR 20

GoogLeNet: Global Average Pooling

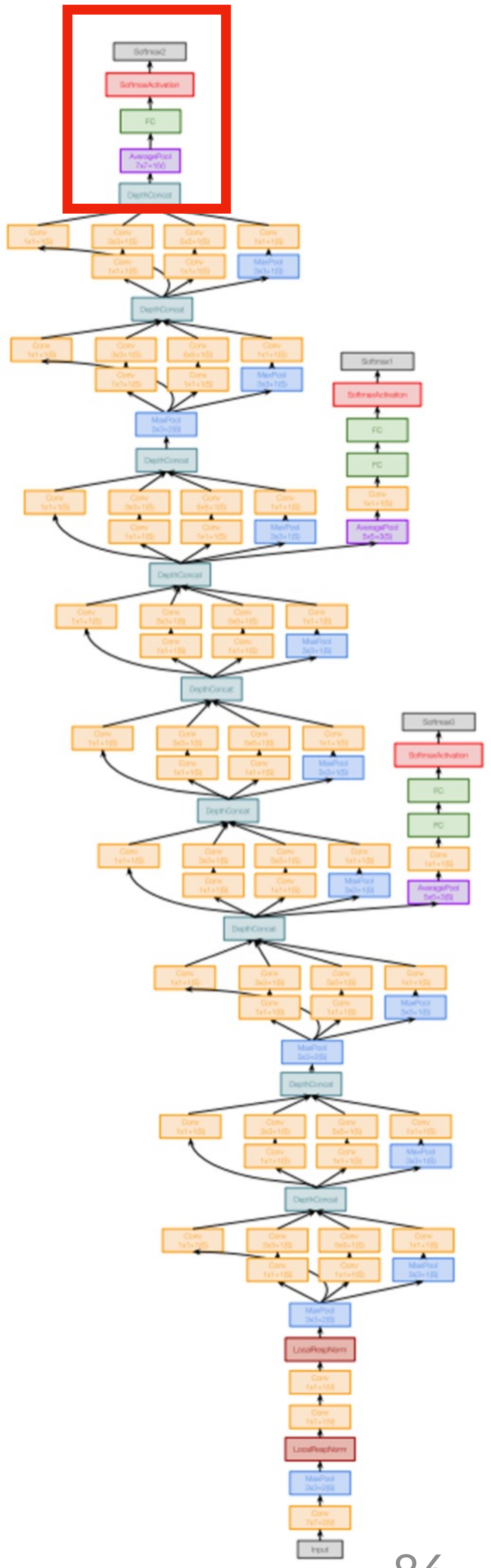
No large FC layers at the end!

Instead use **global average pooling** to collapse spatial dimensions, and one linear layer to produce class scores
(Recall VGG-16: Most parameters were in the FC layers!)

	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params	Flop (M)
avg-pool	1024	7		7	1	0	1024	1	4	0	0
fc	1024		1000				1000	0	0	1025	1

Compare with VGG-16:

	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params	Flop (M)
Flatten	512	7					25088		98		
FC6	25088			4096			4096		16	102760	103
FC7	4096			4096			4096		16	16777	17
FC8	4096			1000			1000		4	4096	4

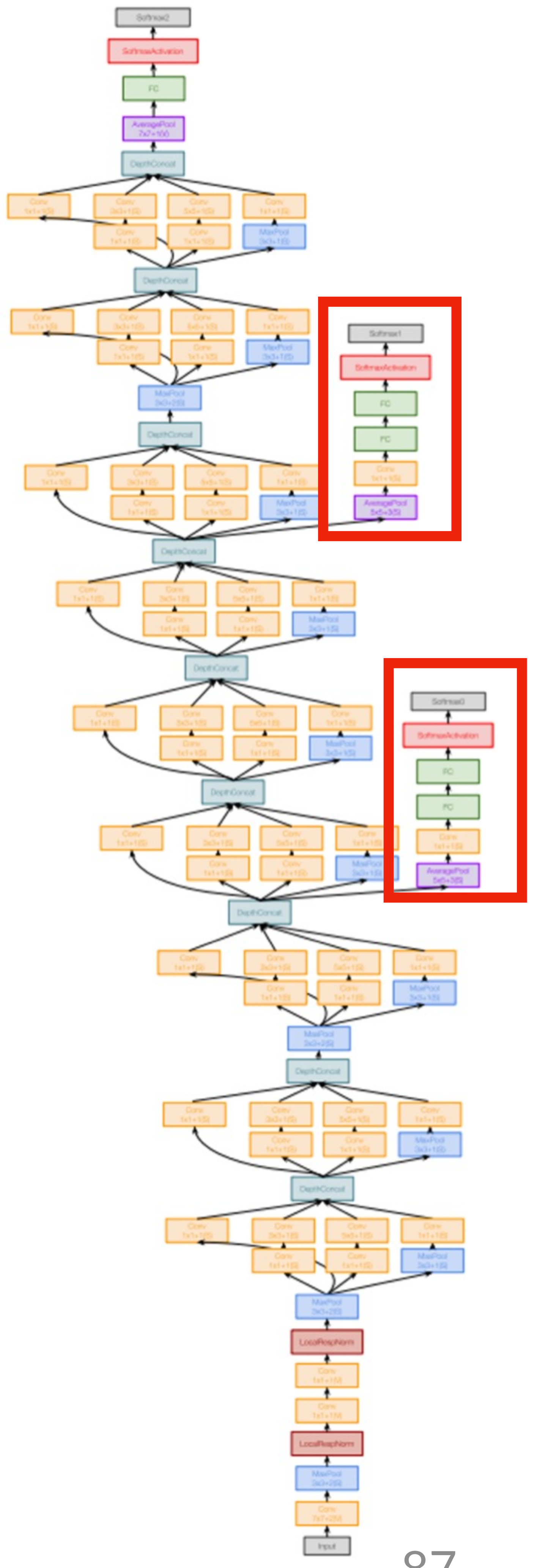


GoogLeNet: Auxiliary Classifiers

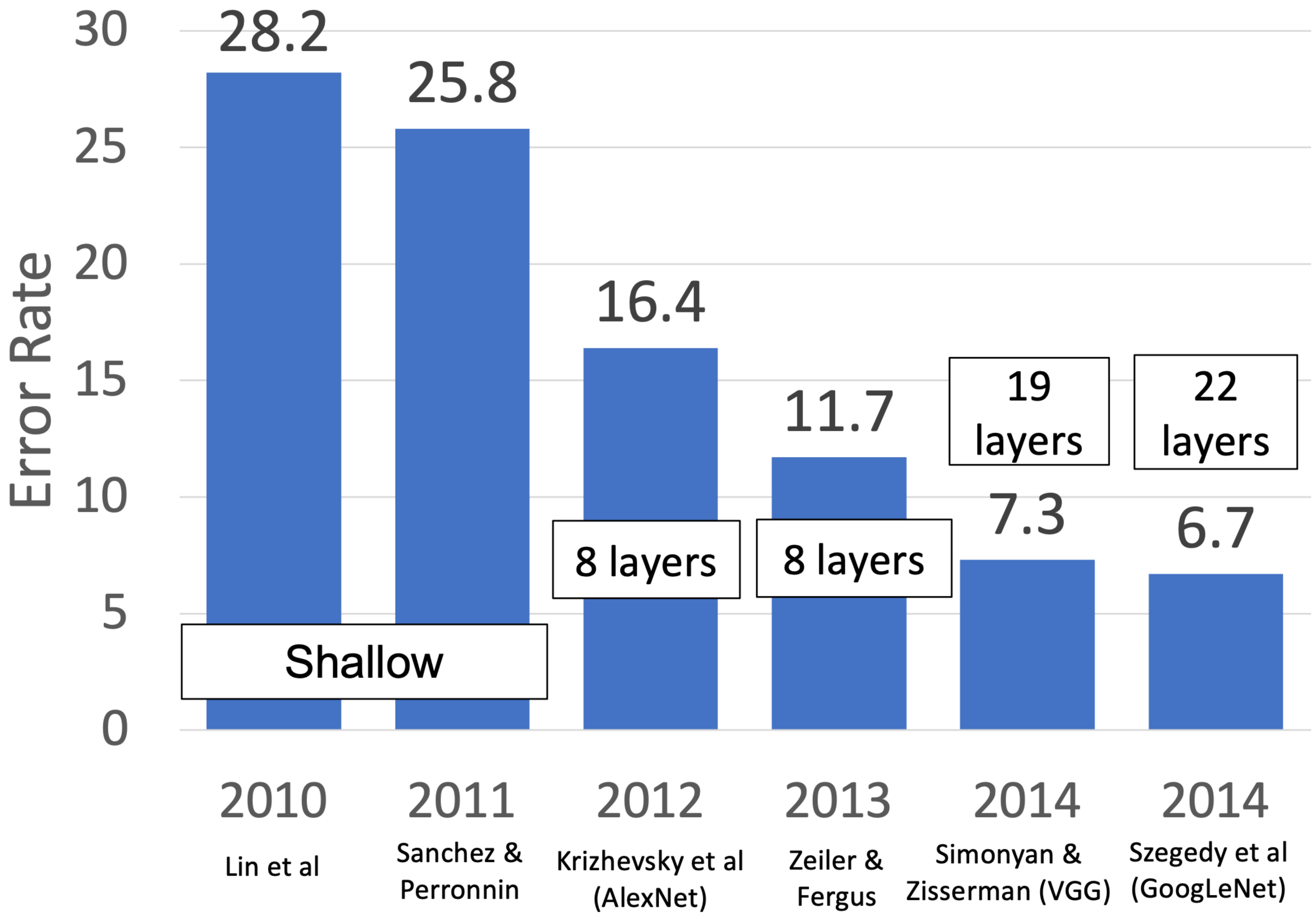
Training using loss at the end of the network didn't work well: Network is too deep, gradients don't propagate cleanly

As a hack, attach "auxiliary classifiers" at several intermediate points in the network that also try to classify the image and receive loss

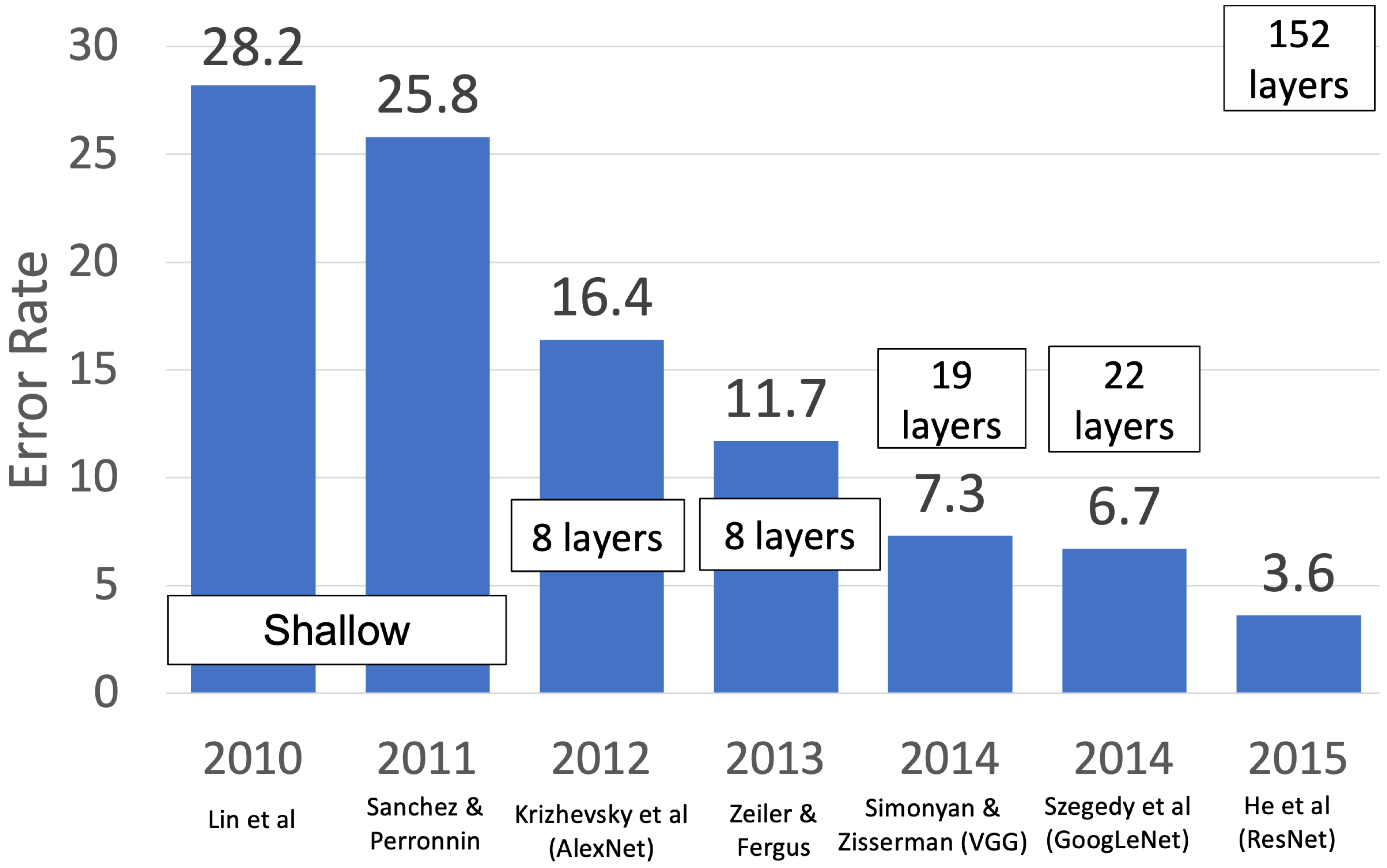
GoogLeNet was before batch normalization! With BatchNorm, we no longer need to use this trick



ImageNet Classification Challenge



ImageNet Classification Challenge



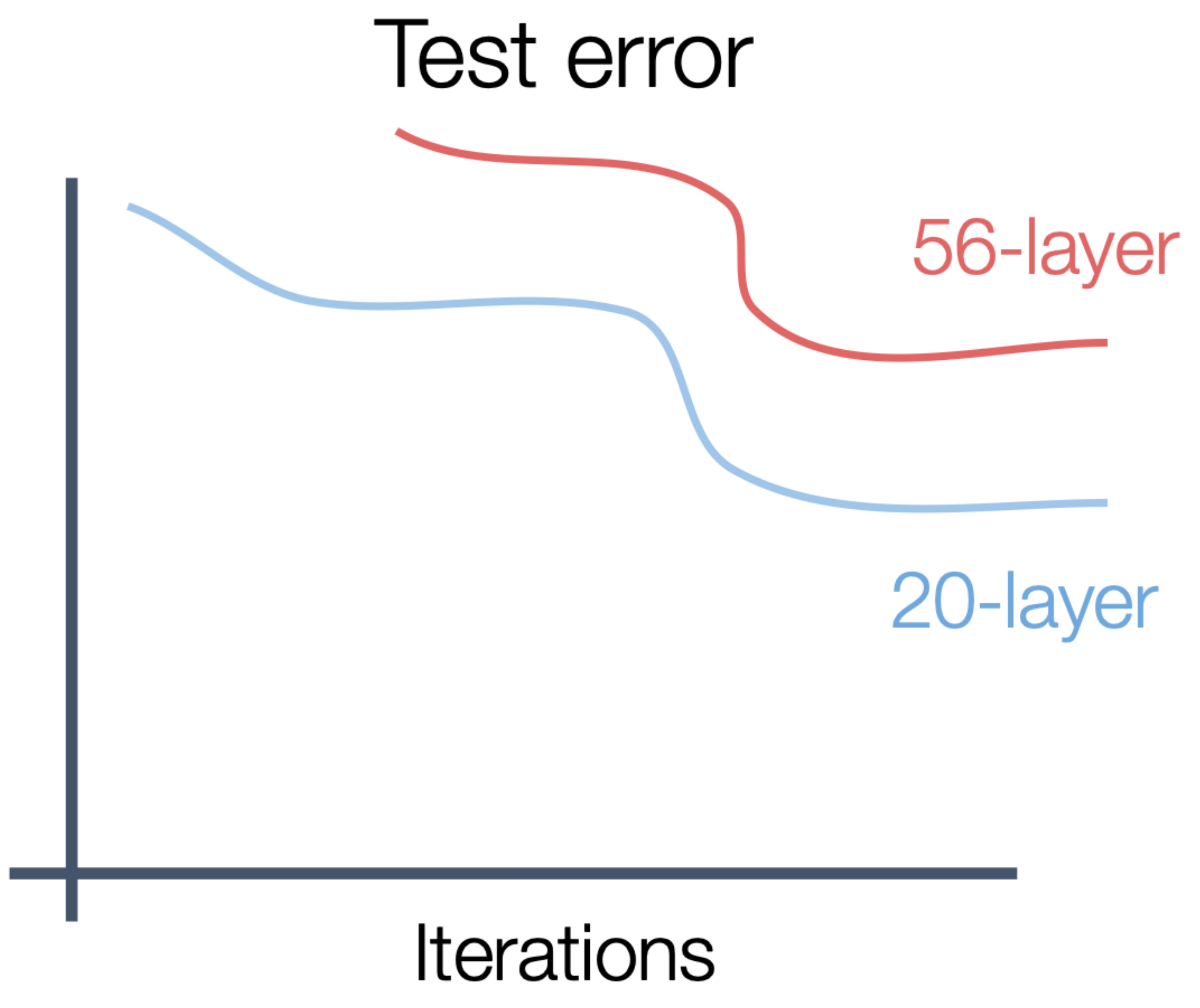
Residual Networks

Once we have Batch Normalization, we can train networks with 10+ layers.

What happens as we go deeper?

Deeper model does worse than shallow model!

Initial guess: Deep model is **overfitting** since it is much bigger than the other model



Residual Networks

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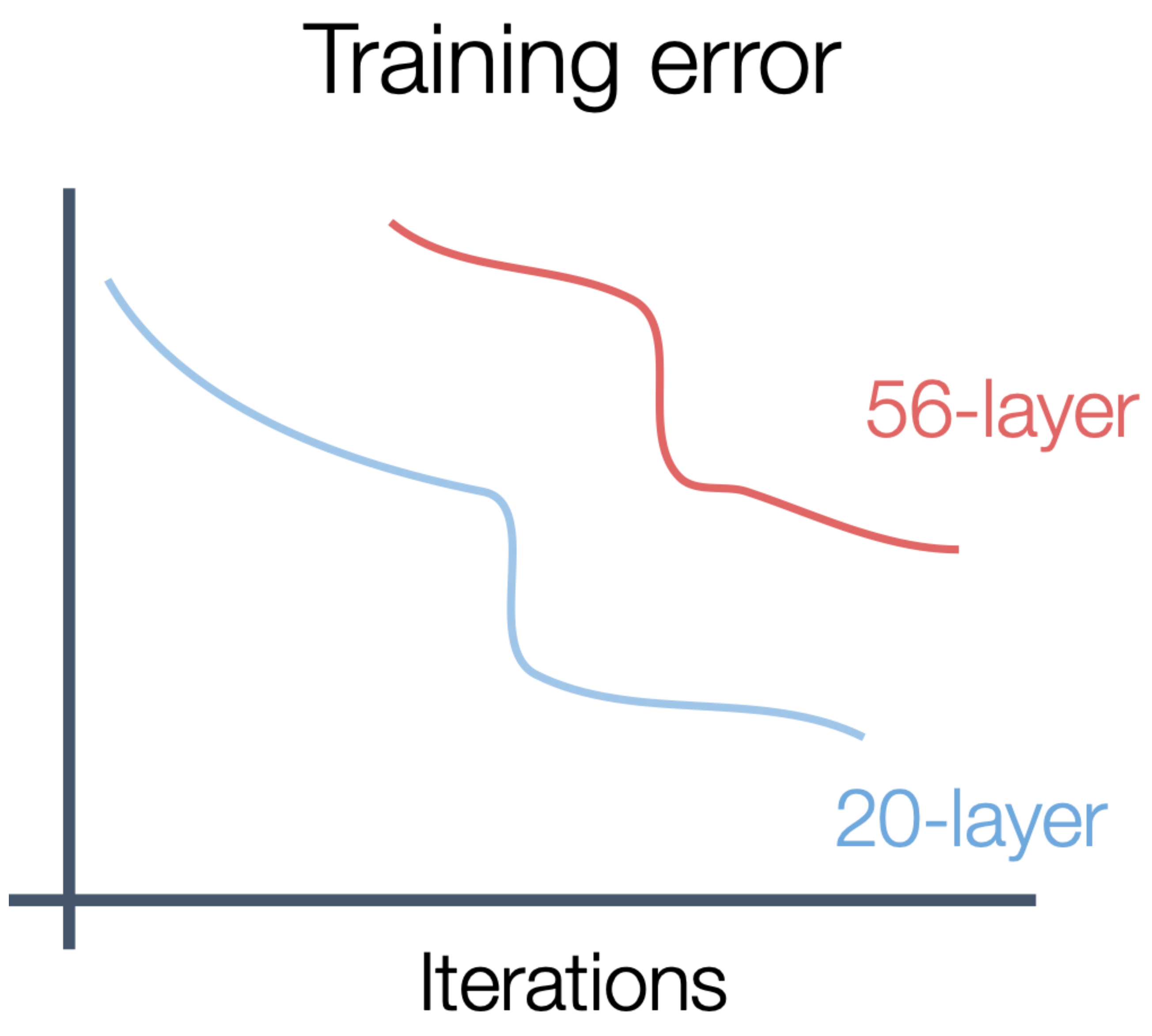
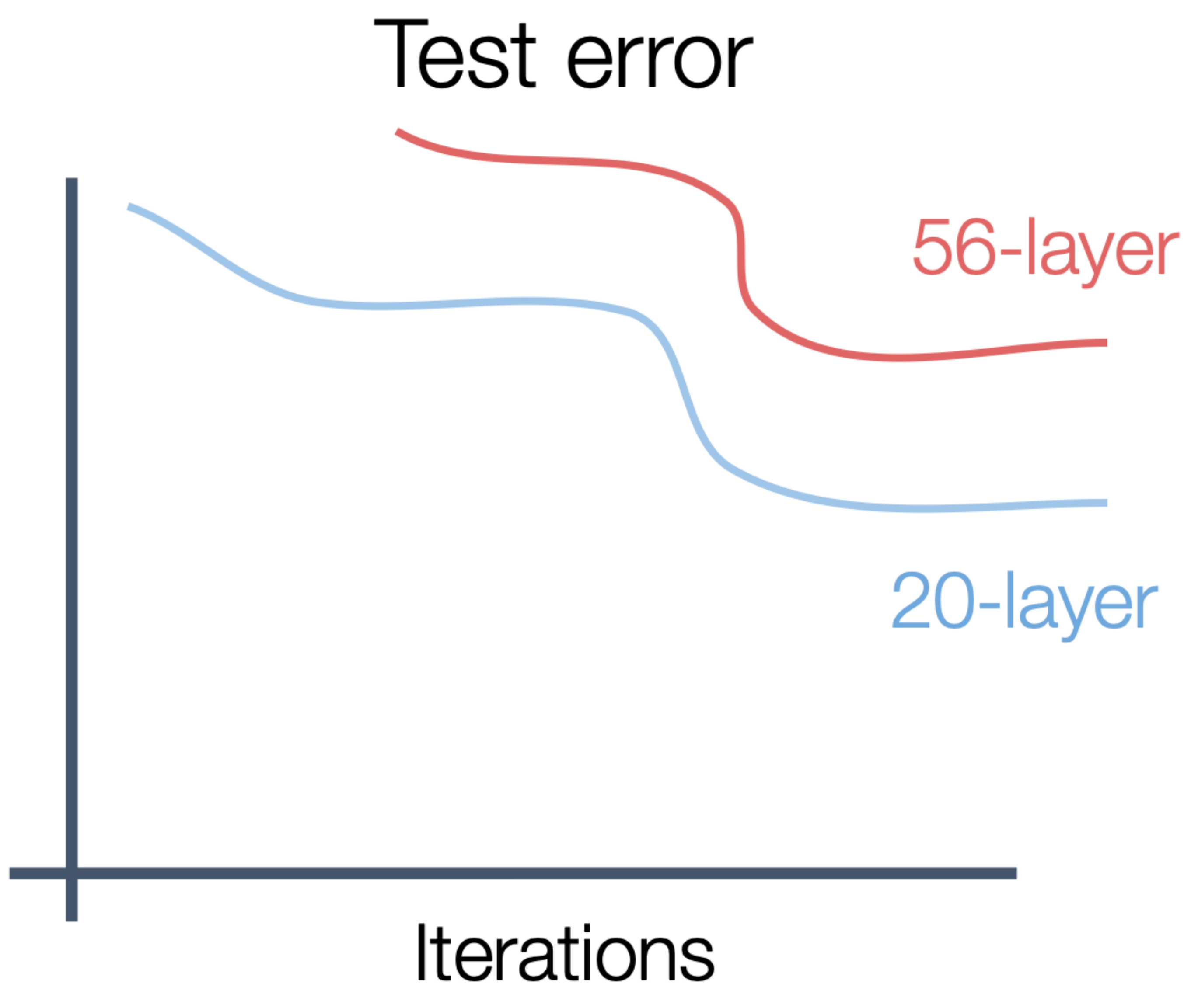
What happens as we go deeper?





In fact the deep model seems to be **underfitting** since it also performs worse than the shallow model on the training set! It is actually **underfitting**

Residual Networks

A deeper model can emulate a shallower model: copy layers from shallower model, set extra layers to identity

Thus deeper models should do at least as good as shallow models

Hypothesis: This is an optimization problem. Deeper models are harder to optimize, and in particular don't learn identity functions to emulate shallow models

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Hypothesis: This is an optimization problem. Deeper models are harder to optimize, and in particular don't learn identity functions to emulate shallow models

Solution: Change the network so learning identity functions with extra layers is easy!

Residual Networks

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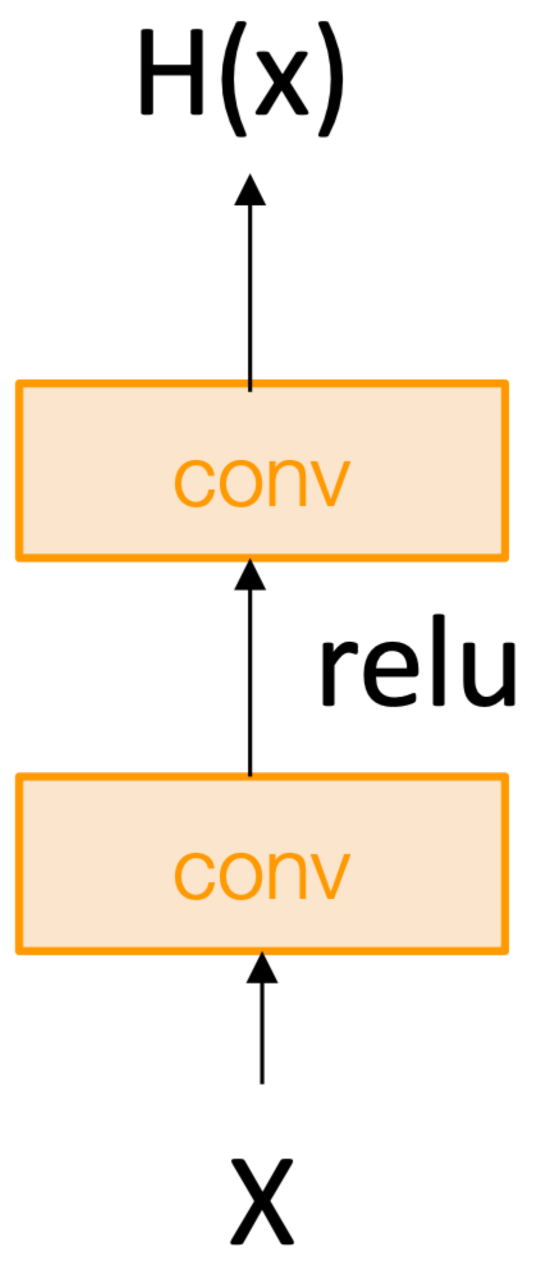
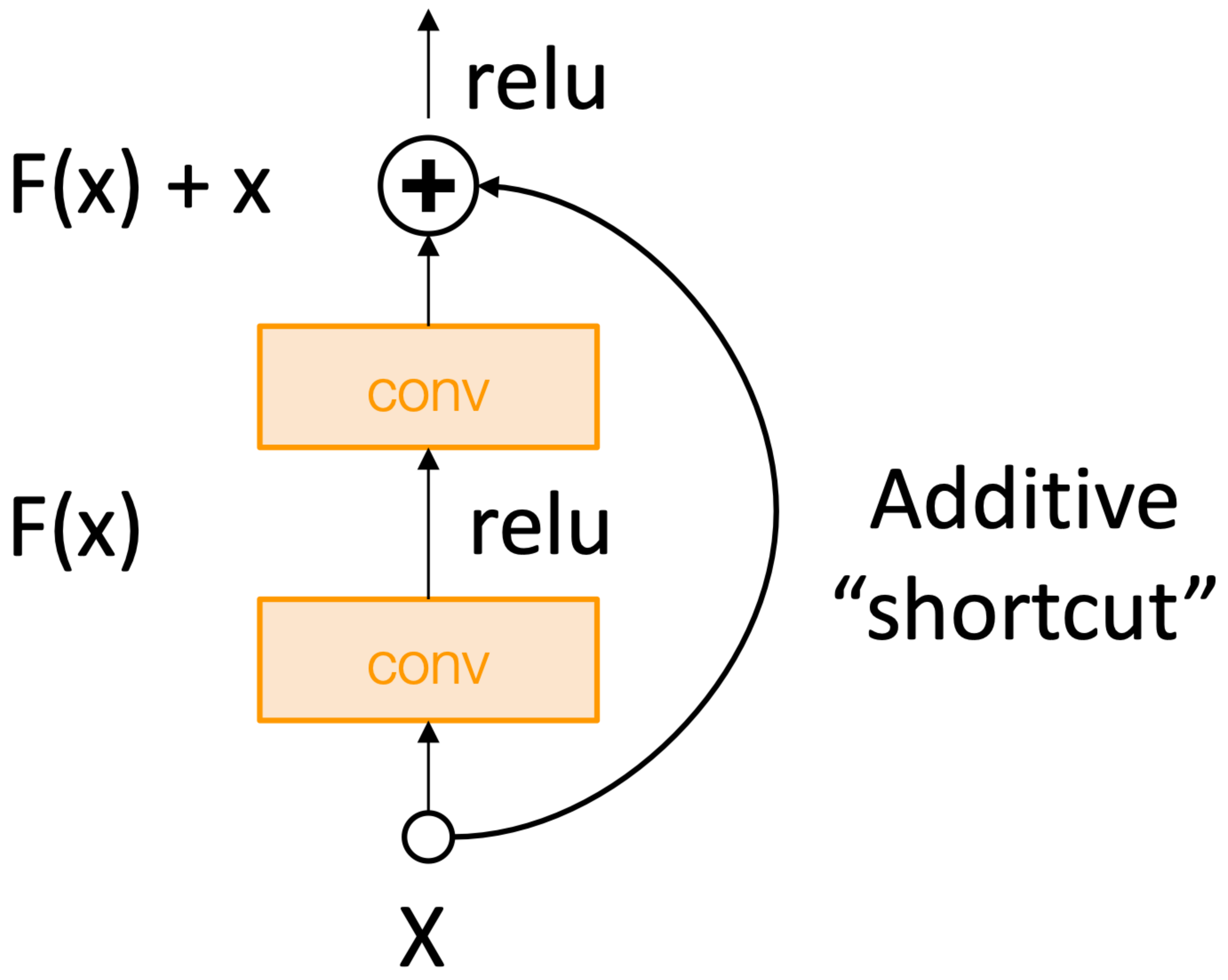


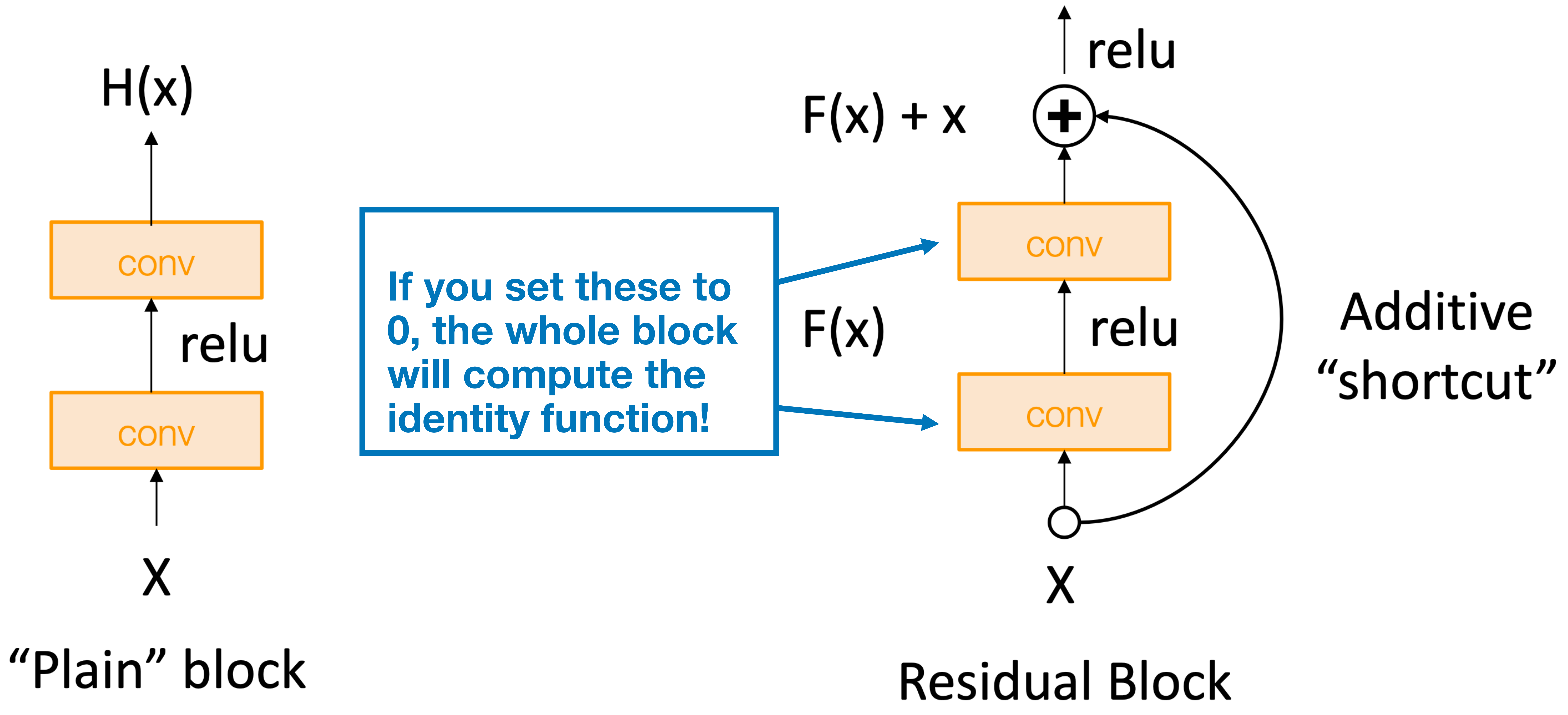
"Plain" block



Residual Block

Residual Networks

Solution: Change the network so learning identity functions with extra layers is easy!

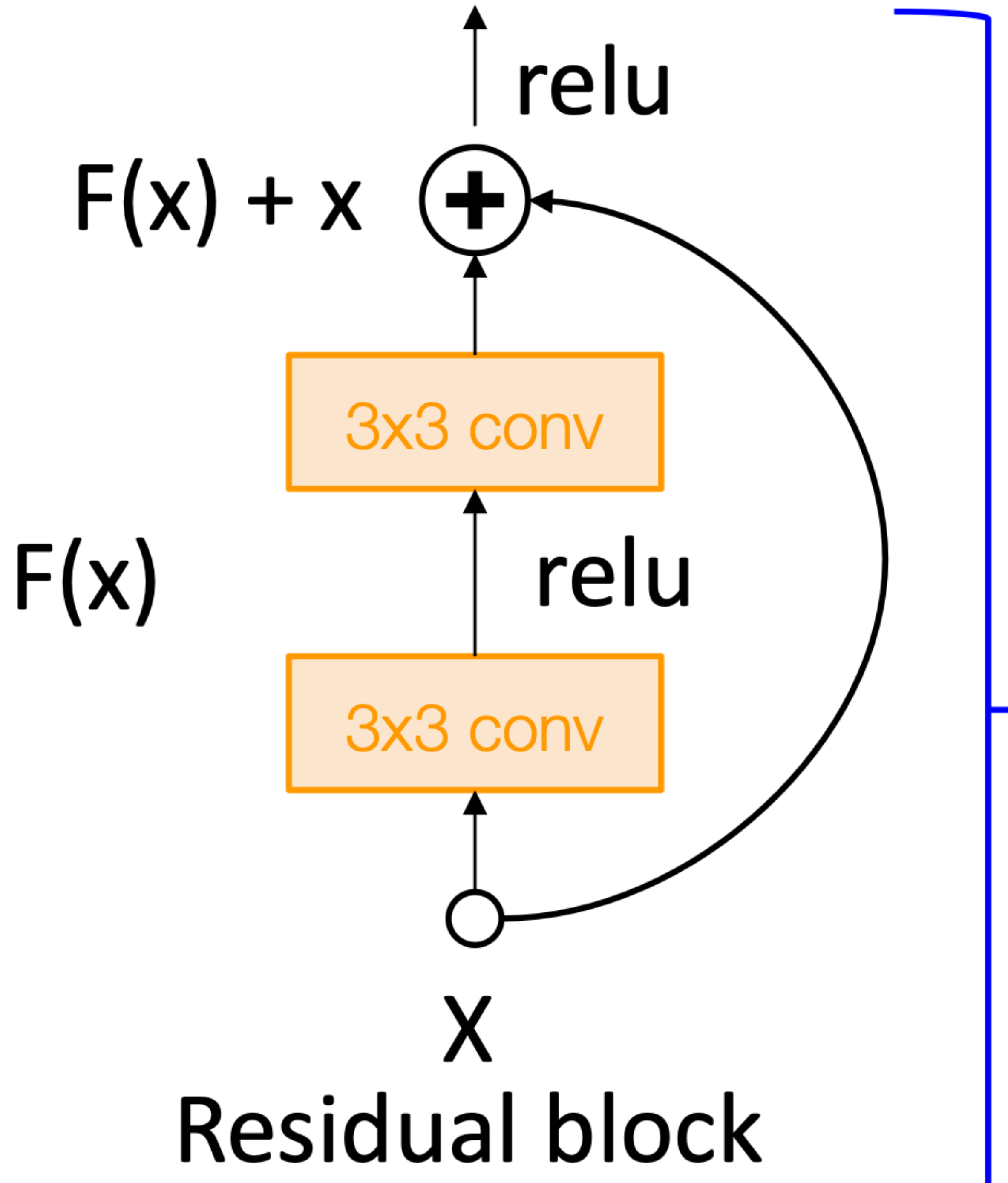


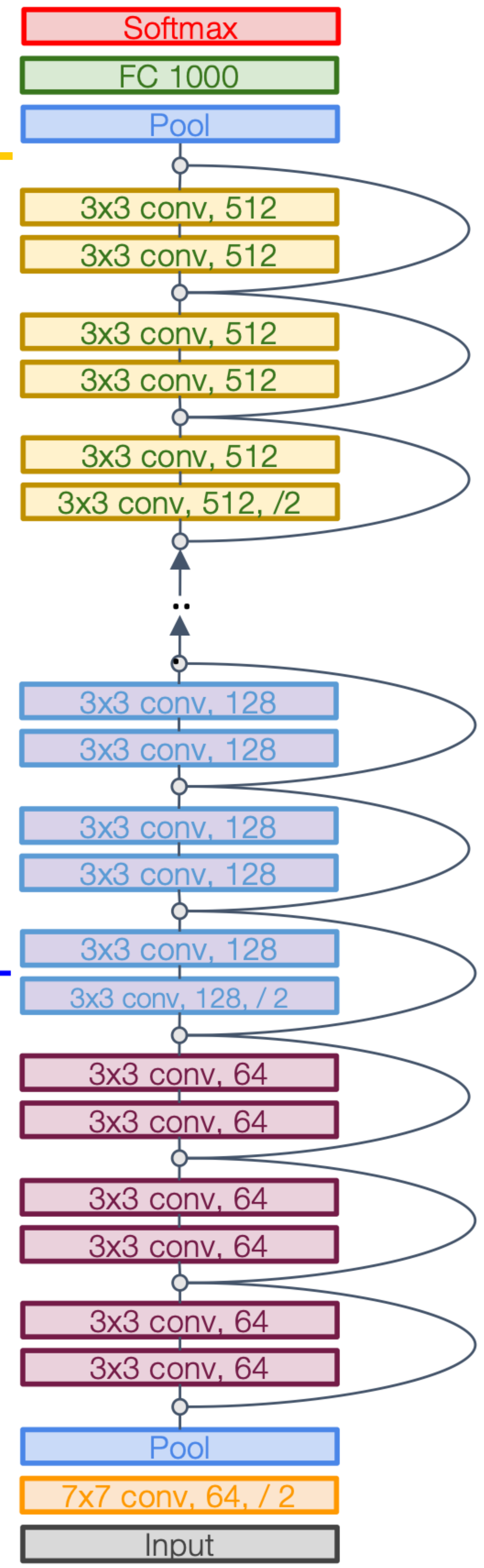
Residual Networks

A residual network is a stack of many residual blocks

Regular design, like VGG: each residual block has two 3x3 conv

Network is divided into **stages**: the first block of each stage halves the resolution (with stride-2 conv) and doubles the number of channels

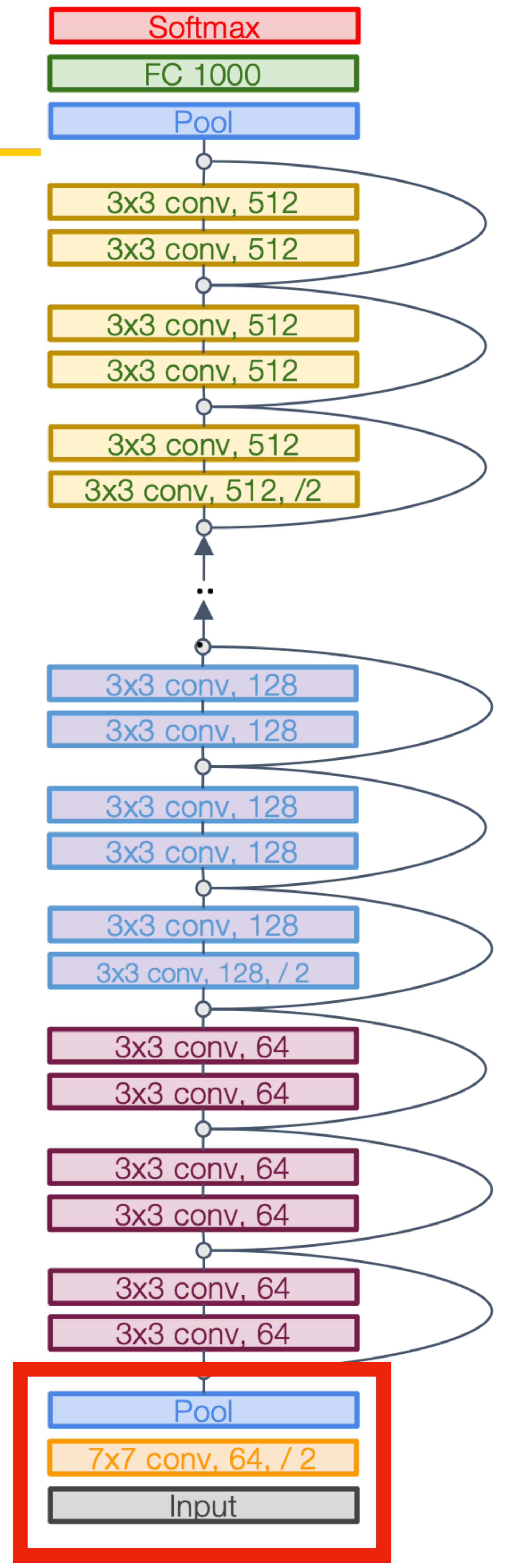




Residual Networks

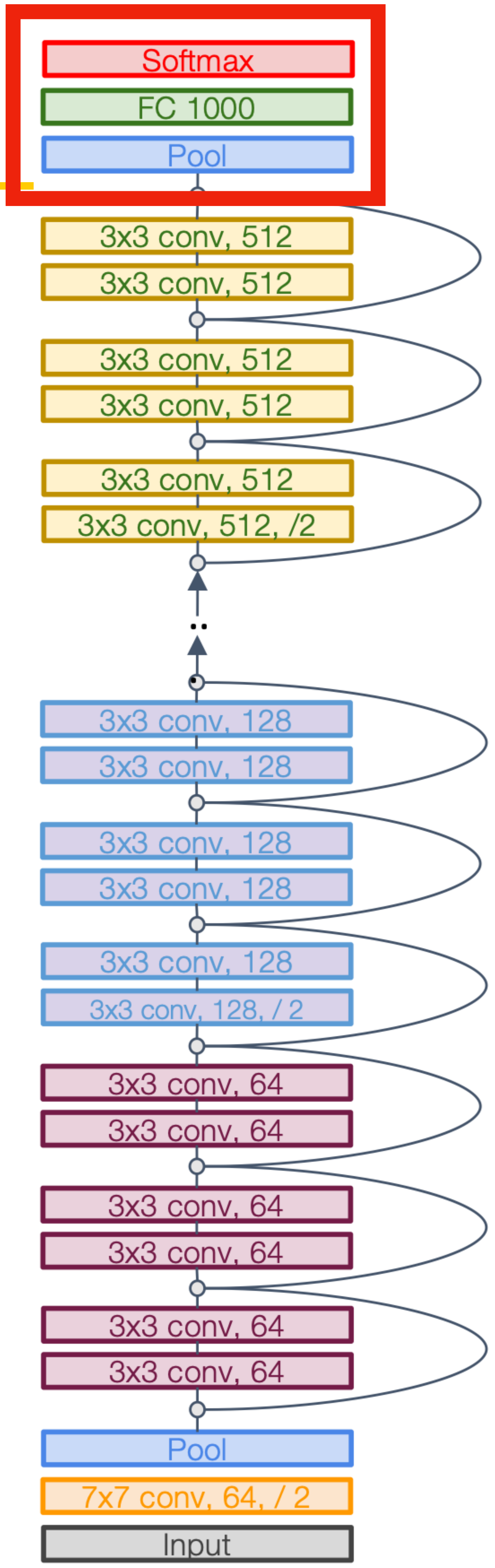
Uses the same aggressive **stem** as GoogleNet to downsample the input 4x before applying residual blocks:

	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv Poo	3	224	64	7	2	3	64	112	3136	9	118
Max-pool	64	112		3	2	1	64	56	784	0	2



Residual Networks

Like GoogLeNet, no big fully-connected-layers: Instead use **global average pooling** and a single linear layer at the end



Residual Networks

ResNet-18:
Stem: 1 conv layer
Stage 1 (C=64): 2 res. block = 4 conv

Stage 2 (C=128): 2 res. block = 4 conv

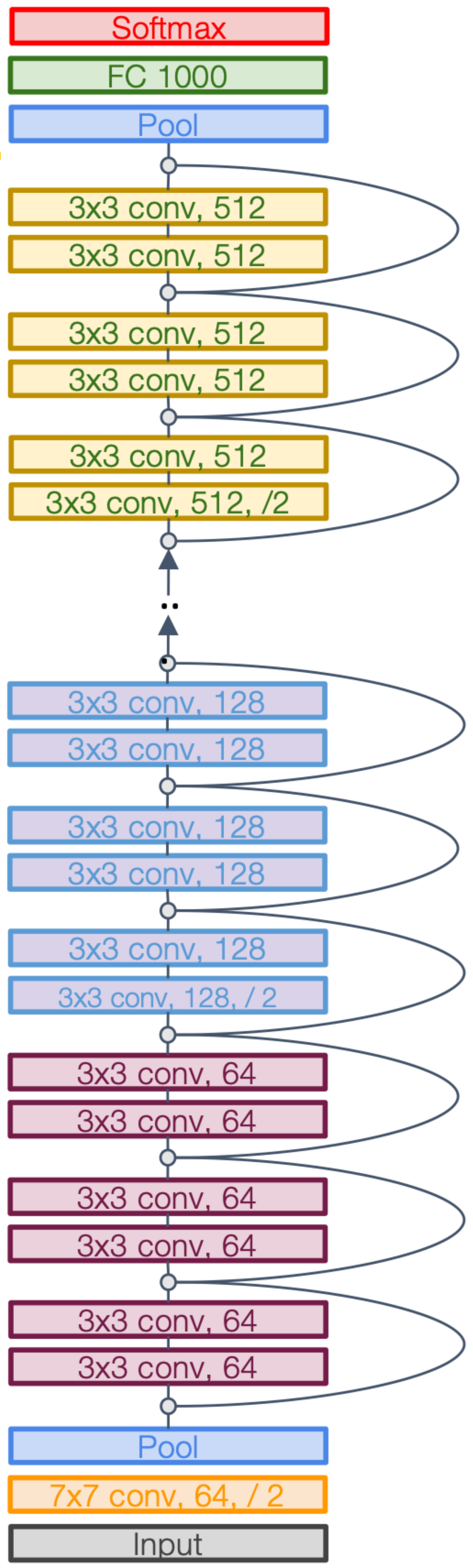
Stage 3 (C=256): 2 res. block = 4 conv

Stage 4 (C=512): 2 res. block = 4 conv

Linear

ImageNet top-5 error: 10.92

GFLOP: 1.8



Error rates are 224x224 single-crop testing, reported by torchvision

Residual Networks

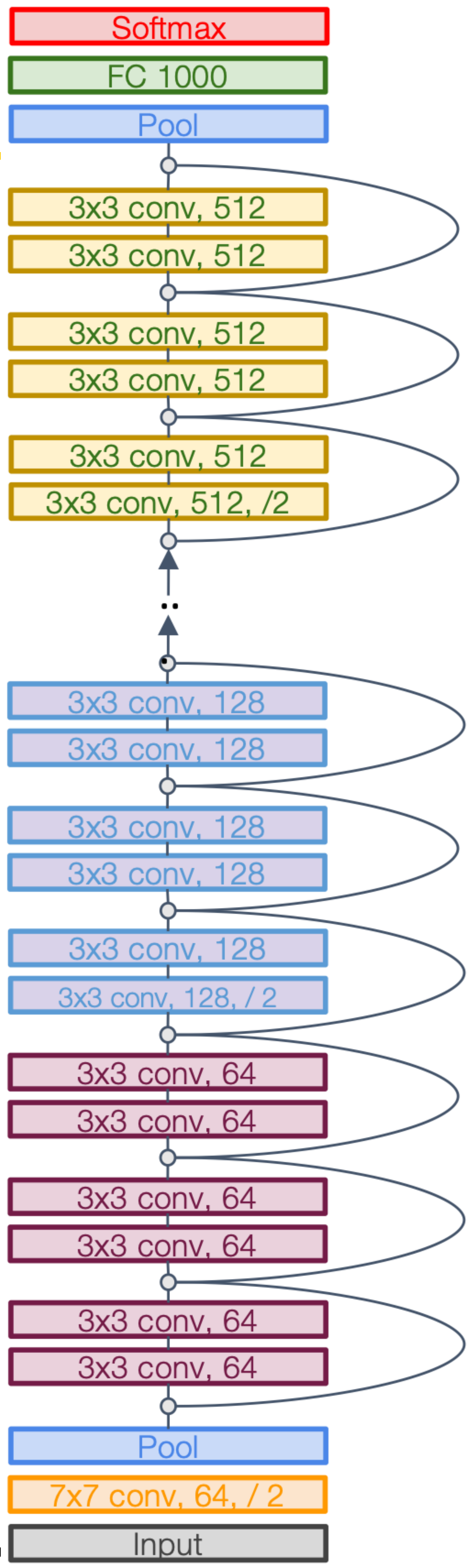
ResNet-18:
Stem: 1 conv layer
Stage 1 (C=64): 2 res. block = 4 conv
Stage 2 (C=128): 2 res. block = 4 conv
Stage 3 (C=256): 2 res. block = 4 conv
Stage 4 (C=512): 2 res. block = 4 conv
Linear
ImageNet top-5 error: 10.92
GFLOP: 1.8

ResNet-34:
Stem: 1 conv layer
Stage 1: 3 res. block = 6 conv
Stage 2: 4 res. block = 8 conv
Stage 3: 6 res. block = 12 conv
Stage 4: 3 res. block = 6 conv
Linear
ImageNet top-5 error: 8.58
GFLOP: 3.6

VGG-16:

ImageNet top-5 error: 9.62

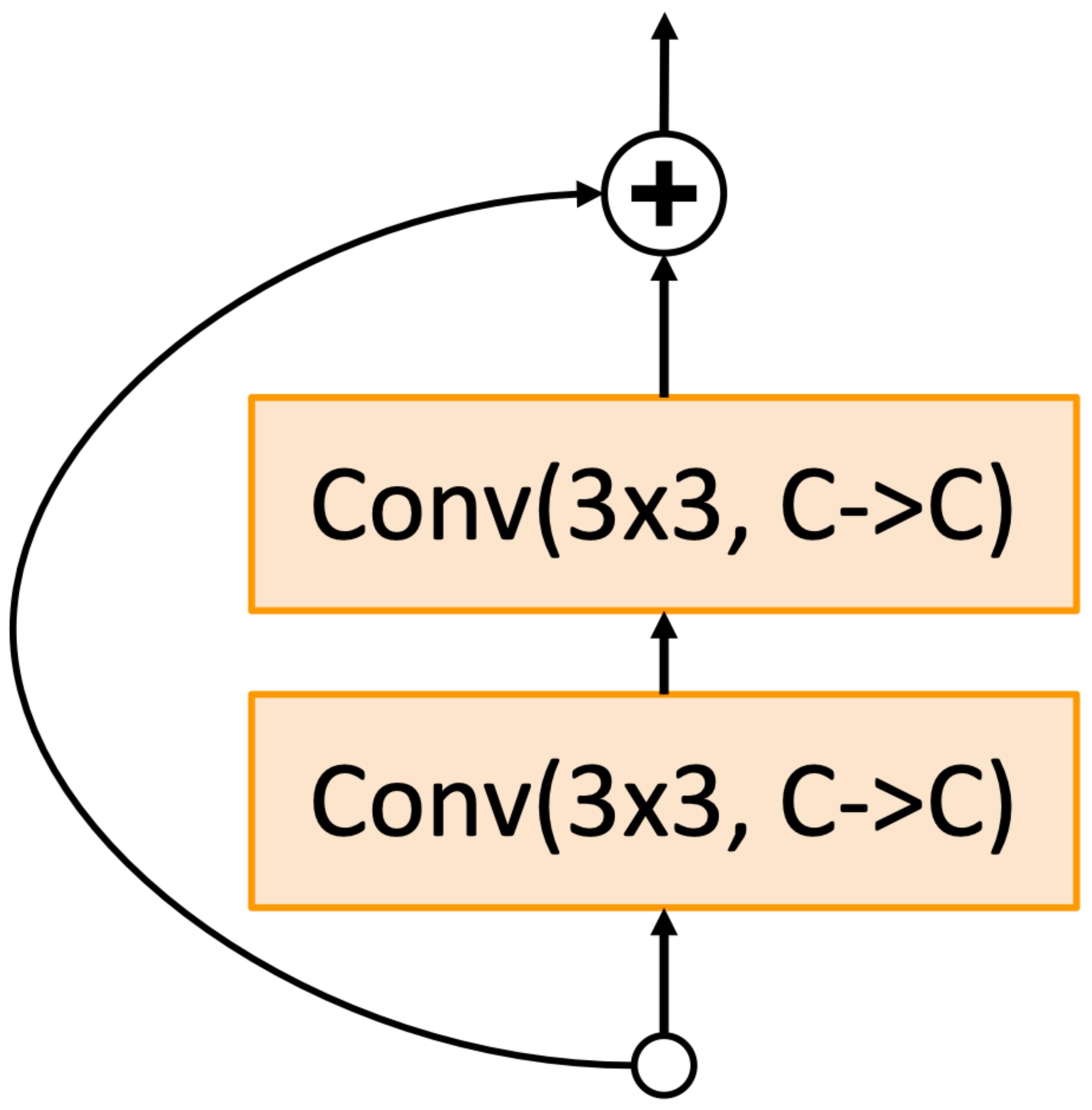
GFLOP: 13.6



He et al, “Deep Residual Learning for Image Rec… , CV

Error rates are 224x224 single-crop testing, reported by torch

Residual Networks: Basic Block



"Basic"
Residual block

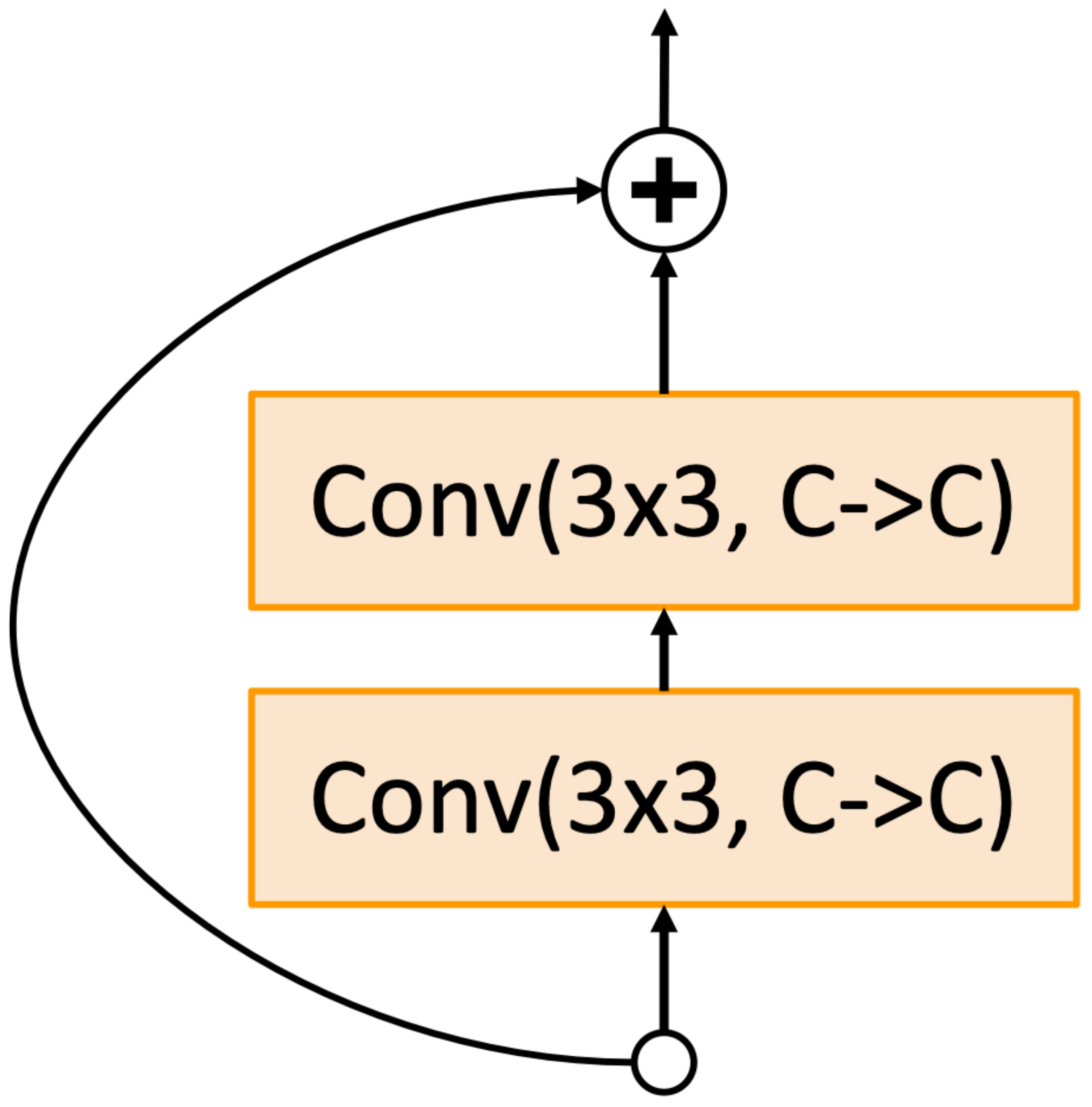
FLOPs: $9HWC^2$

FLOPs: $9HWC^2$

Total FLOPs:

$18HWC^2$

Residual Networks: Bottleneck Block



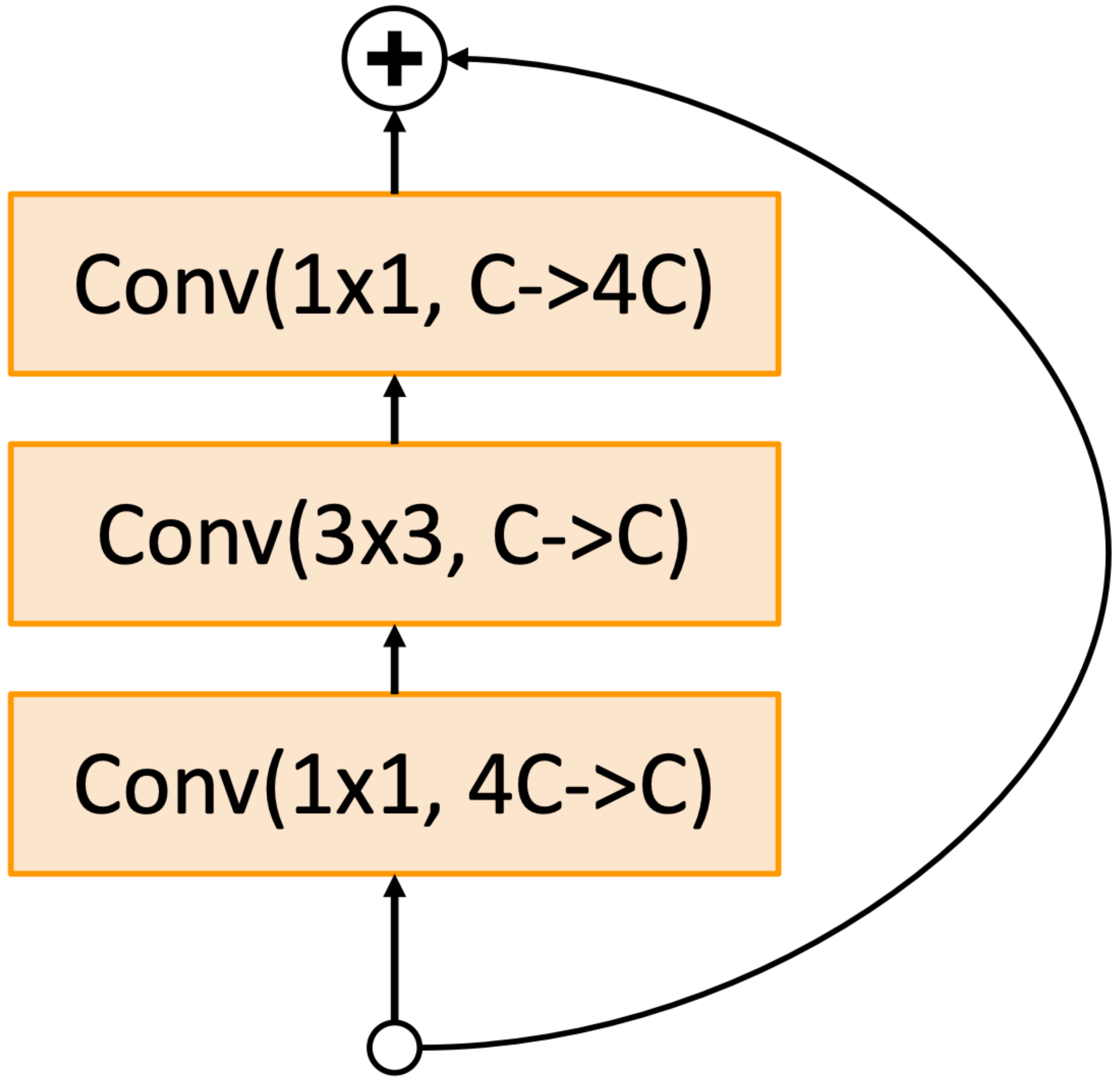
FLOPs: $9HWC^2$

FLOPs: $9HWC^2$

"Basic"
Residual block

Total FLOPs:

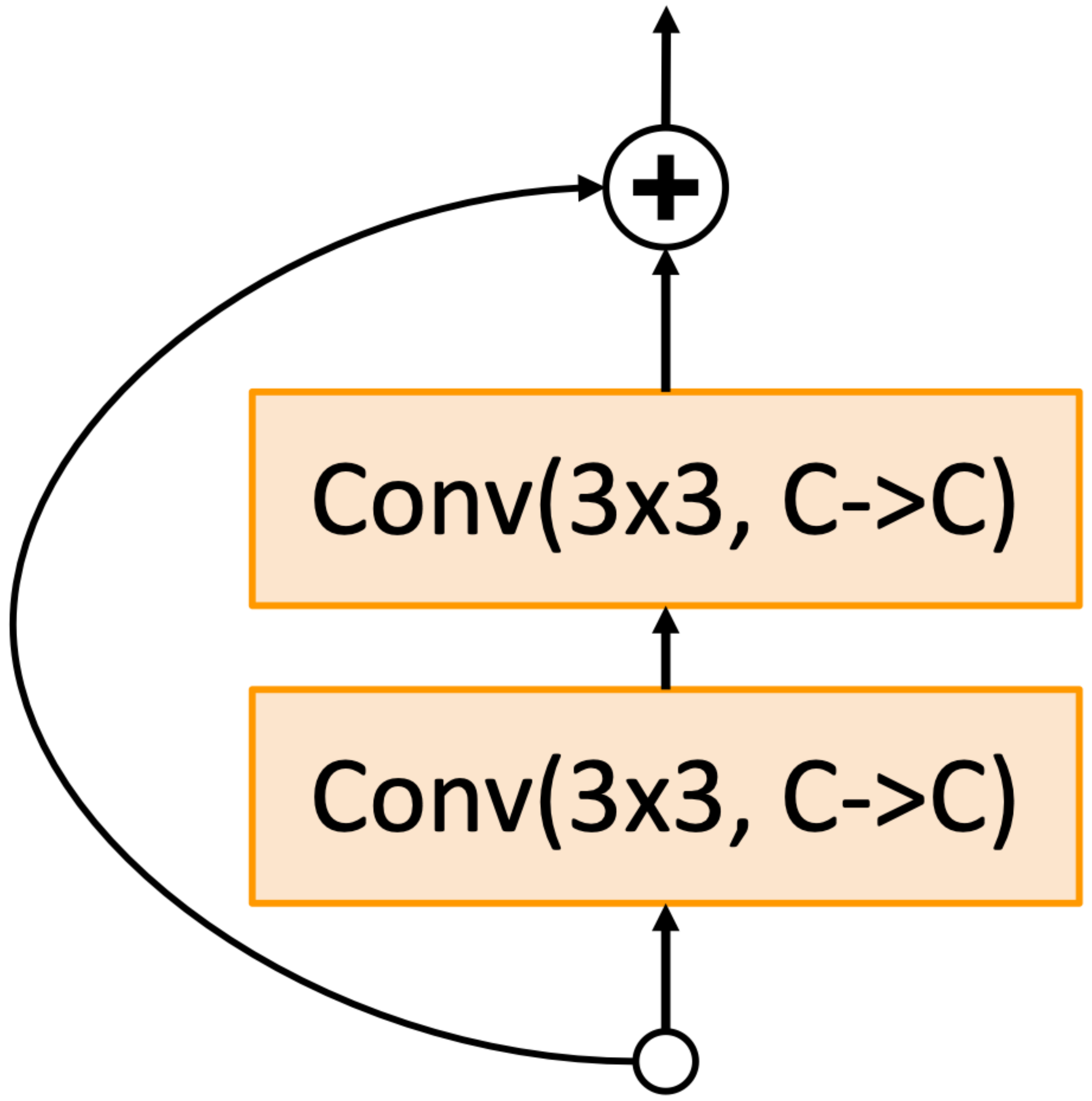
$18HWC^2$



"Bottleneck"
Residual block

Residual Networks: Bottleneck Block

More layers, less computational cost!



“Basic”
Residual block

FLOPs: $9HWC^2$

FLOPs: $9HWC^2$

Total FLOPs:

$18HWC^2$

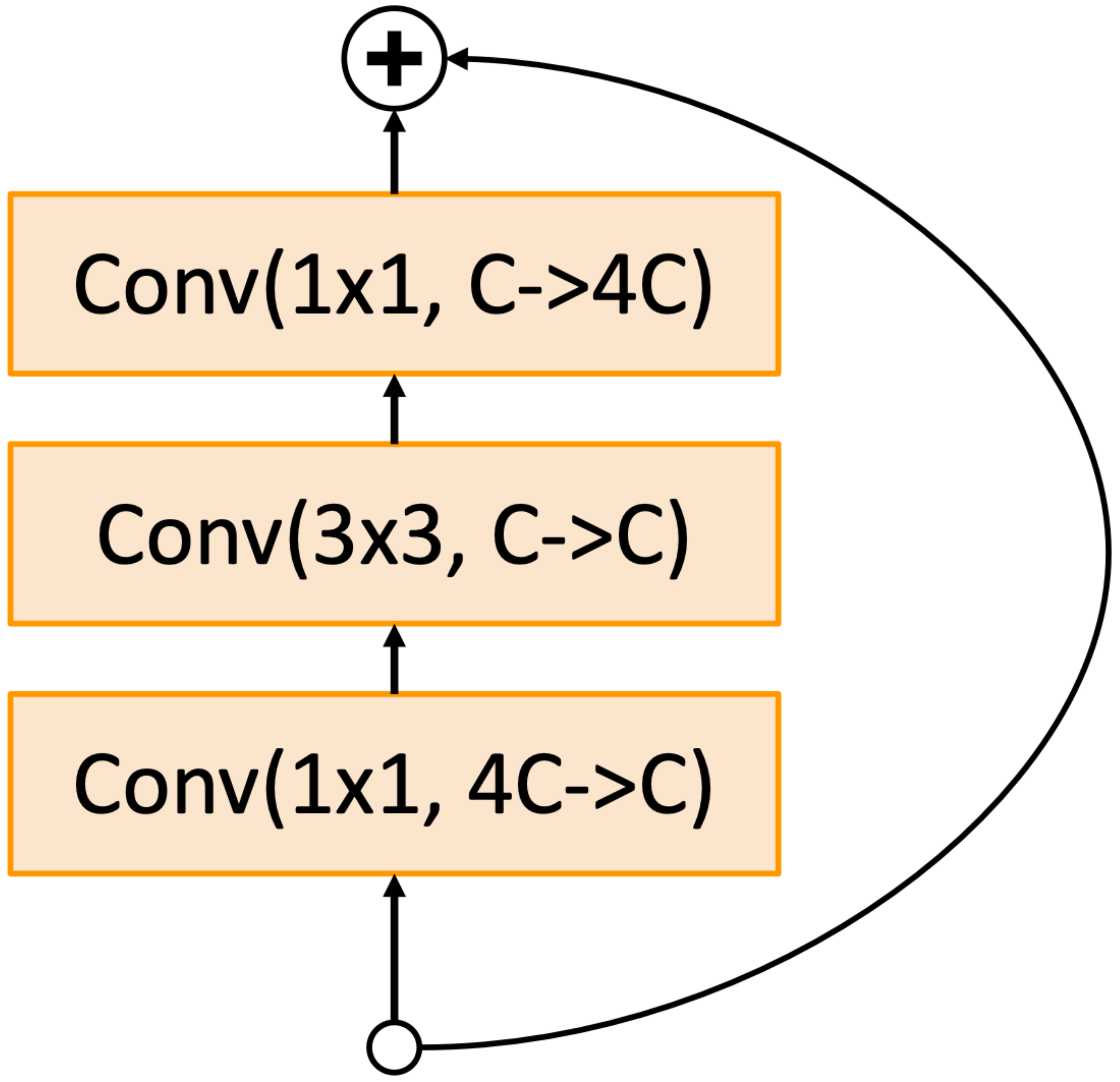
FLOPs: $4HWC^2$

FLOPs: $9HWC^2$

FLOPs: $4HWC^2$

Total FLOPs:

$17HWC^2$



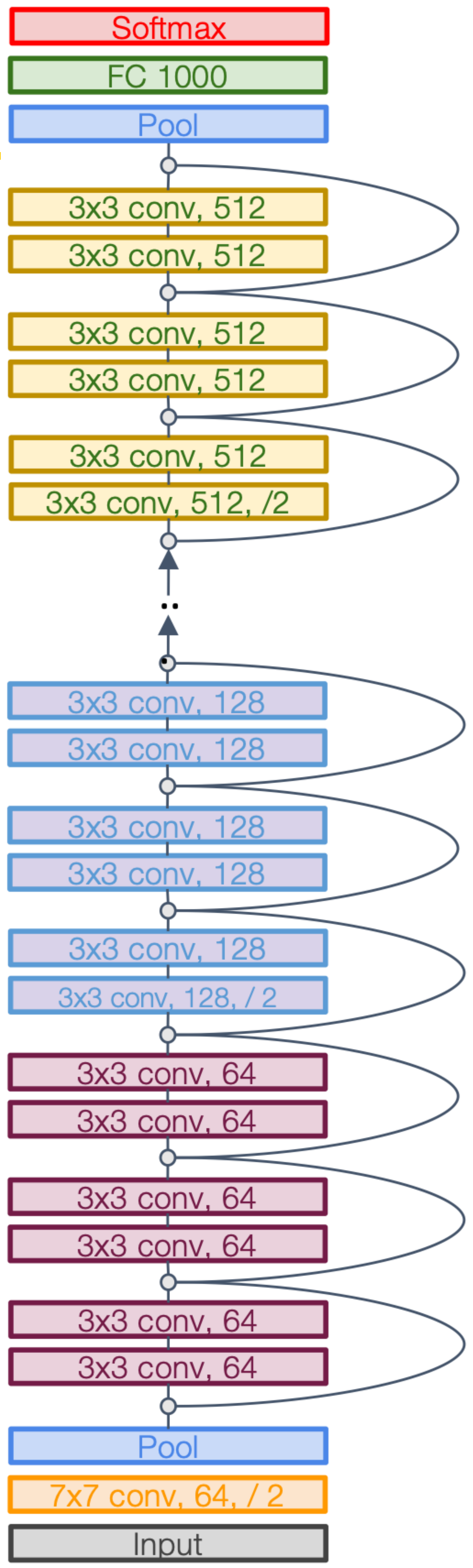
“Bottleneck”
Residual block

Residual Networks

ResNet-50 is the same as ResNet-34, but replaces Basic blocks with Bottleneck Blocks. This is a great baseline architecture for many tasks even today!

Deeper ResNet-101 and ResNet-152 models are more accurate, but also more computationally heavy

			Stage 1		Stage 2		Stage 3		Stage 4				
	Block type	Stem layers	Blocks	Layers	Blocks	Layers	Blocks	Layers	Blocks	Layers	FC Layers	GFLOP	ImageNet
ResNet-18	Basic	1	2	4	2	4	2	4	2	4	1	1.8	10.92
ResNet-34	Basic	1	3	6	4	8	6	12	3	6	1	3.6	8.58
ResNet-50	Bottle	1	3	9	4	12	6	18	3	9	1	3.8	7.13
ResNet-101	Bottle	1	3	9	4	12	23	69	3	9	1	7.6	6.44
ResNet-152	Bottle	1	3	9	8	24	36	108	3	9	1	11.3	5.94



Residual Networks

- Able to train very deep networks
- Deeper networks do better than shallow networks (as expected)
- Swept 1st place in all ILSVRC and COCO 2015 competitions
- Still widely used today

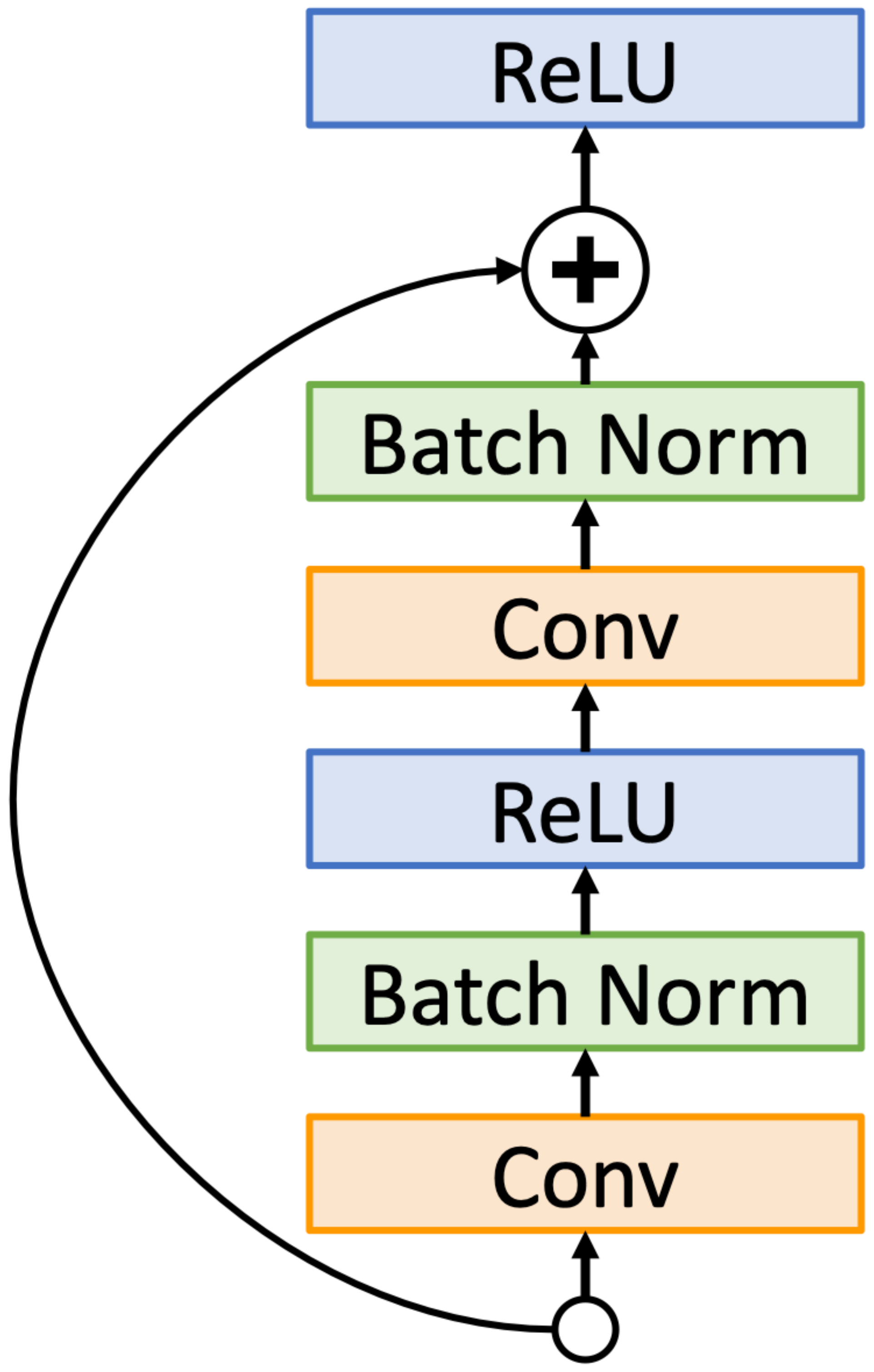
MSRA @ ILSVRC & COCO 2015 Competitions

- **1st places in all five main tracks**
  - ImageNet Classification: *"Ultra-deep"* (quote Yann) 152-layer nets
  - ImageNet Detection: 16% better than 2nd
  - ImageNet Localization: 27% better than 2nd
  - COCO Detection: 11% better than 2nd
  - COCO Segmentation: 12% better than 2nd

He et al, "Deep Residual Learning for Image Recognition", CV

Improving Residual Networks: Block Design

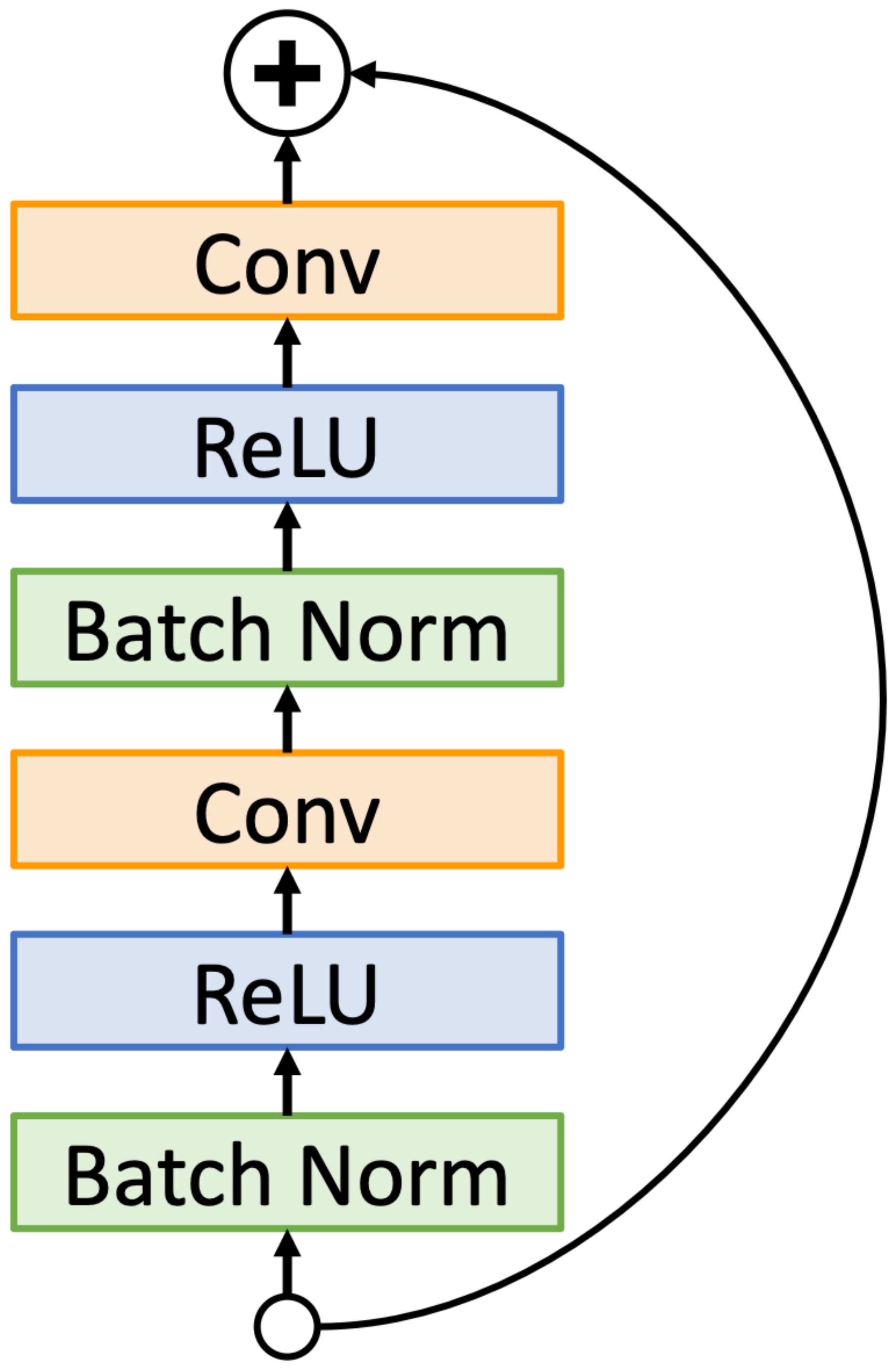
Original ResNet block



Note ReLU **after** residual:

Cannot actually learn identity function since outputs are nonnegative!

"Pre-Activation" ResNet Block



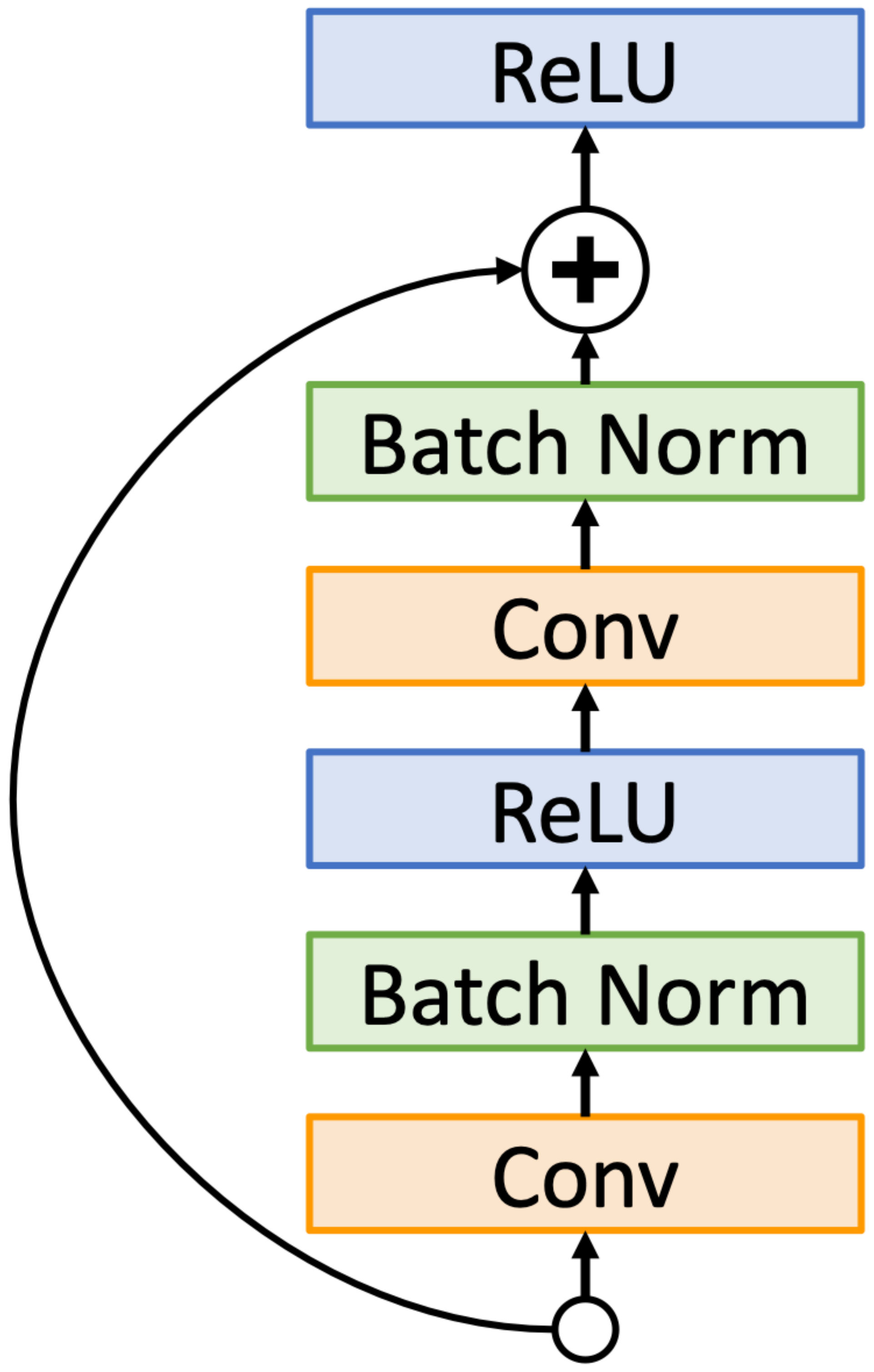
Note ReLU **inside** residual:

Can learn identity function by setting Conv weights to zero

He et al, "Identity mappings in deep residual networks", ECCV

Improving Residual Networks: Block Design

Original ResNet block



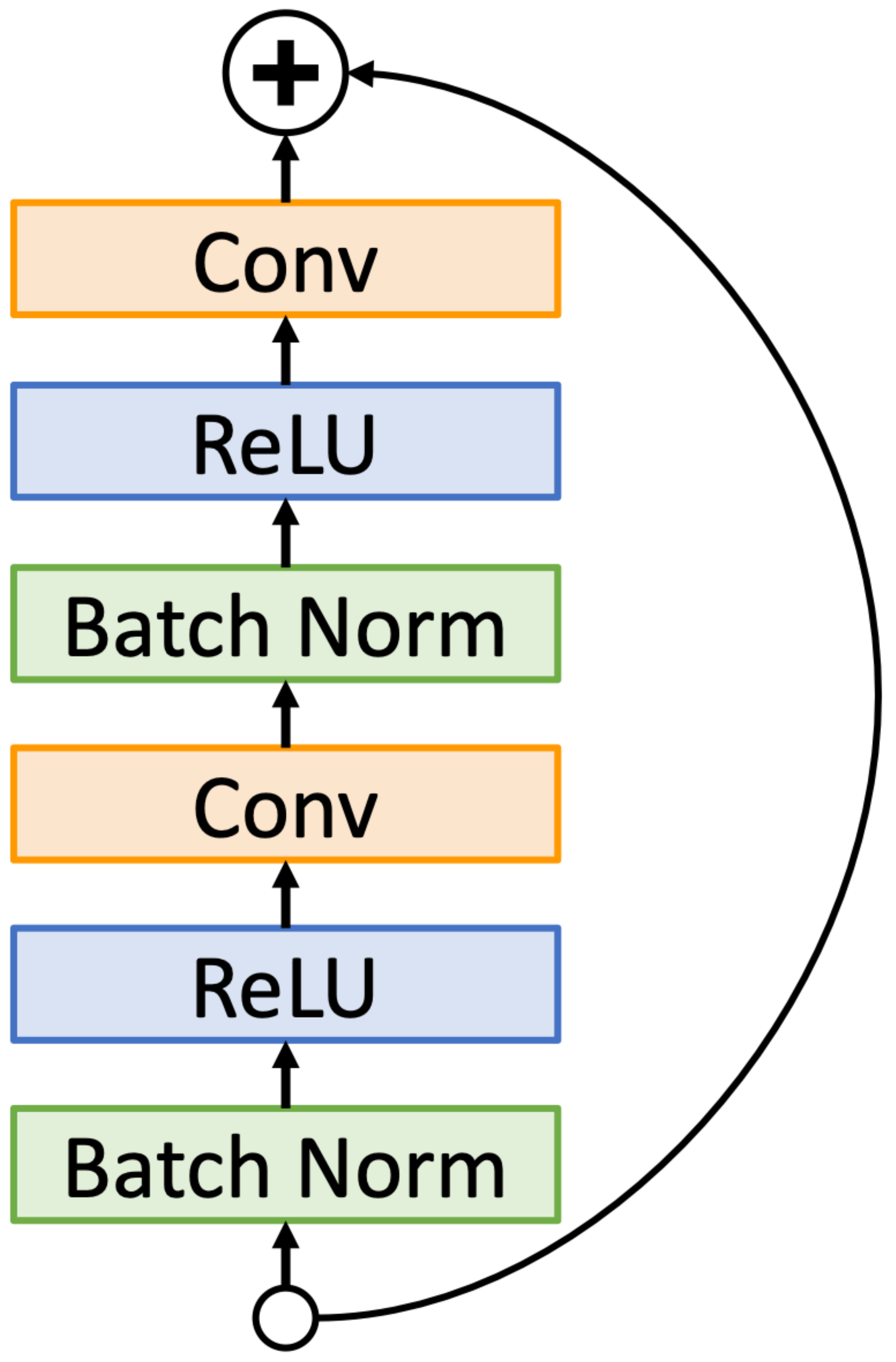
Slight improvement in accuracy (ImageNet top-1 error)

ResNet-152: 21.3 vs **21.1**

ResNet-200: 21.8 vs **20.7**

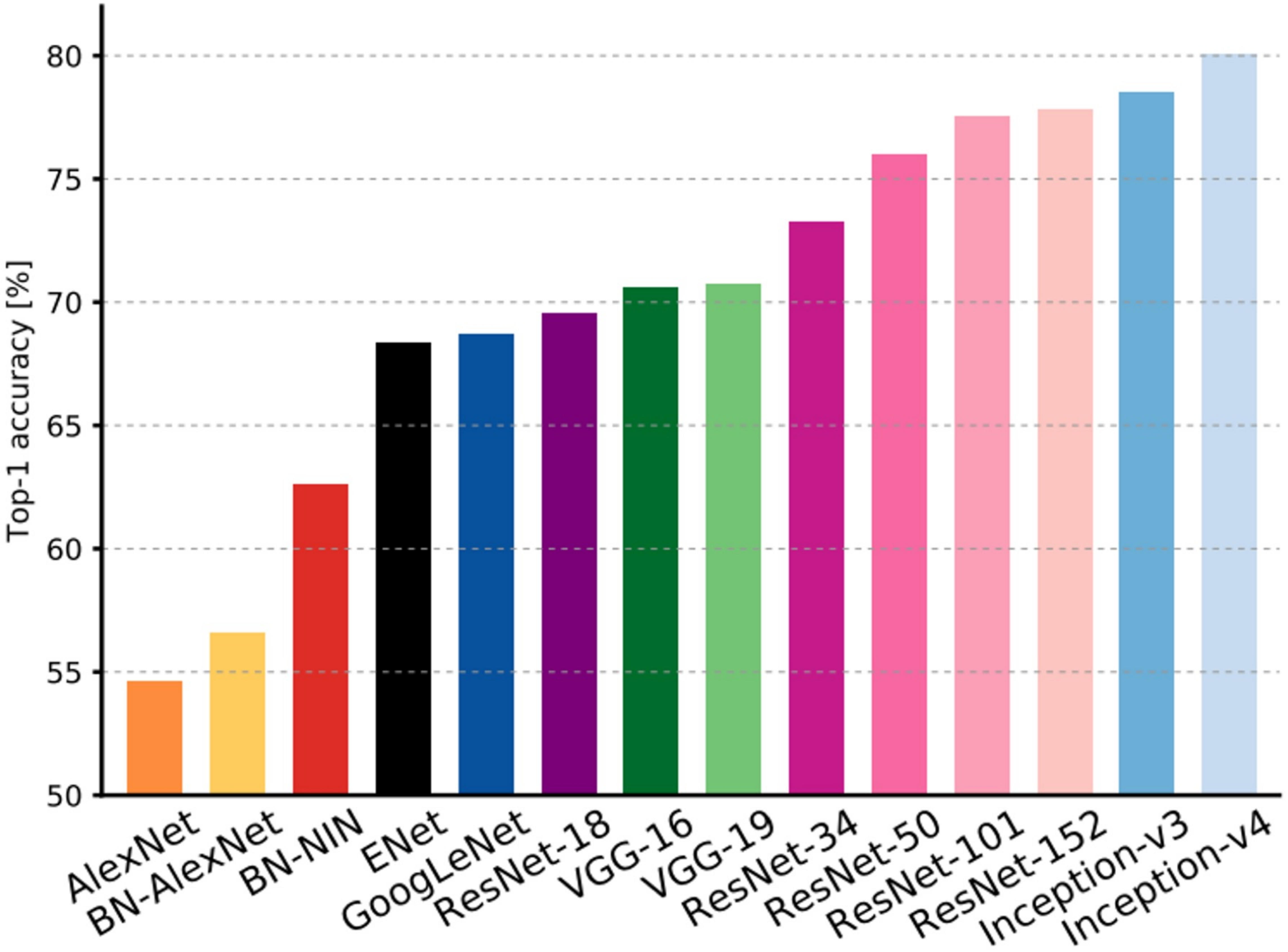
Not actually used that much in practice

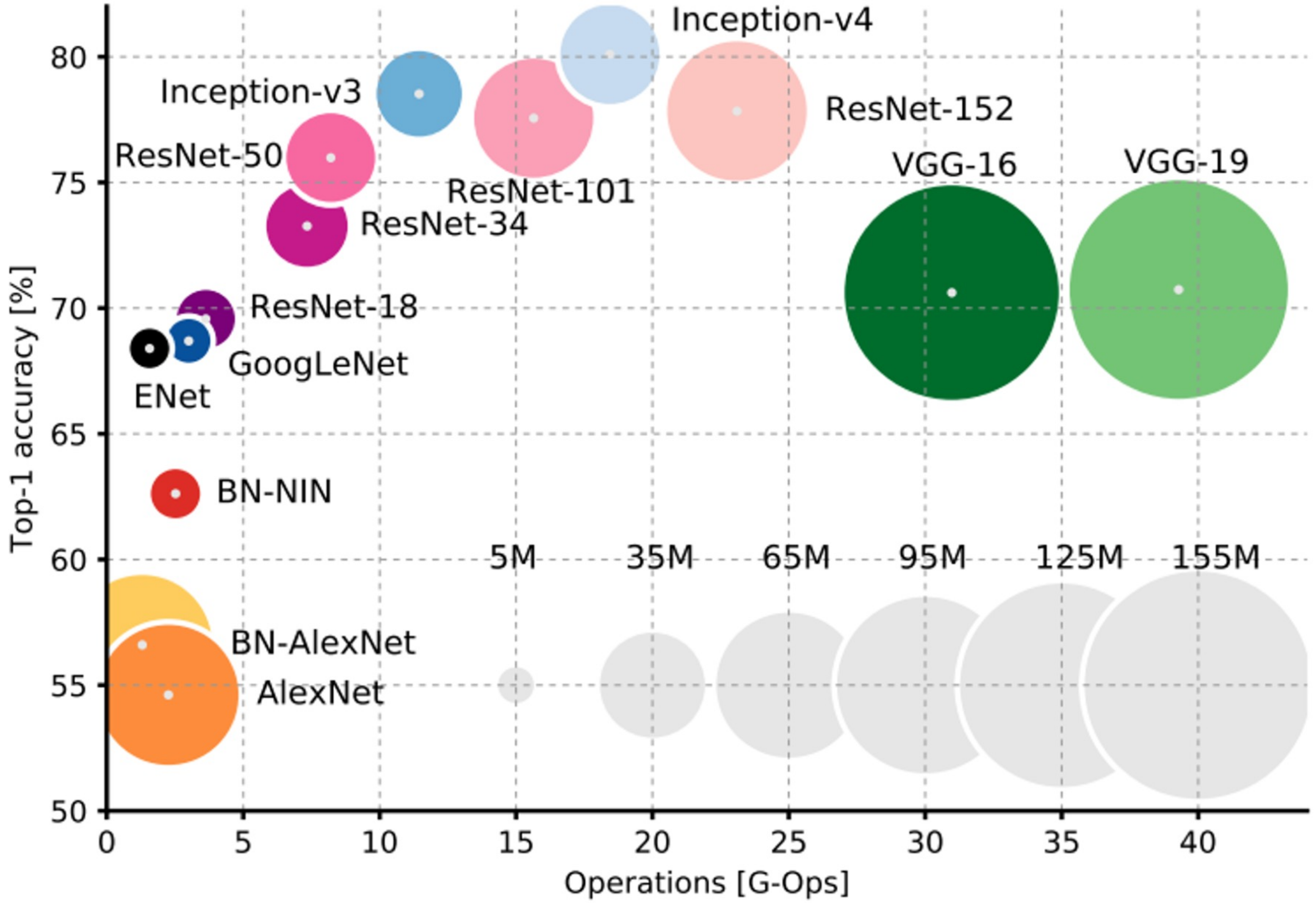
"Pre-Activation" ResNet Block



He et al, "Identity mappings in deep residual networks", ECCV

Comparing Complexity

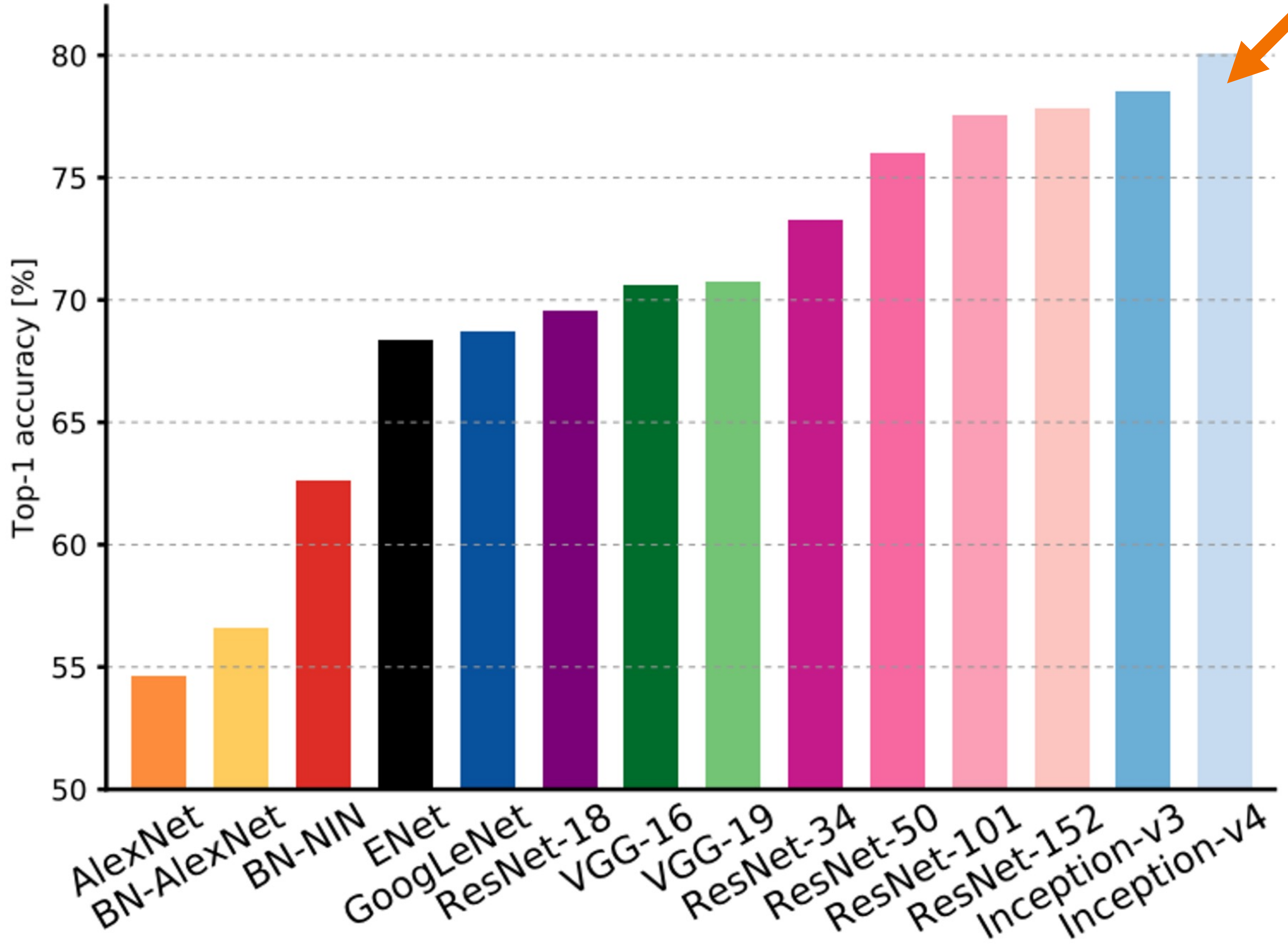


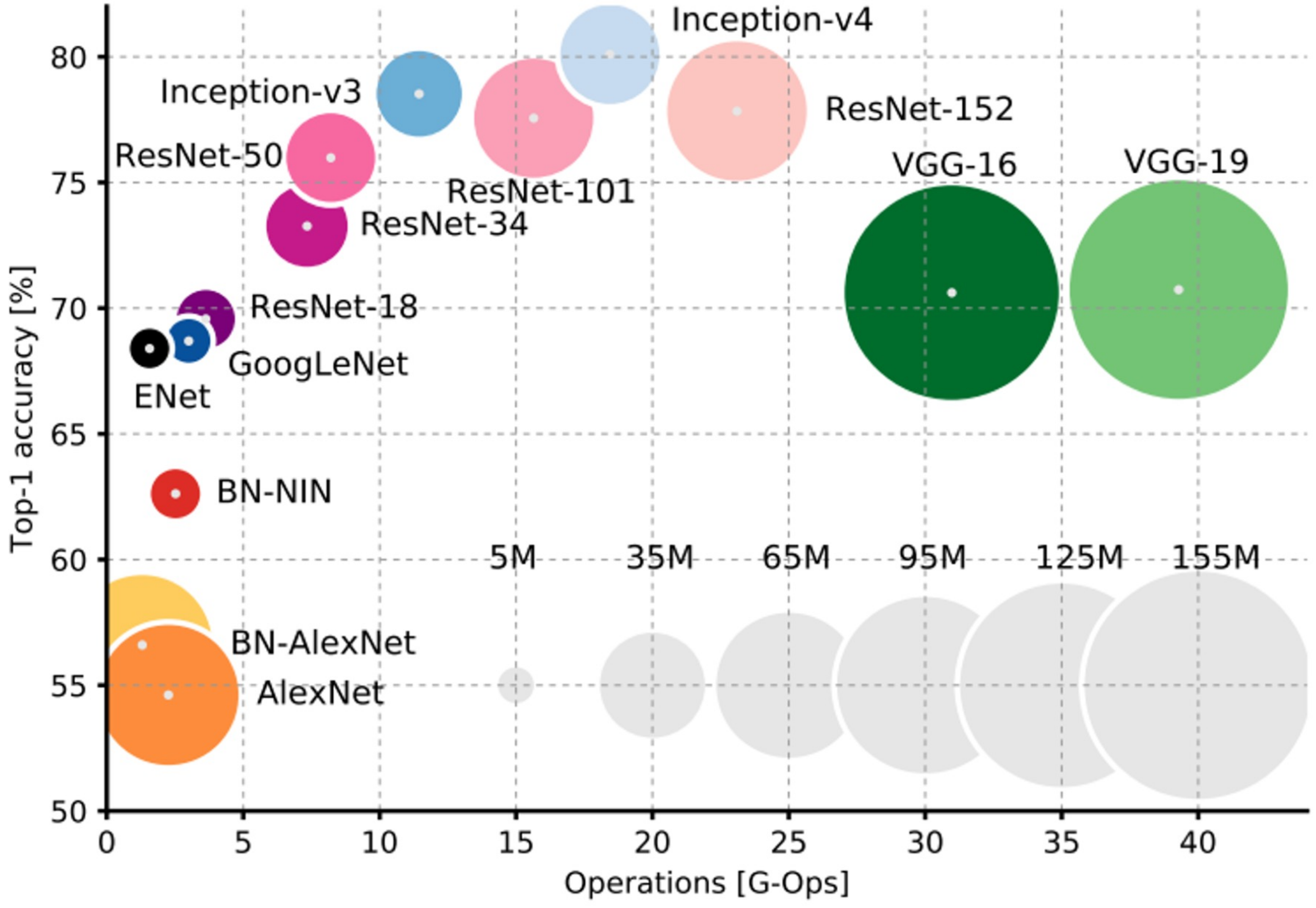


Canziani et al, "An analysis of deep neural network models for pract

Comparing Complexity

Inception-v4: ResNet + Inception!



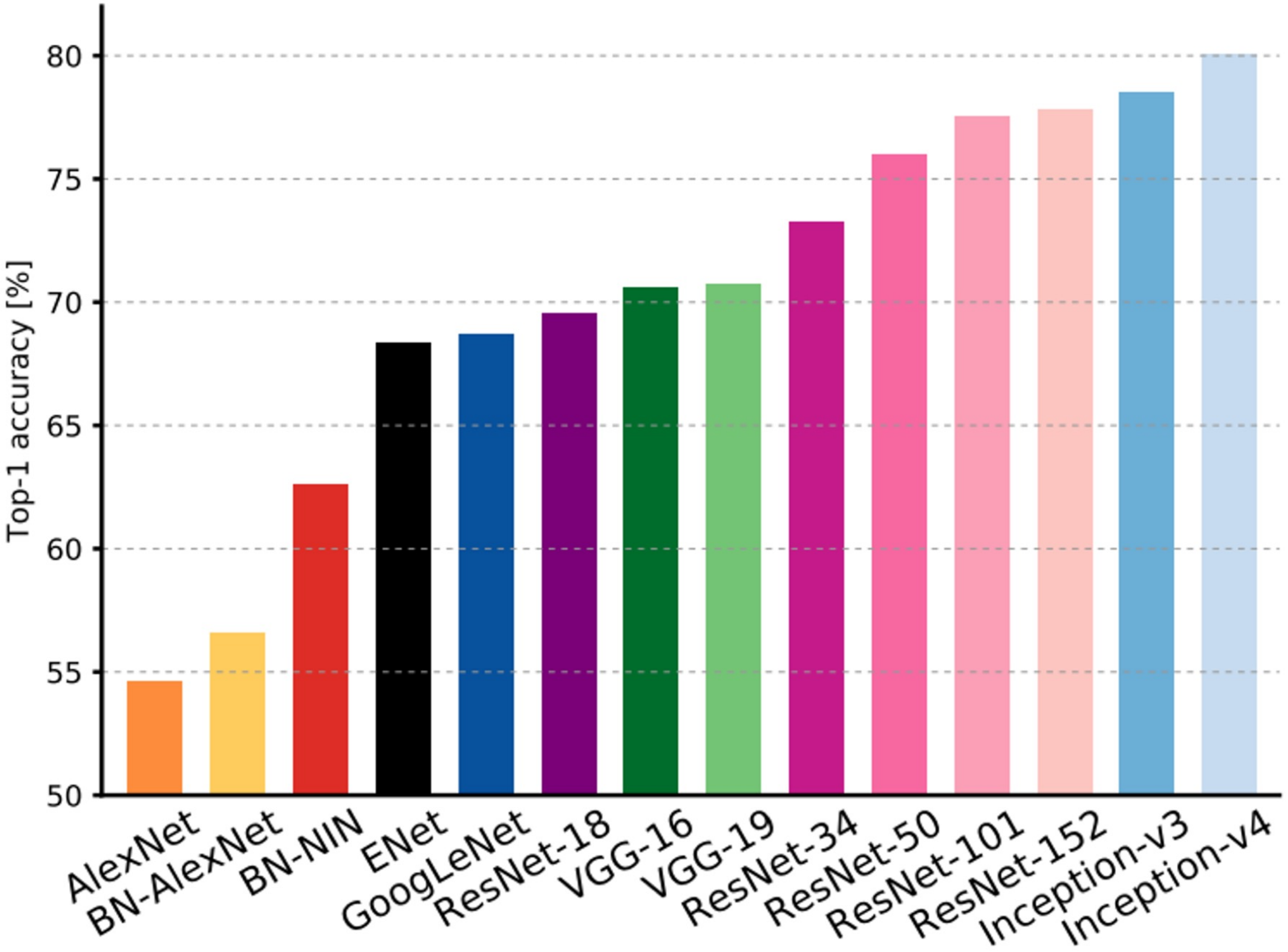


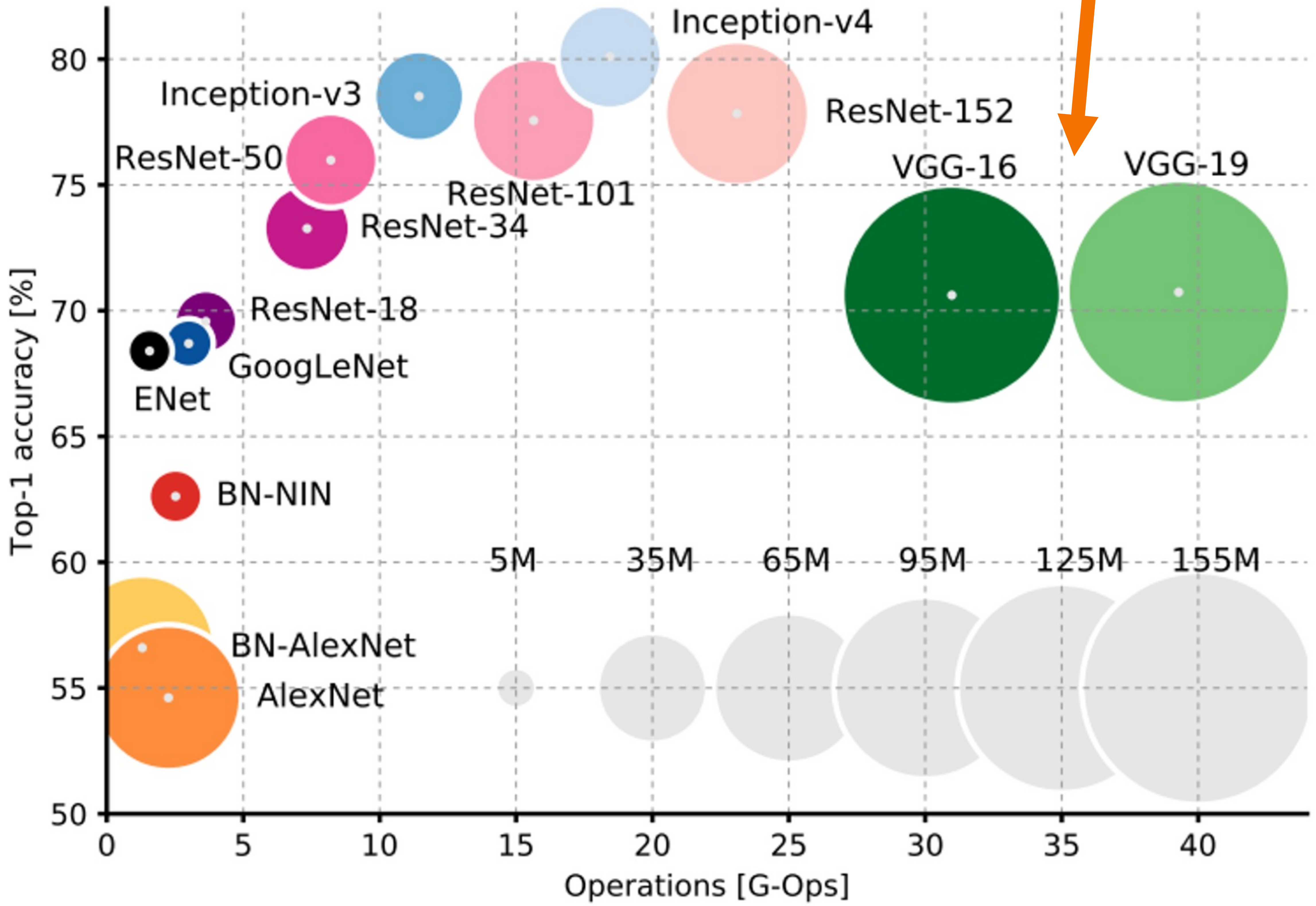
Canziani et al, "An analysis of deep neural network models for pract

Comparing Complexity

VGG:

Highest memory, most operations



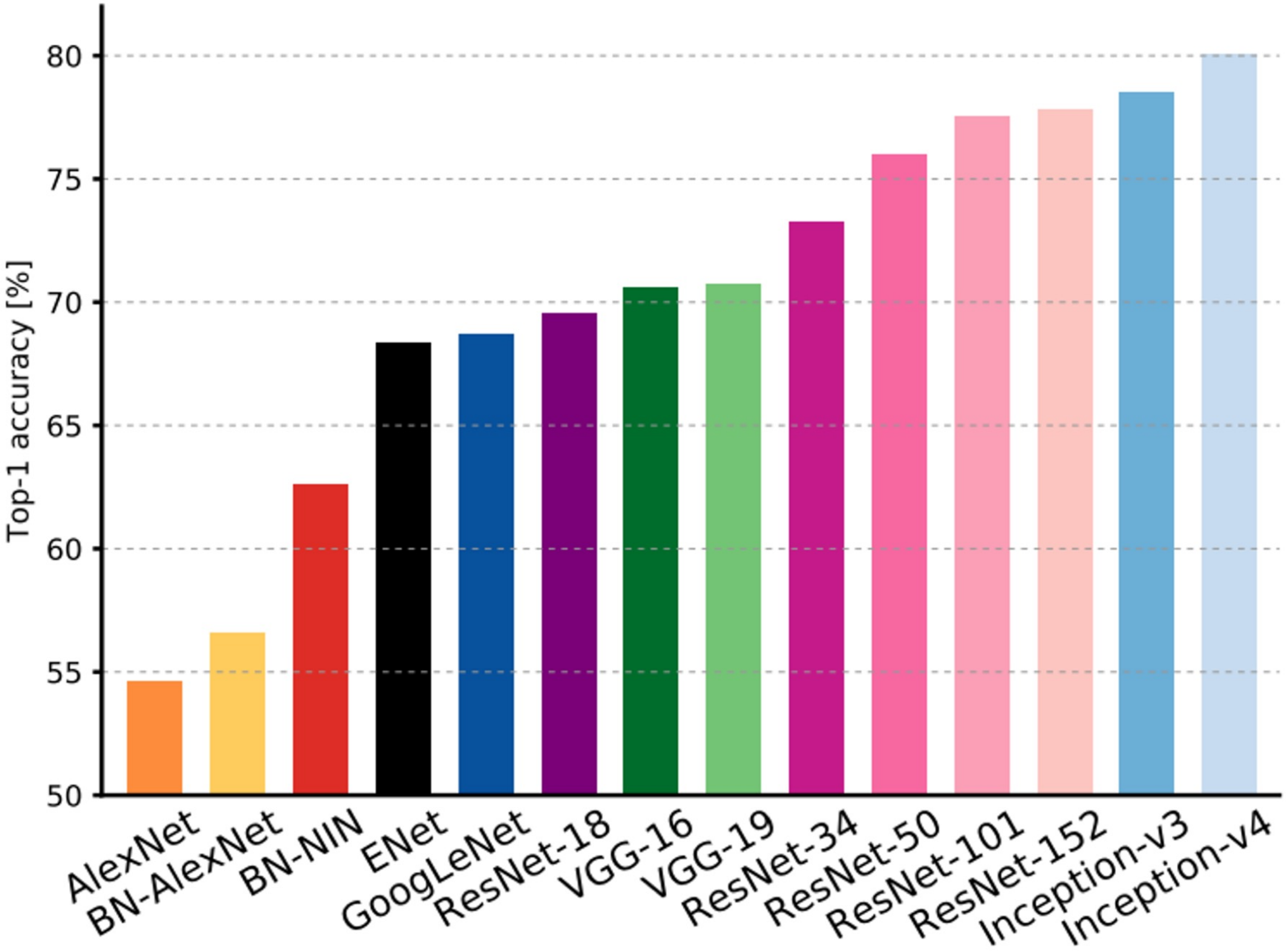


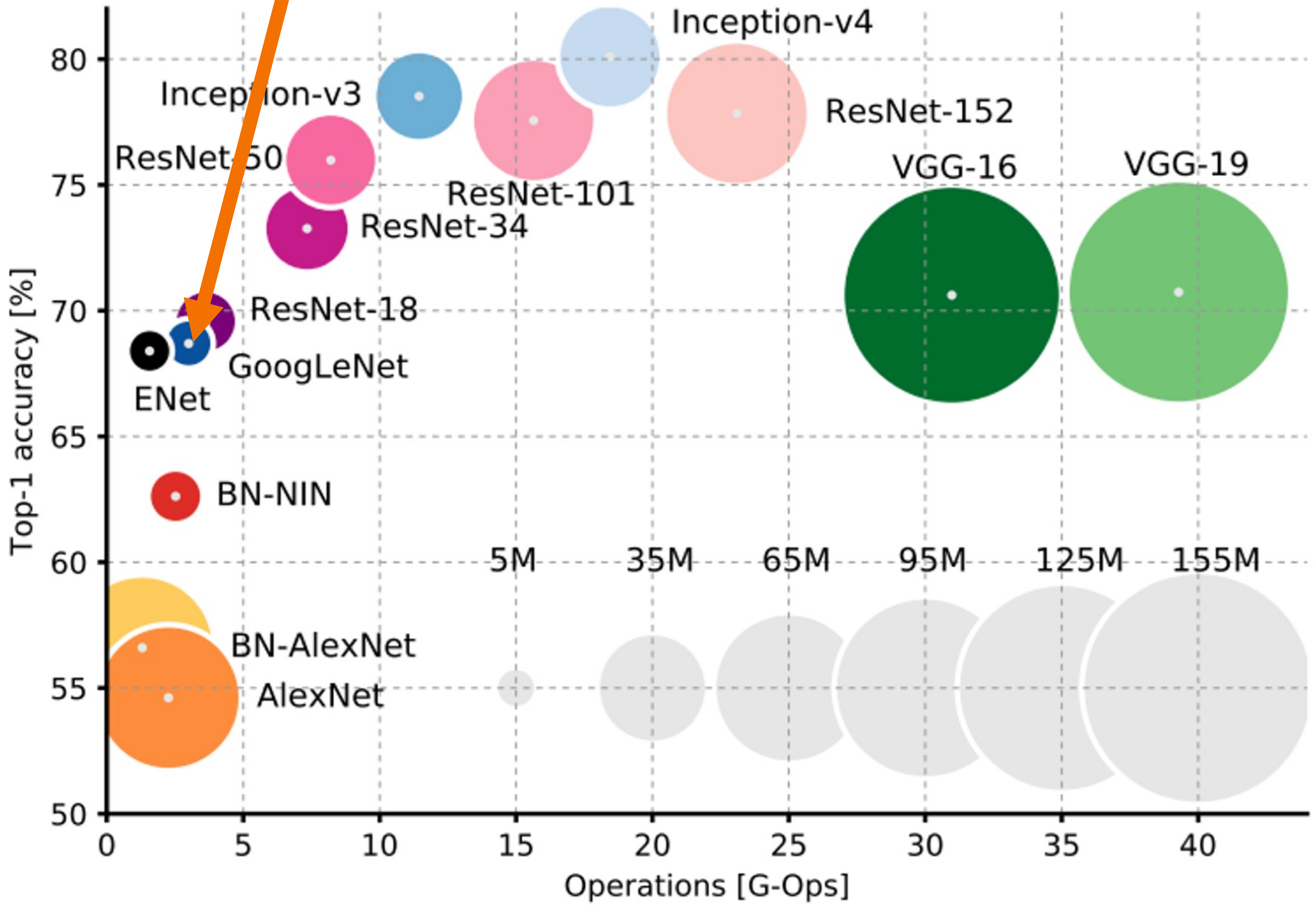
Canziani et al, "An analysis of deep neural network models for pract

Comparing Complexity

GoogLeNet:

Very efficient!

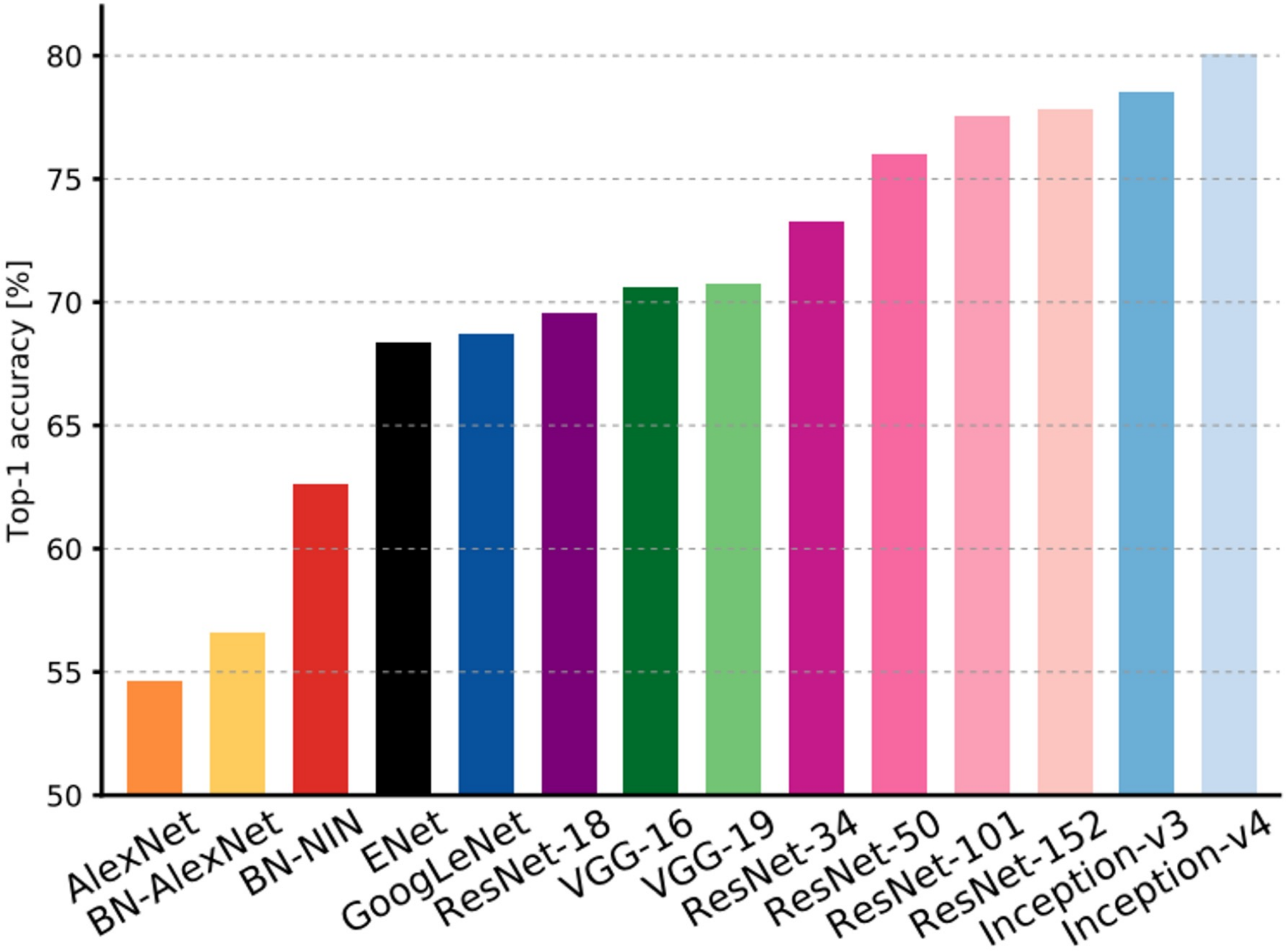


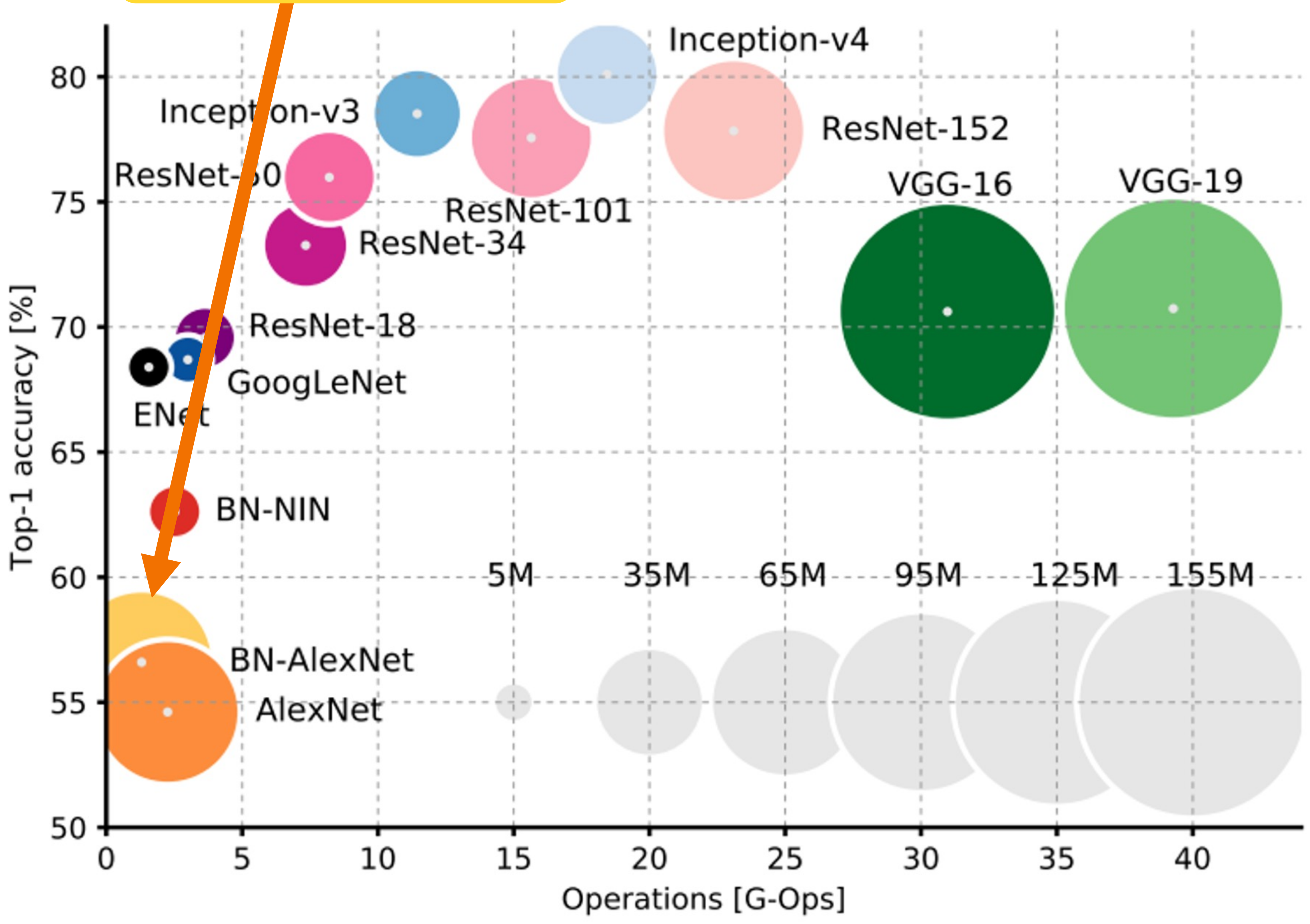


Canziani et al, "An analysis of deep neural network models for pract

Comparing Complexity

AlexNet: Low compute, lots of parameters

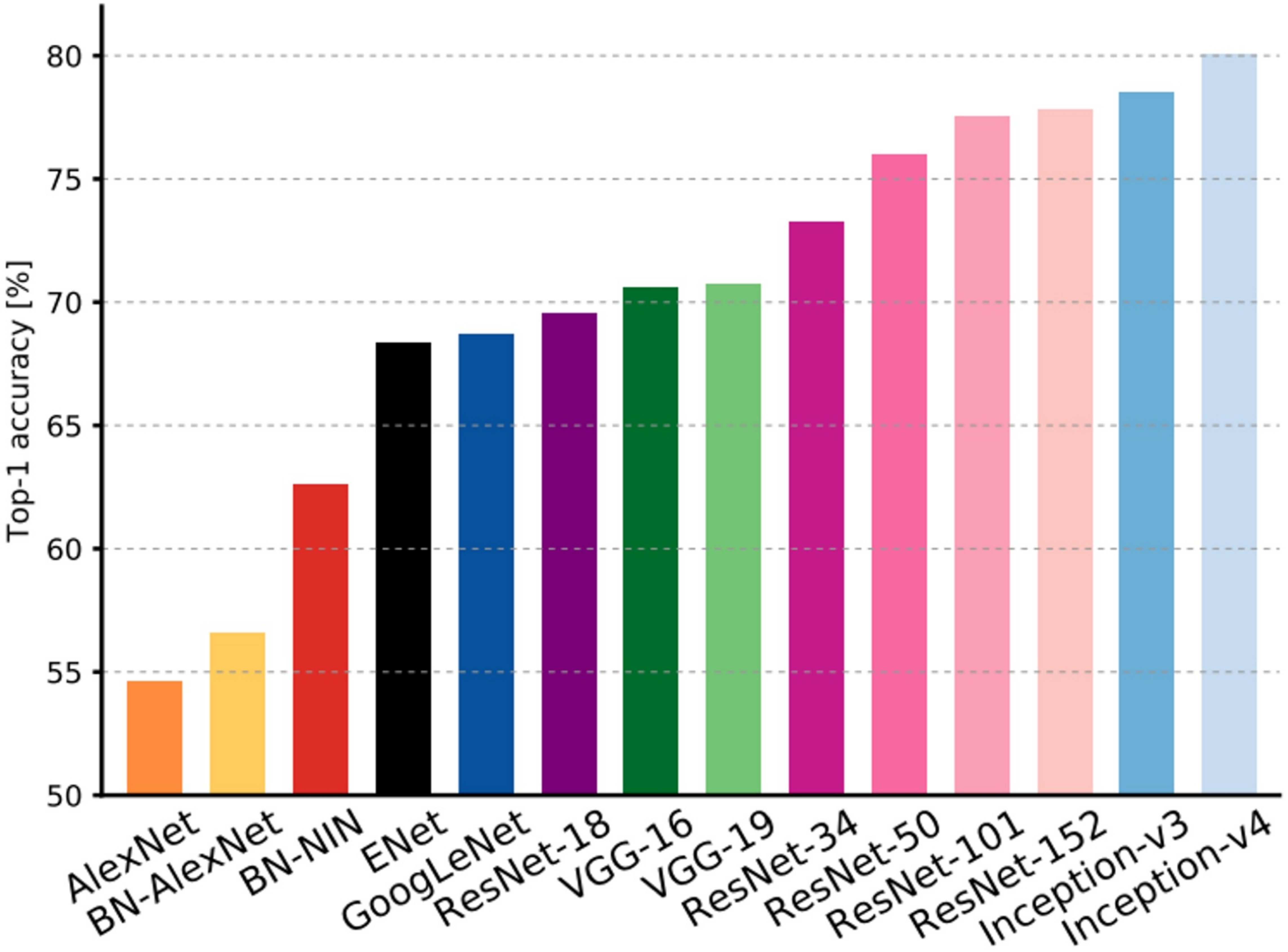


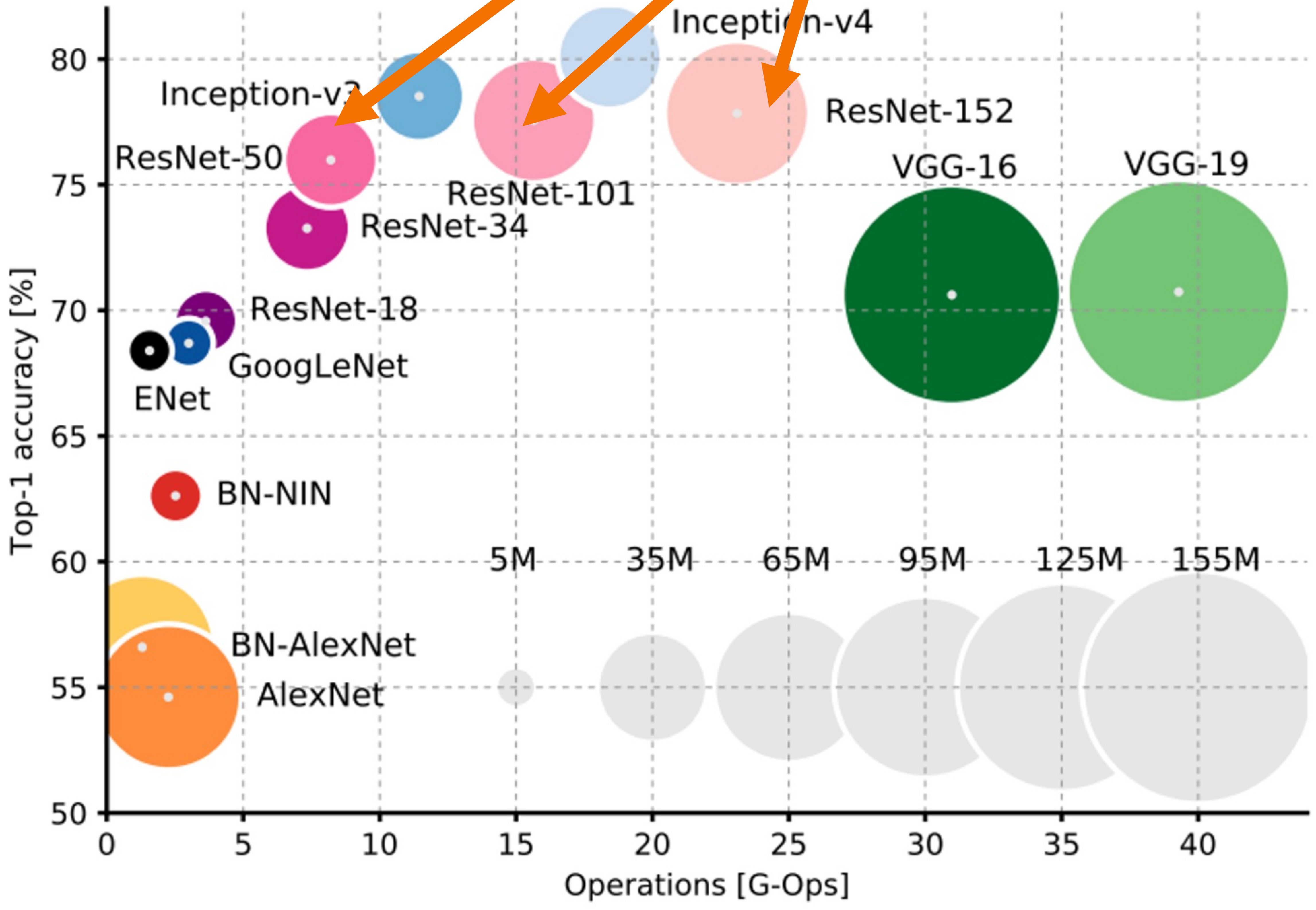


Canziani et al, "An analysis of deep neural network models for pract

Comparing Complexity

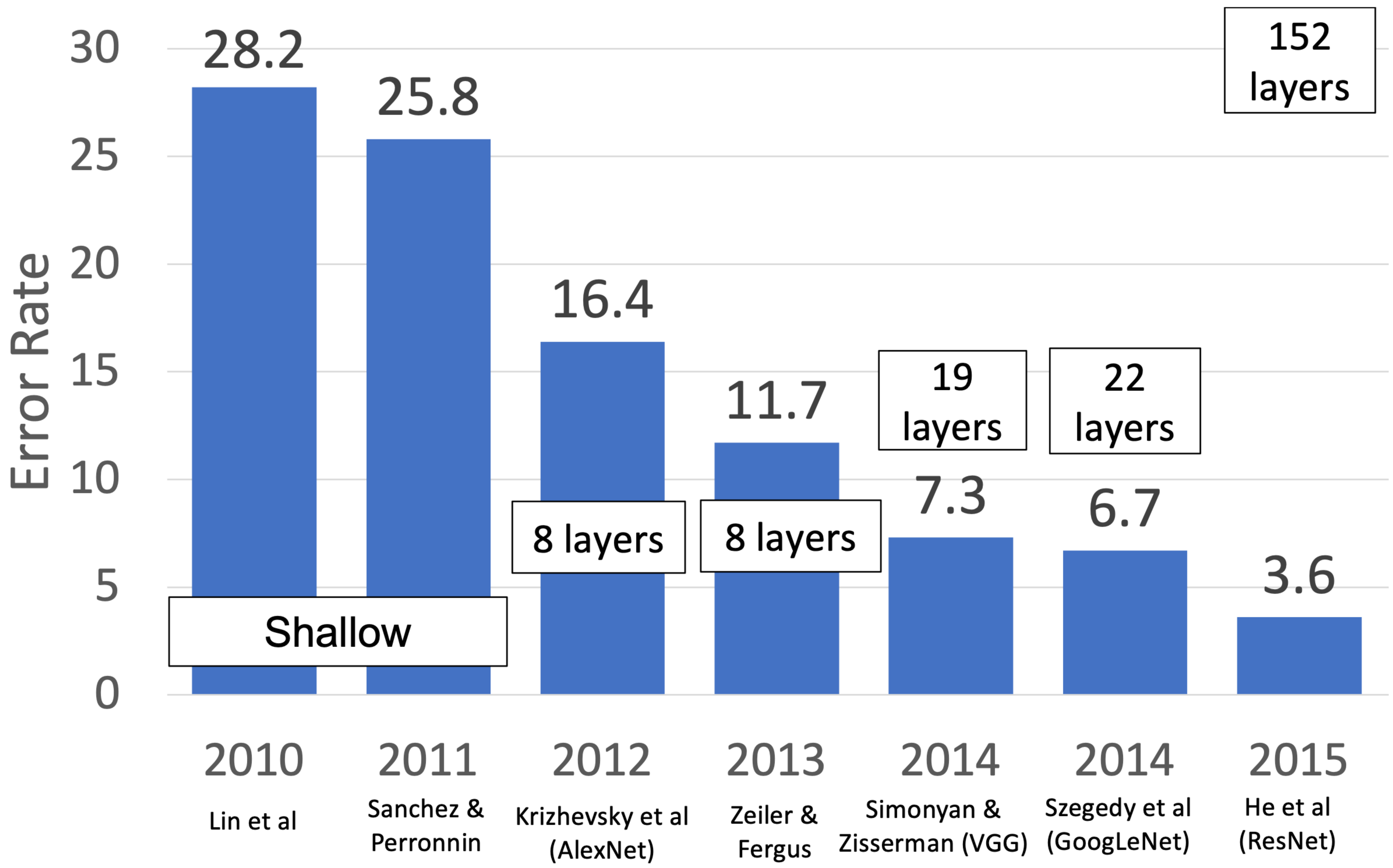
ResNet: Simple design, moderate efficiency, high accuracy





Canziani et al, "An analysis of deep neural network models for pract

ImageNet Classification Challenge



CNN architectures have continued to evolve!

DeepRob

Lecture 7
CNN Architectures
University of Michigan | Department of Robotics