CNN Architectures

Neural Networks Design And Application

LetNet-5

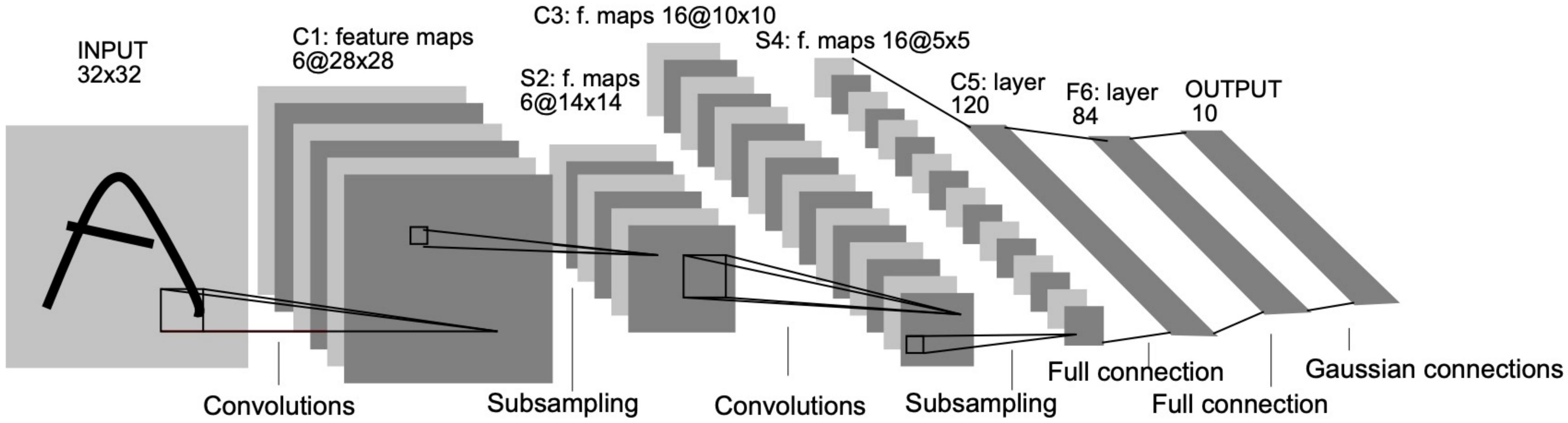
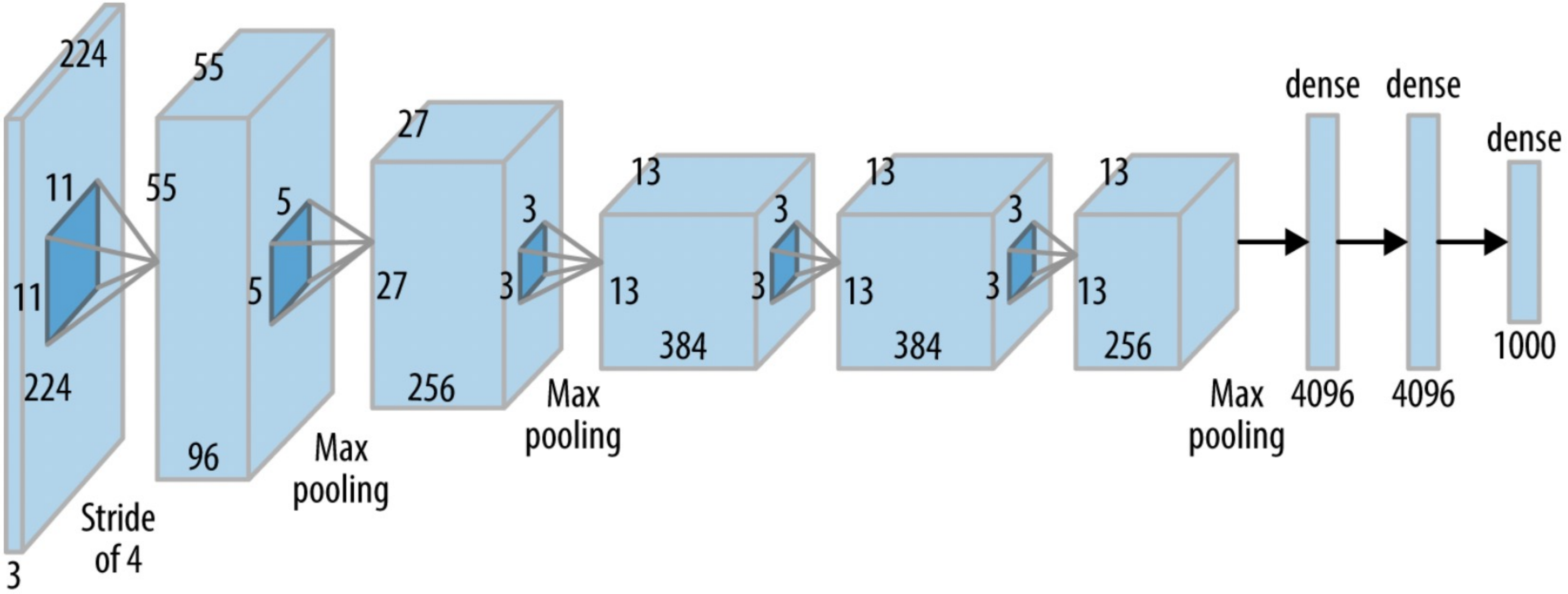


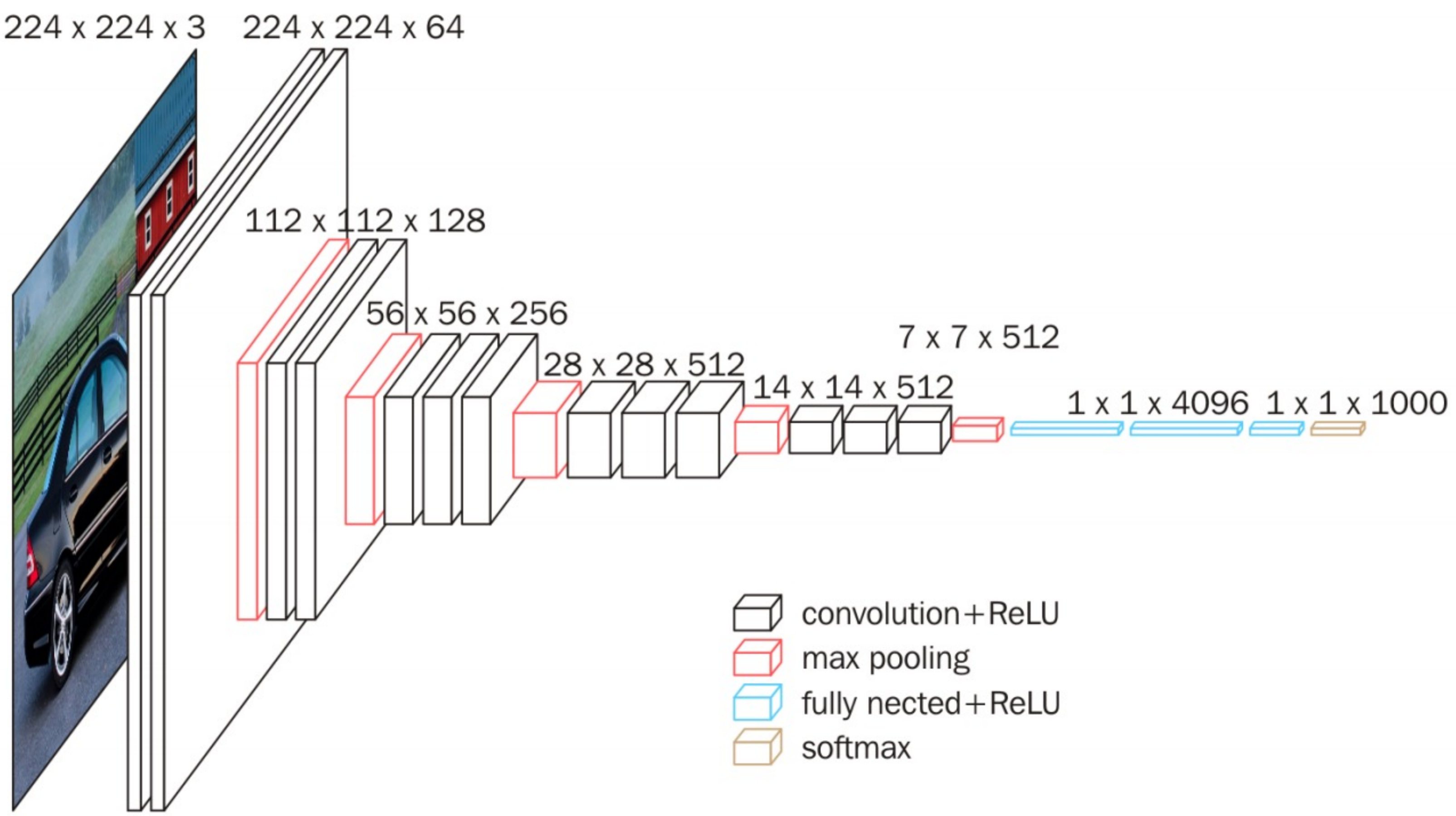
Fig. 1. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

AlexNet

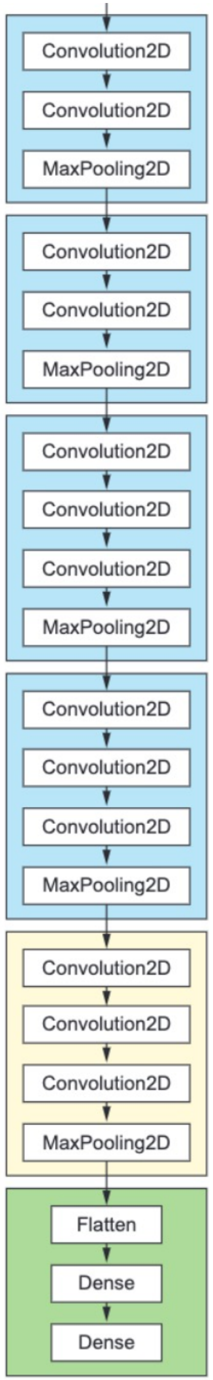


224
55
27
13
13
13
dense
dense
dense
11
55
5
3
3
3
11
5
27
3
13
3
13
3
13
384
384
256
1000
224
256
Max
pooling
Max
pooling
4096
4096
96
Max
pooling
Stride
of 4
3

VGG-16



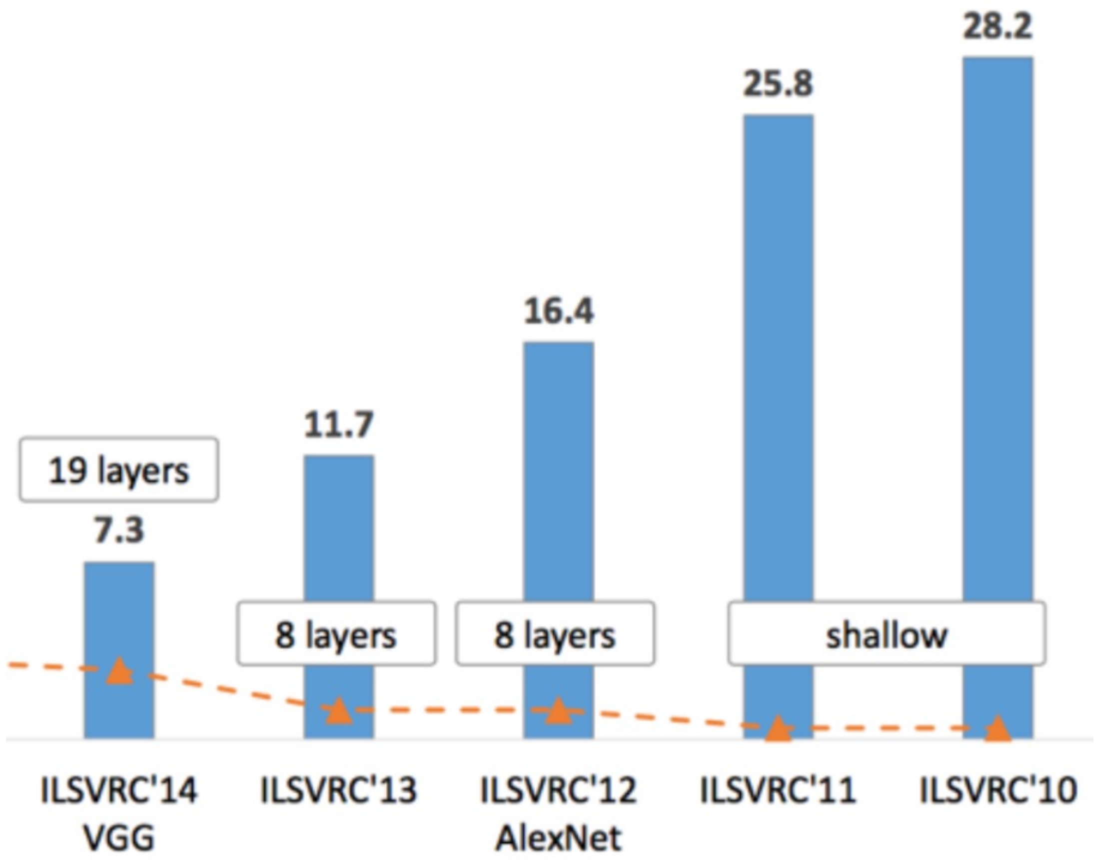
224 x 224 x 3
224 x 224 x 64
112 x 112 x 128
56 x 56 x 256
28 x 28 x 512
14 x 14 x 512
7 x 7 x 512
1 x 1 x 4096
1 x 1 x 1000
convolution+ReLU
max pooling
fully nected+ReLU
softmax



Convolution2D
Convolution2D
MaxPooling2D
Convolution2D
Convolution2D
MaxPooling2D
Convolution2D
Convolution2D
Convolution2D
MaxPooling2D
Convolution2D
Convolution2D
Convolution2D
MaxPooling2D
Convolution2D
Convolution2D
Convolution2D
MaxPooling2D
Flatten
Dense
Dense

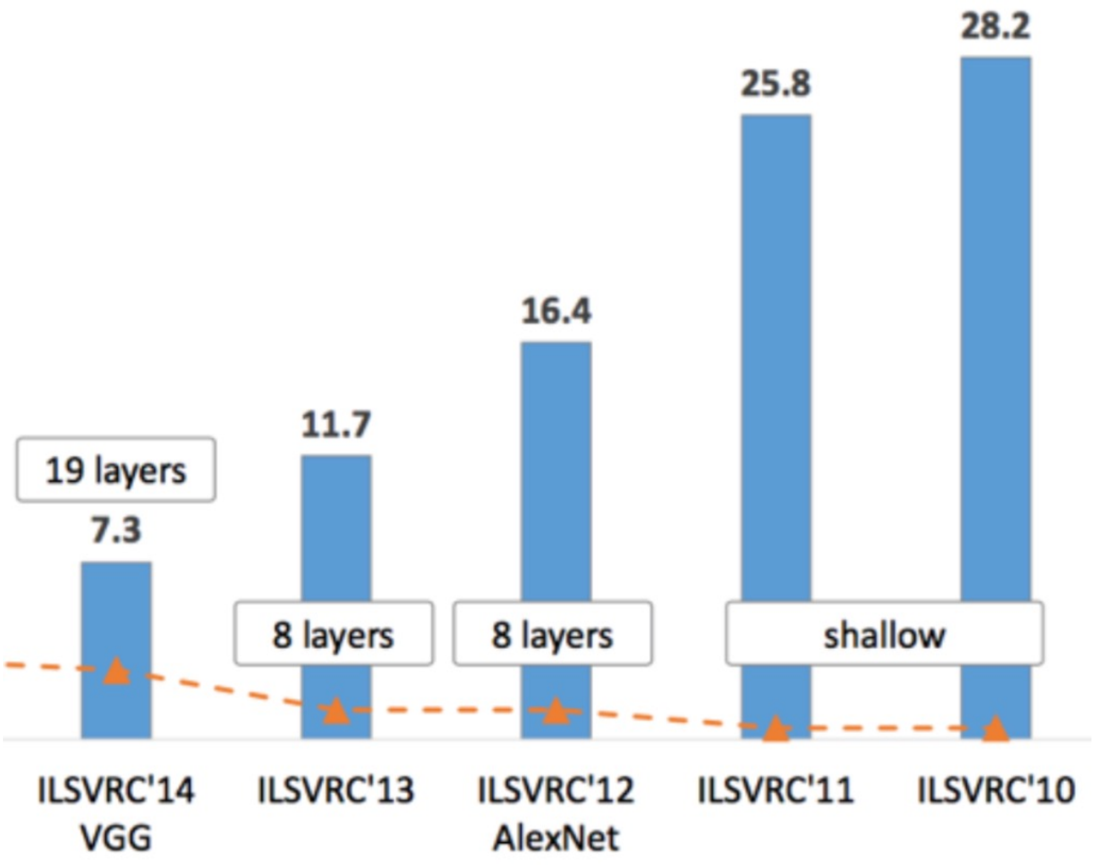
[VGG]

ImageNet competition



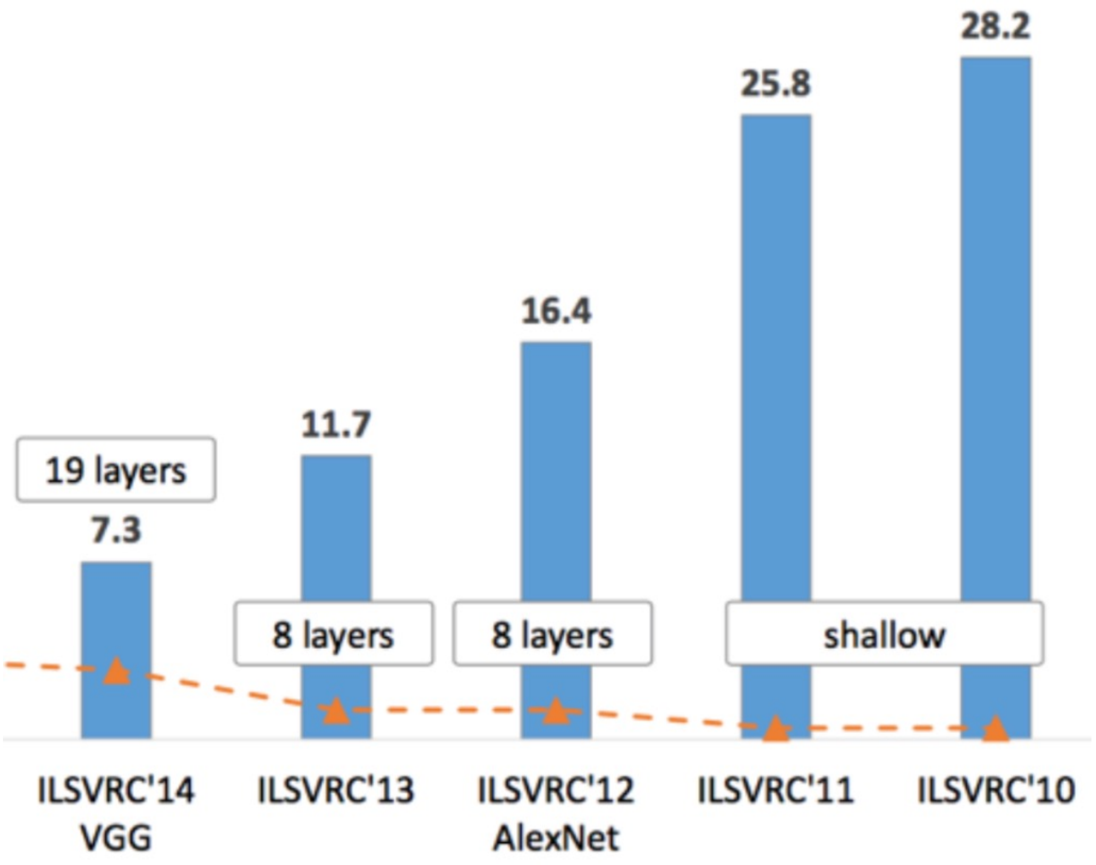
ImageNet competition

More layers



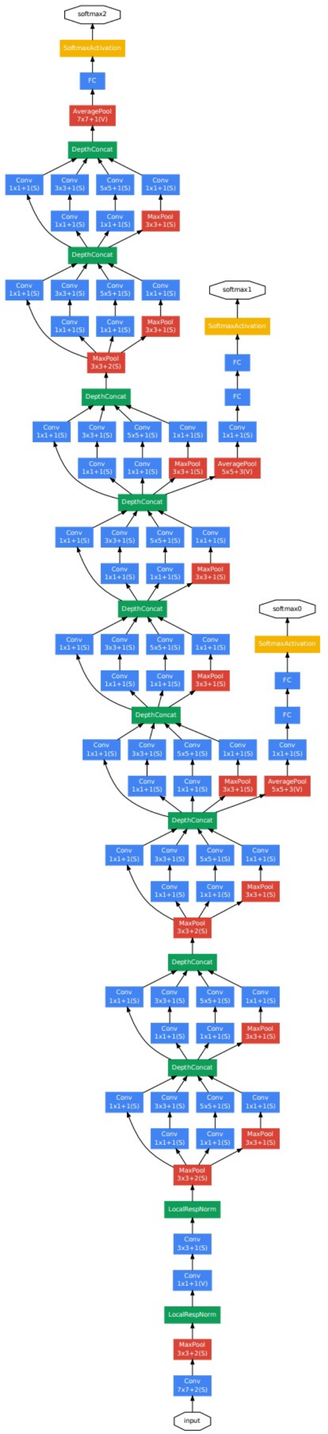
ImageNet competition

More layers

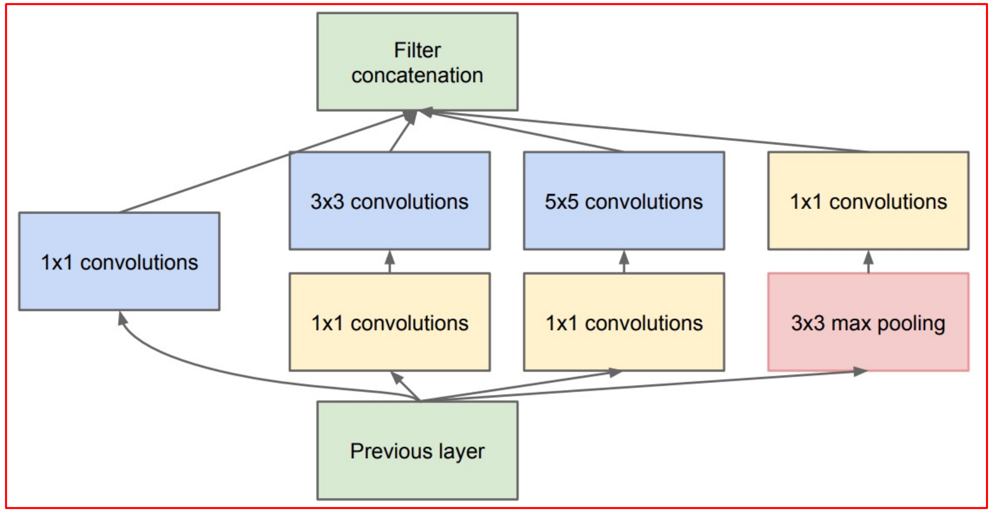


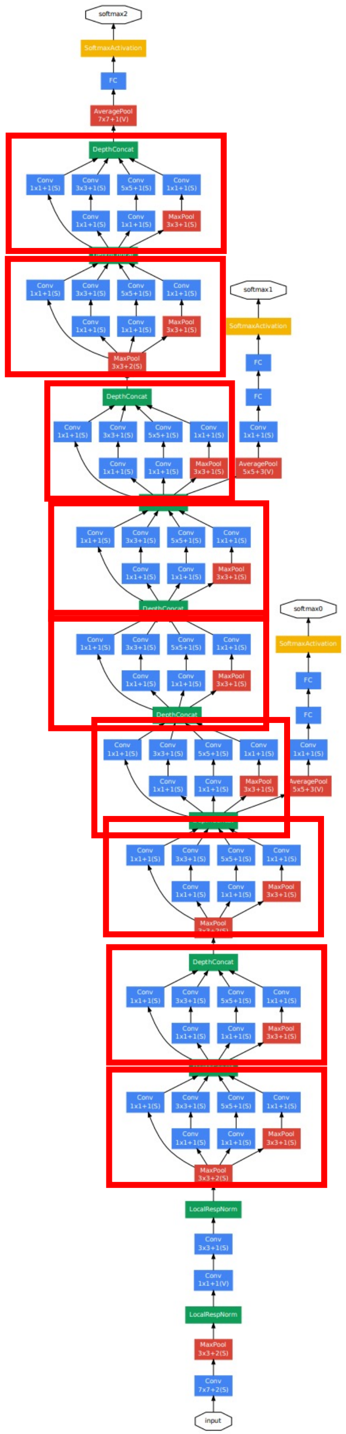
Better performance

Inception (GoogLeNet)

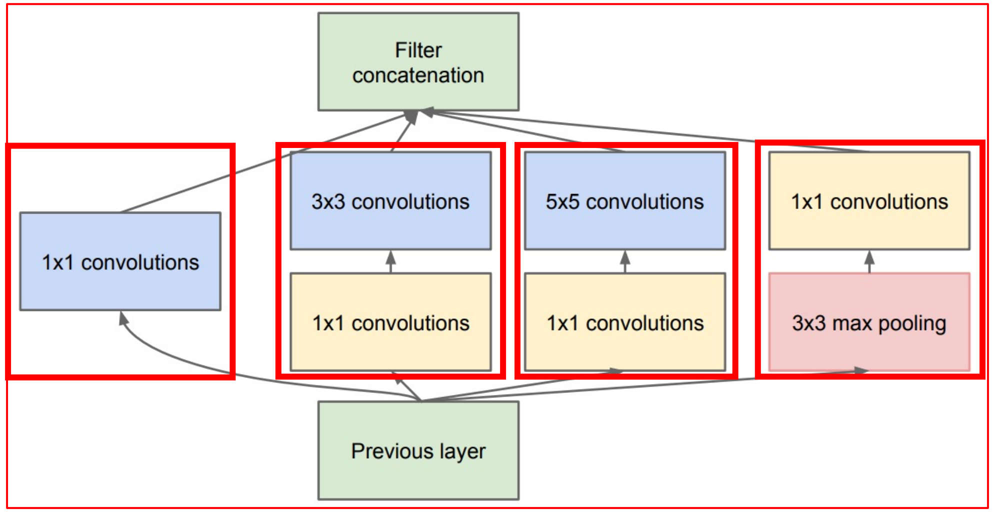


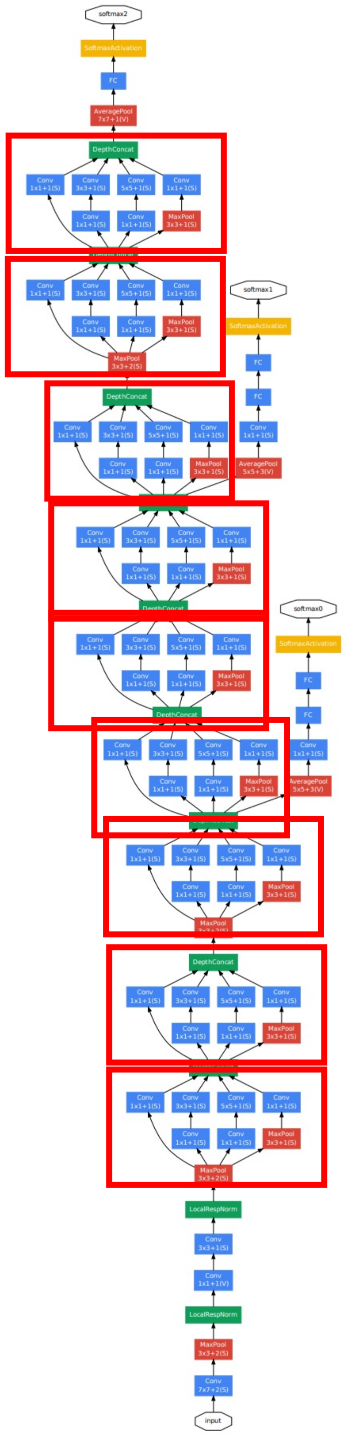
Inception (GoogLeNet)



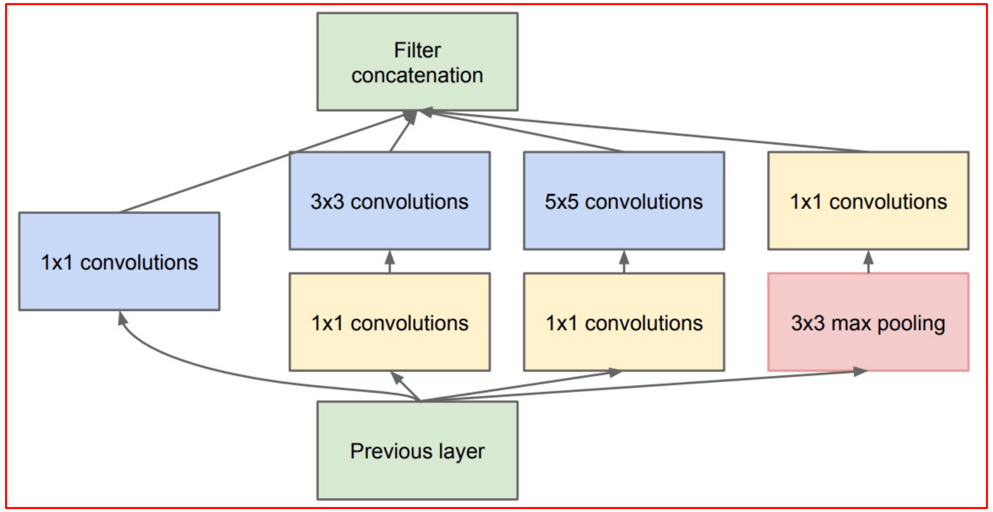


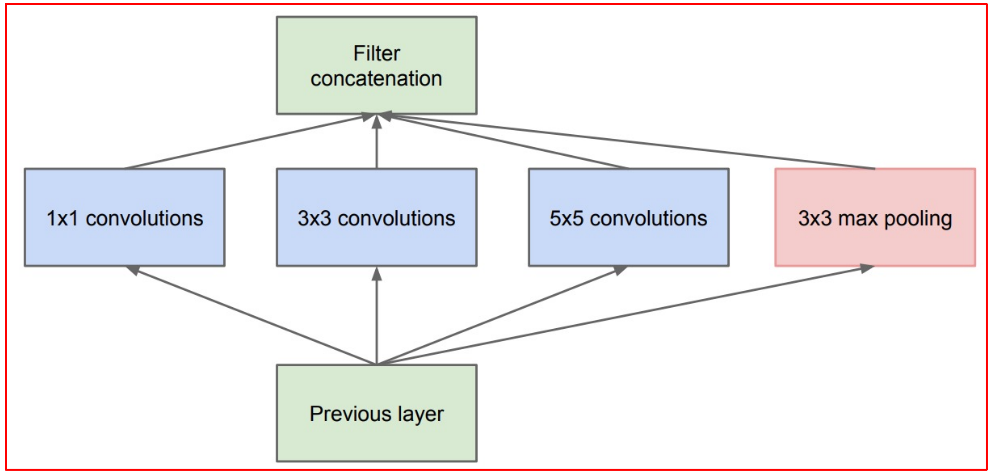
Inception (GoogLeNet)

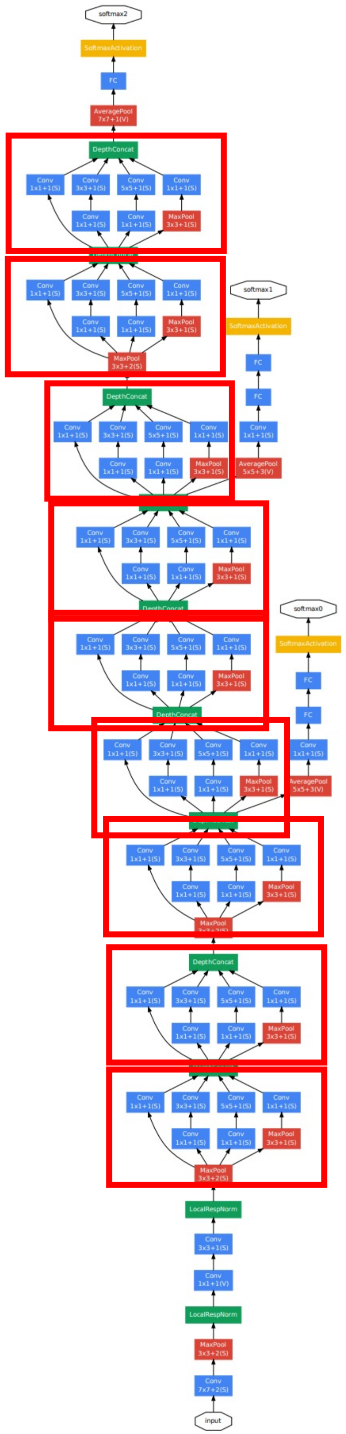




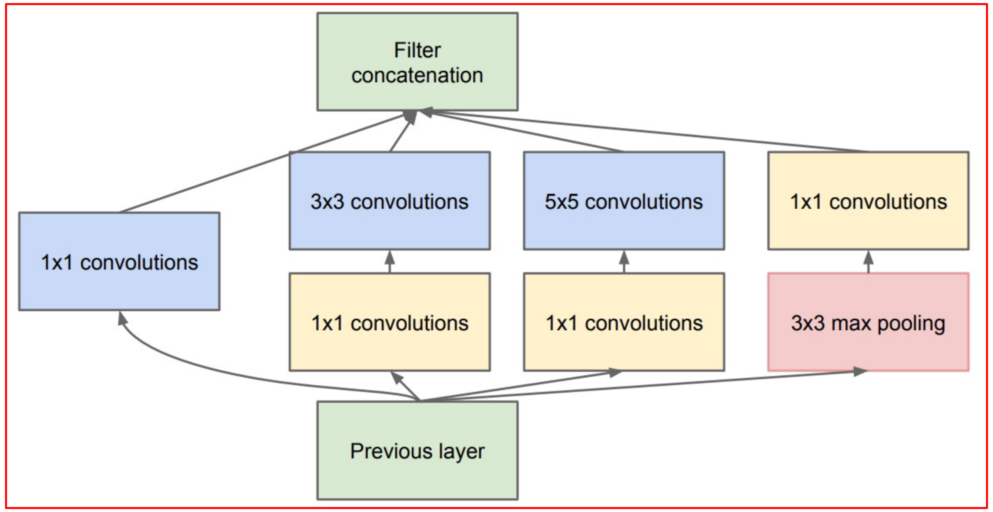
Inception (GoogLeNet)



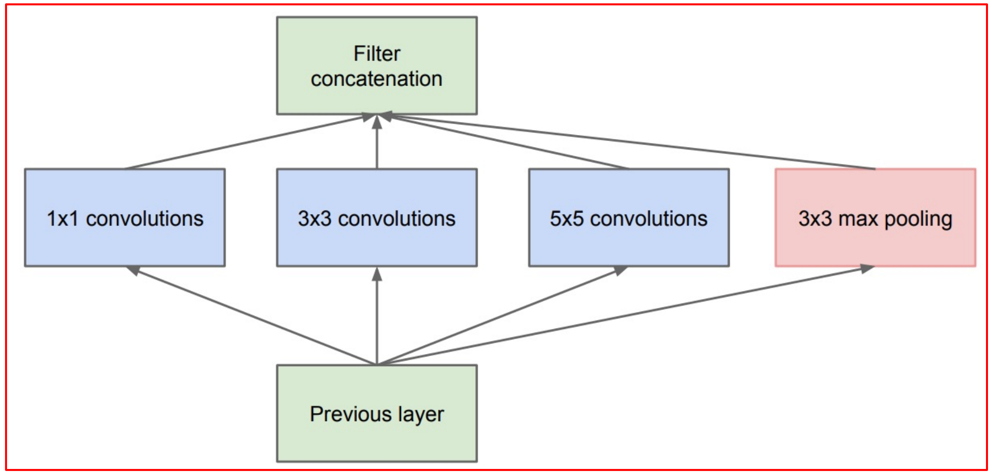


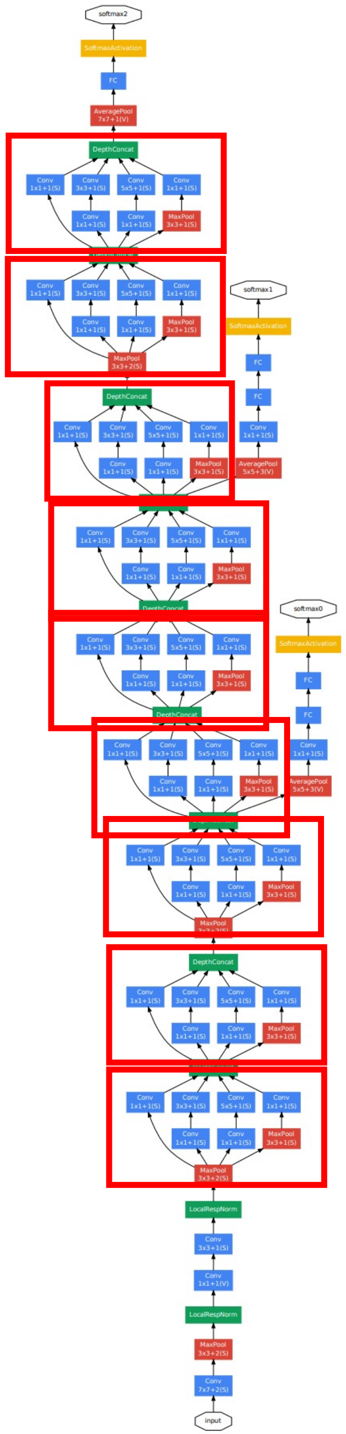


Inception (GoogLeNet)

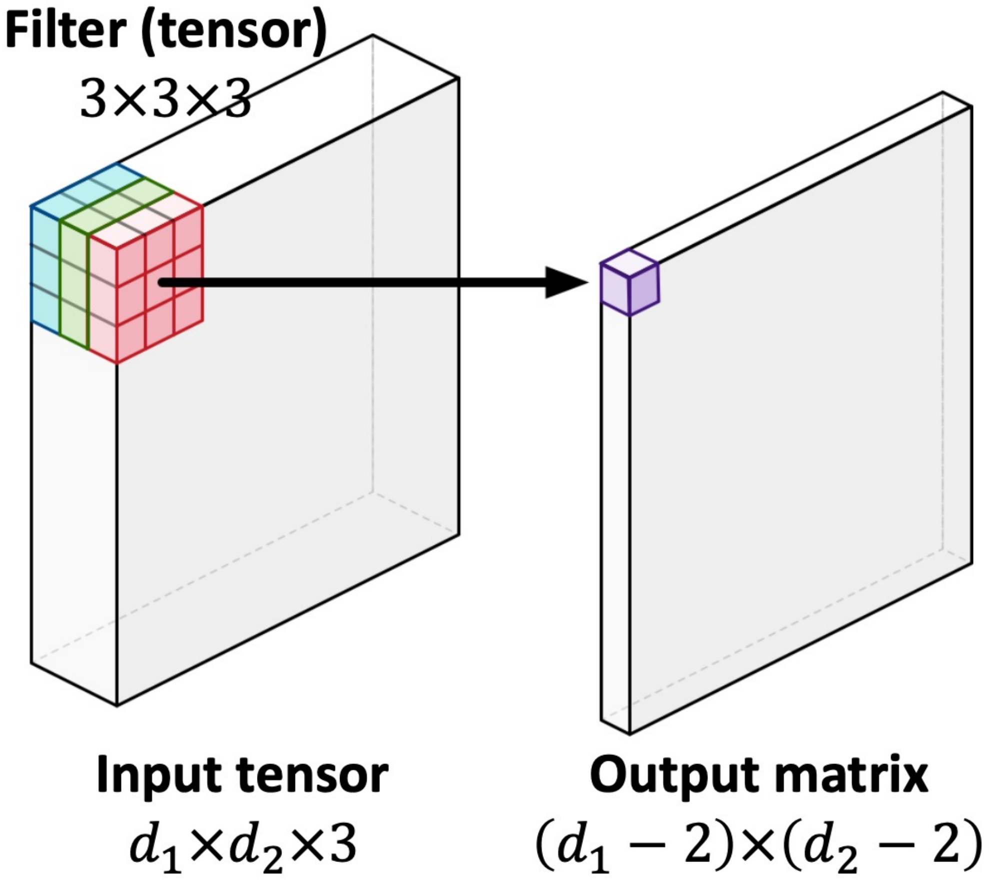


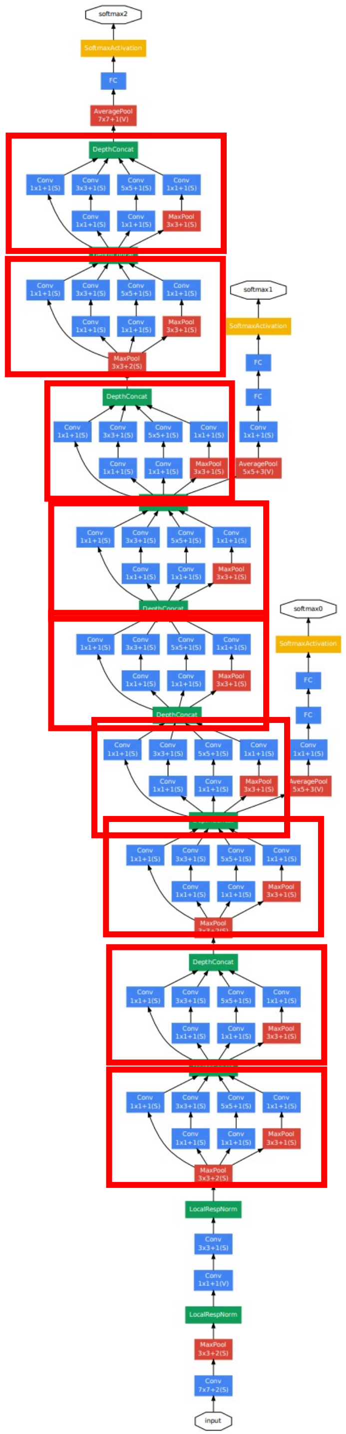
Q: difference between those two variants?



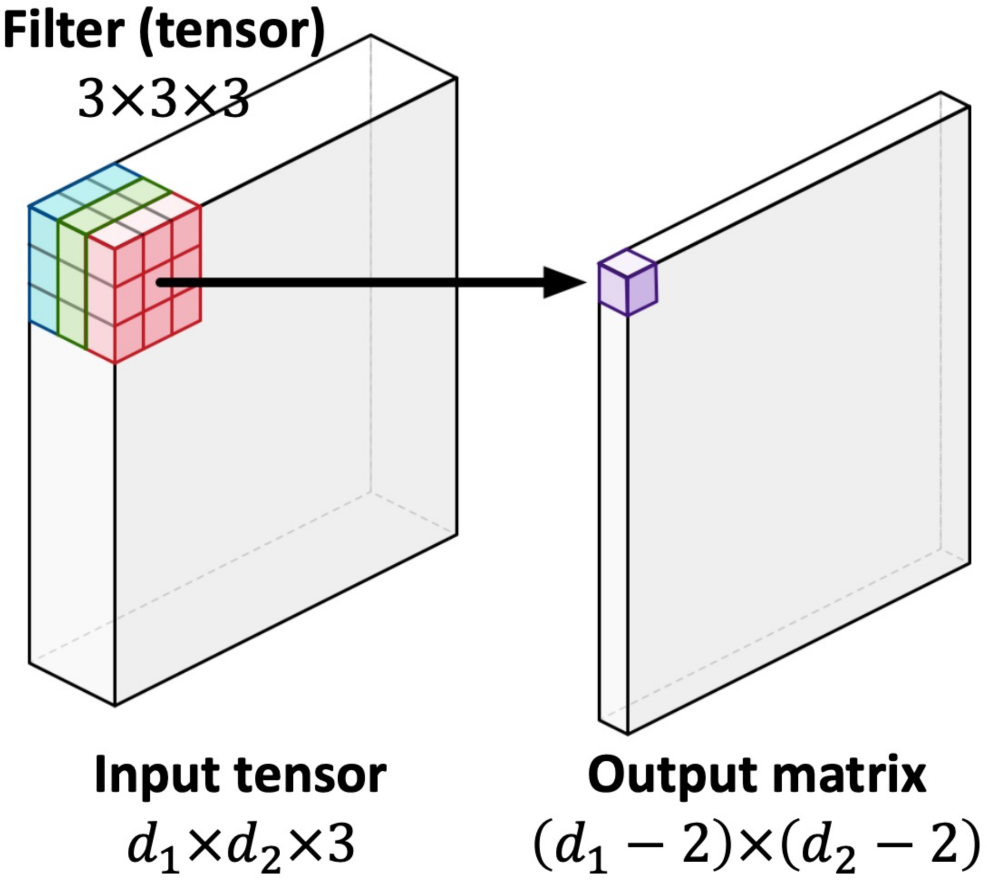


Inception (GoogLeNet)



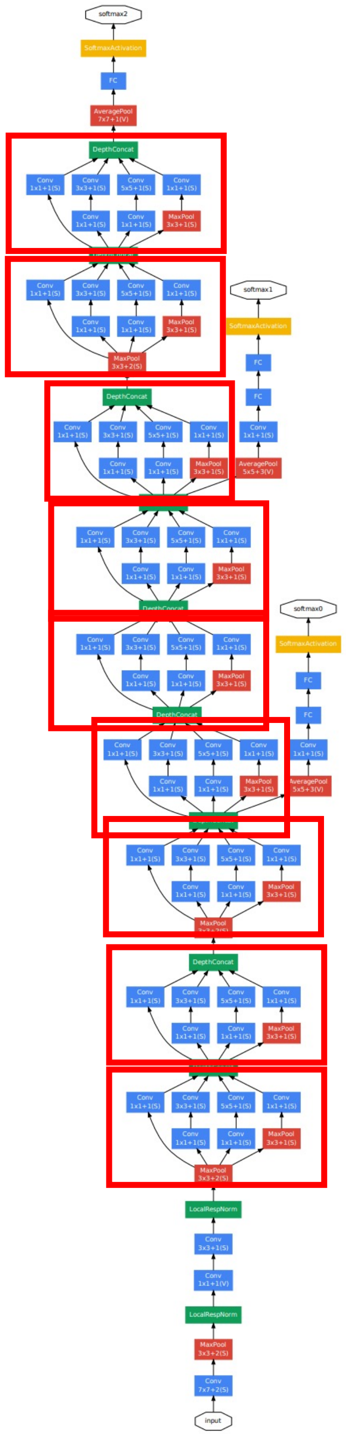


Inception (GoogLeNet)

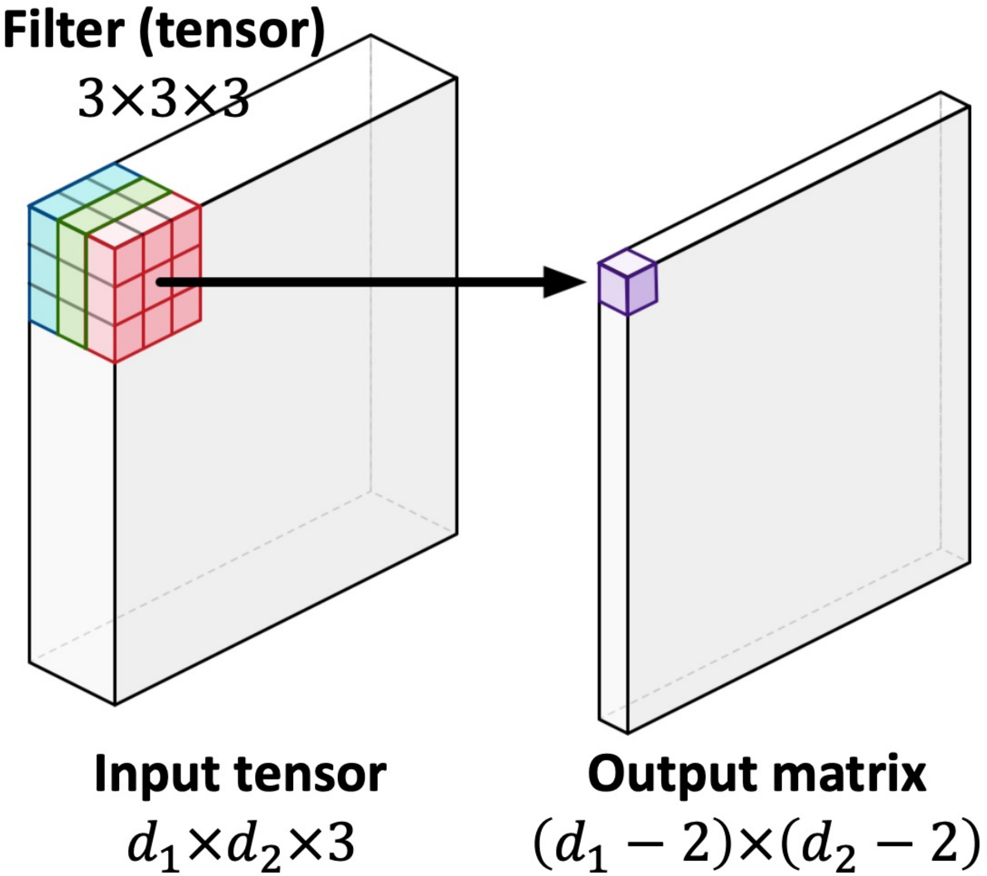


a tensor → a matrix (channel)

a filter/kernel

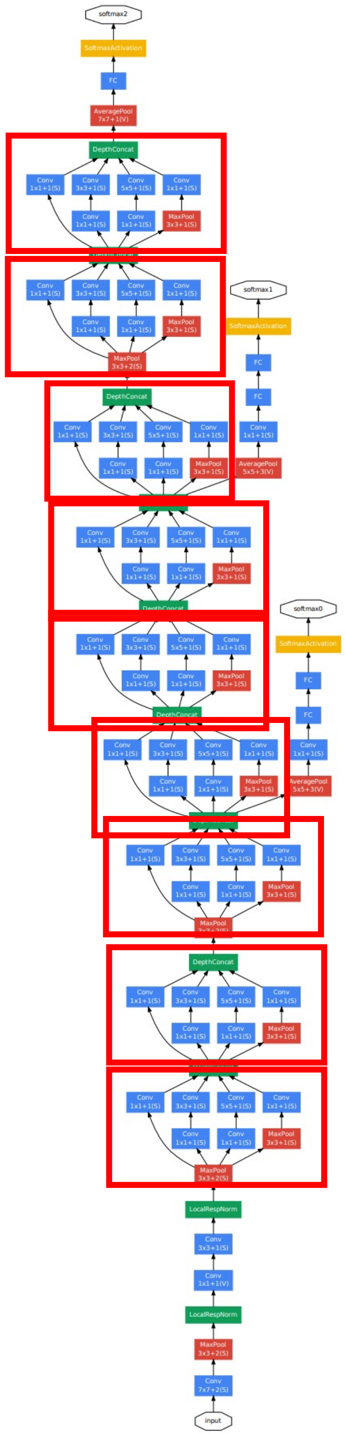


Inception (GoogLeNet)



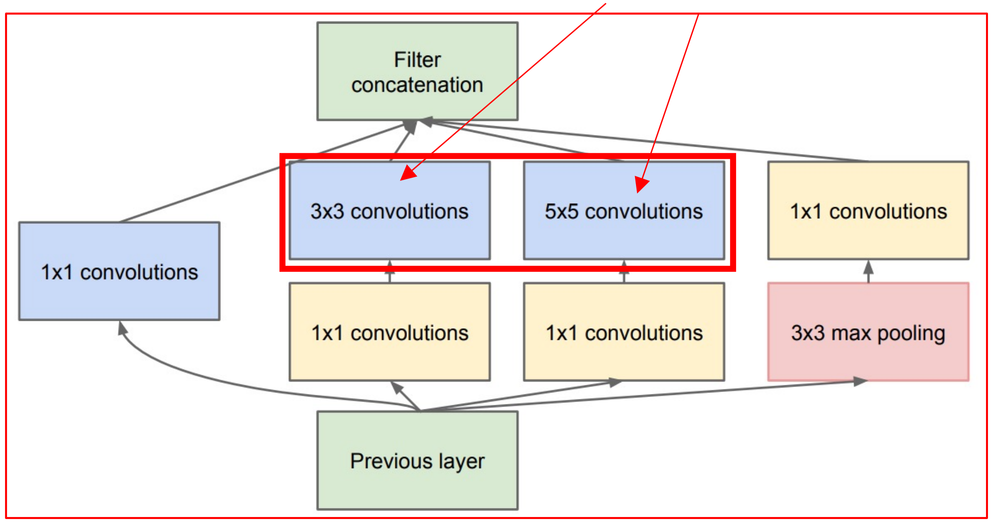
a tensor → m matrices (channels)

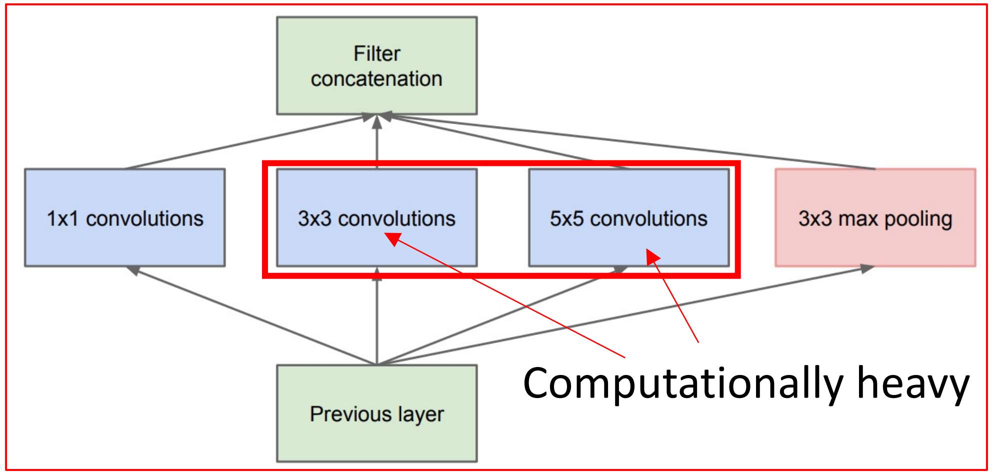
m filter/kernel

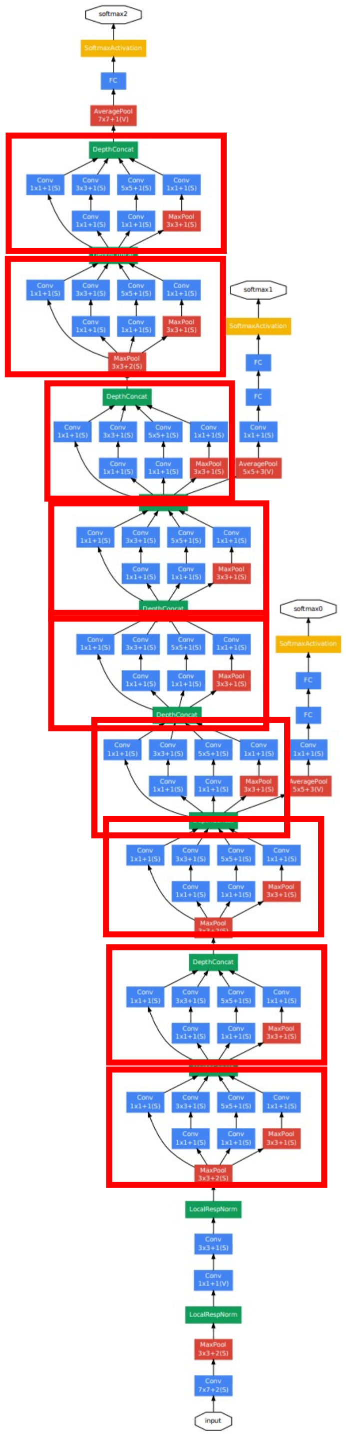


Inception (GoogLeNet)

Computationally heavy

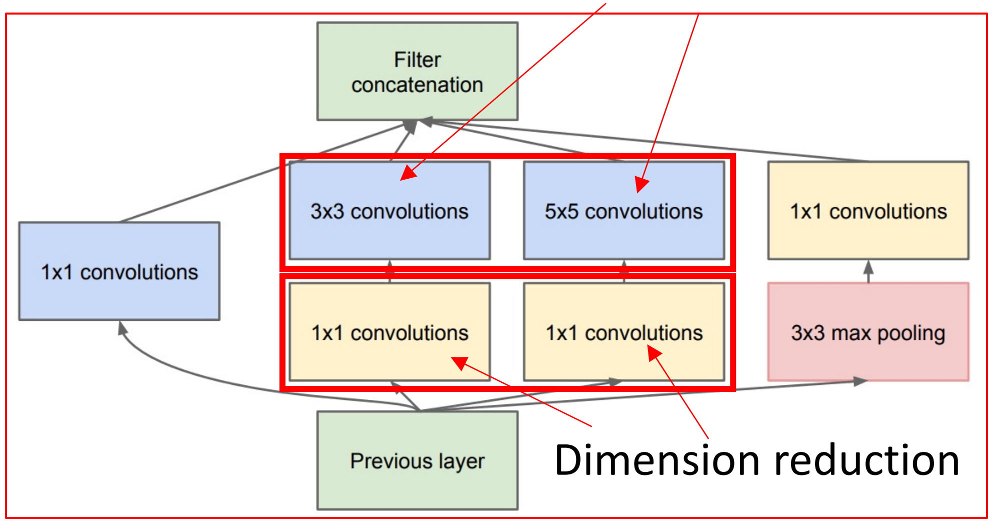


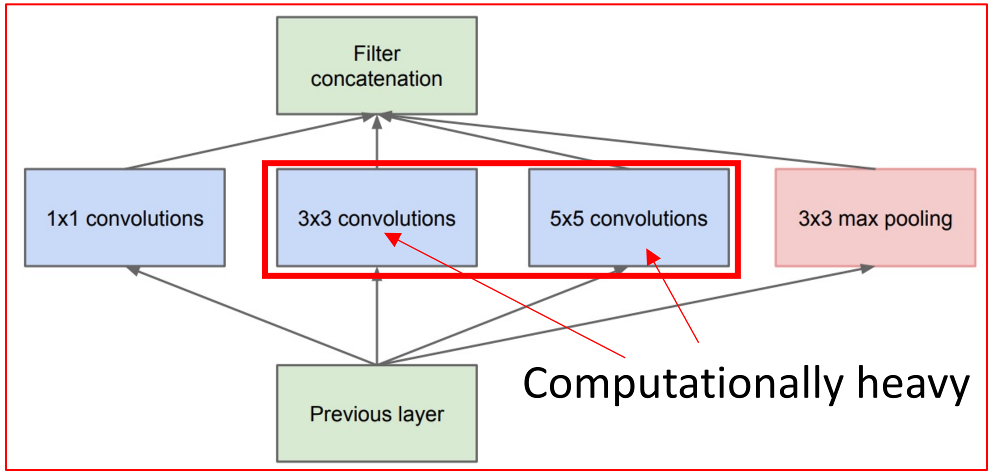


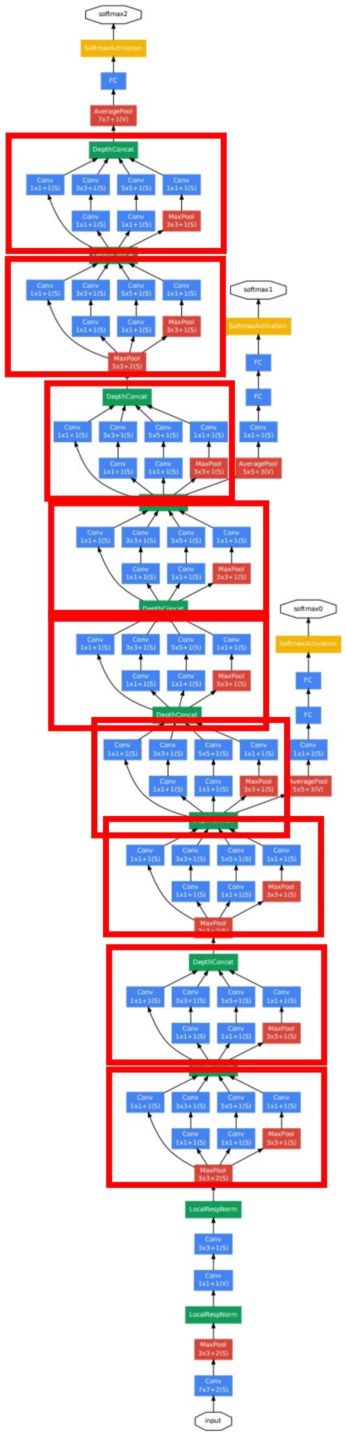


Inception (GoogLeNet)

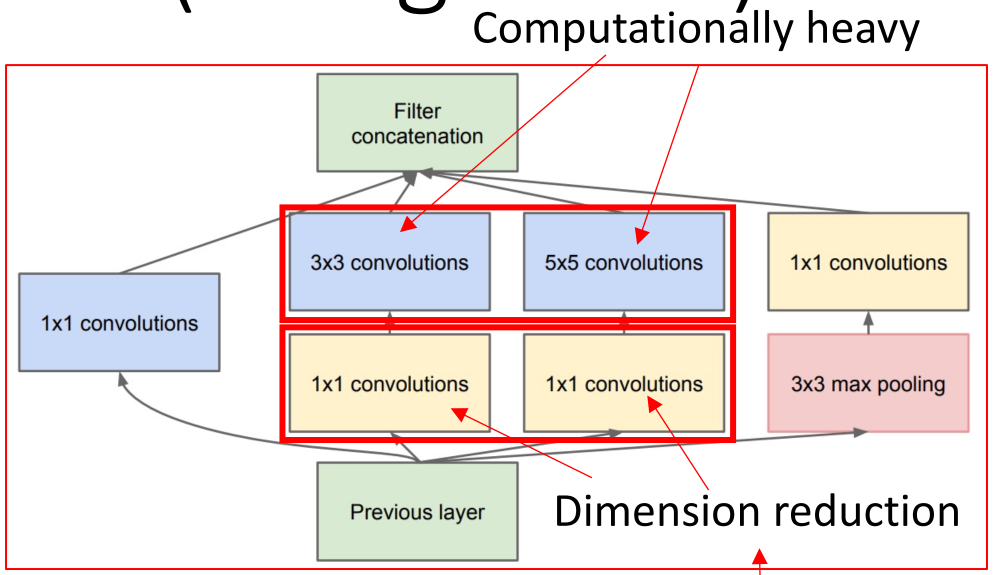
Computationally heavy



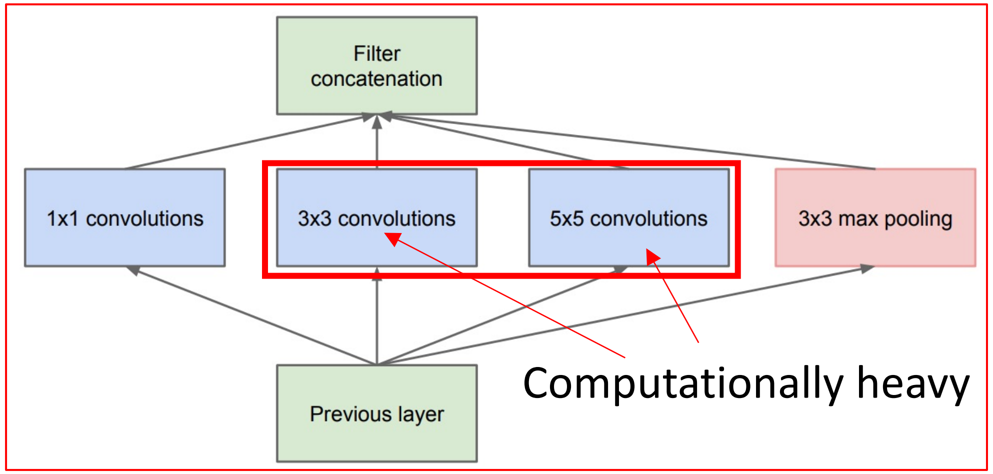


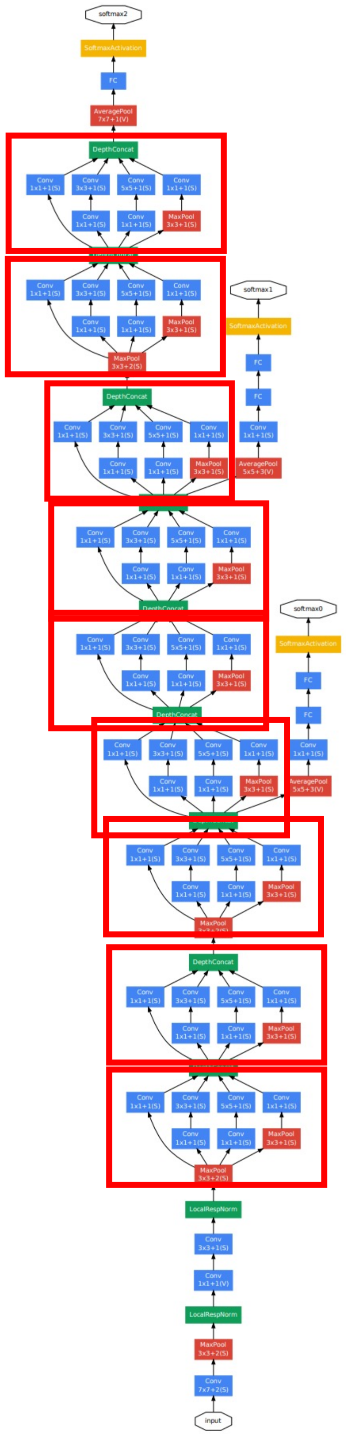


Inception (GoogLeNet)

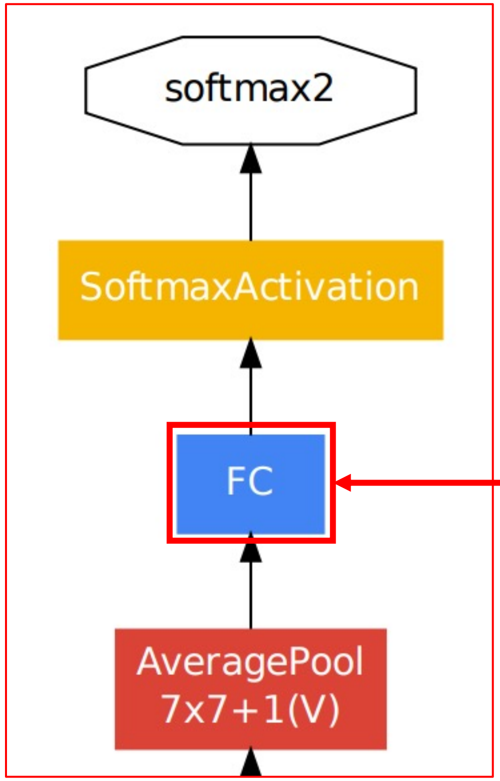


Less channels

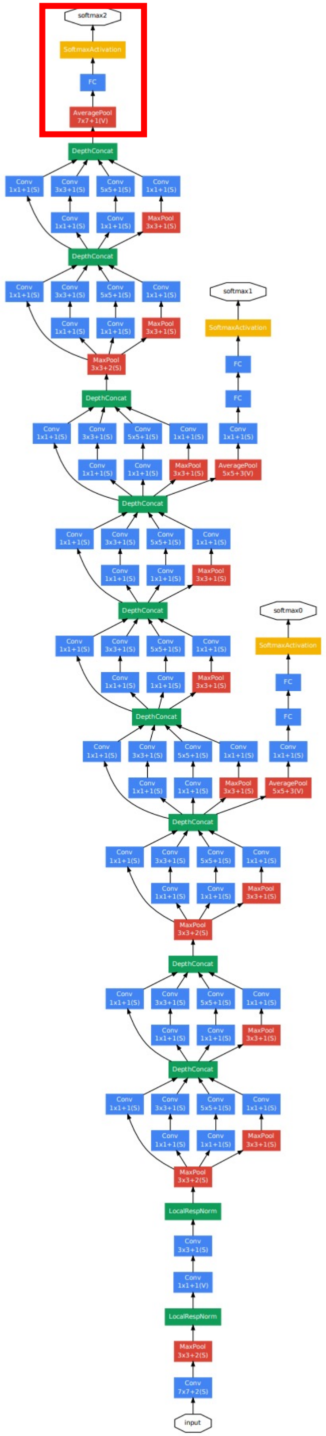




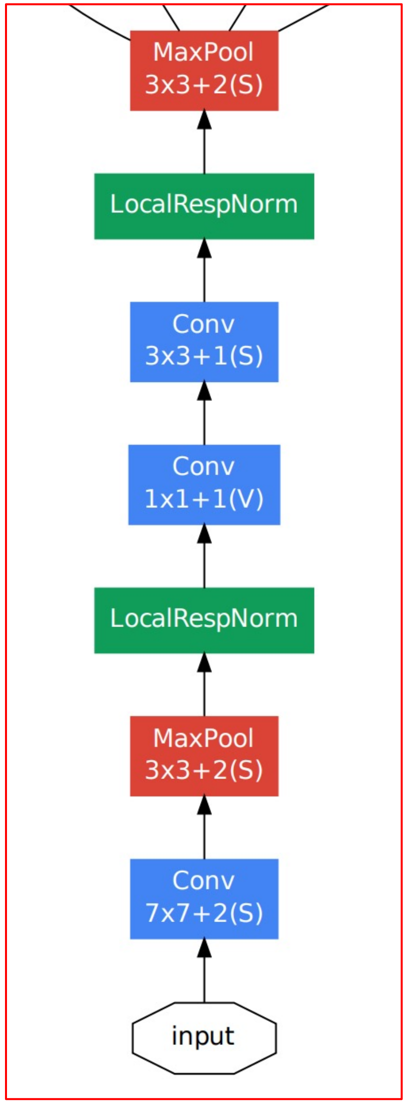
Inception (GoogLeNet)

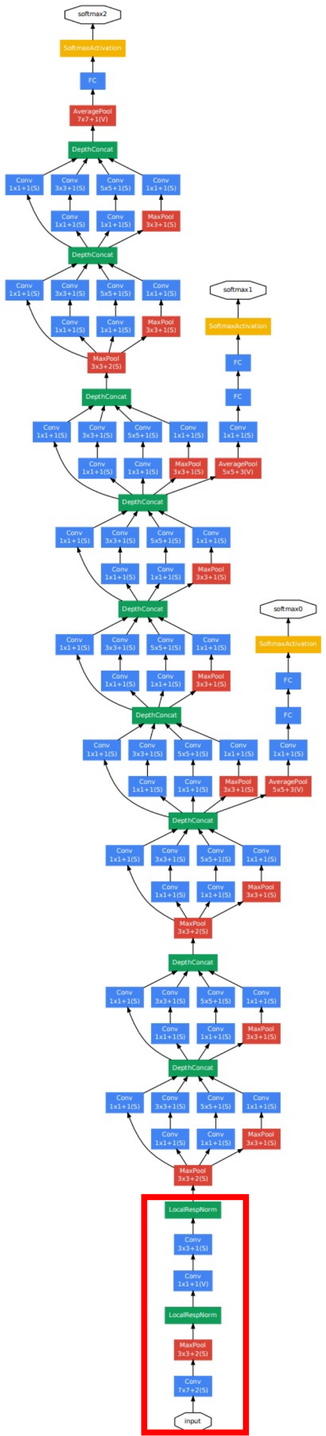


a linear model

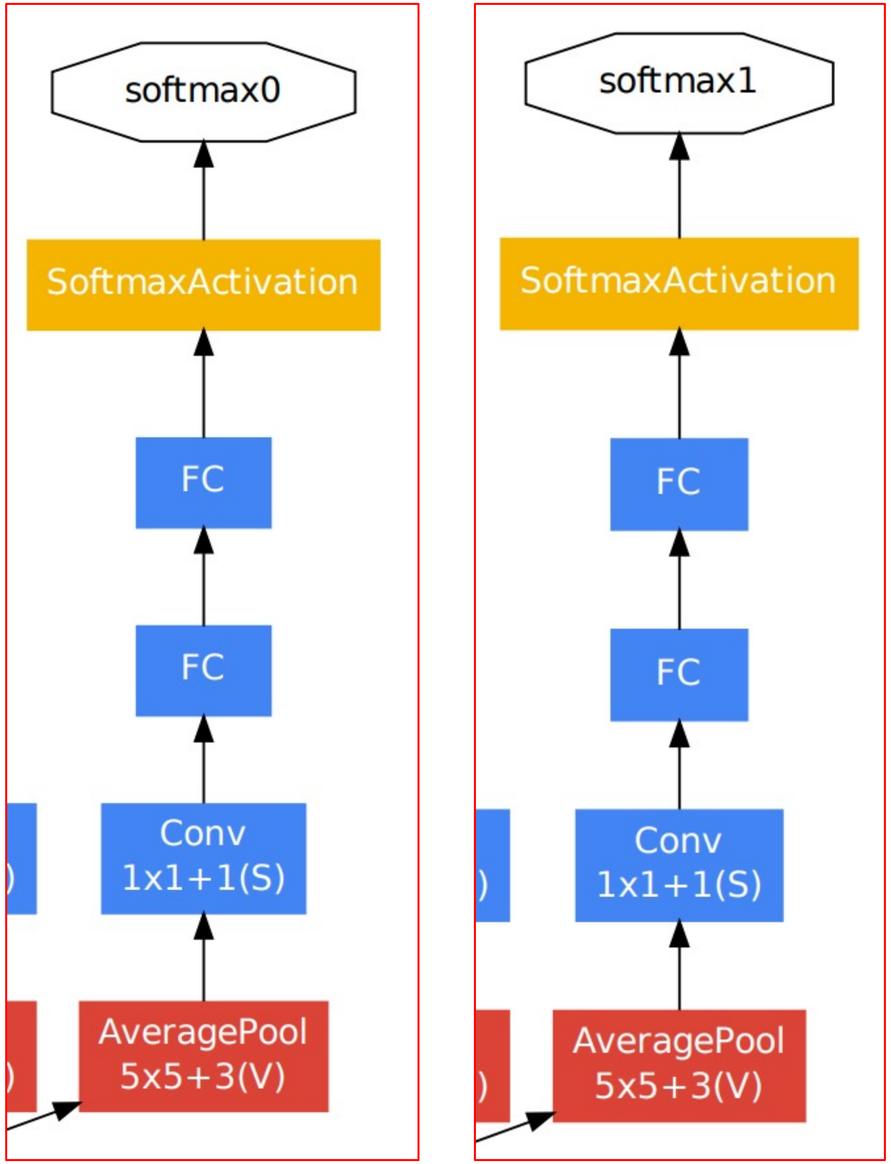


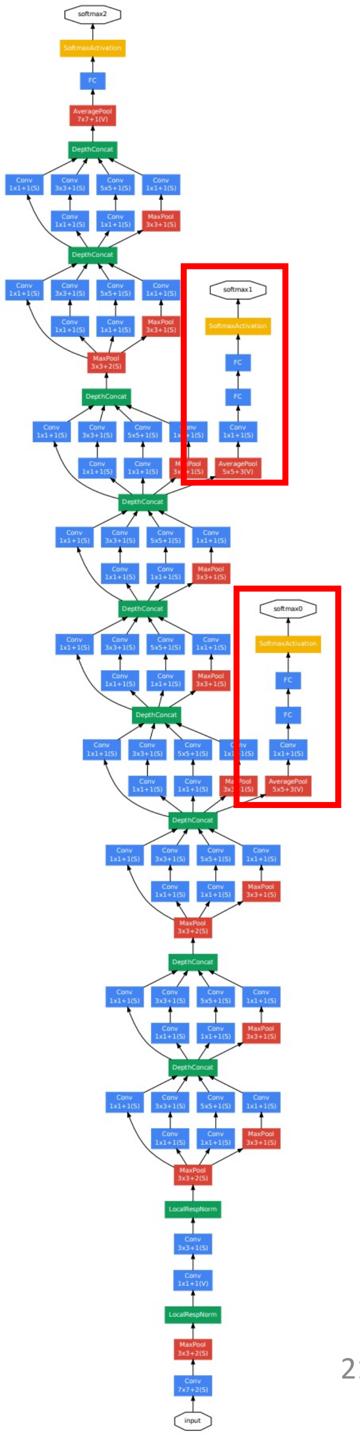
Inception (GoogLeNet)



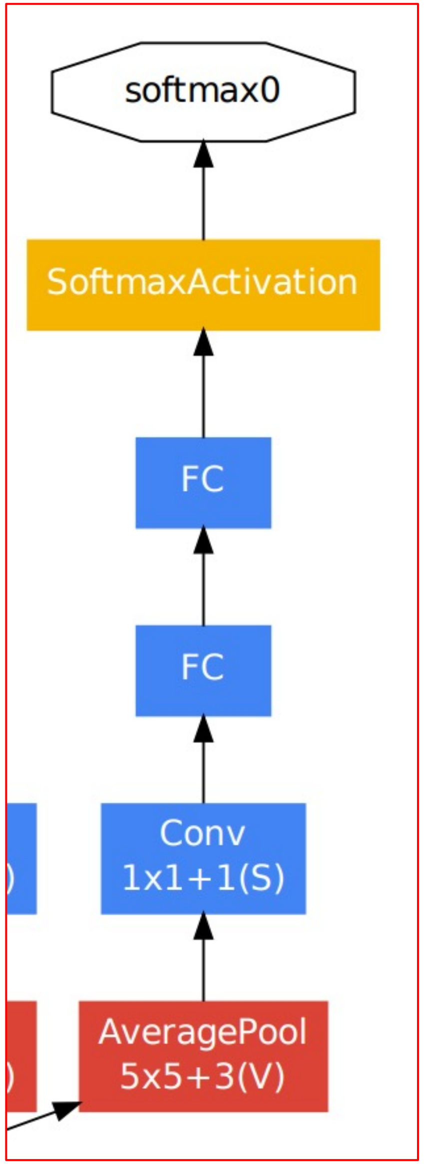


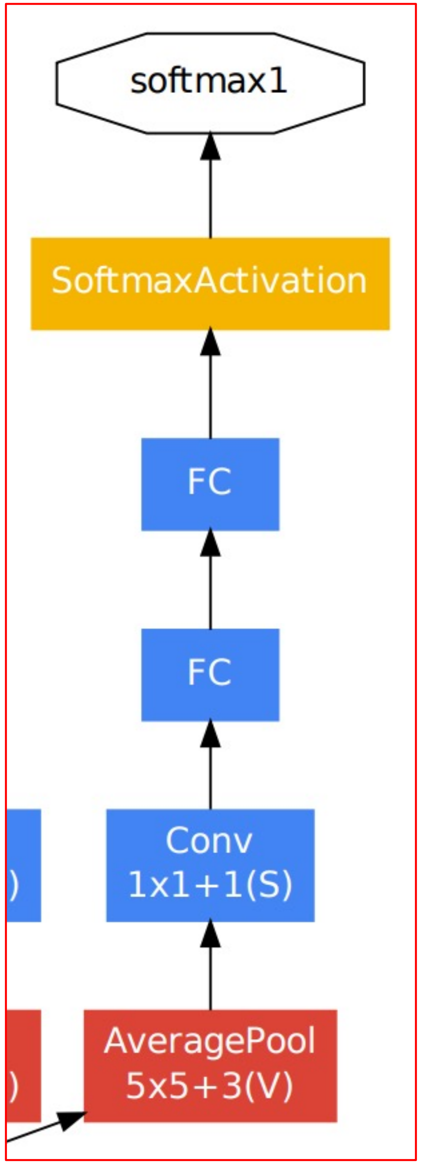
Inception (GoogLeNet)

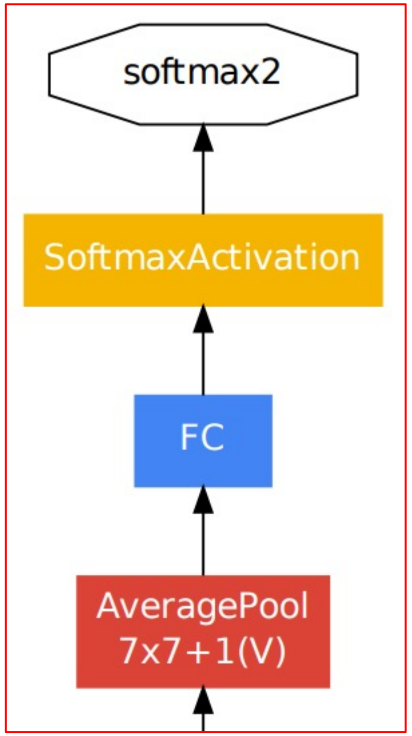


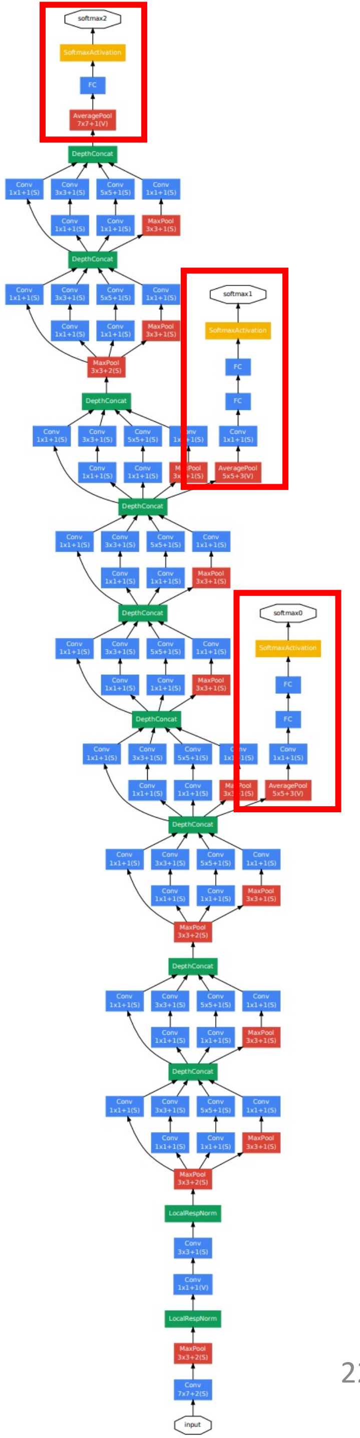


Inception (GoogLeNet)



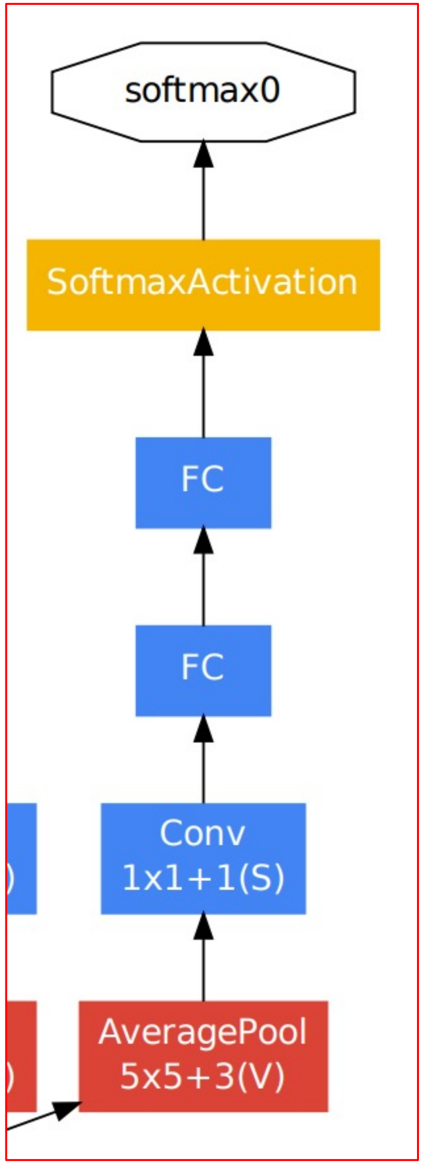


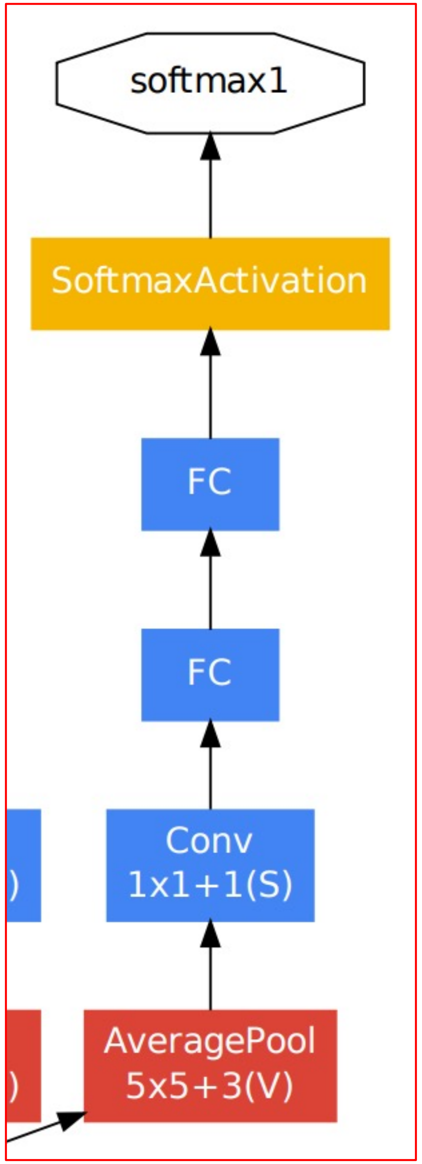


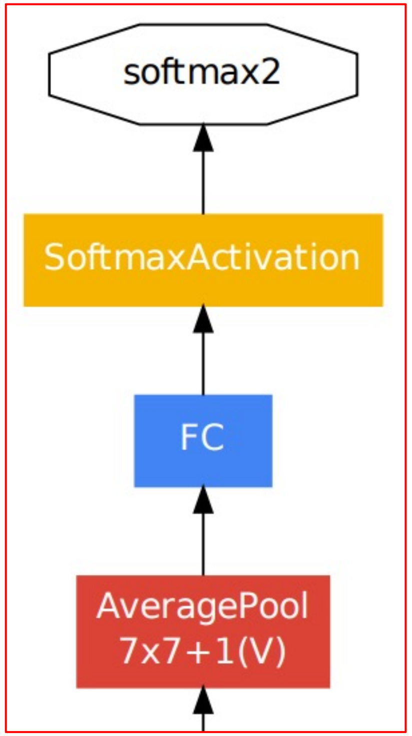


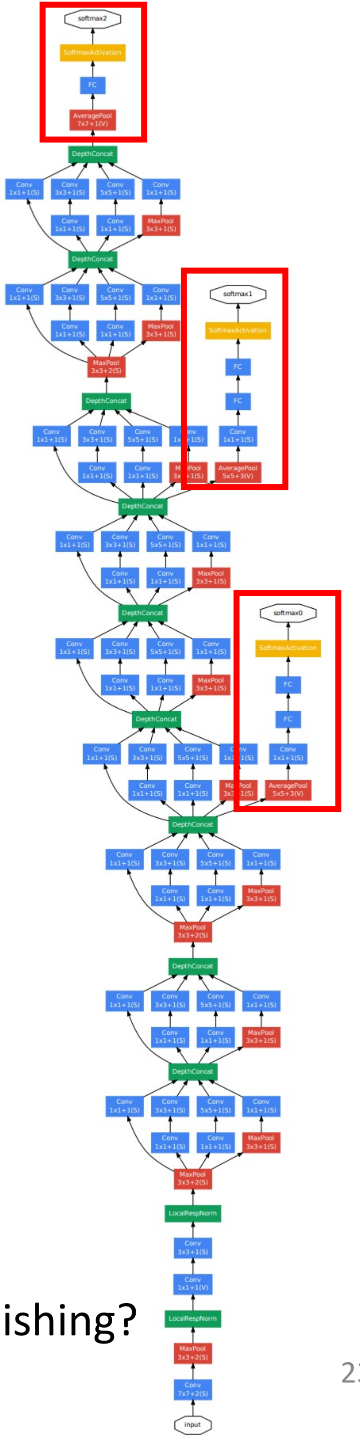
Q: why output prediction from lower layers?

Inception (GoogLeNet)









Q: why output prediction from lower layers?

Hint: remember gradient vanishing?

of layers

- LeNet-5: 3 conv + 2 fc
- AlexNet: 5 conv + 2 fc
- VGG-16: 13 conv + 2 fc

More conv layers

of layers

- LeNet-5: 3 conv + 2 fc
- AlexNet: 5 conv + 2 fc
- VGG-16: 13 conv + 2 fc

More conv layers

Q: why they did not develop some architecture with more layers?

of layers

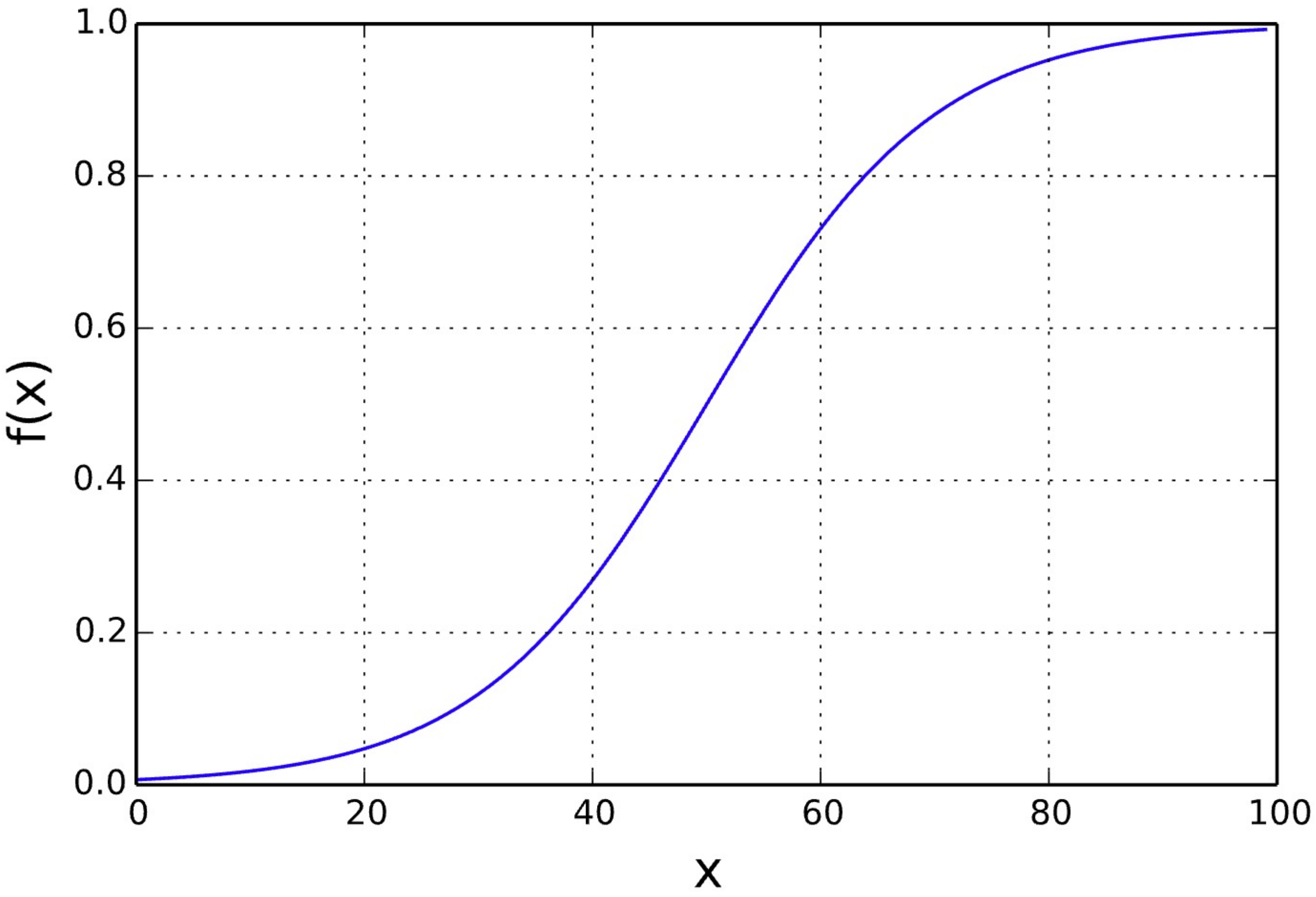
- LeNet-5: 3 conv + 2 fc
- AlexNet: 5 conv + 2 fc
- VGG-16: 13 conv + 2 fc

More conv layers

Q: why they did not develop some architecture with more layers?

Hint (again): remember gradient vanishing?

Gradient vanish



Sigmoid function

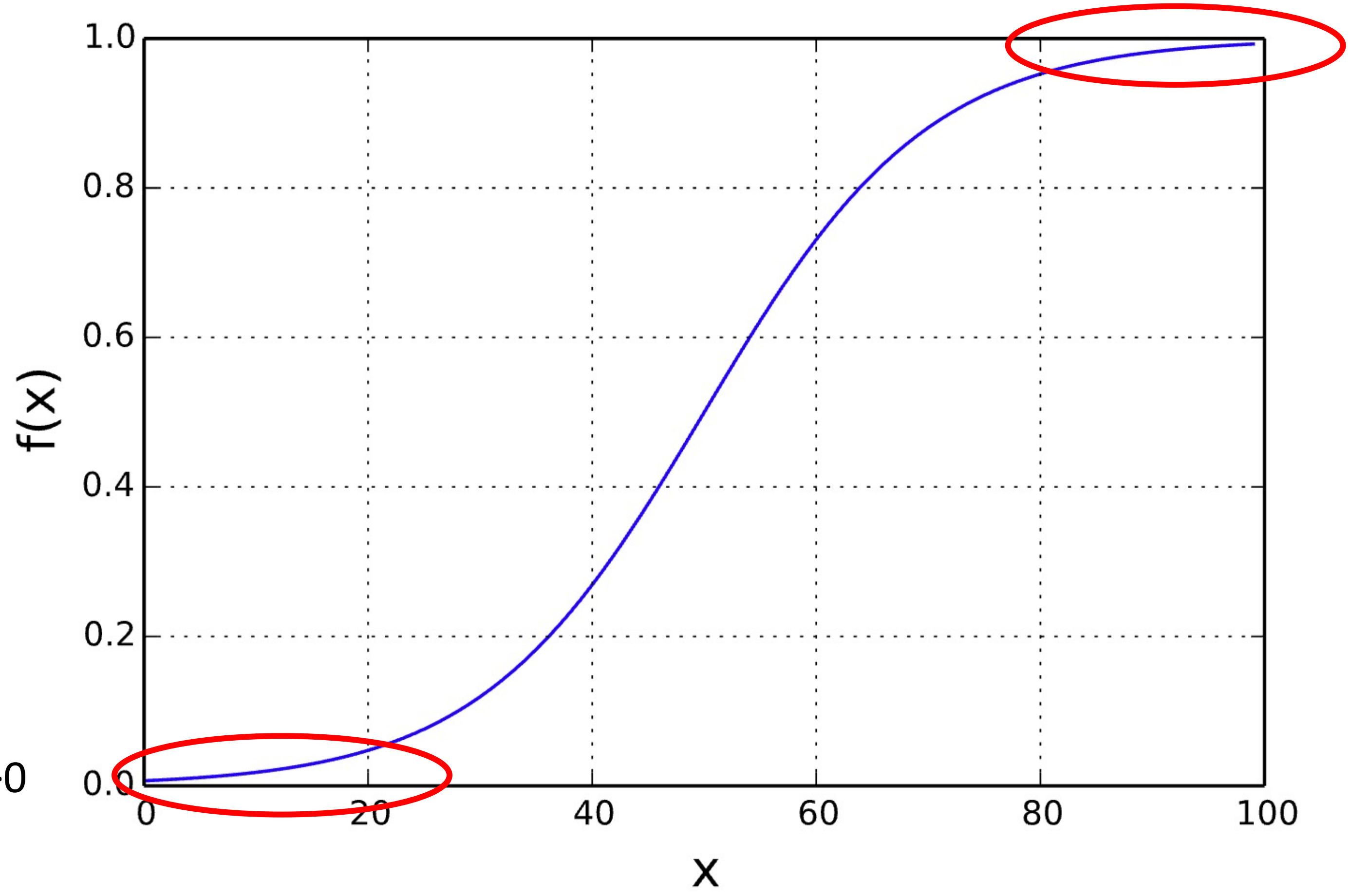
Gradient vanish

$$f_n\left(\dots\left(f_2\left(f_1(x)\right)\right)\right) \to ?$$

$$f_i \to x_i$$

$$\frac{dx_n}{dx_1} = \frac{dx_n}{dx_{n-1}} \cdot \dots \cdot \frac{dx_2}{dx_1} \cdot \frac{dx_1}{dx}$$

gradients->0



gradients->0

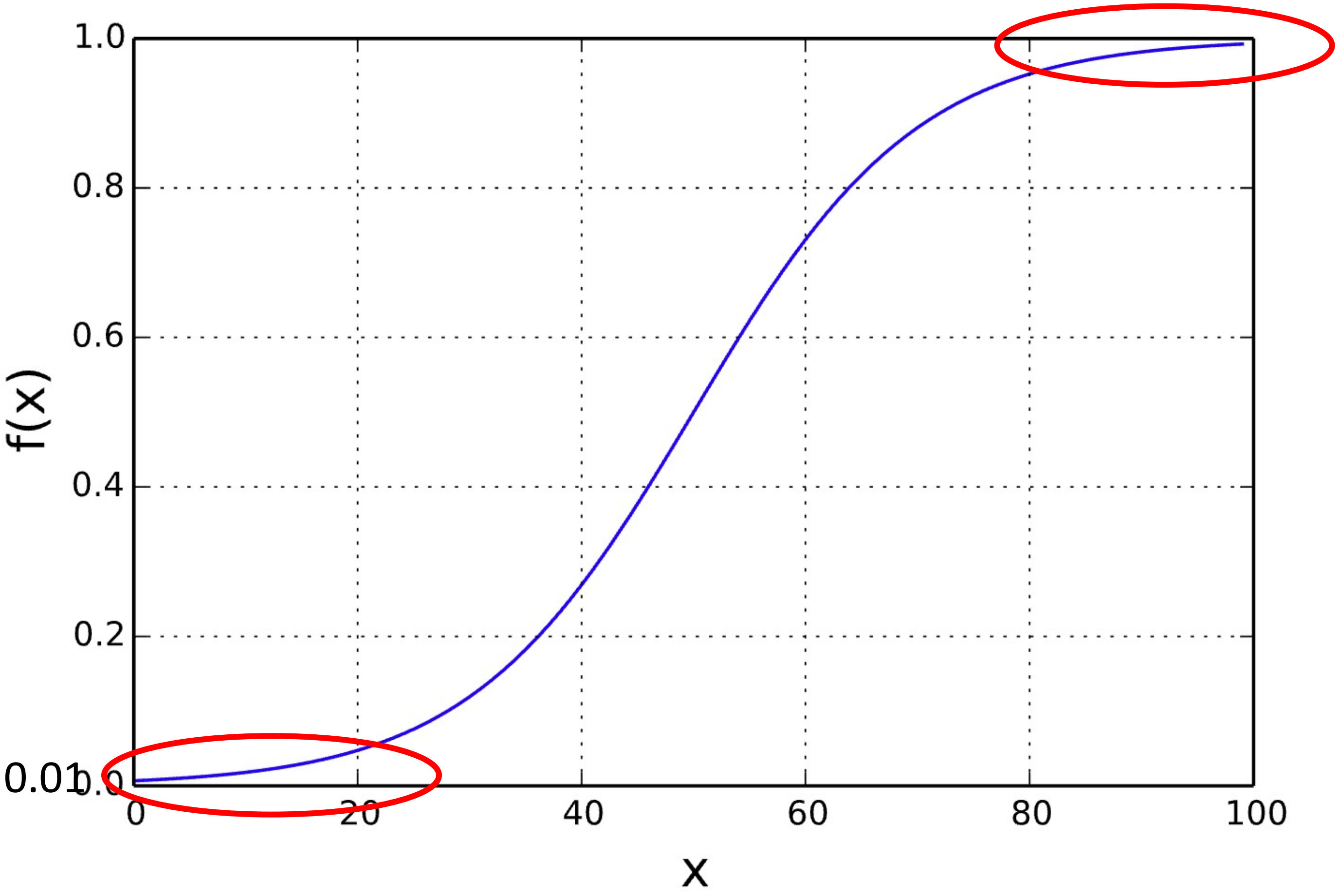
Sigmoid function

Gradient vanish

$$f_n\left(\dots\left(f_2\left(f_1(x)\right)\right)\right) \rightarrow ?$$

$$f_i \rightarrow x_i$$

$$\frac{dx_n}{dx_1} = \frac{dx_n}{dx_{n-1}} \cdot \dots \cdot \frac{dx_2}{dx_1} \cdot \frac{dx_1}{dx}$$



gradients-> 0.01

gradients-> 0.01

Sigmoid function

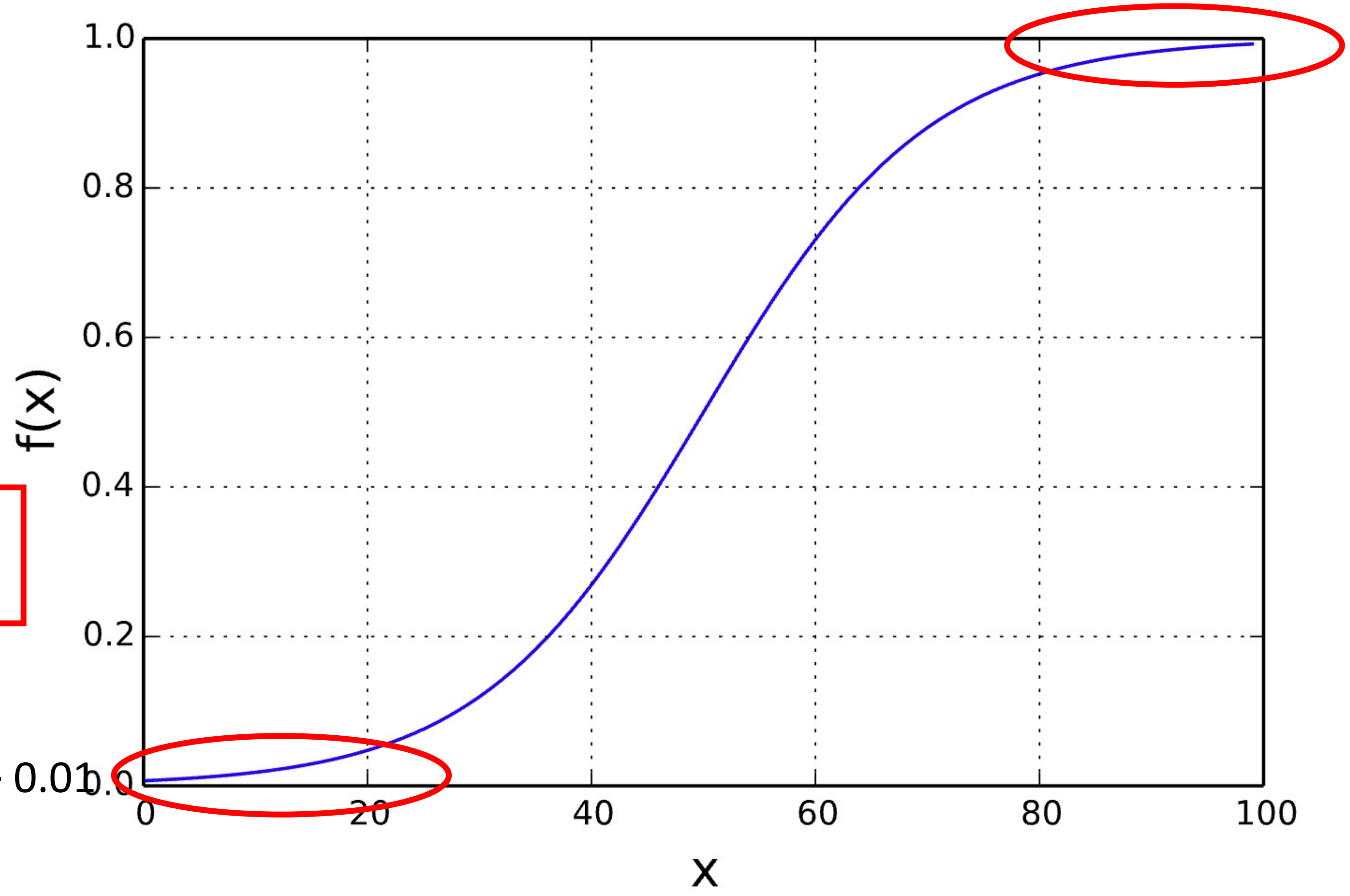
Gradient vanish

$$f_n\left(\dots\left(f_2\left(f_1(x)\right)\right)\right) \to ?$$

$$f_i \to x_i$$

$$\frac{dx_n}{dx_1} = \boxed{\frac{dx_n}{dx_{n-1}}} \cdot \dots \cdot \boxed{\frac{dx_2}{dx_1}} \cdot \boxed{\frac{dx_1}{dx}}$$

gradients-> 0.01



gradients-> 0.01

Sigmoid function

Gradient vanish

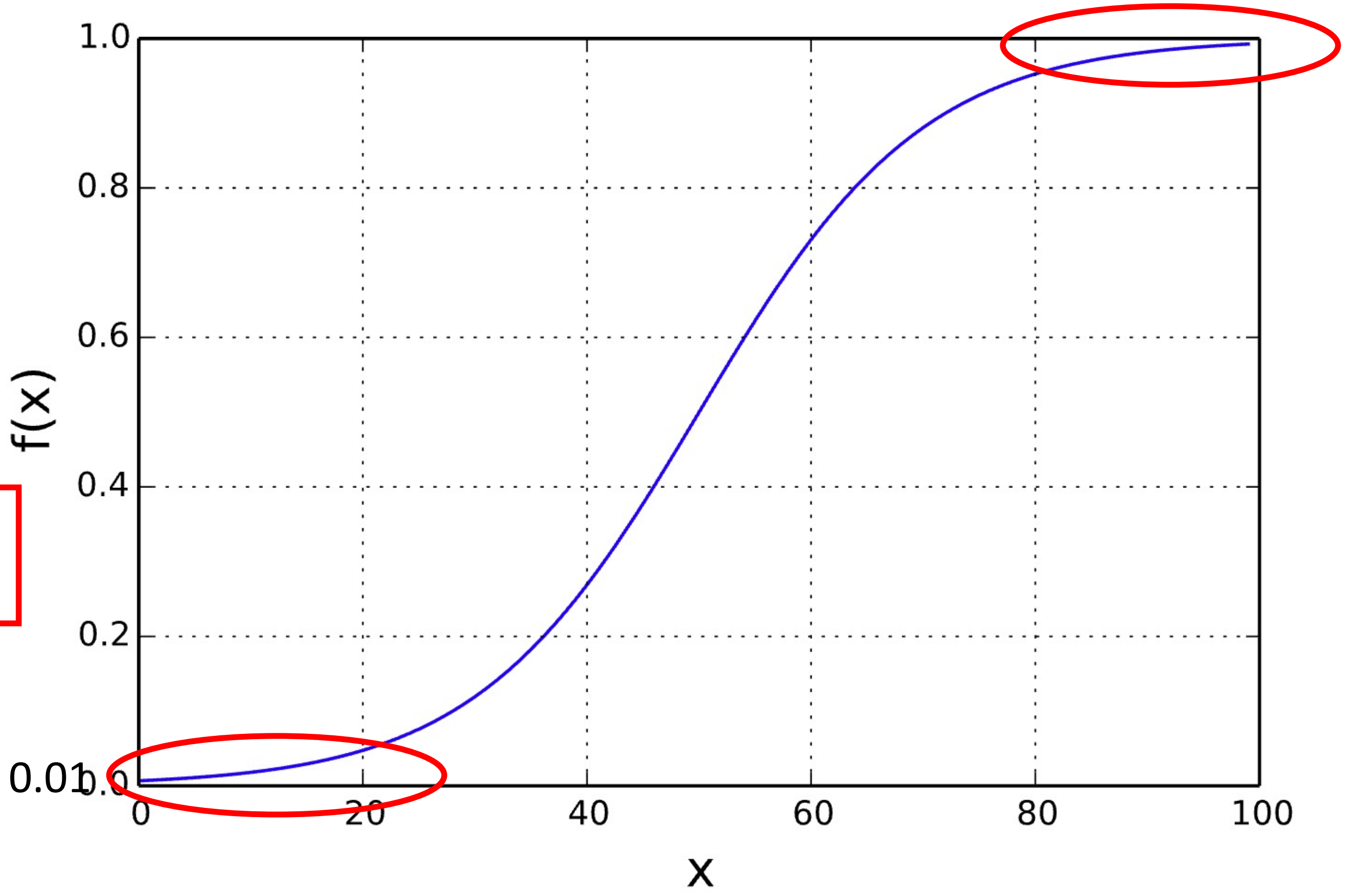
$$f_n\left(\dots\left(f_2(f_1(x))\right)\right) \to ?$$

$$f_i \to x_i$$

$$\frac{dx_n}{dx_1} = \boxed{\frac{dx_n}{dx_{n-1}}} \cdot \dots \cdot \boxed{\frac{dx_2}{dx_1}} \cdot \boxed{\frac{dx_1}{dx}}$$

$\to 0.01^n$

gradients-> 0.01



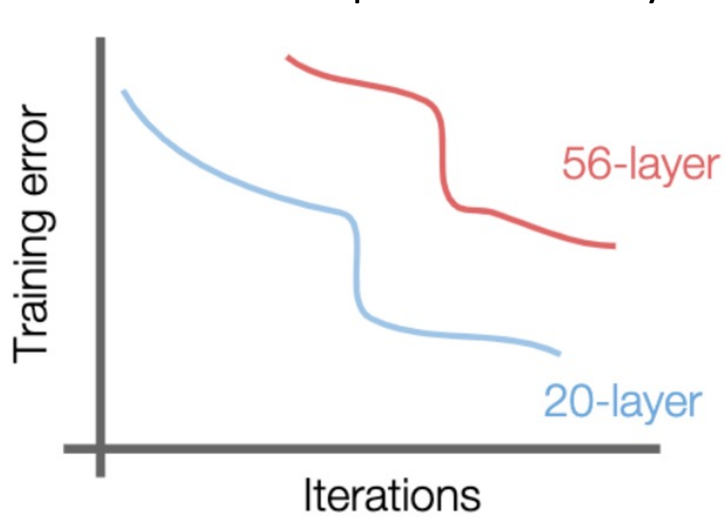
gradients-> 0.01

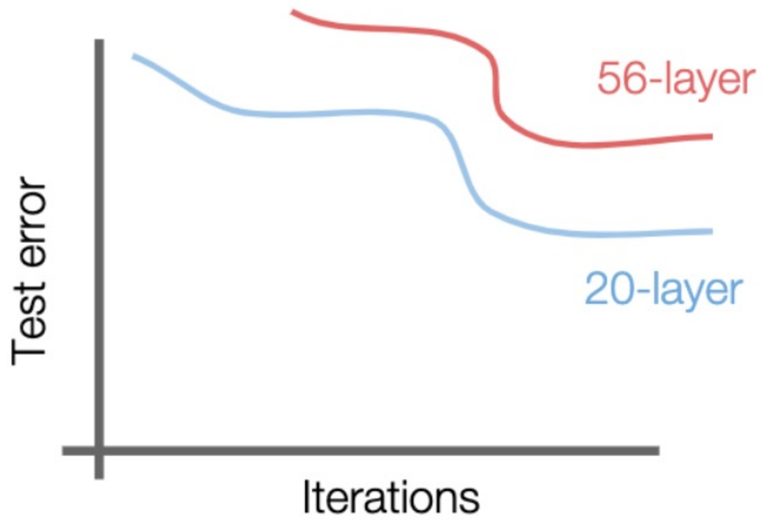
Sigmoid function

of layers

- LeNet-5: 3 conv + 2 fc
- AlexNet: 5 conv + 2 fc
- VGG-16: 13 conv + 2 fc

Q: why they did not develop some architecture with more layers?
Optimization may be difficult.



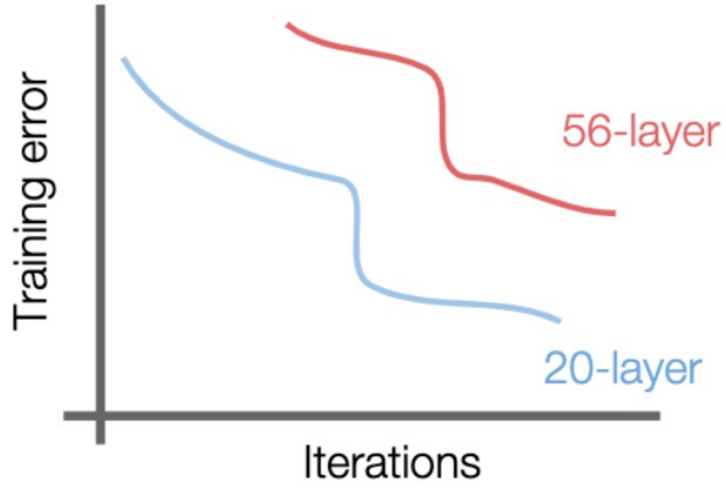


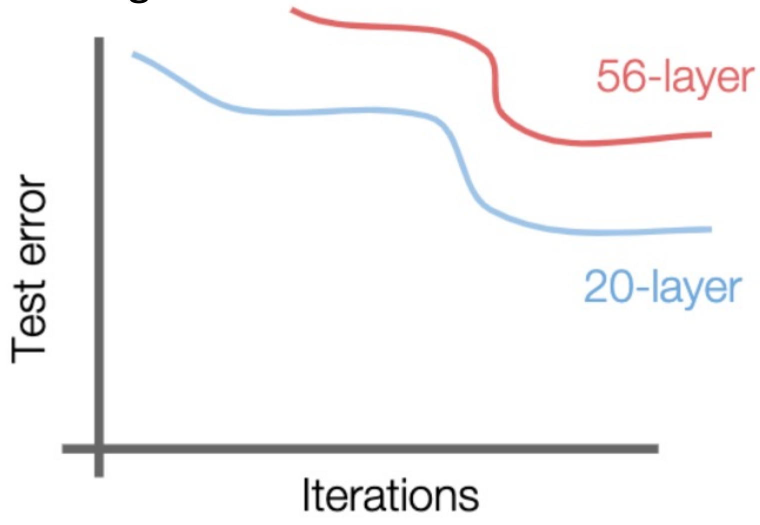
of layers

- LeNet-5: 3 conv + 2 fc
- AlexNet: 5 conv + 2 fc
- VGG-16: 13 conv + 2 fc

Q: why they did not develop some architecture with more layers?

Optimization may be difficult. We do not have a good solution as our model.



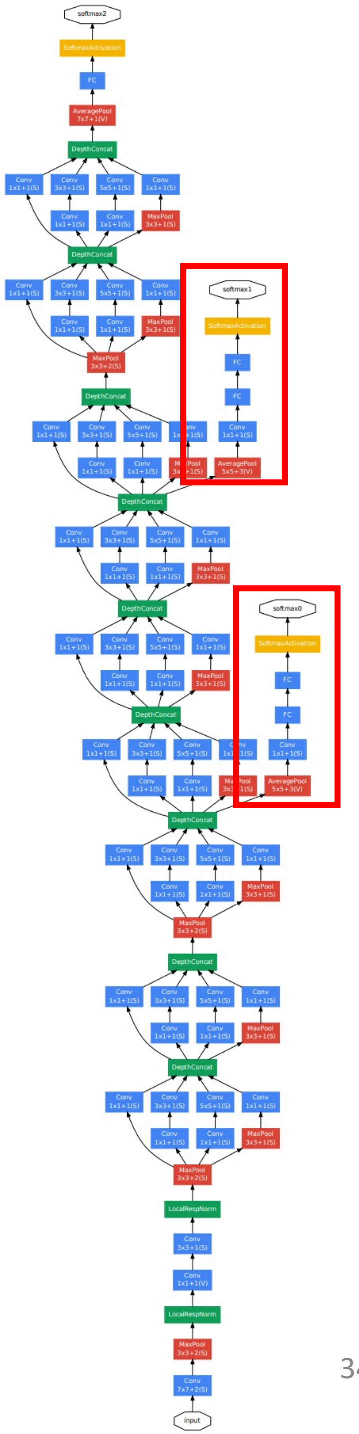


Inception

$$f_n\left(\dots\left(f_2\left(f_1(x)\right)\right)\right) \rightarrow ?$$

$$\frac{dx_n}{dx_1} = \boxed{\frac{dx_n}{dx_{n-1}}} \cdot \dots \cdot \boxed{\frac{dx_2}{dx_1}} \cdot \boxed{\frac{dx_1}{dx}}$$

$\rightarrow 0.01^n$

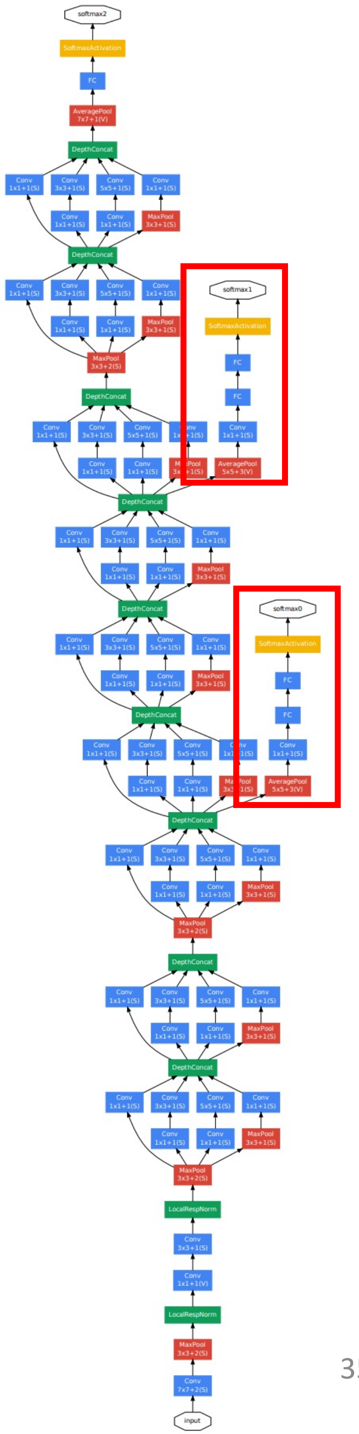


Inception

$$f_n\left(\dots\left(f_2\left(f_1(x)\right)\right)\right) + f_m\left(\dots\left(f_{n+2}\left(f_{n+1}(x)\right)\right)\right)$$

$$\frac{dx_n}{dx_1} = \boxed{\frac{dx_n}{dx_{n-1}}} \cdot \dots \cdot \boxed{\frac{dx_2}{dx_1}} \cdot \boxed{\frac{dx_1}{dx}}$$

$\rightarrow 0.01^n$

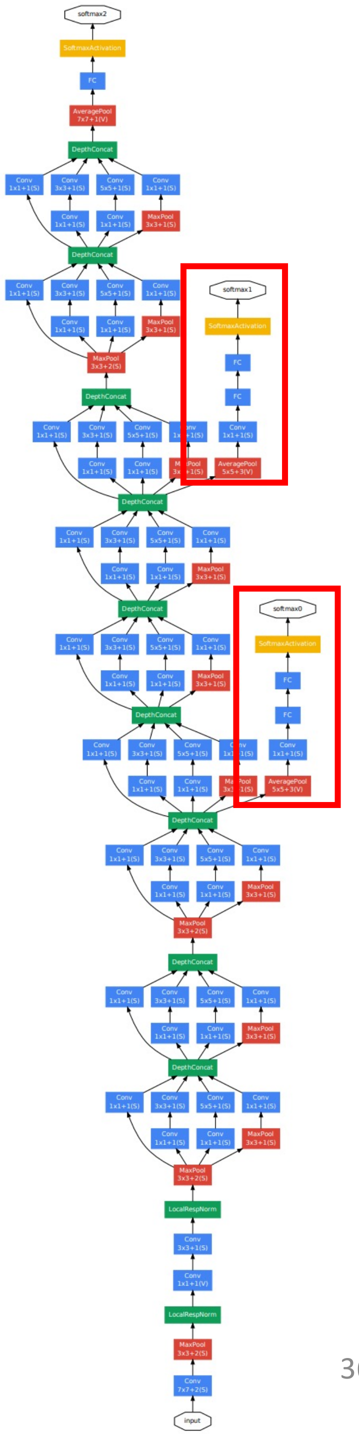


Inception

$$f_n\left(\cdots\left(f_2\left(f_1(x)\right)\right)\right) + f_m\left(\cdots\left(f_{n+2}\left(f_{n+1}(x)\right)\right)\right)$$

$$\boxed{\frac{dx_n}{dx_1}} = \underbrace{\boxed{\frac{dx_n}{dx_{n-1}} \cdot \ldots \cdot \frac{dx_2}{dx_1} \cdot \frac{dx_1}{dx}}}_{\to 0.01^n} + \underbrace{\boxed{\frac{dx_m}{dx_{m-1}} \cdot \ldots \cdot \frac{dx_{n+2}}{dx_{n+1}} \cdot \frac{dx_{n+1}}{dx}}}_{>> 0}$$

Will not be very small



Residual neural networks (ResNet)

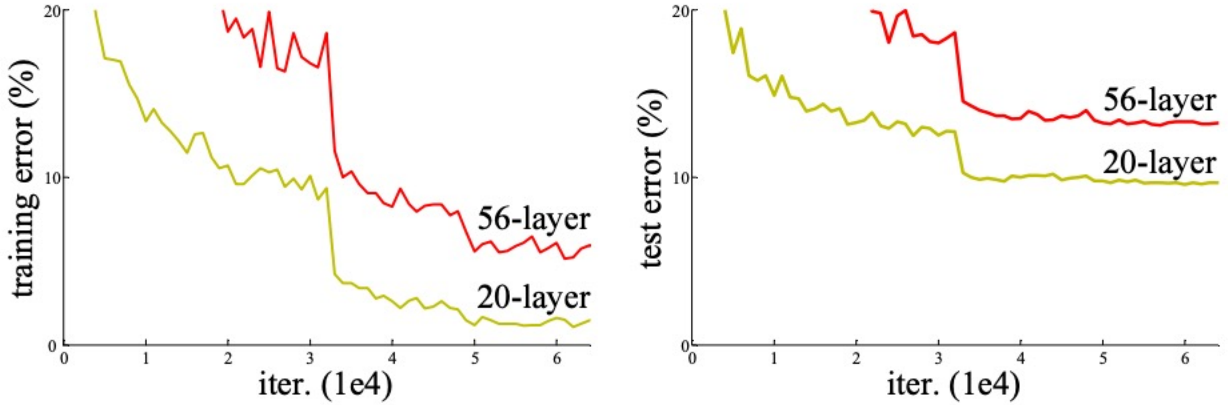


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

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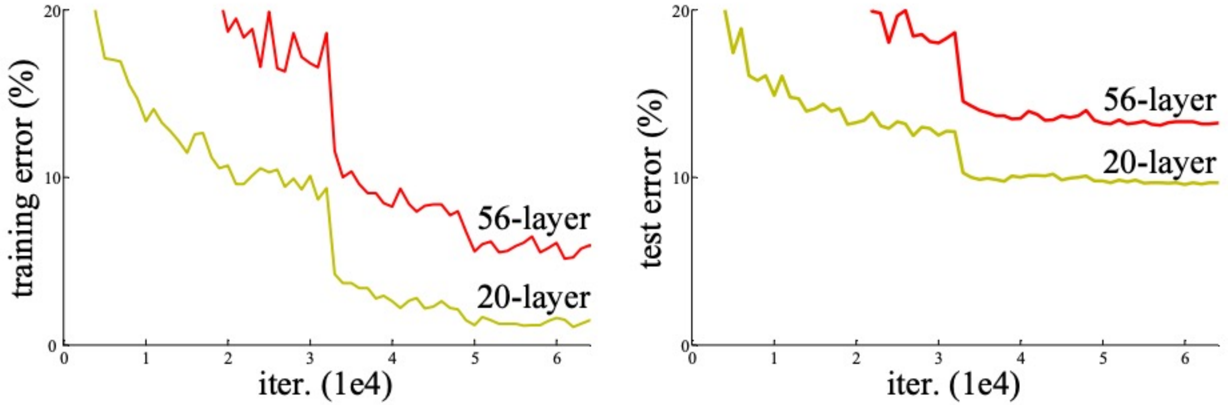

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Without special structure other than conv/fc layers

ResNet: shortcut connection

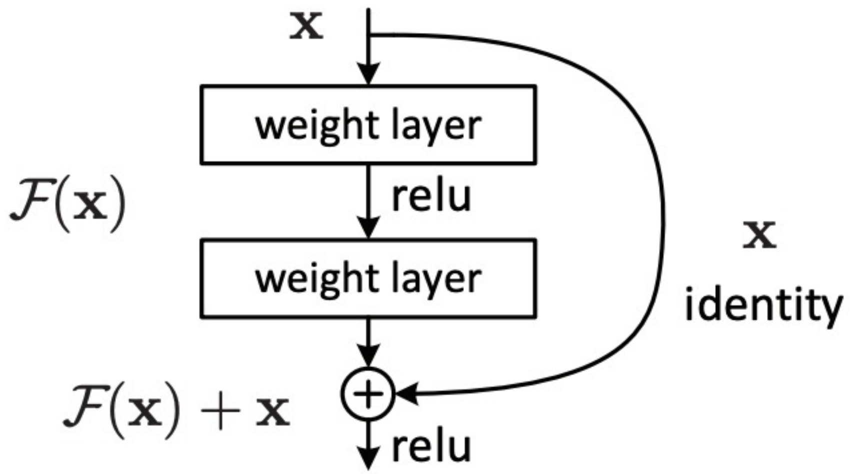
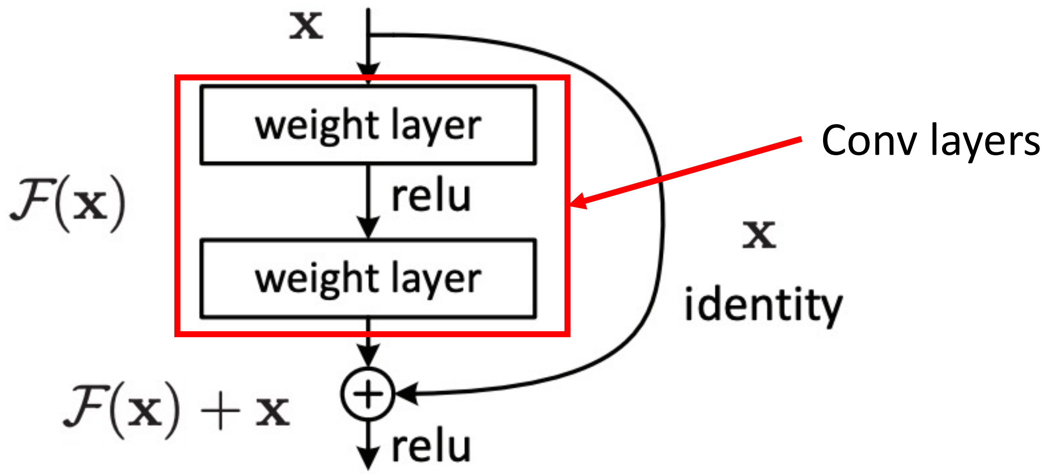


Figure 2. Residual learning: a building block.

ResNet: shortcut connection



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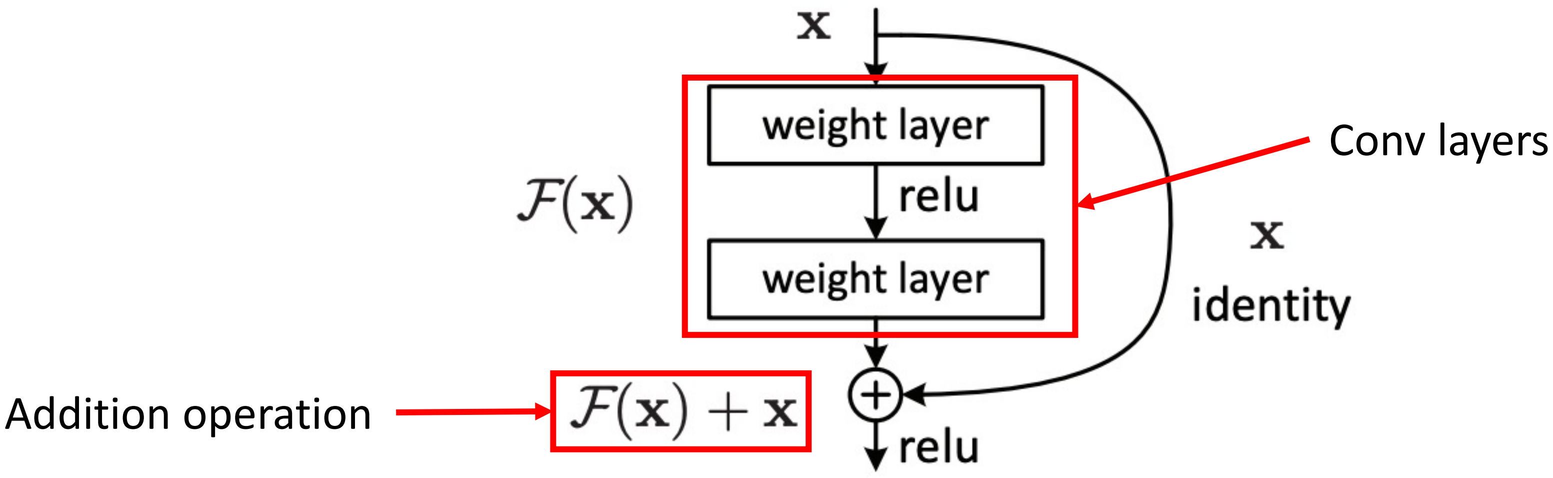

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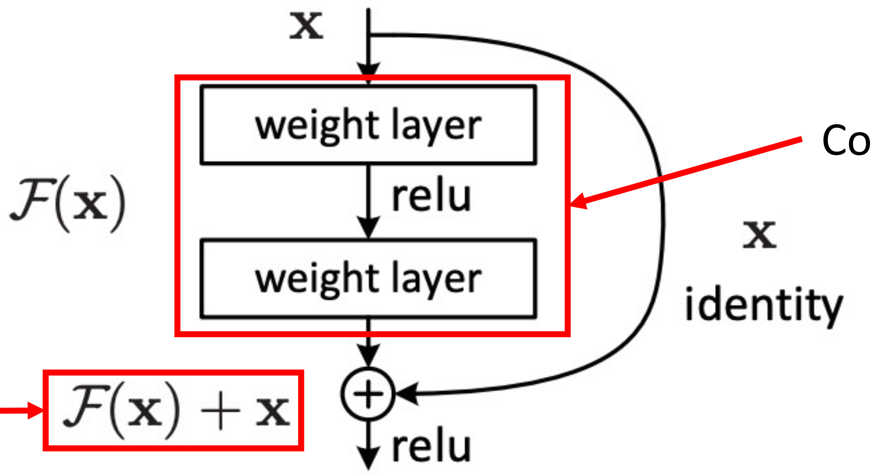
ResNet: shortcut connection

Conv layers

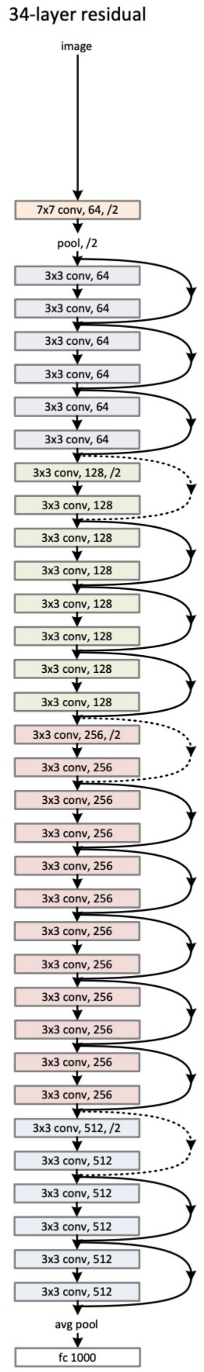


Addition operation

Figure 2. Residual learning: a building block.

implication: same dimension

ResNet



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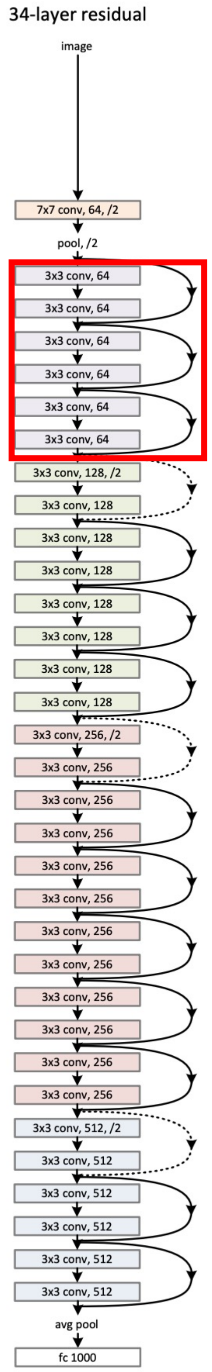
ResNet



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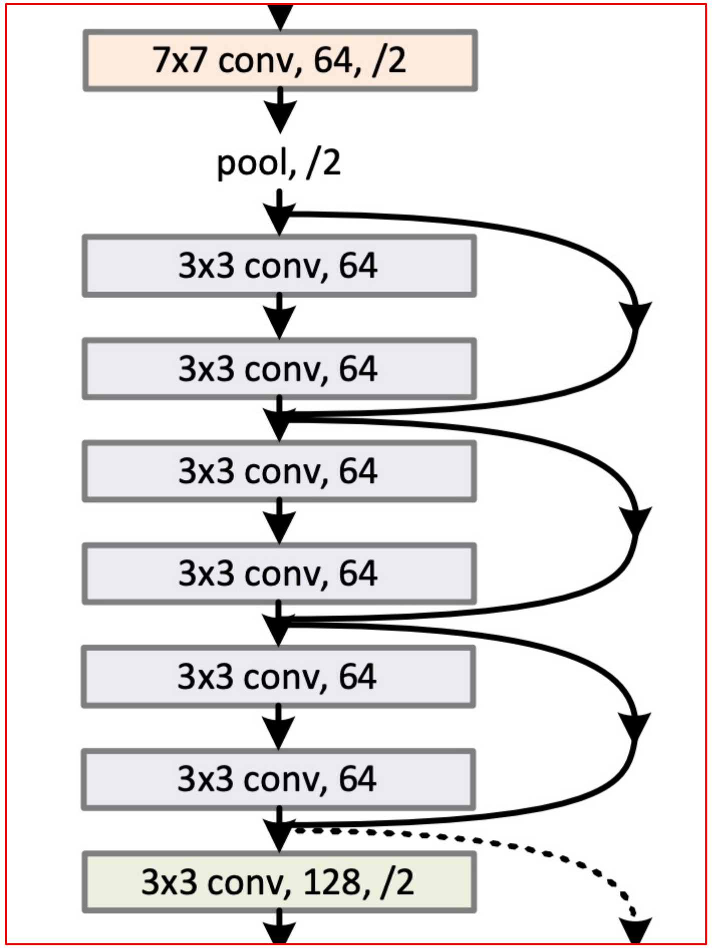
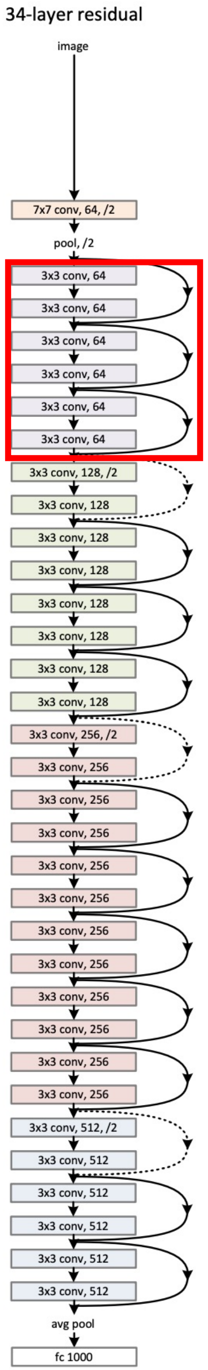
ResNet





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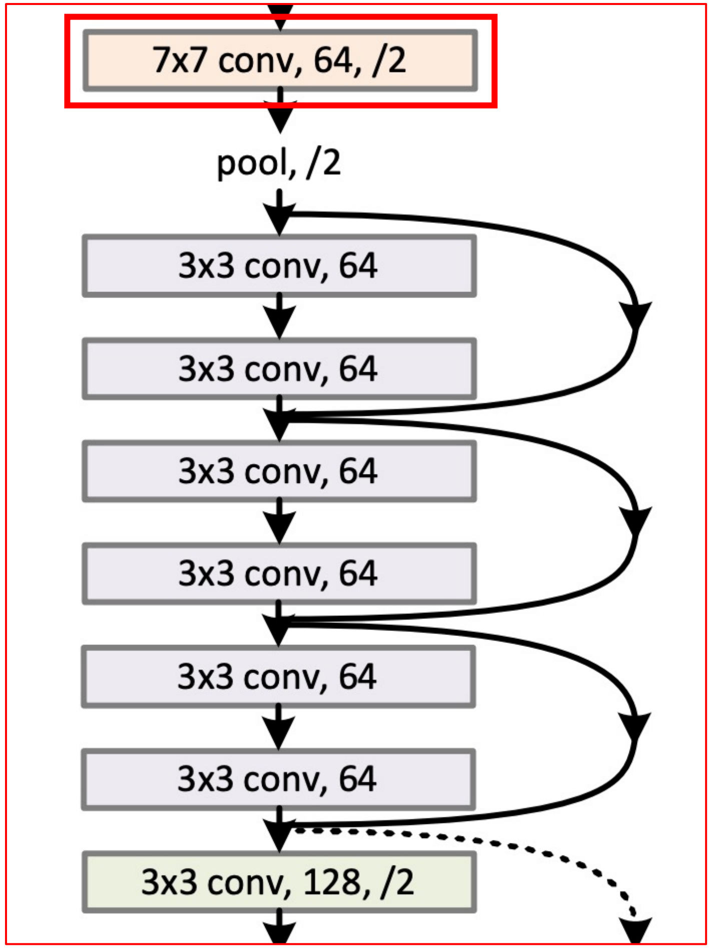
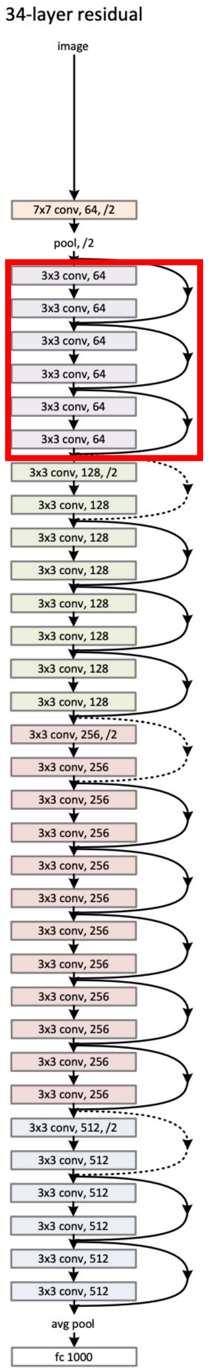
ResNet





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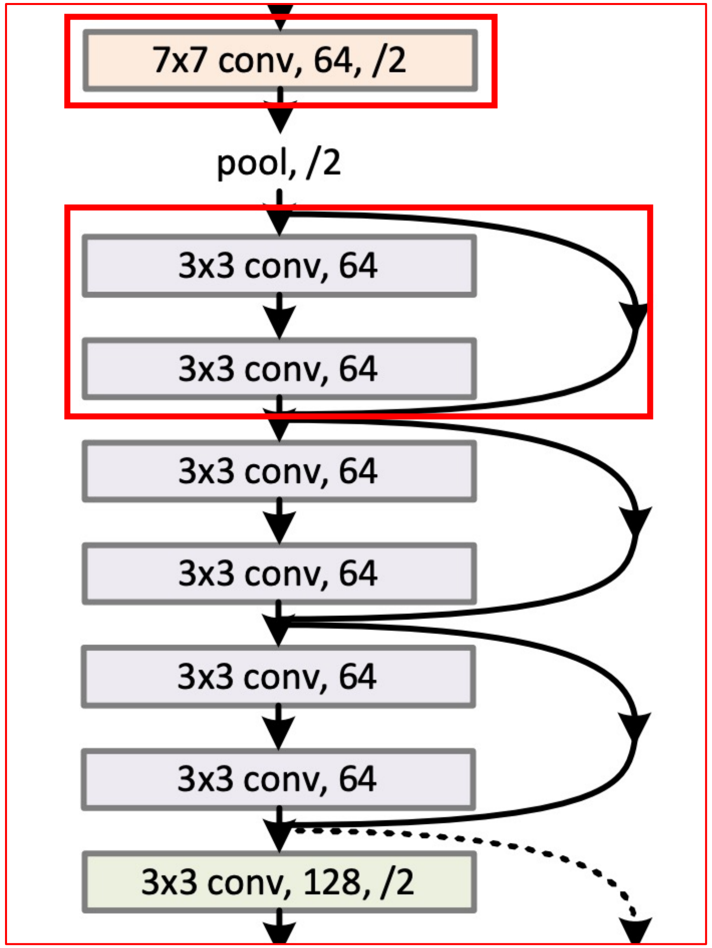

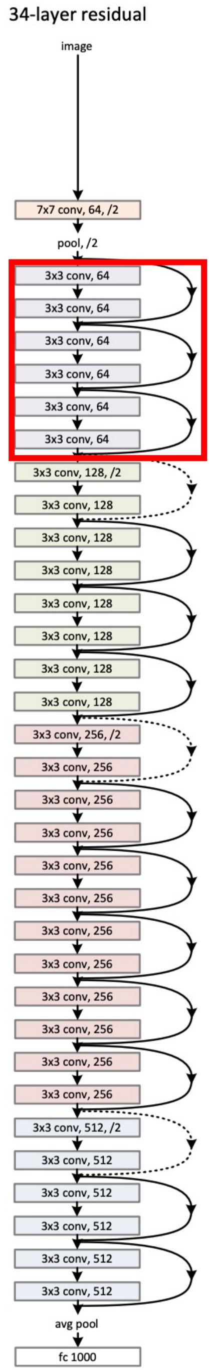

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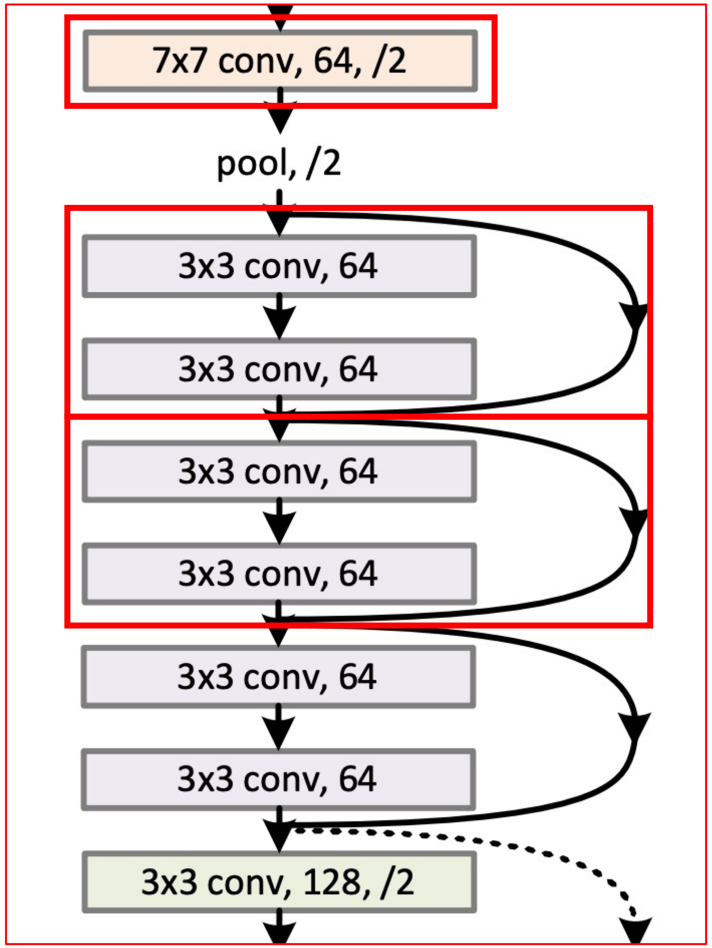

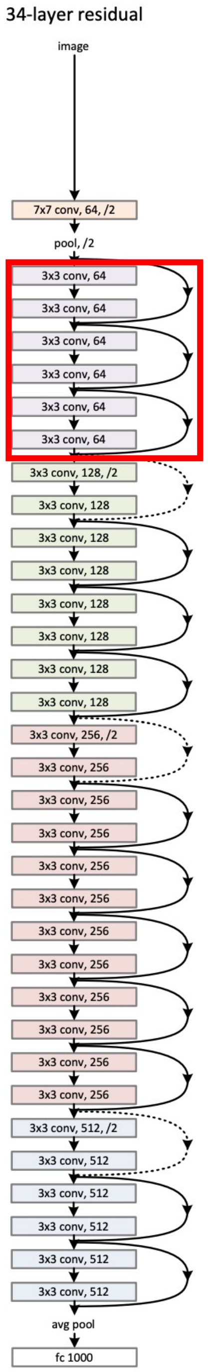

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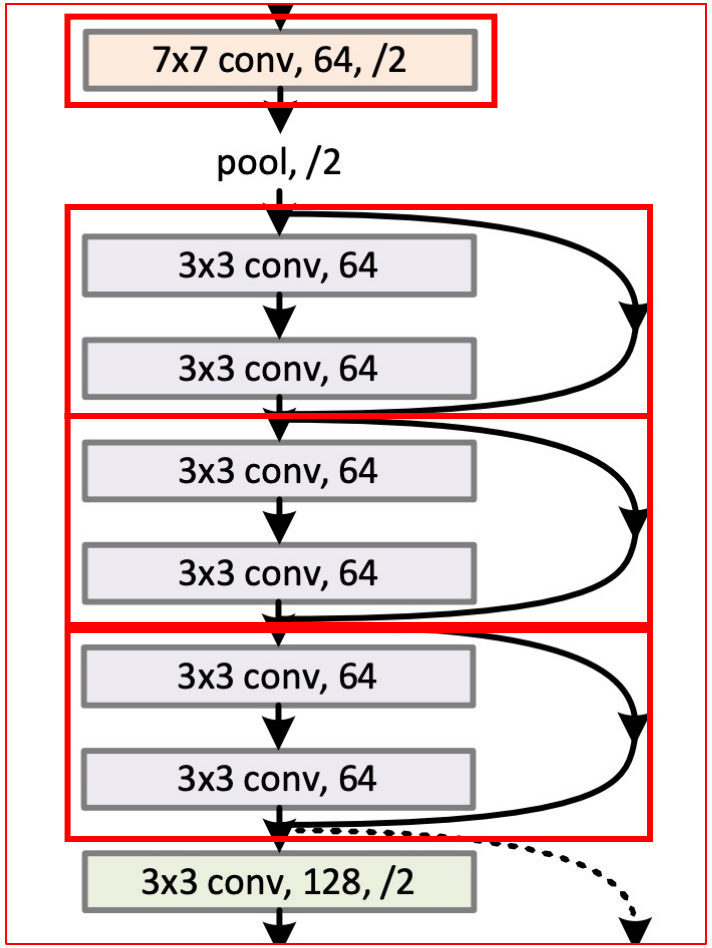
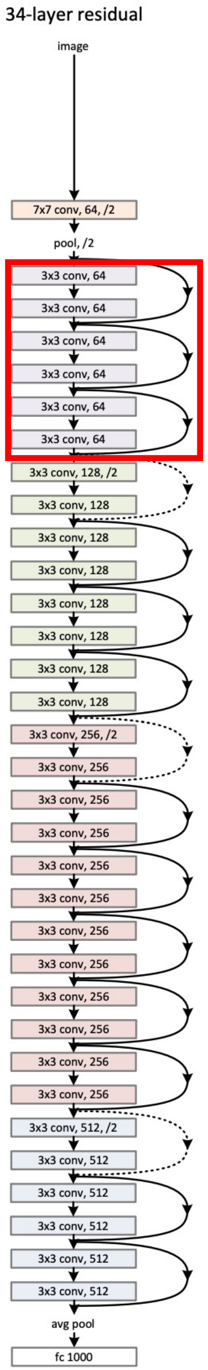
ResNet





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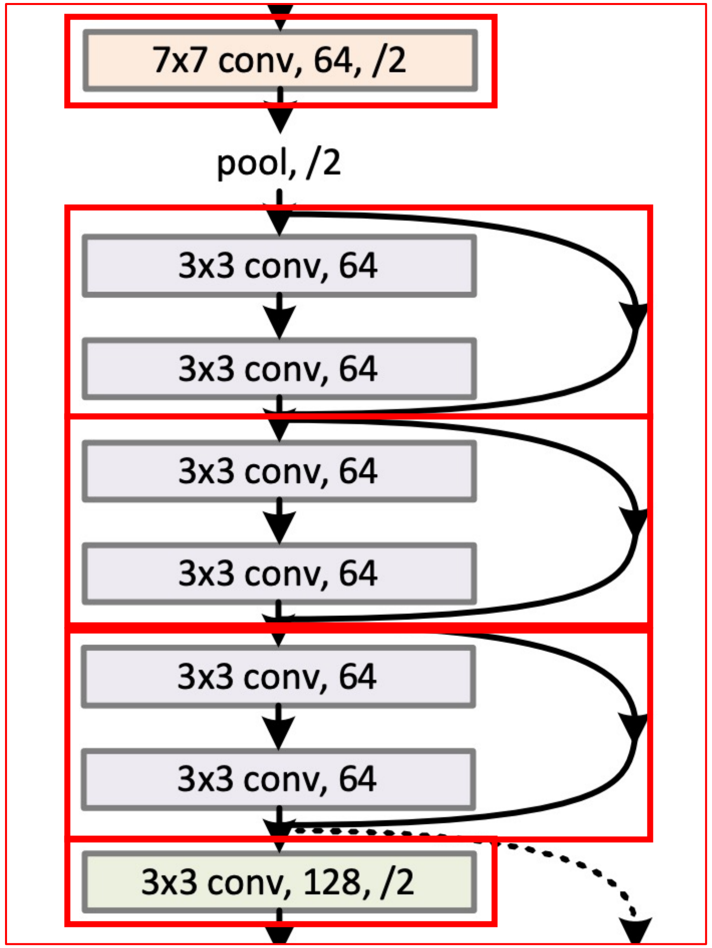

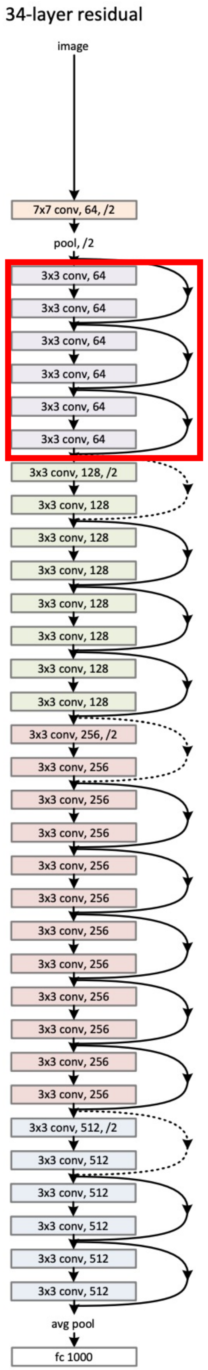

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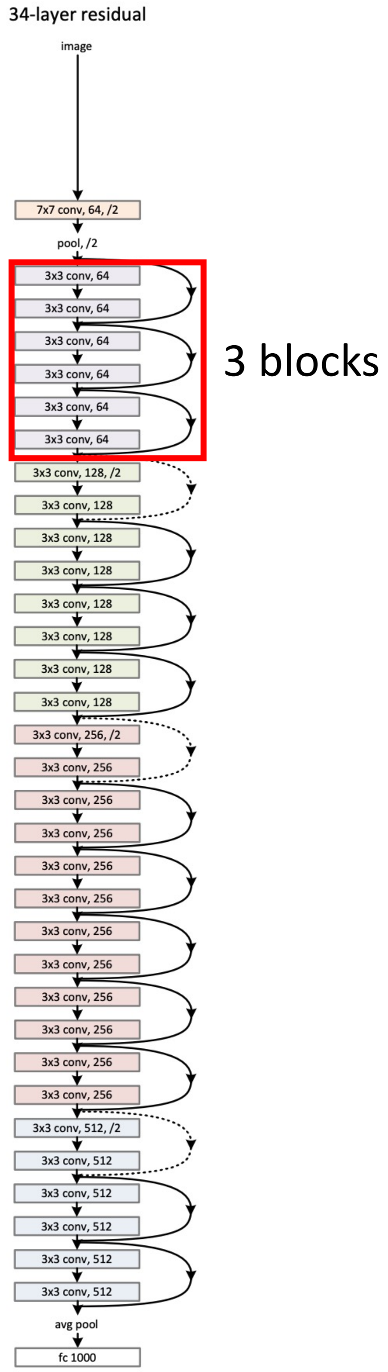
ResNet



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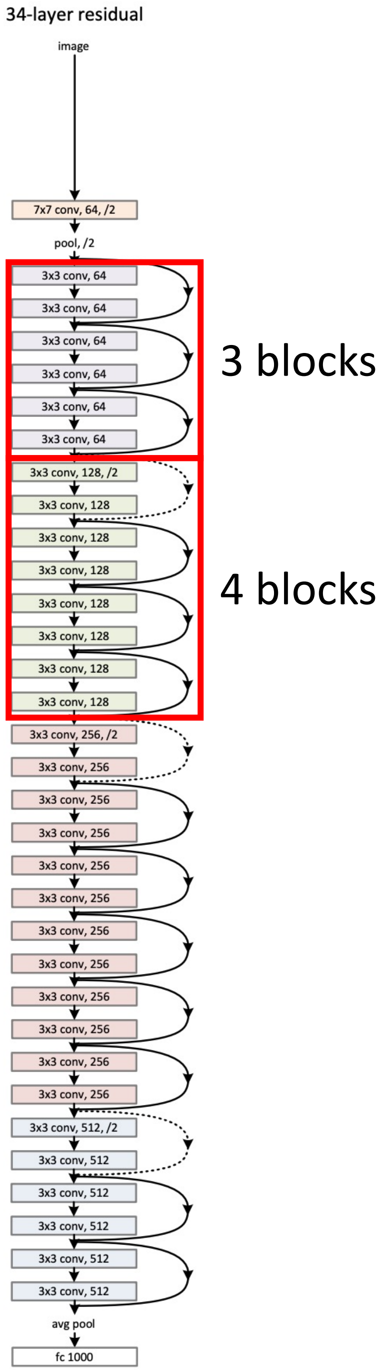

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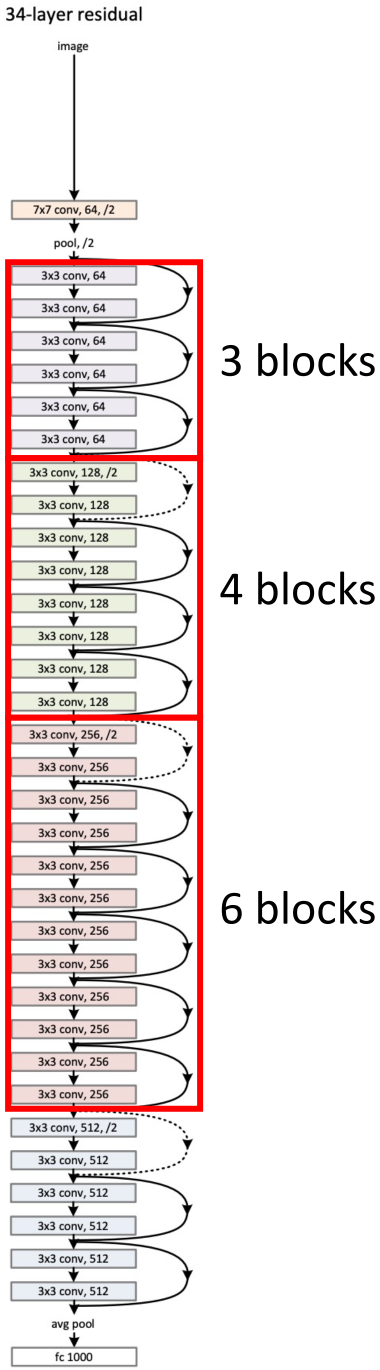

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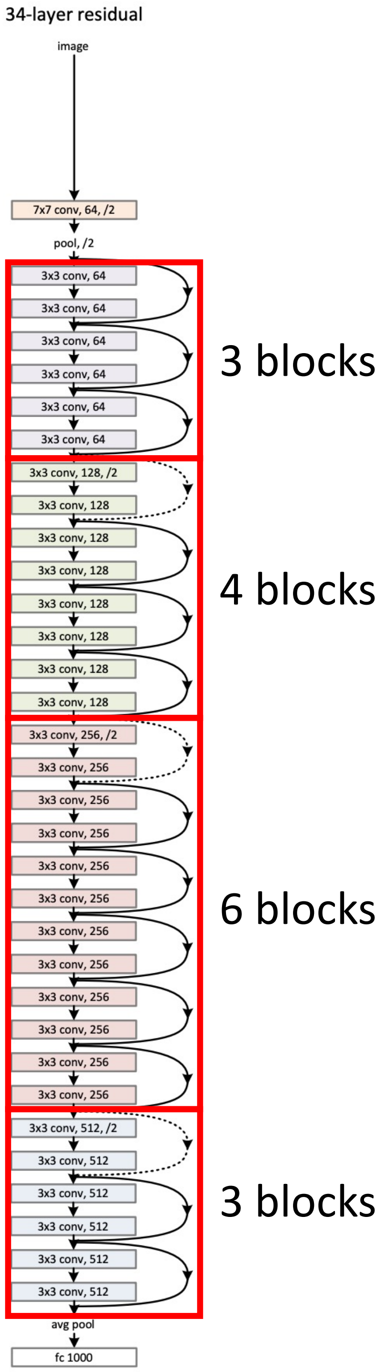

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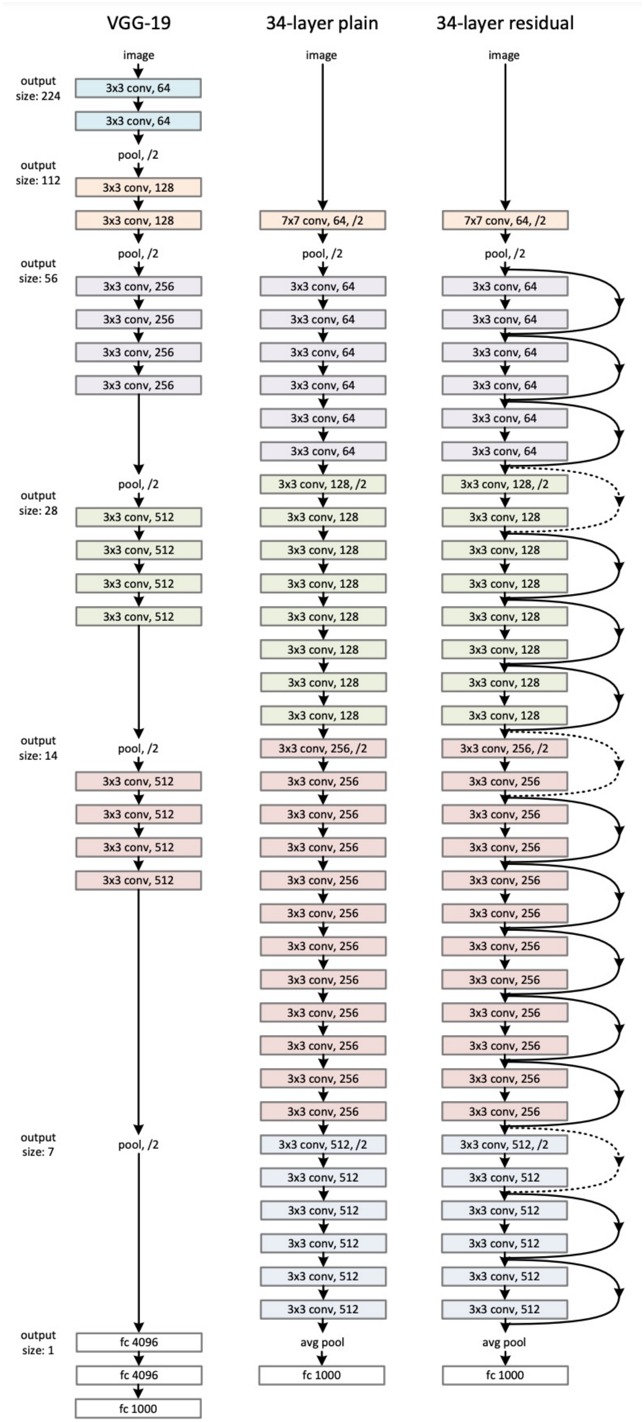

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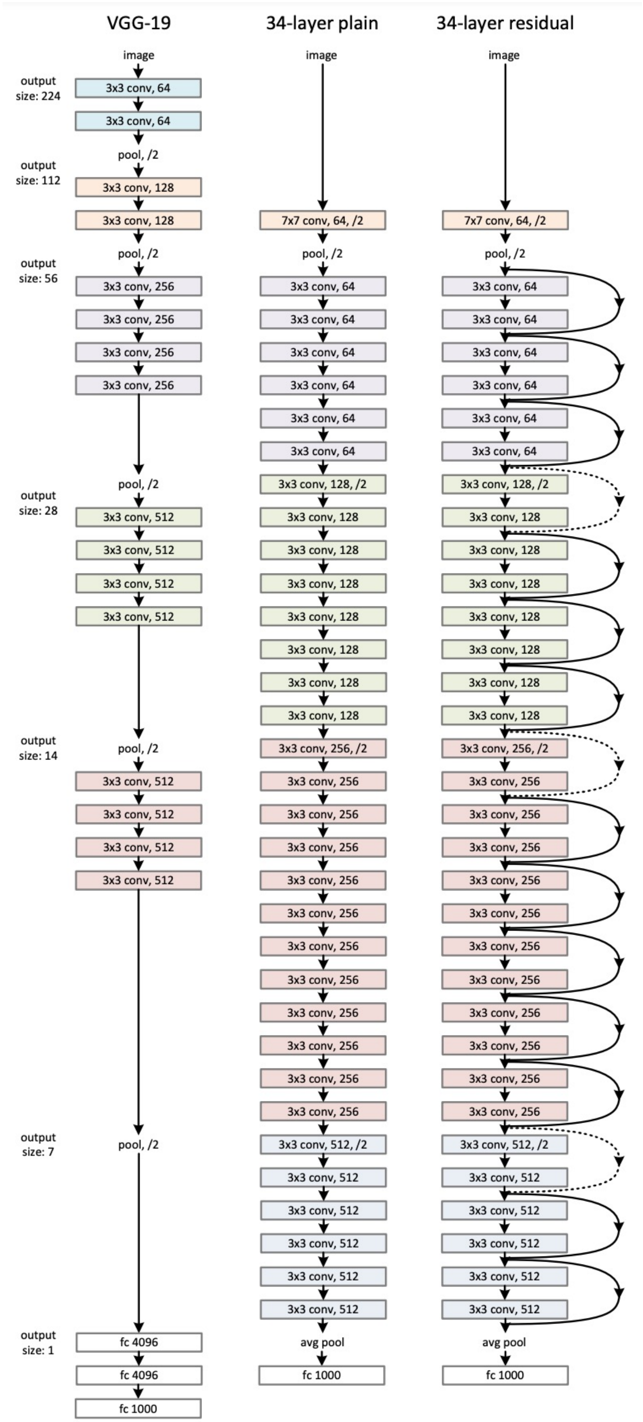

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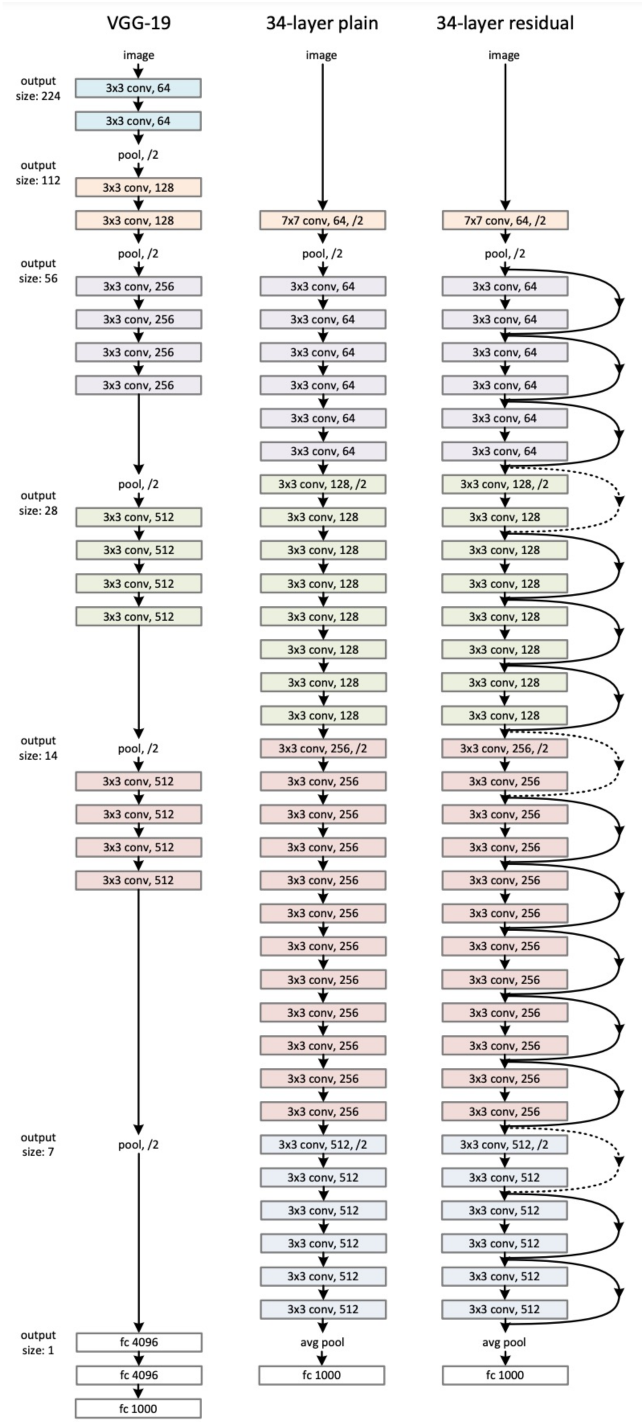
ResNet



floating point operations per second

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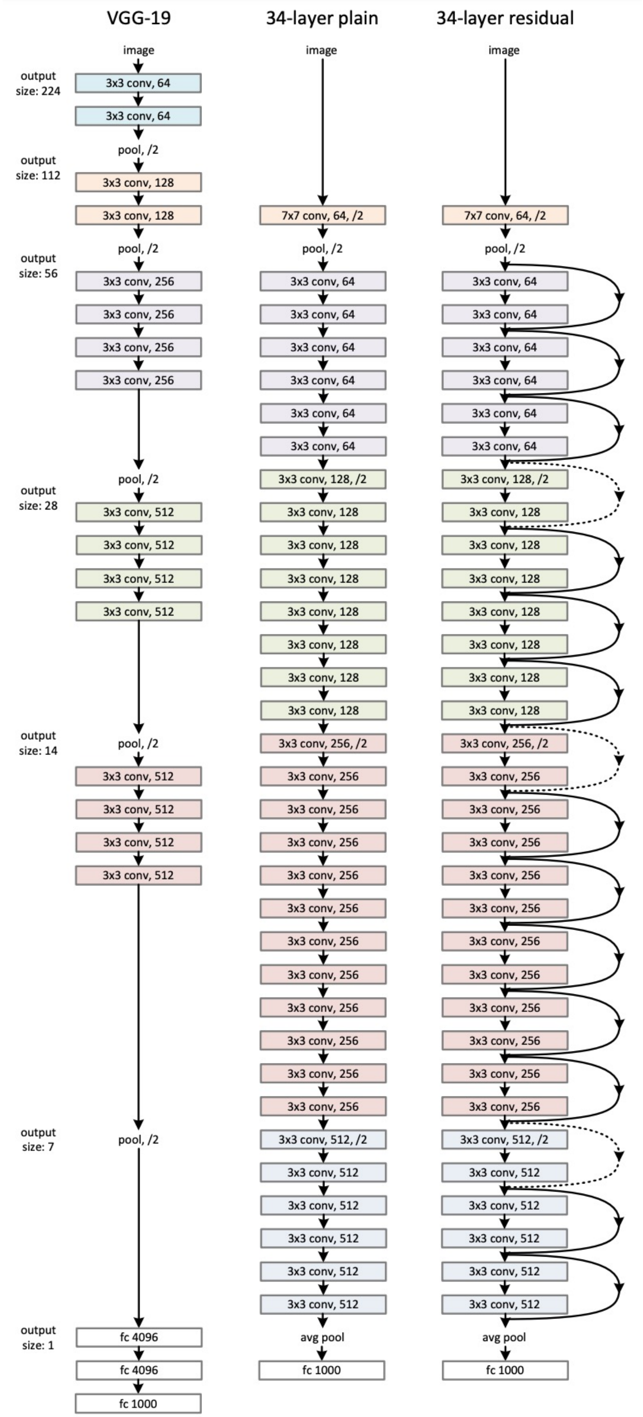

Measure: how complicated the model is

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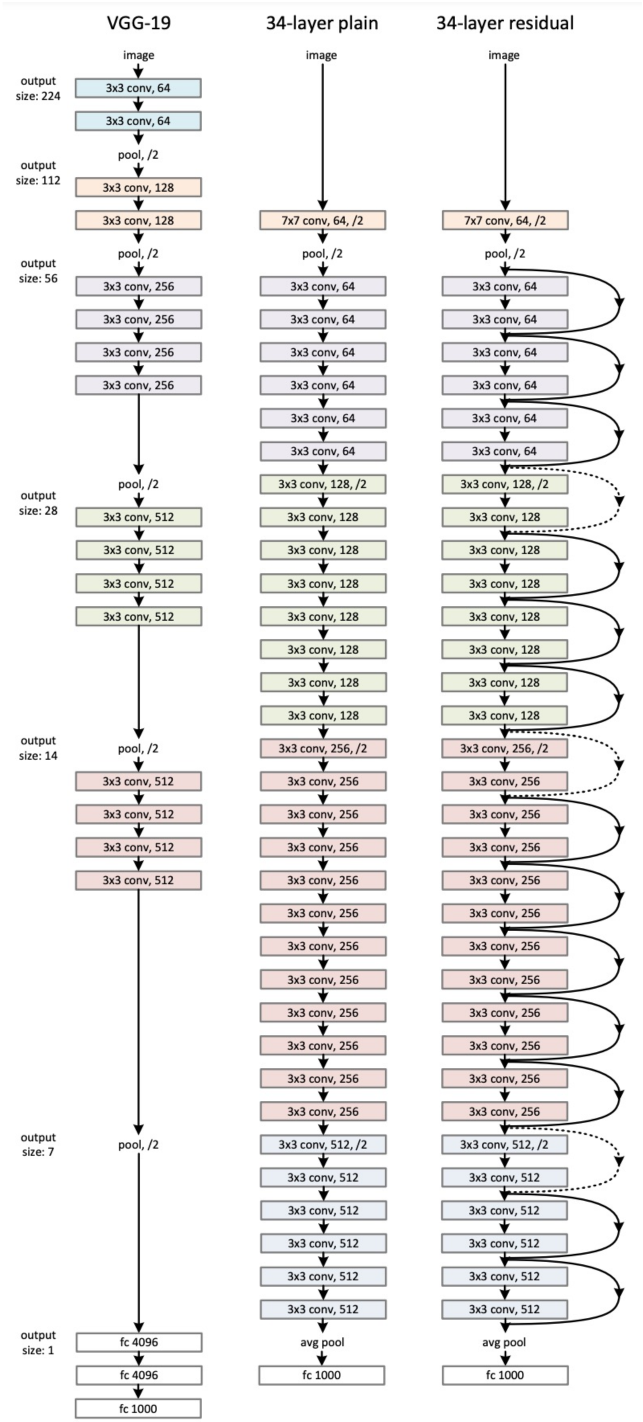
ResNet



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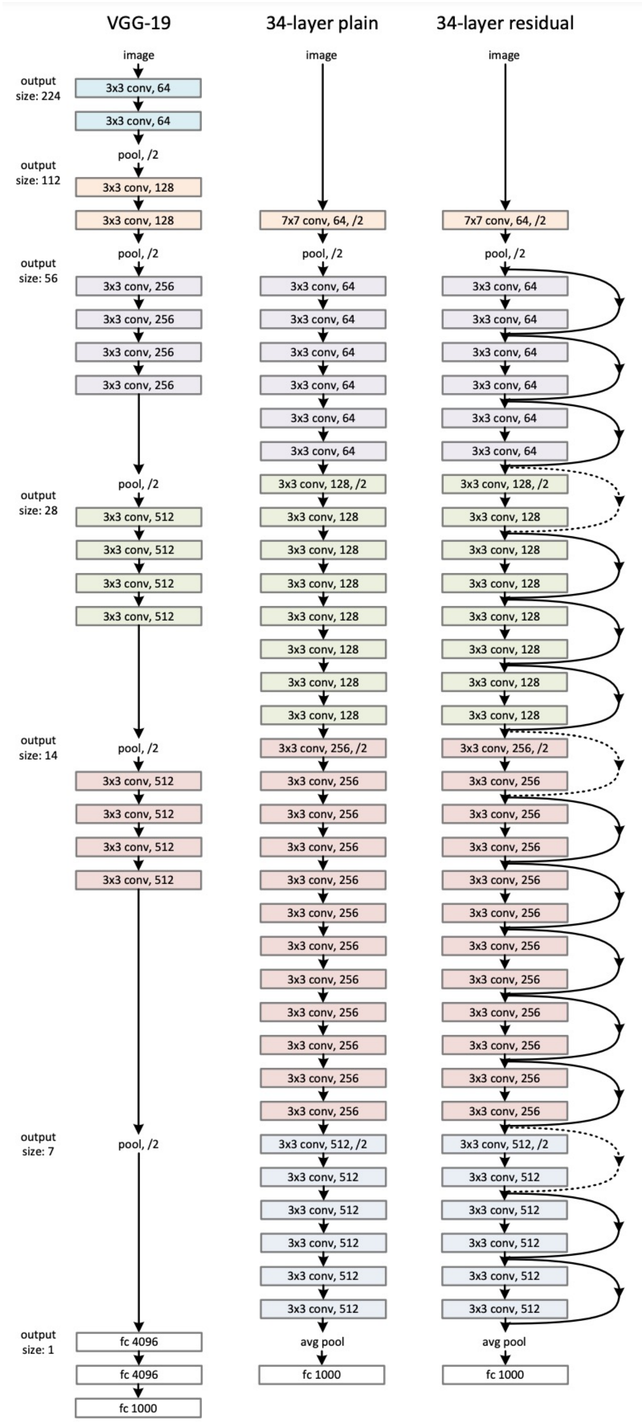

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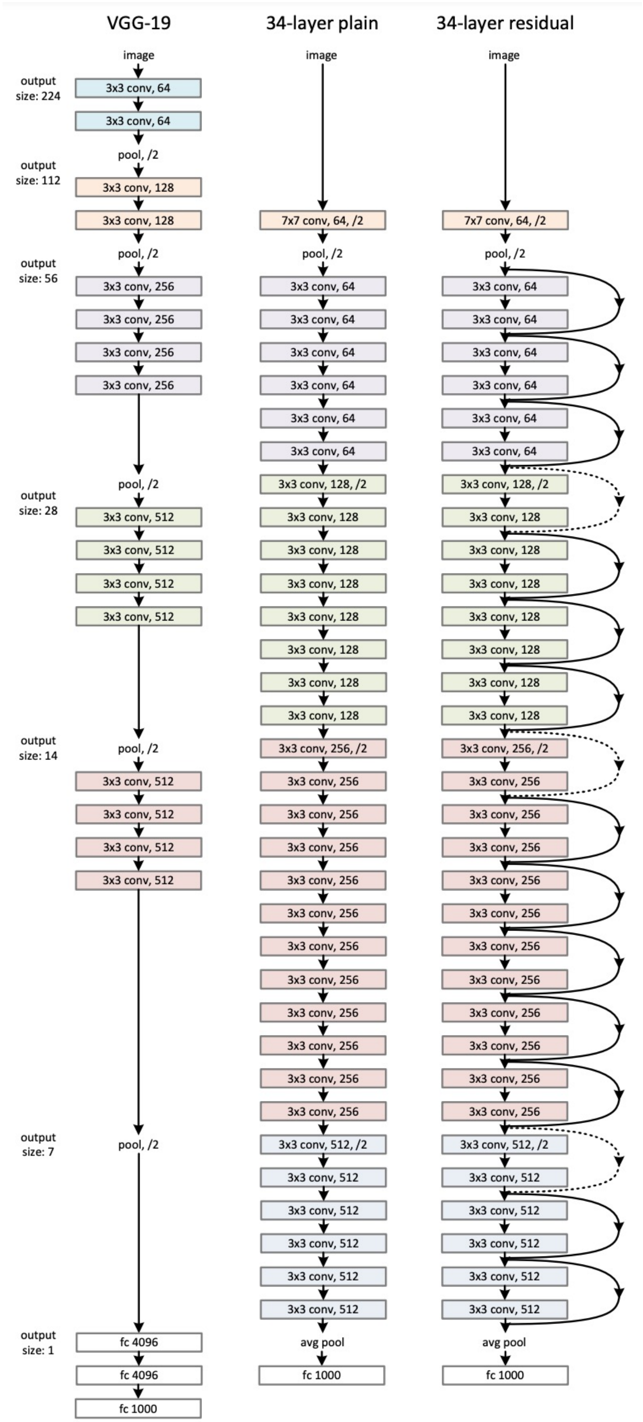

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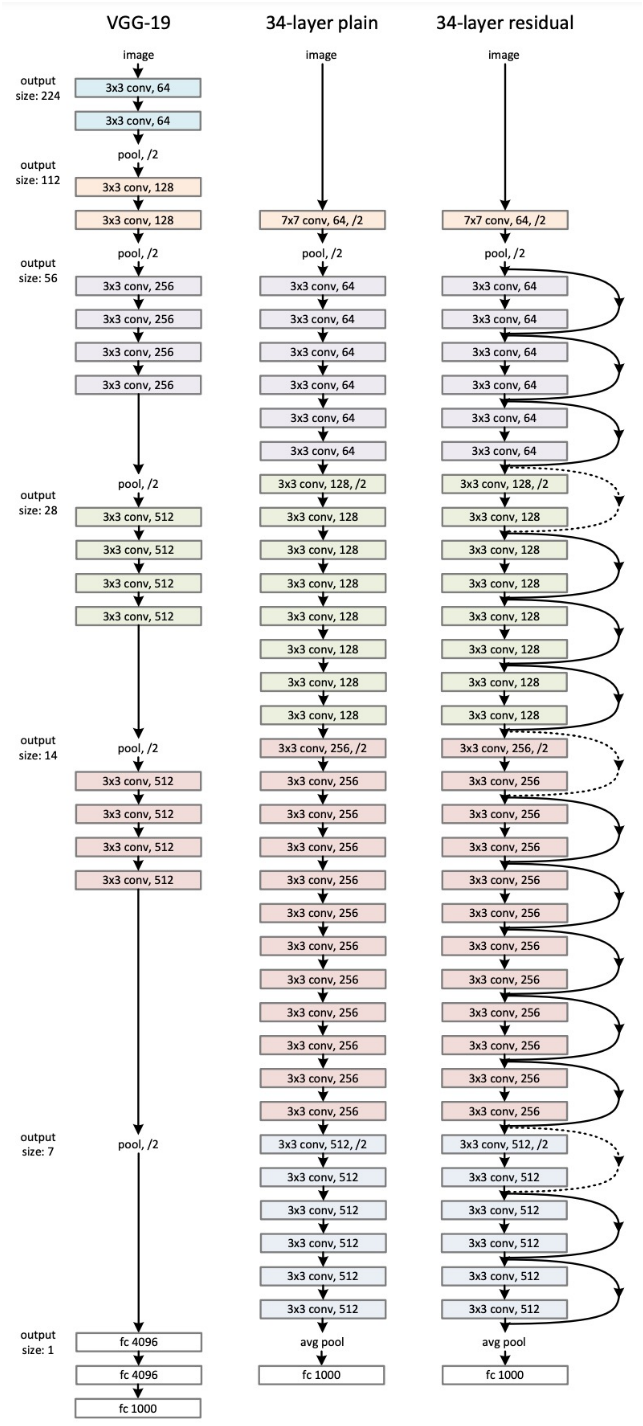
Q: VGG-19 has much more FLOPS than 34-layer plain network and 34-layer ResNet?

ResNet



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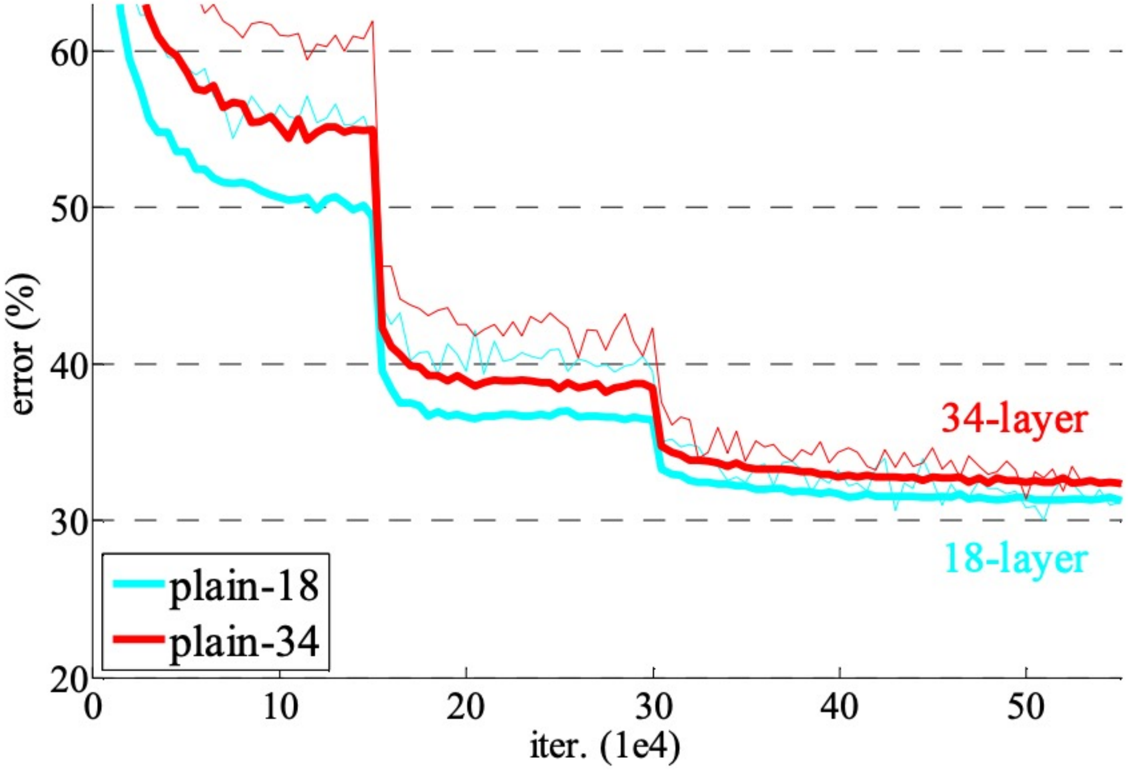
Reading material

ResNet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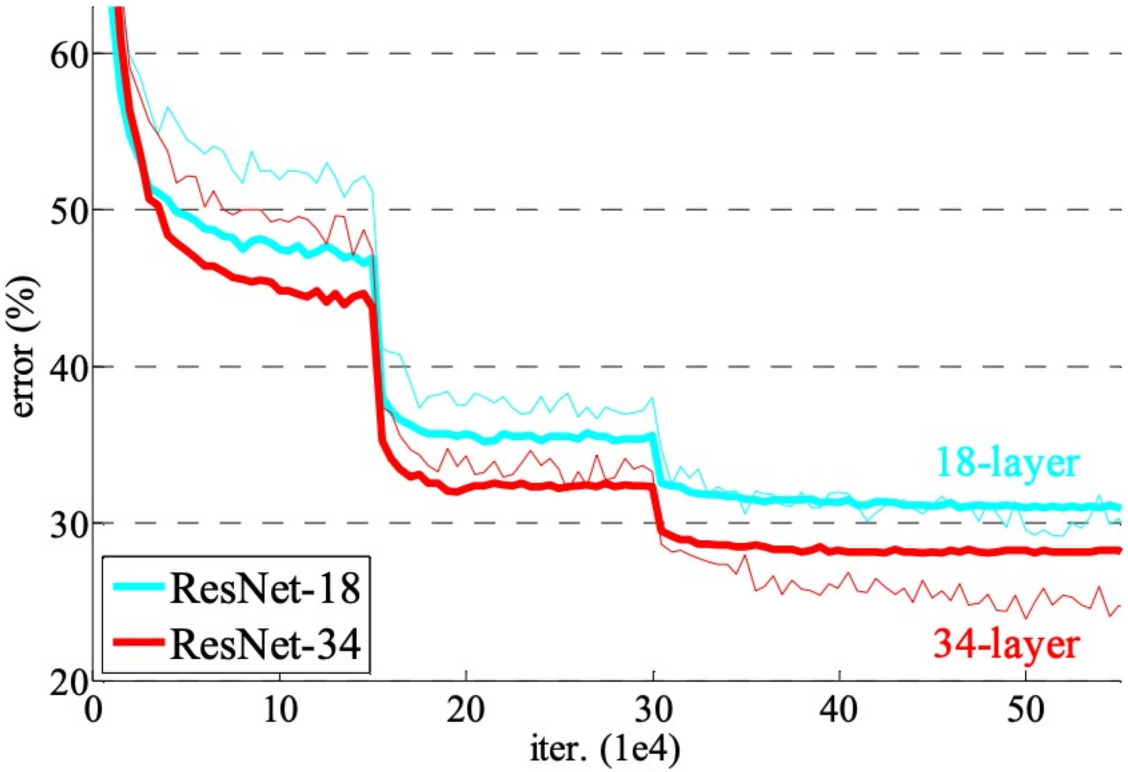
plain-18
plain-34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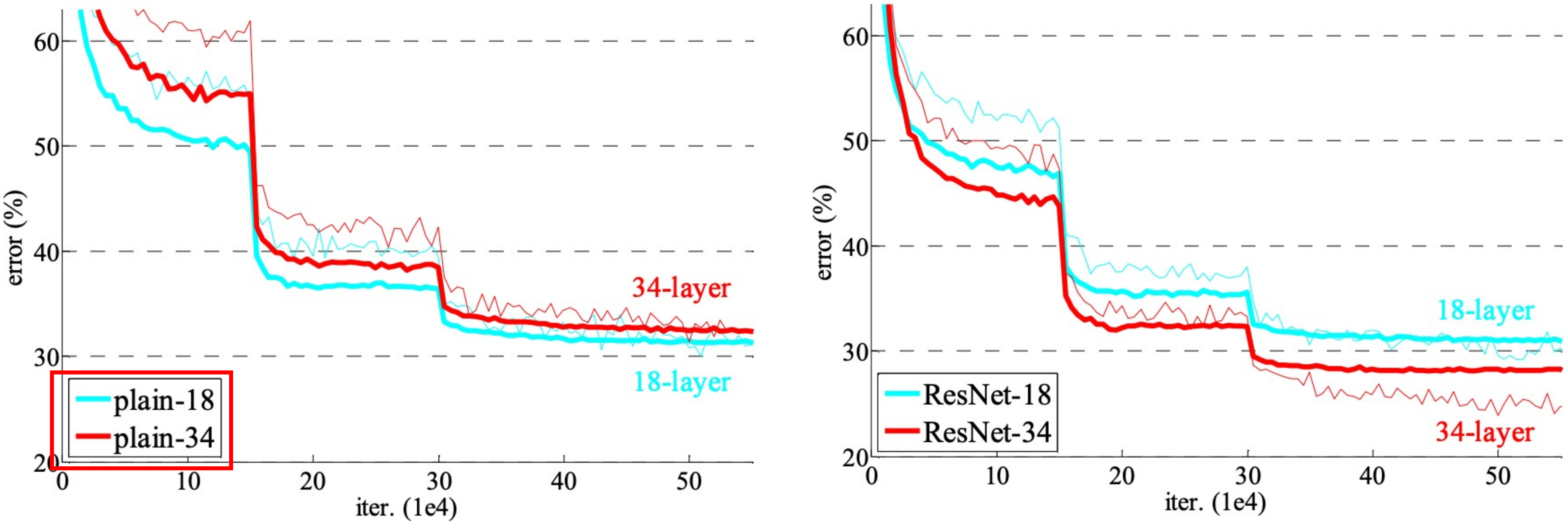
ResNet-18
ResNet-34

ResNet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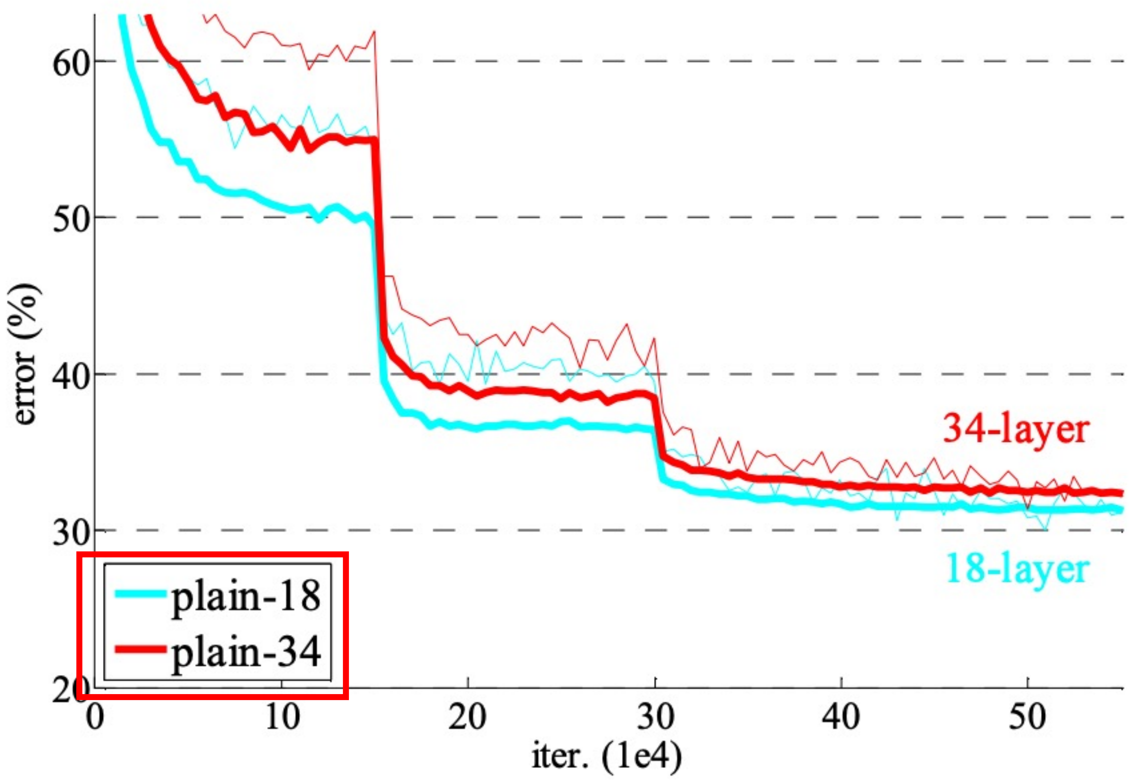
ResNet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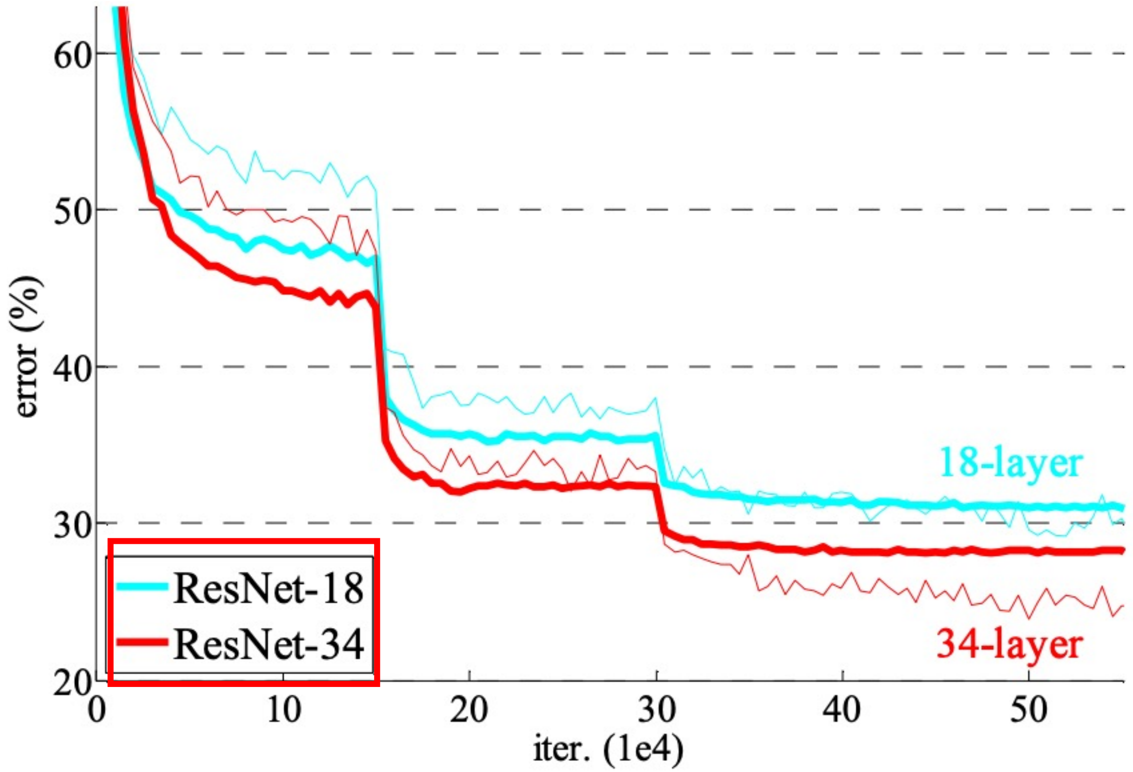
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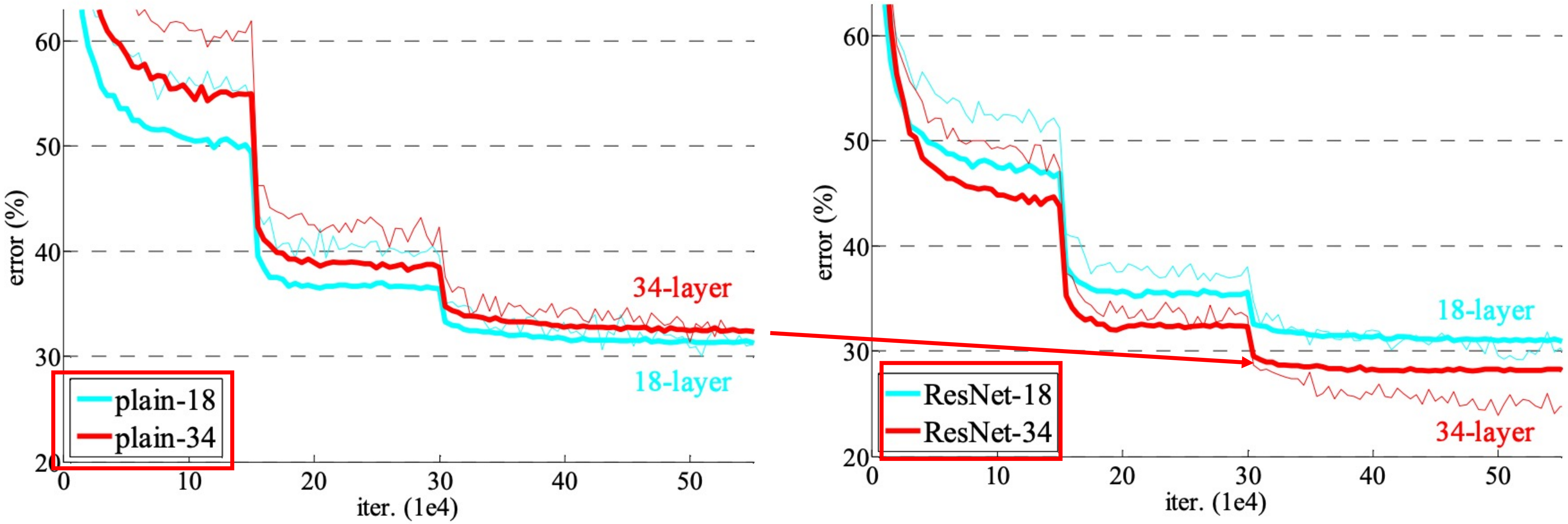
ResNet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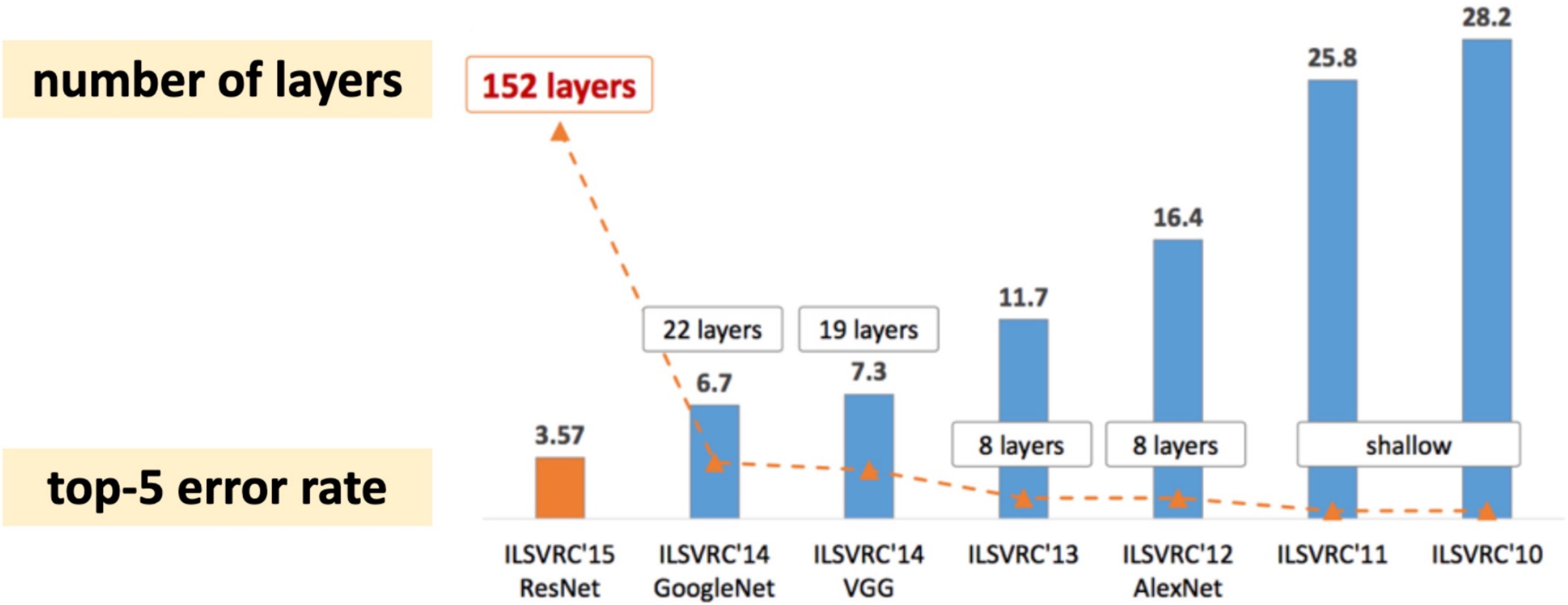
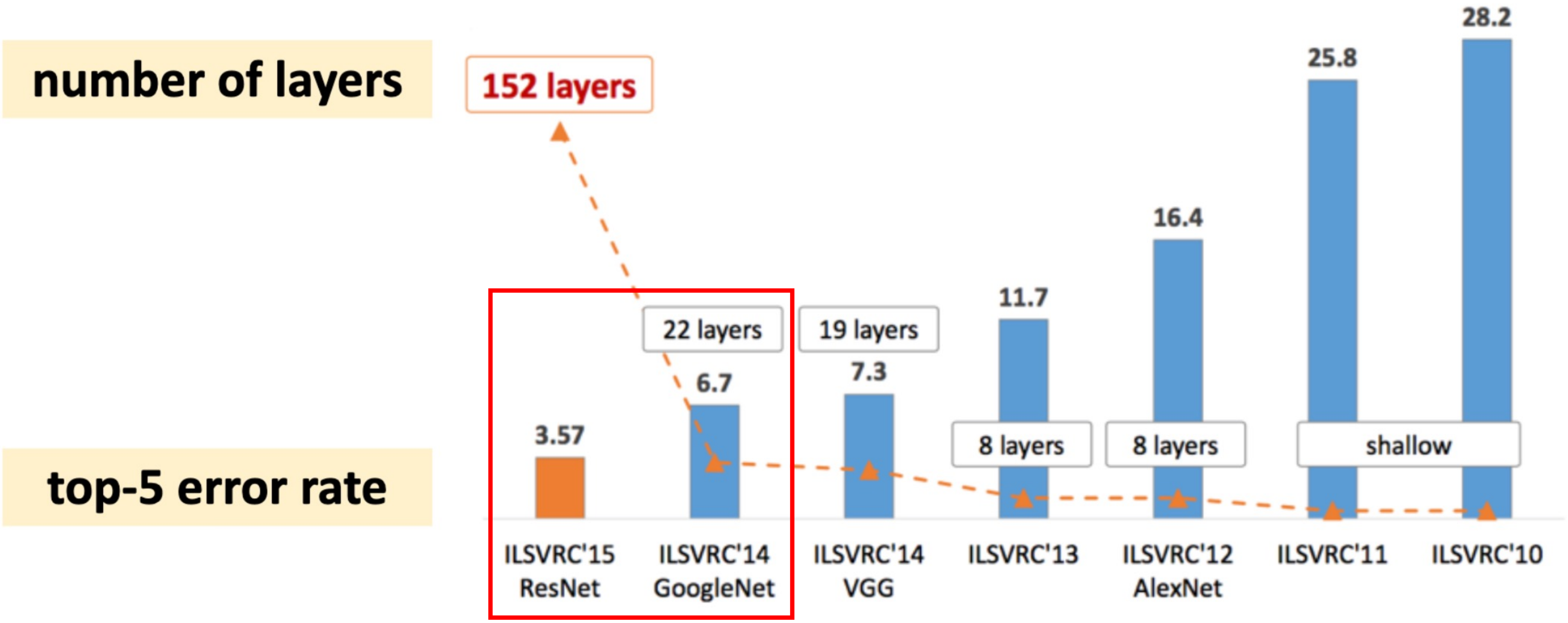
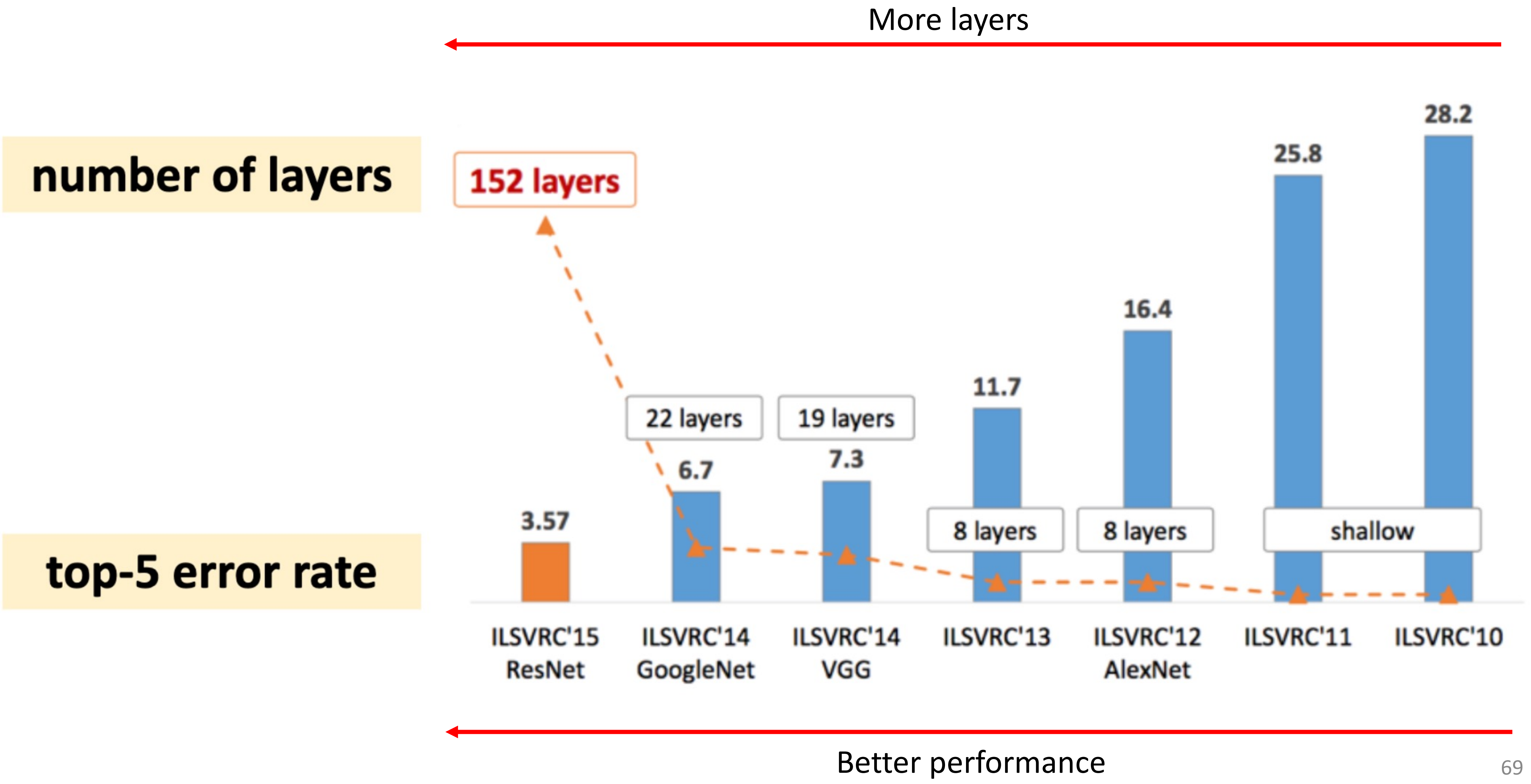
ImageNet competition winners



ImageNet competition winners



ImageNet competition winners



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- [ResNet] He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Deep residual learning for image recognition." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770-778. 2016. ArXiv at https://arxiv.org/pdf/1512.03385.pdf (*Section 3.1, 3.2 and 3.3)*