CNN Architectures

Neural Networks Design And Application

Input resolution issue

- Global average pooling

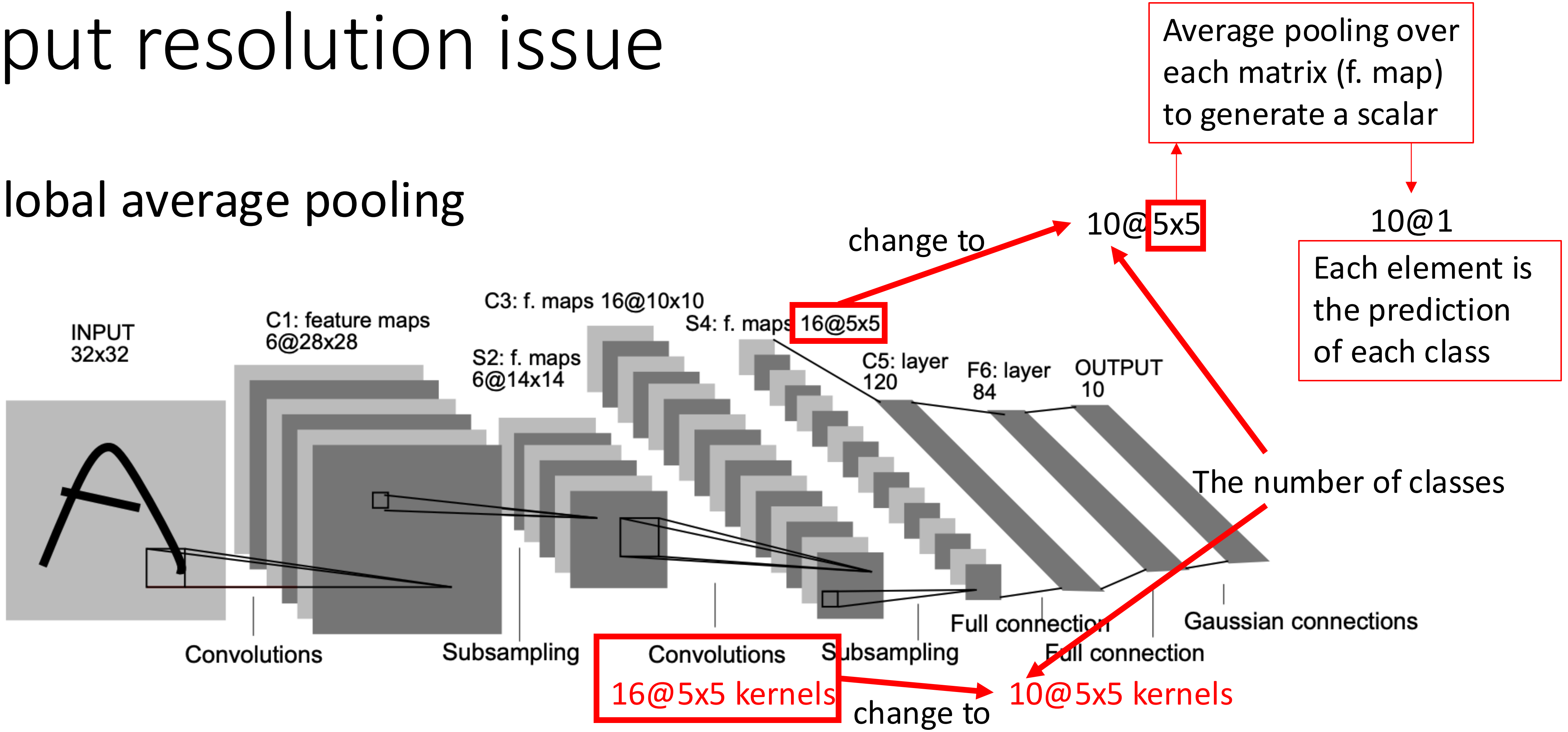
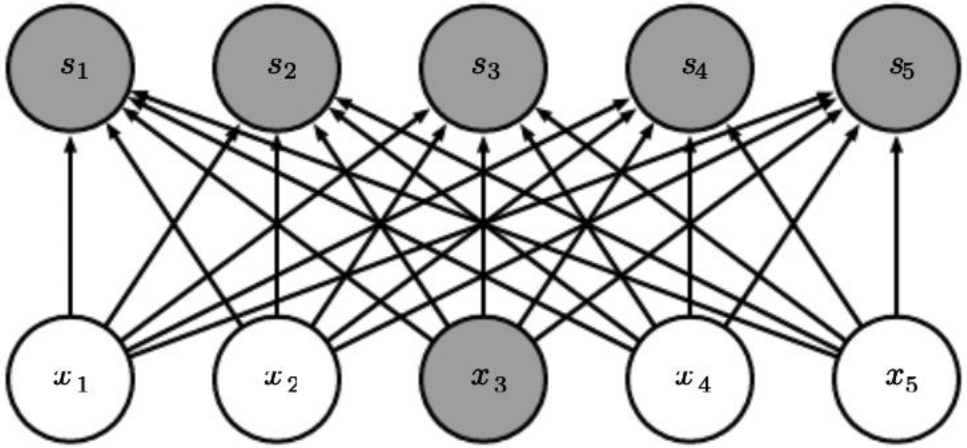


Fig. 1. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

Difference between ConvNet and MLP

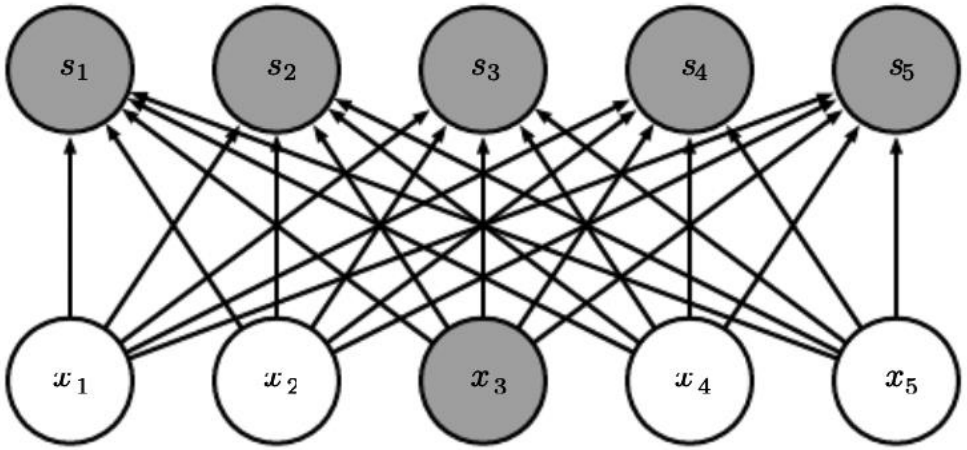
- Sparse connectivity
- Parameter sharing
- Equivariant representations

Sparse connectivity of convolution



Feedforward network (fully connected layer)

Sparse connectivity of convolution



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Q: how many arrows we have?

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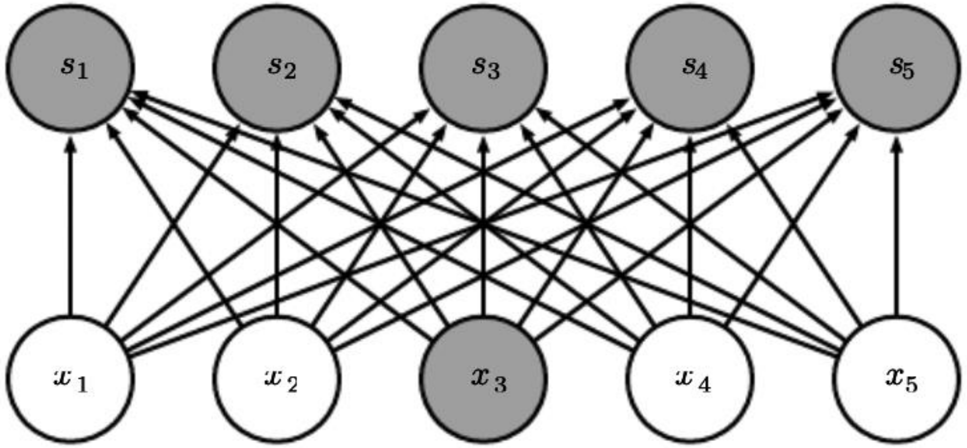

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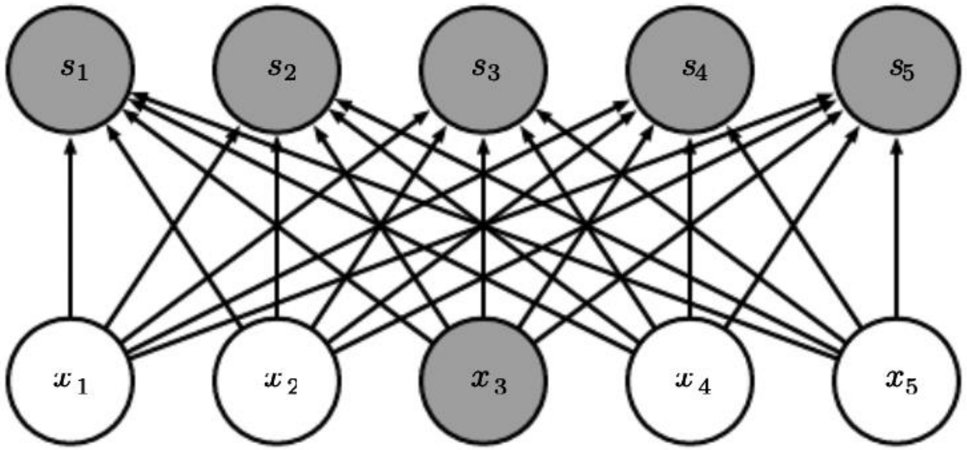
Q: how many arrows we have?

For each x_i: from s_1 to s_5 → 5 arrows
$x_1, \dots, x_5$ → 25 arrows

Sparse connectivity of convolution

$x'w \to s$



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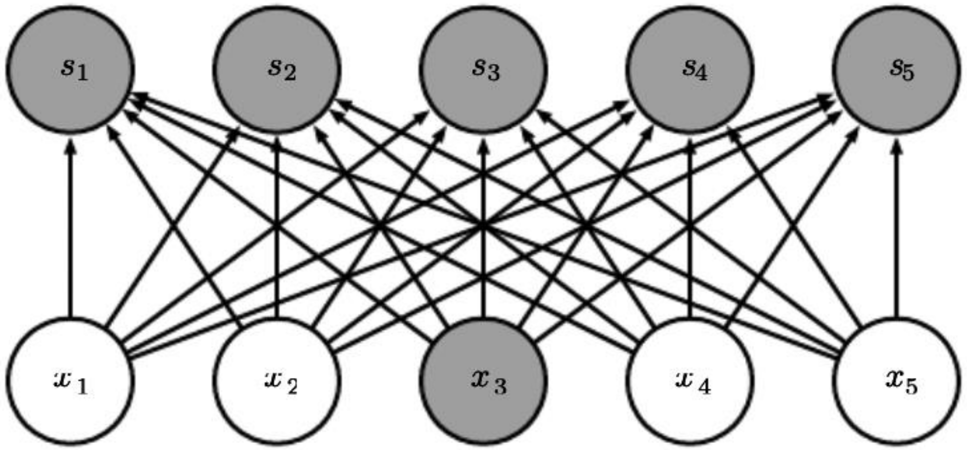
x and w are vectors; s is a scalar number

$x'w \rightarrow s$



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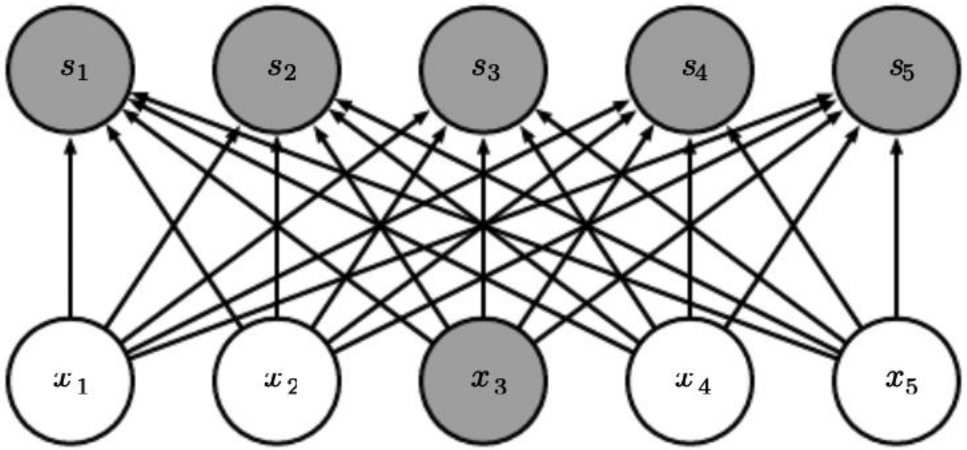
$$x'w_1 = \sum_{i=1}^{5} x_i w_{1,i}$$



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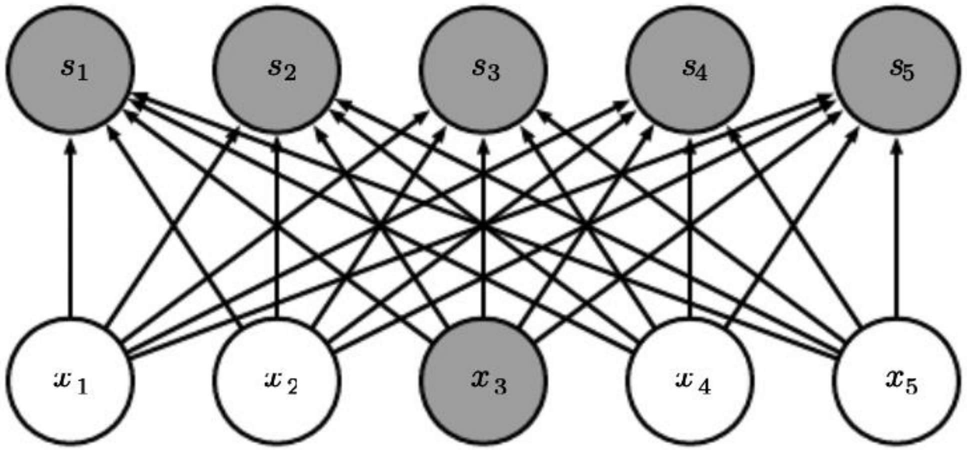

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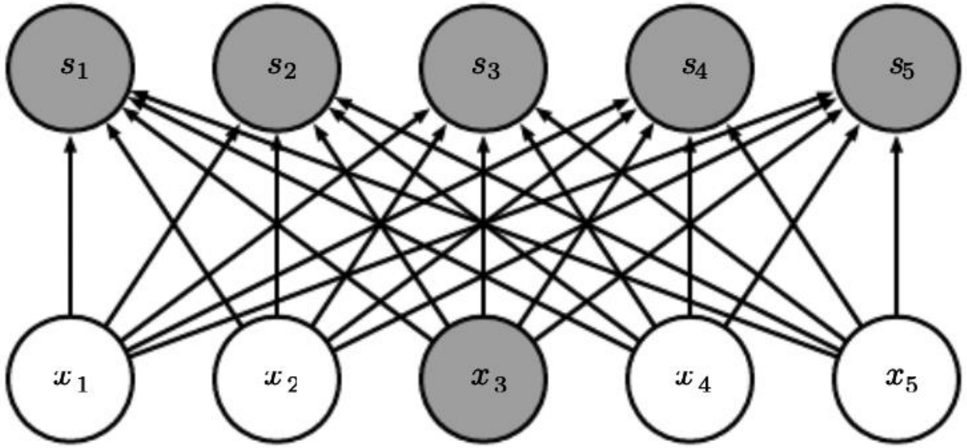

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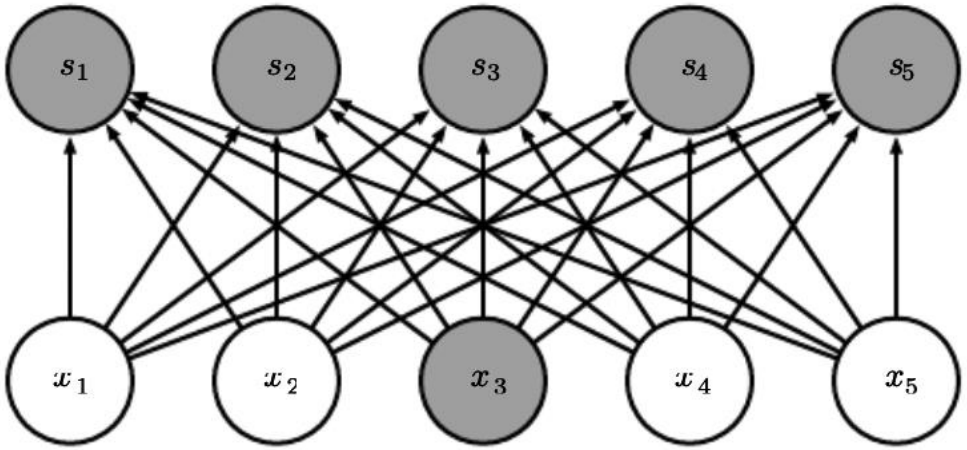
$W = [w_1, w_2, w_3, w_4, w_5]$



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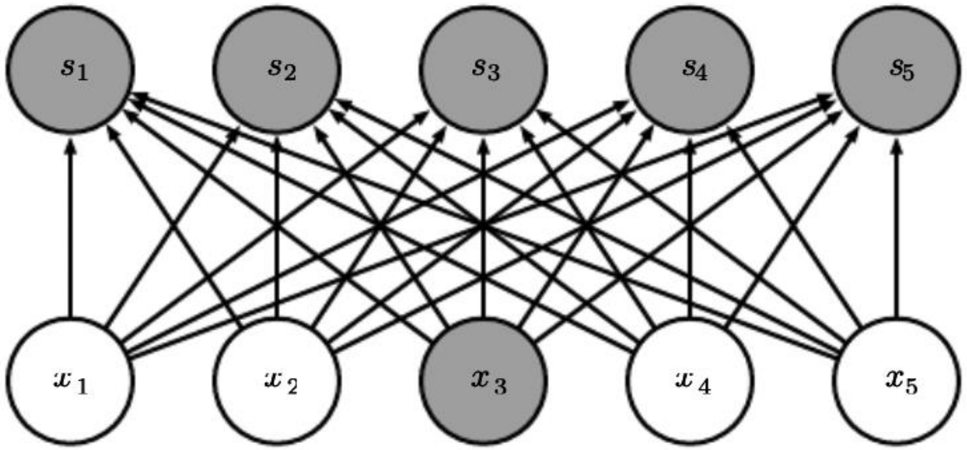
W

$=$

$[w_1, w_2, w_3, w_4, w_5]$

(5x5 weight matrix)



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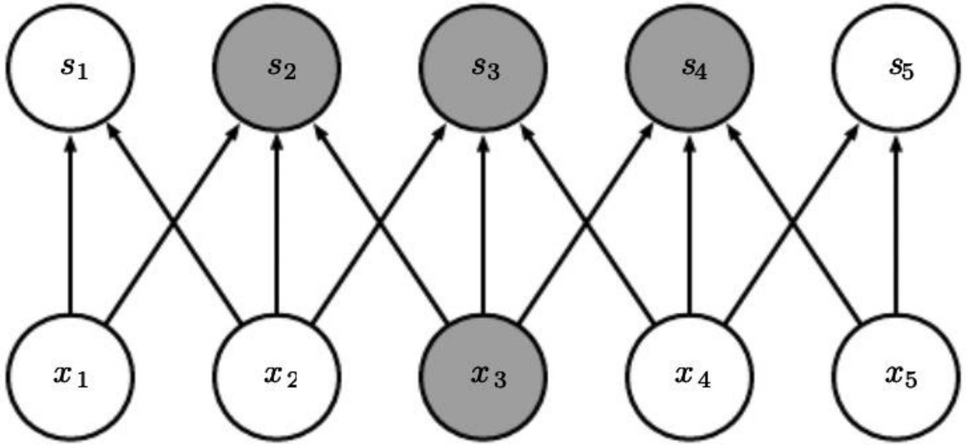
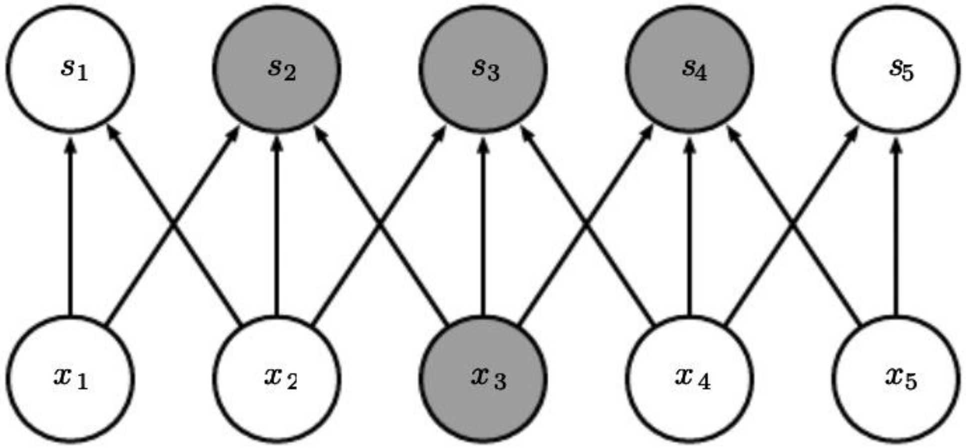


Convolutional layers

Sparse connectivity of convolution



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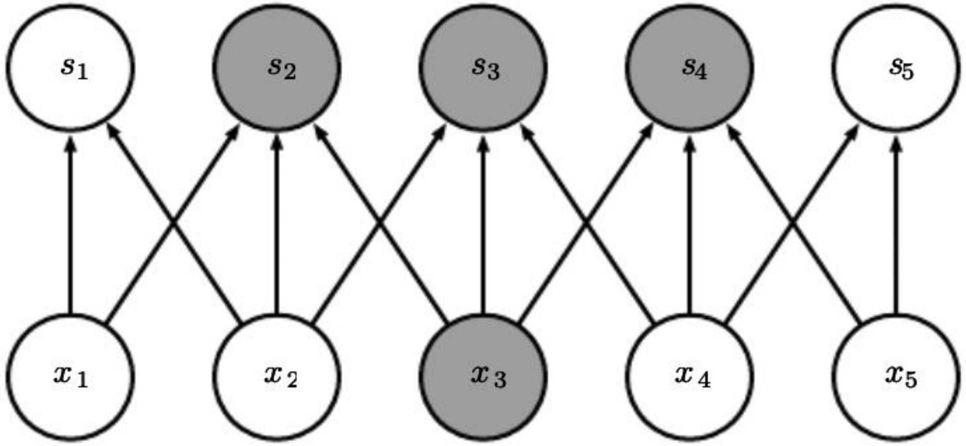
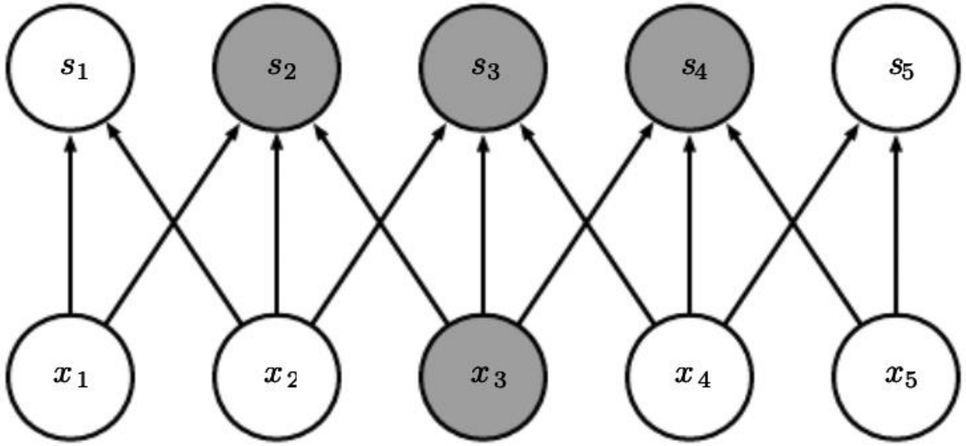


Convolutional layers

Q: how many arrows we have?

For each x_i: connect to 3 s outputs

Sparse connectivity of convolution



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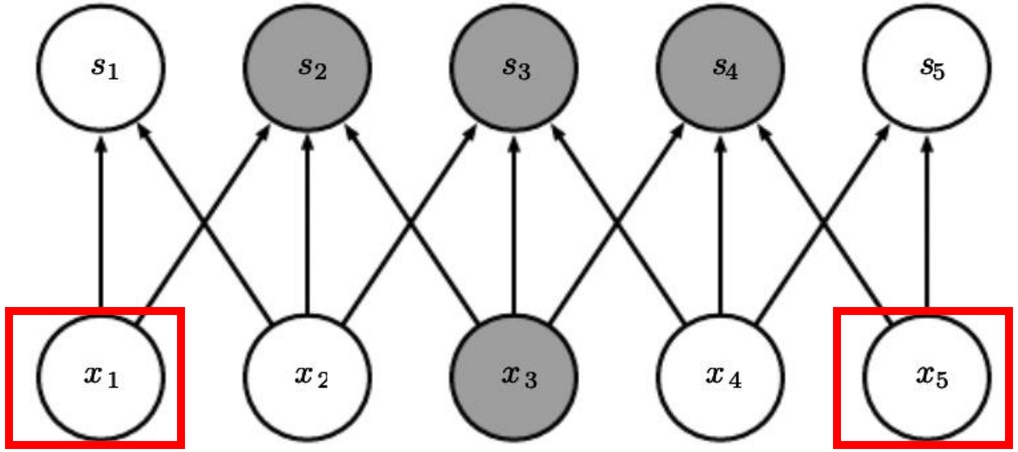

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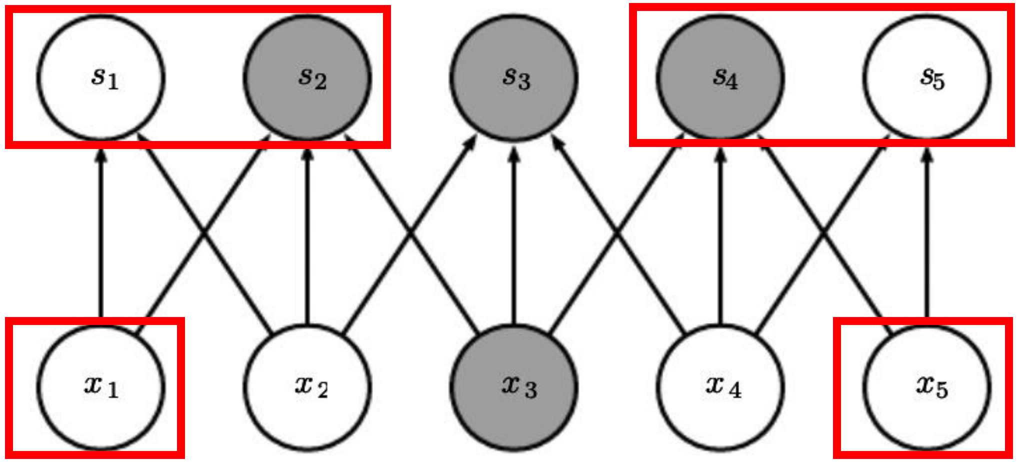

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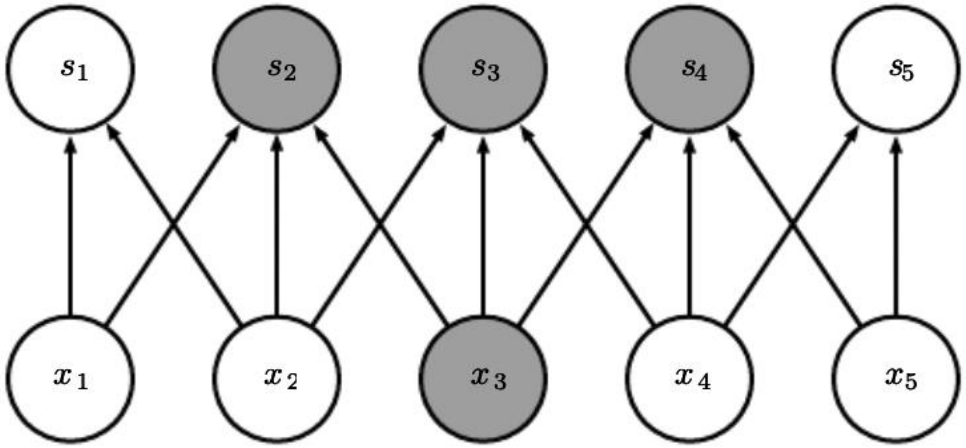
Sparse connectivity of convolution

The view of convolutional kernel/filter



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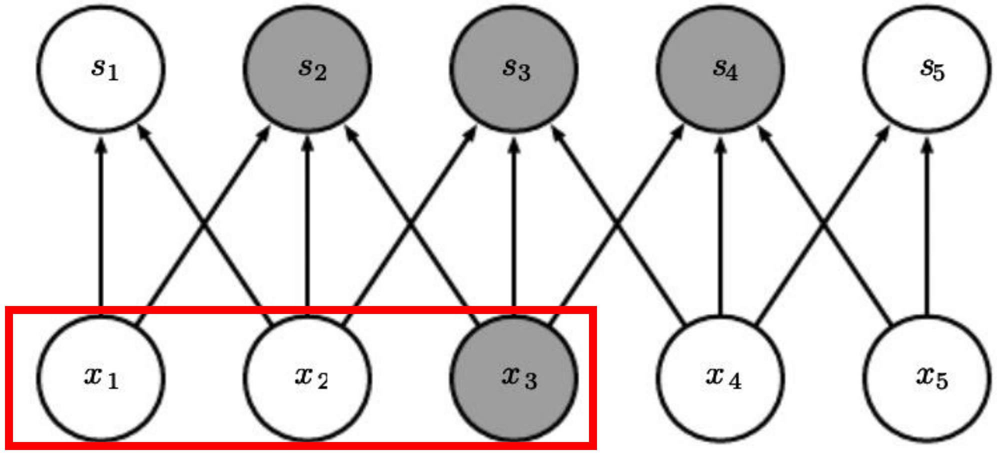

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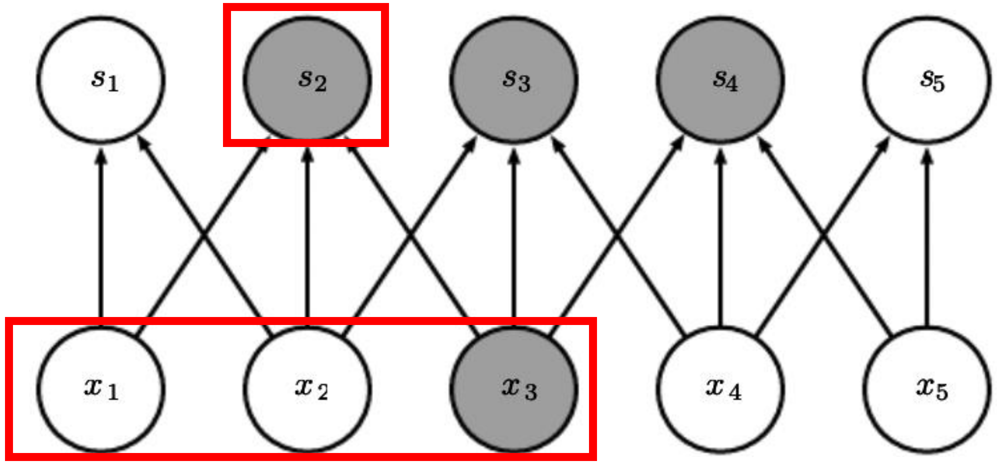

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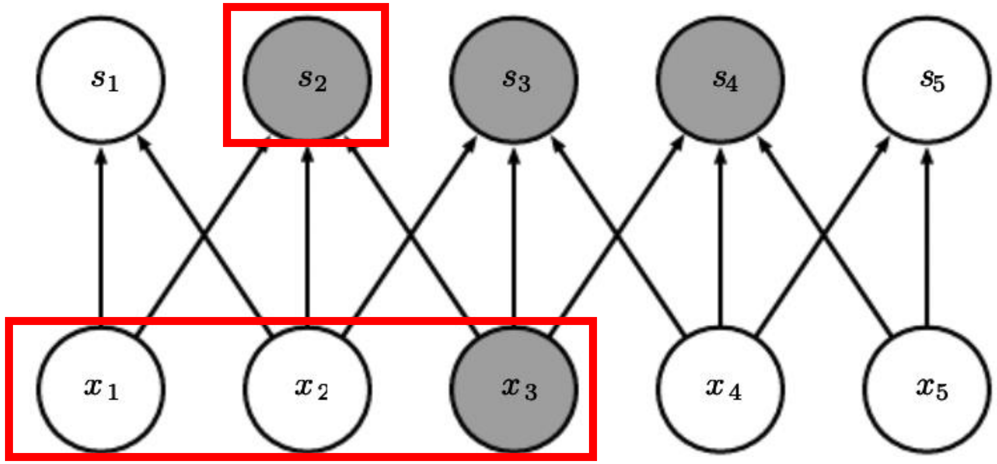
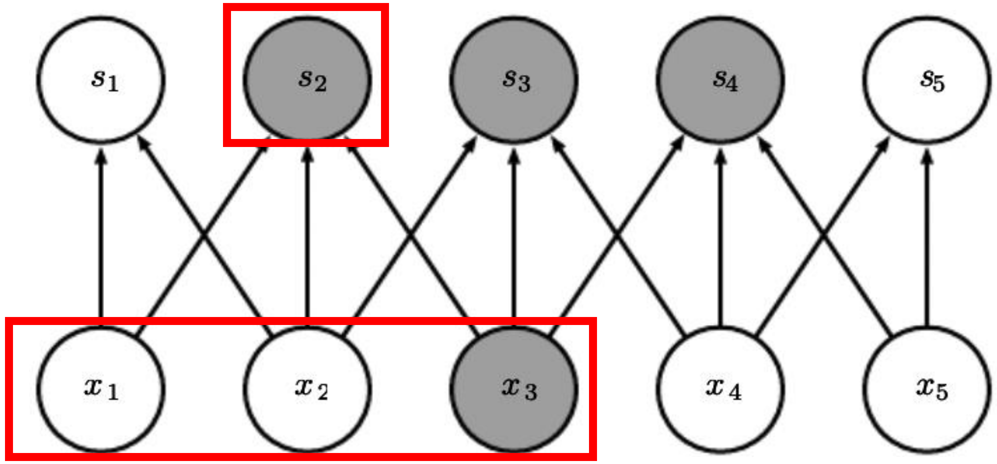


Q: filter size and stride?

Sparse connectivity of convolution

The view of convolutional kernel/filter



Q: filter size and stride?

Filter size = 3 + stride = 1 with 0-pading

Sparse connectivity of convolution

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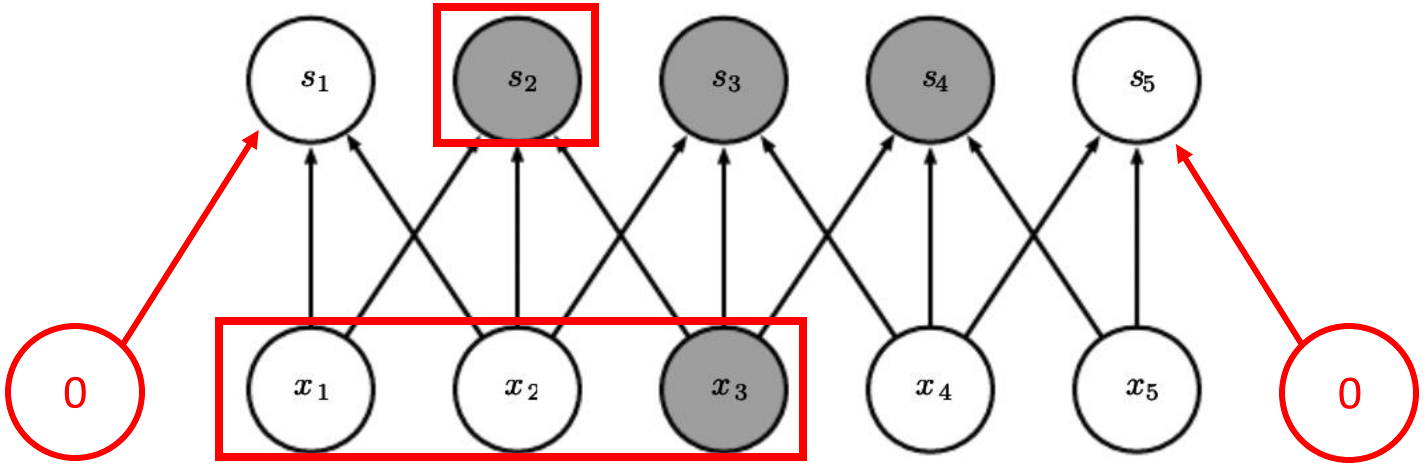

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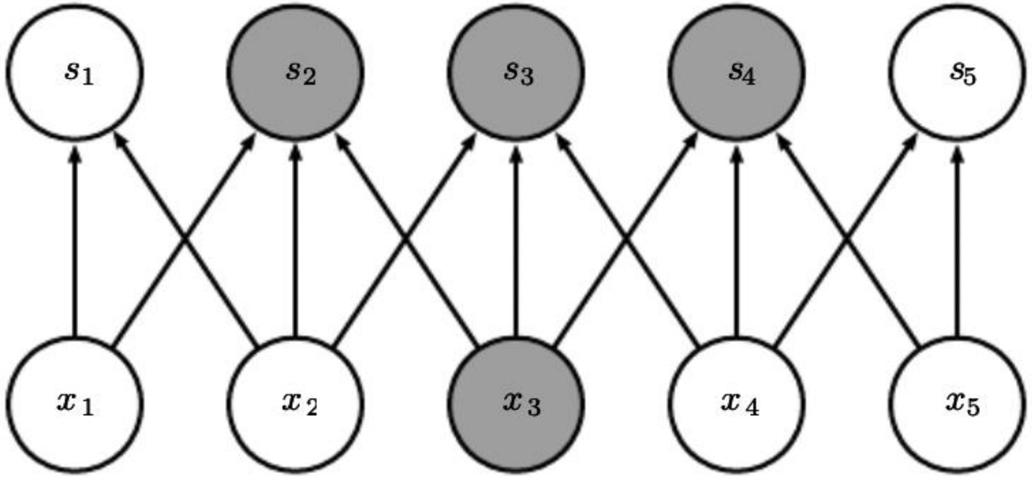
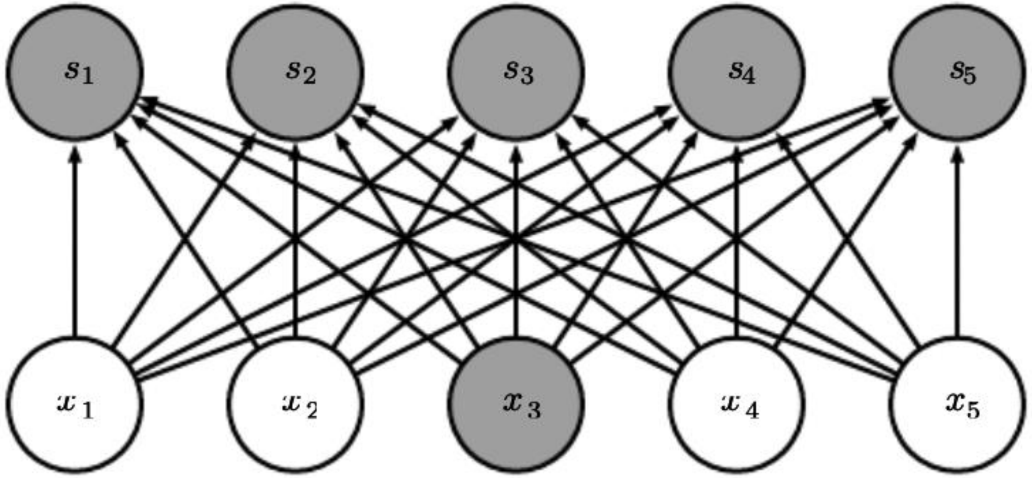
Sparse connectivity of convolution

Sparse connection



Weights→13 scalar numbers

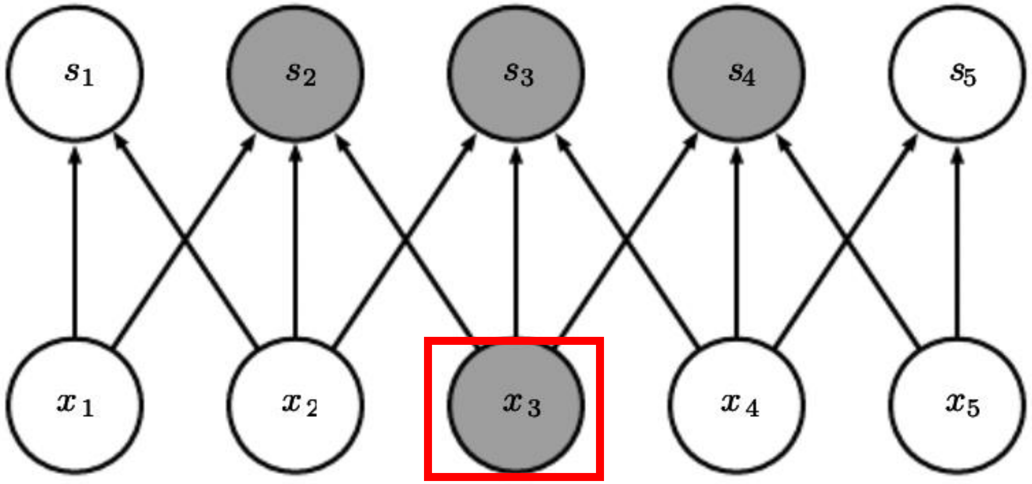
Dense connection



Weights→25 scalar numbers

Sparse connectivity of convolution

Sparse connection



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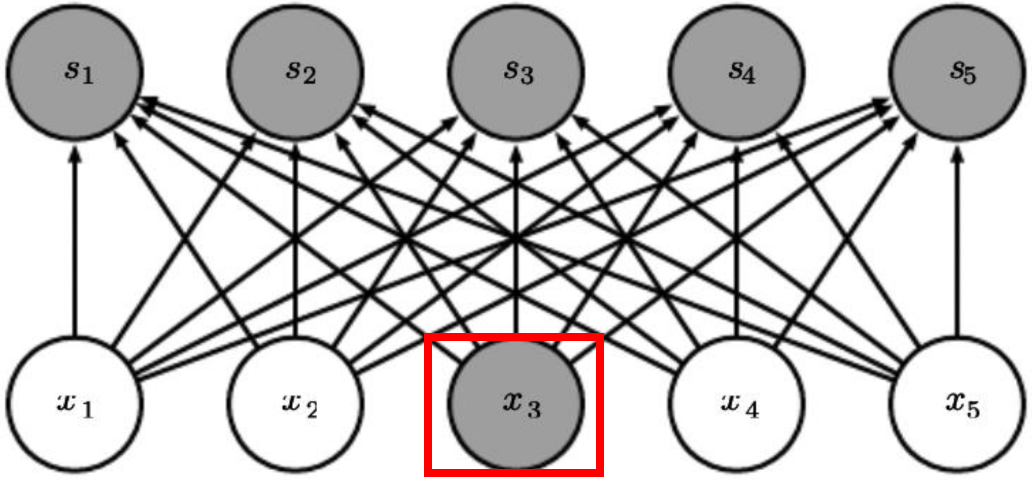

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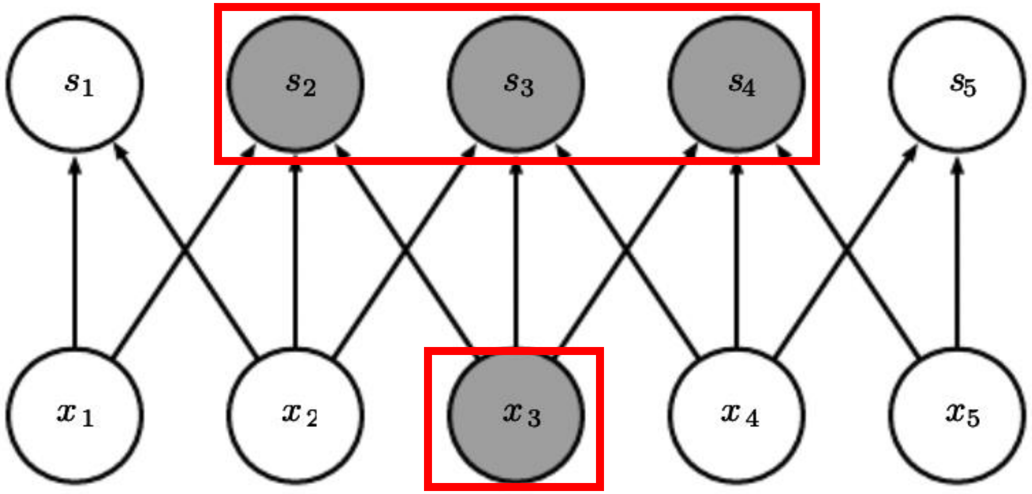

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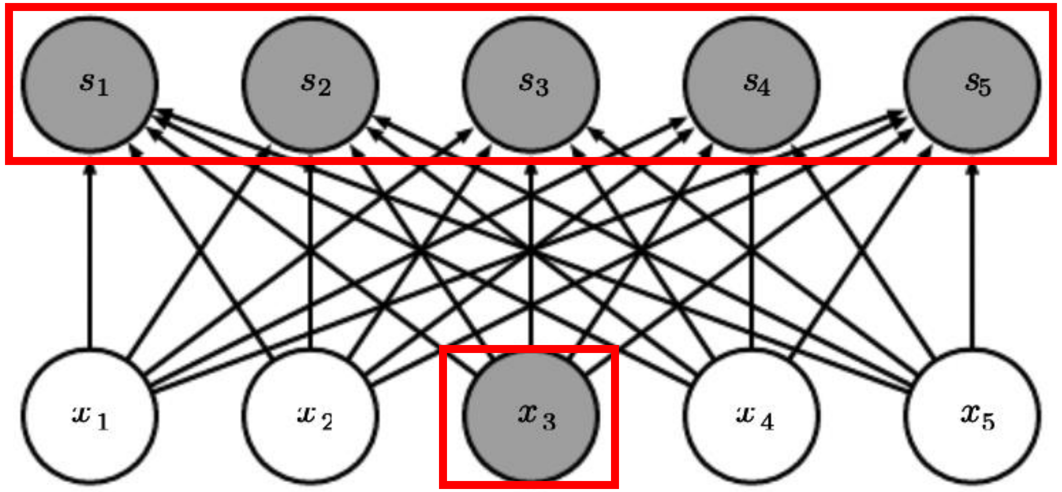

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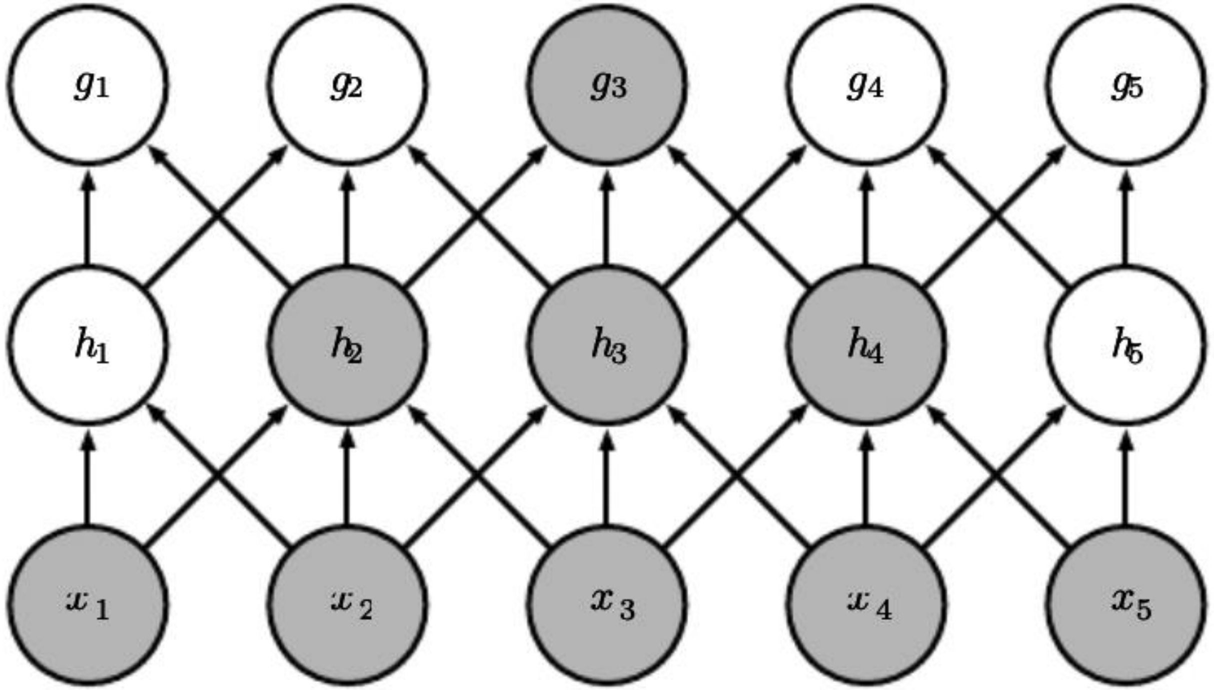
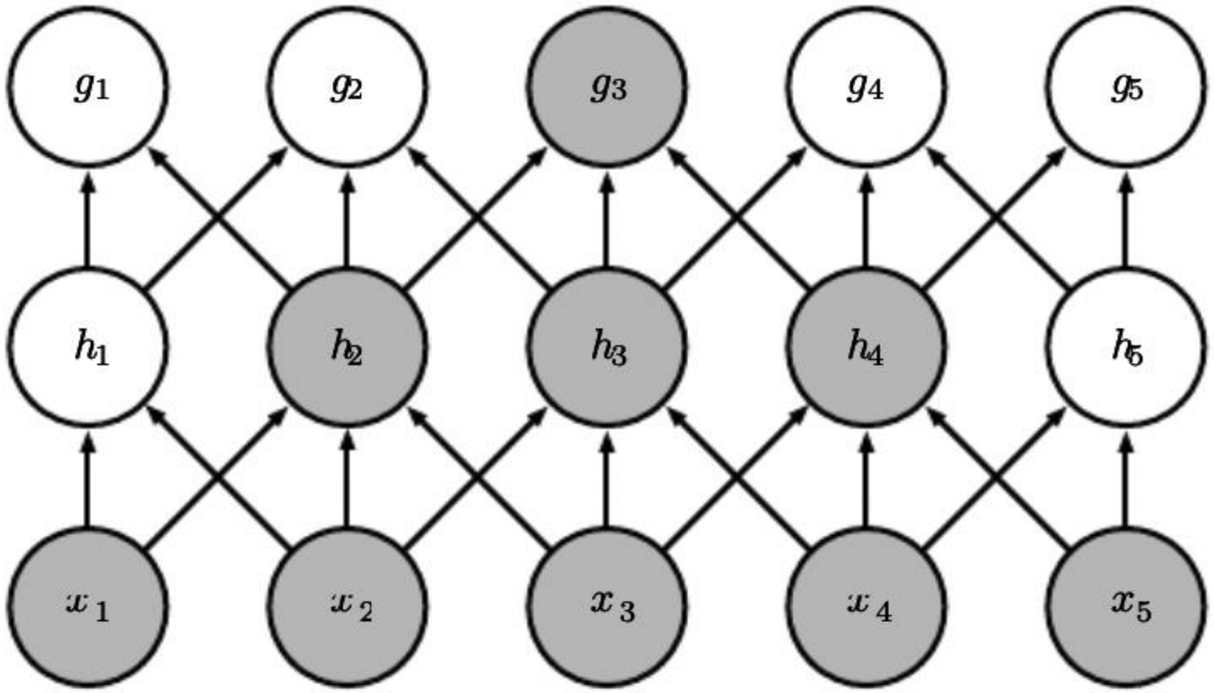


Sparse connectivity of convolution

3 layers



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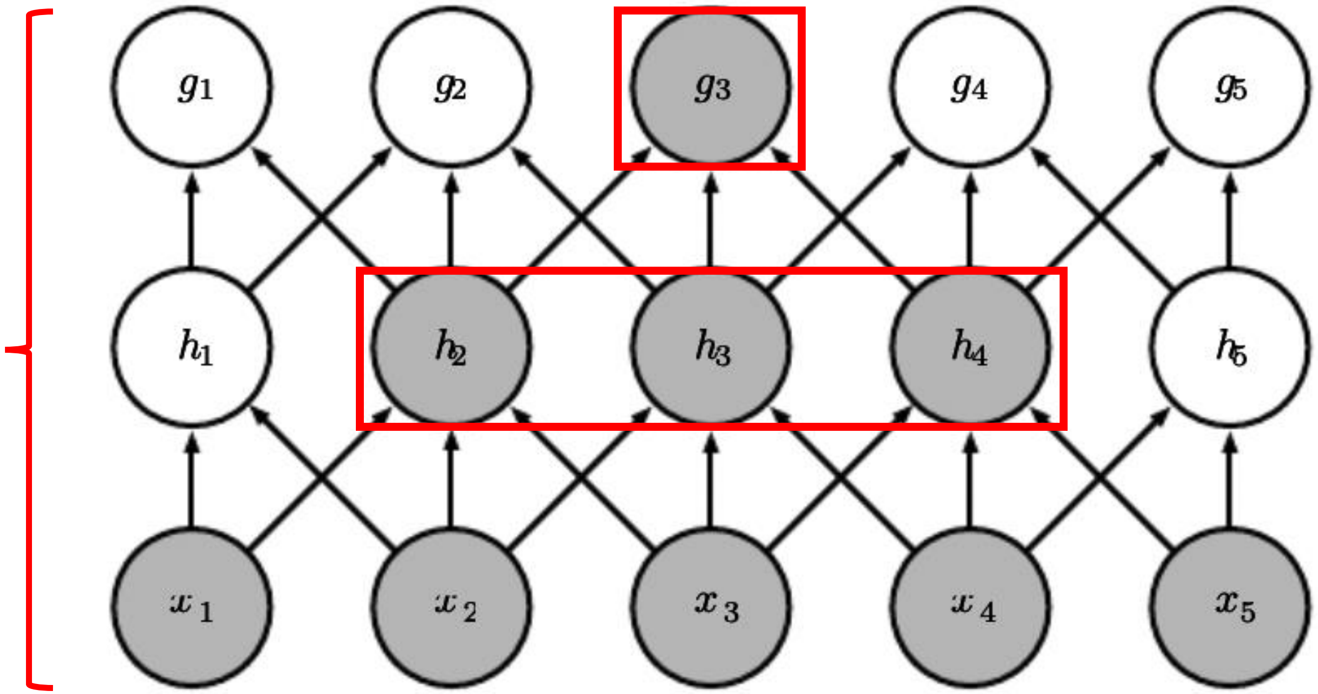

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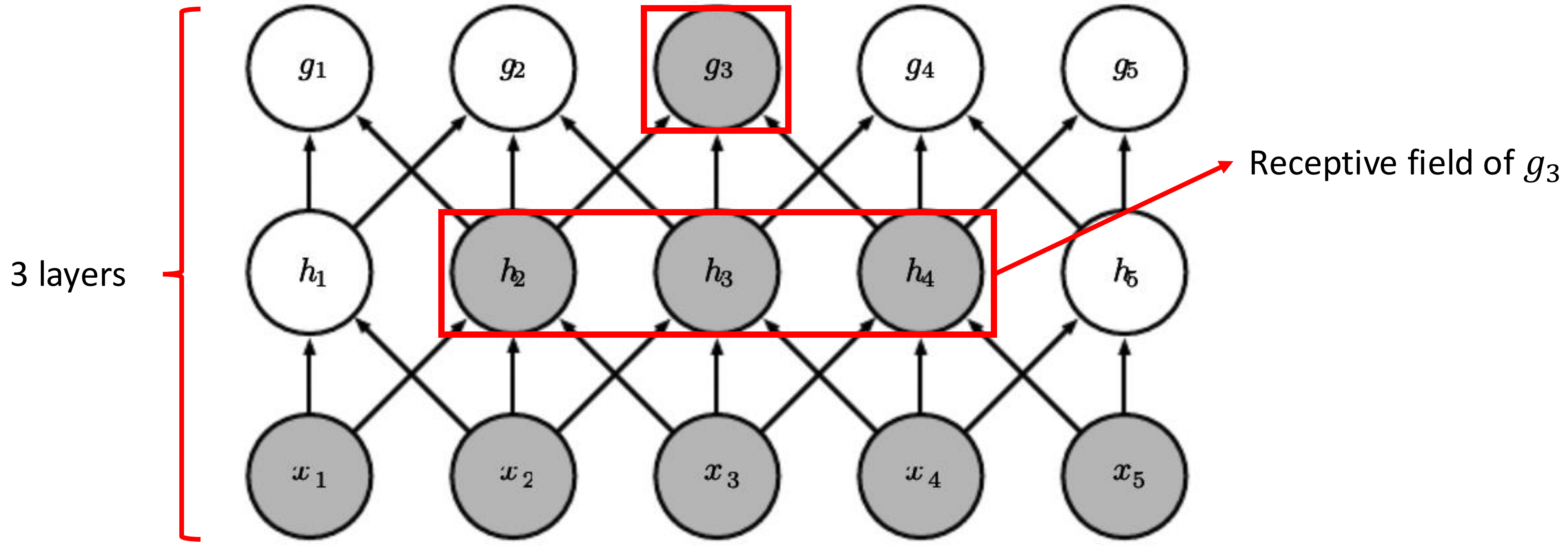

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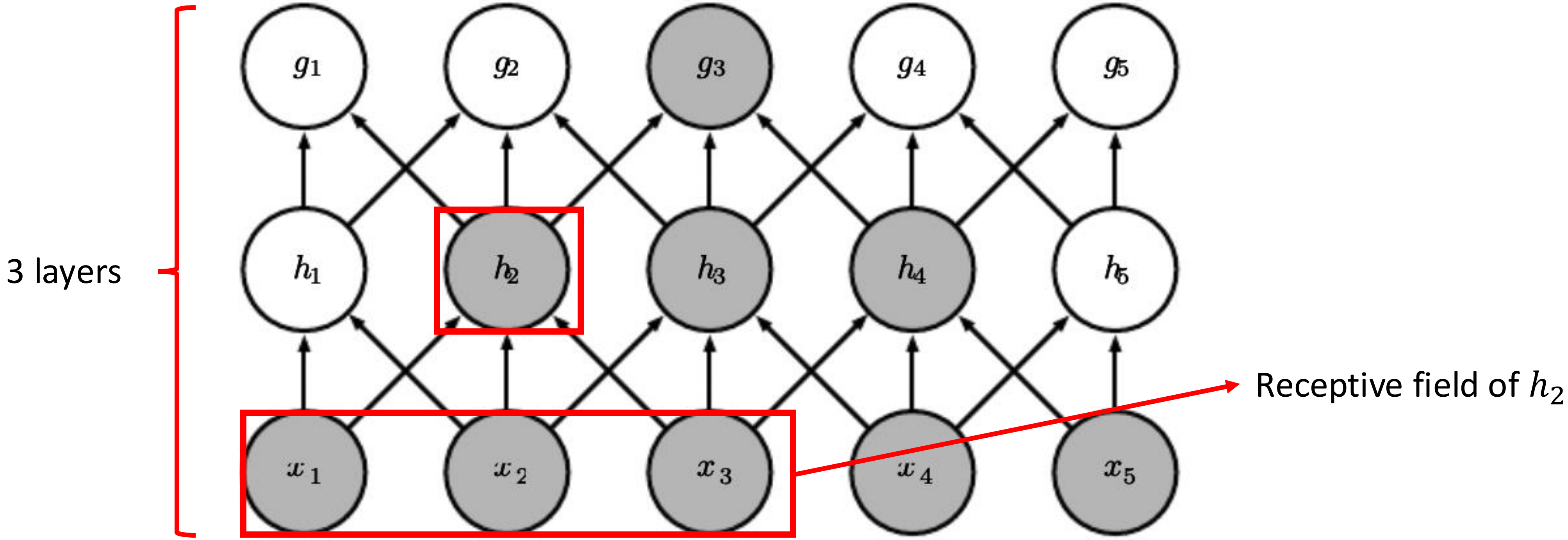

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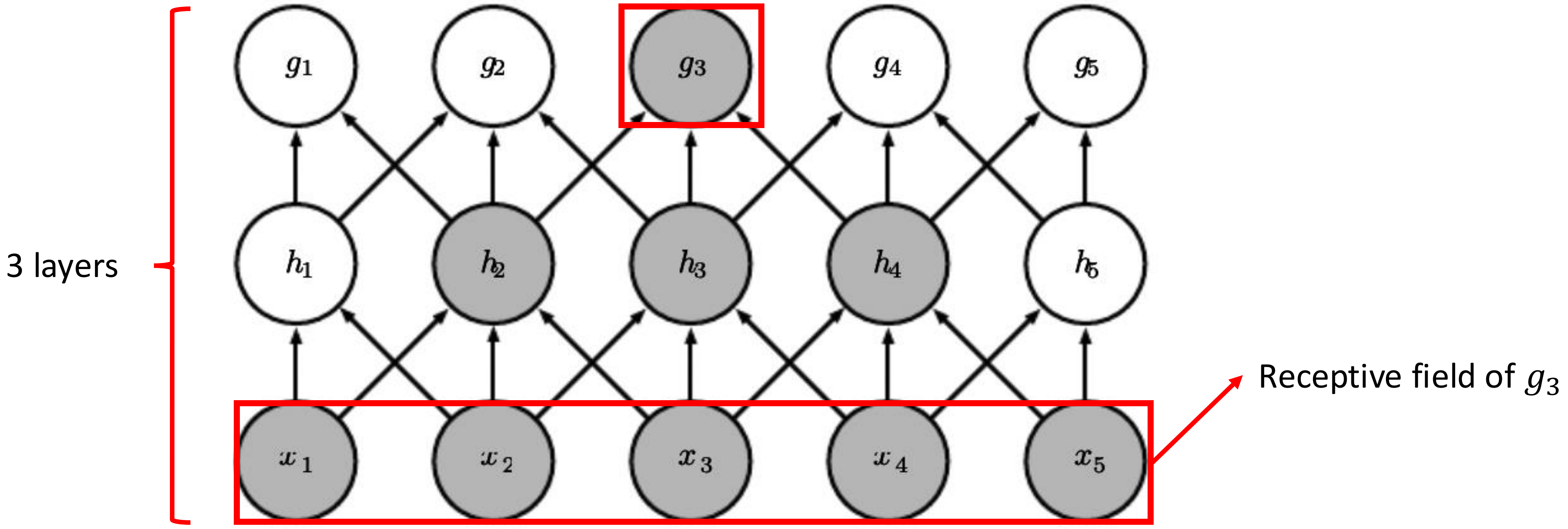

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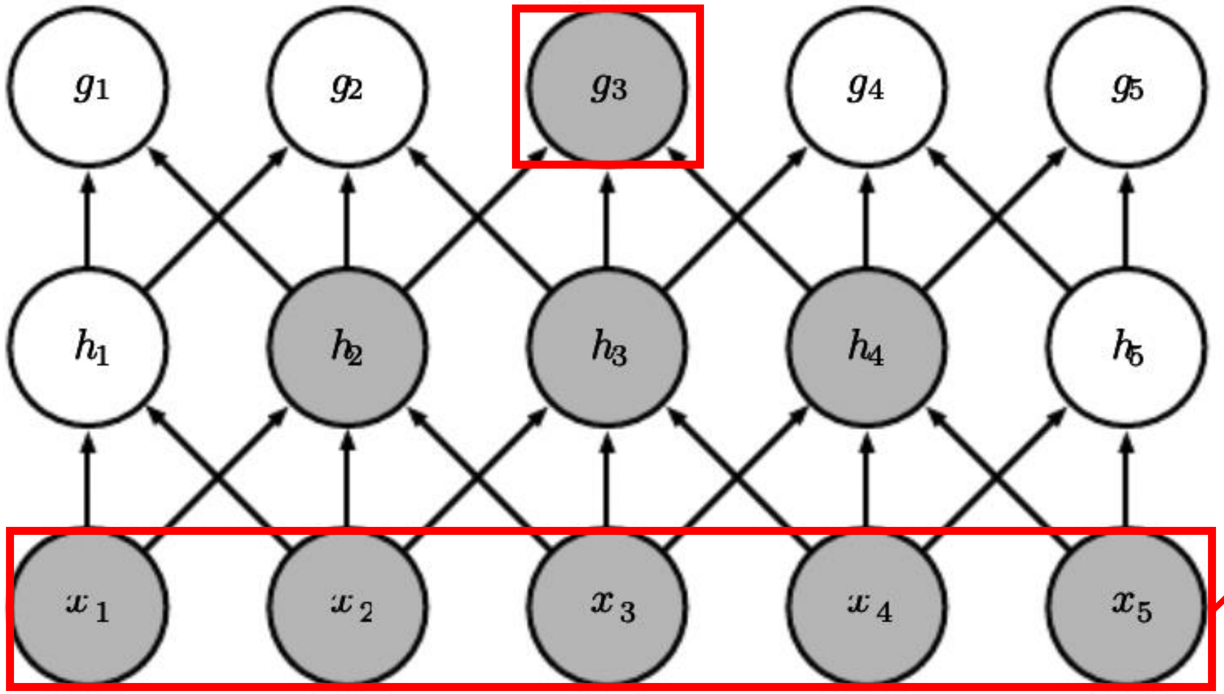
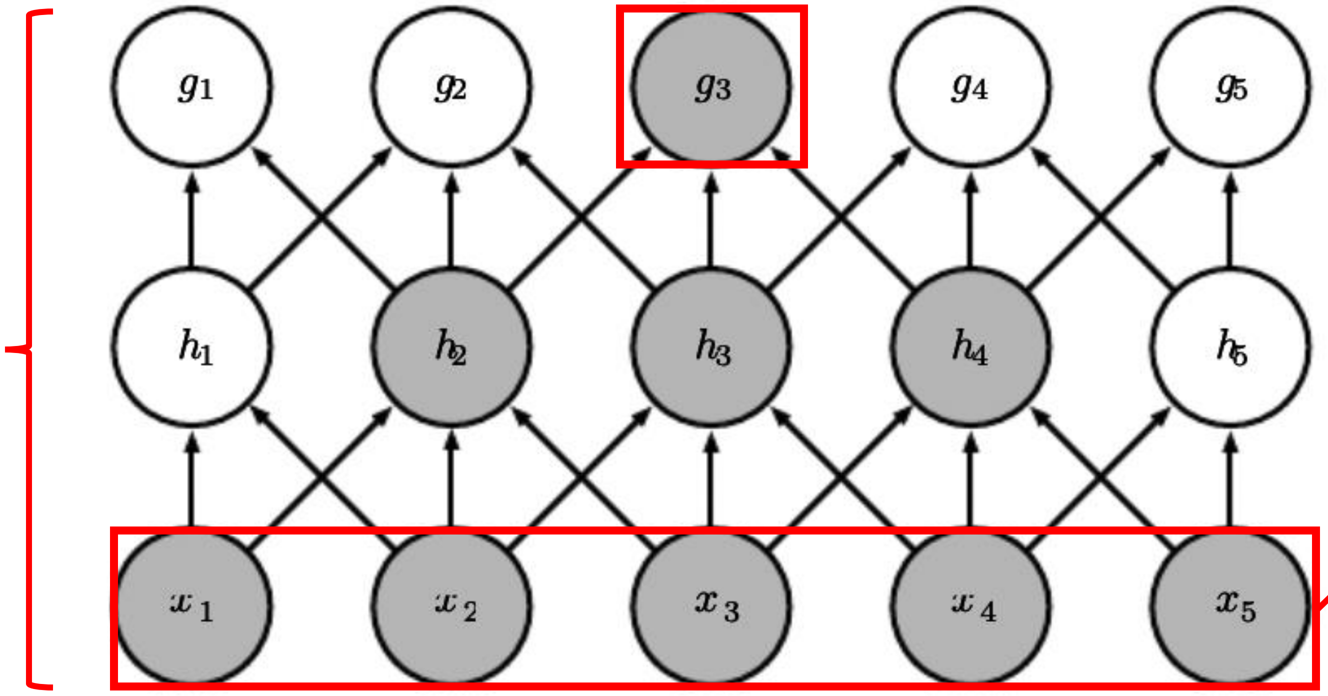


Receptive field of g_3

Deep layers has larger receptive field than shallow layers

Sparse connectivity of convolution

3 layers

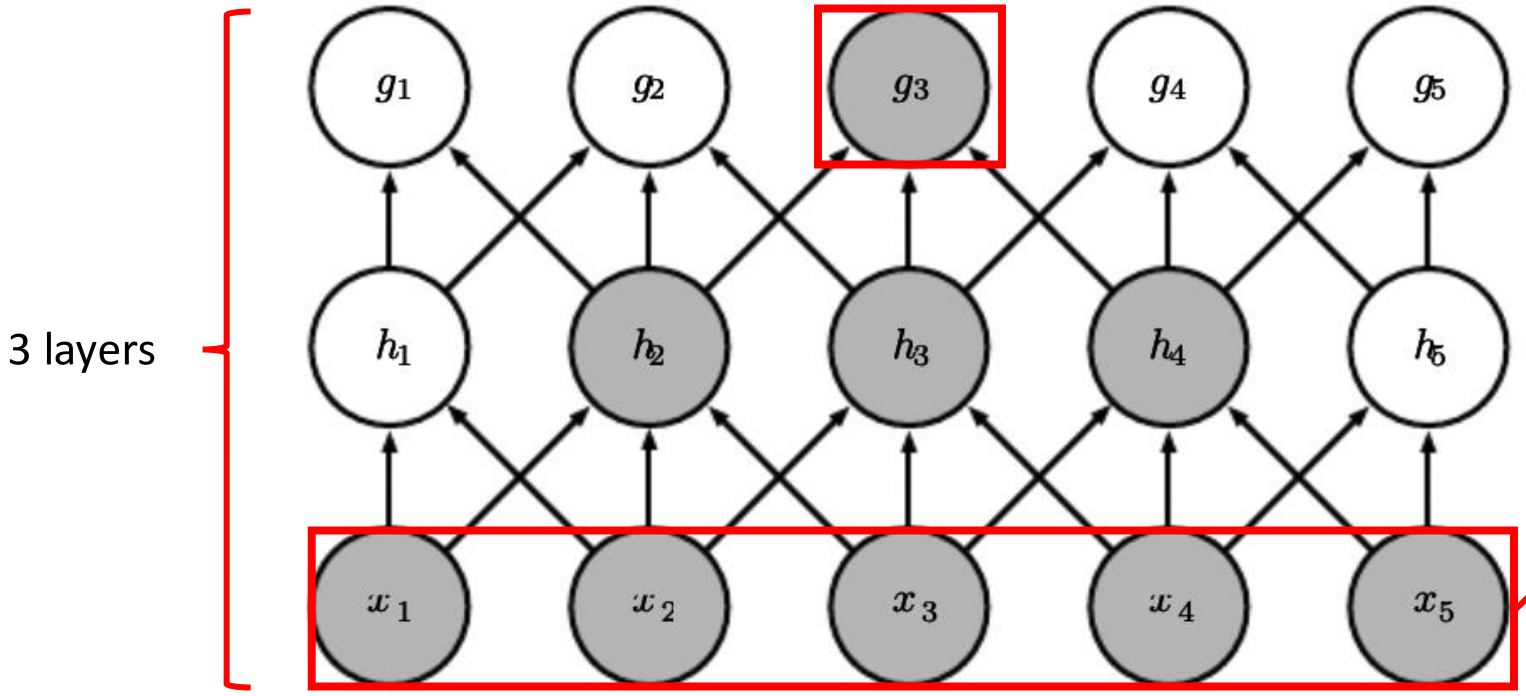


Receptive field of g_3

Units in deep layer indirectly connect to all/most input image

Deep layers has larger receptive field than shallow layers

Sparse connectivity of convolution



Receptive field of g_3

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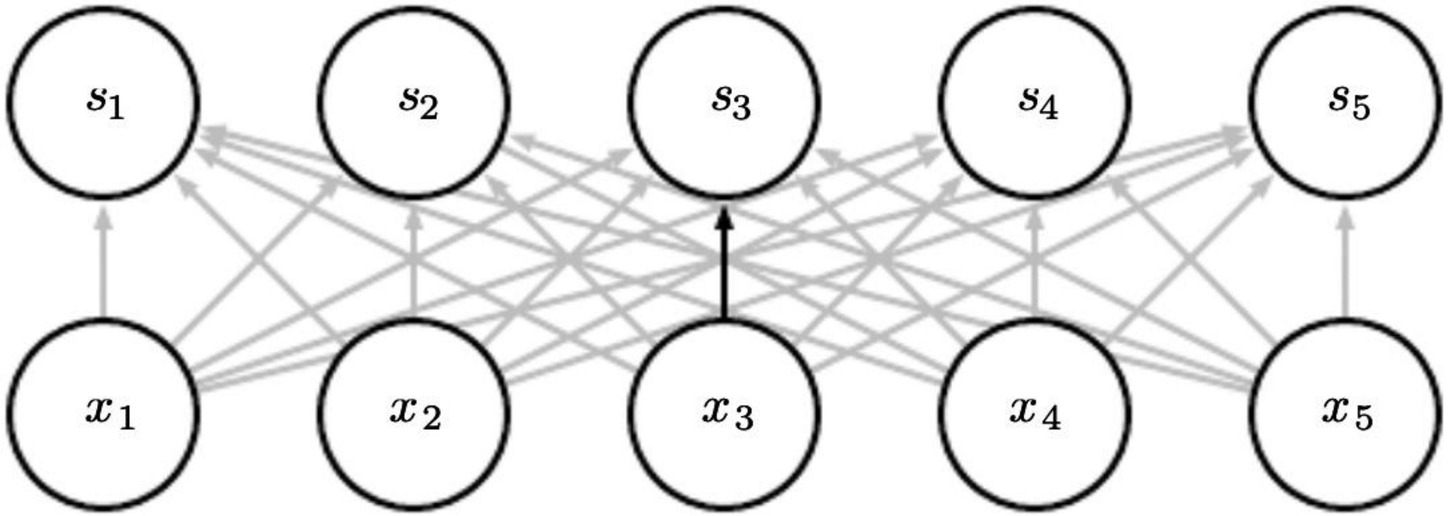
Q: larger stride of convolution filter → increase receptive field?

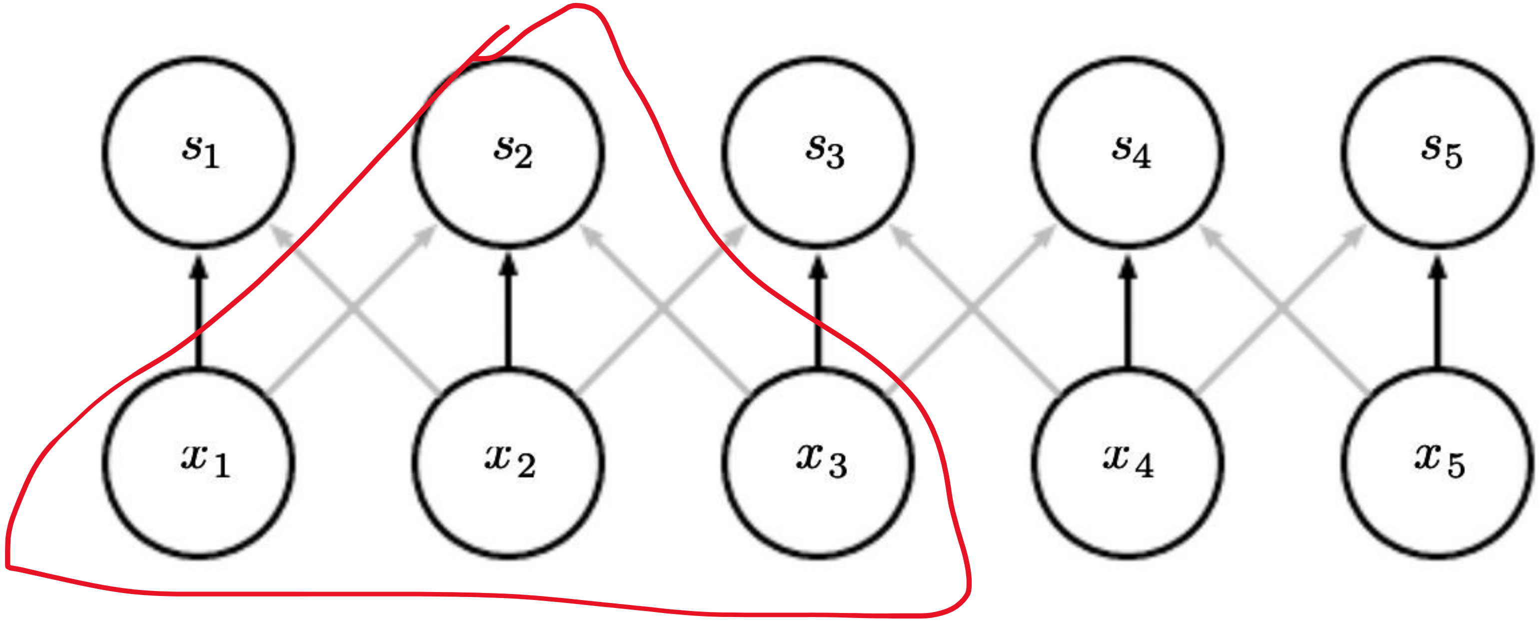
Parameter sharing



In MLP (FC layer): $w^T x$

Parameter sharing

Consider the same filter



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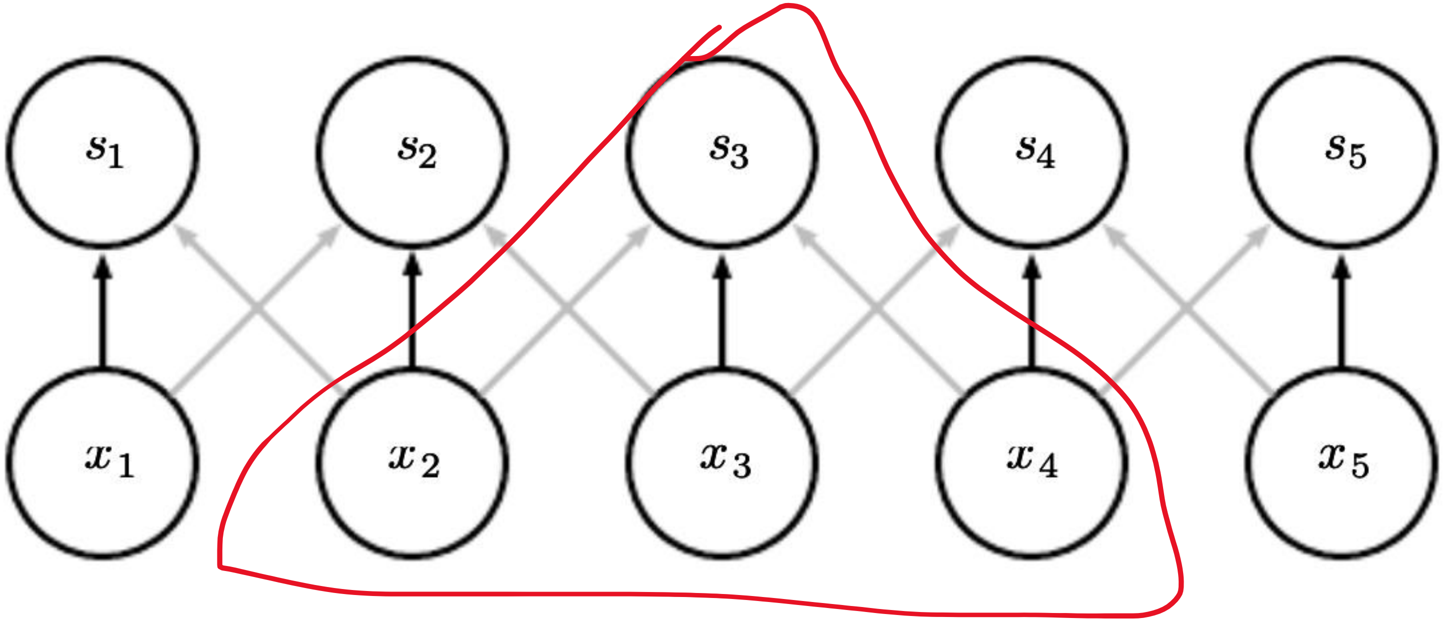

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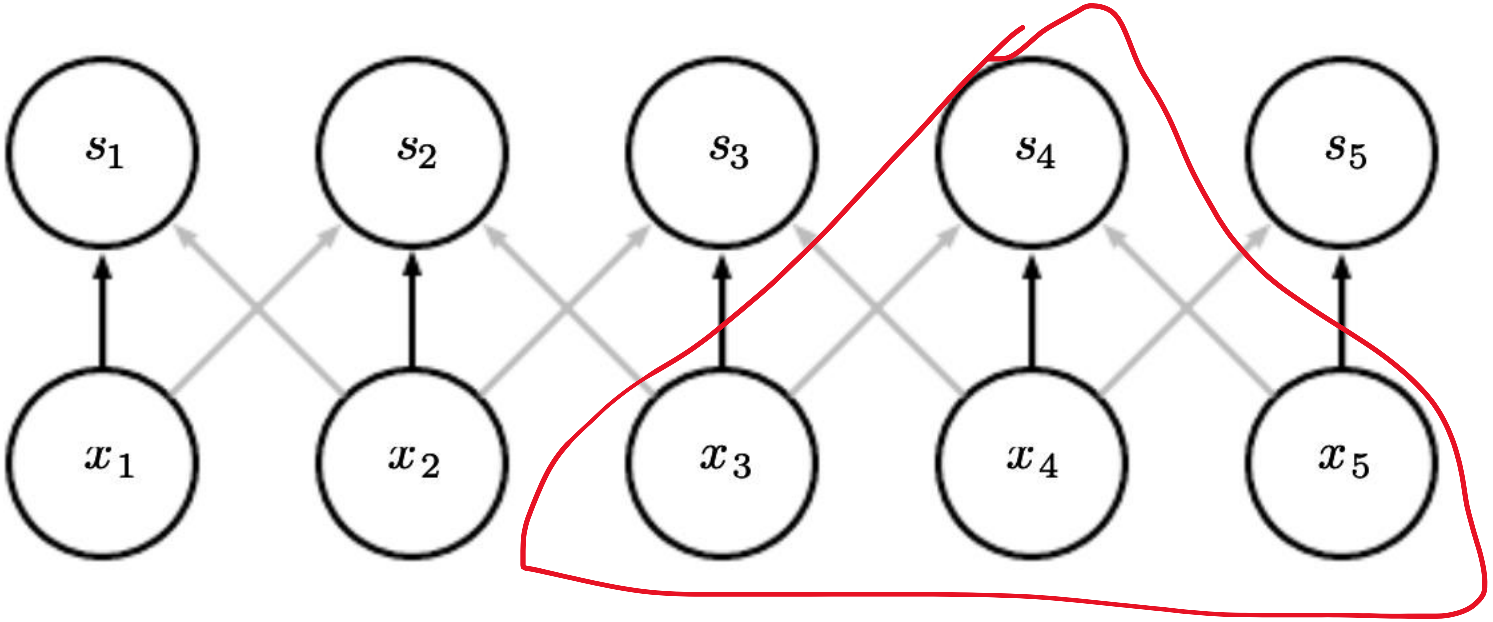
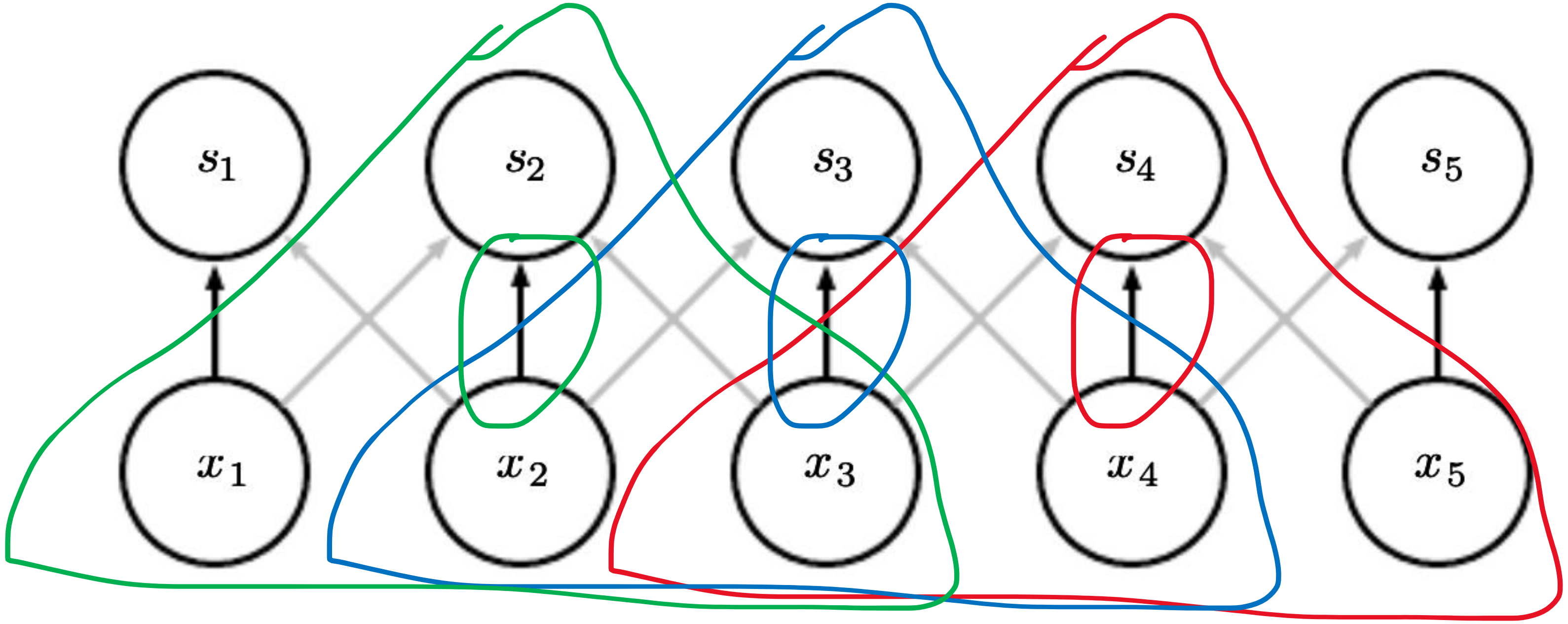


Parameter sharing

Consider the same filter (but different part of input feat. map)



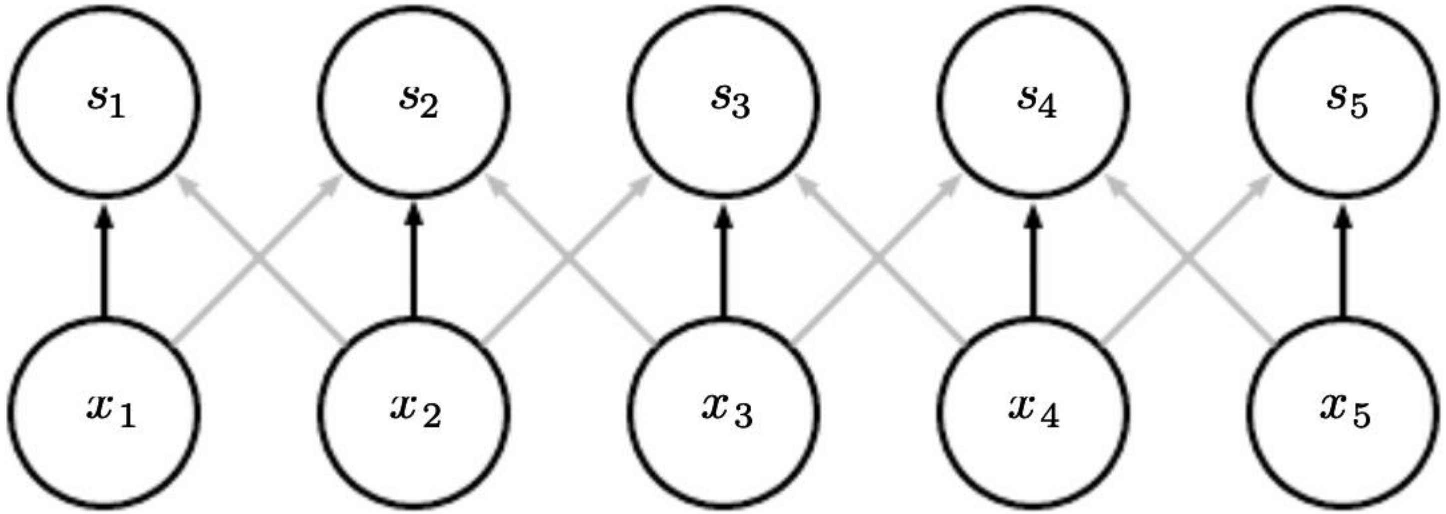
In convlayer:

$w^T(x_1; x_2; x_3)$

$w^T(x_2; x_3; x_4)$

$w^T(x_3; x_4; x_5)$

Equivariance



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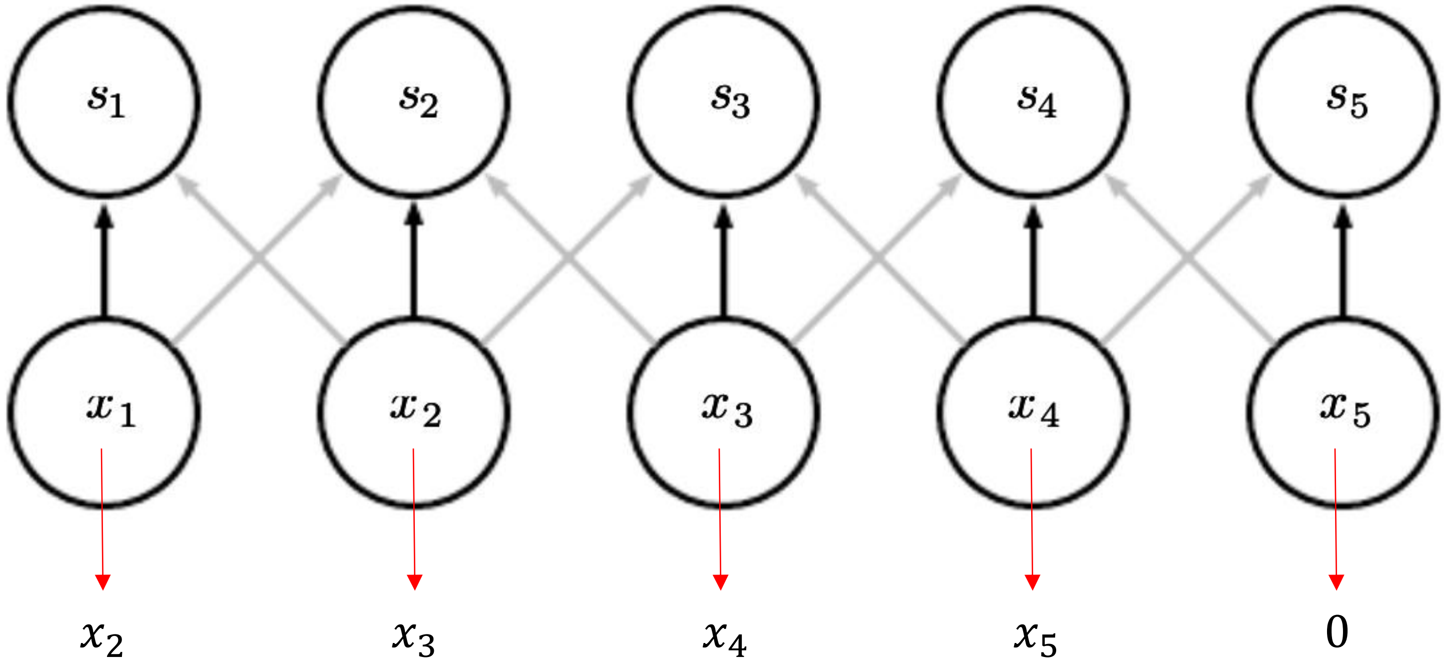

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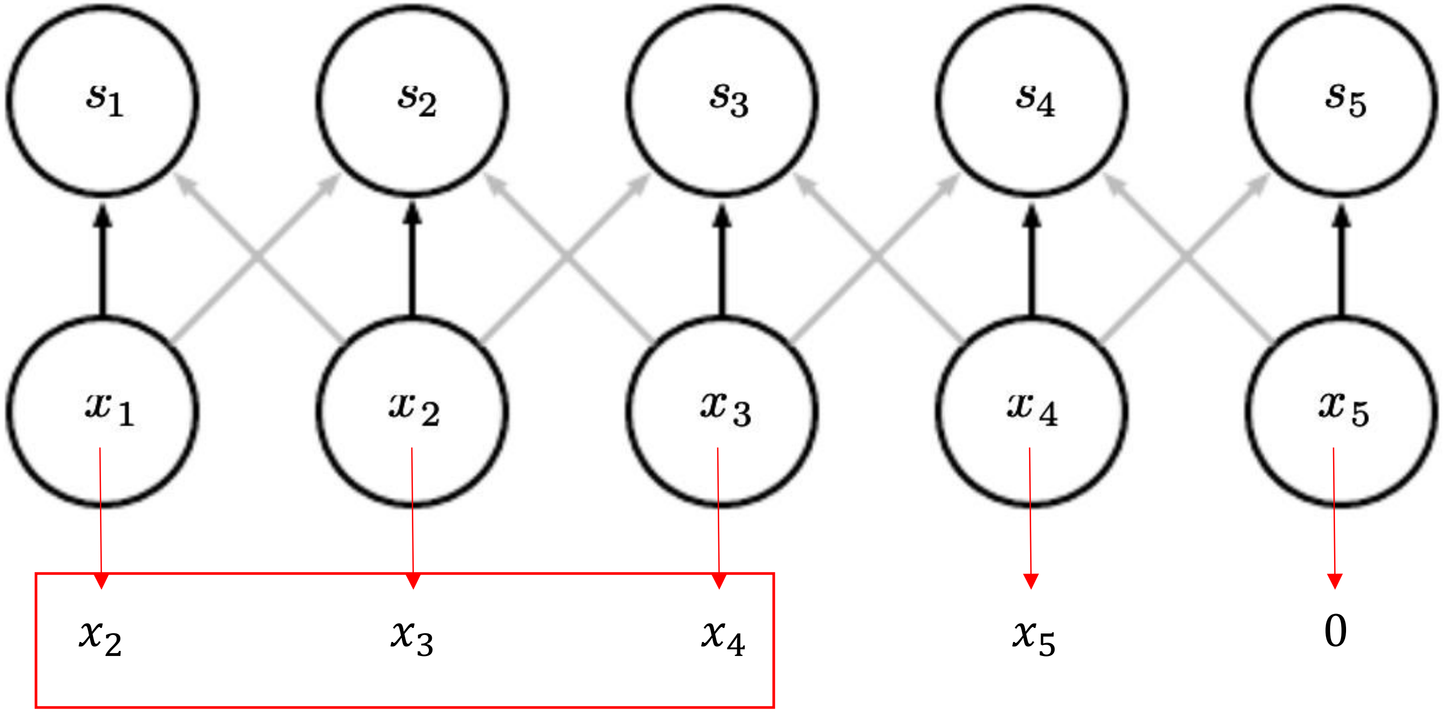

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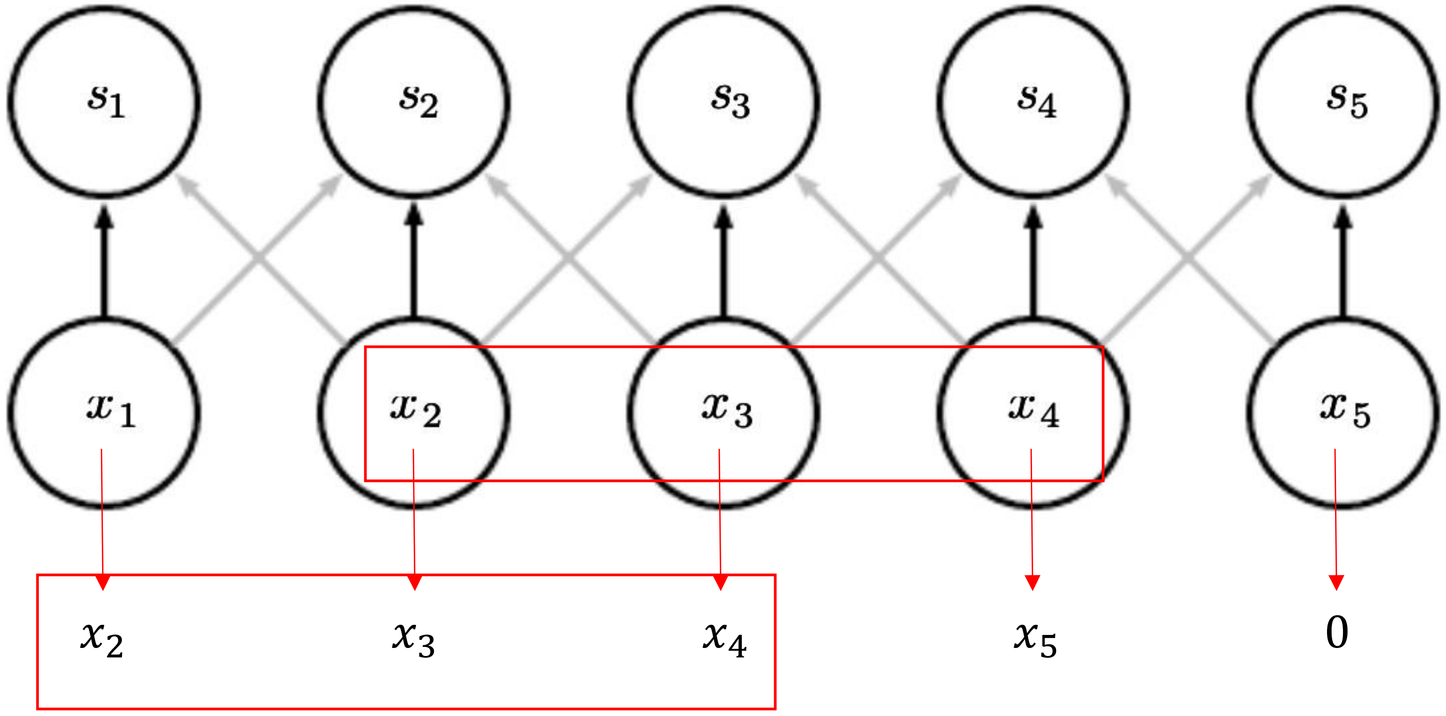

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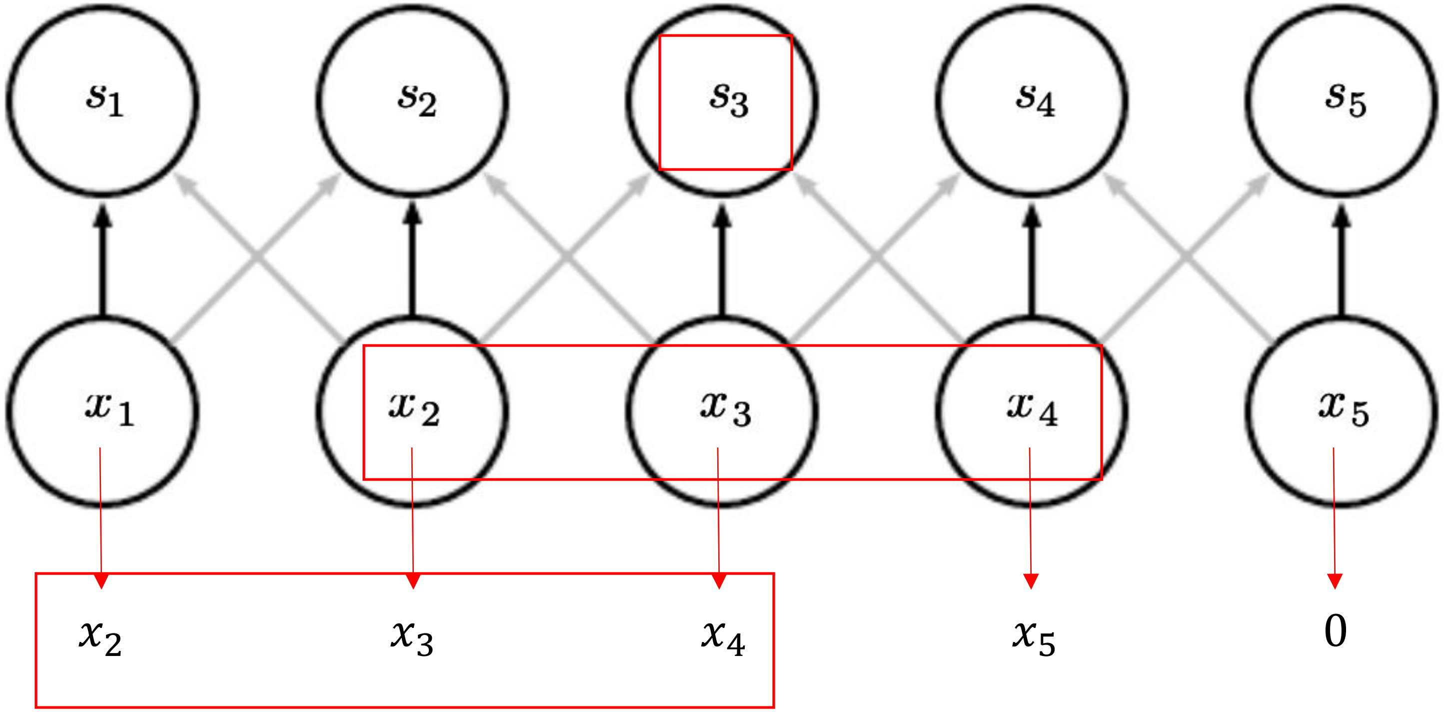
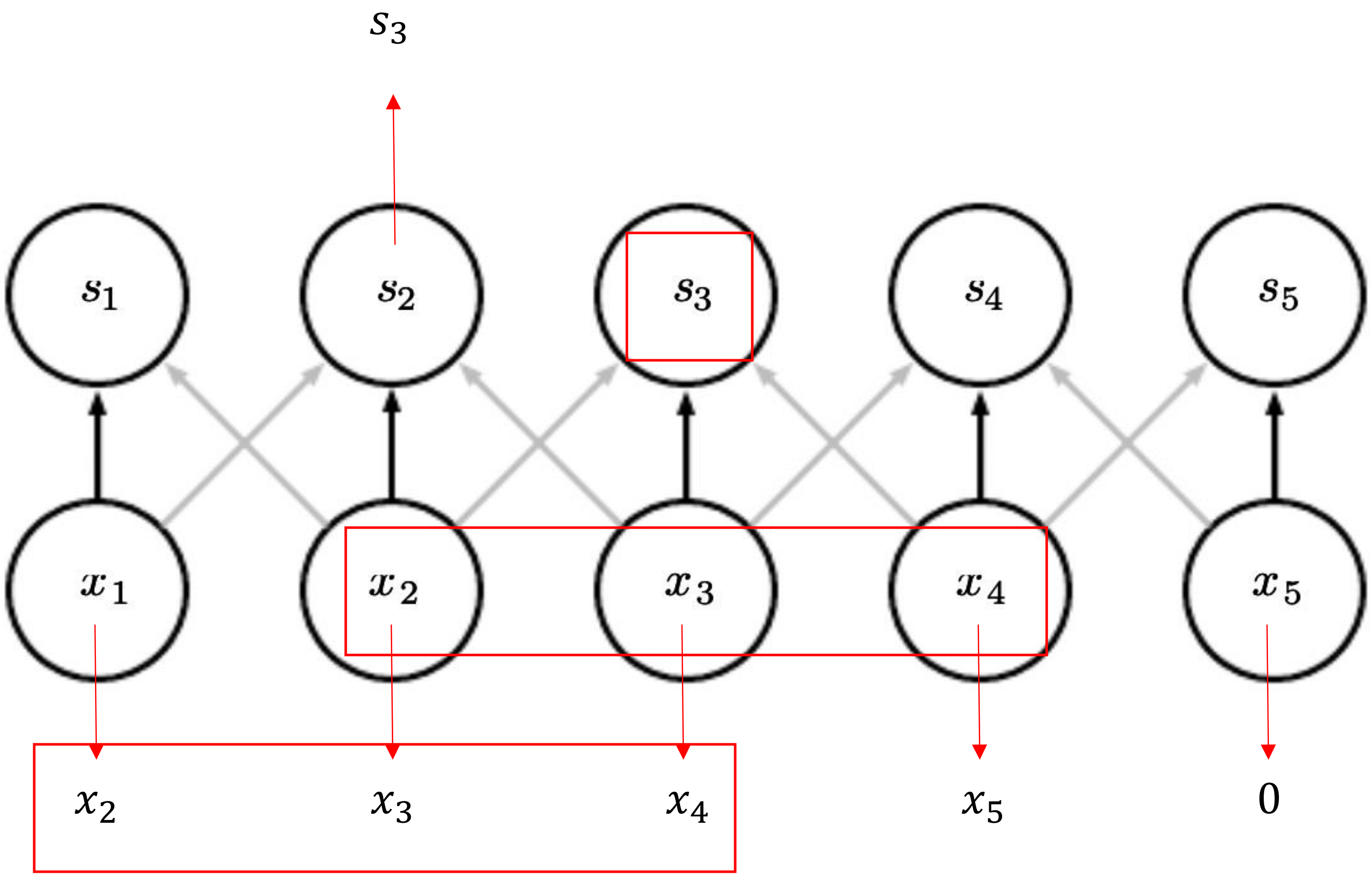


Equivariance



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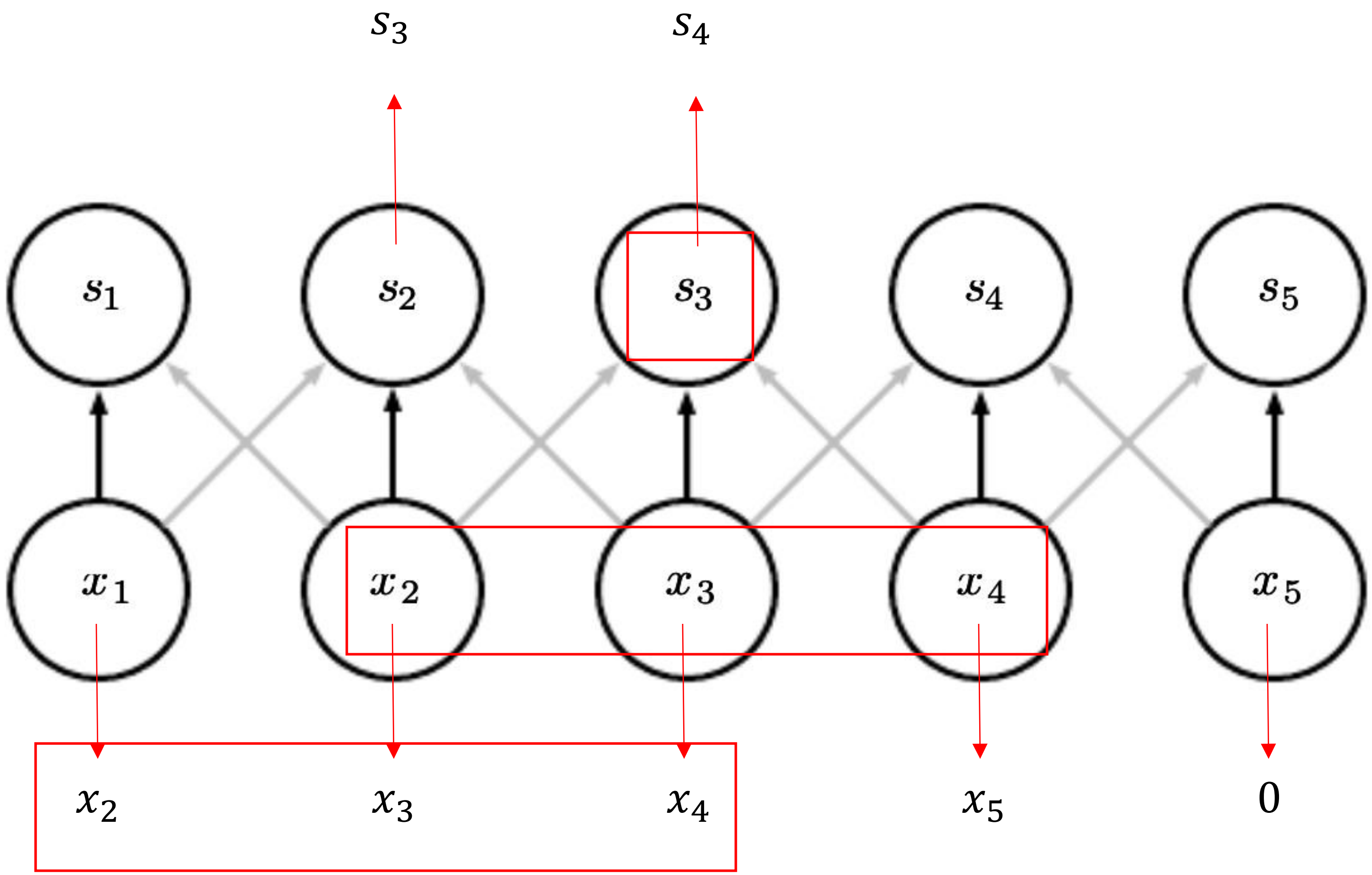

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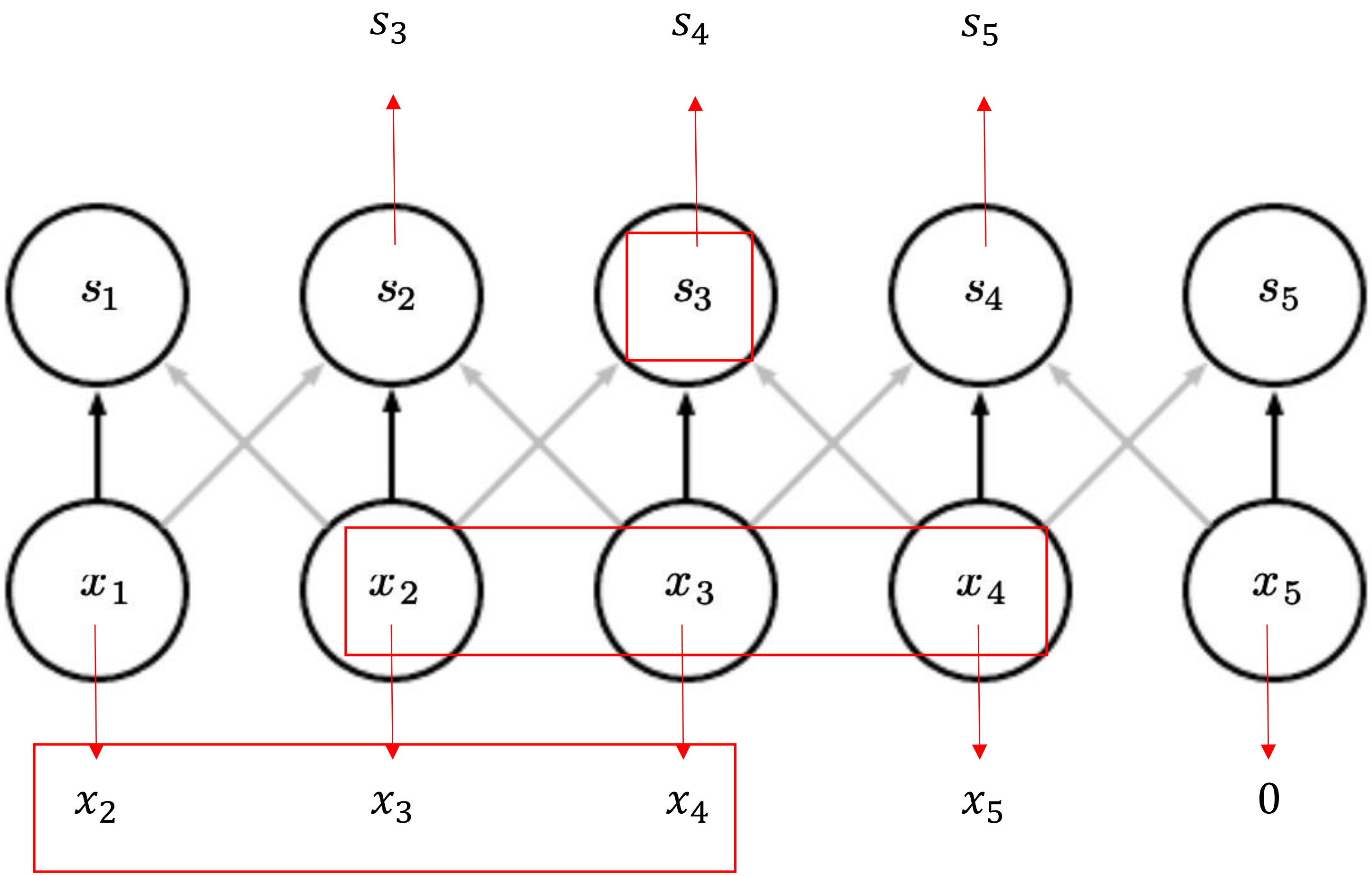

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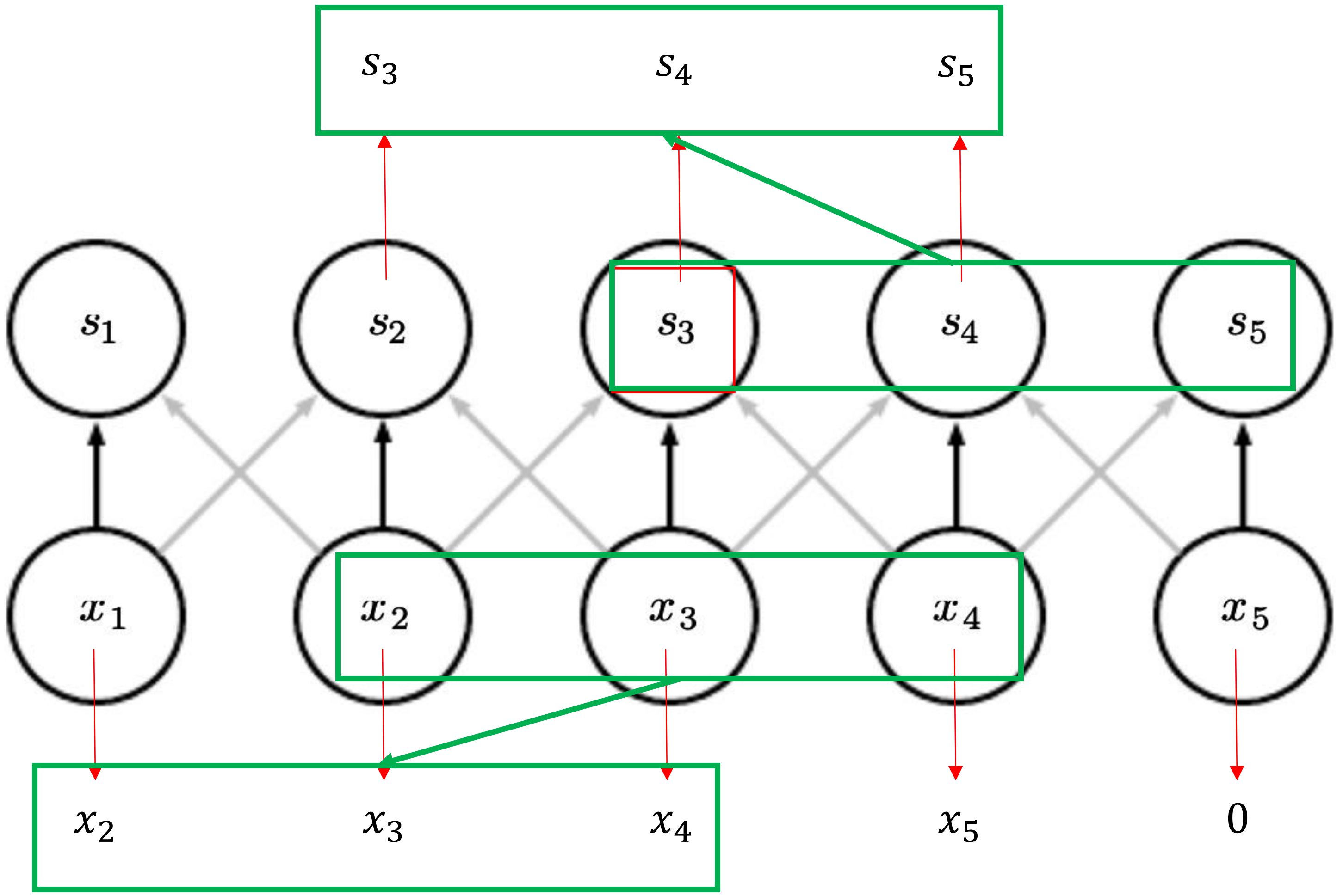
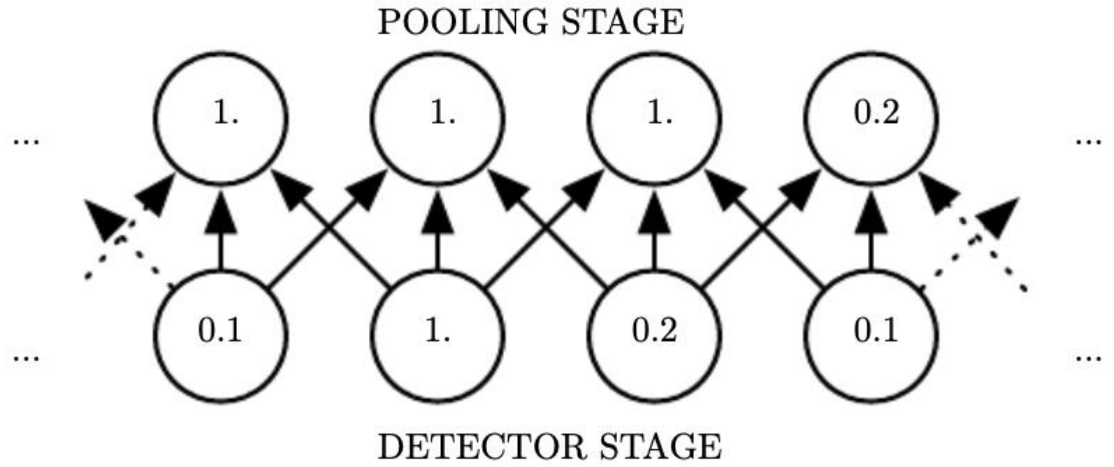
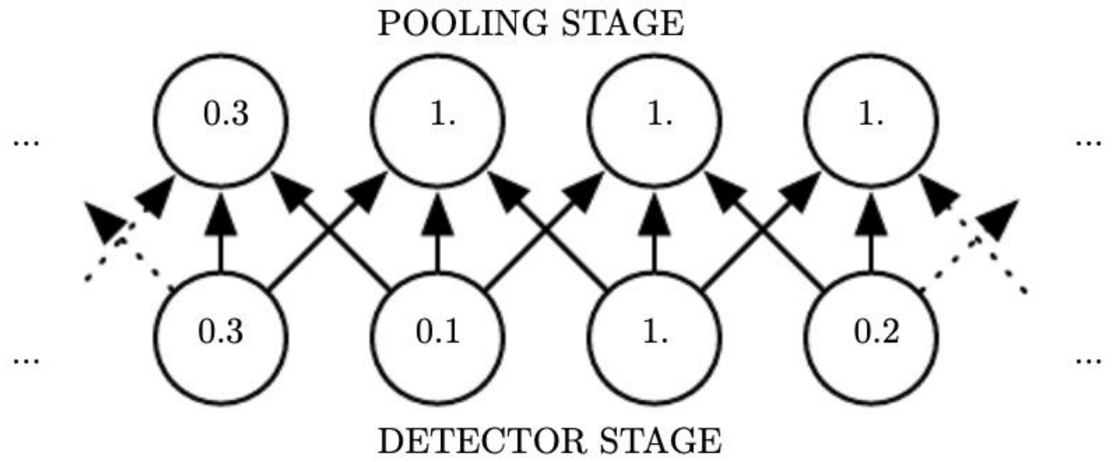


Pooling: invariance to small translation





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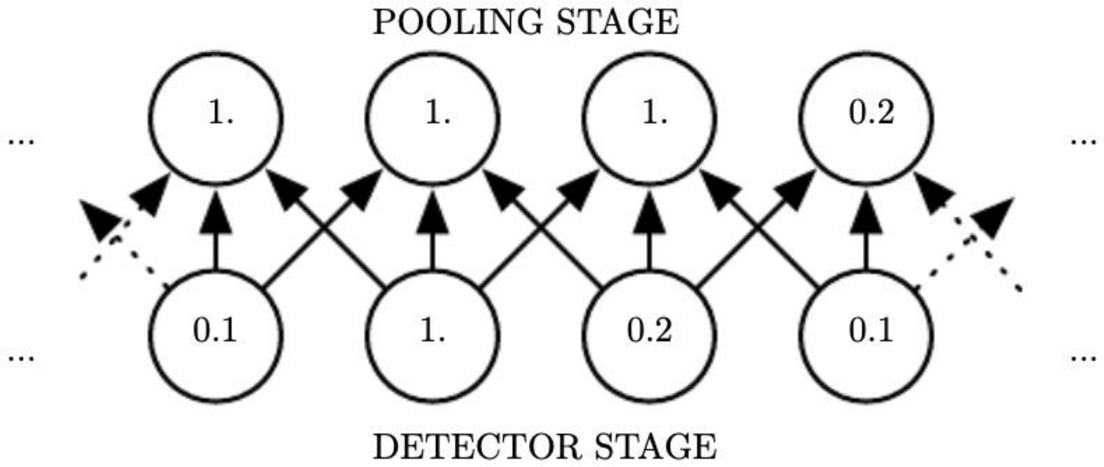
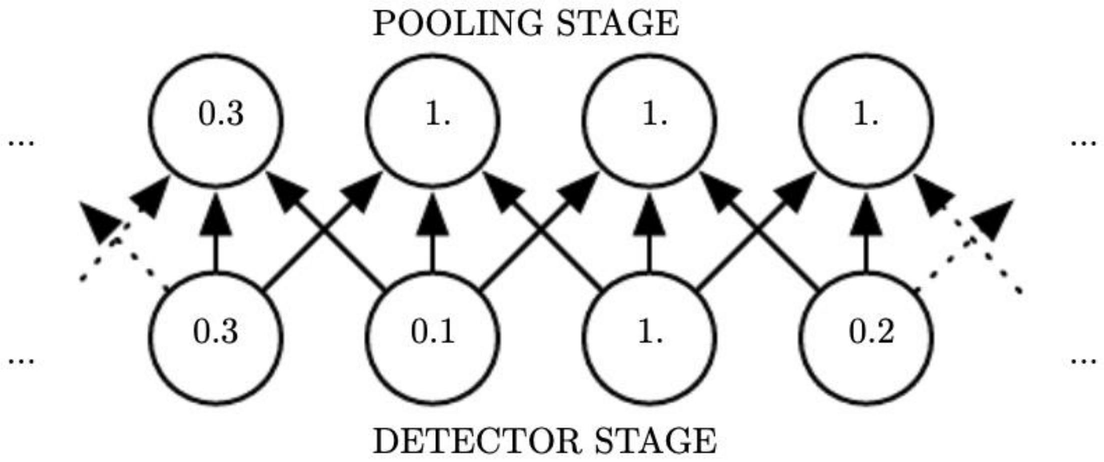
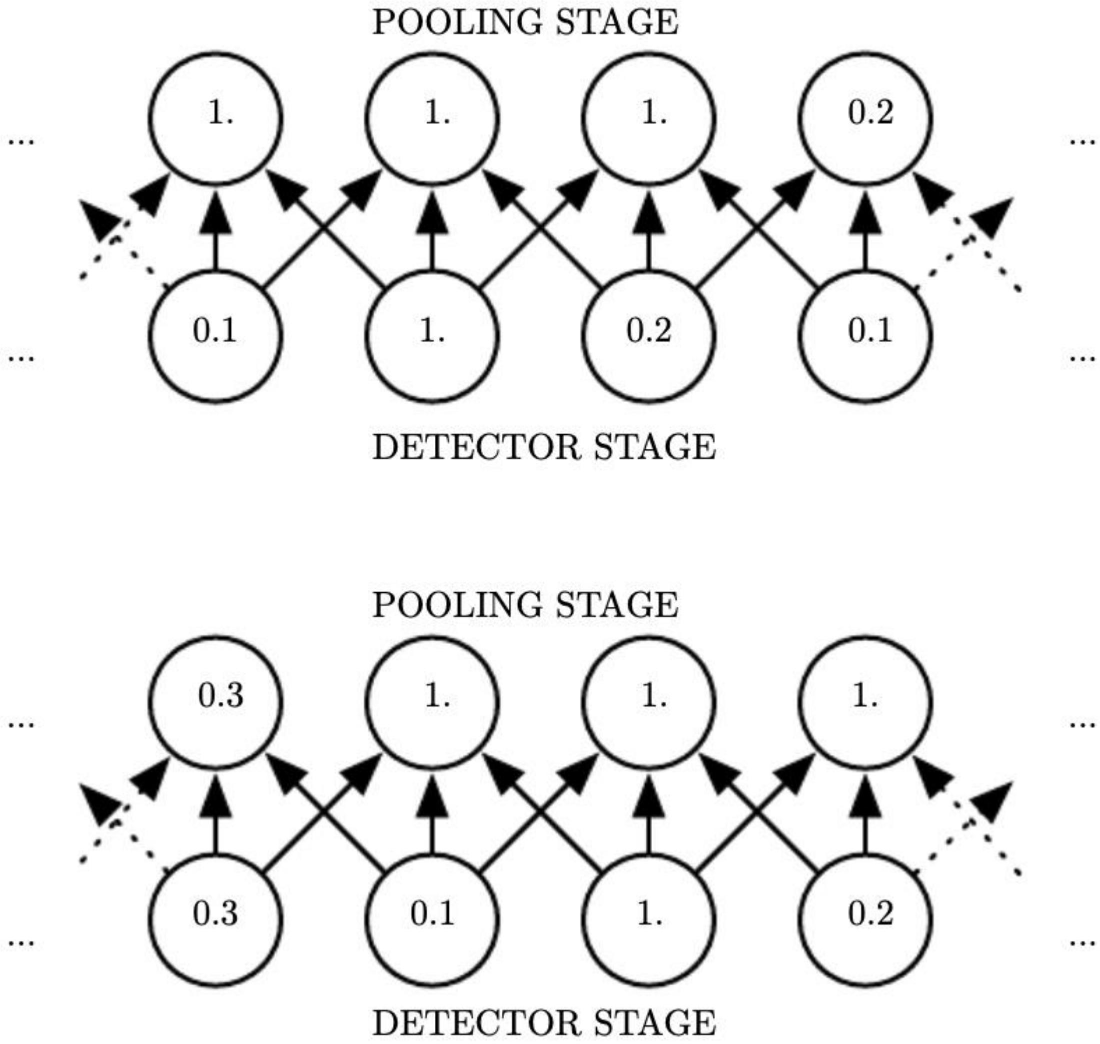




Q: what is type of pooling?
Max or average pooling?

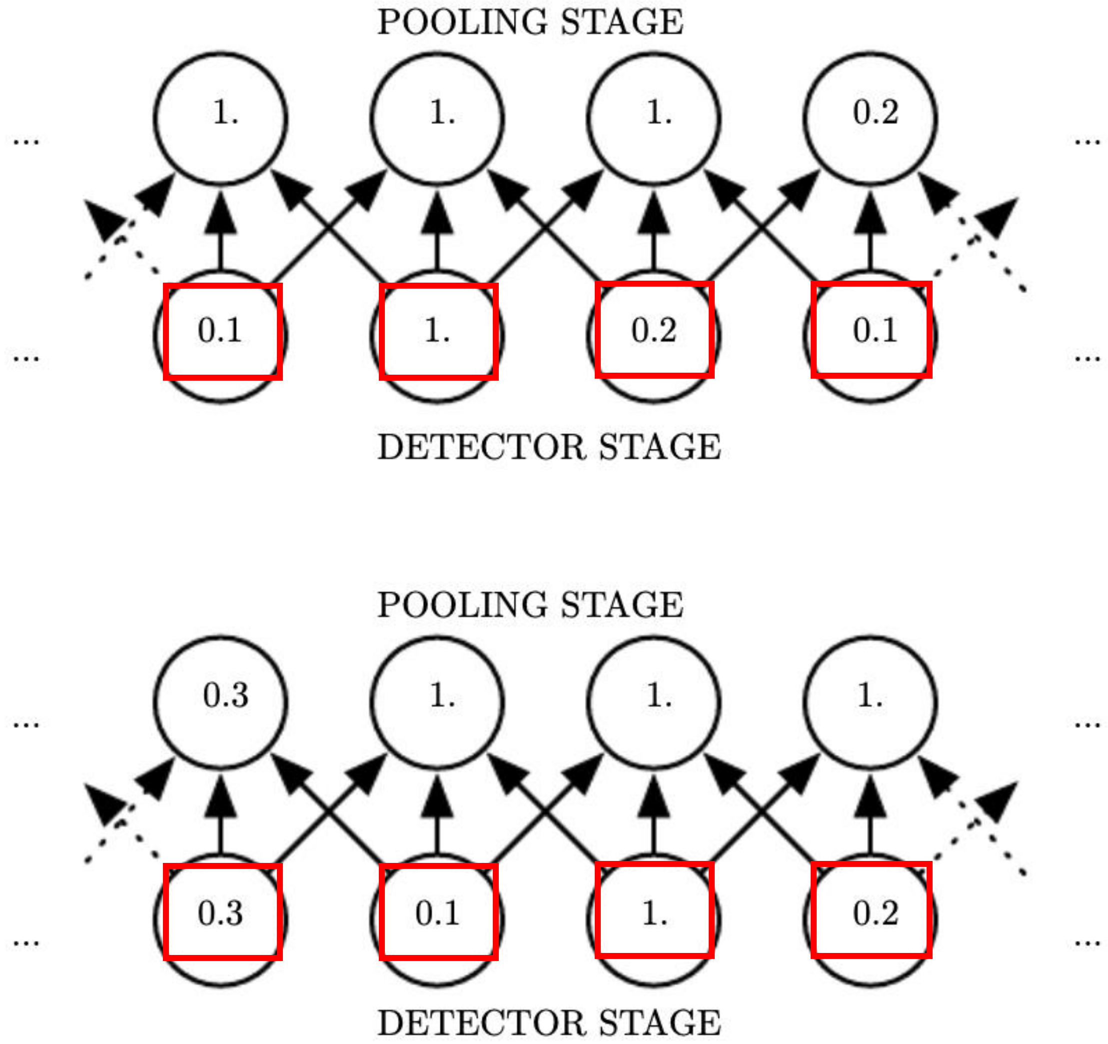
Pooling: invariance to small translation



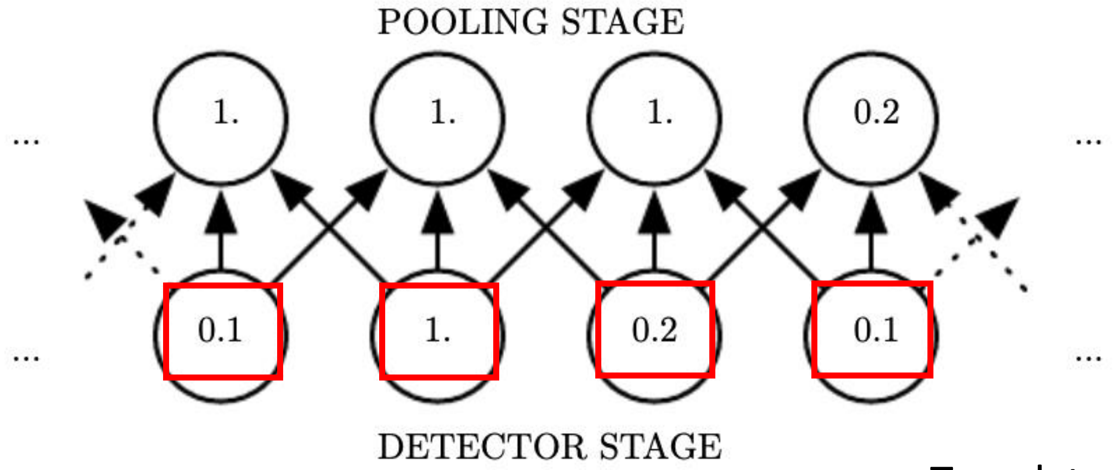
Q: what is type of pooling?
Max or average pooling?

Max pooling

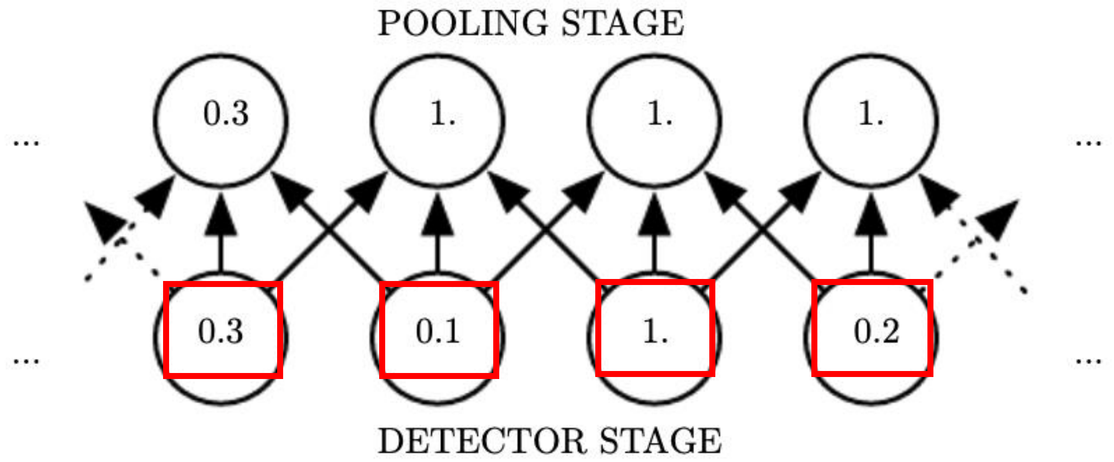
Pooling: invariance to small translation



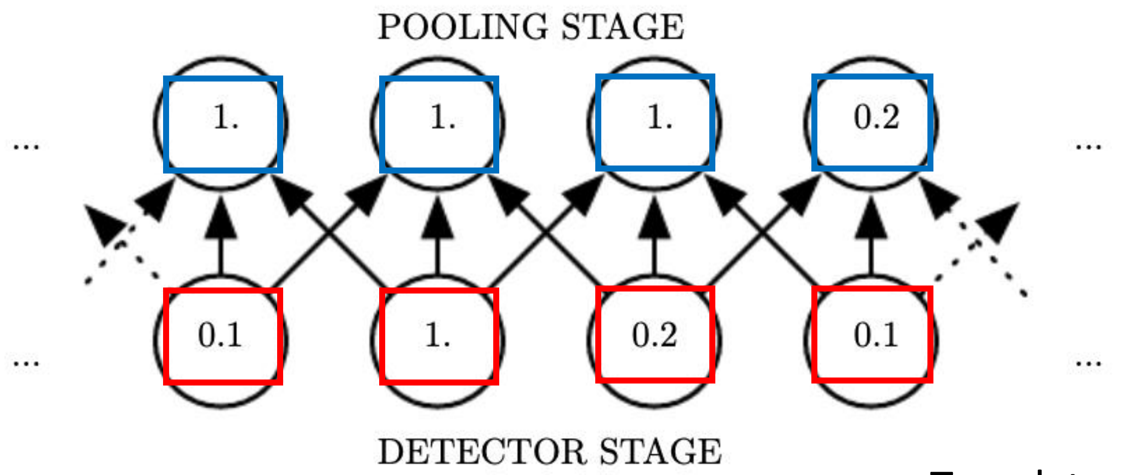
Pooling: invariance to small translation



Translate: change the input value a little bit
+ change their positions



Pooling: invariance to small translation



Translate: change the input value a little bit
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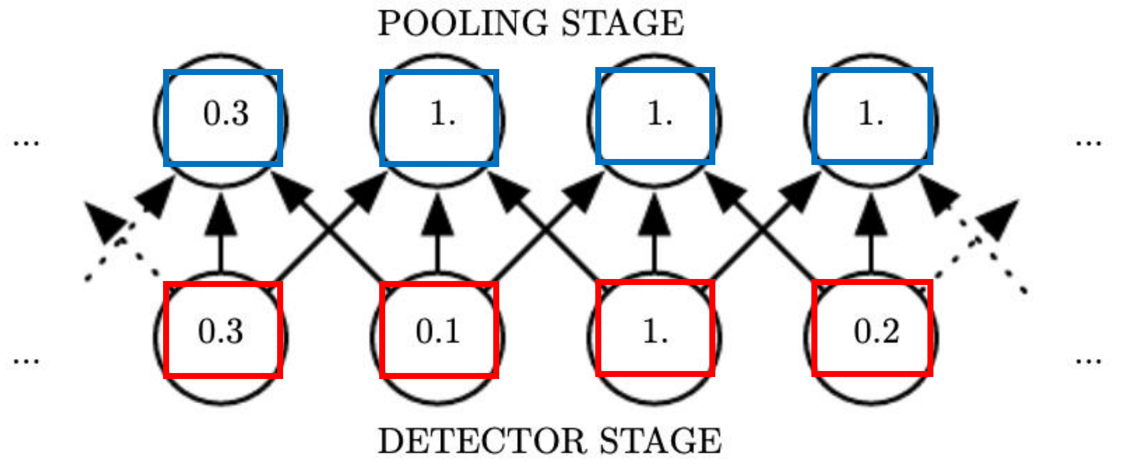


Seagull = 1?

Seagull = 1?

Seagull is in the center

Seagull = 1?

Seagull = 1?

Seagulls are present, but not in the center

Seagull = 1?

Seagulls are present, but not in the center

Seagull = 1?

Seagulls are present, but not in the center

CNNs can tell:
whether seagulls are present
Not tell:
their positions in the image

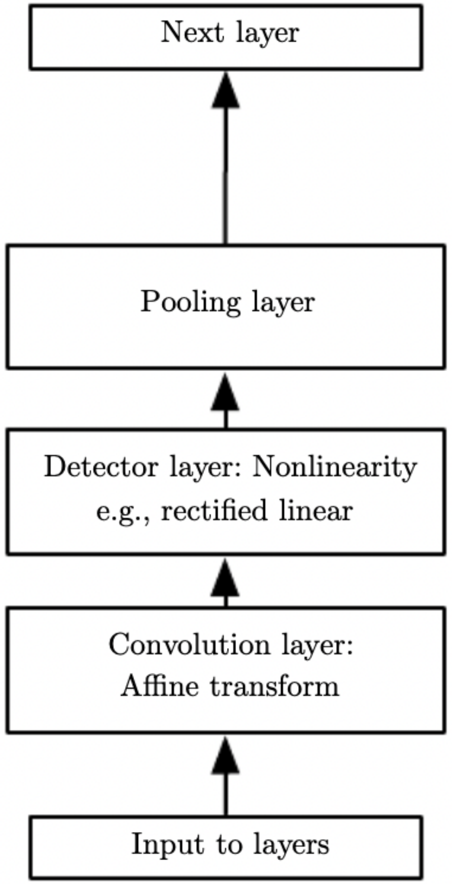
Seagull = 1?

Seagulls are present, but not in the center

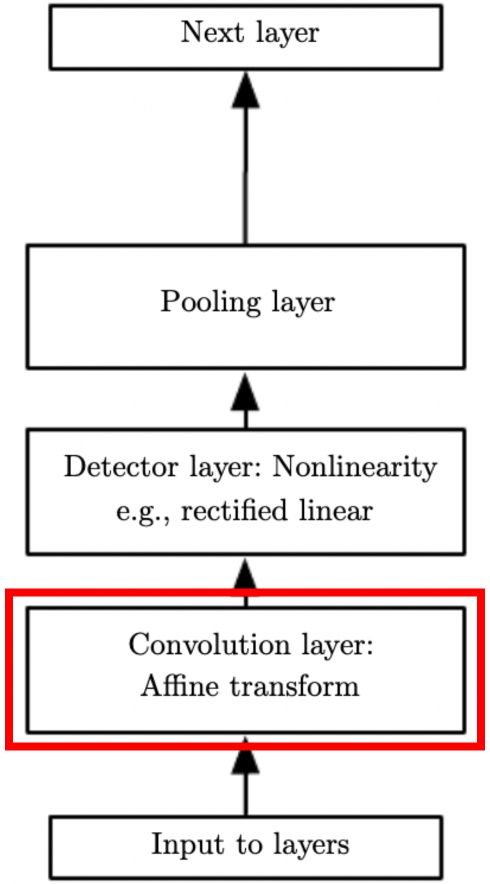
CNNs can tell:
whether seagulls are present
Not tell:
their positions in the image

Invariant to small translations

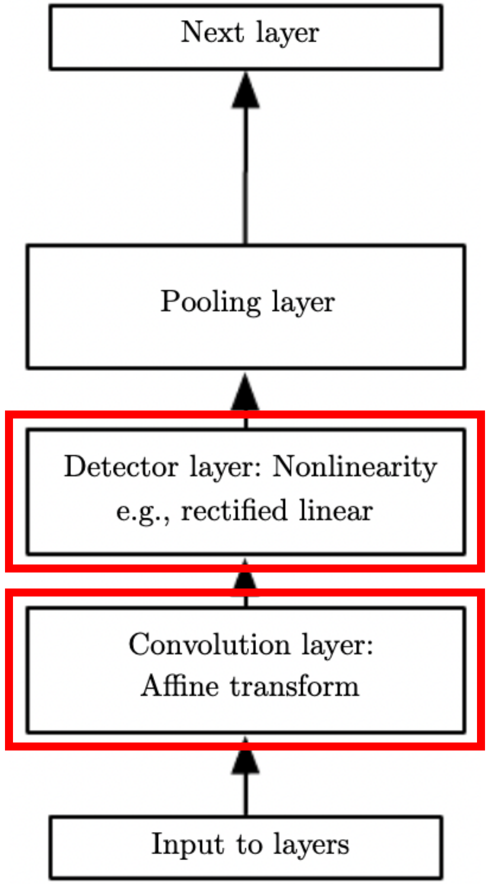
A typical convolutional layer



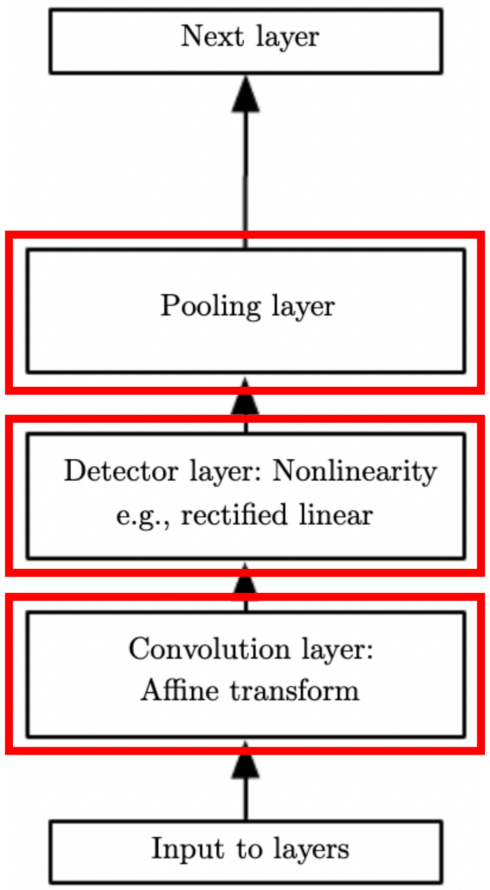
A typical convolutional layer



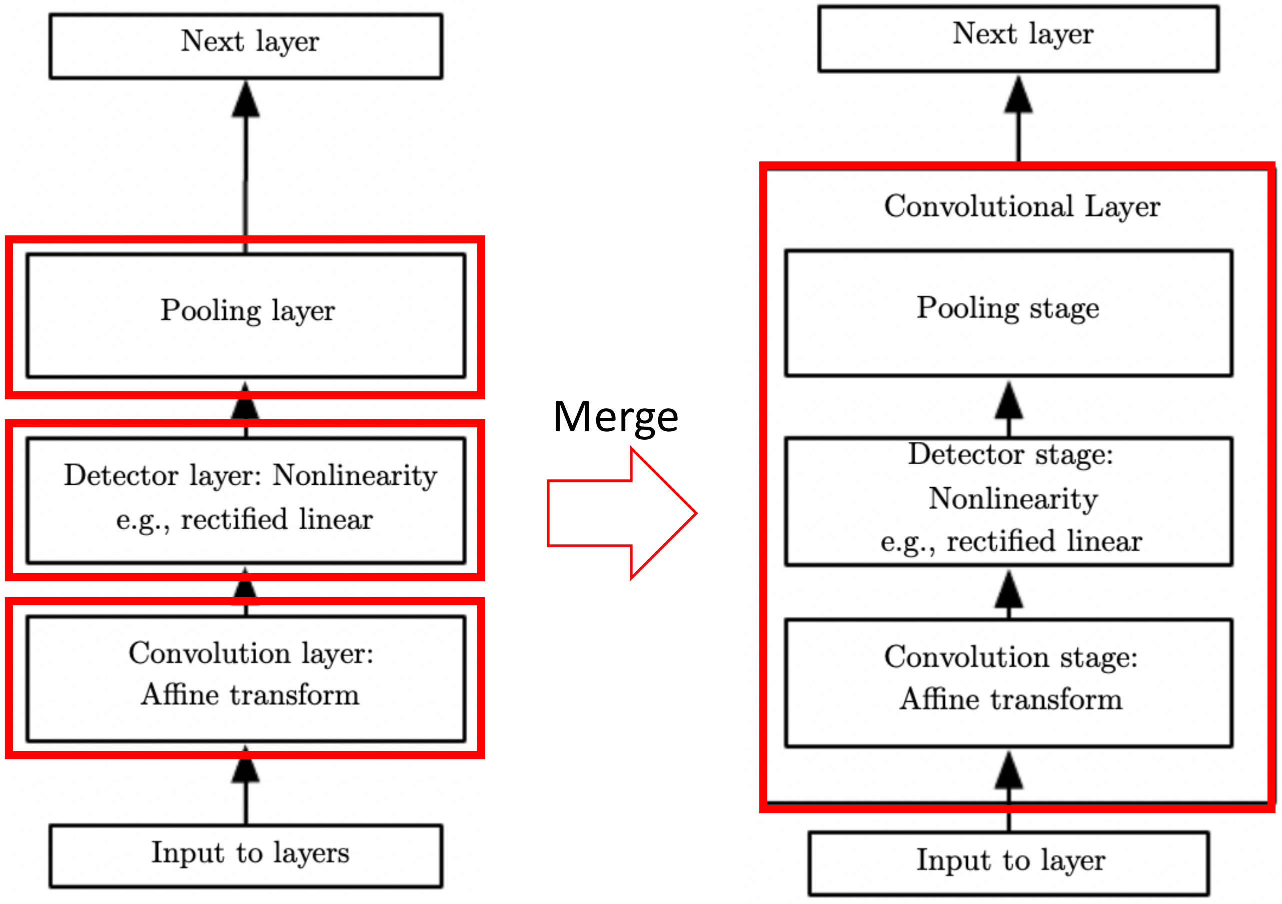
A typical convolutional layer

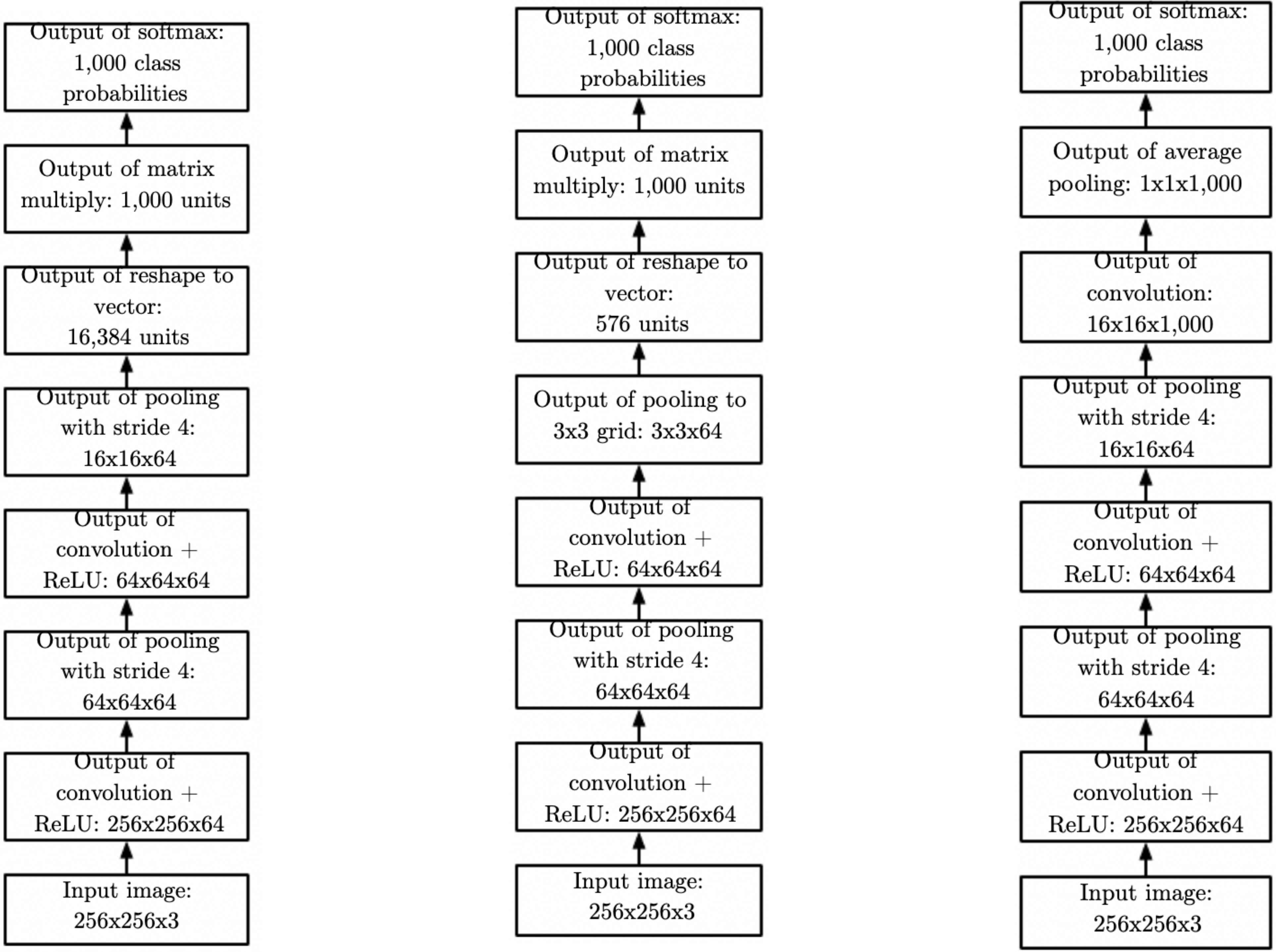


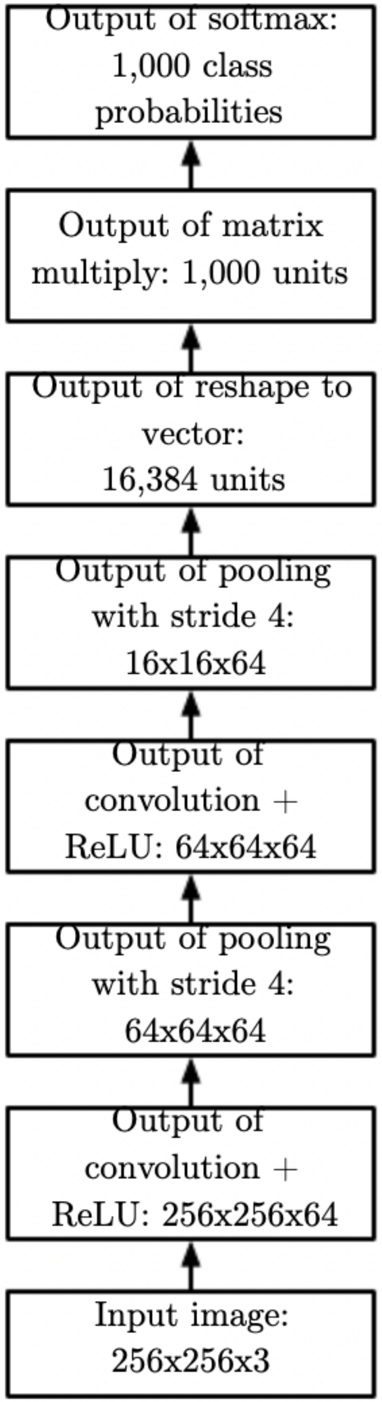
A typical convolutional layer

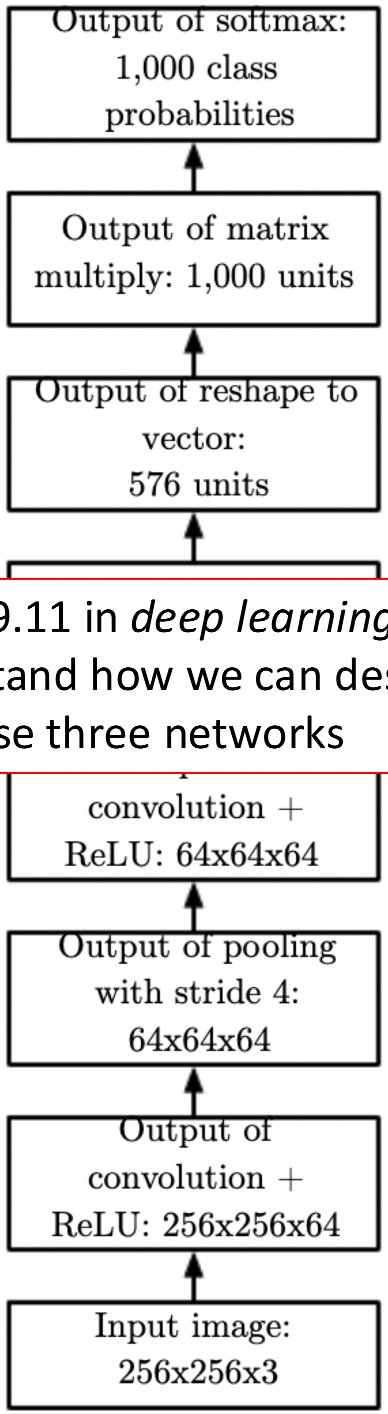


A typical convolutional layer

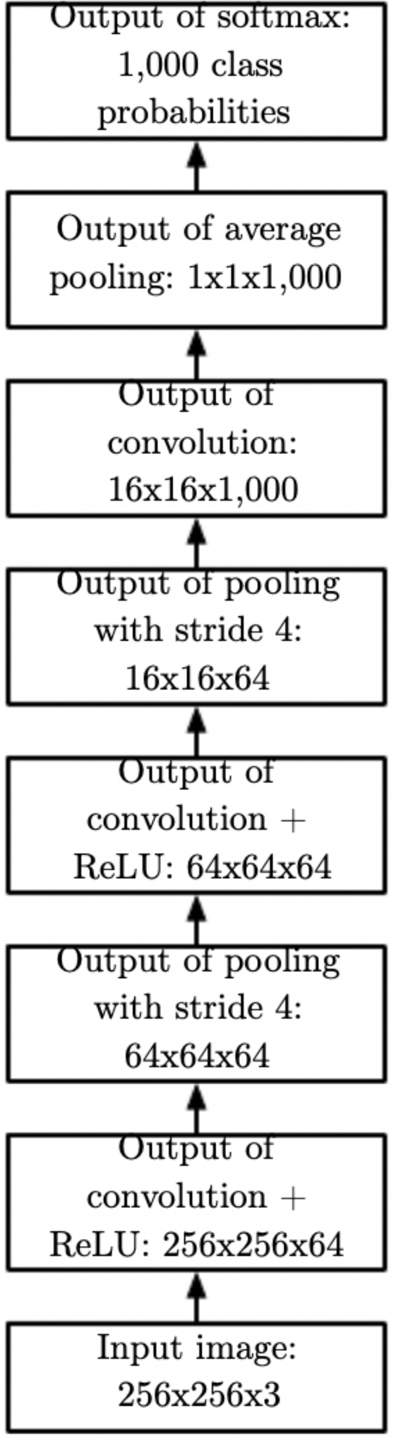



Output of softmax: 1,000 class probabilities
Output of matrix multiply: 1,000 units
Output of reshape to vector: 16,384 units
Output of pooling with stride 4: 16x16x64
Output of convolution + ReLU: 64x64x64
Output of pooling with stride 4: 64x64x64
Output of convolution + ReLU: 256x256x64
Input image: 256x256x3
Output of softmax: 1,000 class probabilities
Output of matrix multiply: 1,000 units
Output of reshape to vector: 576 units
Output of pooling to 3x3 grid: 3x3x64
Output of convolution + ReLU: 64x64x64
Output of pooling with stride 4: 64x64x64
Output of convolution + ReLU: 256x256x64
Input image: 256x256x3
Output of softmax: 1,000 class probabilities
Output of average pooling: 1x1x1,000
Output of convolution: 16x16x1,000
Output of pooling with stride 4: 16x16x64
Output of convolution + ReLU: 64x64x64
Output of pooling with stride 4: 64x64x64
Output of convolution + ReLU: 256x256x64
Input image: 256x256x3

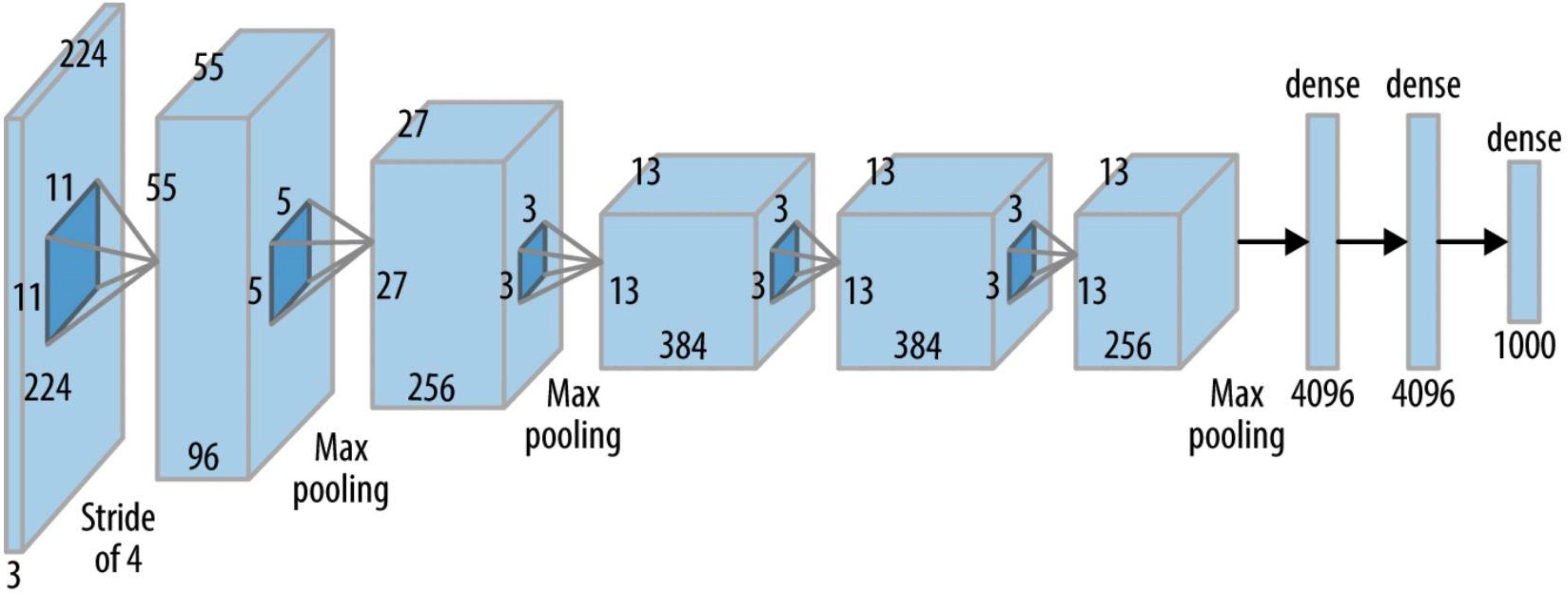




Read: Figure 9.11 in *deep learning* book
Try to understand how we can design architecture and build these three networks

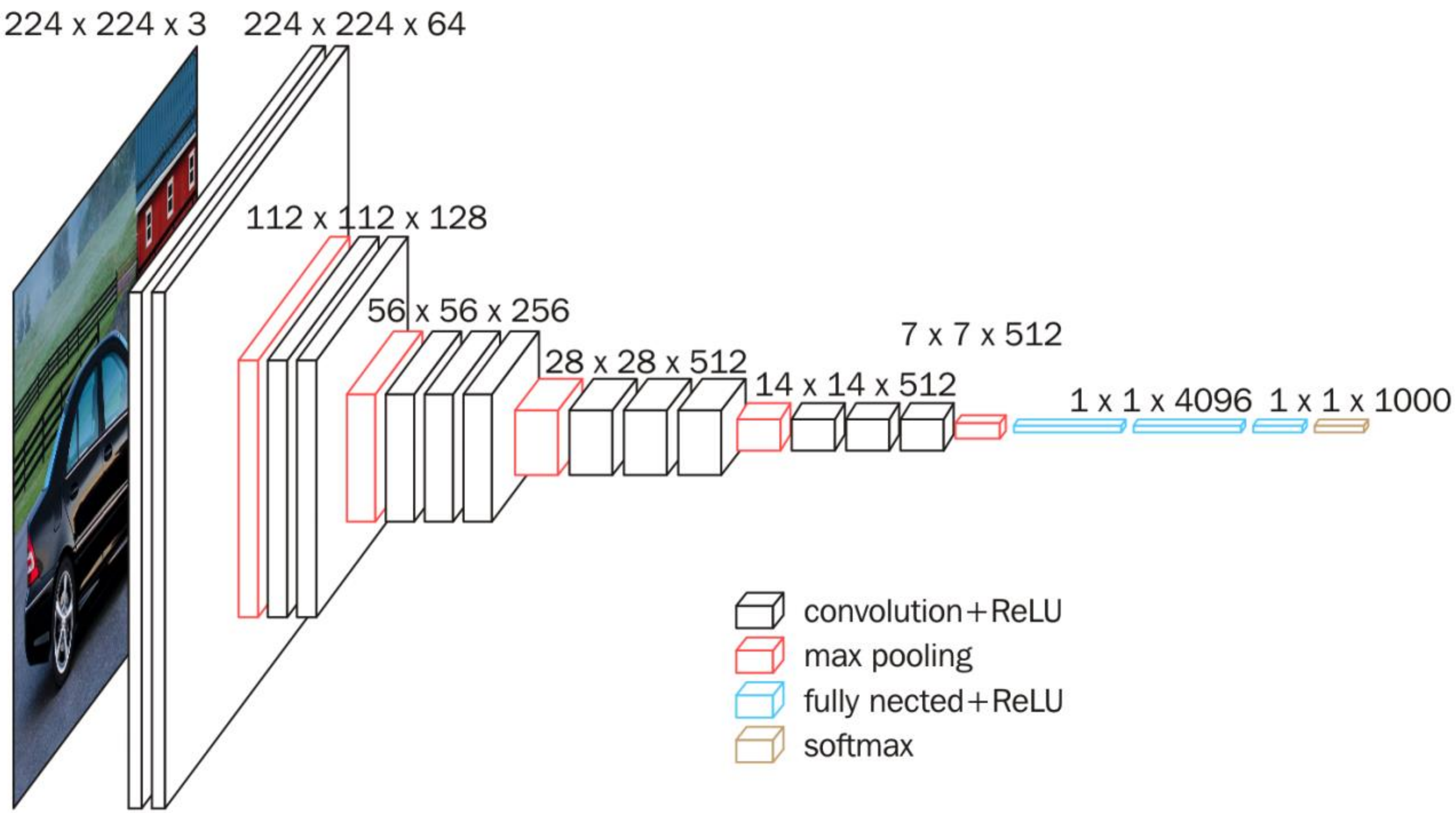


AlexNet

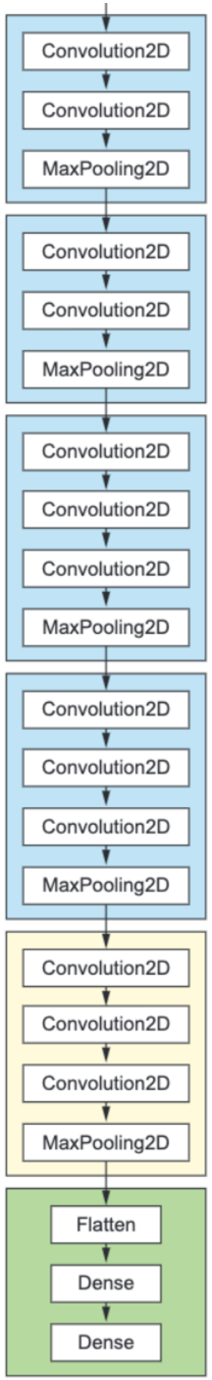


224
224
11
11
3
Stride
of 4
55
55
96
5
5
Max
pooling
27
27
256
3
3
Max
pooling
13
13
384
3
3
13
13
384
3
3
13
13
256
Max
pooling
dense
dense
dense
4096
4096
1000

VGG-16



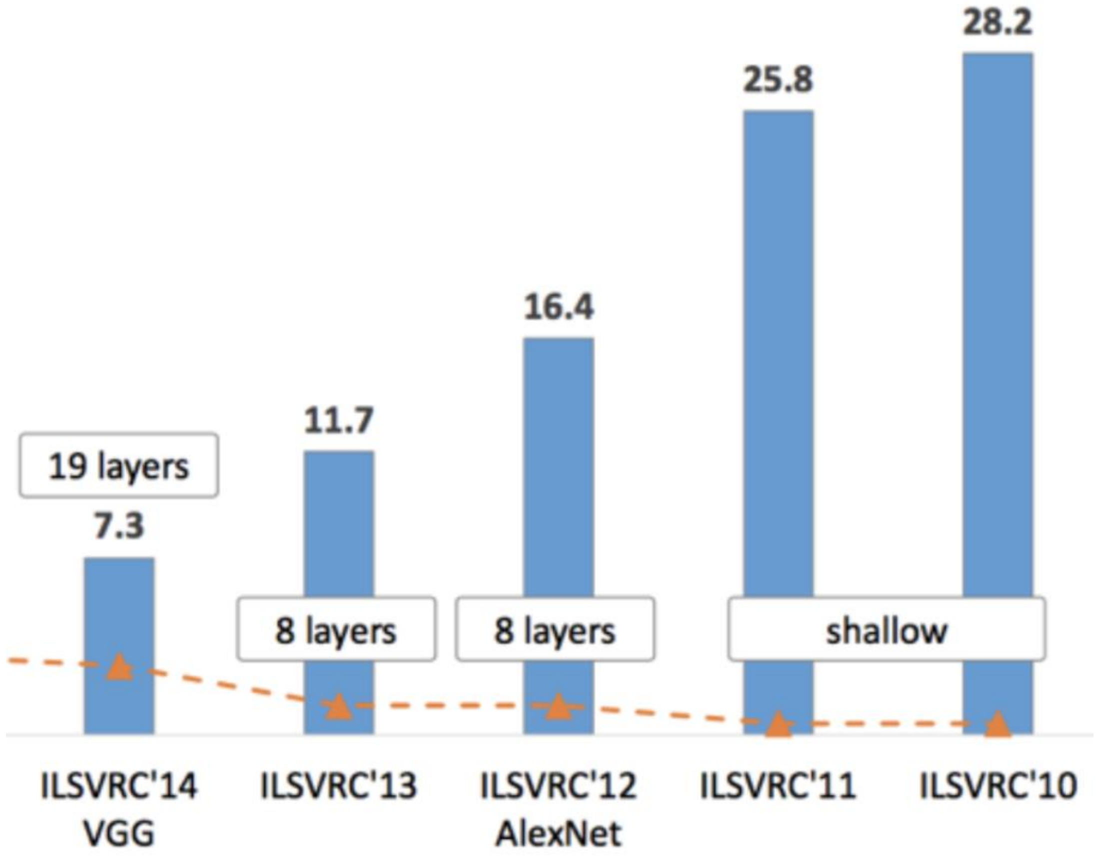
224 x 224 x 3
224 x 224 x 64
112 x 112 x 128
56 x 56 x 256
28 x 28 x 512
14 x 14 x 512
7 x 7 x 512
1 x 1 x 4096
1 x 1 x 1000
convolution+ReLU
max pooling
fully nected+ReLU
softmax



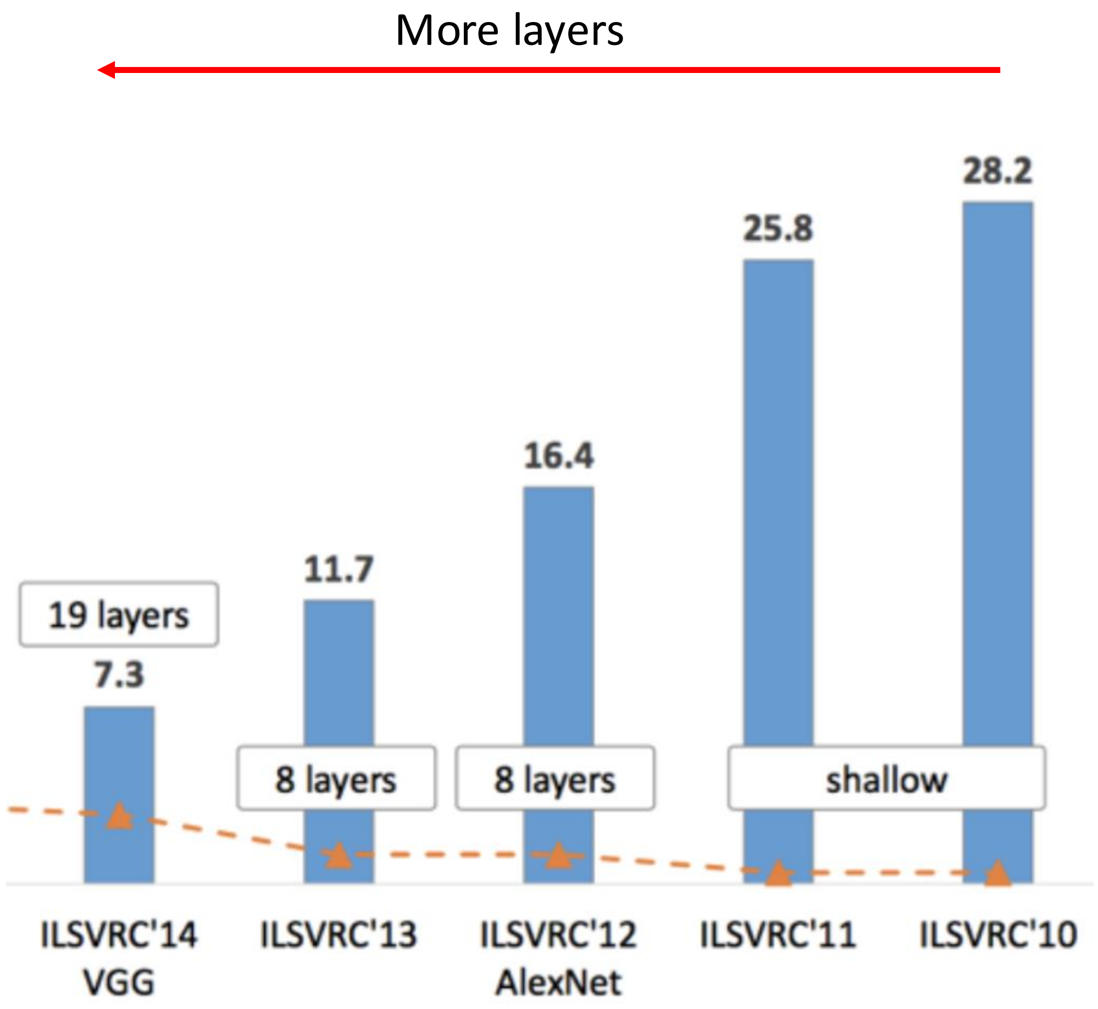
Convolution2D
Convolution2D
MaxPooling2D
Convolution2D
Convolution2D
MaxPooling2D
Convolution2D
Convolution2D
Convolution2D
MaxPooling2D
Convolution2D
Convolution2D
Convolution2D
MaxPooling2D
Convolution2D
Convolution2D
Convolution2D
MaxPooling2D
Flatten
Dense
Dense

[VGG]

ImageNet competition

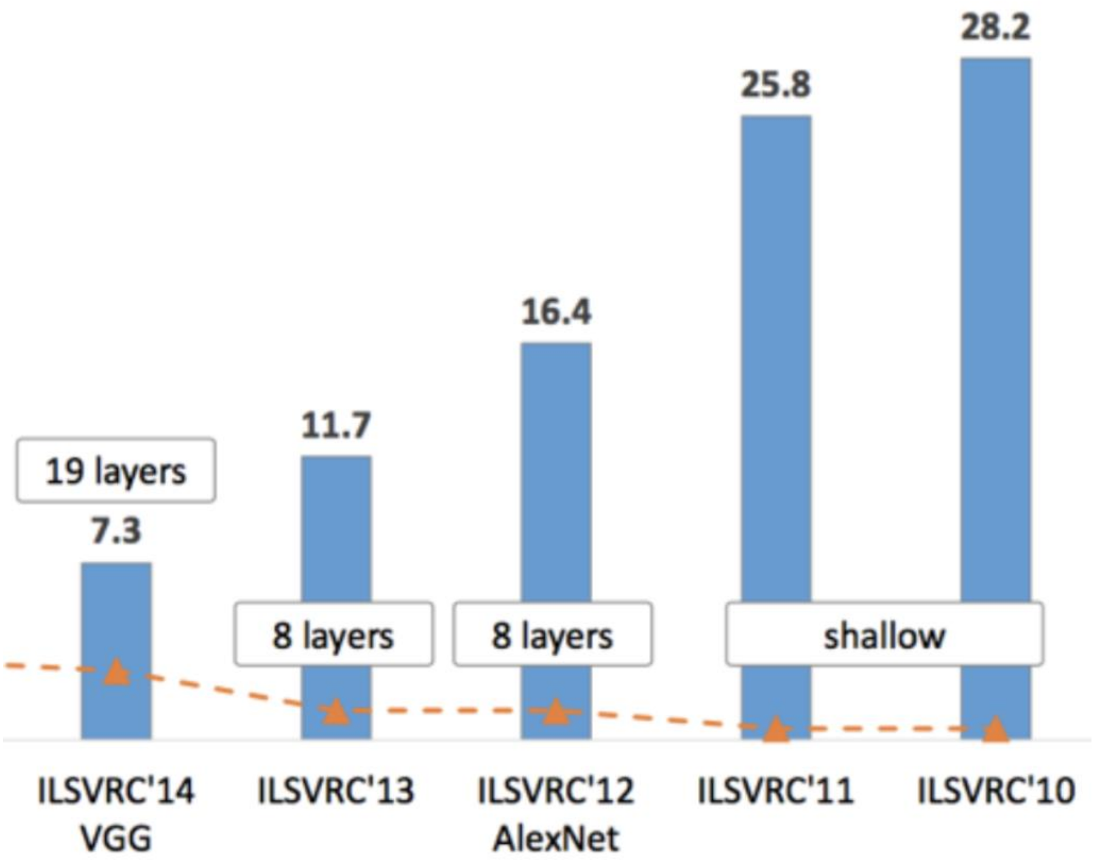


ImageNet competition



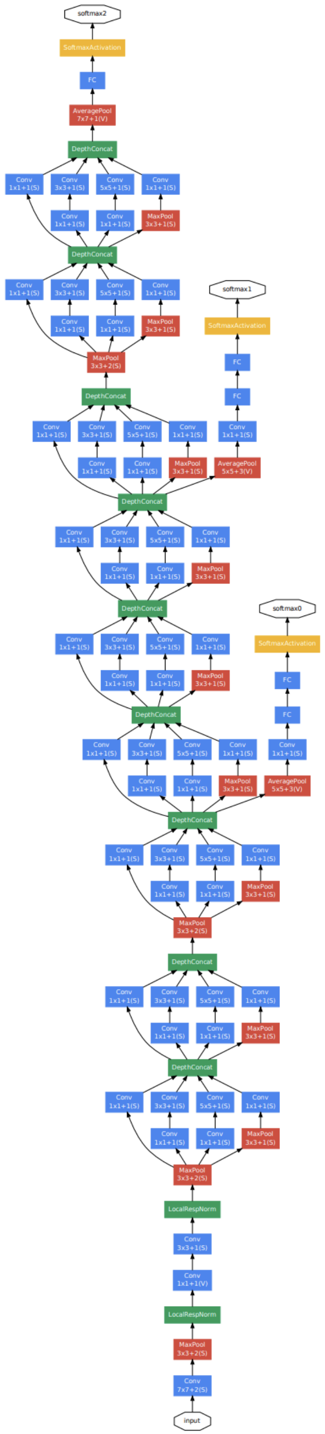
ImageNet competition

More layers

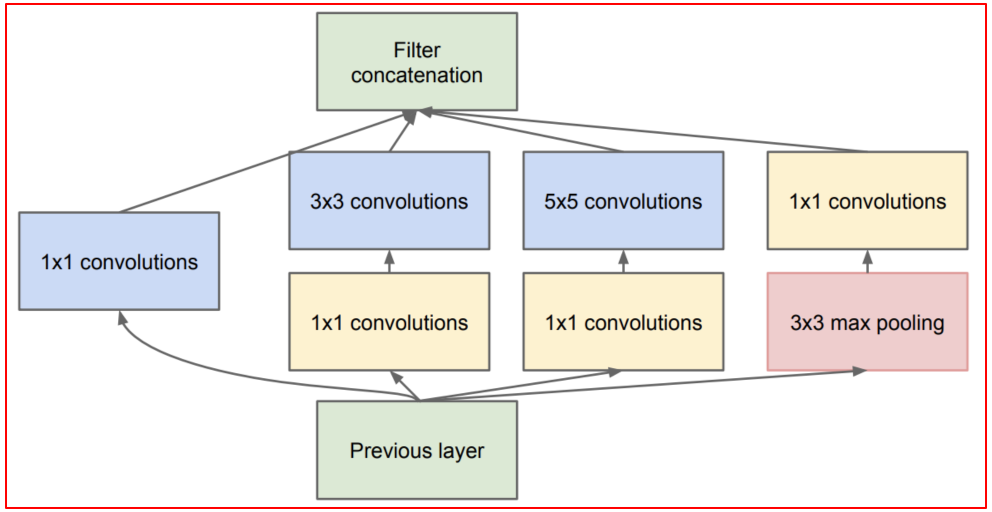


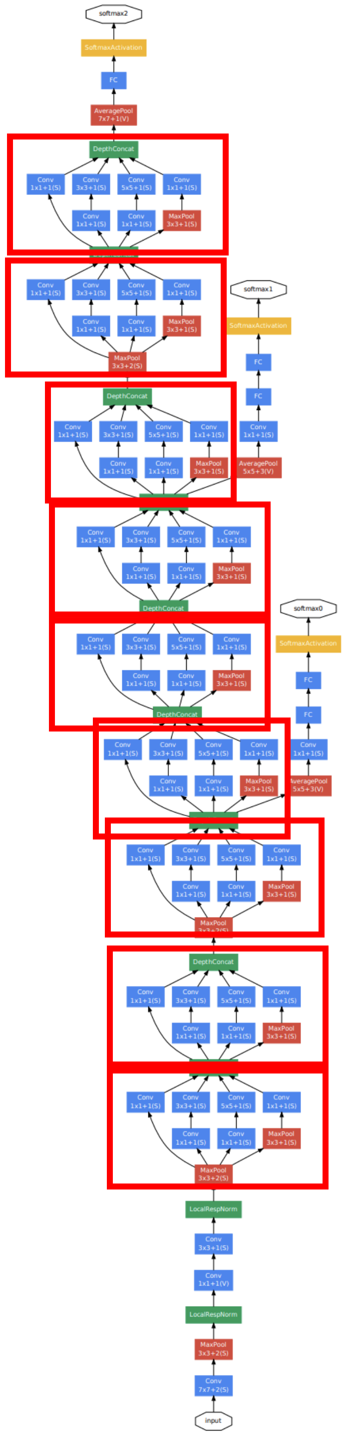
Better performance

Inception (GoogLeNet)

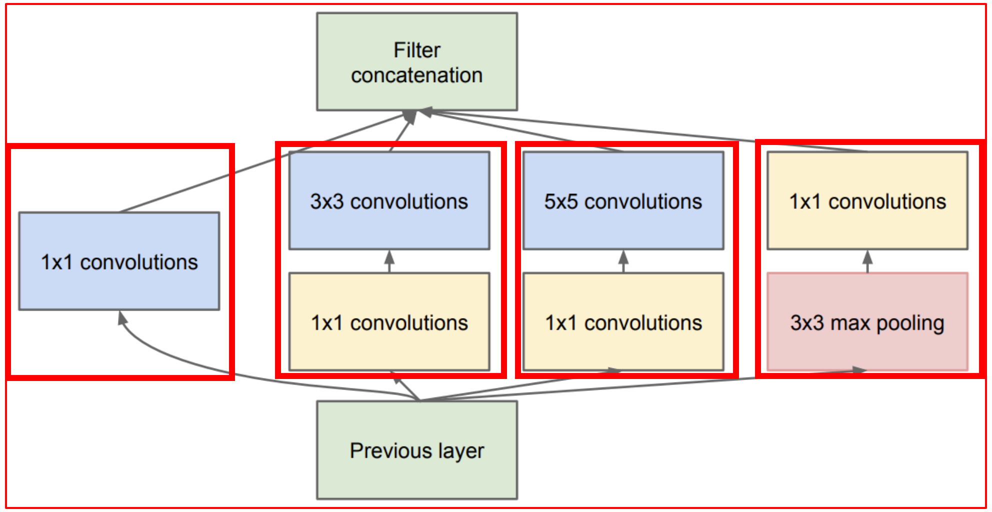


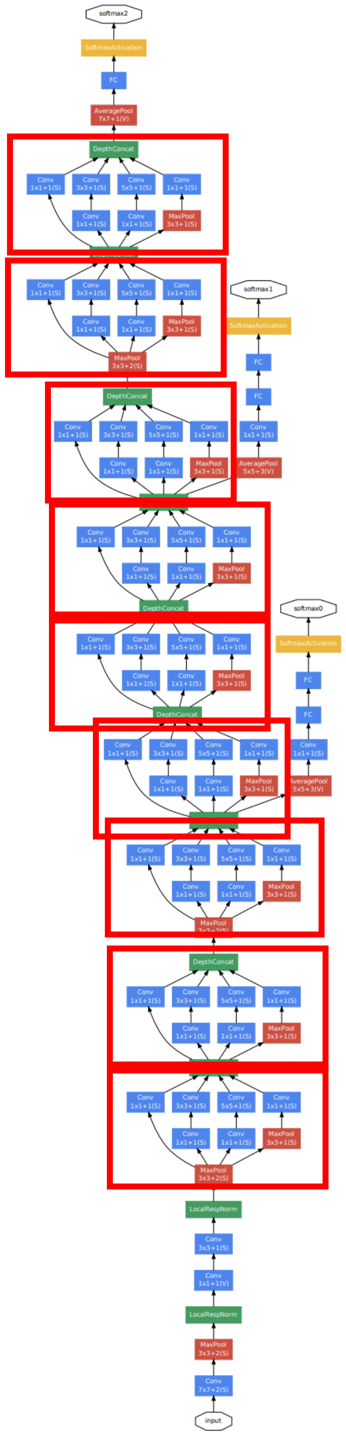
Inception (GoogLeNet)



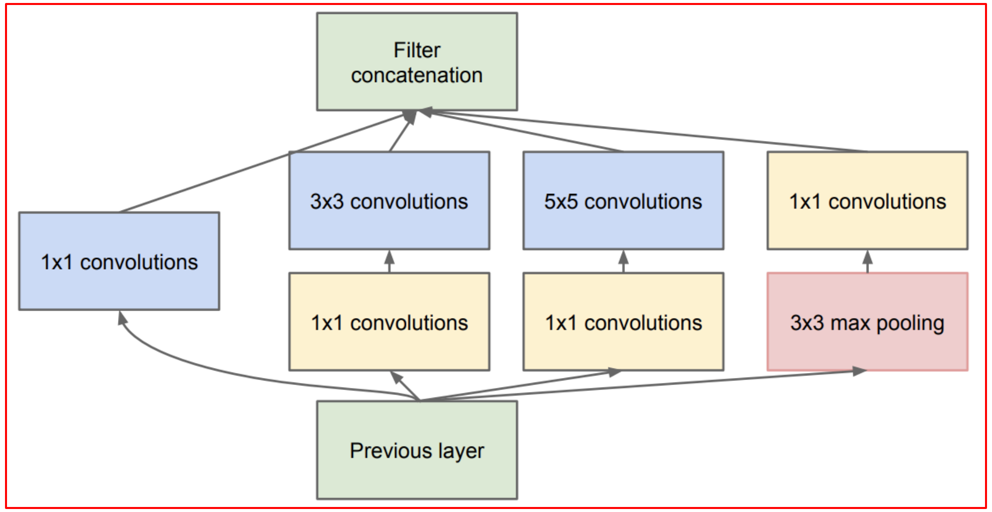


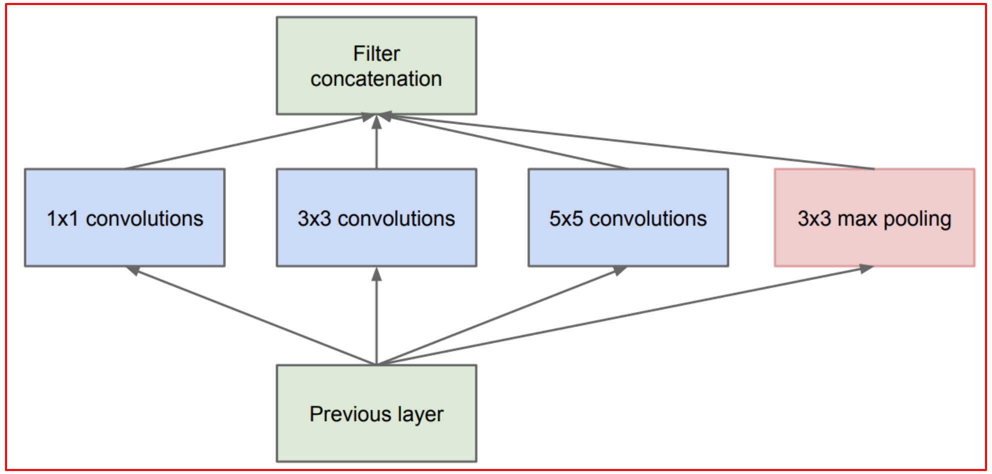
Inception (GoogLeNet)

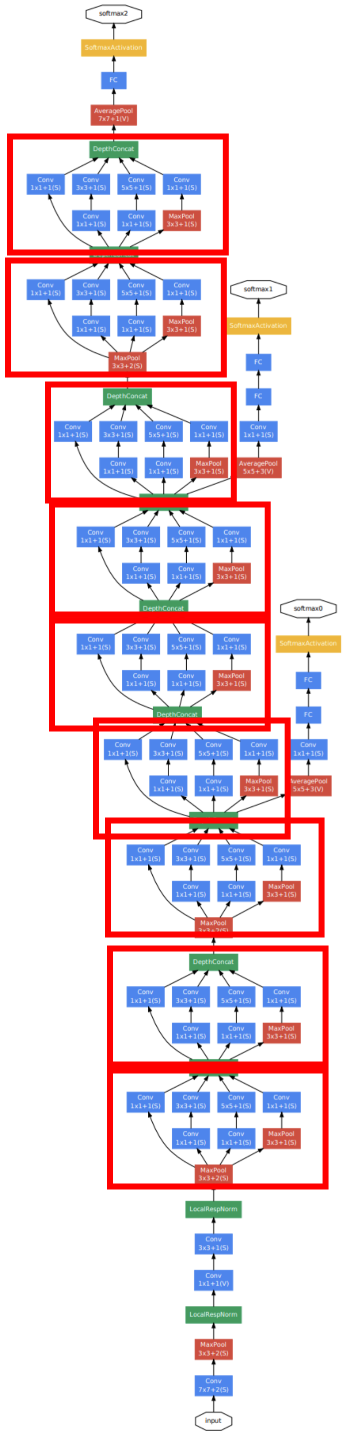




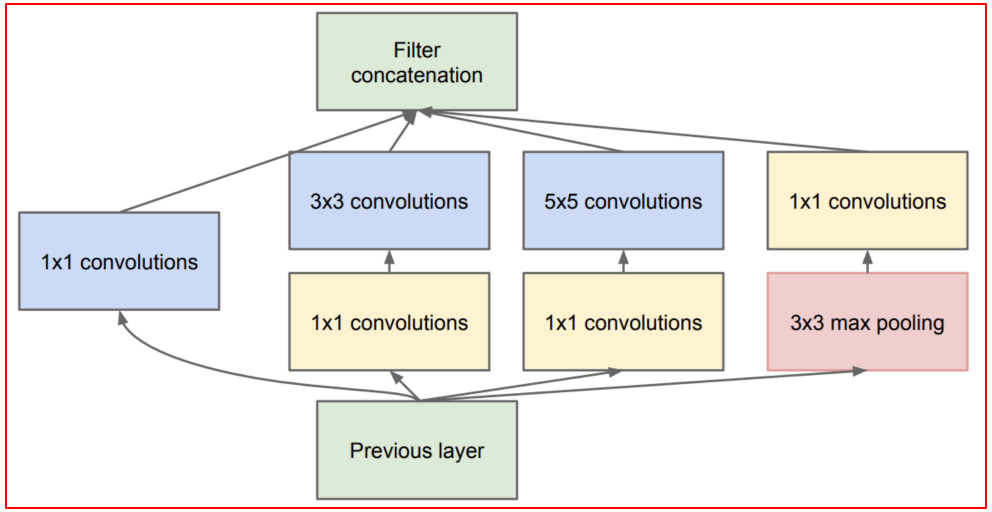
Inception (GoogLeNet)



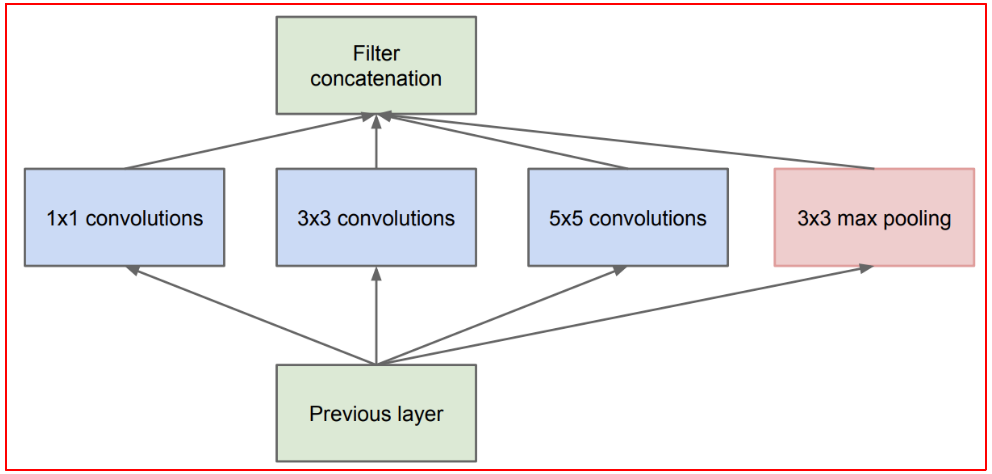


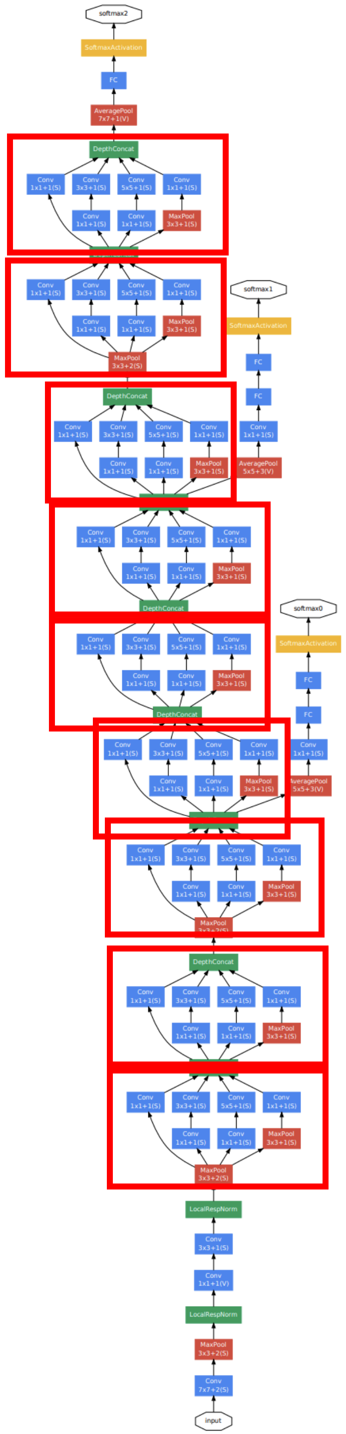


Inception (GoogLeNet)

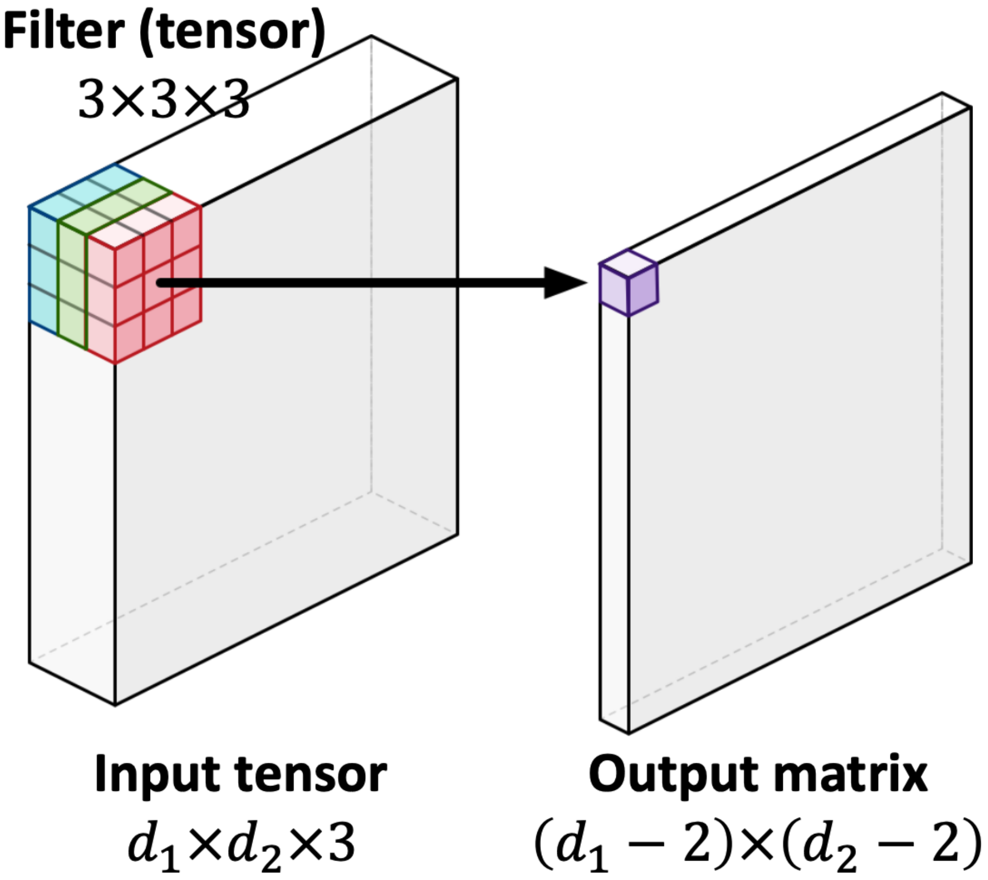


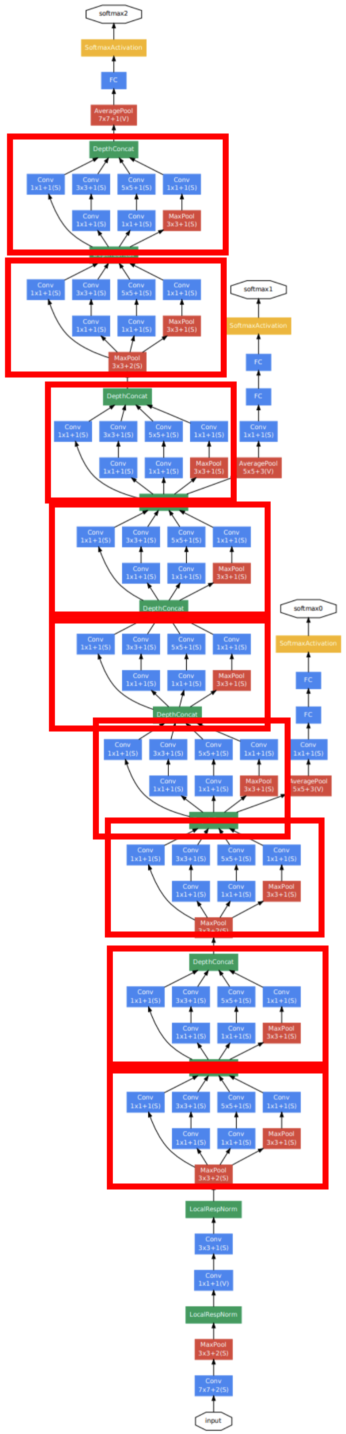
Q: difference between those two variants?



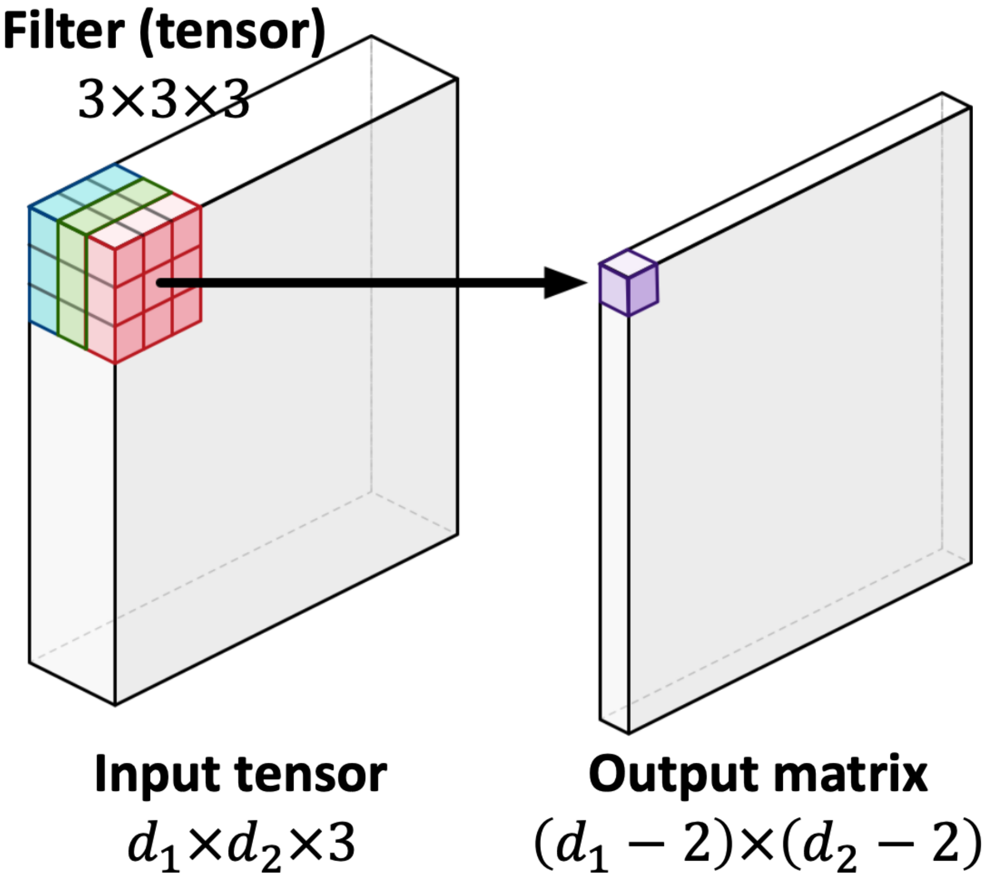


Inception (GoogLeNet)





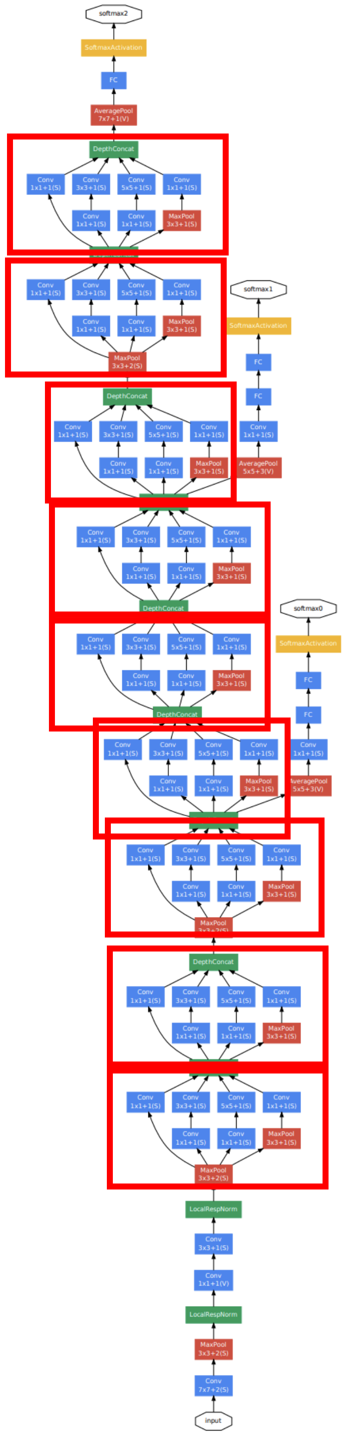
Inception (GoogLeNet)



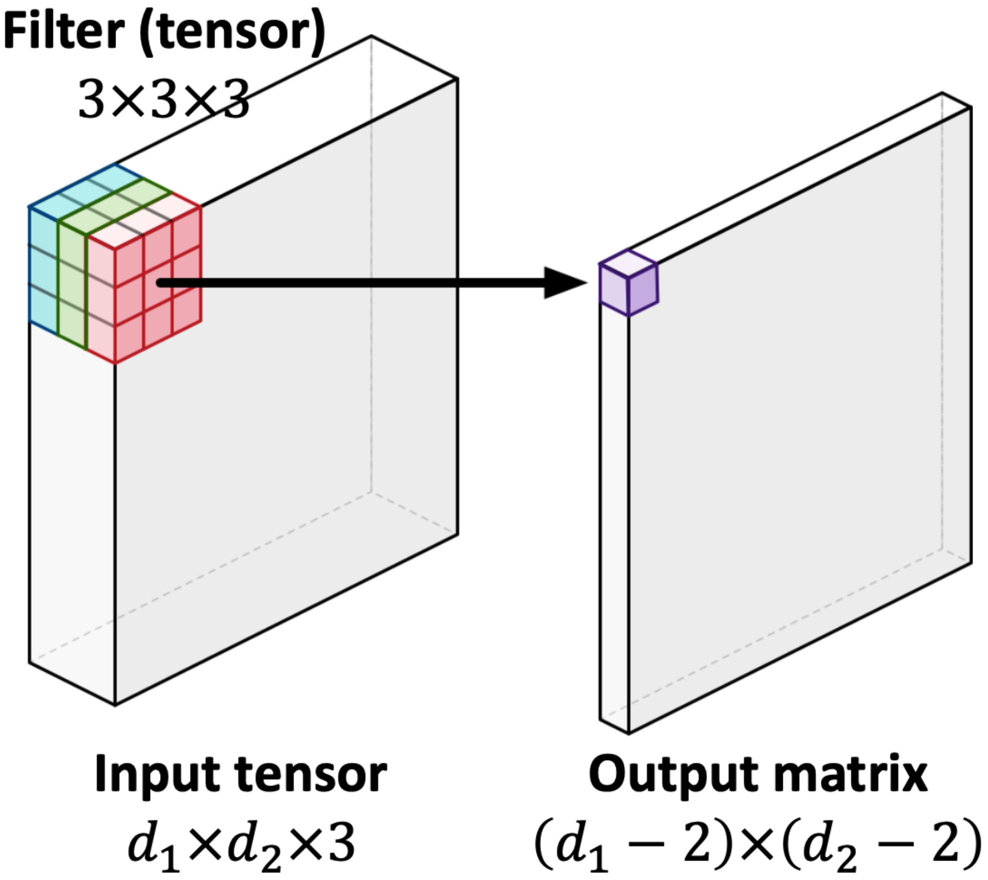
a tensor → a matrix (channel)

↑

a filter/kernel

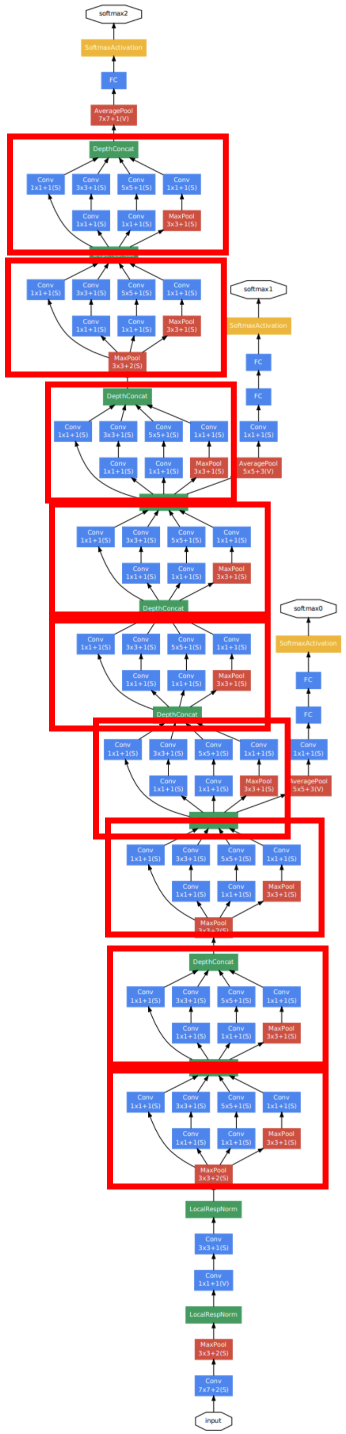


Inception (GoogLeNet)



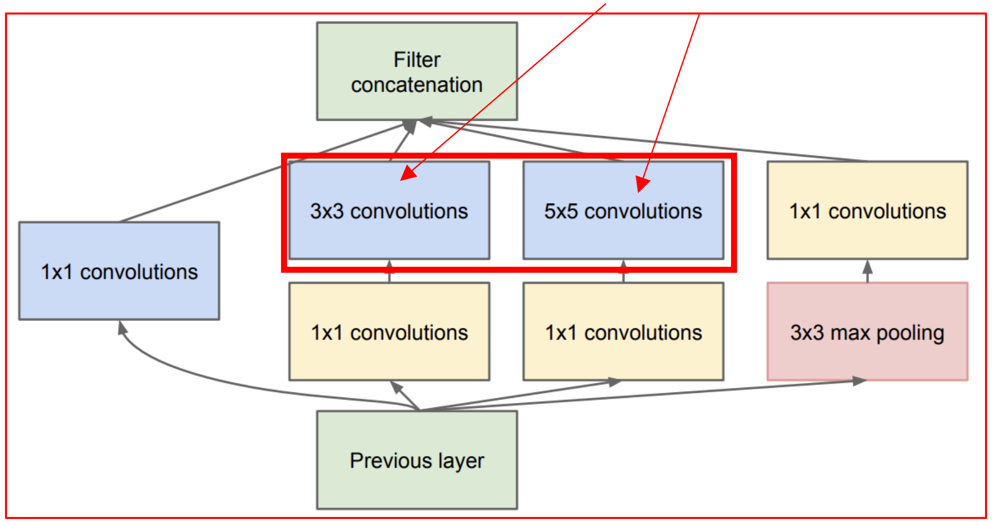
a tensor → m matrices (channels)

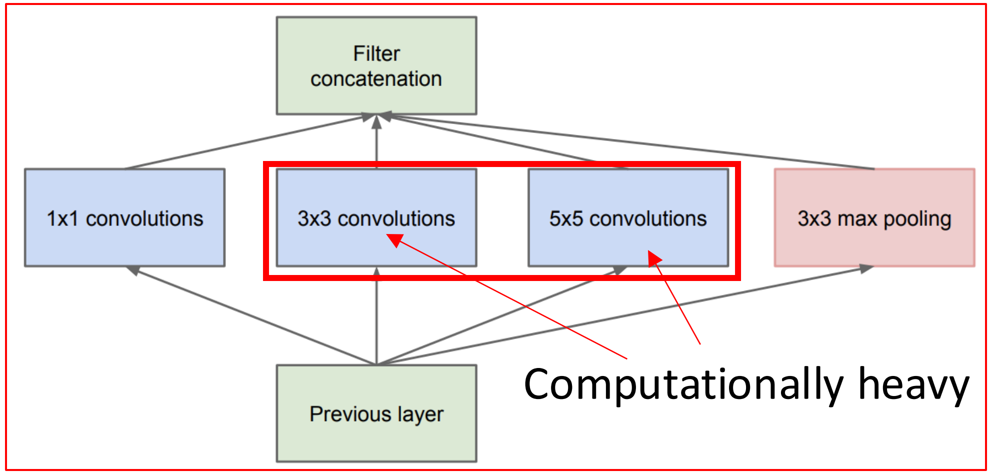
m filter/kernel

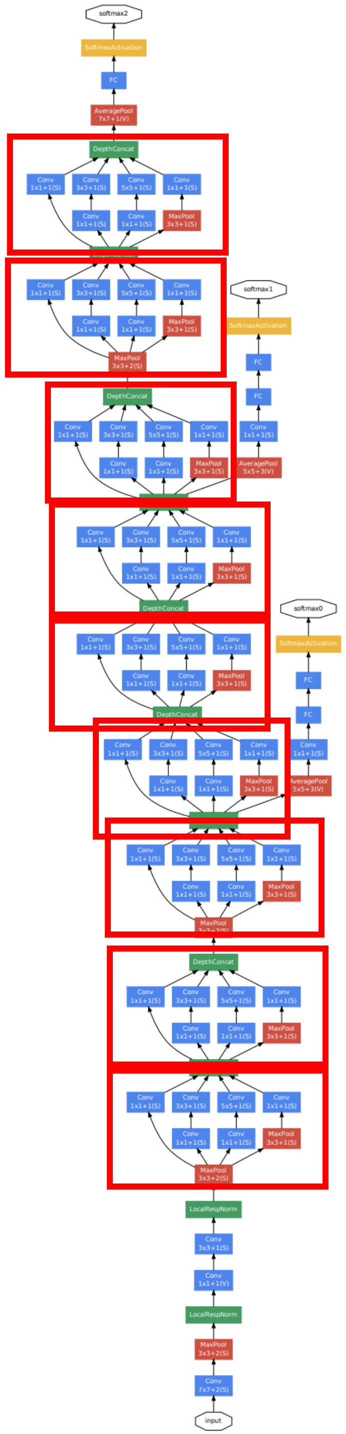


Inception (GoogLeNet)

Computationally heavy







Inception (GoogLeNet)

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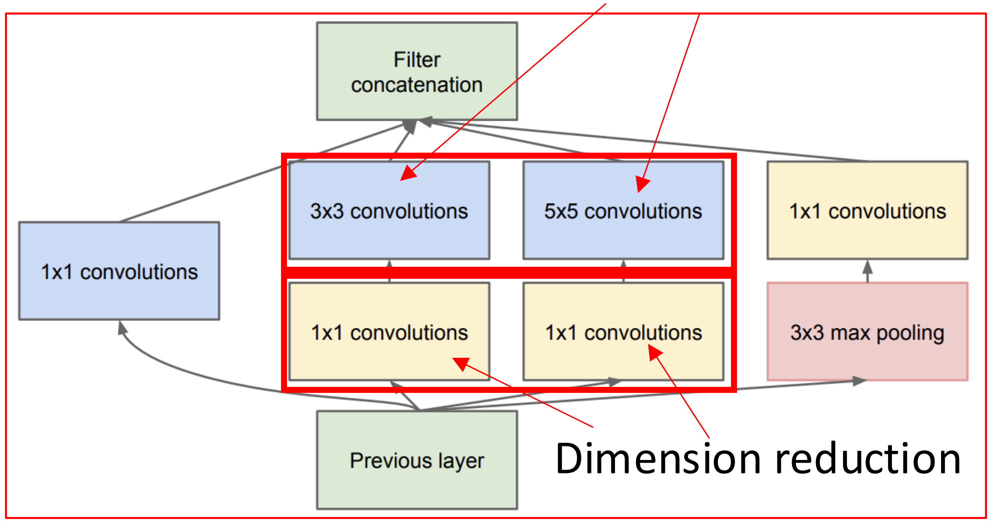
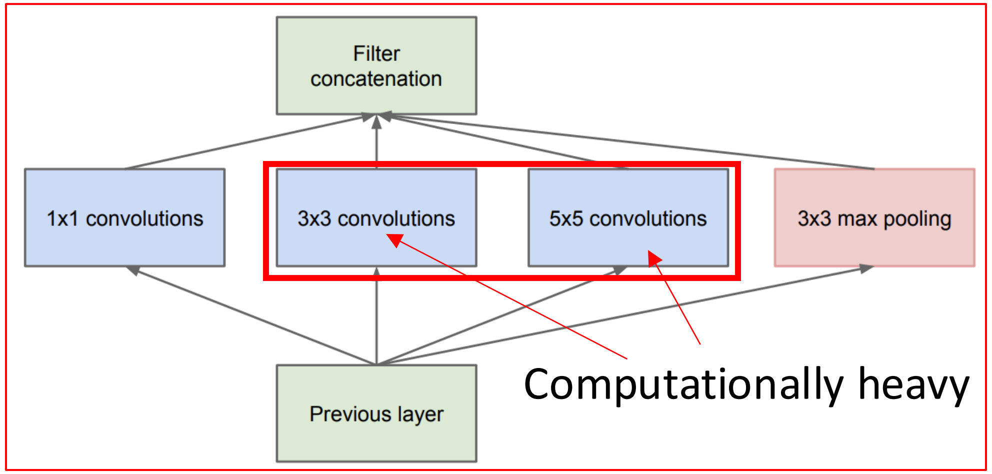
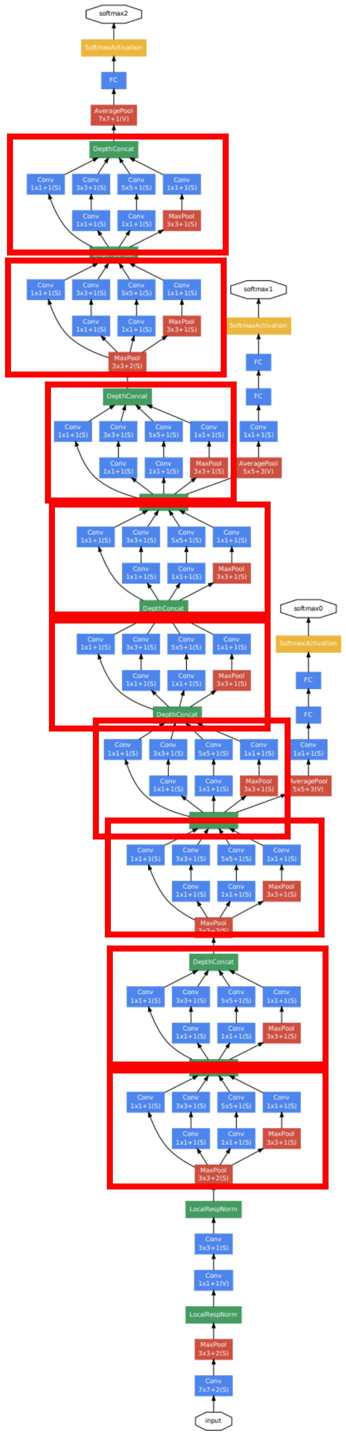
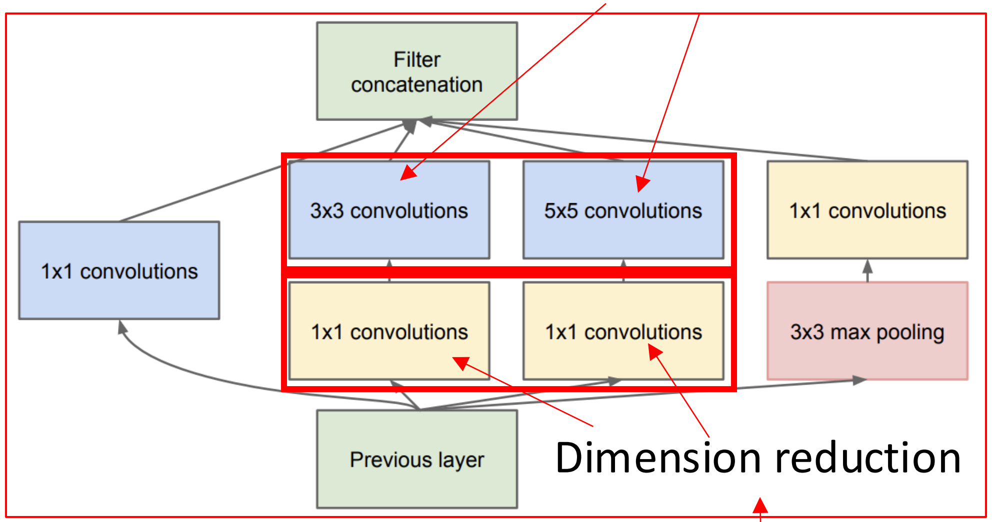




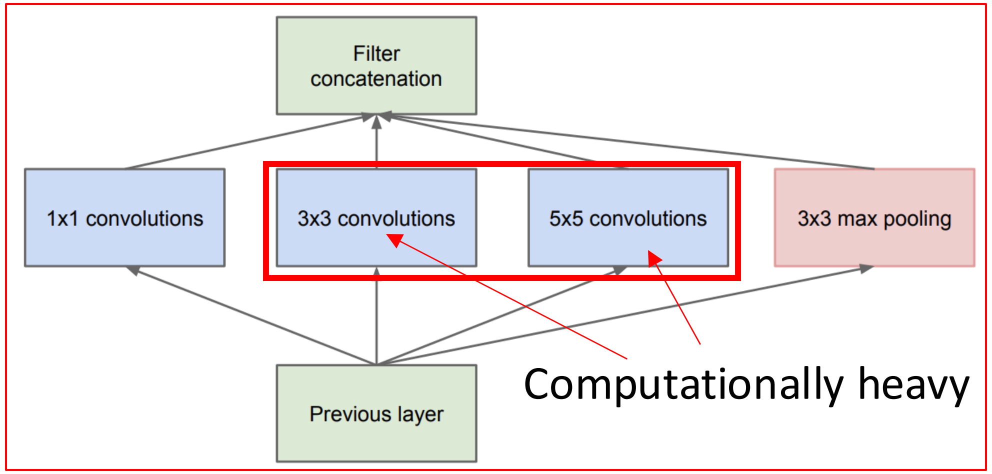


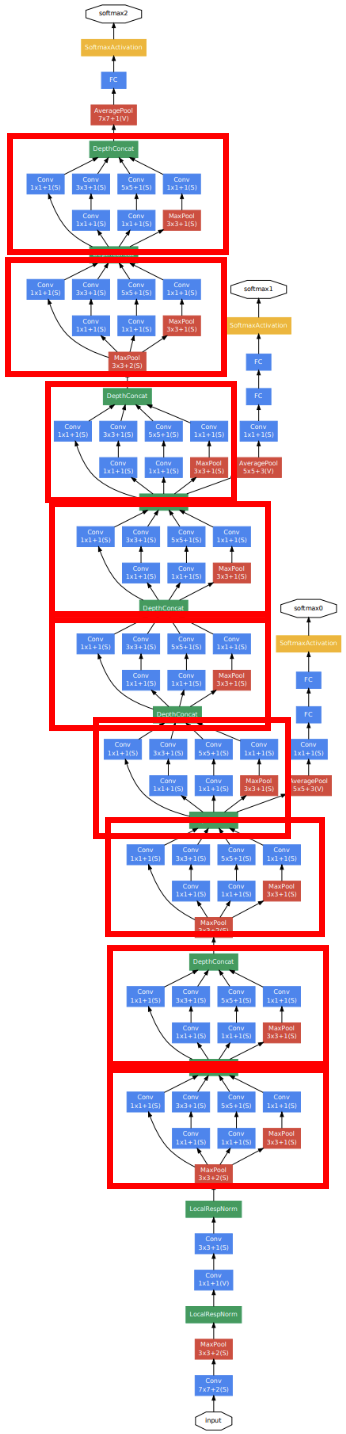
Inception (GoogLeNet)

Computationally heavy

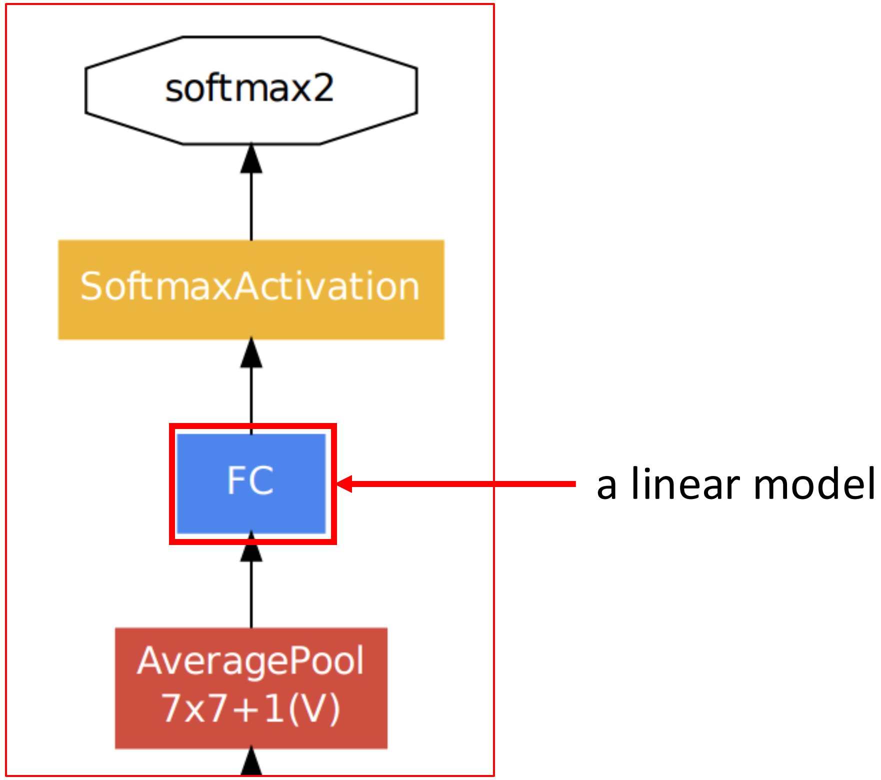


Less channels

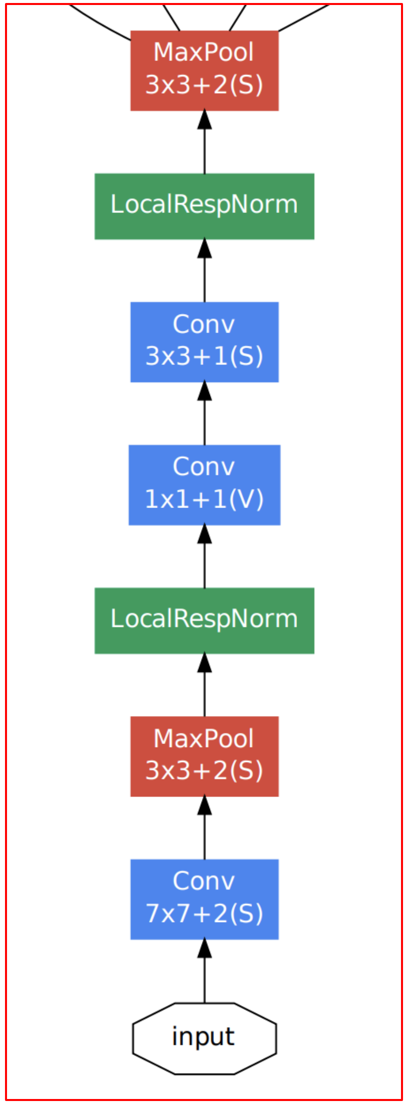


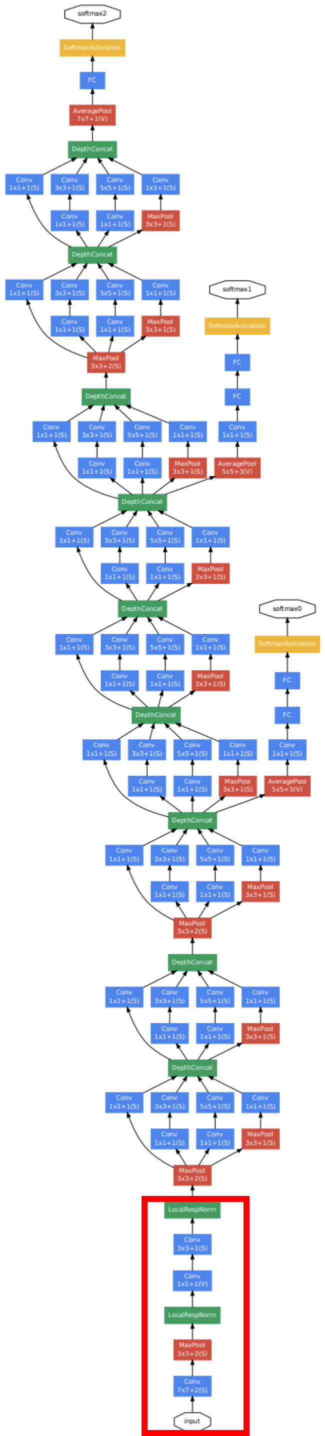


Inception (GoogLeNet)

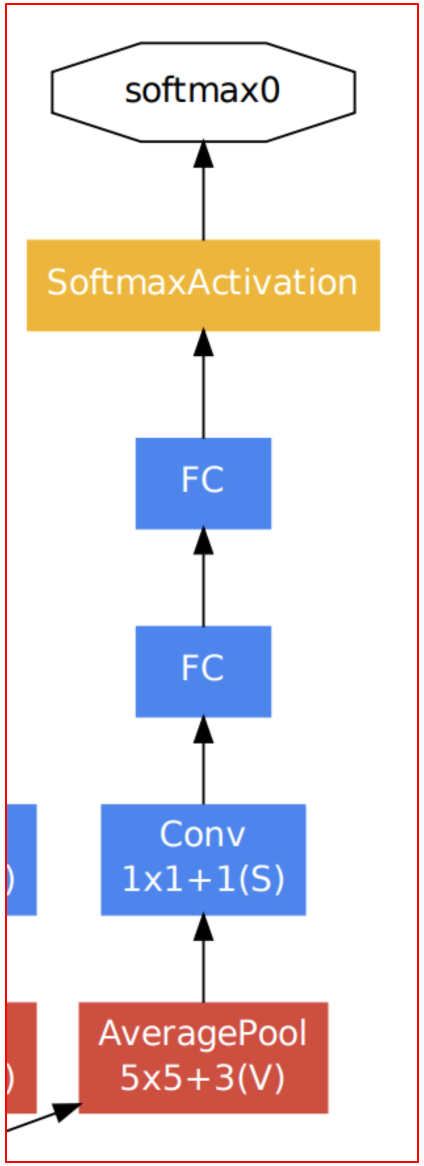


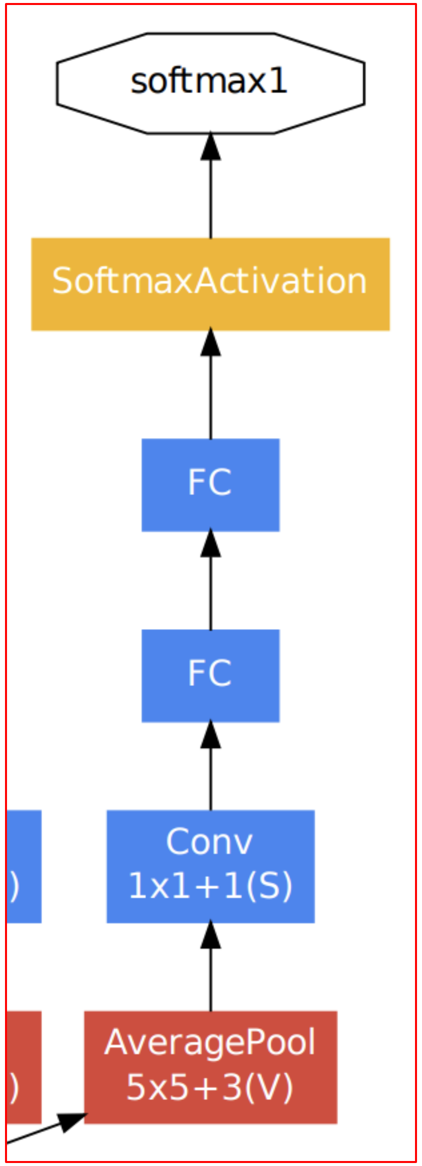
Inception (GoogLeNet)

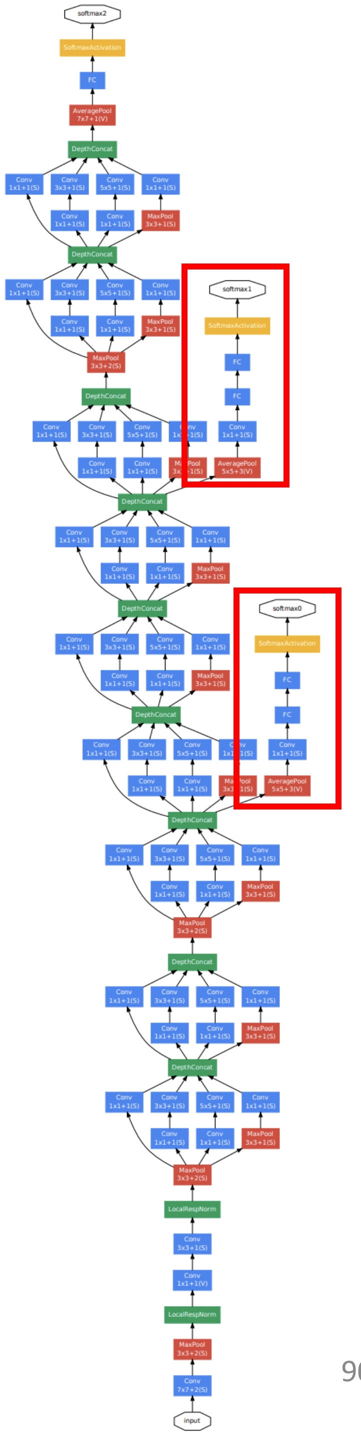




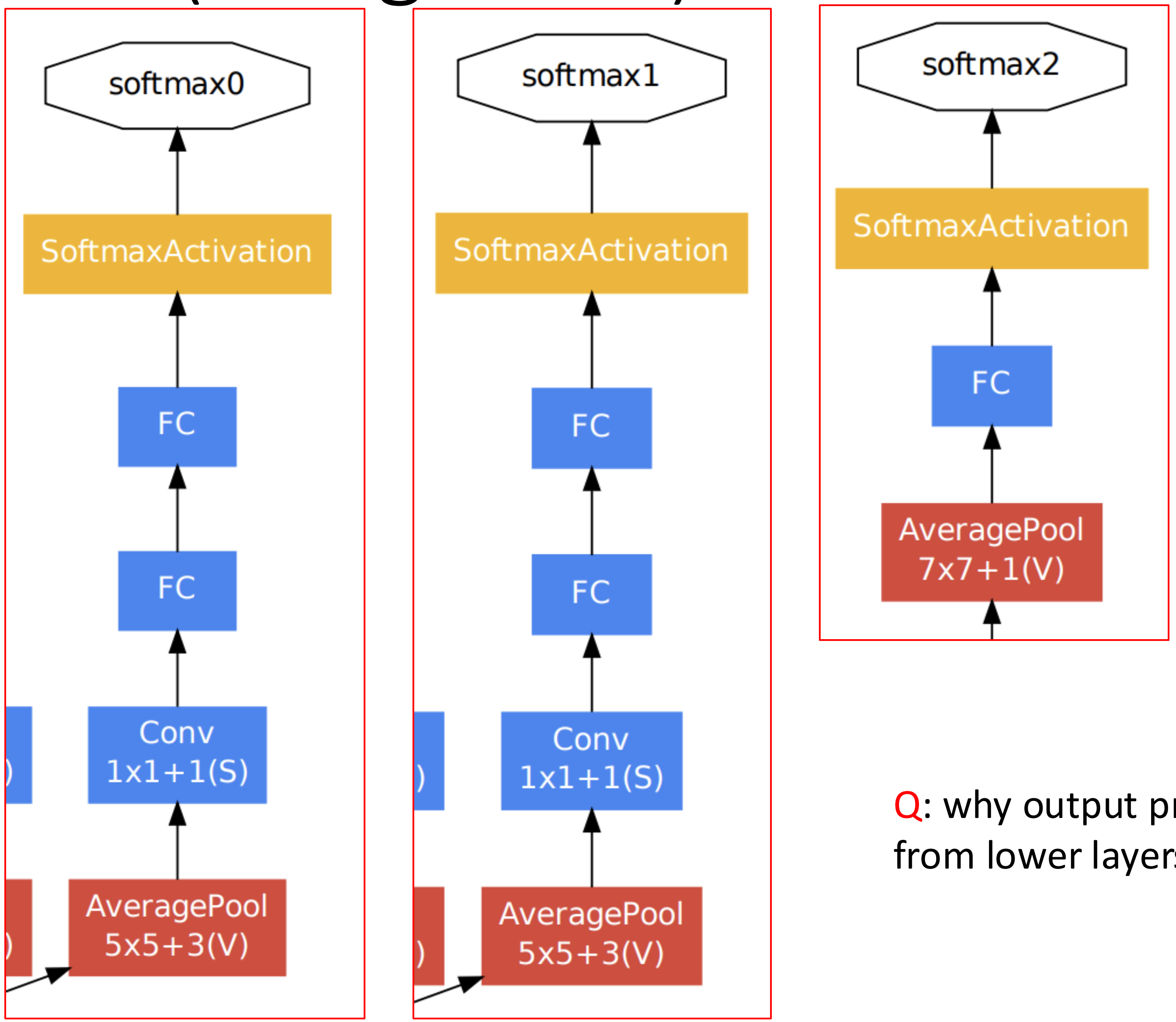
Inception (GoogLeNet)



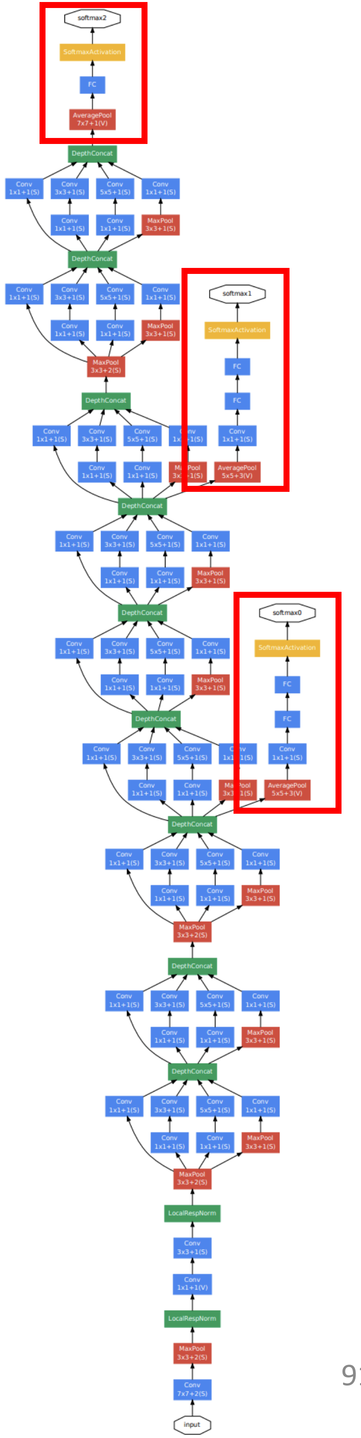




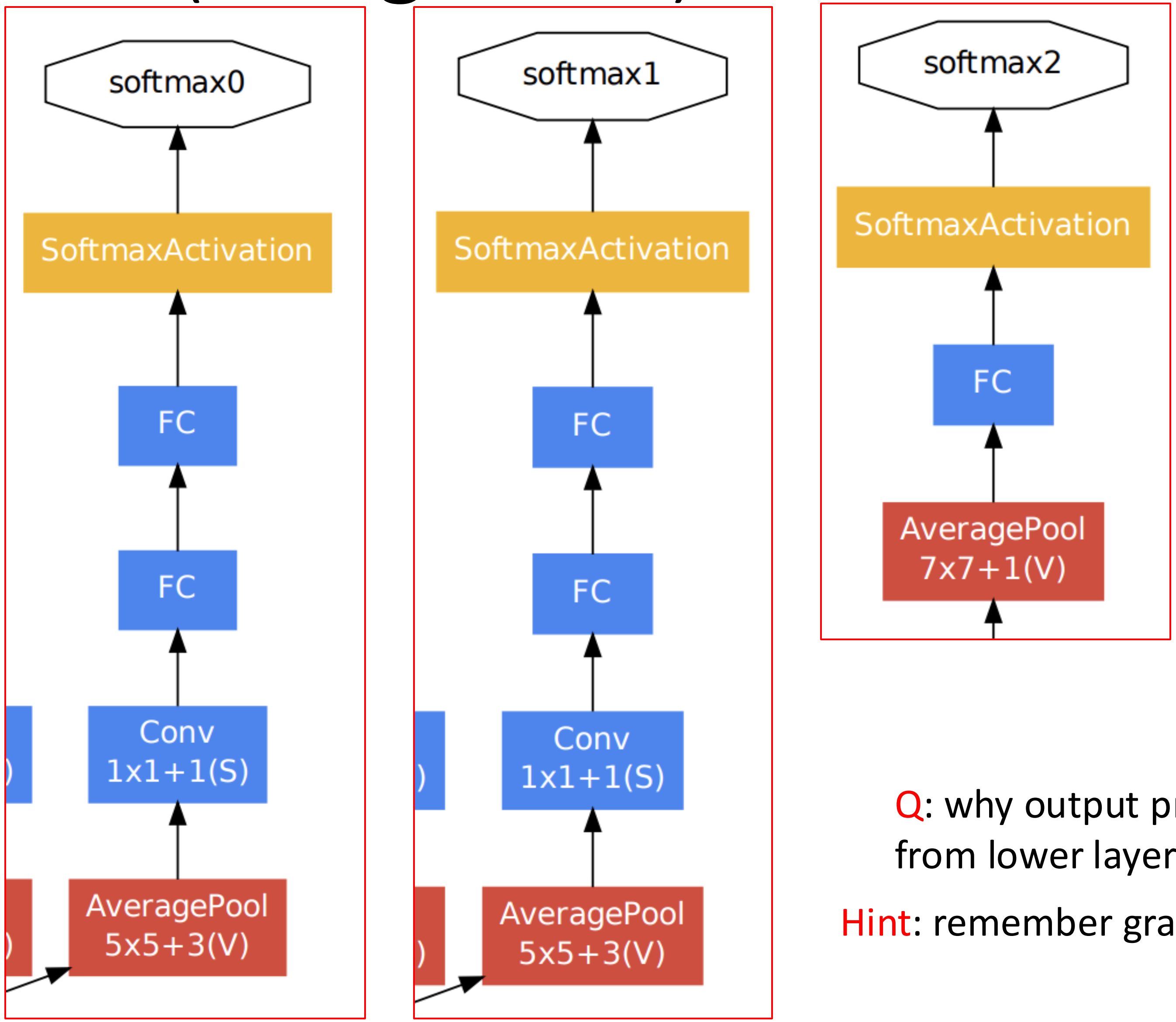
Inception (GoogLeNet)

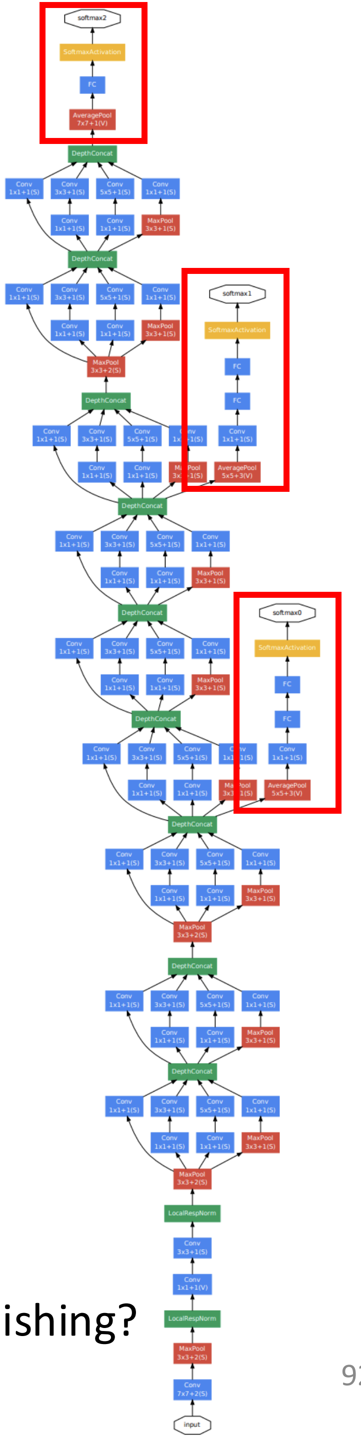


Q: why output prediction from lower layers?



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

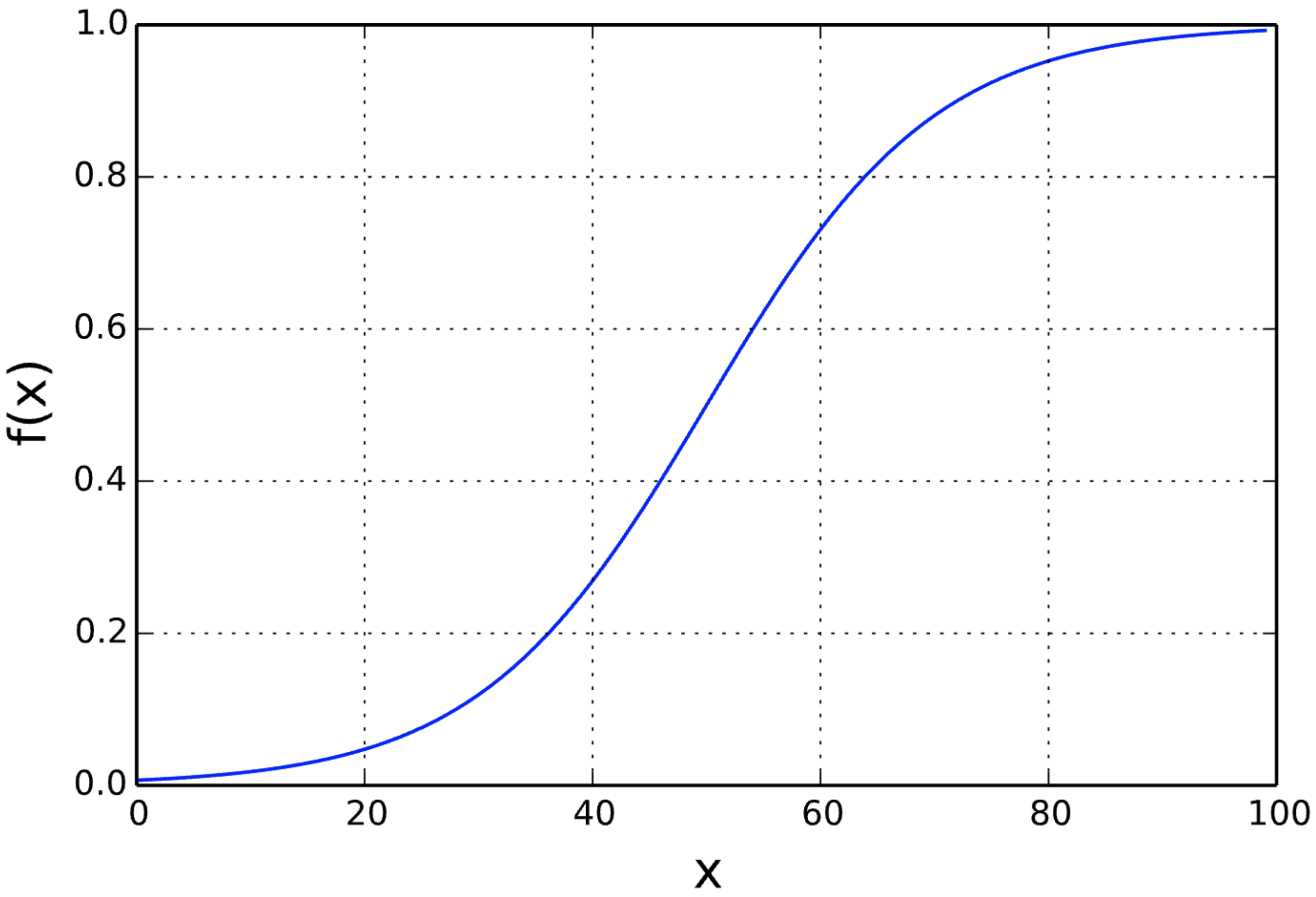
- LeNet-5: 3 conv + 2 fc
- AlexNet: 5 conv + 2 fc
- VGG-16: 13 conv + 2 fc

More conv layers

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

Hint (again): remember gradient vanishing?

Gradient vanish



Sigmoid function

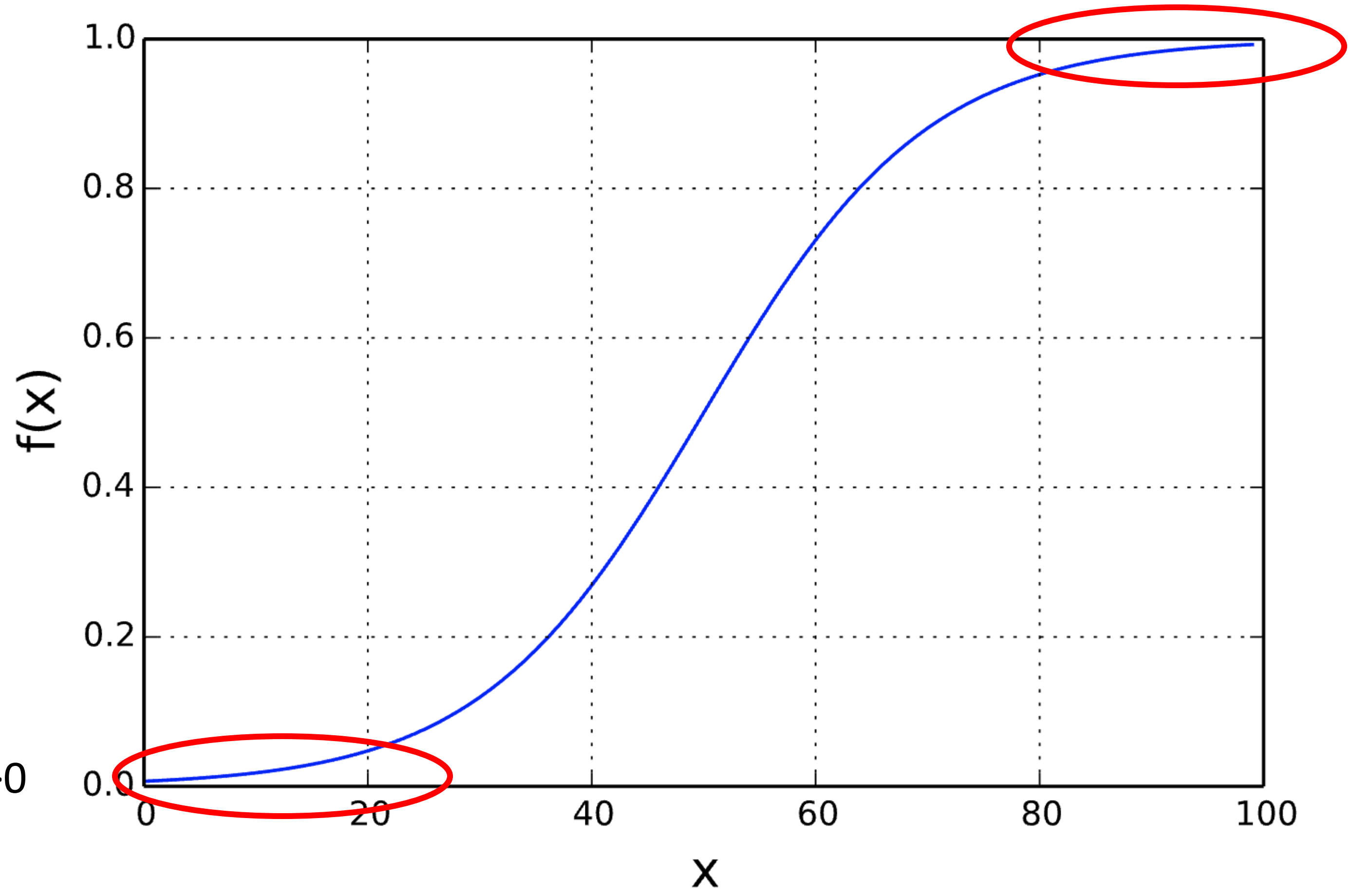
Gradient vanish

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

$$f_i \to x_i$$

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

gradients->0



gradients->0

Sigmoid function

Gradient vanish

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

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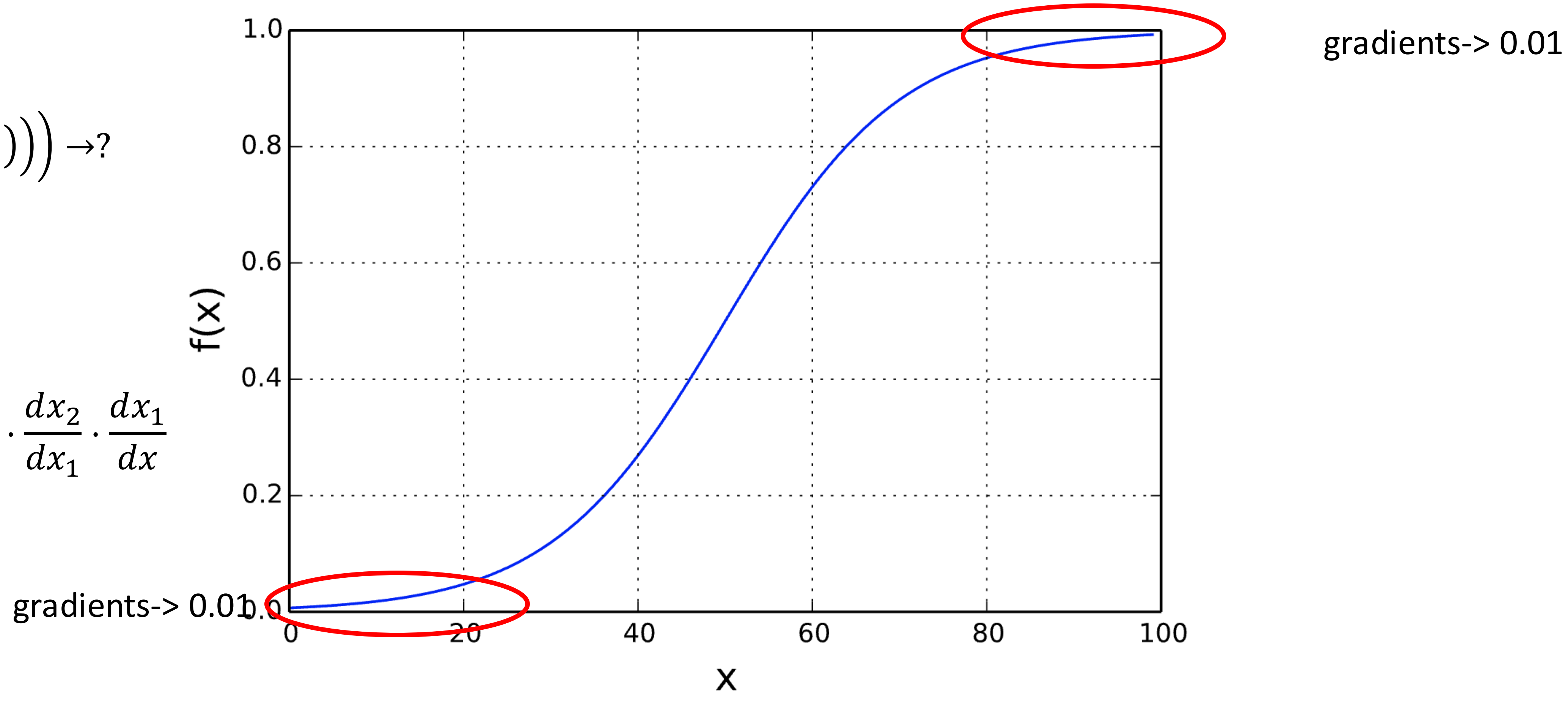


Sigmoid function

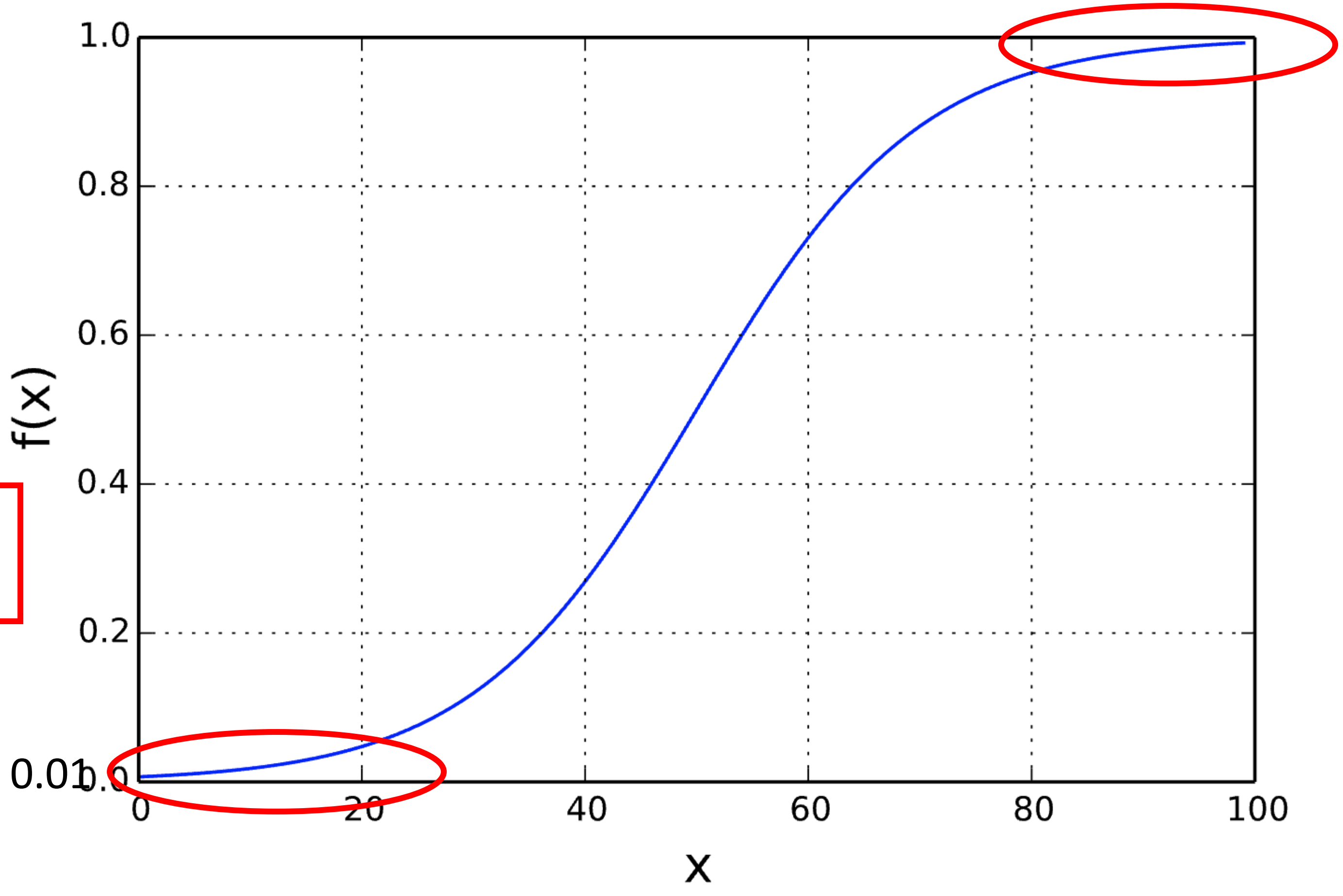
Gradient vanish

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

$$f_i \to x_i$$

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

gradients-> 0.01



gradients-> 0.01

Sigmoid function

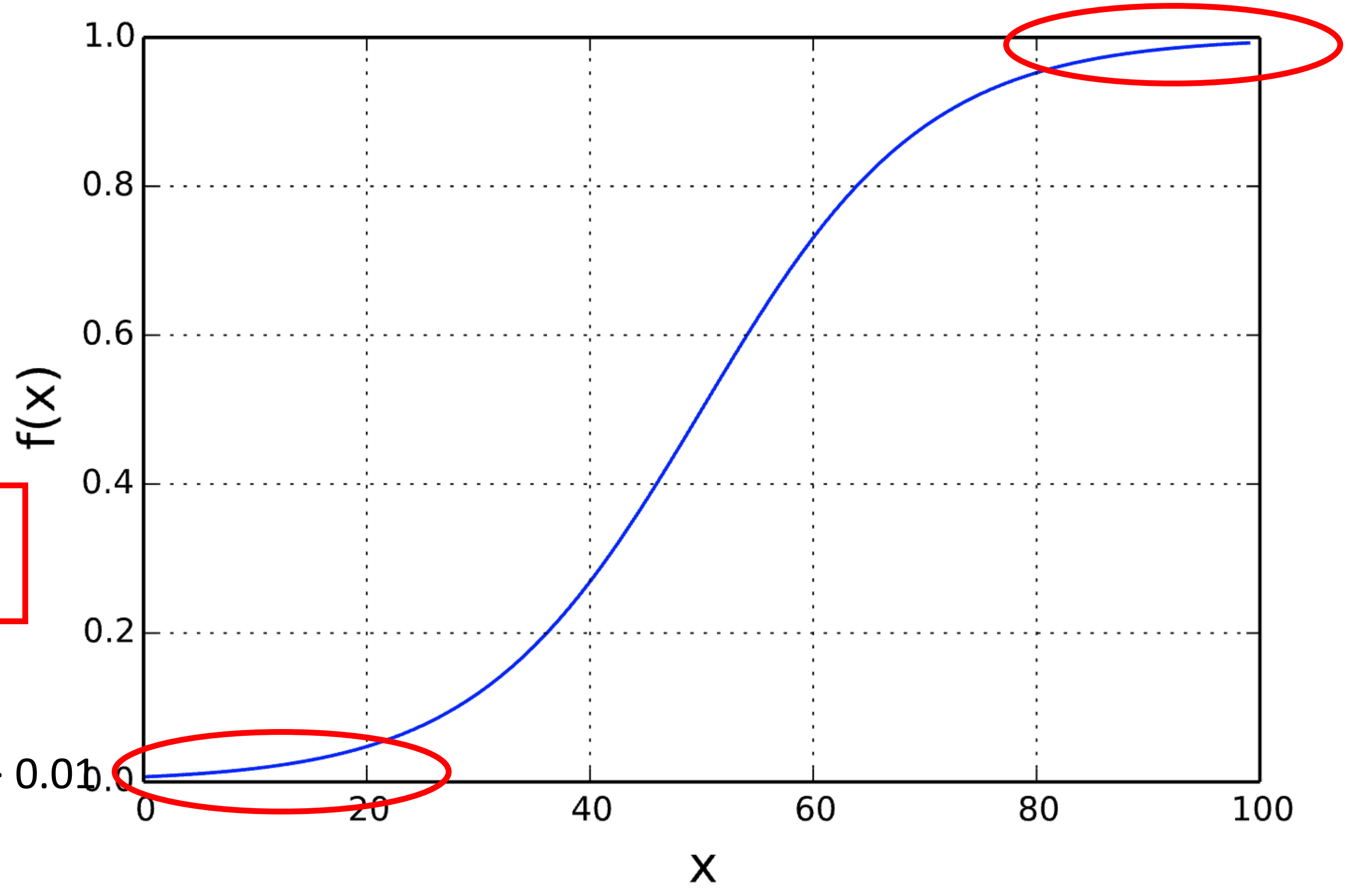
Gradient vanish

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

$$f_i \to x_i$$

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

$\to 0.01^n$



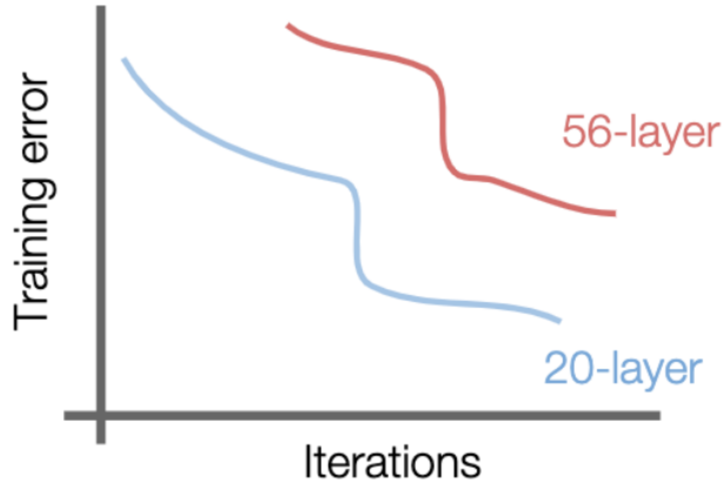
Sigmoid function

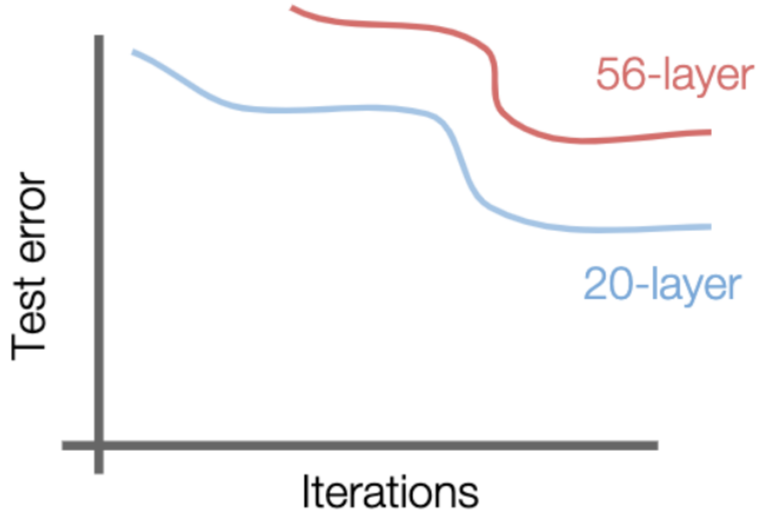
of layers

- 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.



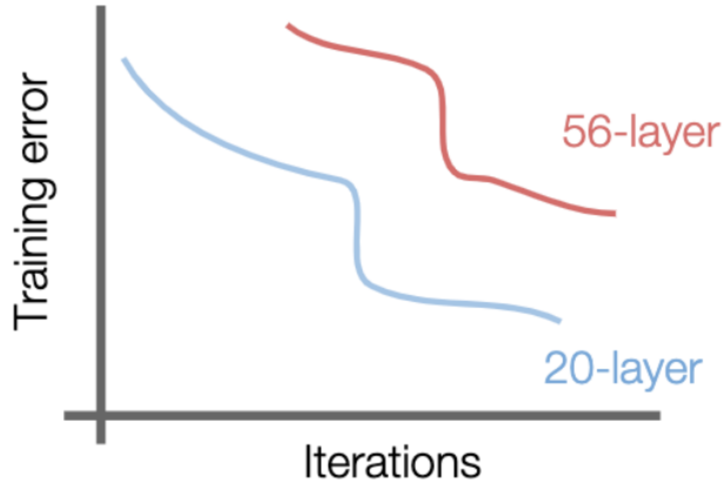


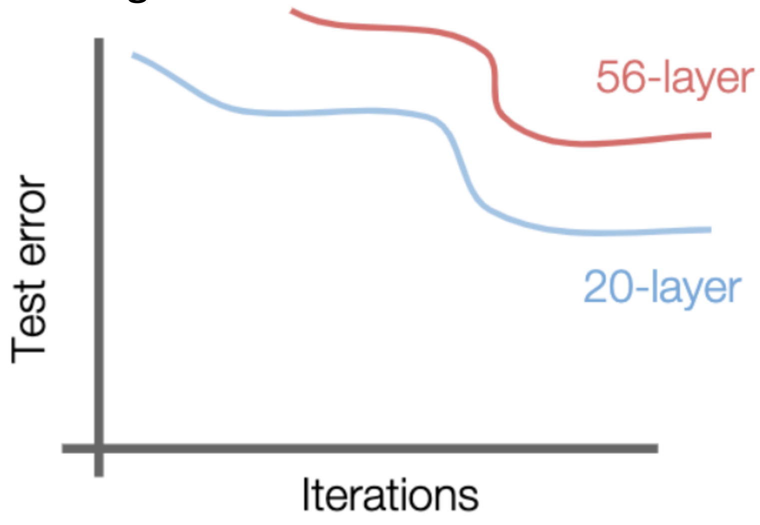
of layers

- 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.



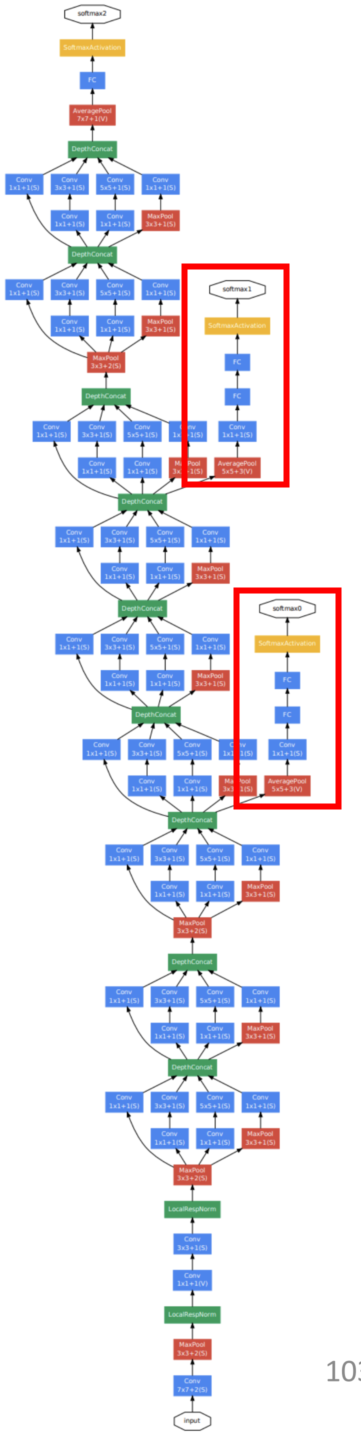


Inception

$$f_n\Big(\dots\big(f_2(f_1(x))\big)\Big) \rightarrow ?$$

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

$\rightarrow 0.01^n$

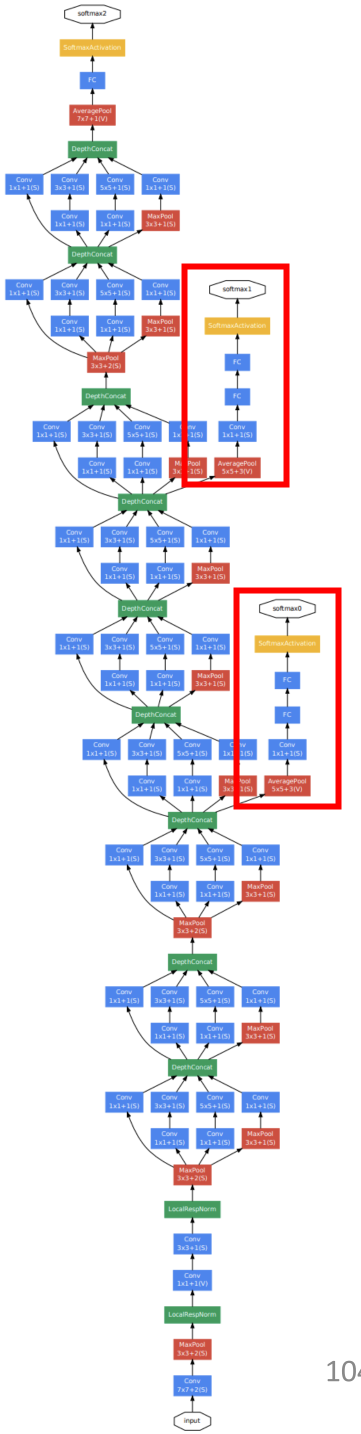


Inception

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

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

$\rightarrow 0.01^n$



Inception

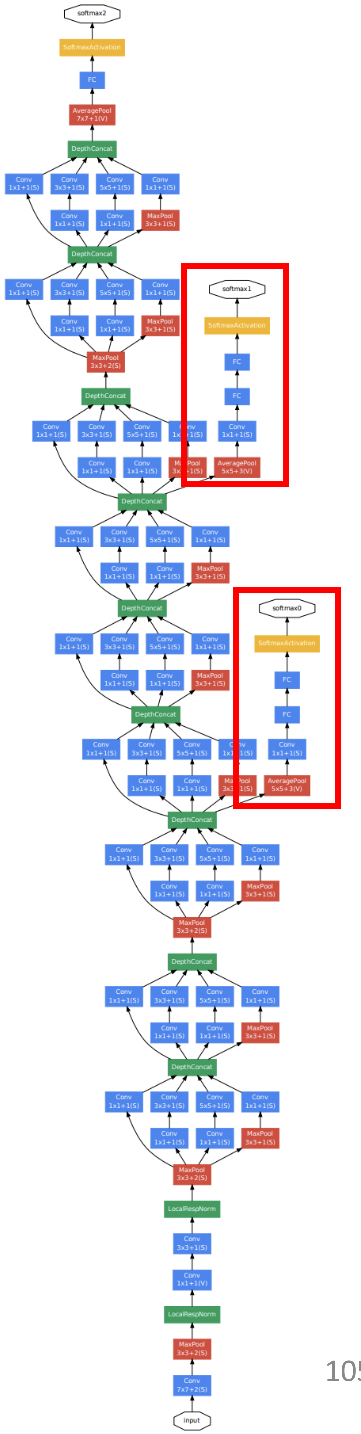
$$f_n\left(\dots\left(f_2\left(f_1(x)\right)\right)\right) + f_m\left(\dots\left(f_{n+2}\left(f_{n+1}(x)\right)\right)\right)$$

$$\boxed{\frac{dx_n}{dx_1}} = \boxed{\frac{dx_n}{dx_{n-1}} \cdot \dots \cdot \frac{dx_2}{dx_1} \cdot \frac{dx_1}{dx}} + \boxed{\frac{dx_m}{dx_{m-1}} \cdot \dots \cdot \frac{dx_{n+2}}{dx_{n+1}} \cdot \frac{dx_{n+1}}{dx}}$$

$\to 0.01^n$

>> 0

Will not be very small



Residual neural networks (ResNet)

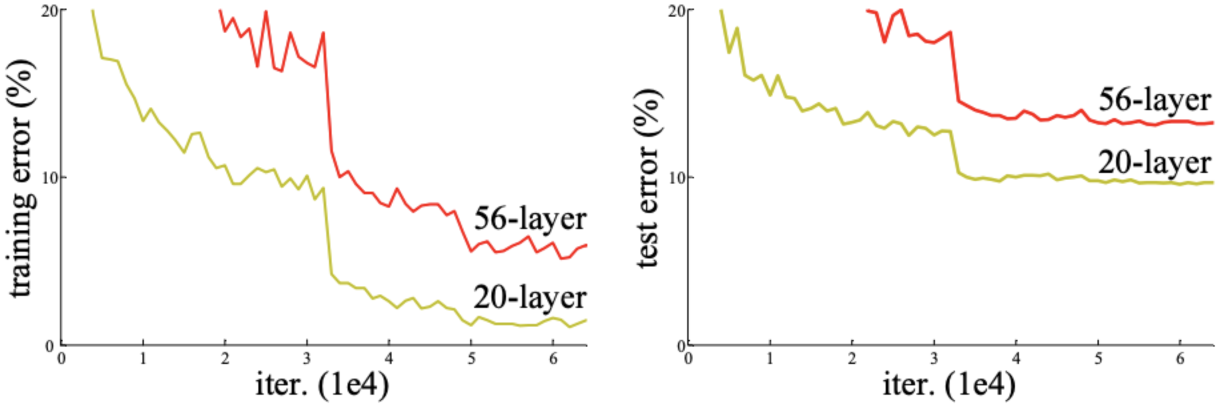


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

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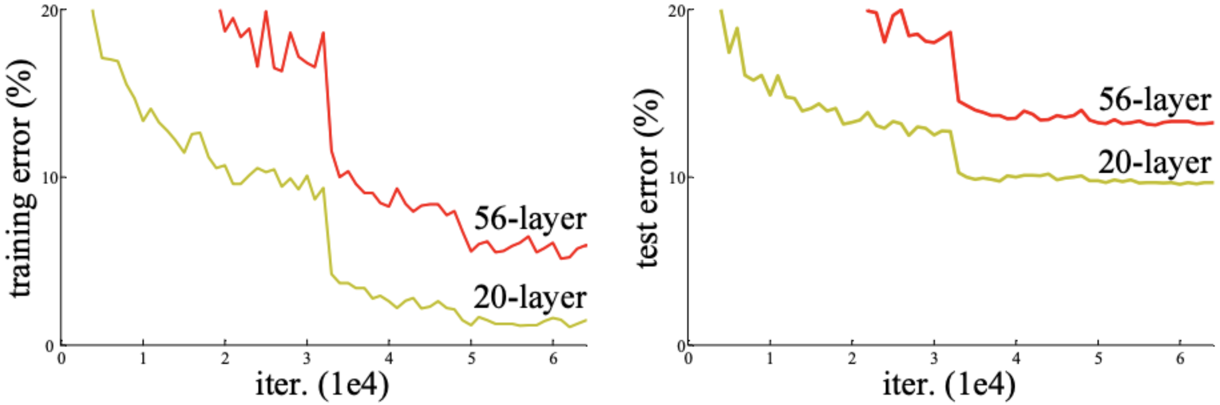


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer “plain” networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

Without special structure other than conv/fc layers

ResNet: shortcut connection

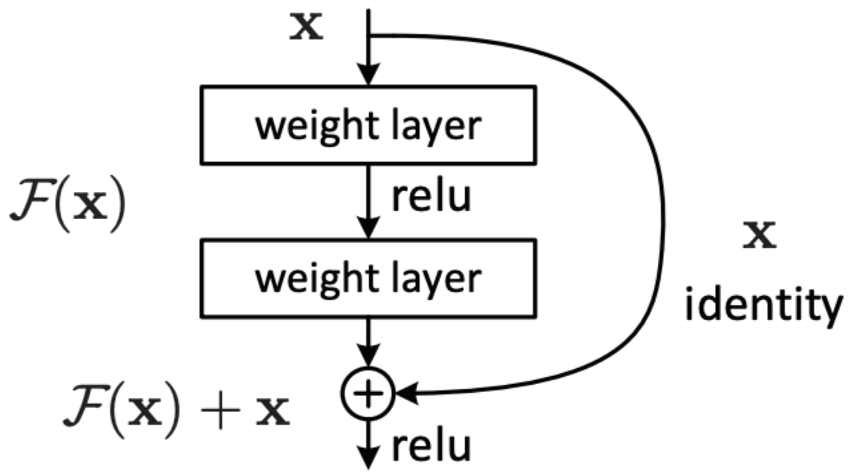
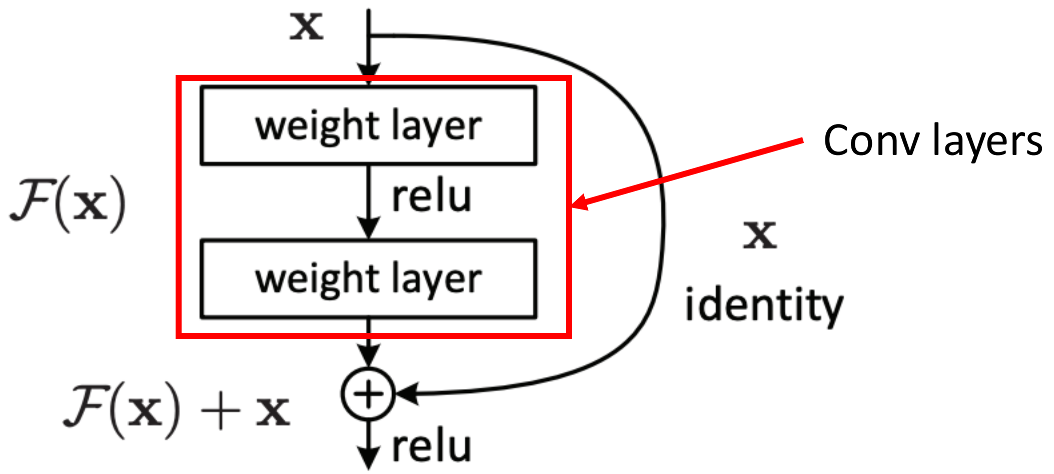


Figure 2. Residual learning: a building block.

ResNet: shortcut connection



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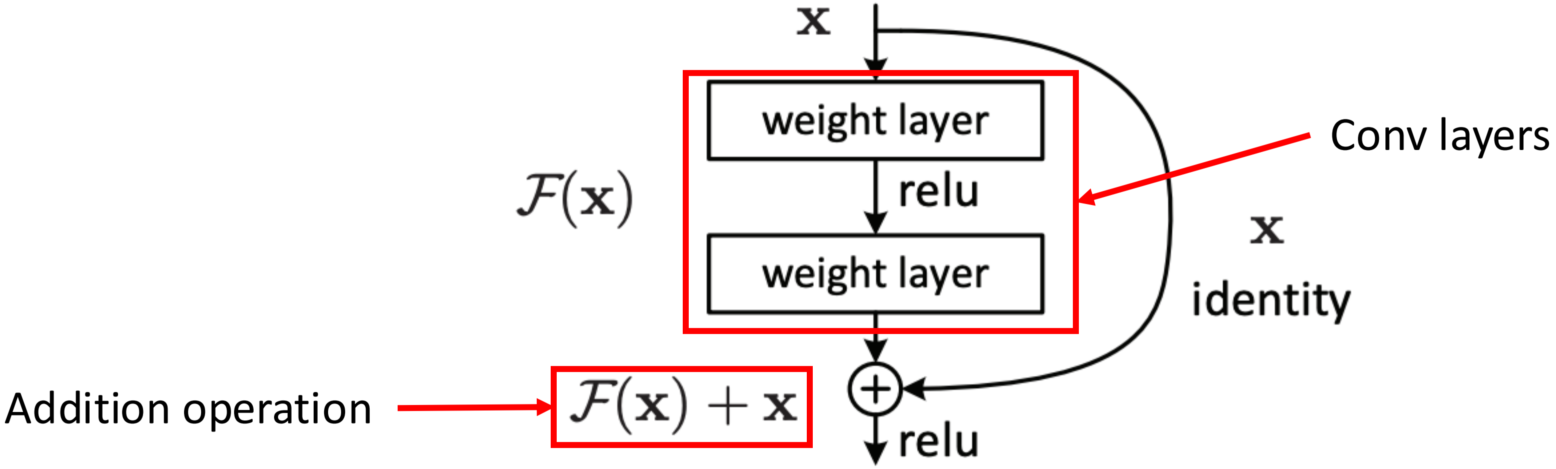

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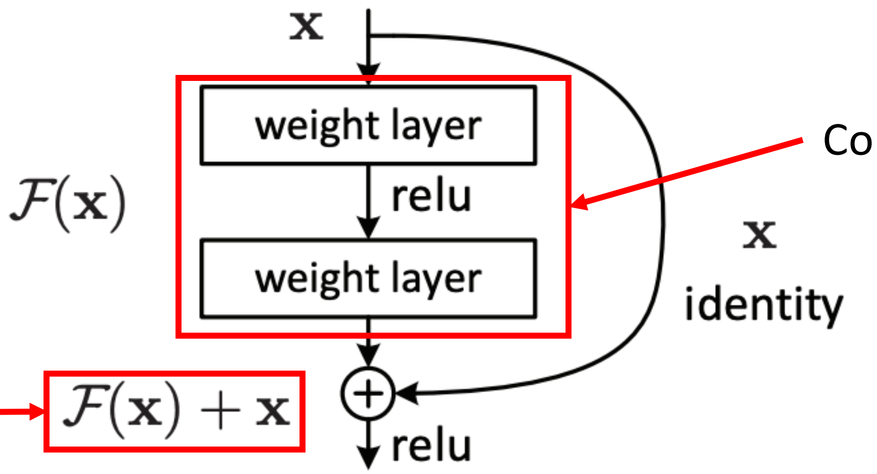


Conv layers

Addition operation

implication: same dimension

Figure 2. Residual learning: a building block.

ResNet

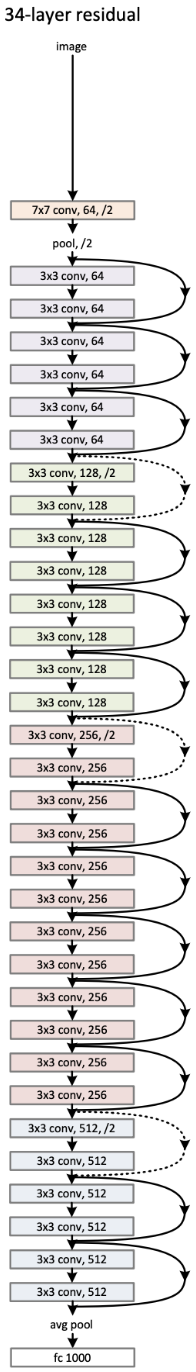
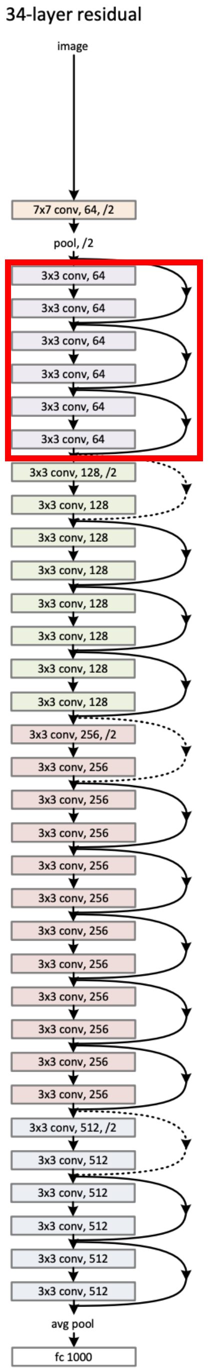


Figure 3. Example network architectures for ImageNet. **Left**: the VGG-19 model [41] (19.6 billion FLOPs) as a reference. **Middle**: a plain network with 34 parameter layers (3.6 billion FLOPs). **Right**: a residual network with 34 parameter layers (3.6 billion FLOPs). The dotted shortcuts increase dimensions. **Table 1** shows more details and other variants.

ResNet



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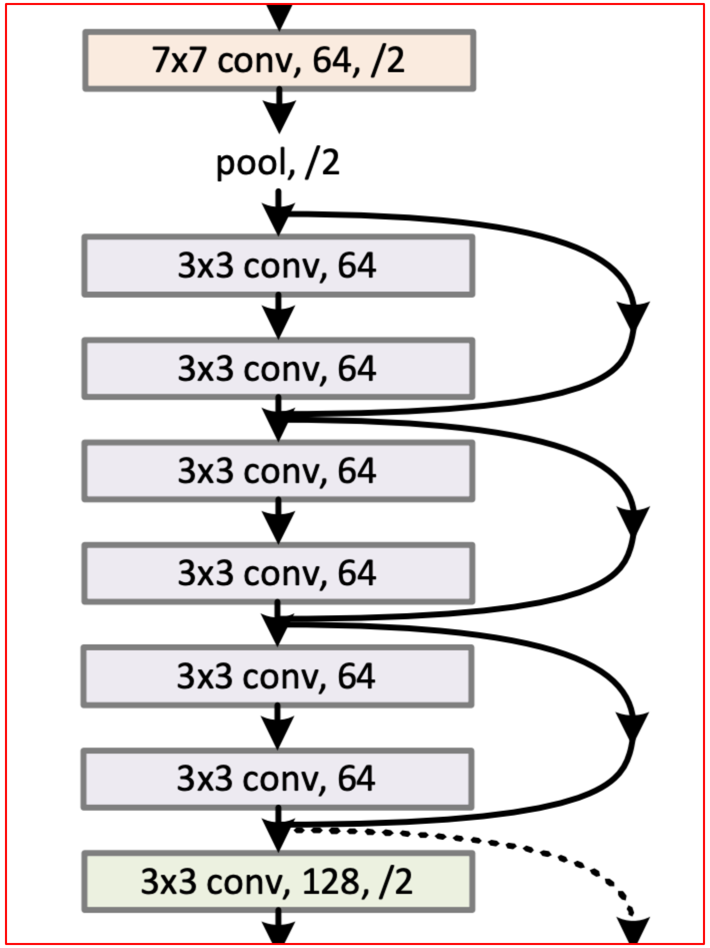
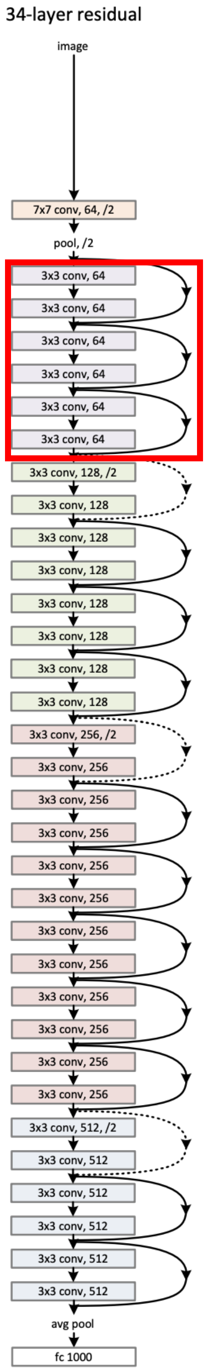
ResNet





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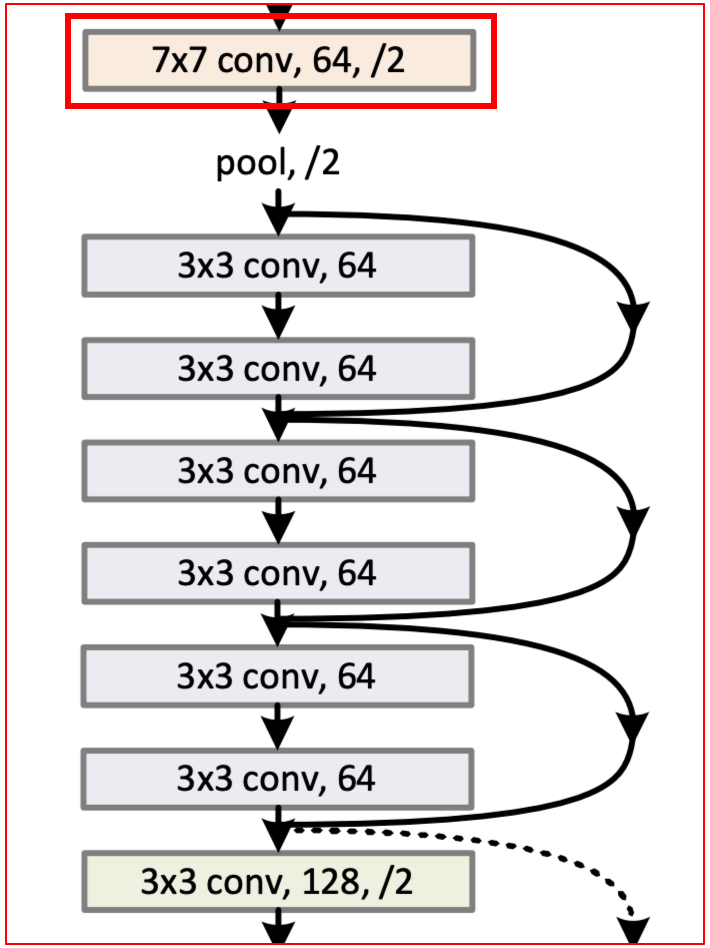
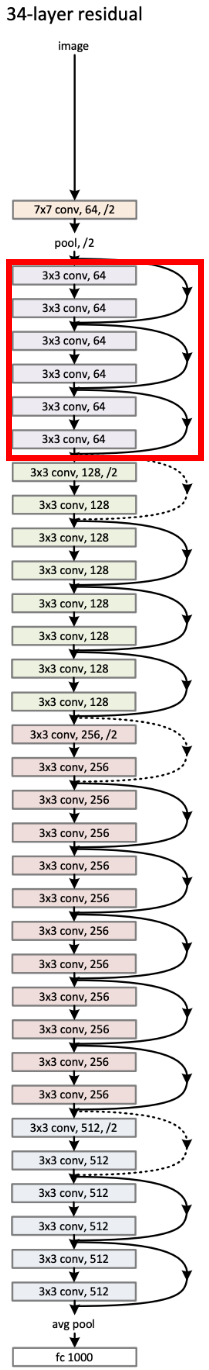
ResNet





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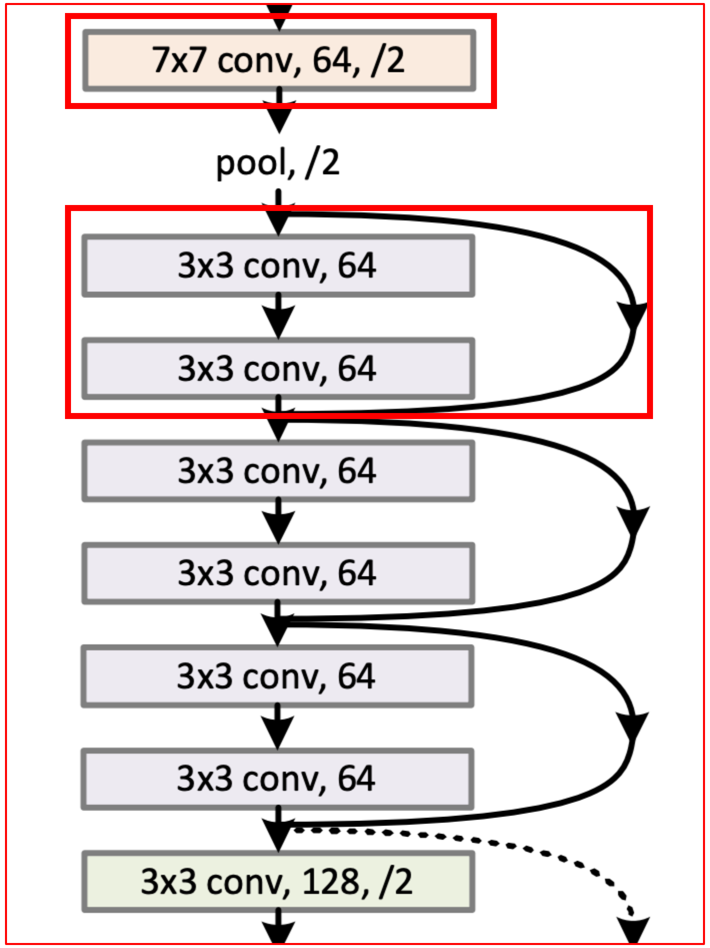
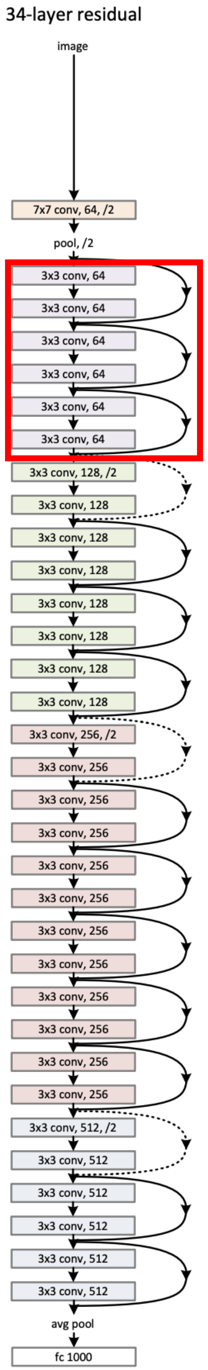
ResNet





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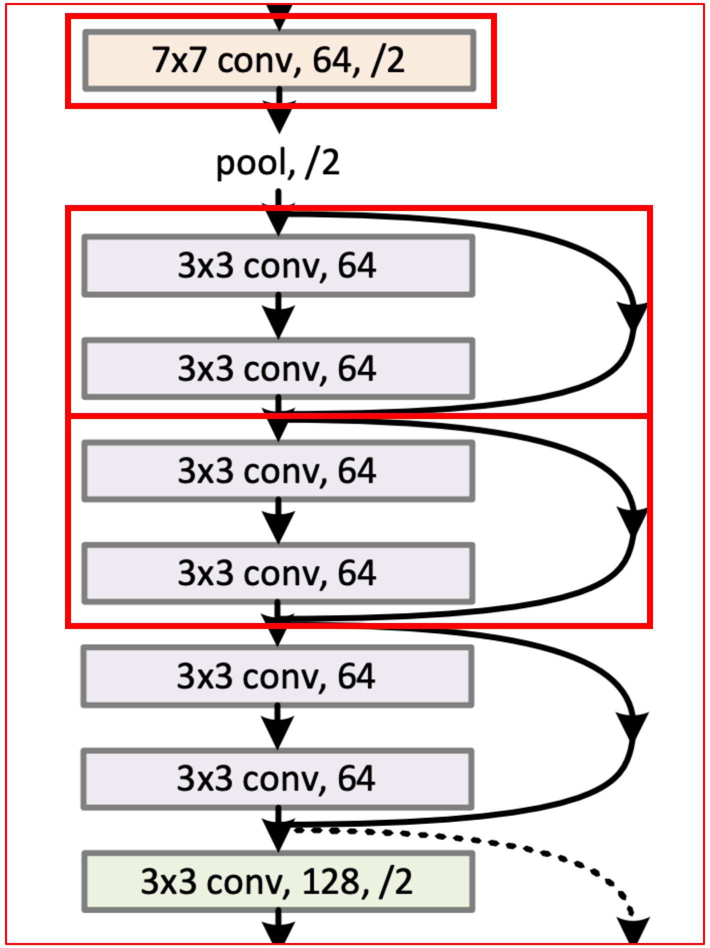
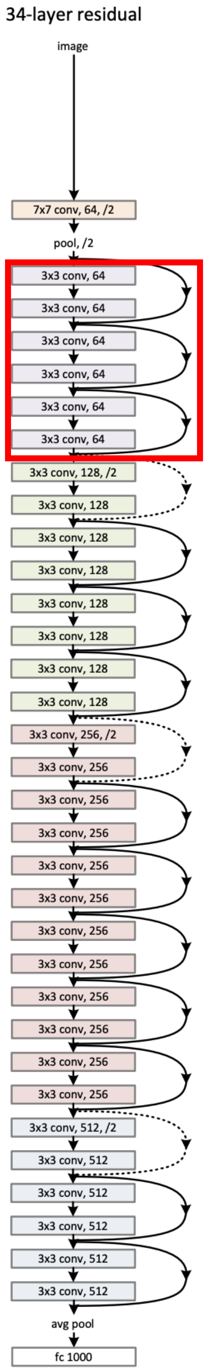
ResNet





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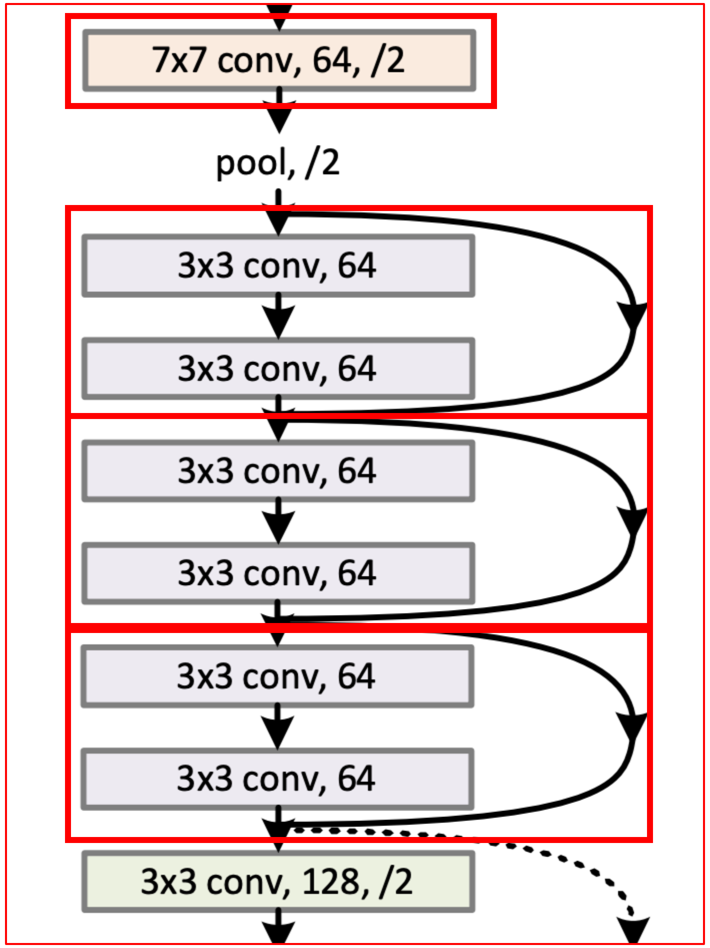
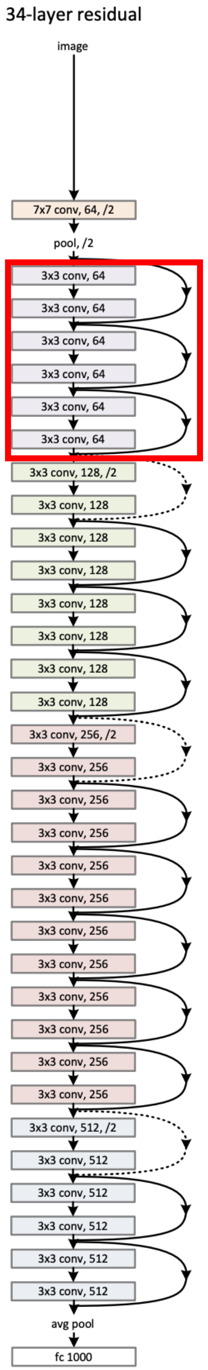
ResNet





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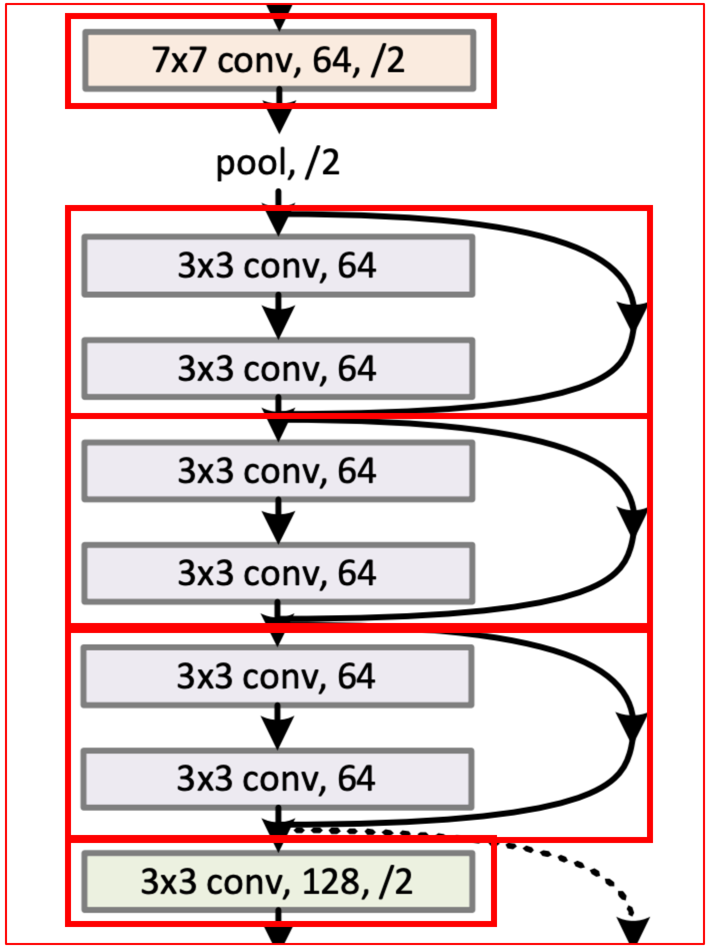
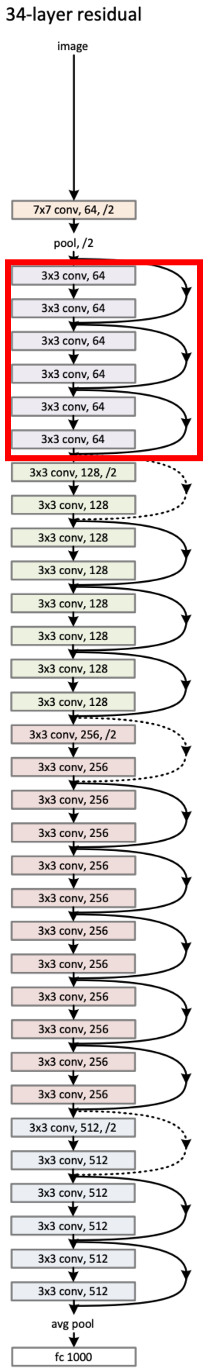
ResNet





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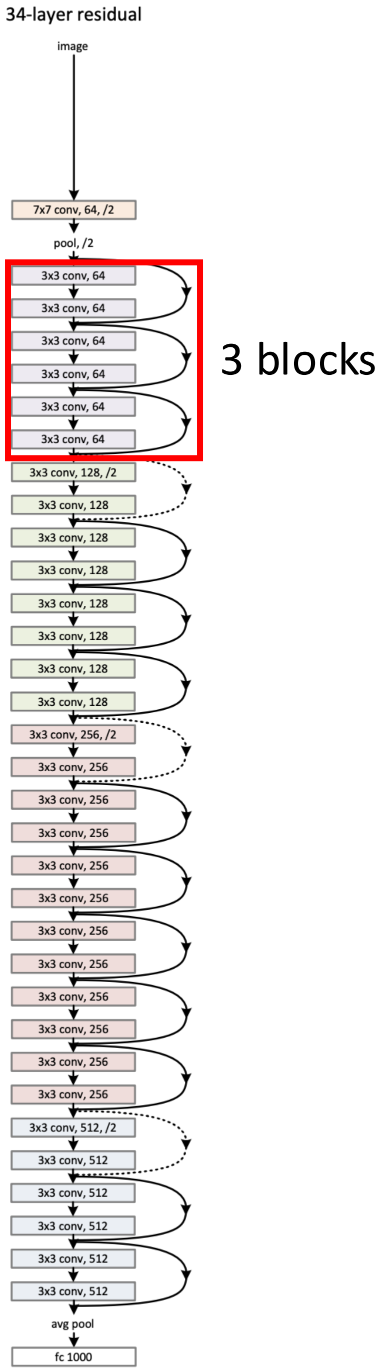

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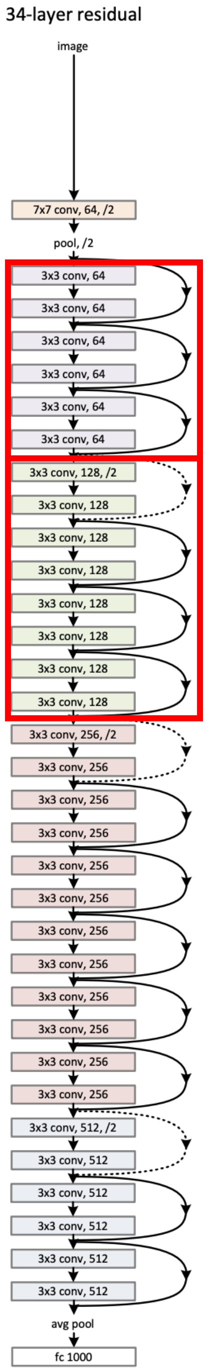
ResNet



3 blocks

4 blocks

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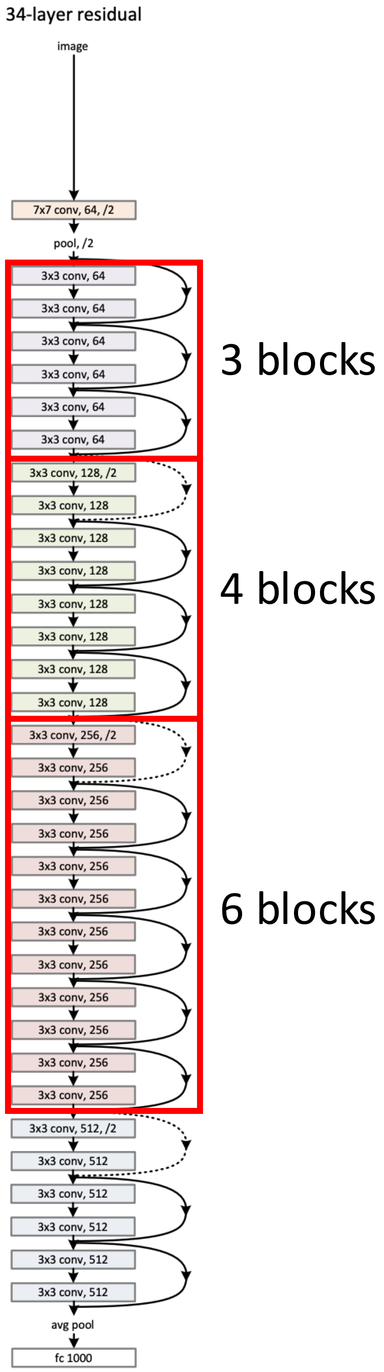
ResNet



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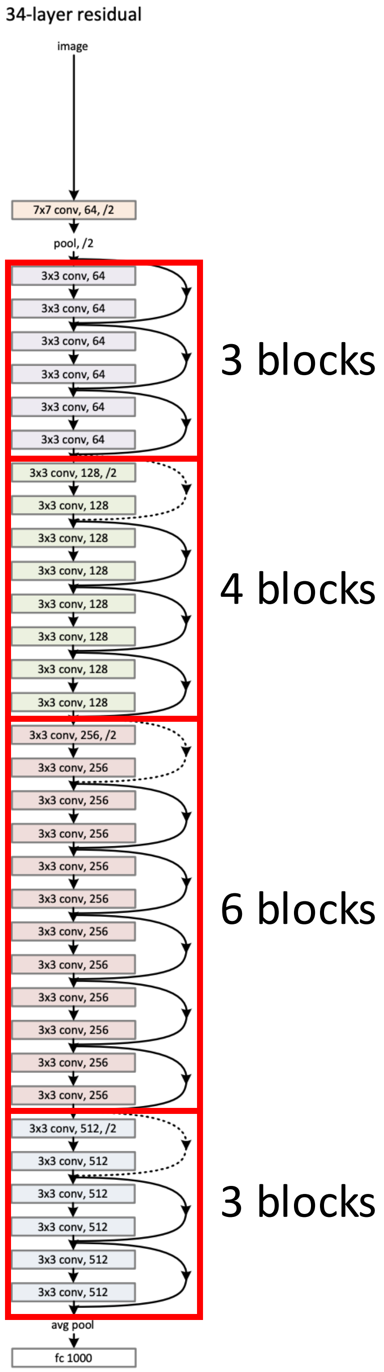
ResNet



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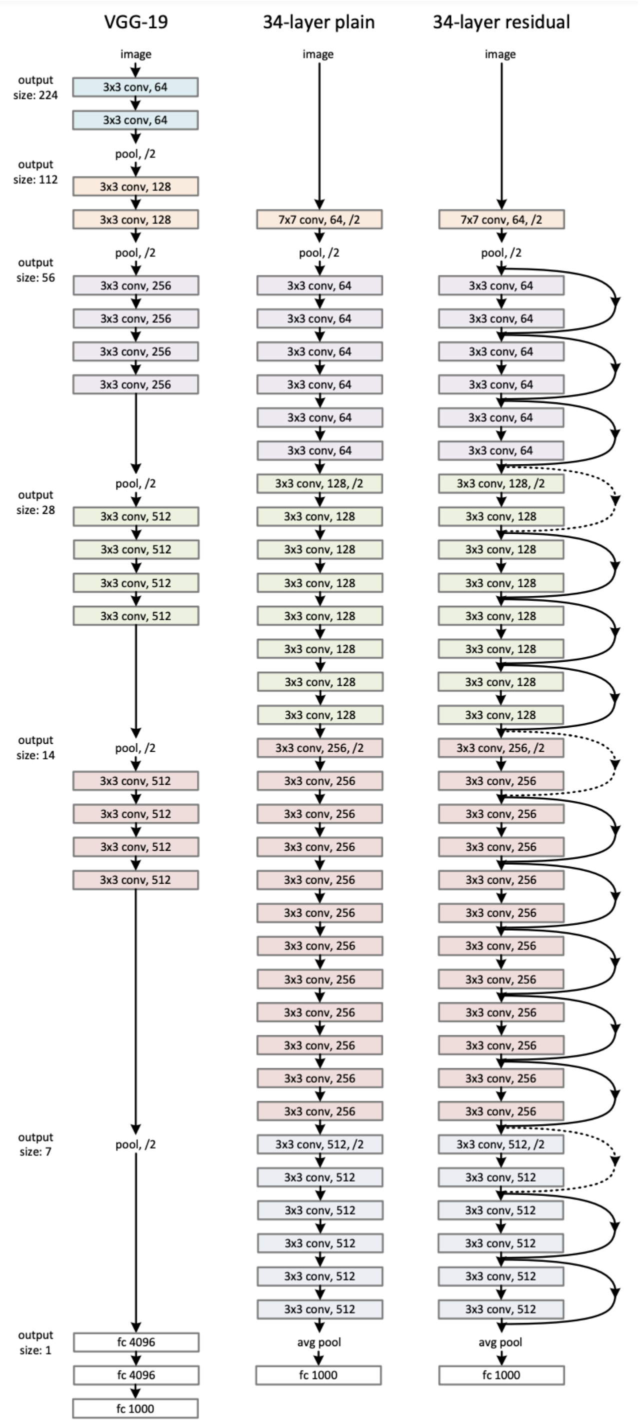

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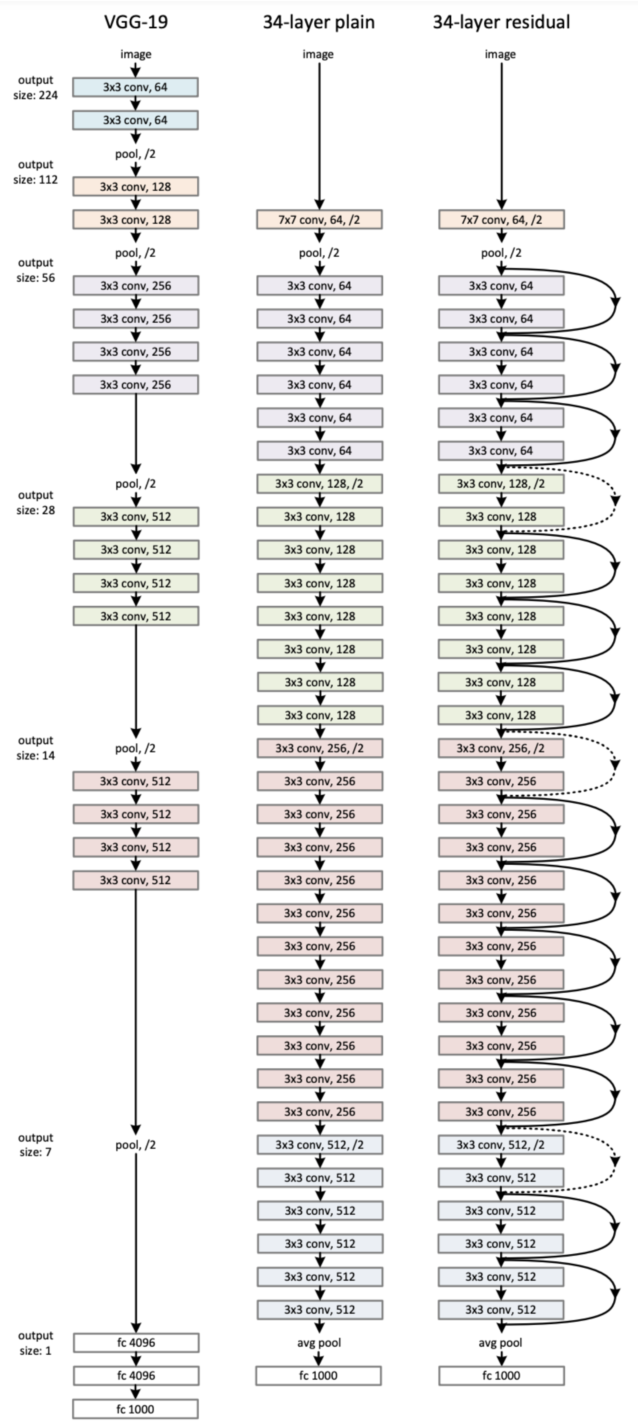

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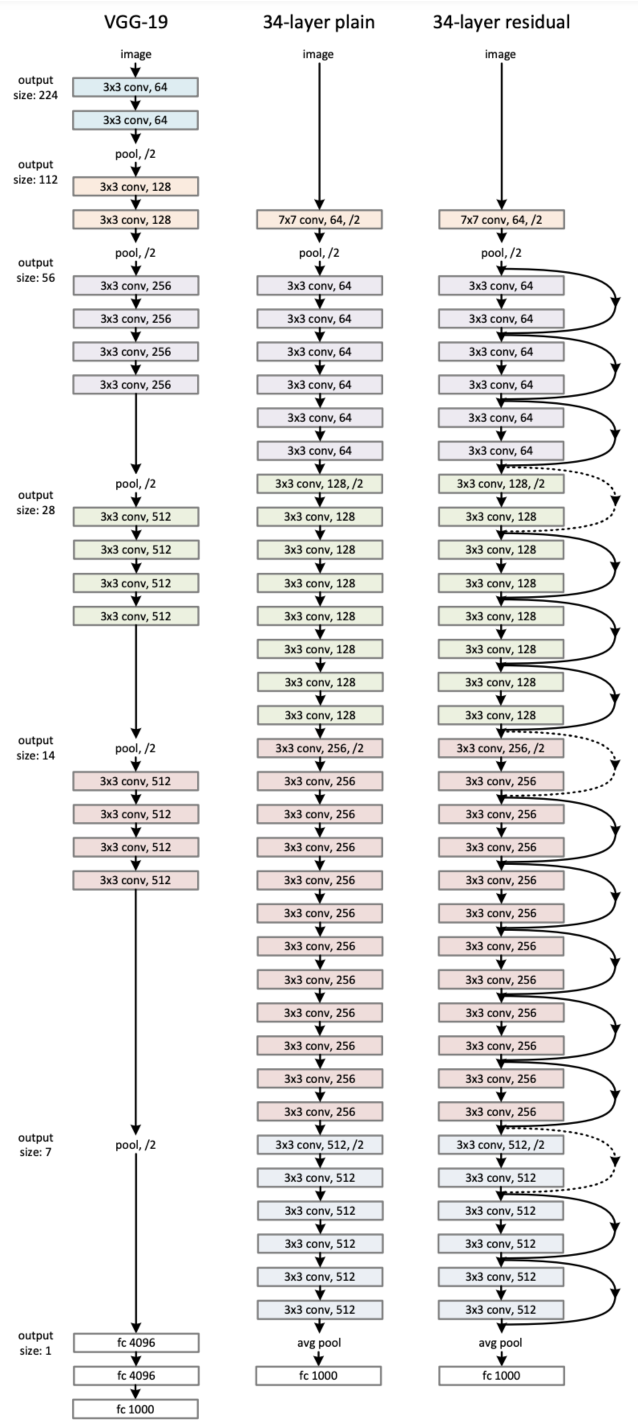
ResNet



floating point operations per second

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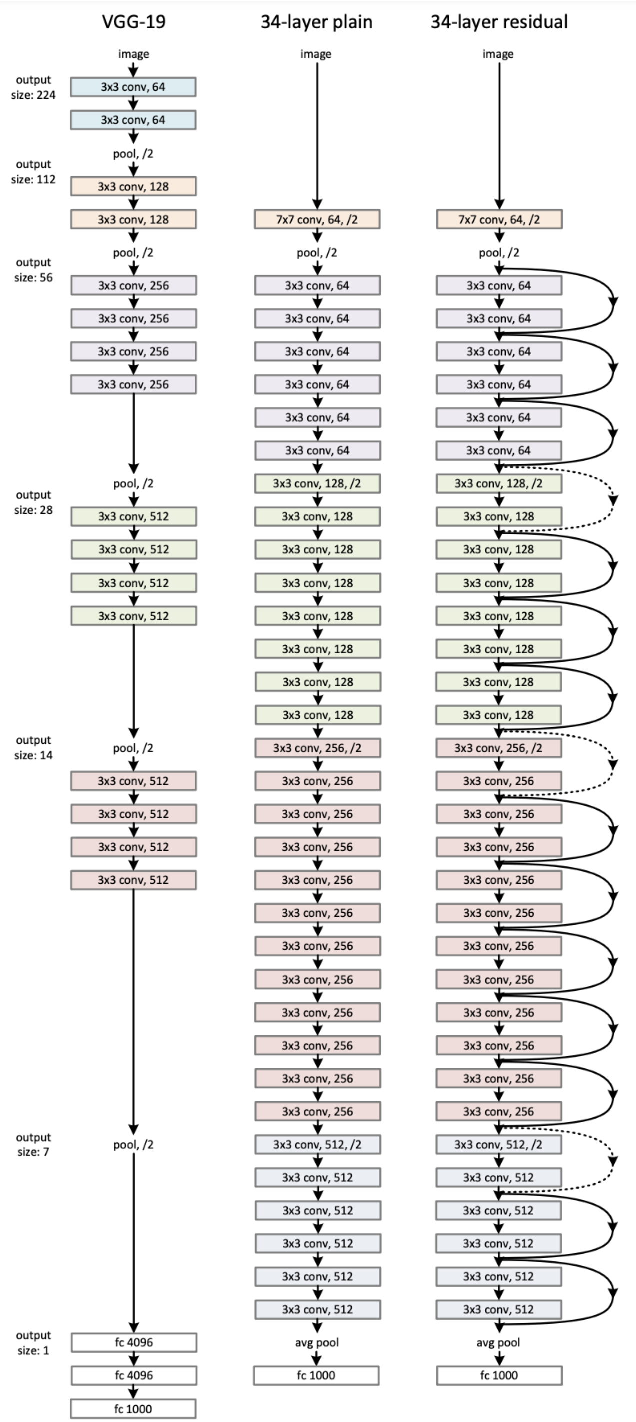
ResNet



Measure: how complicated the model is

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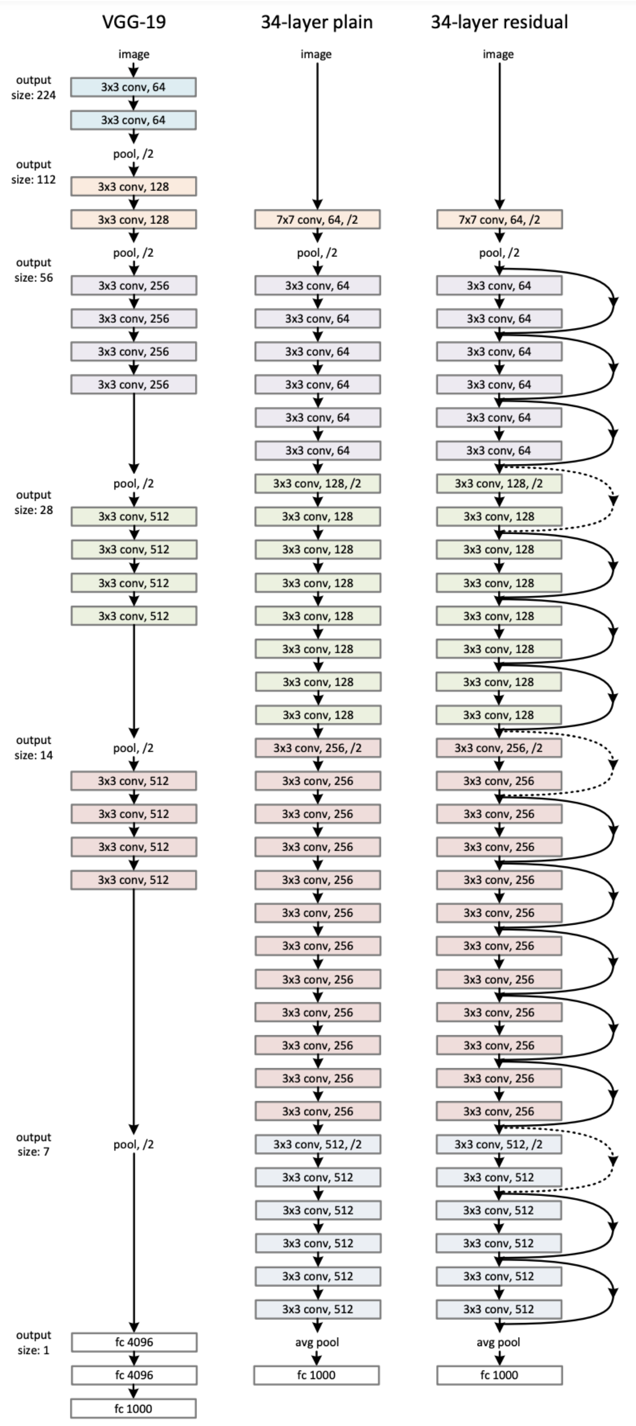
ResNet



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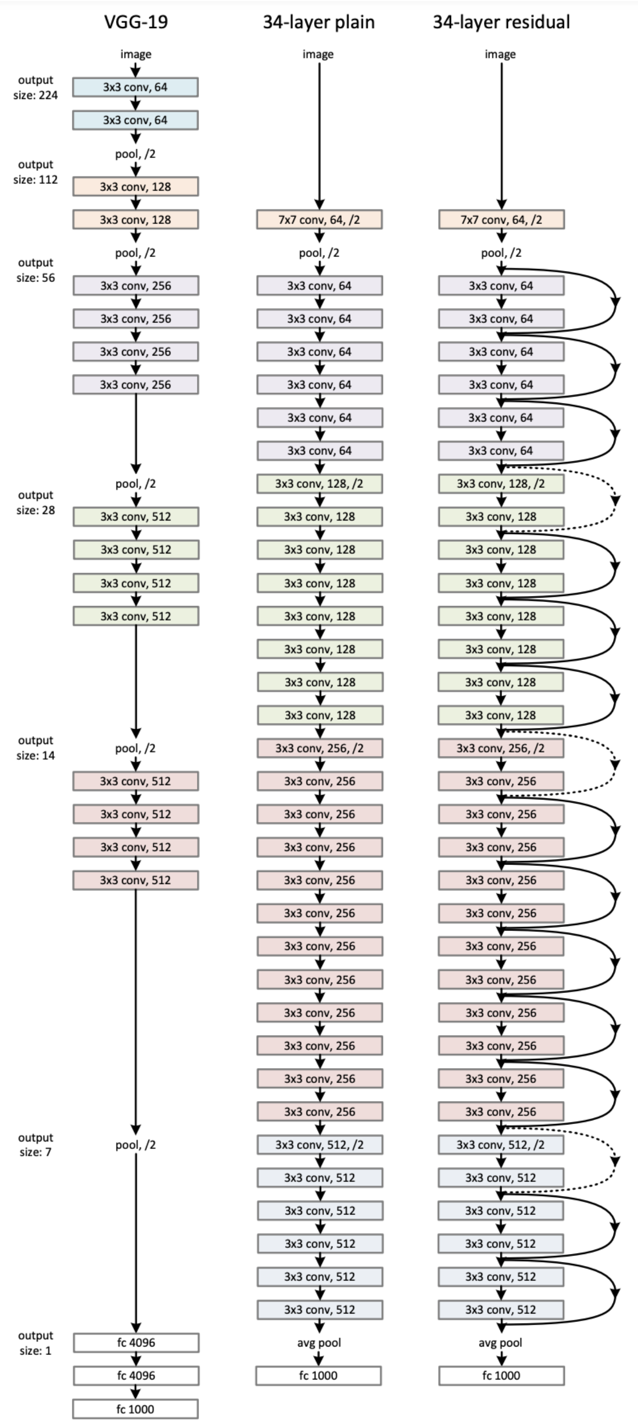

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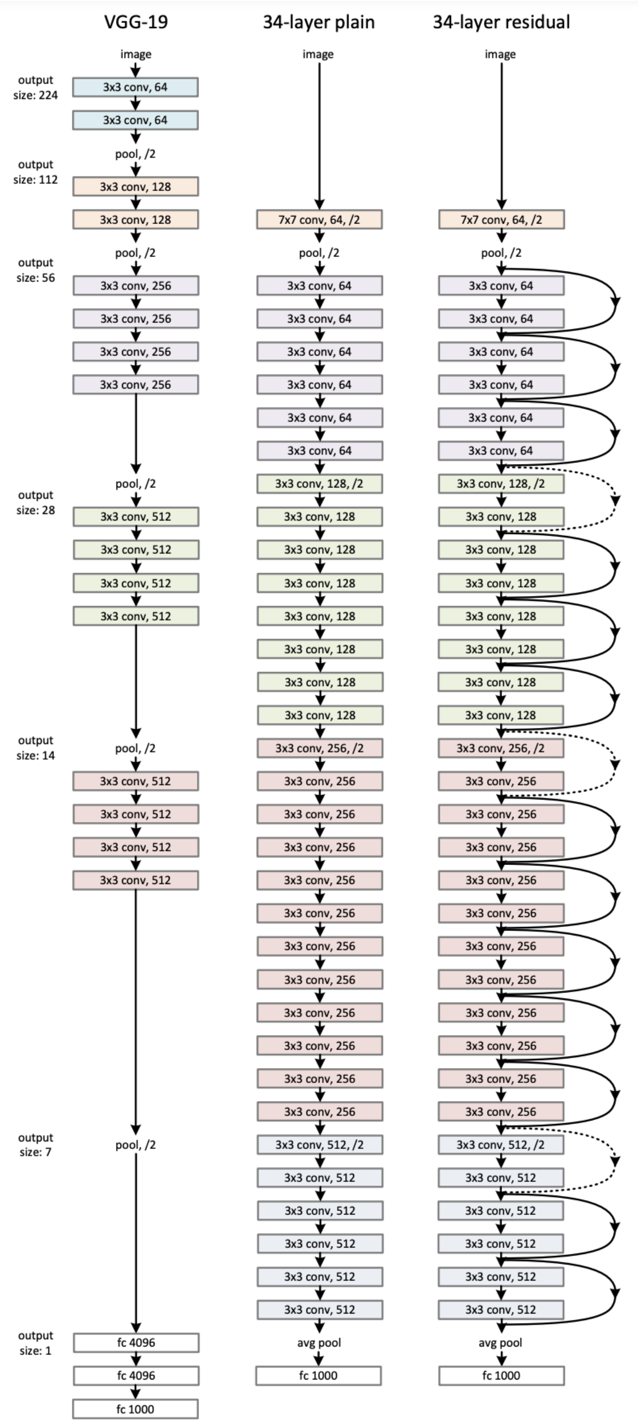
ResNet



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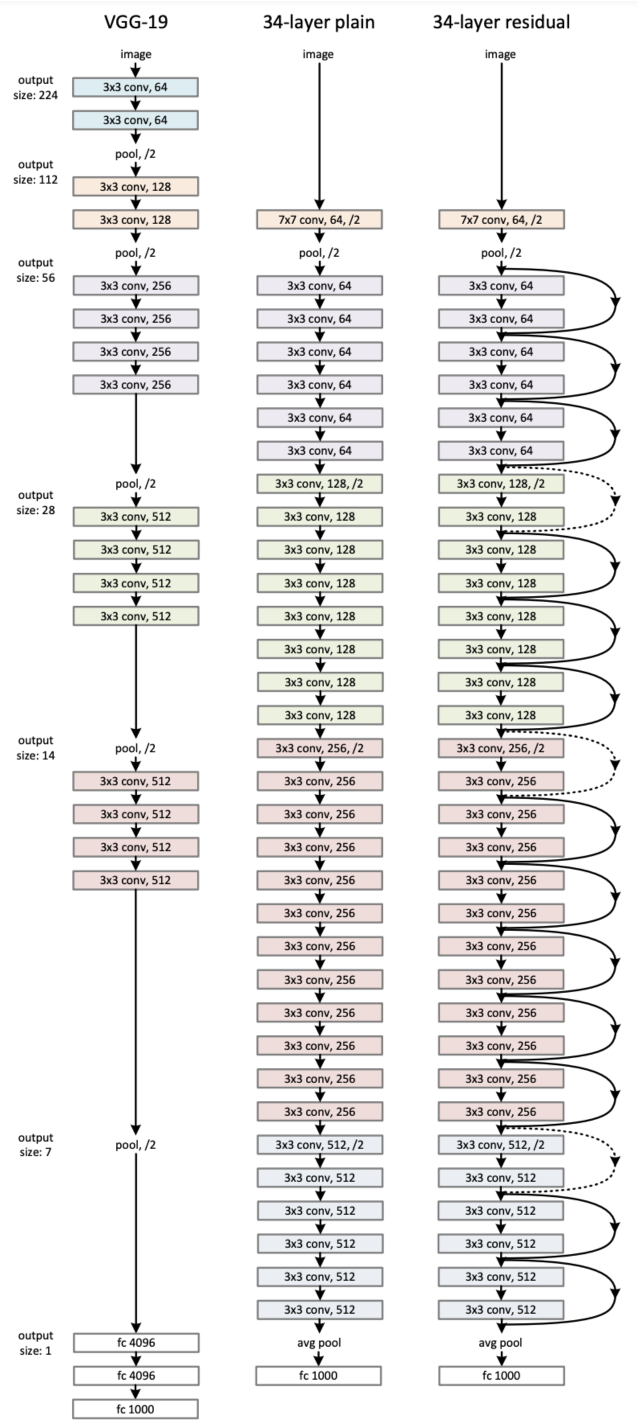
Q: VGG-19 has much more FLOPS than 34-layer plain network and 34-layer ResNet?

ResNet



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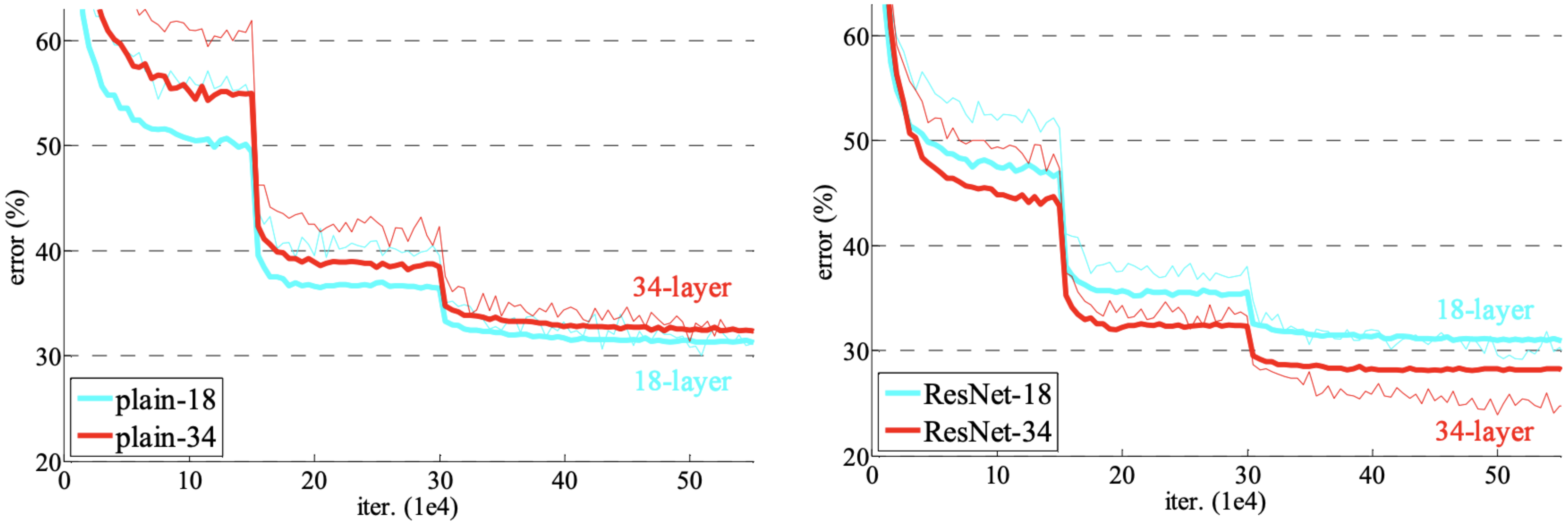
[Reading material]

ResNet



60
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error (%)
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iter. (1e4)
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18-layer
plain-18
plain-34
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error (%)
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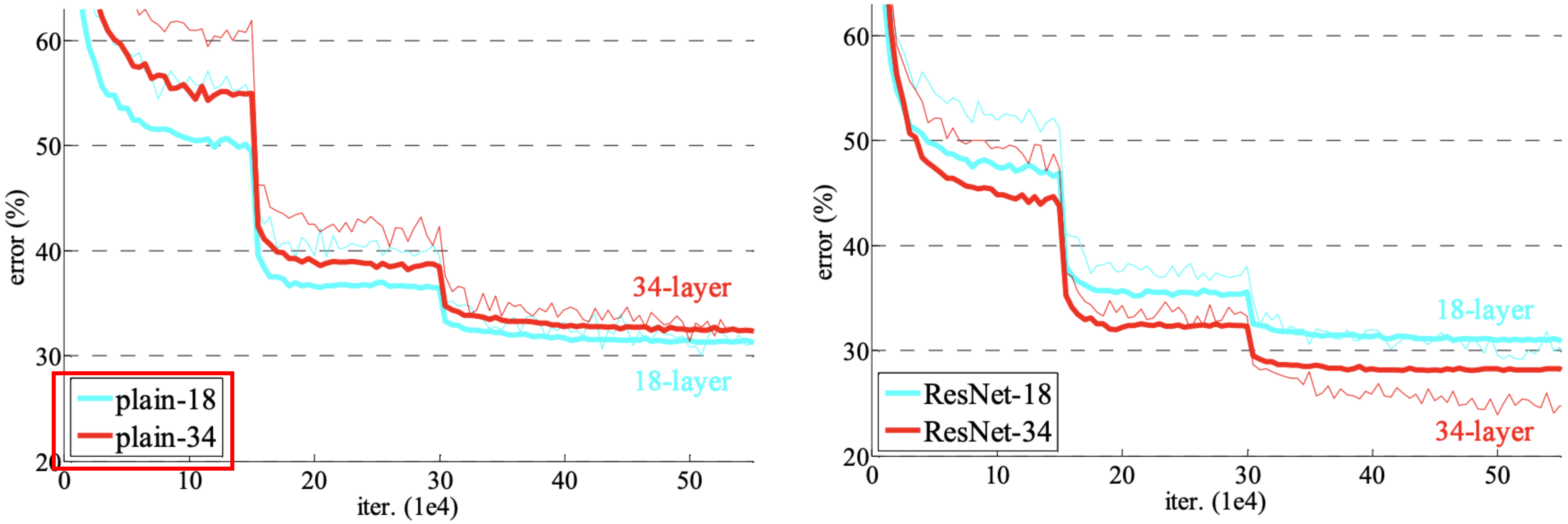
iter. (1e4)
18-layer
34-layer
ResNet-18
ResNet-34

ResNet



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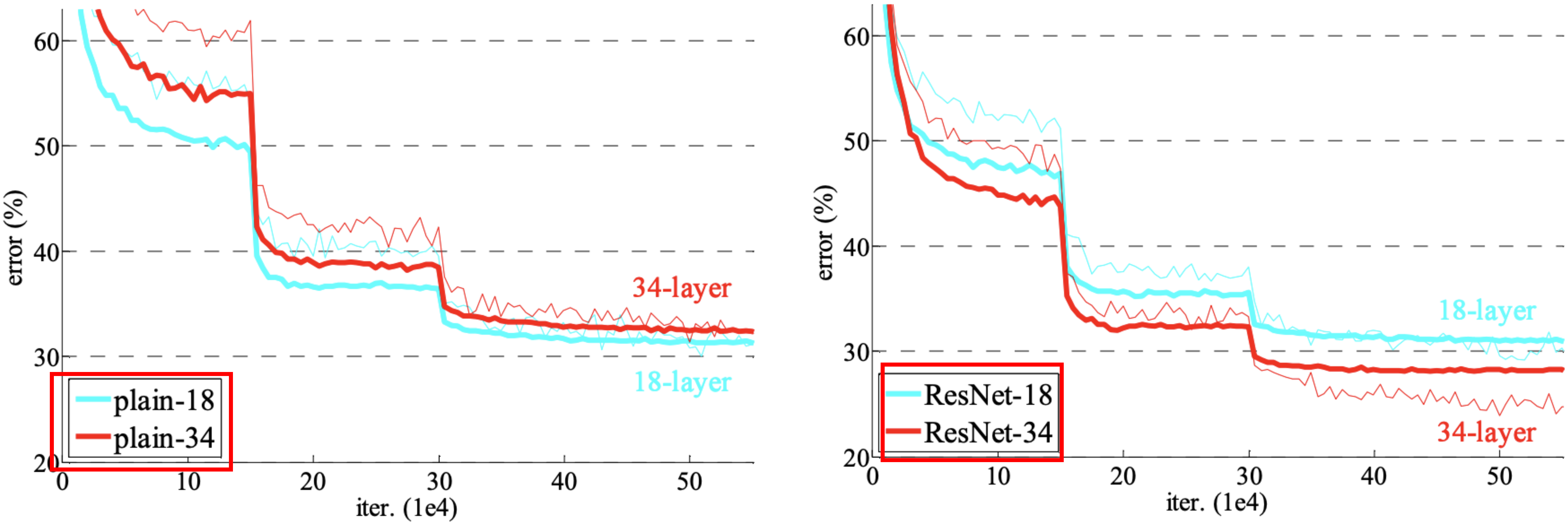
ResNet-34

ResNet



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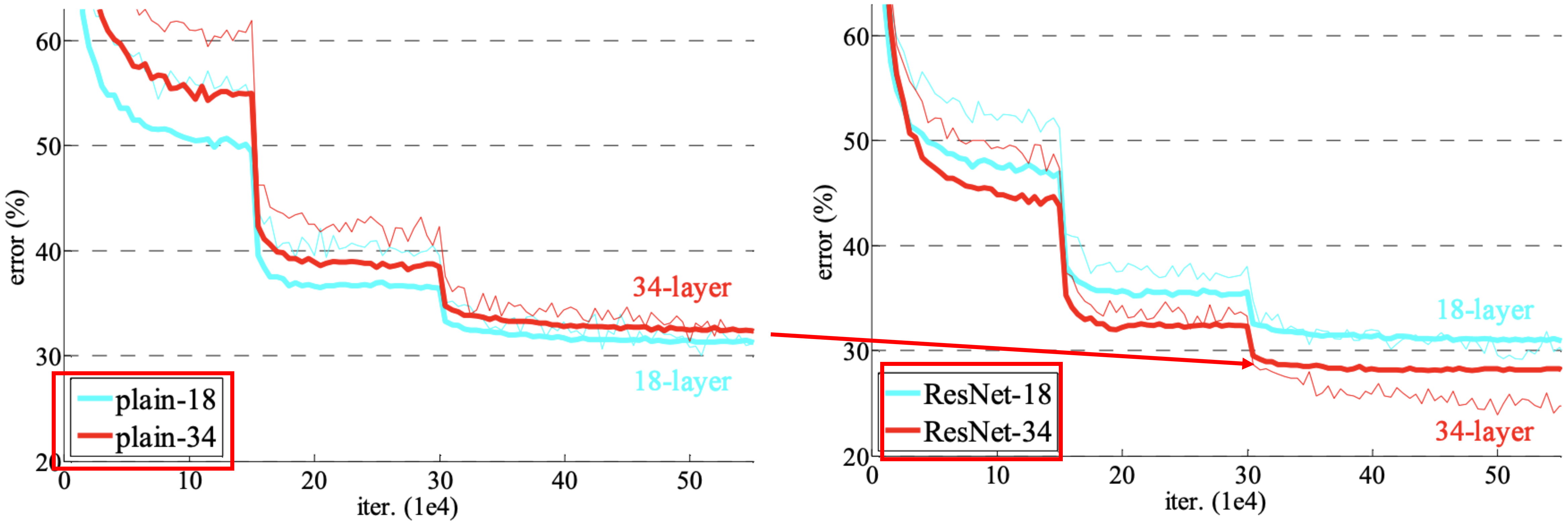
ResNet-34

ResNet



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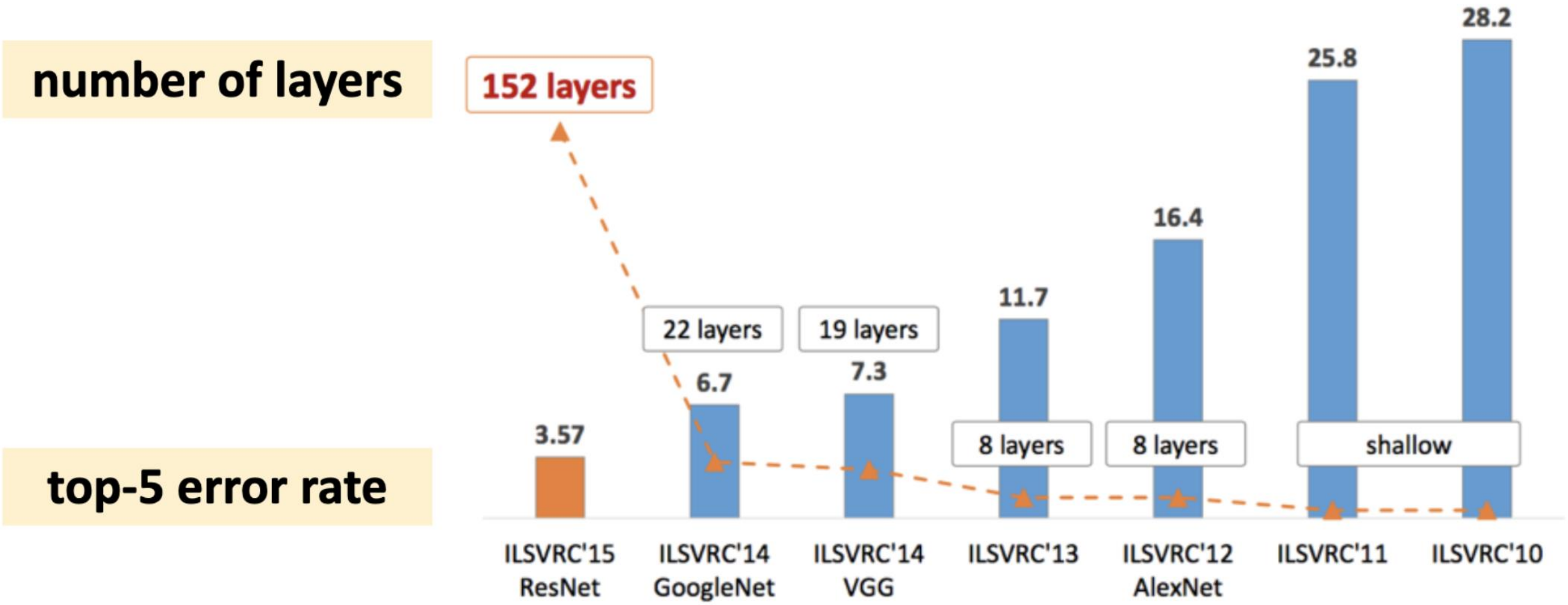
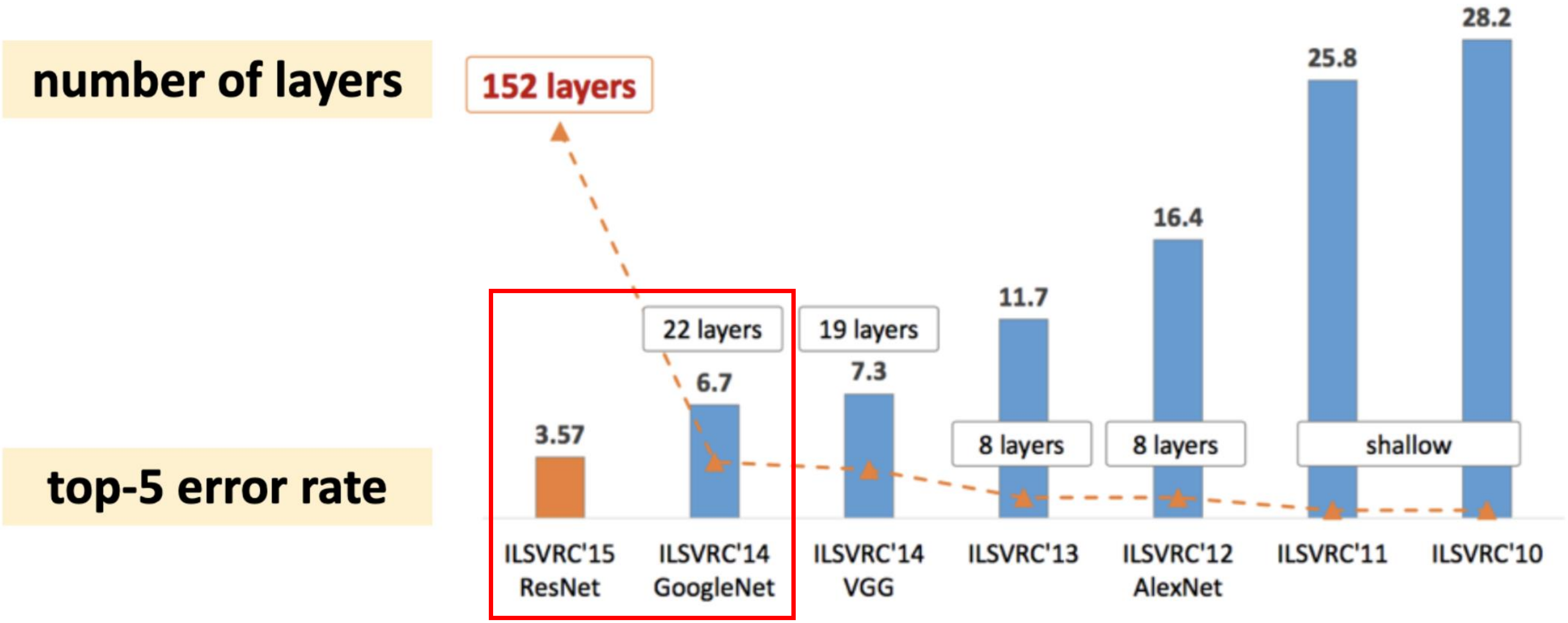
ResNet-34

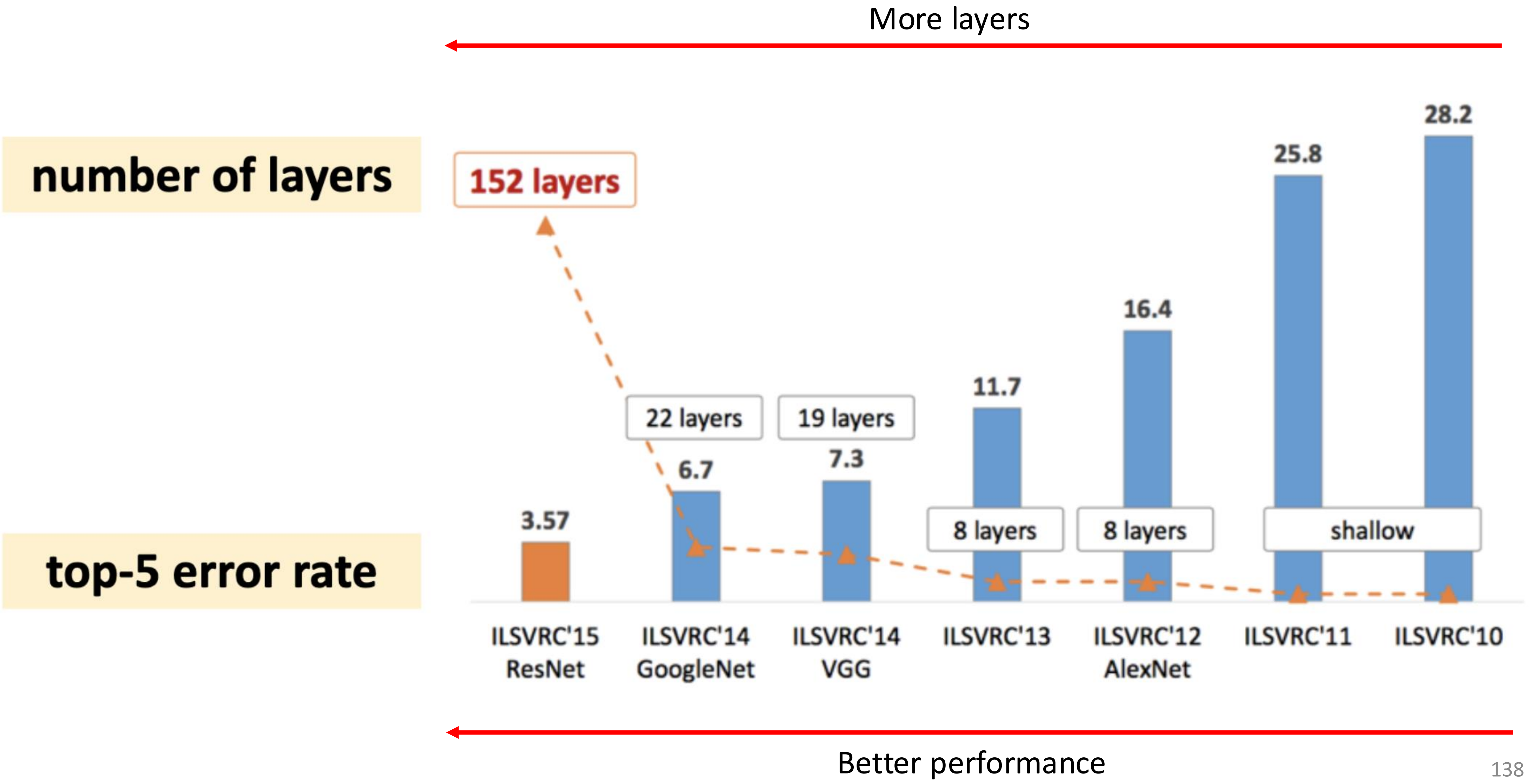
ImageNet competition winners



ImageNet competition winners



ImageNet competition winners



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