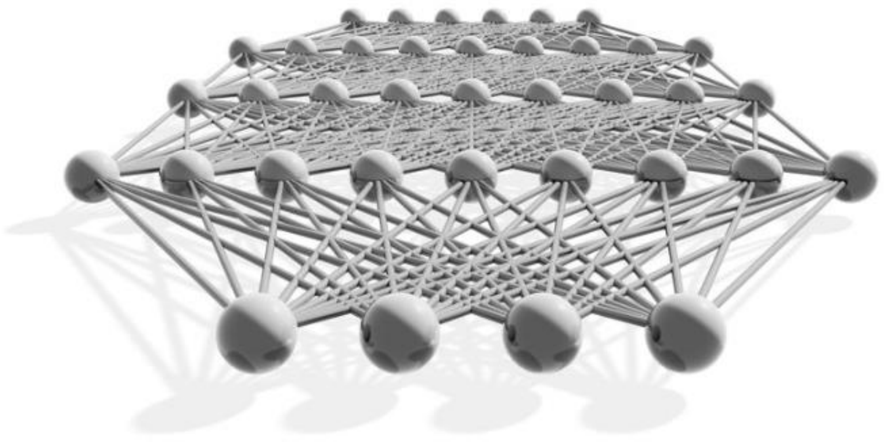
Recap: Last Lecture

- Neural Networks
- Multilayer Neural Networks
- Backpropagation



Today:

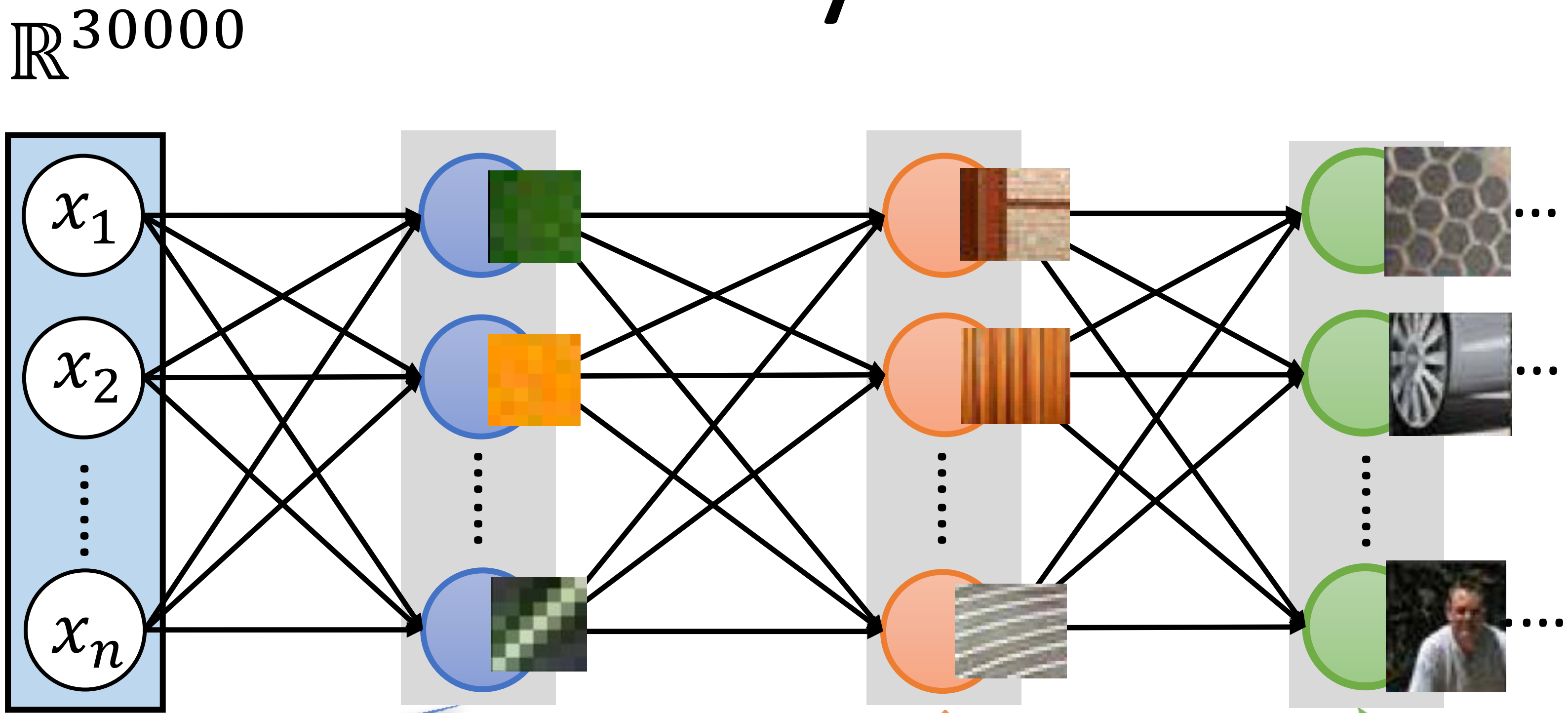
Convolutional Neural Networks

- CNN Basics
- Typical CNN Architectures

Why CNN for Image?

100*100*3

Represented as pixels



The most basic classifiers

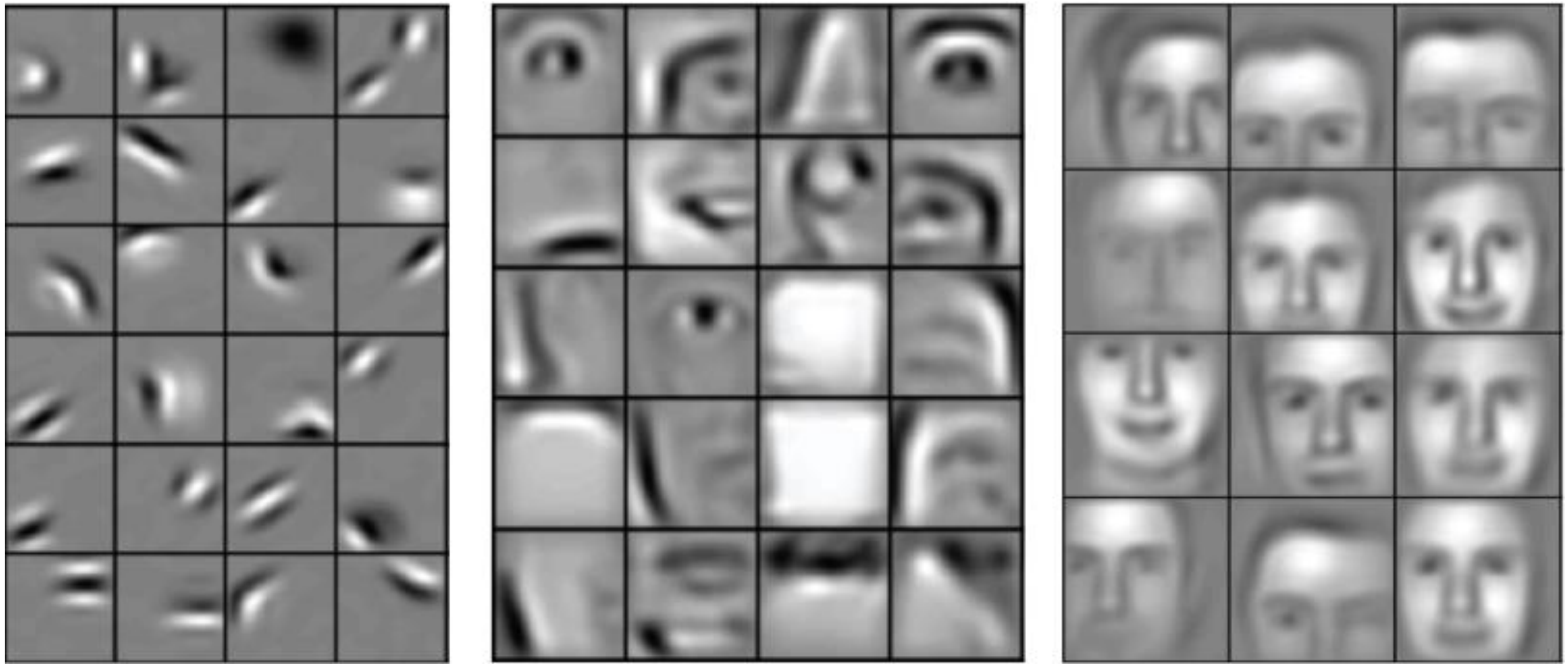
Use 1st layer as module to build classifiers

Use 2nd layer as module ……

Can the network be simplified by considering the properties of images?

Why CNN for Image

- Hierarchical structure of objects.
  - Objects consist of object parts.
  - Object parts consist of simple, local patterns.



Low level features Mid level features High level features

Why CNN for Image

- Some patterns are much smaller than the whole image

A neuron does not have to see the whole image to discover the pattern.

Connecting to small region with less parameters

"beak" detector

Why CNN for Image

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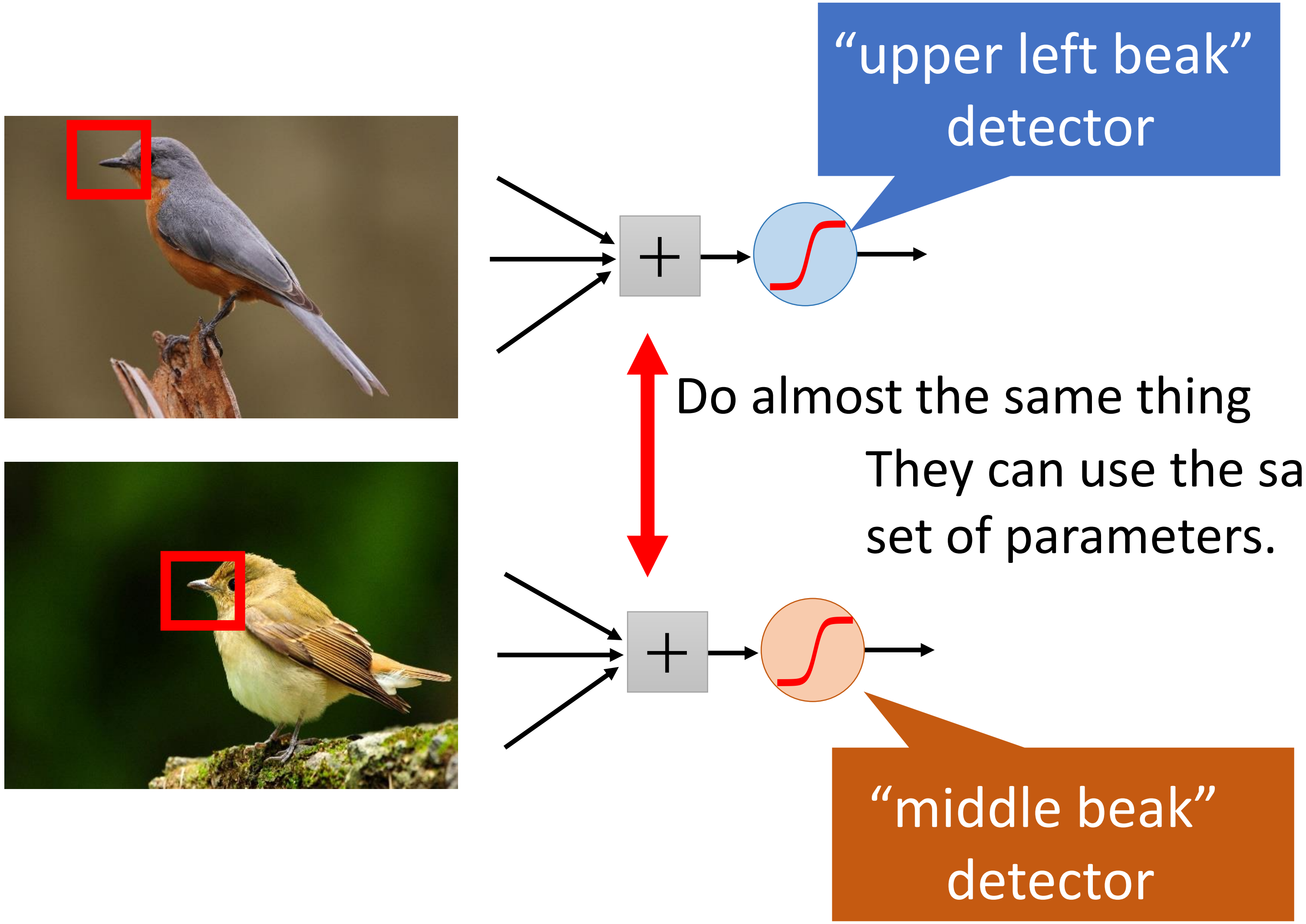
- Same objects or same patterns appear at different places of images.



Why CNN for Image

- Subsampling/scaling the pixels will not change the object category

bird

subsampling

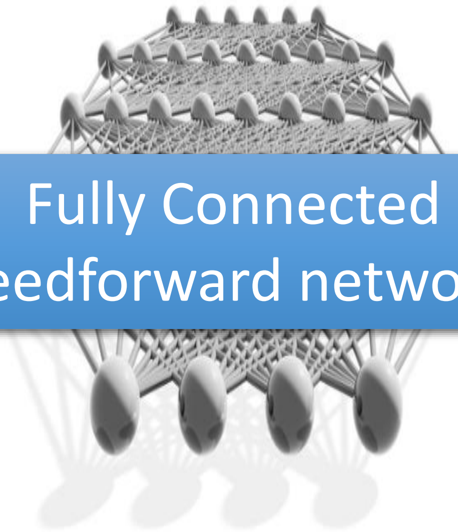
bird

We can subsample the pixels to make image smaller

Less parameters for the network to process the image

The whole CNN

dog, cat, horse ……



Fully Connected Feedforward network

Convolution

Max Pooling

Convolution

Max Pooling

Can repeat many times

Flatten

The whole CNN

Property 1

- Some patterns are much smaller than the whole image

Property 2

- The same patterns appear in different regions.

Property 3

- Subsampling the pixels will not change the object
- Can obtain local invariance

Convolution

Max Pooling

Convolution

Max Pooling

Can repeat many times

Flatten

The whole CNN

Convolution

Max Pooling

Convolution

Max Pooling

Can repeat many times

Flatten

dog, cat, horse ……

CNN – Convolution

Those are the network parameters to be learned.

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 ×6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

Matrix

-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

Matrix

⋮

Property 1 Each filter detects a small pattern (3 × 3).

CNN – Convolution

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6×6 image

3 -1

CNN – Convolution

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

If stride=2

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6×6 image

3 -3

We set stride=1 below

CNN – Convolution

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 × 6 image

3	-1	-3	-1
-3	1	0	-3
-3	-3	0	1
3	-2	-2	-1

Property 2

CNN – Convolution

-1	1	-1
-1	1	-1
-1	1	-1

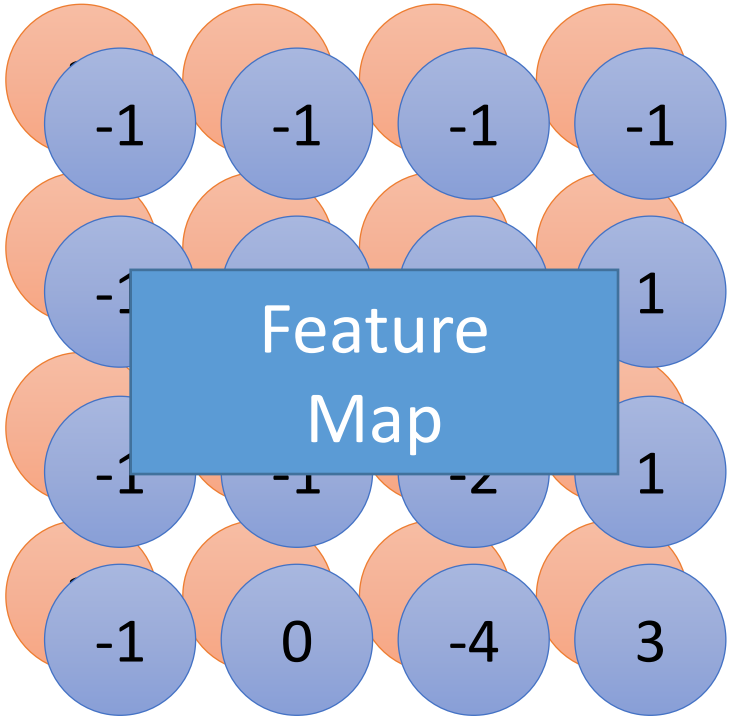
Filter 2

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6×6 image

Do the same process for every filter



4×4 image

CNN – Color Image

Filter 1

1	-1	-1
-1	1	-1
-1	-1	1

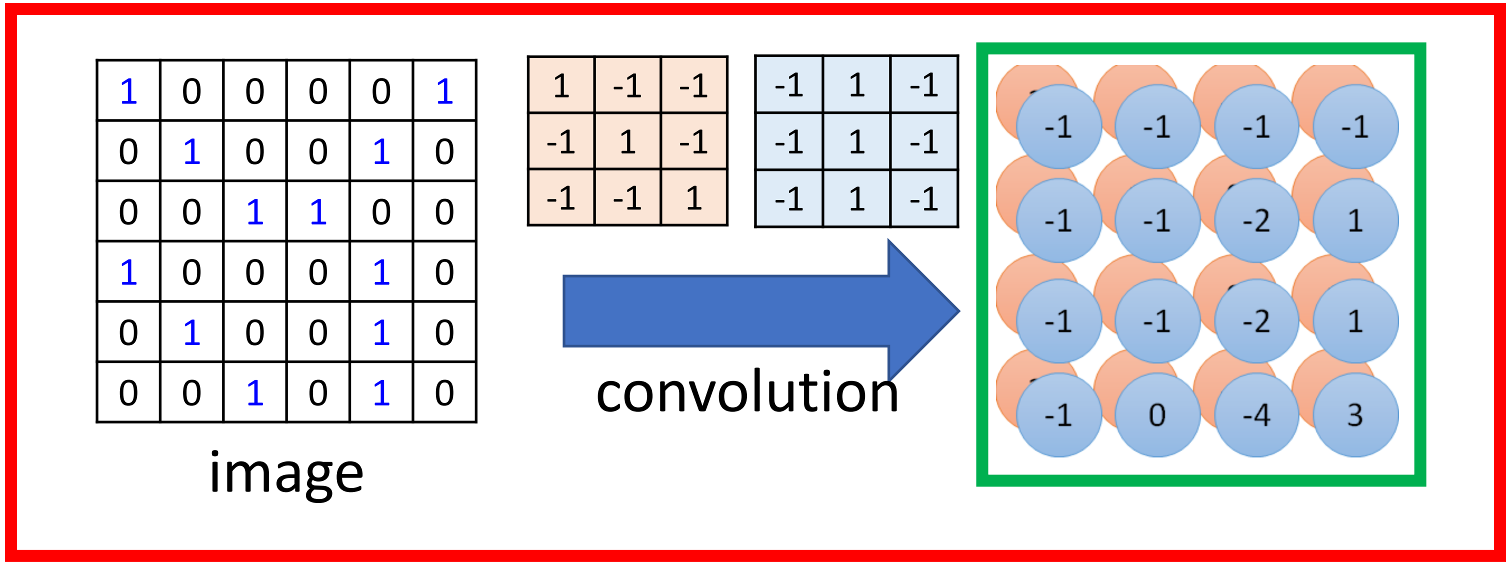
Filter 2

-1	1	-1
-1	1	-1
-1	1	-1

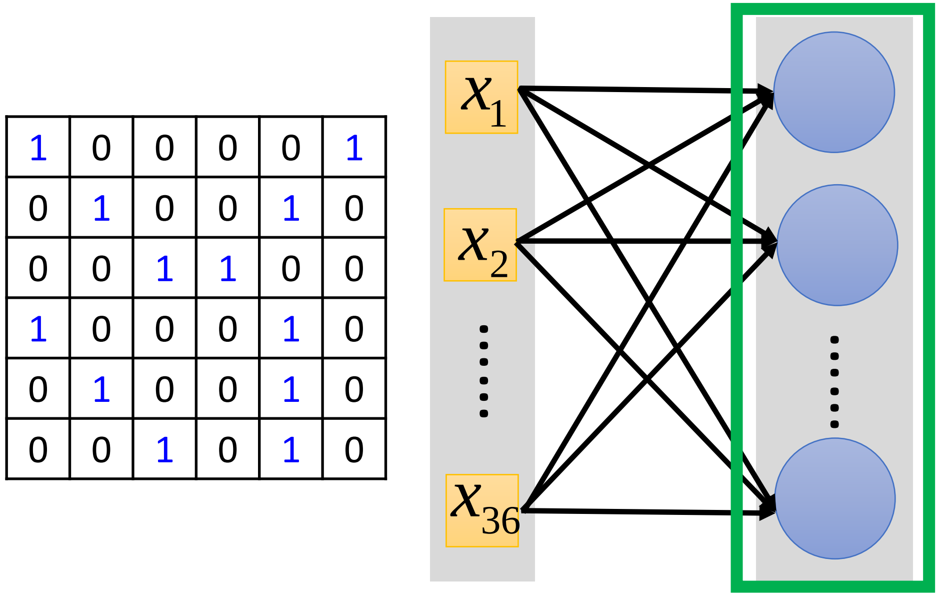
Color image

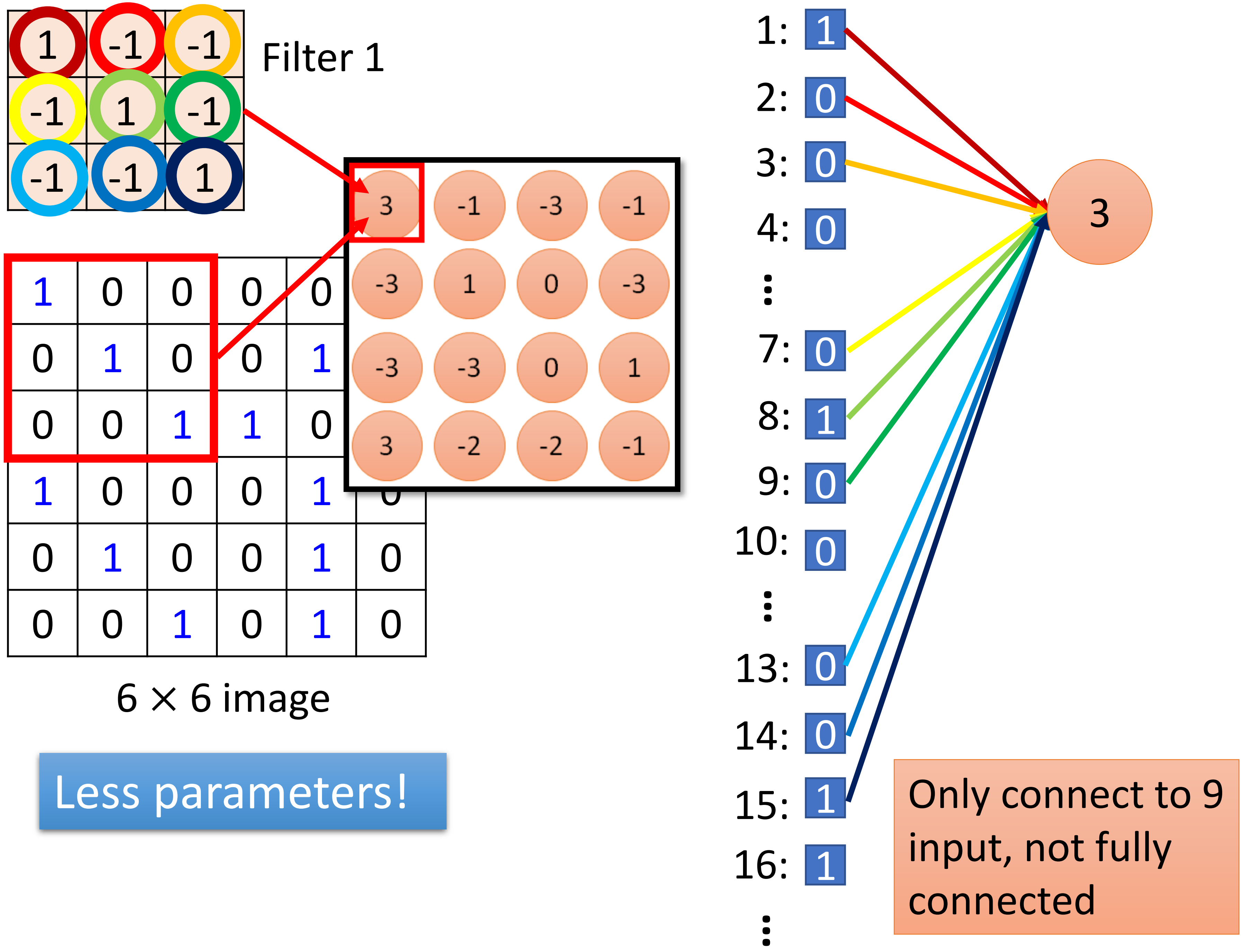
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

Convolution v.s. Fully Connected



Fully Connected





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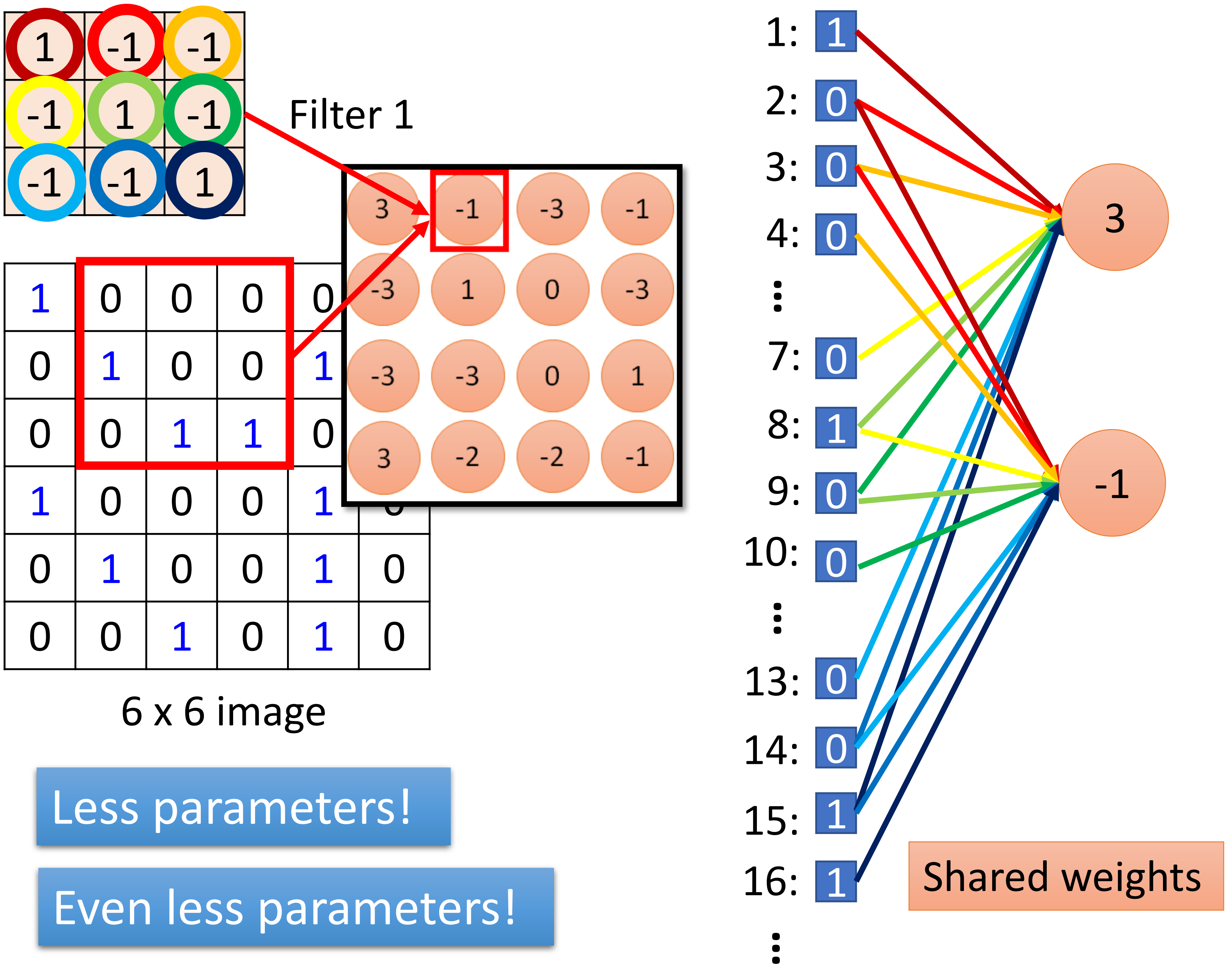
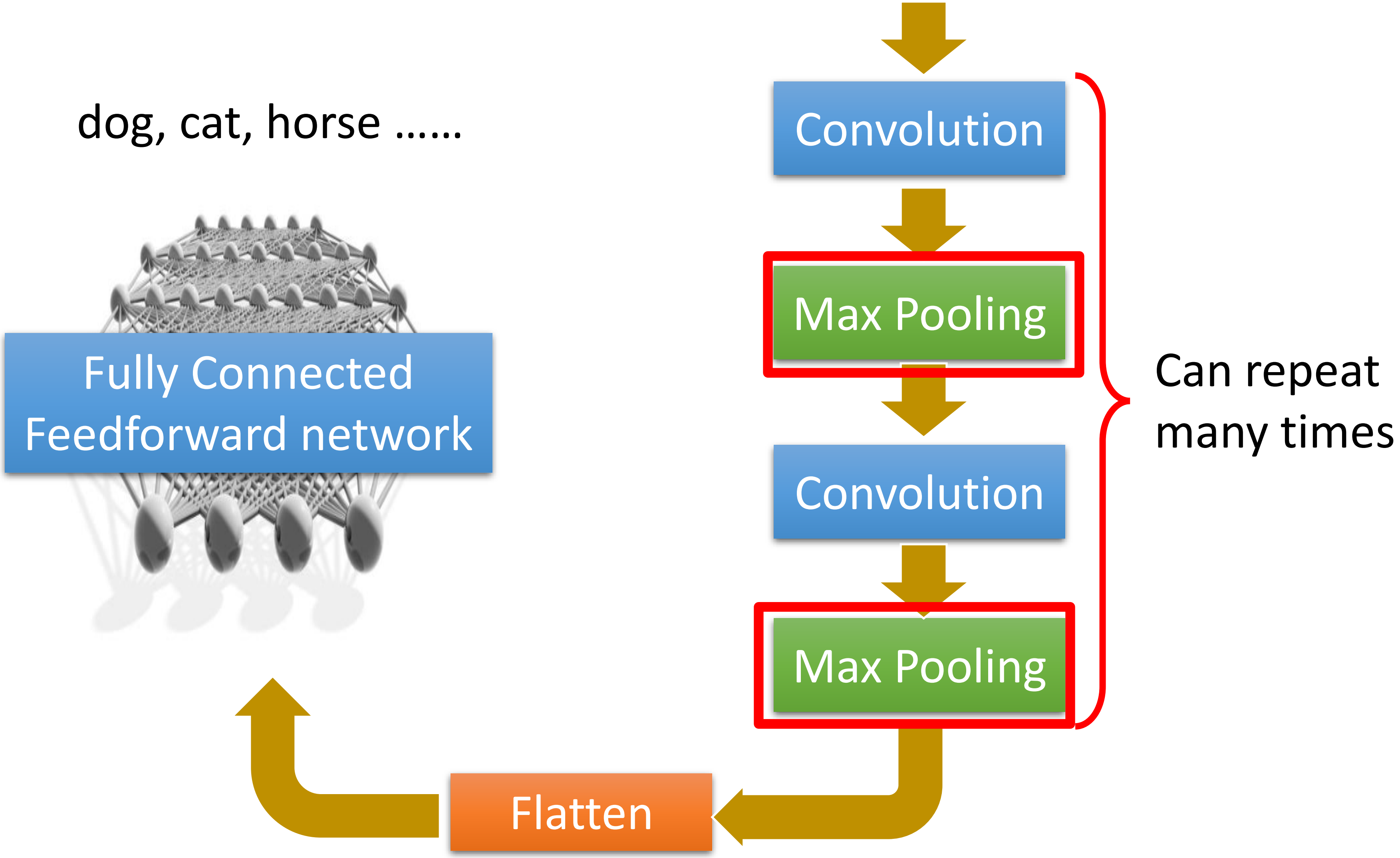


Filter 1
6 x 6 image
Less parameters!
Even less parameters!
Shared weights

The whole CNN



CNN – Max Pooling

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

3	-1	-3	-1
-3	1	0	-3
-3	-3	0	1
3	-2	-2	-1

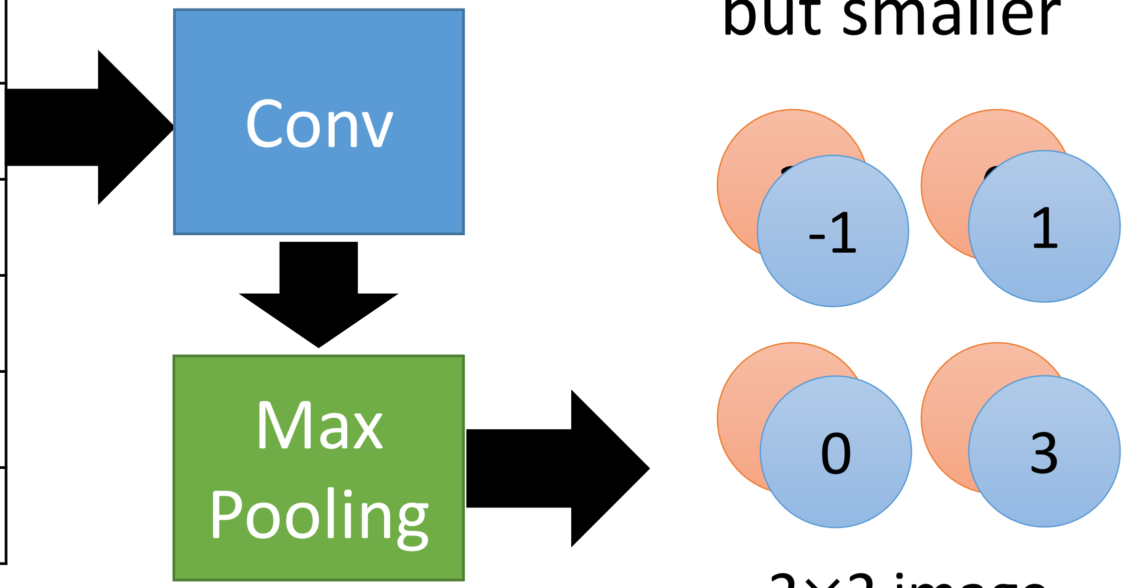
-1	-1	-1	-1
-1	-1	-2	1
-1	-1	-2	1
-1	0	-4	3

CNN – Max Pooling

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 × 6 image

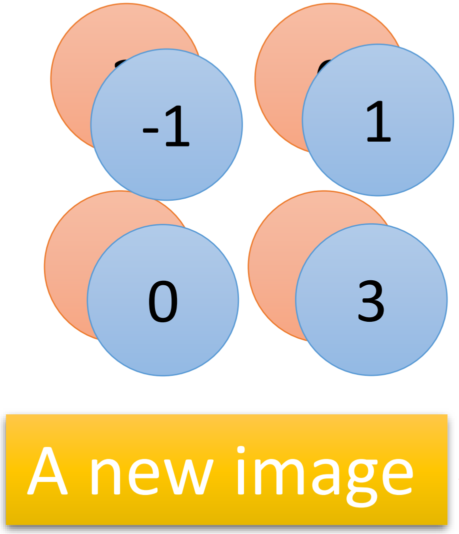
New image
but smaller

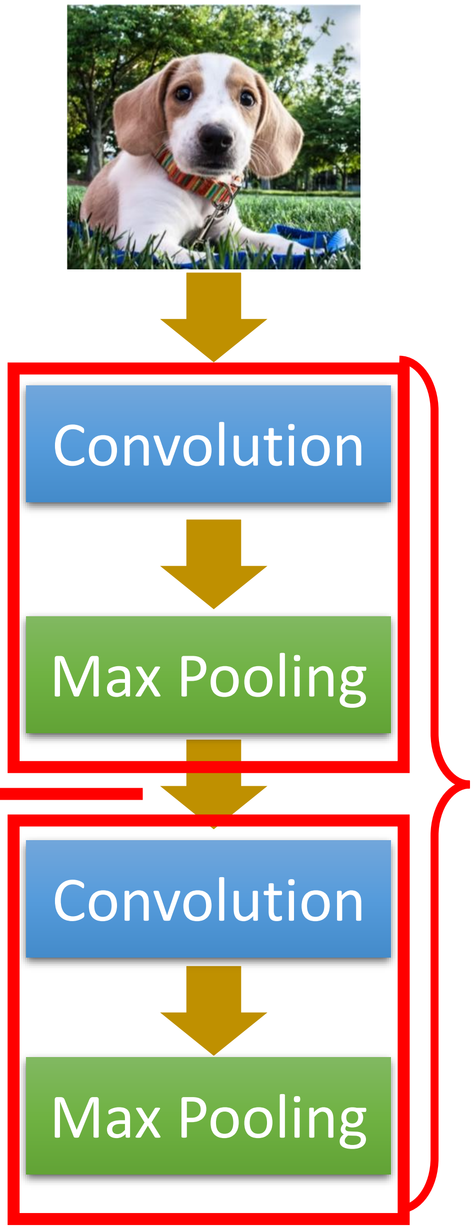


2×2 image

Each filter
is a channel

The whole CNN



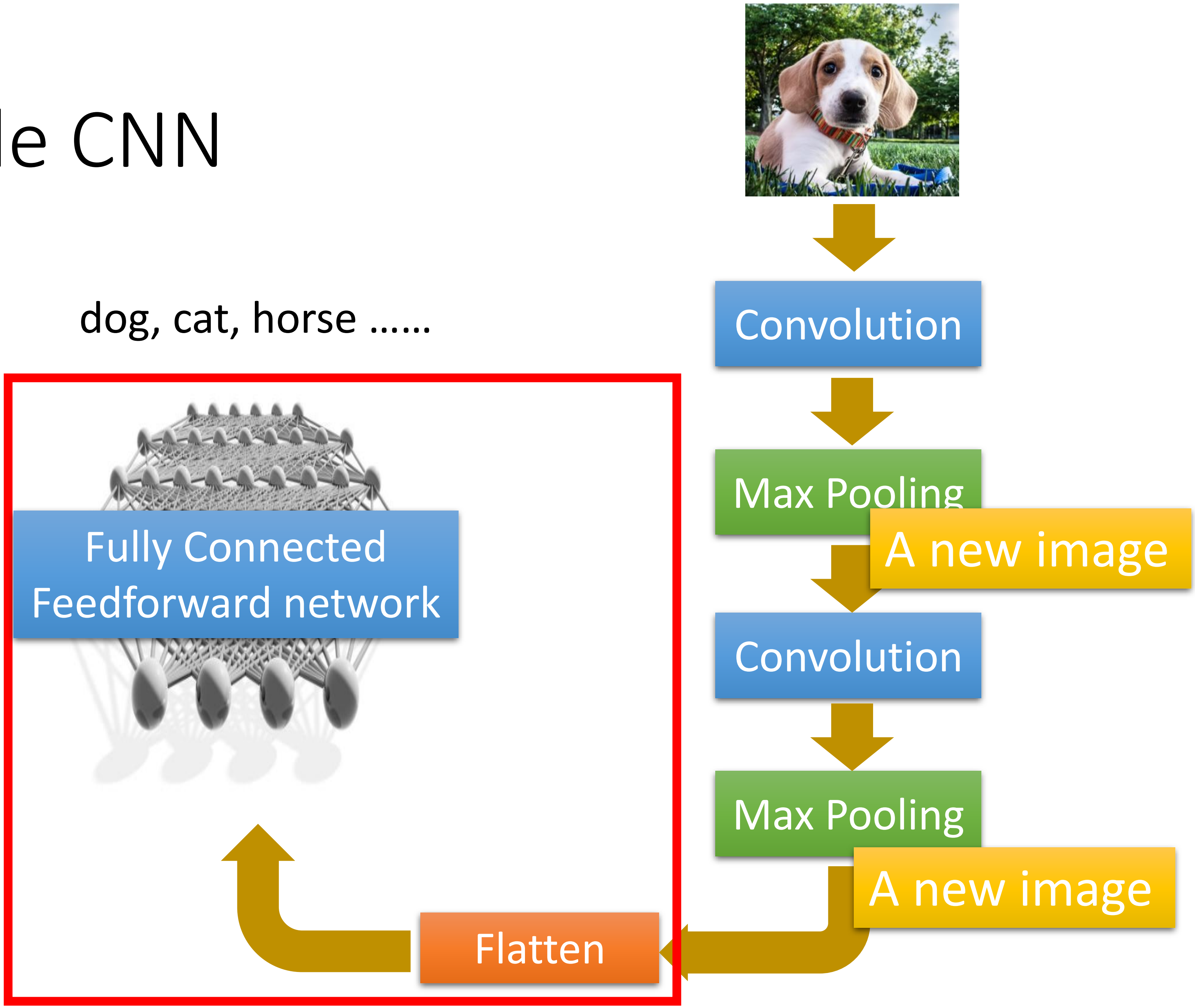


Can repeat many times

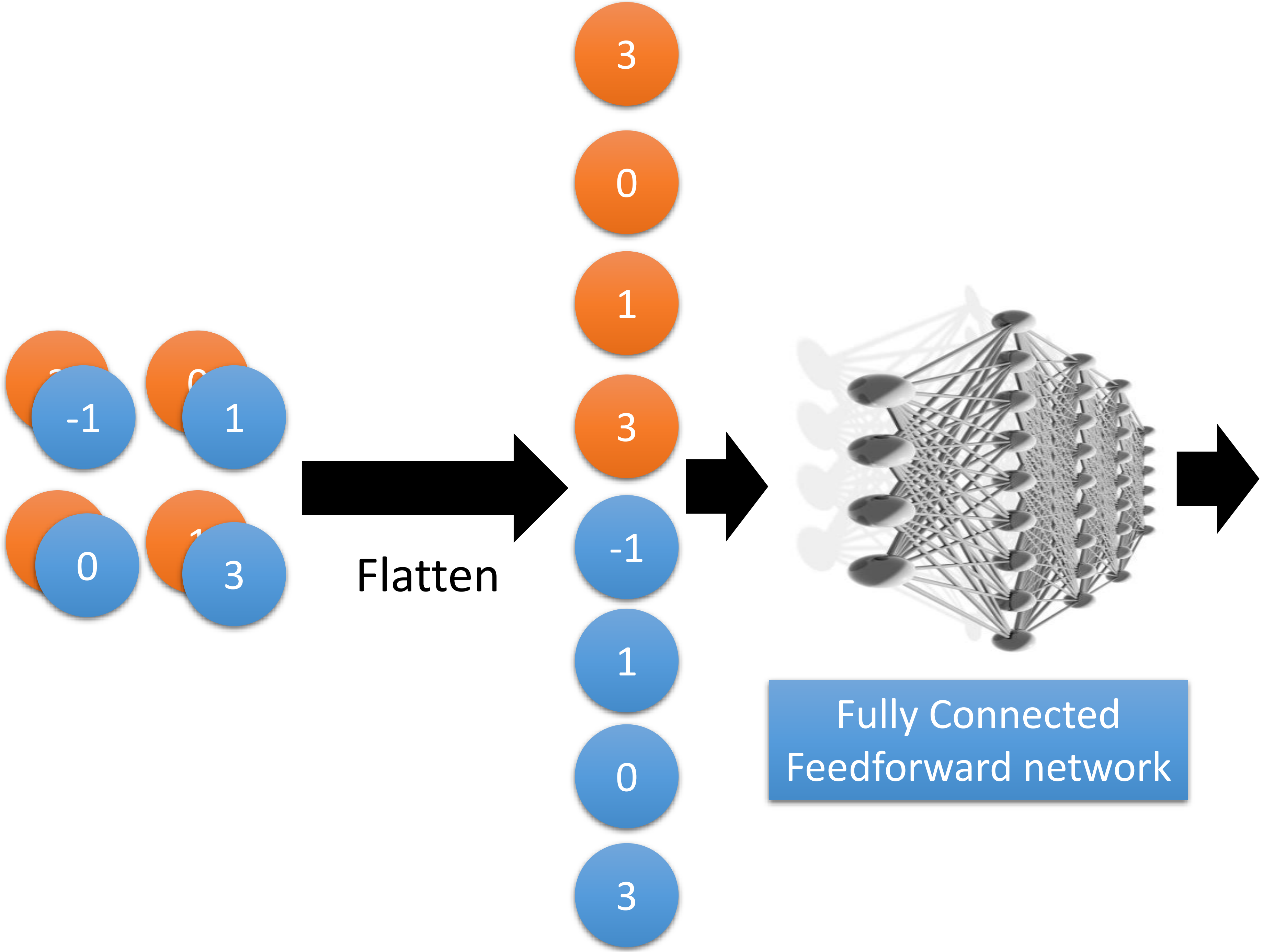
Smaller than the original image

The number of the channel is the number of filters

The whole CNN

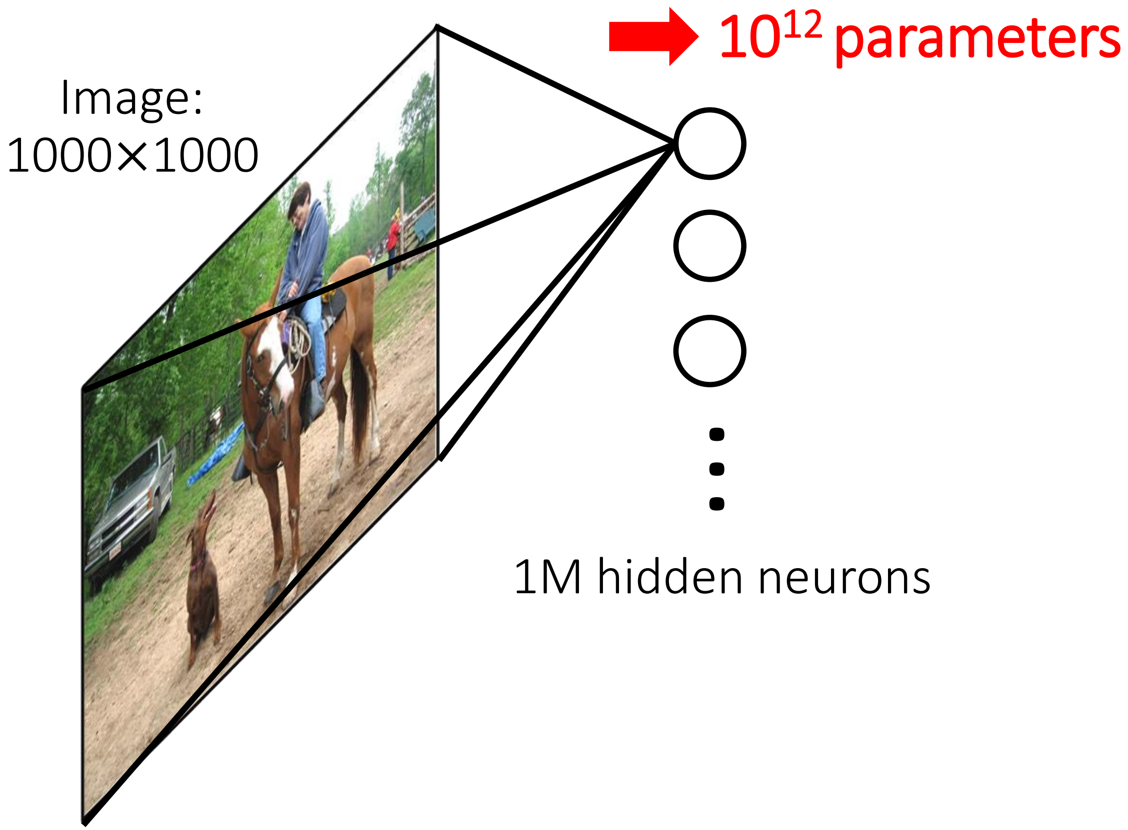


Flatten


Flatten
3
0
1
3
-1
1
0
3
-1
1
0
3
Fully Connected
Feedforward network

CNN-Summary

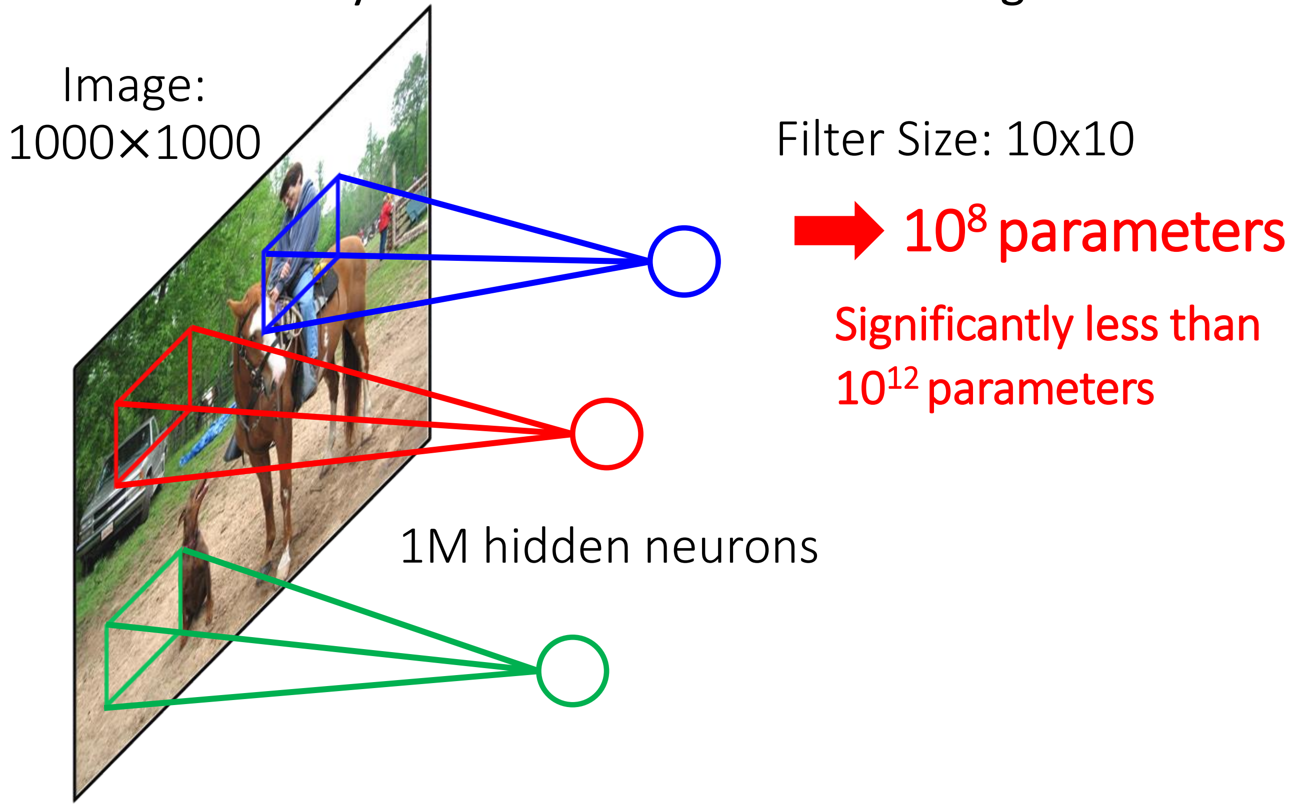
- Problems of fully connected neural networks
  - Every output unit interacts with every input unit (pixel)
  - The number of weights grows largely with the size of the input image
  - Pixels in distance are less correlated



CNN-Summary

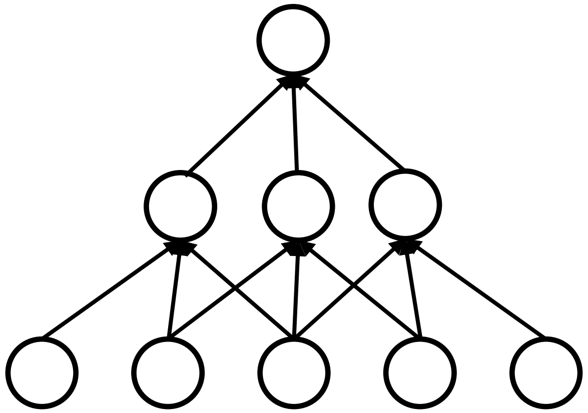
◻ Locally connected neural networks

- Sparse connectivity: a hidden unit is only connected to a local patch (weights connected to the patch are called filter or kernel)
- Inspired by biological systems, where a cell is sensitive to a small subregion of the input space, called a receptive field. Many cells are tiled to cover the entire visual field.
- The design of such sparse connectivity is based on domain knowledge.



CNN-Summary

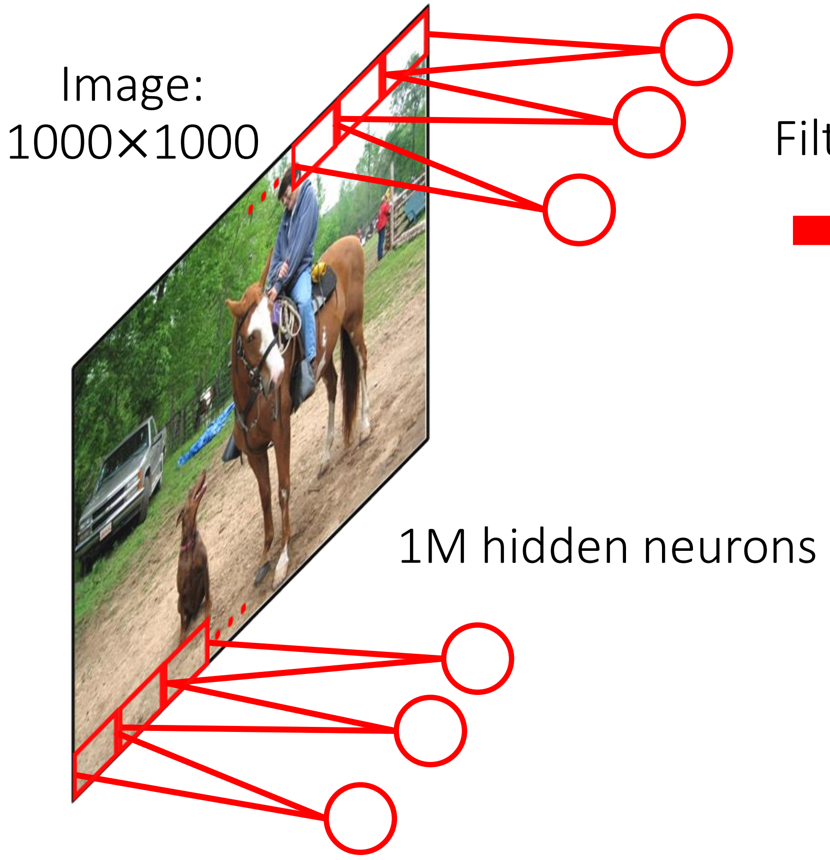
- Locally connected neural networks
  - The learned filter is a spatially local pattern
  - A hidden node at a higher layer has a larger receptive field in the input
  - Stacking many such layers leads to “filters” which become increasingly “global”



CNN-Summary

□ Share weights

- Translation invariance: capture statistics in local patches and they are independent of locations. (Similar edges appear at different locations)
- Hidden nodes at different locations share the same weights. It greatly reduces the number of parameters to learn.
- We may only locally share weights or not share weights at top layers.



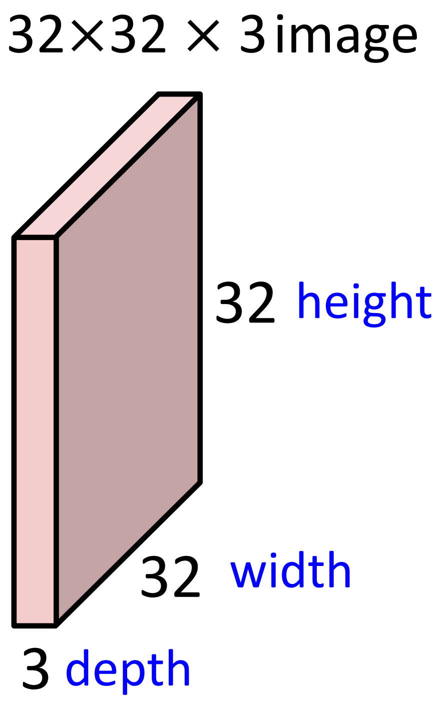
Filter Size: 10x10

➡ 10^2 parameters

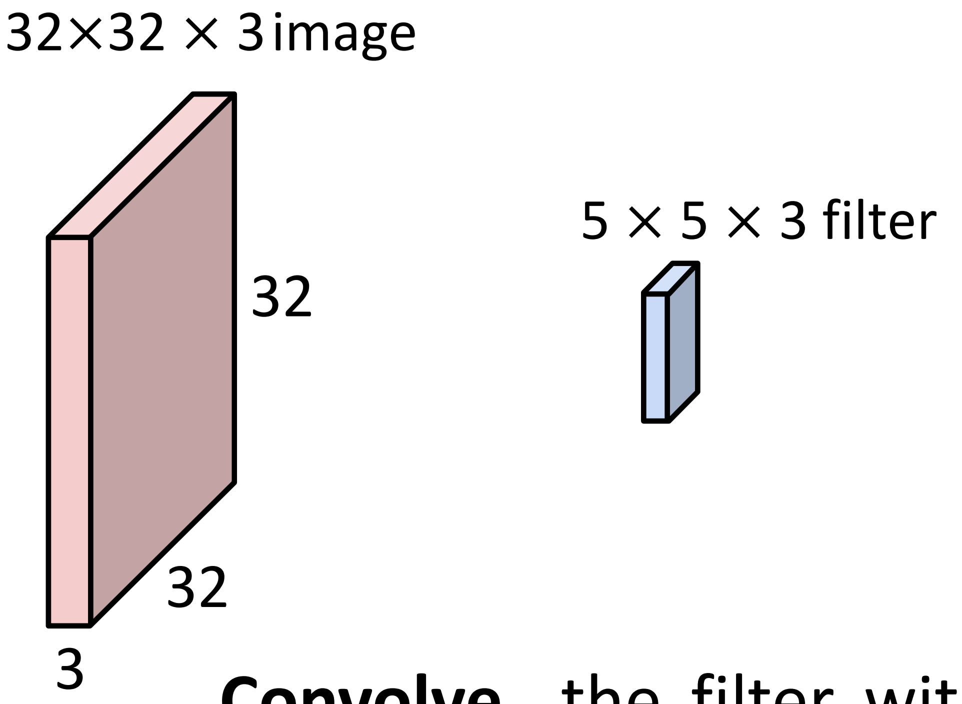
Significantly less than 10^{12} parameters

CNN: Practices

Convolution Layer



Convolution Layer

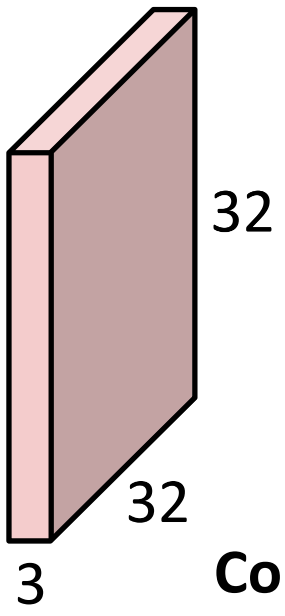


Convolve the filter with the image *i.e.* “slide over the image spatially, computing dot products”

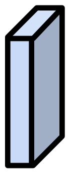
Convolution Layer

- $32 \times 32 \times 3$ image

Filters always extend the full depth of the input volume

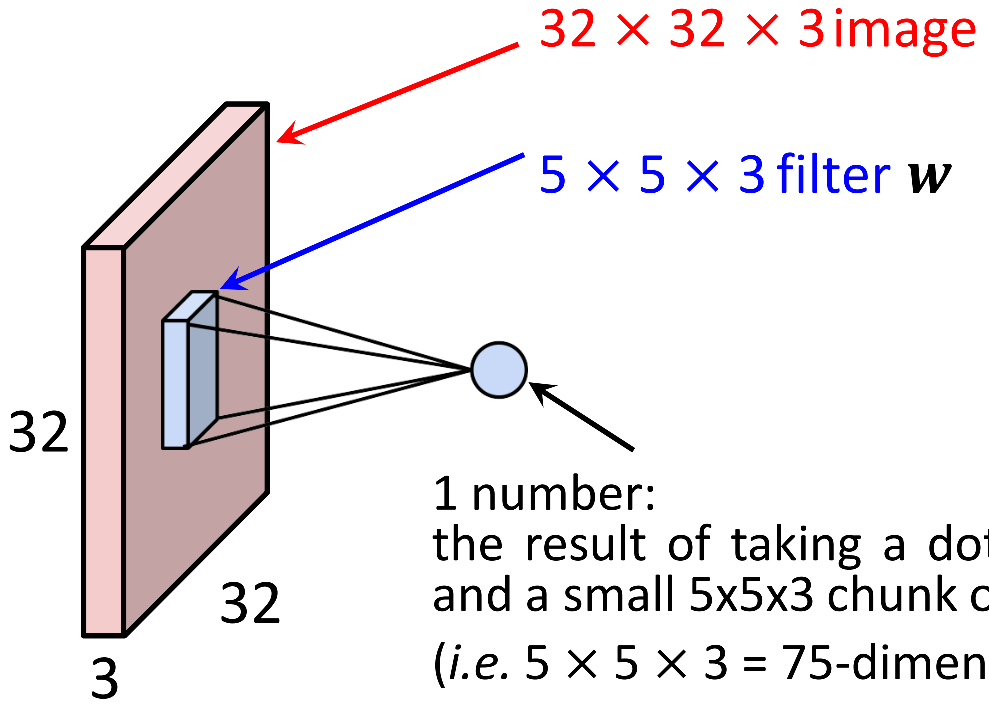


$5 \times 5 \times 3$ filter



Convolve the filter with the image *i.e.* “slide over the image spatially, computing dot products”

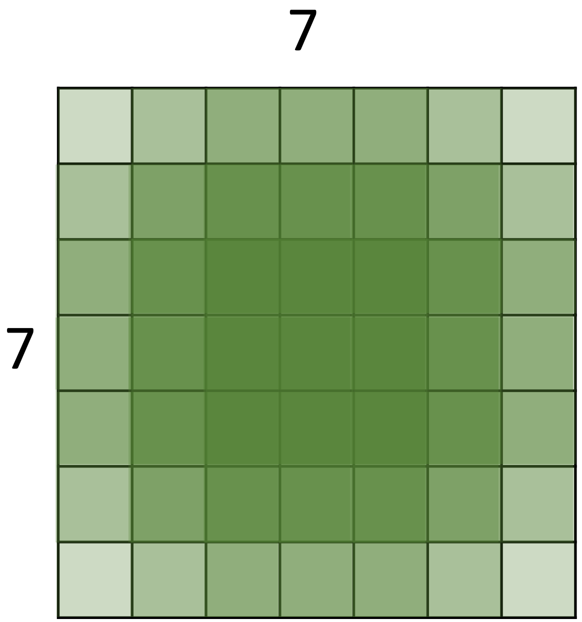
Convolution Layer



1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(*i.e.* $5 \times 5 \times 3 = 75$-dimensional dot product + bias)

$$\boldsymbol{w}^T \boldsymbol{x} + b$$

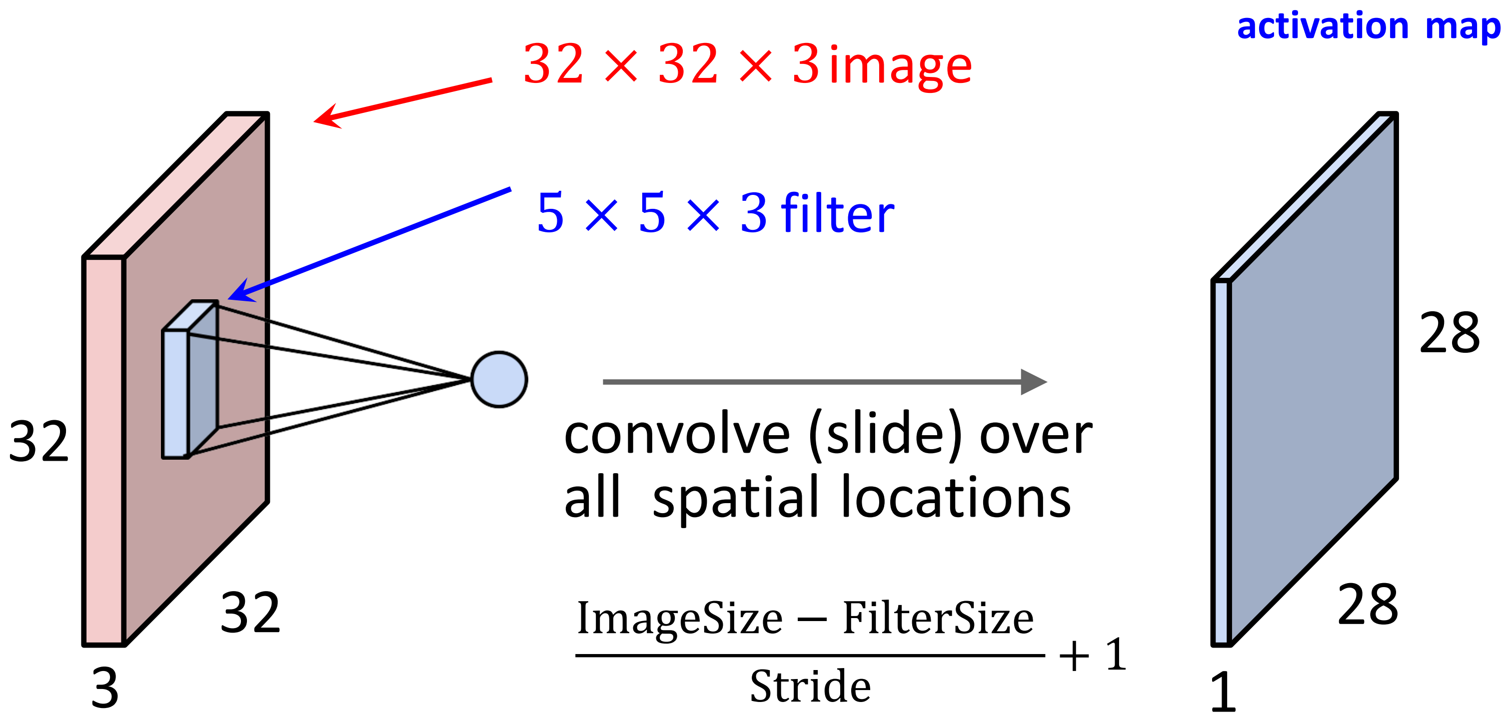
Convolution Layer



7×7 input (spatially)
assume 3×3 filter

$\Rightarrow$ **5×5 output**

Convolution Layer

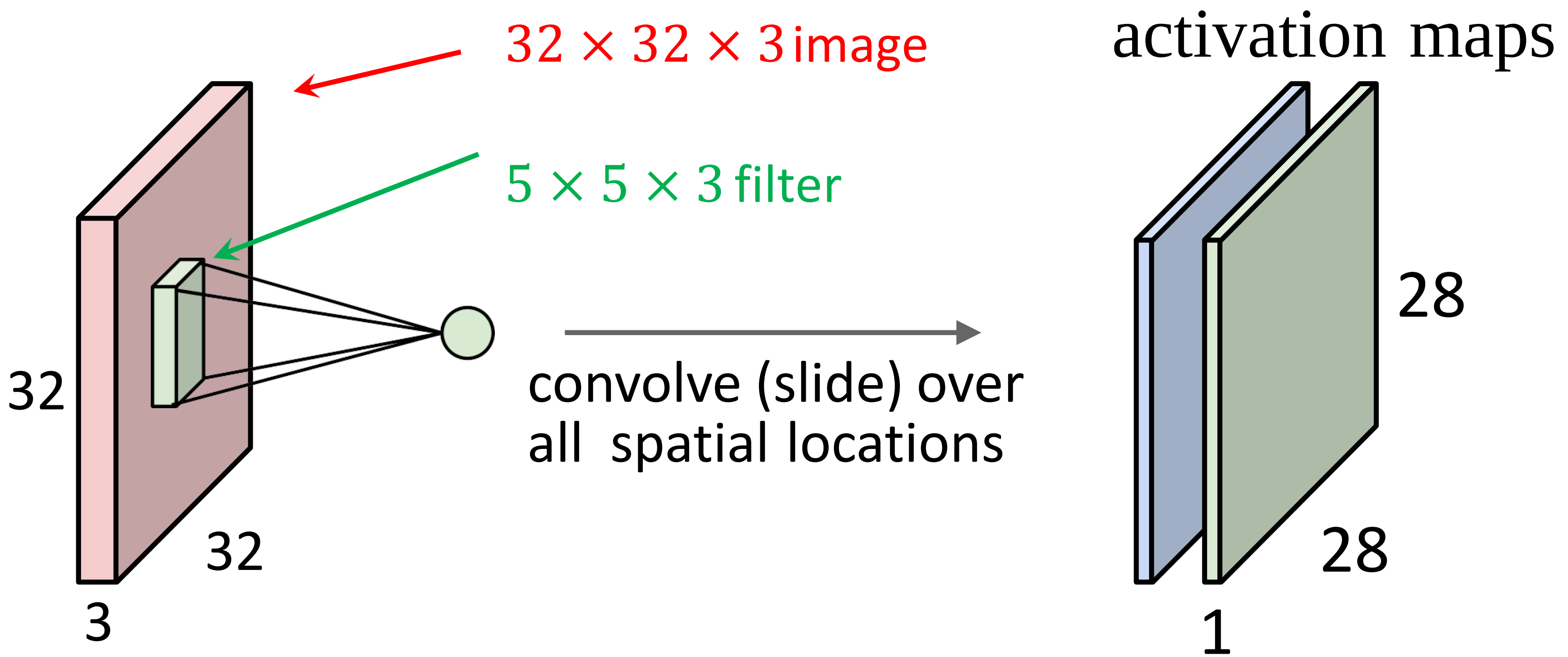


$$\frac{\text{ImageSize} - \text{FilterSize}}{\text{Stride}} + 1$$

$$\frac{32 - 5}{1} + 1 = 28$$

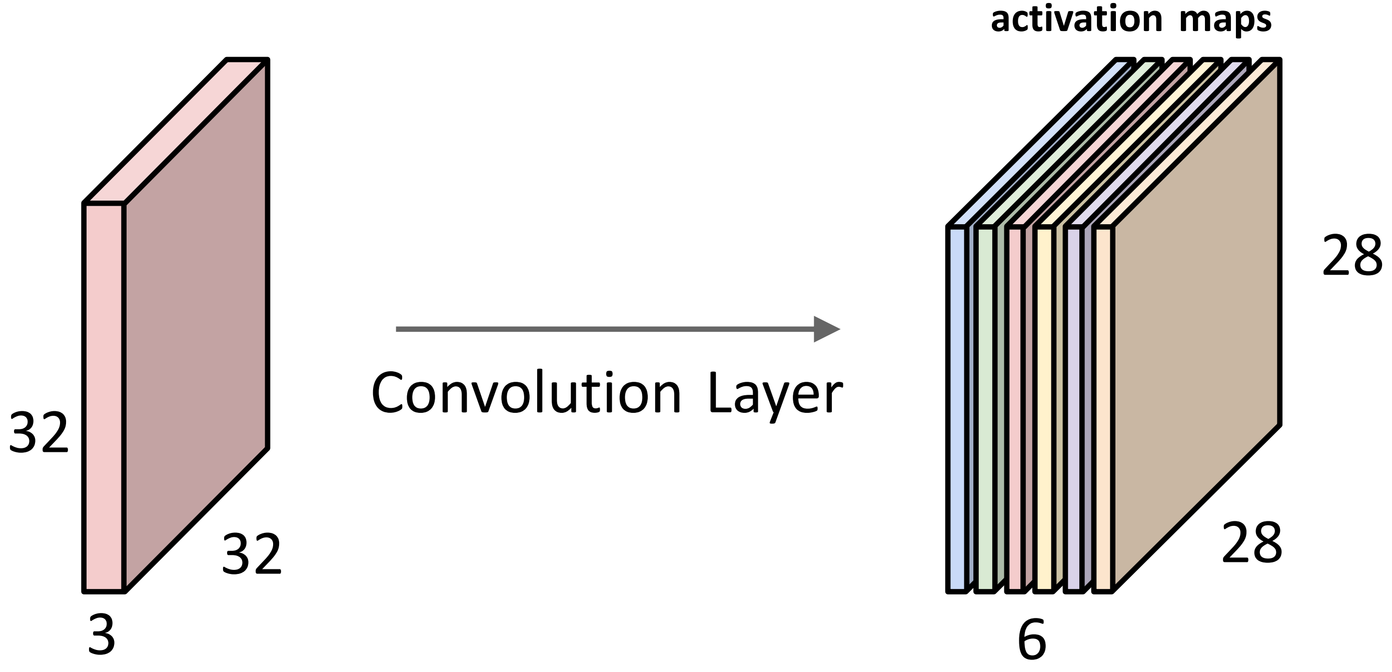
Convolution Layer

consider a second, green filter



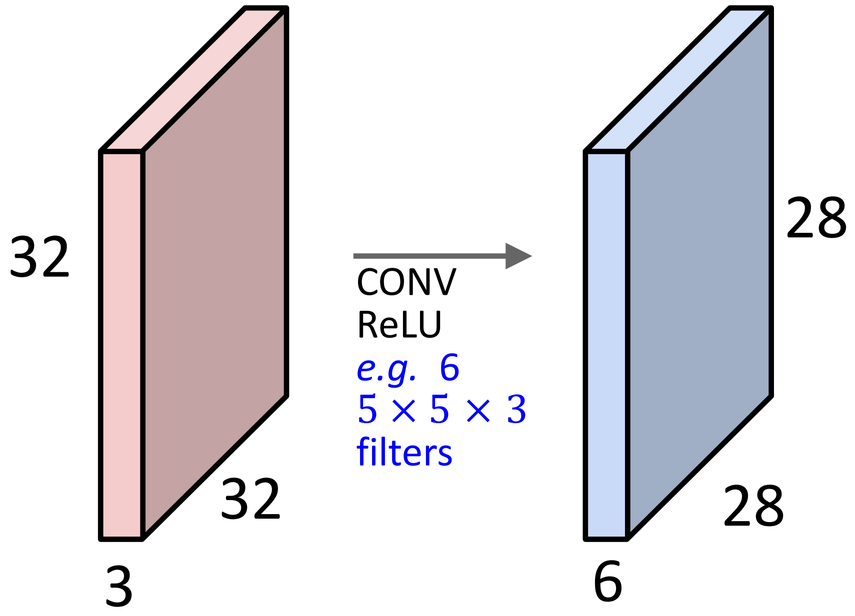
Convolution Layer

For example, if we had 6 filters of size $5 \times 5 \times 3$, we'll get 6 separate activation maps:

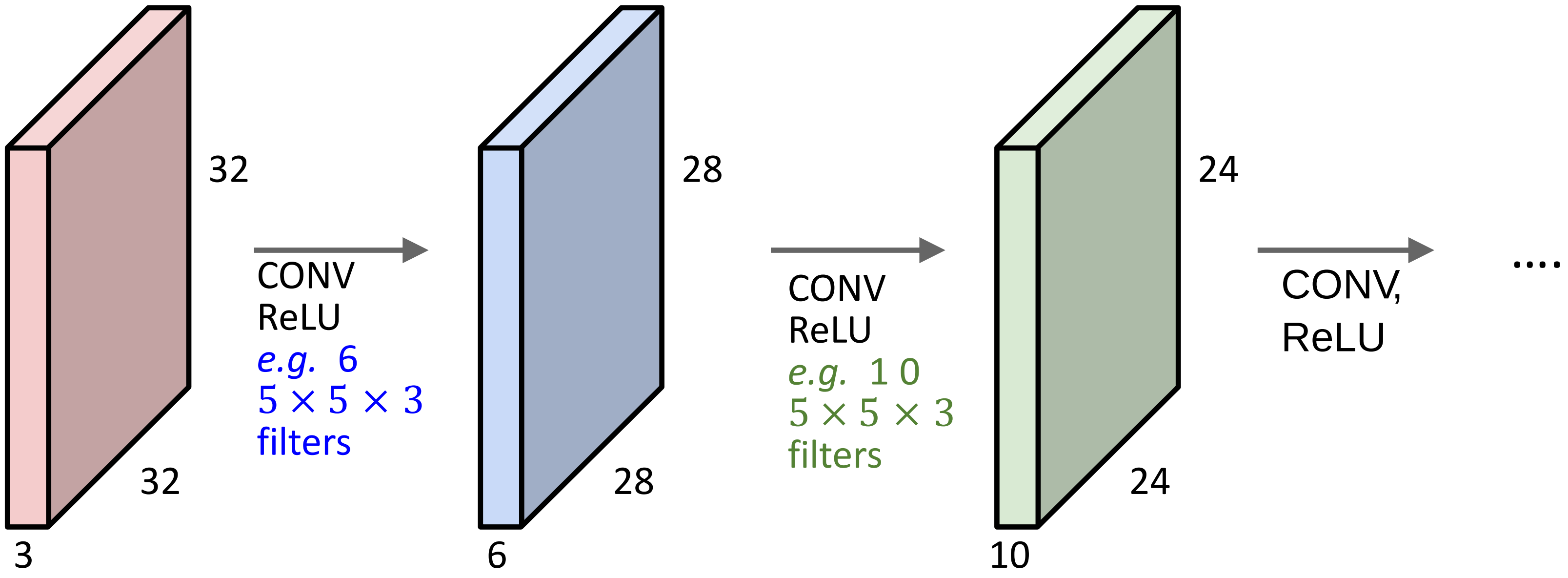


We stack these up to get a "new image" of size 28x28x6!

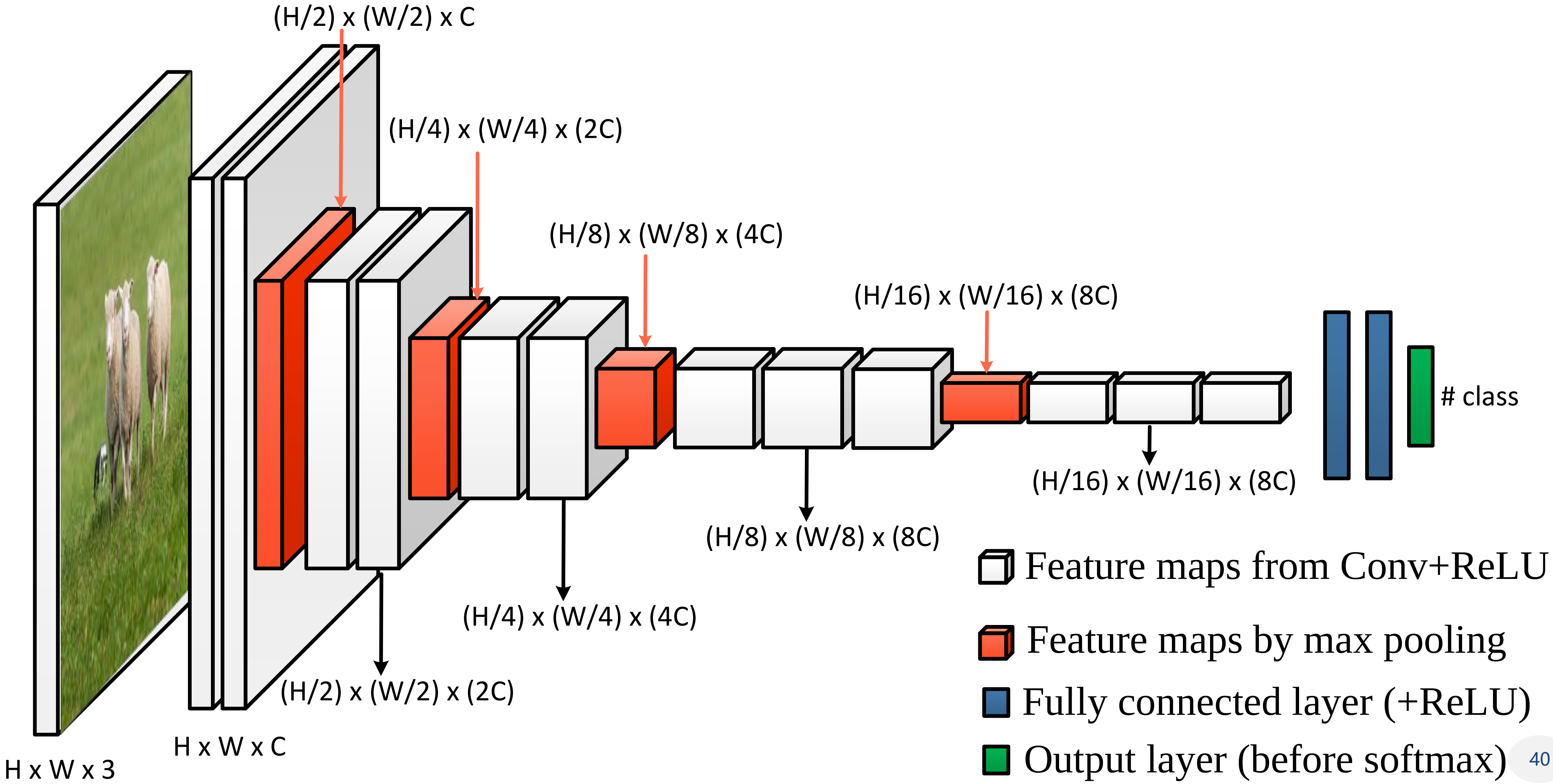
Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions.



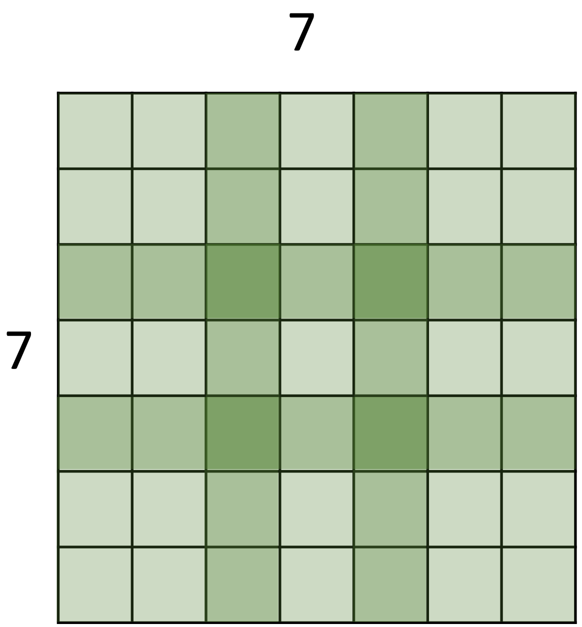
Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions.



32×32 input convolved repeatedly with 3×3 filters shrinks volumes spatially!
Shrinking too fast is not good, doesn't work well.



A closer look at spatial dimensions:



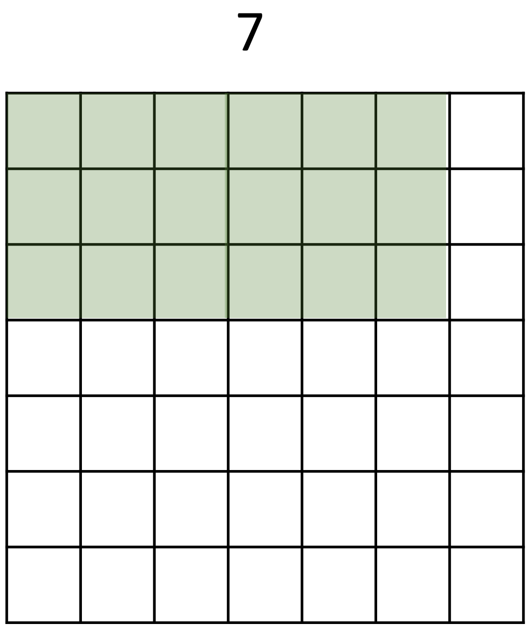
7×7 input (spatially)
assume 3×3 filter
applied **with stride 2**

$\Rightarrow$ 3×3 output

$$\frac{\text{ImageSize} - \text{FilterSize}}{\text{Stride}} + 1$$

$$\frac{7-3}{2} + 1 = 3$$

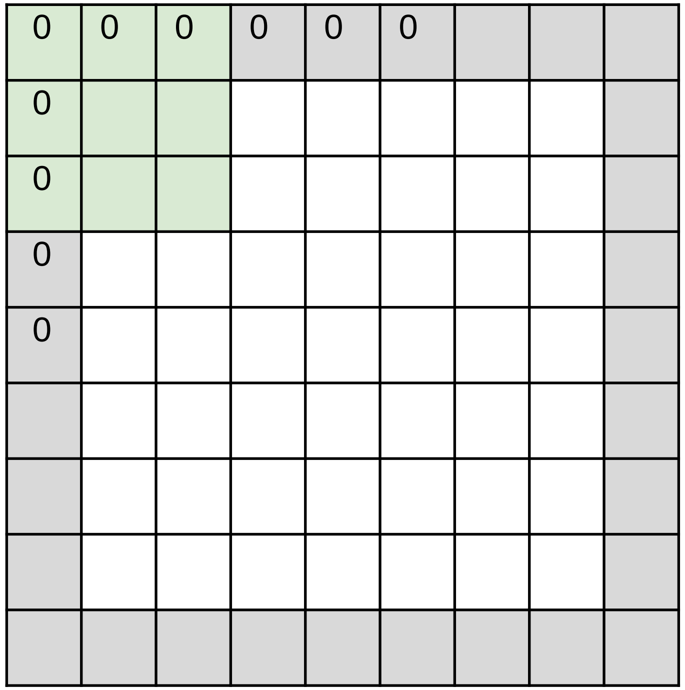
A closer look at spatial dimensions:



7×7 input (spatially)
assume 3×3 filter
applied **with stride 3?**

doesn't fit!
cannot apply 3×3 filter on
7×7 input with stride 3.

In practice: Common to zero pad the border

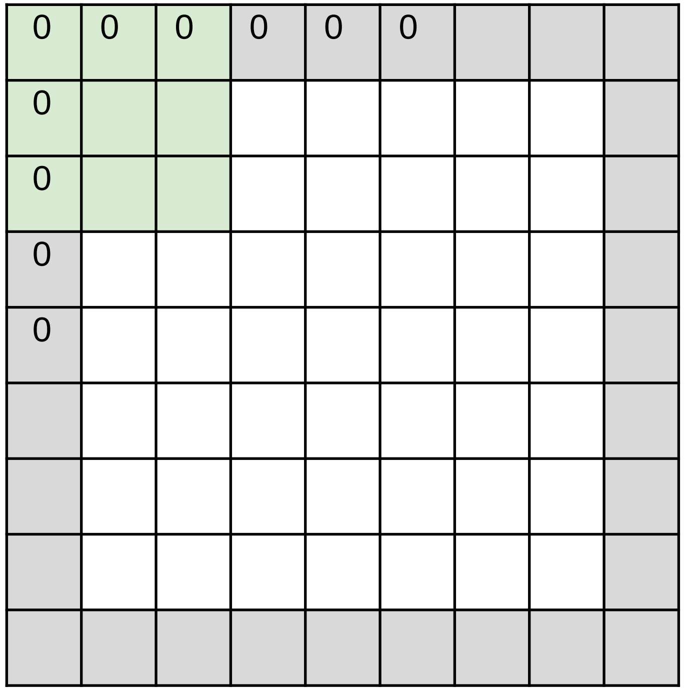


e.g. input$\mathbf{7} \times \mathbf{7}$

$\mathbf{3} \times \mathbf{3}$ filter, applied with **stride 1**
pad with 1 pixel border $\Longrightarrow$ what is the output?

7 × 7 output!

In practice: Common to zero pad the border

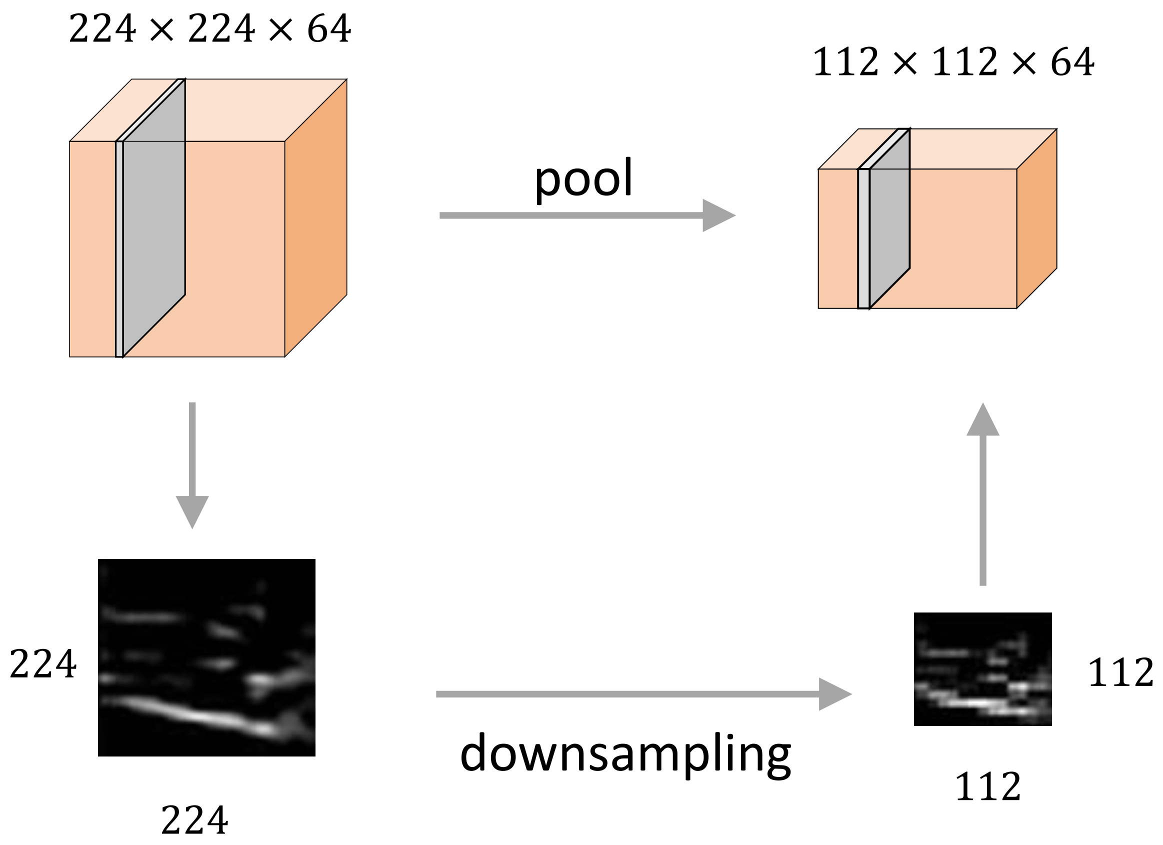


e.g. input 7×7
3×3 filter, applied with **stride 1**
pad with 1 pixel border $\Longrightarrow$ what is the output?

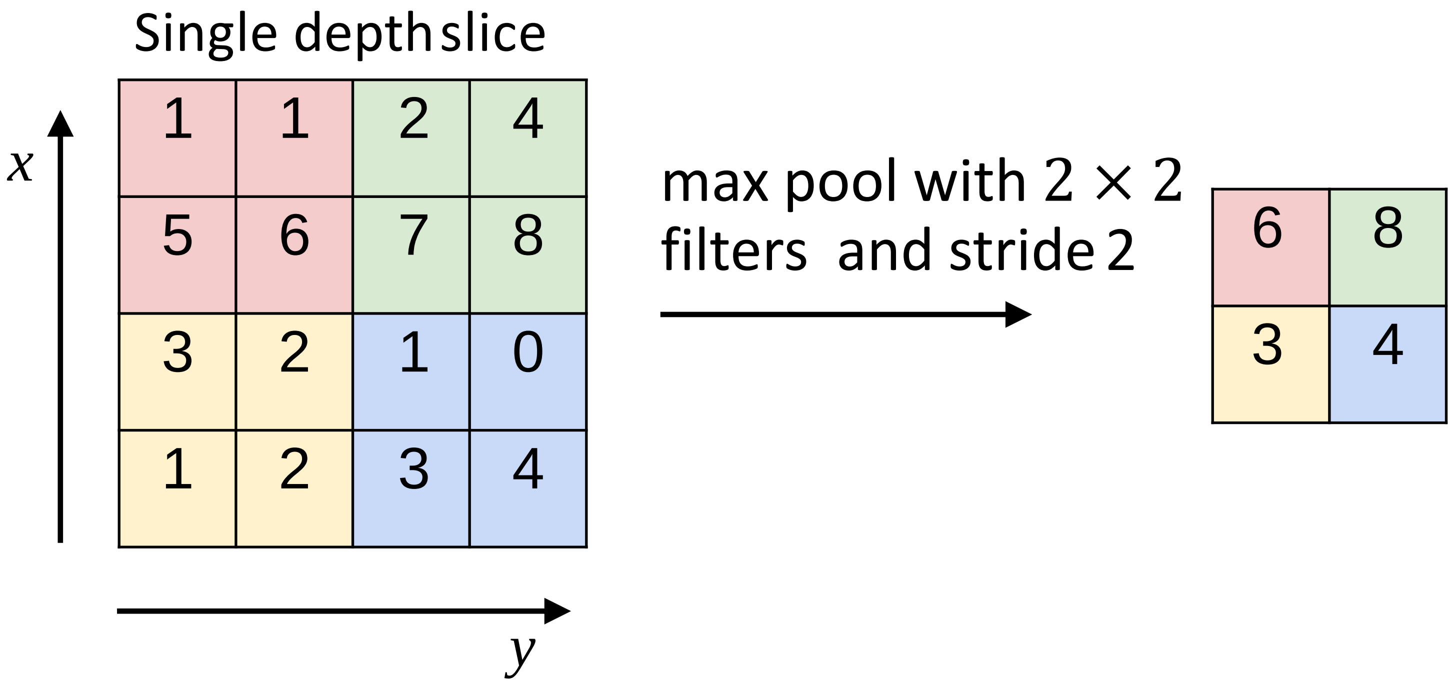
7×7 output!
in general, common to see CONV layers with stride 1, filters of size $F \times F$, and zero-padding with $(F-1)/2$. (will preserve size spatially)
e.g. F = 3 → zero pad with 1
F = 5 → zero pad with 2
F = 7 → zero pad with 3

Pooling layer

- makes the representations smaller and more manageable
- operates over each activation map independently



MAX Pooling


Single depth slice
x
1 1 2 4
5 6 7 8
3 2 1 0
1 2 3 4
y
max pool with 2 × 2
filters and stride 2
6 8
3 4

Lecture 4

Convolutional Neural Networks

- CNN Basics
- Typical CNN Architectures

Typical CNN Architectures

Case Studies

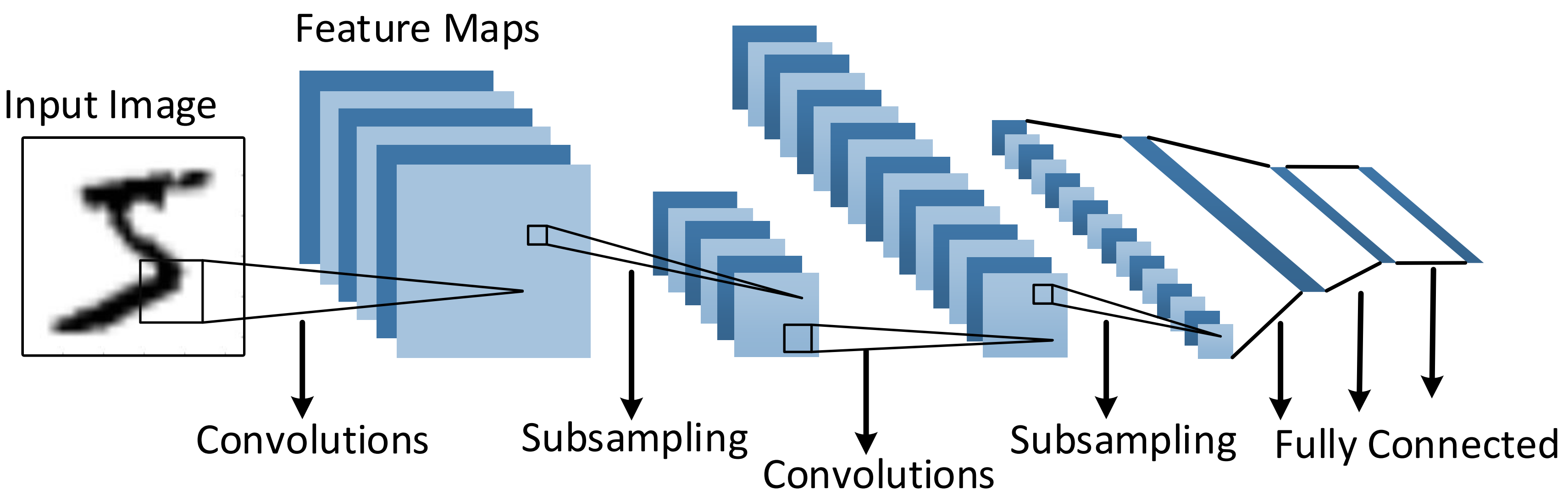
- AlexNet
- VGG
- GoogLeNet
- ResNet

Briefly talk about ...(if time allows)

- NIN (Network in Network)
- Wide ResNet
- ResNeXT
- Stochastic Depth
- DenseNet
- SENet
- FractalNet
- SqueezeNet

Review: LeNet

[LeCun *et al.* 1998]



Conv filters were 5×5, applied at stride 1

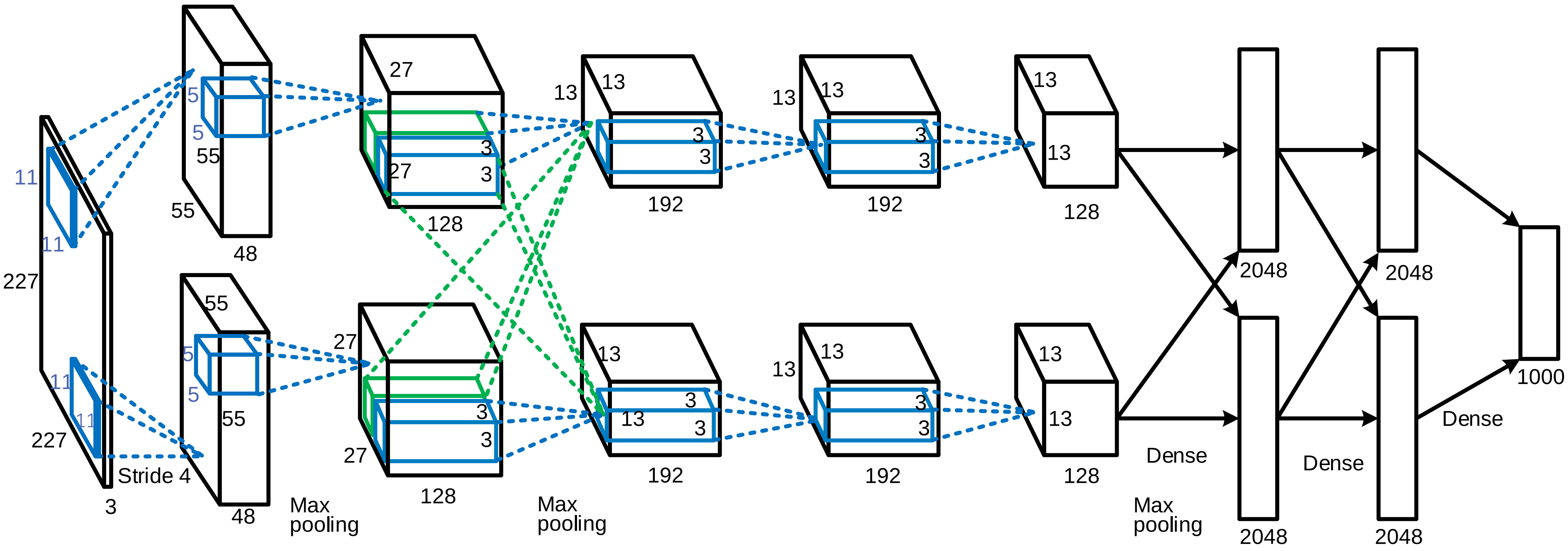
Subsampling (Pooling) layers were 2 × 2 applied at stride 2

i.e. architecture is [CONV→POOL → CONV → POOL → FC → FC]

Case Study: AlexNet

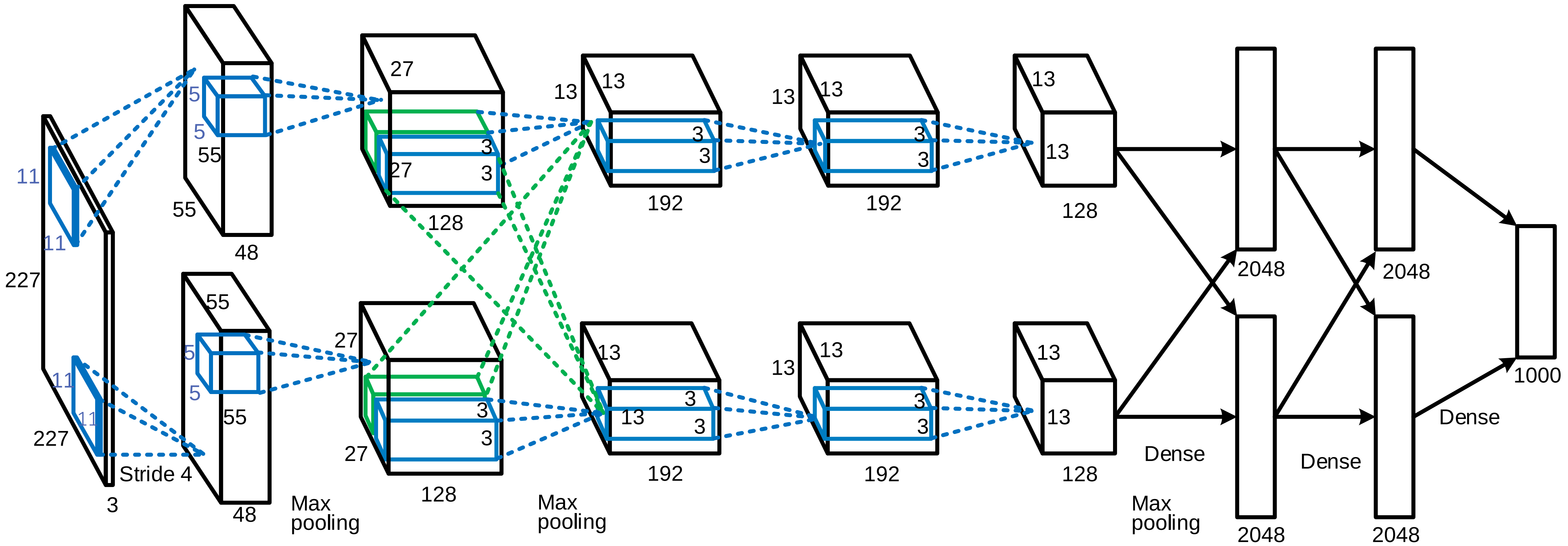
[Krizhevsky *et al.* 2012]

Architecture:
CONV1
MAX POOL1
NORM1
CONV2
MAX POOL2
NORM2
CONV3
CONV4
CONV5
Max POOL3
FC6
FC7
FC8



Case Study: AlexNet

[Krizhevsky *et al.* 2012]



Input: 227×227 × 3 images

First layer (CONV1): 96 11 × 11 filters applied at stride 4

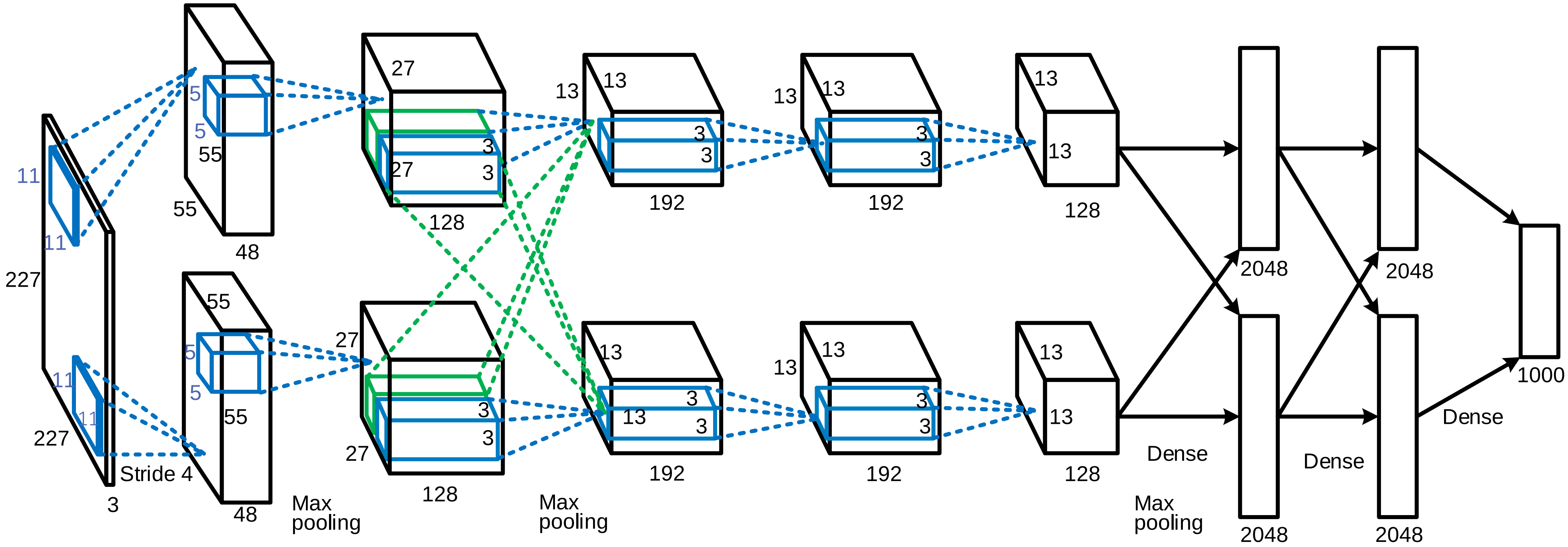
Q: what is the output volume size?

$$\frac{\text{ImageSize} - \text{FilterSize}}{\text{Stride}} + 1$$

(227-11)/4+1 = 55

Case Study: AlexNet

[Krizhevsky *et al.* 2012]



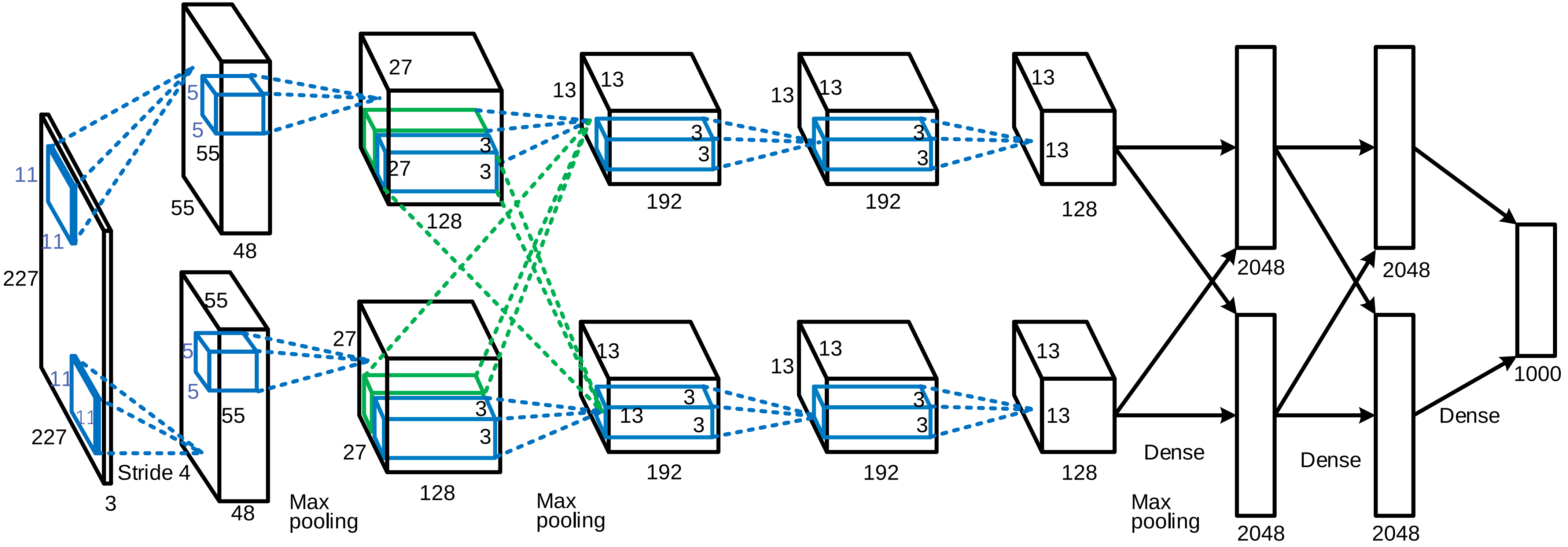
Input: 227×227×3 images

First layer (CONV1): 96 11×11 filters applied at stride 4
Output volume **[55×55×96]**

Q: What is the total number of parameters in this layer?

Case Study: AlexNet

[Krizhevsky *et al.* 2012]



Input: 227×227×3 images

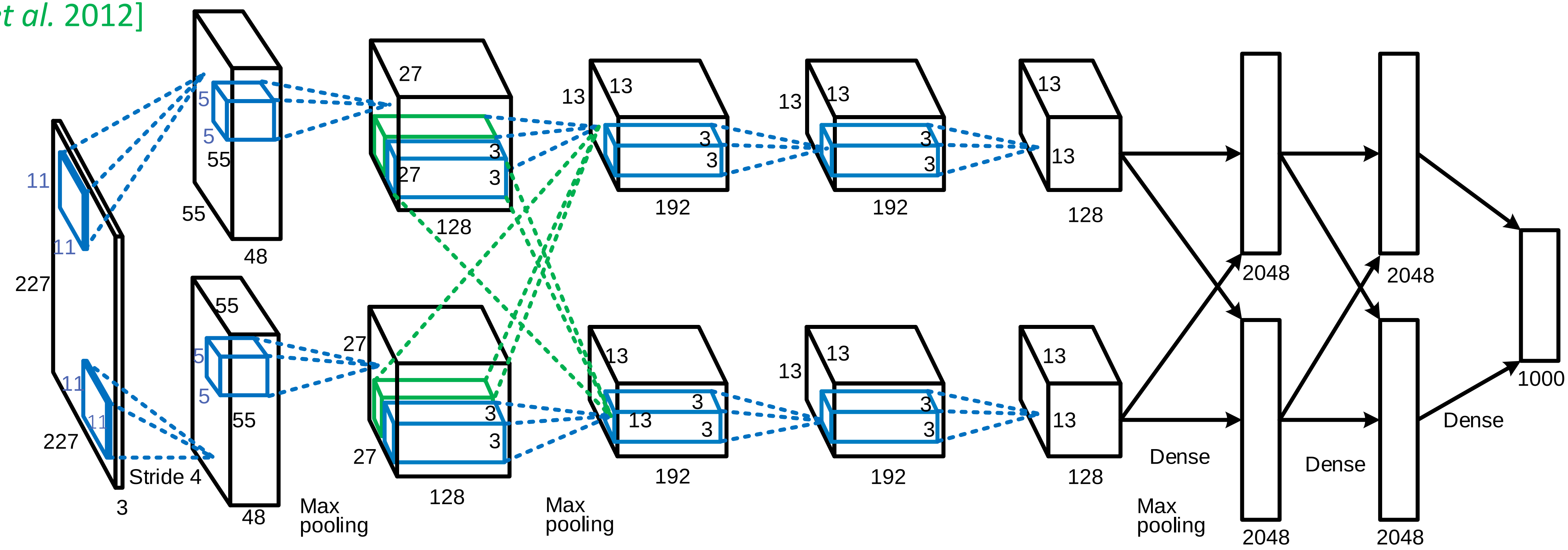
First layer (CONV1): 96 11×11 filters applied at stride 4

Output volume **[55×55×96]**

Parameters: (11*11*3)*96 = **35K**

Case Study: AlexNet

[Krizhevsky *et al.* 2012]



Input: 227×227×3 images

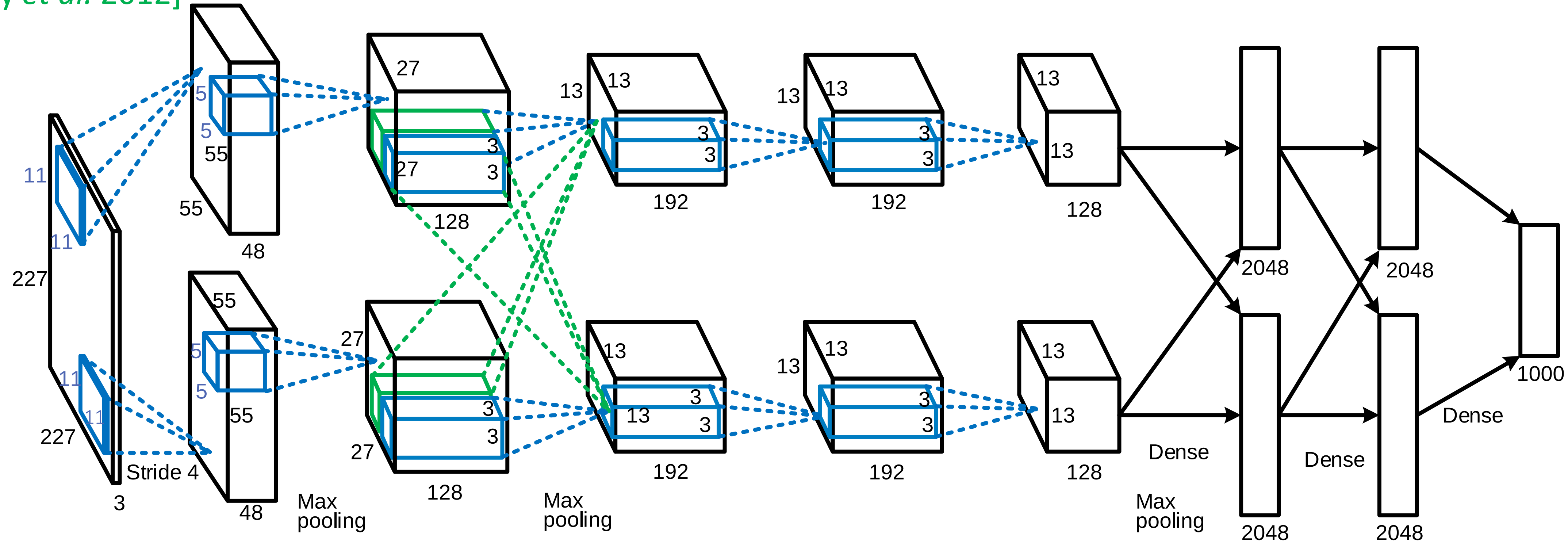
After CONV1: 55×55×96

Second layer (POOL1): 3×3 filters applied at stride 2

Q: what is the output volume size? Hint: (55-3)/2+1 = 27

Case Study: AlexNet

[Krizhevsky *et al.* 2012]



Input: 227×227×3 images

After CONV1: 55×55×96

Second layer (POOL1): 3×3 filters applied at stride 2

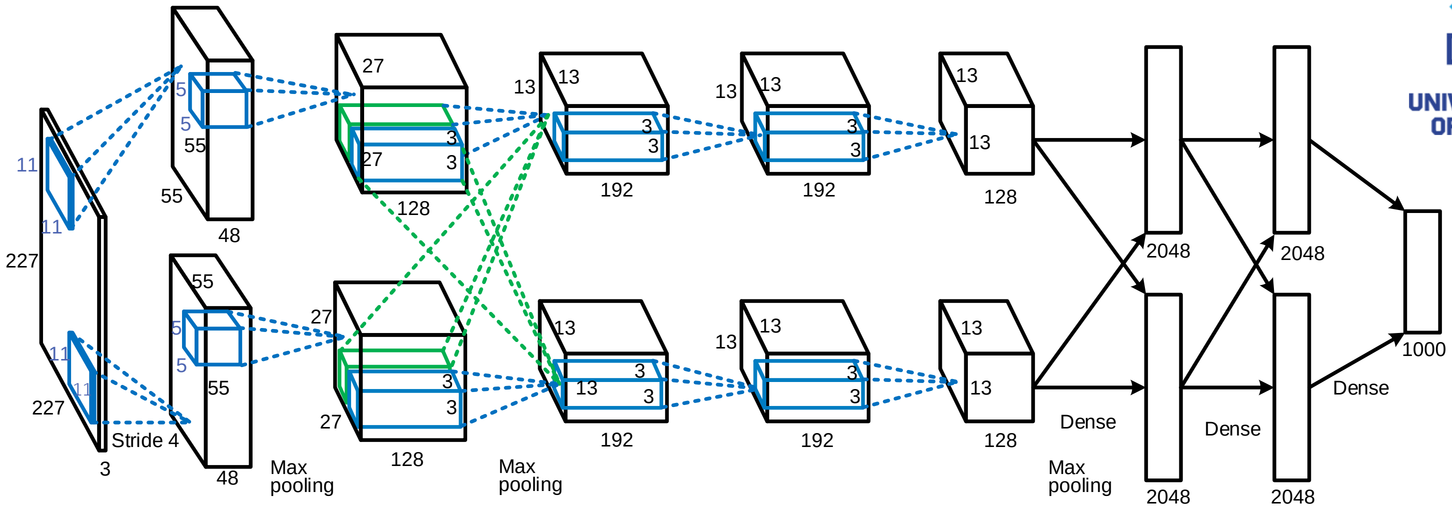
Output volume: 27×27×96

Q: what is the number of parameters in this layer?

Parameters: 0!

Case Study: AlexNet

[Krizhevsky *et al.* 2012]



Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

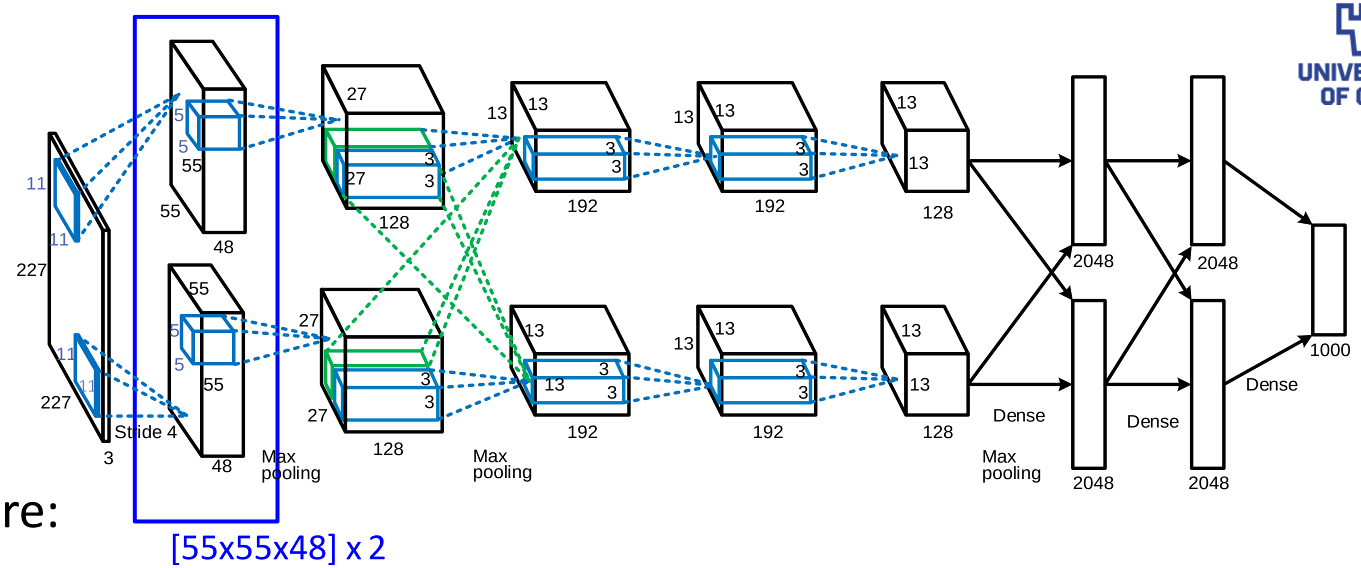
Details:

- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 0.01, reduced by 10 manually when val accuracy plateaus
- L2 weight decay 0.0005

7 CNN ensemble: 18.2%→ 15.4%

Case Study: AlexNet

[Krizhevsky *et al.* 2012]

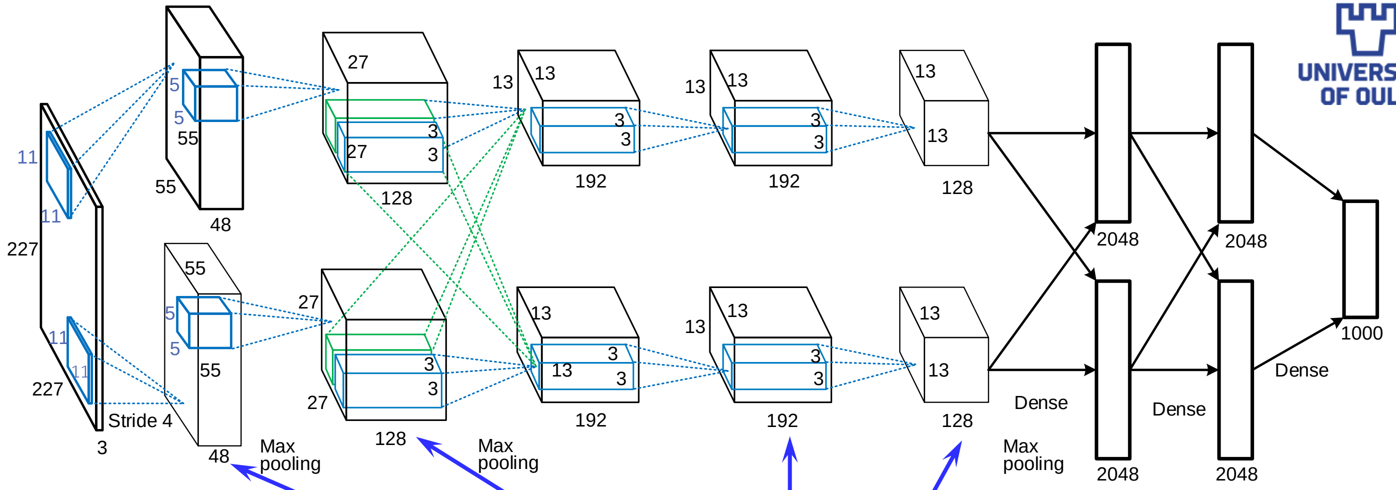


Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Historical note: Trained on GTX 580 GPU with only 3 GB of memory. Network spread across 2 GPUs, half the neurons (feature maps) on each GPU.

Case Study: AlexNet

[Krizhevsky *et al.* 2012]



CONV1, CONV2, CONV4, CONV5:
Connections only with feature maps on same GPU

Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
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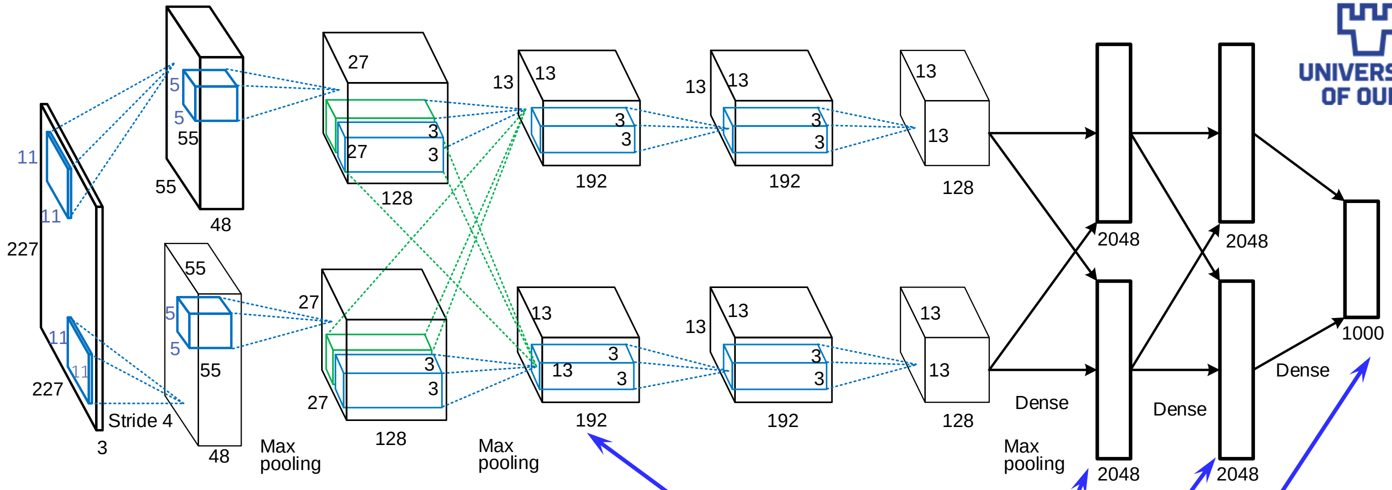
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Case Study: AlexNet

[Krizhevsky *et al.* 2012]



Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
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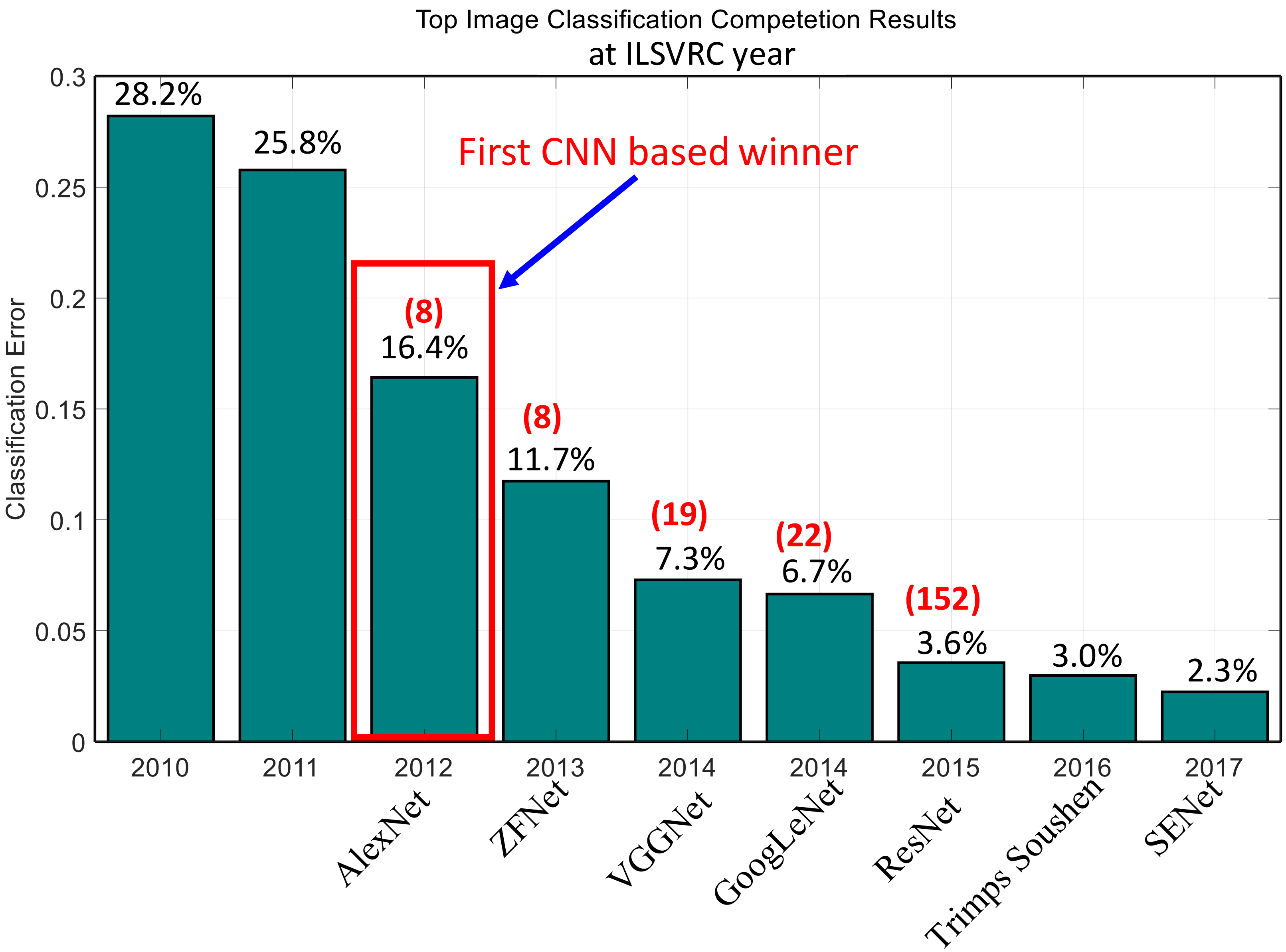
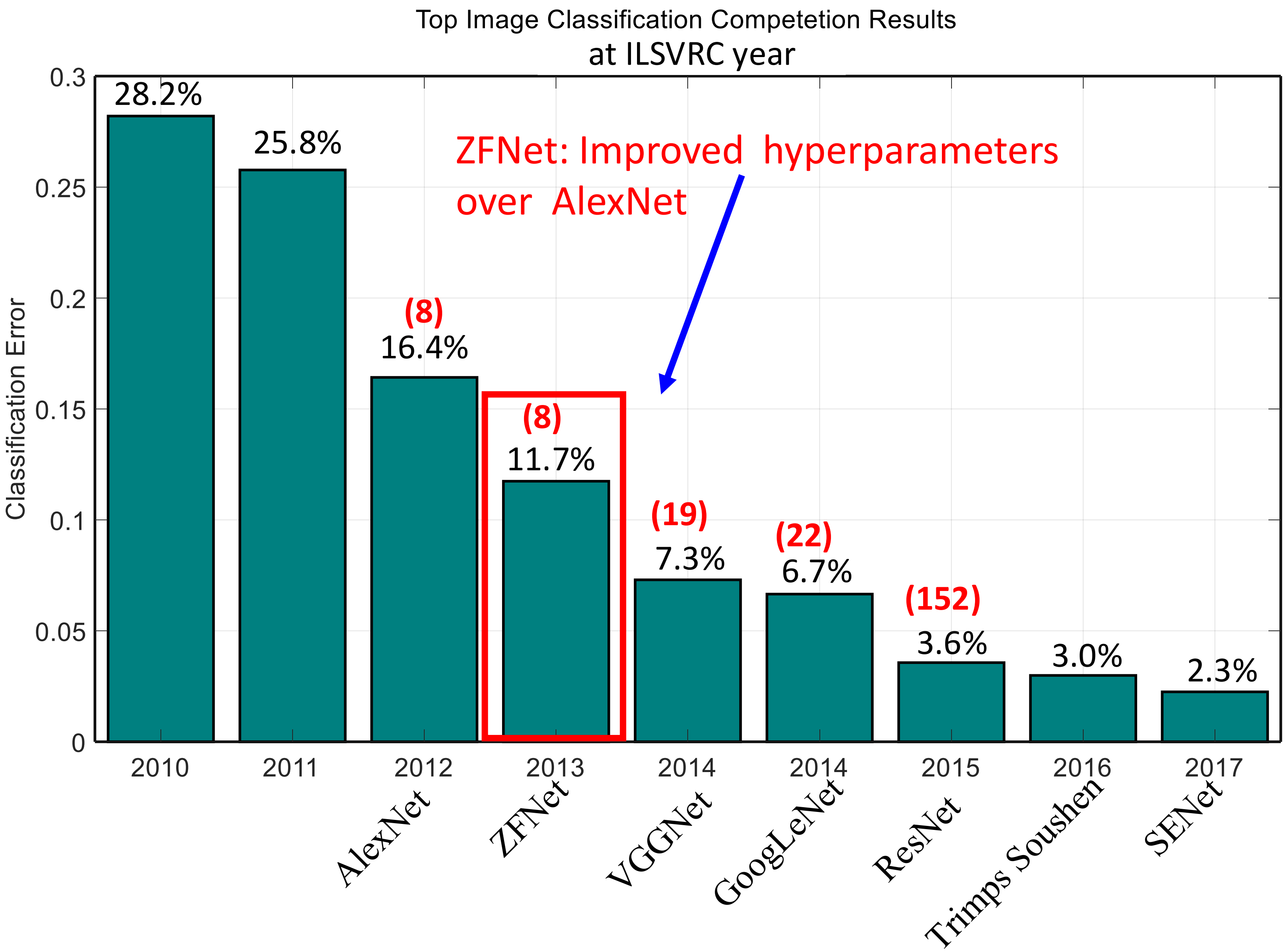
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

CONV3, FC6, FC7, FC8:
Connections with all feature maps in preceding layer, communication across GPUs



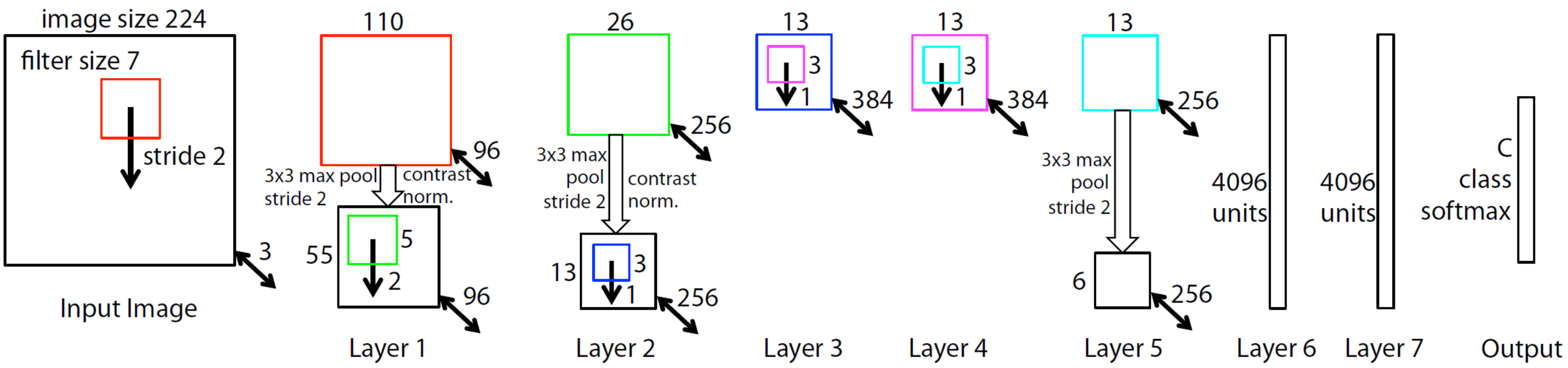
Li Liu et al., Deep Learning for Generic Object Detection: A Survey, IJCV, 2019.



Li Liu et al., Deep Learning for Generic Object Detection: A Survey, IJCV, 2019.

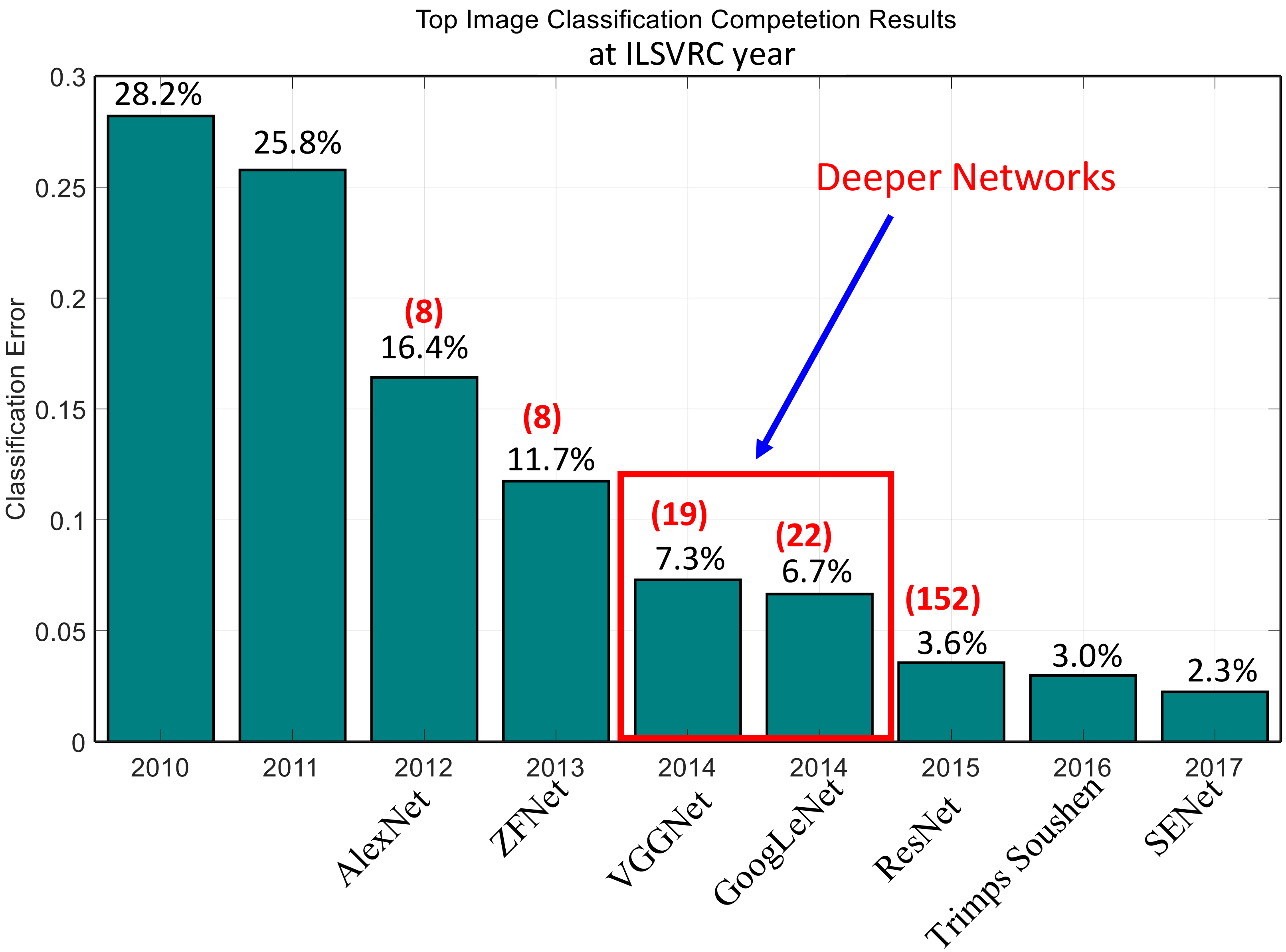
ZFNet

[Zeiler and Fergus, 2013]



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

ImageNet top 5 error: 16.4% →11.7%



Li Liu et al., Deep Learning for Generic Object Detection: A Survey, IJCV, 2019.

Case Study: VGGNet

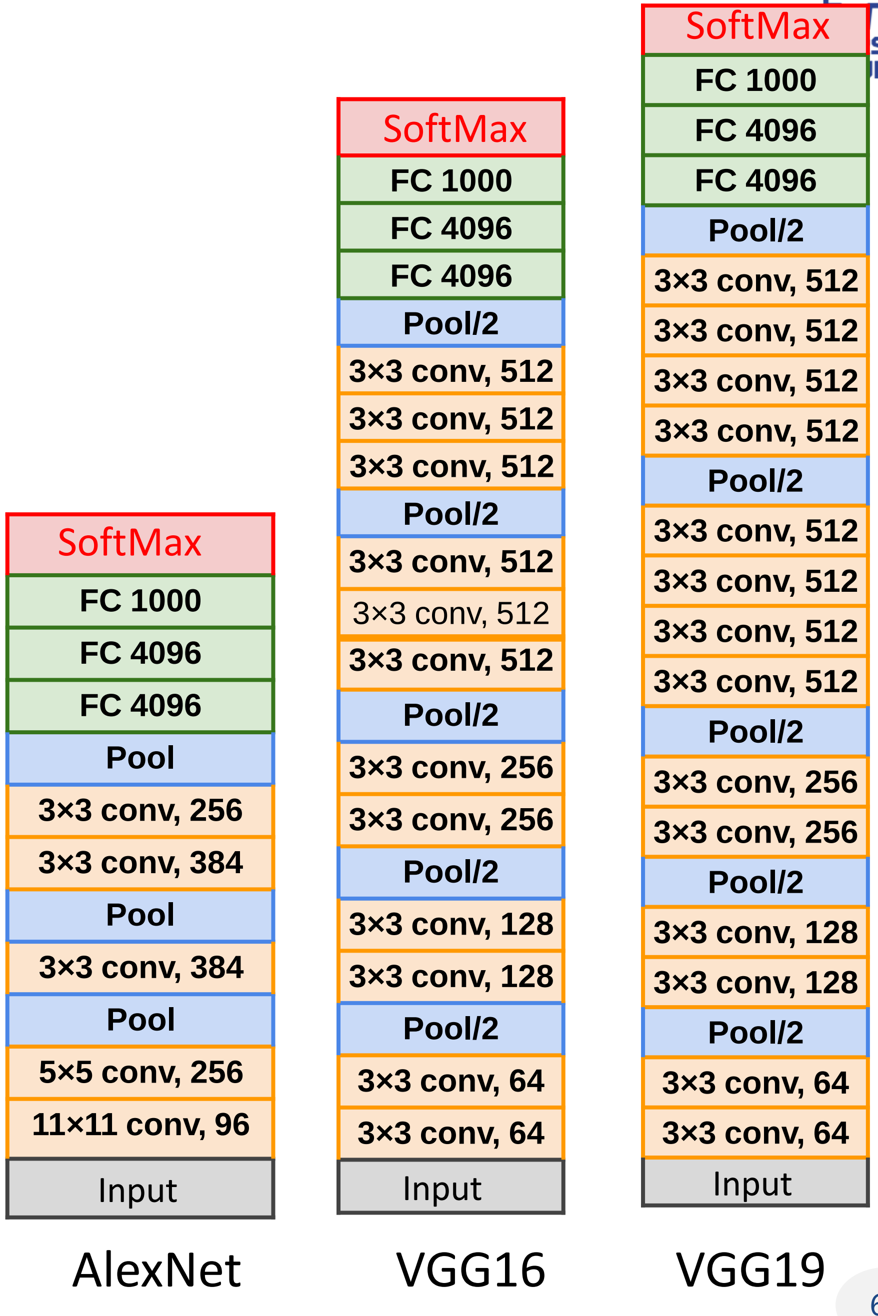
[Simonyan and Zisserman, 2014]

Small filters, Deeper networks

8 layers (AlexNet)
→ 16−19 layers (VGG16Net)

Only 3 × 3 CONV stride 1, pad 1 and 2 × 2 MAX POOL stride 2

11.7% top 5 error in ILSVRC’13 (ZFNet)
→ 7.3% top 5 error in ILSVRC’14



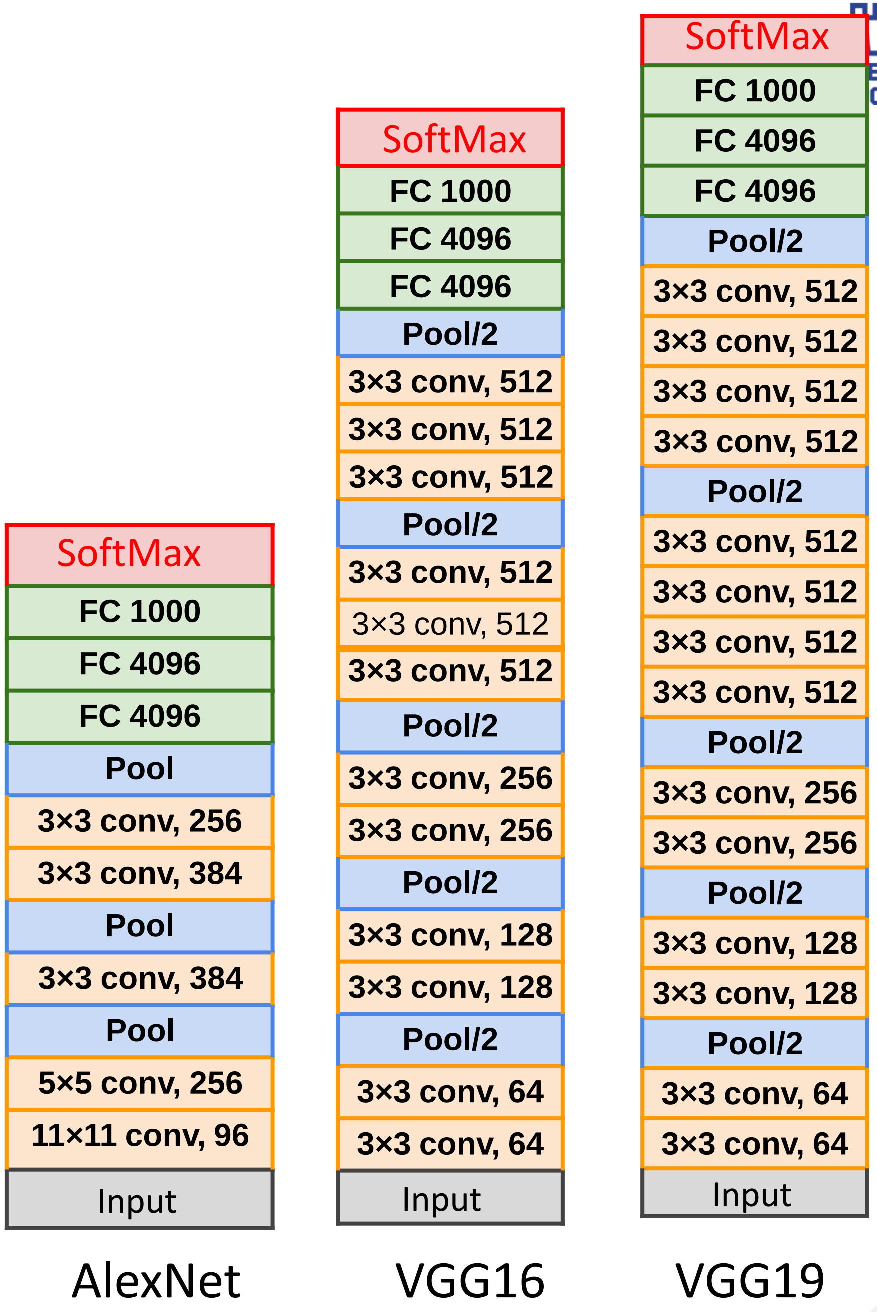
Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Q: Why use smaller filters? (3×3 conv)

Stack of three 3×3 conv (stride 1) layers has same **effective receptive field** as one 7×7 conv layer

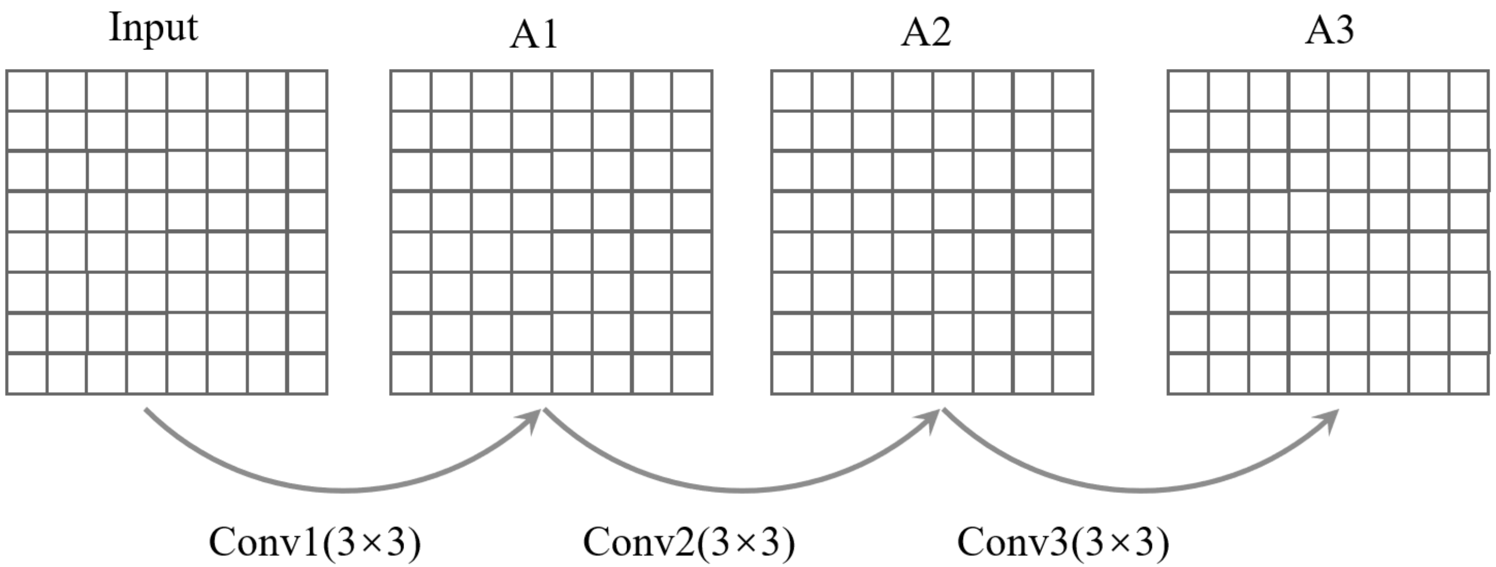
Q: What is the effective receptive field of three 3×3 conv (stride 1) layers?

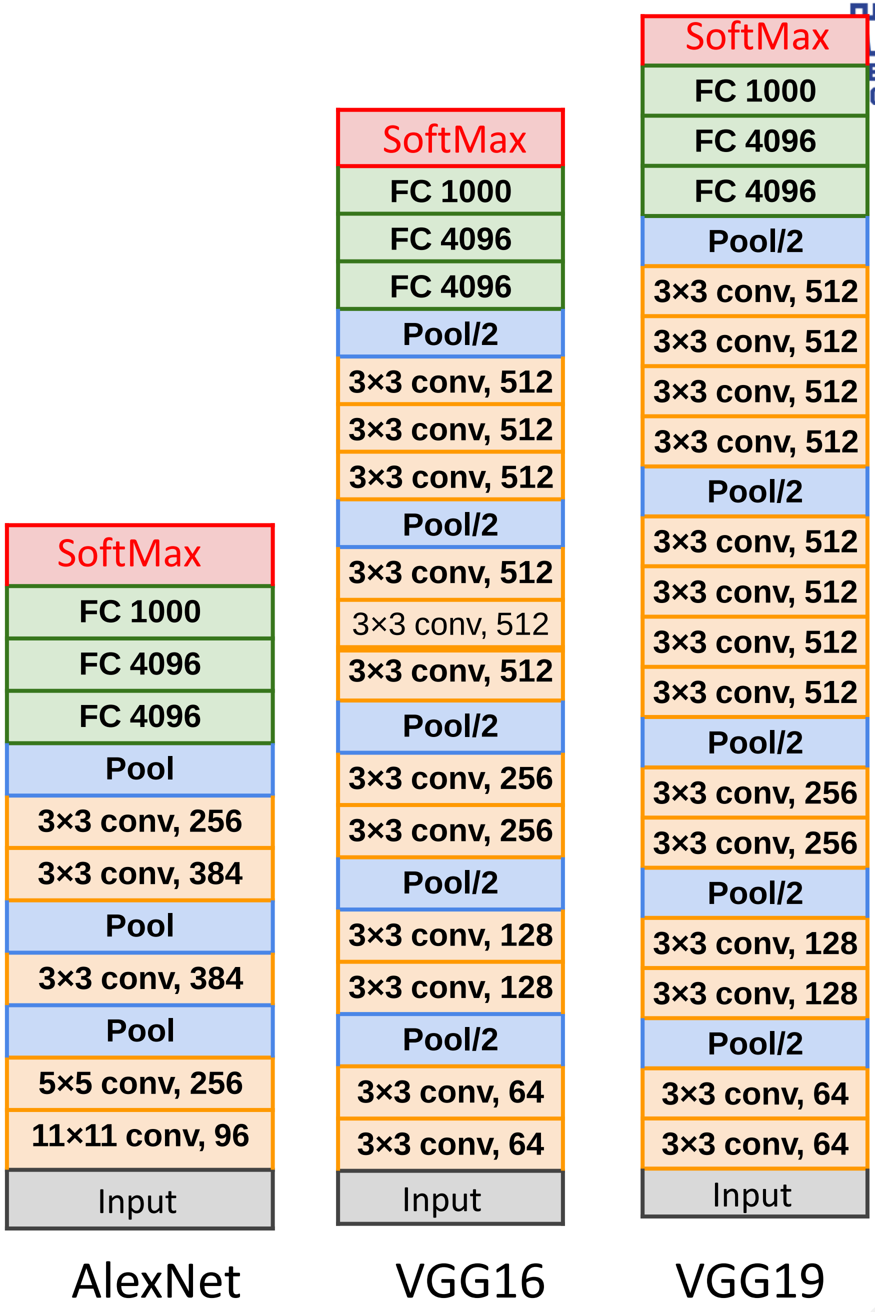


Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Q: What is the effective receptive field of three 3×3 conv (stride 1) layers?

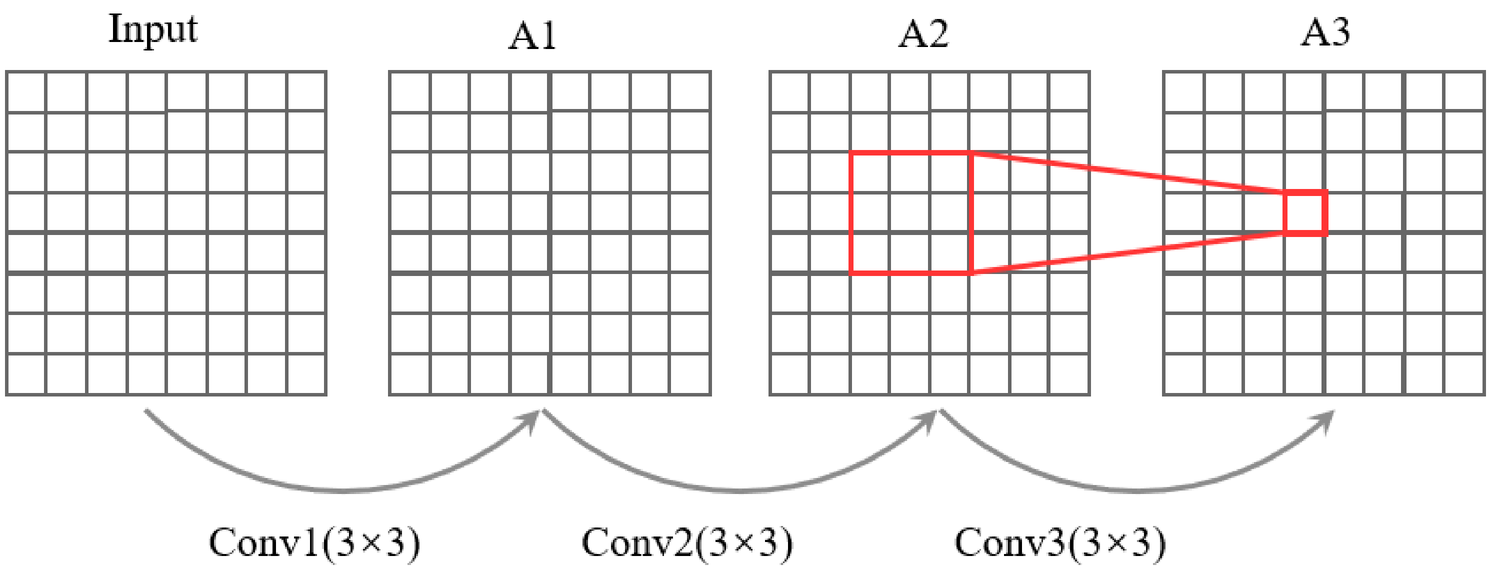


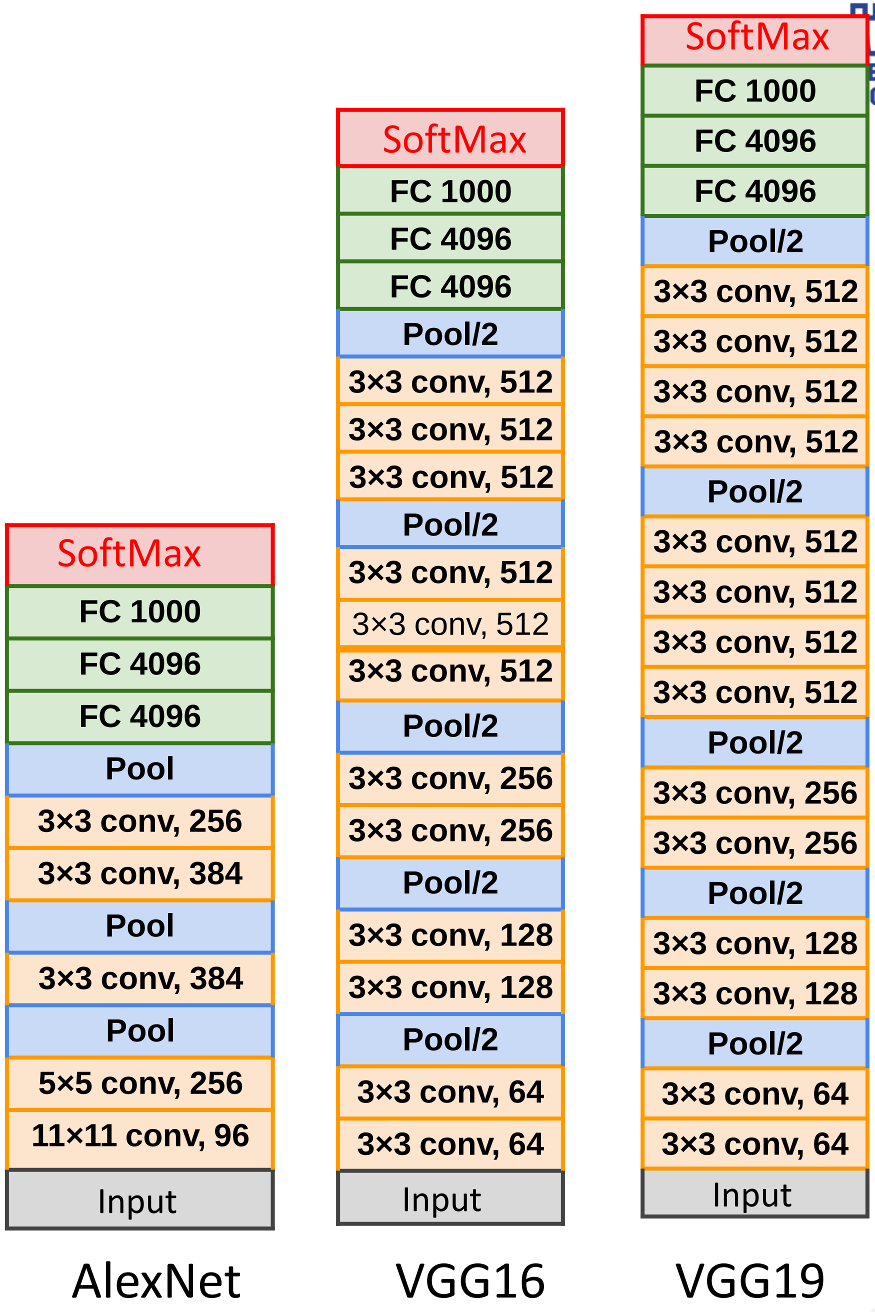


Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Q: What is the effective receptive field of three 3×3 conv (stride 1) layers?





Case Study: VGGNet

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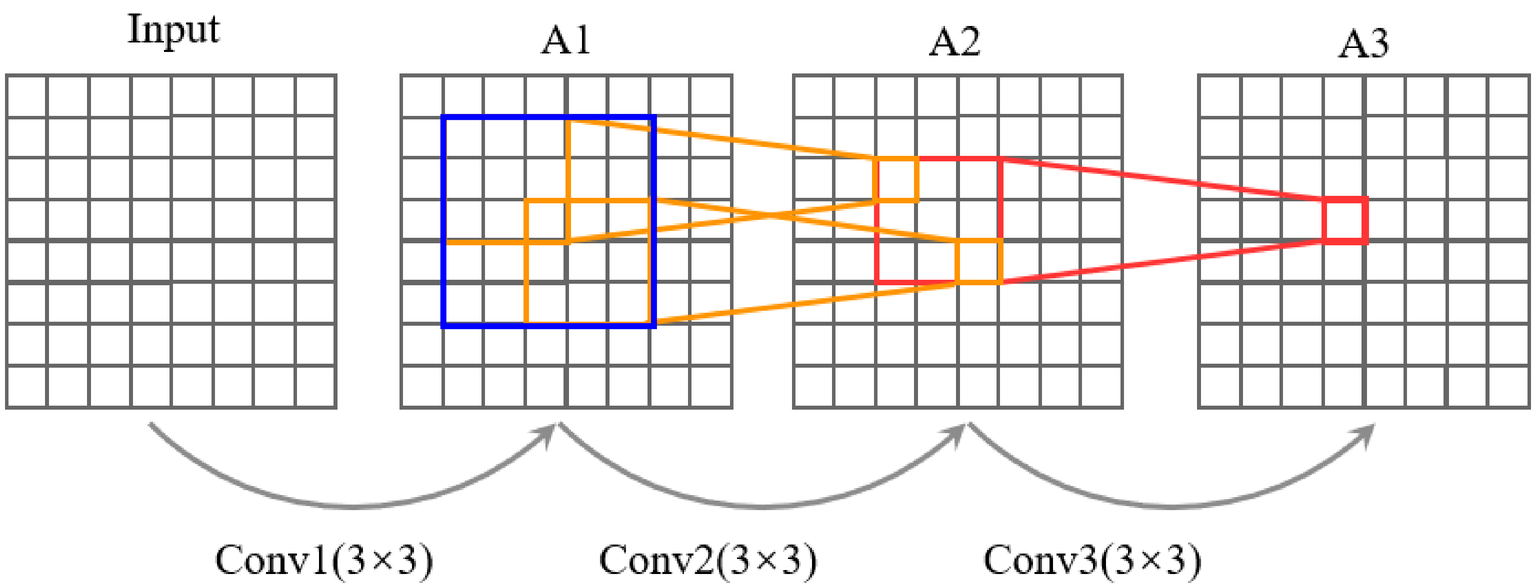
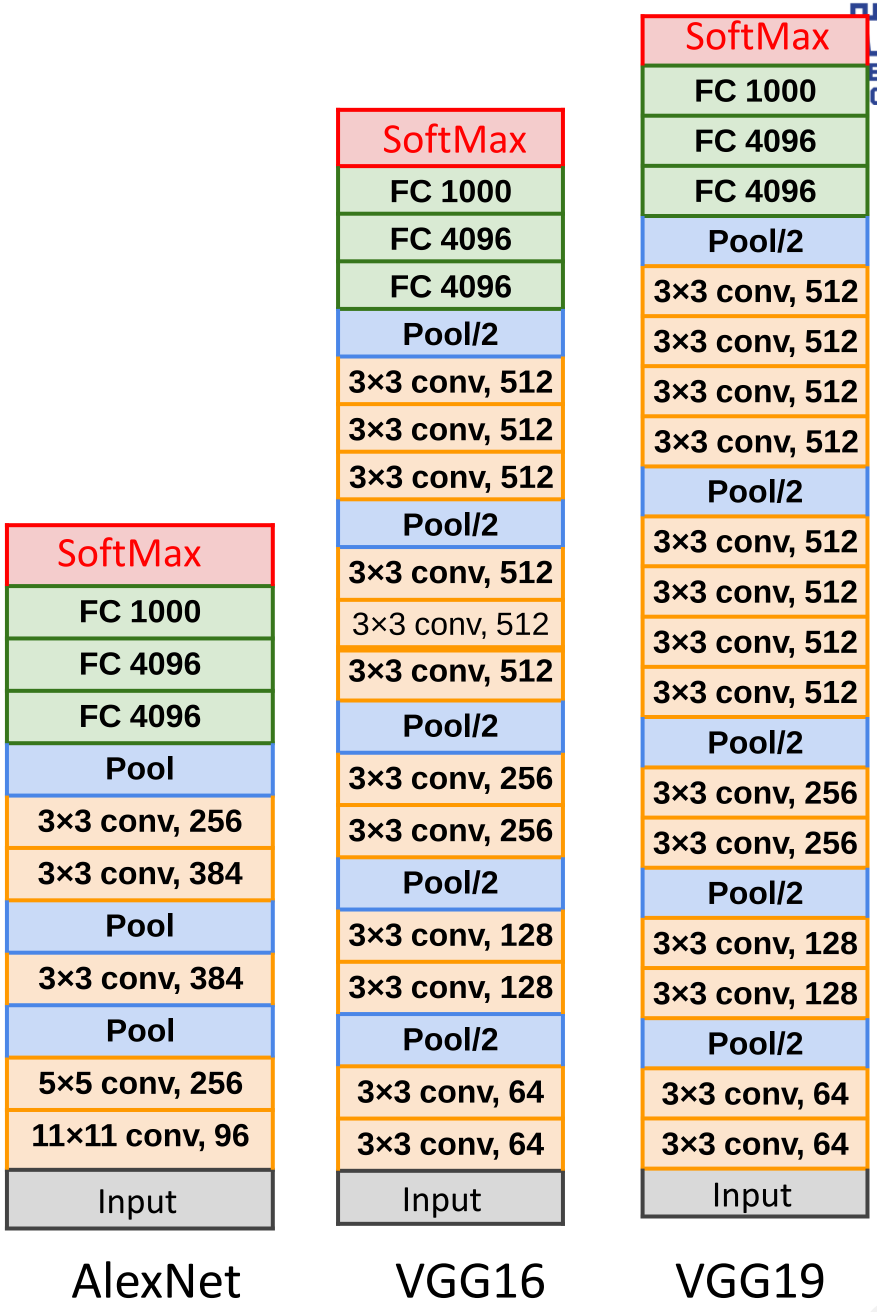
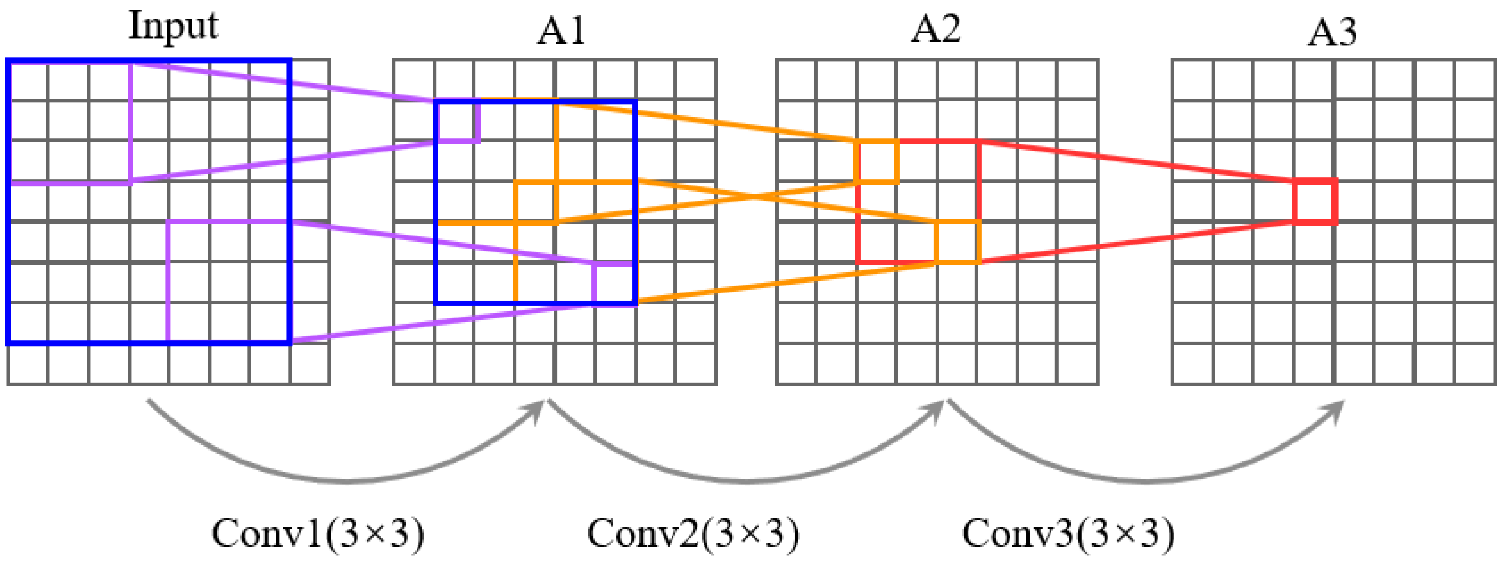


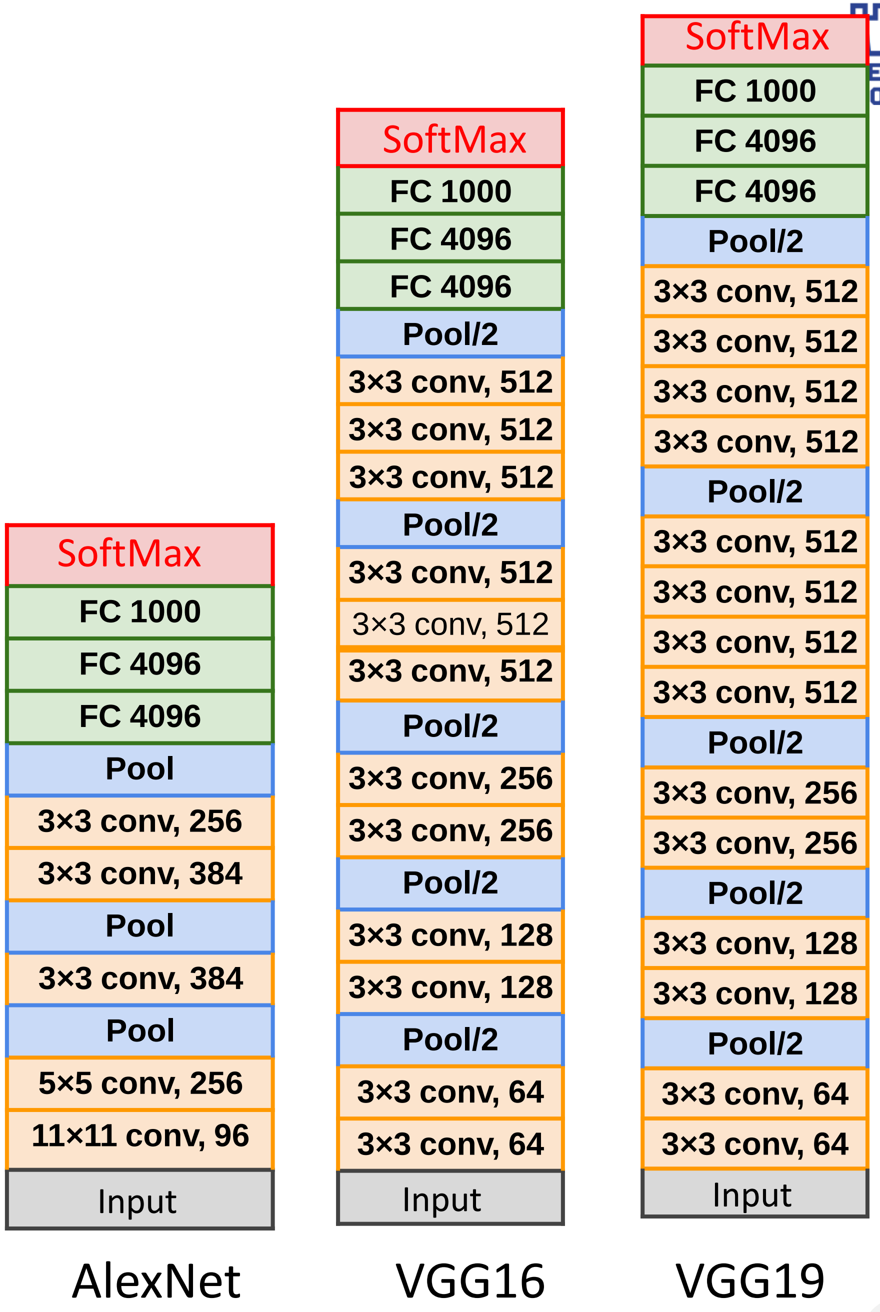


Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Q: What is the effective receptive field of three 3×3 conv (stride 1) layers?





Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Q: Why use smaller filters? (3 × 3 conv)

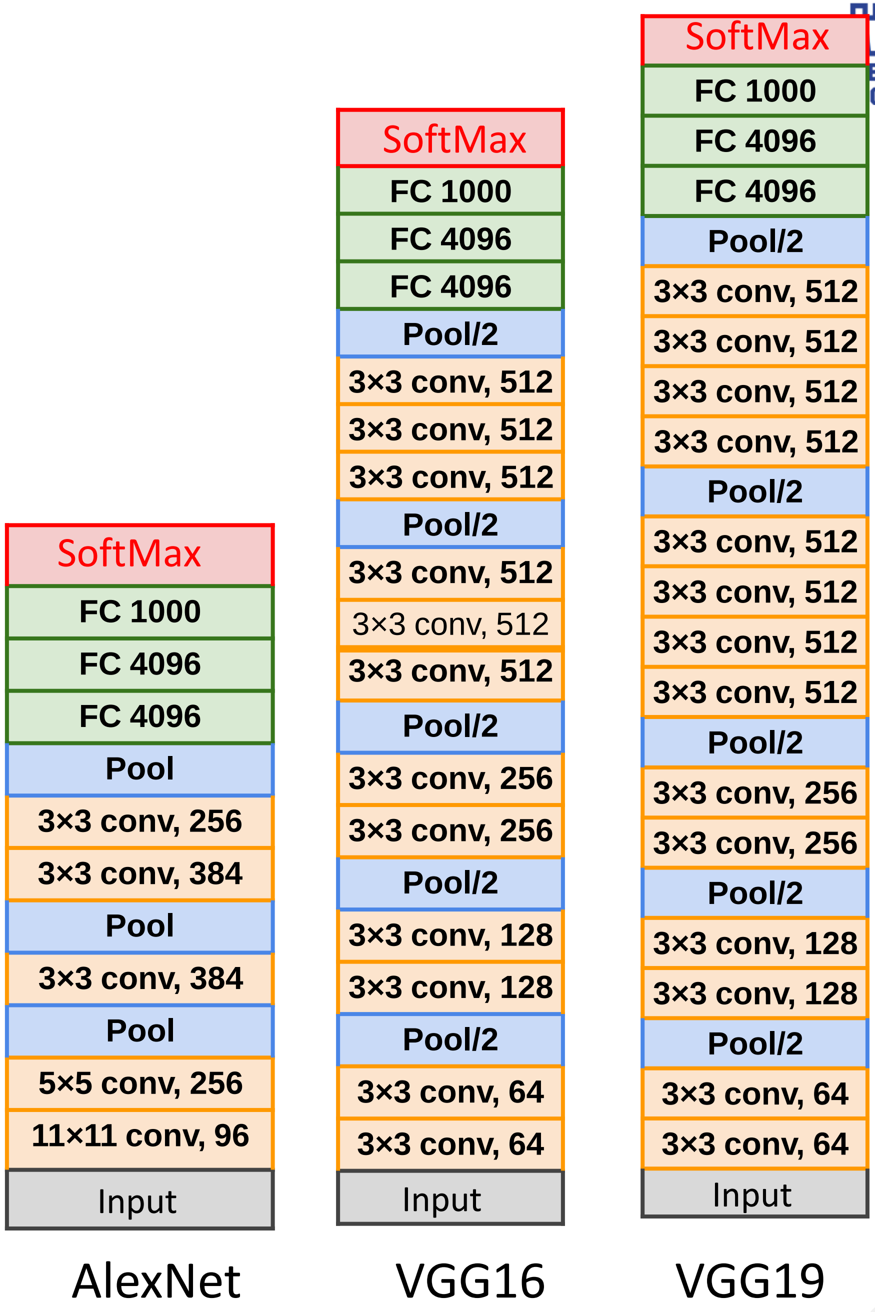
Stack of three 3×3 conv (stride 1) layers has same **effective receptive field** as one 7 × 7 conv layer

Q: What is the effective receptive field of three 3×3 conv (stride 1) layers?

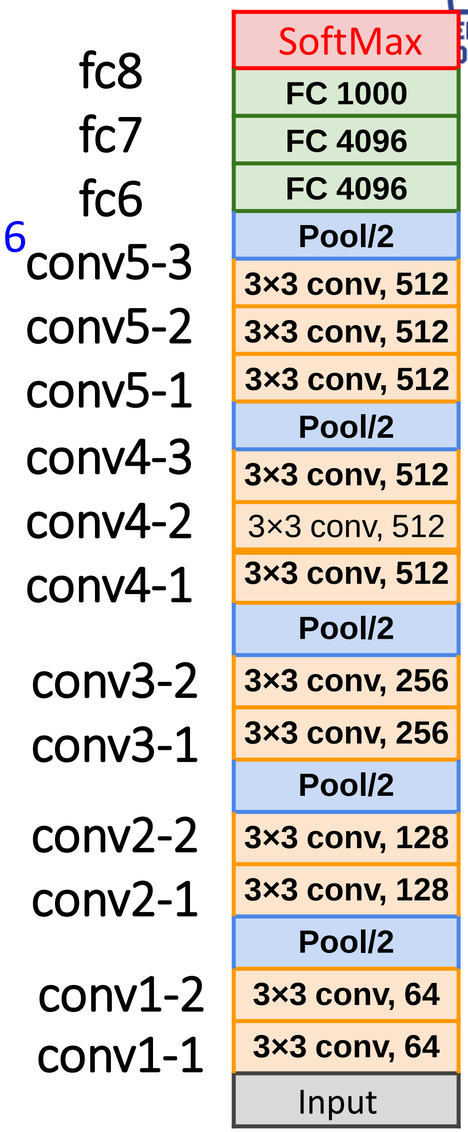
[7×7]

But deeper, more nonlinearities

And fewer parameters:
$3*(3^2C^2)$ vs. 7^2C^2 for C channels per layer



INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000



VGG16

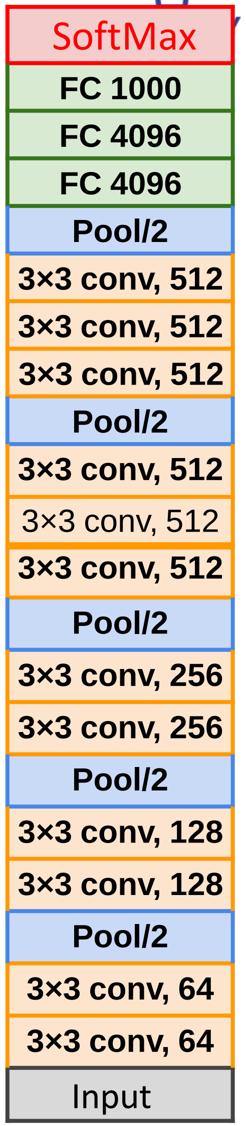
TOTAL memory: 24M * 4 bytes ~= 96MB / image (only forward! about*2 for bwd)
TOTAL params: 138M parameters

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

Most memory is in early CONV

Most params are in late FC

TOTAL memory: 24M * 4 bytes ~= 96MB / image (only forward! about*2 for bwd)
TOTAL params: 138M parameters



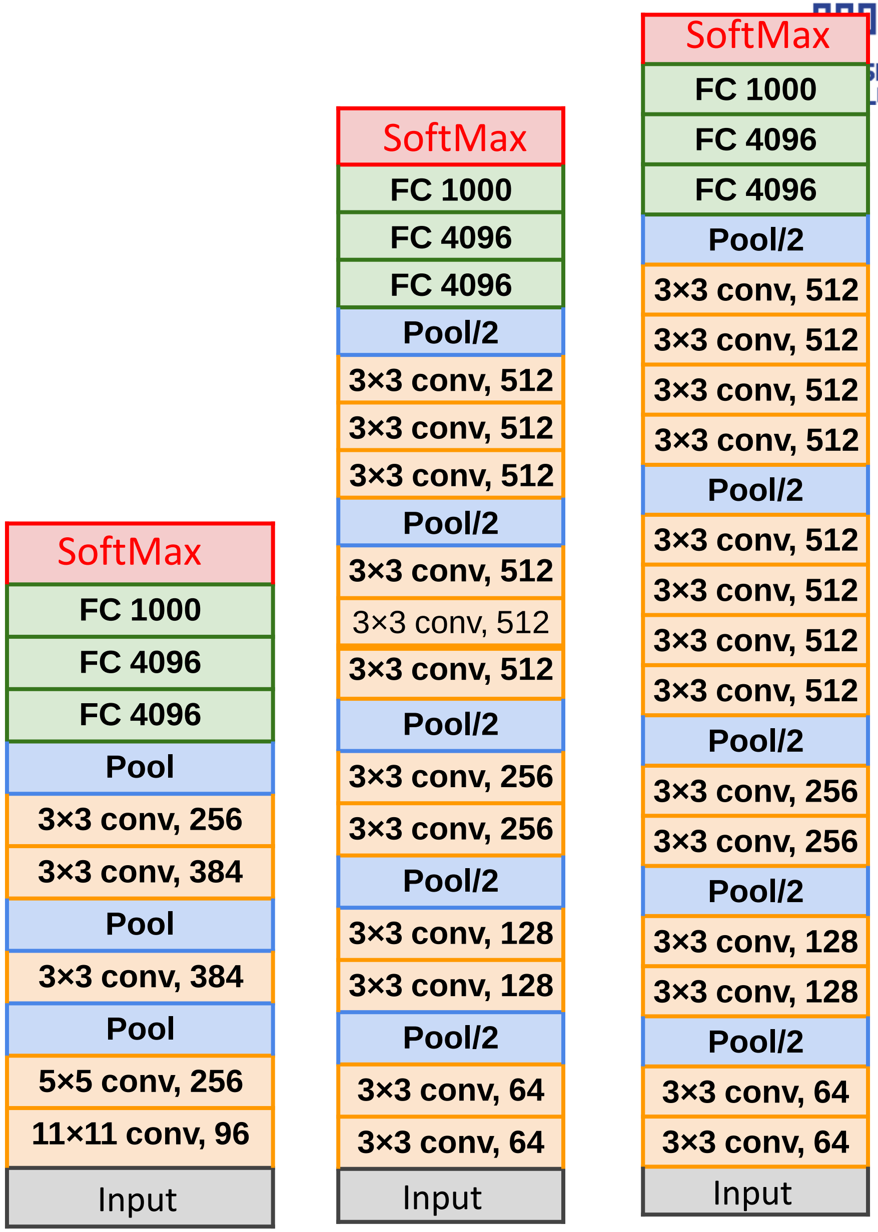
VGG16

Case Study: VGGNet

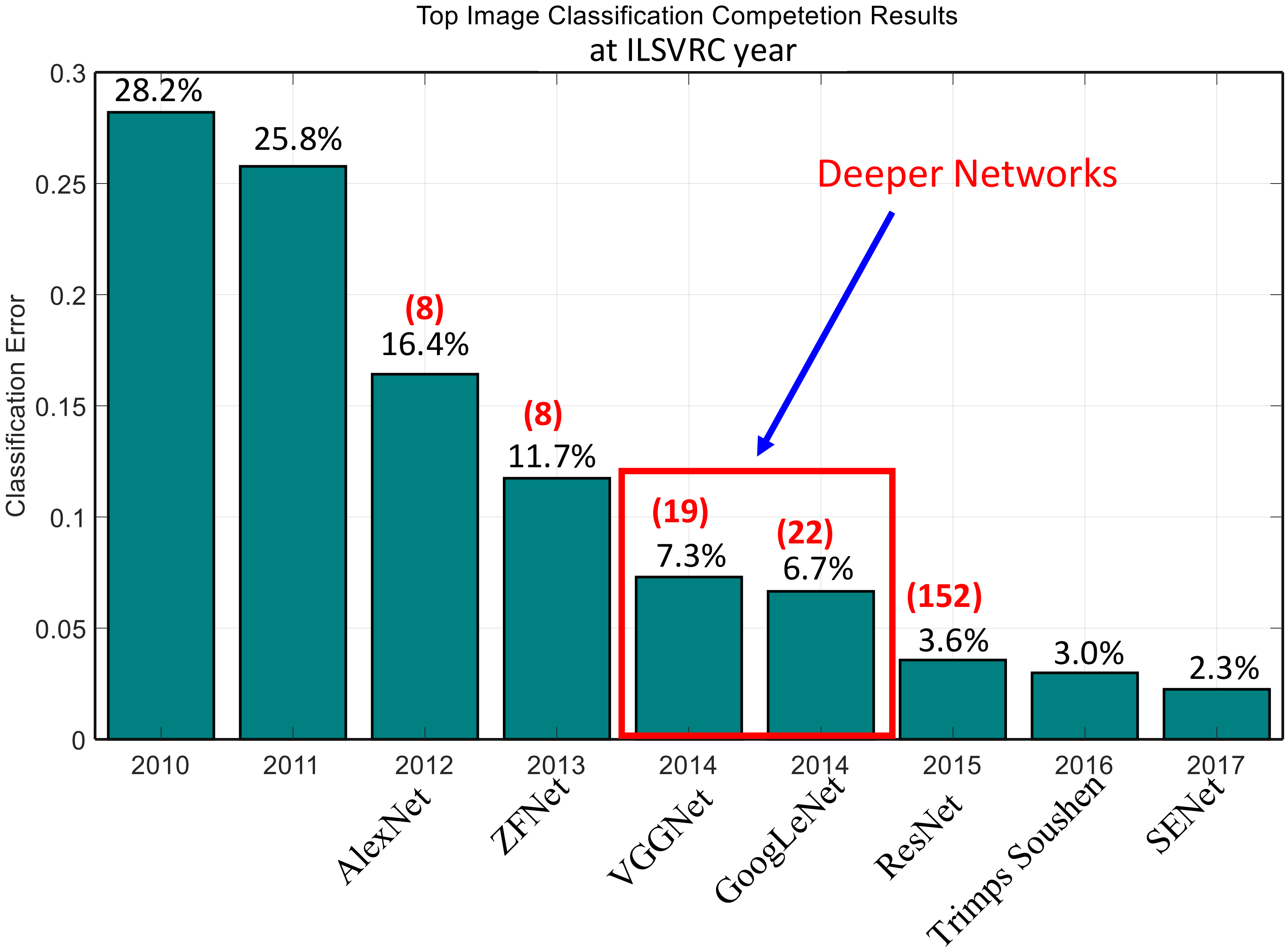
[Simonyan and Zisserman, 2014]

Summary

- ILSVRC'14 2nd in classification, 1st in localization
- Similar training procedure as AlexNet
- No Local Response Normalization (LRN)
- Use VGG16 or VGG19 (VGG19 only slightly better, more memory)
- Use ensembles for best results
- FC7 features generalize well to other tasks



AlexNet VGG16 VGG19



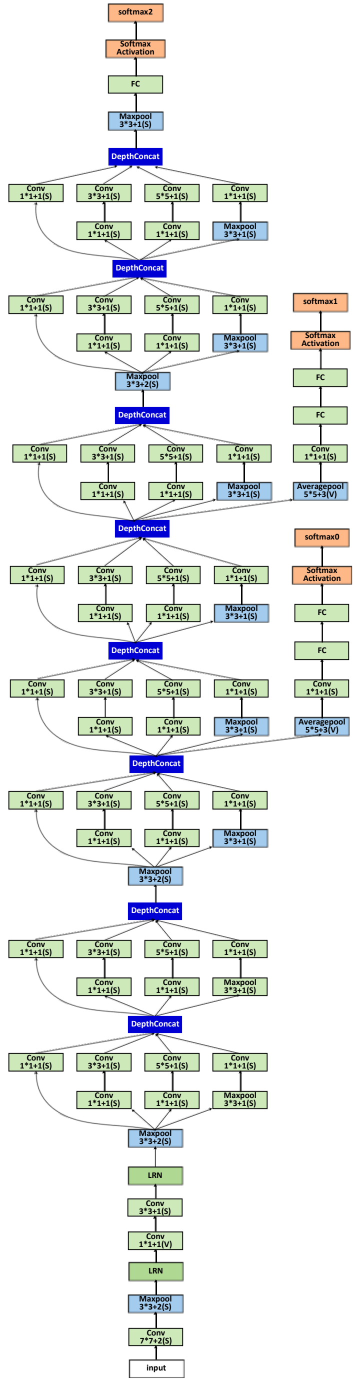
Li Liu et al., Deep Learning for Generic Object Detection: A Survey, IJCV, 2019.

Case Study: GoogLeNet

[Szegedy et al., 2014]

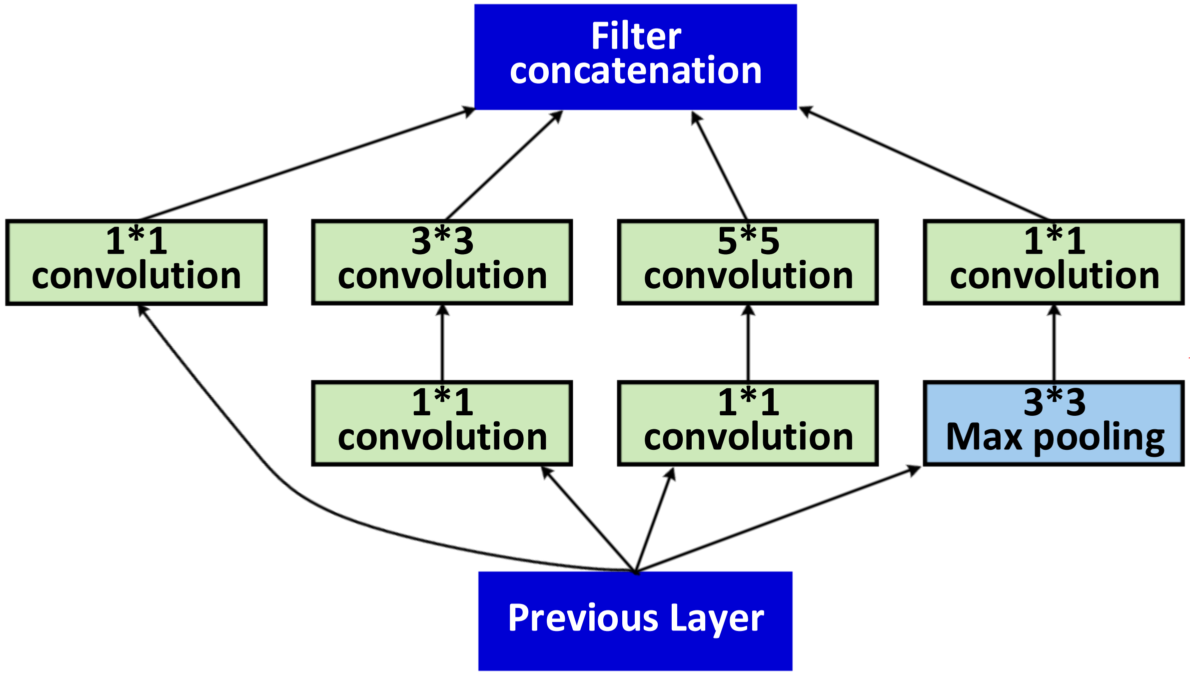
Deeper networks and computational efficiency

- 22 layers
- Efficient “Inception” module
- No FC layers
- Only 5 million parameters!
  - 12× less than AlexNet
- ILSVRC’14 classification winner (6.7% top 5 error)

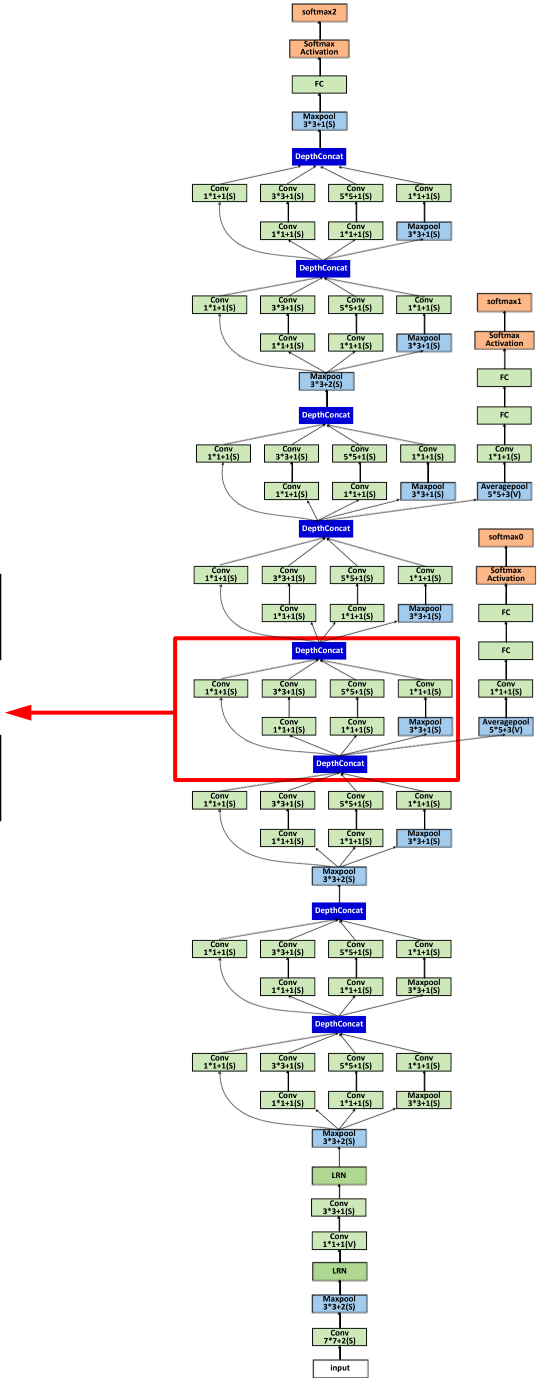


Case Study: GoogLeNet

[Szegedy et al., 2014]



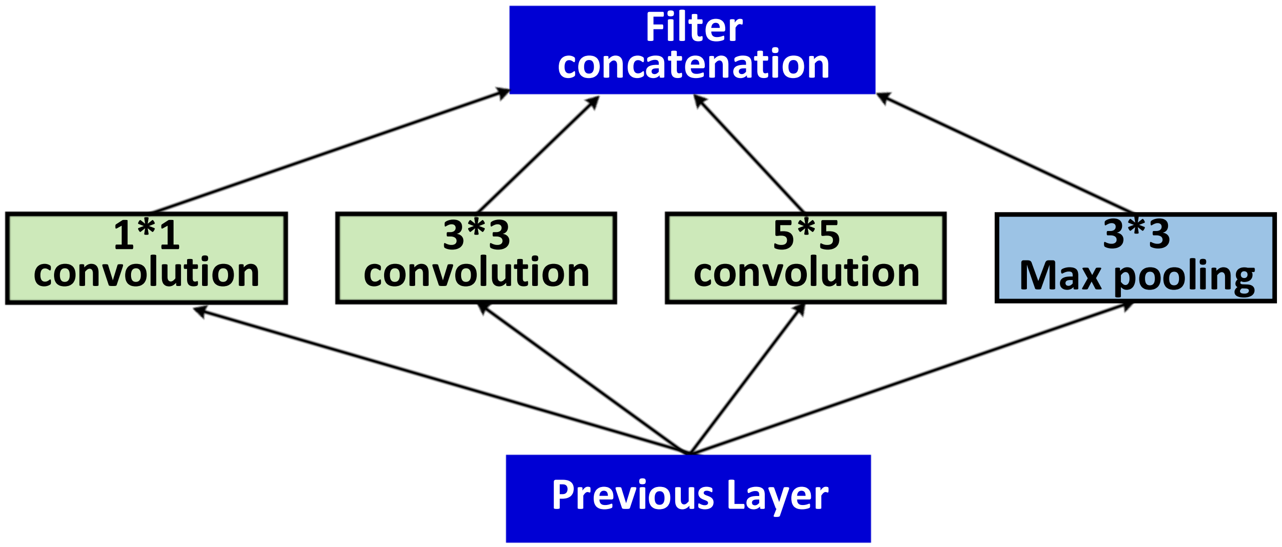
Inception module



"Inception module": design a good local network topology (network within a network) and then stack these modules on top of each other

Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

Apply parallel filter operations on the input from previous layer:

- Multiple receptive field sizes for convolution (1×1, 3×3, 5×5)
- Pooling operation (3×3)

Concatenate all filter outputs together depthwise.

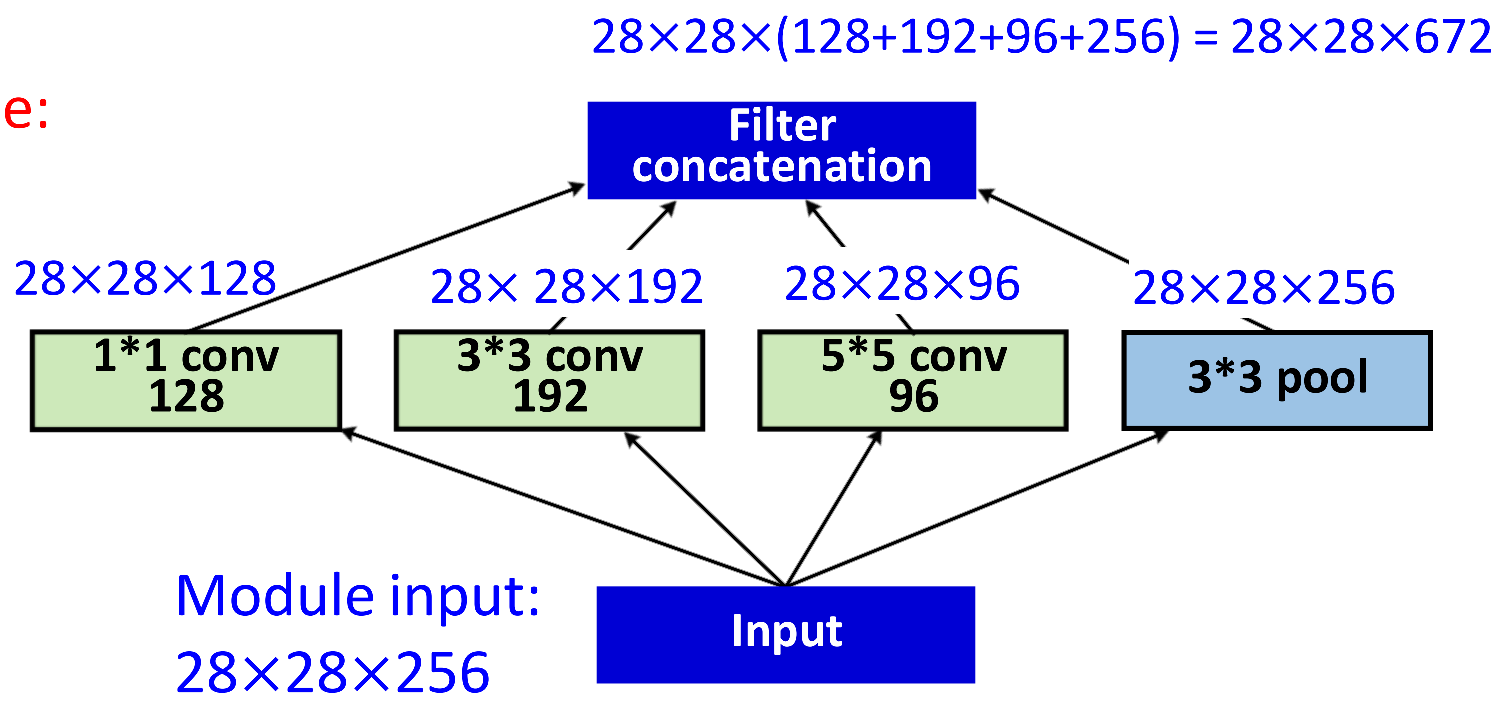
Q: What is the problem with this?
[Hint: Computational complexity]

Case Study: GoogLeNet

[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:



Naive Inception module

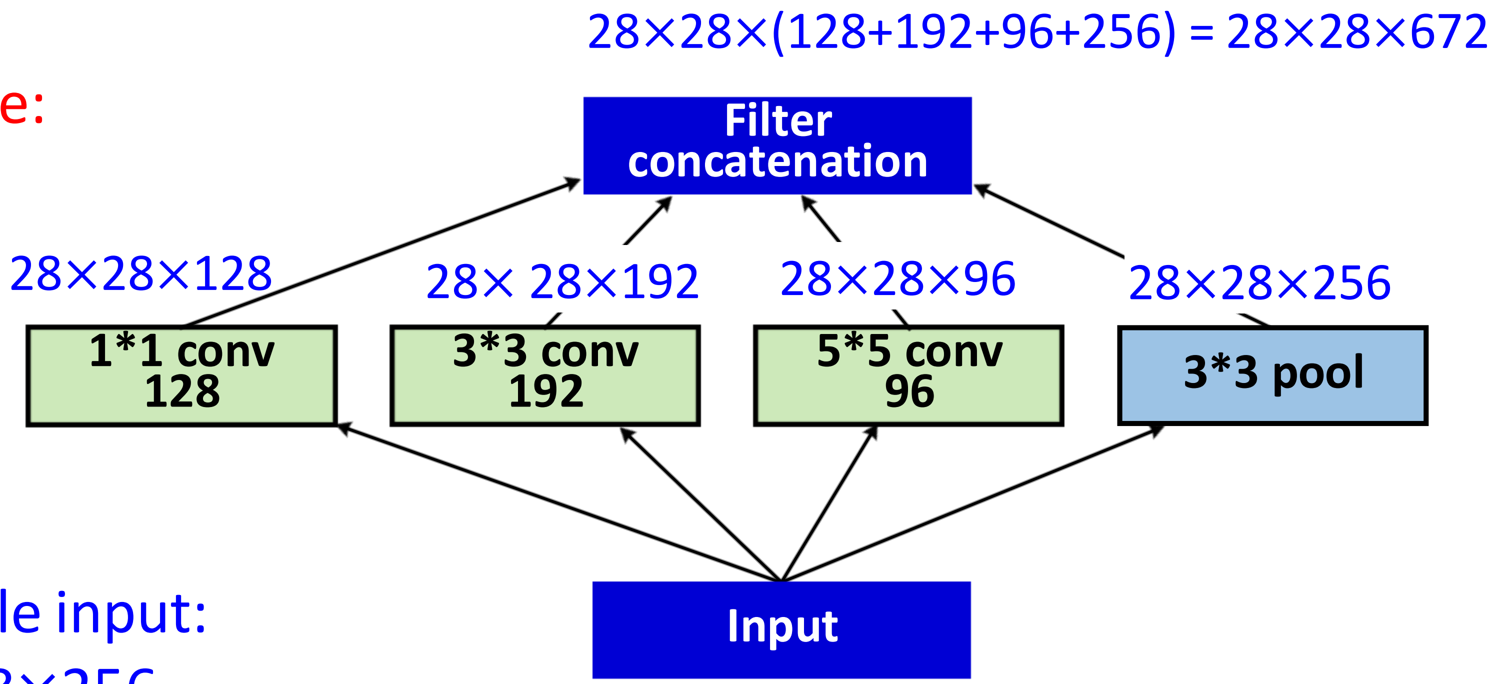
Q1: What is the output size of the 1×1 conv, with 128 filters?
Q2: What are the output sizes of all different filter operations?
Q3: What is output size after filter concatenation?

Case Study: GoogLeNet

[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:



Module input:
28×28×256

Naive Inception module

Conv Ops:
[1×1 conv, 128] 28*28*128*1*1*256
[3×3 conv, 192] 28*28*192*3*3*256
[5×5 conv, 96] 28*28*96*5*5*256
Total: 854M ops

Very expensive compute

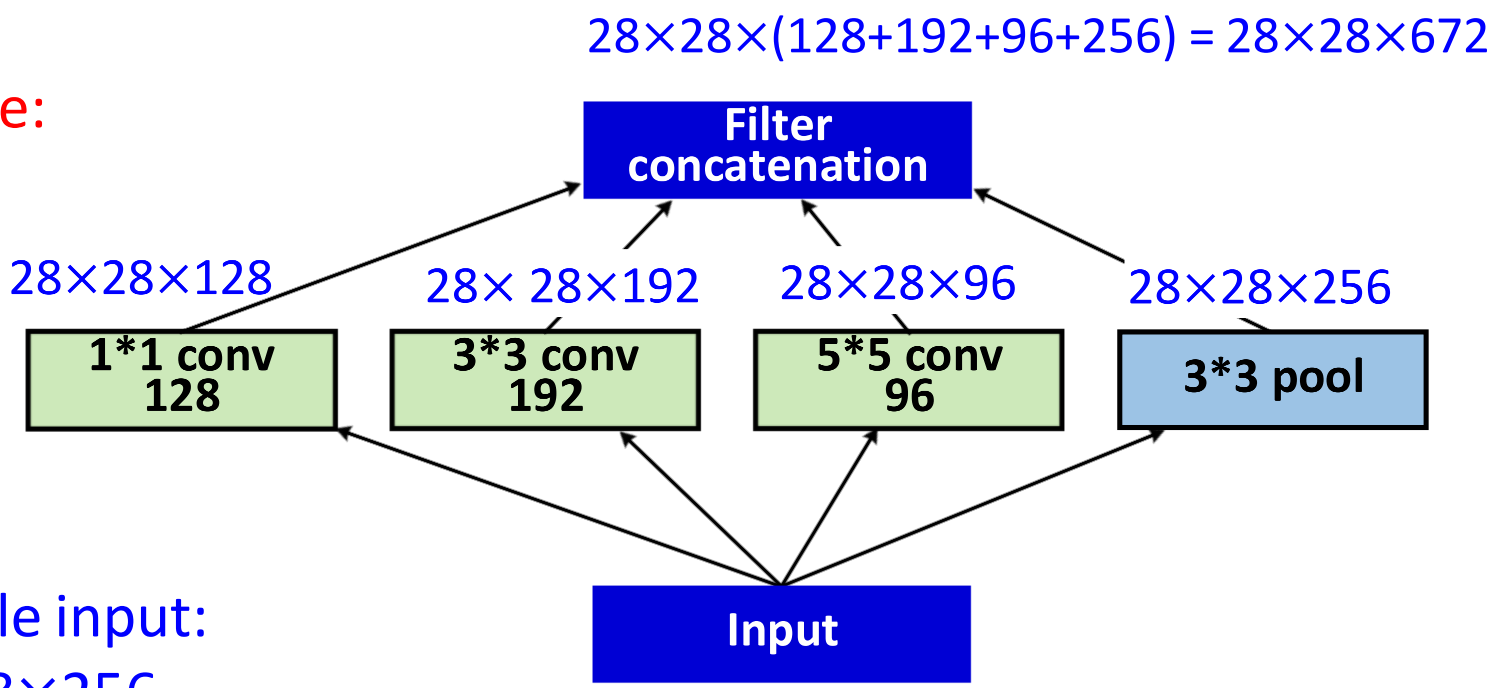
Pooling layer also preserves feature depth, which means total depth after concatenation can only grow at every layer!

Case Study: GoogLeNet

[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:

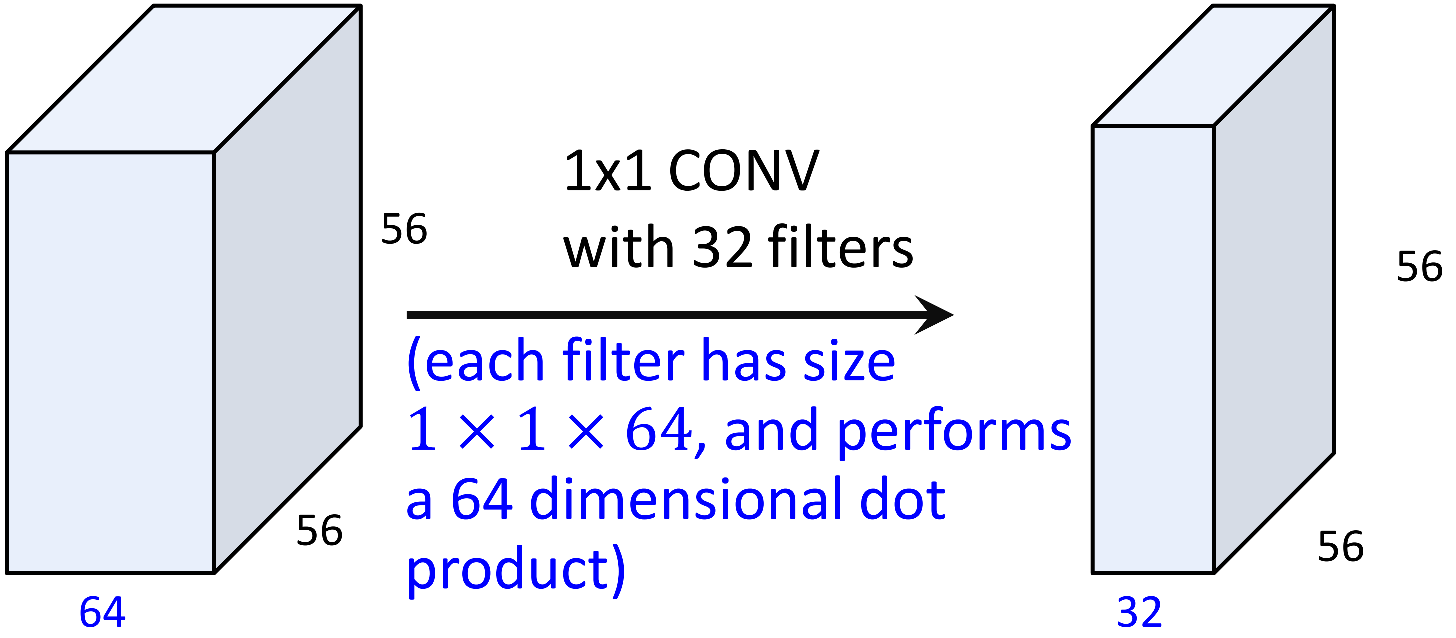


Module input: 28×28×256

Naive Inception module

Solution: “bottleneck” layers that use 1×1 convolutions to reduce feature depth.

Reminder: 1x1 convolutions

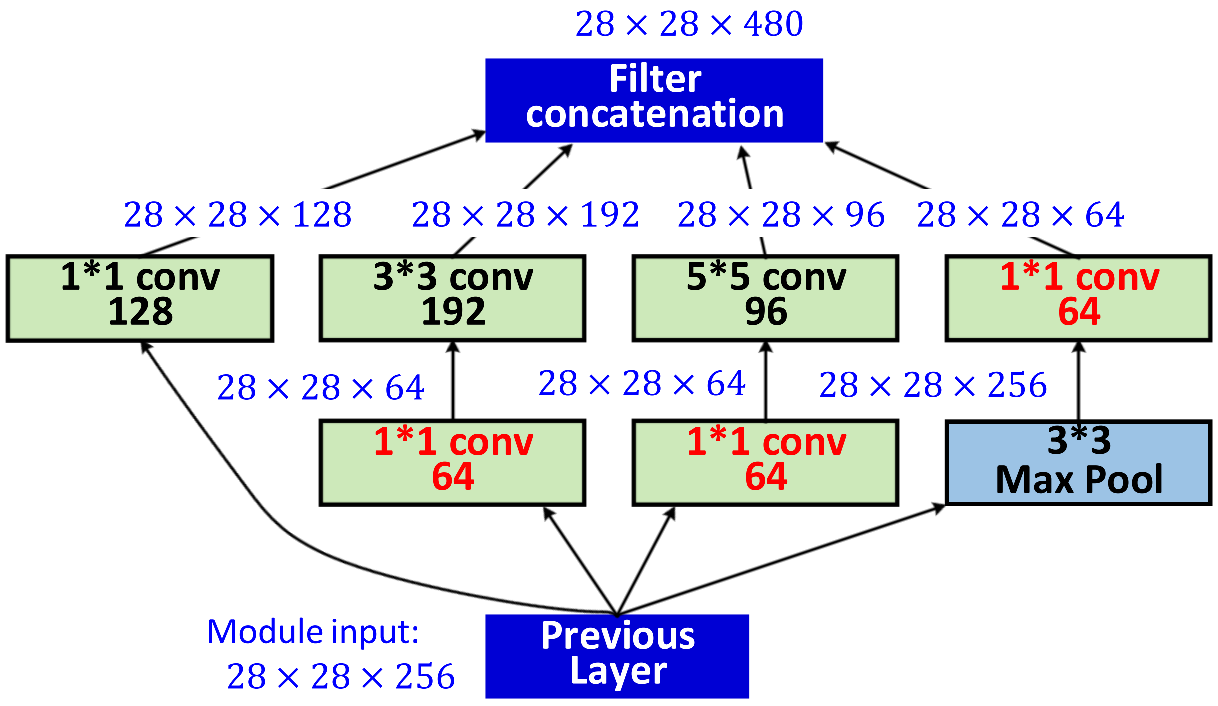


Preserves spatial dimensions, reduces depth!

Projects depth to lower dimension (combination of feature maps)

Case Study: GoogLeNet

[Szegedy et al., 2014]



Inception module with dimension reduction

Using same parallel layers as naive example, and adding "1×1 conv, 64 filter" bottlenecks:

Conv Ops:

$[1 \times 1\ conv, 64]\ 28 \times 28 \times 64 \times 1 \times 1 \times 256$

$[1 \times 1\ conv, 64]\ 28 \times 28 \times 64 \times 1 \times 1 \times 256$

$[1 \times 1\ conv, 128]\ 28 \times 28 \times 128 \times 1 \times 1 \times 256$

$[3 \times 3\ conv, 192]\ 28 \times 28 \times 192 \times 3 \times 3 \times 64$

$[5 \times 5\ conv, 96]\ 28 \times 28 \times 96 \times 5 \times 5 \times 64$

$[1 \times 1\ conv, 64]\ 28 \times 28 \times 64 \times 1 \times 1 \times 256$

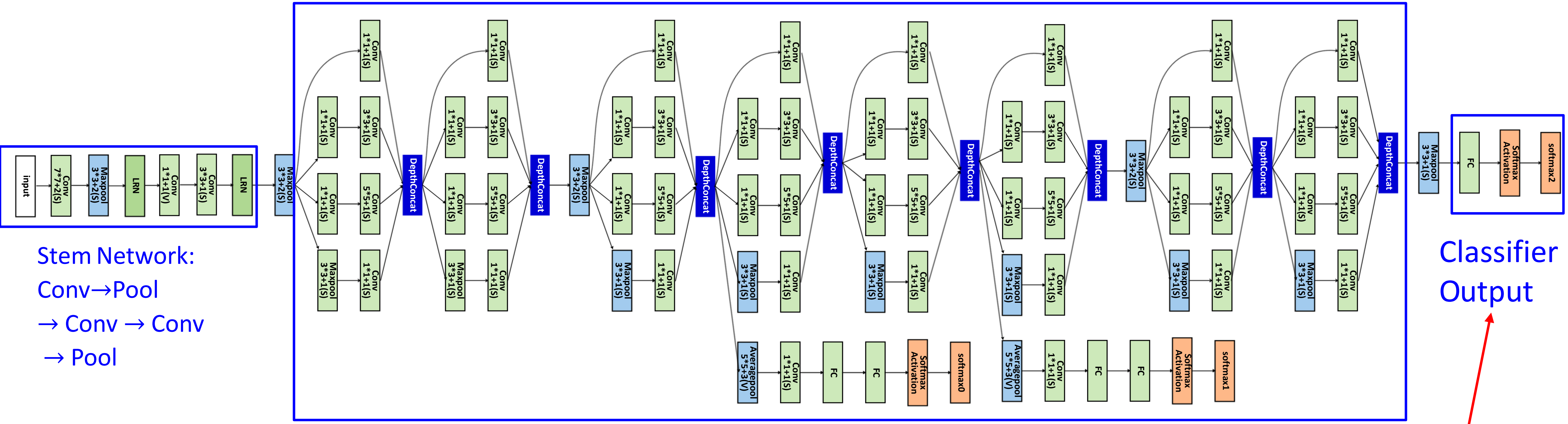
Total: 358M ops

Compared to 854M ops for naive version Bottleneck can also reduce depth after pooling layer

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture

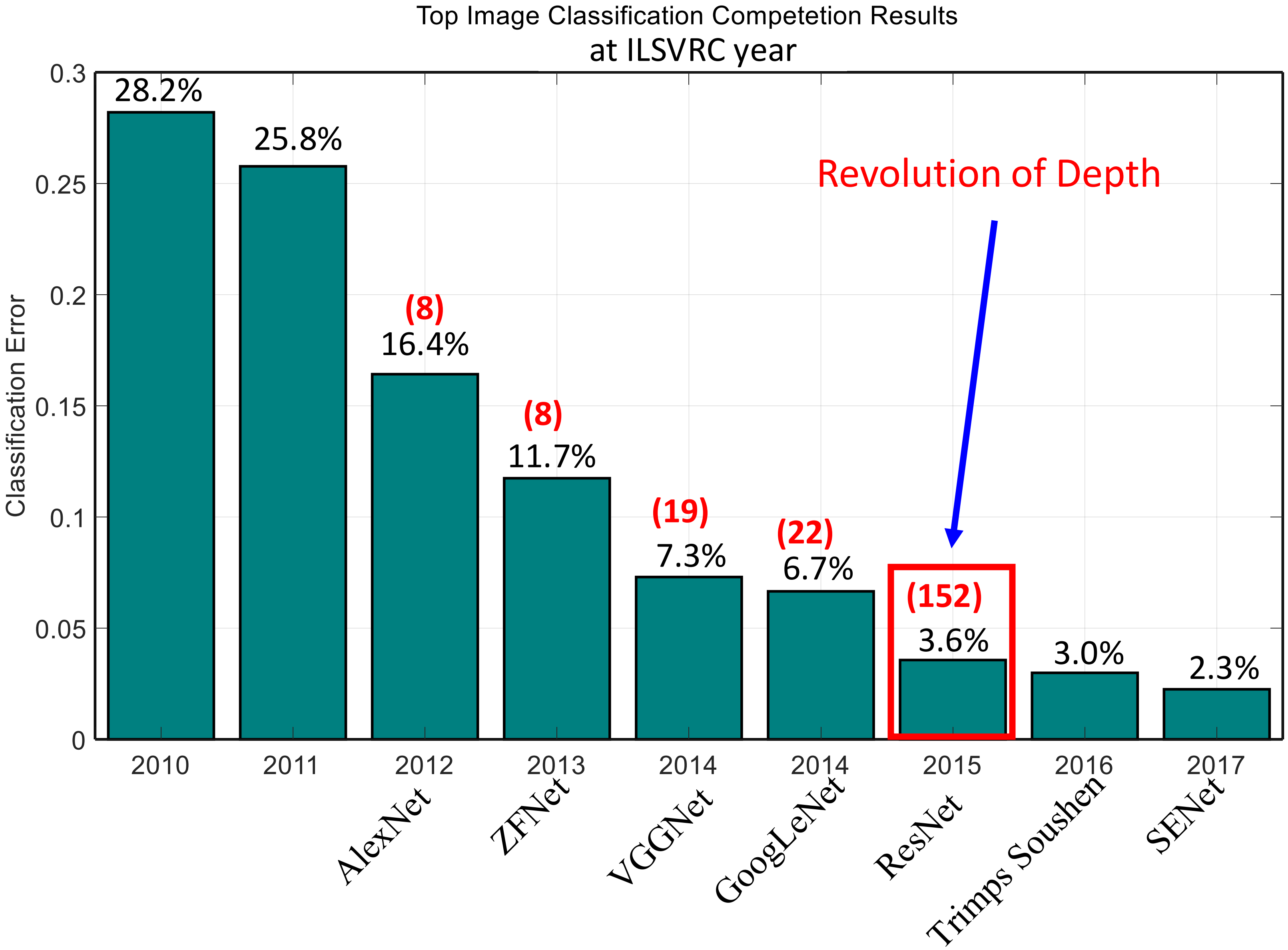


Stem Network:
Conv→Pool
→ Conv → Conv
→ Pool

Stacked Inception Modules

Classifier Output

(removed expensive FC layers!)



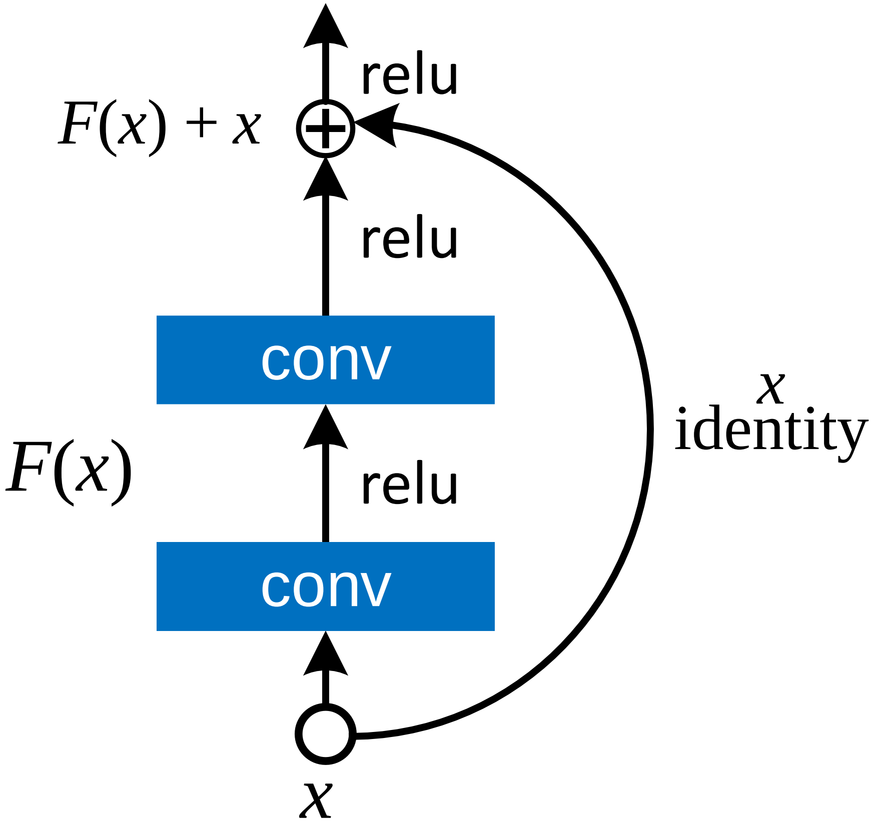
Li Liu et al., Deep Learning for Generic Object Detection: A Survey, IJCV, 2019.

Case Study: ResNet

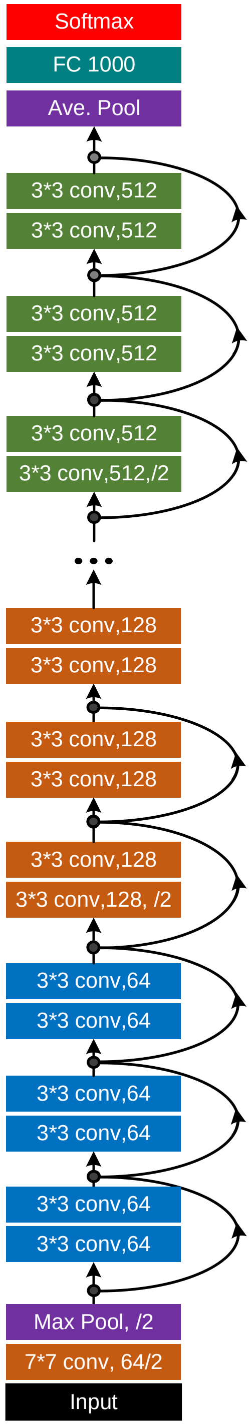
[He et al., 2015]

Very deep networks using residual connections

- 152-layer model for ImageNet
- ILSVRC’15 classification winner (3.57% top 5 error)
- Swept all classification and detection competitions in ILSVRC’15 and COCO’15!



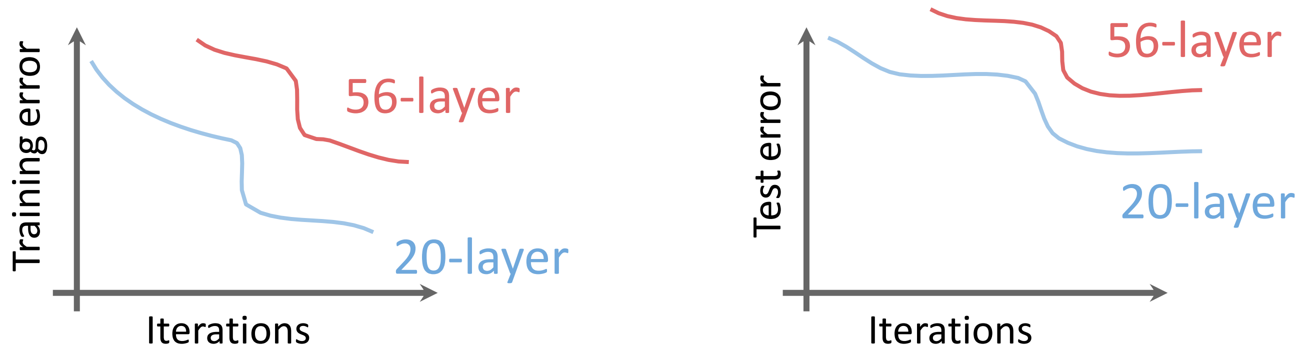
Residual block



Case Study: ResNet

[He et al., 2015]

What happens when we continue stacking deeper layers on a “plain” convolutional neural network?



Q: What’s strange about these training and test curves?
[Hint: look at the order of the curves]

56-layer model performs worse on both training and test error.
→The deeper model performs worse, but it’s not caused by overfitting!

Case Study: ResNet

[He et al., 2015]

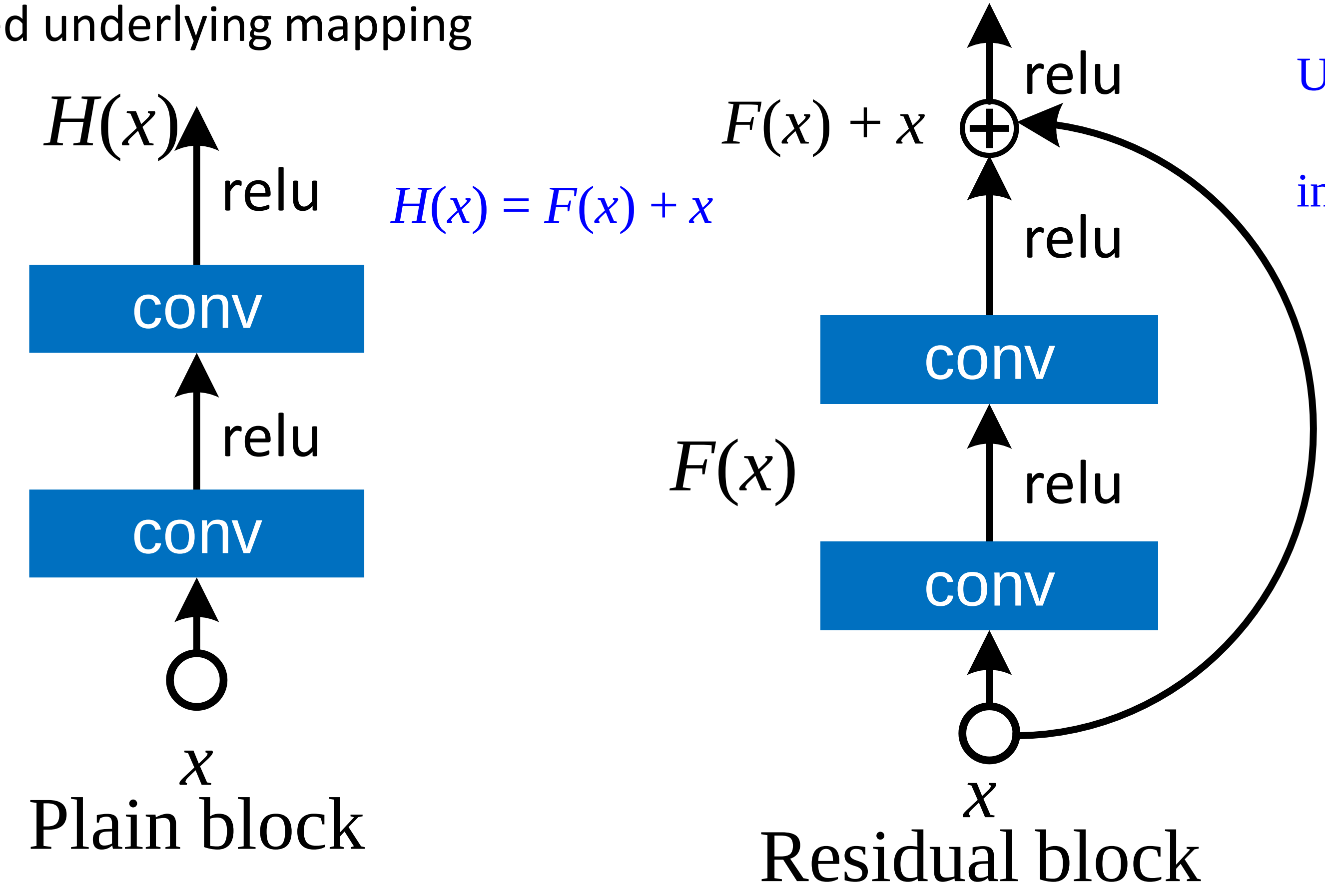
Hypothesis: the problem is an *optimization* problem, deeper models are harder to optimize

- The deeper model should be able to perform at least as well as the shallower model.
- A solution by construction is copying the learned layers from the shallower model and setting additional layers to identity mapping.

Case Study: ResNet

[He et al., 2015]

Solution: Use network layers to fit a residual mapping instead of directly trying to fit a desired underlying mapping



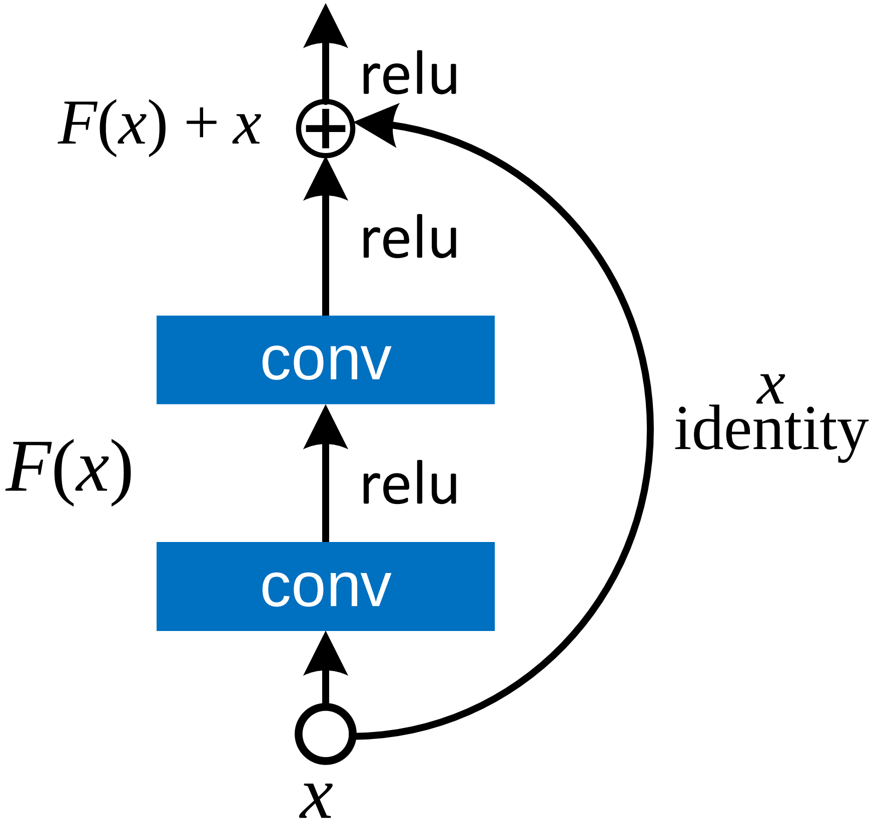
Use layers to fit residual
$F(x) = H(x) - x$
instead of $H(x)$ directly

Case Study: ResNet

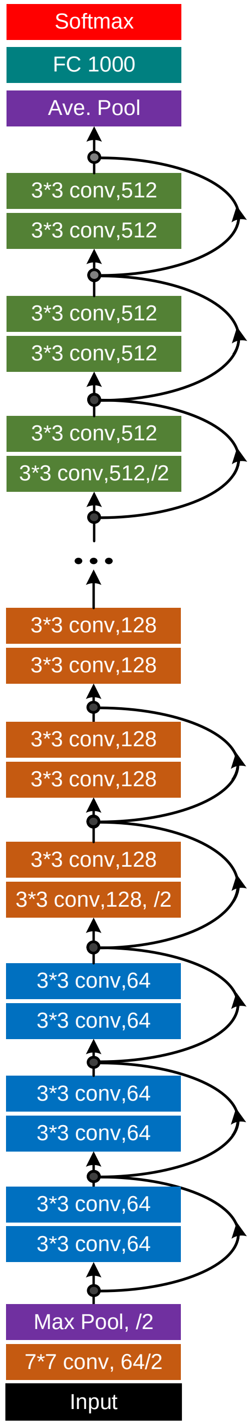
[He et al., 2015]

Full ResNet architecture:

- Stack residual blocks
- Every residual block has two 3x3 conv layers
- Periodically, double the number of filters and subsample spatially using stride 2
- Additional conv layer at the beginning
- No FC layers at the end (only FC 1000 to output classes)



Residual block



Total depths of 34, 50, 101, or 152 layers for ImageNet

Case Study: ResNet

[He et al., 2015]

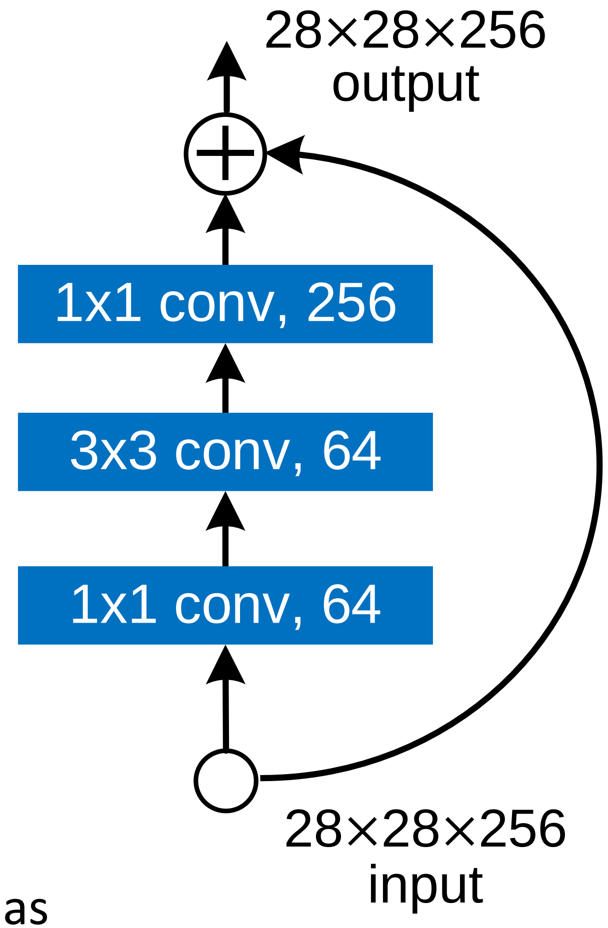
For deeper networks (ResNet50+), use “bottleneck” layer to improve efficiency (similar to GoogLeNet)

ILSVRC 2015 classification winner (3.6% top 5 error)→better than “human performance”!

1x1 conv, 256 filters projects back to 256 feature maps (28x28x256)

3x3 conv operates over only 64 feature maps

1x1 conv, 64 filters to project to 28x28x64



Experimental Results

- Able to train very deep networks without degrading (152 layers on ImageNet, 1202 on Cifar)
- Deeper networks now achieve lowing training error as expected
- Swept 1st place in all ILSVRC and COCO 2015 competitions

Typical CNN Architectures

Case Studies
- AlexNet
- VGG
- GoogLeNet
- ResNet

about other architecture…

- NIN (Network in Network)
- Wide ResNet
- ResNeXT
- Stochastic Depth
- DenseNet
- SENet
- FractalNet
- SqueezeNet

No time to talk about, leave for yourself

Summary: CNN Architectures

- VGG, GoogLeNet, ResNet all in wide use, available in model zoos
- ResNet current best default
- Trend towards extremely deep networks
- Significant research centers around design of layer / skip connections and improving gradient flow
- Even more recent trend towards examining necessity of depth vs. width and residual connections
- Lots of research in network compression and acceleration
- Lots of research in network architecture search

Next time: Training Tips for DNNs