



CS540 Introduction to Artificial Intelligence

Convolutional Neural Networks (II)

University of Wisconsin-Madison
Spring 2024

Today's goals

- Review (some of) convolutional computations.
 - 2D convolutions, multiple input channels, pooling.
- Understand how convolutions are used as layers in a (deep) neural network.
- Build intuition for output of convolutional layers.
- Overview the evolution of deeper convolutional networks

How to classify

Cats vs. dogs?



Dual
12MP
wide-angle and
telephoto cameras

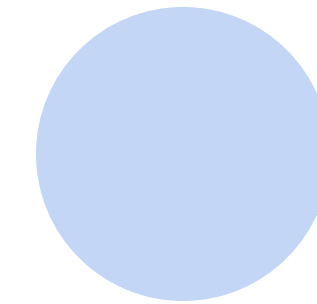
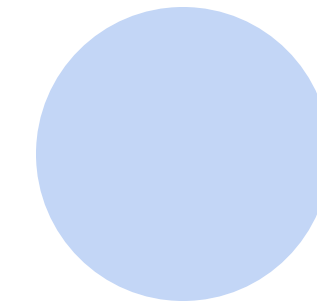
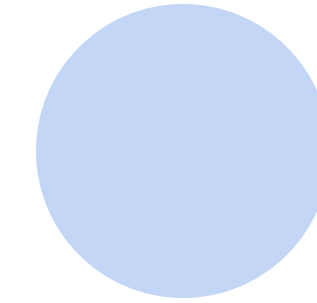
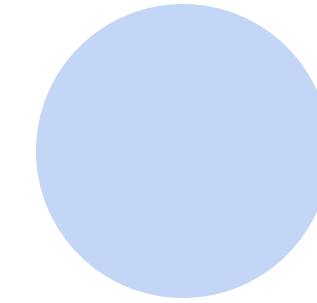
36M floats in a RGB image!

Fully Connected Networks

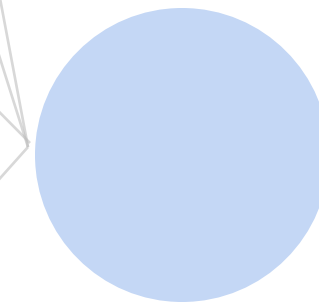
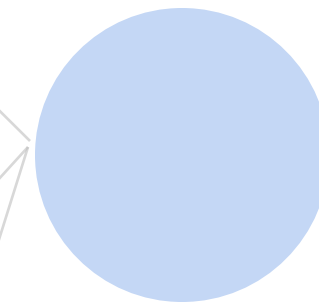
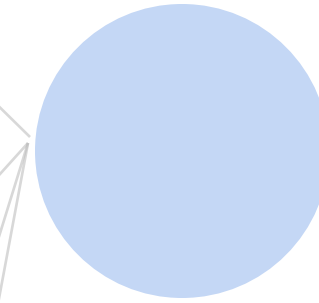
Cats vs. dogs?



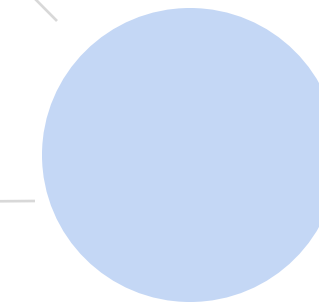
Input



Hidden layer
100 neurons



Output



36M elements x 100 = **3.6B** parameters!

Review: 2-D Convolution

Input

0	1	2
3	4	5
6	7	8

*

Kernel

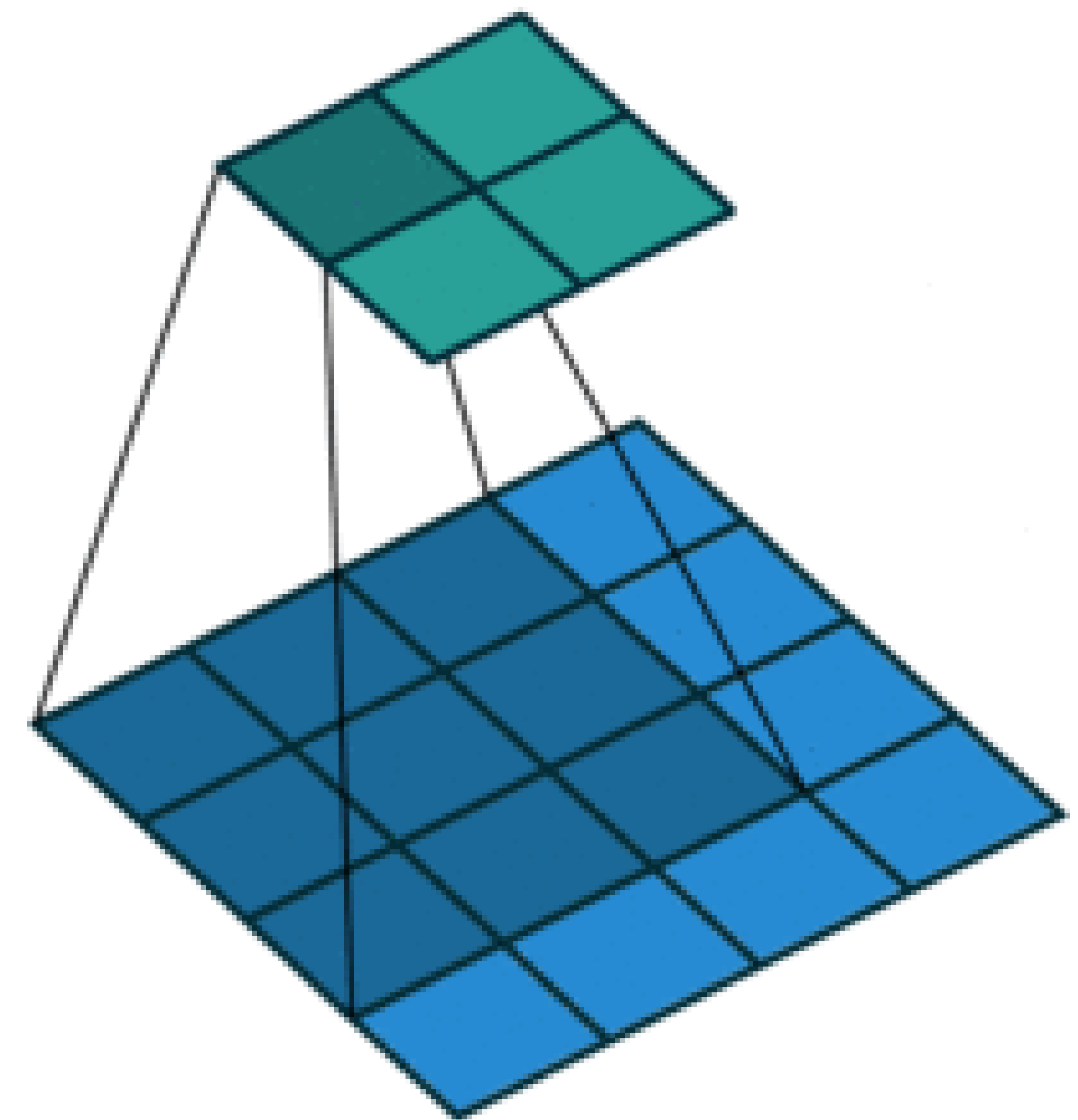
0	1
2	3

=

Output

19	25
37	43

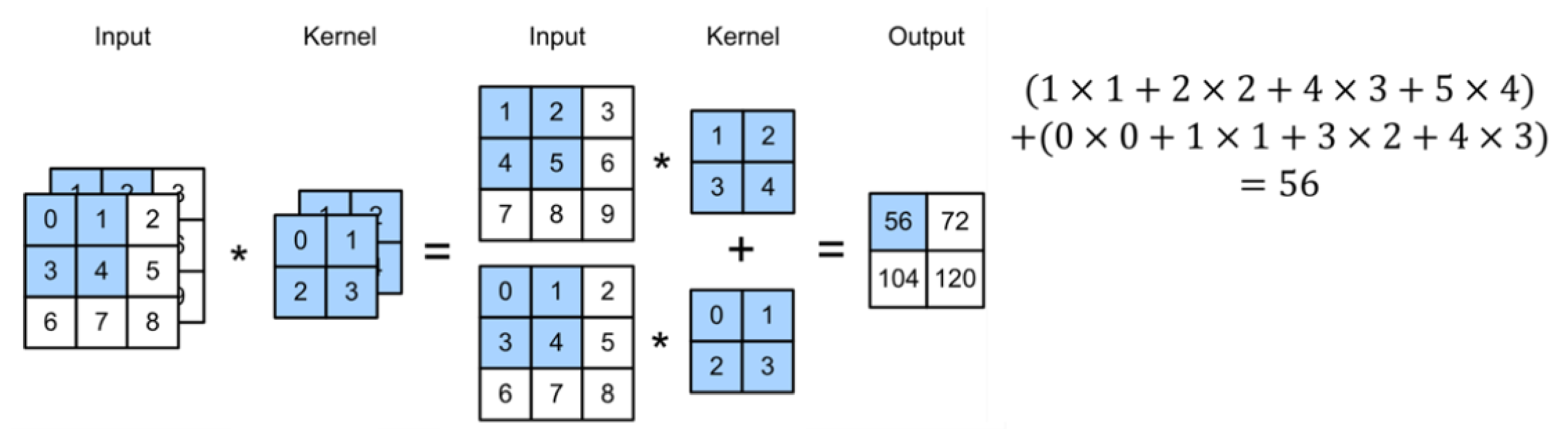
$$\begin{aligned}0 \times 0 + 1 \times 1 + 3 \times 2 + 4 \times 3 &= 19, \\1 \times 0 + 2 \times 1 + 4 \times 2 + 5 \times 3 &= 25, \\3 \times 0 + 4 \times 1 + 6 \times 2 + 7 \times 3 &= 37, \\4 \times 0 + 5 \times 1 + 7 \times 2 + 8 \times 3 &= 43.\end{aligned}$$



(vdumoulin@ Github)

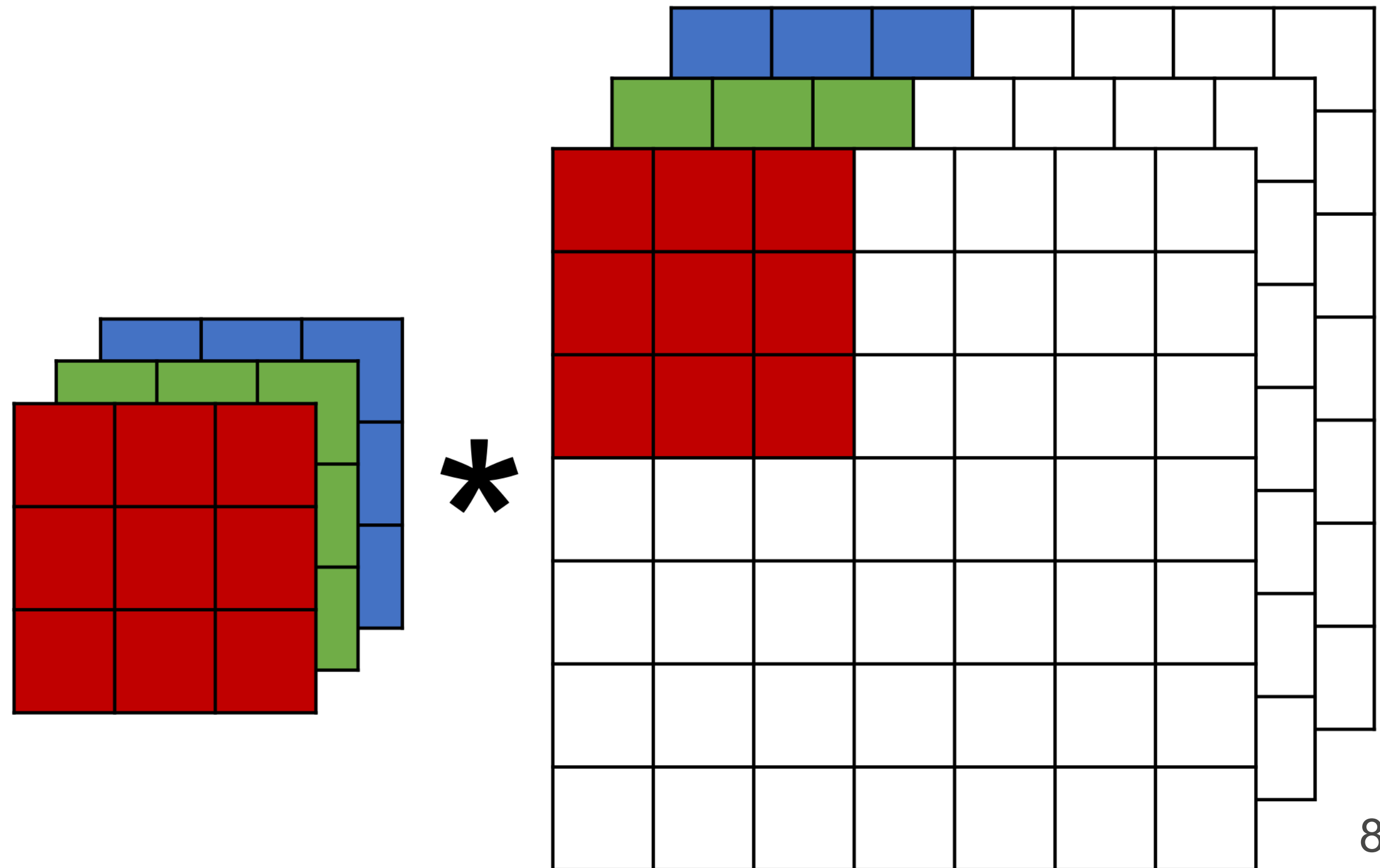
Review: Multiple Input Channels

- Input and kernel can be 3D, e.g., an RGB image have 3 channels
- Have a kernel for each channel, and then sum results over channels



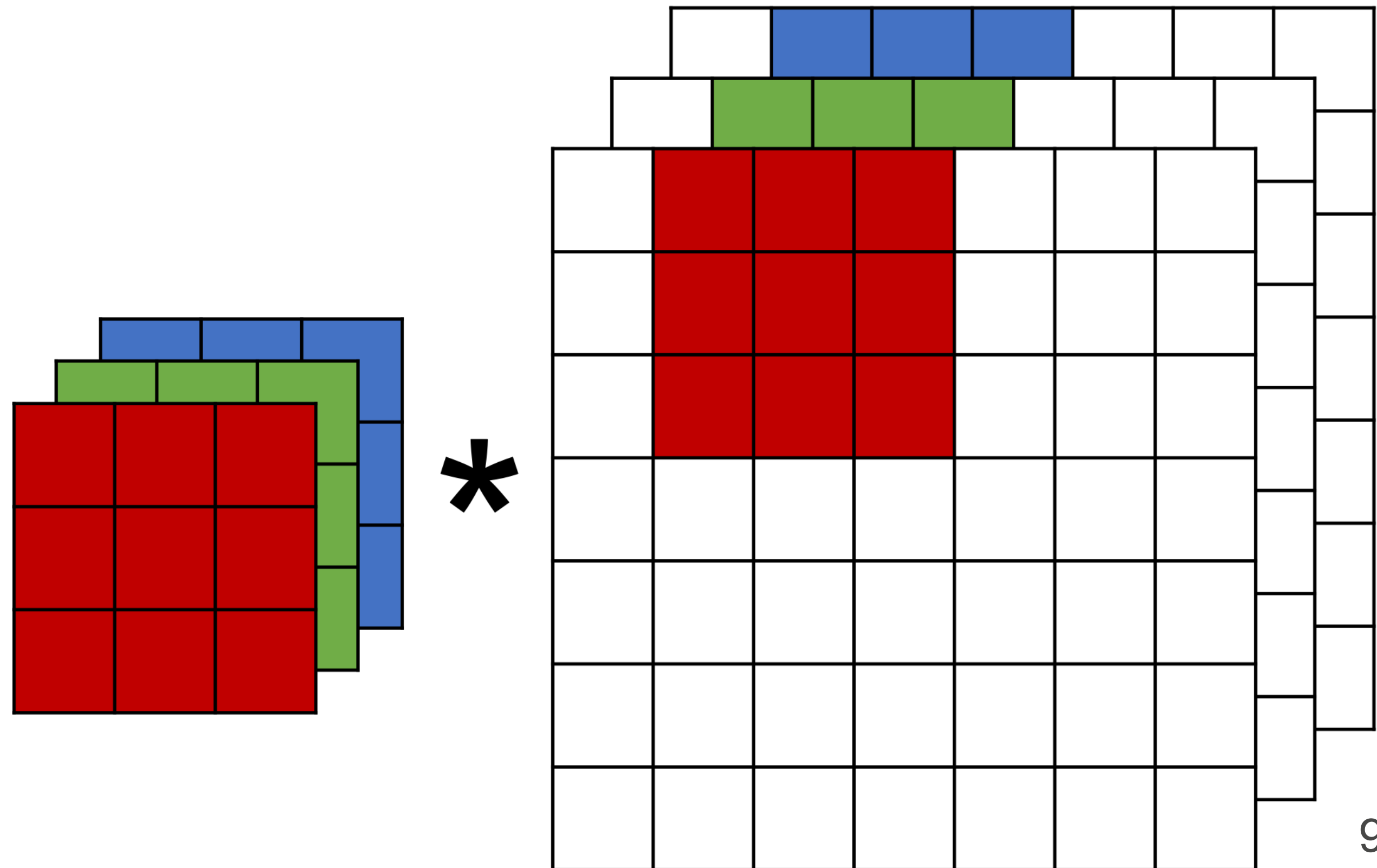
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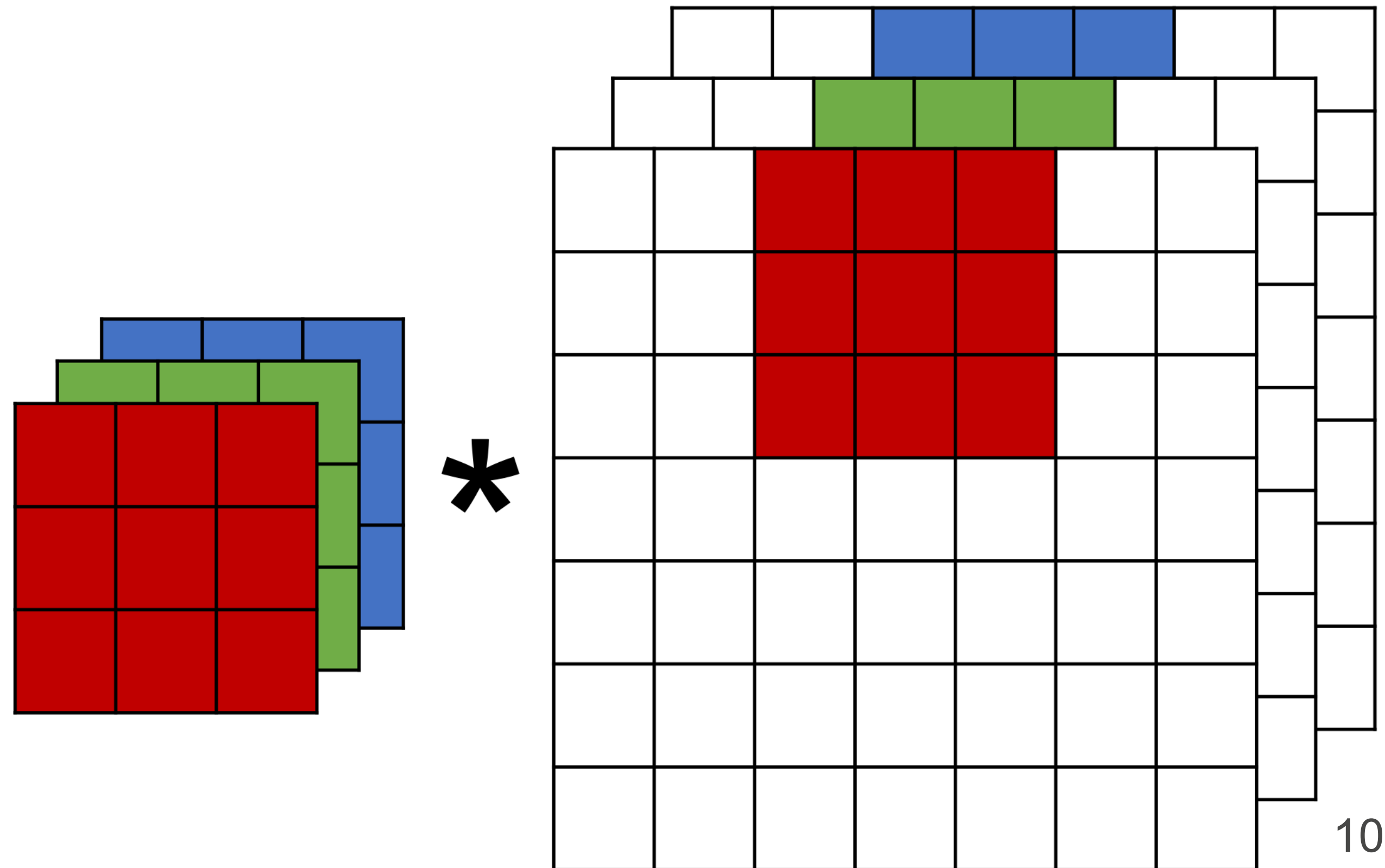
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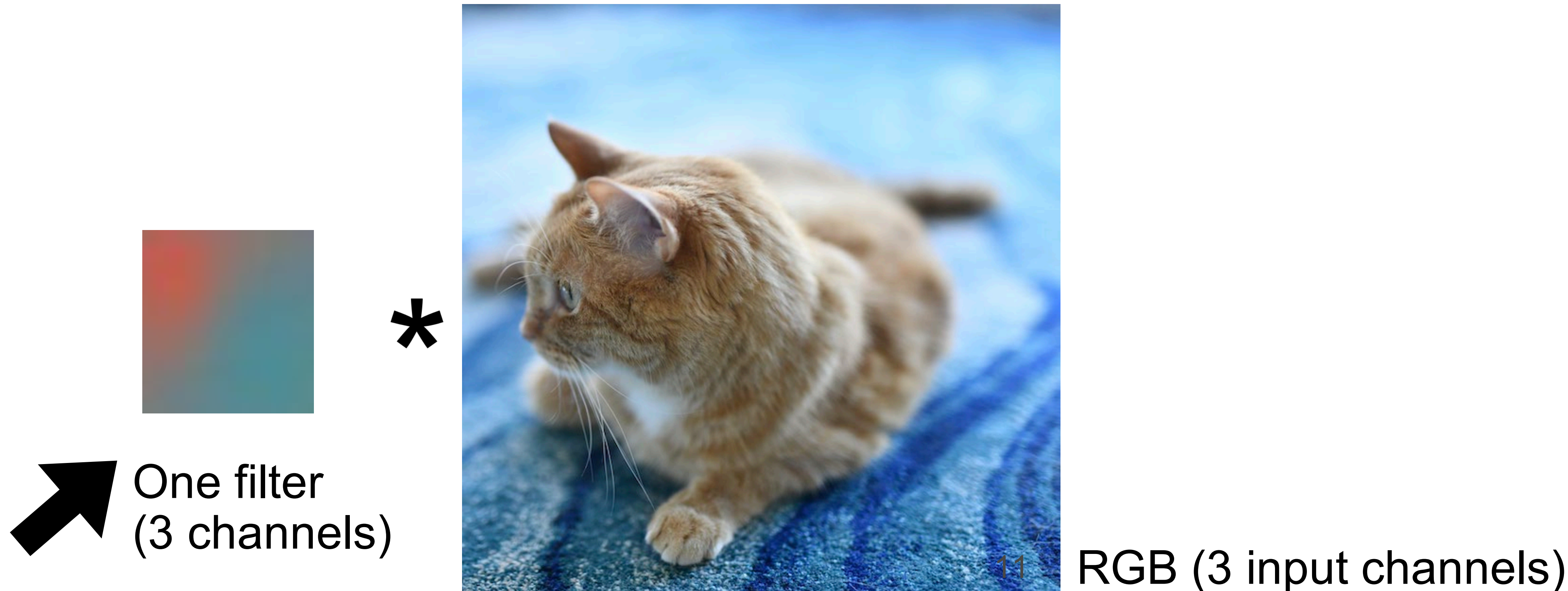
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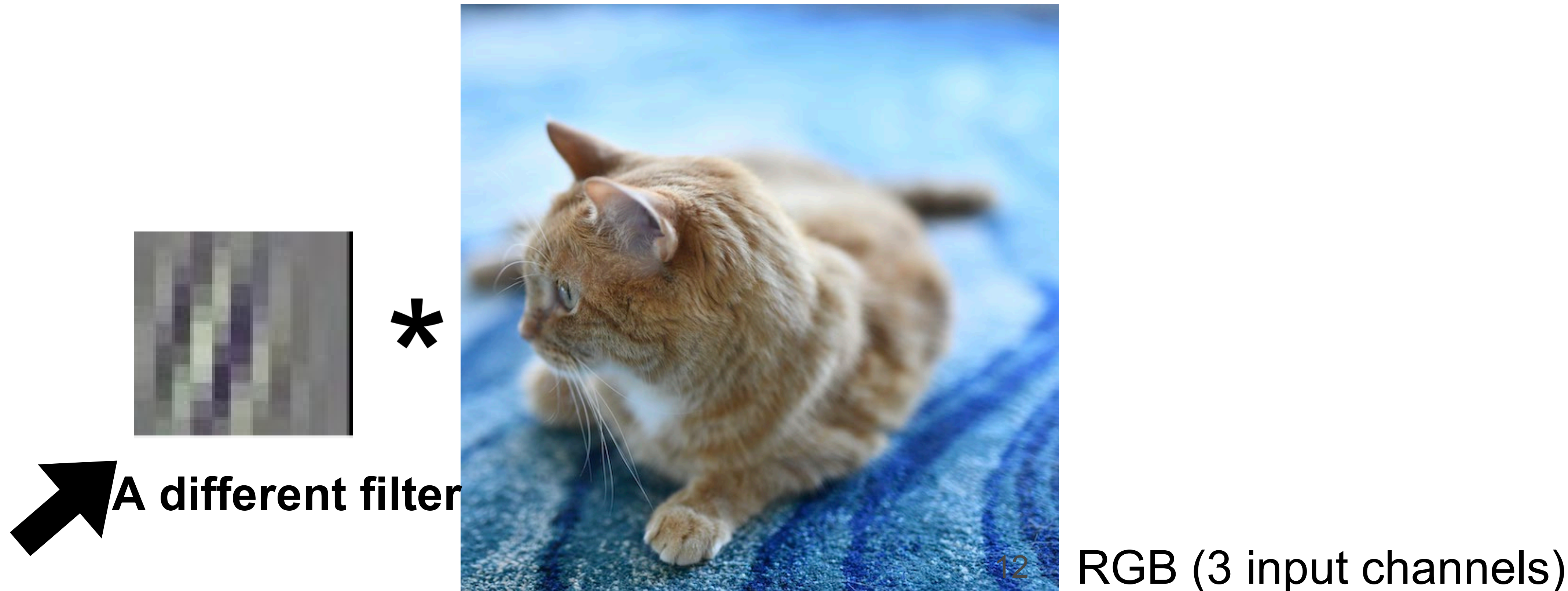
Multiple Input Channels

- Input and kernel can be 3D, e.g. RGB image has 3 channels
- Also call each 3D kernel a “**filter**”, which produces only **one** output channel (due to summation over channels)



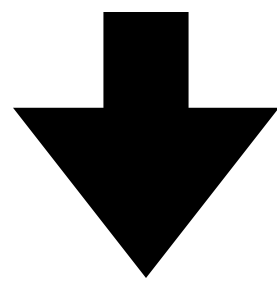
Multiple filters (in one layer)

- Apply multiple filters on the input
- Each filter may learn different features about the input
- Each filter (3D kernel) produces one output channel

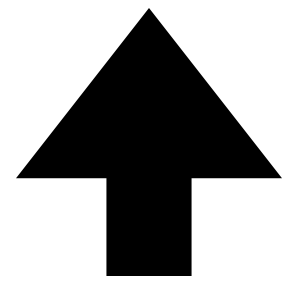


Output shape

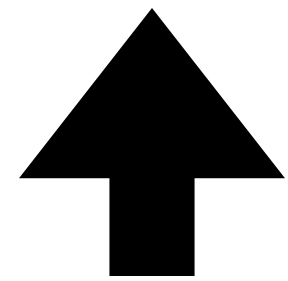
Kernel/filter size



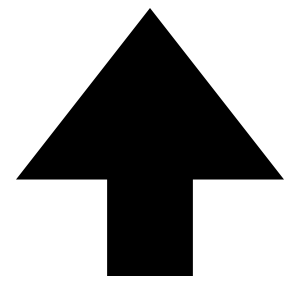
$$\lfloor (n_h - k_h + p_h + s_h) / s_h \rfloor \times \lfloor (n_w - k_w + p_w + s_w) / s_w \rfloor$$



Input size



Pad



Stride

Consider a convolution layer with 16 filters. Each filter has a size of $11 \times 11 \times 3$, a stride of 2×2 . Given an input image of size $22 \times 22 \times 3$, if we don't allow a filter to fall outside of the input, what is the output size?

- $11 \times 11 \times 16$
- $6 \times 6 \times 16$
- $7 \times 7 \times 16$
- $5 \times 5 \times 16$

Consider a convolution layer with 16 filters. Each filter has a size of 11x11x3, a stride of 2x2. Given an input image of size 22x22x3, if we don't allow a filter to fall outside of the input, what is the output size?

- 11x11x16

- 6x6x16

- 7x7x16

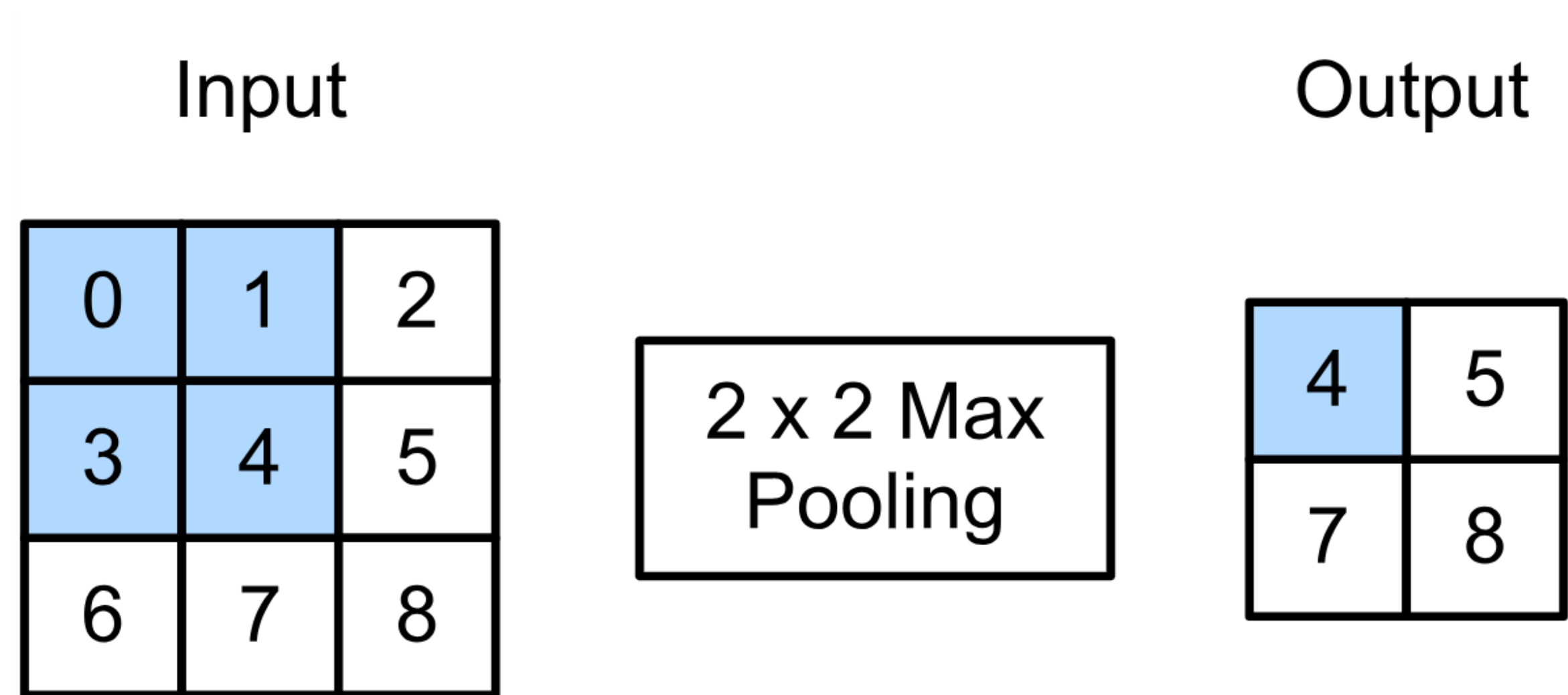
- 5x5x16

$$\lfloor (n_h - k_h + p_h + s_h) / s_h \rfloor \times \lfloor (n_w - k_w + p_w + s_w) / s_w \rfloor$$

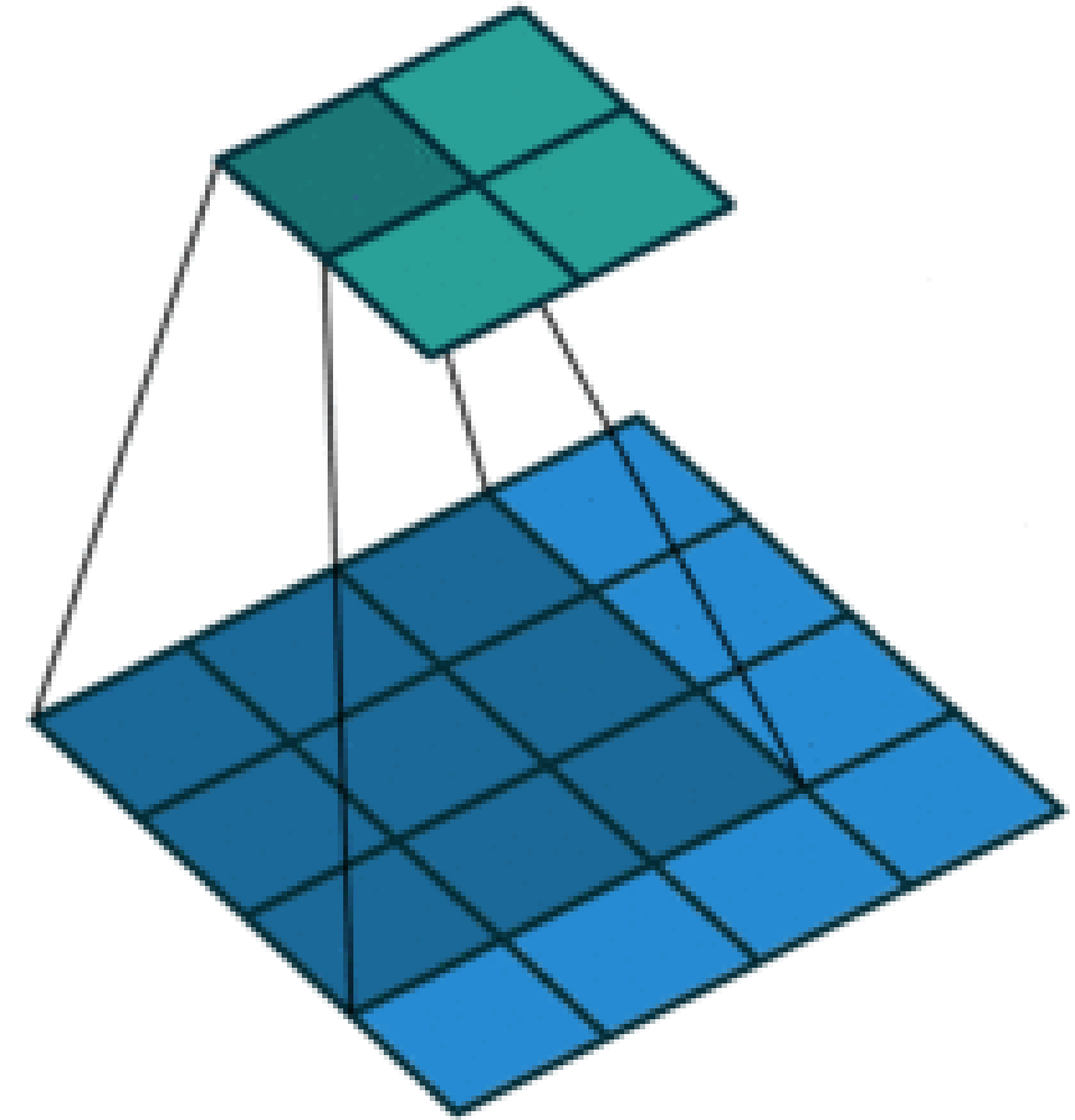
Pooling Layer

2-D Max Pooling

- Returns the maximal value in the sliding window



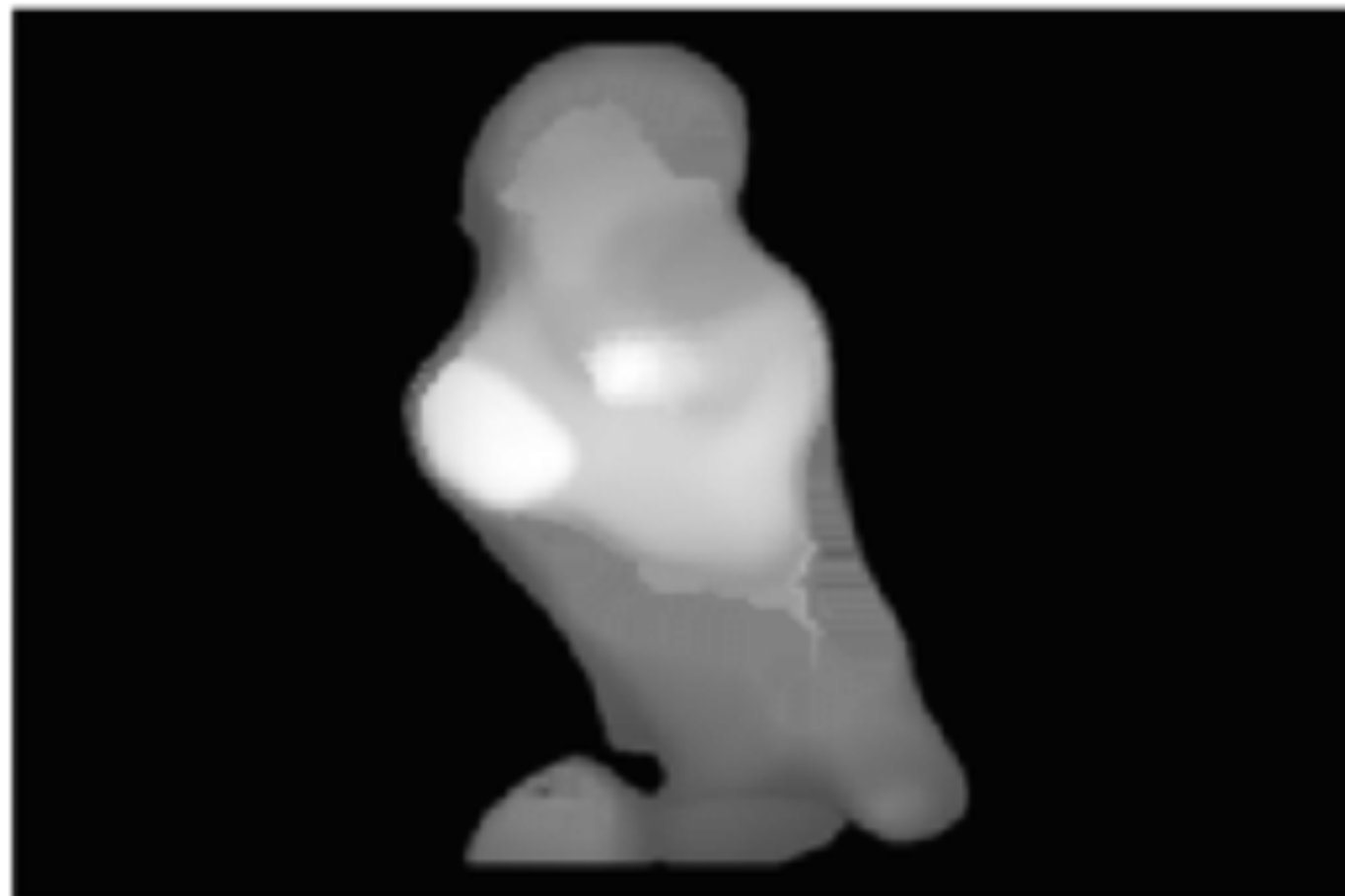
$$\max(0, 1, 3, 4) = 4$$



Average Pooling

- Max pooling: the strongest pattern signal in a window
- Average pooling: replace max with mean in max pooling
 - The average signal strength in a window

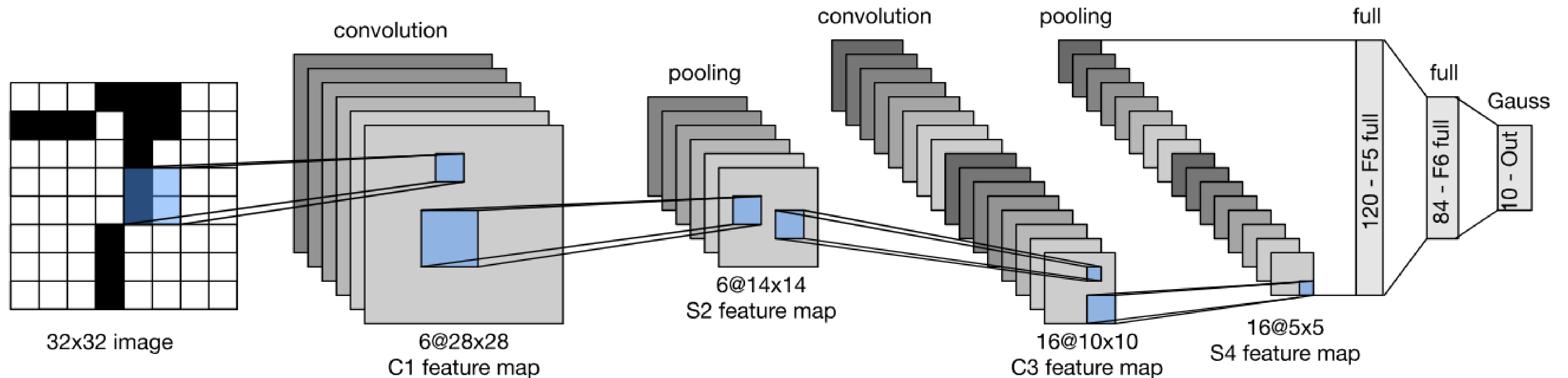
Max pooling



Average pooling



Convolutional Neural Network Architecture



Convolutional Neural Network Intuition

Early layers recognize simple visual features, later layers recognize more complex visual features.

Suppose we want to classify pictures of cats or dogs. How would you do this?

Look for features of cats or dogs in the image and use for decision.

- Example: cats have cat-like faces, dogs have dog-like faces.
- How do you determine what is a “cat-like” face vs a “dog-like” face?

Look for features of “cat-like” faces and “dog-like” faces.

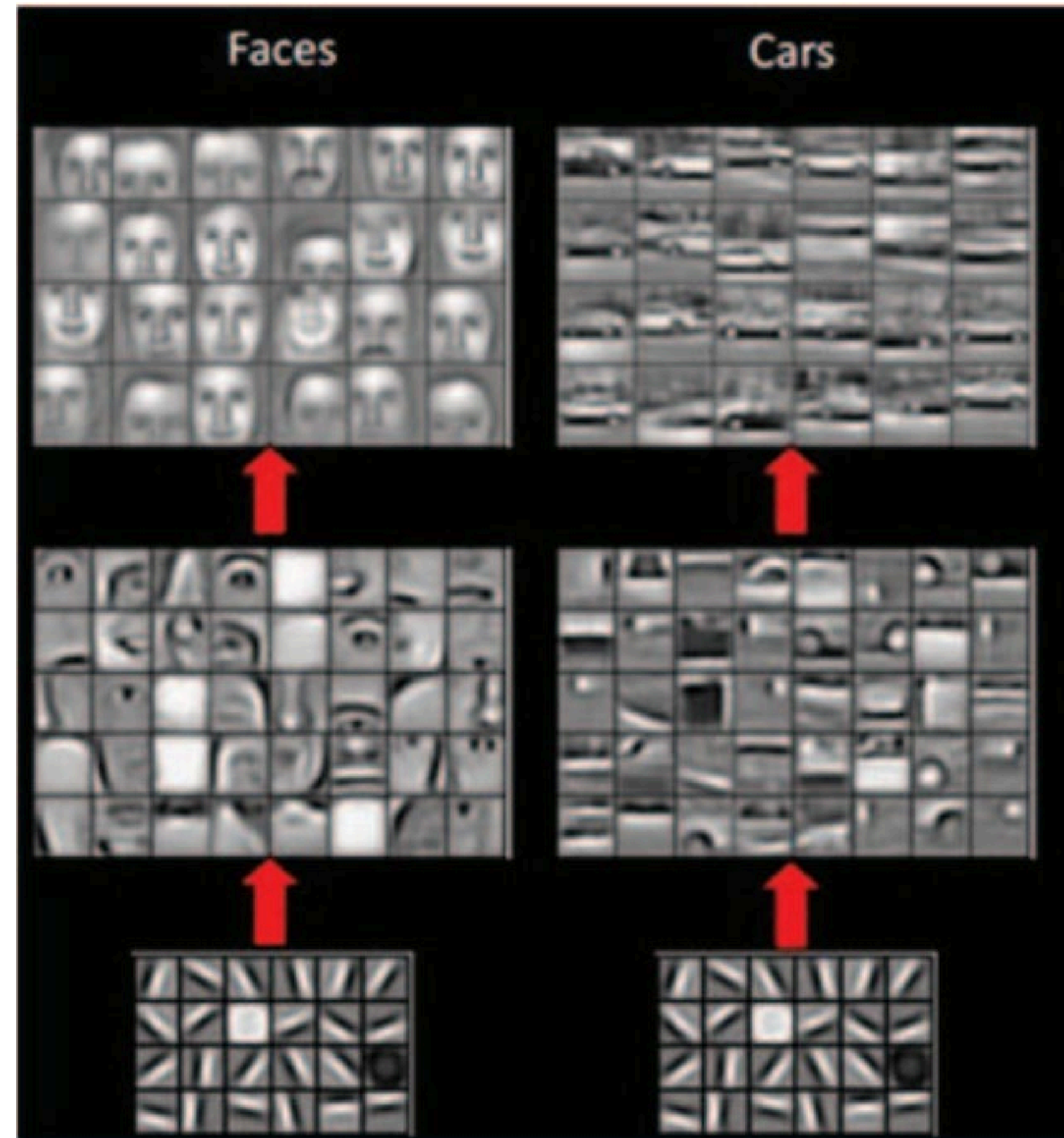
- Example: Dogs have longer snouts.
- How do you determine what is a long snout?

Feature Learning

Later layers recognize complete objects

Middle layers recognize parts of objects

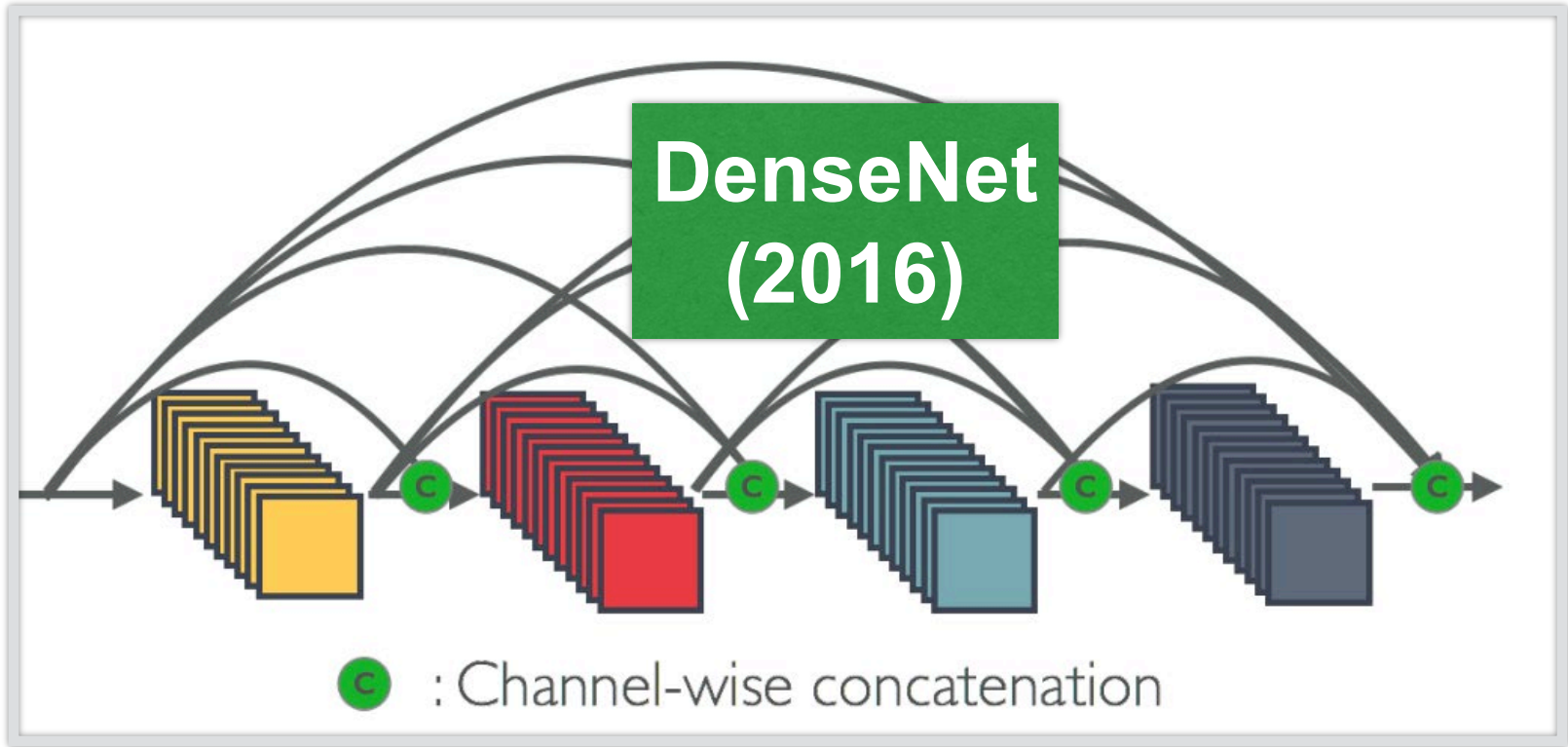
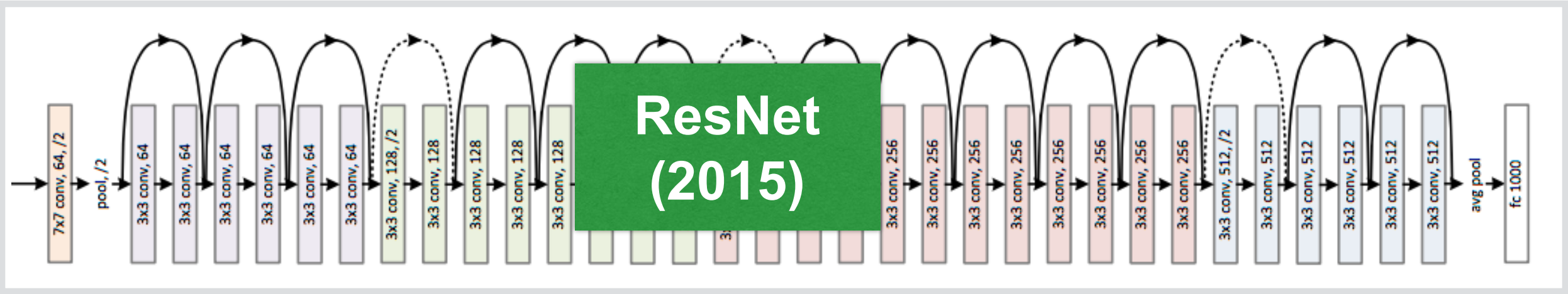
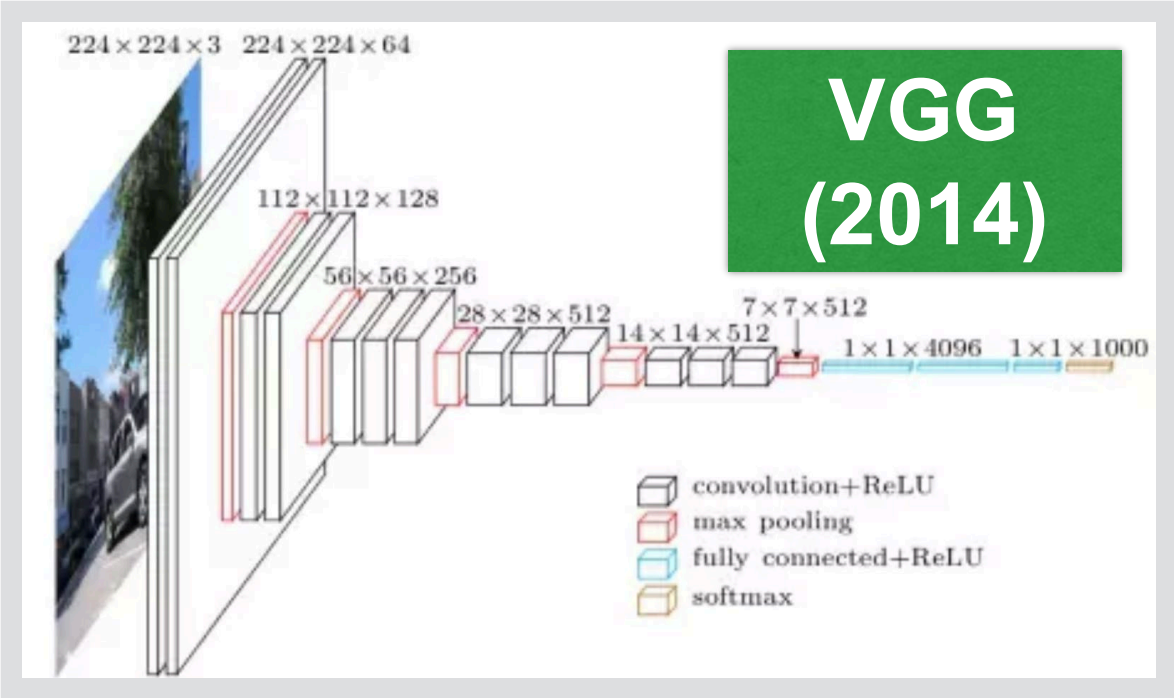
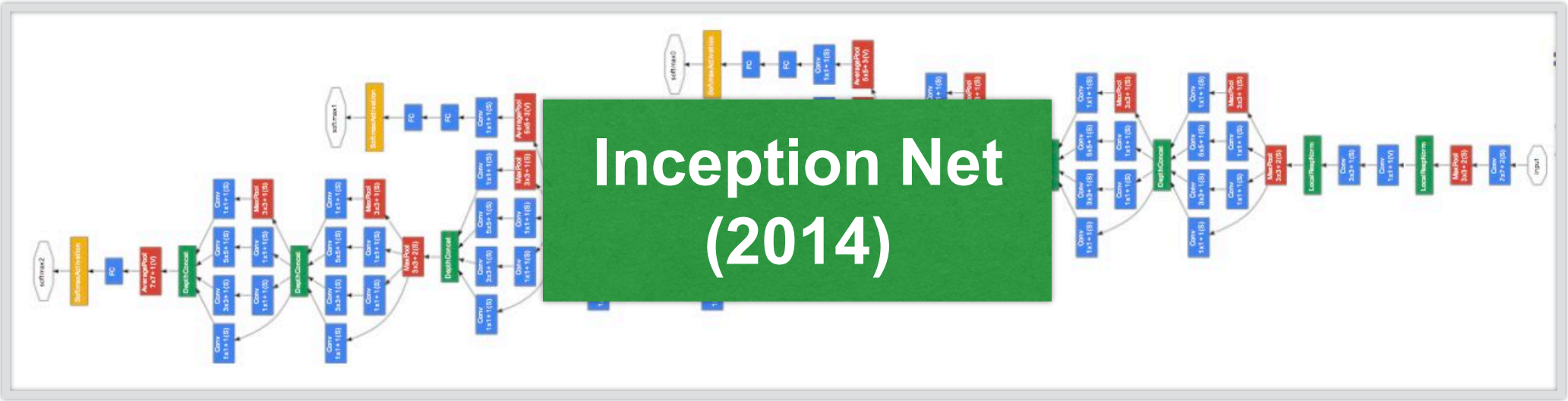
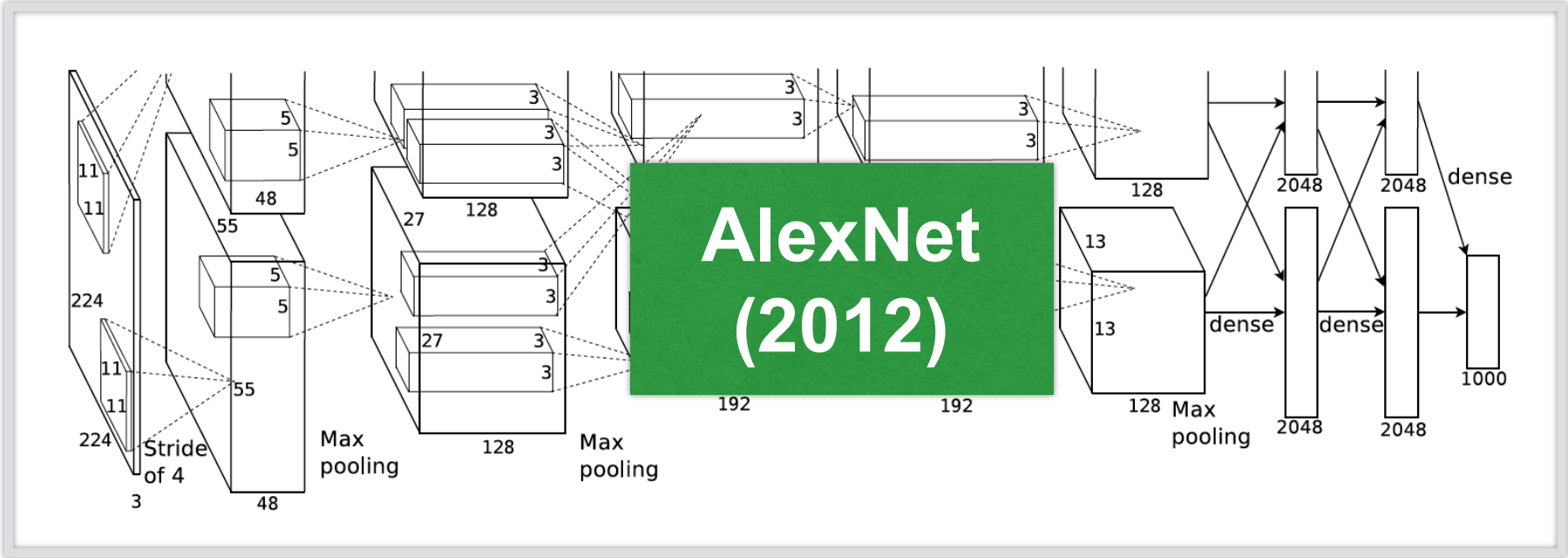
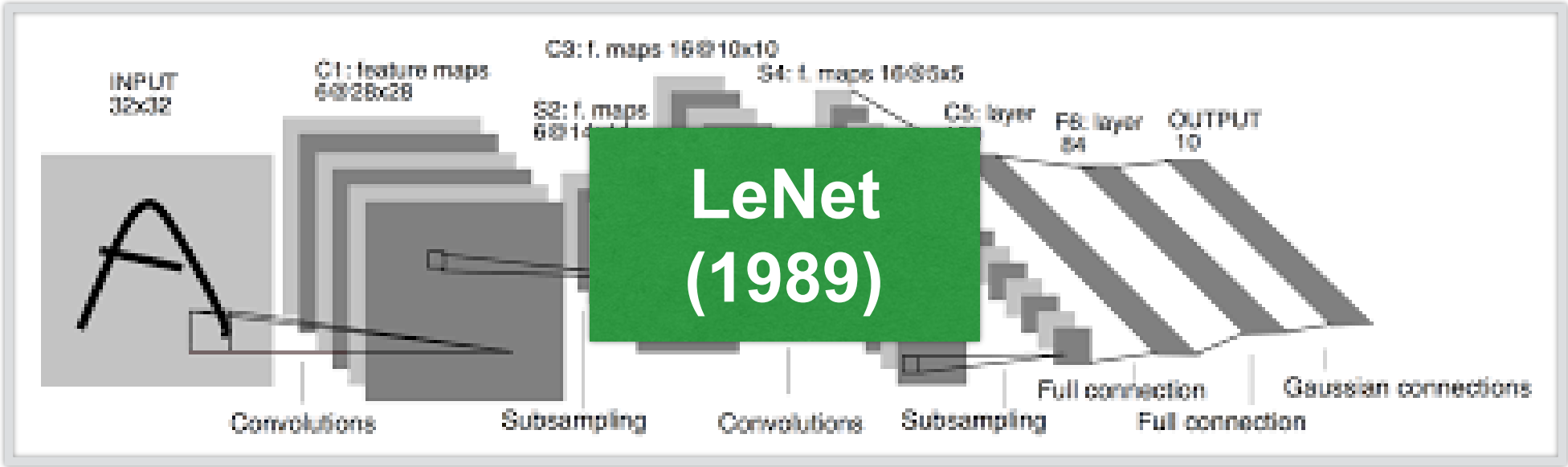
Early layers recognize simple patterns



Convolutional Neural Networks

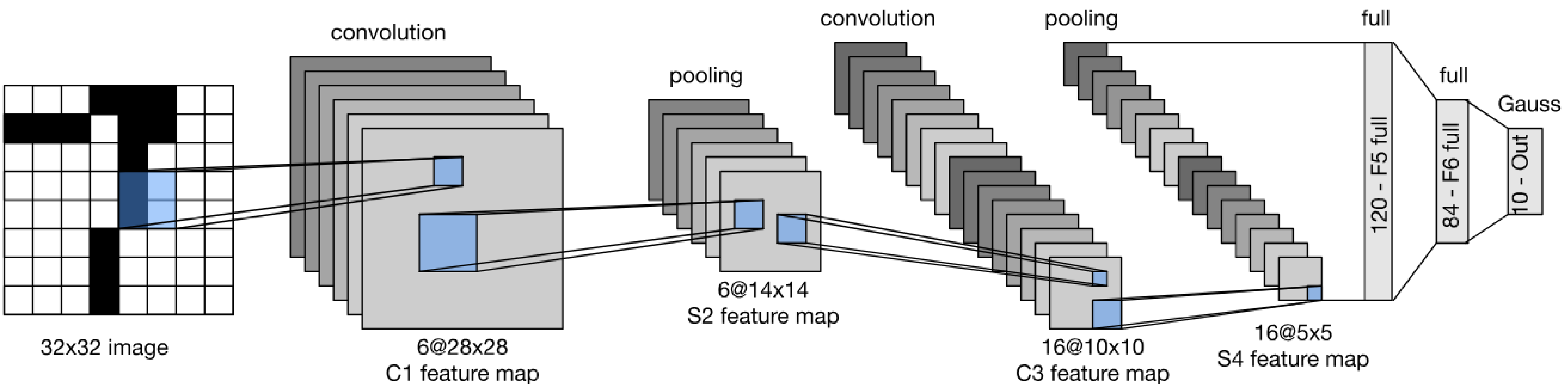
Examples

Evolution of neural net architectures

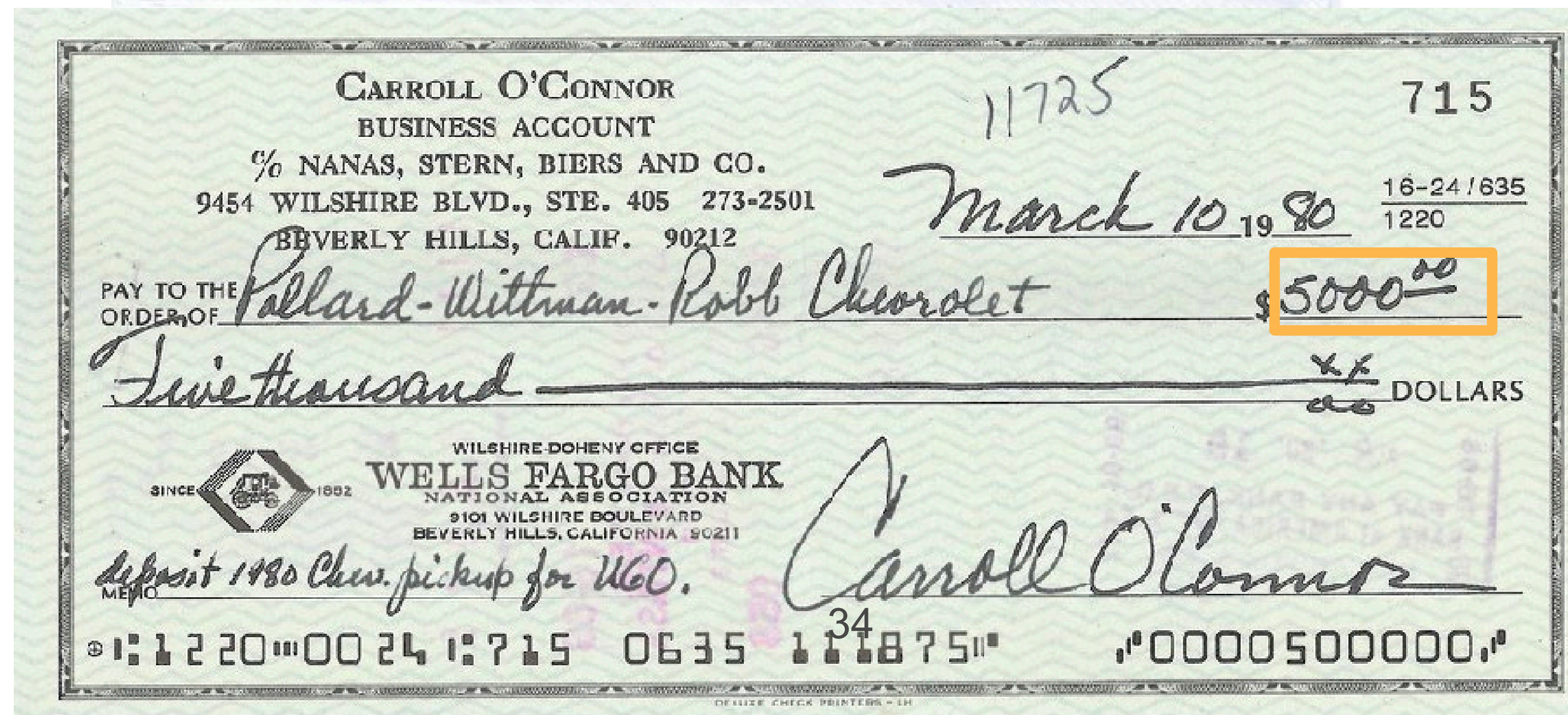
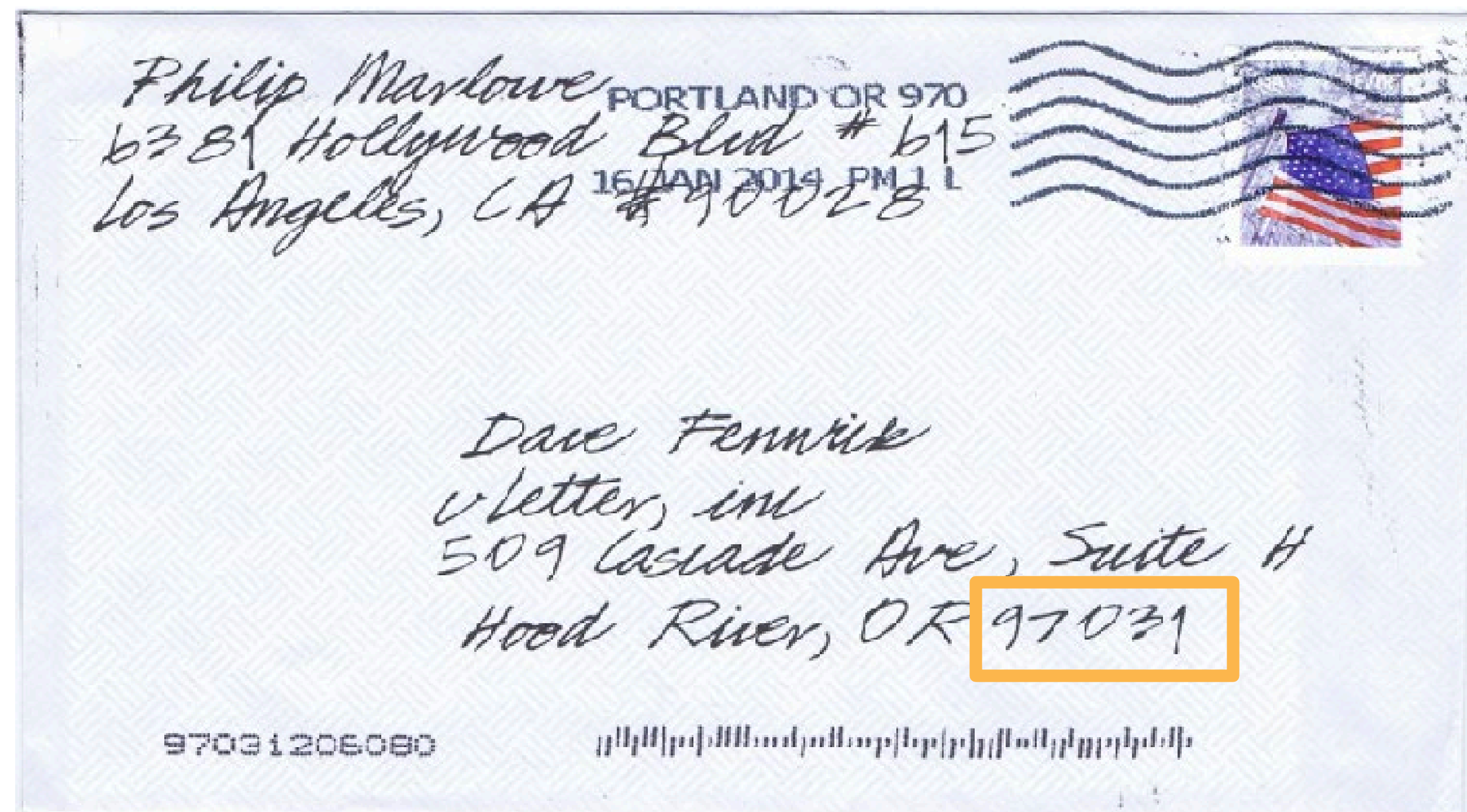


LeNet Architecture

(first convolutional neural net; 1989)

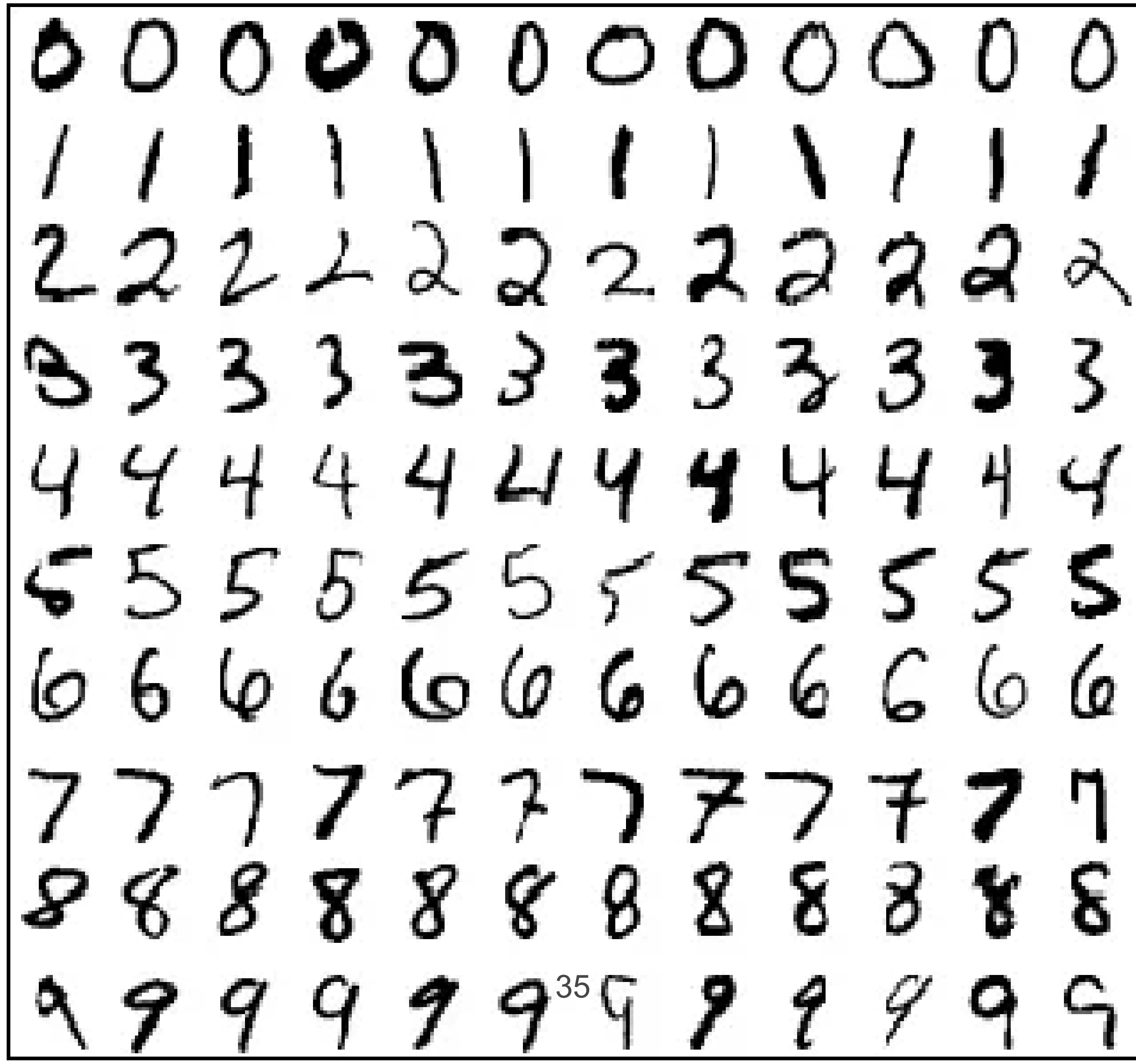


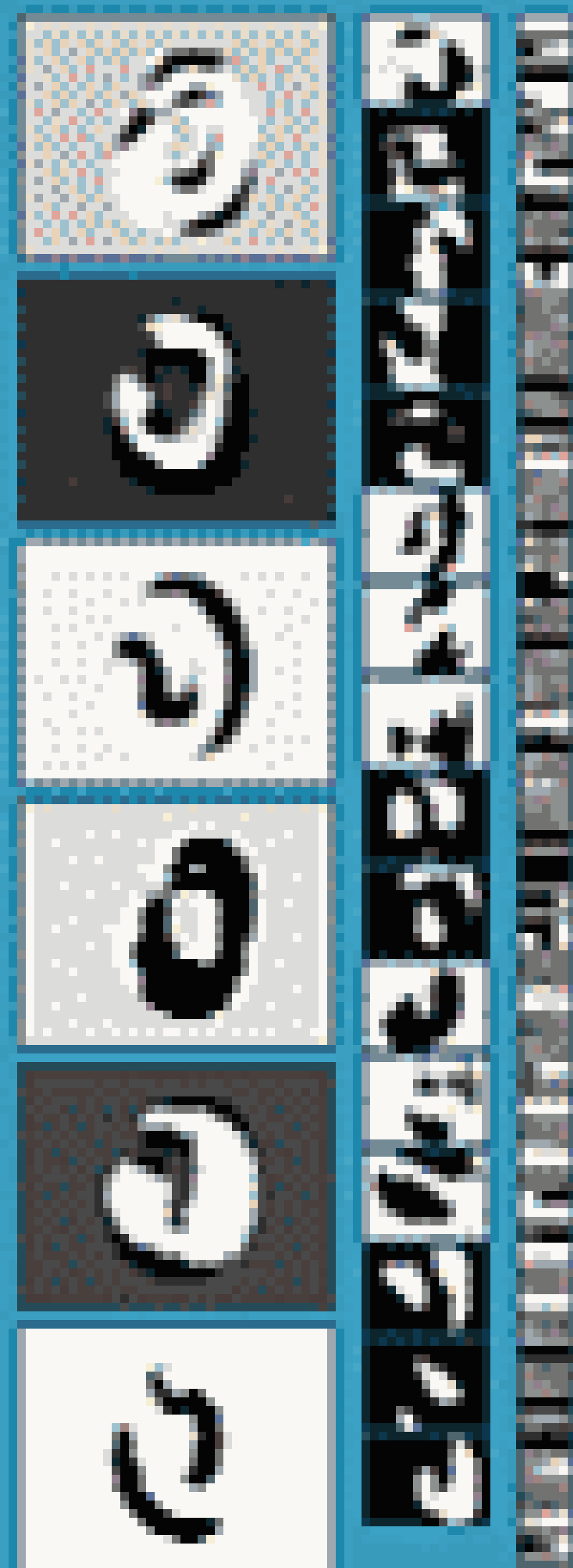
Handwritten Digit Recognition



MNIST

- Centered and scaled
- 50,000 training data
- 10,000 test data
- 28 x 28 images
- 10 classes



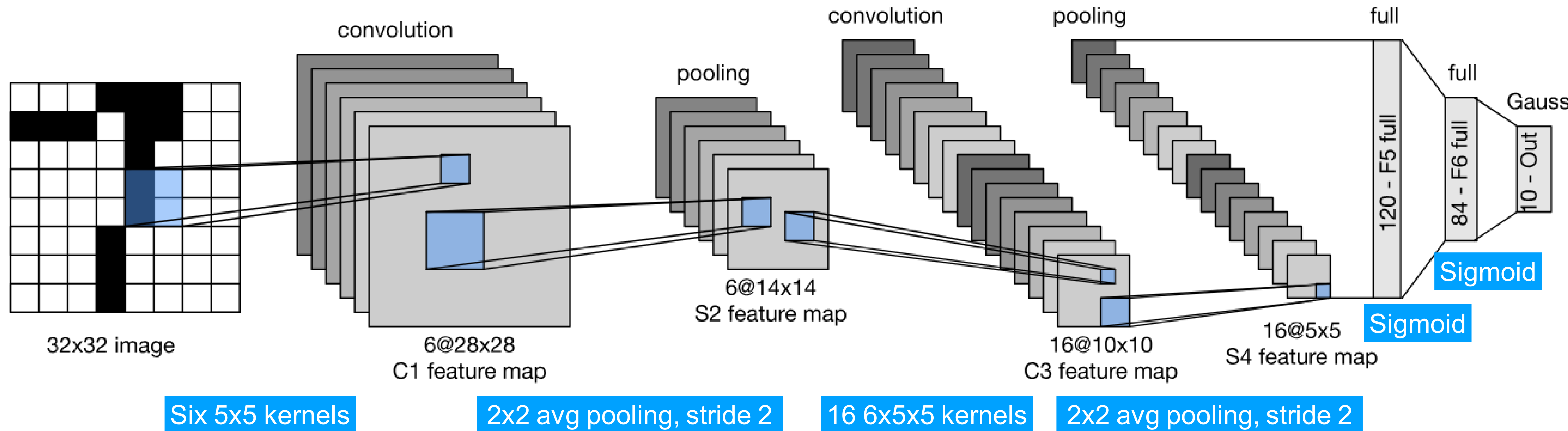


0
103



Y. LeCun, L.
Bottou, Y. Bengio,
P. Haffner, 1998
Gradient-based
learning applied to
document
recognition

LeNet Architecture



LeNet in Pytorch

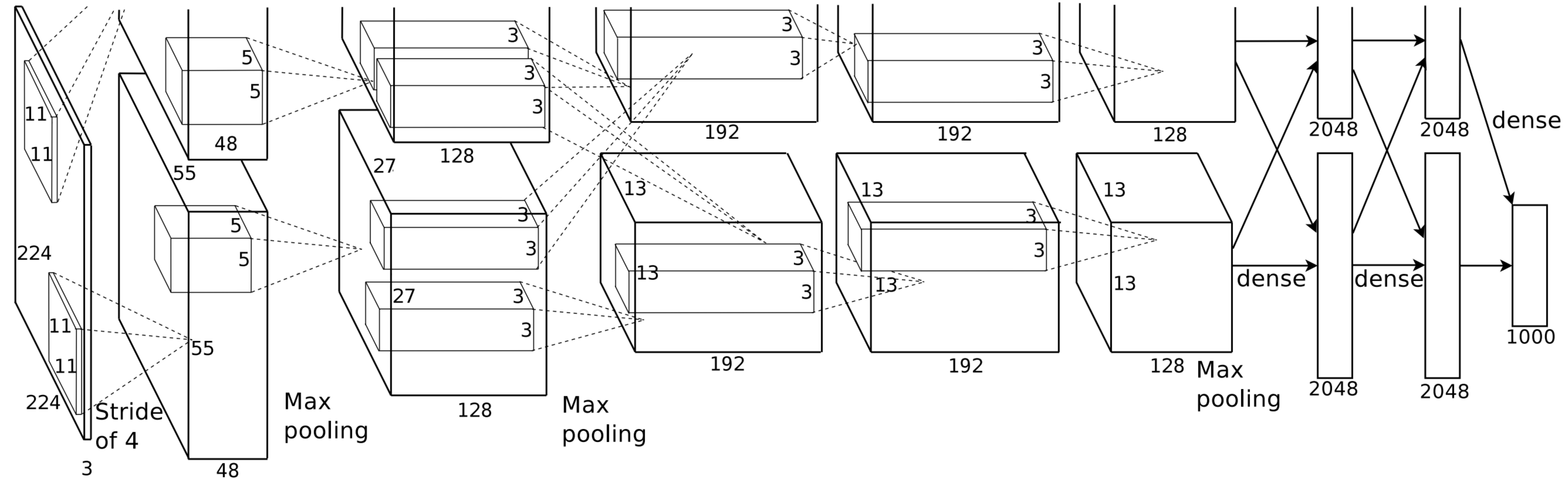
```
def __init__(self):
    super(LeNet5, self).__init__()
    # Convolution (In LeNet-5, 32x32 images are given as input. Hence padding of 2 is done below)
    self.conv1 = torch.nn.Conv2d(in_channels=1, out_channels=6, kernel_size=5, stride=1, padding=2, bias=True)
    # Max-pooling
    self.max_pool_1 = torch.nn.MaxPool2d(kernel_size=2)
    # Convolution
    self.conv2 = torch.nn.Conv2d(in_channels=6, out_channels=16, kernel_size=5, stride=1, padding=0, bias=True)
    # Max-pooling
    self.max_pool_2 = torch.nn.MaxPool2d(kernel_size=2)
    # Fully connected layer
    self.fc1 = torch.nn.Linear(16*5*5, 120)    # convert matrix with 16*5*5 (= 400) features to a matrix of 120 features (columns)
    self.fc2 = torch.nn.Linear(120, 84)       # convert matrix with 120 features to a matrix of 84 features (columns)
    self.fc3 = torch.nn.Linear(84, 10)        # convert matrix with 84 features to a matrix of 10 features (columns)
```

```
def forward(self, x):
    # convolve, then perform ReLU non-linearity
    x = torch.nn.functional.relu(self.conv1(x))
    # max-pooling with 2x2 grid
    x = self.max_pool_1(x)
    # convolve, then perform ReLU non-linearity
    x = torch.nn.functional.relu(self.conv2(x))
    # max-pooling with 2x2 grid
    x = self.max_pool_2(x)
    # first flatten 'max_pool_2_out' to contain 16*5*5 columns
    # read through https://stackoverflow.com/a/42482819/7551231
    x = x.view(-1, 16*5*5)
    # FC-1, then perform ReLU non-linearity
    x = torch.nn.functional.relu(self.fc1(x))
    # FC-2, then perform ReLU non-linearity
    x = torch.nn.functional.relu(self.fc2(x))
    # FC-3
    x = self.fc3(x)

    return x
```

LeNet in Pytorch

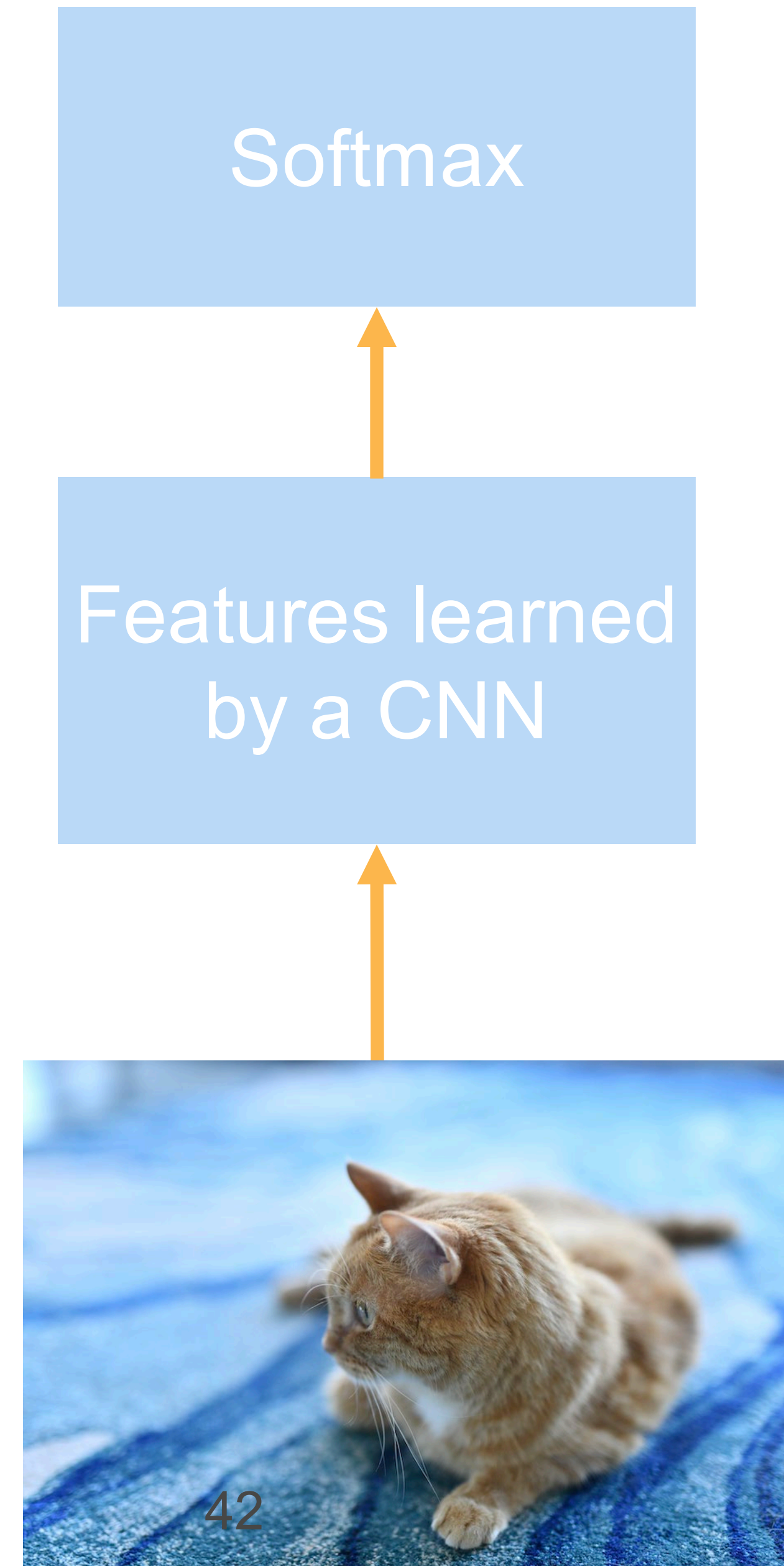
AlexNet



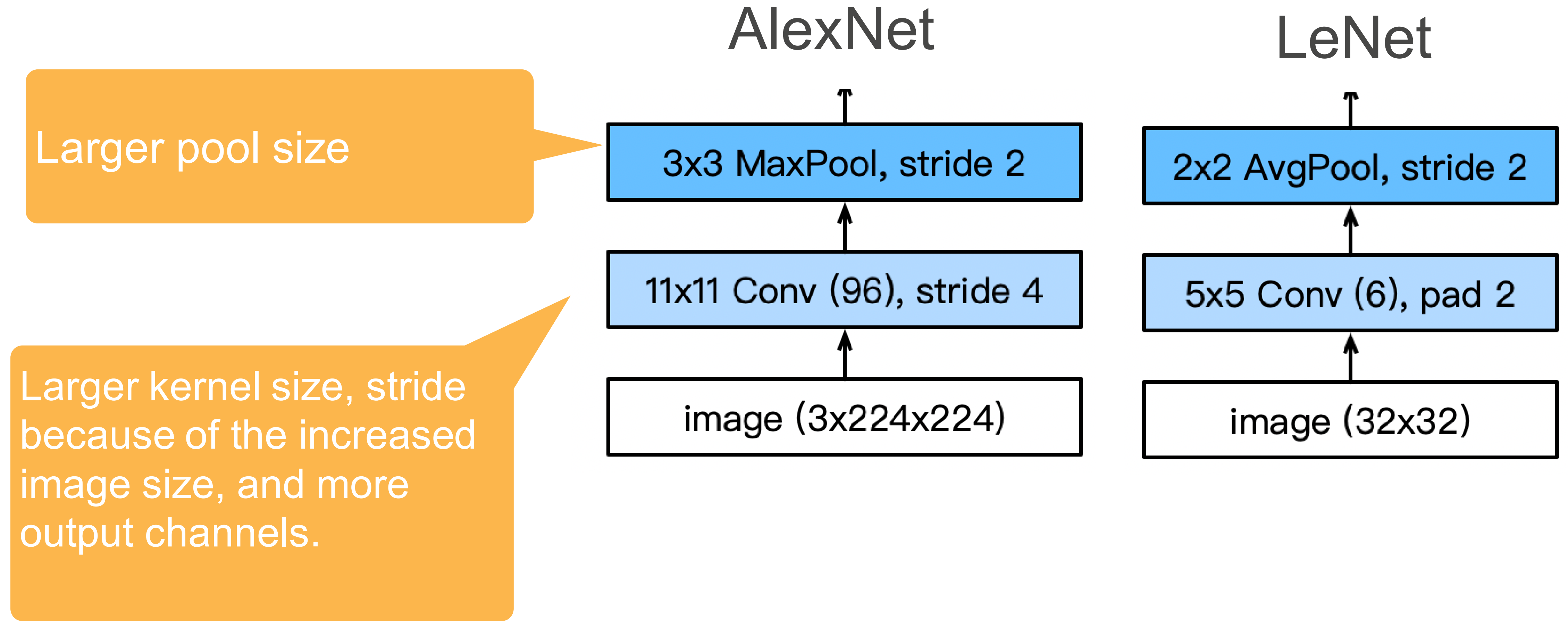


AlexNet

- AlexNet won ImageNet competition in 2012
- Deeper and bigger LeNet
- Paradigm shift for computer vision

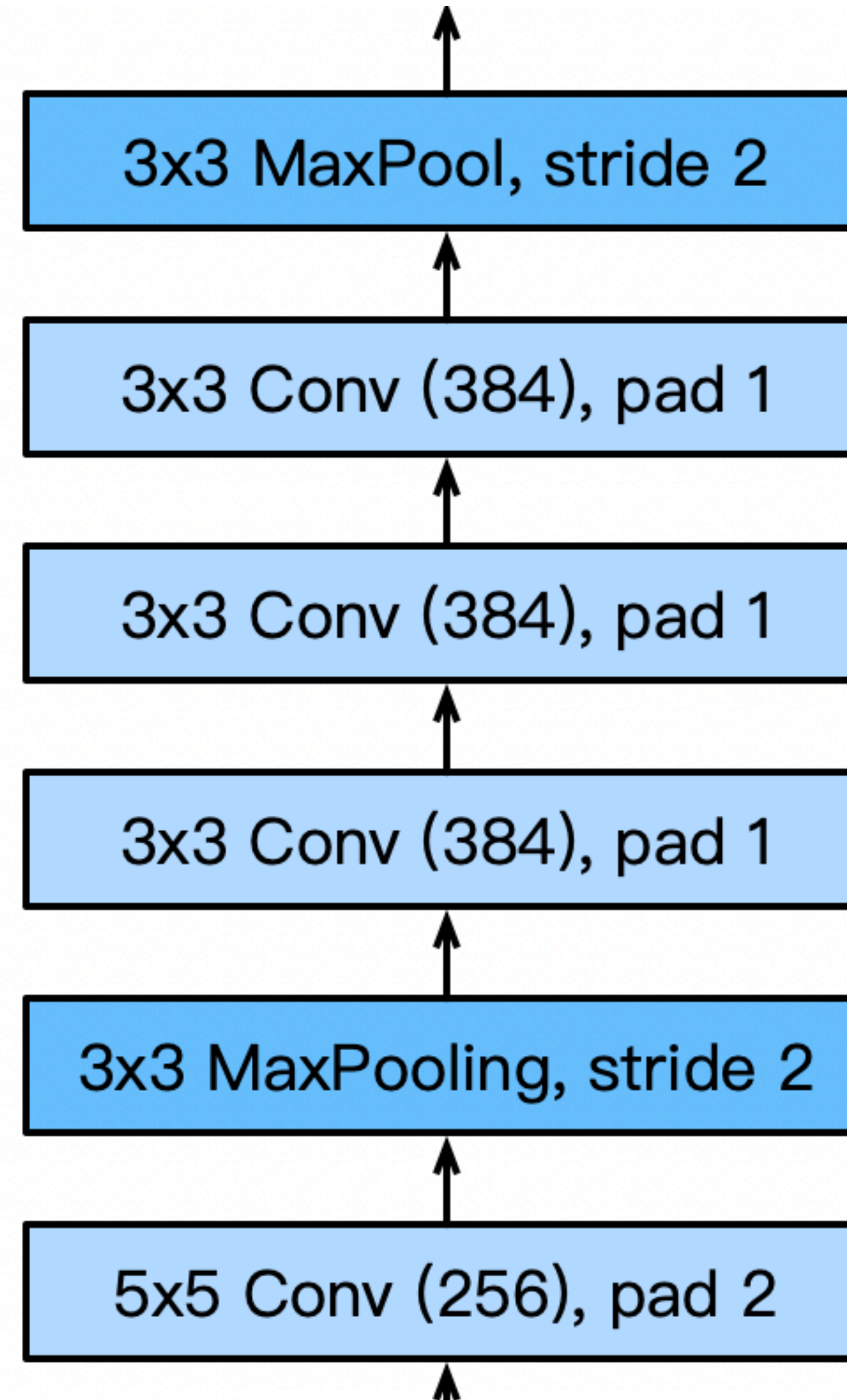


AlexNet Architecture



AlexNet Architecture

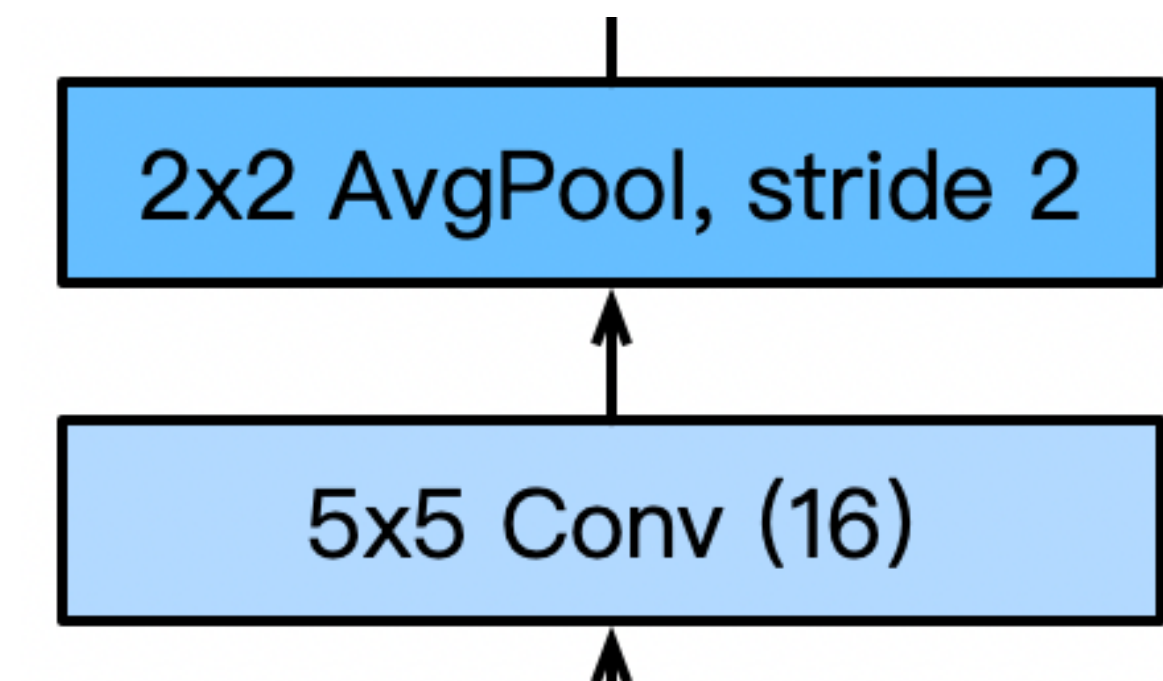
AlexNet



3 additional
convolutional layers

More output channels.

LeNet

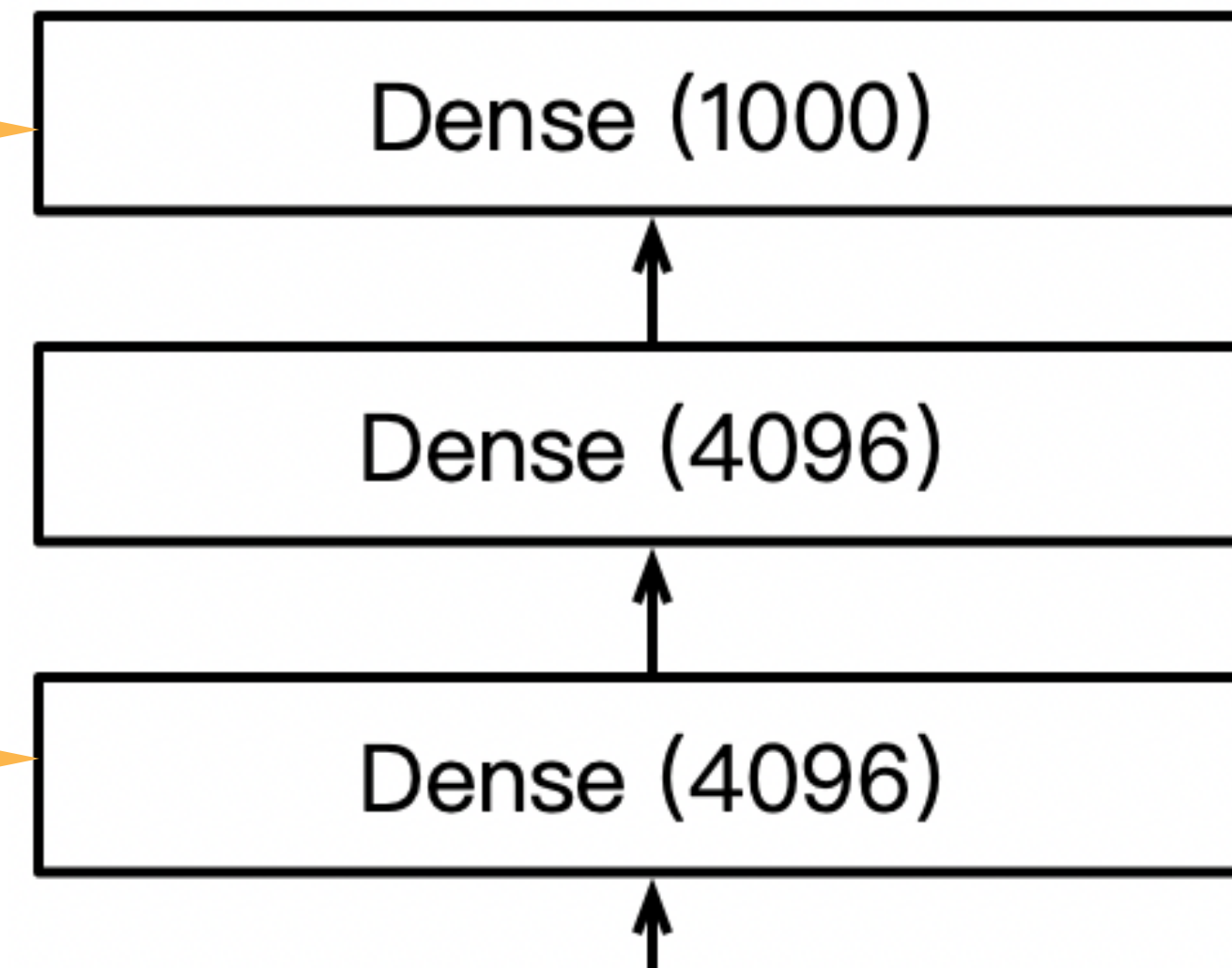


AlexNet Architecture

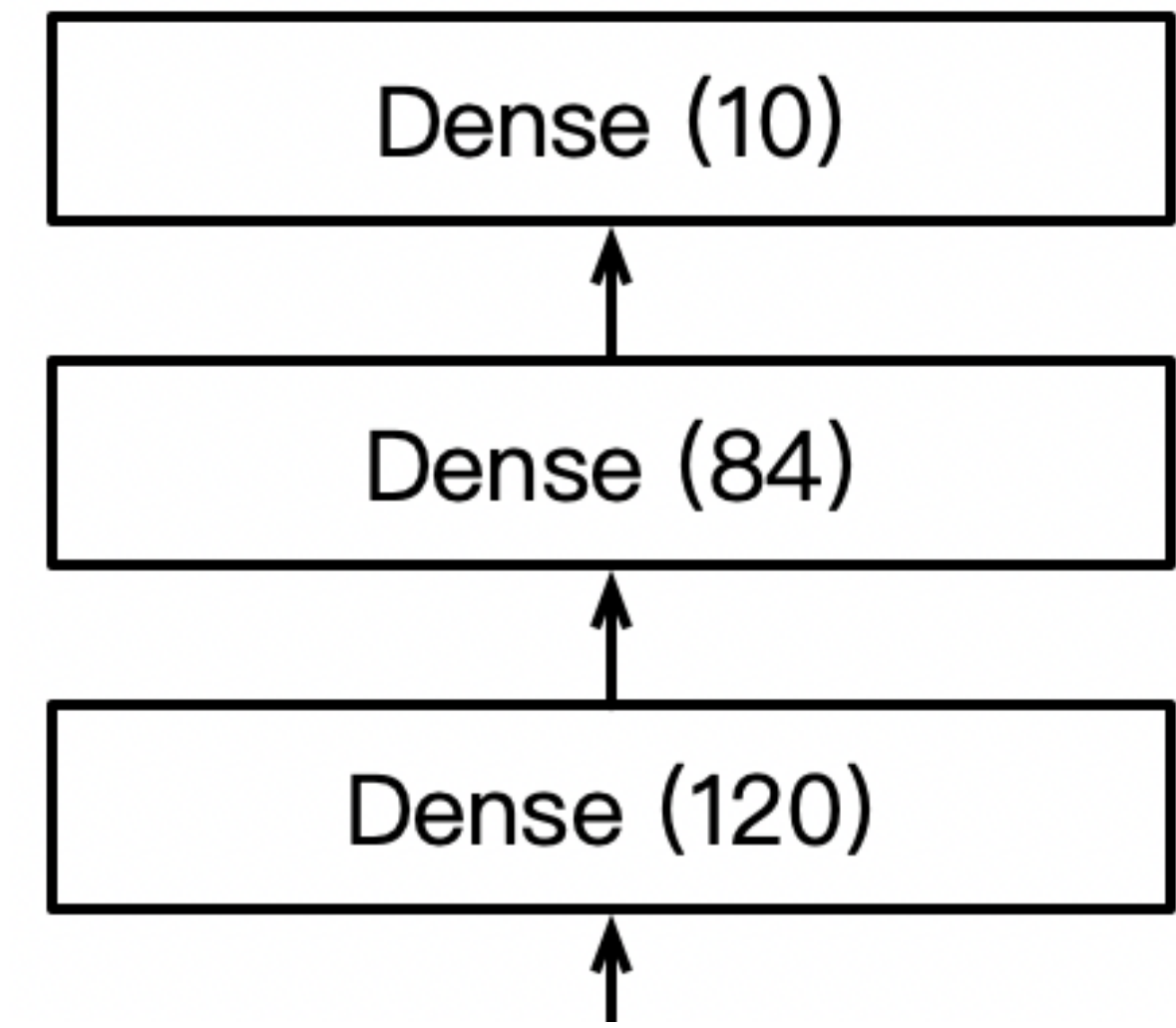
AlexNet

1000 classes output

Increase hidden size
from 120 to 4096

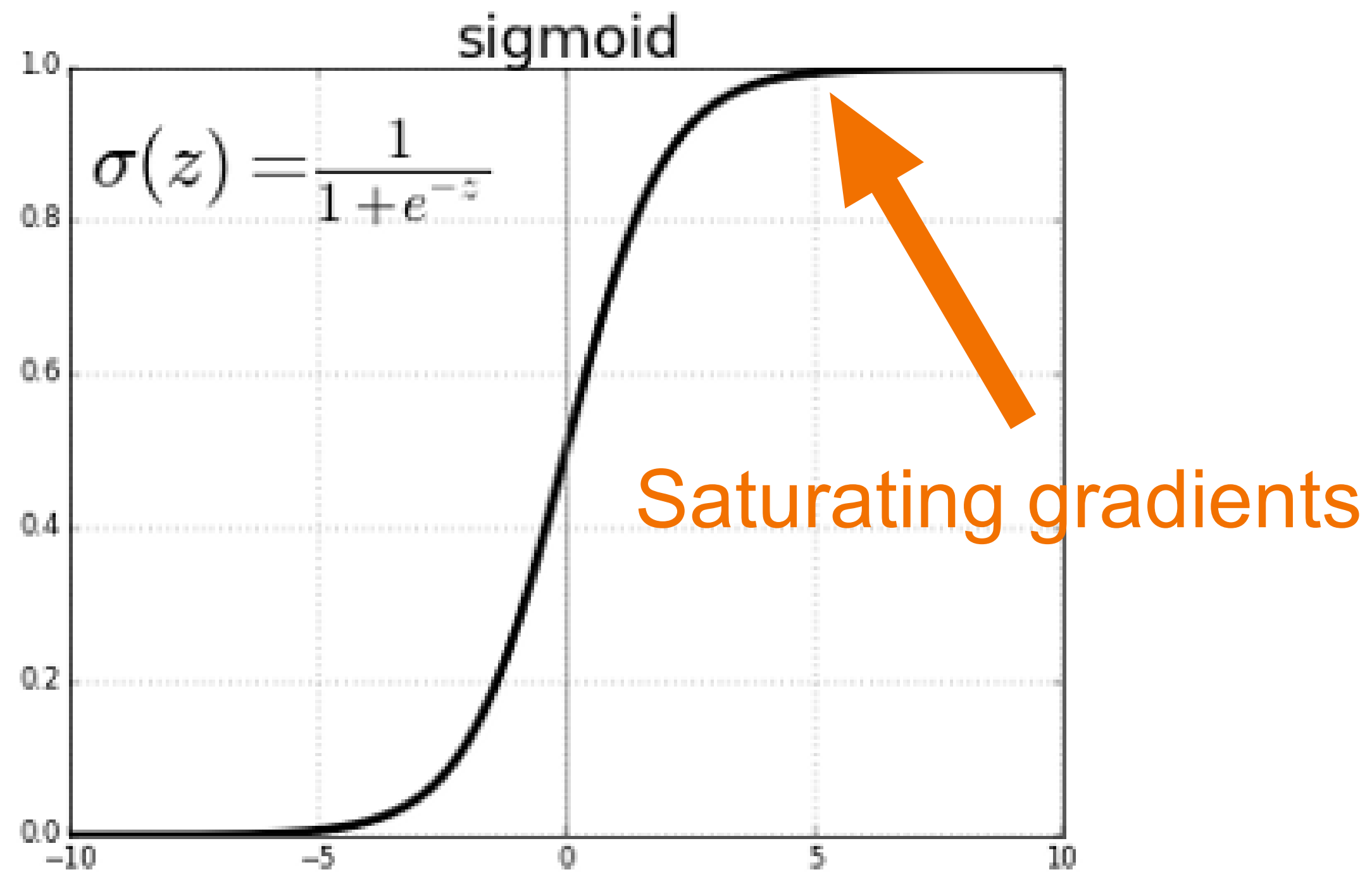


LeNet



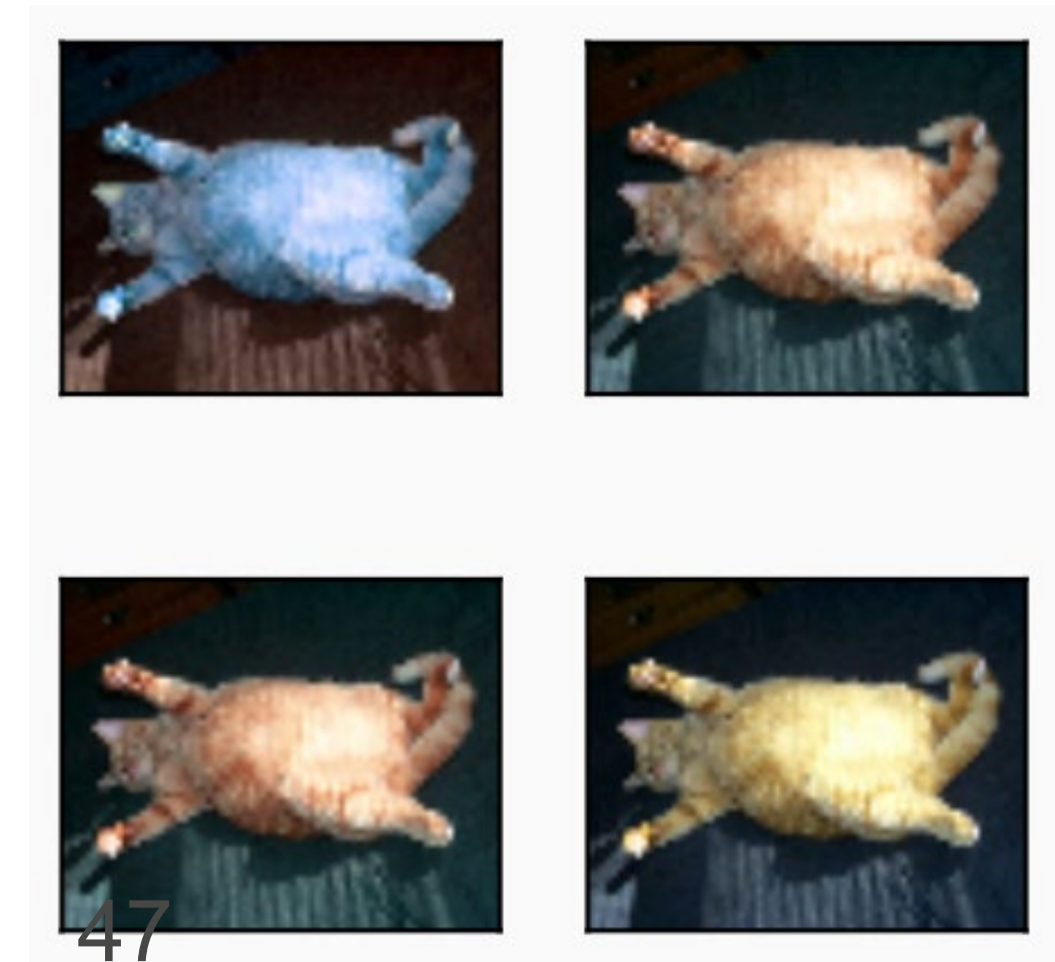
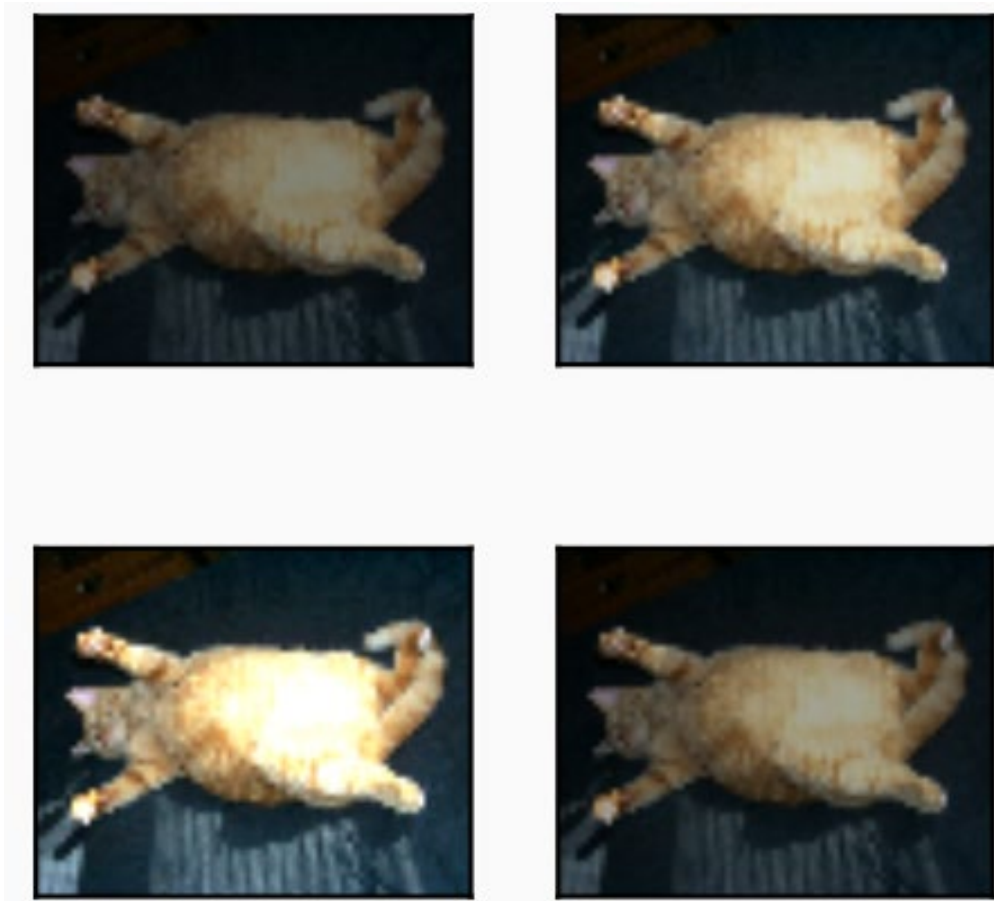
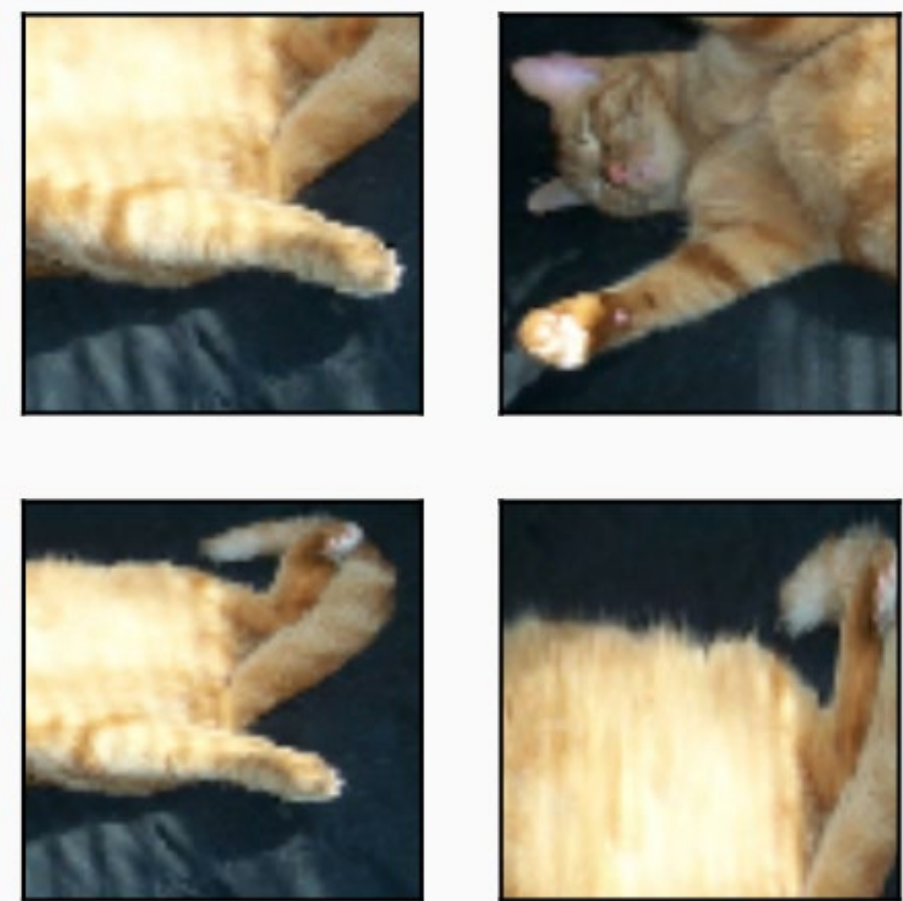
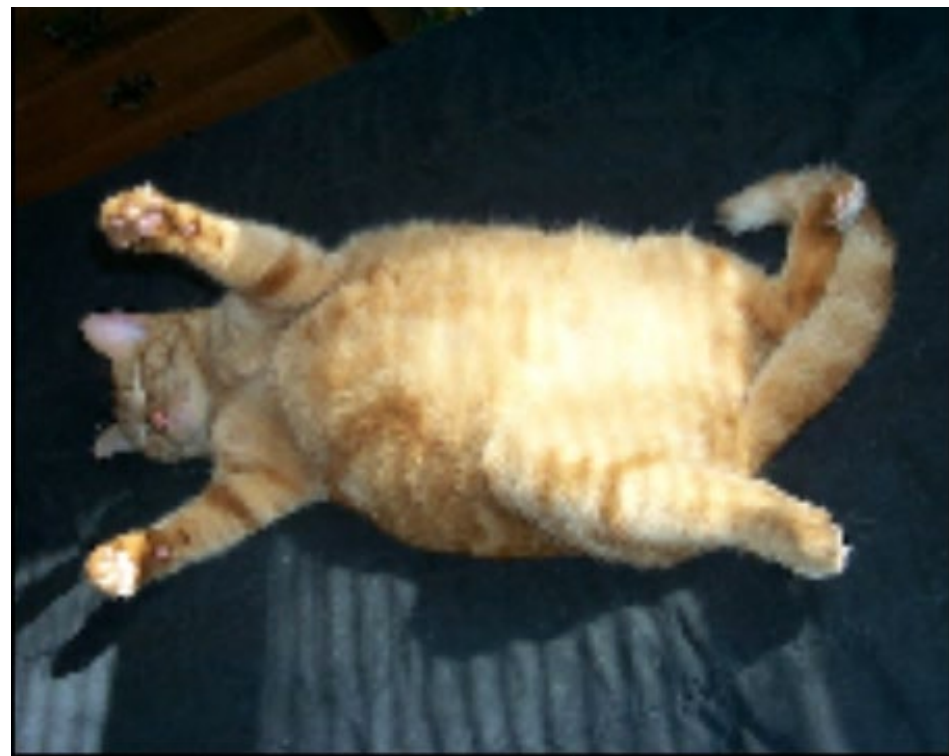
More Differences...

- Change activation function from sigmoid to ReLu (no more vanishing gradient)



More Differences...

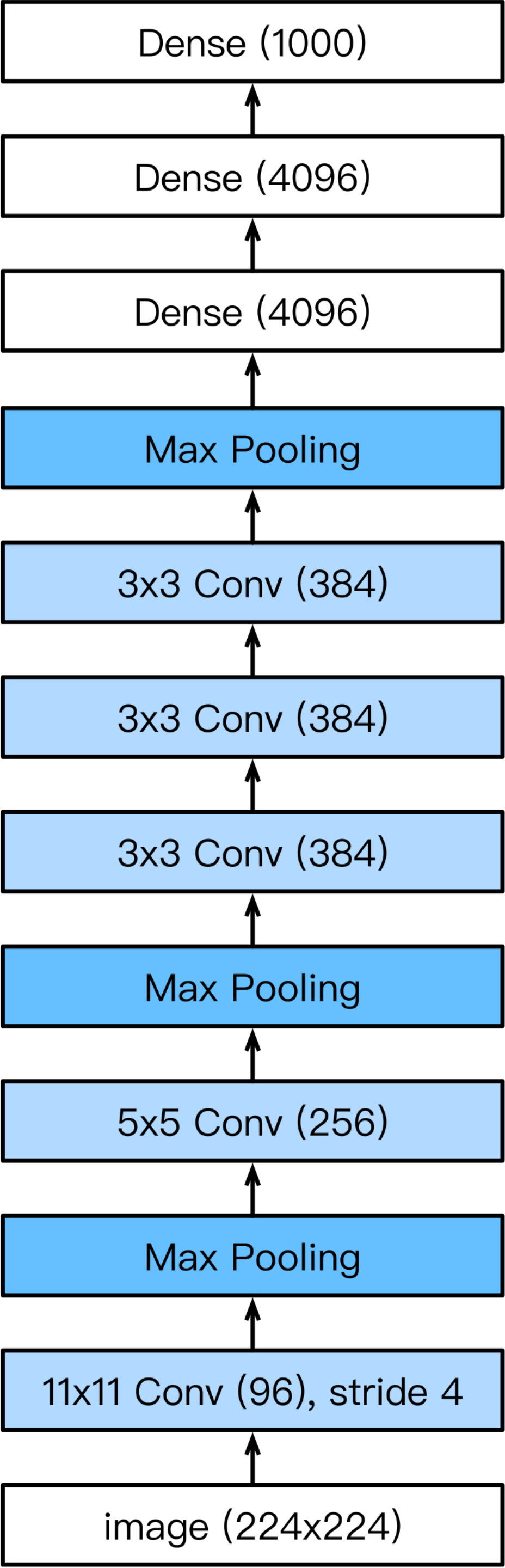
- Change activation function from sigmoid to ReLu (no more vanishing gradient)
- Data augmentation



Complexity

	#parameters	
	AlexNet	LeNet
Conv1	35K	150
Conv2	614K	2.4K
Conv3-5	3M	
Dense1	26M	0.048M
Dense2	16M	0.01M
Total	46M	0.06M

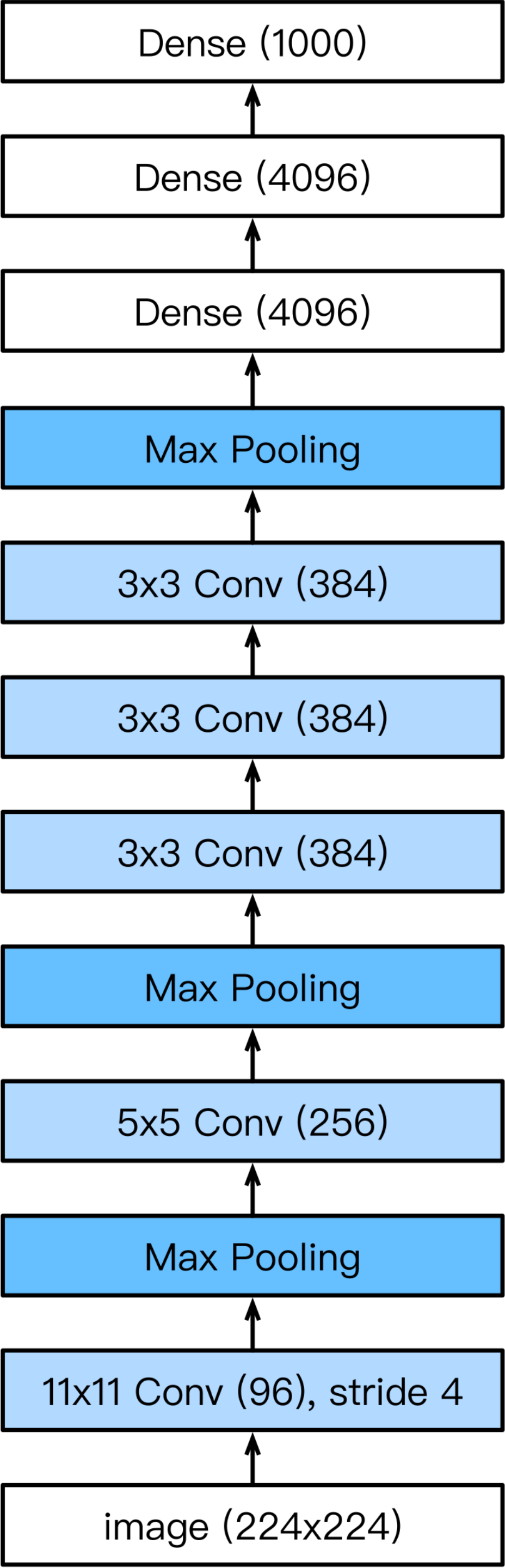
48

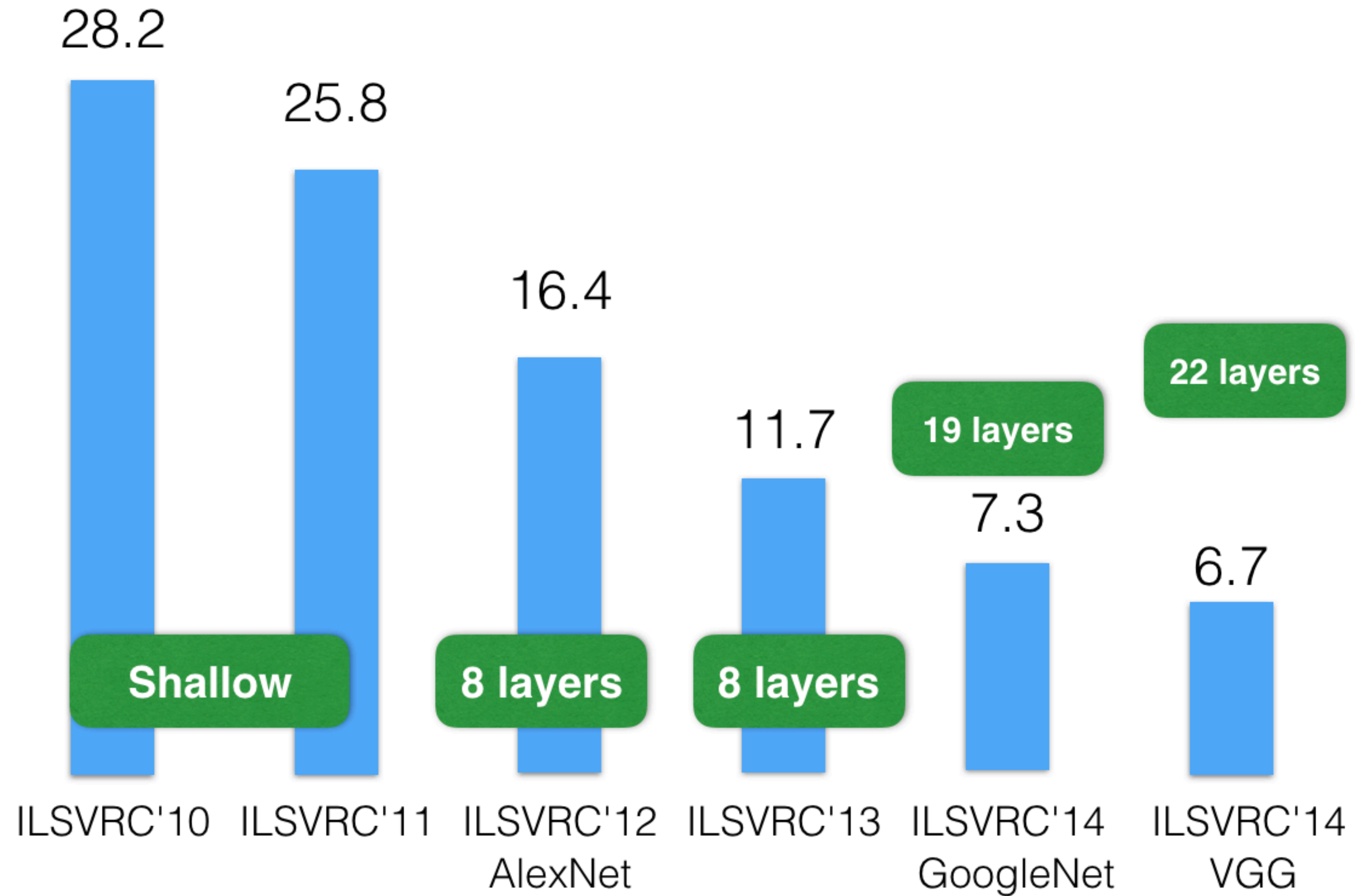


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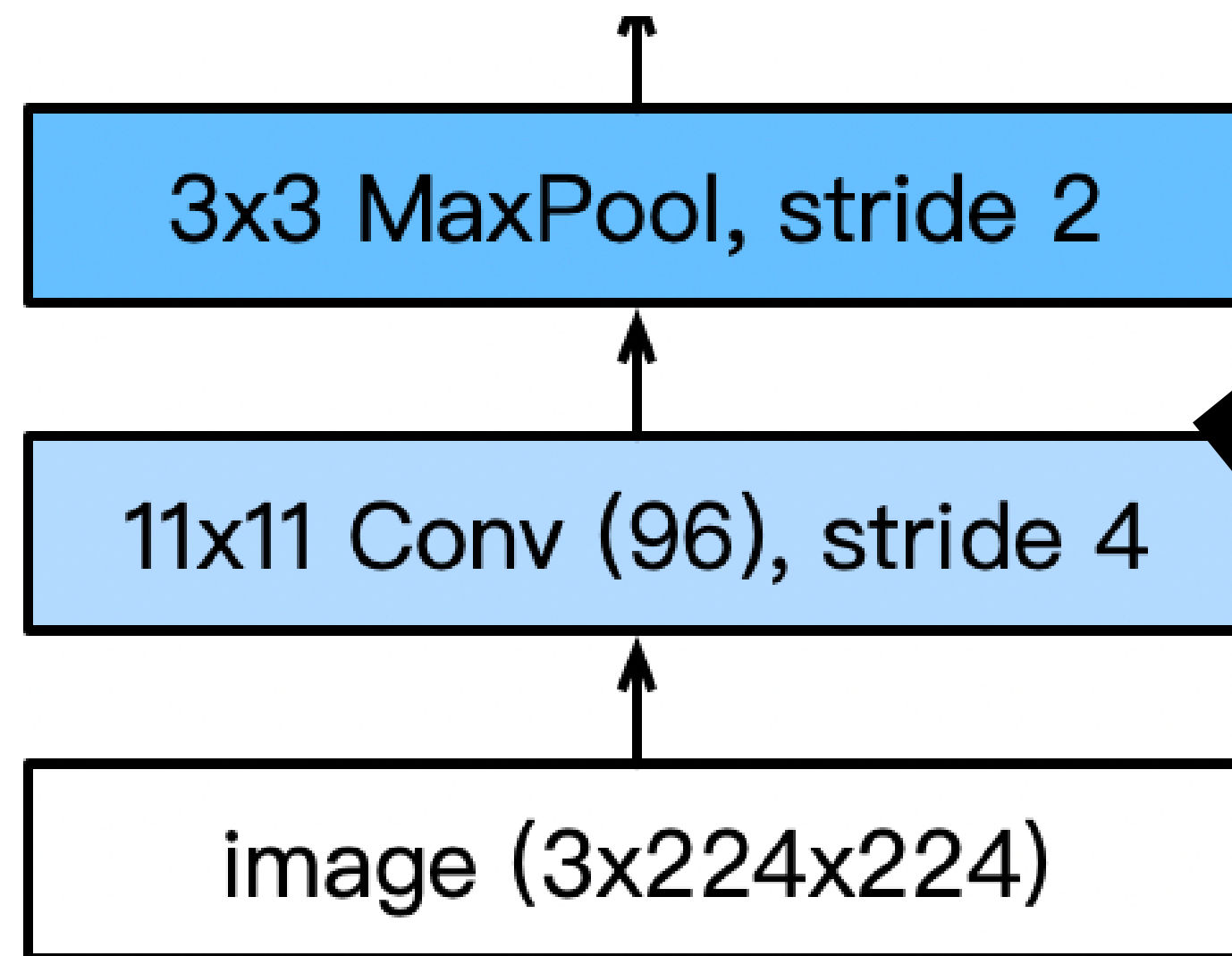
$11 \times 11 \times 3 \times 96 = 35k$



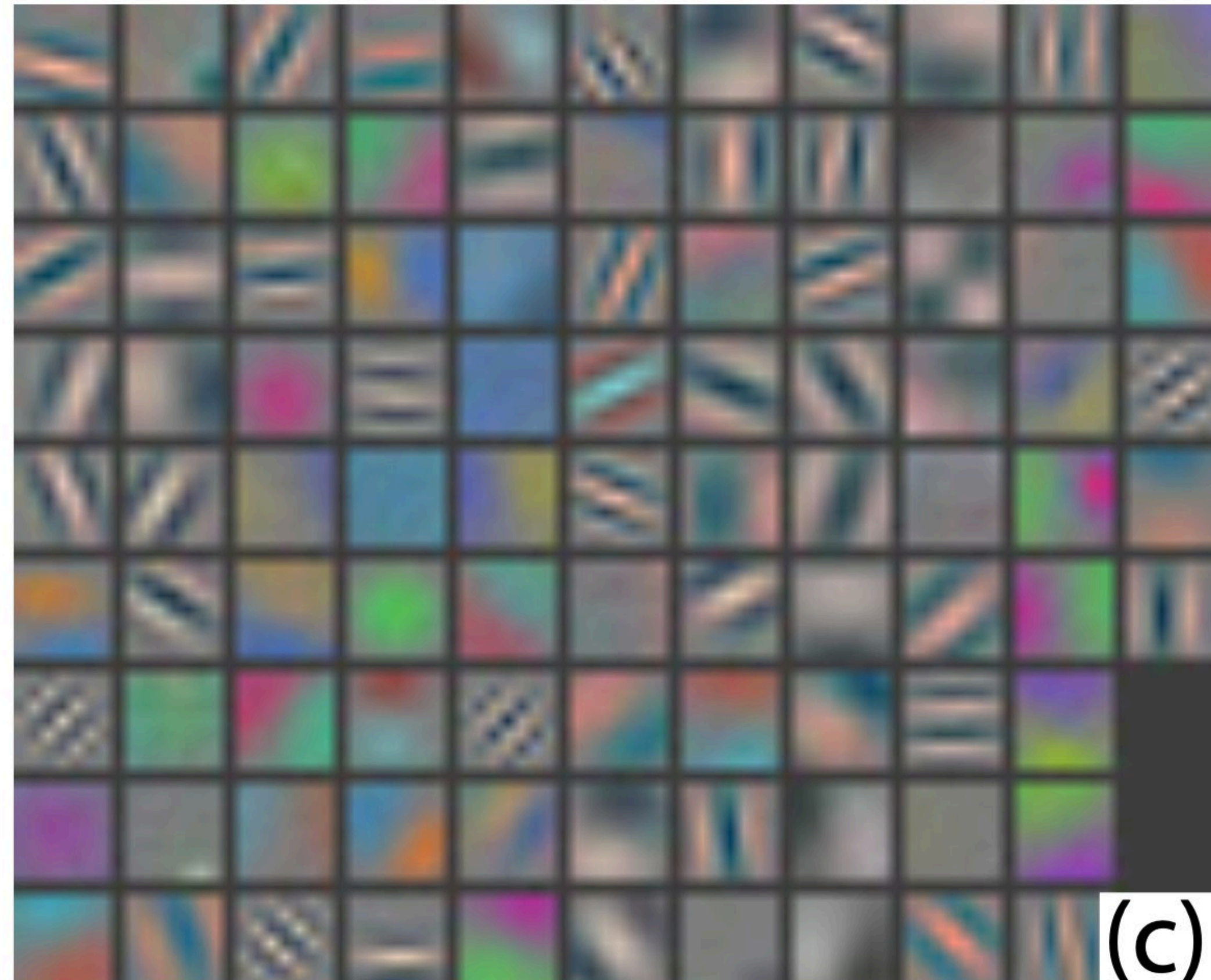


ImageNet Top-5 Classification Error (%)

AlexNet



Each Conv1 kernel is 3x11x11, can be visualized as an RGB patch:



[Visualizing and Understanding Convolutional Networks. M Zeiler & R Fergus 2013]

Which of the following are true about AlexNet? Select all that apply.

- A. AlexNet contains 8 conv/fc layers. The first five are convolutional layers.
- B. The last three layers are fully connected layers.
- C. some of the convolutional layers are followed by [max-pooling](#) (layers).
- D. AlexNet achieved excellent performance in the 2012 ImageNet challenge.

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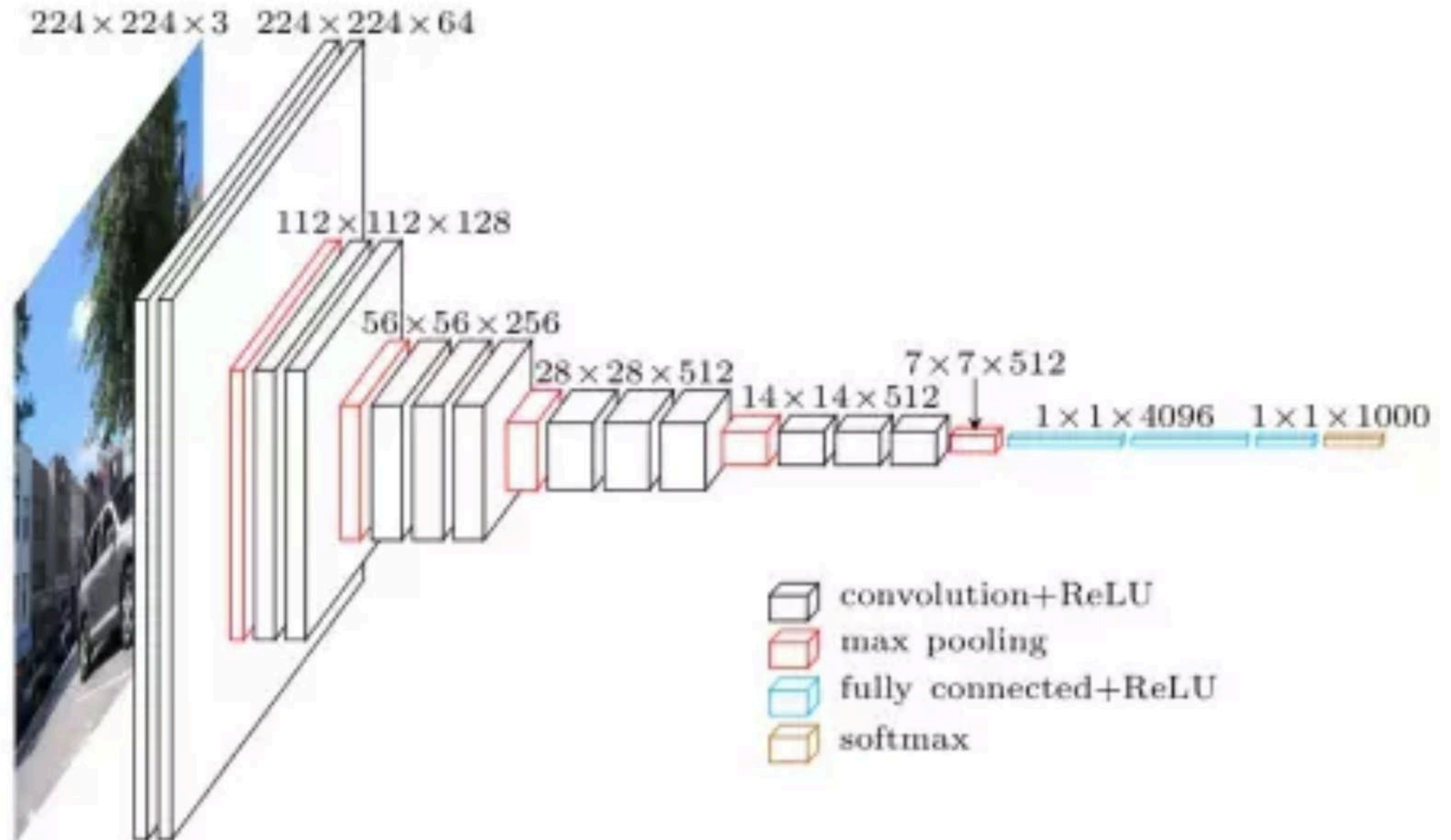
All options are true!

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks.

Advances in neural information processing systems (pp. 1097–1105).



VGG



VGG Block: Multiple convolution layers followed by pooling.

Progress

- LeNet (1995)
 - 2 convolution + pooling layers
 - 2 hidden dense layers
- AlexNet
 - Bigger and deeper LeNet
 - ReLu, preprocessing
- VGG
 - Bigger and deeper AlexNet (repeated VGG blocks)

Which of the following statement is True for the success of deep models?

- Better design of the neural networks
- Large scale training dataset
- Available computing power
- All of the above

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Suggested Reading

Example using PyTorch:

https://pytorch.org/tutorials/beginner/blitz/cifar10_tutorial.html

Summary of today

- Reviewed (some of) convolutional computations.
 - 2D convolutions, multiple input channels, pooling.
- Shown how convolutions are used as layers in a (deep) neural network.
- Built intuition for output of convolutional layers.
- Overviewed the evolution of deeper convolutional networks



Acknowledgement:

Some of the slides in these lectures have been adapted/borrowed from materials developed by Yin Li (<https://happyharrycn.github.io/CS540-Fall20/schedule/>), Alex Smola and Mu Li: <https://courses.d21.ai/berkeley-stat-157/index.html>