CS540 Introduction to Artificial Intelligence

Convolutional Neural Networks (II)

University of Wisconsin-Madison

Spring 2025

Announcements

- **Homeworks**:
  - HW7 online, deadline on Monday **April 7th at 11:59 PM**

- Class roadmap and schedule:

Machine Learning: Deep Learning II
Machine Learning: Deep Learning III
Spring Recess March 22-30

Deep Learning

it matters

Take the Healthy Minds Survey by March 24.

Complete the survey to be entered into a drawing to win a Wiscard deposit:

400 students will receive $10, and 10 students will receive $200.

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

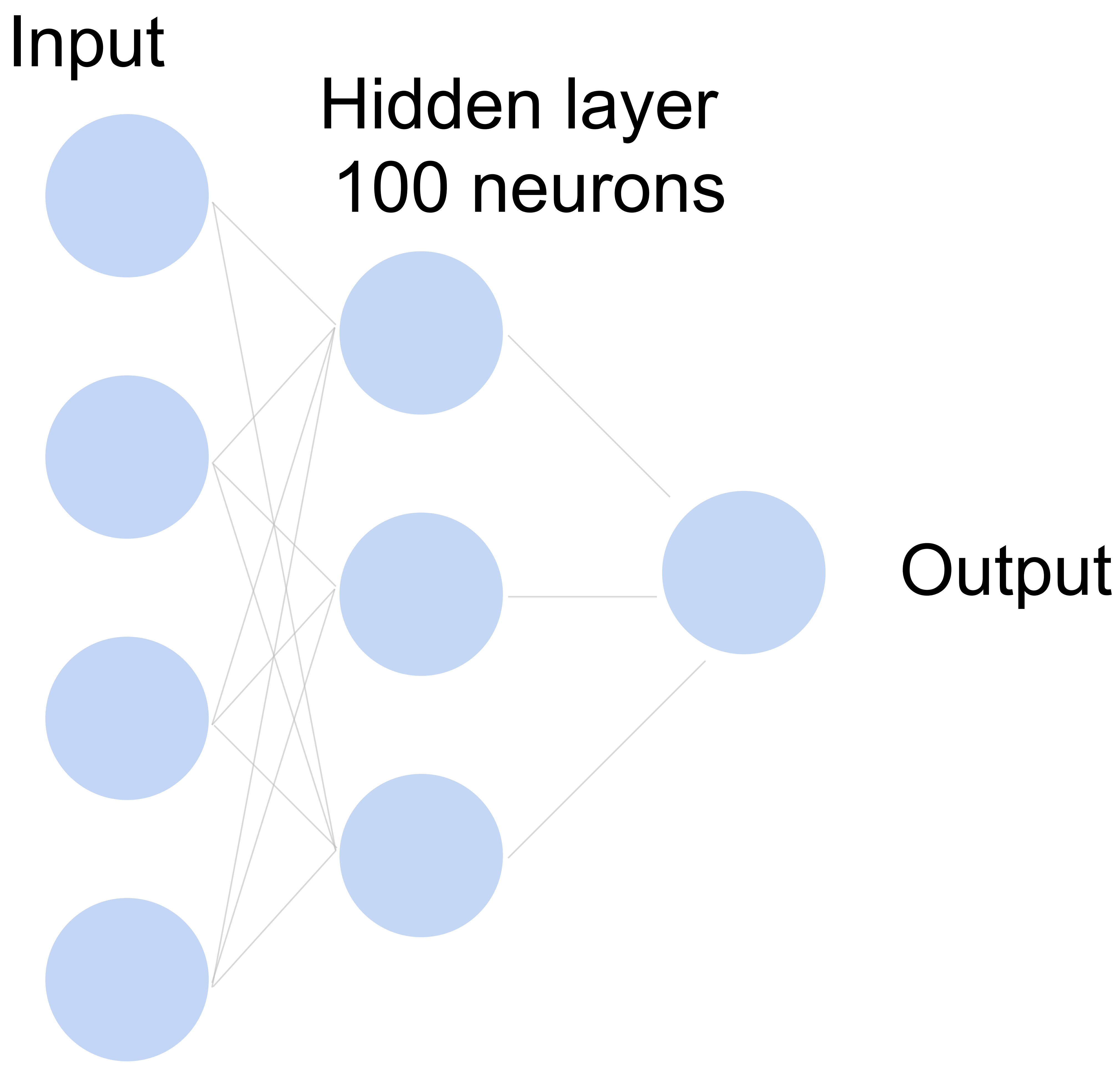
How to classify

Cats vs. dogs?

36M floats in a RGB image!

Fully Connected Networks

Cats vs. dogs?

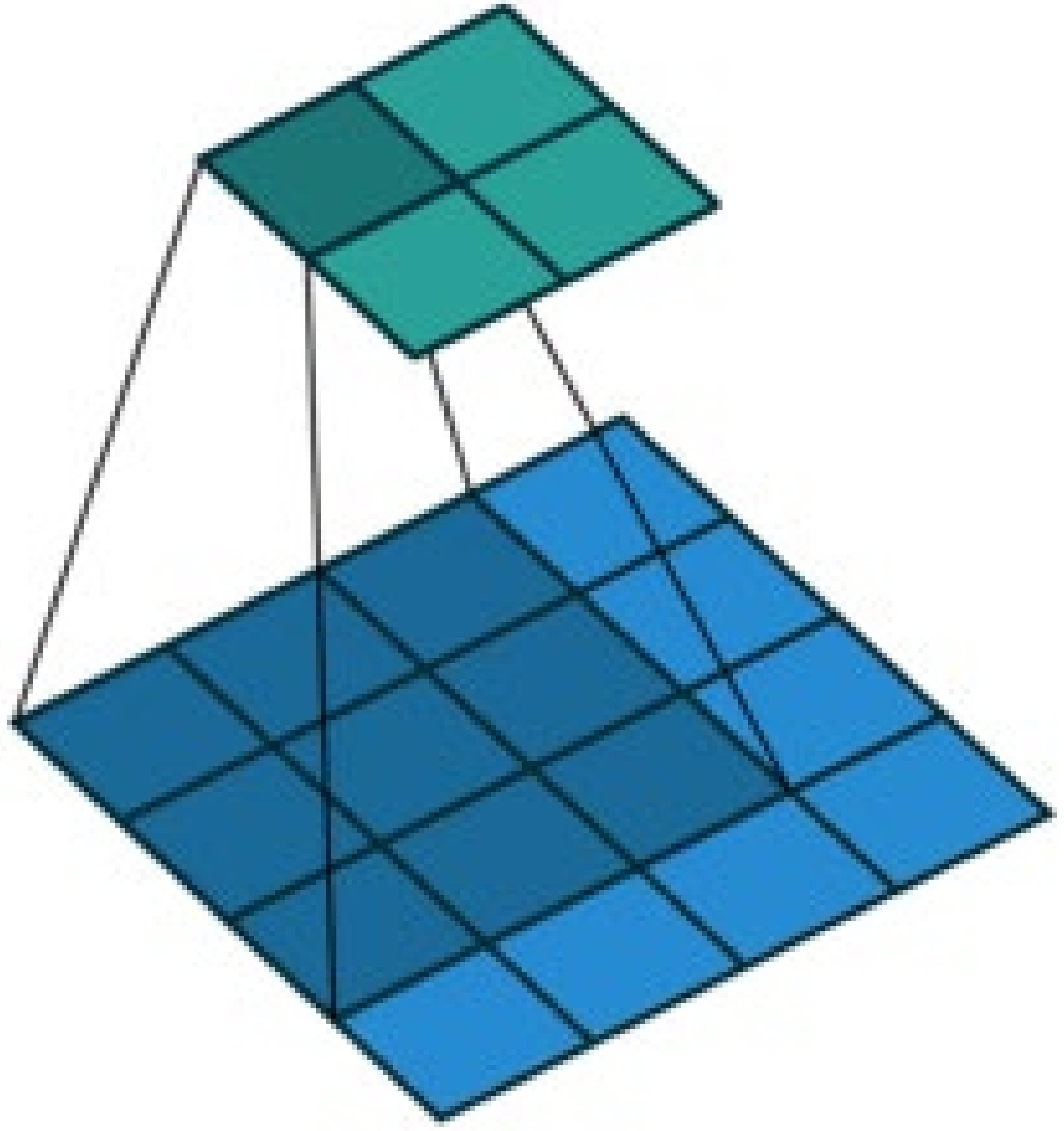


36M elements x 100 = **3.6B** parameters!

Review: 2-D Convolution

Input		Kernel		Output
$\begin{bmatrix} 0 & 1 & 2 \\ 3 & 4 & 5 \\ 6 & 7 & 8 \end{bmatrix}$	$*$	$\begin{bmatrix} 0 & 1 \\ 2 & 3 \end{bmatrix}$	$=$	$\begin{bmatrix} 19 & 25 \\ 37 & 43 \end{bmatrix}$

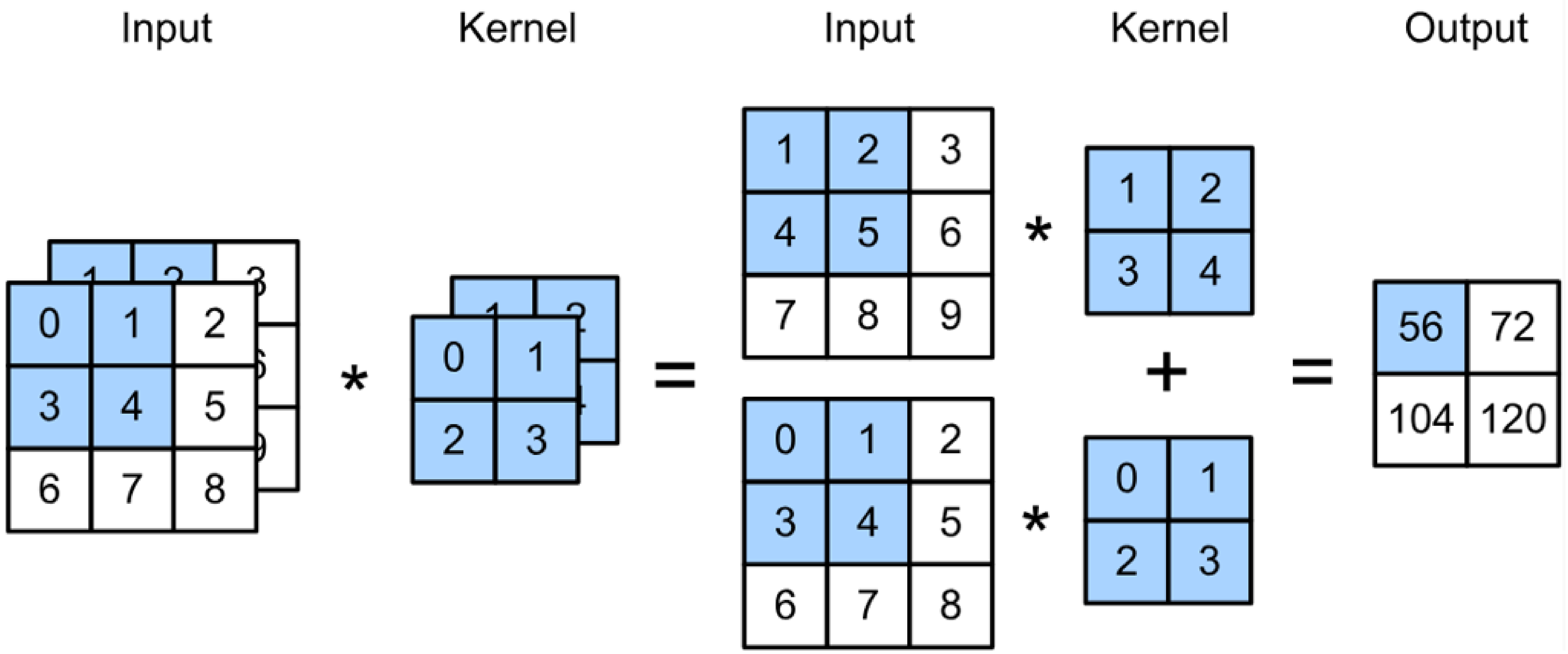
$$
\begin{aligned}
0 \times 0 + 1 \times 1 + 3 \times 2 + 4 \times 3 &= 19, \\
1 \times 0 + 2 \times 1 + 4 \times 2 + 5 \times 3 &= 25, \\
3 \times 0 + 4 \times 1 + 6 \times 2 + 7 \times 3 &= 37, \\
4 \times 0 + 5 \times 1 + 7 \times 2 + 8 \times 3 &= 43.
\end{aligned}
$$



(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



$$(1 \times 1 + 2 \times 2 + 4 \times 3 + 5 \times 4)$$
$$+(0 \times 0 + 1 \times 1 + 3 \times 2 + 4 \times 3)$$
$$= 56$$

Review: Multiple Input Channels

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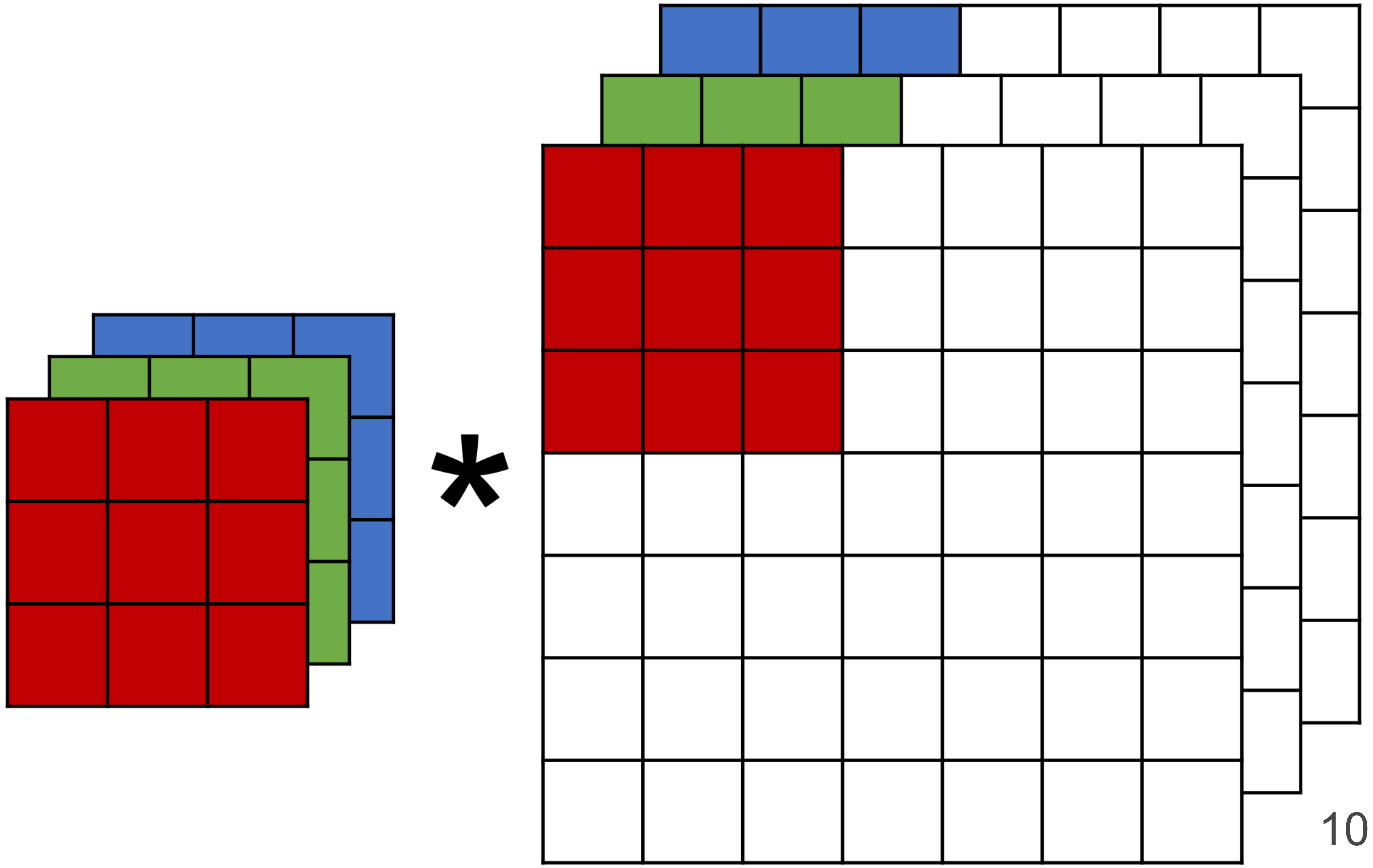

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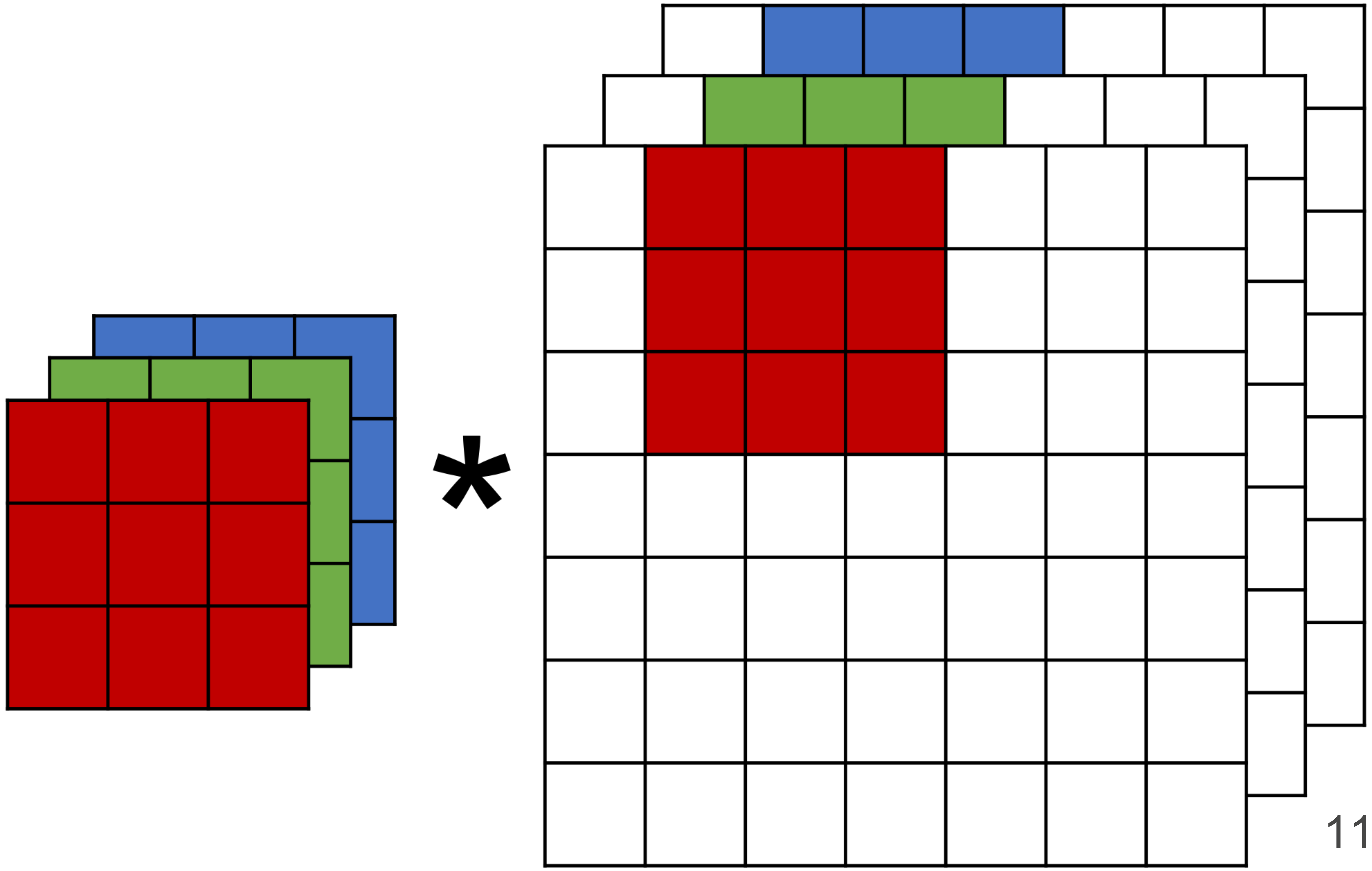

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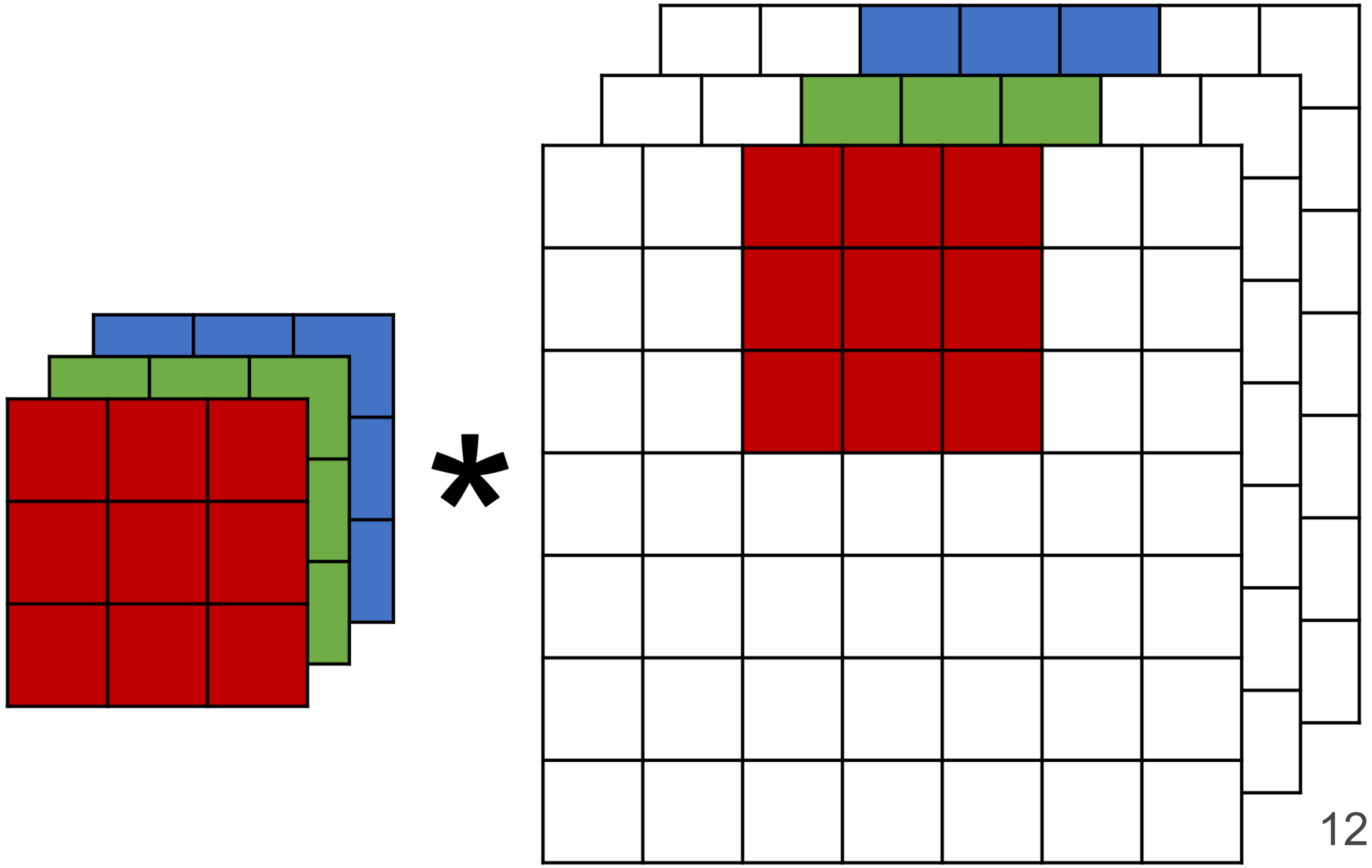
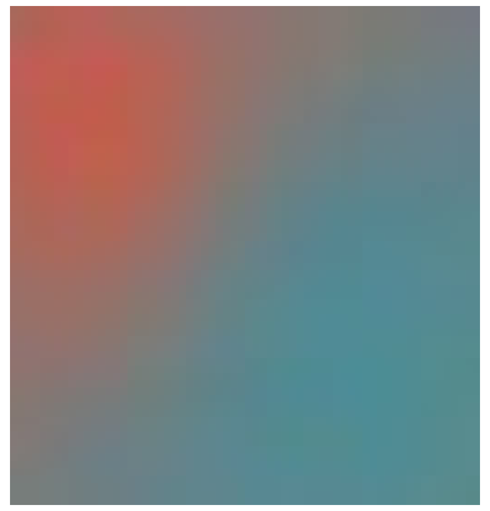


Multiple Input Channels

- 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)



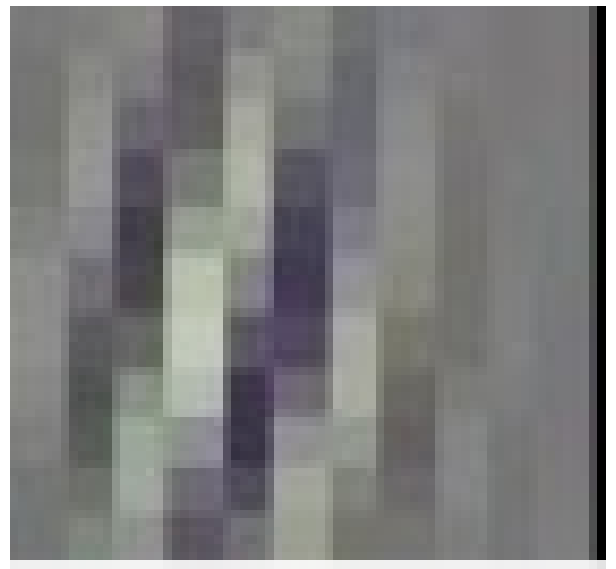
One filter
(3 channels)

$*$

RGB (3 input channels)

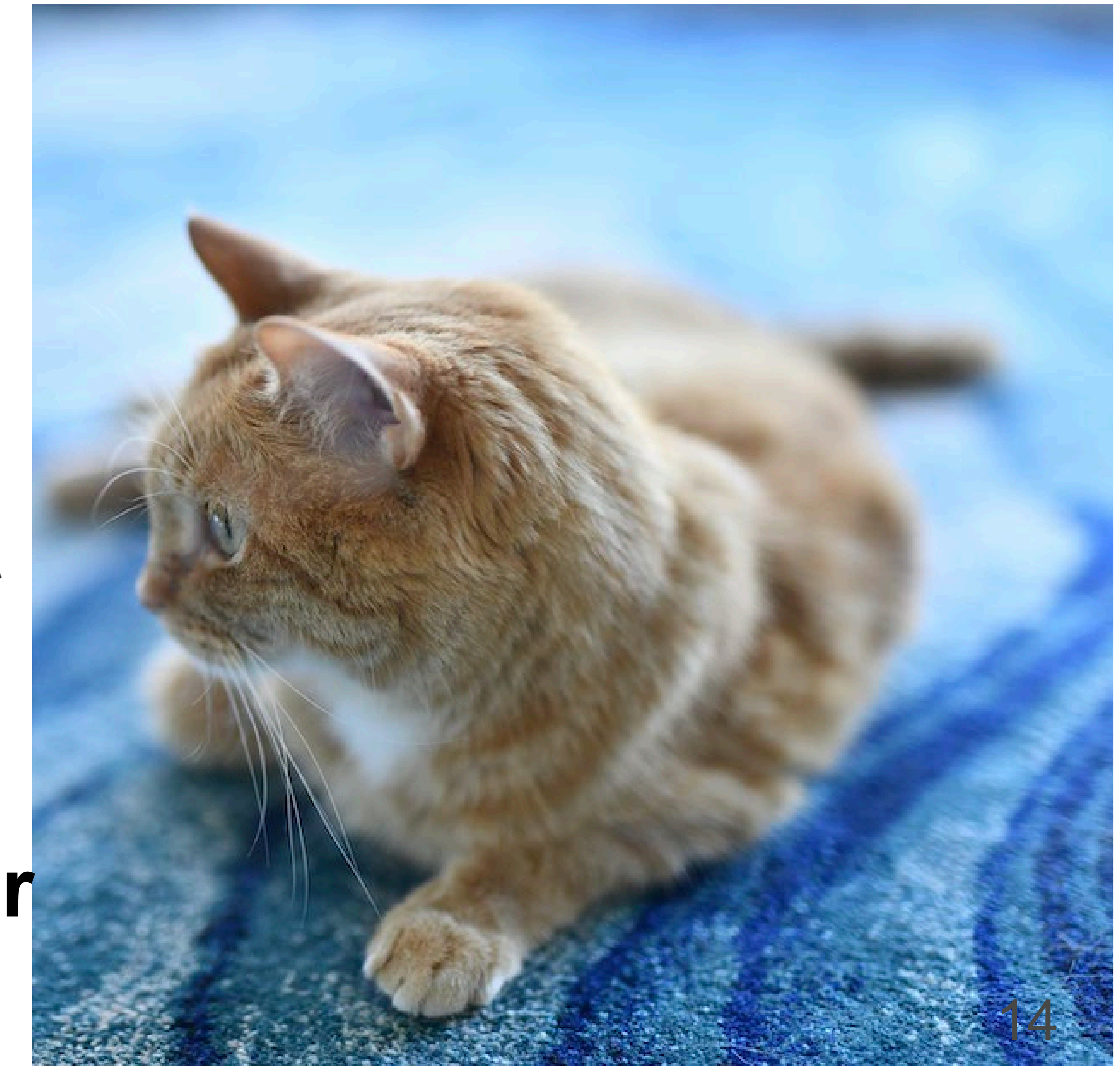
Multiple filters (in one layer)

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



A different filter

*



RGB (3 input channels)

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 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

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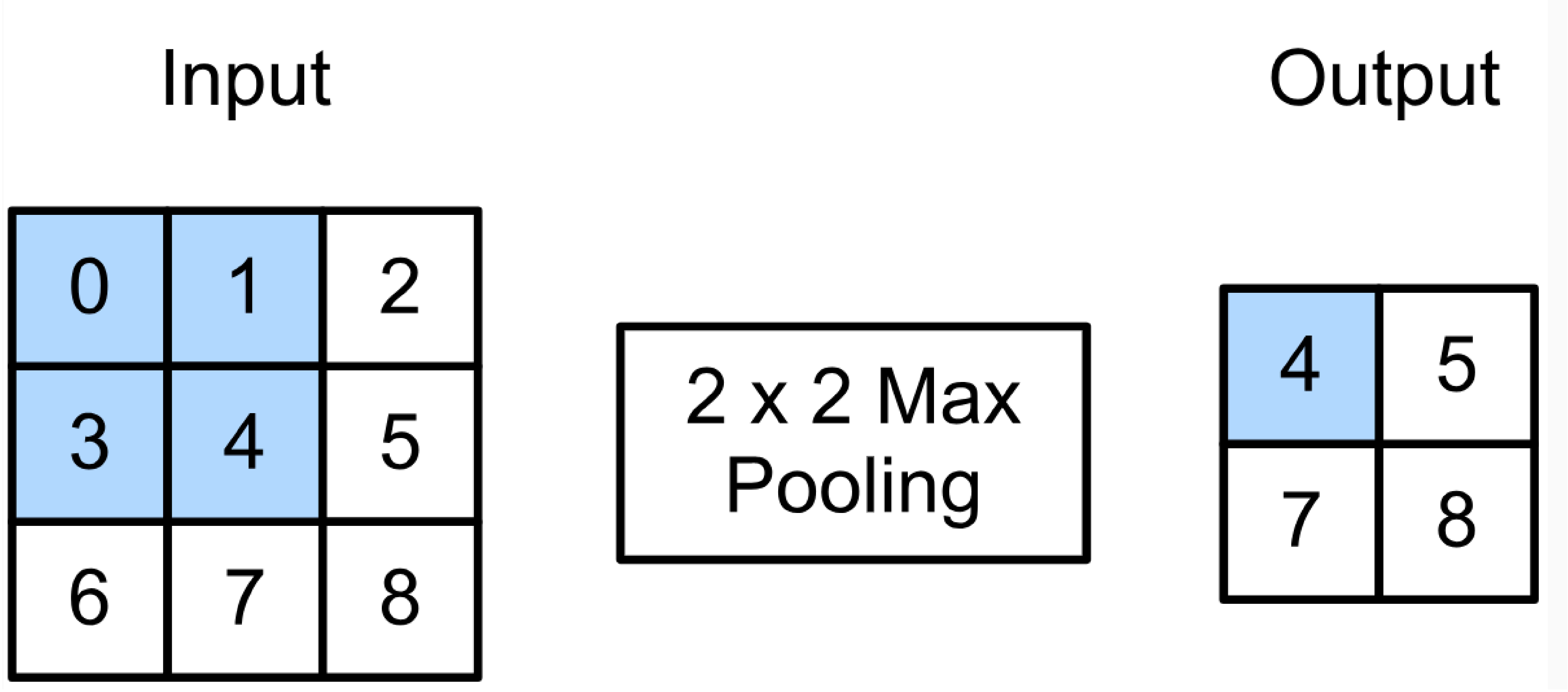
$$\lfloor (n_h - k_h + p_h + s_h)/s_h \rfloor \times \lfloor (n_w - k_w + p_w + s_w)/s_w \rfloor$$

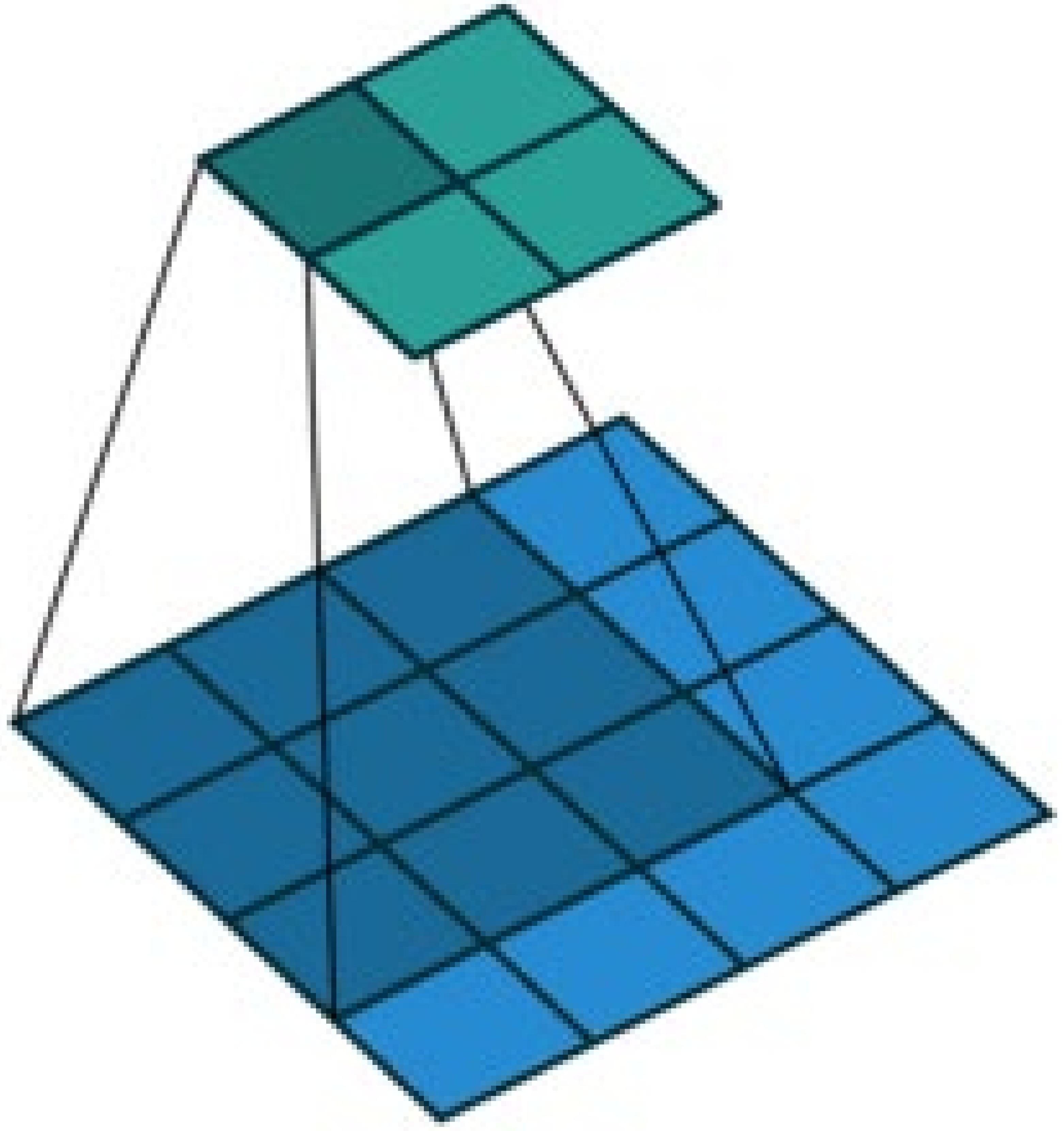
Pooling Layer

2-D Max Pooling

- Returns the maximal value in the sliding window



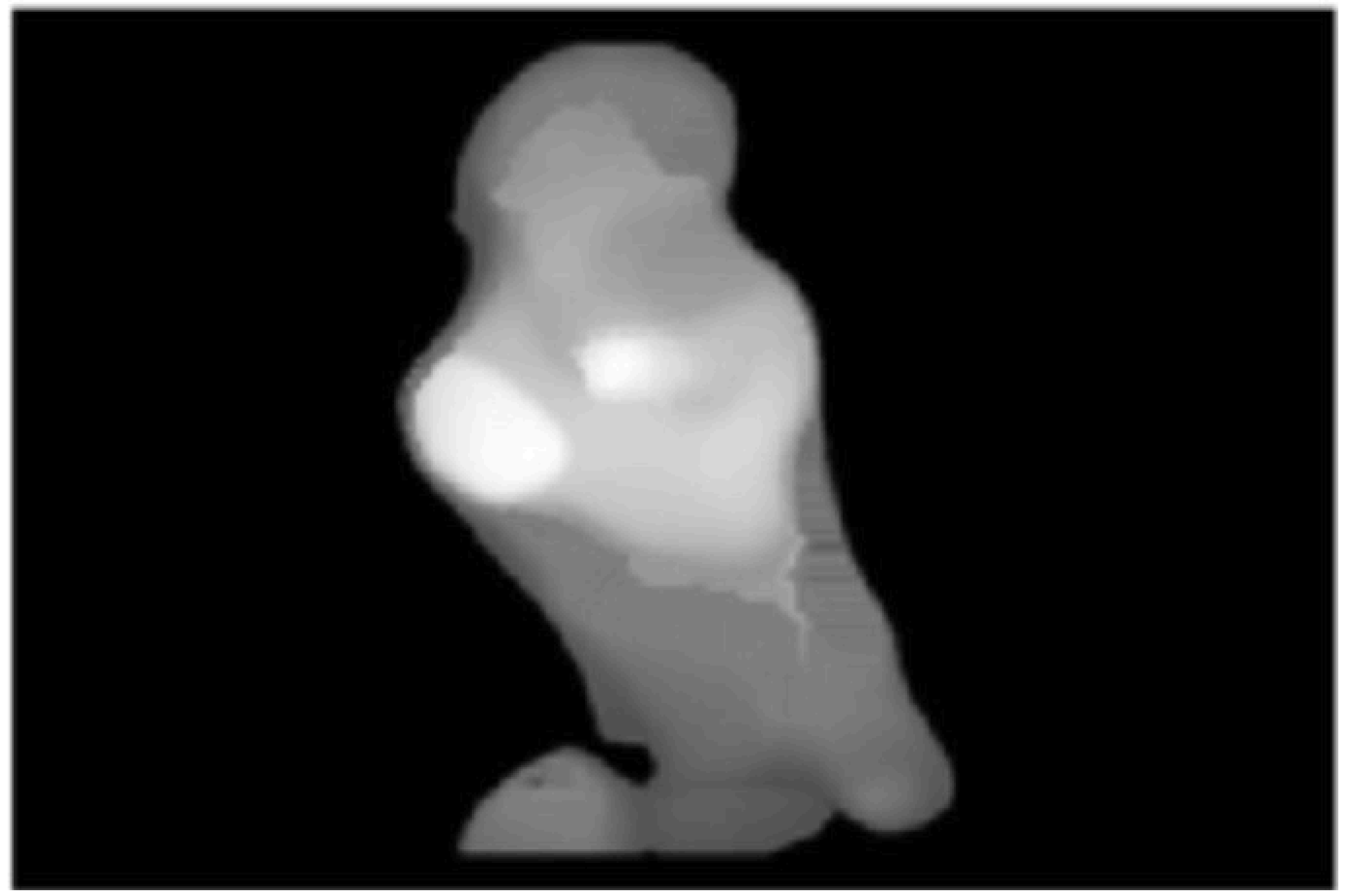
$$max(0,1,3,4) = 4$$



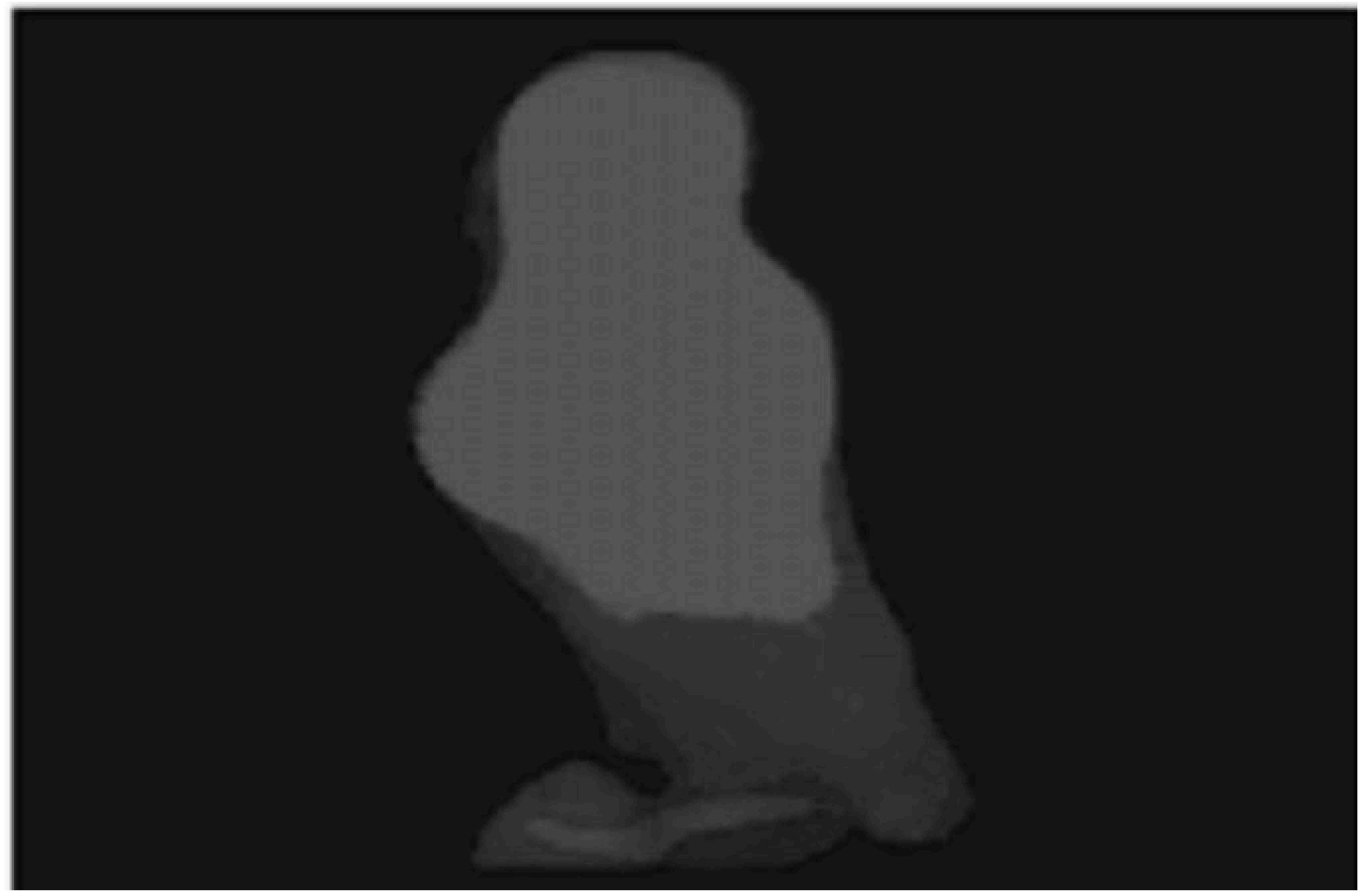
Average Pooling

- 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

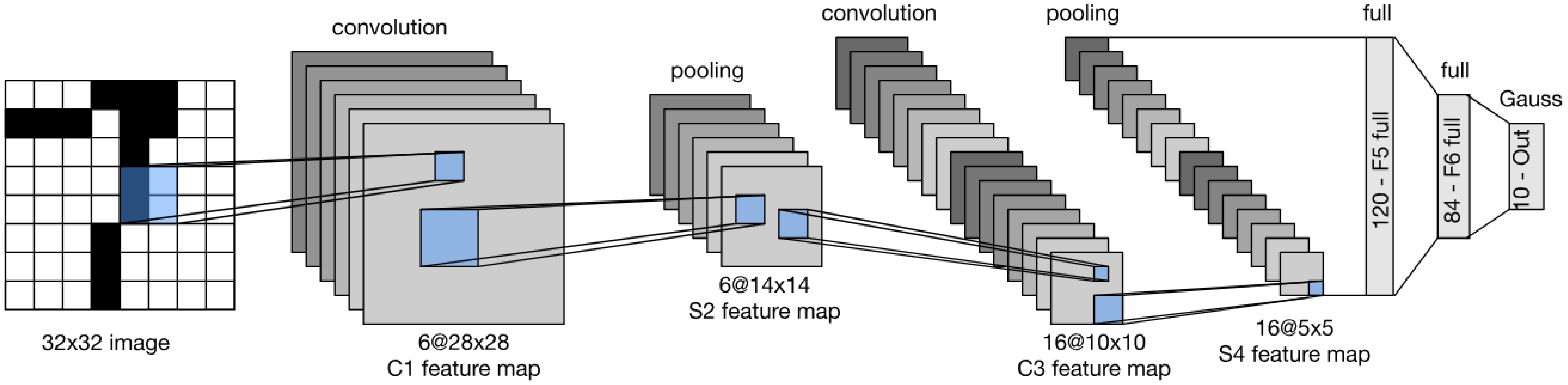
Max pooling



Average pooling



Convolutional Neural Network Architecture



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

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.

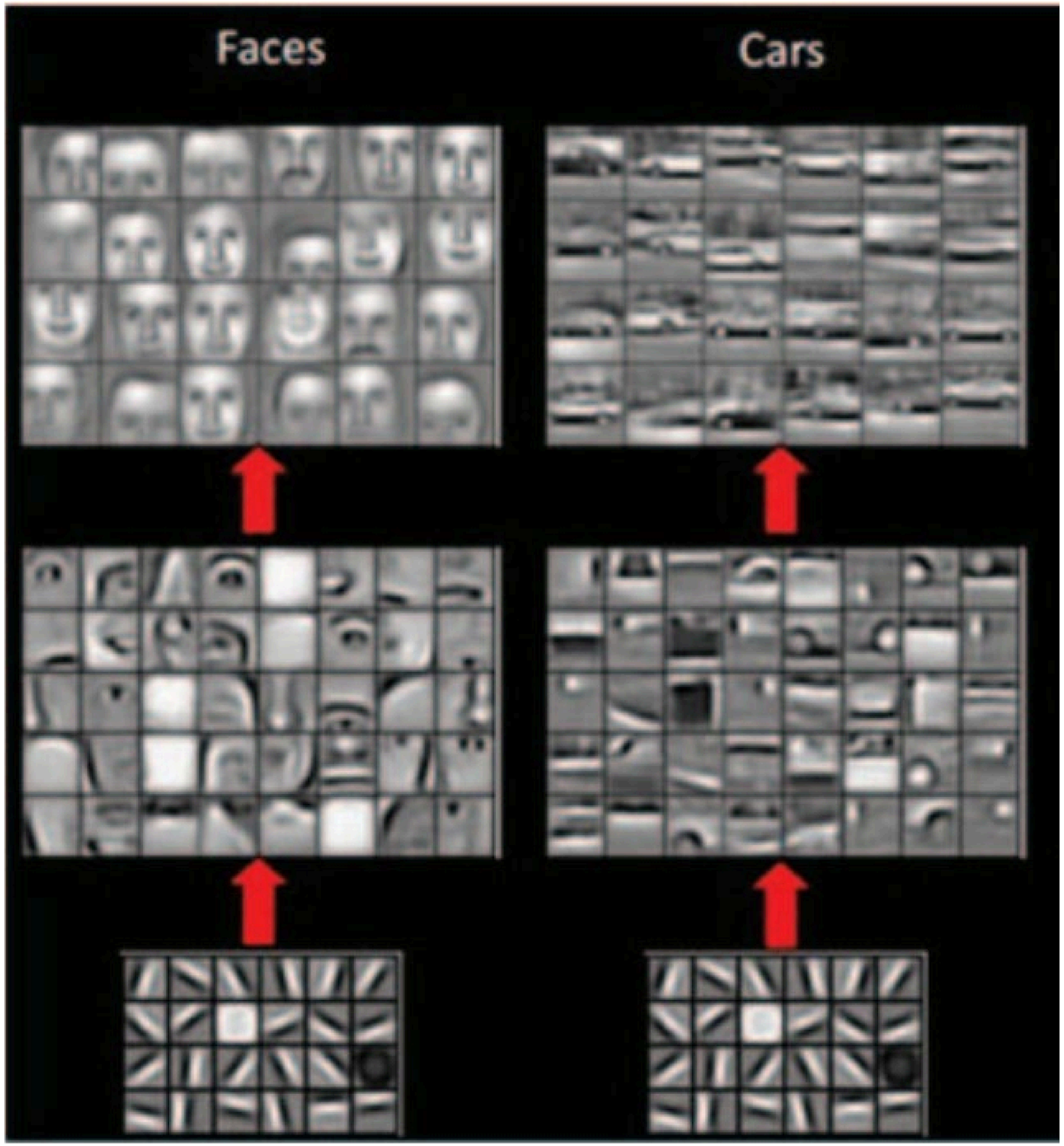
- Example: Dogs have longer snouts.
- How do you determine what is a long snout?

Feature Learning

Later layers recognize complete objects

Middle layers recognize parts of objects

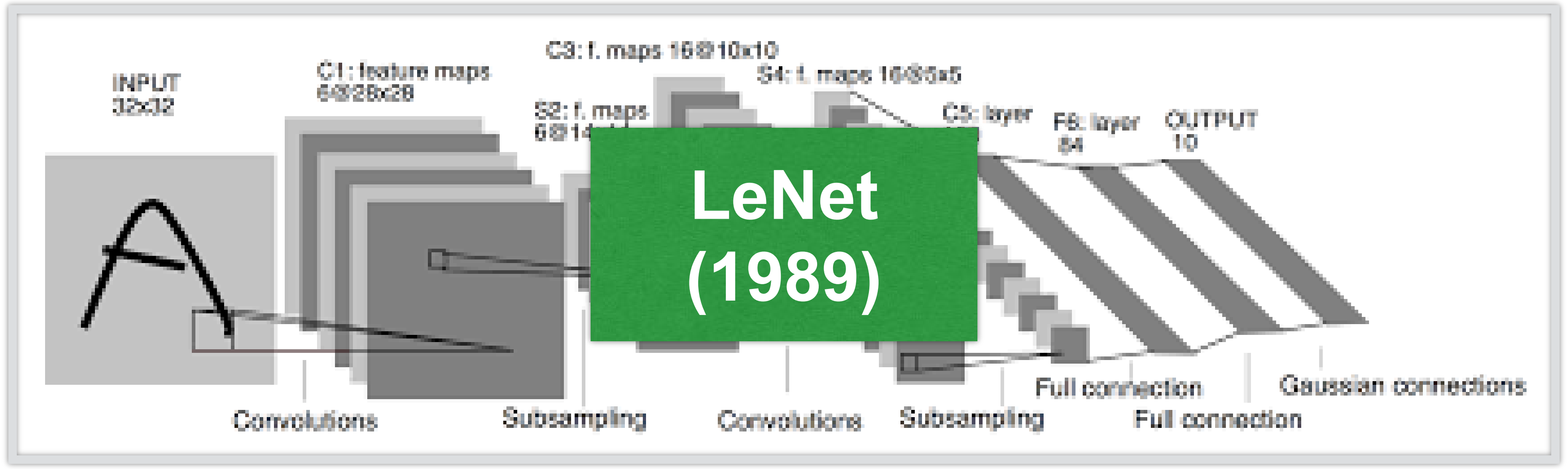
Early layers recognize simple patterns

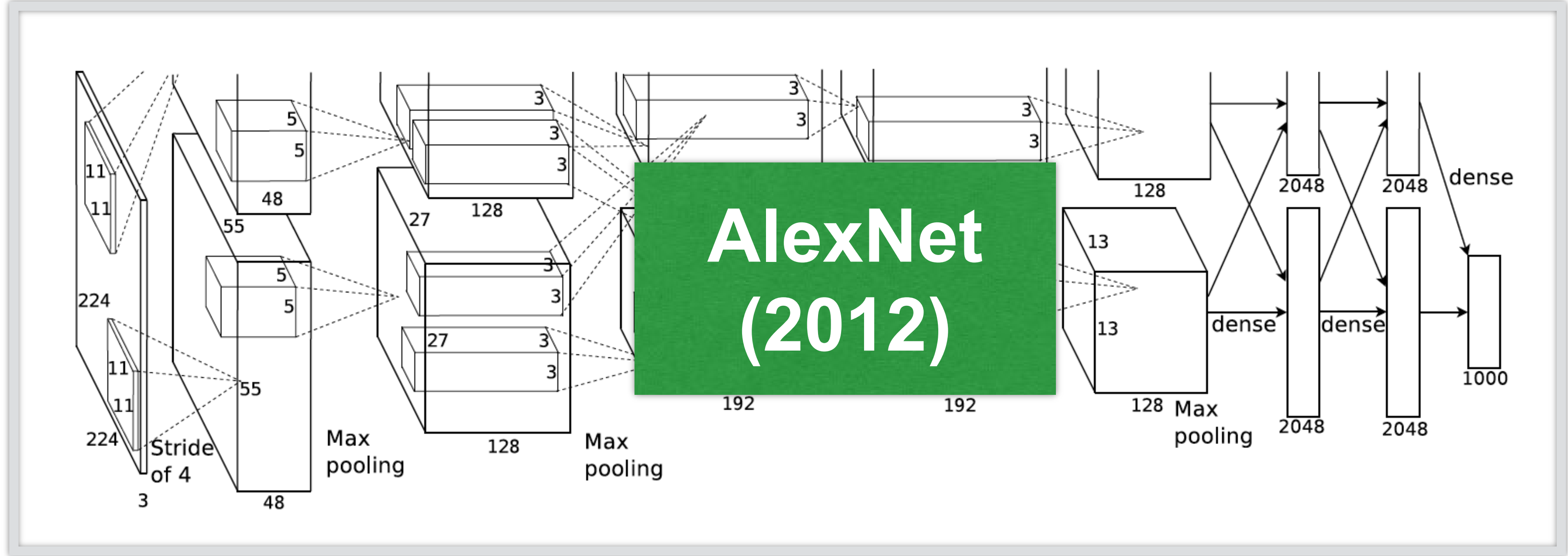


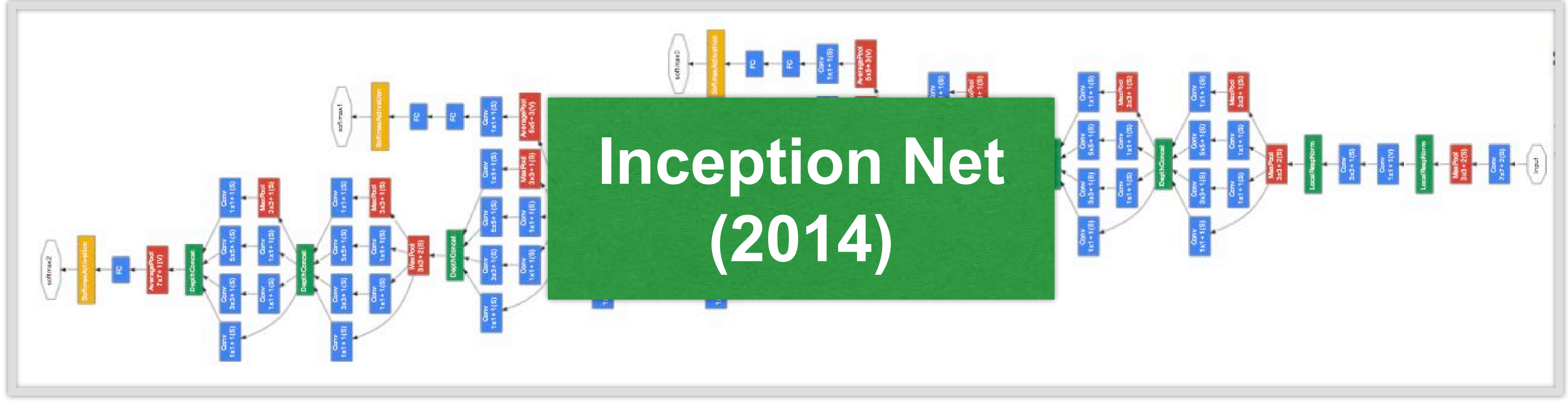
Adaptive Neuron Apoptosis for Accelerating Deep Learning on Large Scale Systems. Seigel et al. 2016.

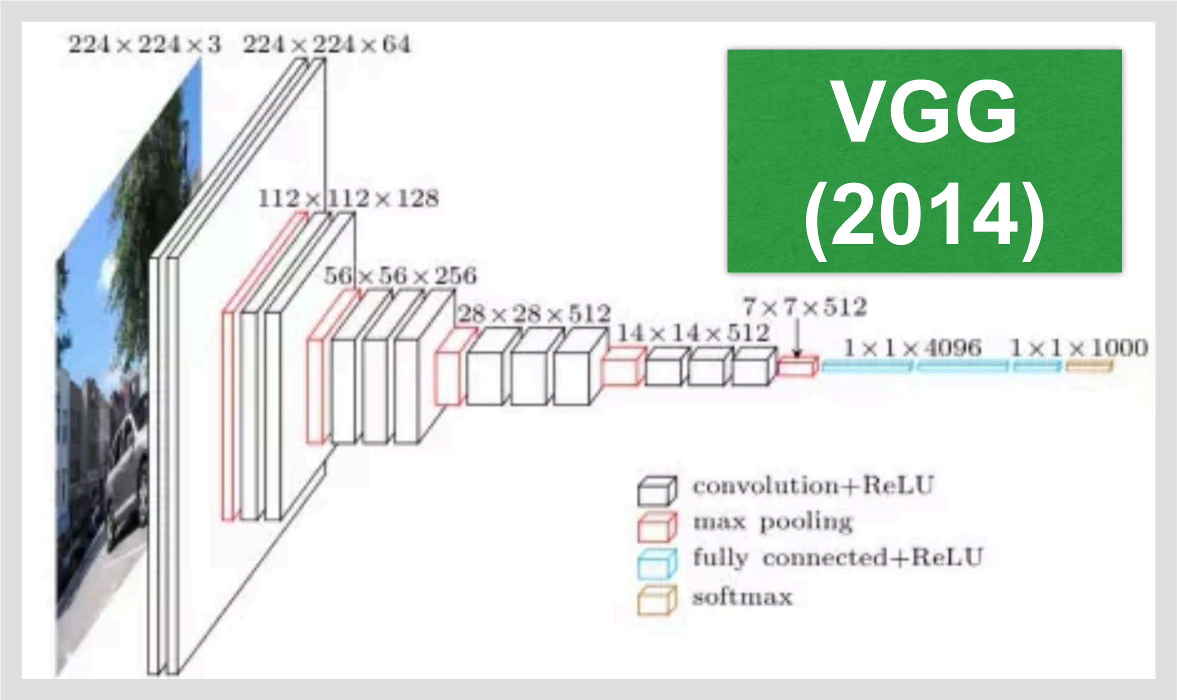
Convolutional Neural Networks Examples

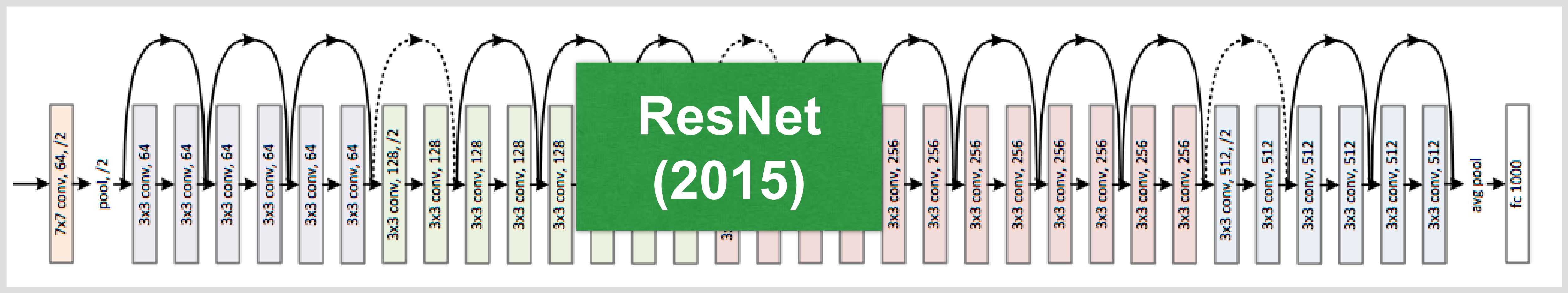
Evolution of neural net architectures

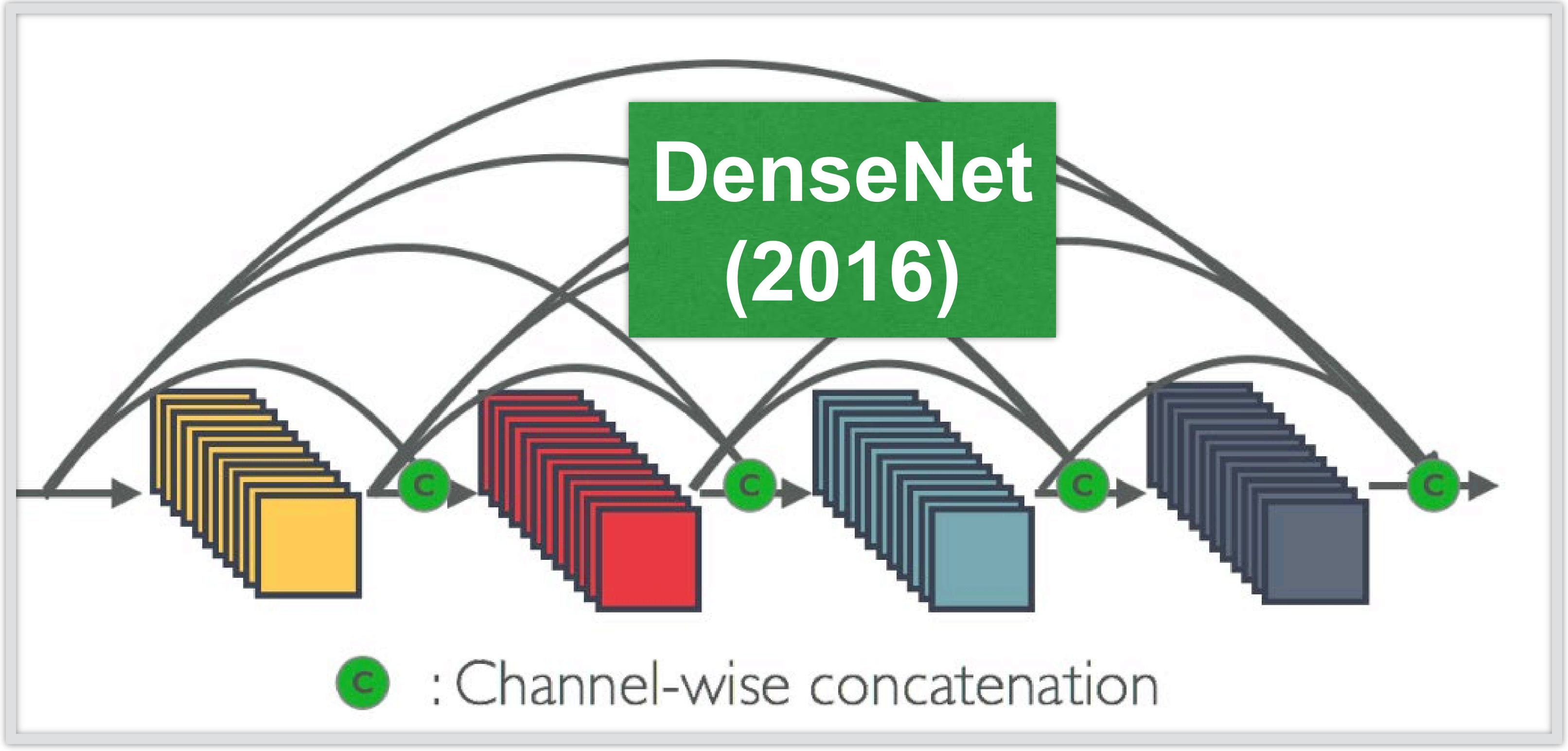








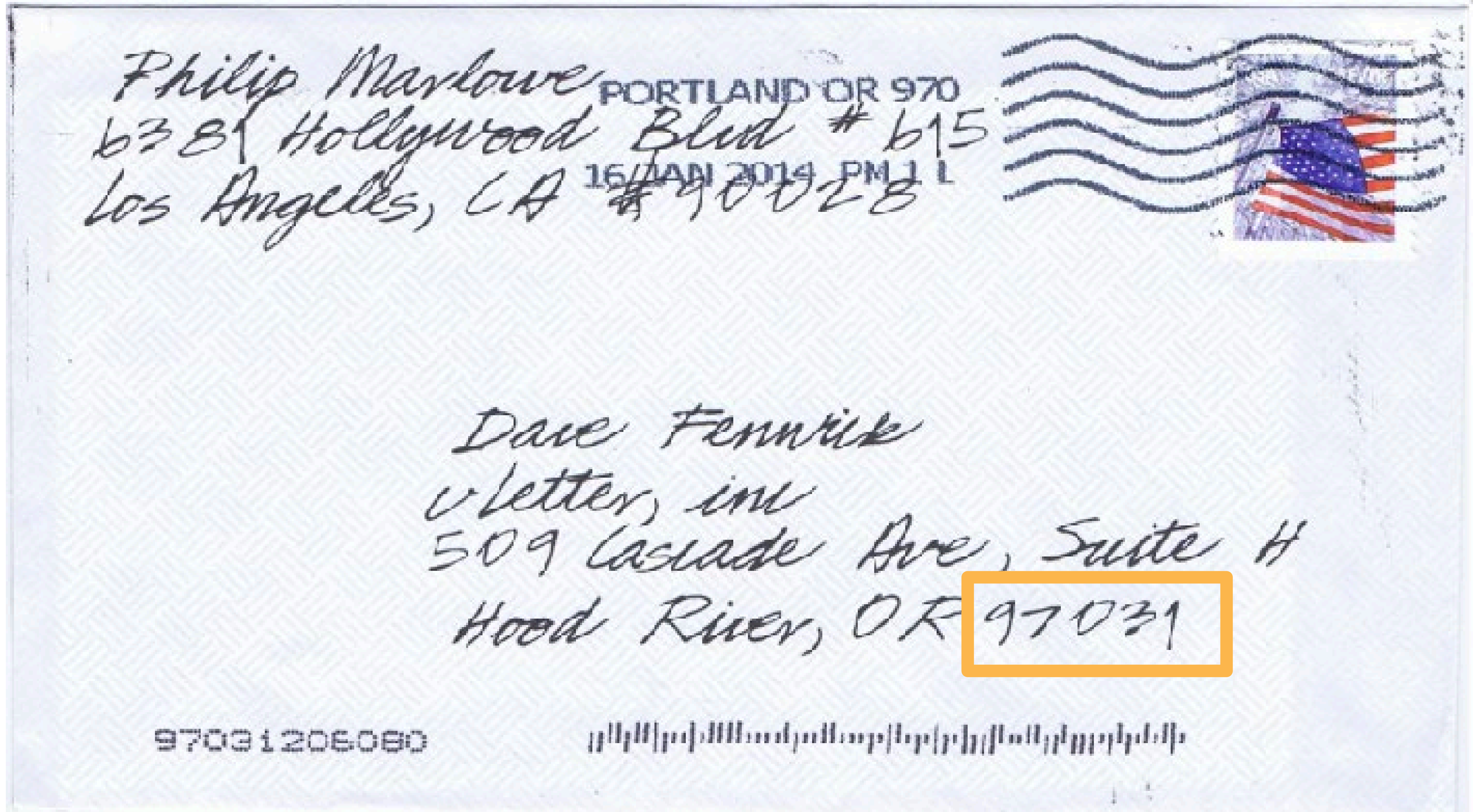


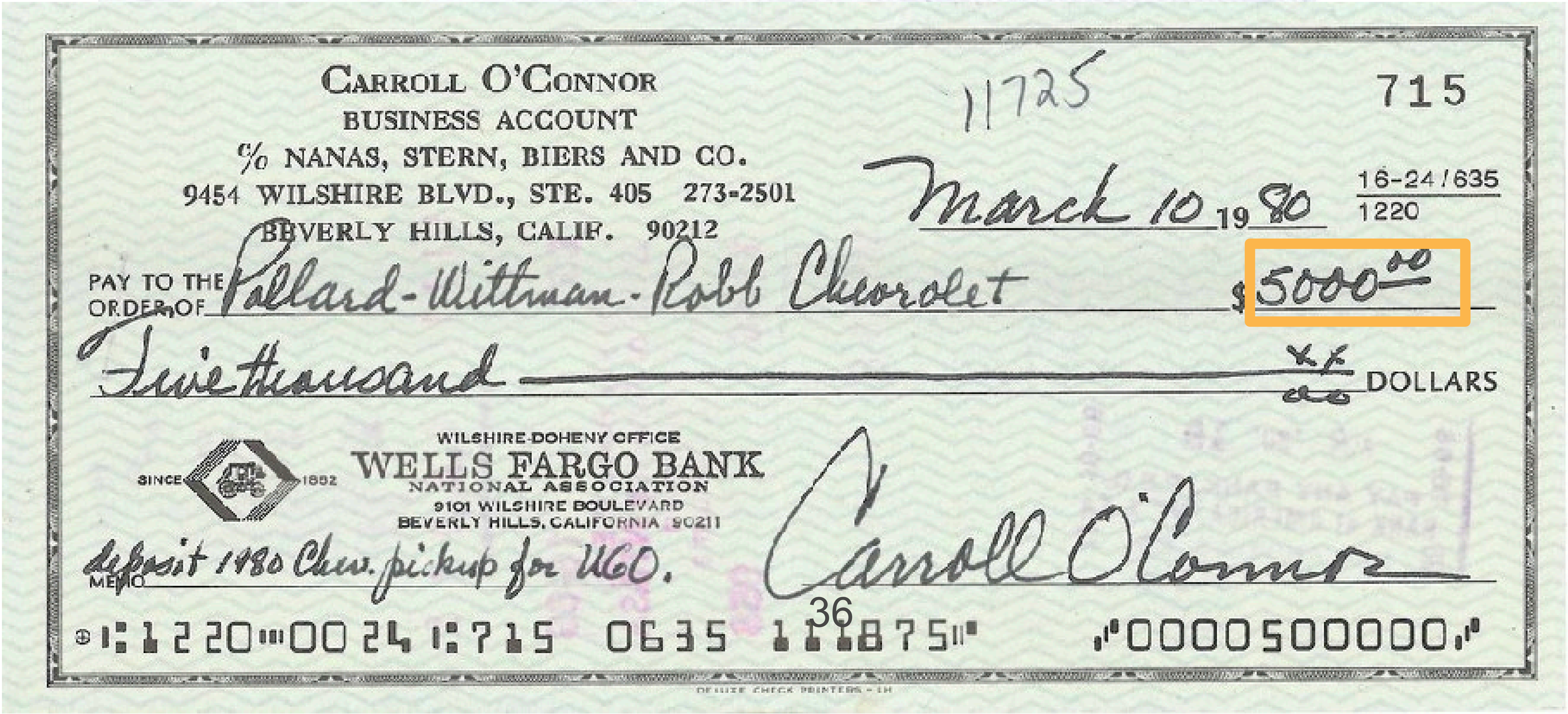


LeNet Architecture
(first convolutional neural net; 1989)

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

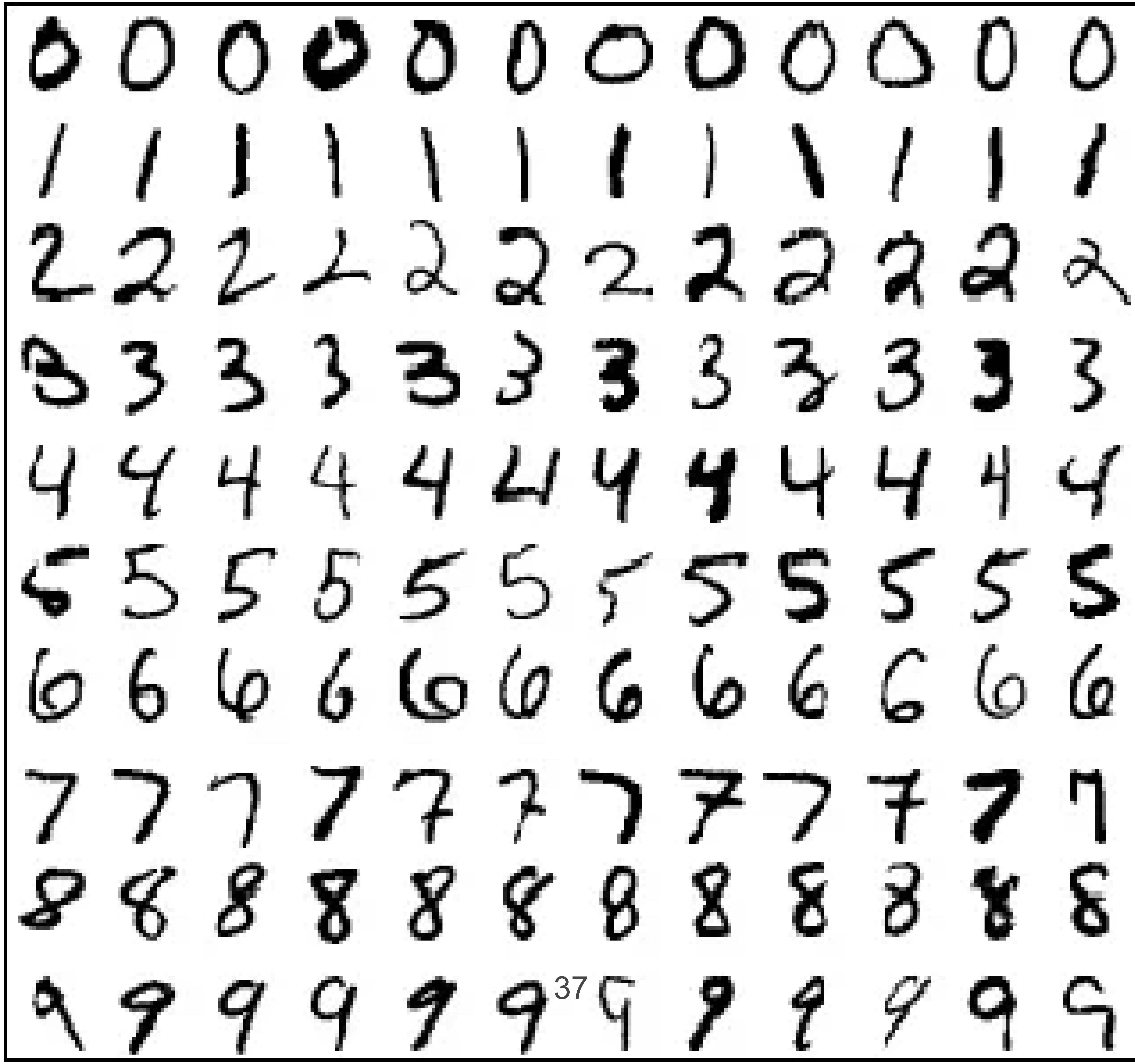
Handwritten Digit Recognition

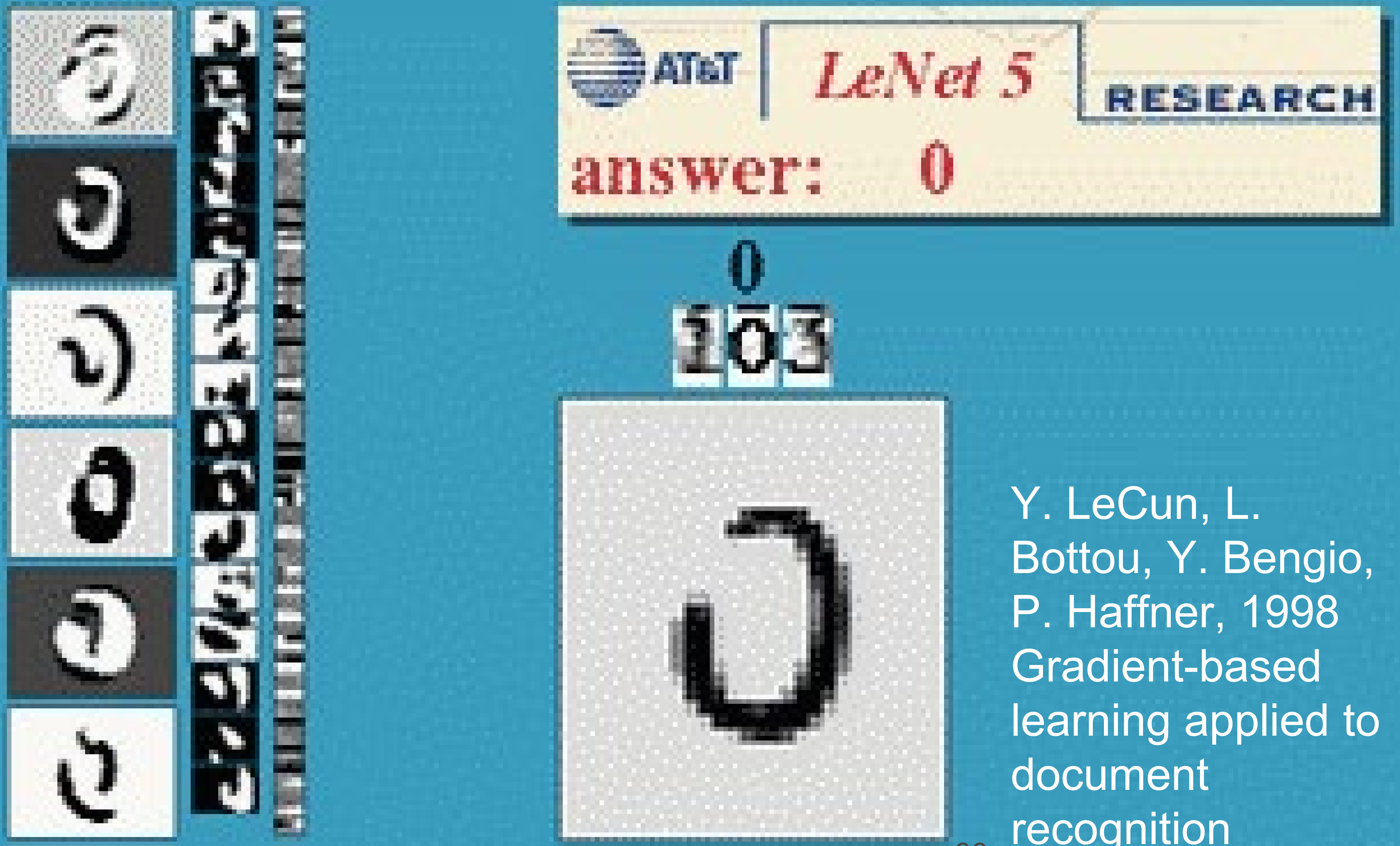




MNIST

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





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

LeNet Architecture

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

LeNet in Pytorch

```python
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)
```

https://github.com/bollakarthikeya/LeNet-5-PyTorch/blob/master/lenet5_gpu.py

LeNet in Pytorch

```
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
```

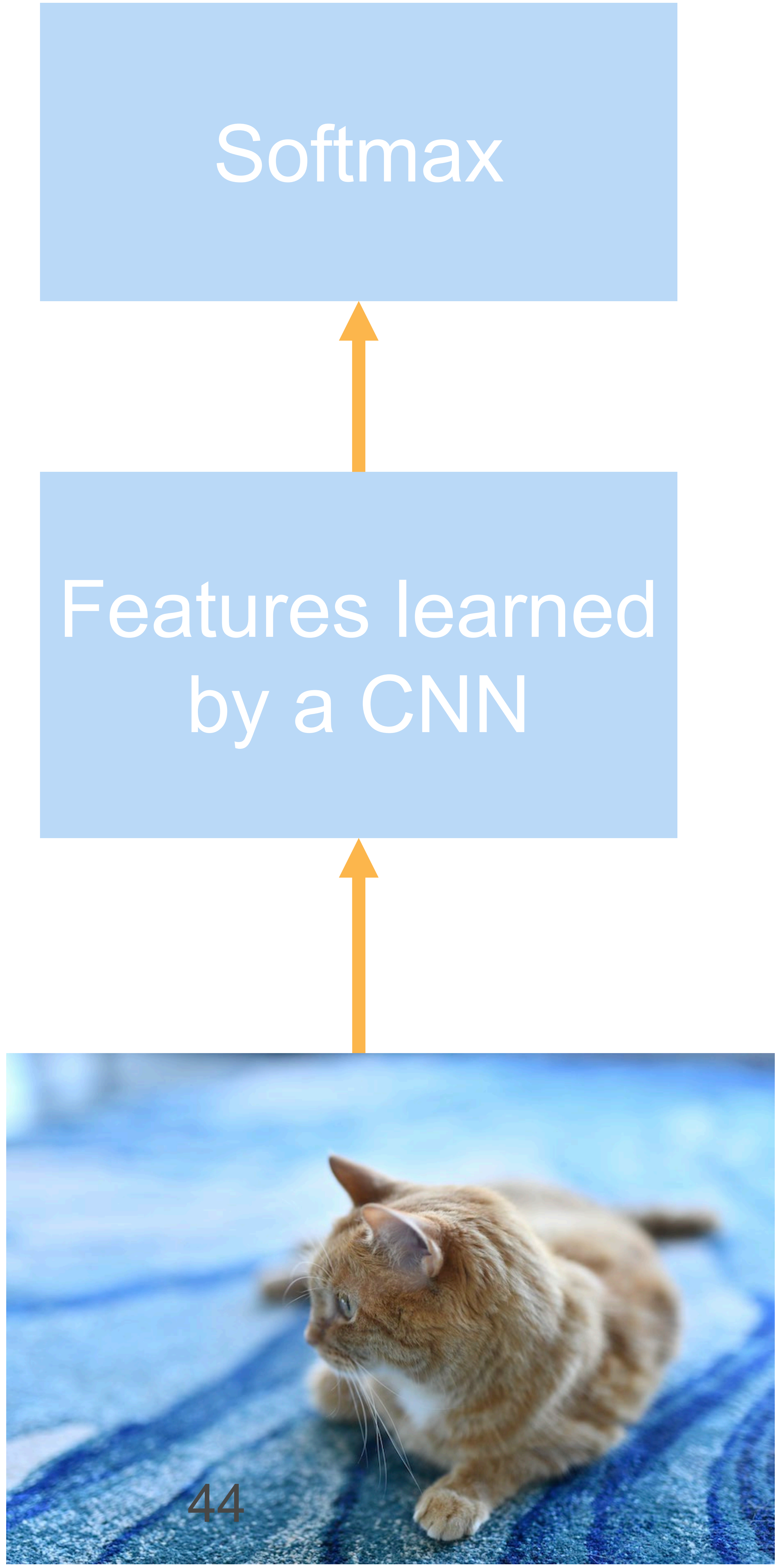
AlexNet

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems.*

Deng et al. 2009

AlexNet

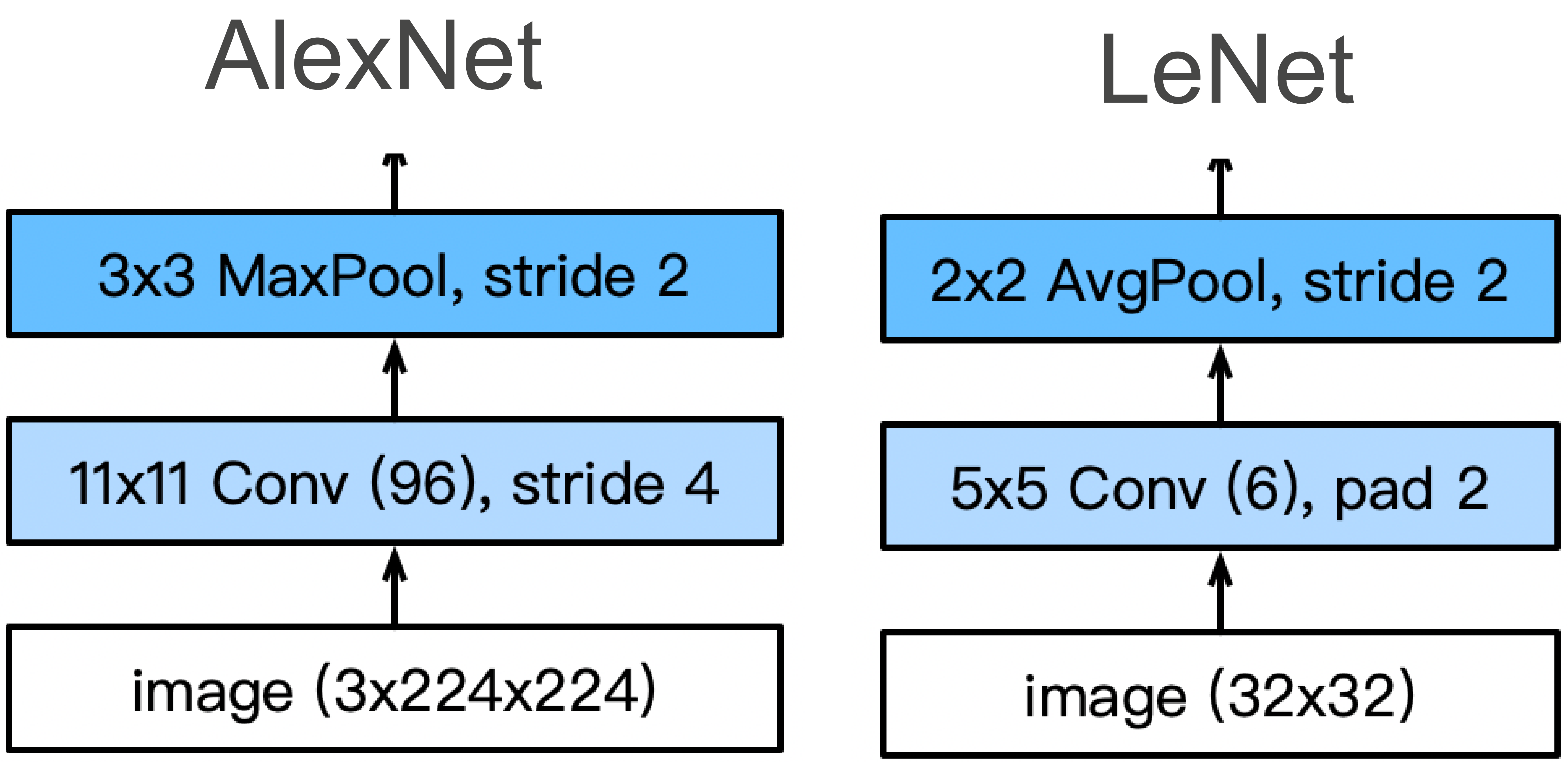
- AlexNet won ImageNet competition in 2012
- Deeper and bigger LeNet
- Paradigm shift for computer vision



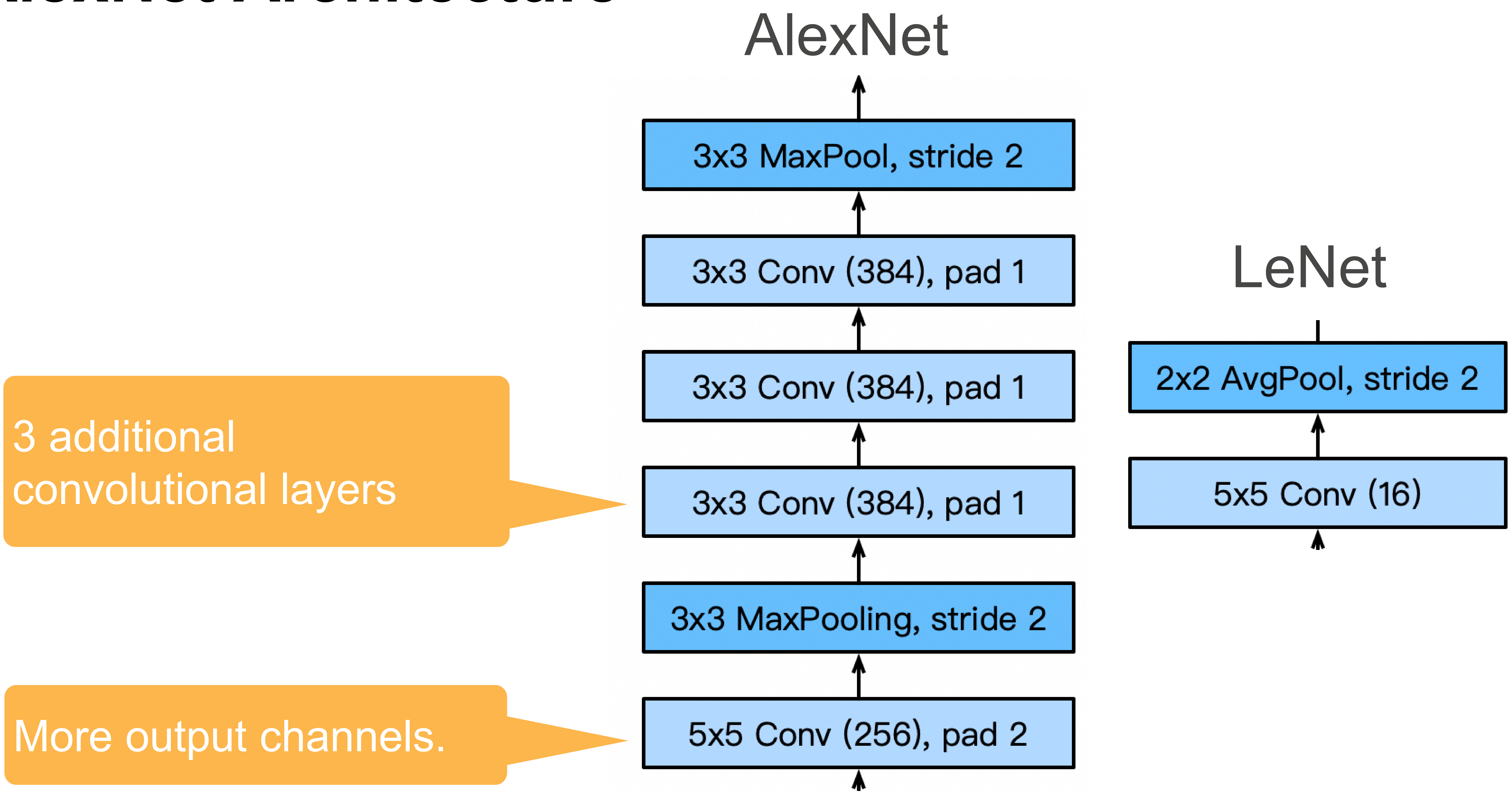
AlexNet Architecture

Larger pool size

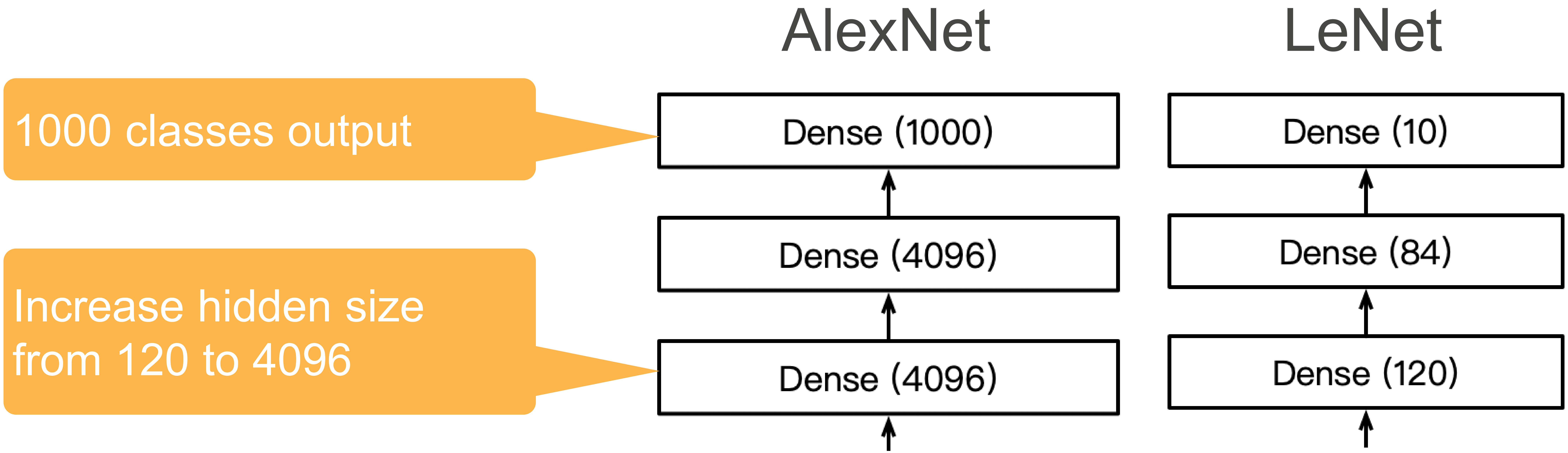
Larger kernel size, stride because of the increased image size, and more output channels.



AlexNet Architecture

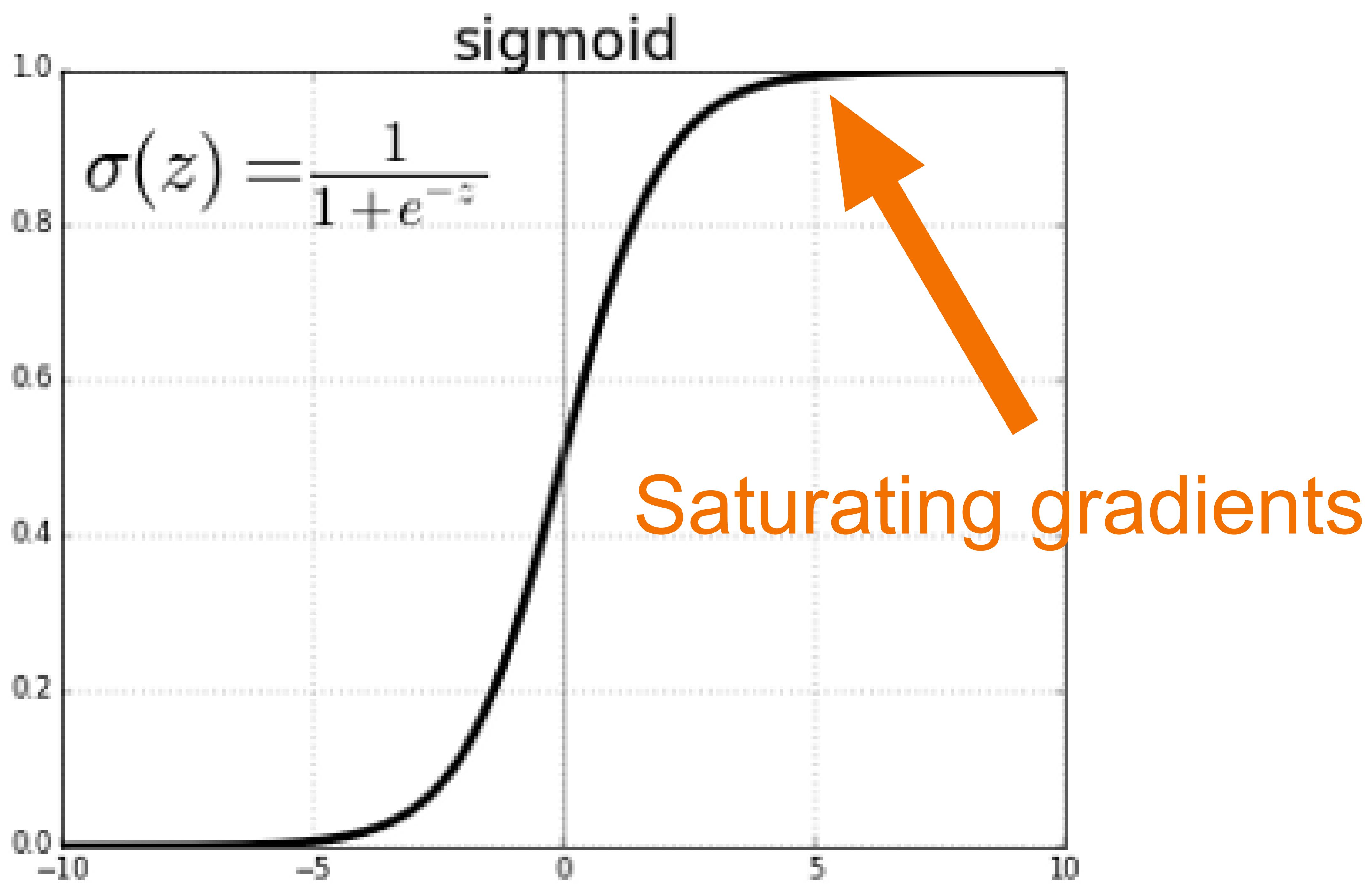


AlexNet Architecture



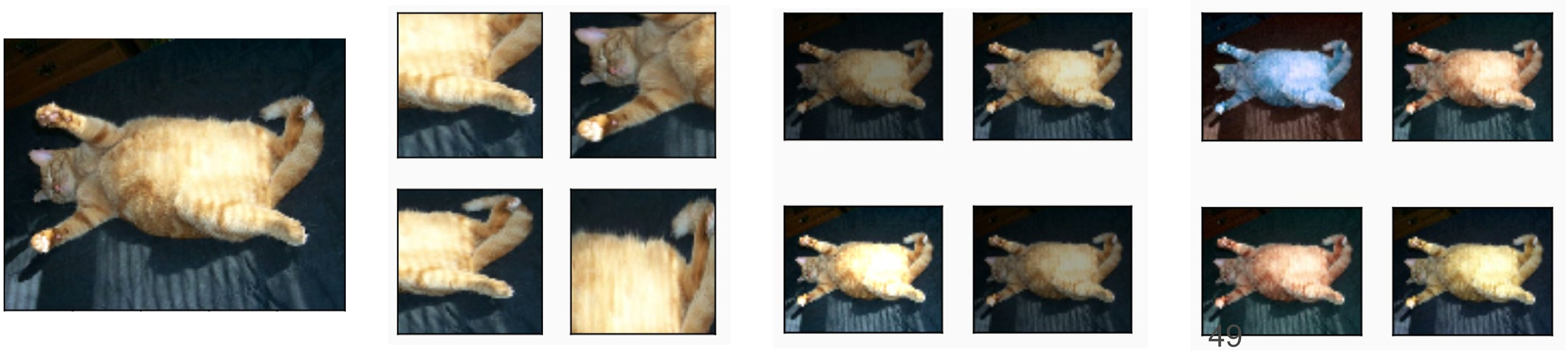
More Differences…

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



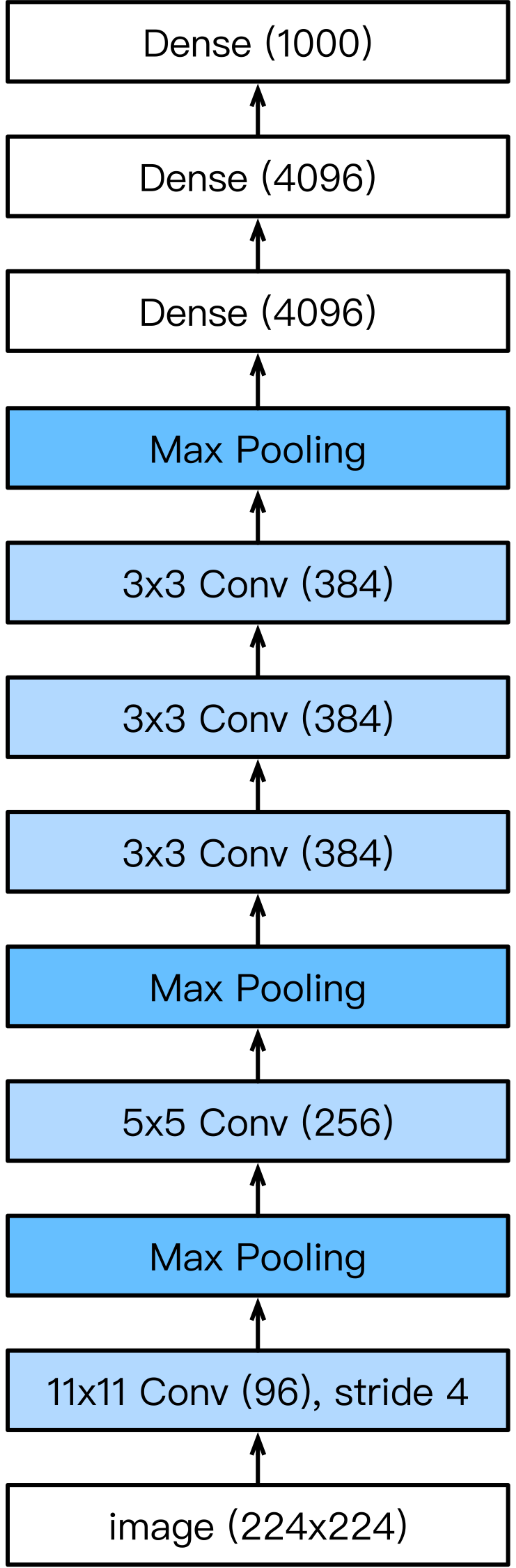
More Differences…

- 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



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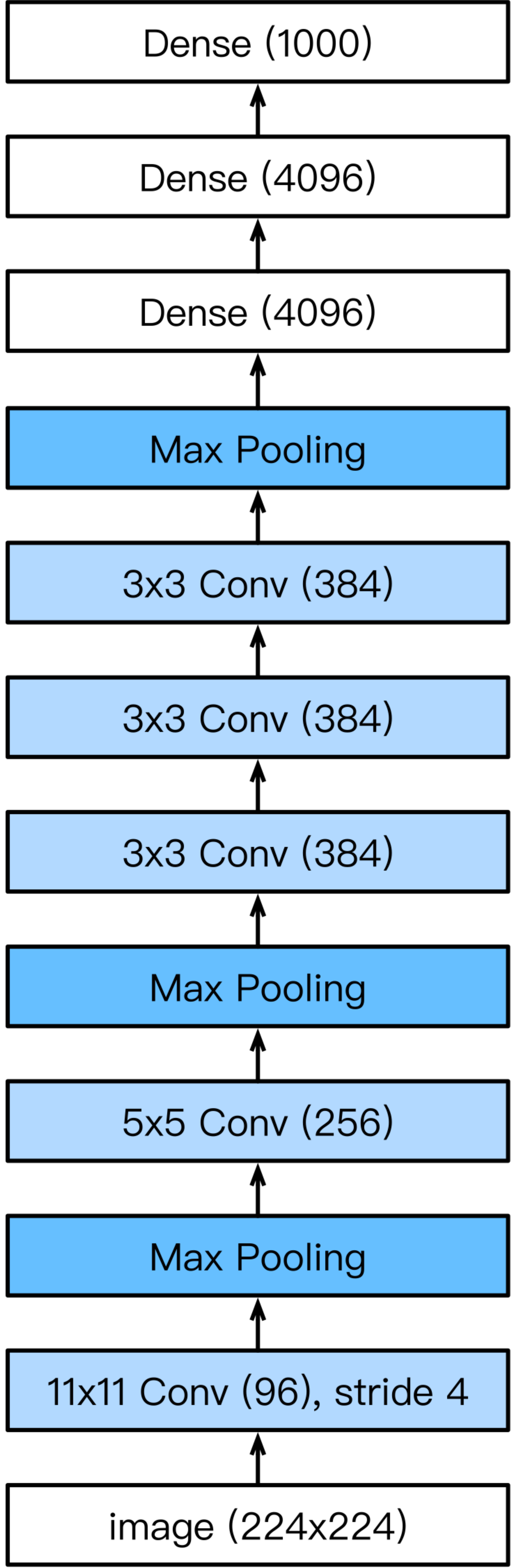
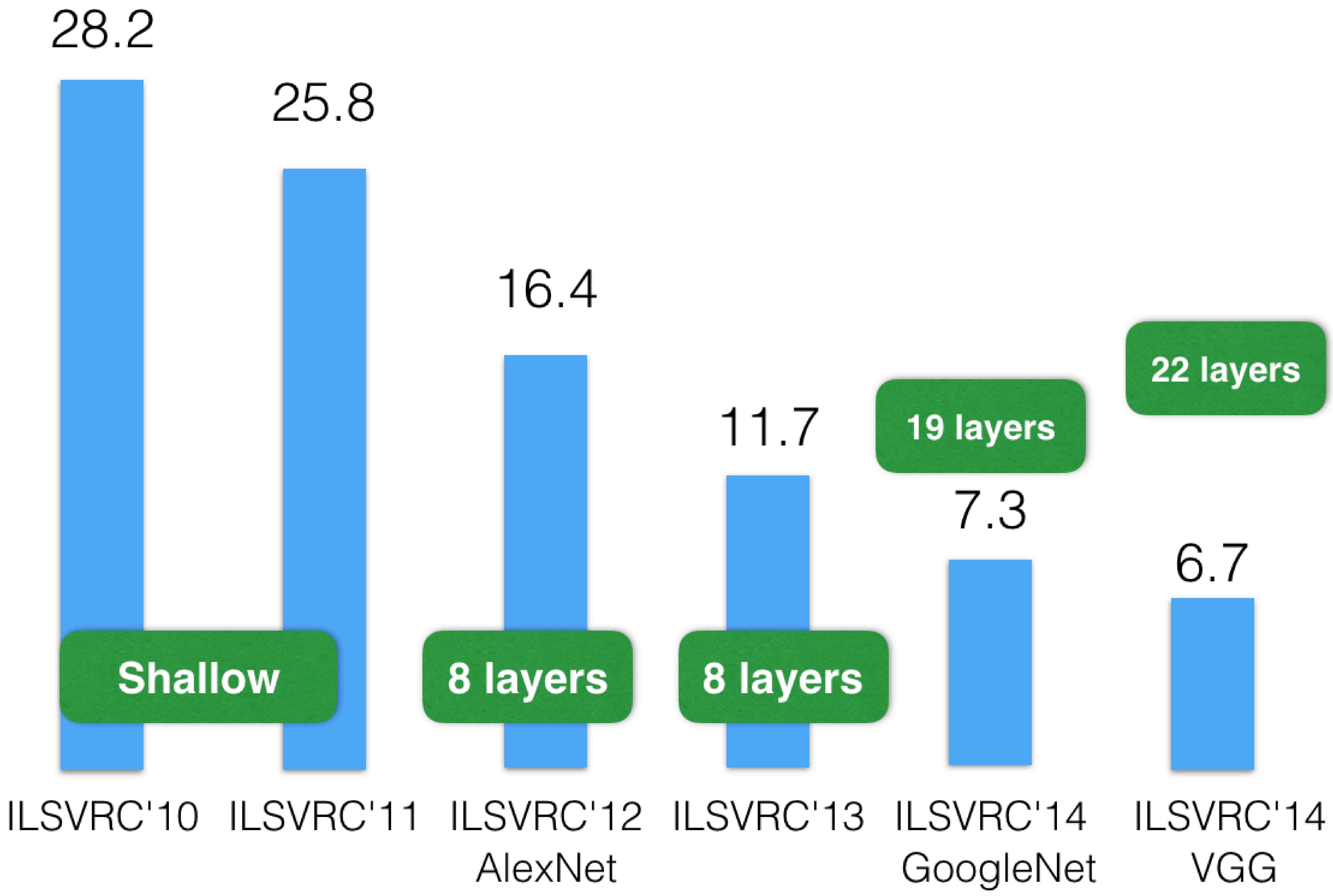
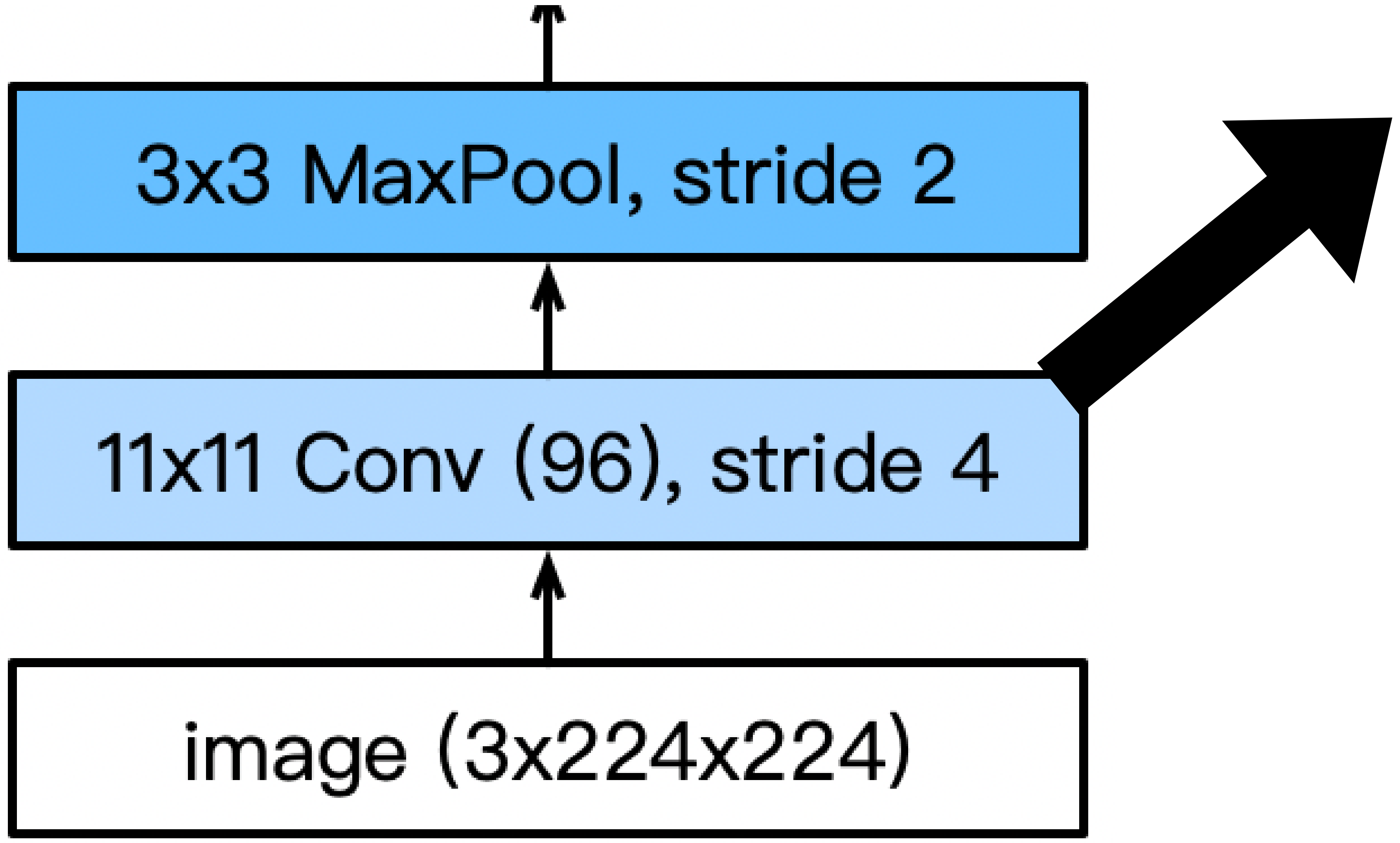
11x11x3x96=35k



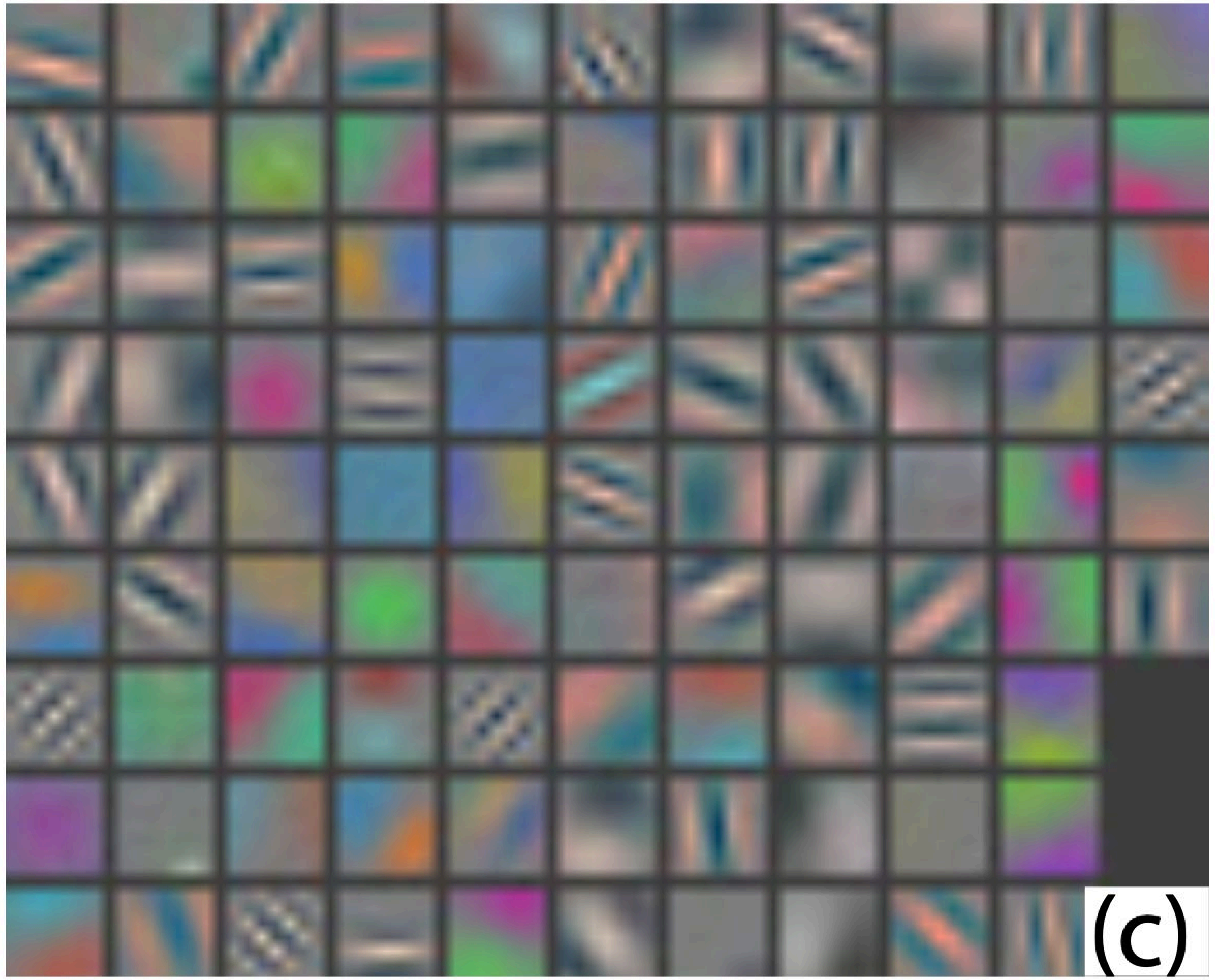


ImageNet Top-5 Classification Error (%)

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.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems* (pp. 1097–1105).

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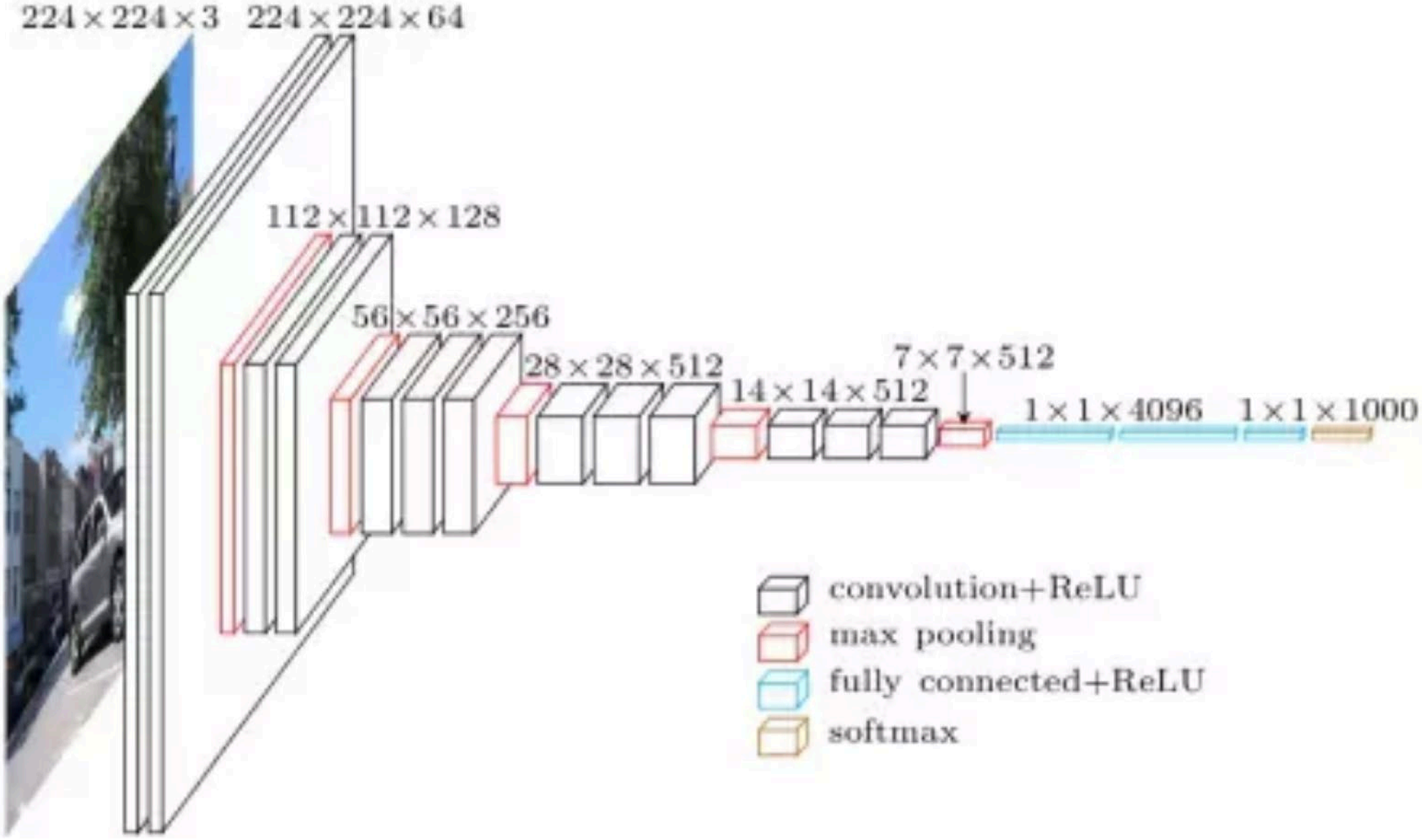
All options are true!

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.d2l.ai/berkeley-stat-157/index.html