CS540 Introduction to Artificial Intelligence

Deep Learning II: Convolutional Neural Networks

University of Wisconsin-Madison

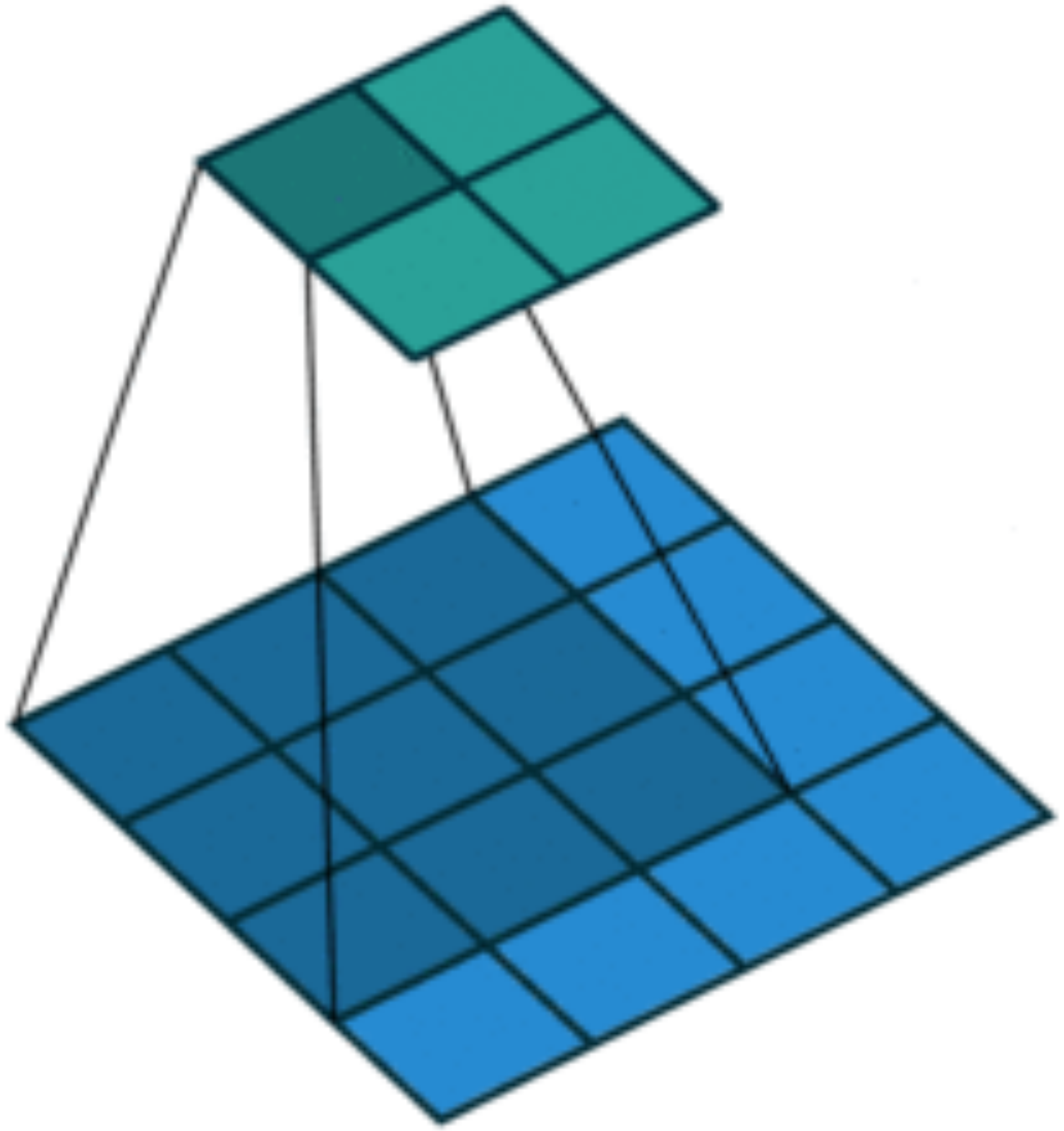
Outline

- Brief review of convolutional computations
- Convolutional Neural Networks
    - LeNet (first conv nets)
    - AlexNet
    - ResNet

Review: 2-D Convolution

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

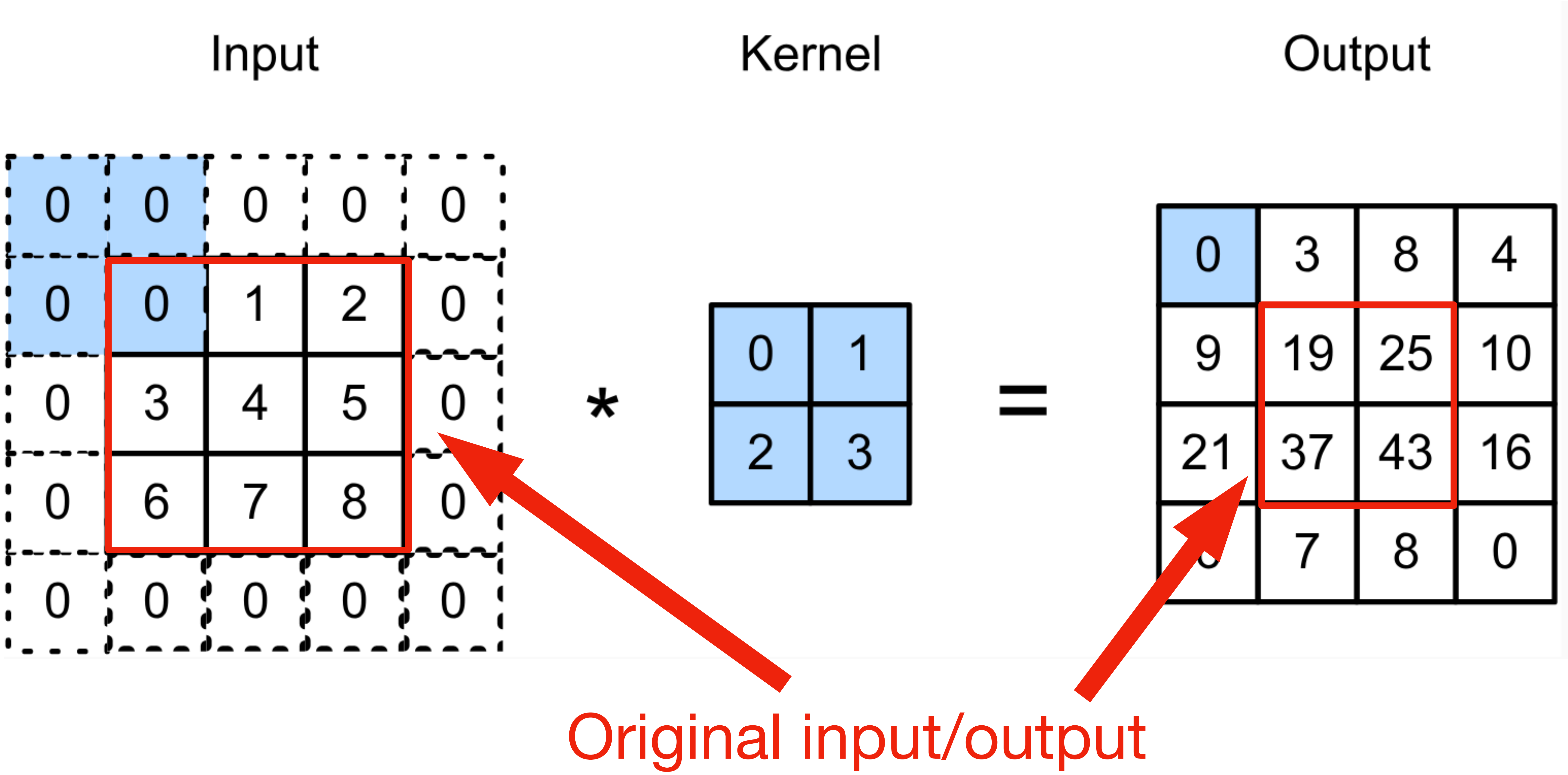
$$0\times0 + 1\times1 + 3\times2 + 4\times3 = 19,$$
$$1\times0 + 2\times1 + 4\times2 + 5\times3 = 25,$$
$$3\times0 + 4\times1 + 6\times2 + 7\times3 = 37,$$
$$4\times0 + 5\times1 + 7\times2 + 8\times3 = 43.$$



(vdumoulin@ Github)

Padding

Padding adds rows/columns around input

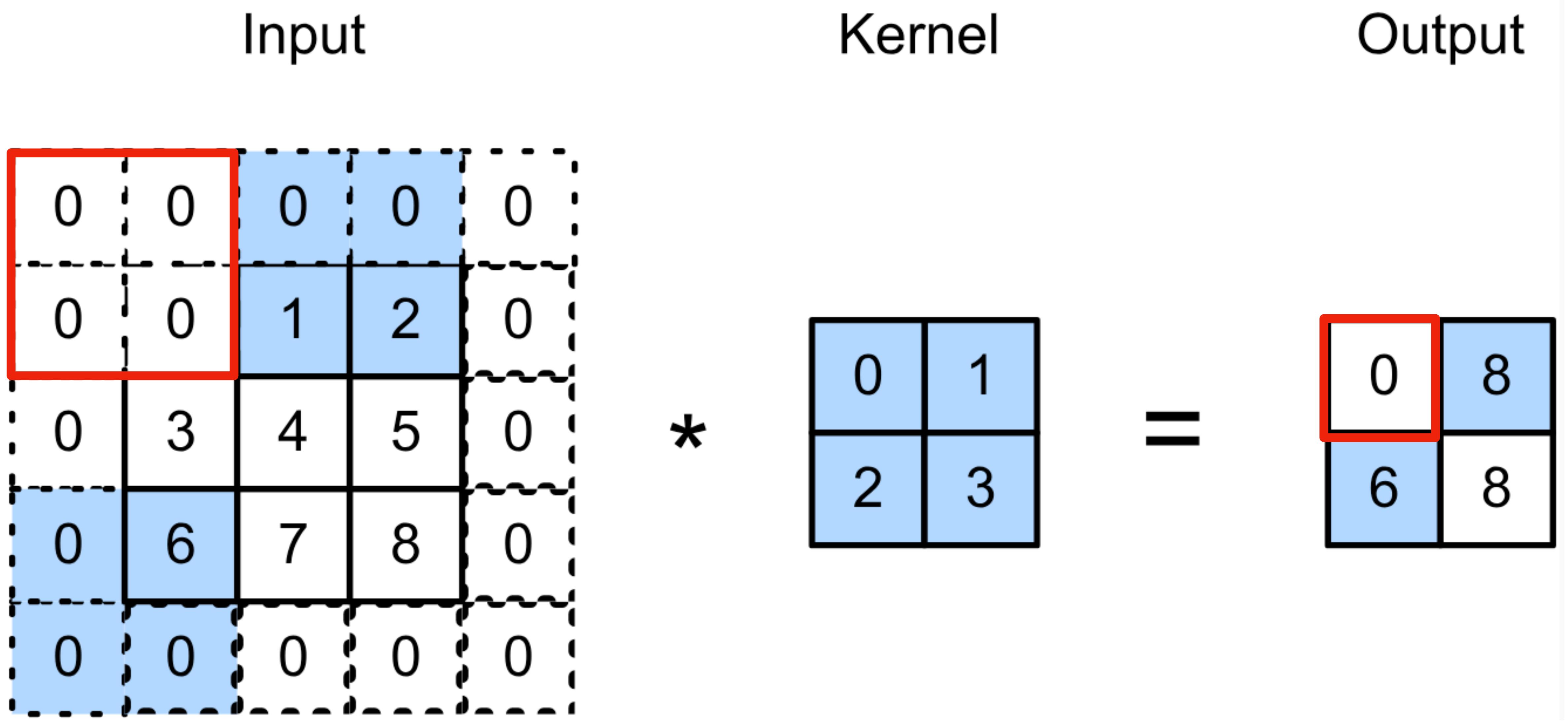


$$0{\times}0 + 0{\times}1 + 0{\times}2 + 0{\times}3 = 0$$

Stride

- Stride is the #rows/#columns per slide

Strides of 3 and 2 for height and width



$$0\times0 + 0\times1 + 1\times2 + 2\times3 = 8$$
$$0\times0 + 6\times1 + 0\times2 + 0\times3 = 6$$

Output shape

Kernel/filter size

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

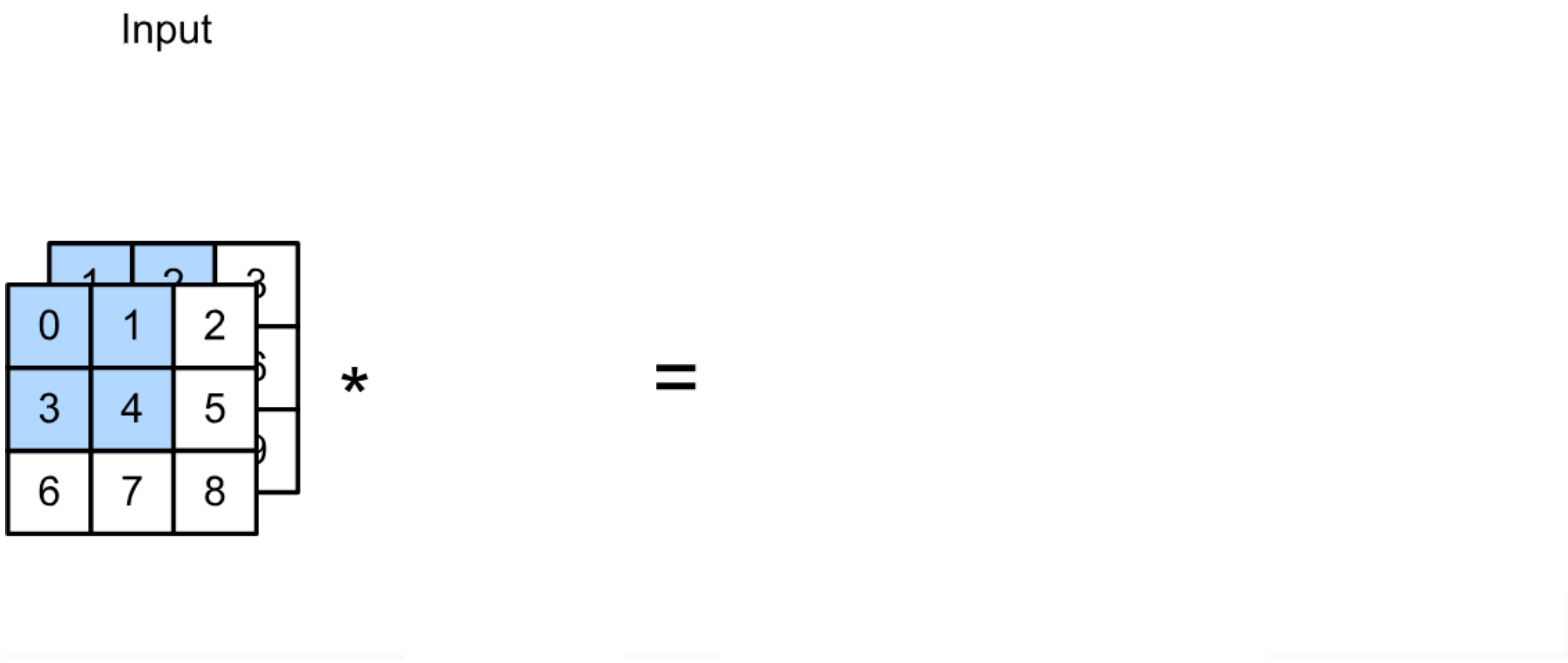
Input size

Pad

Stride

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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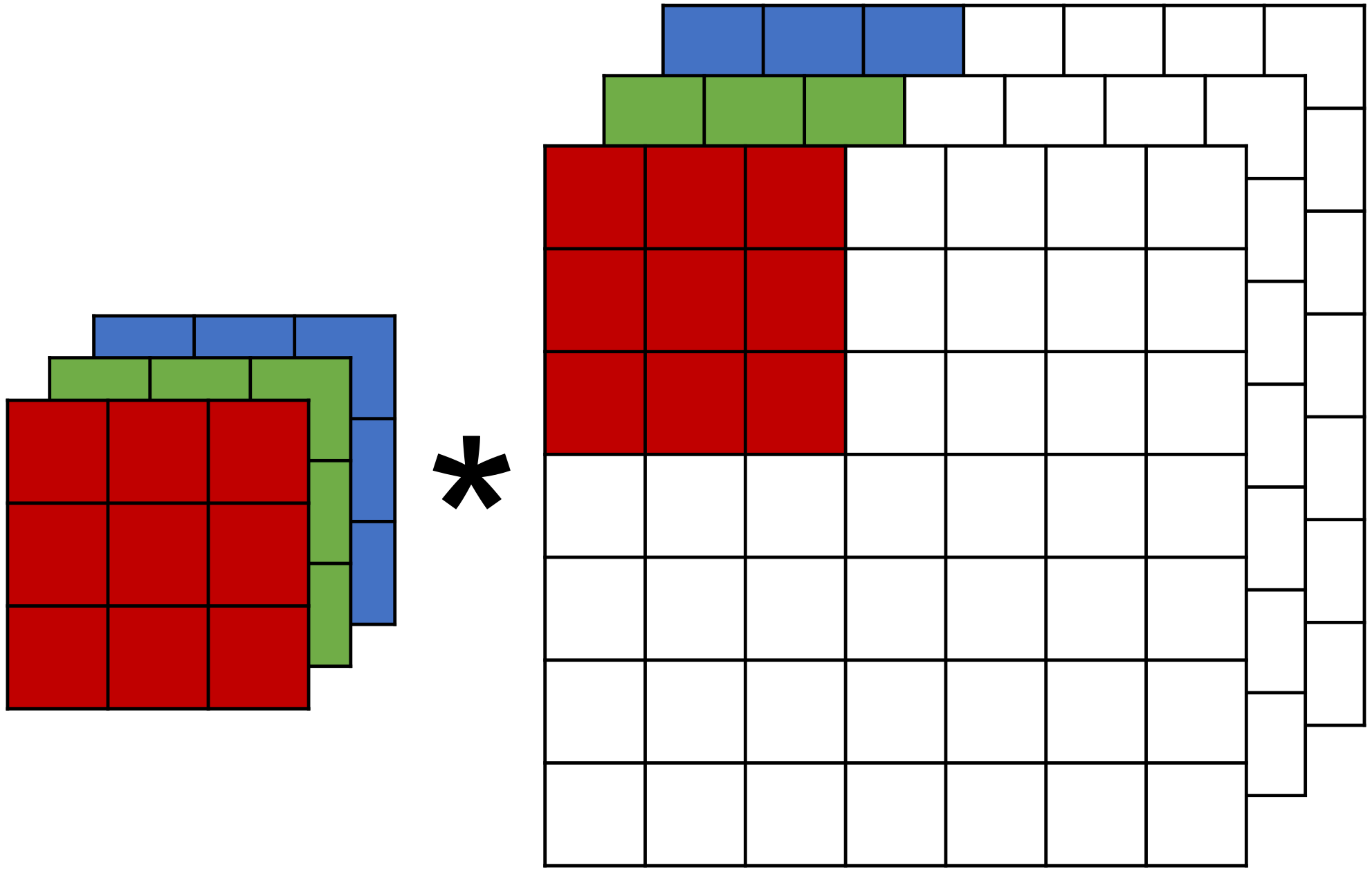

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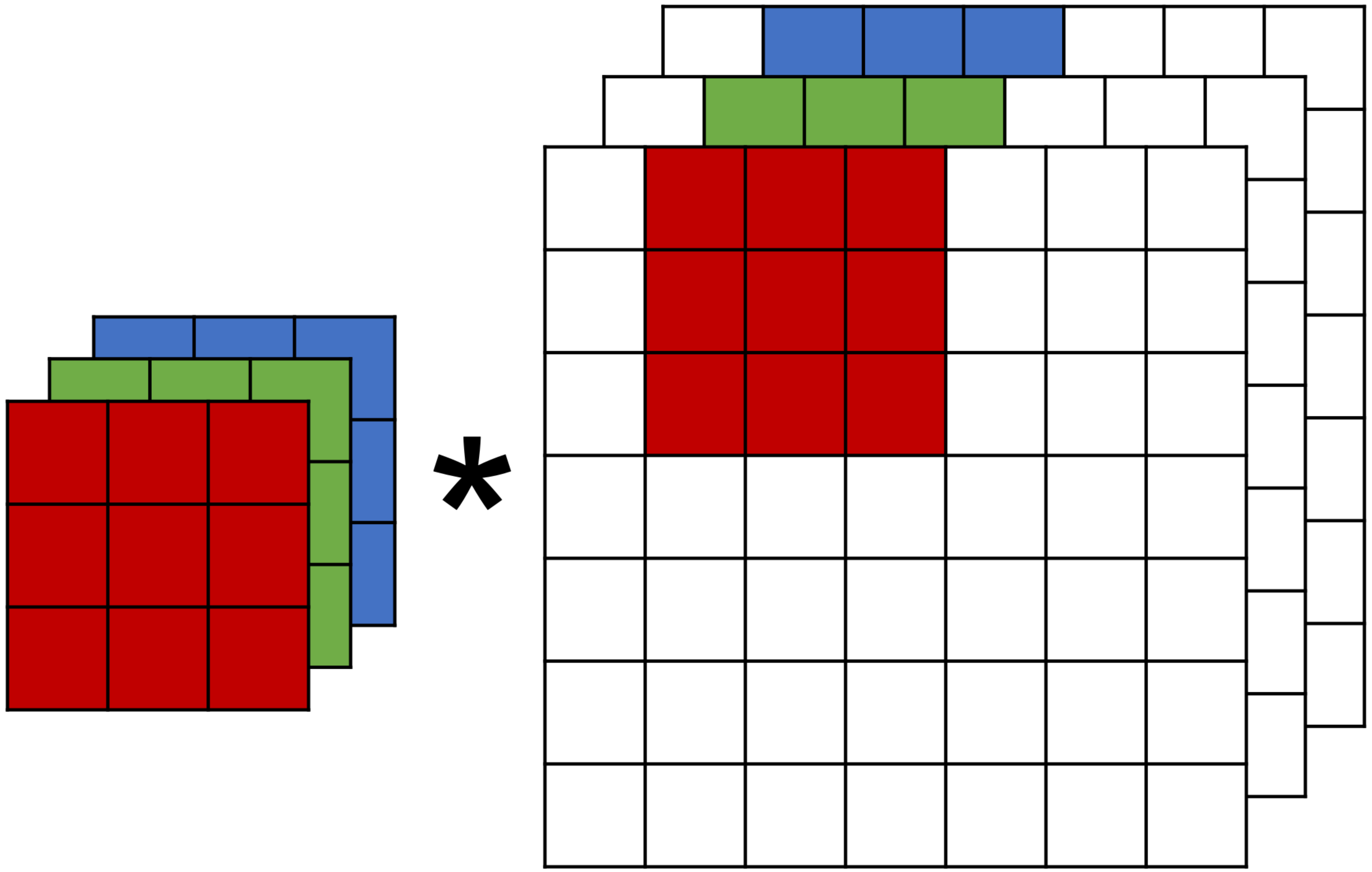

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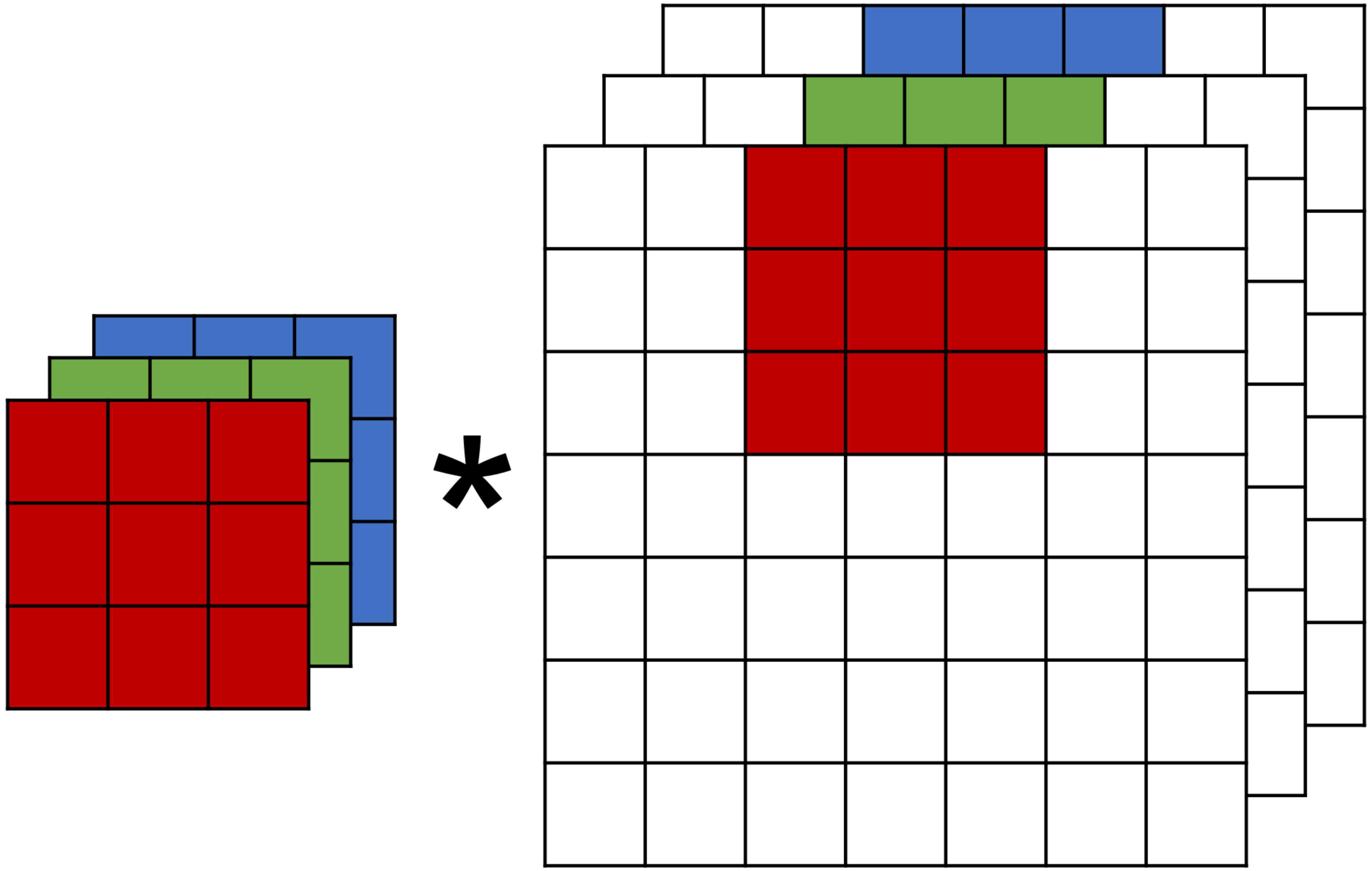
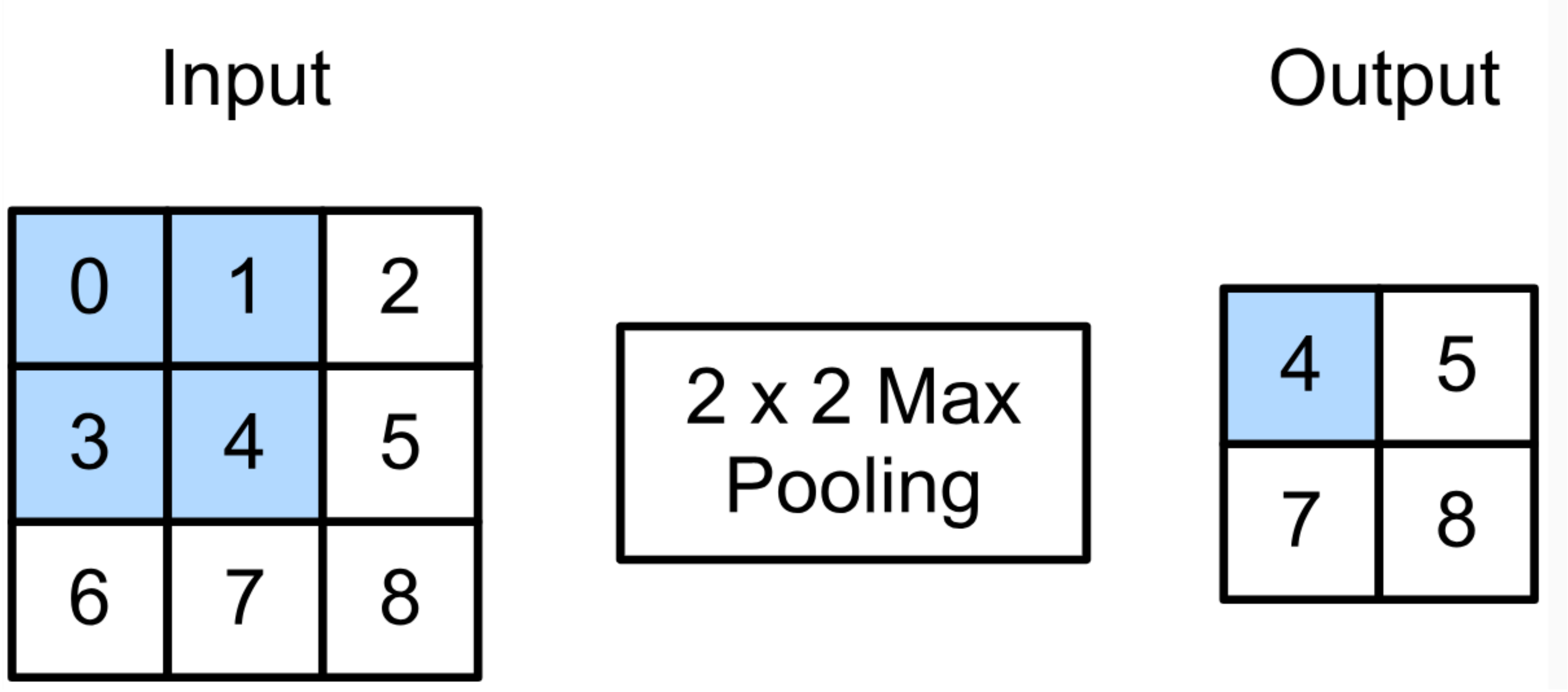
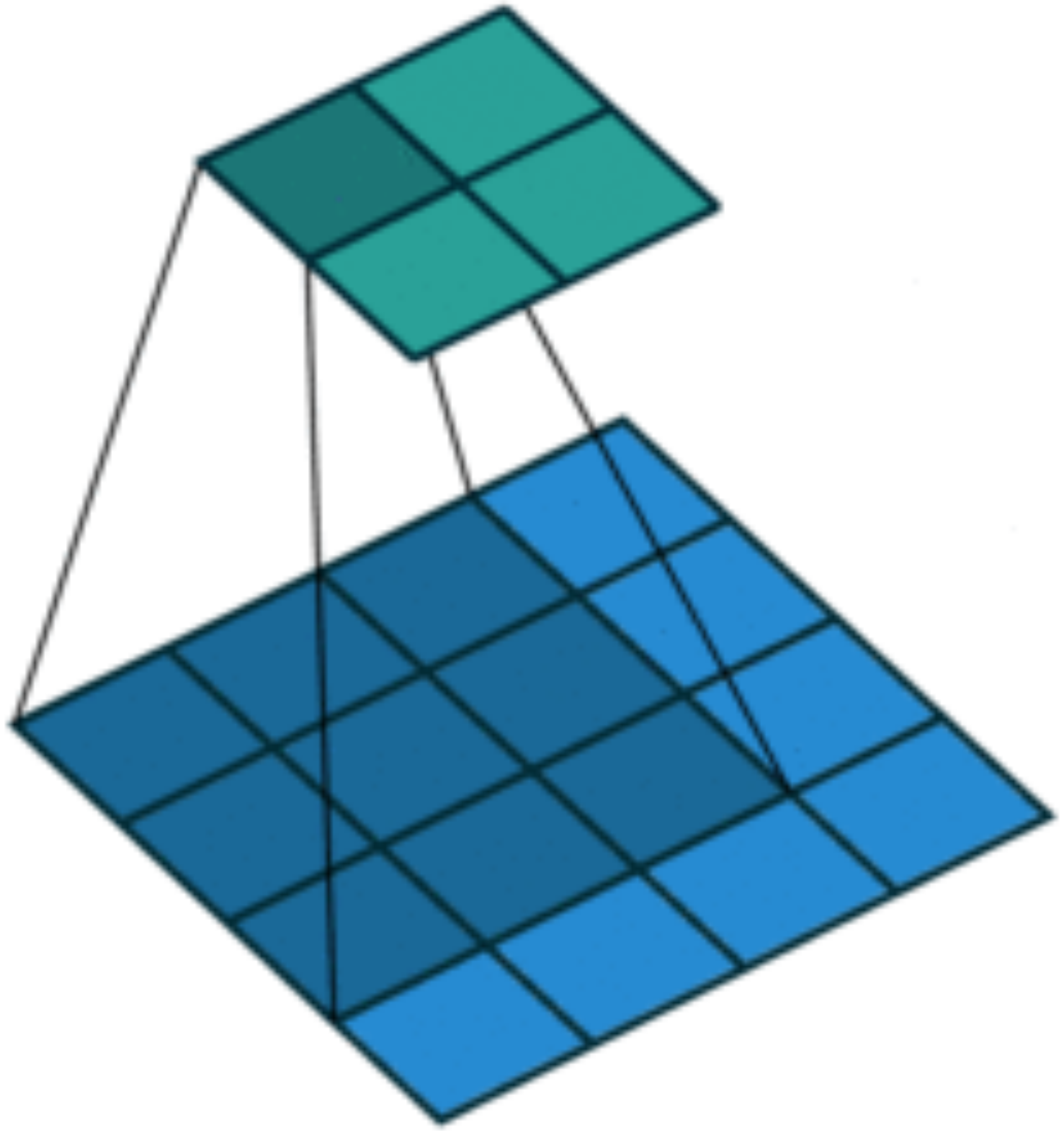


Review: 2-D Max Pooling

- Returns the maximal value in the sliding window



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



Q1: 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 (no padding), what is the output size?

A. 11x11x16
B. 6x6x16
C. 7x7x16
D. 5x5x16

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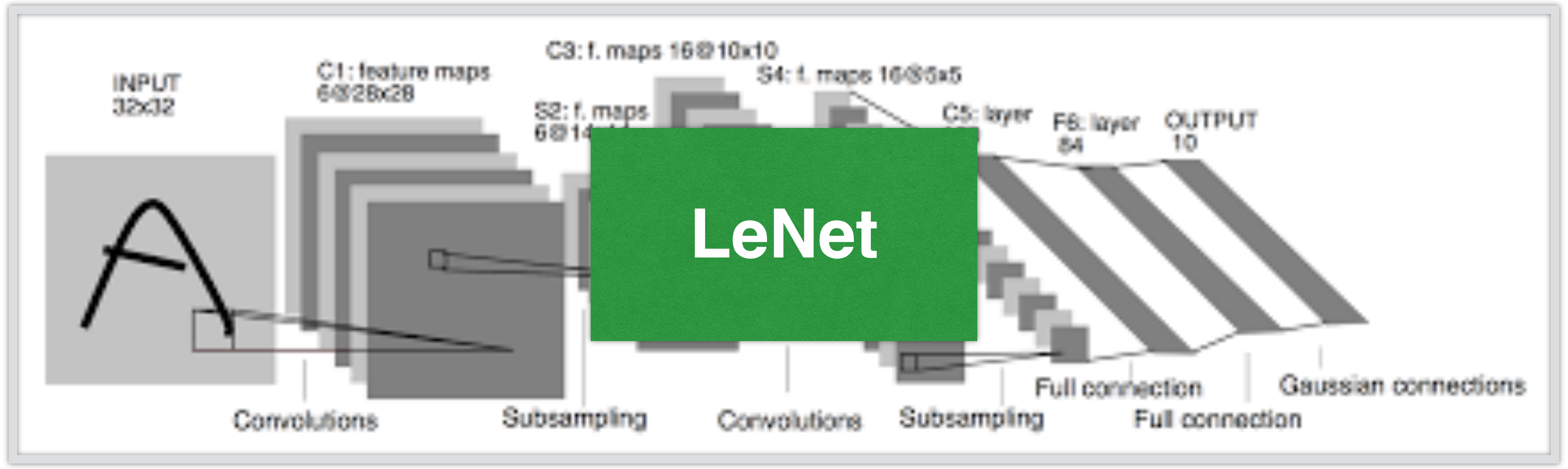
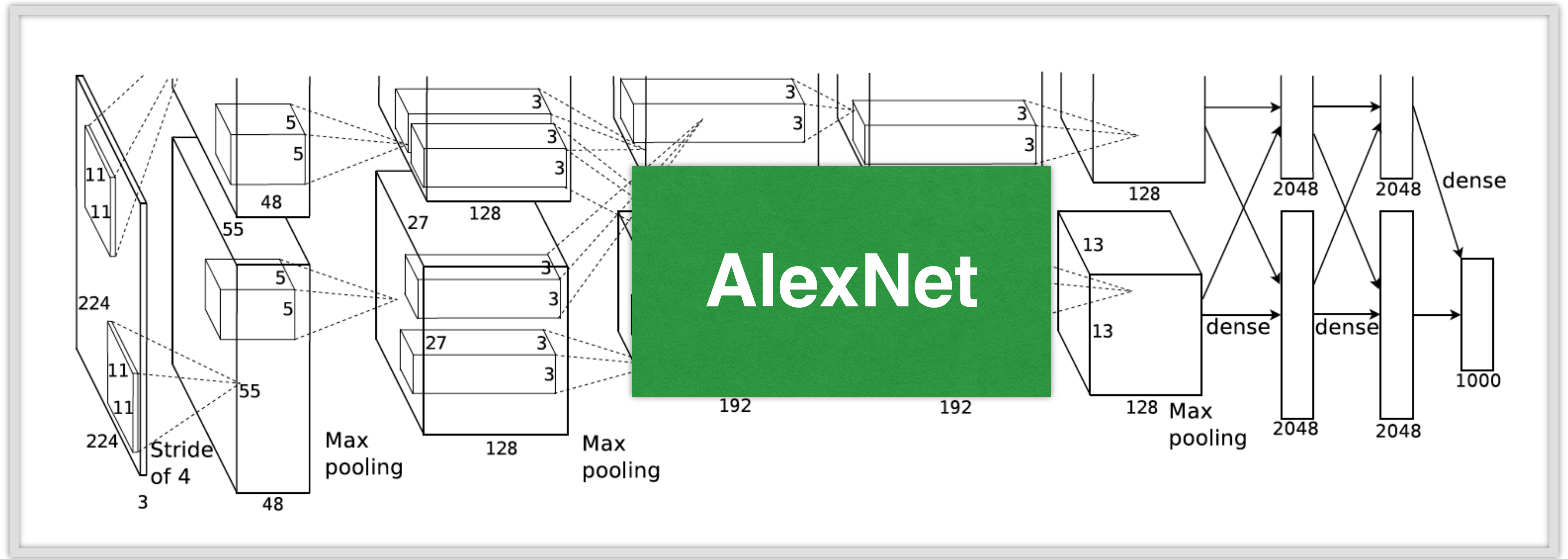
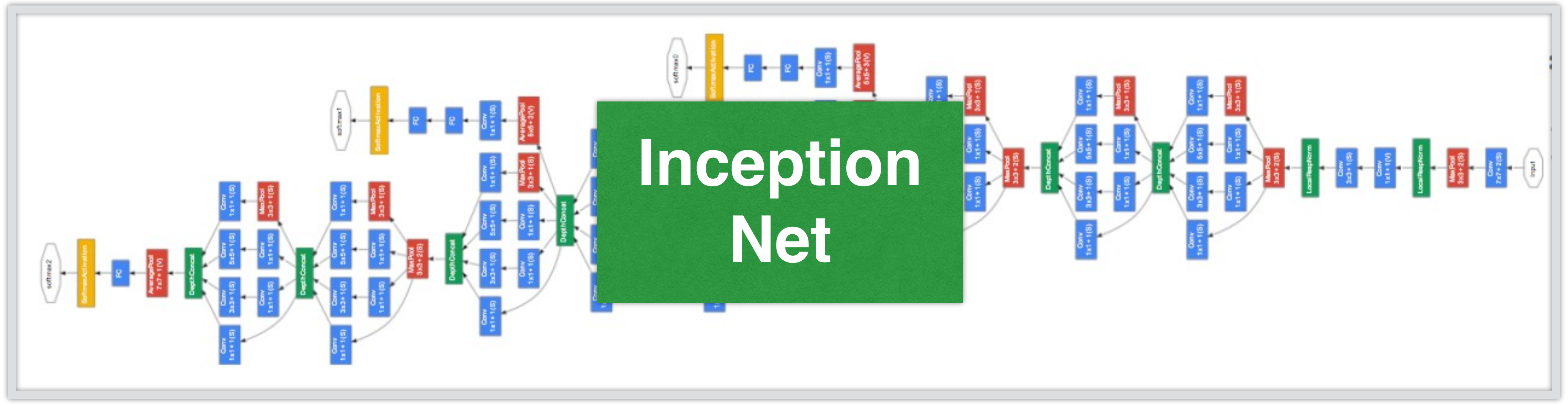
$$\lfloor (n_h - k_h + p_h + s_h)/s_h \rfloor \times \lfloor (n_w - k_w + p_w + s_w)/s_w \rfloor$$

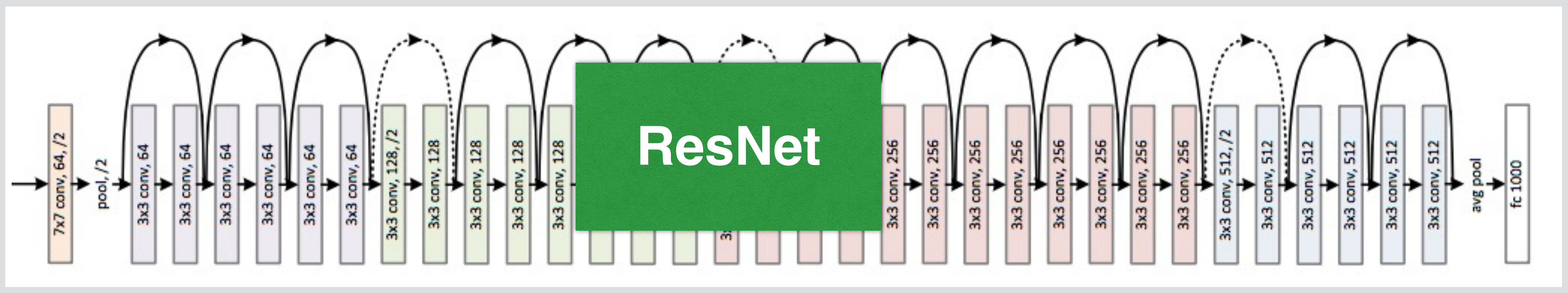
Convolutional Neural Networks

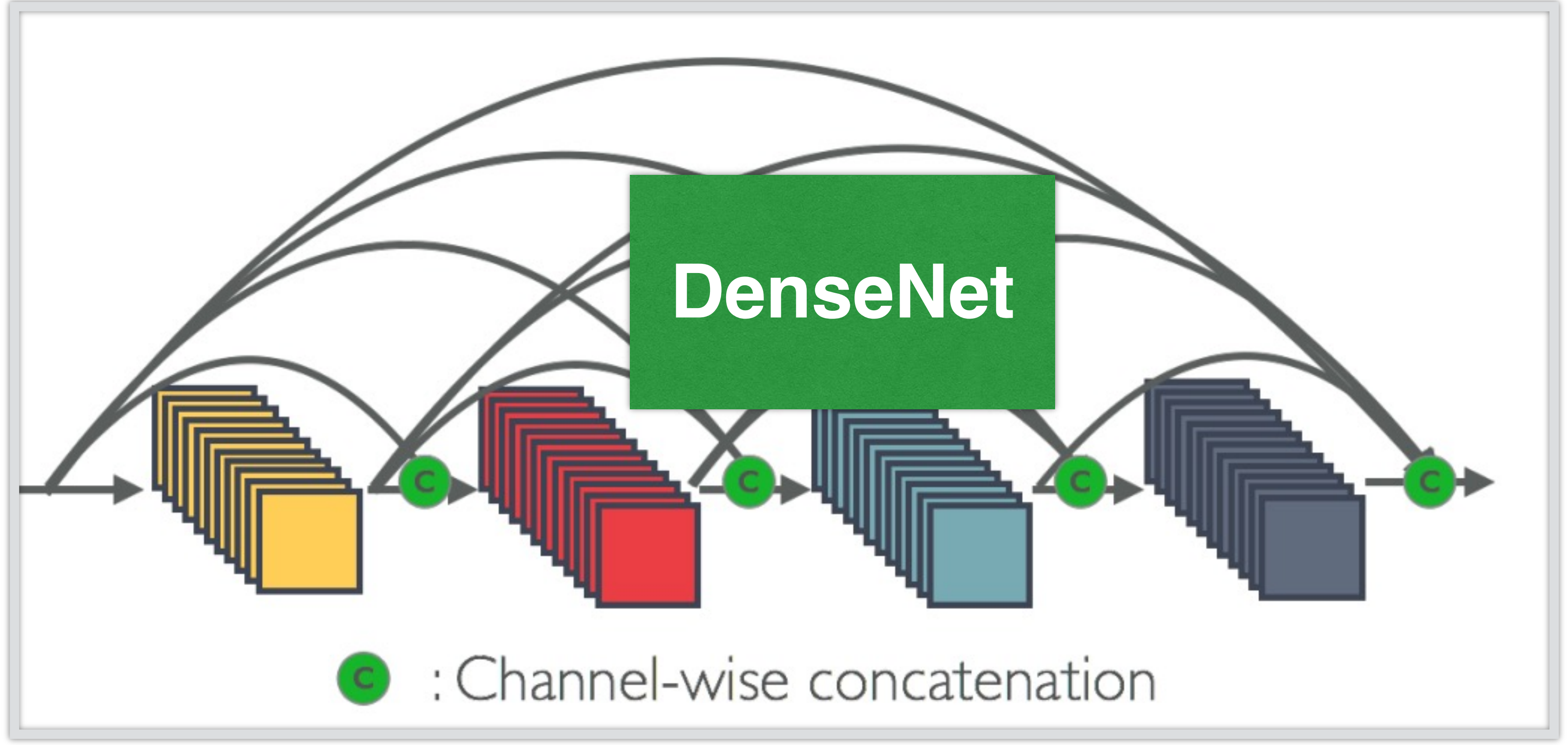
Evolution of neural net architectures



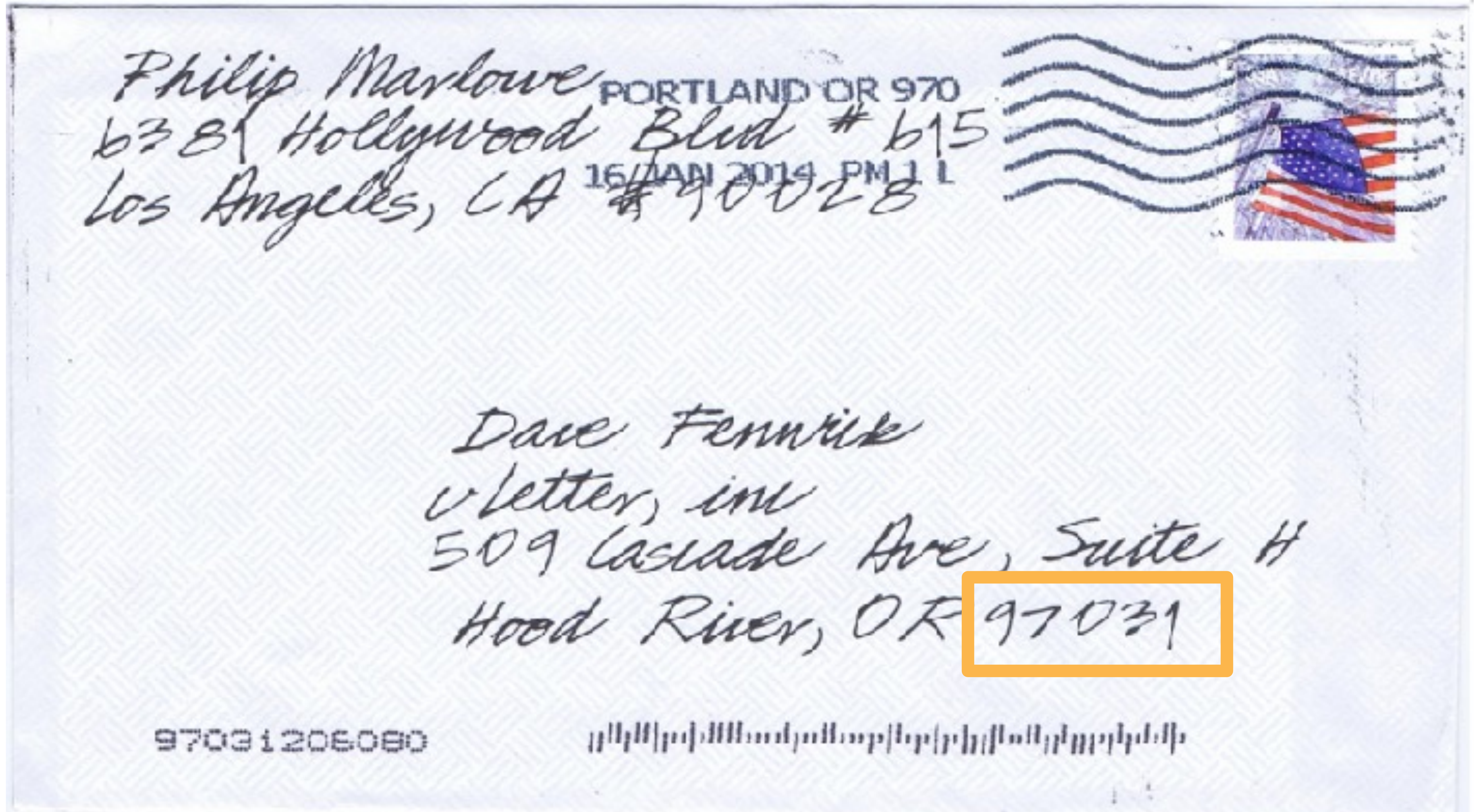


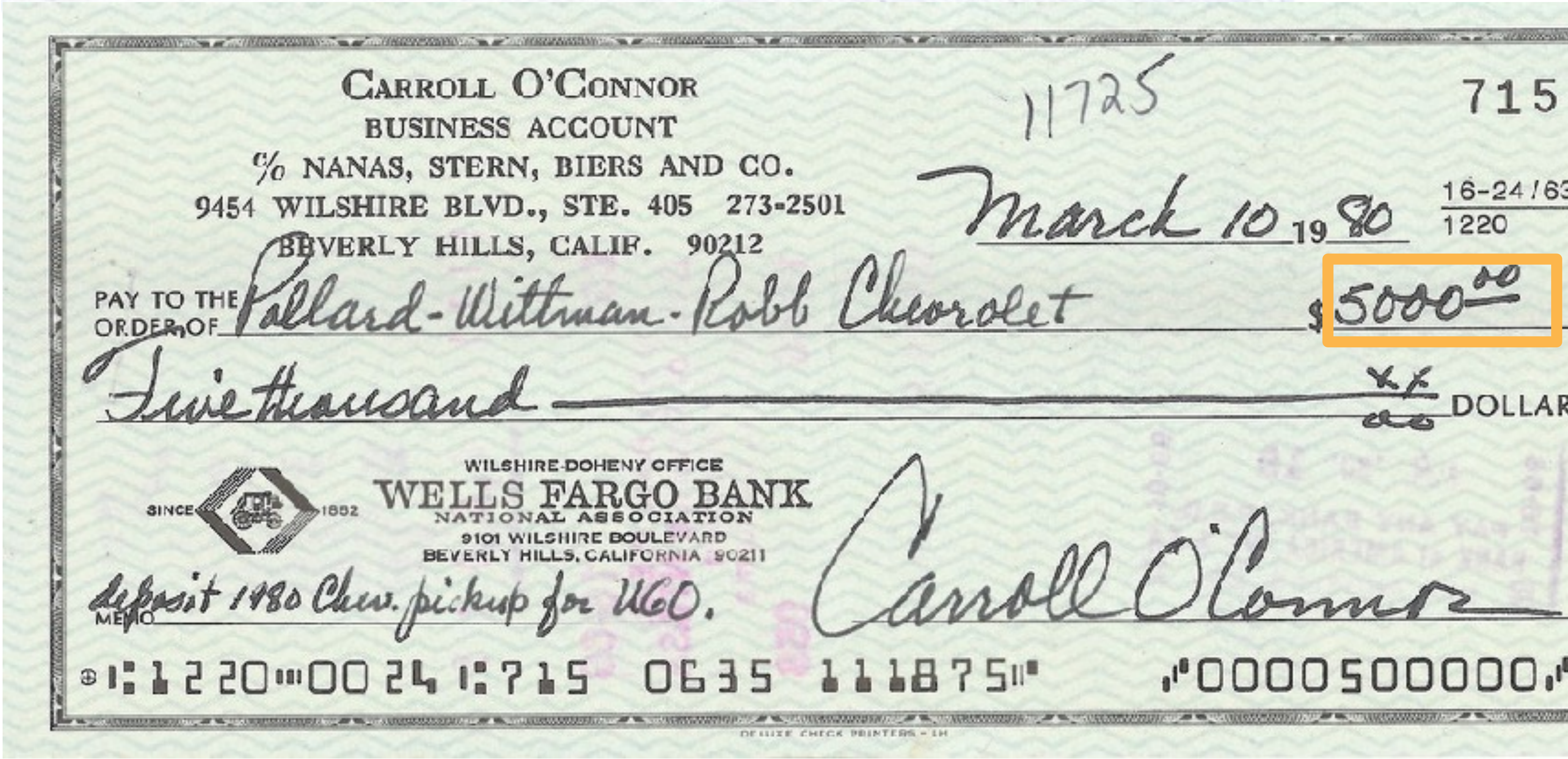






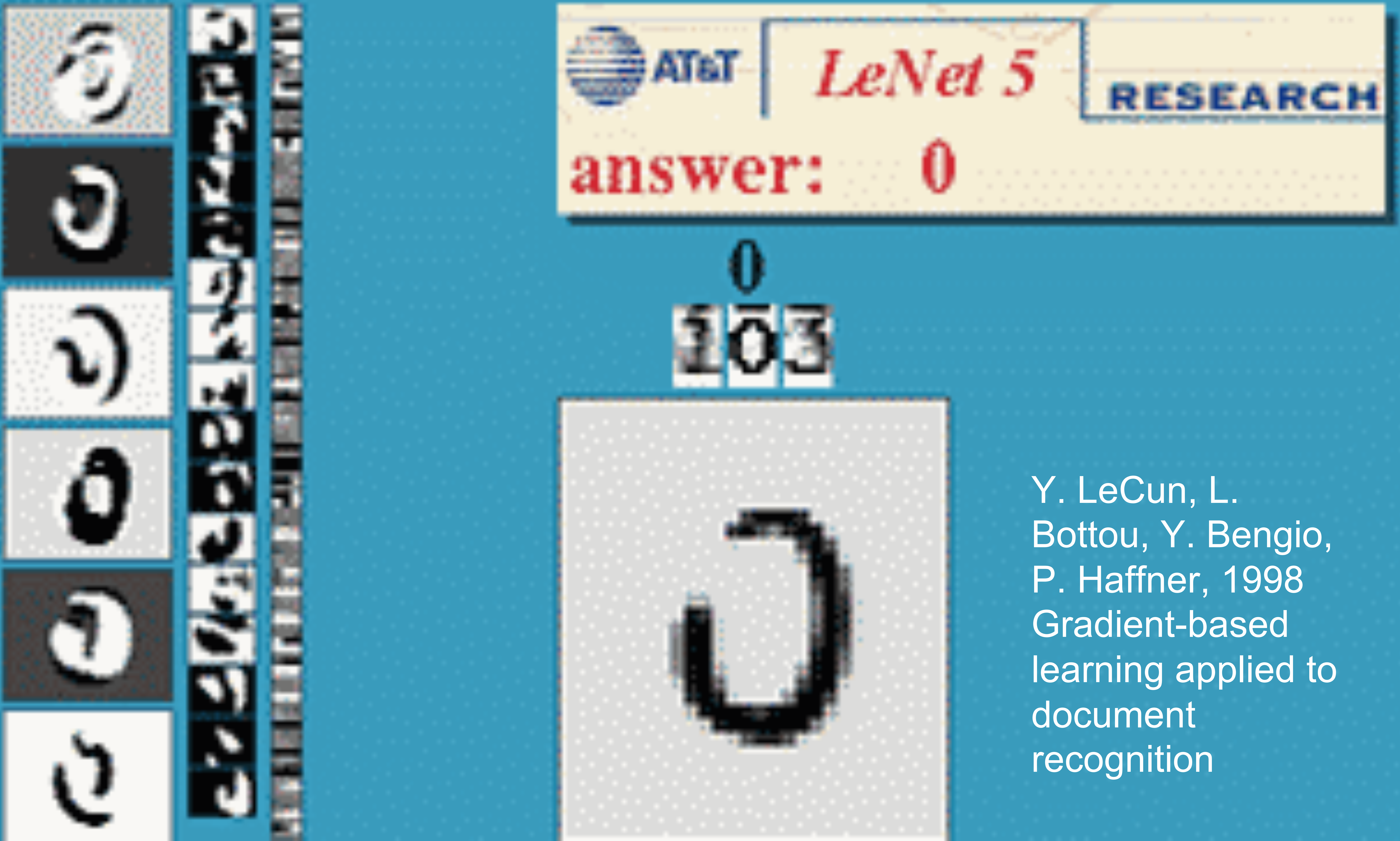
Handwritten Digit Recognition





MNIST

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

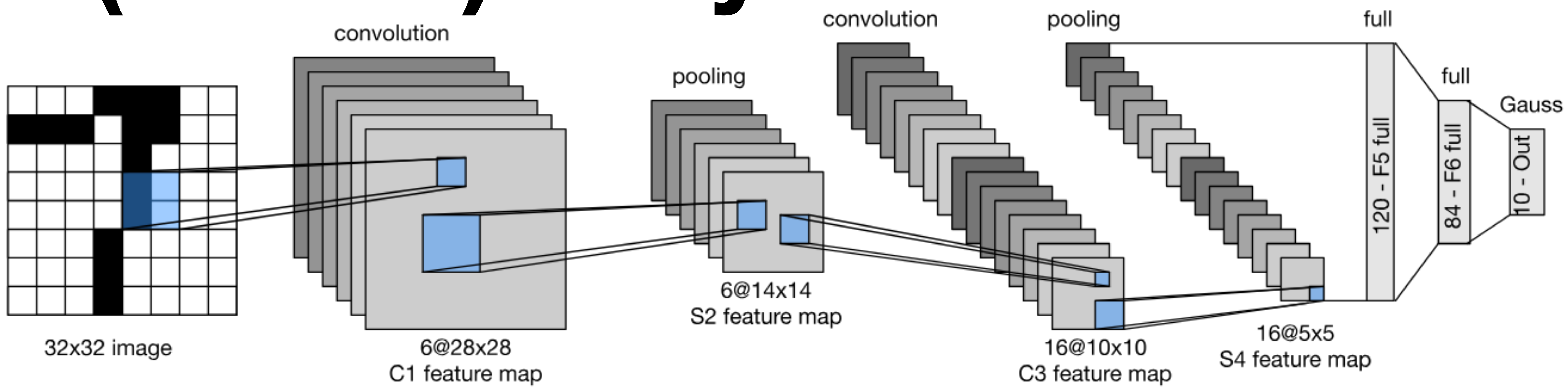


Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, 1998 Gradient-based learning applied to document recognition

LeNet Architecture
(first conv nets)

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

LeNet(variant) in Pytorch

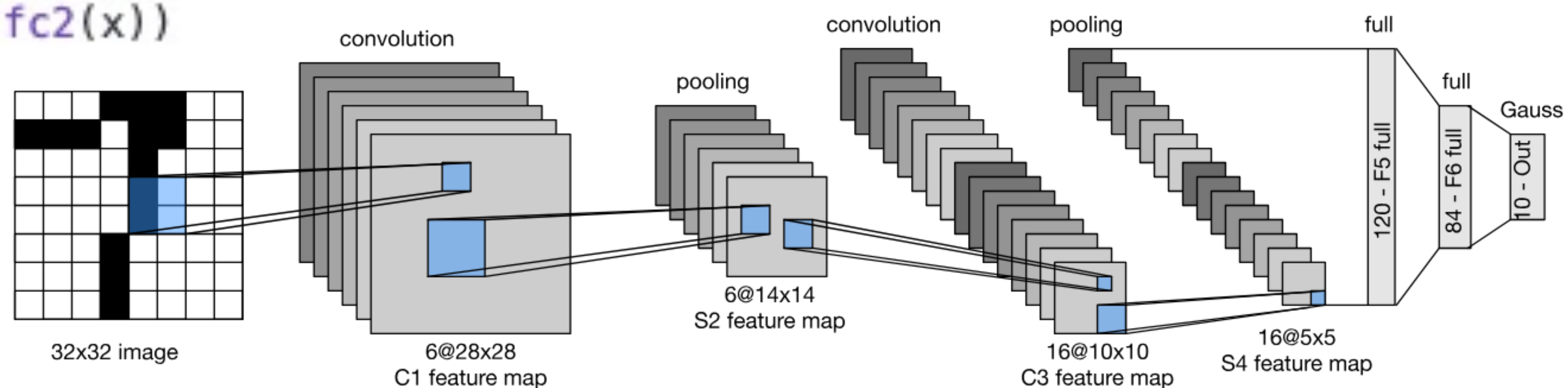



```python
def __init__(self):
    super(LeNet5, self).__init__()
    # Convolution (In LeNet-5, 32x32 images are given as input. Hence padding of 2 is done below)
    self.conv1 = torch.nn.Conv2d(in_channels=1, out_channels=6, kernel_size=5, stride=1, padding=2, bias=True)
    # Max-pooling
    self.max_pool_1 = 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 (column
    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(variant) in Pytorch

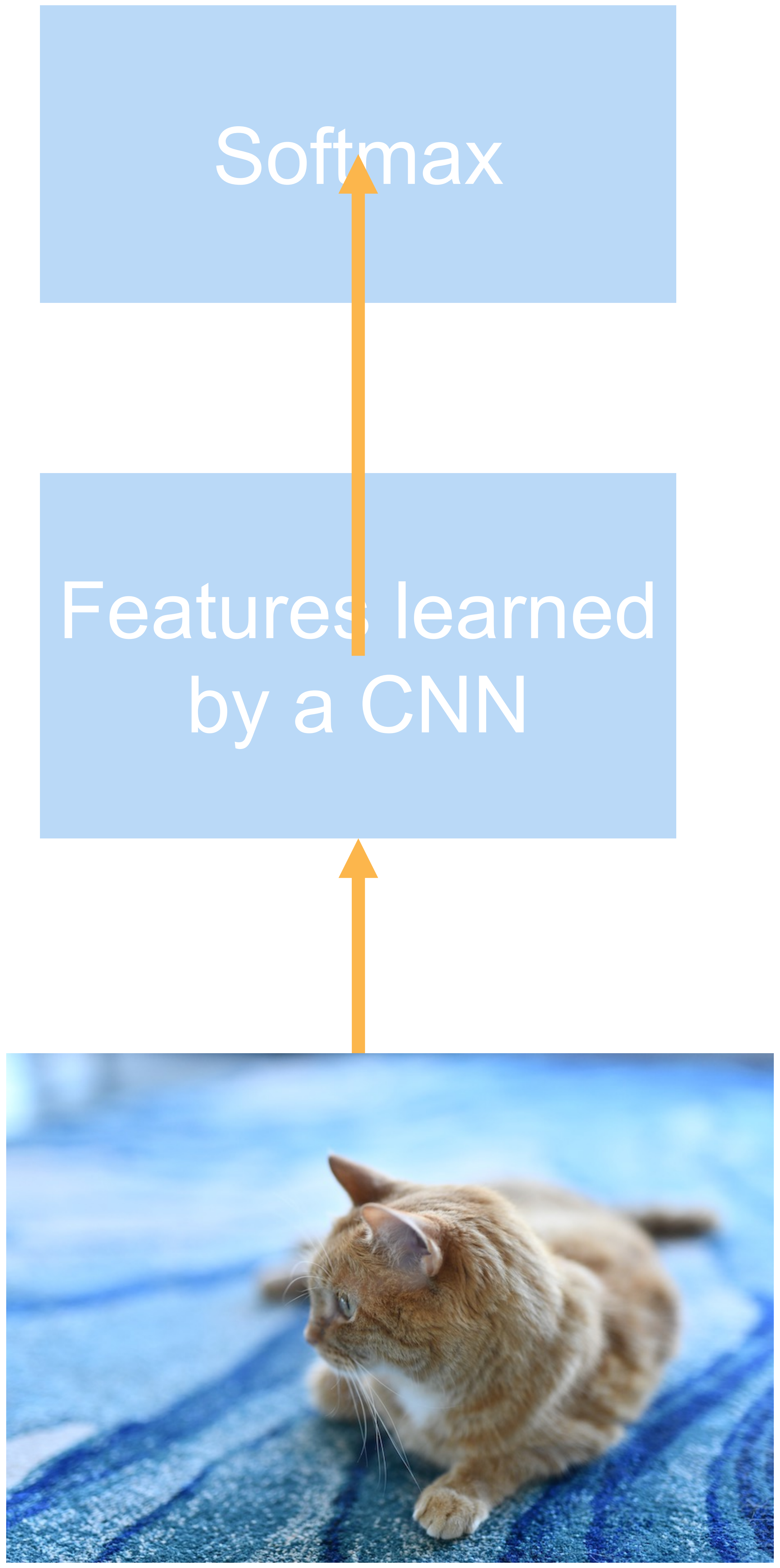
```python
def forward(self, x):
    # convolve, then perform ReLU non-linearity
    x = torch.nn.functional.relu(self.conv1(x))
    # max-pooling with 2x2 grid
    x = self.max_pool_1(x)
    # convolve, then perform ReLU non-linearity
    x = torch.nn.functional.relu(self.conv2(x))
    # max-pooling 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
```

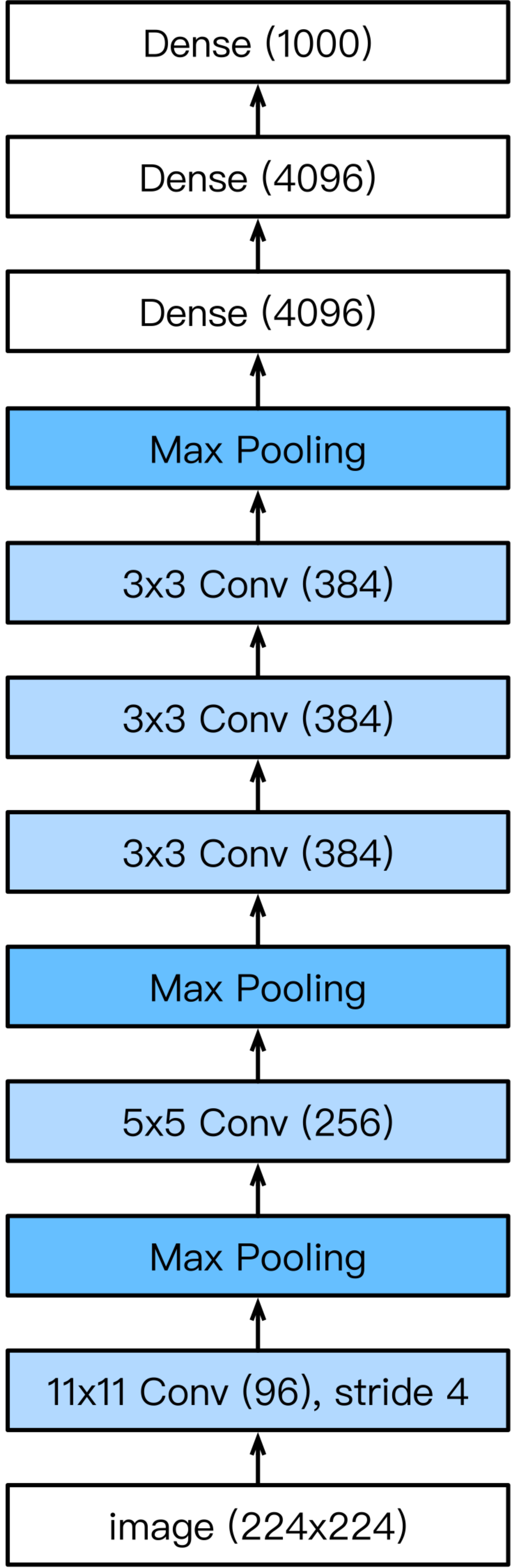


Deng et al. 2009

AlexNet

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

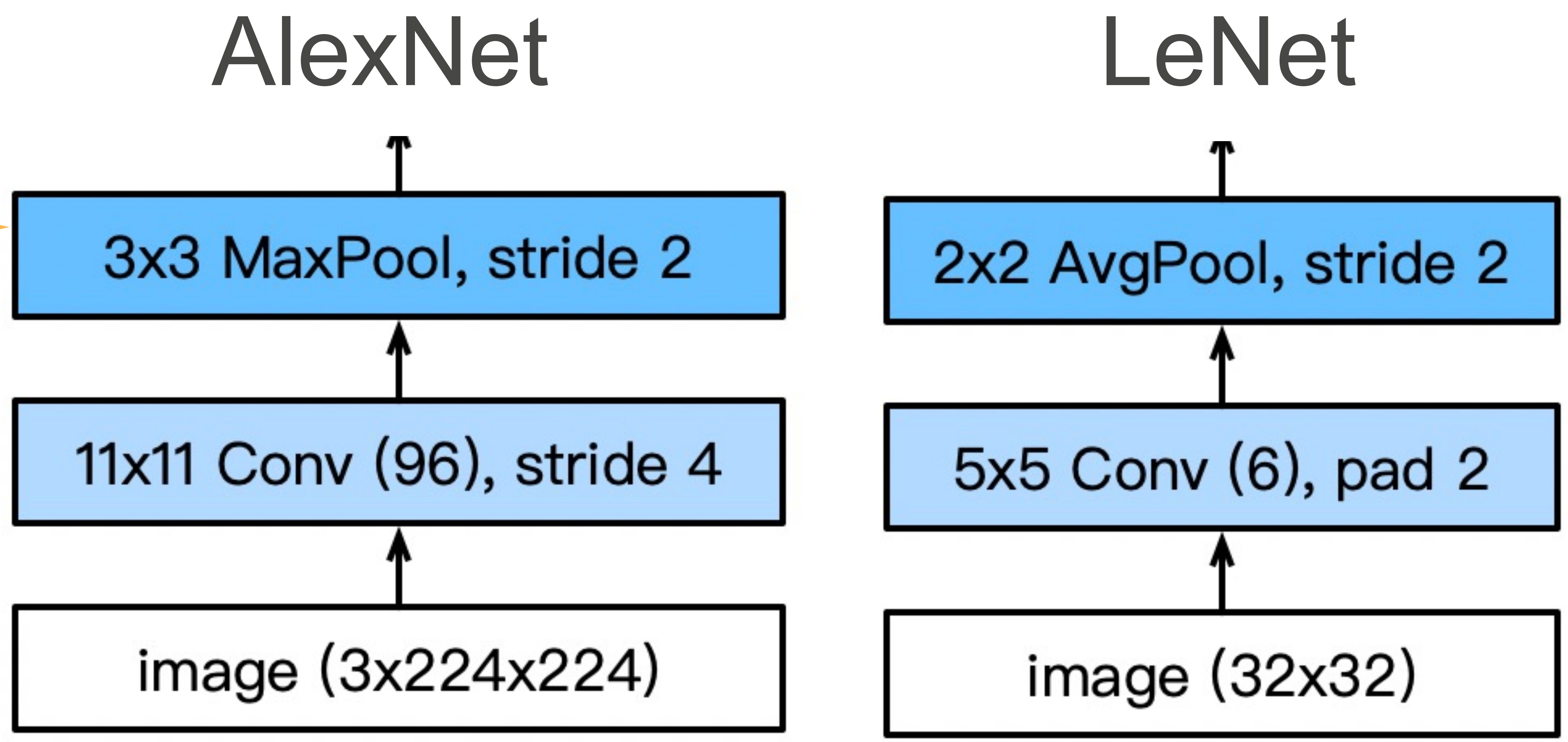




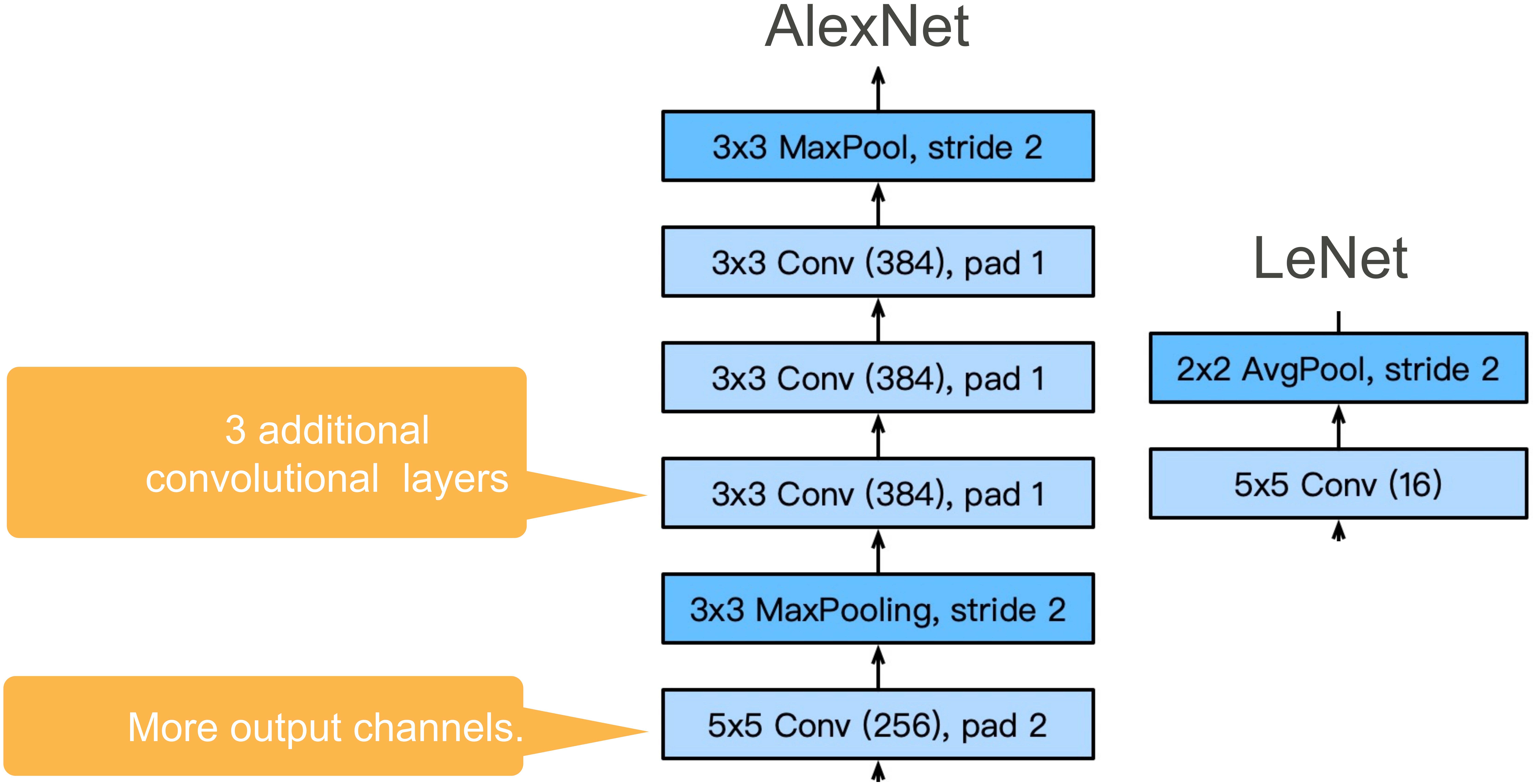
AlexNet Architecture

Larger pool size

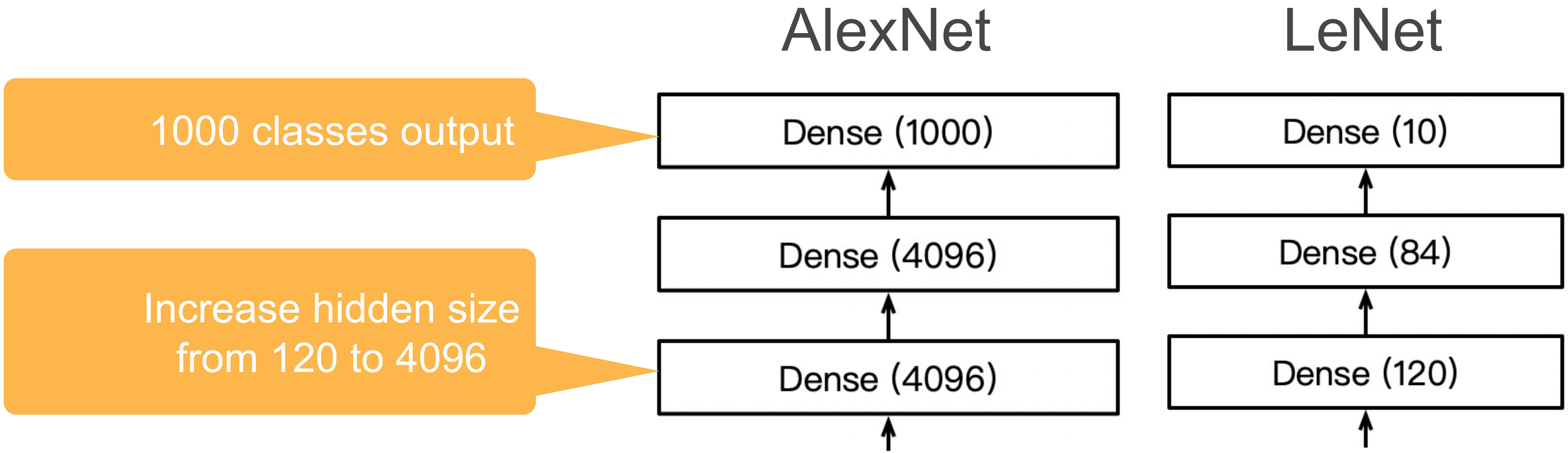
Larger kernel size, stride because of the increased image size, and more output channels.



AlexNet Architecture

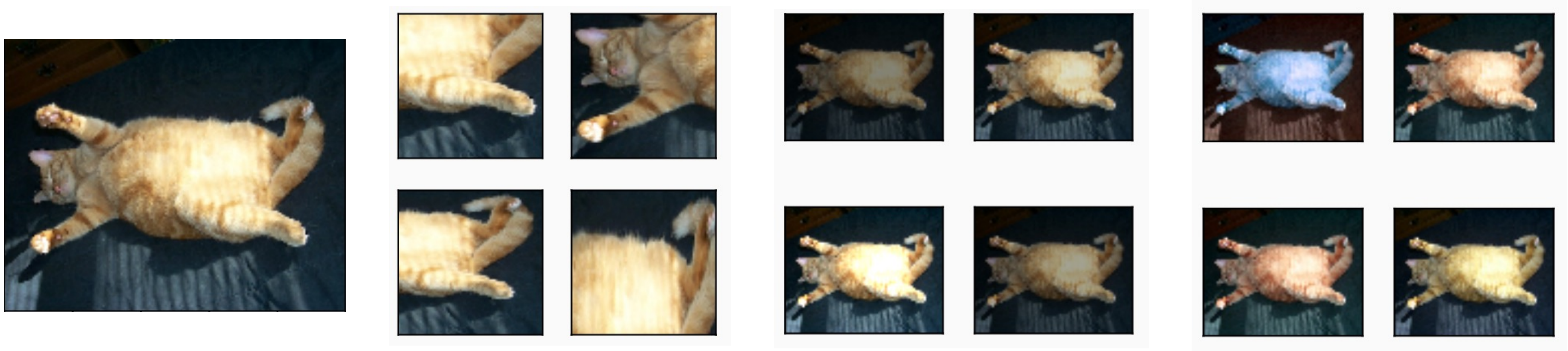


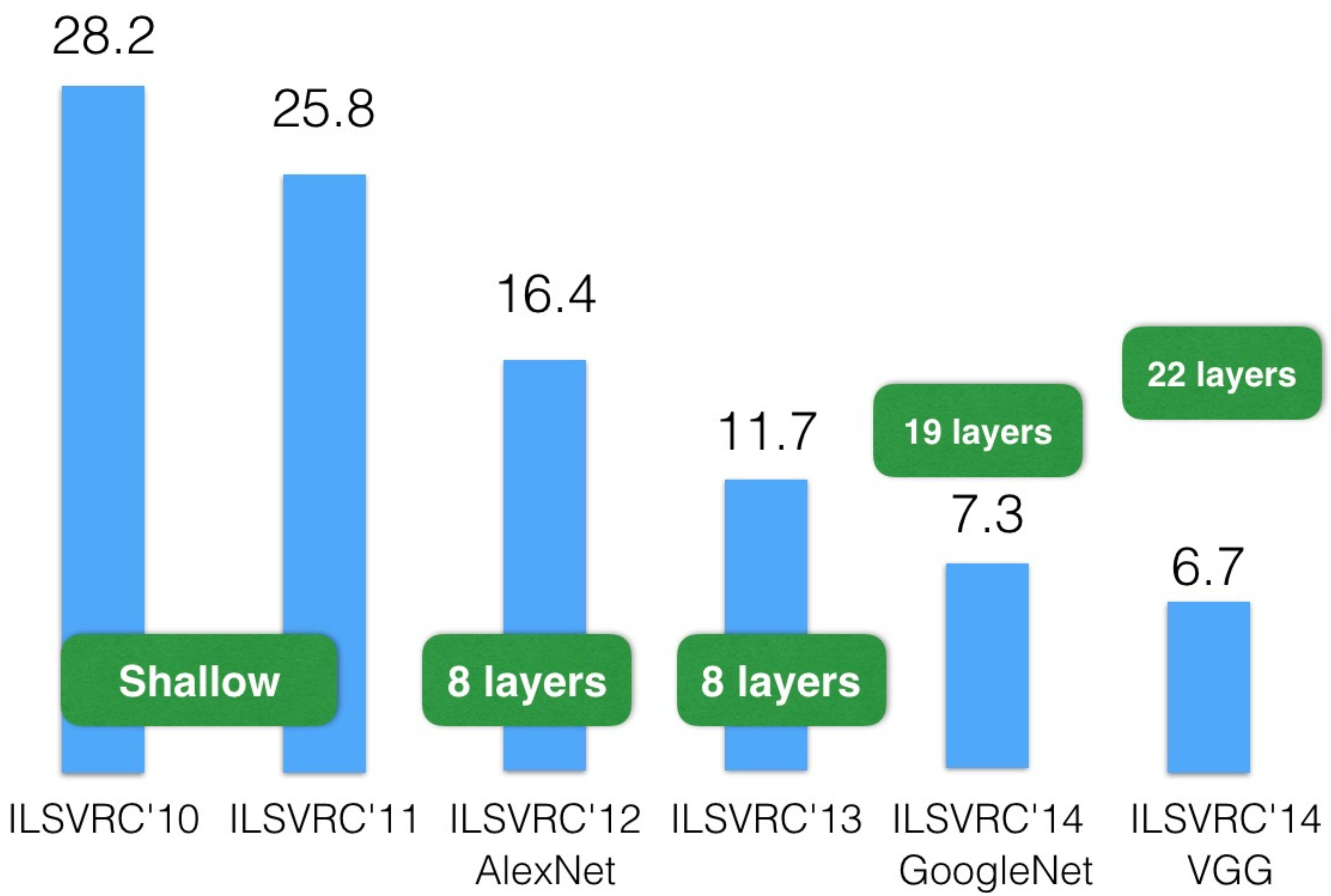
AlexNet Architecture



More Differences…

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





ImageNet Top-5 Classification Error (%)

Q2: Which of the following are true about AlexNet? Select all that apply.

A. Let’s view convolution+pooling as a composition convolutional layer. Then AlexNet contains 8 layers. The first five are (standard or composition)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. 10

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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. 10

Q3: Which of the following is true about the success of deep learning models?

A. Better design of the neural networks

B. Large scale training dataset

C. Available computing power

D. All of the above

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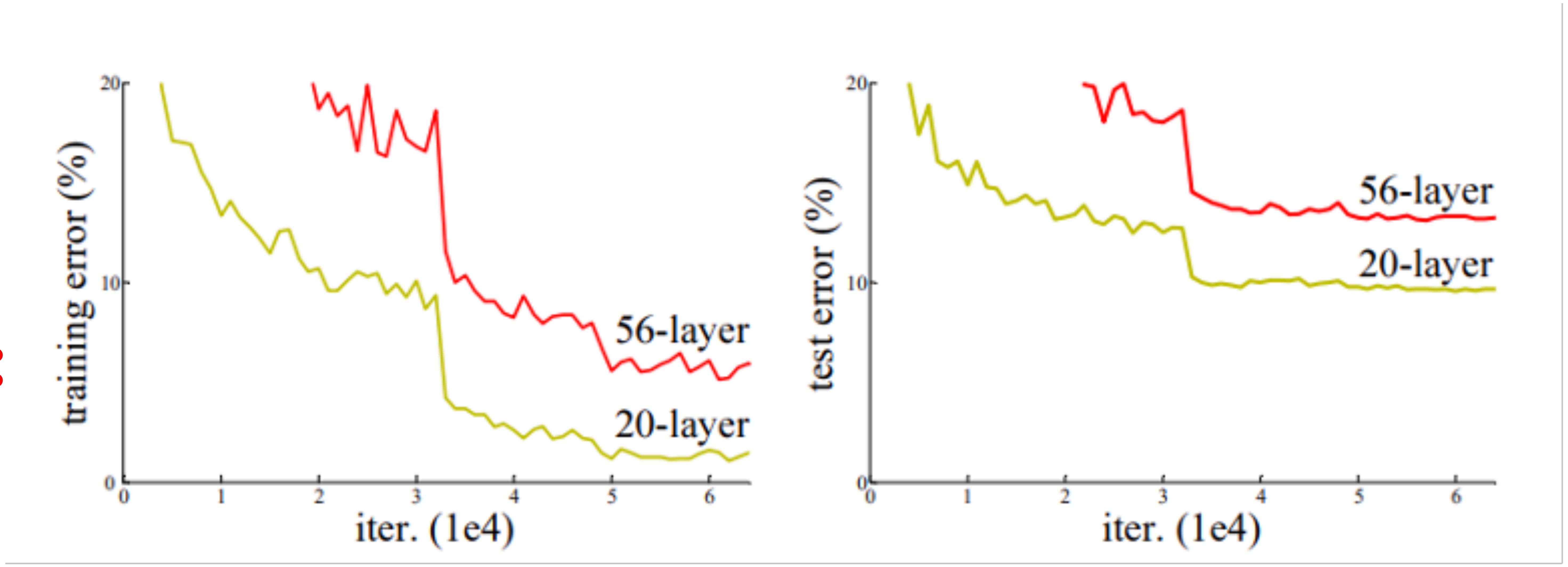
Simple Idea: Add More Layers

- VGG: 19 layers. ResNet: 152 layers. Add more layers sufficient?
- No! Some problems:
  - Vanishing gradients: more layers more likely
  - Instability: can't guarantee we learn identity maps

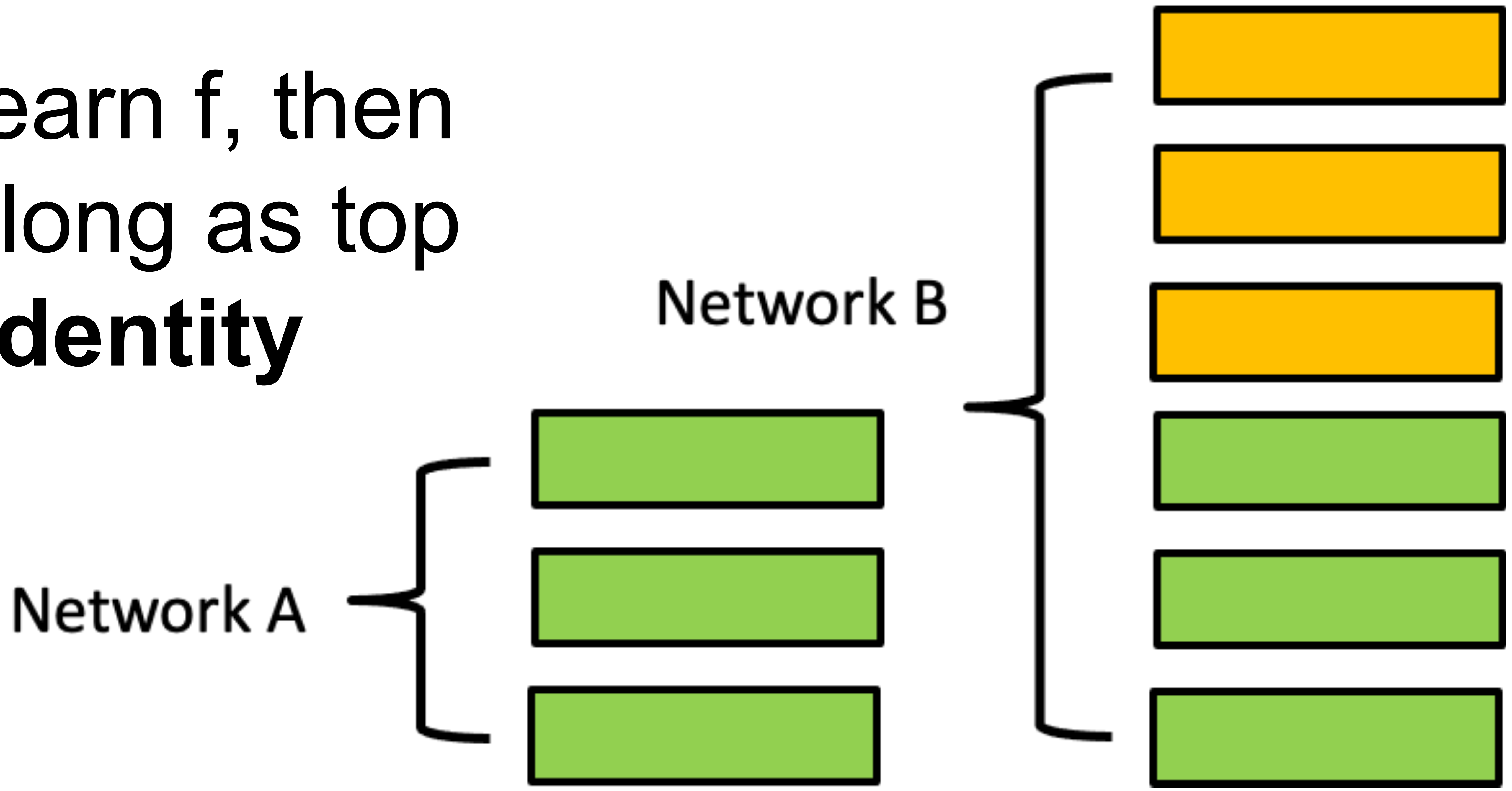
Reflected in training error:



He et al: "Deep Residual Learning for Image Recognition"

Depth Issues & Learning Identity

- Why would more layers result in worse performance
  - Same architecture, etc.
  - If the A can learn f, then so can B, as long as top layers learn **identity**

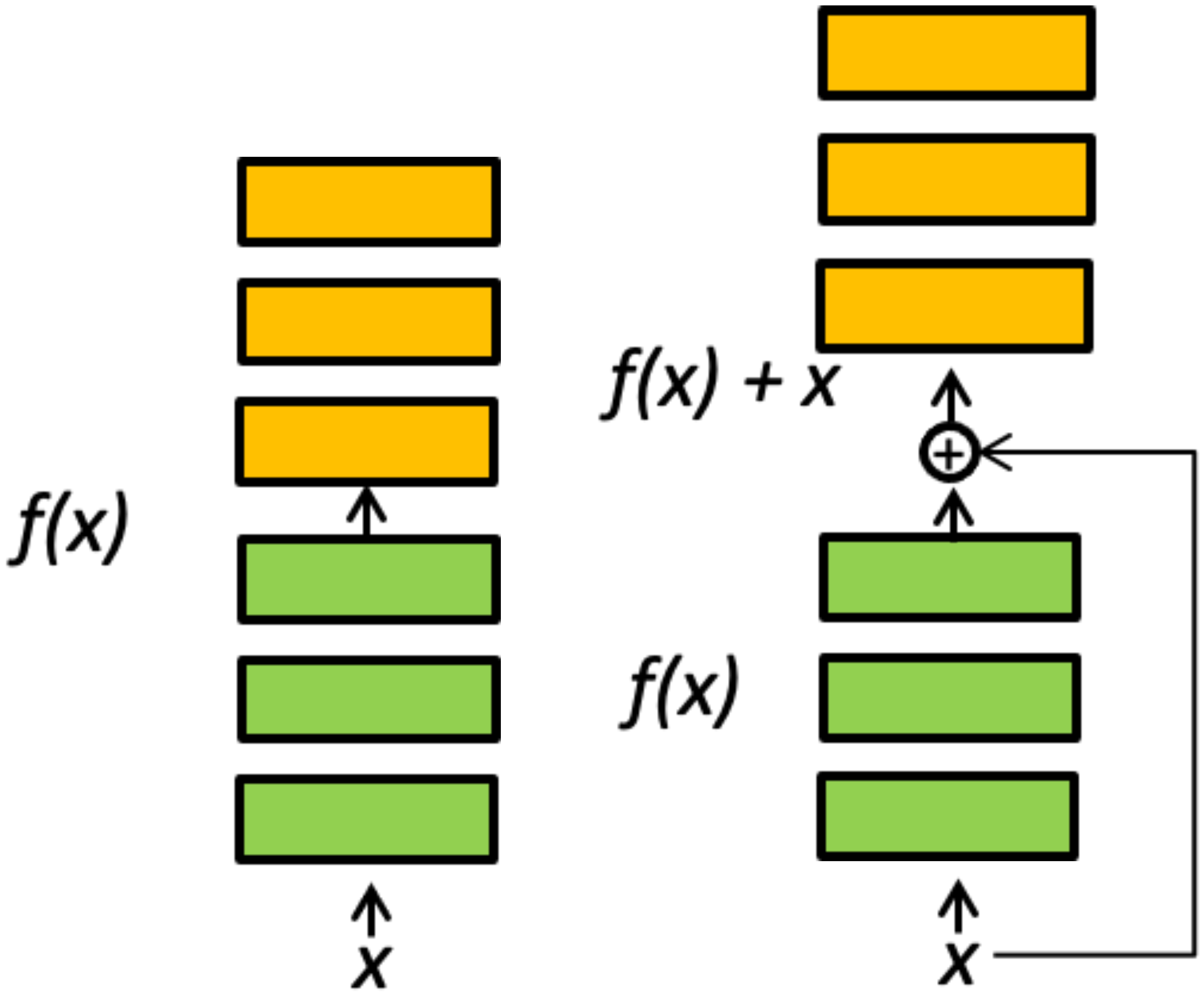


Q: can we learn identity here?

Idea: if layers can learn identity, **can't get** worse.

Residual Connections

- **Idea:** identity might be hard to learn, but zero is easy!
  - Make all the weights tiny, produces zero for output
  - Can easily transform learning identity to learning zero:



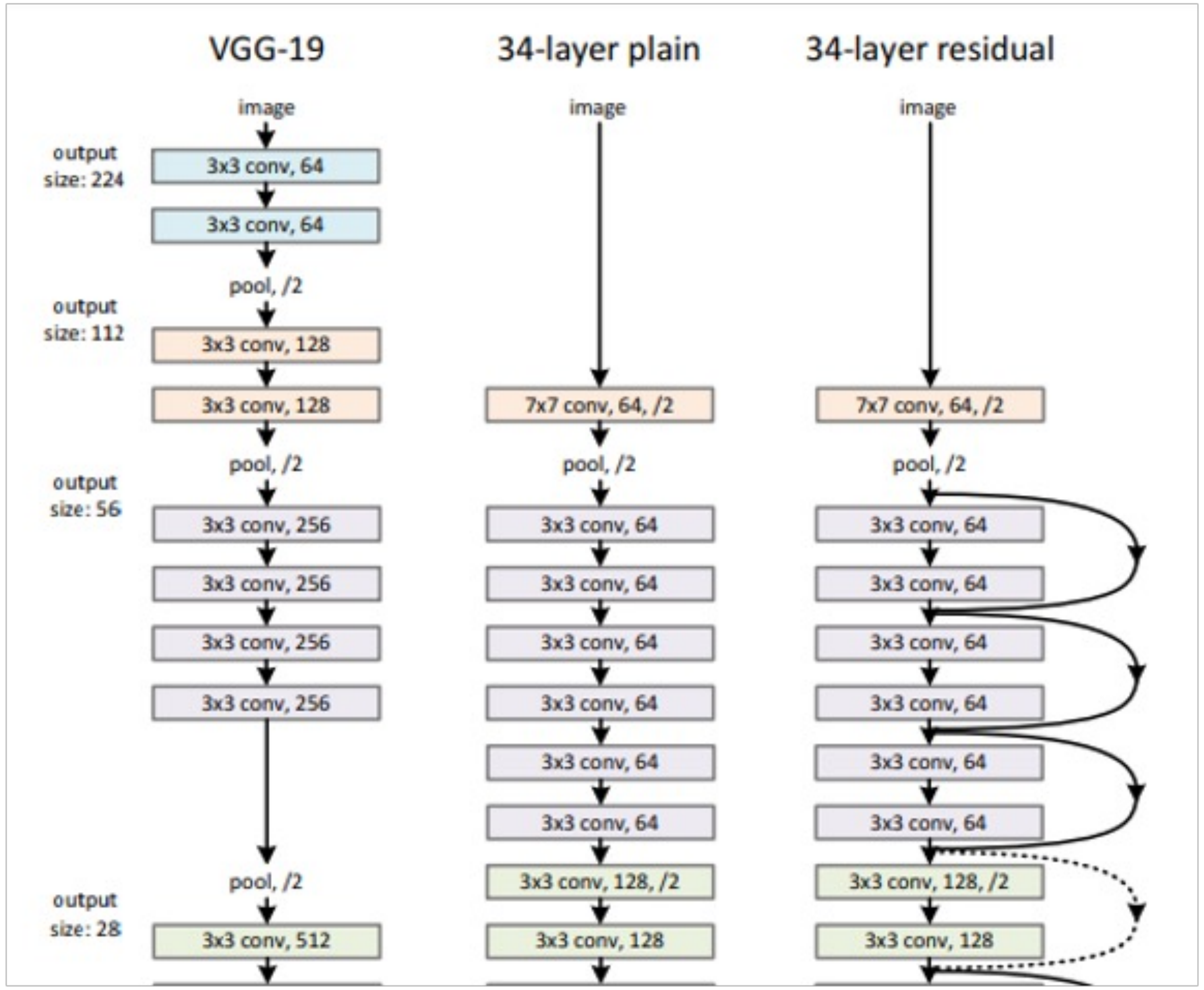
Left: Conventional layer blocks

Right: Residual layer blocks

To learn identity f(x) = x, layers now need to learn f(x) = 0 ➔ easier

ResNet Architecture

- **Idea:** Residual (skip) connections help make learning easier
  - Example architecture:
  - Note: residual connections
    - Every two layers for ResNet34
  - **Vastly better** performance
    - No additional parameters!
    - Records on many benchmarks



He et al: “Deep Residual Learning for Image Recognition”

Q4: Which of the following is **NOT** true?

- A. Adding more layers can improve the performance of a neural network.
- B. Residual connections help deal with vanishing gradients.
- C. CNN architectures use no more than ~20 layers to avoid problems such as vanishing gradients.
- D. It is usually easier to learn a zero mapping than the identity mapping.

Q4: Which of the following is **NOT** true?

- A. Adding more layers can improve the performance of a neural network. (Yes, as long as we're careful, e.g., ResNets.)
- B. Residual connections help deal with vanishing gradients. (Yes, this is an explicit consideration for residual connections.)
- C. CNN architectures use no more than ~20 layers to avoid problems such as vanishing gradients. (No, much deeper networks.)
- D. It is usually easier to learn a zero mapping than the identity mapping. (Yes: simple way to learn zero is to make weights zero)

What we’ve learned today

- Brief review of convolutional computations
- Convolutional Neural Networks
    - LeNet (first conv nets)
    - AlexNet
    - ResNet

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 Sr

https://courses.d2l.ai/berkeley-stat-157/index.html