CS540 Introduction to Artificial Intelligence

Deep Learning II: Convolutional Neural Networks

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Nov 4, 2021

Slides created by Sharon Li [modified by Yingyu Liang]

Outline

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

Review: 2-D Convolution

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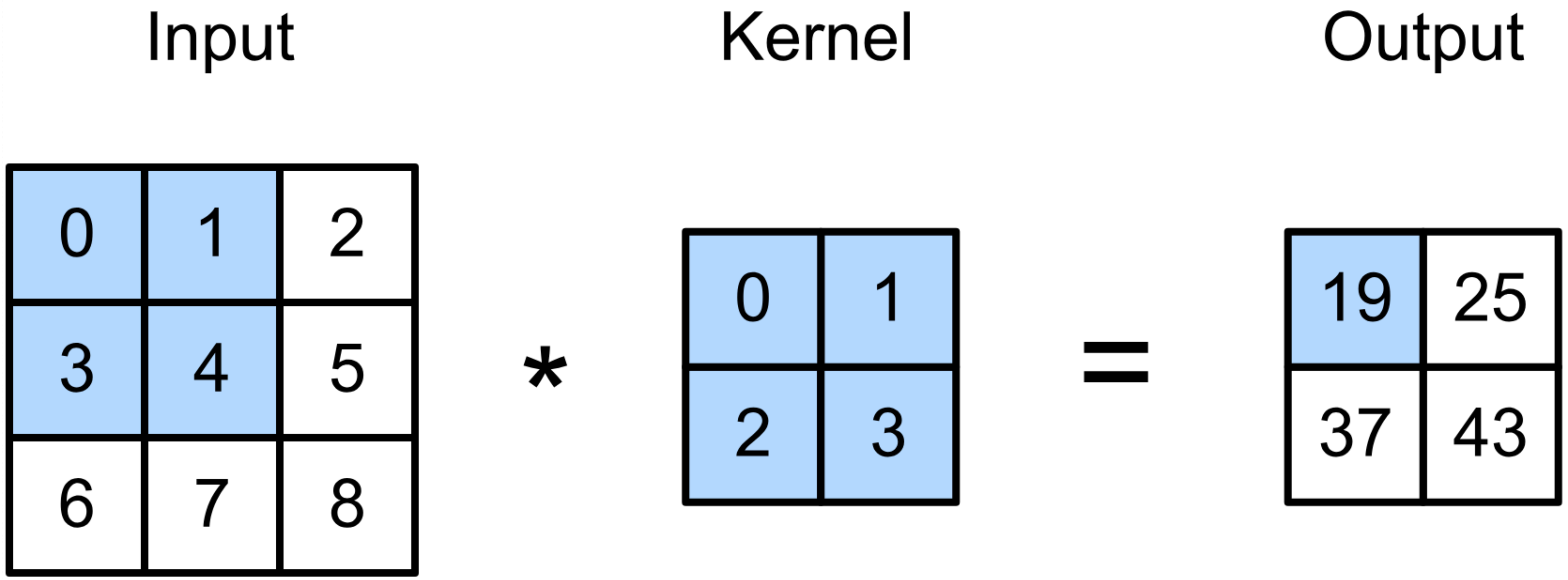
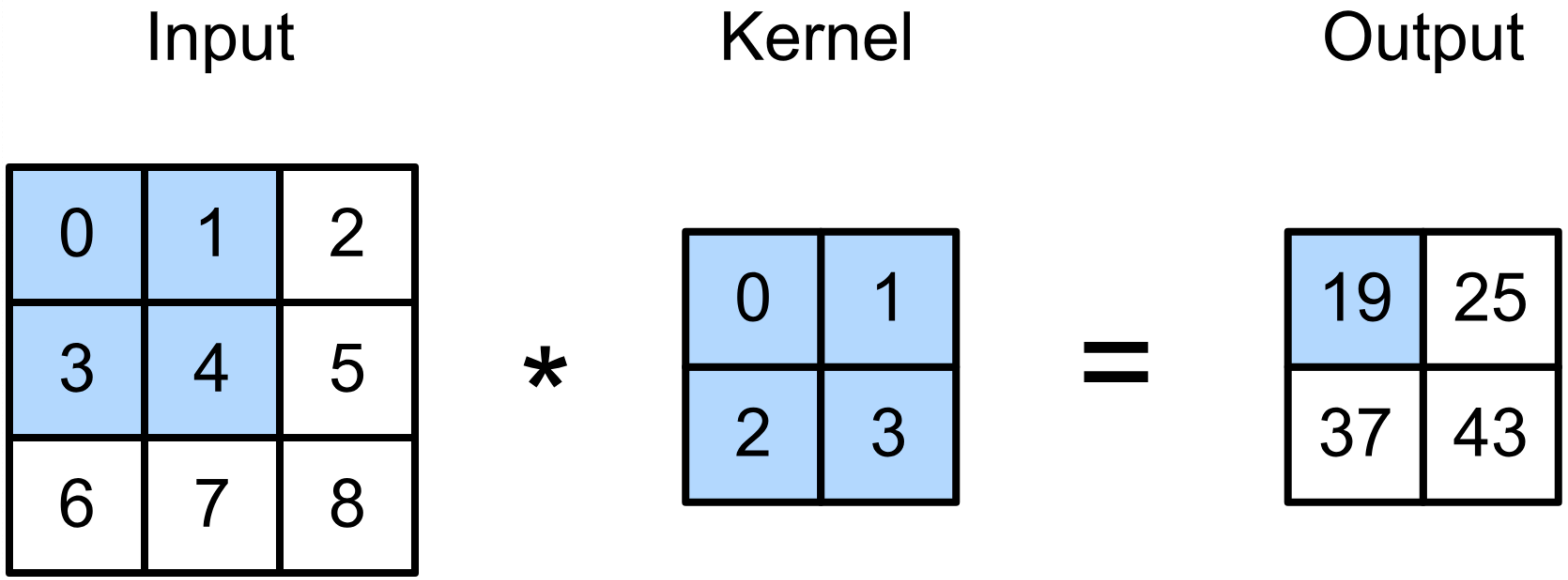


Review: 2-D Convolution



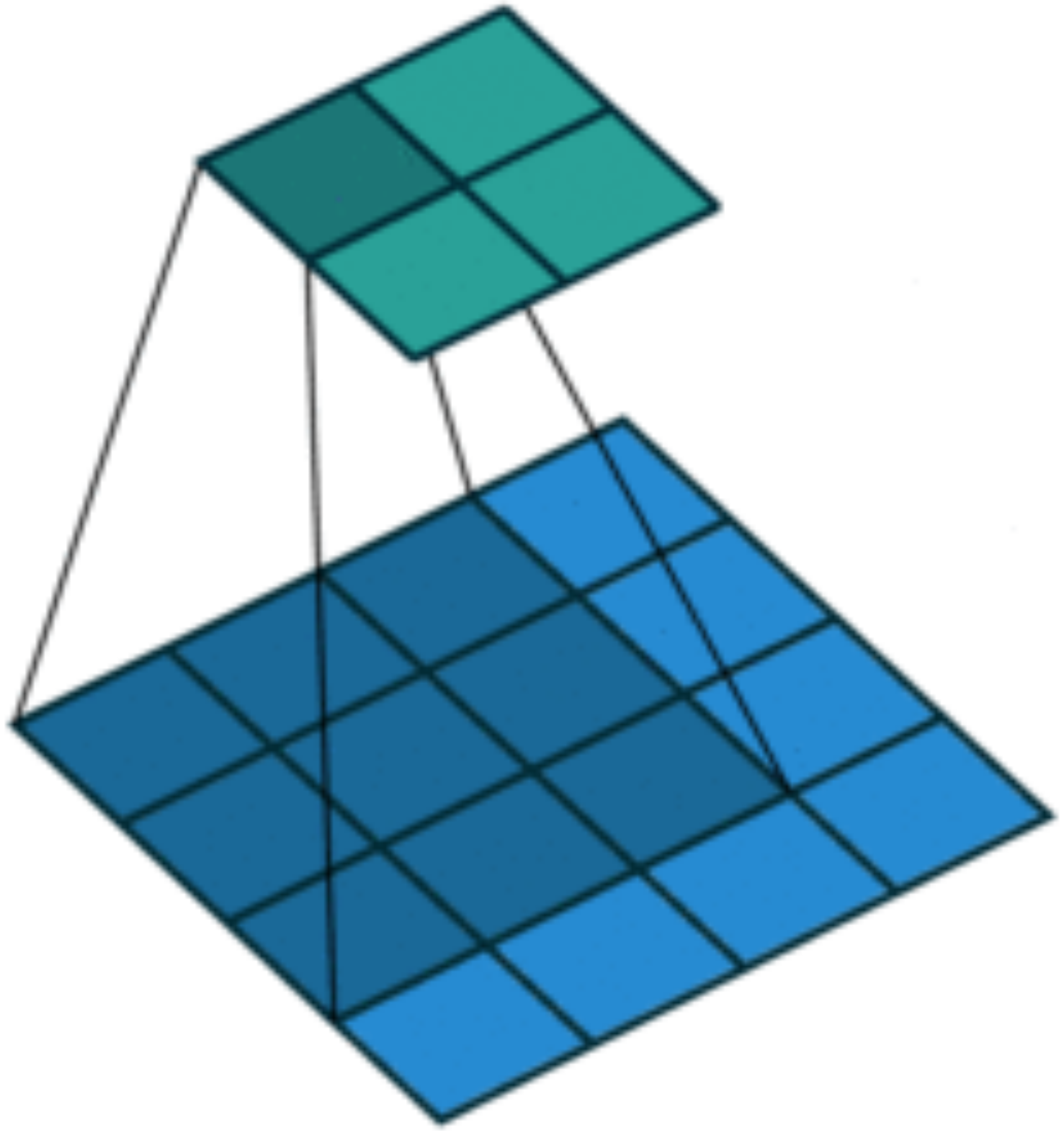
$$
\begin{aligned}
0 \times 0 + 1 \times 1 + 3 \times 2 + 4 \times 3 &= 19, \\
1 \times 0 + 2 \times 1 + 4 \times 2 + 5 \times 3 &= 25, \\
3 \times 0 + 4 \times 1 + 6 \times 2 + 7 \times 3 &= 37, \\
4 \times 0 + 5 \times 1 + 7 \times 2 + 8 \times 3 &= 43.
\end{aligned}
$$

Review: 2-D Convolution

Input * Kernel = Output

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

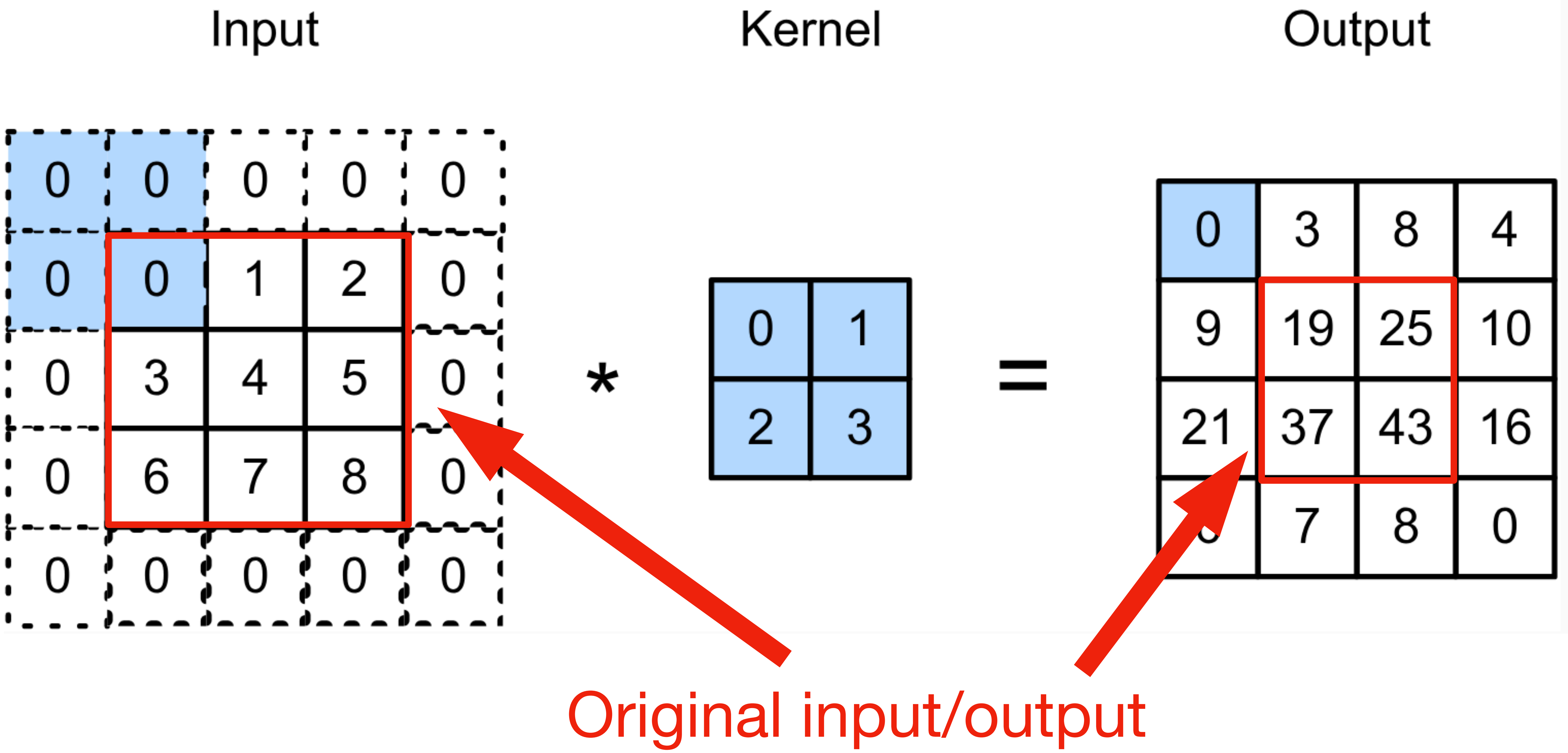
$$0 \times 0 + 1 \times 1 + 3 \times 2 + 4 \times 3 = 19,$$
$$1 \times 0 + 2 \times 1 + 4 \times 2 + 5 \times 3 = 25,$$
$$3 \times 0 + 4 \times 1 + 6 \times 2 + 7 \times 3 = 37,$$
$$4 \times 0 + 5 \times 1 + 7 \times 2 + 8 \times 3 = 43.$$



(vdumoulin@ Github)

Padding

Padding adds rows/columns around input

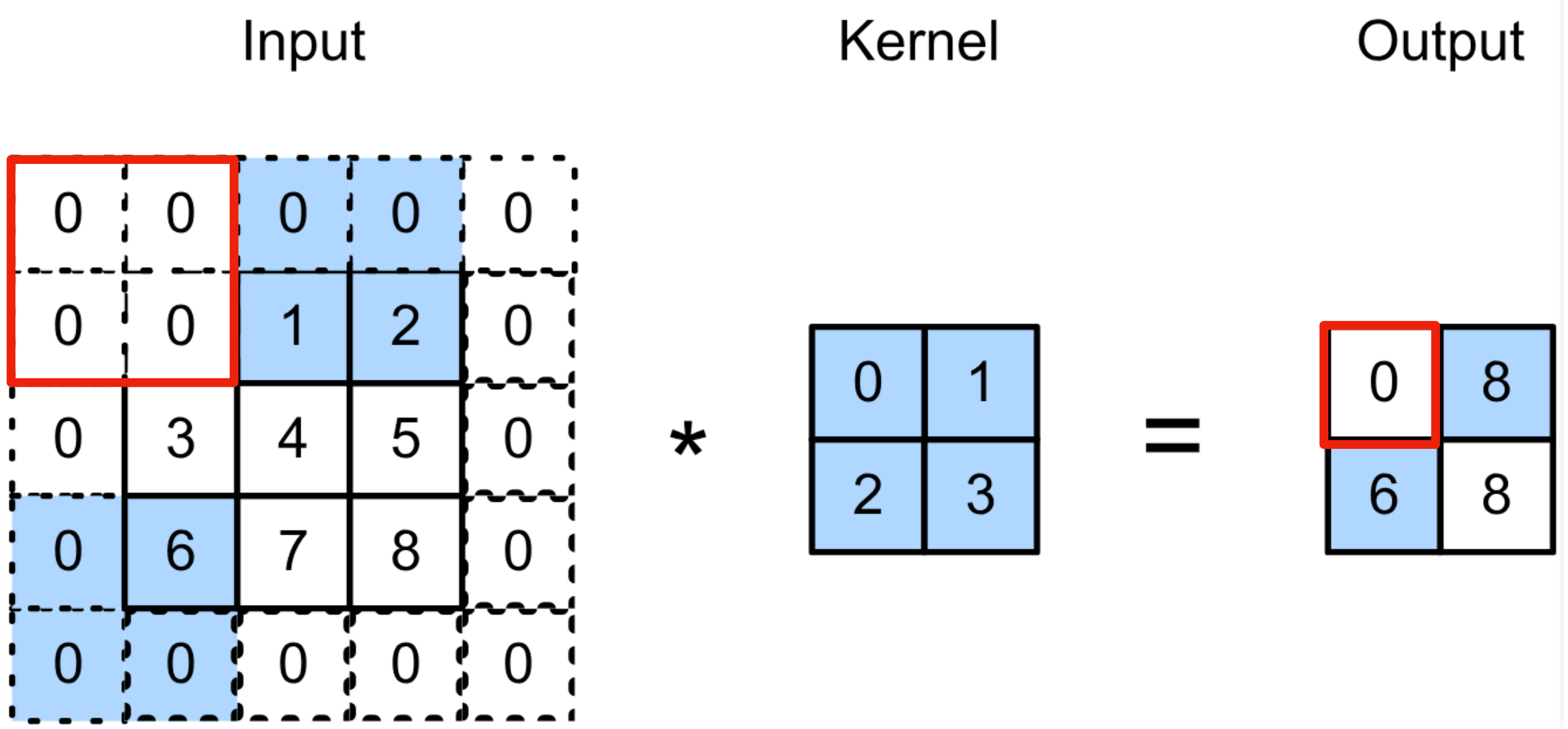


$$0 \times 0 + 0 \times 1 + 0 \times 2 + 0 \times 3 = 0$$

Stride

- Stride is the #rows/#columns per slide

Strides of 3 and 2 for height and width



$$0 \times 0 + 0 \times 1 + 1 \times 2 + 2 \times 3 = 8$$
$$0 \times 0 + 6 \times 1 + 0 \times 2 + 0 \times 3 = 6$$

Output shape

Kernel/filter size

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

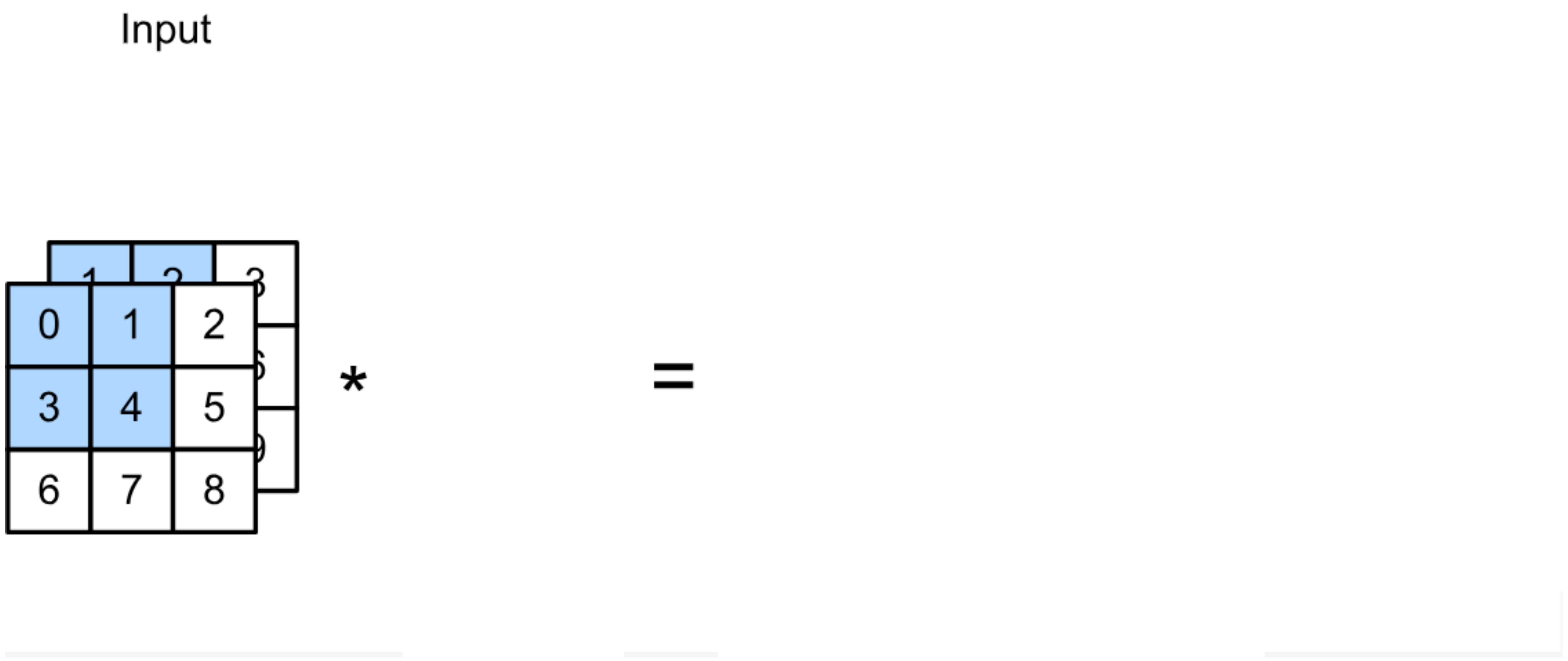
Input size

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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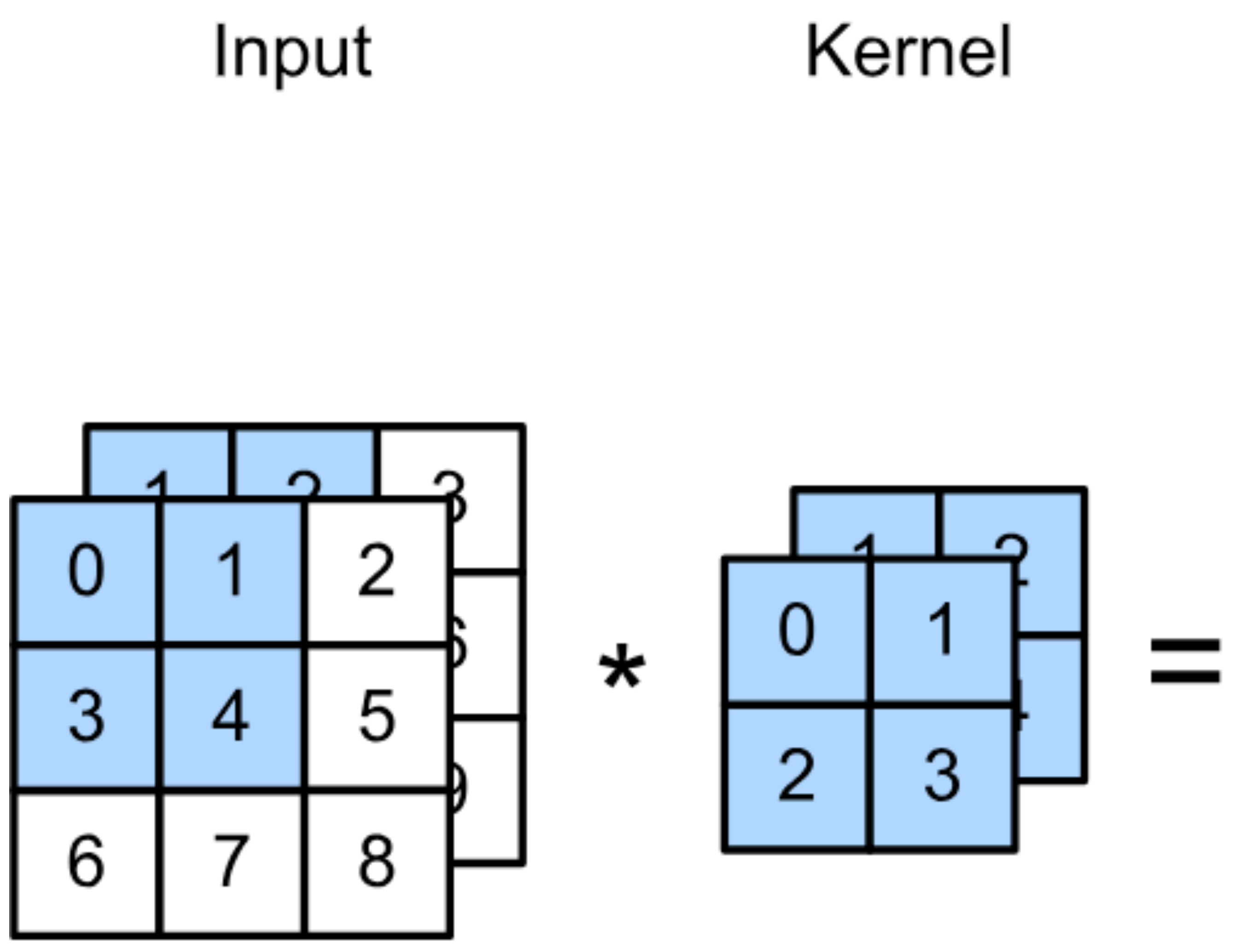

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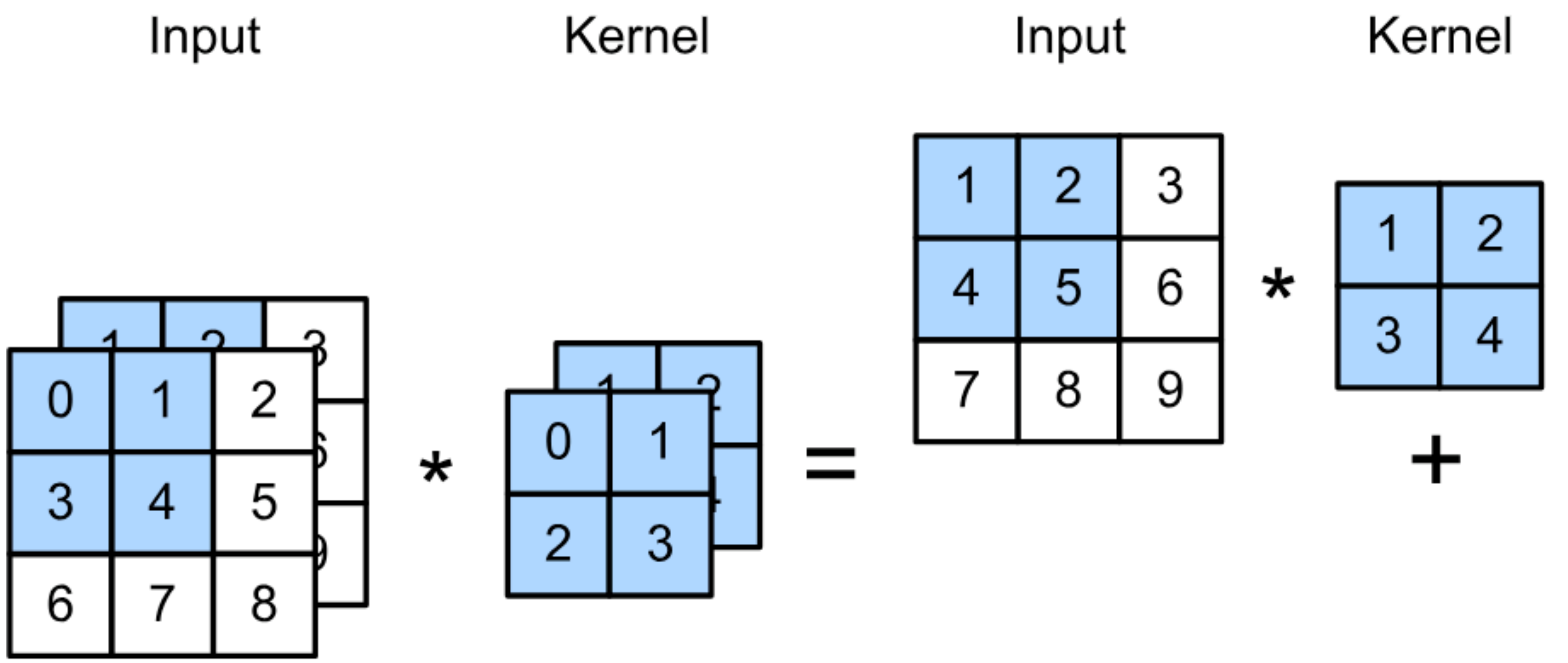

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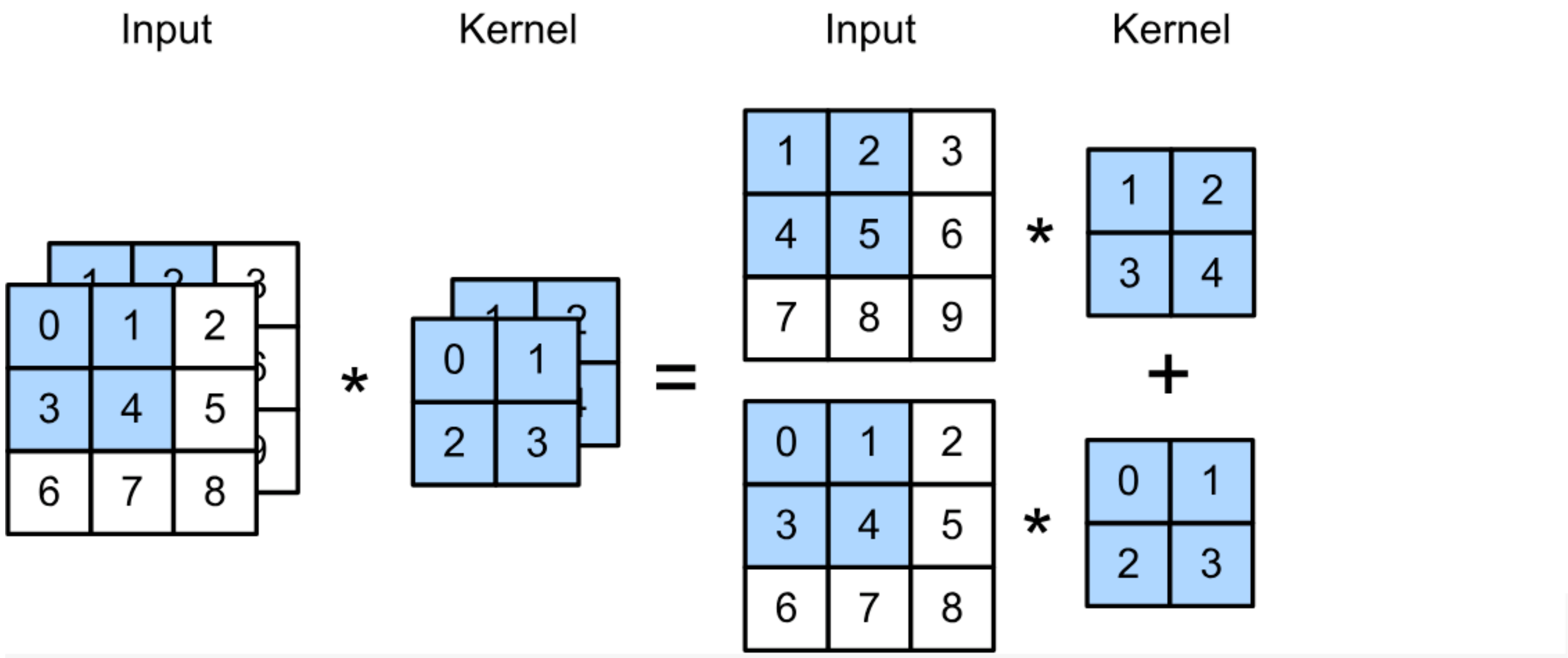

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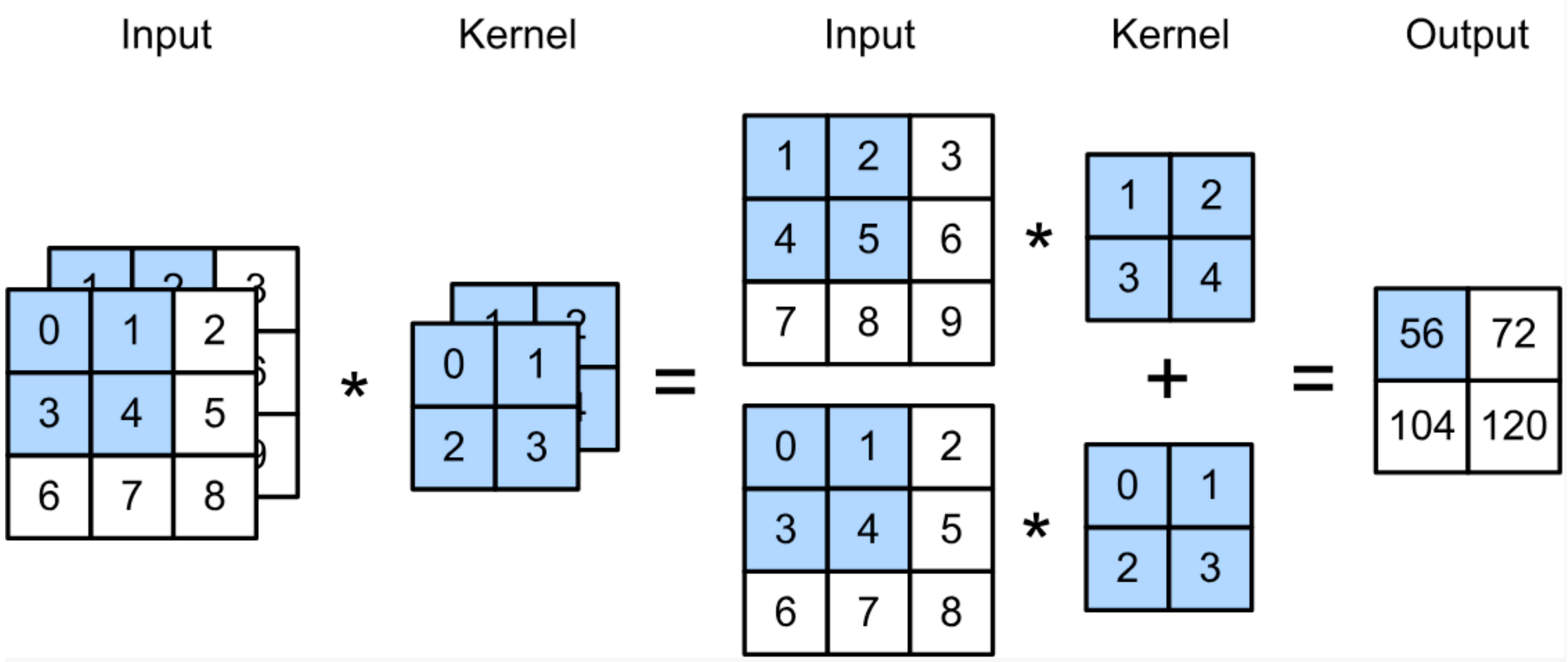

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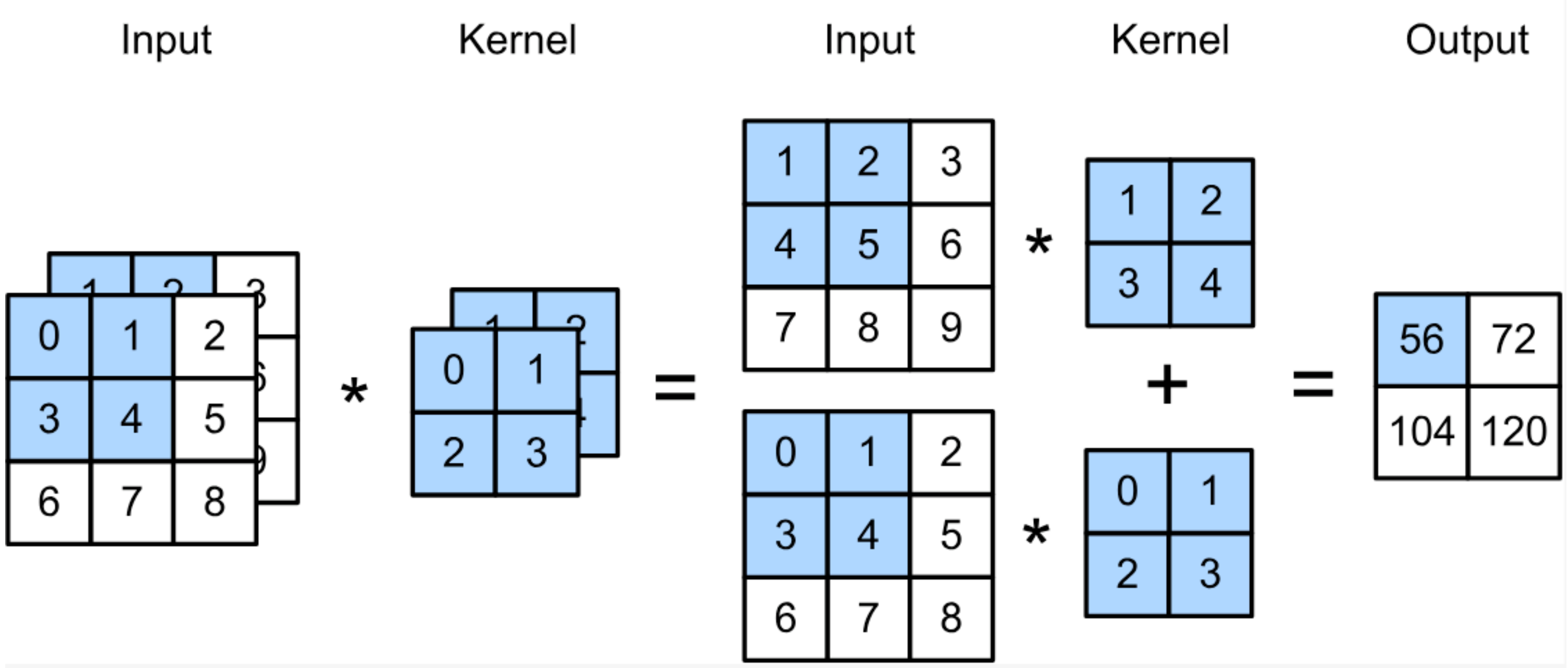

$$
\begin{aligned}
&(1\times 1+2\times 2+4\times 3+5\times 4)\\
&+(0\times 0+1\times 1+3\times 2+4\times 3)\\
&=56
\end{aligned}
$$

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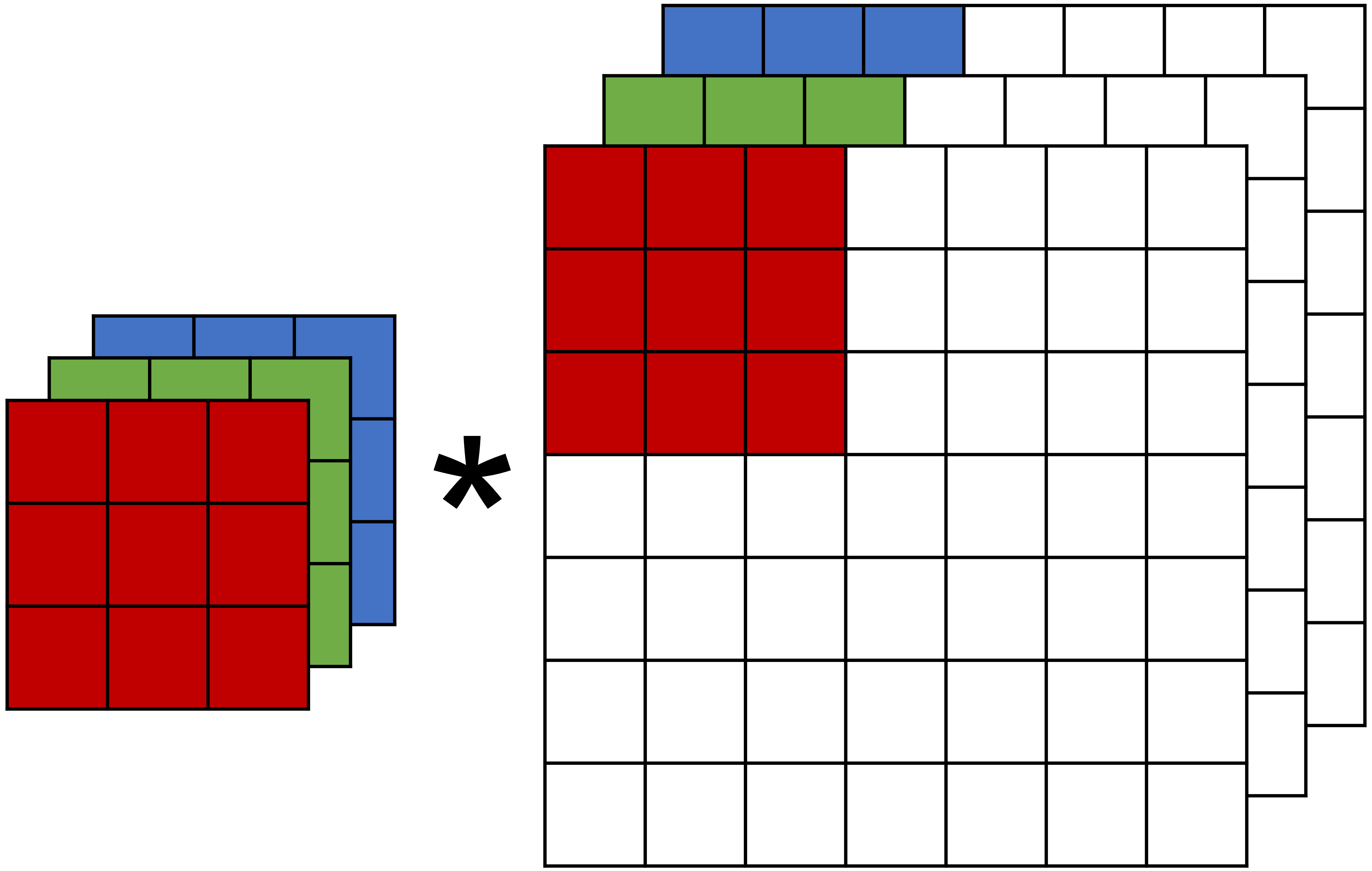

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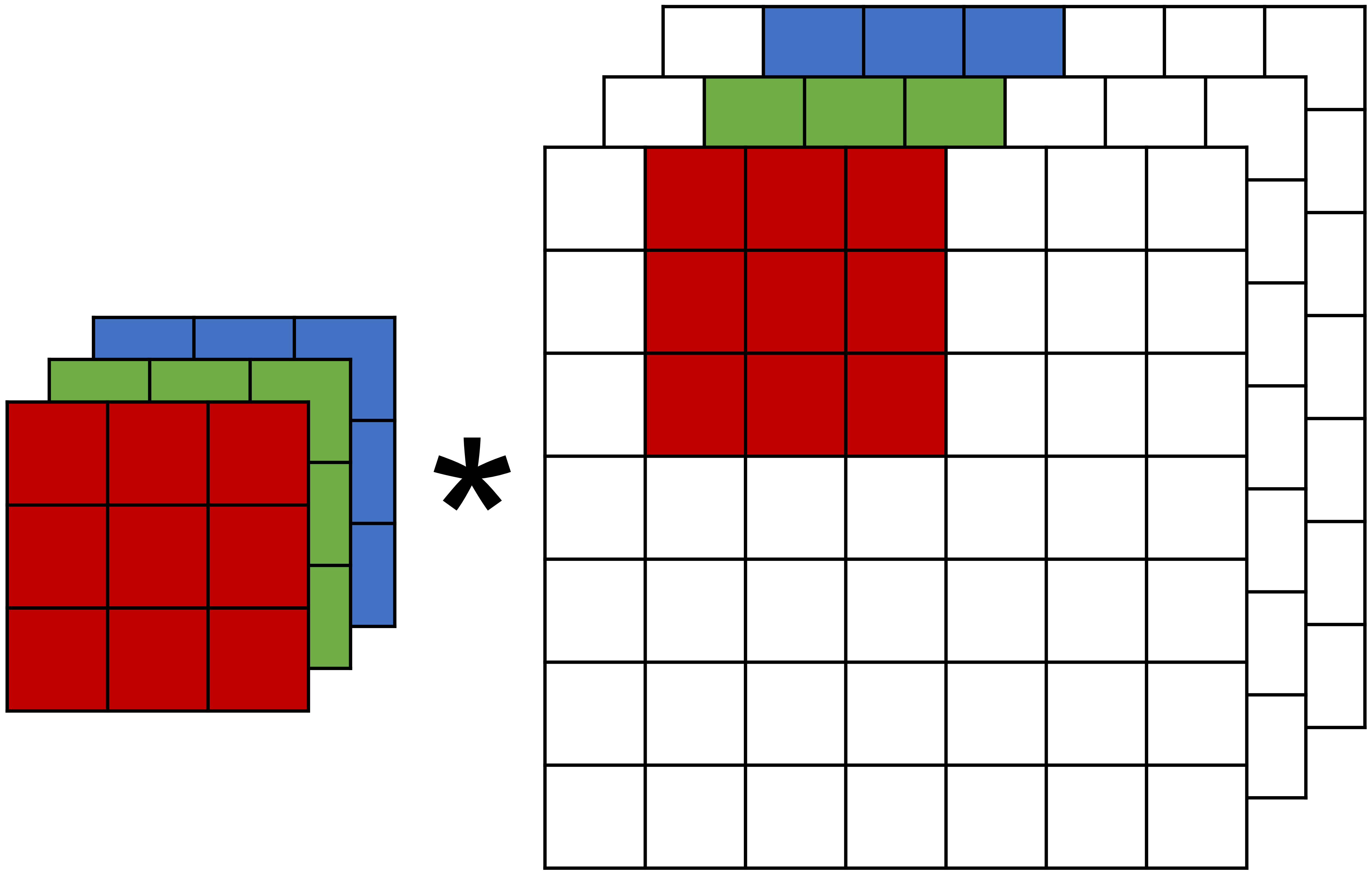

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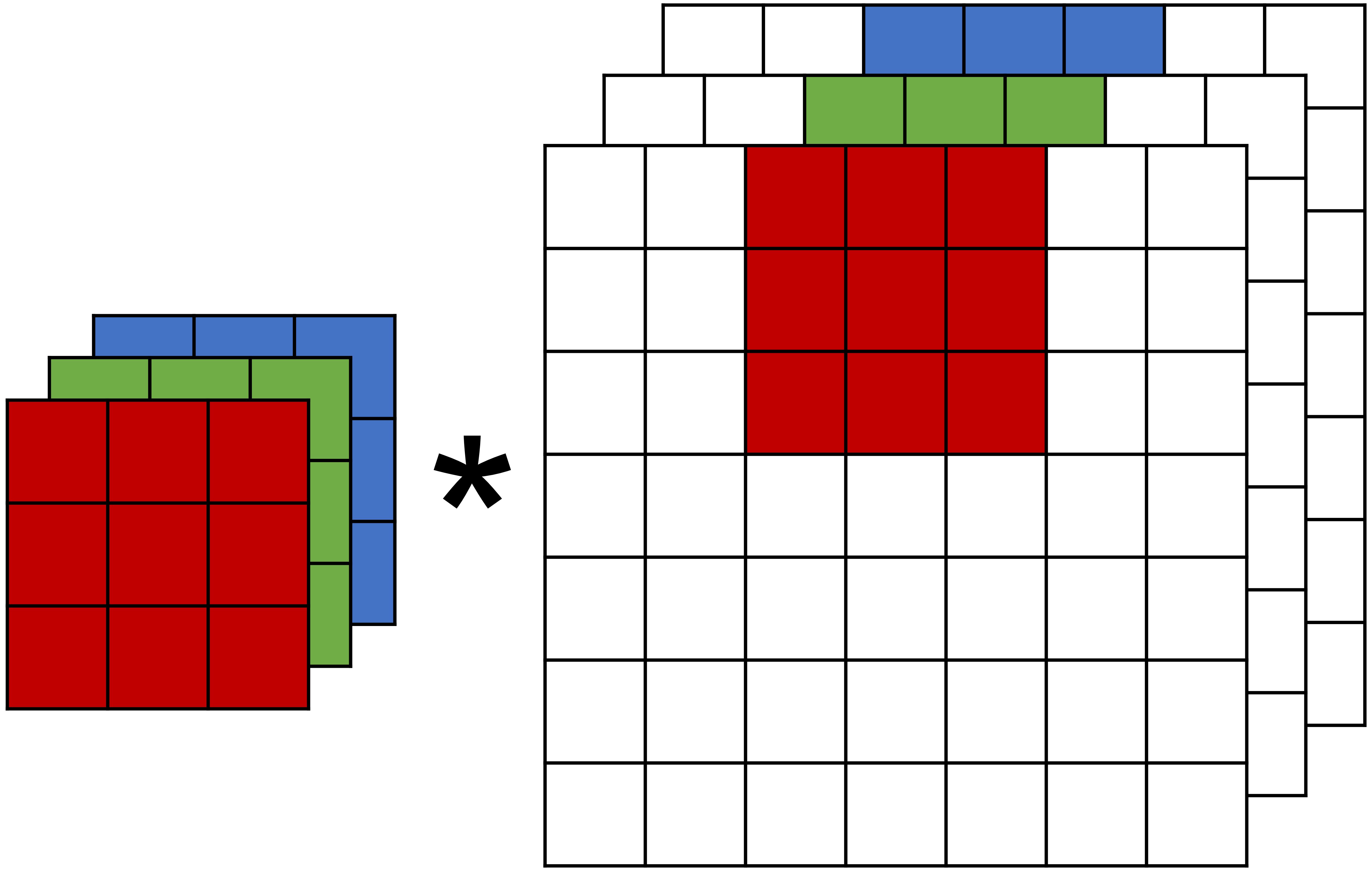
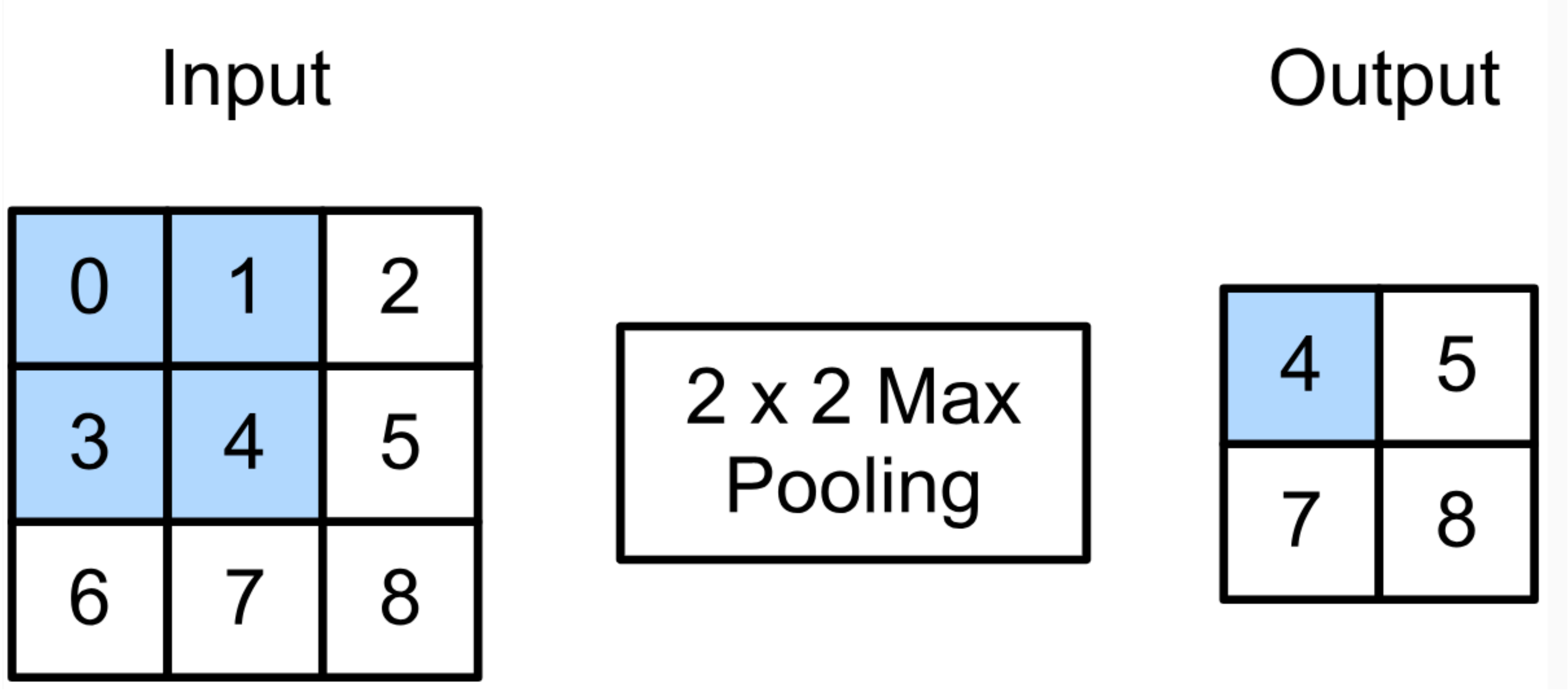
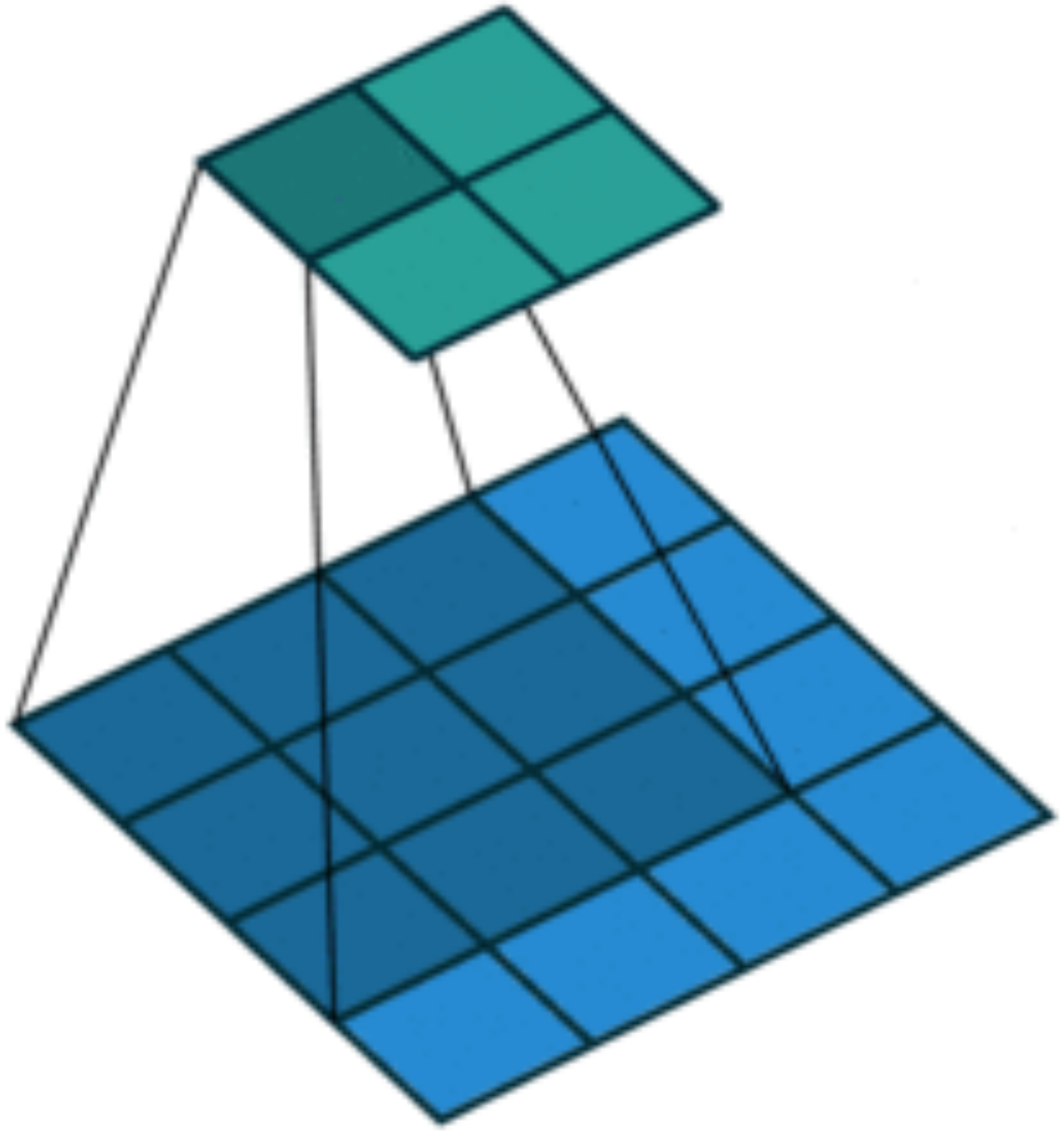


Review: 2-D Max Pooling

- Returns the maximal value in the sliding window



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



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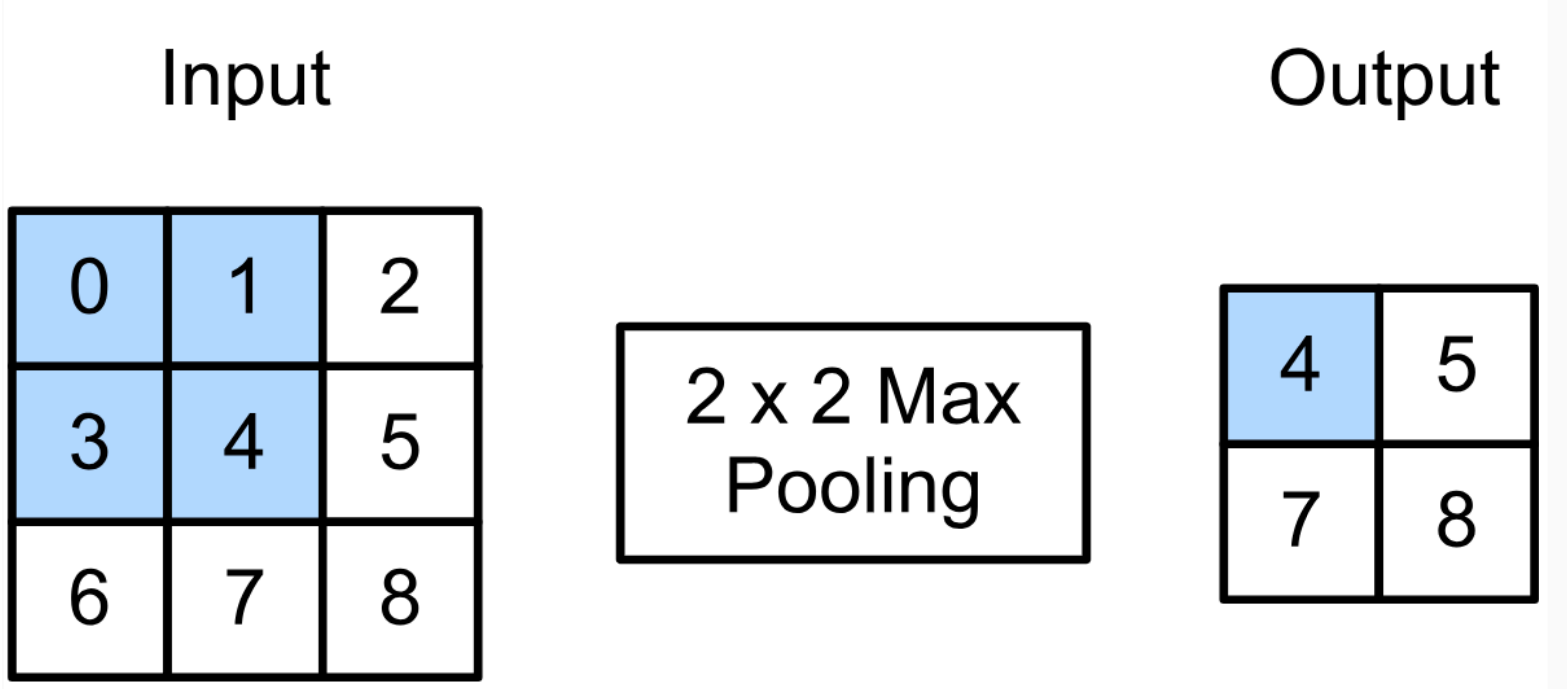

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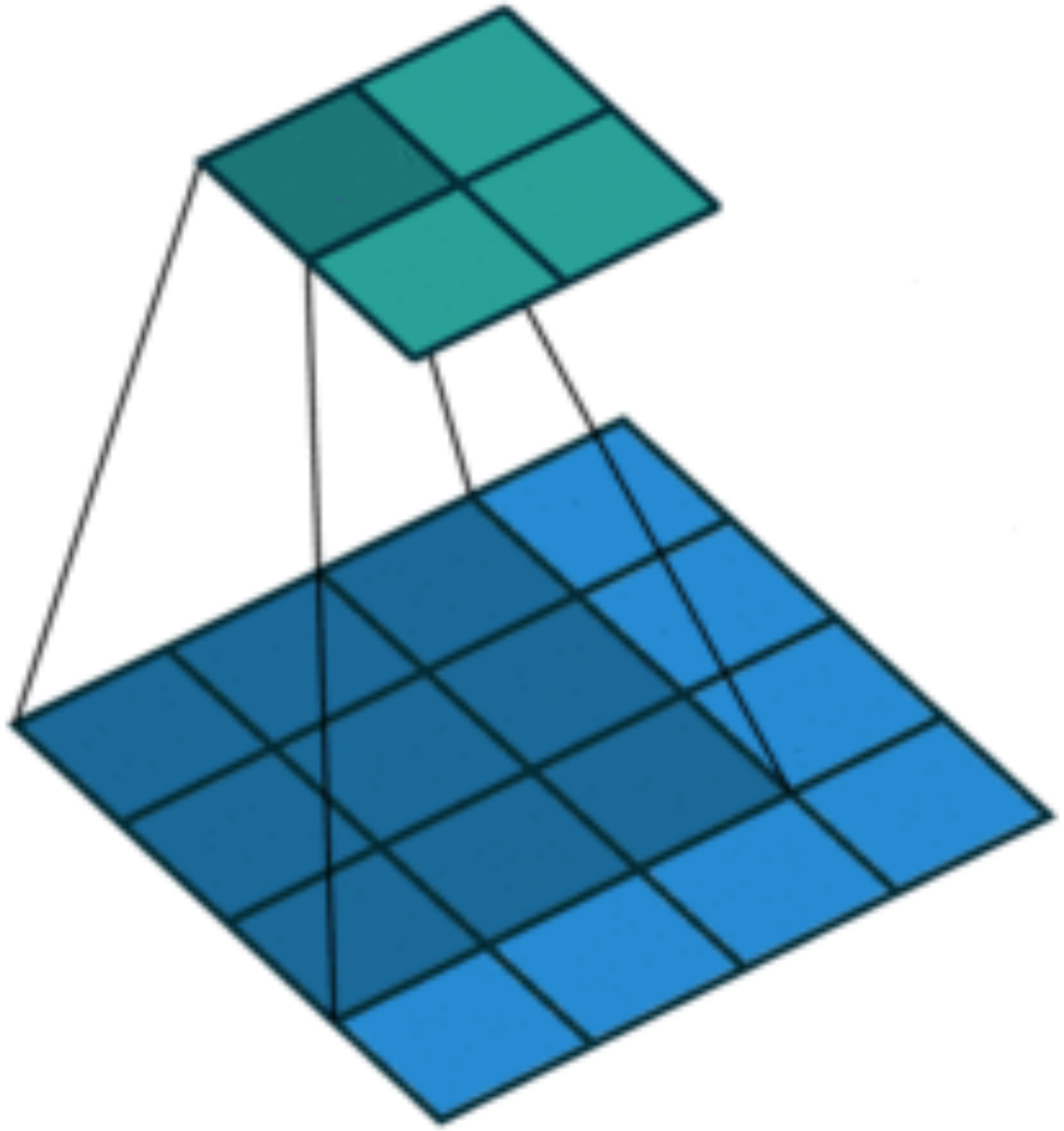

Convolutional Neural Networks

Evolution of neural net architectures

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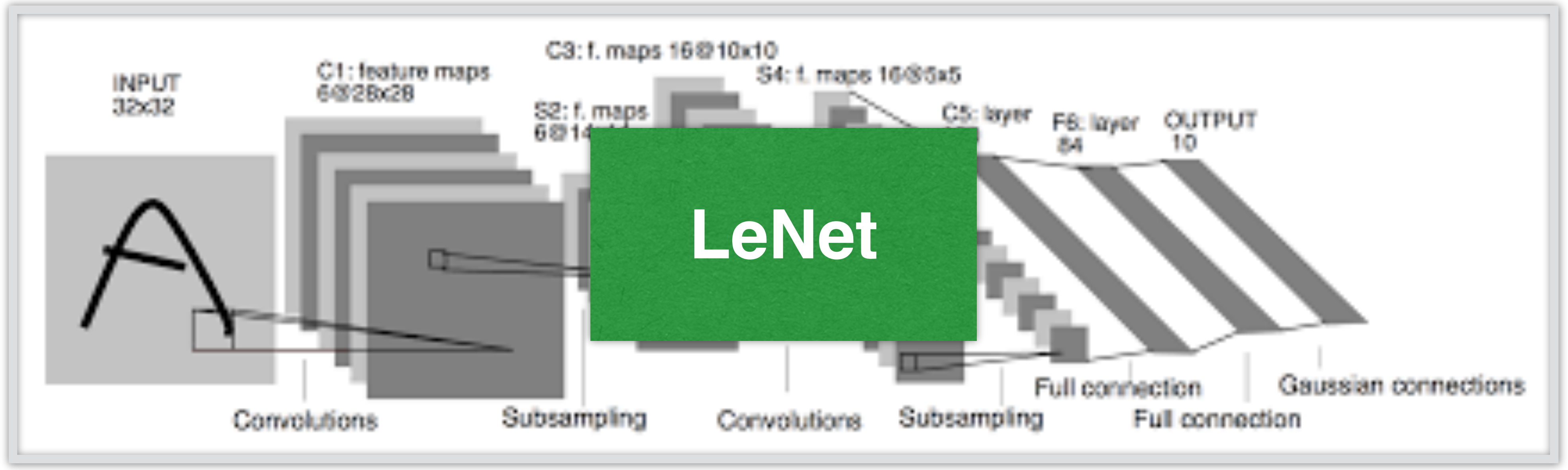
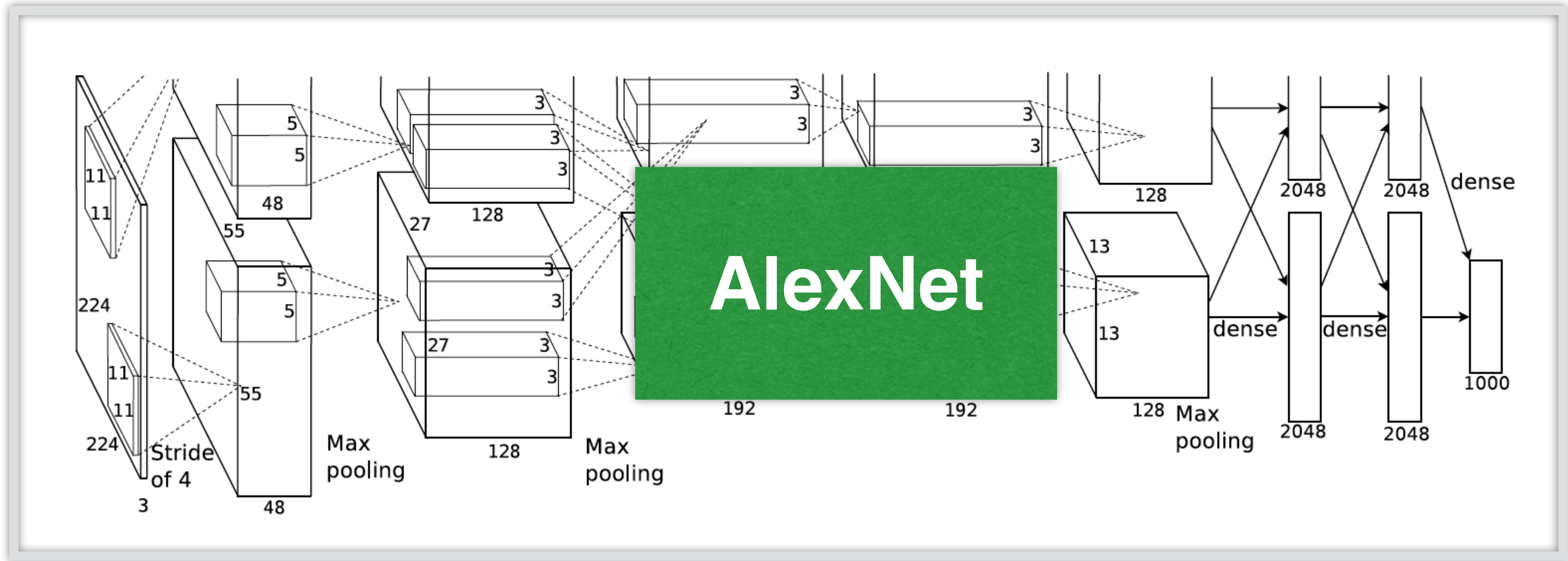
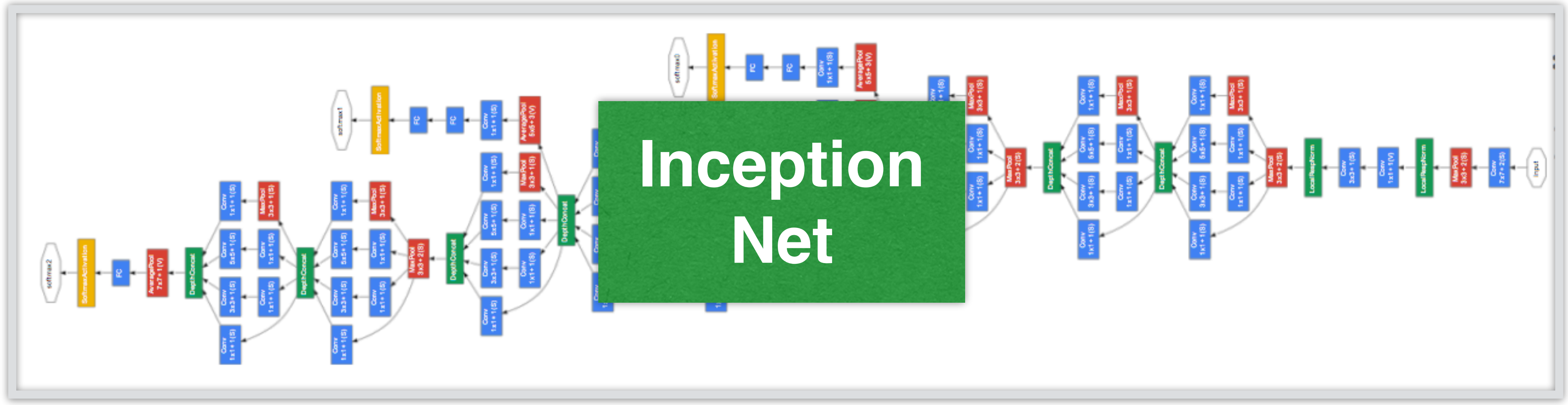
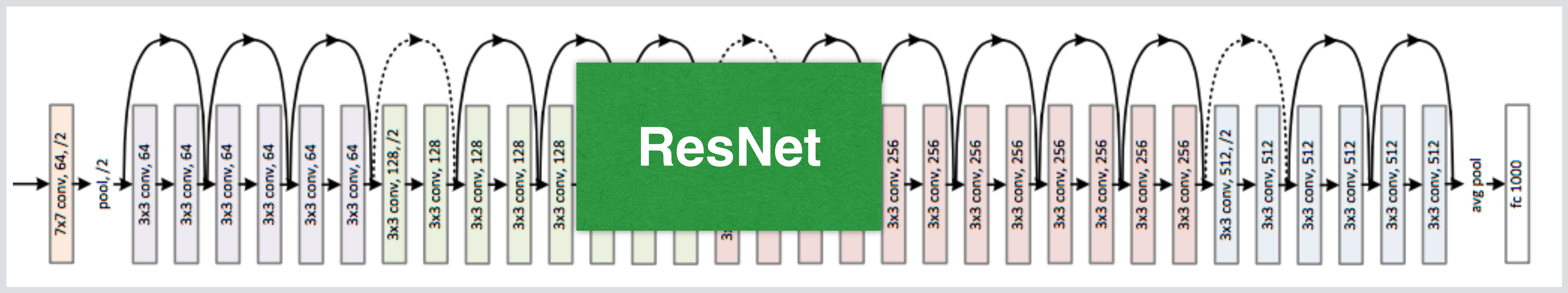
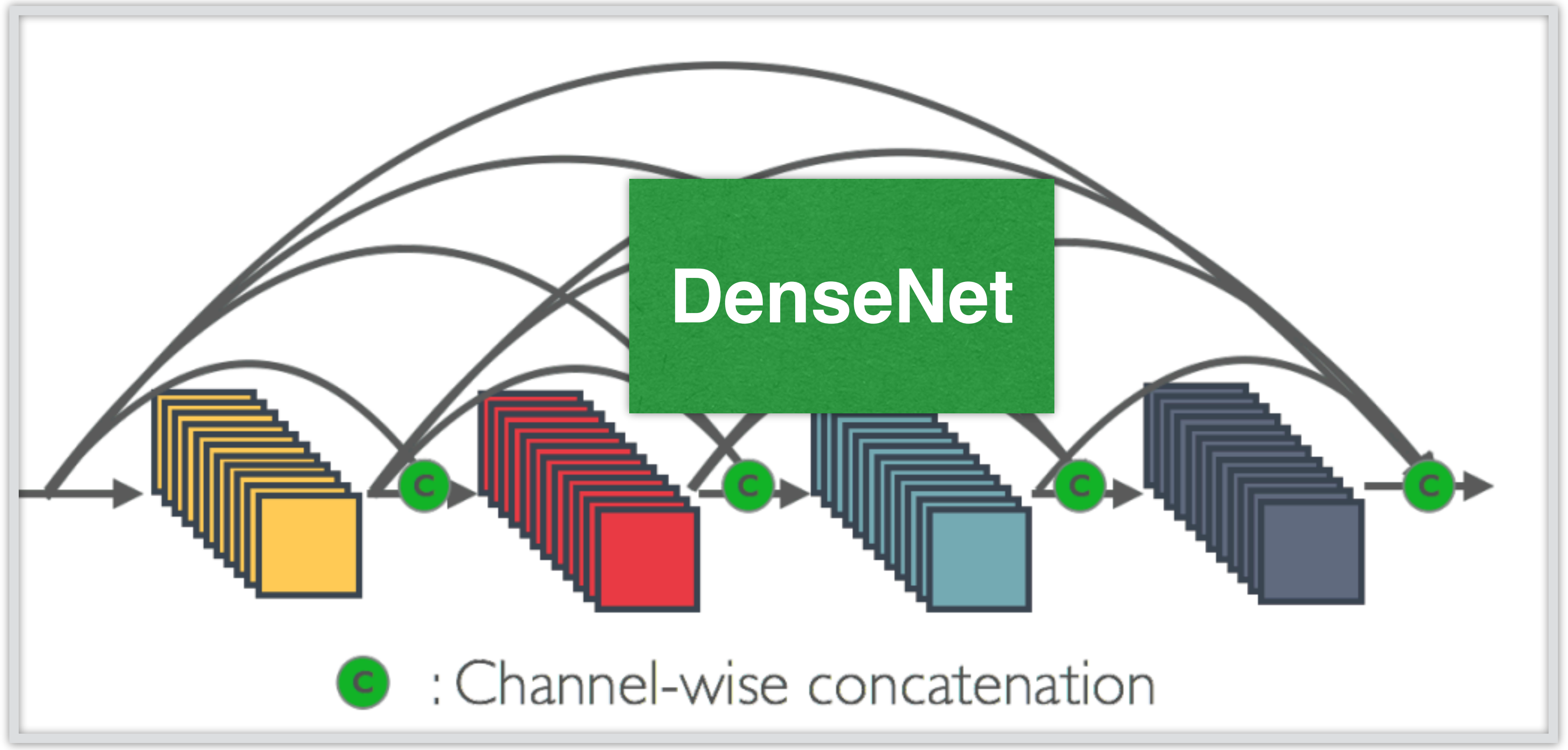


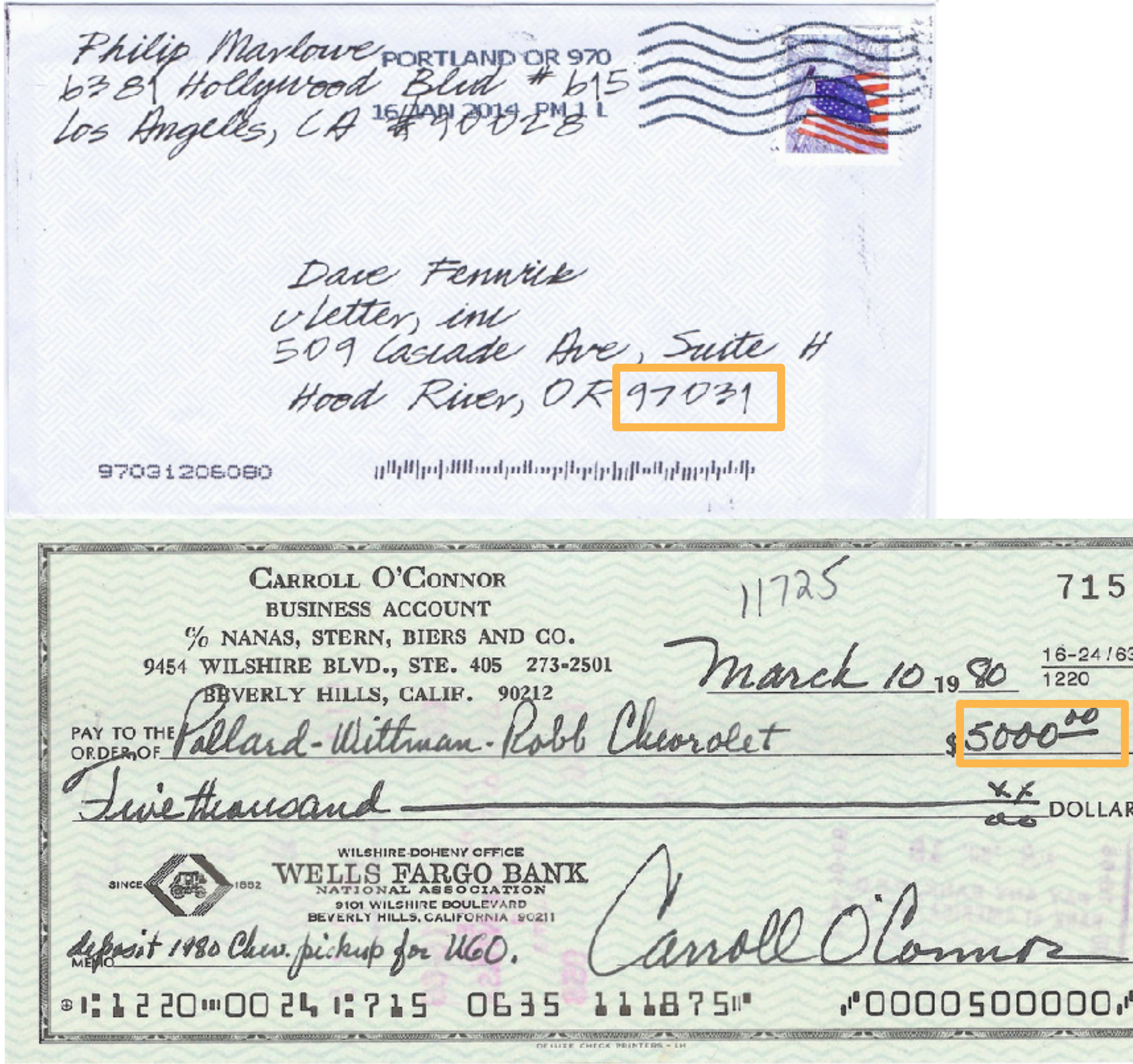






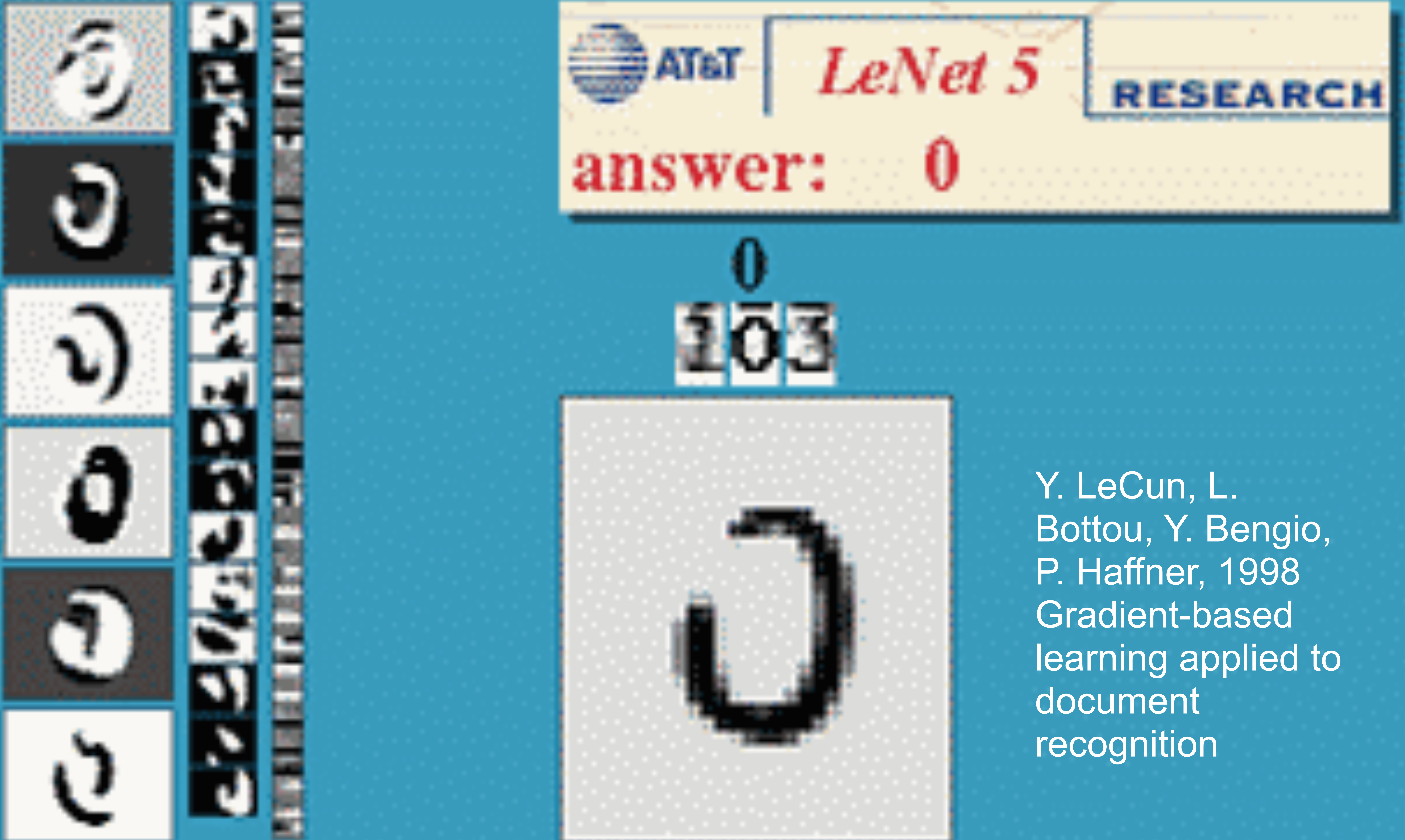


Handwritten Digit Recognition

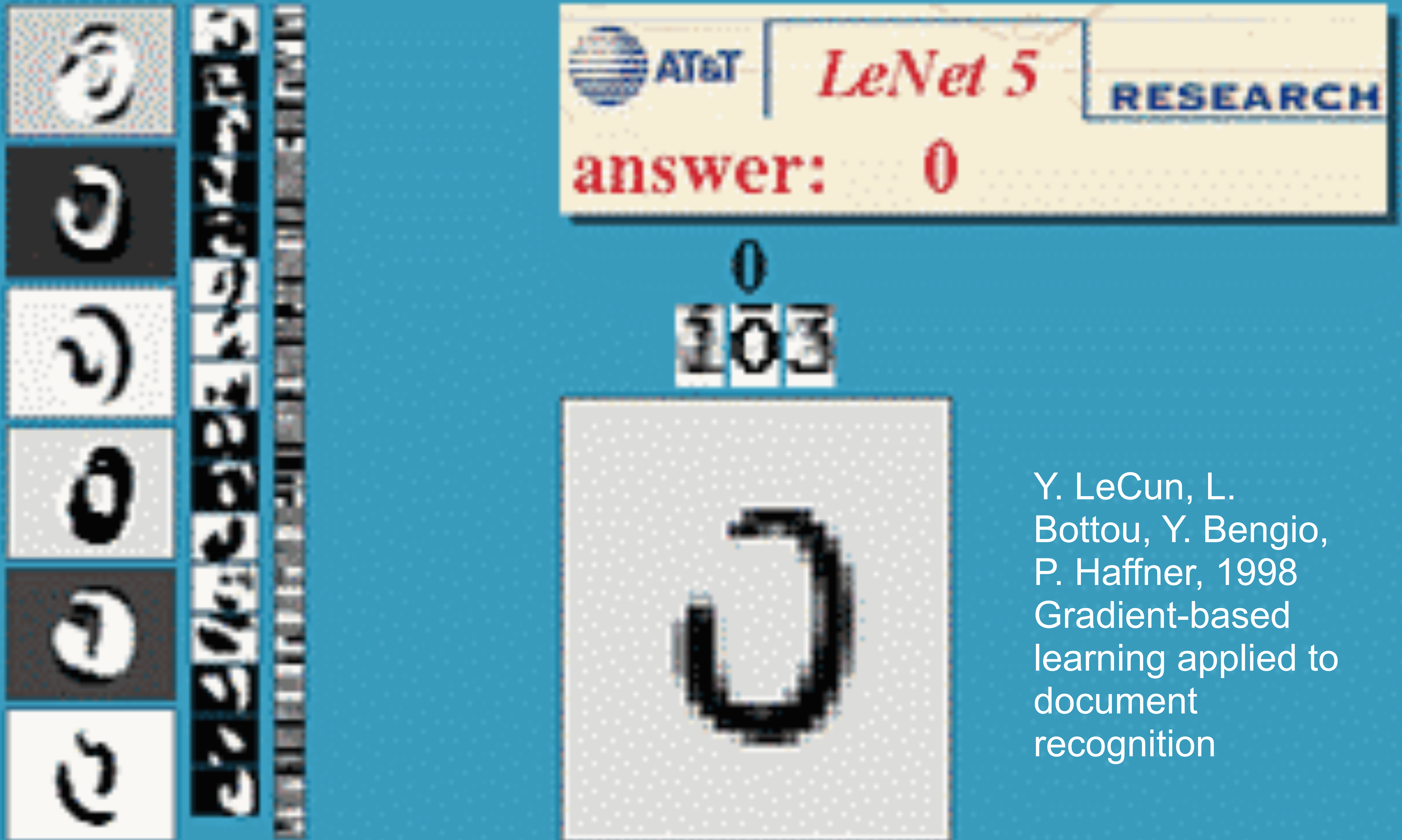


MNIST

- 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



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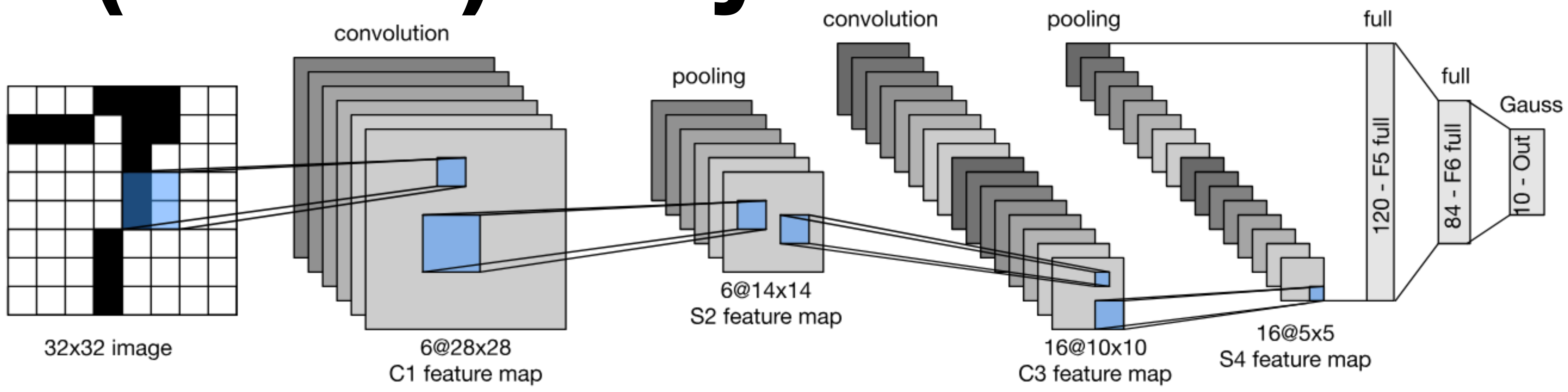
LeNet Architecture (first conv nets)

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

LeNet(variant) in Pytorch



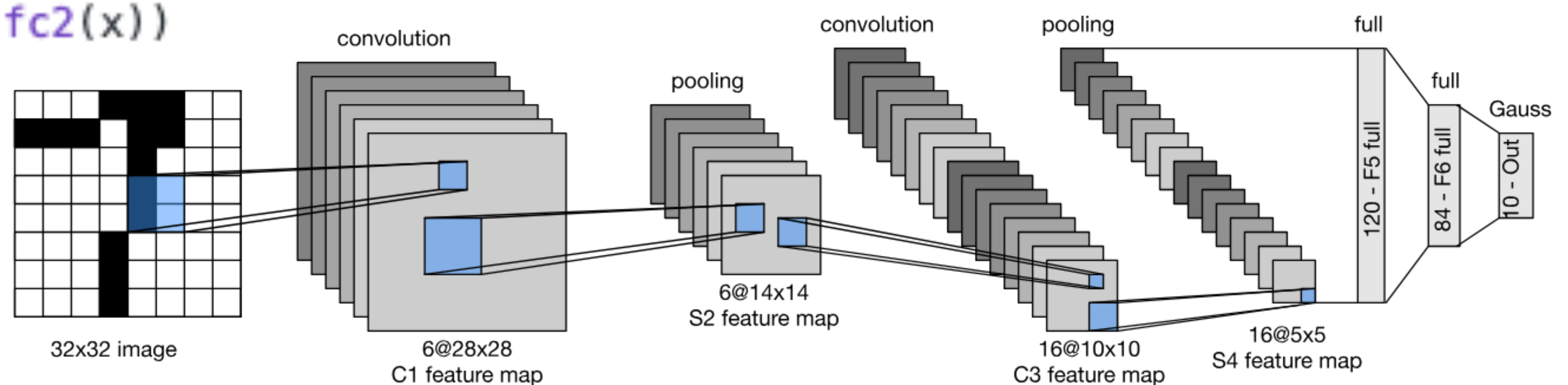

```python
def __init__(self):
    super(LeNet5, self).__init__()
    # Convolution (In LeNet-5, 32x32 images are given as input. Hence padding of 2 is done below)
    self.conv1 = torch.nn.Conv2d(in_channels=1, out_channels=6, kernel_size=5, stride=1, padding=2, bias=True)
    # Max-pooling
    self.max_pool_1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

```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
```

LeNet(variant) in Pytorch



Deng et al. 2009

AlexNet

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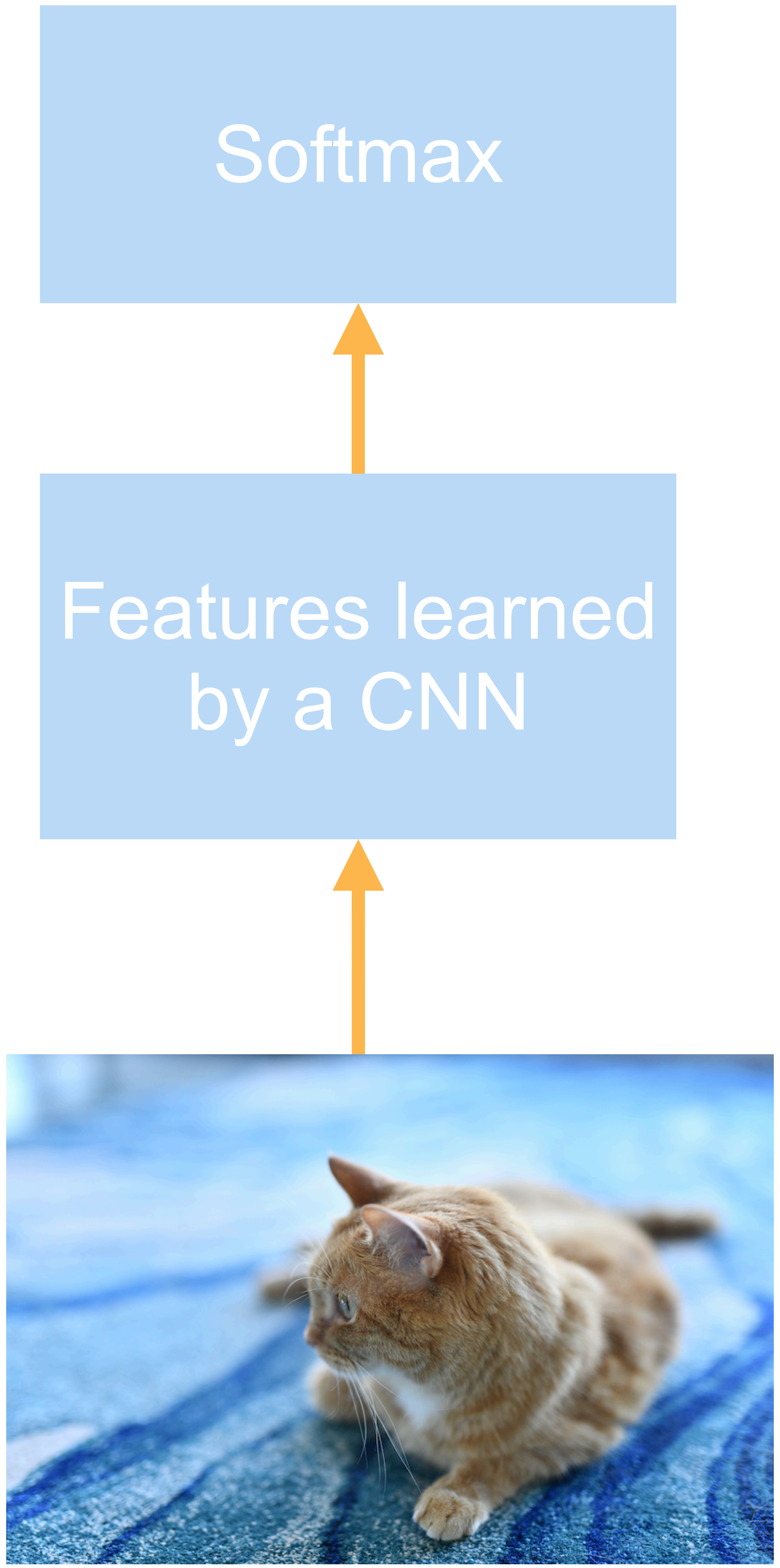

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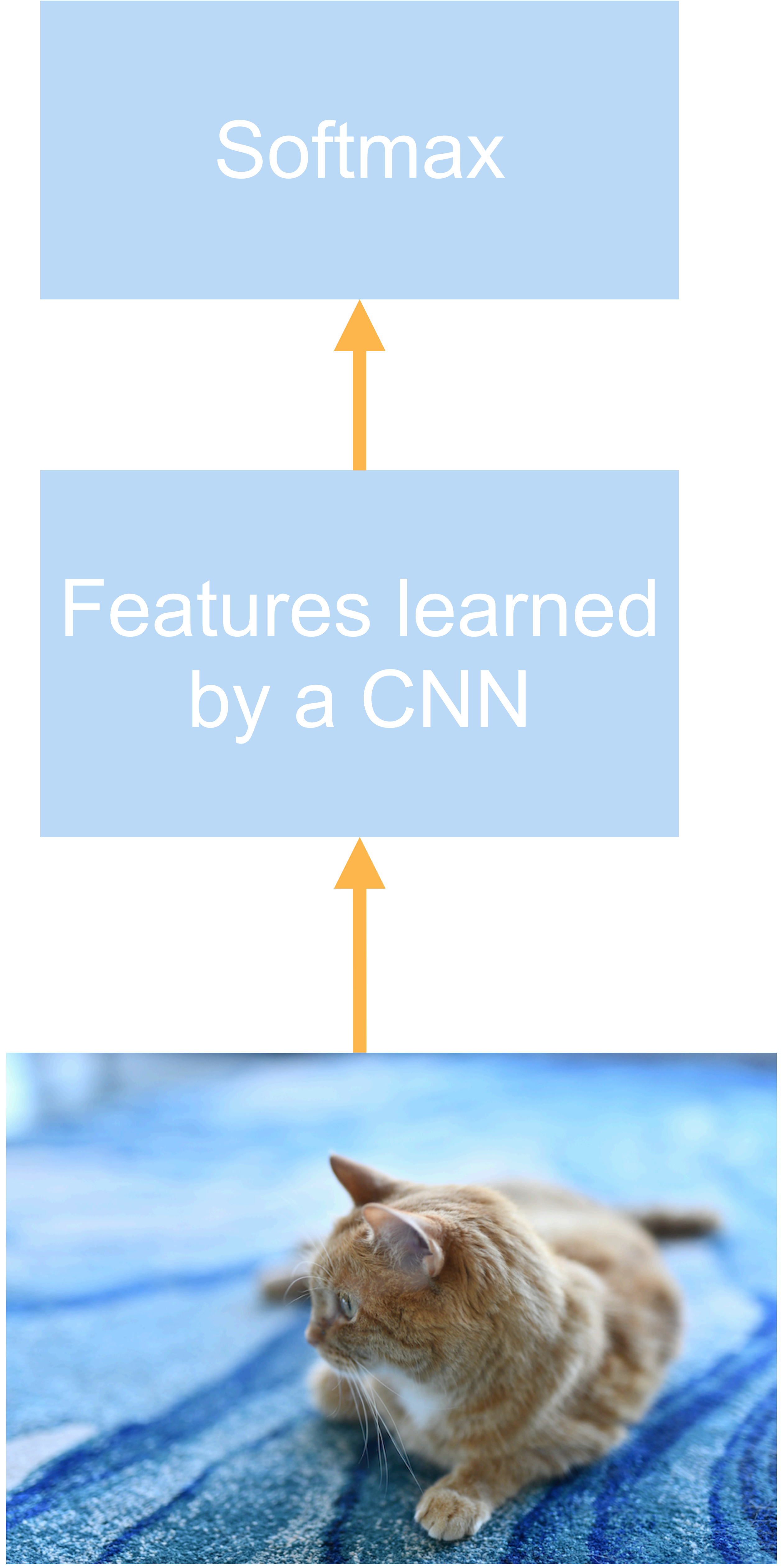
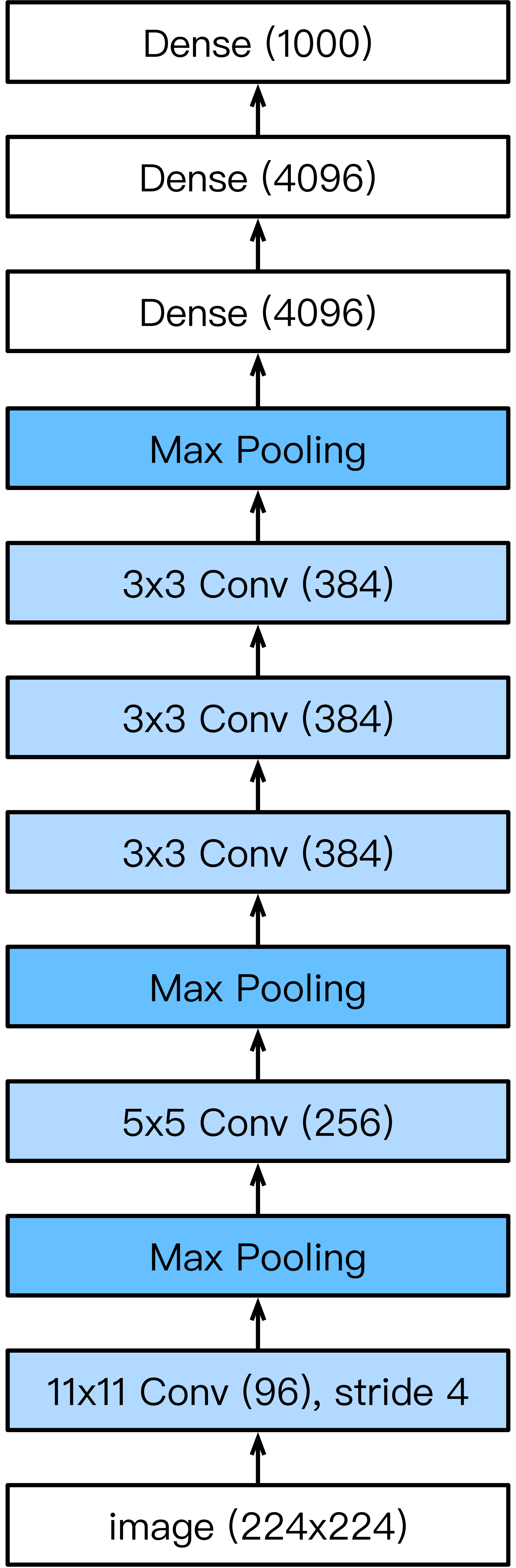
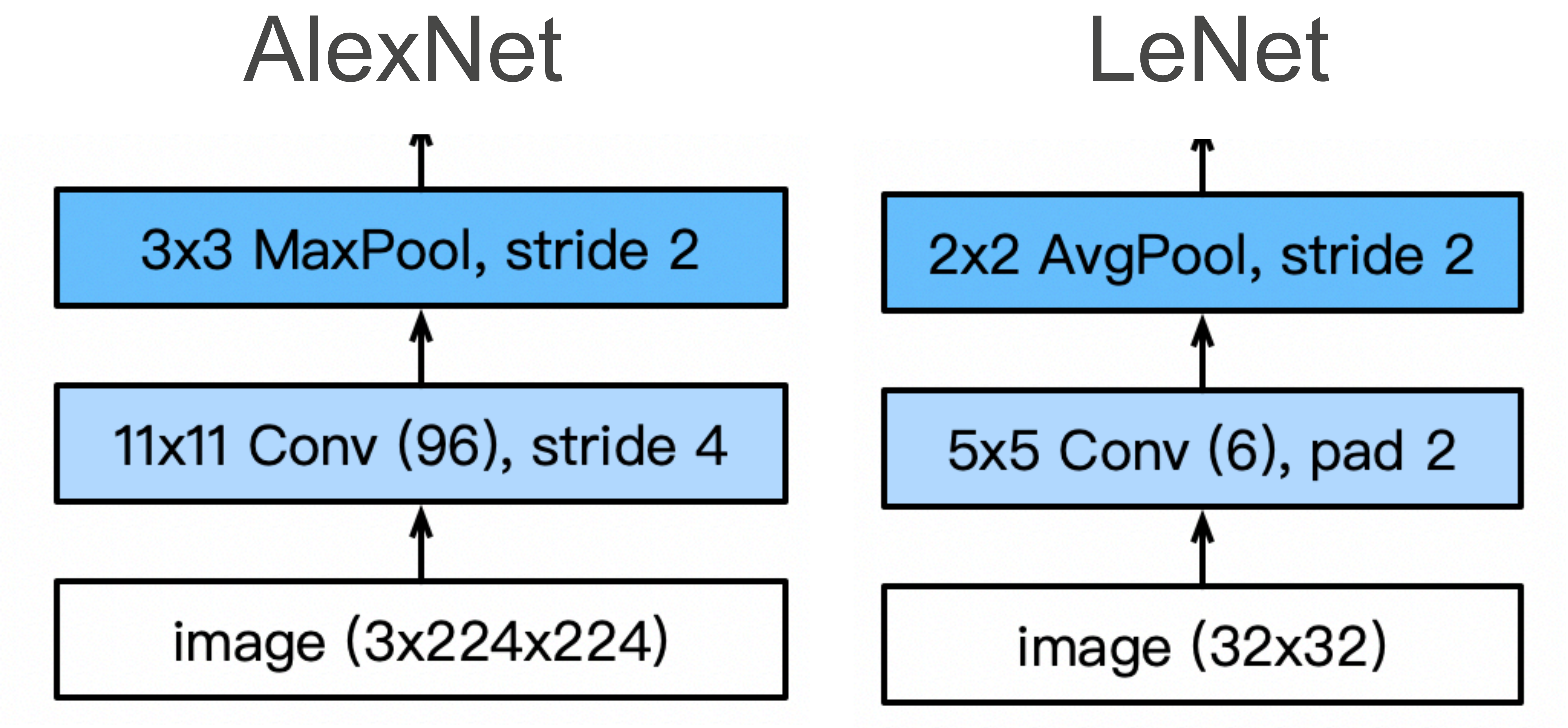


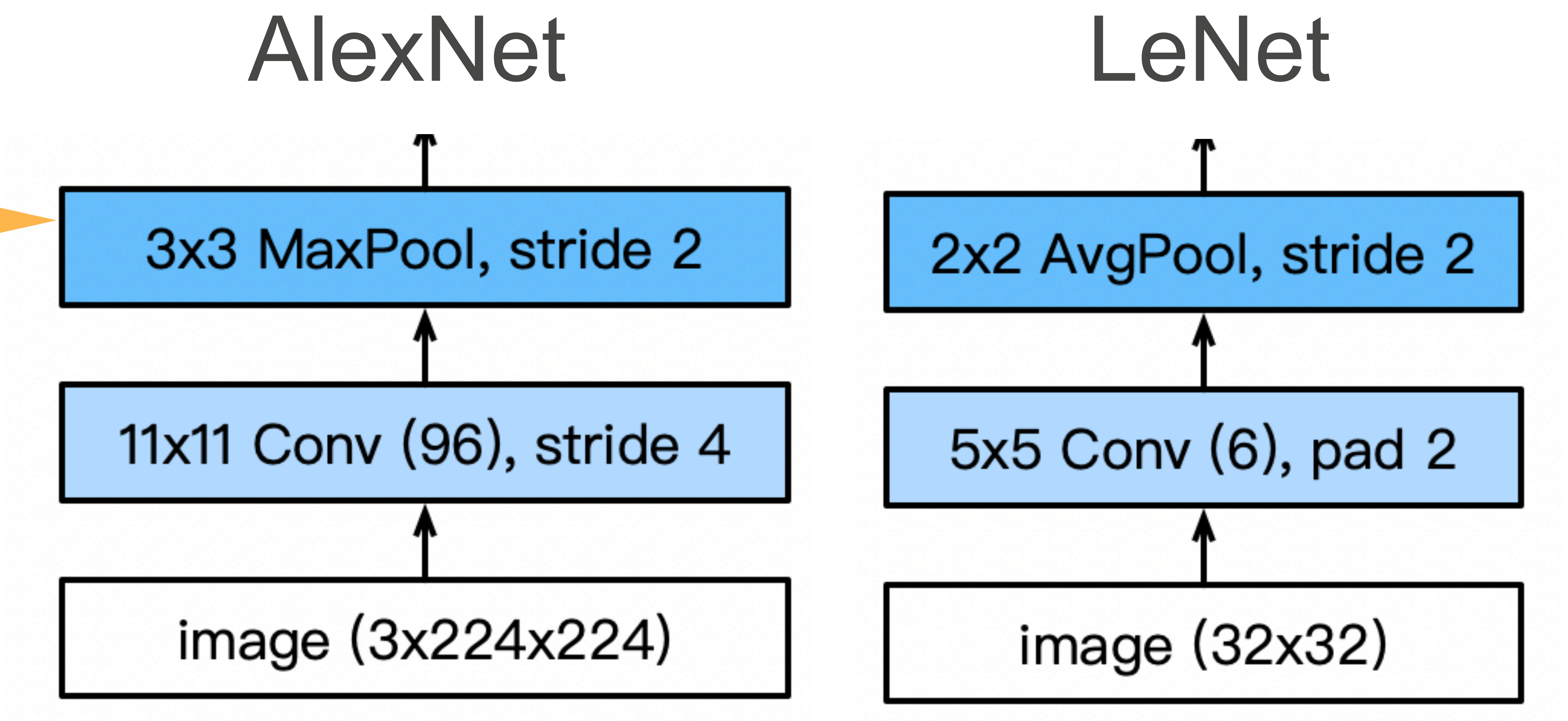


AlexNet Architecture



AlexNet Architecture

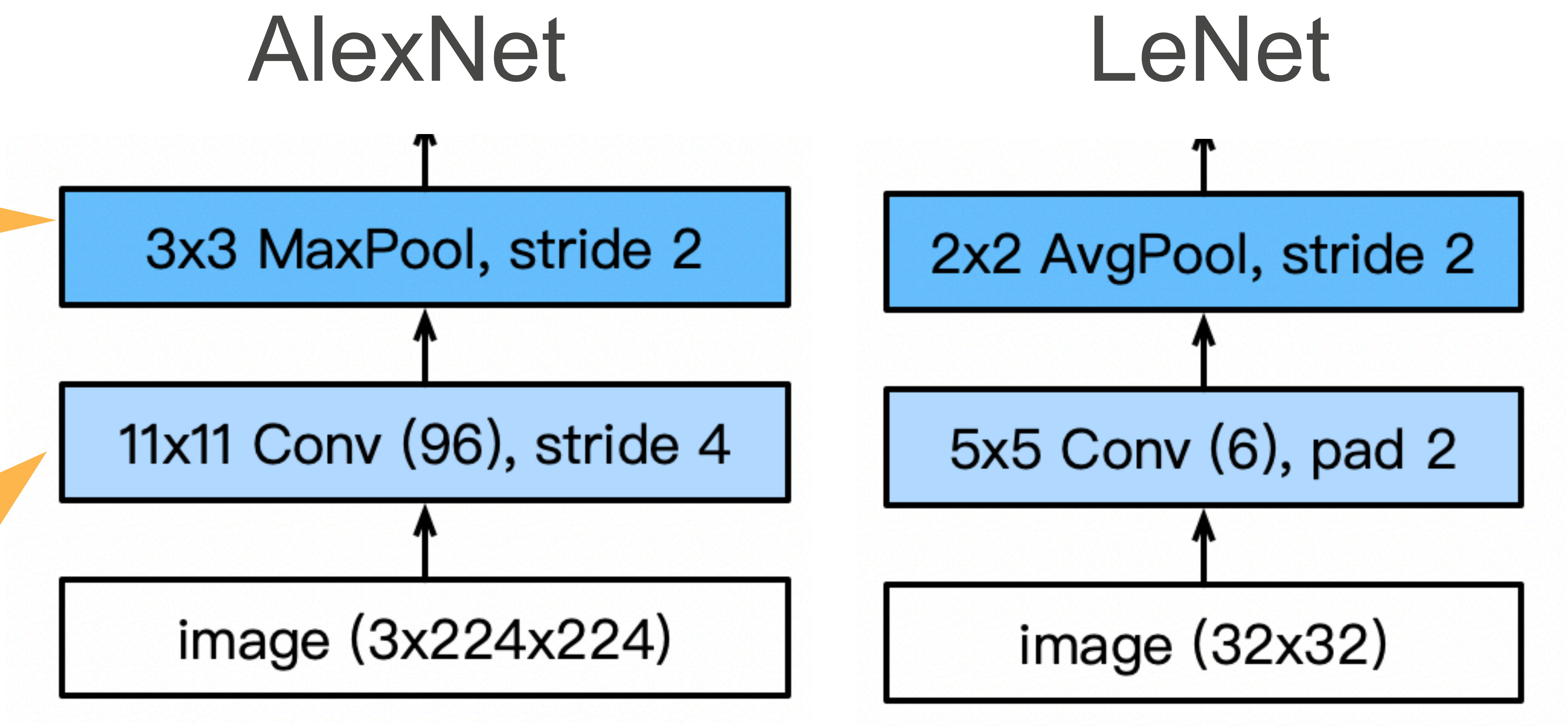
Larger pool size



AlexNet Architecture

Larger pool size

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



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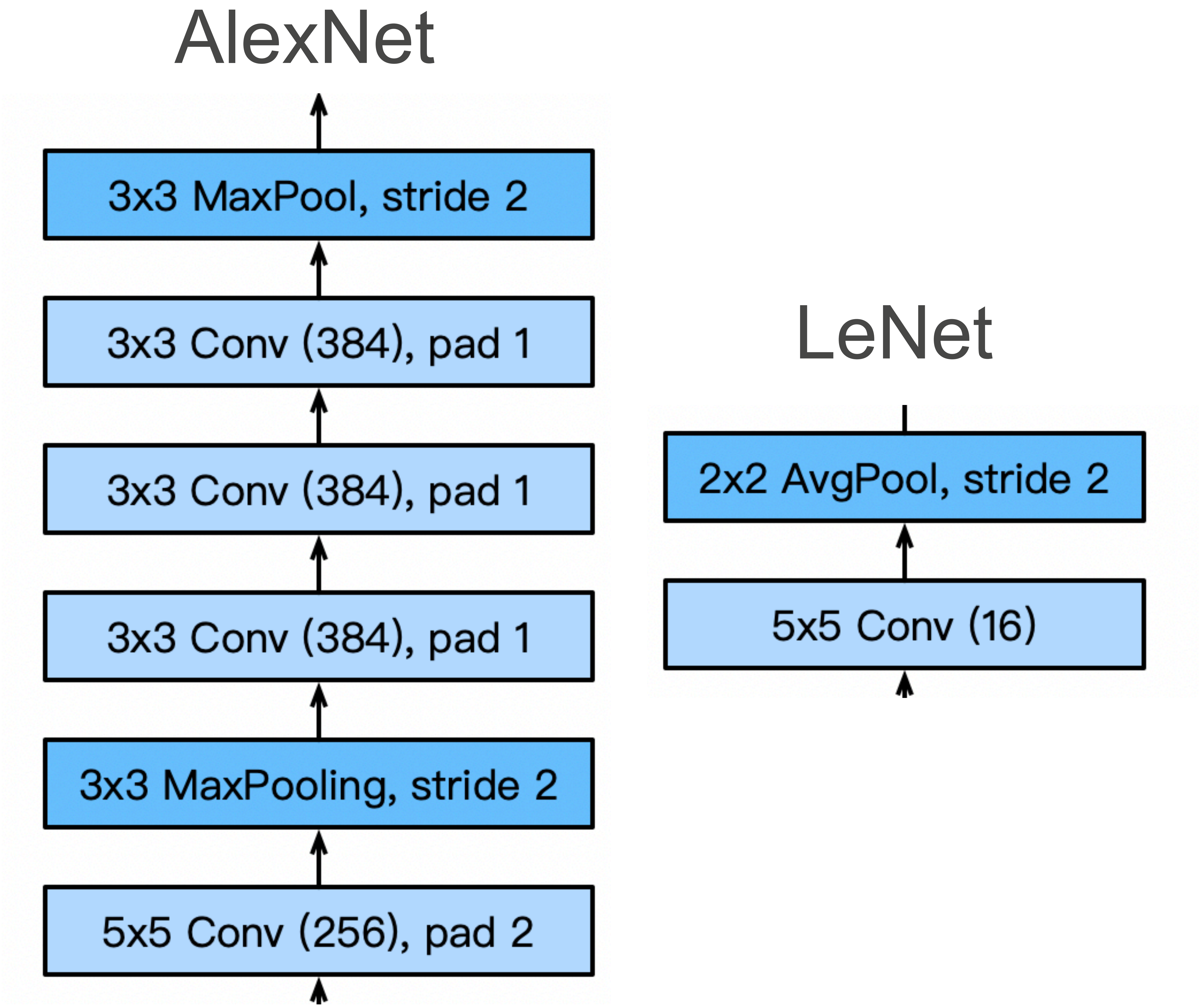

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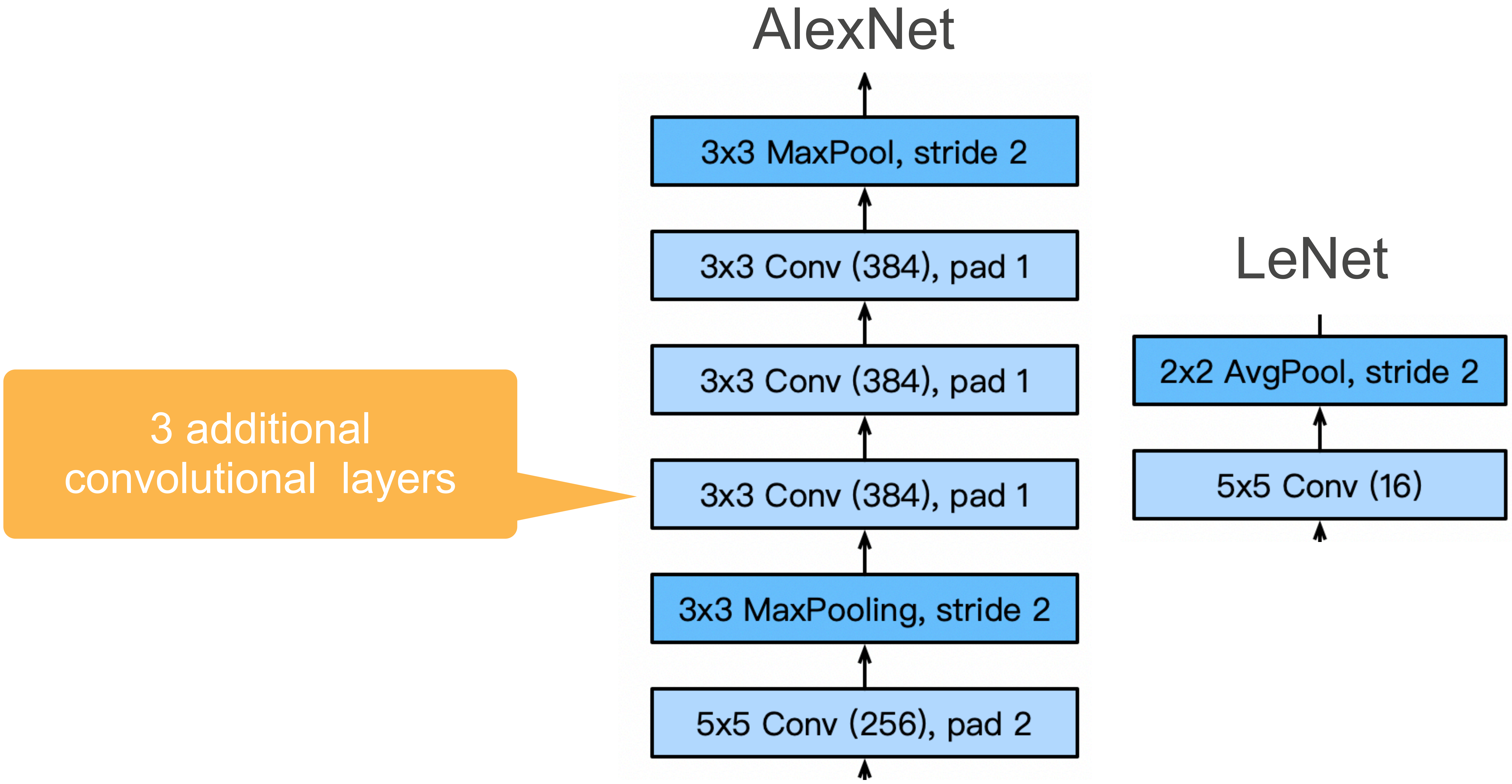
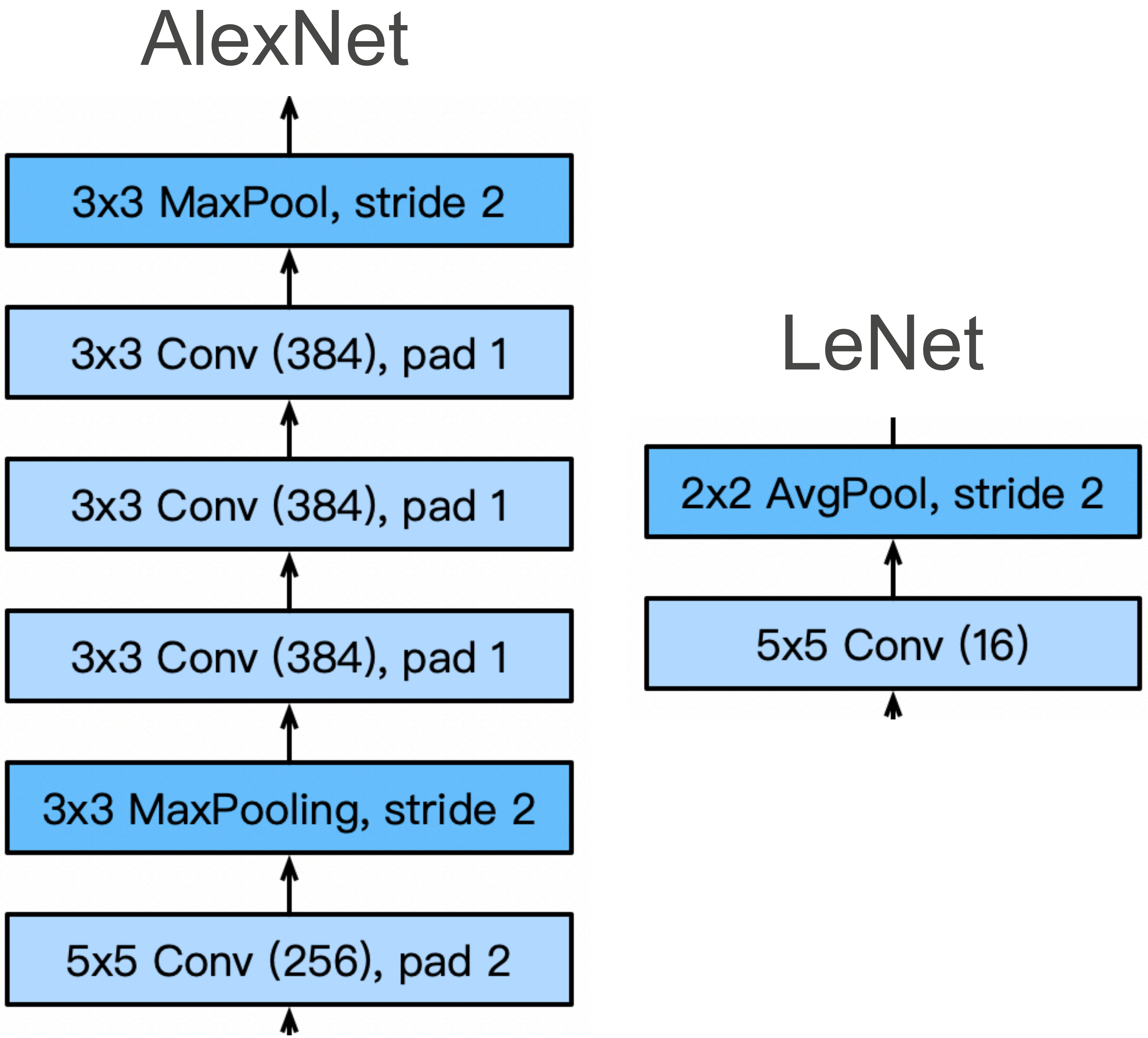


AlexNet Architecture

3 additional convolutional layers

More output channels.



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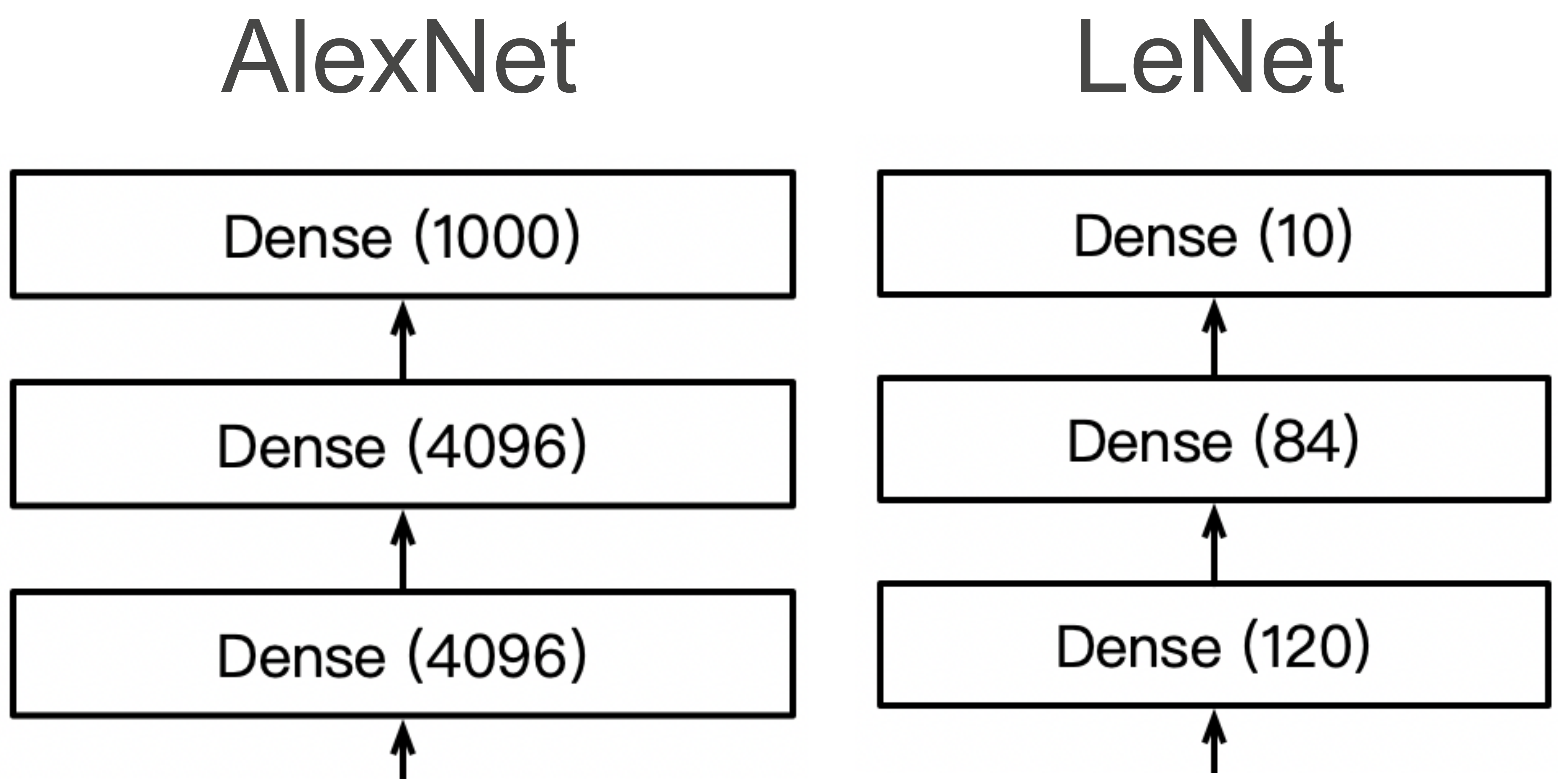
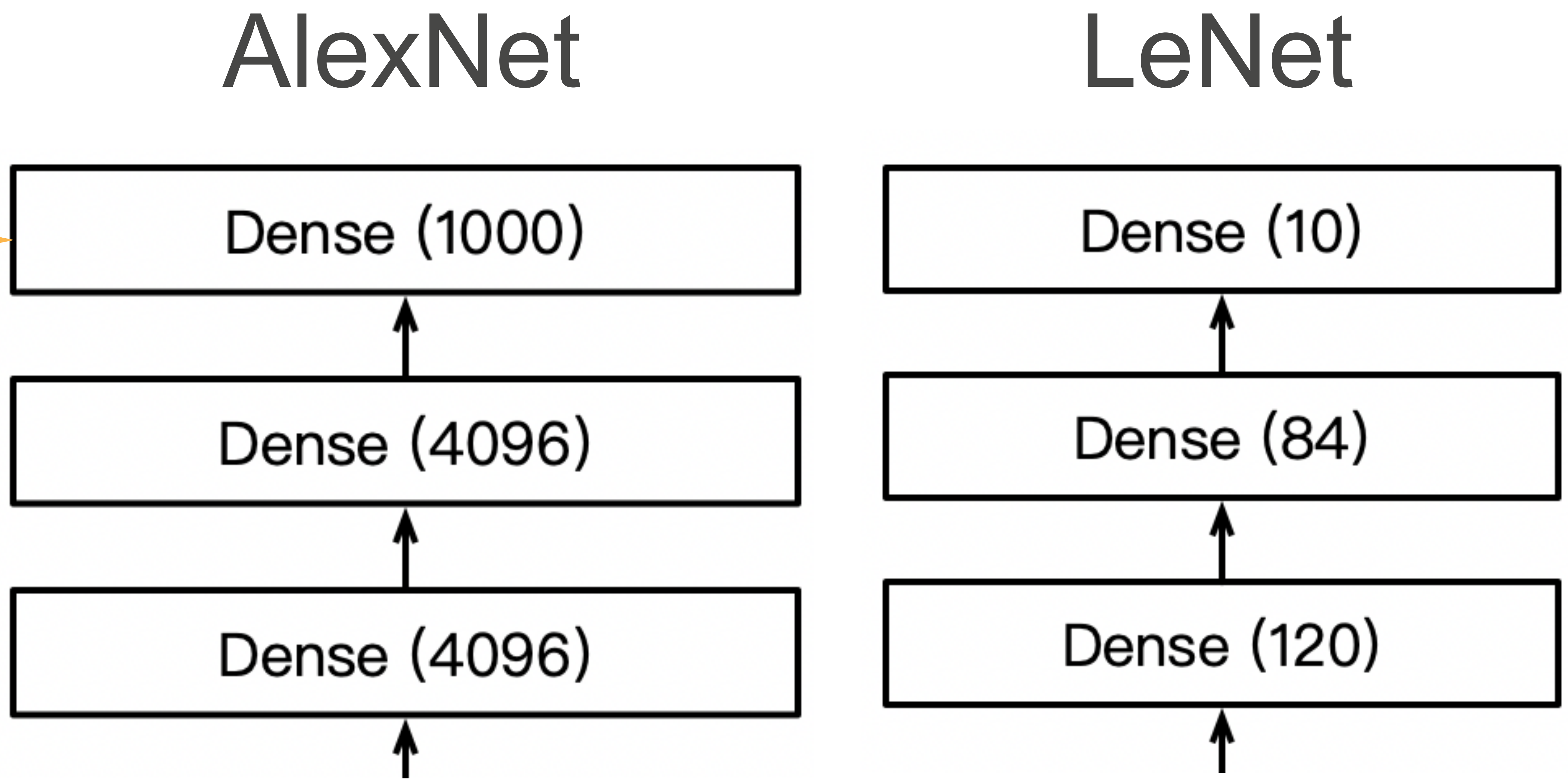
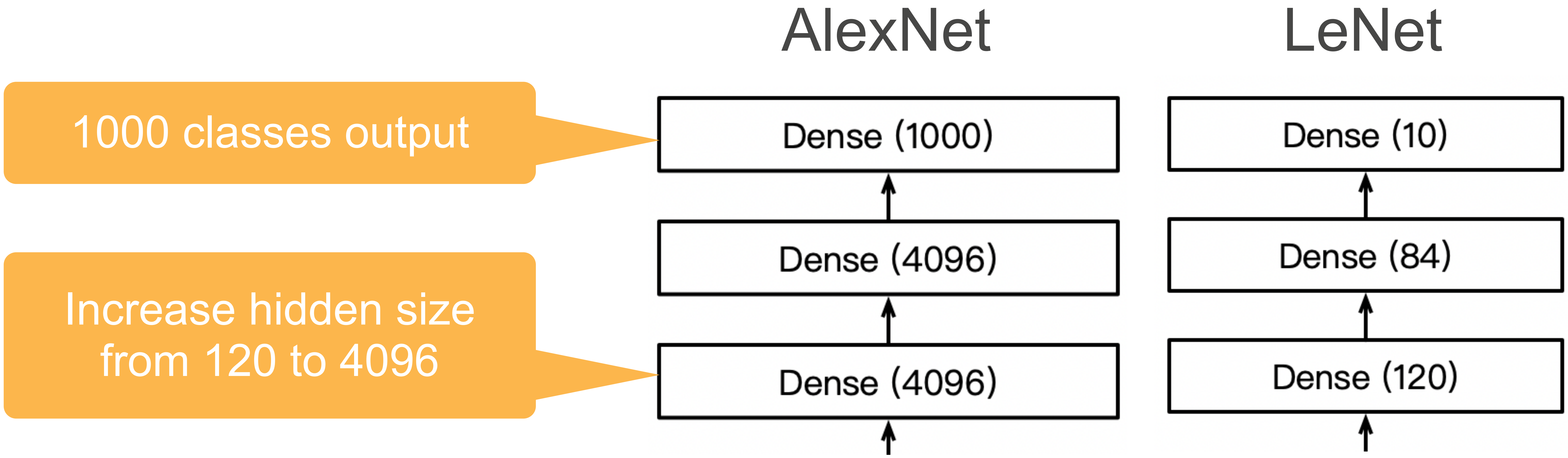


AlexNet Architecture

1000 classes output

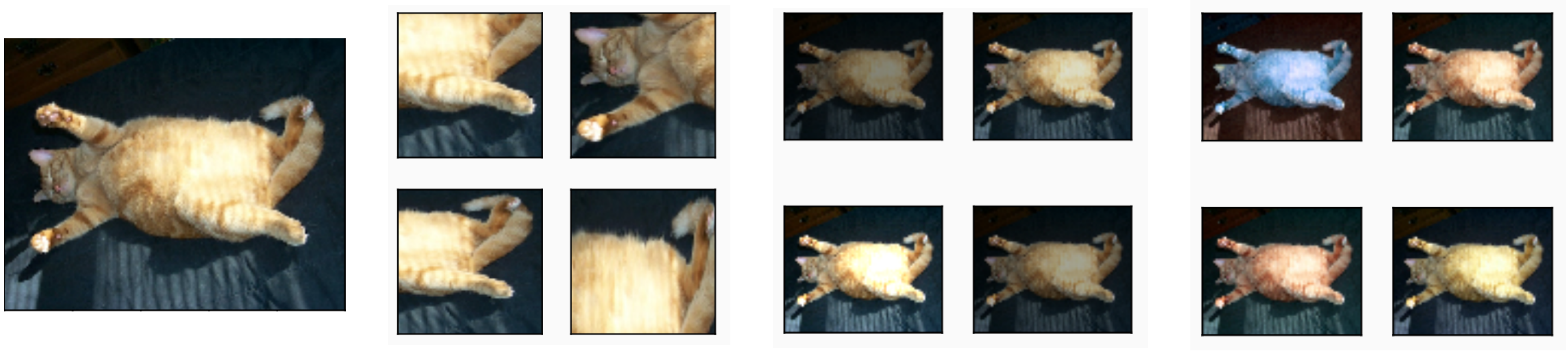


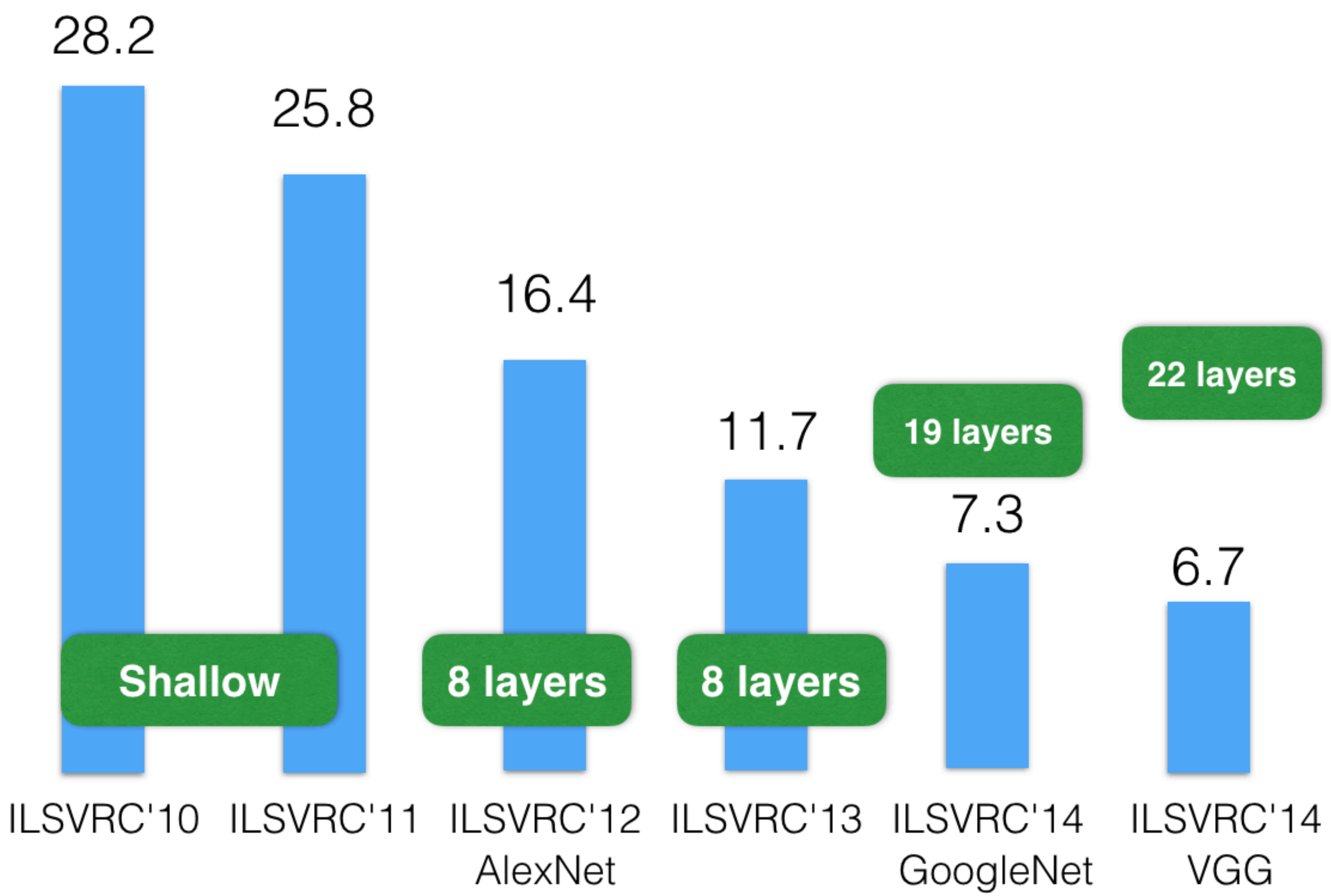
AlexNet Architecture



More Differences…

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





ImageNet Top-5 Classification Error (%)

Simple Idea: Add More Layers

- VGG: 19 layers. ResNet: 152 layers. Add more layers sufficient?

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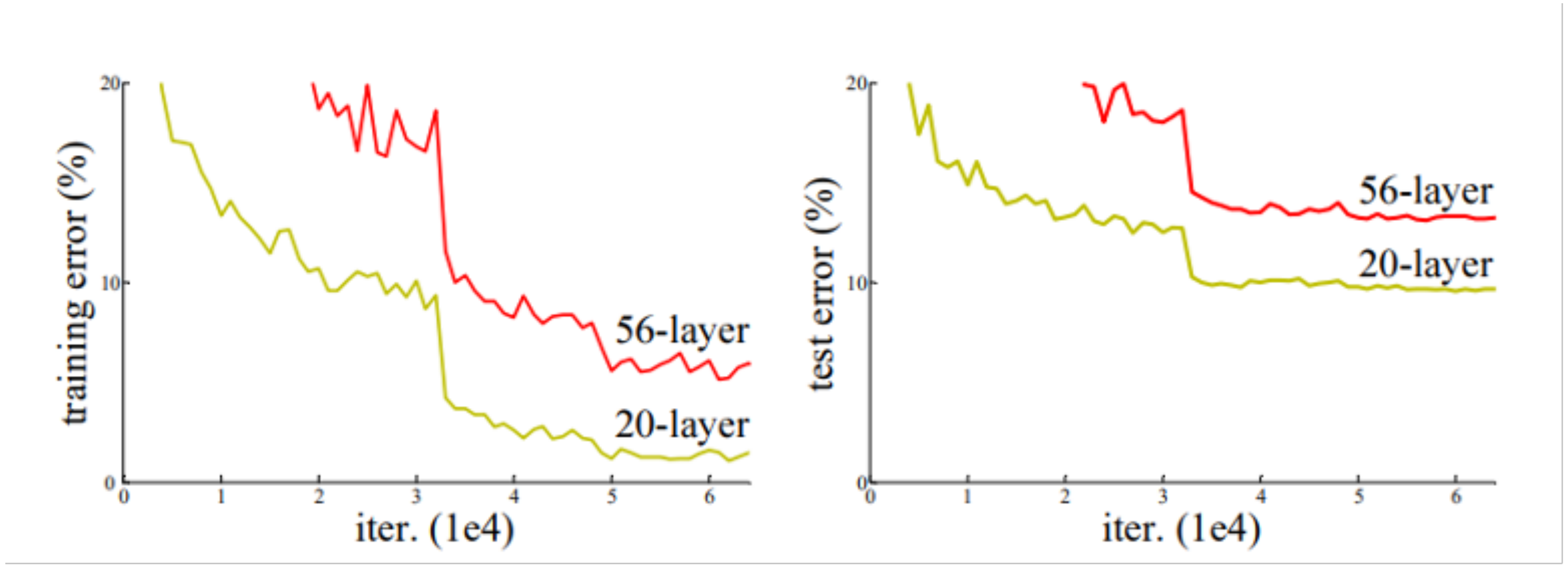
Reflected in training error:



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

Depth Issues & Learning Identity

- Why would more layers result in worse performance

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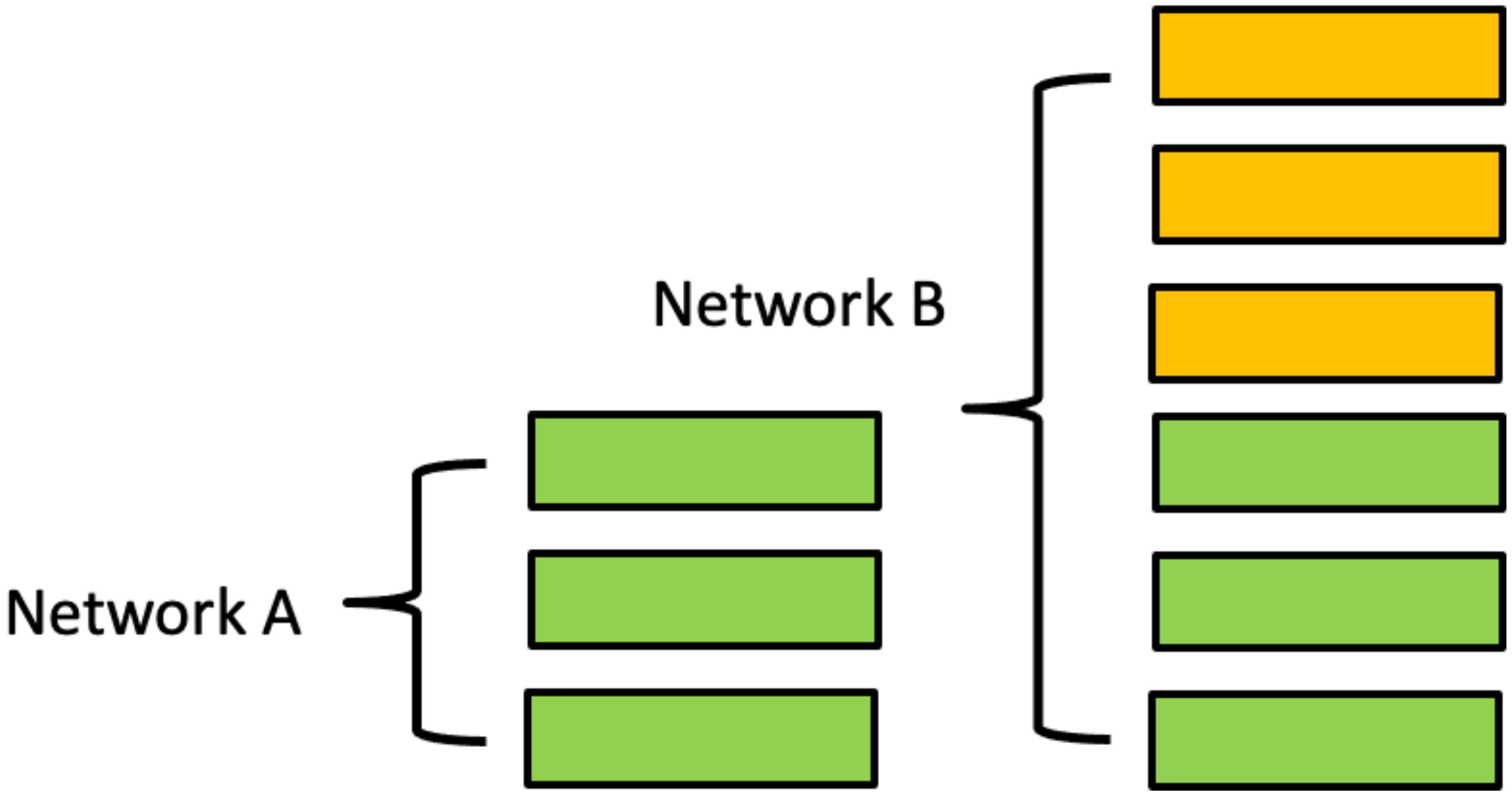

Depth Issues & Learning Identity

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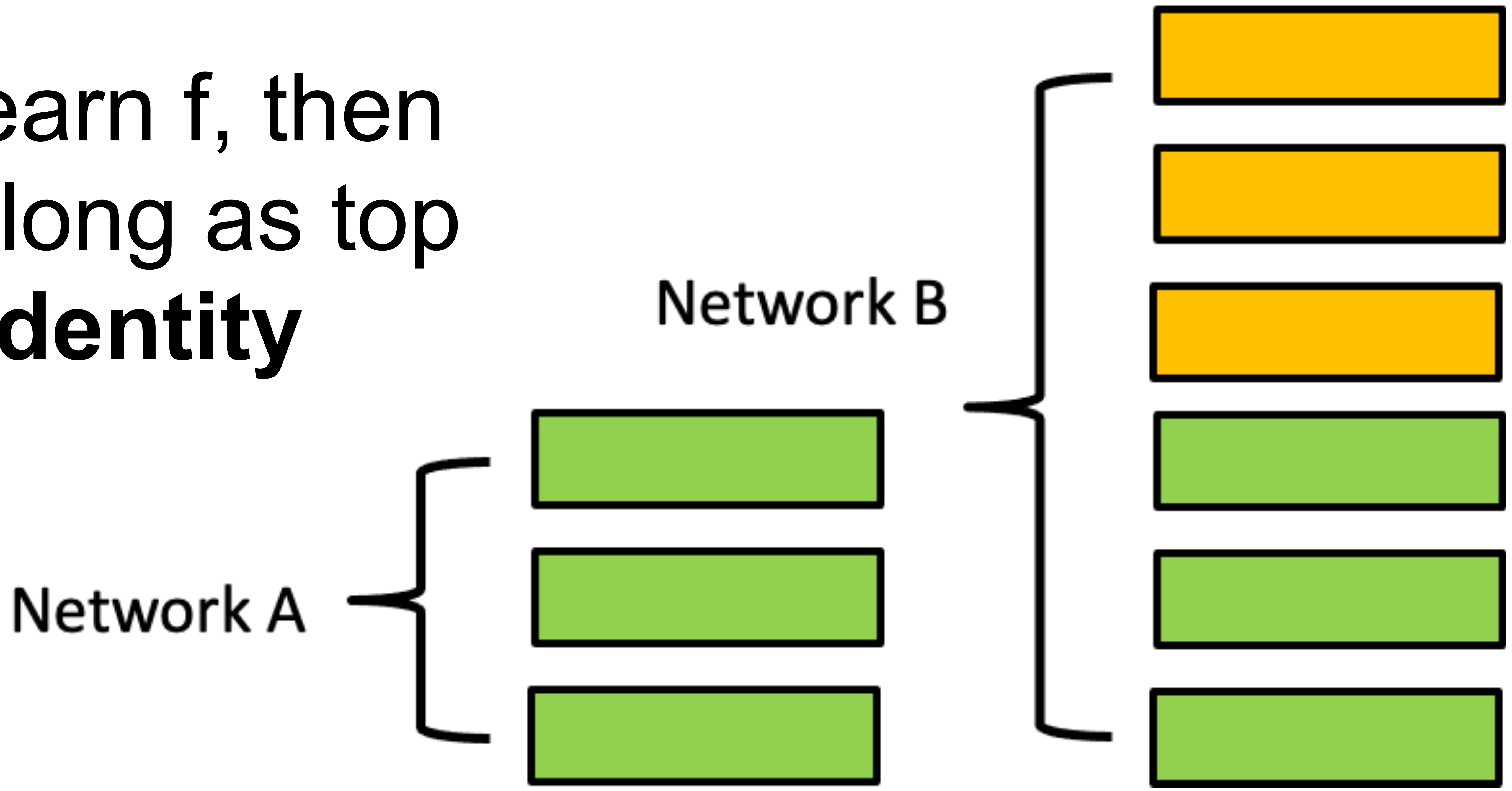

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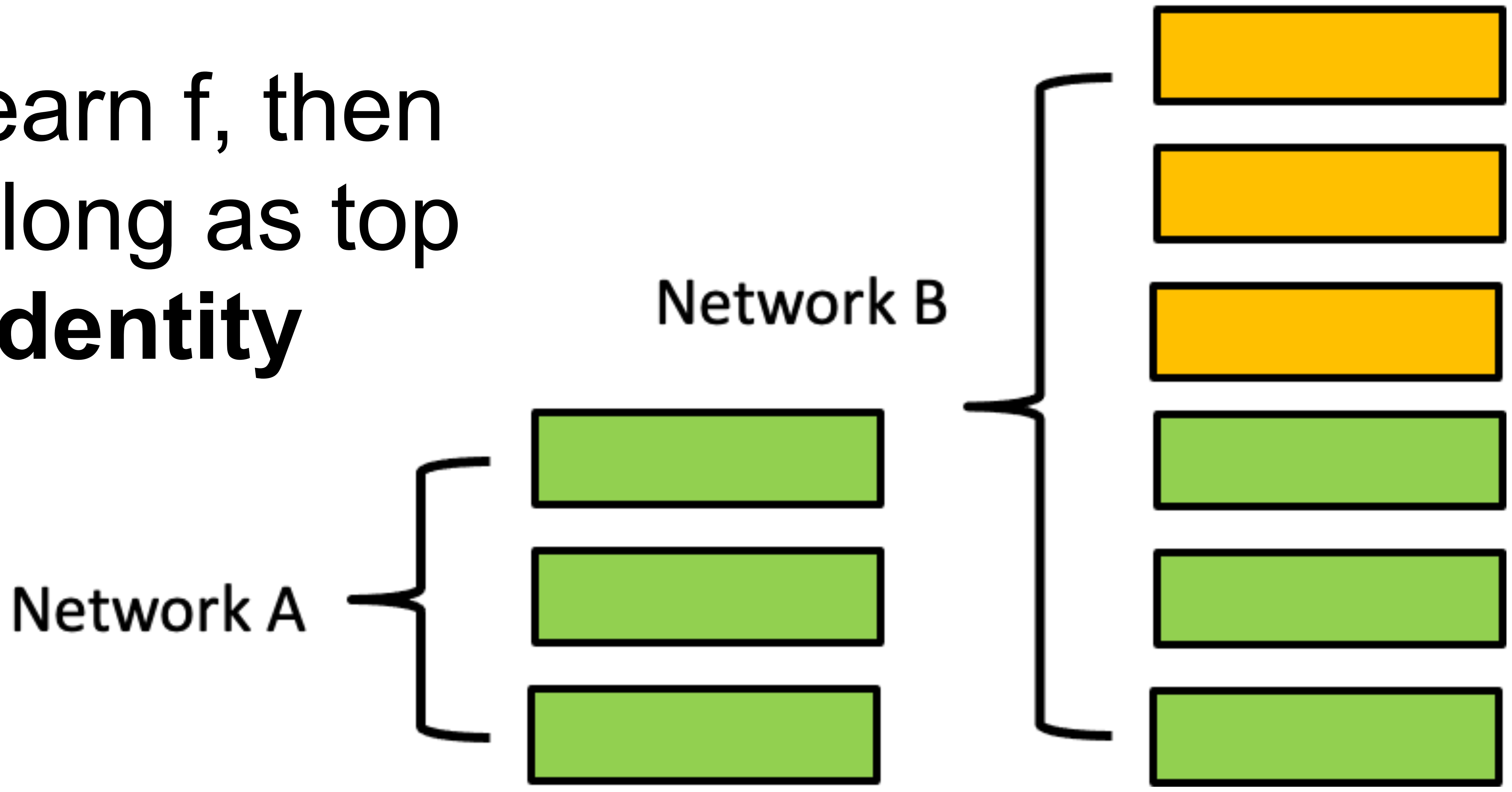

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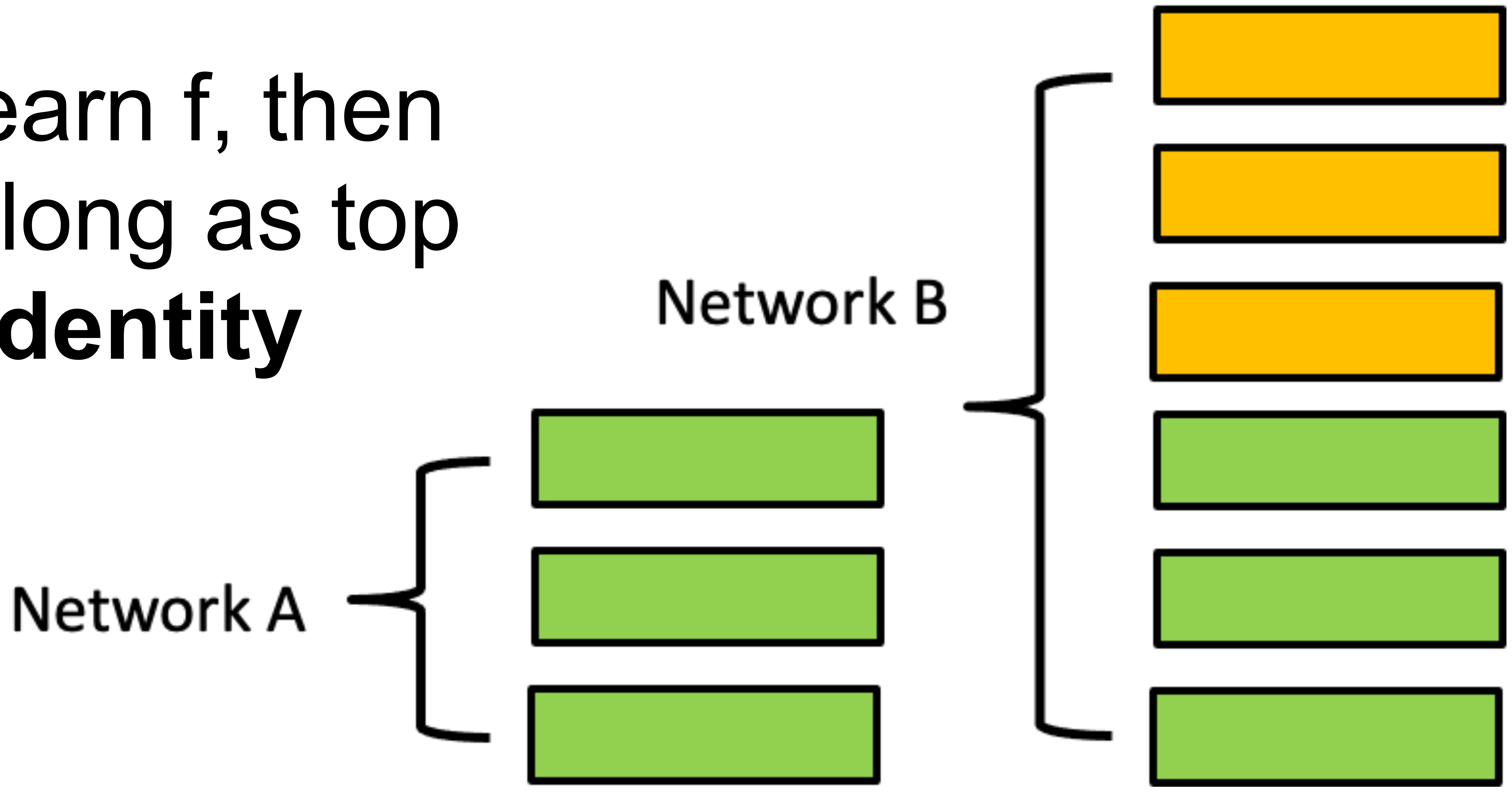

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Idea: if layers can learn identity, **can't get** worse.

Residual Connections

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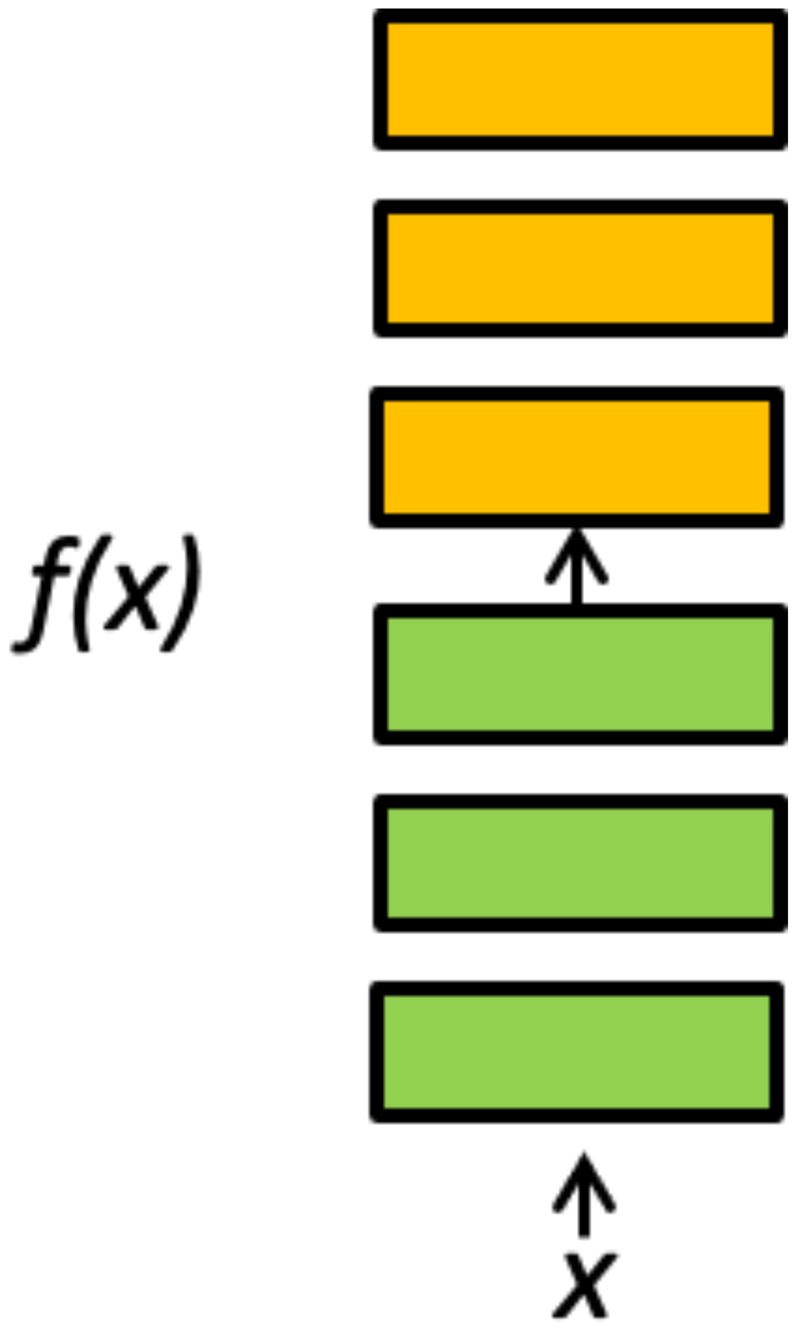

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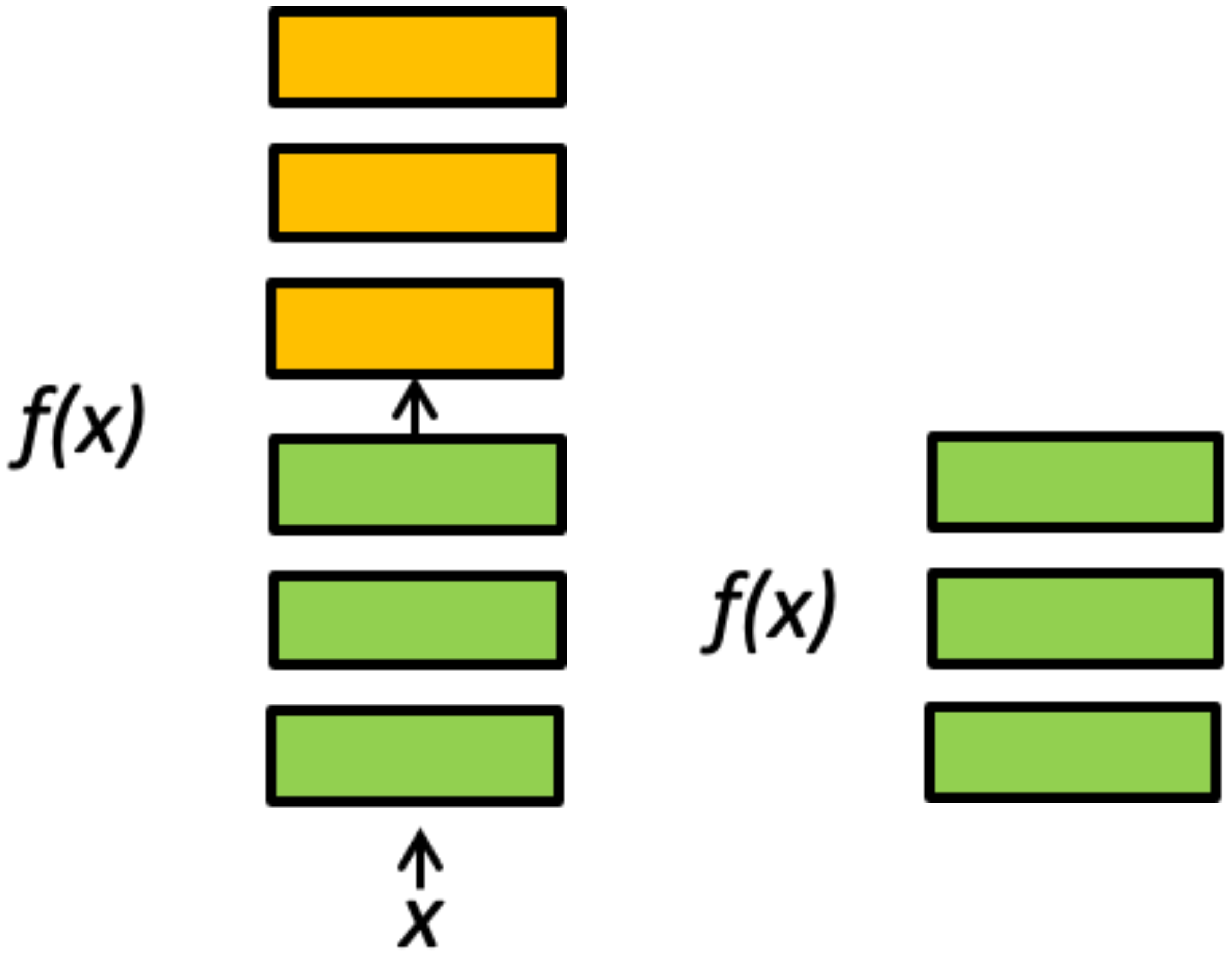

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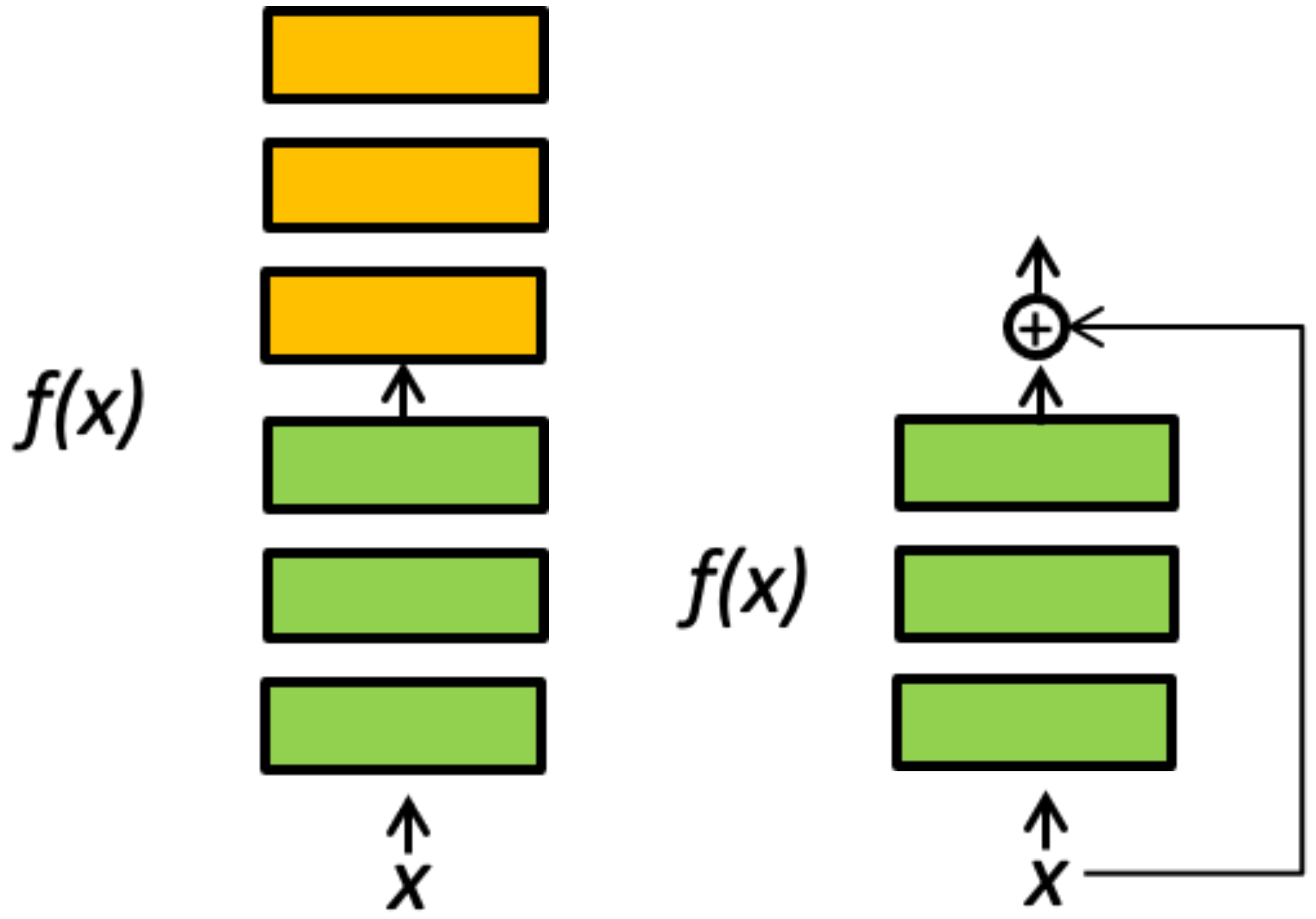

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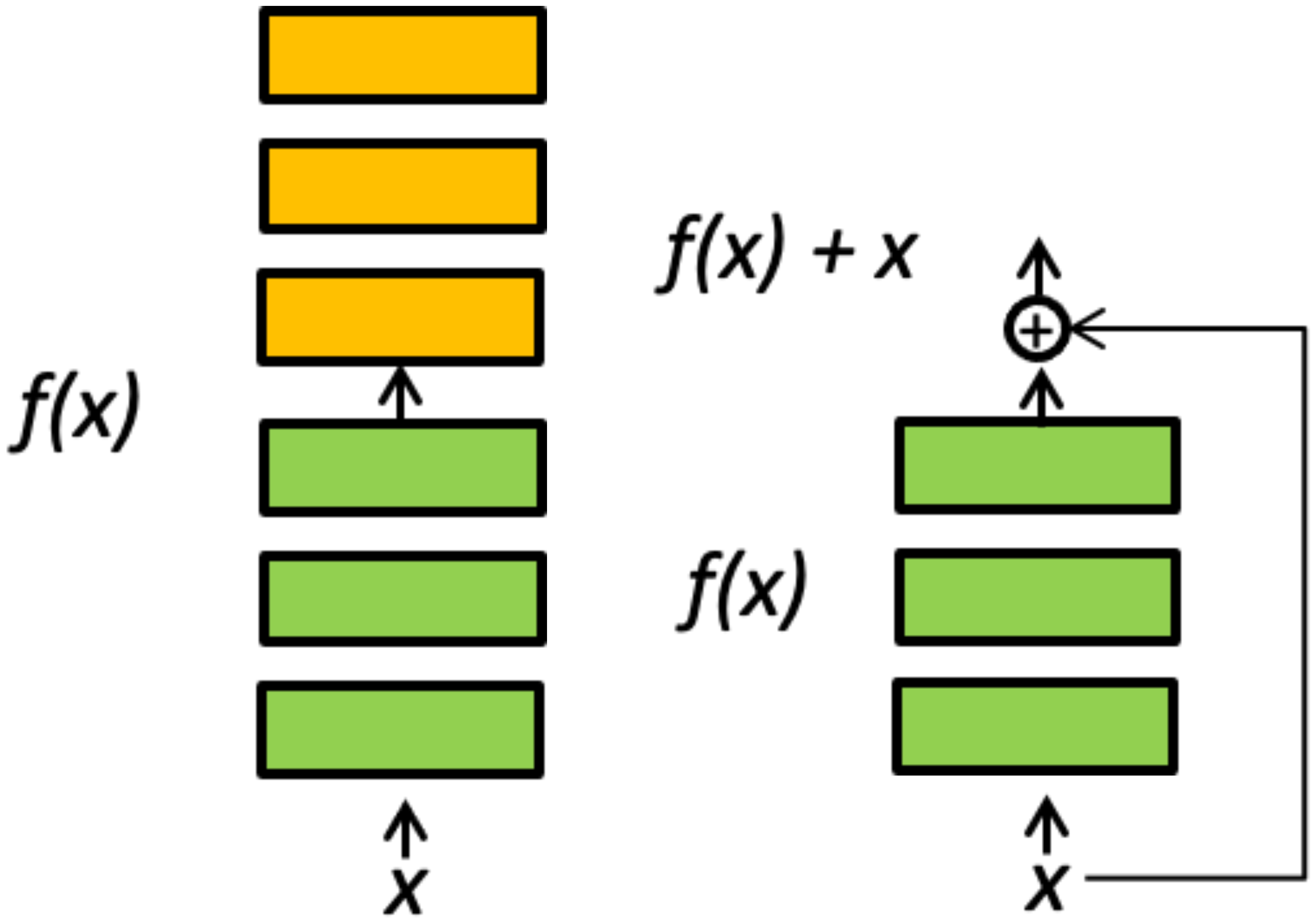

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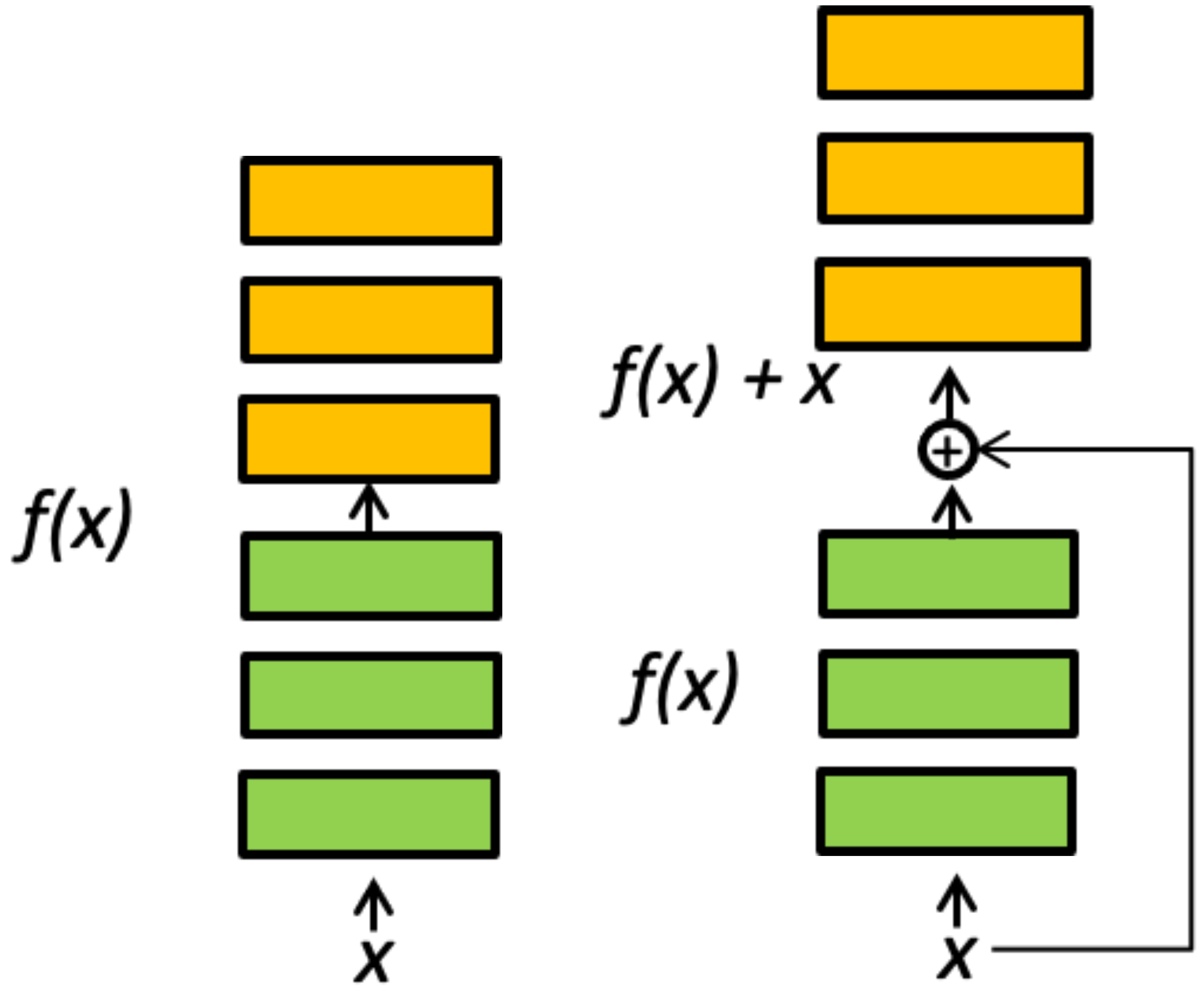

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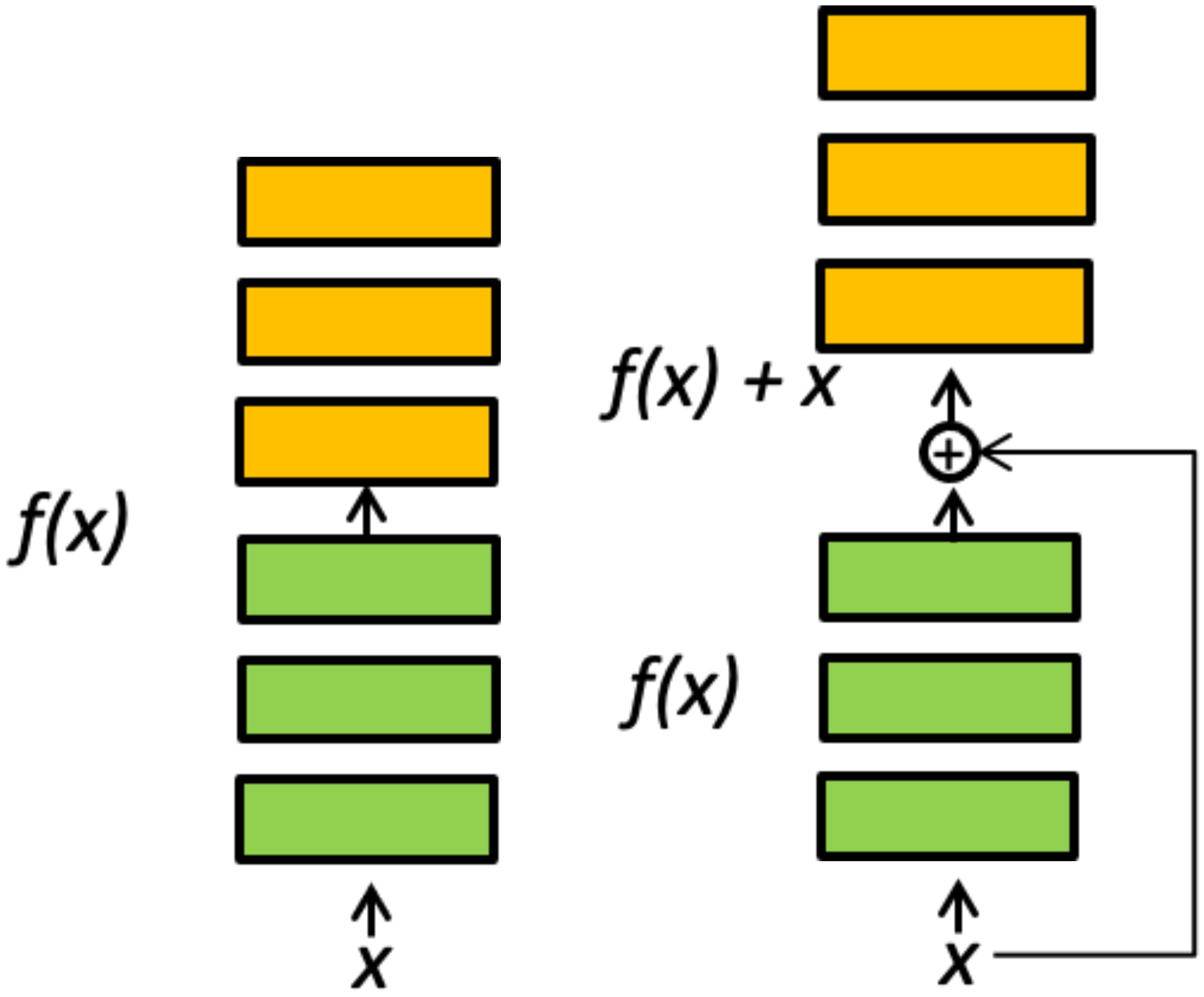

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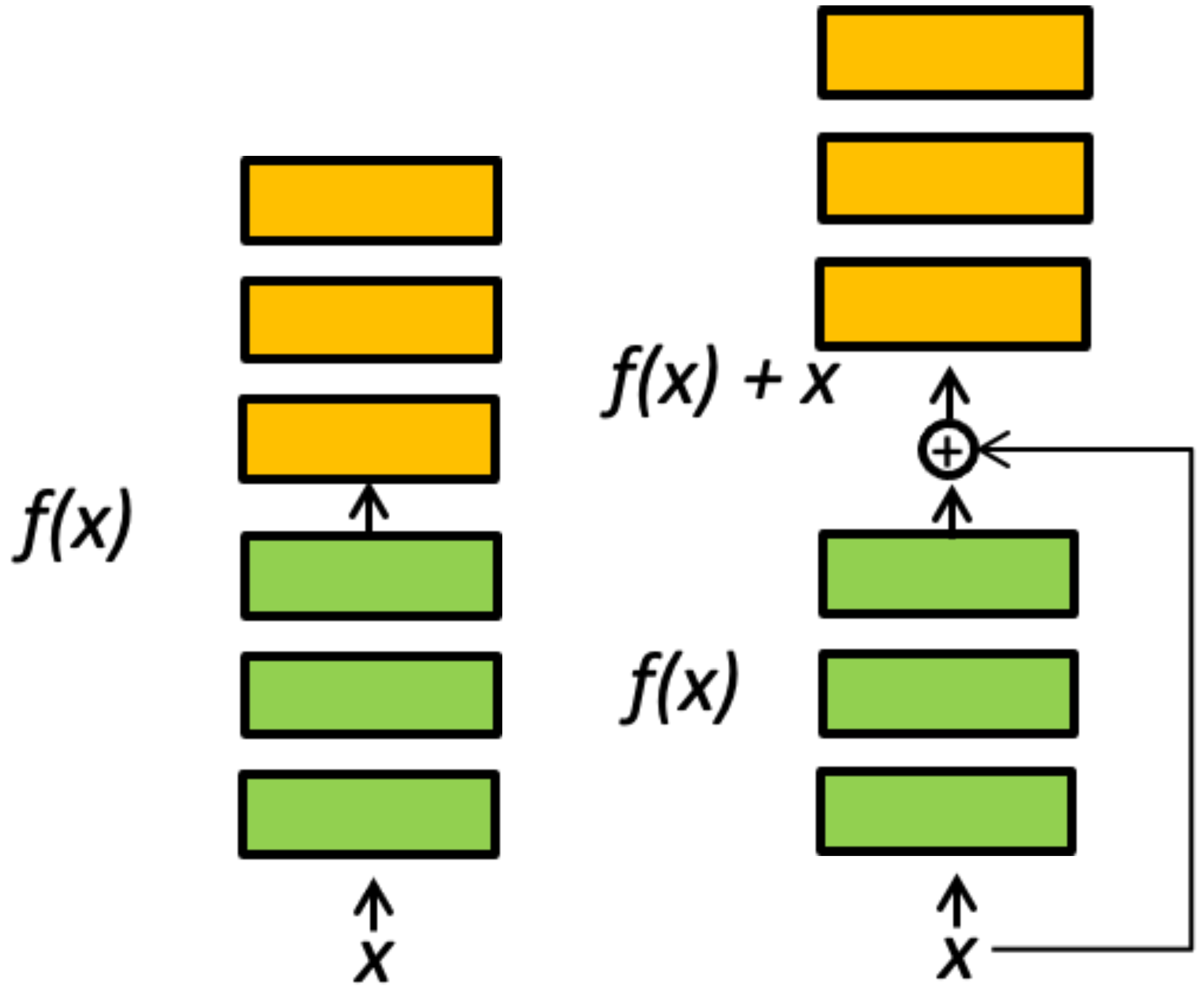

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Right: Residual layer blocks

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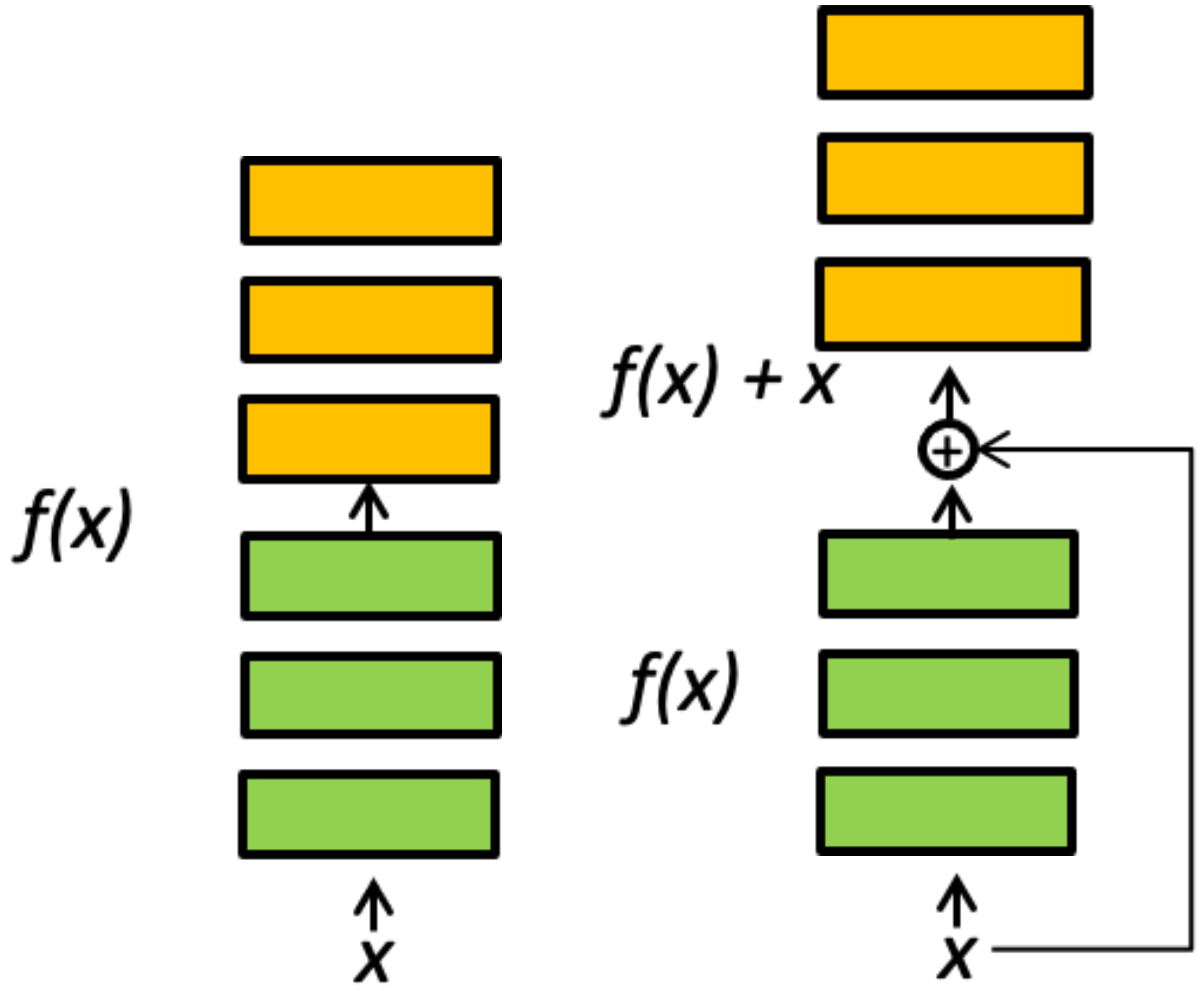

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To learn identity f(x) = x, layers now need to learn f(x) = 0 ➔ easier

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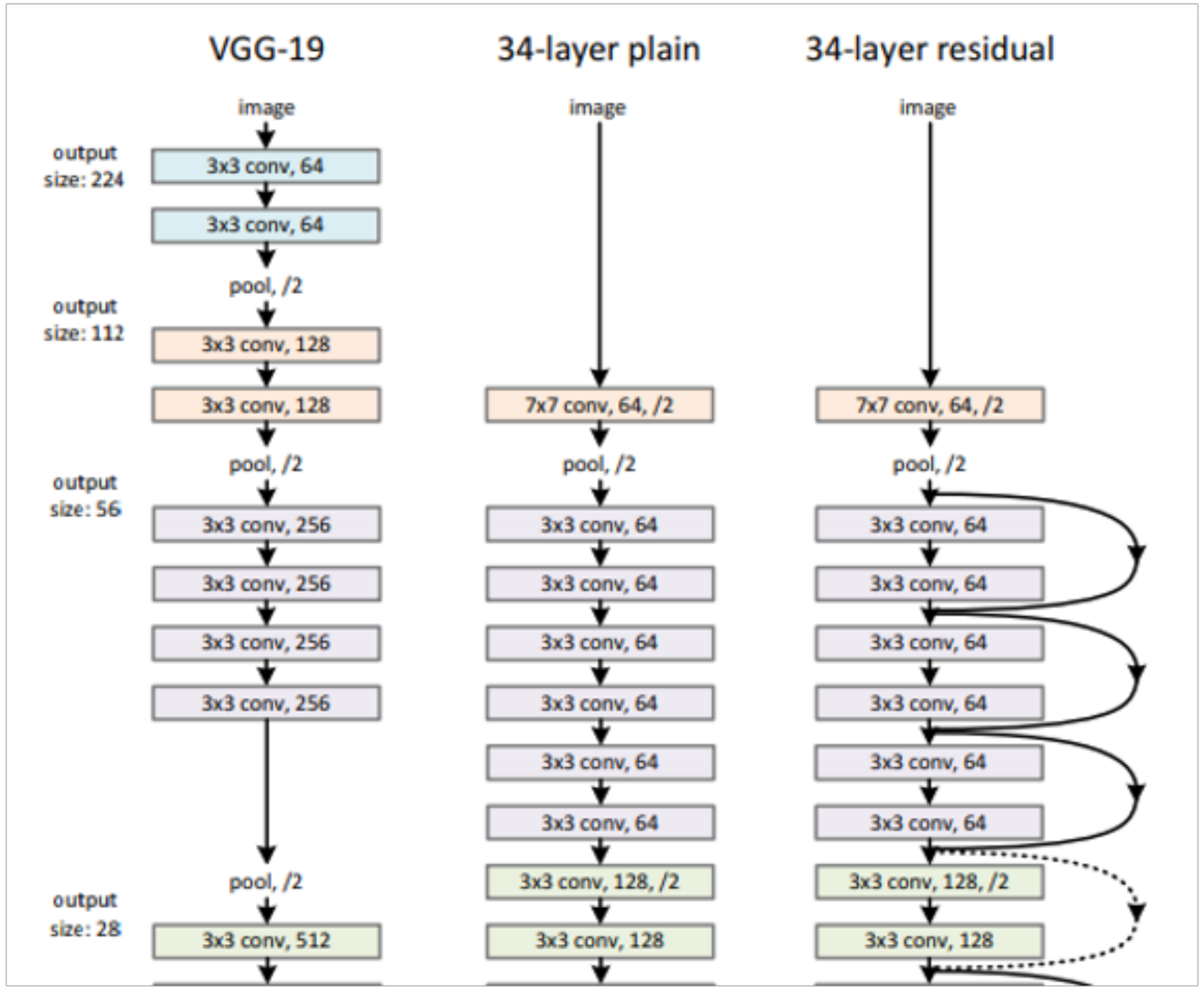

He et al: "Deep Residual Learning for Image Recognition"

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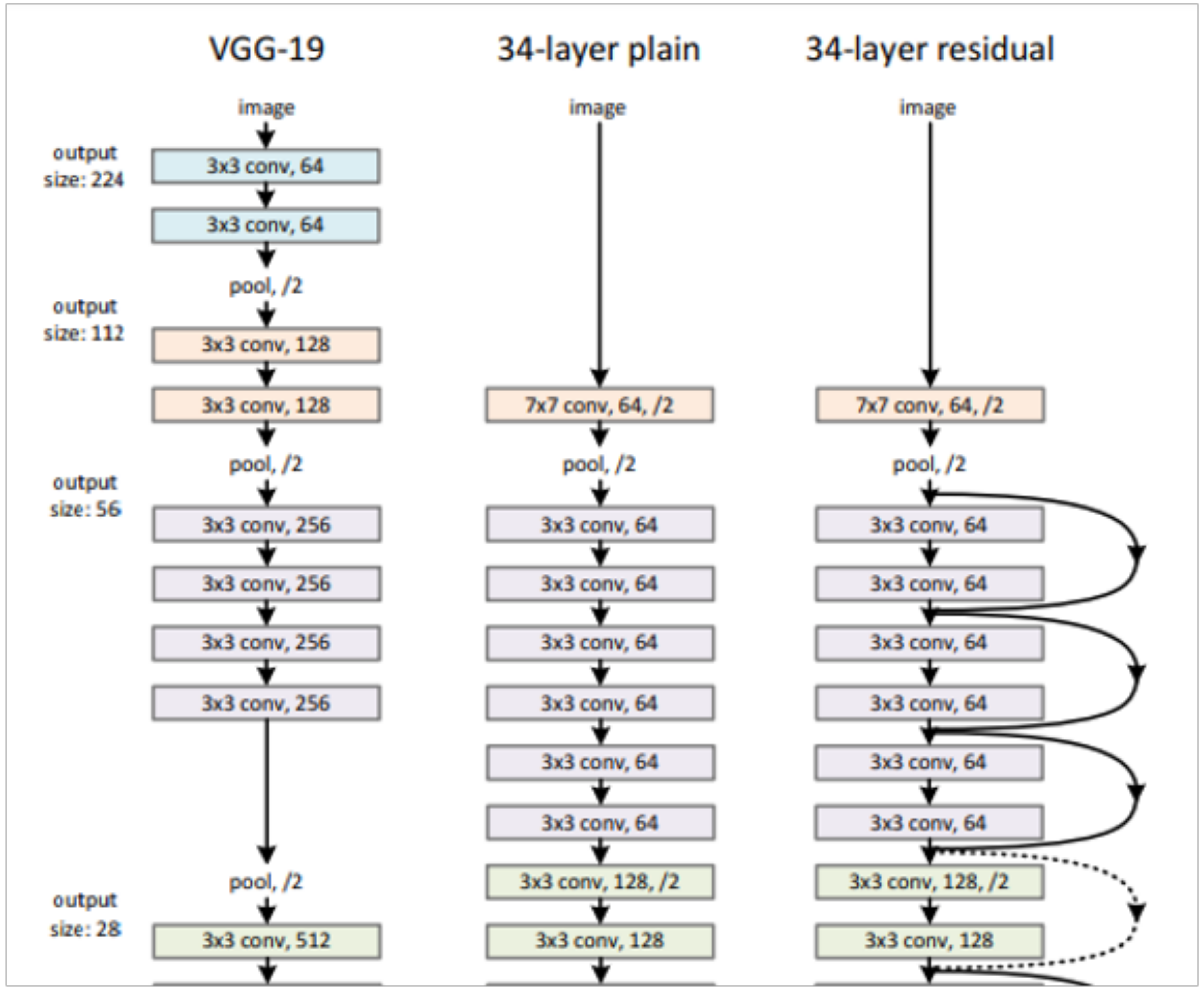
    - Every two layers for ResNet34



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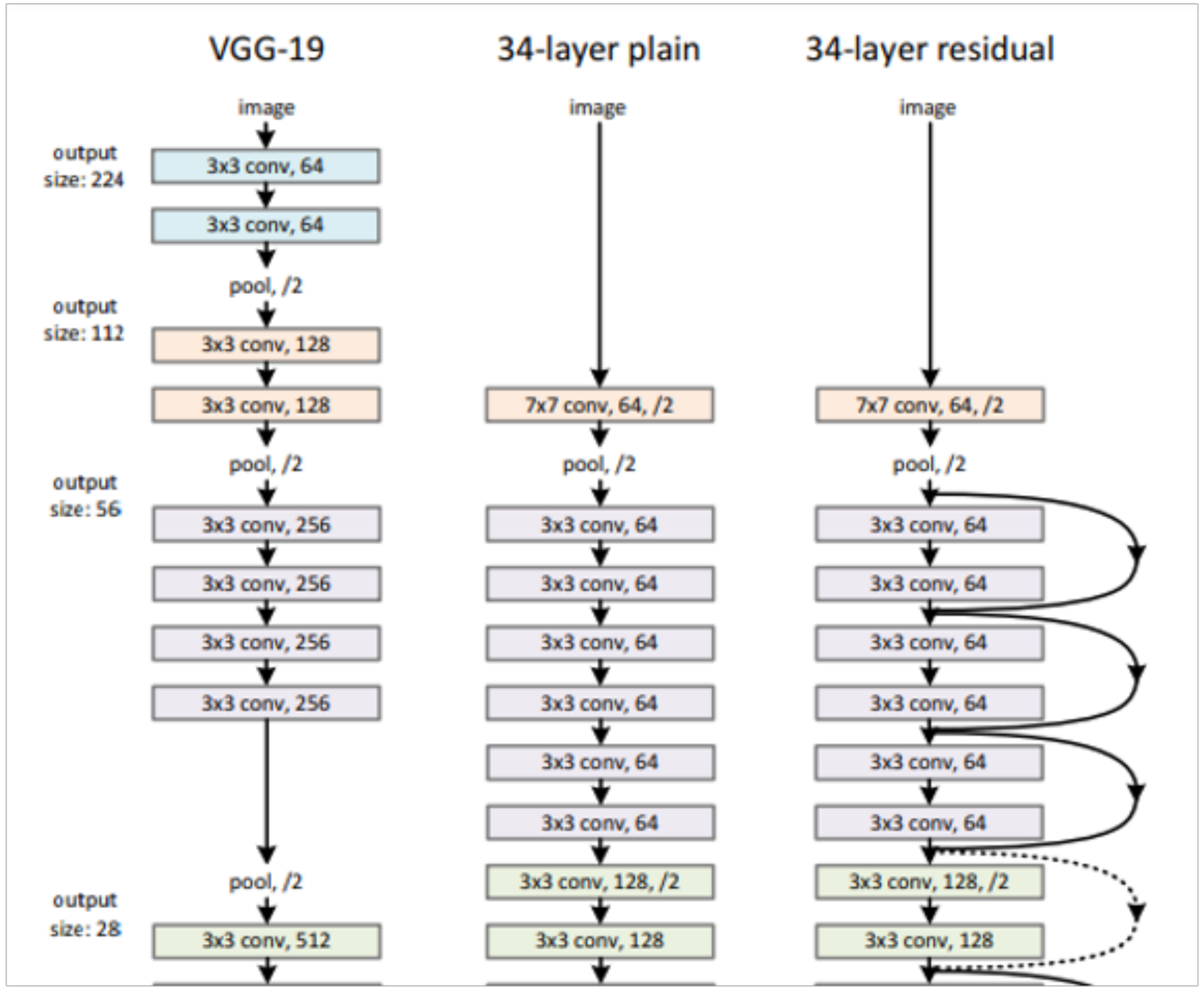
ResNet Architecture

- **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



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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