# CS540 Introduction to Artificial Intelligence

## Convolutional Neural Networks (II)

University of Wisconsin-Madison

**Spring 2022**

# Outline

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

# How to classify

## Cats vs. dogs?

Dual

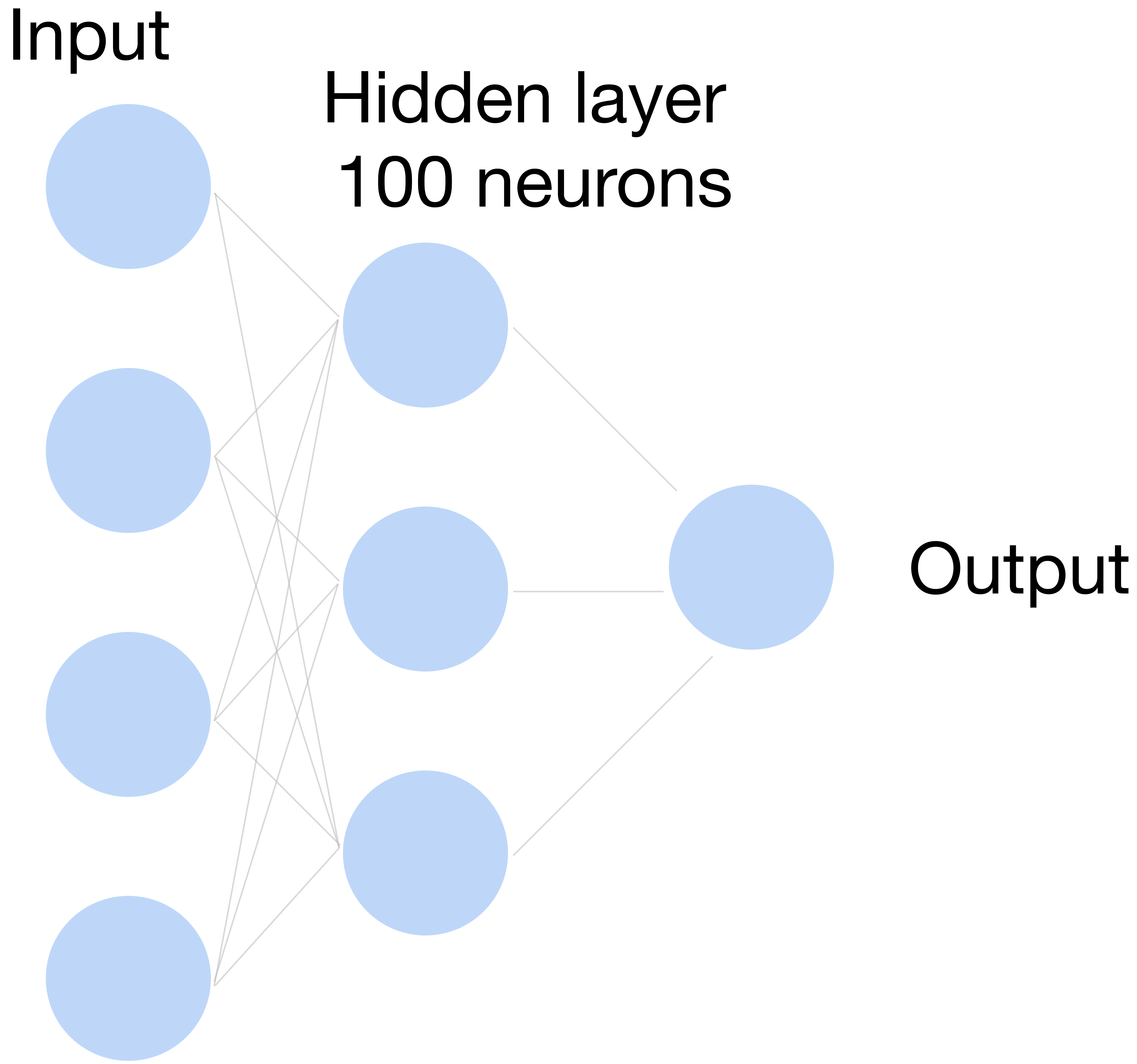
**12MP**

wide-angle and
telephoto cameras

**36M** floats in a RGB image!

# Fully Connected Networks

**Cats vs. dogs?**




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

# Review: 2-D Convolution

Input

| | | |
|---|---|---|
| 0 | 1 | 2 |
| 3 | 4 | 5 |
| 6 | 7 | 8 |

*

Kernel

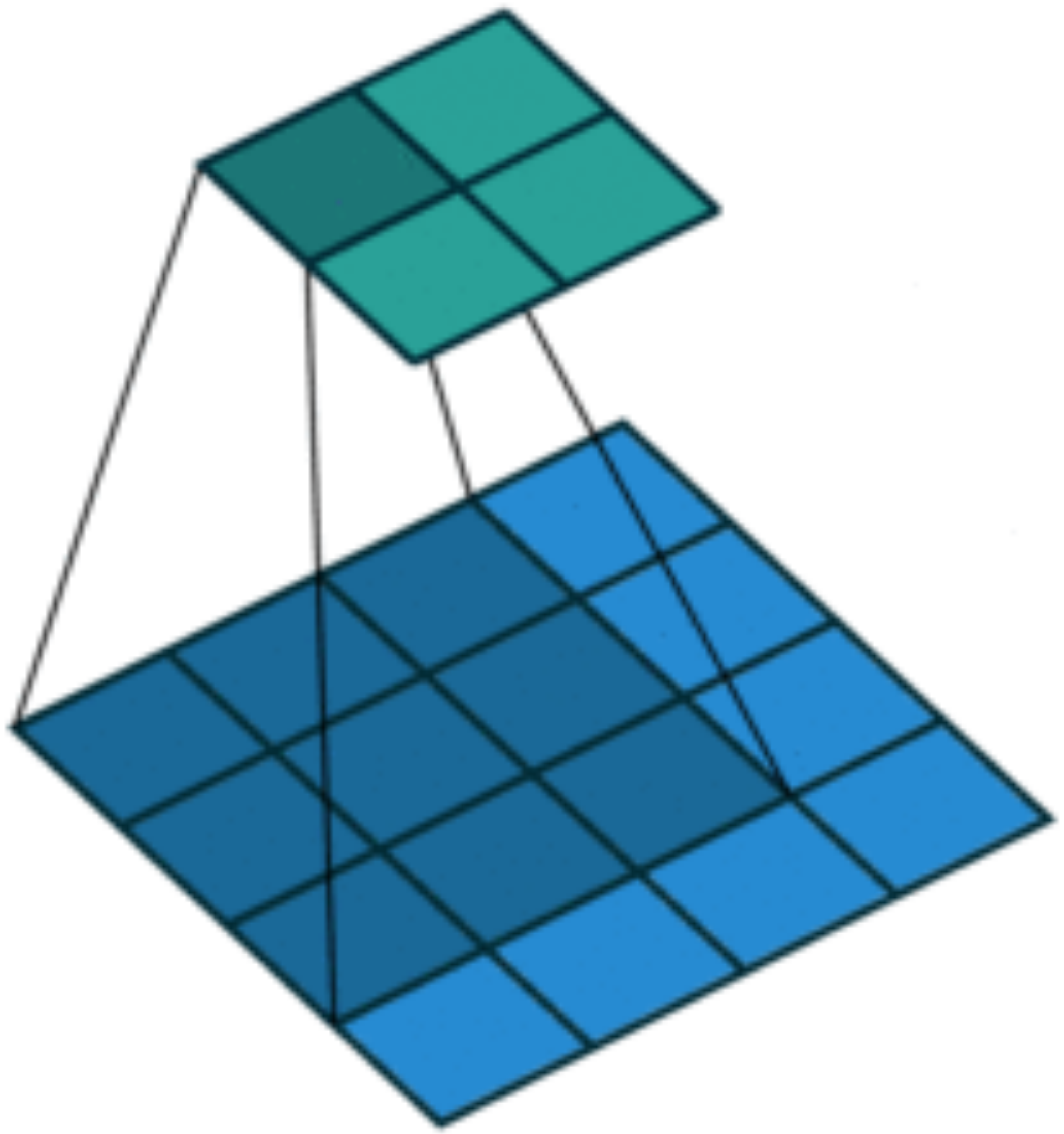
| | |
|---|---|
| 0 | 1 |
| 2 | 3 |

=

Output

| | |
|---|---|
| 19 | 25 |
| 37 | 43 |

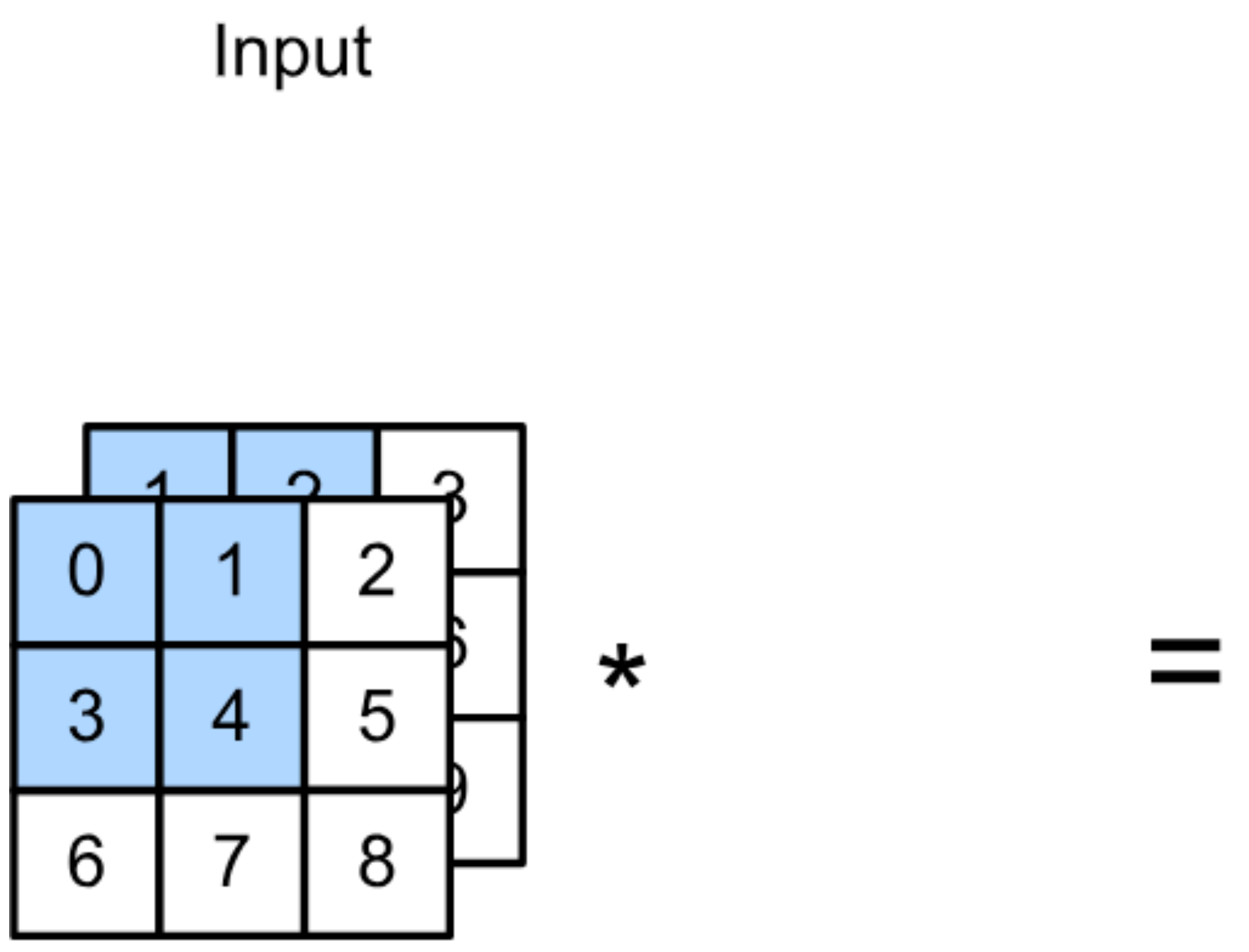
$$0 \times 0 + 1 \times 1 + 3 \times 2 + 4 \times 3 = 19,$$
$$1 \times 0 + 2 \times 1 + 4 \times 2 + 5 \times 3 = 25,$$
$$3 \times 0 + 4 \times 1 + 6 \times 2 + 7 \times 3 = 37,$$
$$4 \times 0 + 5 \times 1 + 7 \times 2 + 8 \times 3 = 43.$$



(vdumoulin@ Github)

# 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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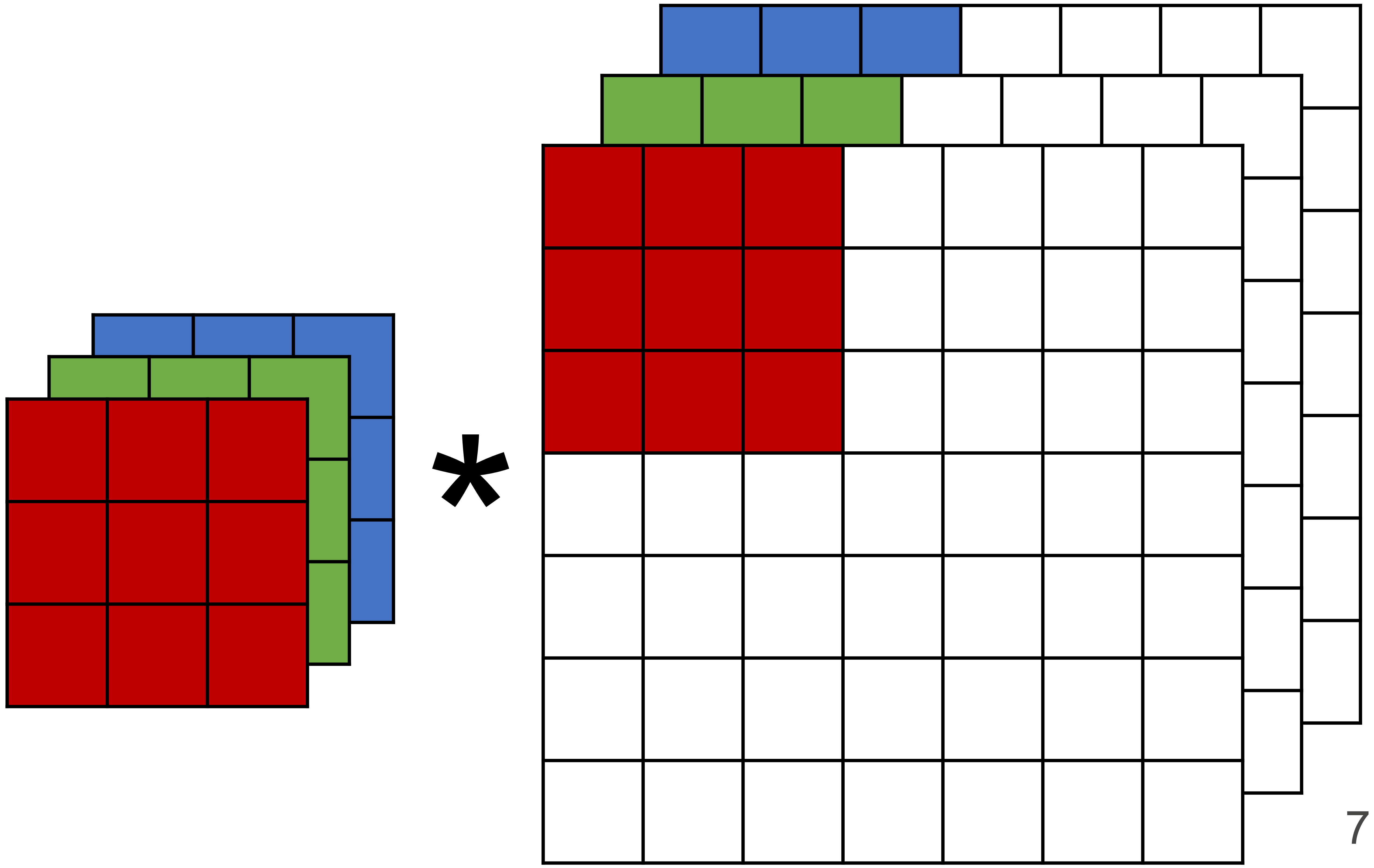

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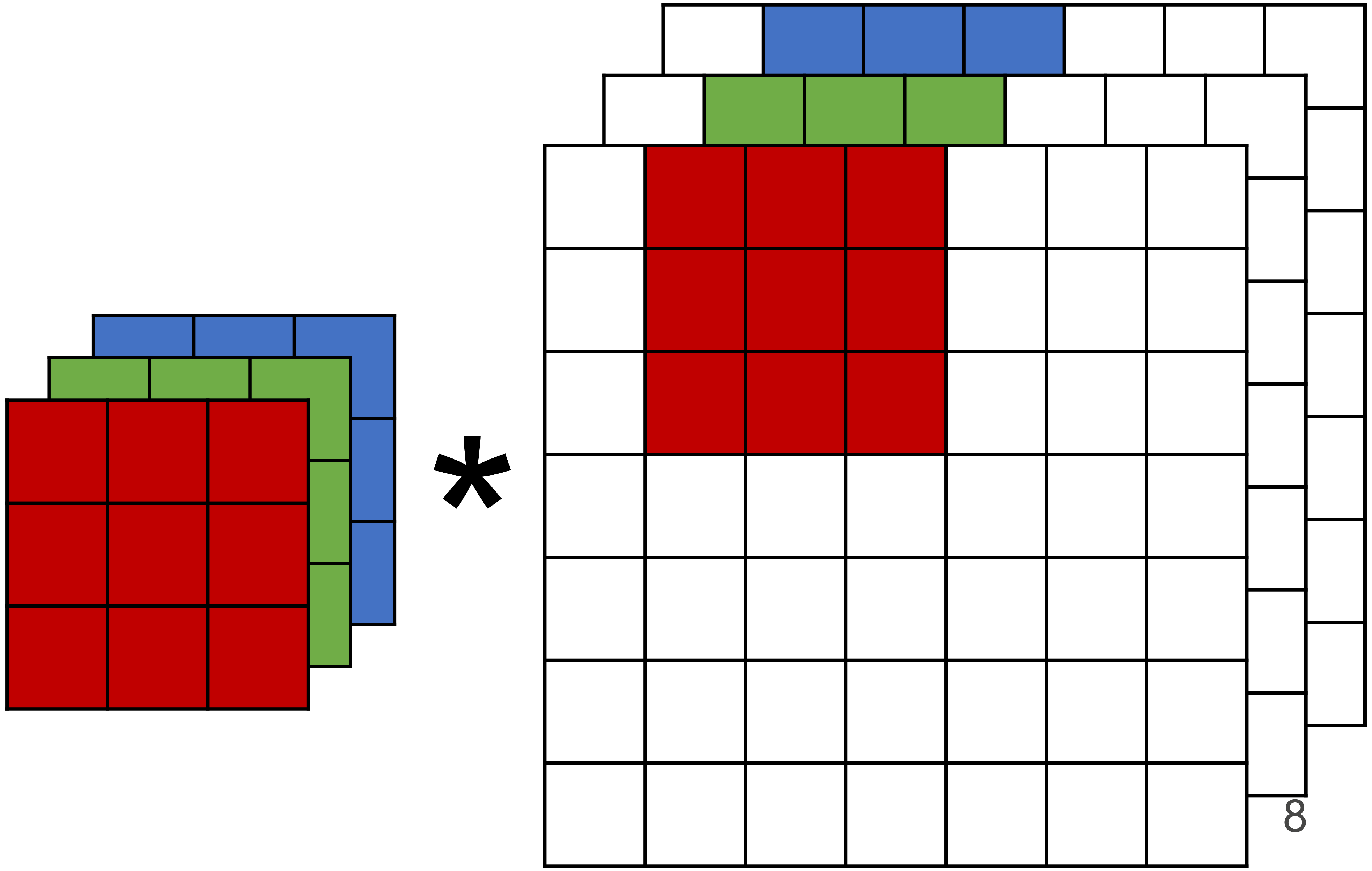

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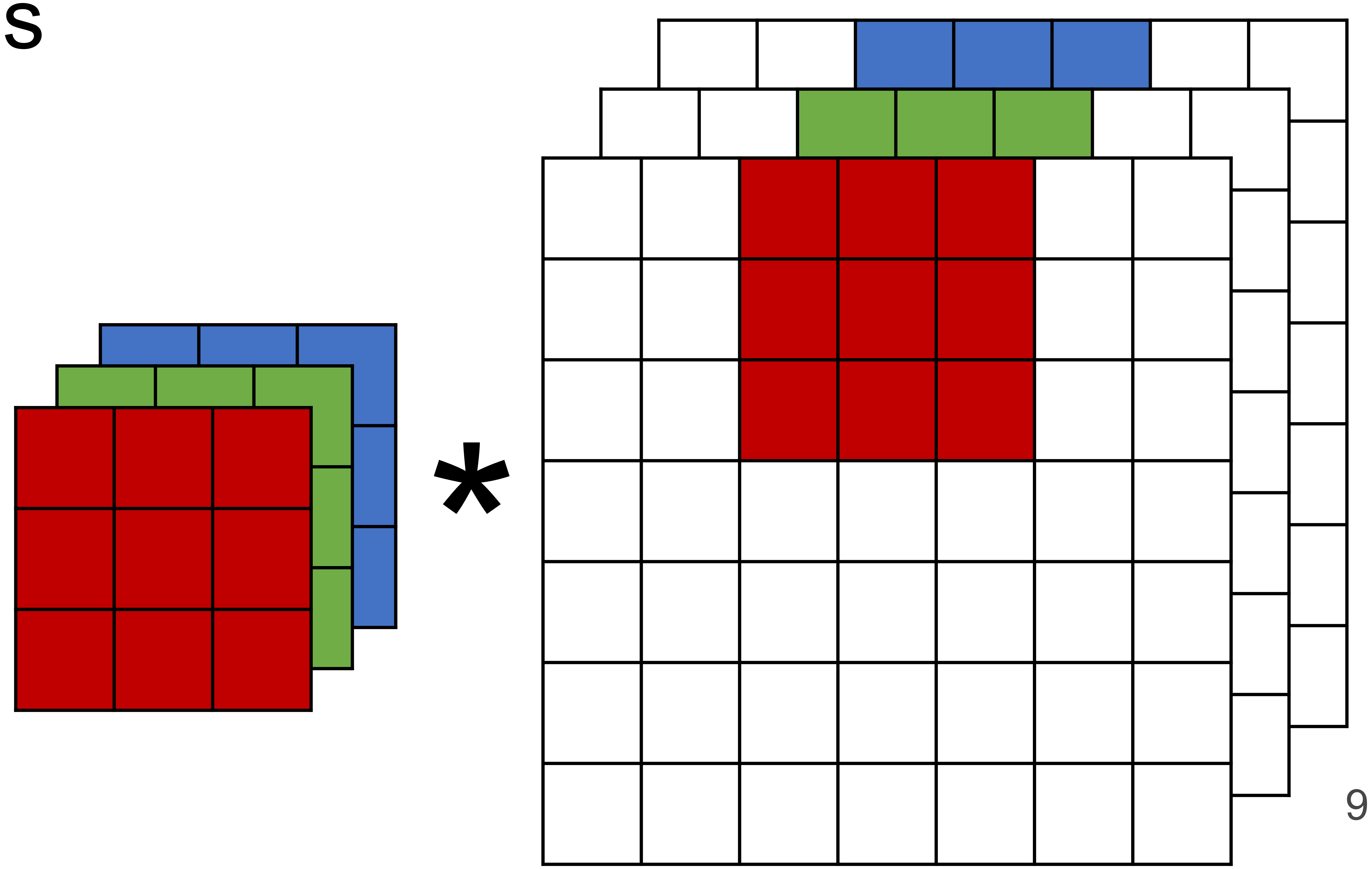
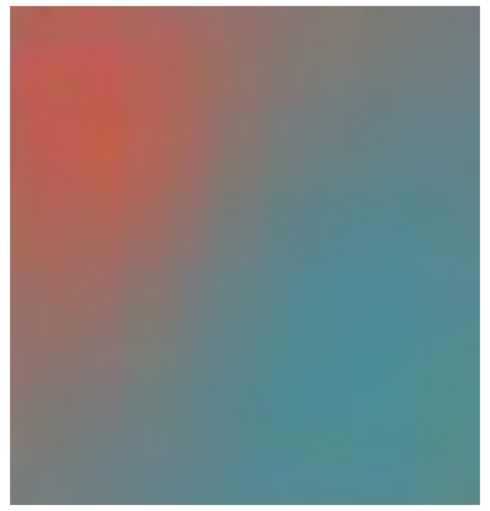


# Multiple Input Channels

- Input and kernel can be 3D, e.g., an RGB image have 3 channels
- Also call each 3D kernel a "**filter**", which produce 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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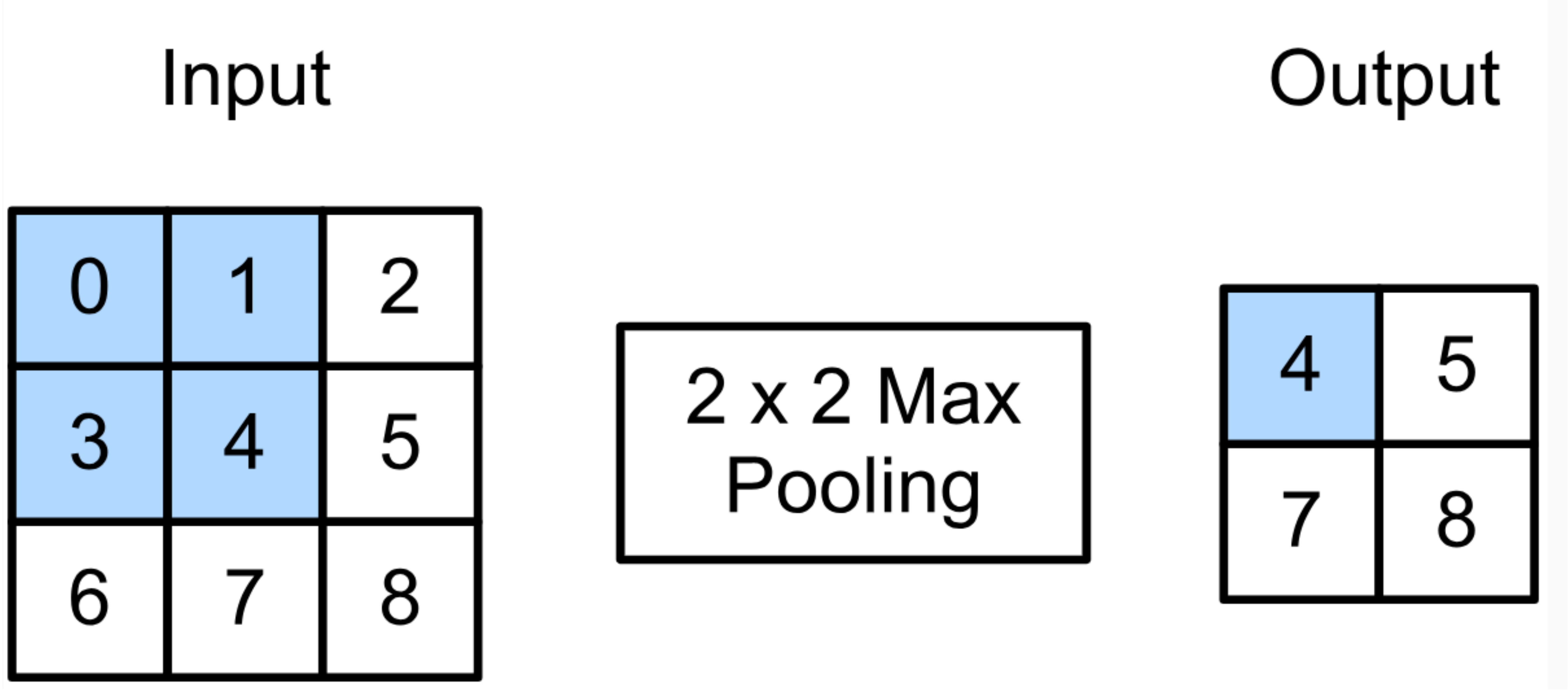
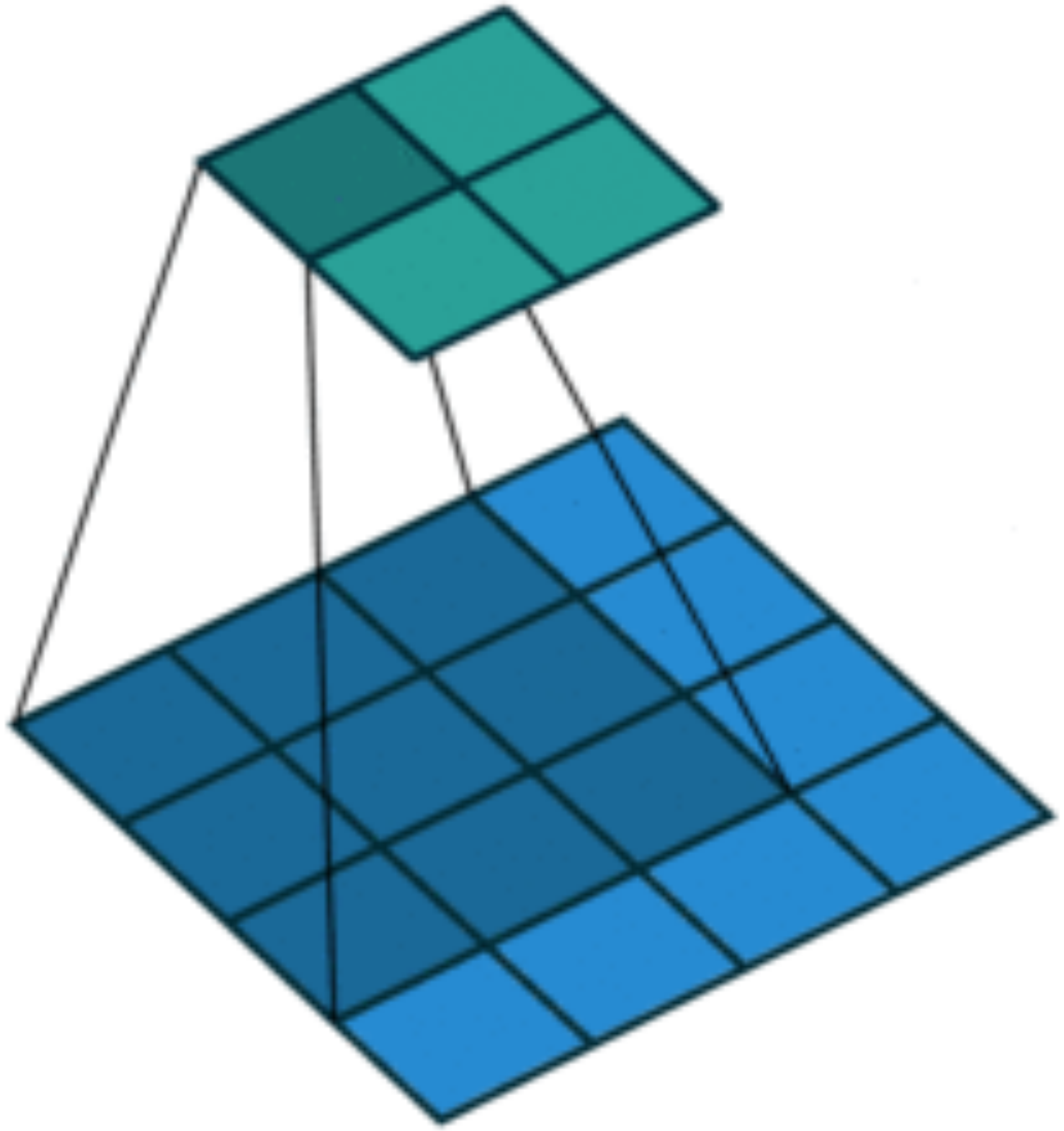
# Pooling Layer

# 2-D Max Pooling

- Returns the maximal value in the sliding window



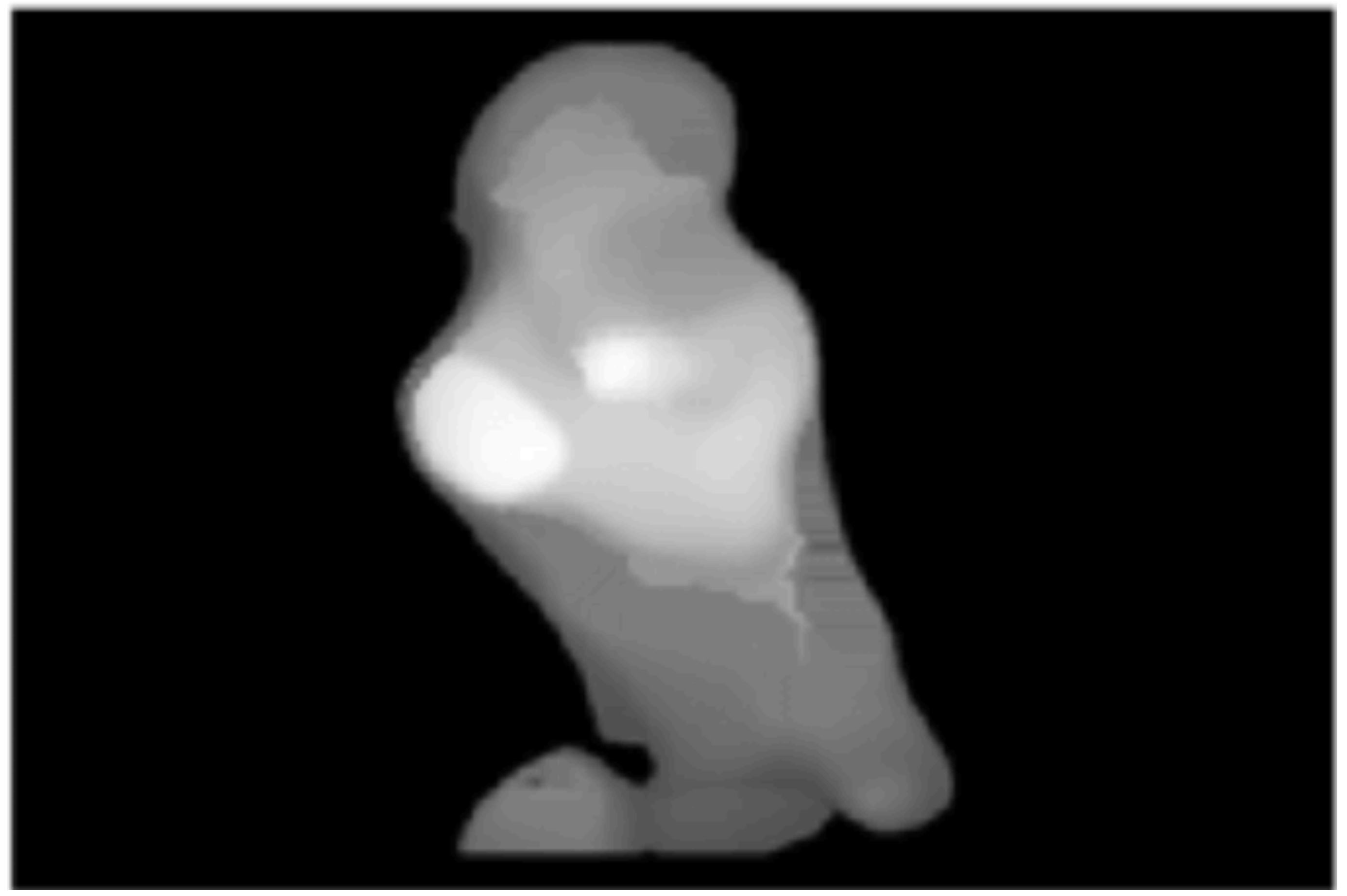

$$\max(0,1,3,4) = 4$$



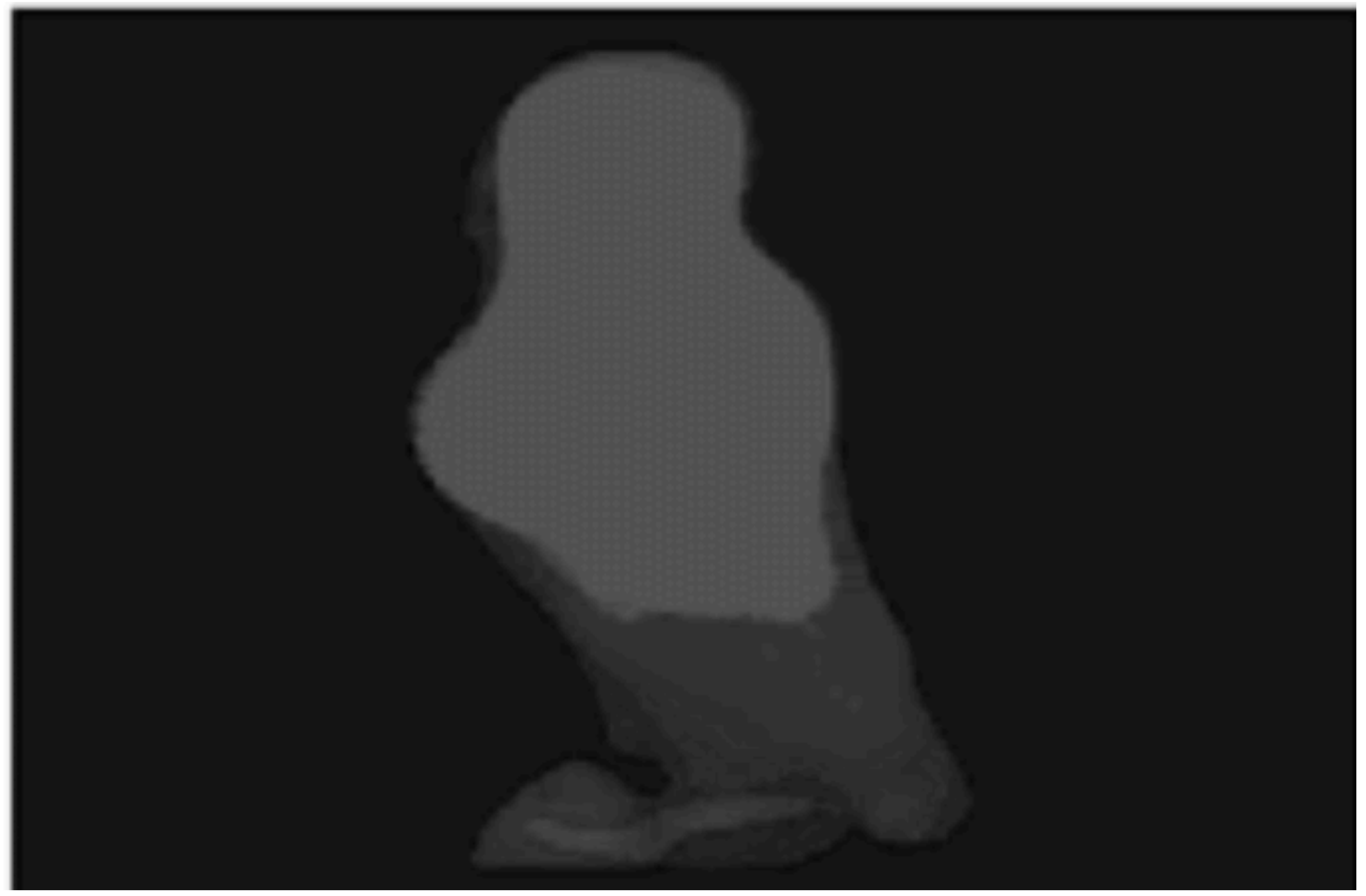
# Average Pooling

- 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



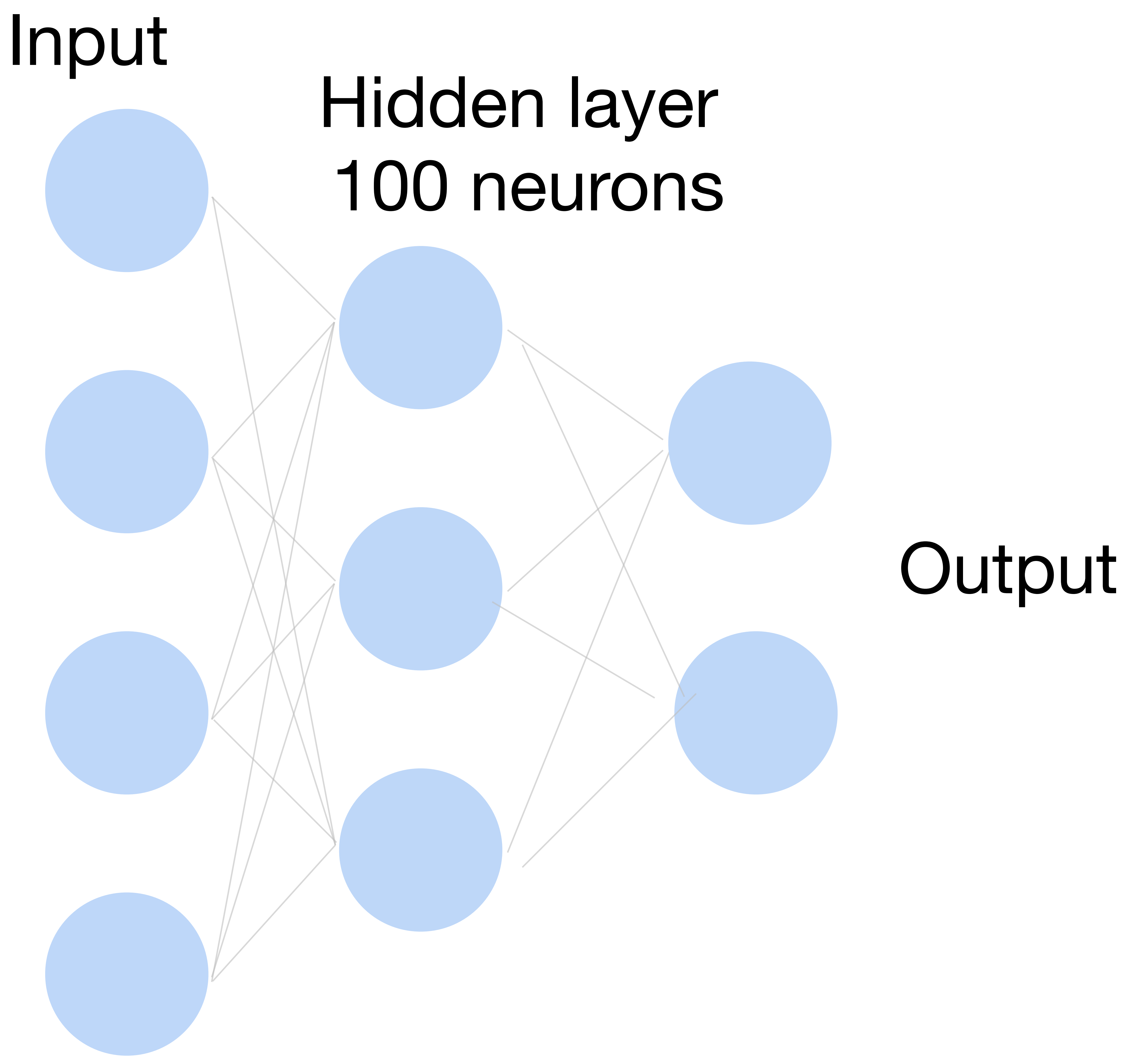
# How to train a neural network?

**Loss function:** $$\frac{1}{|D|}\sum_{i}\ell(\mathbf{x}_i, y_i)$$

**Per-sample loss:**

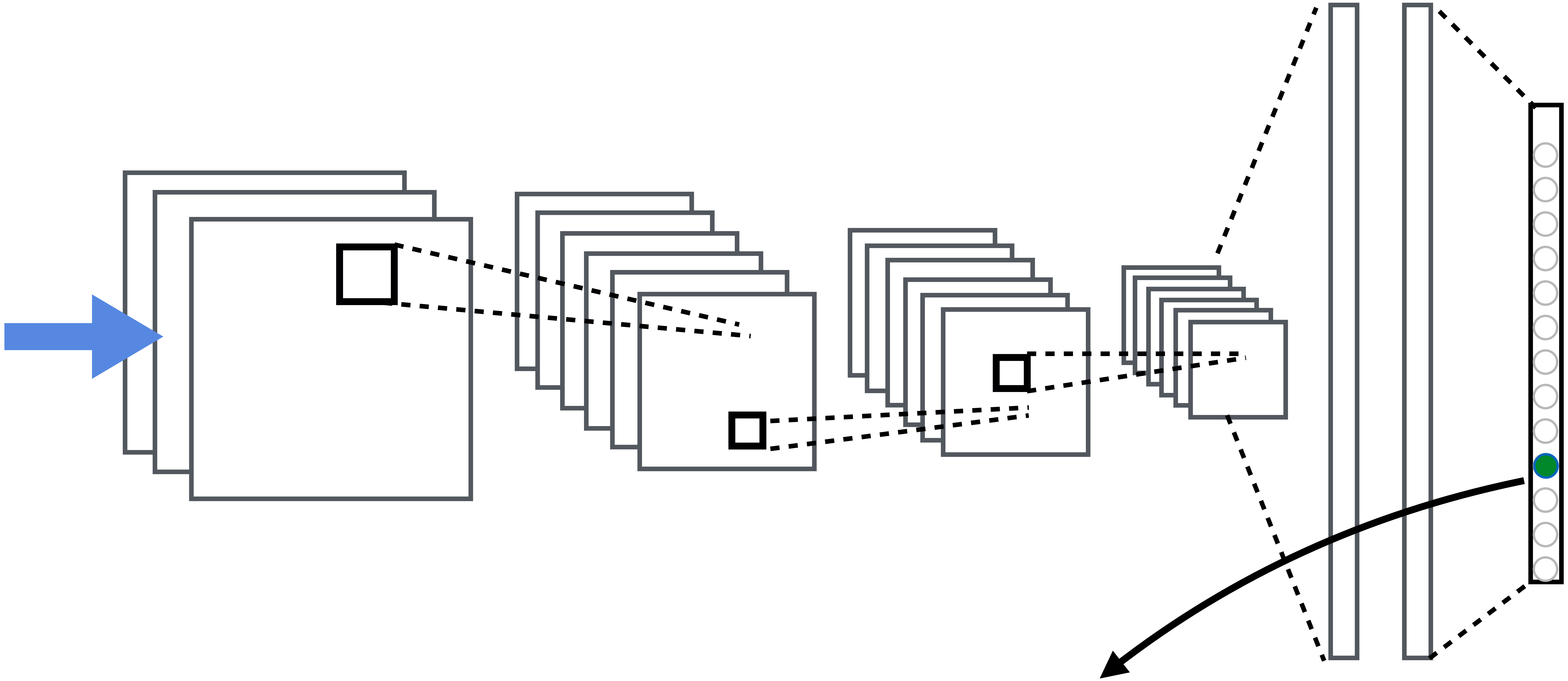
$$\ell(\mathbf{x}, y) = \sum_{j=1}^{K} -y_j \log p_j$$

**Also known as** **cross-entropy loss or softmax loss**



# How to train a convolutional neural network?

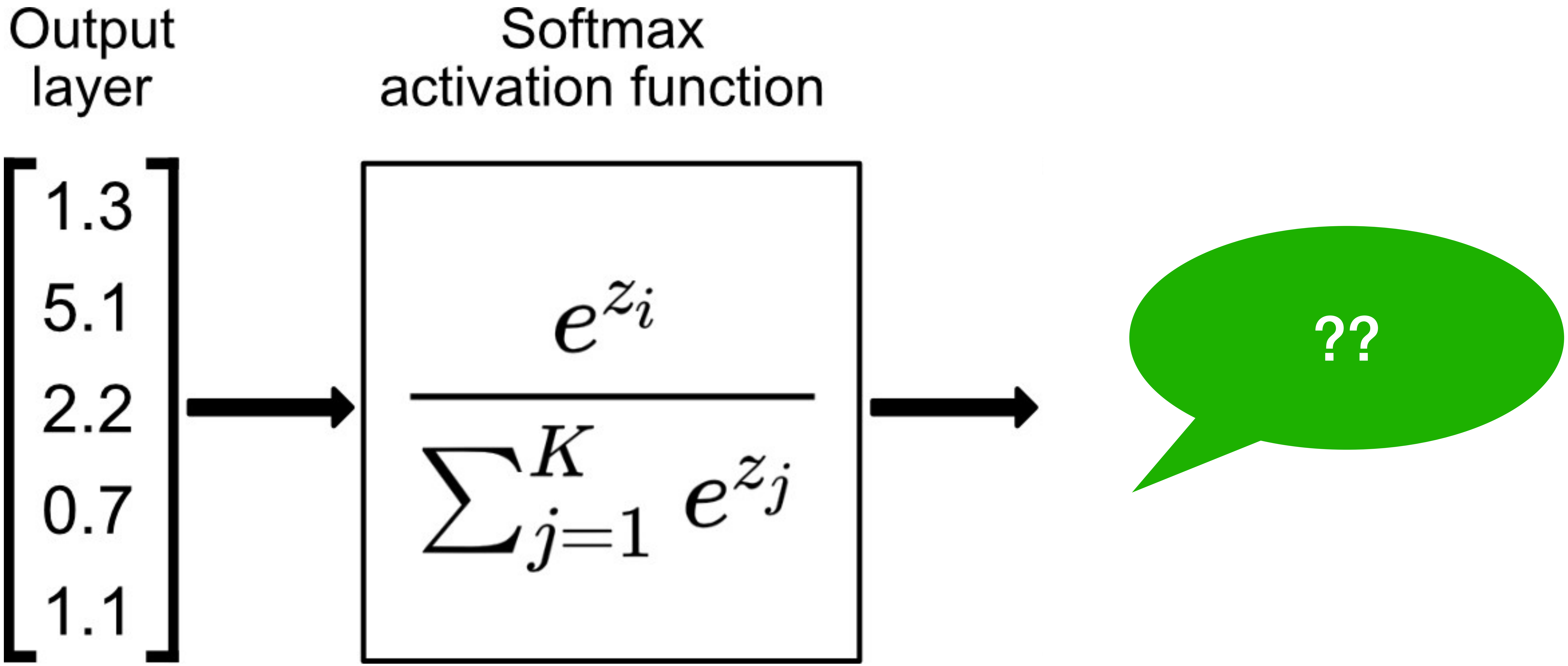
**Input**



$$p_i(\boldsymbol{x}) = \frac{\exp\left(f_i(\boldsymbol{x})\right)}{\sum_{j=1}^{N} \exp\left(f_j(\boldsymbol{x})\right)},$$ softmax

# Recall Softmax

Turns outputs f into probabilities (sum up to 1 across k classes)



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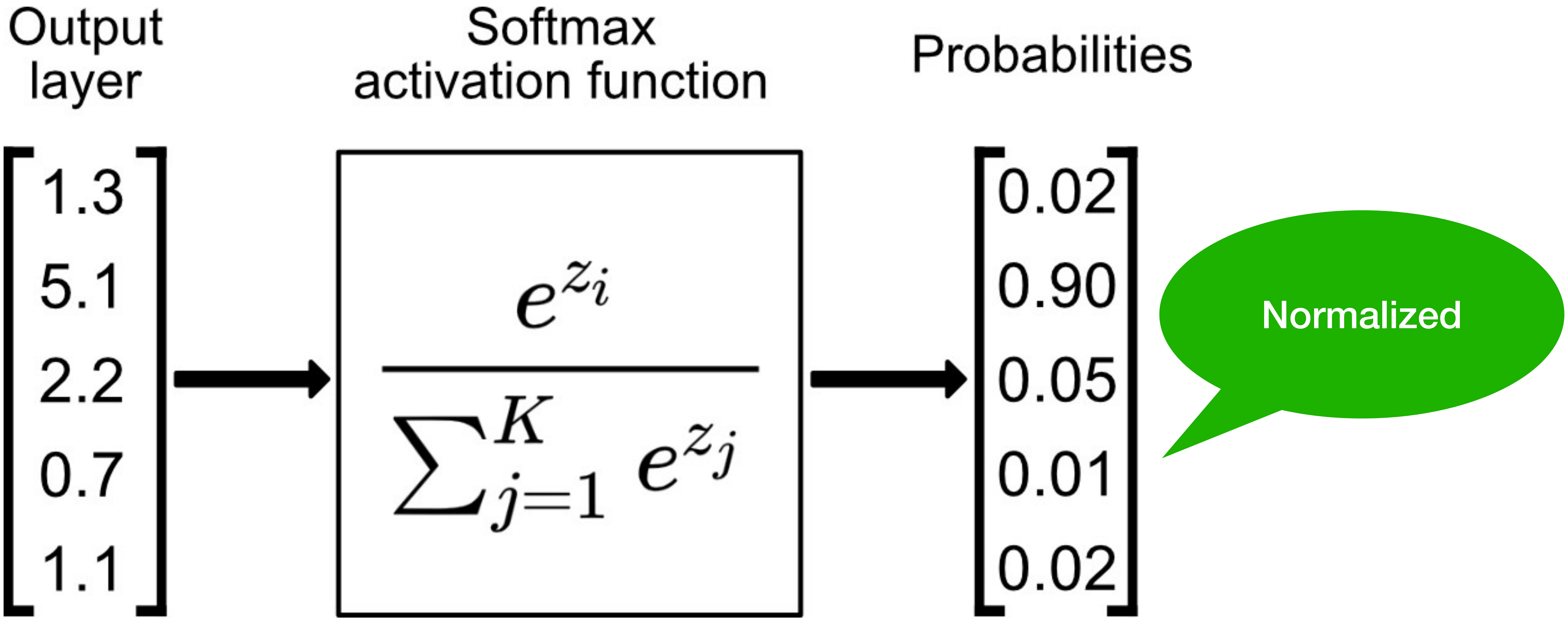
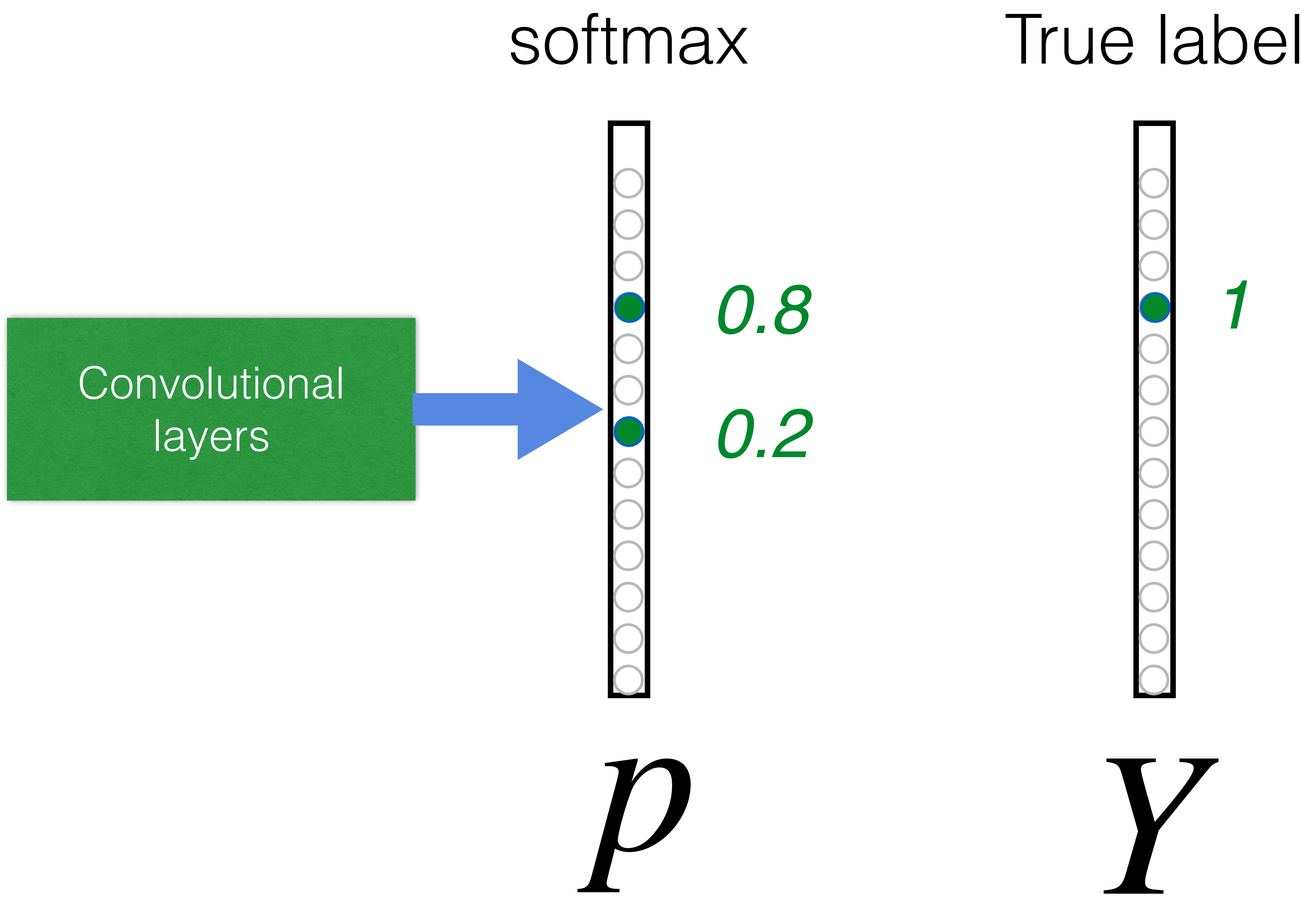


# Cross-Entropy Loss



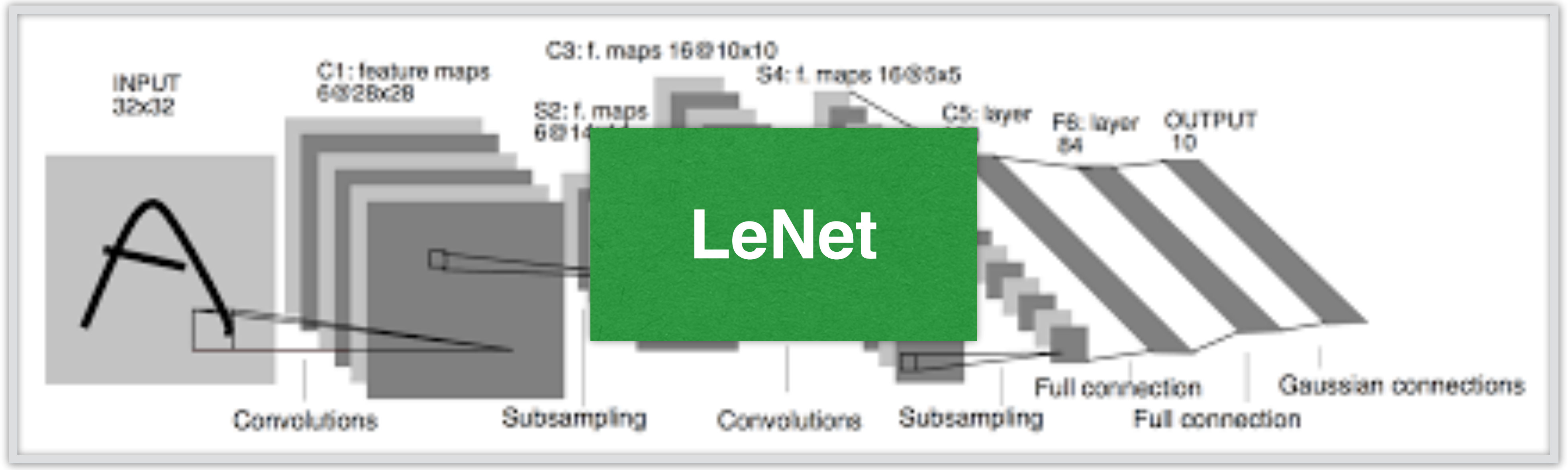

$$L_{CE} = \sum_i -Y_i \log(p_i)$$

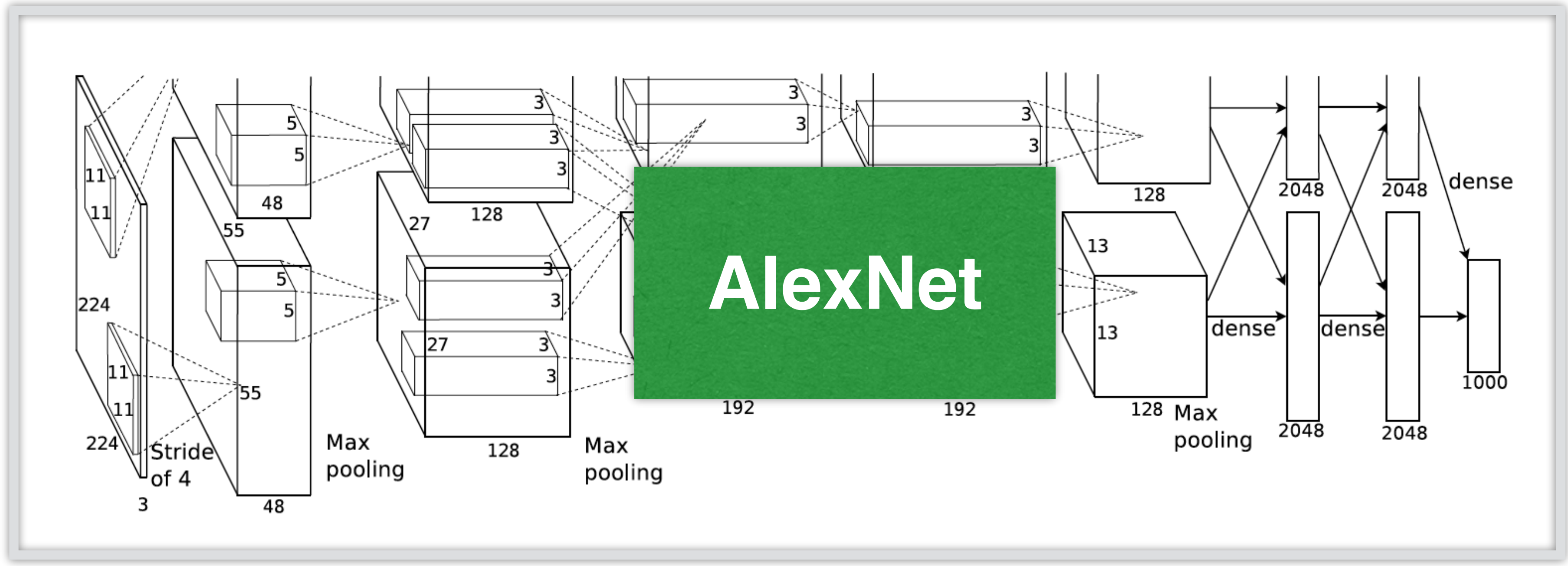
$$= -\log(0.8)$$

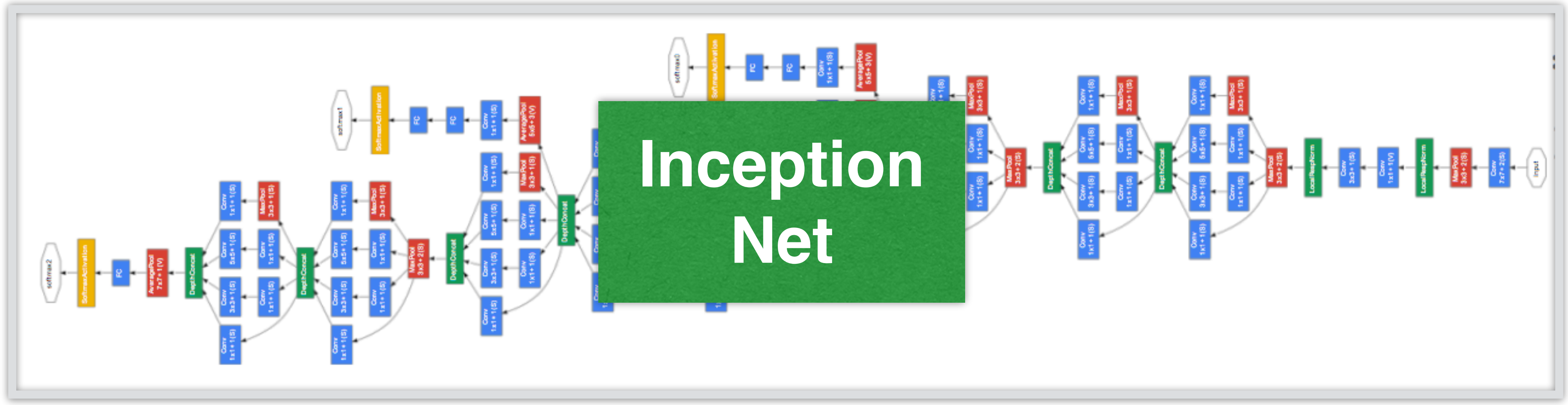
**Goal**: push **p** and **Y** to be identical

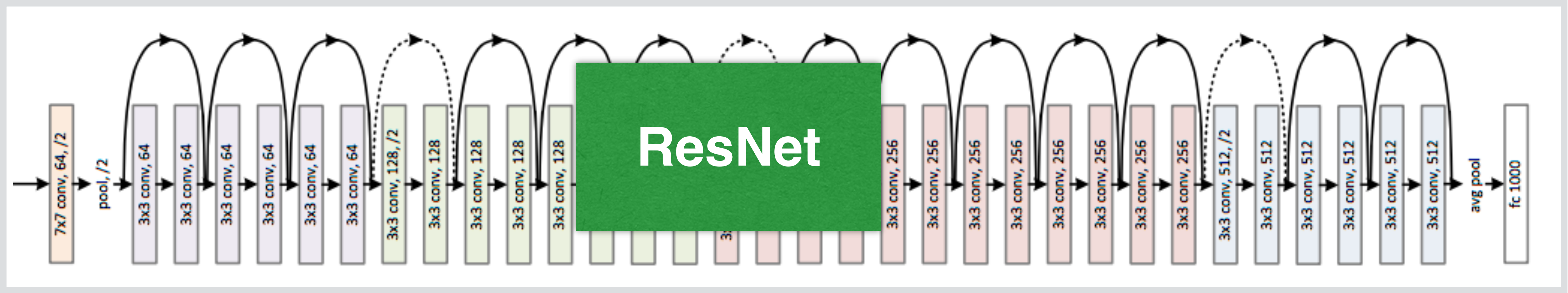
# Convolutional Neural Networks

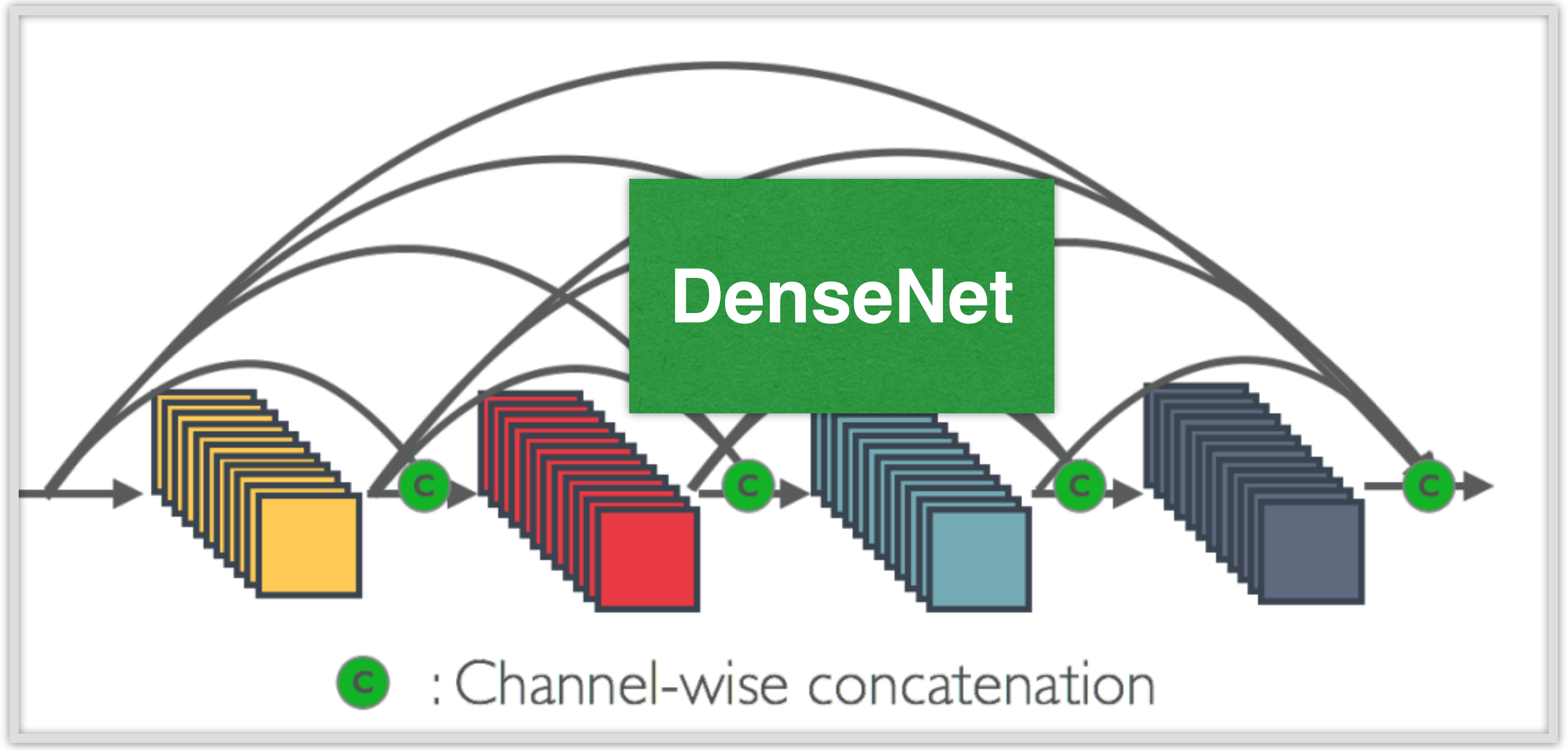
# Evolution of neural net architectures



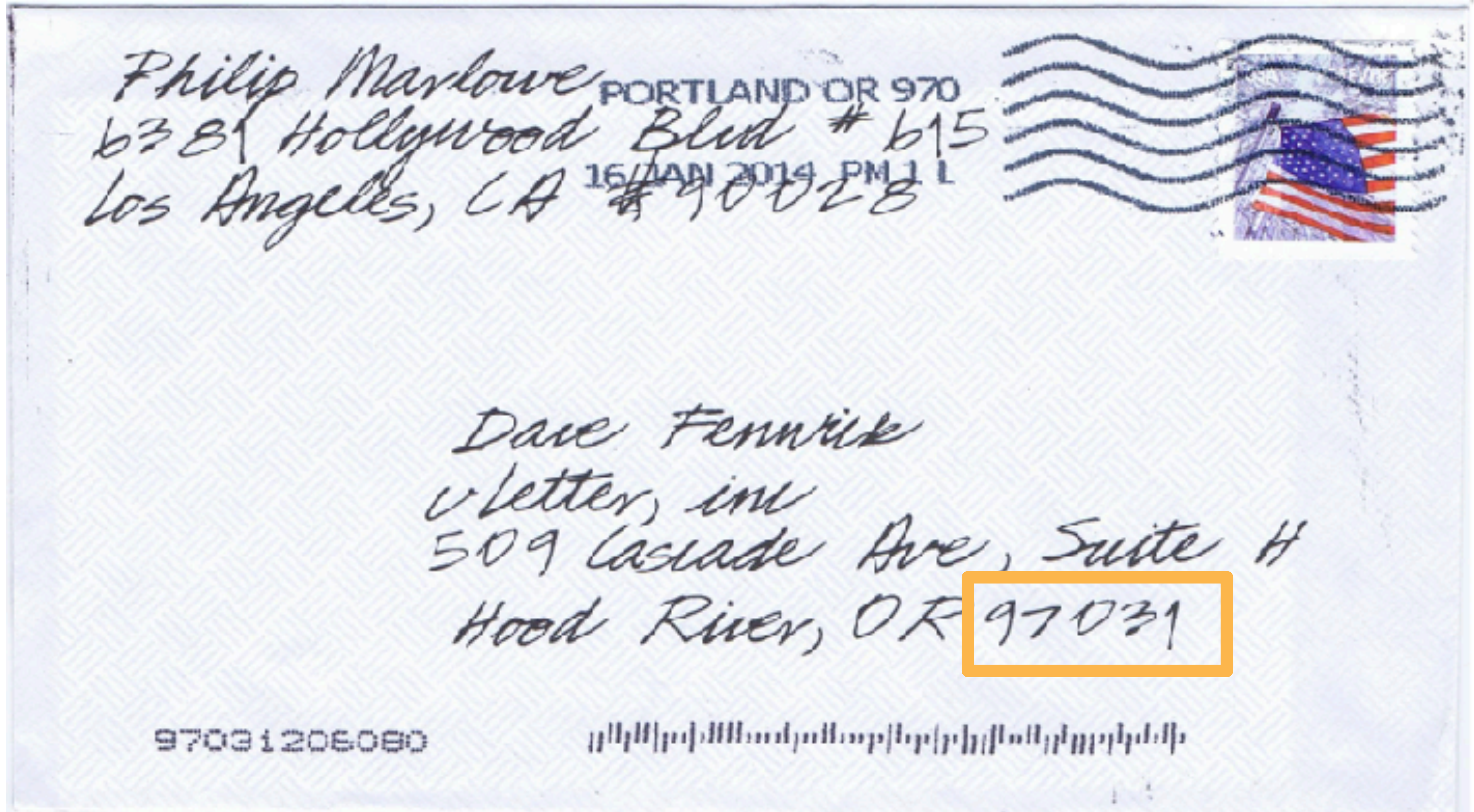



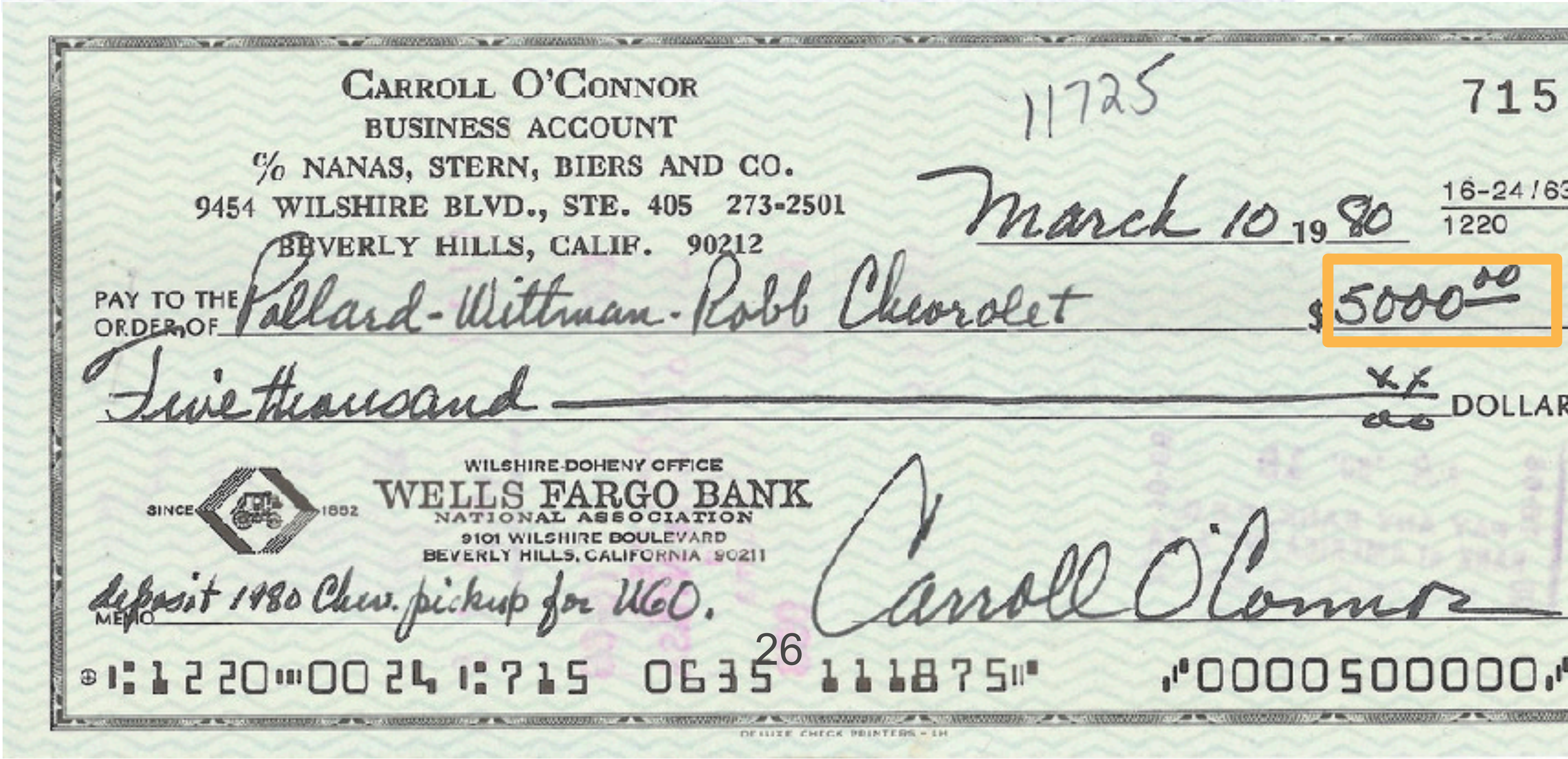
# LeNet Architecture (first conv nets)




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

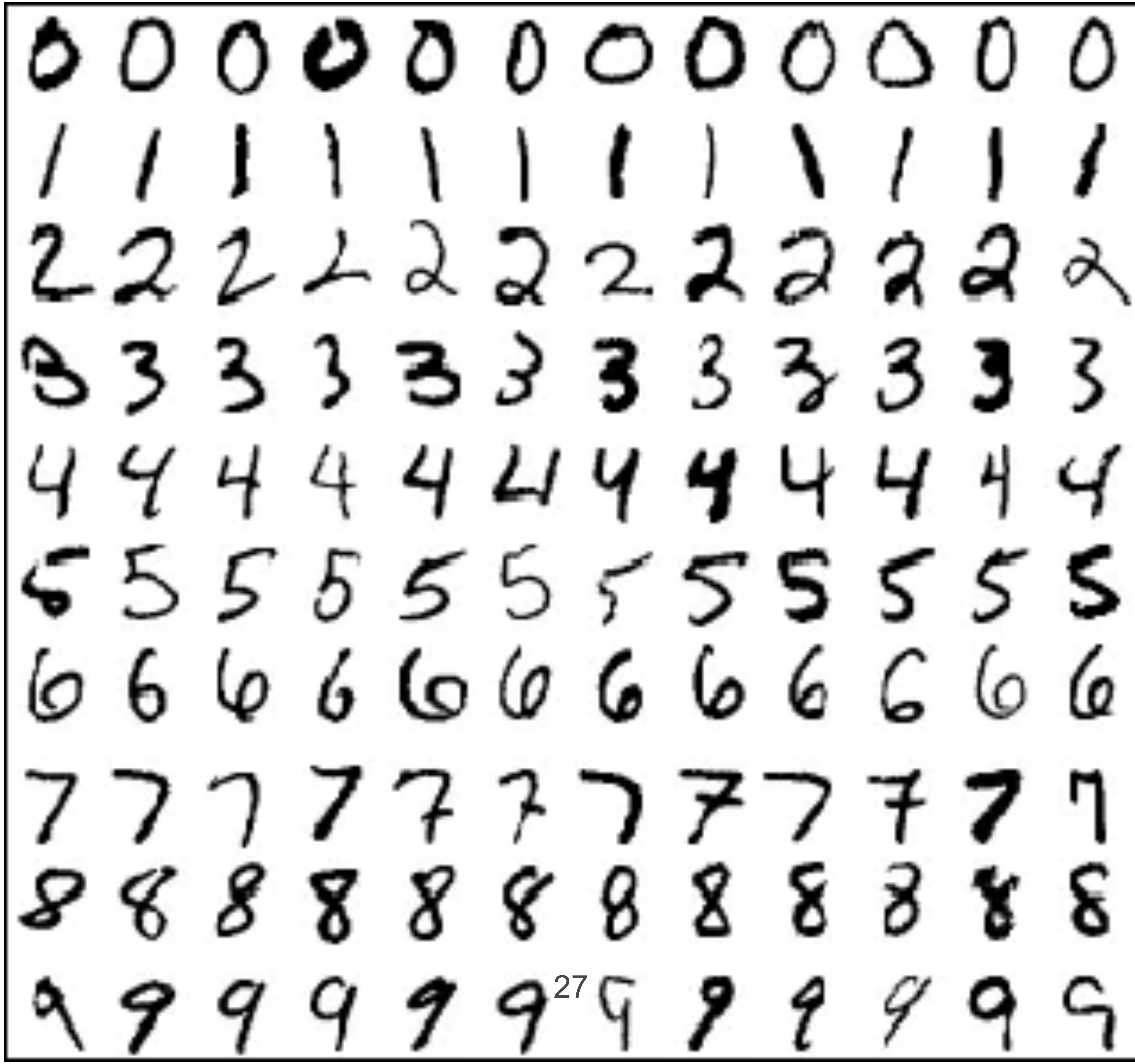
# Handwritten Digit Recognition

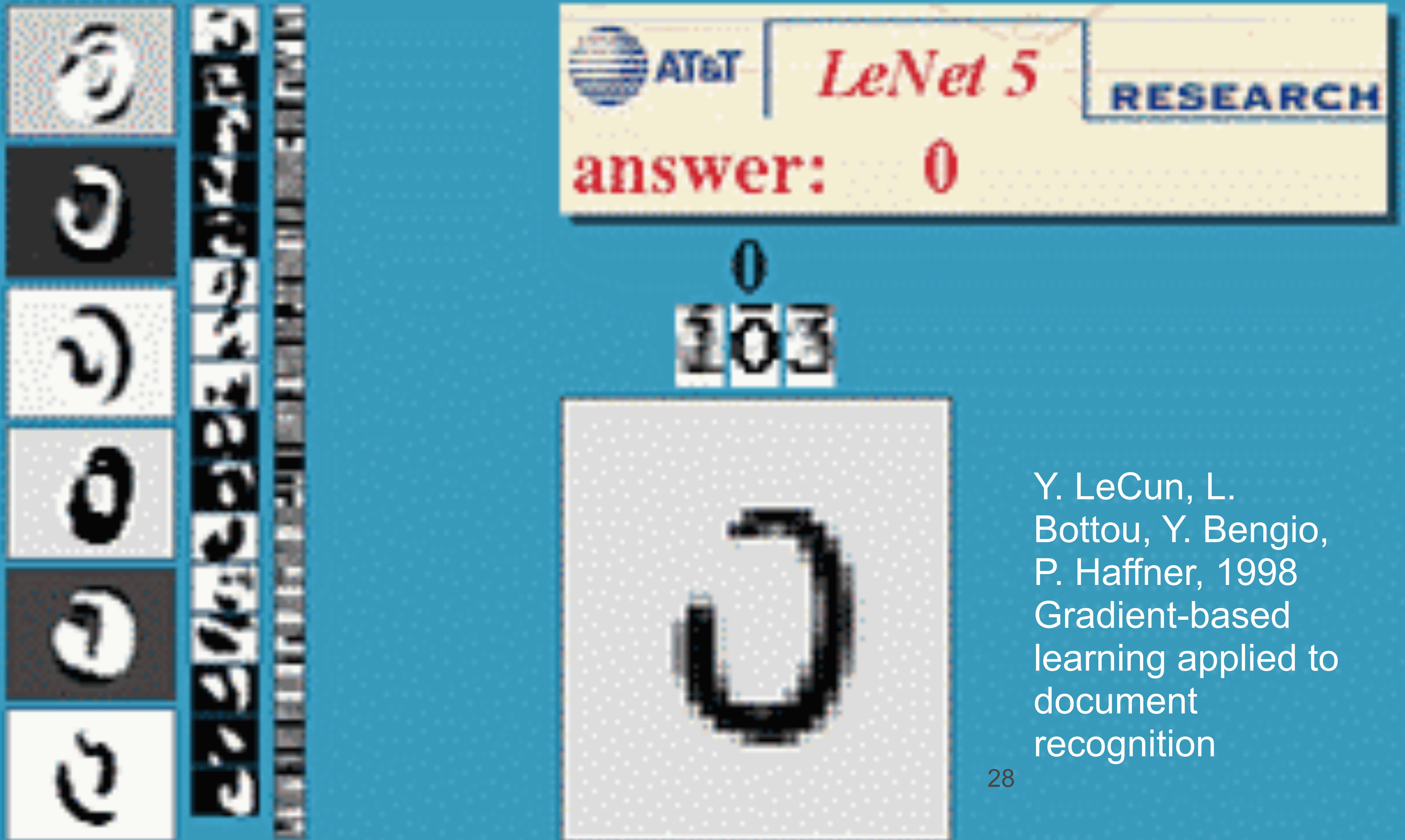


# MNIST

- 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

```
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 (col
    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 in Pytorch

# Let's walk through an example using PyTorch

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

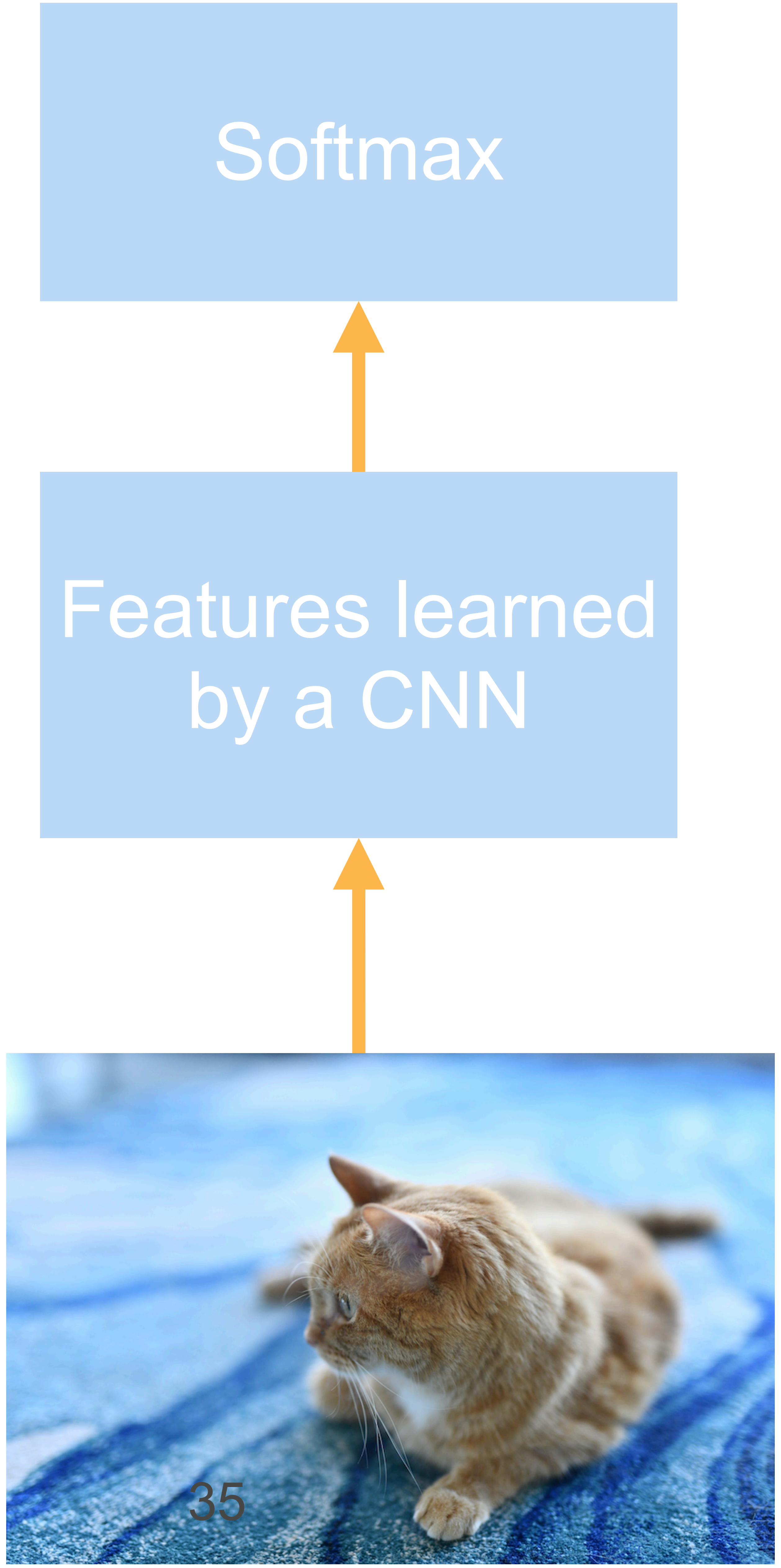
# AlexNet

11
11
224
11
11
224
Stride of 4
3
5
5
48
55
5
5
55
48
Max pooling
3
3
3
3
128
27
3
3
27
3
3
128
Max pooling
3
3
192
13
13
3
3
192
3
3
192
13
13
3
3
192
128
13
13
128
Max pooling
dense
2048
2048
dense
dense
2048
2048
dense
1000


Deng et al. 2009

# AlexNet

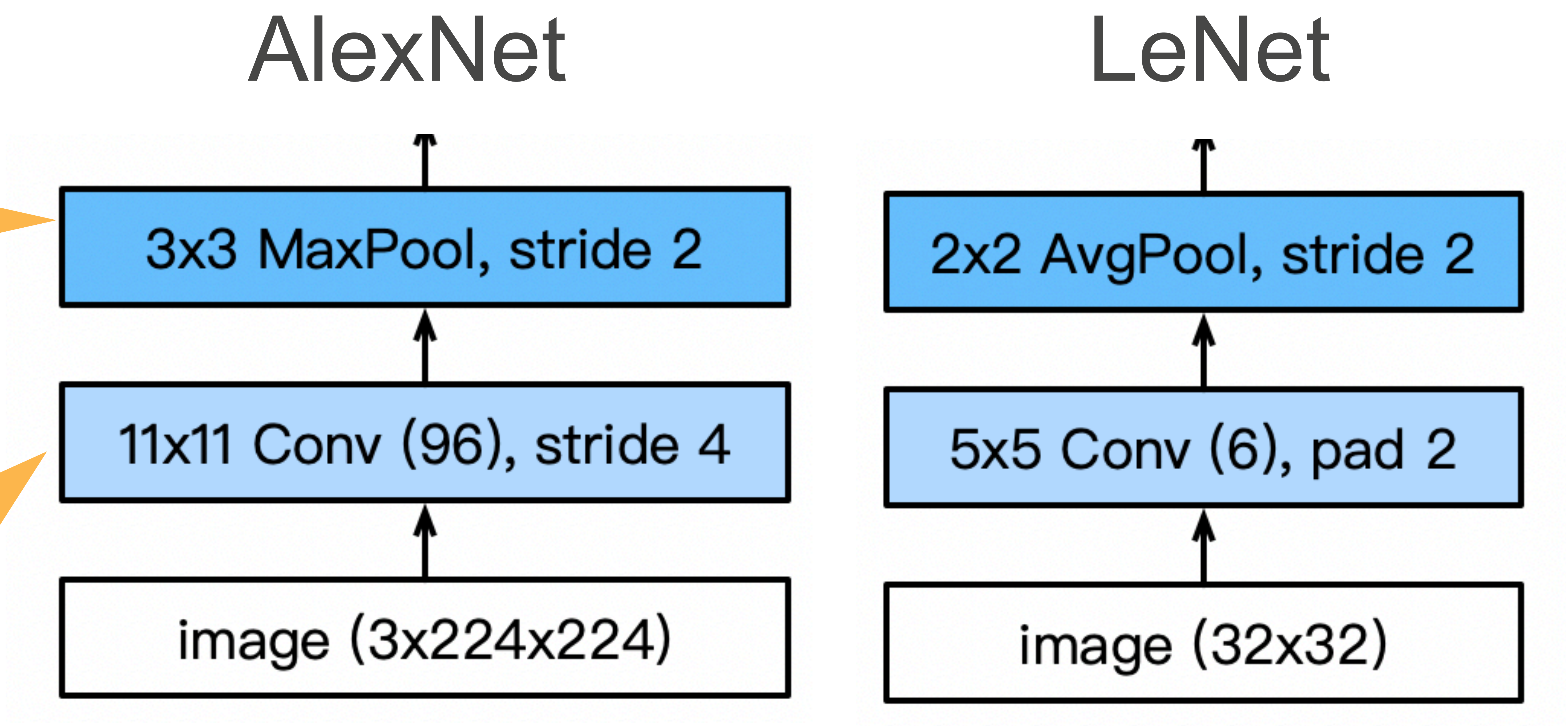
- AlexNet won ImageNet competition in 2012
- Deeper and bigger LeNet
- Paradigm shift for computer vision



# AlexNet Architecture

Larger pool size

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



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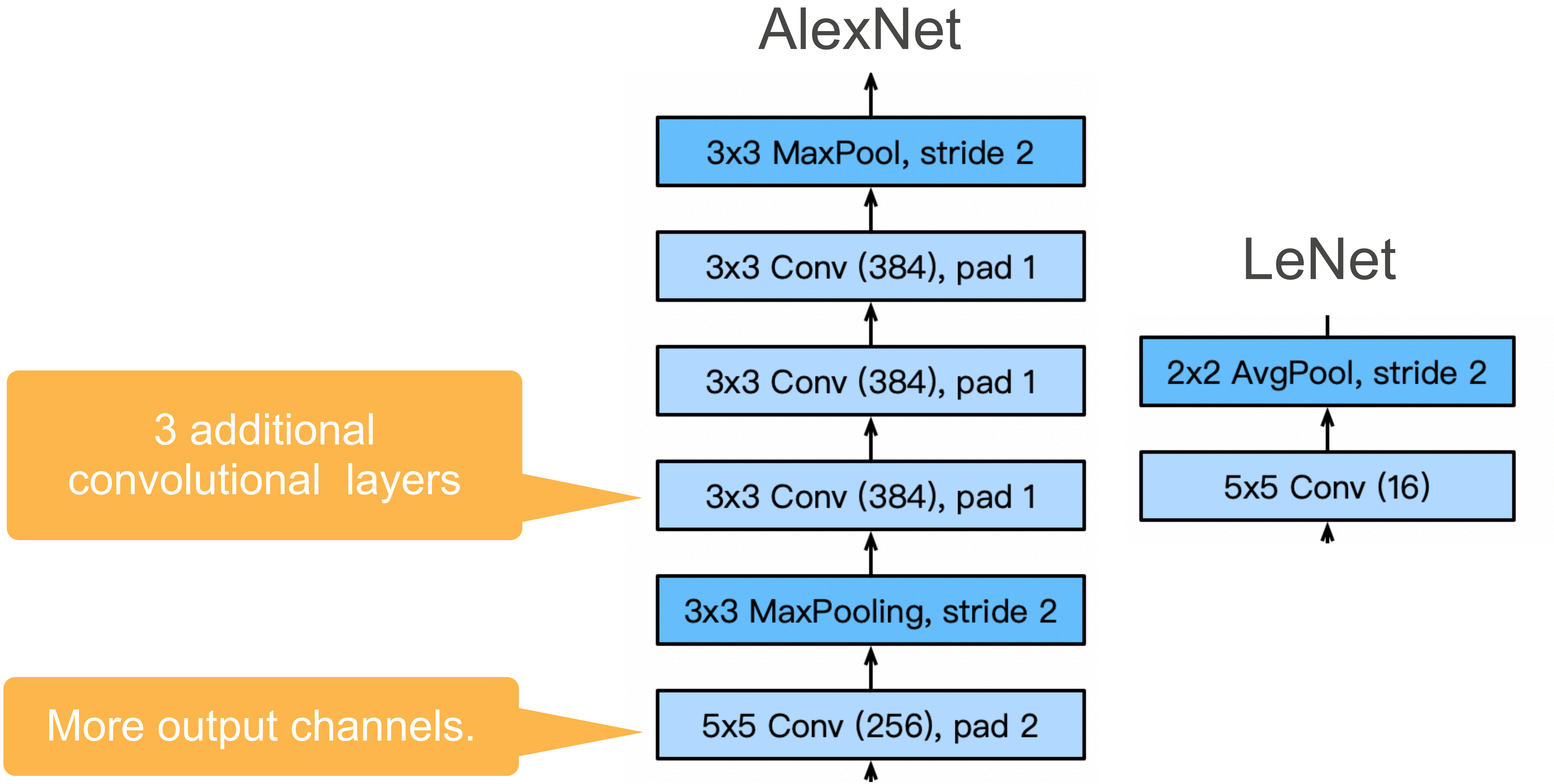
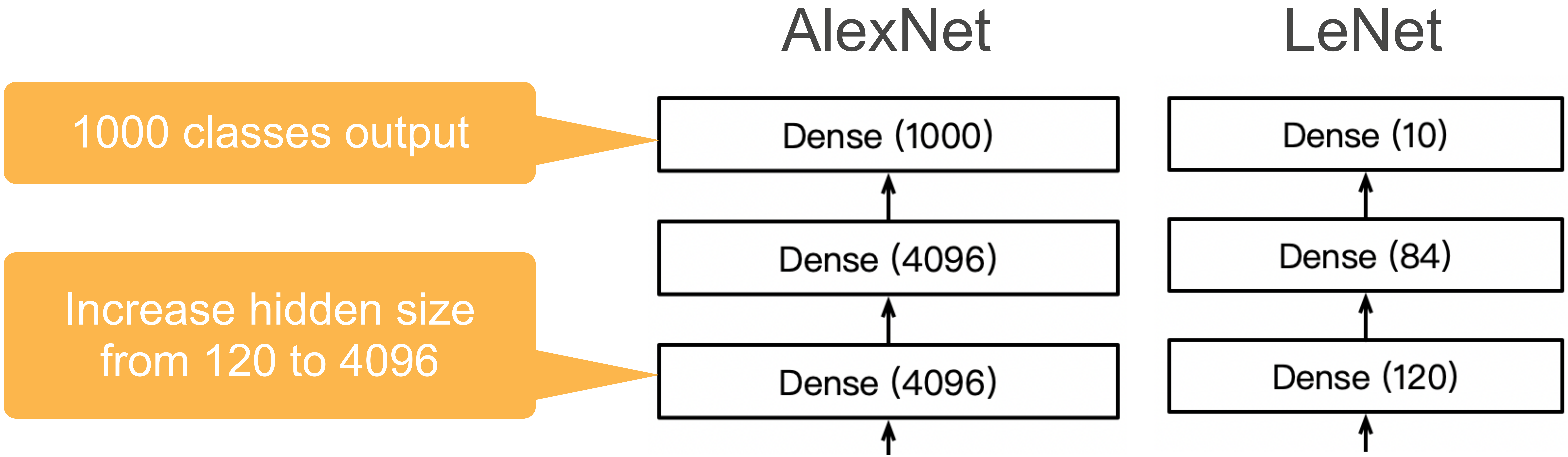
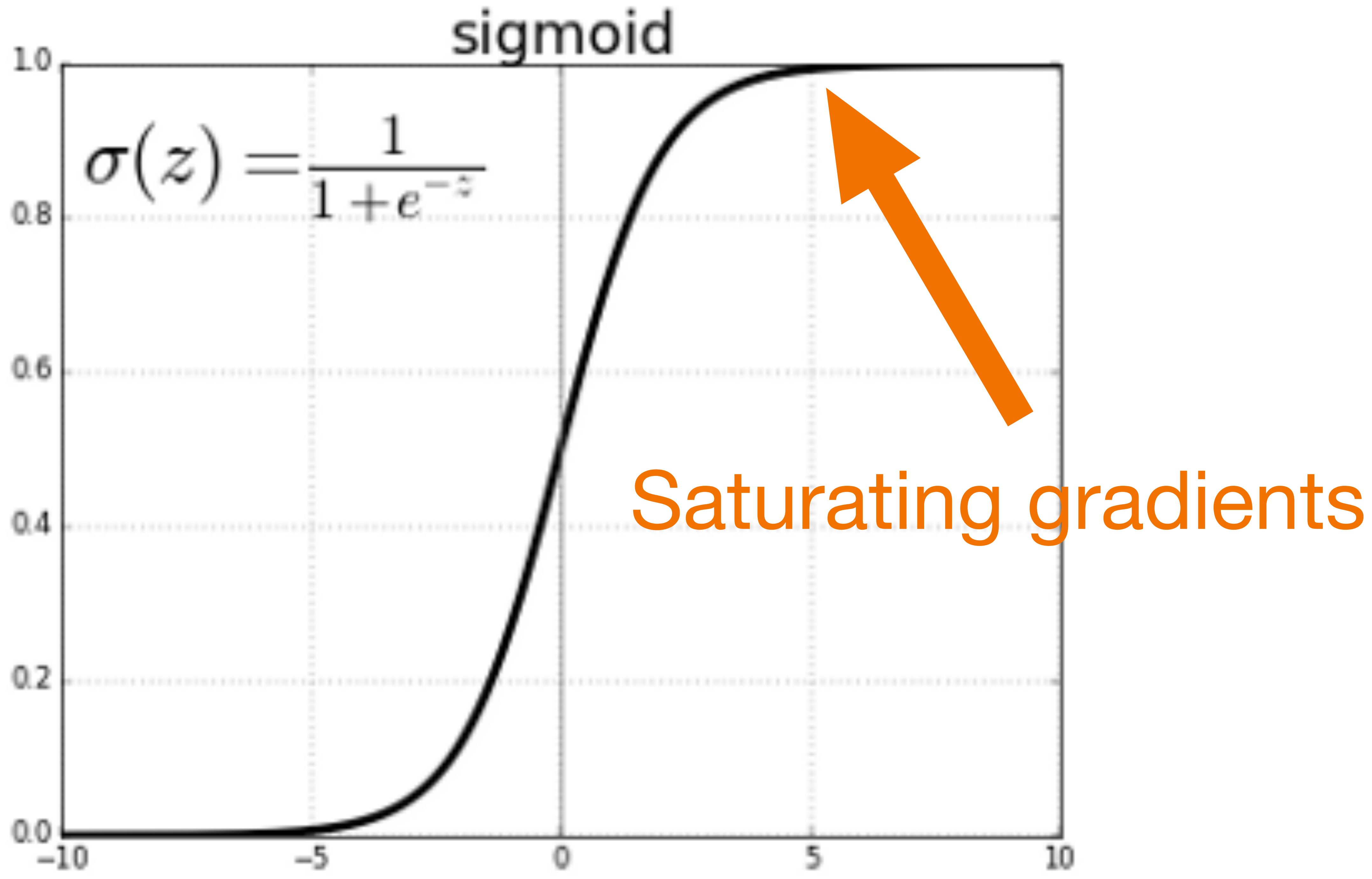


# AlexNet Architecture



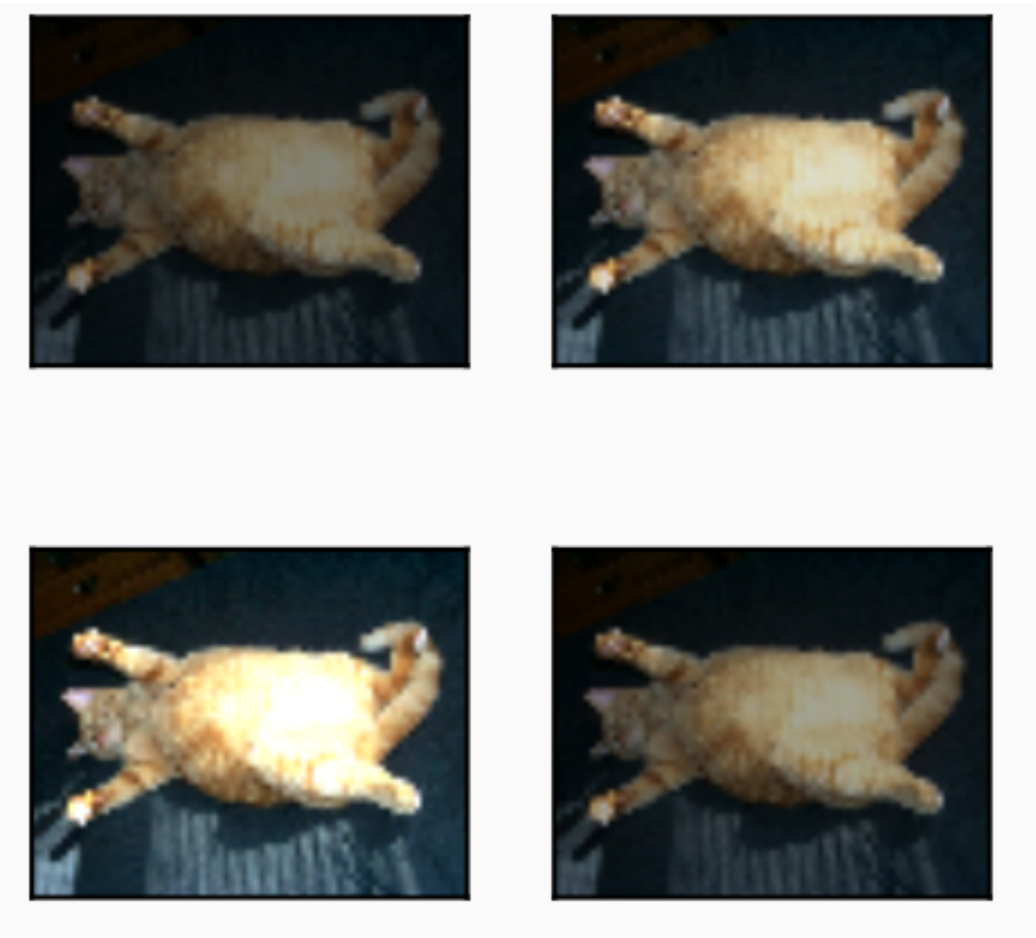
# More Differences…

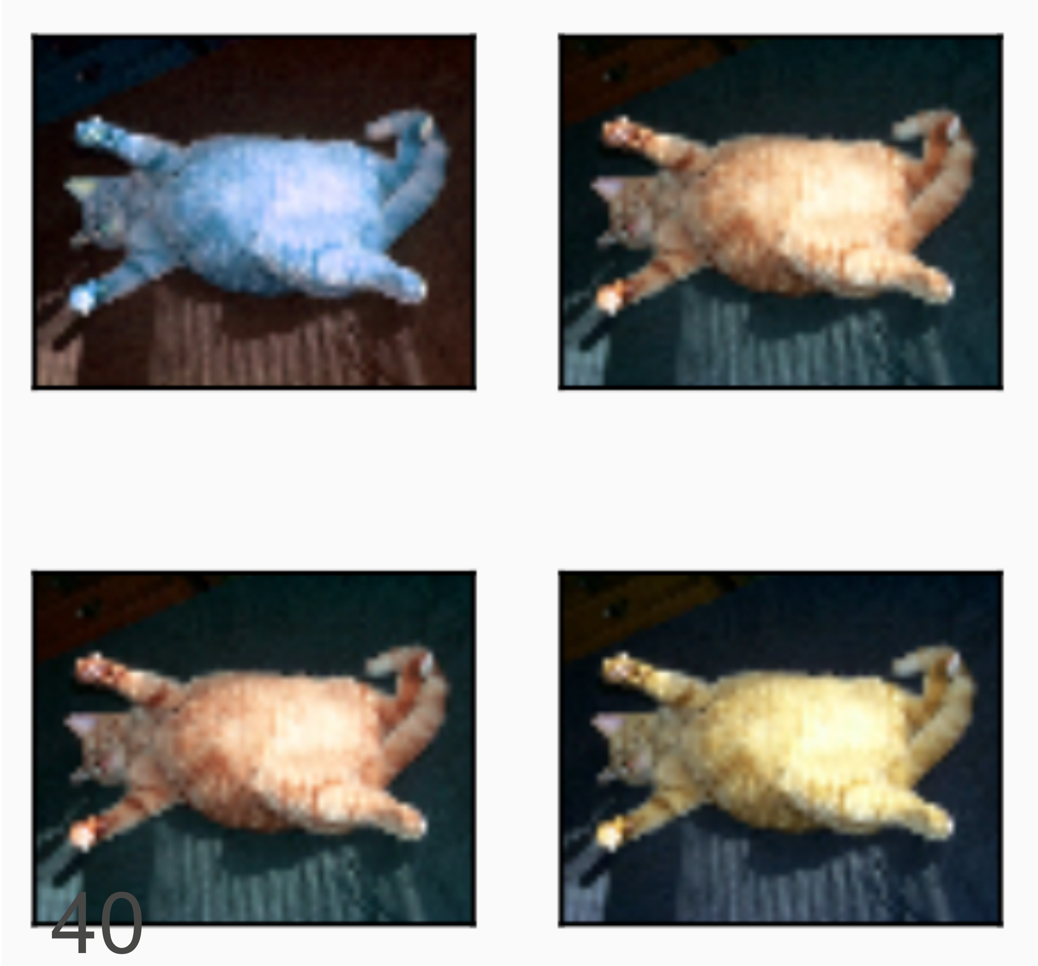
- Change activation function from sigmoid to ReLu (no more vanishing gradient)



# More Differences…

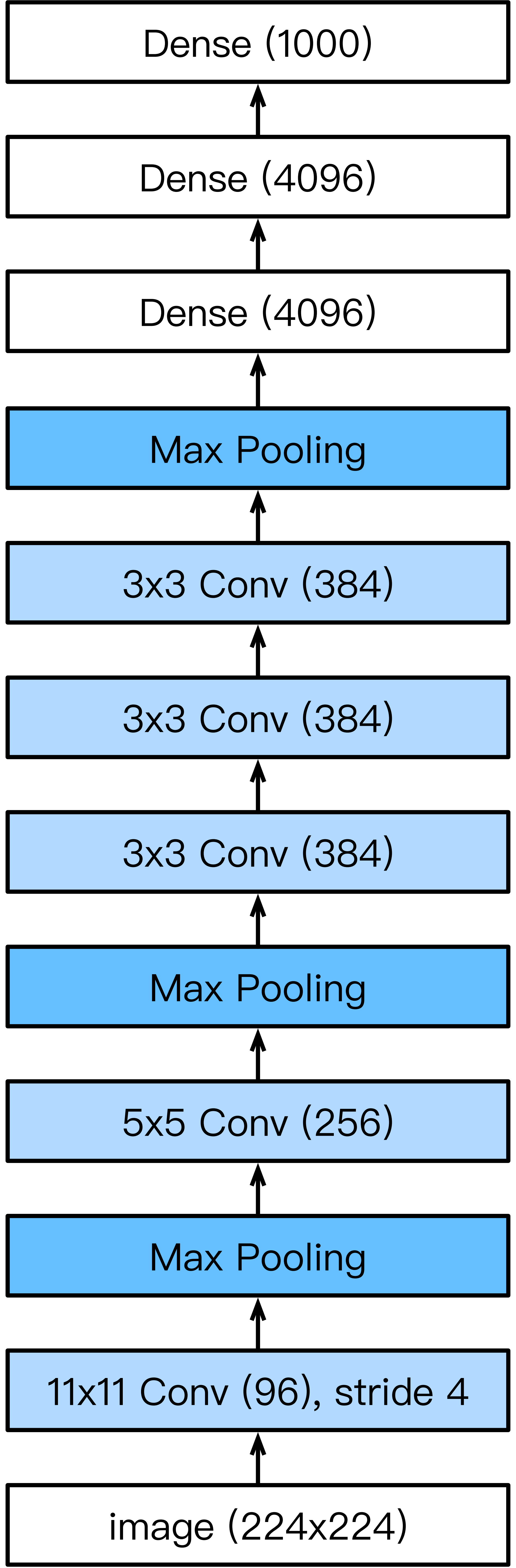
- Change activation function from sigmoid to ReLu (no more vanishing gradient)
- Data augmentation





# 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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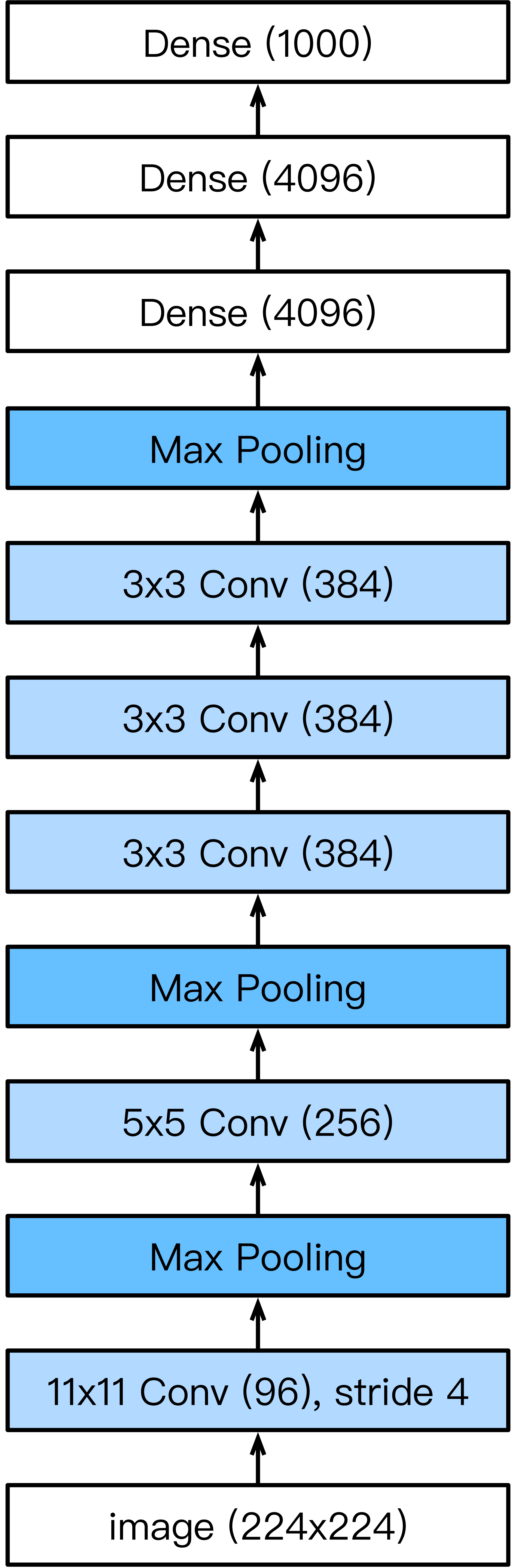
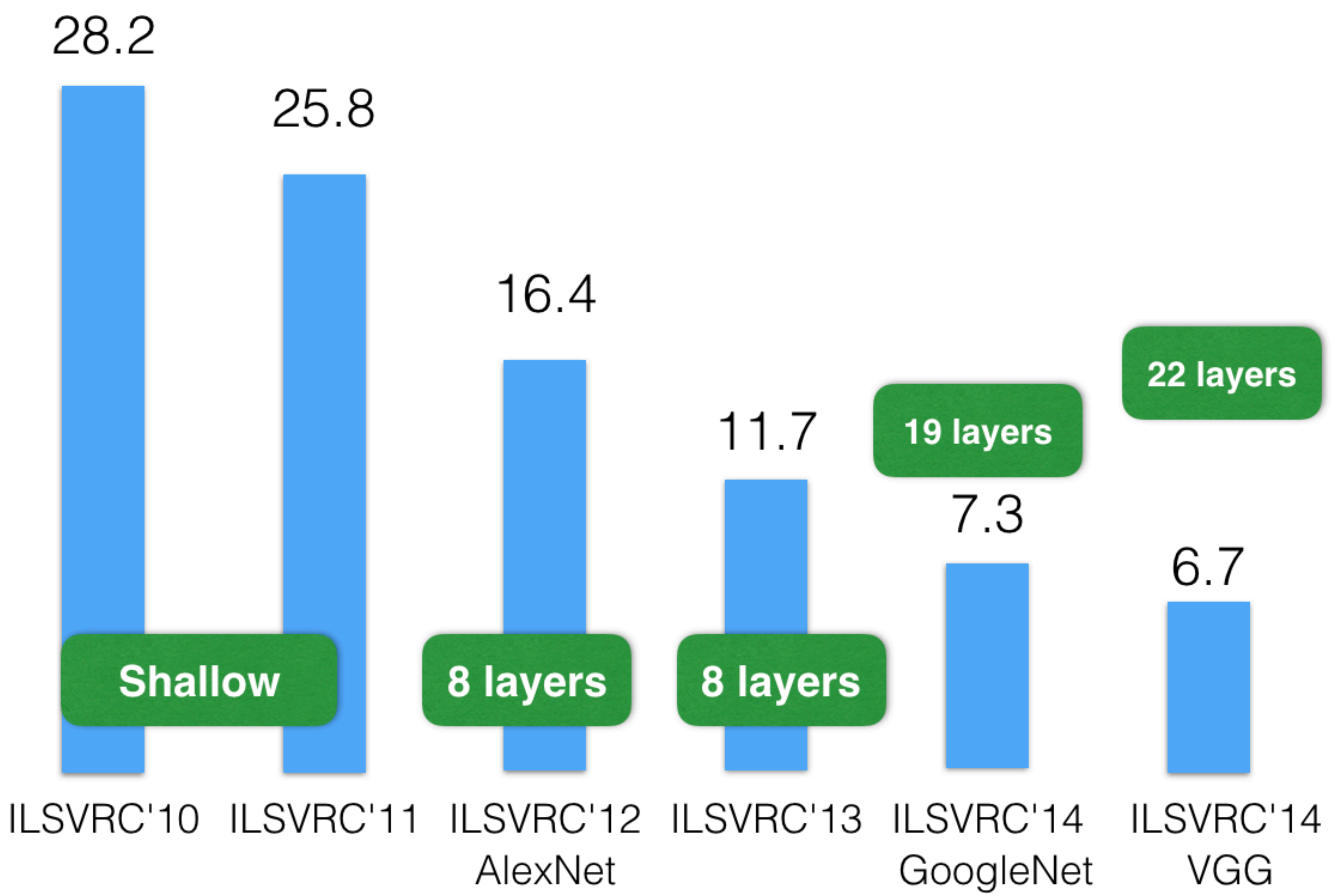
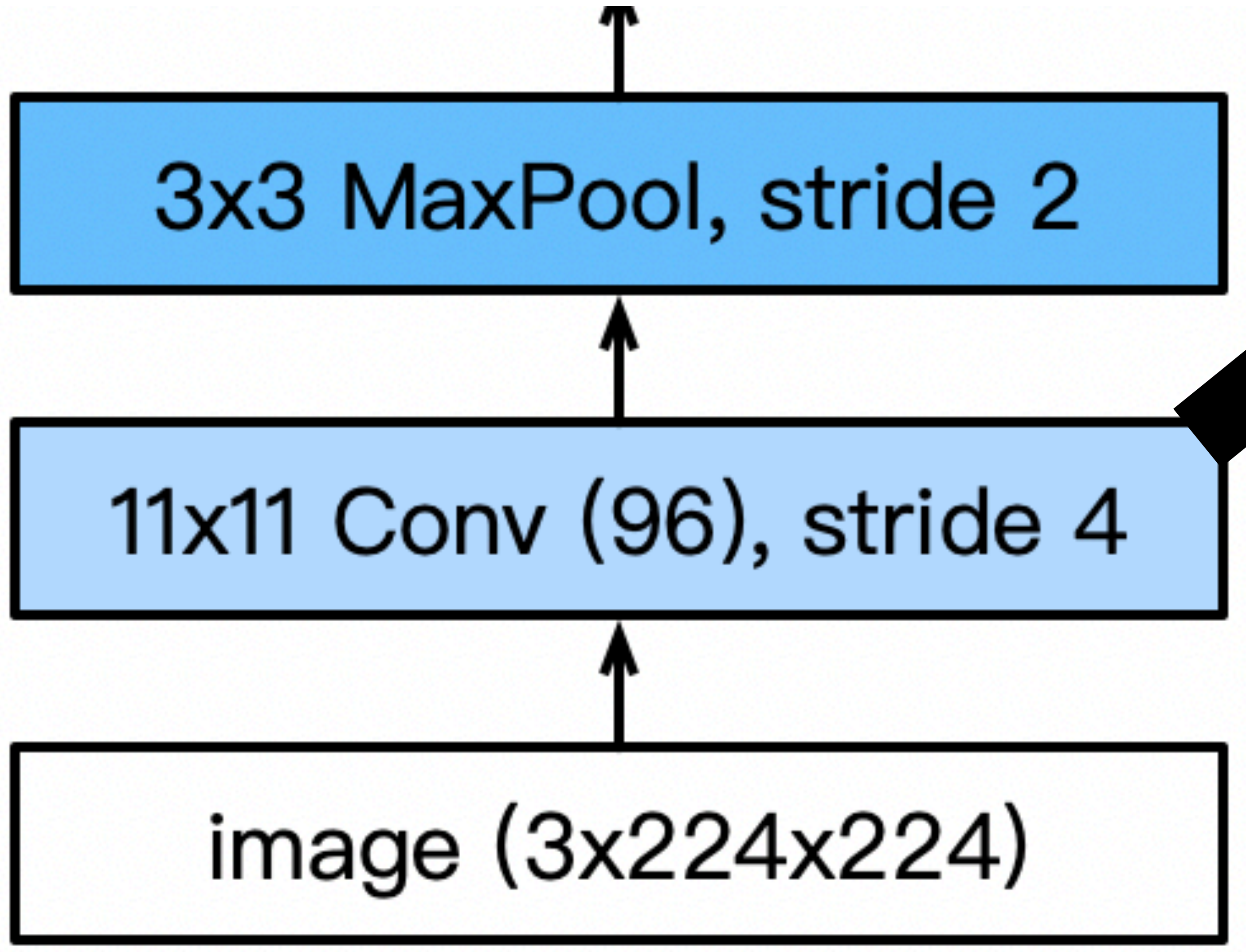
11x11x3x96=35k



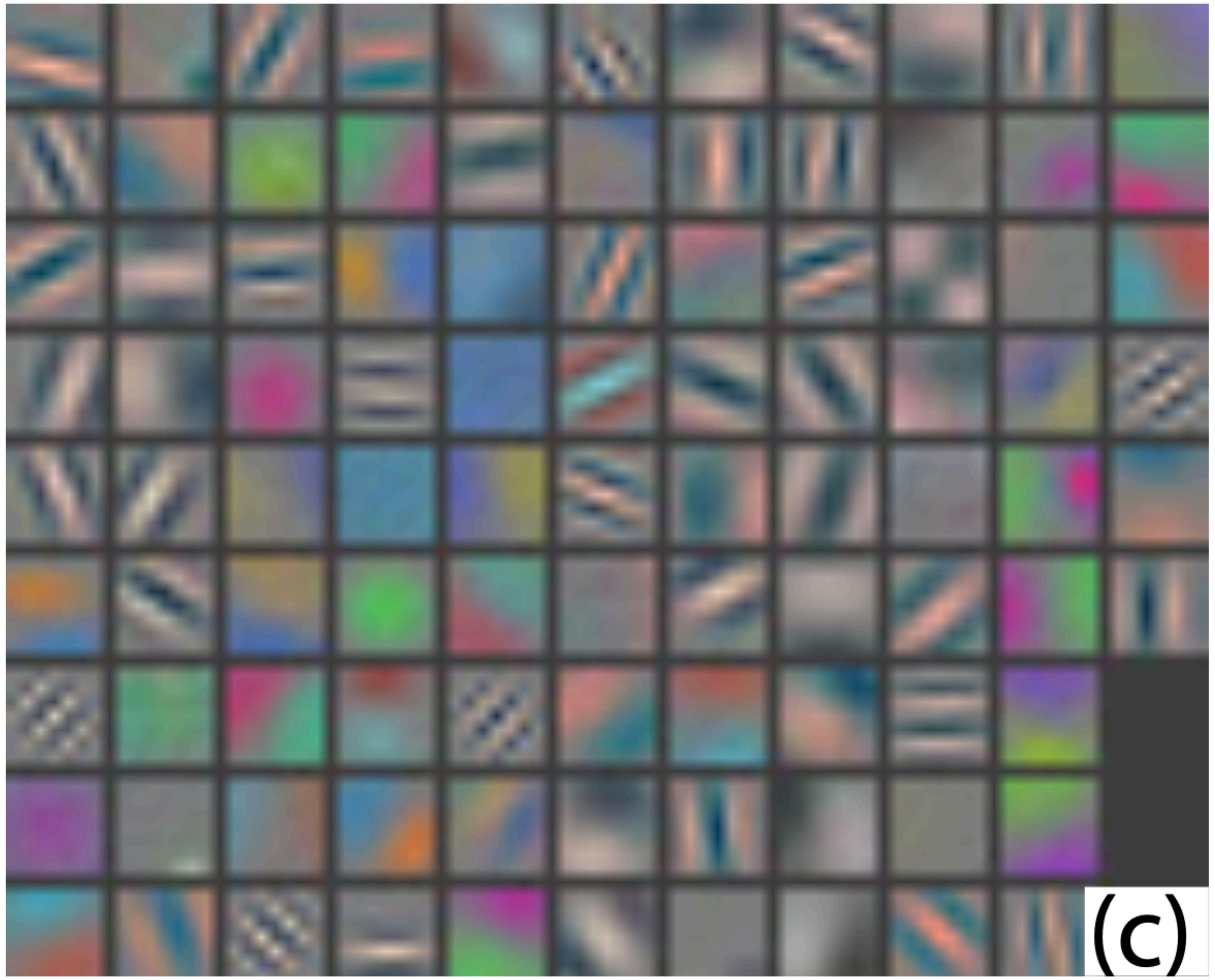



ImageNet Top-5 Classification Accuracy (%)

# 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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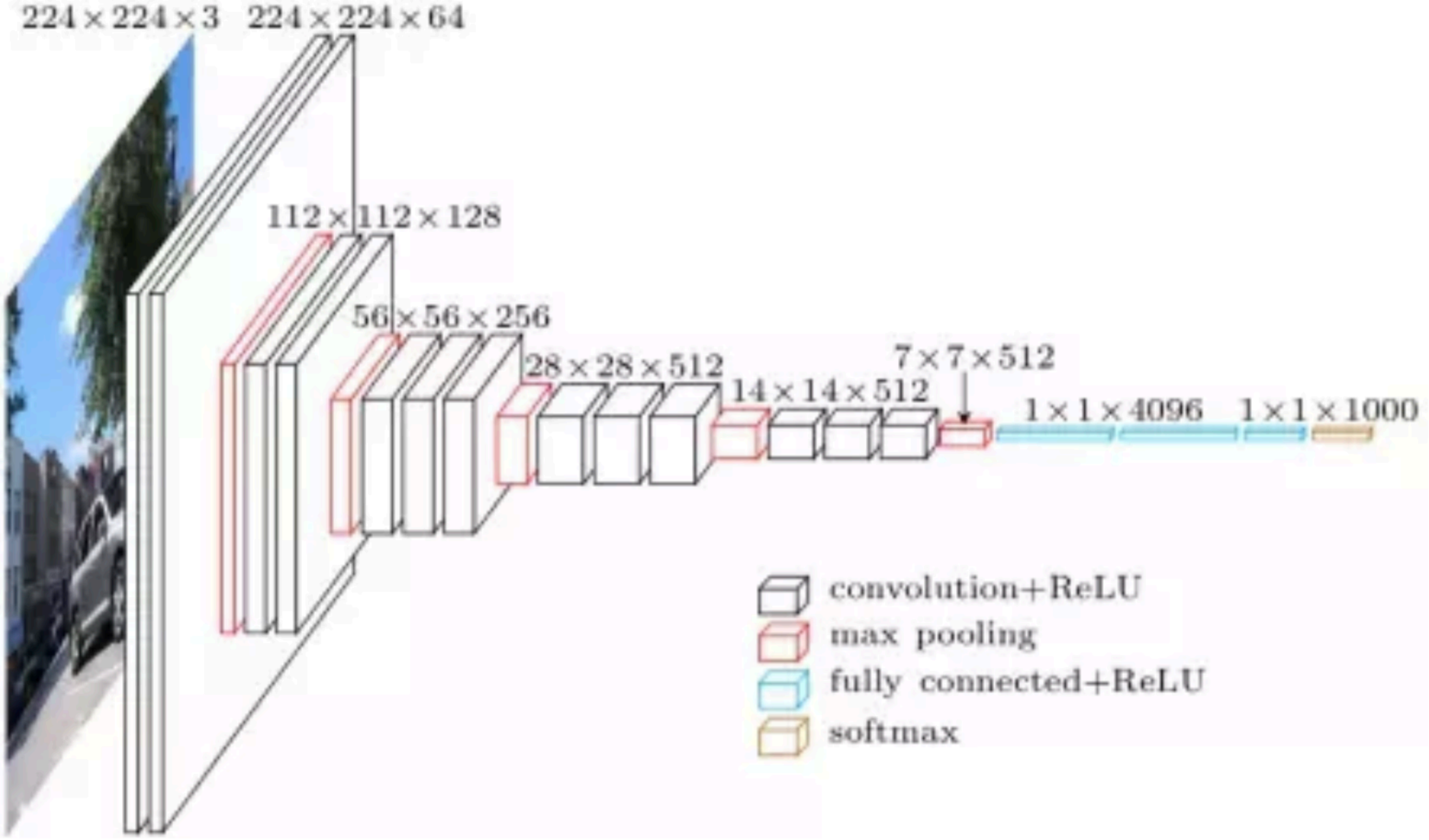
All options are true!

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



224 × 224 × 3
224 × 224 × 64
112 × 112 × 128
56 × 56 × 256
28 × 28 × 512
14 × 14 × 512
7 × 7 × 512
1 × 1 × 4096
1 × 1 × 1000
convolution+ReLU
max pooling
fully connected+ReLU
softmax

# 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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# What we’ve learned today

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


# **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