香港科技大學
THE HONG KONG
UNIVERSITY OF SCIENCE
AND TECHNOLOGY

COMP 5212
Machine Learning
Lecture 19

Neural Networks, Architectures

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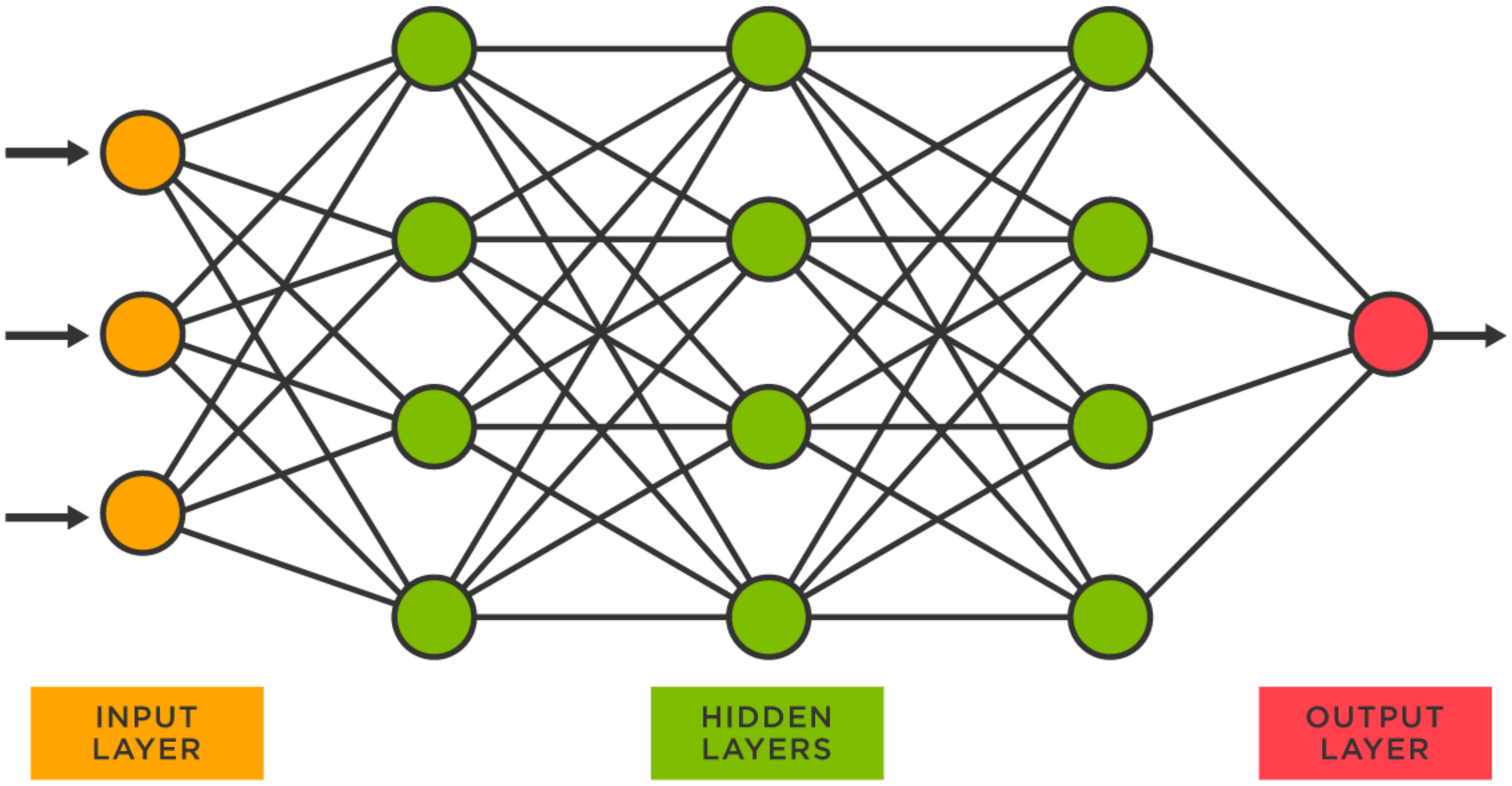
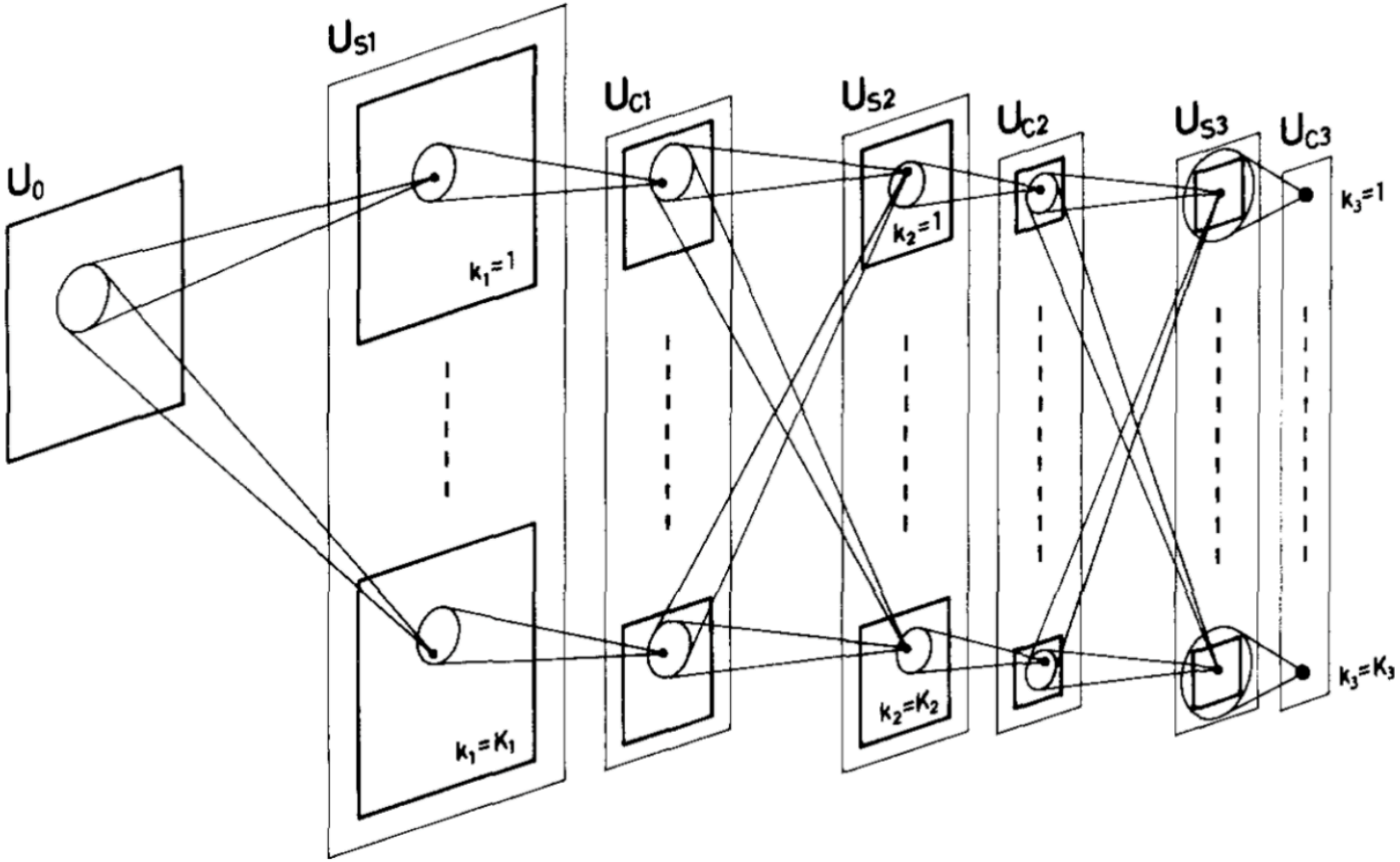
Apr 17, 2024

Recap: Multilayer Perceptron Neural Networks (MLP)

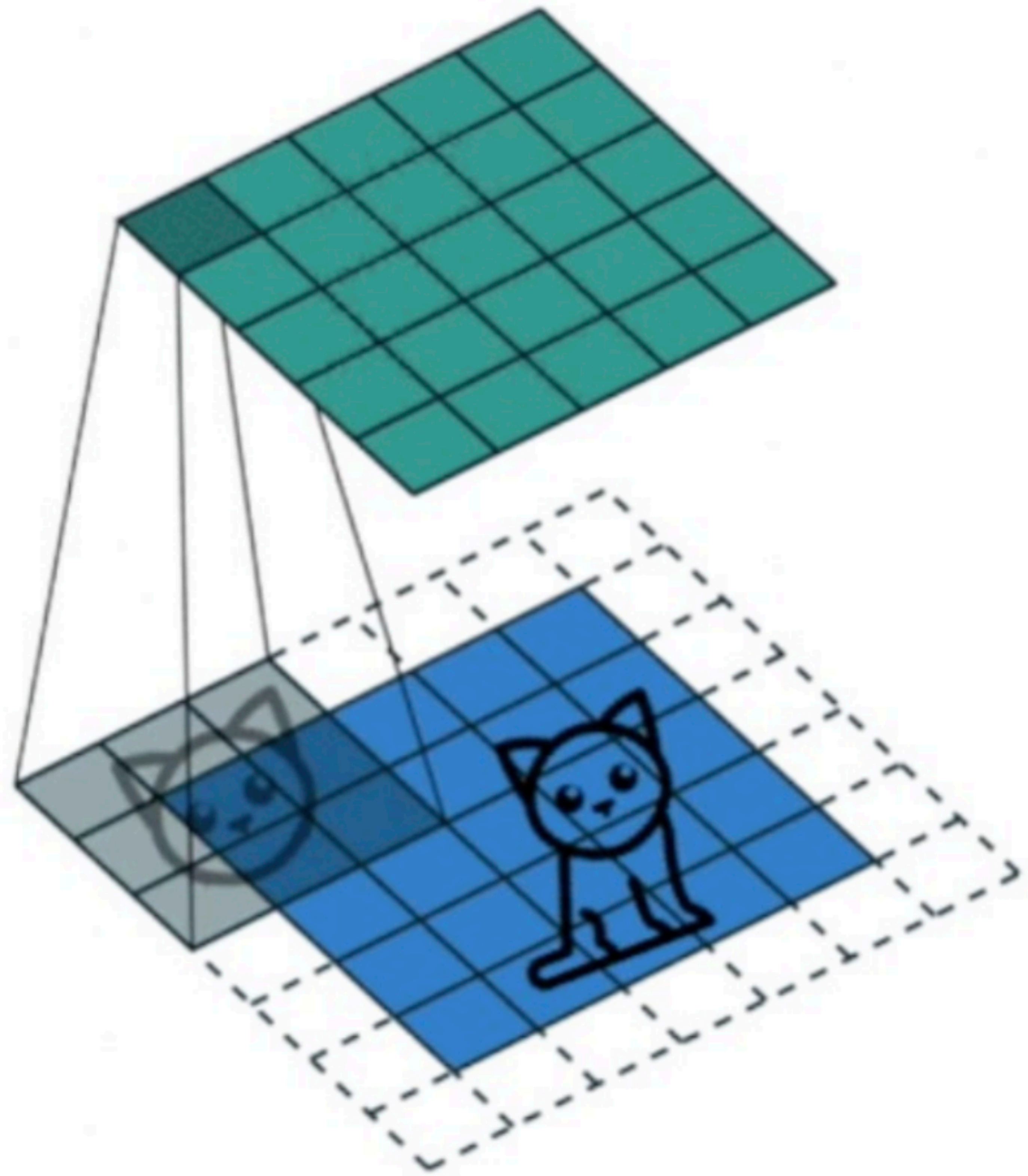


Convolutional Neural Networks



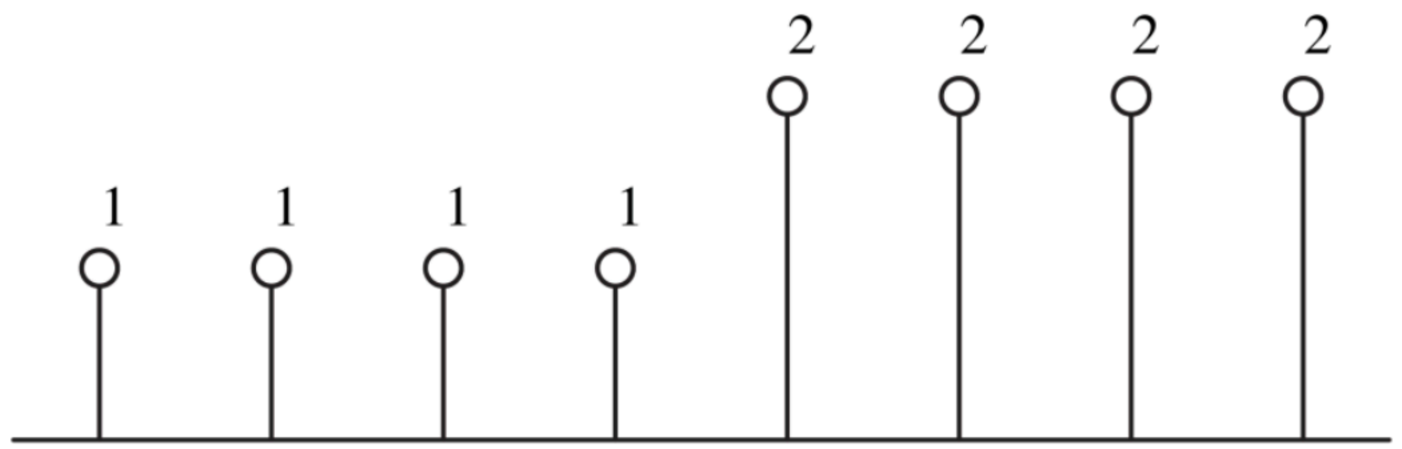
Convolution is template matching

- with a sliding window
- abstract templates
- similarity measured by dot product
- stronger activation, better matching

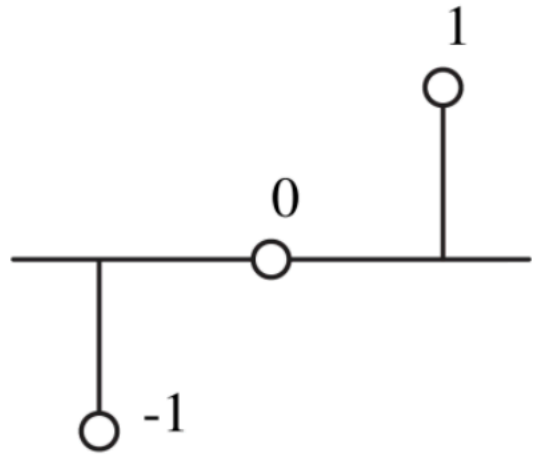


Convolution: a 1-D example

input

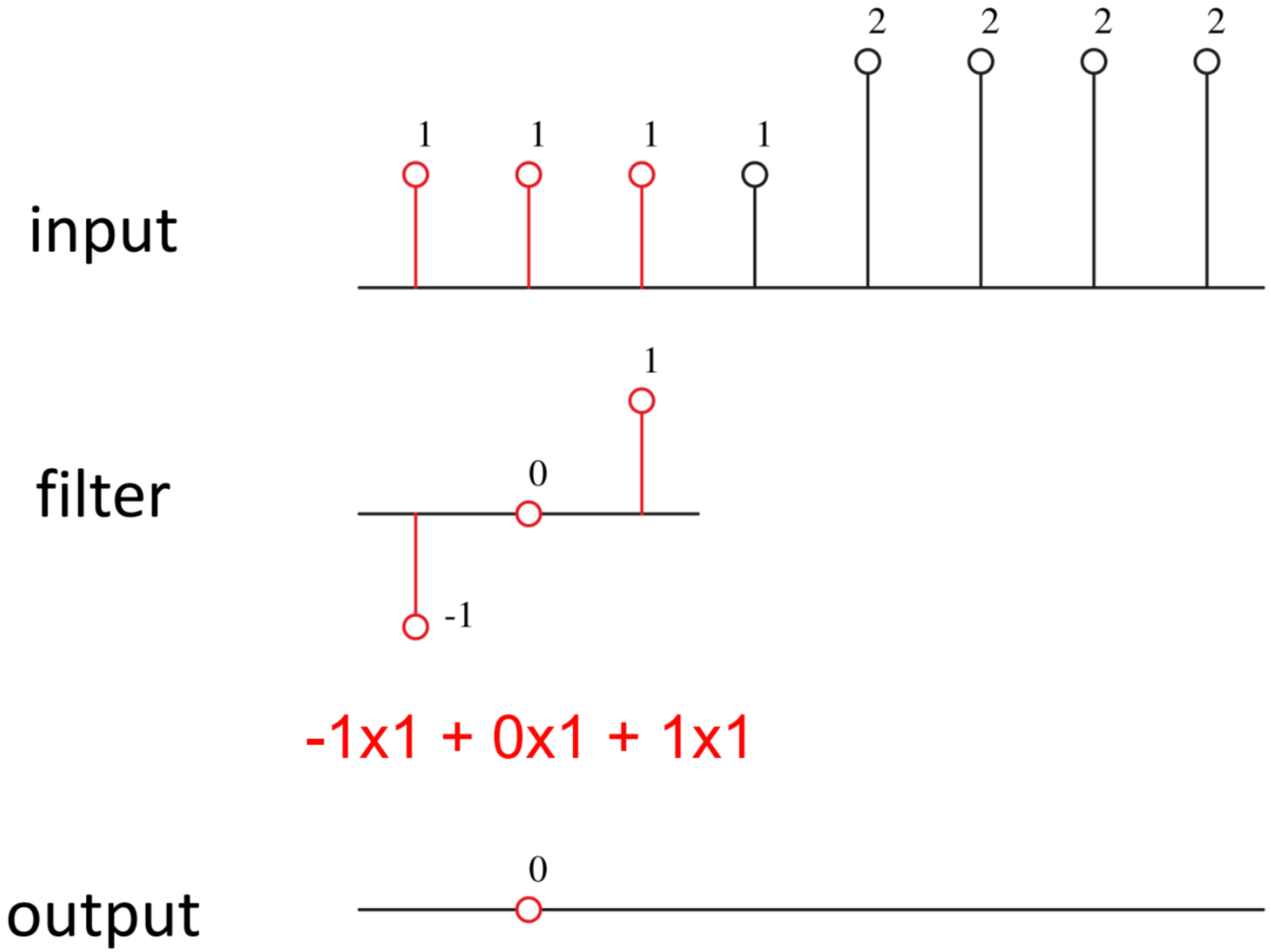


filter



Convolution: a 1-D example

- sliding window
- dot product



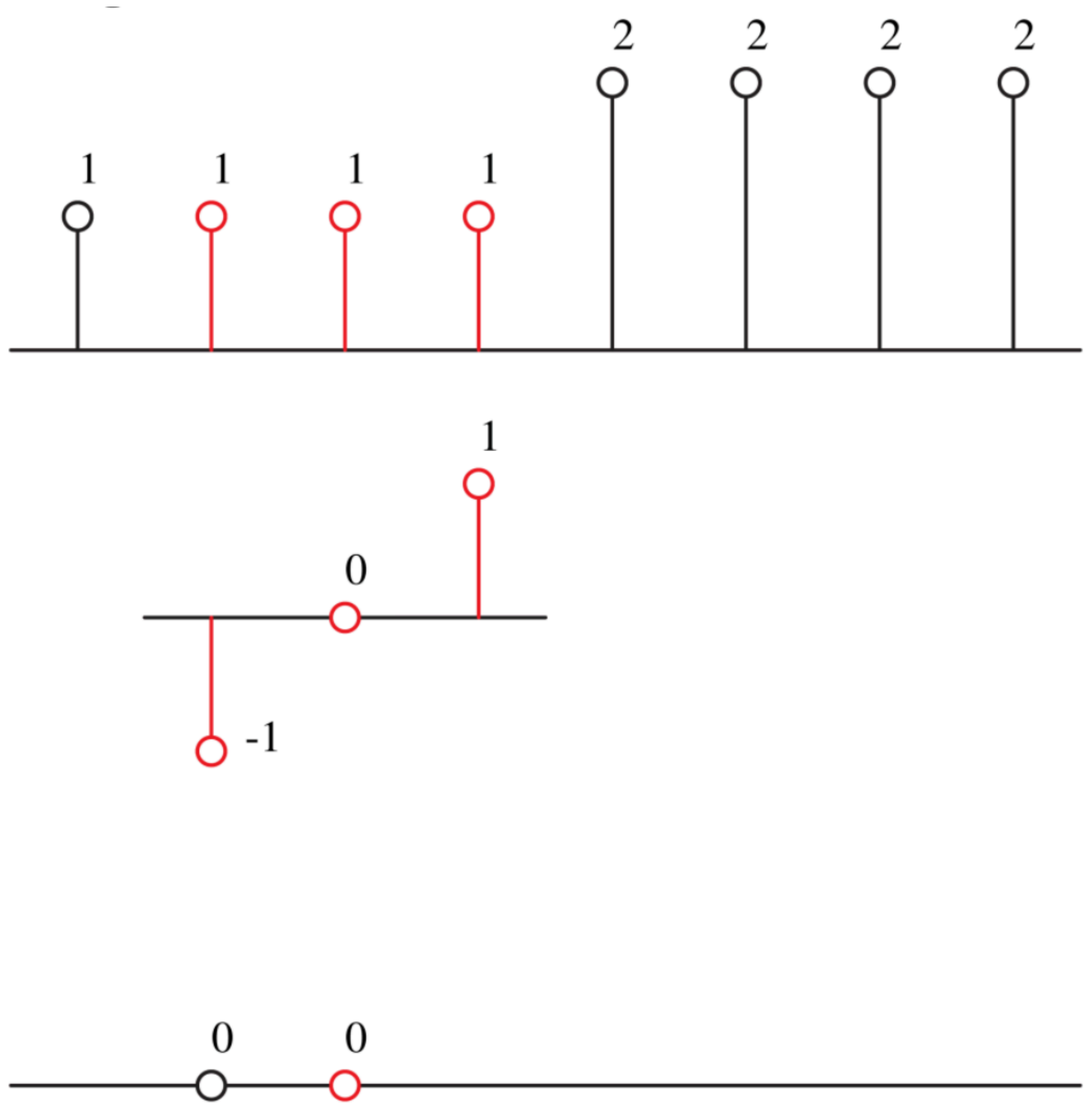
Convolution: a 1-D example

- sliding window
- dot product

input

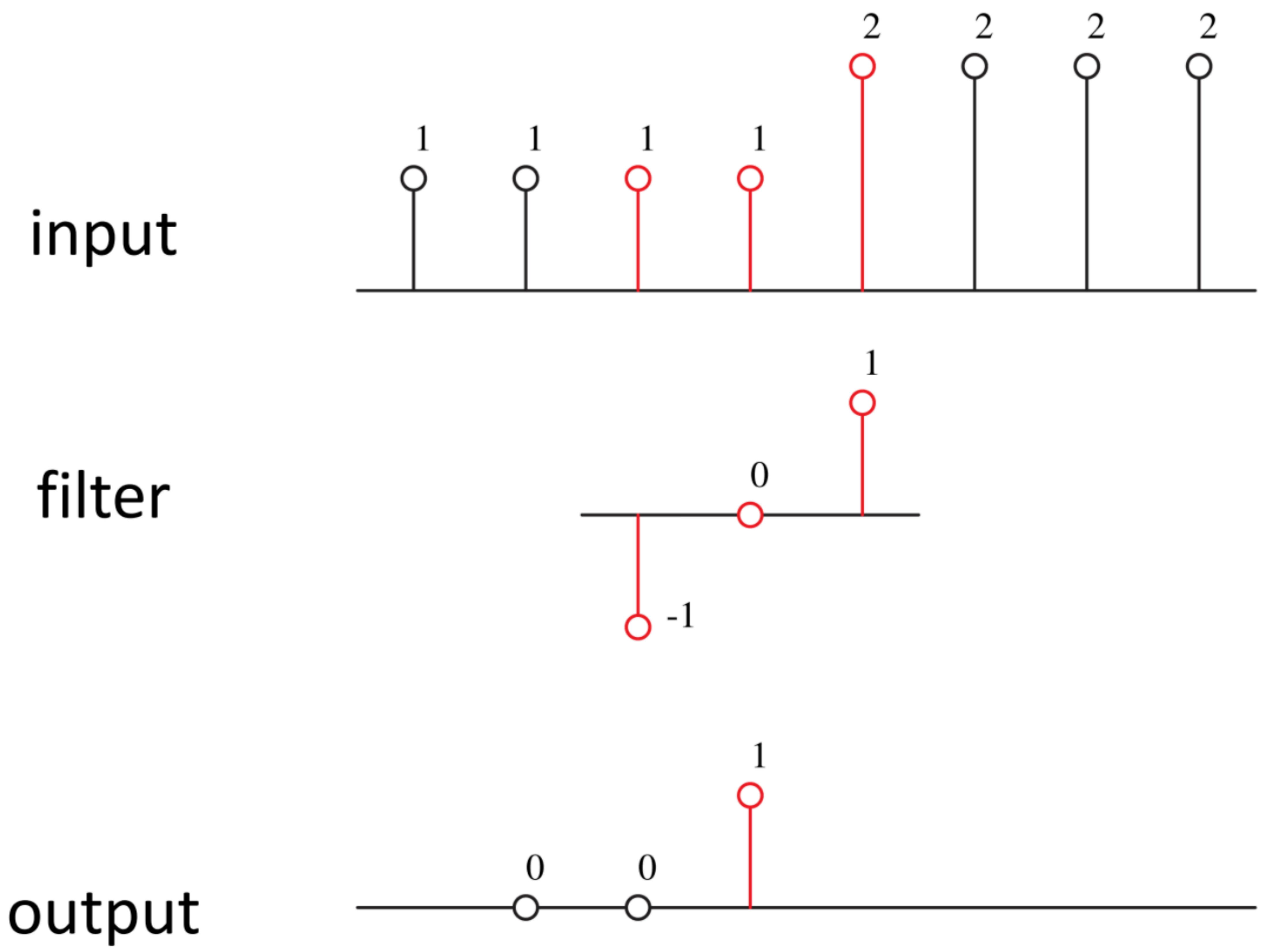
filter

output



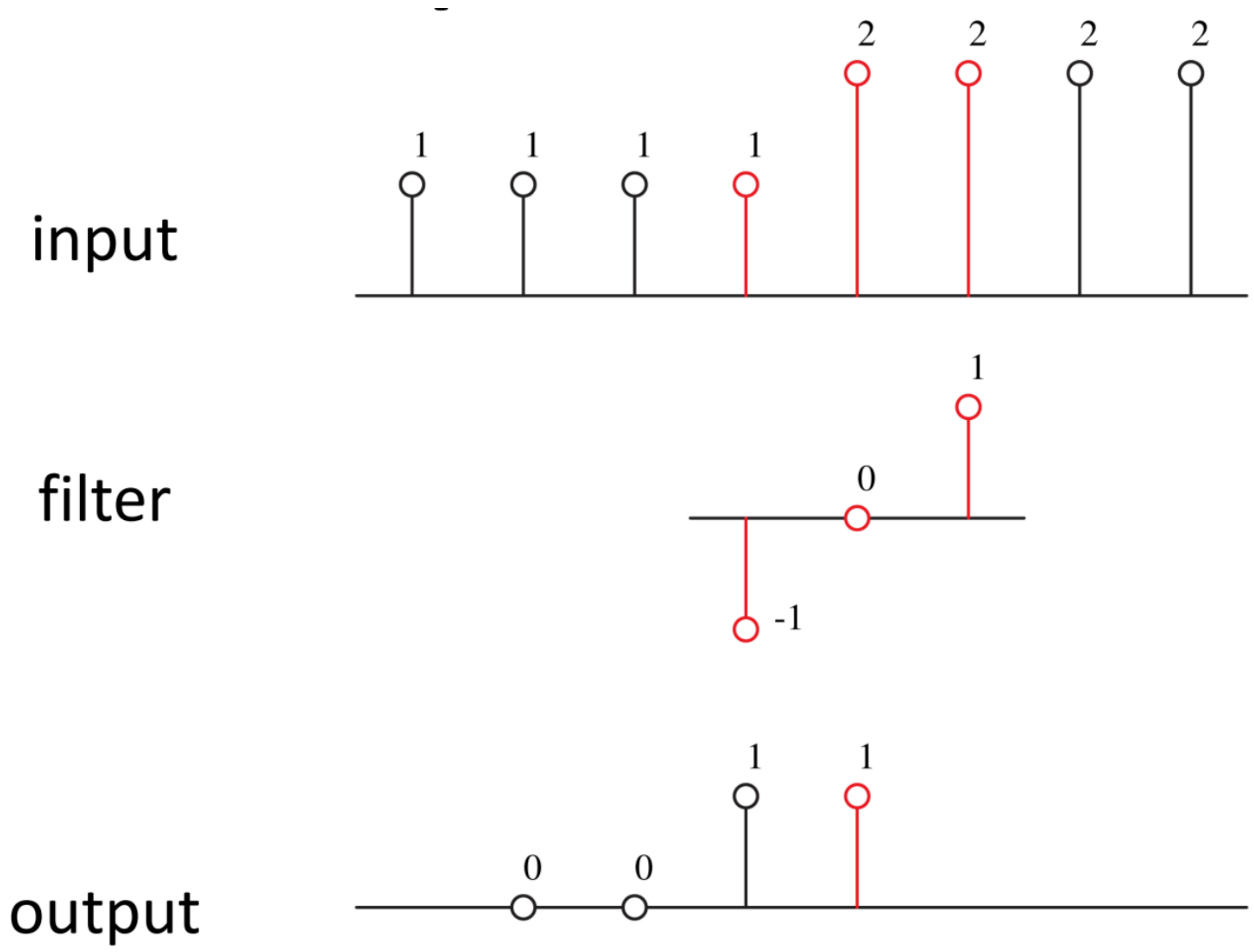
Convolution: a 1-D example

- sliding window
- dot product



Convolution: a 1-D example

- sliding window
- dot product



Convolution: a 2-D example

input

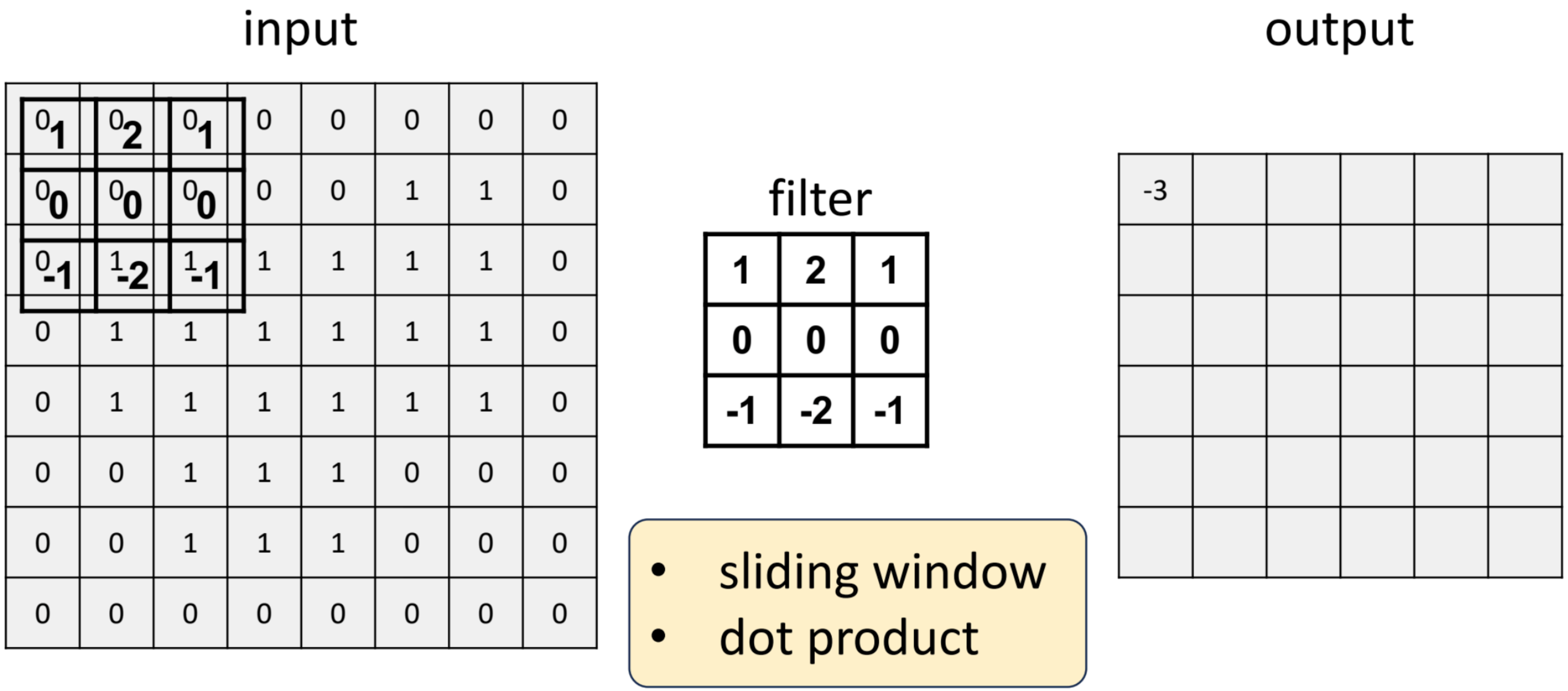
0	0	0	0	0	0	0	0
0	0	0	0	0	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	0	1	1	1	0	0	0
0	0	1	1	1	0	0	0
0	0	0	0	0	0	0	0

filter

1	**2**	**1**
0	**0**	**0**
-1	**-2**	**-1**

output

Convolution: a 2-D example



Convolution: a 2-D example

input

0	$^{0}\mathbf{1}$	$^{0}\mathbf{2}$	$^{0}\mathbf{1}$	0	0	0	0
0	$^{0}\mathbf{0}$	$^{0}\mathbf{0}$	$^{0}\mathbf{0}$	0	1	1	0
0	$^{1}\mathbf{-1}$	$^{1}\mathbf{-2}$	$^{1}\mathbf{-1}$	1	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	0	1	1	1	0	0	0
0	0	1	1	1	0	0	0
0	0	0	0	0	0	0	0

filter

1	**2**	**1**
0	**0**	**0**
-1	**-2**	**-1**

- sliding window
- dot product

output

-3	-4				

Convolution: a 2-D example

input

0	0	0 **1**	0 **2**	0 **1**	0	0	0
0	0	0 **0**	0 **0**	0 **0**	1	1	0
0	1	1 **-1**	1 **-2**	1 **-1**	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	0	1	1	1	0	0	0
0	0	1	1	1	0	0	0
0	0	0	0	0	0	0	0

filter

1	**2**	**1**
0	**0**	**0**
-1	**-2**	**-1**

- sliding window
- dot product

output

-3	-4	-4			

Convolution: a 2-D example

input

0	0	0	0	0	0	0	0
0	0	0	0	0	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	0	1	1	1	0 1	0 2	0 1
0	0	1	1	1	0 0	0 0	0 0
0	0	0	0	0	0 -1	0 -2	0 -1

filter

1	**2**	**1**
0	**0**	**0**
-1	**-2**	**-1**

- sliding window
- dot product

output

-3	-4	-4	-4	-4	-3
-3	-4	-4	-3	-1	0
0	0	0	0	0	0
2	1	0	1	3	3
2	1	0	1	3	3
1	3	4	3	1	0

Convolution: a 2-D example

input map

coordinates in
a local window

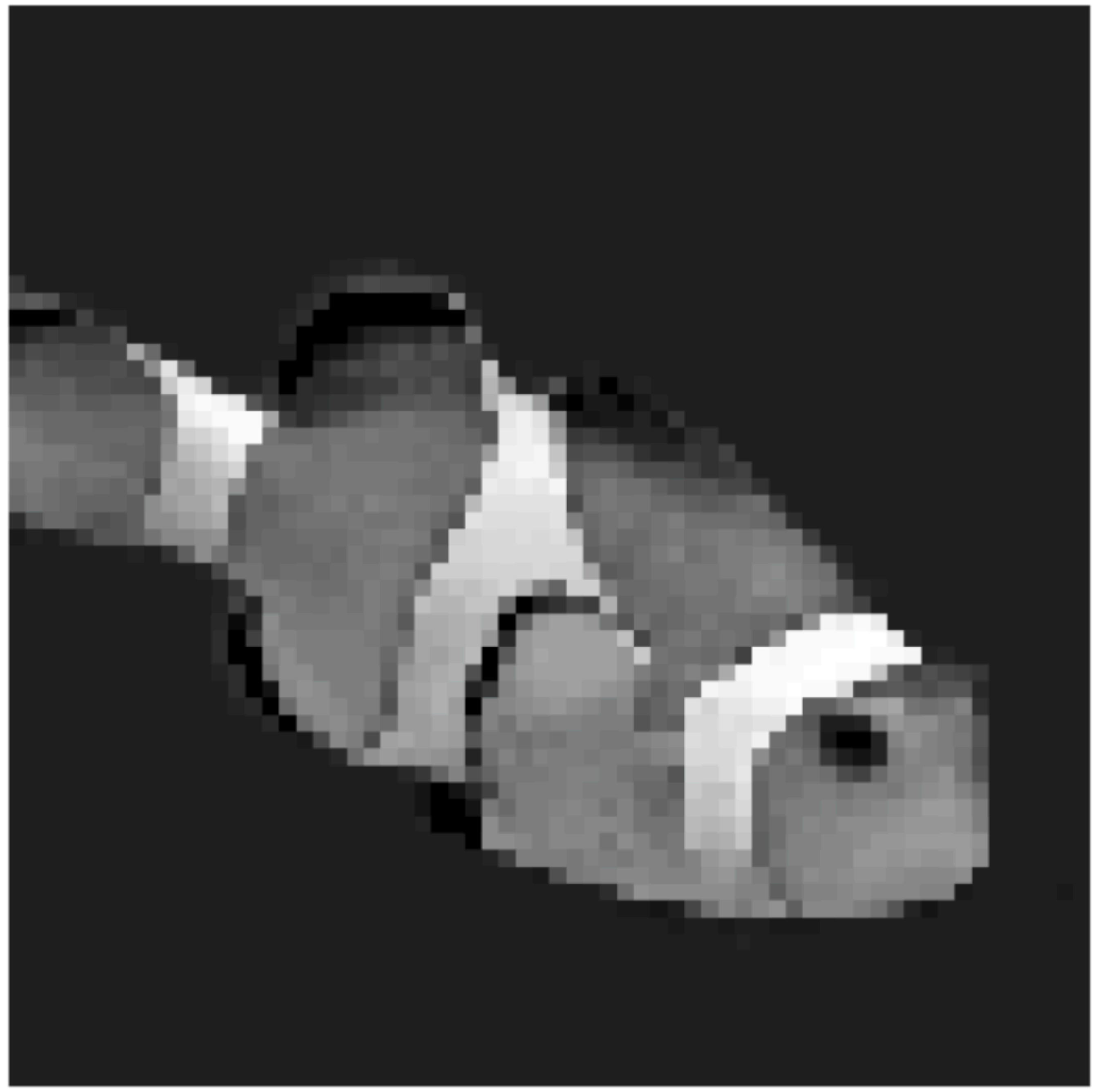
filter weights

$$\boldsymbol{y}[n, m] = \sum_{i=-r}^{r} \sum_{j=-r}^{r} \boldsymbol{w}[i, j]\boldsymbol{x}[n + i, m + j]$$

output map

r: kernel radius
kernel size = $2r + 1$

Convolution: 2-D



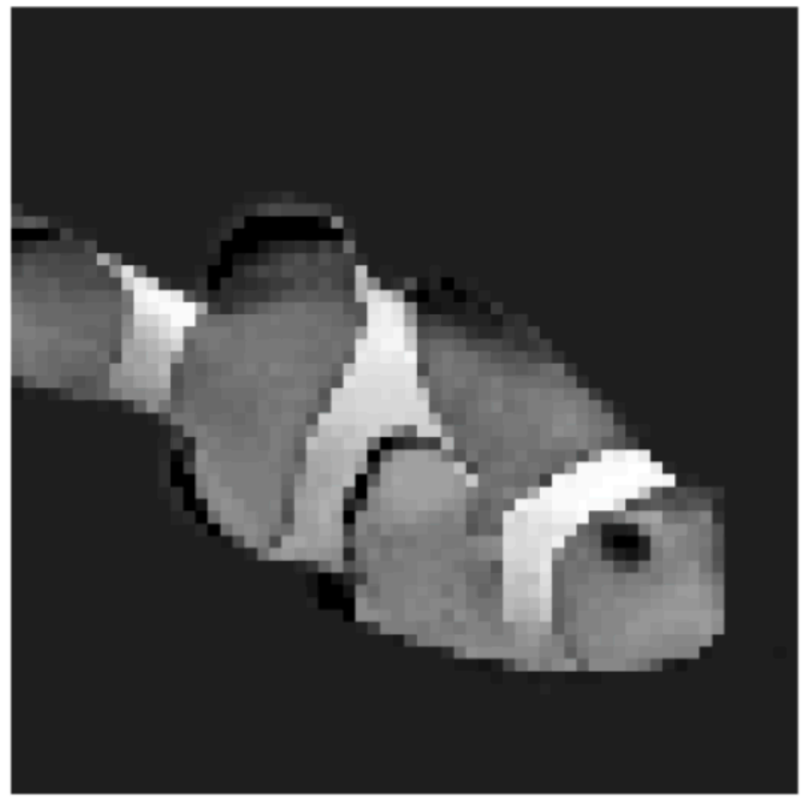
*

filter

1	2	1
0	0	0
-1	-2	-1

=

Convolution: Multi-channel outputs



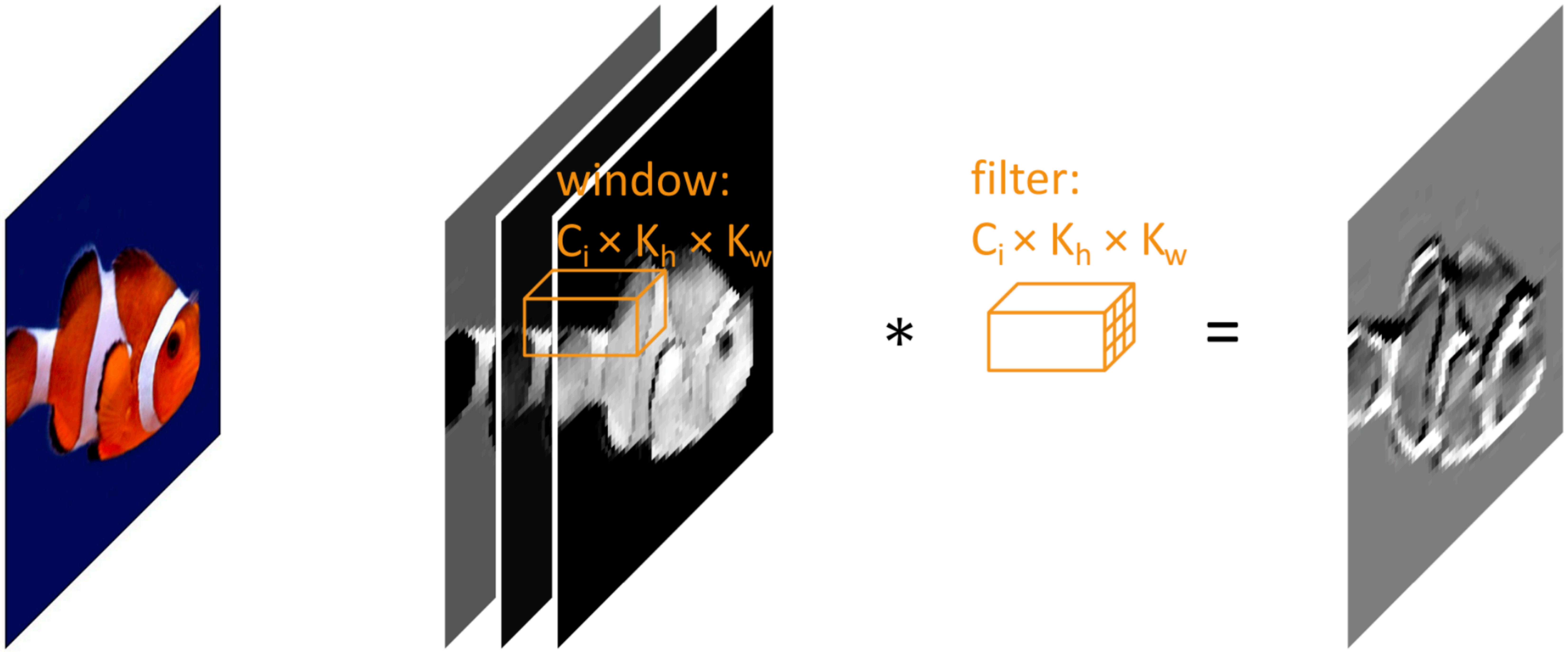
$$* \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} =$$

one filter, one feature

$$* \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} =$$

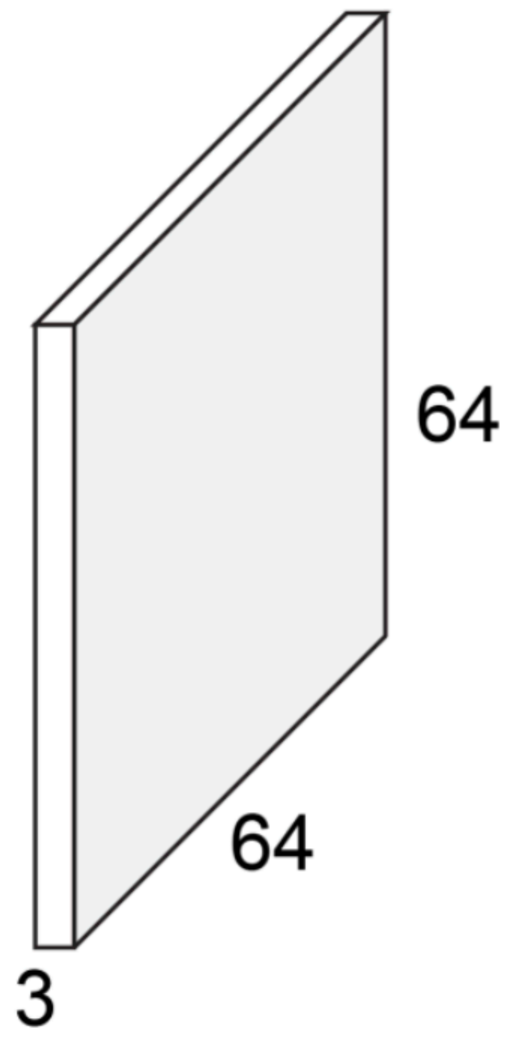
Understanding the filter/kernel as feature extractors

Convolution: Multi-channel inputs



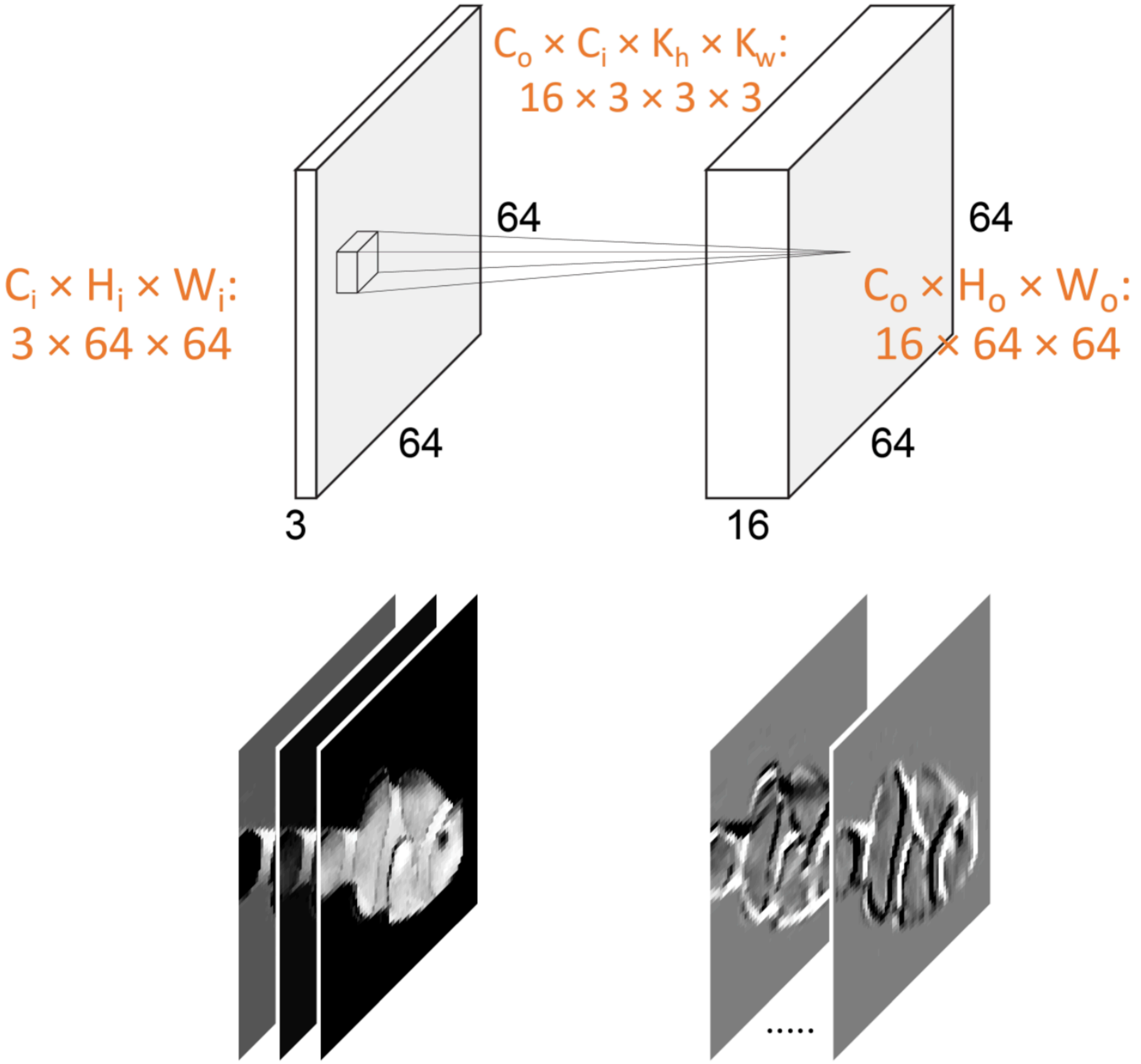
Like (R, G, B) color notations have three features

Convolution: tensor views



- Tensor: high-dimension array
- feature maps
  - 3-D tensor: C × H × W
  - C: channels
  - H: height
  - W: width

Convolution: tensor view



- Tensor: high-dimension array

- feature maps
  - 3-D tensor: $C \times H \times W$
  - C: channels
  - H: height
  - W: width

- filters
  - 4-D tensor: $C_o \times C_i \times K_h \times K_w$
  - C_o: output channels
  - C_i: input channels
  - K_h, K_w: filter height, width

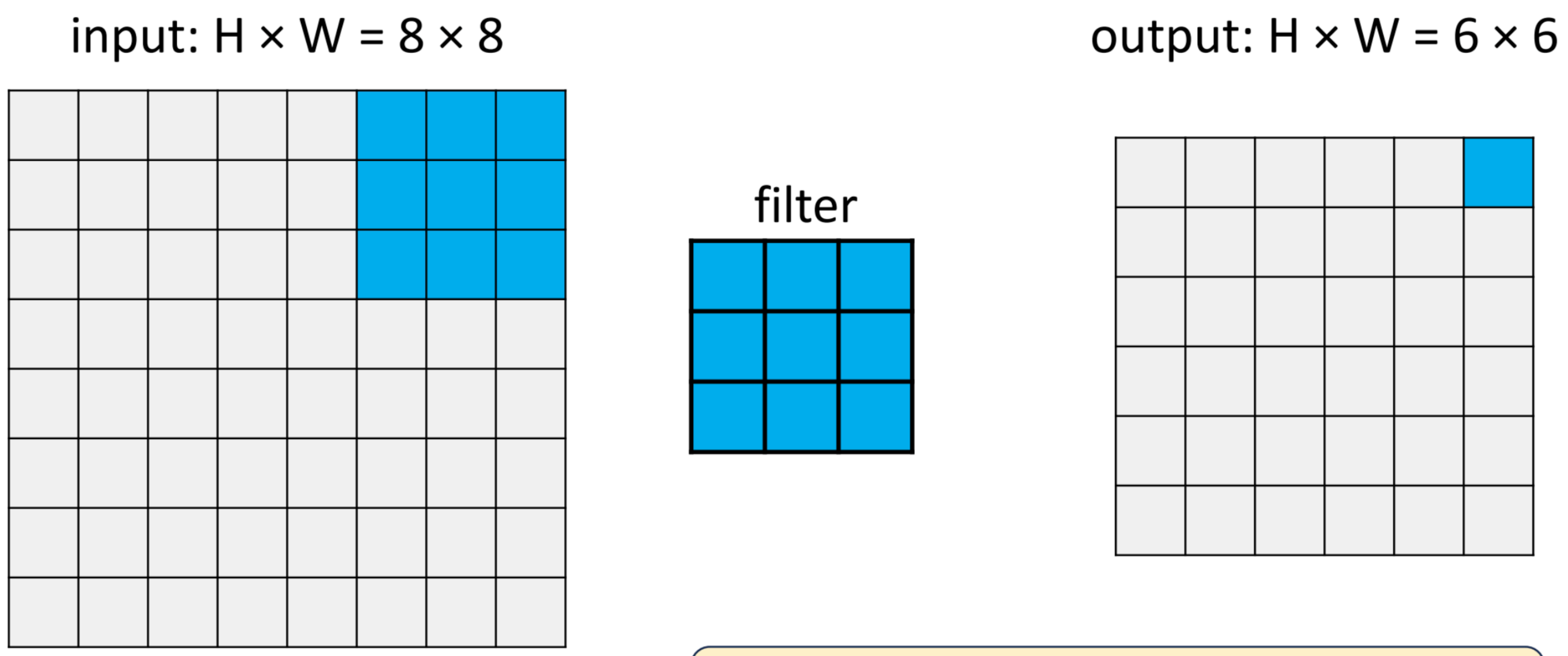
The same filter tensor applies to different locations

Convolution: # parameters and # operations

- # parameters
  - weights: $C_o \times C_i \times K_h \times K_w$
  - bias: C_o

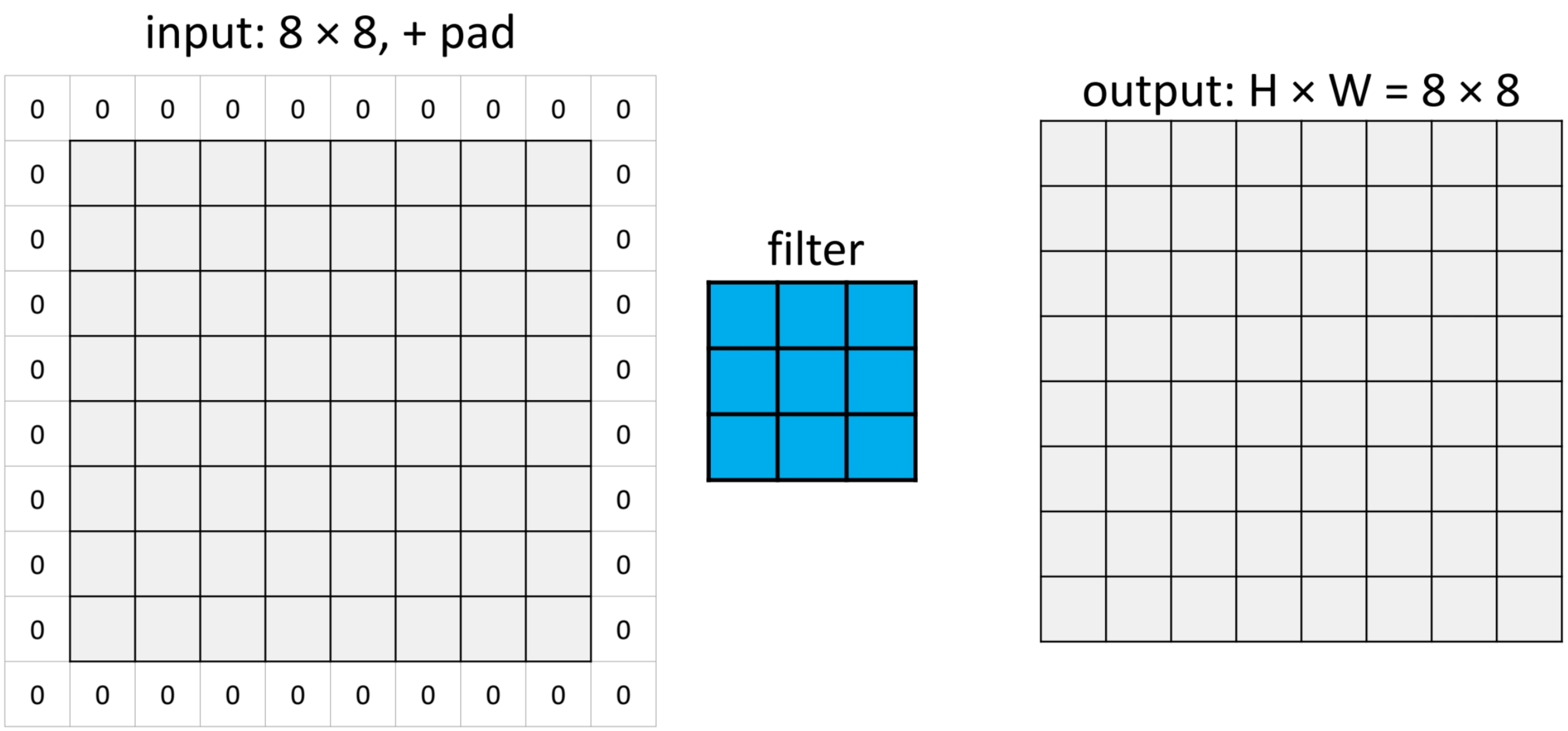
- # floating-point operations (FLOPs)
  - # params $\times H_o \times W_o$

Convolution: padding



$$H_{out} = H_{in} - K_h + 1$$

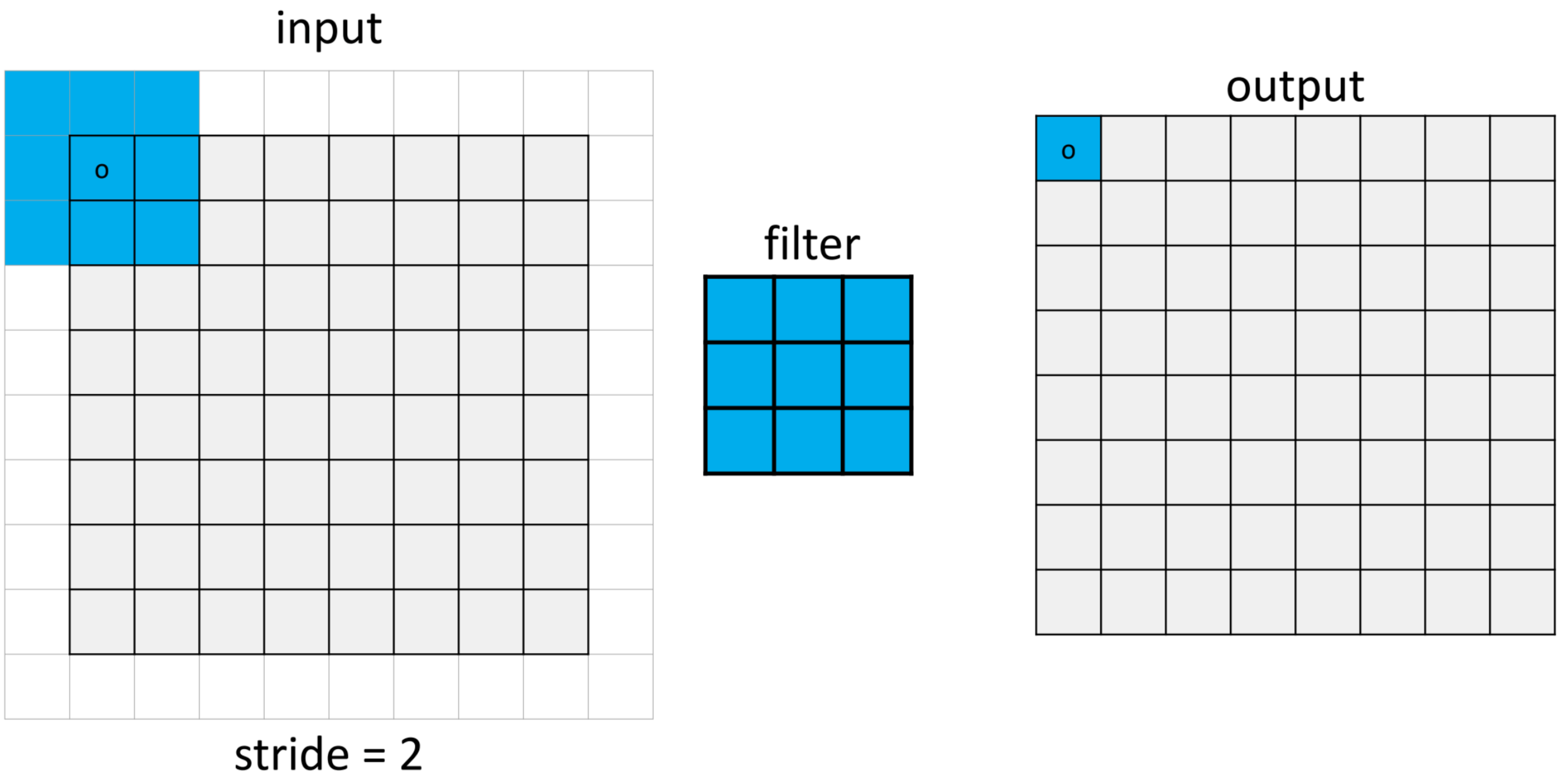
Convolution: padding



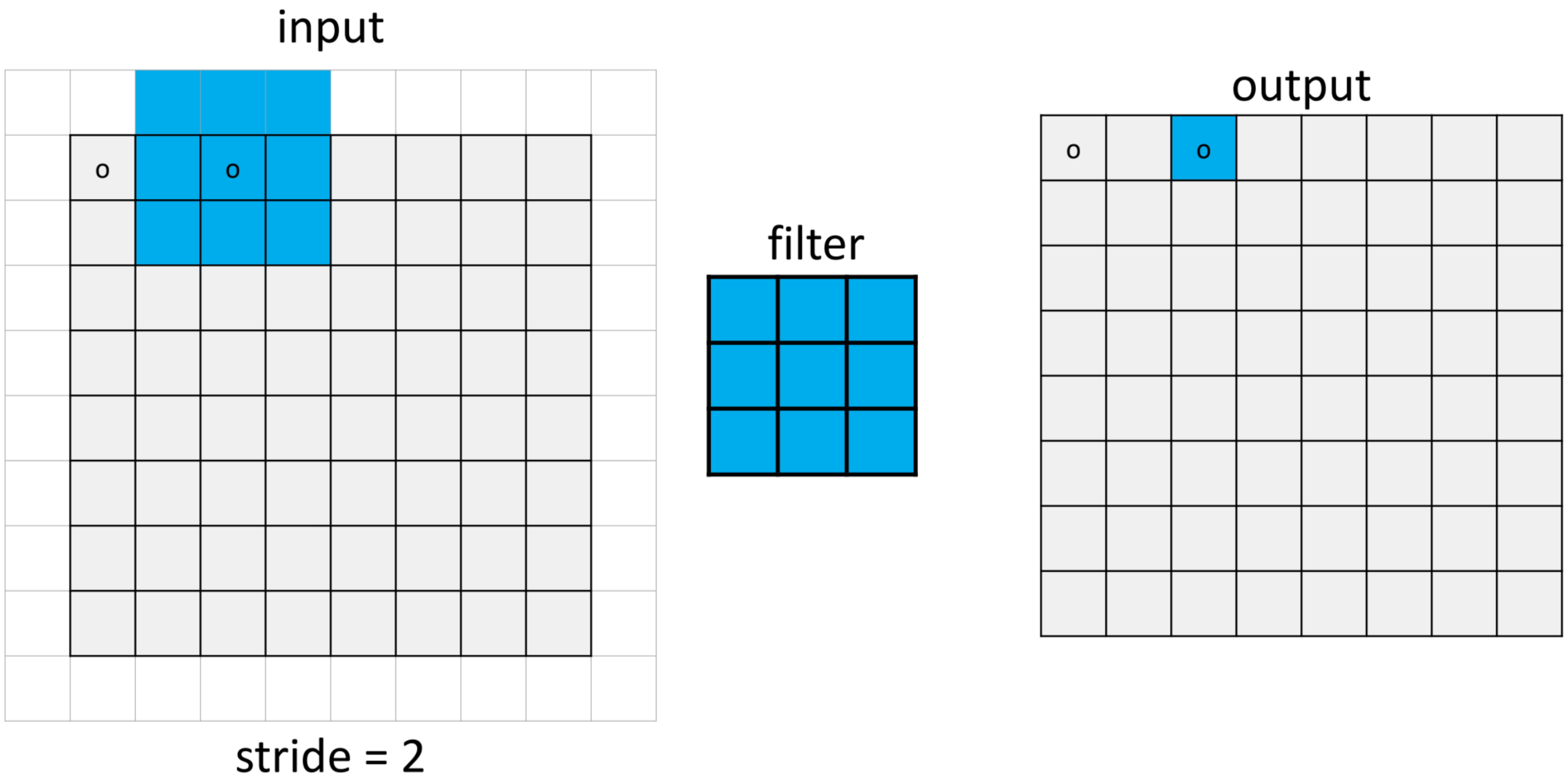
- pad = ⌊kernel_size / 2⌋
- maintains feature map size

$$H_{out} = H_{in} + 2pad_h - K_h + 1$$

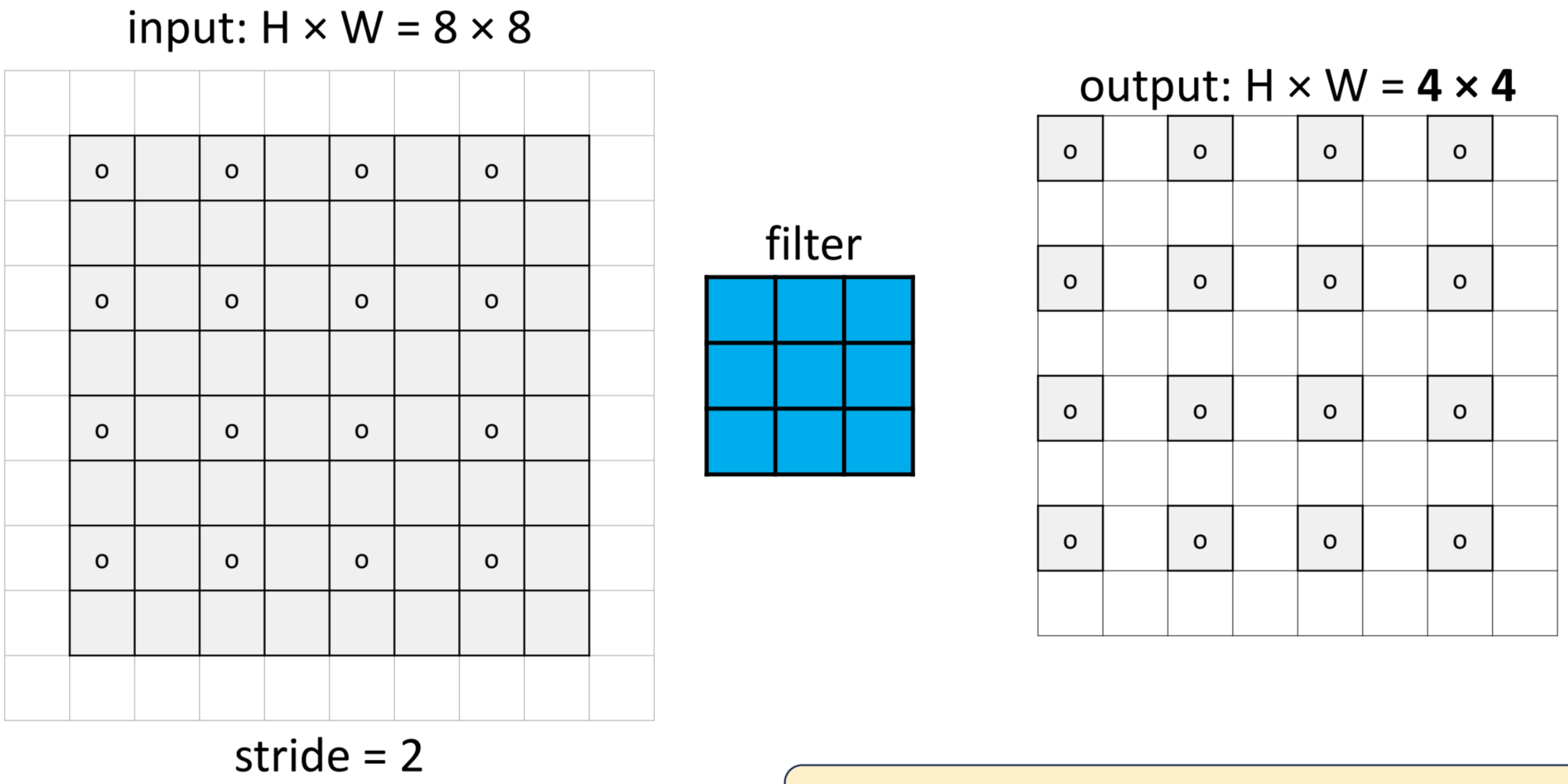
Convolution: stride



Convolution: stride



Convolution: stride

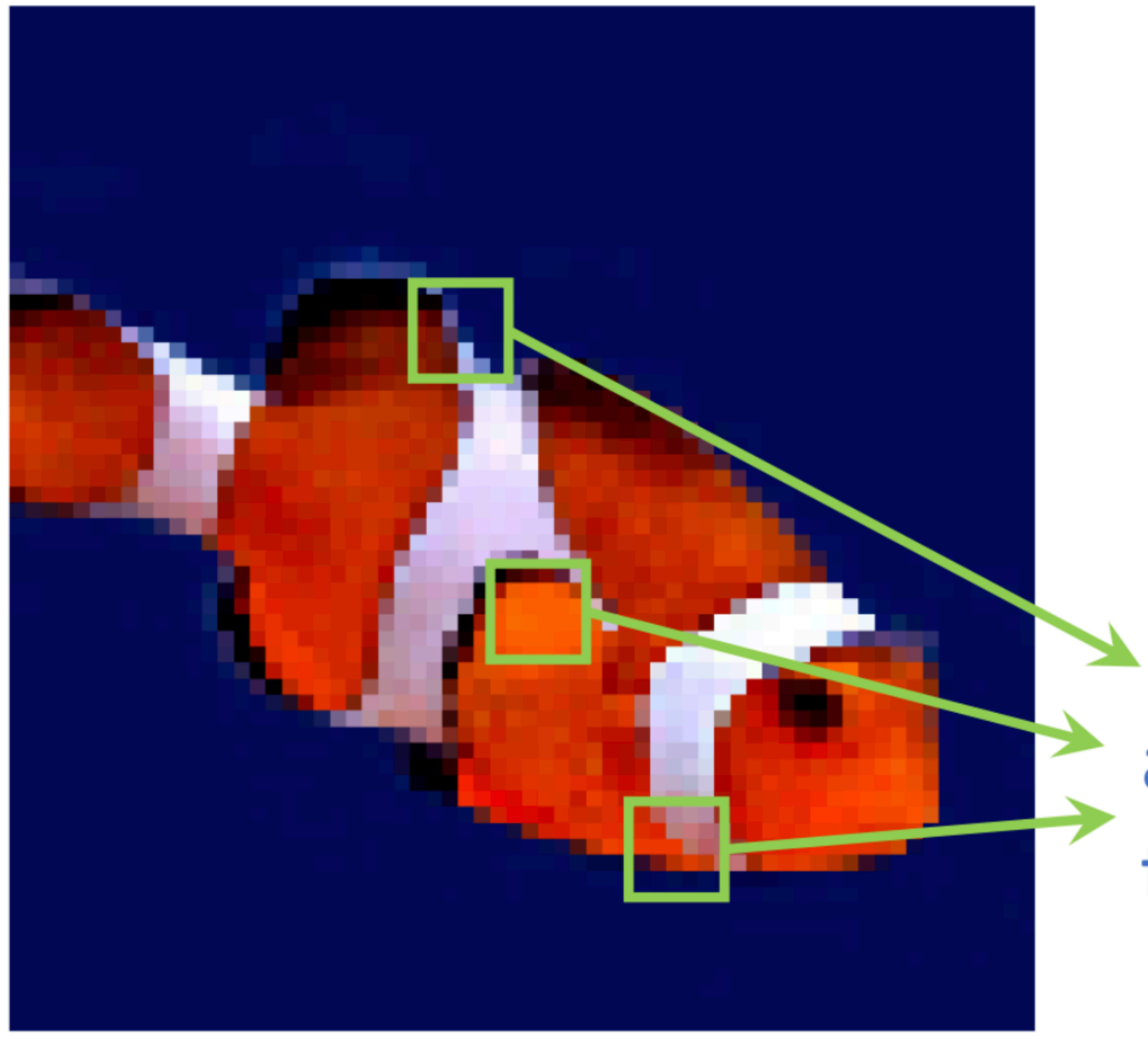


- reduces feature map size
- compress and abstract

$$H_{out} = \lfloor (H_{in} + 2pad_h - K_h) / str \rfloor + 1$$

Convolution: translation-invariance

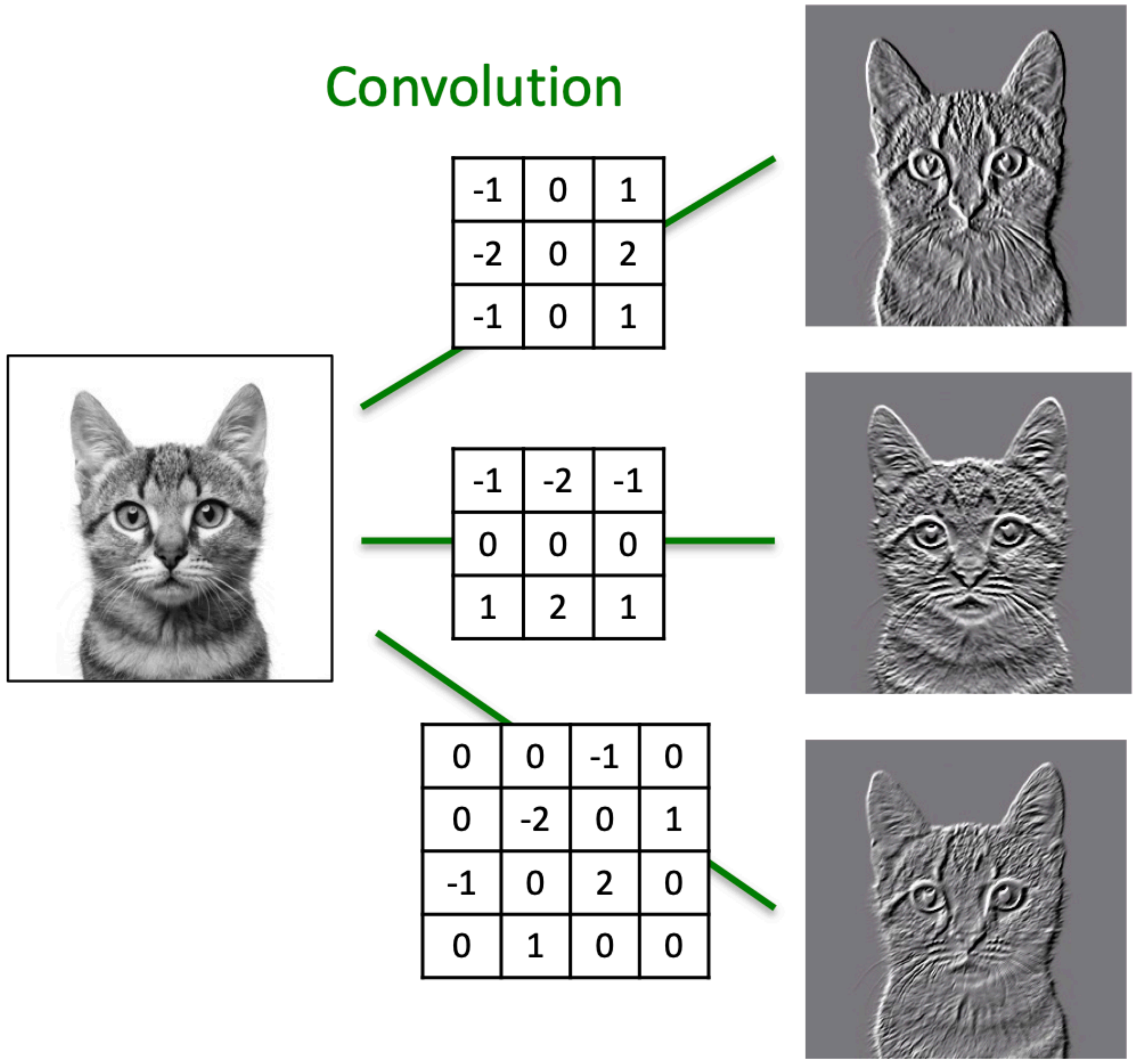
- Process each window in the same way

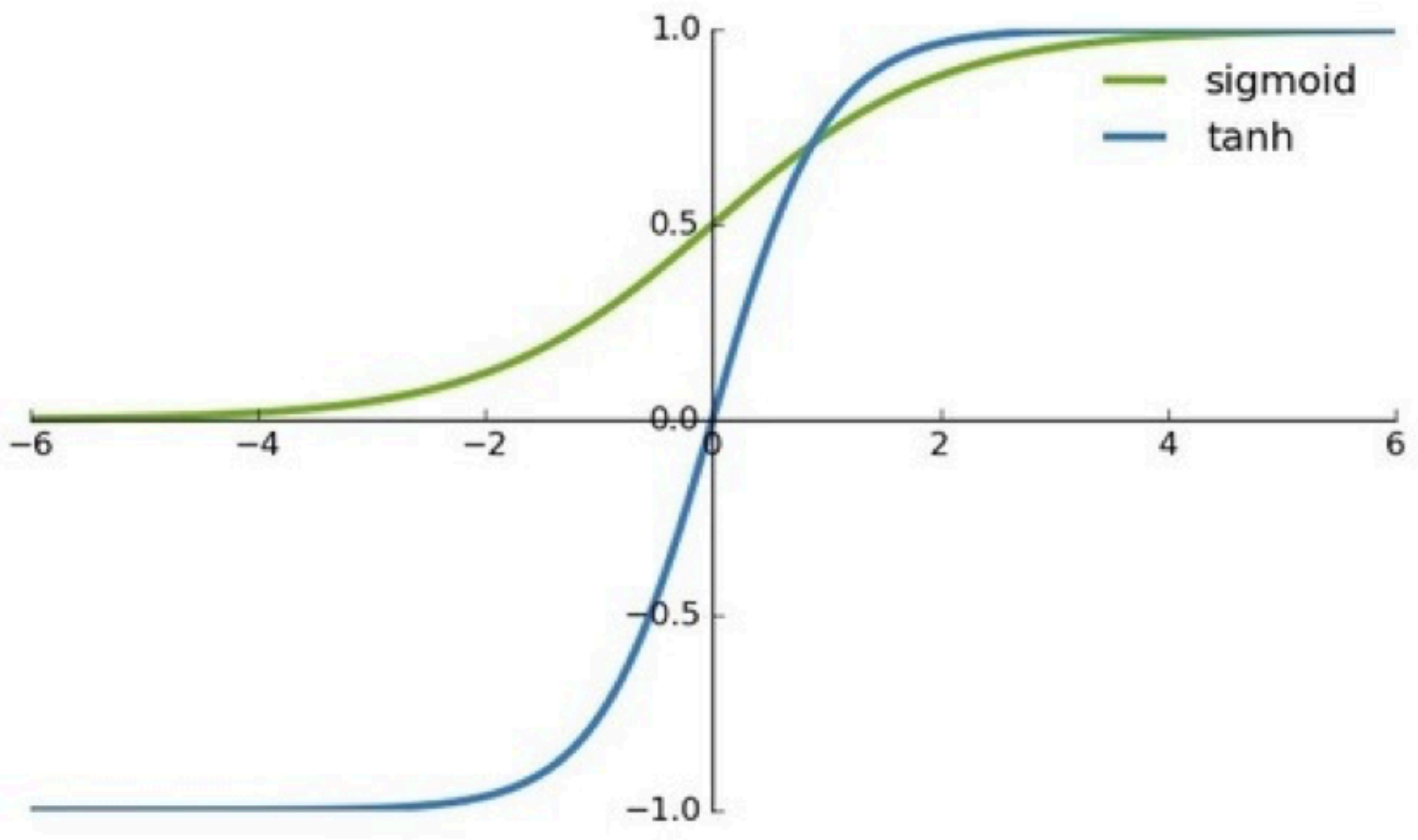


apply the same weights regardless of the window location

Deep Convolutional Networks

[Convolution + Nonlinear activation] + Pooling



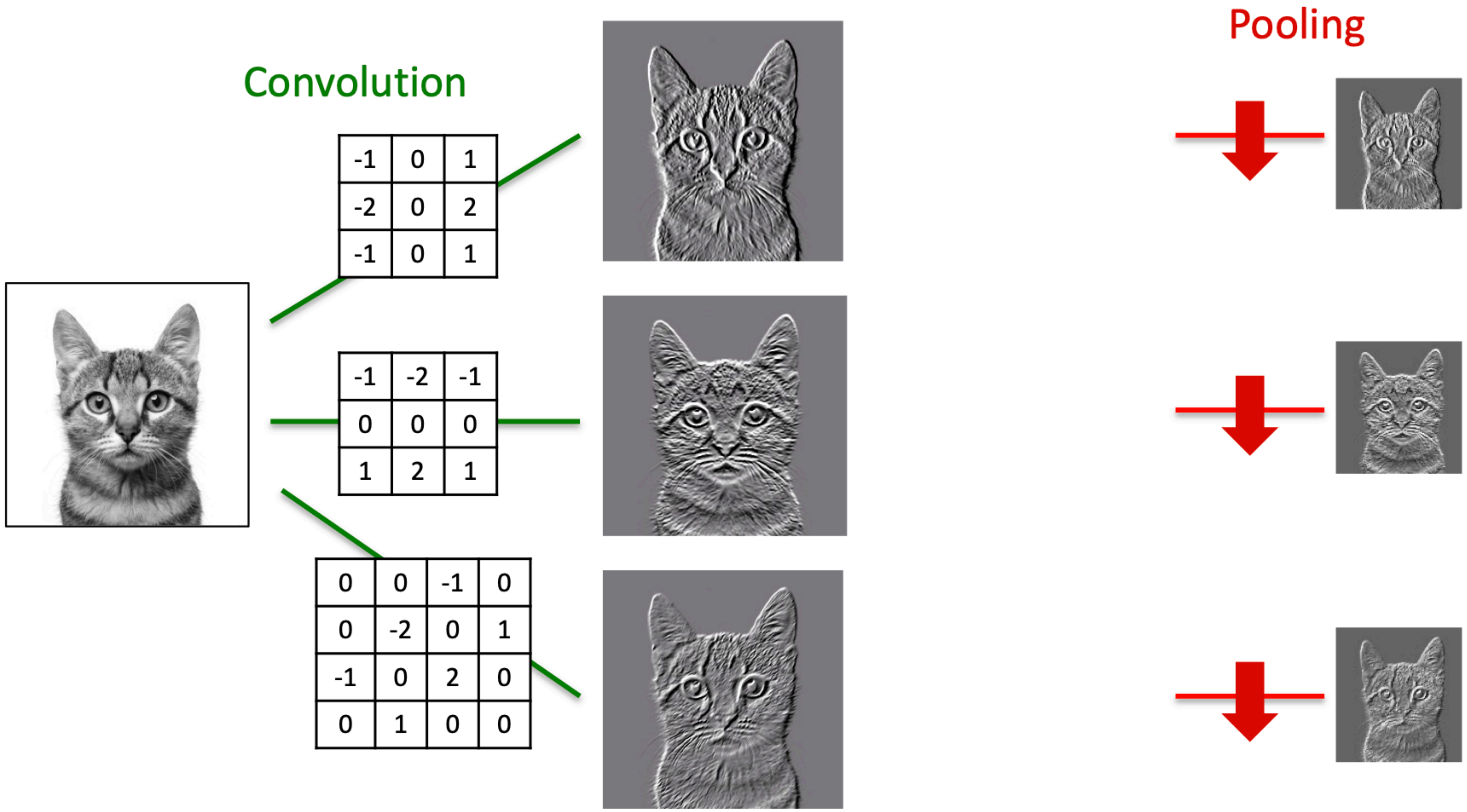


LeNet – tanh activation

$$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

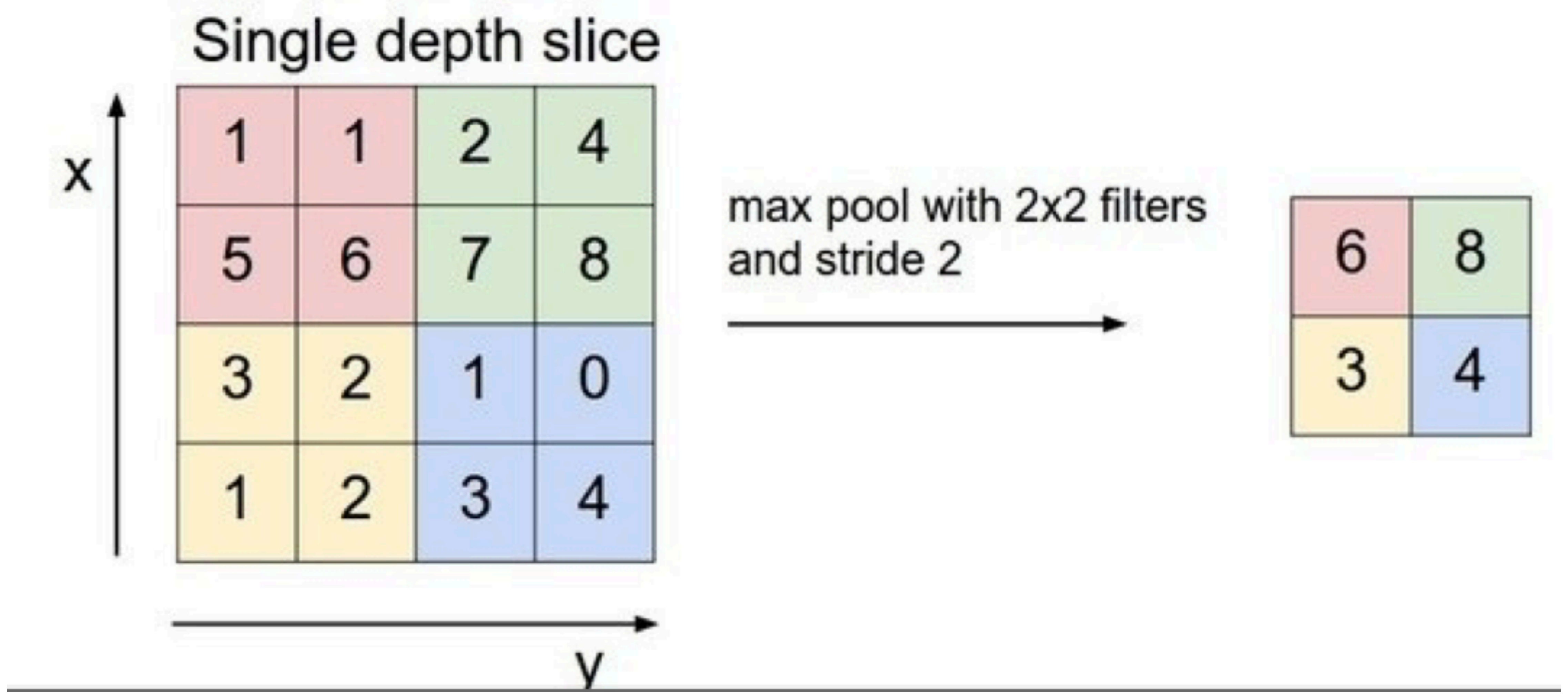
Deep Convolutional Networks

[Convolution + Nonlinear activation] + Pooling

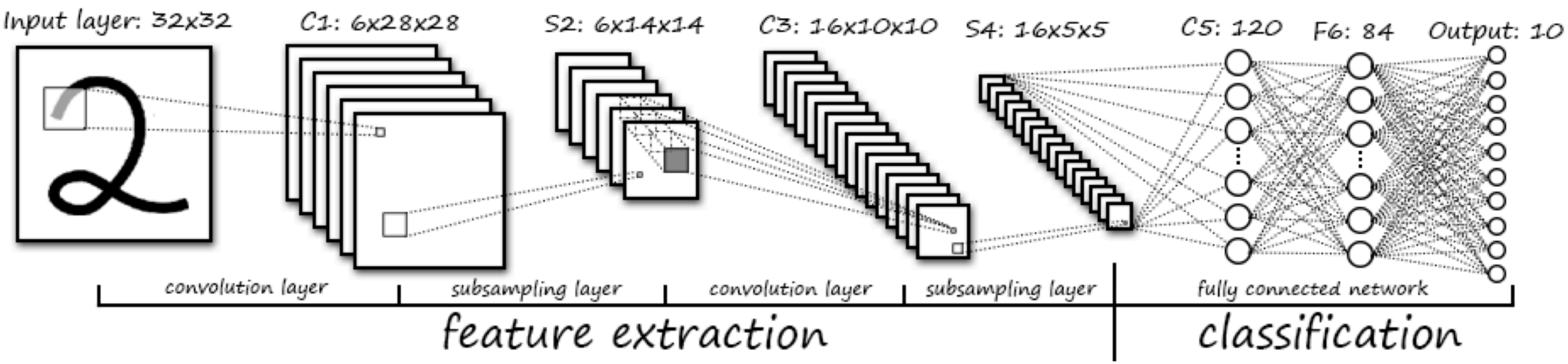


Pooling = Down-sampling

Max pooling



Deep Convolutional Networks



MNIST

60,000 original dataset

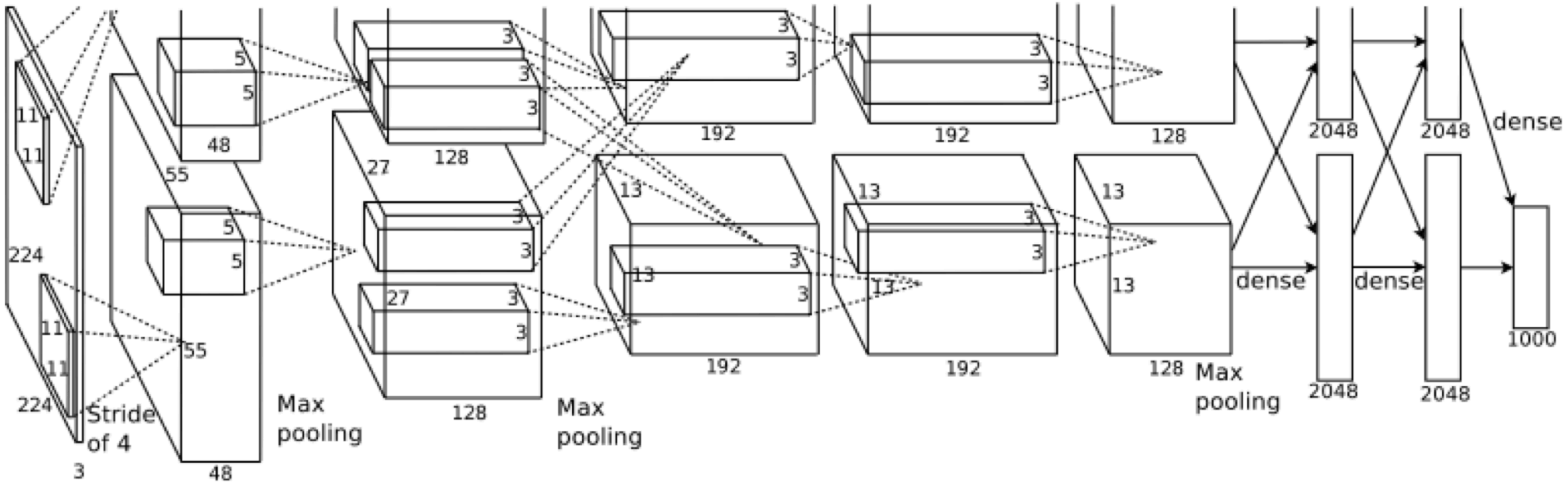
Test error: 0.95%

[1] LeNet 5, LeCun et al. 1998

Misclassified examples on MNIST

True label -> Predicted label

Alex Net

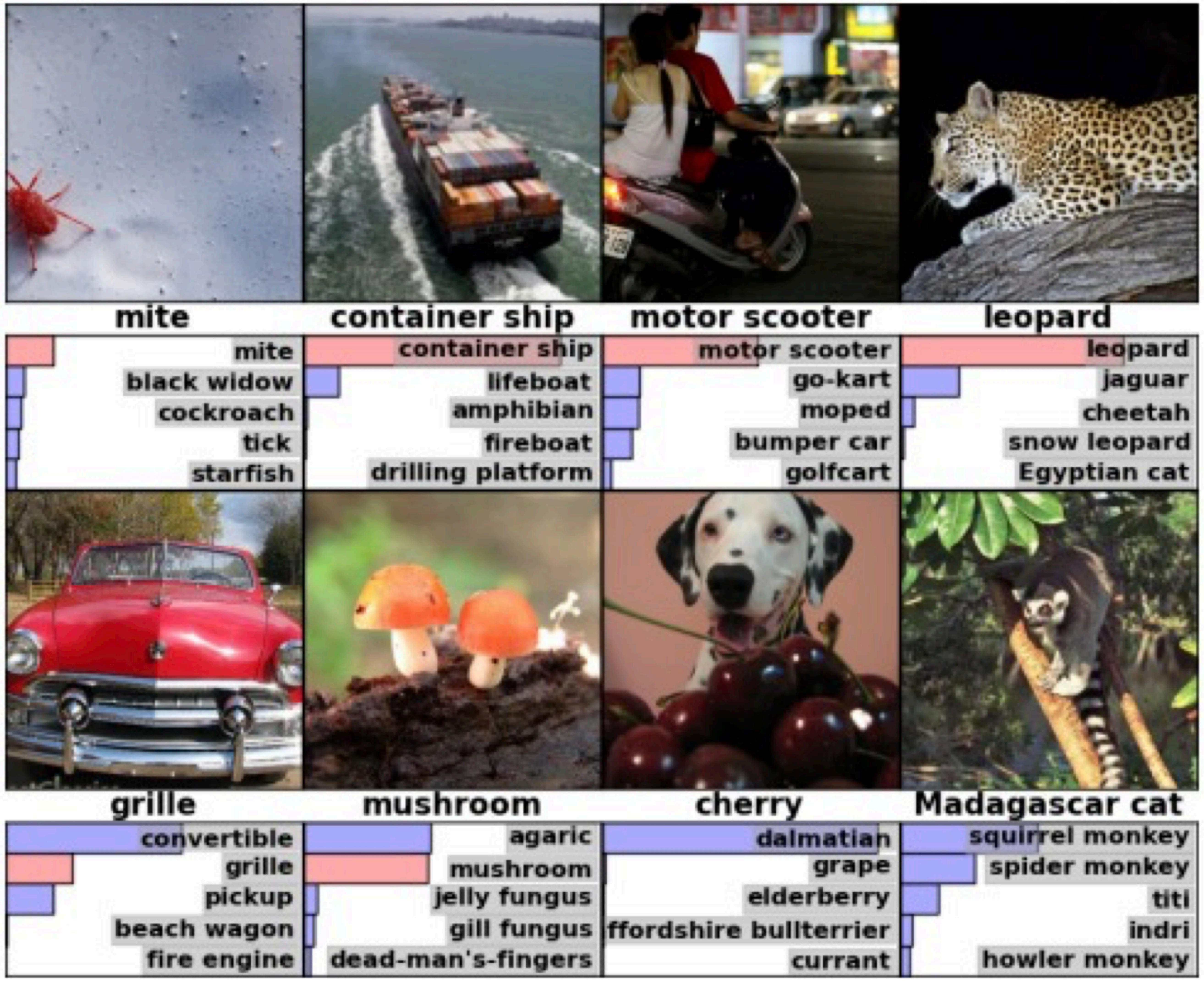


[1] Alex Krizhevsky, Ilya Sutskever, Geoffrey Hinton. ImageNet Classification with Deep Convolutional Neural Networks. NeurIPS 2012.

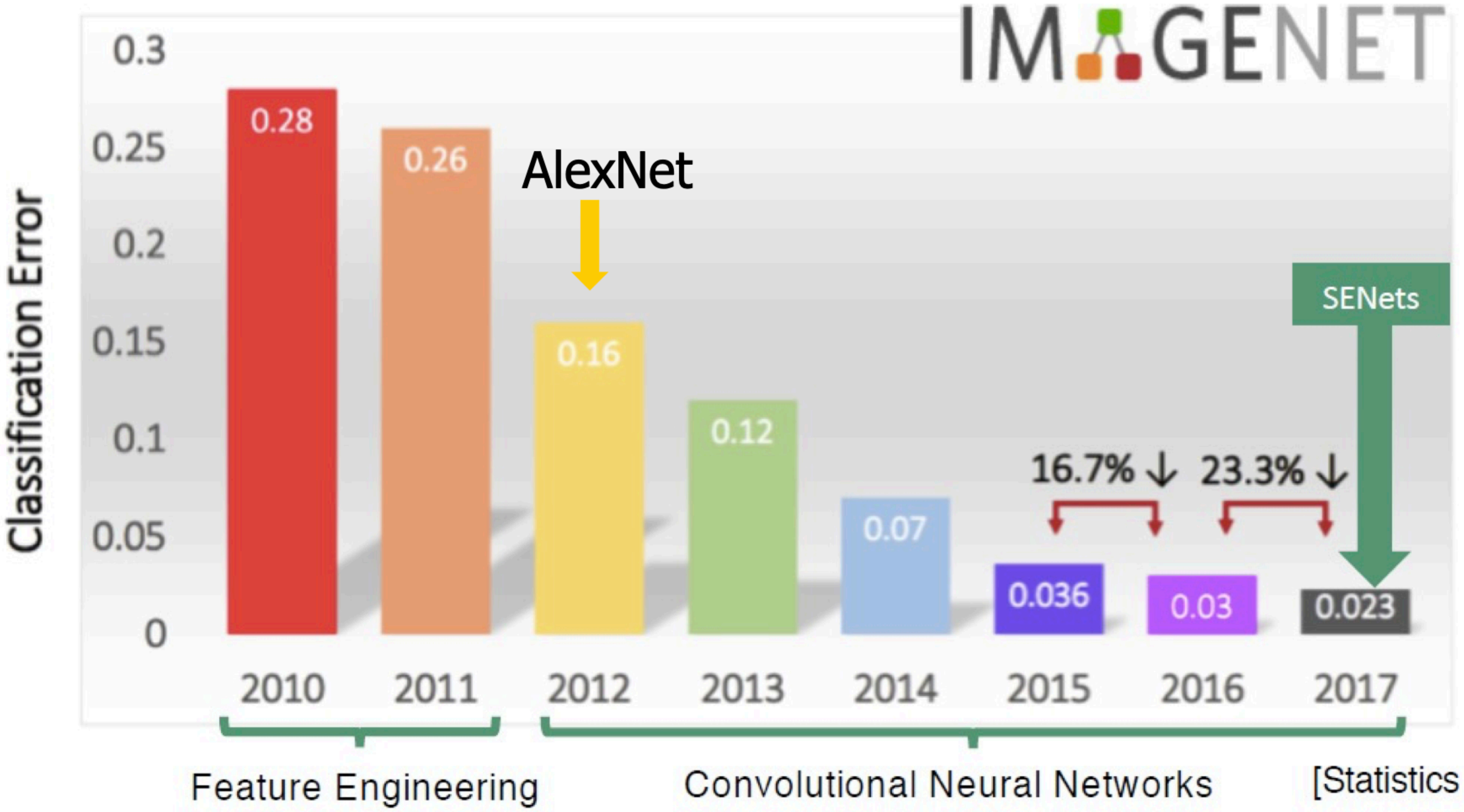
ImageNet

- 15M images
- 22K categories
- Images collected from Web
- Human labelers (Amazon's Mechanical Turk crowd-sourcing)
- ImageNet Large Scale Visual Recognition Challenge (ILSVRC-2010)
  - 1K categories
  - 1.2M training images (~1000 per category)
  - 50,000 validation images
  - 150,000 testing images
- RGB images
- Variable-resolution, but this architecture scales them to 256x256 size

ImageNet Results

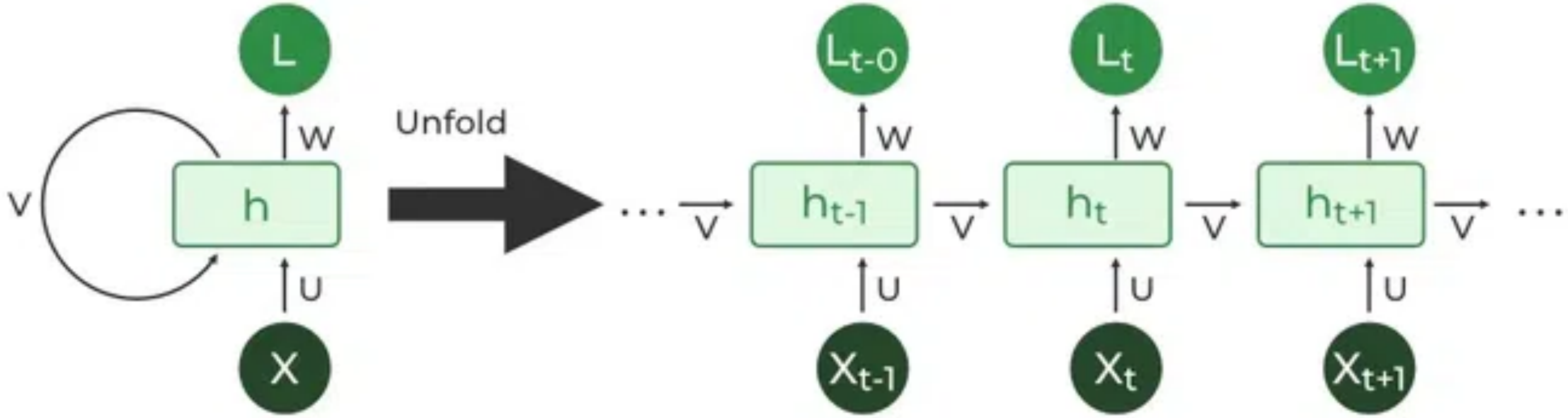


ImageNet Results



[Statistics provided by ILSVRC]

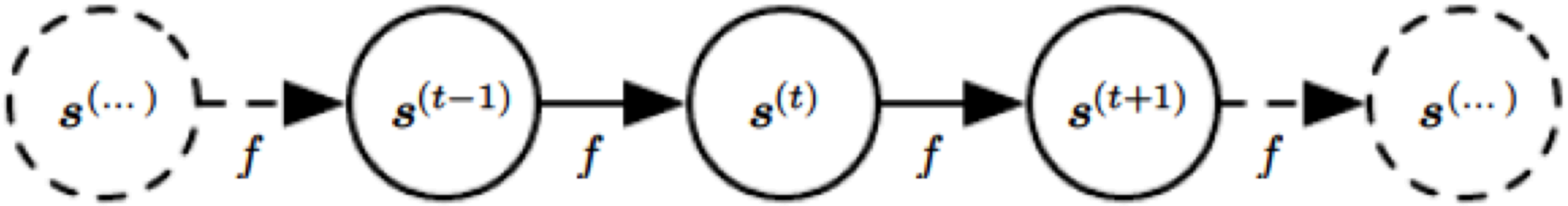
Recurrent Neural Networks (RNNs)



Recurrent Neural Networks

- Dates back to (Rumelhart *et al.*, 1986)
- A family of neural networks for handling sequential data, which involves variable length inputs or outputs
- Especially, for natural language processing (NLP)

Computation Graph

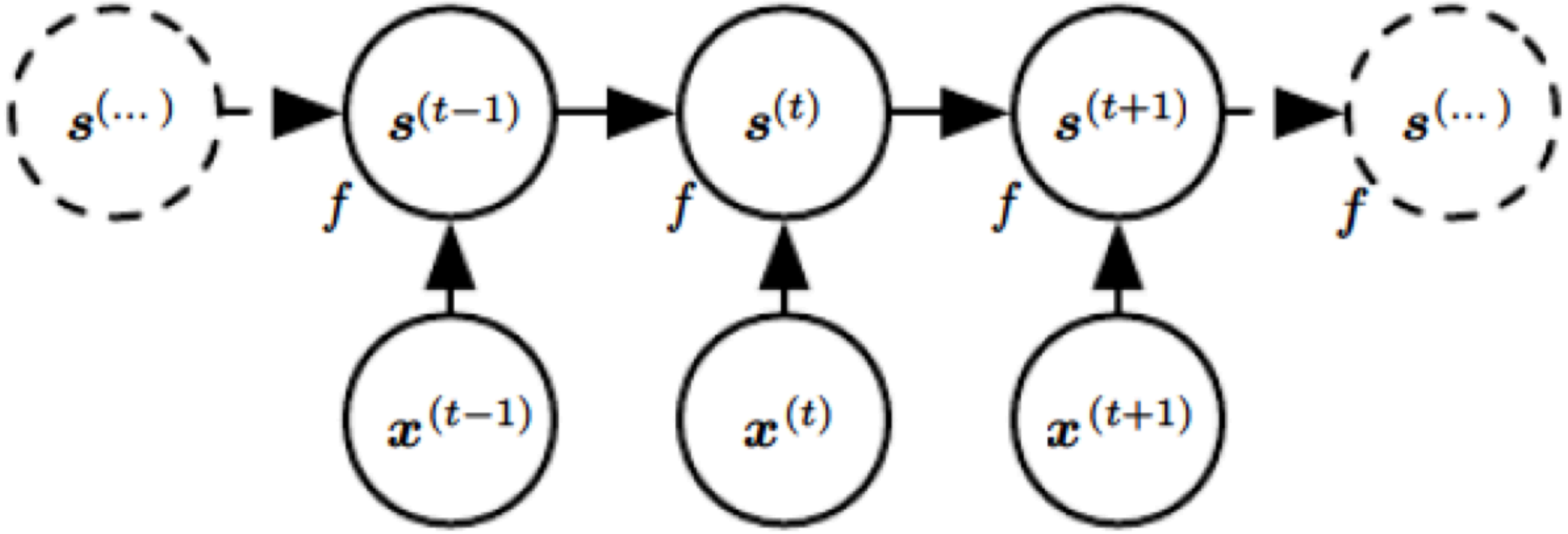


$$s^{(t+1)} = f(s^{(t)}; \theta)$$

Figure from *Deep Learning*, Goodfellow, Bengio and Courville

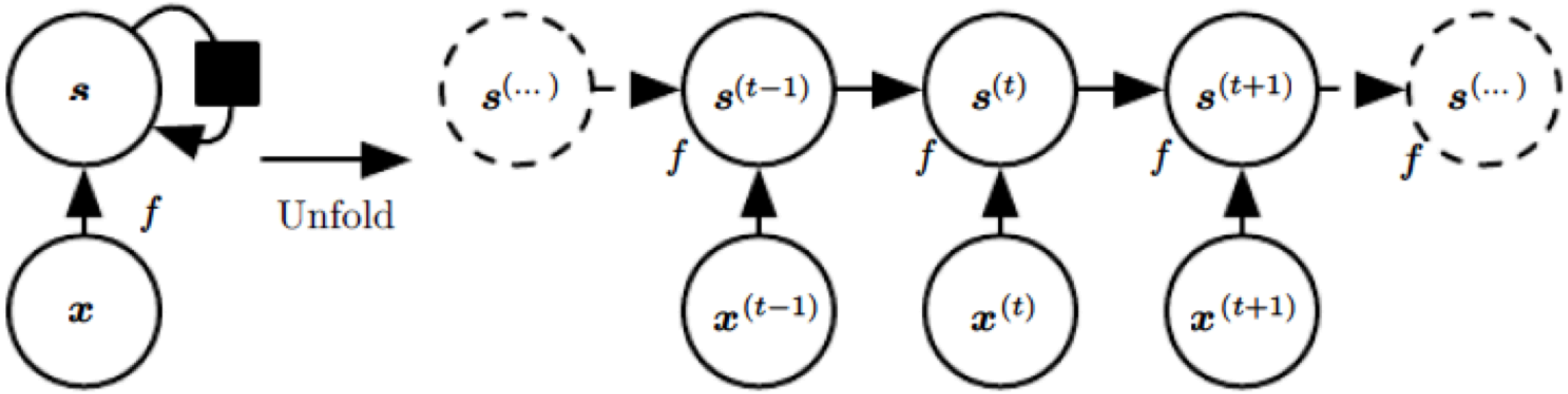
Like Markov model, but here $s^{(t+1)}$ is deterministic given $s^{(t)}$

Computation Graph



$$s^{(t+1)} = f(s^{(t)}, x^{(t+1)}; \theta)$$

Compact view



$$s^{(t+1)} = f(s^{(t)}, x^{(t+1)}; \theta)$$

Key: the same f and θ for all time steps

Like stationary HMM

Recurrent Neural Networks

- Use the same computational function and parameters across different time steps of the sequence

- Each time step: takes the input entry and the previous hidden state to compute the output entry

- Loss: typically computed every time step

Recurrent Neural Networks

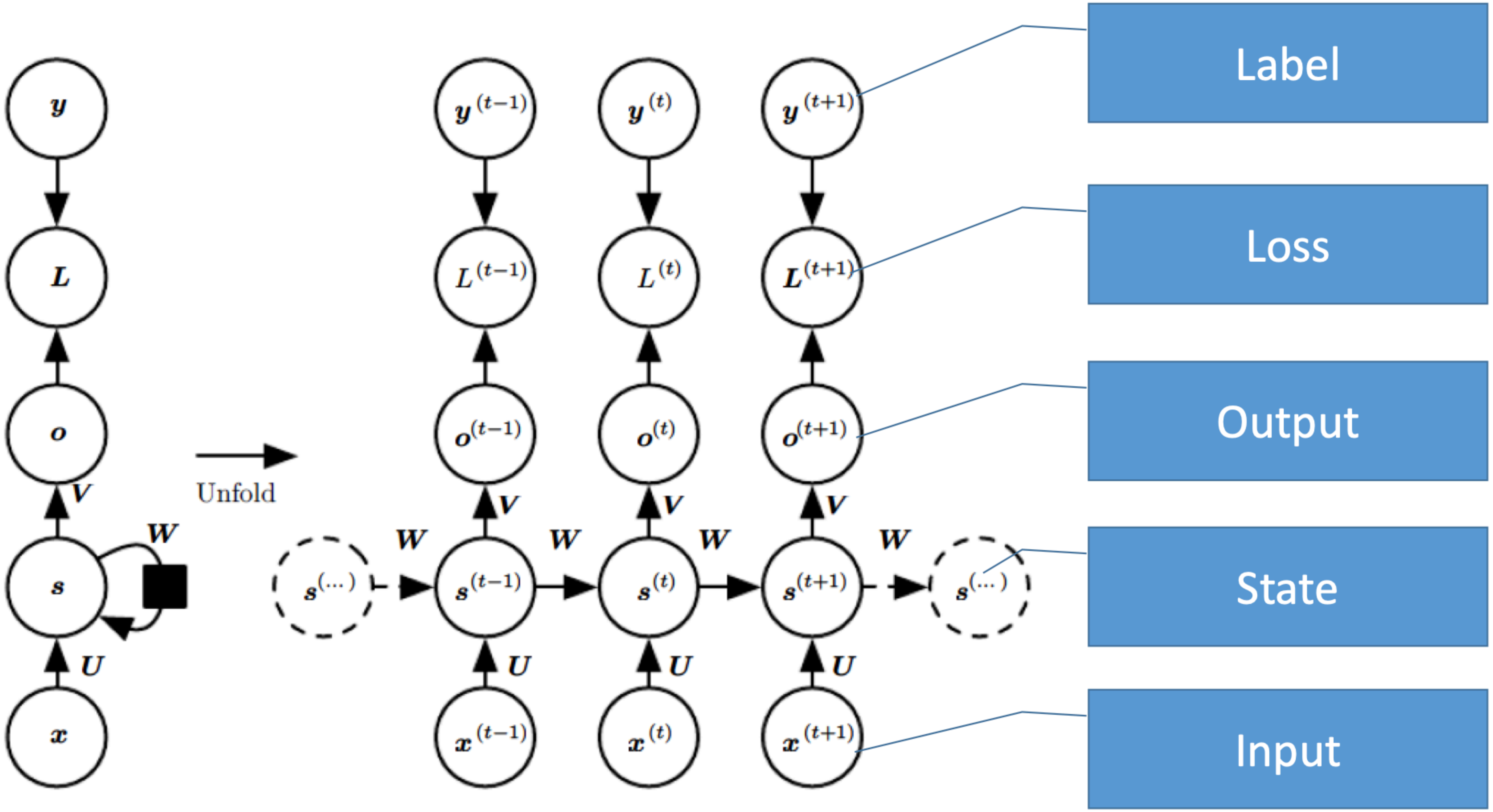
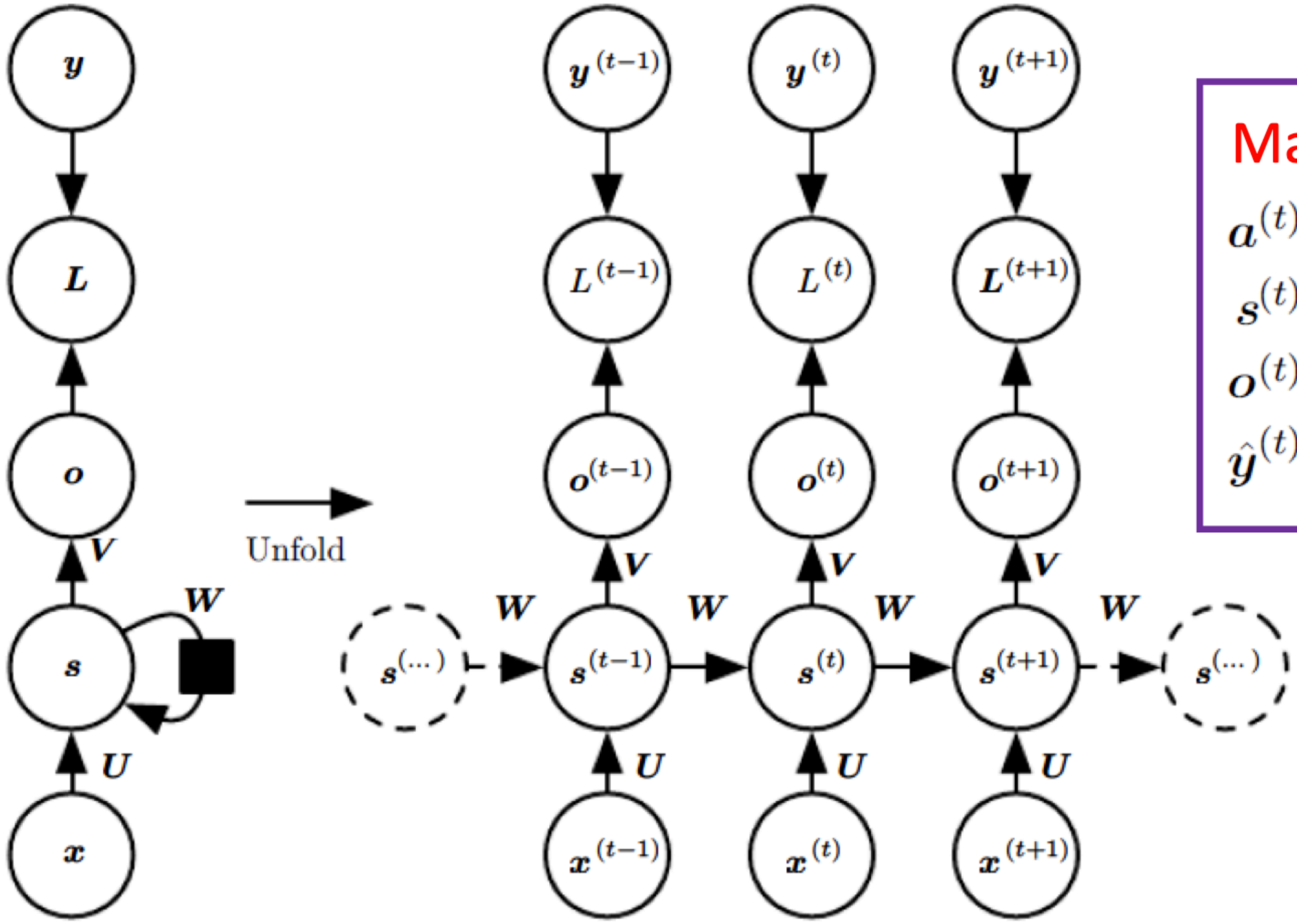


Figure from *Deep Learning*, by Goodfellow, Bengio and Courville

Recurrent Neural Networks



Math formula:

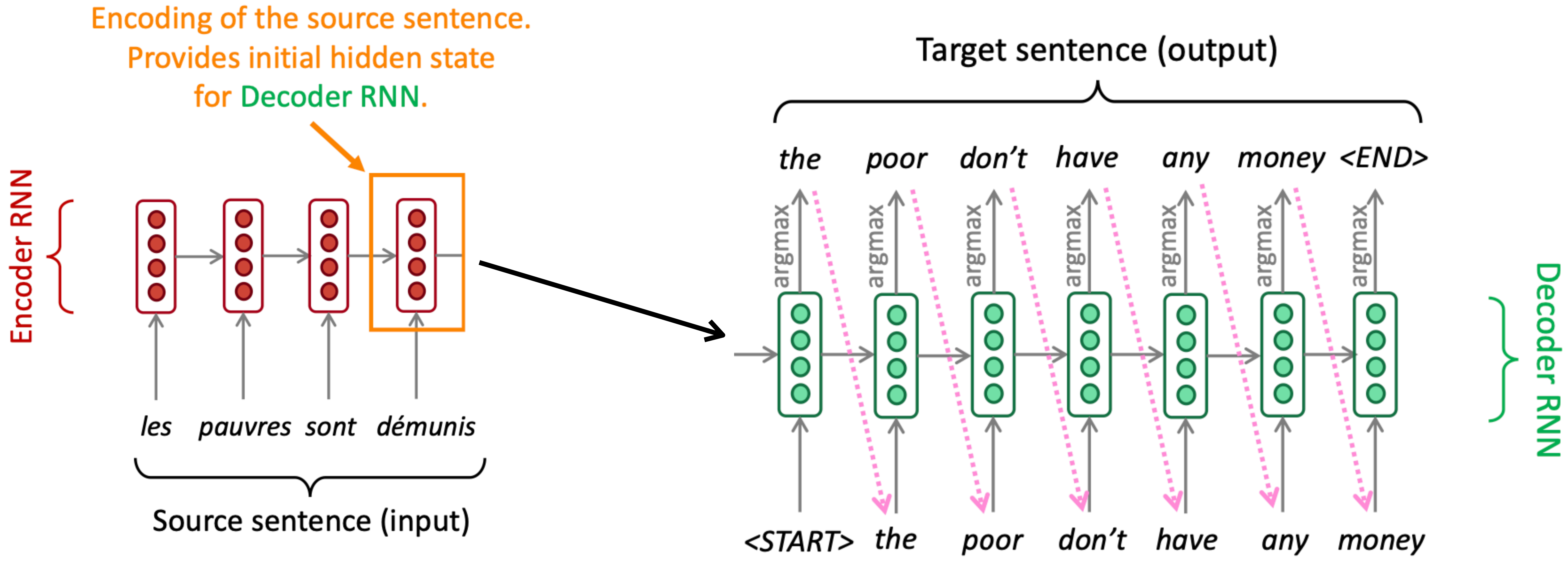
$$\begin{aligned} \boldsymbol{a}^{(t)} &= \boldsymbol{b} + \boldsymbol{W}\boldsymbol{s}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)} \\ \boldsymbol{s}^{(t)} &= \tanh(\boldsymbol{a}^{(t)}) \\ \boldsymbol{o}^{(t)} &= \boldsymbol{c} + \boldsymbol{V}\boldsymbol{s}^{(t)} \\ \hat{\boldsymbol{y}}^{(t)} &= \mathrm{softmax}(\boldsymbol{o}^{(t)}) \end{aligned}$$

Figure from *Deep Learning*,
Goodfellow, Bengio and Courville

There are many variants of RNNs since the functional form to compute $s^{(t)}$ can vary, e.g., LSTM

Sequence-to-Sequence Learning

Example of Neural Machine Translation



Encoder RNN produces an encoding of the source sentence.

Decoder RNN is a Language Model that generates target sentence conditioned on encoding.

Residual Connection

We want deeper and deeper NNs, but going deep is difficult

- Troubles accumulate w/ more layers
- Signals get distorted when propagated
- in forward and backward passes

Commonly used techniques to train “Deep” NNs:

Weight initialization

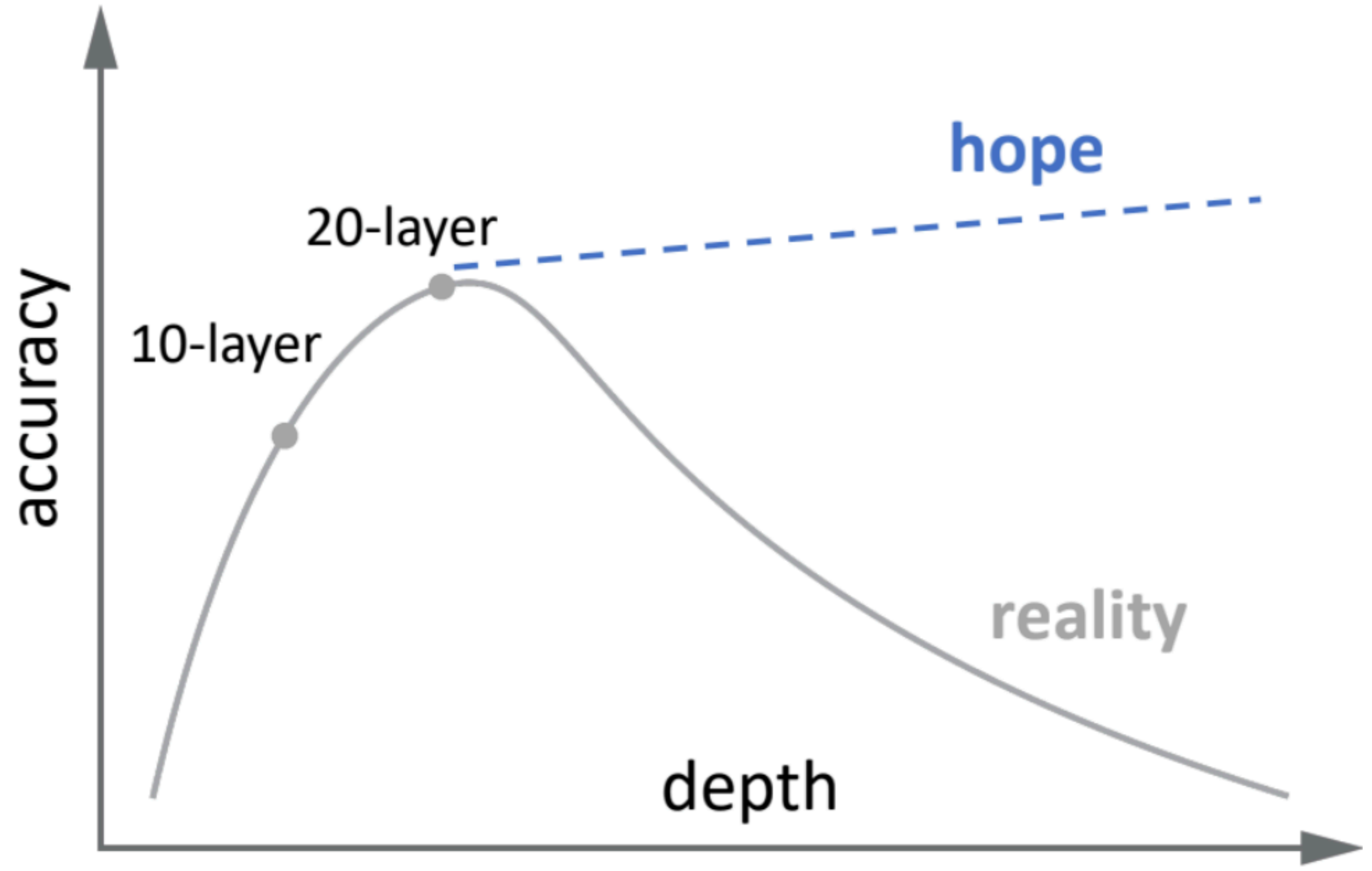
Normalization modules

Deep residual learning

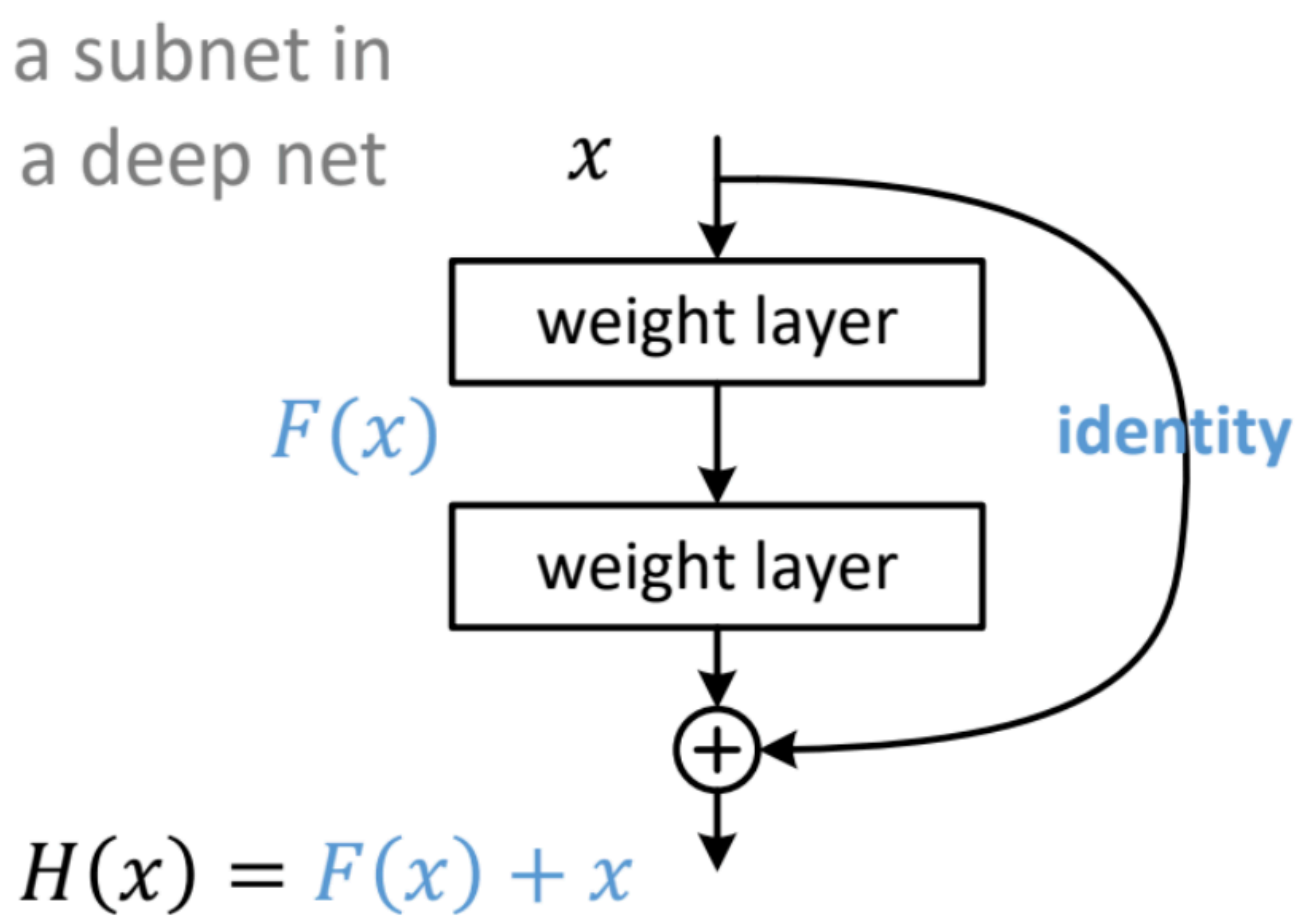
The Degradation Problem

- Good init + norm enable training deeper models
- Simply stacking more layers?

- Degrade after ~20 layers
- Not overfitting
- Difficult to train

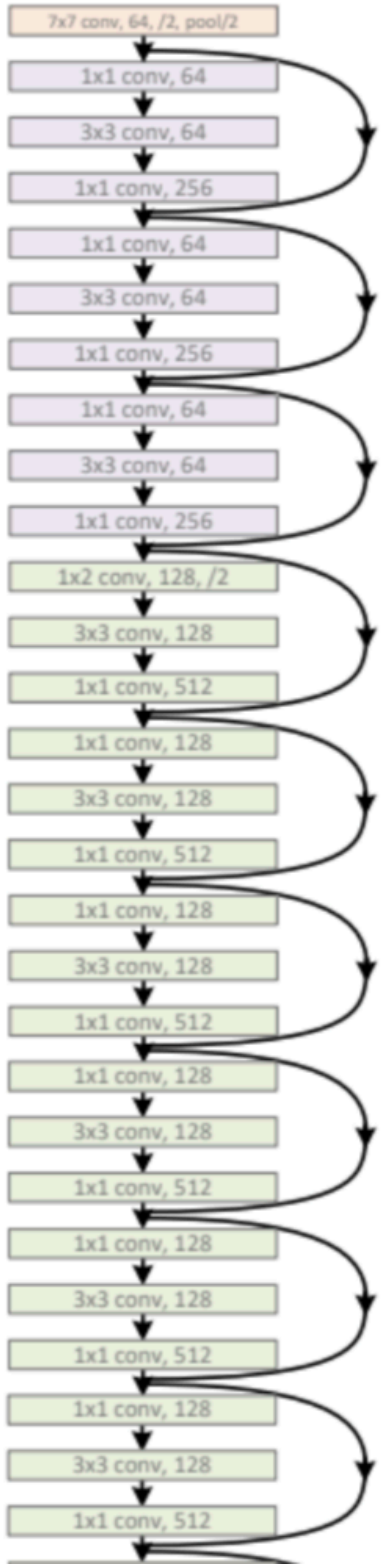


Deep Residual Learning



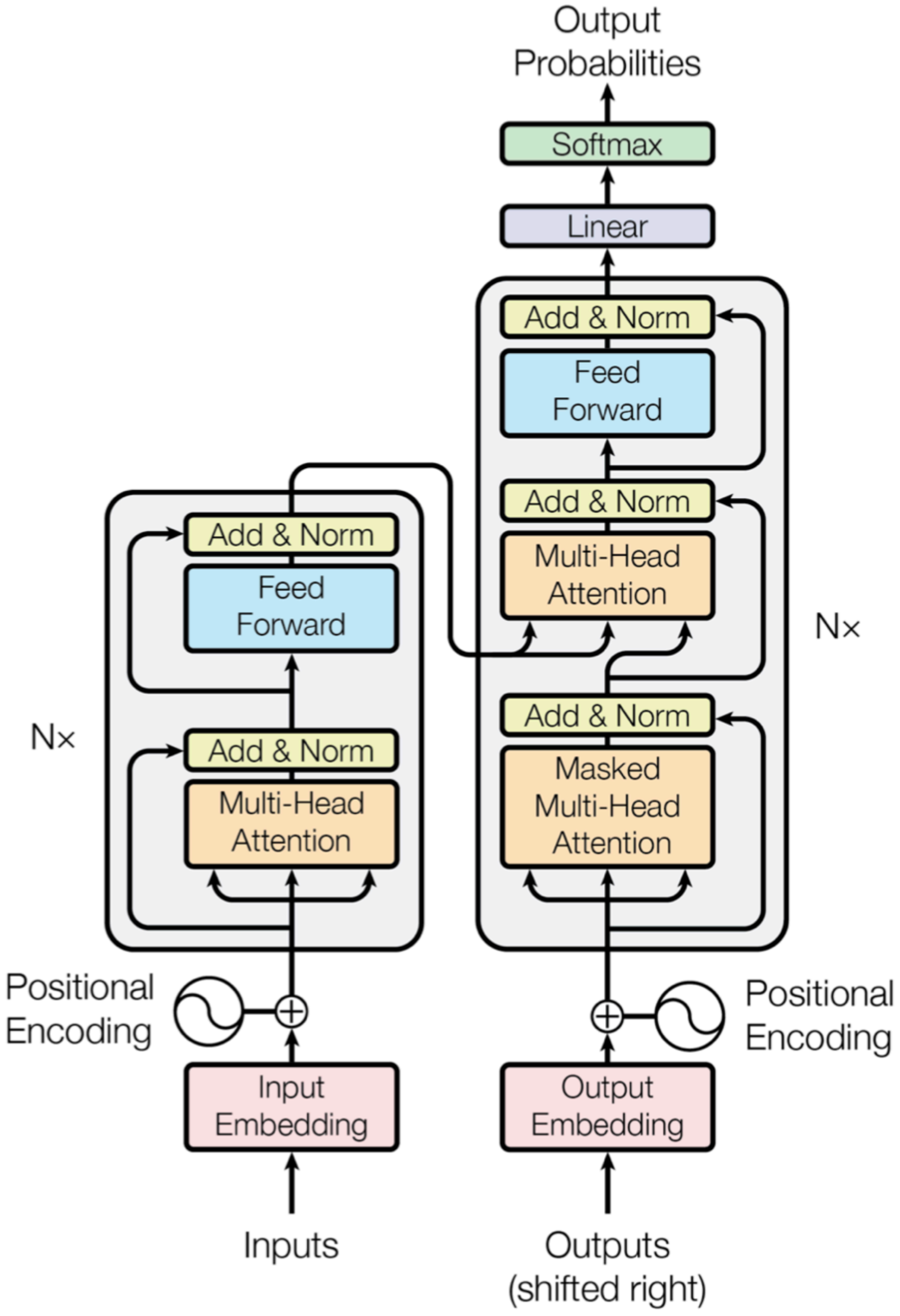
Deep Residual Networks (ResNet)

ResNet-152



Kaiming He et al. Deep Residual Learning for Image Recognition. CVPR 2016.

Transformers



Vaswani et al. Attention is All You Need. NeurIPS 2017.