Artificial Neural Networks and Deep Learning

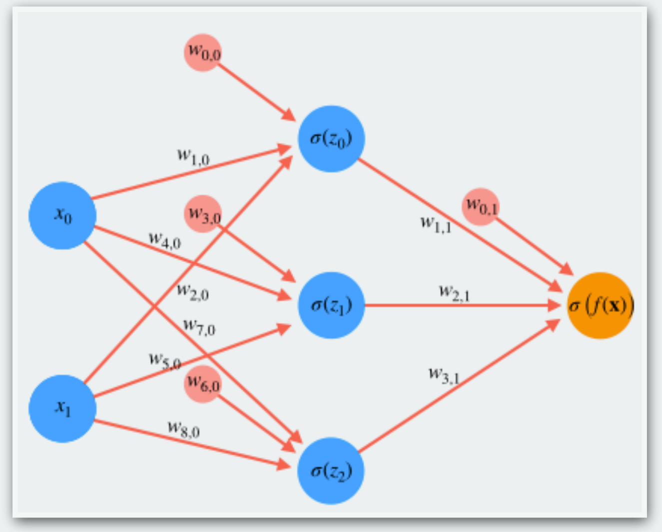
Week 4

Convolutional neural networks

Quick recap…

Find the gradients with **Backpropagation** … this week

(1) The model



Input ⟶ **Neural network function** ⟶ **Output**

Datapoints, **X**

Parameters: Weights, **W**

Prediction, $\tilde{\mathbf{y}}$

(2) Its performance

Input ⟶ **Cost function** ⟶ **Output**

Weights, **W**

Many training examples

One number, **the cost**

$$
\begin{aligned}
C(\mathbf{W}) &= \frac{1}{N}\sum_i (\tilde{y}_i - y_i)^2 \\
&= (0.96-1)^2 \\
&+ (0.10-0)^2 \\
&+ (0.04-0)^2 \\
&+ \ldots \\
&+ (0.70-1)^2 \\
&+ (0.02-0)^2 \\
&+ (0.99-1)^2
\end{aligned}
$$

(3) The cost function gradient in **W**

$$
-\nabla C(\mathbf{W}) = \begin{bmatrix} -0.23 \\ 1.32 \\ 0.20 \\ 0.38 \\ -1.23 \\ 0.01 \\ 1.20 \\ -2.12 \\ 0.73 \\ 2.17 \\ 0.54 \\ -0.23 \\ -0.93 \\ 0.45 \end{bmatrix}
$$

(4) Updating **W**

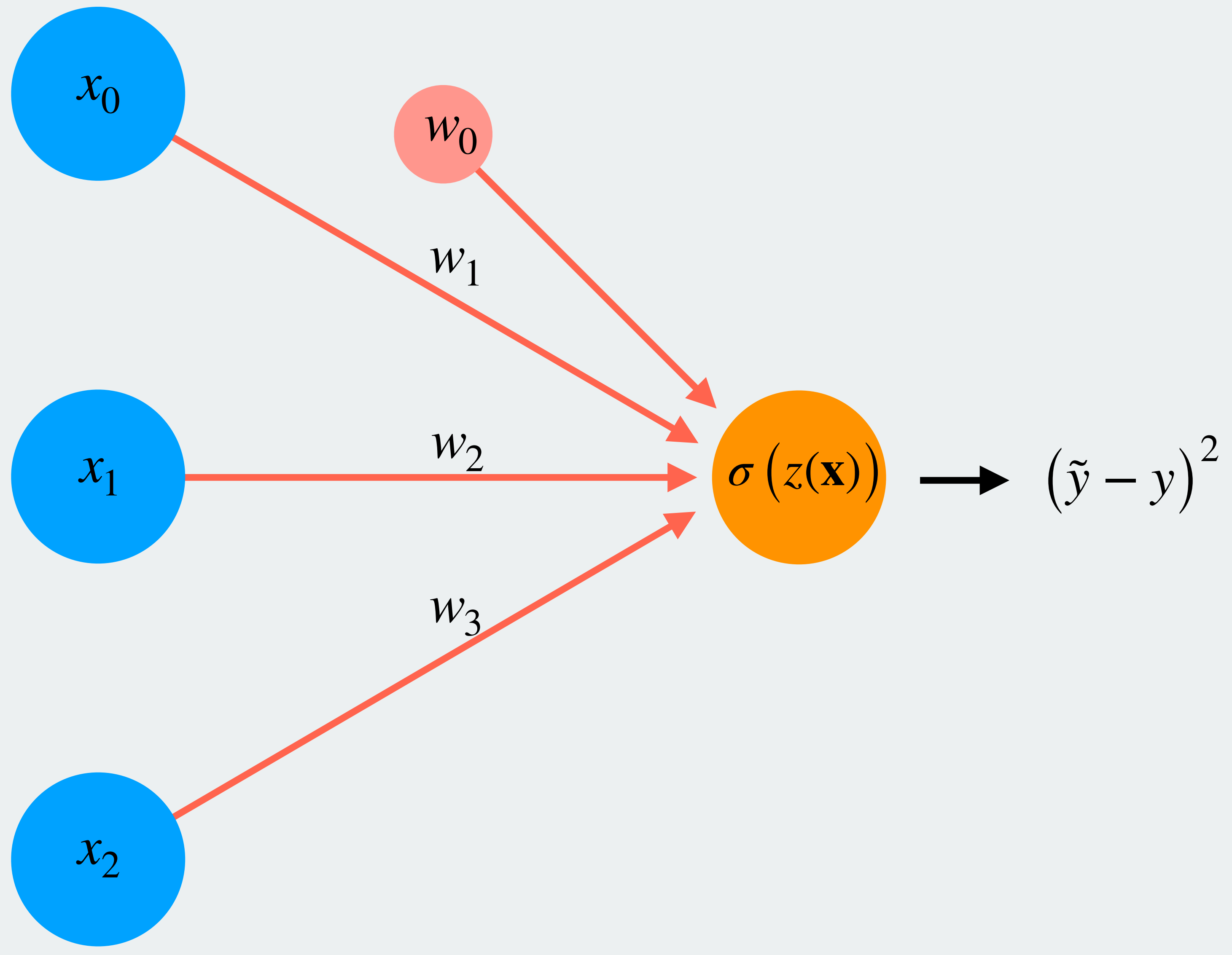
$$
\mathbf{W} = \mathbf{W}^{\mathbf{old}} + r\left(-\nabla C(\mathbf{W}^{\mathbf{old}})\right)
$$

(5) Repeat 3 and 4

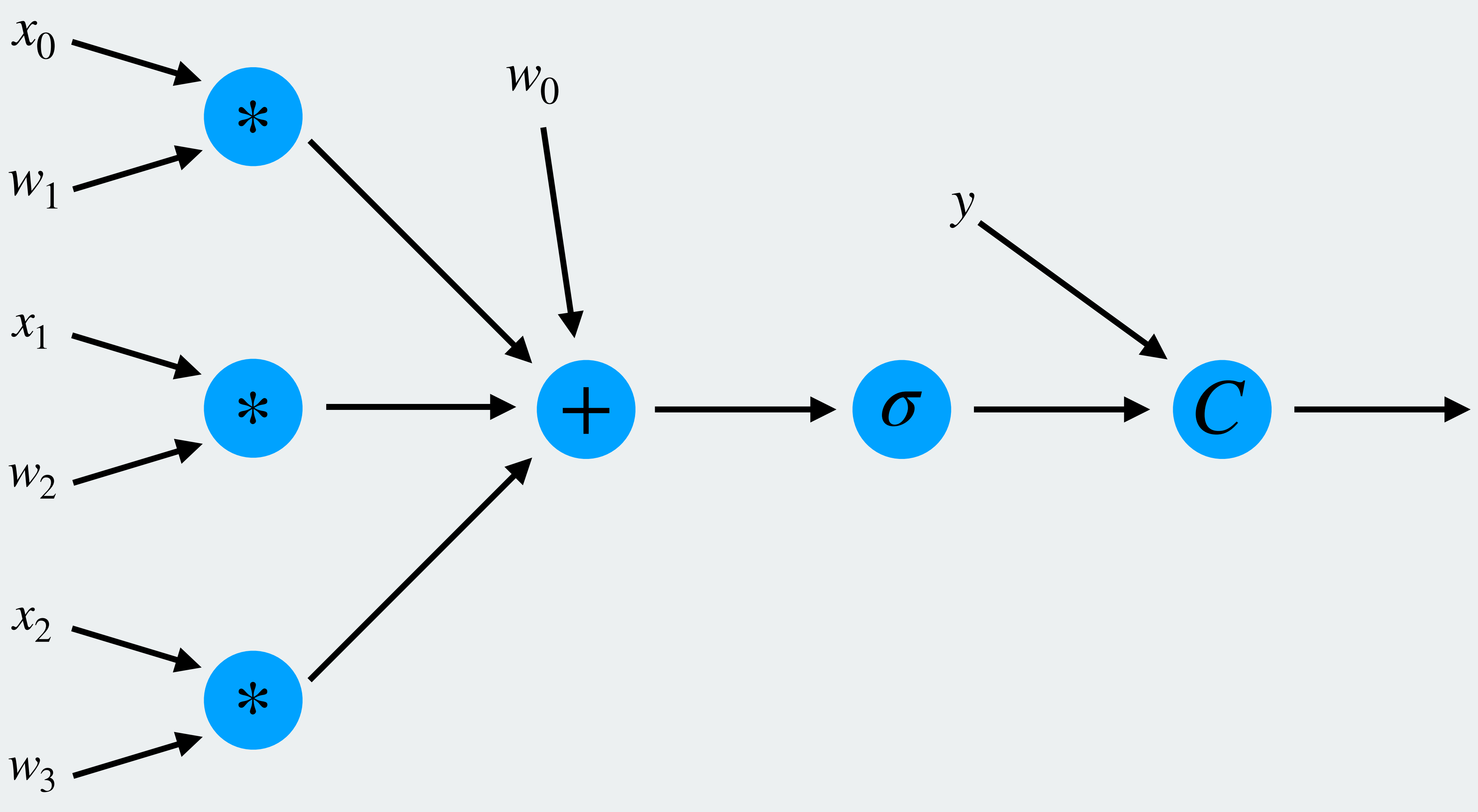
r is usually called the *learning rate*

Quick recap…

Neural network



Computational graph



Quick recap…

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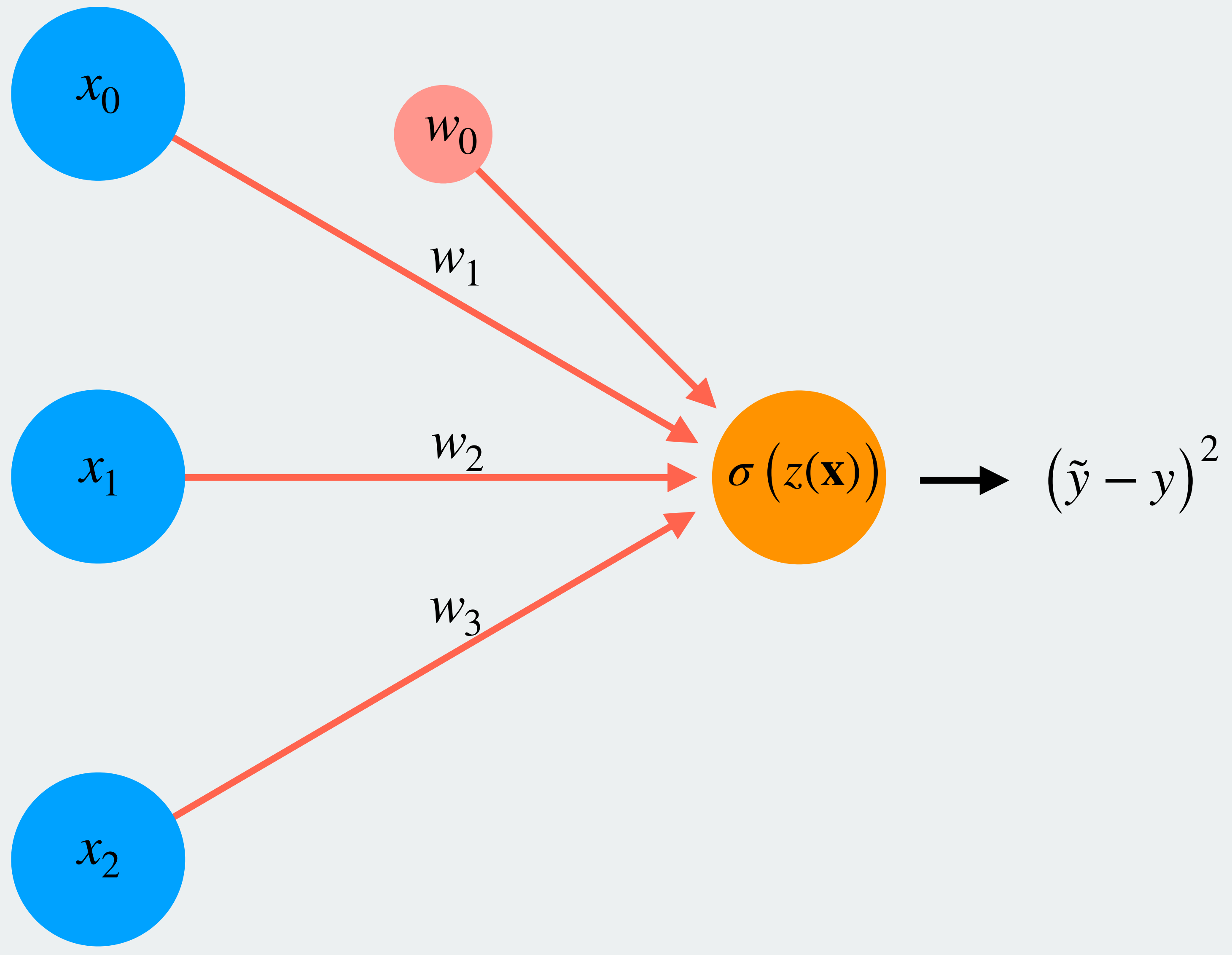

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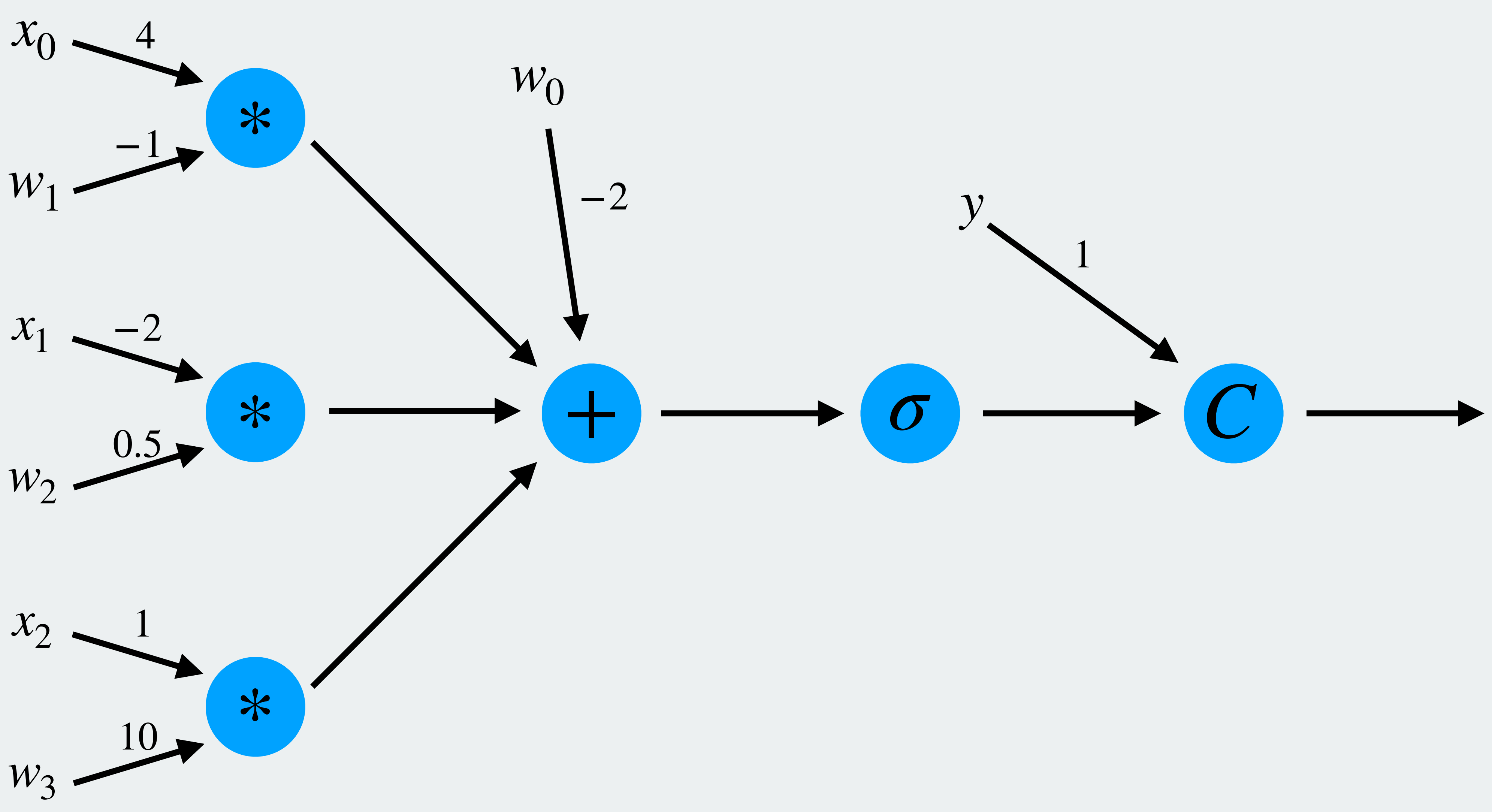
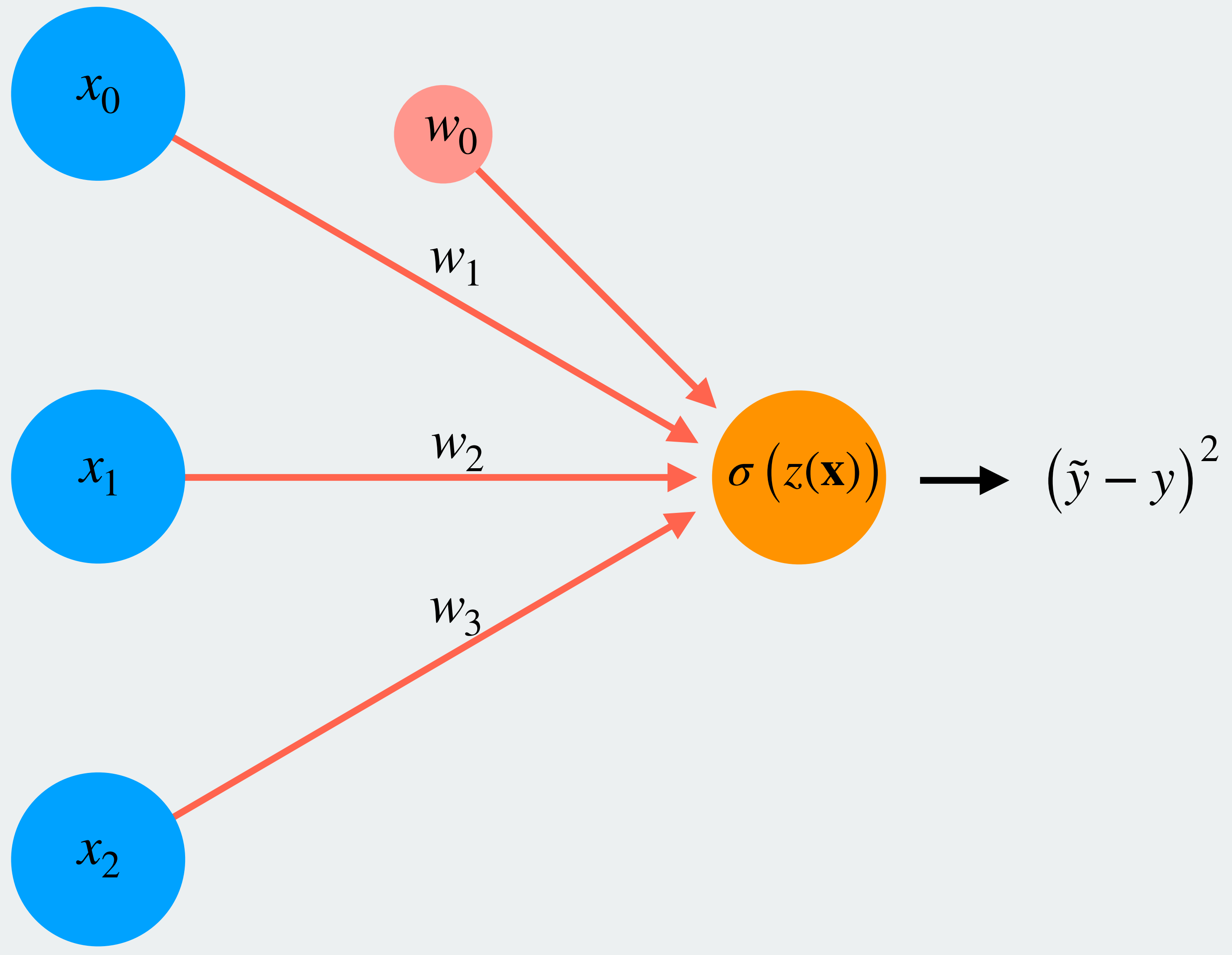


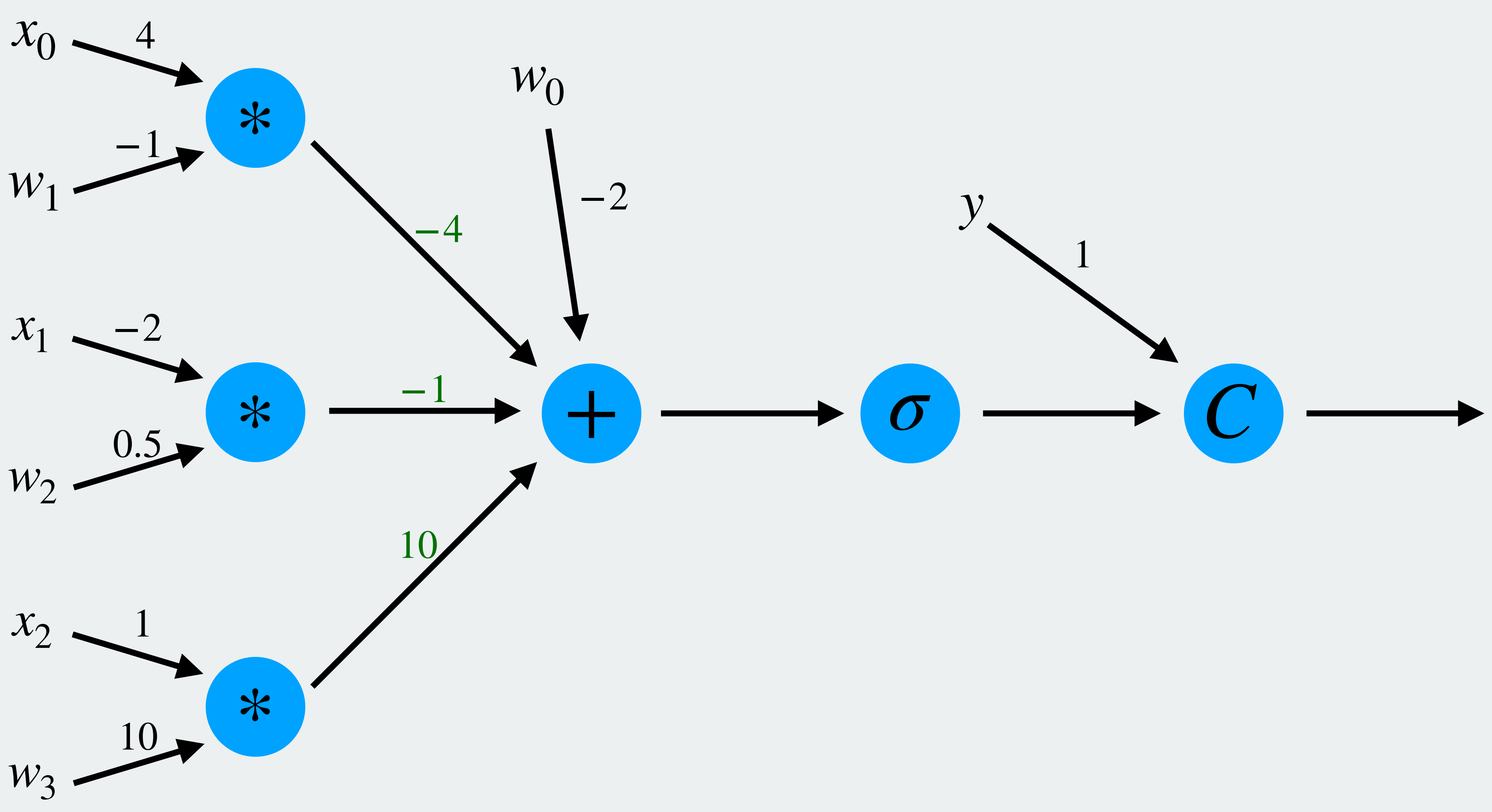
Quick recap…

Neural network



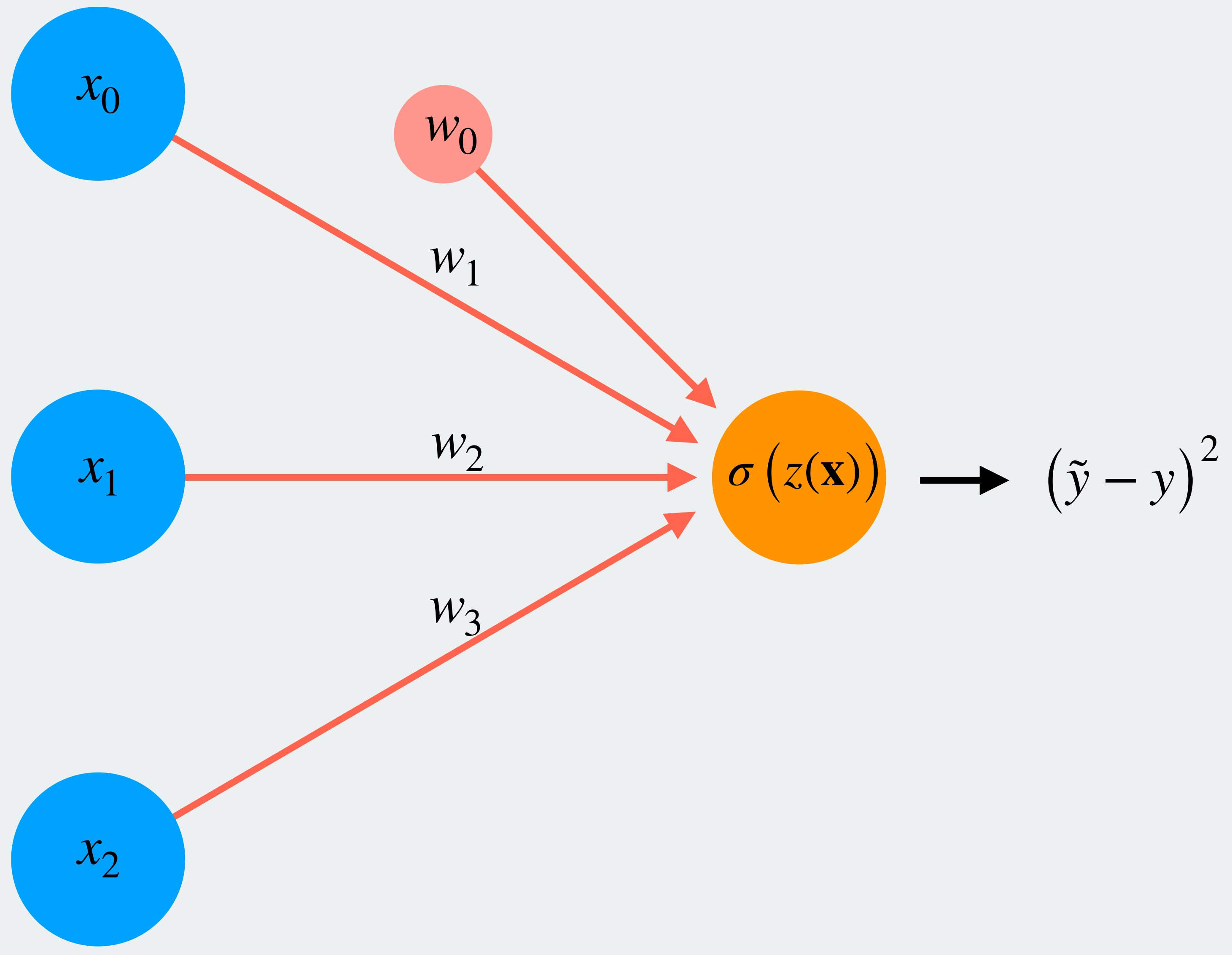
Computational graph

Forward pass



Quick recap…

Neural network



Computational graph

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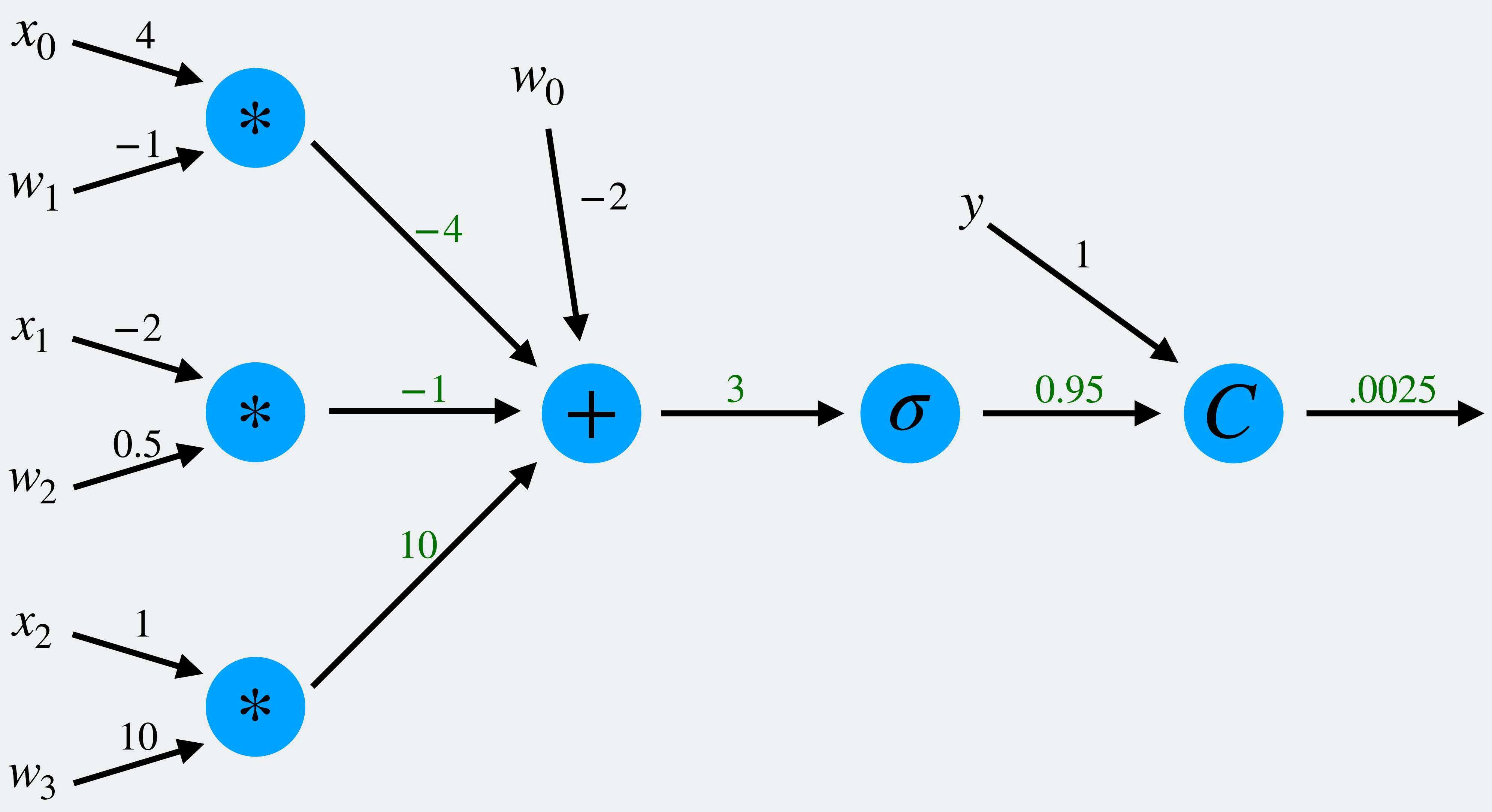

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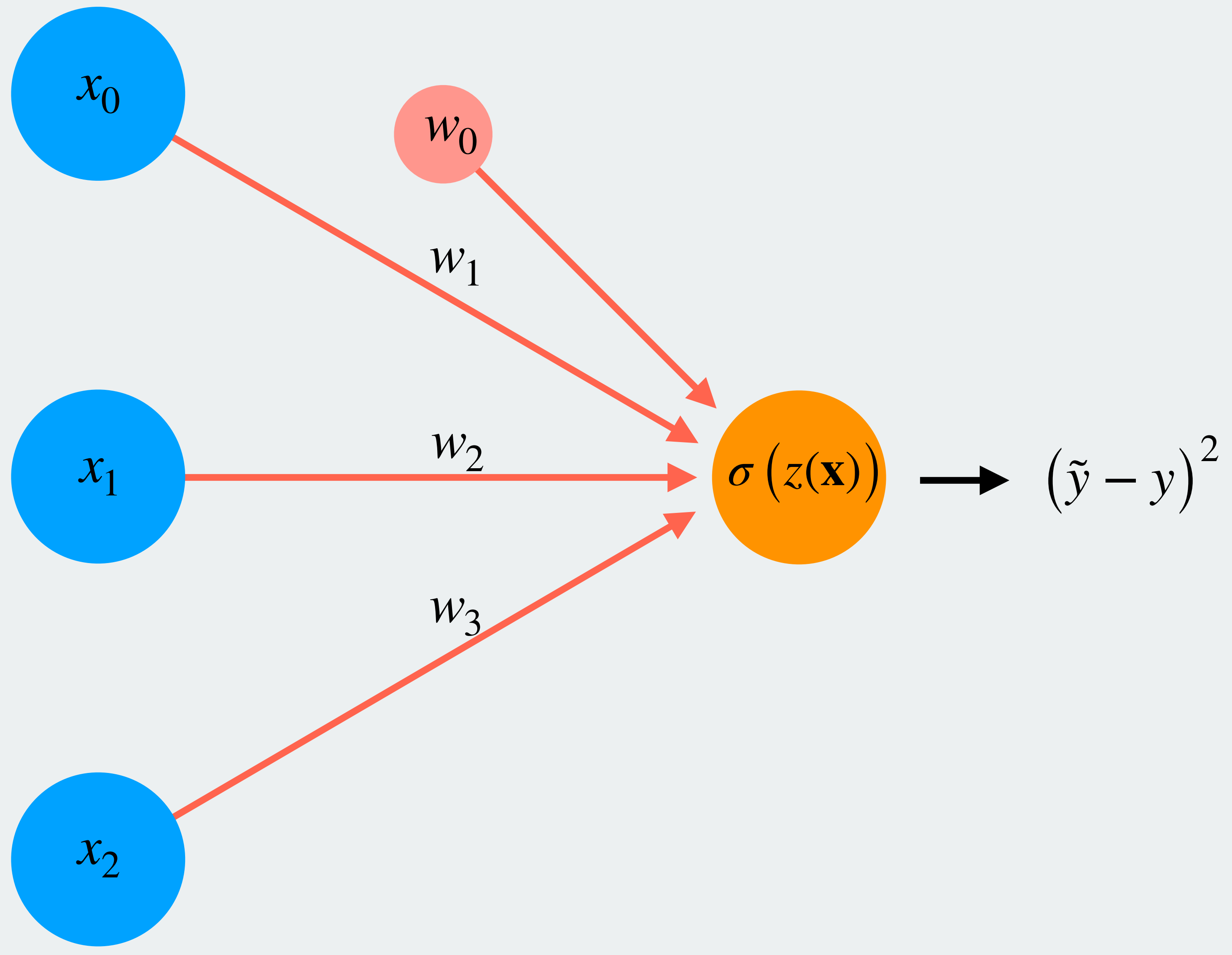
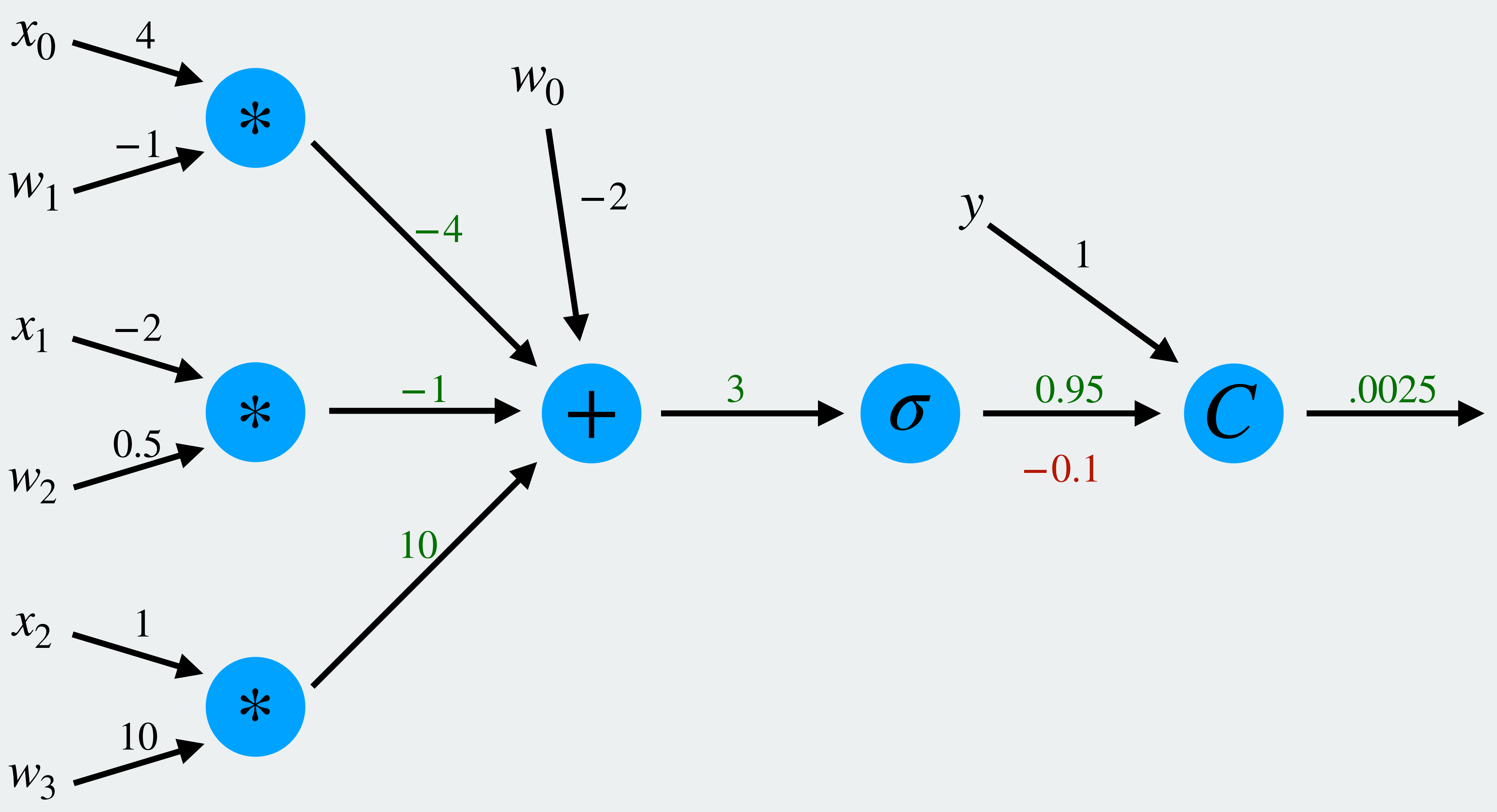
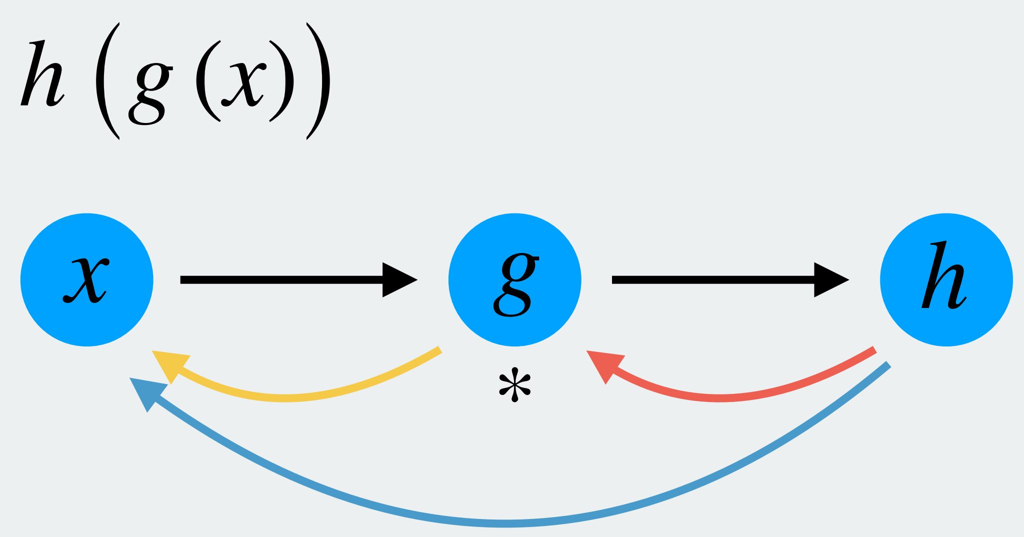
Neural network



Computational graph

Backward pass



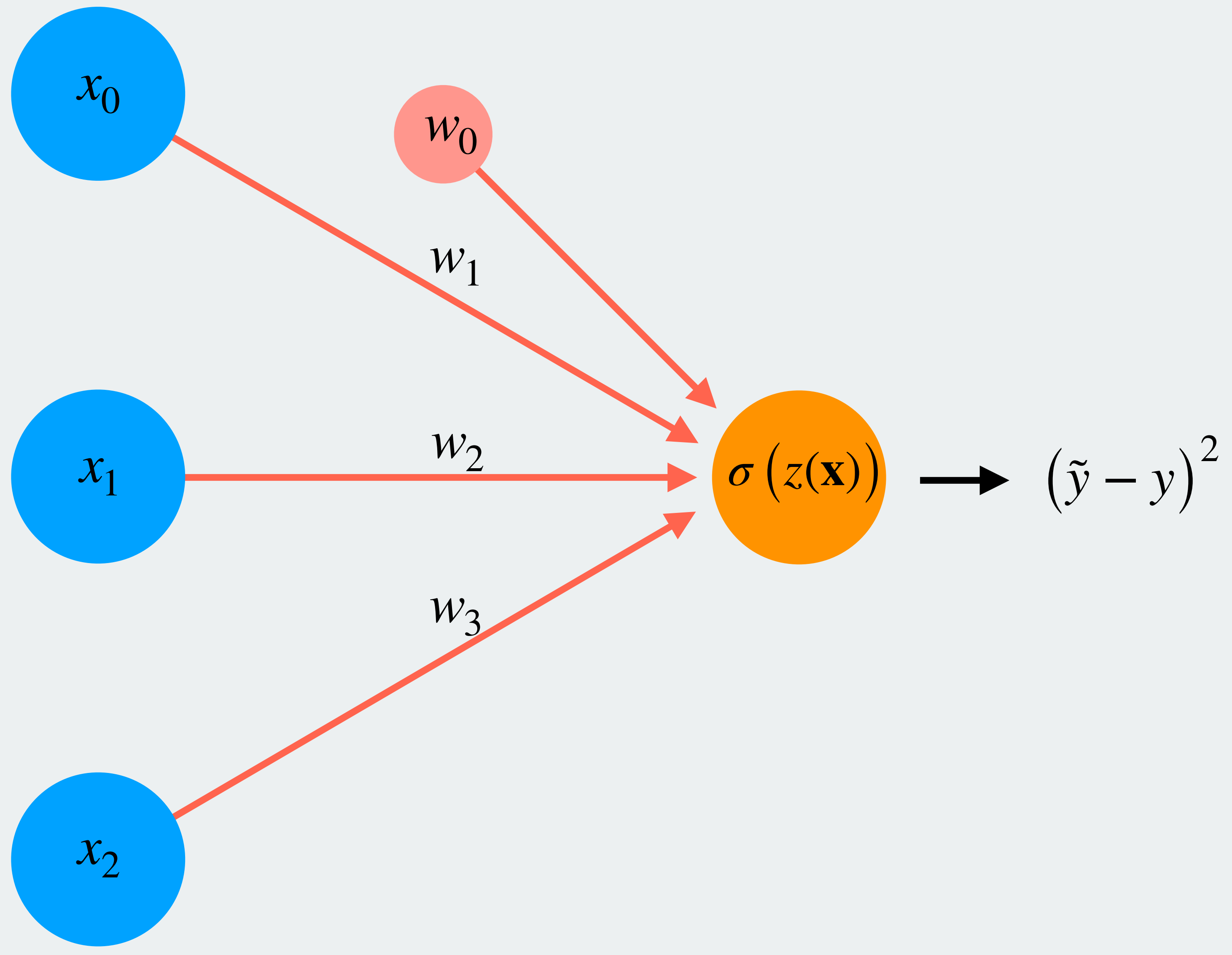


Chain rule says:

$$\frac{dh}{dx} = \frac{dh}{dg}\frac{dg}{dx}$$

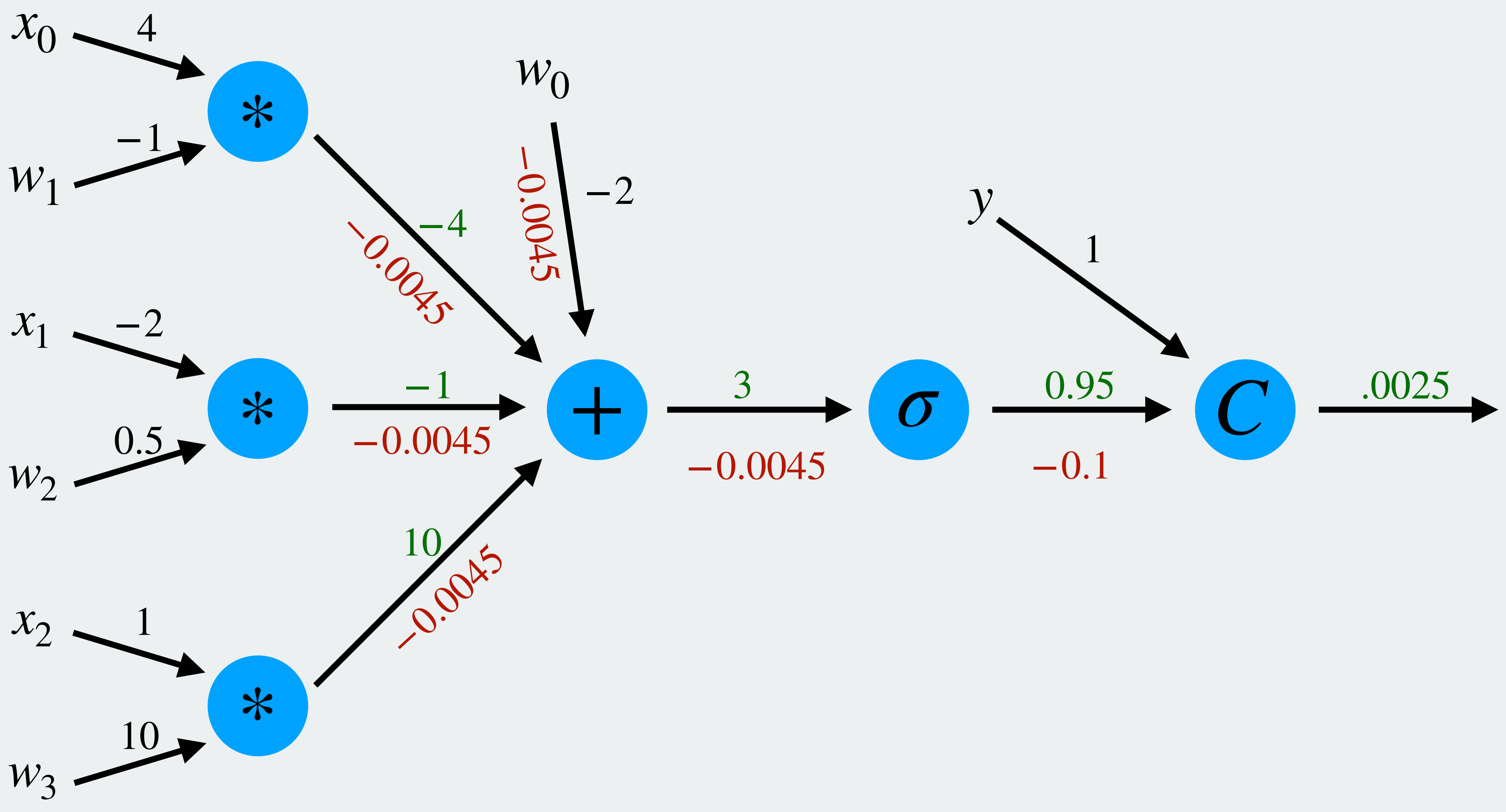
Quick recap...

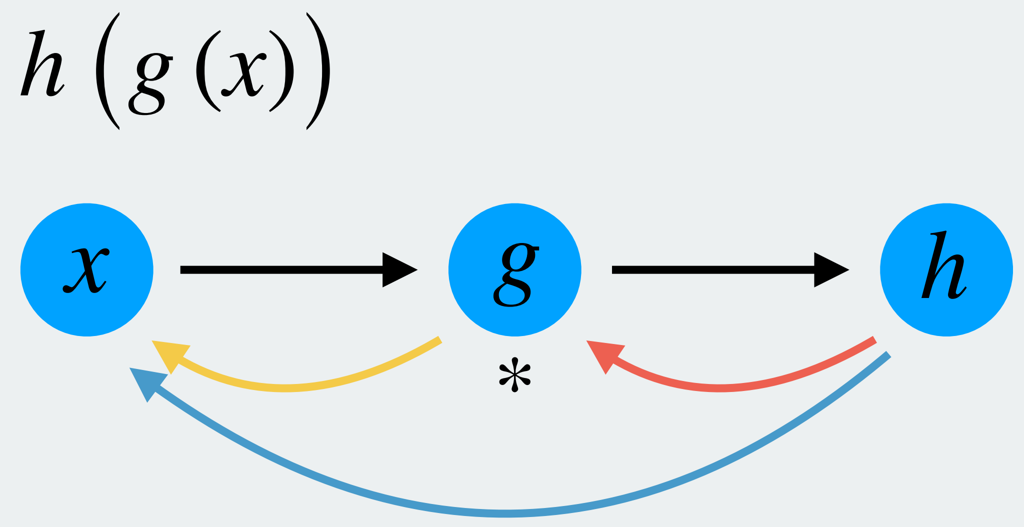
Neural network



Computational graph

Backward pass





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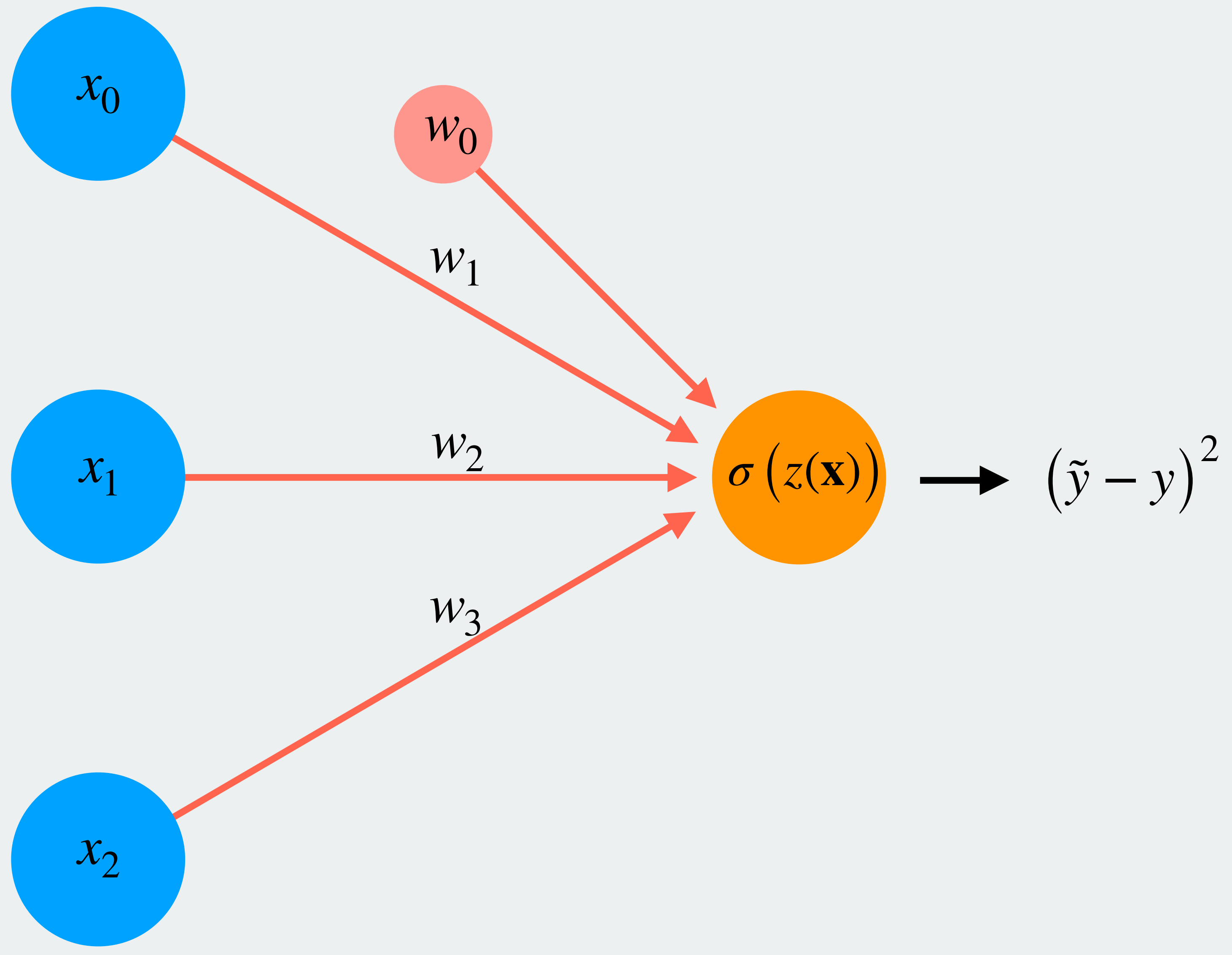
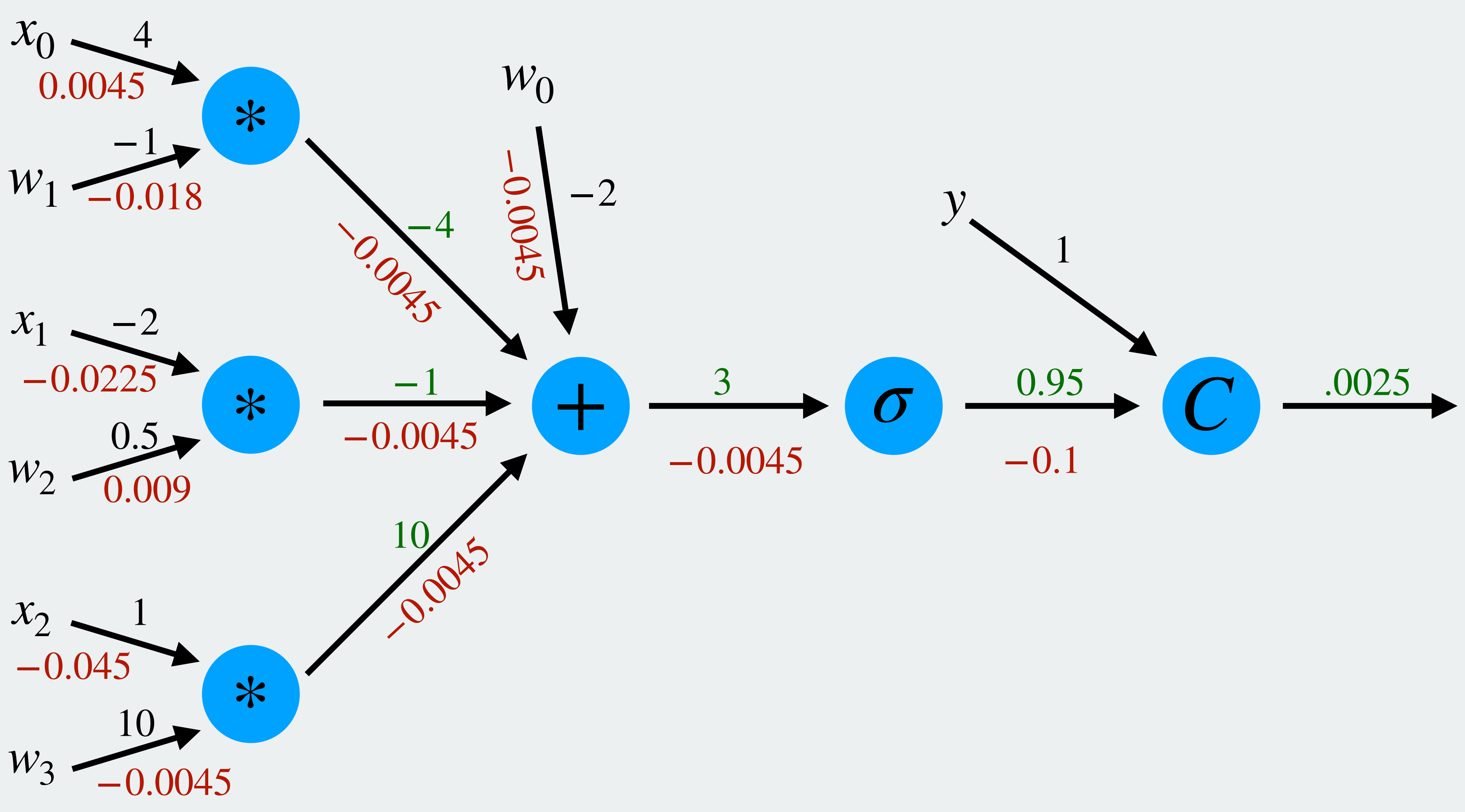
Quick recap…

Neural network

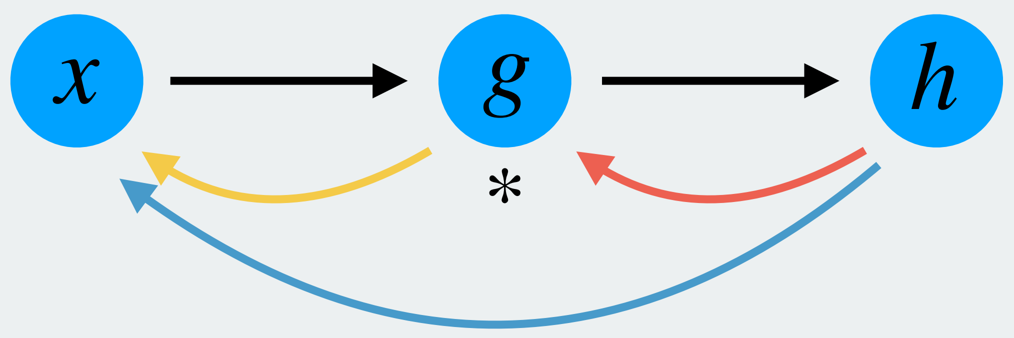


Computational graph

Backward pass



$h(g(x))$



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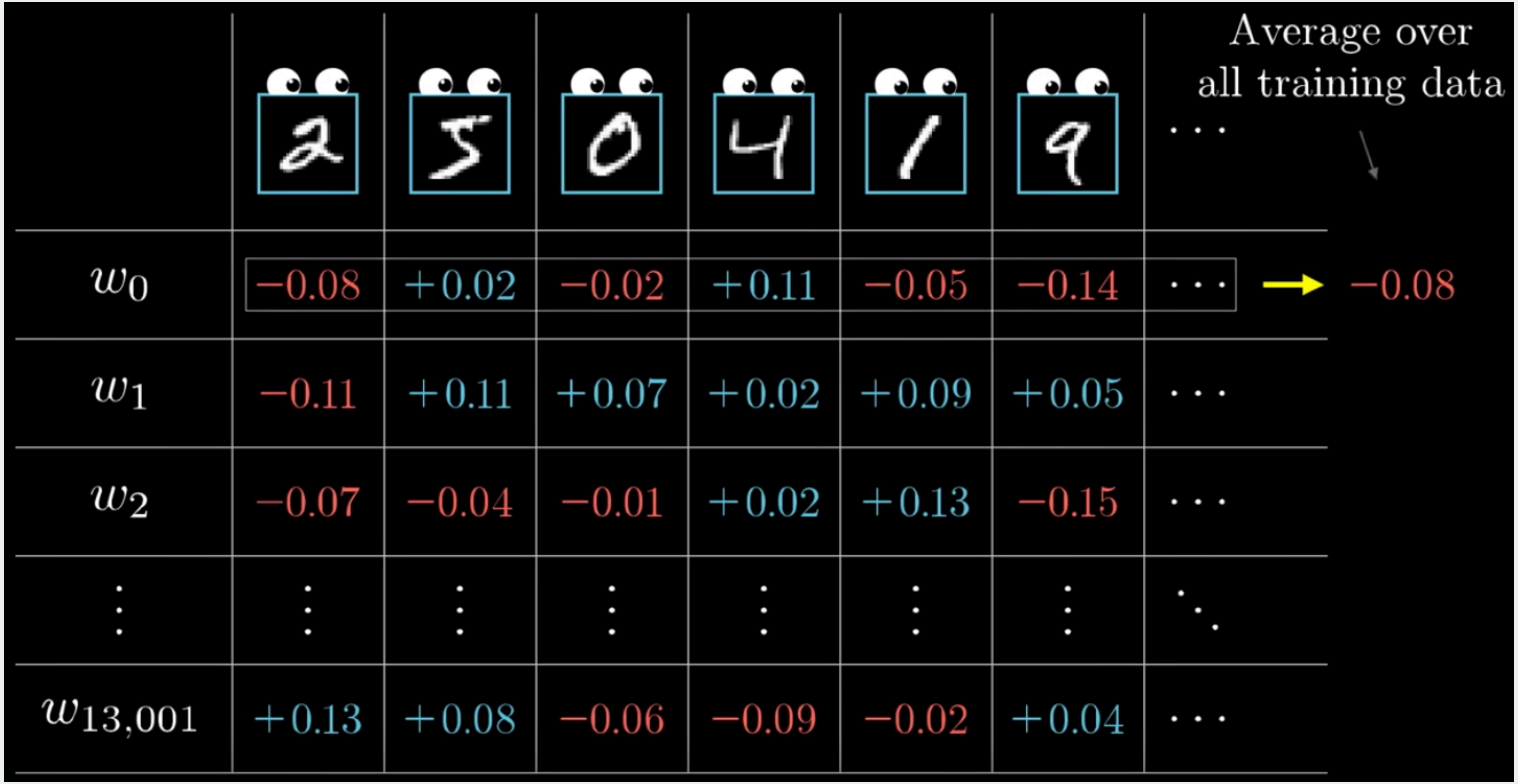
Quick recap…

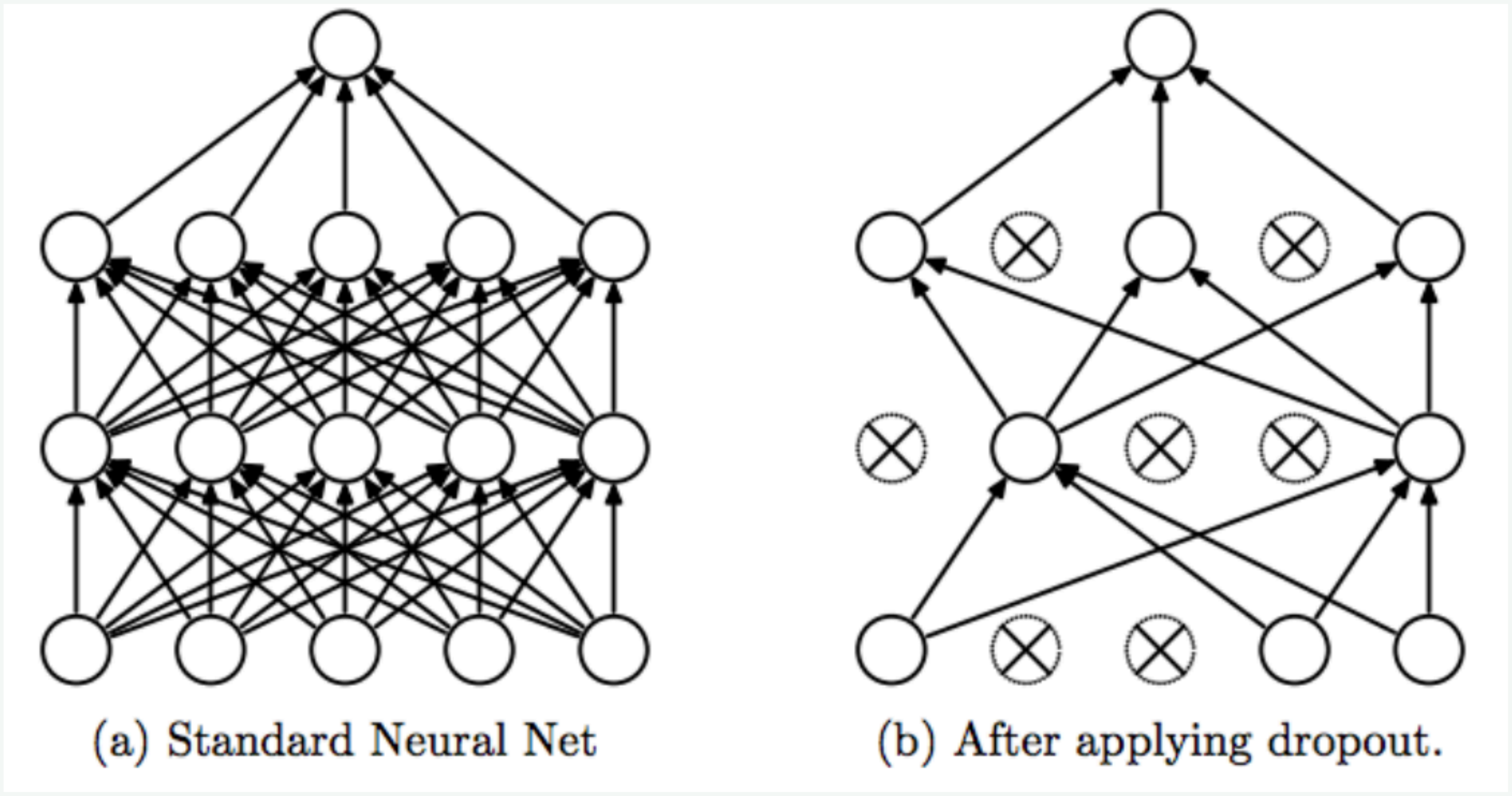


	2	5	0	4	1	9	…	Average over all training data
w_0	−0.08	+0.02	−0.02	+0.11	−0.05	−0.14	…	→ −0.08
w_1	−0.11	+0.11	+0.07	+0.02	+0.09	+0.05	…	
w_2	−0.07	−0.04	−0.01	+0.02	+0.13	−0.15	…	
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋱	
$w_{13,001}$	+0.13	+0.08	−0.06	−0.09	−0.02	+0.04	…	

Quick recap…

Dropout:

“In each SGD step, randomly ignore a fraction *p* of neurons”



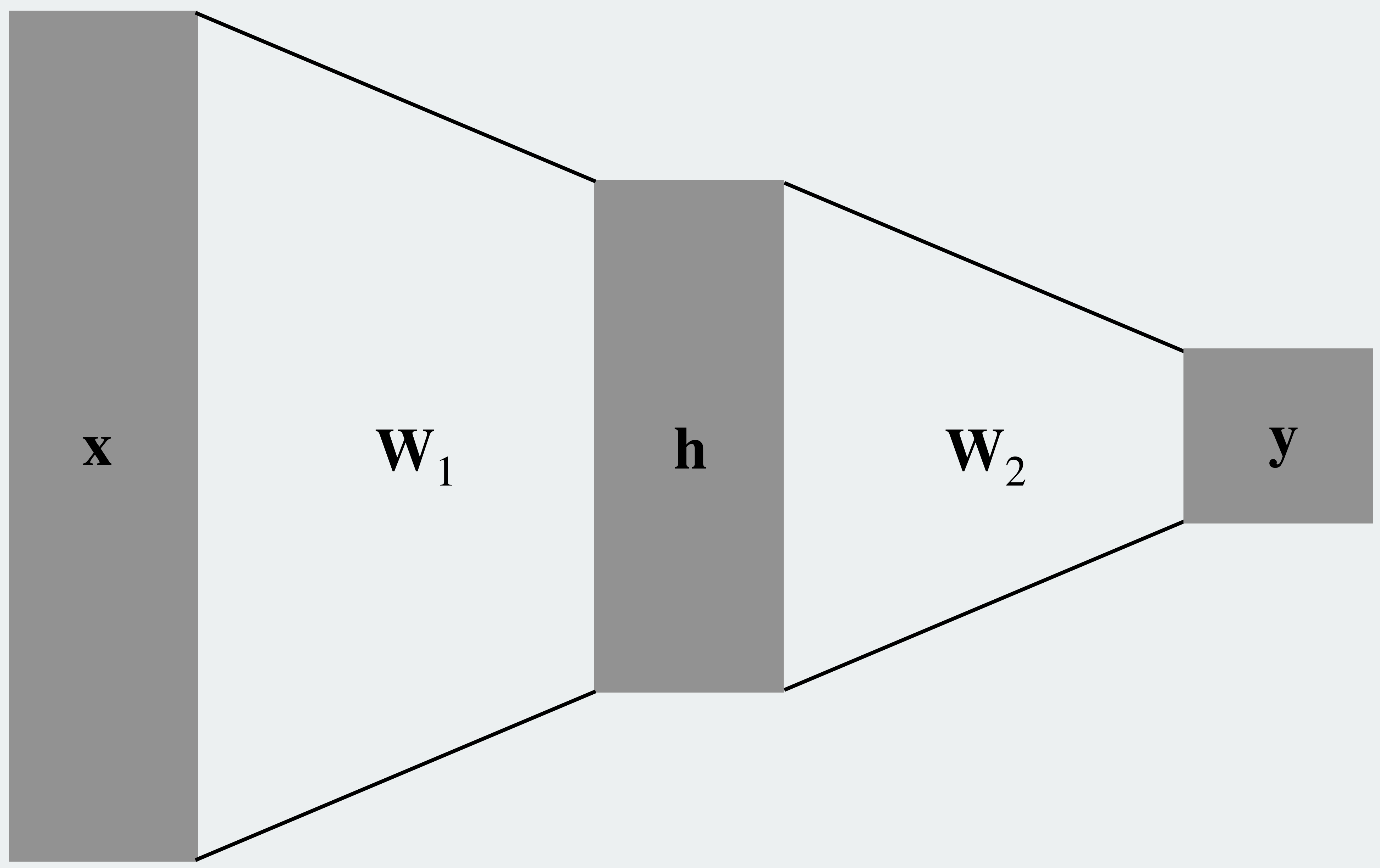
Srivastava, Nitish, et al. ”Dropout: a simple way to prevent neural networks from overfitting”, JMLR 2014

- Can select *p* in wide range. Typical is 0.2 – 0.8, dependent on size of ANN
- Can apply only in specific layers. It is typical to only do dropout in a designated “dropout layer” somewhere close to output.

Convolutional Neural Networks

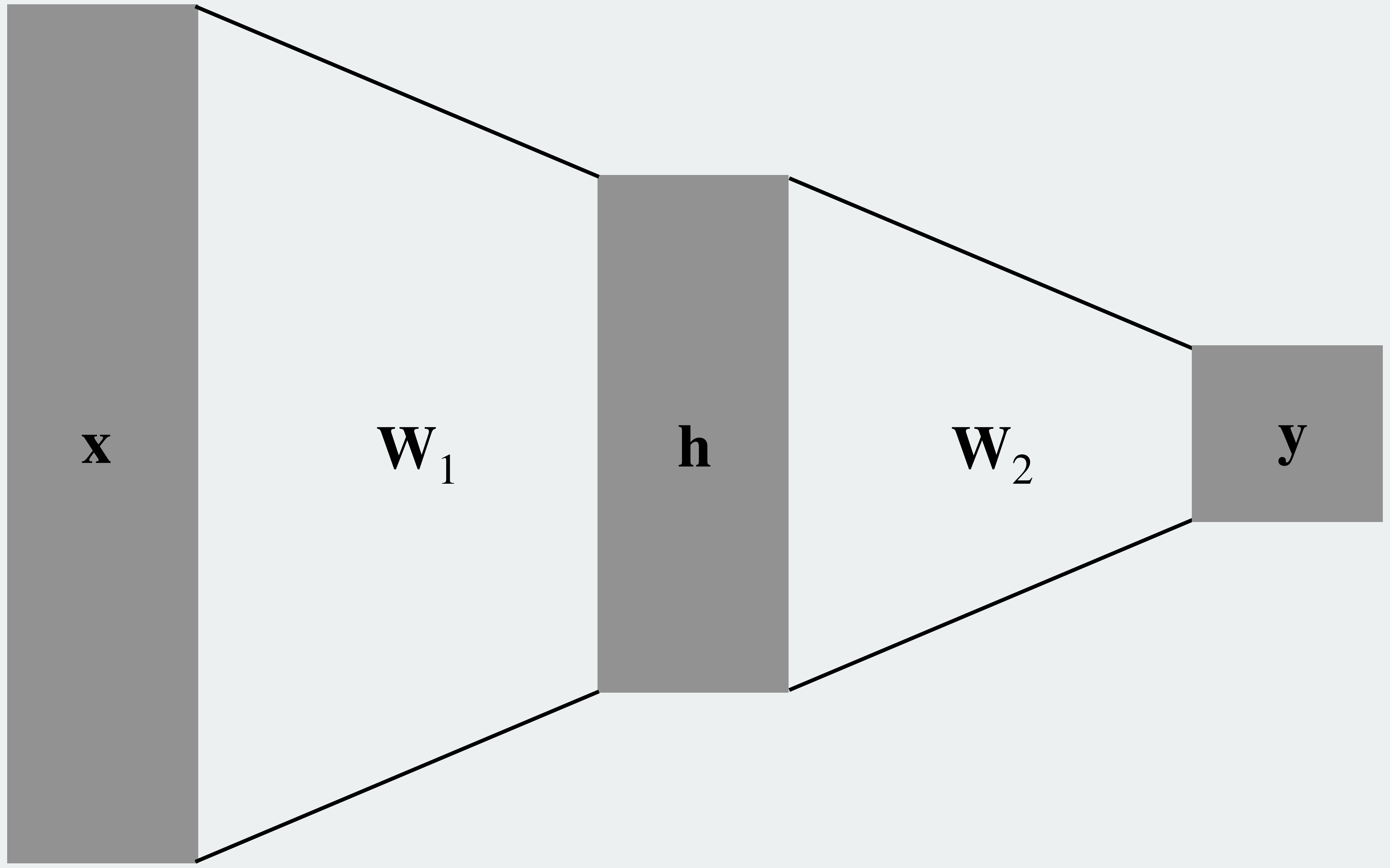
THE neural network architecture to use for image data

The problem with vanilla neural networks

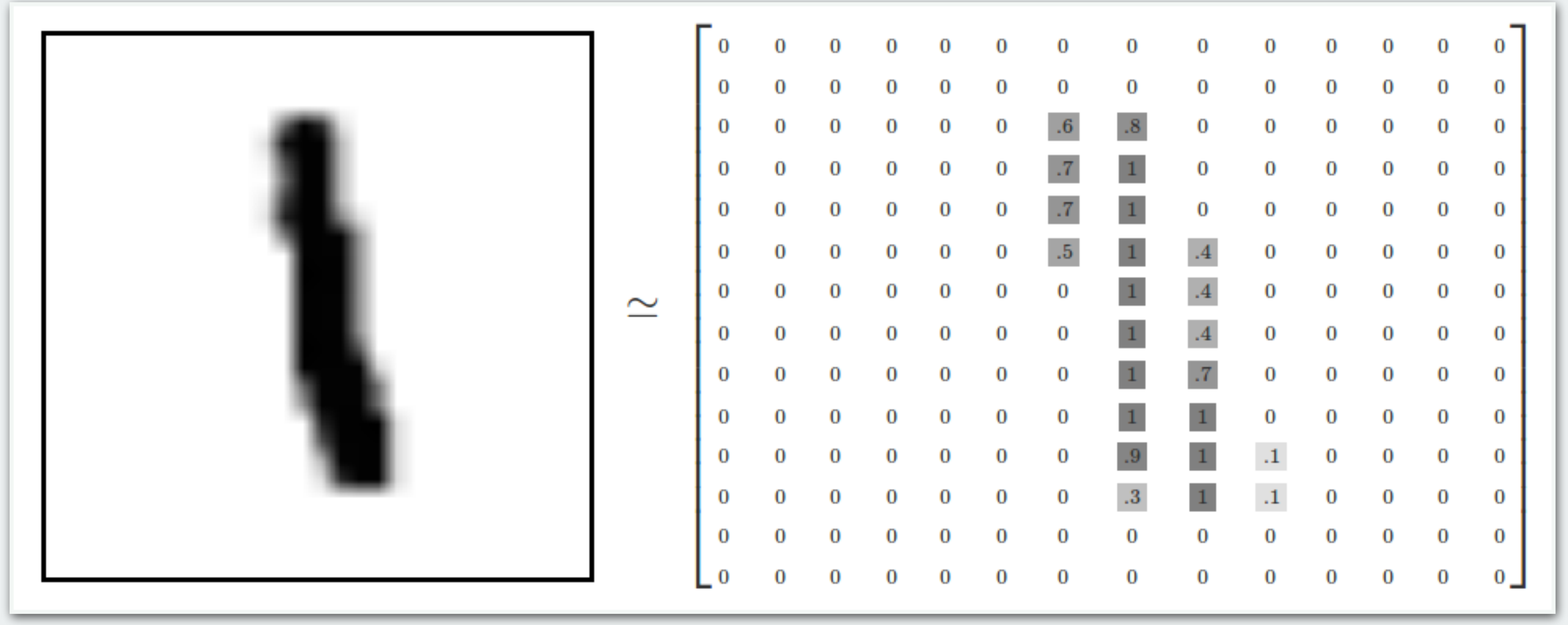


- Single operation on whole input
- Each neuron reacts to specific inputs

The problem with vanilla neural networks

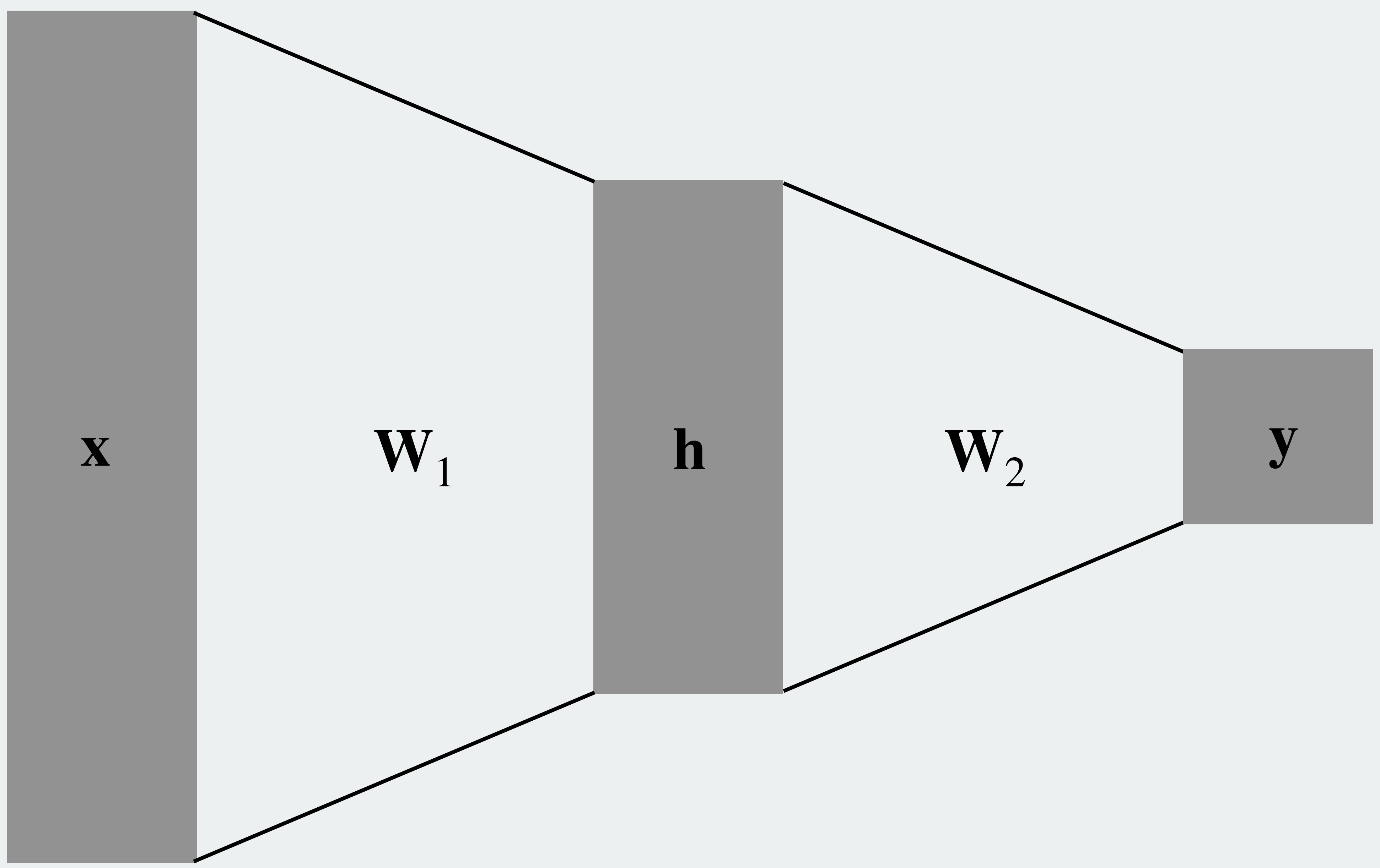


- Single operation on whole input
- Each neuron reacts to specific inputs
- Bad for images: objects move around
- No attention to spatial adjacency



The problem with vanilla neural networks

> Solution: “slide” the weight matrix over the input



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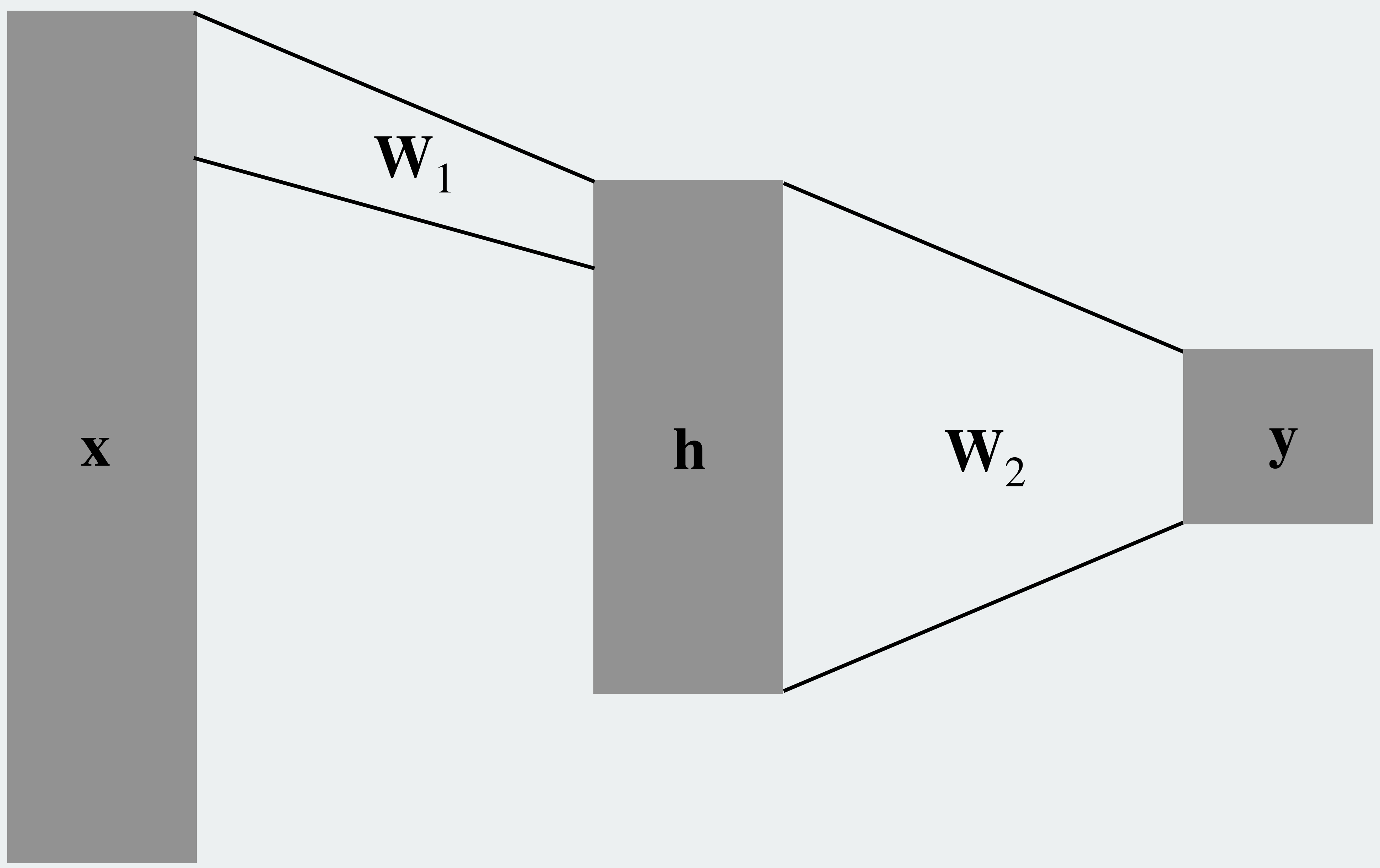

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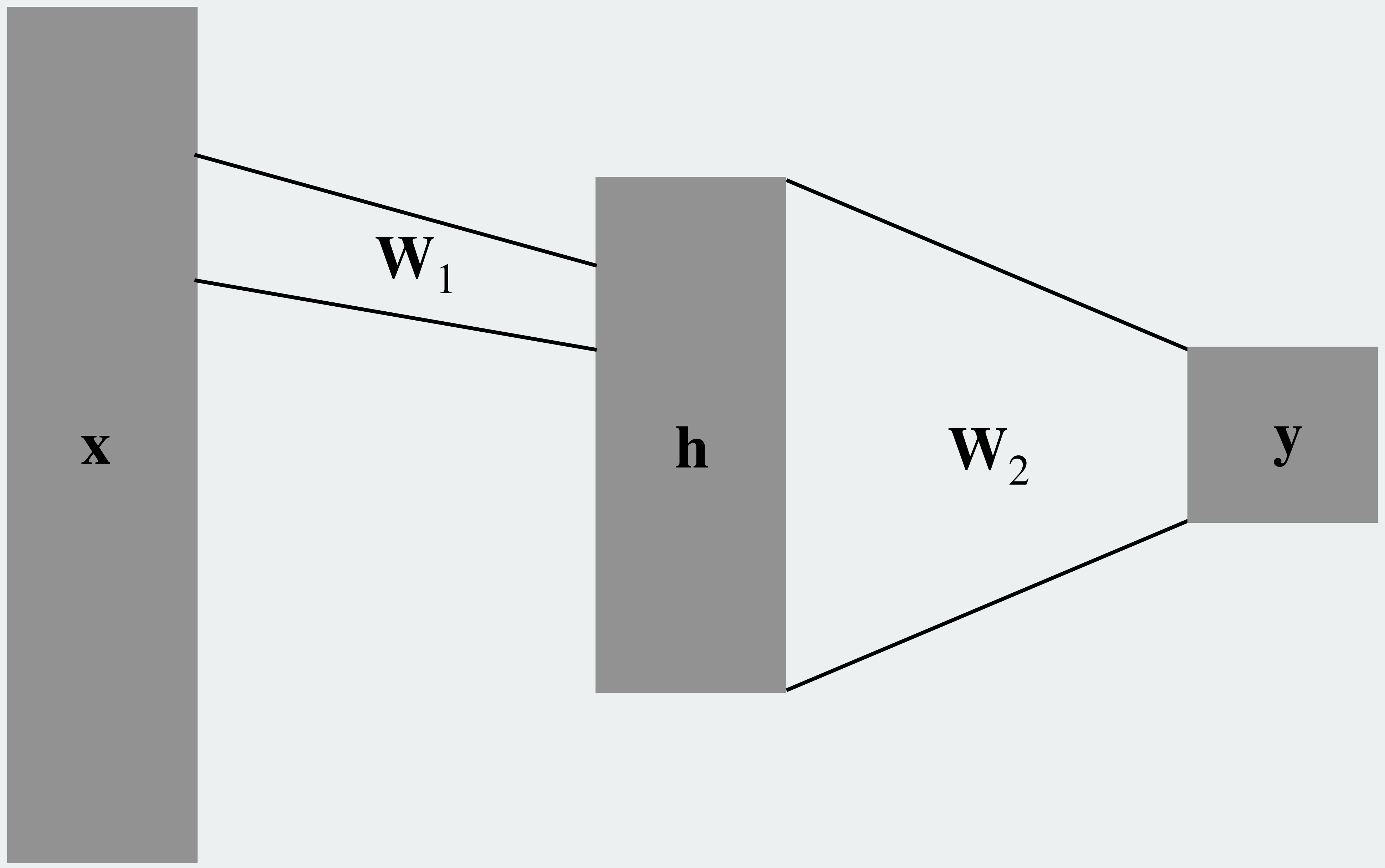

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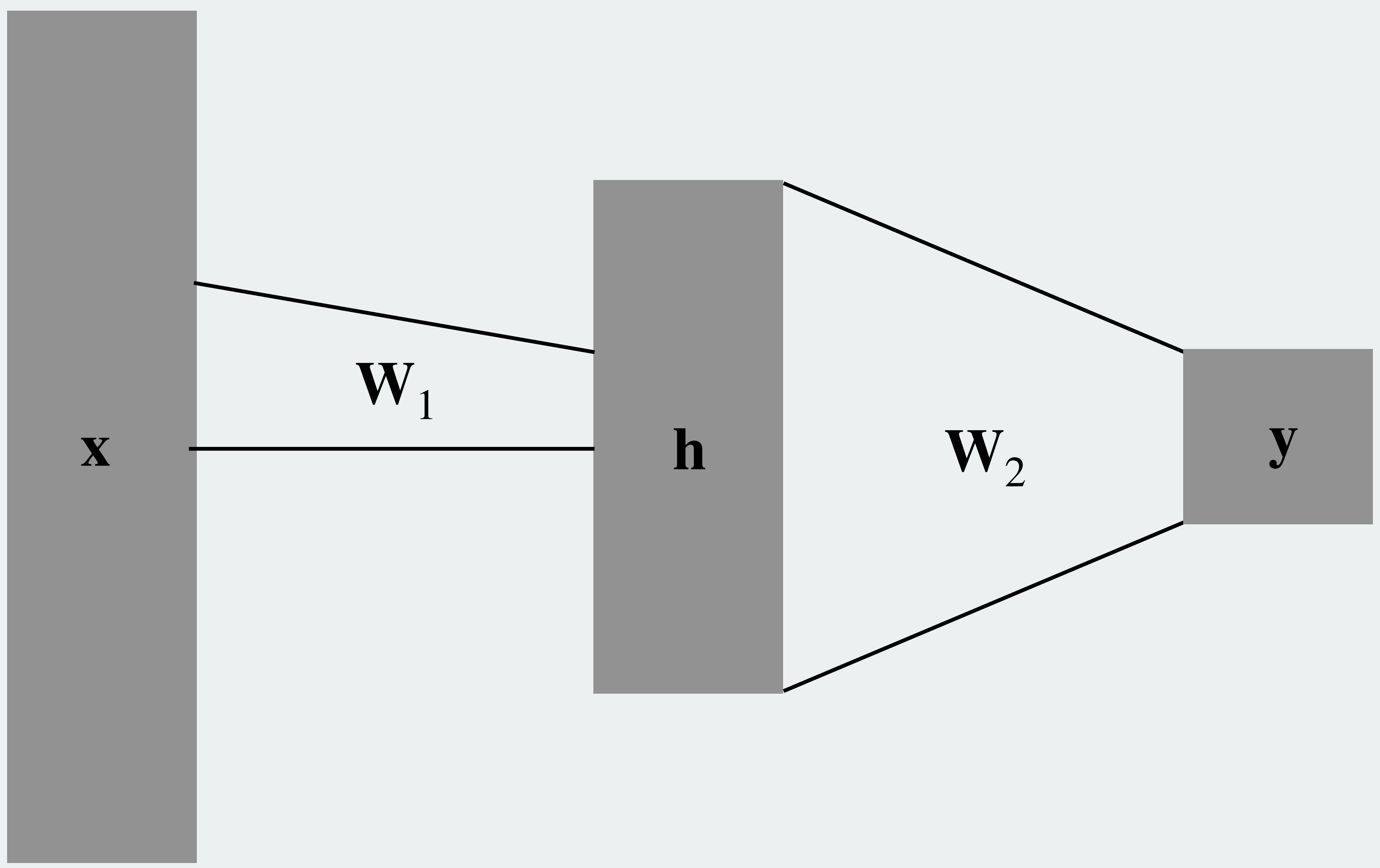
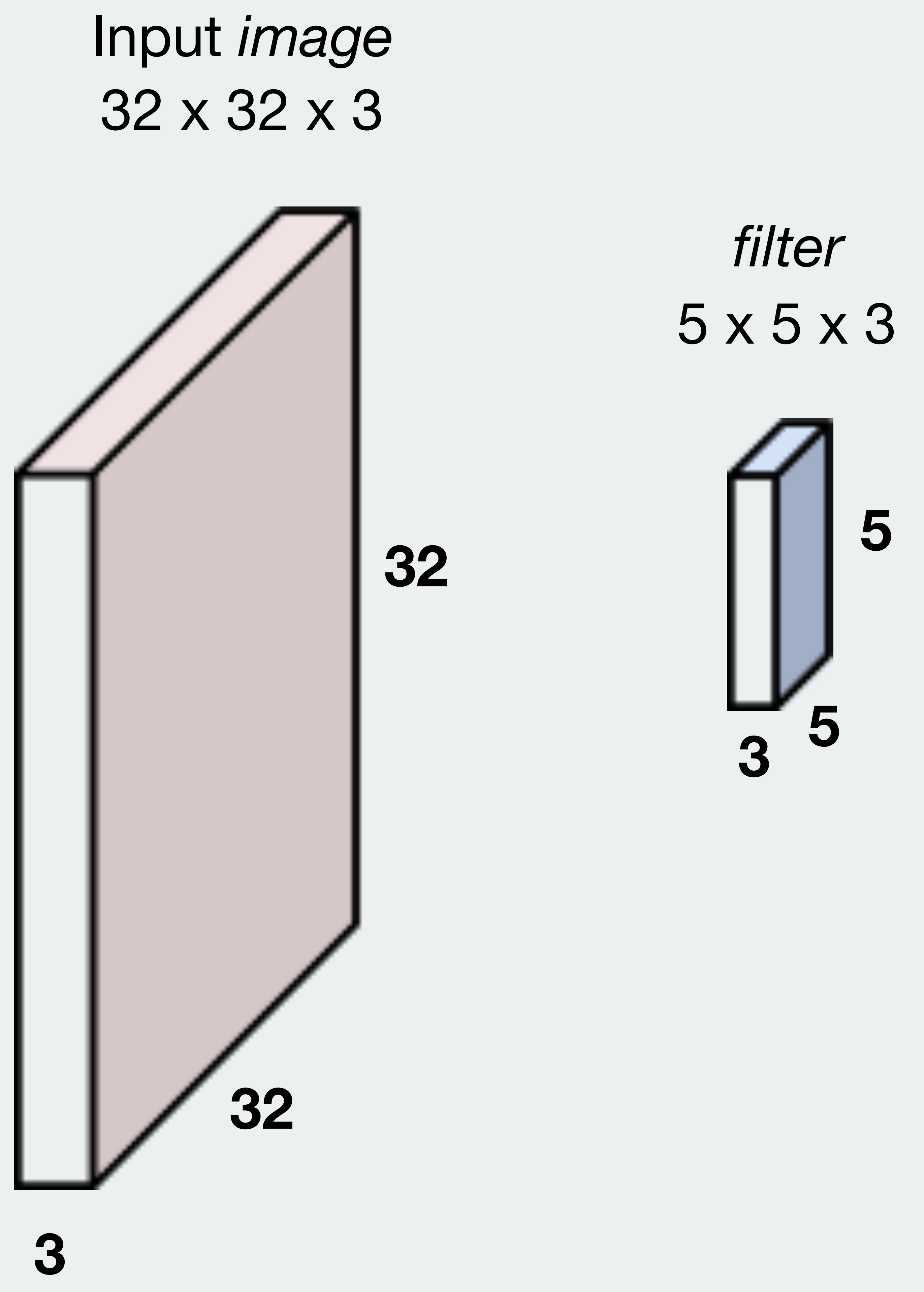
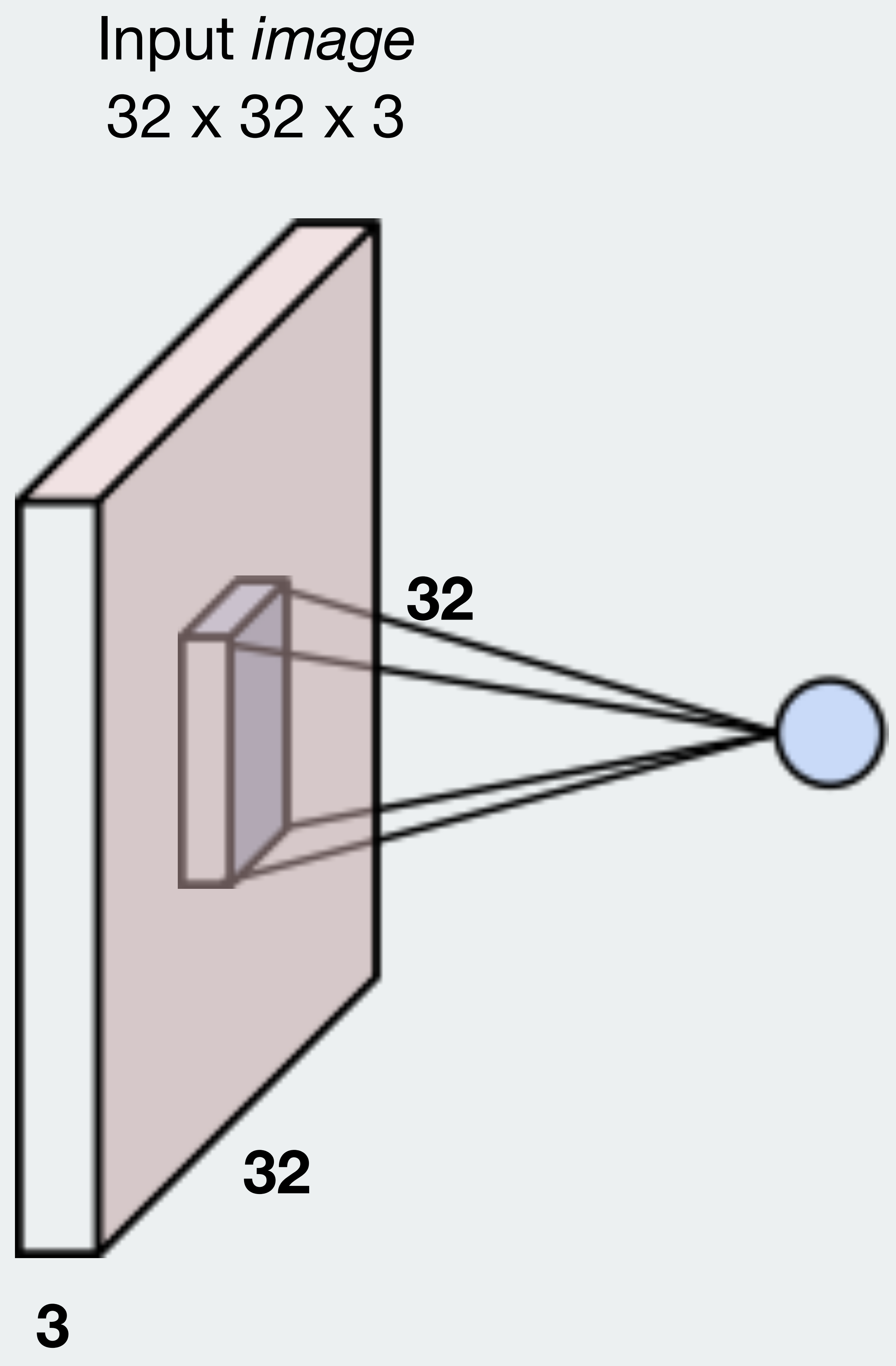


Convolutional neural networks



Convolutional neural networks

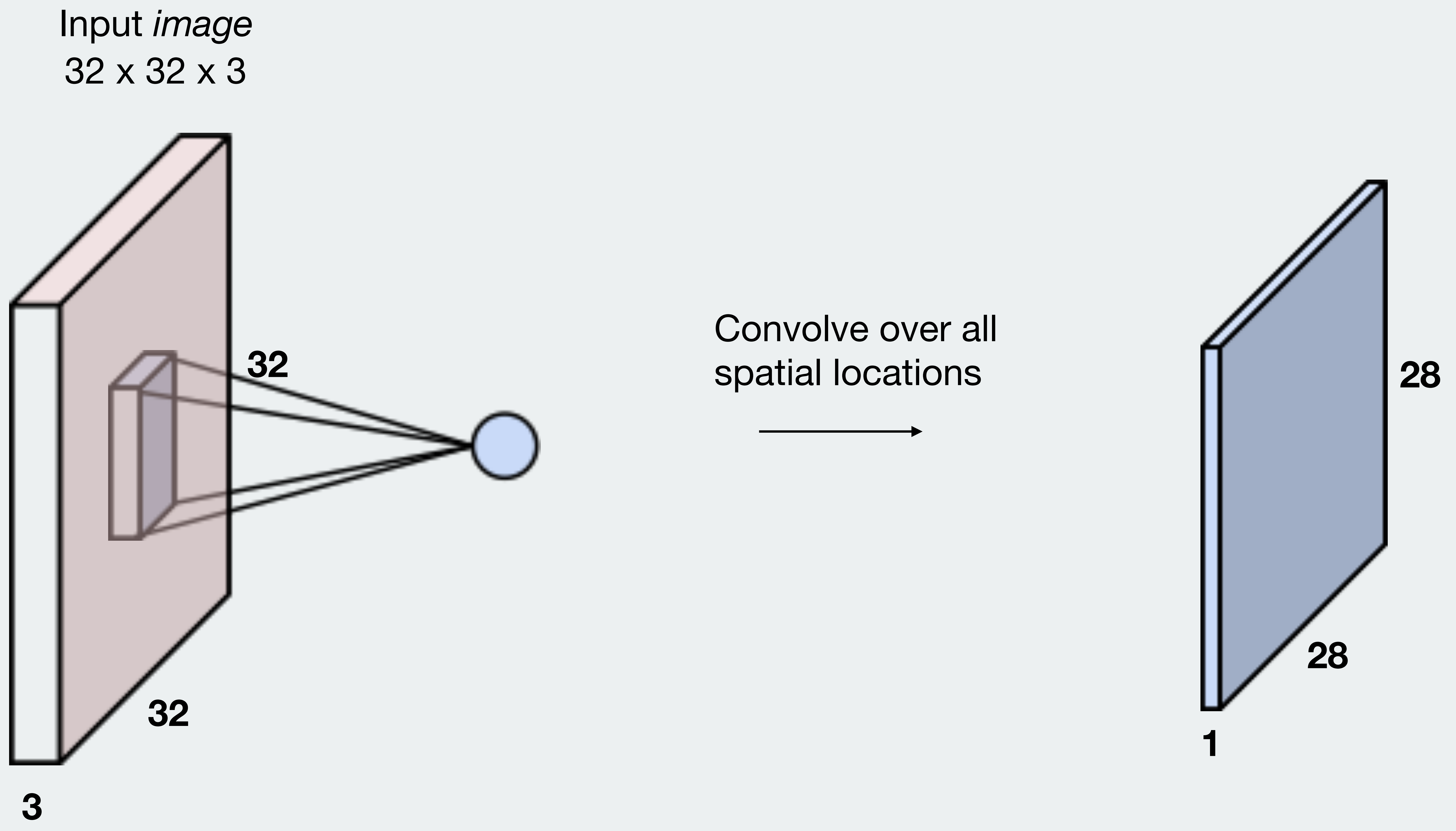
> Convolve the filter across the input image to computing dot products



1 number: the result of taking the dot product between the filter and one chunk of the image (5*5*3 = 75-dimensional dot product + bias)

Convolutional neural networks

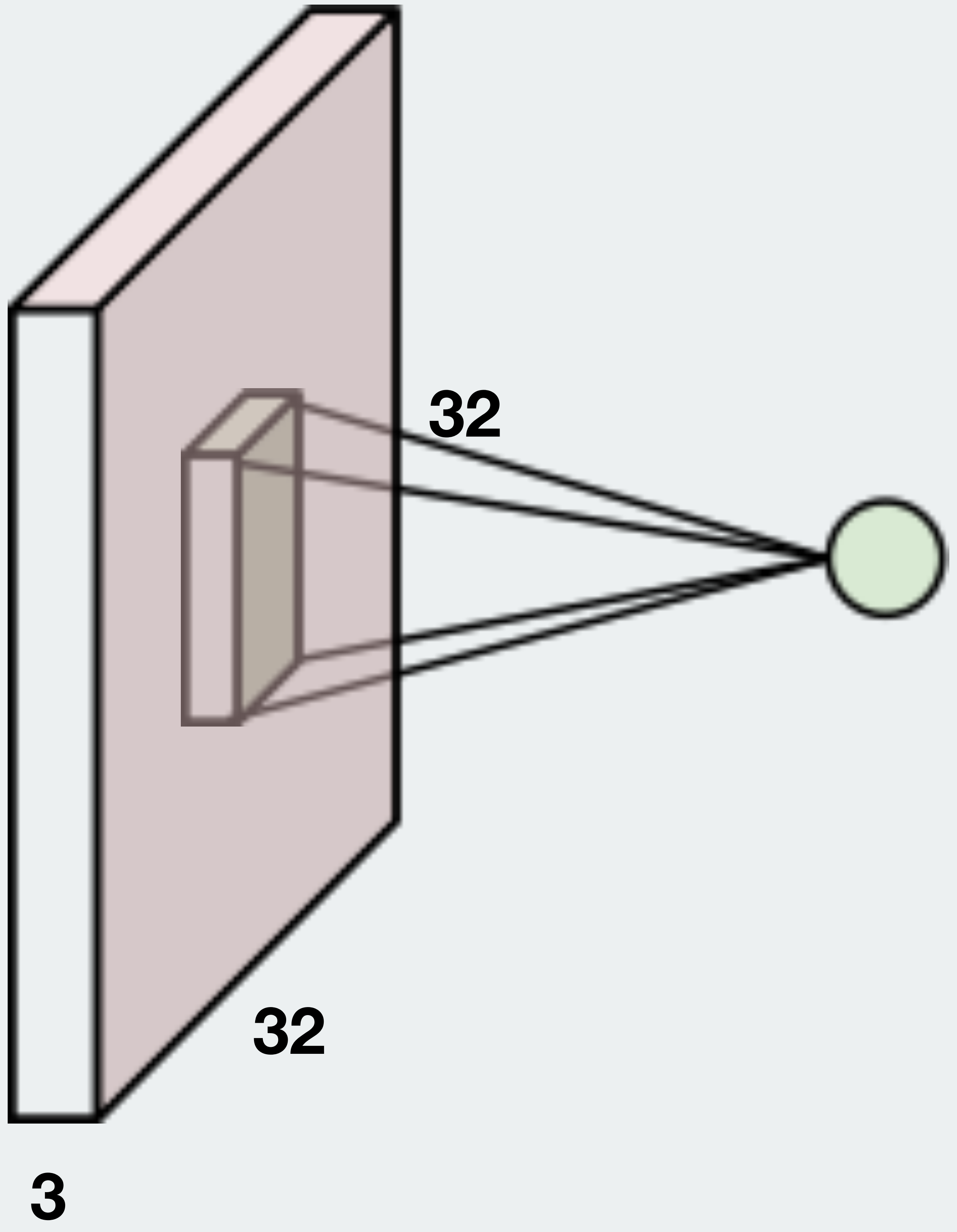
> Convolution by 1 filter produces new *activation map* of depth 1



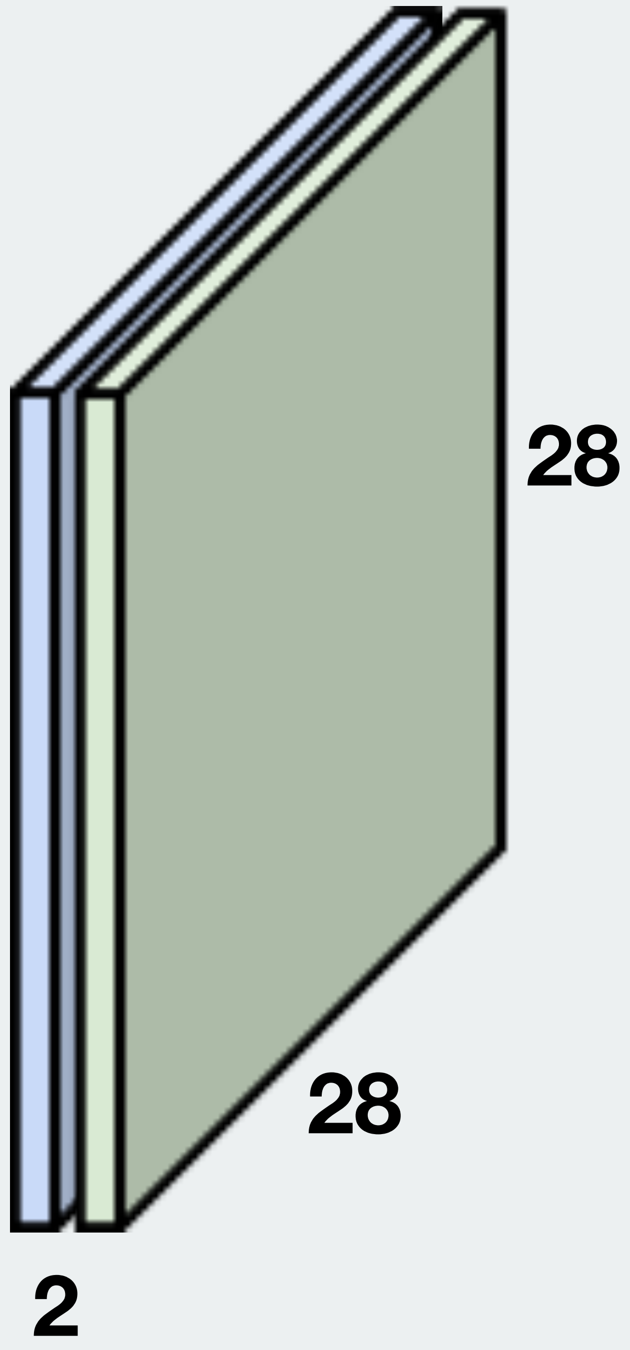
Convolutional neural networks

> Convolution by 2 filters produces new *activation map* of depth 2

Input *image*
32 x 32 x 3

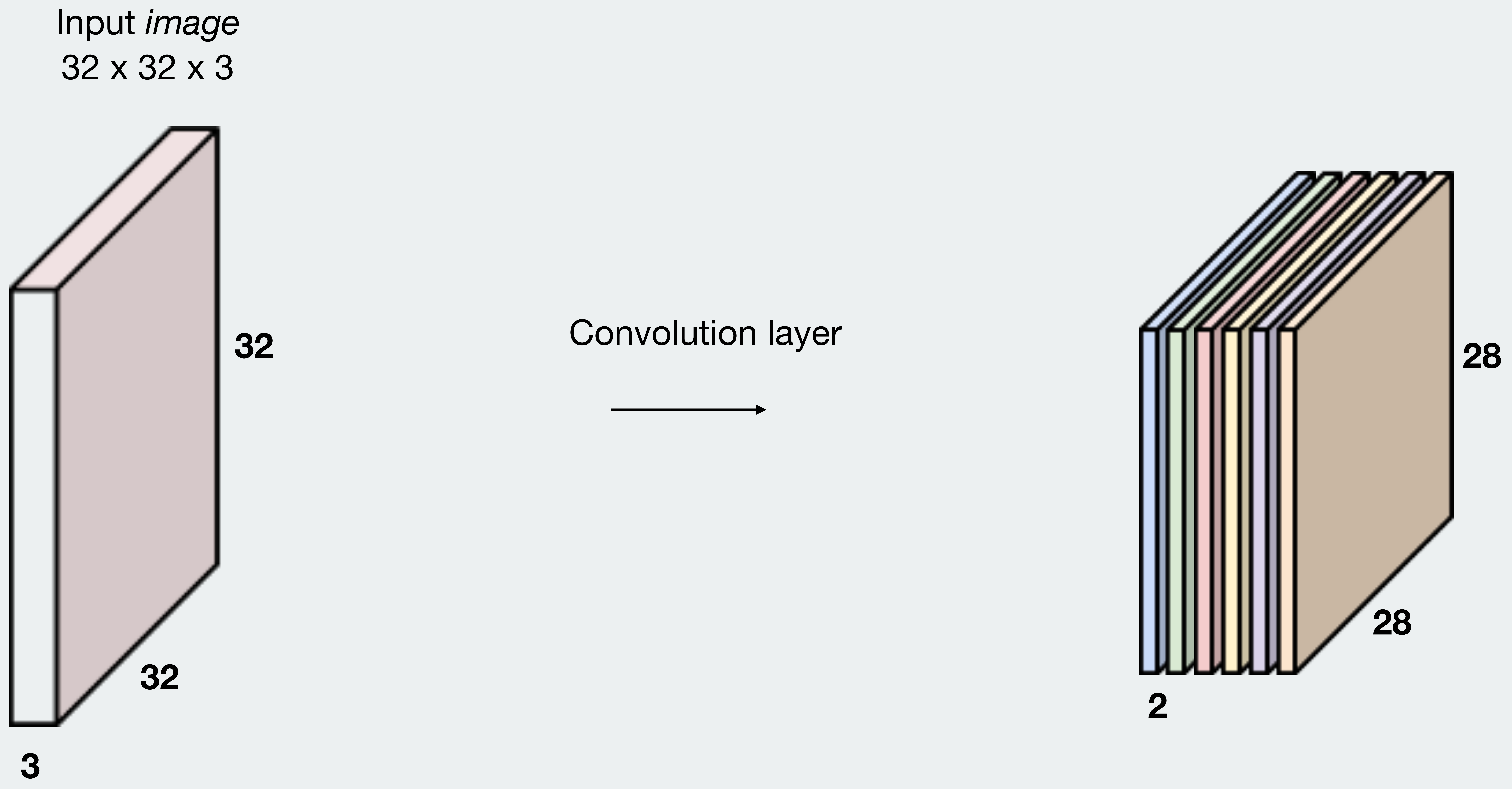


Convolve over all spatial locations



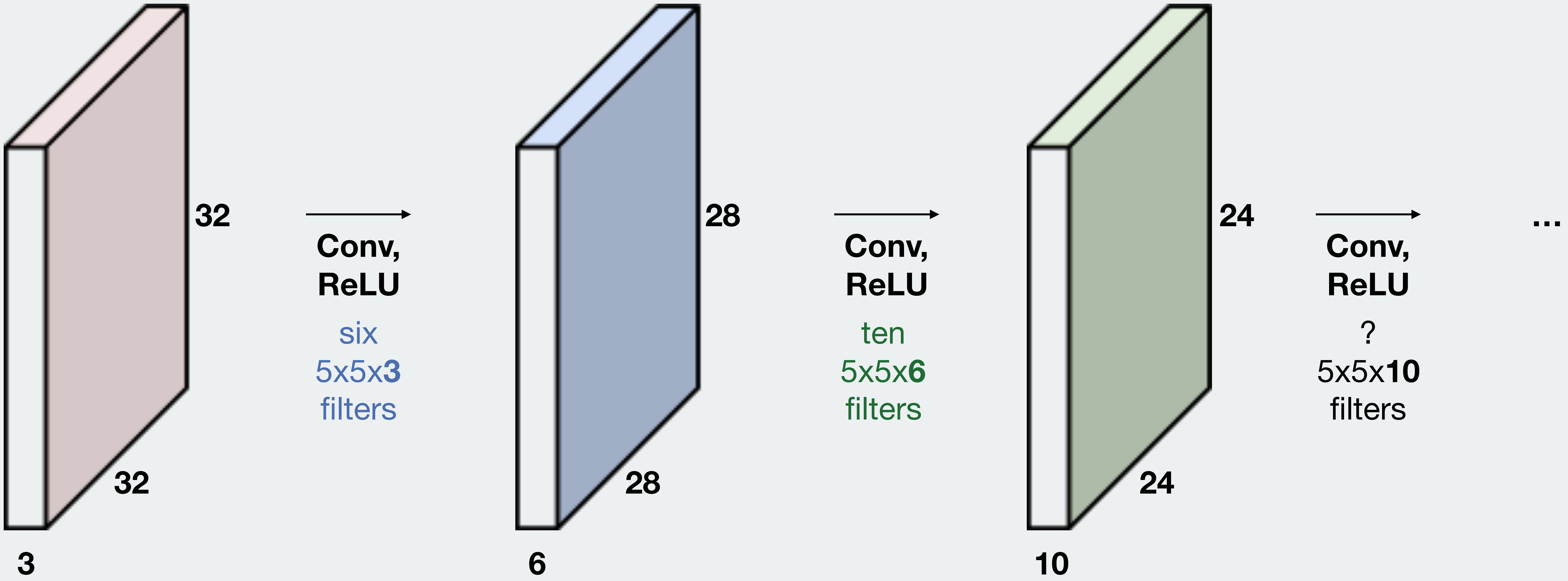
Convolutional neural networks

> Convolution by *n* filters produces new *activation map* of depth *n*



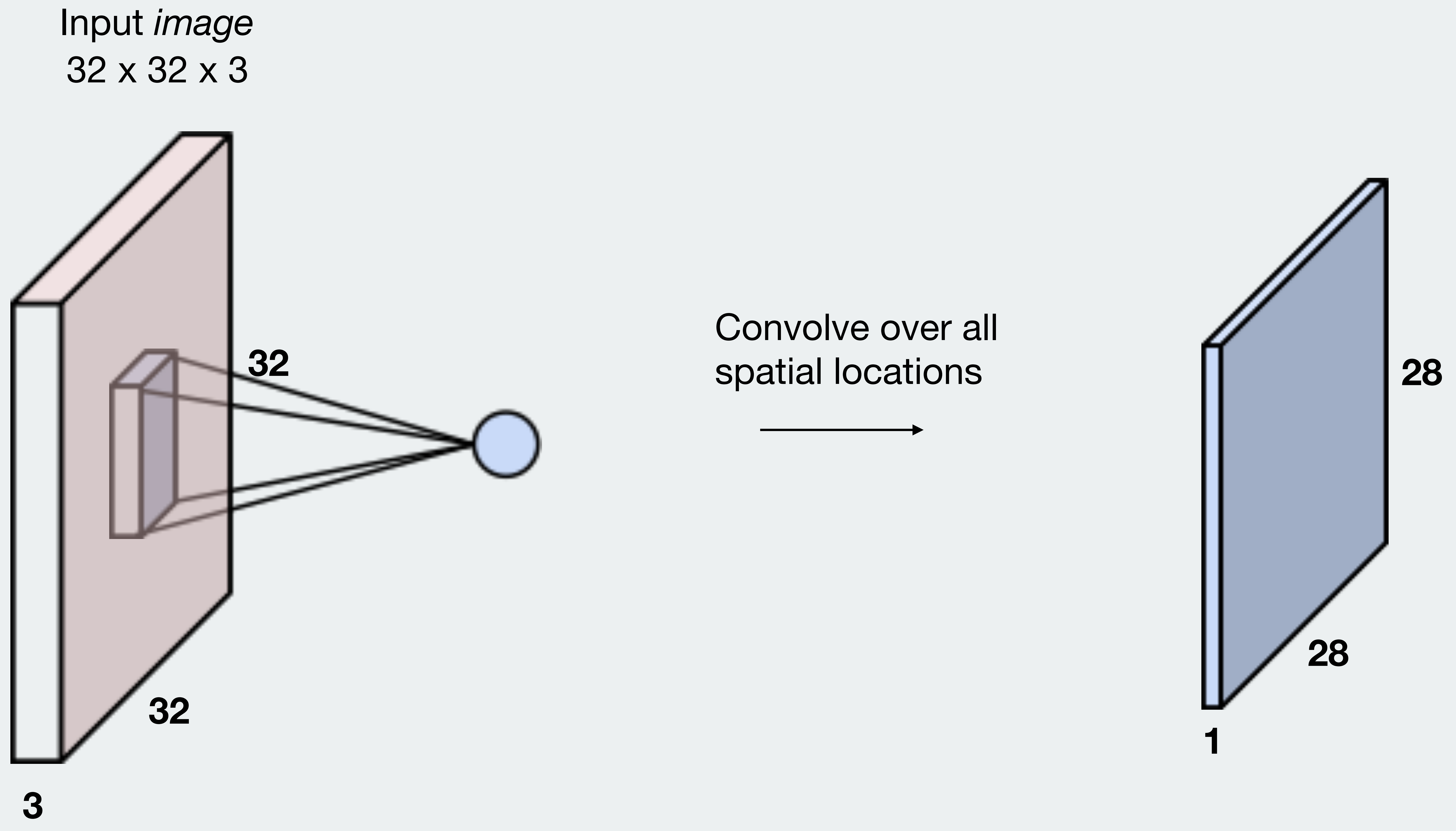
Convolutional neural networks

> Stack these operations



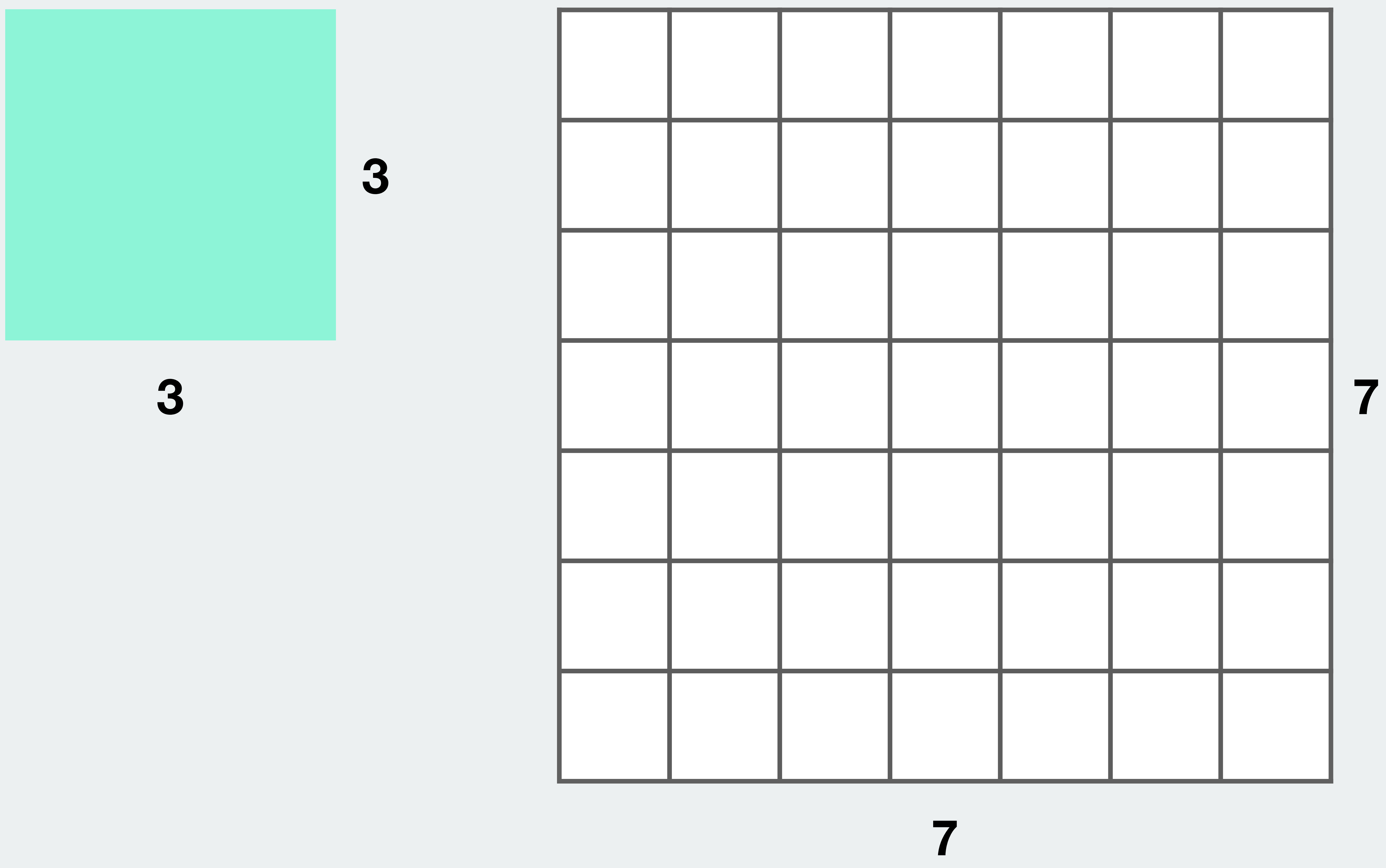
Convolutional neural networks

> Dimensions



Example: 7 x 7 input
3 x 3 filter

Question: What is the dimensions of the resulting activation map?



Convolutional neural networks

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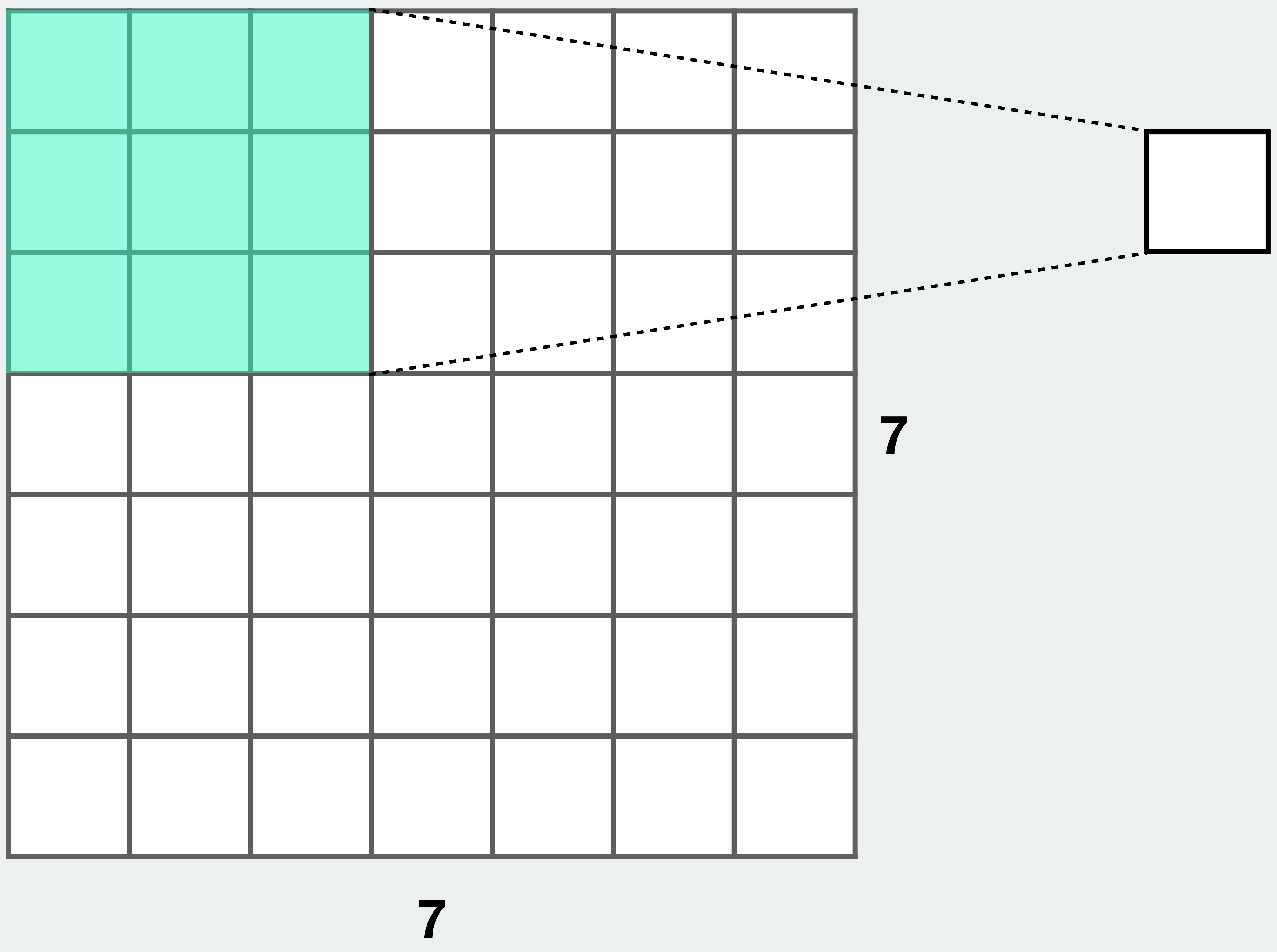

Convolutional neural networks

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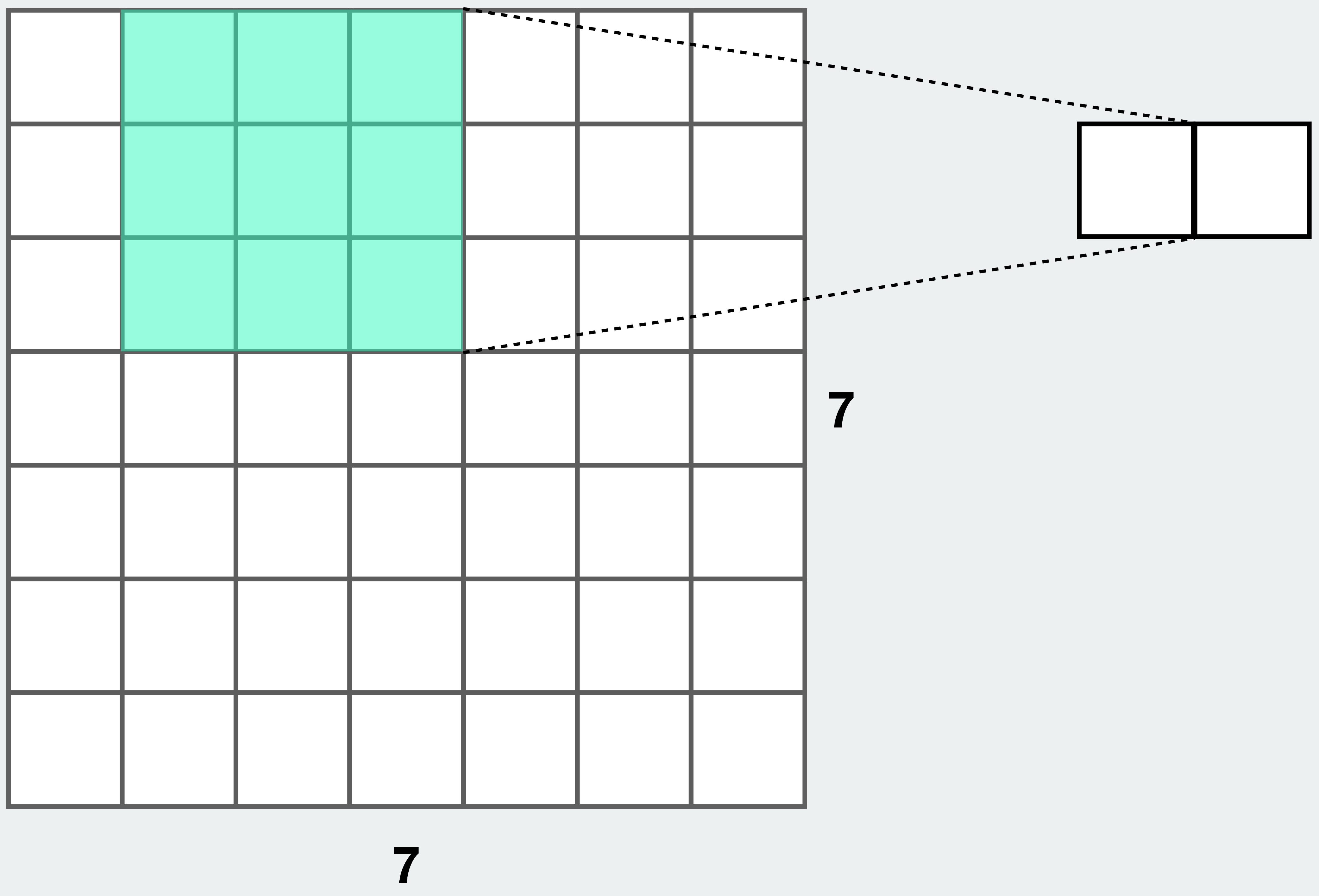

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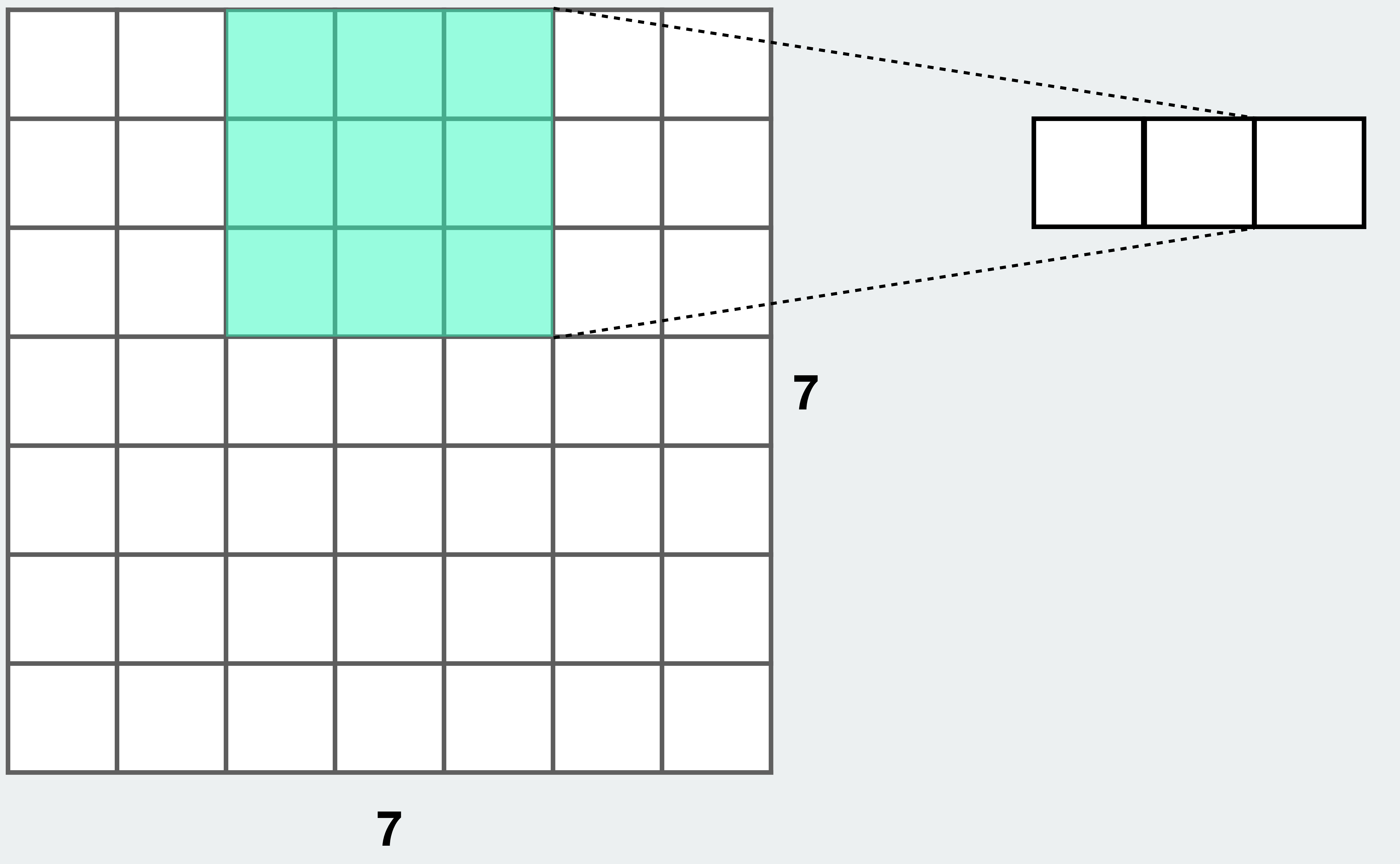

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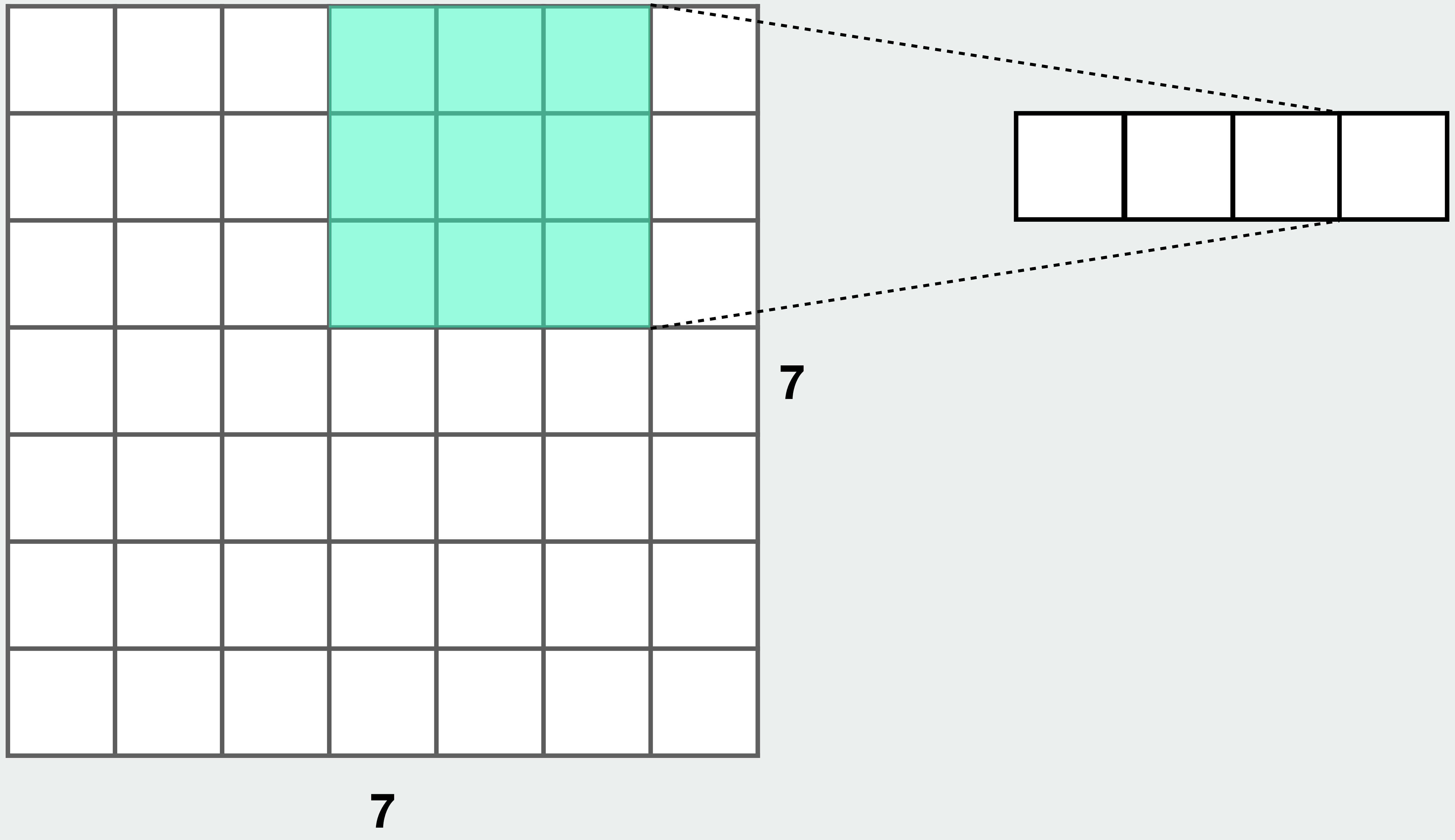

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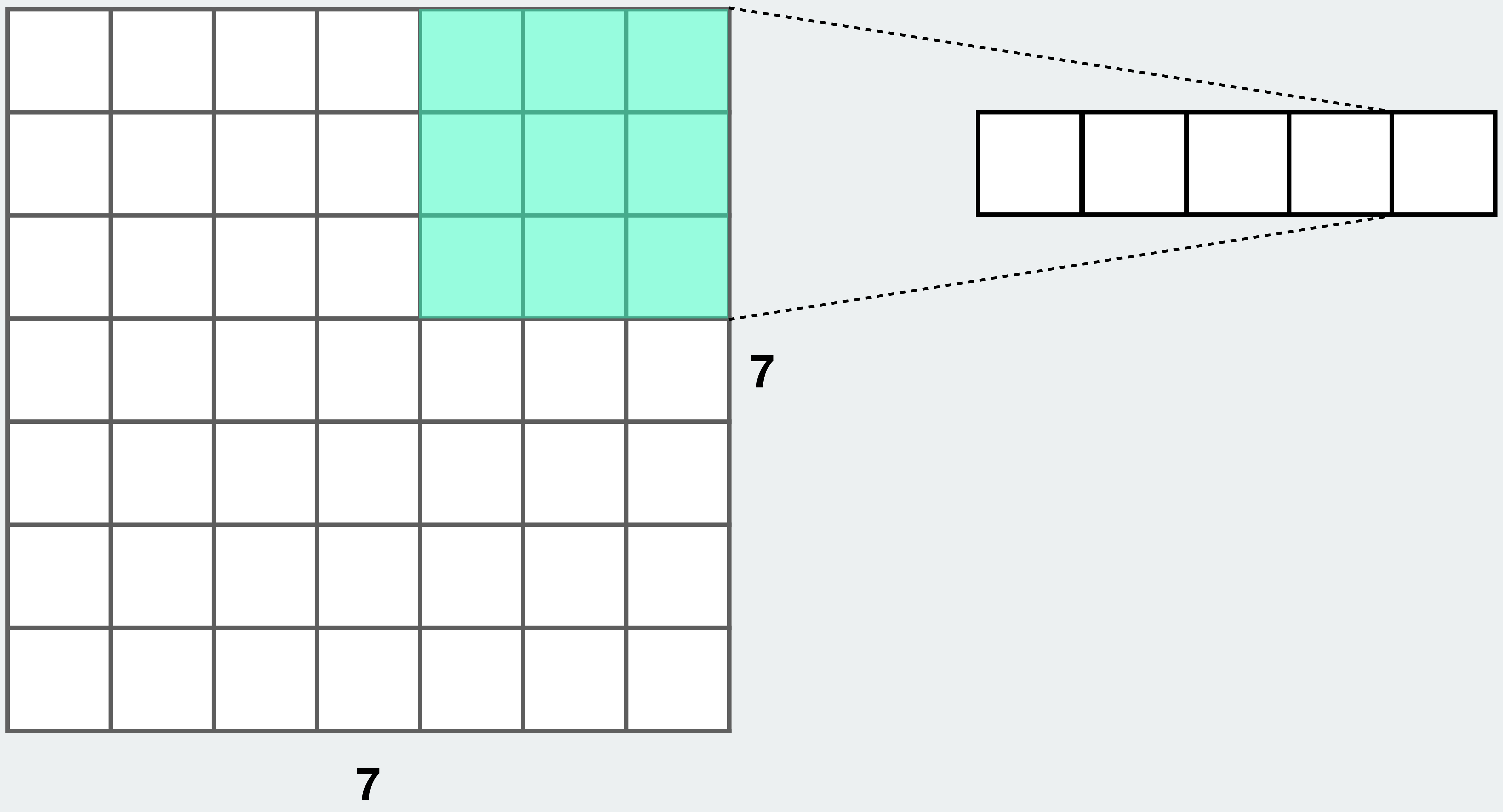

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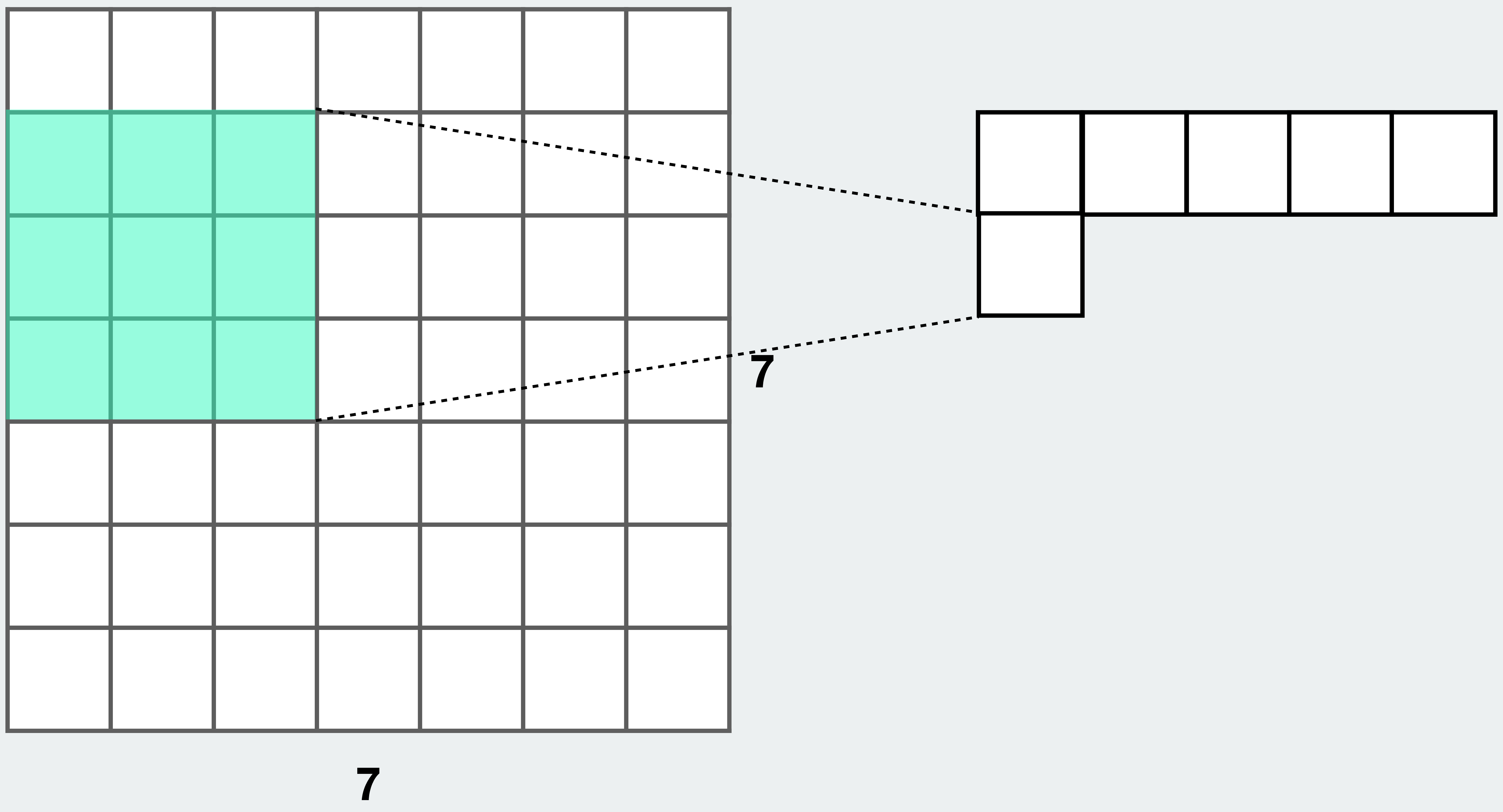

Convolutional neural networks

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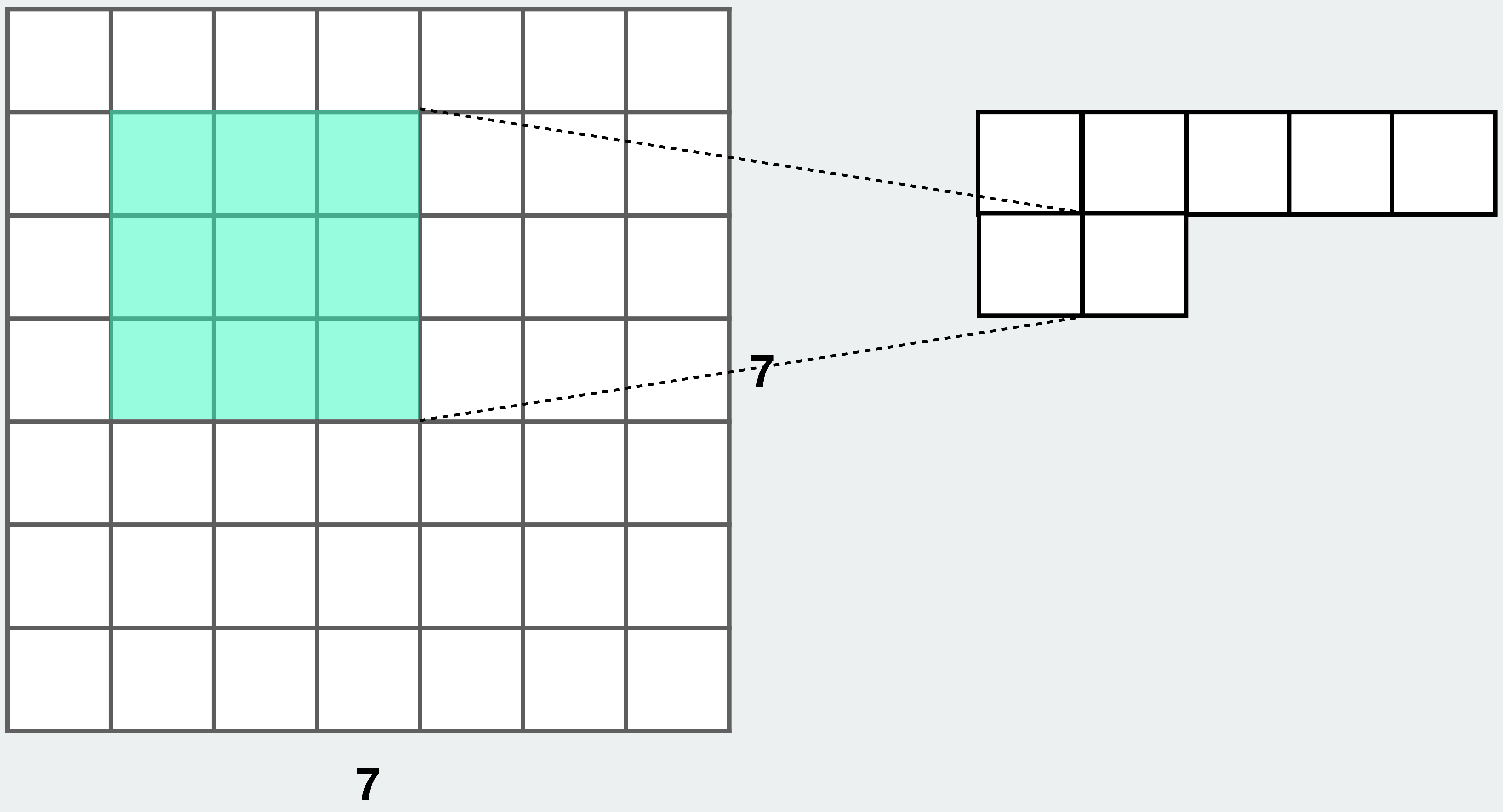
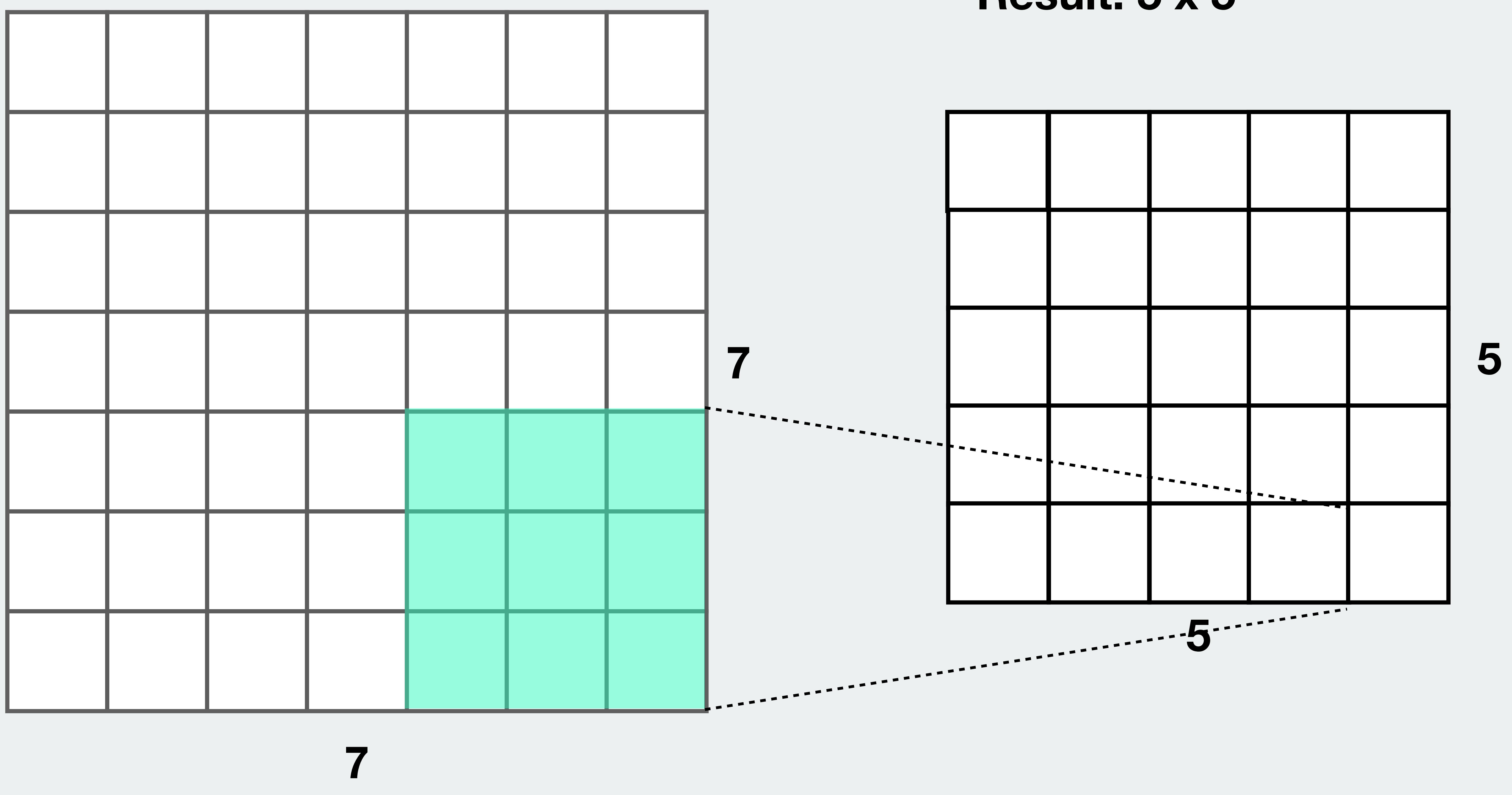


Example: 7 x 7 input
3 x 3 filter

Question: What is the dimensions of the resulting activation map?

Result: 5 x 5

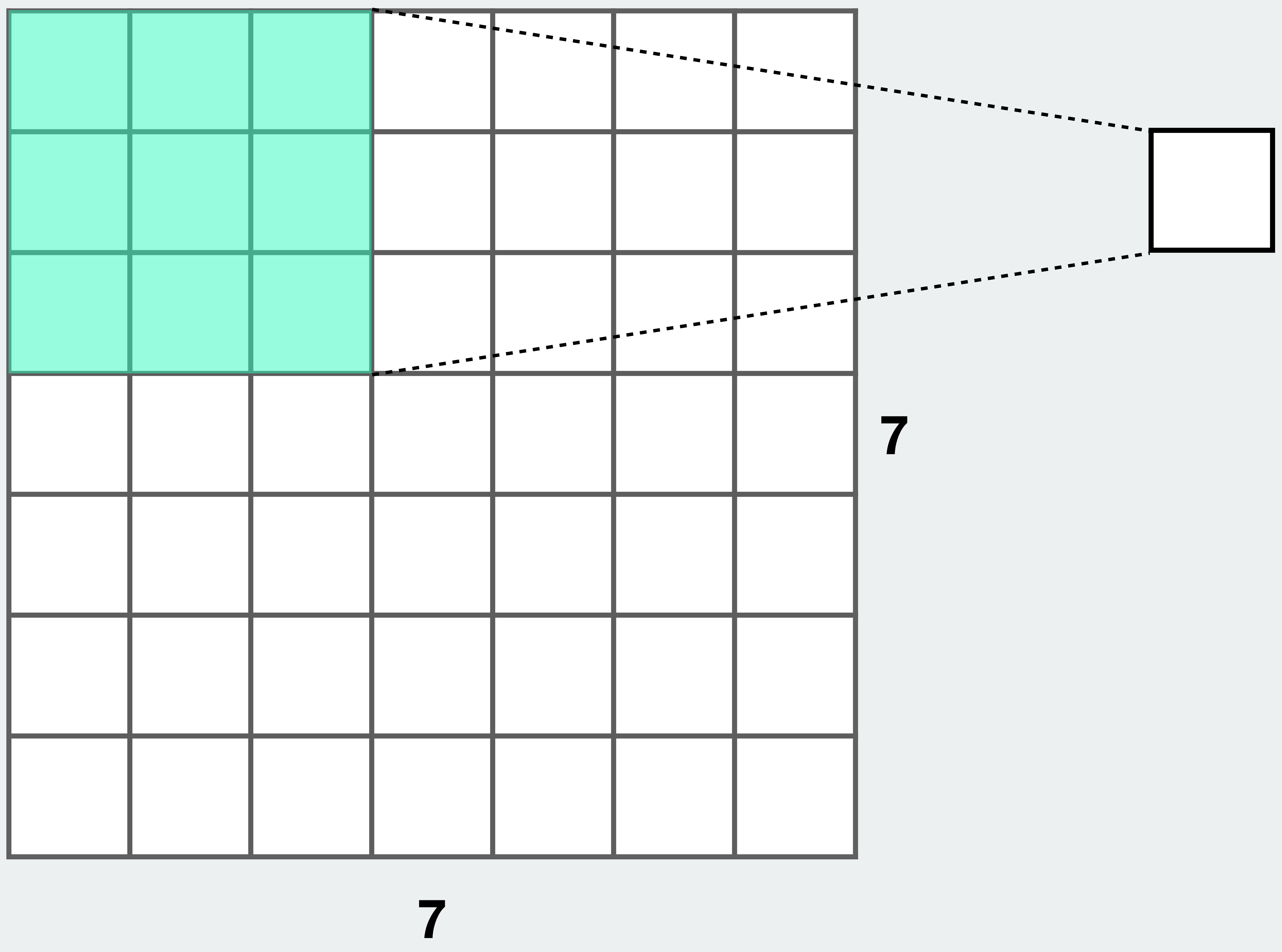


Convolutional neural networks

> Dimensions

Example: 7 x 7 input
3 x 3 filter

Question: What if we use stride 2?



Convolutional neural networks

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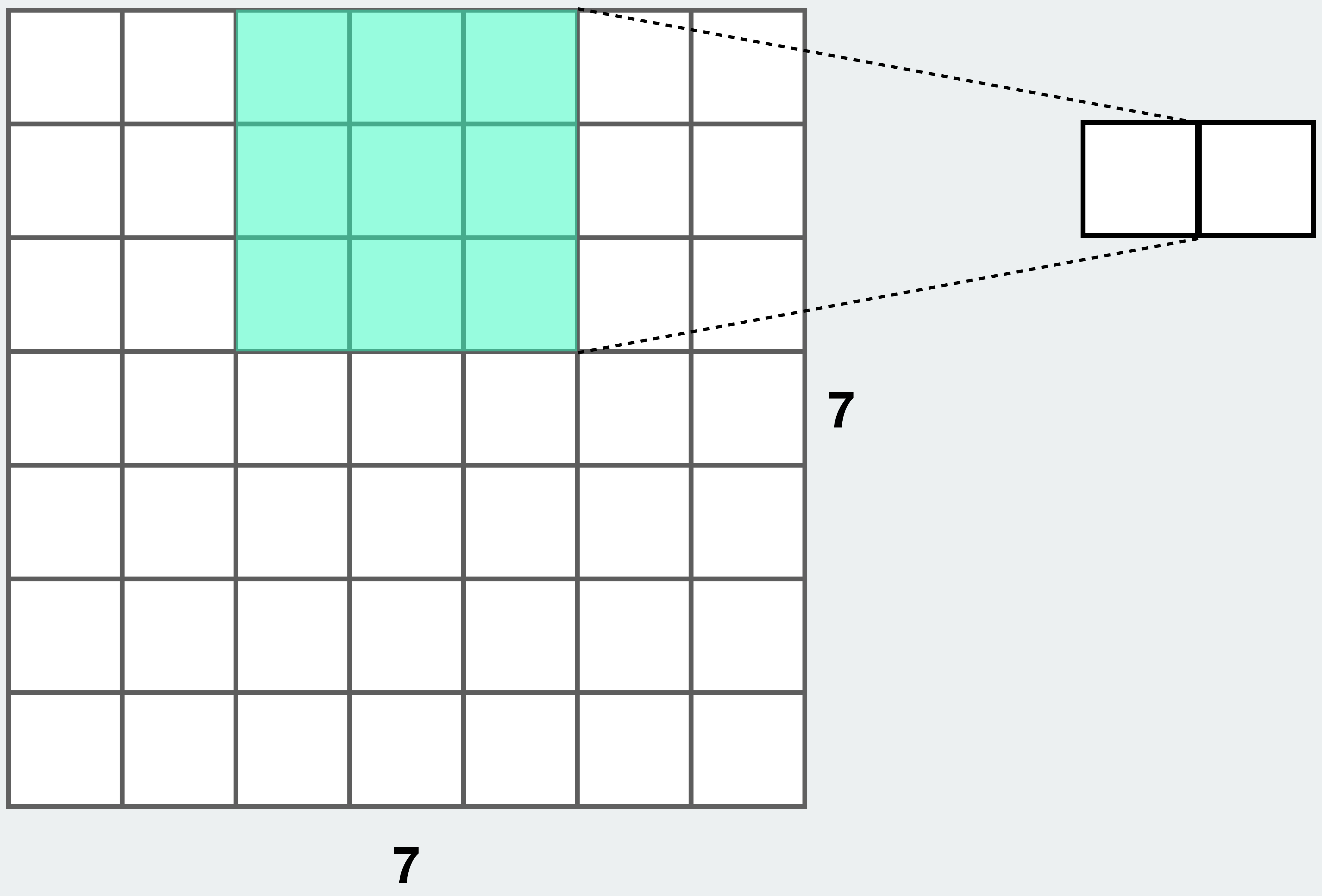


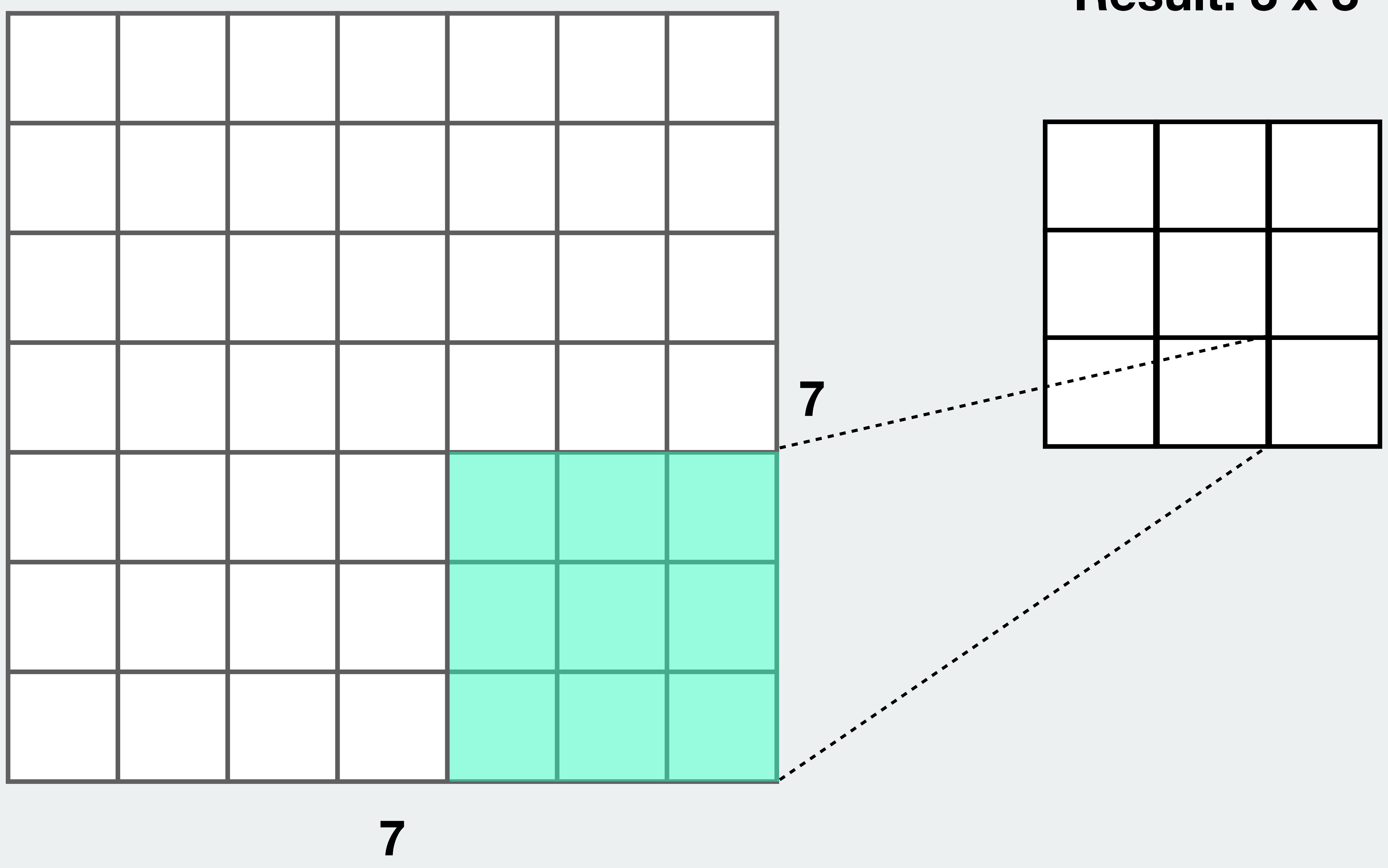
Convolutional neural networks

> Dimensions

Example: 7 x 7 input
3 x 3 filter

Question: What if we use stride 2?

Result: 3 x 3

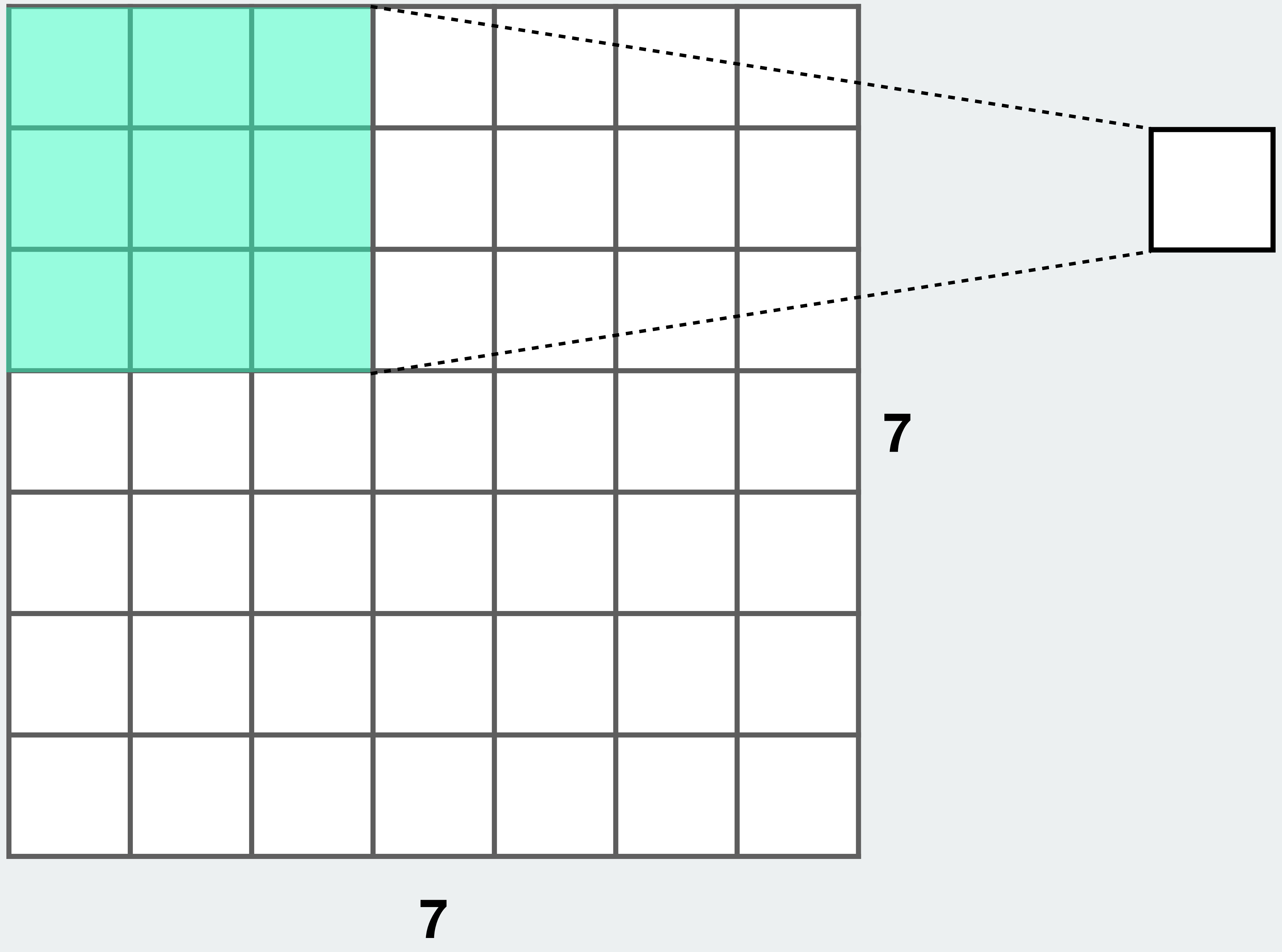


Convolutional neural networks

> Dimensions

Question: Stride 3?

Example: 7 x 7 input
3 x 3 filter



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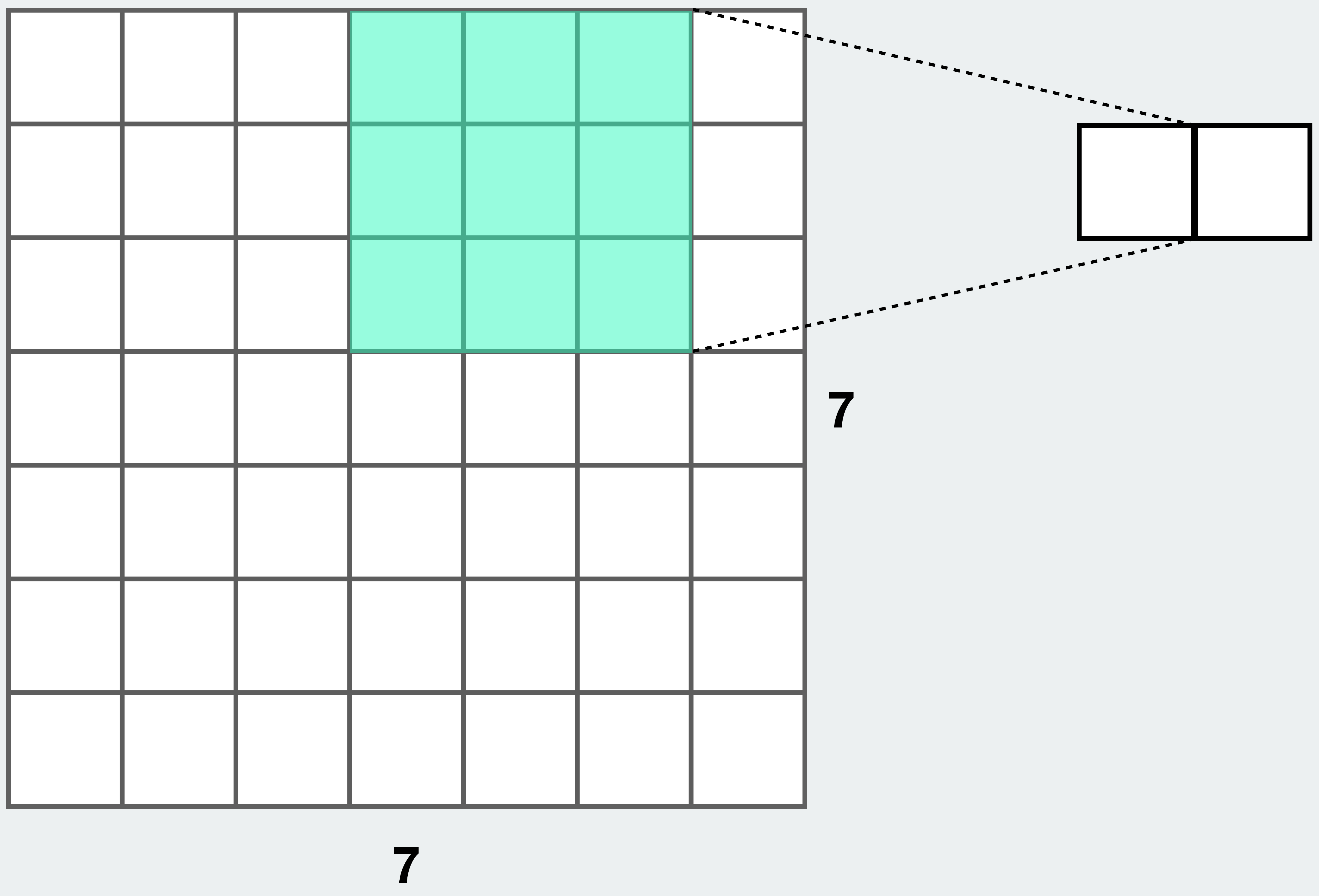

Convolutional neural networks

> Dimensions

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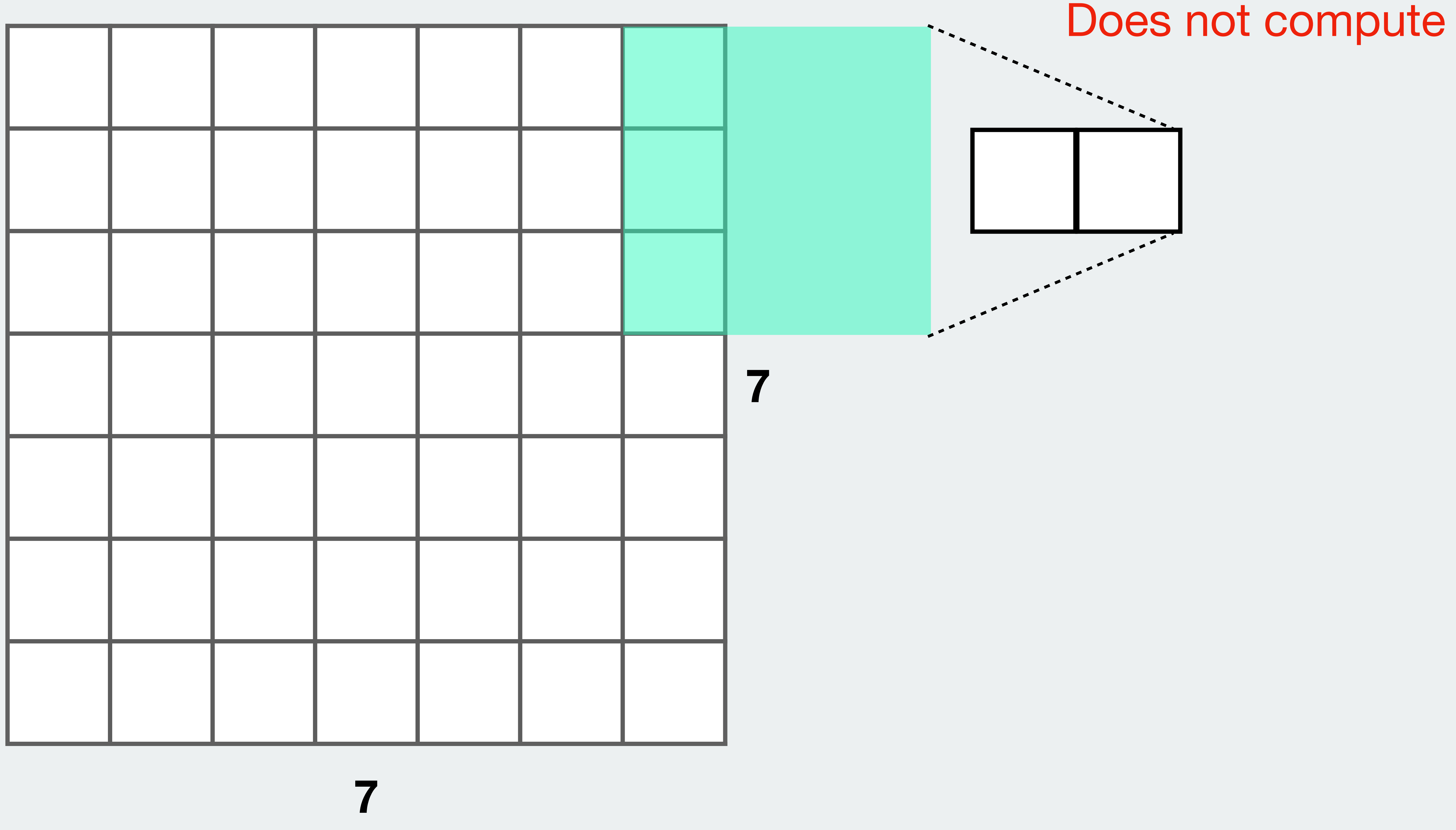
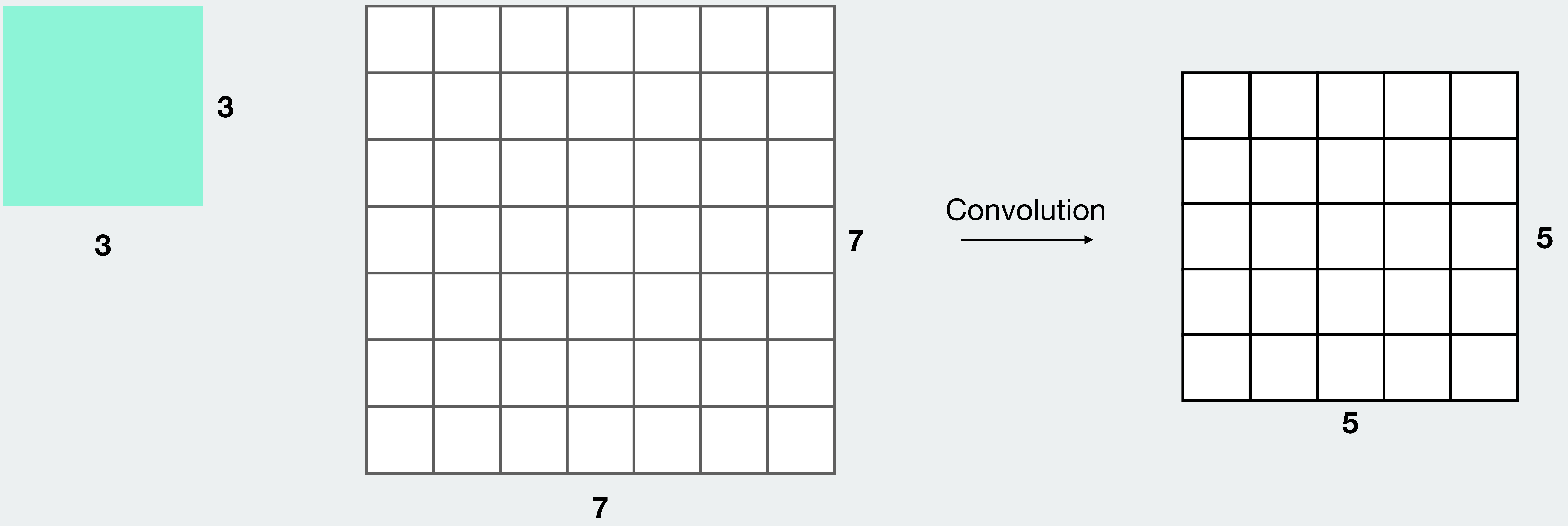


Problem: The image *shrinks*

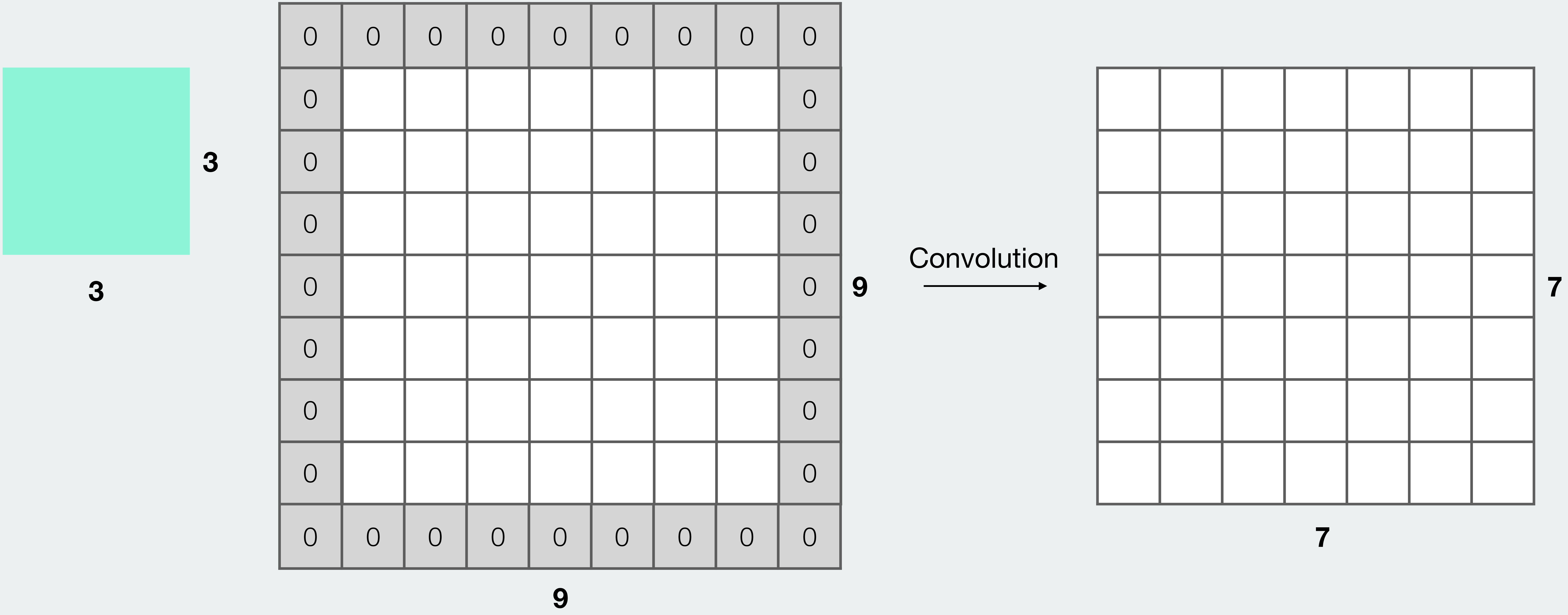
7 x 7 => **5 x 5**



Problem: The image *shrinks*

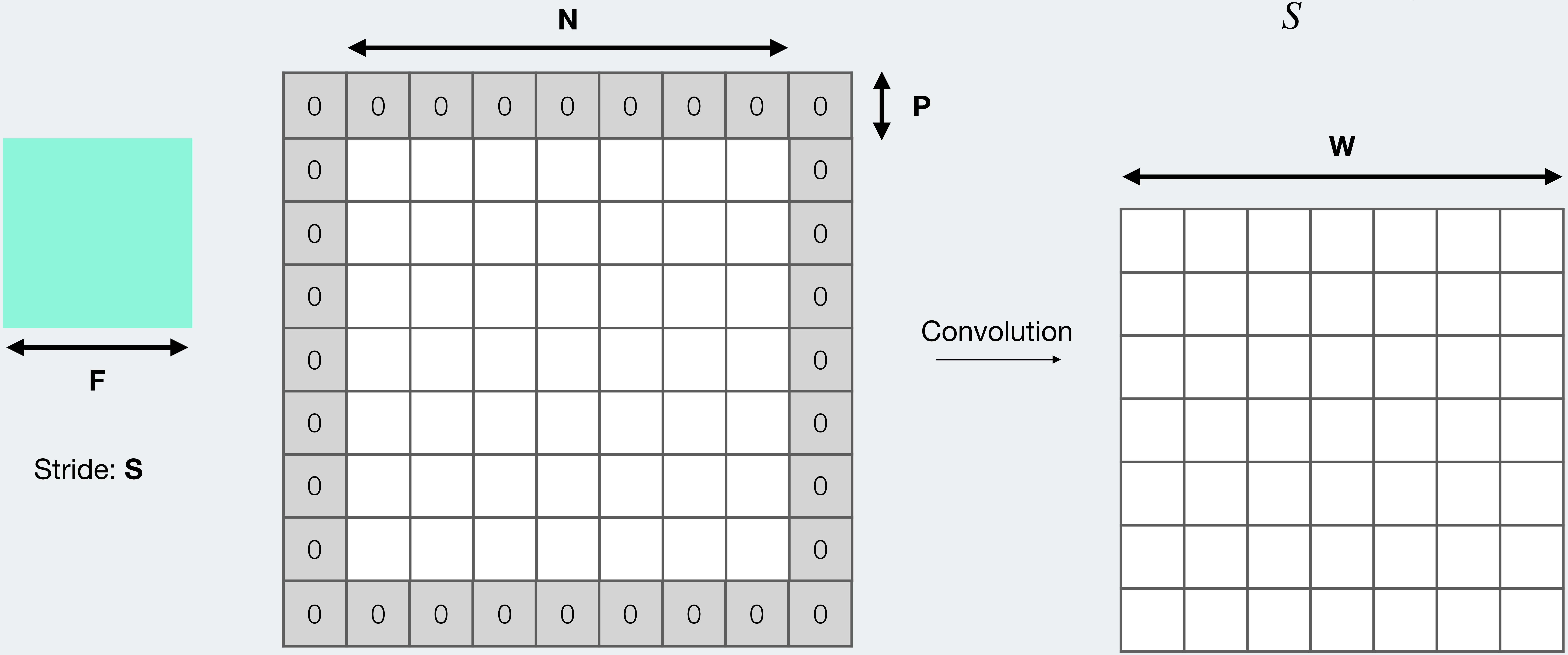
Solution: *Padding!*

7 x 7 => 5 x 5



Convolutional neural networks

> Dimensions



General formula

$$W = \frac{N + 2P - F}{S} + 1$$

Animations

Given: 128 x 128 x 3 input

Ten 5 x 5 x 3 filters

Padding: 2

Stride: 1

Question 1: What are the output dimensions?

Question 2: What is the number of parameters?

Question 3: What if $F = N + 2P$?

Given: 128 x 128 x 3 input

Ten 5 x 5 x 3 filters

Padding: 2

Stride: 1

Question 1: What are the output dimensions?

Question 2: What is the number of parameters?

Question 3: What if $F = N + 2P$?

Answer 1:

$$W = \frac{128 + 2 \cdot 2 - 5}{1} + 1 = 128$$

Answer 2:

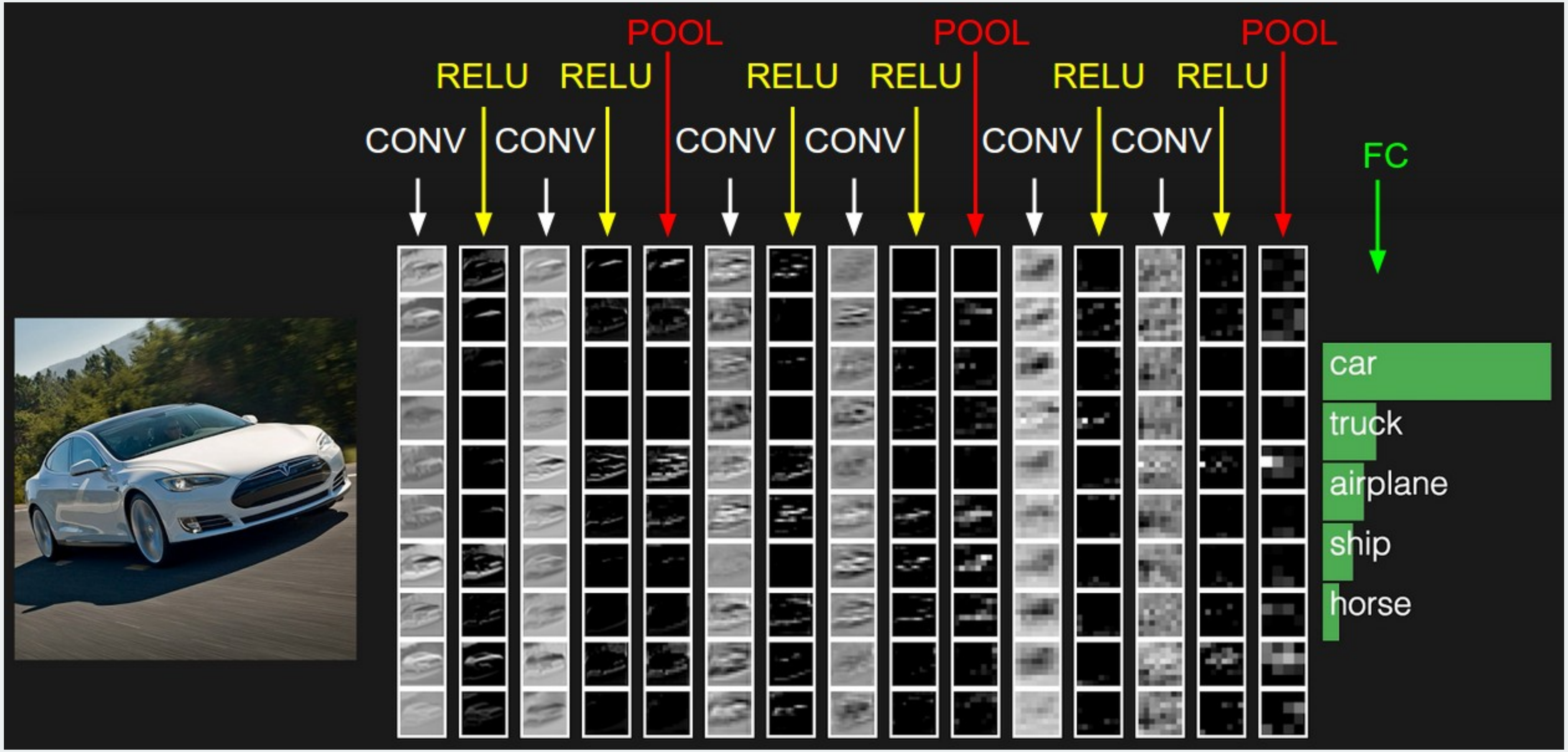
$$5 \cdot 5 \cdot 3 \cdot 10 + 10 = 760$$

Answer 3:

Then it's just a VNN!

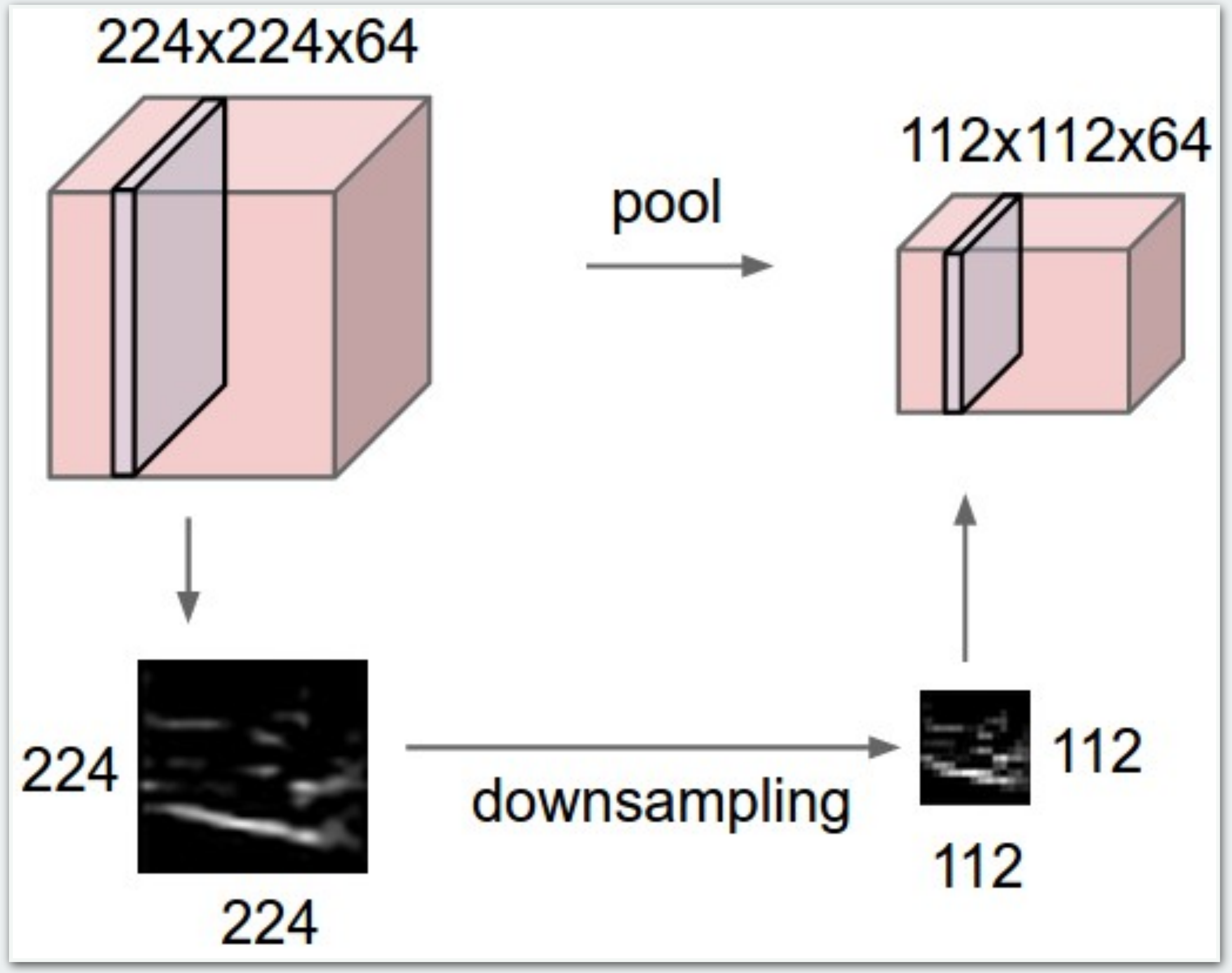
Convolutional neural networks

> Example of a bigger network



http://cs231n.github.io/convolutional-networks/

- Method used for downsampling
- Reduces number of parameters and computations
- Lowers width and height of volume by an integer factor
- Preserved depth

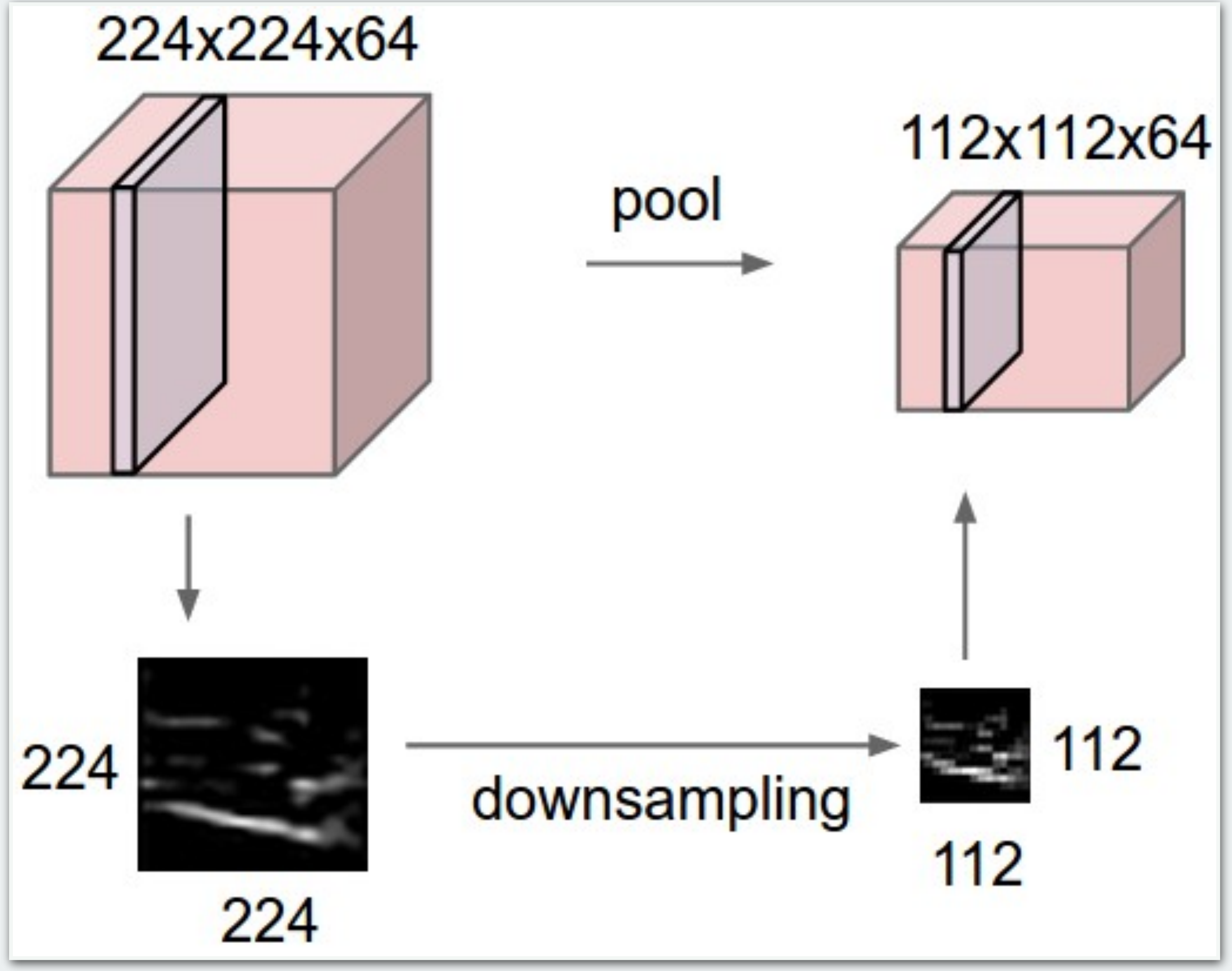


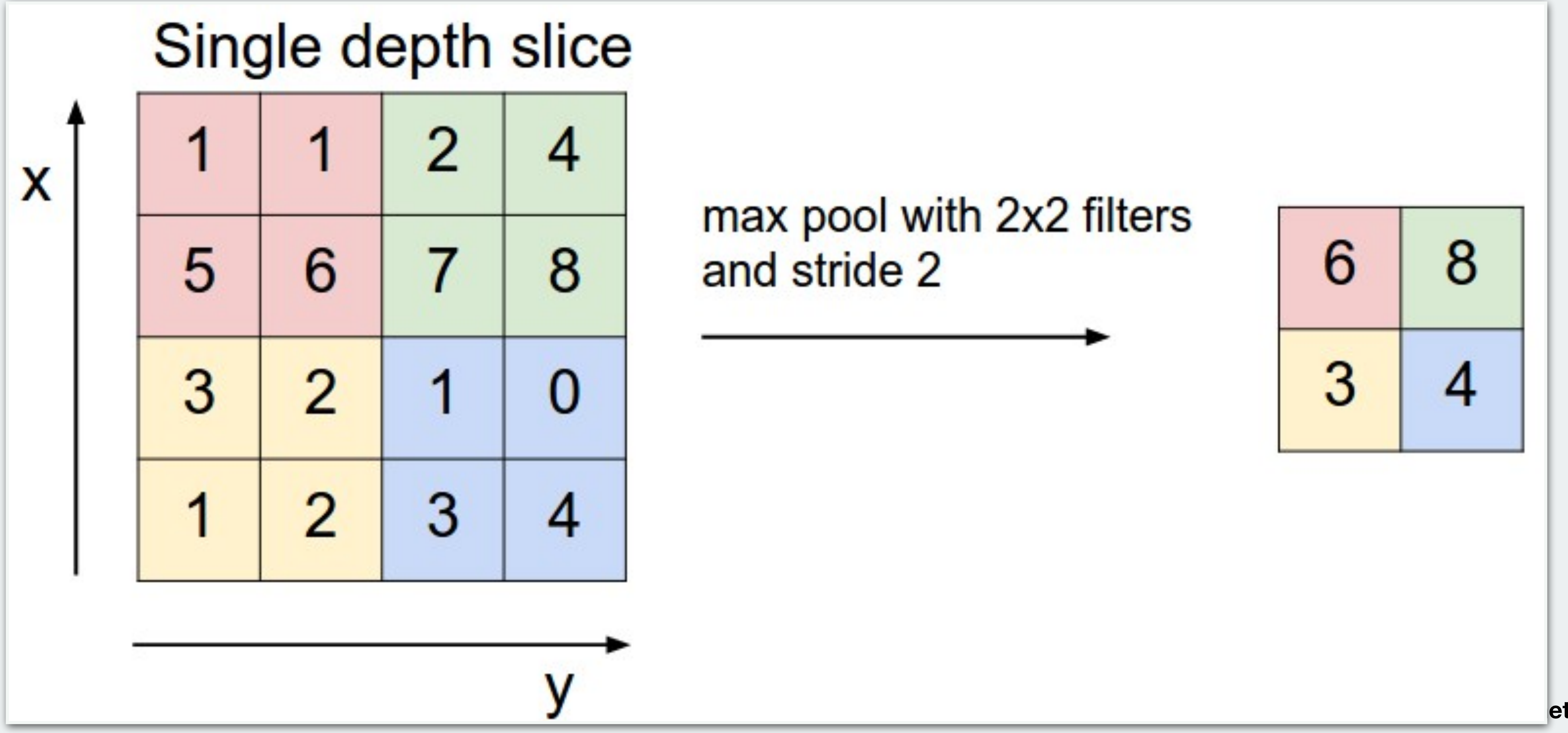
http://cs231n.github.io/convolutional-networks/

Convolutional neural networks

> Pooling

- Method used for downsampling
- Reduces number of parameters and computations
- Lowers width and height of volume by an integer factor
- Preserved depth





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