Applied Deep Learning

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Learning objectives of today

Goals:

- Discuss the importance of computer vision for different business applications
- Understand how convolution works and how it can be implemented in TensorFlow
- Apply CNNs to medical diagnosis

How will we do this?

- We will start with a look at Zebra Medical Vision, which provides diagnostic services based on medical imaging
- We will see how convolutional layers drastically simplify the task of analyzing images
- We then turn to the impact of developments in computer vision more broadly

But first: the group assignment

The importance of transparency

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The importance of transparency

Trust

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The importance of transparency

Trust

Fairness

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The importance of transparency

Trust

Fairness

Regulation

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The importance of transparency

Trust

Fairness

Regulation

Informativeness

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Zebra Medical Vision

The startup

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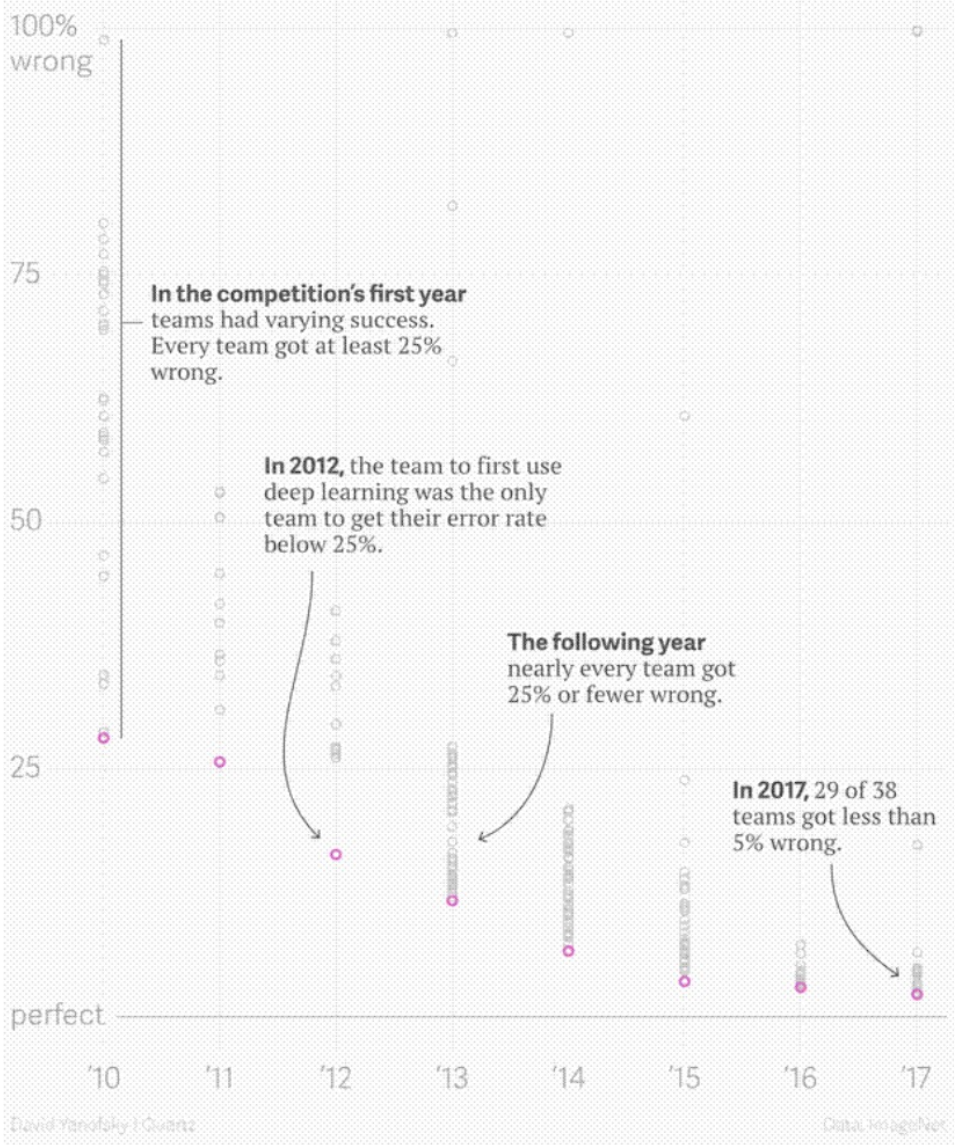
Why now? Why not a decade ago?

ImageNet Large Scale Visual Recognition Challenge Results



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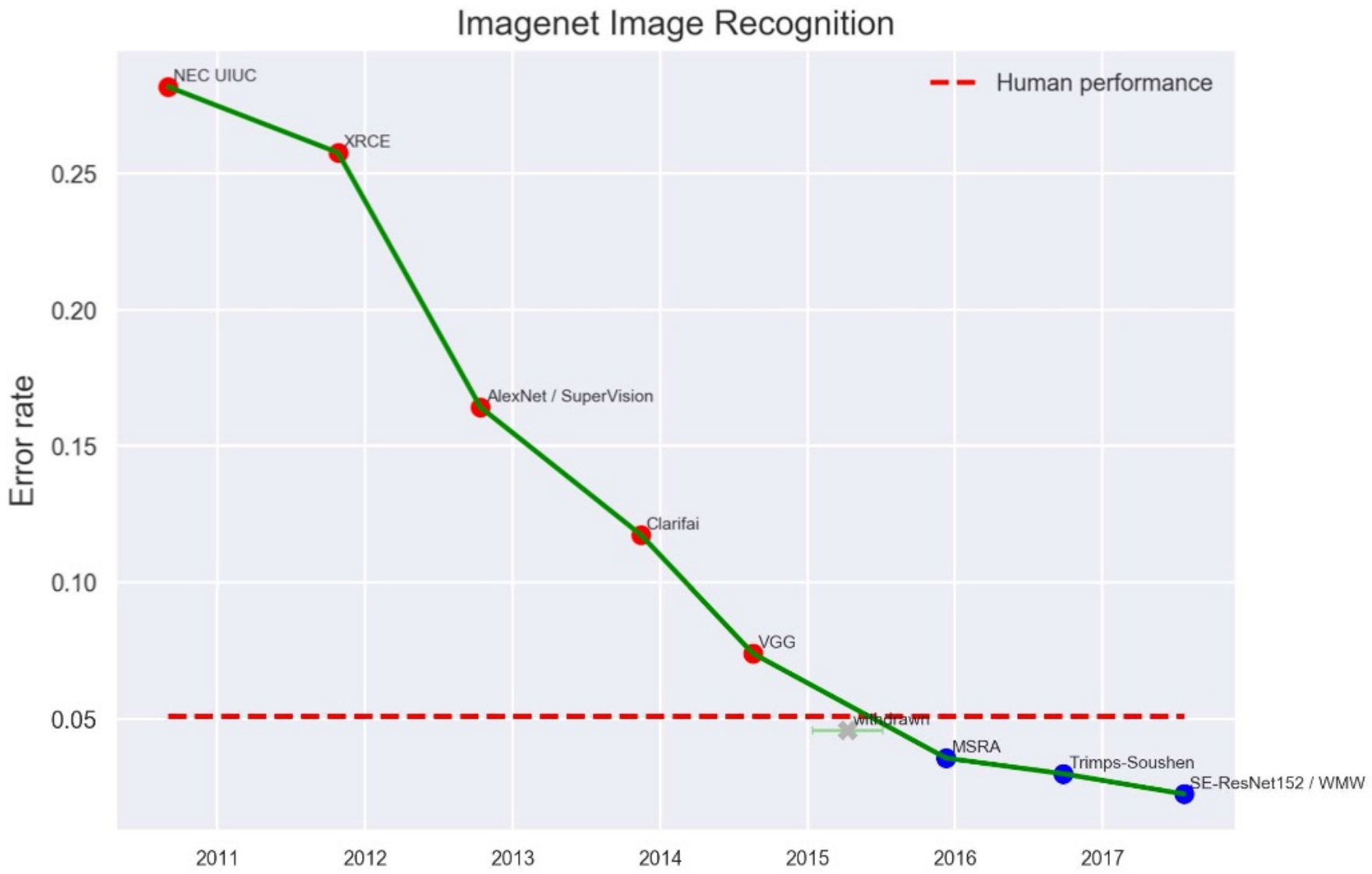
ImageNet Large Scale Visual Recognition Challenge Results



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Why now? Why not a decade ago?

What is Zebra fundamentally doing?

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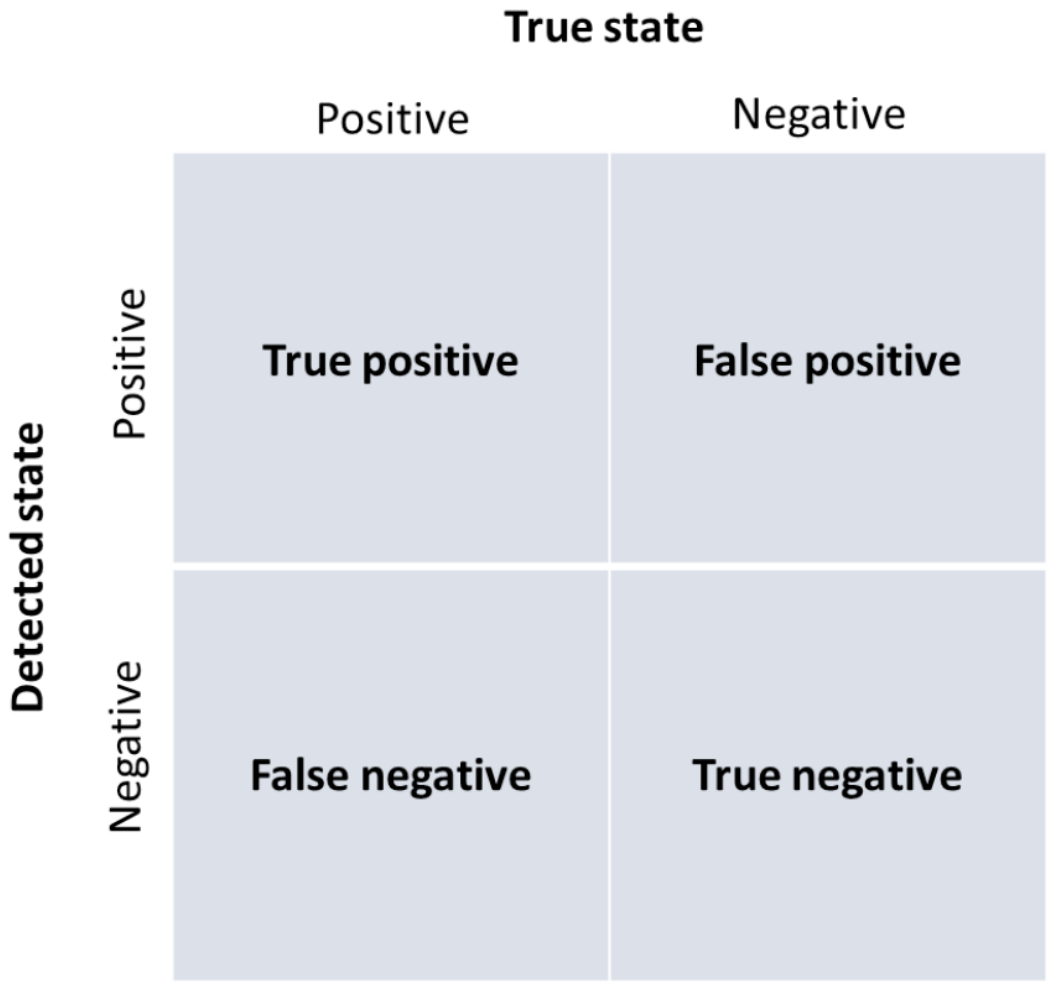
What is Zebra fundamentally doing?



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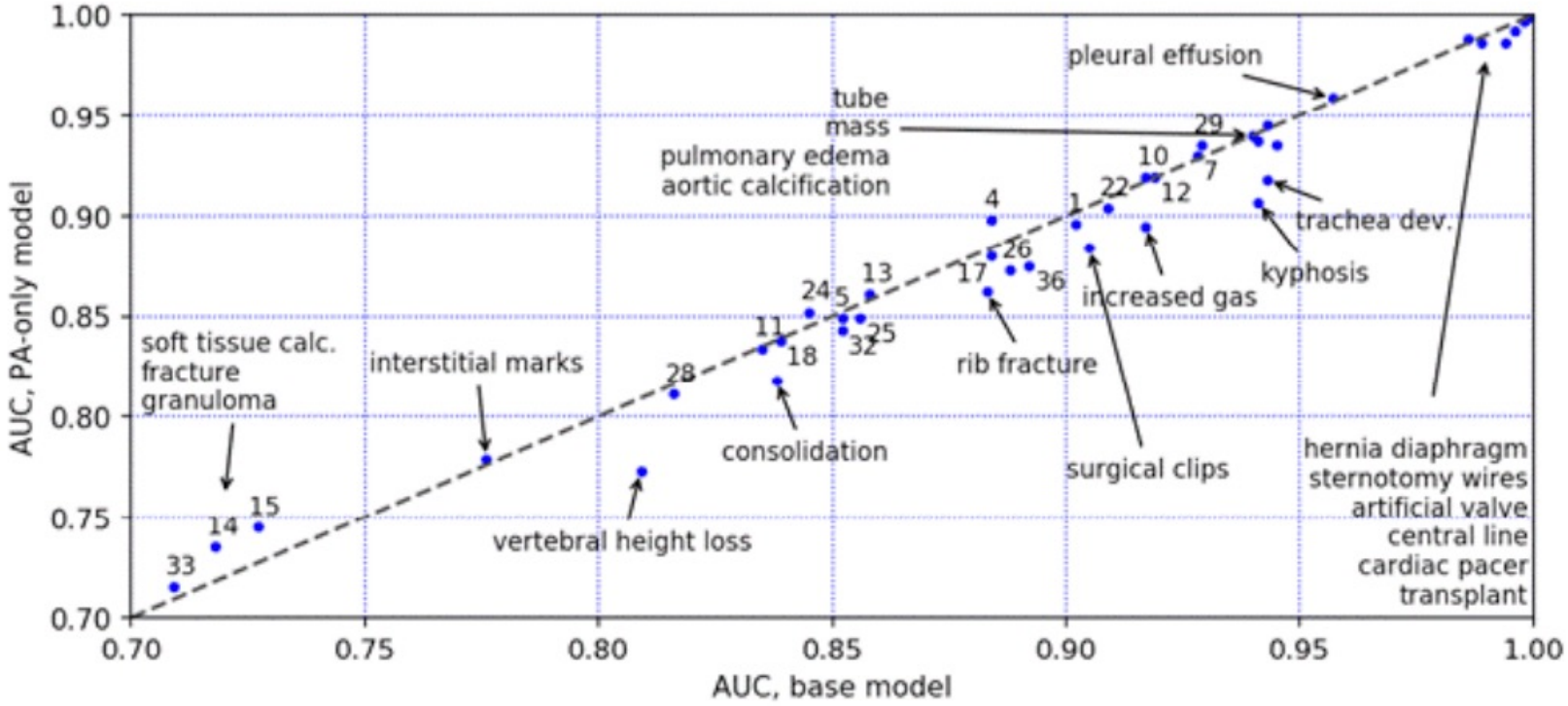
Predictions based on lung X-rays



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Let’s try classifying lung X-rays ourselves

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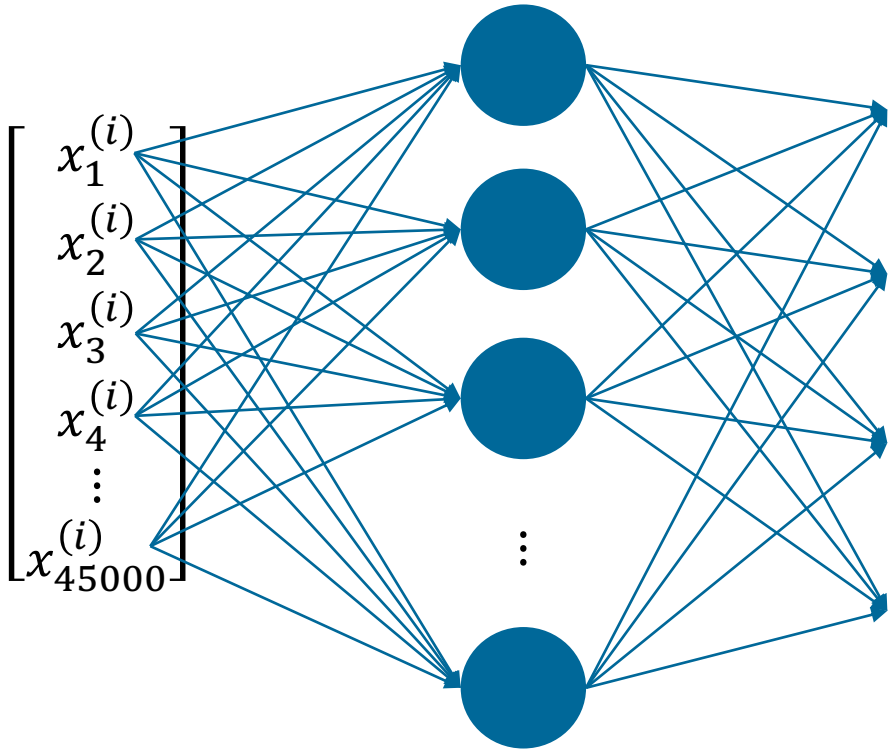
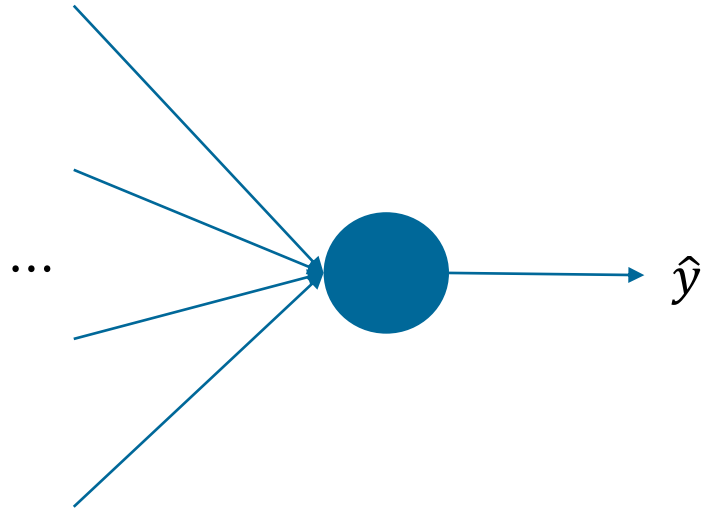
Basics of convolution

Challenges to deep learning using large images

150x100x3



$y = 1$, if it's a cat
$y = 0$, if it's a BA student



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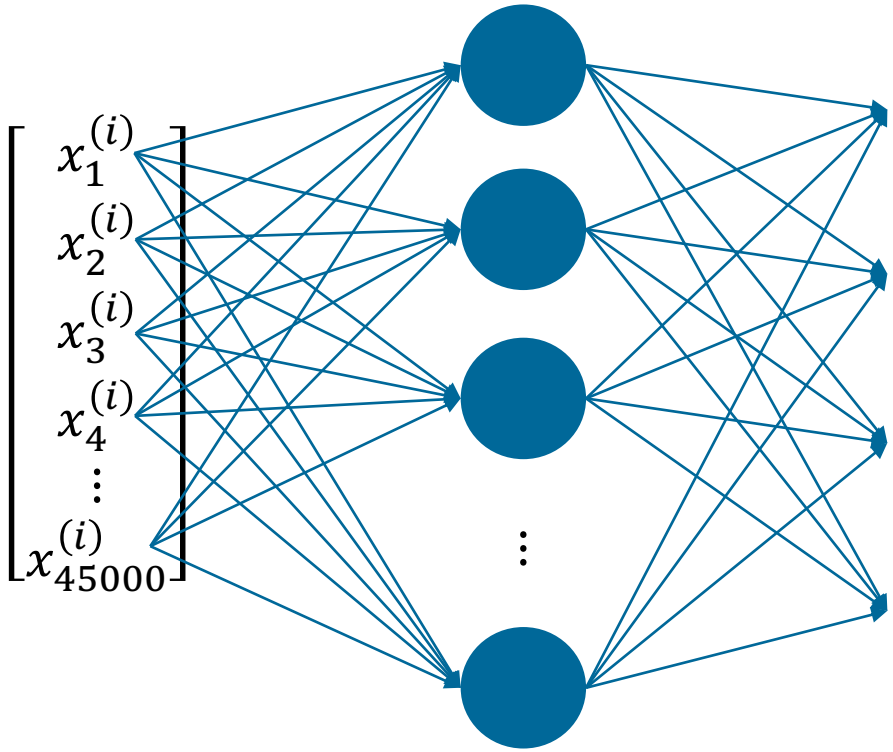

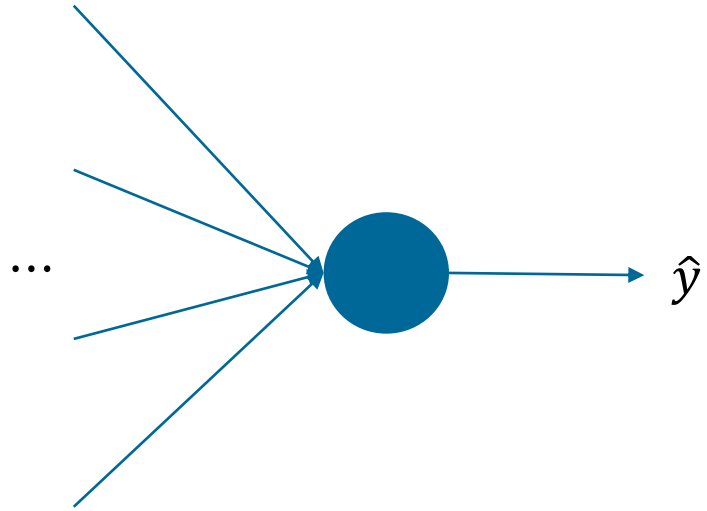

Say we have 100 neurons at the first layer.
Then we need 100*(45000+1)=4.5 mio parameters, just for the first layer!

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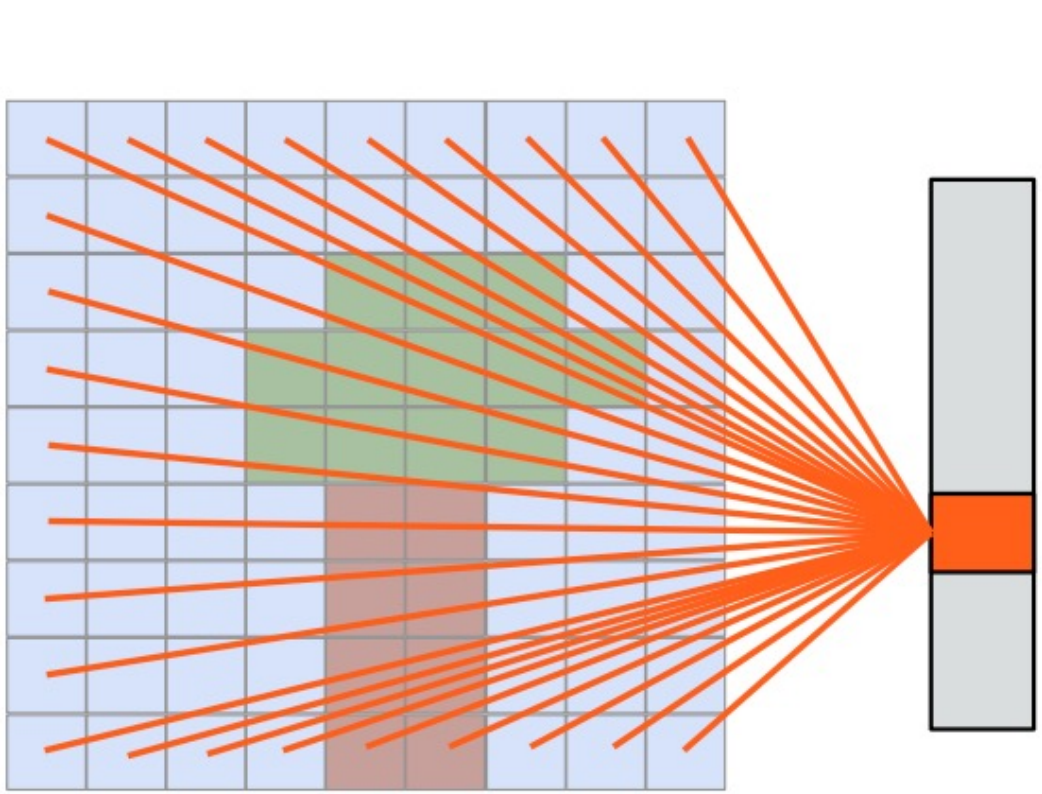
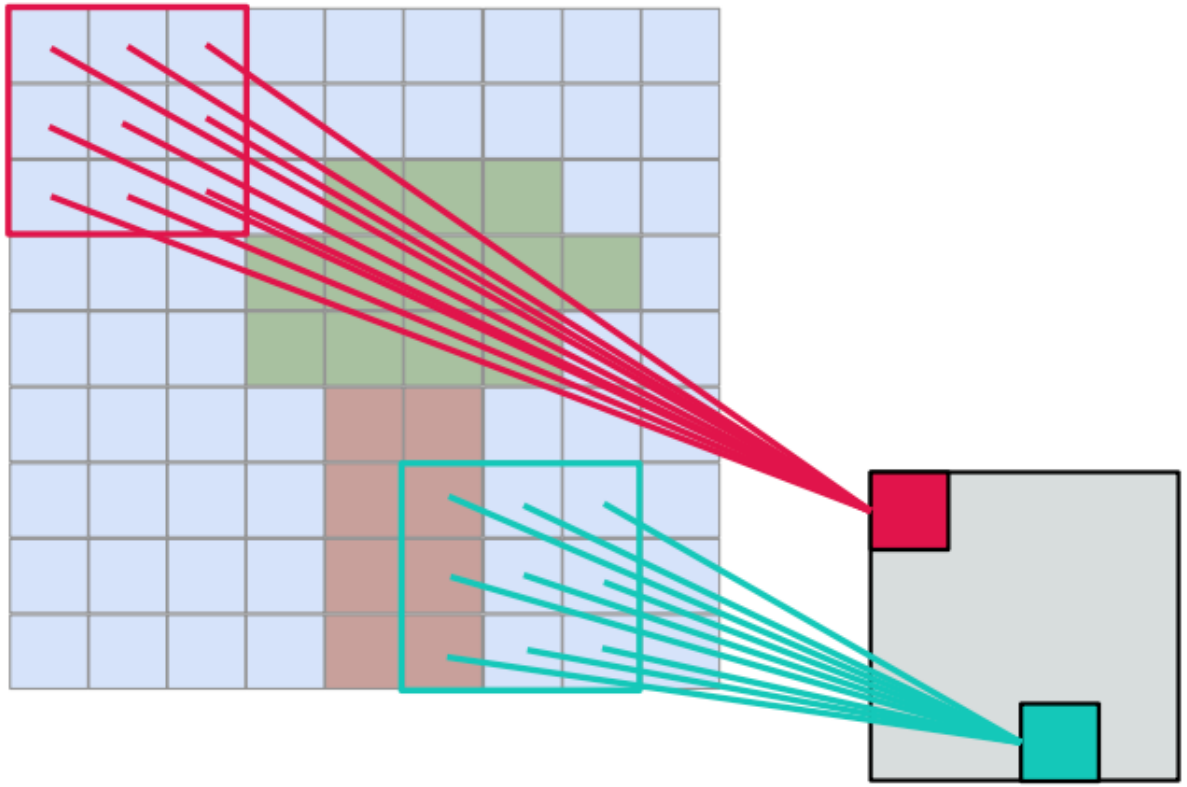
From fully connected to locally connected





Source: Dieleman

An image filter

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

*

1	0	-1
1	0	-1
1	0	-1

=

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An image filter

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

*

1	0	-1
1	0	-1
1	0	-1

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0			

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An image filter

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

*

1	0	-1
1	0	-1
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0			

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An image filter

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

*

1	0	-1
1	0	-1
1	0	-1

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0	30		

An image filter

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

*

1	0	-1
1	0	-1
1	0	-1

=

0	30		

An image filter

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

*

1	0	-1
1	0	-1
1	0	-1

=

0	30	30	

An image filter

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

*

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0	30	30	

An image filter

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10	10	10	0	0	0
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10	10	10	0	0	0

*

1	0	-1
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1	0	-1

=

0	30	30	0

An image filter

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

*

1	0	-1
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1	0	-1

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0	30	30	0
0	30	30	0
0	30	30	0

An image filter

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
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10	10	10	0	0	0

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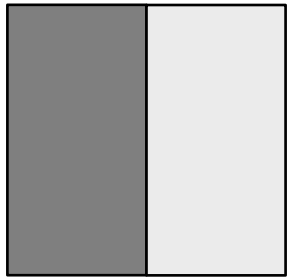
0	30	30	0
0	30	30	0
0	30	30	0



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10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

*

1	0	-1
1	0	-1
1	0	-1

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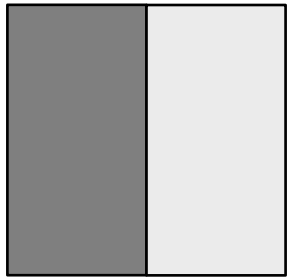
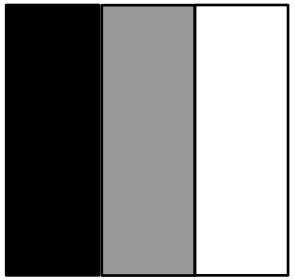
0	30	30	0
0	30	30	0
0	30	30	0





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*

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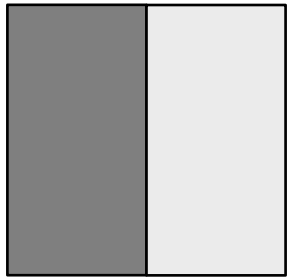
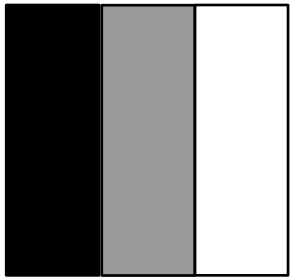
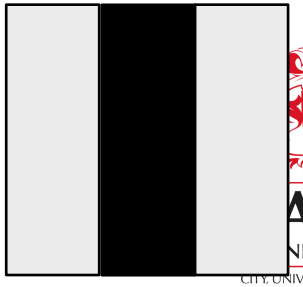
=

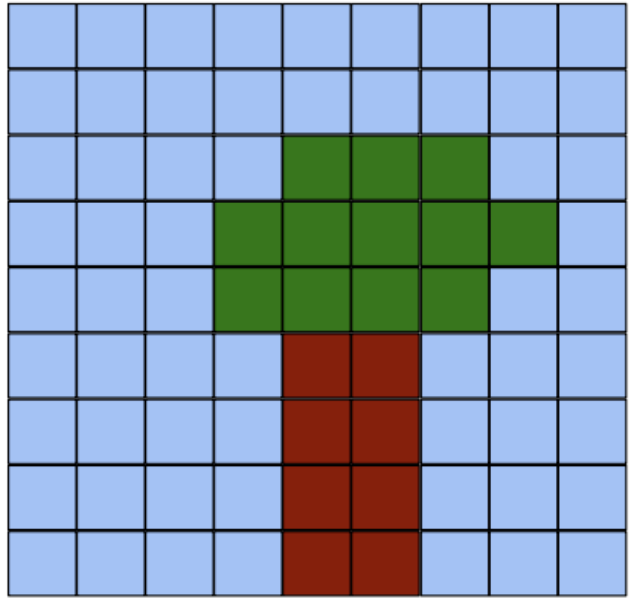
0	30	30	0
0	30	30	0
0	30	30	0







Convolutional layers: learning the filter

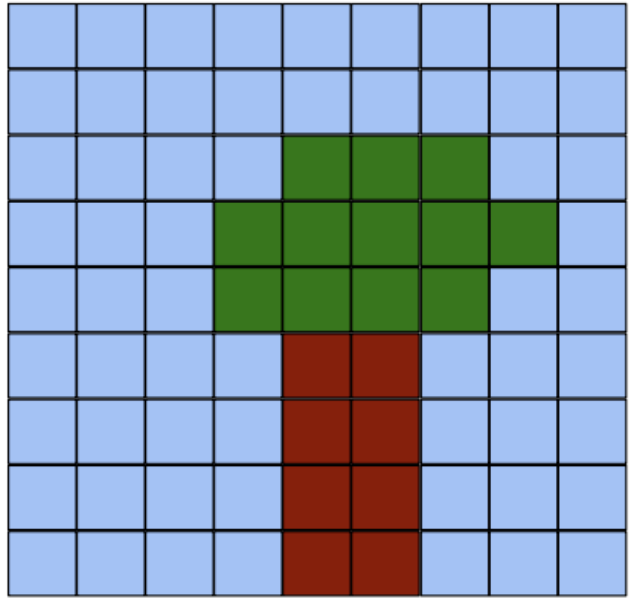


$*$

$w_{1,1}$	$w_{1,2}$	$w_{1,3}$
$w_{2,1}$	$w_{2,2}$	$w_{2,3}$
$w_{3,1}$	$w_{3,2}$	$w_{3,3}$

Source: Dieleman

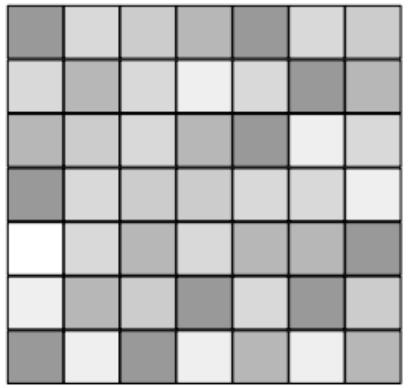
Convolutional layers: learning the filter



$*$

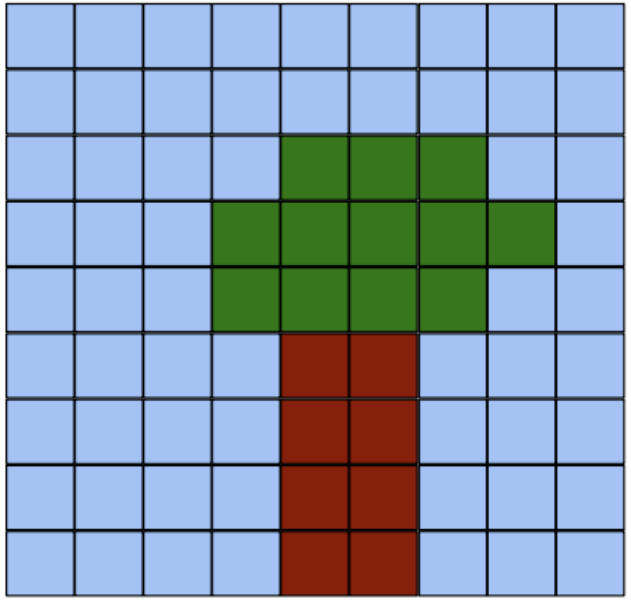
$w_{1,1}$	$w_{1,2}$	$w_{1,3}$
$w_{2,1}$	$w_{2,2}$	$w_{2,3}$
$w_{3,1}$	$w_{3,2}$	$w_{3,3}$

$+ \quad b \quad =$



Source: Dieleman

Convolutional layers: learning the filter



$*$

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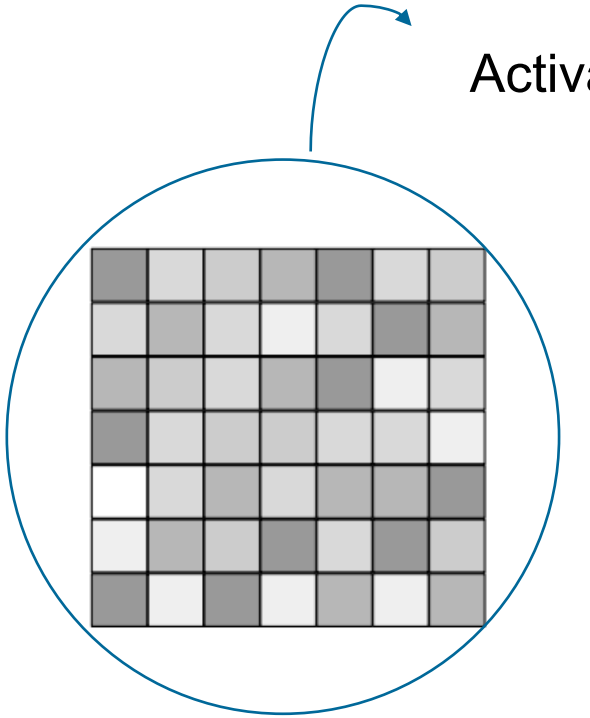
$w_{2,1}$	$w_{2,2}$	$w_{2,3}$
$w_{3,1}$	$w_{3,2}$	$w_{3,3}$

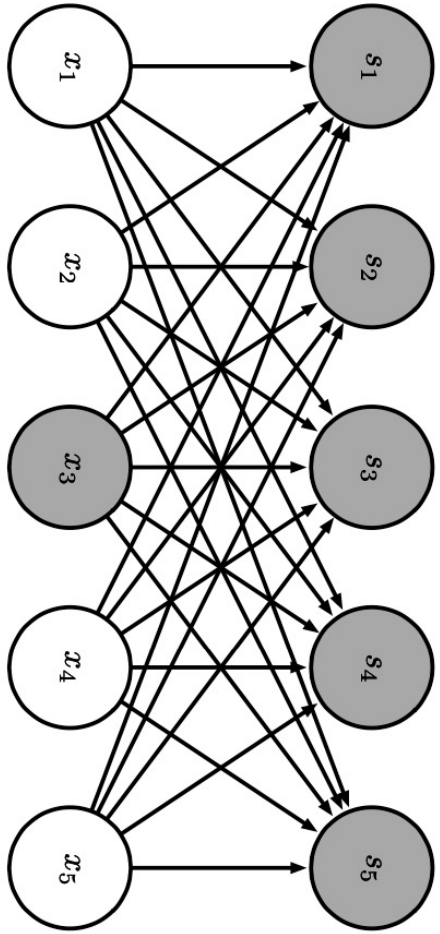
$+ \quad b \quad =$

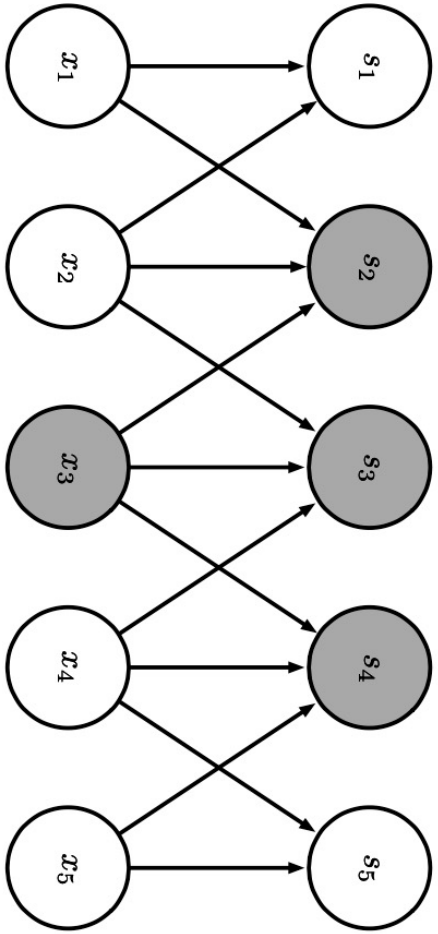


Activation function

Source: Dieleman

Less parameters required





Source: Goodfellow

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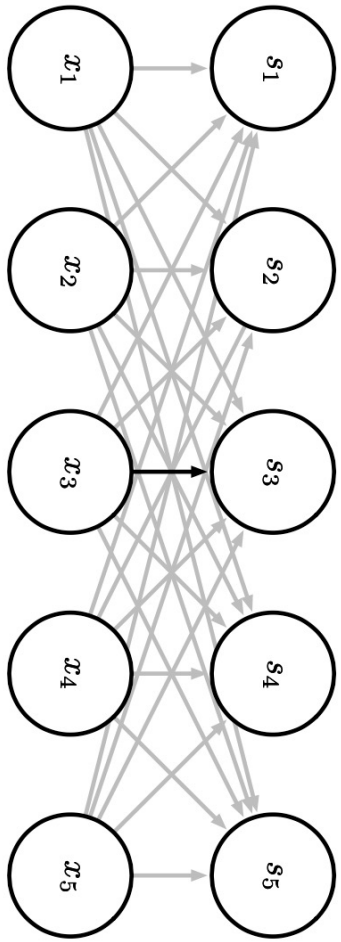
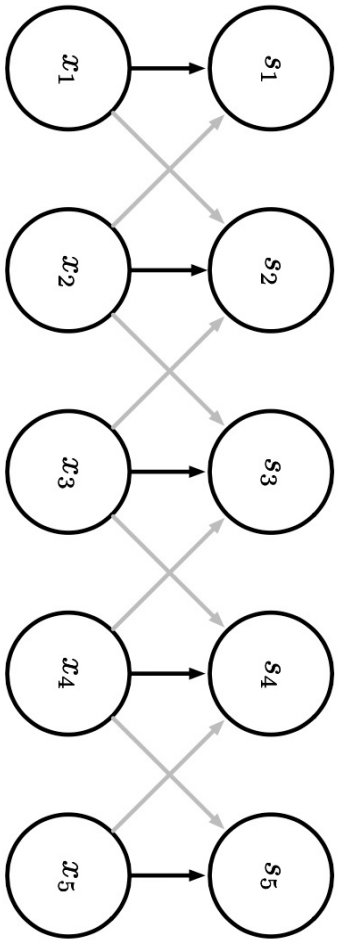
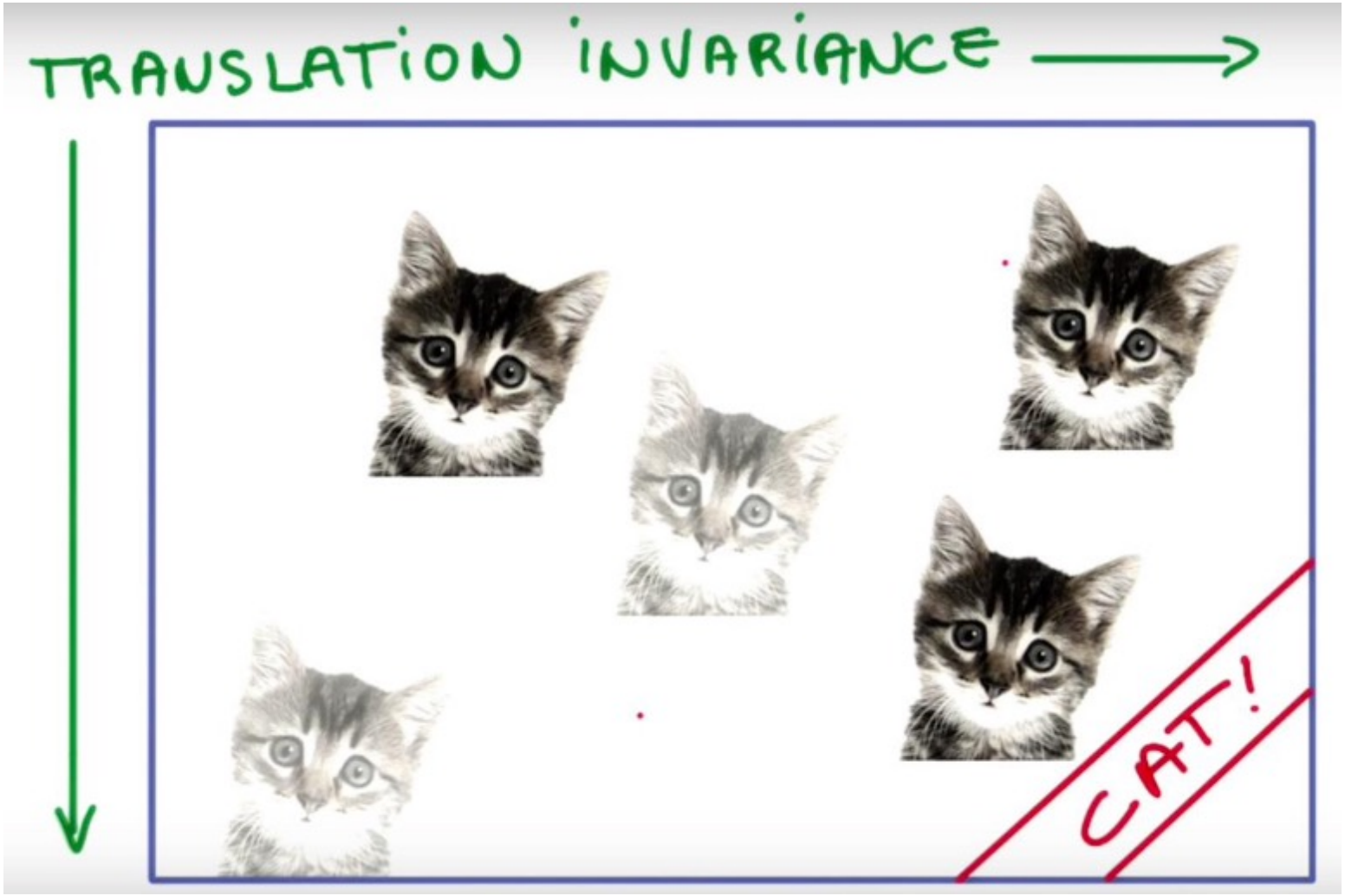
Parameters are shared





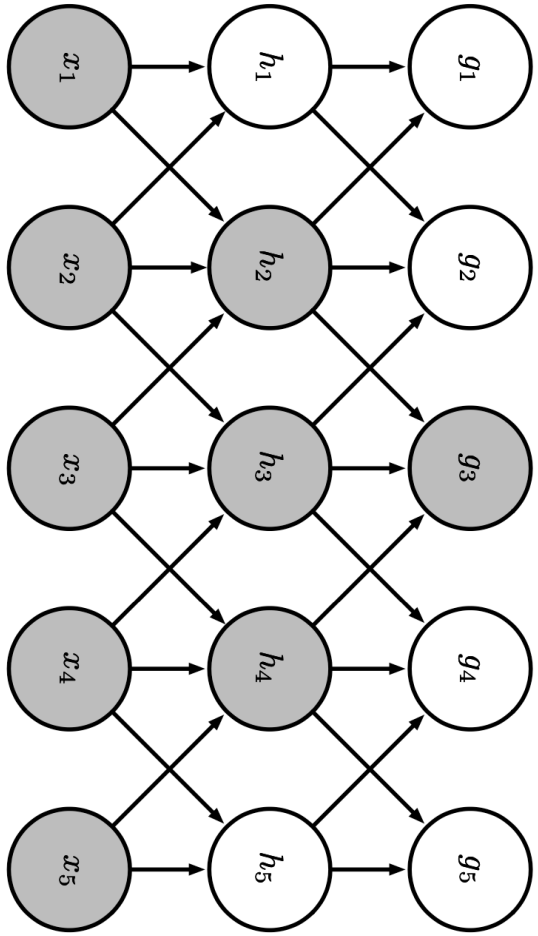
Source: Goodfellow

Shared parameters lead to translation invariance



Source: Bhaskhar

Hierarchical setup



Source: Goodfellow

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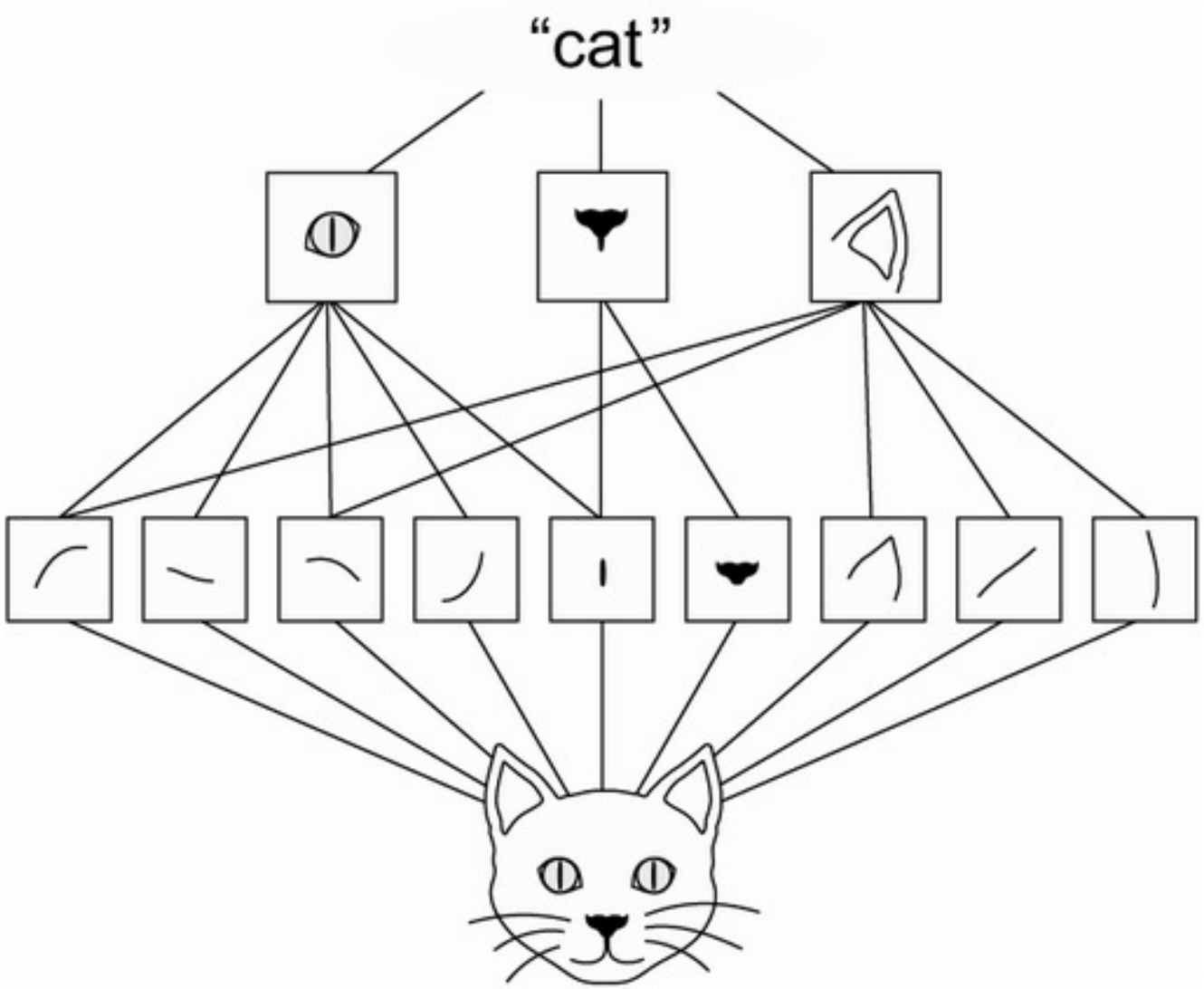
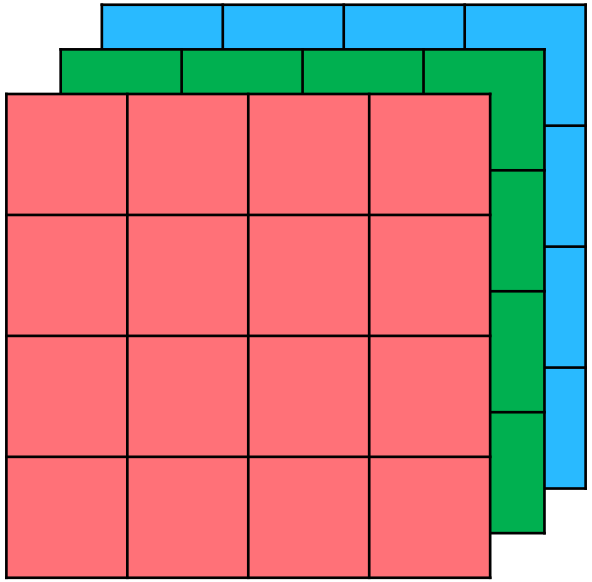
Hierarchical structure supports a spatial hierarchy of learning



Source: Chollet

From convolution to CNNs

Convolution on a 3D array



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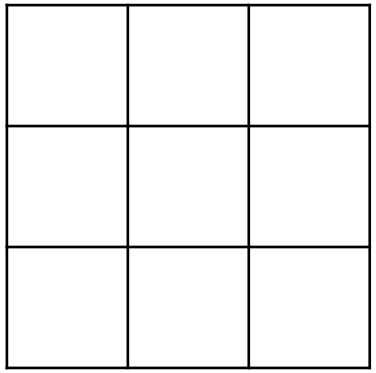
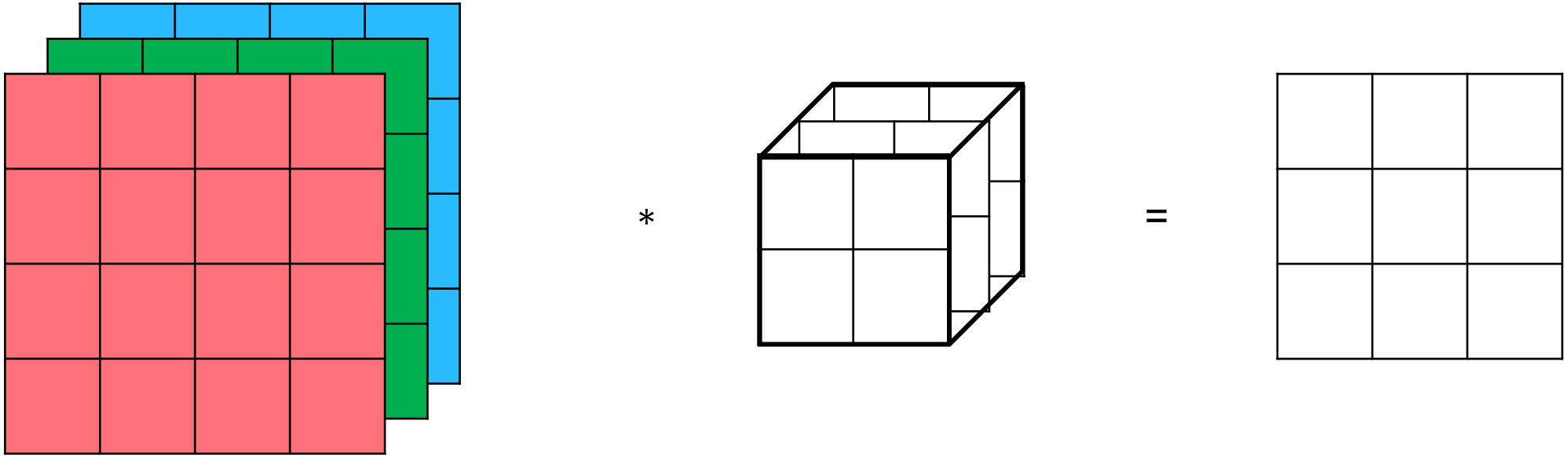
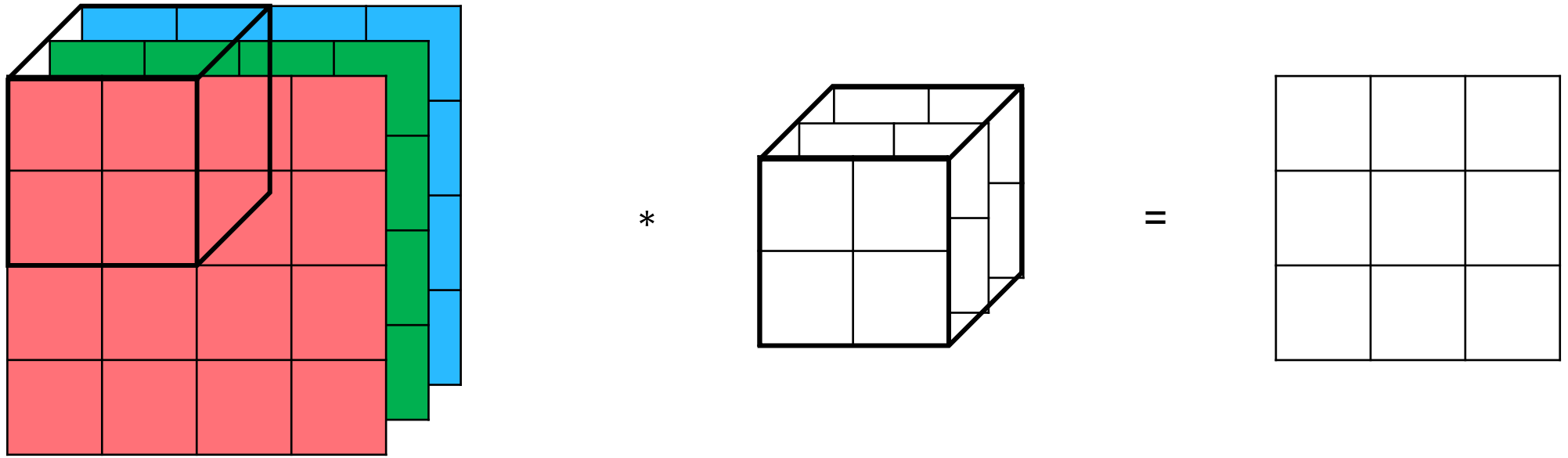


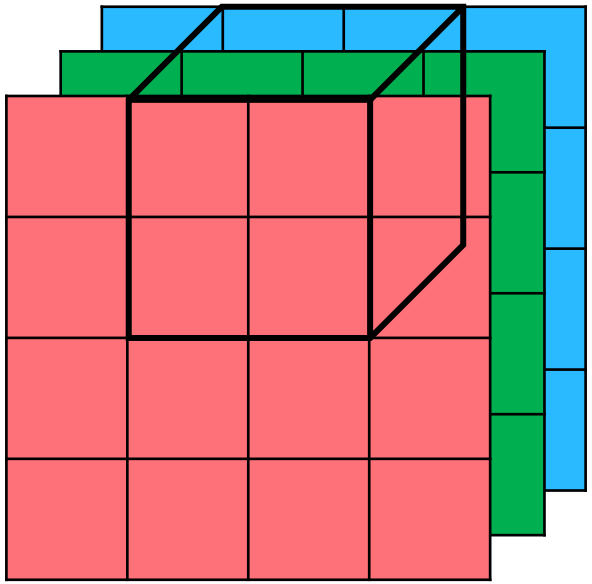
Convolution on a 3D array



Convolution on a 3D array



Convolution on a 3D array



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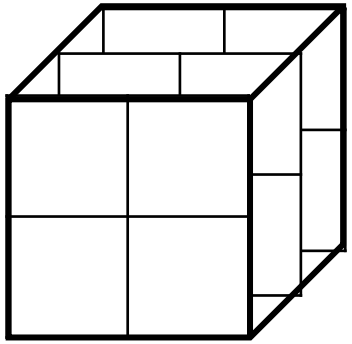

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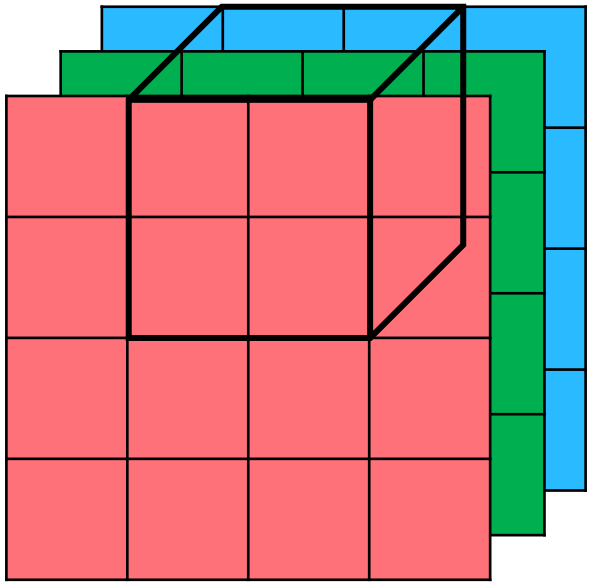
Convolution on a 3D array



4x4x3

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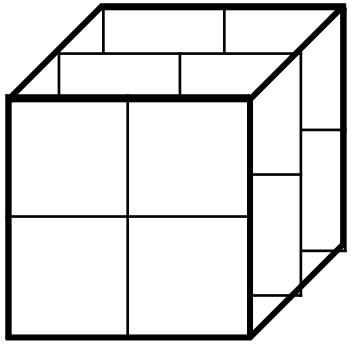

2x2x3

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3x3

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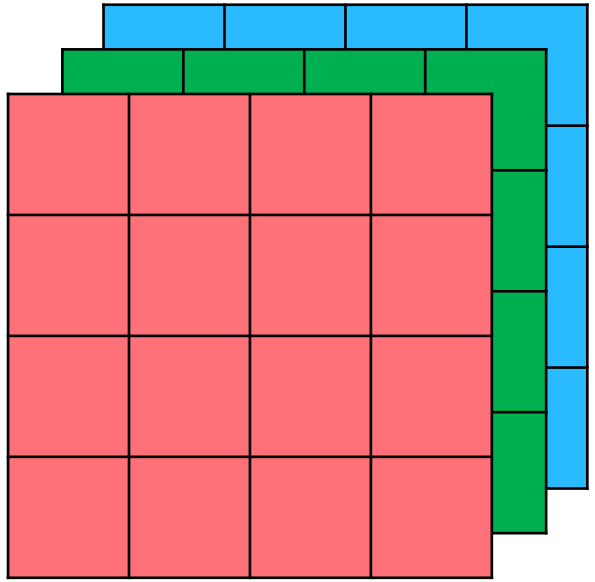
Multiple 3D convolutions



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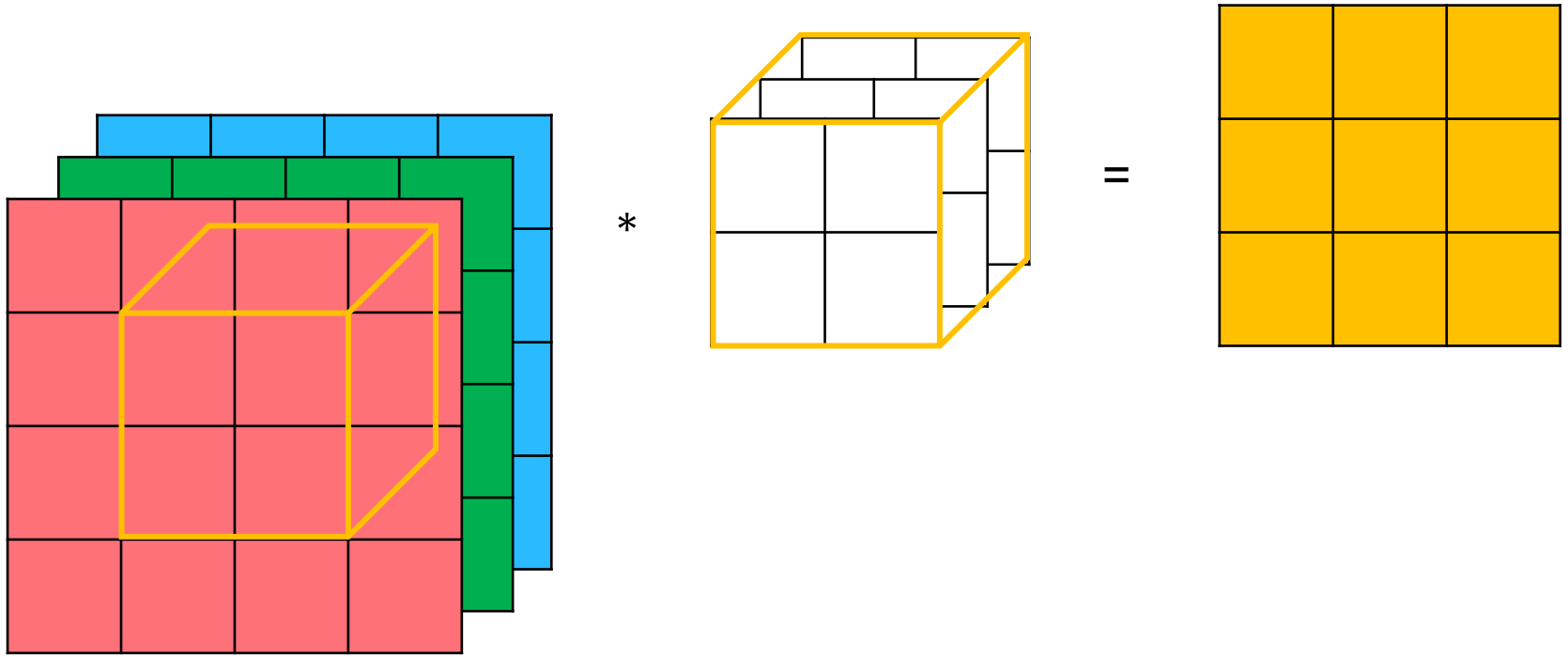
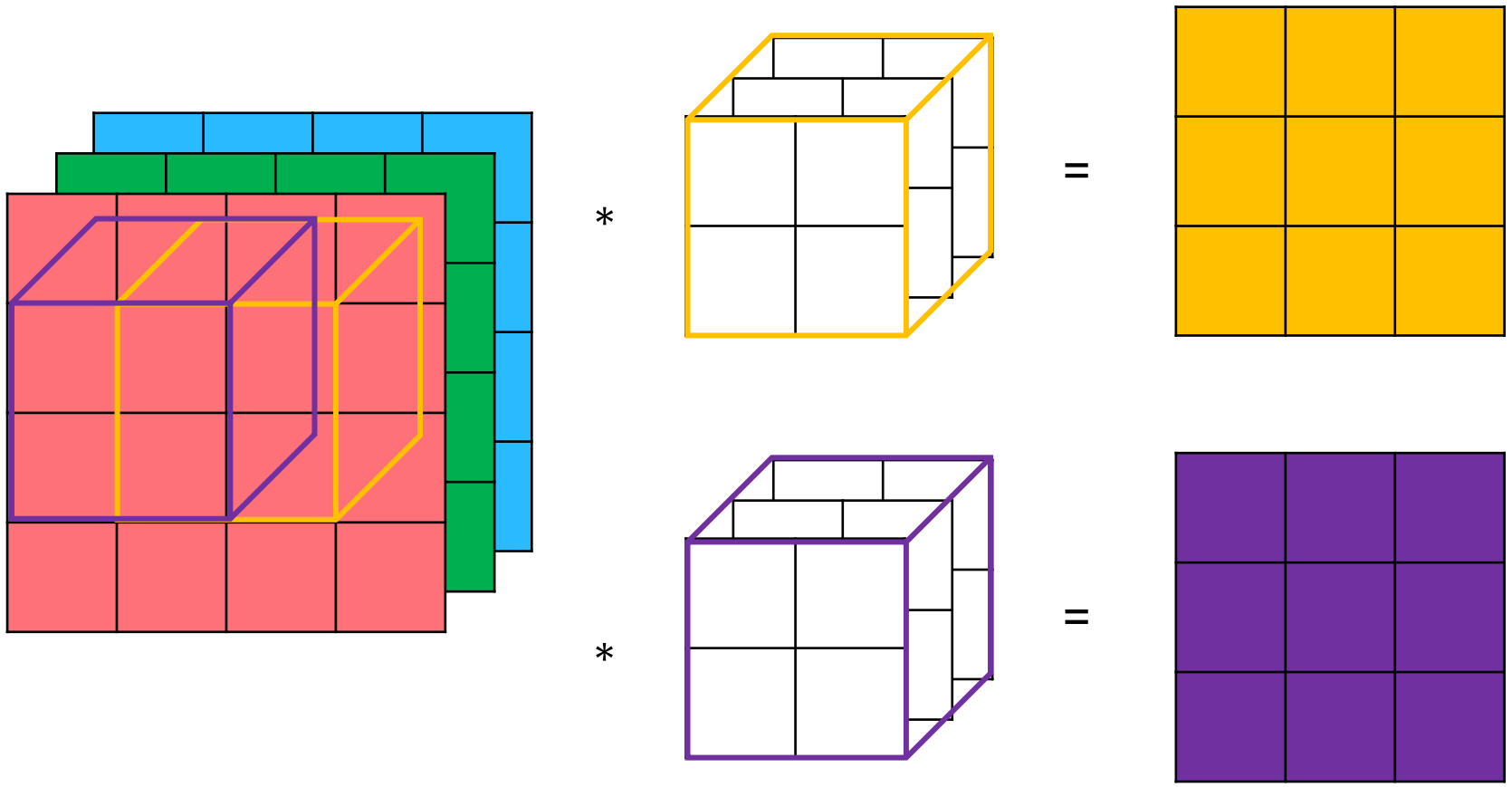
Multiple 3D convolutions



Multiple 3D convolutions



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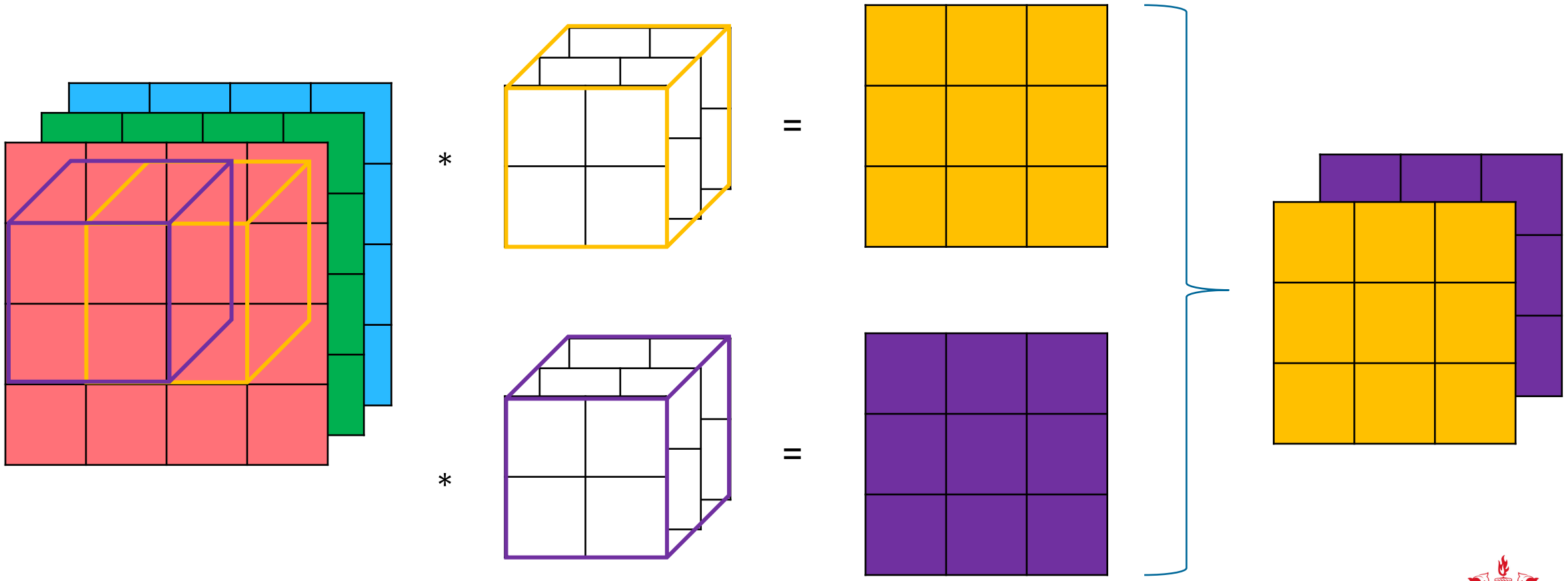
Multiple 3D convolutions



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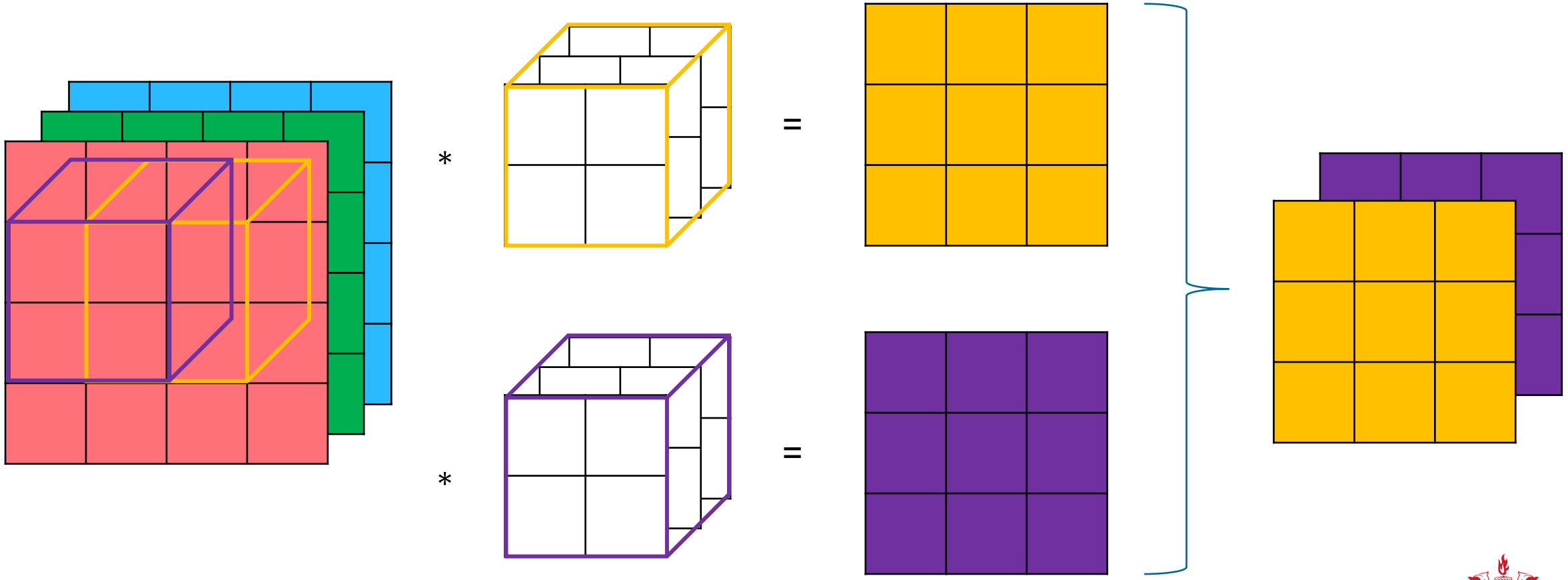
Multiple 3D convolutions



4x4x3

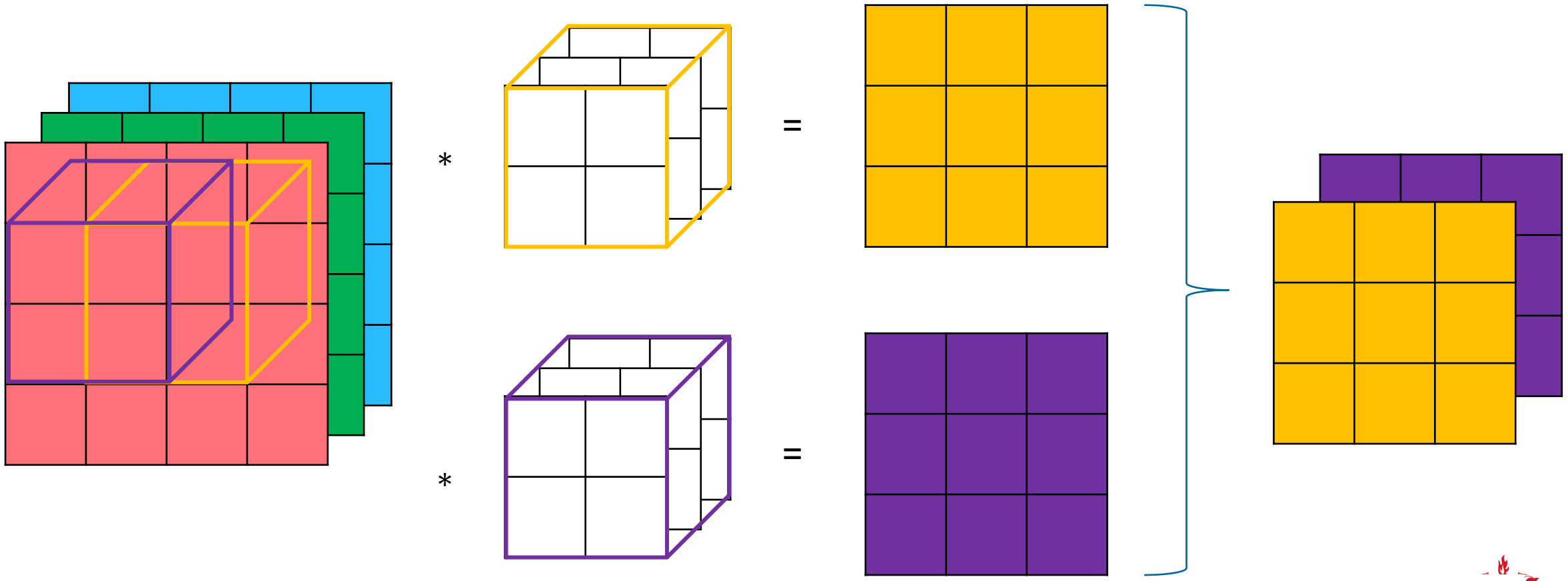
$(n_H^{[0]}, n_W^{[0]}, \mathrm{n}_\mathrm{C}^{[0]})$

2x2x3

$(f_H, f_W, \mathrm{n}_\mathrm{C}^{[0]})$

$n_C^{[1]}$= number of filters

Multiple 3D convolutions



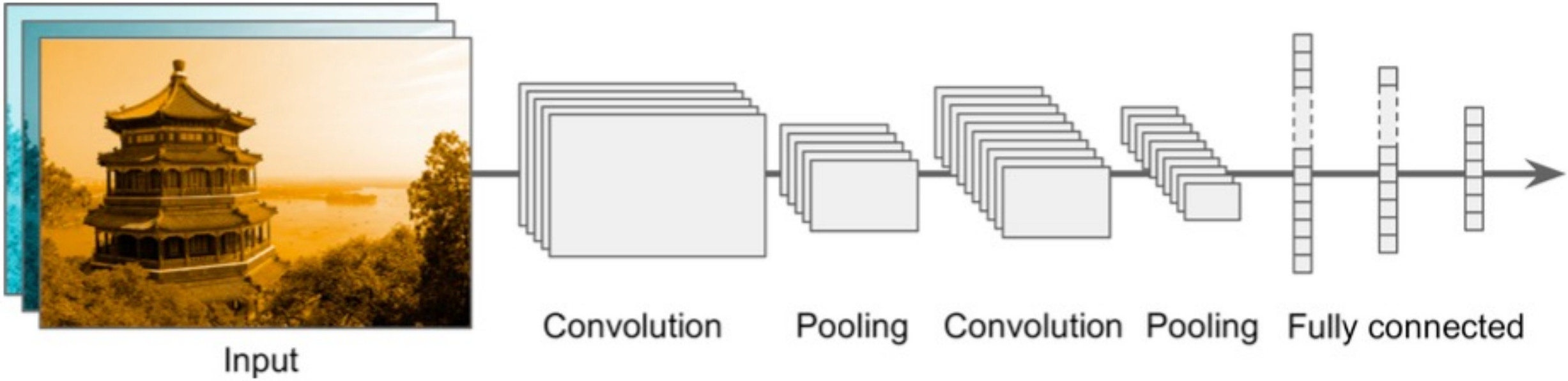
4x4x3
$(n_H^{[0]}, n_W^{[0]}, \mathrm{n}_\mathrm{C}^{[0]})$

2x2x3
$(f_H, f_W, \mathrm{n}_\mathrm{C}^{[0]})$

$n_C^{[1]}$= number of filters

3x3x2
$(n_H^{[1]}, n_W^{[1]}, \mathrm{n}_\mathrm{C}^{[1]})$

Typical architecture

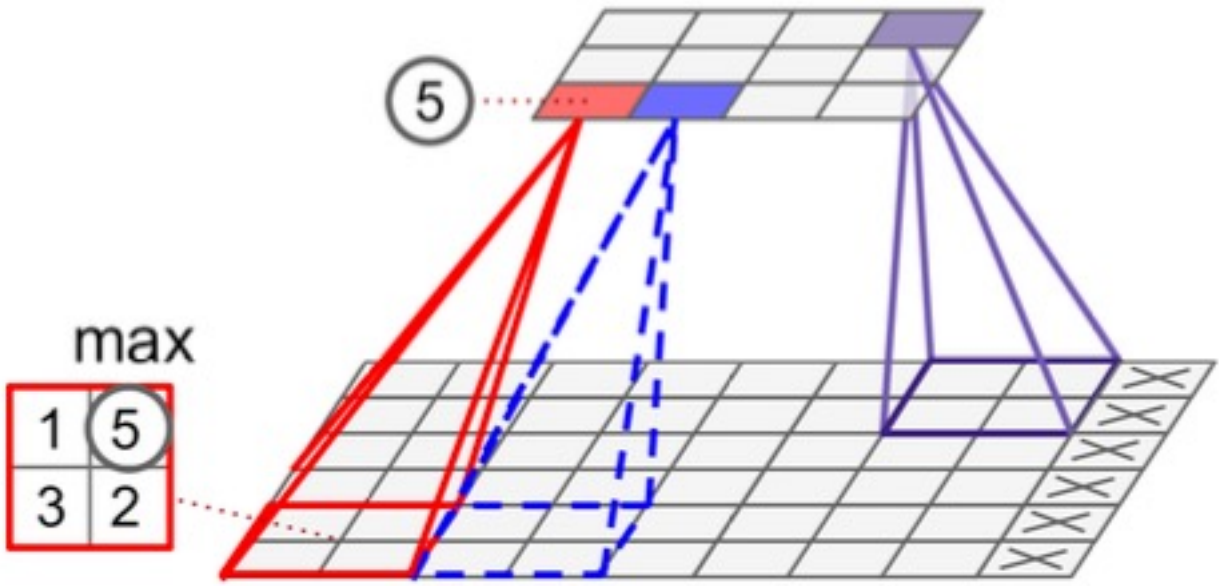


Source: Géron

Pooling layers

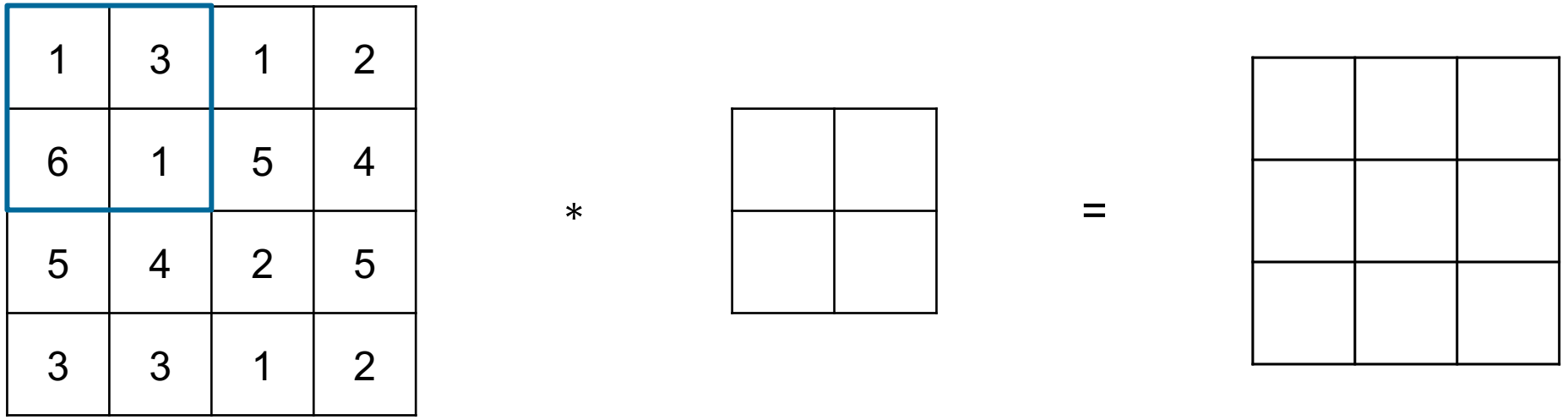
- Subsample (i.e., summarize) the input
  - Reduced computational load
  - Reduced memory usage
  - Fewer parameters (and, thus, less overfitting)

Max pooling



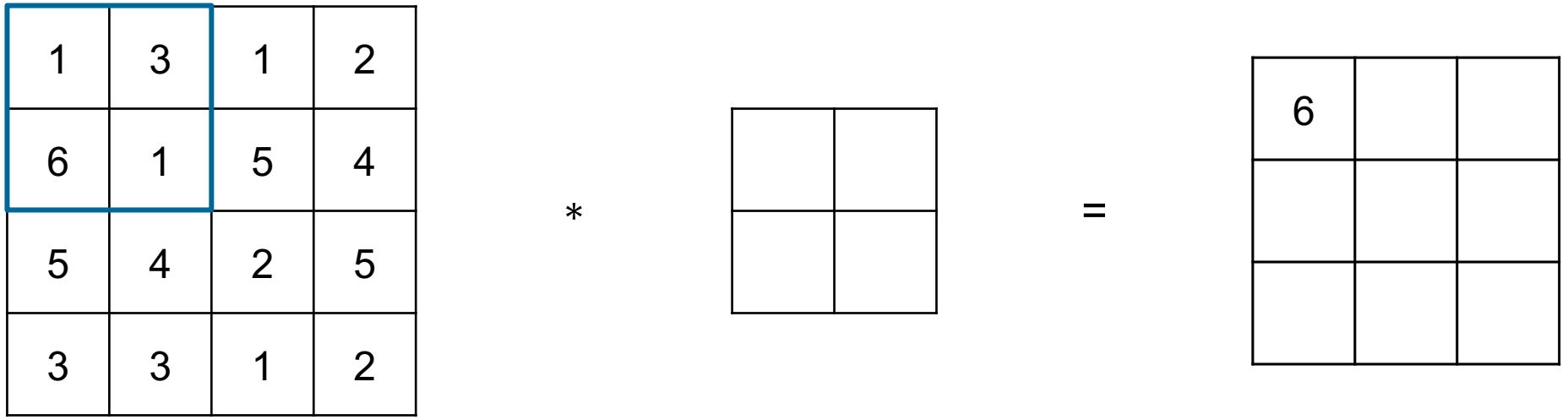
Source: Géron

Max pooling in practice



Source: Géron

Max pooling in practice



Source: Géron

Max pooling in practice

1	3	1	2
6	1	5	4
5	4	2	5
3	3	1	2

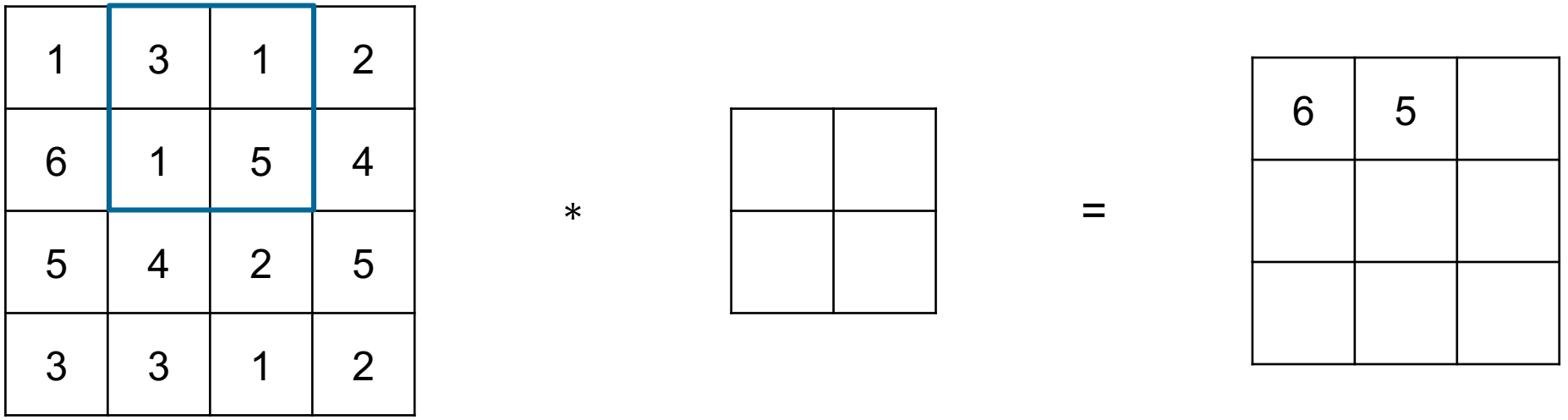
*

=

6		

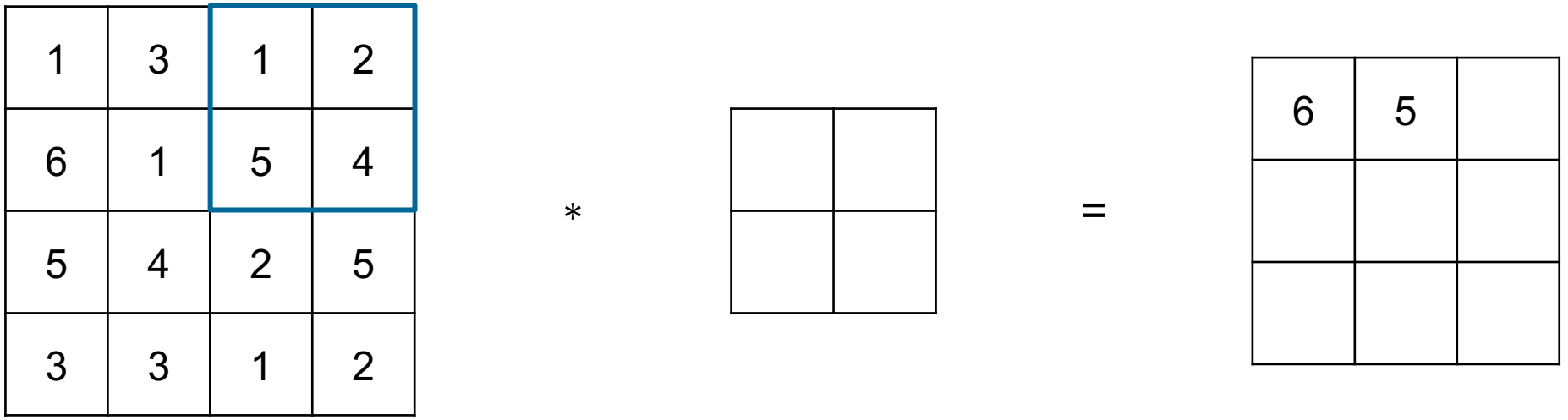
Source: Géron

Max pooling in practice



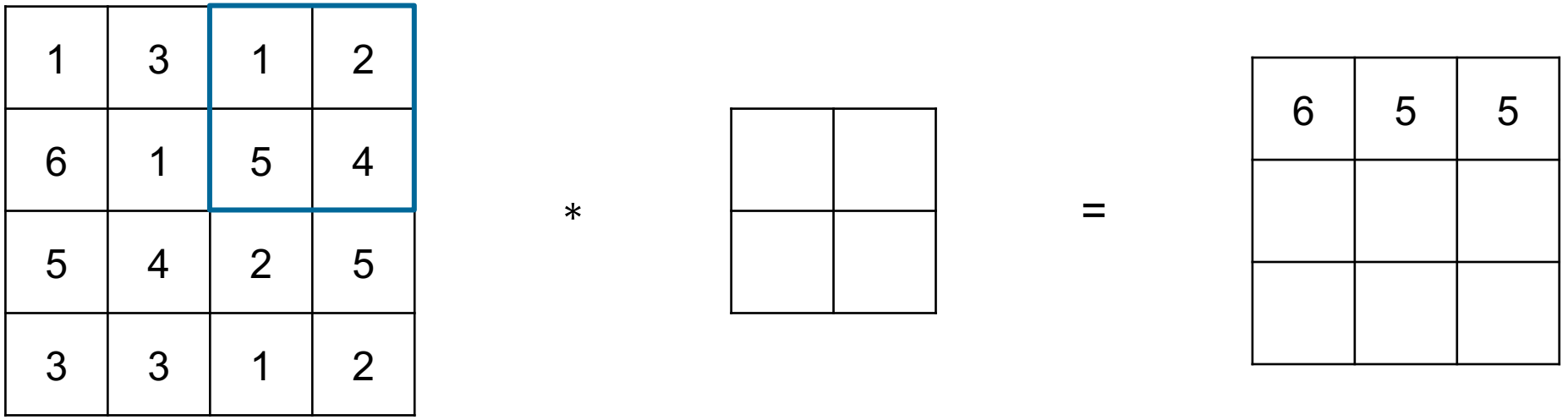
Source: Géron

Max pooling in practice



Source: Géron

Max pooling in practice



Source: Géron

Max pooling in practice

1	3	1	2
6	1	5	4
5	4	2	5
3	3	1	2

*

=

6	5	5
6	5	5
5	4	5

Source: Géron

Timer permitting – additional details on convolutions

With convolution, the center matters more

1	3	1	2
6	1	5	4
5	4	2	5
3	3	1	2

*

1	2
2	1

=

20	12	19
22	21	22
22	15	16

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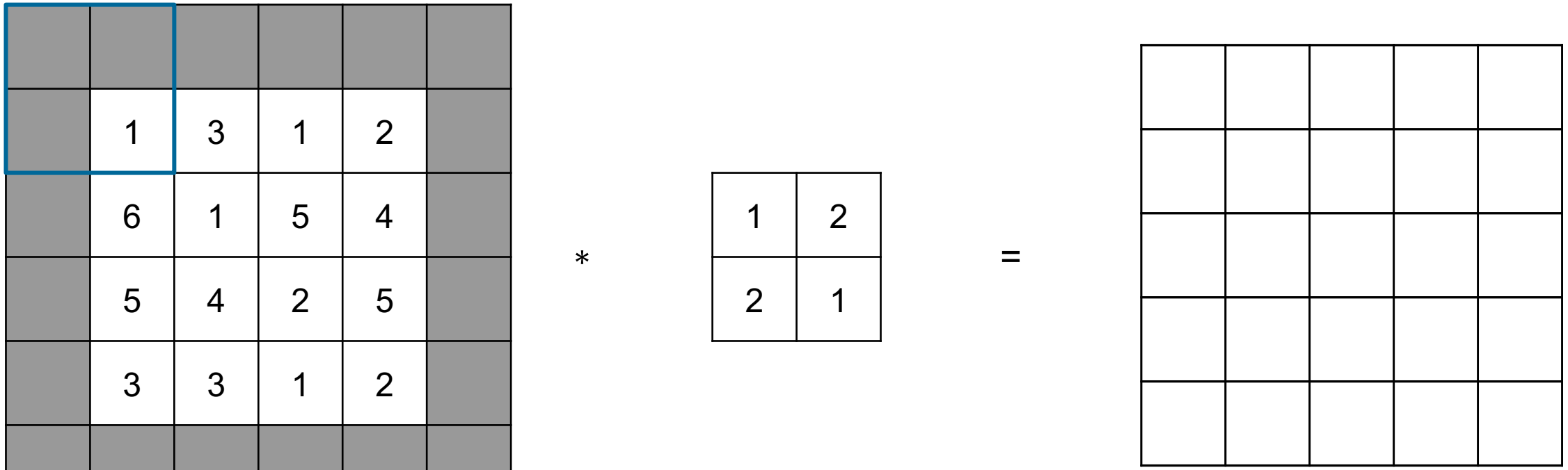
The convolution operator with padding



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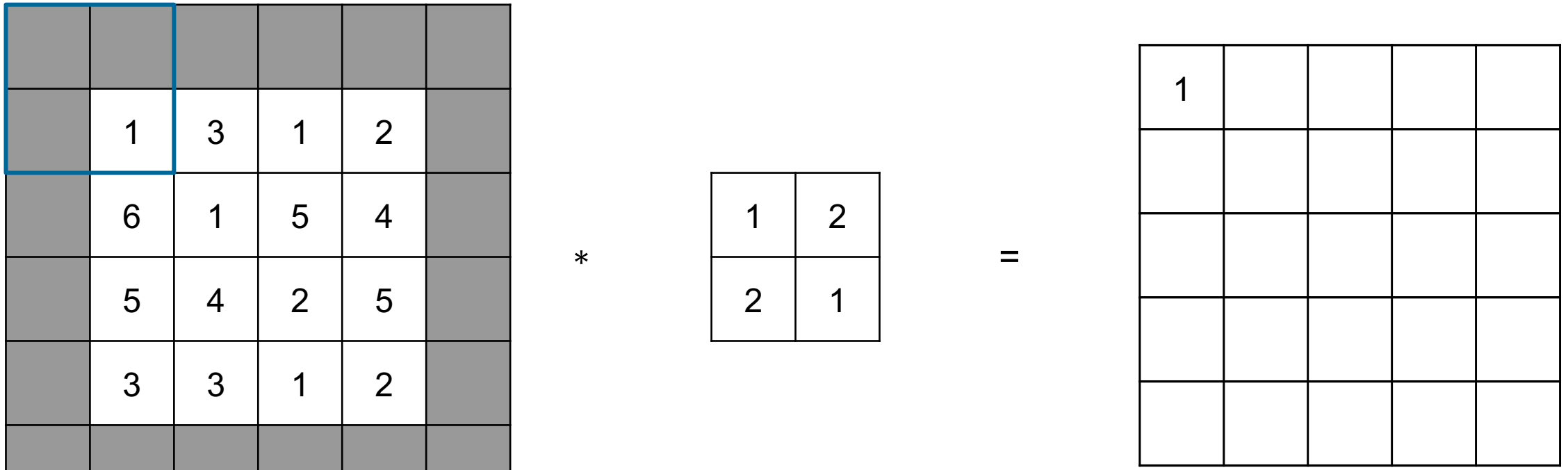
The convolution operator with padding



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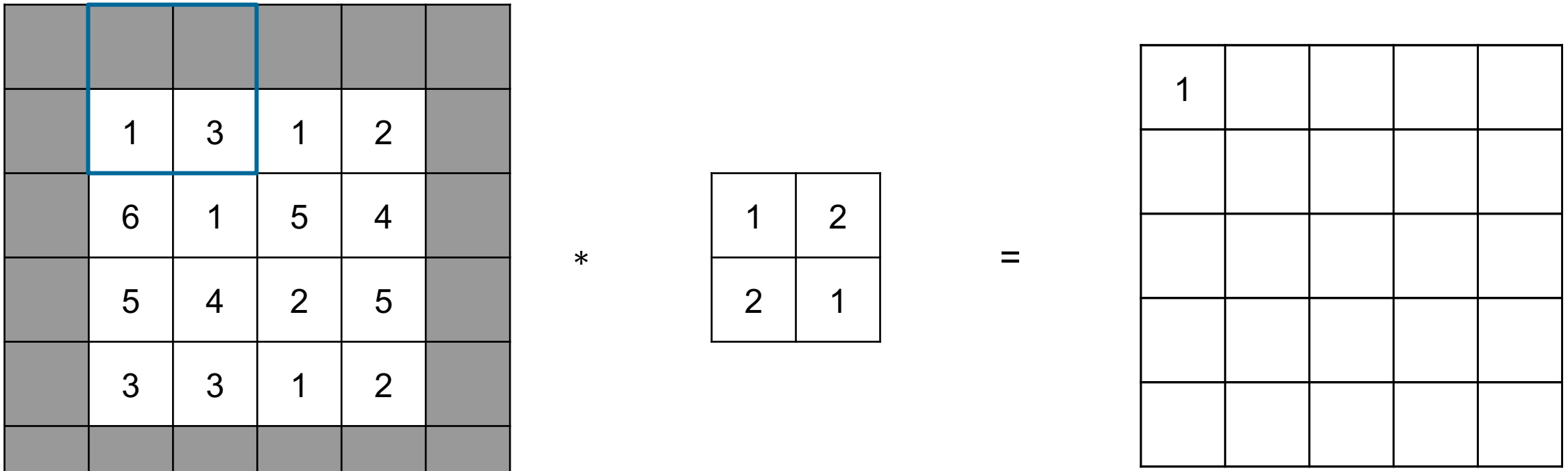
The convolution operator with padding



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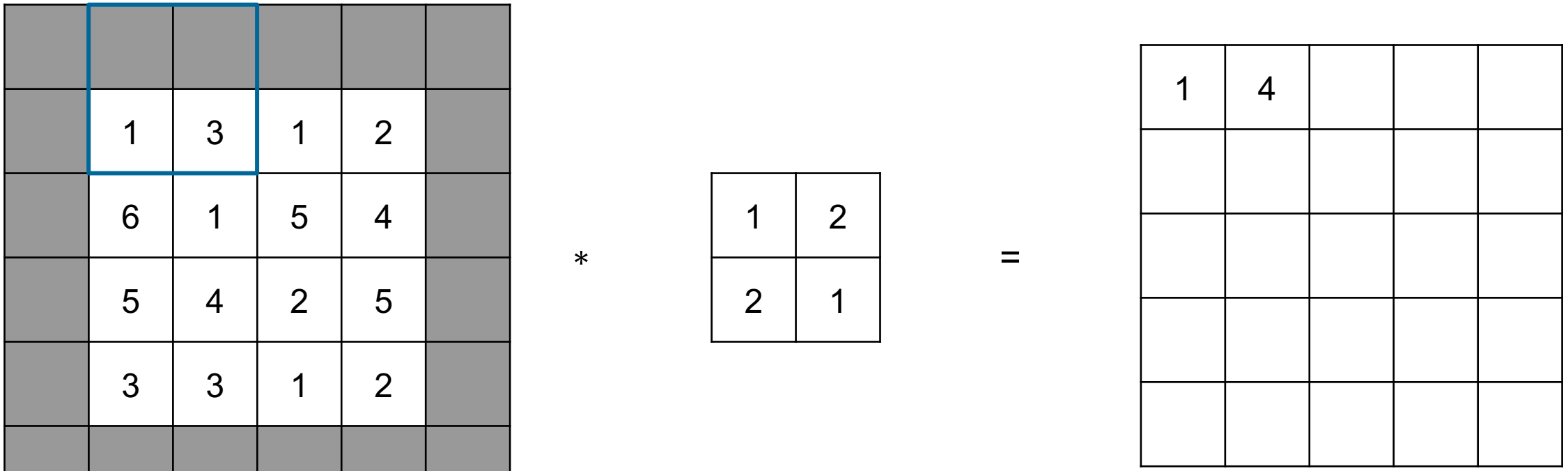
The convolution operator with padding



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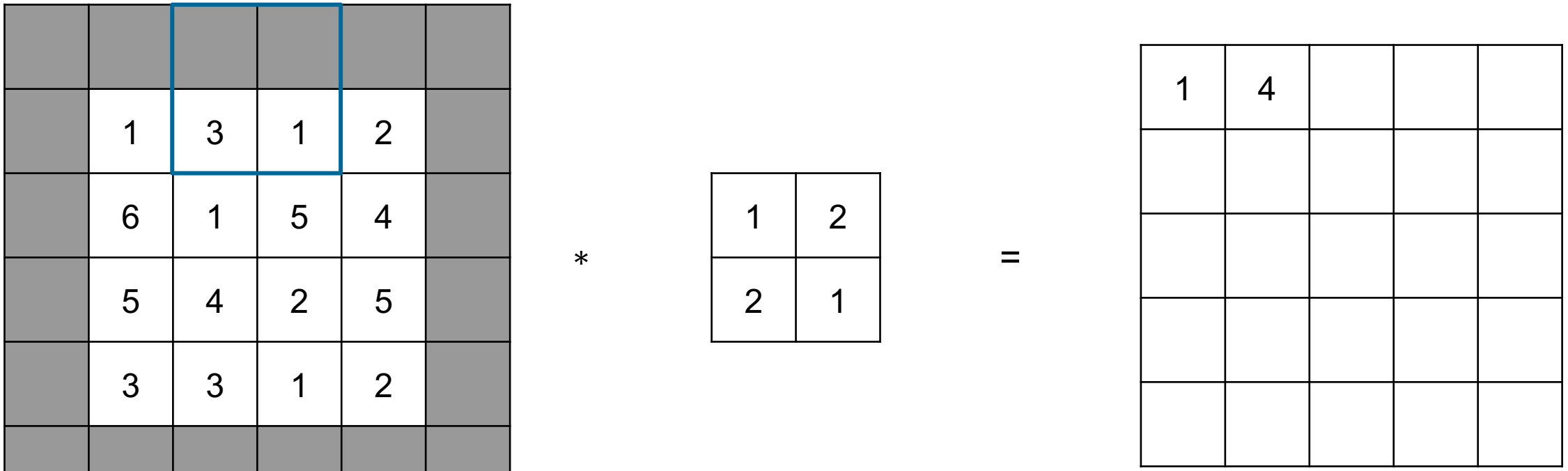
The convolution operator with padding



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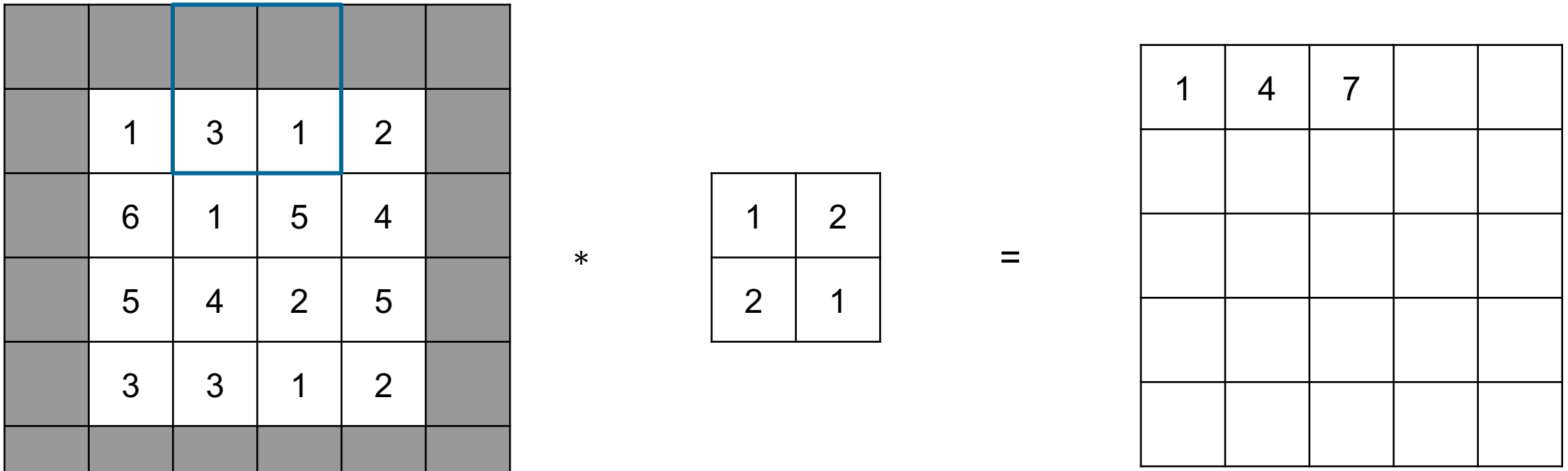
The convolution operator with padding



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The convolution operator with padding

	1	3	1	2	
	6	1	5	4	
	5	4	2	5	
	3	3	1	2	

*

1	2
2	1

=

1	4	7	4	4
8	20	12	19	10
17	22	21	22	14
13	22	15	16	9
6	9	5	5	2

The convolution operator with padding

	1	3	1	2	
	6	1	5	4	
	5	4	2	5	
	3	3	1	2	

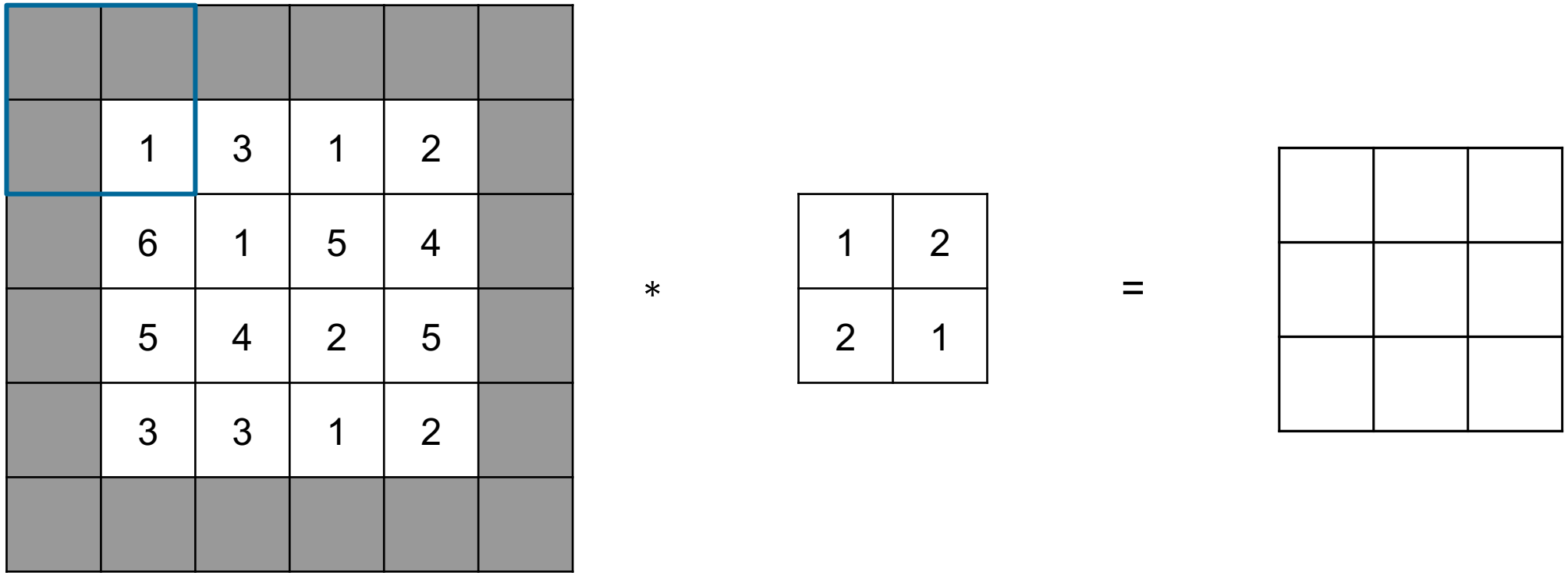
*

1	2
2	1

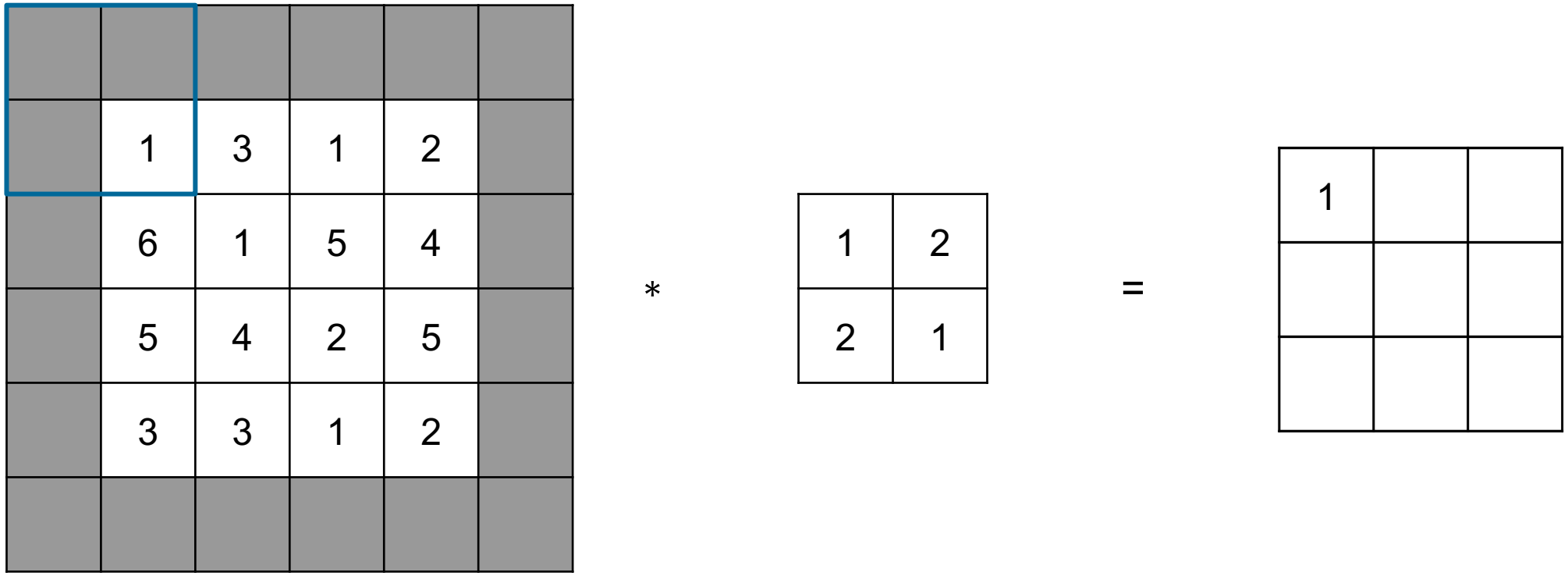
=

1	4	7	4	4
8	20	12	19	10
17	22	21	22	14
13	22	15	16	9
6	9	5	5	2

The convolution operator with padding and stride



The convolution operator with padding and stride



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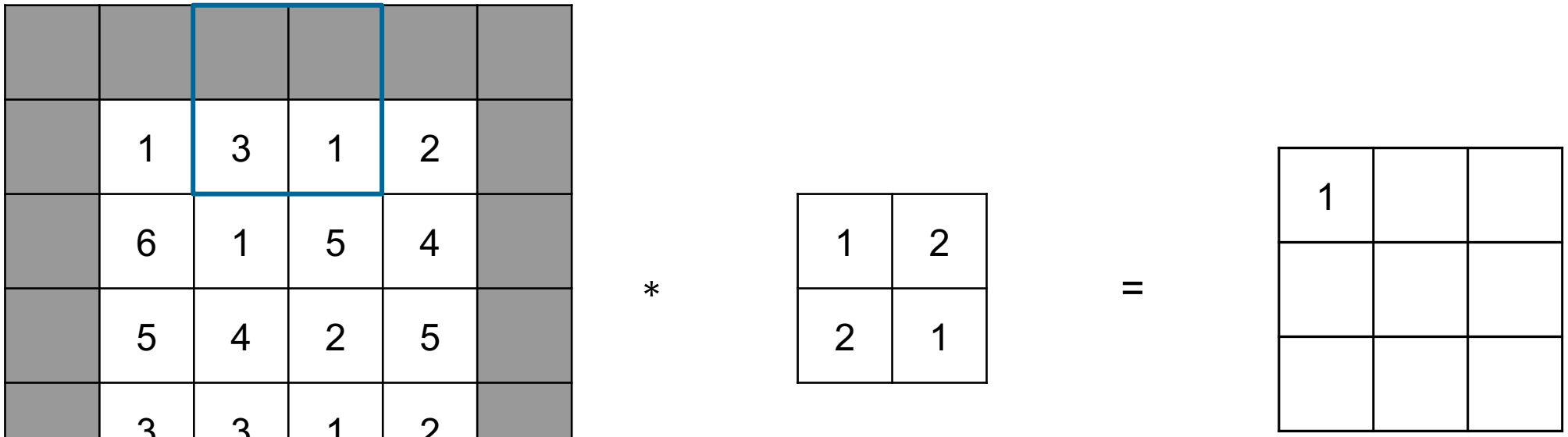
The convolution operator with padding and stride



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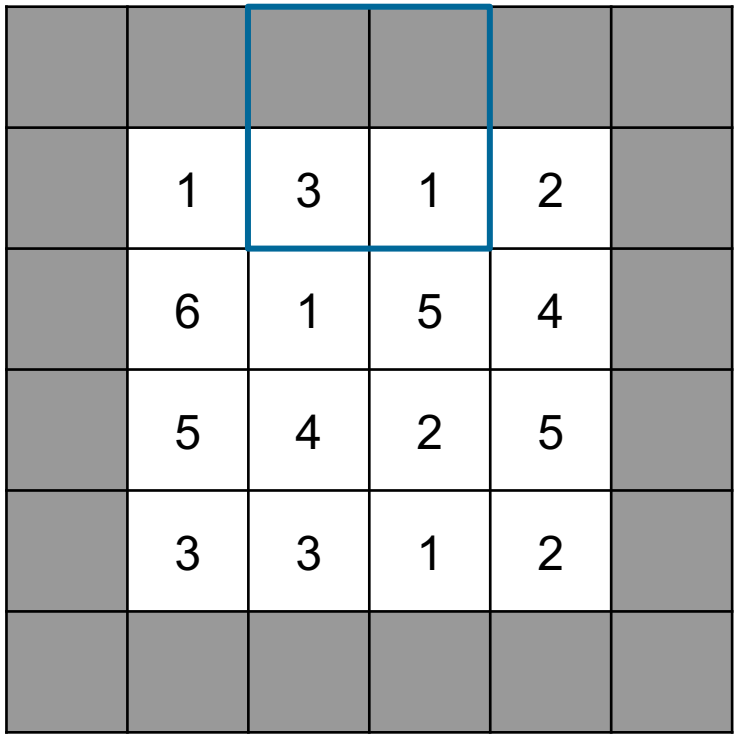
The convolution operator with padding and stride



*

1	2
2	1

=

1	7	

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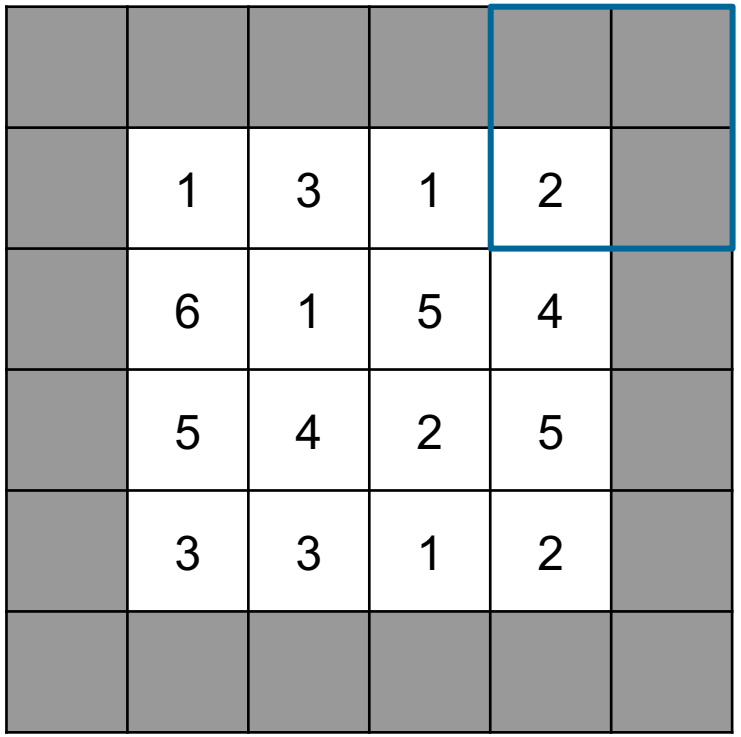
The convolution operator with padding and stride



*

1	2
2	1

=

1	7	

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The convolution operator with padding and stride

	1	3	1	2	
	6	1	5	4	
	5	4	2	5	
	3	3	1	2	

*

1	2
2	1

=

1	7	4

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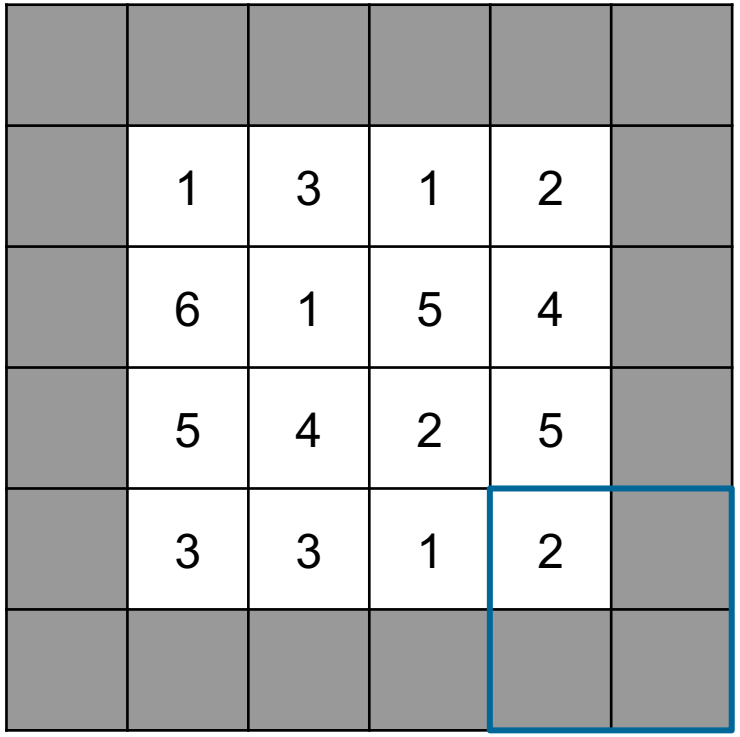
The convolution operator with padding and stride



*

1	2
2	1

=

1	7	4
17	21	14
6	5	2

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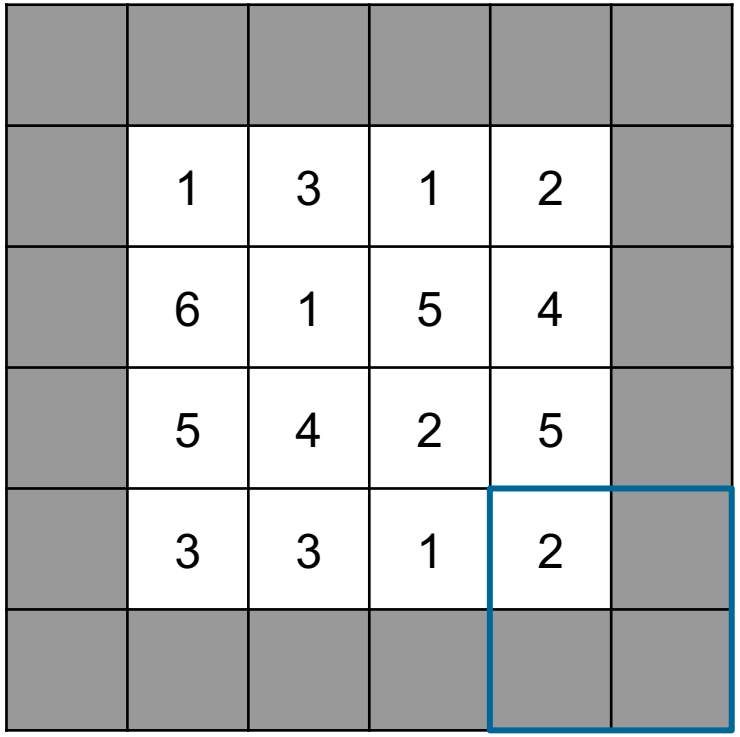
The convolution operator with padding and stride



*

1	2
2	1

=

1	7	4
17	21	14
6	5	2

4x4
$(n_H^{[0]}, n_W^{[0]})$

2x2 with padding 1x1 and stride 2x2
(f_H, f_W) with (p_H, p_W) and (s_H, s_W)

3x3
$(n_H^{[1]}, n_W^{[1]})$

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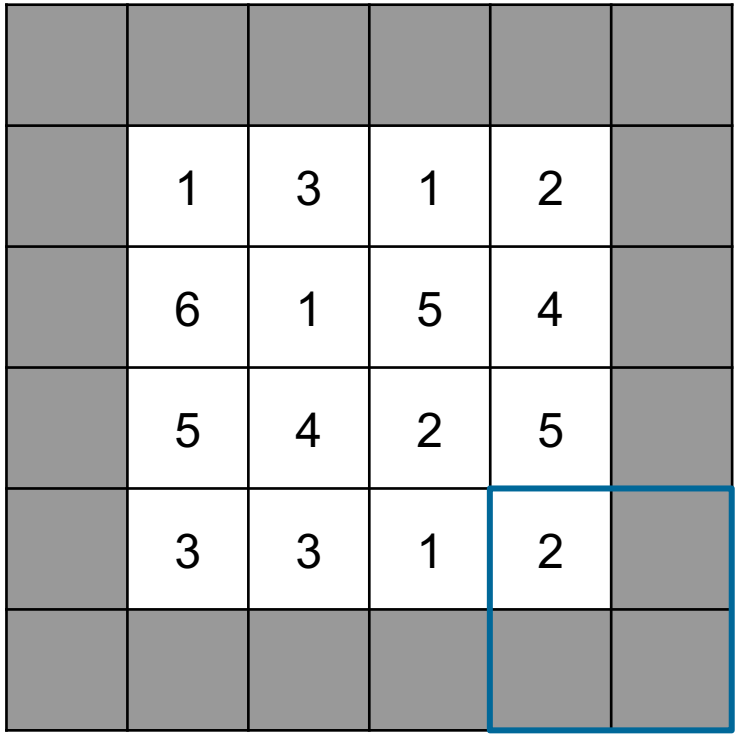
The convolution operator with padding and stride



*

1	2
2	1

=

1	7	4
17	21	14
6	5	2

4x4
$(n_H^{[0]}, n_W^{[0]})$

2x2 with padding 1x1 and stride 2x2
(f_H, f_W) with (p_H, p_W) and (s_H, s_W)

3x3
$(n_H^{[1]}, n_W^{[1]})$

$$n_H^{[1]} = \left\lfloor \frac{n_H^{[0]} + 2p_H - f_H}{s_H} + 1 \right\rfloor \quad n_W^{[1]} = \left\lfloor \frac{n_W^{[0]} + 2p_W - f_W}{s_W} + 1 \right\rfloor$$

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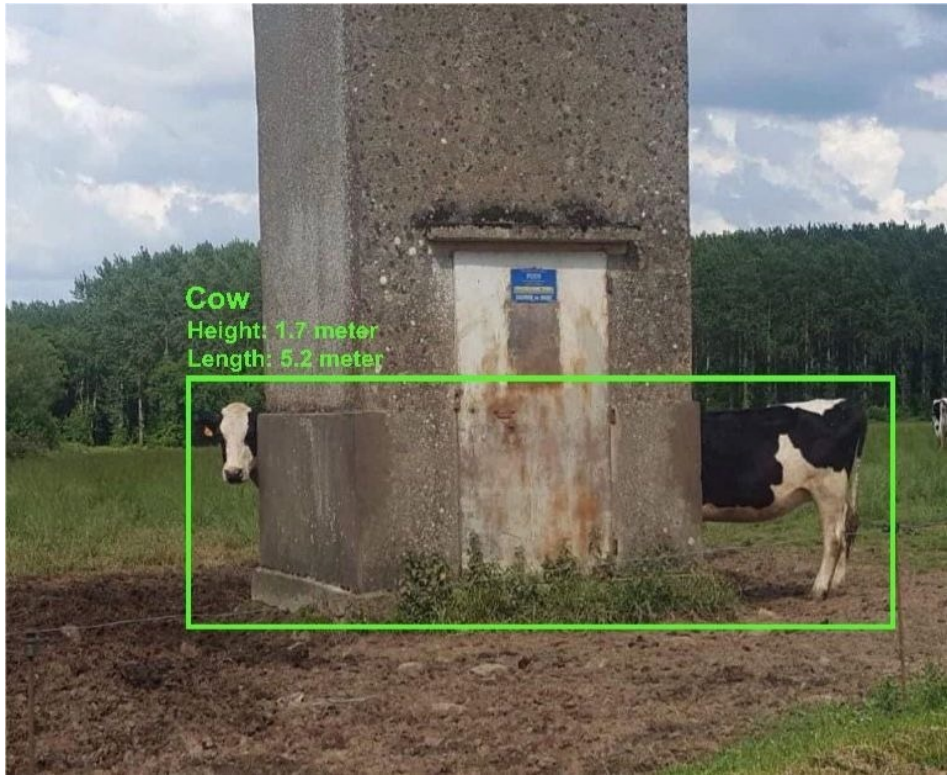
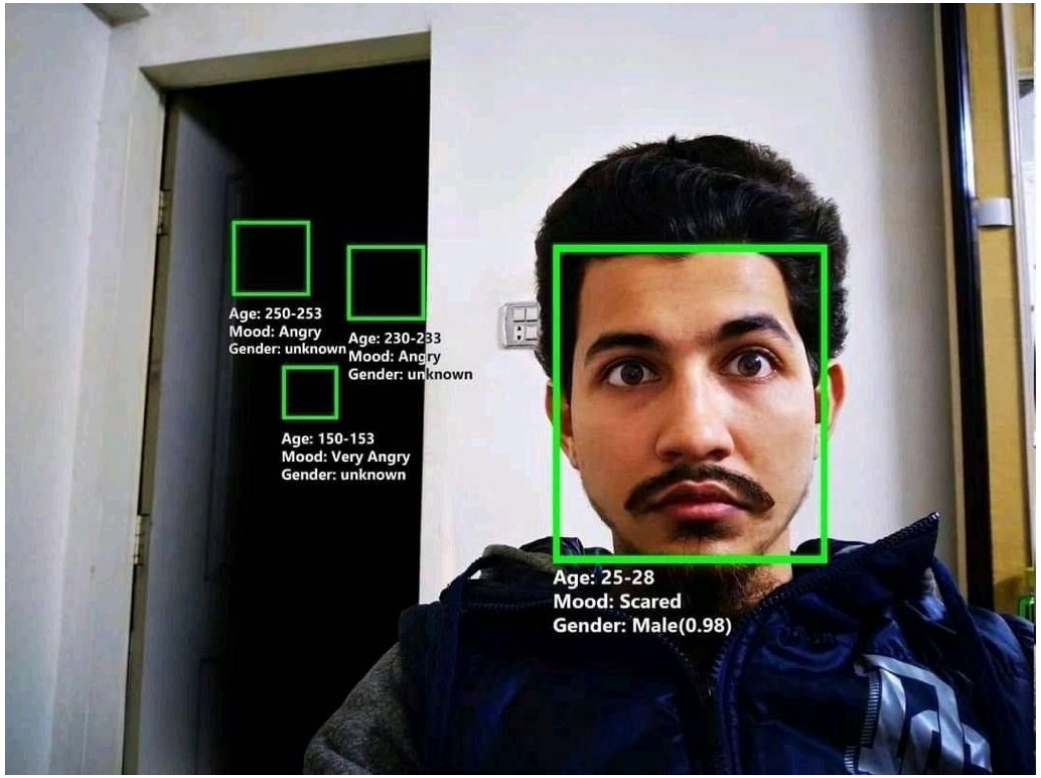
Image classification as a business

Use cases and challenges

Beyond image classification

Object detection





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Semantic segmentation

Source: Towards AI, 2021

Image generation

DALL·E History Collections

Edit the detailed description

Surprise me Upload

A lecture theatre full of students in business analytics

Generate




Source: OpenAI

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See you next week!

Sources

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