

Convolutional neural networks

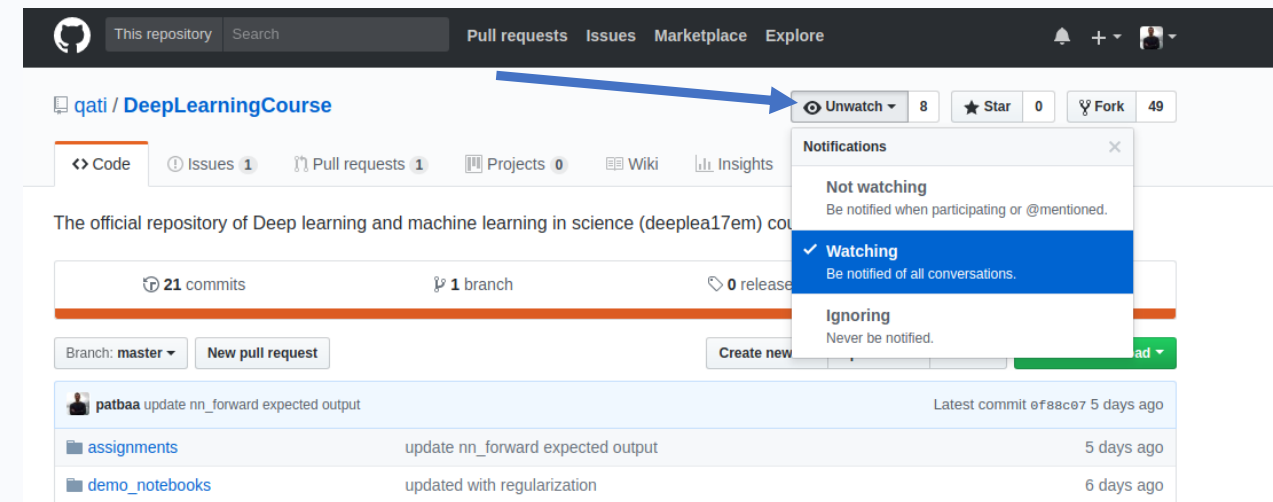
Bálint Ármin Pataki

13 March 2018

Deep learning and machine learning in science

- Homework02 (deadline: today):
 - nn_train → update **b** too
- kaggle ELTE_phys_photoz (deadline: 2018.03.20.):
 - 7 people submitted
 - 6 outperformed baseline

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- github watch to get e-mail notifications



- Random numbers (they are not random)

```
import numpy as np  
np.random.seed(0)  
np.random.randn(3)
```

```
array([ 1.76405235,  0.40015721,  0.97873798])
```

Homework

- Random numbers (they are not random)
 - rand vs randn (later will be explicitly mentioned)

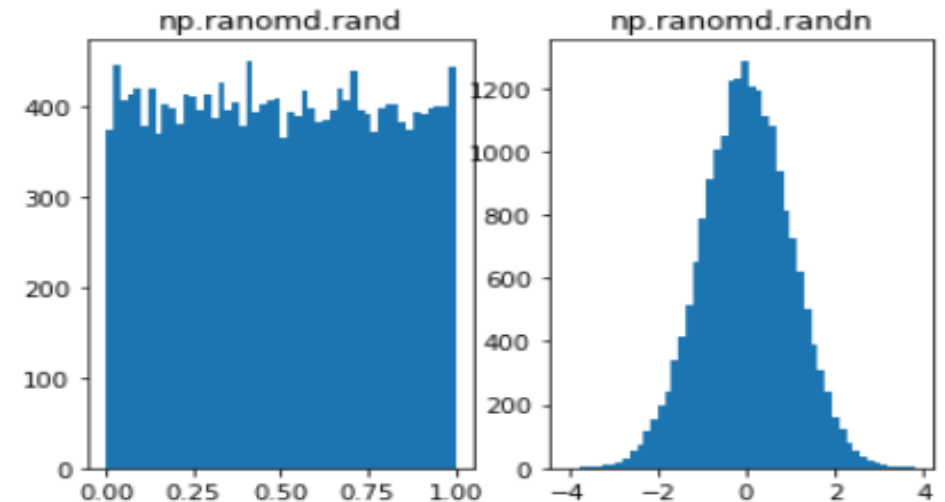
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import numpy as np
np.random.seed(0)
np.random.randn(3)
```

```
array([ 1.76405235,  0.40015721,  0.97873798])
```

```
import matplotlib.pyplot as plt
import numpy as np
%matplotlib inline

plt.subplot(1, 2, 1)
plt.hist(np.random.rand(20000), bins=50)
plt.title('np.random.rand')

plt.subplot(1, 2, 2)
plt.hist(np.random.randn(20000), bins=50)
plt.title('np.random.randn')
plt.show()
```



- Random numbers (they are not random)
 - rand vs randn (later will be explicitly mentioned)

```
import numpy as np
np.random.seed(0)
np.random.randn(3)
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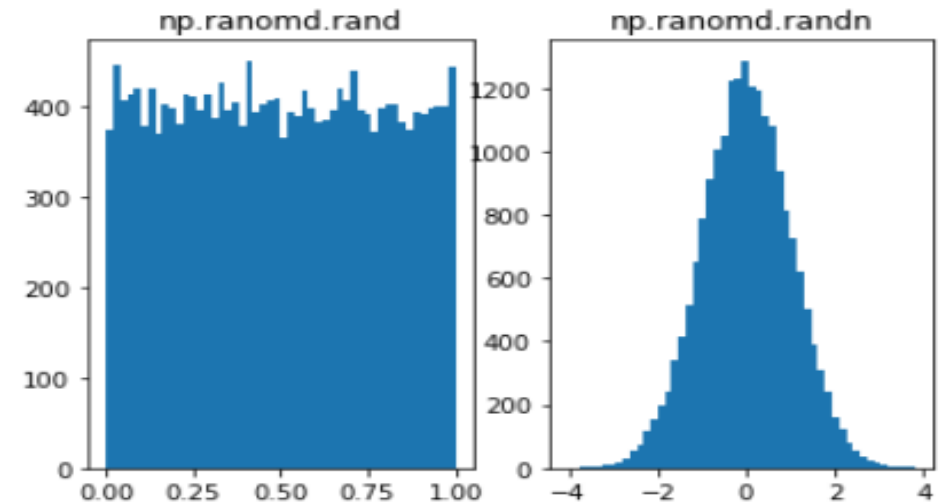
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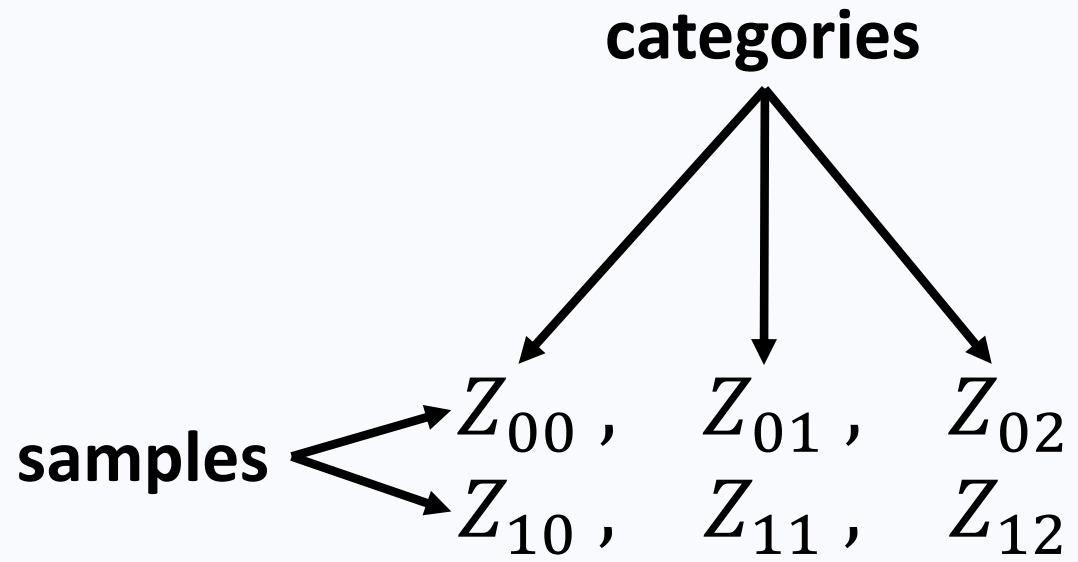
- Grading
 - Tested for different seeds
 - Tested for different inputs
 - You can correct your errors (resubmitting is allowed)

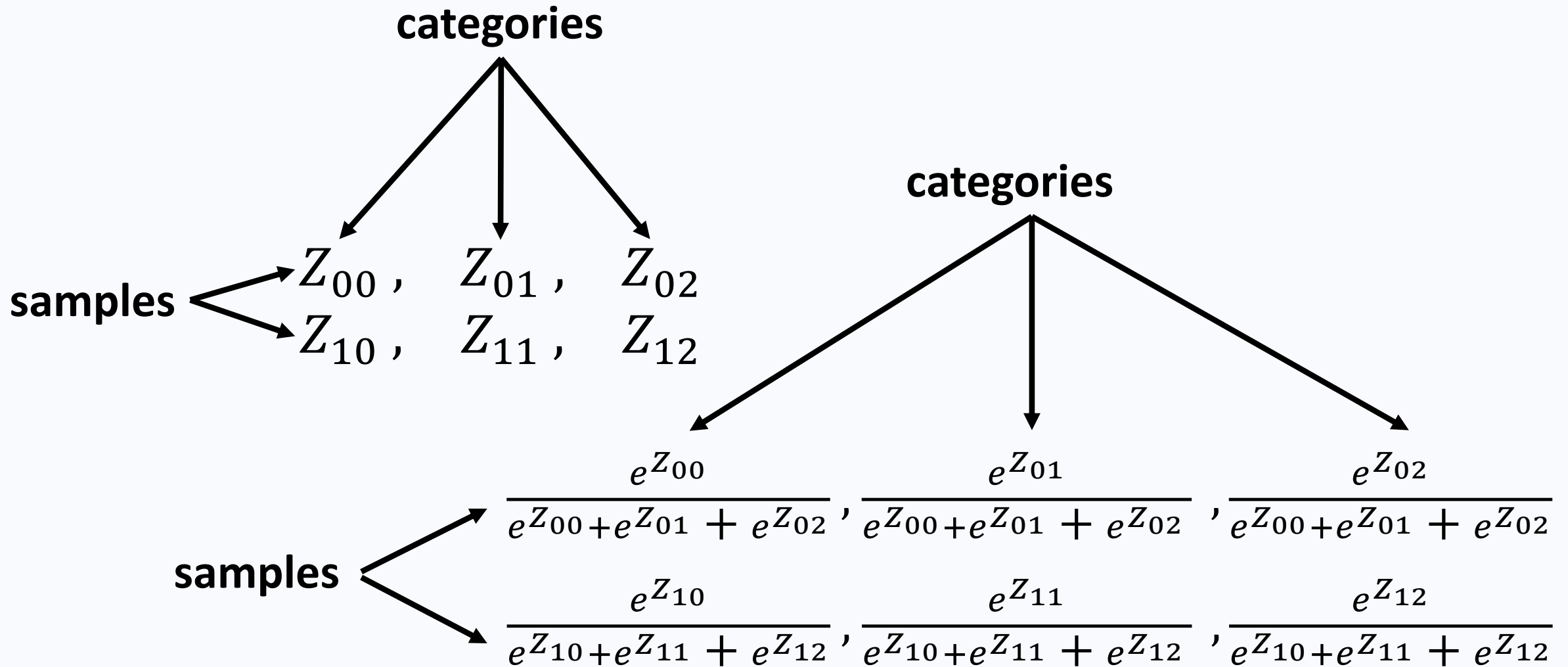
```
import matplotlib.pyplot as plt
import numpy as np
%matplotlib inline

plt.subplot(1, 2, 1)
plt.hist(np.random.rand(20000), bins=50)
plt.title('np.random.rand')

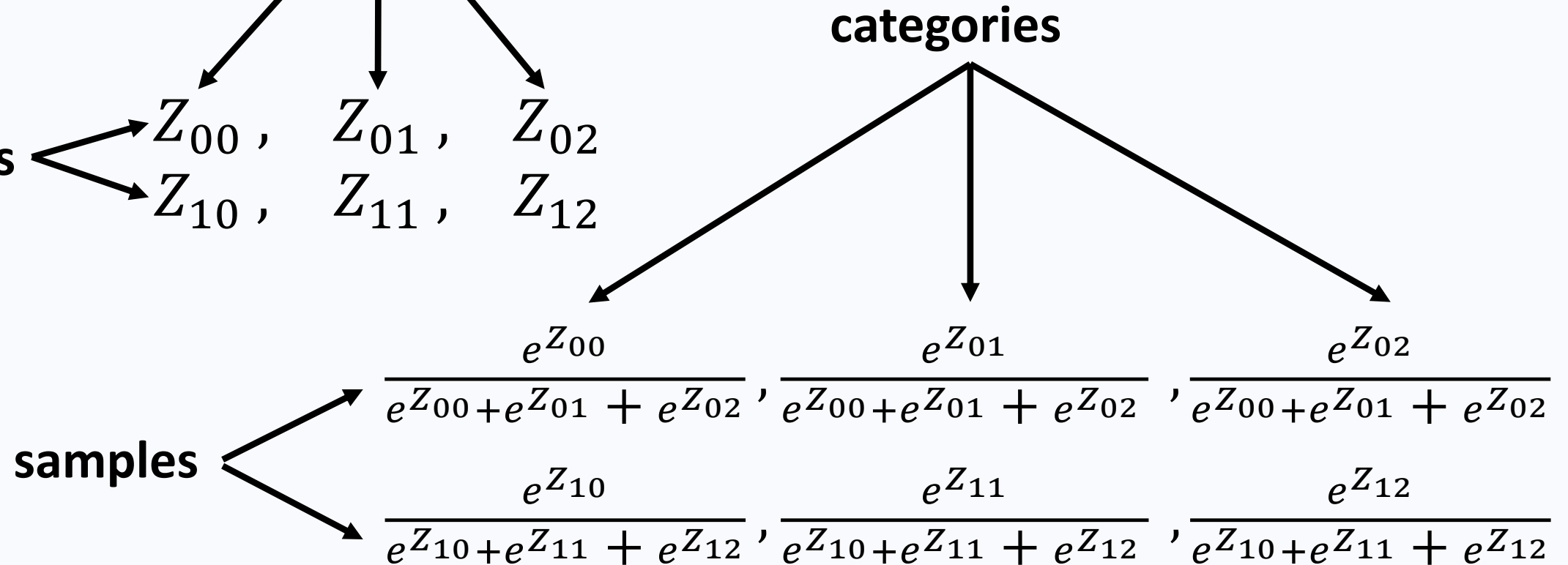
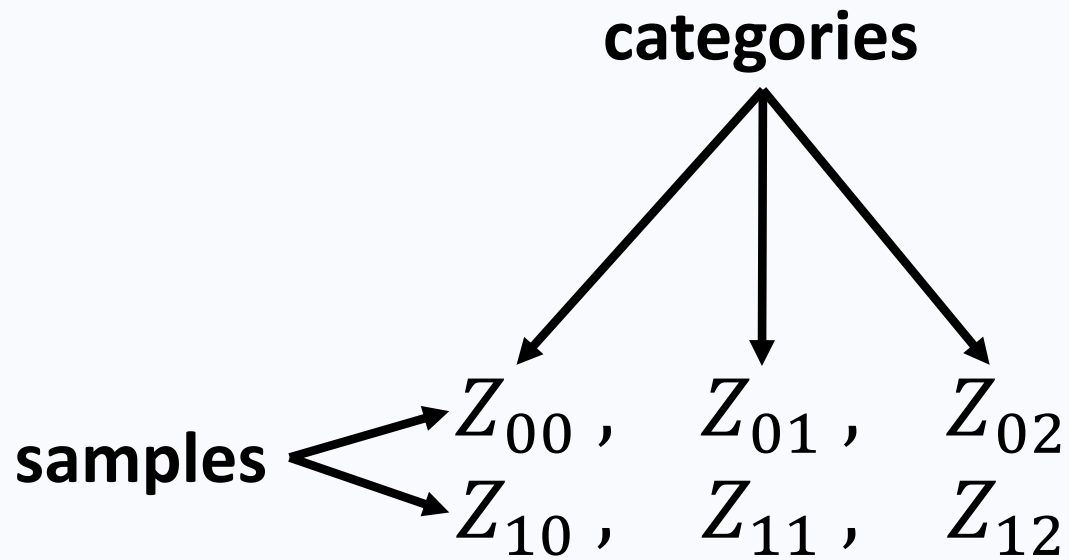
plt.subplot(1, 2, 2)
plt.hist(np.random.randn(20000), bins=50)
plt.title('np.random.randn')
plt.show()
```








```
np.exp(Z)/(np.exp(Z).sum(axis=1, keepdims=True))
np.exp(Z)/(np.exp(Z).sum(axis=1).reshape(Z.shape[0], 1))
```



L-layer neural network: reminder

$x \in \mathbb{R}^N, y \in \mathbb{R}^K$, neural network: $\mathbb{R}^N \rightarrow \mathbb{R}^K$

$$z^{[1]} = W^{[1]}x + b^{[1]}, \quad W: n^{[1]} \times N, \quad b: n^{[1]} \times 1$$
$$a^{[1]} = g(z^{[1]})$$

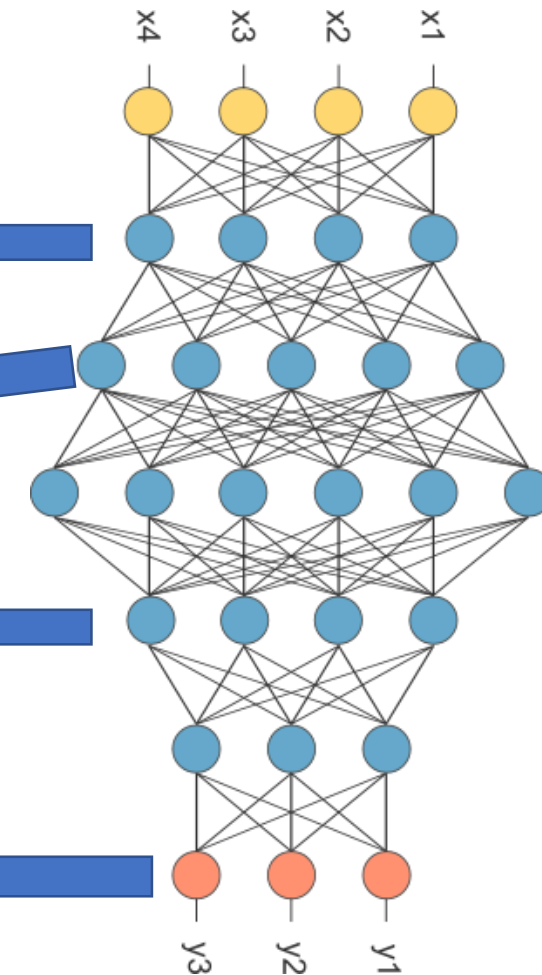
$$z^{[2]} = W^{[2]}a^{[1]} + b^{[2]}, \quad W: n^{[2]} \times n^{[1]}, \quad b: n^{[2]} \times 1$$
$$a^{[2]} = g(z^{[2]})$$

\vdots

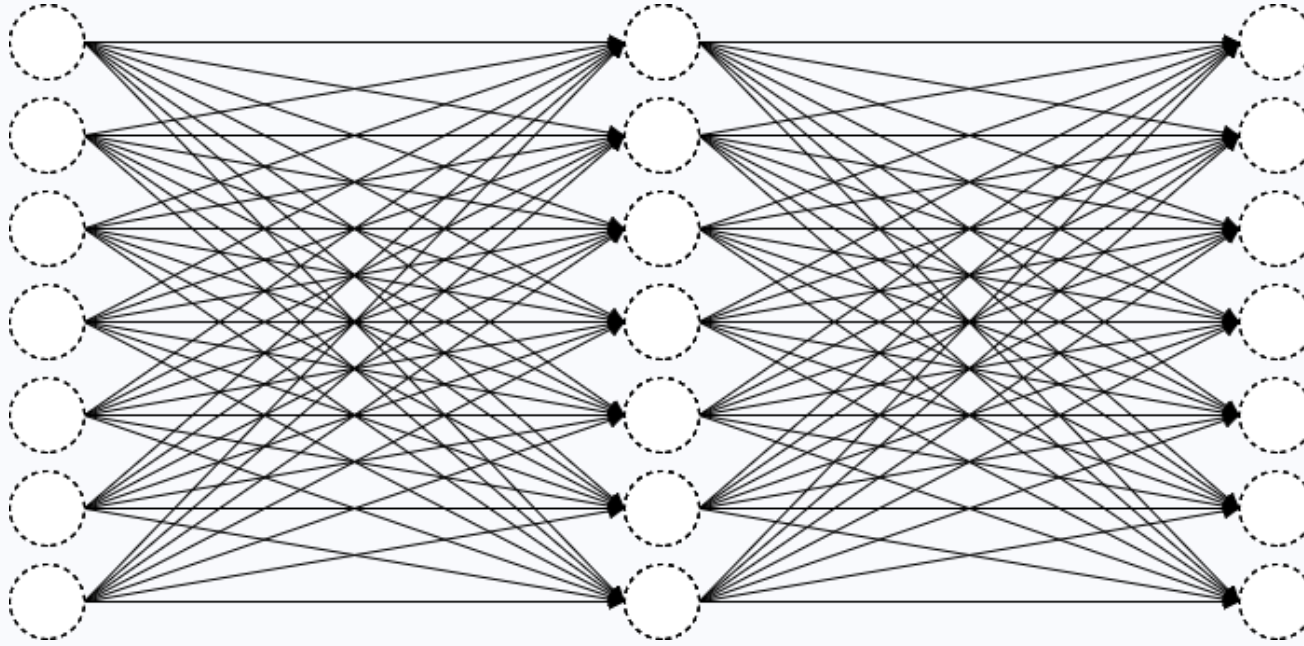
$$z^{[i]} = W^{[i]}a^{[i-1]} + b^{[i]}, \quad W: n^{[i]} \times n^{[i-1]}, \quad b: n^{[i]} \times 1$$
$$a^{[i]} = g(z^{[i]})$$

\vdots

$$z^{[L]} = W^{[L]}a^{[L-1]} + b^{[L]}, \quad W: n^{[L]} \times n^{[L-1]}, \quad b: n^{[L]} \times 1$$
$$y = a^{[L]} = \text{softmax}(z^{[L]})$$



Credit: [OpenNN](#)



- Exploding parameter number:
 - 200x200 pixel input \rightarrow 40000 input
 - $40000^2 + 40000 \approx 1.6 \cdot 10^9$ parameters per layer
 - float32: 4 byte/number \rightarrow 6.4 GB/layer
 - color images have 3 color channels (RGB) \rightarrow 57.6 GB/layer

Question: How do you recognize the content of this picture?



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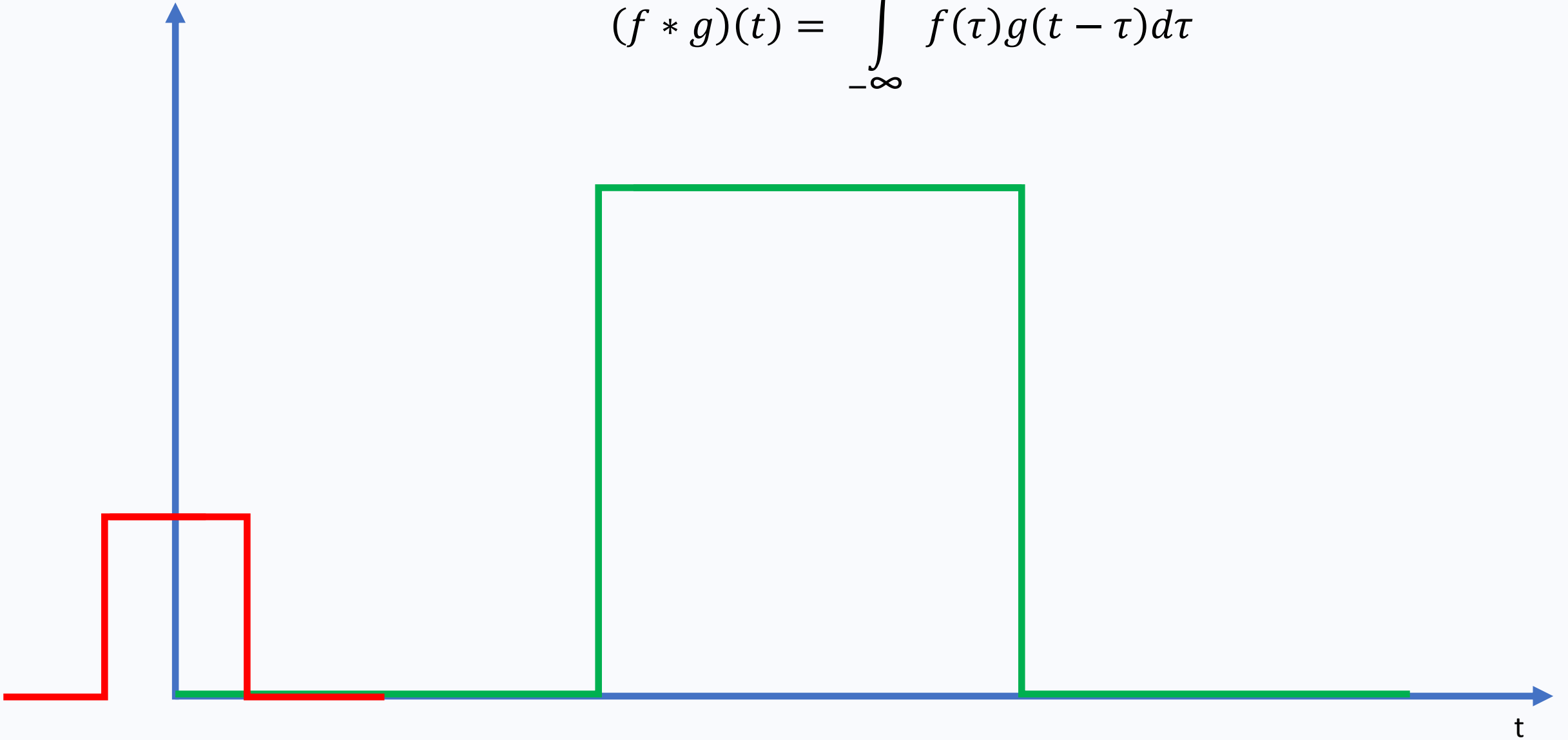
Feature locality (pixels are relevant only to their neighbours)

Question: How do you recognize the content of this picture?

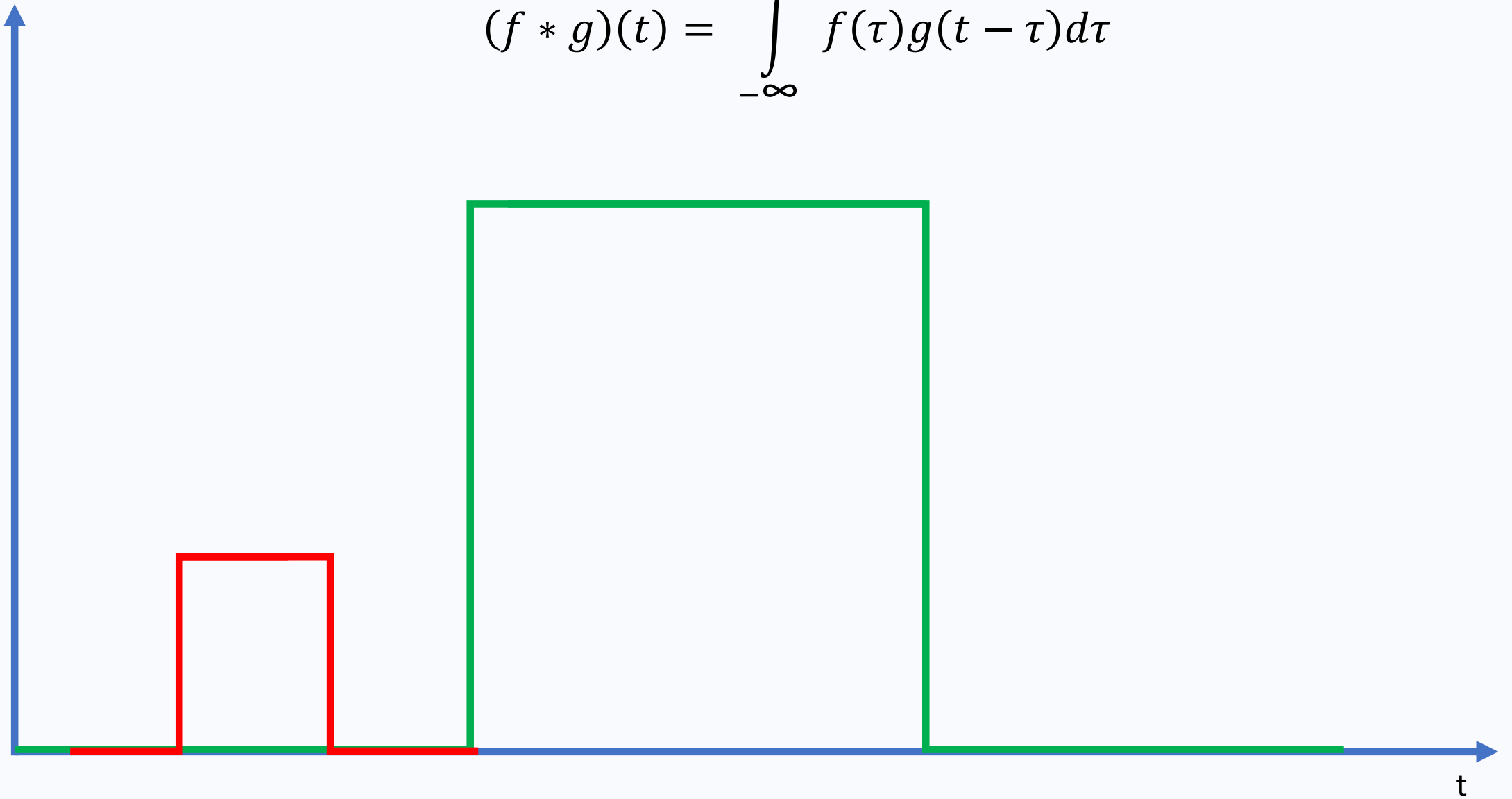


Feature locality (pixels are relevant only to their neighbours)
Goal: to have a „window detector” with a few parameters.

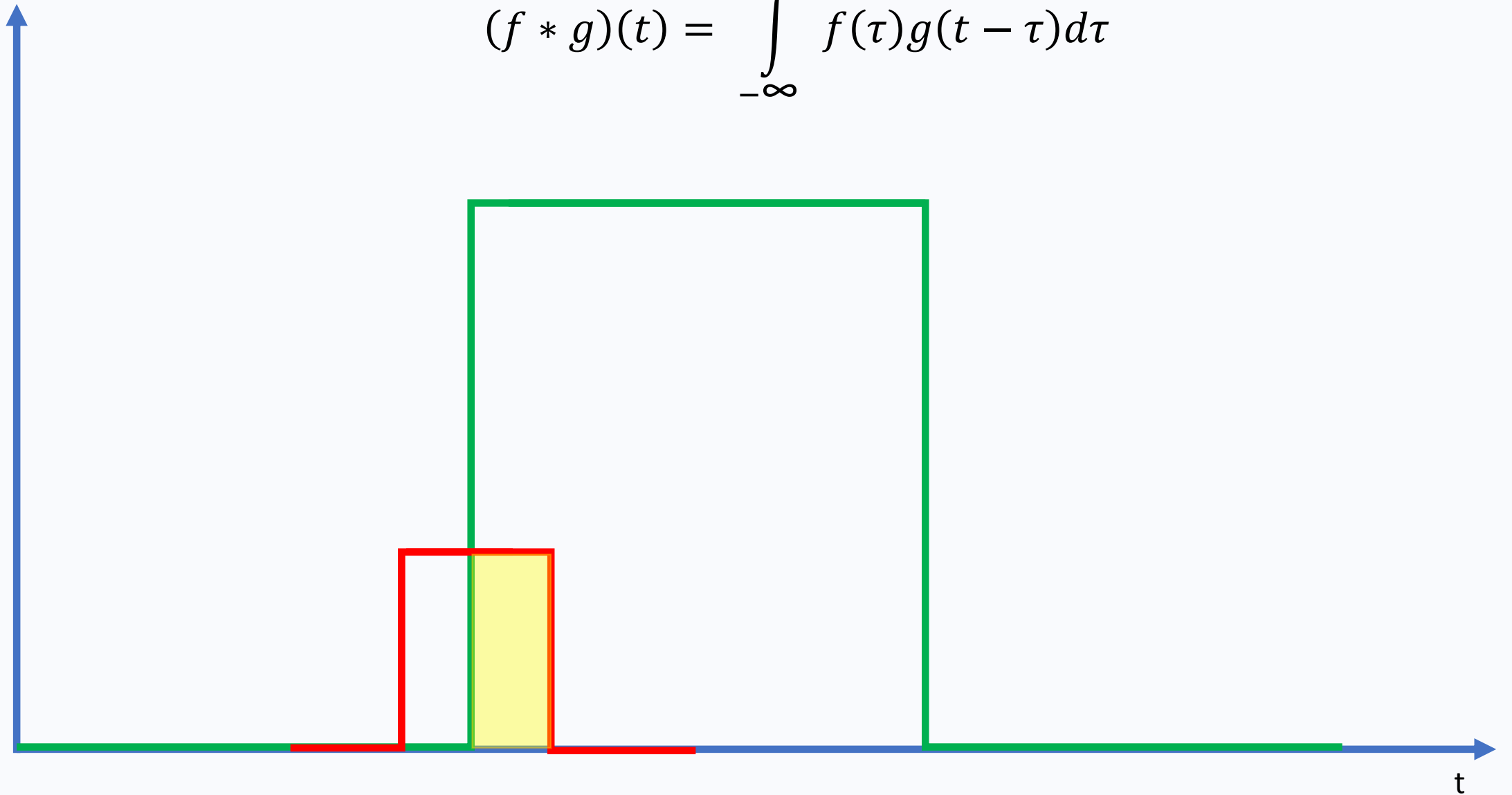
$$(f * g)(t) = \int_{-\infty}^{+\infty} f(\tau)g(t - \tau)d\tau$$



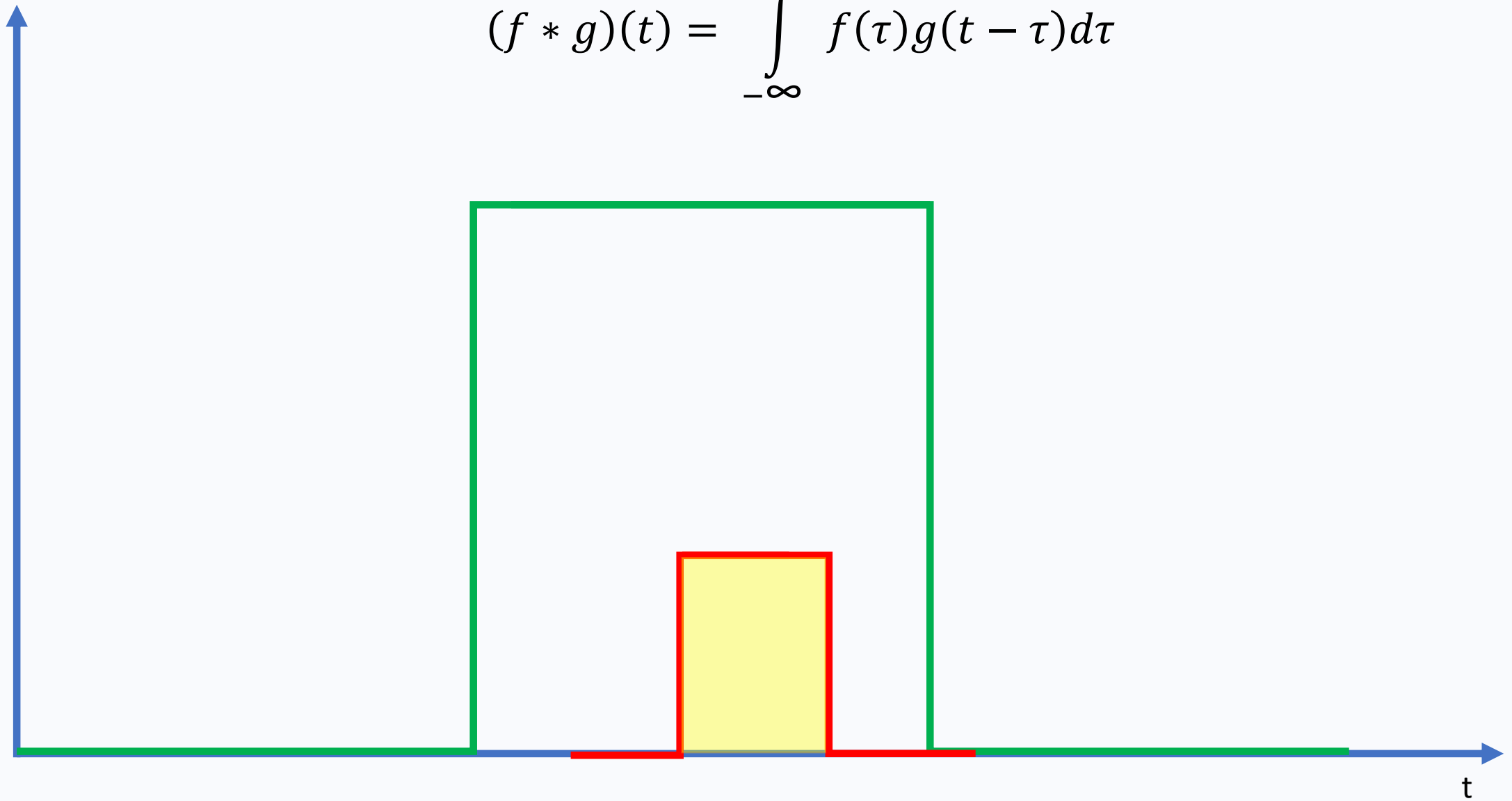
$$(f * g)(t) = \int_{-\infty}^{+\infty} f(\tau)g(t - \tau)d\tau$$



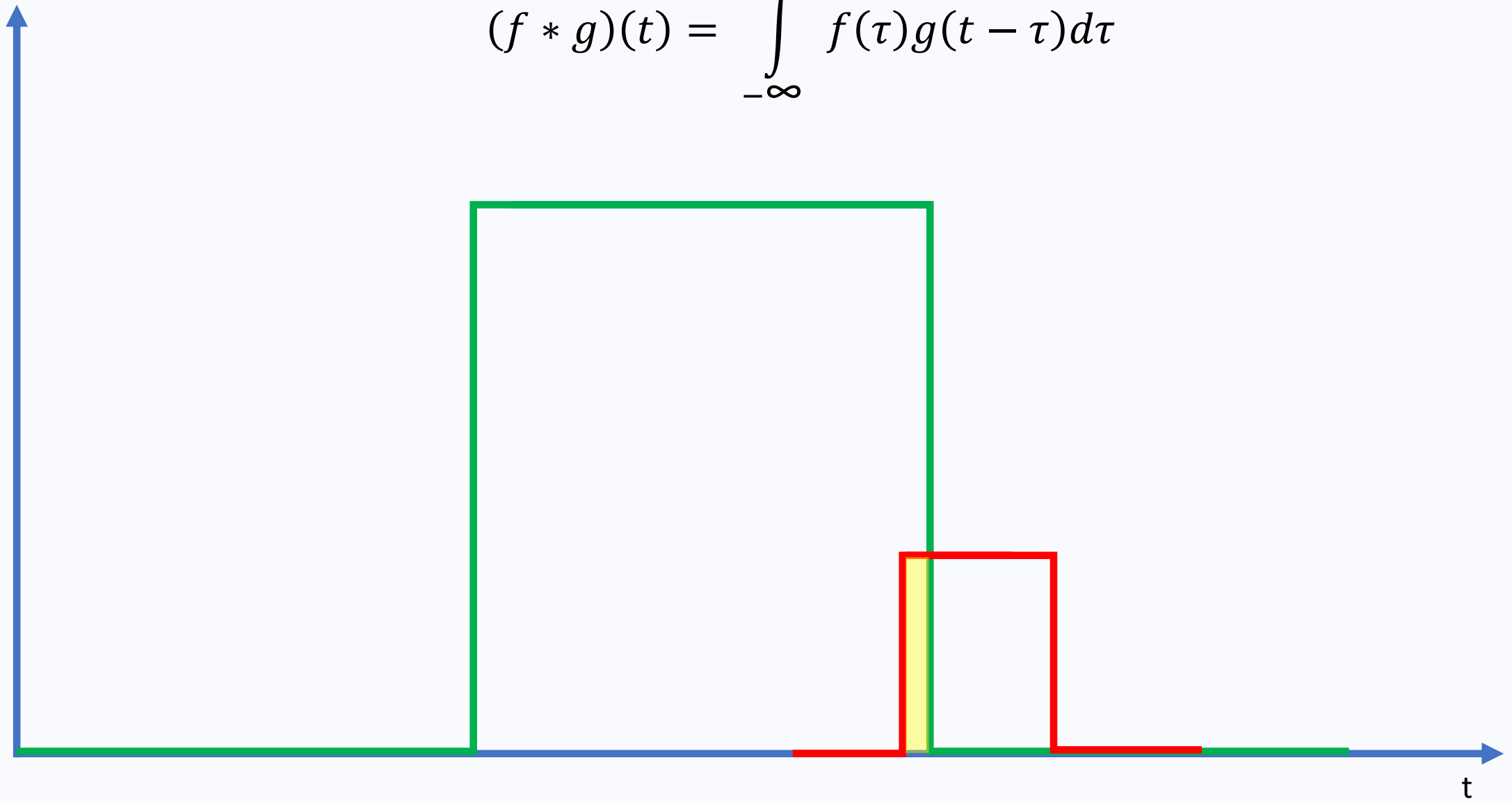
$$(f * g)(t) = \int_{-\infty}^{+\infty} f(\tau)g(t - \tau)d\tau$$



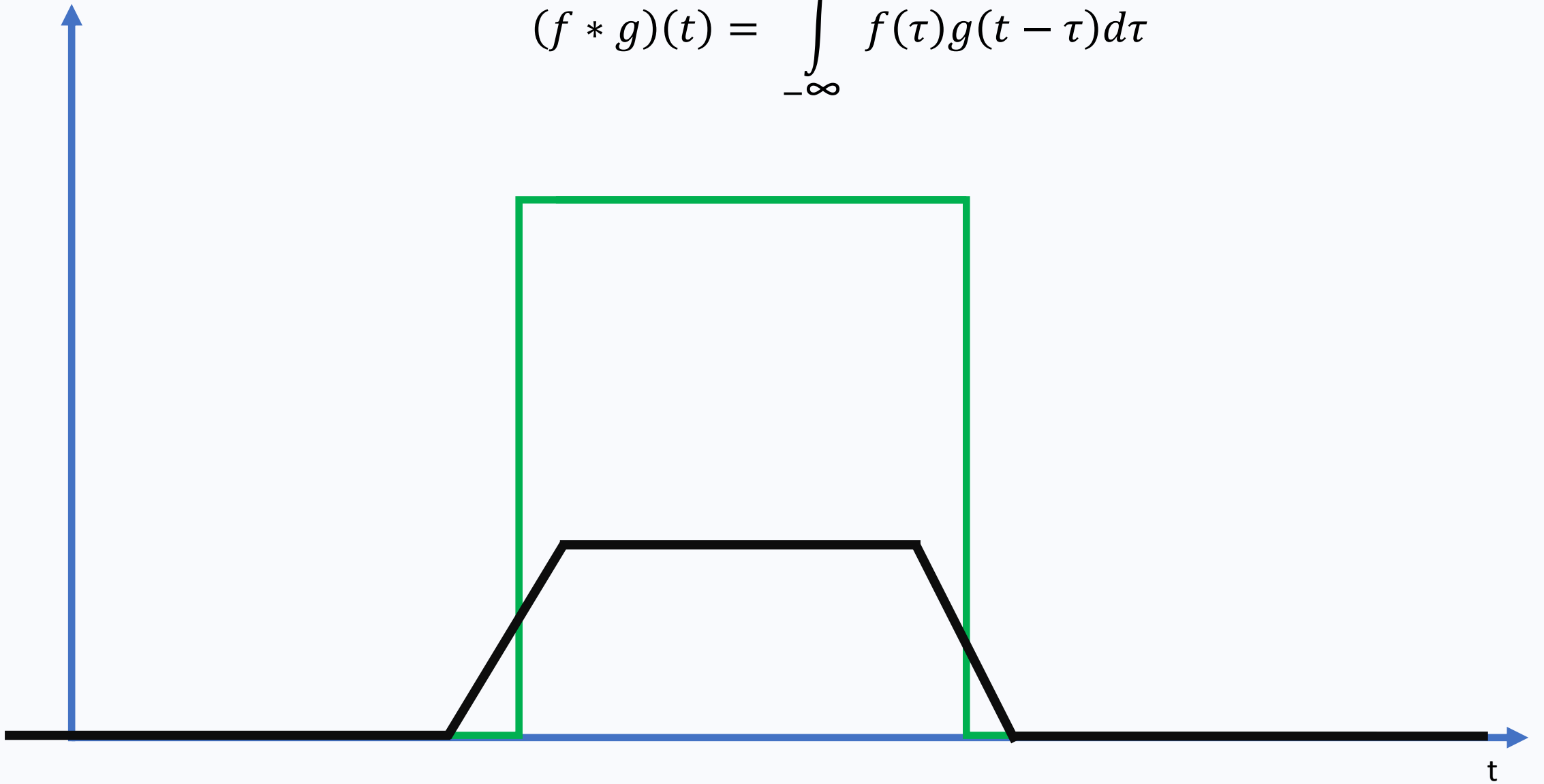
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filter

w_{00}	w_{01}	w_{02}
w_{10}	w_{11}	w_{12}
w_{20}	w_{21}	w_{22}

Image

a_{00}	a_{01}	a_{02}	a_{03}	a_{04}	a_{05}
a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}
a_{20}	a_{21}	a_{22}	a_{23}	a_{24}	a_{25}
a_{30}	a_{31}	a_{32}	a_{33}	a_{34}	a_{35}
a_{40}	a_{41}	a_{42}	a_{43}	a_{44}	a_{45}
a_{50}	a_{51}	a_{52}	a_{53}	a_{54}	a_{55}

filter

w_{00}	w_{01}	w_{02}
w_{10}	w_{11}	w_{12}
w_{20}	w_{21}	w_{22}

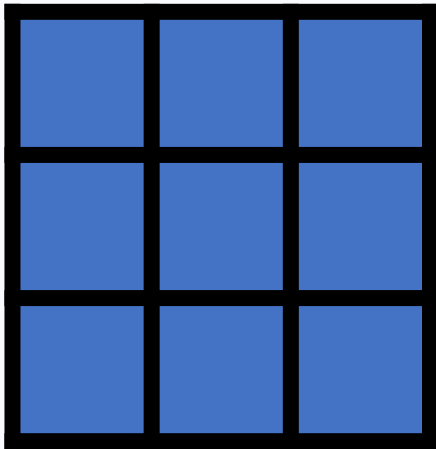
Image

a_{00}	a_{01}	a_{02}	a_{03}	a_{04}	a_{05}
a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}
a_{20}	a_{21}	a_{22}	a_{23}	a_{24}	a_{25}
a_{30}	a_{31}	a_{32}	a_{33}	a_{34}	a_{35}
a_{40}	a_{41}	a_{42}	a_{43}	a_{44}	a_{45}
a_{50}	a_{51}	a_{52}	a_{53}	a_{54}	a_{55}

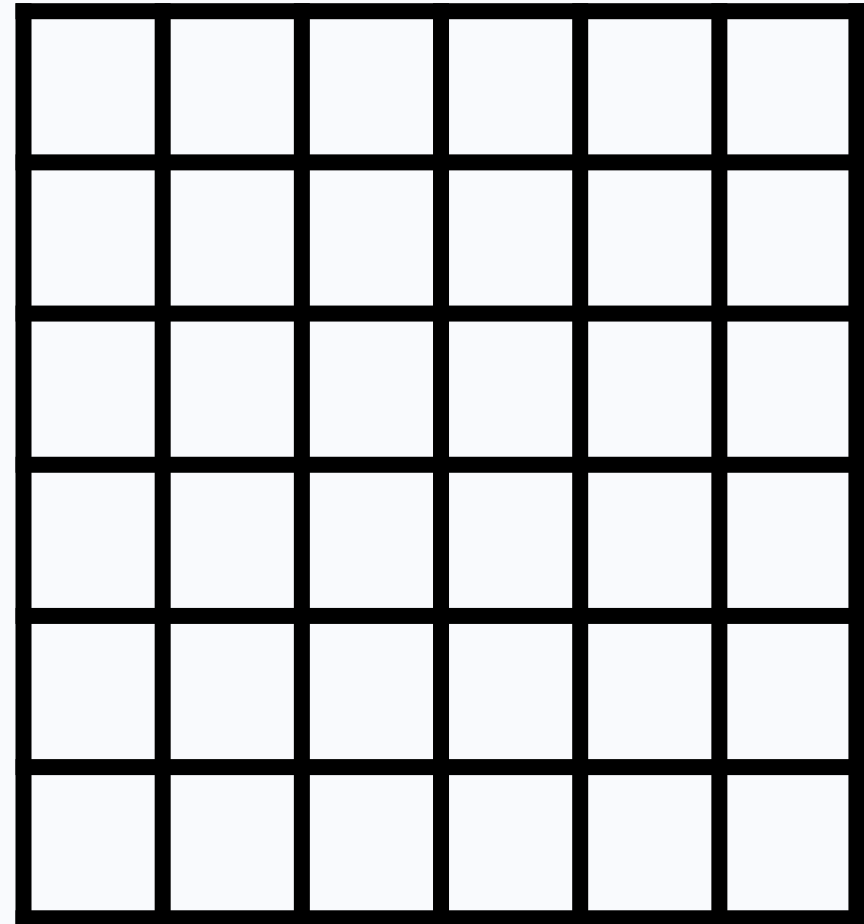
Note: Image-processing/math convolution is slightly different.
The kernel/filter is flipped around both axes before the multiplication.

$$a'_{11} = w_{00} \cdot a_{00} + w_{01} \cdot a_{01} + w_{02} \cdot a_{02} + w_{10} \cdot a_{10} + w_{11} \cdot a_{11} + \\ + w_{12} \cdot a_{12} + w_{20} \cdot a_{20} + w_{21} \cdot a_{21} + w_{22} \cdot a_{22}$$

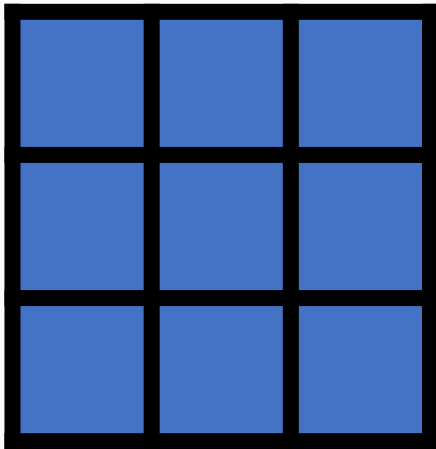
filter



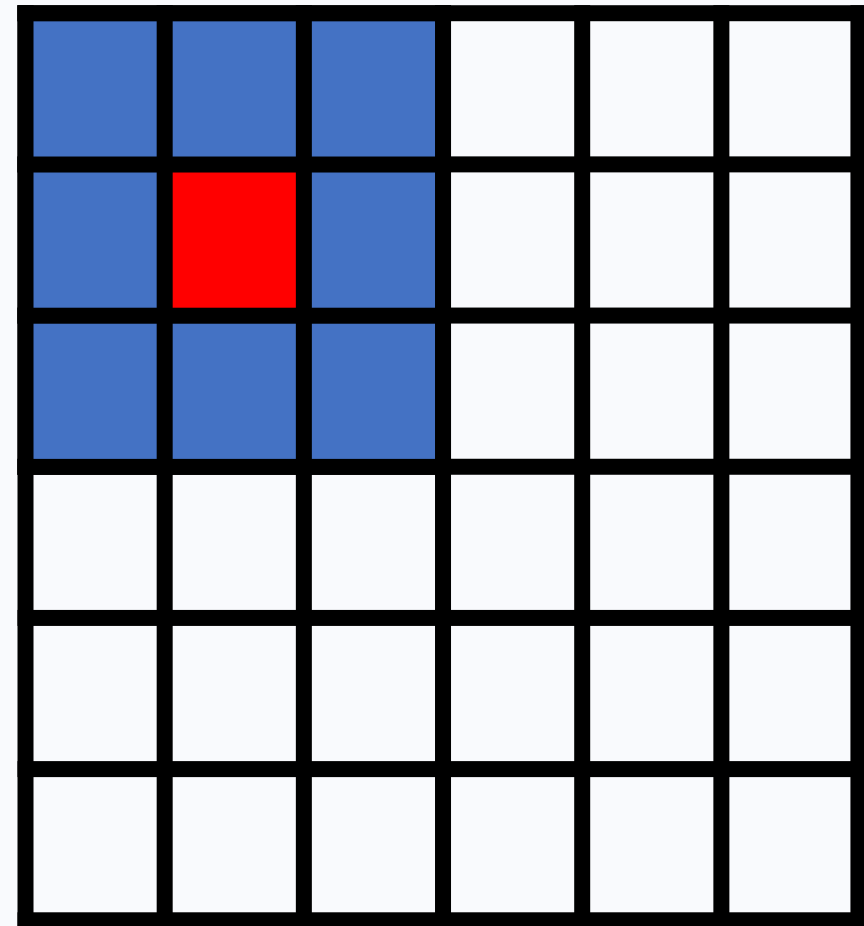
Image



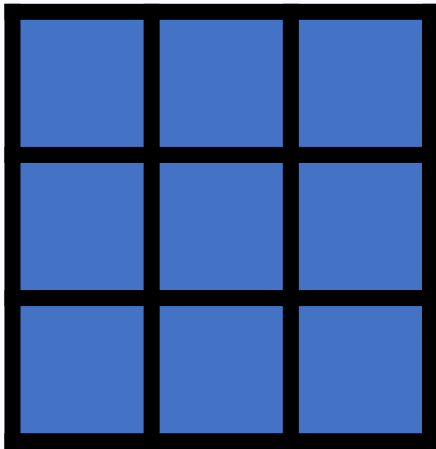
filter



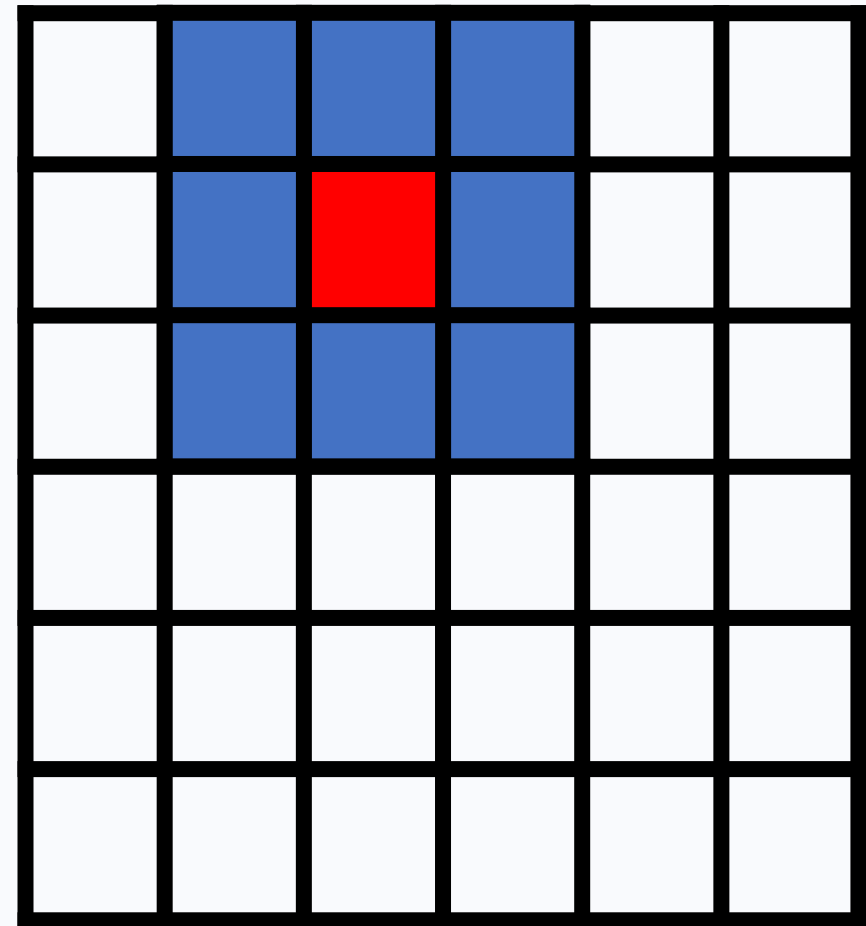
Image



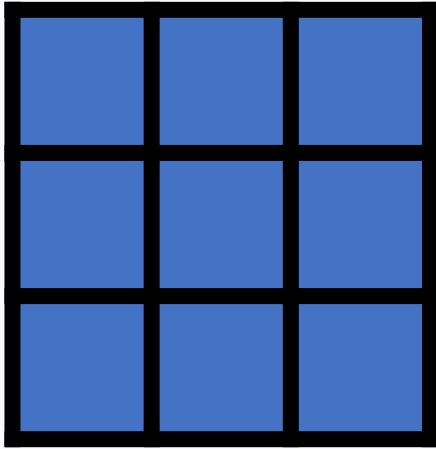
filter



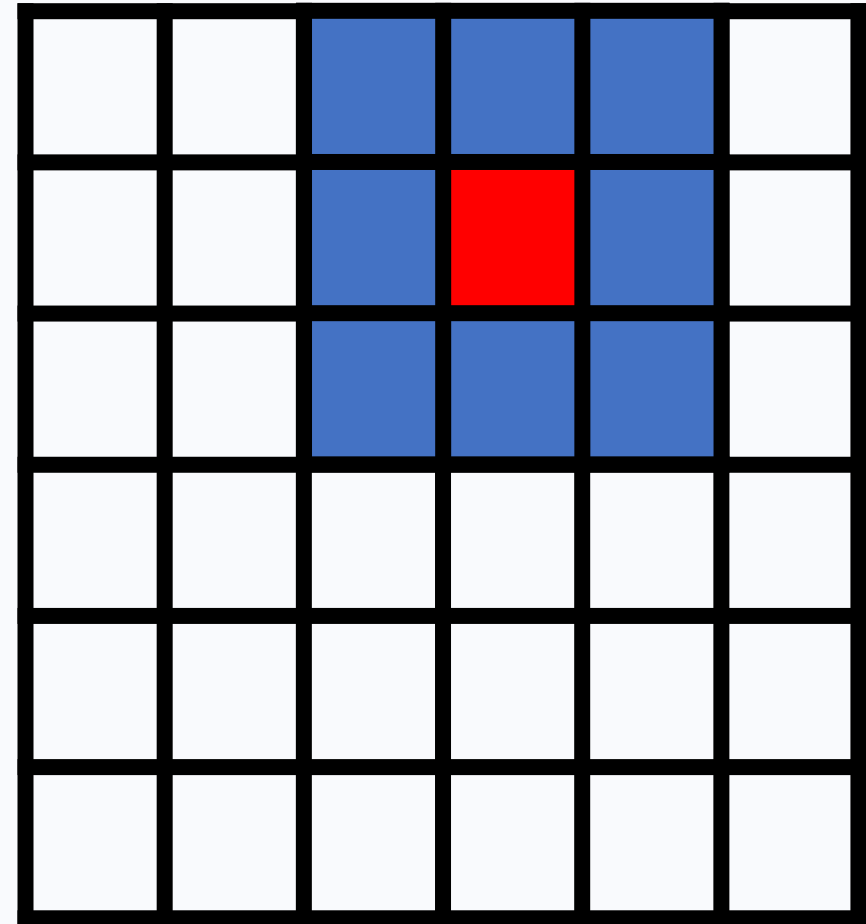
Image



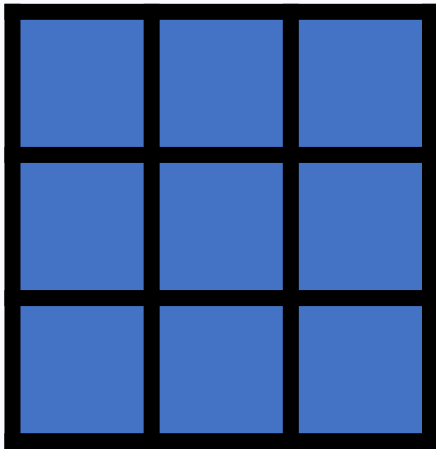
filter



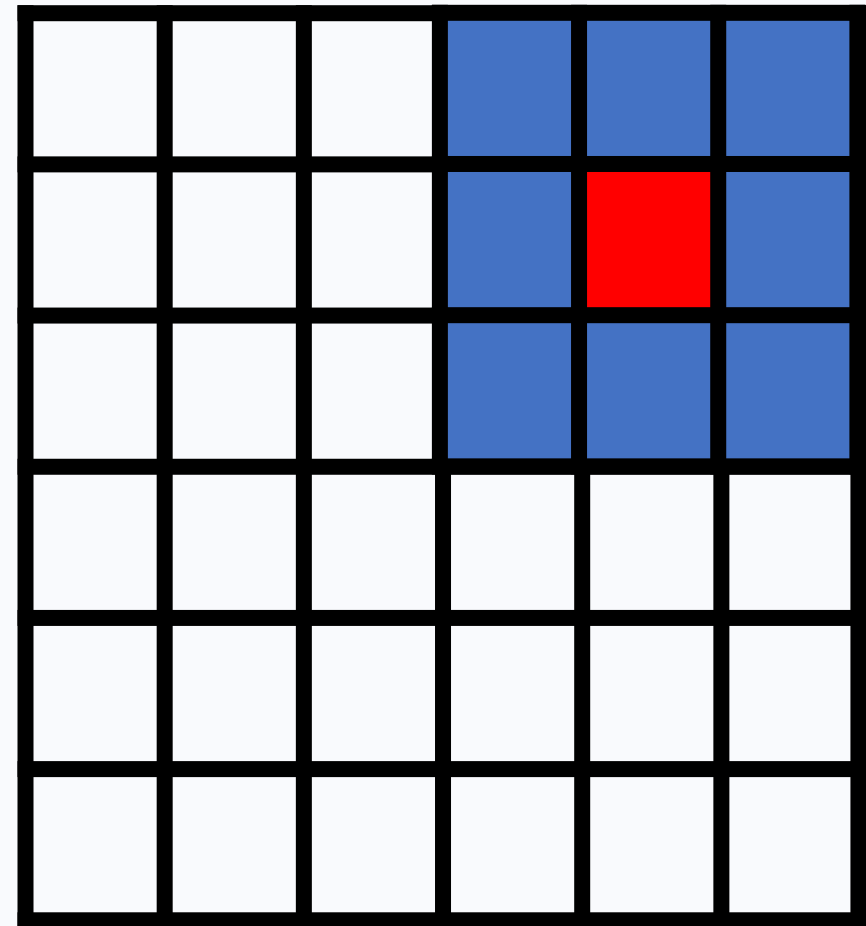
Image



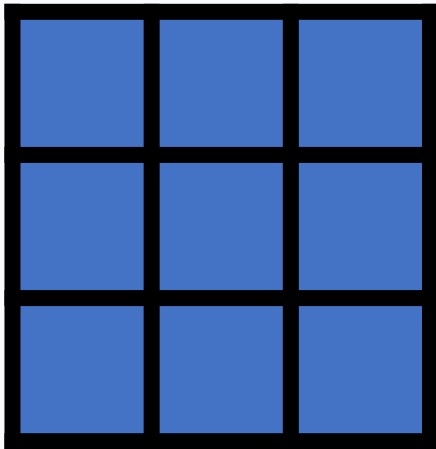
filter



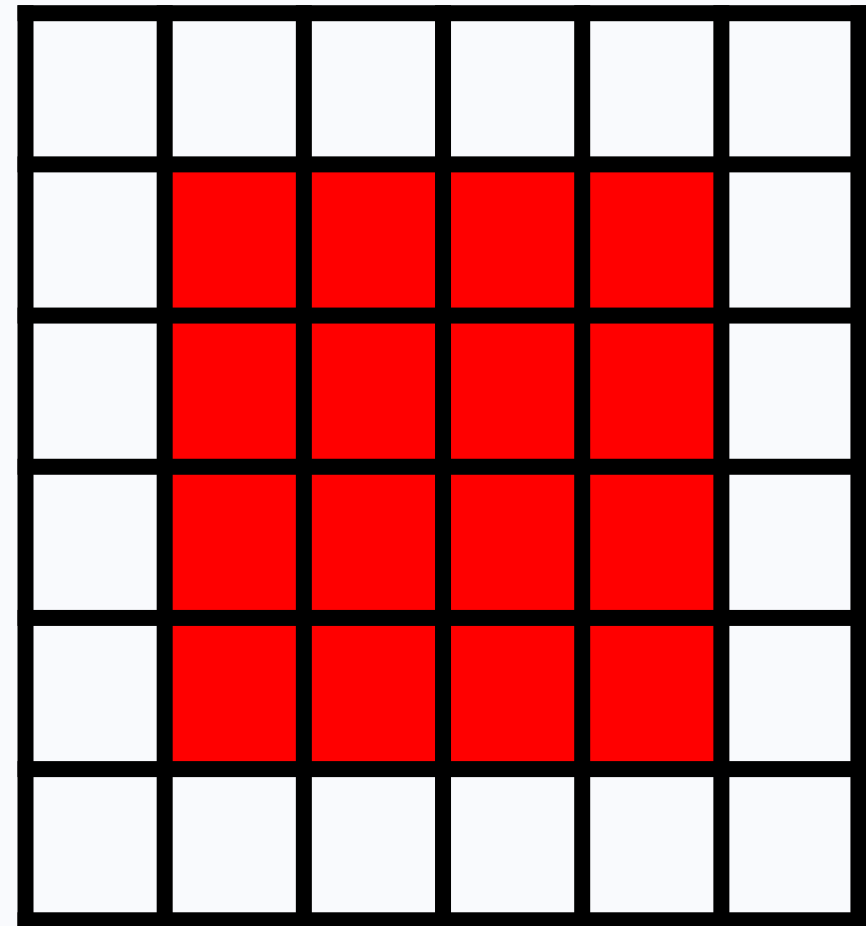
Image



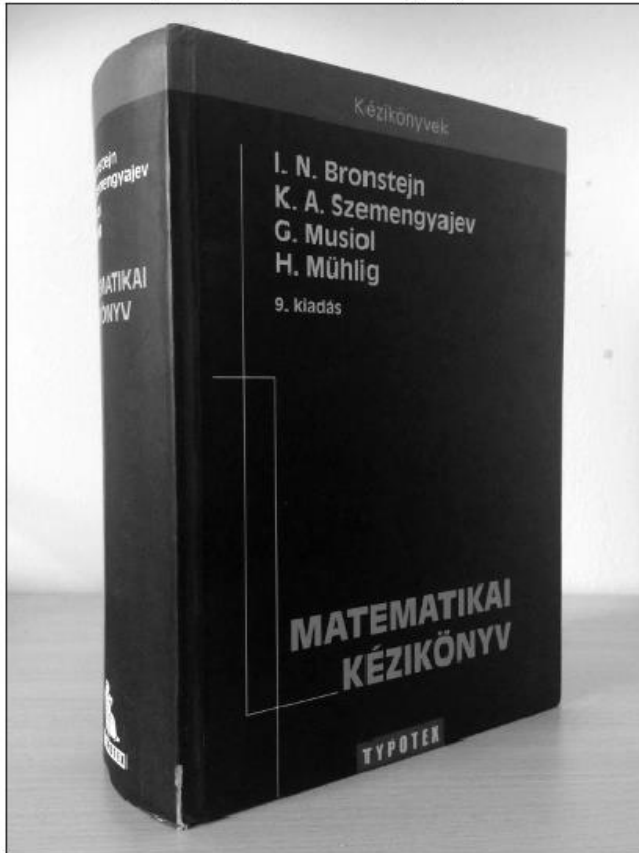
filter



Image



Original picture as grayscale



*

filter

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

Question: what do you expect?

Original picture as grayscale



*

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

=

Horizontal edges



Original picture as grayscale

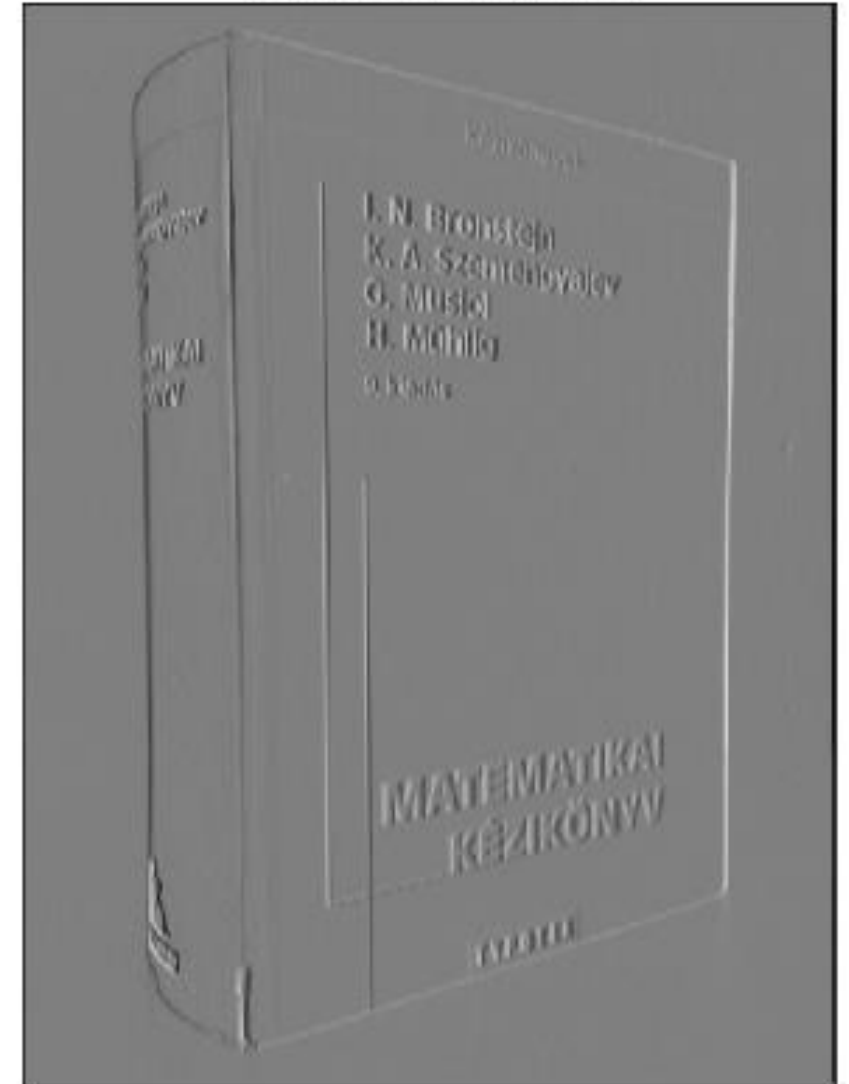


*

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

=

Vertical edges



Original picture as grayscale

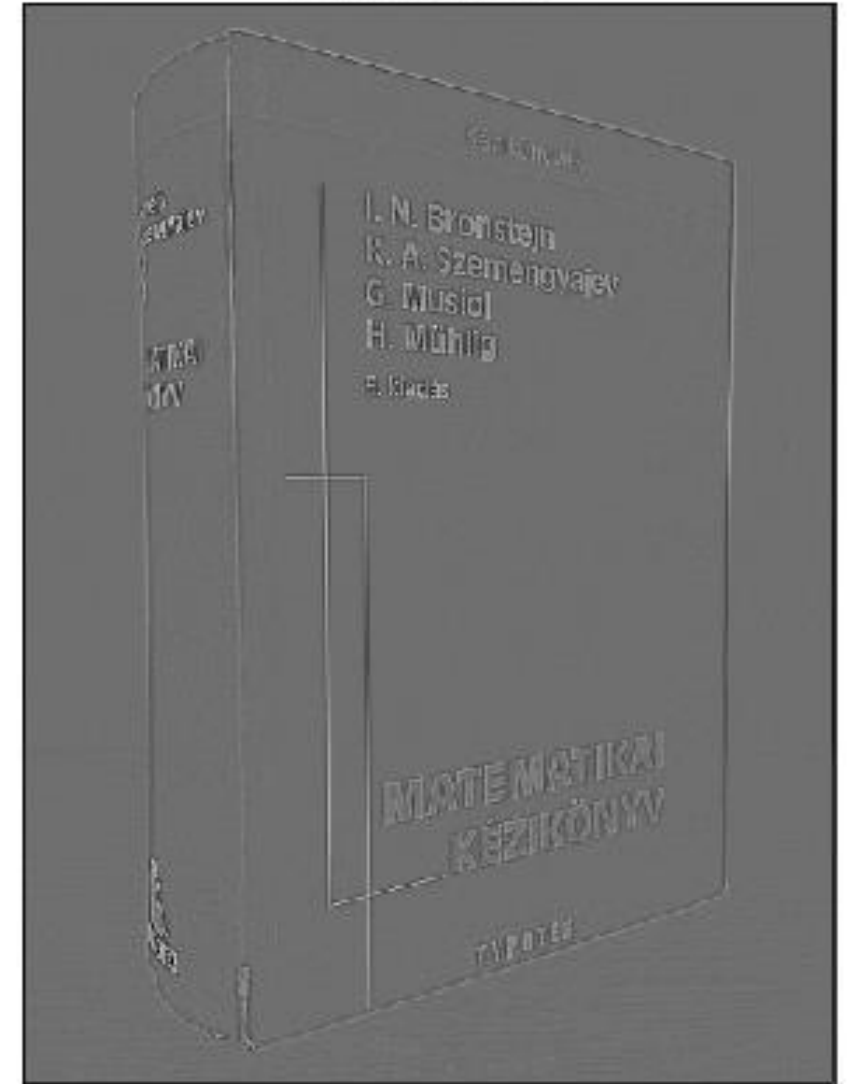


*

-1	-1	-1
-1	8	-1
-1	-1	-1

=

All edges



Original picture as grayscale

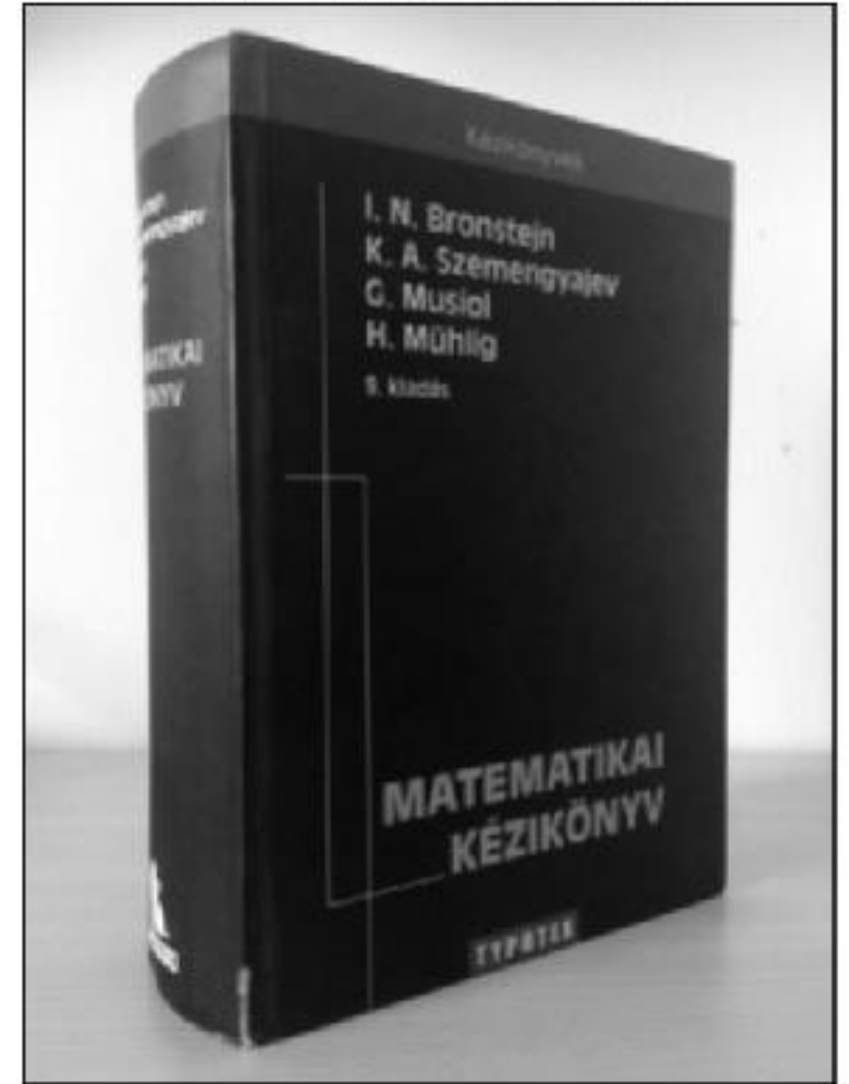


*

$1/9$	$1/9$	$1/9$
$1/9$	$1/9$	$1/9$
$1/9$	$1/9$	$1/9$

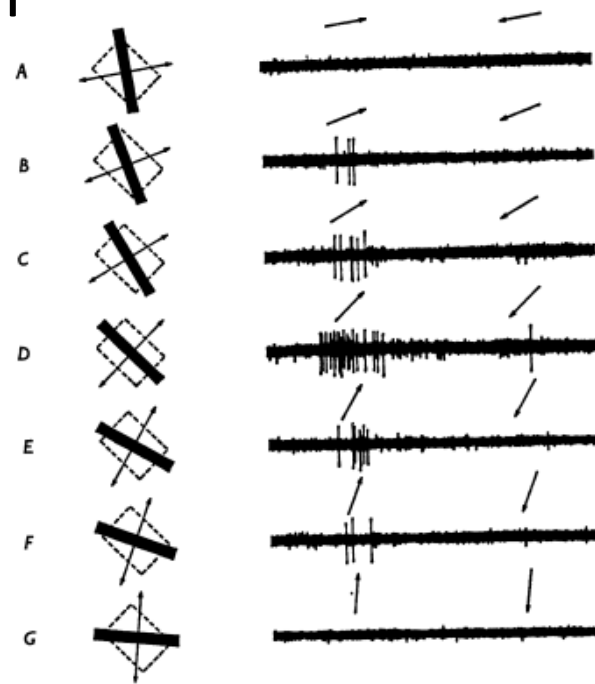
=

Smoothed picture

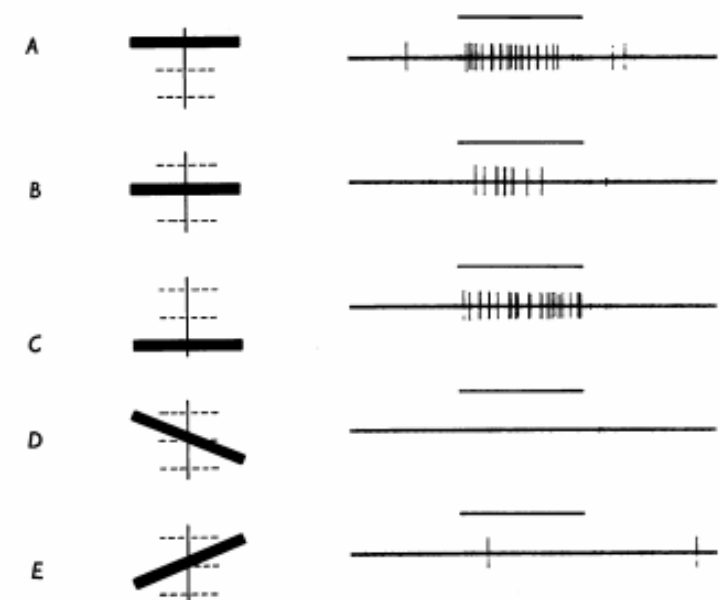


Neuroscientific experiments

- Hubel, Wiesel, Sperry
- cat's & monkey's vision
- Electrodes to the brain
- 1981 Nobel prize



Text-fig. 2. Responses of a complex cell in right striate cortex (layer IV A) to various orientations of a moving black bar. Receptive field in the left eye indicated by the interrupted rectangles; it was approximately $\frac{1}{2} \times \frac{1}{2}^\circ$ in size, and was situated 4° below and to the left of the point of fixation. Ocular-dominance group 4. Duration of each record, 2 sec. Background intensity $1.3 \log_{10} \text{ cd/m}^2$, dark bars $0.0 \log_{10} \text{ cd/m}^2$



Text-fig. 7. Cell activated only by left (contralateral) eye over a field approximately $5 \times 5^\circ$, situated 10° above and to the left of the area centralis. The cell responded best to a black horizontal rectangle, $\frac{1}{2} \times 6^\circ$, placed anywhere in the receptive field (A-C). Tilting the stimulus rendered it ineffective (D-E). The black bar was introduced against a light background during periods of 1 sec, indicated by the upper line in each record. Luminance of white background, $1.0 \log_{10} \text{ cd/m}^2$; luminance of black part, $0.0 \log_{10} \text{ cd/m}^2$. A lesion, made while recording from the cell, was found in layer 2 of apical segment of post-lateral gyrus.

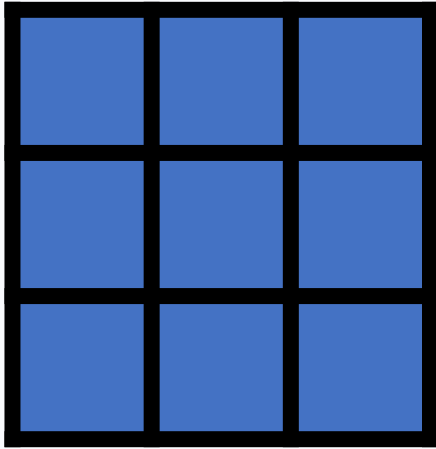
[Hubel, Wiesel: Receptive fields, binocular interaction and functional architecture in the cat's visual cortex, 1961]

[Hubel, Wiesel: Receptive fields and functional architecture of monkey striate cortex, 1968]

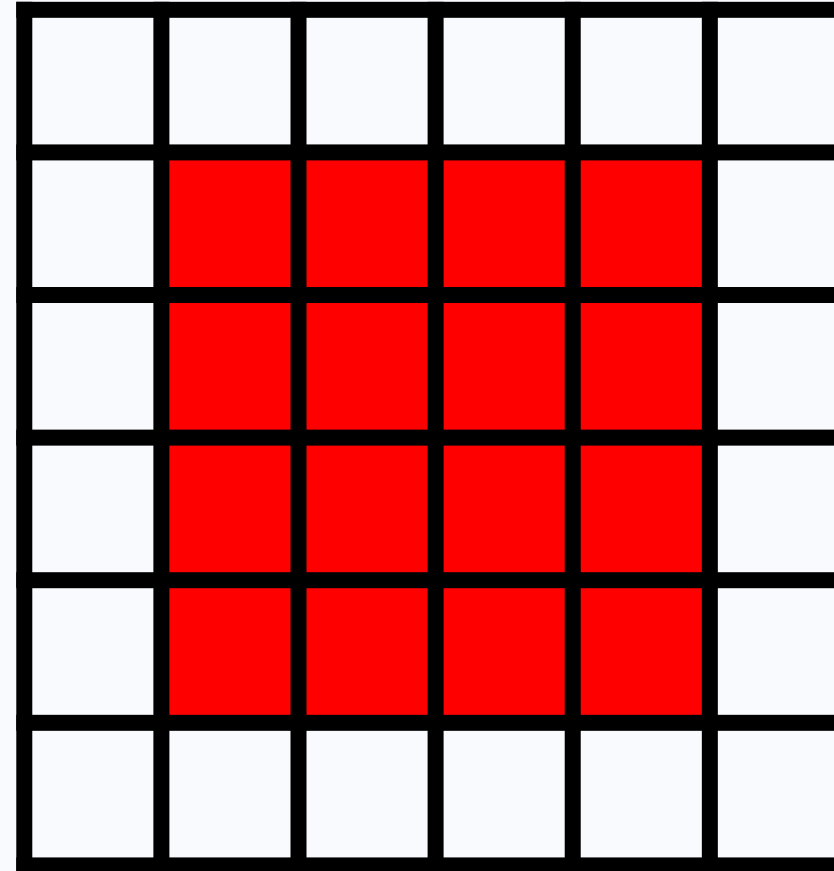
Demo convoluton notebook

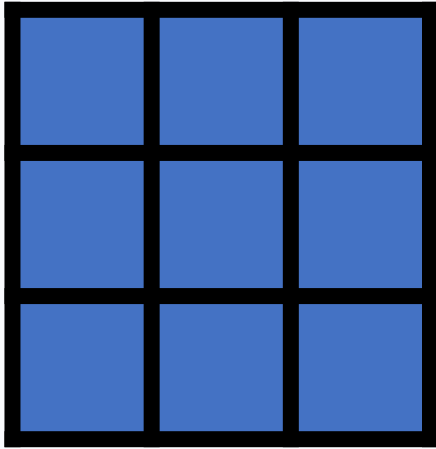
https://github.com/qati/DeepLearningCourse/tree/master/demo_notebooks/lecture_05

filter



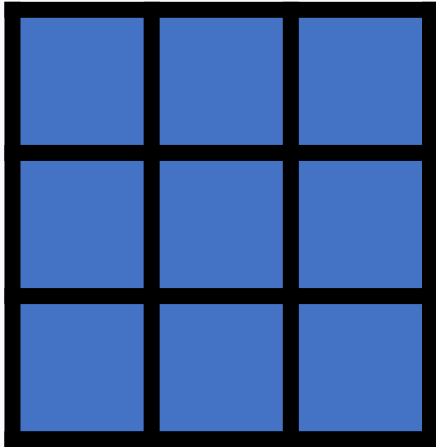
Image



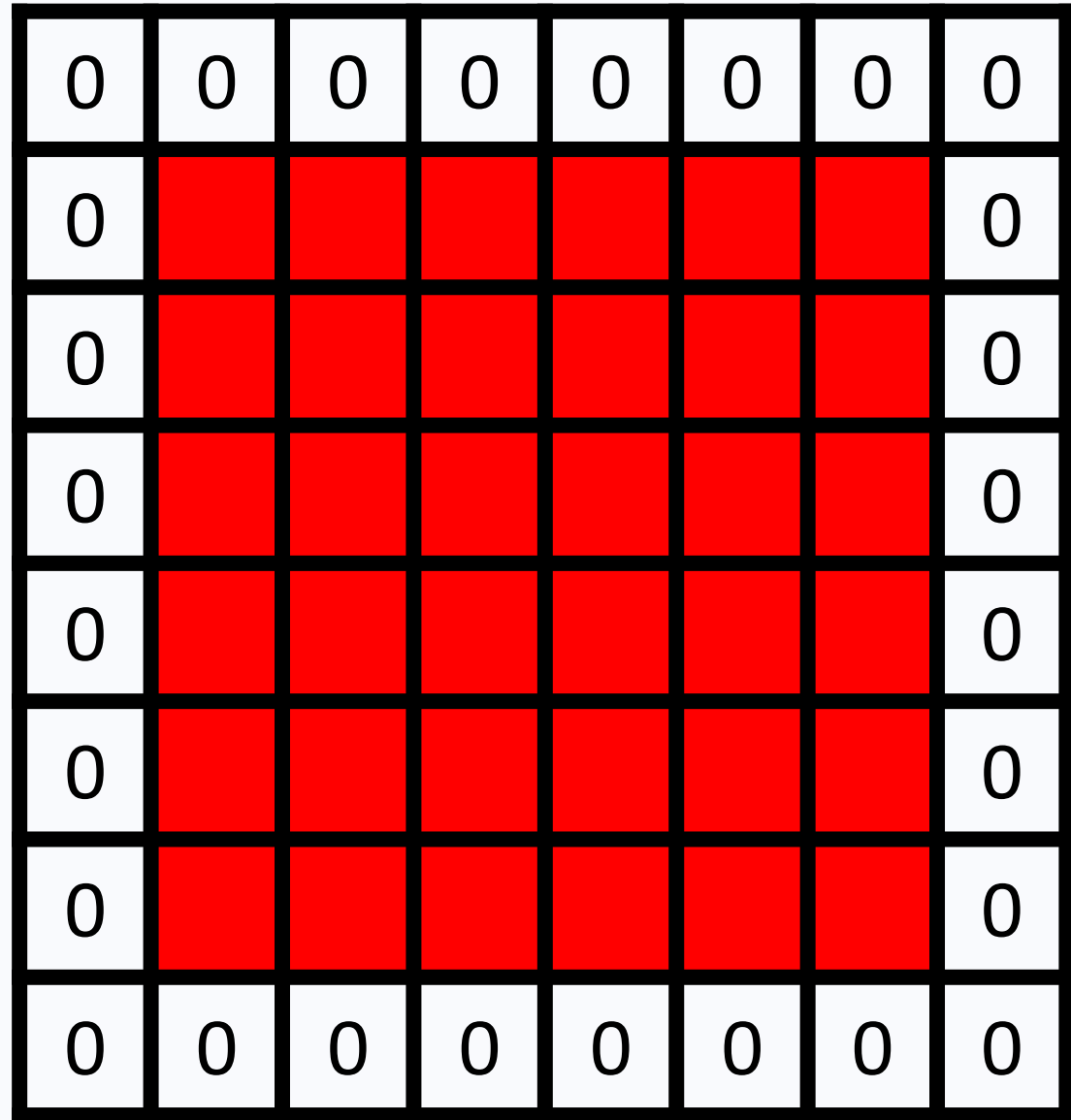
filter**Image**

0	0	0	0	0	0	0	0
0							0
0							0
0							0
0							0
0							0
0							0
0	0	0	0	0	0	0	0

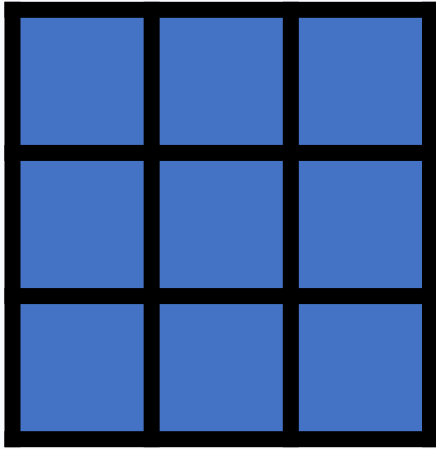
filter



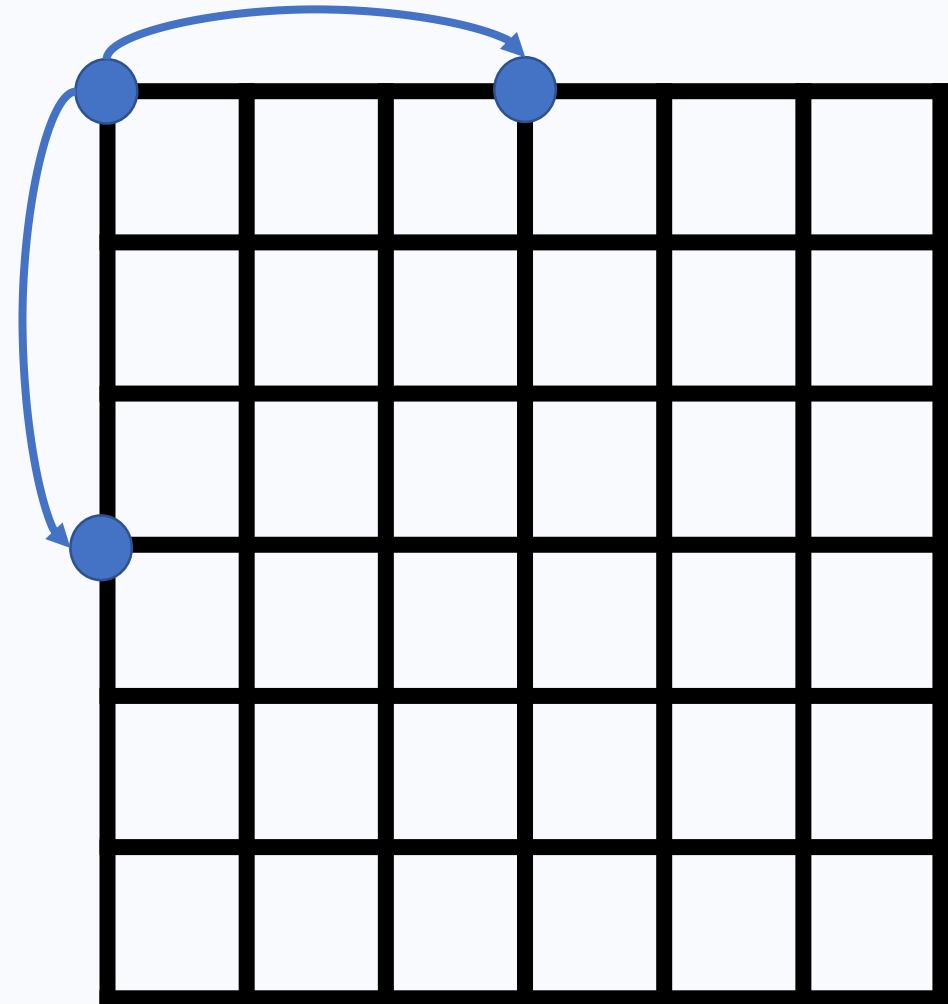
Image



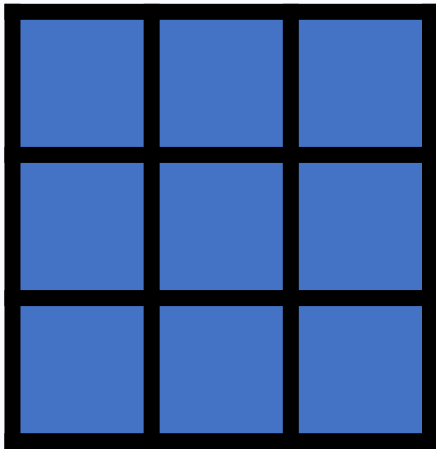
filter



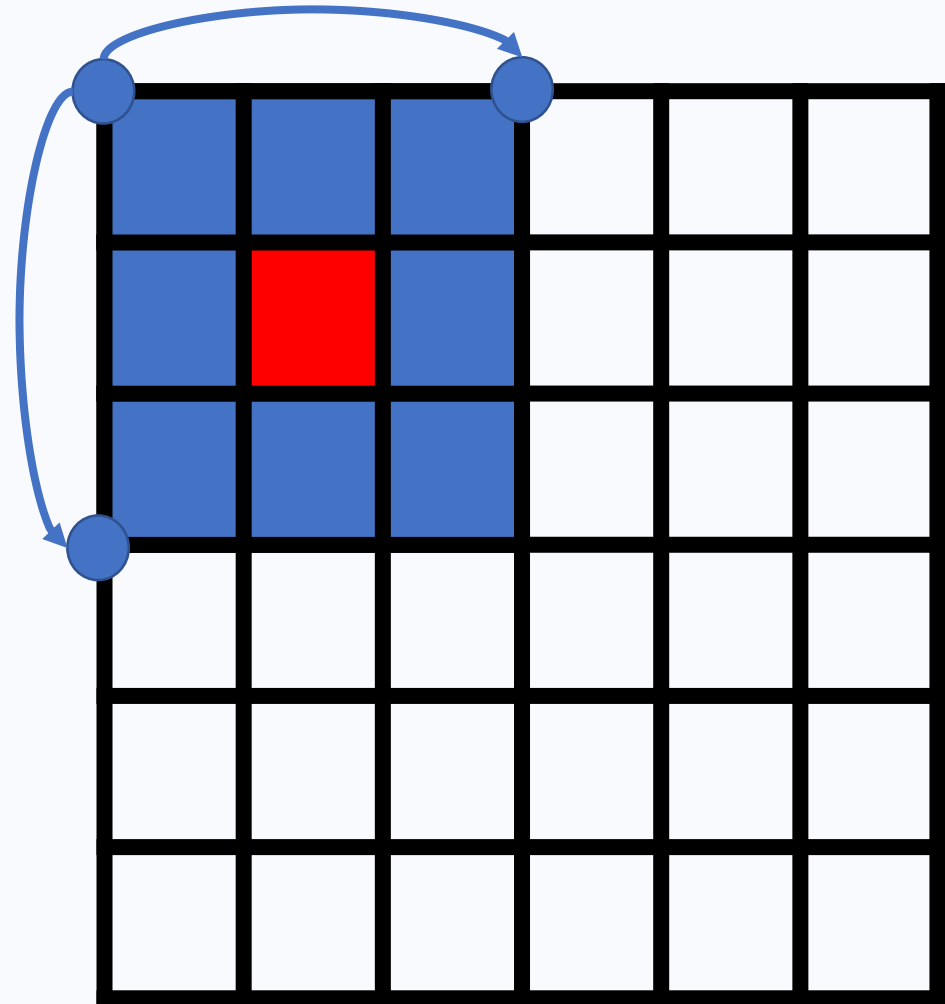
Image

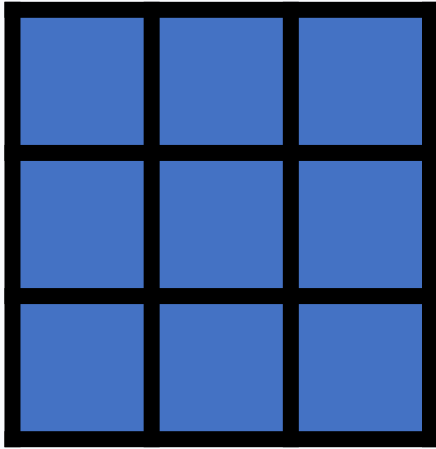
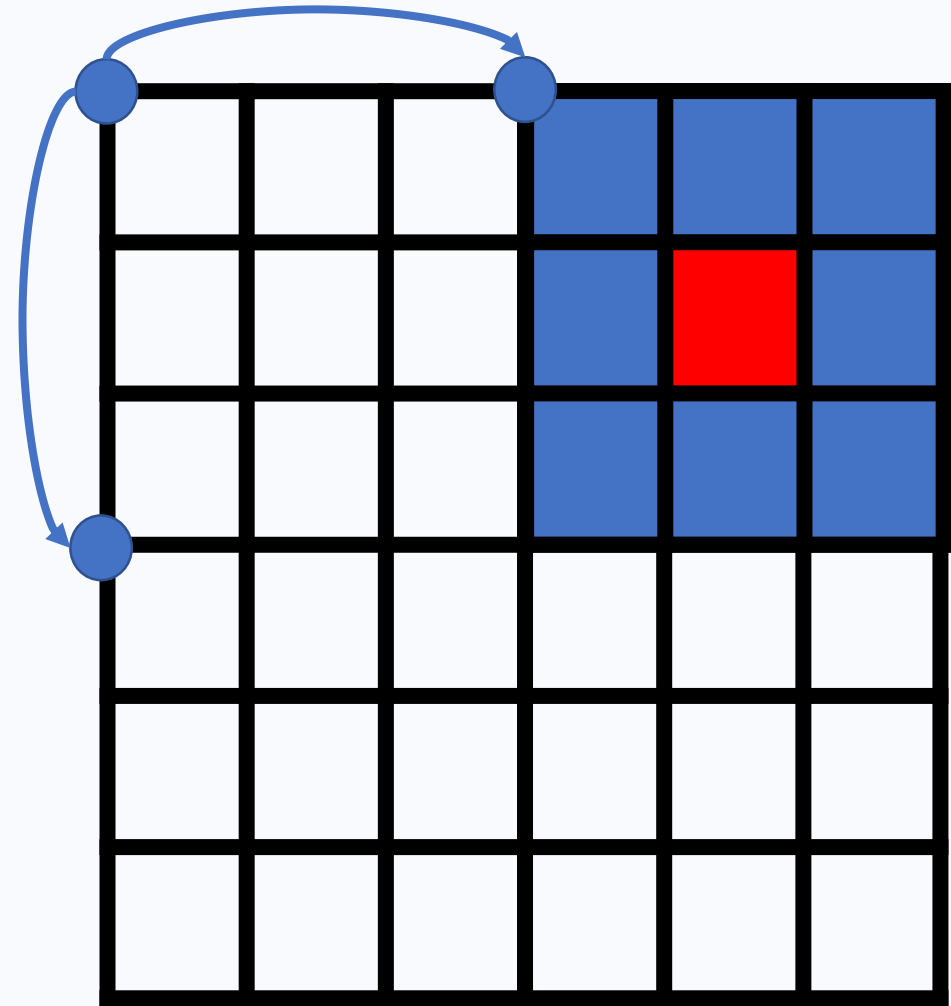


filter

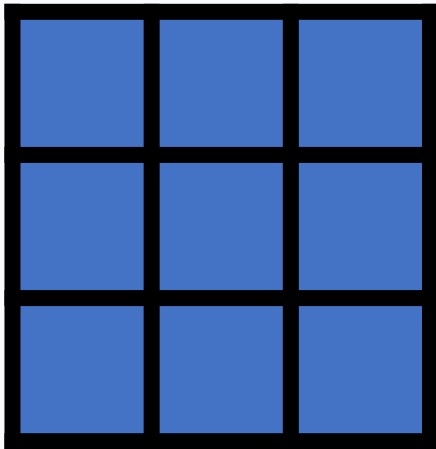


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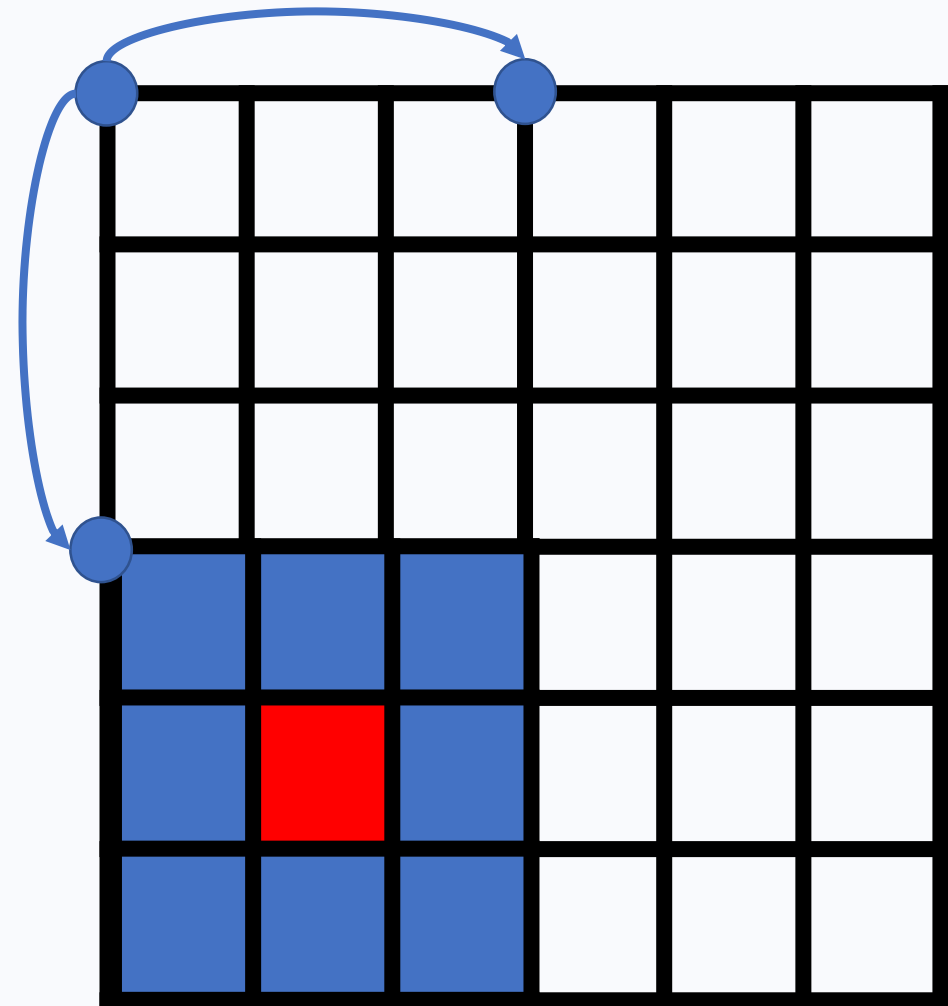


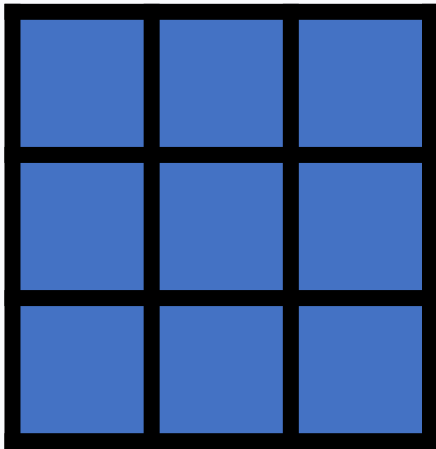
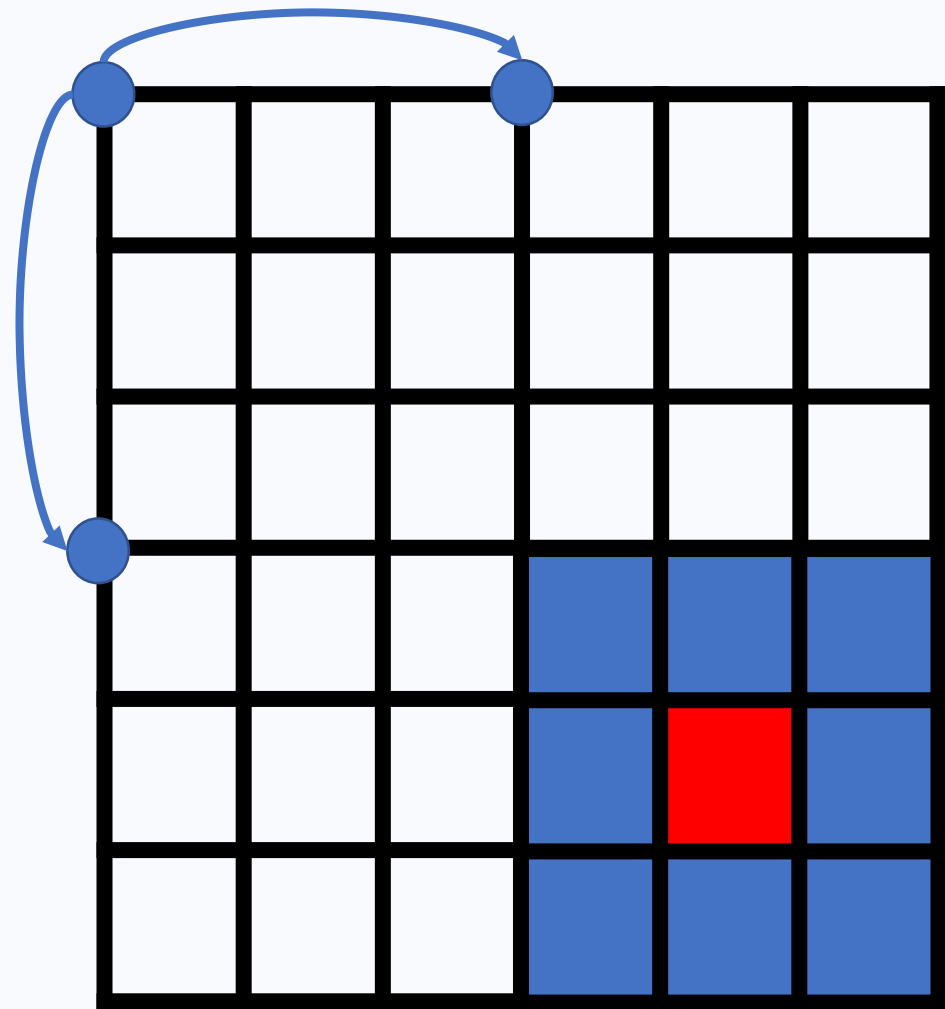
filter**Image**

filter

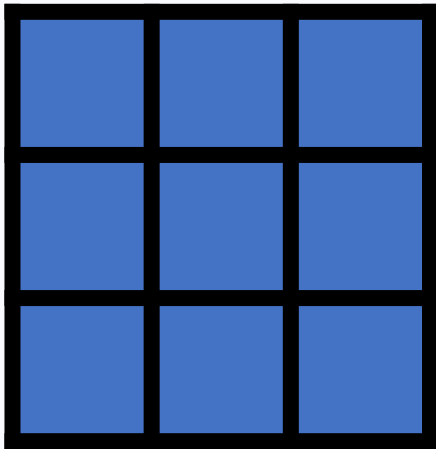


Image

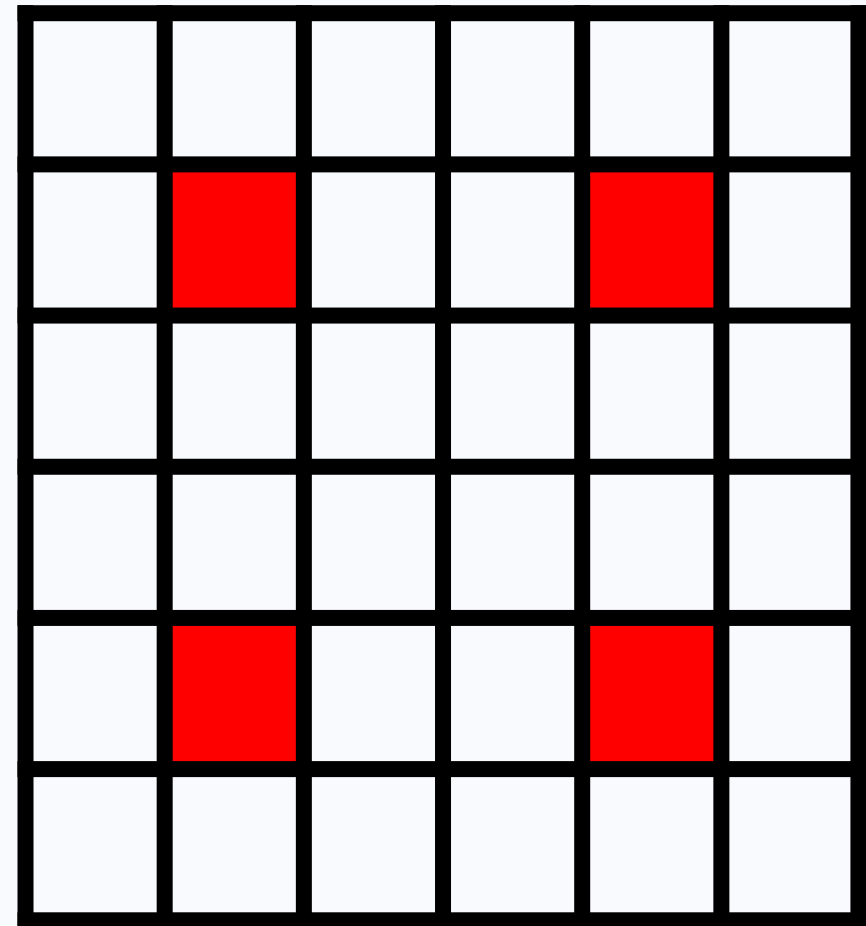


filter**Image**

filter



Image



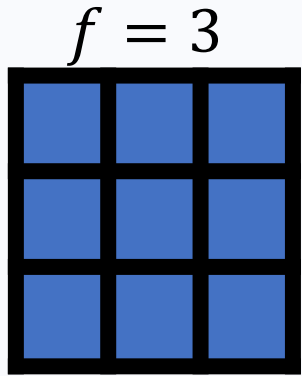
stride: s

padding: p

filter: $f \times f$

image: $n \times n$

result



stride: s

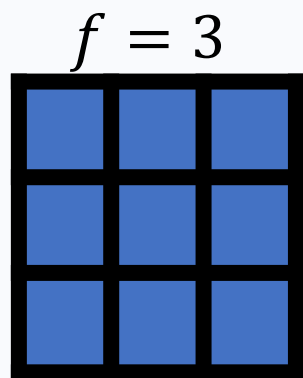
padding: p

filter: $f \times f$

image: $n \times n$

result

Notations for convolutions



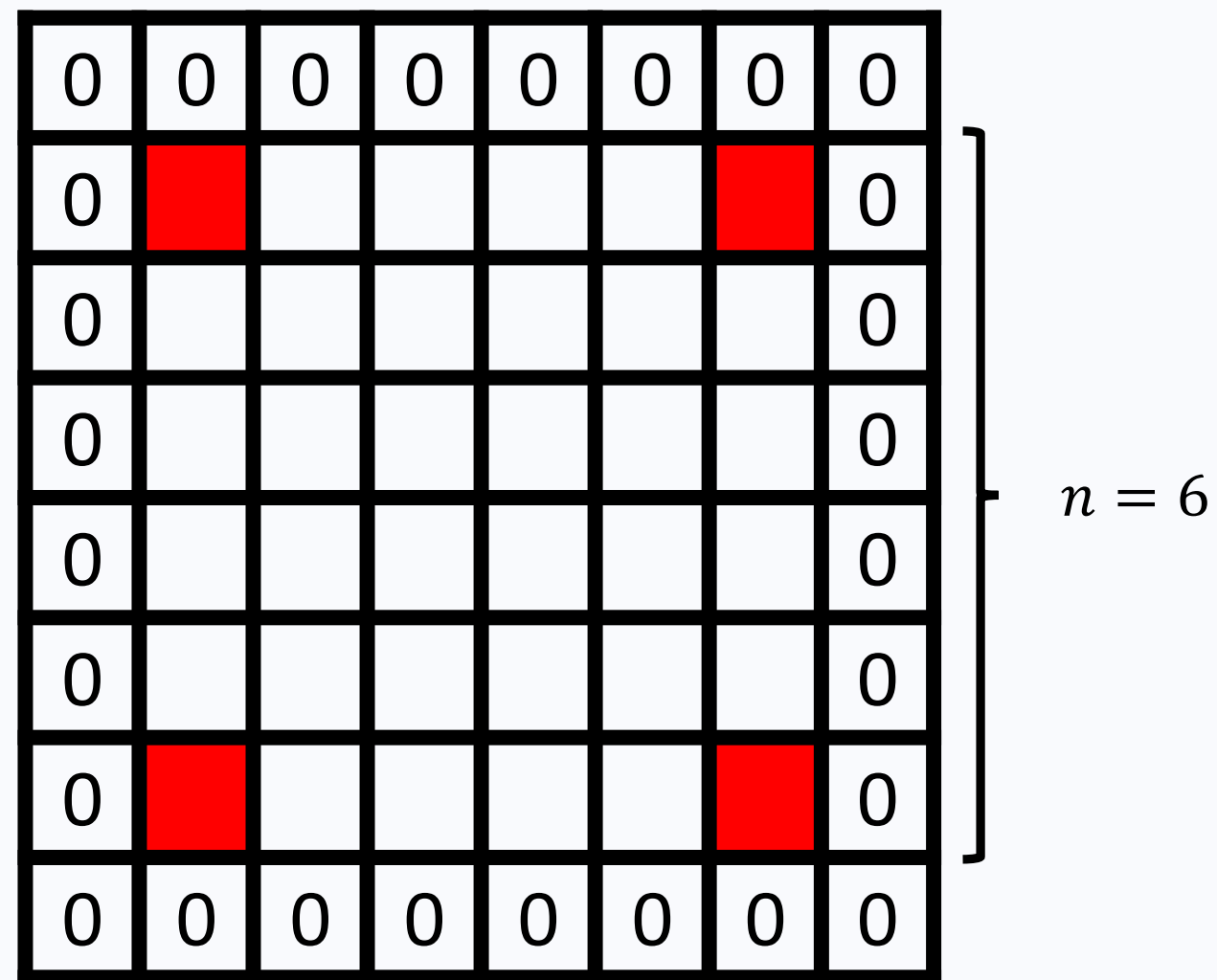
stride: s

padding: p

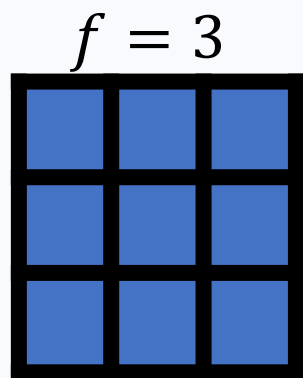
filter: $f \times f$

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Notations for convolutions



stride: s

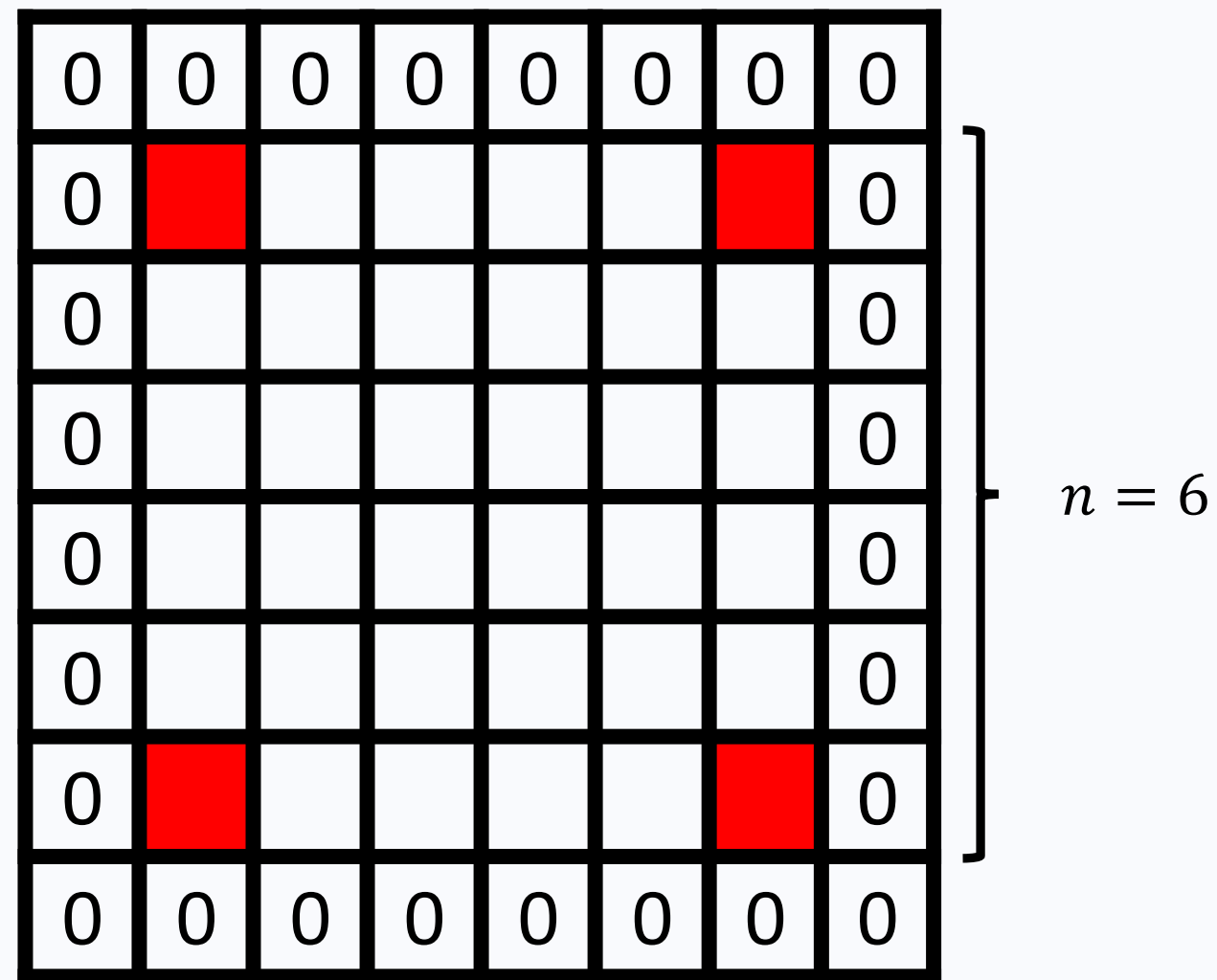
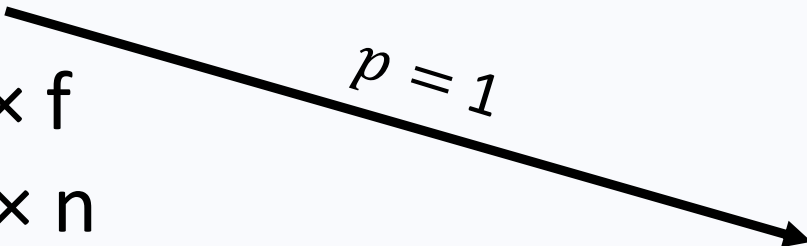
padding: p

filter: $f \times f$

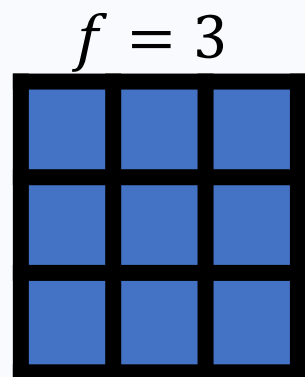
image: $n \times n$

result

$p = 1$



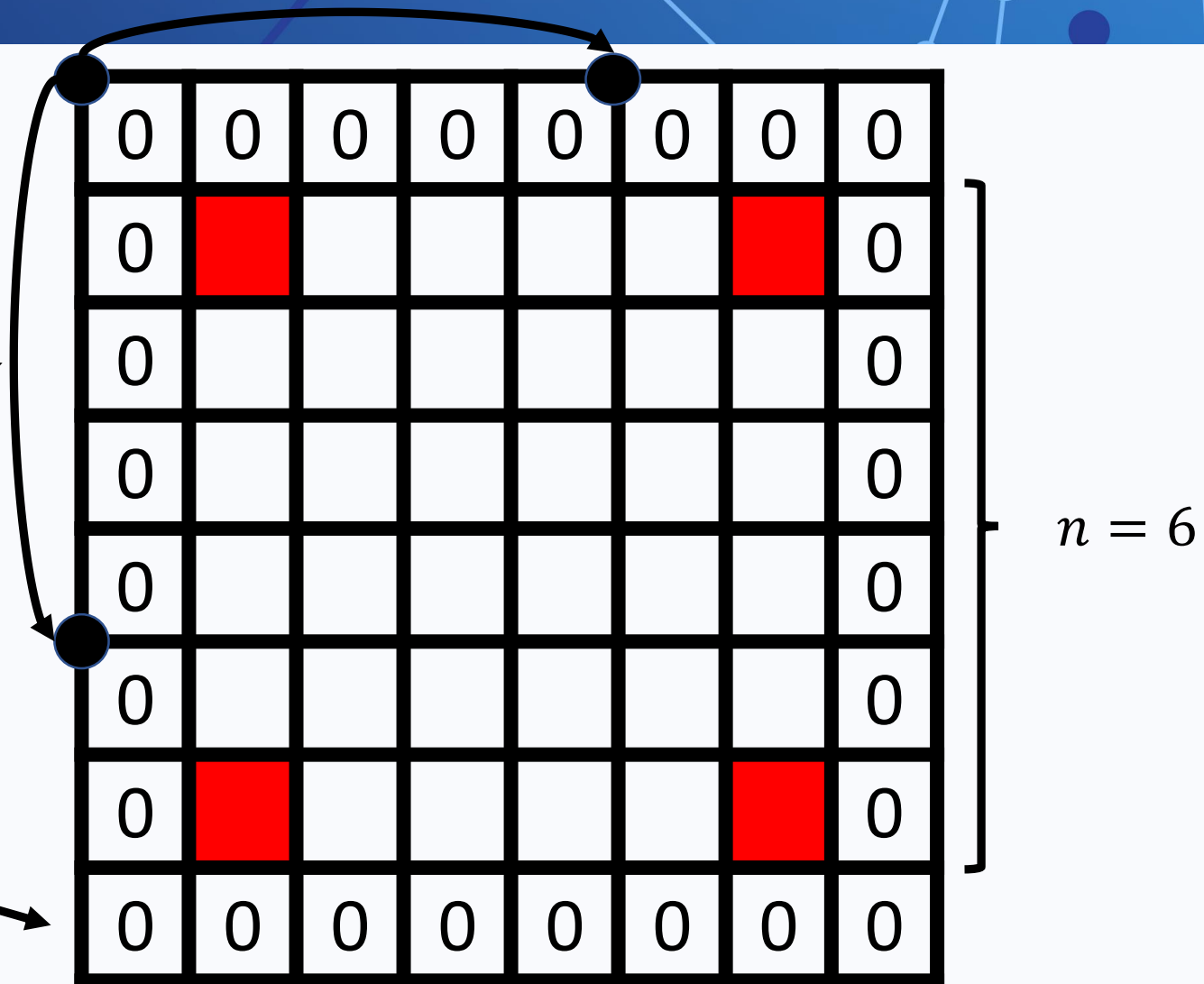
Notations for convolutions



stride: s
padding: p
filter: $f \times f$
image: $n \times n$
result

$s = 5$

$p = 1$



Notations for convolutions

stride: s

padding: p

filter: $f \times f$

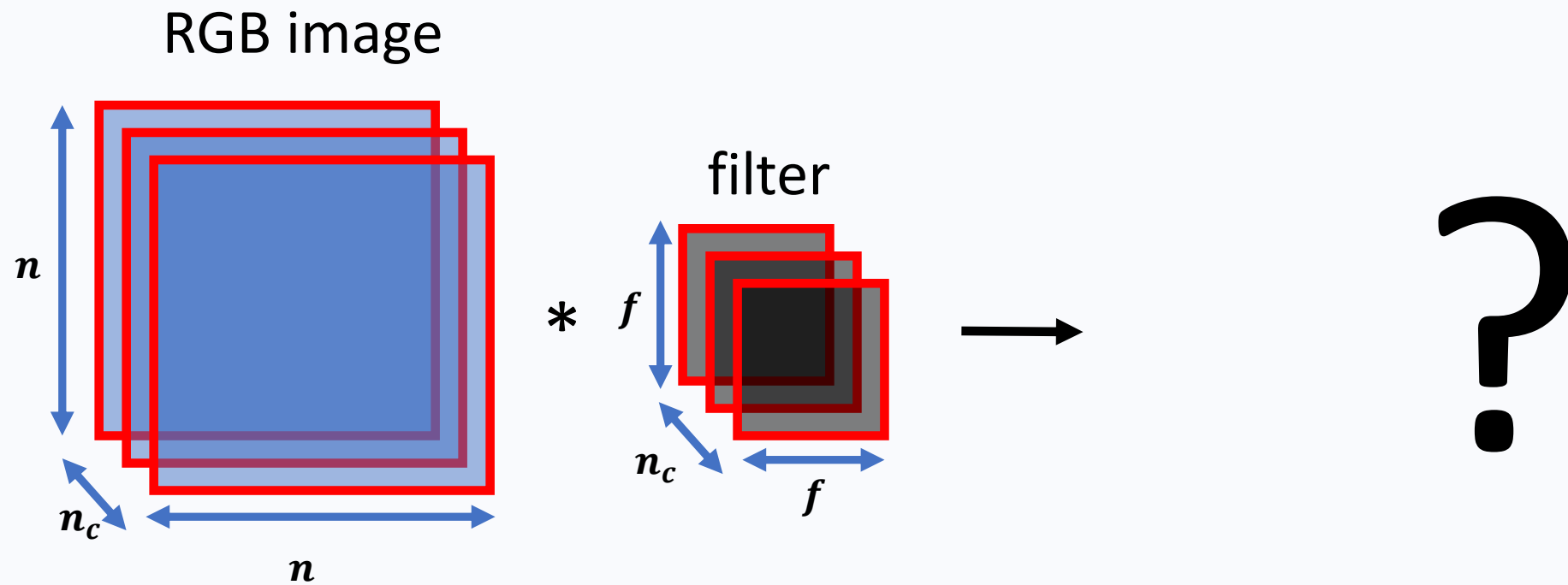
image: $n \times n$

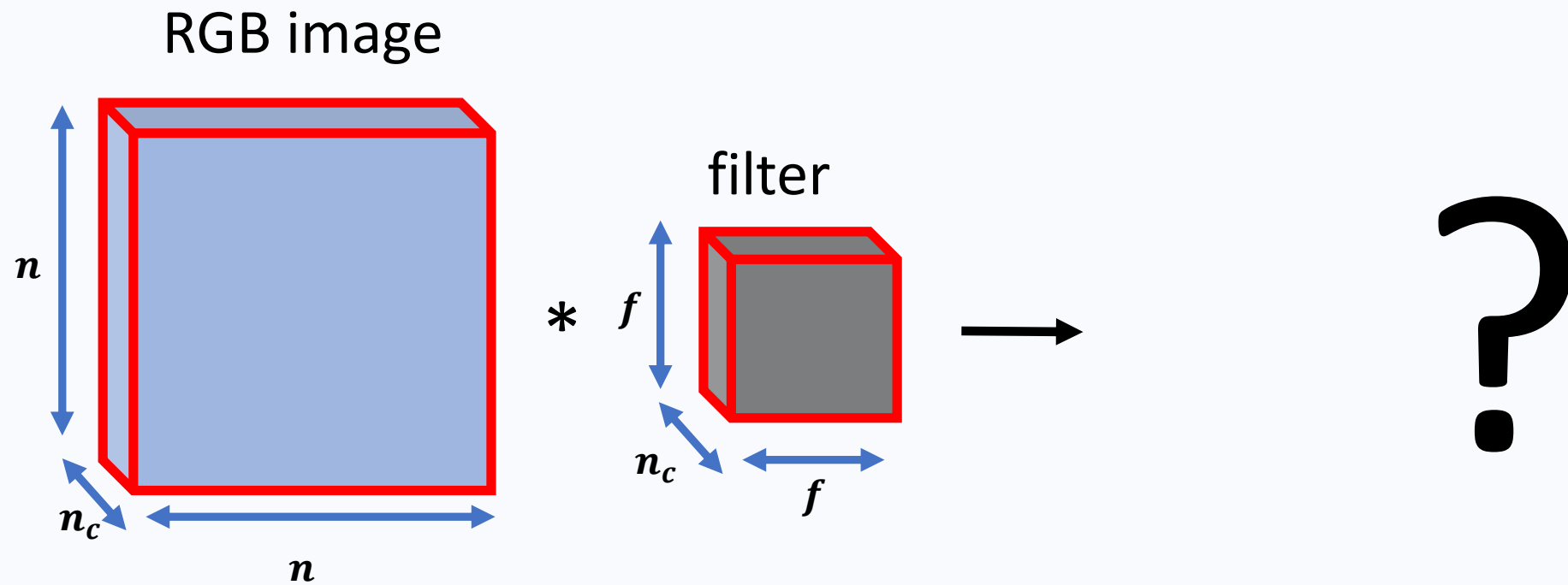
$$= 6 + 2 * 1 - 3 \quad 5 \quad 6 + 2 * 1 - 3 \quad 5 + 1 \quad \times \left| \frac{6 + 2 * 1 - 3}{5} + 1 \right| = 2 \times 2$$

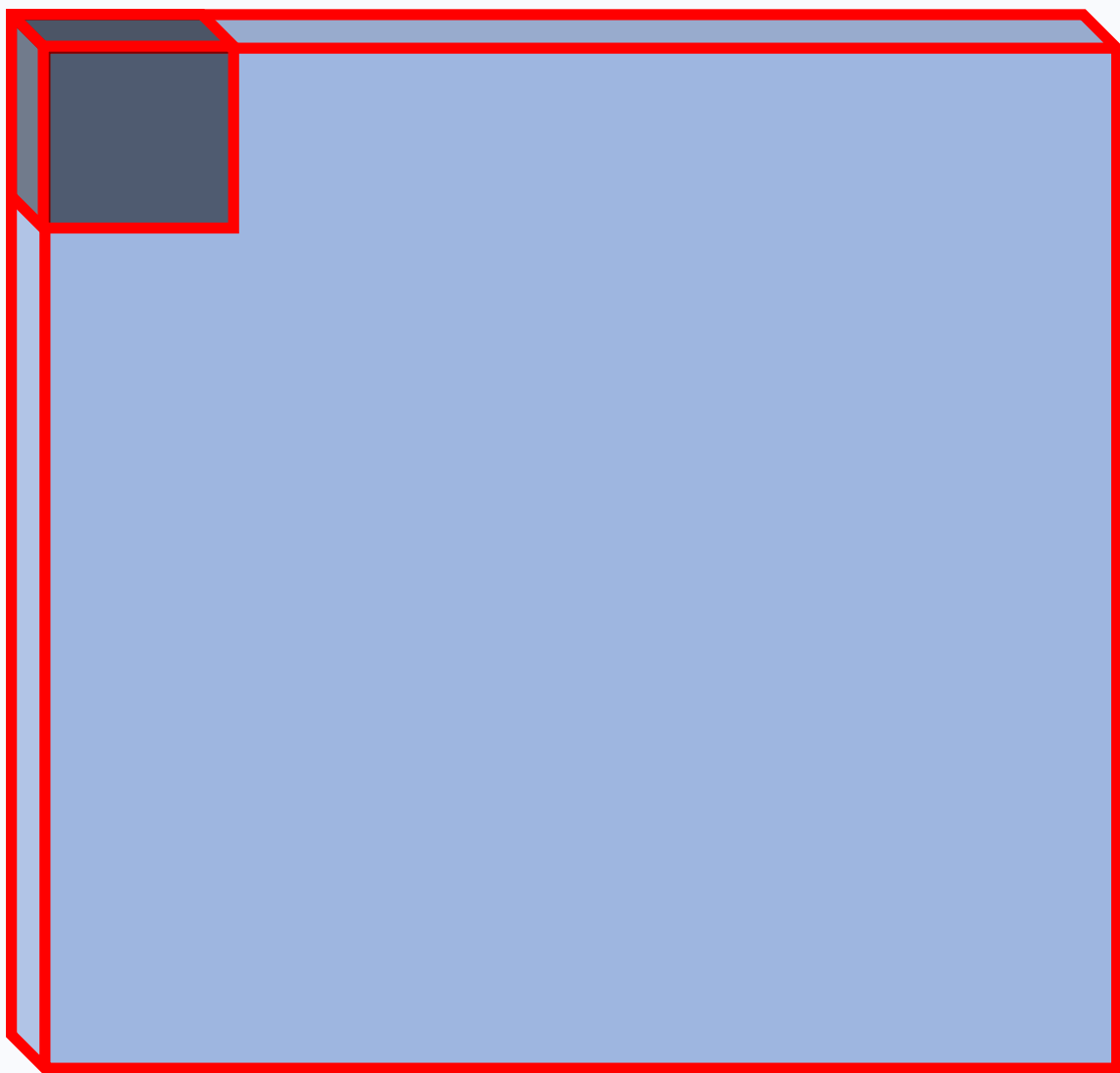
13 March 2018

Deep learning and machine learning in science

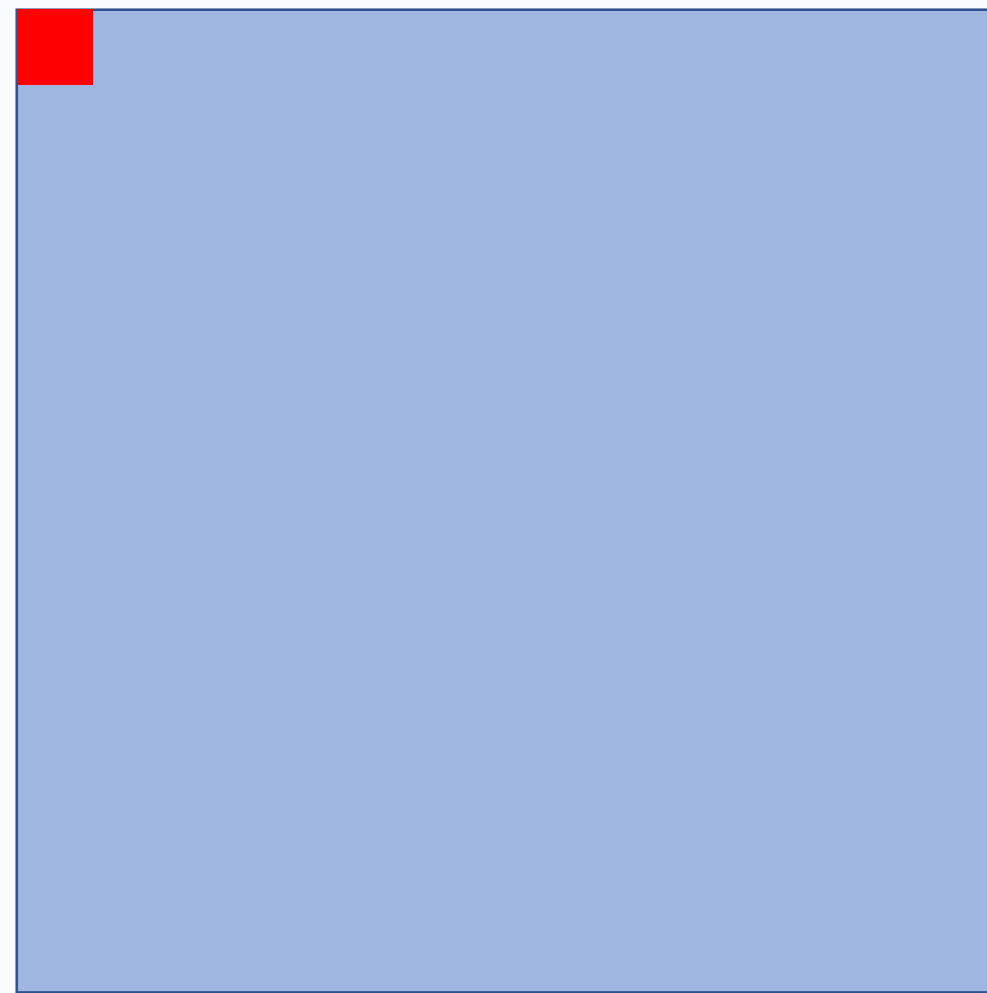
24



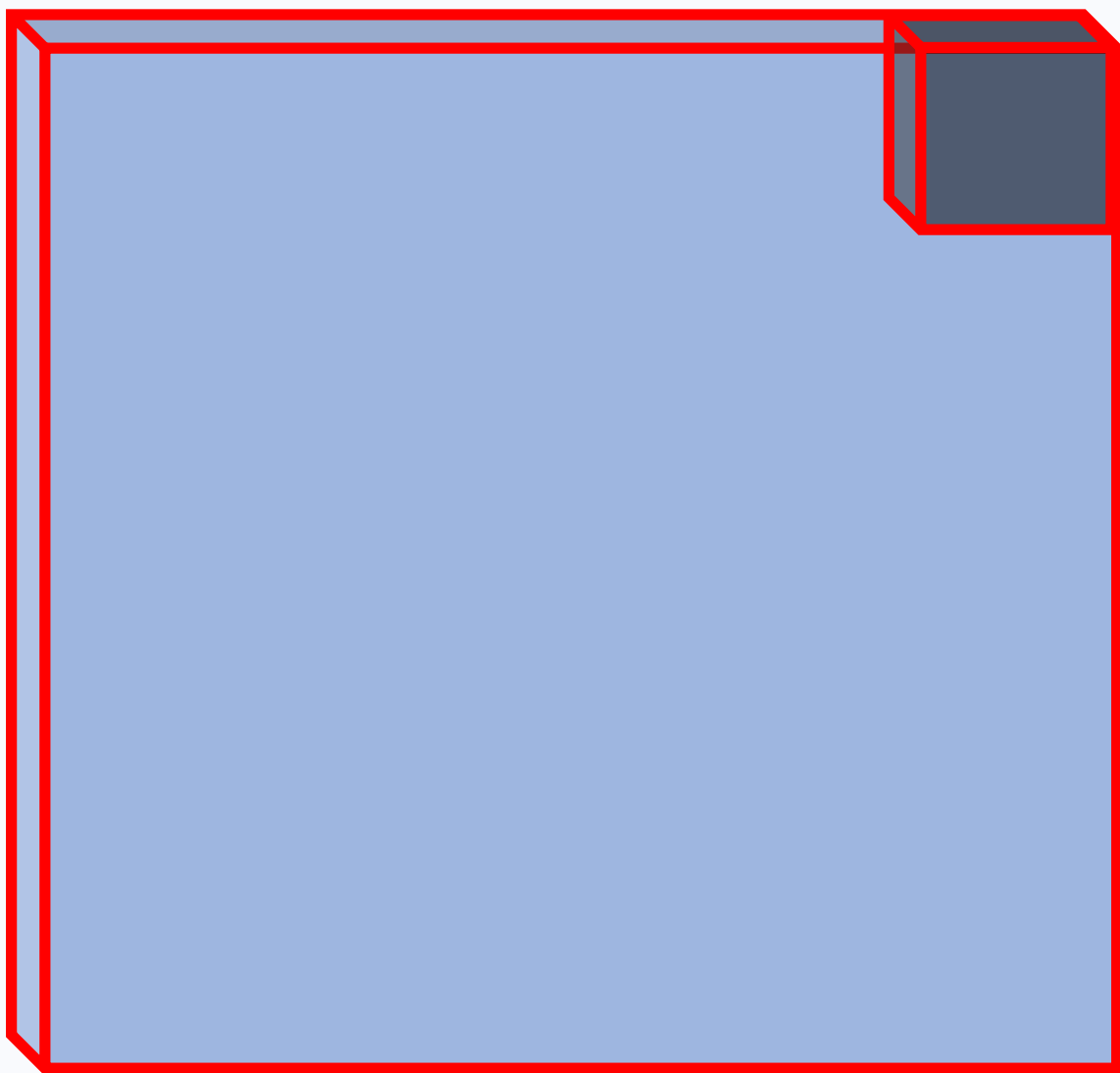




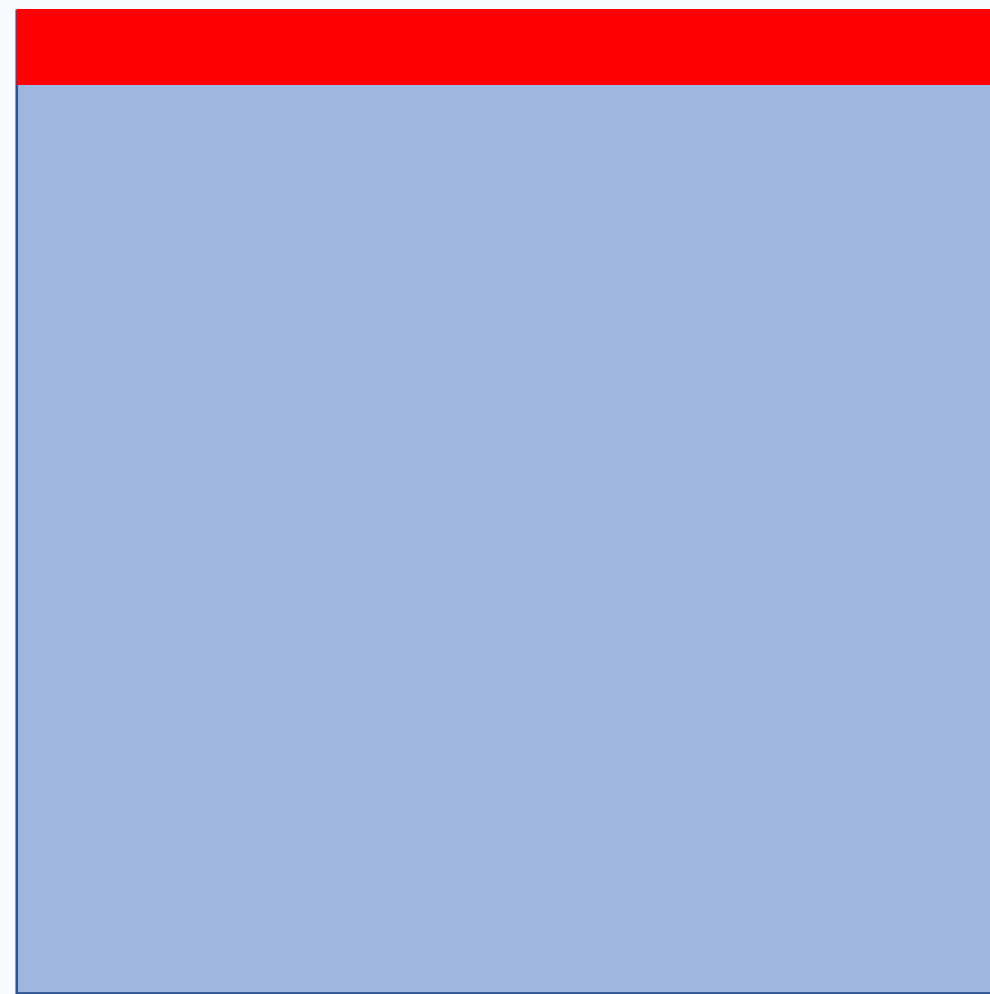
$n_c = 3$ (RGB)



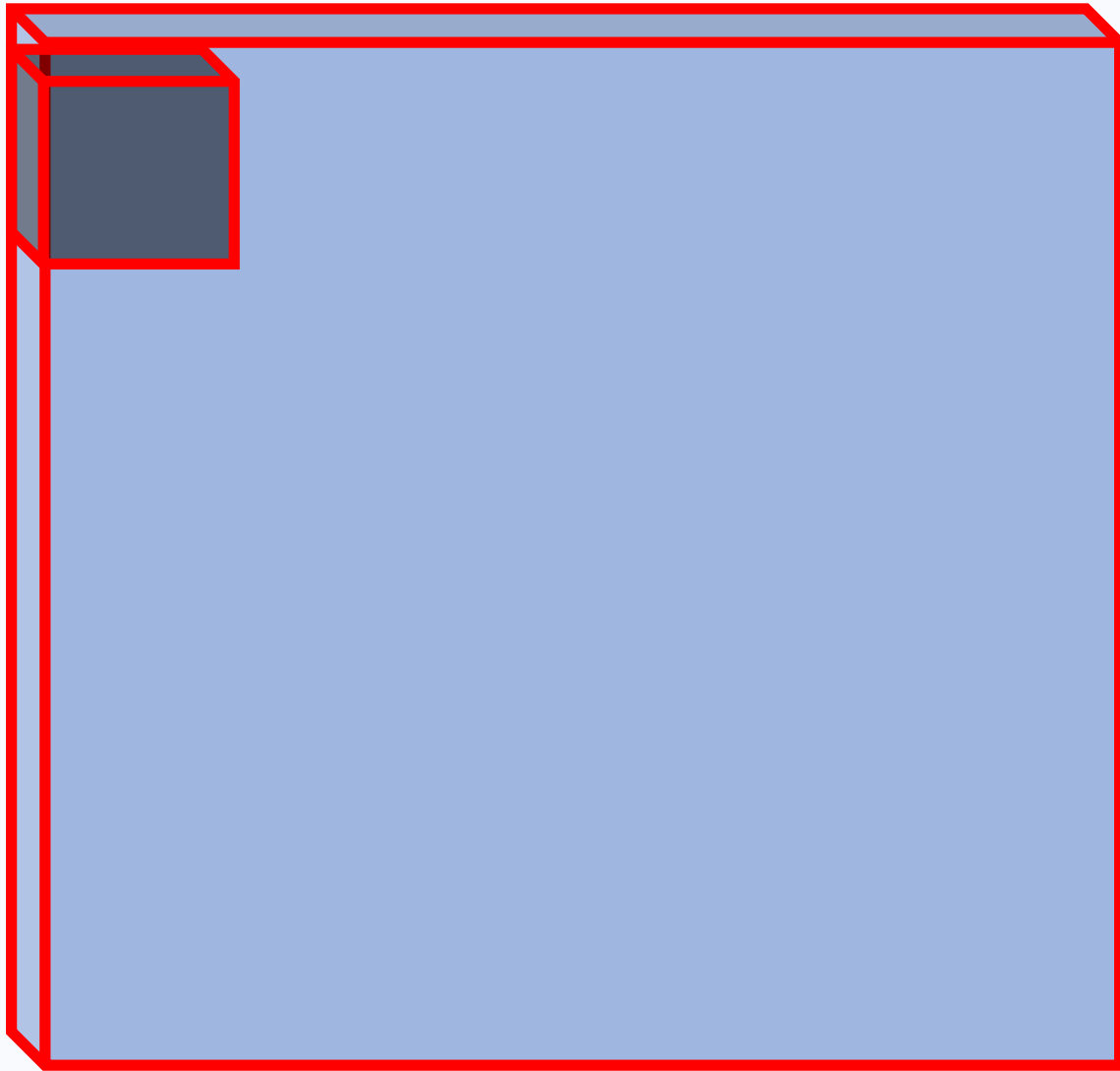
$n_c = 1$



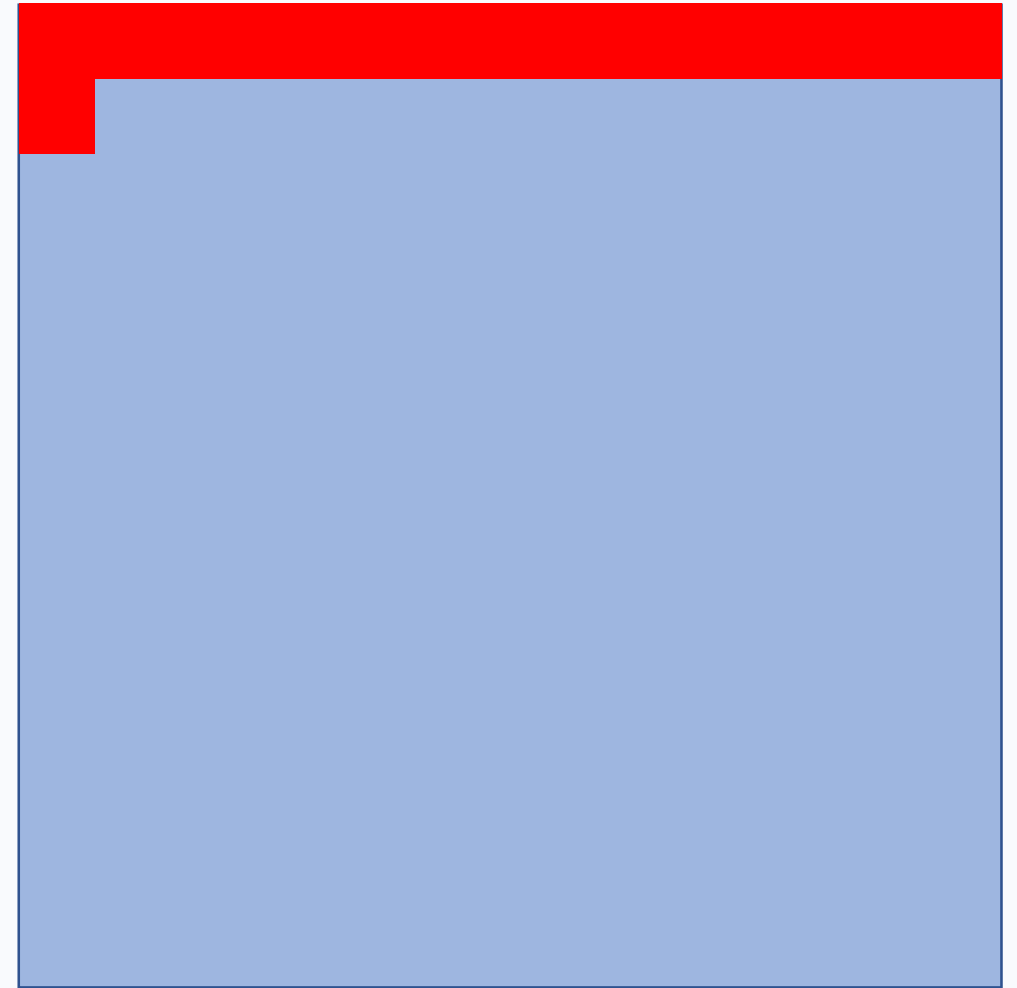
$n_c = 3$ (RGB)



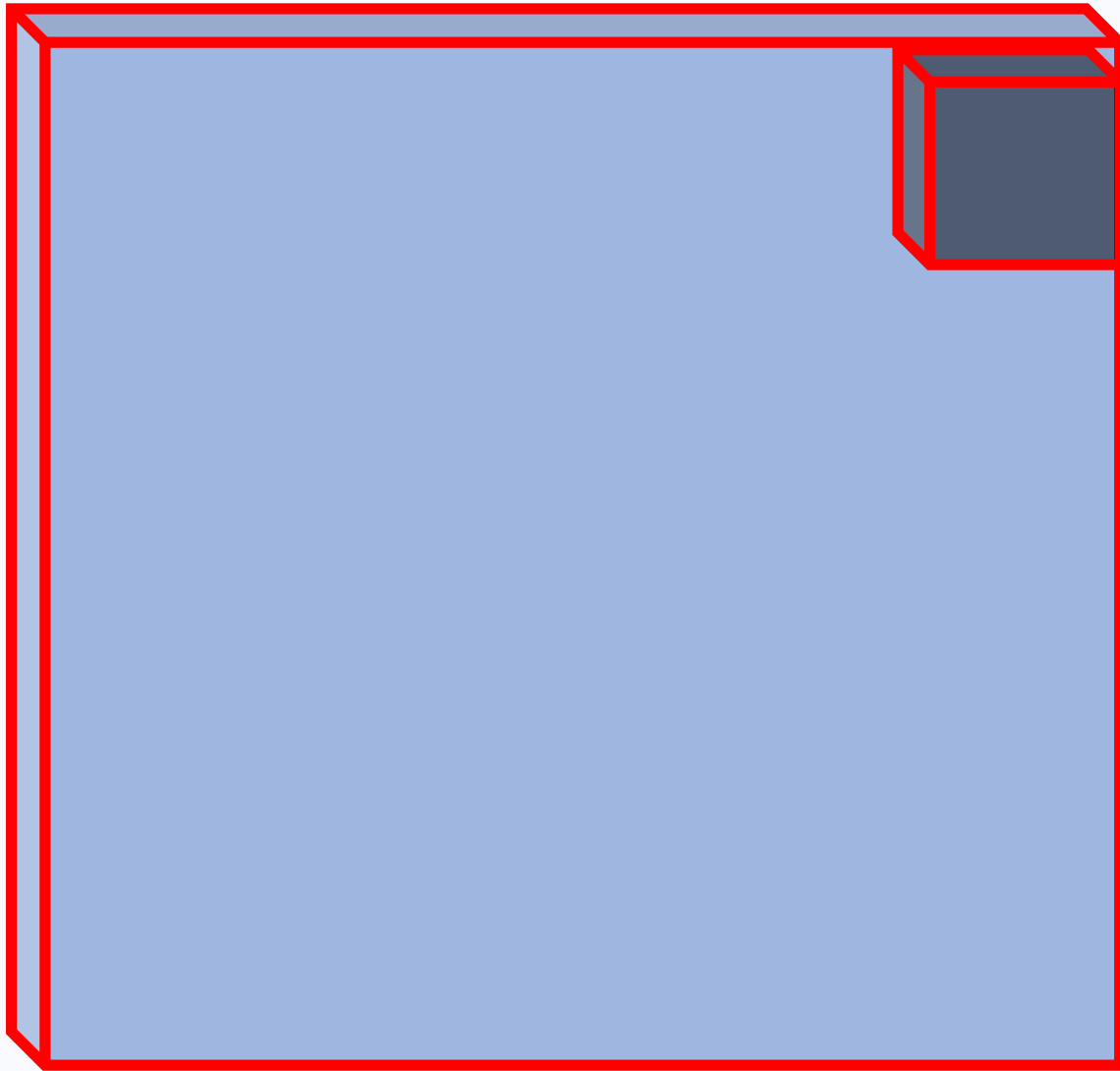
$n_c = 1$



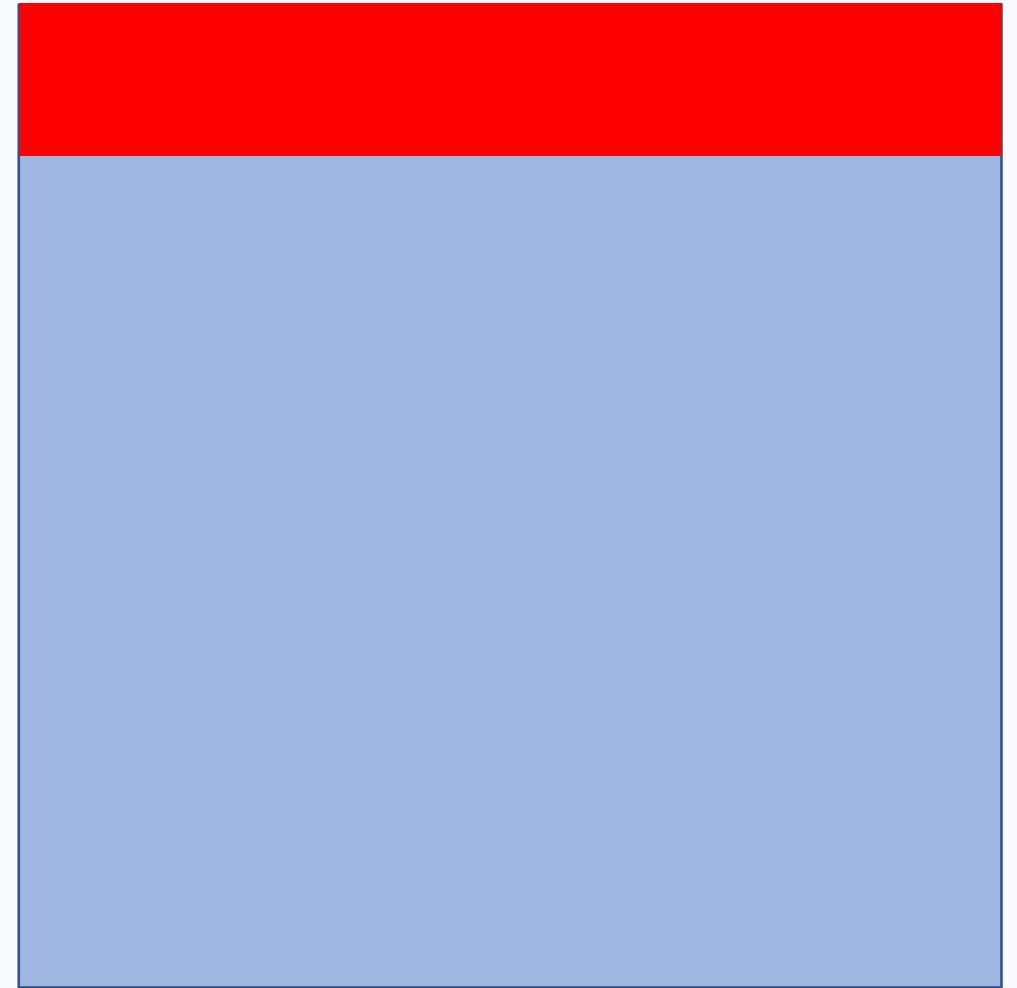
$n_c = 3$ (RGB)



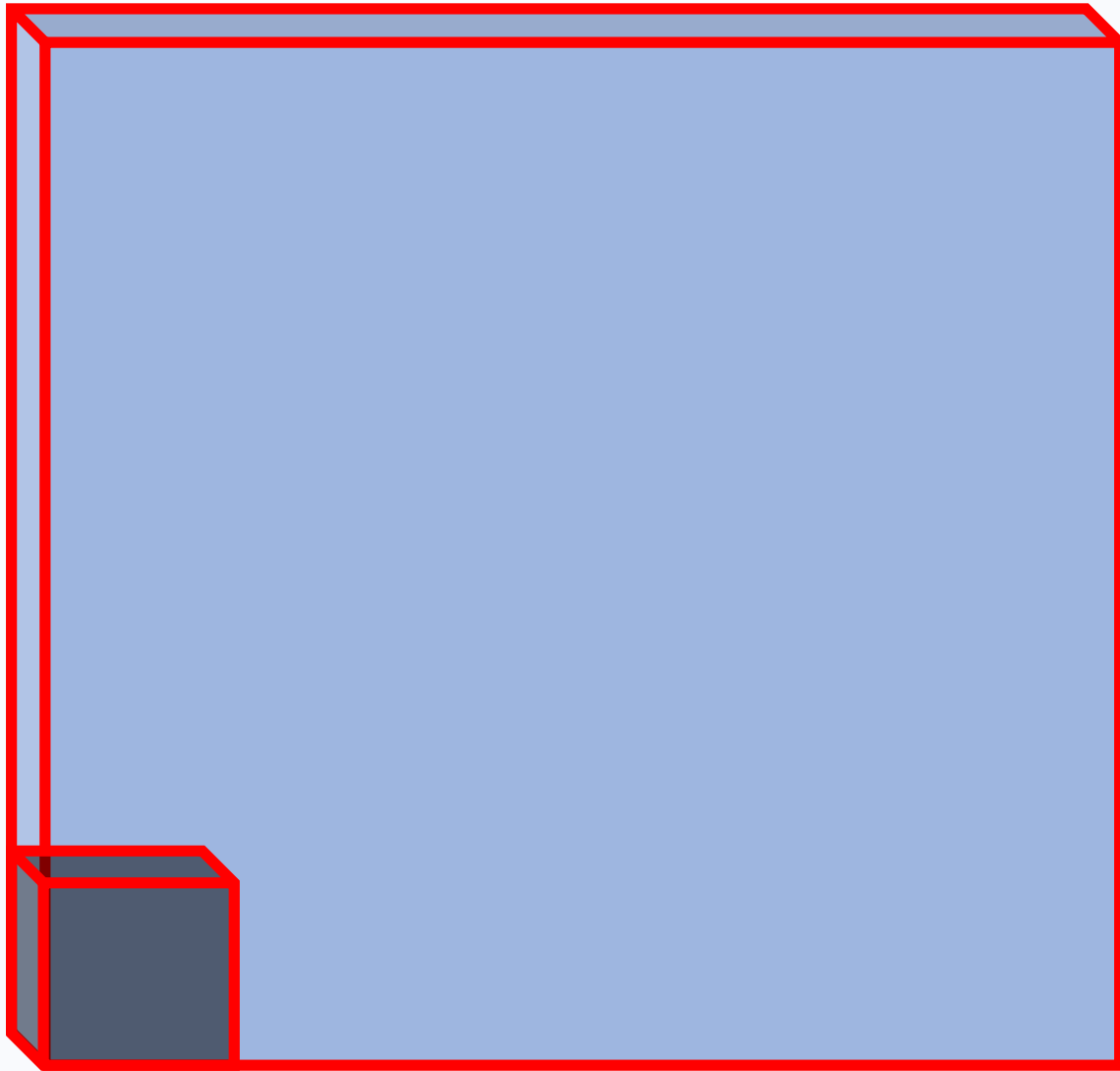
$n_c = 1$



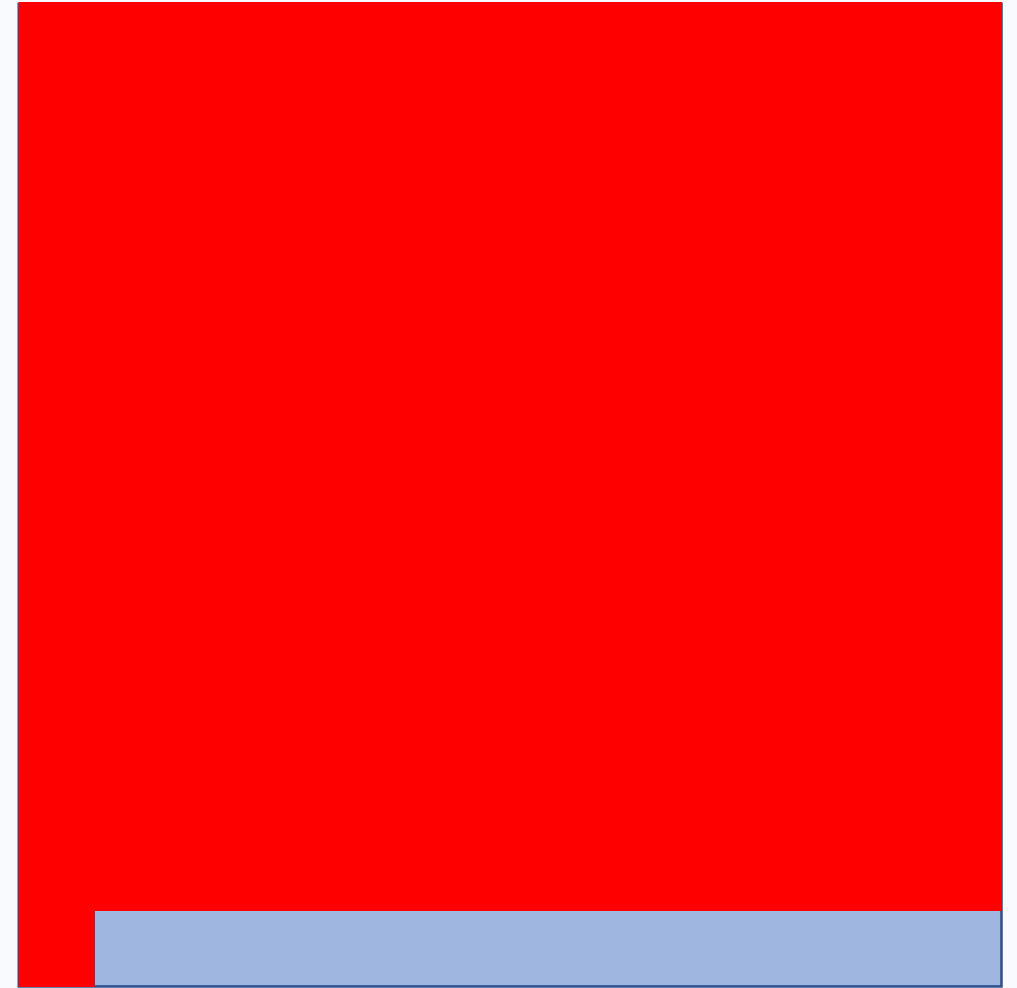
$n_c = 3$ (RGB)



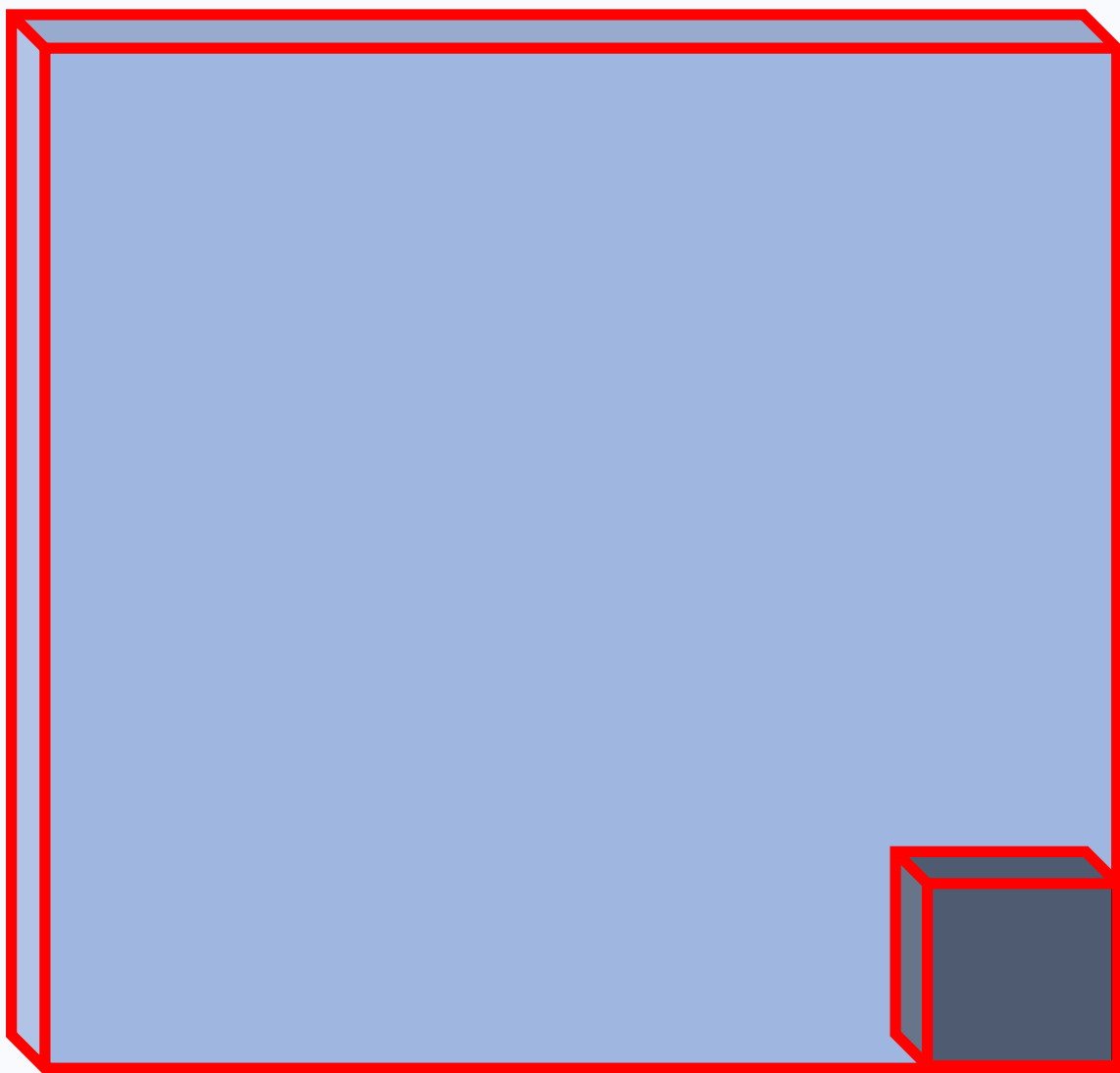
$n_c = 1$



$n_c = 3$ (RGB)



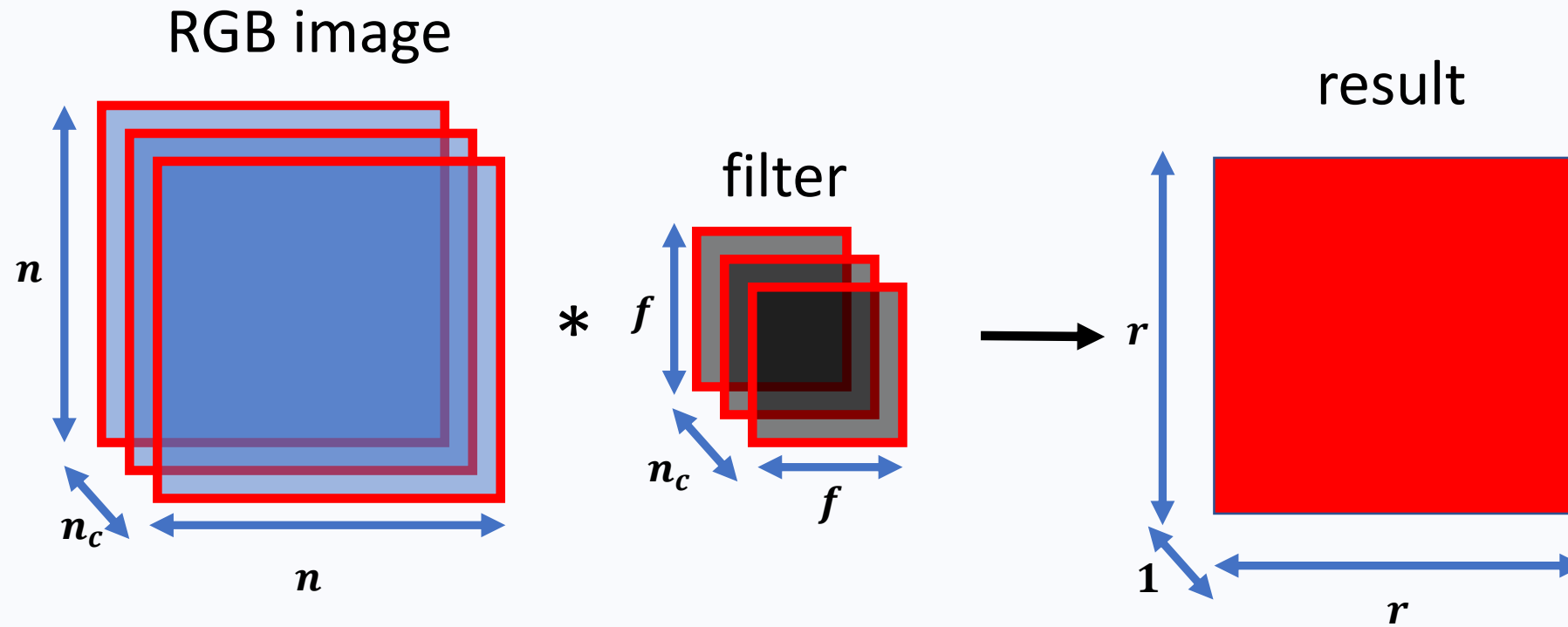
$n_c = 1$



$n_c = 3$ (RGB)

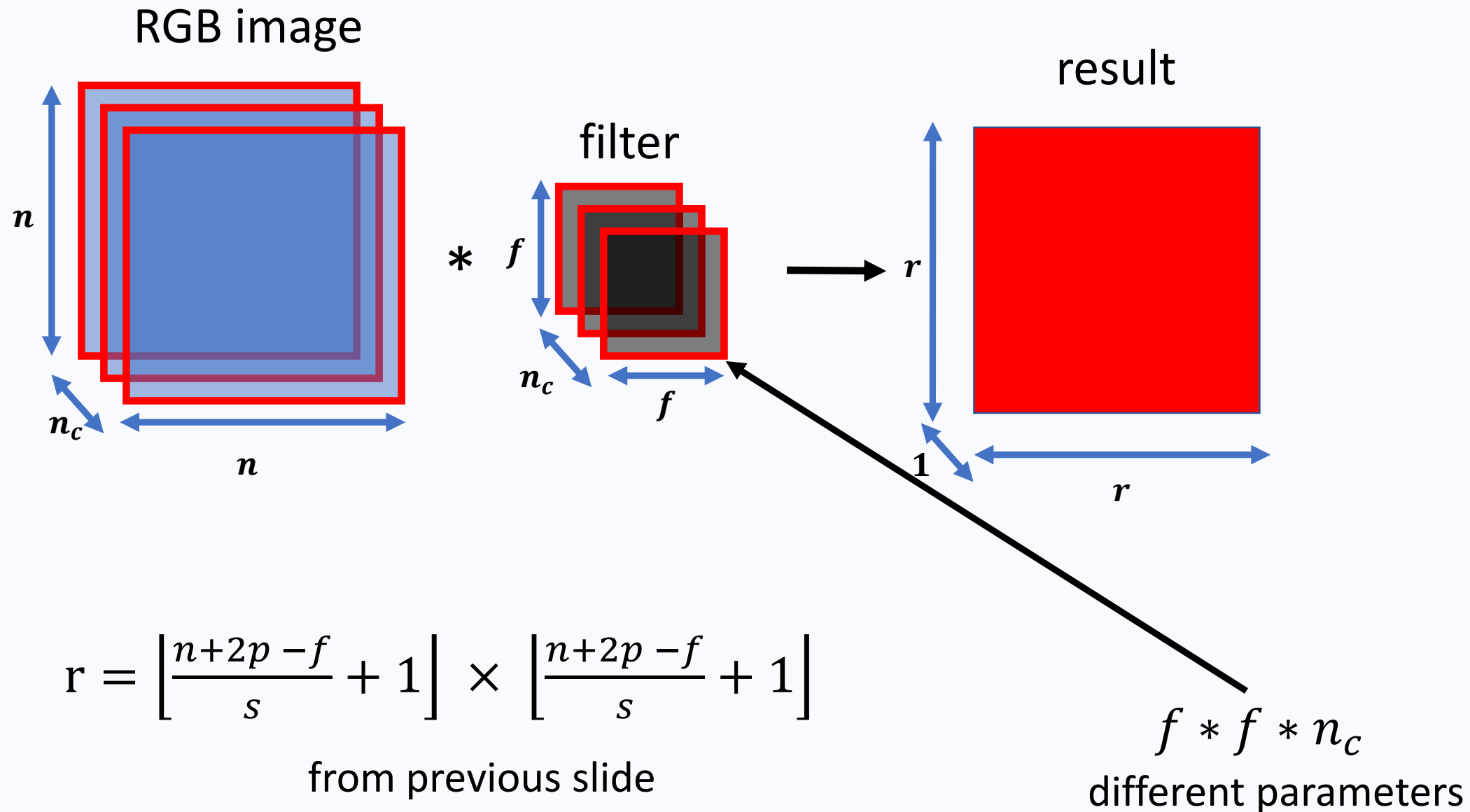


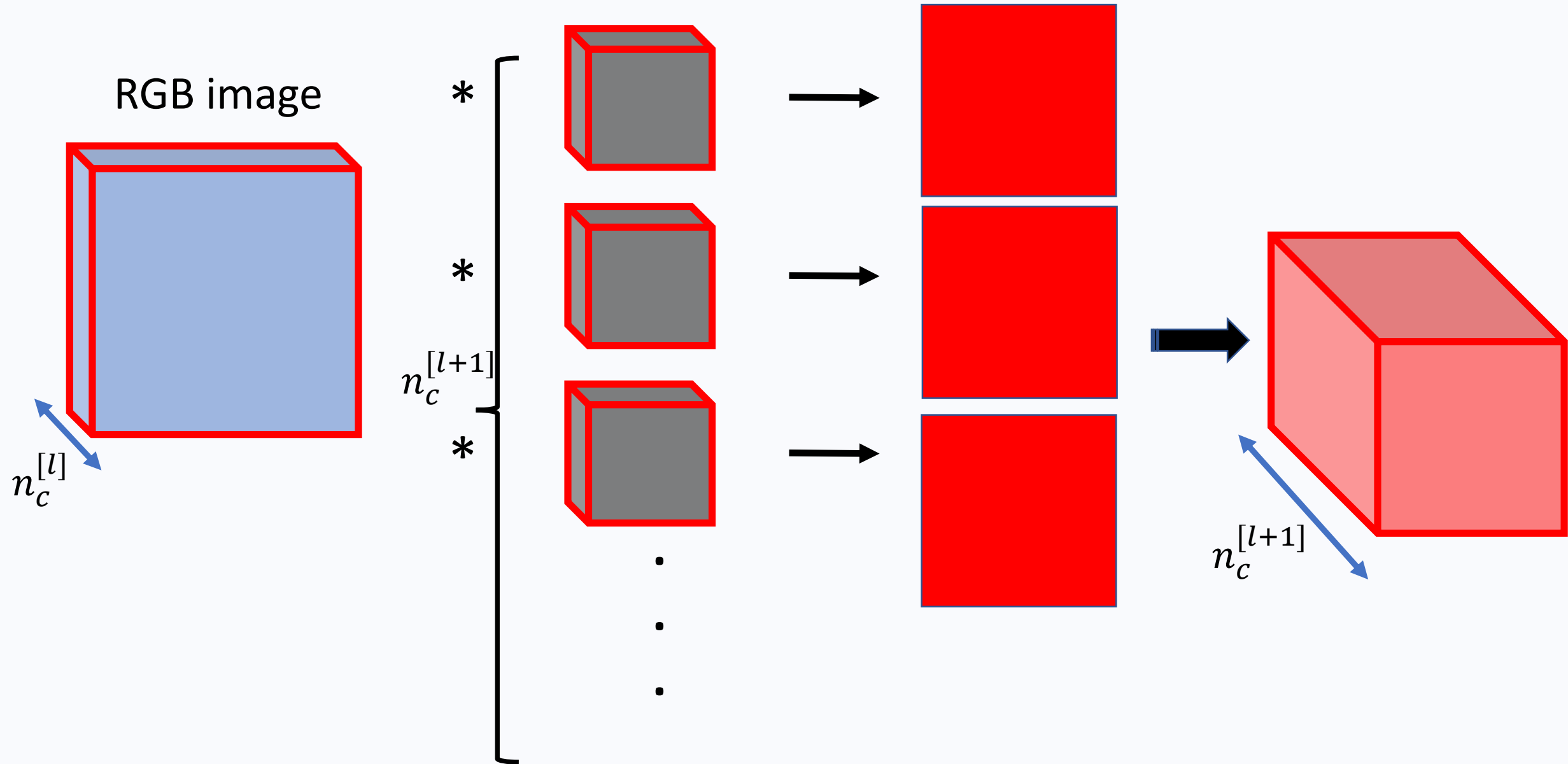
$n_c = 1$



$$r = \left\lfloor \frac{n+2p-f}{s} + 1 \right\rfloor \times \left\lfloor \frac{n+2p-f}{s} + 1 \right\rfloor$$

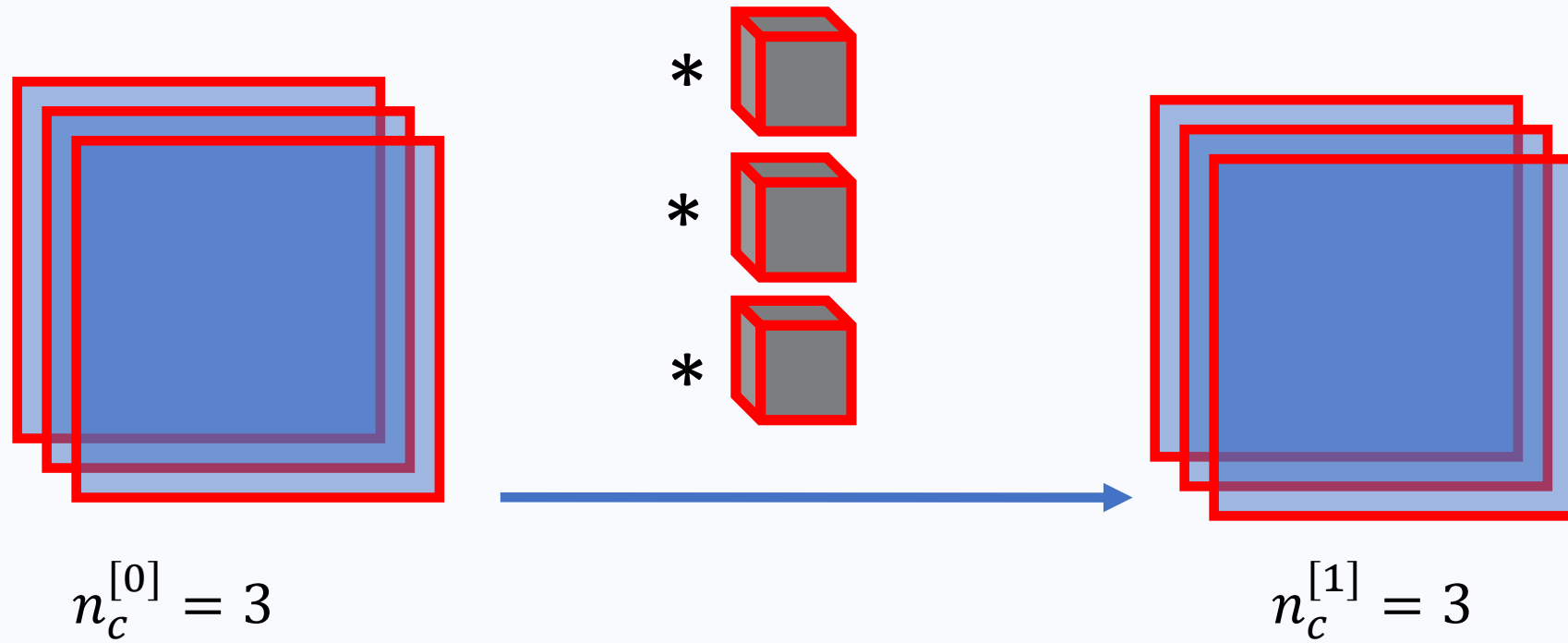
from previous slide





1 layer of convolution in neural networks

#channels in layer l : $n_c^{[l]}$



Difference from the previous: 1 bias per filter

Each filter has a parameter number of: $f \cdot f \cdot n_c + 1$

1 layer of convolution in neural networks

Input: 200 x 200 pixel RGB image, in the first layer we want 200 x 200 x 3 neurons

How many parameters does it have?

Fully connected layer

- weights: $(200 \cdot 200 \cdot 3)^2$
- bias: $200 \cdot 200 \cdot 3$
- *Total* $\approx 1.4 \cdot 10^{10}$

1 layer of convolution in neural networks

Input: 200 x 200 pixel RGB image, in the first layer we want 200 x 200 x 3 neurons

How many parameters does it have?

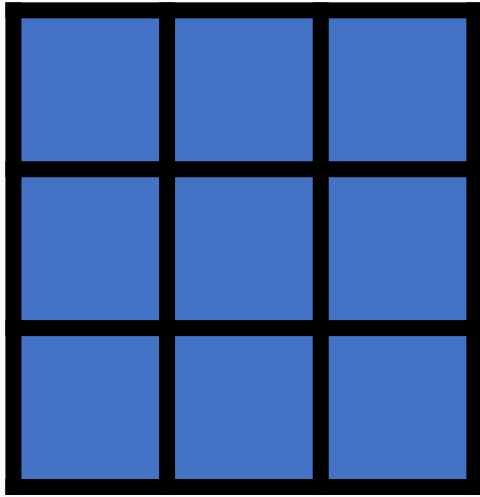
Fully connected layer

- weights: $(200 \cdot 200 \cdot 3)^2$
- bias: $200 \cdot 200 \cdot 3$
- *Total* $\approx 1.4 \cdot 10^{10}$

Convolutional layer ($f = 3$)

- Weights per filter: $f \cdot f \cdot n_c^{[0]} + 1$
- Number of filters: $n_c^{[1]}$
- *Total* = 84

'filter'



Image

a_{00}	a_{01}	a_{02}	a_{03}	a_{04}	a_{05}
a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}
a_{20}	a_{21}	a_{22}	a_{23}	a_{24}	a_{25}
a_{30}	a_{31}	a_{32}	a_{33}	a_{34}	a_{35}
a_{40}	a_{41}	a_{42}	a_{43}	a_{44}	a_{45}
a_{50}	a_{51}	a_{52}	a_{53}	a_{54}	a_{55}

$$a'_{11} = \max(a_{00}, a_{01}, a_{02}, a_{10}, a_{11}, a_{12}, a_{20}, a_{21}, a_{22})$$

Default stride = pool size (f)

- Objects are not position dependents



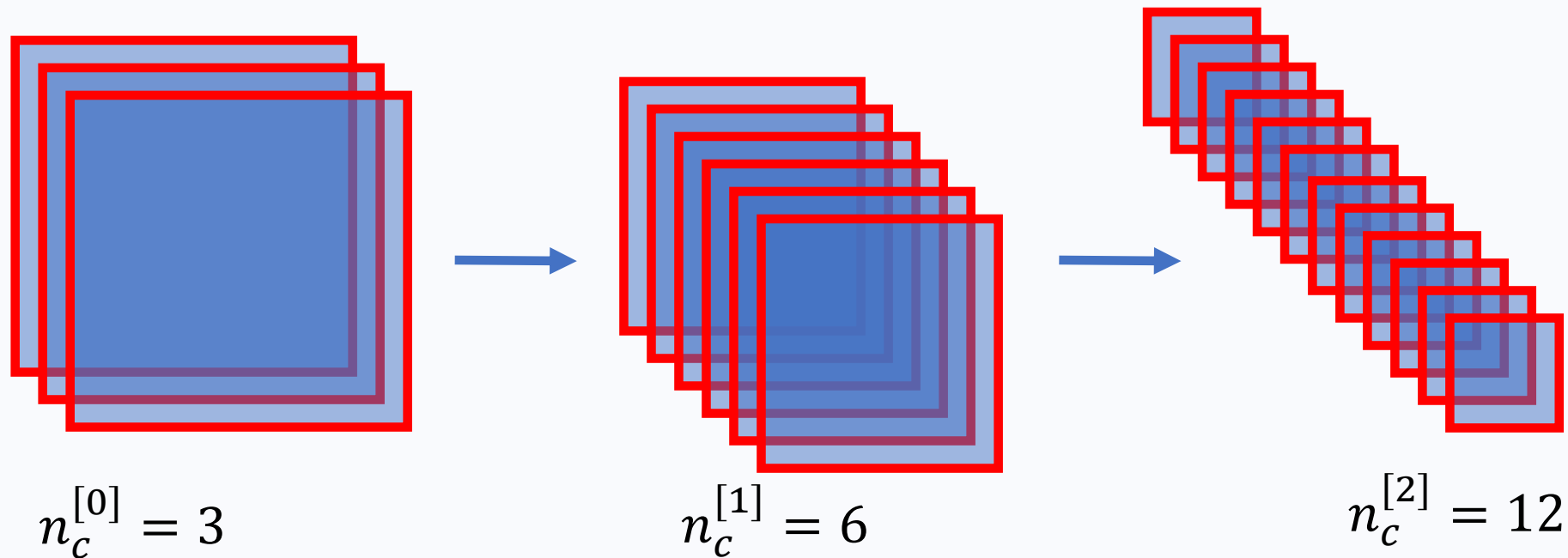
- Objects are not position dependents
- ✓ A convolution filter



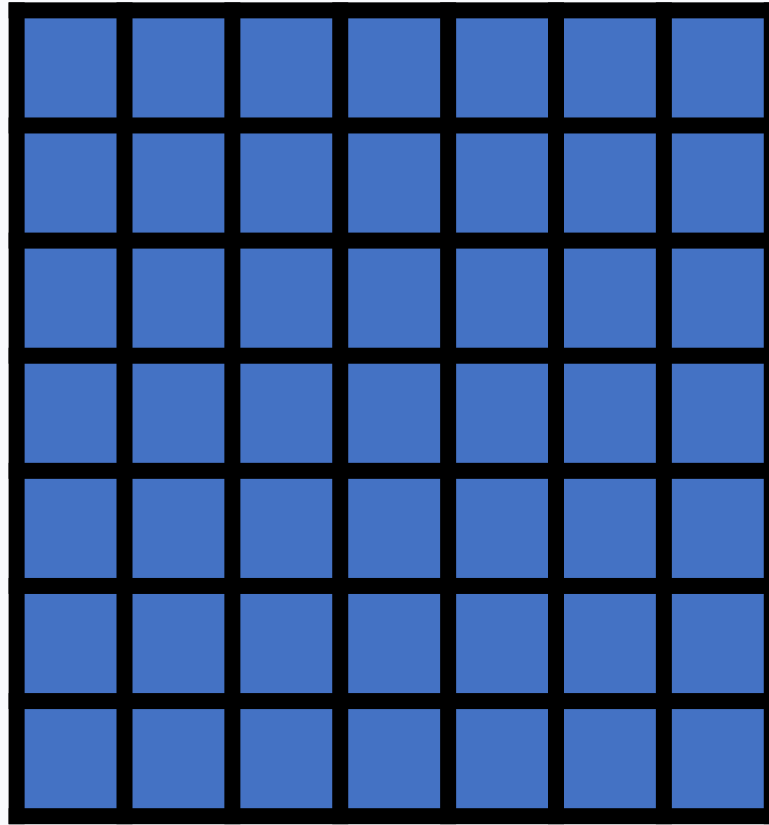
- Objects are not position dependents
- ✓ A convolution filter
- ✓ Maxpooling: best value from a region (exact position doesn't matter for image classification)



#channels in layer l : $n_c^{[l]}$

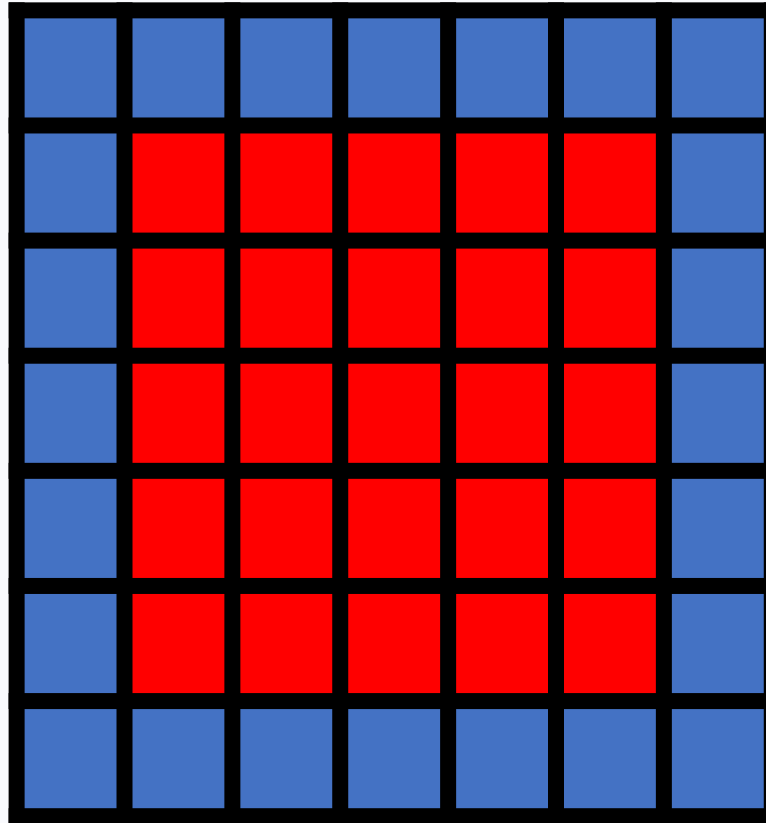


Three 3×3 convolution after each other
No padding, stride=1, $f=3$



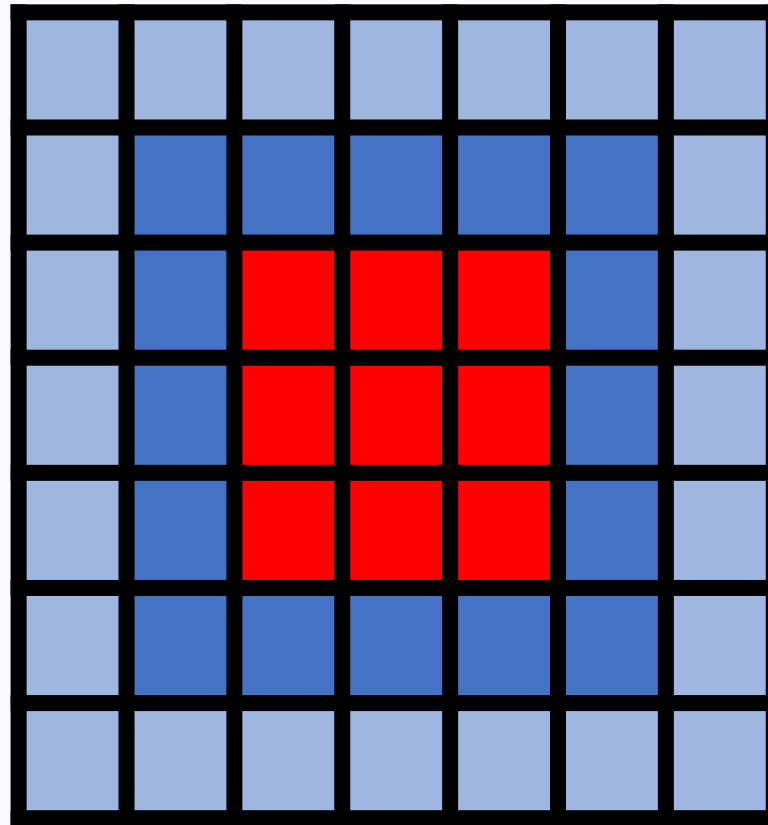
Three 3×3 convolution after each other
No padding, stride=1, $f=3$

After 1 layer:



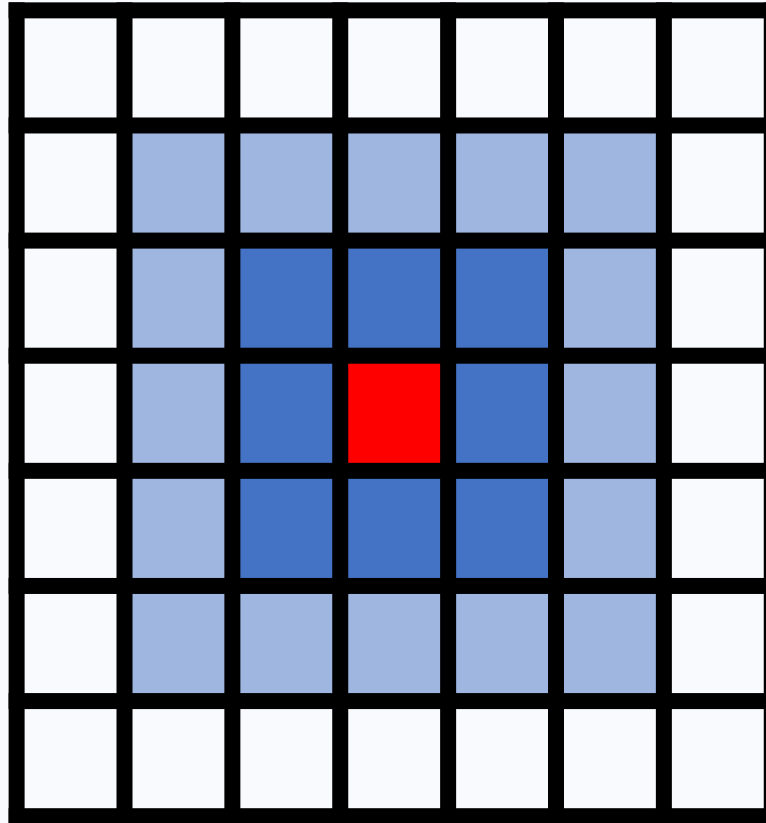
Three 3×3 convolution after each other
No padding, stride=1, $f=3$

After 2 layer:



Three 3×3 convolution after each other
No padding, stride=1, $f=3$

After 3 layer:

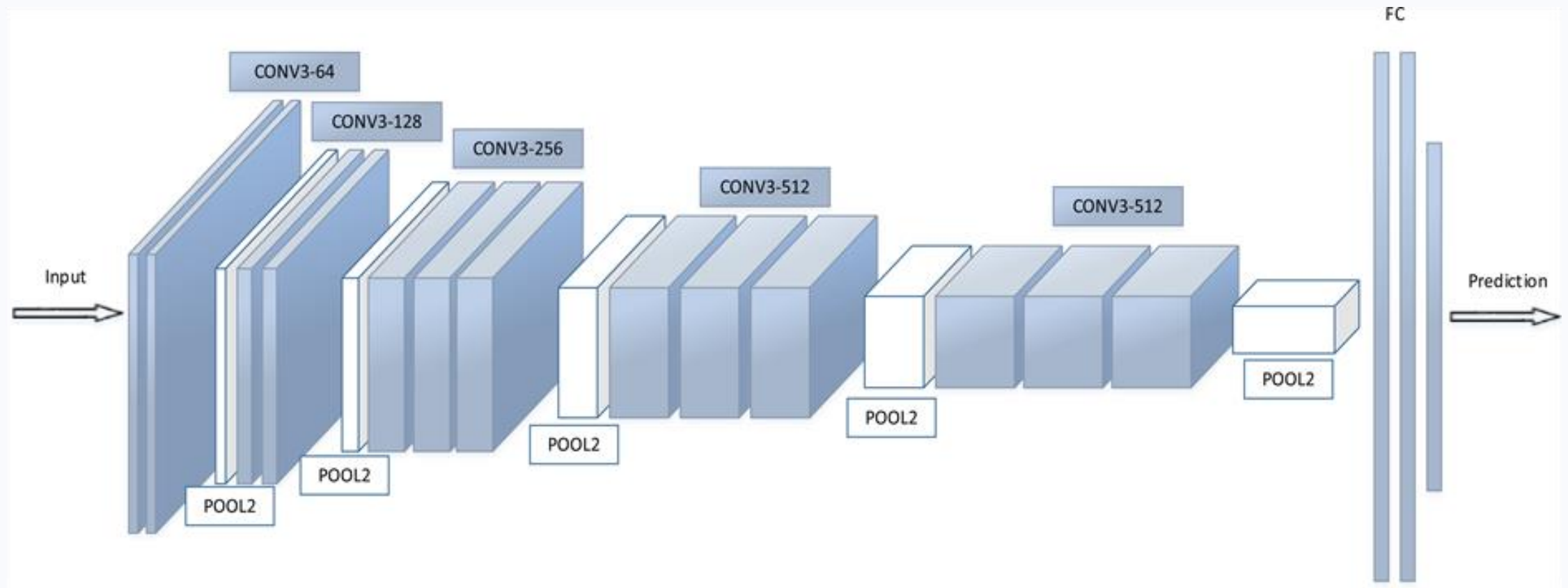


After three 3 x 3 convolution each neuron can see 7 x 7 field from the input

#parameters in three 3 x 3 conv: $3 \cdot (3 \cdot 3 + 1) = 30$

#parameters in one 7 x 7 conv: $1 \cdot (7 \cdot 7 + 1) = 50$

3 convolutions → more 'non-linearity'



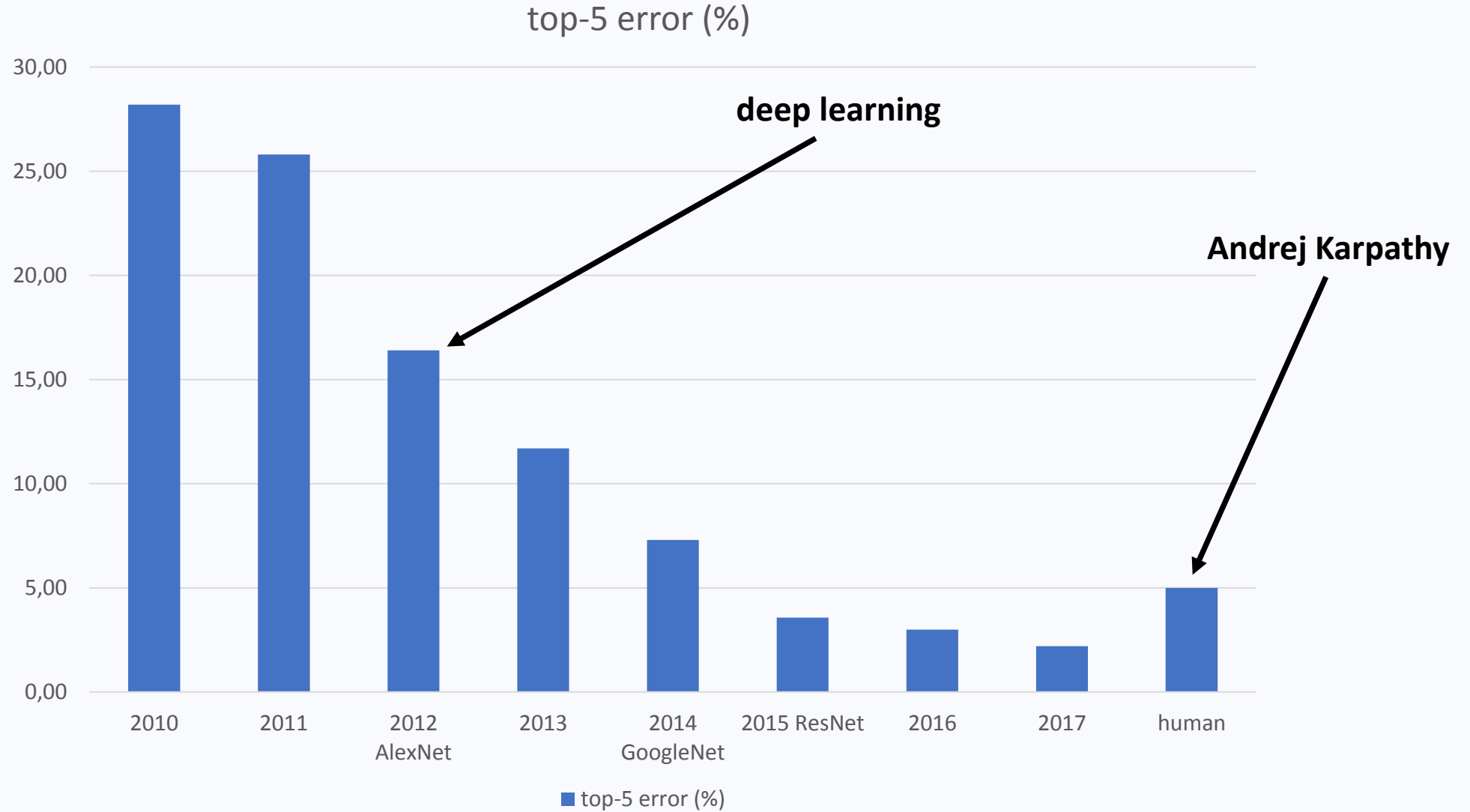
[http://file.scirp.org/Html/4-7800353_65406.htm]

Keras notebook

https://github.com/qati/DeepLearningCourse/tree/master/demo_notebooks/lecture_05

ImageNet Large Scale Visual Recognition Challenge

- 2010 –
- 1.2M images (100K test set)
- 1000 categories
- 'Image classification world cup',
- top-5 error (still not that easy...)



<https://cs.stanford.edu/people/karpathy/ilsvrc/>