Deep Learning (CS324)

5. Convolutional Neural Networks*

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SUSTech

*Based on http://www.deeplearningbook.org chapter 9 + referenced papers

What’s special about images?


WIDTH
HEIGHT


ATIAL STRUCTURE

What does the computer see?

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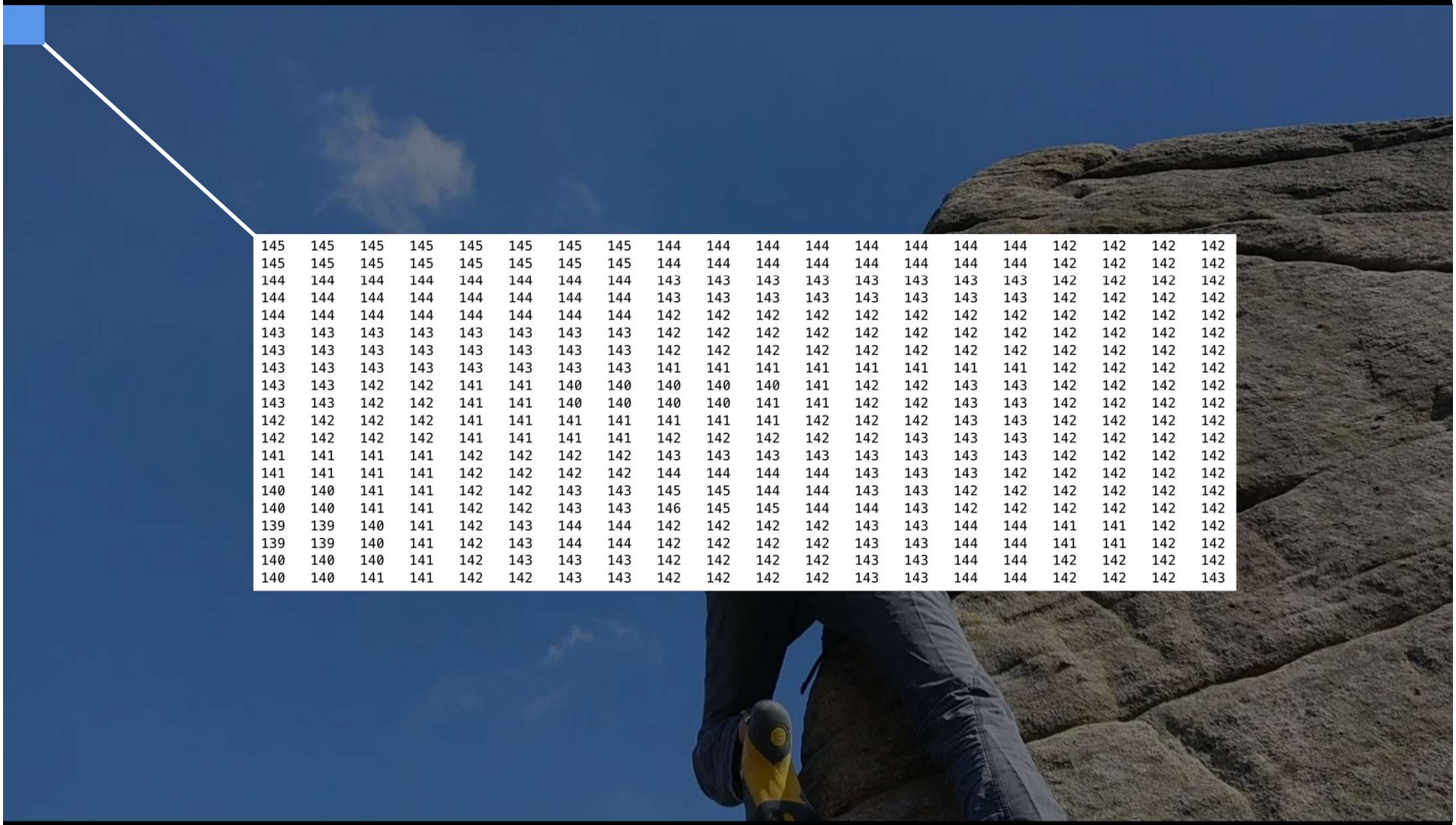

First 20 x 20 = 400 pixels

1920 (w) x 1080 (h) pixels = 2,073,600 input variables

1920 (w) x 1080 (h) x 3 (RGB) pixels = 6,220,800 input variables

1920 (w) x 1080 (h) x 3 (RGB) pixels = 6,220,800 input variables

What if you feed this to an MLP with 1 hidden layer of 100 units

1920 (w) x 1080 (h) x 3 (RGB) pixels = 6,220,800 input variables

What if you feed this to an MLP with 1 hidden layer of 100 units

Spot the difference…

Spot the difference…

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We shifted it of 1 px to the right

Spot the difference…

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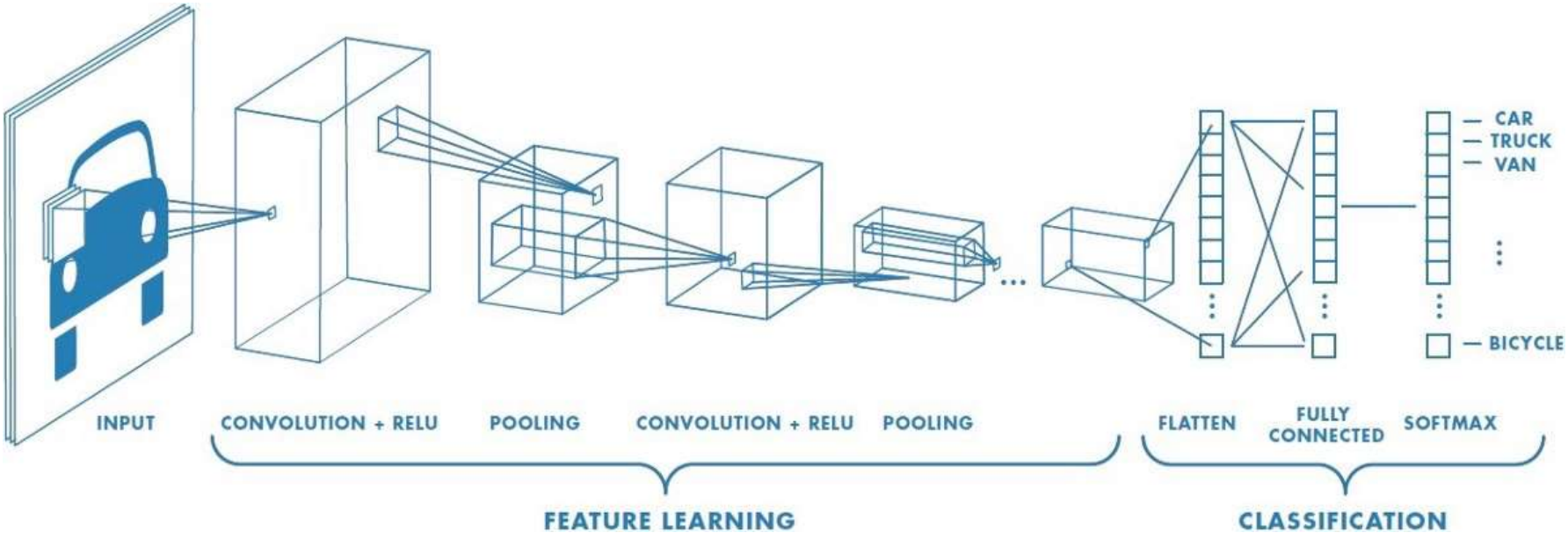
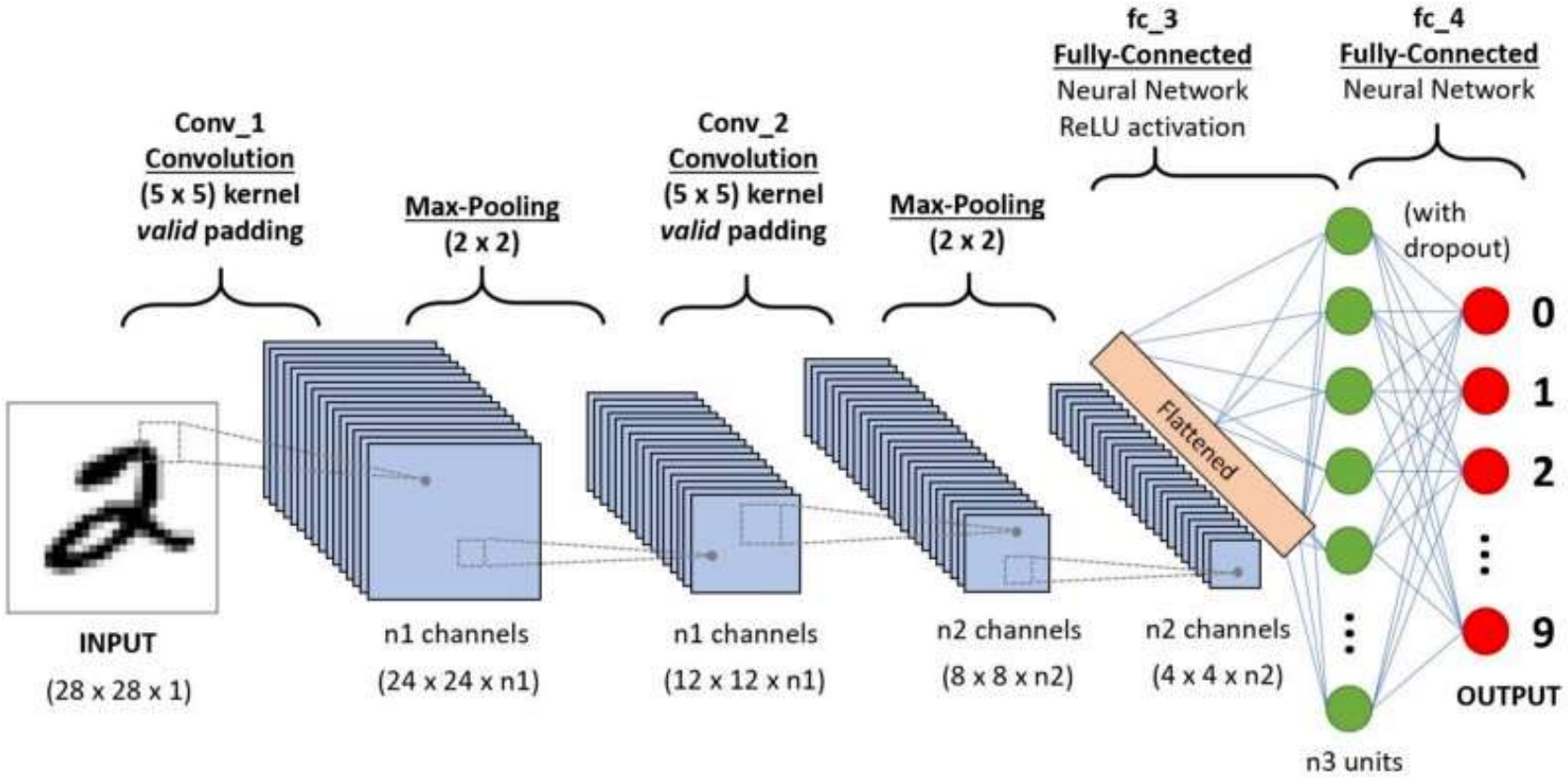
Convolutional neural networks



Source: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Convolutional neural networks



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Convolutional neural networks

- Preserve spatial structure by
  - Convolutional filters
- Scale up to process very large inputs (laid out on a grid) using
  - Sparse connections
  - Parameter sharing
- Robust to local variances thanks to
  - Spatial pooling

Neighbouring variables are locally correlated

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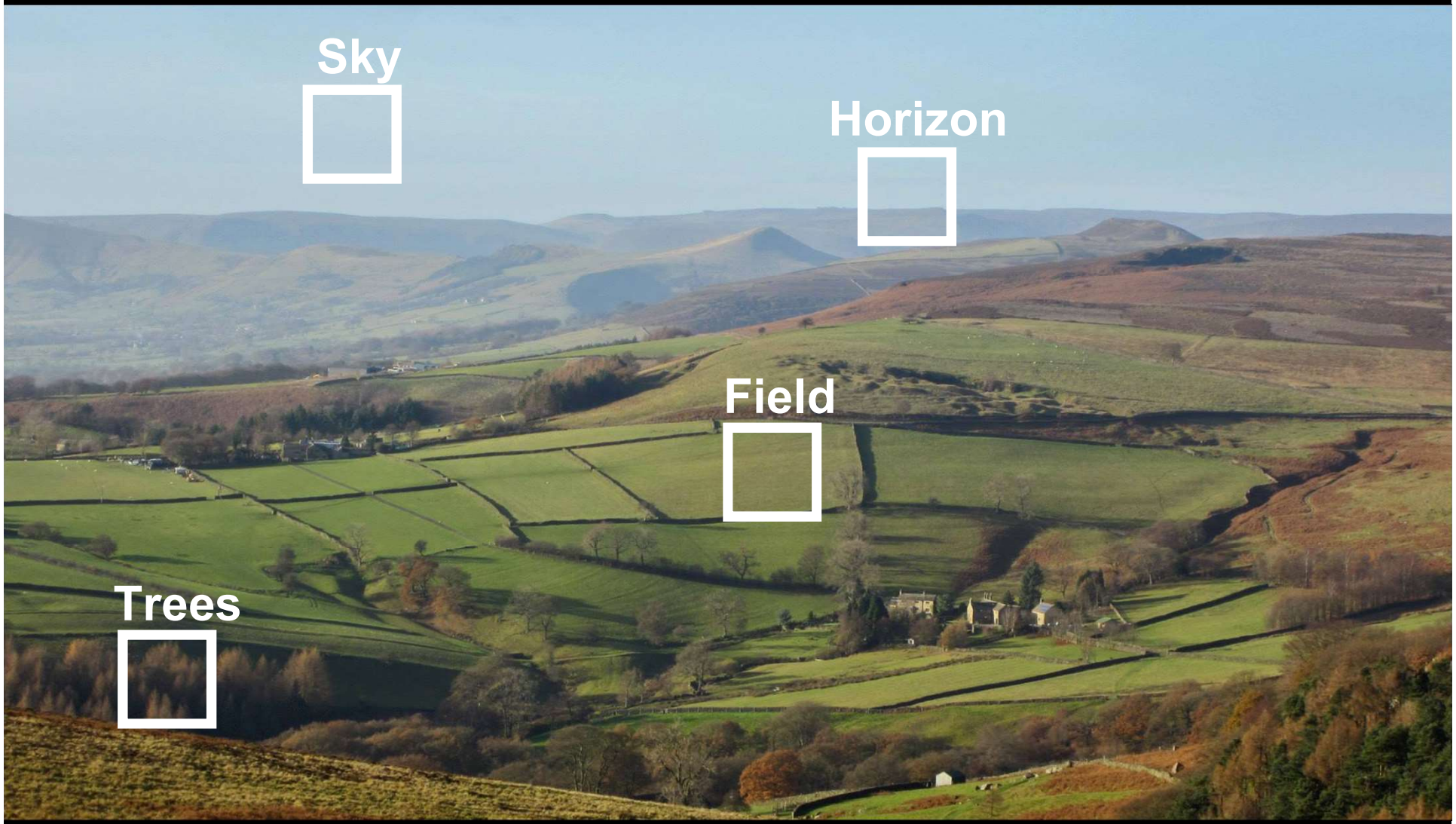
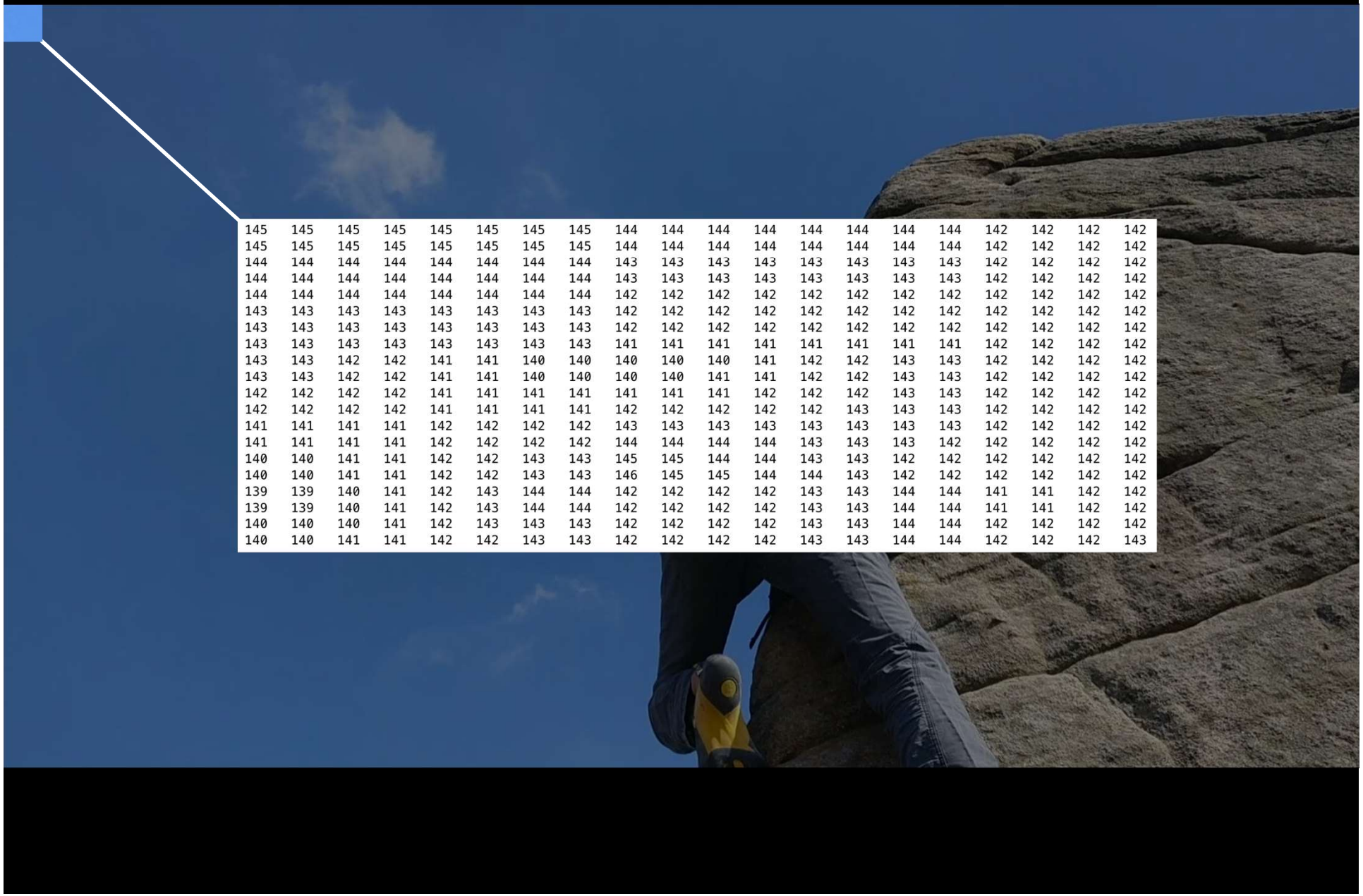


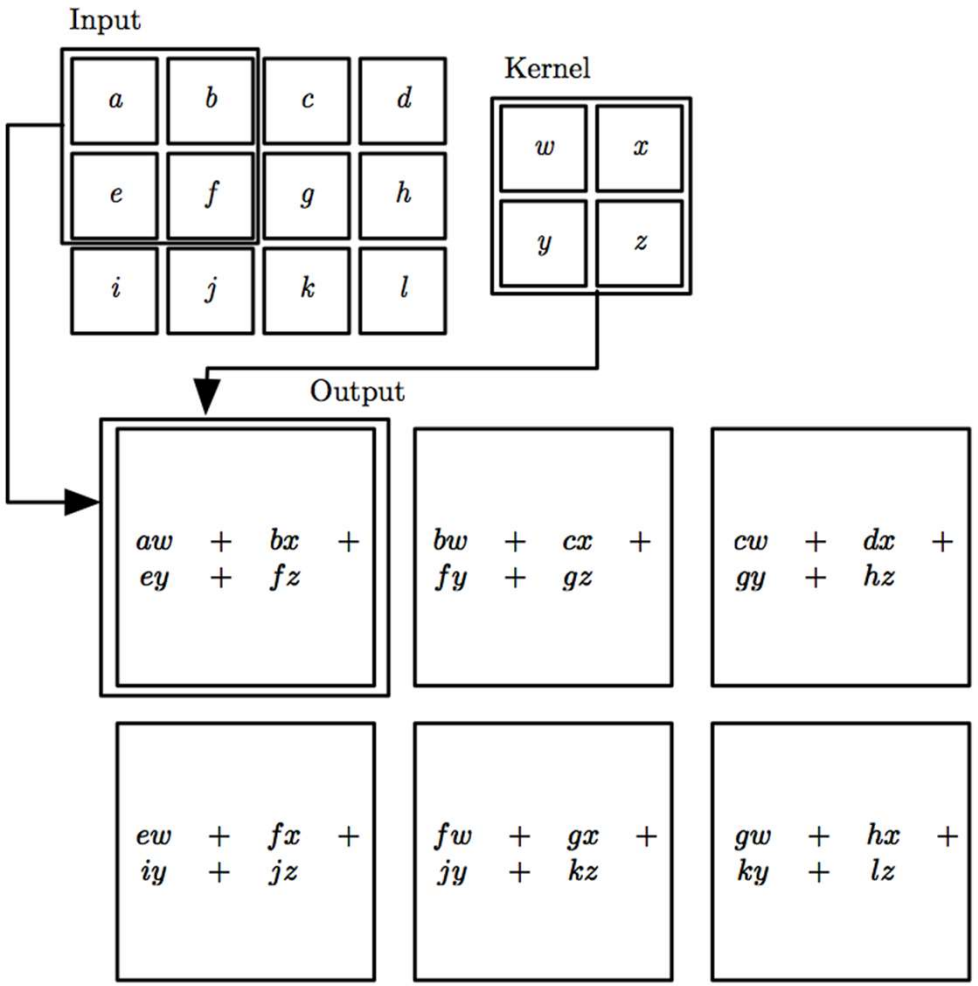
We say it already here…



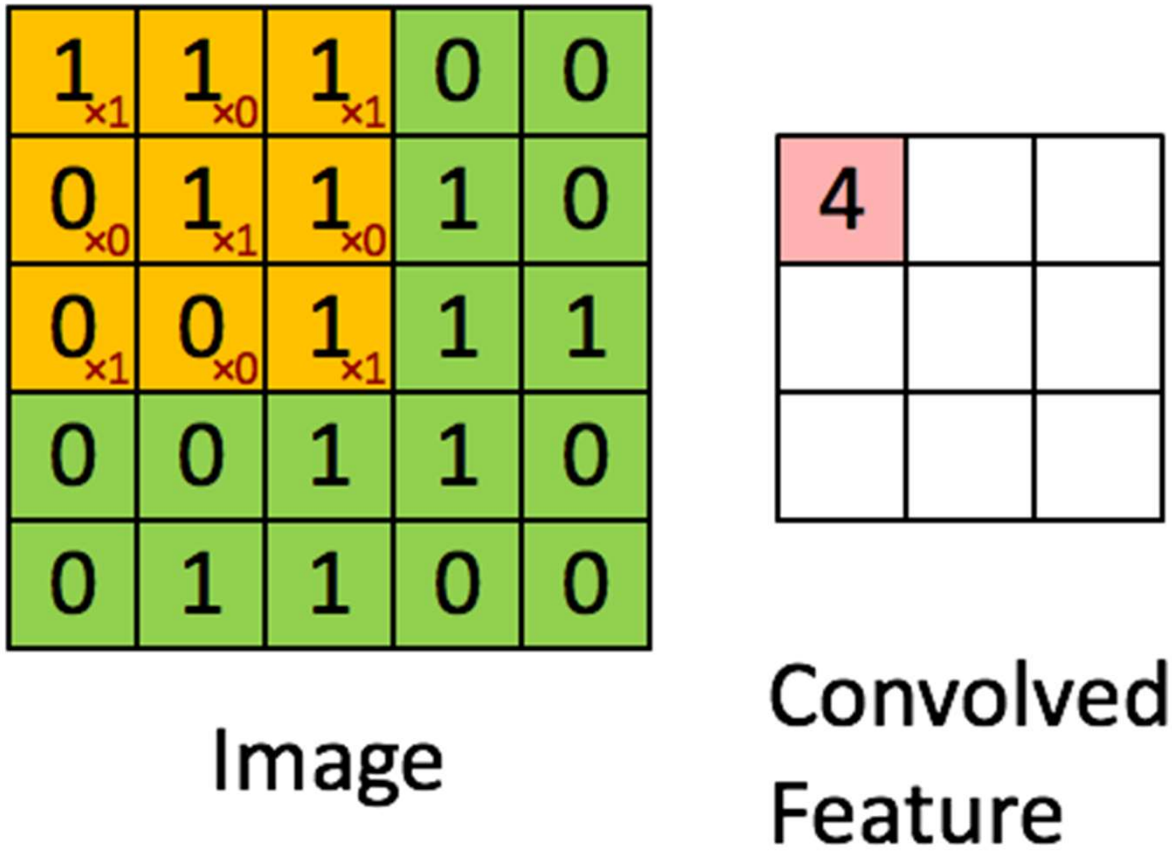
Key idea of CNNs

- **Replace first layers of matrix multiplications with convolution operations**
- Everything else stays the same
  - Maximum likelihood
  - Back-propagation
  - etc.

2D convolution



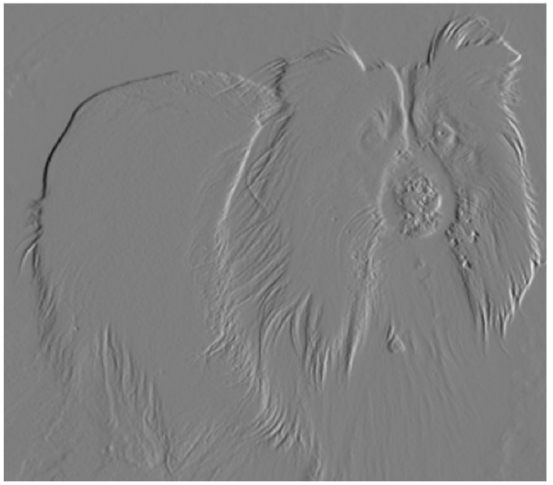
2D convolution



Source:https://hackernoon.com/visualizing-parts-of-convolutional-neural-networks-using-keras-and-cats-5cc01b214e59

Edge detection by convolution

Input



Output

1	-1

Kernel

Example: Sobel filter

$$\mathbf{G}_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * \mathbf{A} \quad \text{and} \quad \mathbf{G}_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} * \mathbf{A}$$

Source: https://en.wikipedia.org/wiki/Sobel_operator

Example: Sobel filter

```
%% MATLAB code
clear
img = imread('test_image.jpg');
img = rgb2gray(img);
imshow(edge(img,'sobel'));
```

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Sobel filter is handcrafted: **can we learn filters from data instead?**

Example: Sobel filter

```
%% MATLAB code
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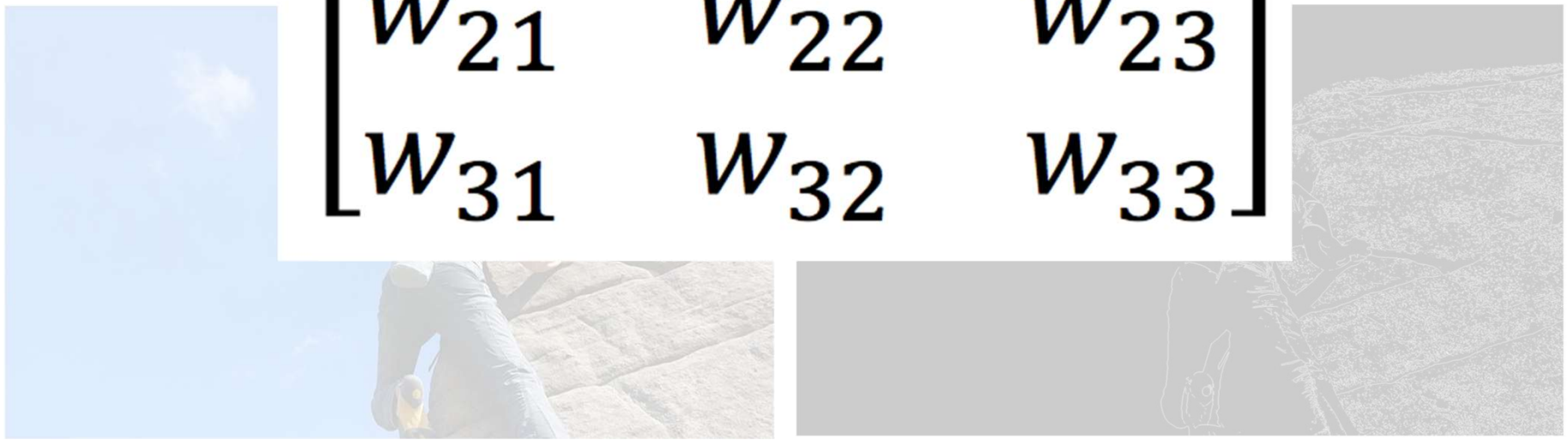
$$\begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{32} & w_{33} \end{bmatrix}$$



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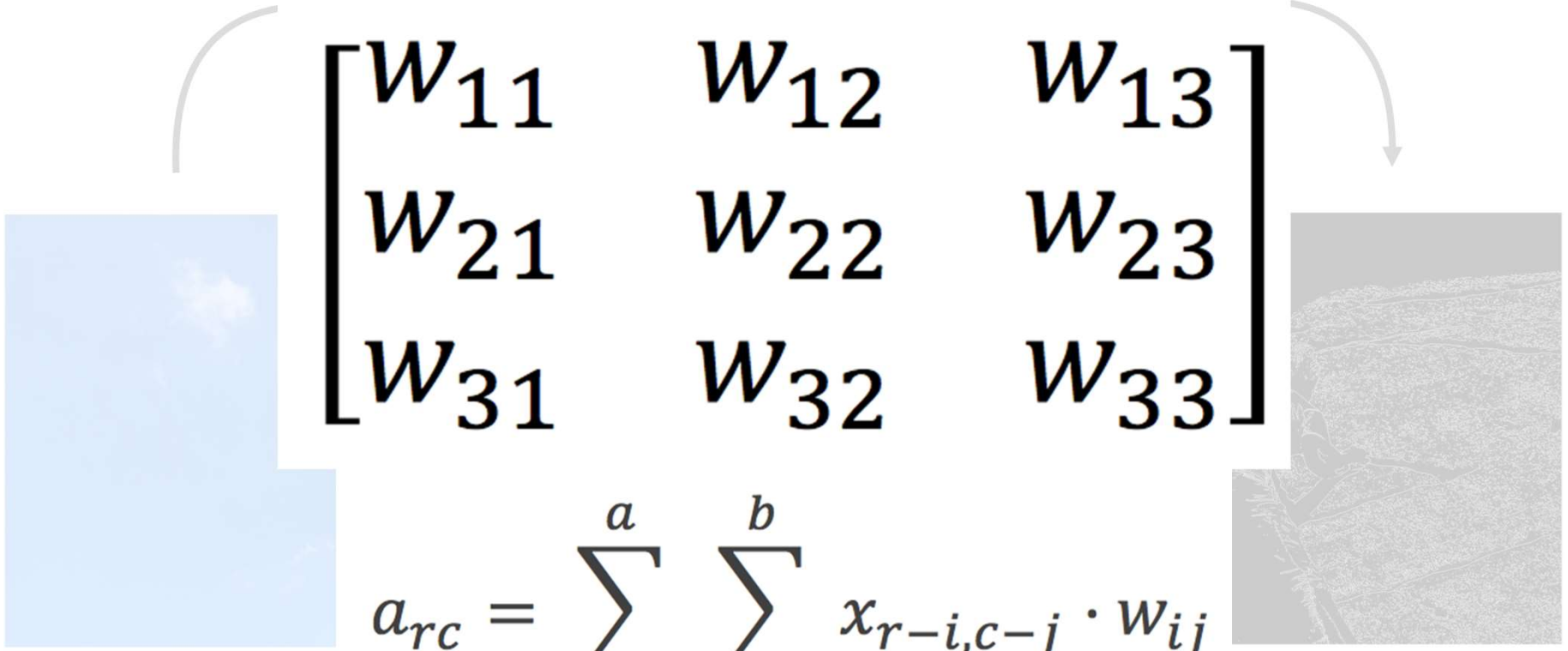

$$\begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{32} & w_{33} \end{bmatrix}$$

$$a_{rc} = \sum_{i=-a}^{a} \sum_{j=-b}^{b} x_{r-i,c-j} \cdot w_{ij}$$

Convolution is essentially a dot product, just like linear layers

Example: Sobel filter

```
%% MATLAB code
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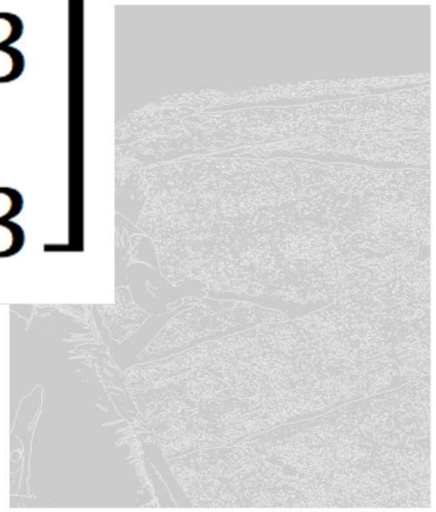
```

$$\begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{32} & w_{33} \end{bmatrix}$$



$$\frac{\partial a_{rc}}{\partial w_{ij}} = \sum_{i=-a}^{a} \sum_{j=-b}^{b} x_{r-i,c-j}$$

Example: Sobel filter

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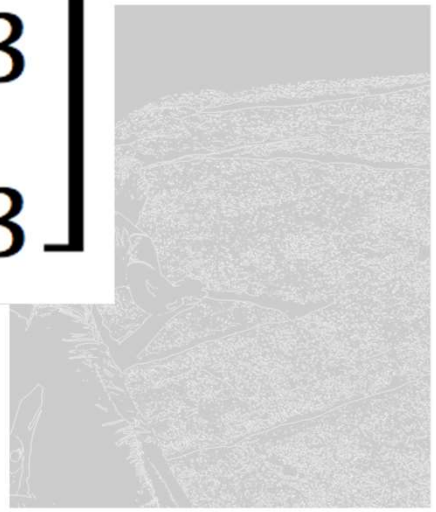
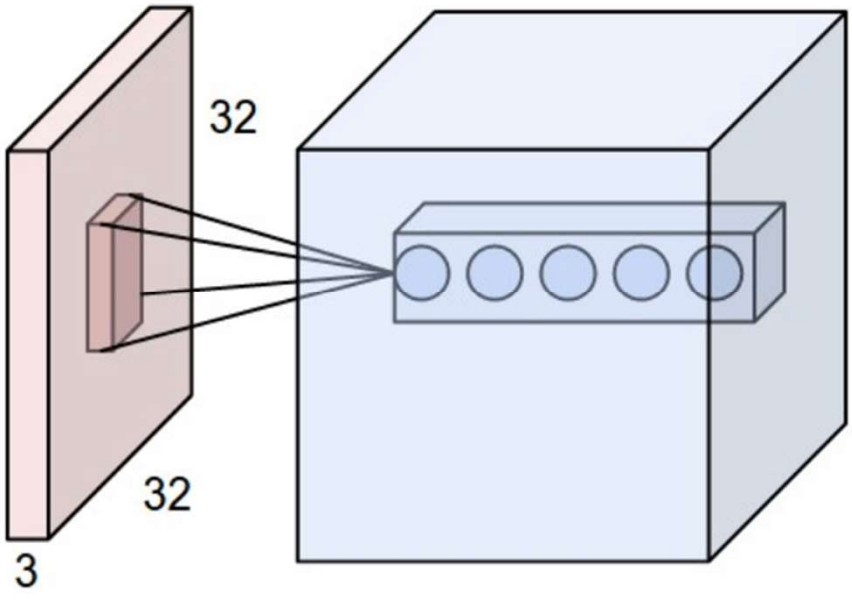
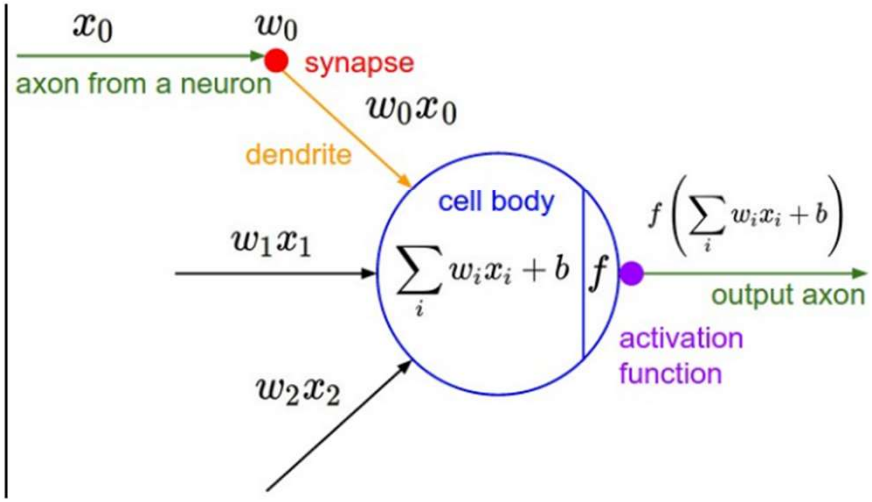


$$\frac{\partial a_{rc}}{\partial w_{ij}} = \sum_{i=-a}^{a} \sum_{j=-b}^{b} x_{r-i,c-j}$$

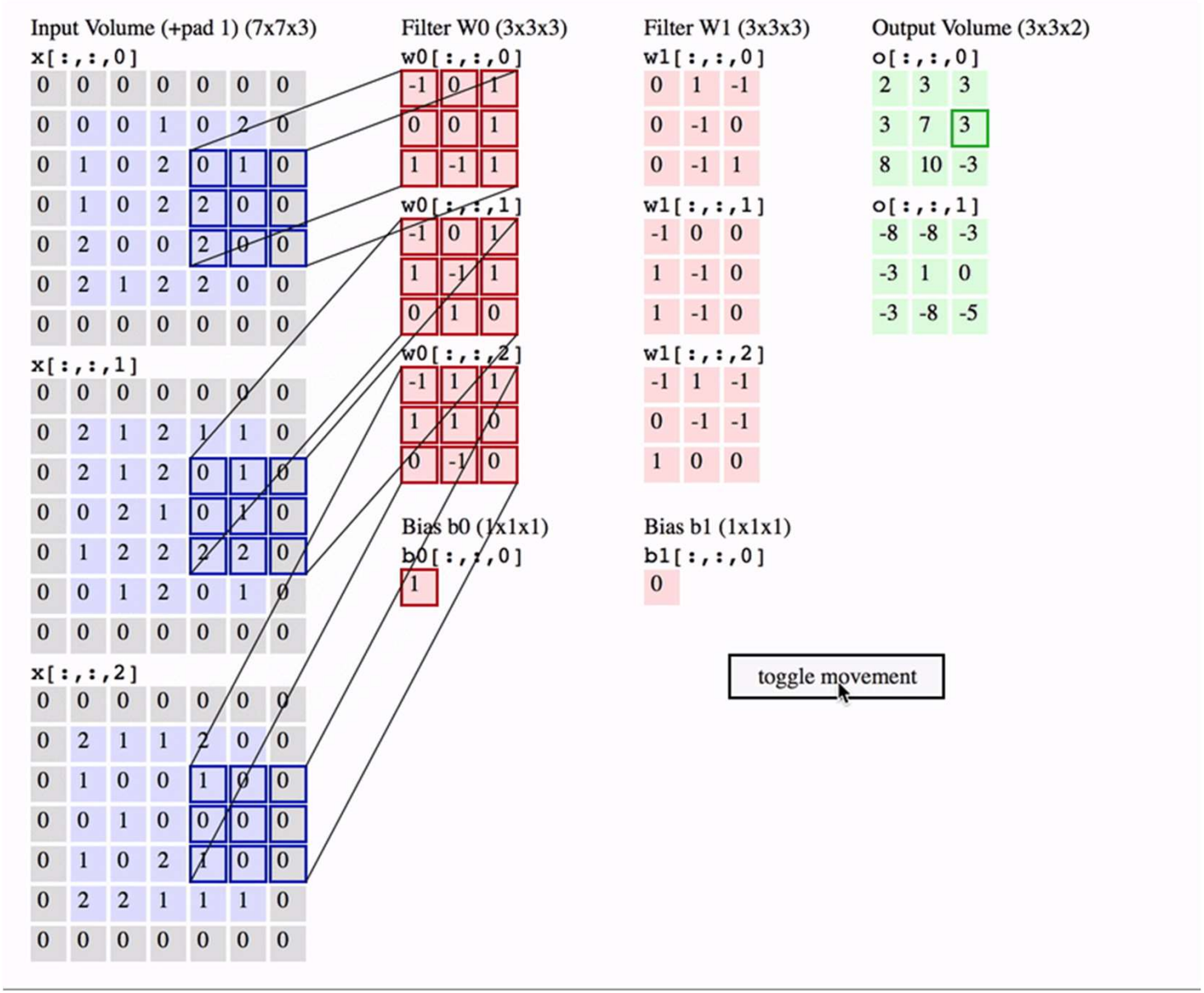
We can learn ***W***

Convolutional layers





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



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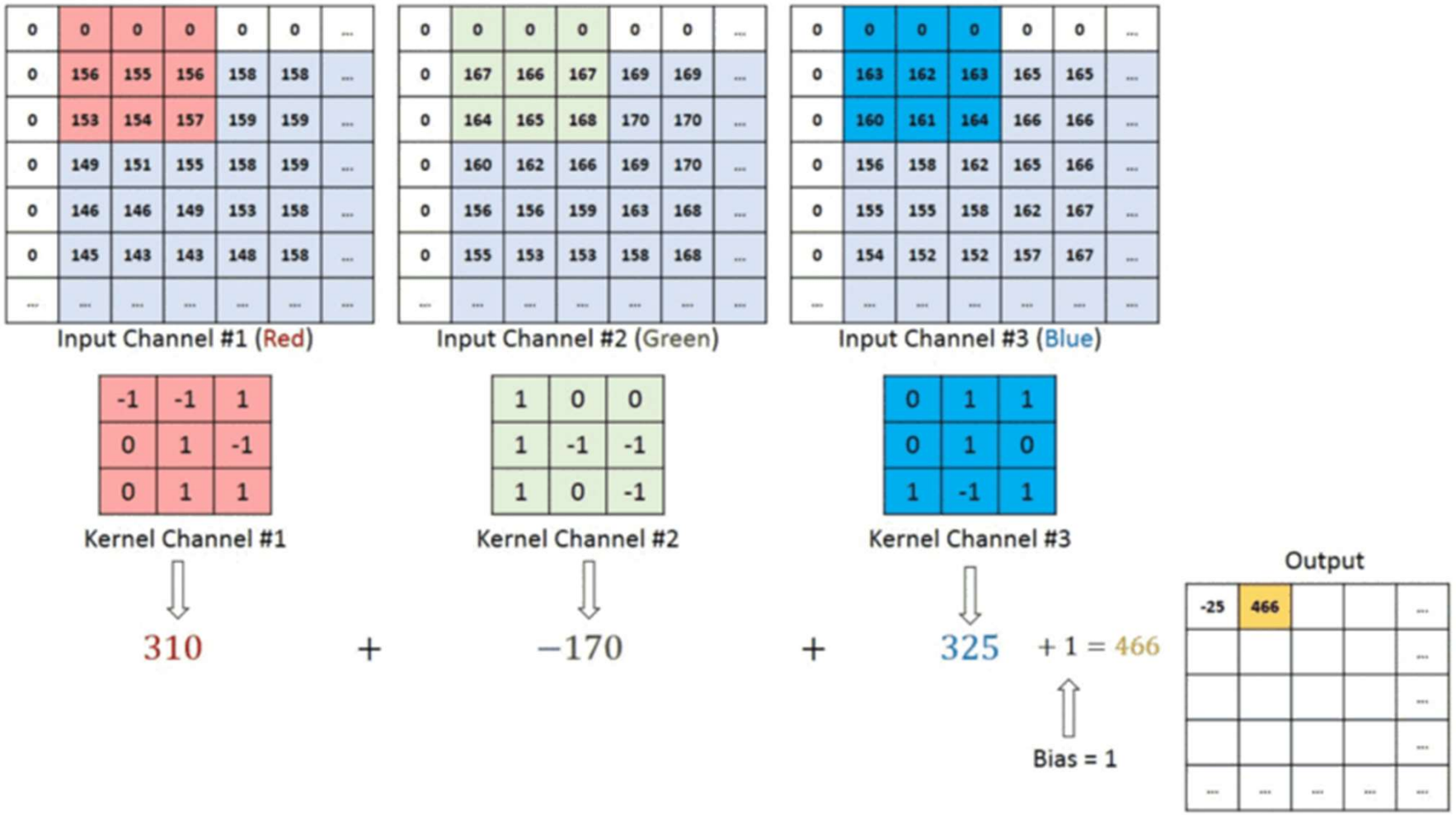

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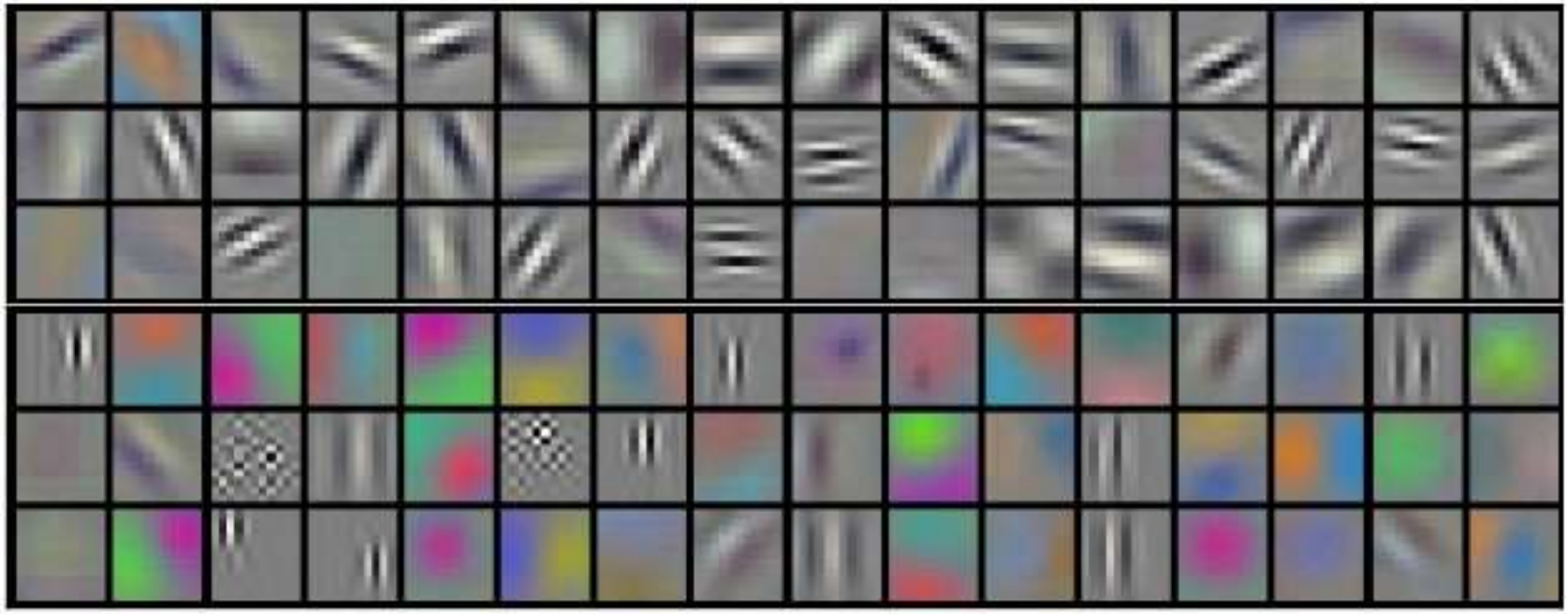
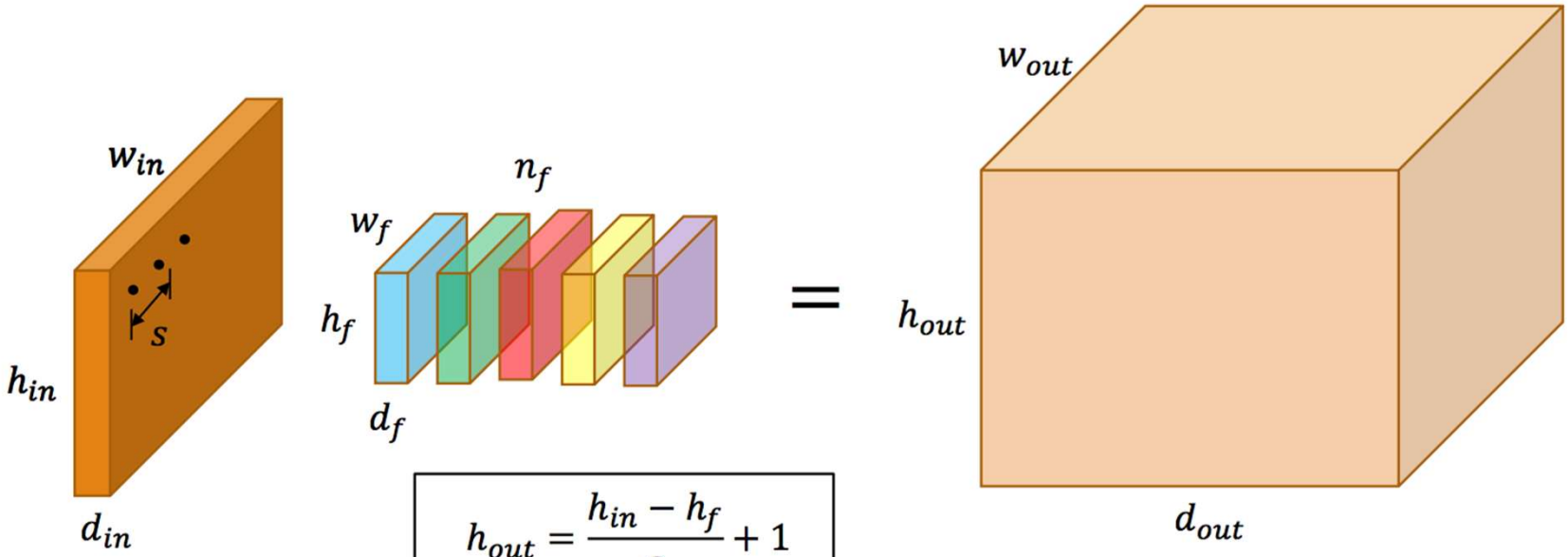


Example filters learned by Krizhevsky et al. Each of the 96 filters shown here is of size [11x11x3], a

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

Dimensions after convolution



$$h_{out} = \frac{h_{in} - h_f}{s} + 1$$

$$w_{out} = \frac{w_{in} - w_f}{s} + 1$$

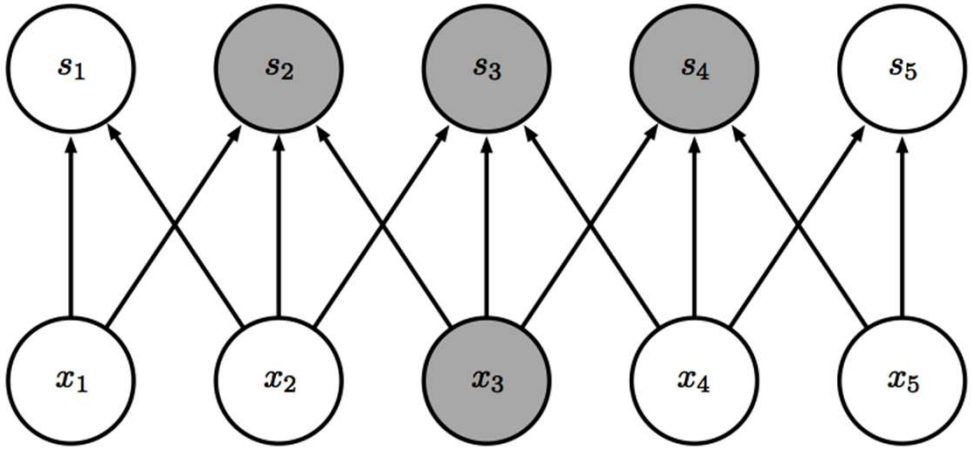
$$d_{out} = n_f$$

$$d_f = d_{in}$$

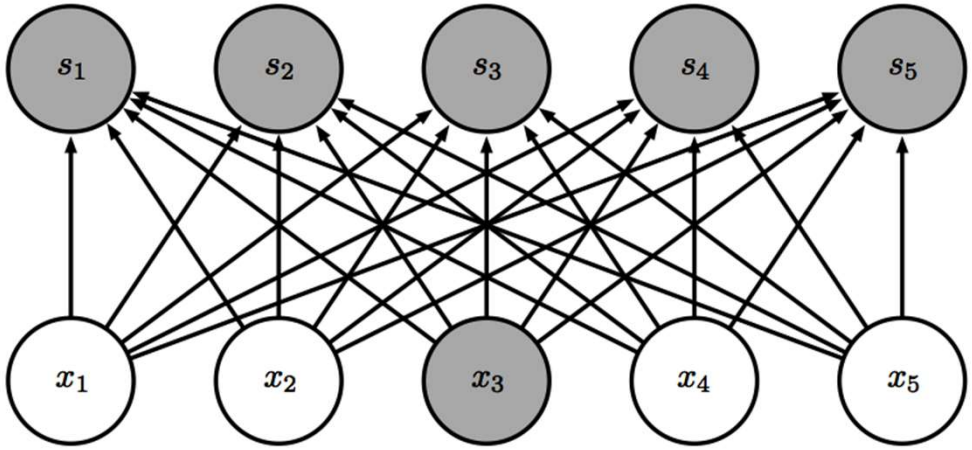
Source Dr. Efstratios Gavves UVA lectures

Sparse connectivity

Sparse connections due to small convolution kernel

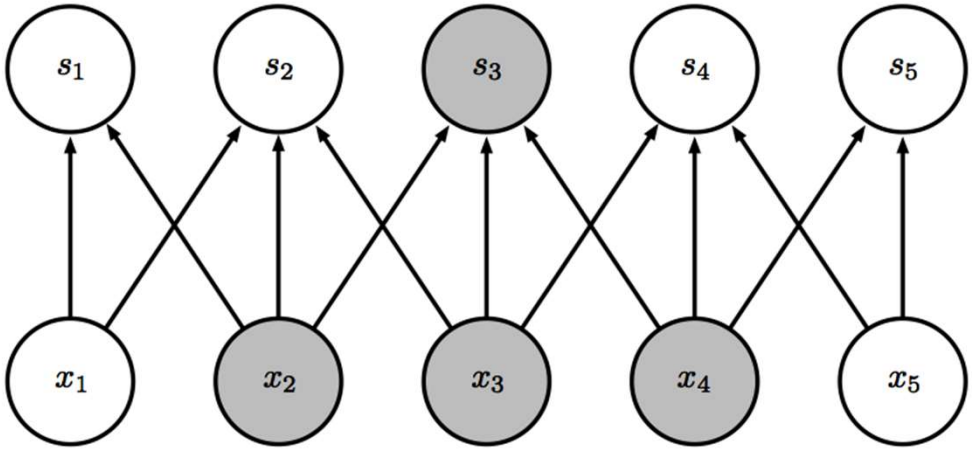


Dense connections



Sparse connectivity

Sparse connections due to small convolution kernel



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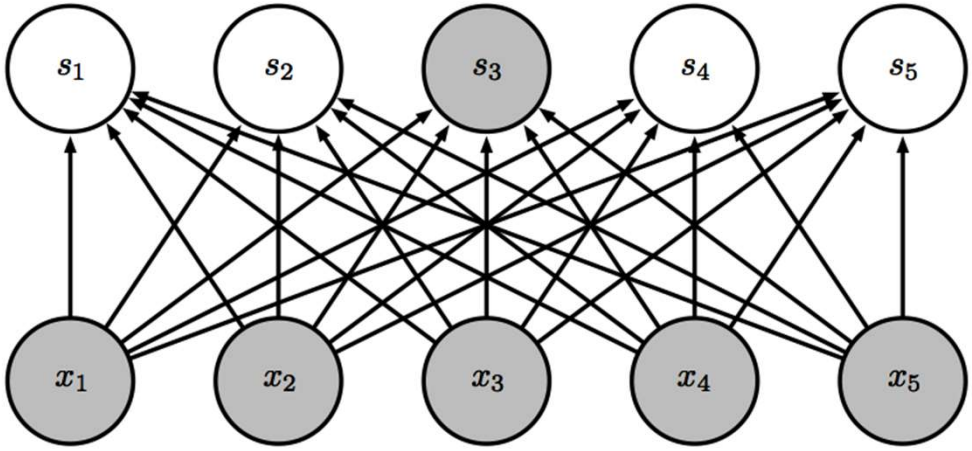
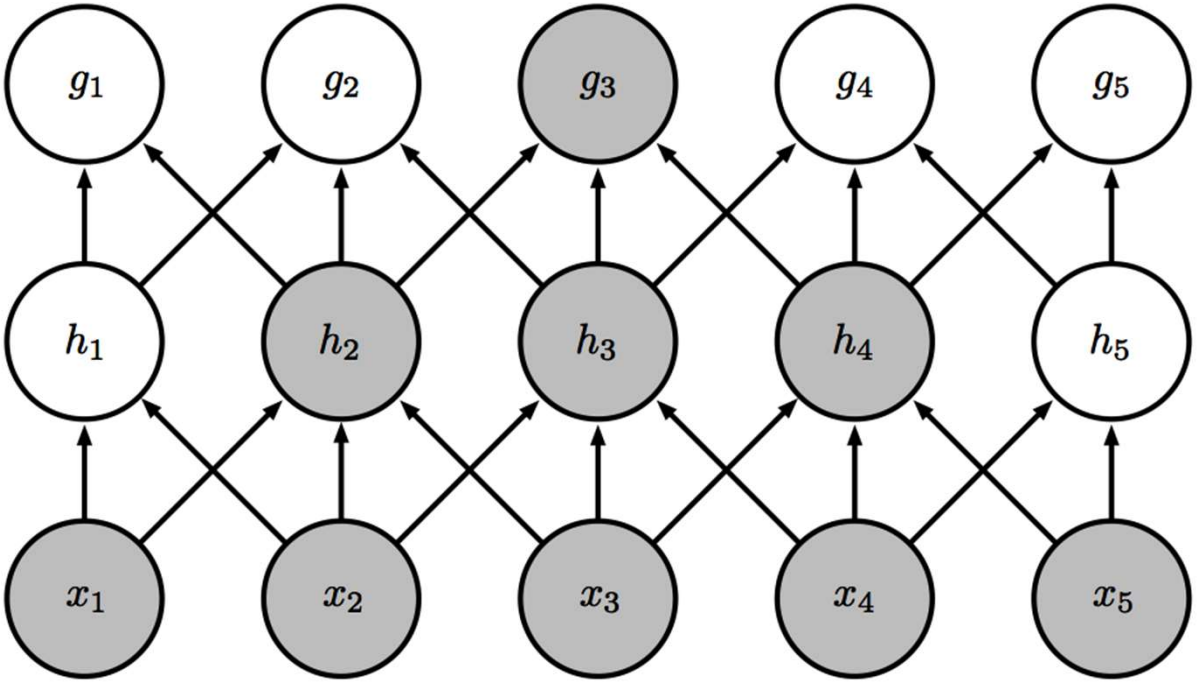
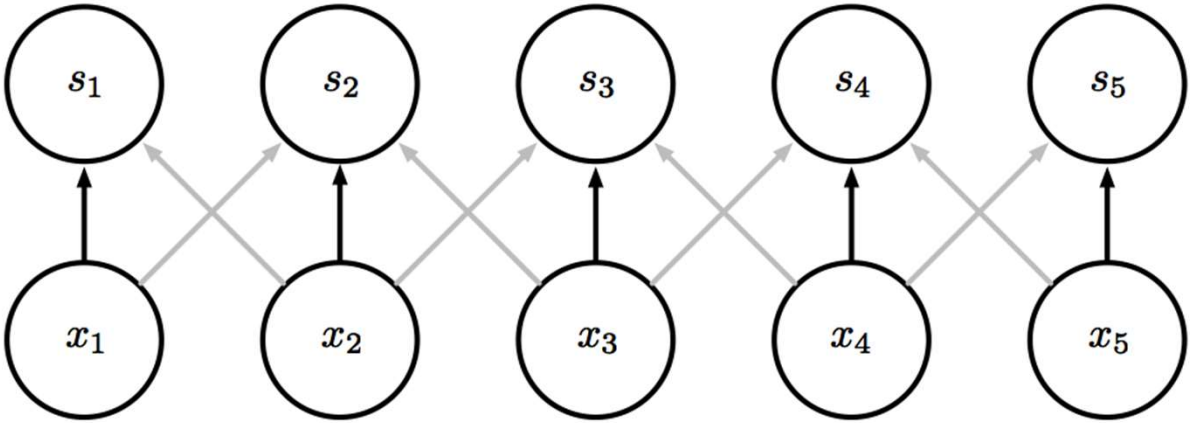


Growing receptive fields

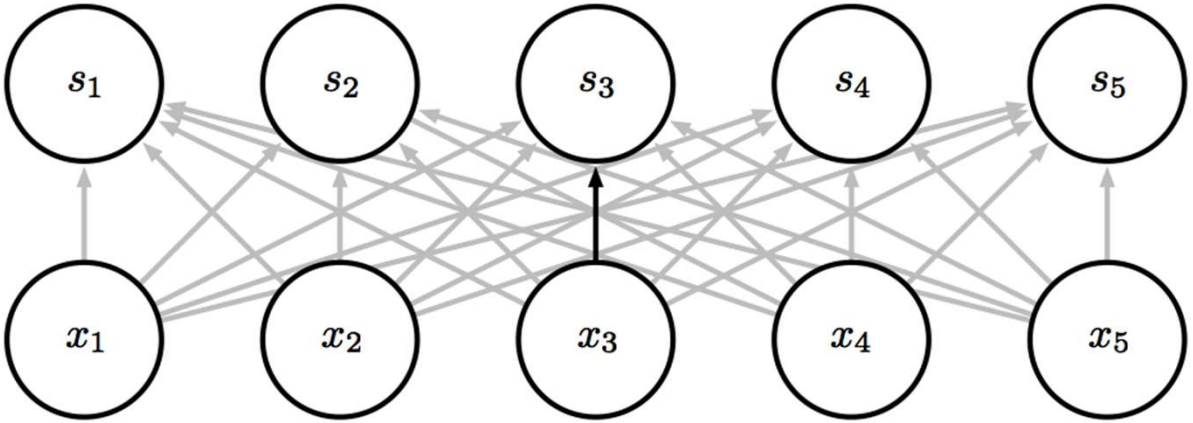


Parameter sharing

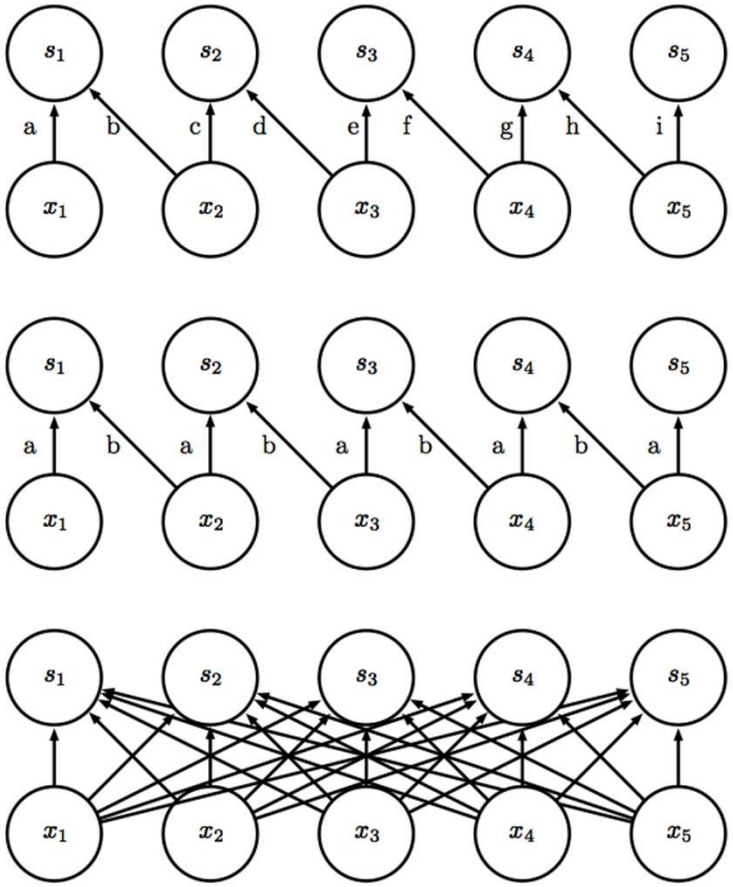
Convolution shares the same parameters across all spatial locations



Traditional matrix multiplication does not share any parameters



Local connectivity vs convolution

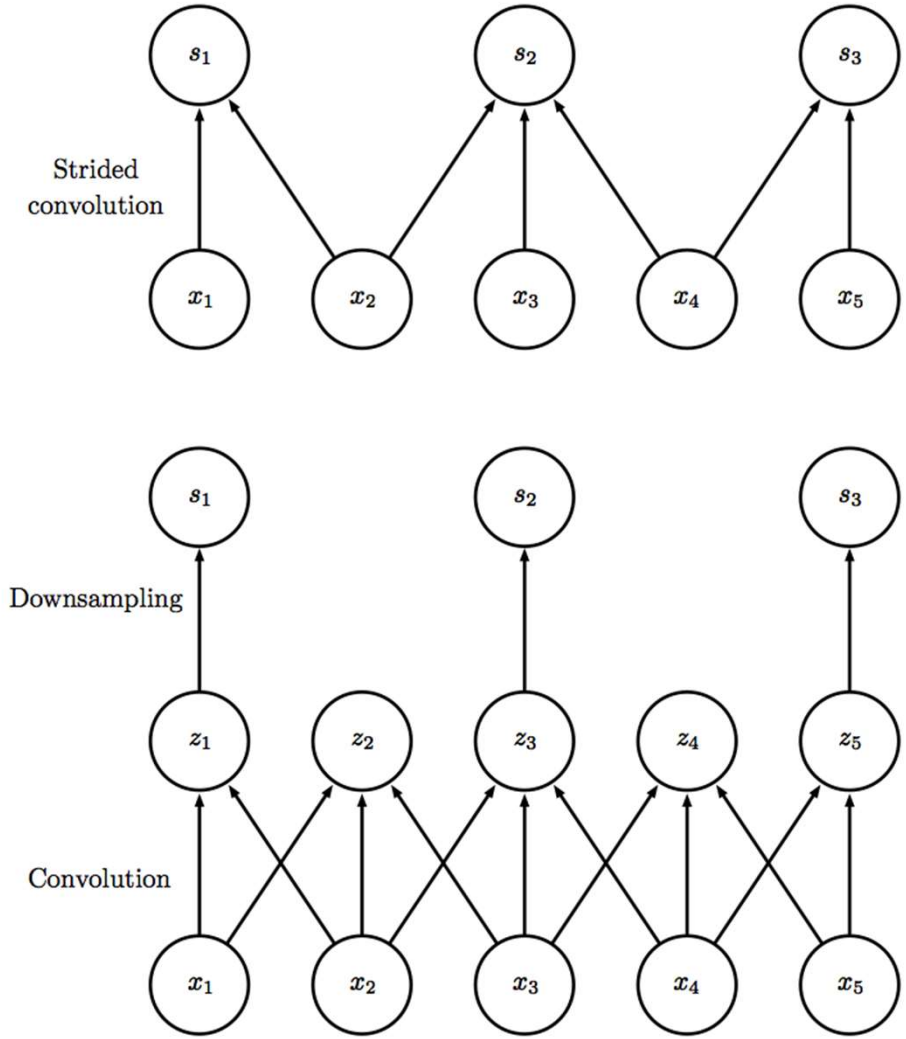


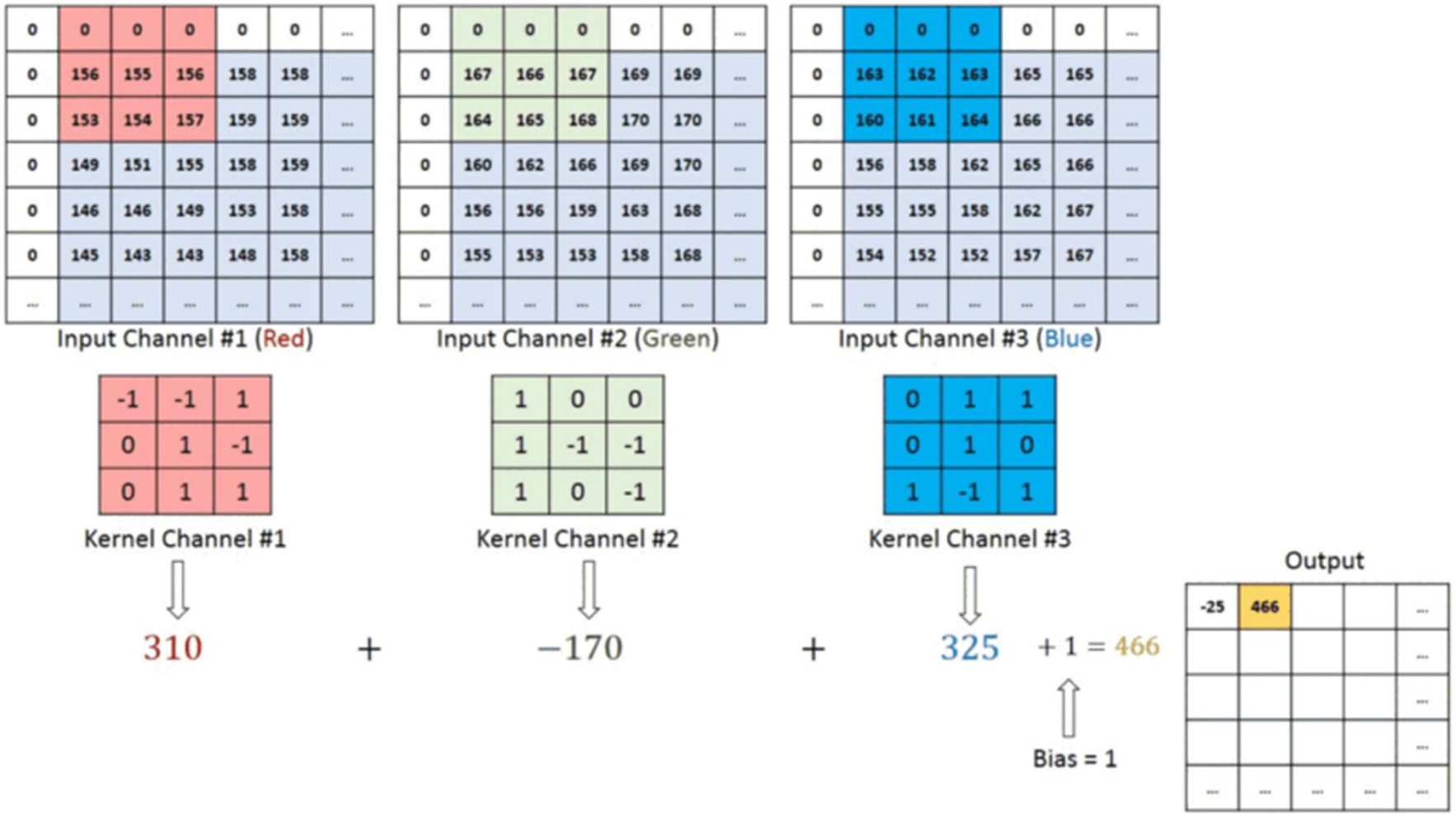
Local connection: like convolution, but no sharing

Convolution

Fully connected

Convolution with stride





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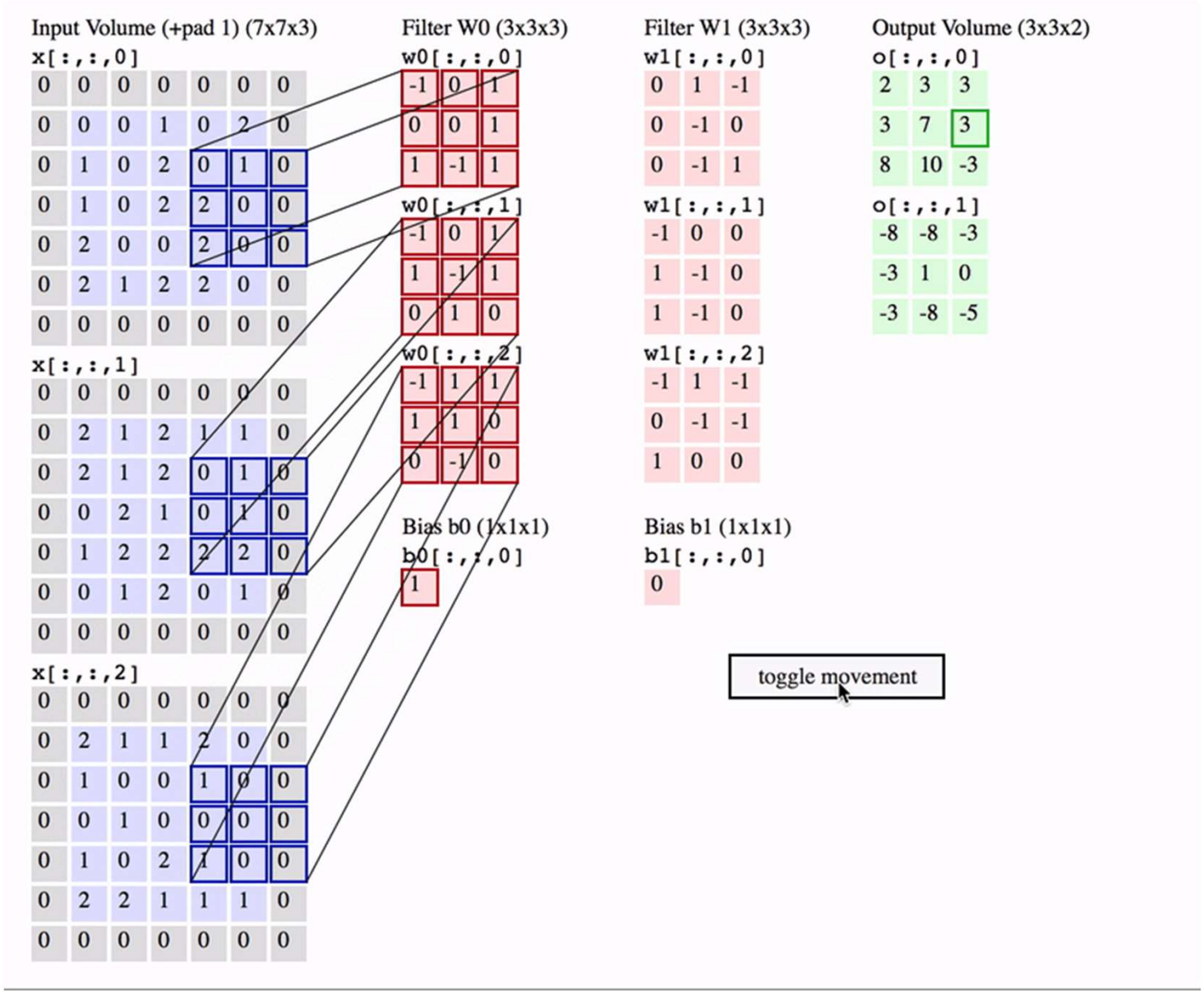

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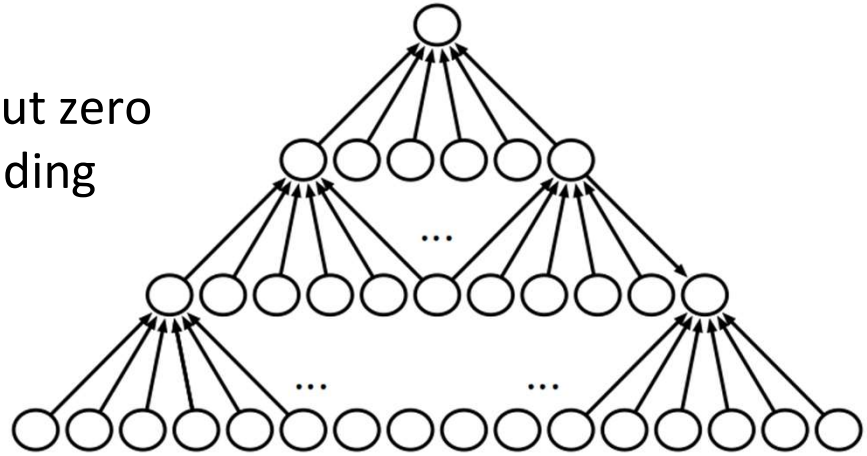
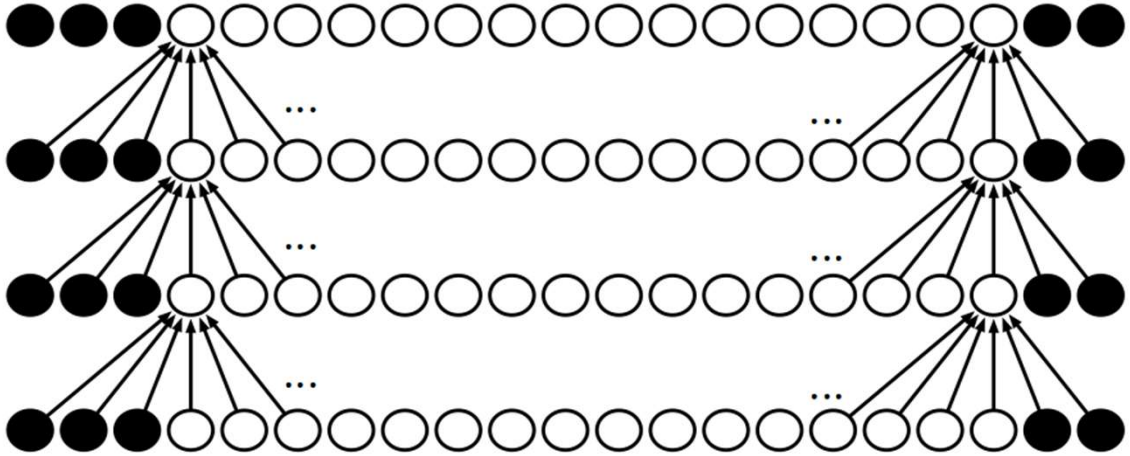
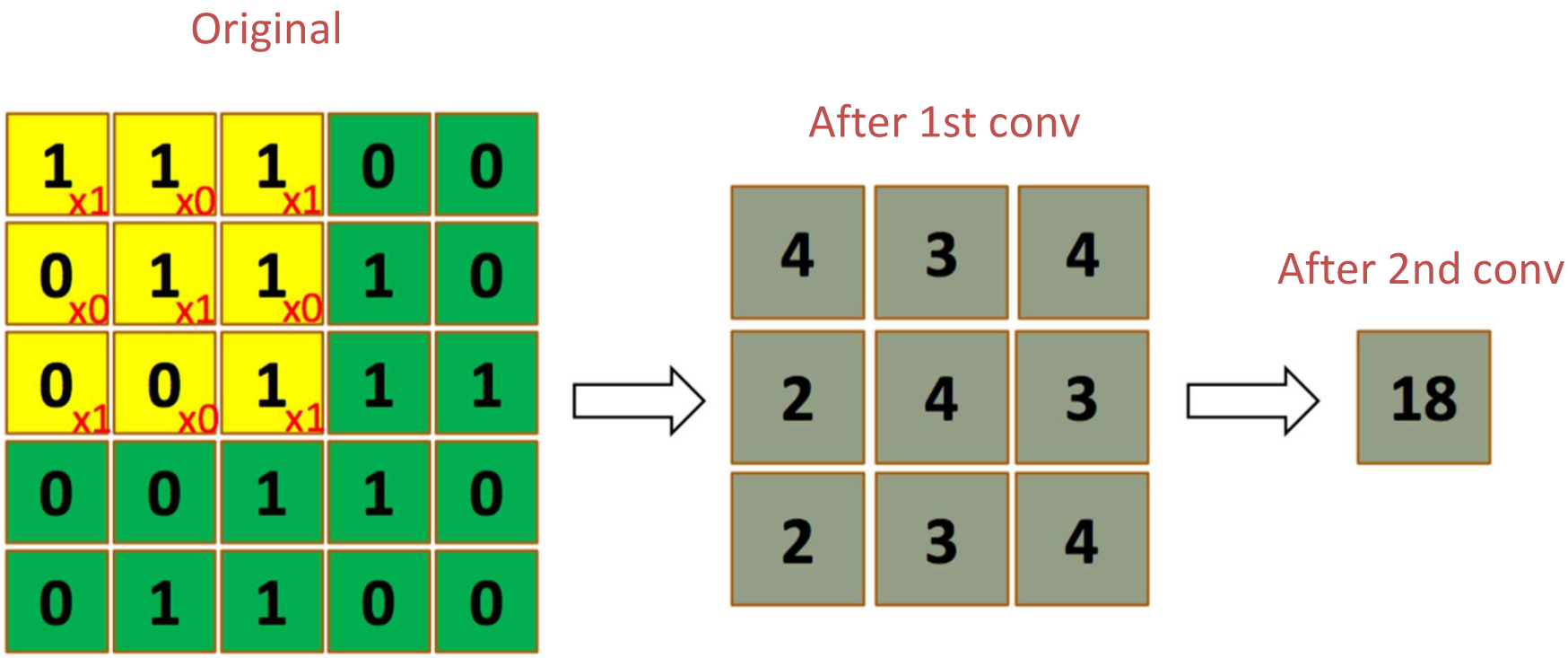
Zero padding controls size

Without zero padding



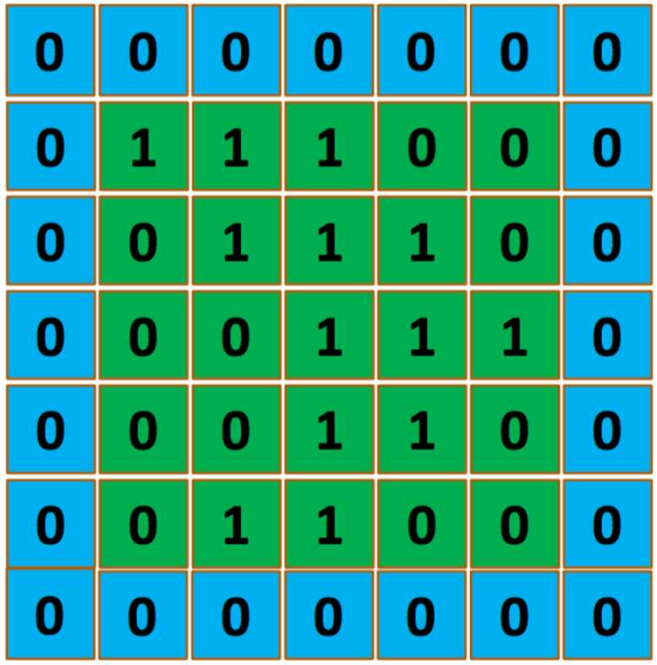
With zero padding

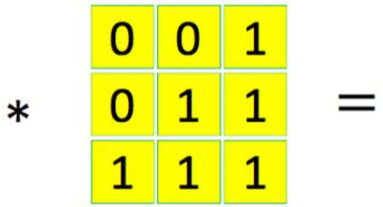




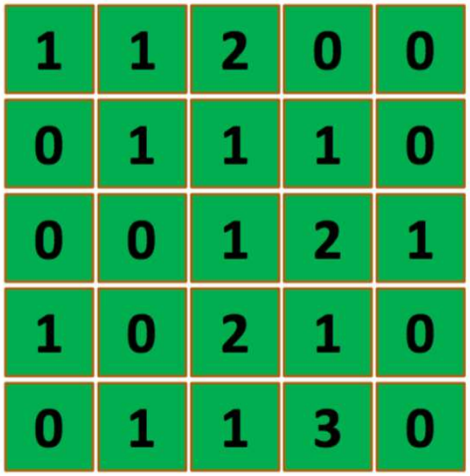
Without padding the image shrinks!

Original



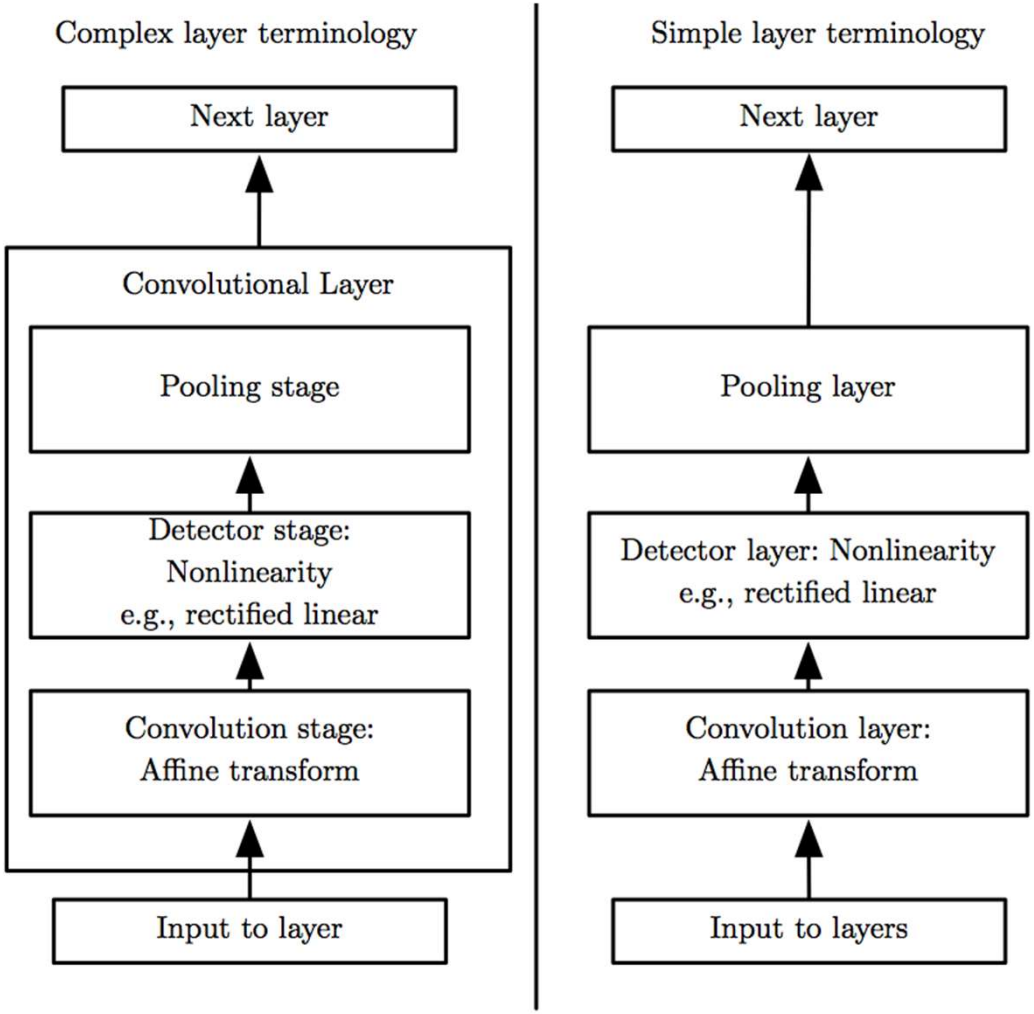


After 1st conv

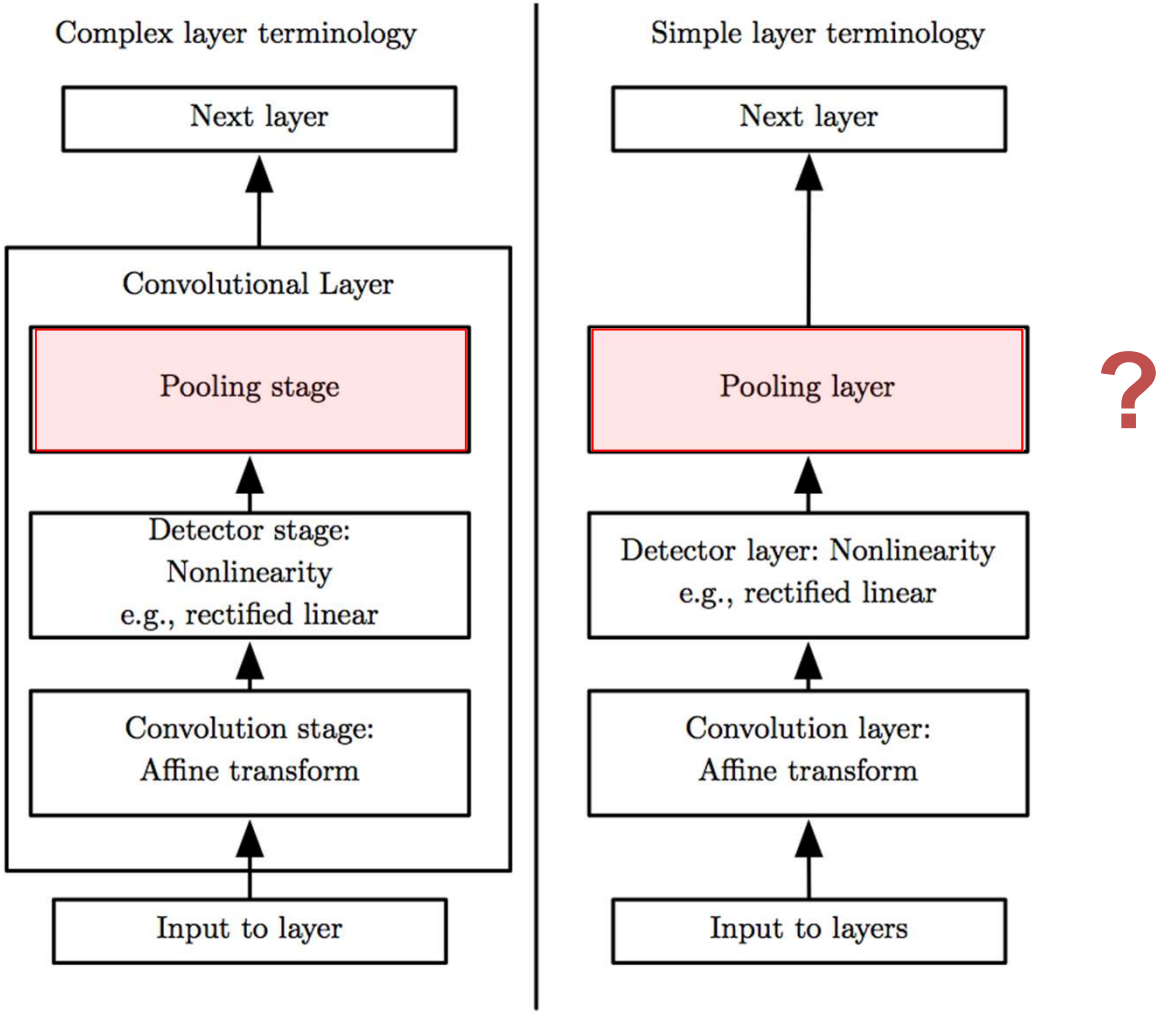


With padding the image doesn't shrinks!

CNN components

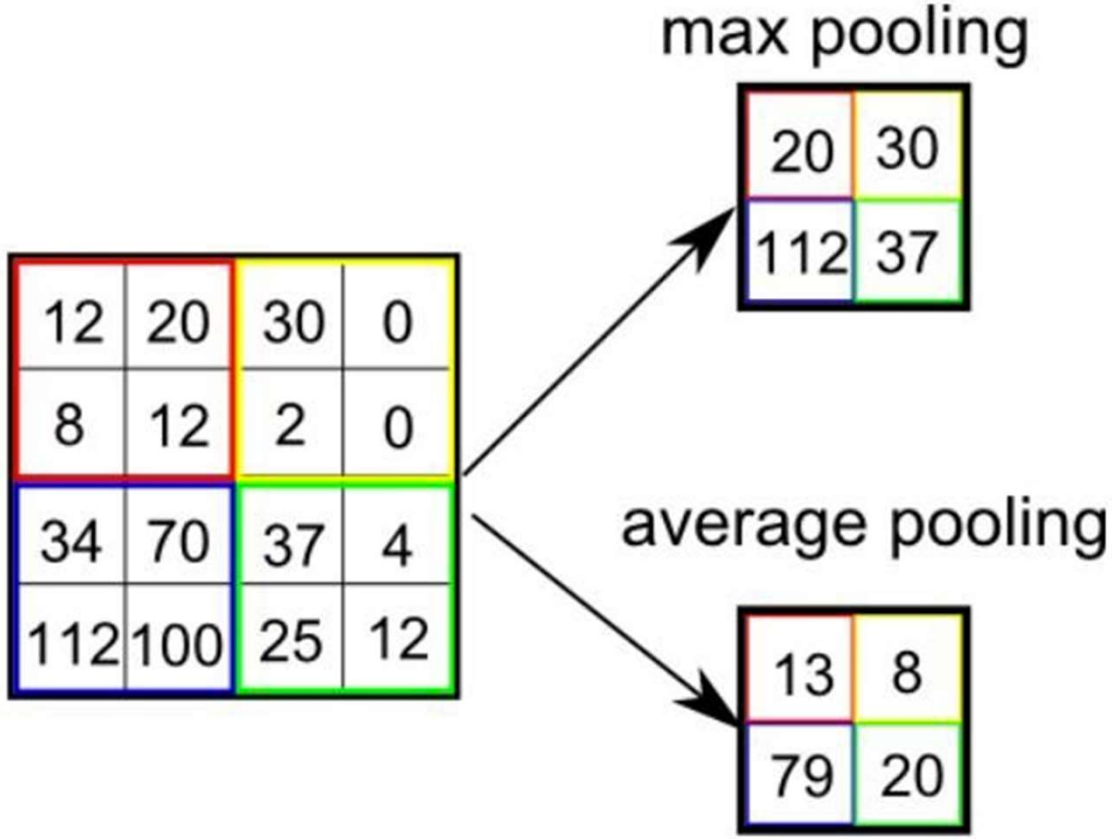


CNN components



Pooling

- Aggregate multiple values into a single value
  - Reduce size of layer (speed up computation)
  - Keep most important information for next layer
  - Invariance to small transformation



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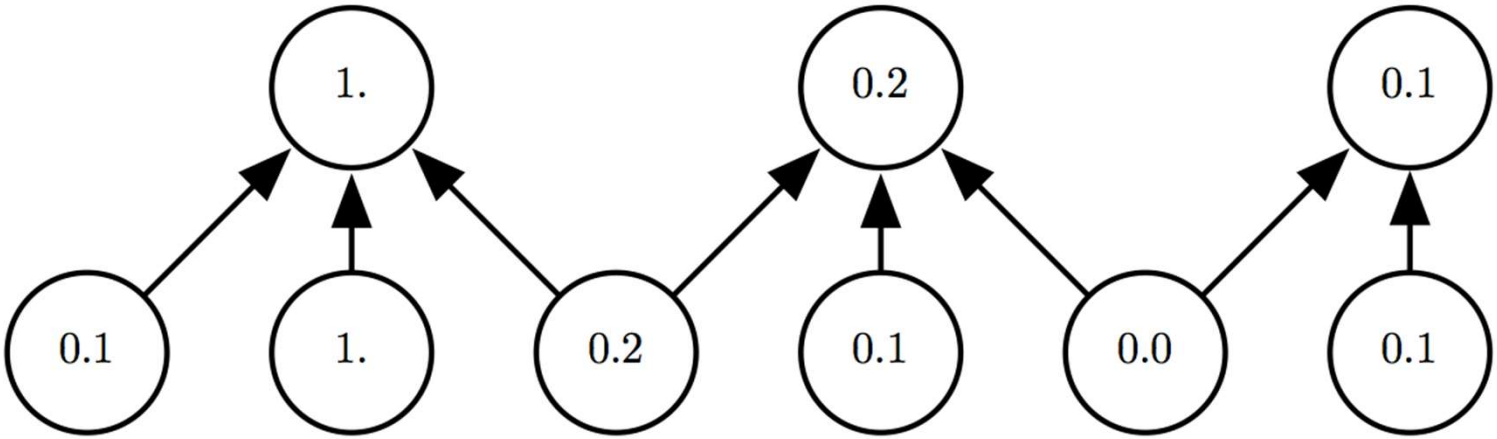
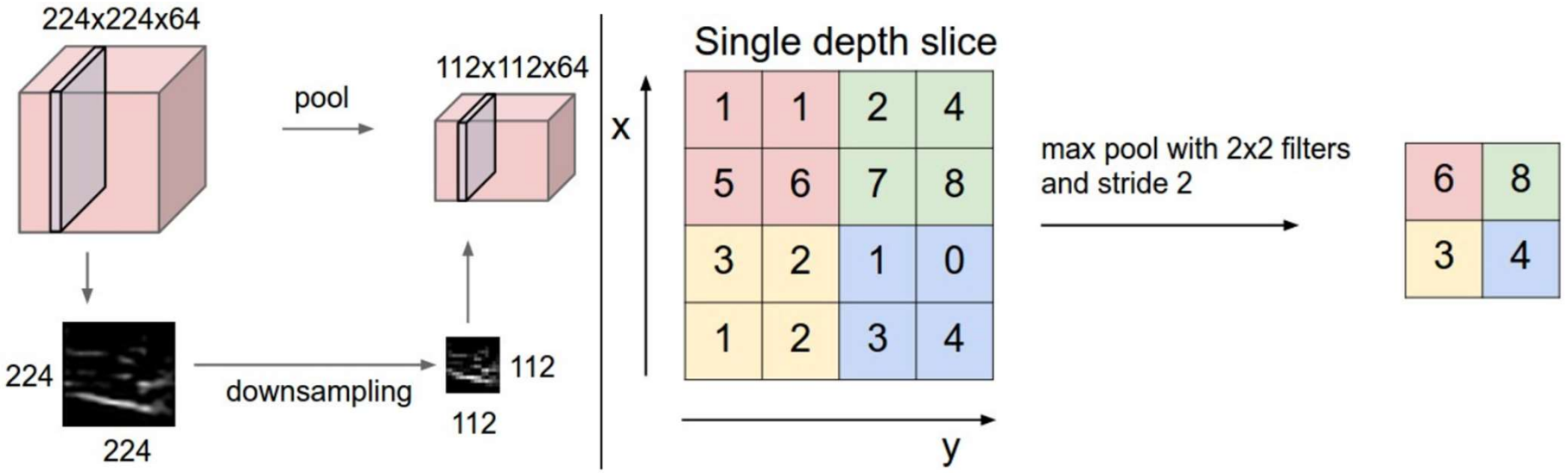
Downsampling with pooling



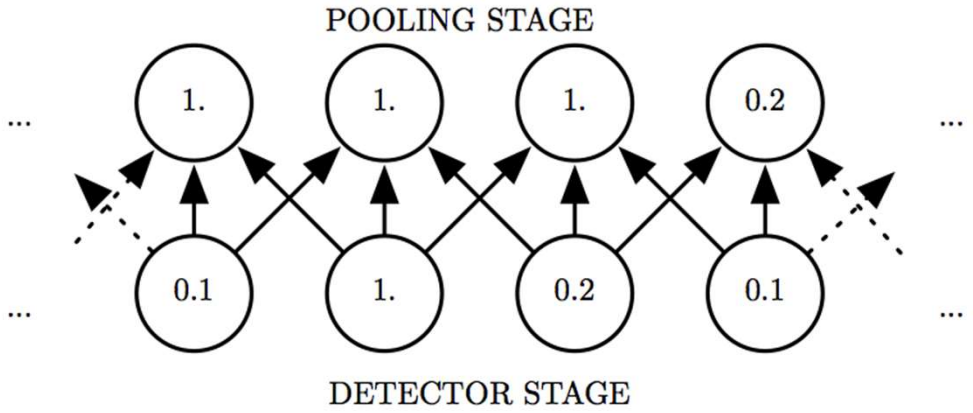
(When stride size > 1)

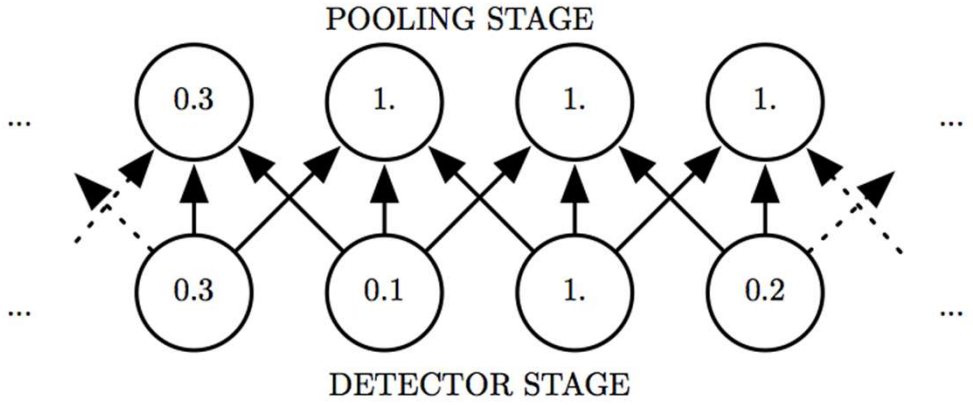


Pooling layer downsamples the volume spatially, independently in each depth slice of the input volume. Left: In this example, the input volume of size [224x224x64] is pooled with filter size 2, stride 2 into output volume of size [112x112x64]. Notice that the volume depth is preserved. Right: The most common downsampling operation is max, giving rise to max pooling, here shown with a stride of 2. That is, each max is taken over 4 numbers (little 2x2 square).

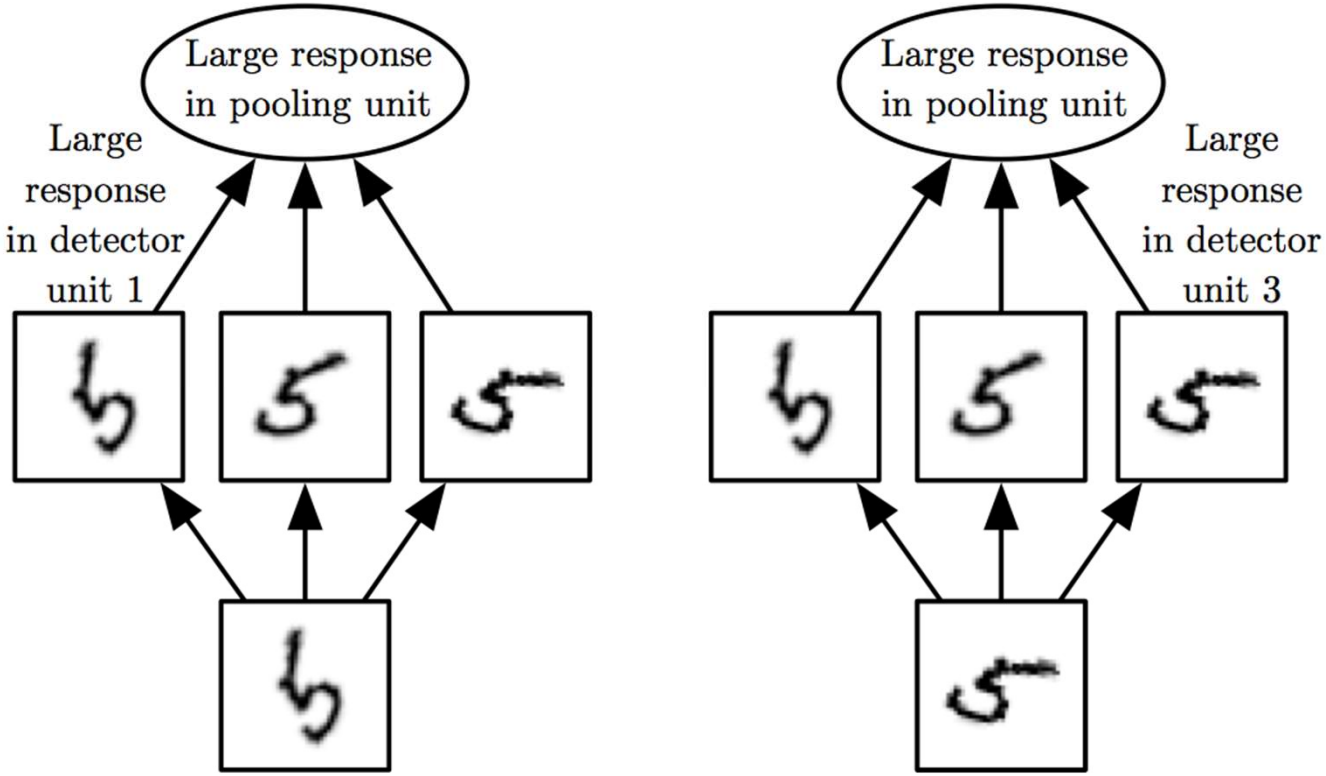
Source: http://cs231n.github.io/convolutional-networks/

Invariance through pooling





Cross-channel pooling



Do we really need pooling?

- Increasing the stride size of the kernel also reduces the size of the image…so why not doing that instead of pooling? Yes you can

Table 2: Model description of the three networks derived from base model C used for evaluating the importance of pooling in case of classification on CIFAR-10 and CIFAR-100. The derived models for base models A and B are built analogously. The higher layers are the same as in Table 1 .

Model		
Strided-CNN-C	ConvPool-CNN-C	All-CNN-C
Input 32×32 RGB image		
3×3 conv. 96 ReLU 3×3 conv. 96 ReLU with stride $r = 2$	3×3 conv. 96 ReLU 3×3 conv. 96 ReLU 3×3 conv. 96 ReLU	3×3 conv. 96 ReLU 3×3 conv. 96 ReLU
	3×3 max-pooling stride 2	3×3 conv. 96 ReLU with stride $r = 2$
3×3 conv. 192 ReLU 3×3 conv. 192 ReLU with stride $r = 2$	3×3 conv. 192 ReLU 3×3 conv. 192 ReLU 3×3 conv. 192 ReLU	3×3 conv. 192 ReLU 3×3 conv. 192 ReLU
	3×3 max-pooling stride 2	3×3 conv. 192 ReLU with stride $r = 2$

⋮

See: https://arxiv.org/pdf/1412.6806.pdf and
https://towardsdatascience.com/iclr-2015-striving-for-simplicity-the-all-convolutional-net-with-interactive-code-manual-b4976e206760

Summary

- The concept of convolutional NN
  - Why it is helpful in image recognition?
- What is convolution
- Convolutional layer and its basic components
- The special characteristics of convolutional layer
  - Sparse connectivity
  - Parameter sharing
  - Pooling: different type of Invariance

Next Week:

  - Variants of CNN and the introduction of RNN