


浙江大学爱丁堡大学联合学院

ZJU-UoE Institute

Lecture 11 - Convolutional Neural Networks (CNN)

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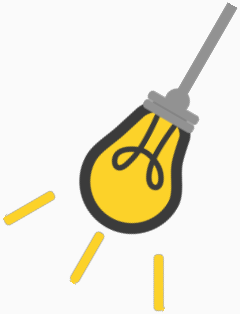
Learning objectives

- LO 1
- LO 2
- LO 3

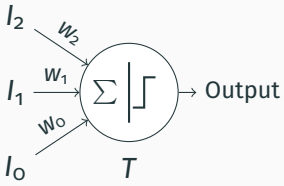


Introduction

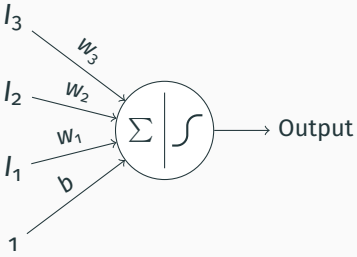
From shallow to deep networks

In Lecture 11 we introduced neural networks. With increasing depth, neural networks can solve more complex problems. This comes at the cost of increased computational complexity (more parameters to learn).

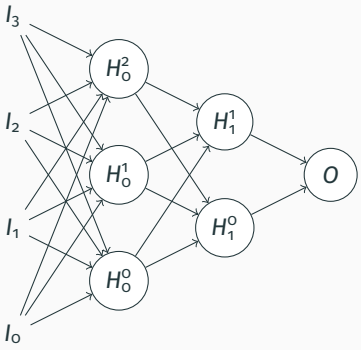
McCulloch-Pitts neuron



Single layer perceptron



Multi-layer perceptron



Neural networks for image analysis

Can we use a MLP to analyze images?

- Input image: shape(w, h, c)
- Linearize image: shape(w x h x c)
- Use this vector as input to MLP
- Train and predict

Any problem with this?

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- **It is impractical** for anything other than extremely small images.
  A small 256 x 256 RGB image gives 256 x 256 x 3 = 196608 inputs. Add a few hidden layers and the number of parameters to estimate becomes unmanageable.

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  If our network learns to detect a cell in the top-left part of the image, it won't be able to detect it in the bottom-right part.

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- MLP are not **translation invariant**.
  If our network learns to detect a cell in the top-left part of the image, it won't be able to detect it in the bottom-right part.
- **We lose spatial information** when we flatten the image.
  Closeby pixels are more similar to each other than they are to the rest of the image. Problem for all other ML methods we have seen so far.

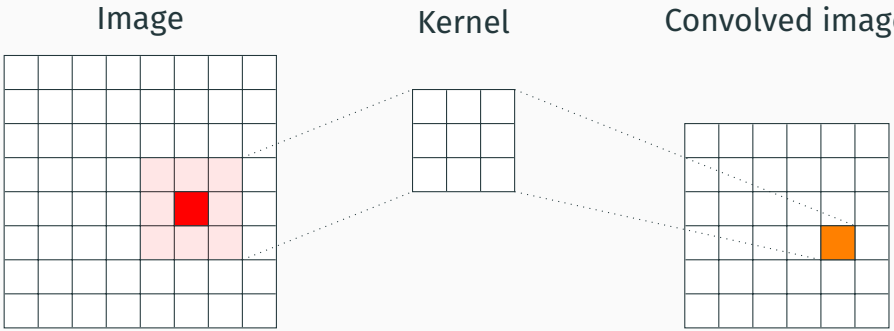
The solution?

Use convolutional filters!

(and have a neural network decide which to use!)

Convolutional filters

Convolutional filters



$$O = \sum_i \sum_j I_{i,j} K_{i,j}$$

- A 3x3 filter only has 9 parameters to learn, independently of image size.
- Convolutional filters are translation invariant.
- Convolution retains spatial information.

Some CNN convolution terminology

In CNN we define convolutional filters using:

- **Stride**: the number of pixels to skip between each filter application. Strides greater than 1 **reduce the size of the output**.
- **Padding**: the number of pixels to add to the input image to make it divisible by the filter size. Normally, zero-padding is used in CNN.

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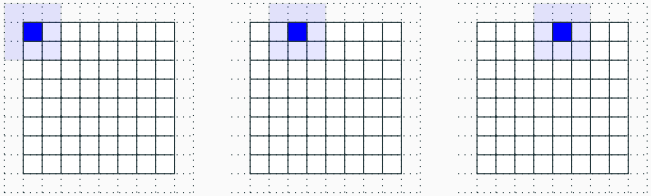
- Some CNN terminology related to padding: beginitemize
- **Same padding**: we pad with the same amount of zeros on each side. If we use a stride of 1 we will have the same image shape after convolution.
- **Valide padding**: only **valid** data is used, meaning no padding. The output image is smaller than the input image, since we cannot process edge pixels.

Stride and padding - examples

3 x 3 kernel, stride: 2, same padding



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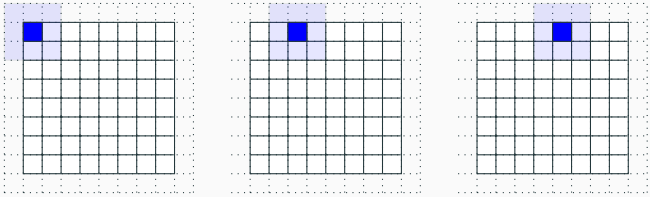
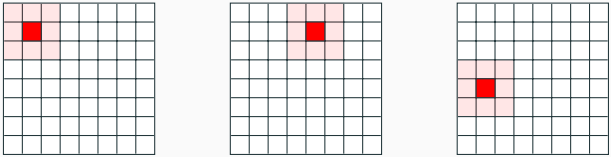


3 x 3 kernel, stride: 3, valid padding



Convolved image size

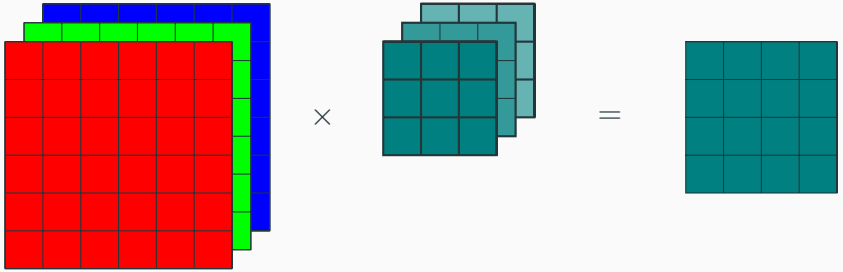
Given an image of size $n \times n$, a filter of size $k \times k$, stride s and padding p the output image size is:

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

Convolution of a volume

When applying convolution to a volume, we need to do it with a 3D filter.

For example, we can convolve an RGB image with a $3 \times 3 \times 3$ filter.



6×6 RGB image $\quad$ $3 \times 3 \times 3$ filter $\quad$ 4×4 image

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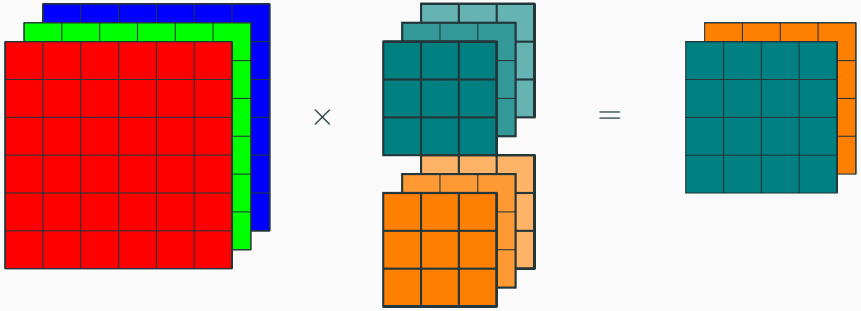
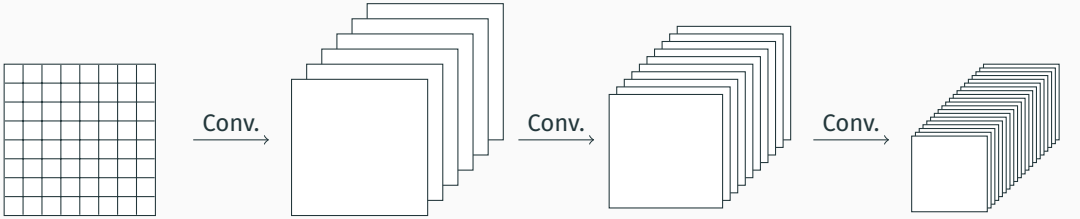


6×6 RGB image | Two $3 \times 3 \times 3$ filters | $4 \times 4 \times 2$ image

Using convolution in an ANN

How can we make use of convolution in an ANN?

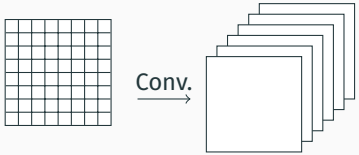
The general idea behind convolutional neural networks



Building a CNN

Convolutional layer

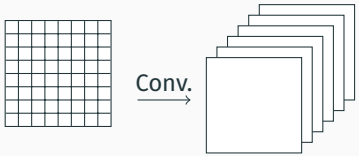
- Arguably the most important part of a CNN



Convolutional layer, 6 convolutions

Convolutional layer

- Arguably the most important part of a CNN
- Performs a series of convolutions on the input image.



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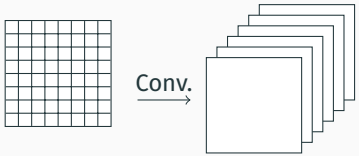
- Hyperparameters: number of convolutions, filter size, stride, padding.
  Note: the size, stride and padding are the same for all convolutions in the same layer.



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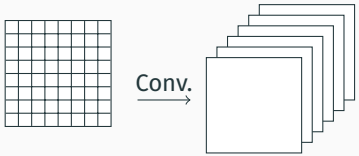

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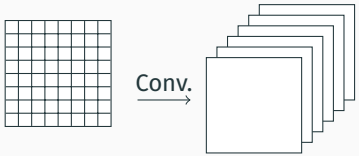

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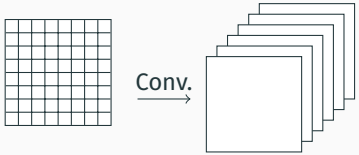
- Parameters to learn: filter weights and biases.
- Number of parameters: num filters $\times$ filter size.
- After convolution a non-linearity is introduced through the **activation function**. **ReLU** is the most commonly used.

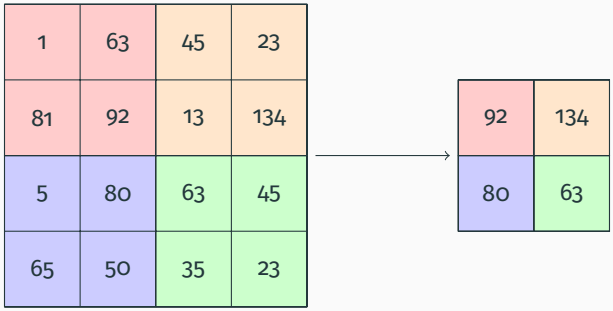


Convolutional layer, 6 convolutions

Pooling layers - max pooling

Max-pooling layer

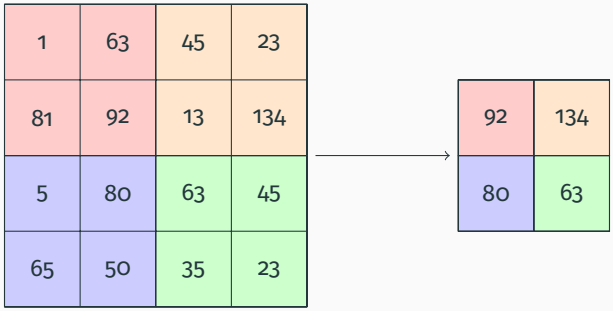
- Performs a maximum filters on the input.



Pooling layers - max pooling

Max-pooling layer

- Performs a maximum filters on the input.
- Hyperparameters: filter size.



Pooling layers - max pooling

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- Hyperparameters: filter size.
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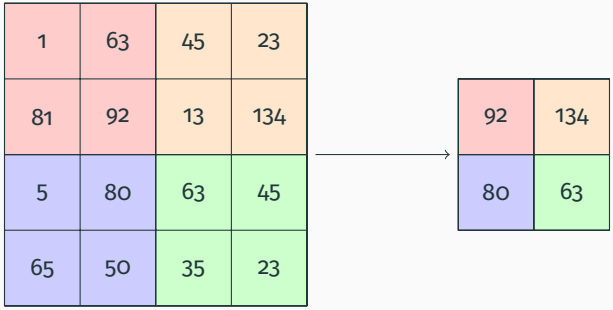
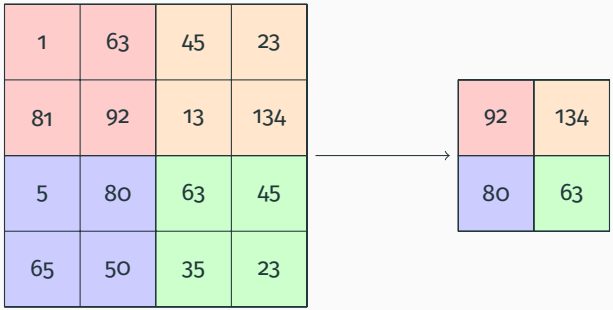


Pooling layers - max pooling

Max-pooling layer

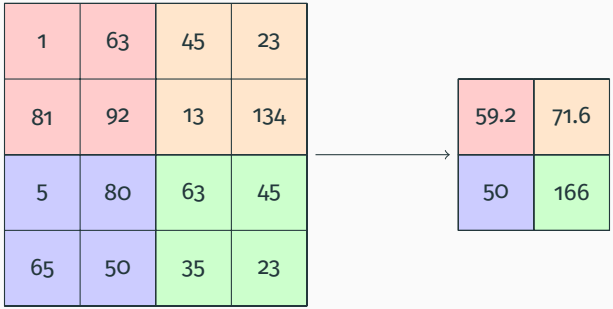
- Performs a maximum filters on the input.
- Hyperparameters: filter size.
- Parameters to learn: none.
- Mostly used after a convolutional layer (thus some people call "convolutional + max pooling" a layer, others will consider them two layers, there is no consensus).



Pooling layers - average pooling

Average-pooling layer

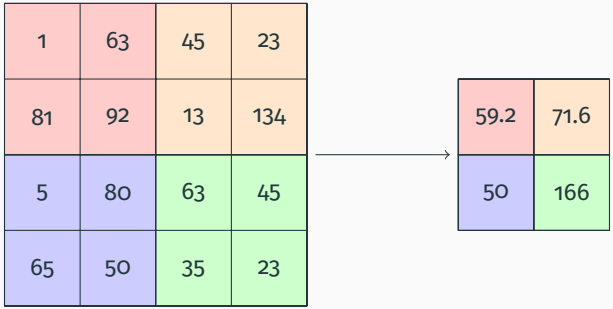
- Performs average filtering on the input.



Pooling layers - average pooling

Average-pooling layer

- Performs average filtering on the input.
- Hyperparameters: filter size, stride.



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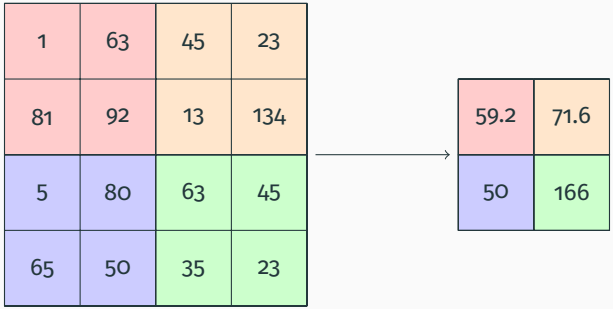

Pooling layers - average pooling

Average-pooling layer

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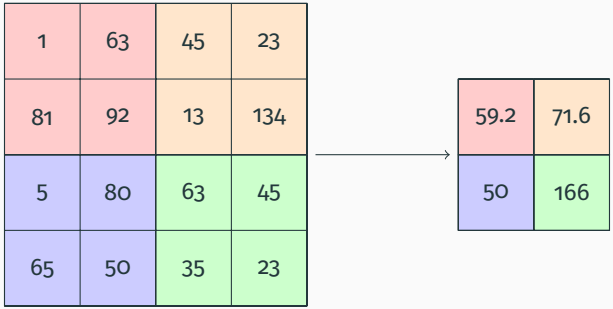
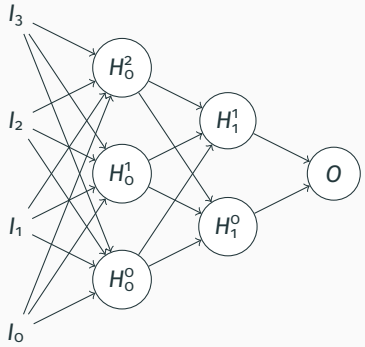
- Hyperparameters: filter size, stride.
- Parameters to learn: none.
- Rarely used nowadays



After the convolutions - flatten and FC

Eventually, after all the convolutions we will need to flatten our output and feed it to a **fully-connected layer** (that is, a **multi-layer perceptron**!).

This will take care, for example, of the final classification task.



Putting it all together

We are now ready to put everything together.

Example, we want to create a CNN that can classify an image as one of two classes (e.g. illness vs no illness).

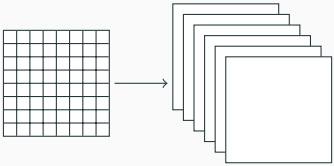


Image
32×32

6 filters,
size 5,
s=1, p=0
$32 \times 32 \times 6$

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$\mathbf{32} \times \mathbf{32}$

6 filters,
size 5,
s=1, p=0
$\mathbf{32} \times \mathbf{32} \times \mathbf{6}$

2x2 max
pooling, s=2
$\mathbf{14} \times \mathbf{14} \times \mathbf{6}$

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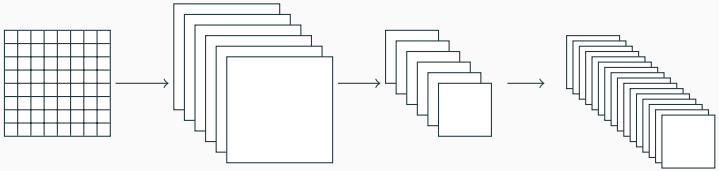

Image
32 × 32

6 filters,
size 5,
s=1, p=0
32 × 32 × 6

2x2 max
pooling, s=2
14 × 14 × 6

16 filters,
size 5, s=1
10 × 10 × 16

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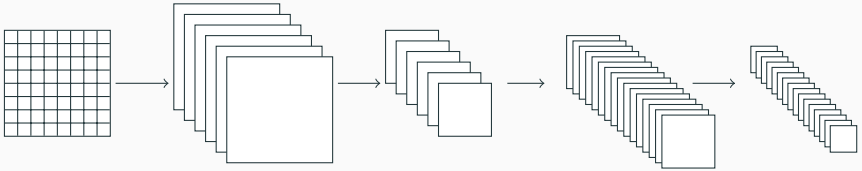

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6 filters,
size 5,
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2x2 max
pooling, s=2
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16 filters,
size 5, s=1
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2 × 2 max
pooling, s=2
5 × 5 × 16

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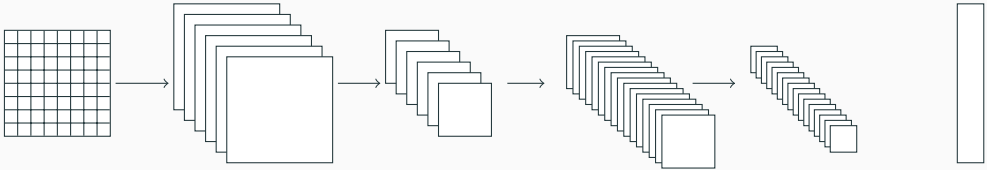

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2x2 max
pooling, s=2
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