AARHUS UNIVERSITY

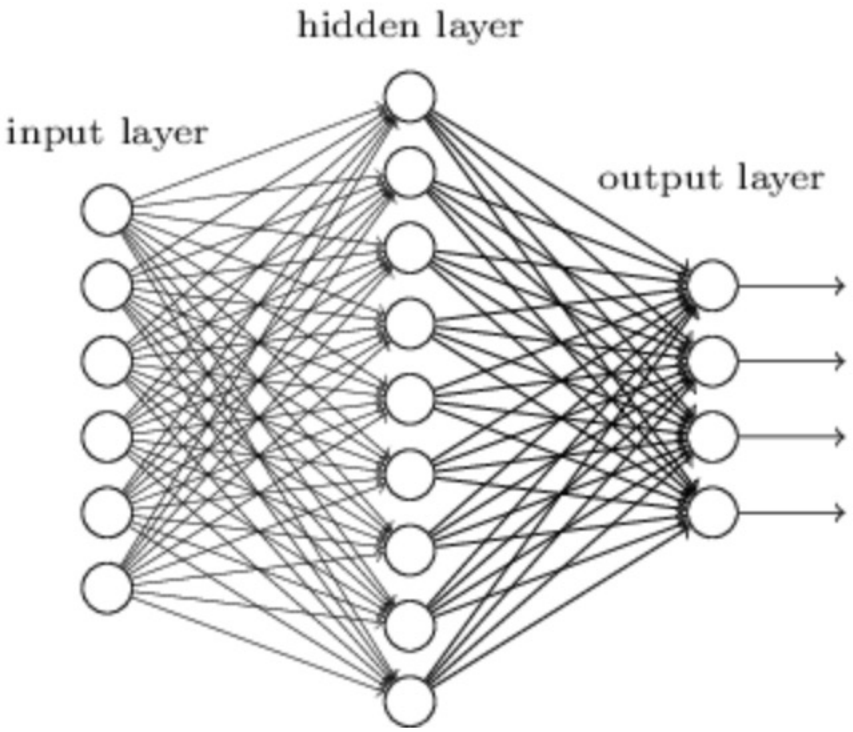
Data Science 6

Chris Mathys

Master's Degree Programme in Cognitive Science

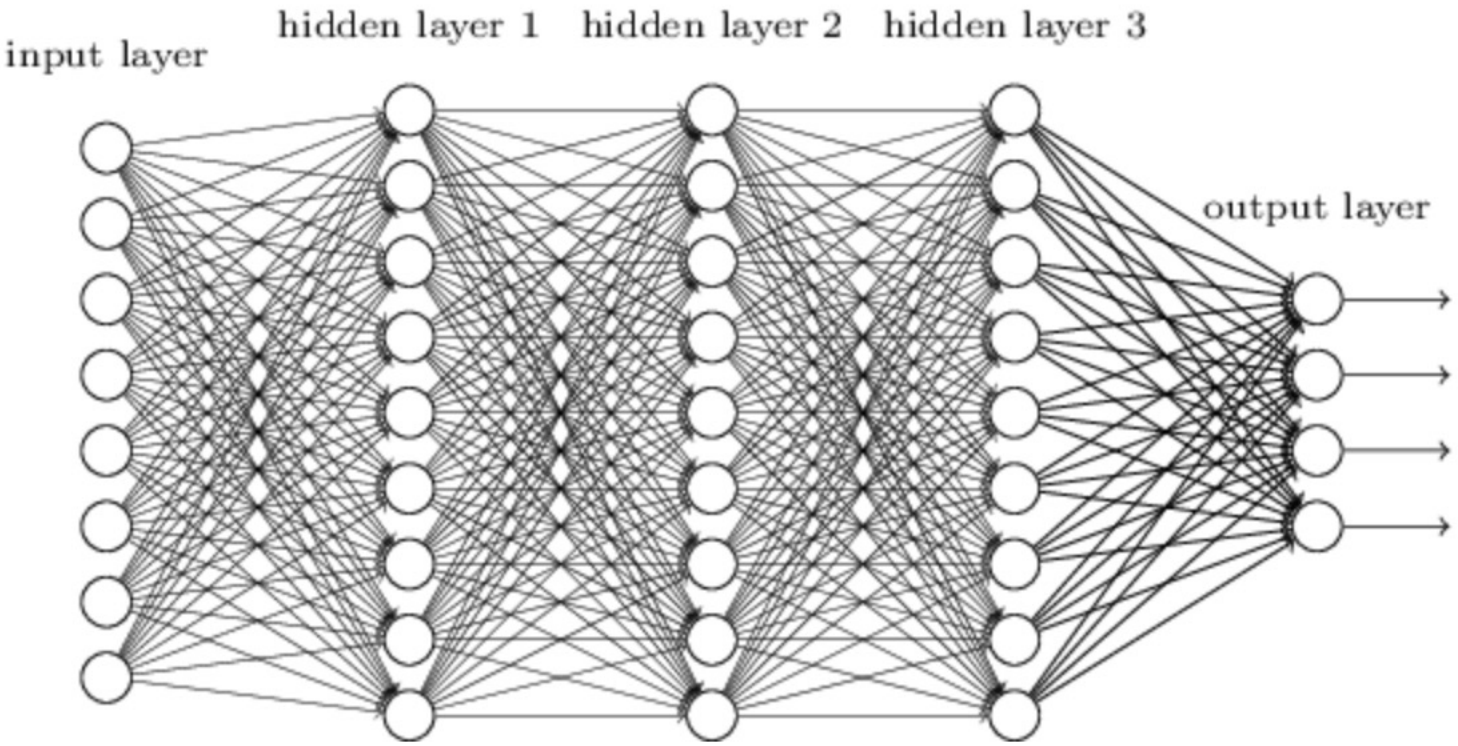
Spring 2022

Shallow neural networks



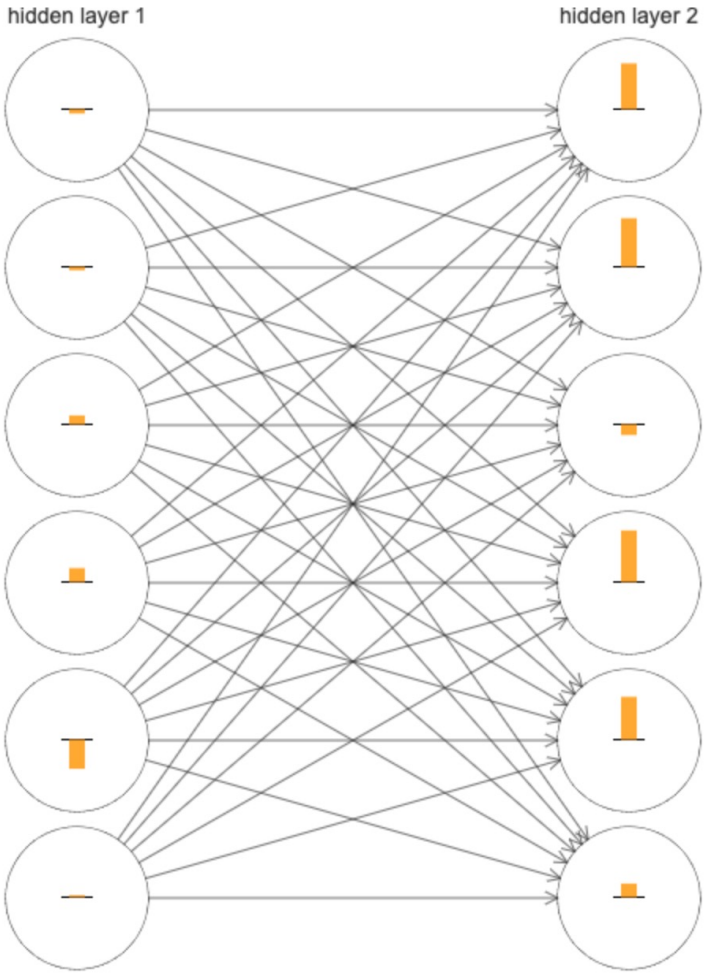
Source: Michael Nielsen, http://neuralnetworksanddeeplearning.com

Deep neural networks



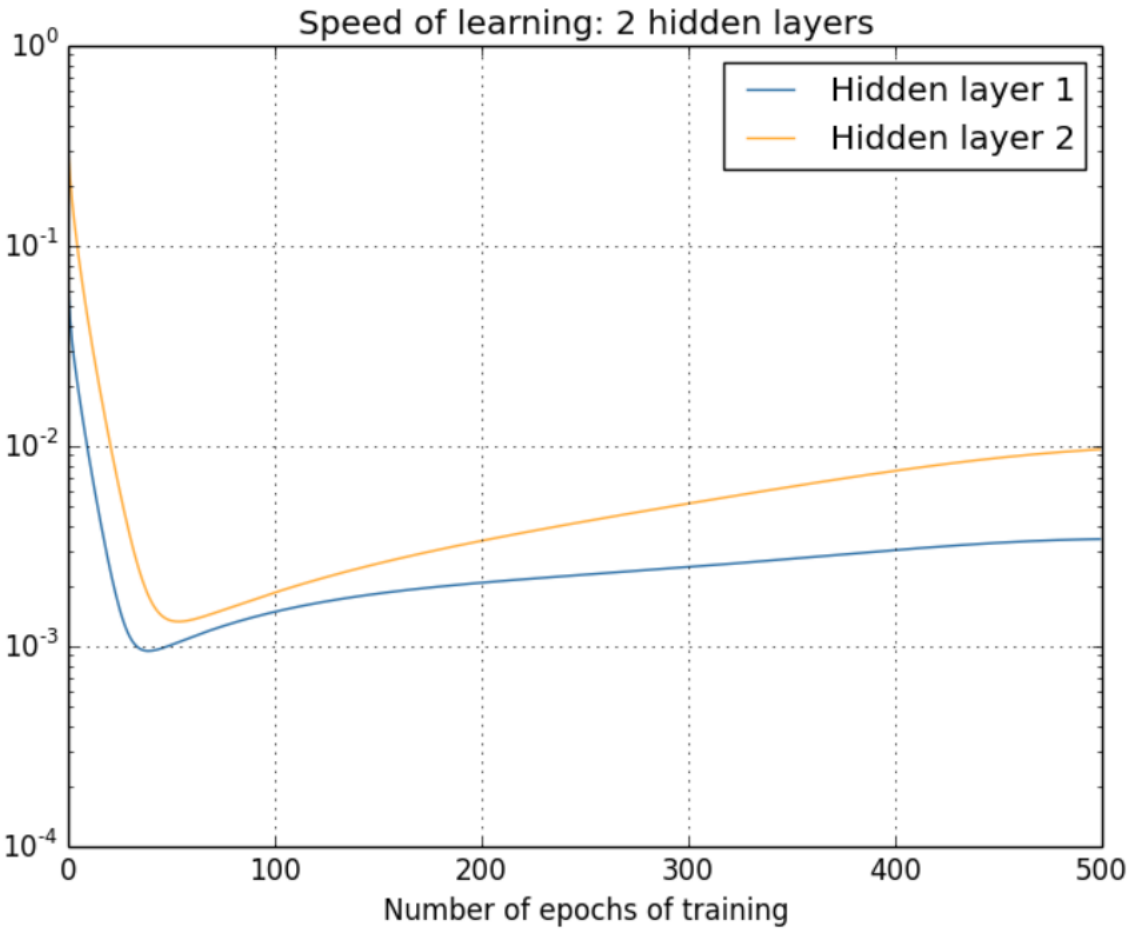
Source: Michael Nielsen, http://neuralnetworksanddeeplearning.com

As we backpropagate errors through the layers, gradients become smaller



Source: Michael Nielsen, http://neuralnetworksanddeeplearning.com

Slower learning in earlier layers



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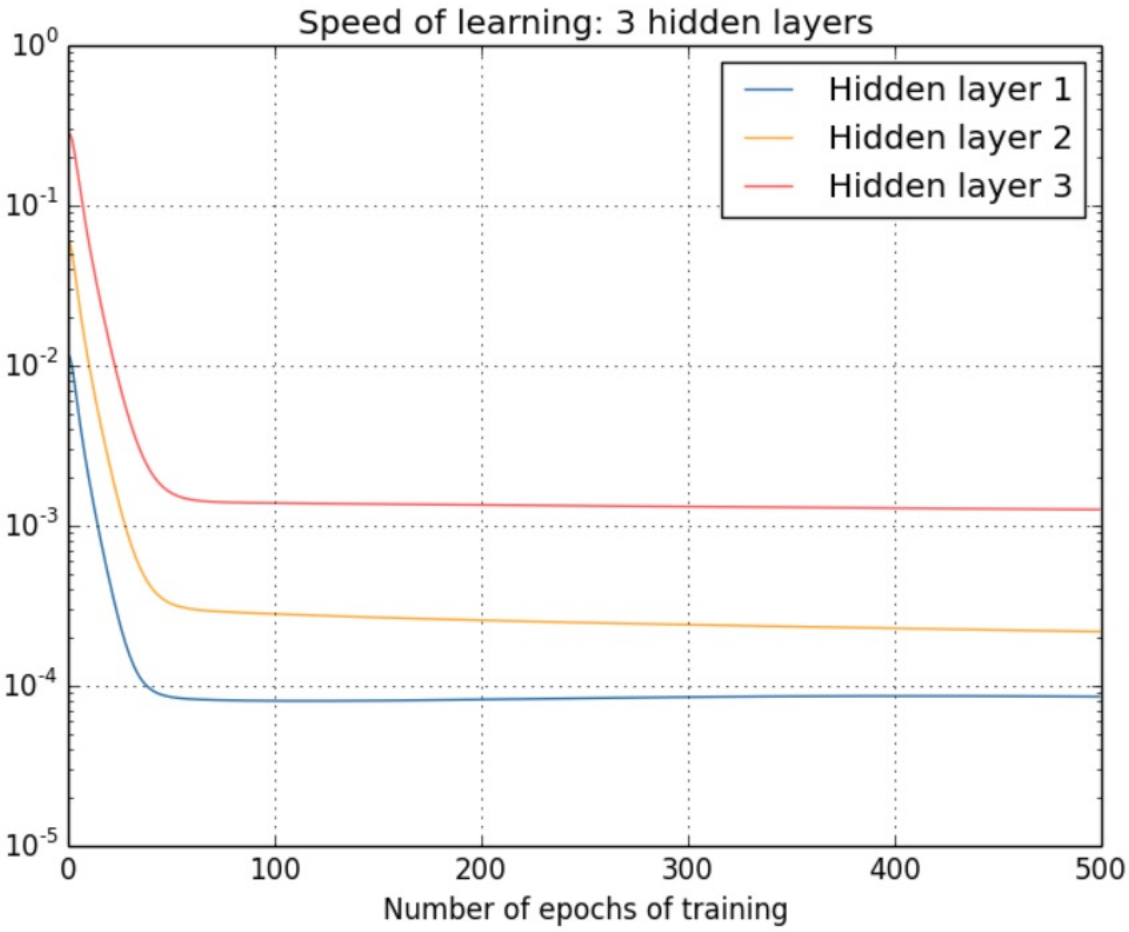
Slower learning in earlier layers



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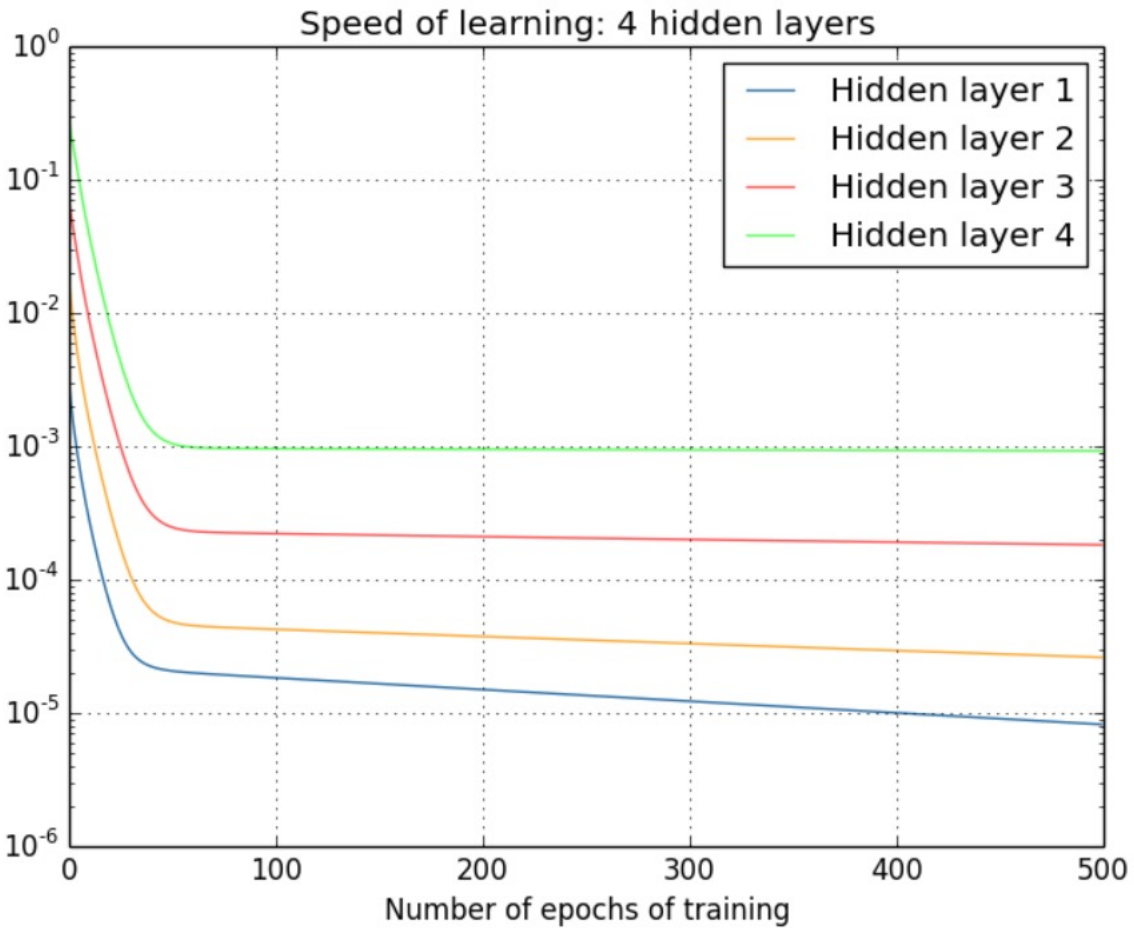
Slower learning in earlier layers



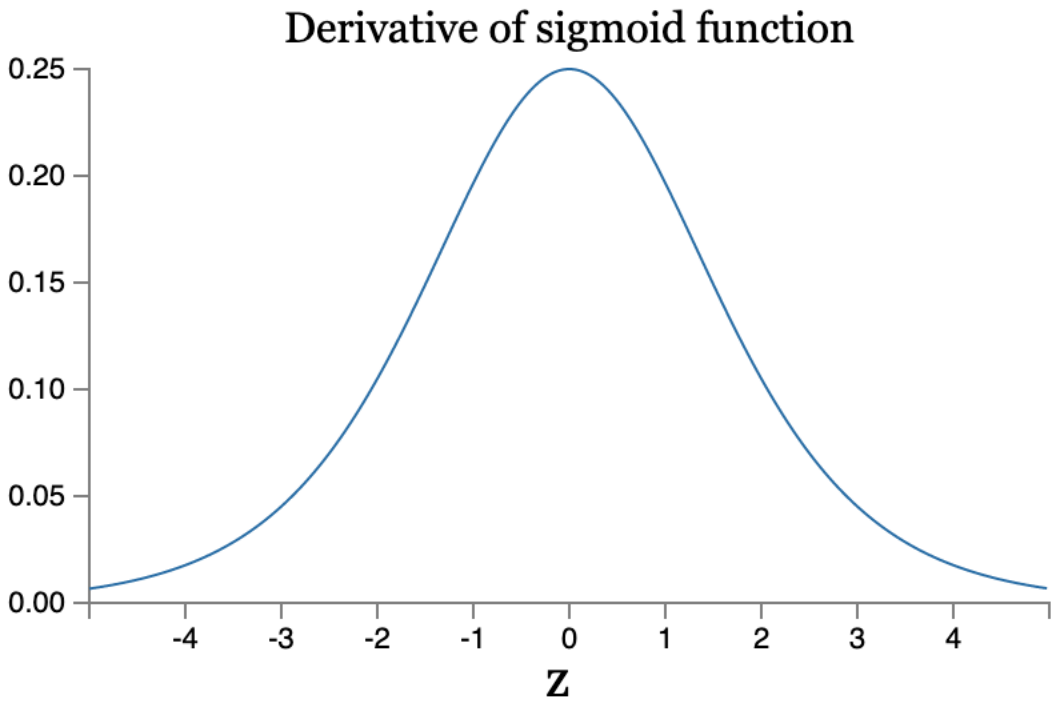
Source: Michael Nielsen, http://neuralnetworksanddeeplearning.com

Why are gradients unstable?

$$\frac{\partial C}{\partial b_1} = \sigma'(z_1) \times w_2 \times \sigma'(z_2) \times w_3 \times \sigma'(z_3) \times w_4 \times \sigma'(z_4) \times \frac{\partial C}{\partial a_4}$$

Source: Michael Nielsen, http://neuralnetworksanddeeplearning.com

Why are gradients unstable?



Source: Michael Nielsen, http://neuralnetworksanddeeplearning.com

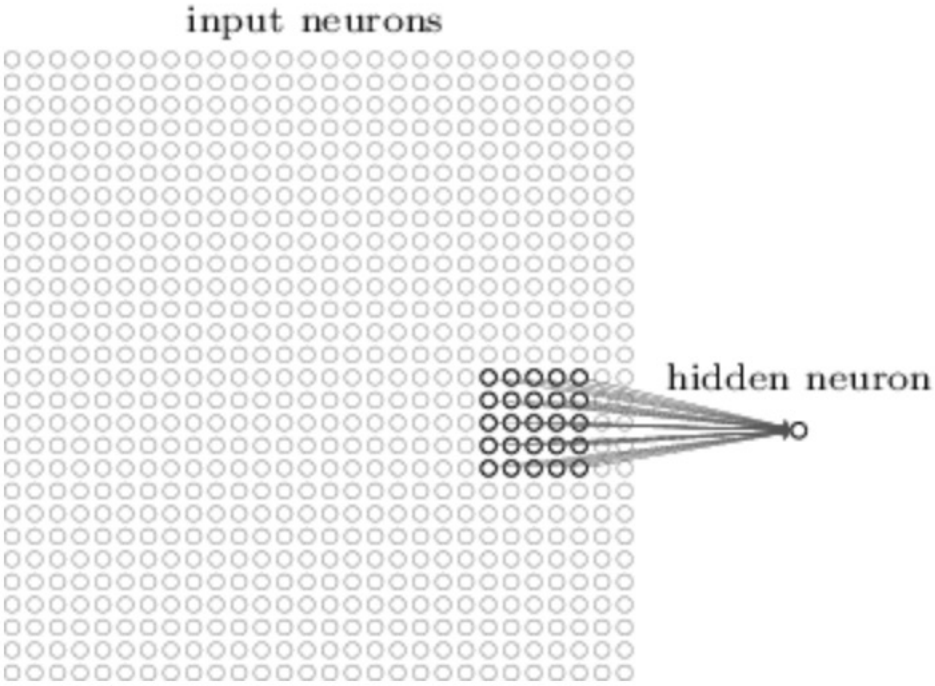
Why are gradients unstable?

- They are the products of many factors
- The earlier the layer, the more factors the gradients are composed of
- This is an unstable situation
- Mostly, we get vanishing gradients in early layers
- However, by the same multiplication of many factors, we can get exploding gradients

Source: Michael Nielsen, http://neuralnetworksanddeeplearning.com

Convolutional neural networks

Local receptive fields



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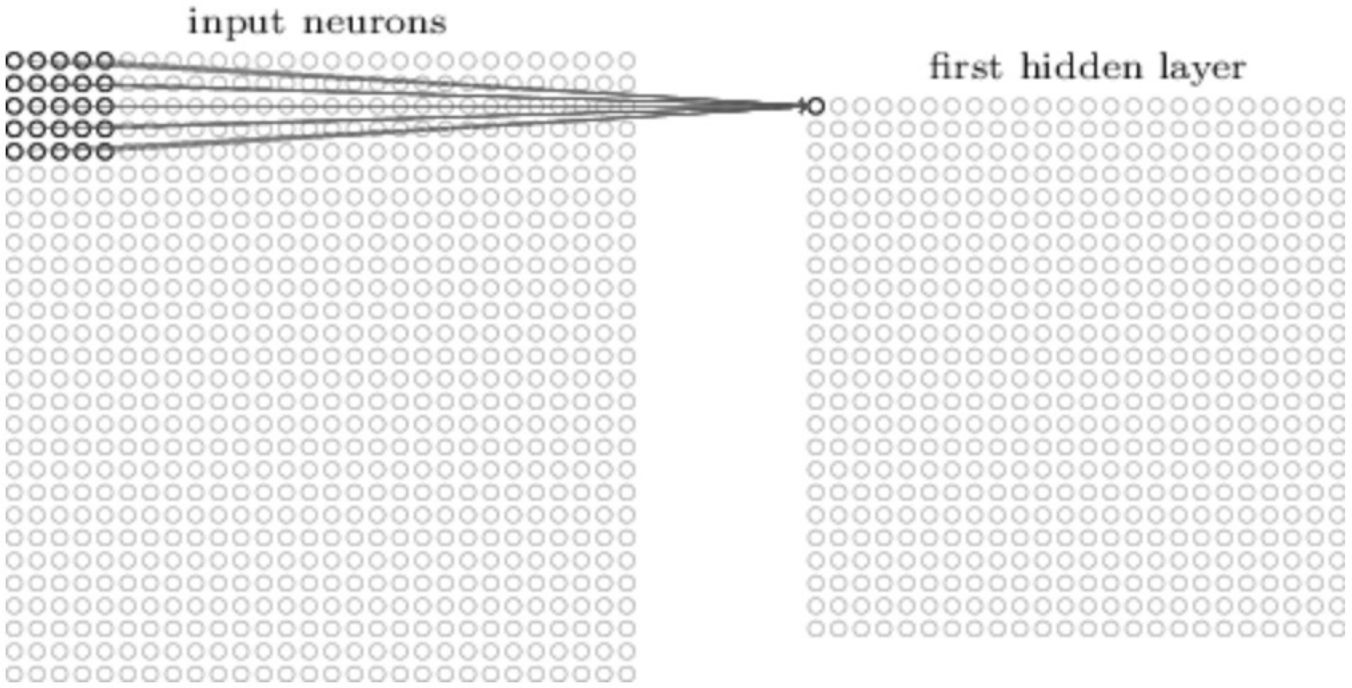
Convolutional neural networks

Local receptive fields



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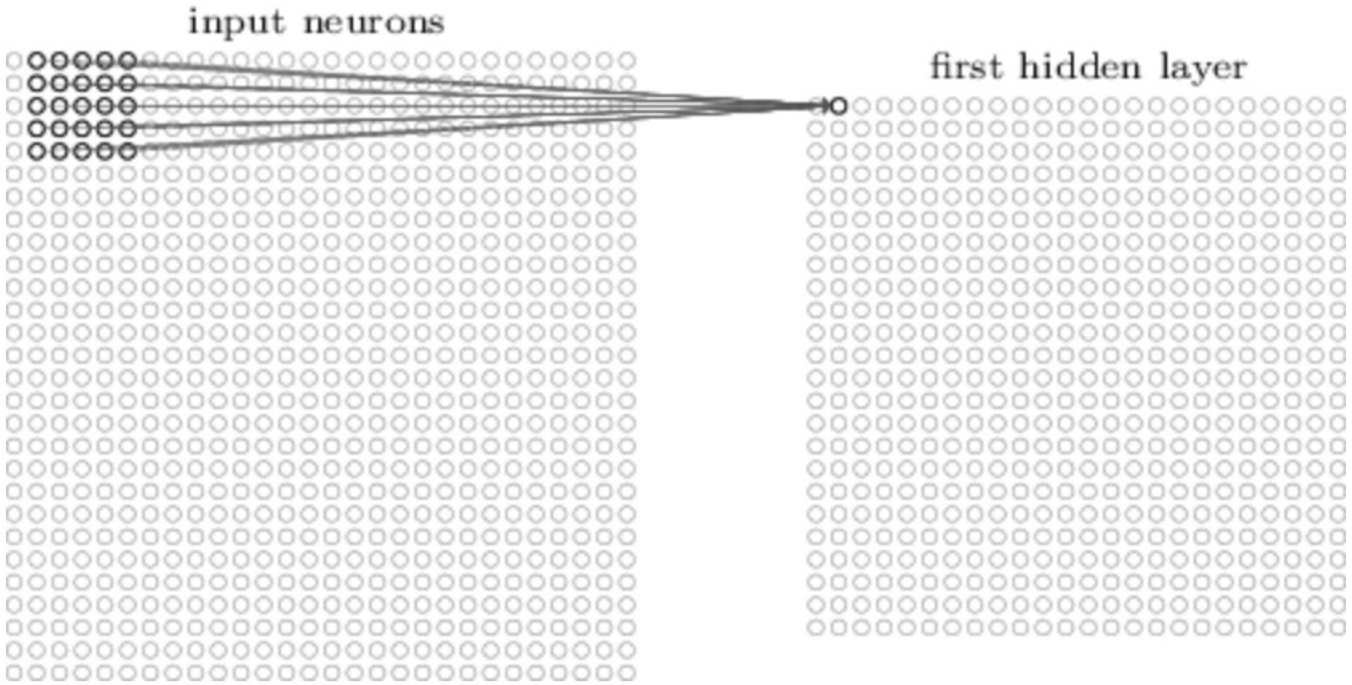
Convolutional neural networks

Local receptive fields



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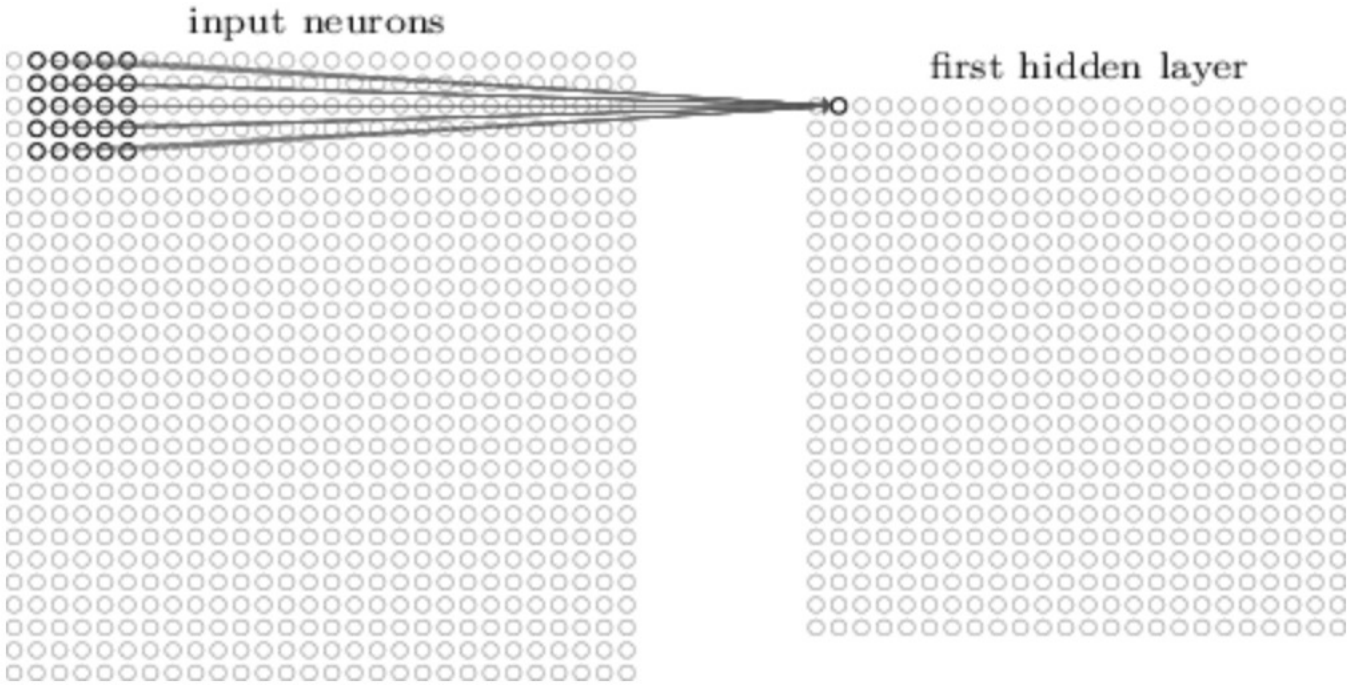
Convolutional neural networks

Local receptive fields



Source: Michael Nielsen, http://neuralnetworksanddeeplearning.com

Convolutional neural networks

Shared weights and biases: I've said that each hidden neuron has a bias and 5×5 weights connected to its local receptive field. What I did not yet mention is that we're going to use the *same* weights and bias for each of the 24×24 hidden neurons. In other words, for the j, kth hidden neuron, the output is:

$$\sigma\left(b + \sum_{l=0}^{4}\sum_{m=0}^{4} w_{l,m} a_{j+l,k+m}\right). \tag{125}$$

Here, σ is the neural activation function - perhaps the sigmoid function we used in earlier chapters. b is the shared value for the bias. $w_{l,m}$ is a 5×5 array of shared weights. And, finally, we use $a_{x,y}$ to denote the input activation at position x, y.

Source: Michael Nielsen, http://neuralnetworksanddeeplearning.com

Convolutional neural networks

This means that all the neurons in the first hidden layer detect exactly the same feature*, just at different locations in the input image. To see why this makes sense, suppose the weights and bias are such that the hidden neuron can pick out, say, a vertical edge in a particular local receptive field. That ability is also likely to be useful at other places in the image. And so it is useful to apply the same feature detector everywhere in the image. To put it in slightly more abstract terms, convolutional networks are well adapted to the translation invariance of images: move a picture of a cat (say) a little ways, and it's still an image of a cat*.

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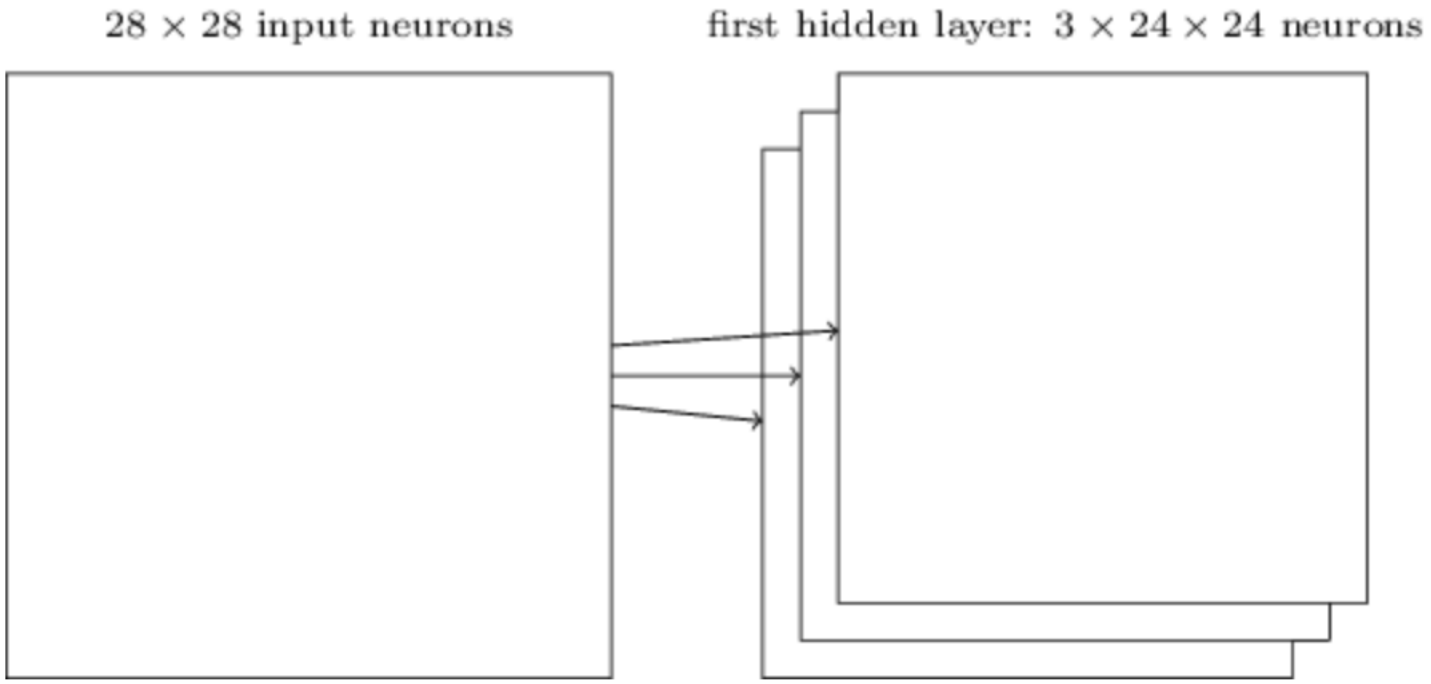
Convolutional neural networks

Feature maps



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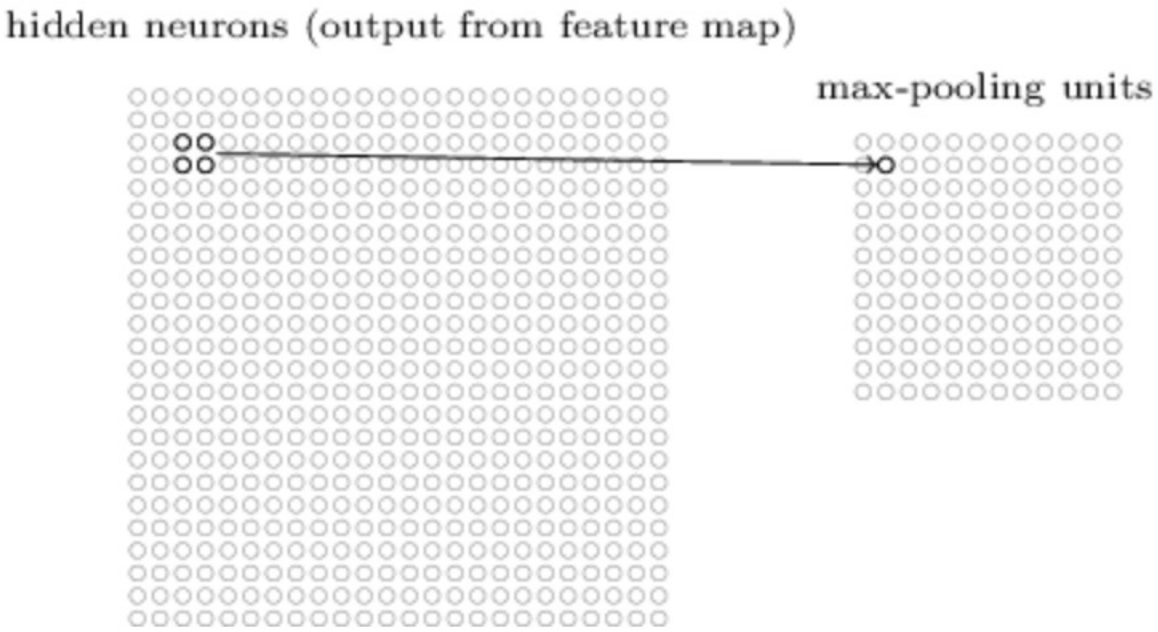
Convolutional neural networks

Pooling layers are used to condense feature maps



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Convolutional neural networks

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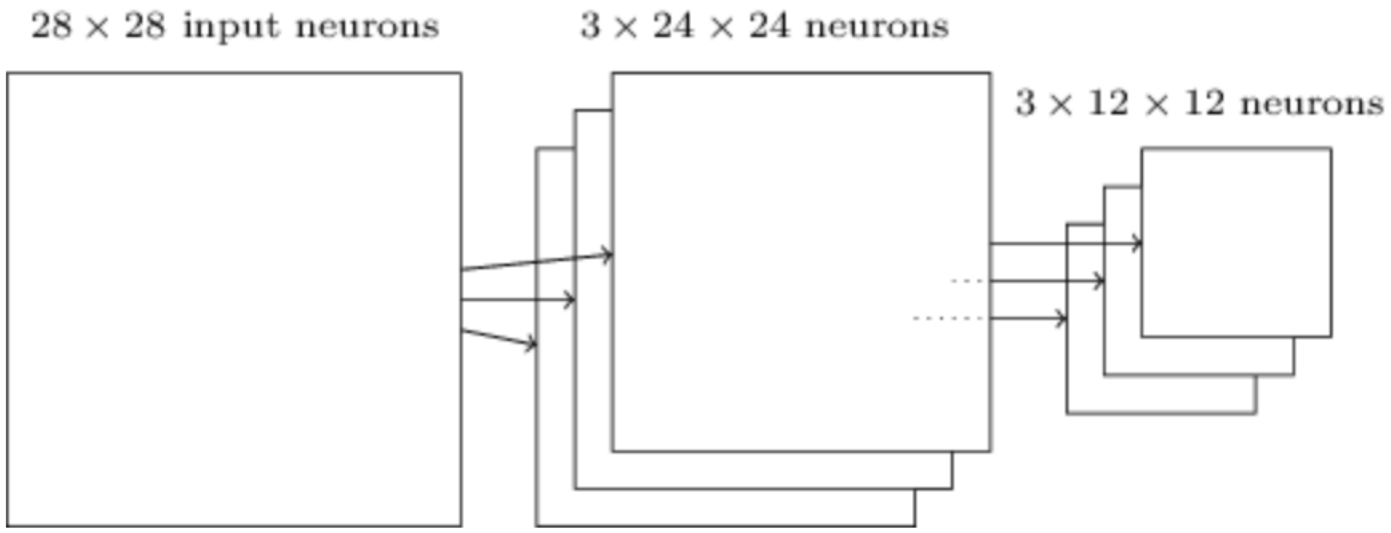

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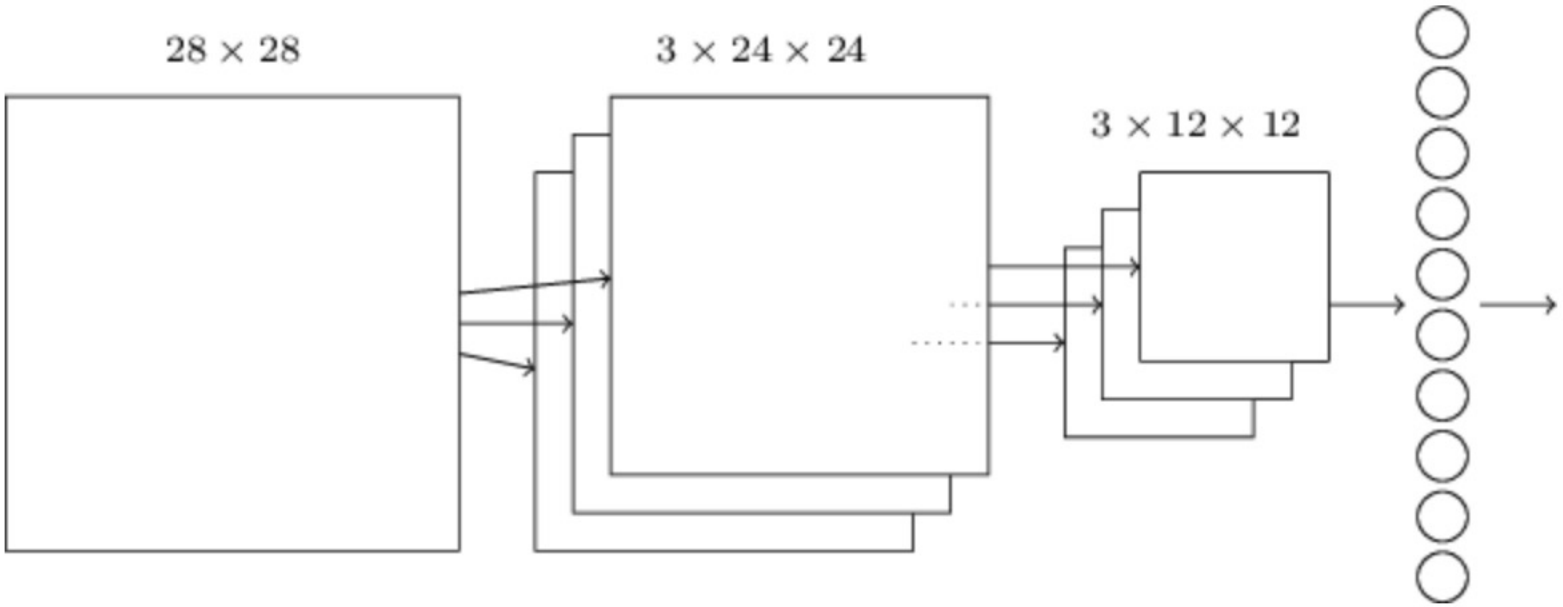
Convolutional neural networks

Putting it all together



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Convolutional neural networks

Further resources:

ICTP Winter School on Learning and Artificial Intelligence

https://indico.ictp.it/event/8339/

Materials and videos:

https://indico.ictp.it/event/8339/other-view?view=ictptimetable

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