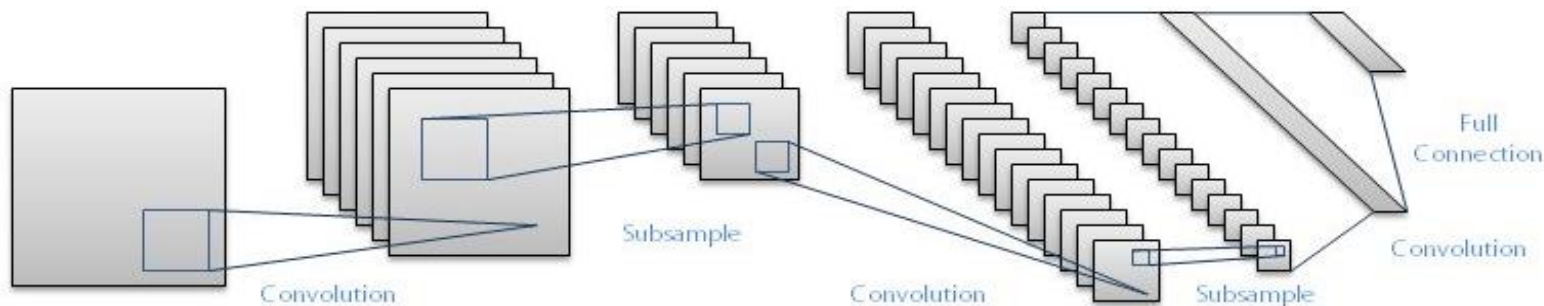


## *Convolutional Neural Networks (CNNs)*

*Beate Sick*

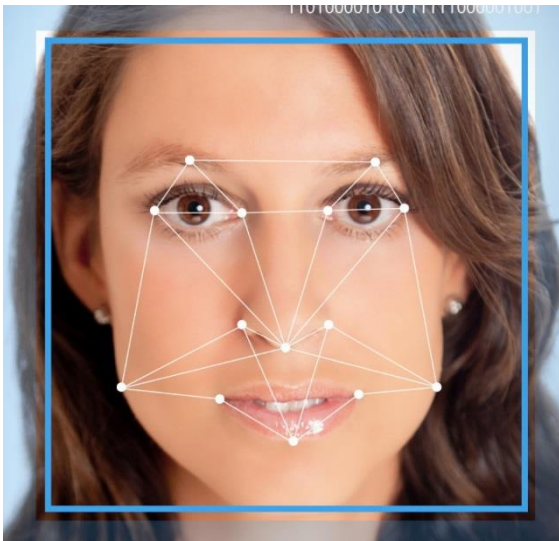
Institut für Datenanalyse und Prozessdesign

Zürcher Hochschule für Angewandte Wissenschaften



Winterthur, 22th Sep 2017

# What is new in the deep learning approach?

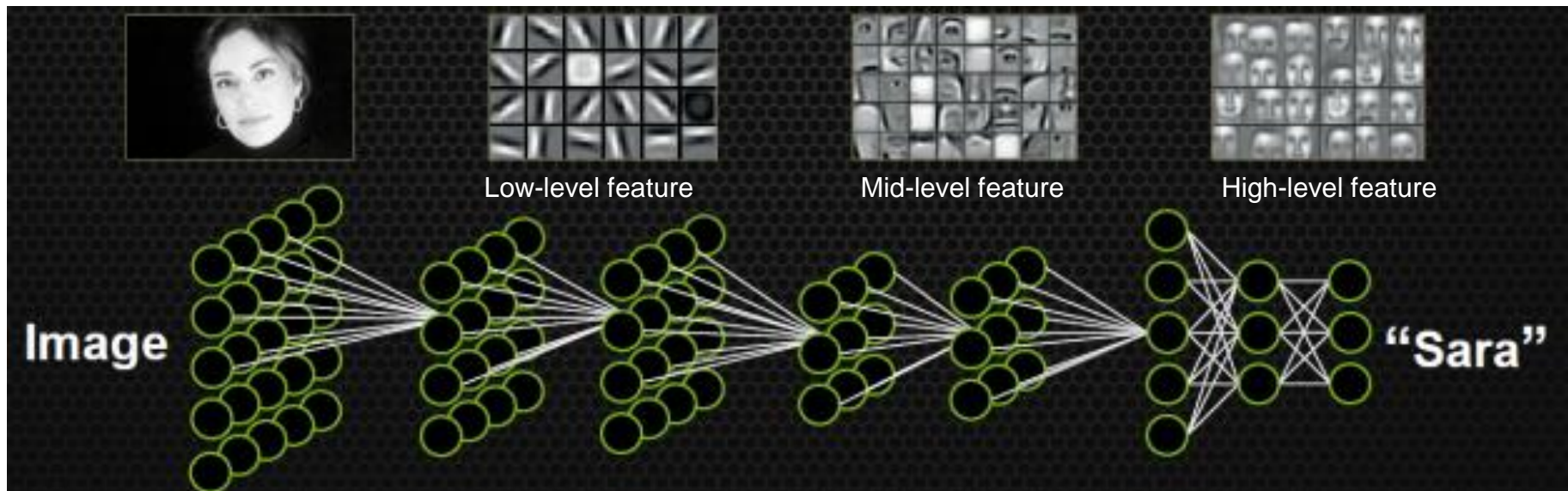


## Traditional:

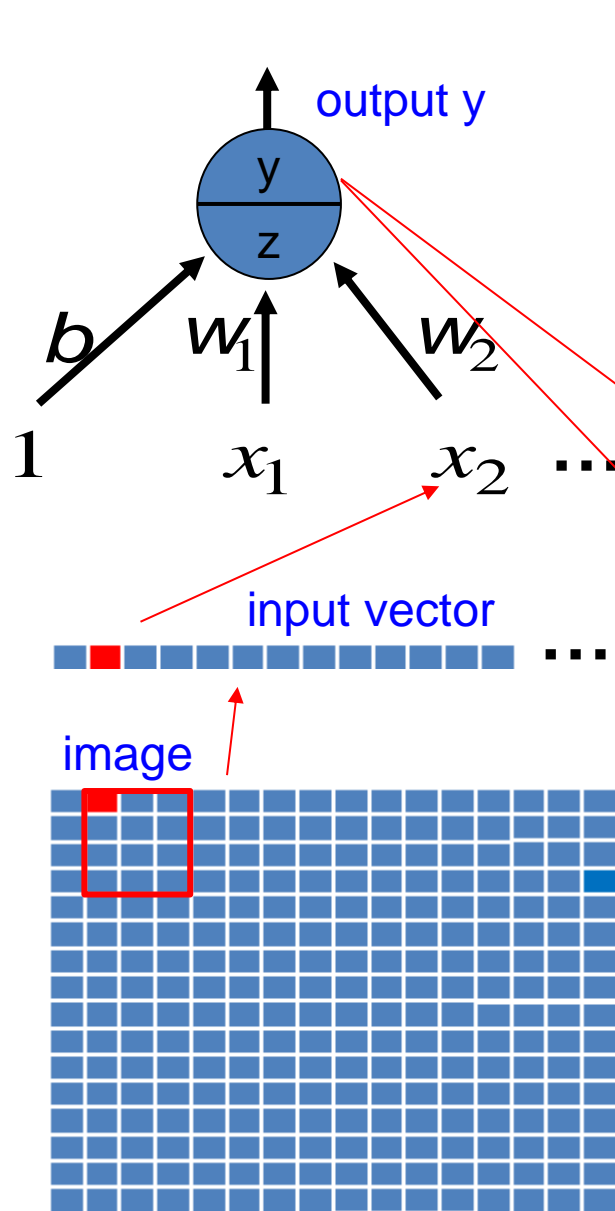
Extract **handcrafted features** & use these features to **train / fit a model** (e.g. SVM, RF) and use fitted model to perform classification/prediction.

## Deep learning:

In **deep neural networks** start with raw data and **learn** during training/fitting to extract appropriate **hierarchical features** and to use them for classification/prediction.



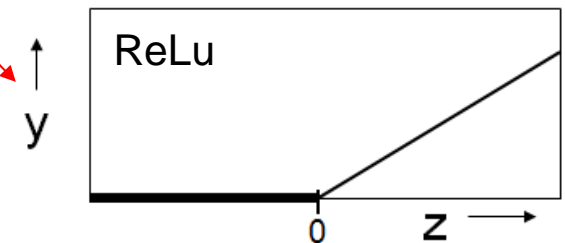
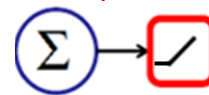
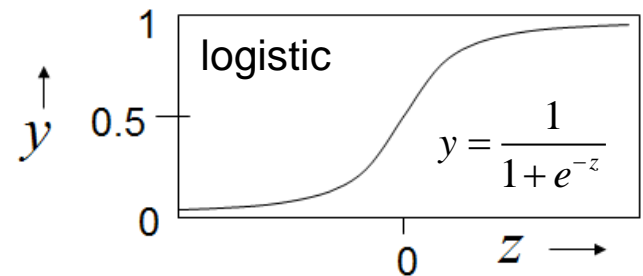
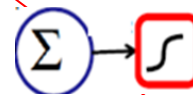
# An artificial neuron



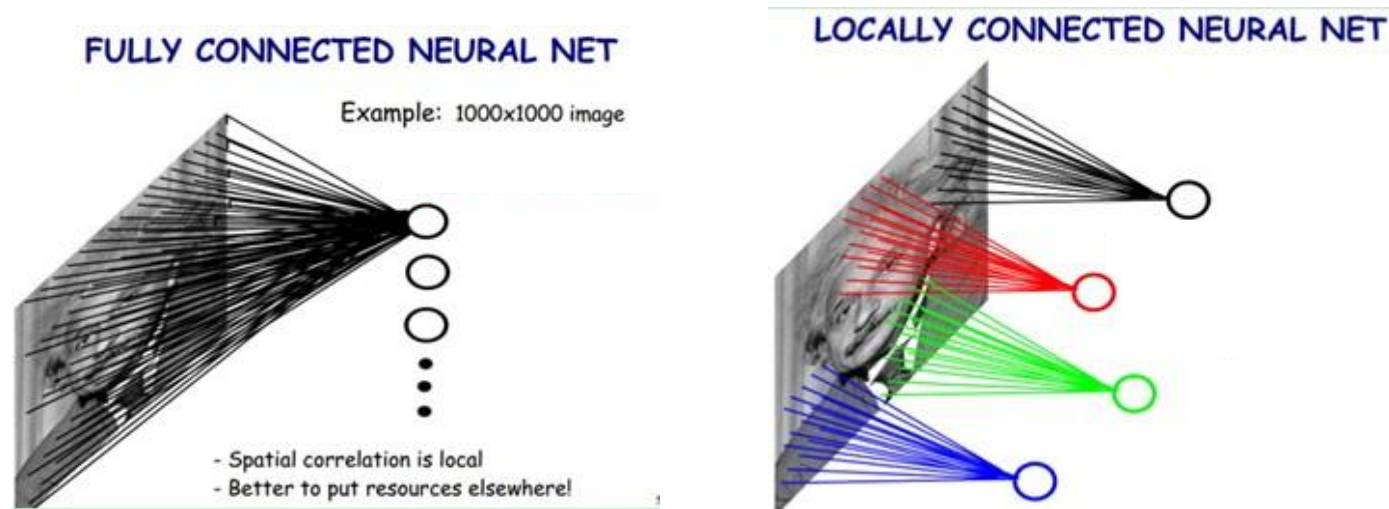
bias                      weights

$$z = b + \sum_i x_i w_i$$

Different non-linear transformations are used to get from  $z$  to output  $y$



# Convolution extracts local information using few weights



## Shared weights:

by using the **same weights for each patch** of the image we need much **less parameters** than in the fully connected NN and get from each patch the same kind of **local feature information** such as the presence of a edge.

# Convolutional networks use neighborhood information and replicated local feature extraction

In a locally connected network the calculation rule

$$z = b + \sum_i x_i w_i$$

Pixel values in a small image patch are element-wise multiplied with weights of a small filter/kernel:

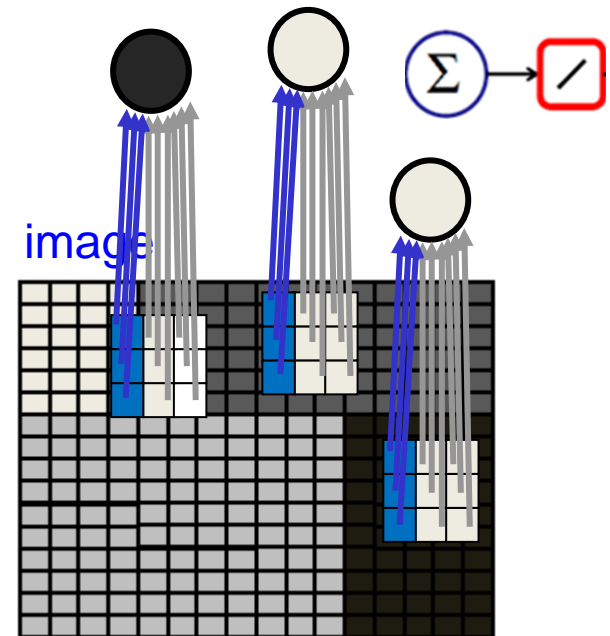
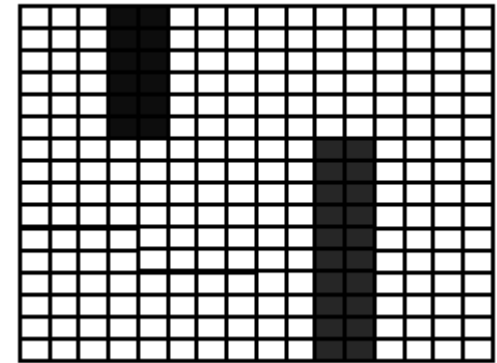
$w_1$	$w_2$	$w_3$
$w_4$	$w_5$	$w_6$
$w_7$	$w_8$	$w_9$

0.9	0.1	0.1
0.9	0.1	0.1
0.9	0.1	0.1

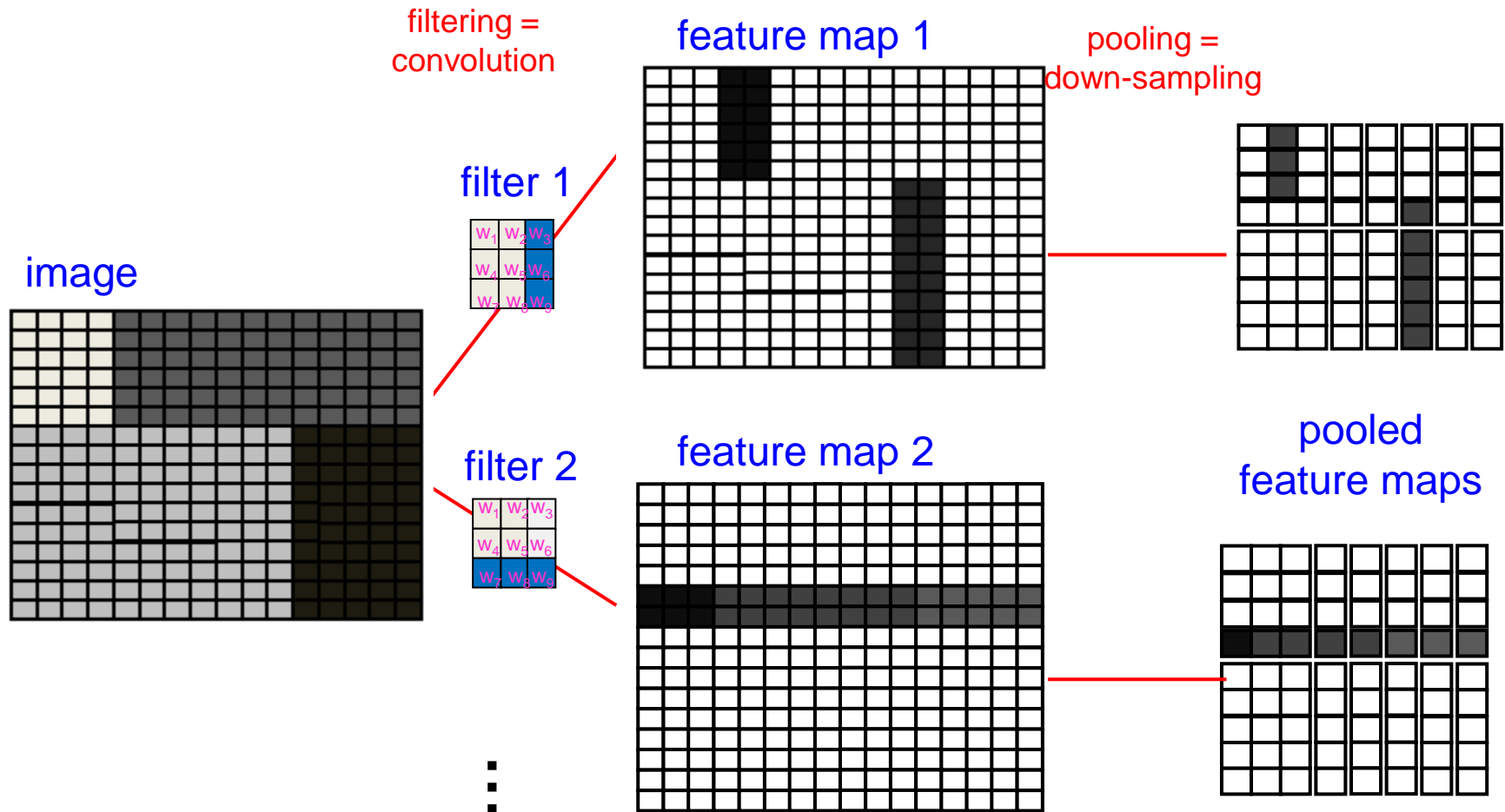
The filter is applied at each position of the image and it can be shown that the **result is maximal if the image pattern corresponds to the weight pattern**.

The results form again an image called **feature map (=activation map)** which shows at which position the feature is present.

feature/activation map



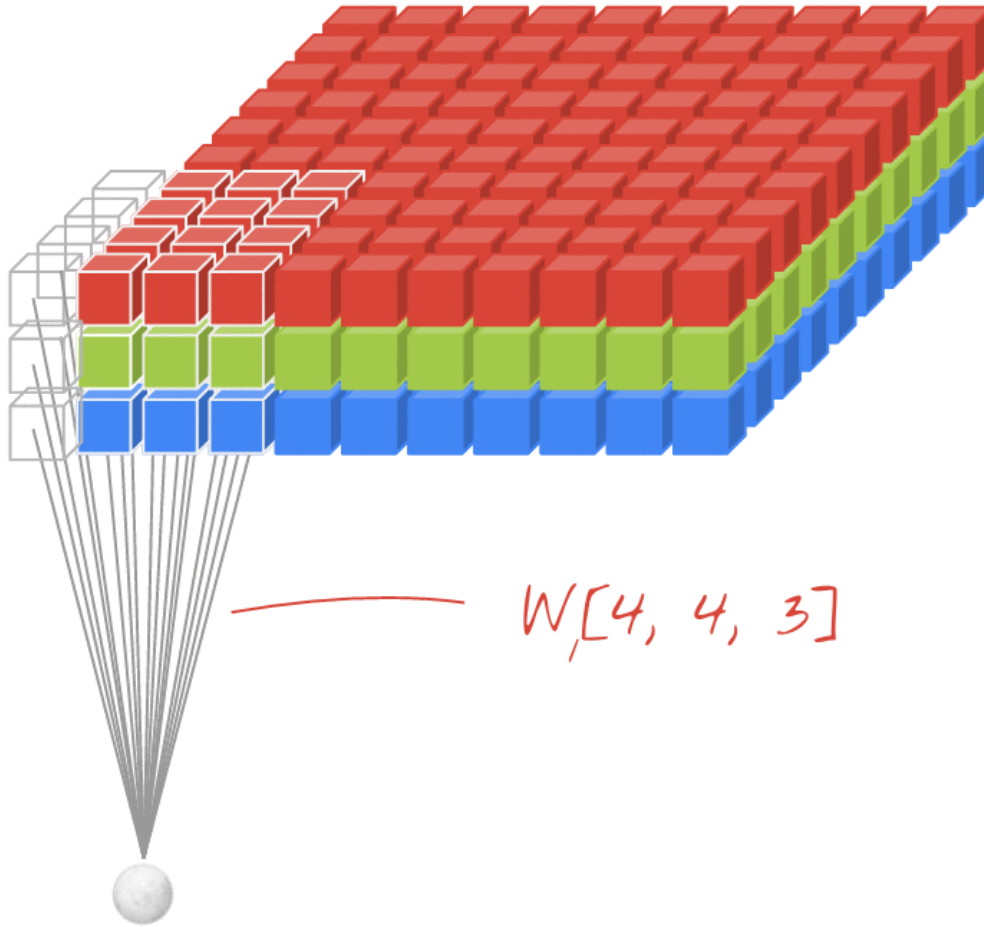
# Convolutional networks use neighborhood information and replicated local feature extraction



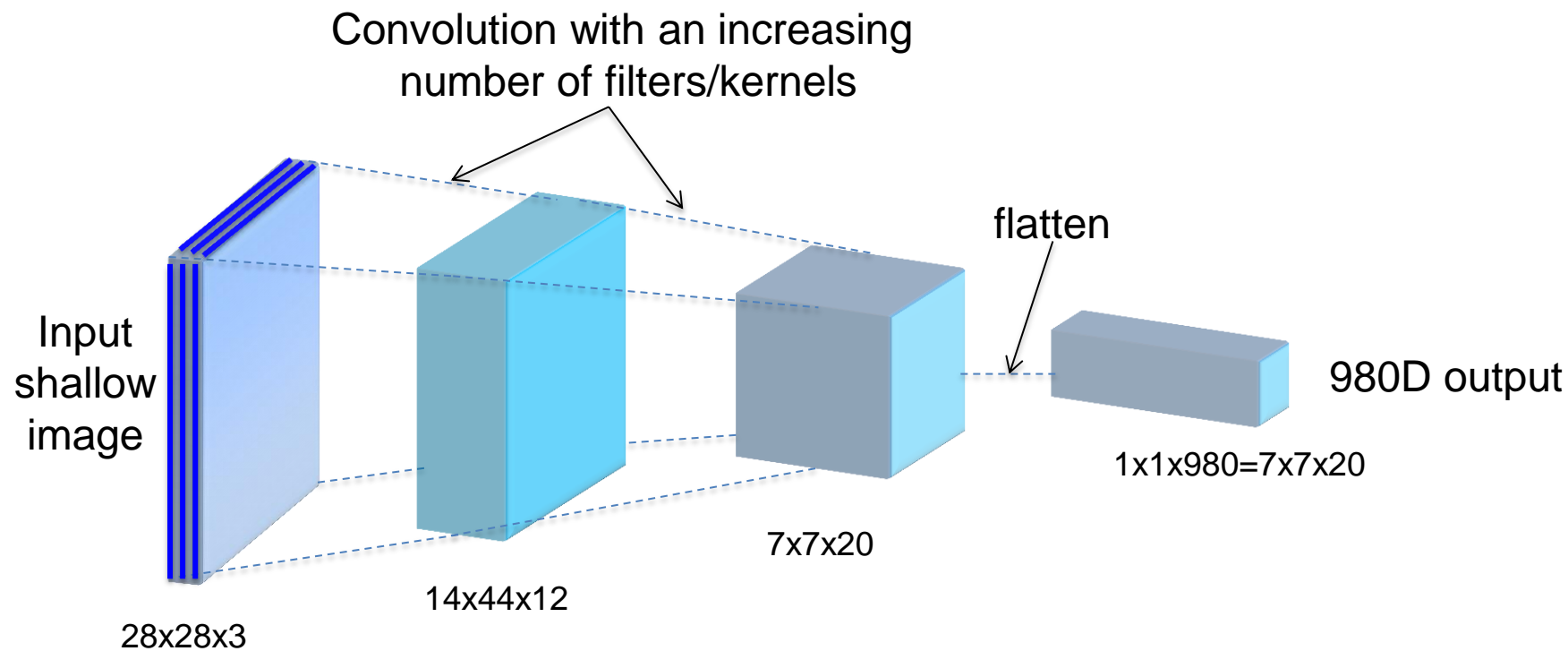
The weights of each filter are randomly initiated and then adapted during the training.

# Animated convolution with 3 input channels

3 color channel input image



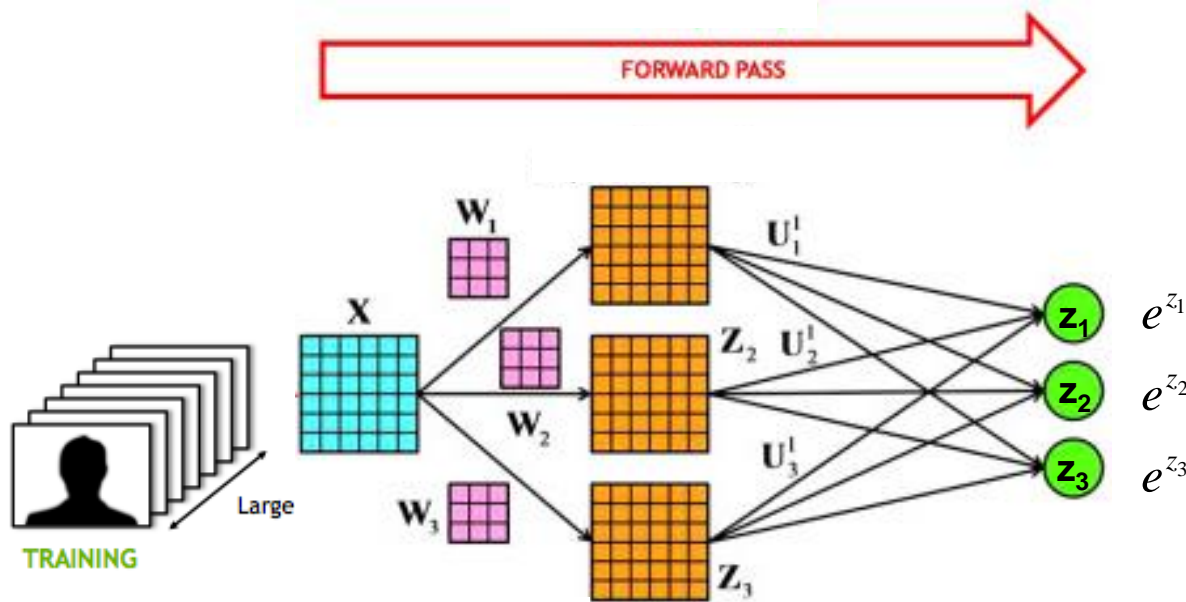
# Typical shape of a classical CNN



Spatial resolution is decreased e.g. via max-pooling while more abstract image features are detected in deeper layers.

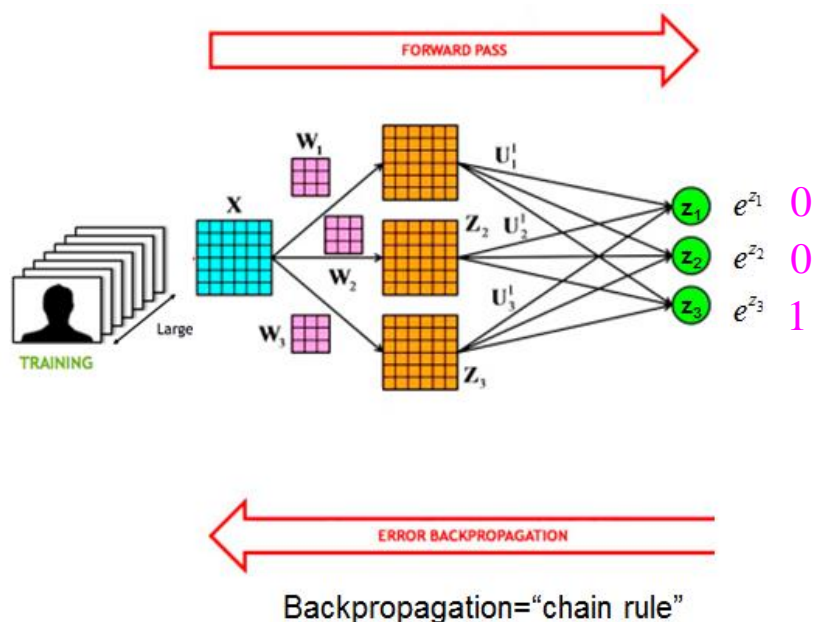


# A CNN yields for each image a vector of output values



Output depends on input and on the weights of the CNN.

# Training of a CNN is based on gradient backpropagation



For the training we need the **true label** for each image which we then compare with the **output** of the CNN.

We want to **adjust the weights** in a way so that difference between true label and output is minimal.

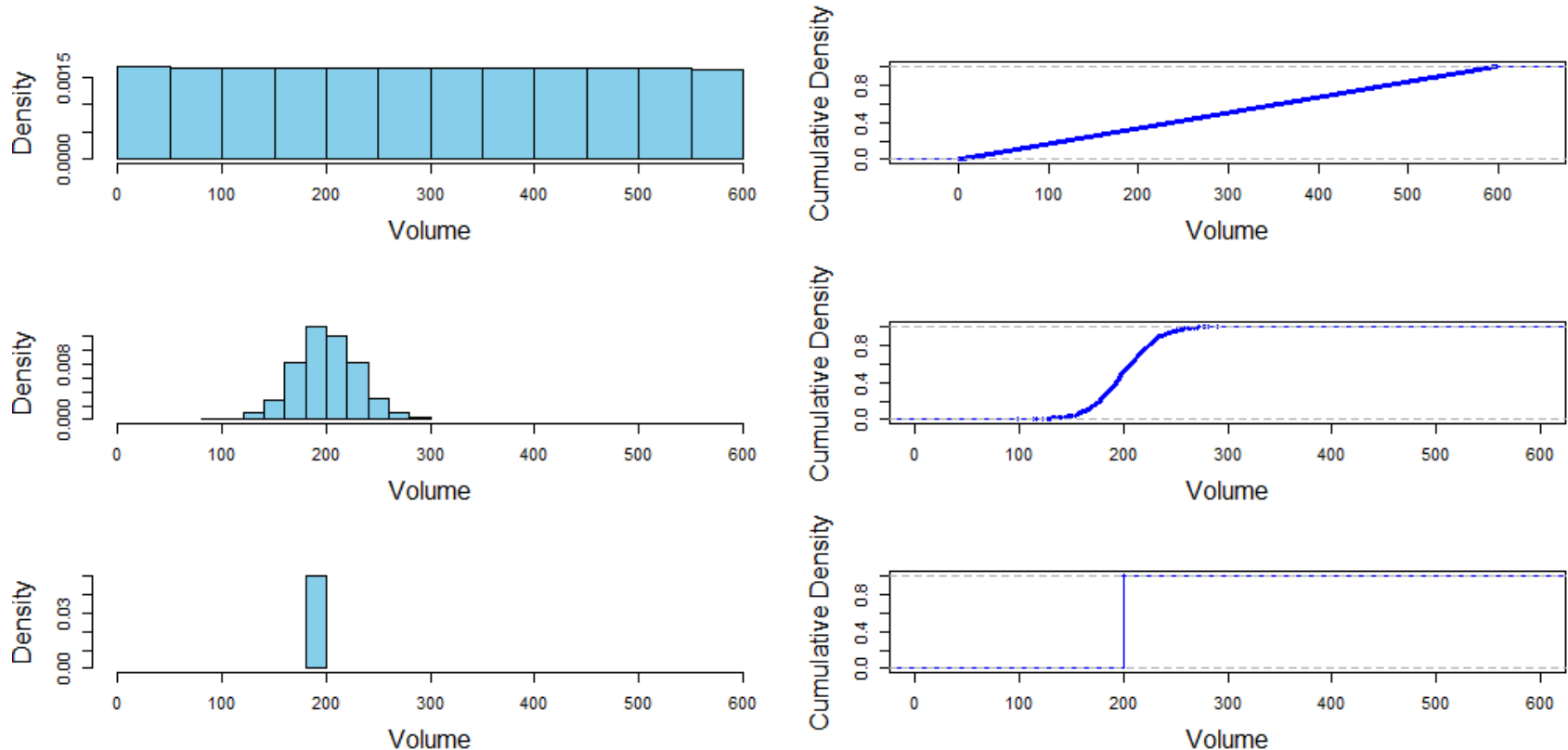
Minimize Loss-function:

**$L = \text{distance}(\text{truth}, \text{output}(w))$**

$$w_i^{(t)} = w_i^{(t-1)} - \underset{\substack{\uparrow \\ \text{learning rate}}}{l^{(t)}} \frac{\partial L(w)}{\partial w_i} \bigg|_{w_i = w_i^{(t-1)}}$$

# Task in tutorial 1

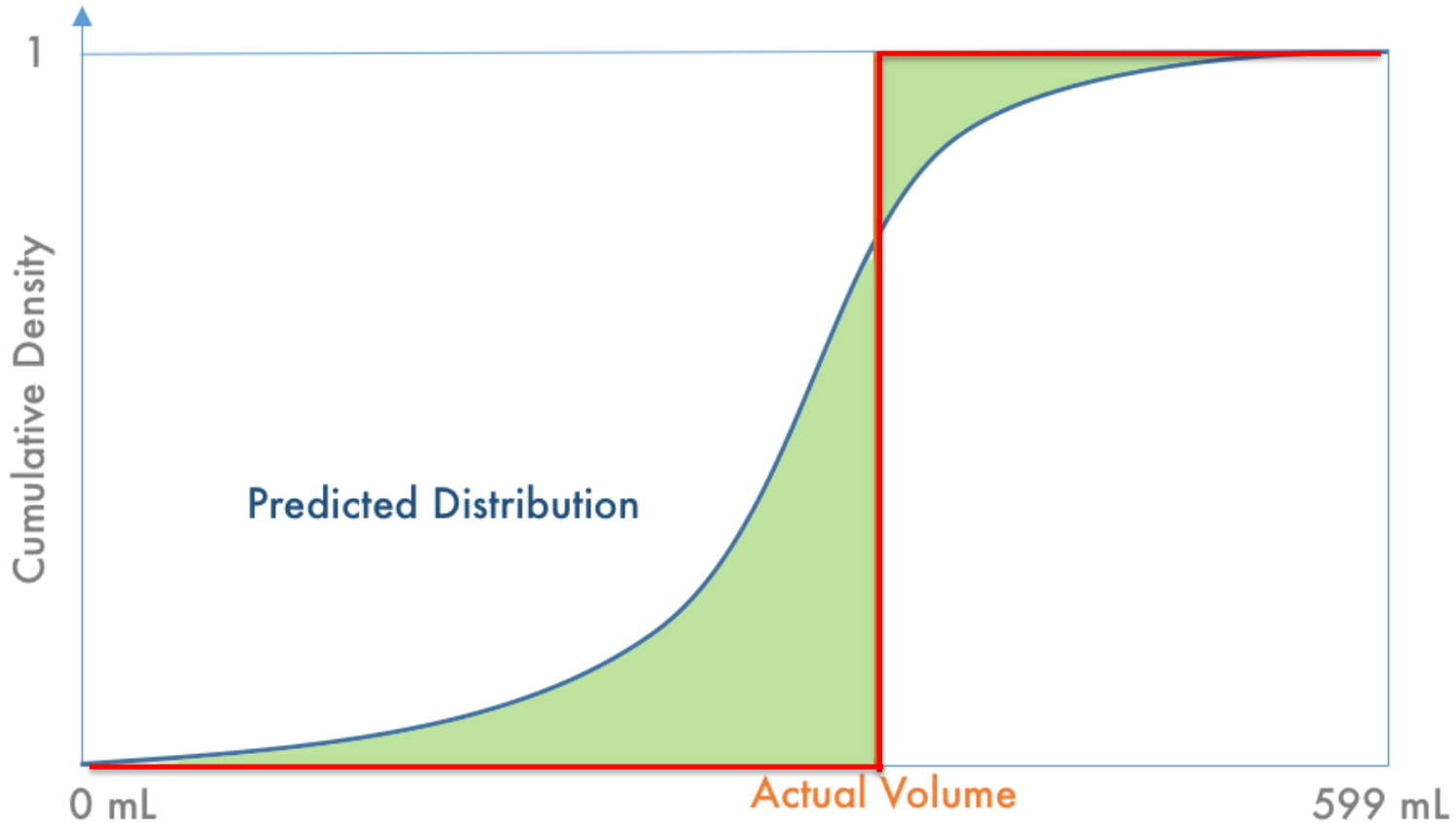
- **Input:** stack of MRI heart images **Output:** plausible heart volumes
- The heart volume can be between 0ml and 599ml.
- Our output layer has 600 neurons – each corresponding to the cumulative probability of each possible Volume  $e^{z_i} = P(V \leq X\text{ml})$  with  $X \in \{0, 1, \dots, 599\}$



# Cost or loss function in tutorial 1

**Loss-function L:**  $L = \text{distance}(\text{truth}, \text{CNN-output})$   
 $= \text{green area} = \text{sum}(|\text{label} - \text{pred}|)$

Note in code the square of the areas is used.



# Next

9:15 - 9:35	Oliver and Beate	Welcome and short intro to CNNs
9:30 - 10:15	Kevin Mader (4 Quant)	<a href="#">Approaches and Challenges for using Artificial Intelligence in Medical Imaging</a>
10:15 - 10:30	Coffee Break	Coffee Break
10:30 - 12:15	Gunter Roth (NVIDIA)	<a href="#">Tutorial: Medical Image Analysis with R and MXNet</a>
12:15 - 13:30	--	Lunch at your own expense (e.g. Mensa ZHAW)
13:10 - 13:30	Oliver	Short intro to RNNs (optional)
13:30 - 14:10	Dirk von Grünigen	<a href="#">Natural Language Dialogues with Sequence-to-Sequence Learning</a>
14:10 - 15:30	Gunter Roth (NVIDIA)	<a href="#">Tutorial: Modelling Time Series Data with Recurrent Neural Networks in Keras</a>
15:30 - 16:00	Various	Spotlight Talks and closing
16:00 -	You	<a href="#">Posters</a> and Apero