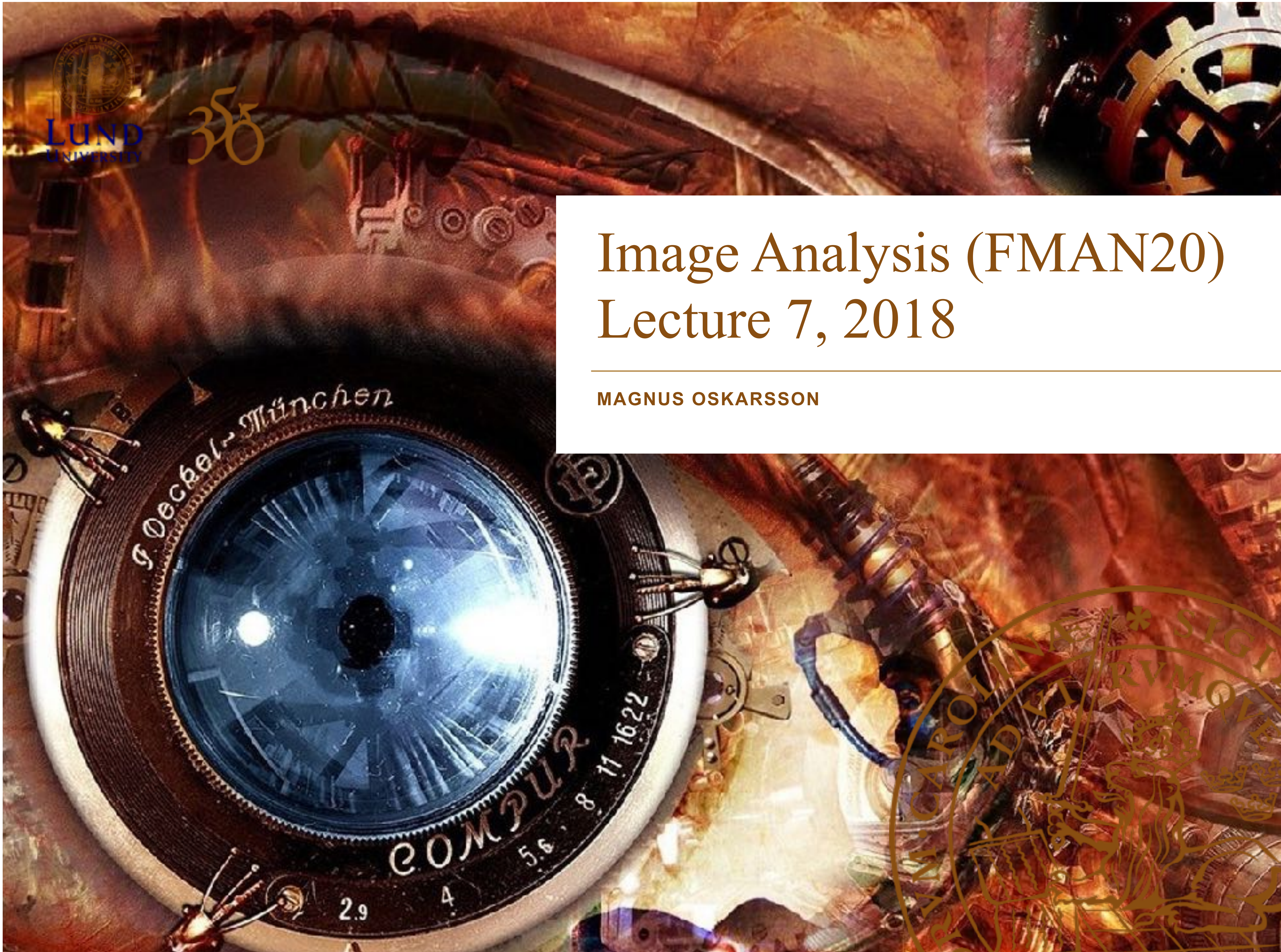


# Image Analysis (FMAN20)
# Lecture 7, 2018

**MAGNUS OSKARSSON**

# Image Analysis - Motivation

Aligning Books and Movies: Towards Story-like Visual Explanations by Watching Movies and Reading Books
Yukun Zhu*, Ryan Kiros*, Richard Zemel, Ruslan Salakhutdinov, Raquel Urtasun, Antonio Torralba, Sanja Fidler
Arxiv, June 2015

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# Overview – Deep Learning

1. History and Motivation
2. Components of Deep Learning
    1. Convolution
    2. Non-linear
    3. Max pooling
    4. Soft-Max
3. Network Design
4. Training
5. Examples

# Computer vision

## bridge the gap between pixels and meaning

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0 | 3 | 2 | 5 | 4 | 7 | 6 | 9 | 8 |
| 3 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 2 | 1 | 0 | 3 | 2 | 5 | 4 | 7 | 6 |
| 5 | 2 | 3 | 0 | 1 | 2 | 3 | 4 | 5 |
| 4 | 3 | 2 | 1 | 0 | 3 | 2 | 5 | 4 |
| 7 | 4 | 5 | 2 | 3 | 0 | 1 | 2 | 3 |
| 6 | 5 | 4 | 3 | 2 | 1 | 0 | 3 | 2 |
| 9 | 6 | 7 | 4 | 5 | 2 | 3 | 0 | 1 |
| 8 | 7 | 6 | 5 | 4 | 3 | 2 | 1 | 0 |

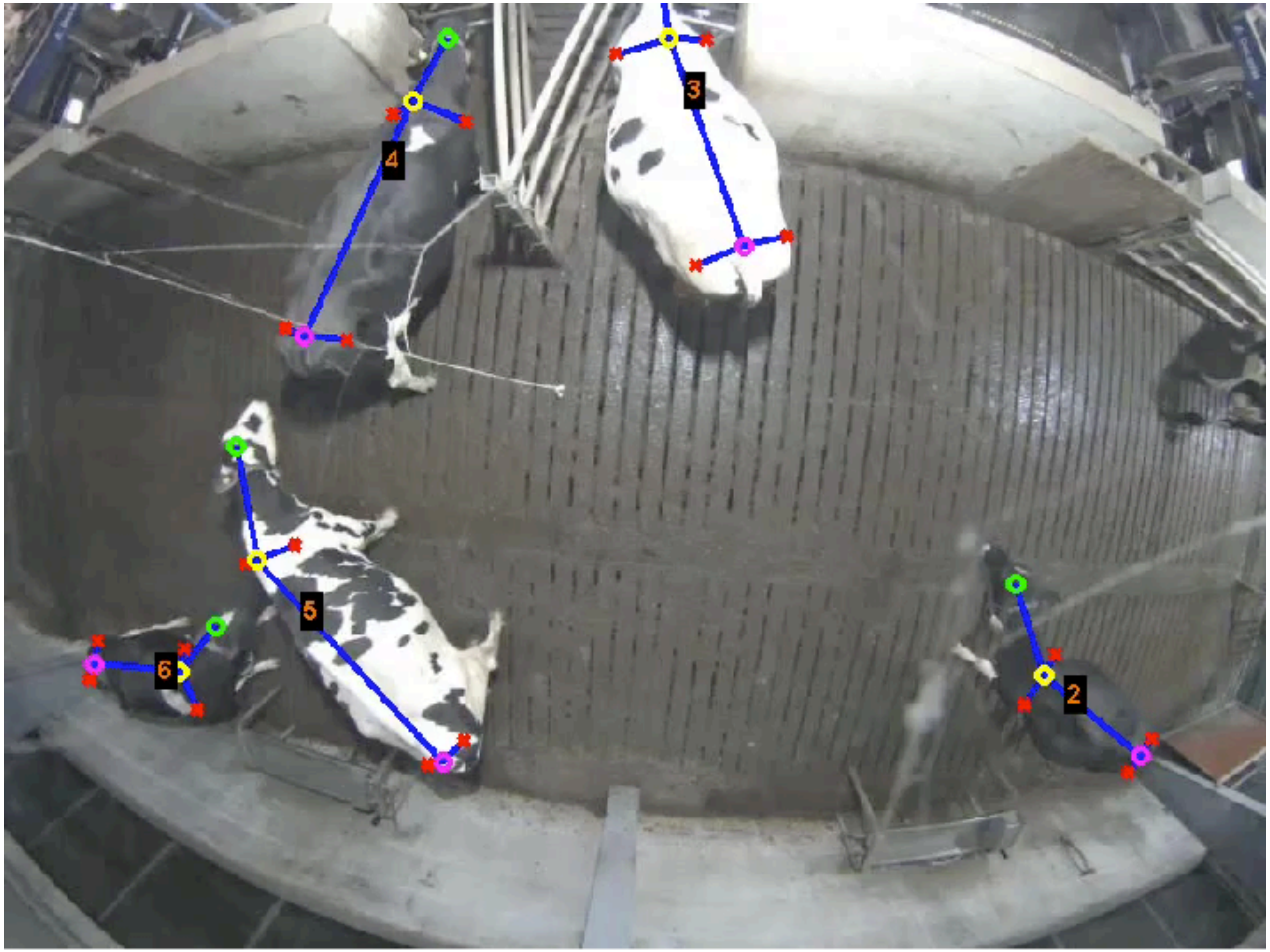
Images are collections of intensity measurements (or RGB, or …)

# Computer vision

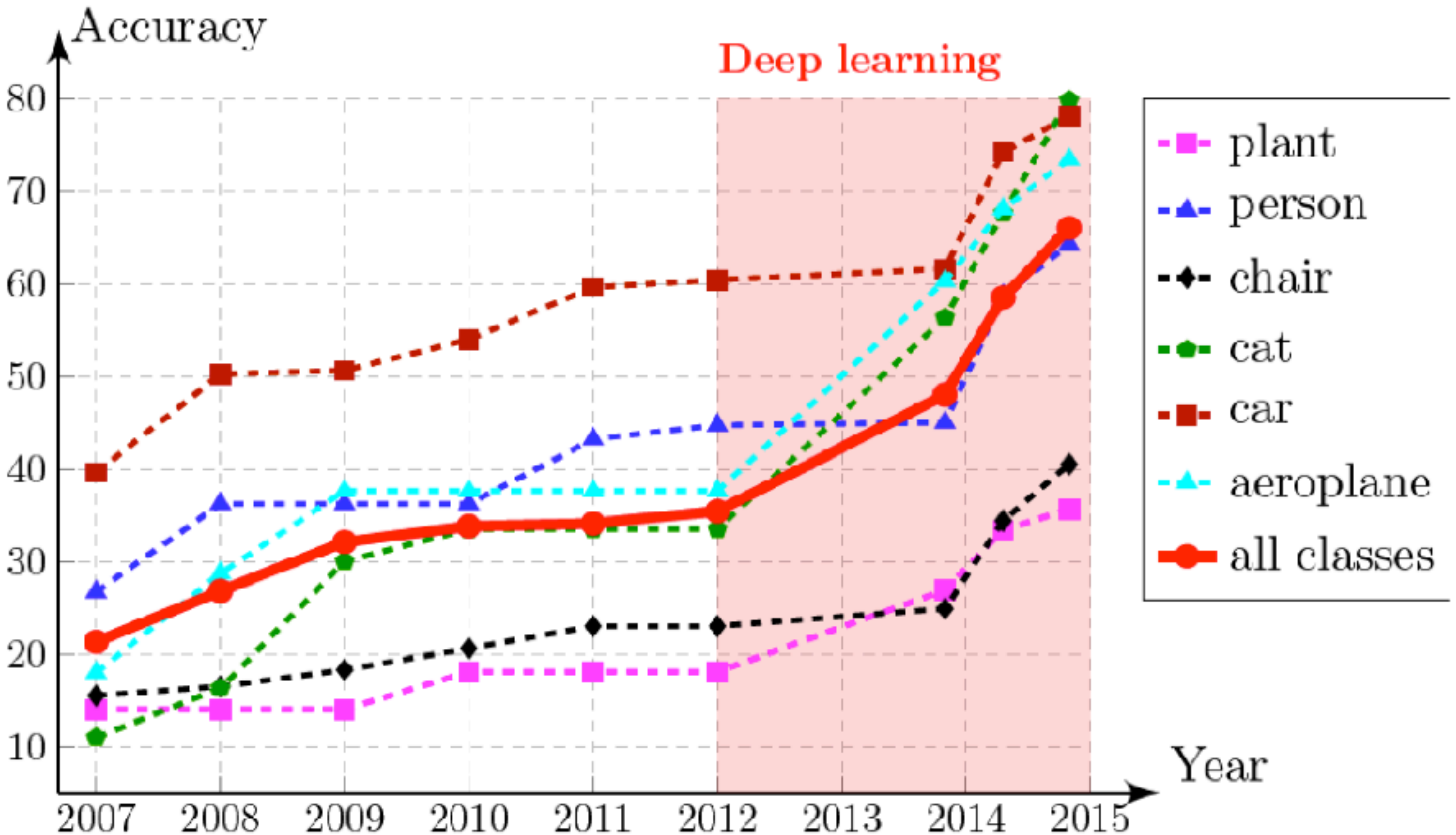
## bridge the gap between pixels and meaning

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0 | 3 | 2 | 5 | 4 | 7 | 6 | 9 | 8 |
| 3 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 2 | 1 | 0 | 3 | 2 | 5 | 4 | 7 | 6 |
| 5 | 2 | 3 | 0 | 1 | 2 | 3 | 4 | 5 |
| 4 | 3 | 2 | 1 | 0 | 3 | 2 | 5 | 4 |
| 7 | 4 | 5 | 2 | 3 | 0 | 1 | 2 | 3 |
| 6 | 5 | 4 | 3 | 2 | 1 | 0 | 3 | 2 |
| 9 | 6 | 7 | 4 | 5 | 2 | 3 | 0 | 1 |
| 8 | 7 | 6 | 5 | 4 | 3 | 2 | 1 | 0 |

# Autonomous
# Precision Livestock Farming



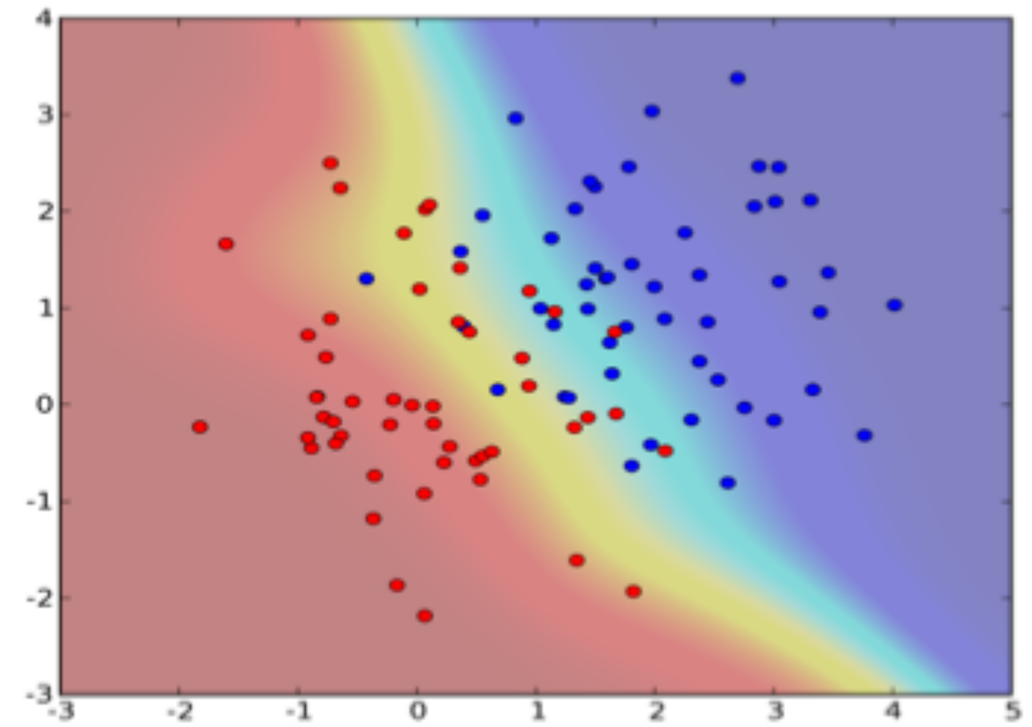
# Deep Learning



# Deep learning
# Convolutional Neural Networks

- Slides and material from
- http://www.cs.nyu.edu/~yann/talks/lecun-ranzato-icml2013.pdf
- MatConvNet
- http://www.robots.ox.ac.uk/~vgg/practicals/cnn/
- Gabrielle Flood's master's thesis
- Anna Gummeson's master's thesis

# Components for deep learning




- One neuron
  - Example: Logistic regression
  - Classification model (x feature vector, (w,b) parameters, s smooth thresholding

$$x \in R^d, w \in R^d, b \in R, f(x) = s(w^T x + b)$$

  - Logistic regression

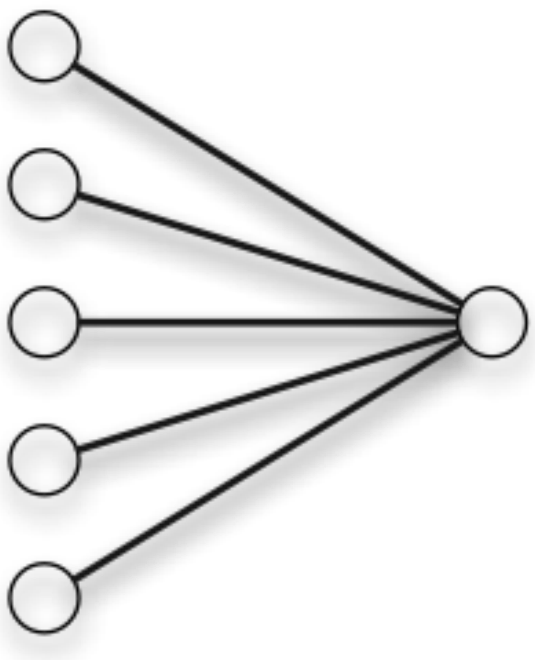
$$s(z) = \frac{1}{1 + e^{-x}}$$

  - ML estimate of parameters (w,b) is a convex optimization problem

# Single Layer Neural Networks One Neuron

- One neuron

$$x \in R^d, w \in R^d, b \in R, f(x) = s(w^T x + b)$$



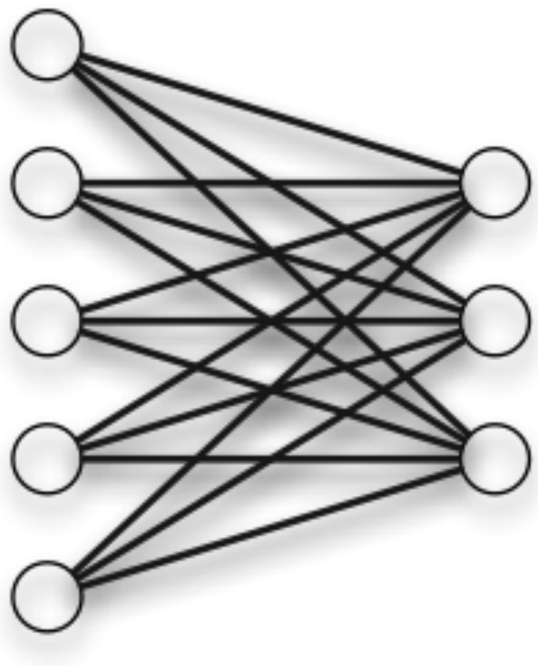
# Single Layer Neural Networks Several Neurons

- Several parallell neurons

$$x \in R^d, y \in R^k, B \in R^d, W - k \times d\text{matrix}$$

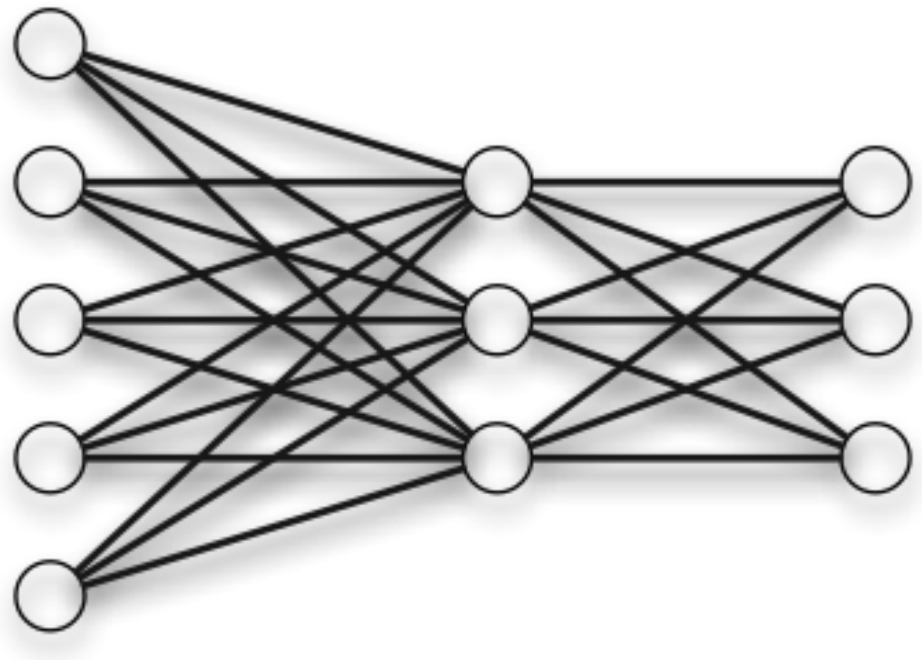
$$y = s(Wx + B)$$

- Elementwise smooth thresholding – s



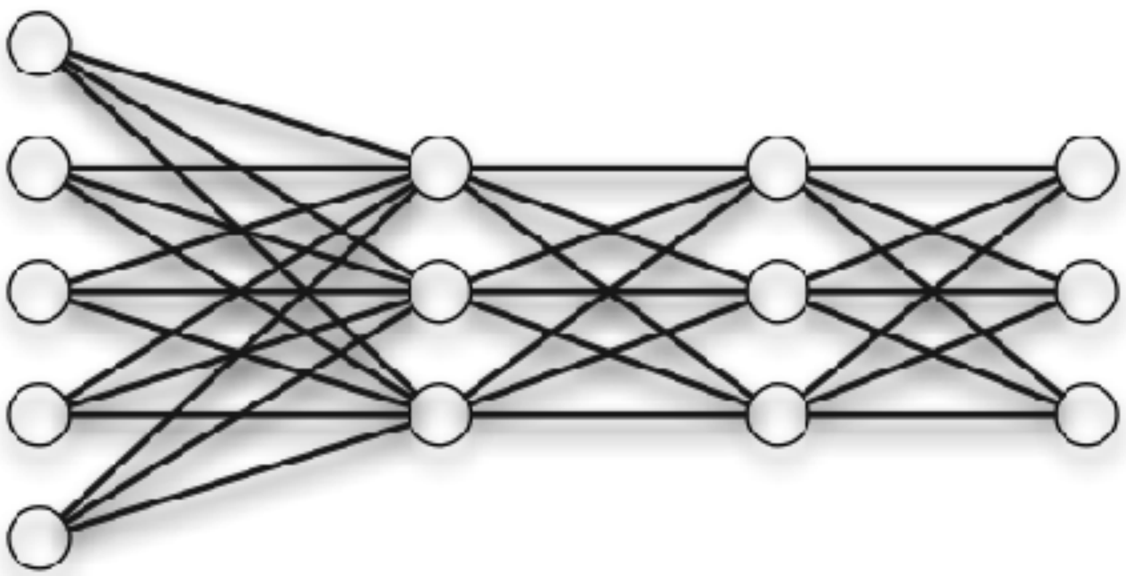
# Artificial Neural Networks
# One hidden layer

- Multi-class classification
- One hidden layer
- Trained by back-propagation
- Popular since the 1990s

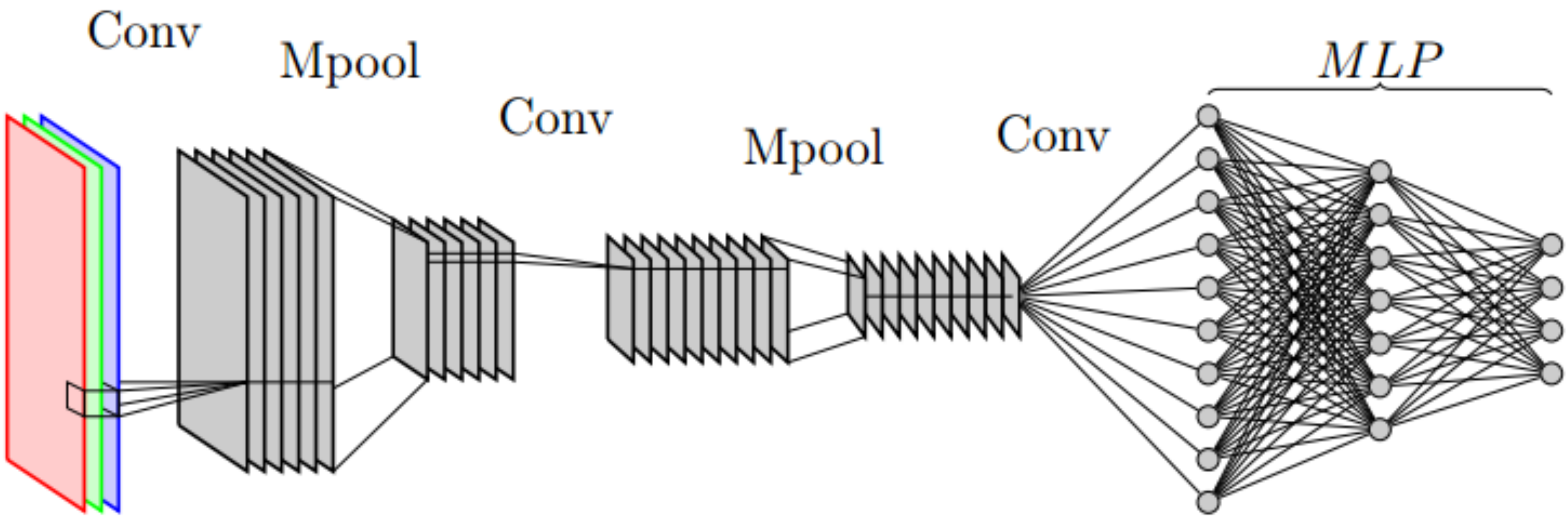


# Deep Neural Networks
# Many layers

- However
- Naively implemented would give to many parameters
- Example
- 1M pixel image
- 1M hidden layers
- $10^{12}$ parameters between each pair of layers

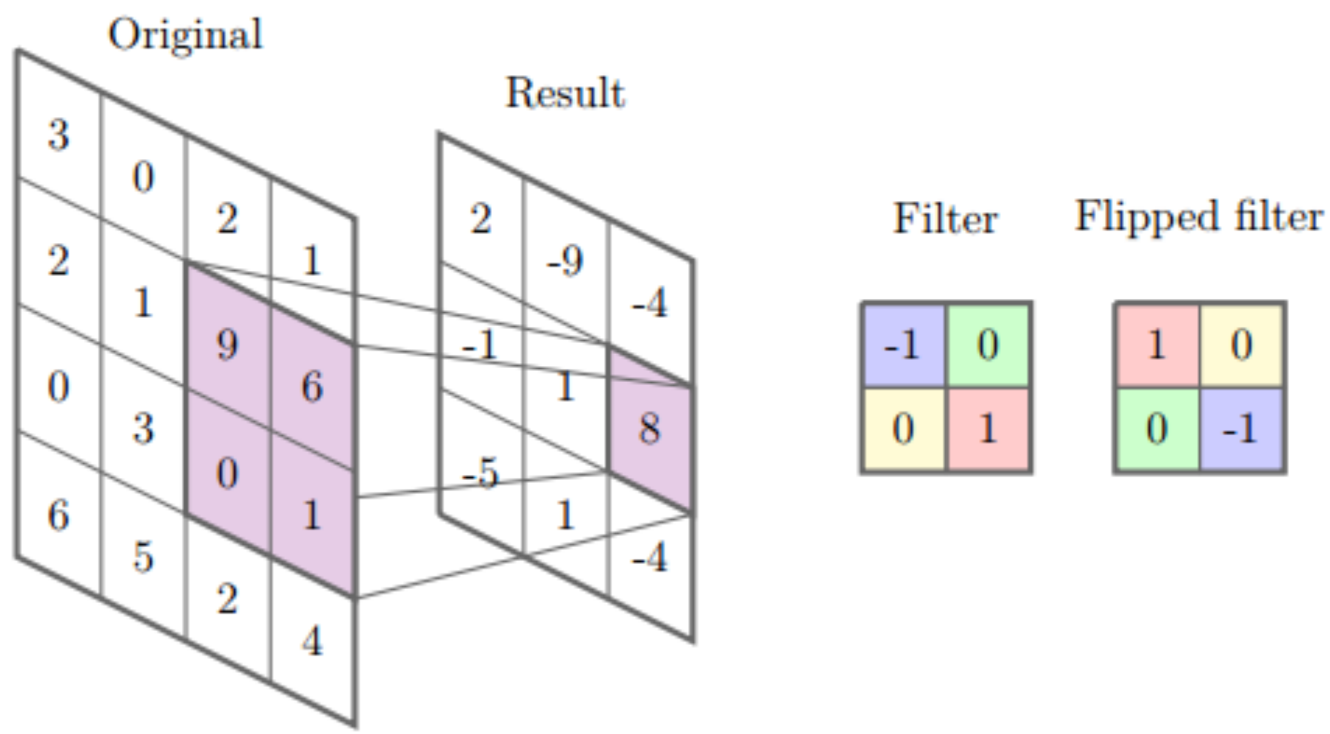


# Convolutional neural network, CNN

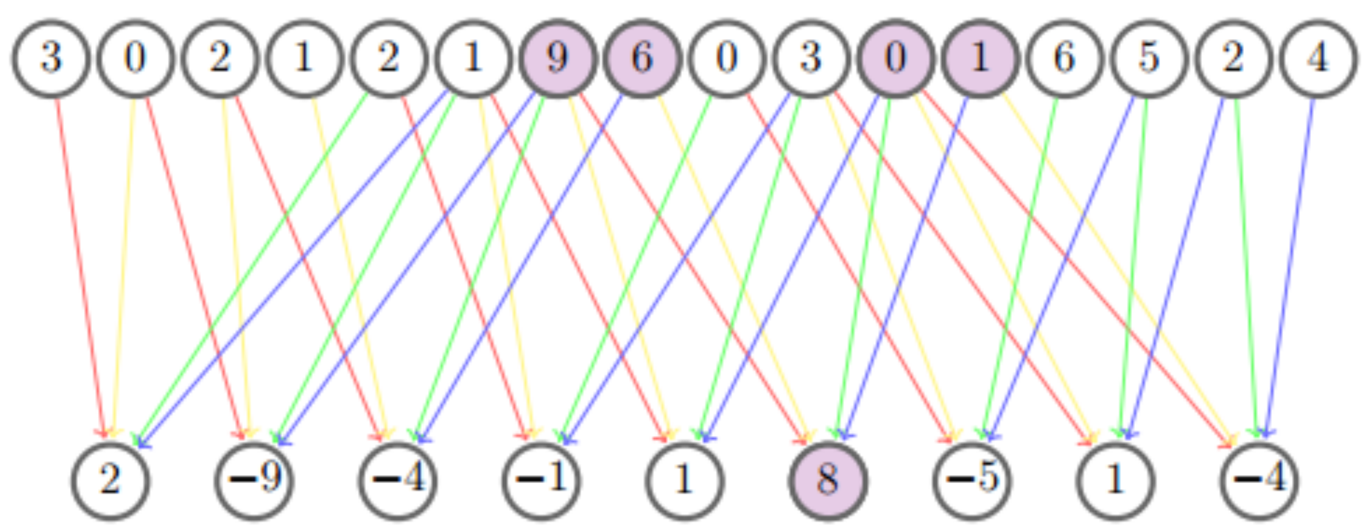


# CNN-Blocks - Convolutional layer

Convolution of an image as a filter-operation.

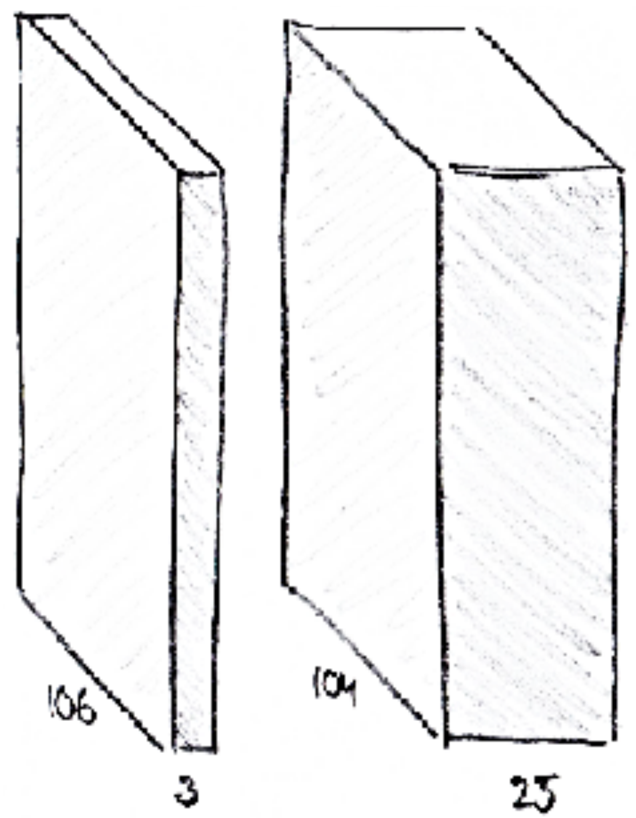



Convolution of an image represented as a sparsely connected ANN.



# CNN-Blocks - Convolutional layer

- Input: Data block x of size
  $$m \times n \times k_1$$
- Output: Data block y of size
  $$m \times n \times k_2$$
- Filter: Filter kernel block w of size
  $$m_w \times n_w \times k_1 \times k_2$$
- Offsets: Vector $w_o$ of length $k_2$

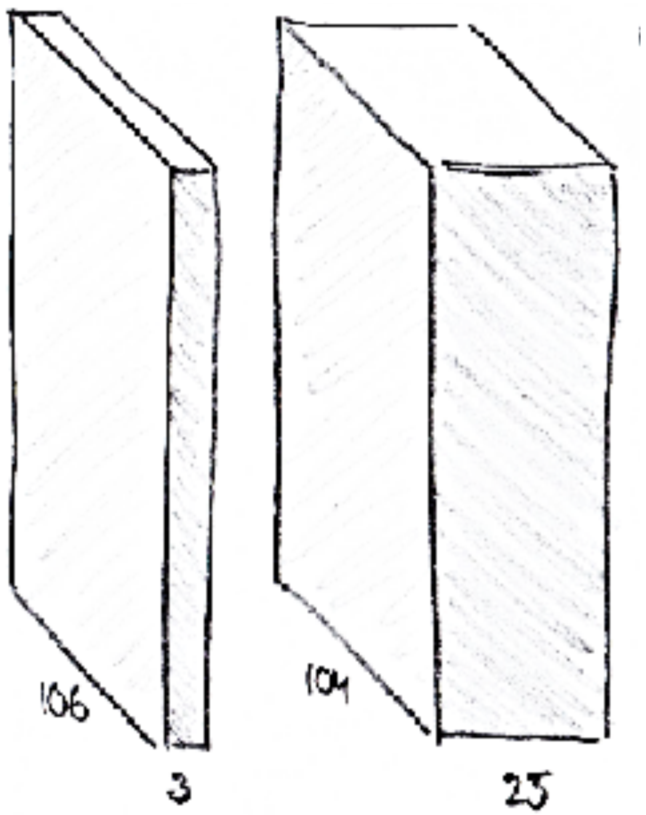



$$y(i,j,k) = w_o(k) + \sum_u \sum_v \sum_l x(i-u, j-v, l) w(u,v,l,k)$$

# CNN-Blocks - Convolutional layer

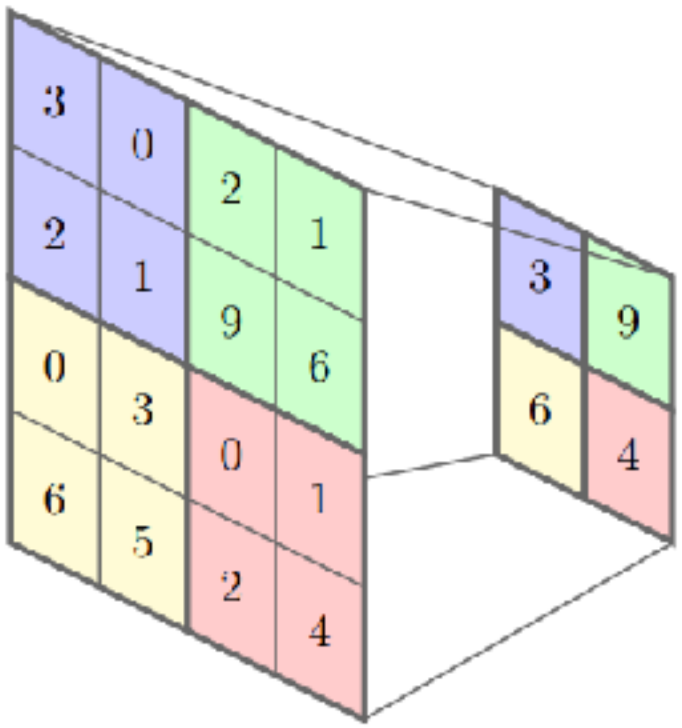
$$y(i,j) = \sum_u \sum_v x(i-u, j-v)w(u,v)$$

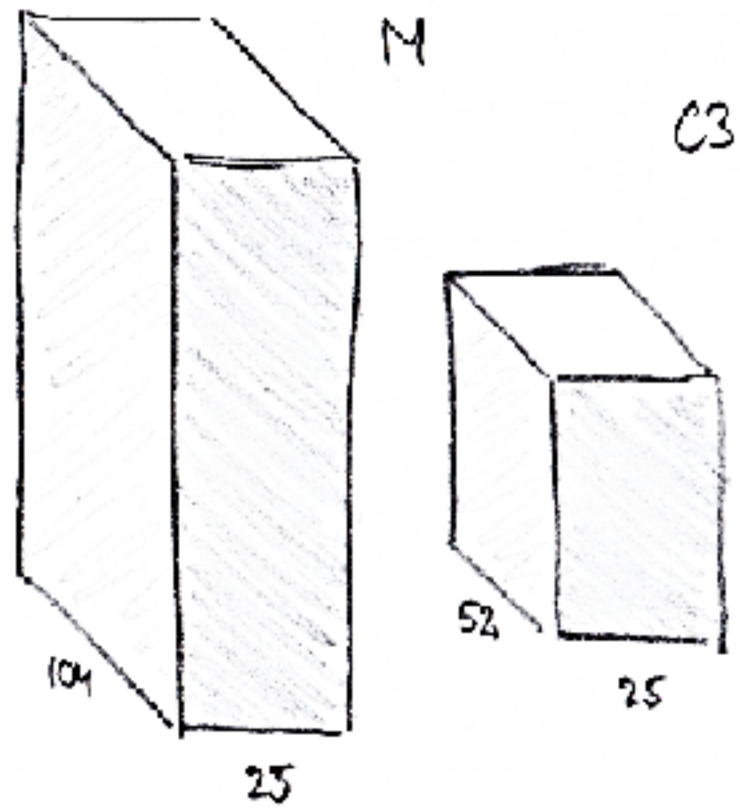
$$y(i,j) = w_o + \sum_l \left( \sum_u \sum_v x(i-u, j-v, l)w(u,v,l) \right)$$




$$y(i,j,k) = w_o(k) + \sum_u \sum_v \sum_l x(i-u, j-v, l)w(u,v,l,k)$$

# CNN-Blocks - Max-pooling

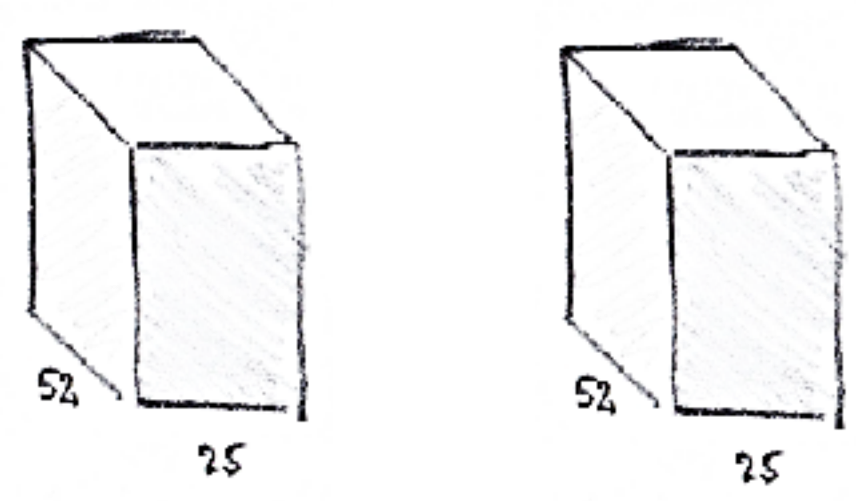


# CNN-Blocks - RELU

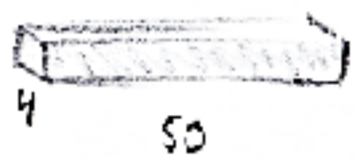
$$f(x) = max(0, x)$$

$$y(i, j, k) = max(x(i, j, k), 0)$$



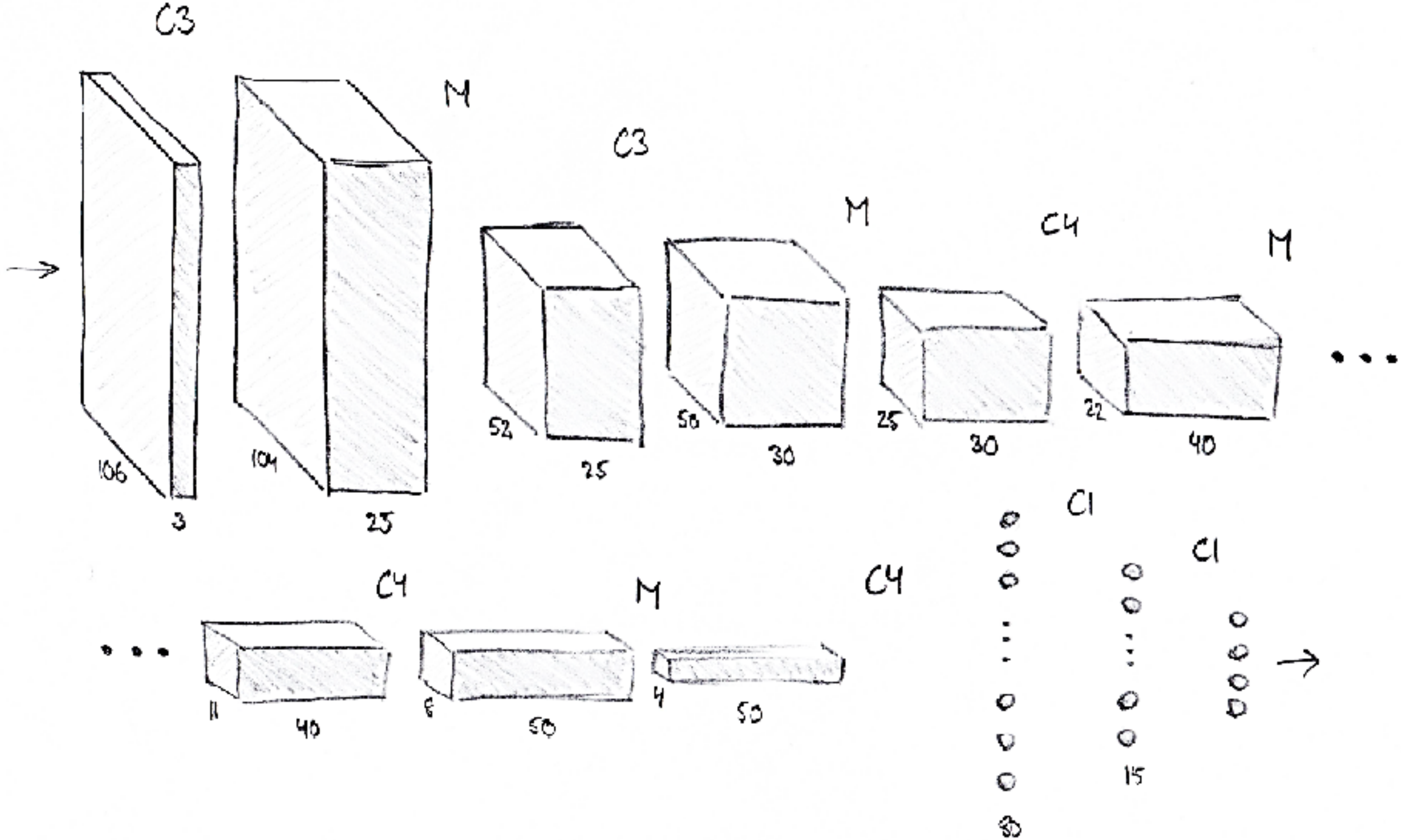
# CNN-Blocks – Softmax
# (convert from ’log probabilites’ dj to ’probabilites’ that sum to 1)

$$p_j = \frac{e^{d_j}}{\sum_{k=1}^{m} e^{d_k}}$$


Gör om till 1x1 stav

# Result, Network design



# CNN-Blocks – input – output


$$y = f(x, w)$$


Input: image x of size m x n x k, typically k=1 (gray-scale) or k=3 (color)
Output: vector y of size 1 x 1 x N, which we interpret as N probabilities y_j
The probability that the image x is of class j

# Training data (x_i, c_i)


$$y = f(x, w)$$


Input: image x of size m x n x k, typically k=1 (gray-scale) or k=3 (colour)
Output: vector y of size 1 x 1 x N, which we interpret as N probabilities y_j
The probability that the image x is of class j $y_{c_i}$

# Training data $T = \{(x_1, c_1), \ldots (x_N, c_N)\}$

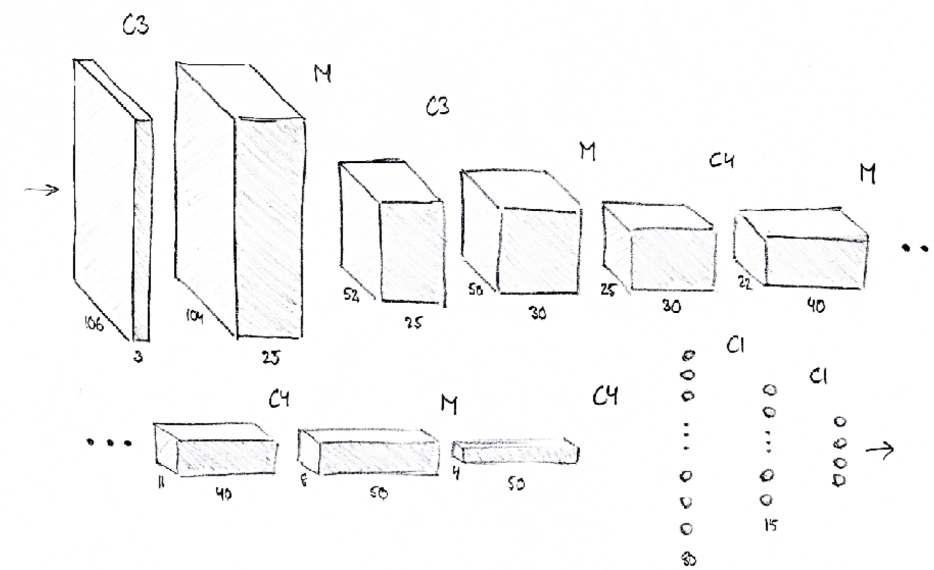
- Classification network $$y = f(x, w)$$
- Evaluate one example $(x_k, c_k)$ (like adding another layer)

$$\sum_{k=1}^{N} -\log y(x_k, w)_{c_k}$$

- Evaluation function: $$g(T, w) = \sum_{k=1}^{N} -\log y(x_k, w)_{c_k}$$
- Solve

$$\min_w g(T, w)$$

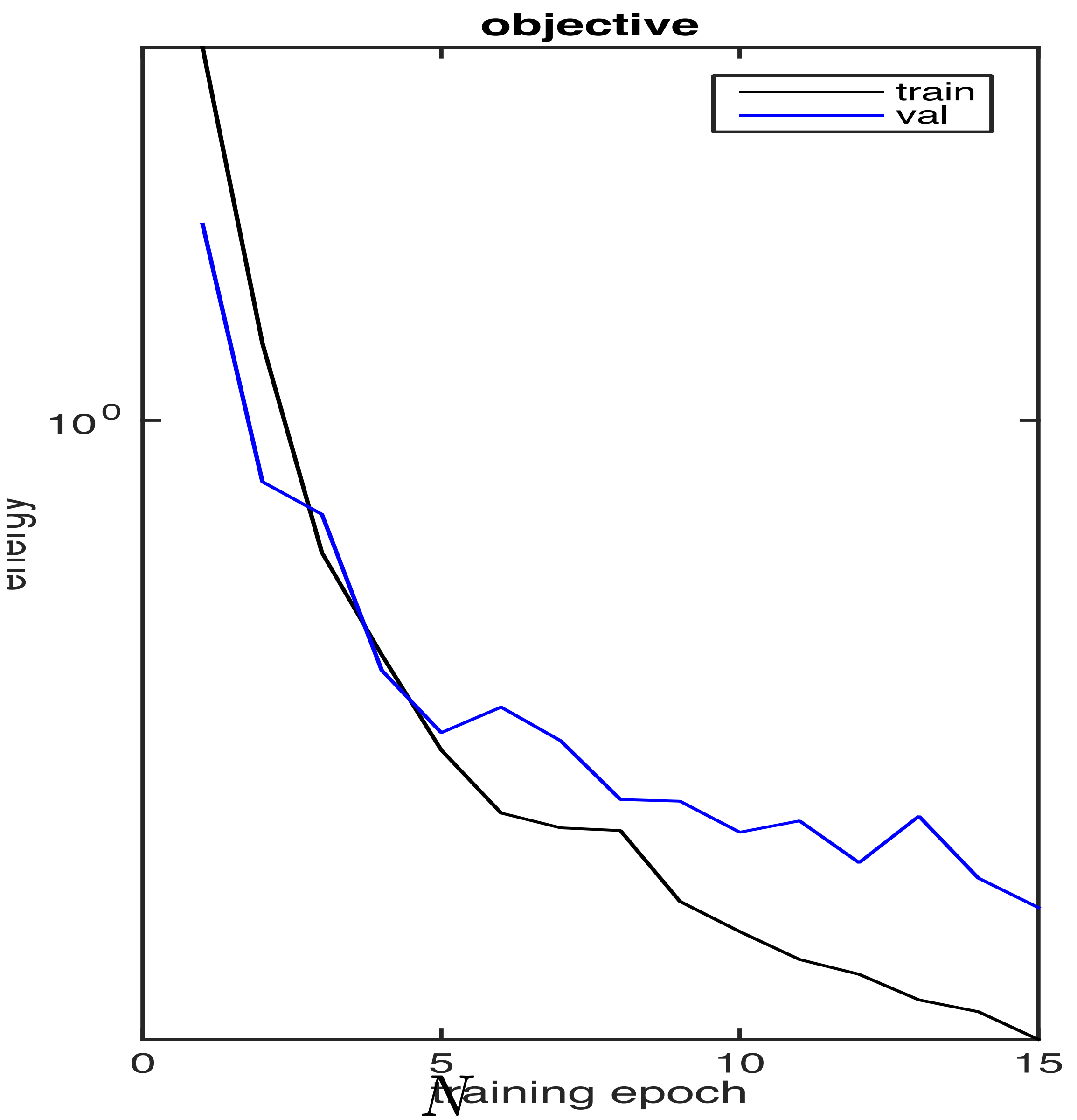
# Example: OCR, classify images as a-z, Network design

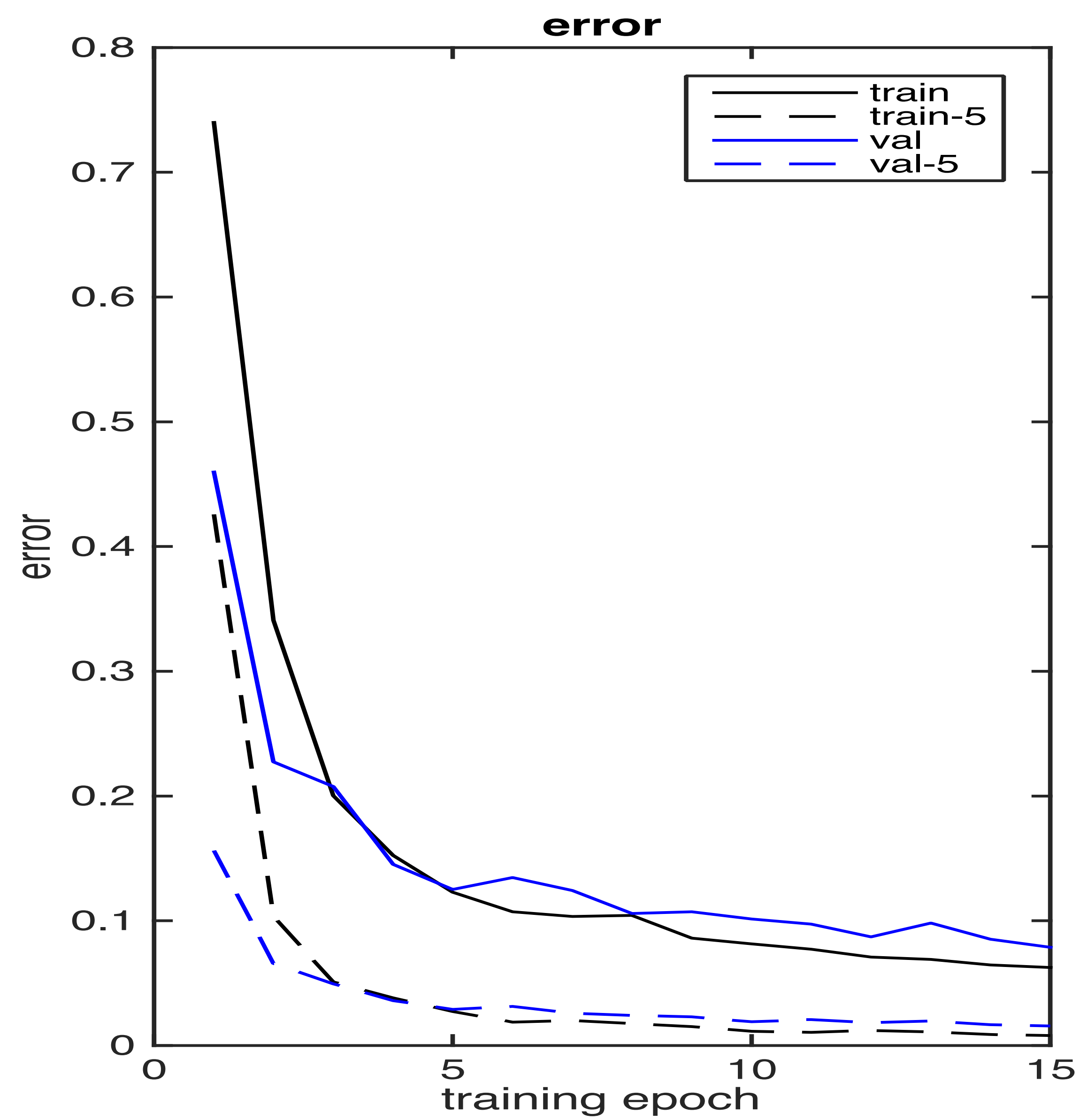



```
>> net

net =

       layers: {1x7 cell}
    imageMean: 0.9176775

>> vl_simplenn_display(net)
      layer|      1|      2|      3|      4|      5|      6|      7|
       type|    cnv|  mpool|    cnv|  mpool|    cnv|   relu|    cnv|
    support|    5x5|    2x2|    5x5|    2x2|    4x4|    1x1|    2x2|
     stride|      1|      2|      1|      2|      1|      1|      1|
        pad|      0|      0|      0|      0|      0|      0|      0|
    out dim|     20|     20|     50|     50|    500|    500|     26|
   filt dim|      1|    n/a|     20|    n/a|     50|    n/a|    500|
rec. field|      5|      6|     14|     16|     28|     28|     32|
c/g net KB|    4/0|    0/0|  196/0|    0/0| 3129/0|    0/0|  406/0|
total network CPU/GPU memory: 3.6/0 MB
>>
```

# Example: OCR, classify images as a-z
# Training data

# Example: OCR, classify images as a-z, Training



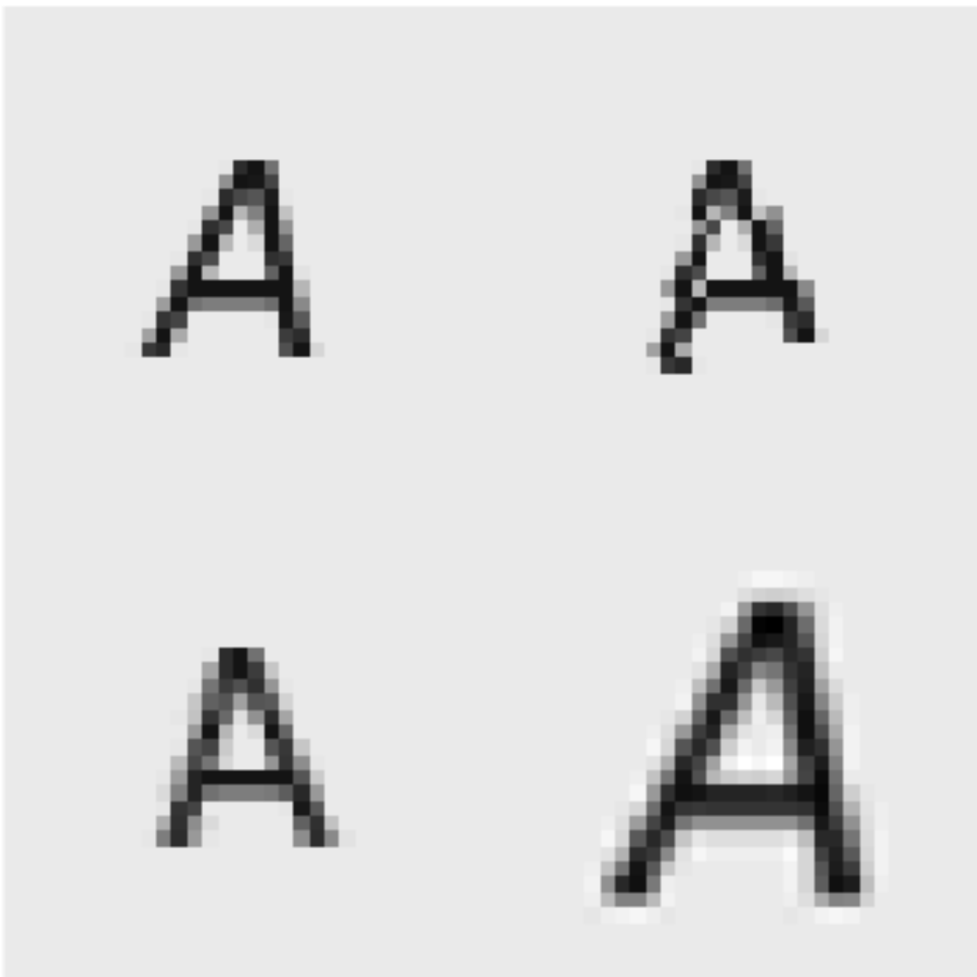

$$g(T, w) = \sum_{k=1}^{N} -\log y(x_k, w)_{c_k}$$

$$\#\{c_k = argmax_i\, y(x_k, w)_i\}$$

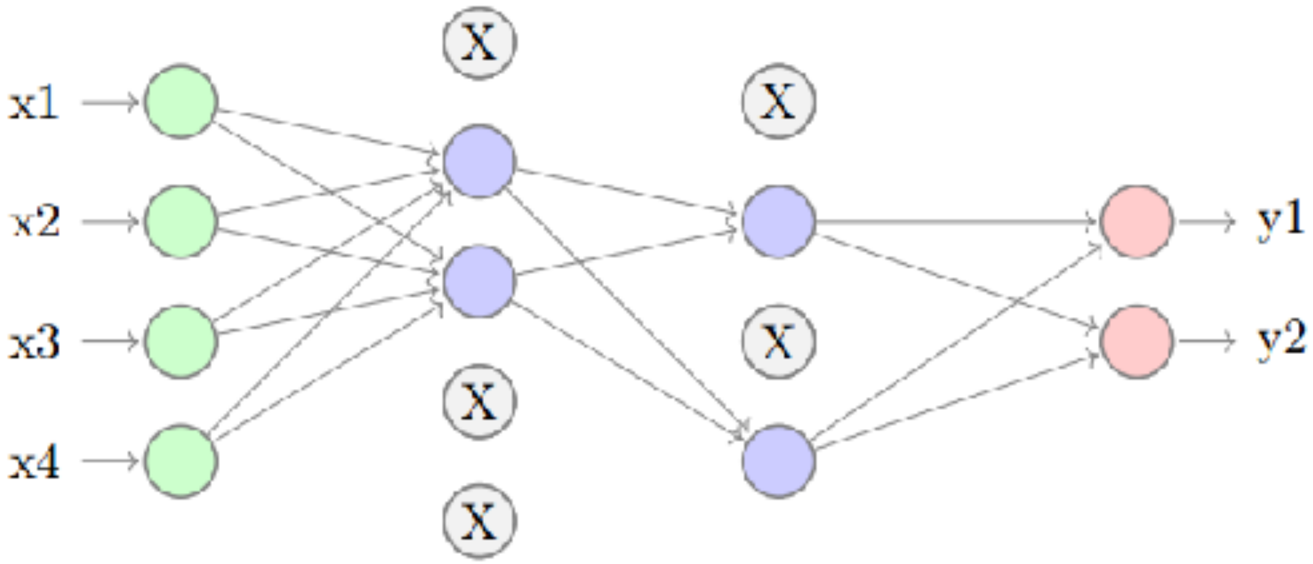
# Tricks

- **Stochastic Gradient Descent**
  - Computation of $$g(T,w) = \sum_{k=1}^{N} -\log y(x_k, w)_{c_k}$$
  - Requires going through all examples (all N).
  - If N is large and/or if computing y(x_k,w) is time-consuming, use stochastic gradient descent, i.e. update parameters using subsets of training data.
- **Jittering** - construct a larger training set by perturbing the examples, jittering, translating images, rotating images, warping, mirroring, adding noise, …'
- **Dropout** – in each computation of y(x_k,w) let a random subset of the neurons die, i e set the output to zero.

# Generalisation, Expand data set



# Generalisation, Dropout



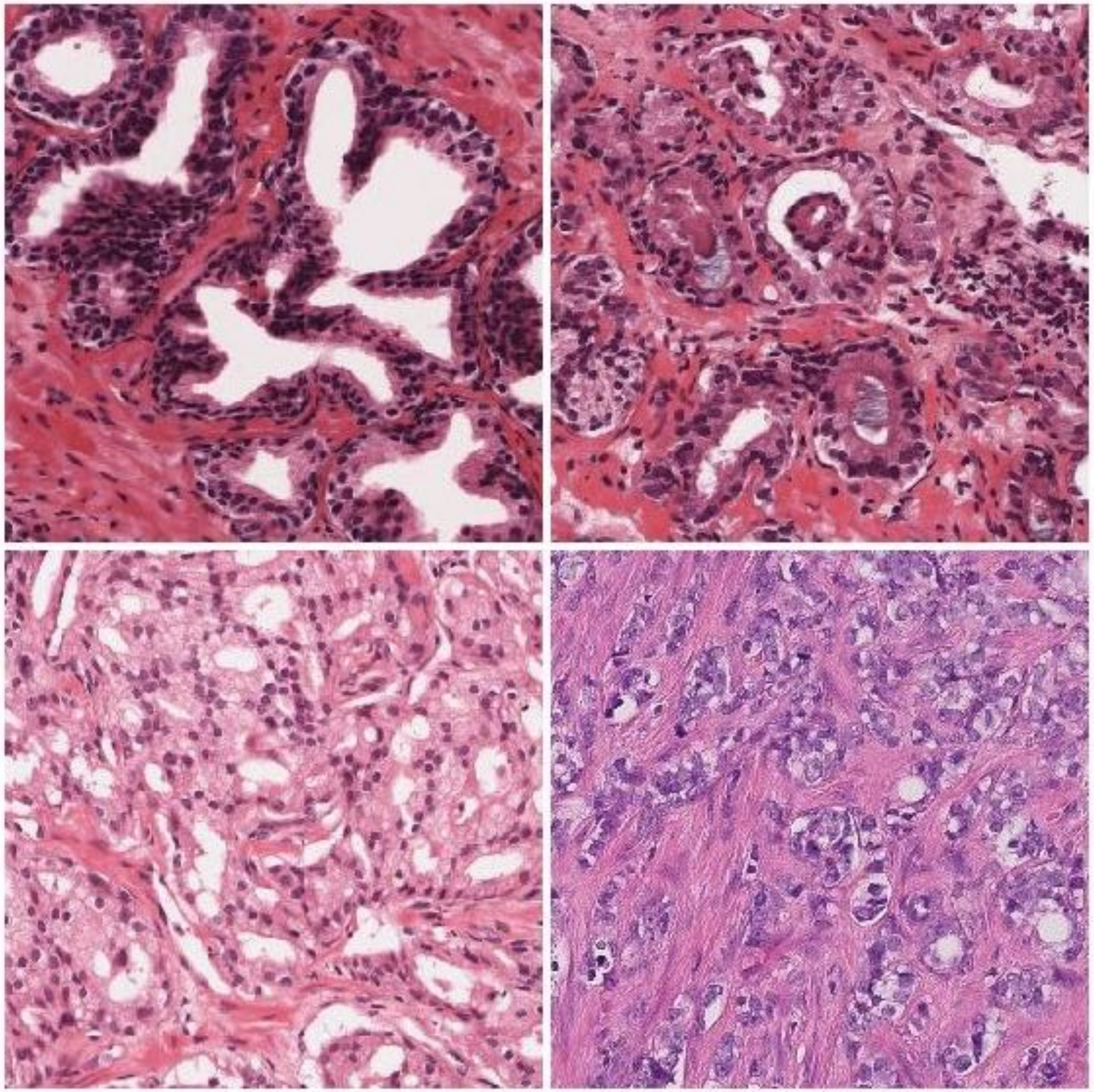
# Generalisation, Weight decay (Prior on small weights)

$$E(w) = -\sum_{n=1}^{N} \log\left(\frac{e^{y_{d(n)}(n)}}{\sum_{i=1}^{k} e^{y_i(n)}}\right) + \frac{\lambda}{2}\sum_{l} w_l^2$$

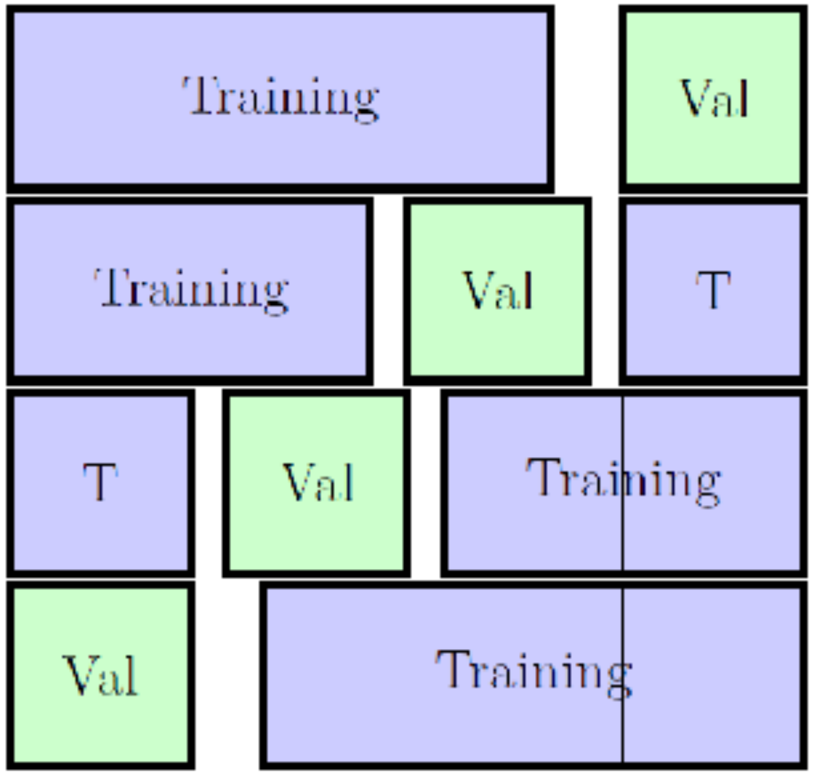
# Thoughts

- Modelling. It takes time to
  - Figure out an appropriate network structure
  - Gather data and ground truth
- The optimization does not always work
  - Parameters explode
  - Nothing happens
- Visualization of the features is important for understanding.
- Feedback in networks

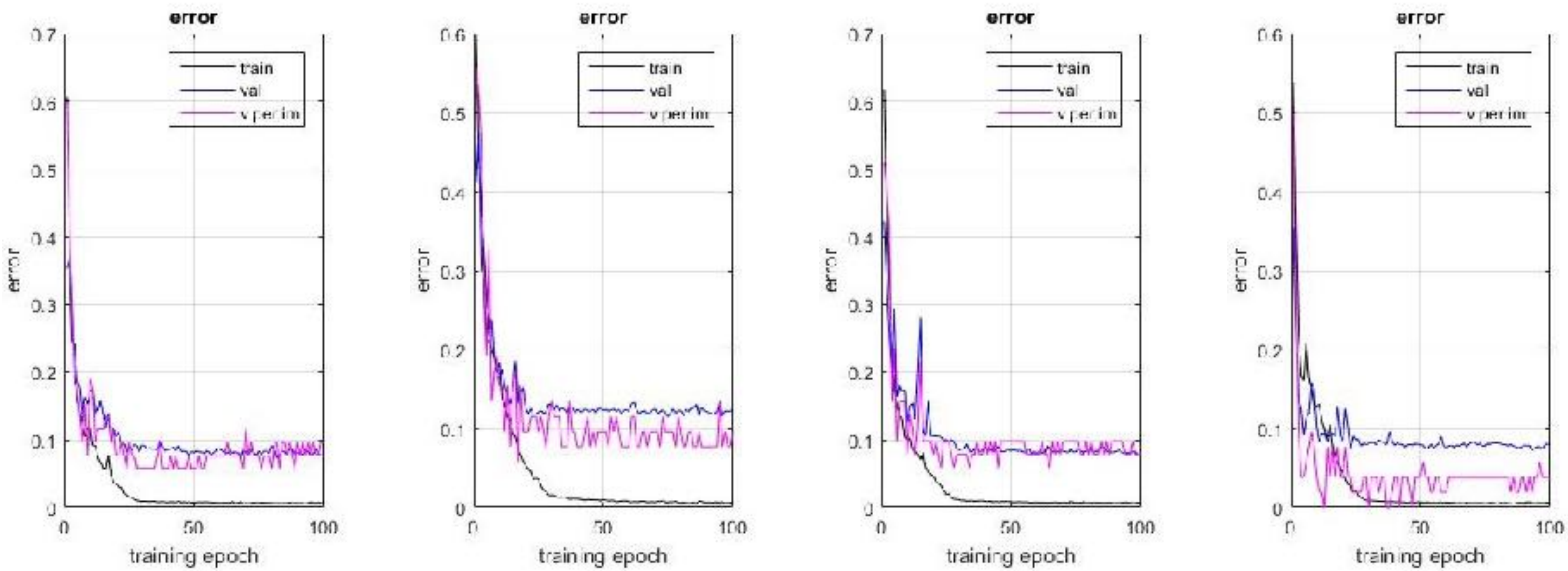
# Example: Prostate cancer Data



# Result, Cross-validation



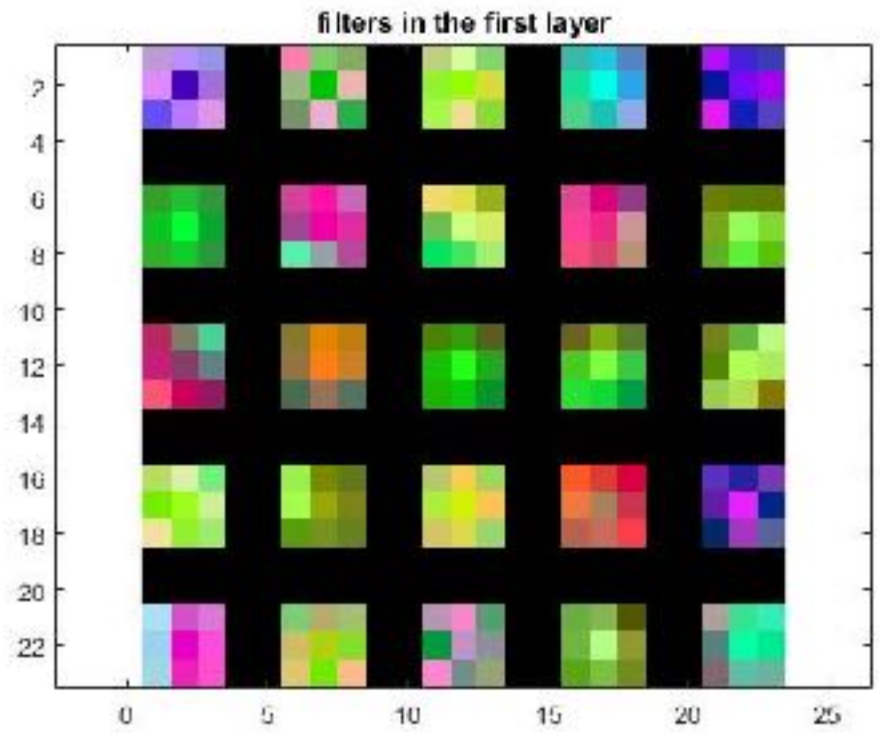
# Example: Prostate cancer Training

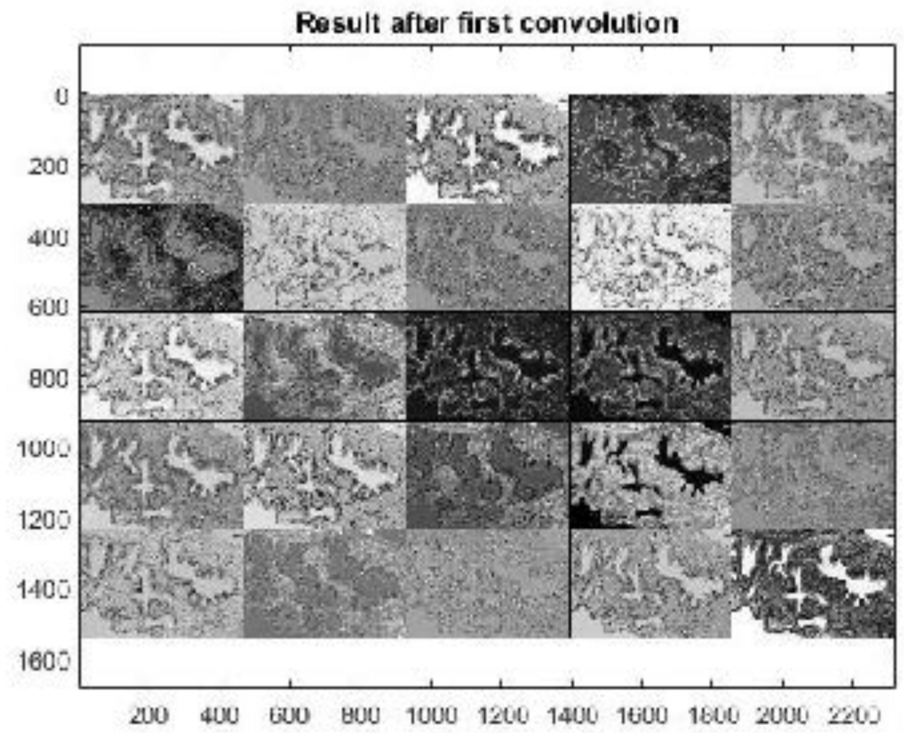


# Example: Prostate cancer
# Results: Confusion matrix

$$\begin{bmatrix} 51 & 0 & 0 & 0 \\ 3 & 46 & 3 & 1 \\ 0 & 6 & 43 & 0 \\ 0 & 3 & 0 & 52 \end{bmatrix}$$

# Visualisation



# Examples: Image net, Data

- ImageNet Large Scale Visual Recognition Challenge
- Yearly challenge since 2010
- 2011 - 25% error
- 2012 - 16% error (using CNN). This kicked off the deep learning hype
- 2015 – 4% error
- By 2015, researchers reported that current software exceeds human ability at the narrow ILSVCR tasks.
- However, as one of the challenge's organisers, Olga Russakovsky, pointed out in 2015, the programs only have to identify images as belonging to one of a thousand categories!

# Training Deep Learning

- Data
  - Obtain data,
  - cut-outs of right size,
  - jittering,
  - Data expansion (translation, rotation, scaling, mirroring, adding noise, …)
- Data
  - Obtain ground truth
  - How should the problem be coded

# Training Deep Learning

- Hyperparameters
  - How many layers
  - Size of convolution kernels
  - Number of channels
  - Order of layers
- Training parameters
  - Initializing weights
  - Momentum
  - …

# Non-linear function

- Different choices of non-linear functions.
- Faster learning
- Rectifier …

$$f(x) = \max(0, x)$$

- … currently most popular, faster training
- Arguments

$$f(x) = \max(0, x)$$

$$f(x) = \ln(1 + e^x)$$

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ 0.01x & \text{otherwise} \end{cases}$$

$$f(x) = (1 + e^{-x})^{-1}$$

$$f(x) = tanh(x)$$

# Training Deep Learning

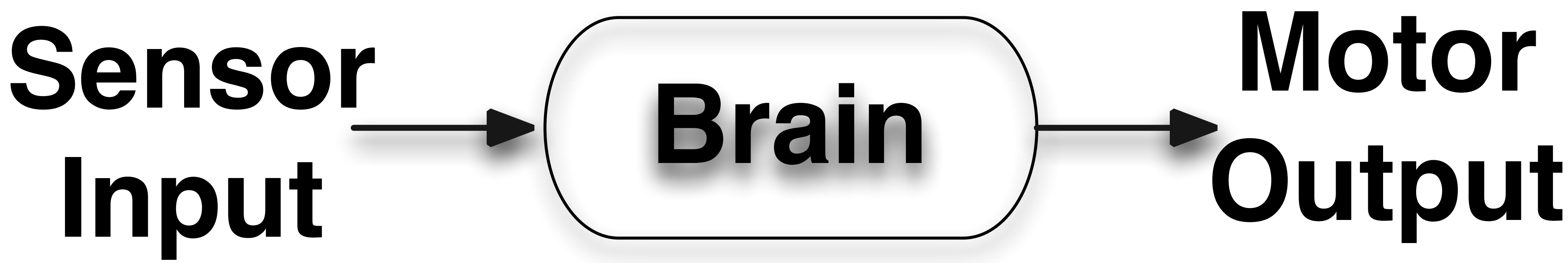
- Once all of these are in place, there are several good systems for optimizing the parameters
  - MatConvNet, TensorFlow, Caffe, Torch7, Theano
  - Can train on single CPU
  - Faster if compiled for GPU
  - Even faster on cluster of computers with multiple GPU (e g LUNARC, http://www.lunarc.lu.se )
- More links on home page for PhD course
- http://www.control.lth.se/Education/DoctorateProgram/deep-learning-study-circle.html

# Deep learning - summary

- What is deep learning
- Supervised vs unsupervised learning
- Goal function, energy function E
- Choice of non-linearity ReLU
- Optimization Back-propagation, SGD
- Tricks dropout
- Examples from speech and vision
- Software
- References
- To learn more – take course on Machine Learning FMAN45

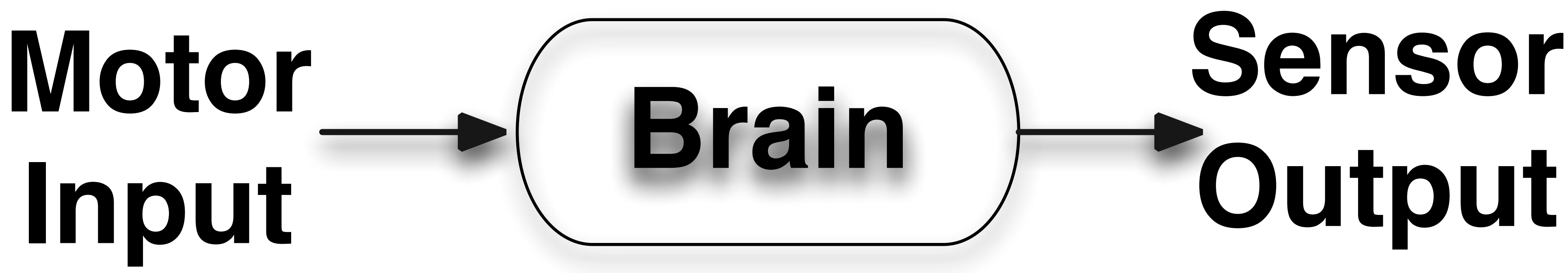
# Master's Thesis Suggestion

# Masters thesis suggestion of the day




- How do we get training data for this?

# Masters thesis suggestion of the day




- Turn it around!
- This is easy to get training data for

# Masters thesis suggestion:
# Action-Based Learning in Brain Circuits and Deep Artificial Neural Networks

Research collaboration with
Christian Balkenius,
Per Petersson,
Jeanette Hellgren Kotaleski

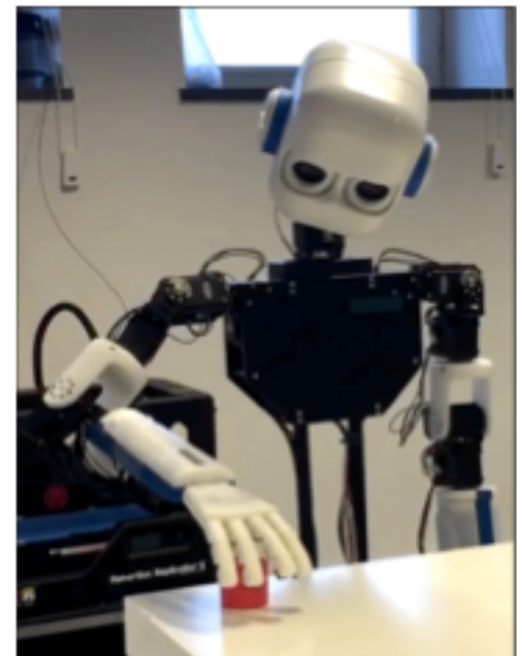


**Figure 1.** The robot Epi grasping an object.

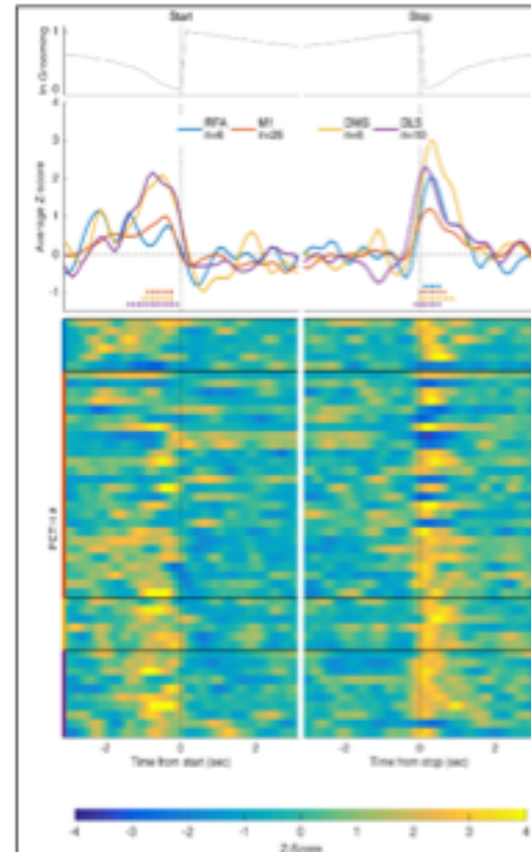


**Figure 4.** Neuronal firing rate modulation in cortico-basal ganglia circuits reveals distinct action bracketing in spontaneous grooming behavior (Tamte et al., unpublished).

**Motor Input** → **Brain** → **Sensor Output**

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