



# **Applied Statistics for Neuroscientists**

## **Part IIa: Neural networks and deep learning**

Dr. Seyed-Ahmad Ahmadi

16.11.2017

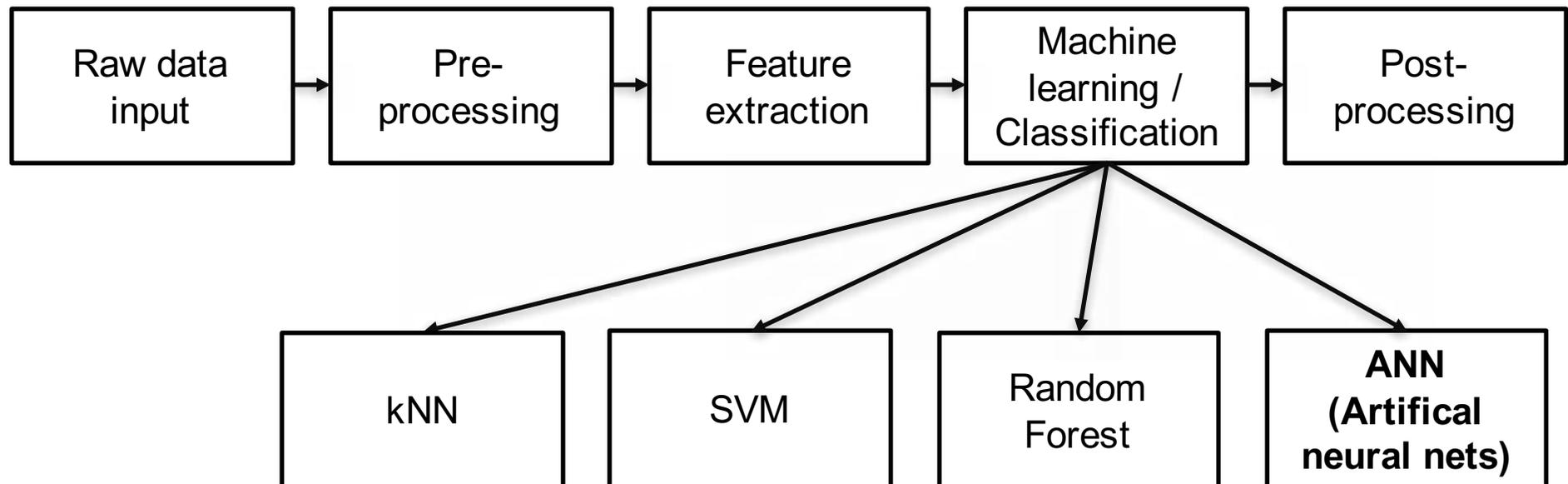


## Outline – Neural networks and Deep Learning

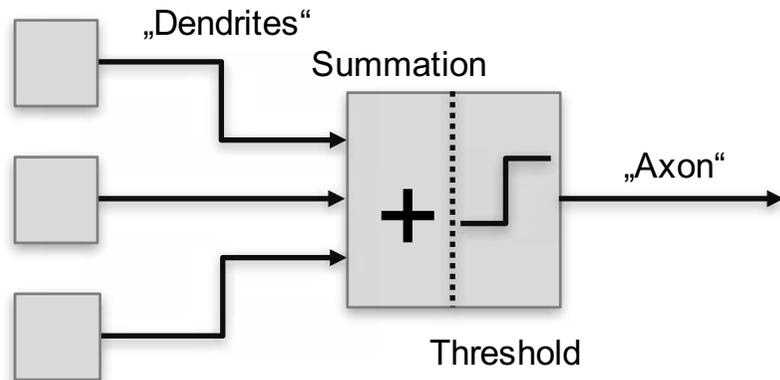
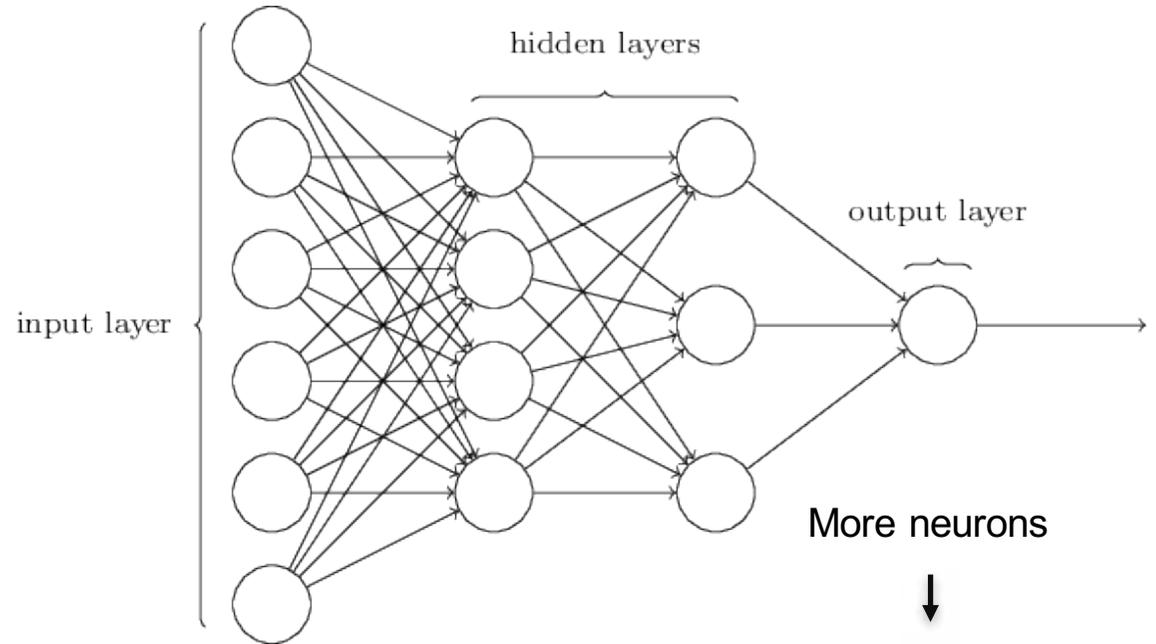
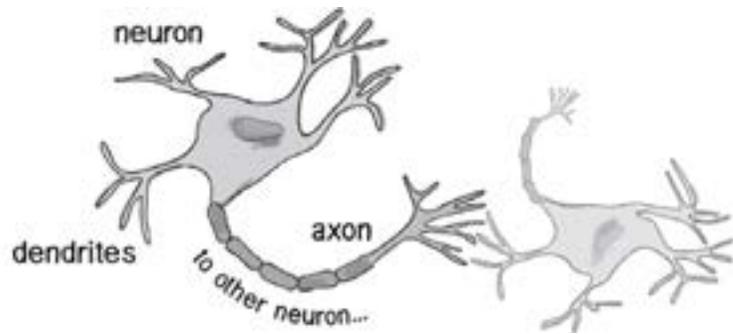
- Artificial neural networks
  - Structure of a MLP
  - Inference via forward-propagation
  - Learning via back-propagation
  - Cost functions: classification vs. regression
- Machine learning vs. representation learning
- Deep learning
  - Successes
- Supervised DL with CNNs
  - Image filters
  - Stacking of hierarchical filters → CNN
- Auto-encoders
- Outlook



## Recap: supervised learning pipeline



# Artificial neural networks (ANN): inspiration

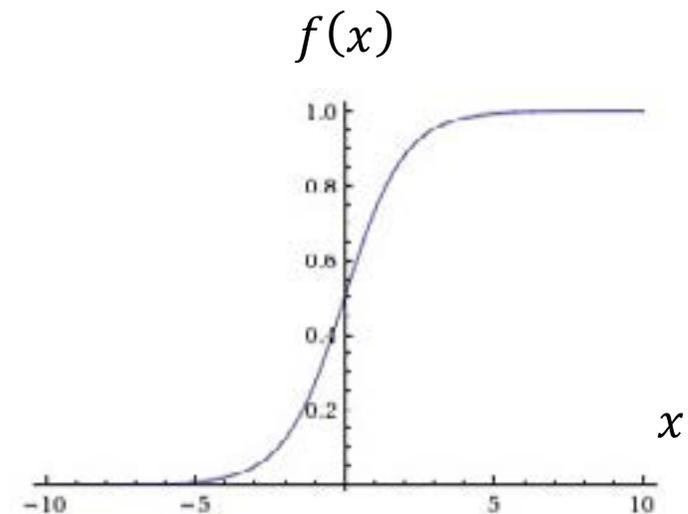
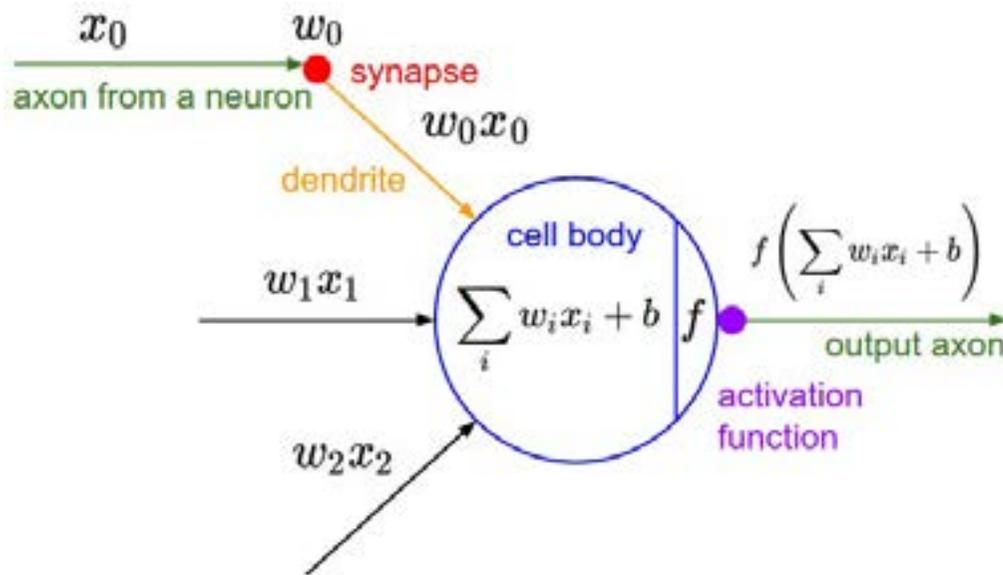


More neurons  
↓  
more modeling capacity



# Mathematical modeling of a neuron

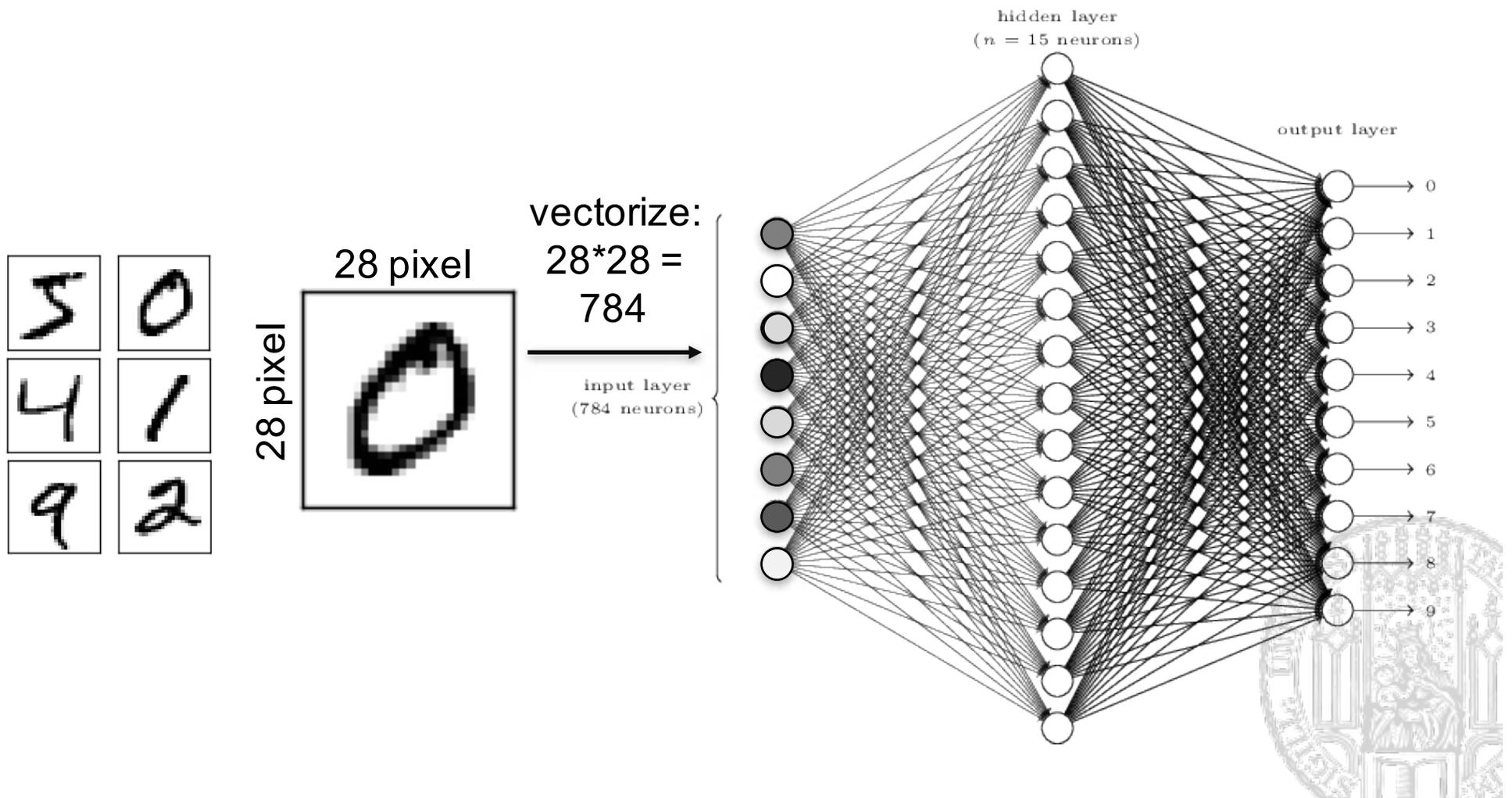
## Non-linear activation function



$$f(x) = \frac{1}{1 + e^{-x}} \longrightarrow f\left(\sum_i w_i x_i + b\right) = \frac{1}{1 + e^{-(\sum_i w_i x_i + b)}}$$

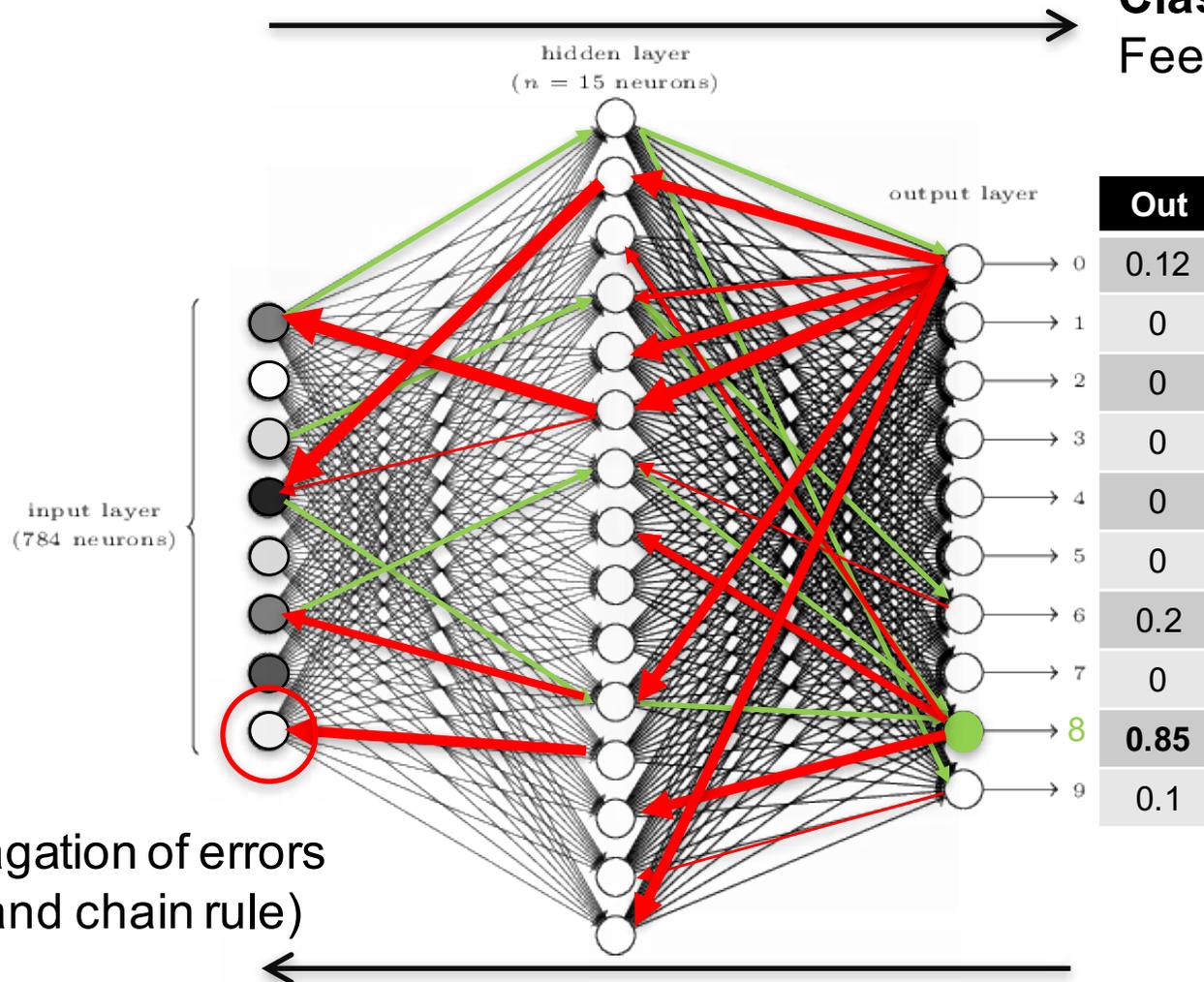
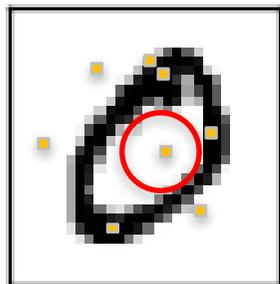


# Neural Networks: Classification of hand-written digits using a fully connected ANN



# Neural Networks: classification by feed-forward, training with backpropagation

**Classification:**  
Feed-forward



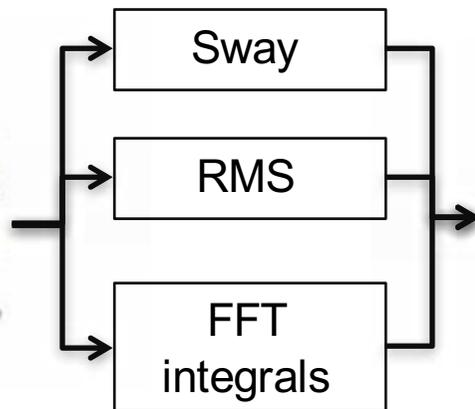
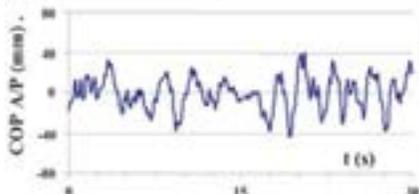
**Training:**  
Back-propagation of errors  
(gradients and chain rule)



# ANN example: posturography platform



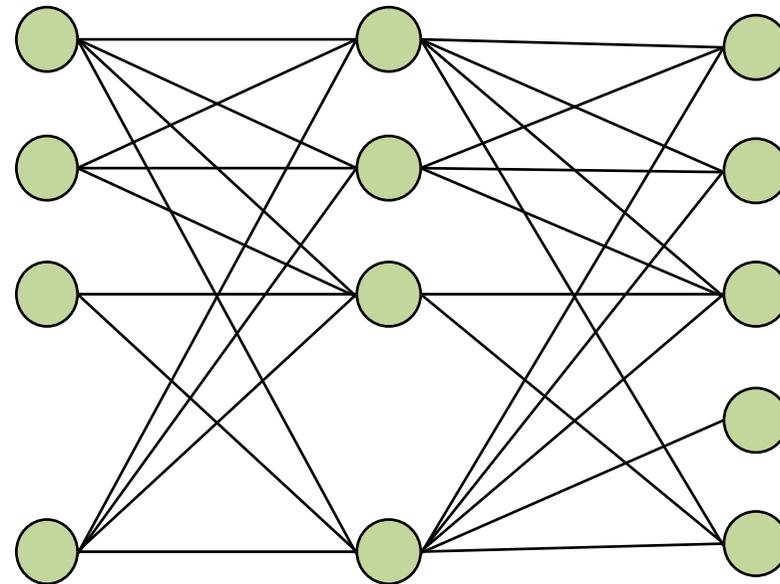
Low-pass filter



160  
input  
neurons

16  
hidden  
neurons

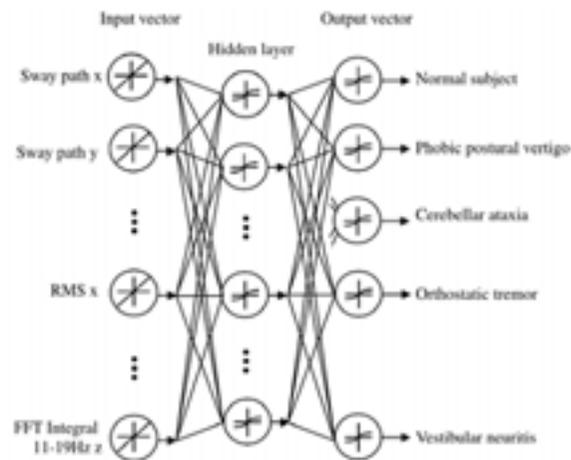
6  
output  
neurons  
(diagnosis  
classification)



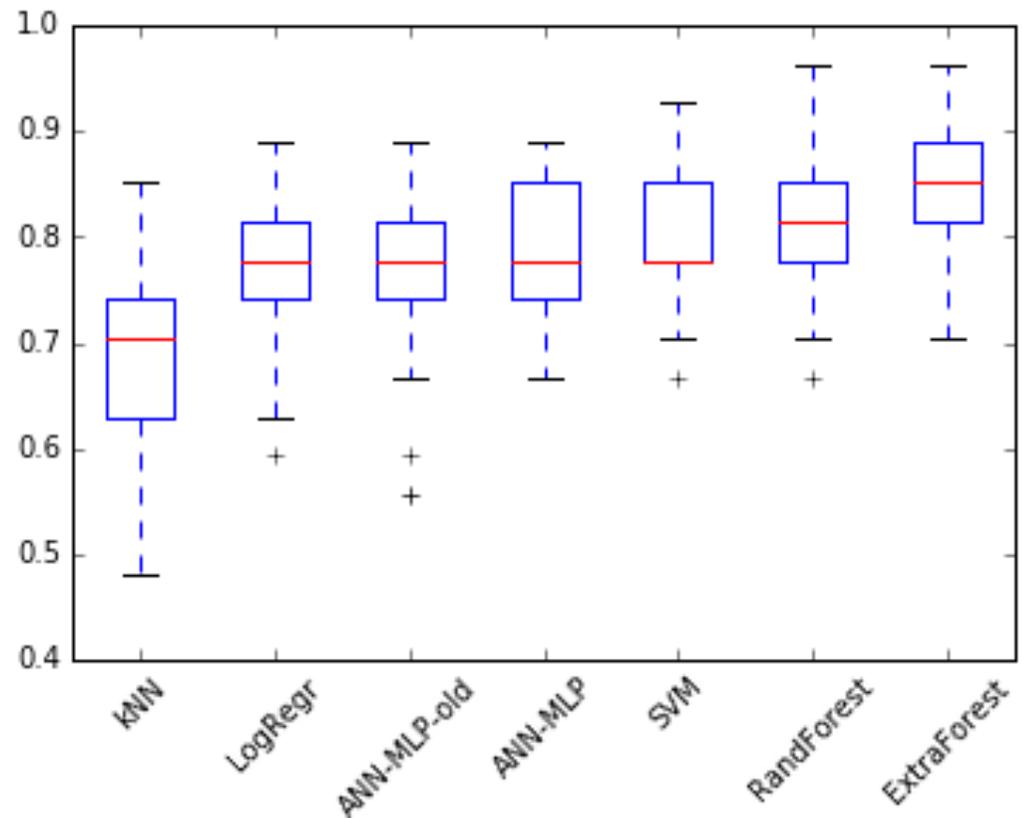
# ANN example: posturography platform

## 2006 model

- 50 train / 50 test, no cross-validation
- One hidden layer MLP (16 hidden neurons)

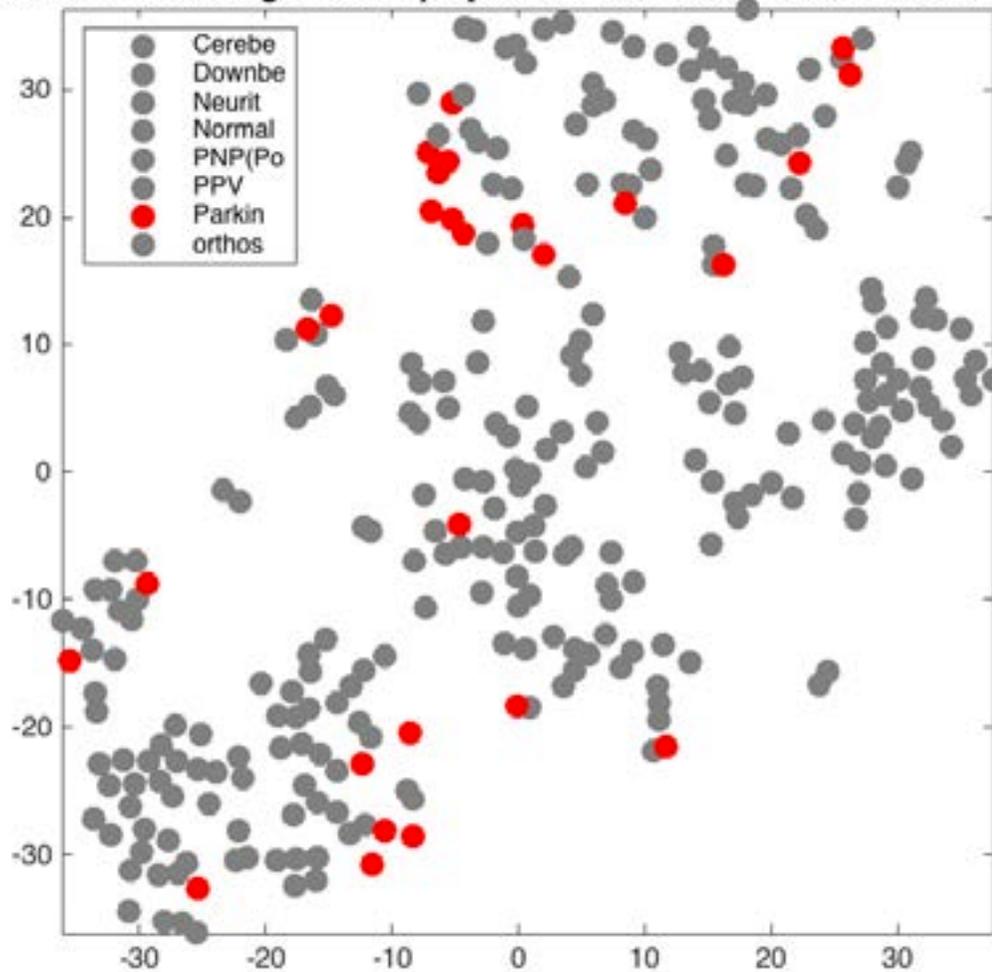


## 2017 models, revisited

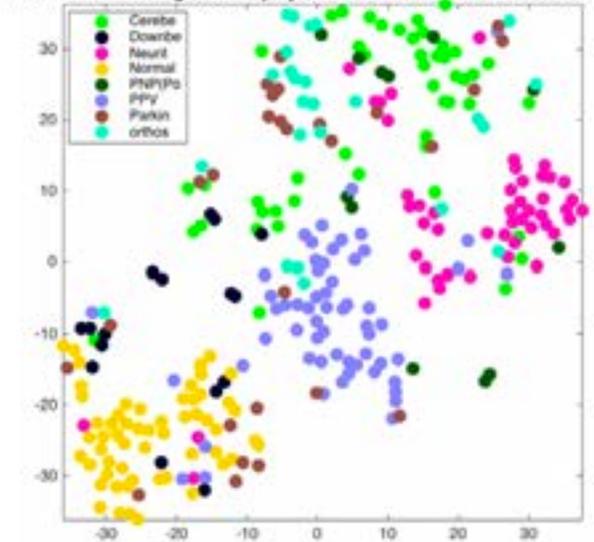


# Posturography feature distribution in 2D

Mean shift clustering of t-SNE projections from outlierCleaned4std features.



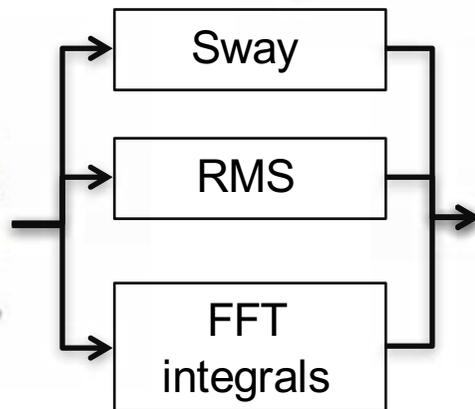
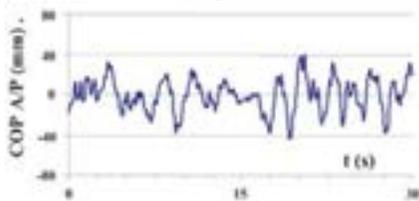
Mean shift clustering of t-SNE projections from outlierCleaned4std features.



# ANN example: posturography platform



Low-pass filter



Are these really the best features to extract from posturography data?  
 Are there maybe features which we are missing in order to distinguish Parkinson patients better from the other classes?

160 input neurons

16 hidden neurons

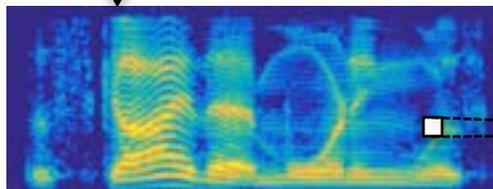
6 output neurons  
 (diagnosis classification)



## Vision: „representation learning“ on posturography data



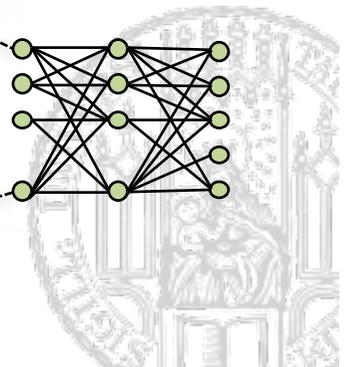
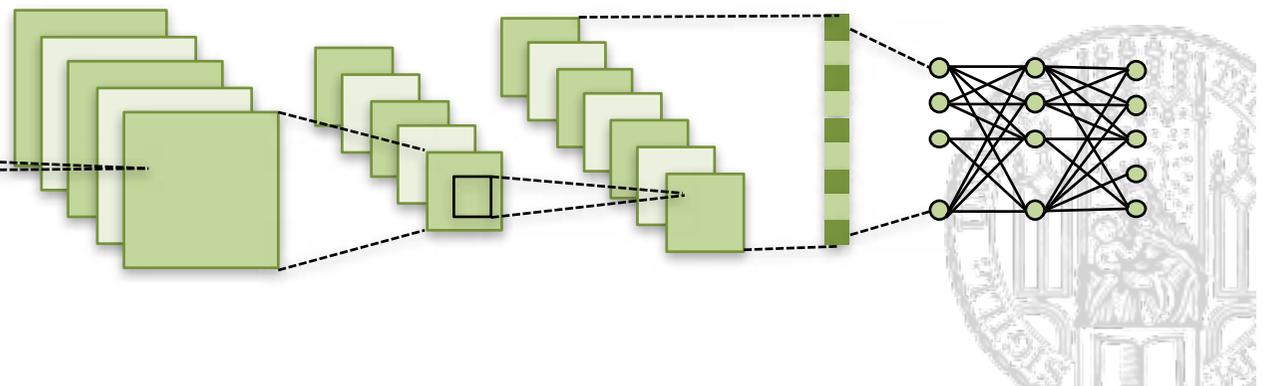
Raw spatio-temporal data



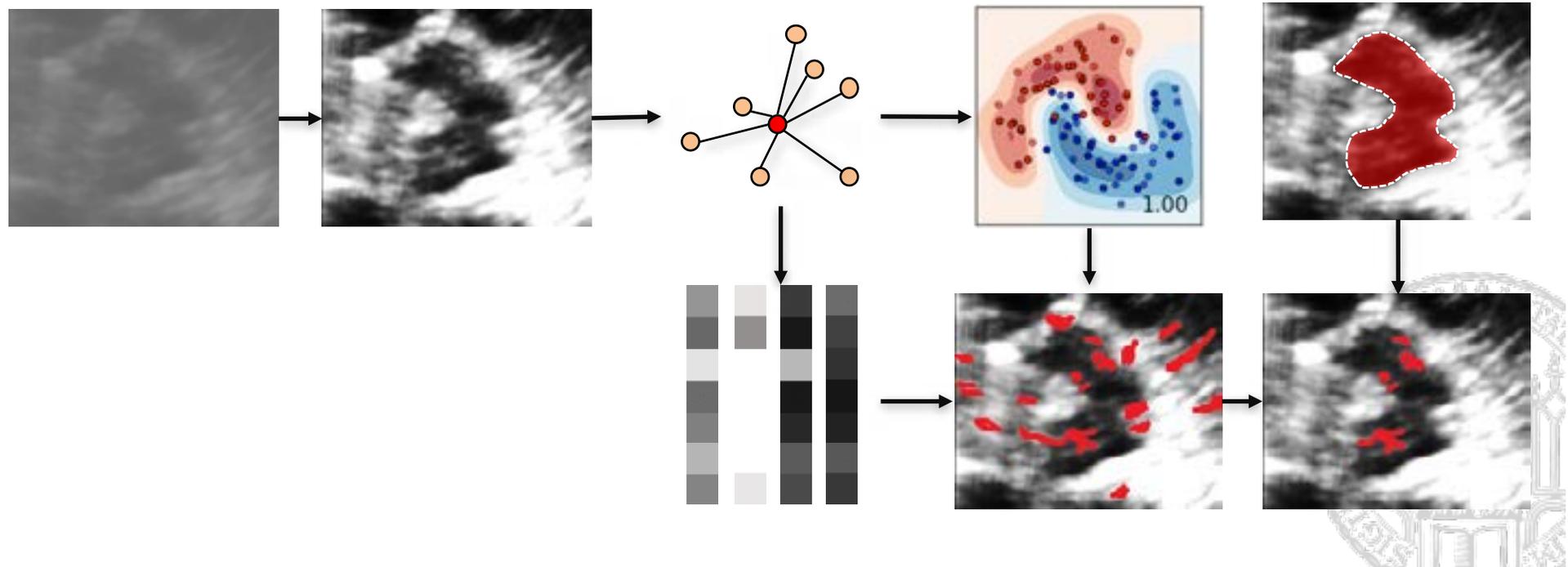
Traditional Machine Learning:  
„Learn the optimal classifier output.“

Deep Learning:  
„Learn the optimal input  
AND classifier output.“

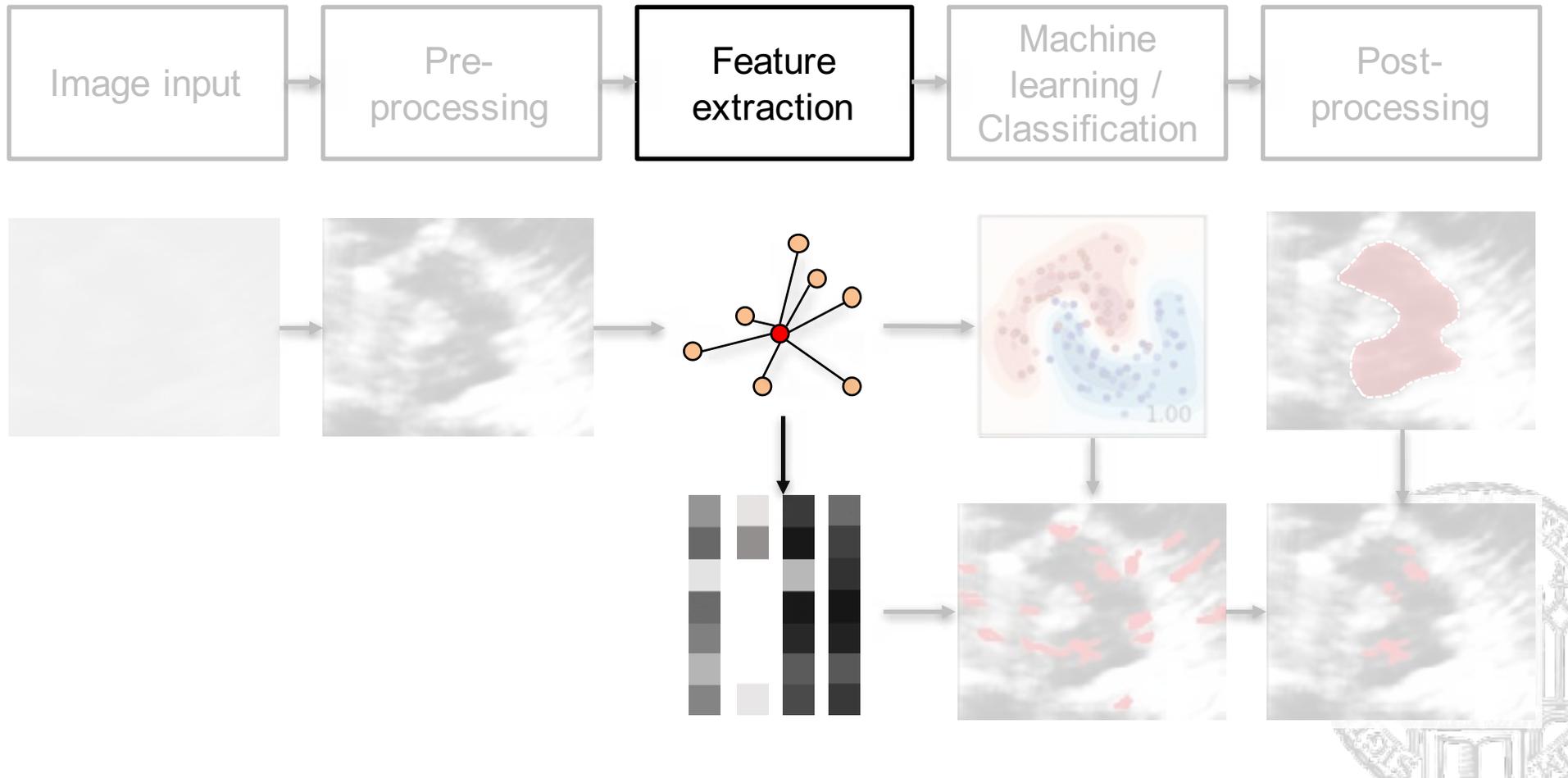
**Deep Learning = Representation learning!**



# Machine learning based image segmentation pipeline



# Most critical point in segmentation pipeline



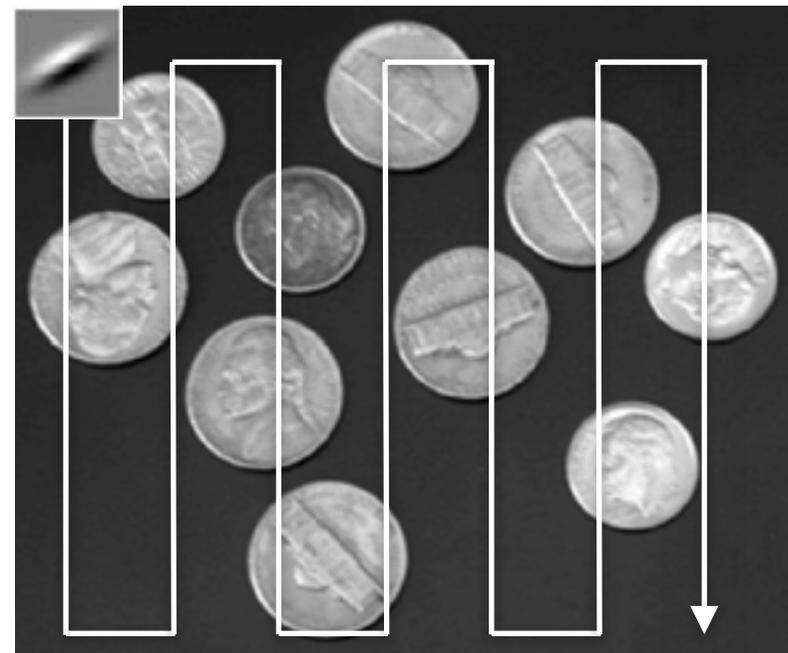
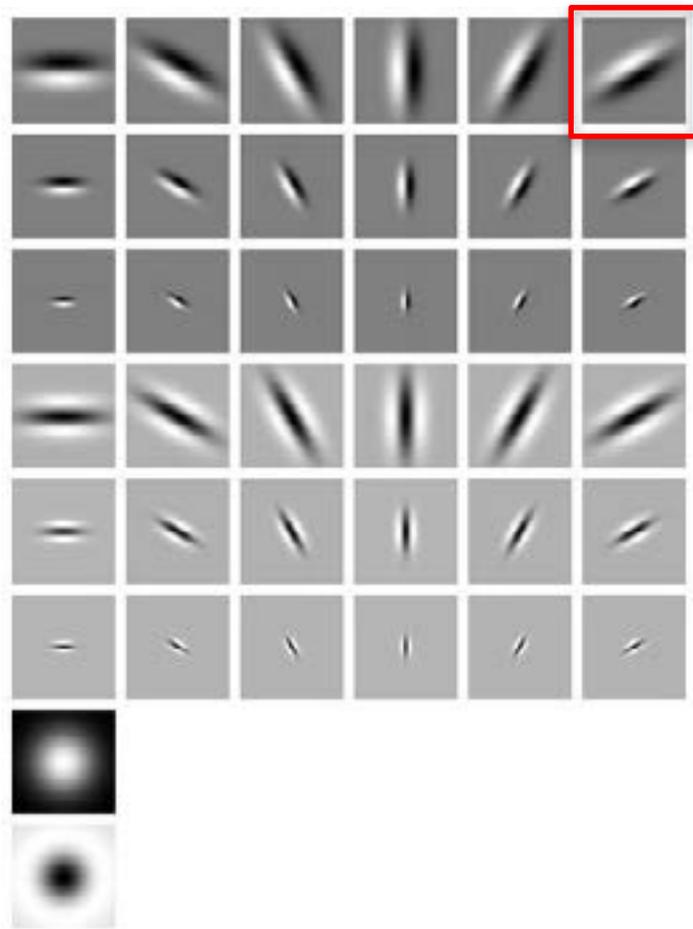


**Short sidestep into computer vision:**

**Filter convolution for feature extraction**



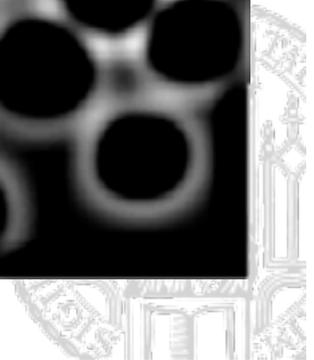
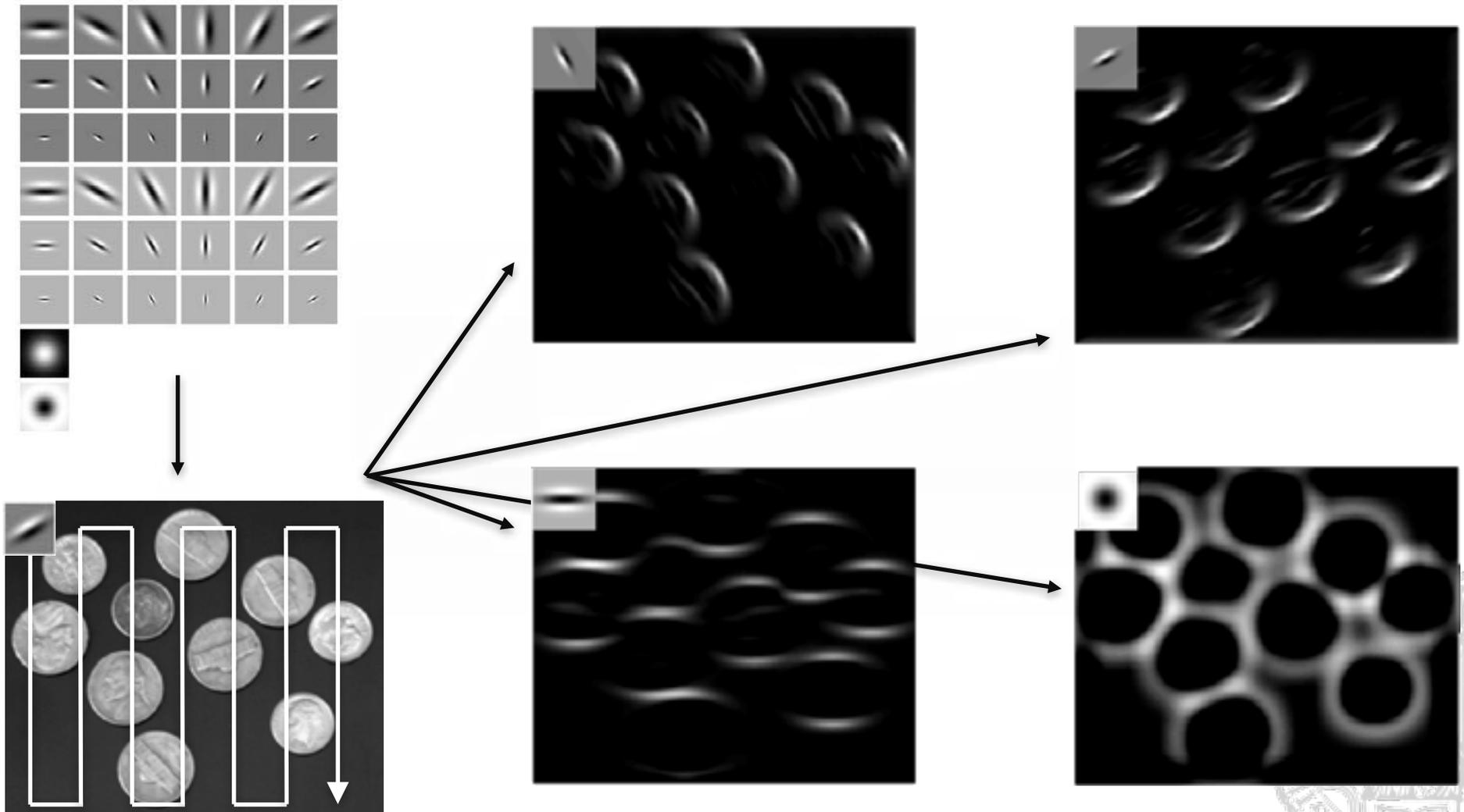
# Computer vision: image filters and convolution



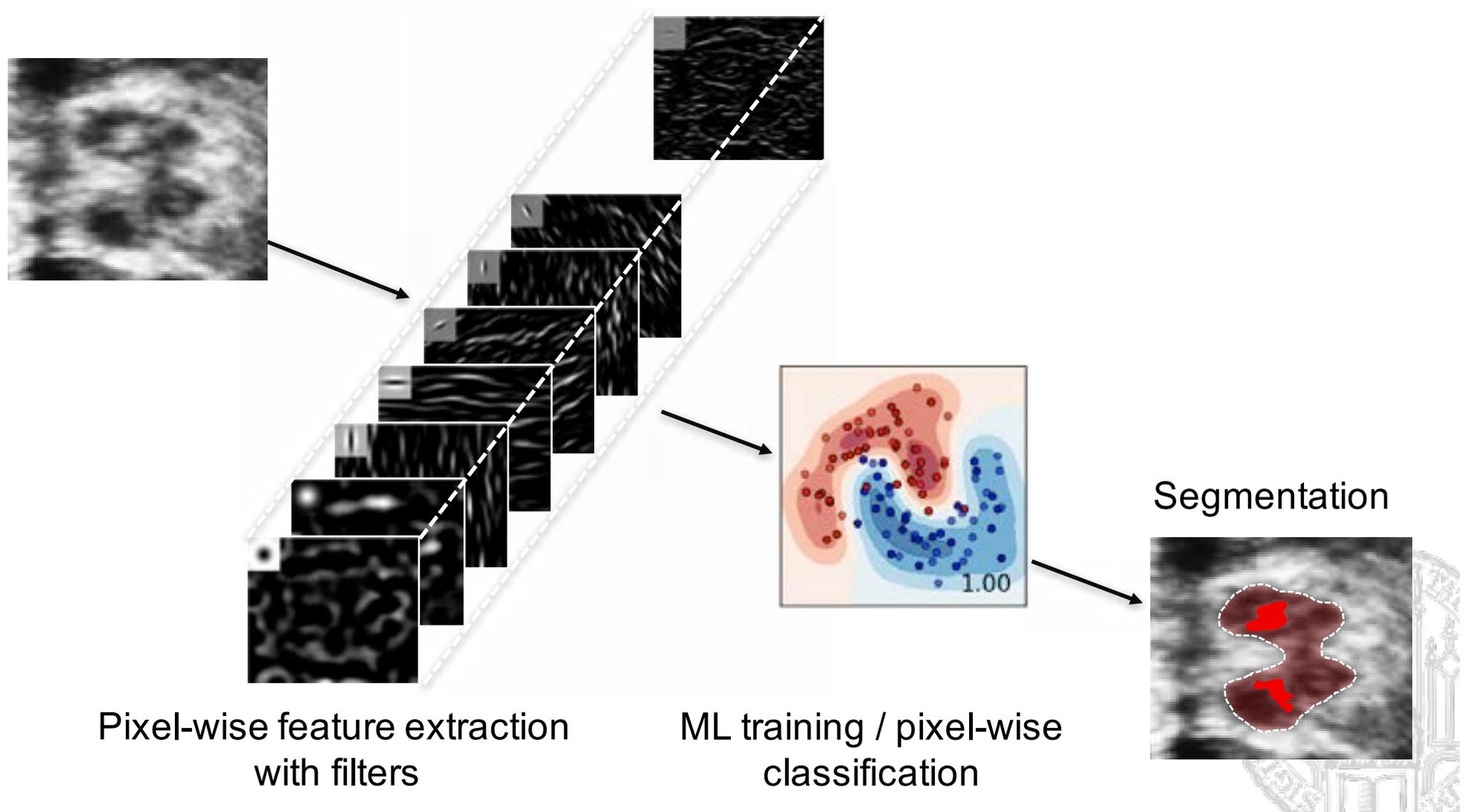
Maximum Response (MR) Filter Bank



# Computer vision: image filters



# Image classification / segmentation with filter banks





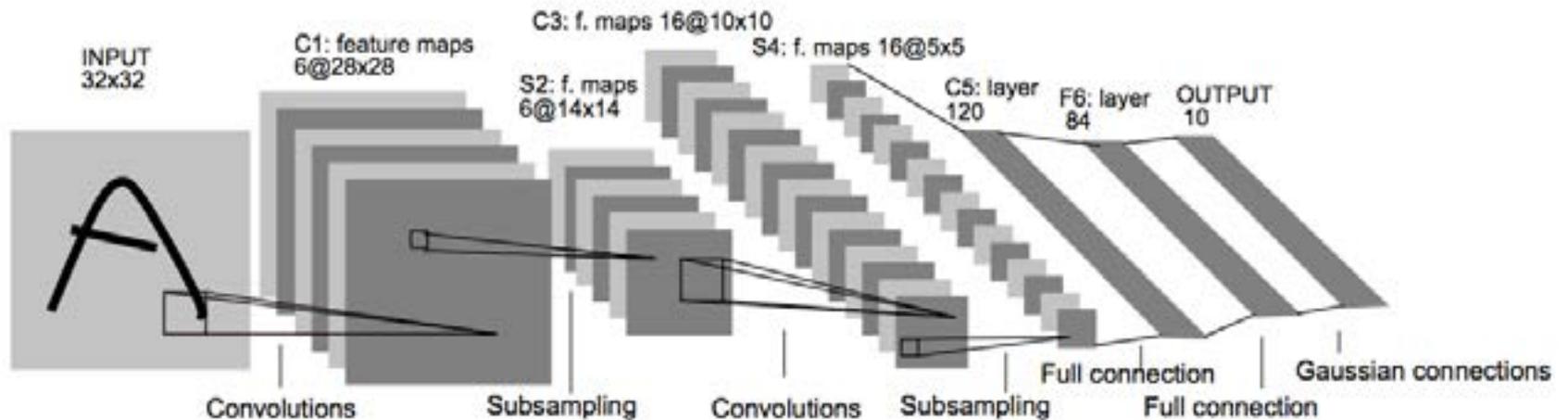
**Back to neural networks and deep learning...**



# Convolutional Neural Networks: combining image filters with neural nets

- Convolutional filter: extracting local salient features
- Provide the ANN with a hierarchical architecture of filter banks
- Instead of applying pre-defined filters, initialize the filter with random “noise” and let the filters be learned by backpropagation!

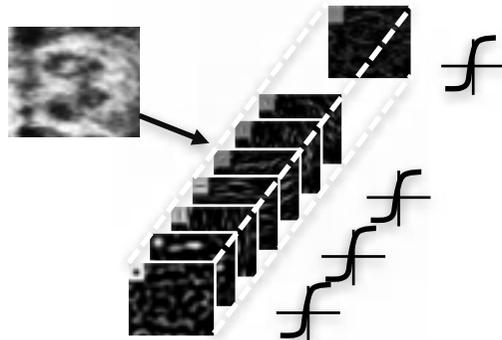
**LeNet  
(1989)**



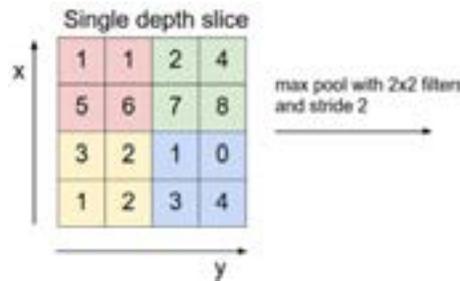
LeCun et al., Backpropagation applied to handwritten zip code recognition, Neural computation 1 (4), 541-551, 1989



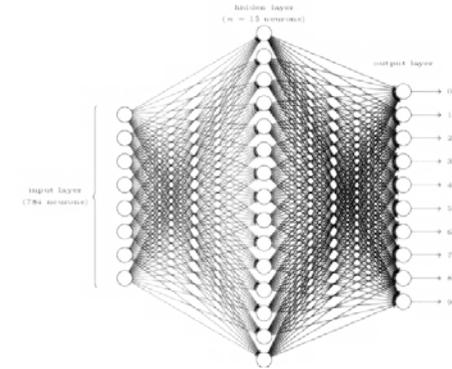
# CNN components: convolutional and pooling layers



Convolutional layer (+act.fct.)

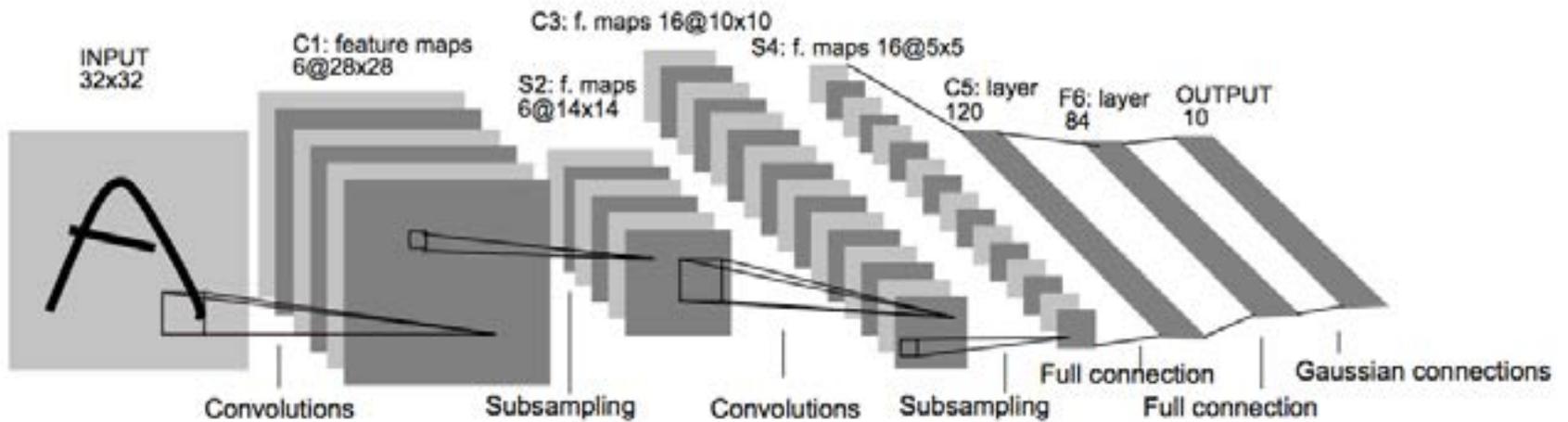


Pooling layer



Multi-layer perceptron

## LeNet (1989)



LeCun et al., Backpropagation applied to handwritten zip code recognition, Neural computation 1 (4), 541-551, 1989





## CNN Demo: LeNet architecture from 1989

Draw your number here

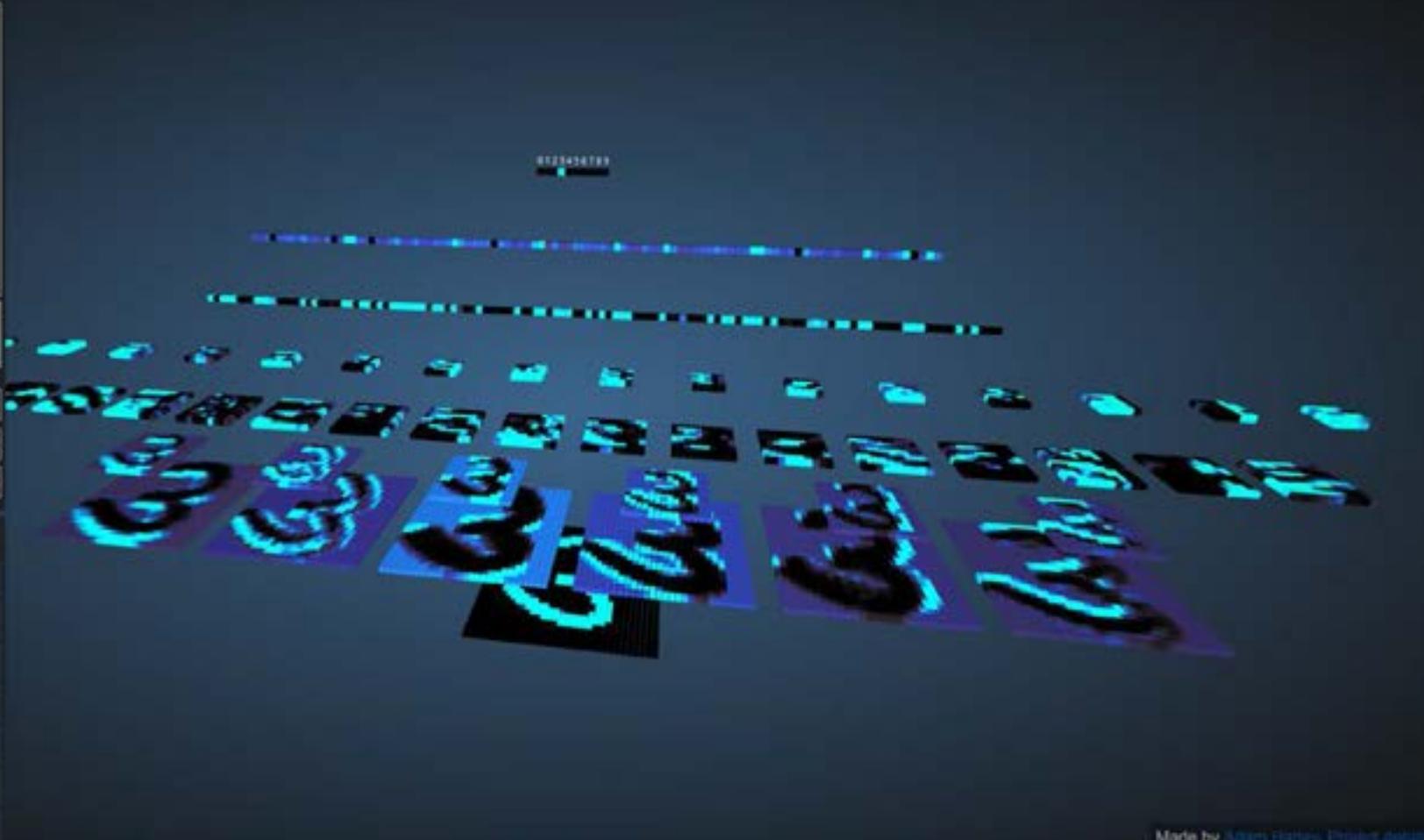


X [Pencil icon] [Eraser icon]

Downsampled drawing: 3  
First guess: 3  
Second guess: 1

Layer visibility

|                         |      |
|-------------------------|------|
| Input layer             | Show |
| Convolution layer 1     | Show |
| Downsampling layer 1    | Show |
| Convolution layer 2     | Show |
| Downsampling layer 2    | Show |
| Fully-connected layer 1 | Show |
| Fully-connected layer 2 | Show |



Made by Adam Harley, Project details

<http://scs.ryerson.ca/~aharley/vis/conv/>



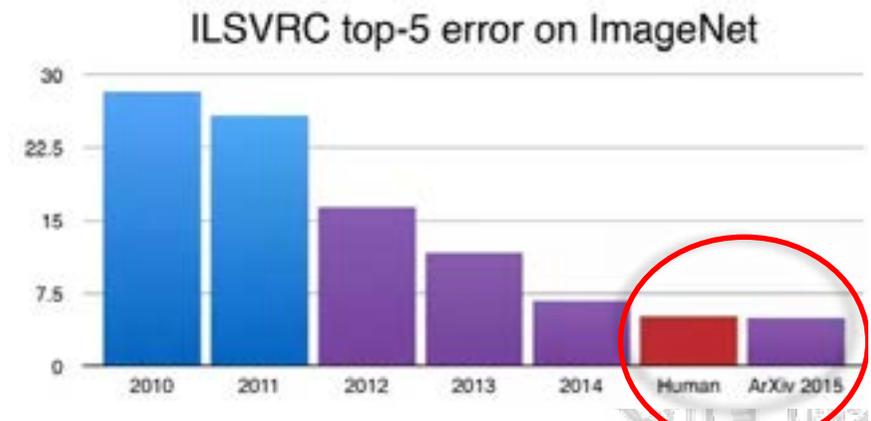
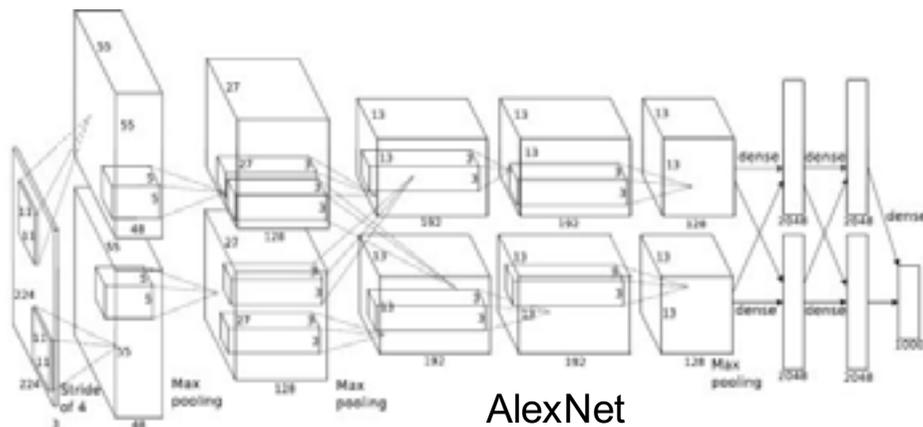
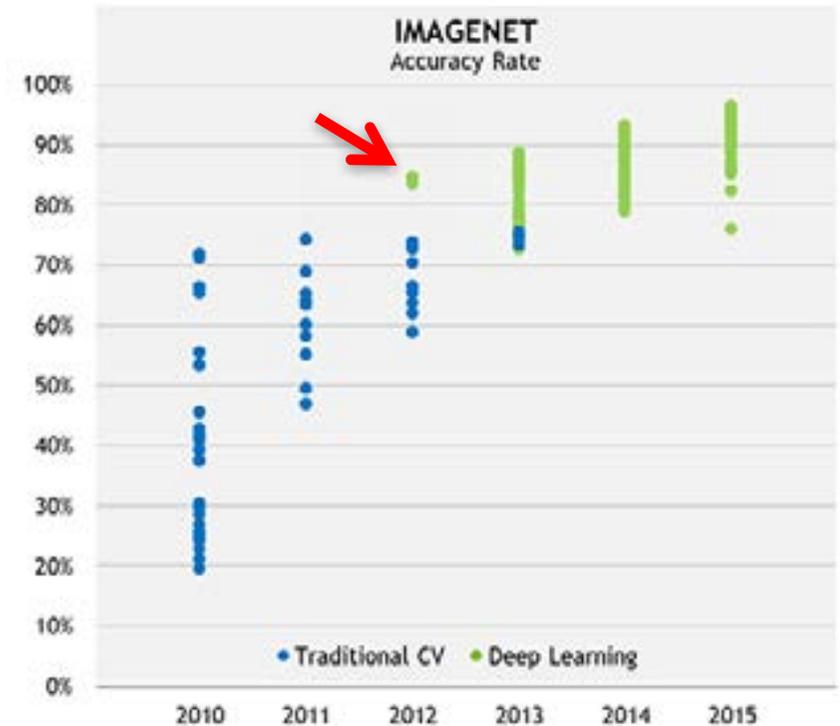
## Modern computer vision datasets: ImageNet

- Published in 2010
- 10 million labeled images with 10.000+ classes

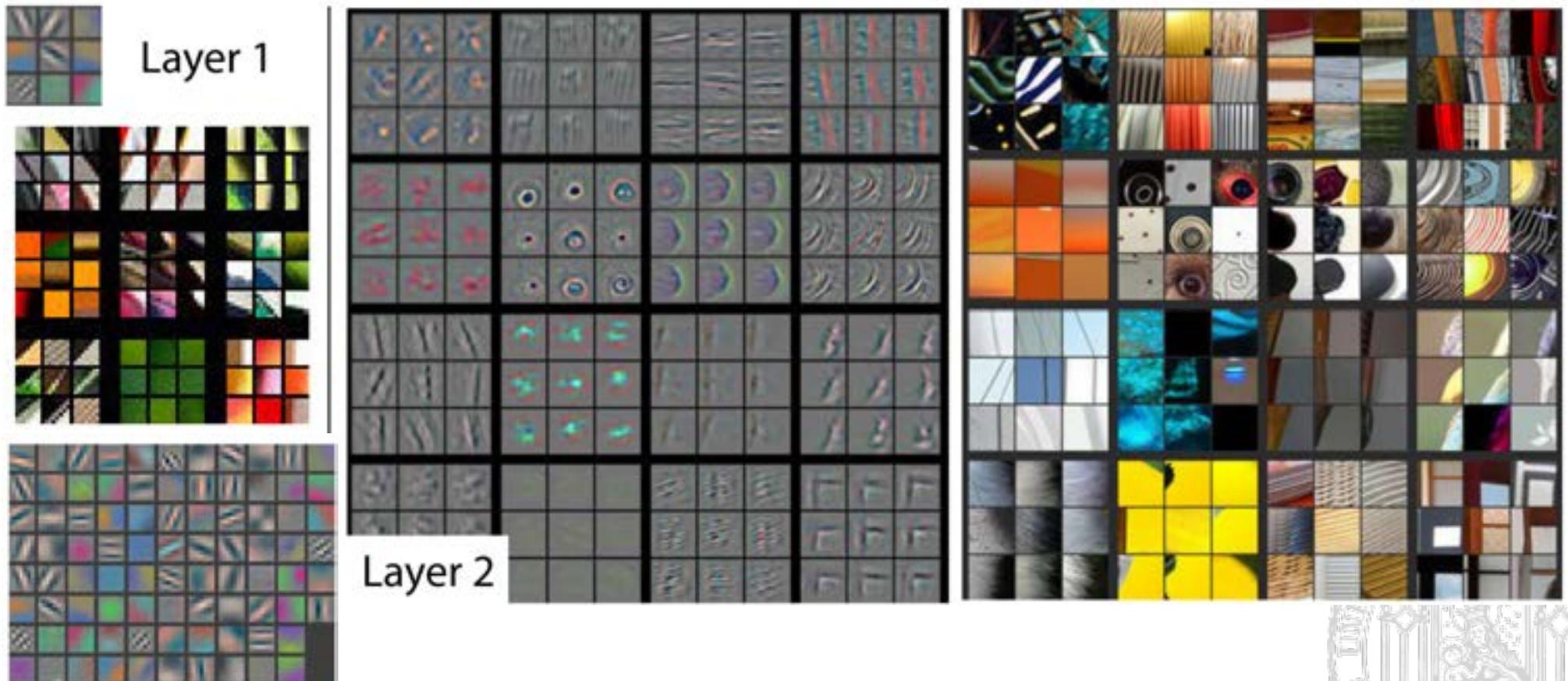


# Breakthrough performances in 2012 and 2015

- ImageNet 2012: 1.3 million images, 1000 classes
- 2012: AlexNet architecture: 5 conv layers, 500.000 neurons, 60 million parameters
- GPU acceleration of training
- 2015: Better than human performance (He et al., ICCV, 2015)

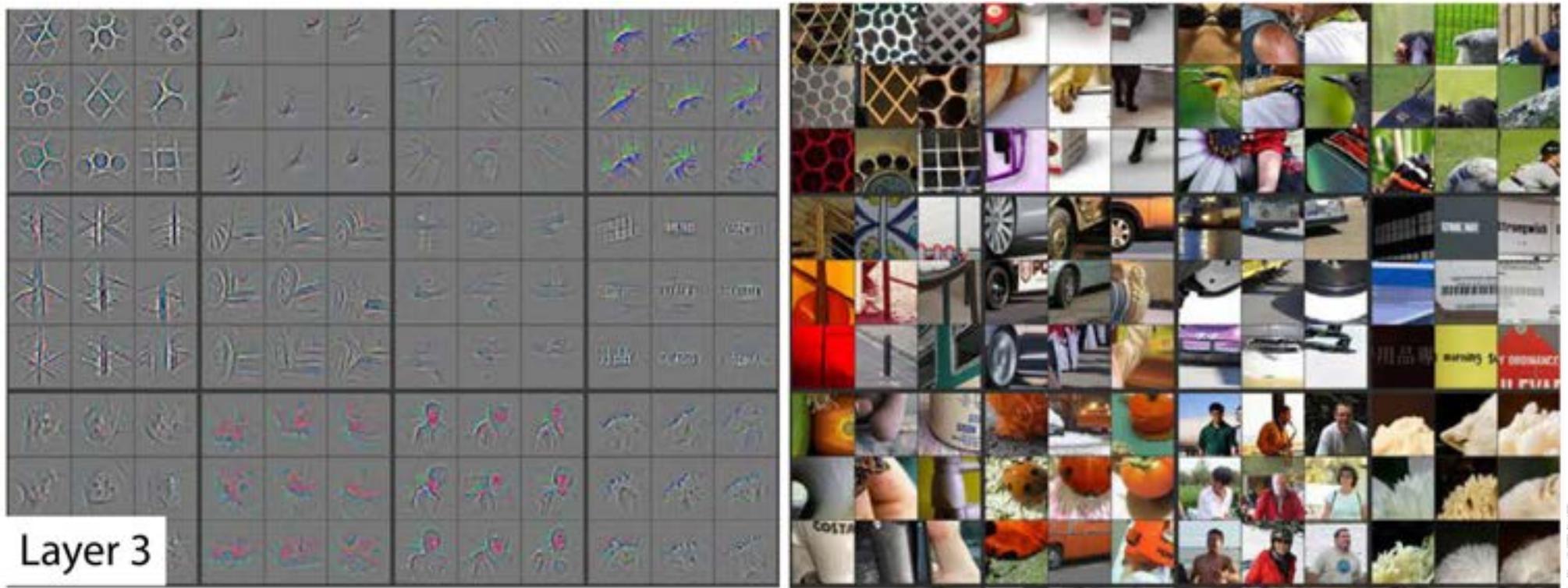


# Visualizing and Understanding CNNs



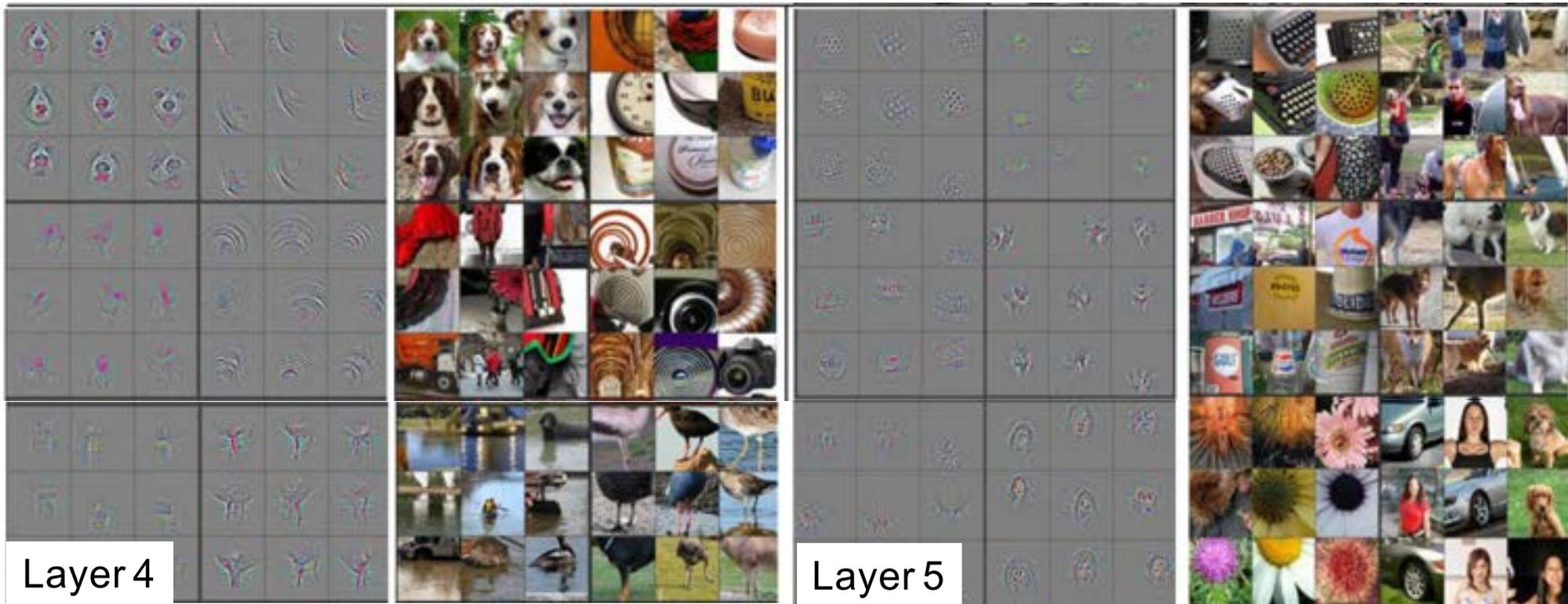


# Visualizing and Understanding CNNs





# Visualizing and Understanding CNNs

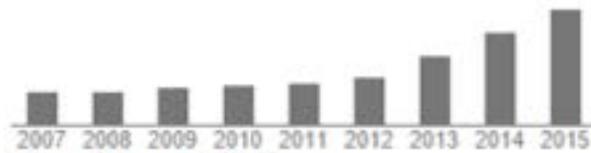




# Deep Learning success

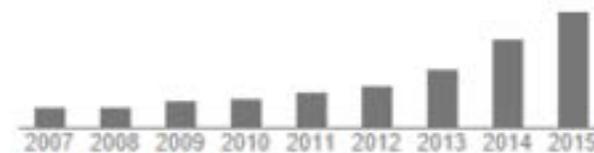


| Citation indices | All    | Since 2010 |
|------------------|--------|------------|
| Citations        | 117120 | 47516      |
| h-index          | 113    | 86         |
| i10-index        | 273    | 200        |



Geoffrey Hinton

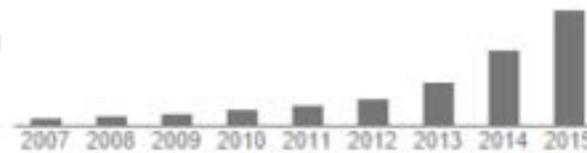
| Citation indices | All   | Since 2010 |
|------------------|-------|------------|
| Citations        | 29582 | 17815      |
| h-index          | 77    | 59         |
| i10-index        | 179   | 141        |



Yann LeCun

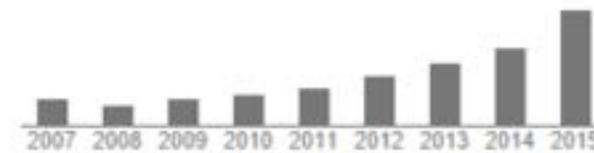


| Citation indices | All   | Since 2010 |
|------------------|-------|------------|
| Citations        | 32736 | 25285      |
| h-index          | 73    | 65         |
| i10-index        | 245   | 200        |



Yoshua Bengio

| Citation indices | All   | Since 2010 |
|------------------|-------|------------|
| Citations        | 15412 | 10292      |
| h-index          | 64    | 48         |
| i10-index        | 242   | 178        |



Juergen Schmidhuber

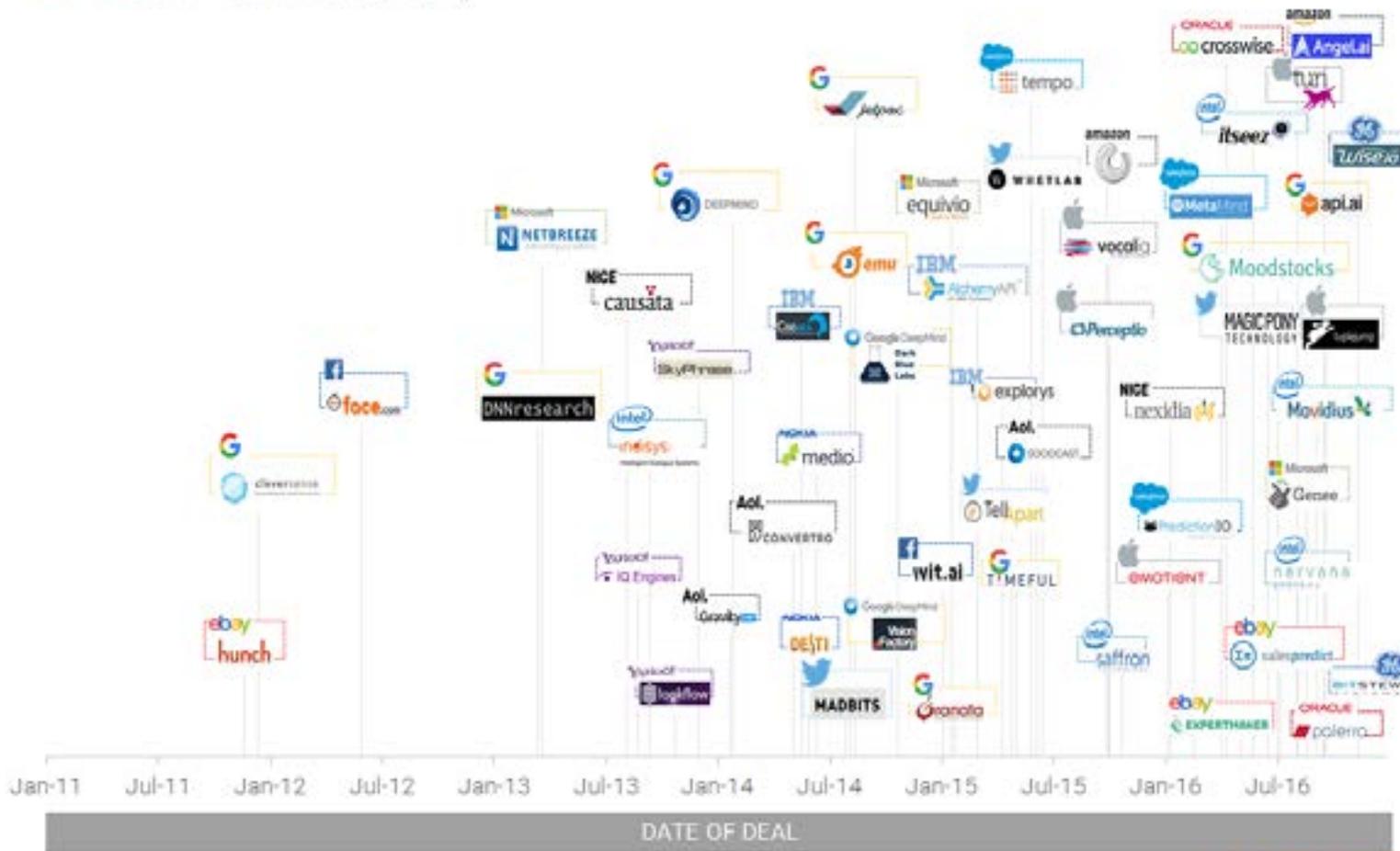
ELEMENT<sup>AI</sup>





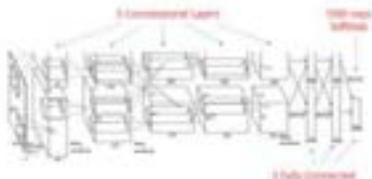
# Deep Learning success

**RACE FOR AI: MAJOR ACQUIRERS IN ARTIFICIAL INTELLIGENCE**  
2011 - 2016 YTD (12/1/16)



# Better training algorithms, faster hardware, deeper models, higher accuracy

AlexNet



VGG



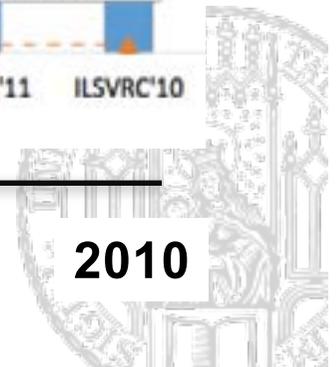
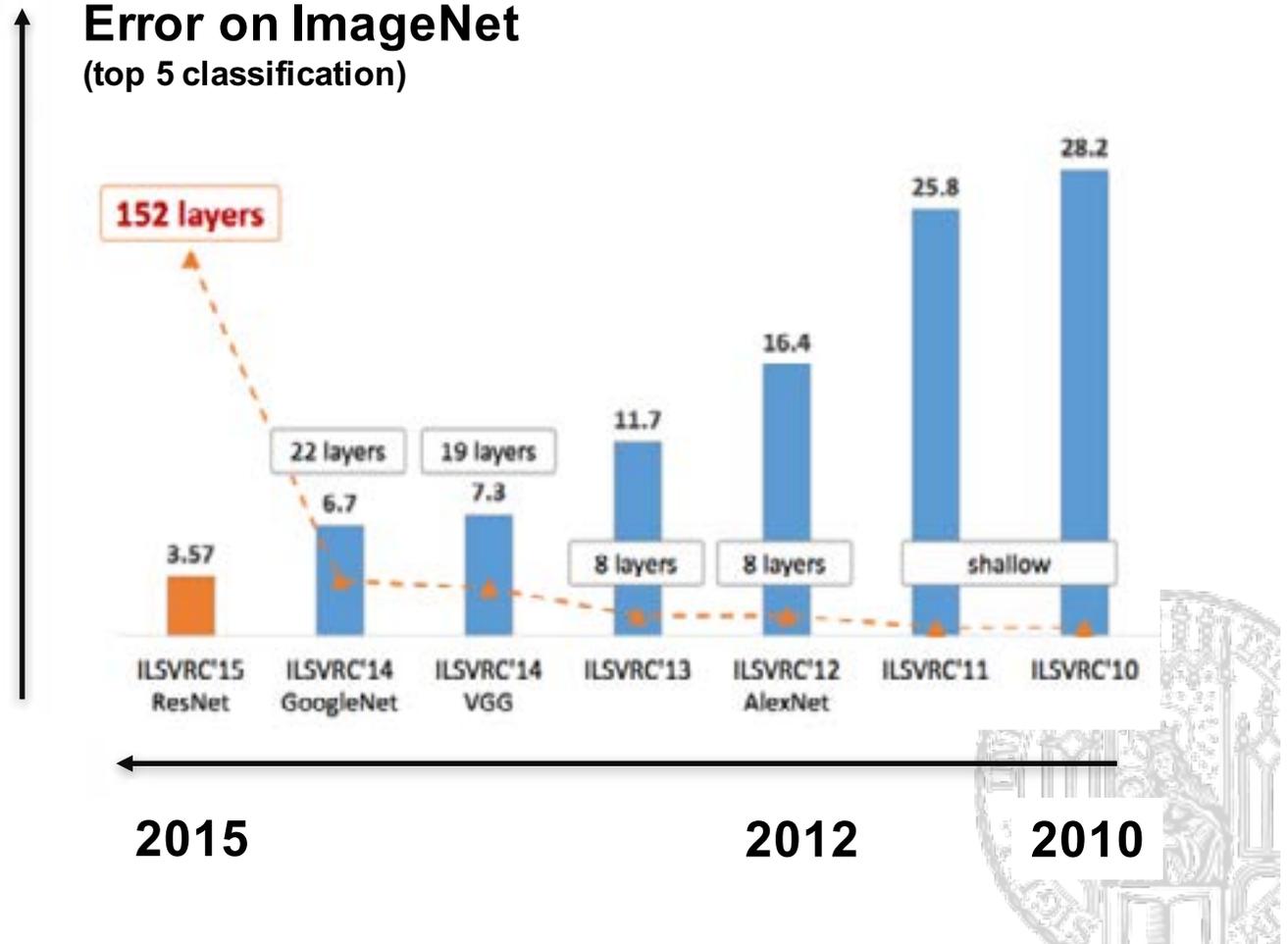
GoogLeNet



ResNet



Error on ImageNet  
(top 5 classification)





## Major Deep Learning achievements

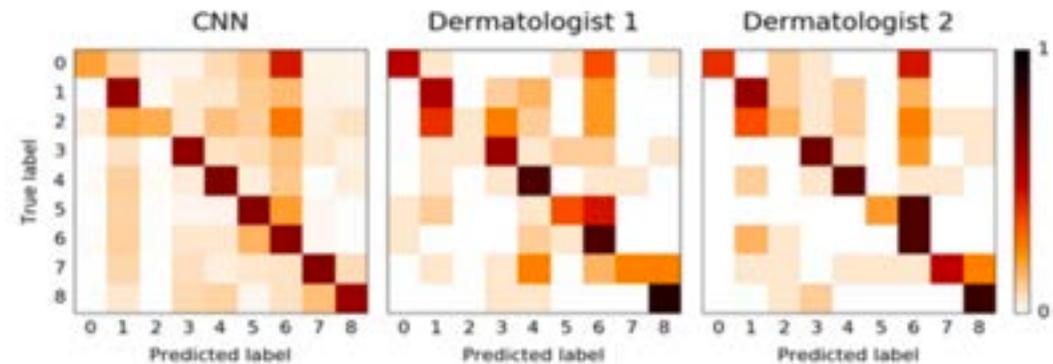
- 2012: AlexNet beats ImageNet challenge by wide margin
- 2013: DeepMind's deep learner teaches itself to play Atari games and beats humans at 31 different games (Google buys DeepMind, starting the „Race for AI“)
- 2014: Facebook's DeepFace achieves human-level performance on face detection of 4000 subjects (from 4 million images)
- 2015: Microsoft surpasses human performance on ImageNet using ResNet architecture with residual connections
- 2016: AlphaGo beats world champion Lee Sedol in Go using deep CNNs and reinforcement learning
- 2017: Dermatologist-level skin cancer identification



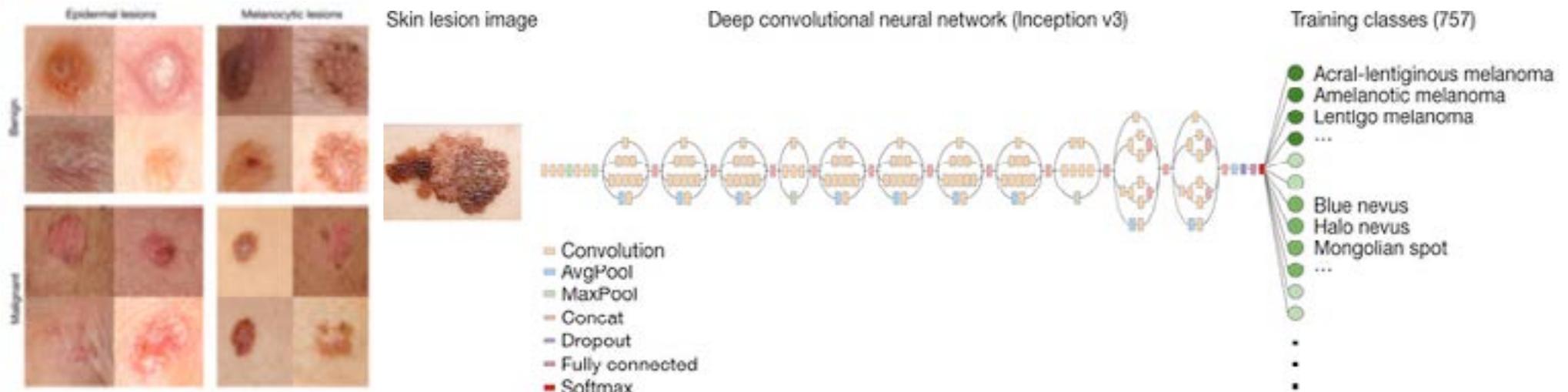


## Dematologist-level skin cancer classification

- Using InceptionV3 CNN architecture
- Pre-trained on natural images!
- 130.000 images, 760 classes

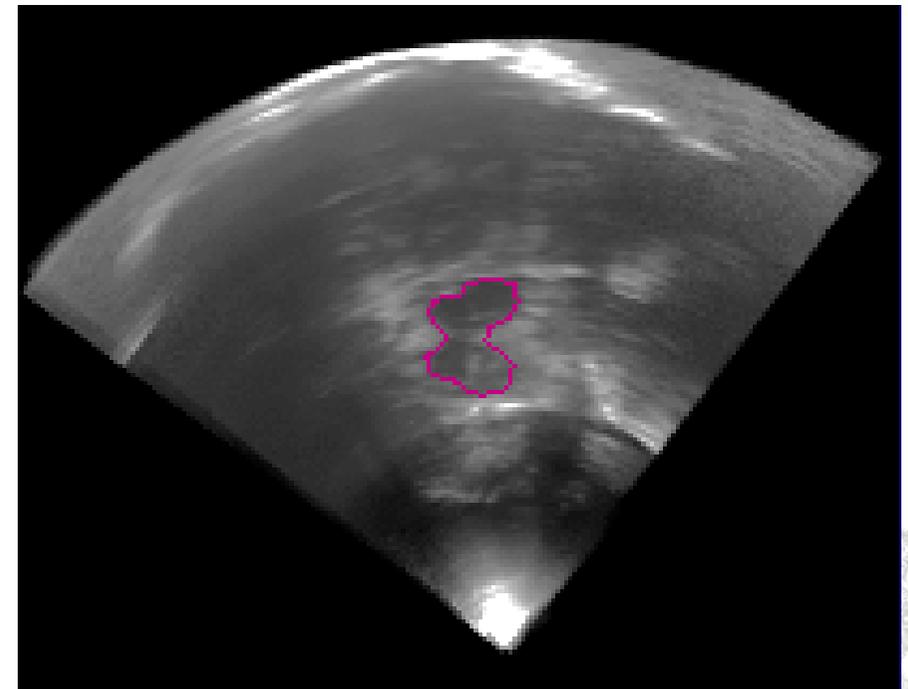
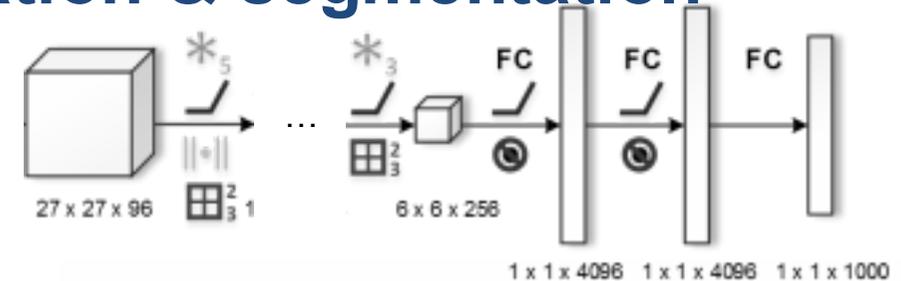


Esteva et al., Dermatologist-level classification of skin cancer with deep neural networks, Nature 542, 115–118, Feb. 2017, doi:10.1038/nature21056



## Hough-CNN: anatomy localization & segmentation

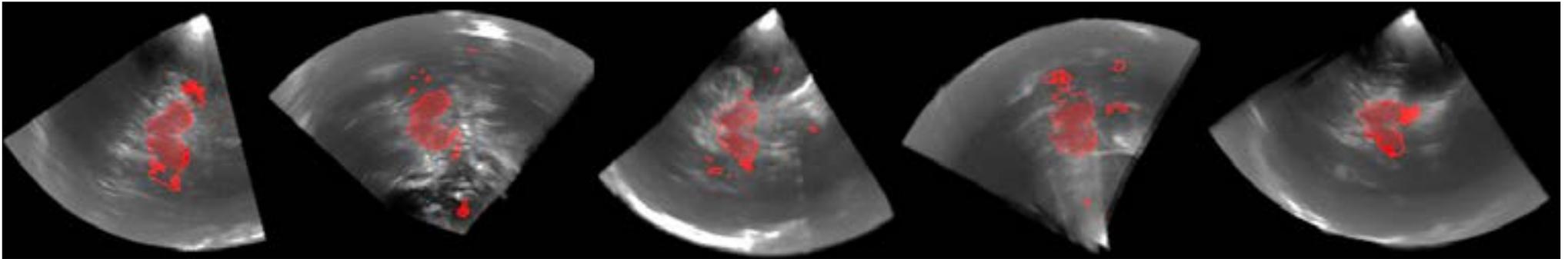
- Perform voxel-wise classification
- Each voxel classified as foreground votes for centroid of classified region
  - a peak in the vote map emerges
- All votes that voted within a radius  $R$  of the peak are considered “correct”
- These patches can now re-project the segmentation patches of kNN patches from the dictionary
  - segmentation volume
  - thresholding yields final contour



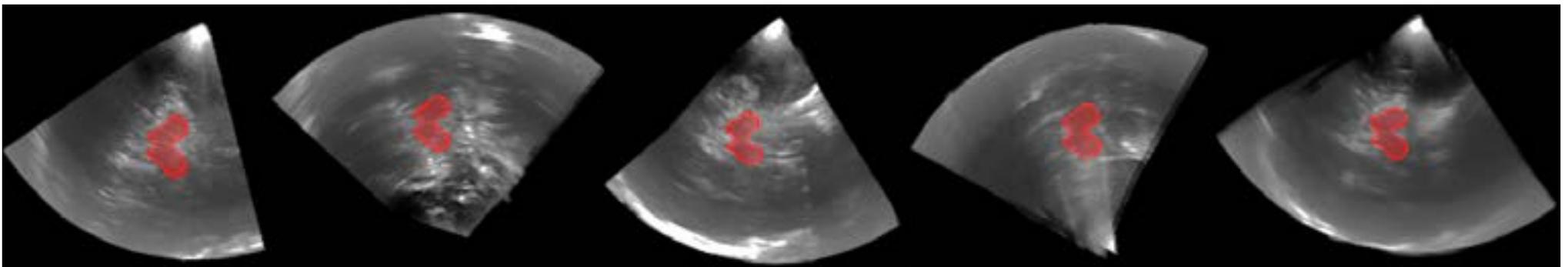
## Hough-CNN Results: Ultrasound

- Training via (5,10,15,...,45) volumes, testing on 114 volumes
- Successful segmentation close to human inter-rater performance in 112 volumes

**Segmentation via voxel-wise classification of volumetric patches:**

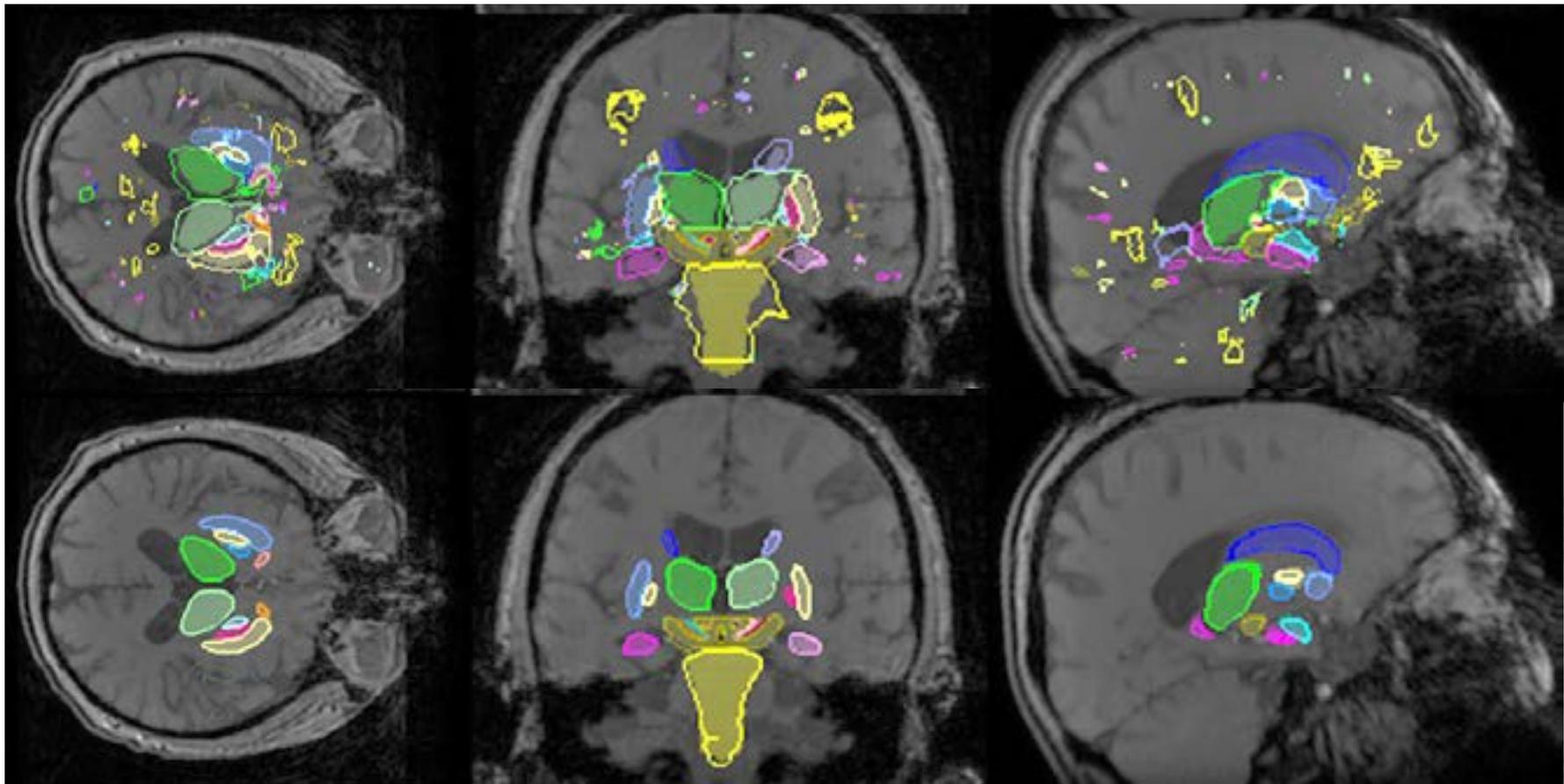


**Segmentation via Hough-CNN**



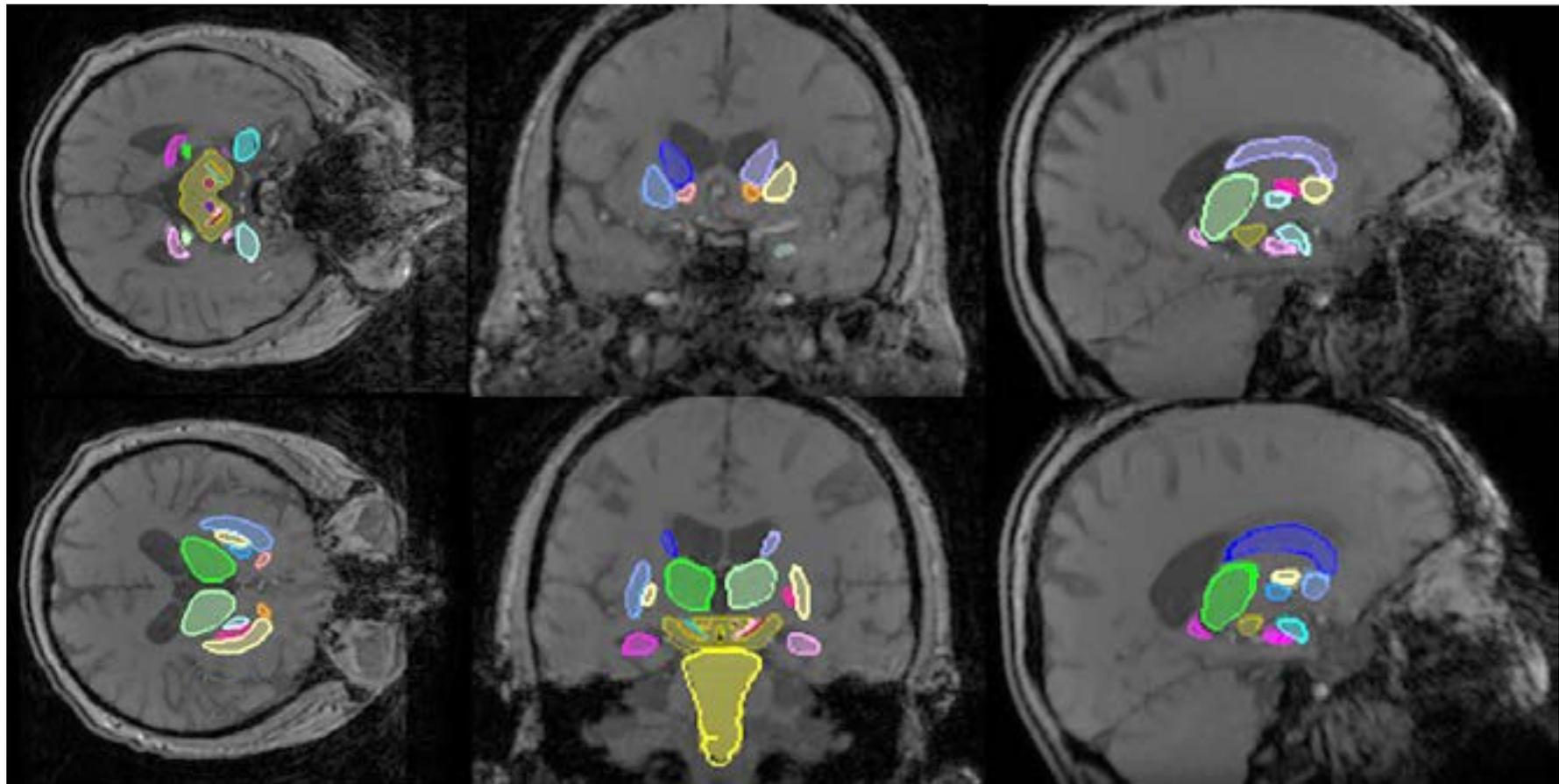
## Hough-CNN Results: Structural MRI

- Voxel-wise classification with patch-wise CNN

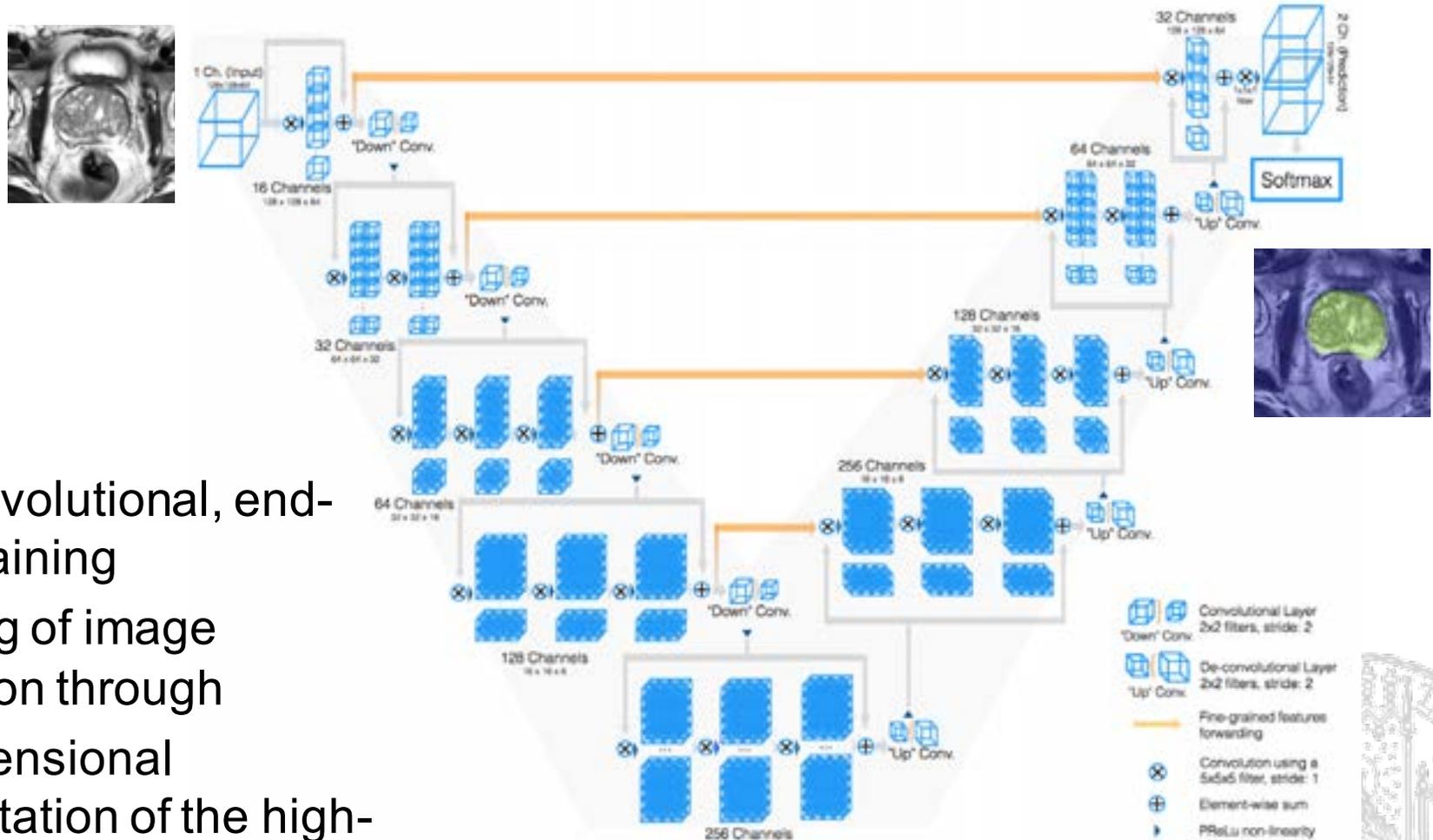


## Hough-CNN Results: Structural MRI

- Voxel-wise classification with Hough-CNN



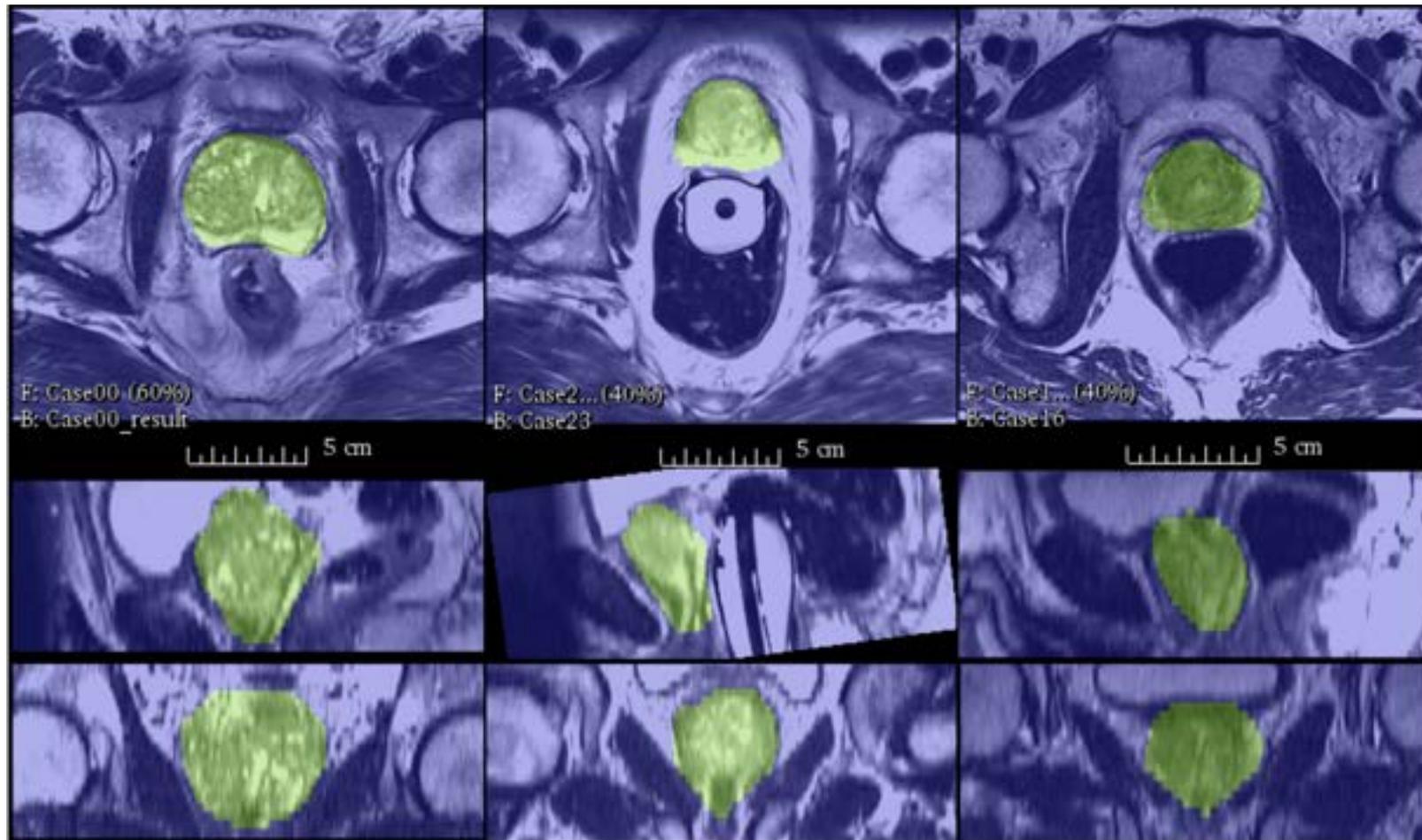
# V-Net Method



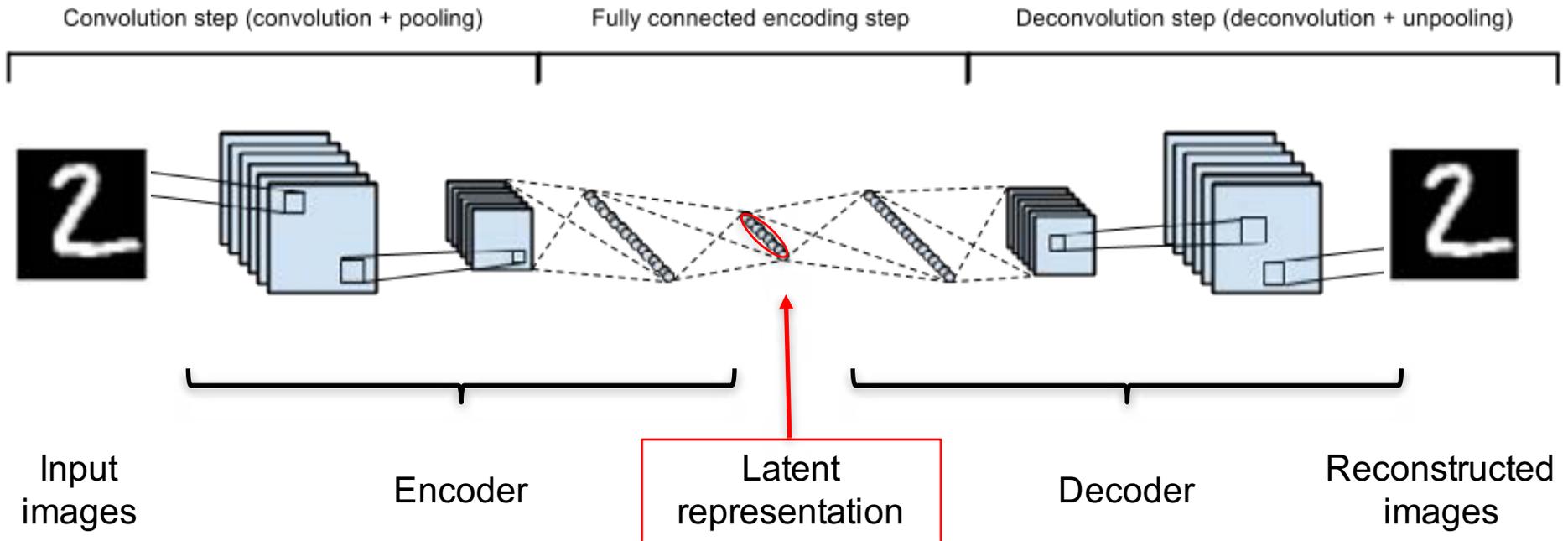
- Fully convolutional, end-to-end training
- Funneling of image information through
- Low-dimensional representation of the high-dimensional input

# V-Net results on prostate MRI

Top 3 on PROMISE12 challenge dataset



# Auto-encoders: when labeled data is scarce...



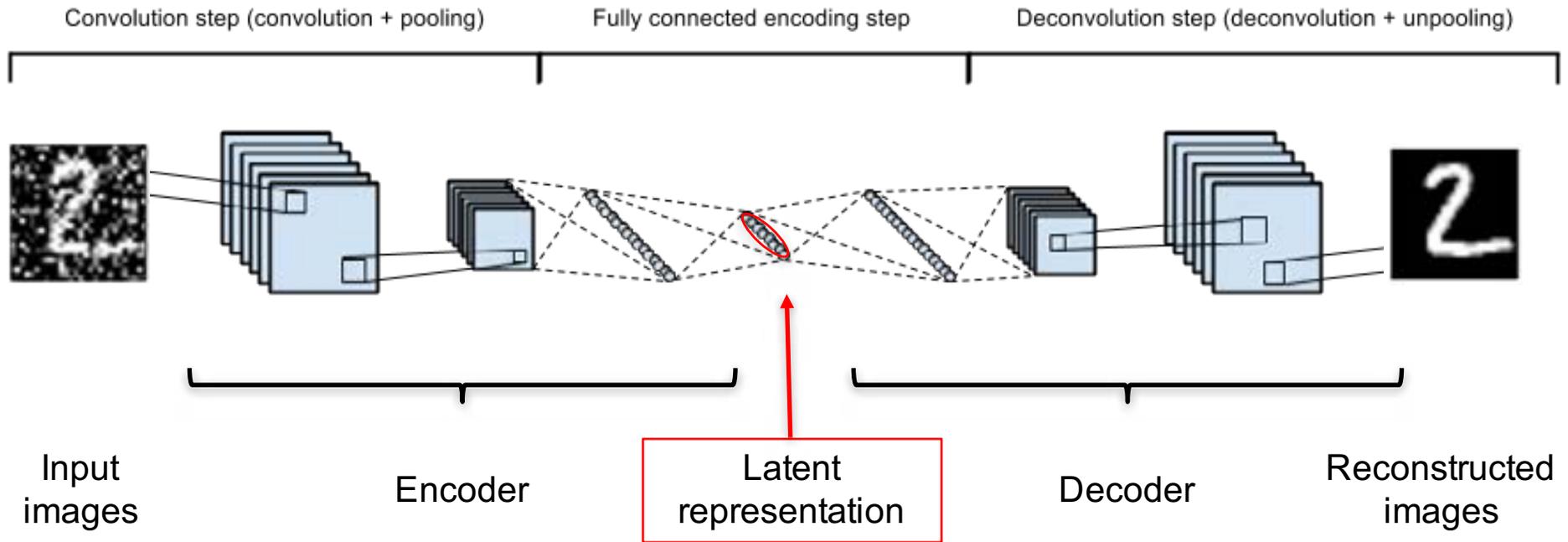
Input images:



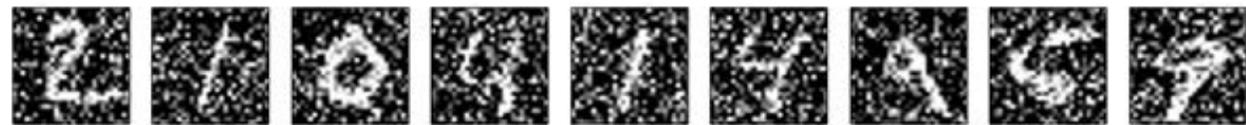
Reconstructed images:



# Denoising auto-encoders for more robust features



Input images:



Reconstructed images:





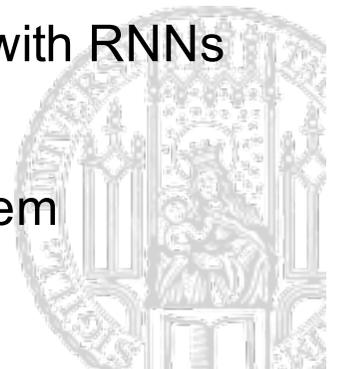
## Conclusion

Recent (dramatic) advances in computer vision using recurrent and convolutional artificial neural networks and deep learning

Application to various medical image and sensor data:

Cutting-edge data analysis for the multi-modal vestibular system

- Structural image segmentation of vestibular system
  - Multi-modal, multi-region using shape-models, atlases and CNNs
- Functional, computer-aided VOG
  - Novel acquisition workflows and features from dynamic analysis with RNNs
- Mining in multi-modal big data
  - Combined structural/functional assessment of the vestibular system





German Center for Vertigo and  
Balance Disorders



# Questions?

**Applied Statistics for Neuroscientists**  
**Part IIa: Neural networks and deep learning**

Dr. Seyed-Ahmad Ahmadi

