Deep Neural Networks

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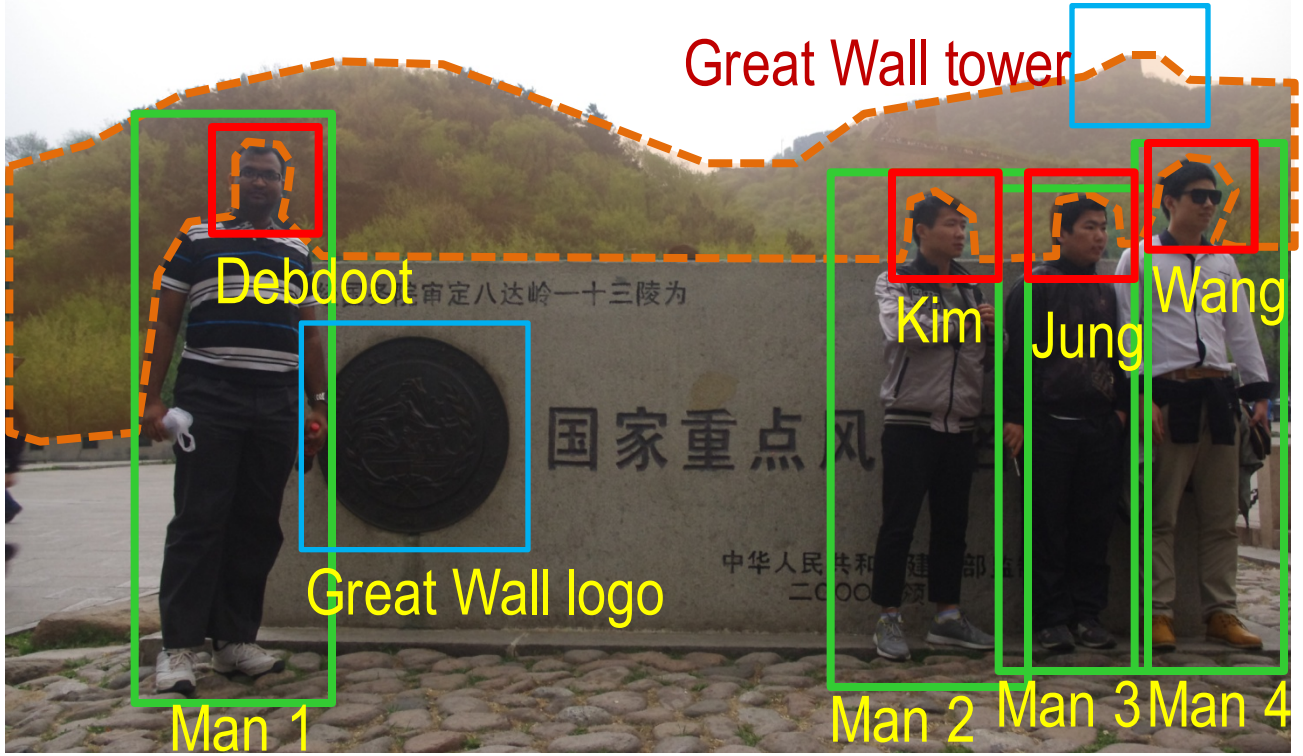
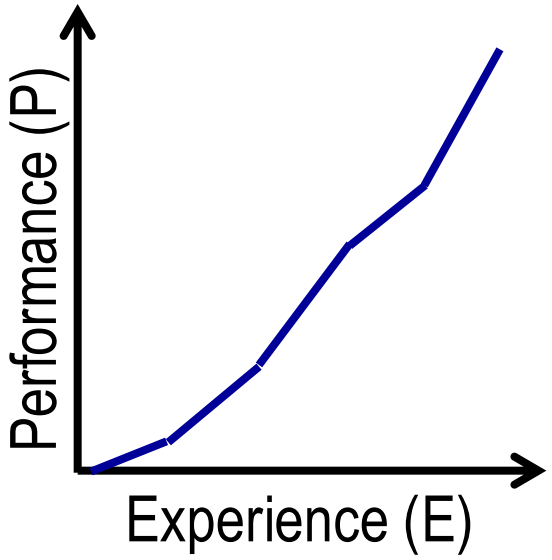
Learning?

A computer program is said to **learn** from **experience E** with respect to some class of **tasks T** and performance **measure P**, if its performance at tasks in **T**, as measured by **P**, improves with experience **E**

-Tom Mitchell

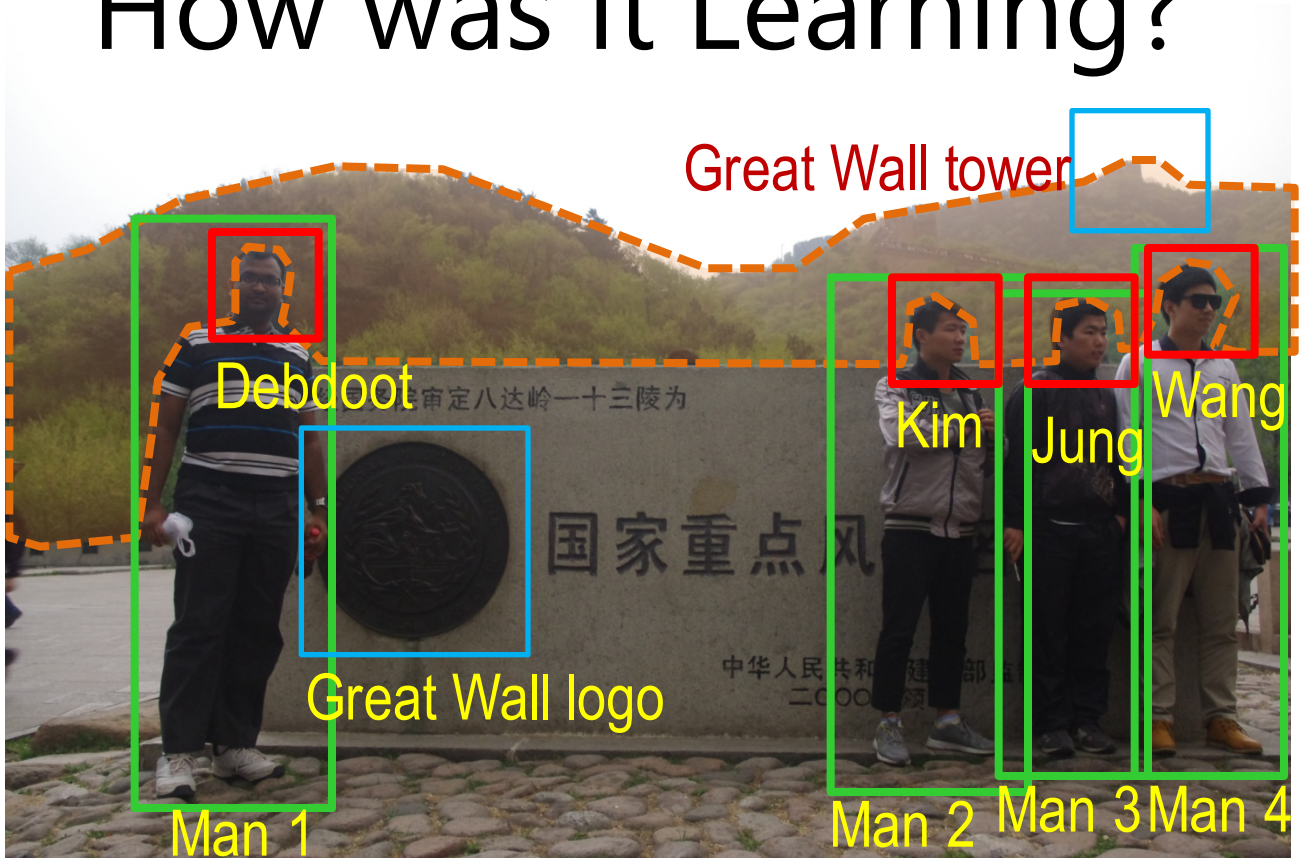
Demystifying Learning

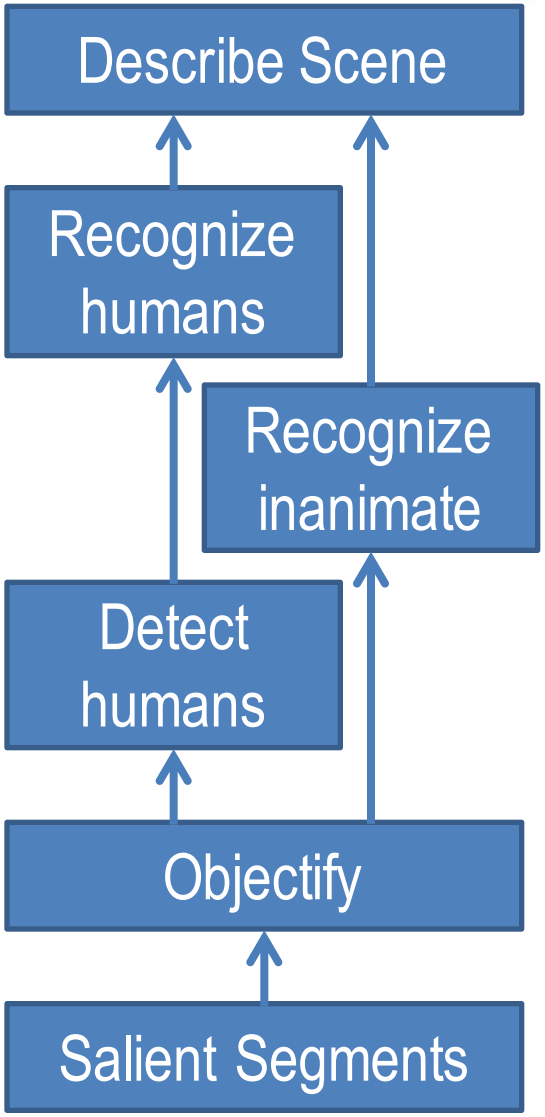




Debdoot, Kim, Jung and Wang are standing near the Great Wall logo and the Great Wall tower is behind them.

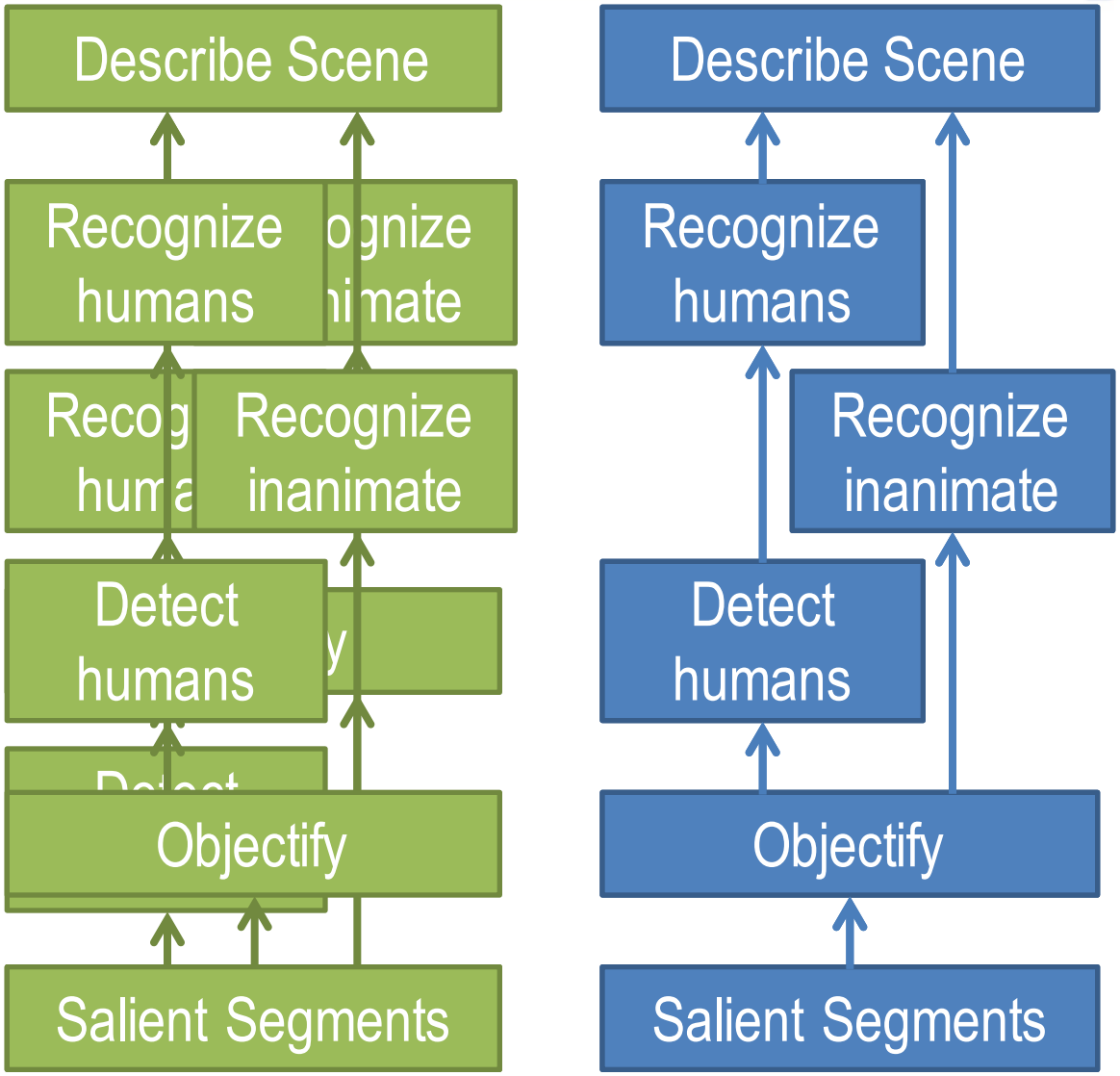
How was it Learning?





Debdoot, Kim, Jung and Wang are standing near the Great Wall logo and the Great Wall tower is behind them.

Challenges


Describe Scene
Recognize humans
Recognize inanimate
Detect humans
Objectify
Salient Segments
Describe Scene
Recognize humans
Recognize inanimate
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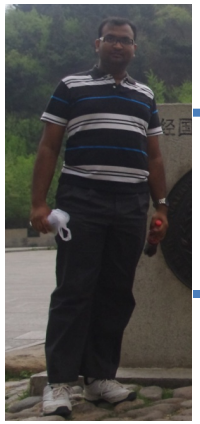
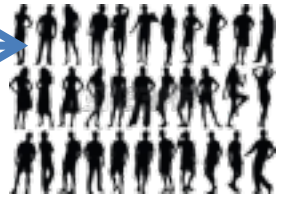
Objectify
Salient Segments

Challenges

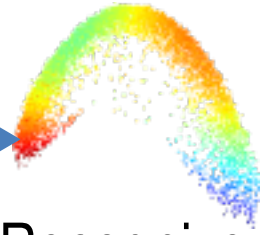


Chroma clustering

Posture realign



Silhouette matching

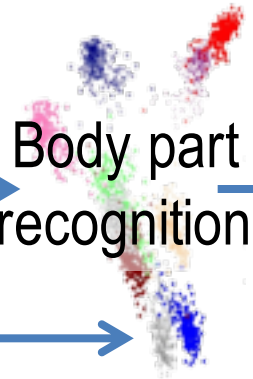


Recognize human

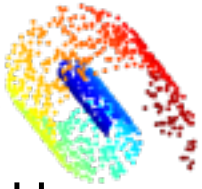
LBP

Wavelets

HoG



Body part recognition



Human appearance

Describe Scene

Recognize humans

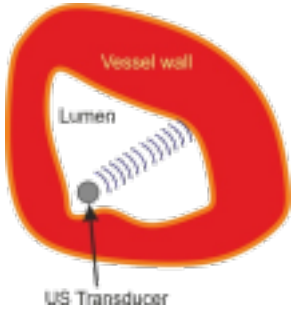
Recognize inanimate

Detect humans

Objectify

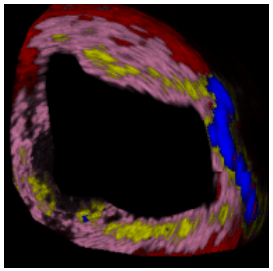
Salient Segments

Sheet, Debdoot, et al. "Deep learning of tissue specific speckle representations in optical coherence tomography and deeper exploration for in situ histology." *IEEE 12th International Symposium on Biomedical Imaging (ISBI)*, 2015.



$$\{f_1(\ _1 \mid \mathbf{x}), \cdots, f_n(\ _n \mid \mathbf{x})\}$$

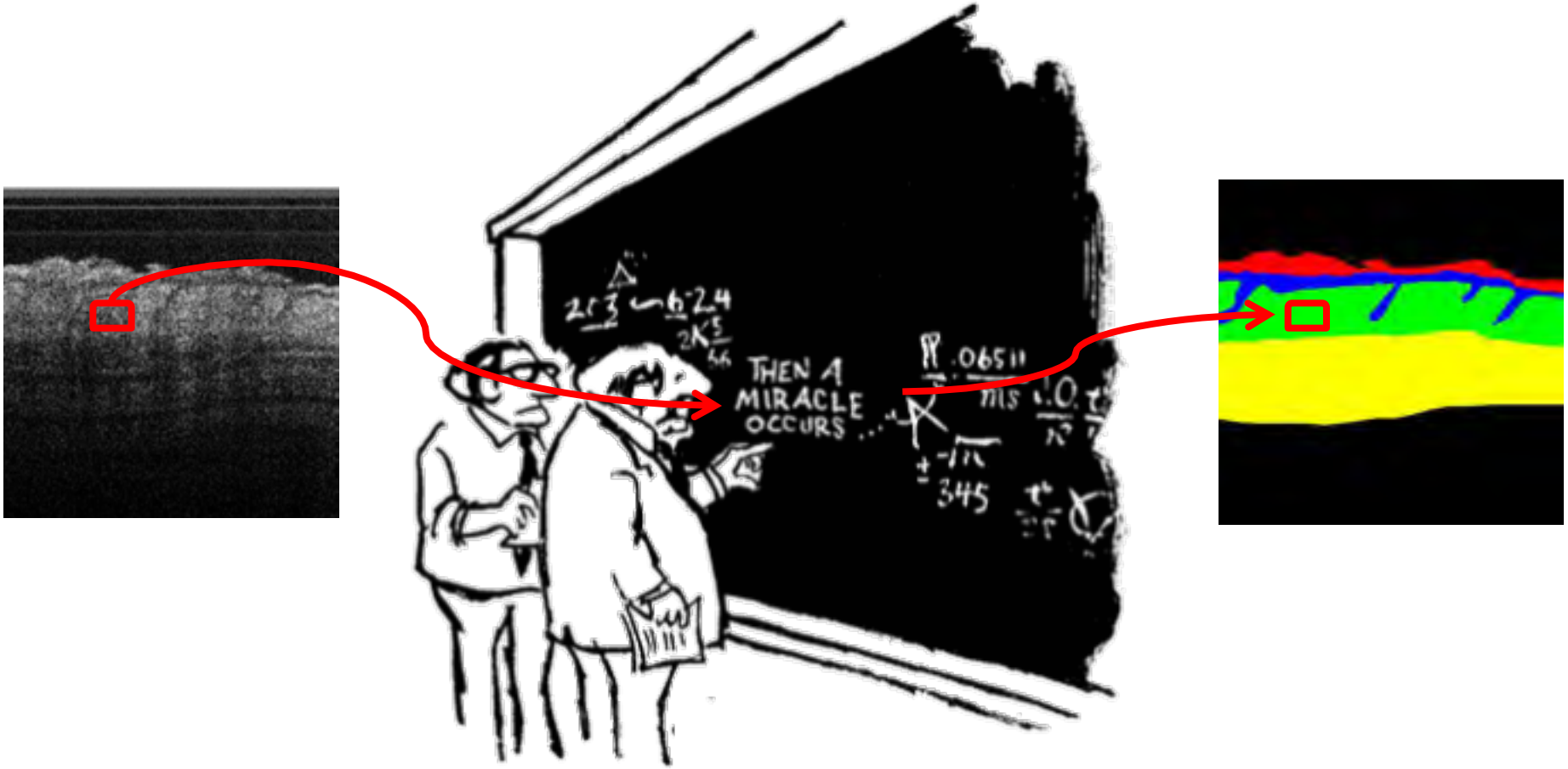
$$g(\ \mid \{\ _1, \cdots,\ _n\}, \mathbf{x})$$



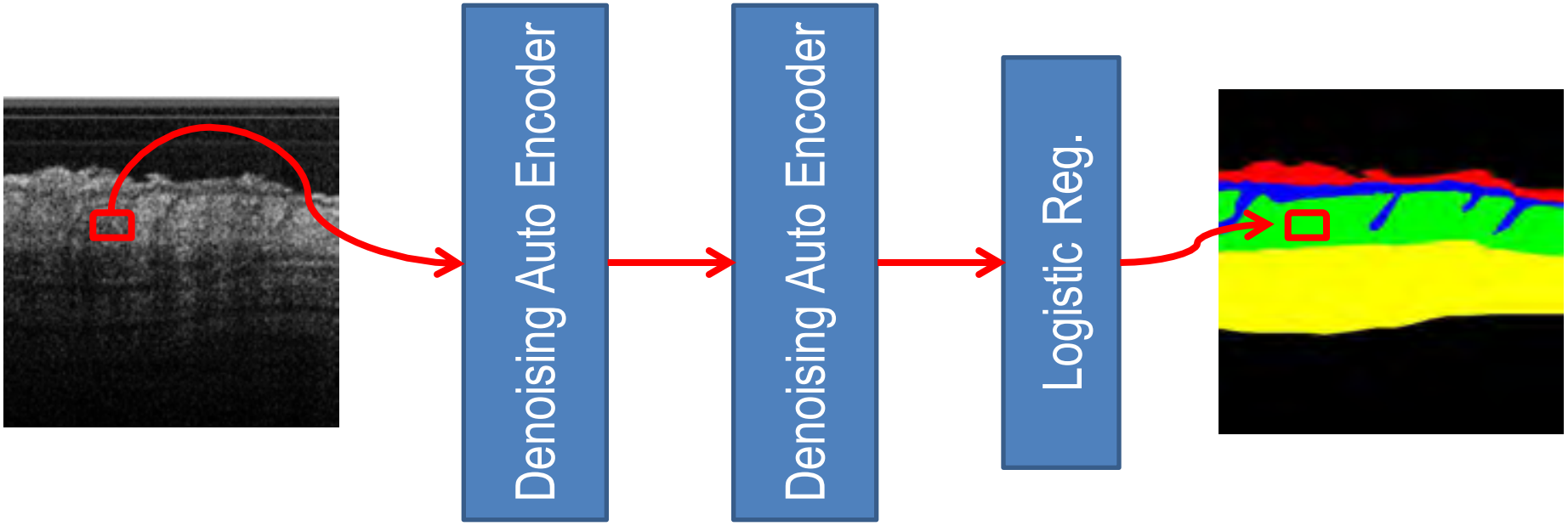
Deep Learning for

COMPUTATIONAL MEDICAL IMAGING

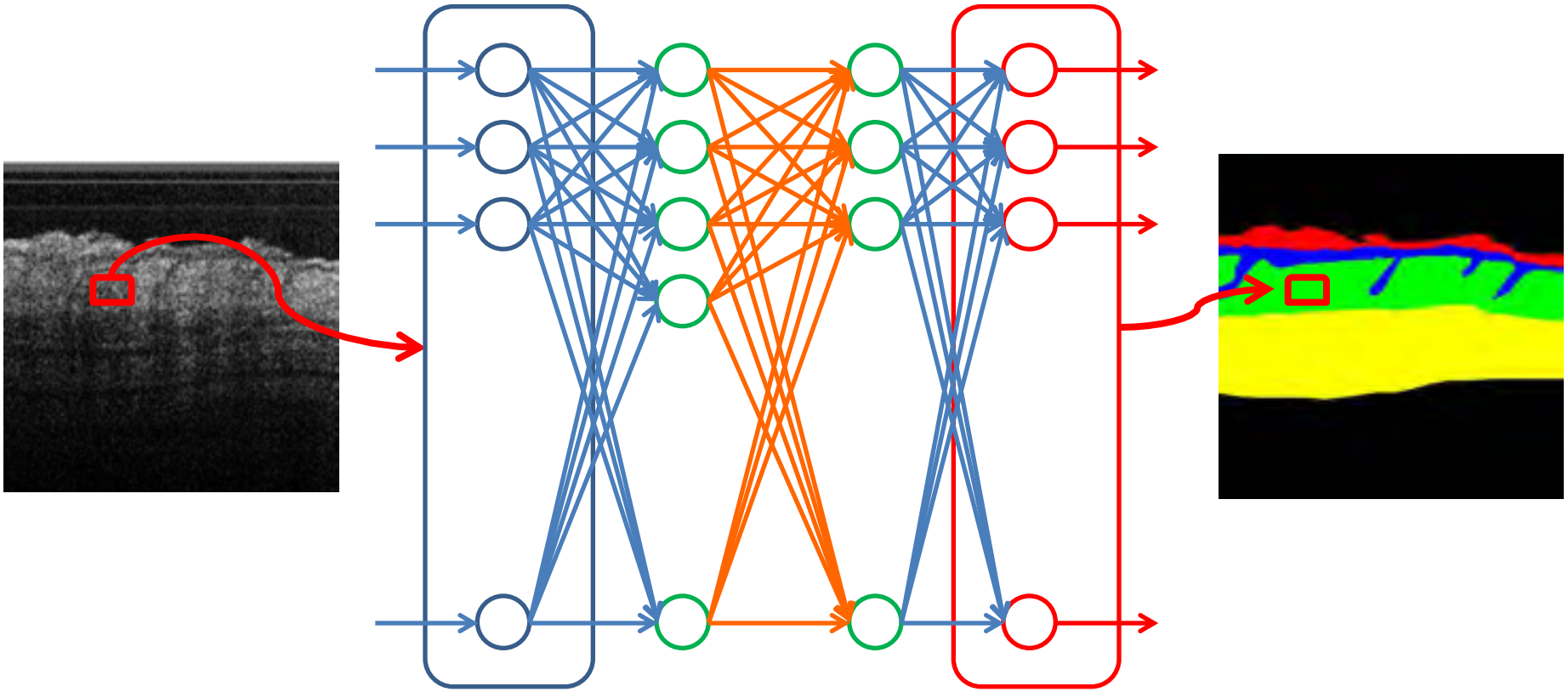
Heuristics in State of Art



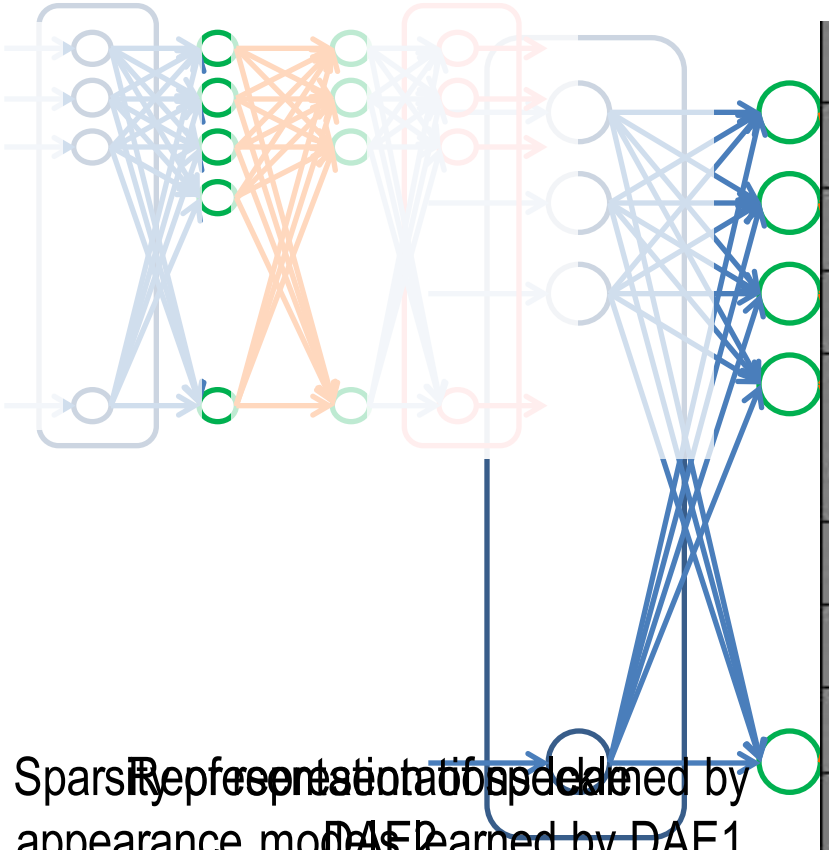
The Solution



Using a Deep Network



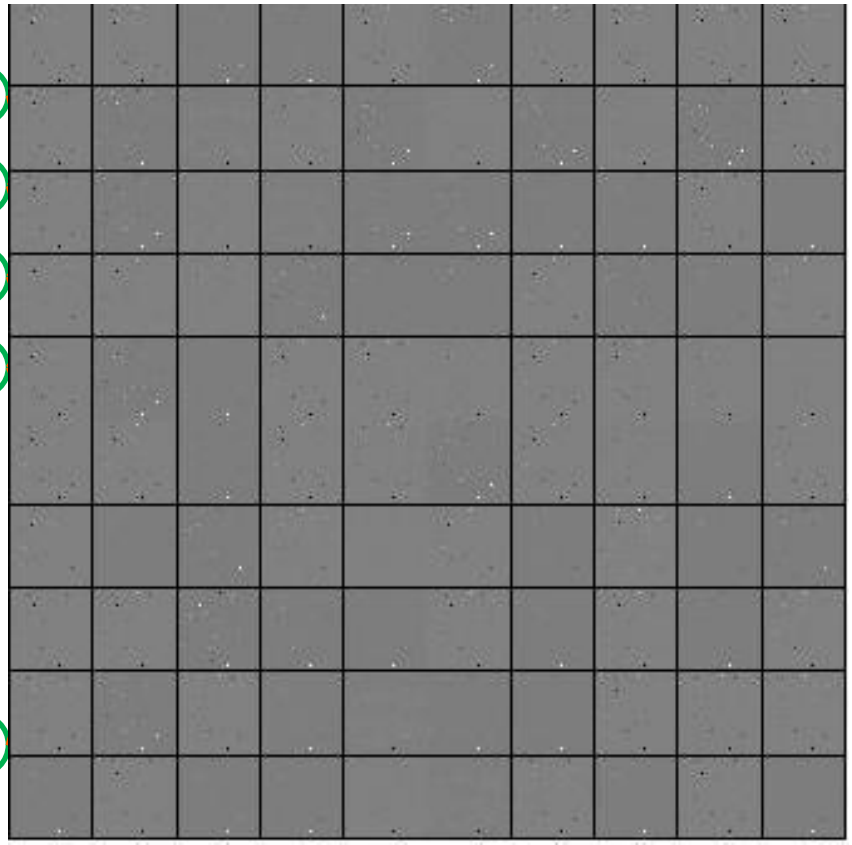
Learning of Representations



Sparsity helps in learning invariant features

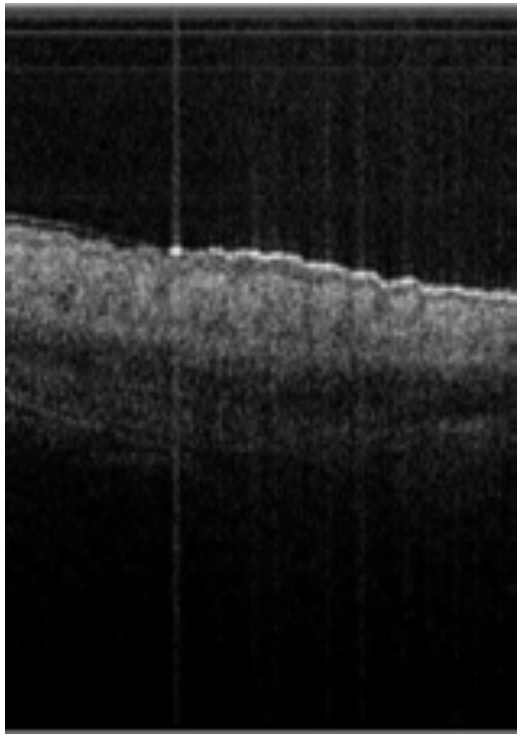
Representation learned by DAE2

Representation learned by DAE1

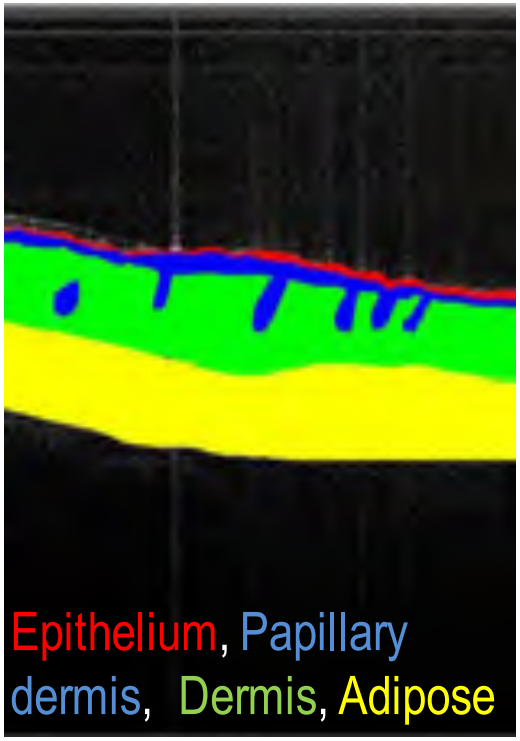


Sparse representation of pose and appearance models

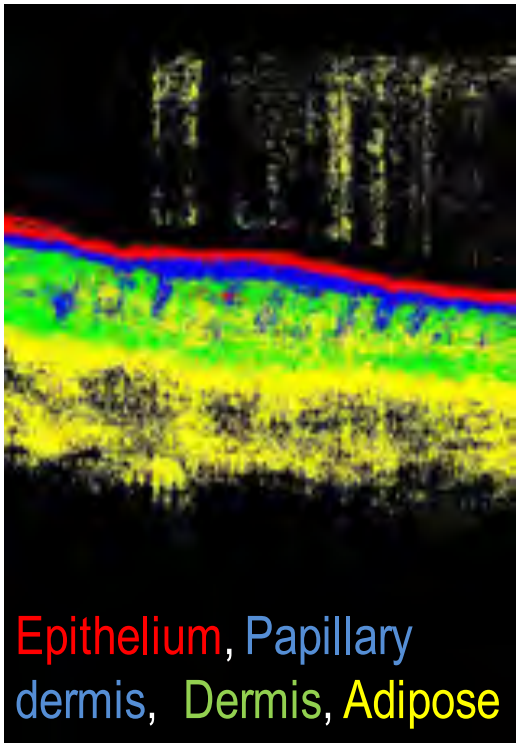
Results in Wounds



(a) OCT image of wound



(b) Ground truth

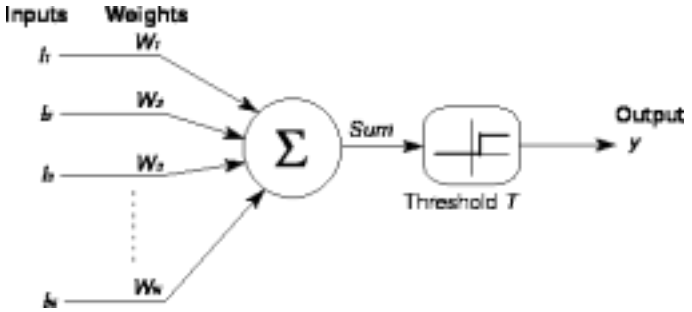


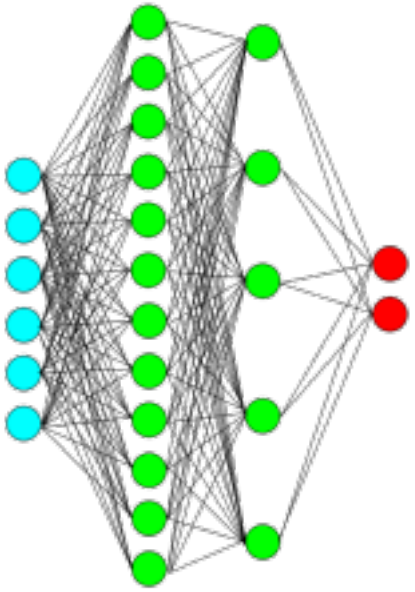
(c) *In situ* histology

FAMILY HISTORY OF DEEP LEARNING

Deep Learning, origin and growth

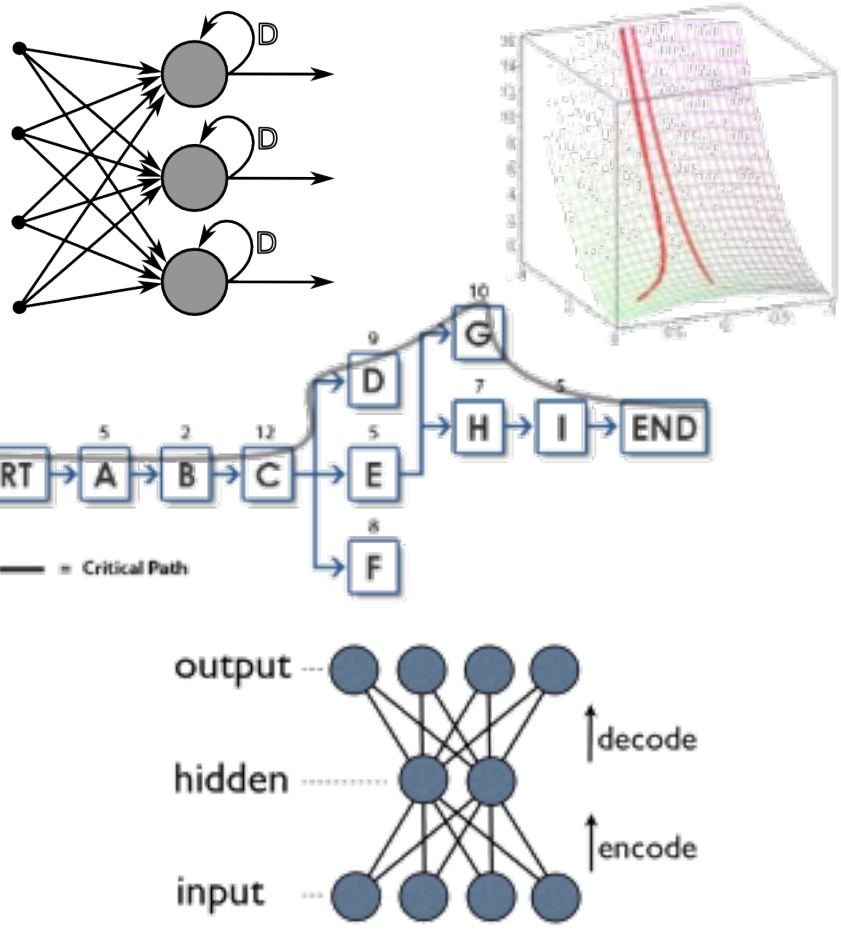
- Around 1950 – NN age
  - Neural Nets (McCulloch and Pitts, 1943)
  - Unsupervised Learn. (Hebb, 1949)
  - Supervised Learn. (Rosenblatt, 1958)
  - Associative Memory (Palm, 1980; Hopfield, 1982)
- 1960
  - Discovery of visual sensory cells that respond to Edges (Hubel and Wiesel, 1962)
  - Feed Forward Multi Layer Perceptron (FF-MLP) (Ivakhnenko, 1968)
- 1980 – Neocognition
  - Convolution + WeightReplication + Subsampling (Fukushima, 1980)
  - Max Pooling
  - Back-propagation (Werbos, 1981; LeCunn, 1985, 1988)





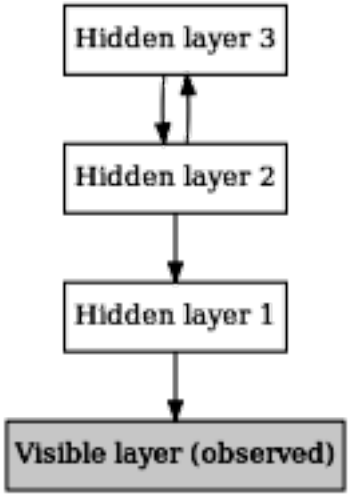
Deep Learning, origin and growth

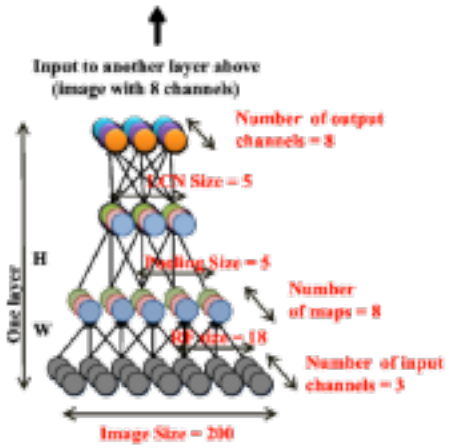
- 1980-2000 – Search for simple, low-complexity, problem-solvers
  - Recurrent Neural Network (RNN) (Hochreiter and Schmidhuber, 1996)
  - Local learning Feed forward NN (Dayan and Hinton, 1996)
  - Advanced gradient descent (Schaback and Werner, 1992)
  - Sequential Network Construction (Honavar and Uhr, 1988)
  - Unsupervised Pre-training (Ritter and Kohonen, 1989)
  - Auto-Encoder (Hinton et al., 1989)
  - Back Propagating Convolutional Neural Networks (LeCun et al., 1989, 1990a, 1998)

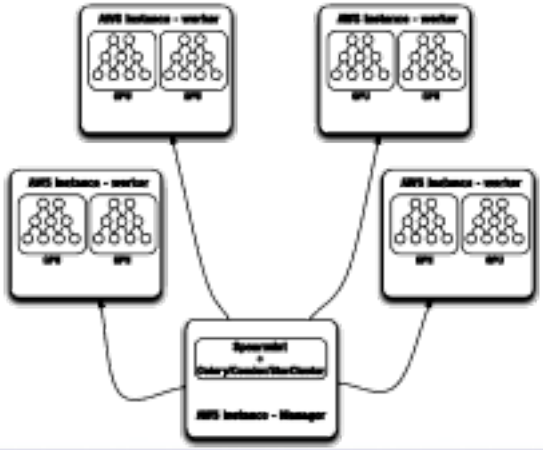


Deep Learning, origin and growth

- 2000 – Era of Deep Learning
  - NIPS 2003 Feature Selection Challenge (Neal and Zhang, 2006)
  - MNIST digit recognition (LeCun et al., 1989)
  - Deep Belief Network (DBN) / Restricted Boltzmann Machines (Hinton et al., 2006)
  - Auto Encoders (Bengio, 2009)
- 2006
  - GPU based CNN (Chellapilla et al., 2006)
- 2009
  - GPU DBN (Raina et al., 2009)
- 2011
  - Max-Pooling CNN on the GPU (Ciresan et al., 2011)
- 2012
  - Image Net (Krizhevsky et al., 2012)







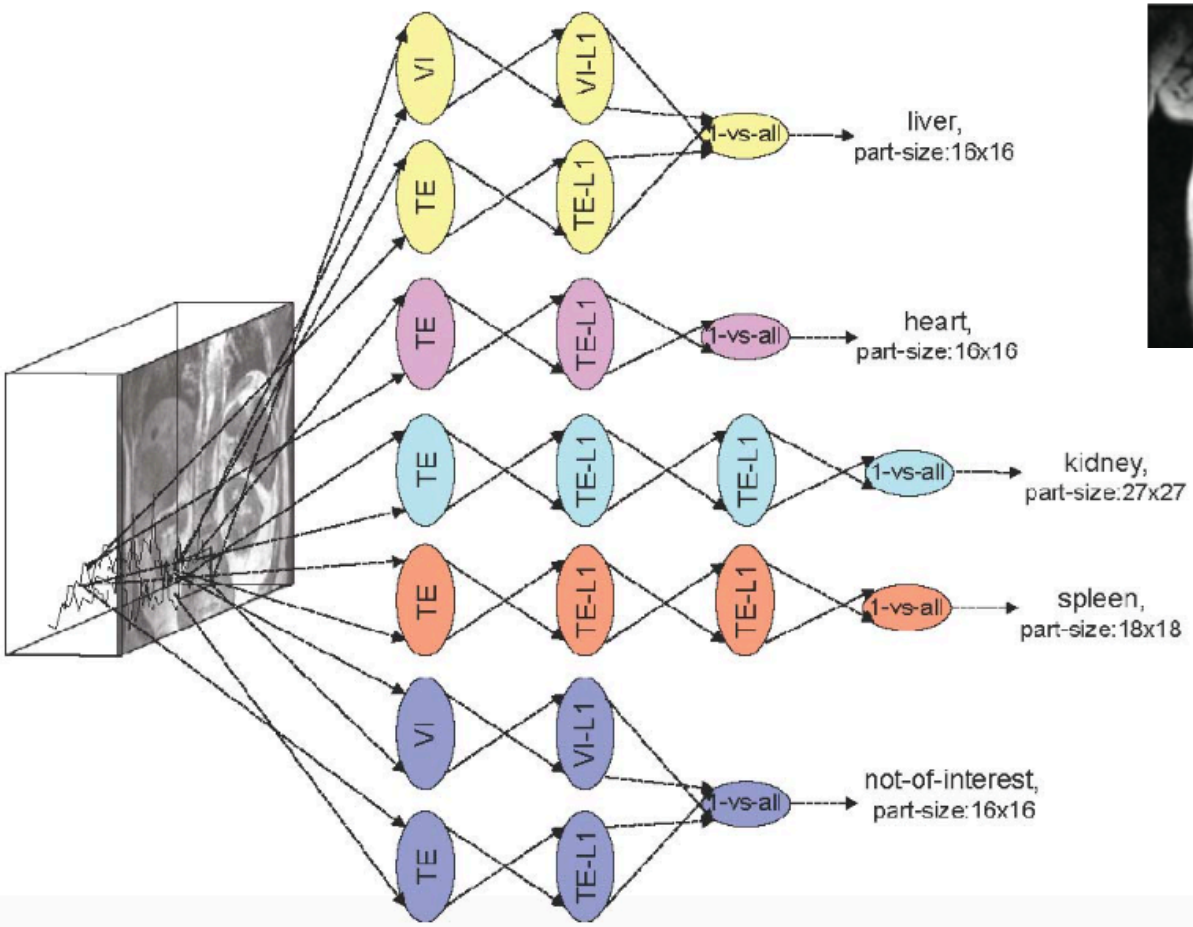
Families of Deep Learning

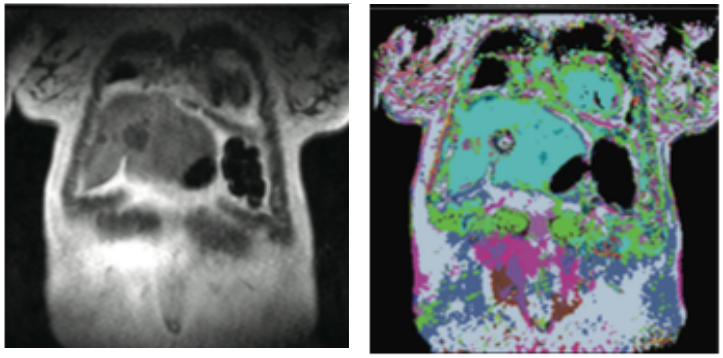
- Fully connected networks
  - Autoencoders
    - Autoencoders
    - Stacked Autoencoder
    - Sparse Autoencoder
    - Denoising Autoencoder
    - Convolutional Autoencoder
  - Belief Networks
    - Restricted Boltzmann Machines
    - Deep Belief Networks
- Convolutional Networks
  - Conv-Nets
  - LeNet, GoogLeNet, AlexNet
  - U-Nets
  - Res-Nets
- Recurrent Neural Networks
  - Long short-term memory (LSTM)

Medical Image Analysis with

DEEP LEARNING TODAY

Organ Detection in MRI





H.-C. Shin, M. R. Orton, D. J. Collins, S. J. Doran, and M. O. Leach, "Stacked Autoencoders for Unsupervised Feature Learning and Multiple Organ Detection in a Pilot Study Using 4D Patient Data," *IEEE Trans. Pat. Anal. Mach. Intell.*, vol. 35, no. 8, pp. 1930-1943, Aug. 2013.

IEEE Trans. Med. Imaging Spl. Issue

IEEE TRANSACTIONS ON

MEDICAL IMAGING

A PUBLICATION OF
THE IEEE ENGINEERING IN MEDICINE AND BIOLOGY SOCIETY
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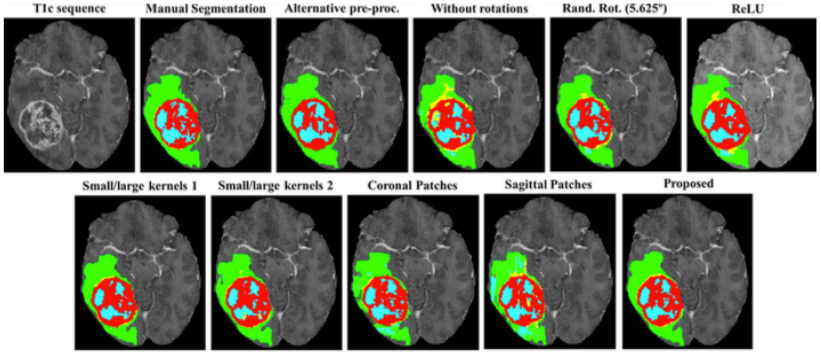
MAY 2016 VOLUME 35 NUMBER 5 ITMID4 (ISSN 0278-0062)

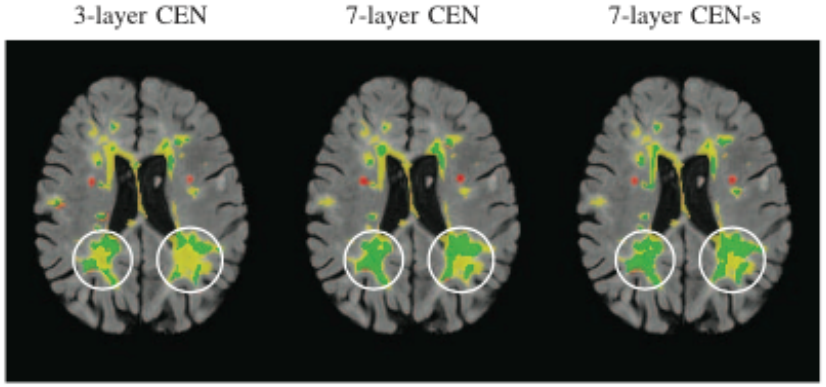
SPECIAL ISSUE ON DEEP LEARNING IN MEDICAL IMAGING

IEEE Trans. Med. Imaging, vol. 35, no. 9, May 2016

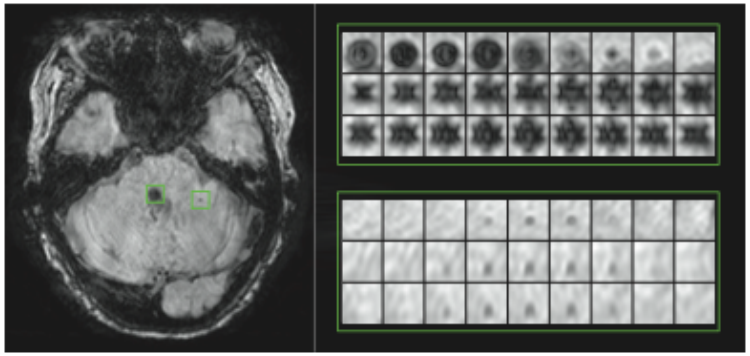
Some Snapshots from the Issue



S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images", *IEEE TMI*, vol. 35, no. 5, May 2016.

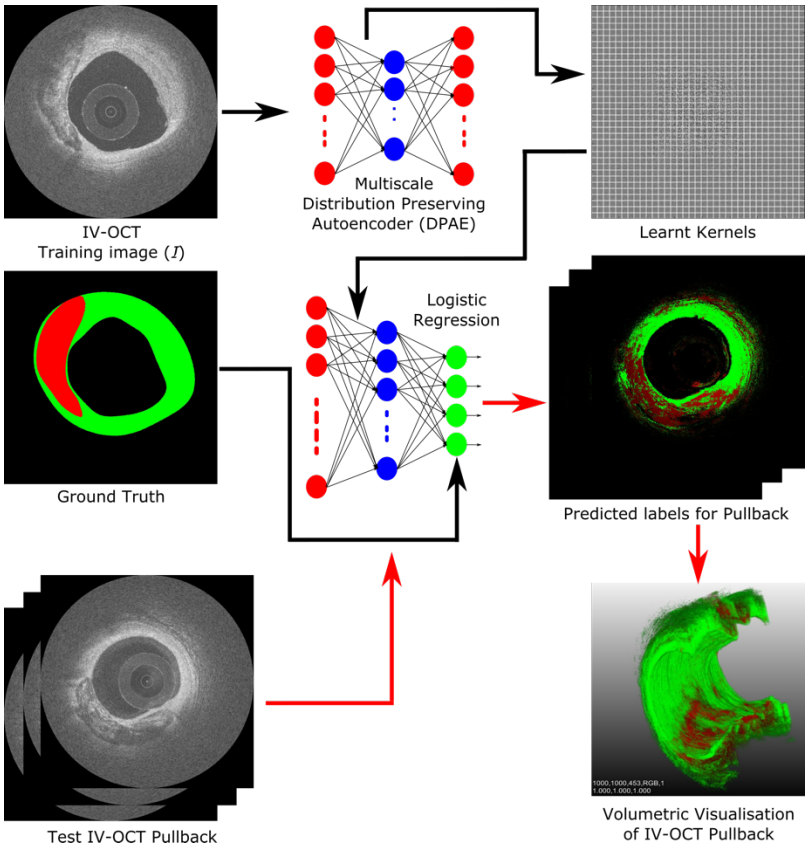


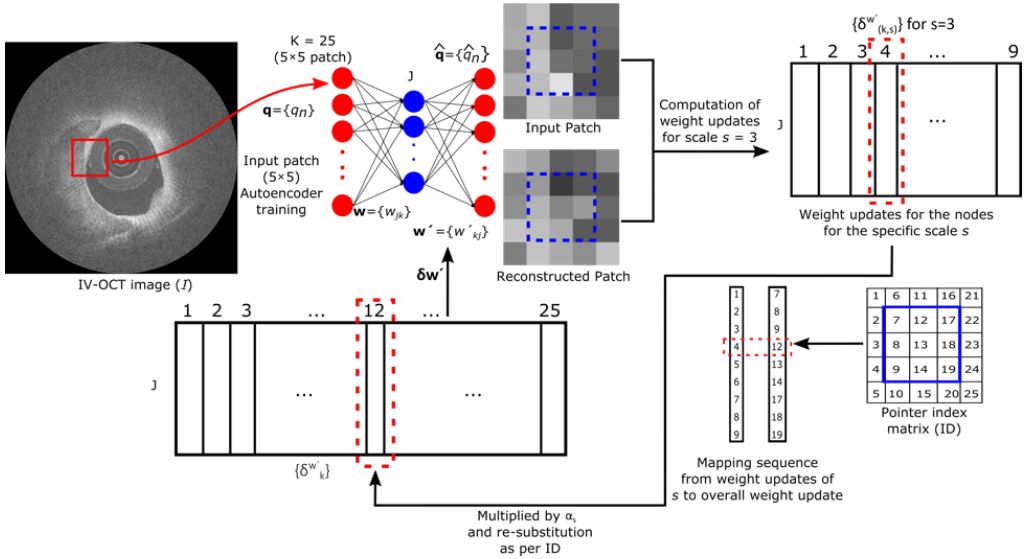
T. Brosch, et al., "Deep 3D Convolutional Encoder Networks With Shortcuts for Multiscale Feature Integration Applied to Multiple Sclerosis Lesion Segmentation", *IEEE TMI*, vol. 35, no. 5, May 2016.



Q. Dou, et al., "Automatic Detection of Cerebral Microbleeds From MR Images via 3D Convolutional Neural Networks", *IEEE TMI*, vol. 35, no. 5, May 2016.

Distribution Preserving Autoencoders





A. Guha Roy, *et al.*, "Multiscale Distribution Preserving Autoencoders for Plaque Detection in Intravascular Optical Coherence Tomography", *Proc. Int. Symp. Biomed. Imaging*, 2016

Endnote (almost there)

"It's like in quantum physics at the beginning of the 20th century" *Trishul Chilimbi* (MSR, DNN, Adam)

"The experimentalists and practitioners were ahead of the theoreticians. They couldn't explain the results. We appear to be at a similar stage with DNNs. We're realizing the power and the capabilities, but we still don't understand the fundamentals of exactly how they work."

Take home message

- Hardware Resources
  - Custom workstations
    - GTX TITAN X / Tesla K40
    - GTX 1080 / GTX 1060
  - Deep Learning Box
    - NVIDIA DGX-1
- Toolboxes
  - Theano + Pylearn2 (Python)
  - Torch (Lua)
  - CUDA + DIGITS + cuDNN (NVIDIA)
  - Matlab DeepLearningToolbox (GitHub)
  - Matlab 2016 NN Toolbox
    - Autoencoders
    - Convolutional Neural Network
- More information
  - www.deeplearningbook.org
  - www.deeplearning.net
  - Schmidhuber (2014). Deep Learning in Neural Networks: An Overview (arXiv:1404.7828)
  - Deng and Yu (2013). *Deep Learning: Methods and Applications*.
- Conferences
  - Int. Conf. Learning Representations (ICLR)
  - Neural Inf. Process. Sys. (NIPS)