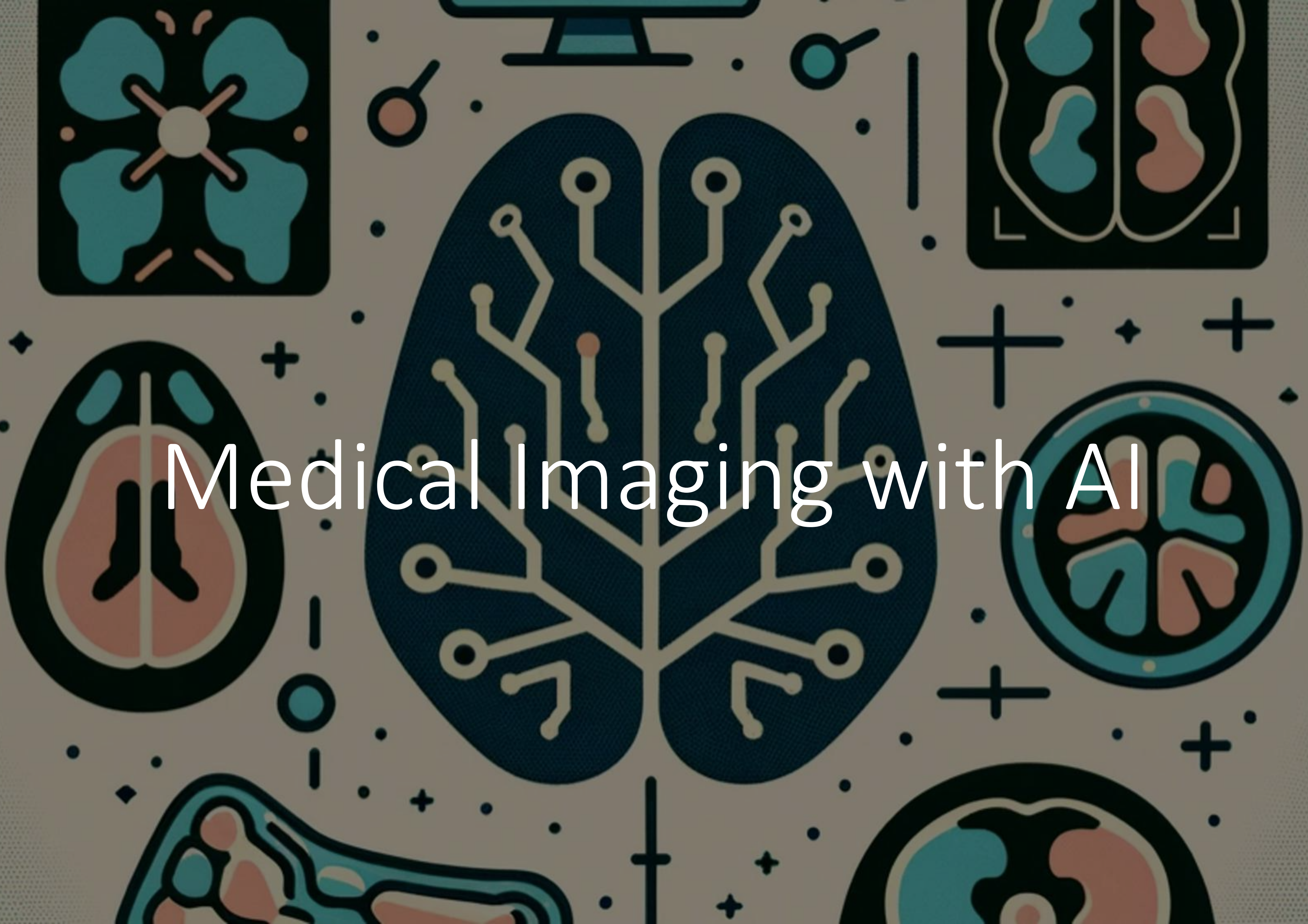


Medical Imaging with AI

Outline

- Course website & logistics
- Syllabus
  - Problem sets
  - Projects
  - Grading
- What is medical imaging?

Course Logistics

Sections:
ENG EC500
M/W 10:10-11:55pm, SOC B59

Instructor:
Kayhan Batmanghelich,
office hours M 12pm-1pm outside PHO 421

Teaching Assistant:
Li Sun (lisun@bu.edu)
Thursday 3PM-4PM, outside of Room PHO 421

Graders/Additional Staff:
Shuyue Jia (brucejia@bu.edu)
Susan Zhang (szha@bu.edu)

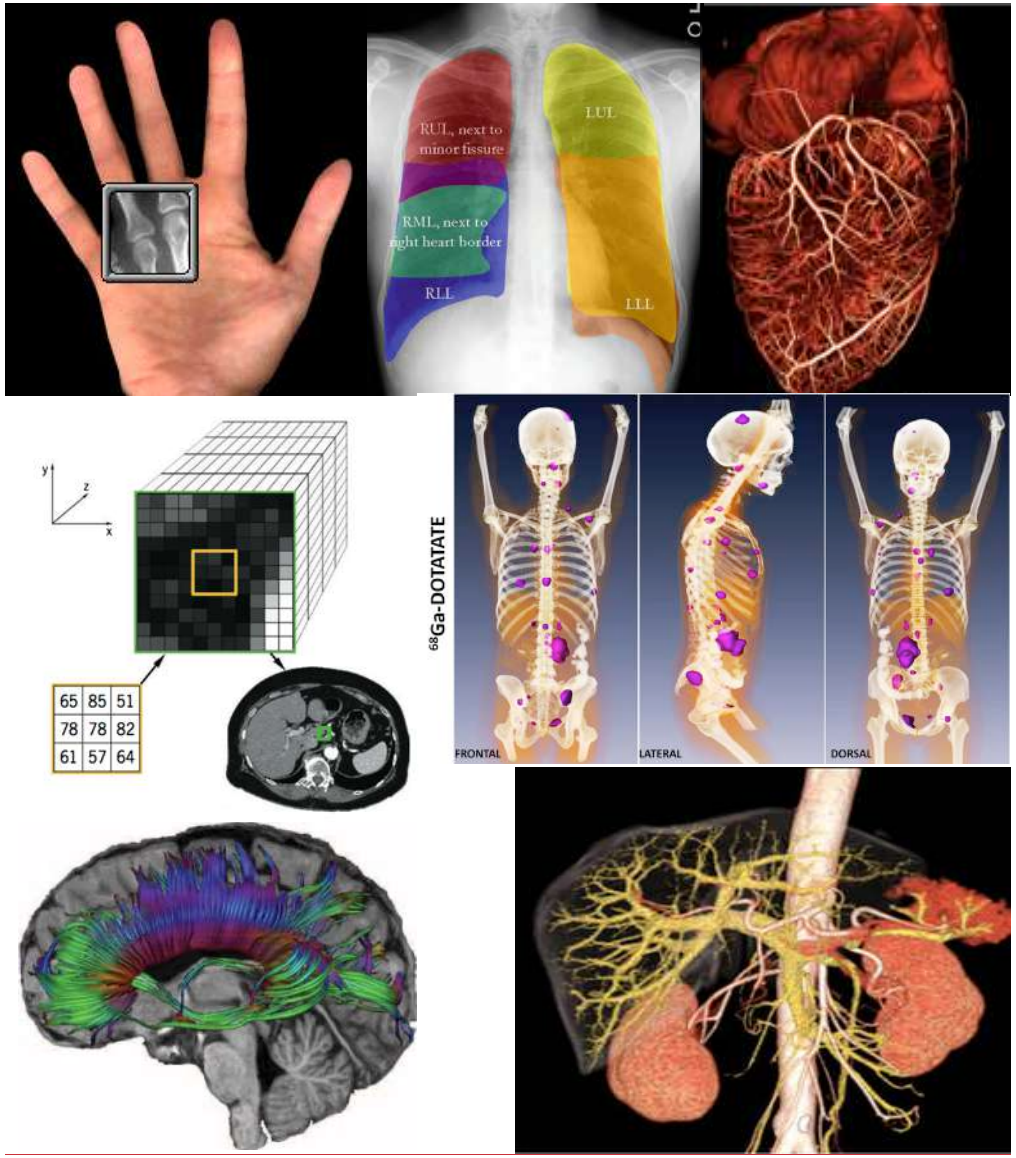


Image Credit: Ulas Bagci, (CAP 5516)- SPRING 2019

The Team

Li Sun (lisun@bu.edu)

Shuyue Jia (brucejia@bu.edu)

Susan Zhang (szha@bu.edu)

Piazza

How to Contact us: Please use Piazza for all communication; if your question is only directed to the instructors, please make a post to “Individual Student(s) / Instructor(s)” and select “Instructors".

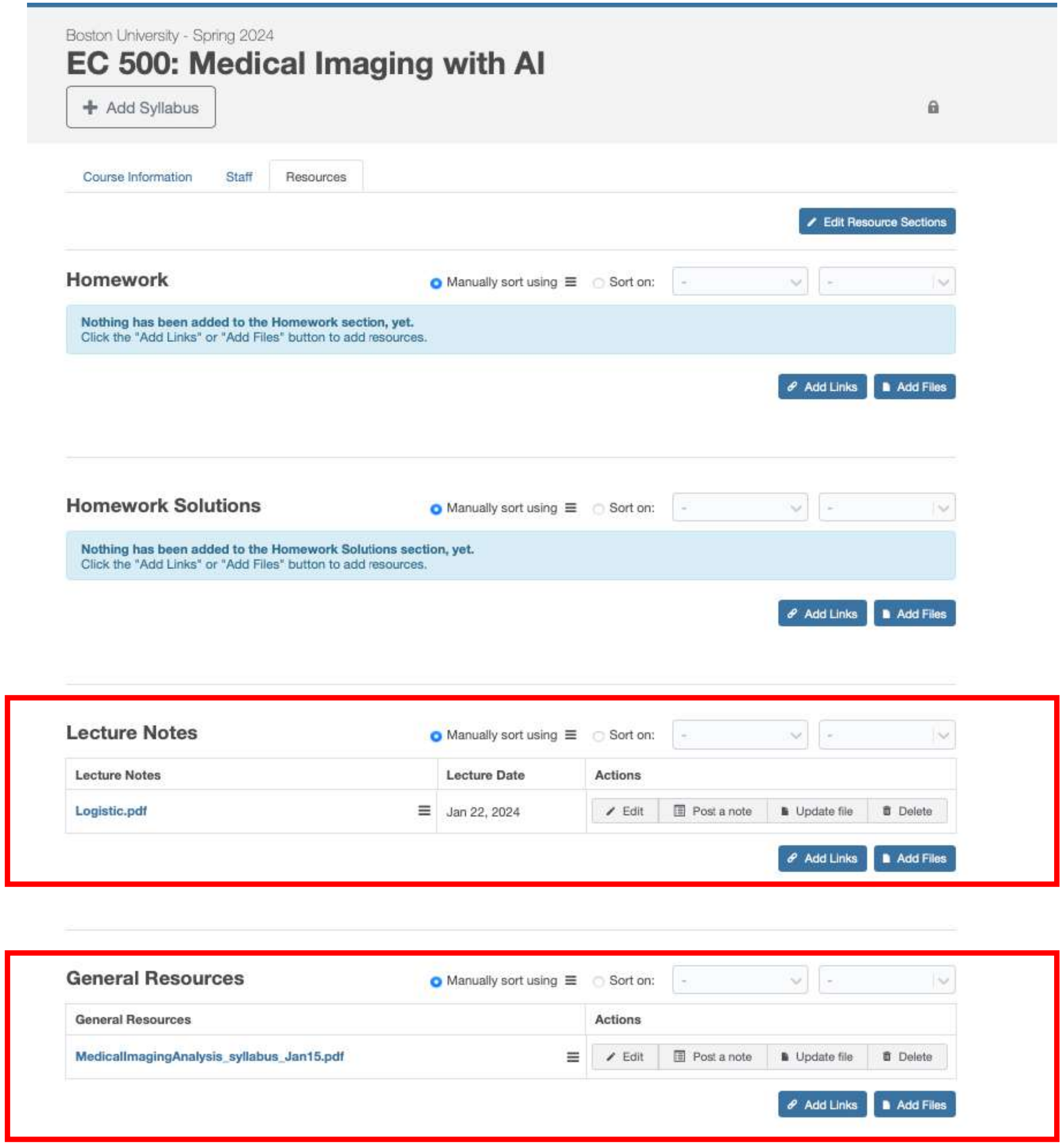
Piazza: https://piazza.com/bu/spring2024/ec500

We will be using piazza for online discussions, questions, and to post assignments.

Gradescope: we will be using Gradescope for submitting and grading assignments.

Link: https://www.gradescope.com/courses/707758, Entry Code:WBZX8R

On Piazza


Boston University - Spring 2024
EC 500: Medical Imaging with AI
Add Syllabus
Course Information
Staff
Resources
Edit Resource Sections
Homework
Manually sort using
Sort on:
Nothing has been added to the Homework section, yet.
Click the "Add Links" or "Add Files" button to add resources.
Add Links
Add Files
Homework Solutions
Manually sort using
Sort on:
Nothing has been added to the Homework Solutions section, yet.
Click the "Add Links" or "Add Files" button to add resources.
Add Links
Add Files
Lecture Notes
Manually sort using
Sort on:
Lecture Notes
Lecture Date
Actions
Logistic.pdf
Jan 22, 2024
Edit
Post a note
Update file
Delete
Add Links
Add Files
General Resources
Manually sort using
Sort on:
General Resources
Actions
MedicalImagingAnalysis_syllabus_Jan15.pdf
Edit
Post a note
Update file
Delete
Add Links
Add Files

Pre-Requisites

Course Pre-requisites

This is an upper-level undergraduate/graduate course. All students should have the following skills:

- Calculus, Linear Algebra
- Probability & Statistics
- Ability to code in Python
- Background in machine learning

Shared Computing Center

- Projects (and possibly some homework) will be done using GPUs from the SCC
  - Can use Google Colab for most/all homework assignments
  - If you have your own GPU resources, feel free to use
- We have access to 28 NVIDIA P100s
- Will have an introduction to using SCC later this month

Deliverables/Graded Work

- There will be five homework assignments, each consisting of written and/or coding problems and a final project.
- The course grade consists of the following:
  - HomeWorks (hw1 and weighted* sum of 2-4) 50%
  - Project (including all components) 45%
  - Class/Piazza participation 5%

- **Weighting**: We sort the scores of HW2, HW3, and HW4 and apply this formula: 30% (HW1) + 30% (1st score) + 30% (2nd score) + 10% (3rd score)

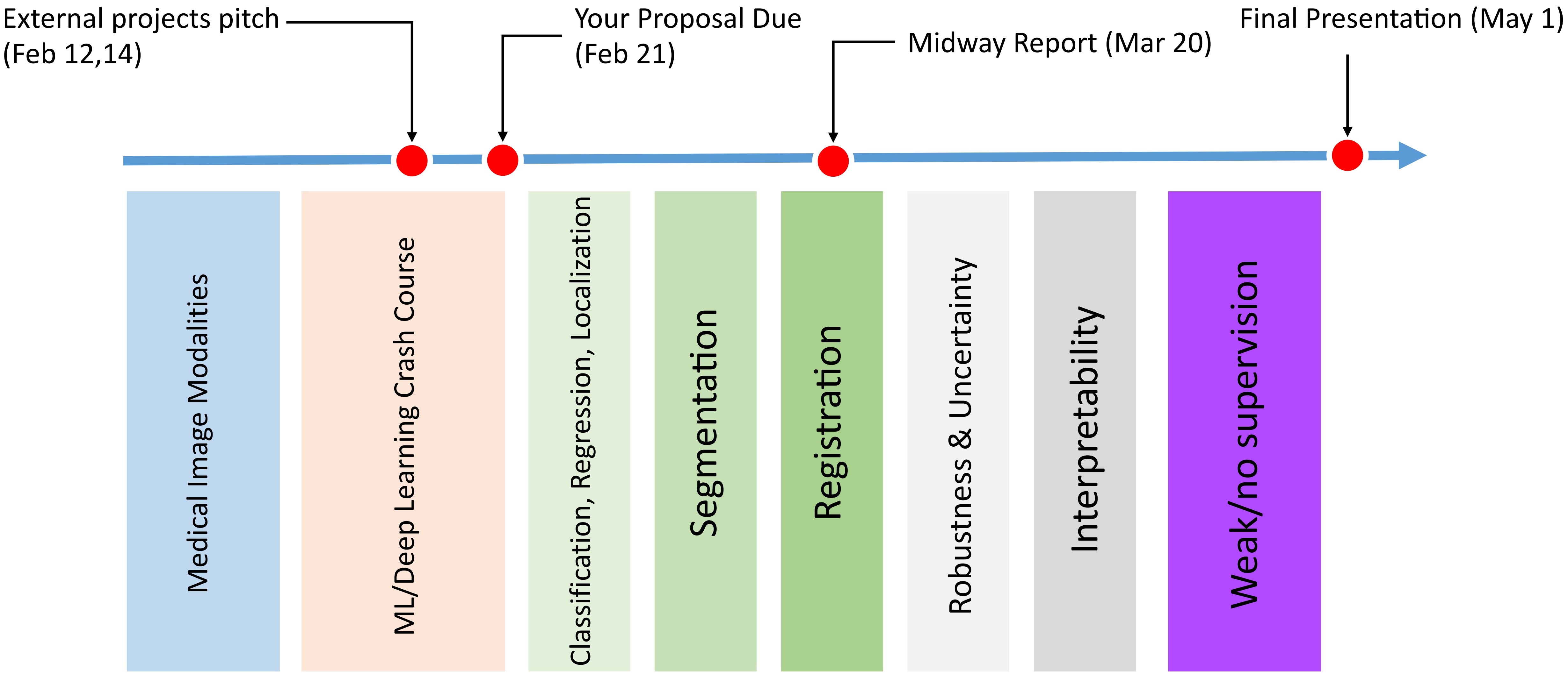
Late policy & academic honesty

- Please see syllabus
- Your work should be your own
- If you consult an online source please cite it in your work

Homeworks

- Four homeworks
- Roughly every three weeks
- A mix of written questions and coding
- Coding for HW2-4 will be in PyTorch
- HW1 out **next session**
    - ML/math review
    - You cannot drop this

(tentative) Schedule and Topics



Projects

- External PI’s will present mini project on Feb 12 and Feb 14 (approximately 5-6 projects) – Please attend the talks.
- Students rank their preferences
- We will create team using a matching algorithm
- PI’s will attend the final project to judge
- Use this opportunity to connect!

Projects

- The project will be done in teams of 3-4 students
- Projects will have several deliverables including
  - a proposal
  - progress update(s)
  - final report
  - Github repository
  - in-class presentation
- Project grade is based on all of the above components

BU Shared Computing Cluster/

Sample Projects

Image Compression Using Deep Learning

H. Kubra Cilingir, M. Ozan Tezcan, Sivaramakrishnan Sankarapandian
kubra@bu.edu, mtezcan@bu.edu , sivark@bu.edu

Figure 1. (left) ort best performing algorithm (CNN-AE-FT), (right) original image

1. Task

Image compression has an important role in data transfer and storage, especially due to the data explosion that is increasing significantly faster than Moore's Law.[1] It is a challenging task since there are highly complex unknown correlations between the pixels, as a result, it is hard to find and recover them. We want to find a well-compressed representation for images and, design and test networks that are able to

addressed the problem of JPEG compression for small images where the amount of redundant information is small. This network follows the classical three stages process of compression: encoding, quantization and decoding. Encoding and decoding are done iteratively using two different architecture of RNNs, Long Short Term Memory (LSTM) and convolutional/ deconvolutional LSTMs. The advantage of this method is that the compression ratio can be increased

Sample Projects

Video Generation with Generative Adversarial Networks

Michael Clifford, Casey Fitzpatrick
{jcliff, cfitz}@bu.edu

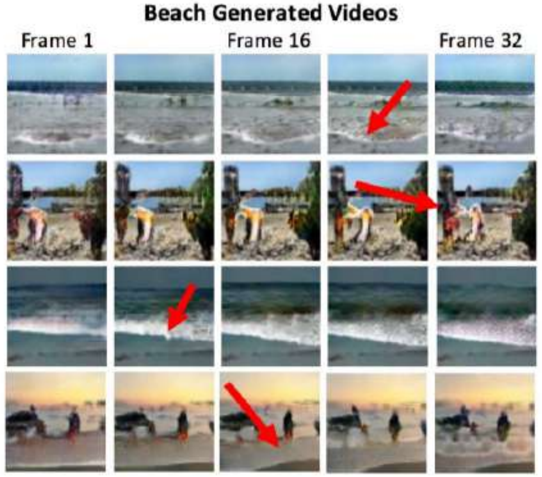


Figure 1. Some generations from the two-stream model. The red arrows highlight motions. Please see http://mit.edu/vondrick/tinyvideo for animated movies. Source [1].

1. Task

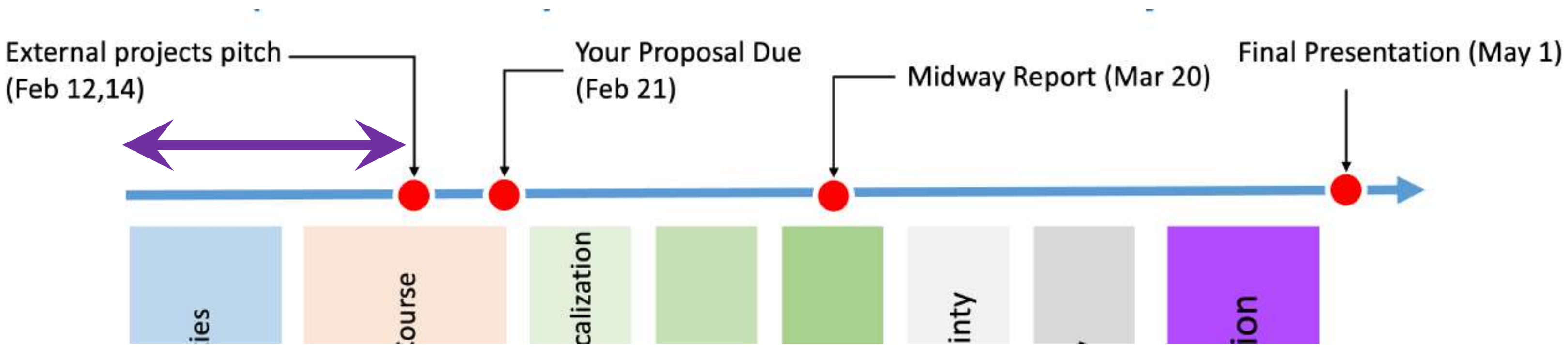
Our ultimate task was to design a generative adversarial network (GAN) capable of conditionally generating realistic, short video clips given a static image input, reproducing the results of [1] in a Keras environment with a TensorFlow backend (as opposed

The second reason this problem is hard is more fundamental with respect to generative video modeling. Namely, the approach used for generation consists of a forked parallel architecture that attempts to distinguish the foreground from background in order generate motion in the foreground while keeping the background fixed. The two streams are them joined together at the end of the generator using a branched mask layer designed to emphasize a fixed background while steadily tracking the motion of the foreground in time. While very interesting, according to Vondrick this approach has not been used in purely generative contexts before. So even the "state-of-the-art" (Vondrick's results) aren't particularly impressive in most cases. This is bleeding edge stuff!

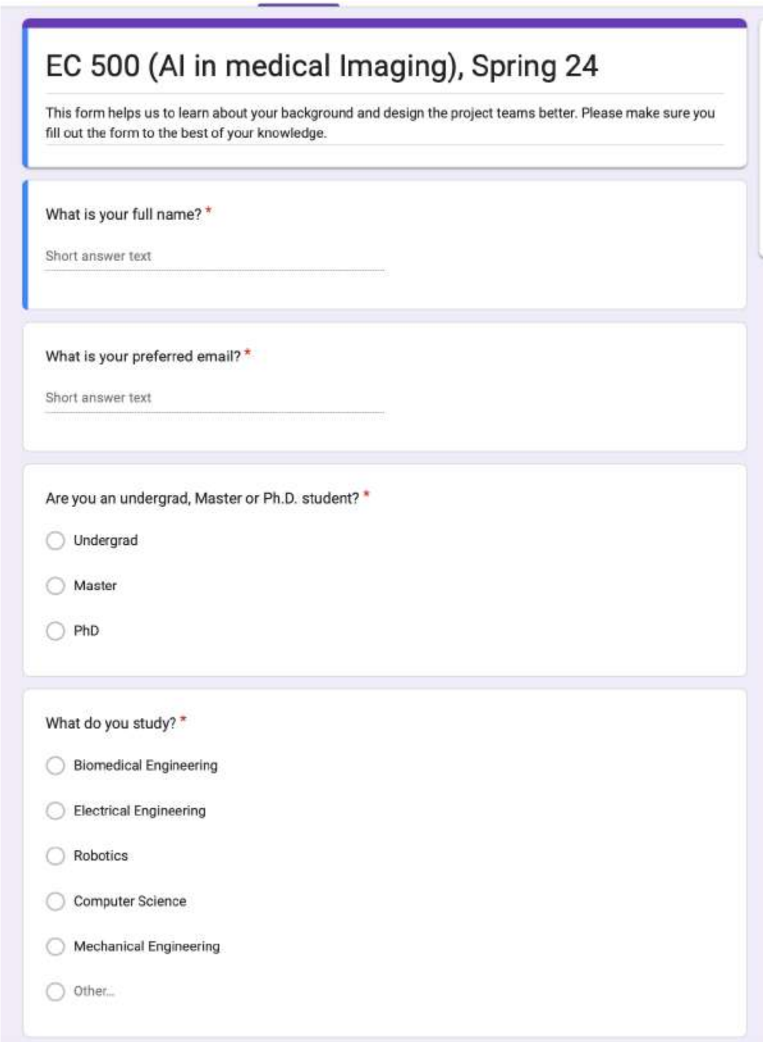
The final reason this problem is difficult is related to the known (and perhaps fundamental) issues with training GAN models. Specifically, since GAN models train based on minimax games, the gradient descent process is seeking a saddle point as opposed to a local minimum. It is inherently a harder to find such a region in a manifold, so convergence guarantees are out the window. Additionally, the models are hard to

About the Deep Learning (DL) Component

- If you have taken EC 523 or equivalent, no action is needed.
- If you are familiar with DL but not comfortable with it, please start this today:
  - https://www.coursera.org/learn/deep-neural-networks-with-pytorch
- If you are not familiar with DL at all, please talk to me.



Now, what about you?



EC 500 (AI in medical Imaging), Spring 24

This form helps us to learn about your background and design the project teams better. Please make sure you fill out the form to the best of your knowledge.

What is your full name? *

Short answer text

What is your preferred email? *

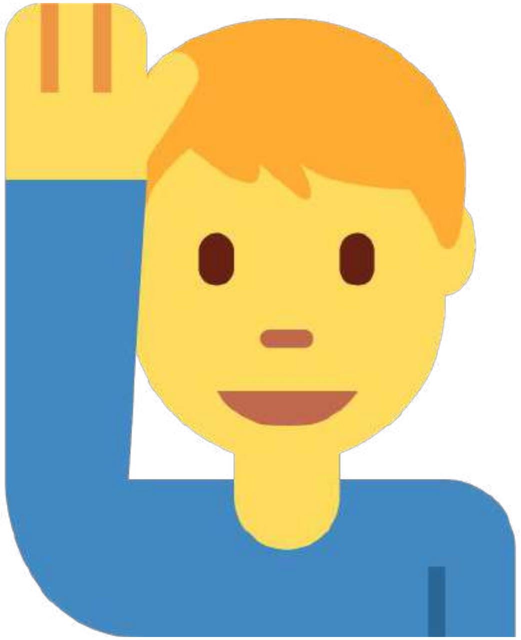
Short answer text

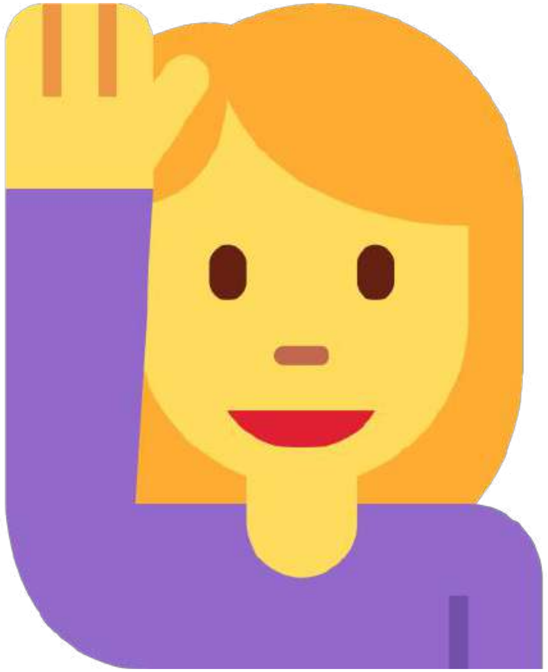
Are you an undergrad, Master or Ph.D. student? *

- Undergrad
- Master
- PhD

What do you study? *

- Biomedical Engineering
- Electrical Engineering
- Robotics
- Computer Science
- Mechanical Engineering
- Other...





https://forms.gle/MuC9BjZZrKMtc48Q7

Questions?

This Course

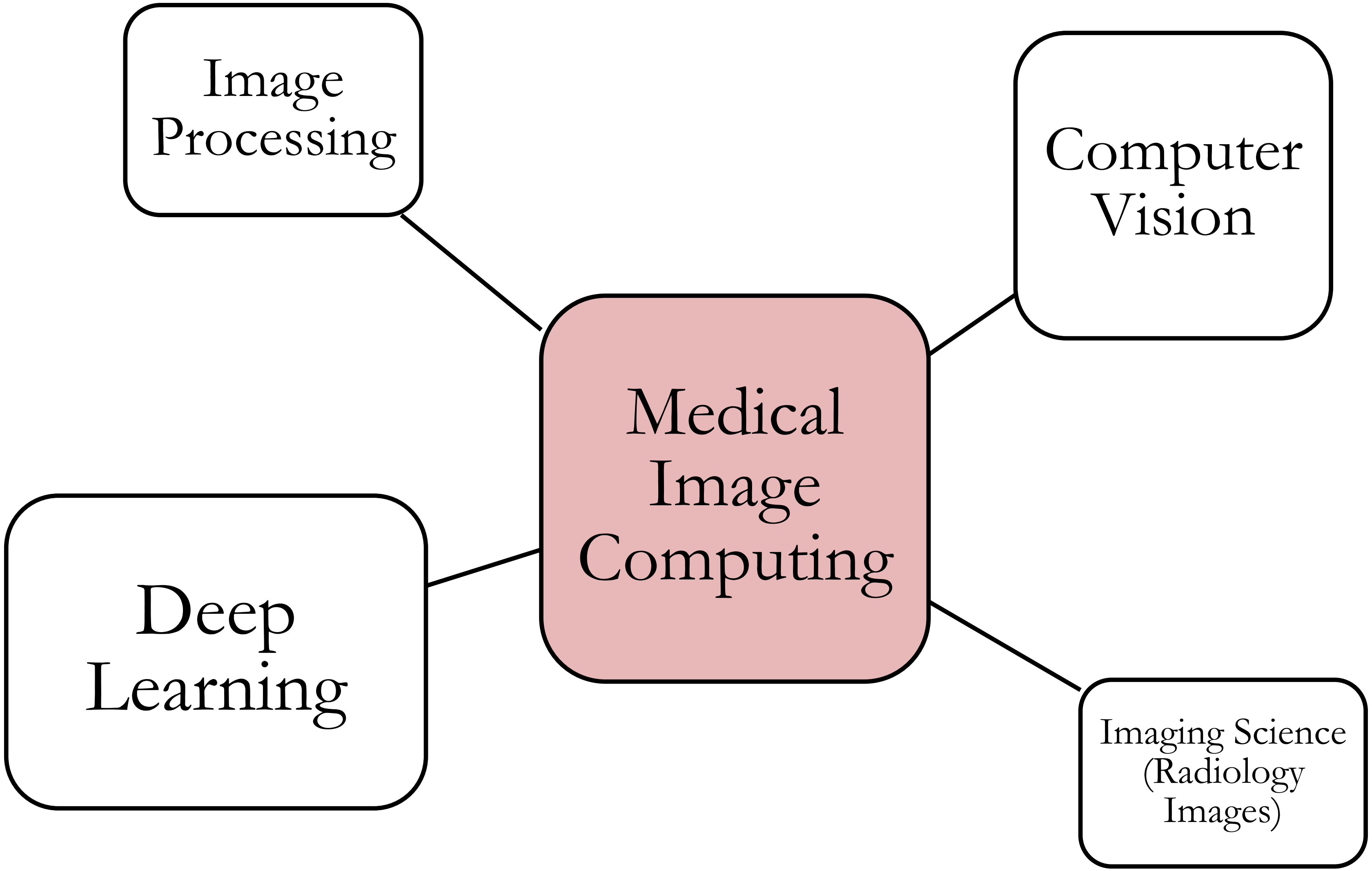
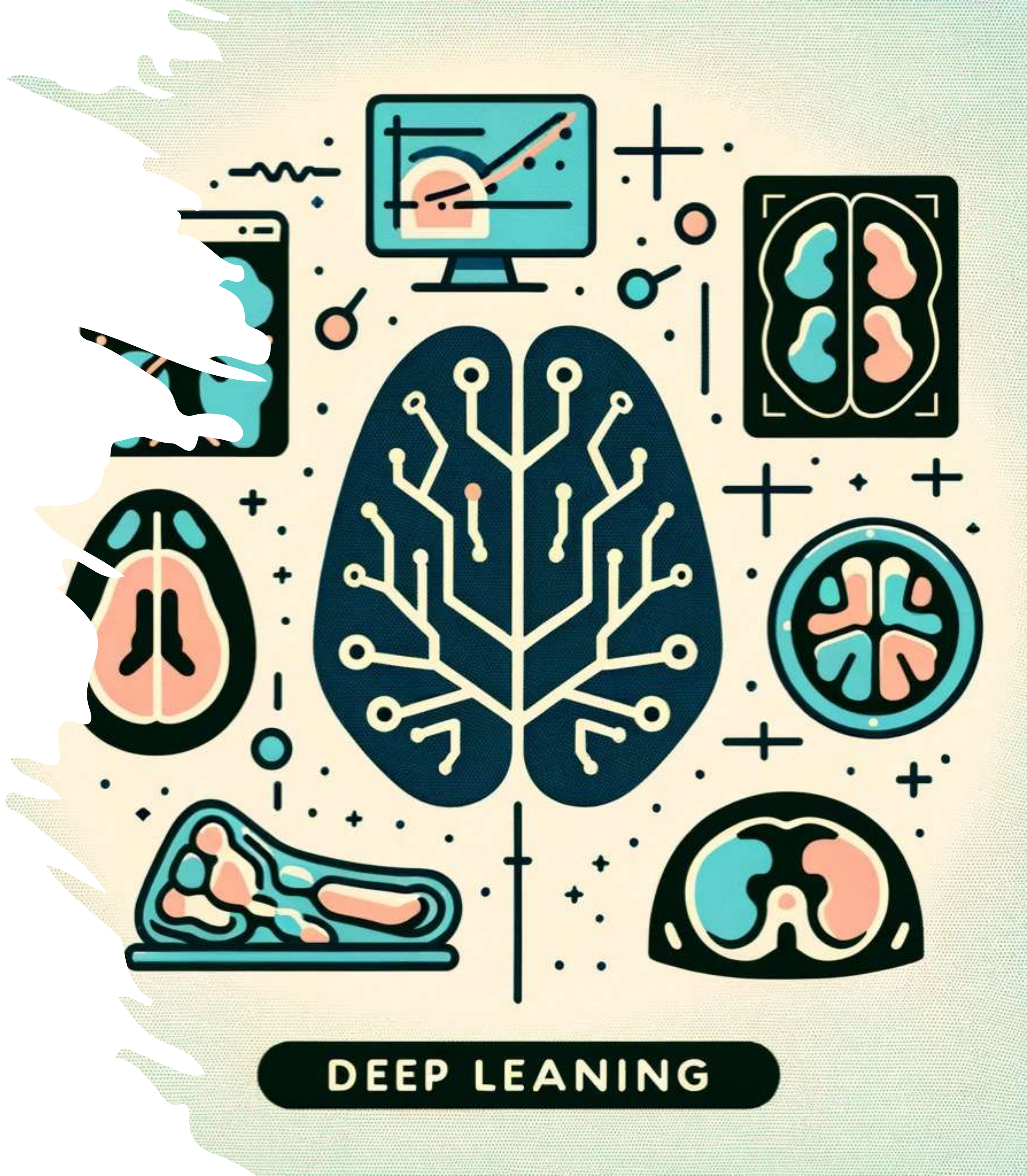


Image Processing
Computer Vision
Medical Image Computing
Deep Learning
Imaging Science (Radiology Images)

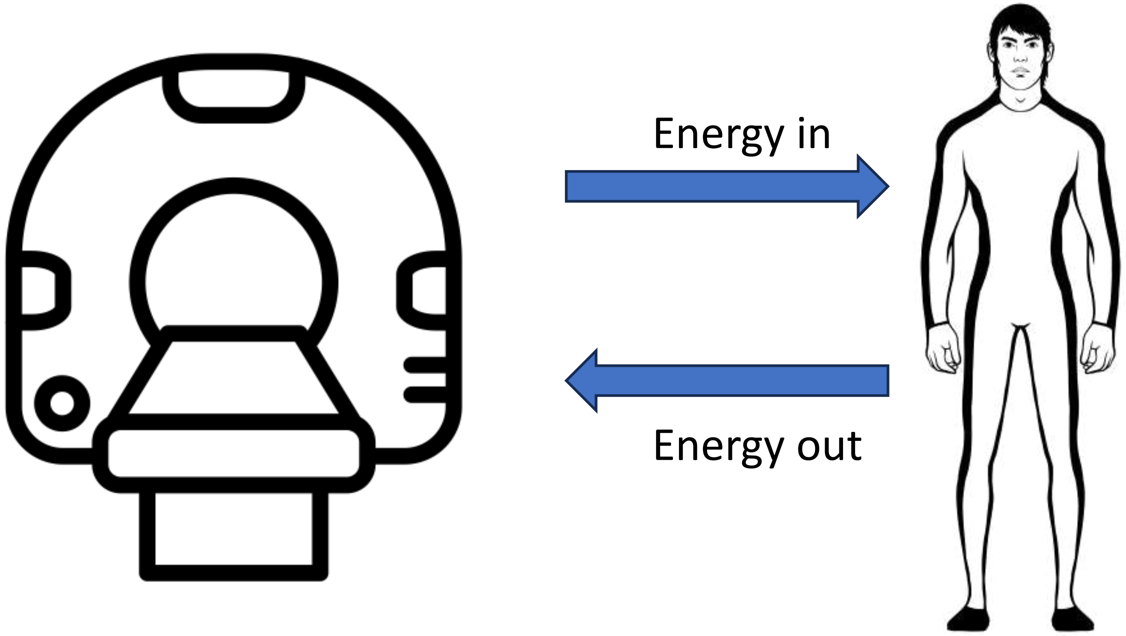
What is Medical Image Computing?



Why Medical Imaging?

- **Why**:
  - Assisting, identifying, intervening medical condition

- **How**:
  - Surgery
  - Endoscopy
  - Medical Imaging

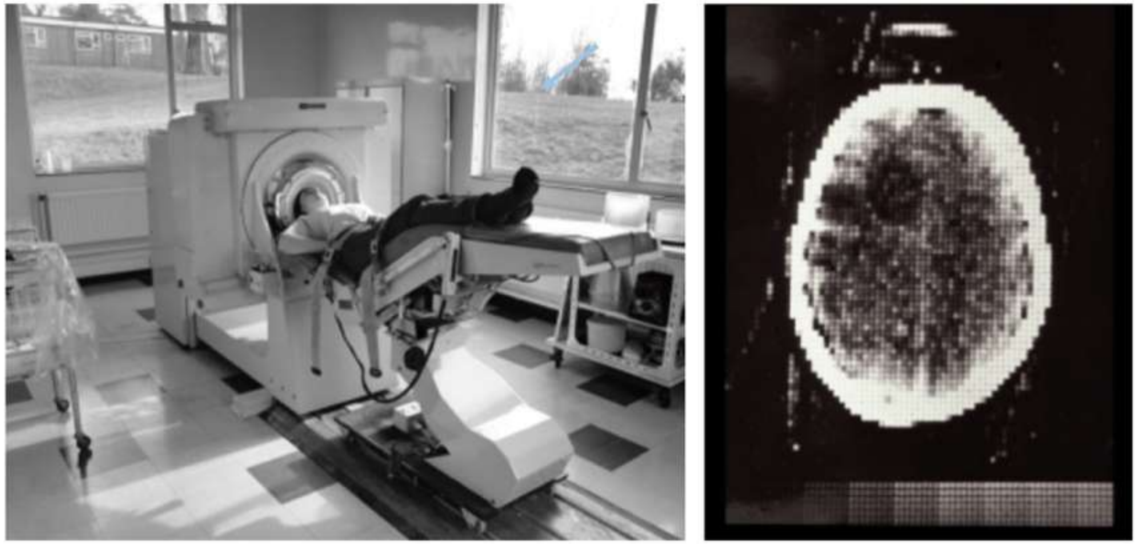


A bit of History

1895- X-Ray (Roentgen)

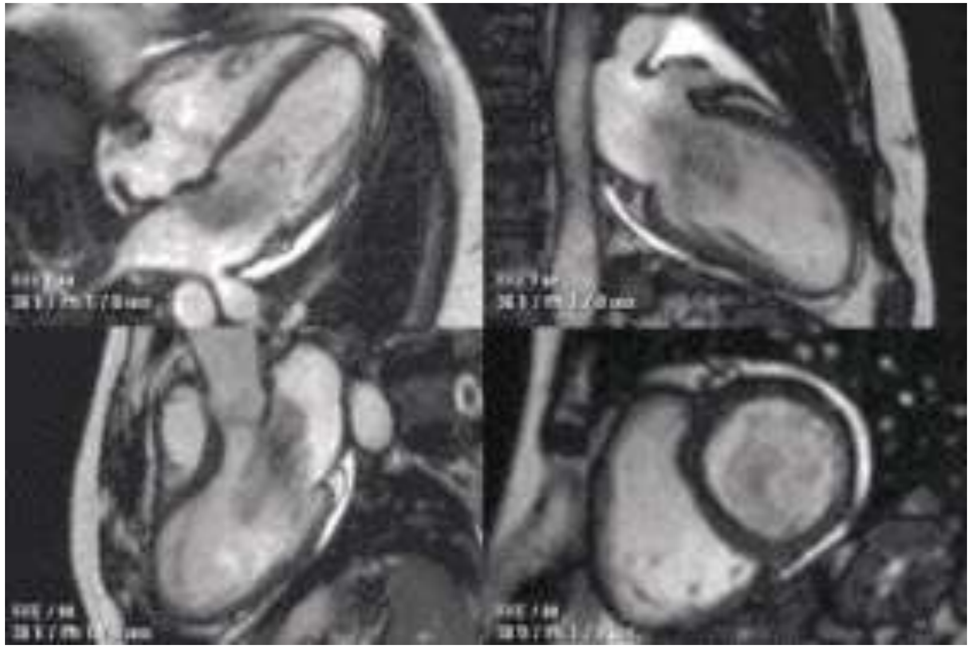
1950 Ultrasound (Wild, Ludwig,…)

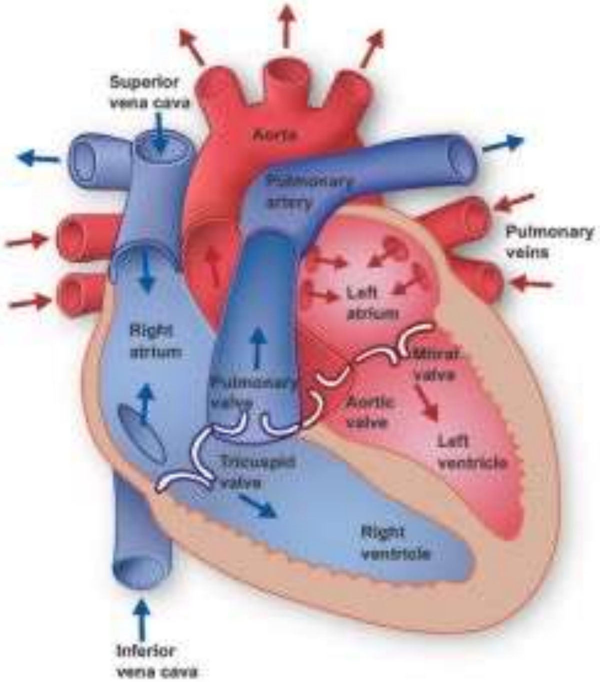
1971 MRI (Damadian)



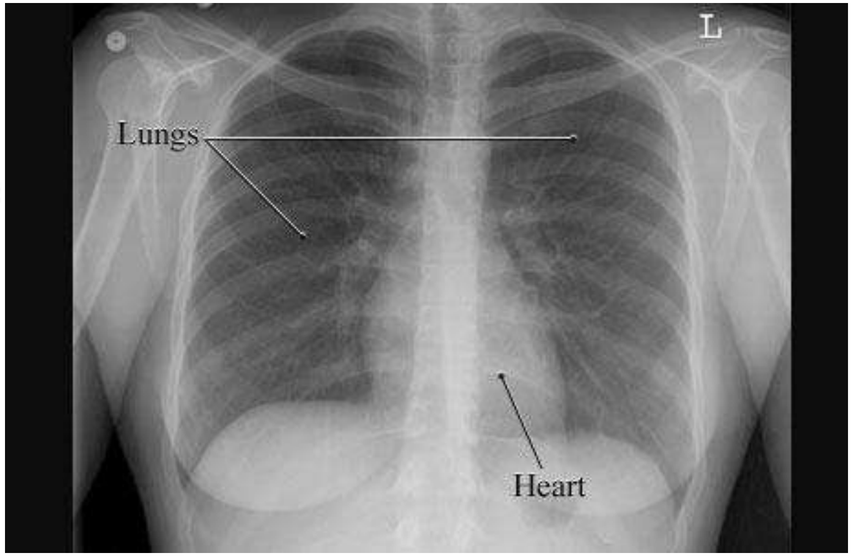
1972 X-Ray CT (Hounsfield and Cormack)

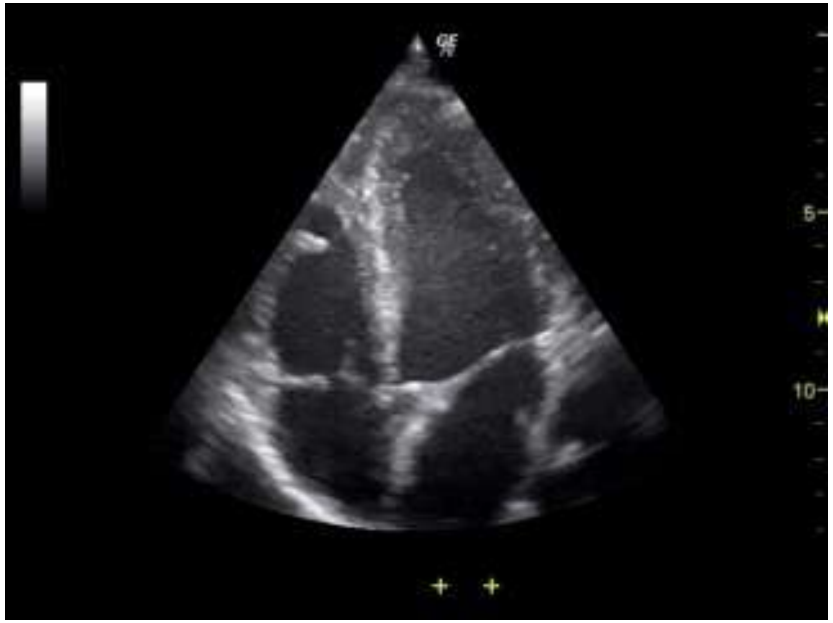
MRI



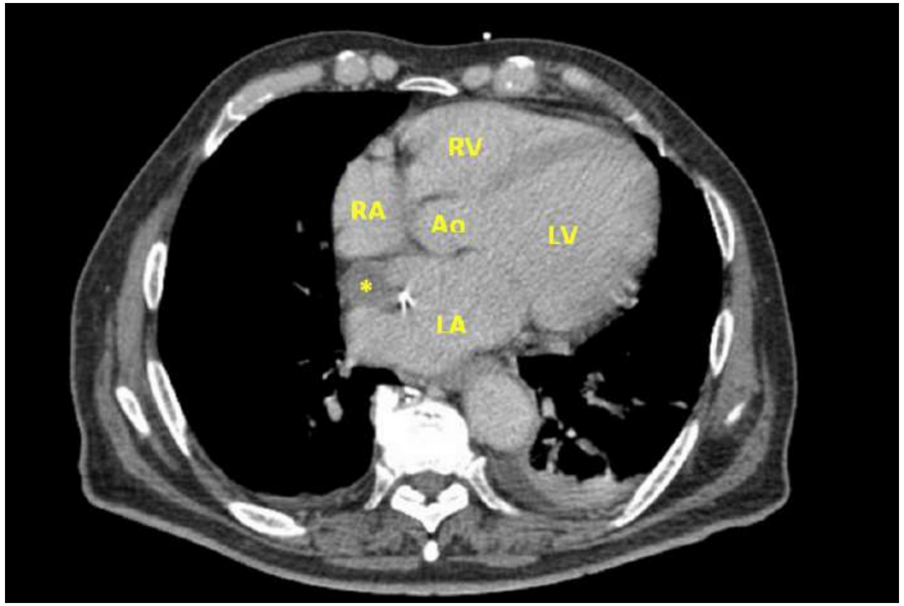


X-ray



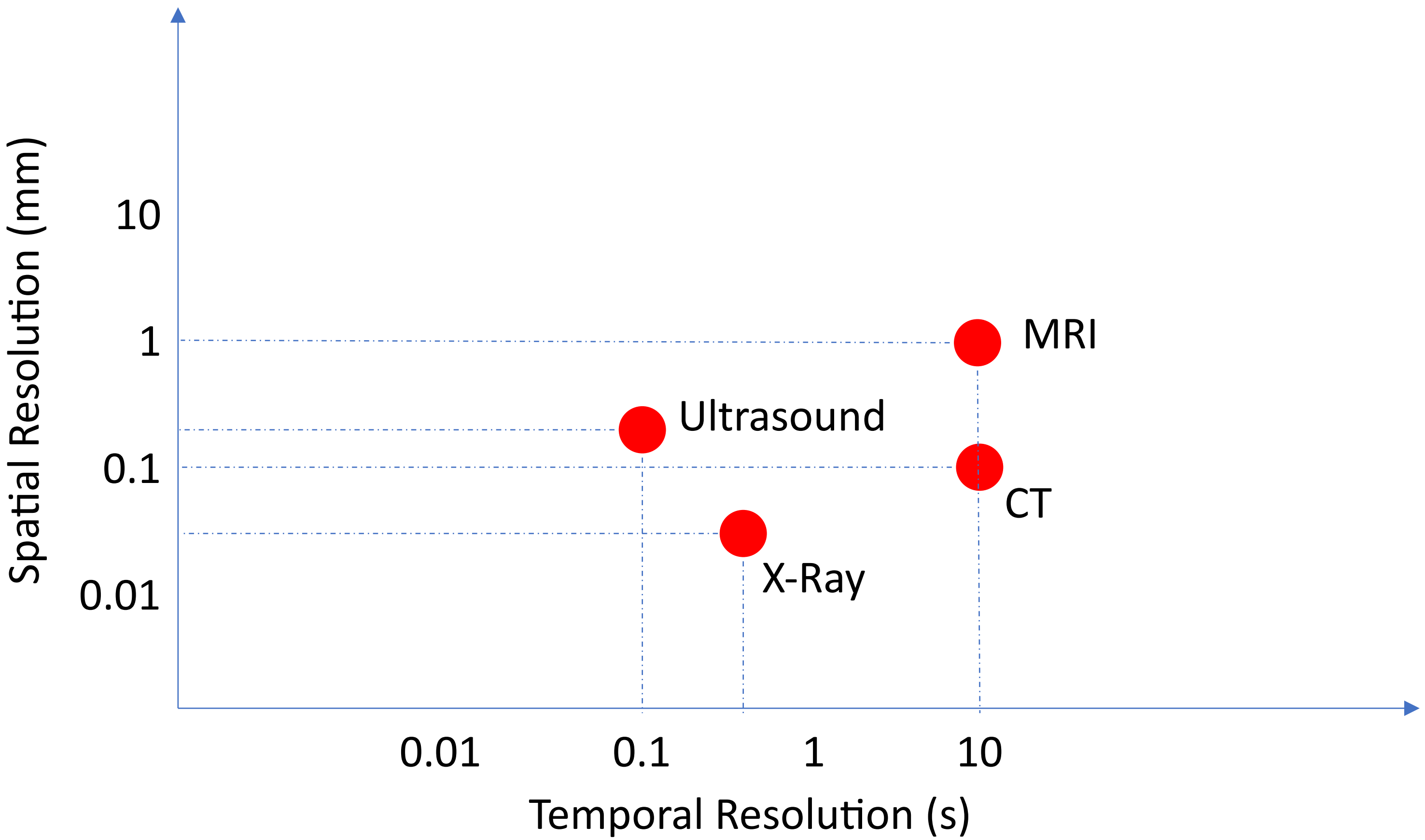


Ultrasound

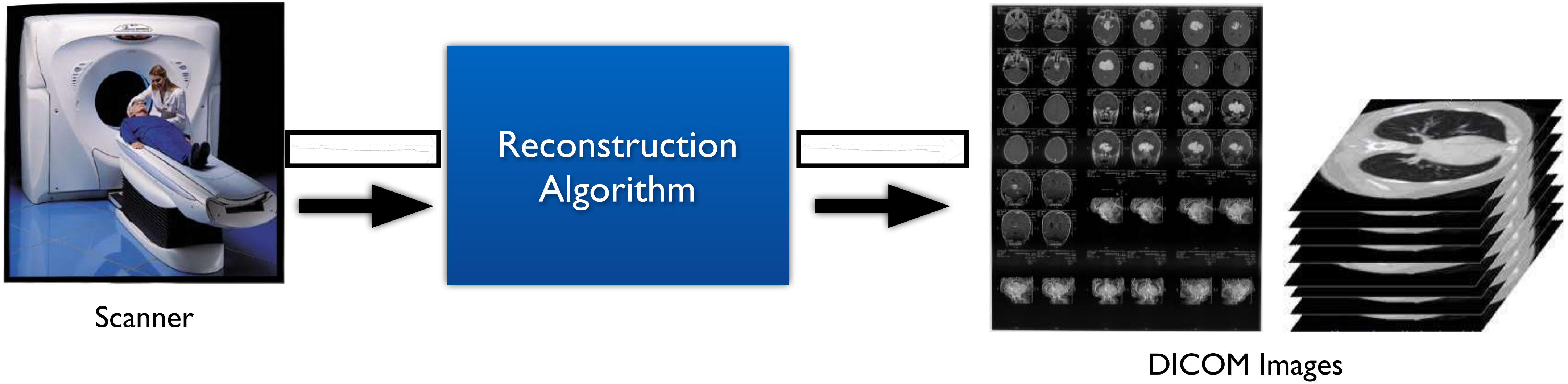


CT

Resolution Imaging Systems

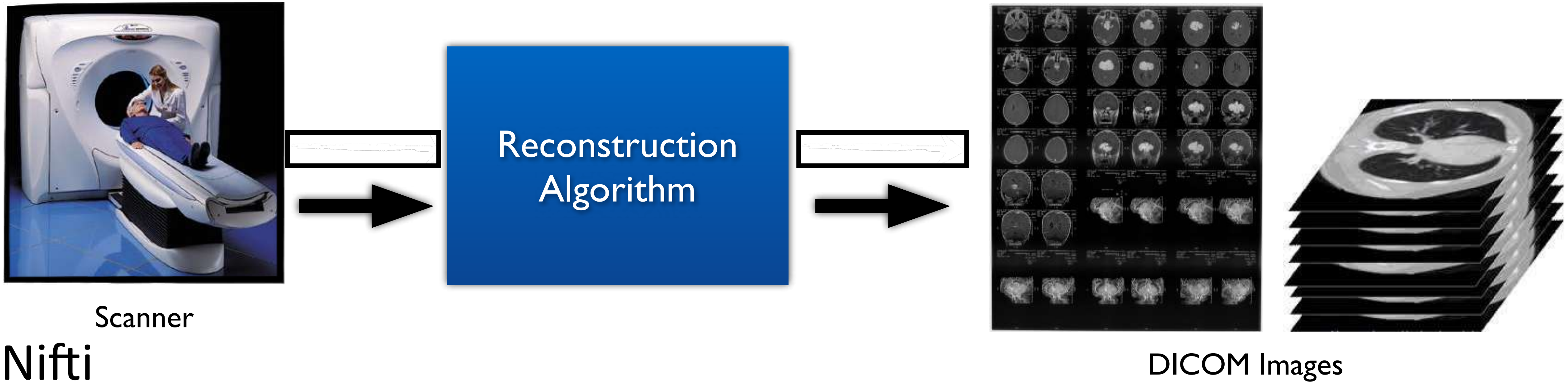


Medical Image Formats



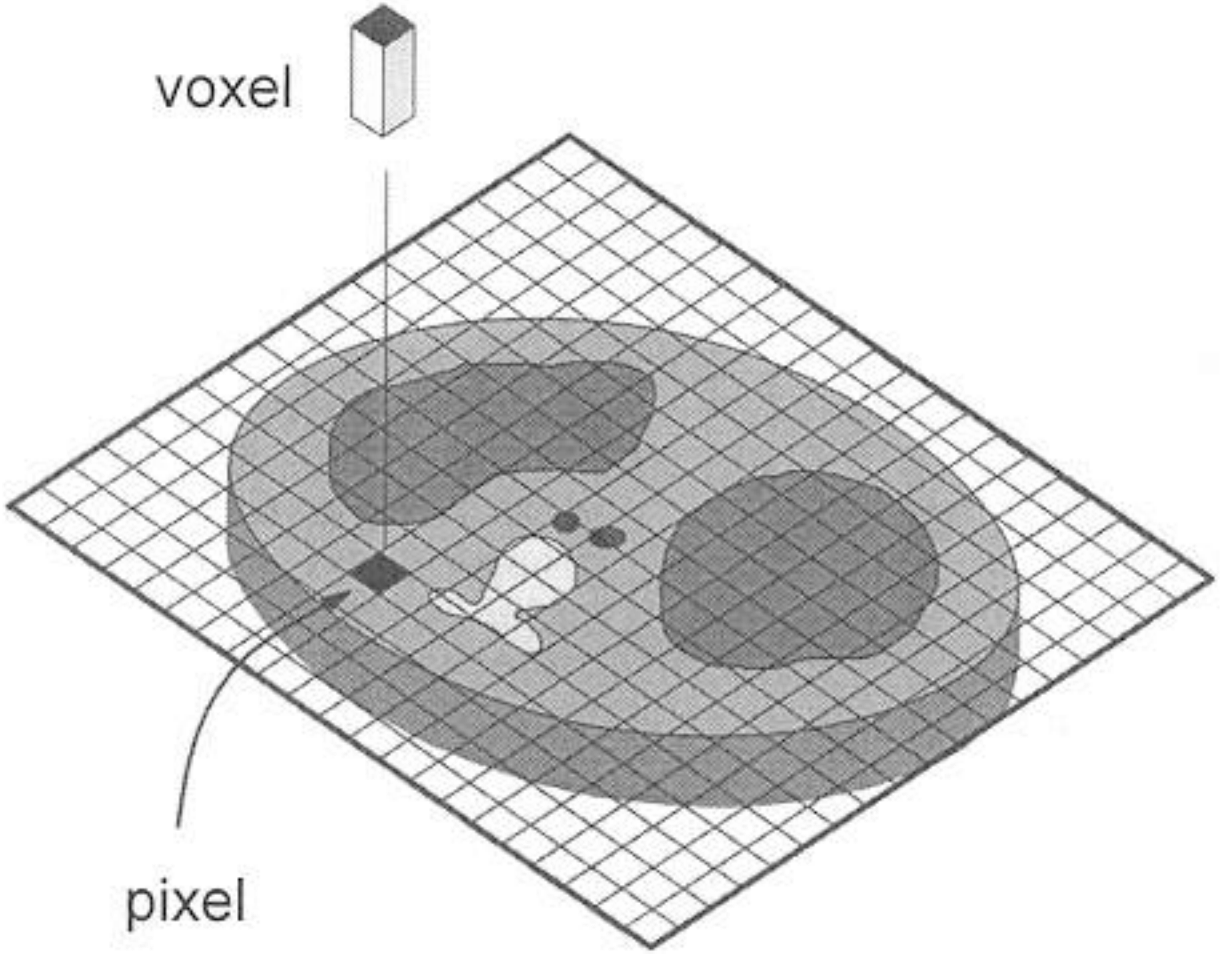
- Digital Imaging and Communications in Medicine standard (DICOM)
- It is *the* international standard for medical images and related information (ISO 12052)
- defines the formats for medical images that can be exchanged with the data and quality necessary for clinical use.

Medical Image Formats



- Nifti
- Analyze (img/hdr)
- Raw data
- …

Pixel vs Voxel



- The thickness of slice is in order of 1-10mm
- CT image consists of pixels
- **Voxel** is a 3D volume element represented by one pixel in a CT image

Image credit: http://Capone.mtsu.edu/phys4600/Syllabus/CT/Lecture_5/lecture_5.html

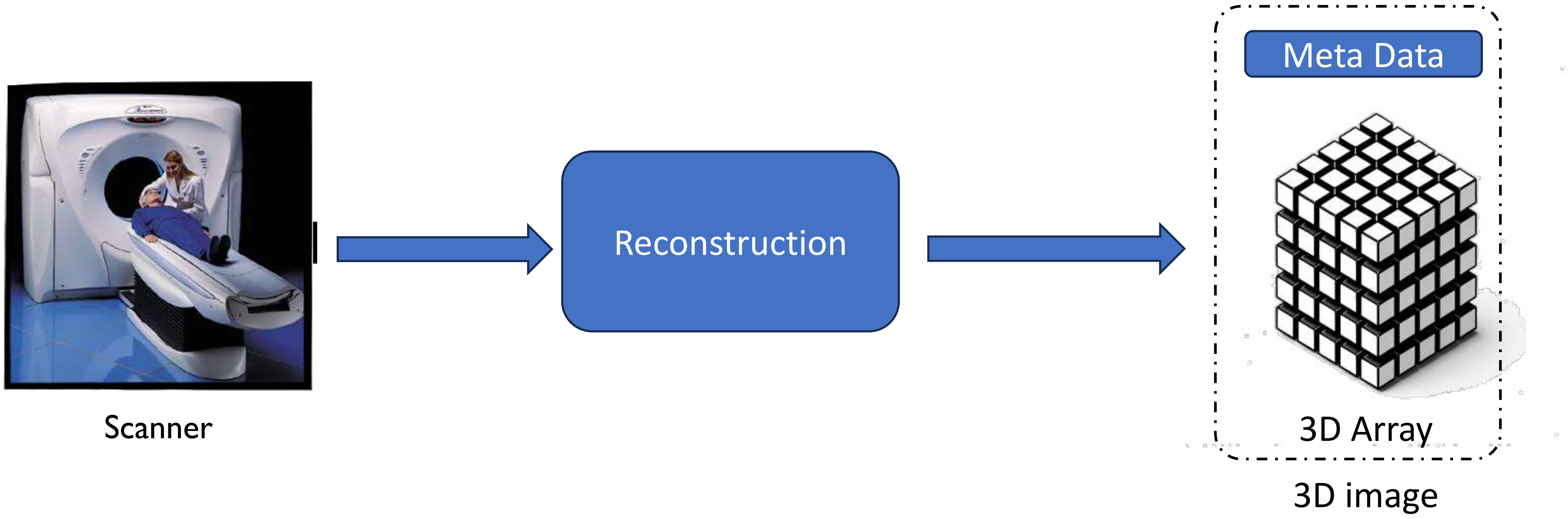
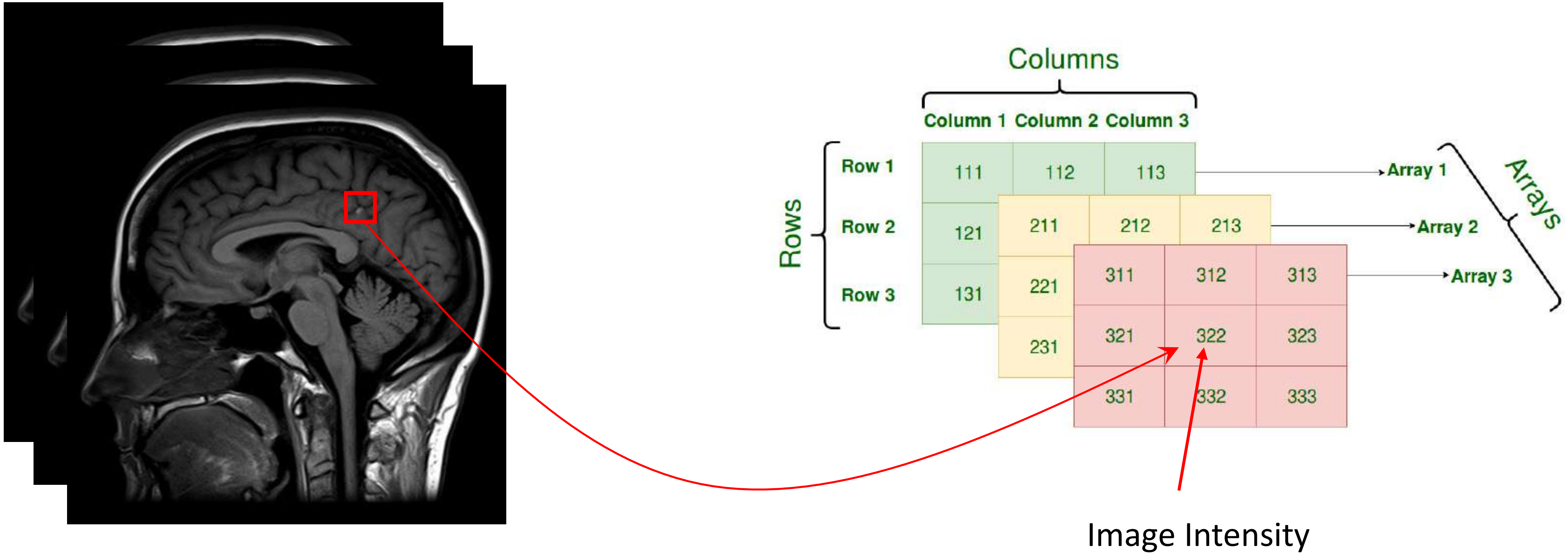
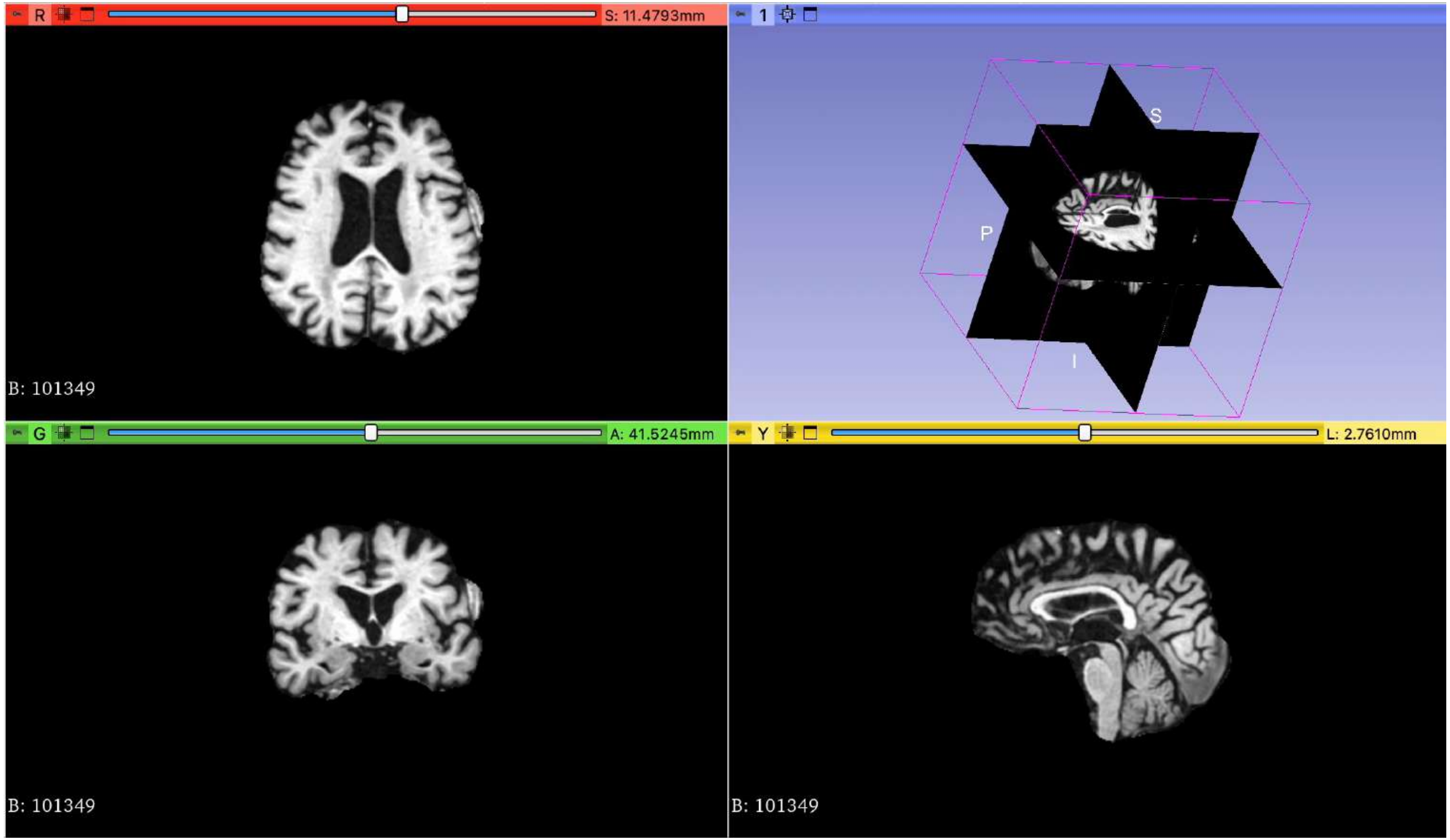

Scanner
Reconstruction
Meta Data
3D Array
3D image

Image Volume as 3D array of voxels



We can cut the three dimensional volume on any plane that we want to visualize it as an image.

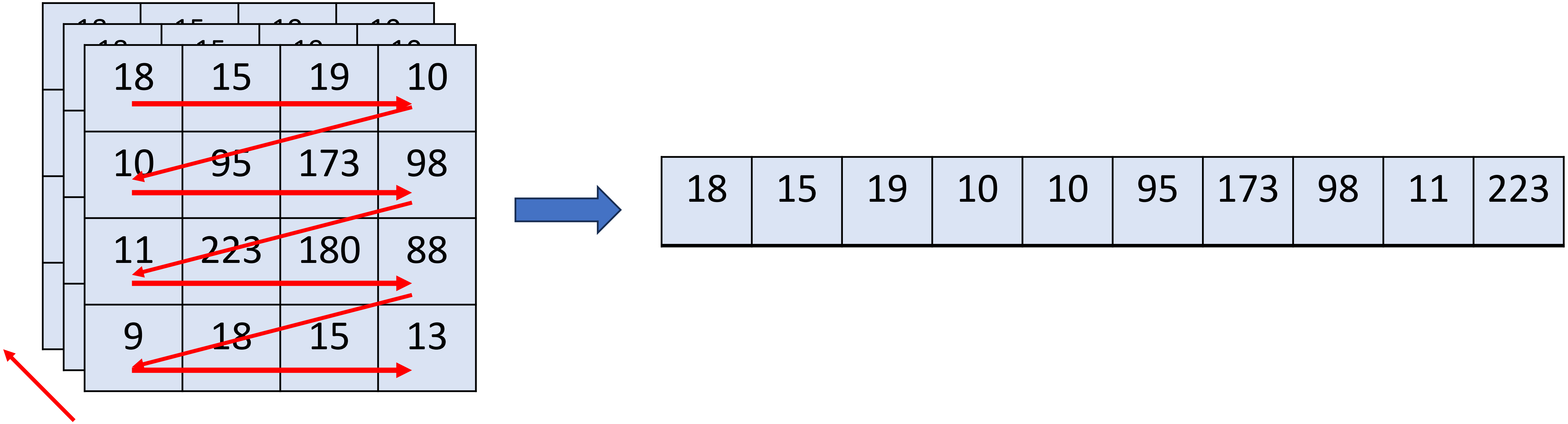


3DSlicer

Meta Data

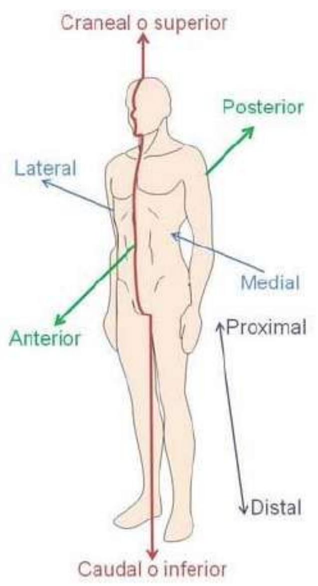
- Subject information
- Scanning parameters (e.g., TR/TE for MR)
- How image array is stored in disk
- Spatial extent, orientation of the image
- Physical meaning of the voxel intensity

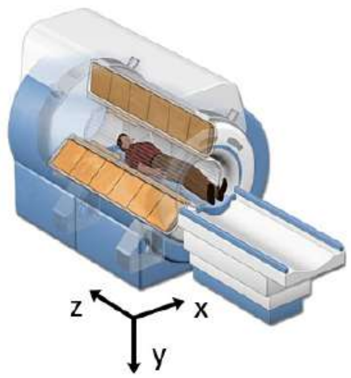
Order of travers is important



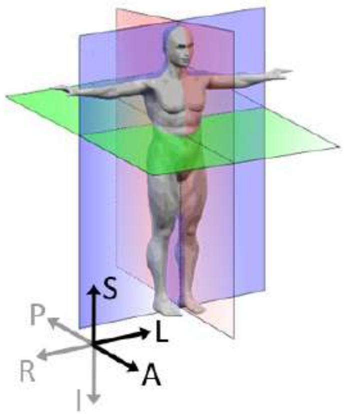
Coordinate System for Reading Files

- Multiple coordinate frames
  - Physical
  - Patient
  - Index





Physical



Patient

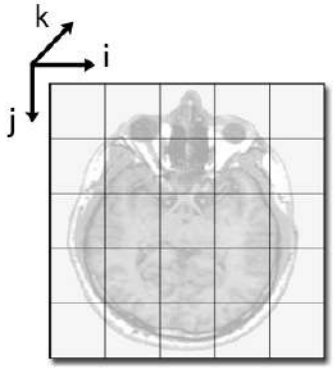
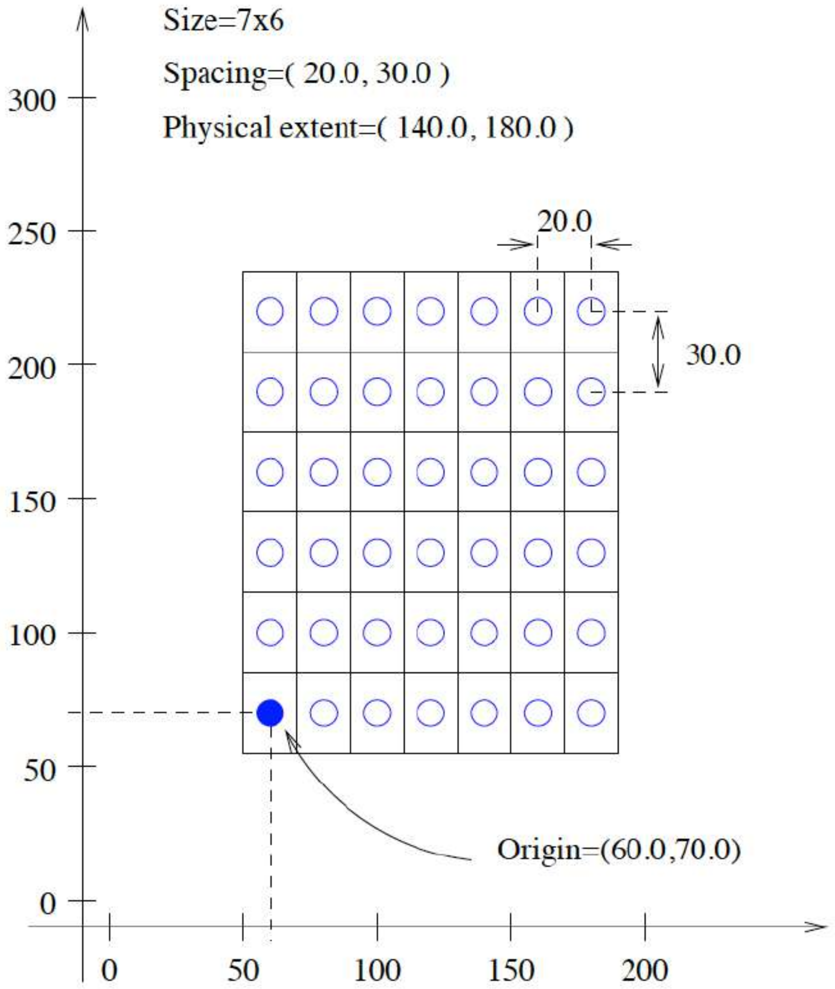


Image Index


Size=7x6
Spacing=(20.0, 30.0)
Physical extent=(140.0, 180.0)
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Origin=(60.0,70.0)
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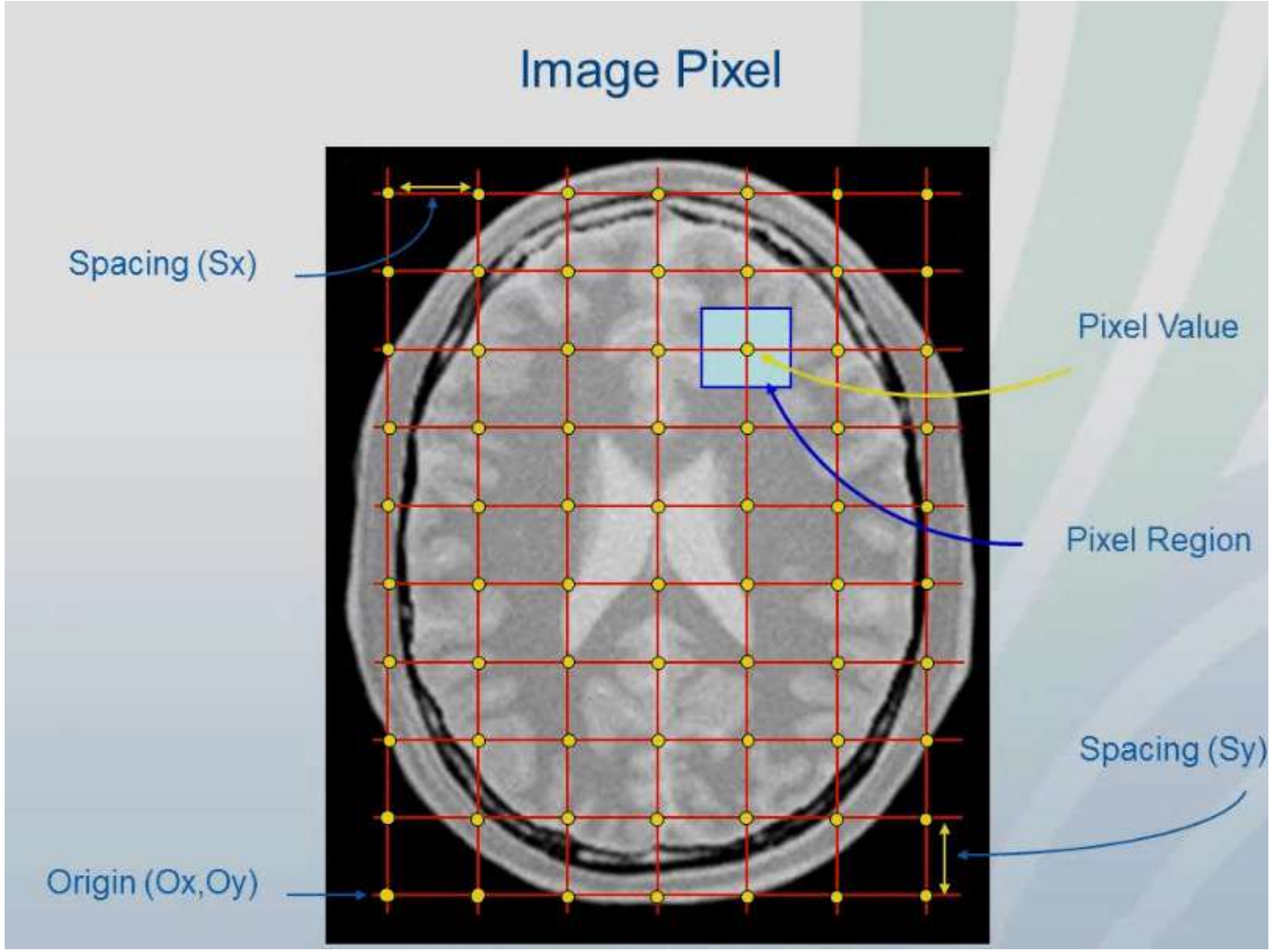


Image Pixel
Spacing (Sx)
Pixel Value
Pixel Region
Spacing (Sy)
Origin (Ox,Oy)

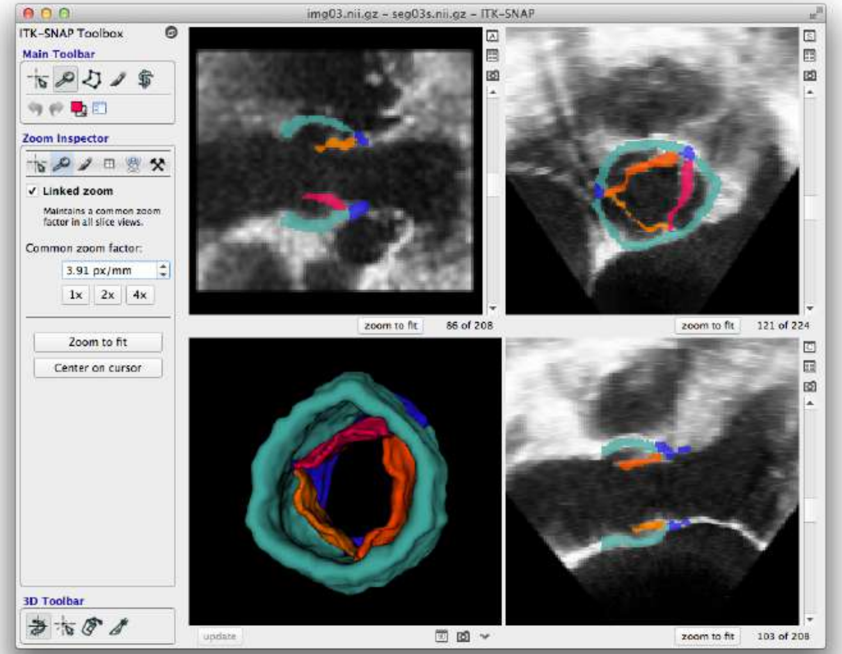
Nifti format (.nii or .nii.gz)

- Image is represented as 3D volume (or 4D or 5D)
- What is the example of 4D image?
- Limited meta-data
  - Spatial extent and orientation
  - Intention (anatomy, segmentation, stat-map, …)
  - No patient identifiers
- Great at storing derived data
- Can be compressed to reduce storage
- Best format to use in research

Free Software and Libraries to use in this course

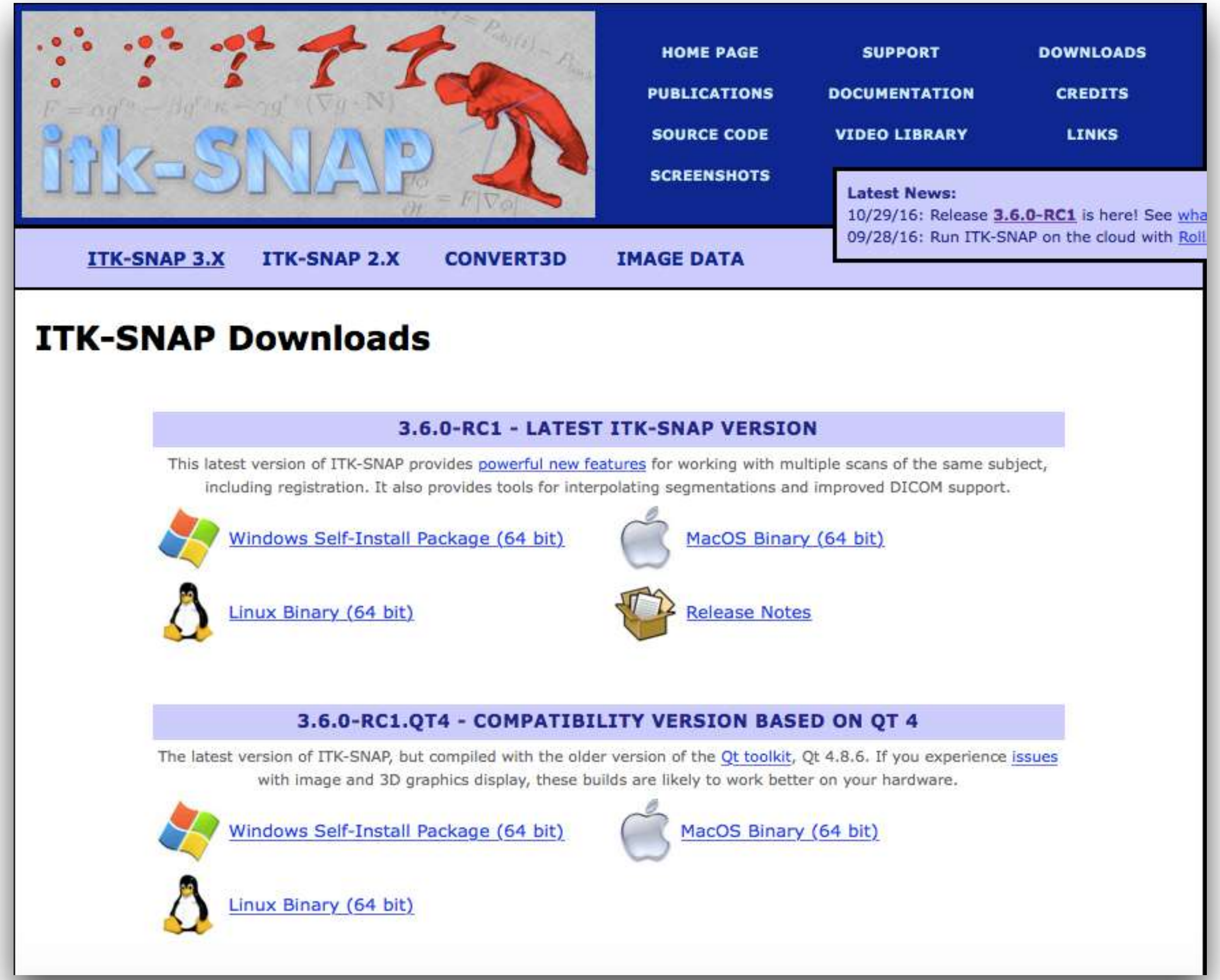
What is ITK-SNAP?

- Interactive tool for labeling structures in 3D medical image volumes
- Open-source C++ software with binaries provided for Windows, MacOS and Linux
- ITK-SNAP vision:
  - Easy to learn and use for clinicians and non-computer researchers
  - Limit features to those that directly support image segmentation
  - Minimize “feature creep”

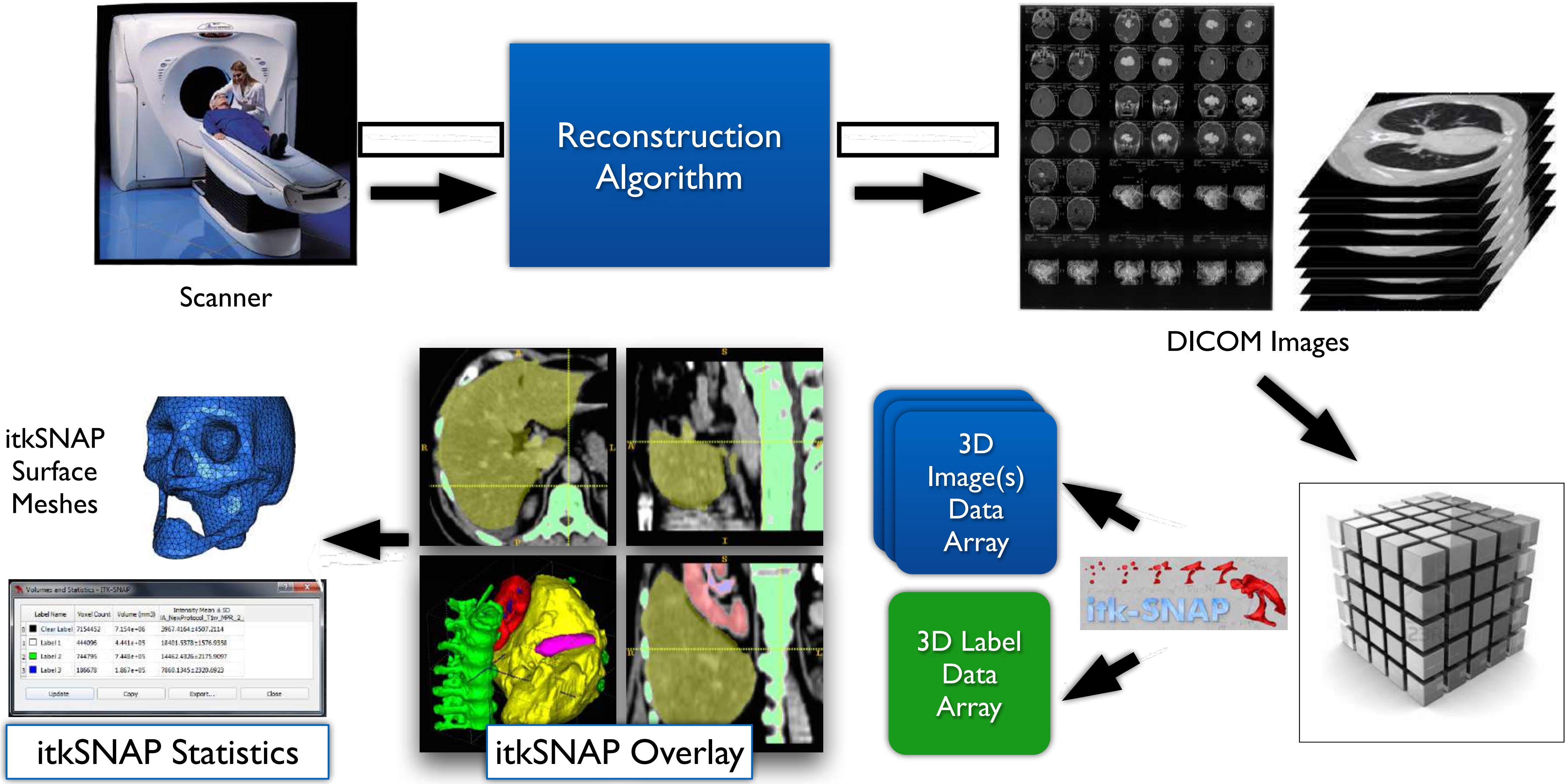


Website / Downloads

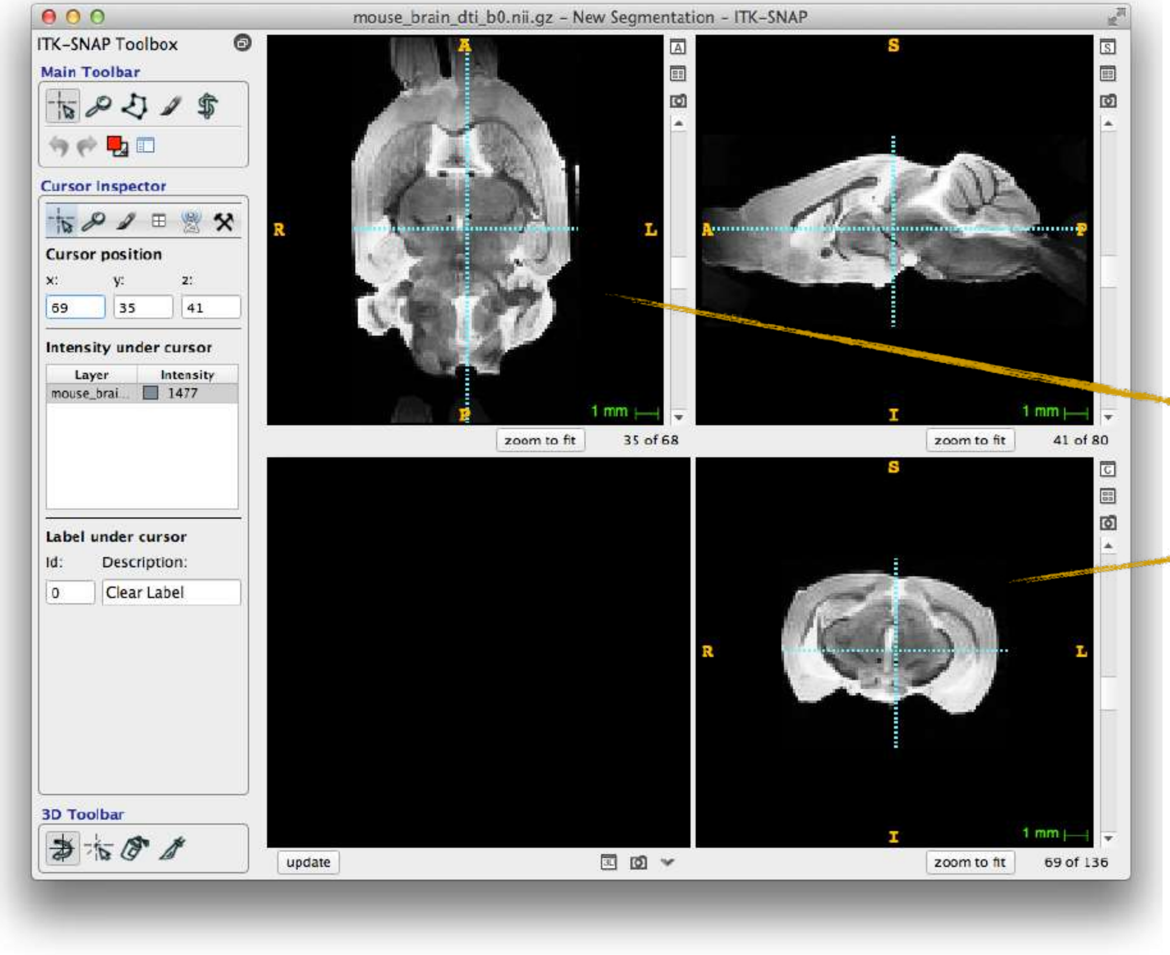
- itksnap.org
- Downloads
- Test Data
- Video Tutorials
- Convert3D

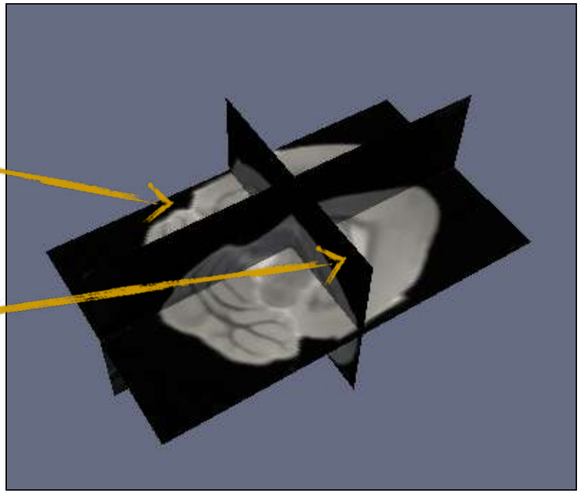


From Imaging to 3D Image Volumes



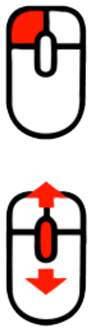
ITK-SNAP shows three orthogonal cuts through the image volume





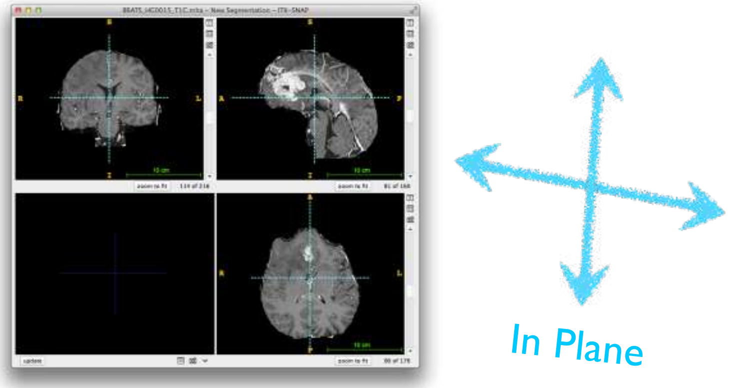
Using Navigation Tools

“Crosshairs Tool”

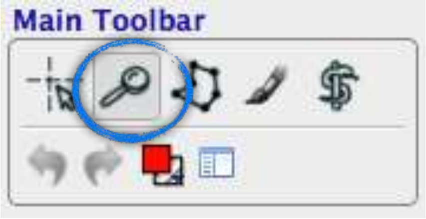


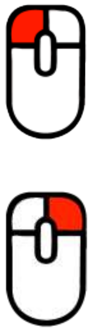
In-plane

Out-of-plane



“Zoom/Pan Tool”





Pan

Zoom

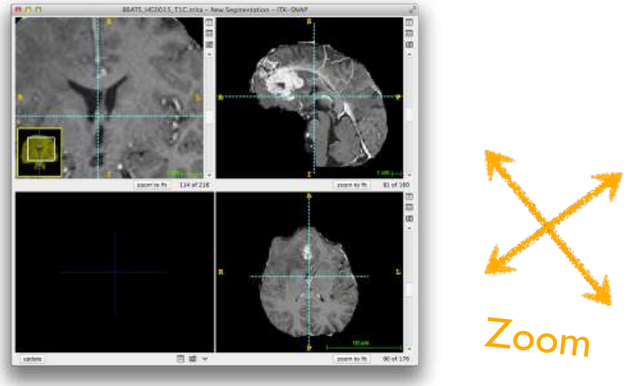
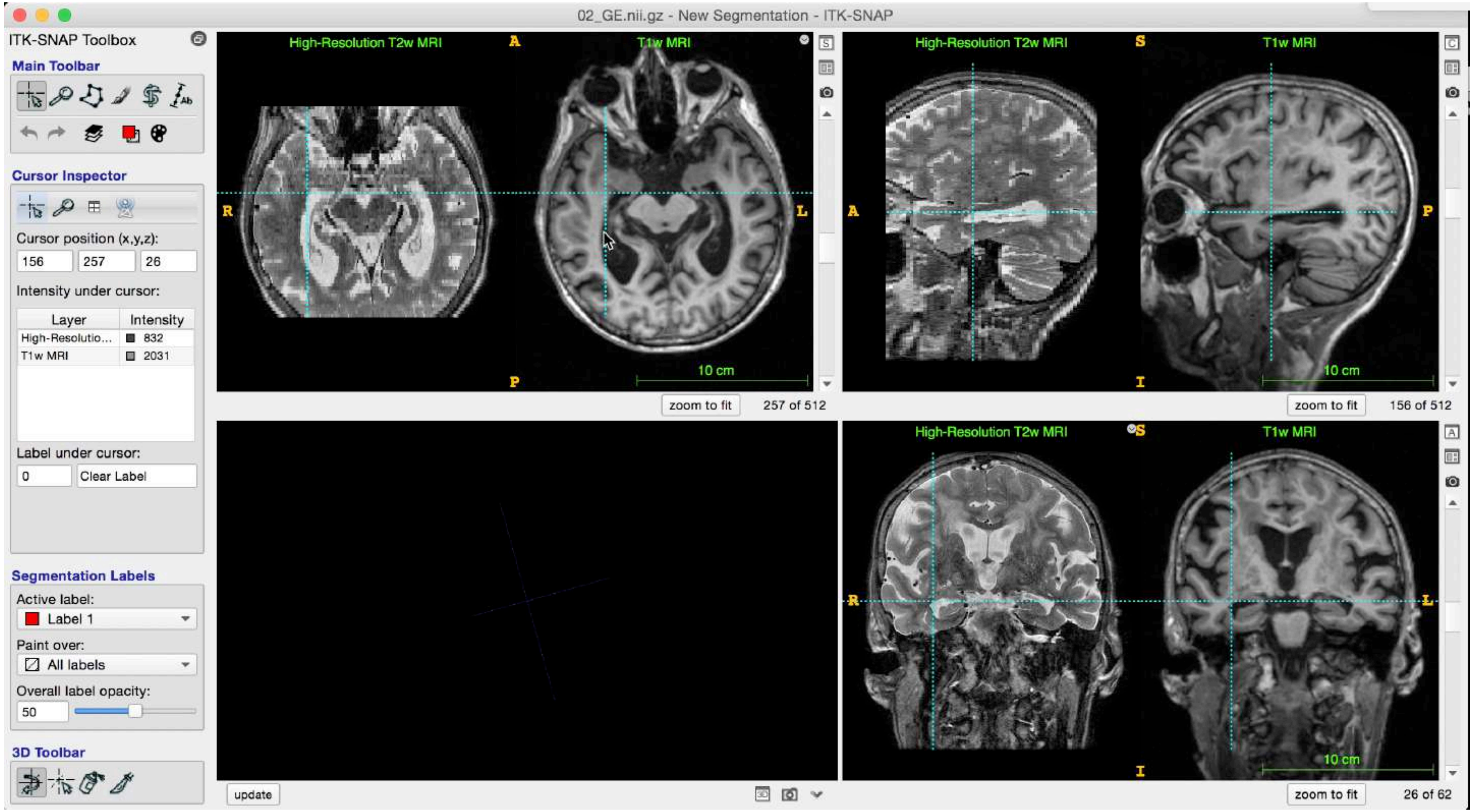
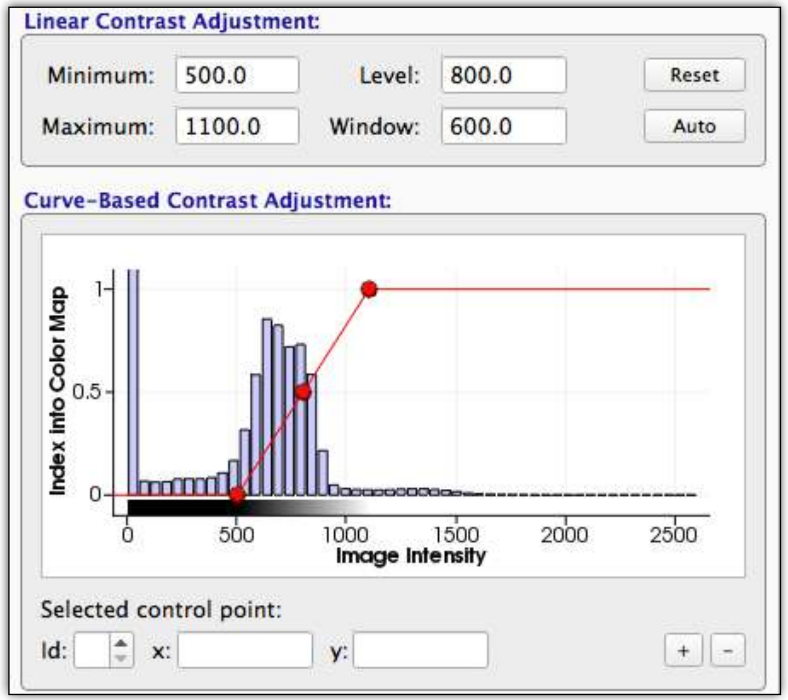
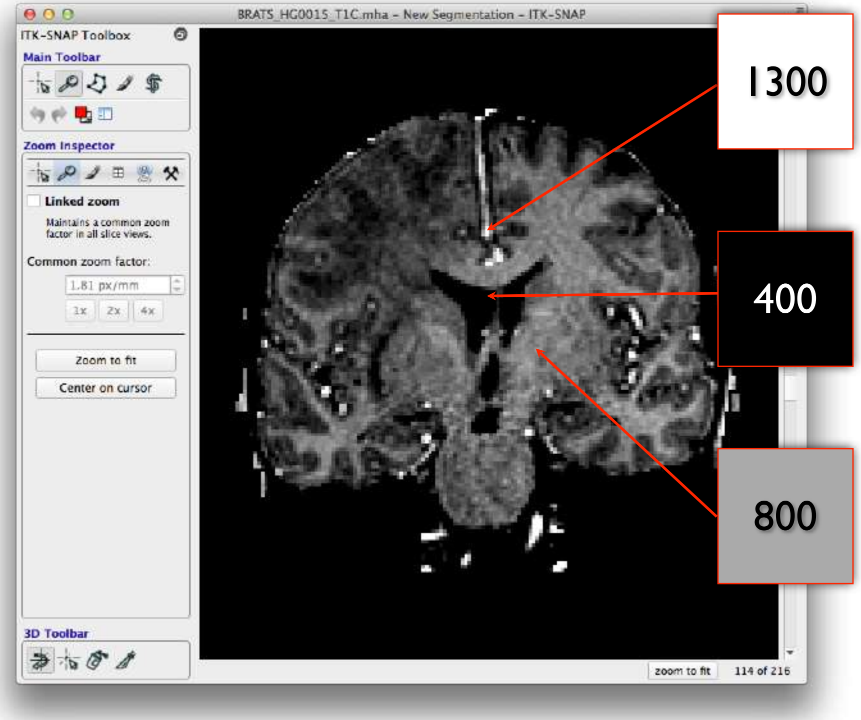


Image navigation with linked cursors



Window and Level

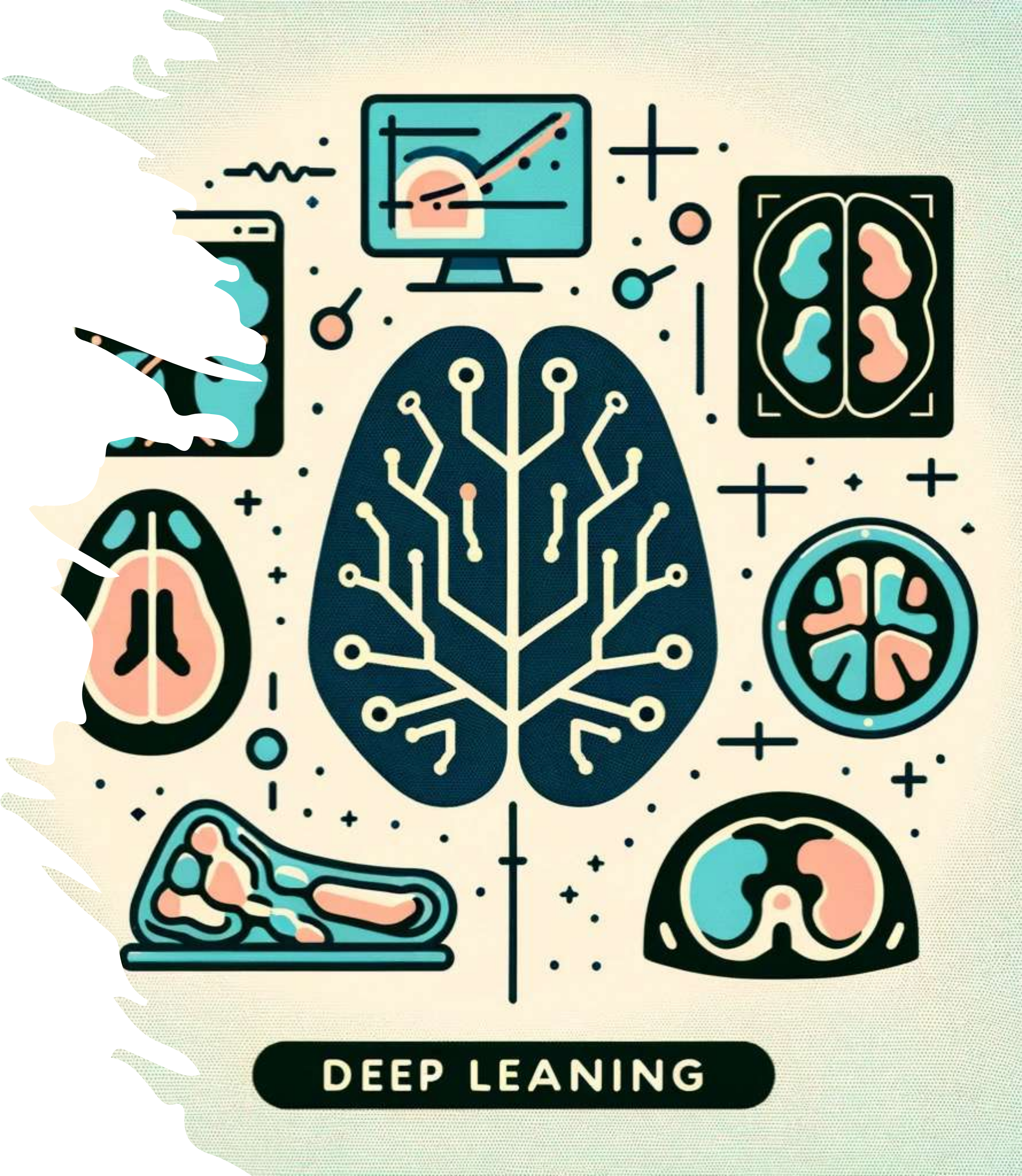




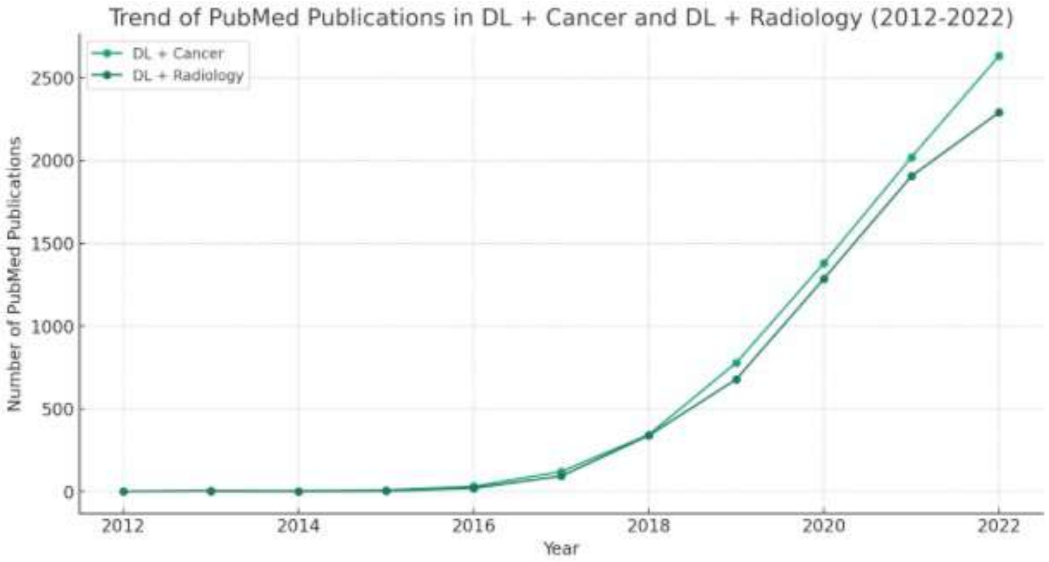
Watch this: https://www.youtube.com/watch?v=-tjVN5GwjKg

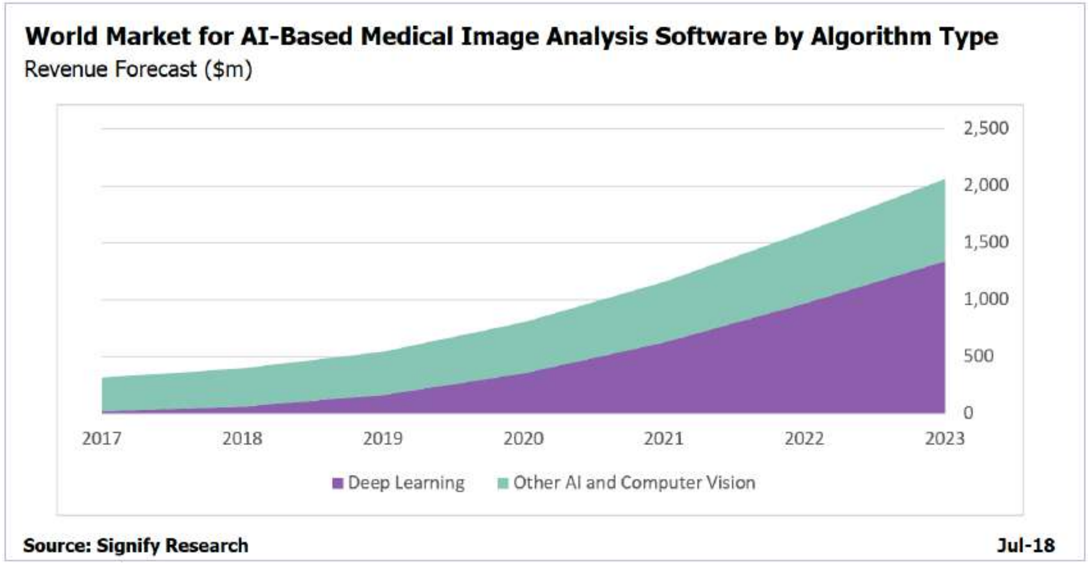
Demo

What is Deep Learning?



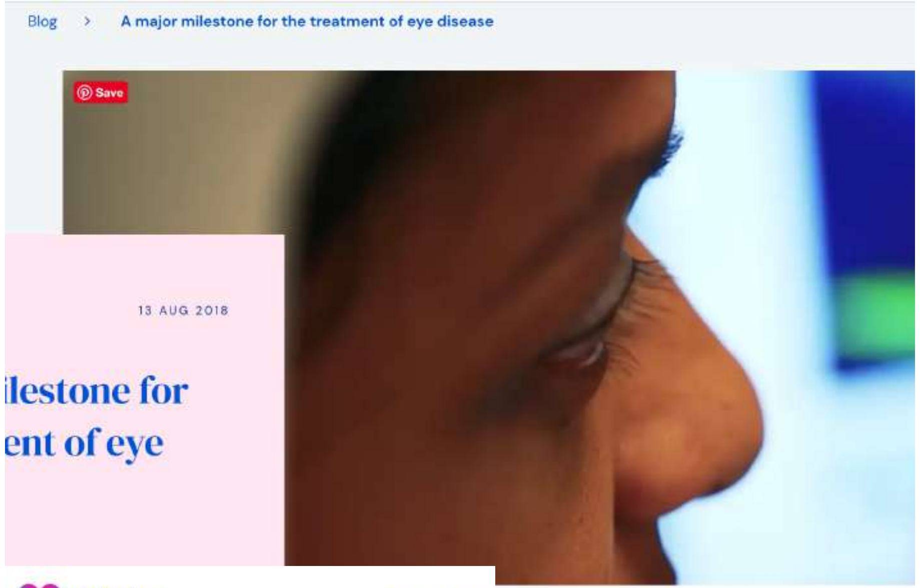
Why should we focus on Deep Learning?

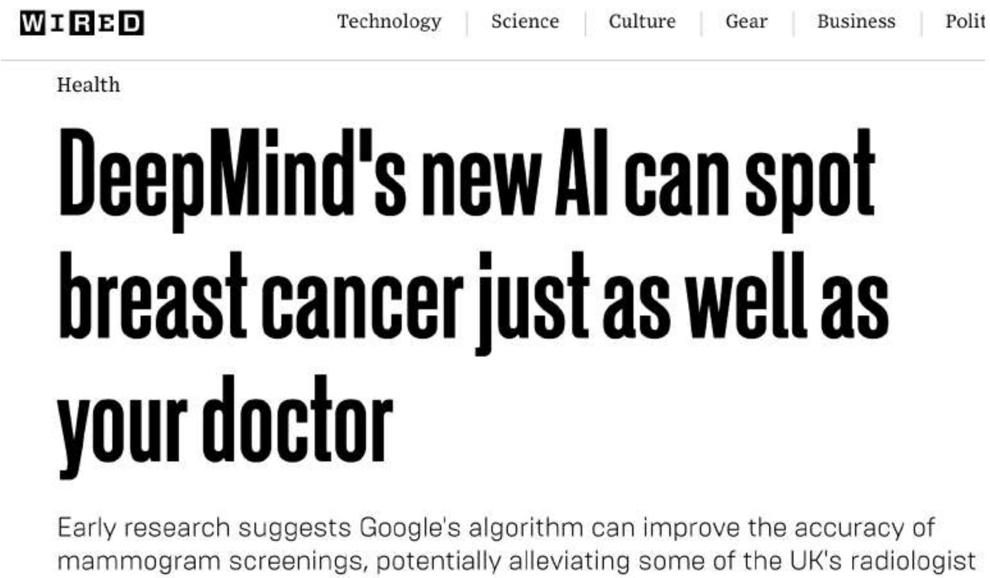




Giger, Maryellen L. "Machine learning in medical imaging." *Journal of the American College of Radiology* 15.3 (2018): 512-520.
https://www.prnewswire.com/news-releases/ai-in-medical-imaging-to-top-2-billion-by-2023-300691229.html

Why should we focus on Deep Learning?





1943: Warren McCulloch and Walter Pitts

- First computational model
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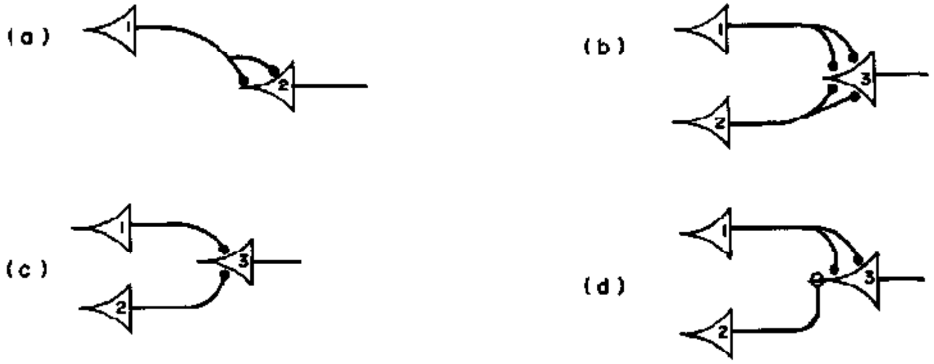
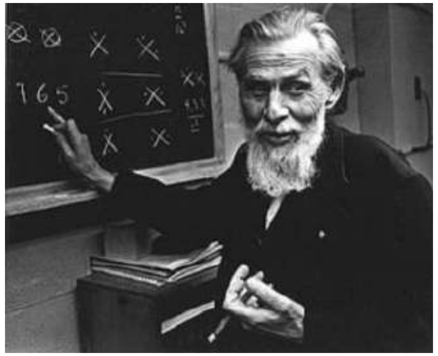
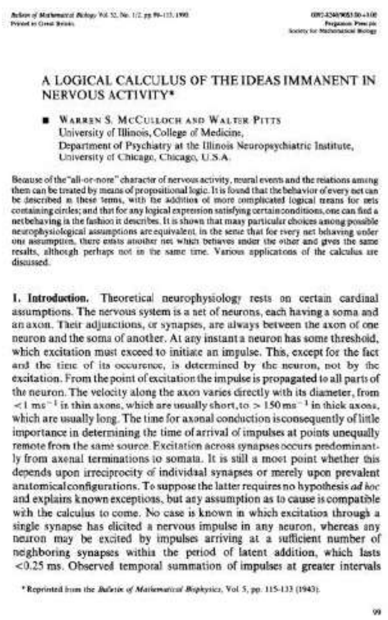
- A neuron model that sums binary inputs and outputs a 1 if the sum exceeds a certain threshold value, and otherwise outputs a 0







Bulletin of Mathematical Biology Vol. 52, No. 1/2, pp. 99-115, 1990
Printed in Great Britain.
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Society for Mathematical Biology

A LOGICAL CALCULUS OF THE IDEAS IMMANENT IN NERVOUS ACTIVITY*

WARREN S. MCCULLOCH AND WALTER PITTS
University of Illinois, College of Medicine,
Department of Psychiatry at the Illinois Neuropsychiatric Institute,
University of Chicago, Chicago, U.S.A.

Because of the "all-or-none" character of nervous activity, neural events and the relations among them can be treated by means of propositional logic. It is found that the behavior of every net can be described in these terms, with the addition of more complicated logical means for nets containing circles; and that for any logical expression satisfying certain conditions, one can find a net behaving in the fashion it describes. It is shown that many particular choices among possible neurophysiological assumptions are equivalent, in the sense that for every net behaving under one assumption, there exists another net which behaves under the other and gives the same results, although perhaps not in the same time. Various applications of the calculus are discussed.

1. Introduction. Theoretical neurophysiology rests on certain cardinal assumptions. The nervous system is a net of neurons, each having a soma and an axon. Their adjunctions, or synapses, are always between the axon of one neuron and the soma of another. At any instant a neuron has some threshold, which excitation must exceed to initiate an impulse. This, except for the fact and the time of its occurence, is determined by the neuron, not by the excitation. From the point of excitation the impulse is propagated to all parts of the neuron. The velocity along the axon varies directly with its diameter, from $<1\ \mathrm{ms}^{-1}$ in thin axons, which are usually short, to $>150\ \mathrm{ms}^{-1}$ in thick axons, which are usually long. The time for axonal conduction is consequently of little importance in determining the time of arrival of impulses at points unequally remote from the same source. Excitation across synapses occurs predominantly from axenal terminations to somata. It is still a moot point whether this depends upon irreciprocity of individual synapses or merely upon prevalent anatomical configurations. To suppose the latter requires no hypothesis *ad hoc* and explains known exceptions, but any assumption as to cause is compatible with the calculus to come. No case is known in which excitation through a single synapse has elicited a nervous impulse in any neuron, whereas any neuron may be excited by impulses arriving at a sufficient number of neighboring synapses within the period of latent addition, which lasts <0.25 ms. Observed temporal summation of impulses at greater intervals

* Reprinted from the *Bulletin of Mathematical Biophysics*, Vol. 5, pp. 115-133 (1943).

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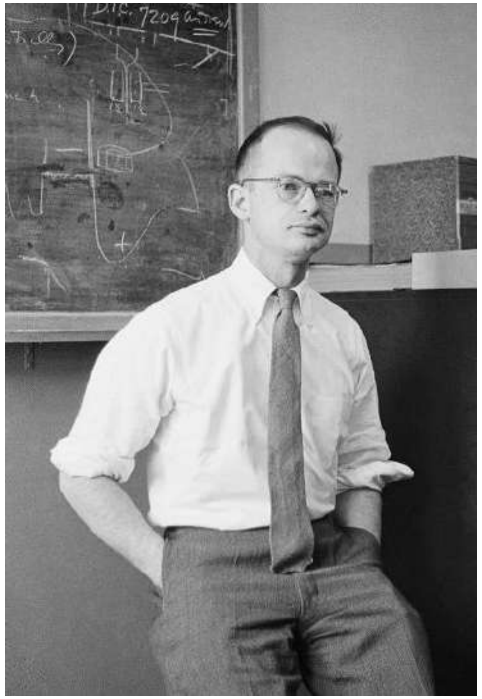

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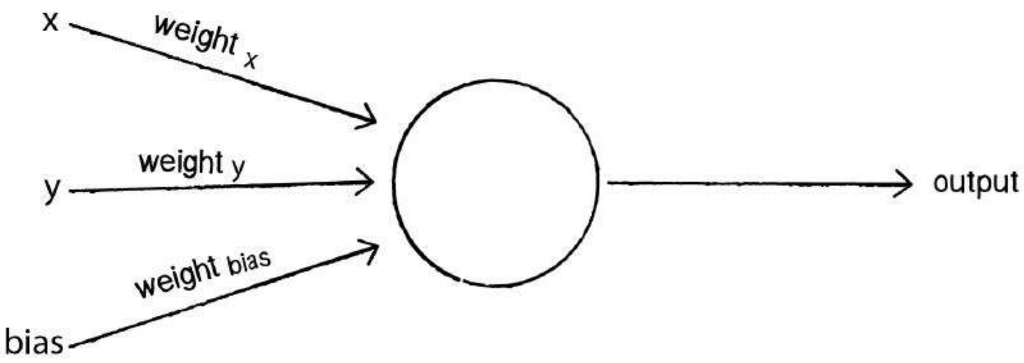
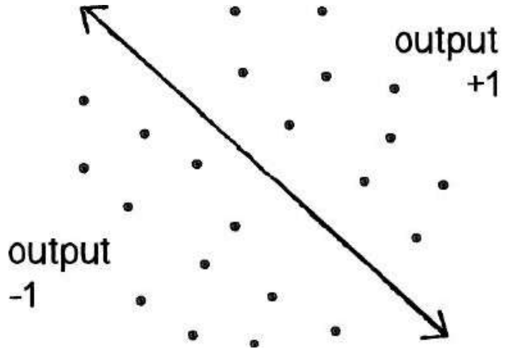
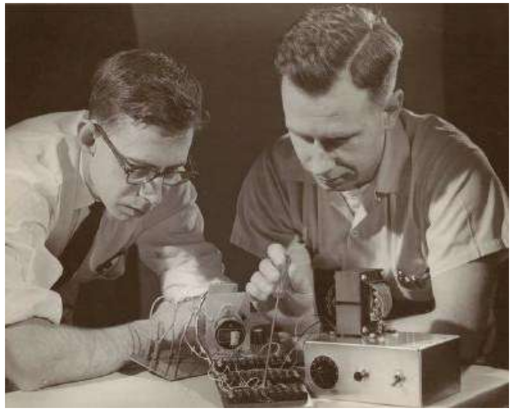
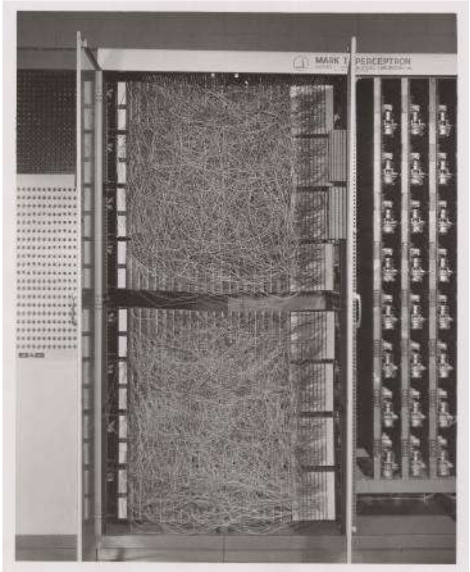
1958: Frank Rosenblatt’s Perceptron

- A computational model of a **single neuron**
- Solves a **binary classification problem**
- Simple training algorithm
- Built using specialized hardware









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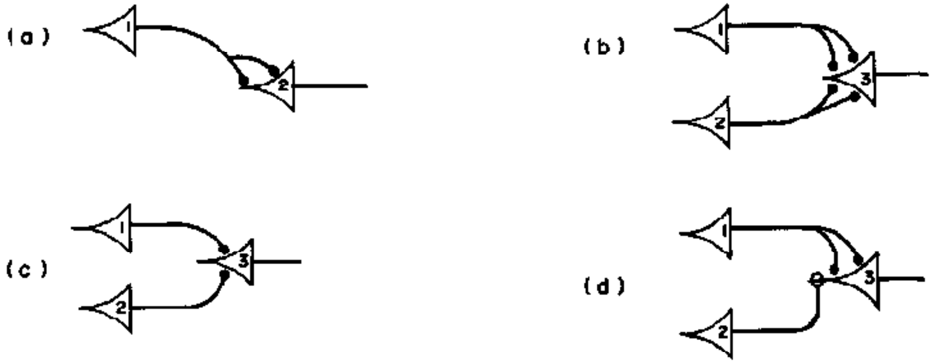

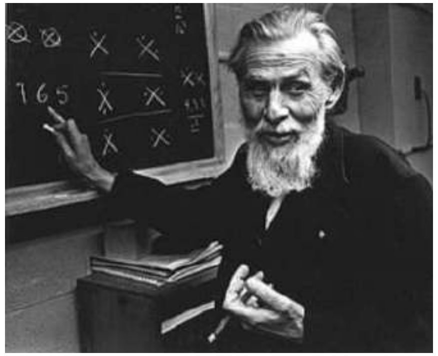

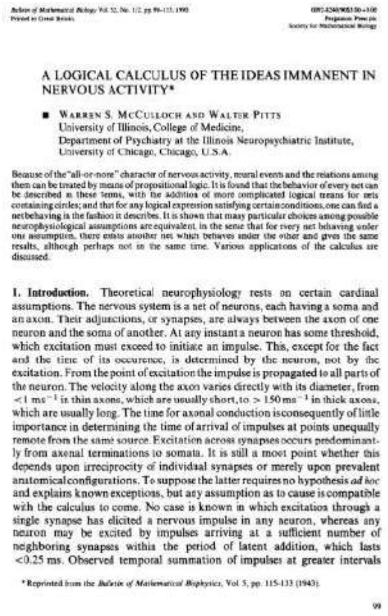

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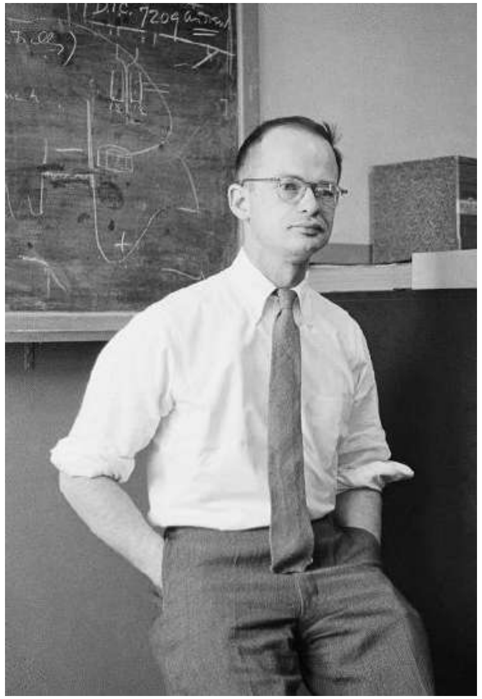

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AI Winter


2012

Slide credit: Deep Learning by Prof. Kosta Derpanis

ImageNet Classification with Deep Convolutional Neural Networks

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kriz@cs.utoronto.ca

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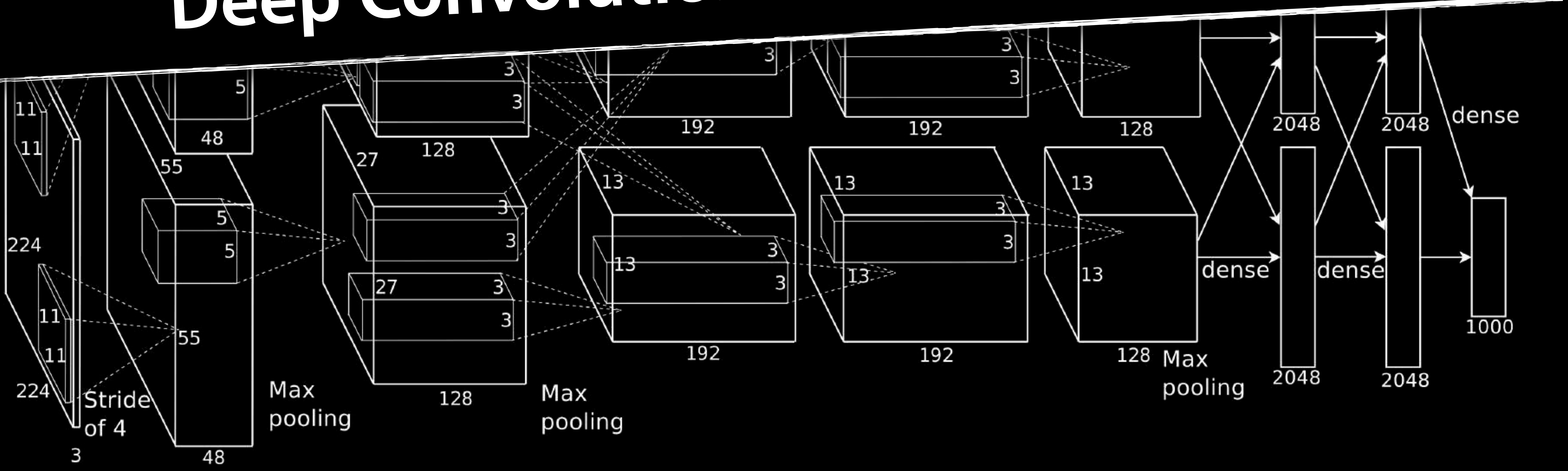
Abstract

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

Deep Convolutional Neural Network



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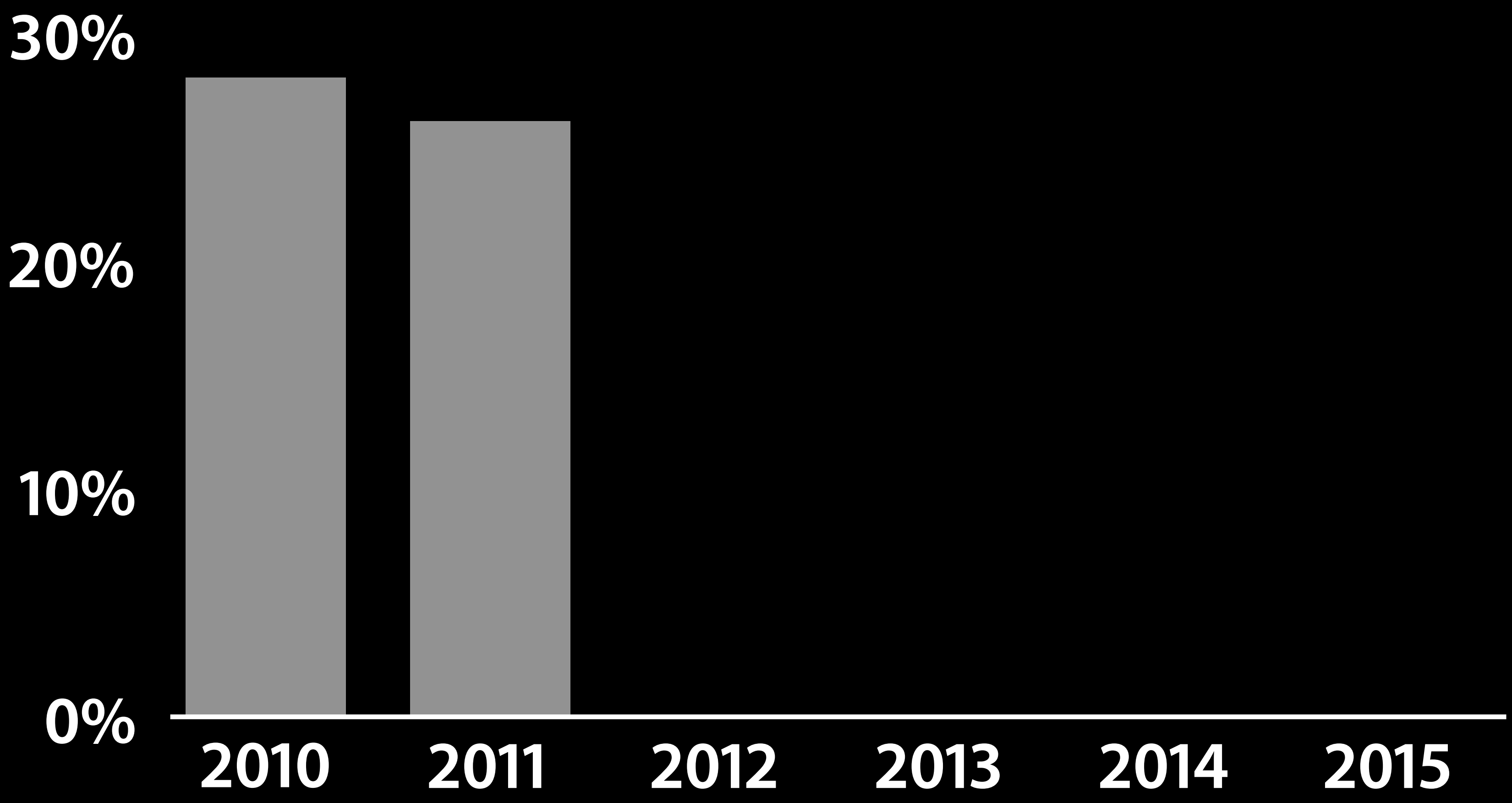
ImageNet Error Rate (Best of 5 Guesses)



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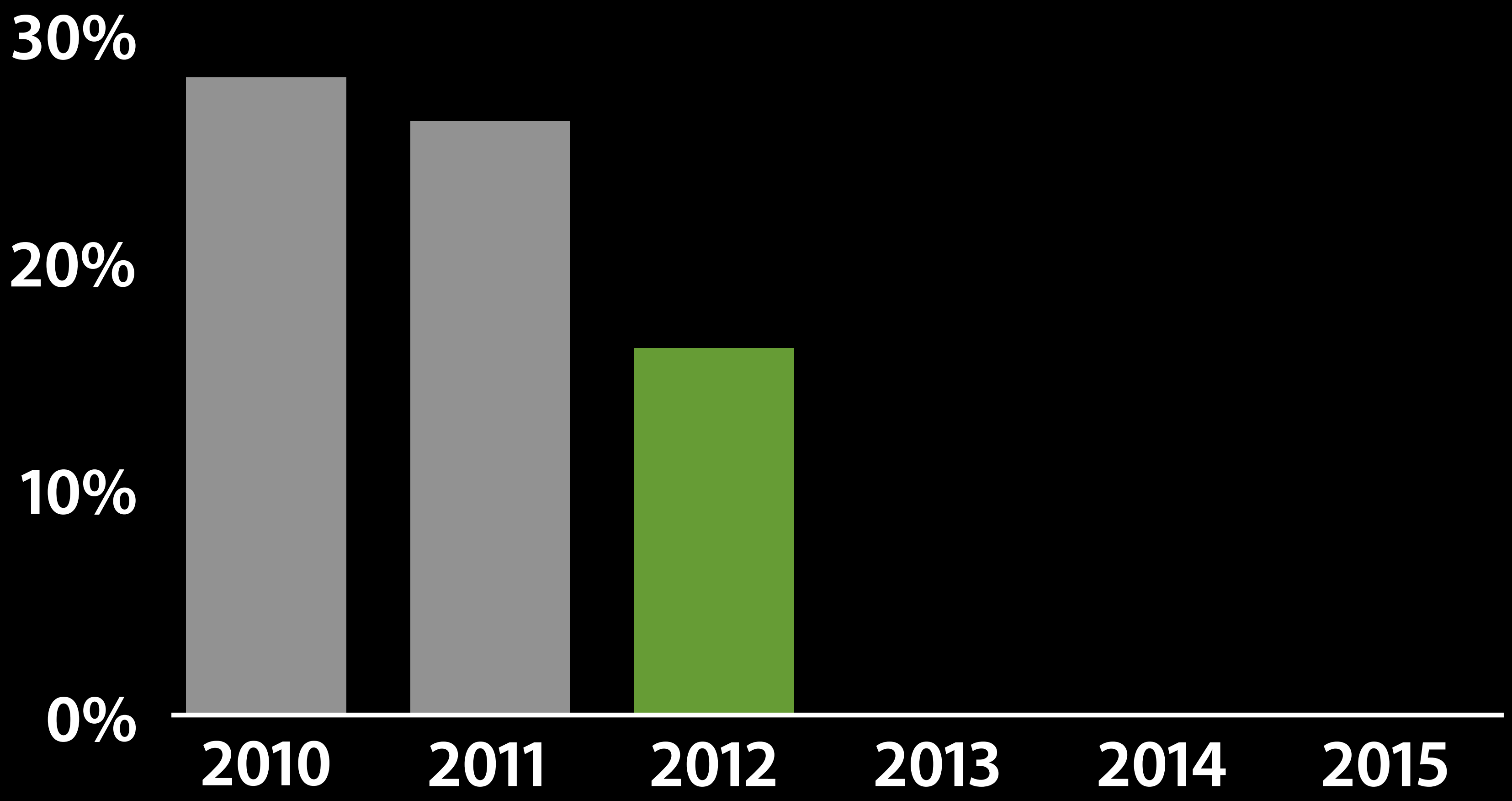

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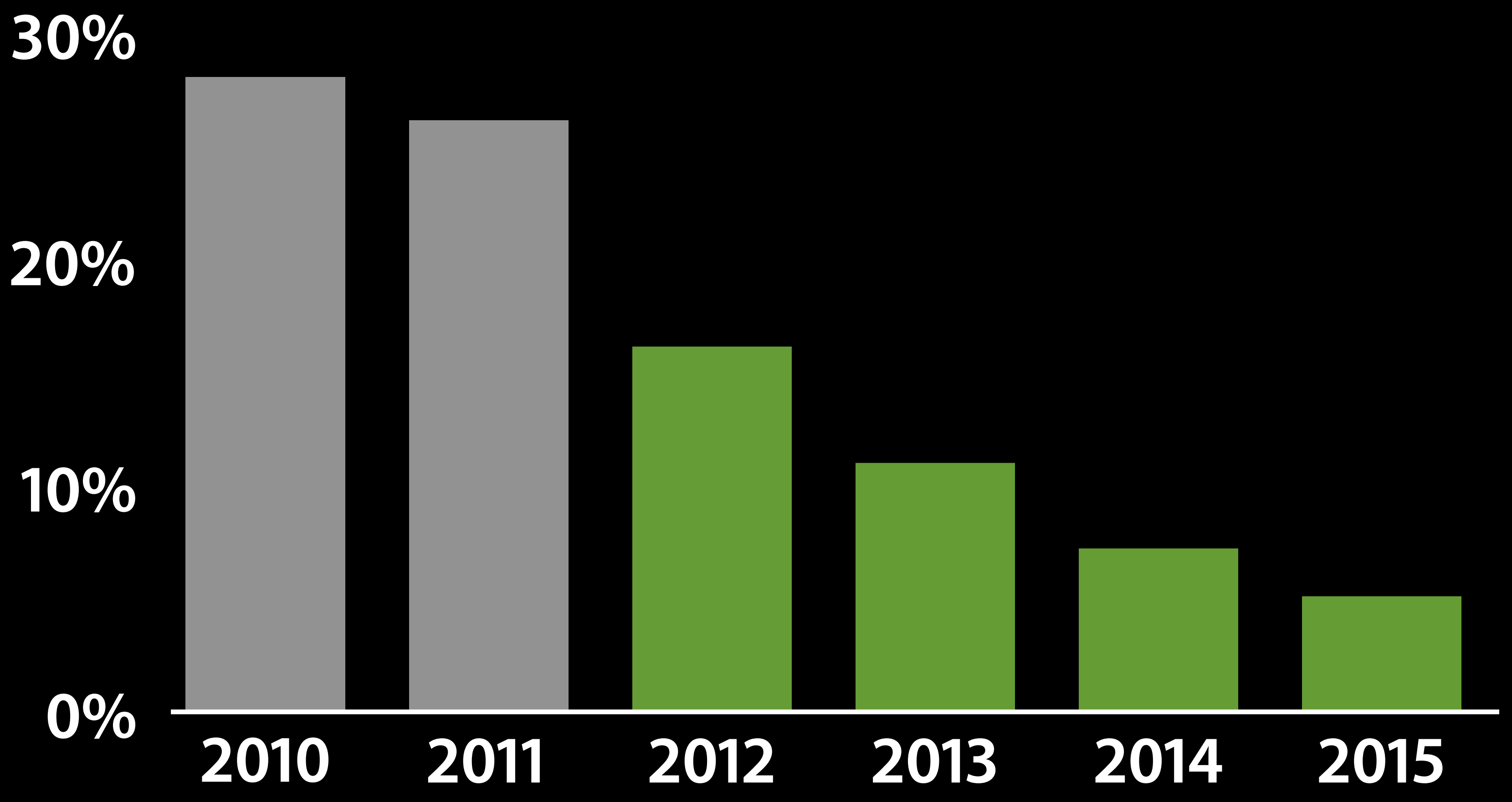
Computer Vision Community
Slide credit: Deep Learning by Prof. Kosta Derpanis

ImageNet Error Rate (Best of 5 Guesses)



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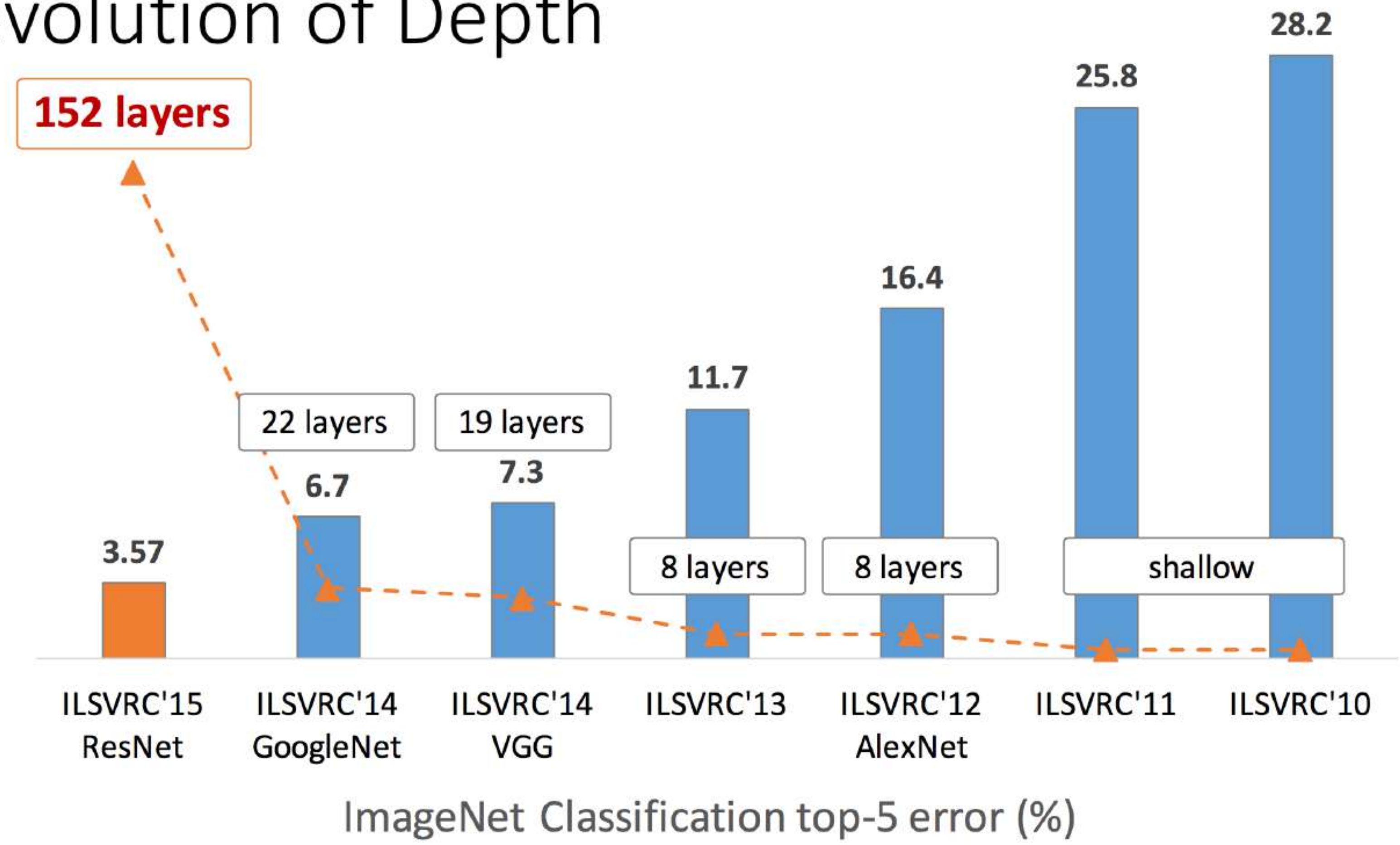
Revolution of Depth



Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

"What's changed?"

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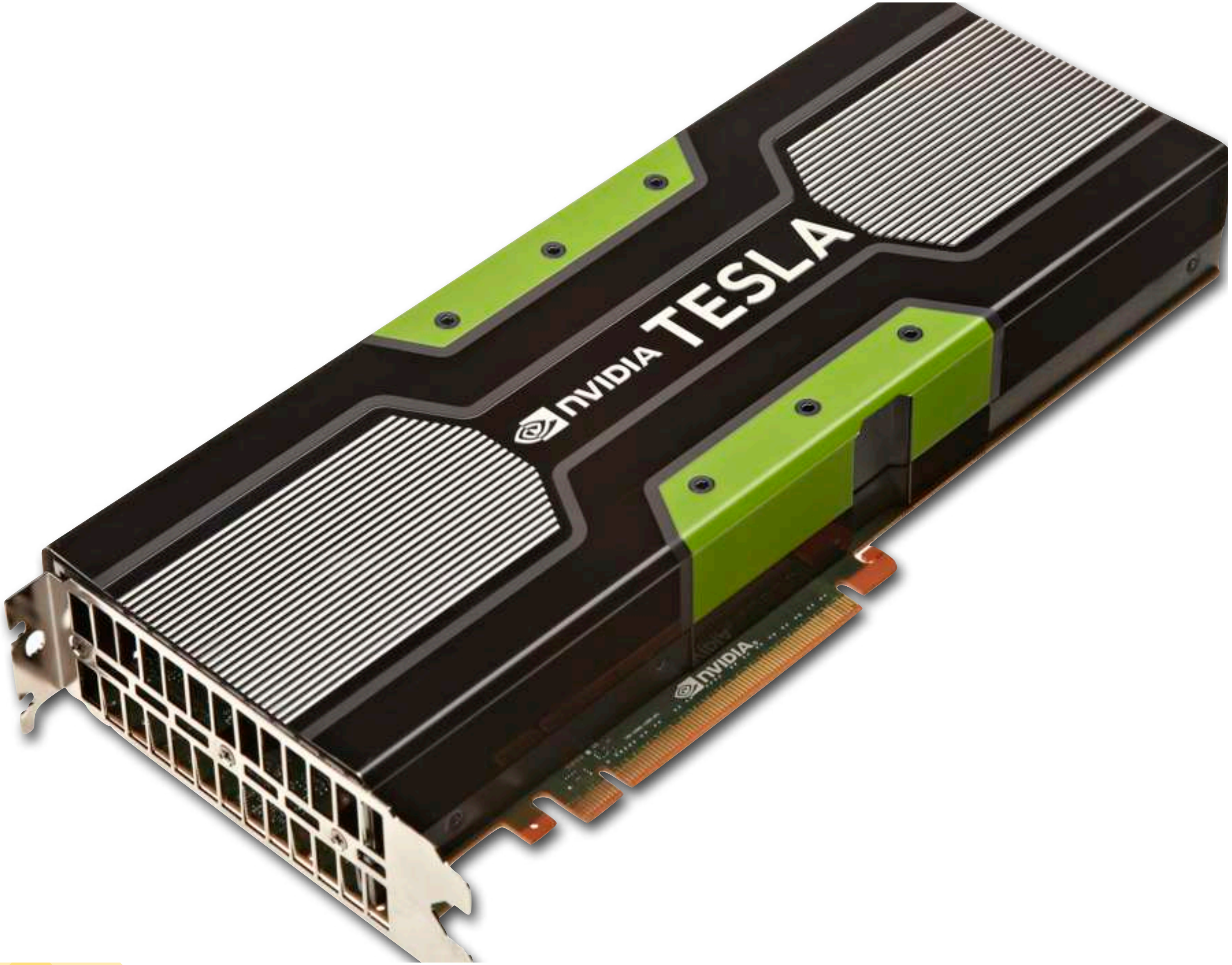
nVIDIA
TESLA

Deep Learning Frameworks

Slide credit: Deep Learning by Prof. Kosta Derpanis

mxnet

Microsoft CNTK

PyTorch

Chainer

TensorFlow

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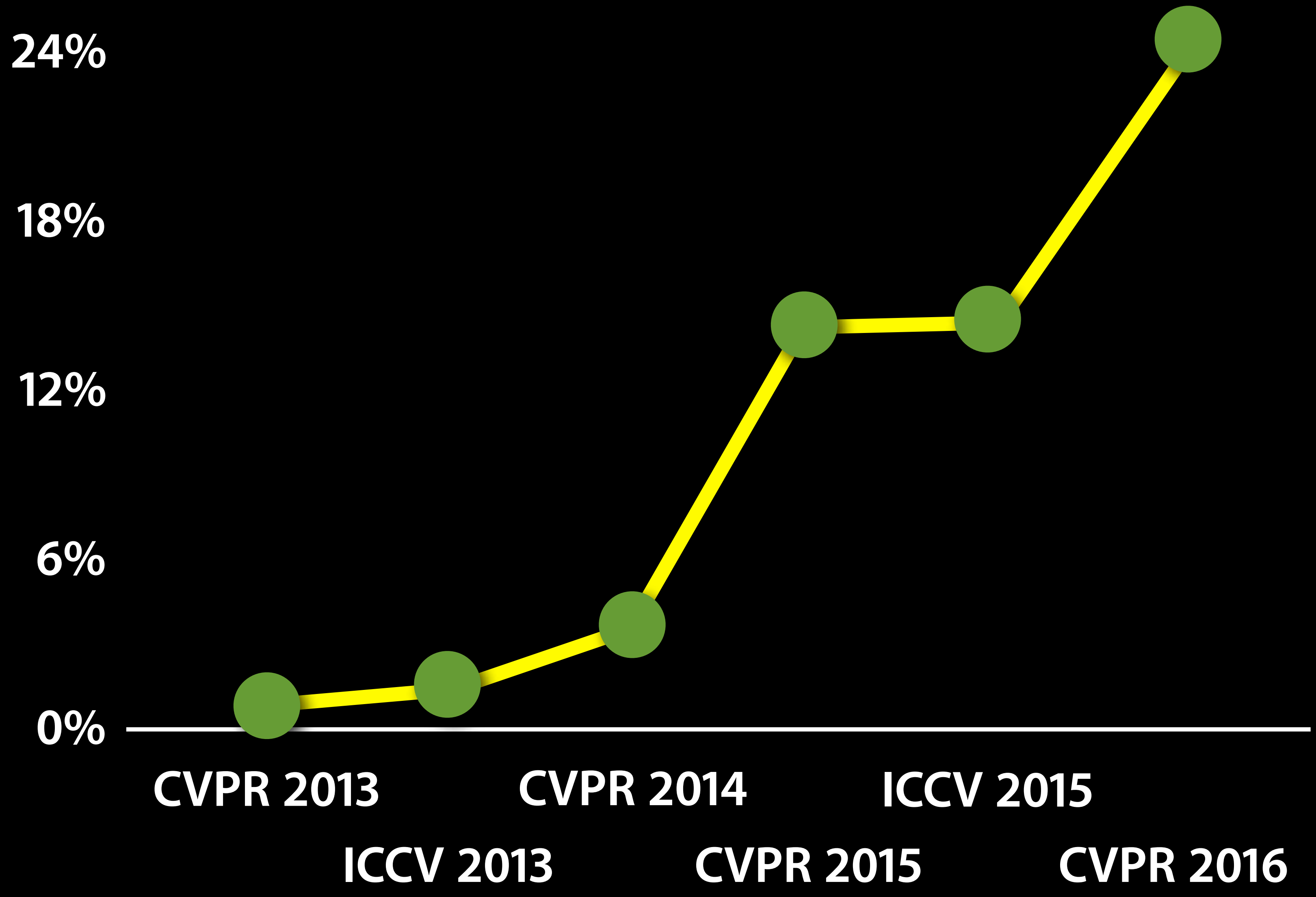
ImageNet

1000 categories, a million images

Deep Learning Takes Over Computer Vision



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Computer vision industry will grow from $1.1 billion in 2016 to $26.2 billion by 2025

Source: Tractica (2020)

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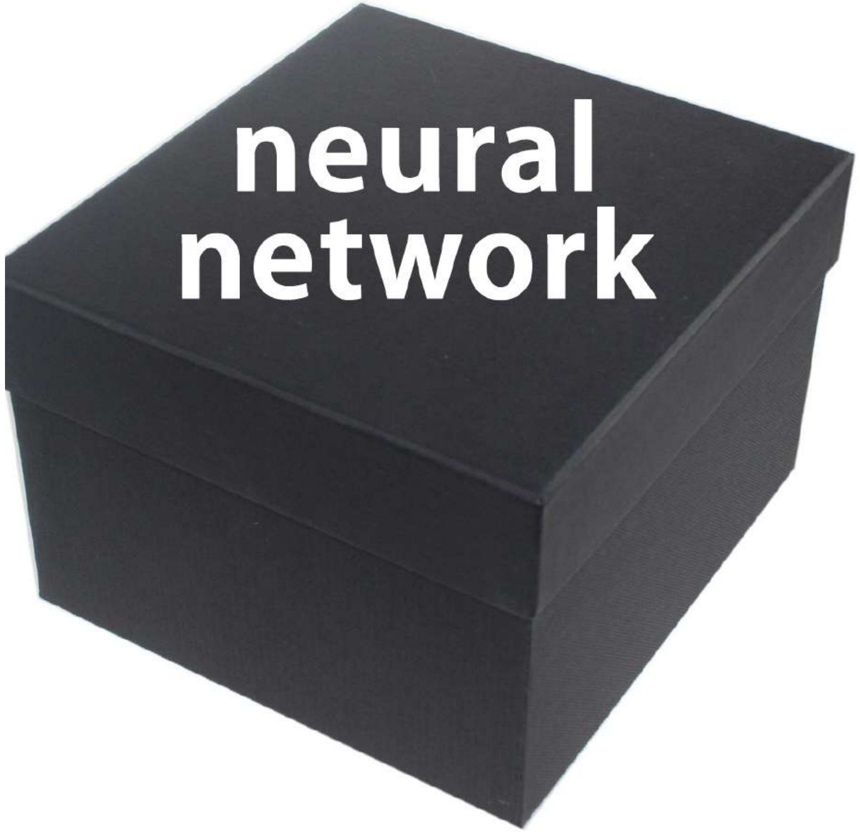

+ **data**

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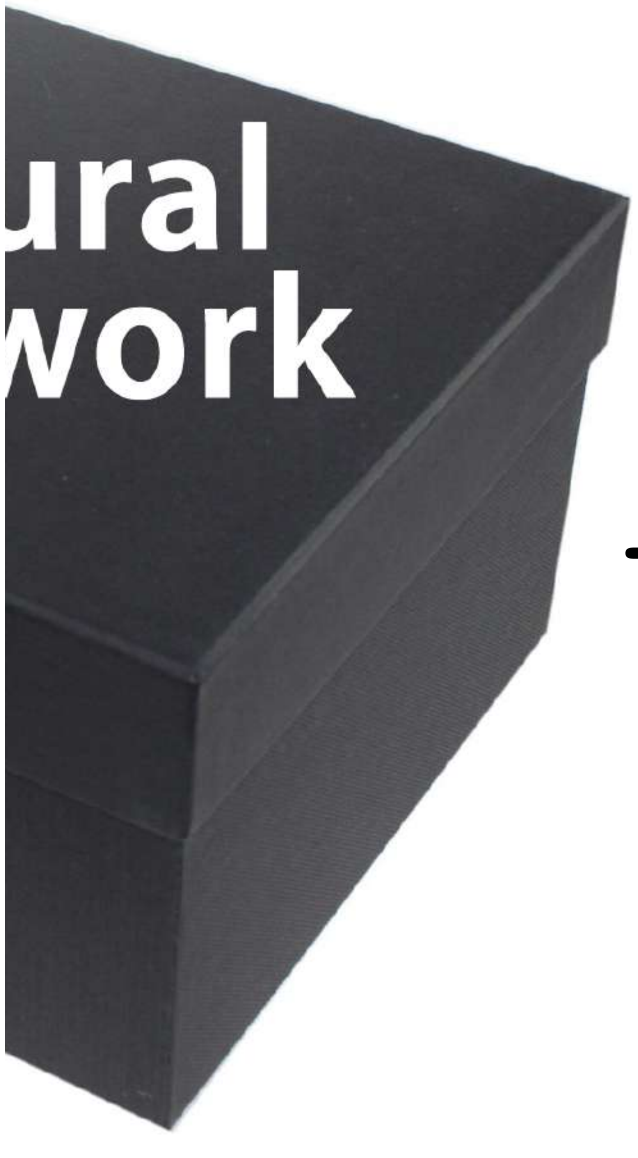
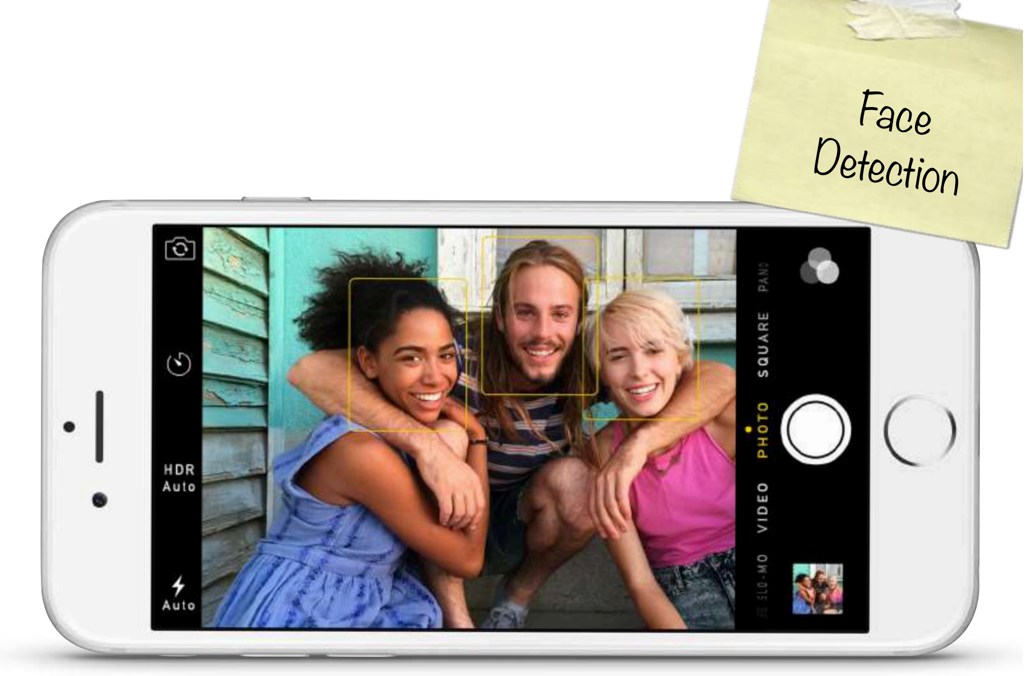


+ **data**

Applications


Face
Detection
HDR
Auto
Auto
VIDEO
PHOTO
SQUARE


What can I help
you with?


amazon


An astronaut riding a horse in a
photorealistic style


LEE SEDOL