Deep Learning for Medical Imaging

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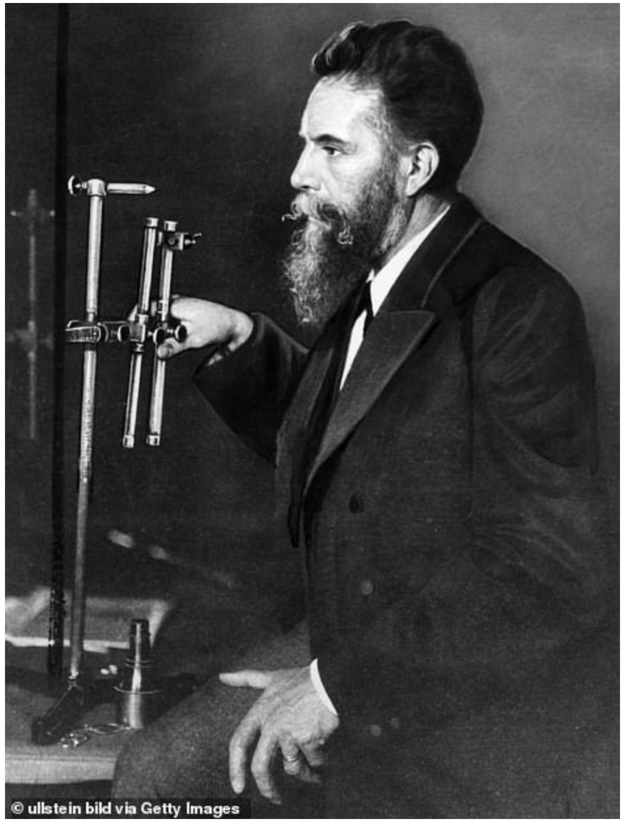
Evaluation

Part 1 – Introduction
1.1 Introduction
1.1.1 What is medical imaging?

What is medical imaging?

Techniques that allow to **see** (*study*) **inside the human body** in vivo and **non-invasively**

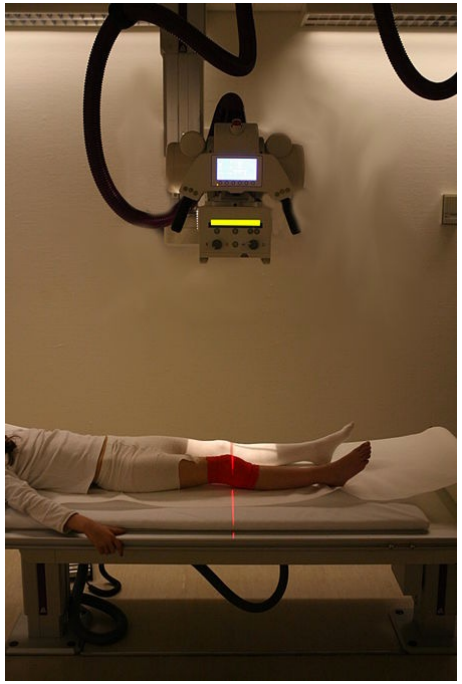


First X-ray radiography (1895) - Wilhelm Röntgen (Nobel Prize in Physics, 1901)

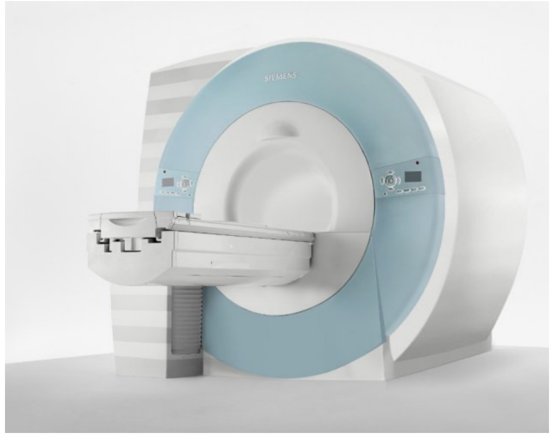
Medical imaging today

Multiple machines

X-ray radiography



MRI



PET / CT

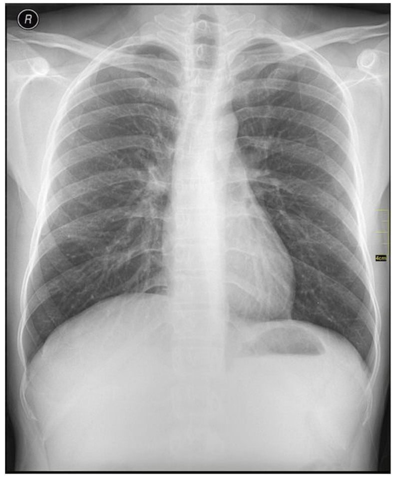
Ultrasound (echography)

Image sources: http://radiologie-abbeville.fr/files/Echographie%20g%C3%A9n%C3%A9rale.jpg, CENIR (ICM), https://fr.wikipedia.org/wiki/Tomographie_par_%C3%A9mission_de_positons, https://en.wikipedia.org/wiki/Radiography

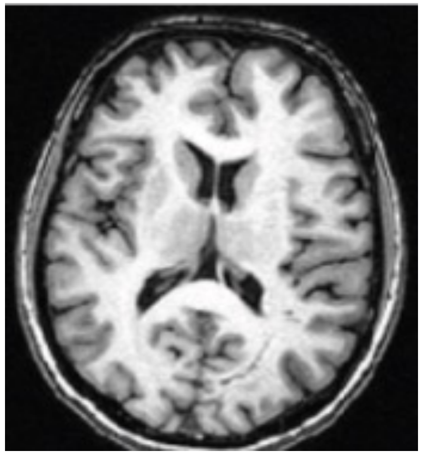
Medical imaging today

Multiple types of images

X-ray radiography



MRI



Ultrasound

PET

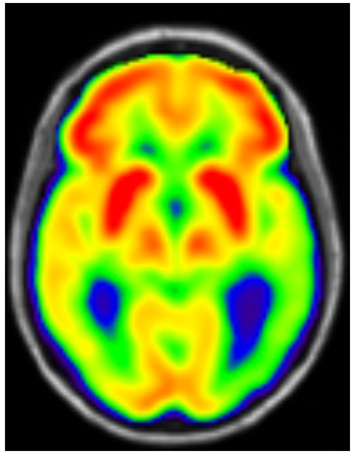
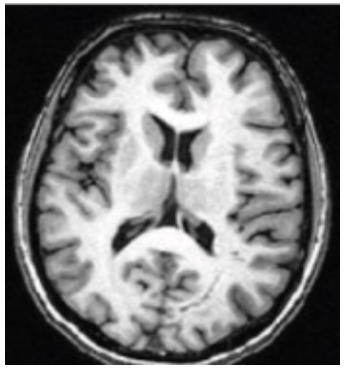


Image sources: https://fr.wikipedia.org/wiki/Radiographie, https://en.wikipedia.org/wiki/Obstetric_ultrasonography, Burgos et al, 2017 https://hal.inria.fr/hal-01567343

Medical imaging today

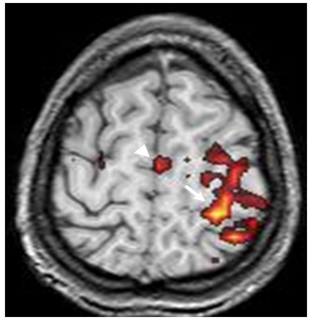
Multiple types of images
with the same machine (MRI)

Anatomical MRI



Angiography

Functional MRI



Diffusion MRI

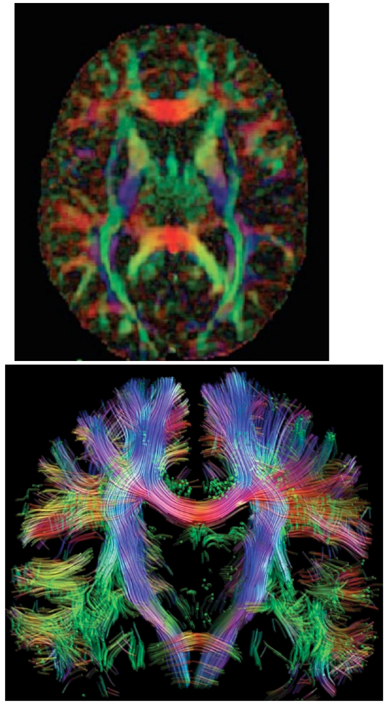


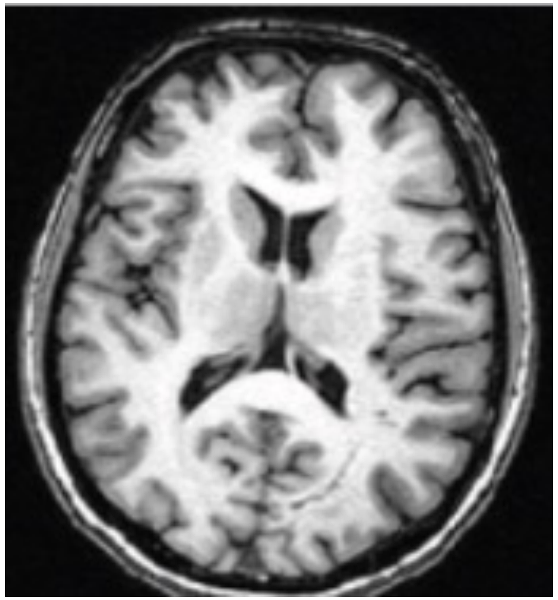
Image sources: https://en.wikipedia.org/wiki/Magnetic_resonance_angiography, Mukerjee et al, Tournier et al

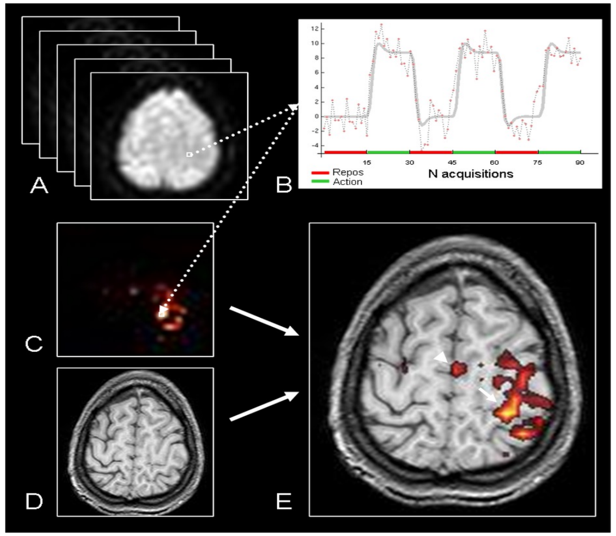
What is medical imaging?

Not only **see inside the human body**

But also **study multiple phenomena** which are inaccessible to the naked eye

- Metabolism
- Oxygenation of the blood
- Molecular structure





Part 1 – Introduction
1.1 Introduction
1.1.2 What is medical imaging used for?

What is medical imaging used for?

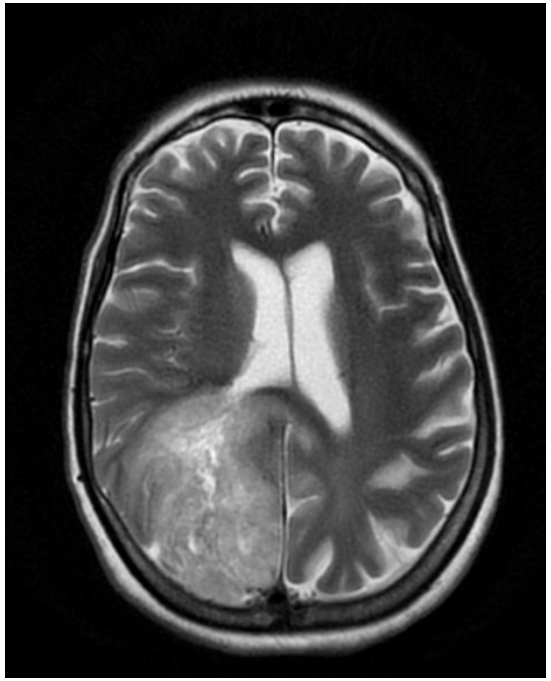
Medical care

- Detect lesions / anomalies
  - Find the cause of a set of symptoms

65-year old female

Presenting with
left-side weakness
and headache

MRI



Glioblastoma (brain tumour)

Source: https://radiopaedia.org/cases/glioblastoma-nos-13?lang=us

What is medical imaging used for?

Medical care

- Screening

Mammography

56-year old female

Routine screening
Asymptomatic

Potential breast tumour
(refered for biopsy)

Source: https://radiopaedia.org/cases/small-breast-cancer?lang=us

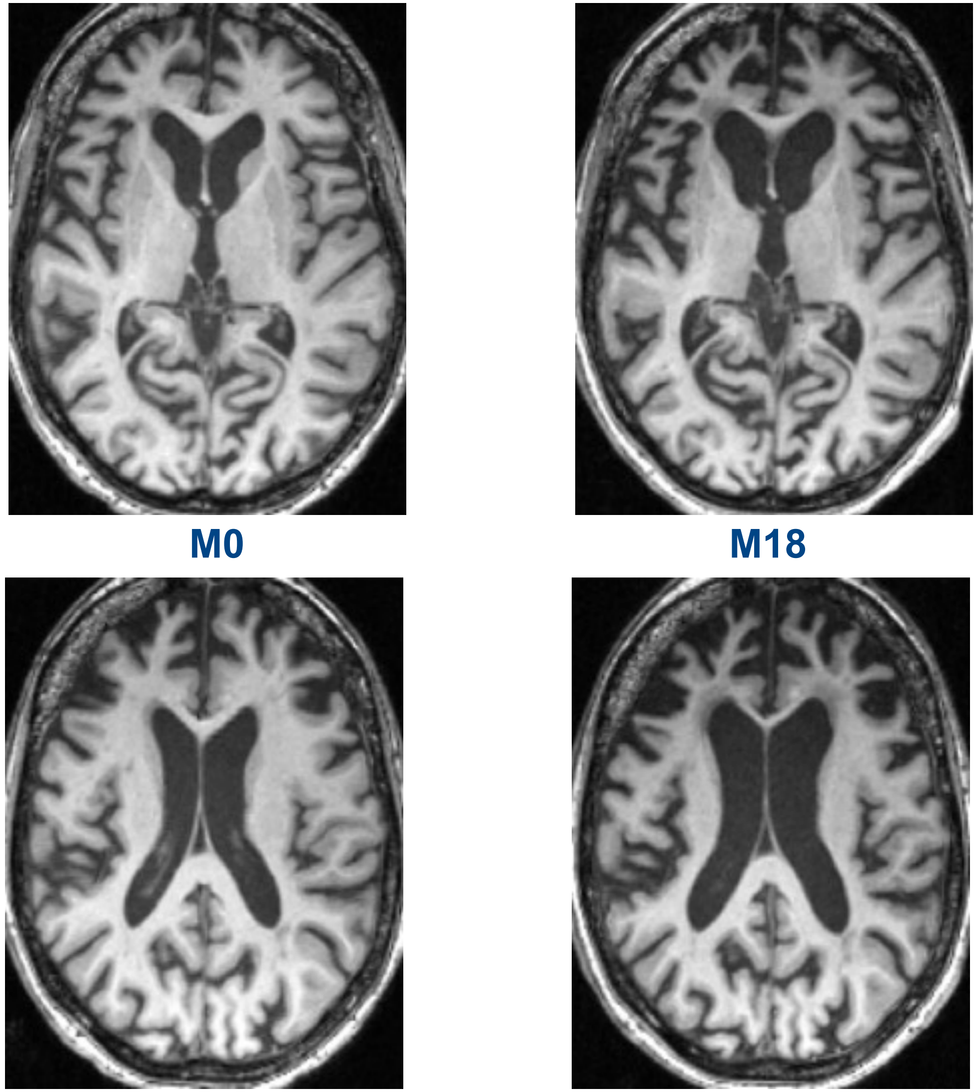
What is medical imaging used for?

Medical care

- Follow up a pathology

Patient with neurodegenerative disease

(followed over 18 months)



What is medical imaging used for?

- Quantify (extract biomarkers)

Medical care

  - For instance, segmentation for volumetric analysis
    - – Reduced volume of specific brain structures: iomarker of neurodegenerative diseases
    - – Enlarged volume of the left ventricle of the heart

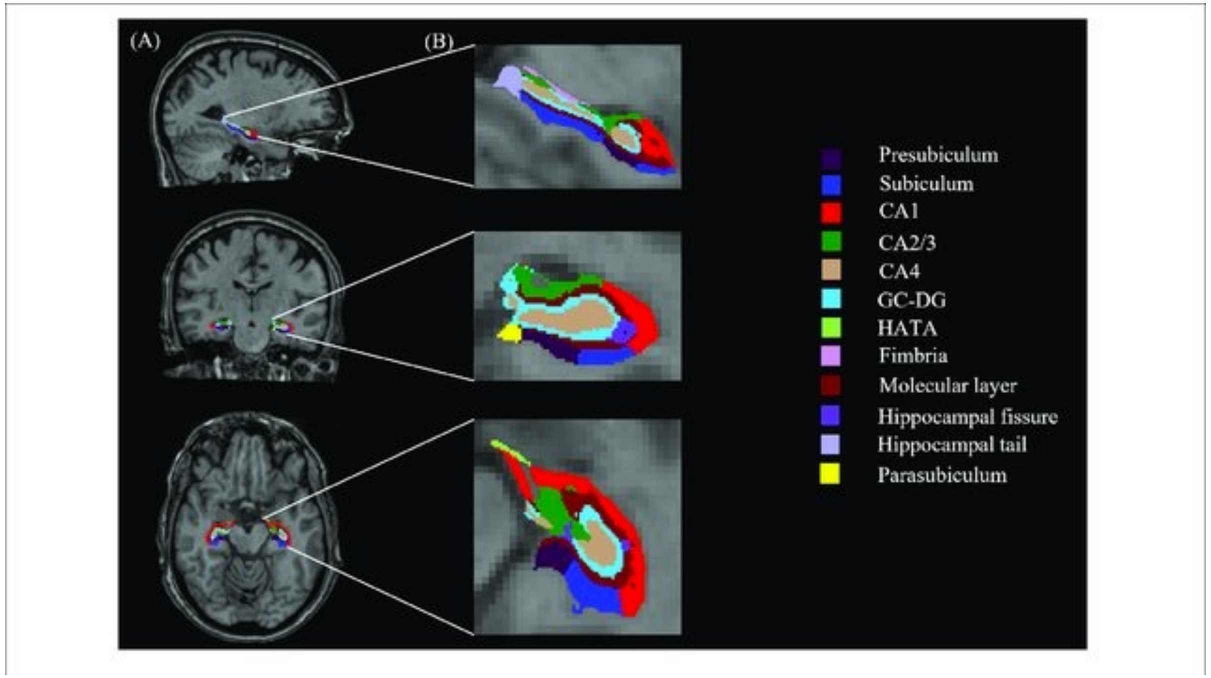


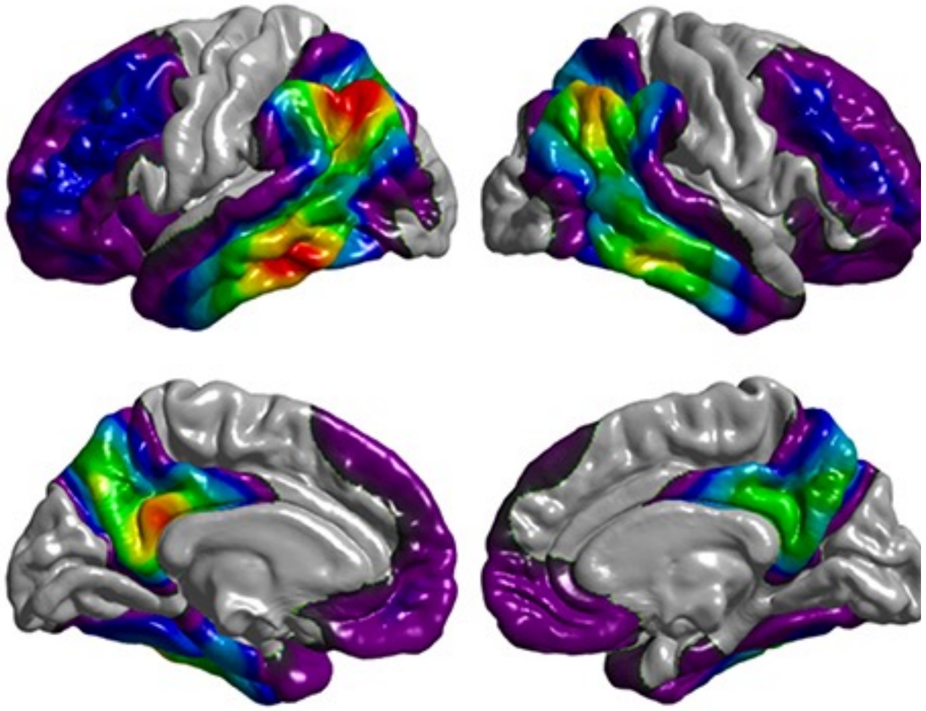
Image source: Zheng et al, The Volume of Hippocampal Subfields in Relation to Decline of Memory Recall Across the Adult Lifespan, 2018

What is medical imaging used for?

Research

- Clinical research
  - Understand the alterations produced by a given disease

Brain alterations associated with Alzheimer's disease



Brain areas with significantly reduced metabolism in patients with Alzheimer's disease compared to healthy controls, as studied with PET imaging

Source: Marcoux et al, Front Neuroinformatics, 2018

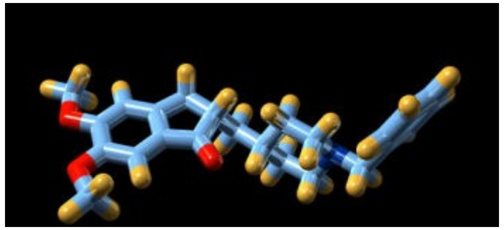
What is medical imaging used for?

- Clinical research
  - Evaluate the effect of a treatment

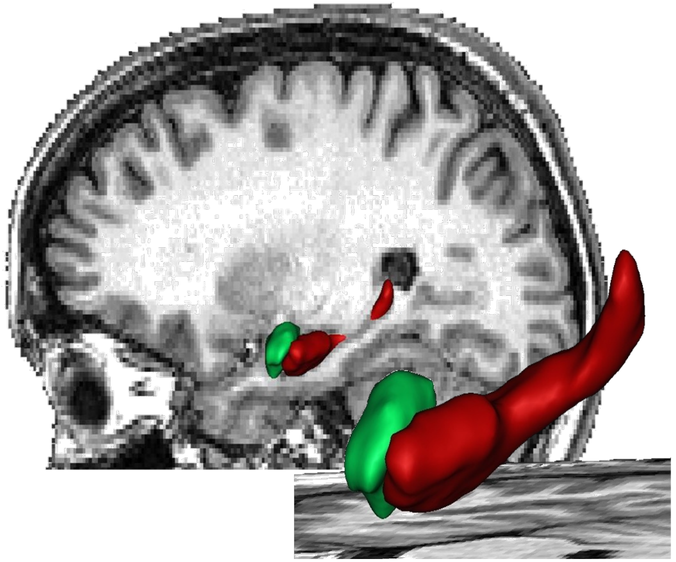
Research

Studying the effect of a treatment (donepezil) on the volume of the hippocampus in Alzheimer's disease

- Double-blind, randomized, placebo-controlled



Hippocampal atrophy was reduced by 45% in one year with donepezil compared to placebo



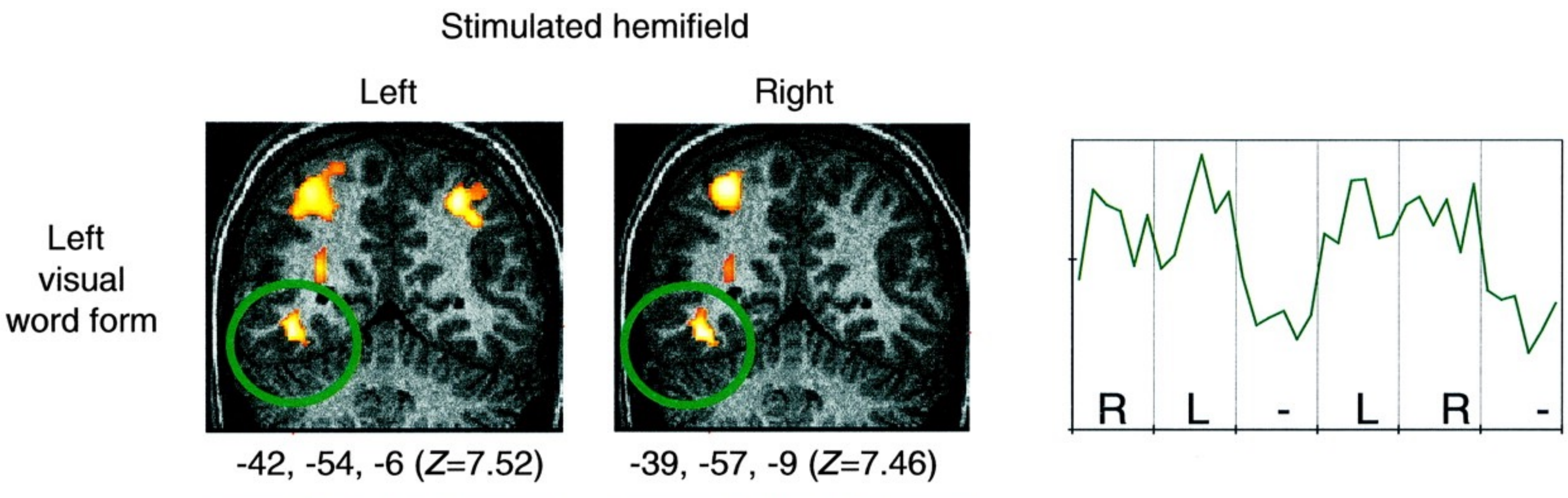
Source: Dubois et al, Alzheimer's and dementia, 2015

What is medical imaging used for?

- Basic research
  - Cognitive neuroscience

Research

Studying which parts of the brain are used for reading



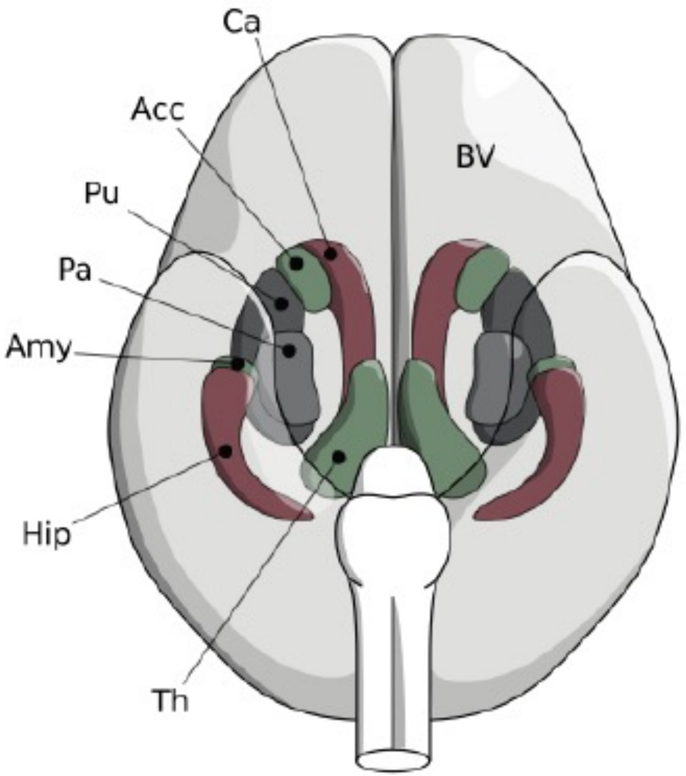
Source: Cohen et al, The visual word form area: Spatial and temporal characterization of an initial stage of reading in normal subjects and posterior split-brain patients, Brain, 2000

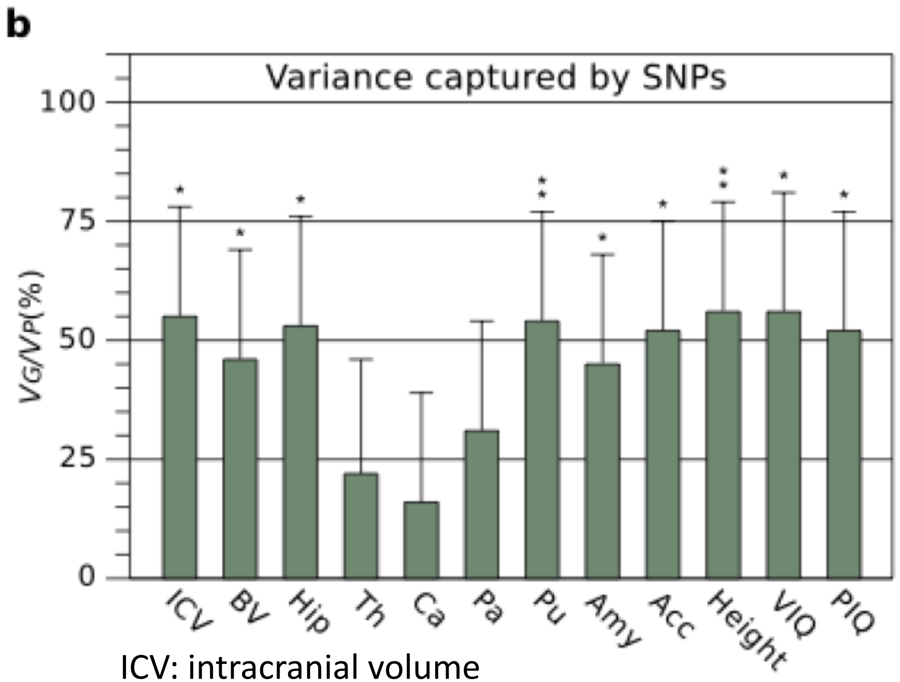
What is medical imaging used for?

- Basic research
  - Genetics and neuroscience

Research

Heritability of the size of brain structures





ICV: intracranial volume
BV: brain volume
VIQ: verbal IQ
PIQ: performance IQ

Source: Toro et al, Genomic architecture of human neuroanatomical diversity, Molecular Psychiatry, 2015

Part 1 – Introduction
1.1 Introduction
1.1.3 Medical image computing

Medical image computing

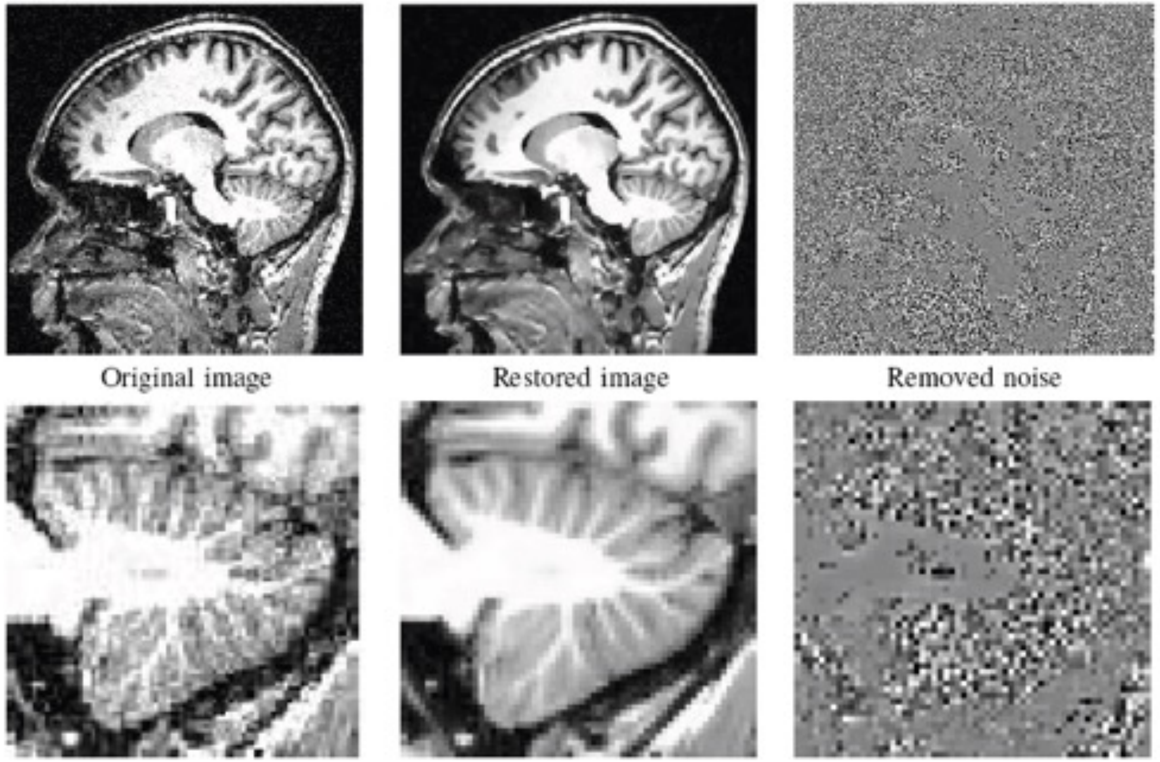
Scientific field dedicated to the computational analysis of medical images

At the cross-road of

- Computer vision / image processing
- Machine learning
- Statistics
- Geometry

Medical image computing – what for?

- Enhance medical images
  - Denoising



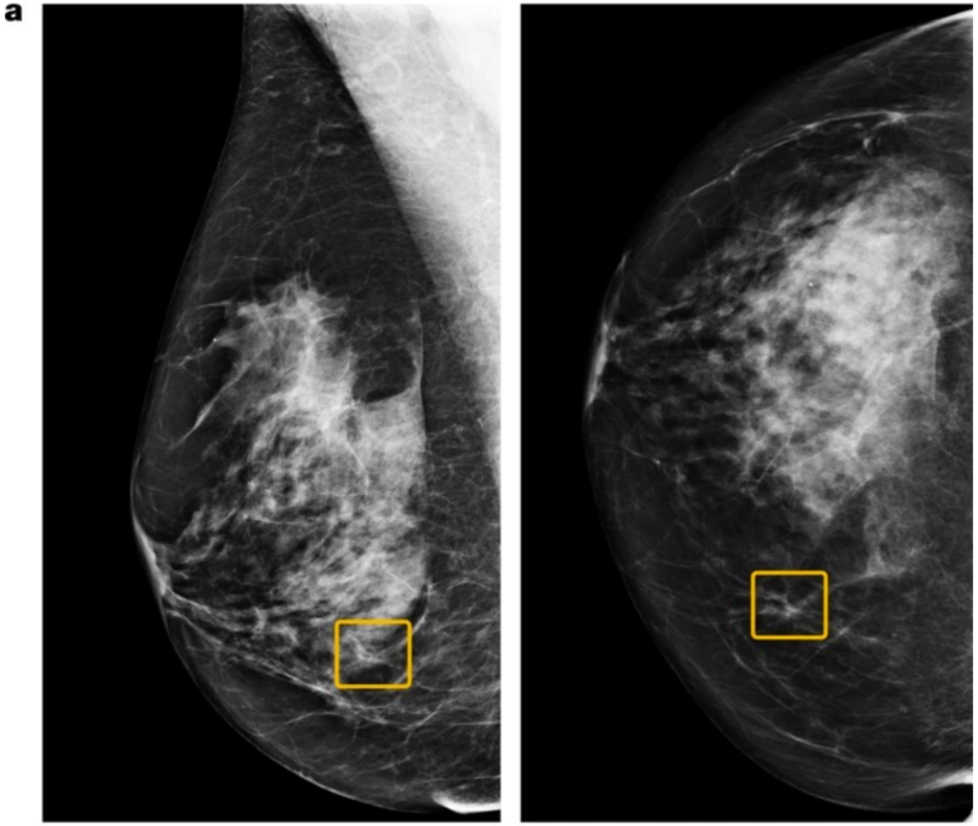
Hellier, TMI 2008

Denoising of brain MRI

Provide higher quality images to the radiologist

Medical image computing – what for?

- Assist medical evaluation
  - Detection
  - Diagnostic classification



Source: McKinney et al International evaluation of an AI system for breast cancer screening, Nature, 2020

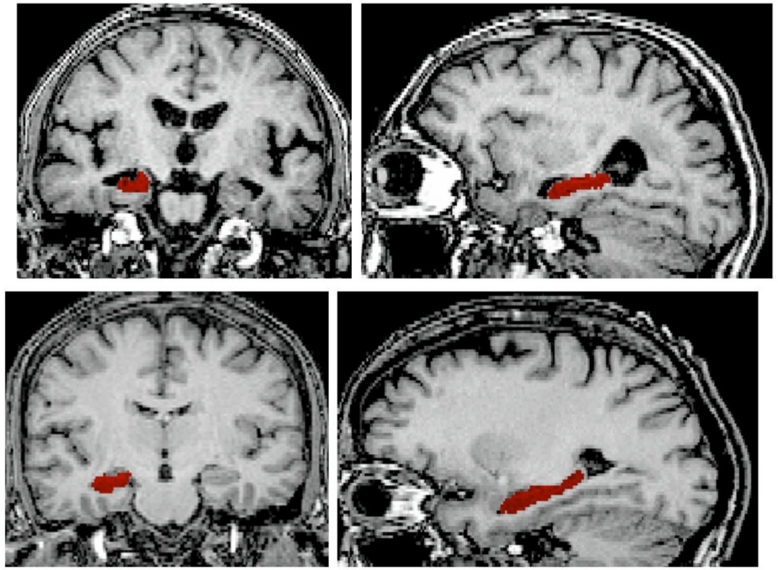
Automatic detection of breast cancer in mammography images

Reduce reading time for the radiologist

In the future: screen automatically and ask the radiologist only for difficult cases?

Medical image computing – what for?

- Quantify
  - Segmentation



	Alzheimer vs controls
Volume reduction	-32%
Sensitivity	84%
Specificity	84%

Automatic segmentation of the hippocampus in Alzheimer's disease

Enrich visual evaluation with quantitative measures

Source: Colliot et al, 2008

Medical image computing – what for?

- Predict
  - Predict the future state of the patient

Predict the future occurrence of Alzheimer's disease (within 3 years)

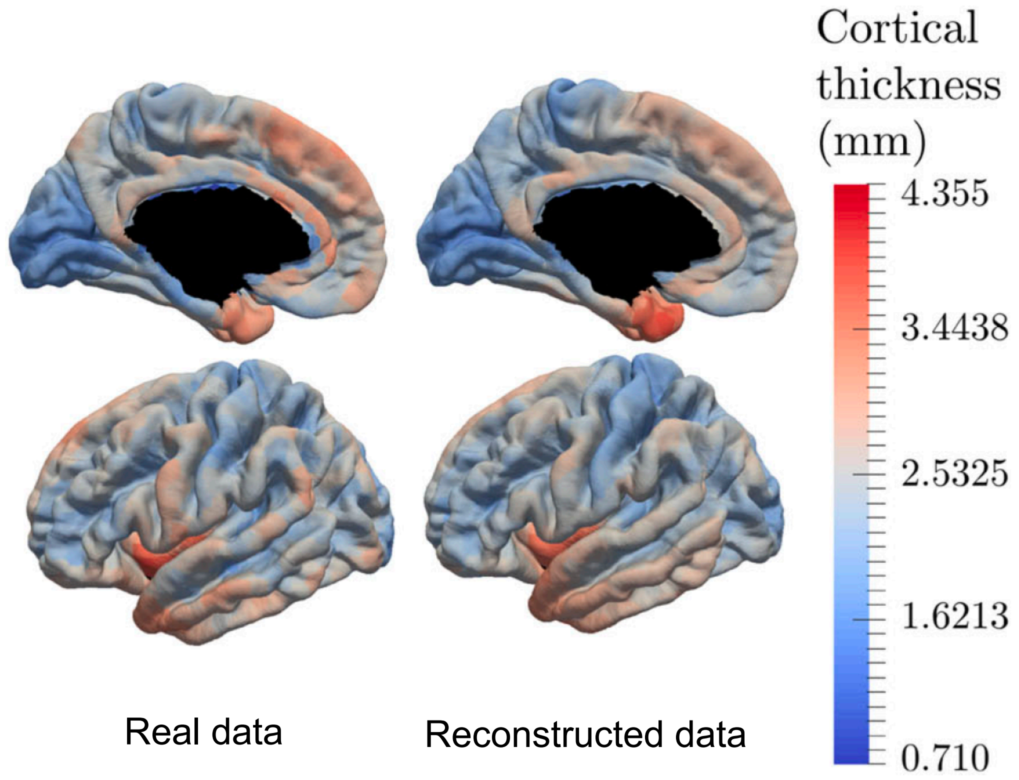
Classifier - Features	Bal. acc.	AUC	Acc.	Sens.	Spec.
SVM - T1w MRI	0.670	0.736	0.698	0.586	0.754
SVM (trained on CN $A\beta$- vs AD $A\beta$+) - T1w MRI	0.679	0.764	0.708	0.547	0.811
SVM - FDG PET	0.708	0.777	0.732	0.633	0.782
SVM (trained on CN $A\beta$- vs AD $A\beta$+) - FDG PET	**0.761**	**0.818**	**0.788**	0.666	0.856
RF - $\text{Clinical}_{\text{base}}$ + Score $_{\text{T1}}$	0.717	0.792	0.732	0.671	0.763
RF - $\text{Clinical}_{\text{base}}$ + Score $_{\text{FDG}}$	0.760	0.831	0.791	0.669	0.852
RF - $\text{Clinical}_{\text{base}}$ + Scores $_{\text{T1,FDG}}$	0.769	0.855	0.796	0.685	0.852
RF - $\text{Clinical}_{\text{base}}$ + RAVLT + Scores $_{\text{T1,FDG}}$	**0.791**	0.881	0.809	0.735	0.846
RF - $\text{Clinical}_{\text{base}}$ + ADAS + Scores $_{\text{T1,FDG}}$	**0.790**	0.873	0.810	0.729	0.851
RF - $\text{Clinical}_{\text{base}}$ + RAVLT + ADAS + Scores $_{\text{T1,FDG}}$	**0.792**	0.888	0.811	0.736	0.849

$\text{Clinical}_{\text{base}}$: gender, education level, MMSE score, sum of boxes of CDR test

Source: Samper-Gonzalez et al, 2019

Medical image computing – what for?

- Predict
  - Predict the future observations

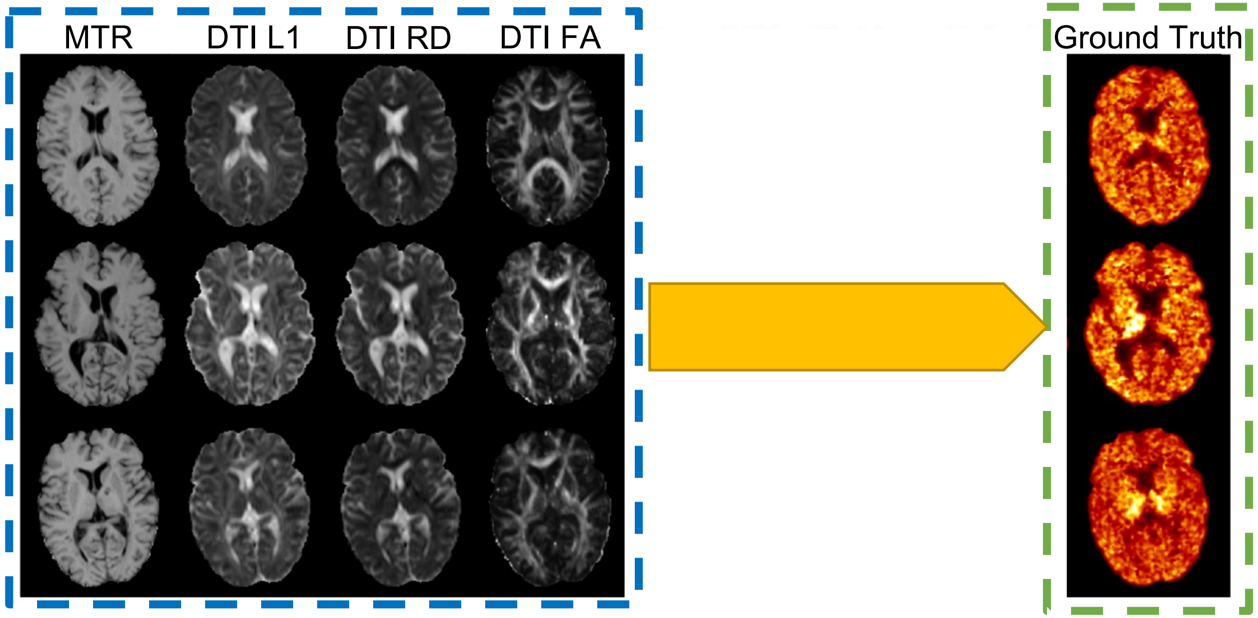


Source: Koval et al, Front Neurosci, 2019

Predict the future MRI data in patients with Alzheimer's disease

Medical image computing – what for?

- Synthesis of medical imaging data



Synthesize PET imaging from MRI imaging

Source: Wei et al, Medical Image Analysis, 2019

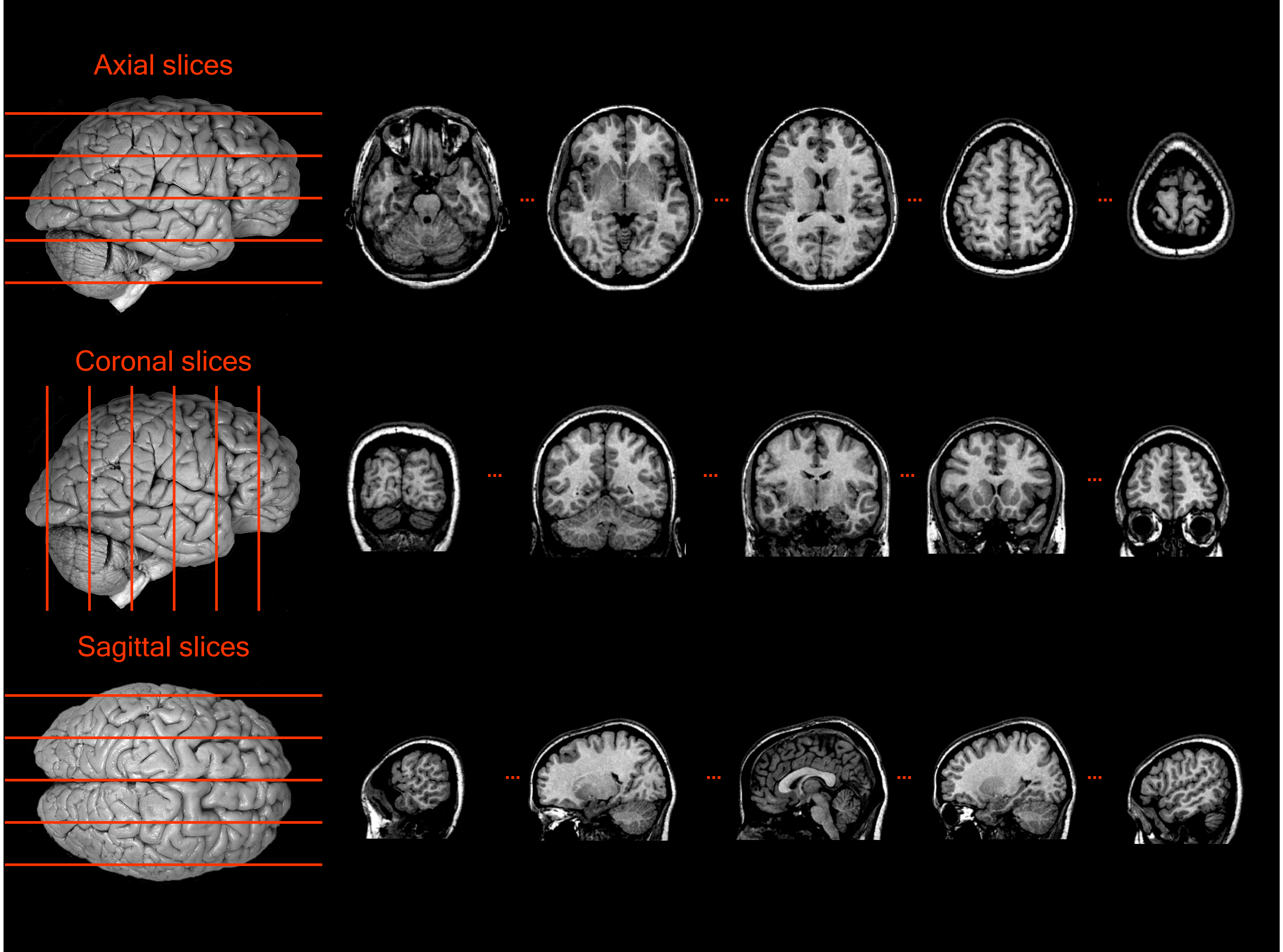
Part 1 – Introduction
1.1 Introduction
1.1.4 Specificities of medical image computing

Specificities of medical image computing

Why it is not only computer vision
applied to medical images

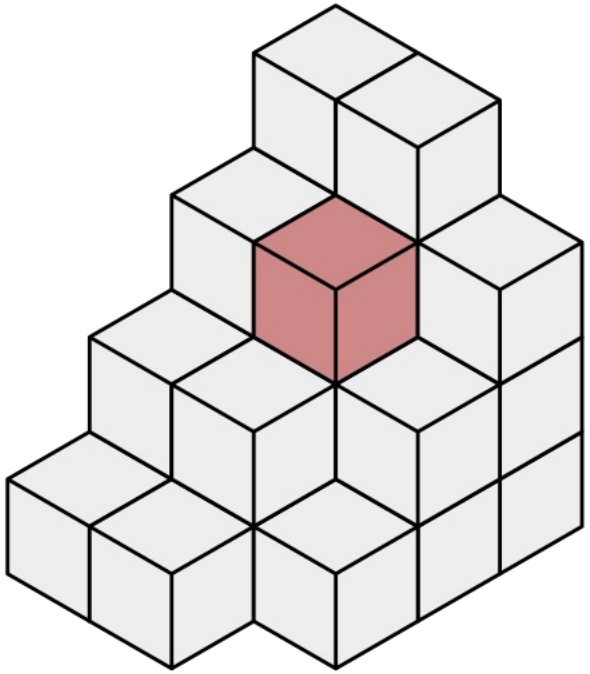
Specificities of medical image computing

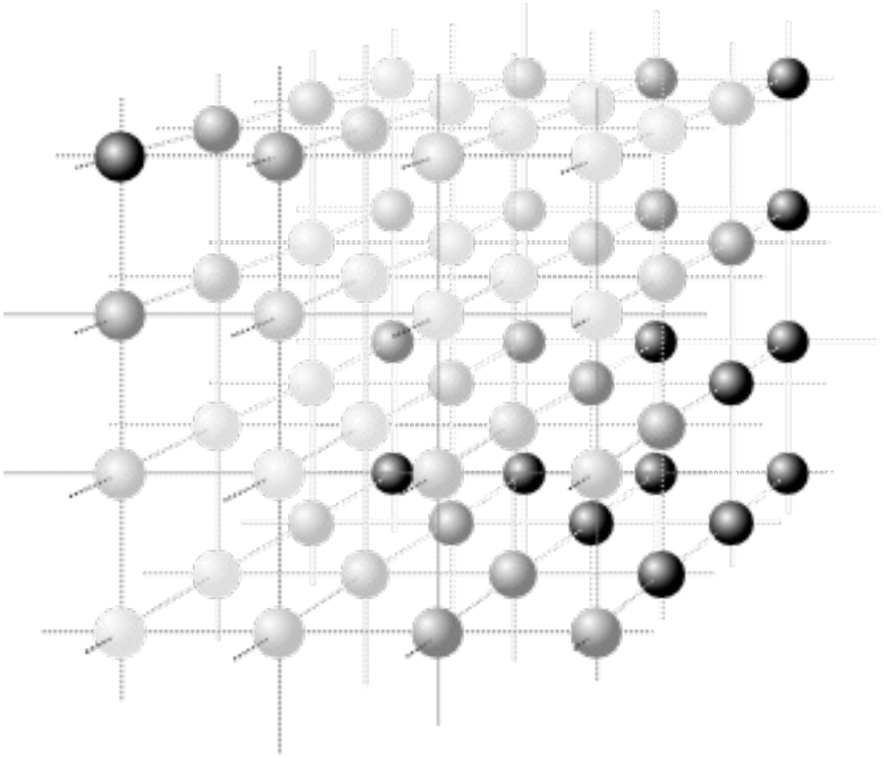
- 3D
  - Most medical images are 3D


Axial slices
Coronal slices
Sagittal slices

Specificities of medical image computing

- 3D
  - Most medical images are 3D



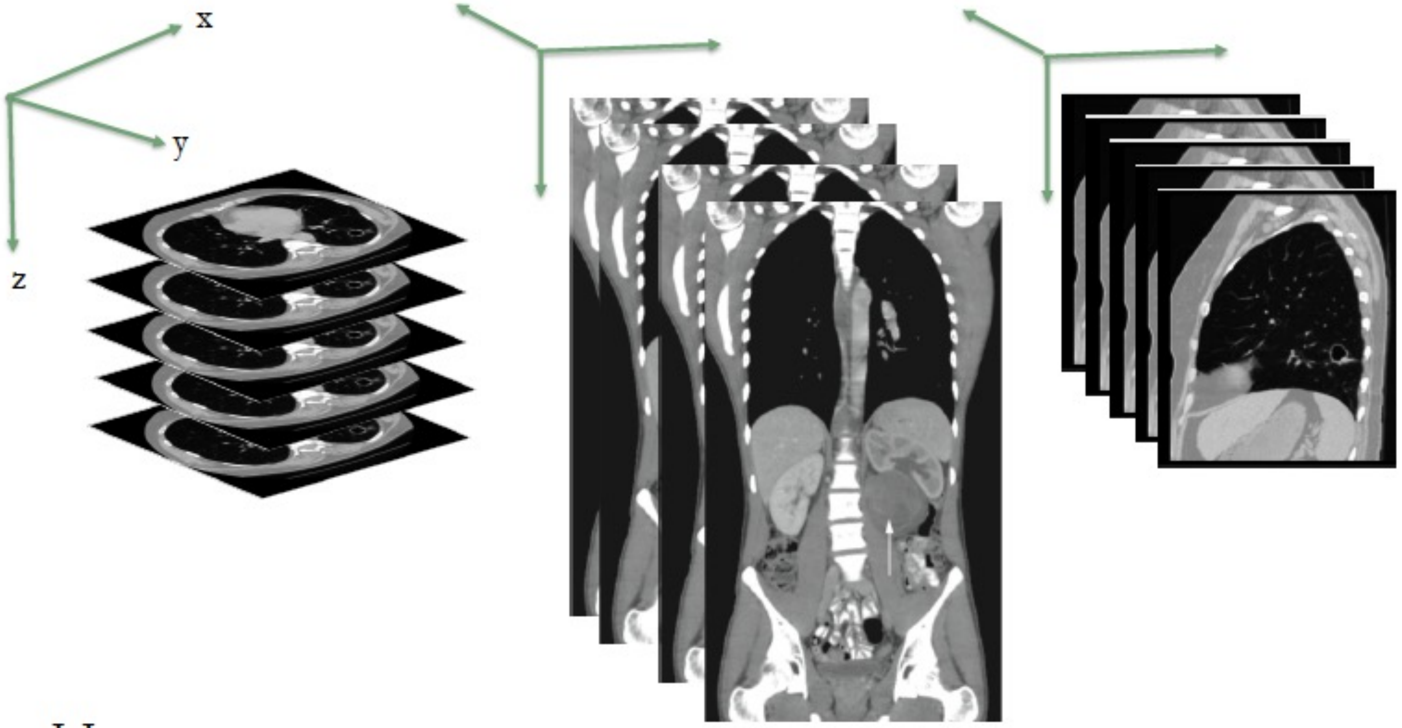


Voxel=volume element

Image source: https://en.wikipedia.org/wiki/Voxel

Specificities of medical image computing

- 3D
  - Most medical images are 3D

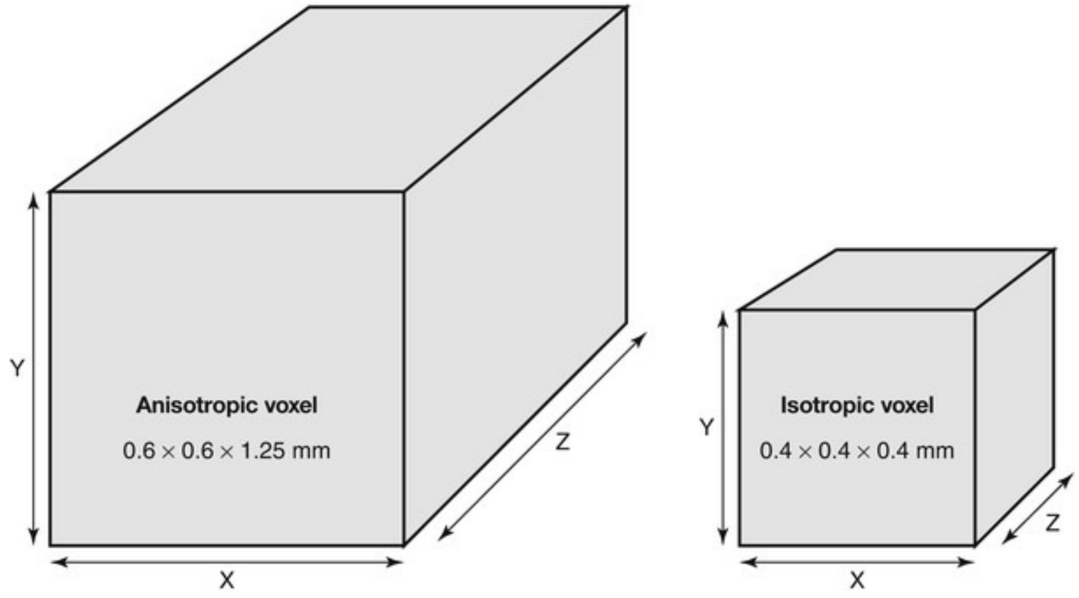


I: Image
I(x,y,z) denotes intensity value at pixel location x,y,z
<u>Note also that whatever you see on the left is right part of the body!</u>

Image source: http://www.cs.ucf.edu/~bagci/teaching/mic17.html

Specificities of medical image computing

- 3D
  - Voxels have a **<u>physical size</u>**
    - Most often, this size needs to be taken into account in the processing
  - Quite often, the voxels are anistropic



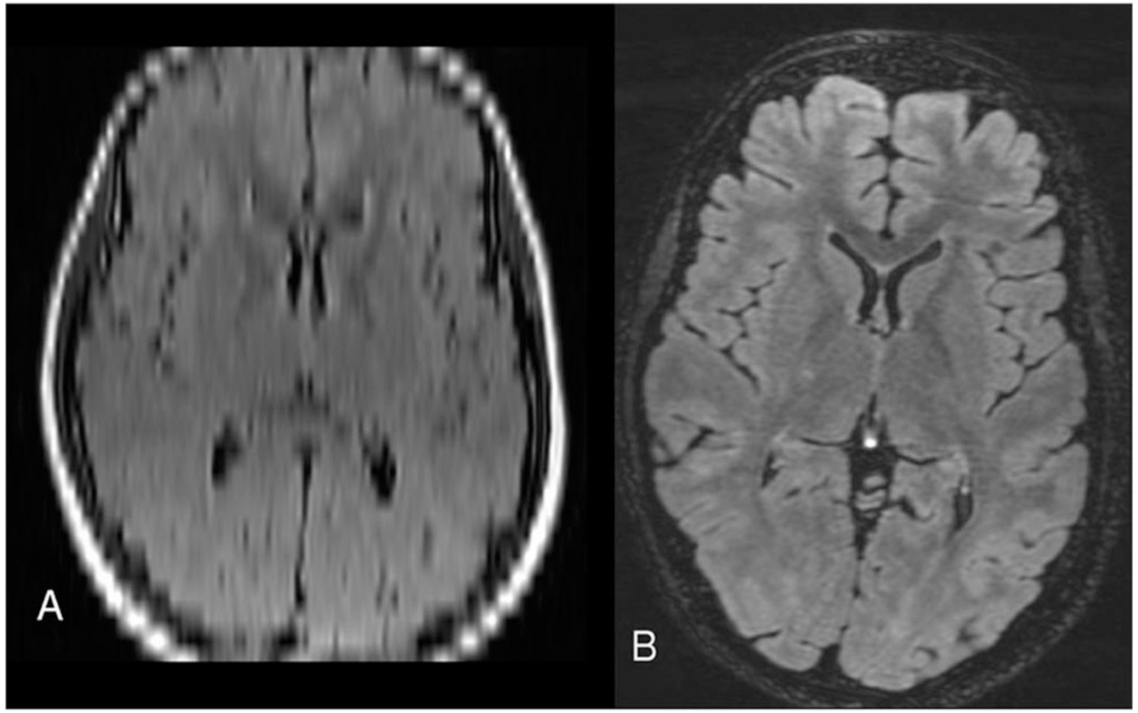
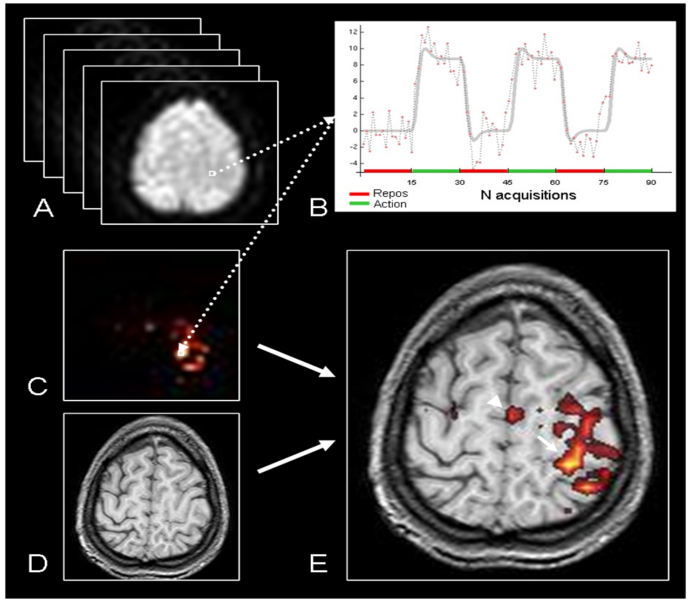
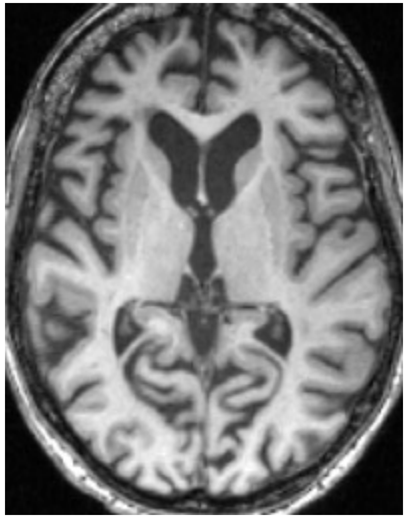


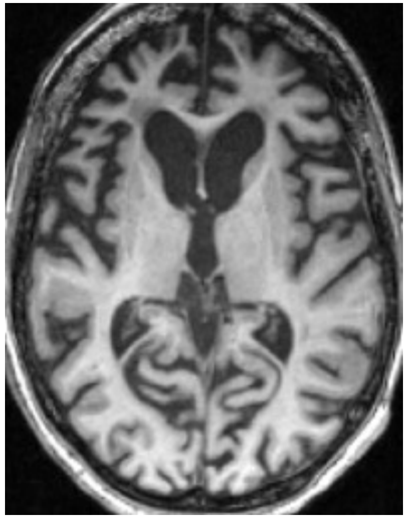
Image source: https://link.springer.com/chapter/10.1007/978-3-319-07560-0_1

Specificities of medical image computing

- Temporal phenomena
  - Across multiple time scales







Second

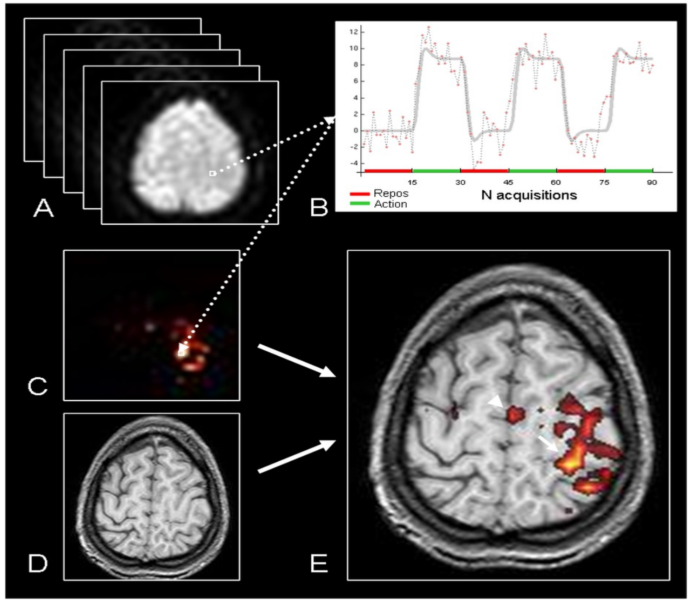
Year

Functional brain images, cardiac images…

Longitudinal studies

Specificities of medical image computing

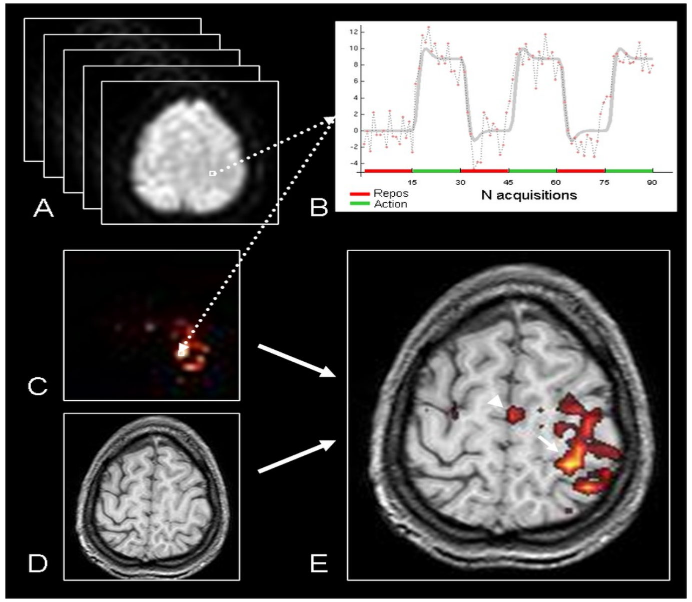
- Multiple phenomena and image types



Anatomical vs functional

Specificities of medical image computing

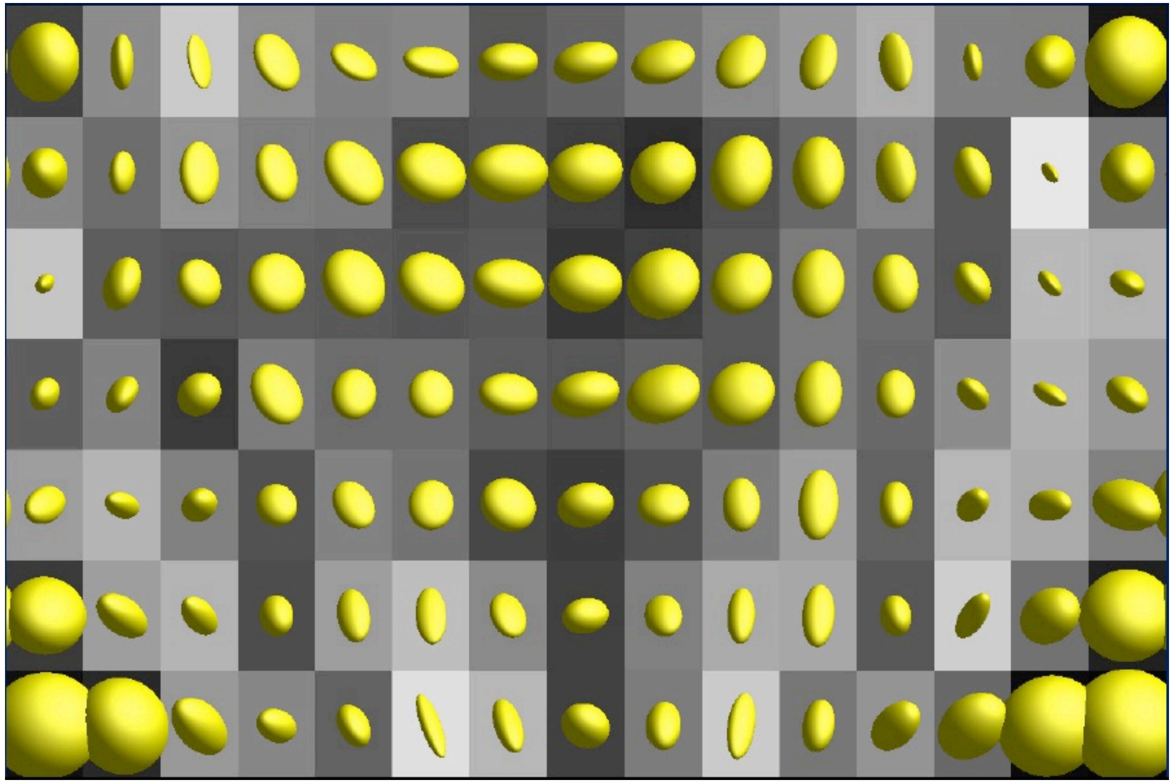
- Multiple phenomena and image types



Time-series

Specificities of medical image computing

- Multiple phenomena and image types



Tensor images

Specificities of medical image computing

- Validation
  - Critical
  - Can be difficult to perform

- Clinical relevance
  - Need close collaboration with physicians to identify relevant problems

- Multidisciplinary collaboration
  - Find a common language

Medical image computing with deep learning

- **Has achieved impressive results, as in other fields (CV, NLP…)**
  - Even though there are some inherent difficulties, in particular the small sample size

- **Is not a universal solution**
  - Other methods may remain competitive for some applications

Part 1 – Introduction
1.1 Introduction
1.1.5 About this course

Course content

- **Content**
  - theoretical and practical aspects of deep learning for medical imaging
  - covers the main tasks involved in medical image analysis (classification, segmentation, registration, generative models…)
  - deep learning techniques are presented, alongside some more traditional image processing and machine learning approaches
  - Emphasis on validation which is critical for medical applications

- **Learning objectives**
  - have knowledge of state-of-the-art deep learning techniques for medical imaging
  - have a deeper understanding of deep learning methods, applicable not only to medical images but also other types of data
  - know how to build and validate deep learning models for medical images

Course content

- Note: today’s course will be very different from the others
  - Presentation of medical image acquisition techniques
    - Closer to physics than machine learning

Part 1 – Introduction
1.2 Main medical imaging modalities

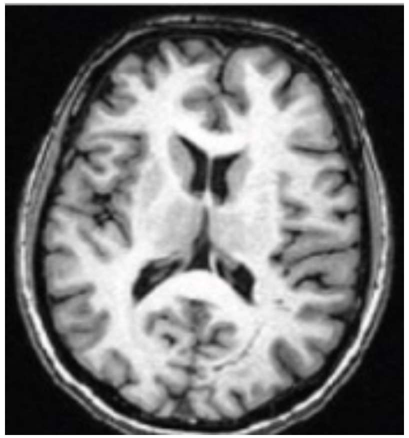
Two main types of medical images

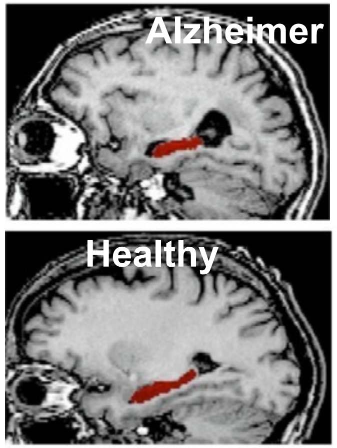
Structural images

Also called morphological or anatomical

Visualize the structures

- Differentiate between tissues (e.g. skin, bone, muscle, fat…)
- Between organs (heart, brain…)
- Between anatomical structures within an organ (e.g. in the heart: ventricles, atria…)

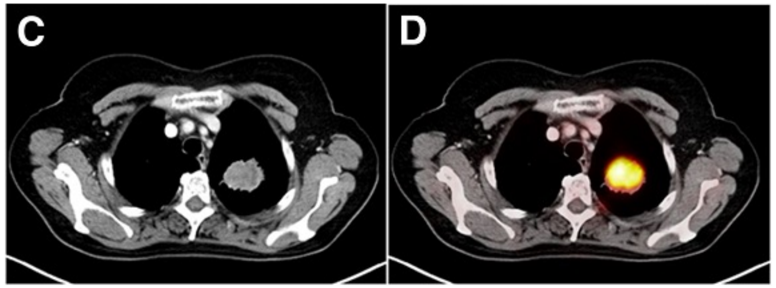




Functional images

Provide information about a functional process

- Metabolism (e.g. glucose consumption)
- Blood flow
- …



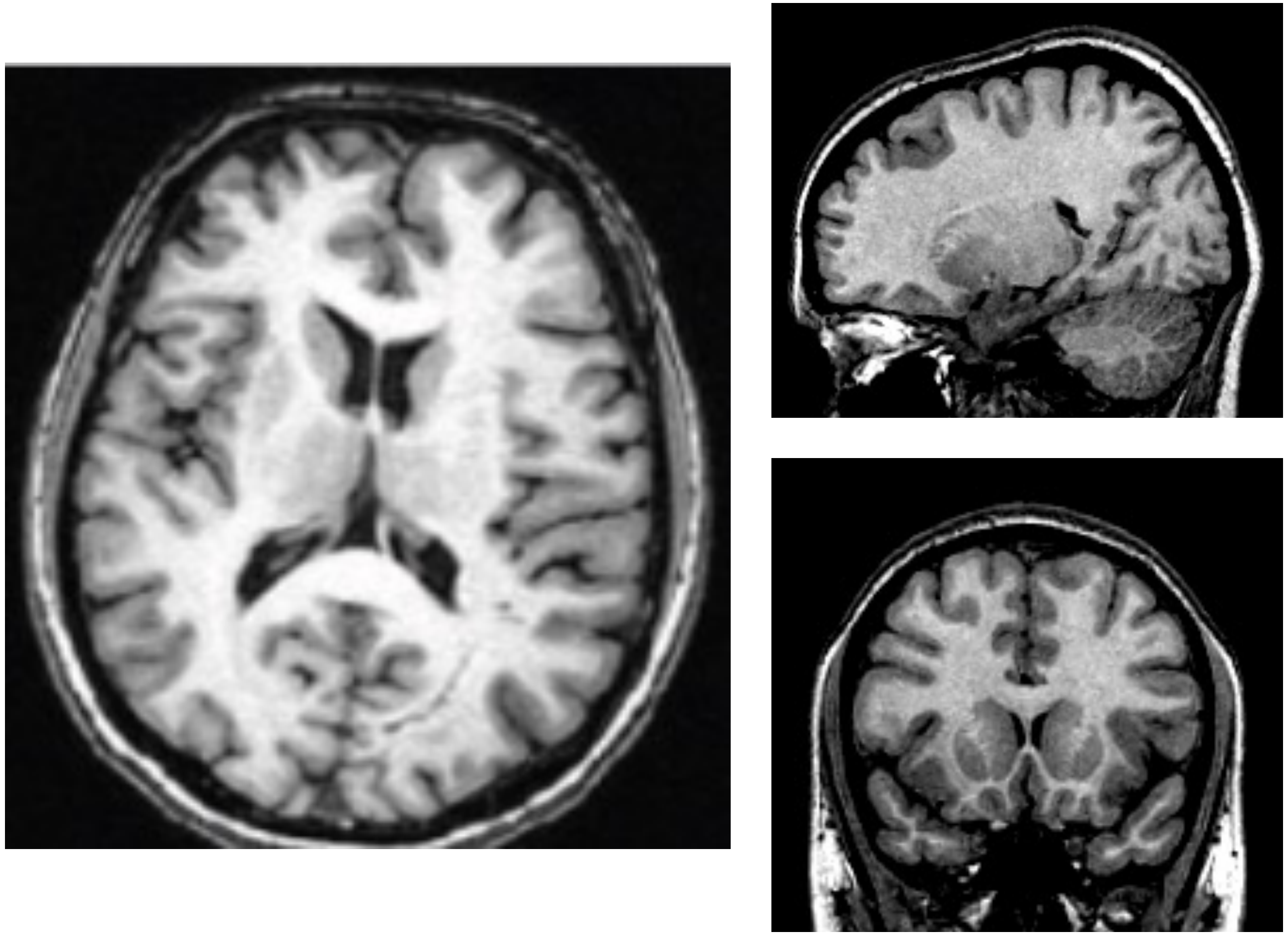
Anatomical image

Functional image (showing malignant lung tumour) superimposed on anatomical image

http://www.snmmi.org/Patients/Procedures/Content.aspx?ItemNumber=13526&navItemNumber=13230

Two main types of medical images

Structural images



Brain MRI

Two main types of medical images

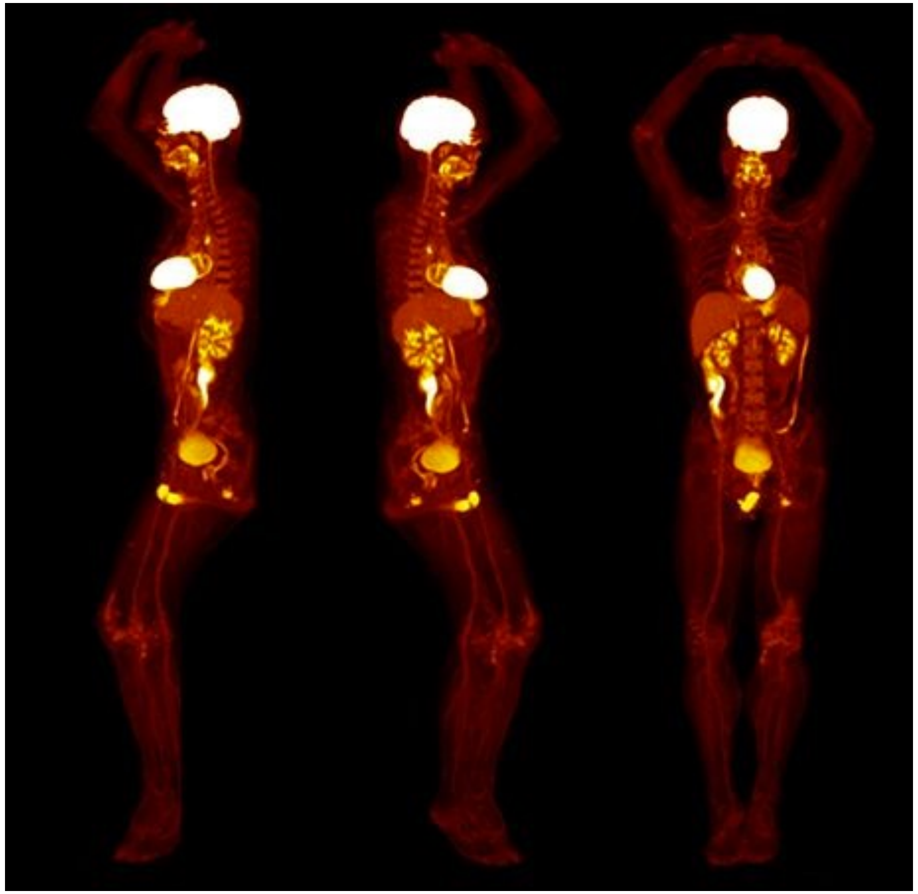
Structural images

Whole Body CT

https://www.siemens-healthineers.com/en-sg/computed-tomography/news/mso-imaging-a-tale-of-two-cities.html

Two main types of medical images

Functional images

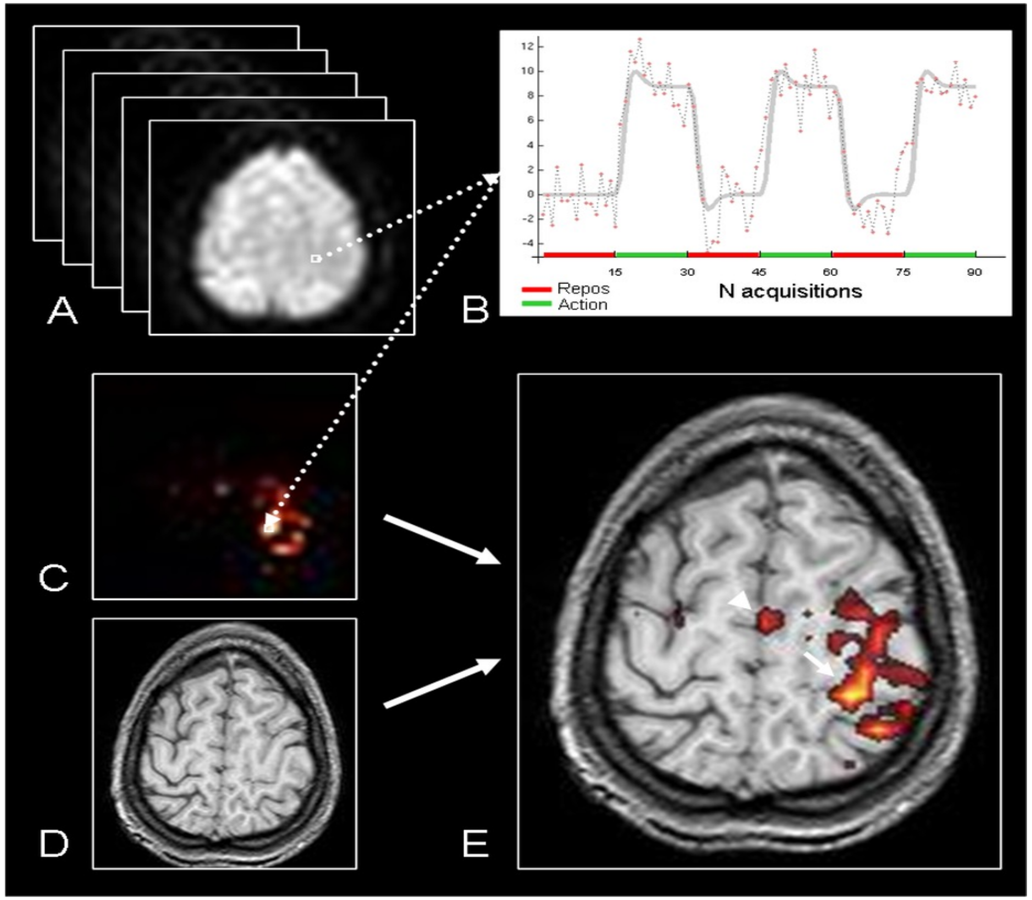


Whole Body PET

https://www.nature.com/articles/d41586-019-01833-z

Two main types of medical images

Functional images



Functional MRI: right hand activation

Two main types of medical images

Structural images

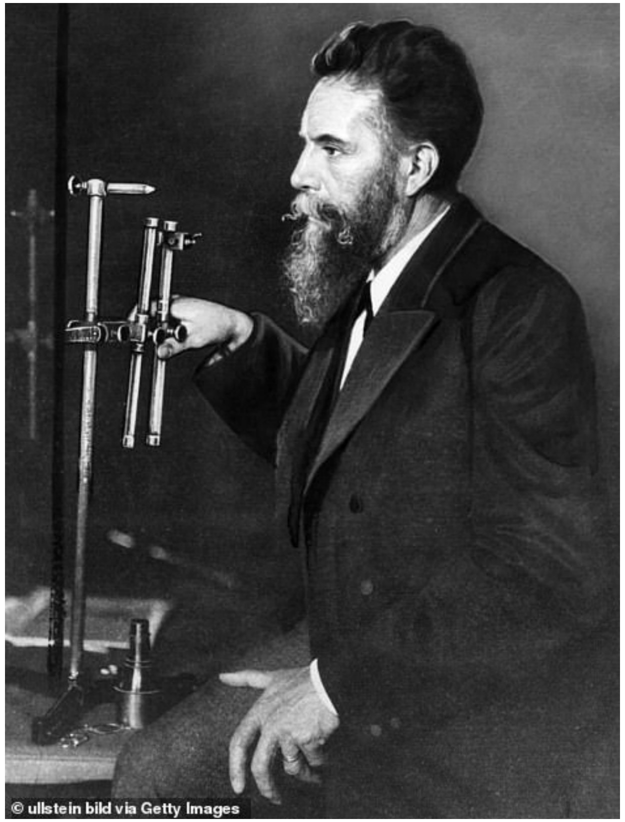
https://media-cdn.tripadvisor.com/media/photo-s/06/bd/47/14/shibuya-crossing-almost.jpg

Functional images

https://www.videezy.com/transportation/39282-ho-chi-minh-city-traffic-at-intersection-vietnam

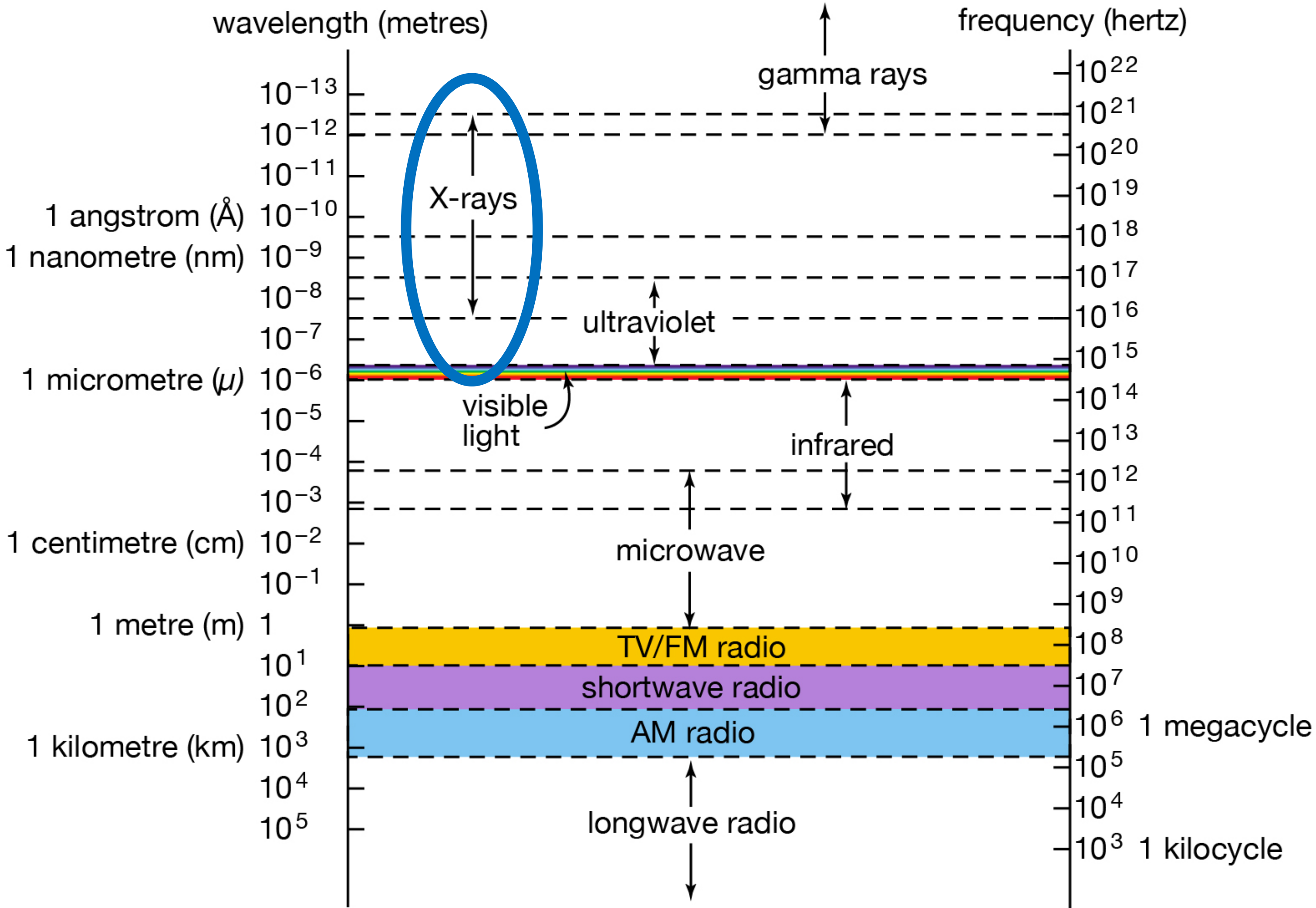
Part 1 – Introduction
1.2.1 Structural imaging
1.2.1.1 X-ray radiography

X-Ray radiography



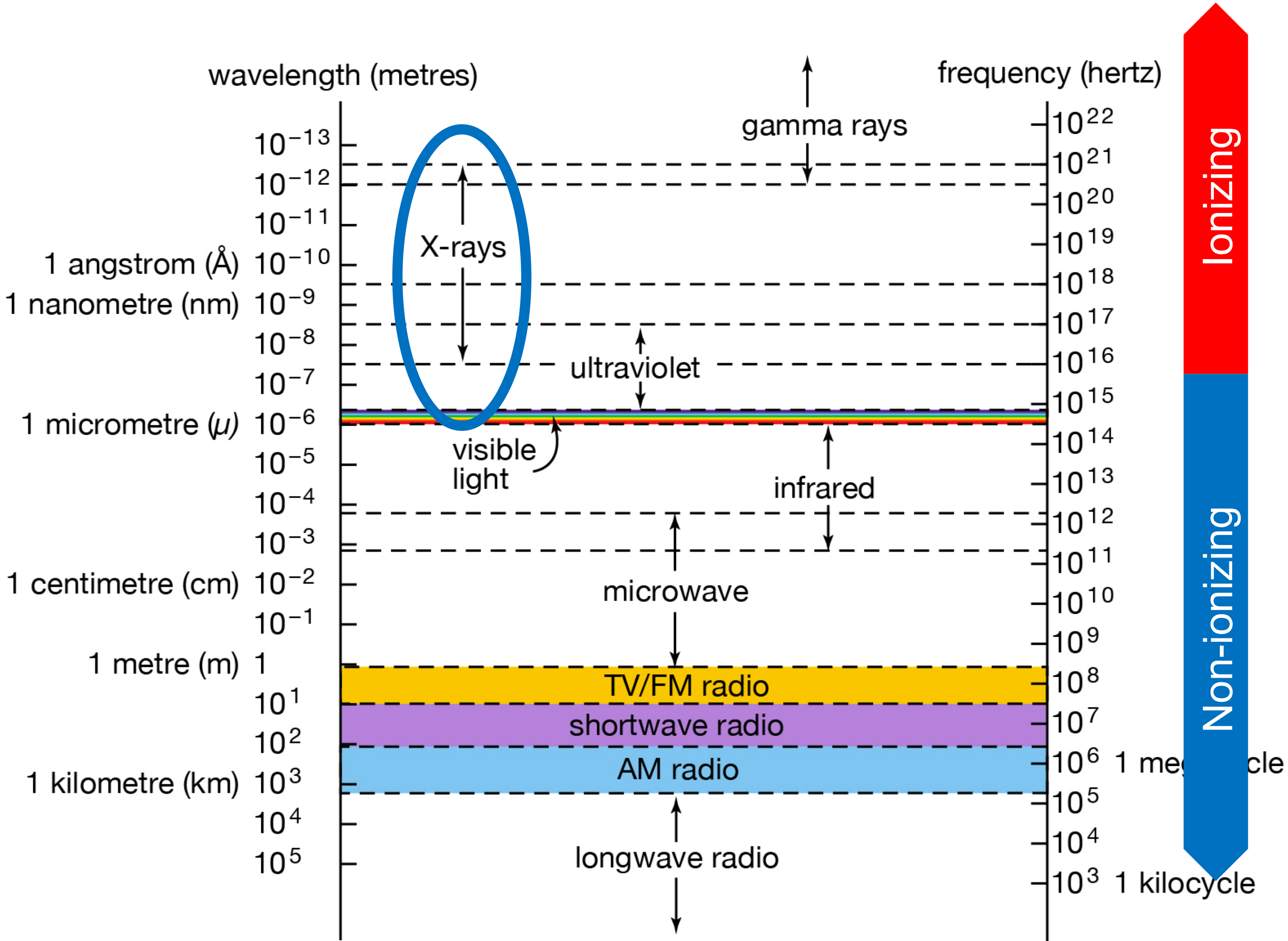
First X-ray radiography (1895) - Wilhelm Röntgen (Nobel Prize in Physics, 1901)

X-Ray radiography



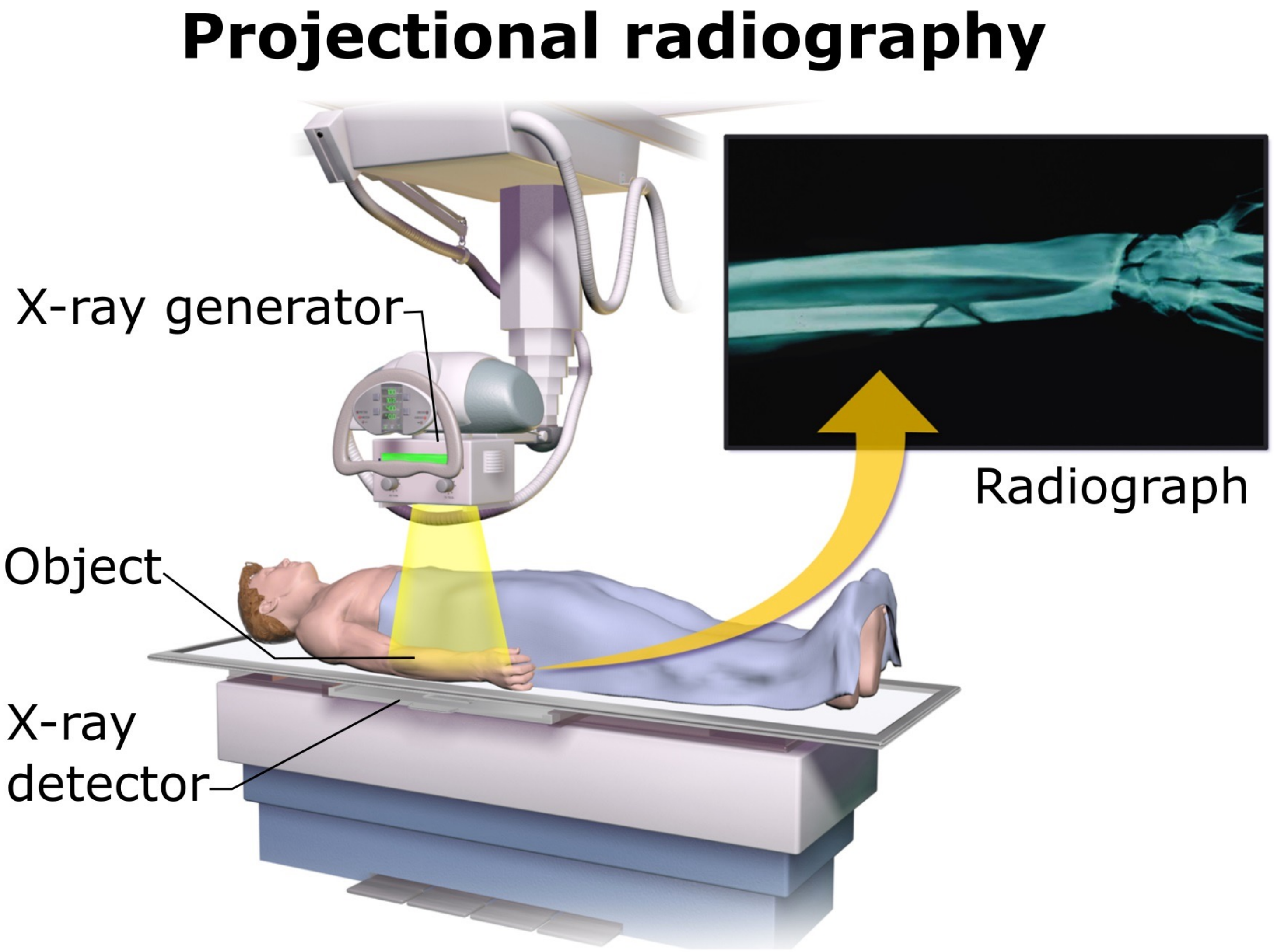
https://cdn.britannica.com/03/203-050-5A9E63DC/relationship-X-rays-electromagnetic-radiation-spectrum.jpg

X-Ray radiography

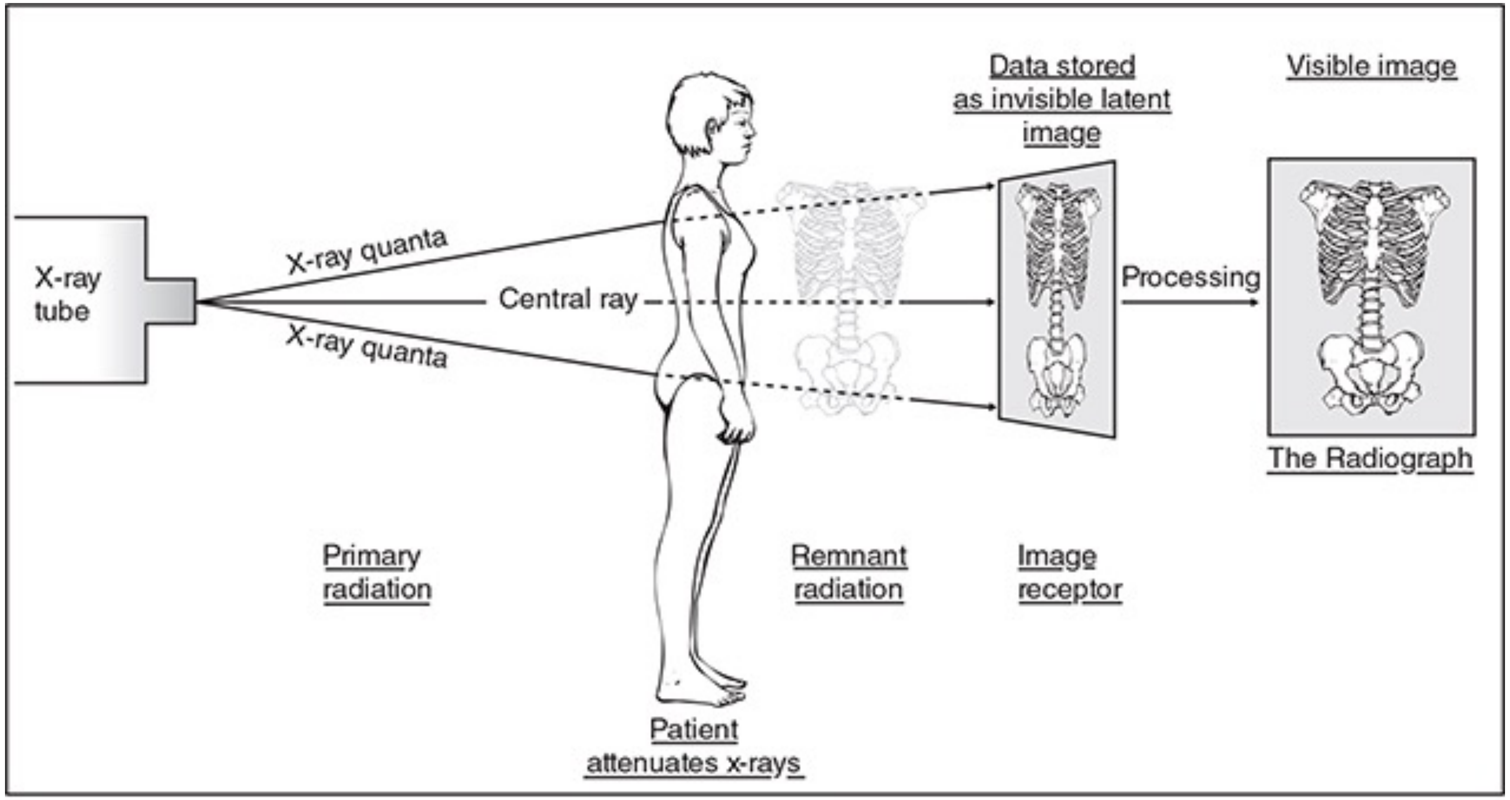


https://cdn.britannica.com/03/203-050-5A9E63DC/relationship-X-rays-electromagnetic-radiation-spectrum.jpg

X-Ray radiography



X-Ray radiography



Source: Lynn N. McKinnis: *Fundamentals of Musculoskeletal Imaging*, 4th Edition: www.FADavisPTCollection.com

X-rays are absorbed by heavy atoms and not by lighter atoms

Bones: high absorbtion

Soft tissues: lower absorbtion

Air: no absorbtion

X-Ray radiography

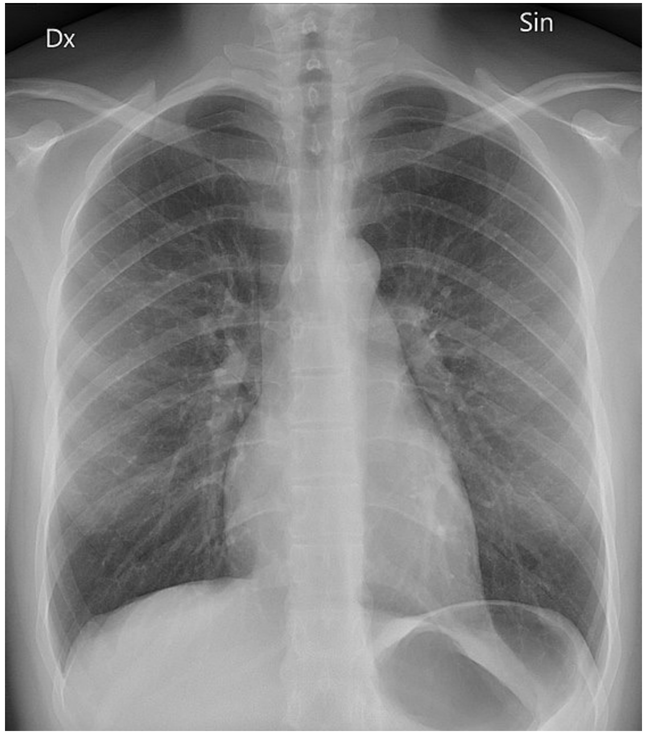


Image source:
https://en.wikipedia.org/wiki/Dental_radiography
https://en.wikipedia.org/wiki/Chest_radiograph

X-rays are absorbed by heavy atoms and not by lighter atoms

Bones: high absorbtion

Soft tissues: lower absorbtion

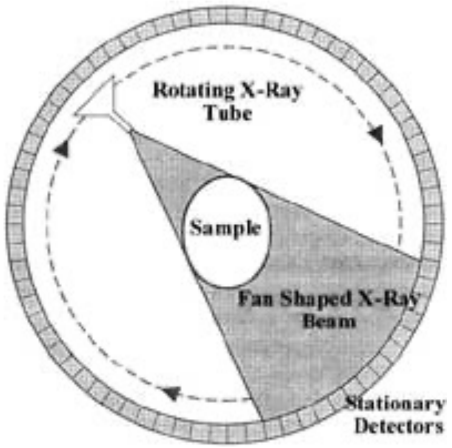
Air: no absorbtion

Part 1 – Introduction
1.2.1 Structural imaging
1.2.1.2 CT

CT

<u>CT: Computed Tomography</u>

<u>Principle :</u> 3D reconstruction from multiple radiographic projections

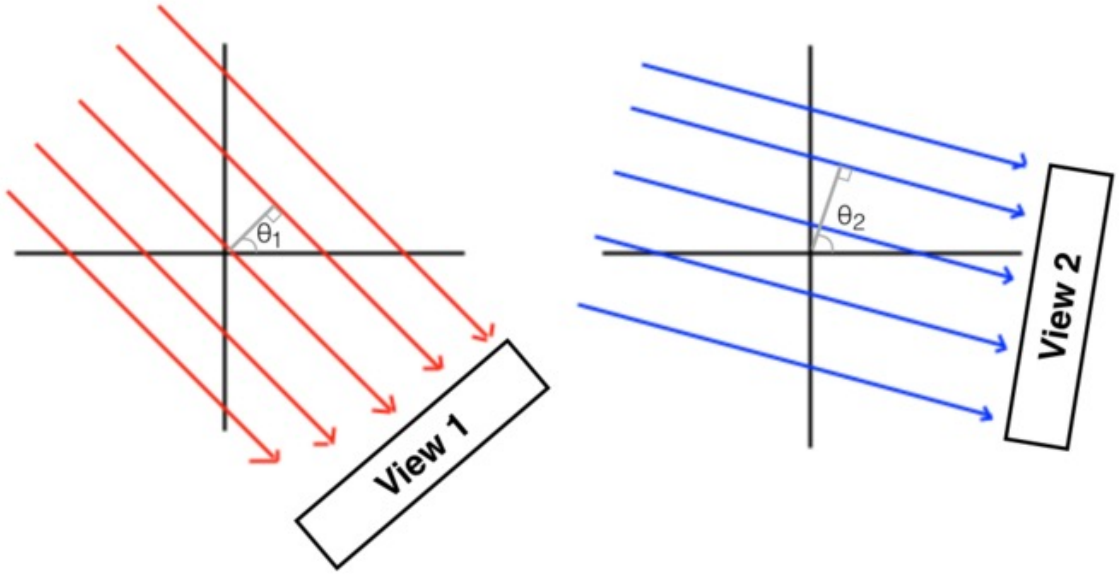


Good visualization of bone

High resolution

Poor visualization of soft tissues (in particular in the brain)

CT

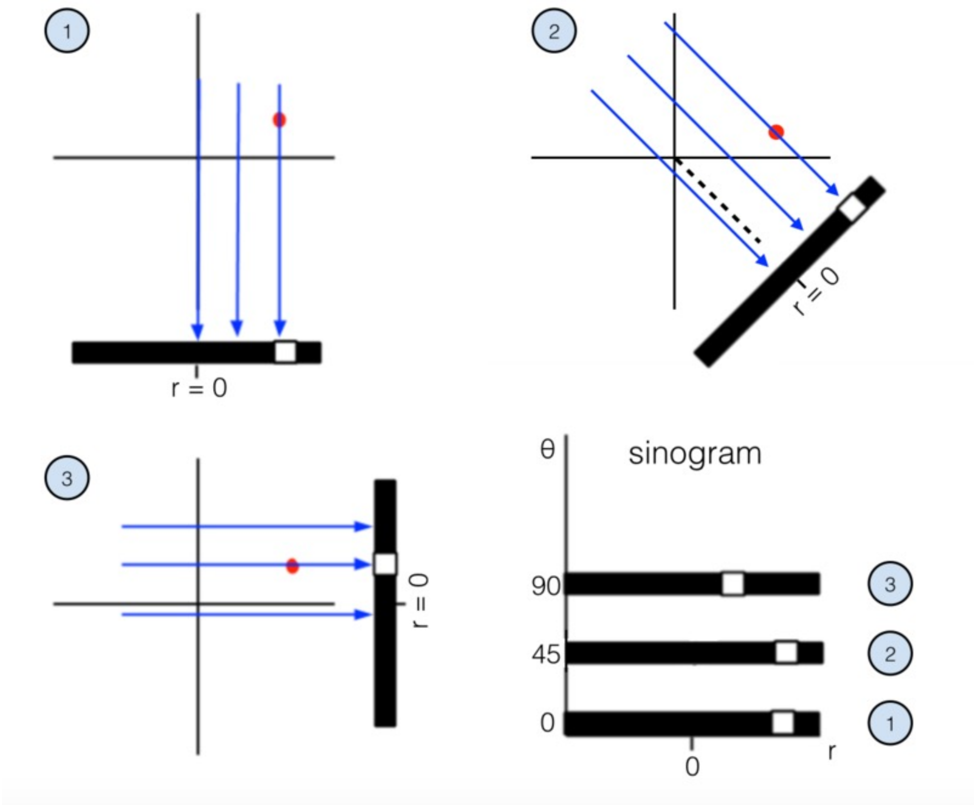


Multiple CT views, each made up of parallel rays incident from a different angle. Theta defines the angle of incidence.

Source: http://199.116.233.101/index.php/Image_Reconstruction_(CT)

CT

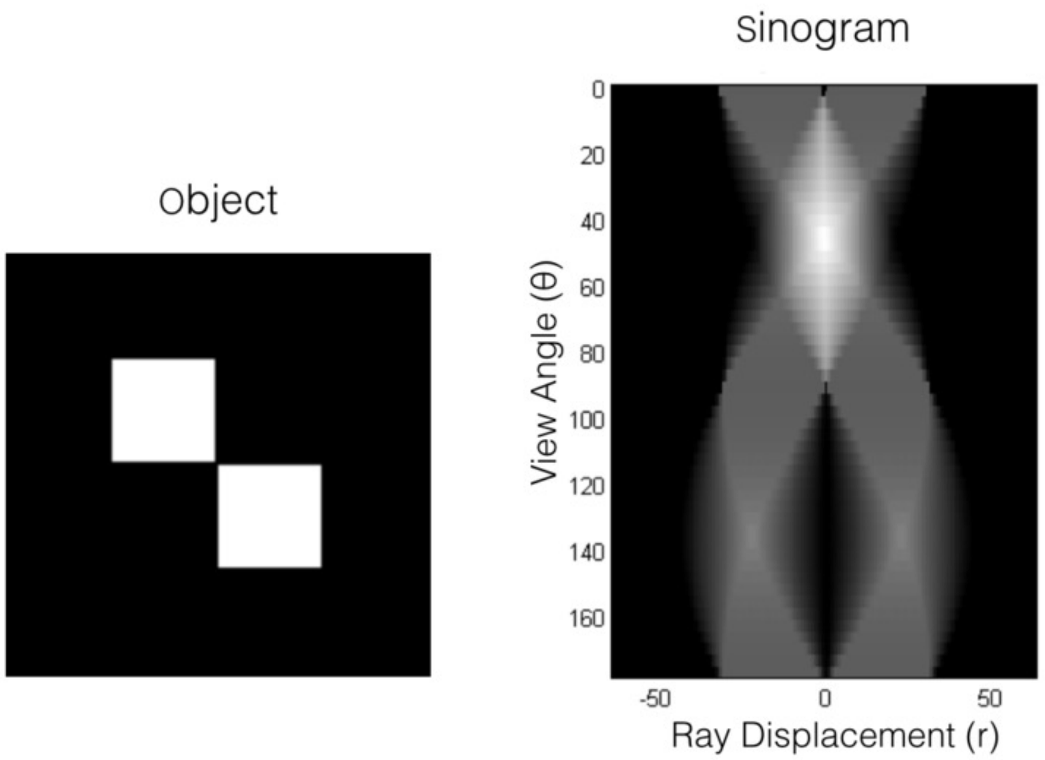
The sinogram draws the signal for each distance r and each angle theta



Sinogram formation from individual projection angles

Source: http://199.116.233.101/index.php/Image_Reconstruction_(CT)

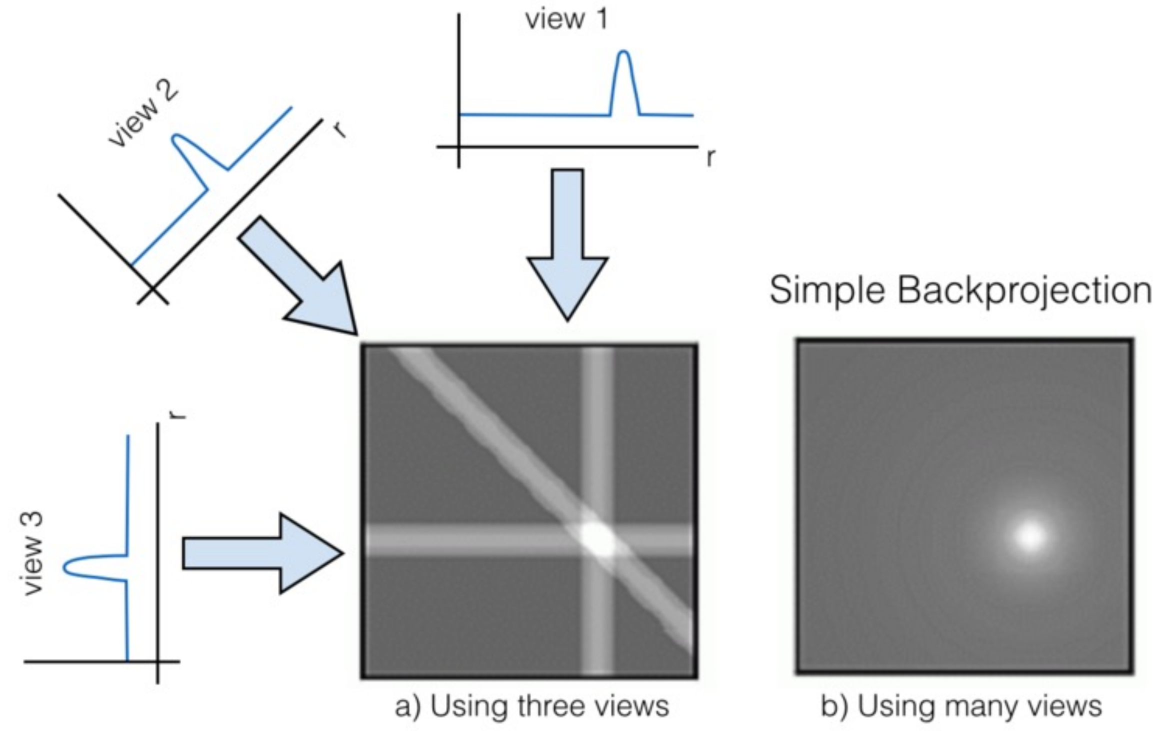
CT



Sinogram of an example object

Source: http://199.116.233.101/index.php/Image_Reconstruction_(CT)

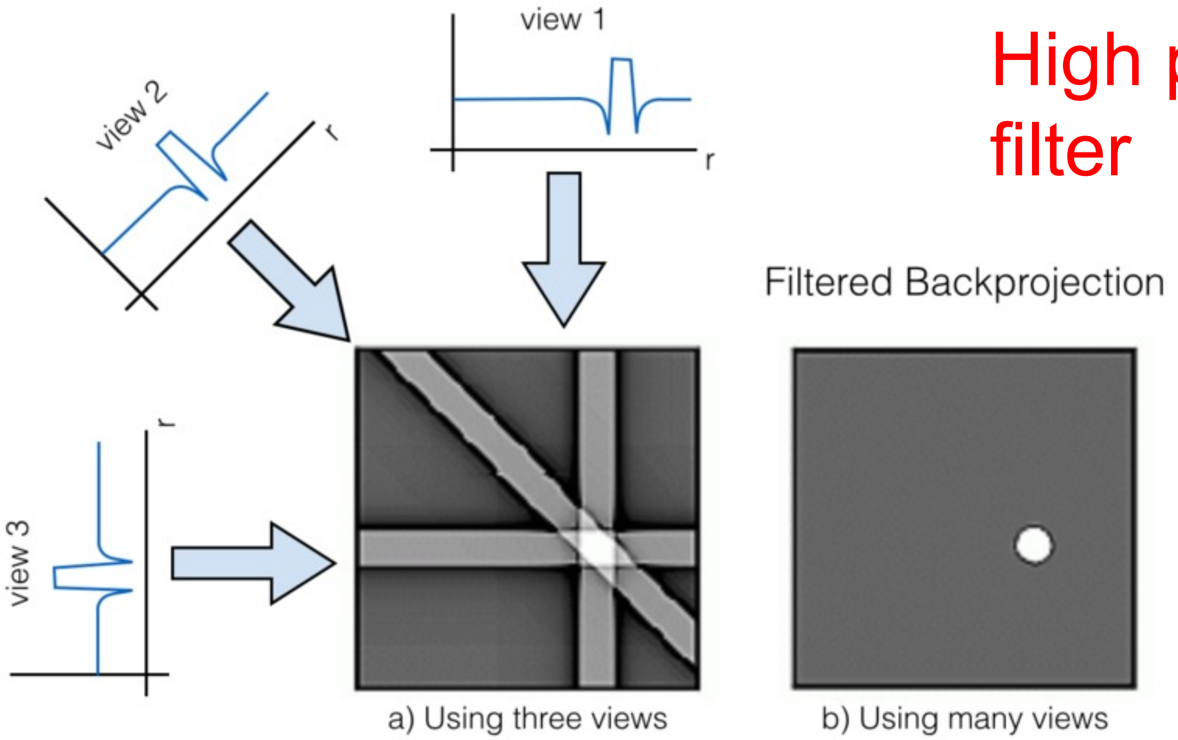
CT



Backprojection. Each view (intensity vs. radius) is stretched backwards in the same direction as the ray and superimposed. Here, three views are used to illustrate the technique (a), and the final result is shown (b).

Source: http://199.116.233.101/index.php/Image_Reconstruction_(CT)

CT

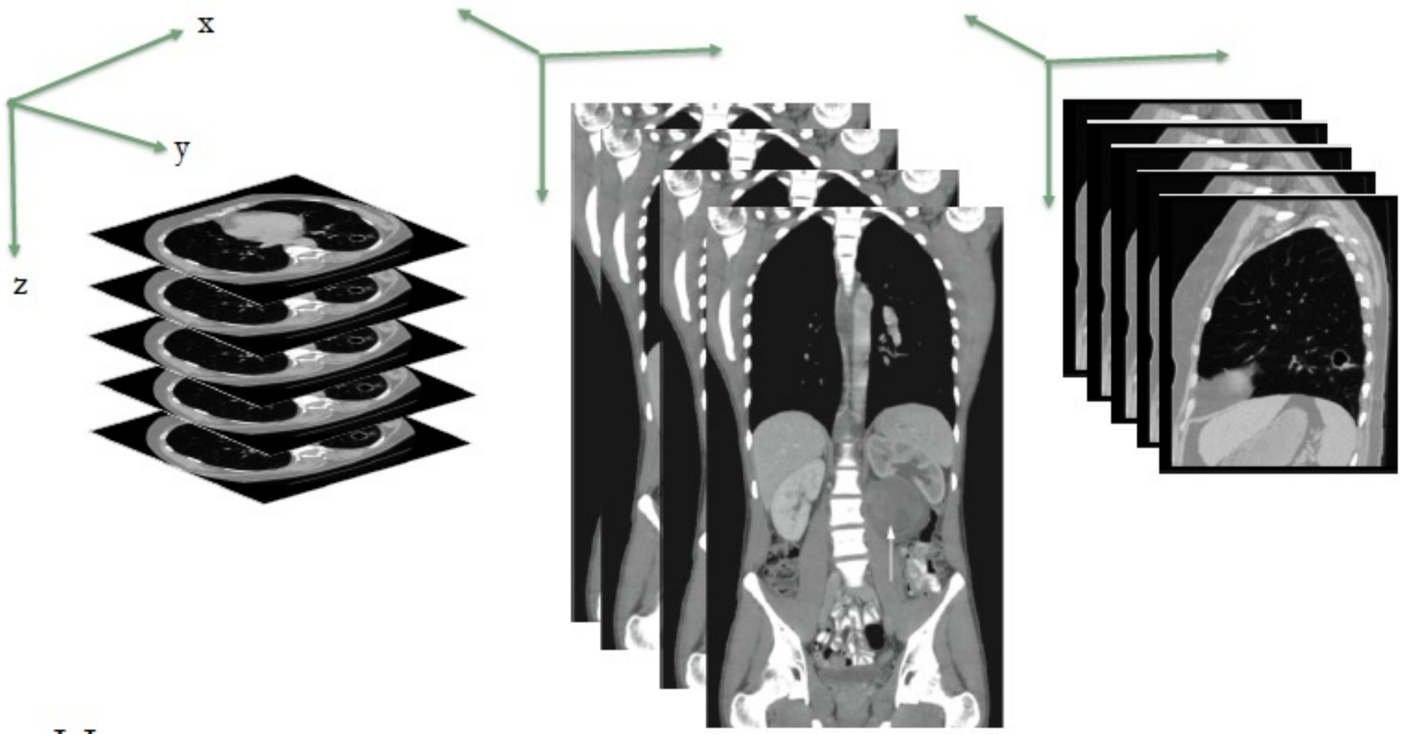


High pass filter

Filtered Backprojection. Each view (intensity vs. radius) is filtered and then stretched backwards in the same direction as the ray. Here, three views are used to illustrate the technique (a), and the final result is shown (b).

Source: http://199.116.233.101/index.php/Image_Reconstruction_(CT)

CT



I: Image
I(x,y,z) denotes intensity value at pixel location x,y,z
<u>Note also that whatever you see on the left is right part of the body!</u>

Part 1 – Introduction
1.2.1 Structural imaging
1.2.1.3 Structural MRI

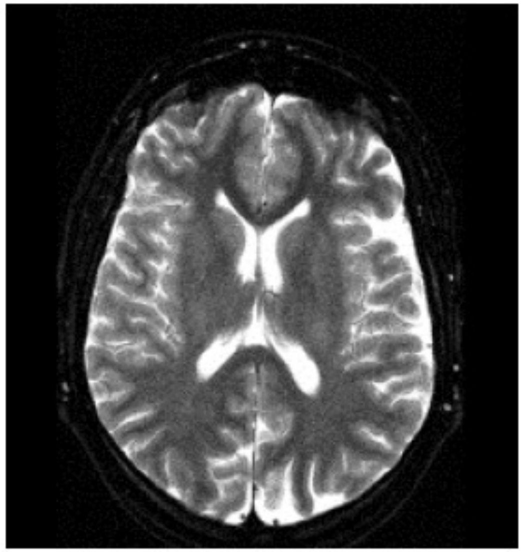
MRI – Magnetic resonance imaging

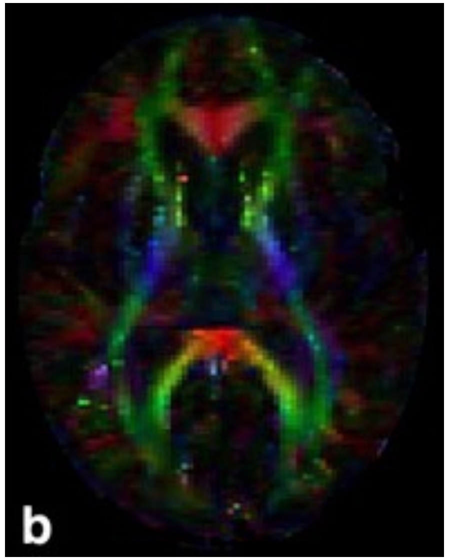
High spatial resolution (millimeter), 3D

Acceptable temporal resolution (second) – for functional imaging

Very versatile modality (multiple types of images, multiple phenomena)

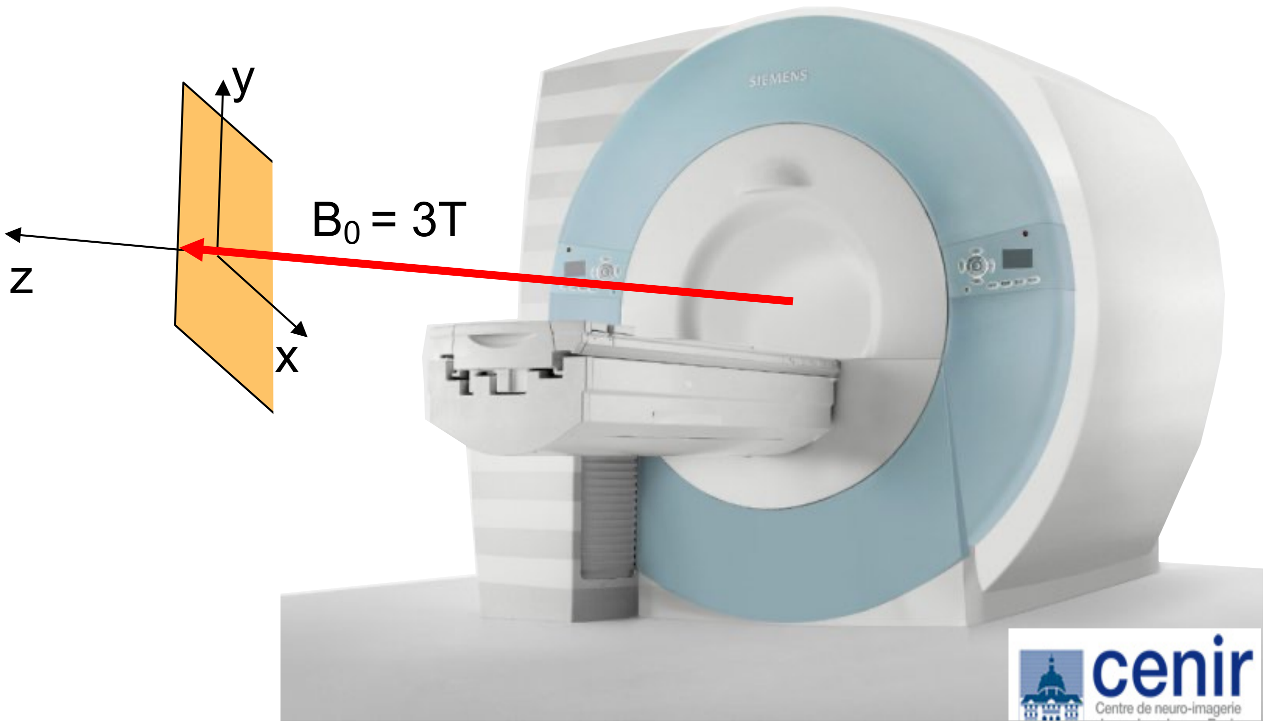
Not radiation





MRI

Magnet



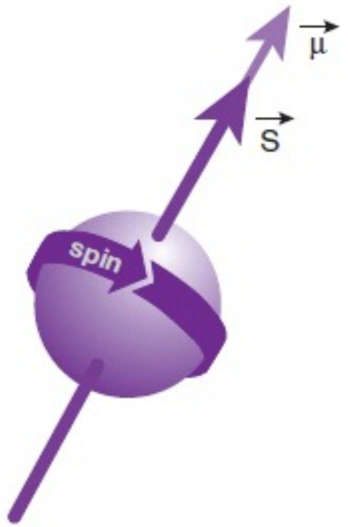
MRI Siemens Magnetom Trio/TIM of the CENIR
Centre for neuroimaging research, Paris

The signal

- It depends on the physico-chemical organization of water within tissues (mobility, chemical liaisons)
- It is produced through excitation at a specific frequency (resonance) and recorded at the return at equilibrium (relaxation)
- It is located in space through additional magnetic fields (field gradients)

The signal

- It is directly related to
  - The magnetic moment of hydrogen nuclei (protons) that are within tissues (in particular, water)
  - To their properties within an external magnetic field B_0



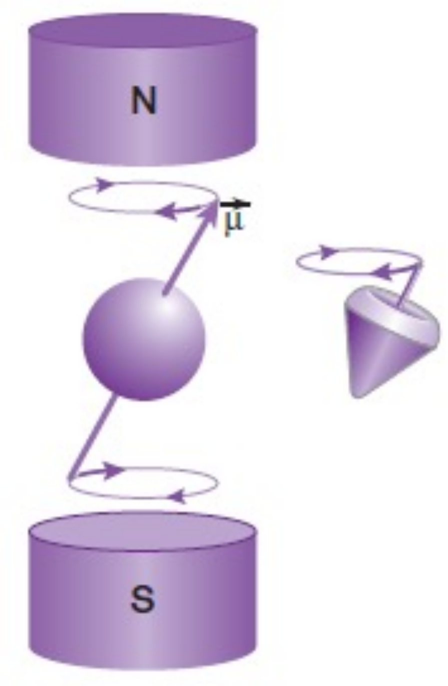
From (Kastler and Vetter)

MRI

- The magnetic moment μ of each proton placed into a static magnetic field B_0
  - orients itself (parallel/anti-parallel)
  - describe a movement of precession at the following angular speed (Larmor relationship)

$$\omega_0 = \gamma . B_0$$

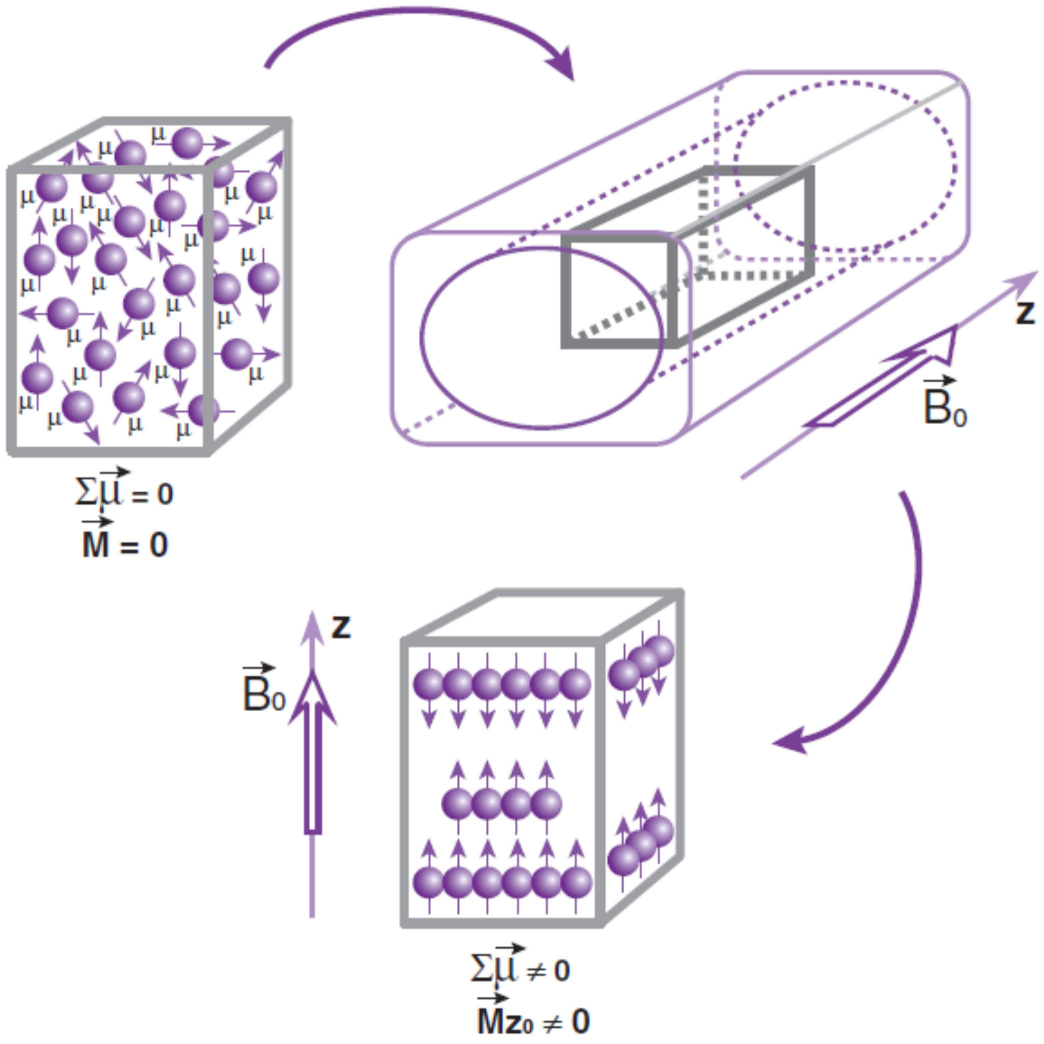
Where B_0 is the external (static) magnetic field and gamma is the gyromagnetic ratio (specific to each nucleus, here protons)



From (Kastler and Vetter)

MRI

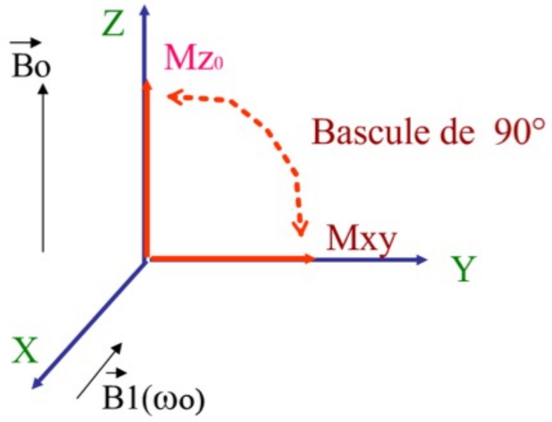
The sum of magnetic moments μ of all protons is oriented along B_0

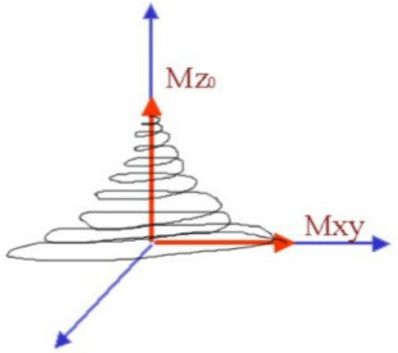


From (Kastler and Vetter)

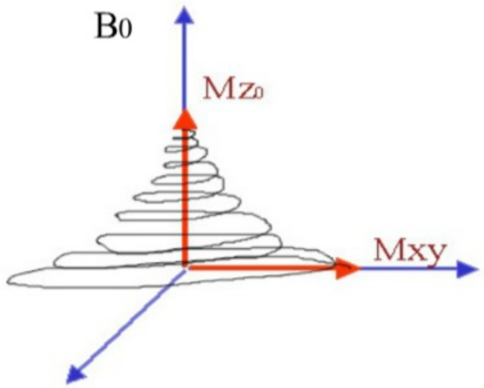
Excitation/relaxation

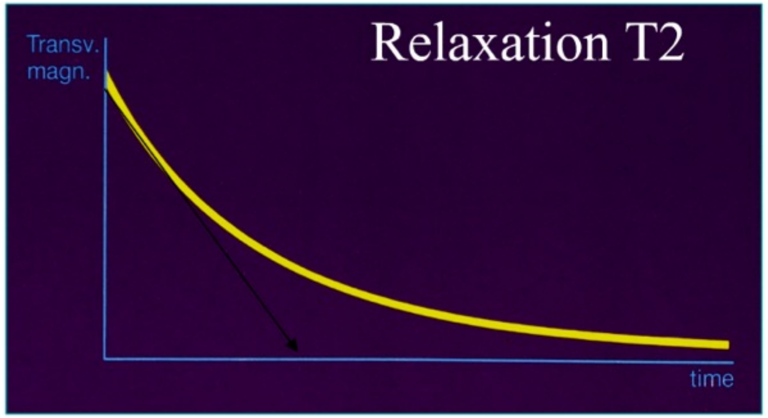
- Excitation by a coil which creates a magnetic field B1 orthogonal to B0
  - B1 is a rotating magnetic field with frequency ω0 (in order to create resonance)
- Rotation of M0 around the direction B1 (resonance). Creation of a component Mxy
- Return to equilibrium: relaxation -> production of the MR signal



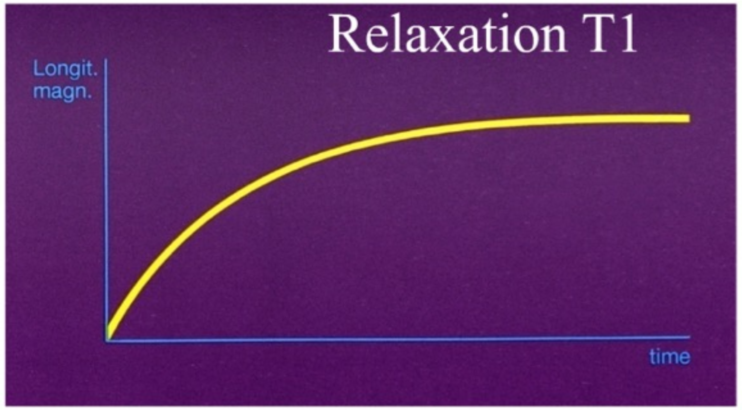


MRI



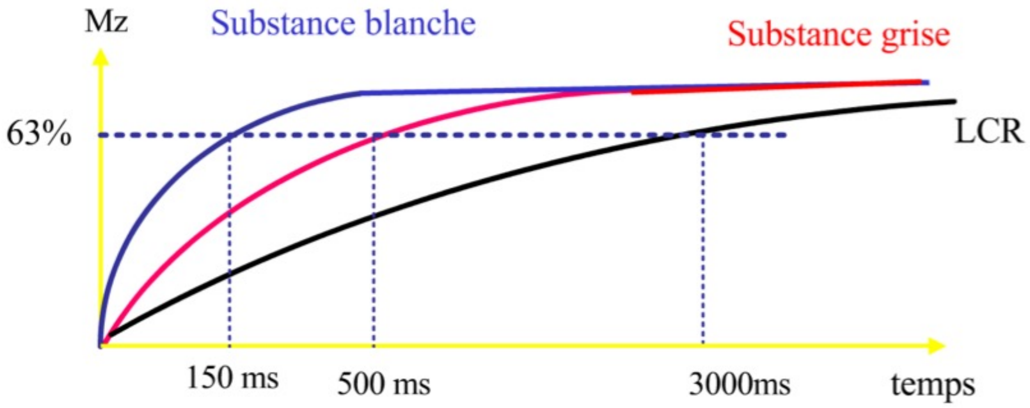


Décroissance de Mxy

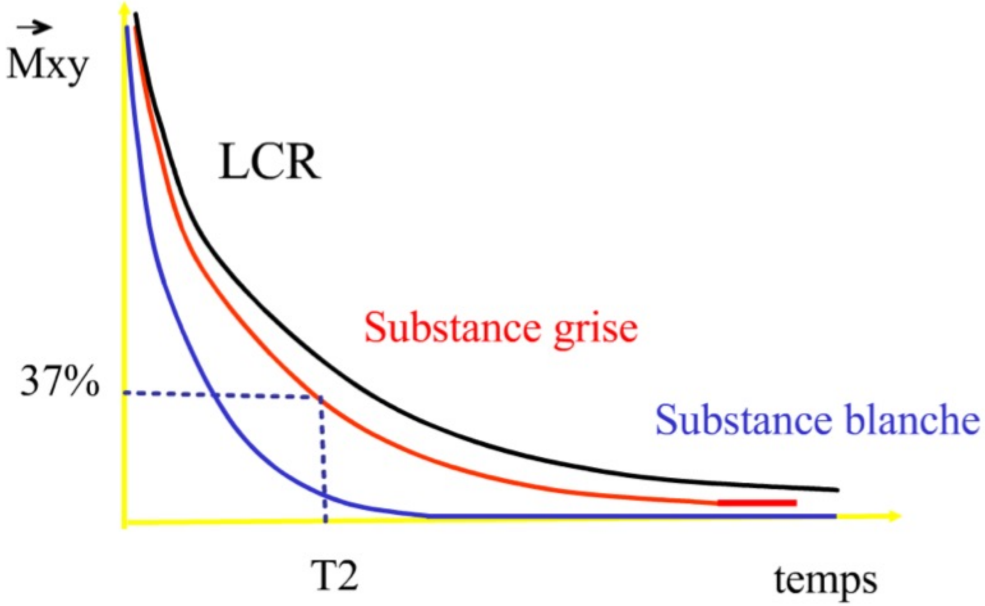


Repousse de Mz

Relaxation T1



Relaxation T2



Obtaining an image

- Spatial coding (x,y,z) relies on the use of magnetic field gradients (Gx, Gy, Gz), with the same direction as B0 but which amplitude varies linearly along directions x, y et z

- It allows to “control” the frequencies of precession at each point, as a function of the magnetic field in this point

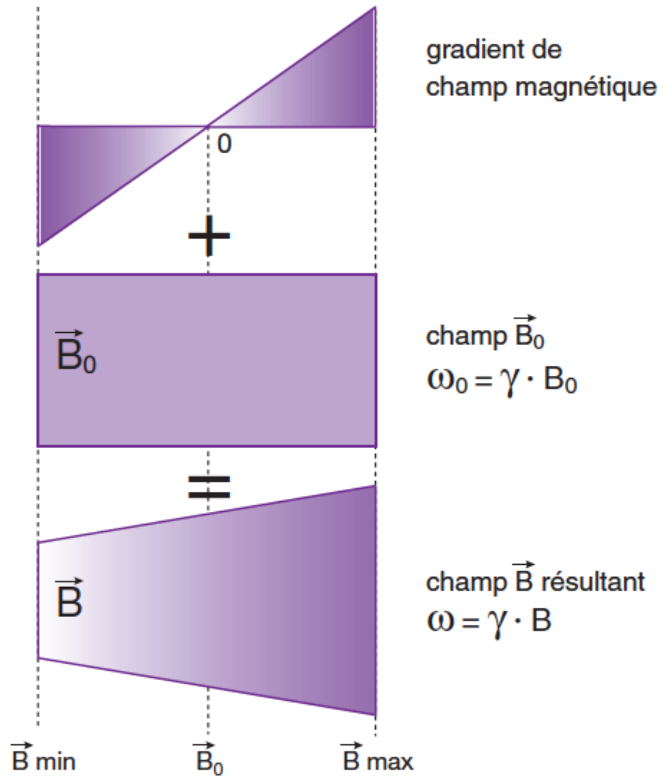
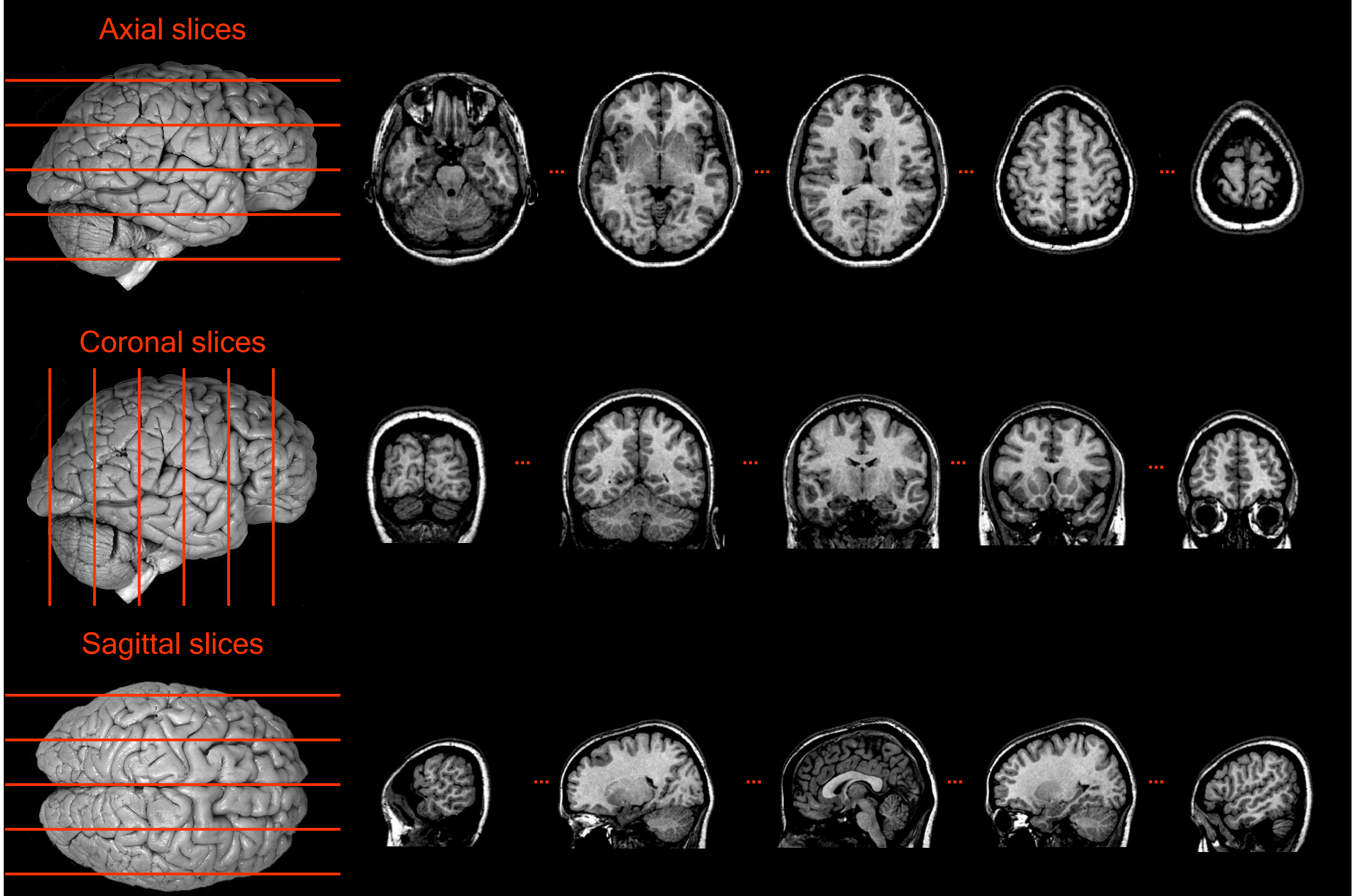
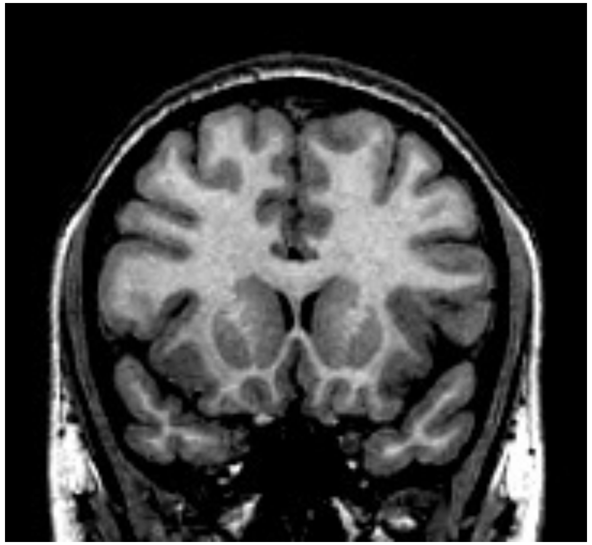


Fig. 6-3. Le gradient de champ magnétique se superpose au champ magnétique principal B_0, les modifications de champ produites se rajoutant ou se retranchant de B_0.
Le champ résultant B croit linéairement dans la direction du gradient (centré par rapport à $\vec{B}_0$). Par conséquent, la fréquence de Larmor croit aussi de manière linéaire, proportionnellement au champ résultant B : on a maintenant $\omega = \gamma \cdot B$. *Schéma : J.-P. Dillenseger.*


Axial slices
Coronal slices
Sagittal slices

Anatomical MRI

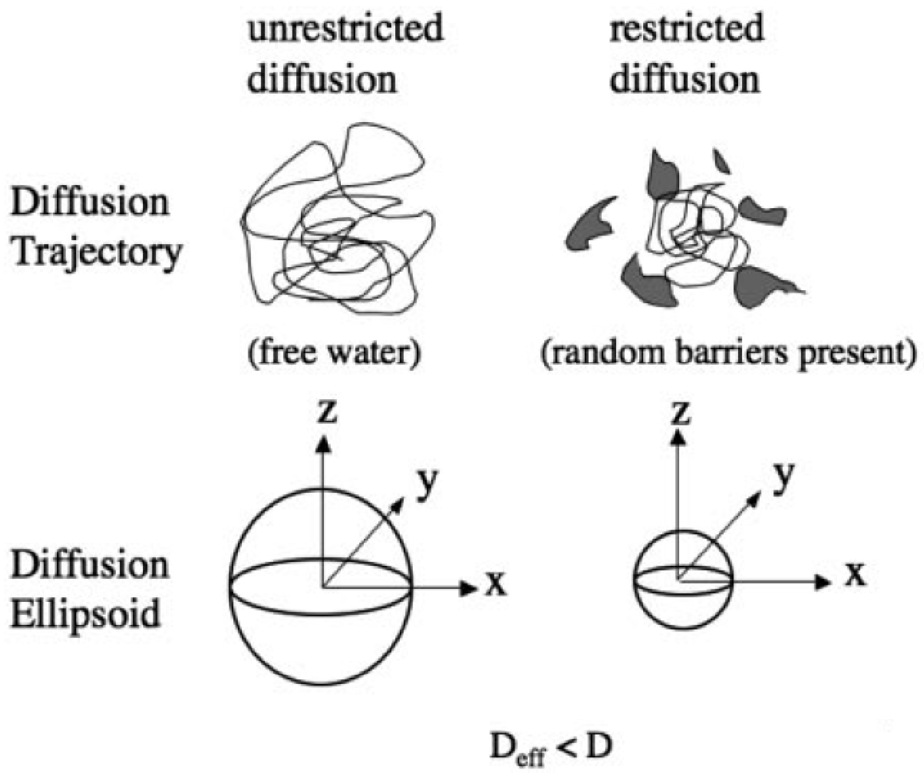
T1-weighted MRI
Resolution ~ 1mm x 1mm x1mm



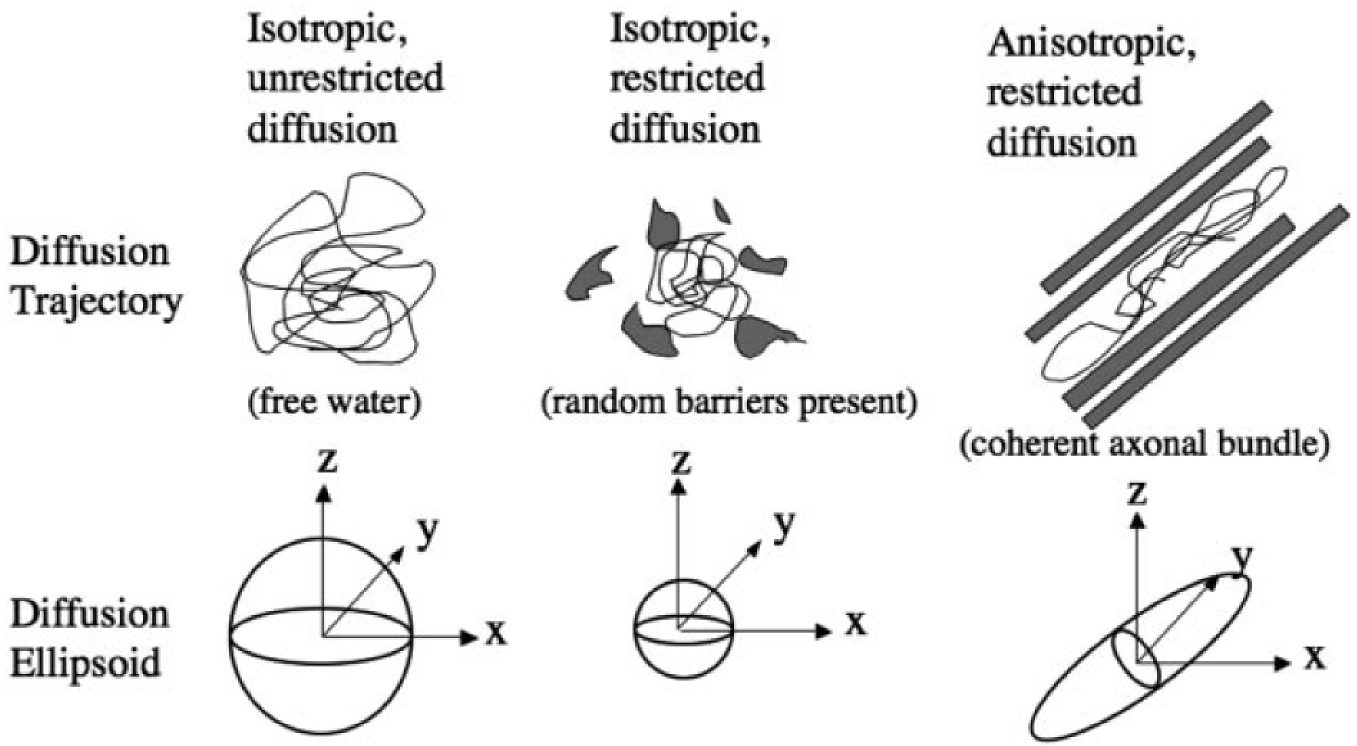
Diffusion MRI

- Brownian motion
- Allow to study the structure of tissues at the microscopic level (cell membranes, fibers…)
- In the brain: allows studying the white matter connections
- Other applications: heart, muscle…

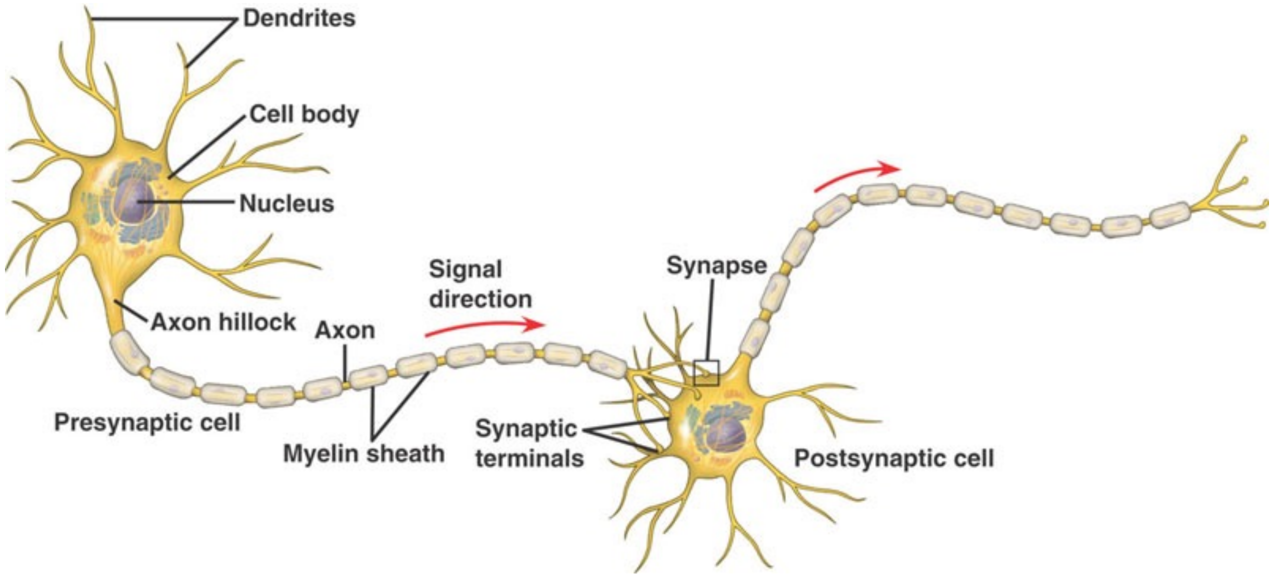
Diffusion MRI

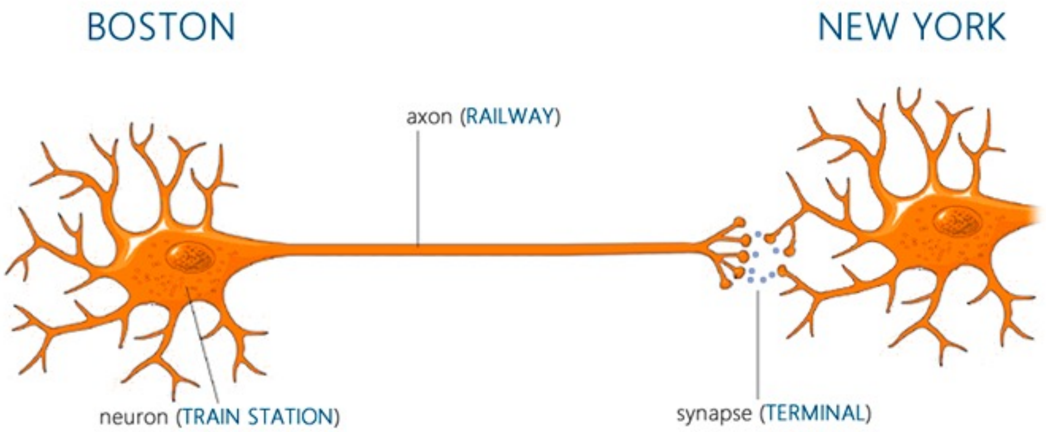


Diffusion MRI

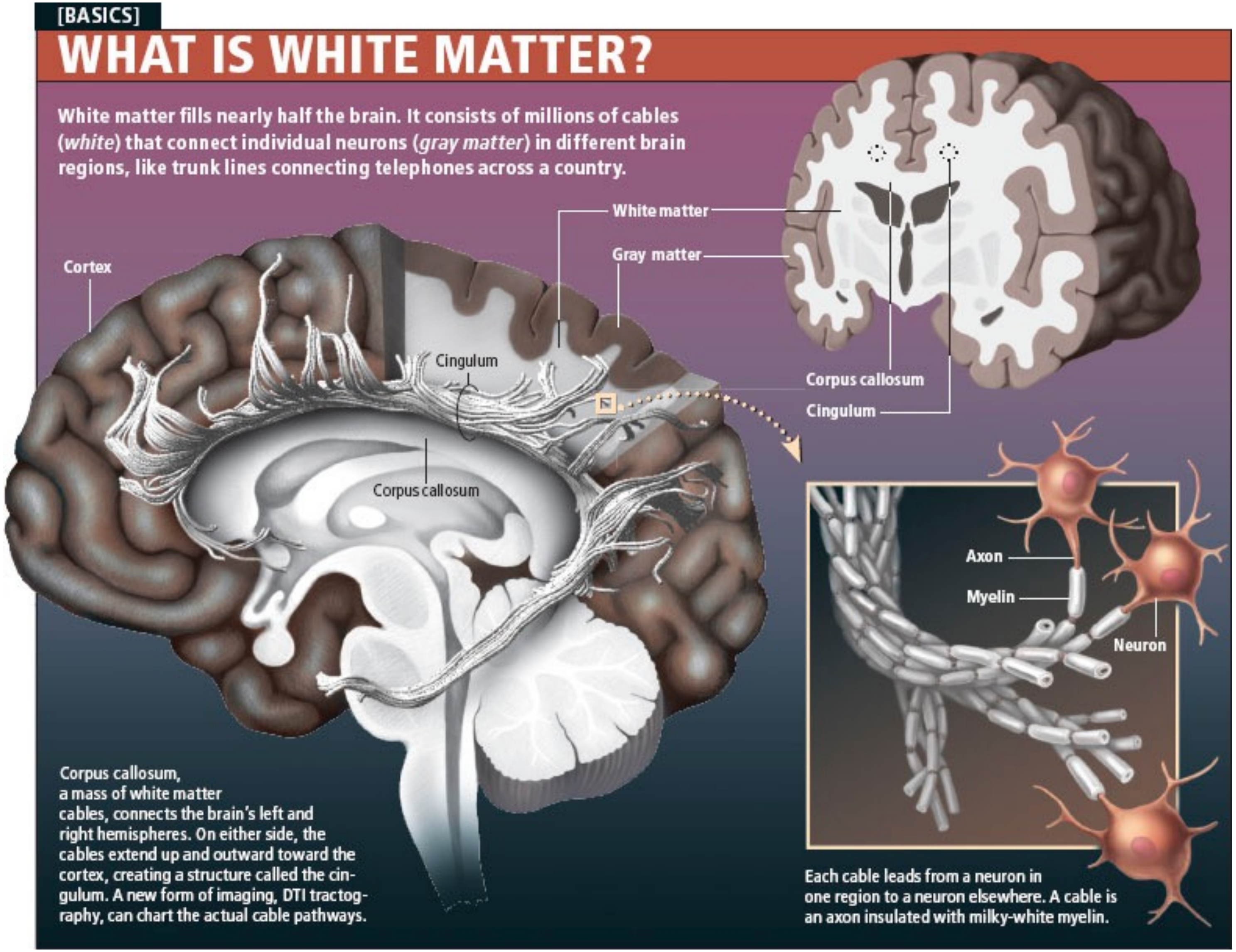


Neurons and axons

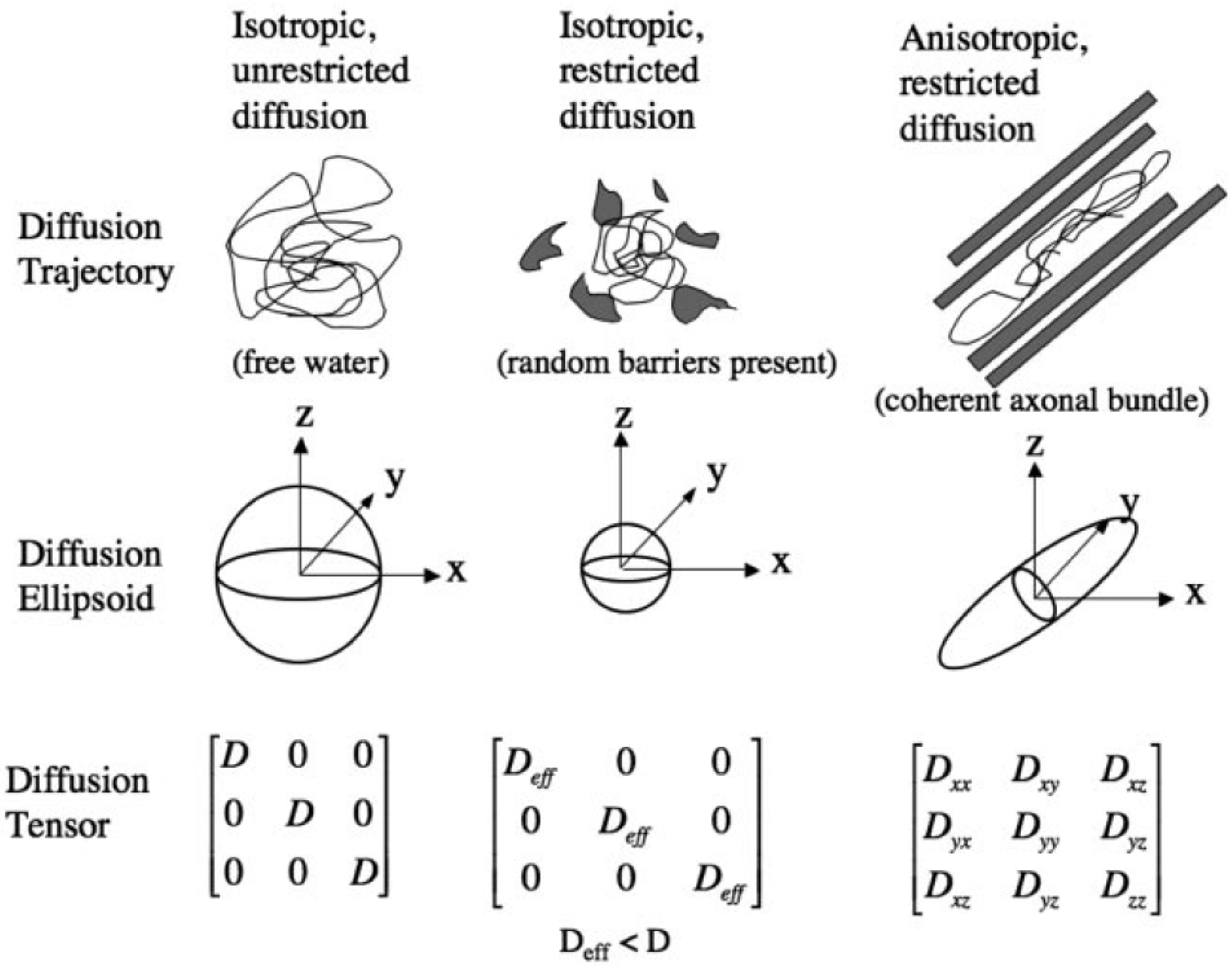




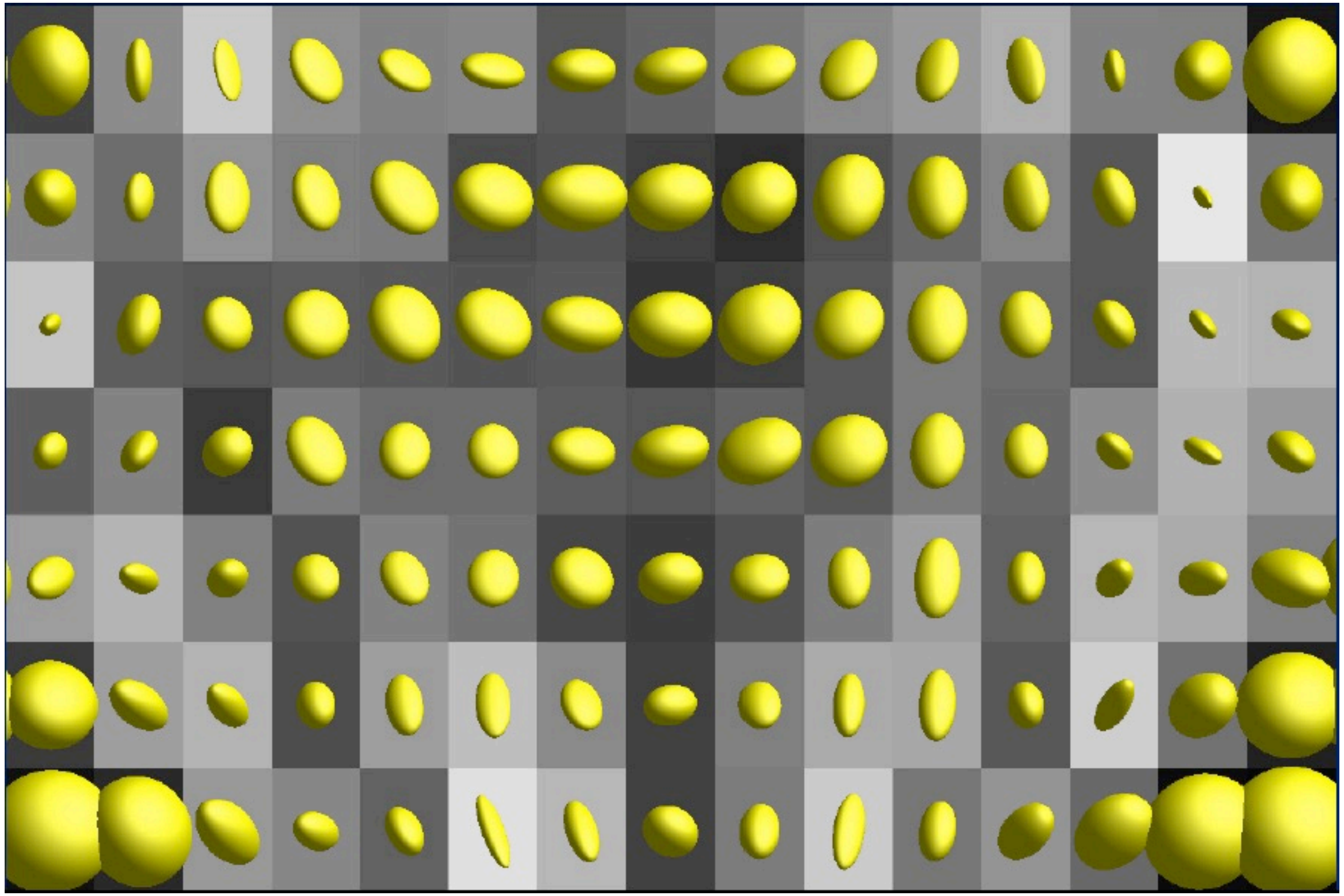
White matter



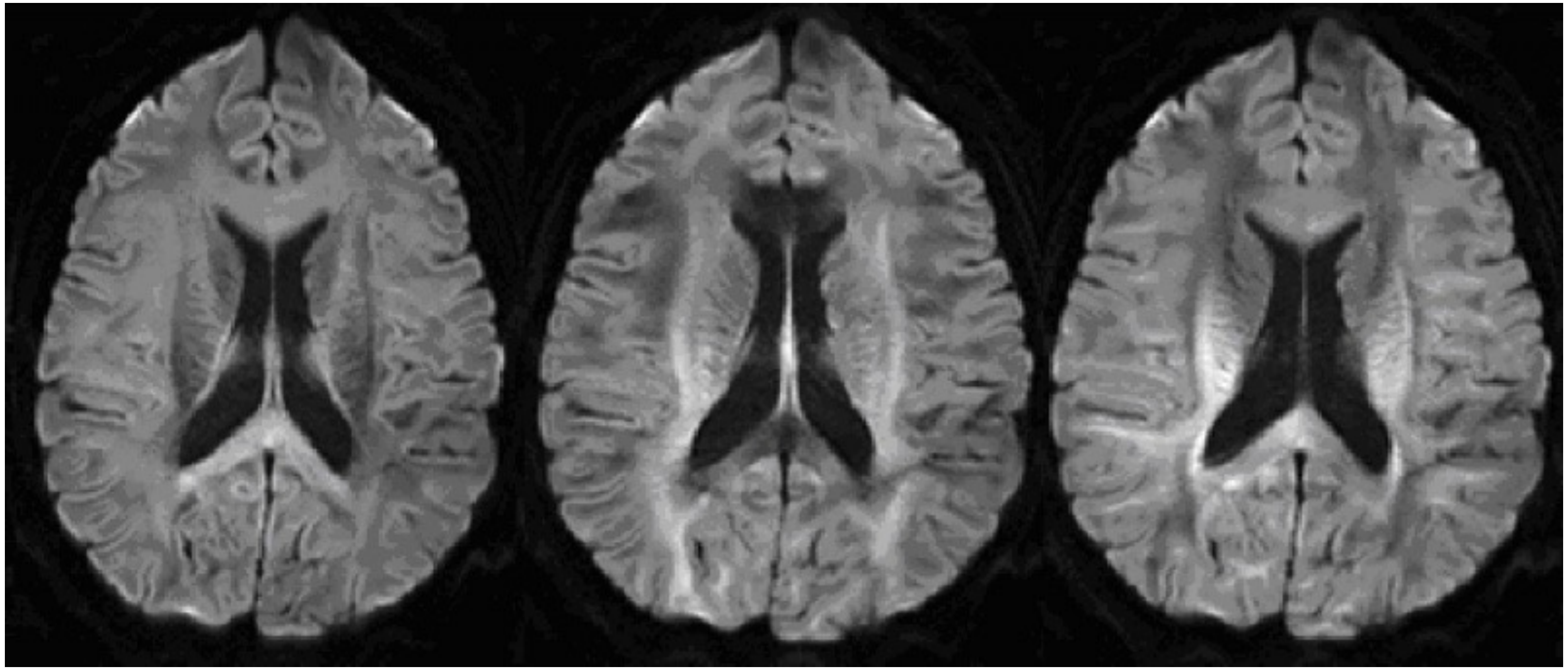
Diffusion MRI



Diffusion MRI



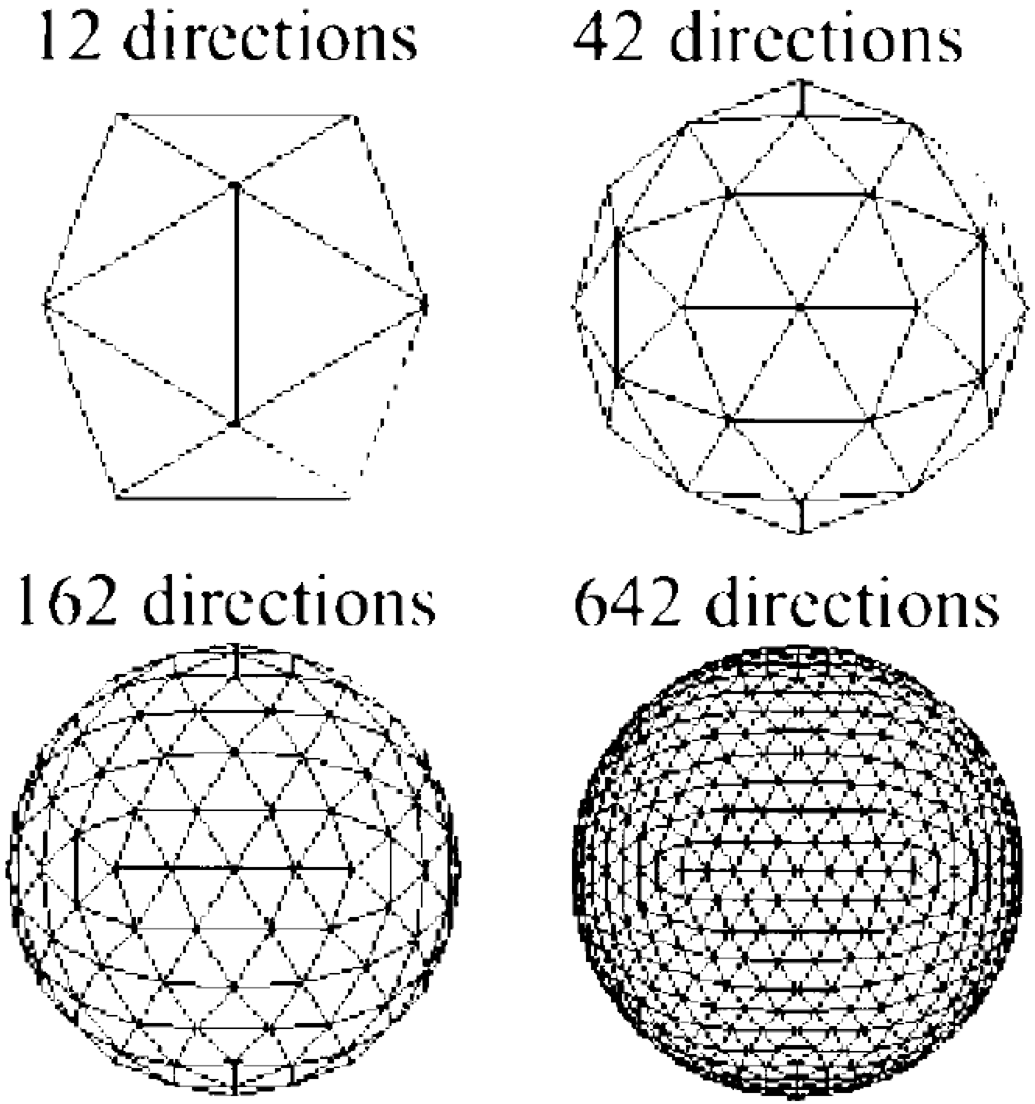
Gradient direction



DWI z DWI x DWI y

(From Cauchi and Yamamoto)

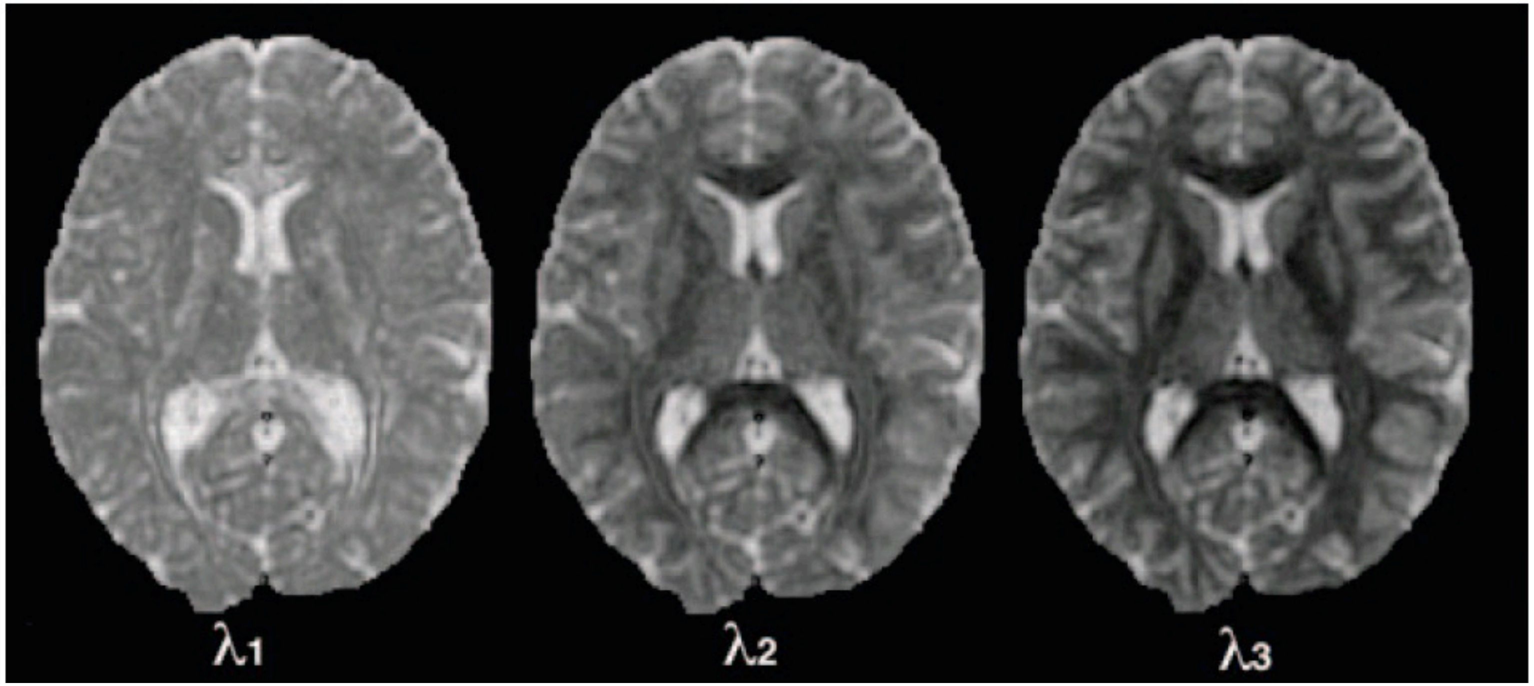
Diffusion MRI



(From Le Bihan et al, 2002)

Diffusion MRI

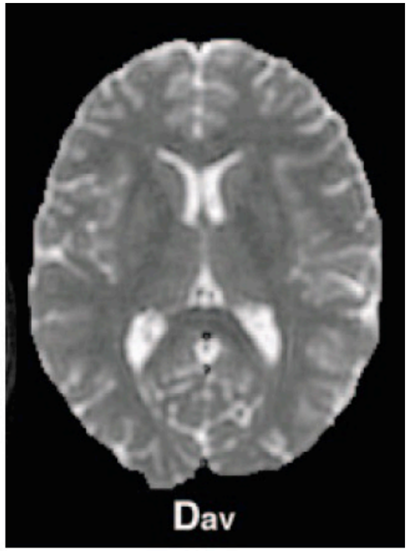
$$\begin{bmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{yx} & D_{yy} & D_{yz} \\ D_{xz} & D_{yz} & D_{zz} \end{bmatrix} \Rightarrow \Lambda = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix} = \mathrm{R} \cdot \mathrm{D} \cdot \mathrm{R}^{\mathrm{T}}.$$



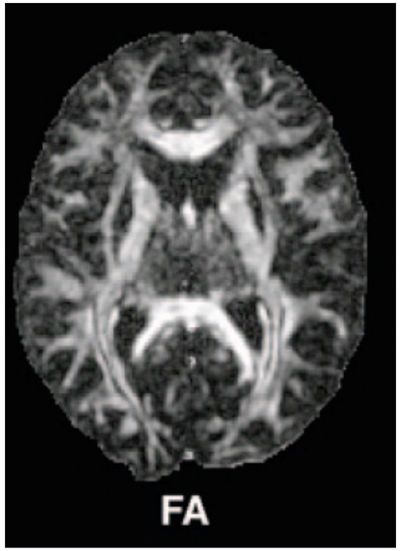
(From Mukerjee et al, 2008)

Diffusion MRI

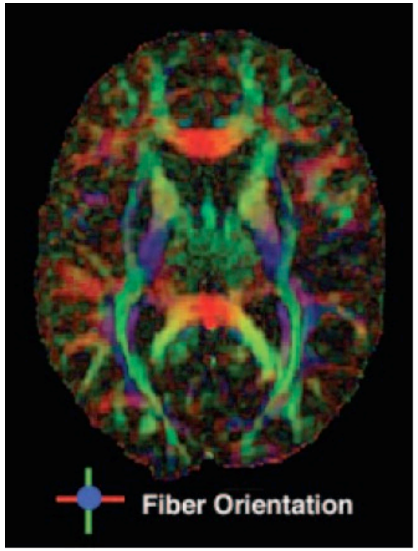
$$\Lambda = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix} = R \cdot D \cdot R^T.$$



Mean diffusivity



Fractional anisotropy



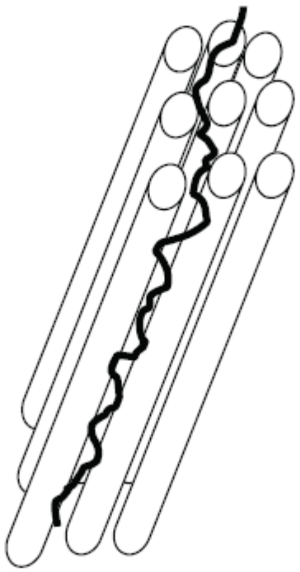
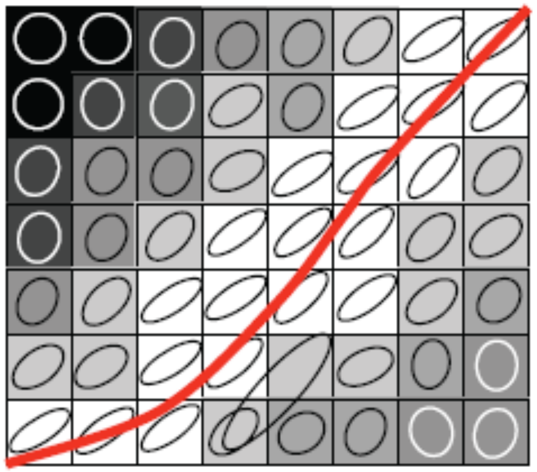
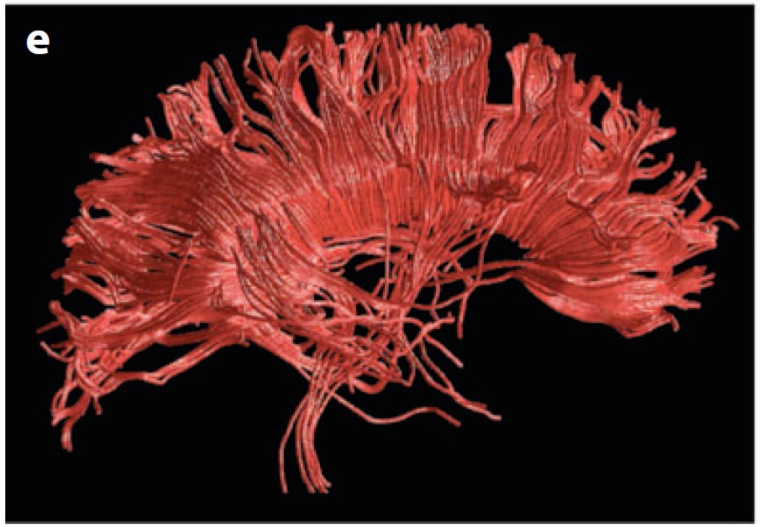
$$D_{av} = \frac{\lambda_1+\lambda_2+\lambda_3}{3} = \text{trace}\,(D)/3$$

$$FA = \frac{\sqrt{(\lambda_1-\lambda_2)^2+(\lambda_2-\lambda_3)^2+(\lambda_3-\lambda_1)^2}}{\sqrt{2}\sqrt{\lambda_1^2+\lambda_2^2+\lambda_3^2}}$$

(From Mukerjee et al, 2008)

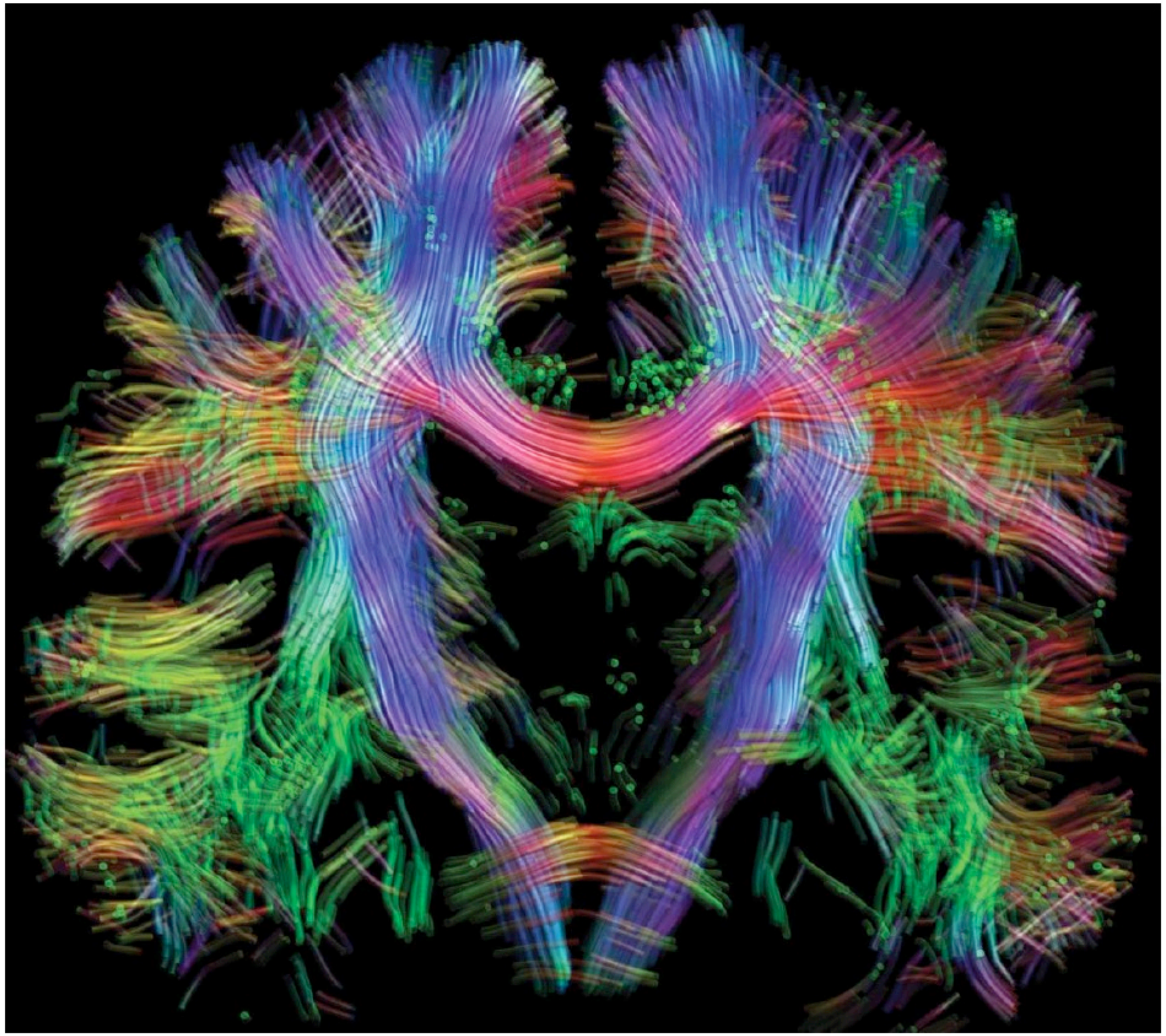
Tractography

- Macroscopic estimate of the trajectories of white matter fiber bundles

(From Johansen-Berg et al, 2009)

Diffusion MRI

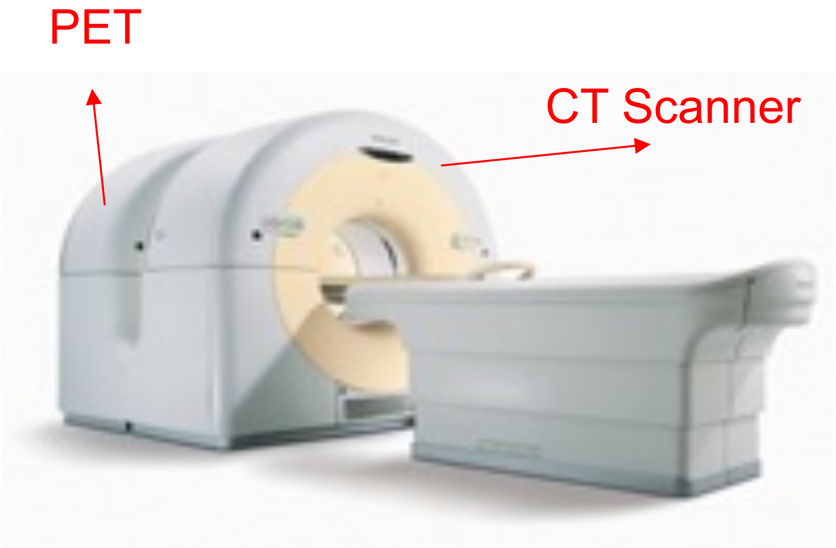


(From Tournier et al, 2011)

Part 1 – Introduction
1.2.2 Functional imaging
1.2.2.1 PET

PET – Positron Emission Tomography

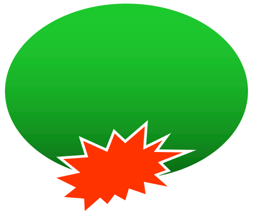
- 1970's
- Uses radioactive compounds which emitt positrons (produced by a cyclotron)
- Short radioactive half-life
- Many types of compounds → multiples functions can be explored
- Spatial resolution ≈ 5 mm
- Quantitative measure
- Expensive



PET

- Intra-veinous injection of a vector, a molecule chosen for its interest regarding the phenomenon one aims to study
- Marked by a radioactive atom

VECTOR



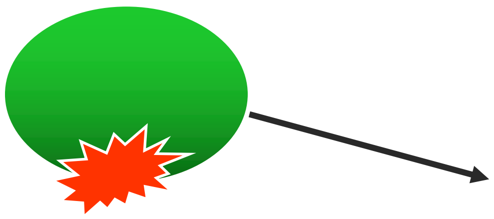
ISOTOPE

^{18}F : T1/2 = 109 mn
^{11}C : T1/2 = 20 mn
^{15}O : T1/2 = 2 mn

PET

- Intra-veinous injection of a vector, a molecule chosen for its interest regarding the phenomenon one aims to study
- Marked by a radioactive atom

VECTOR



β+ (emission of a positron)

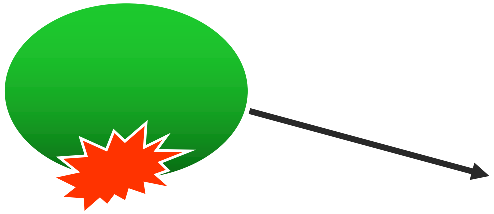
ISOTOPE

^{18}F : T1/2 = 109 mn
^{11}C : T1/2 = 20 mn
^{15}O : T1/2 = 2 mn

PET

- Intra-veinous injection of a vector, a molecule chosen for its interest regarding the phenomenon one aims to study
- Marked by a radioactive atom

VECTOR



β+

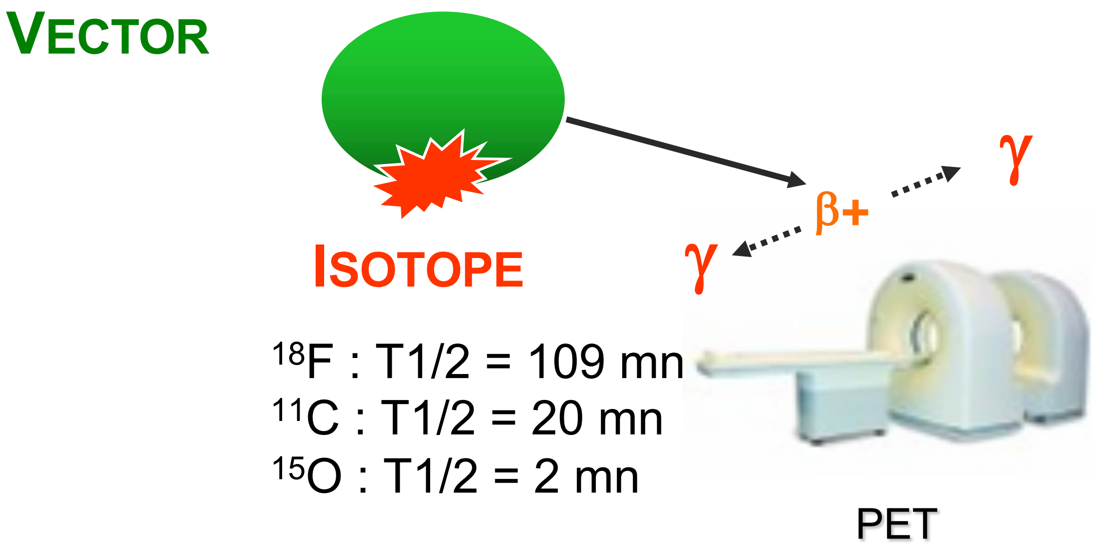
ISOTOPE

^{18}F : T1/2 = 109 mn
^{11}C : T1/2 = 20 mn
^{15}O : T1/2 = 2 mn

Annihilation with an electron of the environment

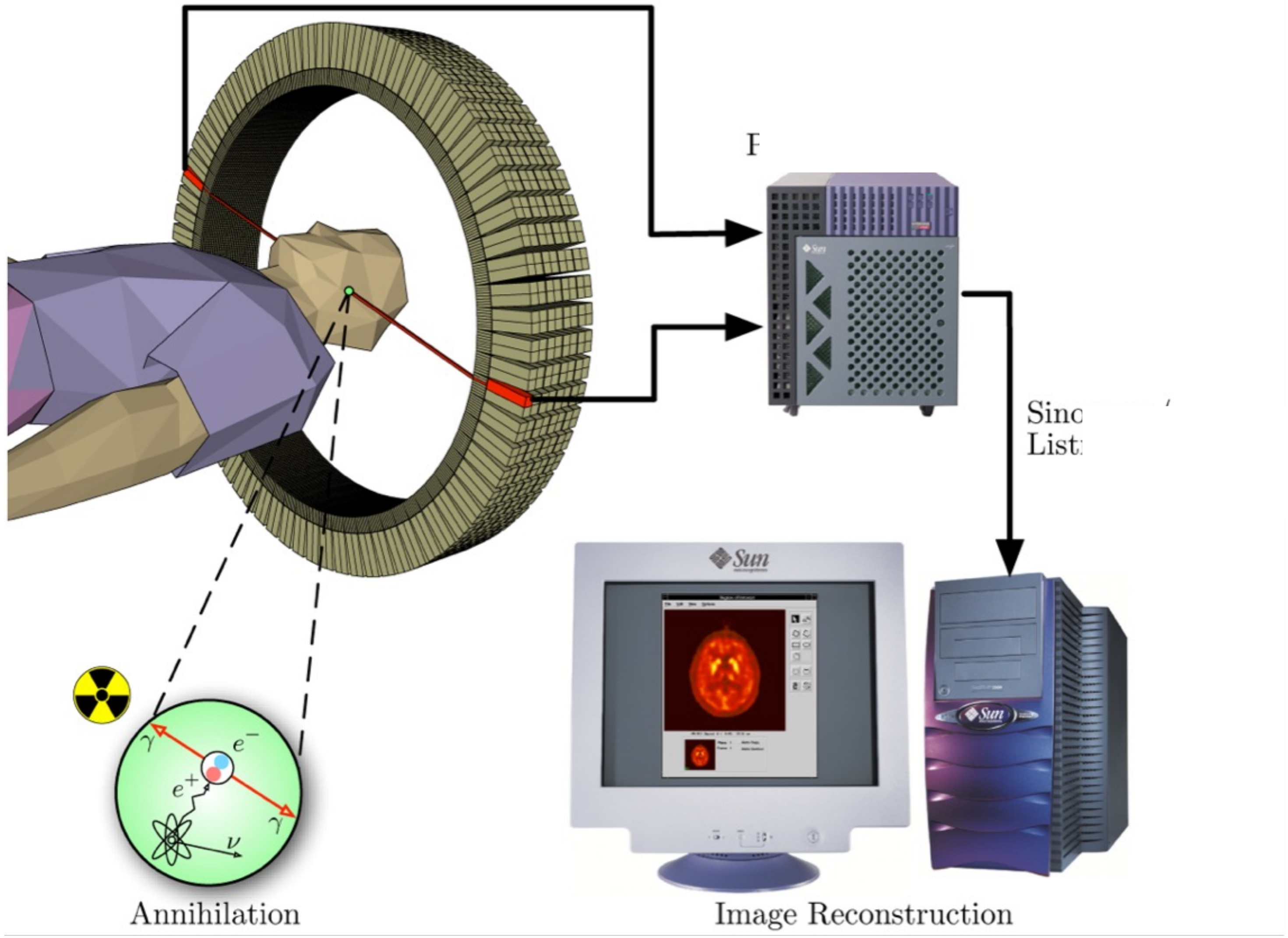
PET

- Intra-veinous injection of a vector, a molecule chosen for its interest regarding the phenomenon one aims to study
- Marked by a radioactive atom



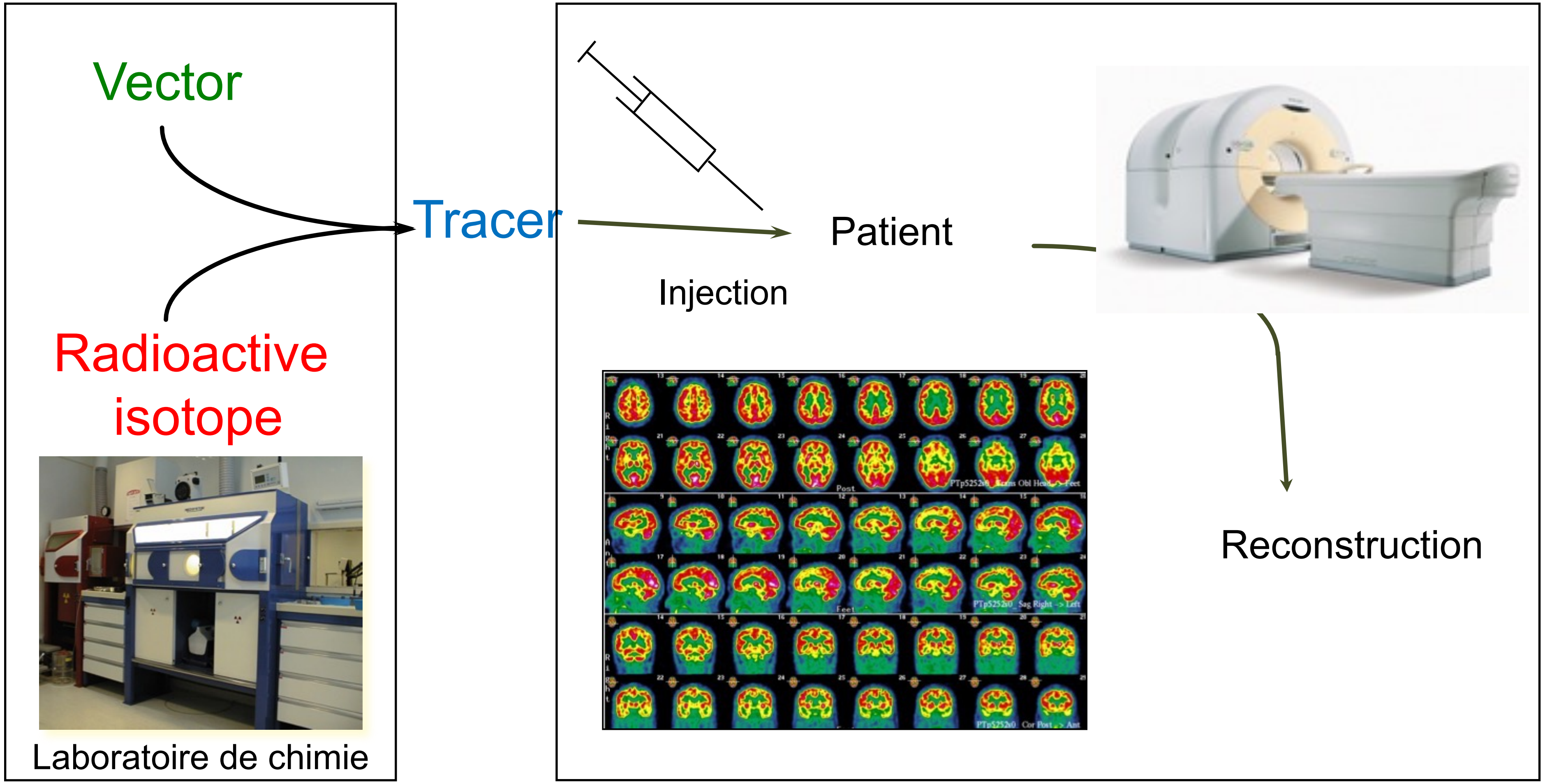
^{18}F : T1/2 = 109 mn
^{11}C : T1/2 = 20 mn
^{15}O : T1/2 = 2 mn

PET



PET

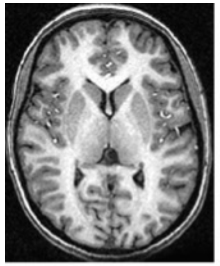
Injection of a radioactive tracer → measures the number of disintegrations ↔ concentration of the tracer

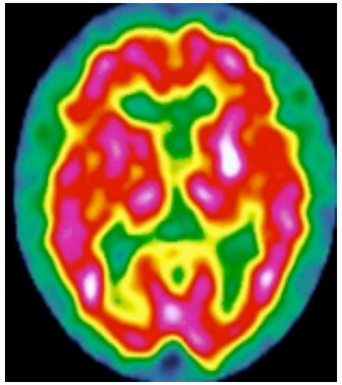


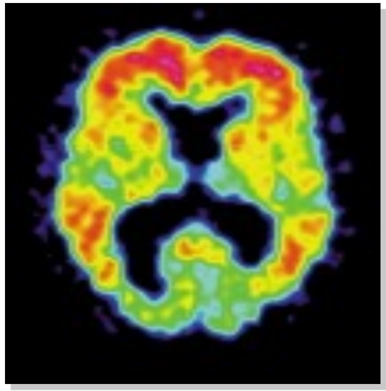
PET

Multiple uses depending on the tracer

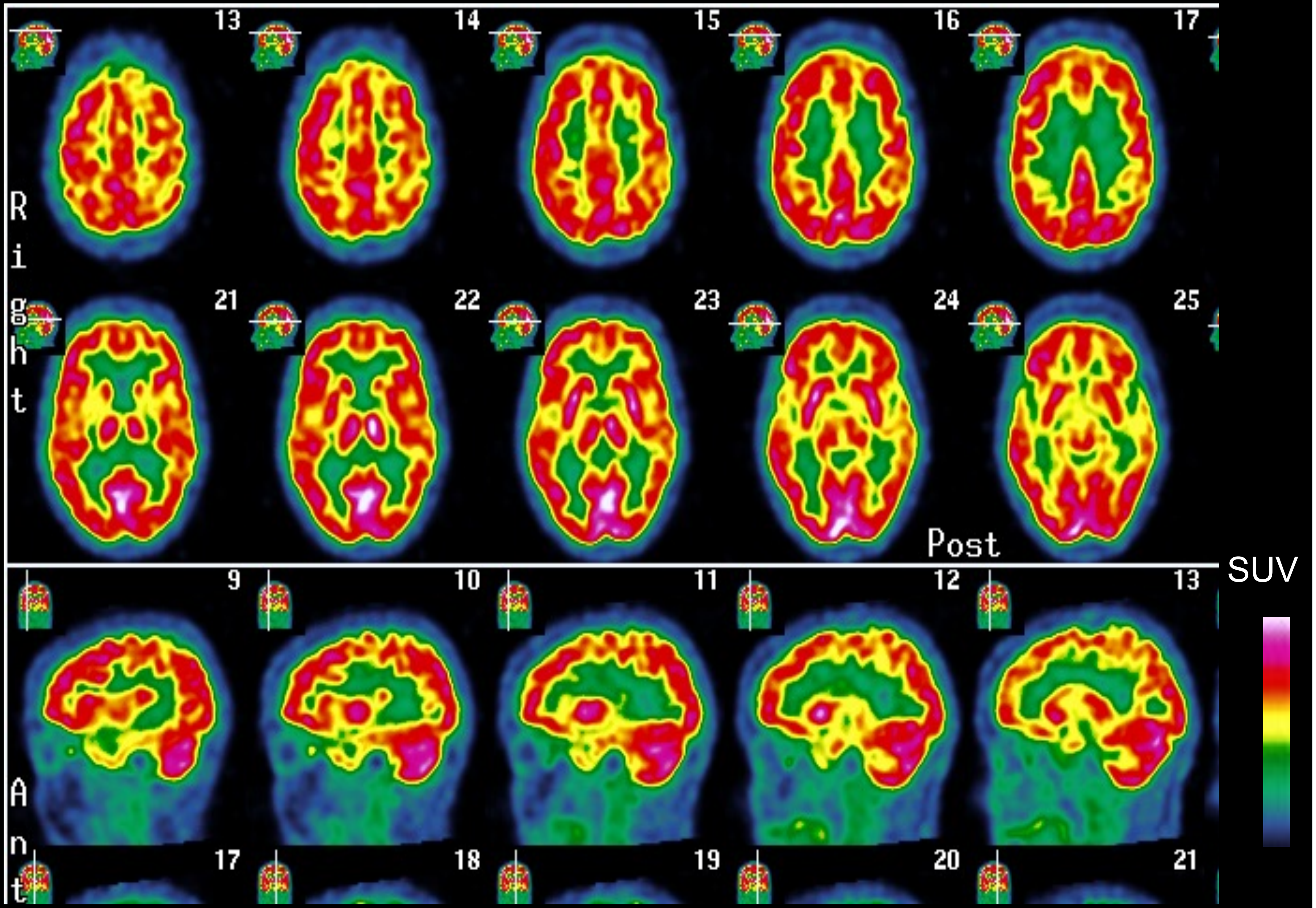
- Study brain metabolism
- Studying neurotransmission, inflammation, amyloid plaques…





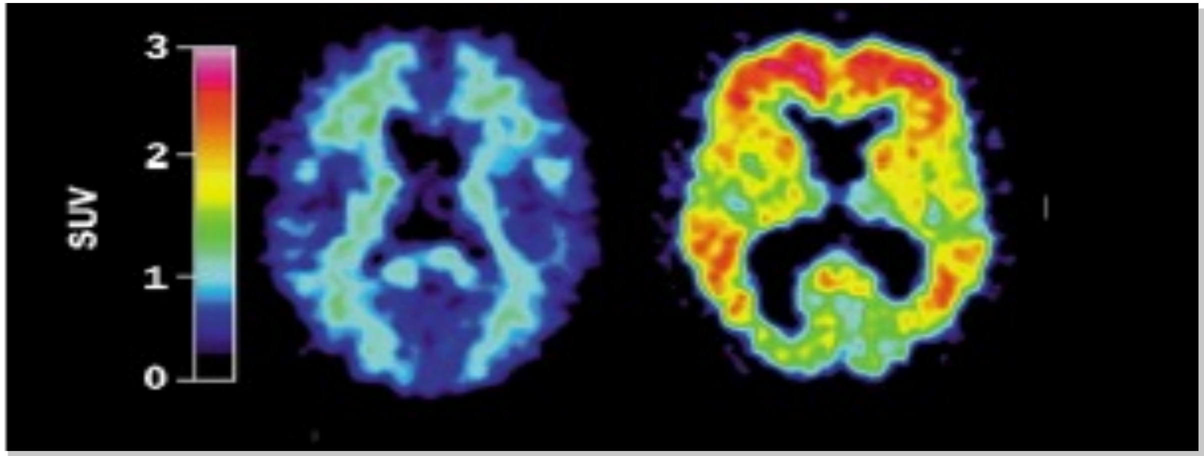


Normal brain FDG PET



Imaging amyloid plaques in Alzheimer's disease

NORMAL ALZHEIMER

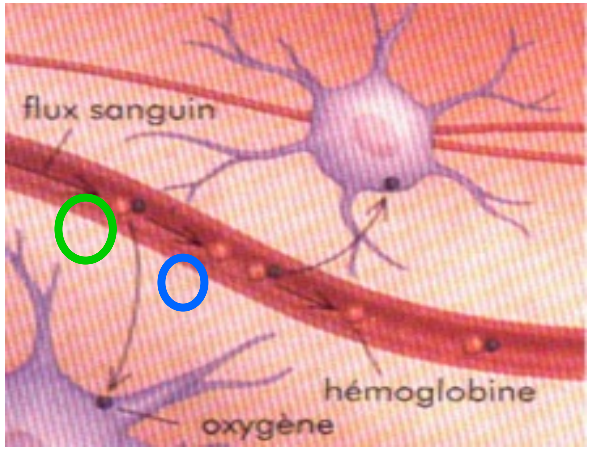


Part 1 – Introduction
1.2.2 Functional imaging
1.2.2.2 Functional MRI

Functional MRI

Direct measure of brain activity
BOLD (Blood Oxygen Level Dependent)

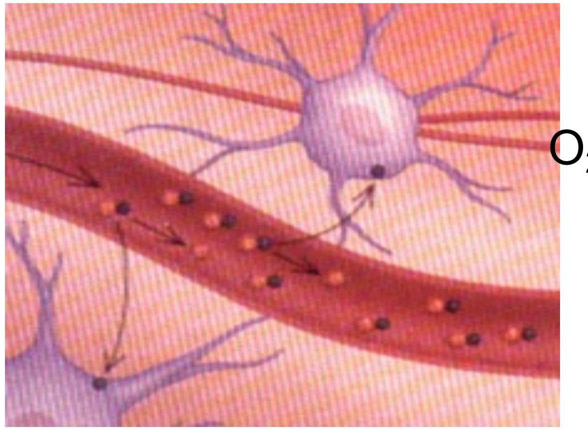
control



oxy-hemoglobin HbO_2

deoxy-hemoglobin Hb
(paramagnetic, T_2^*)

activation



↑ O_2 consumption

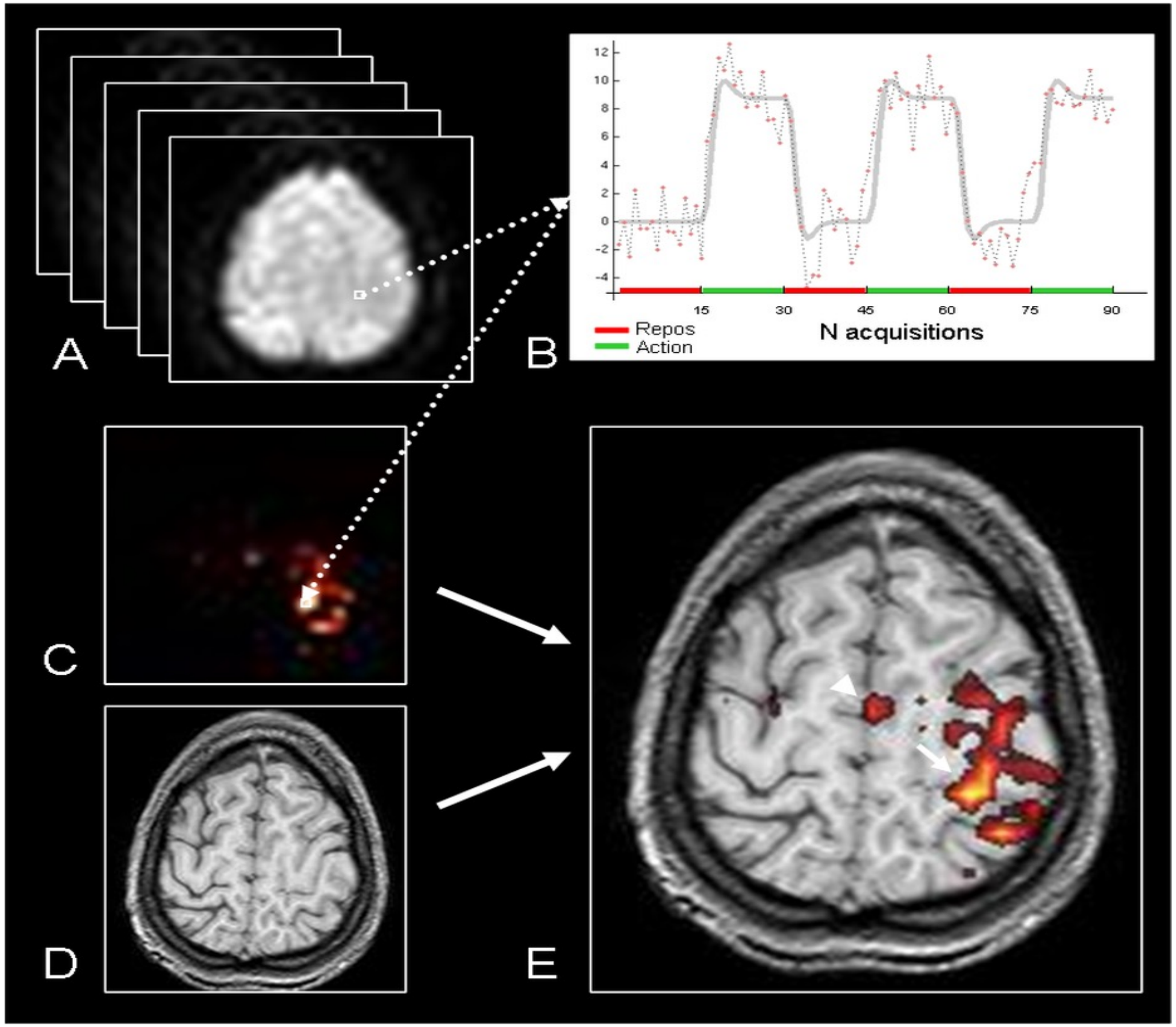
↑↑↑ O_2 supply

↓ [Hb / HbO_2]

↓ T_2^*

↑ signal

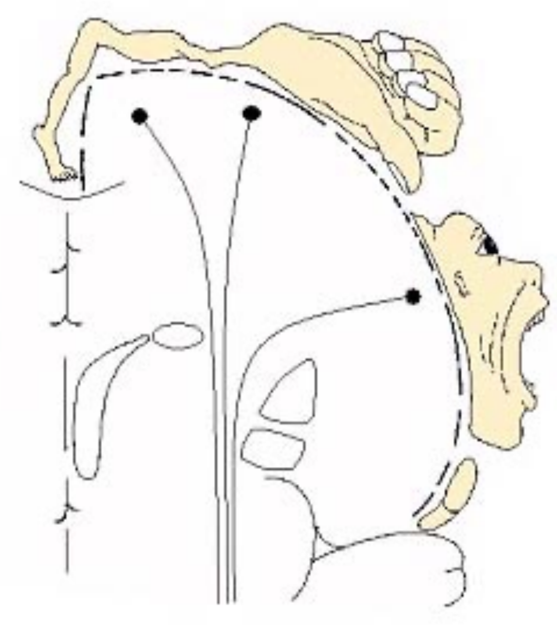
Functional MRI

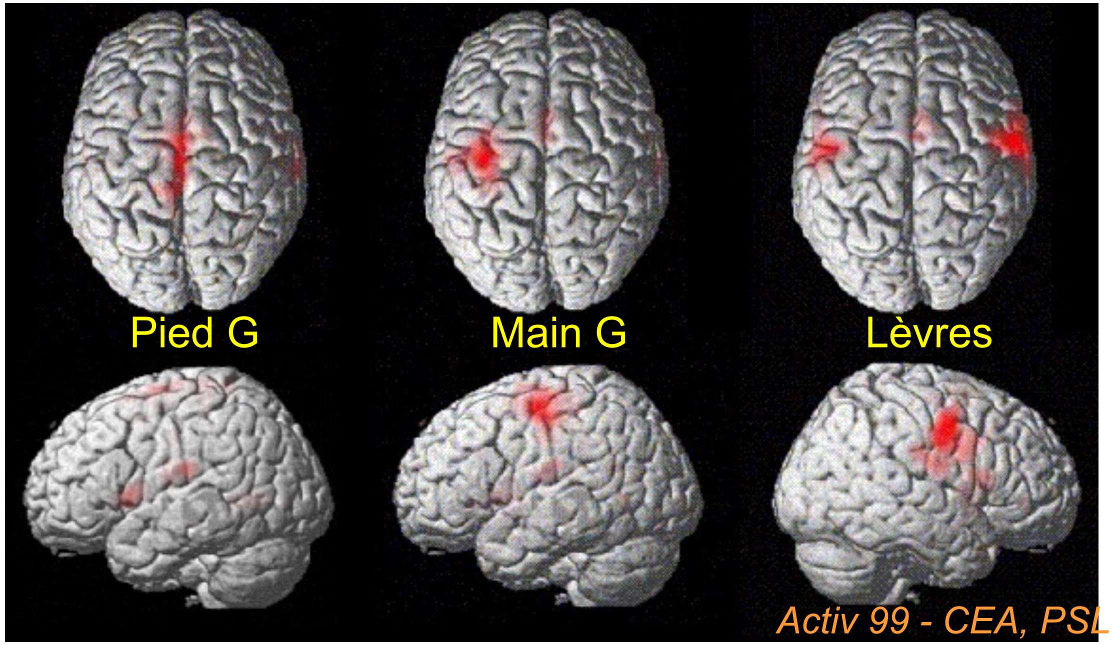


Right hand motion

Motor activations

- **Somatotopy**





MRI

Versatile technique

- Anatomical MRI: tissues and structures
- Diffusion MRI: connections, fibers
- Functional MRI: brain activity

Started a revolution in neuroscience

Application to multiple organs: brain, heat, knee…

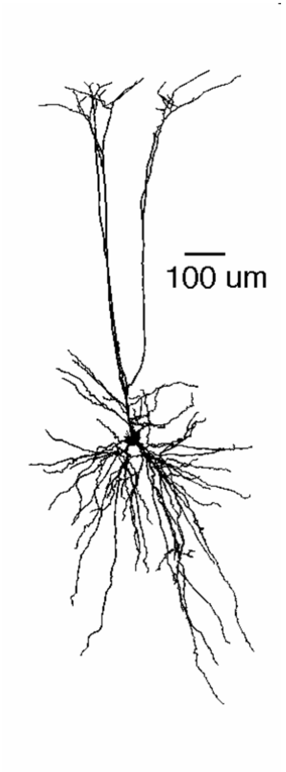
Part 1 – Introduction
1.2.2 Functional imaging
1.2.2.3 EEG/MEG

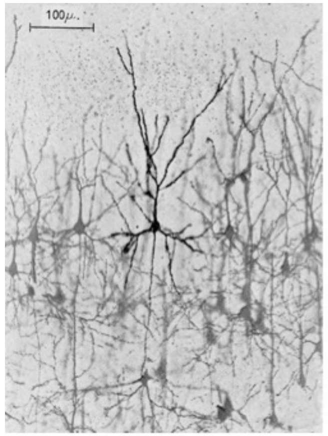
EEG/MEG

- **Surface recording of brain activity**
  - Electrical activity
    - Electro-encephalography - EEG
  - Magnetic activity
    - Magneto-encephalography - MEG

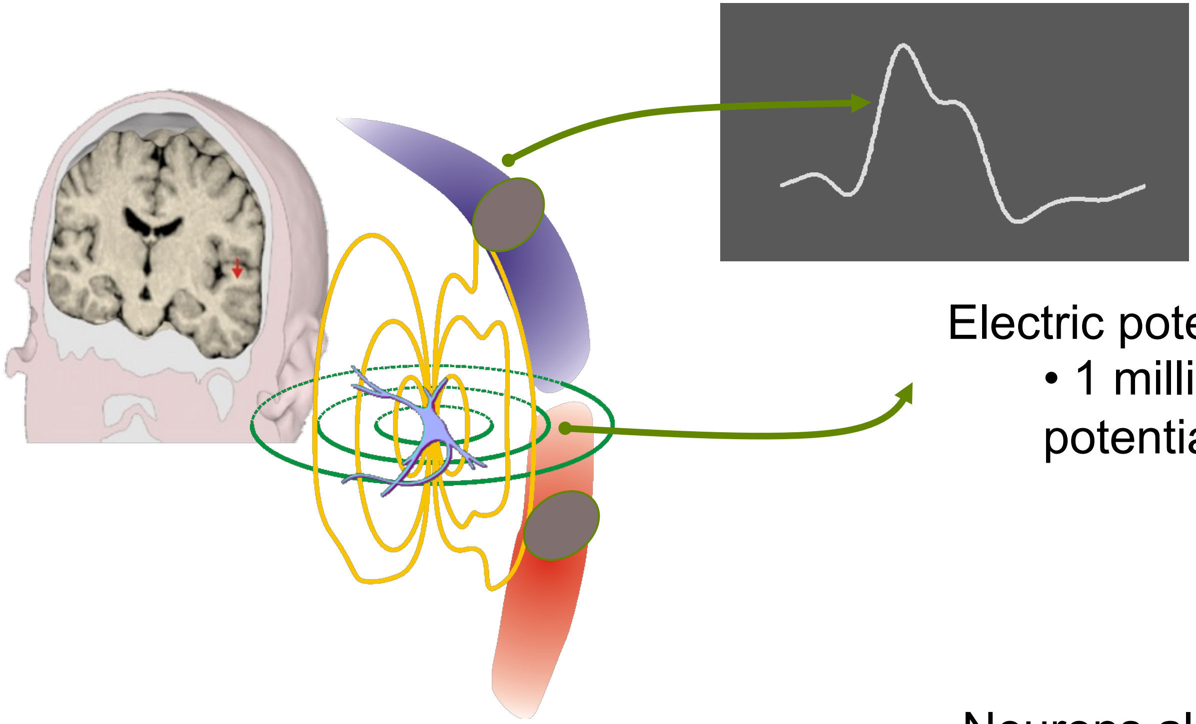
Neuronal electrophysiology

- **Pyramidal neuron**
  - Large cell
  - Organized in parallel in macro-assemblies
  - Superimposition of electrical currents
    - The result is detectable at the surface of the scalp





EEG / MEG



Electric potential

- 1 million de neurones created a potential of around 100μV

Neurons also produce magnetic fields!
Magnetoencephalography (MEG)

Instrumentation: EEG

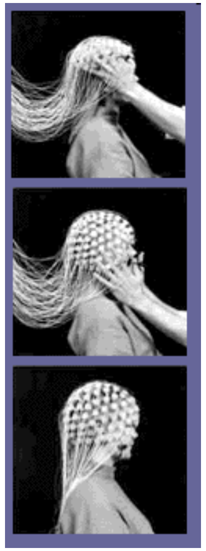
1945

1955

Instrumentation: EEG

- **More sensors**
  - Up to 256
- **High temporal resolution**
  - < 1 millisecond

MicroMed



Electrical Geodesics

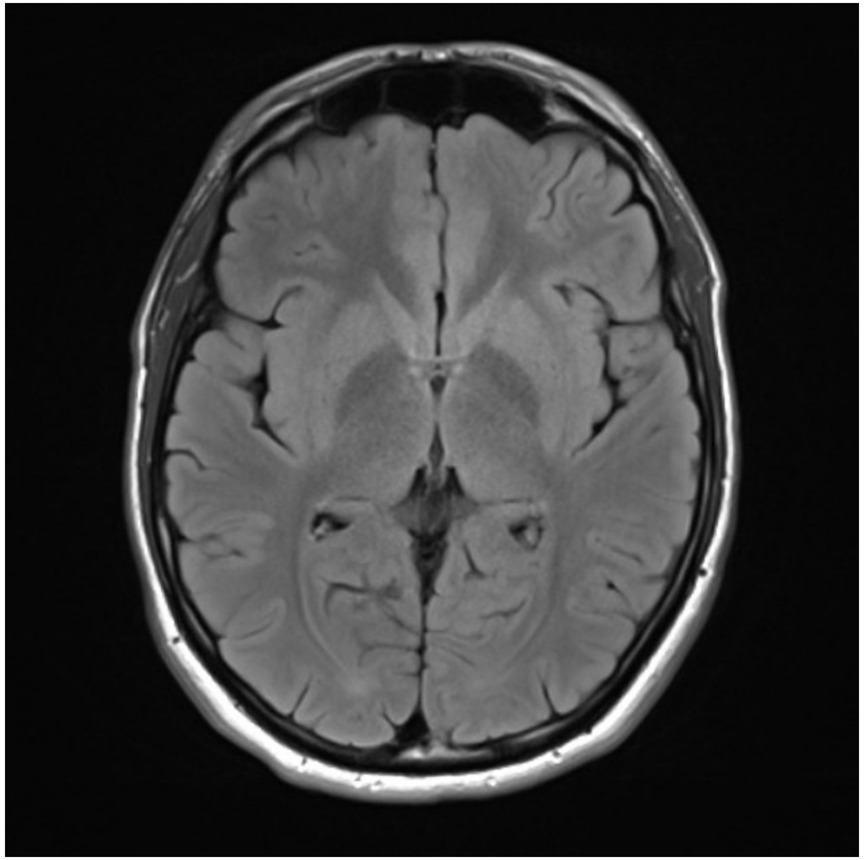
NeuroScan

Instrumentation: MEG

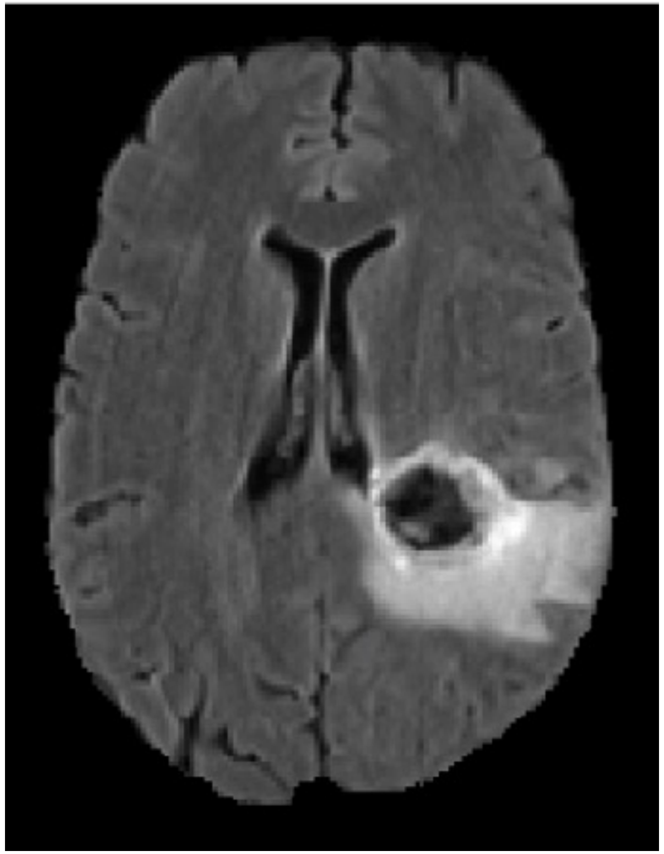
Part 1 – Introduction
1.3 Main tasks in medical image computing

Classification

Assign a label to the image

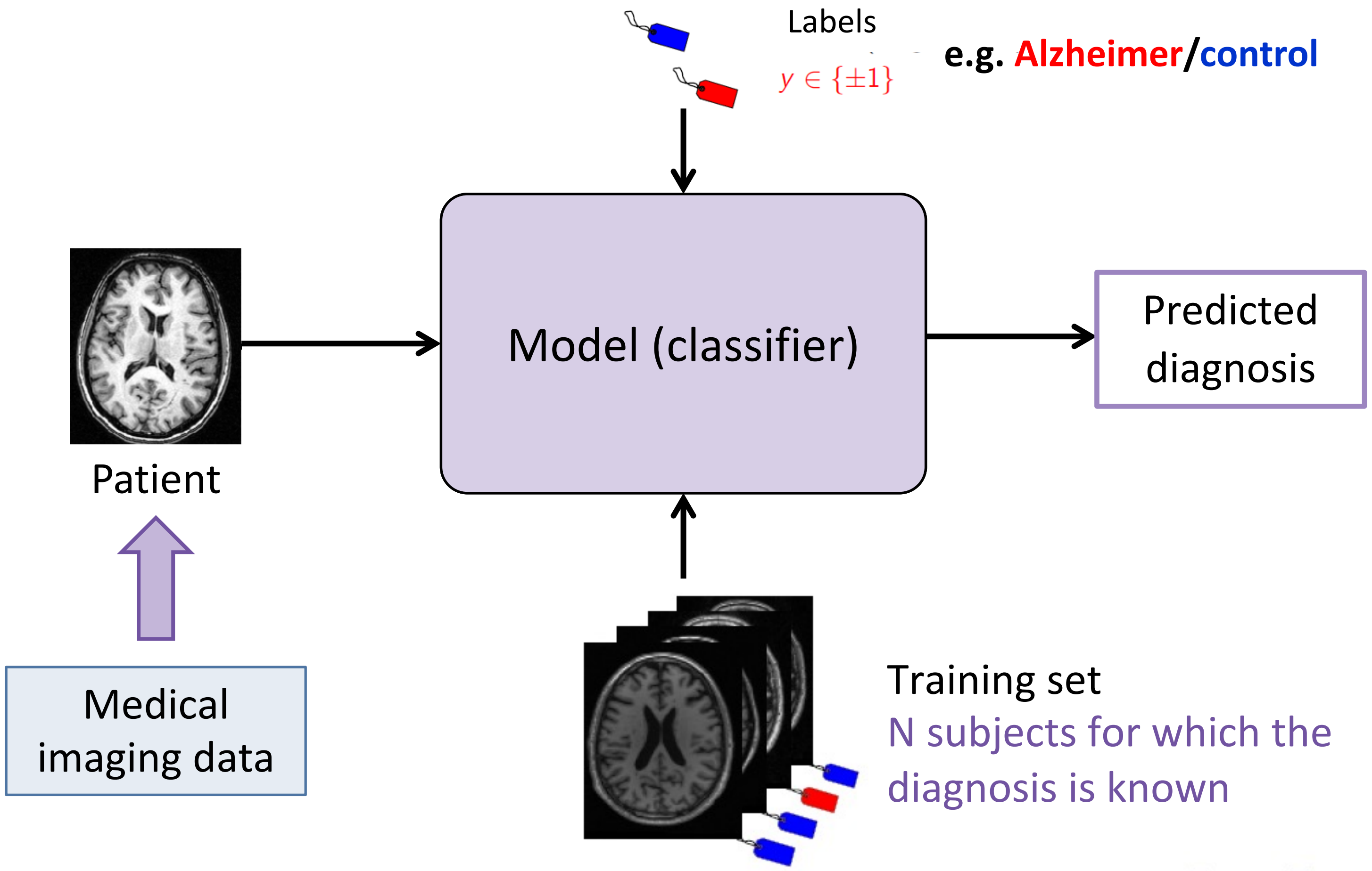


Normal



Tumor

Classification – Diagnosis / Prognosis



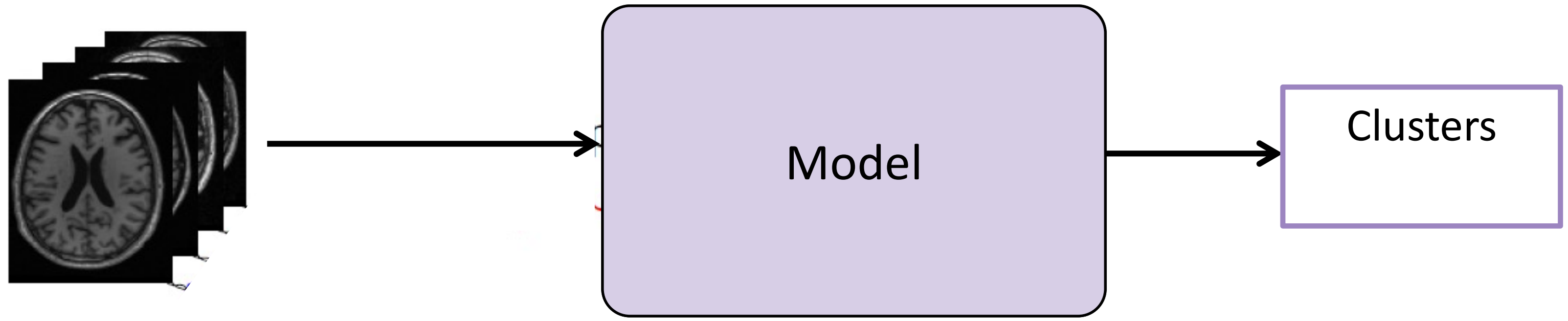
Supervised learning

Classification

Examples:

- Differential diagnosis of neurodegenerative diseases
  - Patient presenting with cognitive deficits, what is the underlying cause?
- Predicting the future clinical state
  - Patient presenting with subtle cognitive decline at baseline, will he have lost autonomy in 5 years ?

Clustering – Discover disease subtypes



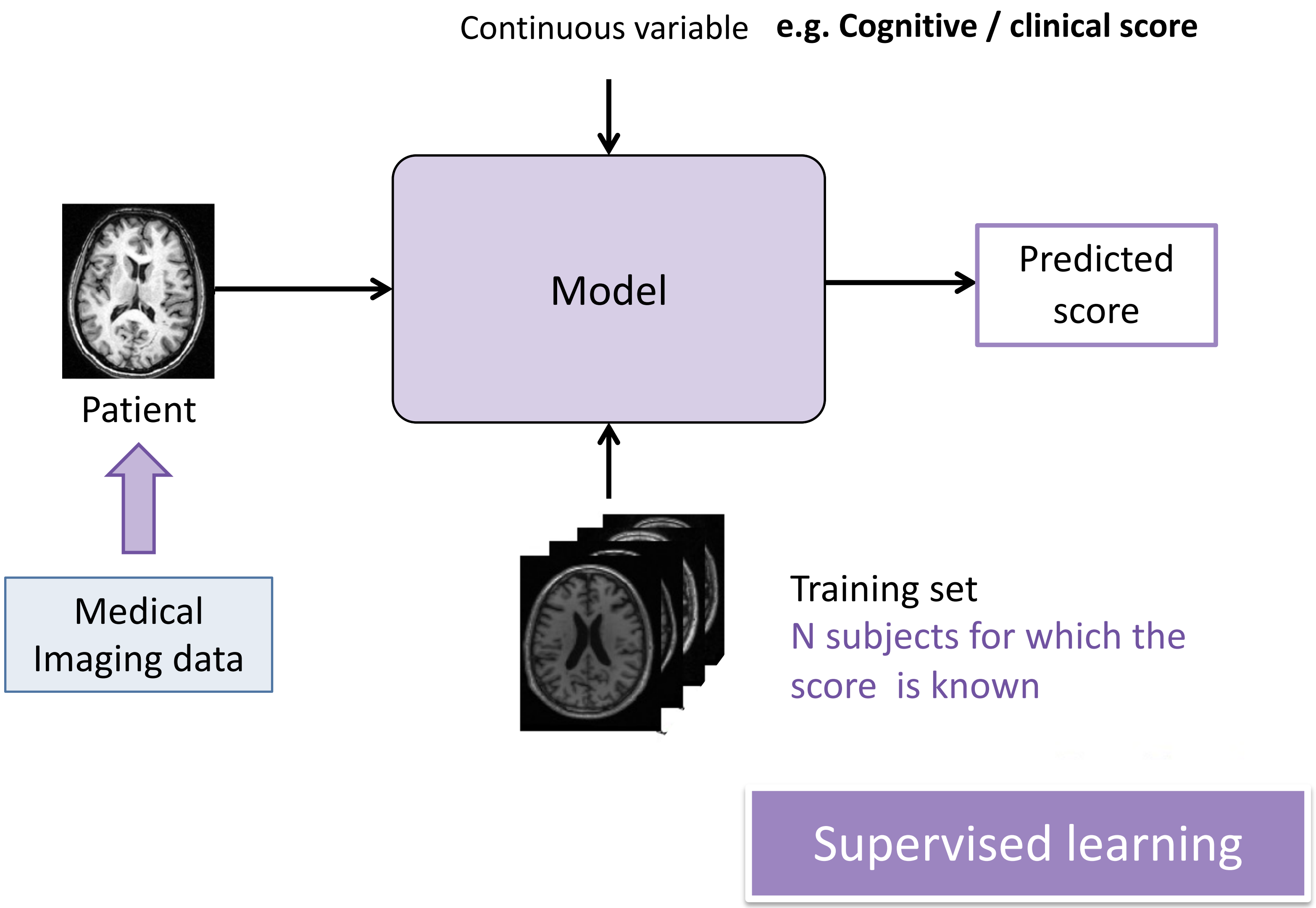
Unsupervised learning

Clustering

- Different symptoms for a given biological cause
- Different biological causes for a given set of symptoms

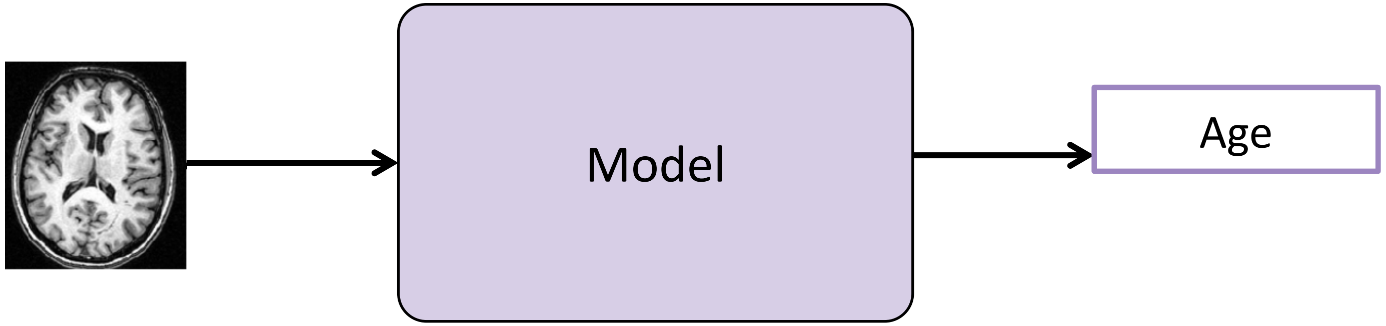
⇨ Find homogeneous subtypes of diseases

Regression – Predict clinical scores



Regression

Example : predict age from brain MRI



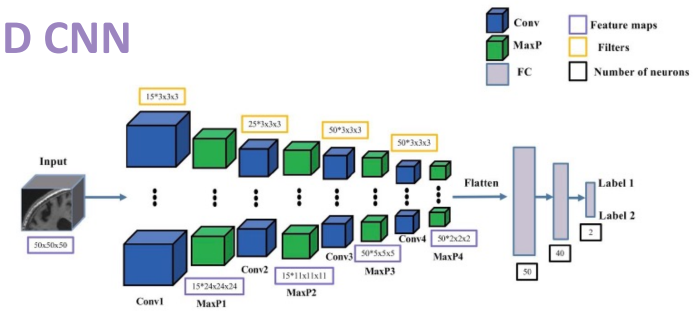
	BLUP mean	**SVM**	**6-layer CNN**	**ResNet**	**Inception V1**	**Ensemble prediction**
MAE (SE)	5.32 (0.19)	5.31 (0.18)	4.18 (0.16)	4.02 (0.15)	3.82 (0.14)	3.46 (0.13)
$\|\rho\|$	0.32	0.58	0.25	0.24	0.41	0.32

(Couvy-Duchesne et al, In preparation)

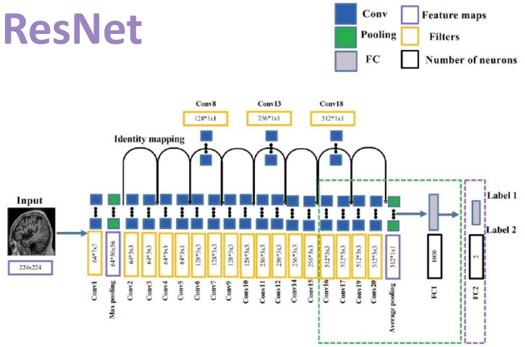
Classification / Regression – typical approaches

Typical approaches: 3D extensions of networks used for natural image classification

3D CNN



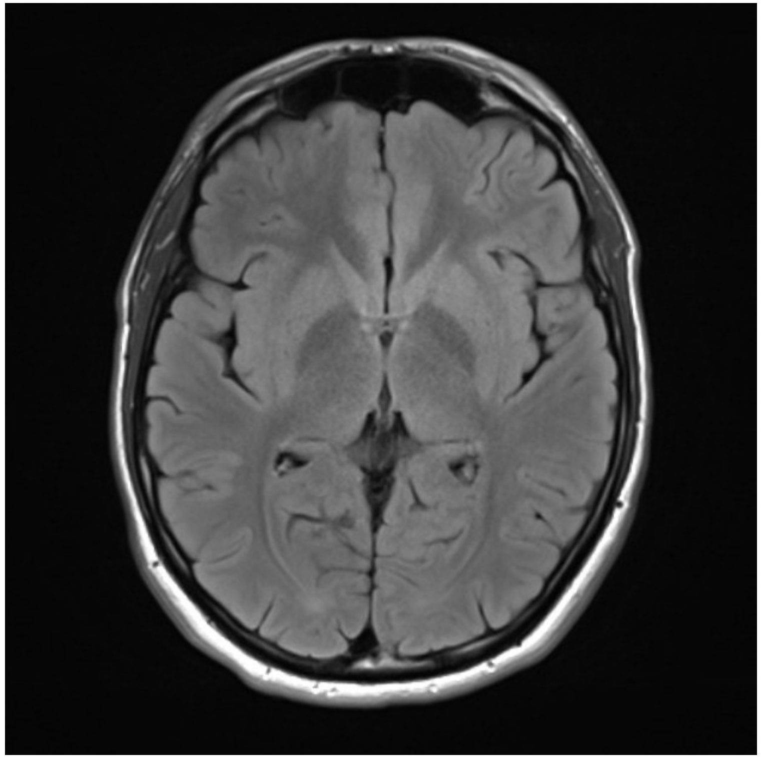
ResNet



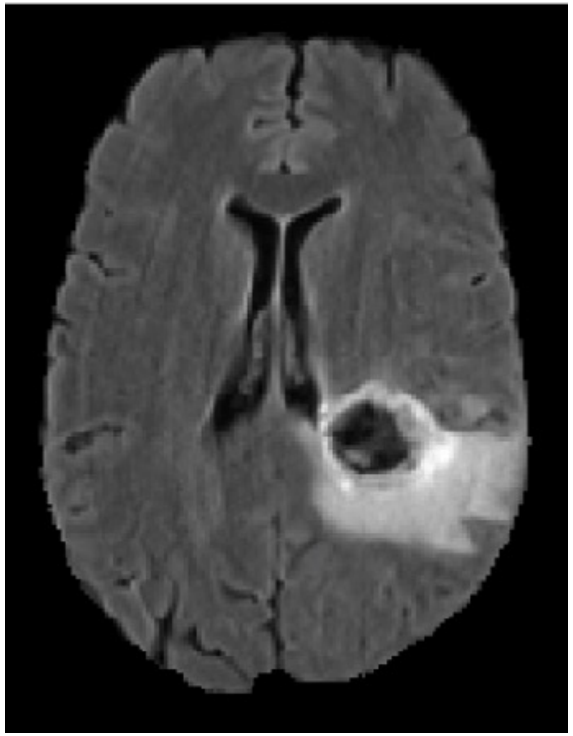
Alternatives: other classification/regression approaches with pre-extracted features

- SVM
- Random forests
- LASSO
- …

Classification



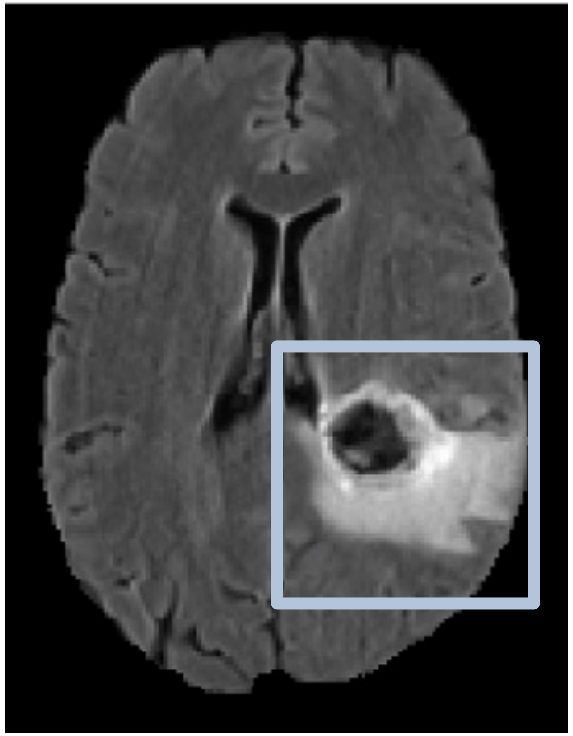
Normal



Tumor

Detection

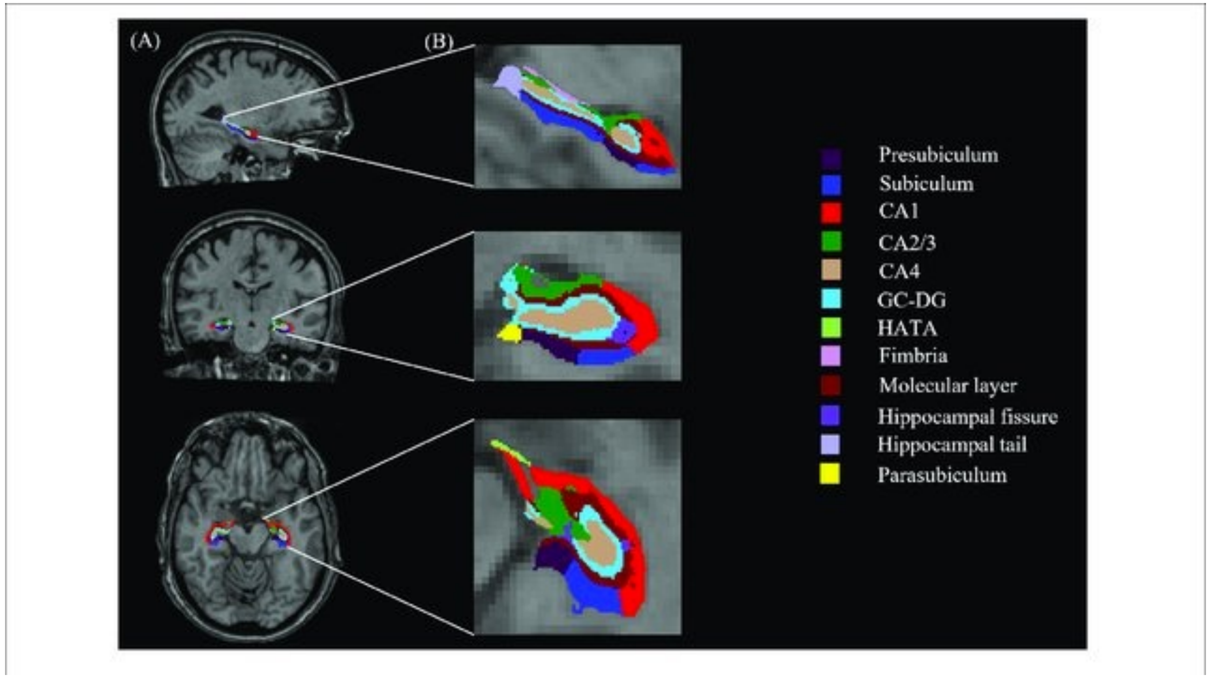
Locate an object in the image (lesion, tumor…)



Tumor

Segmentation

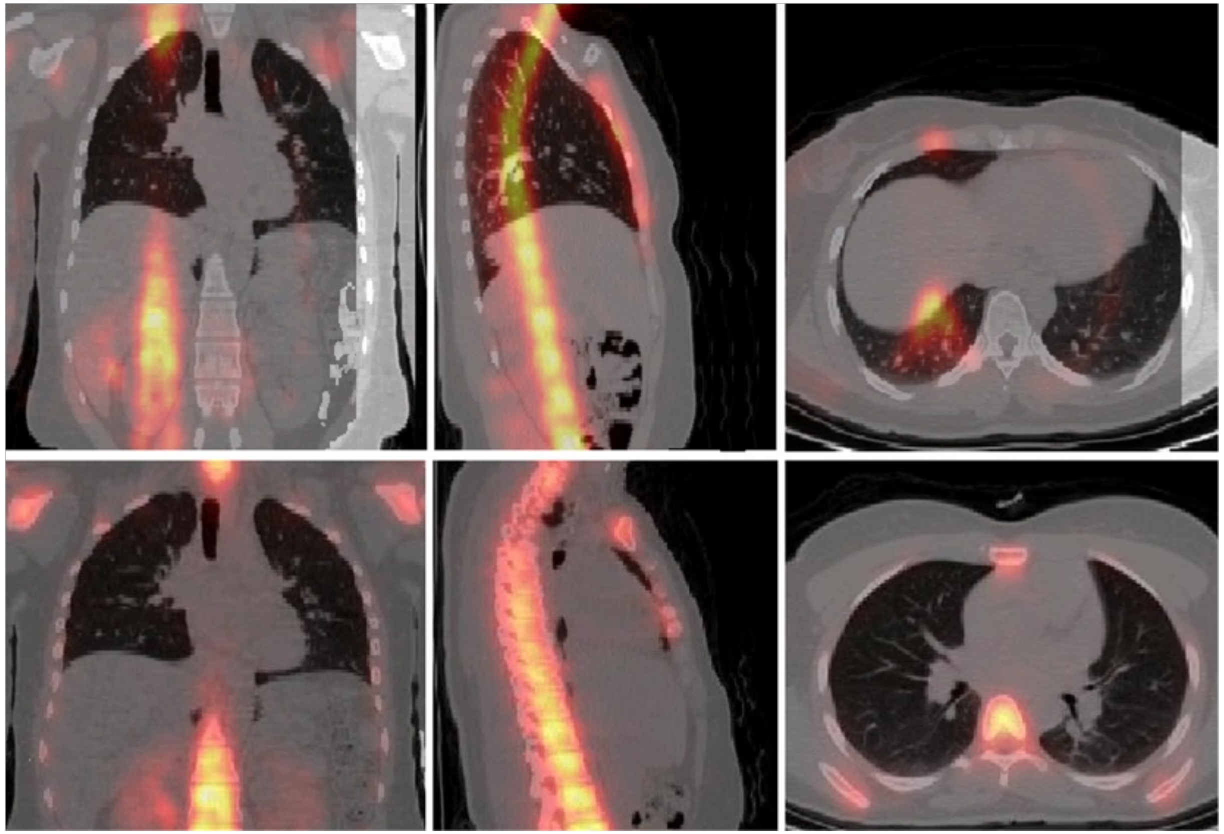
Delineate “objects” in images: tissues, anatomical structures, lesions…



Source: Zheng et al, The Volume of Hippocampal Subfields in Relation to Decline of Memory Recall Across the Adult Lifespan, 2018

Registration

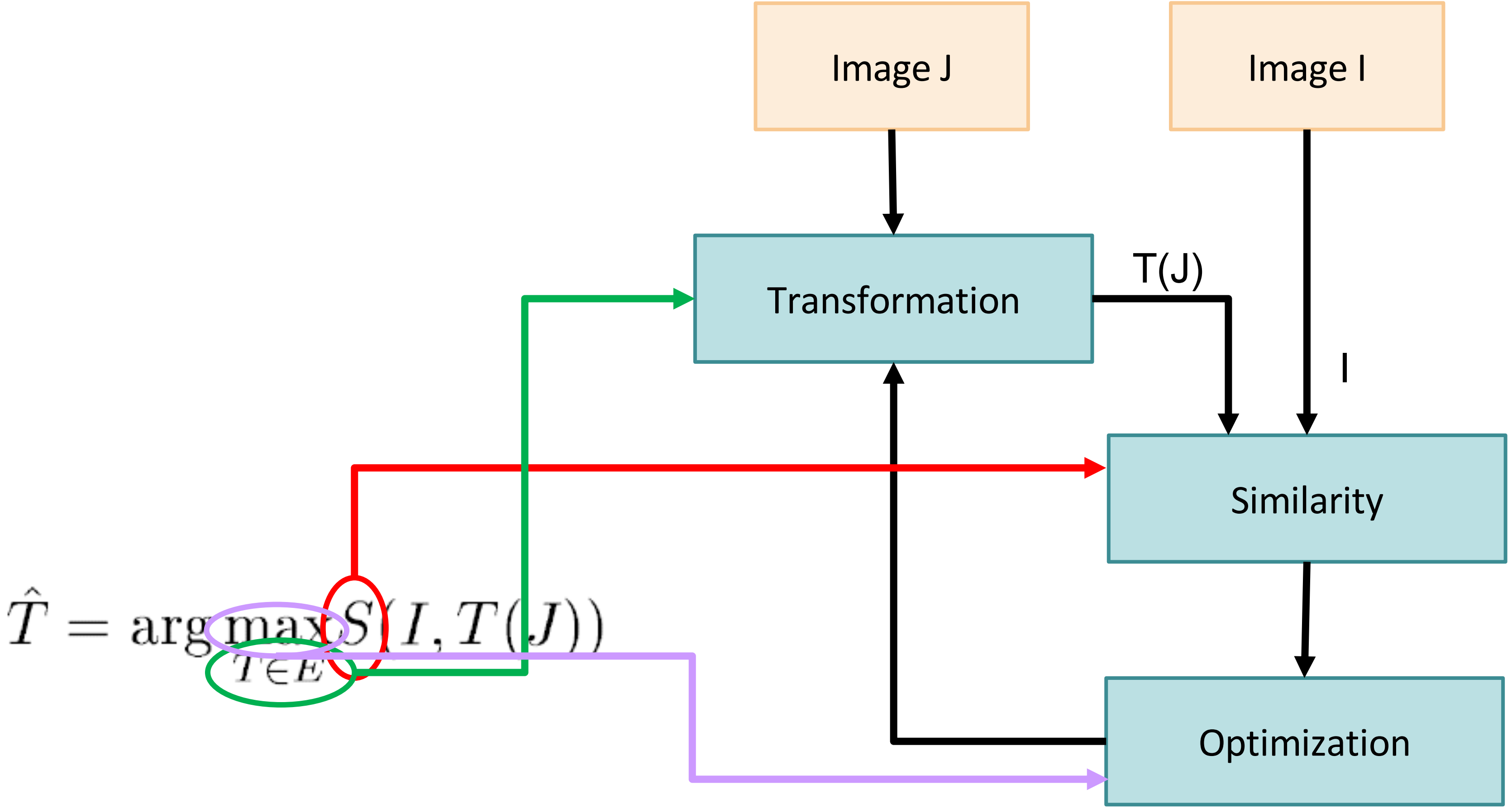
- Definition: put two images in spatial correspondence



[Source Tang et al]

Registration

- Problem setting



$$\hat{T} = \arg\max_{T \in E} S(I, T(J))$$

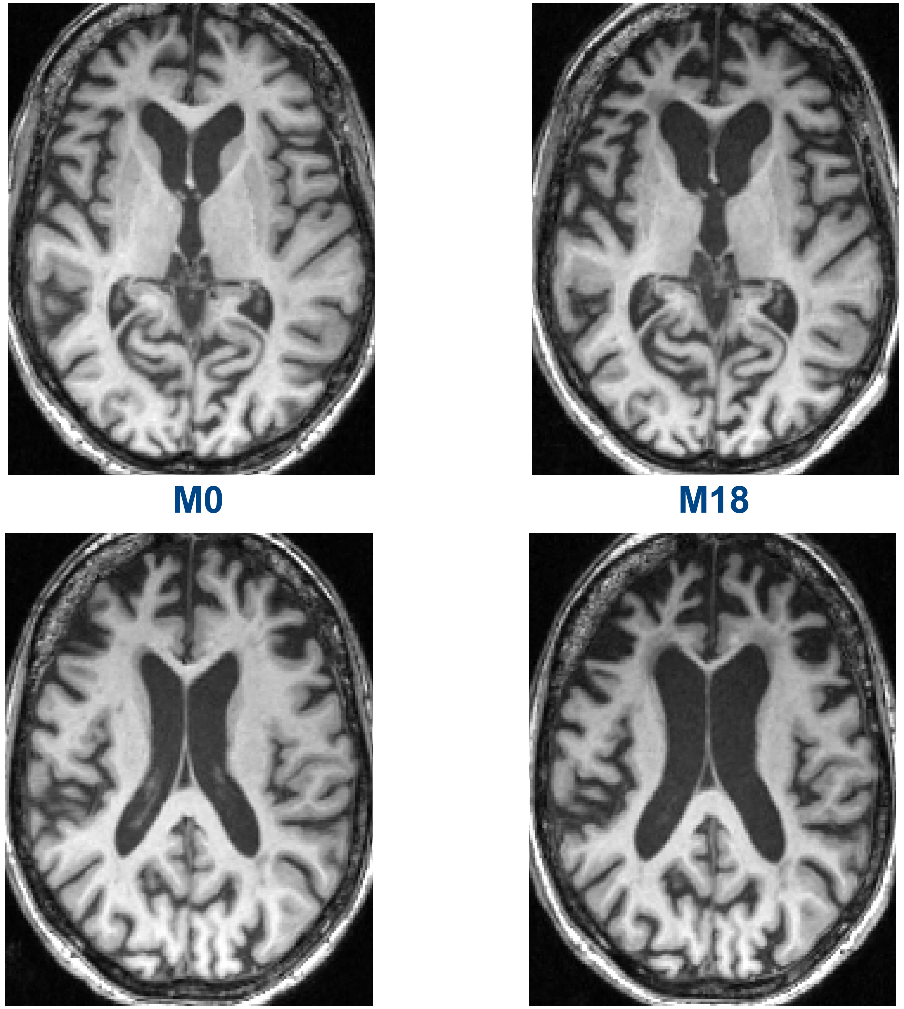
Registration

- Intra-subject, intra-modality
  - Deformation: in general rigid
  - Similarity: simple criterion (e.g. sum of square differences)

Registration

- Intra-subject, intra-modality, longitudinal
  - Deformation: non-linear

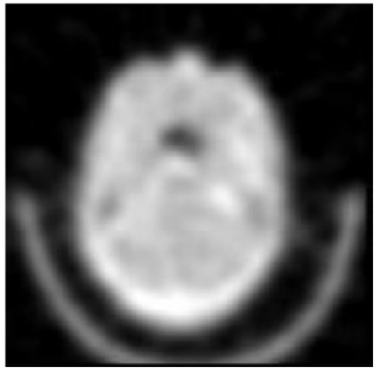
Same patient at different time points (e.g. 18 months after)



Registration

- Intra-subject, inter-modality
  - Deformation: rigid, affine or non-linear
  - Similarity: complex criterion (e.g. mutual information)

Brain imaging


PET

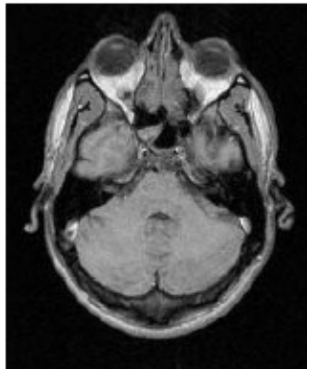
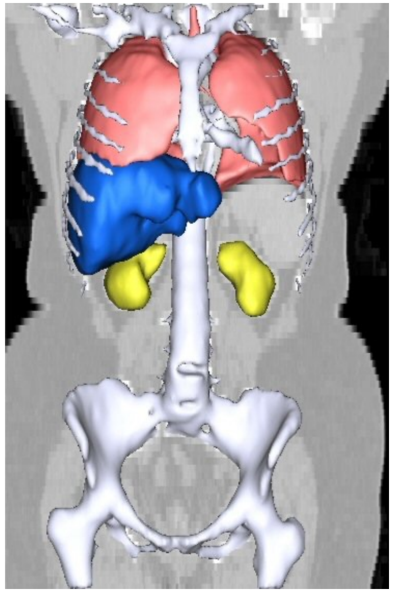

MRI

Image source: (Mangin, 1995)

Thoracico-abdominal imaging


CT


PET

Image source (Camara et al,, 2007)

Registration

- Inter-subject, intra-modality
  - Deformation: non-linear
    - Account for inter-individual variability

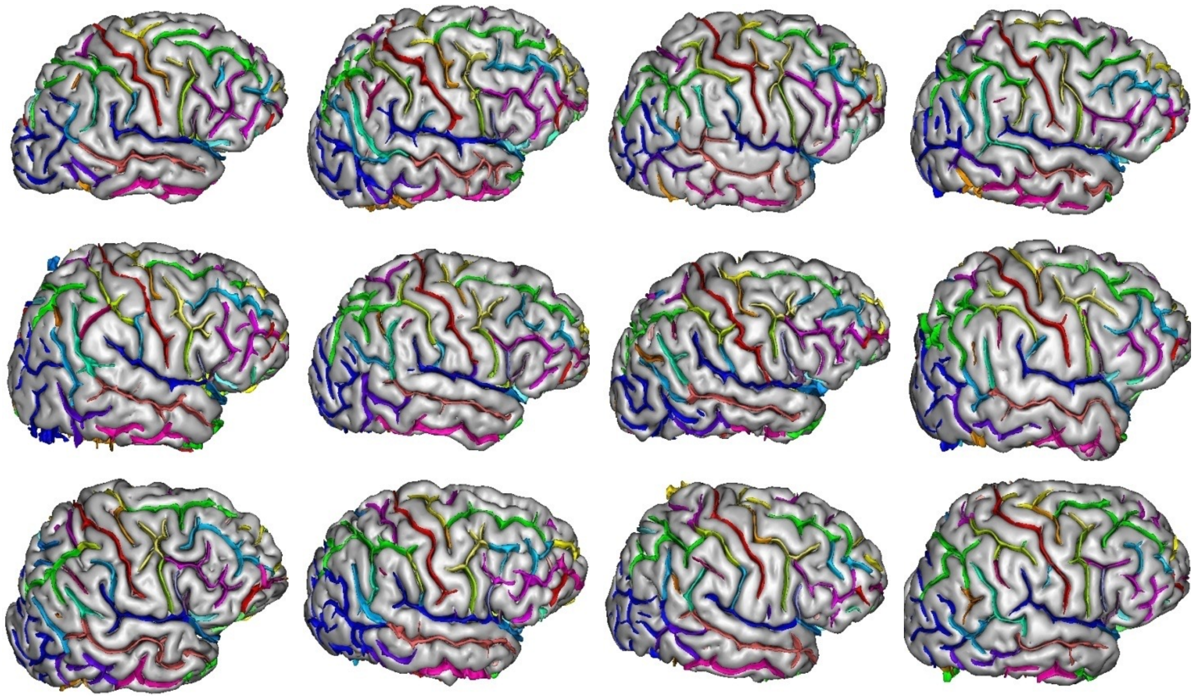
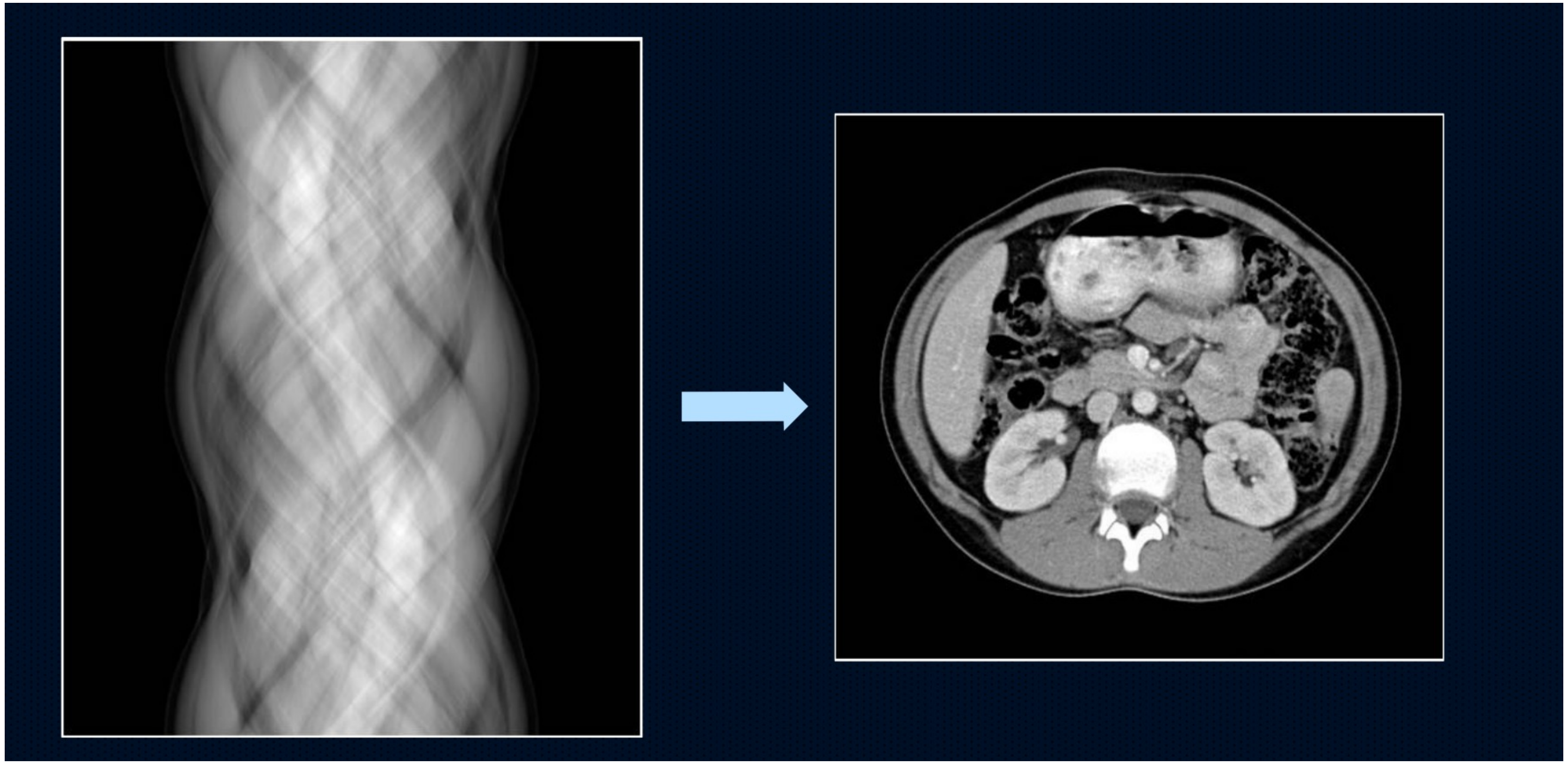


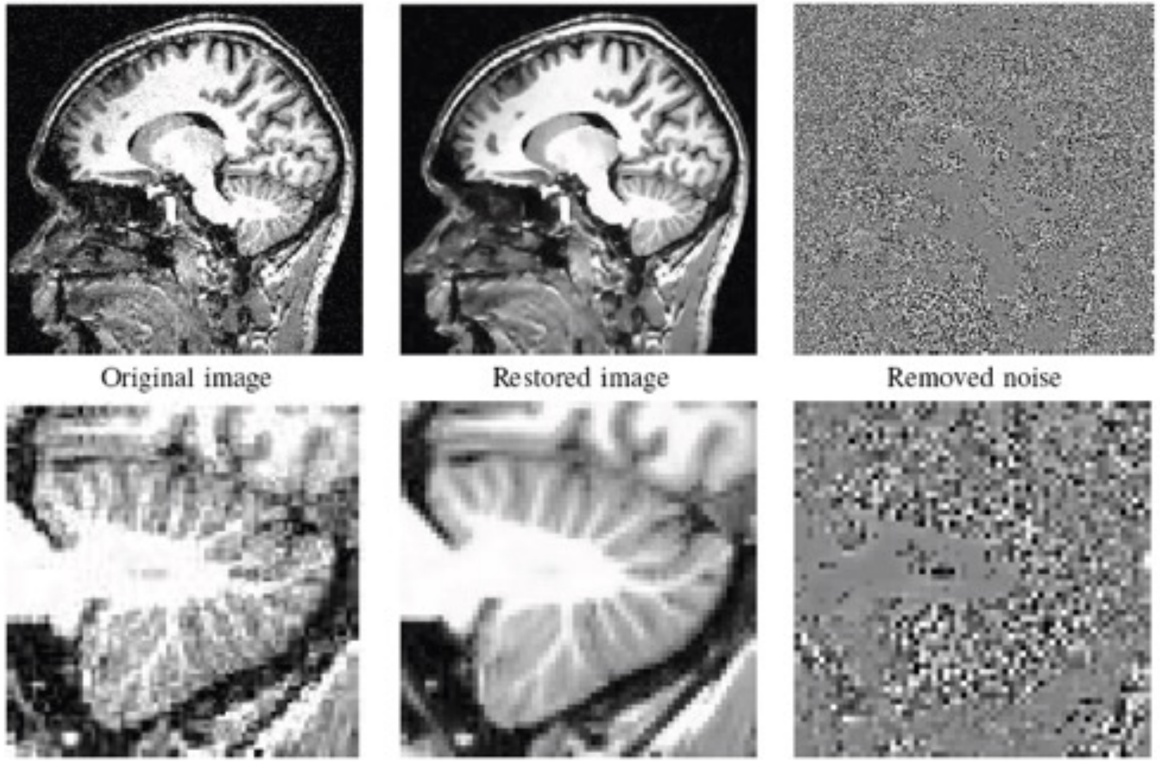
Image source: Mangin et al

Image reconstruction



Source: https://de.medical.canon/wp-content/uploads/sites/17/2016/08/Metal-Artefact-Reduction-in-CT-SEMAR.pdf

Image enhancement - Denoising



Hellier, TMI 2008

Denoising of brain MRI

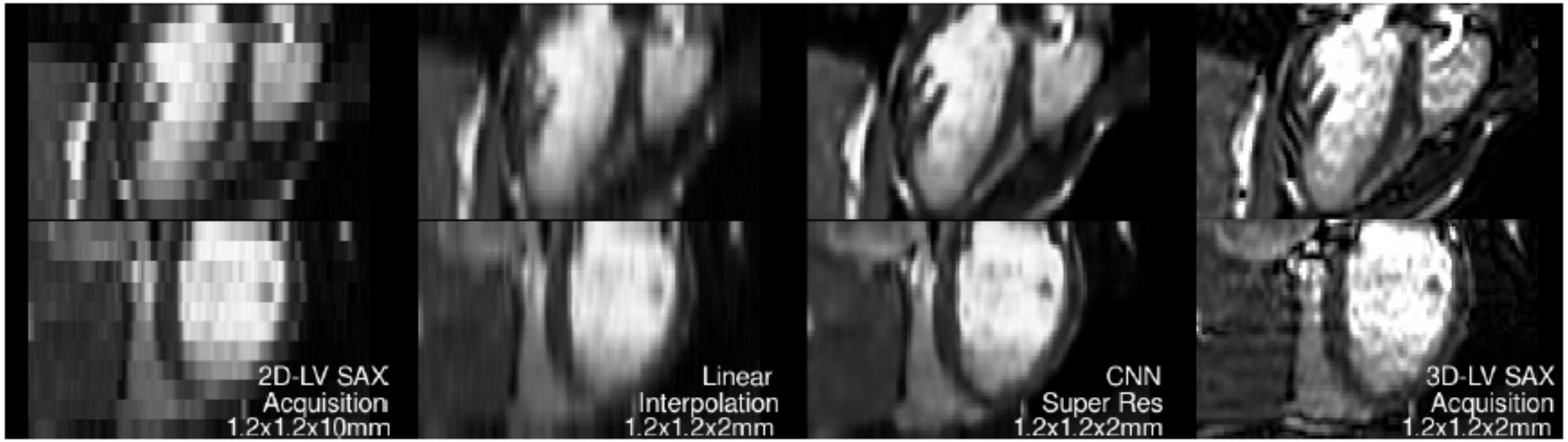
Image enhancement – Super-resolution

Low res acquisition

Baseline super-resolution method (linear interpolation)

Super-resolution using CNN

High resolution acquisition (ground truth)

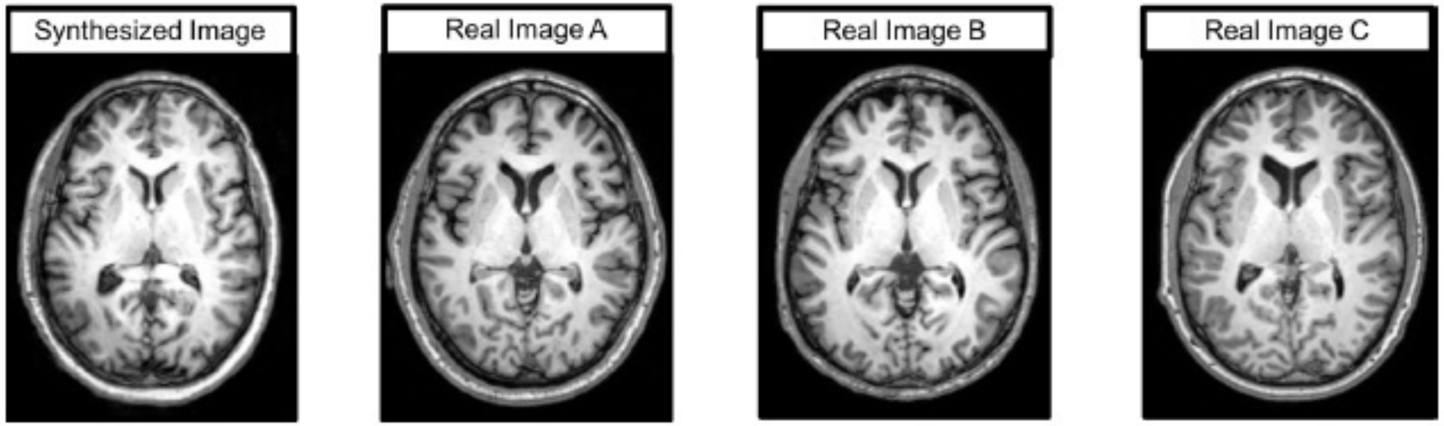


O. Oktay et al. IEEE TMI 2017

Source: Daniel Rueckert, Imperial College London

Image synthesis

Data augmentation



Source: Bermudez et al, Learning Implicit Brain MRI Manifolds with Deep Learning, SPIE MI, 2018

Image translation

Synthesizing one modality from another

MRI to CT

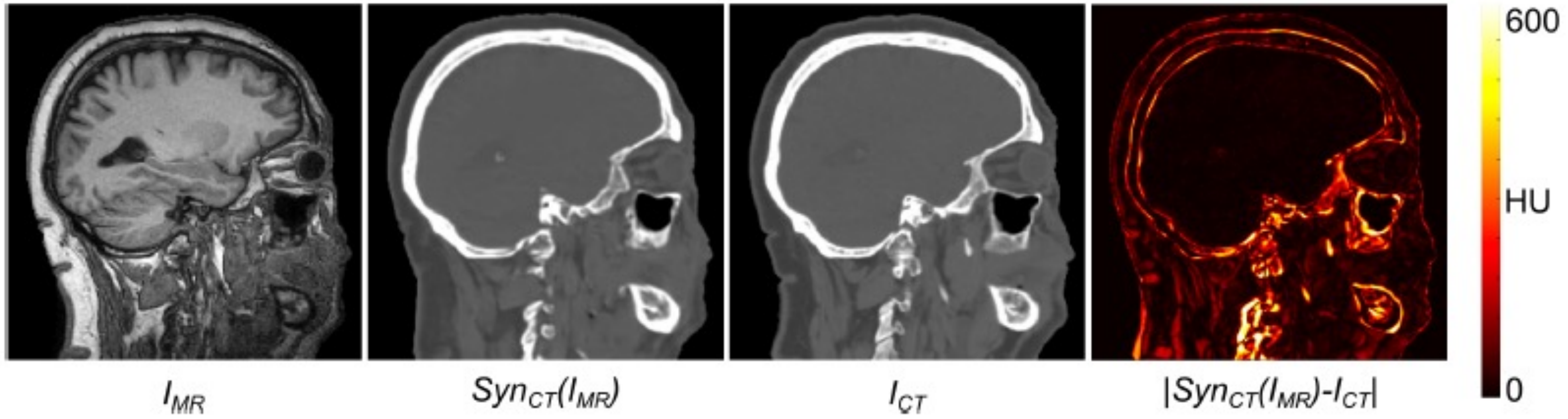
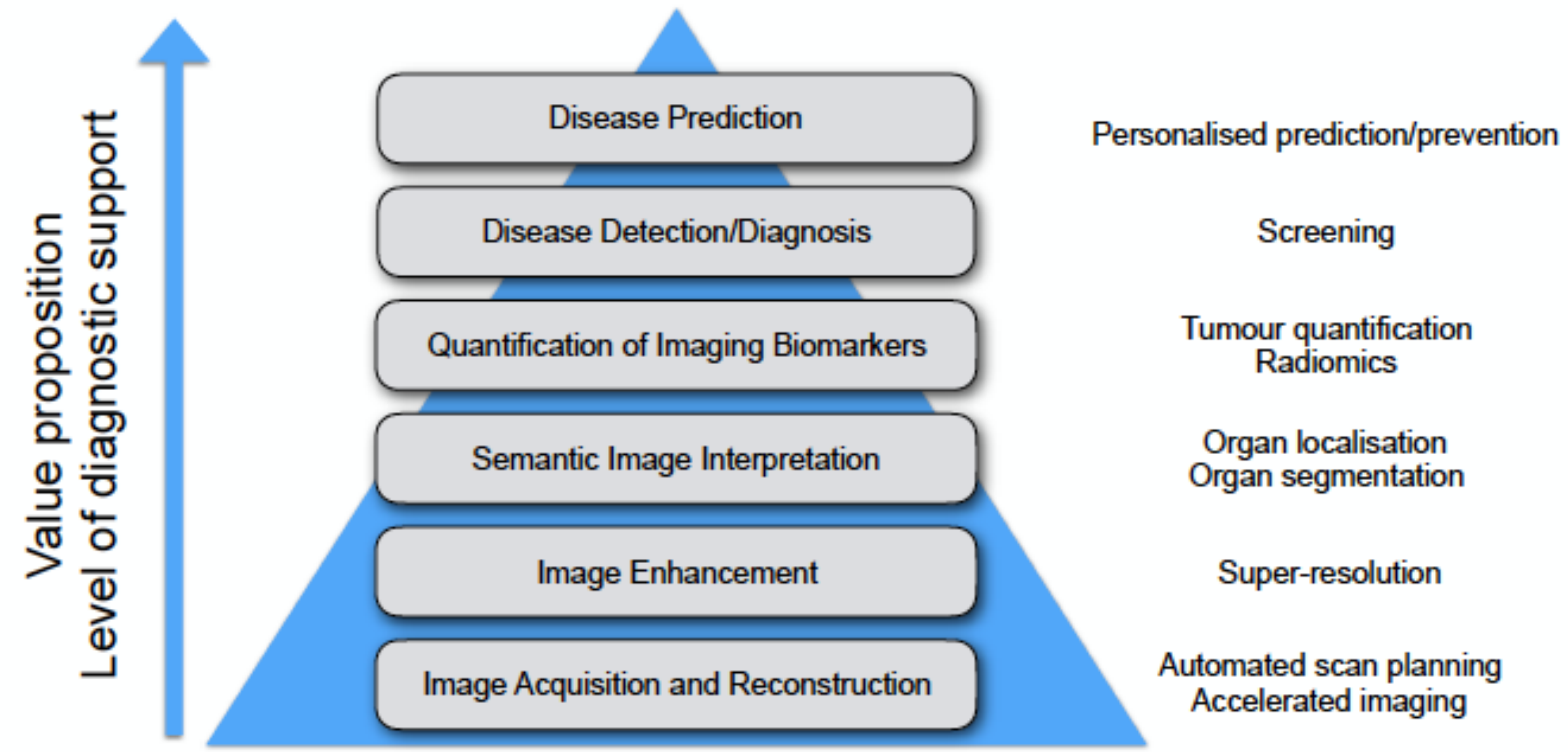


Fig. 4: *From left to right* Input MR image, synthesized CT image, reference real CT image, and absolute error between real and synthesized CT image.

Source: Wolterink et al, Deep MR to CT synthesis using unpaired data, 2017

Tasks



Source: Daniel Rueckert, Imperial College London