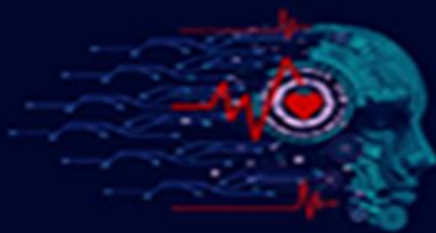


The **First (TvAI) Skyroom**
International **Virtual Congress** on
the practical Application of Artificial
Intelligence in **Medical Sciences**

Date & Time: 1-5 February, 2025 (09:00 Am - 12:00)



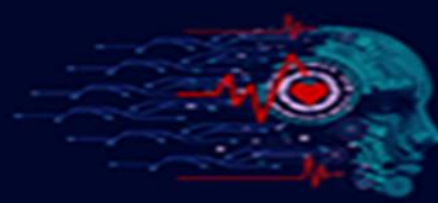
تاریخ و زمان برگزاری: ۱۳ تا ۱۷ بهمن ۱۴۰۳ (۰۹:۰۰ صبح - ۱۲:۰۰)

اولین کنگره بین المللی مجازی
کاربرد هوش مصنوعی
در علوم پزشکی



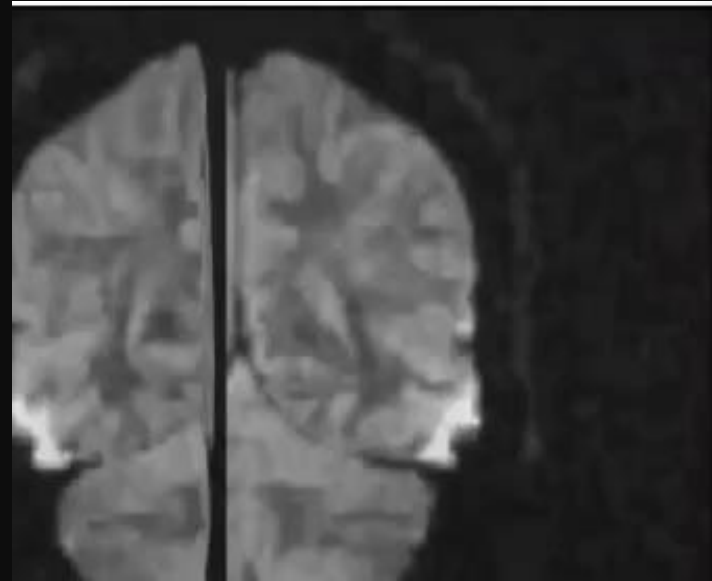
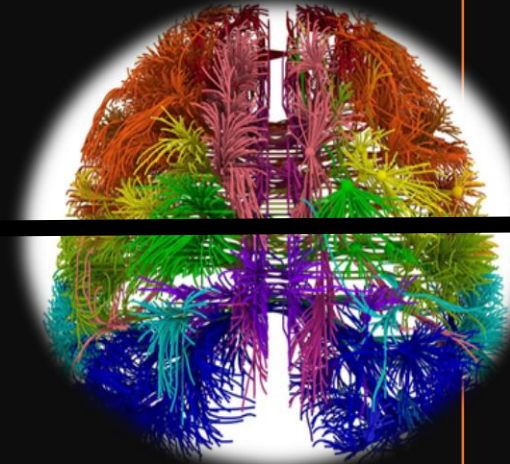
AI-Powered Tractography: Unveiling the Pathways of the Brain from Diffusion MRI

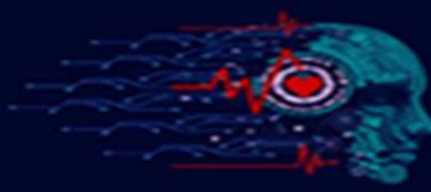
Mahdad Esmaeili, PhD.
Postdoc researcher at AI Virtanen institute
Eastern university of Finland.
Assistant professor of Biomedical
engineering department of Tabriz
university of medical science



“Nothing better defines the function of a neuron than its connections”
Marsel Mesulam (2006)

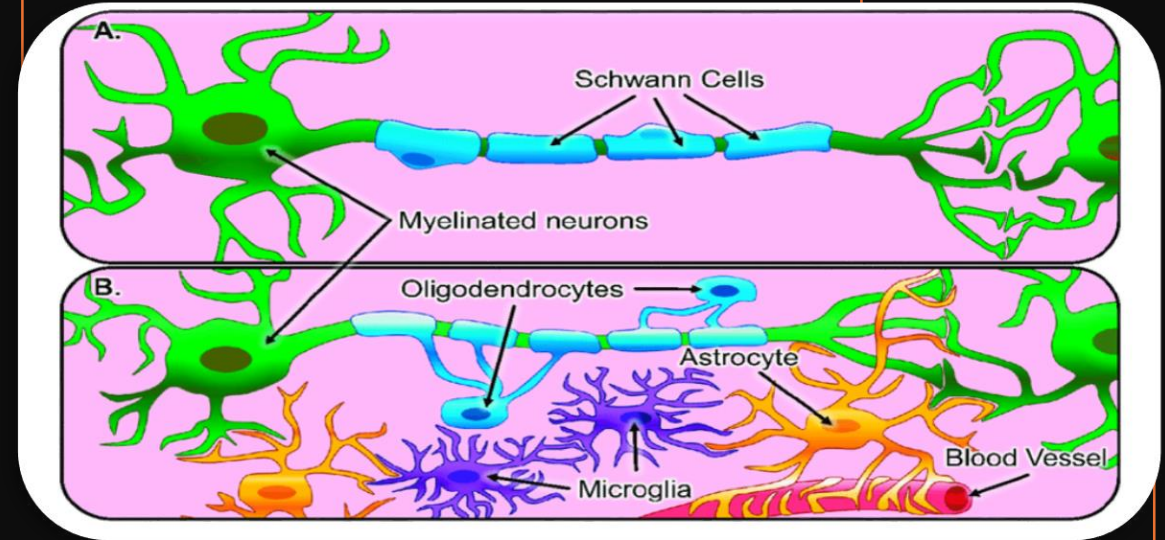
- To better understand the brain, we need to understand its structure and connections, which fundamentally involve white matter



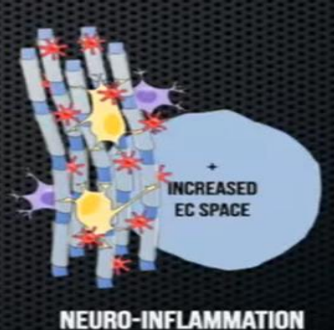
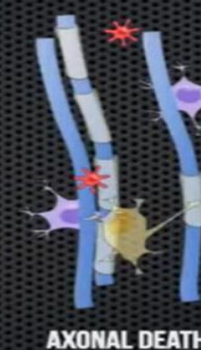
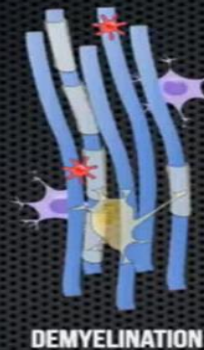


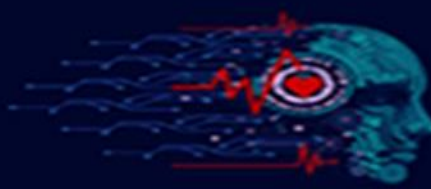
Microstructure of White Matter

- White matter is **very unique Biologically** and Anatomically
- The dream is to have **biomarkers** or **quantitative measures** that can detect whether a bundle of axons is healthy, with healthy myelin and a supportive environment, or if there are **anomalies**:
- Demyelination**
- Axonal loss**
- Axons swelling**
- Neuroinflammation**



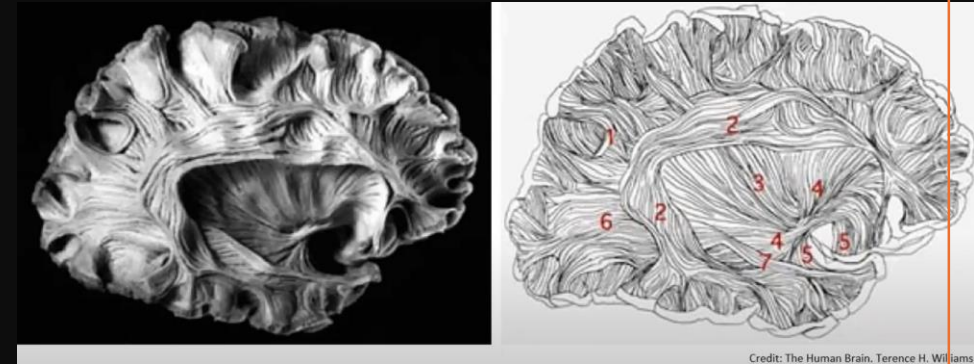
- Figure adapted from 'Electrospun Fiber Scaffolds for Engineering Glial Cell Behavior to Promote Neural Regeneration'



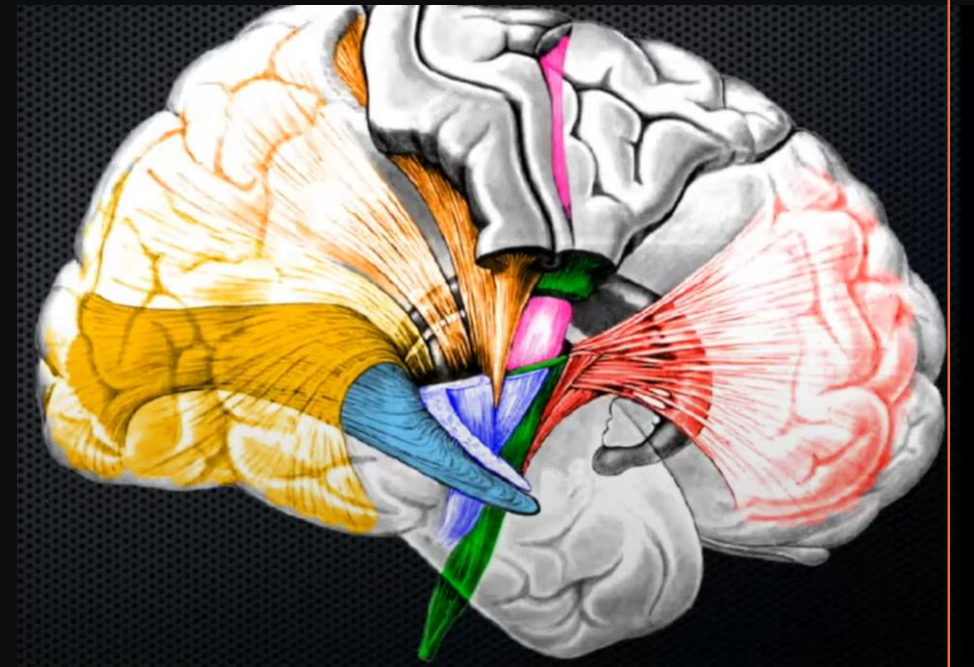


Macrostructure of White Matter

- White matter also has a **macrostructural organization**: axons organize themselves in **families** or **bundles** (fascicles)

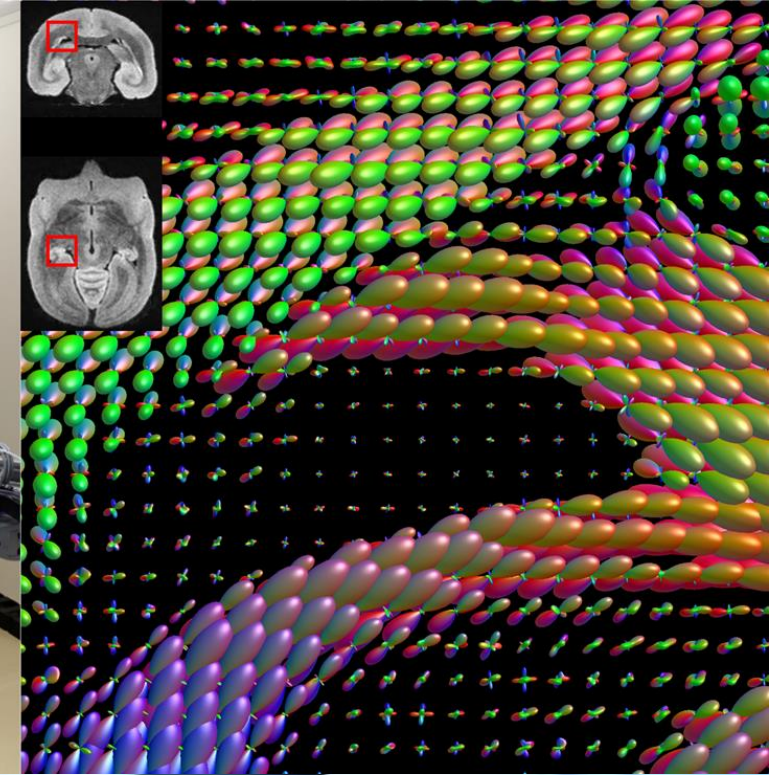
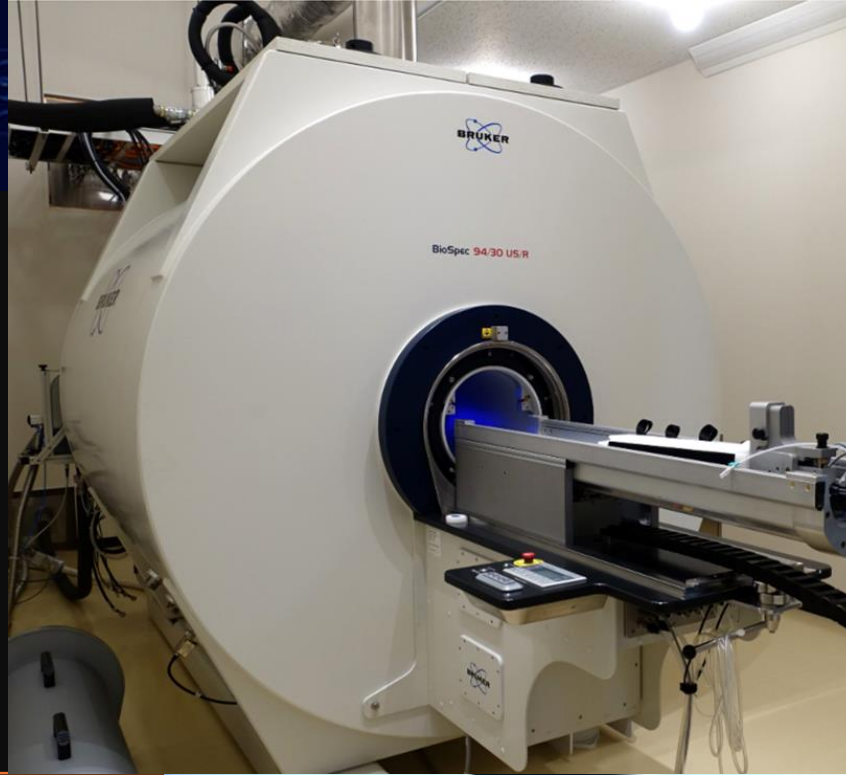


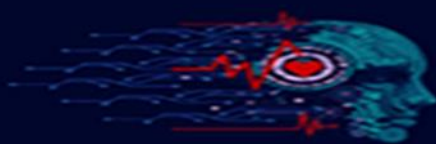
Credit: The Human Brain, Terence H. Williams



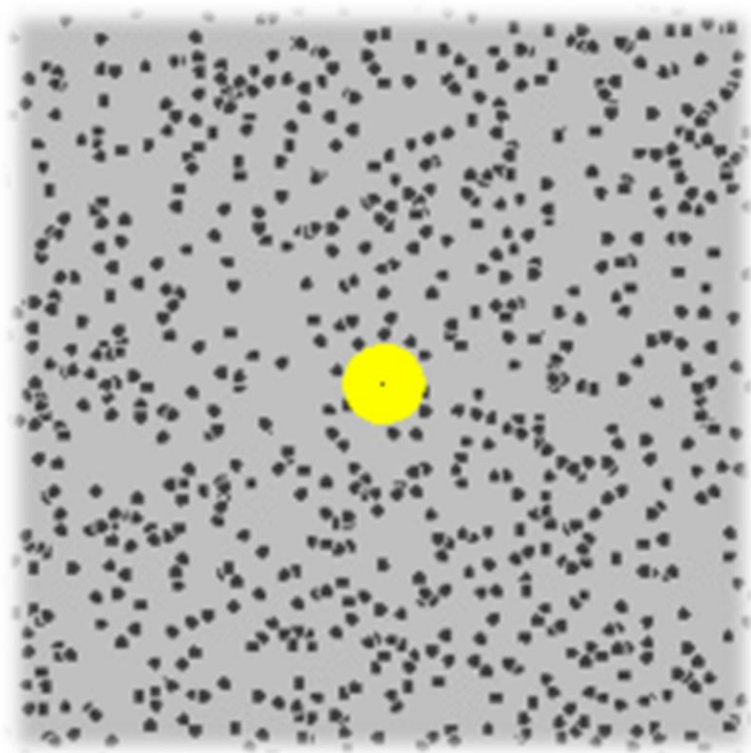
Why Diffusion

How do we **quantitatively** assess this complexity?

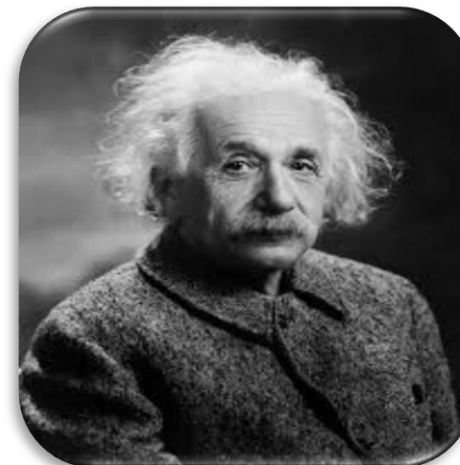




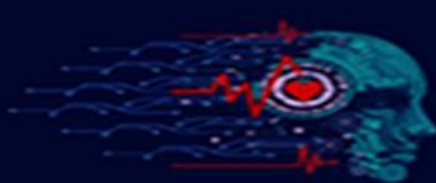
Diffusion is Essentially a Random Walk



Robert Brown, 1827
Brownian motion



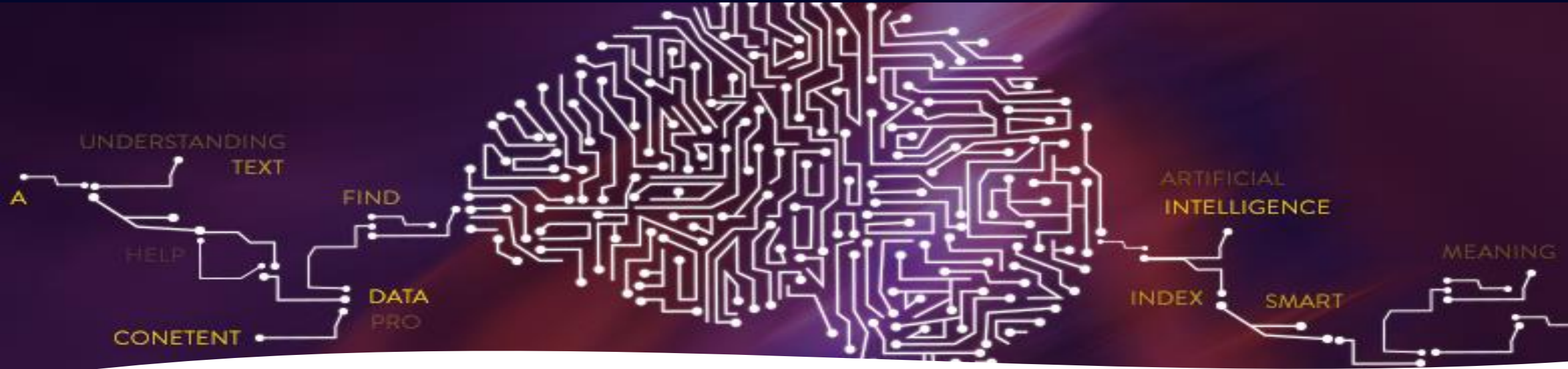
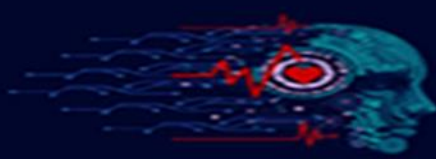
Albert Einstein, 1905
Derived the Diffusion Equation



Google Maps Analogy

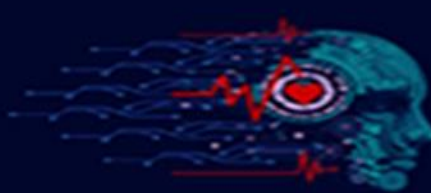


Courtesy of G. Zhang & D Alexander (UC London)]



Challenges That Necessitate Machines

- Number of Neurons
- Total Length of Axons
- Number of Synapses
- High Dimensionality of data
- Need for Precision
- Visualization and Interpretation



The main idea is the Apparent Diffusion Coefficient (ADC)

Le Bihan D, 1985

✓ *b* factor

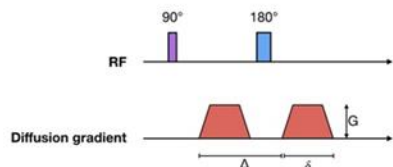
✓ ADC concept

A key paper by **Denis Le Bihan** introduced **Diffusion-Weighted Imaging (DWI)** in the French Academy of Science



b value

$$b = \gamma^2 G^2 \delta^2 \left(\Delta - \frac{\delta}{3} \right)$$



γ = gyromagnetic ratio

G = magnitude of the two balanced DW gradient pulses

δ = width of the two balanced DW gradient pulses

Δ = time between the two balanced DW gradient pulses

Relationship between
signal of $b = 0$, DWI and ADC

$$S_{DWI} = S_{b=0} \times e^{(-b \times D)}$$

equivalent to...

$$D = -\frac{1}{b} \times \ln\left(\frac{S_{DWI}}{S_{b=0}}\right)$$

S_{DWI} = signal intensity of isotropic DWI

$S_{b=0}$ = signal intensity of $b = 0$

b = *b* value

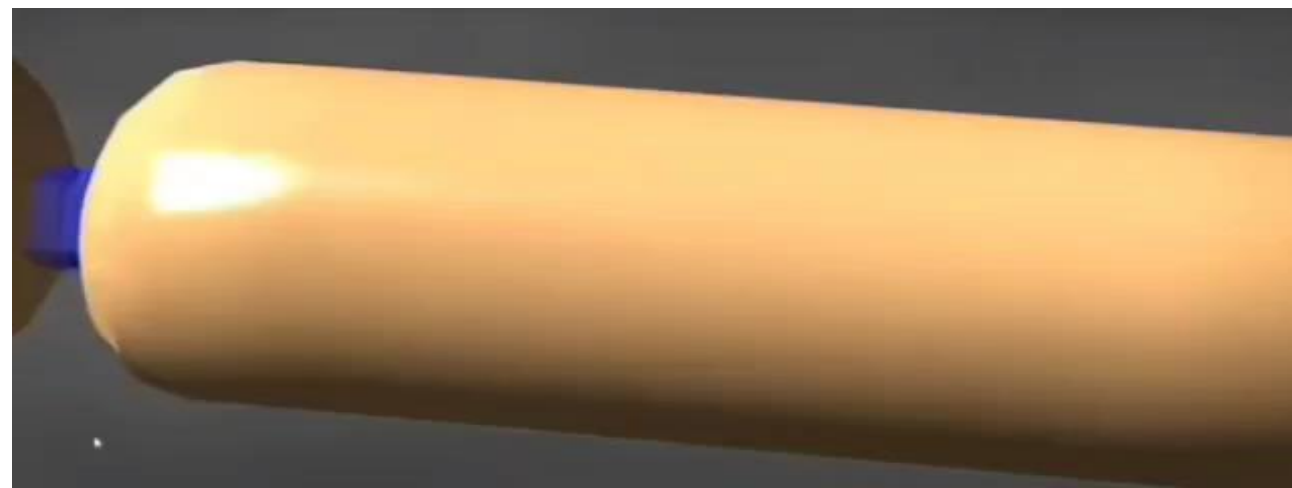
D = apparent diffusion coefficient (ADC)

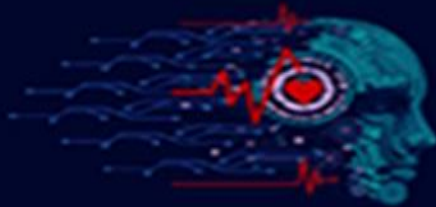


By acquiring enough data, we can find a **normal ADC** for brain tissue; any **tumor, stroke, or other abnormality** causes ADC to deviate from that norm.

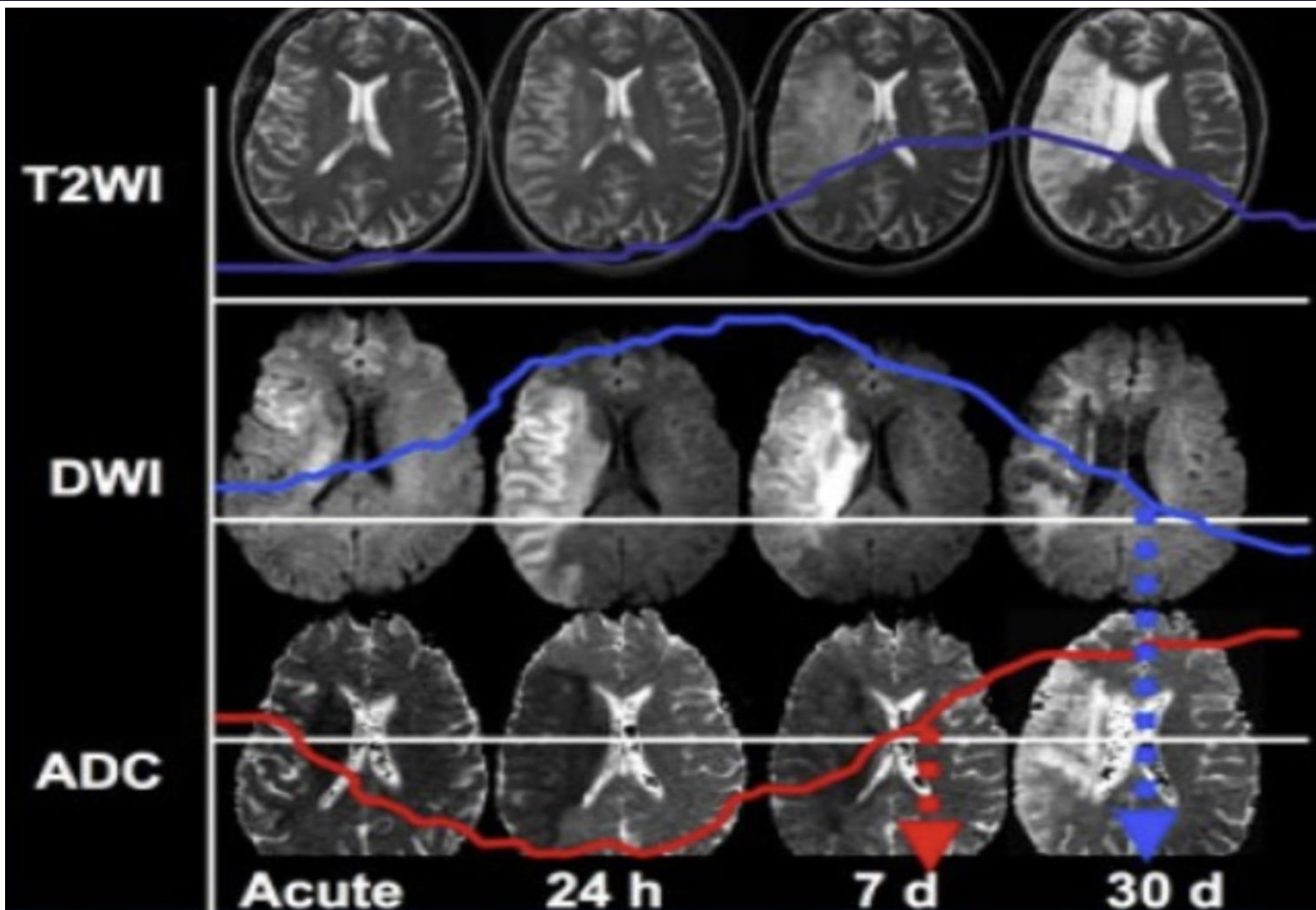


Denis Le Bihan
1985





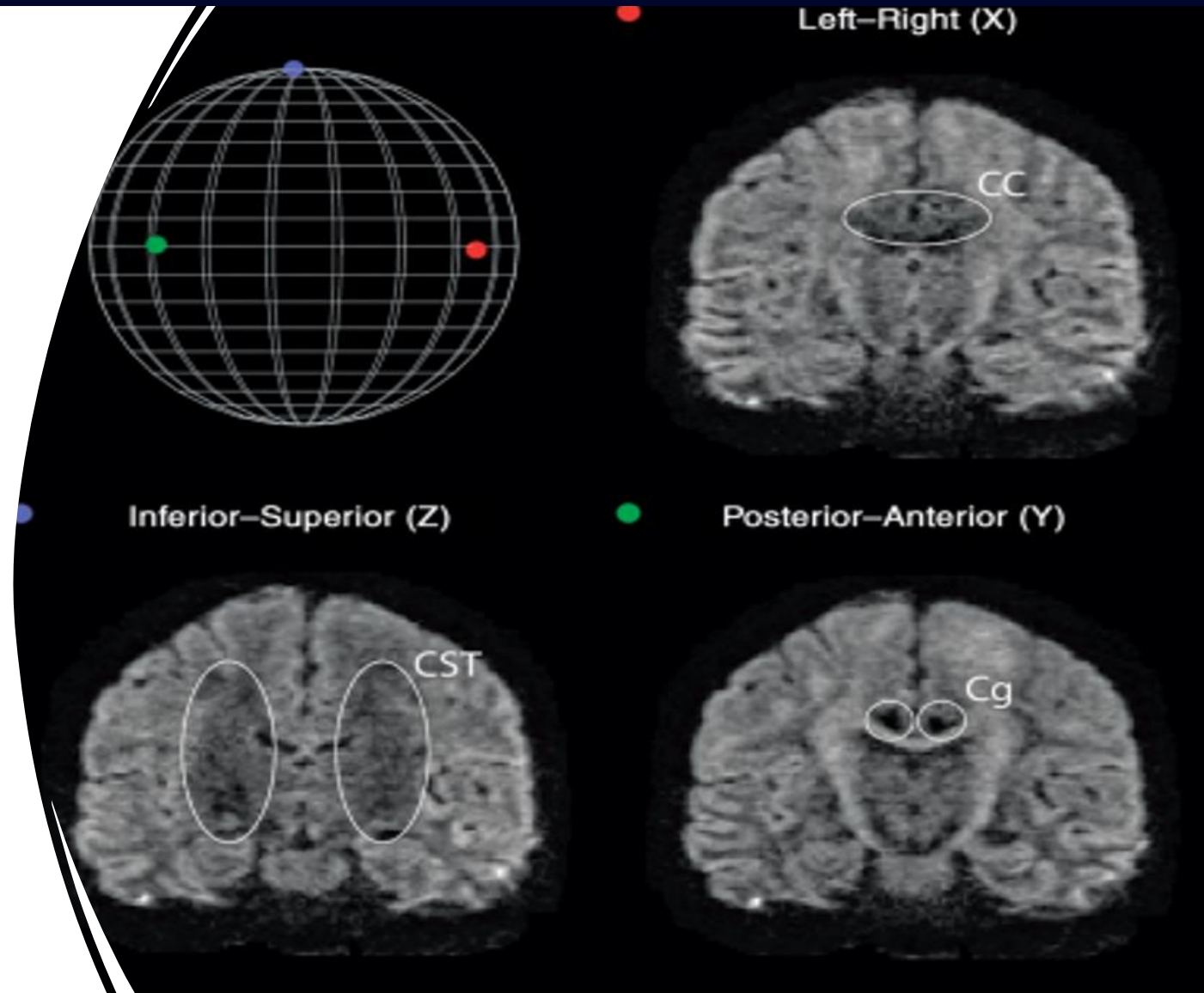
Stroke Imaging

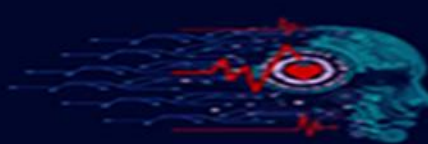




Beyond ADC: Orientation and White Matter Organization

- Diffusion along X, Y, and Z directions. The signal in the left/right oriented corpus callosum is lowest when measured along X, while the signal in the inferior/superior oriented corticospinal tract is lowest when measured along Z.





Diffusion Tensor Imaging (DTI)

- Diffusion Tensor Imaging (DTI) models diffusion in each voxel using a 3*3 tensor:

$$\mathbf{D} = \begin{bmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{yx} & D_{yy} & D_{yz} \\ D_{zx} & D_{zy} & D_{zz} \end{bmatrix}$$

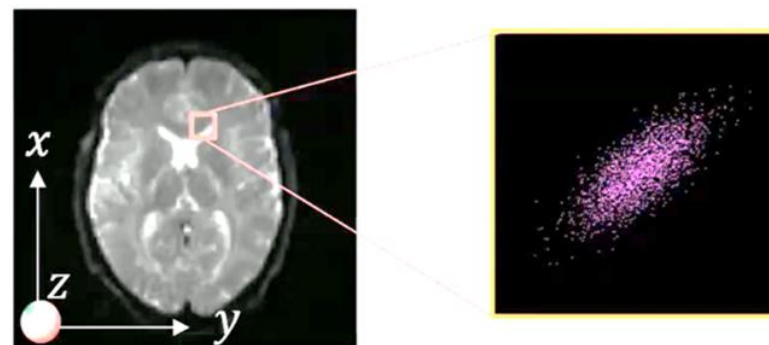
Diffusion Tensor

- AD, RD and MD can be more generally computed from eigen-value decomposition

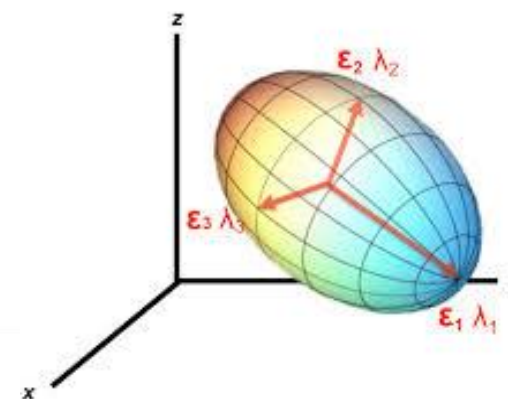
$$\begin{bmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{xy} & D_{yy} & D_{yz} \\ D_{xz} & D_{yz} & D_{zz} \end{bmatrix} = [\mathbf{v}_1 \quad \mathbf{v}_2 \quad \mathbf{v}_3] \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix} \begin{bmatrix} \mathbf{v}_1 \\ \mathbf{v}_2 \\ \mathbf{v}_3 \end{bmatrix}$$

$$AD = \lambda_1 \quad RD = (\lambda_2 + \lambda_3)/2 \quad MD = (\lambda_1 + \lambda_2 + \lambda_3)/3$$

$$FA = \sqrt{\frac{3}{2}} \cdot \frac{\sqrt{(\lambda_1 - MD)^2 + (\lambda_2 - MD)^2 + (\lambda_3 - MD)^2}}{\sqrt{\lambda_1^2 + \lambda_2^2 + \lambda_3^2}}$$



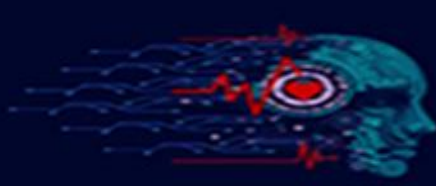
- Ellipsoid representation



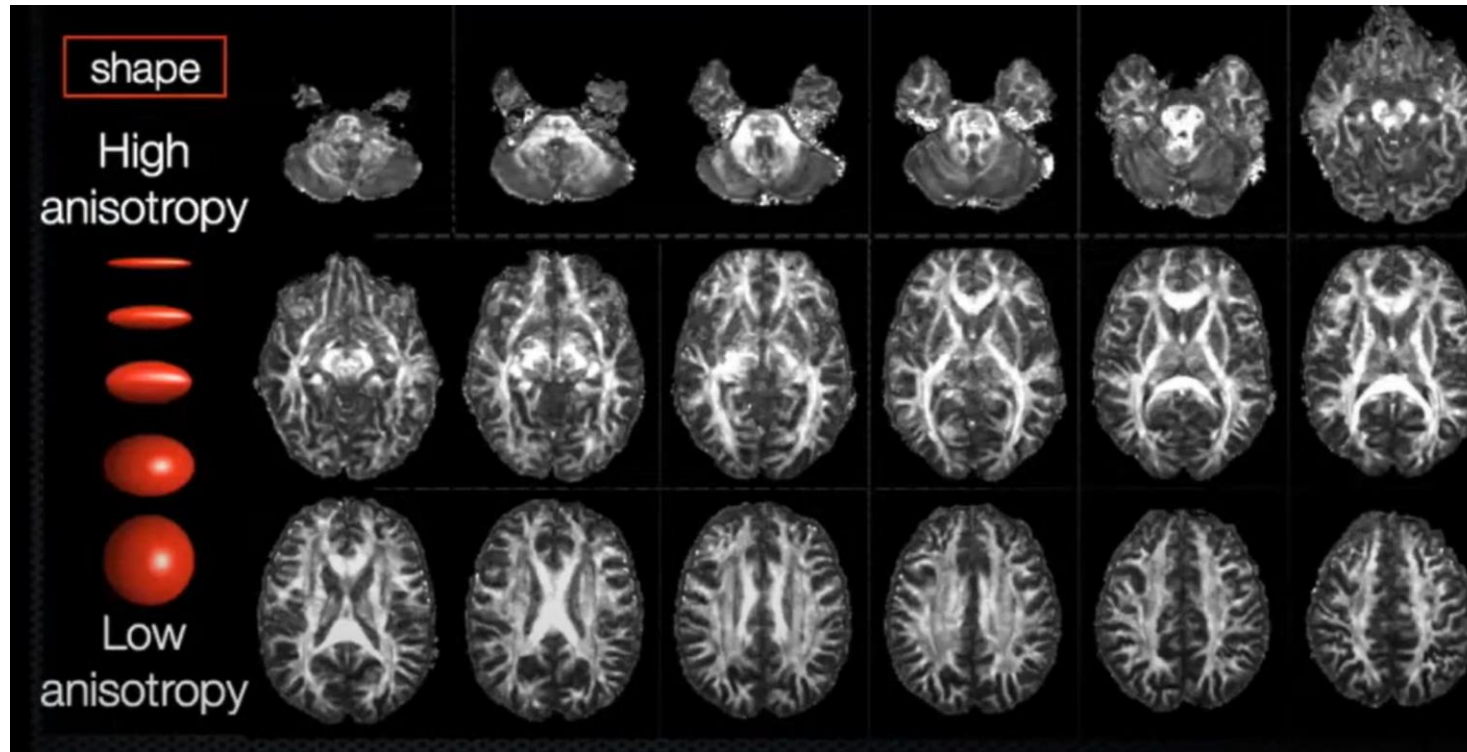
Peter Basser, 1994

$$S(\mathbf{b}) = S_0 e^{-\mathbf{b}^T \mathbf{D} \mathbf{g}}$$

$$\mathbf{g} = [g_x, g_y, g_z]^T$$



Fractional Anisotropy (FA)

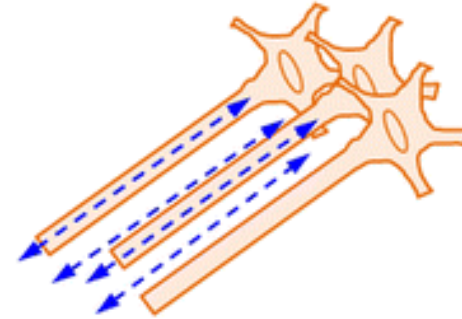


Isotropic

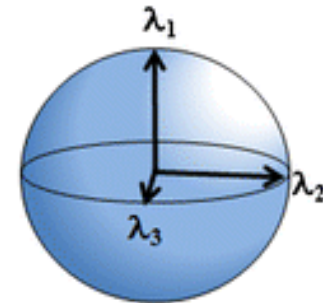
3D Pattern
Of Diffusion



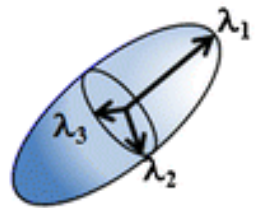
Anisotropic



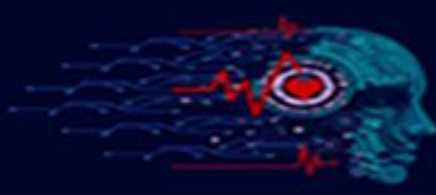
DTI
Model



Low FA



High FA



Limits of DTI



Brain Disorders & Therapy

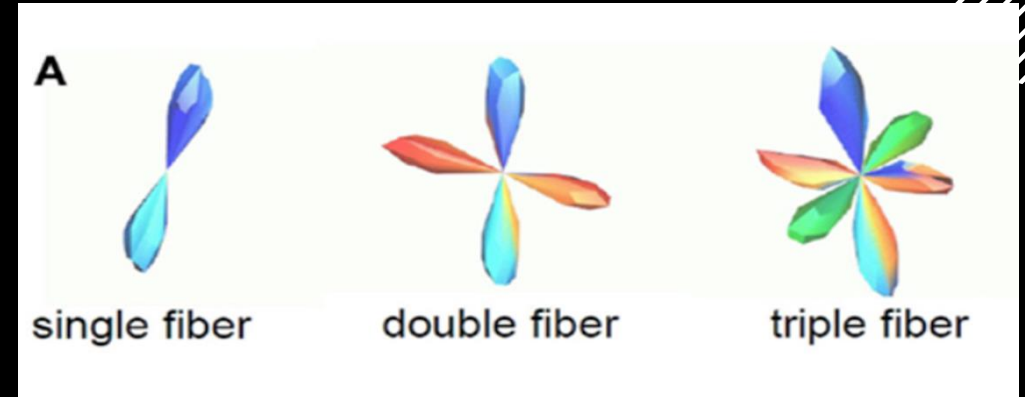
Rajagopalan et al., Brain Disord Ther 2017, 6:2
DOI: 10.4172/2168-975X.1000229

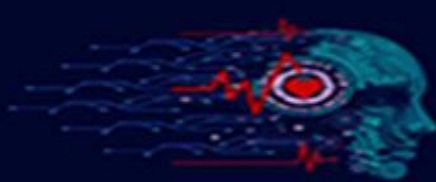
Research Article OMICS International

A Basic Introduction to Diffusion Tensor Imaging Mathematics and Image Processing Steps

Venkateswaran Rajagopalan^{1,2*}, Zhiguo Jiang³, Jelena Stojanovic-Radic⁴, Guang H Yue³, Erik P Pioro^{5,6}, Glenn R Wylie⁴, and Abhijit Das⁴

¹Department of Electrical and Electronics Engineering, Birla Institute of Technology and Sciences Pilani, Hyderabad Campus, Hyderabad, India
²Department of Biomedical Engineering, ND2, Lerner Research Institute, Cleveland Clinic, USA
³Human Performance and Engineering Research, Kessler Foundation, 1199 Pleasant Valley Way, West Orange, New Jersey, USA
⁴Neuroscience and Neuropsychology Laboratory, Kessler Foundation, 300 Executive Drive, Suite 70, West Orange, New Jersey, USA
⁵Neuromuscular Center and Department of Neurology, Neurological Institute, USA
⁶Department of Neurosciences, Lerner Research Institute, Cleveland Clinic, Cleveland, Ohio, USA





Crossing fibers everywhere



[Tournier et al]



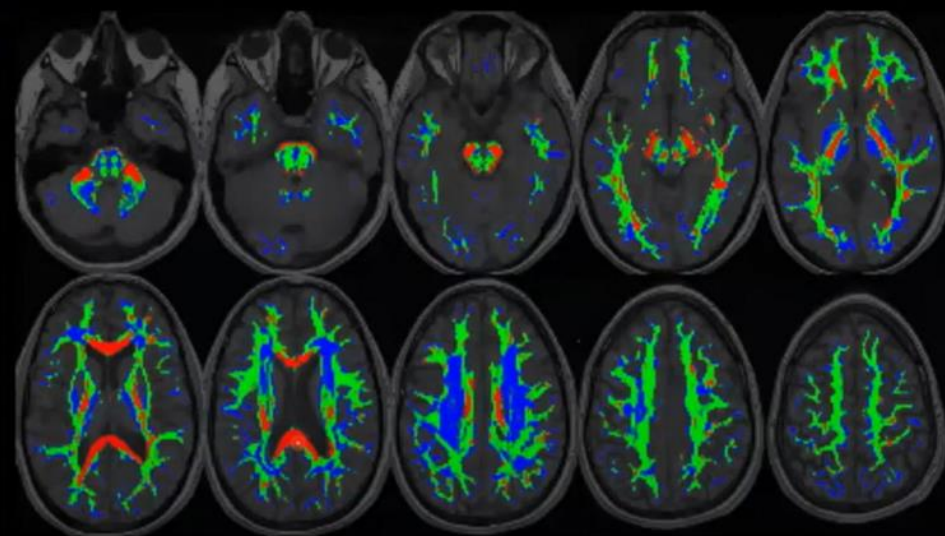
[Dell'Acqua et al]



[Descoteaux et al] **2007**

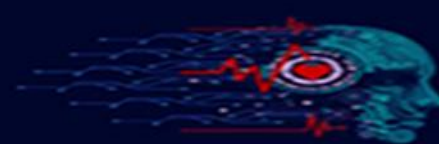
1,000+
"fODF" citations
(3-7 min acquisition)

Crossing fibres affect ~90% of white matter voxels



1 2 >2

Jeurissen et al., HBM 34:2747-2766 (2013)



Constrained Spherical Deconvolution (CSD)

Mathematical Model:

$$S(\mathbf{q}) = \int_{\Omega} E(\mathbf{q}, \mathbf{r}) F(\mathbf{r}) d\mathbf{r},$$

where:

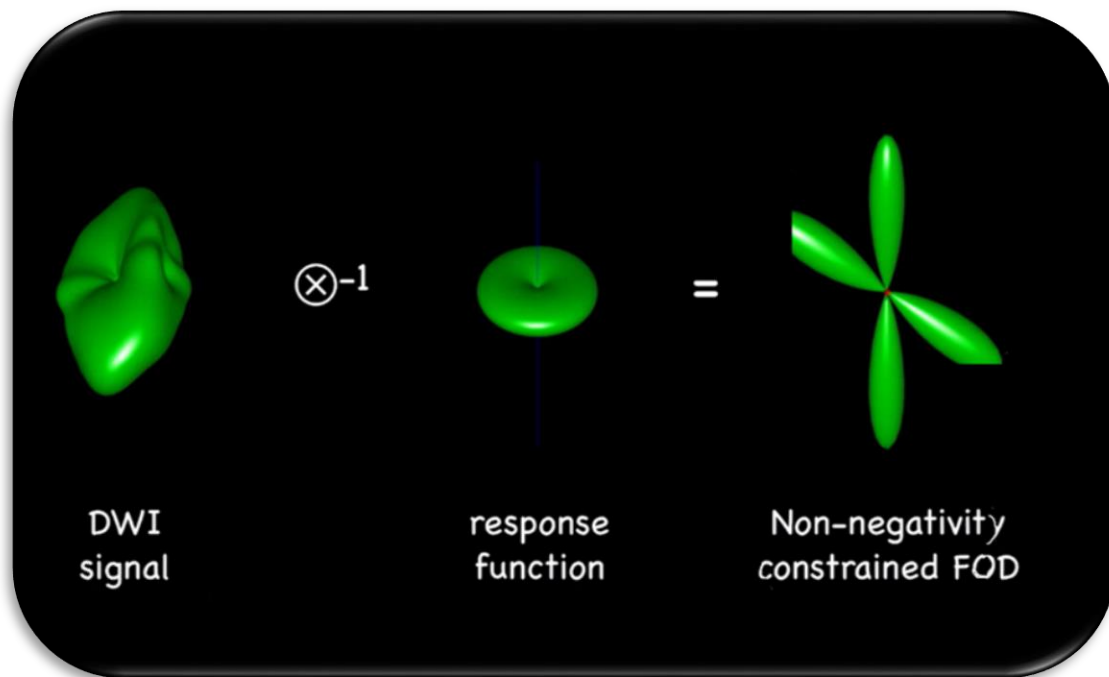
- $S(\mathbf{q})$: Measured diffusion signal.
- $E(\mathbf{q}, \mathbf{r})$: Single-fiber response function (kernel).
- $F(\mathbf{r})$: Fiber Orientation Distribution (FOD).

Model the Problem: The FOD is estimated by solving the optimization problem:

$$\mathbf{F} = \arg \min_{\mathbf{F}} \|\mathbf{S} - \mathbf{E}\mathbf{F}\|^2 + \lambda R(\mathbf{F}),$$

subject to:

$$F(\mathbf{r}) \geq 0 \quad \forall \mathbf{r}.$$

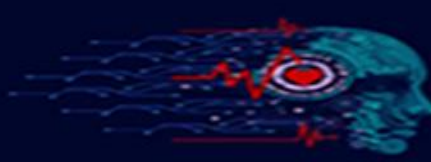


Instead of solving the optimization problem iteratively, the network approximates:

$$\mathbf{F} \approx f_{\text{NN}}(\mathbf{S}),$$

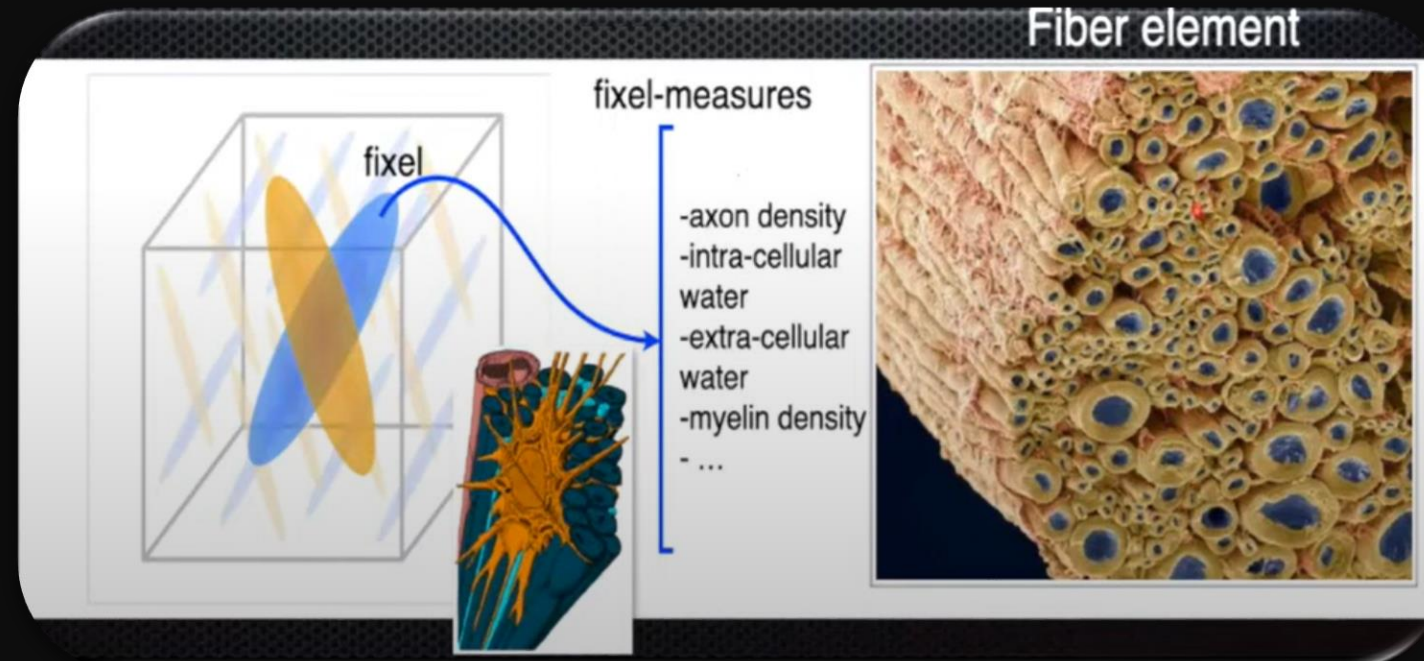
where f_{NN} is parameterized by neural network weights Θ learned by minimizing:

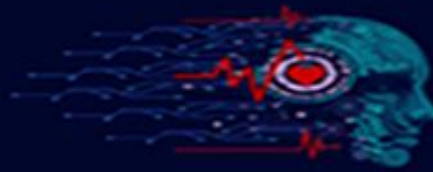
$$\mathcal{L}(\Theta) = \|\mathbf{F}_{\text{true}} - f_{\text{NN}}(\mathbf{S}; \Theta)\|^2 + \lambda R(f_{\text{NN}}(\mathbf{S}; \Theta)).$$



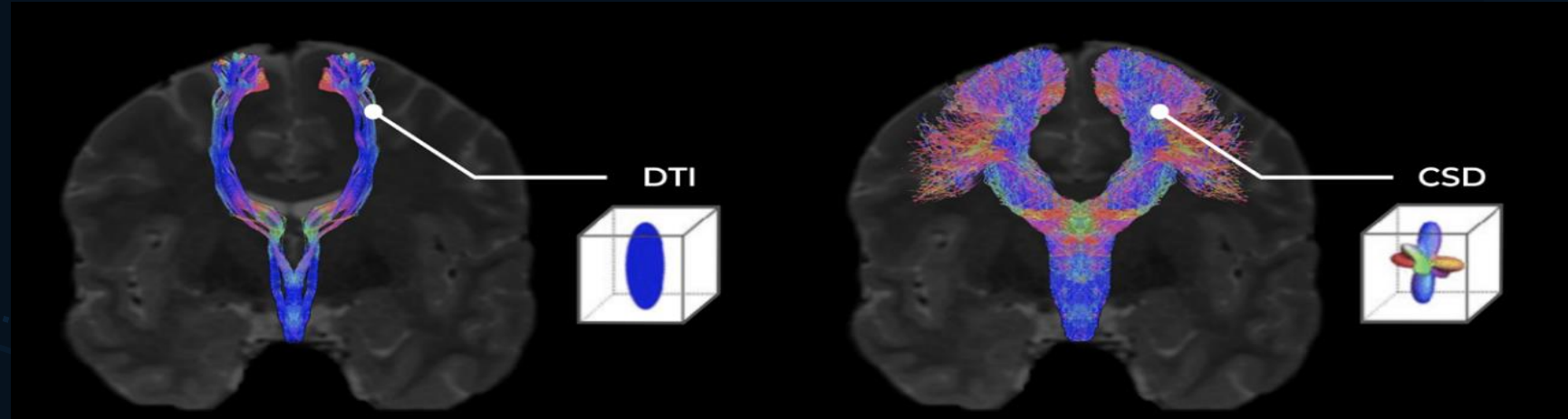
Fixel-Based Analysis (FBA)

- Pixel=picture element (2D)
- Voxel=Volume element (3D)
- Fixel=fiber element (5D)

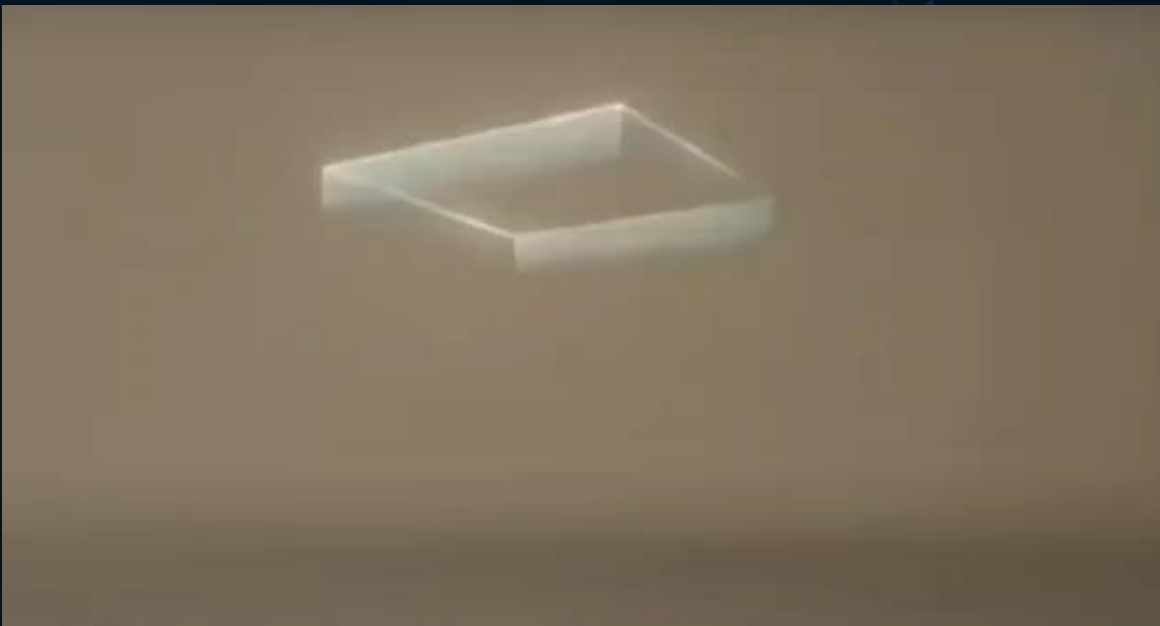




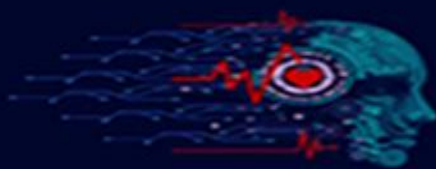
Tractography



- **Tractography** is a brain imaging technique that broadly describes the mapping of the location and direction of white matter bundles and their constituent fibers within the human brain

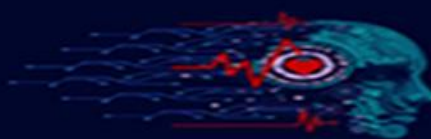


$$x_{i+1} = x_i + \Delta s \cdot d_i$$

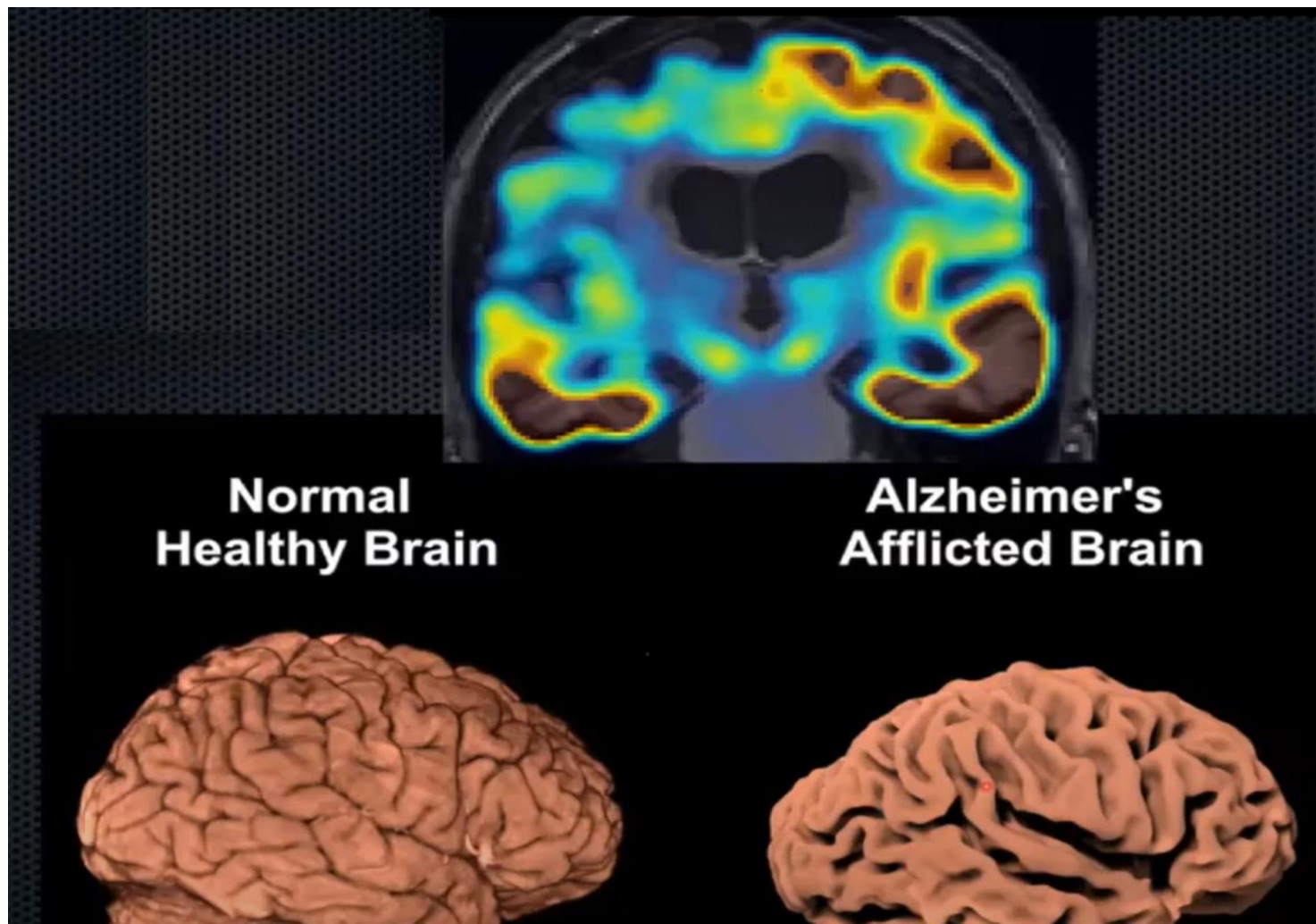


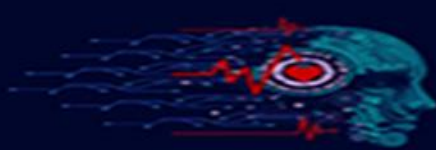
Segmentation and Tractometry



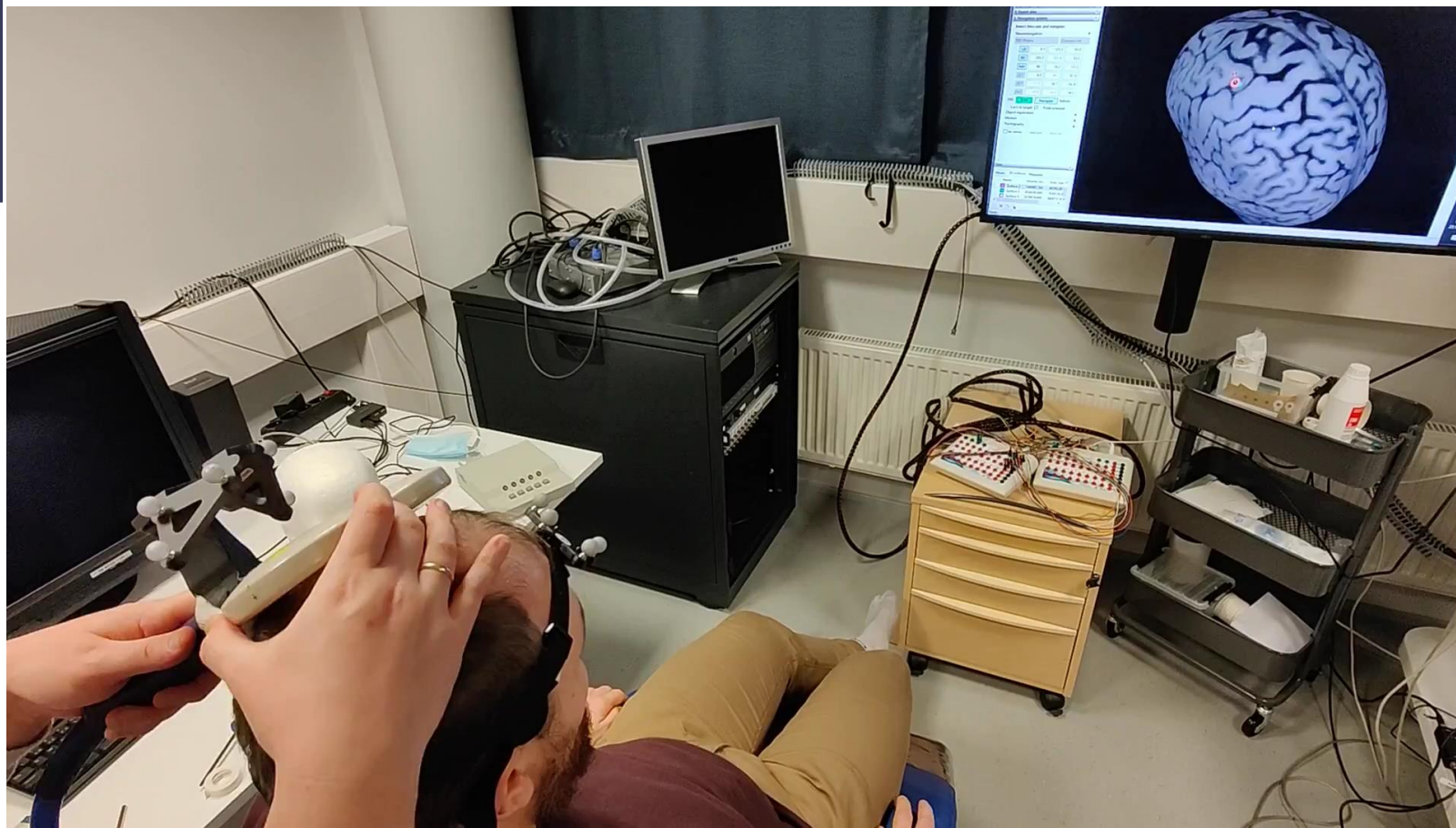


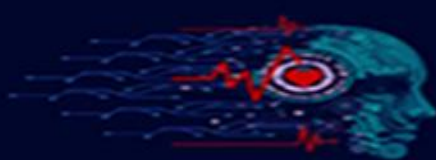
Application of Tractography in Alzheimer's Disease(AD)





Combining TMS and Tractography





DIPY

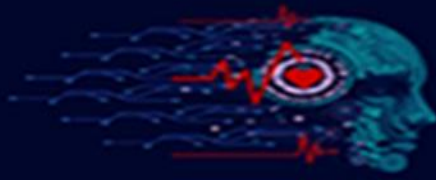
MRtrix3

Open-source
Python
software
designed for
computational
anatomy.

Primarily
focuses on
diffusion MRI
but also
offers general
medical
imaging
algorithms
like denoising
and
registration.

DIPY and
MRtrix3 are
global
initiatives
that foster
collaboration
among
researchers
across
laboratories
and countries

Aims to share
cutting-edge
code and
expertise,
accelerating
progress in
medical
imaging
research.



Diffusion Imaging in Python

An open-source, user-friendly and growing imaging library for 3D/4D+ imaging.

Getting Started Install

Register Now!

DIPY WORKSHOP

17th to 21st March 2025 | Online Edition

MRtrix3

workshop 2024 Taiwan Download Blog Documentation Community Development ▾

MRtrix3

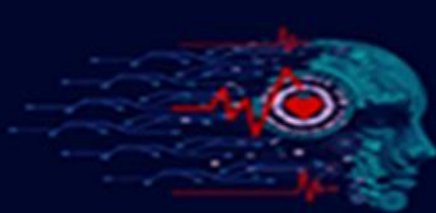
Advanced tools for the analysis of diffusion MRI data

[Download](#) [Use MRtrix3](#)

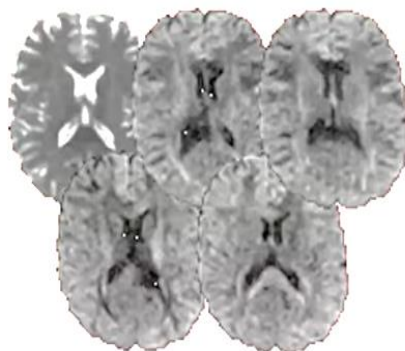
What is MRtrix3?

MRtrix3 provides a set of tools to perform various types of diffusion MRI analyses, from various forms of tractography through to next-generation group-level analyses. It is designed with consistency, performance, and stability in mind, and is freely available under an open-source license. It is developed and maintained by a team of experts in the field, fostering an active community of users from diverse backgrounds.

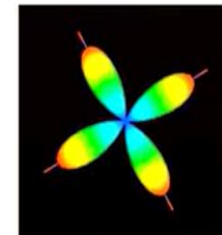
Use Case	Best Tool
High-performance tractography pipelines	MRtrix3
Interactive GUI for diffusion MRI analysis	MRtrix3 (mrview)
Flexible scripting and integration	DIPY
Teaching diffusion MRI principles	DIPY
Python-based workflows or pipelines	DIPY
Multi-modal connectomics	MRtrix3
Large-scale, multi-shell data	MRtrix3



Ongoing Research



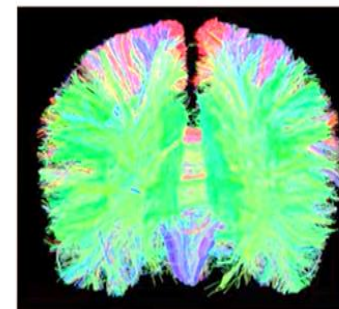
Resolve low X angles?



Voxel reconstruction

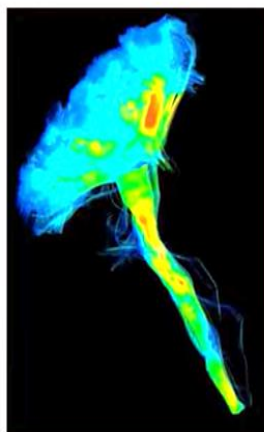


Reduce FP?

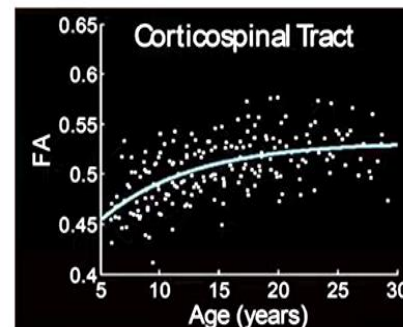


Tractography

Which metric?



Tracts and tractometry



Statistical analysis



Segment
accurately?

Thank you for your attention 😊

