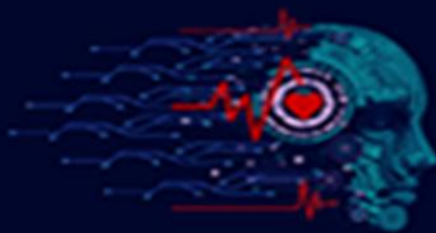


The **First (TVAI) Skyroom**  
International **Virtual Congress** on  
the practical Application of Artificial  
Intelligence in **Medical Sciences**

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



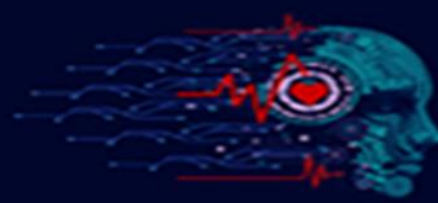
تاریخ و زمان برگزاری: ۱۳ تا ۱۷ بهمن ۱۴۰۳ (۰۹:۰۰ صبح - ۱۲:۰۰)

**اولین کنگره بین المللی مجازی**  
**کاربرد هوش مصنوعی**  
در علوم پزشکی



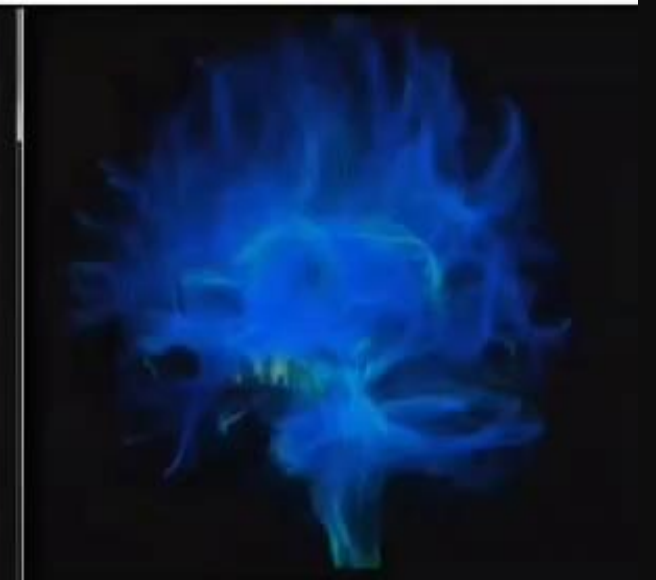
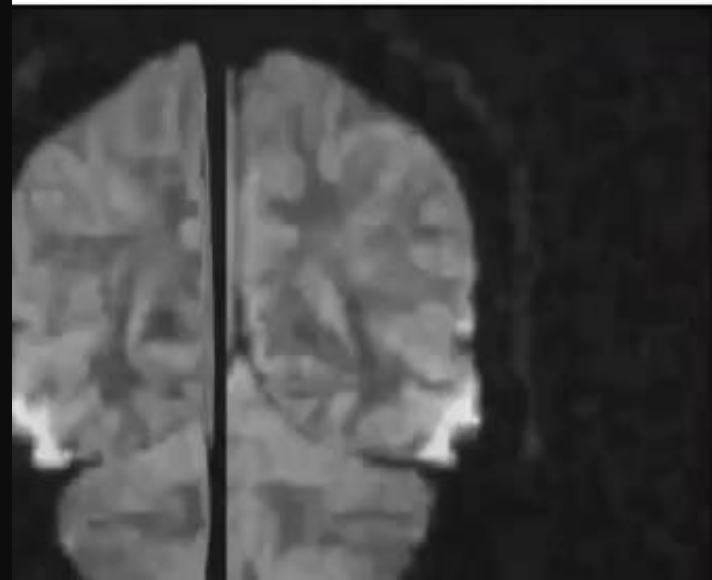
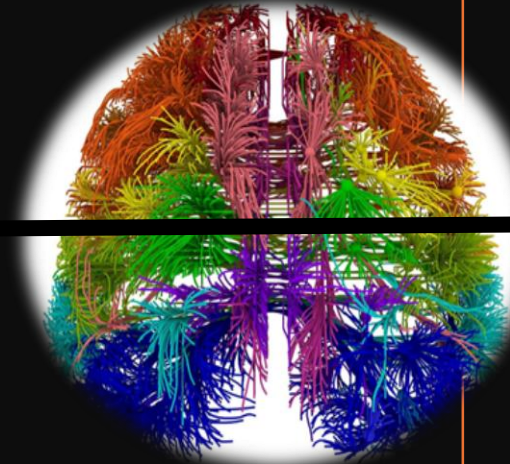
# AI-Powered Tractography: Unveiling the Pathways of the Brain from Diffusion MRI

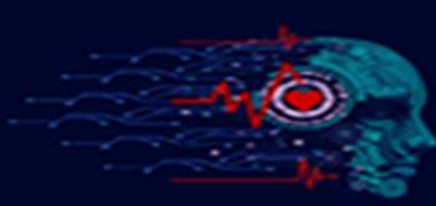
Mahdad Esmaeili, PhD.  
Postdoc researcher at AI Virtanen Institute  
Eastern University of Finland.  
Assistant professor of Biomedical  
engineering department of Tabriz  
university of medical science



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

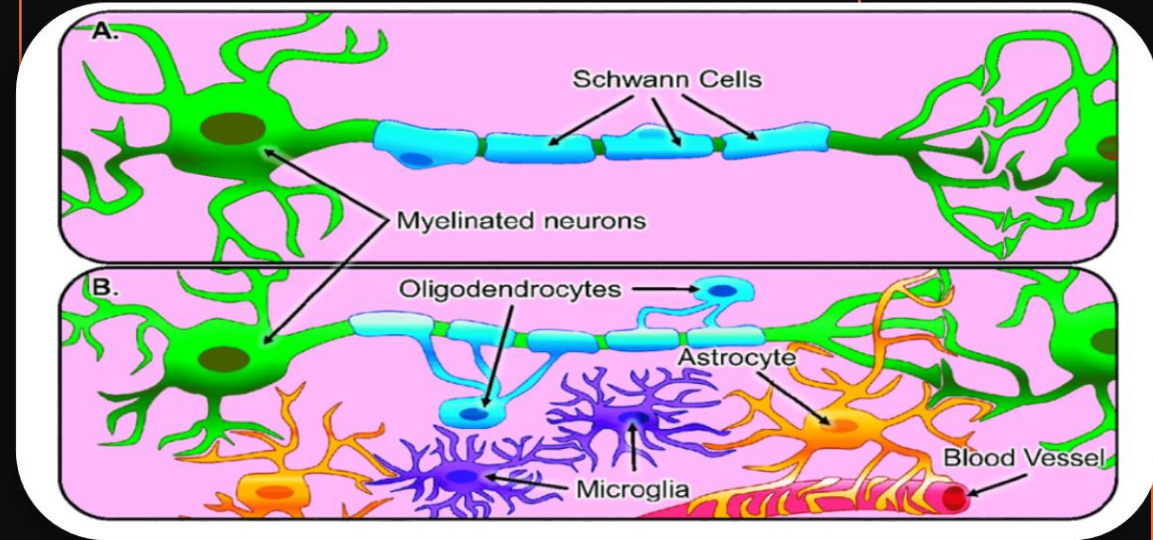
- To better understand the brain, we need to understand its structure and connections, which fundamentally involve white matter



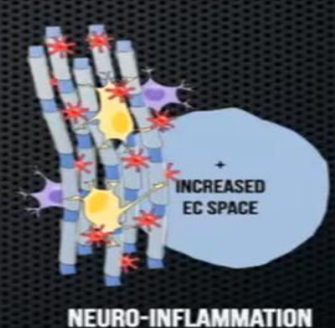
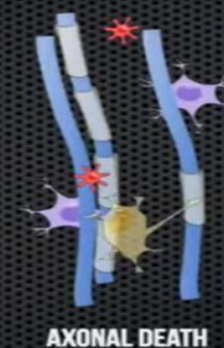
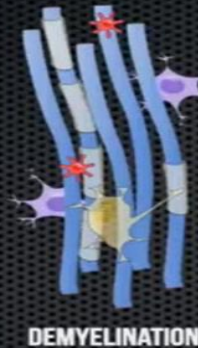
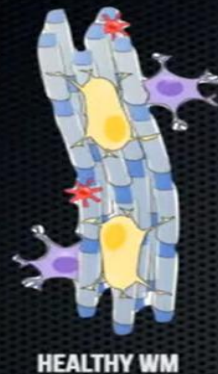


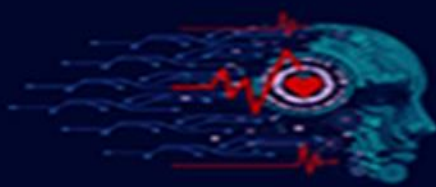
# Microstructure of White Matter

- 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**



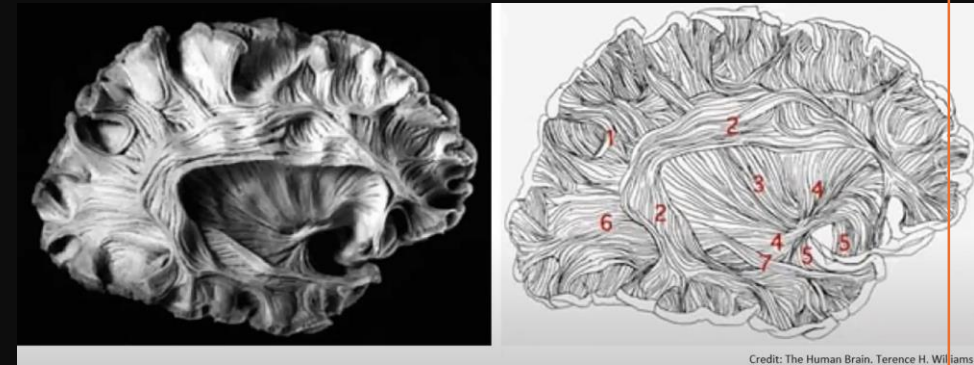
• Figure adapted from 'Electrospun Fiber Scaffolds for Engineering Glial Cell Behavior to Promote Neural Regeneration'



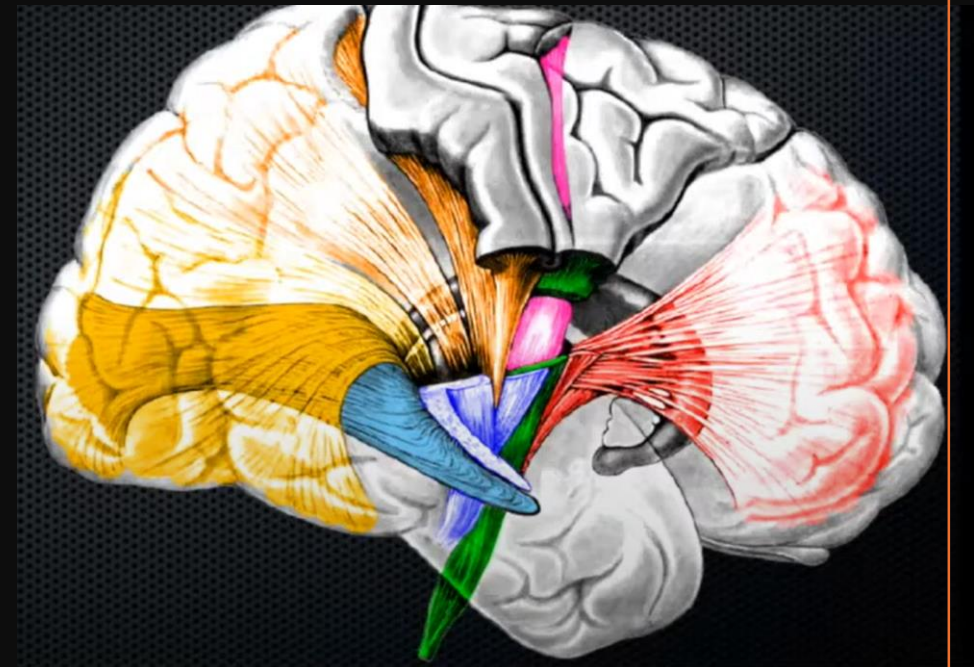


# Macrostructure of White Matter

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

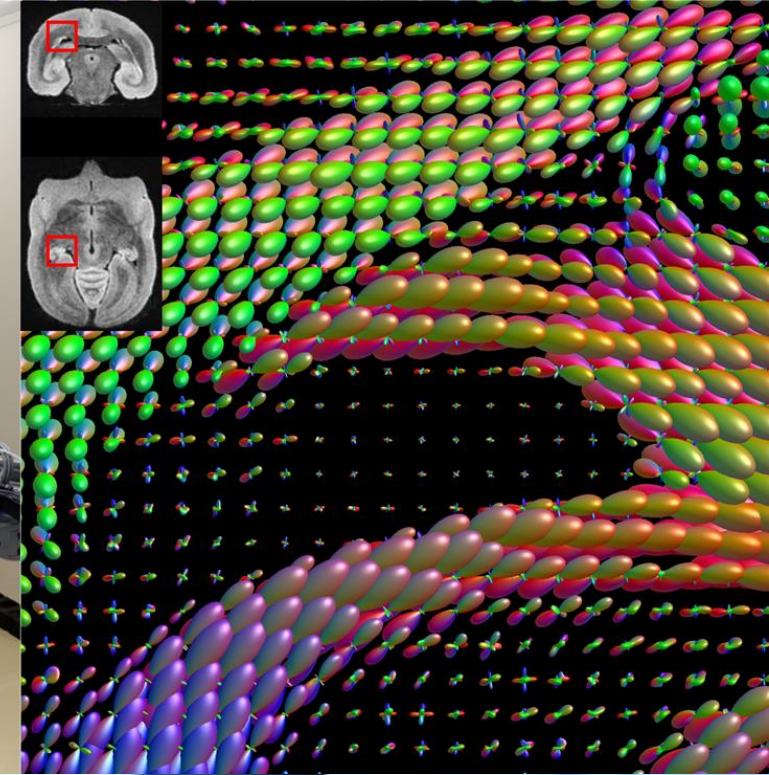
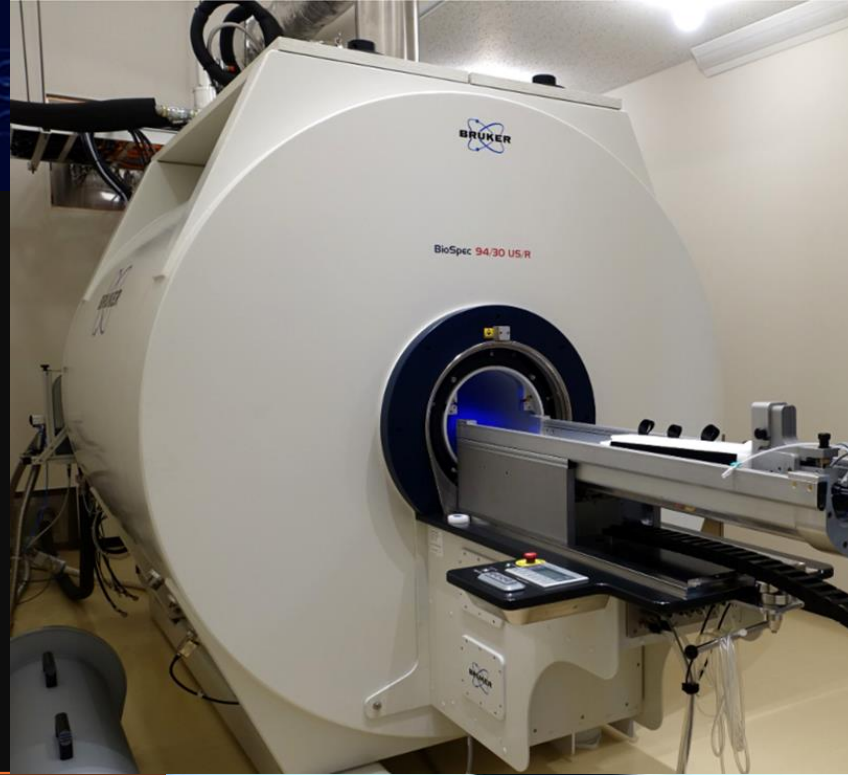


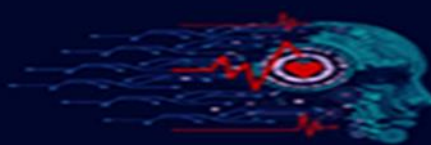
Credit: The Human Brain, Terence H. Williams



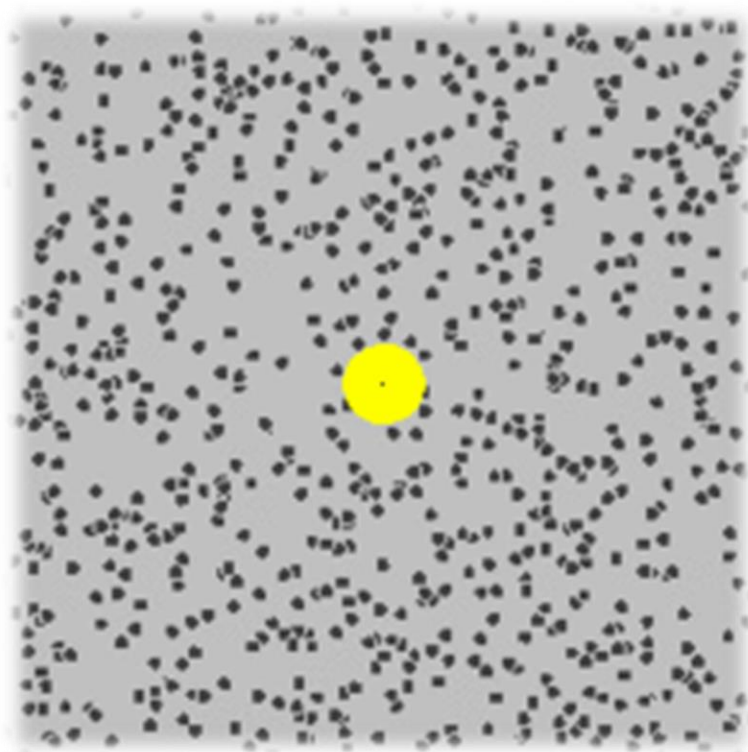
# Why Diffusion

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

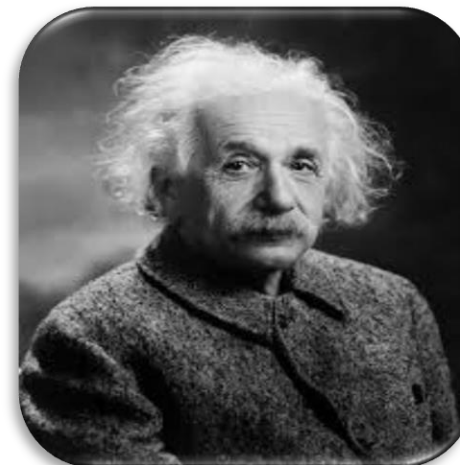




## Diffusion is Essentially a Random Walk

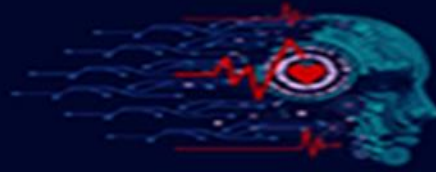


**Robert Brown, 1827**  
Brownian motion



**Albert Einstein, 1905**  
Derived the Diffusion Equation

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: ۱۷ تا ۲۱ بهمن ۱۴۰۳ (۰۹:۰۰ صبح - ۱۲:۰۰)

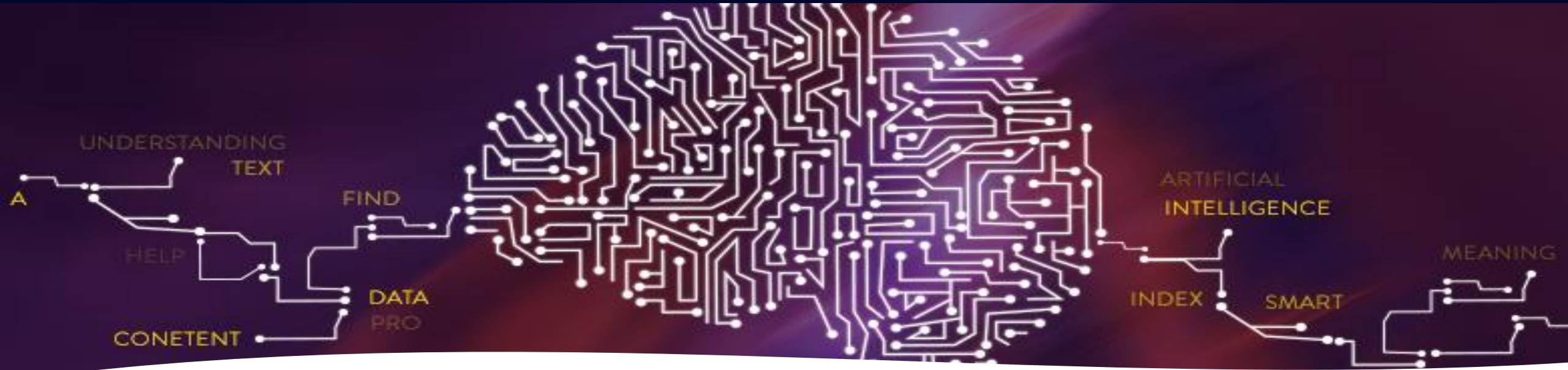
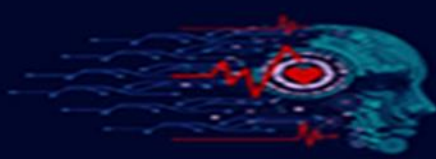
**اولین کنگره بین المللی مجازی**  
**کاربرد هوش مصنوعی**  
در علوم پزشکی



# Google Maps Analogy



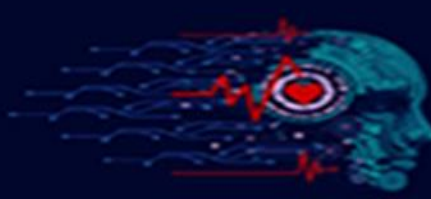
Courtesy of G. Zhang & D Alexander (UC London)]



# Challenges That Necessitate Machines

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





Denis Le Bihan  
 1985

# The main idea is the Apparent Diffusion Coefficient (ADC)

Le Bihan D, 1985

✓ b factor

✓ ADC concept

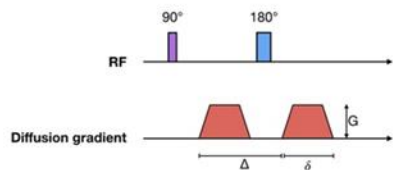
A key paper by **Denis Le Bihan** introduced **Diffusion-Weighted Imaging (DWI)** in the French Academy of Science



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.

**b value**

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



- $\gamma$  = gyromagnetic ratio
- $G$  = magnitude of the two balanced DW gradient pulses
- $\delta$  = width of the two balanced DW gradient pulses
- $\Delta$  = time between the two balanced DW gradient pulses

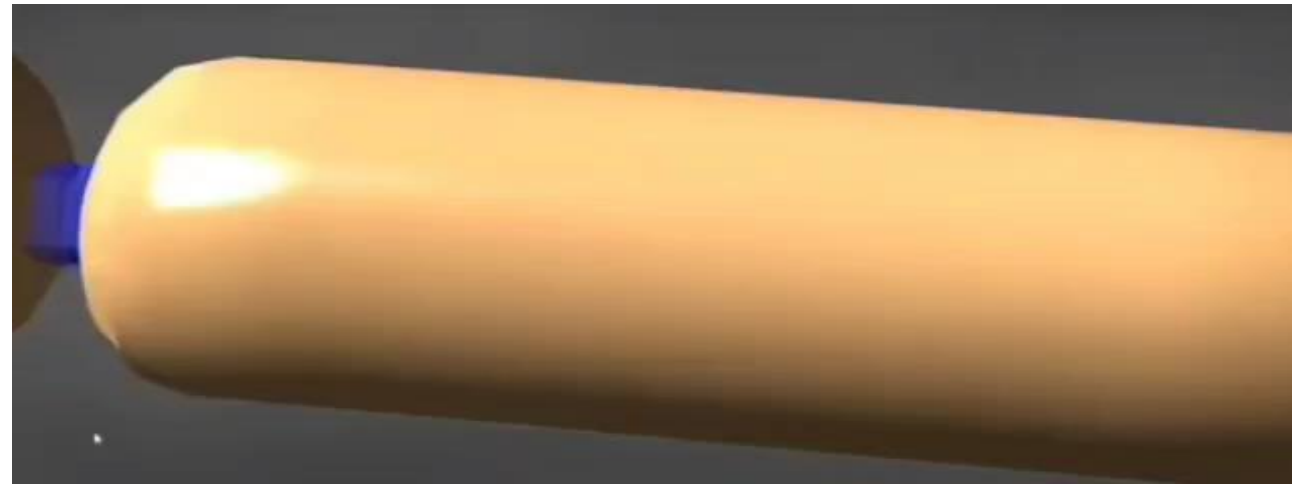
**Relationship between signal of b = 0, DWI and ADC**

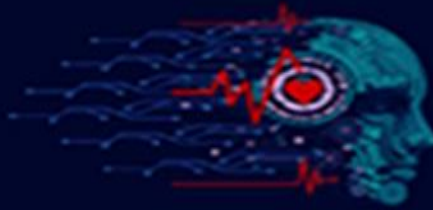
$$S_{DWI} = S_{b=0} \times e^{(-b \times D)}$$

equivalent to...

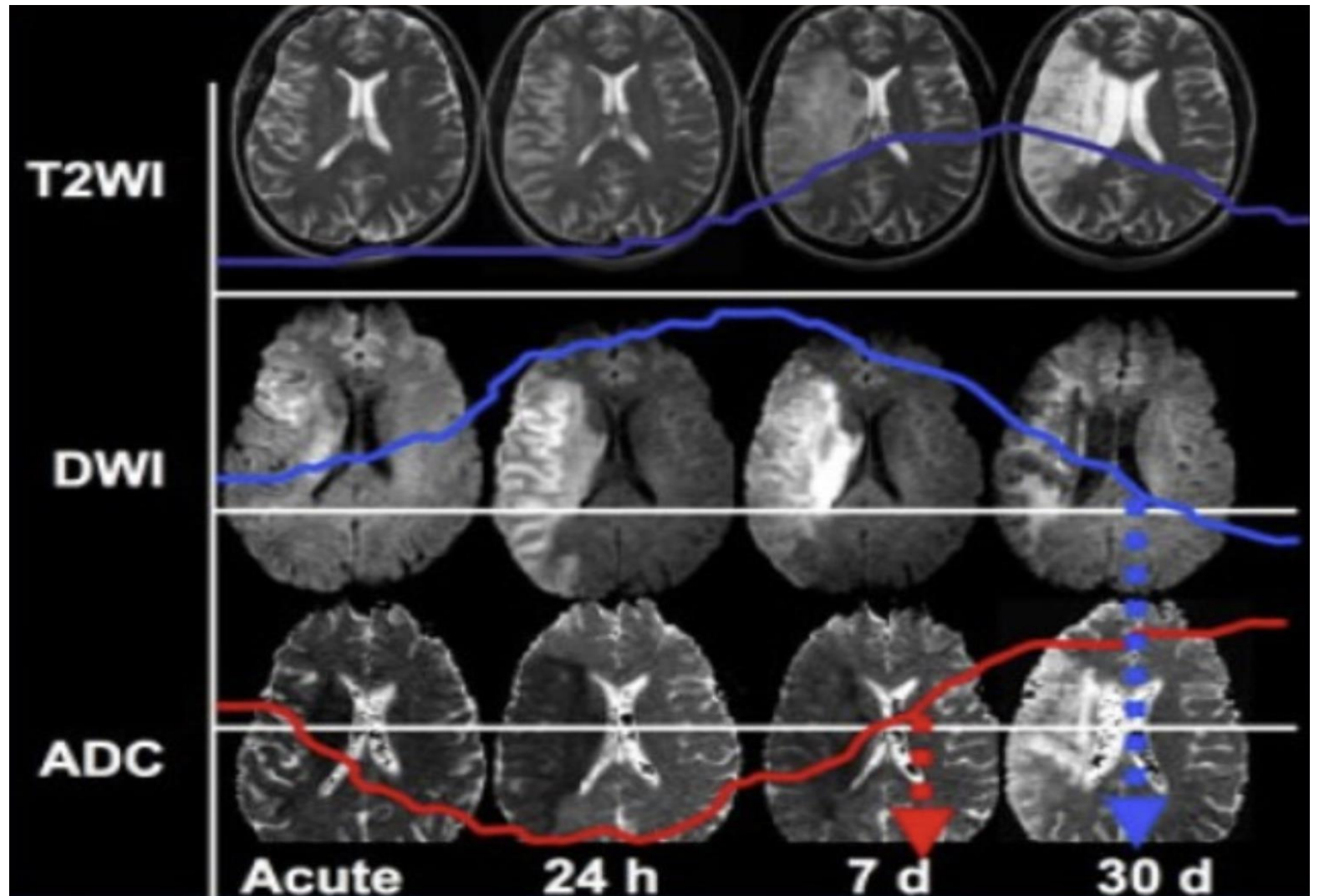
$$D = -\frac{1}{b} \times \ln\left(\frac{S_{DWI}}{S_{b=0}}\right)$$

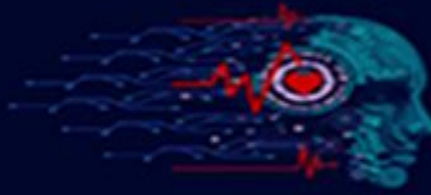
- $S_{DWI}$  = signal intensity of isotropic DWI
- $S_{b=0}$  = signal intensity of b = 0
- $b$  = b value
- $D$  = apparent diffusion coefficient (ADC)





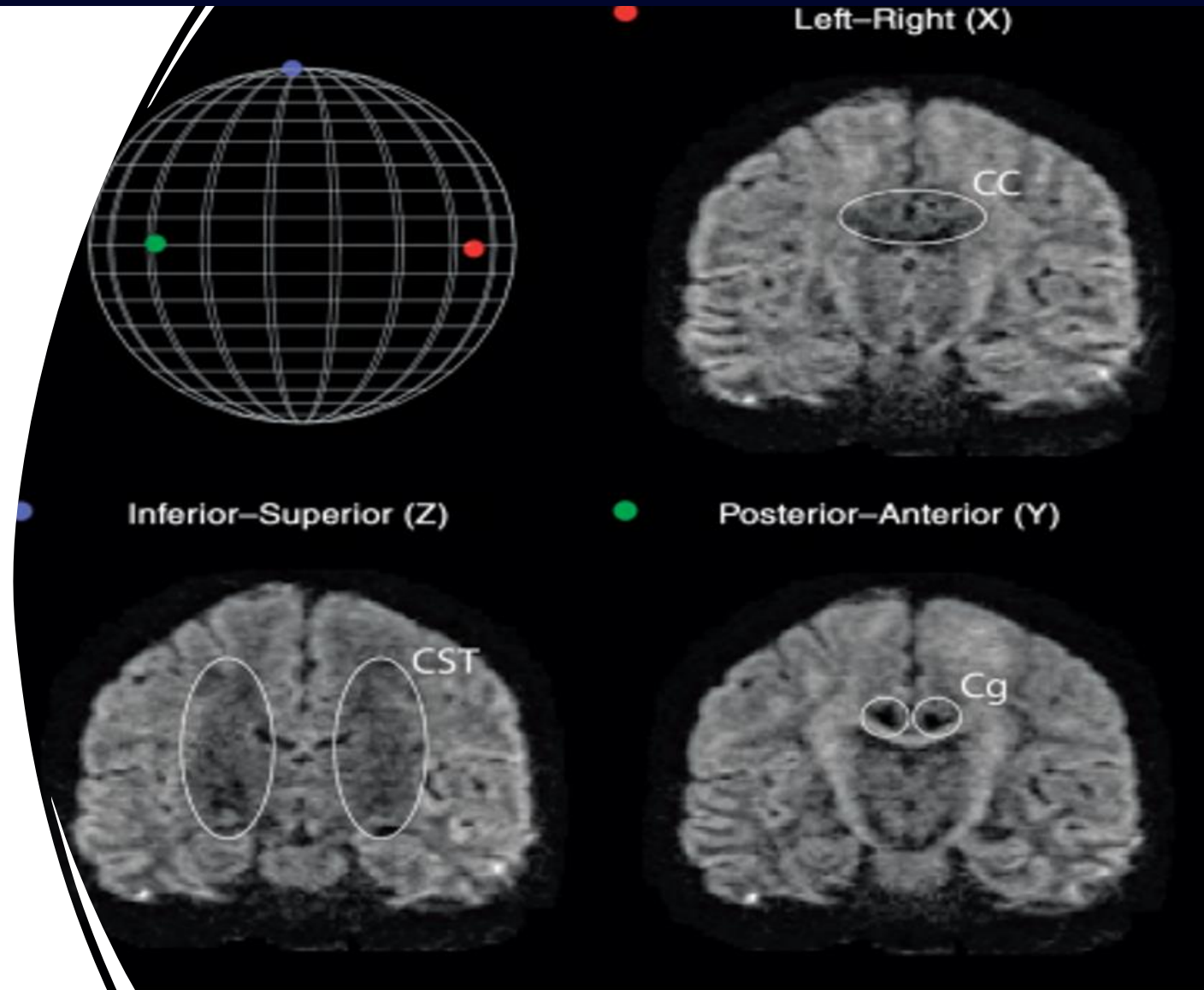
# Stroke Imaging

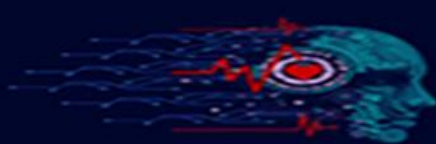




## Beyond ADC: Orientation and White Matter Organization

- 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.



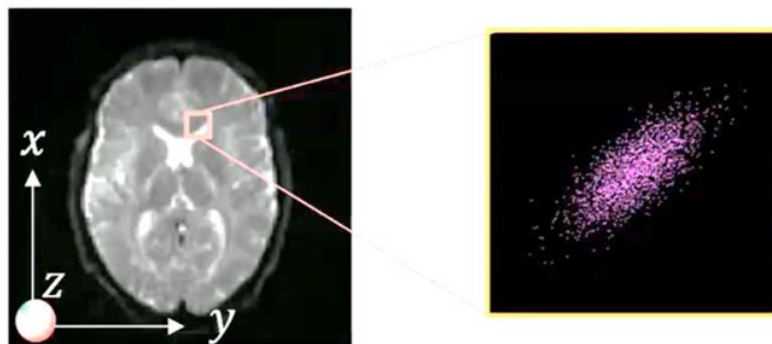


# Diffusion Tensor Imaging (DTI)

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

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

Diffusion Tensor



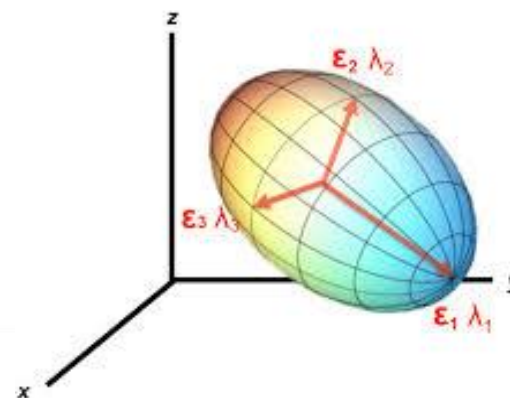
Peter Basser, 1994

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

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

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

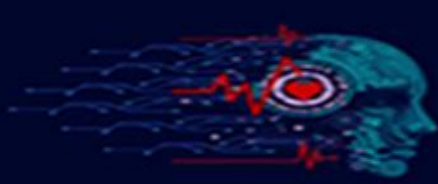
- Ellipsoid representation



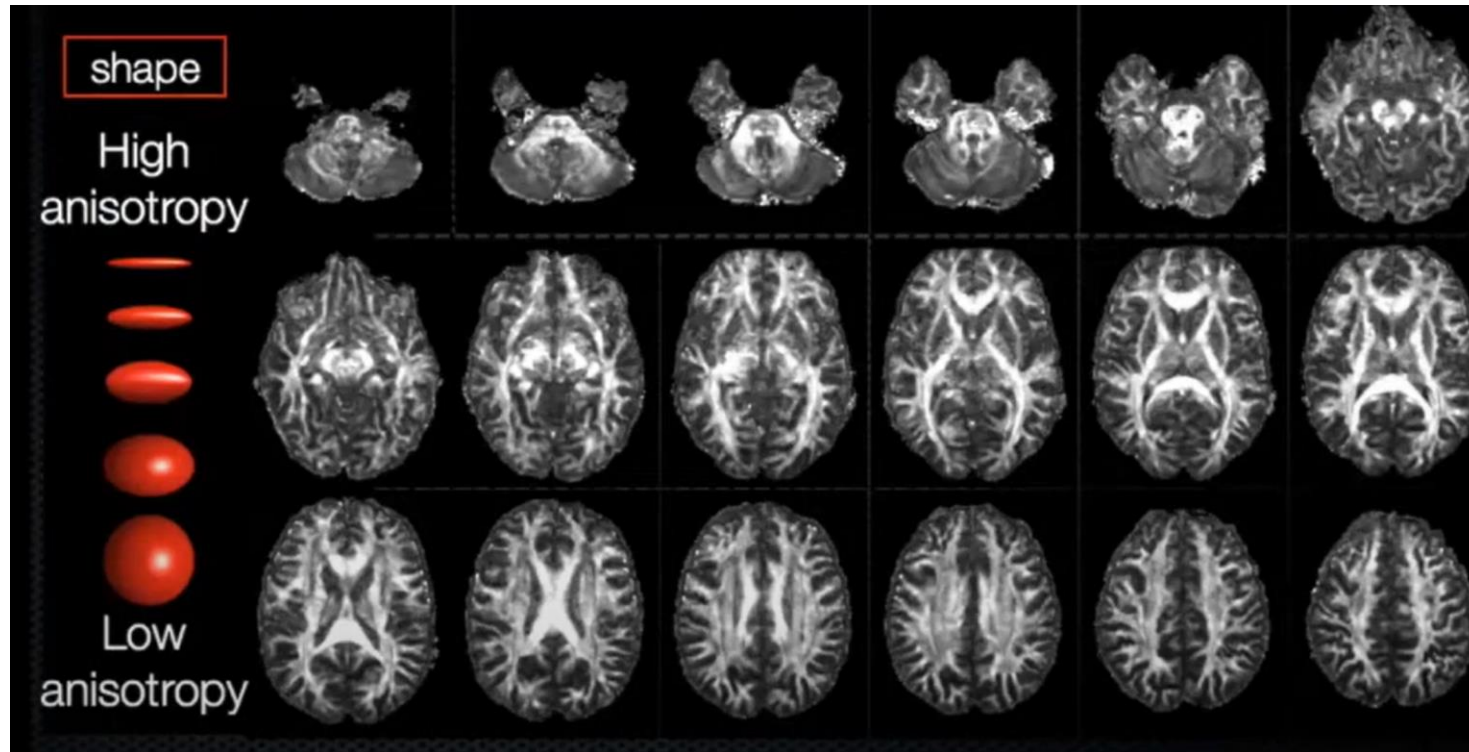
$$S(\mathbf{b}) = S_0 e^{-b \mathbf{g}^T D \mathbf{g}}$$

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

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



# Fractional Anisotropy (FA)



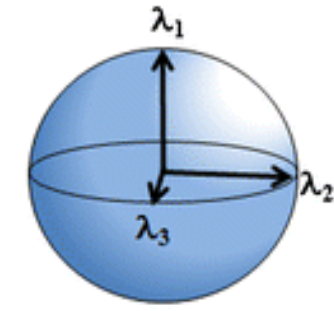
Isotropic

3D Pattern  
Of Diffusion



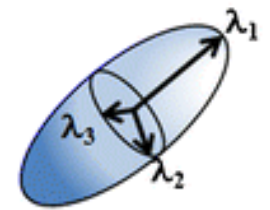
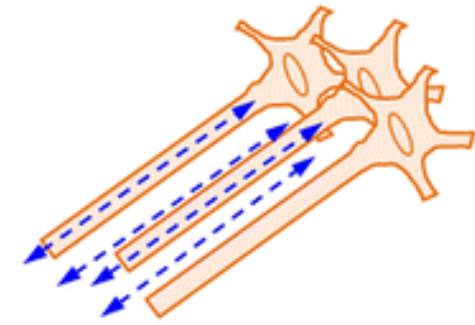
Free water

DTI  
Model



Low FA

Anisotropic



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<sup>1,2\*</sup>, Zhiguo Jiang<sup>3</sup>, Jelena Stojanovic-Radic<sup>4</sup>, Guang H Yue<sup>5</sup>, Erik P Pioro<sup>5,6</sup>, Glenn R Wylie<sup>4</sup>, and Abhijit Das<sup>4</sup>

<sup>1</sup>Department of Electrical and Electronics Engineering, Birla Institute of Technology and Sciences Pilani, Hyderabad Campus, Hyderabad, India

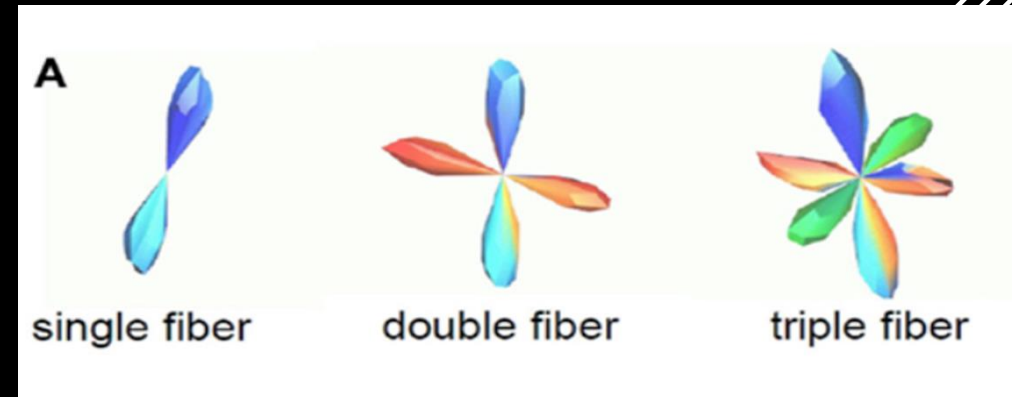
<sup>2</sup>Department of Biomedical Engineering, ND2, Lerner Research Institute, Cleveland Clinic, USA

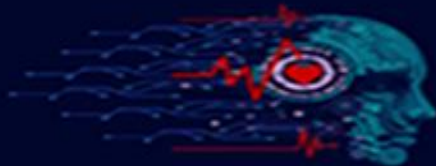
<sup>3</sup>Human Performance and Engineering Research, Kessler Foundation, 1199 Pleasant Valley Way, West Orange, New Jersey, USA

<sup>4</sup>Neuroscience and Neuropsychology Laboratory, Kessler Foundation, 300 Executive Drive, Suite 70, West Orange, New Jersey, USA

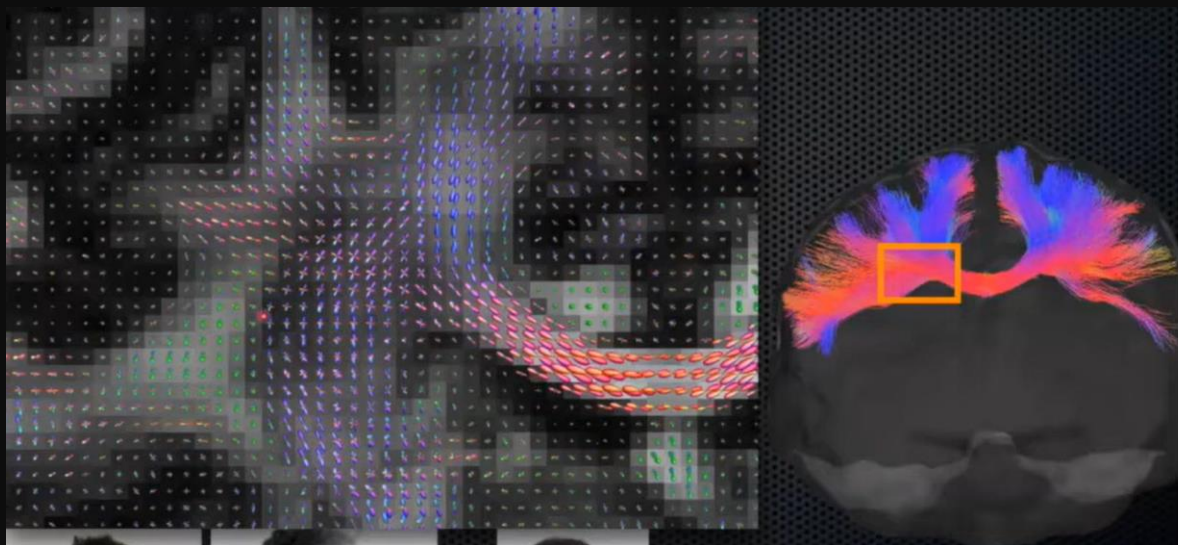
<sup>5</sup>Neuromuscular Center and Department of Neurology, Neurological Institute, USA

<sup>6</sup>Department of Neurosciences, Lerner Research Institute, Cleveland Clinic, Cleveland, Ohio, USA





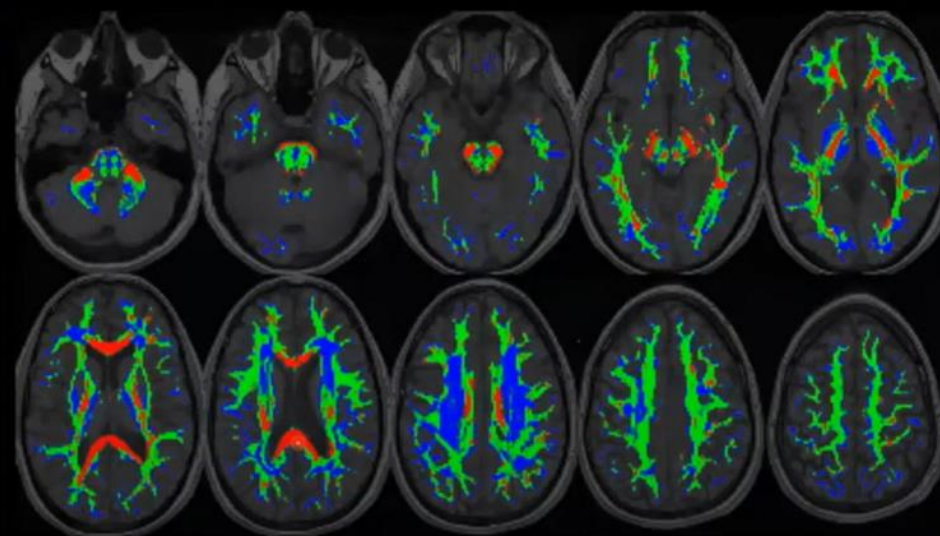
# Crossing fibers everywhere



[Tournier et al] [Dell'Acqua et al] [Descoteaux et al] **2007**

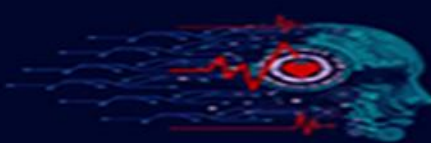
**1,000+**  
"fODF" citations  
(3-7 min acquisition)

Crossing fibres affect ~90% of white matter voxels

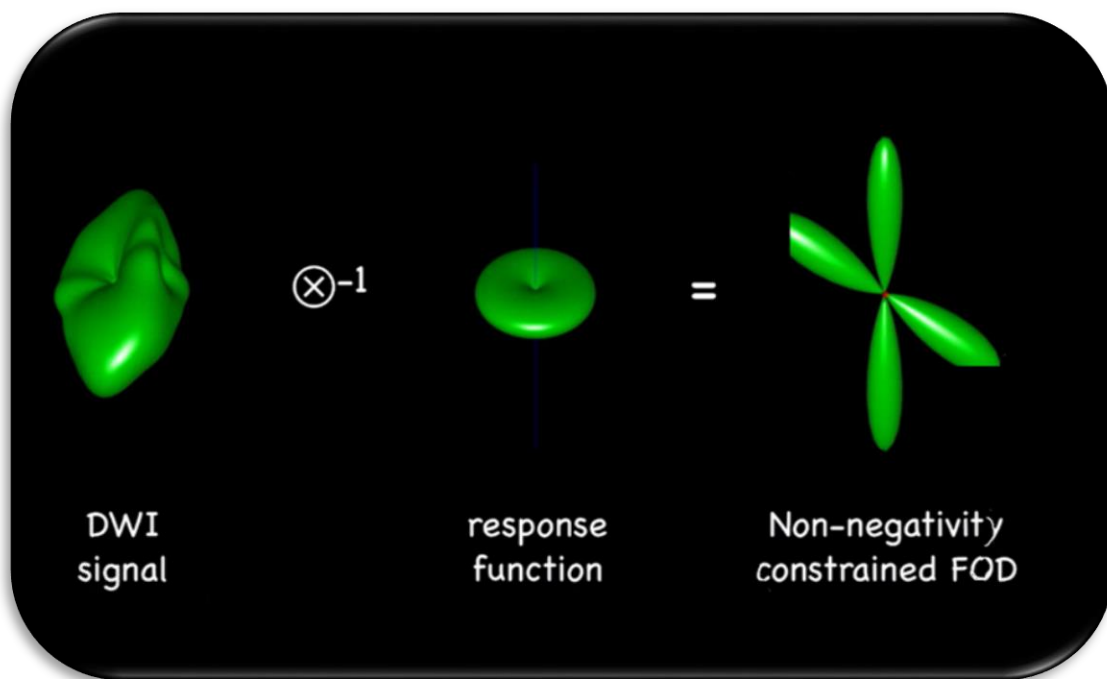


1 2 >2

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:

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

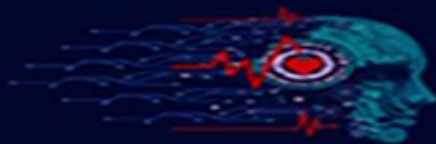
Instead of solving the optimization problem iteratively, the network approximates:

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

where  $f_{\text{NN}}$  is parameterized by neural network weights  $\Theta$  learned by minimizing:

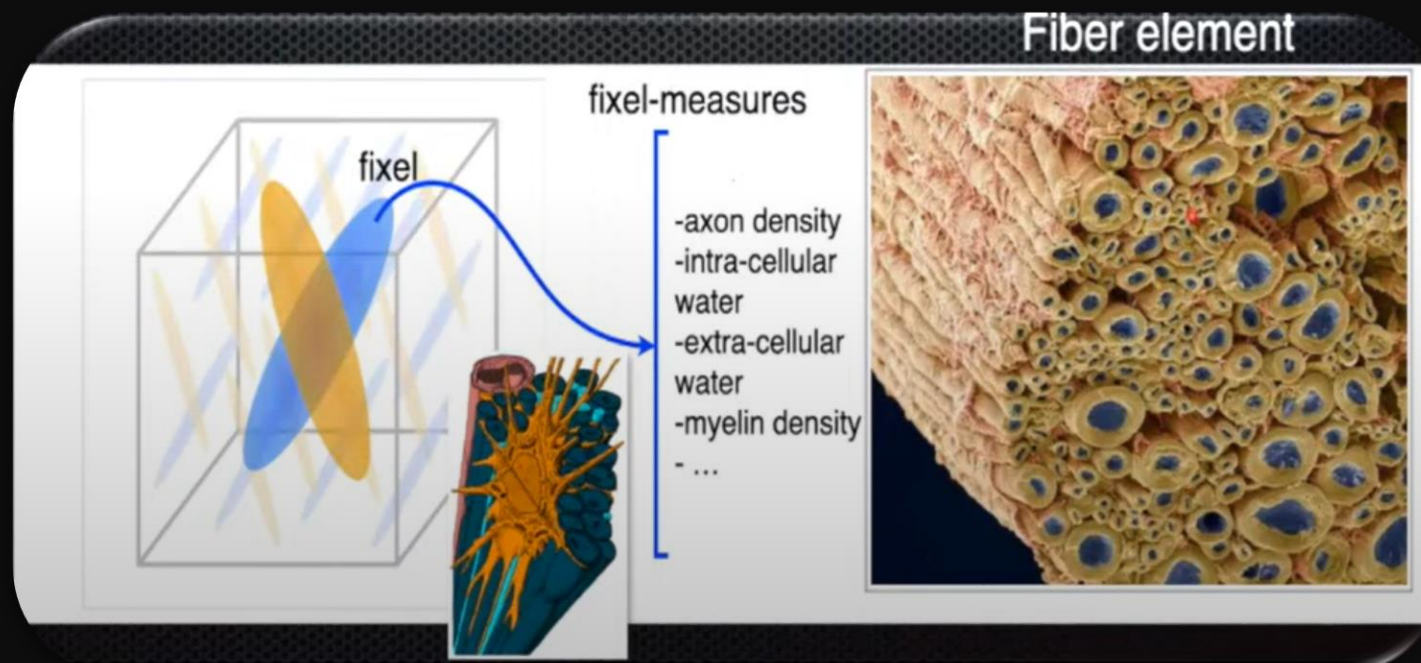
$$\mathcal{L}(\Theta) = \|\mathbf{F}_{\text{true}} - f_{\text{NN}}(\mathbf{S}; \Theta)\|^2 + \lambda R(f_{\text{NN}}(\mathbf{S}; \Theta)).$$

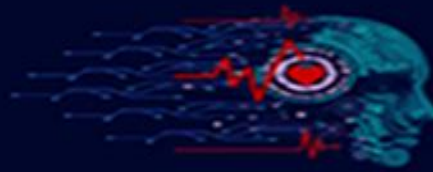




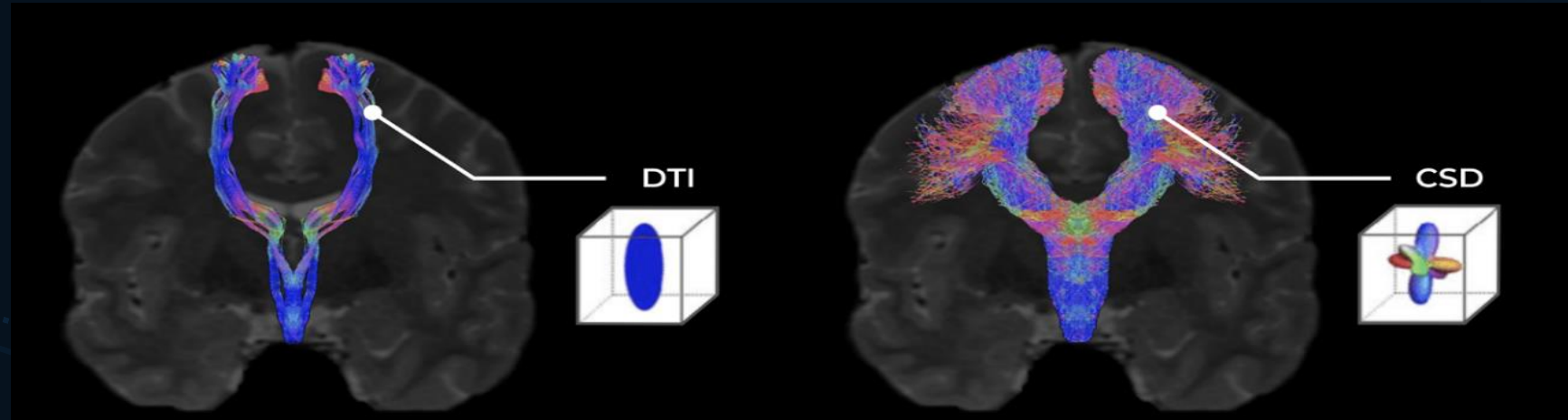
## Fixel-Based Analysis (FBA)

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

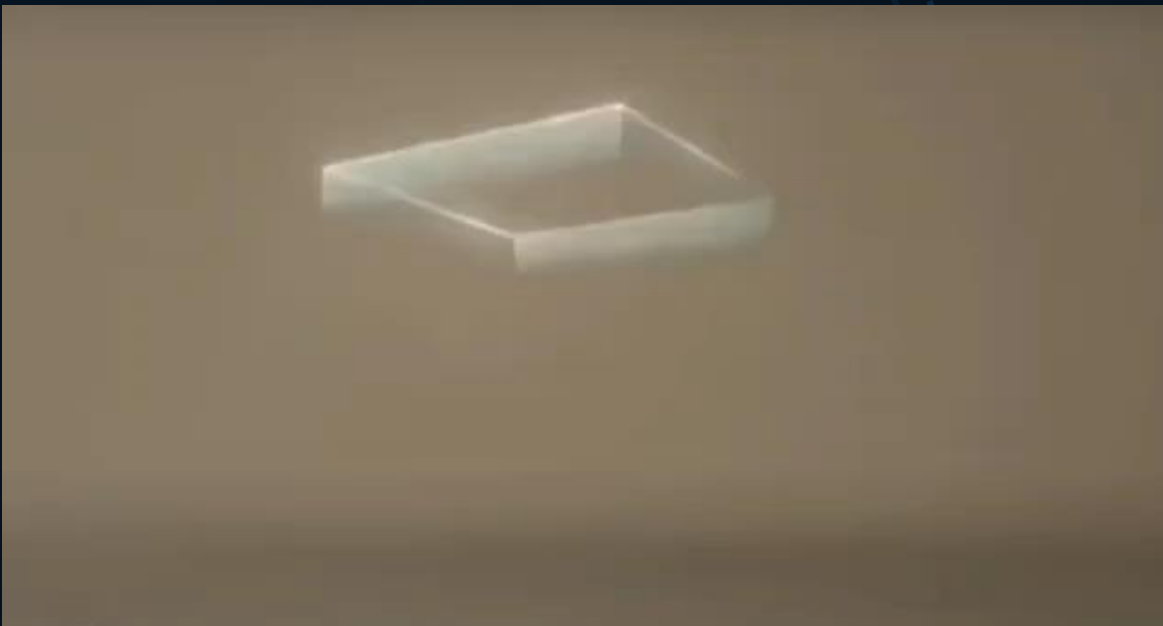




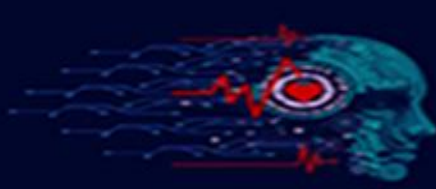
# Tractography



- **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

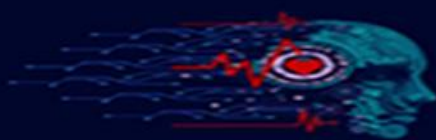


$$x_{i+1} = x_i + \Delta s \cdot d_i$$

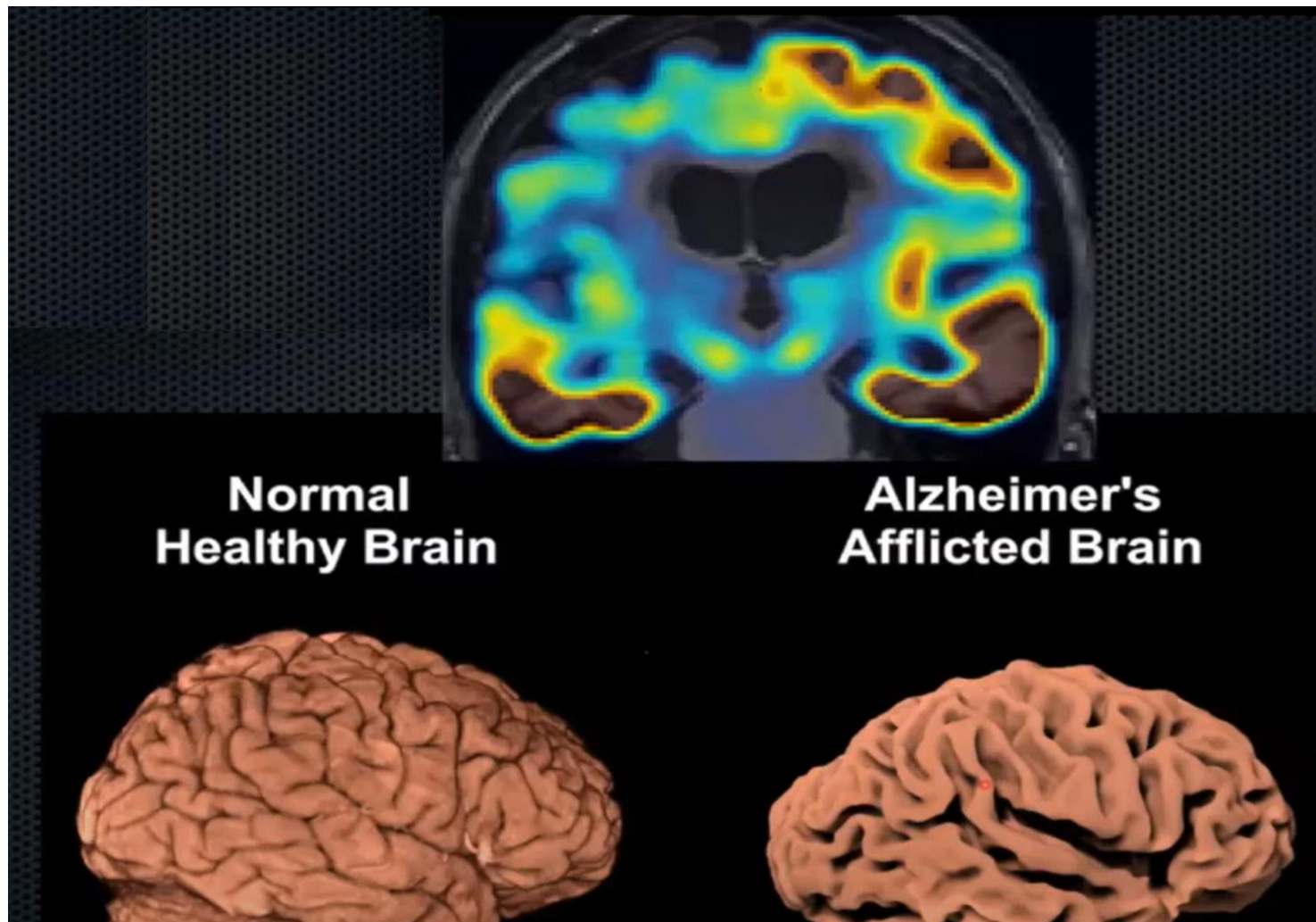


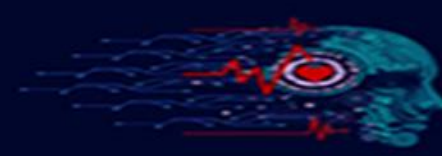
## Segmentation and Tractometry



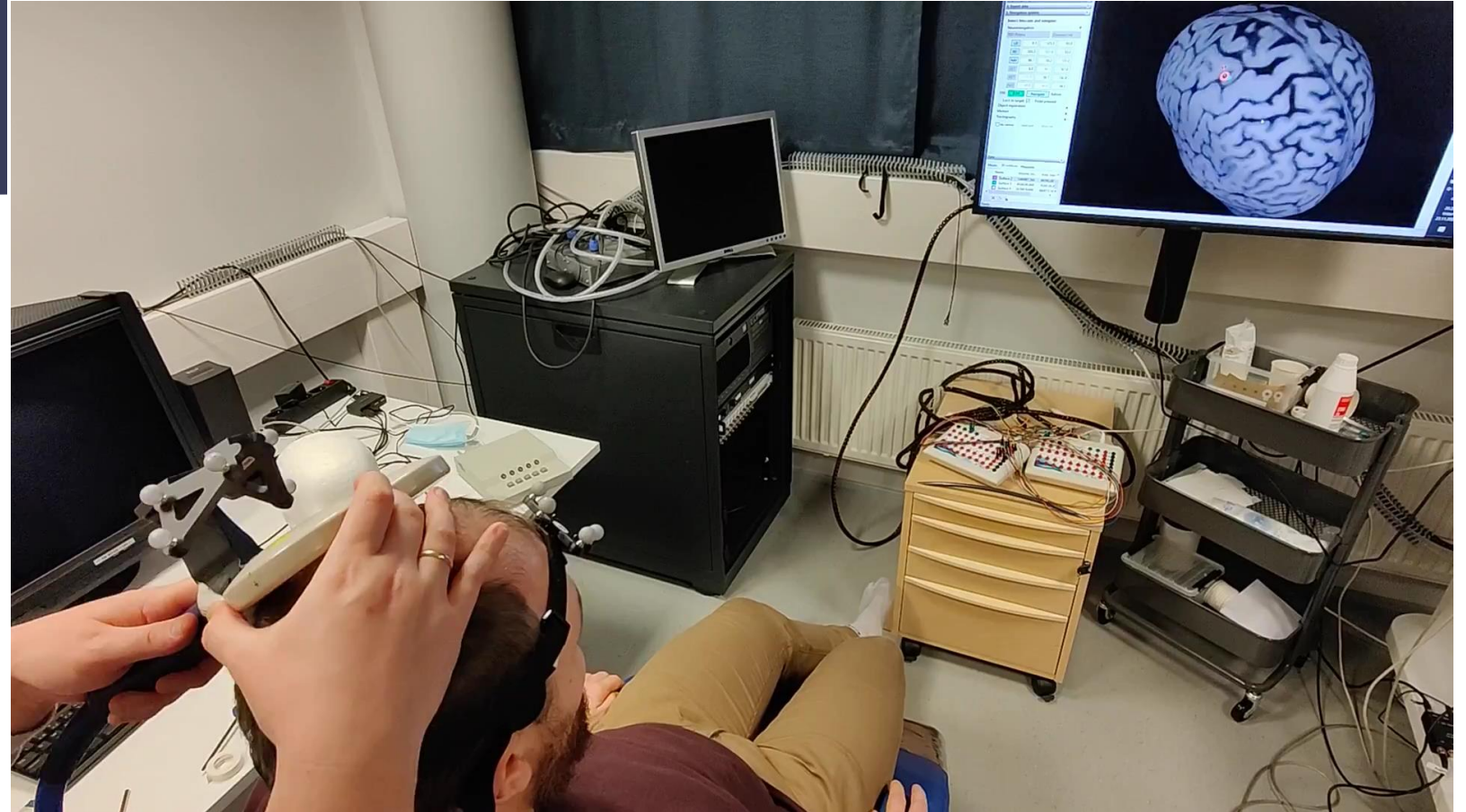


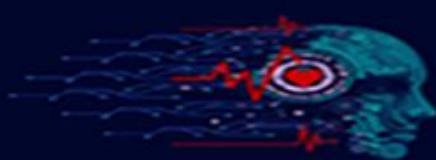
## Application of Tractography in Alzheimer's Disease(AD)





## Combining TMS and Tractography





# DIPY

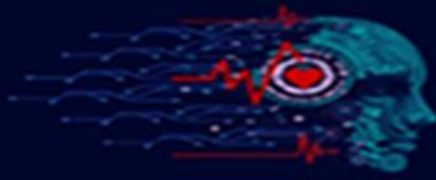
# MRtrix3

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

MRtrix3 workshop 2024 Taiwan Download Blog Documentation Community Development ▾

MRtrix3  
 Advanced tools for the analysis of diffusion MRI data

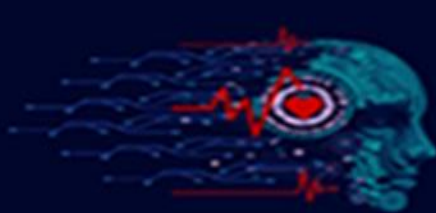
Download Use MRtrix3

Register Now!  
**DIPY WORKSHOP**  
 17<sup>th</sup> to 21<sup>st</sup> March 2025 | Online Edition

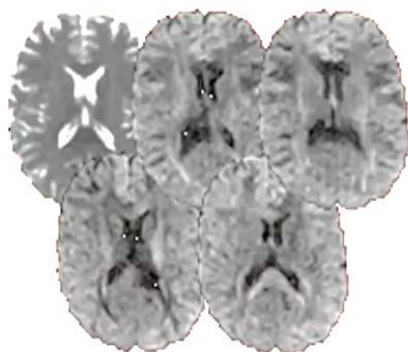
## What is MRtrix3?

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.

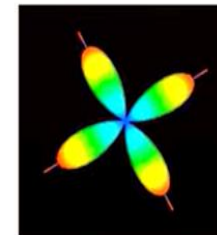
Use Case	Best Tool
High-performance tractography pipelines	MRtrix3
Interactive GUI for diffusion MRI analysis	MRtrix3 ( <a href="#">mrview</a> )
Flexible scripting and integration	DIPY
Teaching diffusion MRI principles	DIPY
Python-based workflows or pipelines	DIPY
Multi-modal connectomics	MRtrix3
Large-scale,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



# Ongoing Research



Resolve low X angles?

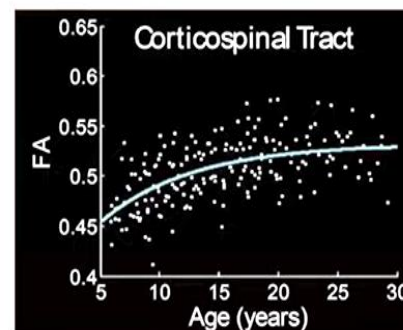


Voxel reconstruction

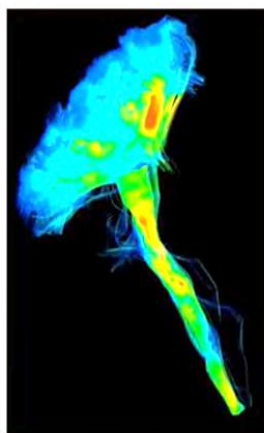


Reduce FP?

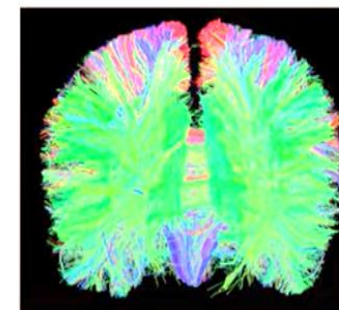
Which metric?



Statistical analysis



Segment accurately?



Tractography

Tracts and tractometry



**Thank you  
for your attention 😊**



Email: [mahdad.esmaeili@uef.fi](mailto:mahdad.esmaeili@uef.fi)