

Machine Learning for Neuroimaging and Neuroscience

Lesson 2 *Structural Connectivity*



AGH UNIVERSITY OF SCIENCE
AND TECHNOLOGY

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Job opportunities (no conflict of interest with me)



GE HealthCare

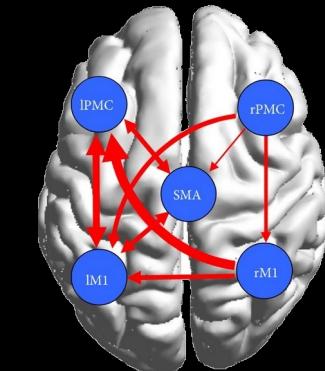
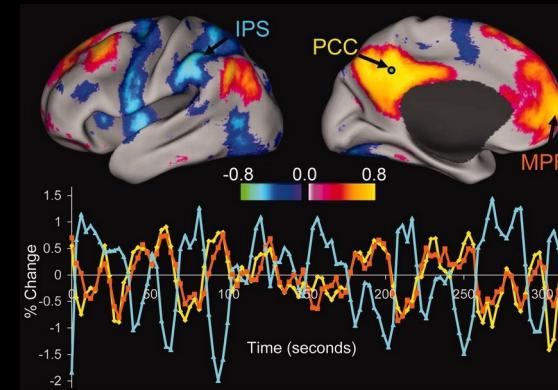
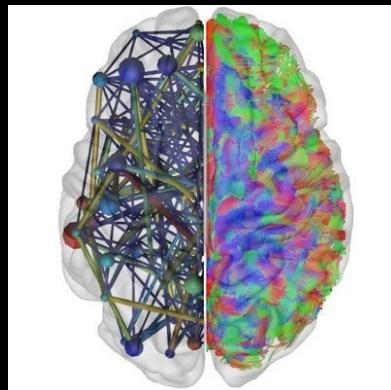
A solid black rectangular box used as a placeholder for a company logo.

Medtronic

The Siemens Healthineers logo, featuring the word "SIEMENS" in teal capital letters above the word "Healthineers" in orange capital letters, with a stylized orange dot pattern to the right.

Some sections of Nvidia and Alphabet (mostly in US or Zurich)
Small but impactful realities as Brainlab, Hyperfine, ect

Structural, functional & effective connectivity



Structural/anatomical connectivity

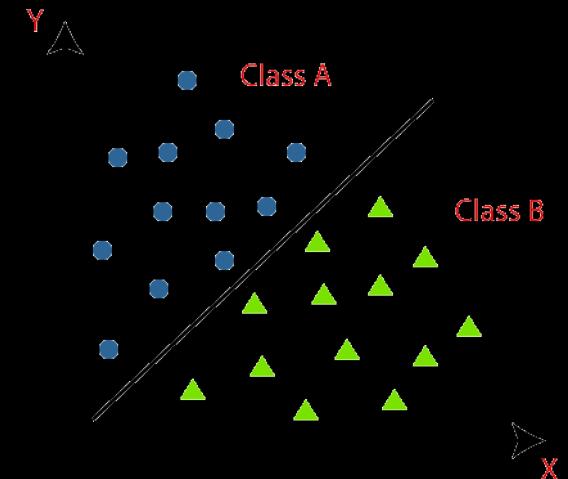
= presence of axonal connections / white matter tracks (eg, DWI, AAV tracers)

Functional connectivity

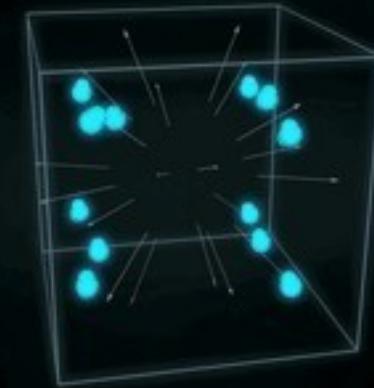
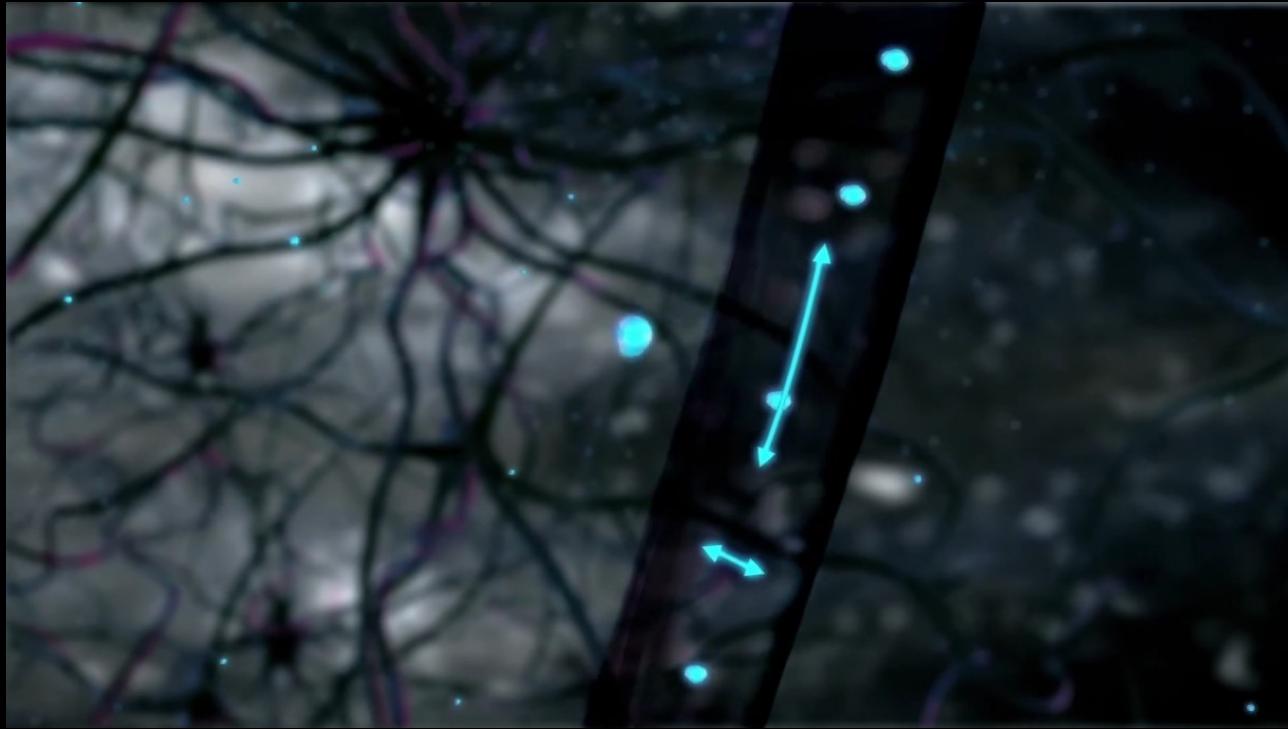
= statistical dependencies between regional time series (eg, Pearson correlation, ICA,...)

Effective connectivity

= causal (directed) influences between neuronal populations (eg, DCM, Granger C., etc)

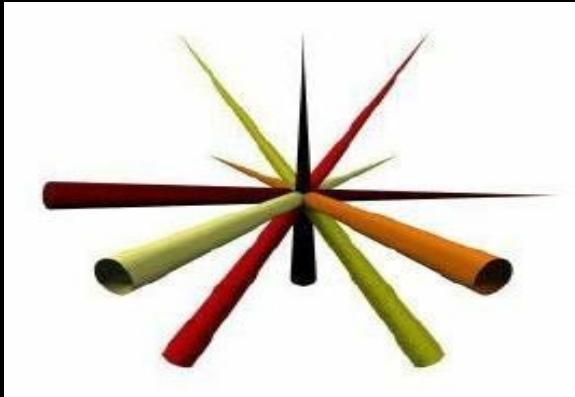


Plenty of water in the brain

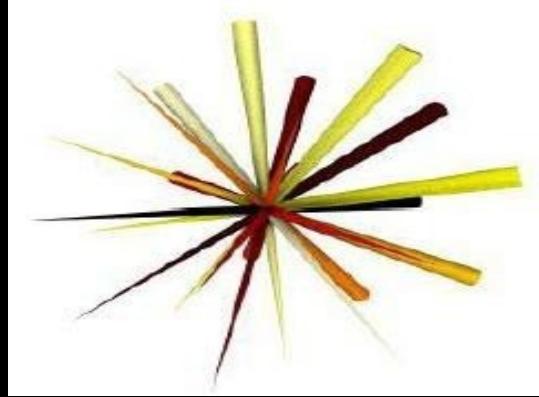


Credit: MaxPlanck
Society

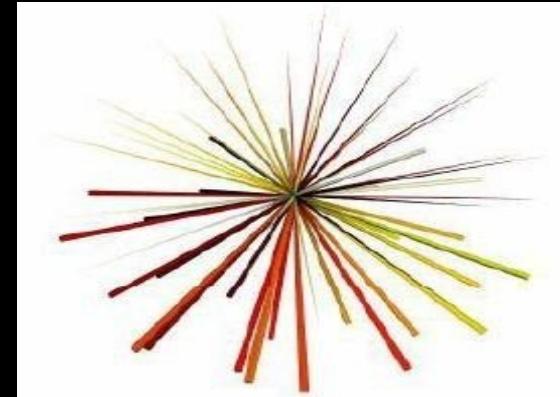
Different Gradient Directions



6
Directions

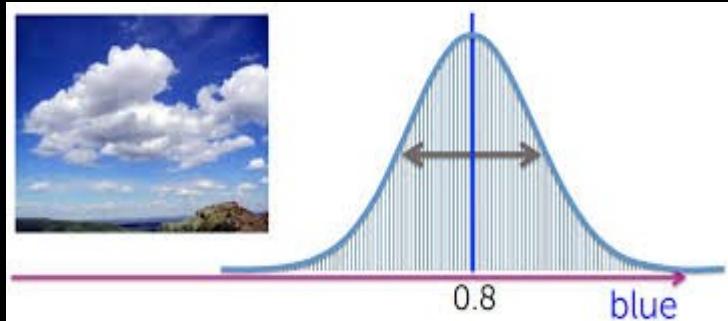


12
Directions

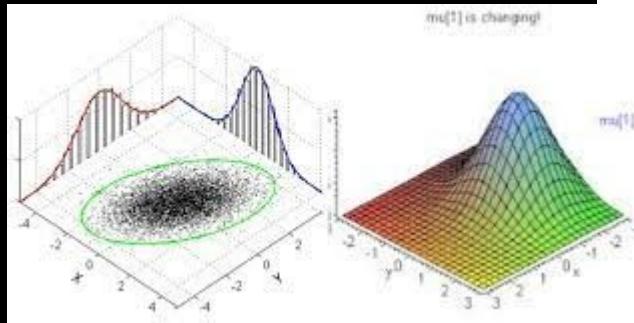


30
Directions

Distributions in different directions

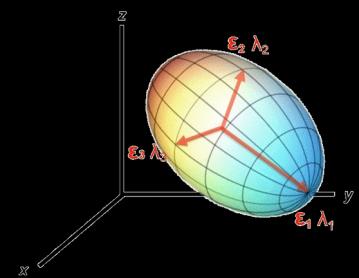


1D



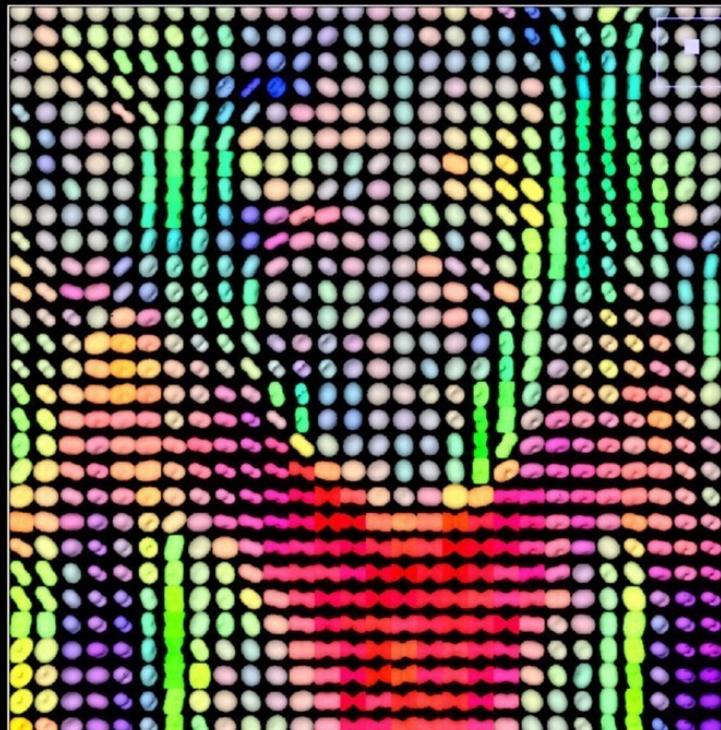
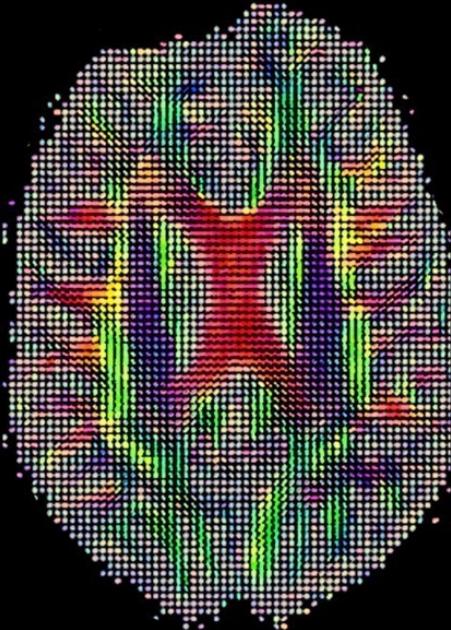
2D

$$\bar{D} = \begin{vmatrix} D_{\textcolor{red}{xx}} & D_{xy} & D_{xz} \\ D_{xy} & D_{\textcolor{red}{yy}} & D_{yz} \\ D_{xz} & D_{yz} & D_{\textcolor{red}{zz}} \end{vmatrix}$$

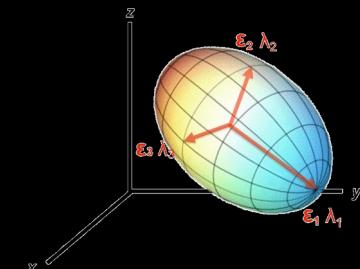


3D

diffusion weighted

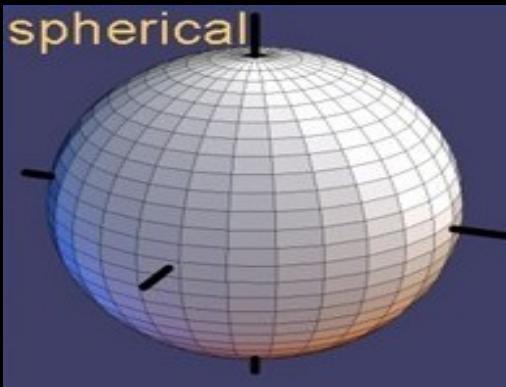


$$\bar{D} = \begin{vmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{xy} & D_{yy} & D_{yz} \\ D_{xz} & D_{yz} & D_{zz} \end{vmatrix}$$

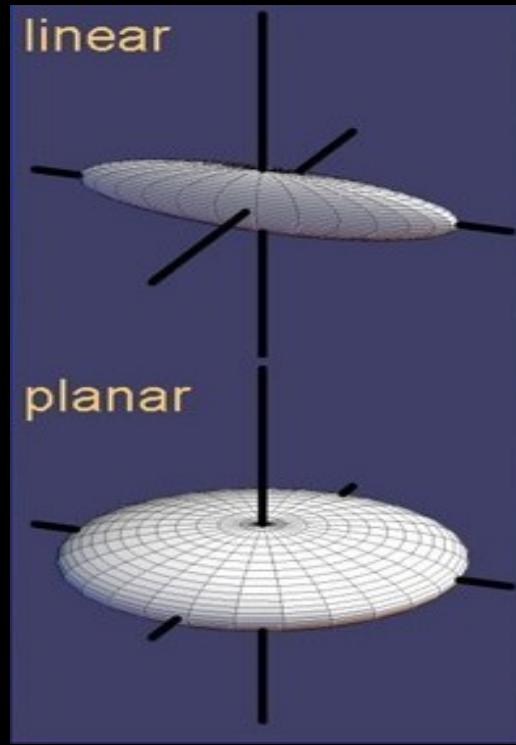


$$FA = \sqrt{\frac{(\lambda_1 - \lambda_2)^2 + (\lambda_2 - \lambda_3)^2 + (\lambda_1 - \lambda_3)^2}{2(\lambda_1^2 + \lambda_2^2 + \lambda_3^2)}}$$

Models of 3D Isotropy



Isotropic



Anisotropic

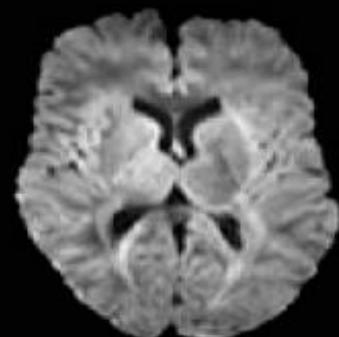
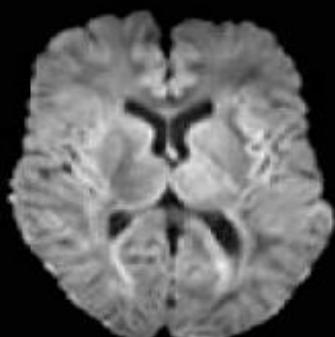
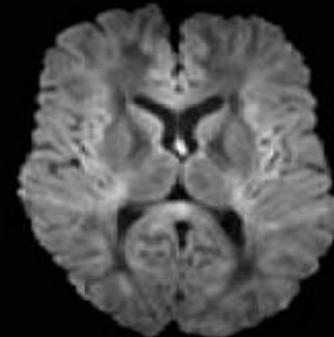
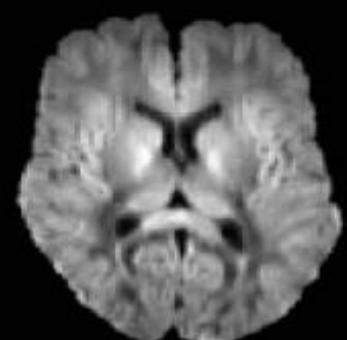
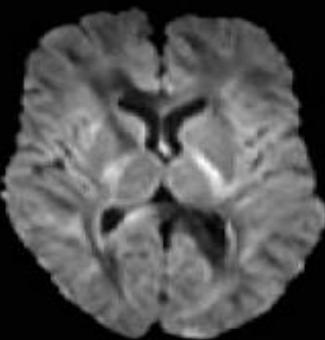
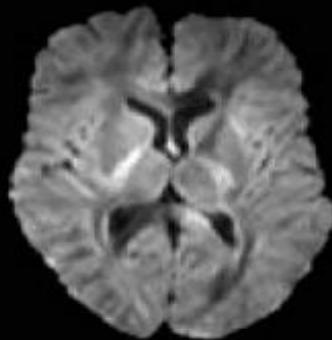
DTI Sequence

- Repeat the DWI sequence with gradients applied in a number of different directions
- From the contribution of all the different directions we can calculate the direction of diffusion as well as the relative rate (ADC)
- Areas with restricted diffusion will have a directional bias which is used to determine the direction of diffusion

Raw Diffusion Images

6 directions

- Diffusion sensitive gradients applied in six directions all with $b=1000$
- Dark areas represent areas with a higher degree of restricted diffusion



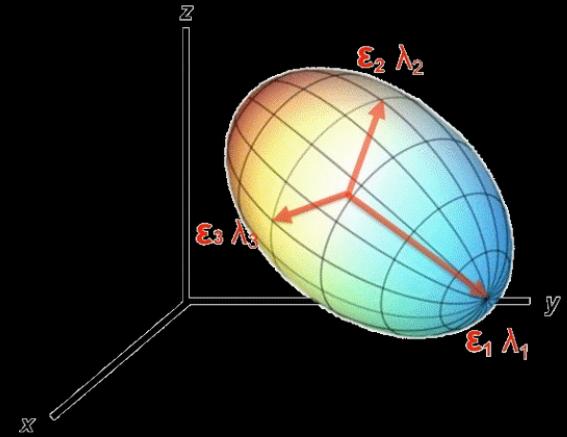
What is the b-value

The b-value is a parameter used to quantify the sensitivity of the DWI sequence to the diffusion of water molecules in biological tissues. It plays a crucial role in characterizing the diffusion properties of tissue and is a key factor in creating diffusion-weighted images.

The b-value influences the degree to which the acquired MRI signal is attenuated by the diffusion of water molecules. A higher b-value results in greater signal attenuation, making the image more sensitive to fast-moving water molecules, such as those in free, unrestricted diffusion. A lower b-value, on the other hand, is less sensitive to diffusion and provides information about tissue microstructure and cellularity.

Diffusion Tensor

Diffusion properties described with
a 3×3 symmetric tensor matrix



Diagonal elements of D (D_{xx} , D_{yy} , D_{zz}) are the ADC values along x, y and z axes respectively

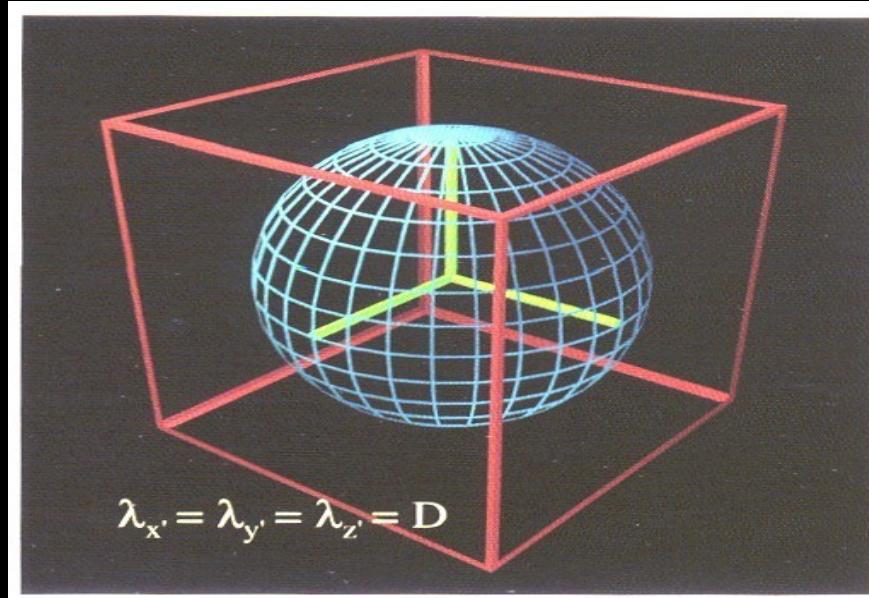
Off-diagonal elements (D_{xy} , D_{xz} , D_{yz}) represent the correlation between molecular displacements in orthogonal directions

DTI Calculation

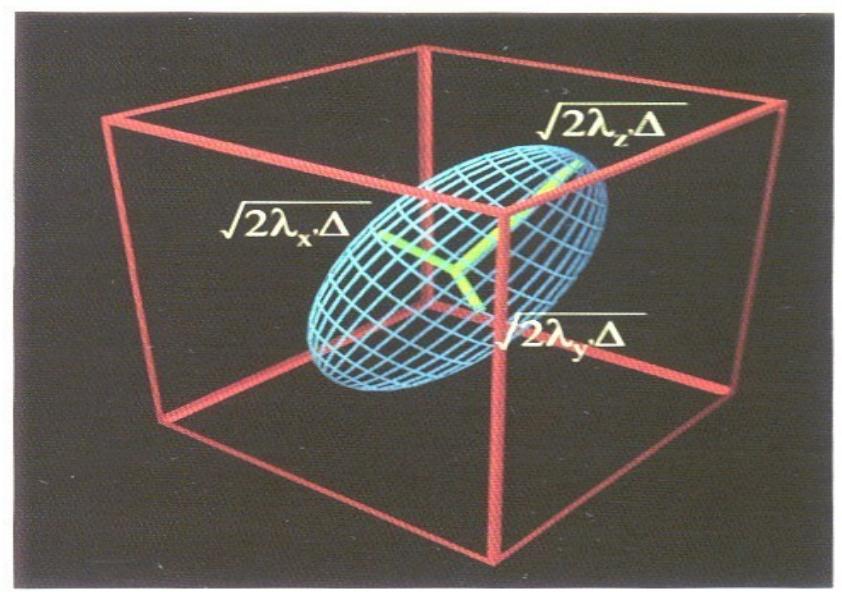
- Eigenvalues of the diffusion tensor (D_x , D_y , and D_z) provides length of the ellipsoid in the three principal directions of diffusivity
- Eigenvectors provide information about the direction of diffusion
- The eigenvector corresponding to the largest eigenvalue is used as the main direction of diffusion

Maps are constructed of various measures of anisotropy from the eigenvalues and eigenvectors

Tensor Model of Isotropy



Isotropic

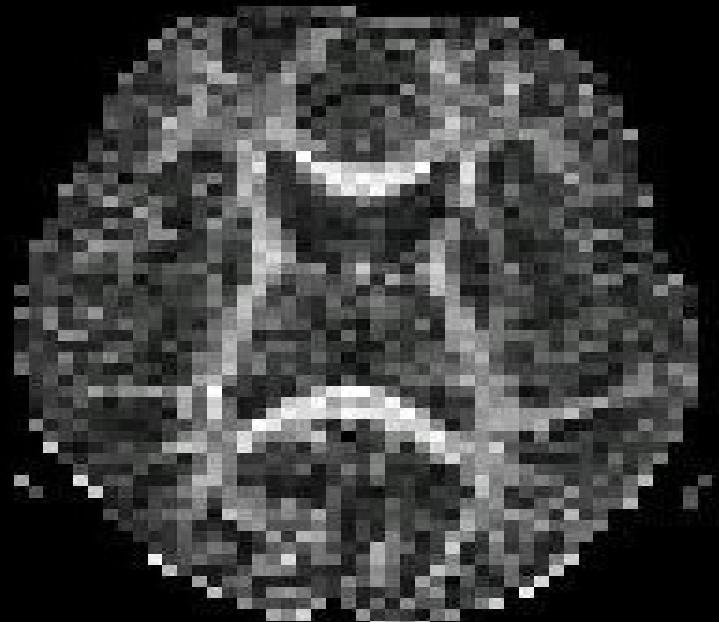


Anisotropic

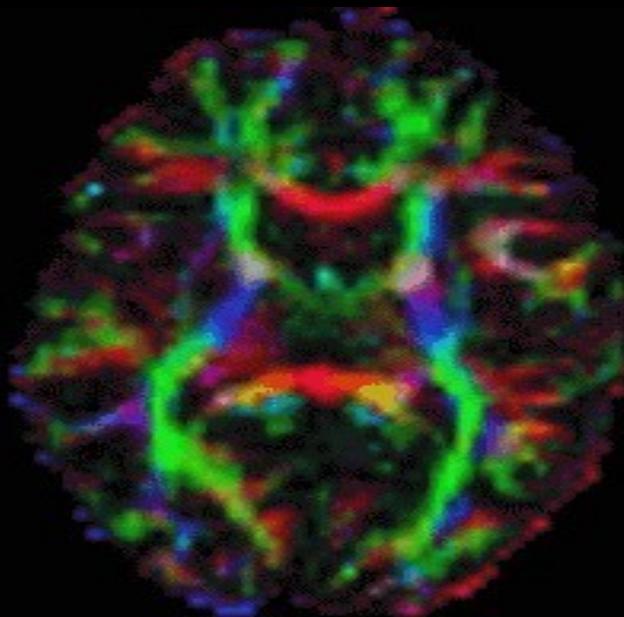
Fractional Anisotropy (FA)

- Measure of degree of anisotropy regardless of direction
- Brighter areas correspond to areas with higher degree of anisotropic diffusion
- Ranges from 0 - 1 where FA=1 corresponds to completely anisotropic

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

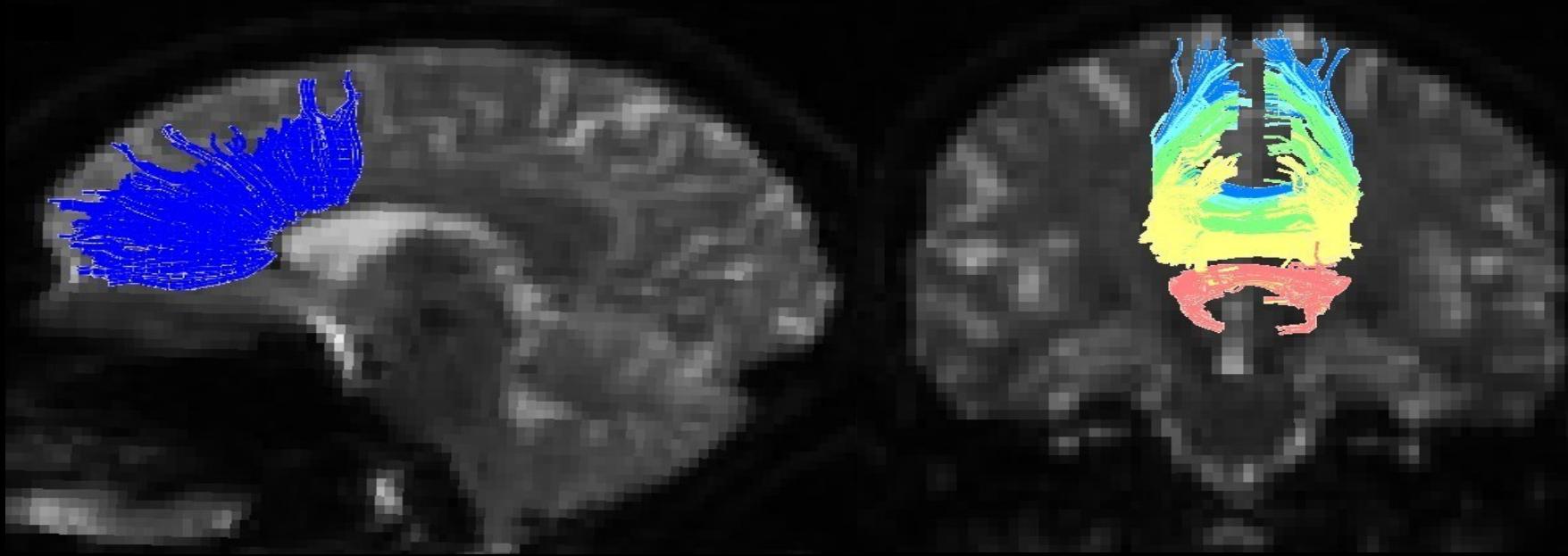


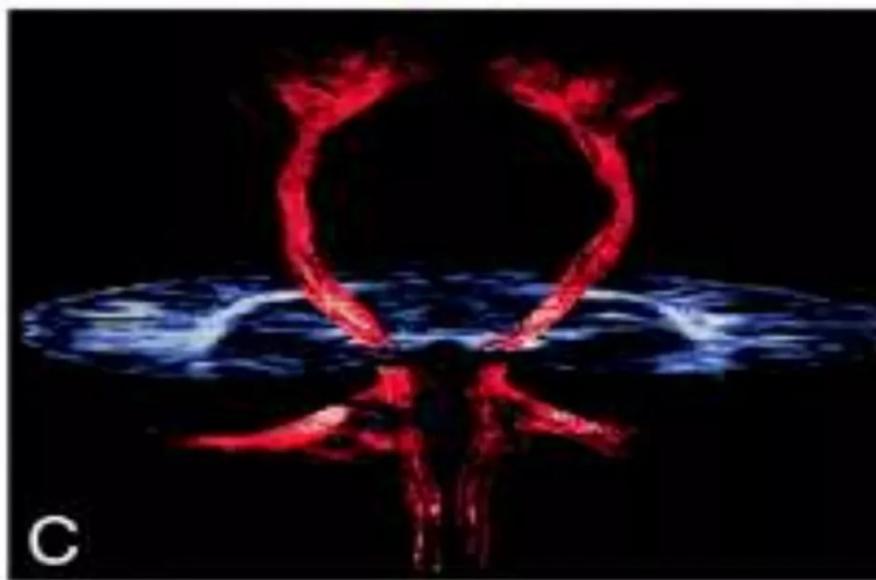
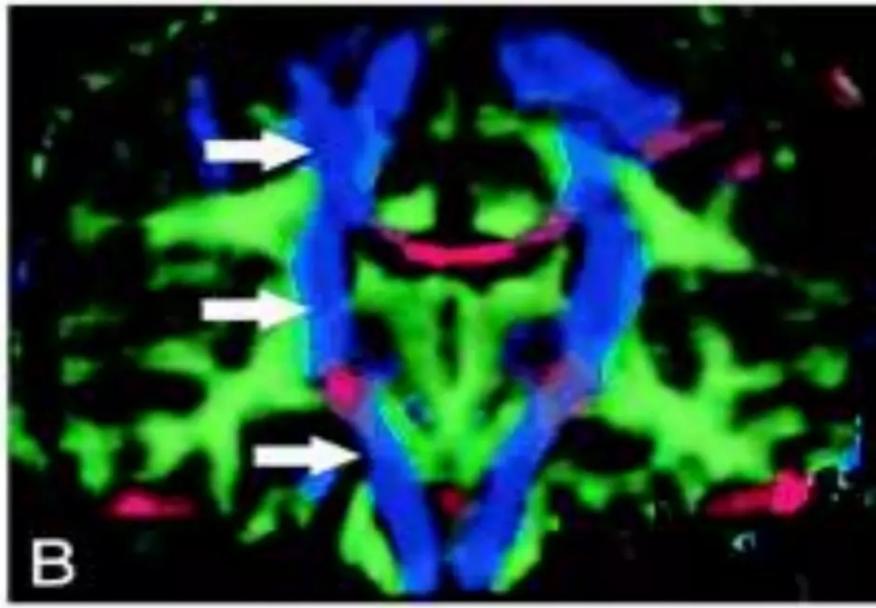
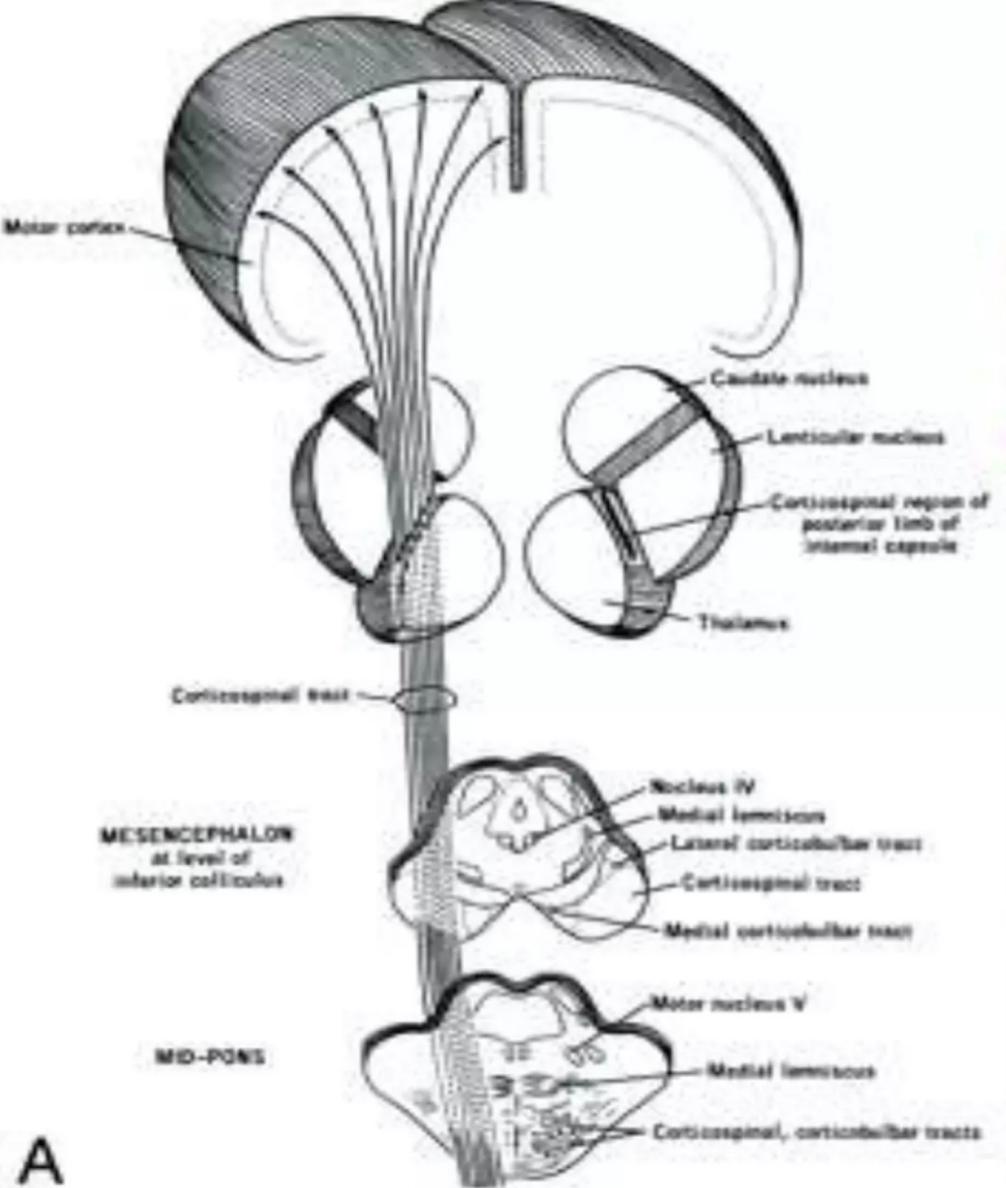
Visualization of Direction of Diffusion (general convention)



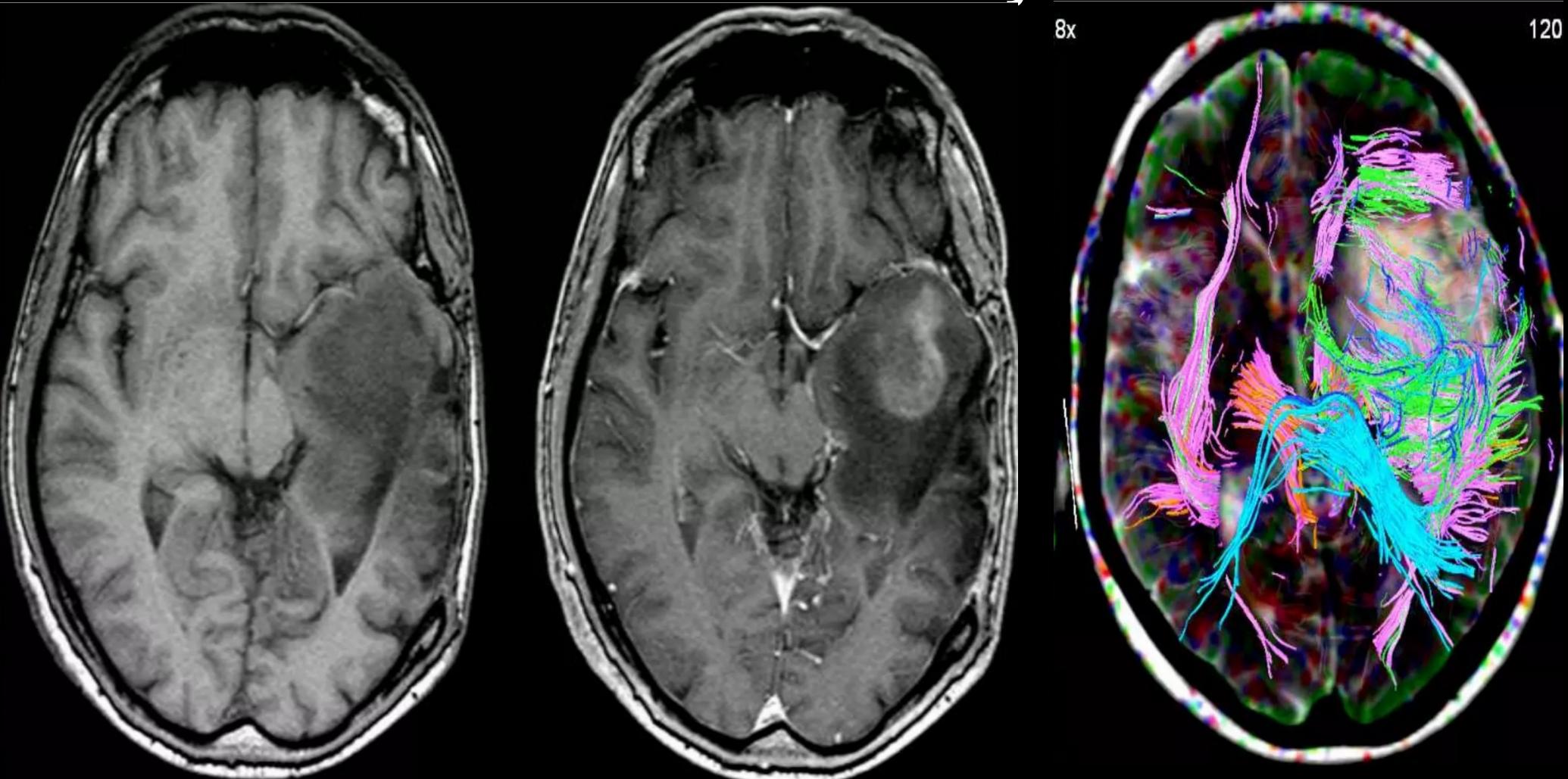
Red = Left-Right
Green = Anterior-
Posterior Blue =
Superior-Inferior

Structural Connectivity: Corpus Callosum



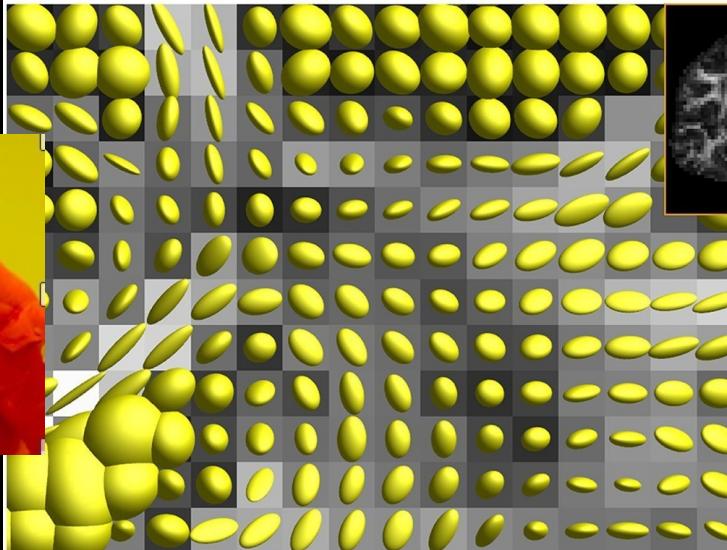


Structural Connectivity with brain

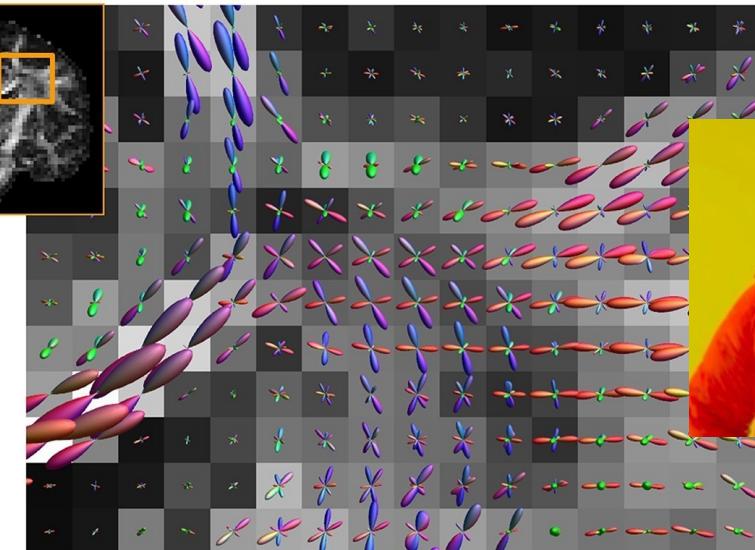


MODELS MATTER

Single Fibre (DTI)



Multiple Fibres (SD)



([Dell'acqua & Tournier NRM in Biomedicine 2018](#))

MODELS MATTER

Diffusion Tensor Tractography



Spherical Deconvolution Tractography



([Dell'acqua & Tournier NRM in Biomedicine](#)
[2018](#))



Break

Constrained spherical deconvolution-based (CSD)

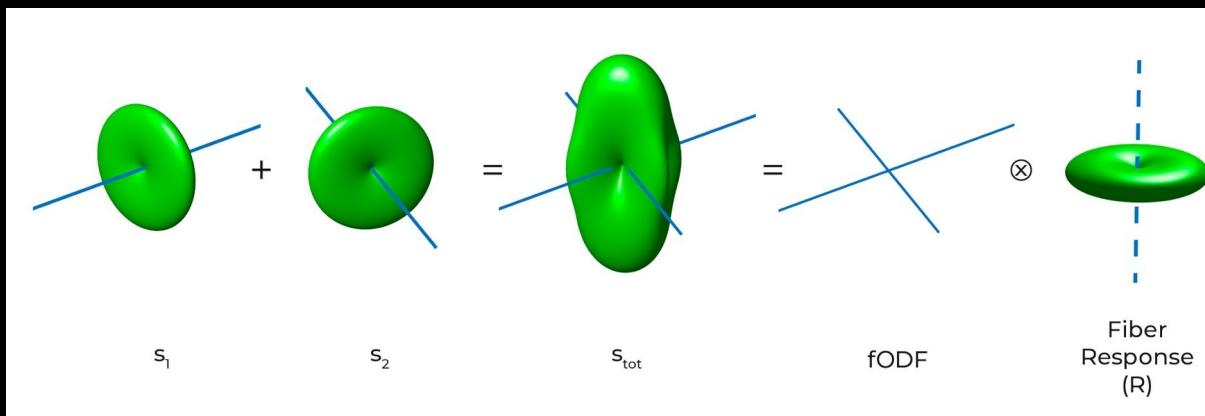
An alternative model to DTI which accommodates the issue of 'crossing fibers' is the fiber orientation distribution (fODF)

With CSD we assume that the DWI signal is a convolution of the true fiber orientation distribution and the response function of the imaging system

CSD calculates multiple tensors in heterogeneous regions and is thus able to support crossing fibers and areas of multiple fiber orientations.

Spherical Harmonics: CSD typically uses spherical harmonics to represent the fODF, which can capture multiple fiber orientations within a single voxel accurately.

CSD



$$Y_\ell^m(\theta, \varphi) = N e^{im\varphi} P_\ell^m(\cos \theta)$$

The CSD model then estimates the fiber orientation distribution (fODF) by assuming that the diffusion weighted signal captured can be adequately described by the fiber

response function (the diffusion

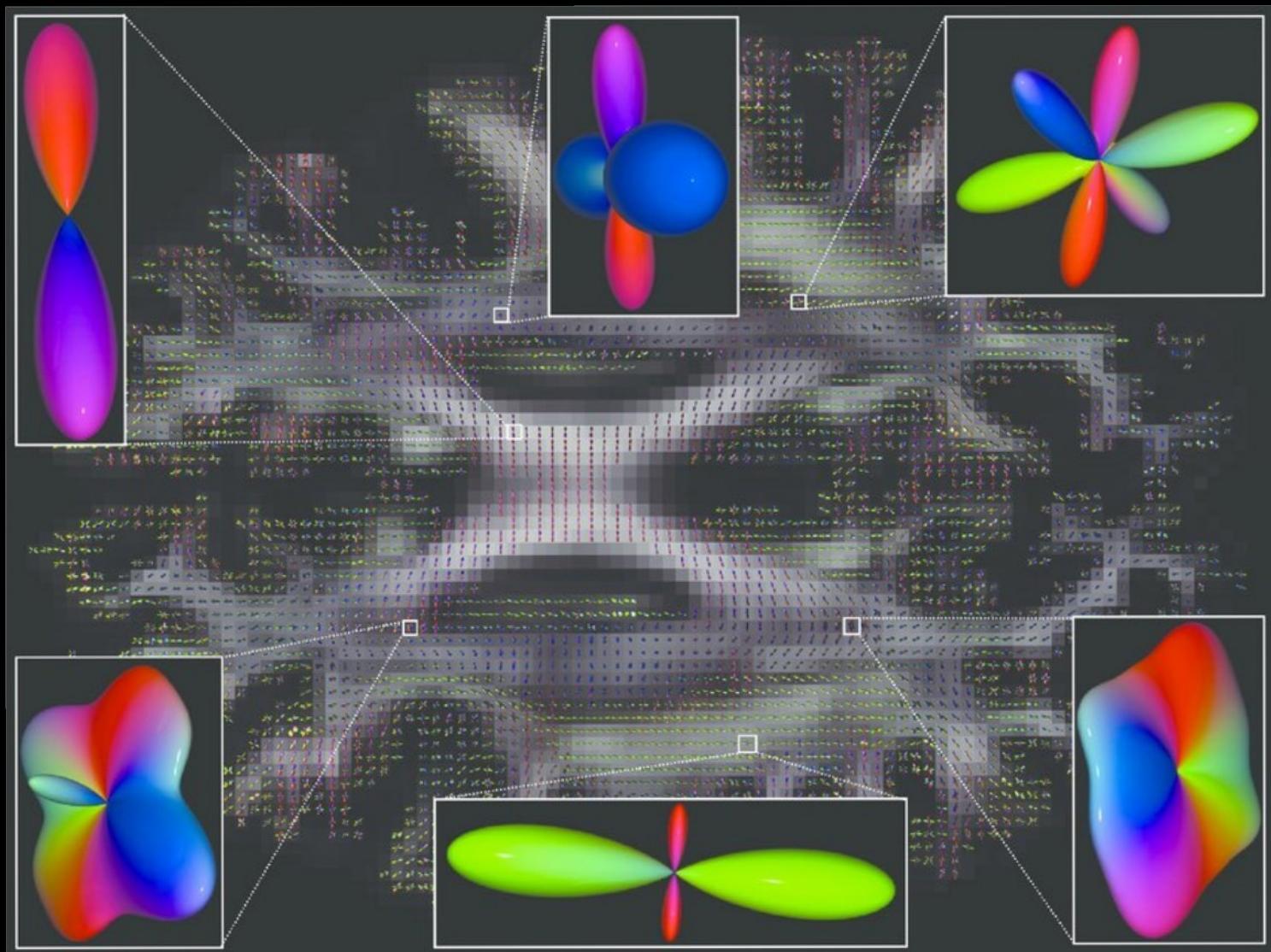
weighted signal in each voxel is a summative

combination of the fiber response from the multiple fibers in each voxel).

We represent fODF in a spherical harmonic basis.

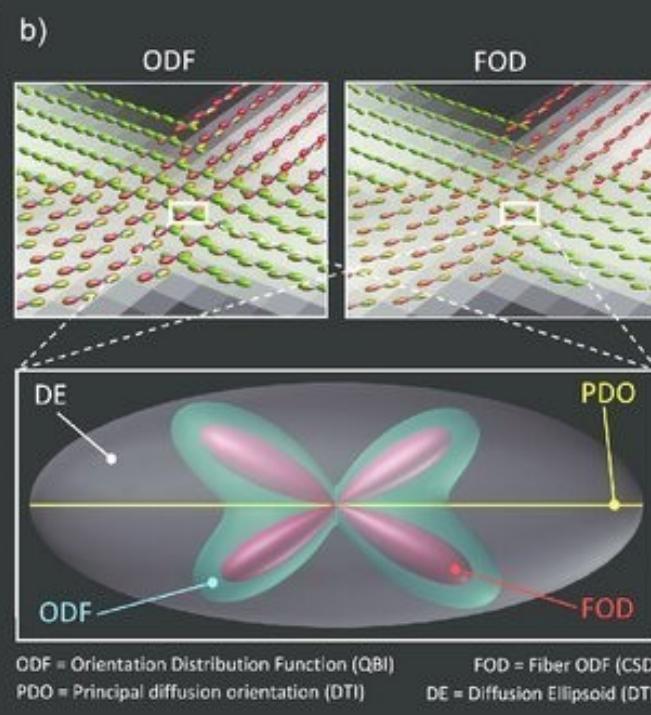
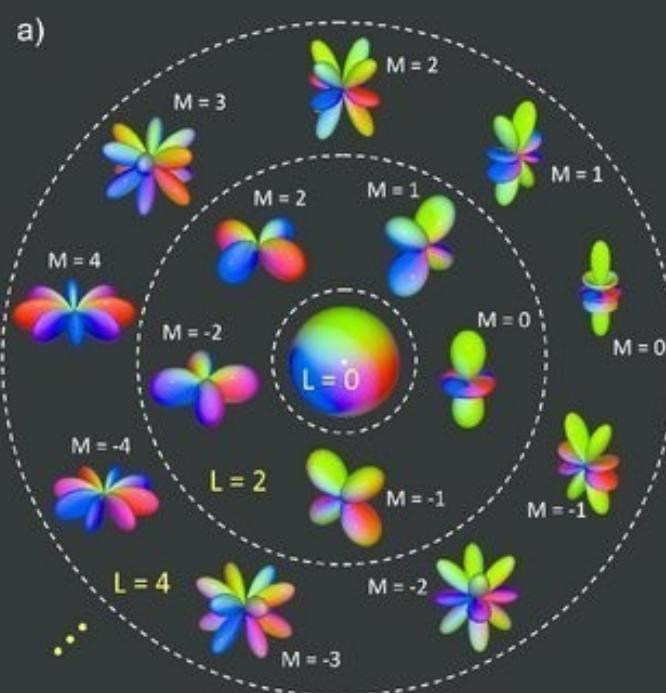
One of the innovations of CSD is therefore to penalize negative amplitudes through a soft regularizer in the least-squares fit of the coefficients of the fODF to the diffusion weighted signal.

This soft regularizer penalises negative amplitudes in the fODF coefficients which does not guarantee a non-negative solution but prefers one.



Spherical harmonics

$$Y_{\ell}^m(\theta, \varphi)$$

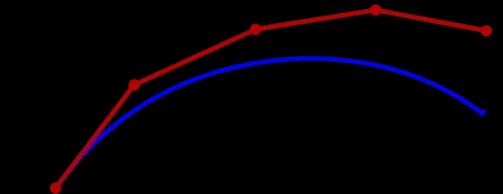
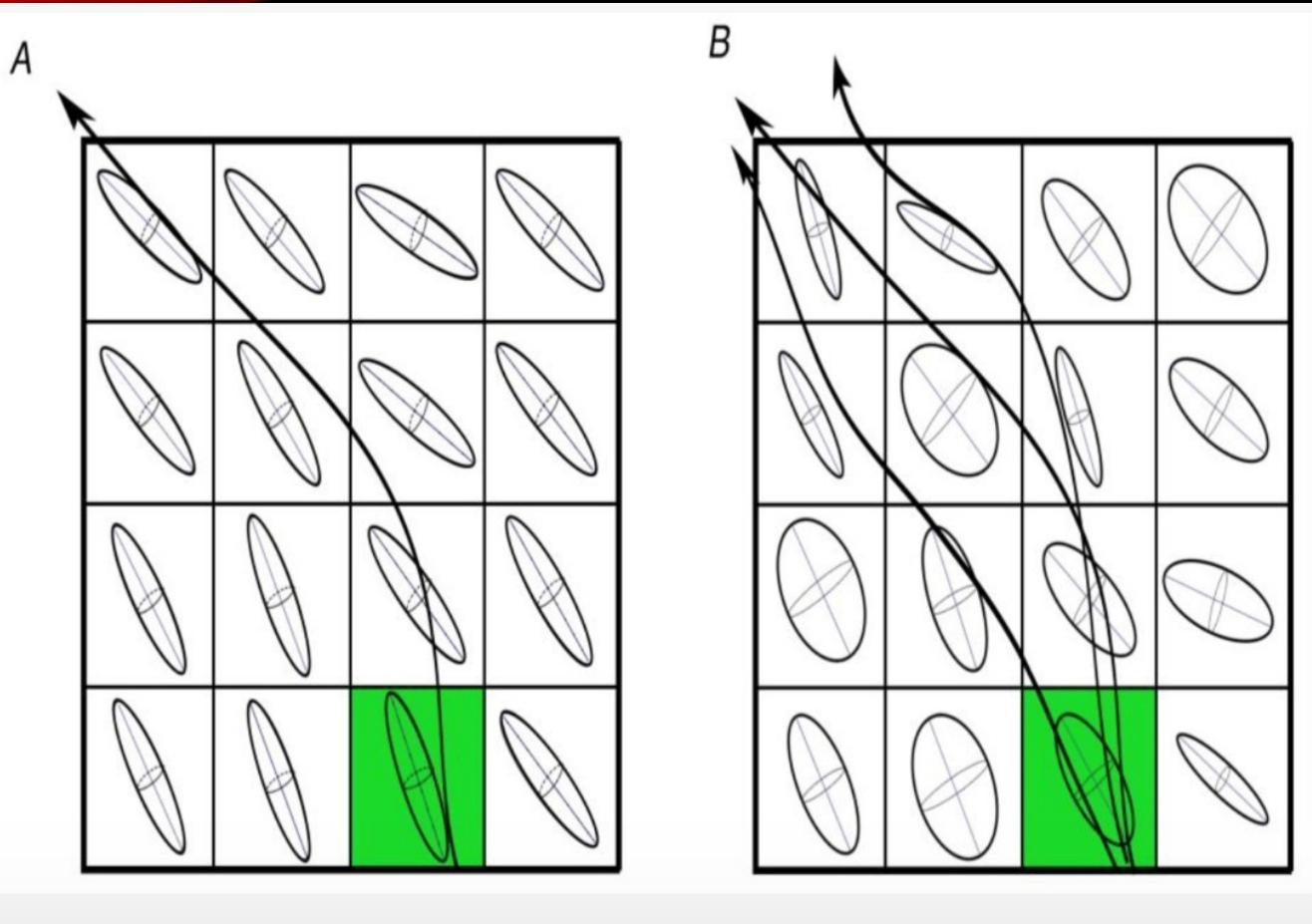


" ℓ " (lowercase L) is called the **azimuthal quantum number** and represents the orbital angular momentum. It determines the shape of the spherical harmonics. The allowed values for " ℓ " are non-negative integers (0, 1, 2, 3, ...). The larger the value of " ℓ ," the more complex and intricate the shape of the spherical harmonics becomes.

" m " is called the **magnetic quantum number** and represents the projection of the orbital angular momentum along a specific axis. " m " can take values ranging from $-l$ to $+l$, including zero. Each value of " m " corresponds to a different orientation or angular distribution of the spherical harmonic. For a given value of " ℓ ," there are $2\ell+1$ possible values of " m ." The orientation of the spherical harmonic depends on the specific value of " m " within the allowed range.

The general expression for spherical harmonics, denoted as $Y_{lm}(\theta, \varphi)$, is a function of two angles, θ (theta) and φ (phi), which represent the polar and azimuthal angles, respectively. The values of " ℓ " and " m " determine which spherical harmonic function you are referring to, and they play a crucial role in characterizing the angular part of a wavefunction or a spherical system.

Deterministic vs Probabilistic



$$y_{n+1} = y_n + h f(t_n, y_n).$$

The Euler method is a first-order method, which means that the local error (error per step) is proportional to the square of the step size,

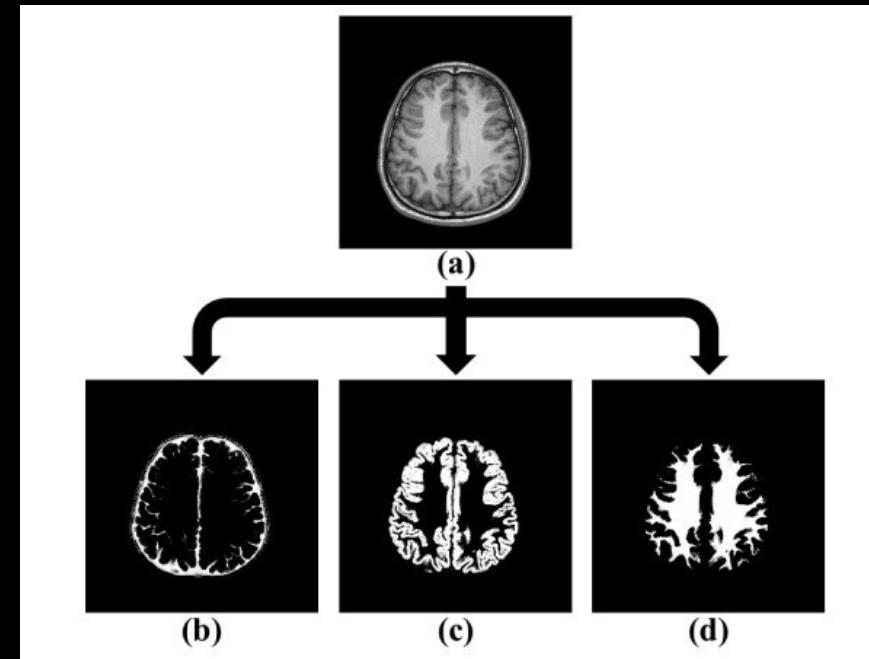
Stopping criteria

- Fractional anisotropy
- Anatomically constrained tractography
- A combination Of both

Isotropic



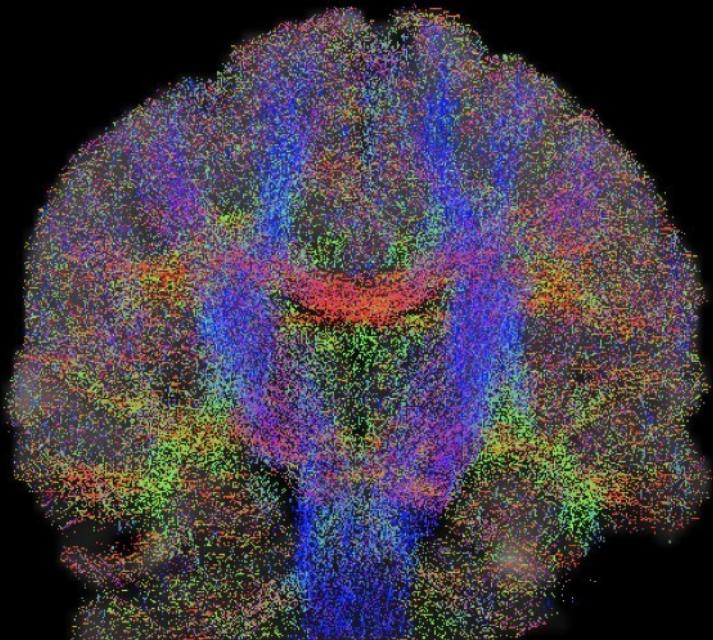
Anisotropic



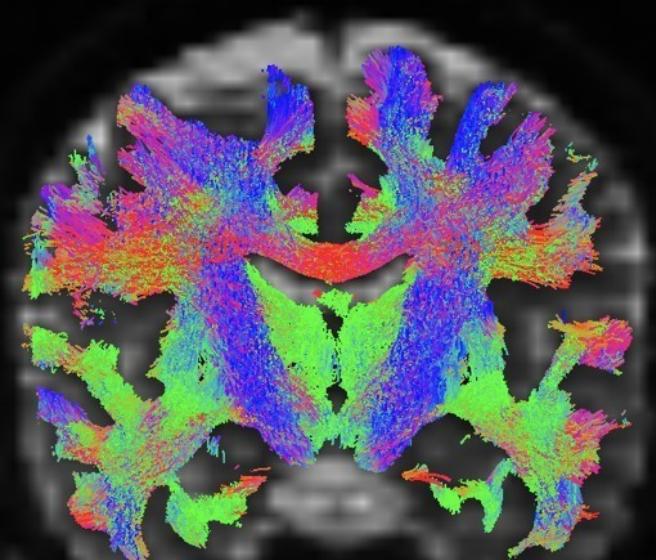
Stopping

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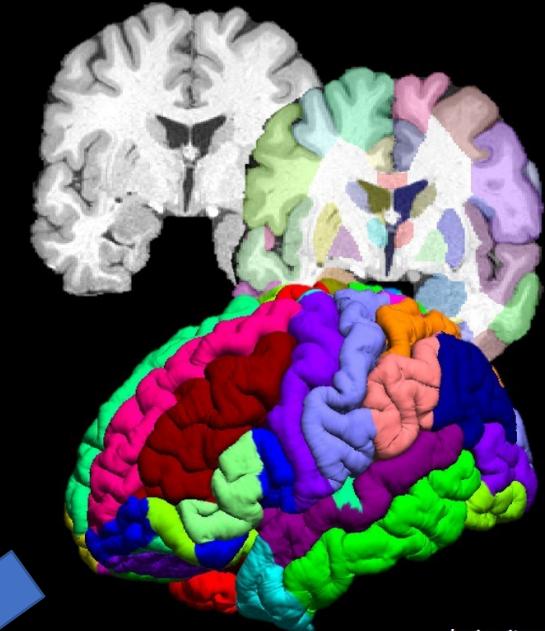
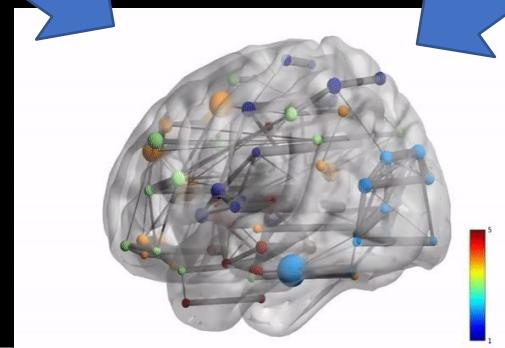
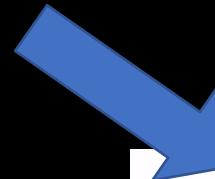
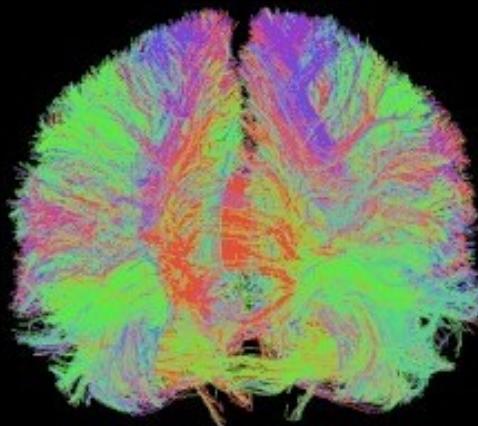
Without ACT



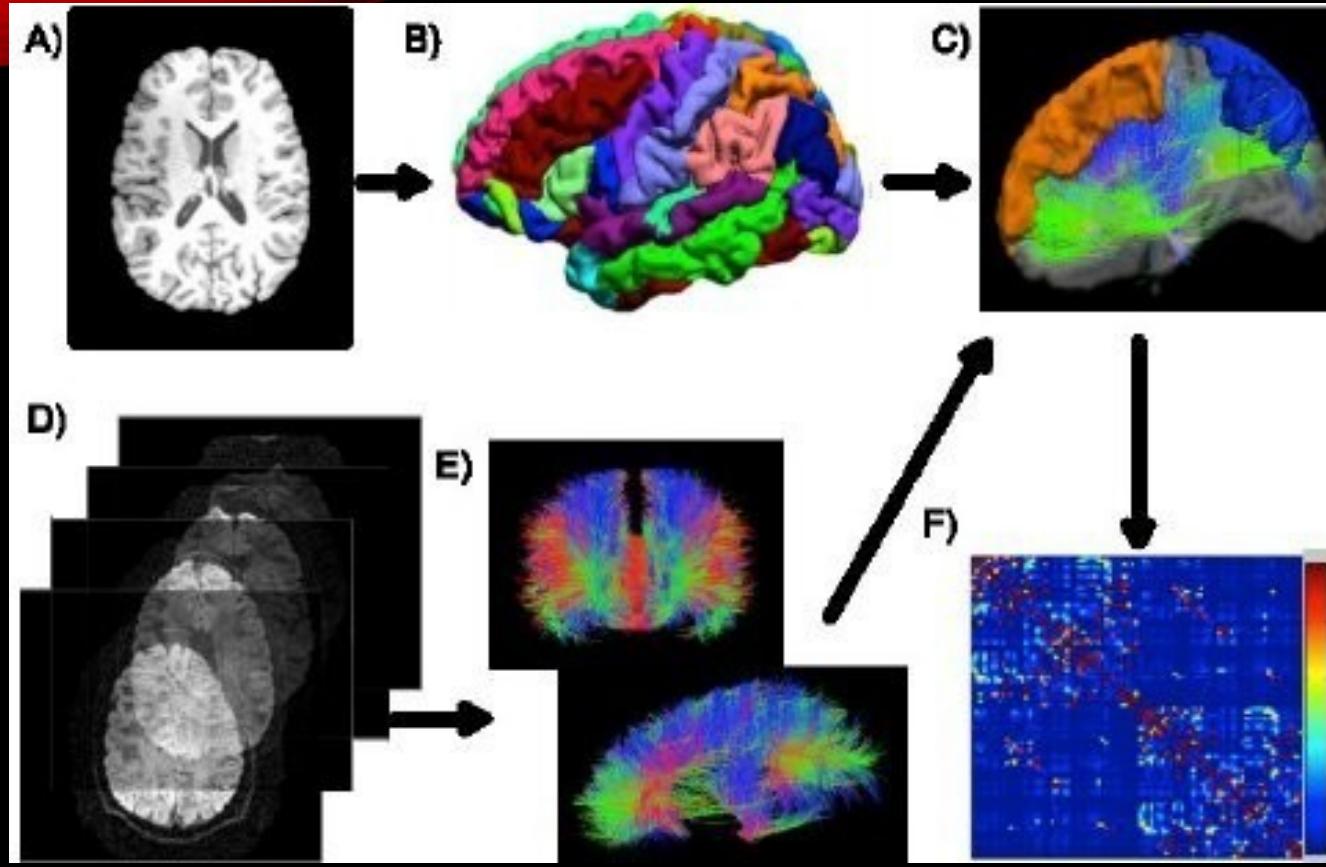
With ACT



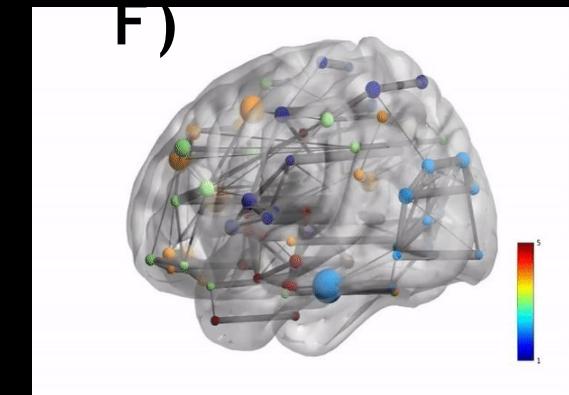
Structural Connectivity

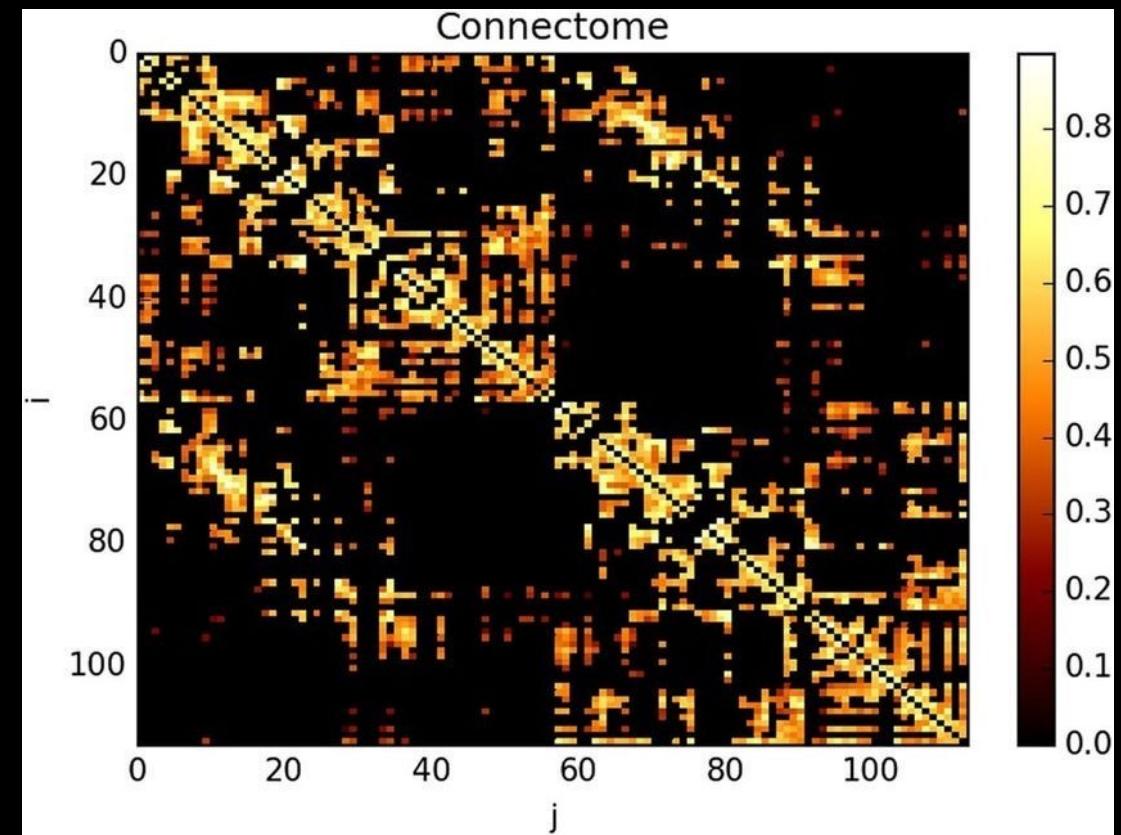
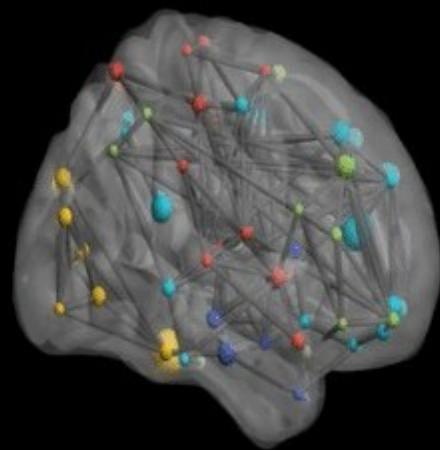


Brain Connectivity

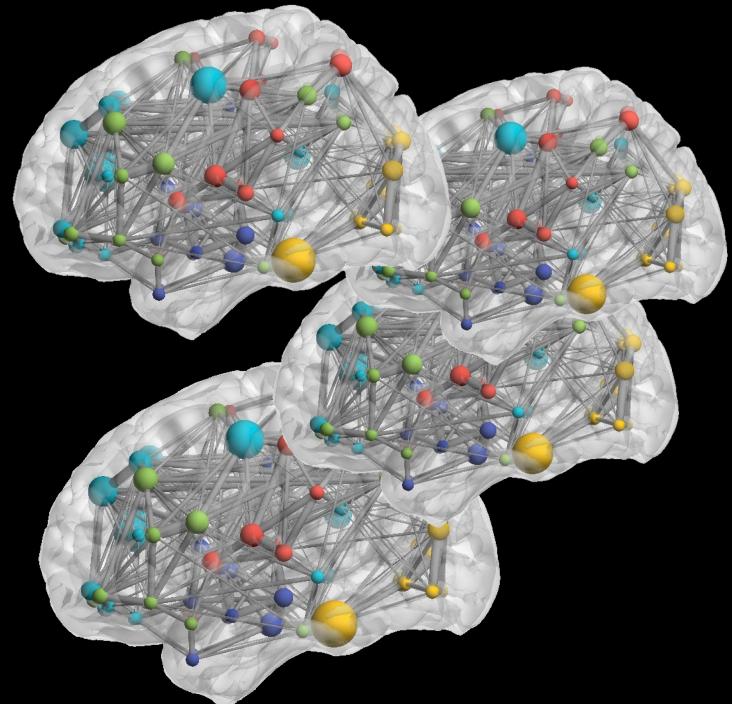


Computationally
the brain
network is
represented
as a
“connectivity
matrix”

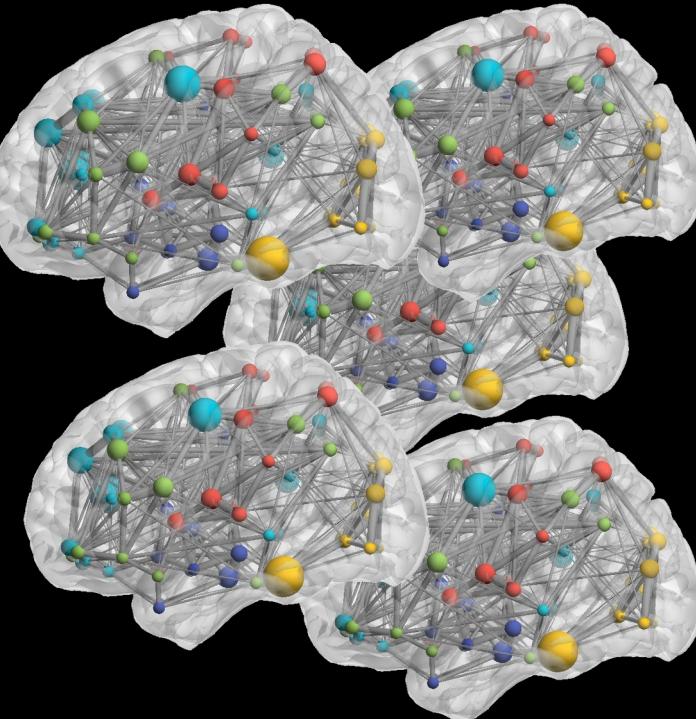




Alzheimer, Schizophrenia,...

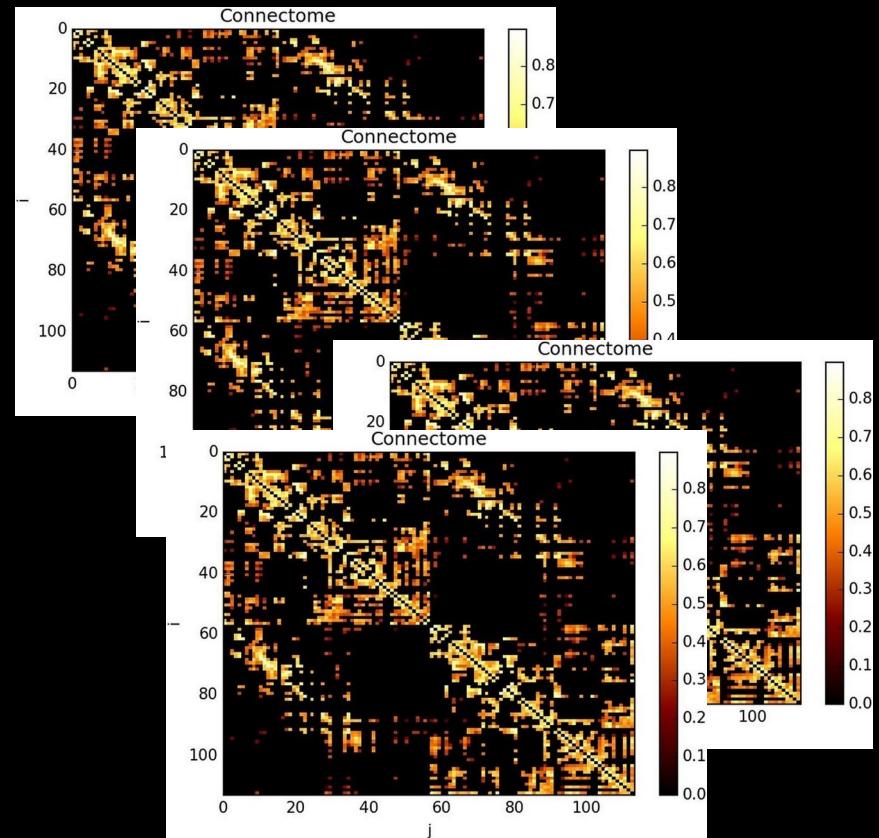
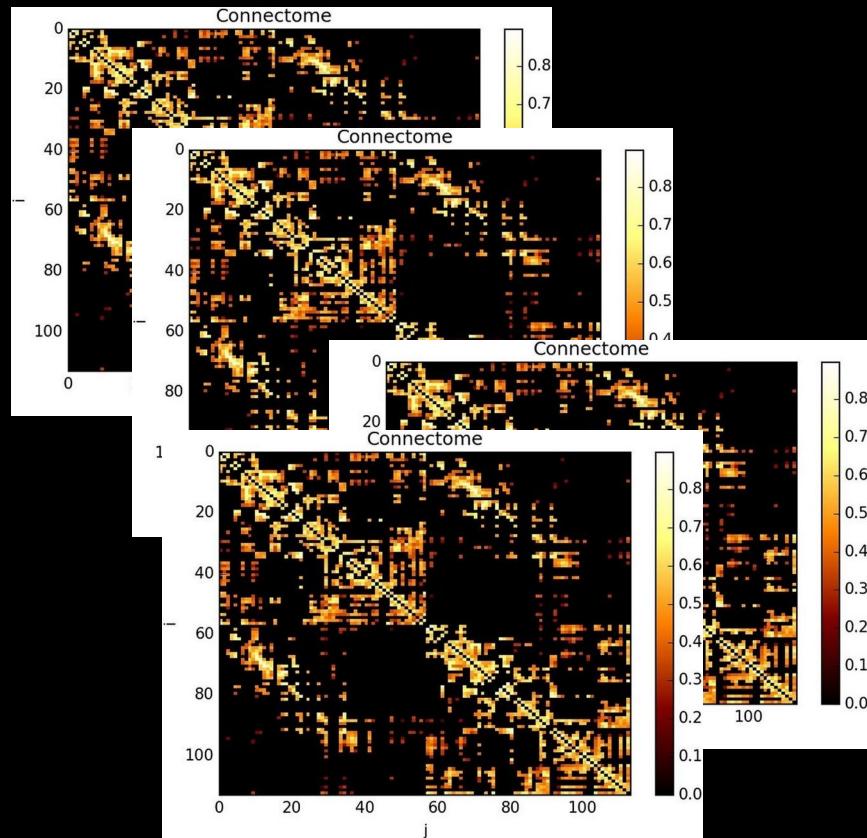


Matched healthy control



Alzheimer, Schizophrenia,...

Matched healthy control



Questions ?

