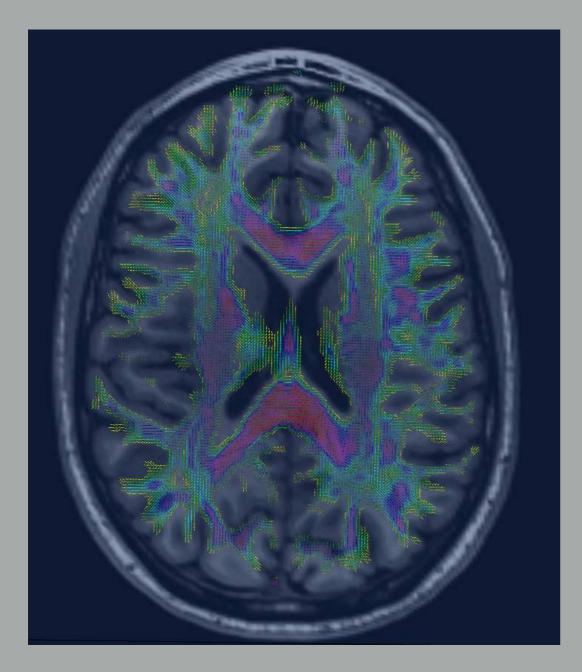
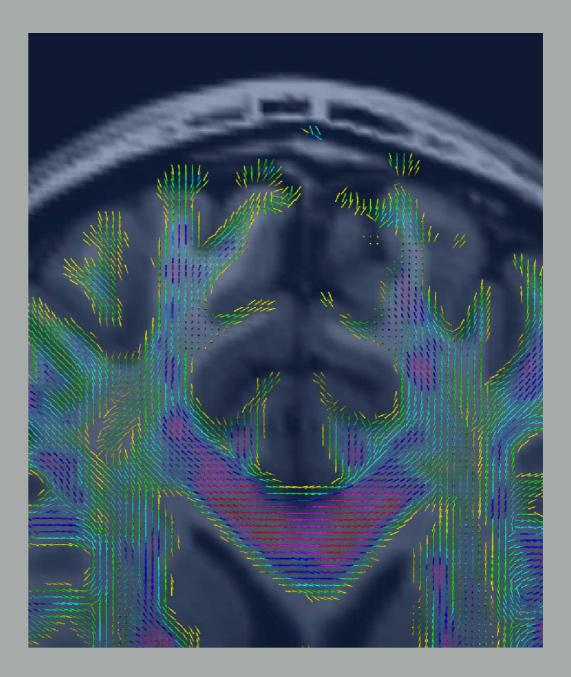
## Lecture 15 Fiber Tract Mapping

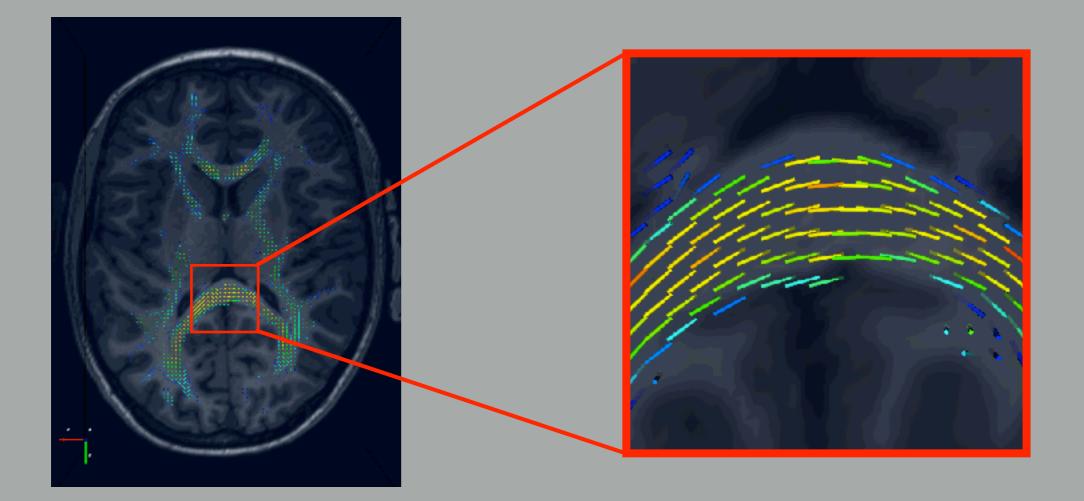
## Principal Eigenvectors





#### FIBER ORIENTATION

#### The Gateway to Connectivity!

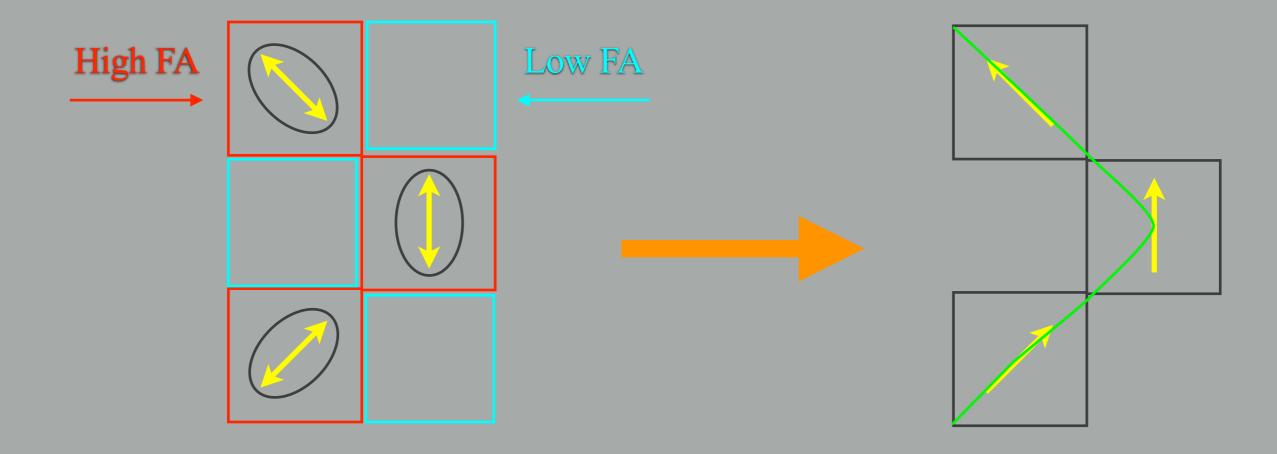


Aligned fibers in the corpus callosum

#### STREAMLINE BASED TRACTOGRAPHY

#### Estimated orientation

#### Flow vector field



principal direction

"tractography"

## Deterministic methods

Connect voxels (Conturo)
FACT (Mori,DTI Studio)
Path integral (Basser, Tuch)

## Deterministic methods

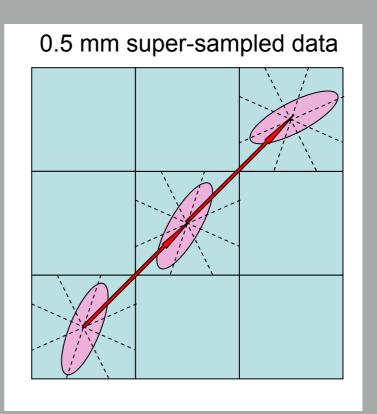
Connect voxels (Conturo)
FACT (Mori,DTI Studio)
Path integral (Basser, Tuch)

#### Connect voxels (Conturo, 1999 PNAS)

Resample tensor (eg from 2.5mm to .5mm)

Follow voxel in direction of PEV (both directions)

Stop when FA low

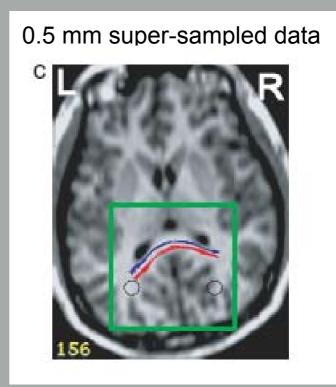


#### Connect voxels (Conturo, 1999 PNAS)

Resample tensor (eg from 2.5mm to .5mm)

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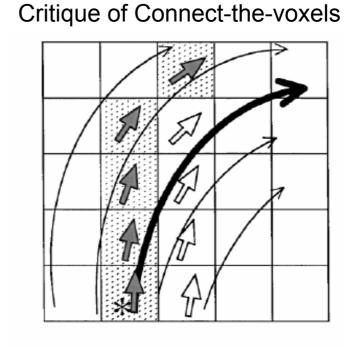


#### Fiber Assignment by Continuous Tracking (FACT) (Mori 1999)

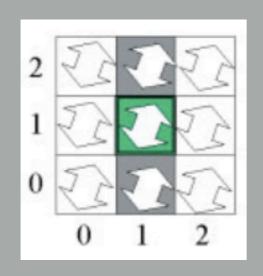
#### Start at seed and follow PEV until hit edge of voxel

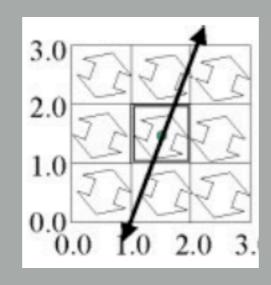
Move to next voxel tensor, repeat

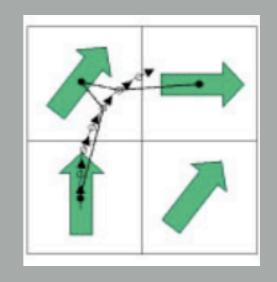




#### Fiber Assignment by Continuous Tracking (FACT)







Discrete: voxel connected to adjacent one to which it "points"

Continuous Linear: Line is propagated

Continuous Non-linear: Line is weighted by distanced weighted average of the surrounding vectors

Mori & Van Zijl, NMR Biomed 2002

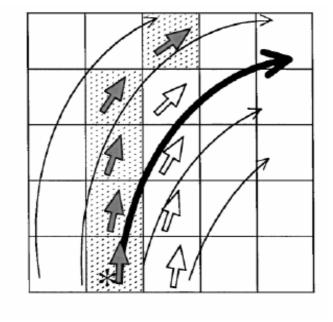
#### Fiber Assignment by Continuous Tracking (FACT) (Mori 1999)

#### Start at seed and follow PEV until hit edge of voxel

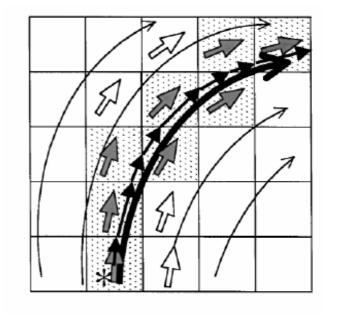
Move to next voxel tensor, repeat

Interpolate between data points

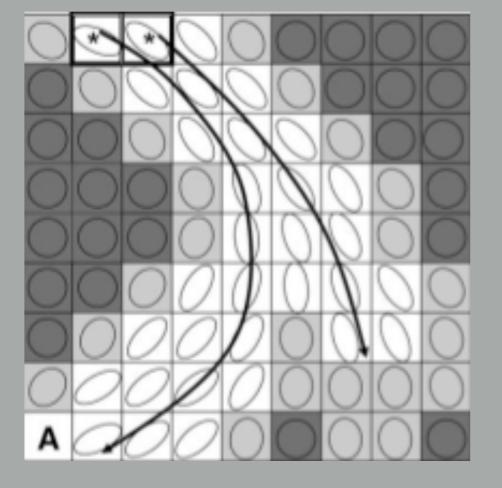


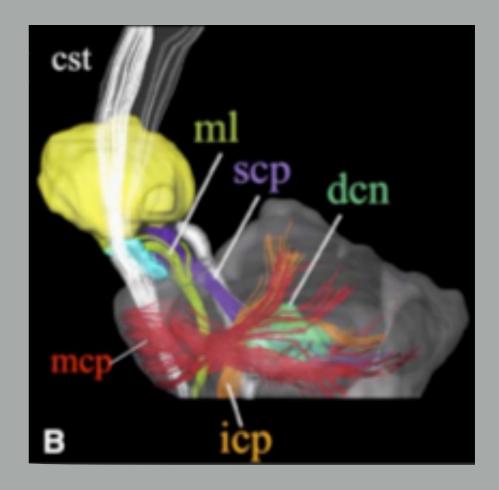


Modified algorithm



## FACT



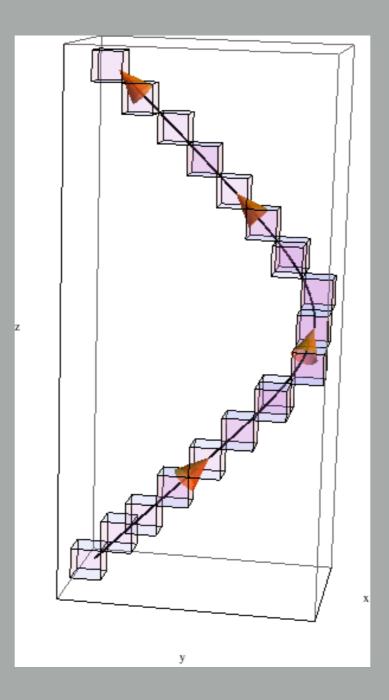


Mori & Zhang, Neuron 2006

Path Integral method (Basser 2000)

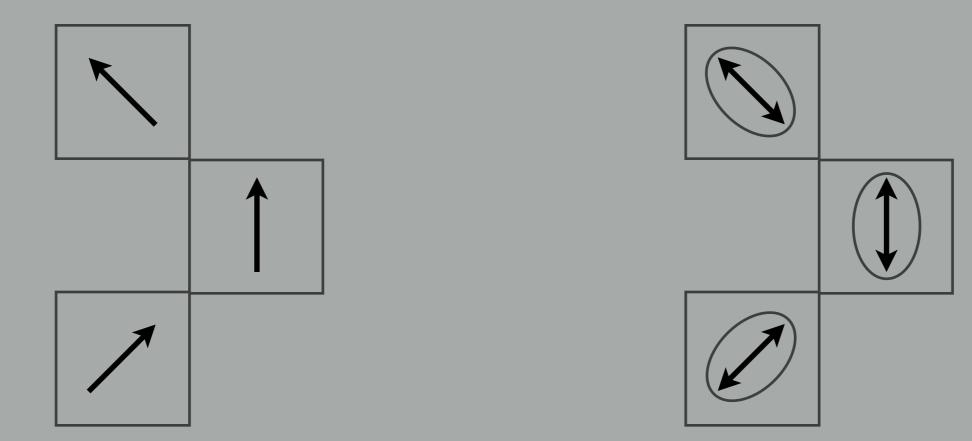
PEV direction is considered to be path tangent

## **Tracing the Principal Eigenvectors**

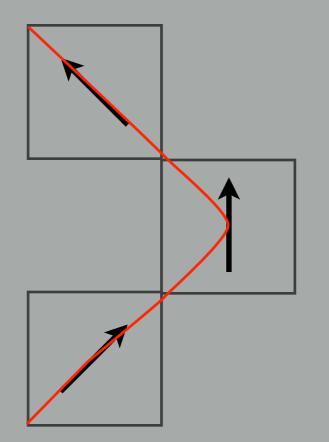


#### Flow vector field

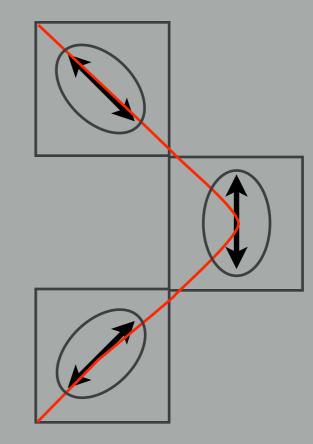
### Principal eigenvector field



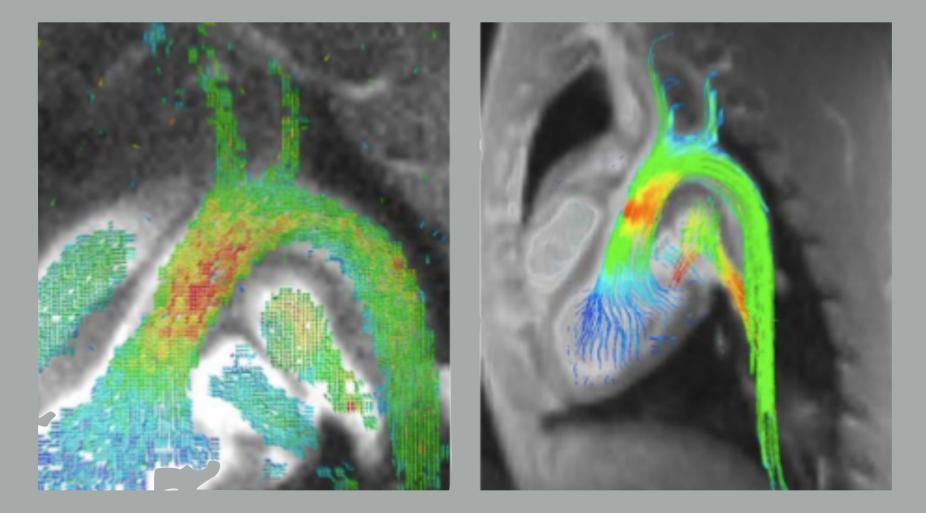
#### Flow vector field



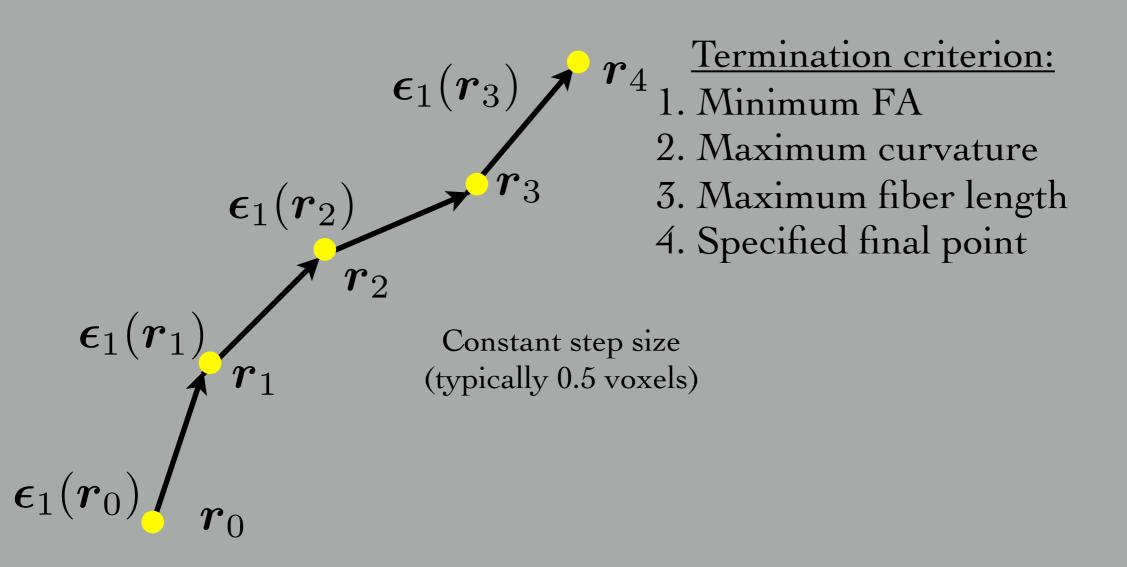
#### Principal eigenvector field



Path traced by a massless particle in a velocity vector field



R. Unterhinninghofen, et. al.



 Deterministic
Integration of principal eigenvector
Requires only diffusion tensor D but does not depend on underlying model for diffusion (i.e., can be any type of fiber)

Space curves (Basser, et. al.)

$$\frac{d\boldsymbol{r}(s)}{ds} = \boldsymbol{t}(s)$$

$$\boldsymbol{r}(s) = ext{trajectory}$$

t(s) = tangent to r(s) at s

 $s = \operatorname{arc} \operatorname{length}$ 

Assert: Principal eigenvector lies in direction of tangent

Assertion: Principal eigenvector  $e_1$  lies in the direction of the tangent t(s)

 $\boldsymbol{t}(s) = \boldsymbol{e}_1(\boldsymbol{r}(s))$ 

$$\frac{d\boldsymbol{r}(s)}{ds} = \boldsymbol{t}(s)$$

#### can then be written

$$\frac{d\boldsymbol{r}(s)}{ds} = \boldsymbol{e}_1(\boldsymbol{r}(s))$$

$$\frac{d\boldsymbol{r}(s)}{ds} = \boldsymbol{e}_1(\boldsymbol{r}(s))$$

$$\boldsymbol{t}(s) = \boldsymbol{e}_1(\boldsymbol{r}(s))$$

#### Solve for $\boldsymbol{r}(s)$ with initial condition

$$\boldsymbol{r}(0) = \boldsymbol{r}_o$$

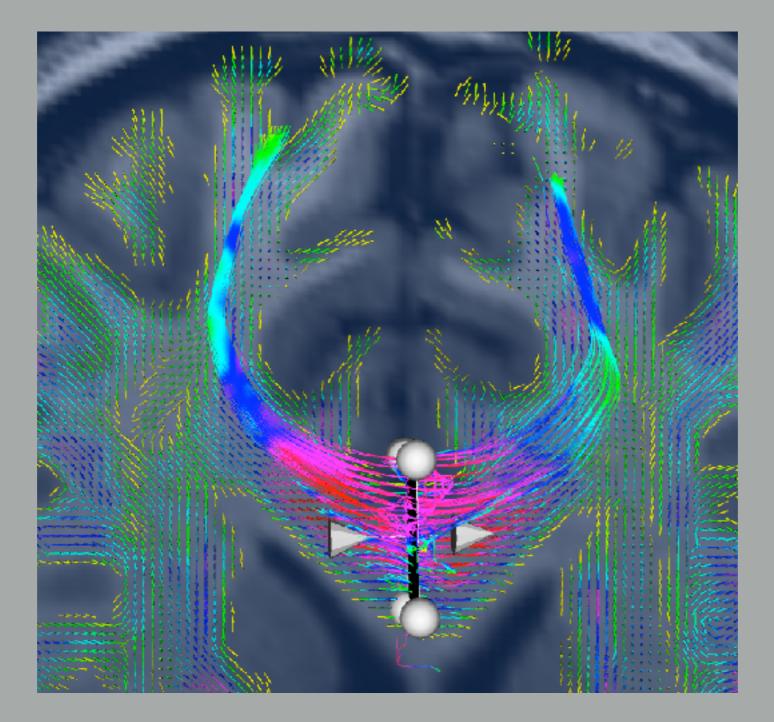
#### **Euler's Method**

$$\frac{d\boldsymbol{r}(s)}{ds} = \boldsymbol{e}_1(\boldsymbol{r}(s))$$

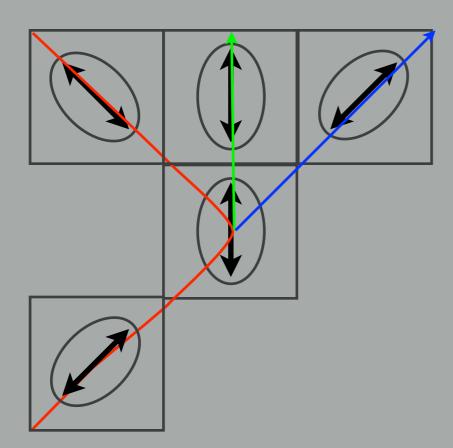
$$\boldsymbol{t}(s) = \boldsymbol{e}_1(\boldsymbol{r}(s))$$

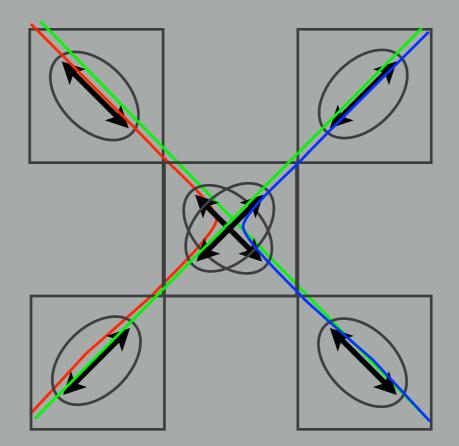
#### Solve for initial conditions

$$\boldsymbol{r}(0) = \boldsymbol{r}_{c}$$



#### **Streamlines: Trouble Ahead?**





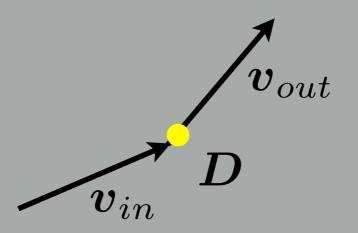
## path ambiguity

crossing fibers

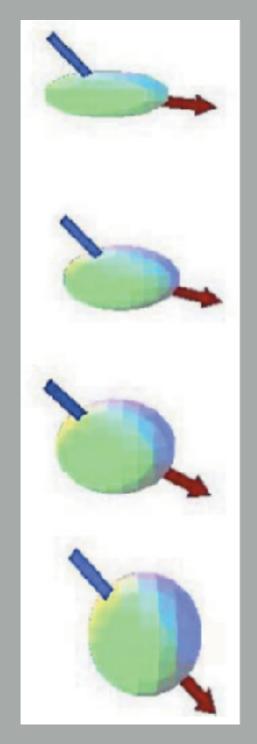
## Tensorlines

# Taking into account regions of low FA $v_{out} = D \, v_{in}$

Fiber direction is deflected by tensor in direction of principal eigenvector



## Tensorlines

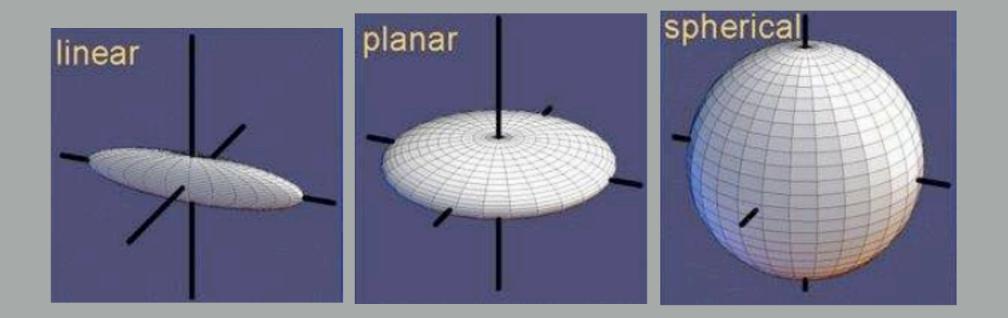


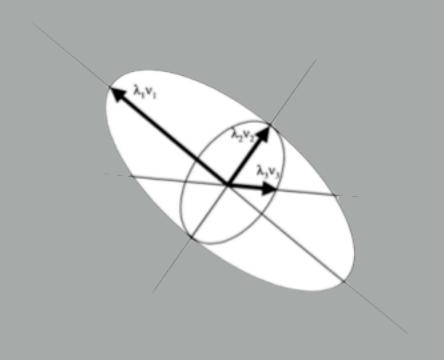
highly anisotropic - large deflection

spherical - no deflection

from Mori & Zhang

## **Anisotropy Indices**





- Let  $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0$ .
- Linear:  $\lambda_1 \gg \lambda_2 \simeq \lambda_3$
- Planar:  $\lambda_1 \simeq \lambda_2 \gg \lambda_3$
- Spherical:  $\lambda_1\simeq\lambda_2\simeq\lambda_3$

## **Anisotropy Indices**

$$c_l = \frac{\lambda_1 - \lambda_2}{\lambda_1 + \lambda_2 + \lambda_3}$$
 linear

$$c_p = \frac{2(\lambda_2 - \lambda_3)}{\lambda_1 + \lambda_2 + \lambda_3}$$
 planar

$$c_s = \frac{3\lambda_3}{\lambda_1 + \lambda_2 + \lambda_3}$$
 spherical

Westin, et. al.

## Tensorlines

Weighted average of tensor deflected vectors

$$\boldsymbol{v}_{new} = c_l \boldsymbol{v}_1 + (1 - c_l) \tilde{\boldsymbol{v}}_l$$

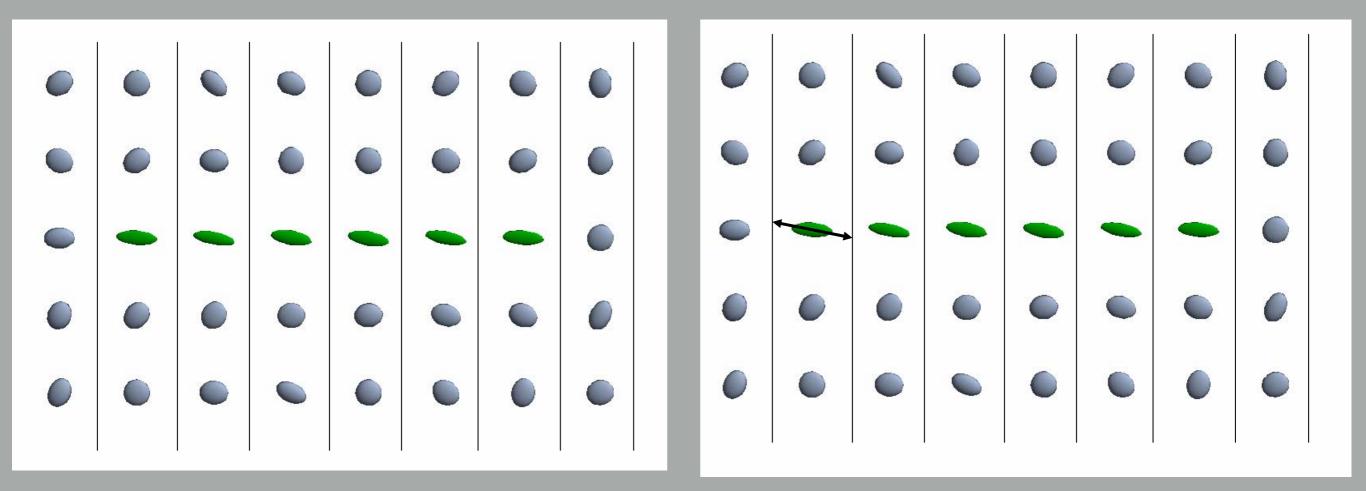
$$\tilde{\boldsymbol{v}} = f\boldsymbol{v}_{in} + (1-f)\boldsymbol{v}_{out} \quad , \quad 0 \le f \le 1$$

$$\boldsymbol{v}_{out} = \boldsymbol{D} \, \boldsymbol{v}_{in}$$

1

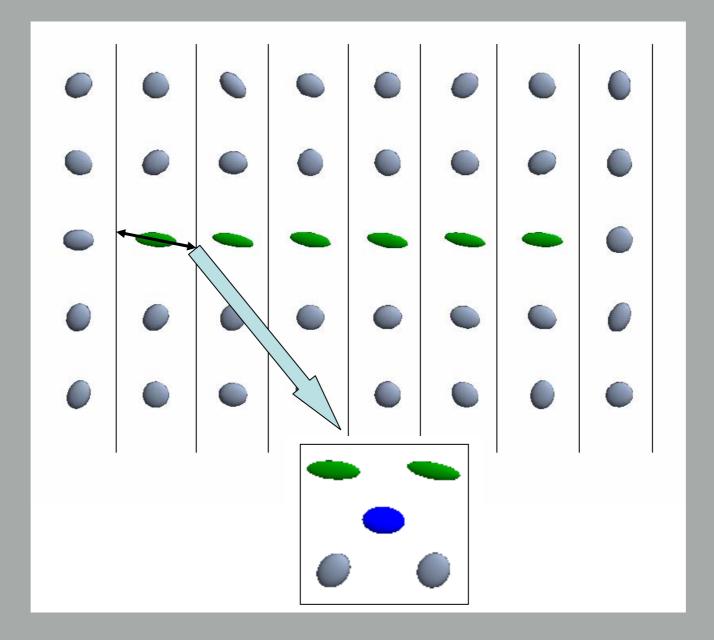
Weinstein, et. al.

## **Tensor interpolation**



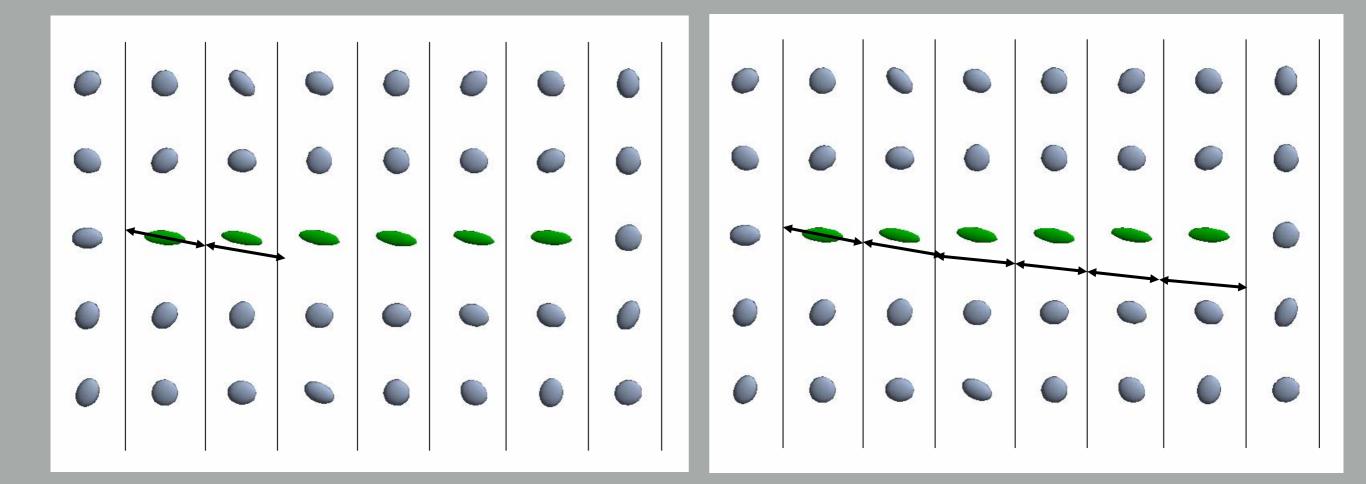
from Wandell

## **Tensor interpolation**



interpolate new tensor at endpoint ... from Wandell

## **Tensor interpolation**

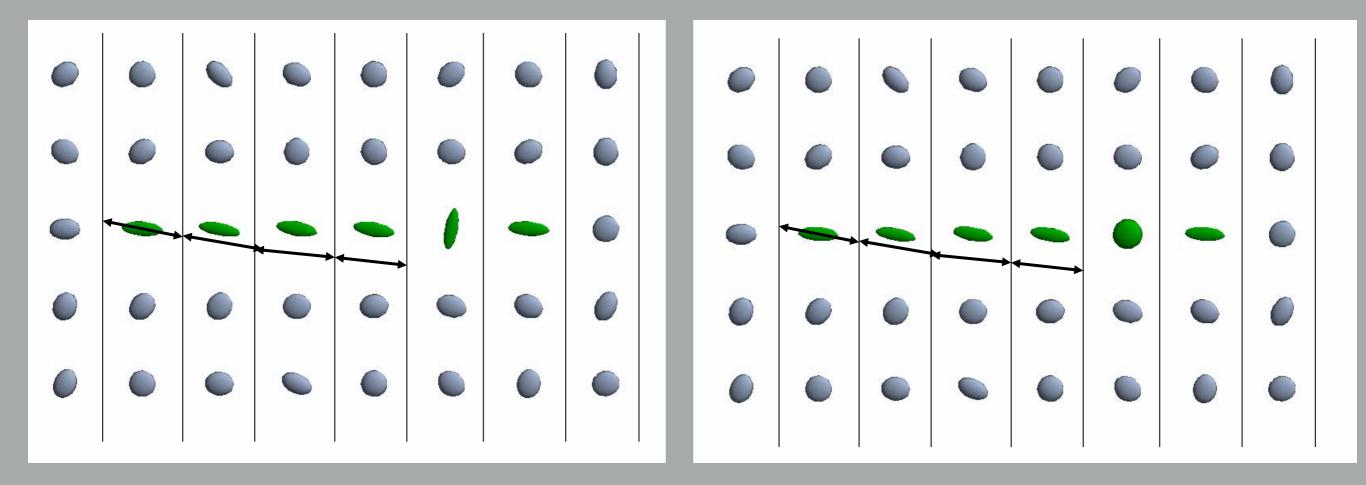


interpolation ...

repeat...

from Wandell

## Termination

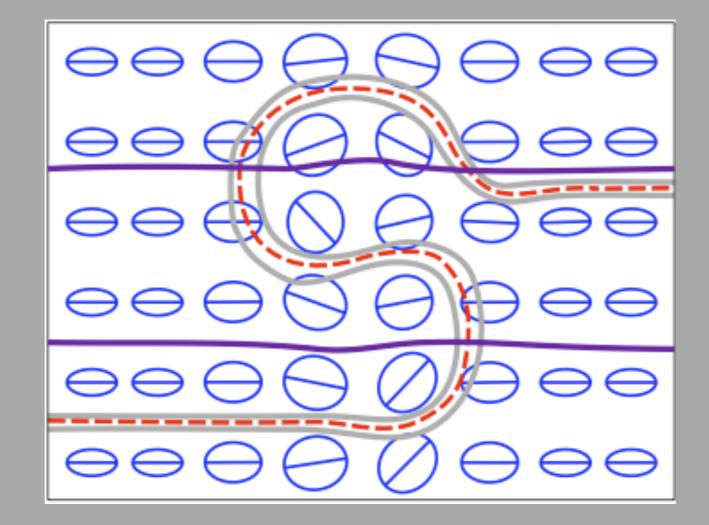


anisotropy

angle

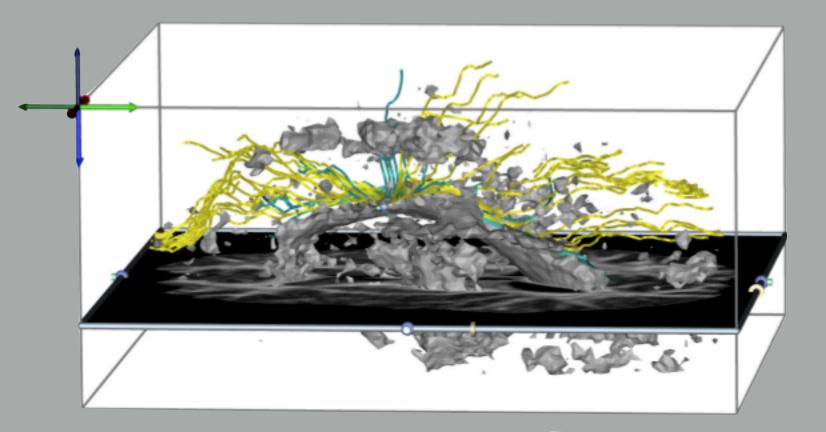
from Wandell

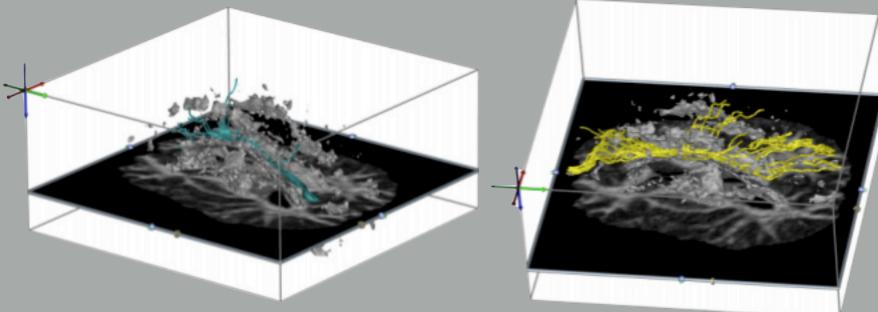
## Tensorlines



Weinstein, et. al.

## Tensorlines

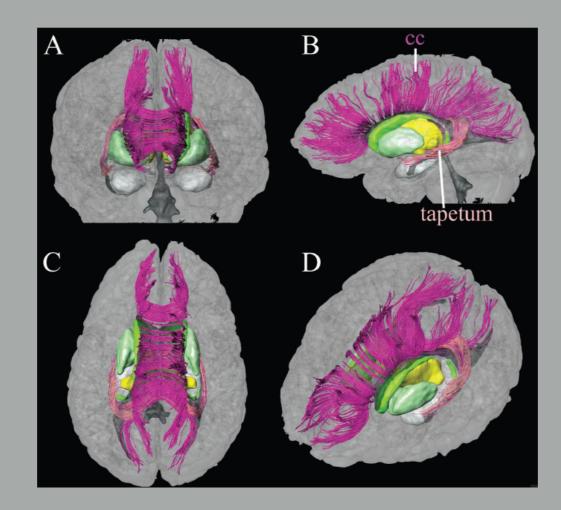




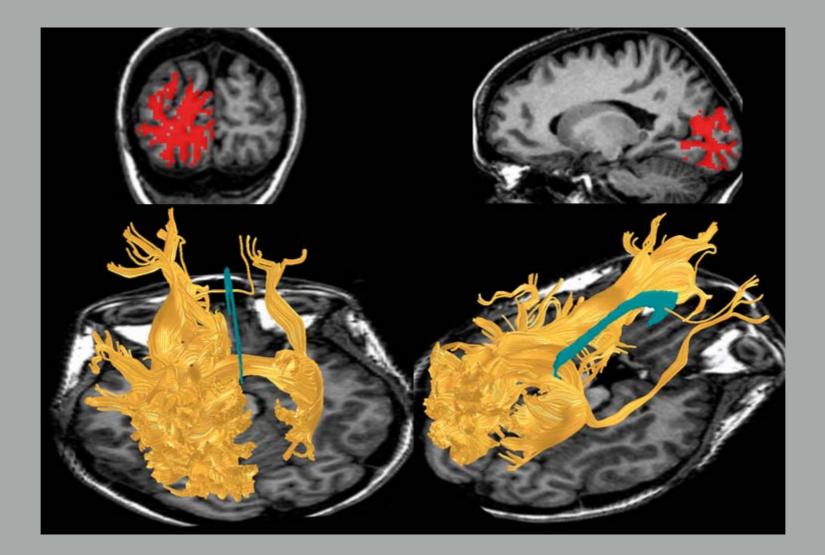
Weinstein, et. al.

## Validation





# Occipital seeds

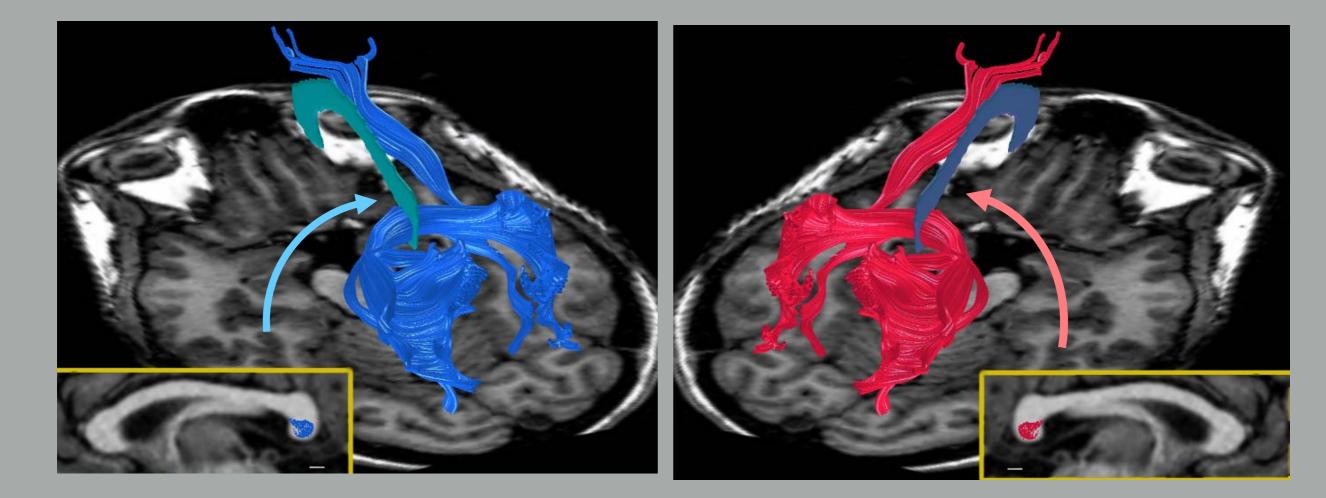


**Dougherty PNAS 2005** 

# Tracking through corpus callosum

### Left occipital seeds

## Right occipital seeds



## **Dougherty PNAS 2005**

- Take into account the uncertainty of fiber orientation
- Allows multiple paths
- Schemes based on
- Regularized stochastic models
- Linear state space models
- Bending energy models
- Monte-Carlo methods

FSL's FDT (Behren's et. al.)

Assume partial volume model for voxels: Some fraction *f* gray matter (isotropic) diffusion and the remaining fraction *(1-f)* is white matter (anisotropic) diffusion

$$\frac{s(b_i)}{s(0)} = f e^{-b_i d} + (1 - f) e^{-b_i \tilde{D}}$$

where  $\tilde{\boldsymbol{D}} = \boldsymbol{R} \boldsymbol{D}_{\Lambda} \boldsymbol{R}^t$ 

$$\frac{s(b_i)}{s(0)} = f e^{-b_i d} + (1 - f) e^{-b_i \tilde{D}}$$

## $ilde{m{D}} = m{R}m{D}_{\Lambda}m{R}^t$

$$\boldsymbol{D}_{\Lambda} = \begin{pmatrix} d & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad \begin{bmatrix} \text{NOT the diffusion} \\ \text{tensor model!} \end{bmatrix}$$

Only models diffusion along fiber direction

$$\begin{split} \frac{s(b_i)}{s(0)} &= fe^{-b_i d} + (1-f)e^{-b_i \tilde{D}} \\ \tilde{D} &= RD_{\Lambda}R^t \quad \text{assumes same d!} \\ D_{\Lambda} &= \begin{pmatrix} d & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \end{split}$$

Behrens, et. al.

$$\frac{s(b_i)}{s(0)} = f e^{-b_i d} + (1 - f) e^{-b_i d\tilde{A}}$$

## $\tilde{A} = RAR^t$

$$\boldsymbol{A} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

Behrens, et. al.

signal model parameters:  $\xi = \{\theta, \phi, d, \sigma, f, s_o\}$ 

$$P(\boldsymbol{y}|\boldsymbol{\xi}, M) = \prod_{i=1}^{n} P(y_i|\boldsymbol{\xi}, M)$$

$$\boldsymbol{y} = \{y_1, y_2, \dots, y_n\}$$

 $P(y_i|\xi, M) \sim N(\mu_i, \sigma)$ 

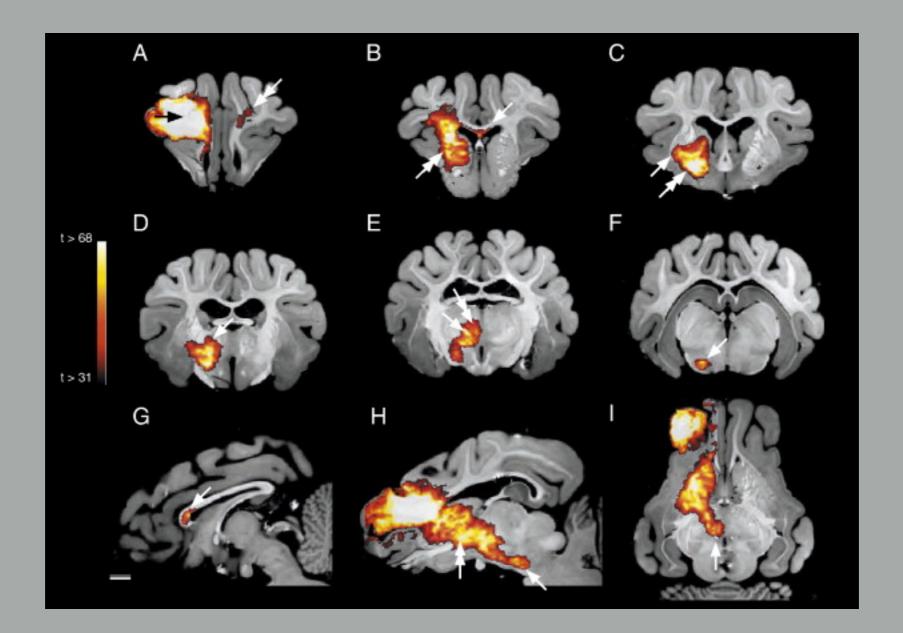
Behrens, et. al.

Bayes' Theorem

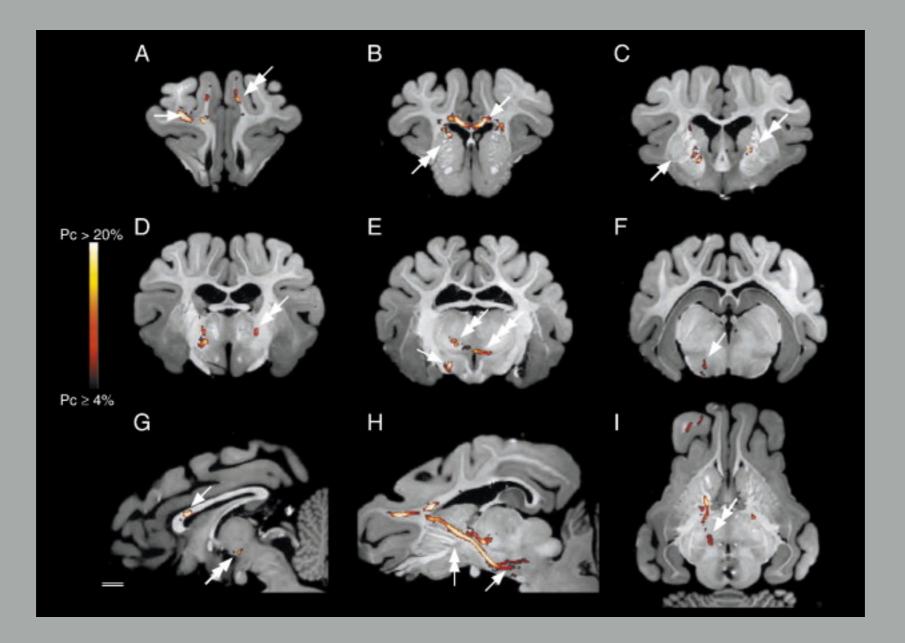
$$P(\xi|\boldsymbol{y}, M) = \frac{P(\boldsymbol{y}|\xi, M)P(\xi|M)}{\int_{\xi} P(\boldsymbol{y}|\xi, M)P(\xi|M)d\xi}$$

 $P(\xi|\boldsymbol{y}, M) = \text{joint distribution of the parameters } \xi$  $P(\xi|M) = \text{prior distribution of the parameters } \xi$ 

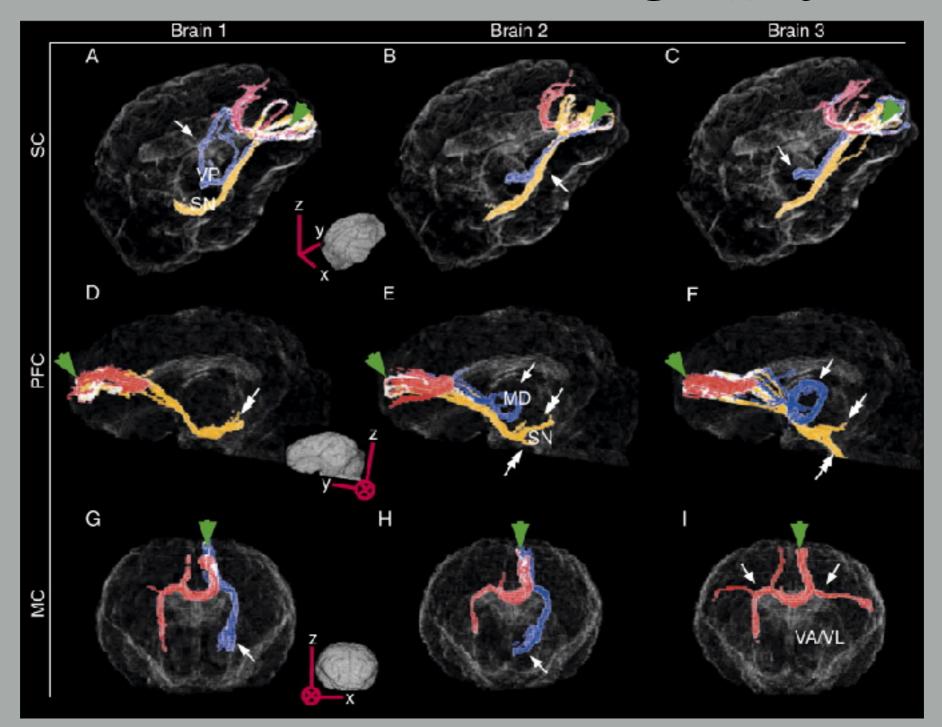
Seek maximum posterior probability of parameters



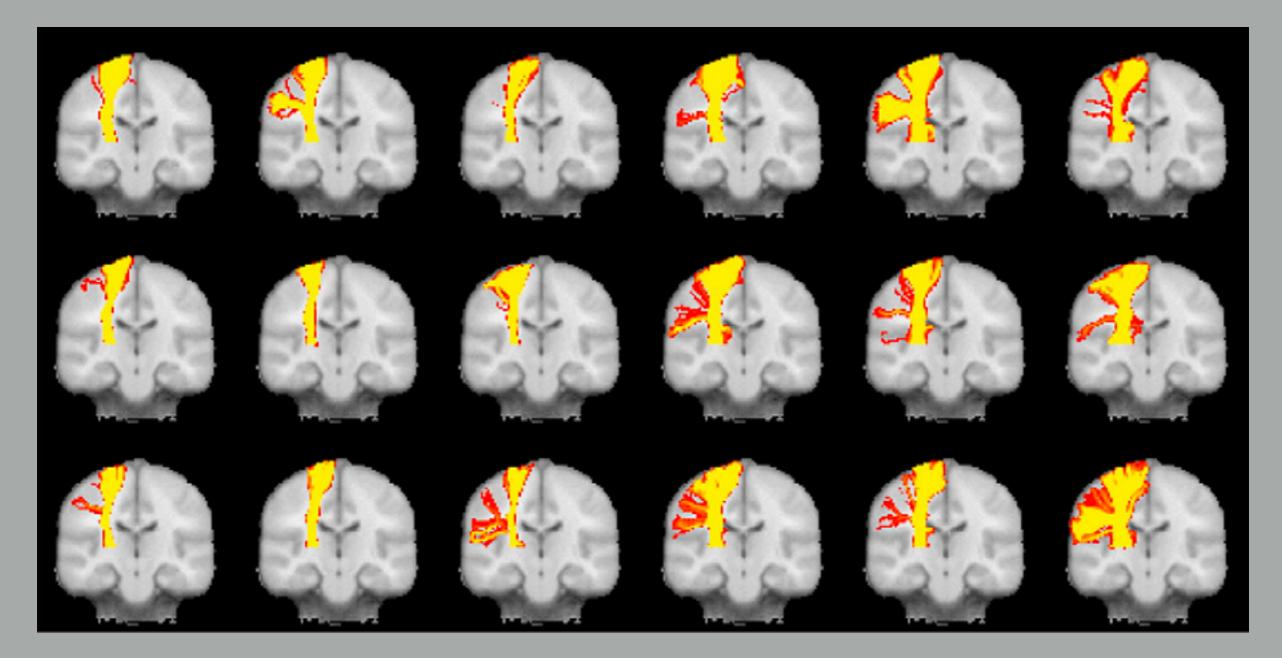
Generation of connected regions Dyrby, NeuroImage 37 (4) 2007



Seeding with constrains on path Dyrby, NeuroImage 37 (4) 2007



Reproducibility Dyrby, NeuroImage 37 (4) 2007



## Multifiber

Behrens, NeuroImage 37 (4) 2007

## Advantages

 Can represent uncertainty in fiber direction so can go in many directions
Robust to noise. Tracks along "noisy" paths tend to be of low probability and so disperse.

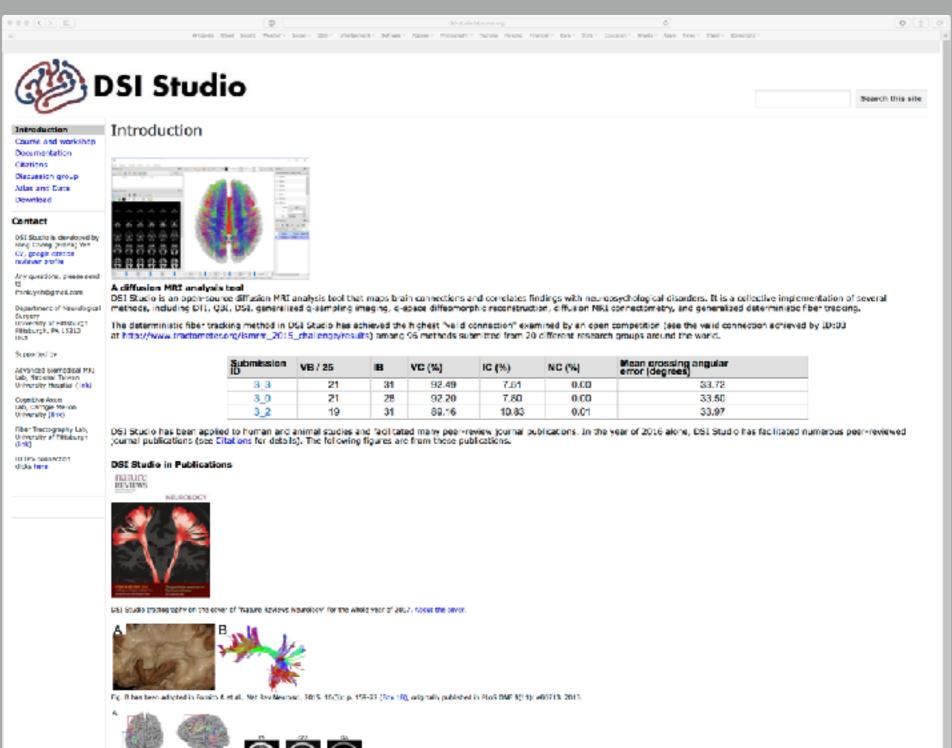
These have the effect of reducing the importance of curvature and anisotropy stopping criteria

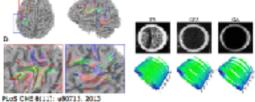
Interpretation:

Connectivity PDF is *not* distribution of connections from a seed point.

It is confidence bounds on location of most probable single connection

## **DSI Studio**



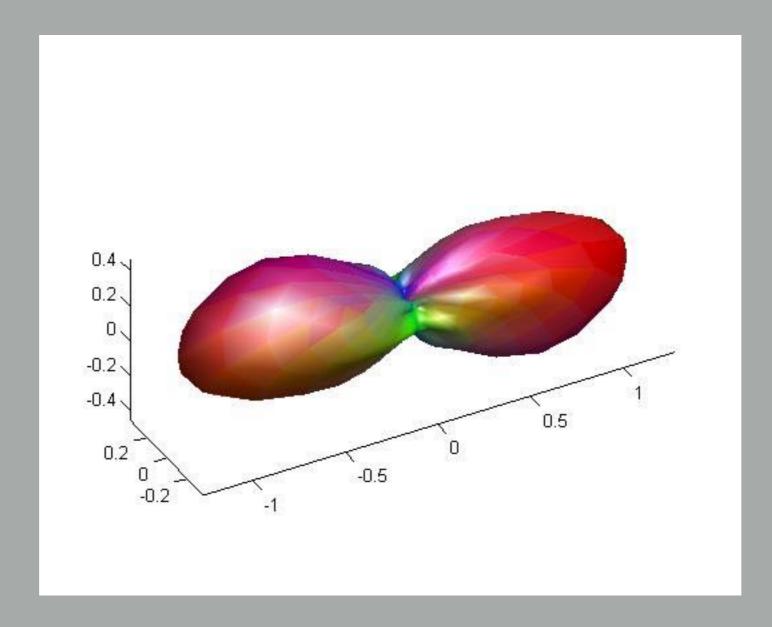


#### Open source, open file format

DSI Sculic is open source. The file format used in DSI Studio can be loaded/save from MATLAB, giving users the greatest flexibility to process the data. DSI Studio supports DICOM file format, Bruker 2dseq, and 4D NIFTI. It was designed to work with other popular tools such as FSL, TrackVis.

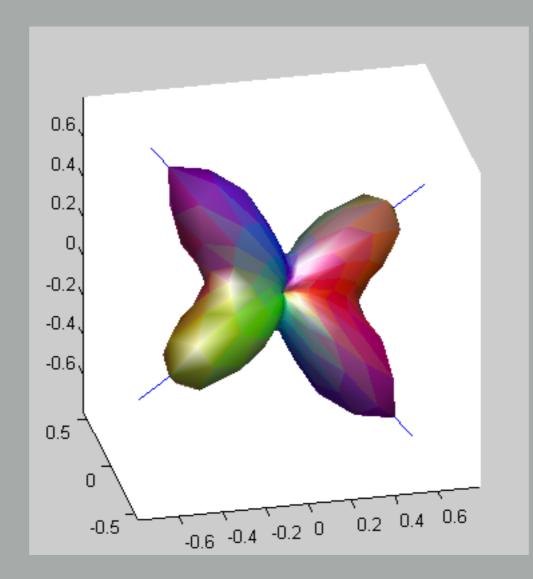
# Track density imaging

3D presentation of the ODFs in Matlab

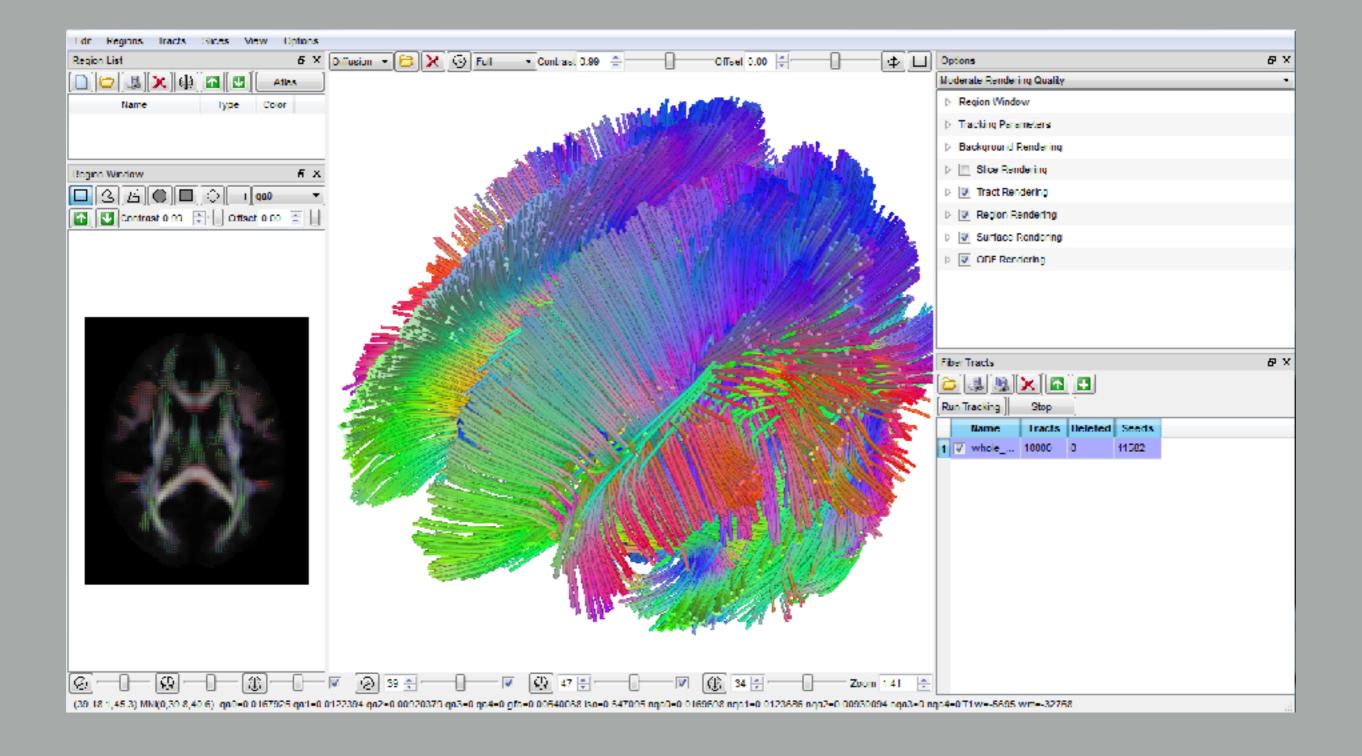


# Track density imaging

3D presentation of the ODFs in Matlab



## **DSI Studio**



# Track density imaging



# The challenge

¥	nature communications					
		Altmetric: 212	Citations: 1			More detail »
Article	OPEN					

## The challenge of mapping the human connectome based on diffusion tractography

Klaus H. Maier-Hein 🏁, Peter F. Neher, 🛛 [...] Maxime Descoteaux 🏁

Nature Communications **8**, Article number: 1349 (2017) doi:10.1038/s41467-017-01285-x Download Citation

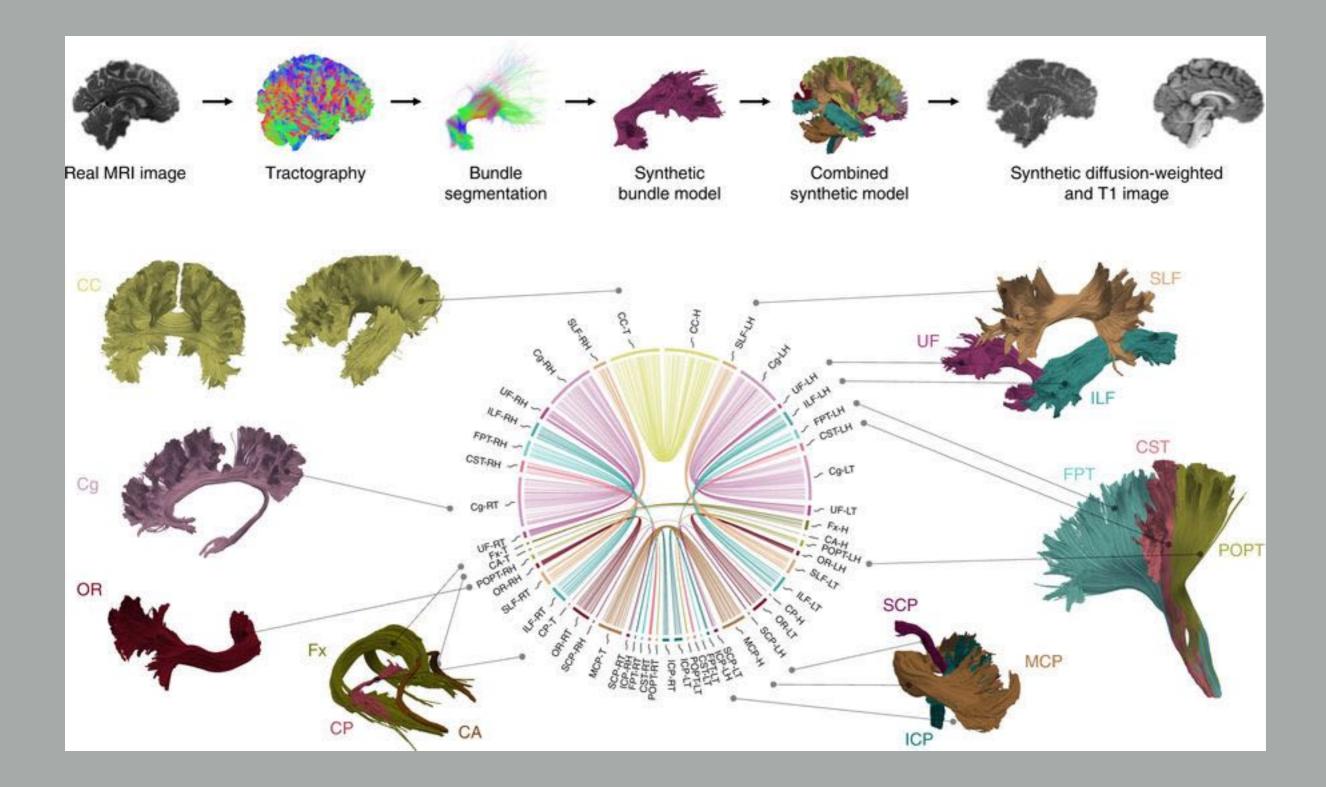
Computational biology and bioinformatics

Medical research Nervous system

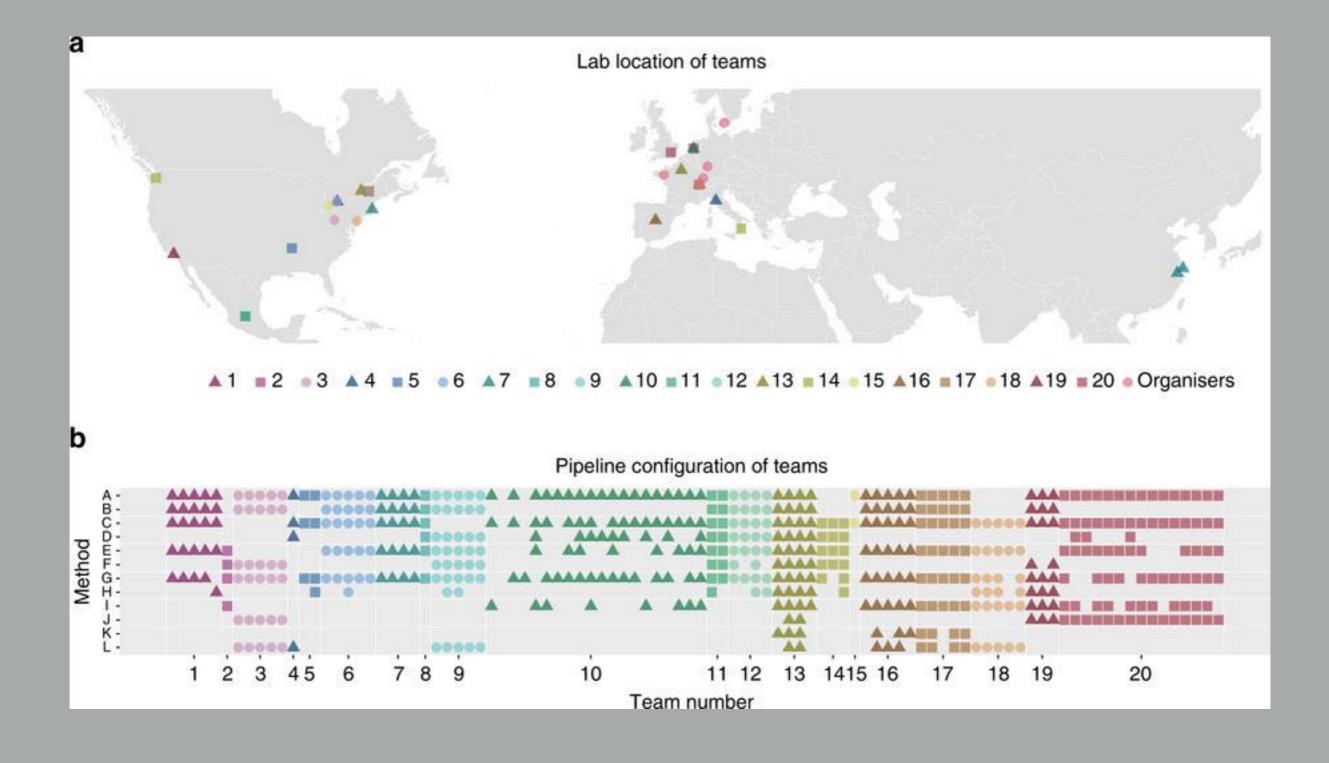
Neuroscience

Received: 21 November 2016 Accepted: 01 September 2017 Published online: 07 November 2017

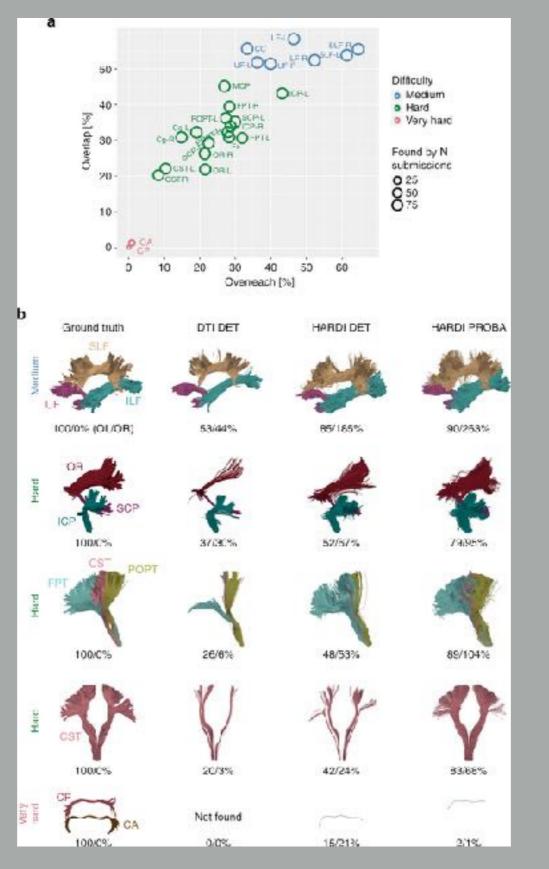
#### Overview of synthetic data set



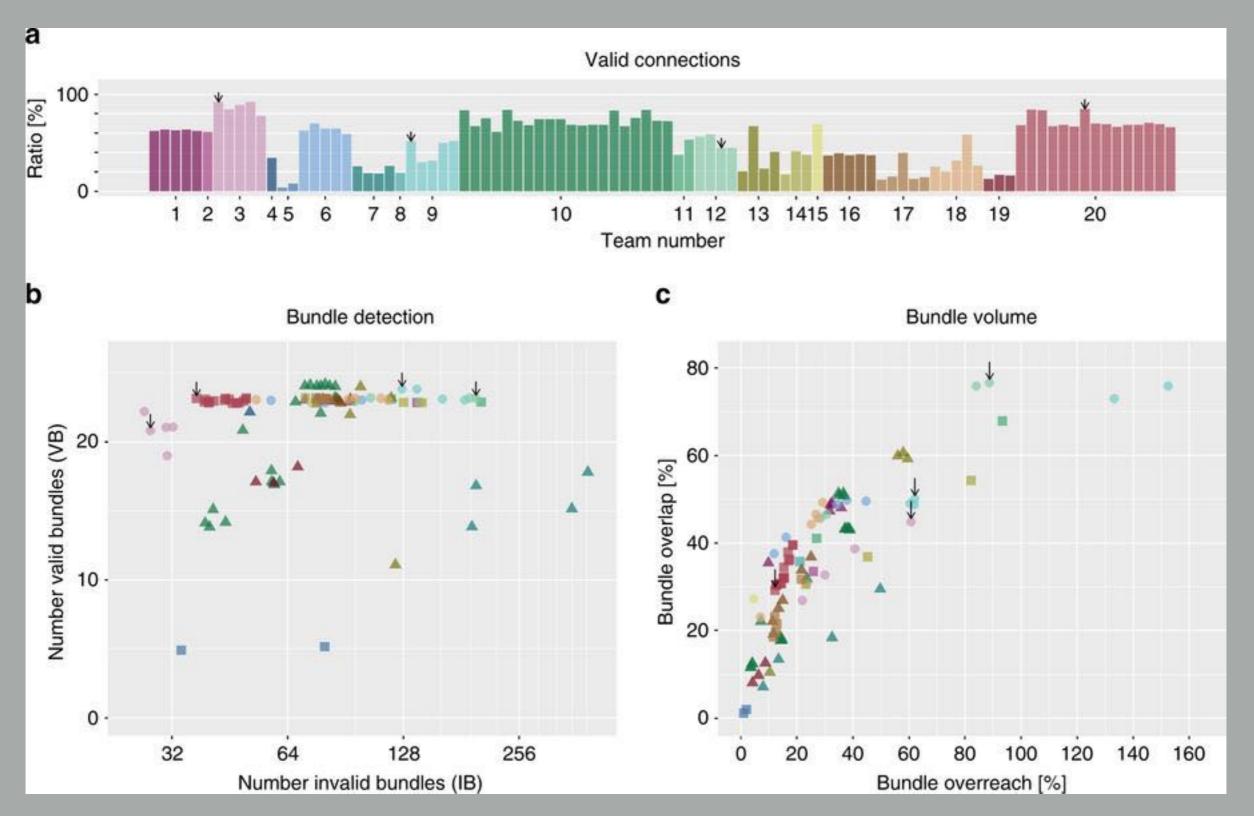
#### Summary of teams and tractography pipeline setups



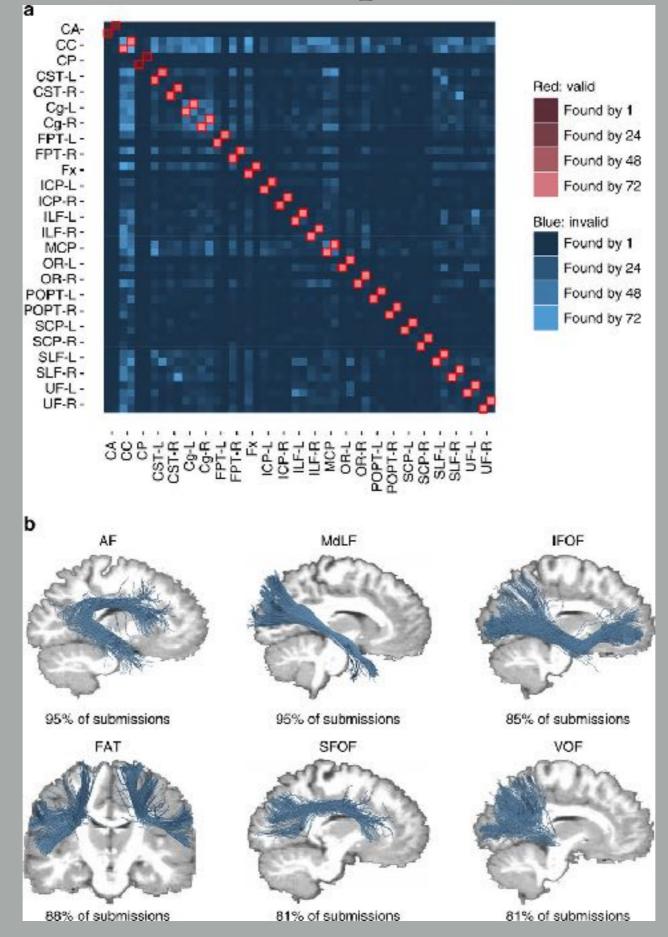
## Tractography identifies most of the ground truth bundles, but not their full extent



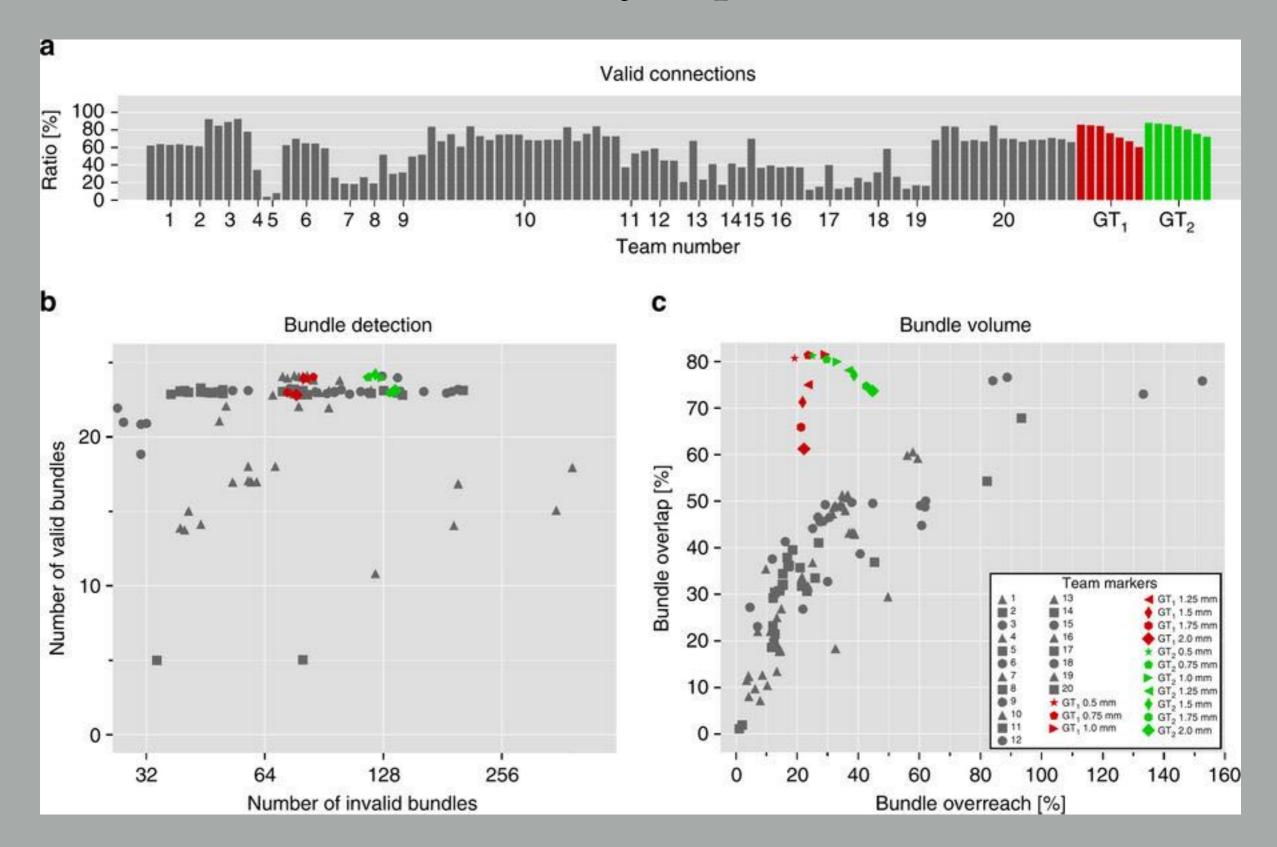
## Between-group differences in tractography reconstructions of VBs and IBs



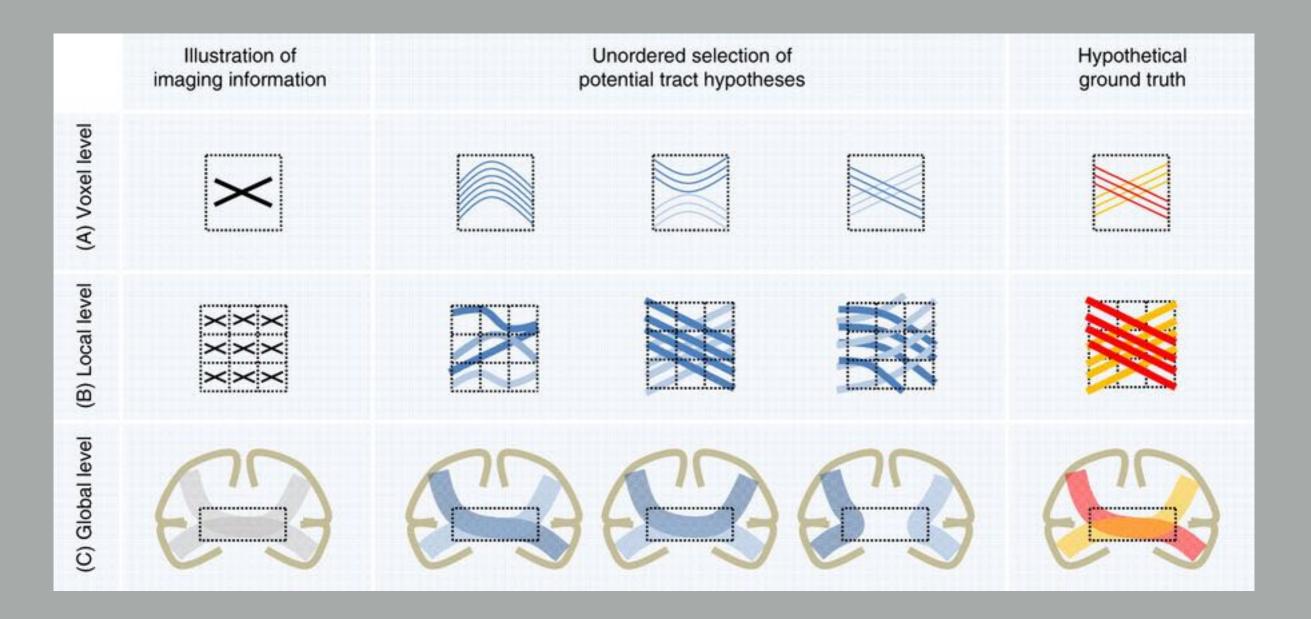
#### Overview of VBs and IBs and examples of invalid streamline clusters



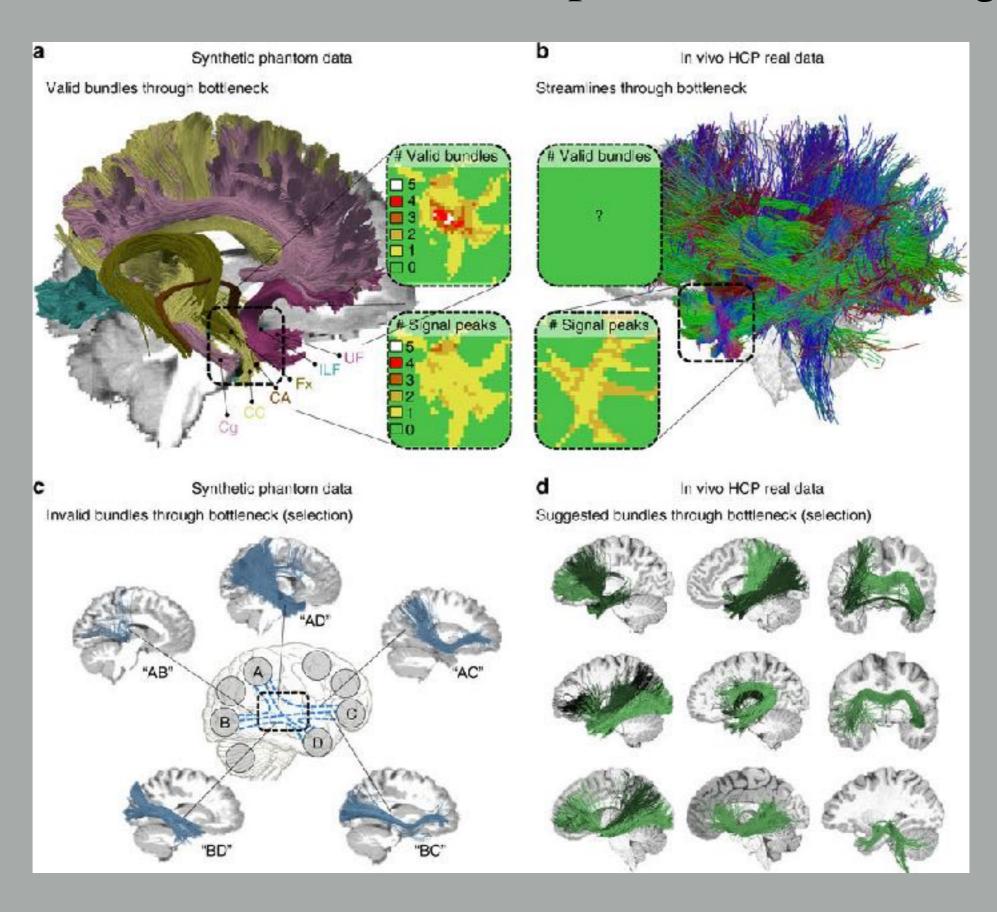
## Tractography on ground truth directions with no noise still affected by IB problem



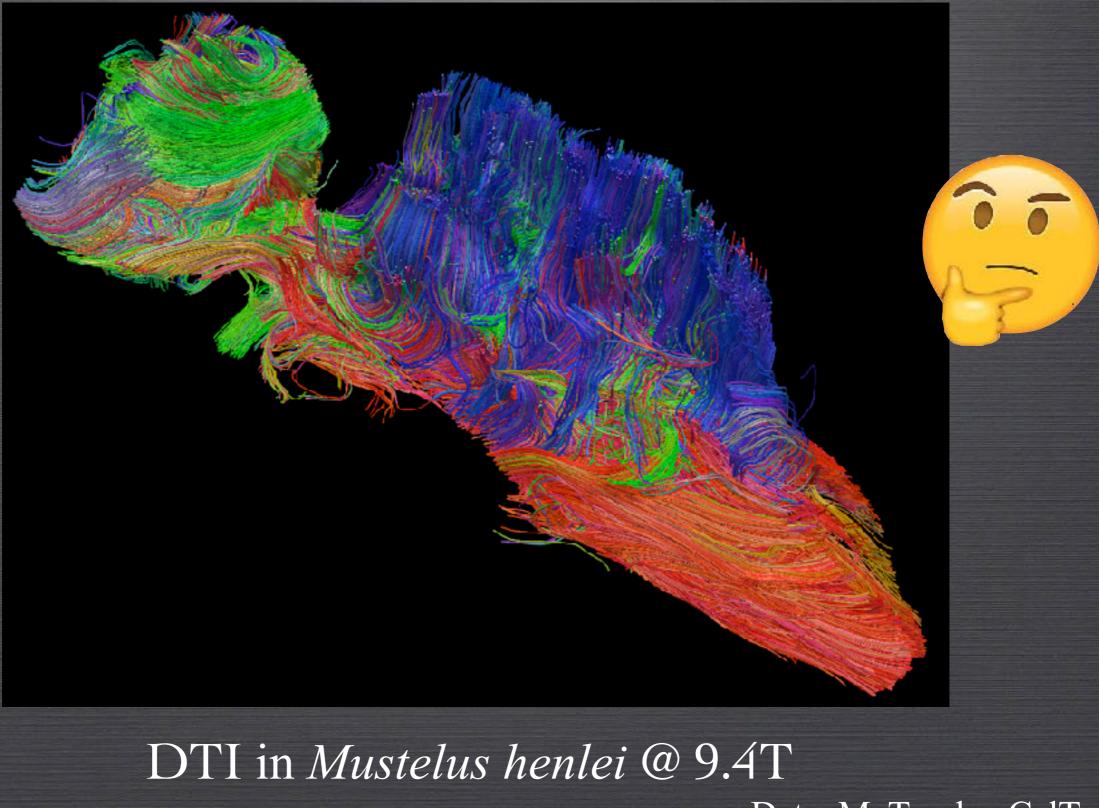
## Ambiguous correspondences between diffusion directions and fiber geometry



#### Bottlenecks and the fundamental ill-posed nature of tractography



## Is this correct??



Data: M. Tyszka, CalTech