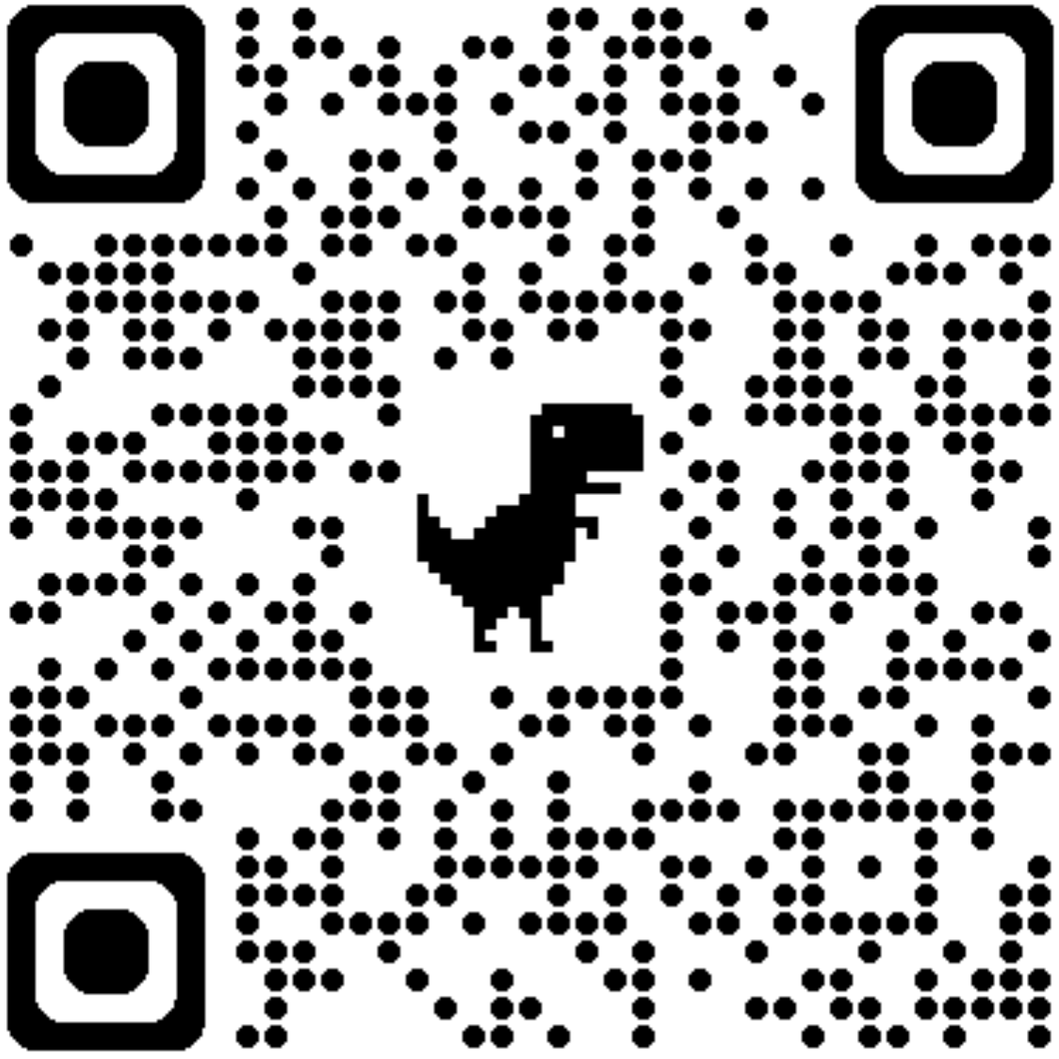
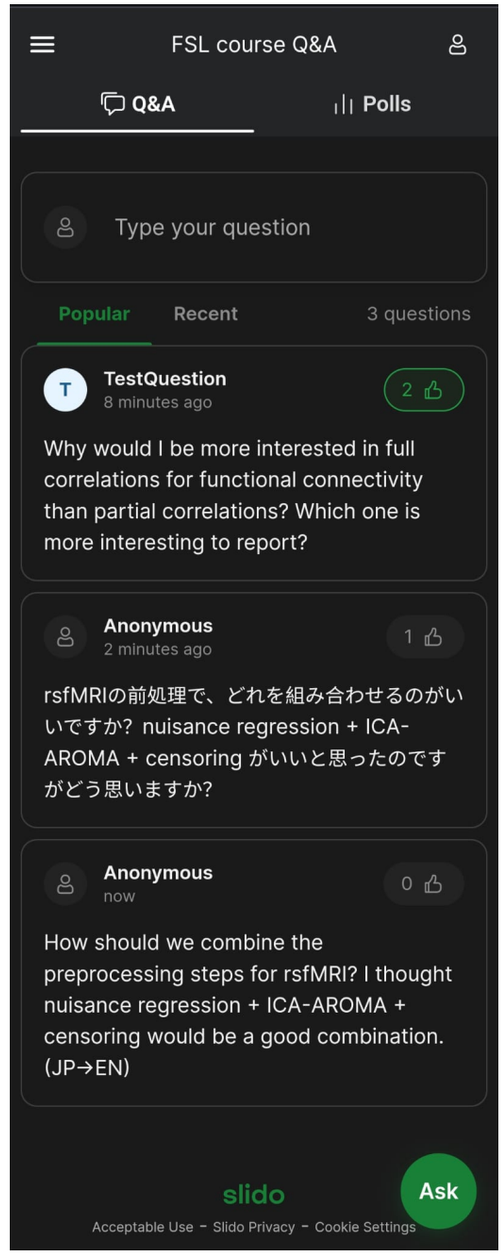
Diffusion MRI Processing and Analysis

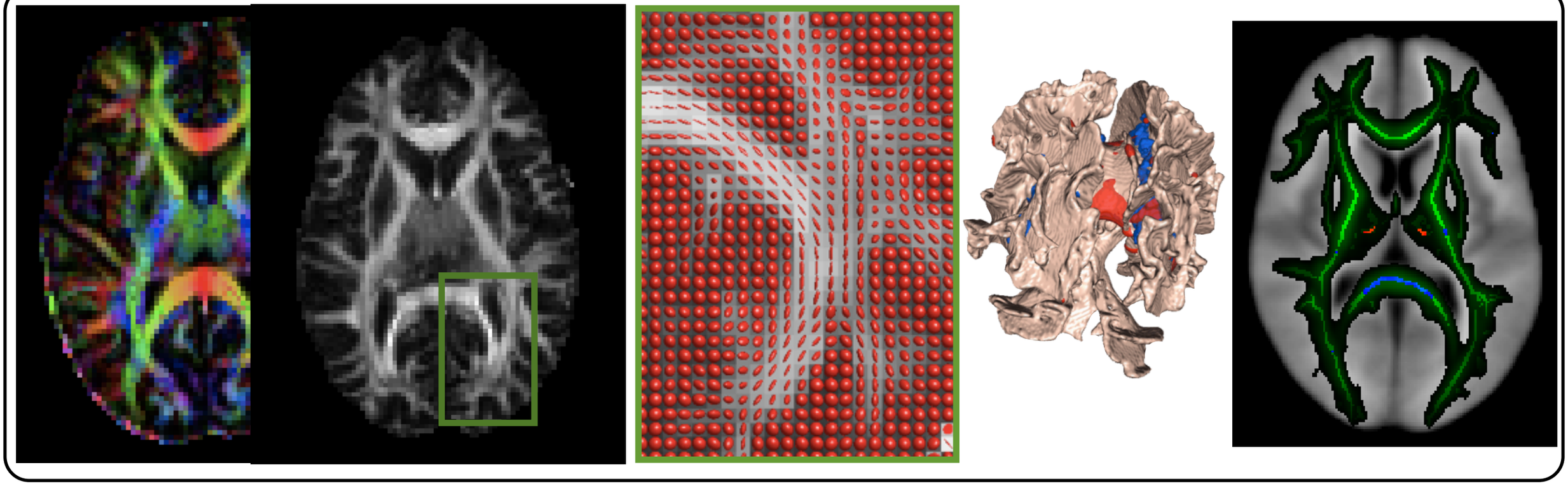
Submit your questions online





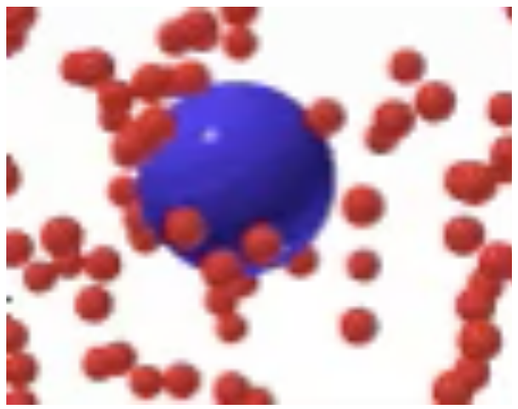
Overview

- What is Diffusion? Diffusion-weighting in MRI
- Diffusion Tensor Model and DTI
- Tract-Based Diffusion analysis (TBSS)
- Distortion Correction for Diffusion MRI



Diffusion - Brownian Motion

Robert Brown (1773-1858)



Molecules are in constant motion at non-zero absolute temperatures (> -273^{o} C)

Diffusion = thermally-driven random motion

Diffusion - Brownian Motion

Albert Einstein (1879-1955)

How can we describe this motion?
For an ensemble of molecules, in *n*-dimensional space:

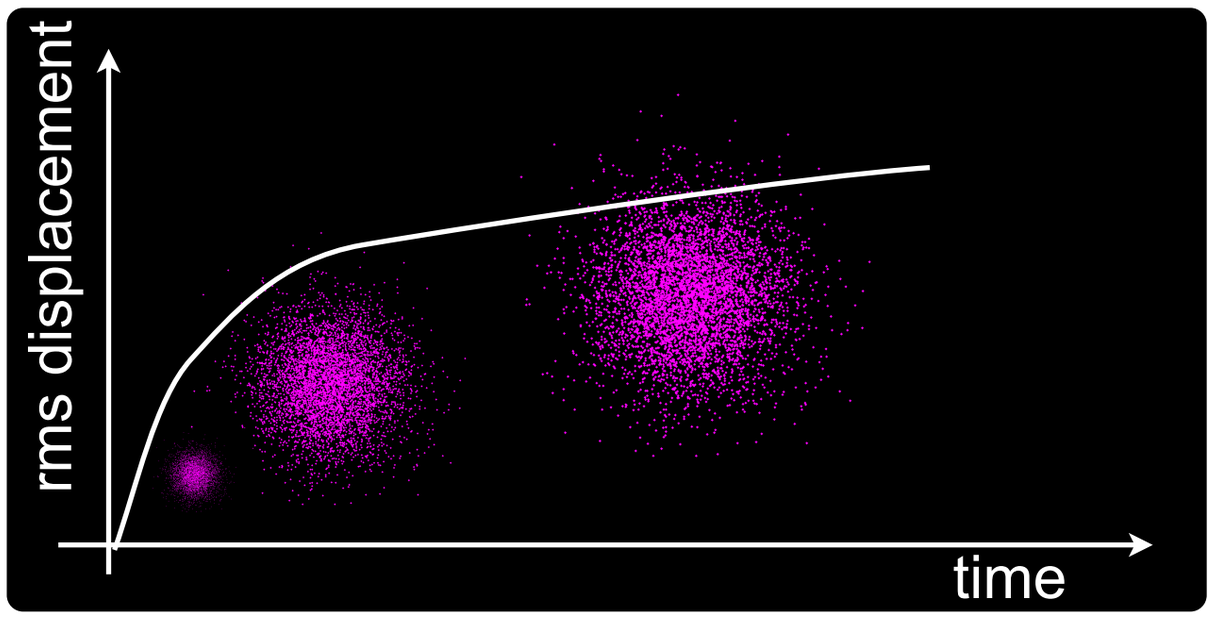
$$< x^2 >= 2nDt$$

mean squared displacement

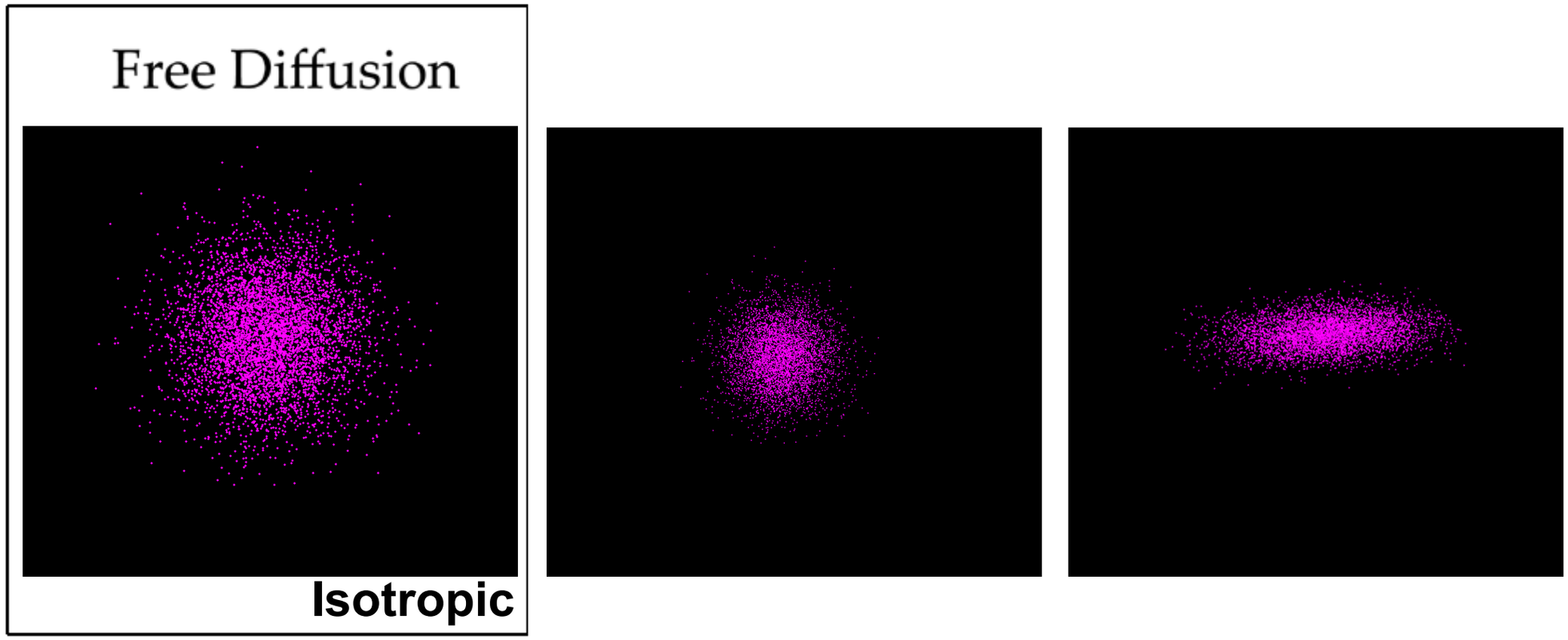
Diffusion coefficient

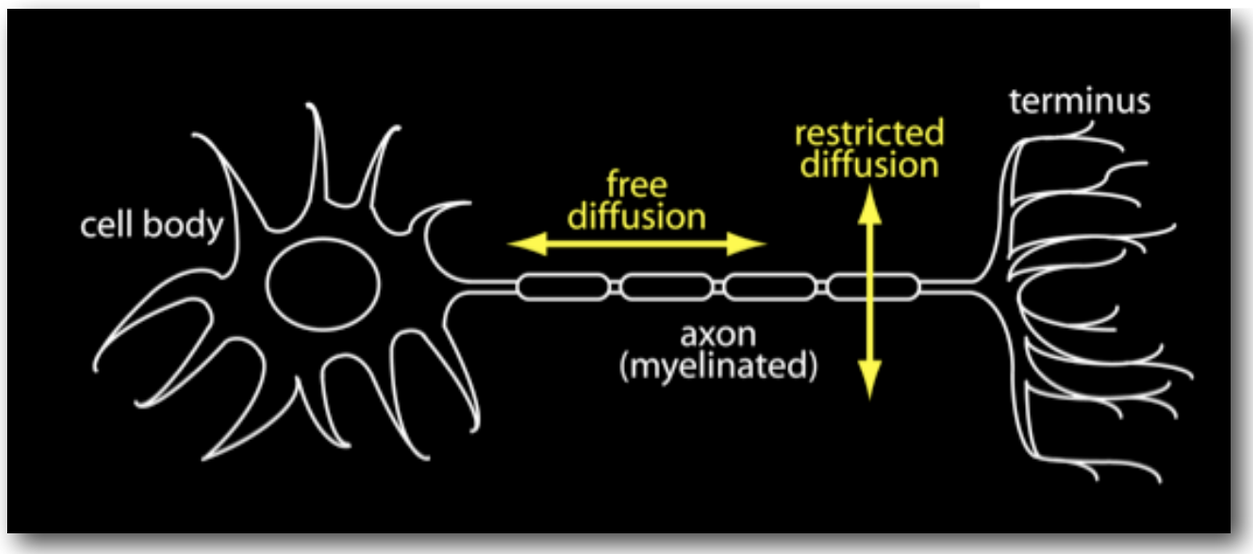
time

Valid for a homogeneous, barrier-free medium.



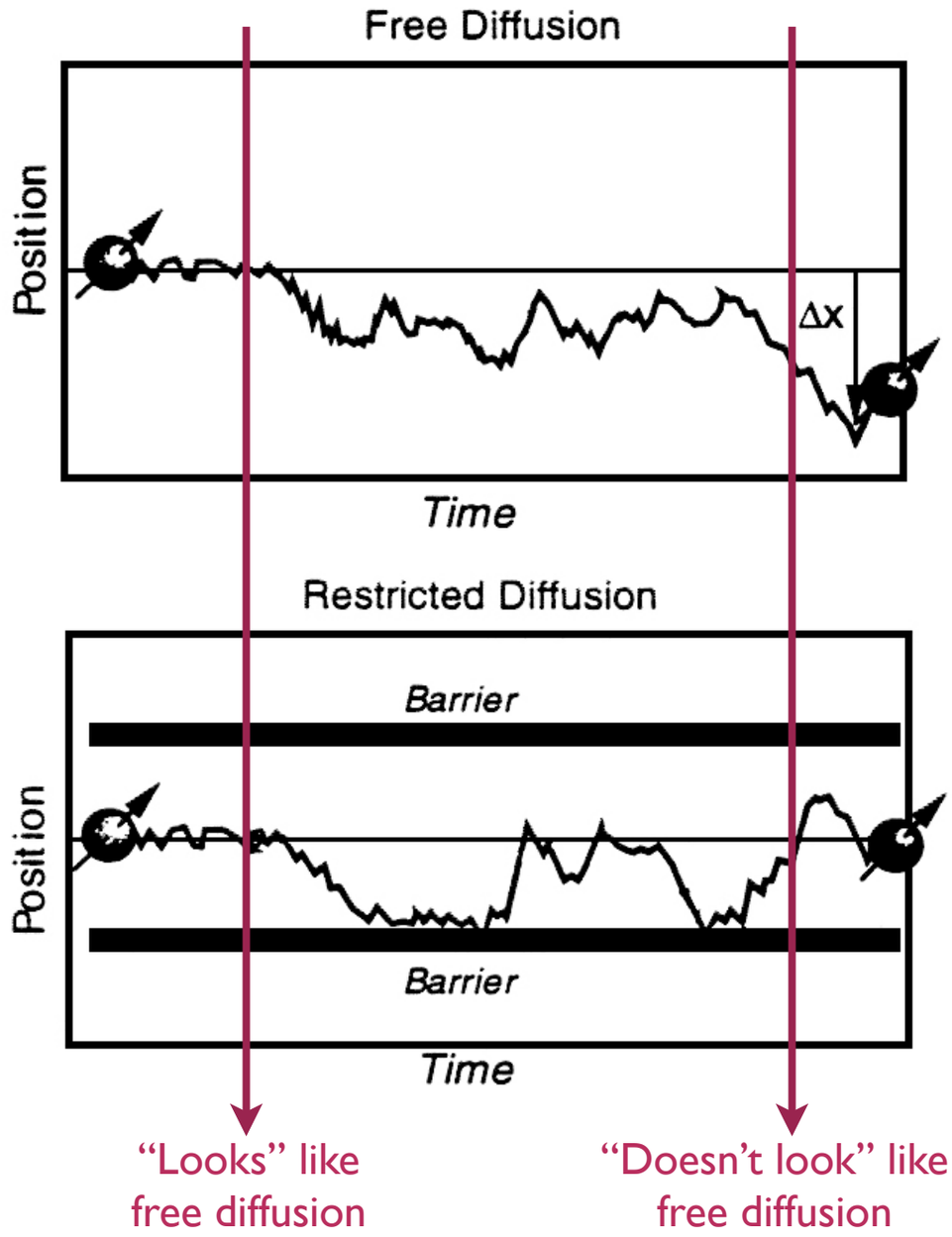
Water Diffusion in the Brain. Why is it Interesting?





Diffusion is restricted by tissue boundaries, membranes, etc.
Marker for tissue microstructure (healthy and pathology)
Diffusion is **anisotropic** in white matter [Beaulieu, NMR Biomed, 2002]

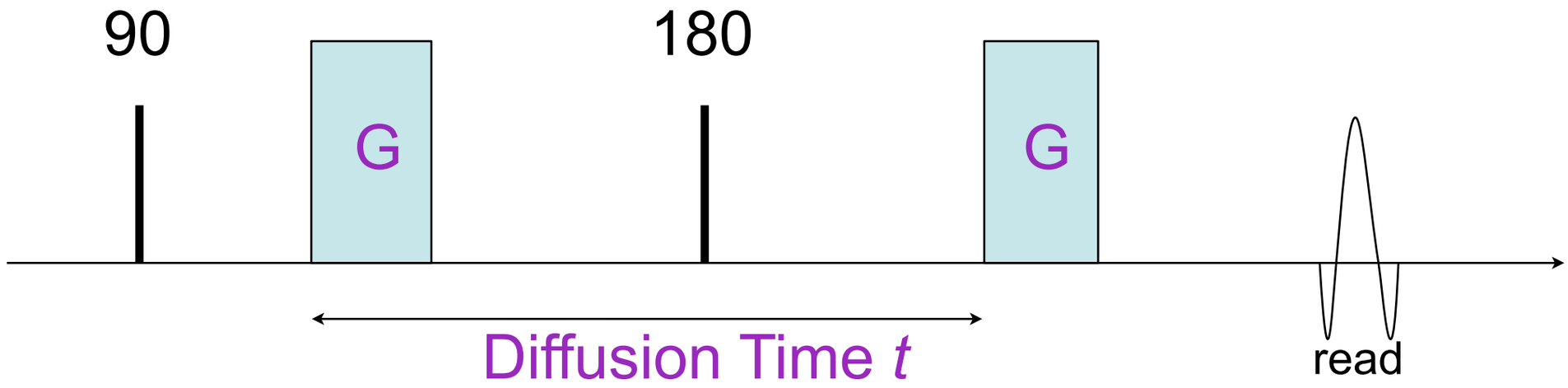
Apparent Diffusion



Observed diffusion in tissues depends on the experiment =
"Apparent diffusion" &
"Apparent diffusion coefficient" (ADC)

Measuring Diffusion with MRI: Diffusion MRI (dMRI)

Pulsed-Gradient Spin-Echo Sequence:
To achieve diffusion-weighting along a direction **x**, apply strong magnetic field gradients along **x**.



If particles diffuse along **x** during the allowed time (DiffTime), a signal attenuation is observed, compared to the signal with G=0.

[Stejskal & Tanner, 1965]

Measuring Diffusion with MRI: Diffusion MRI (dMRI)

Pulsed-Gradient Spin-Echo Sequence:
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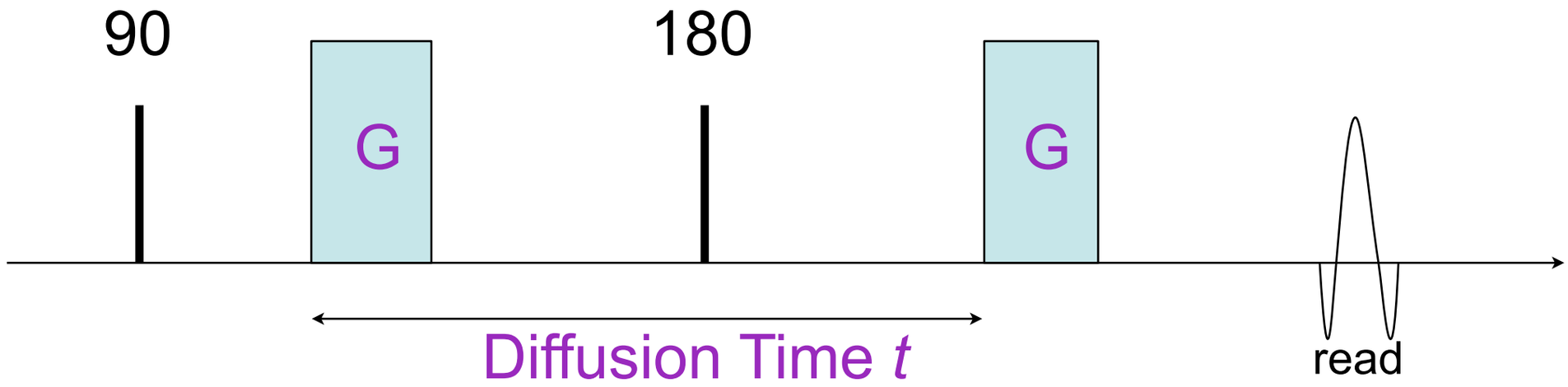


D ~ 2.4 μm²/ms
t~50ms

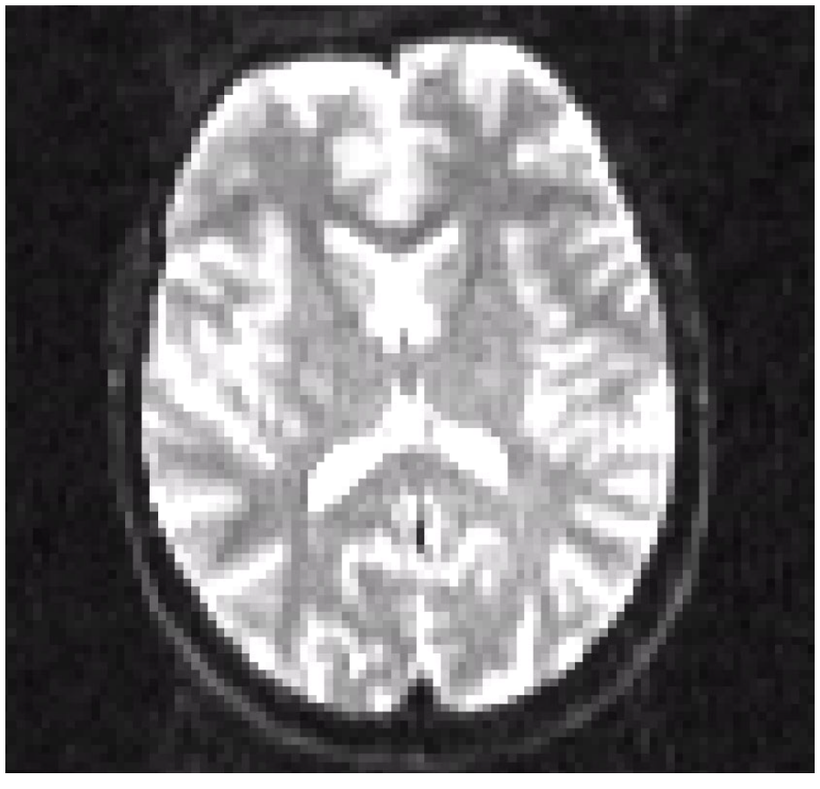
$x=\sqrt{6Dt}$ *~27μm*

st. deviation of displacements

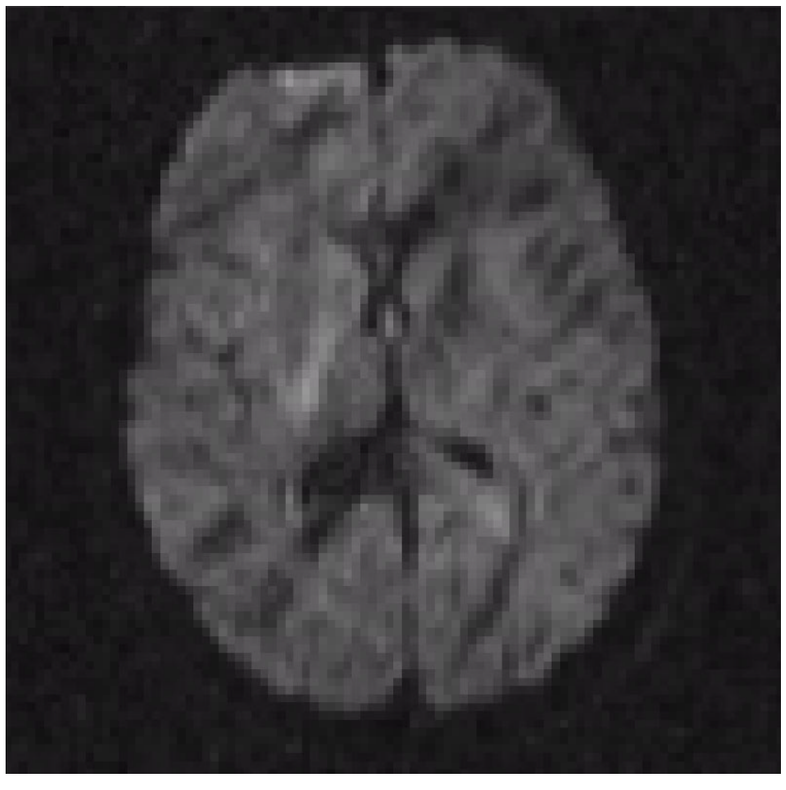
[Stejskal & Tanner, 1965]

Measuring Diffusion with MRI: Diffusion MRI (dMRI)

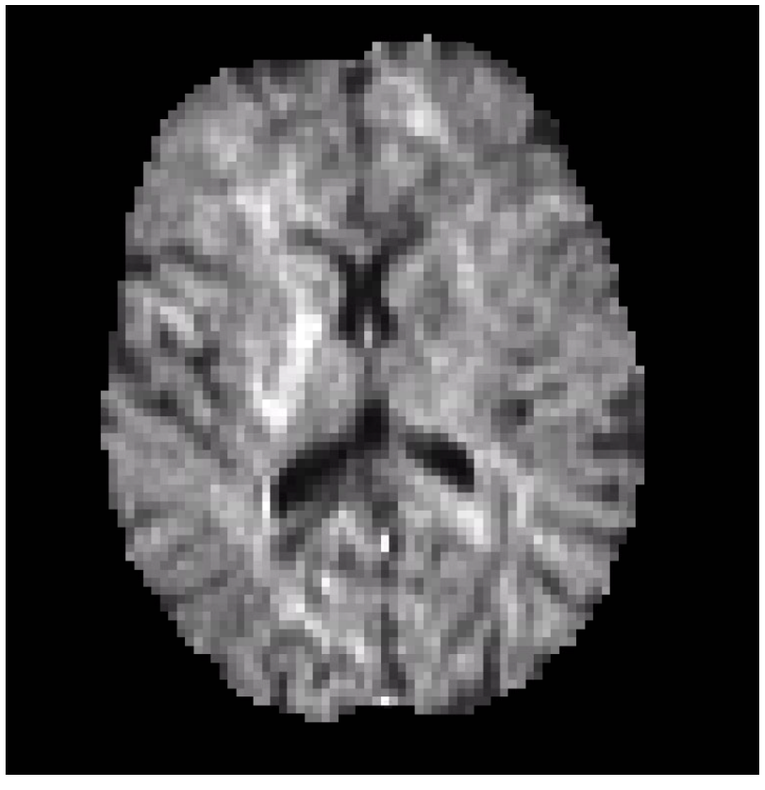
T2w Image
No Diffusion-weighting
(G=0)
S_0



Diffusion-weighted
Image
S



Ratio
S/S_0



Removes T2w contrast

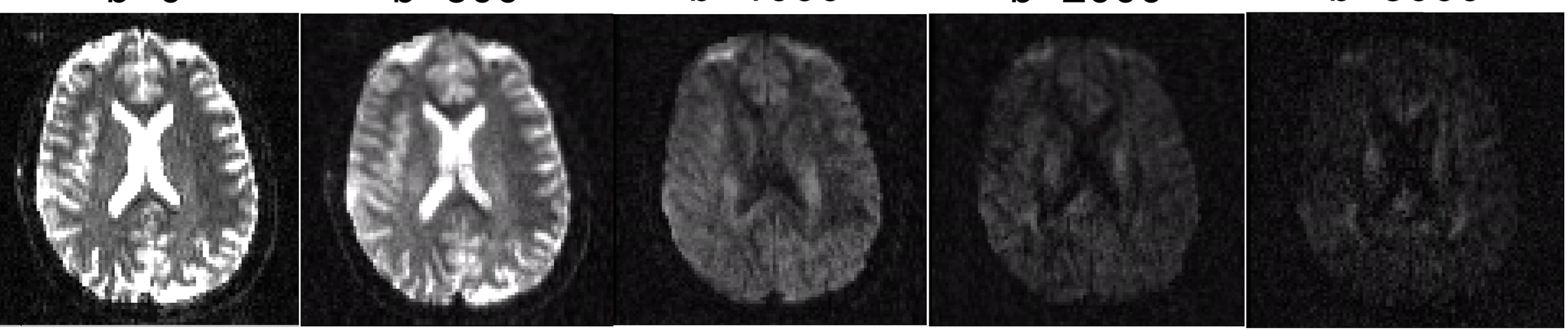
Measuring Diffusion with MRI:
Diffusion MRI (dMRI)

Diffusion contrast can be modulated by:

A) Diffusion weighting: Gradient **strength,** Diffusion **time**

b value ~ G^2 . DiffTime (units in s/mm^2)

b=0 b=300 b=1000 b=2000 b=3000



More diffusion contrast with higher b :)

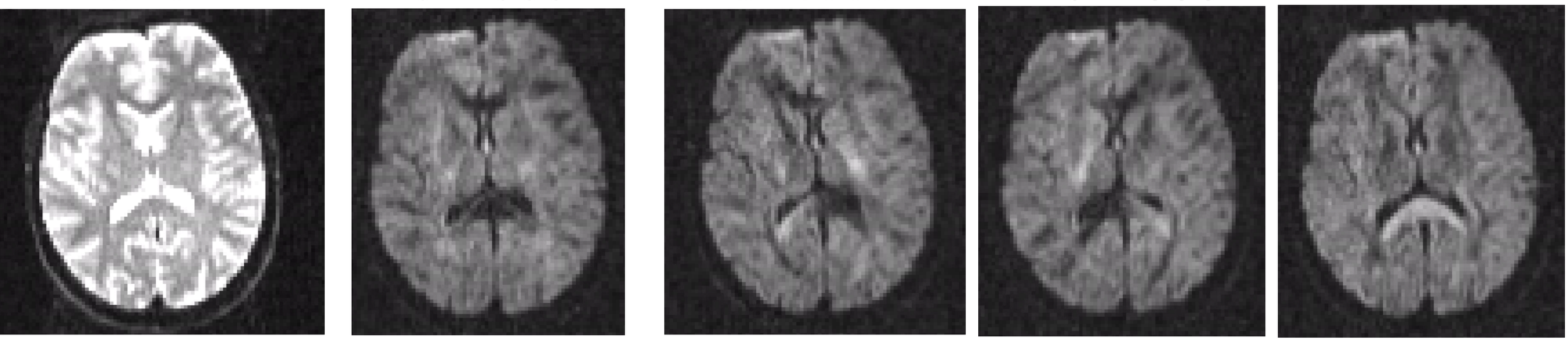
…But less signal left - exponential decay :(

Measuring Diffusion with MRI: Diffusion MRI (dMRI)

Diffusion contrast can be modulated by:

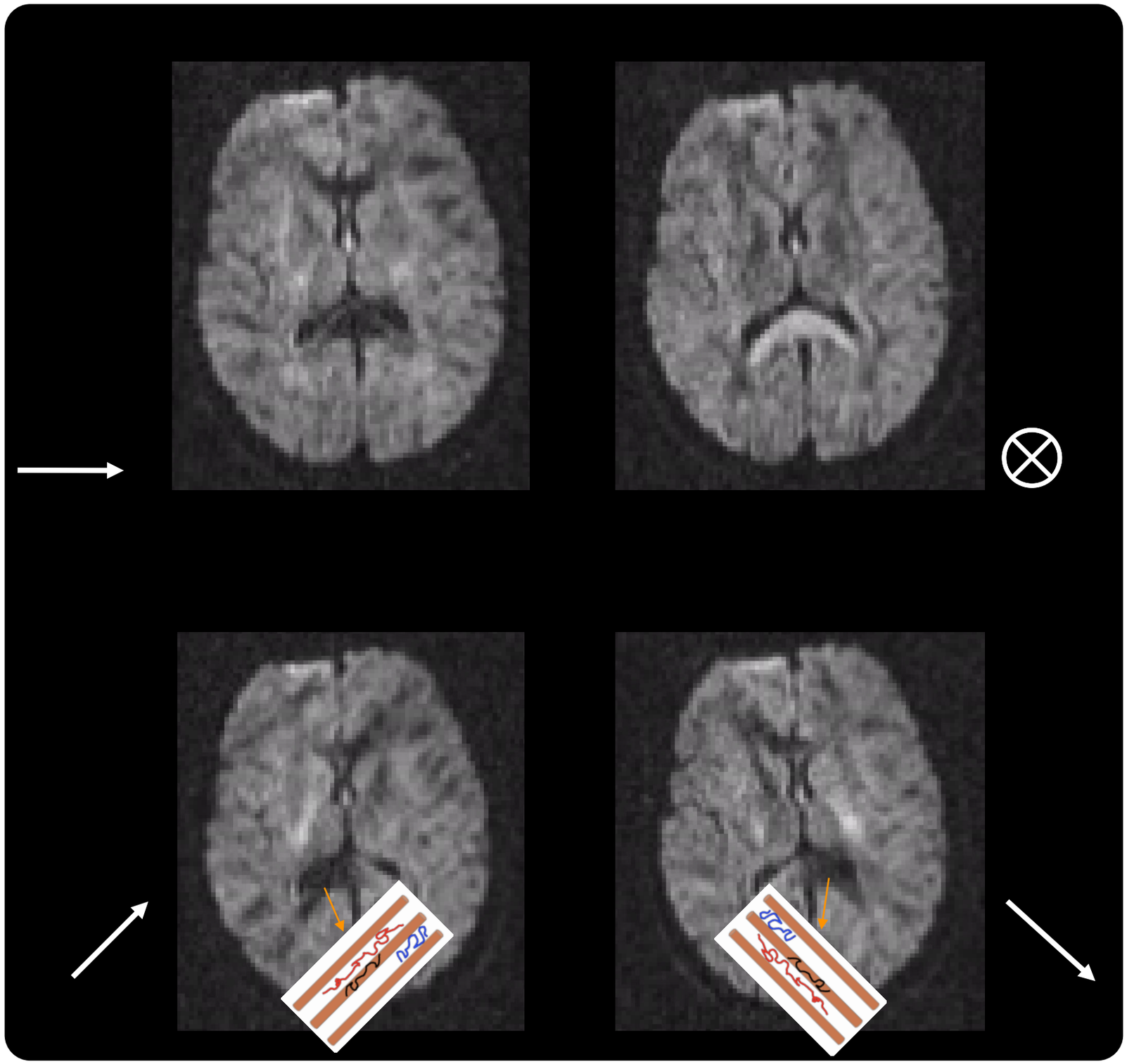
B) Gradient Direction x

b=0 b=1000 b=1000 b=1000 b=1000



x x x x

Orientation Contrast in dMRI



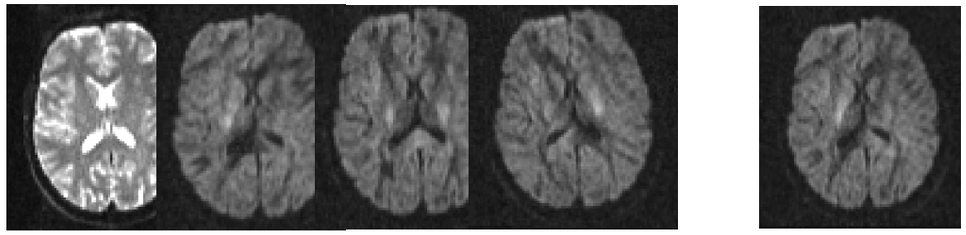
Because diffusion is anisotropic in WM, applying a gradient G along different directions **x**, gives different contrast in WM.

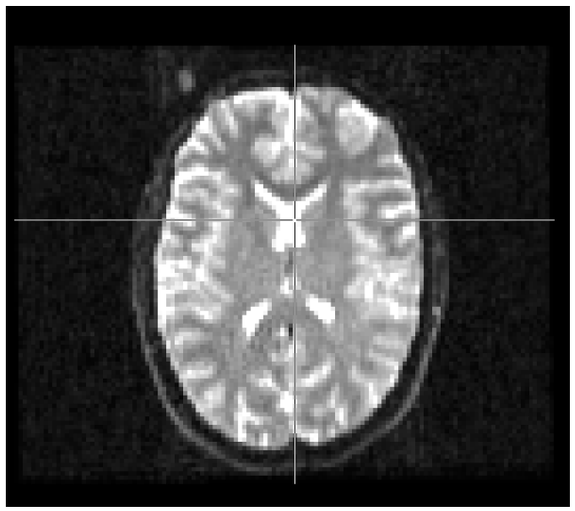
Anisotropic measurements in WM!

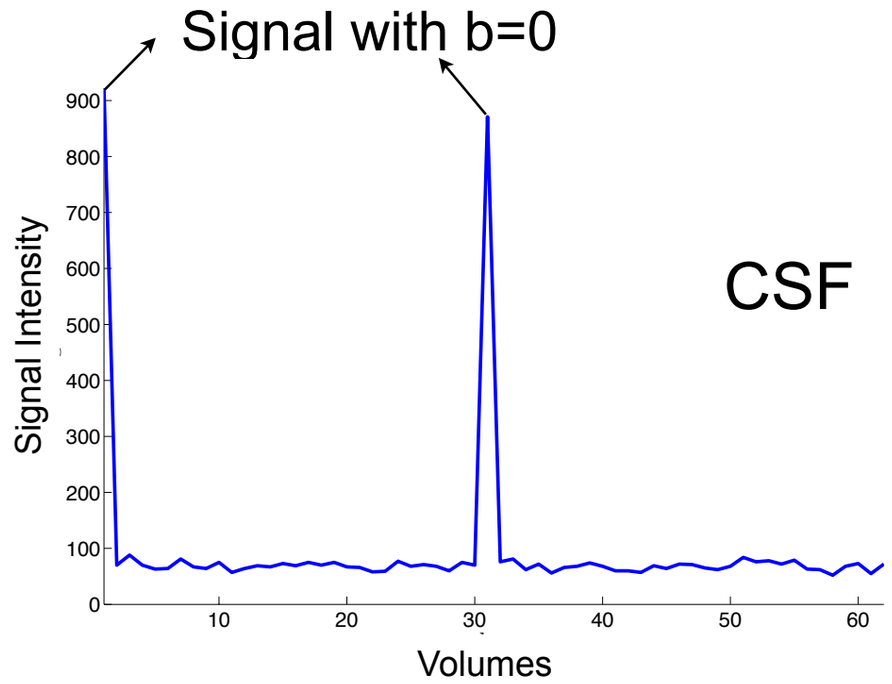
Roughly **Isotropic** in GM and CSF.

A Typical dMRI Protocol

- Normally a few (at least one) b=0 volumes acquired, along with shells at higher b (~1000 s/mm^2).
- A shell is a set of volumes acquired with the same b-value, but different gradient orientation

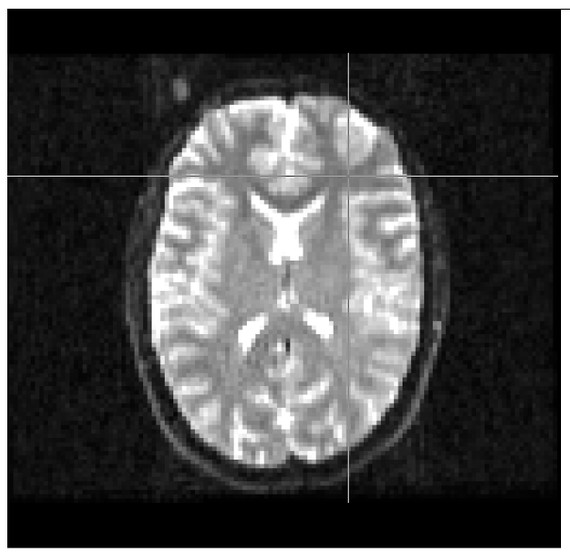


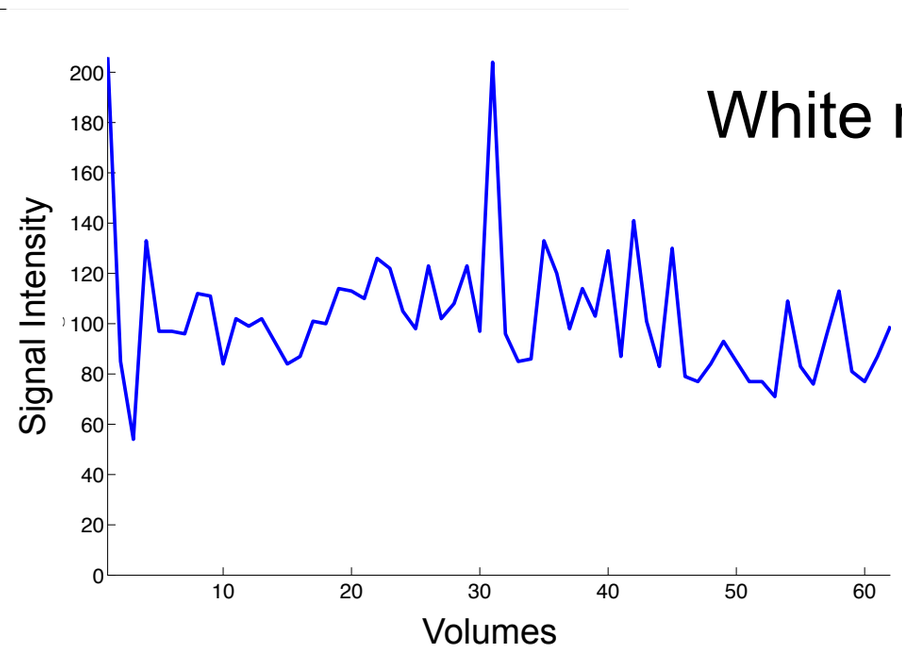




CSF

relates to ADC





White matter

relates to anisotropy

dMRI Summary

- Images acquired with a Gradient along **x**, have contrast that is sensitive to diffusion of water molecules along **x**.

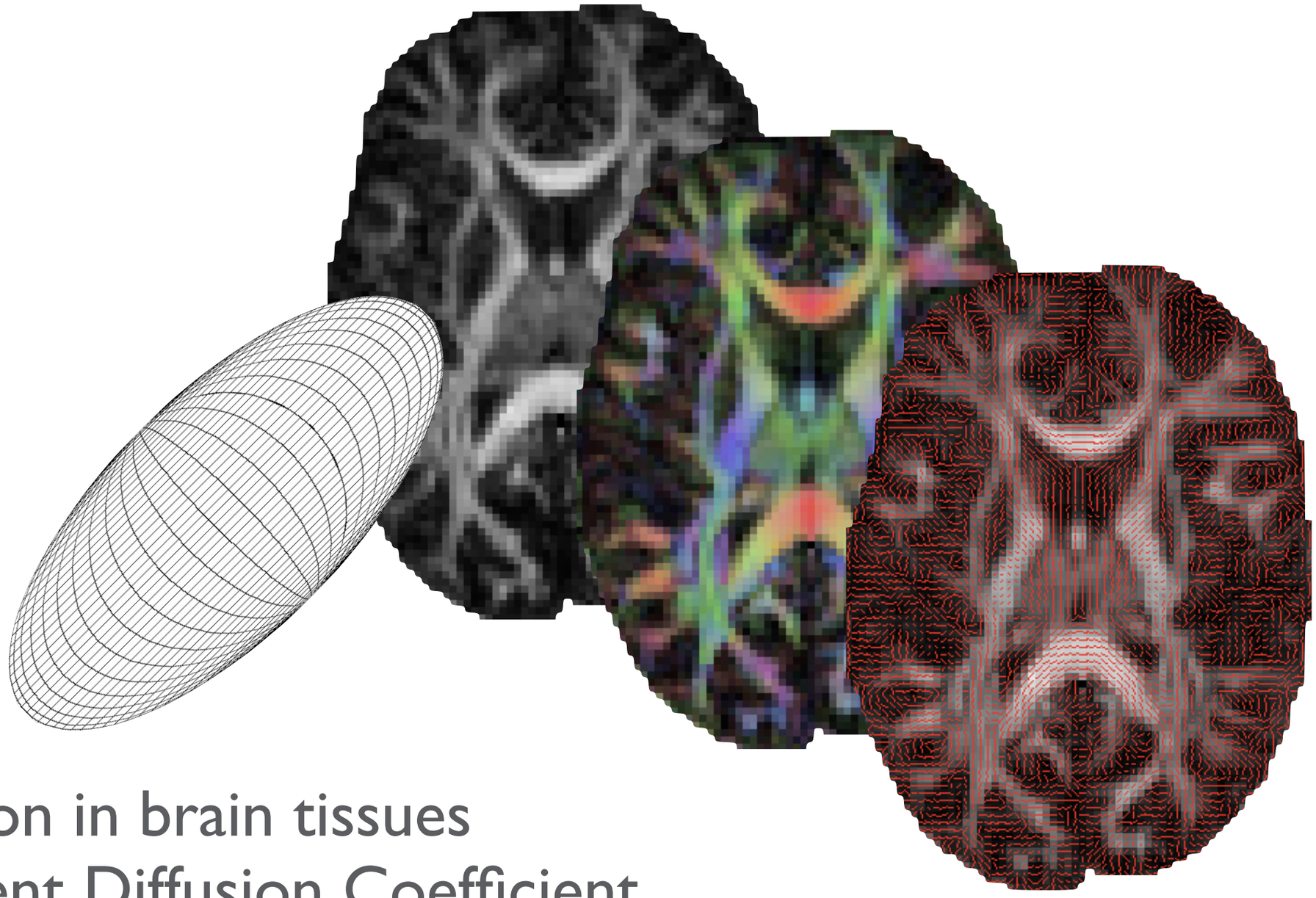
- Images acquired with higher b-values (stronger gradient/ longer diffusion time) are more sensitive to diffusion along **x**.

- When diffusion occurs, signal is attenuated compared to the one with no diffusion-weighting.

- In WM, measurements are anisotropic.

- In GM and CSF, measurements are roughly isotropic.

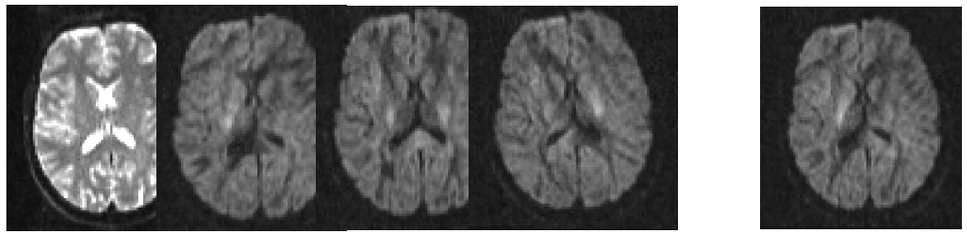
Diffusion Tensor Imaging - basic principles



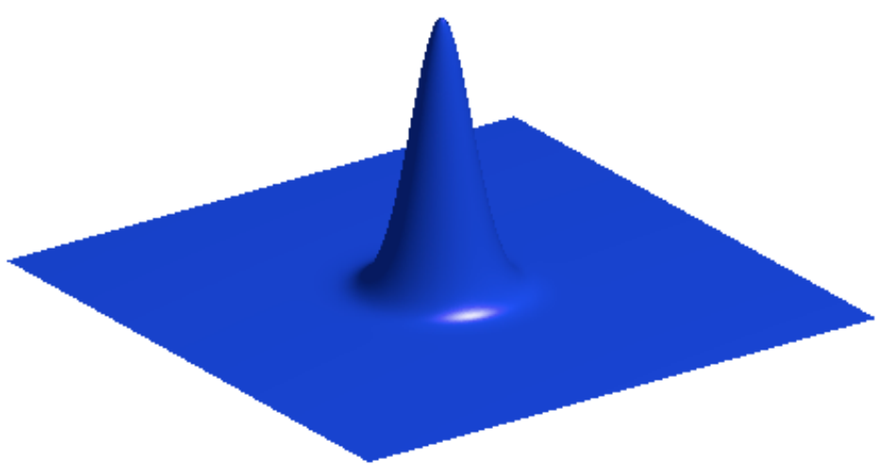
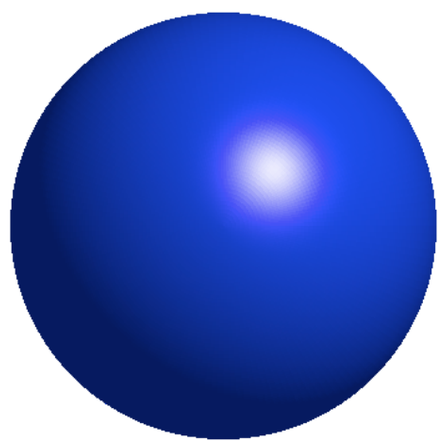
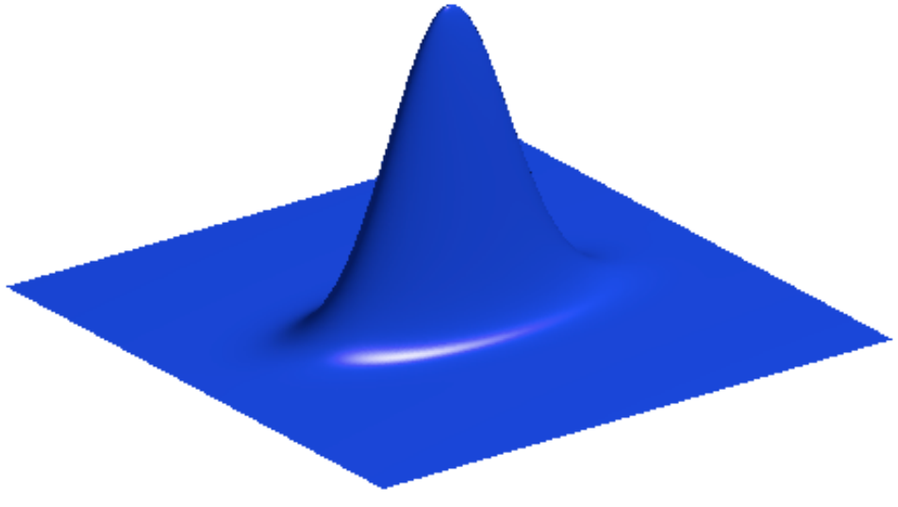
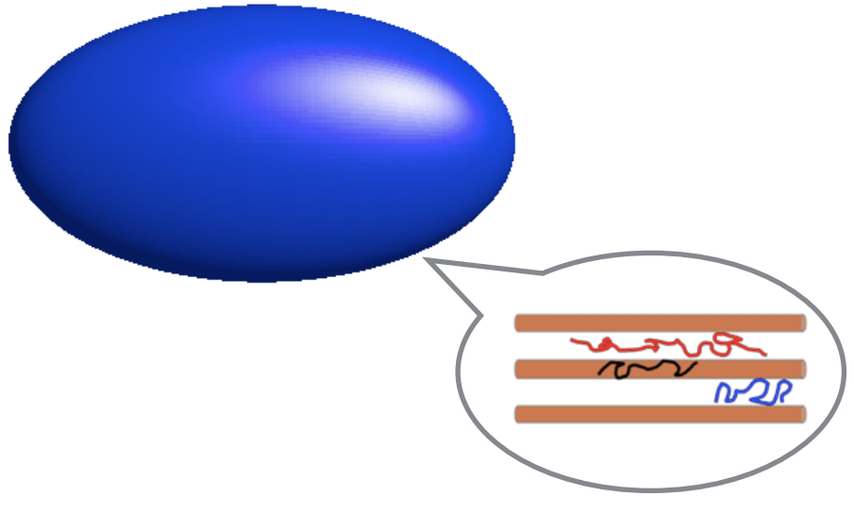
- Diffusion in brain tissues
- Apparent Diffusion Coefficient
- Diffusion Tensor model
- Tensor-derived measures

Diffusion Tensor Imaging (DTI)

- Apply **the diffusion tensor model** to a set of dMRI images.



Diffusion Tensor Imaging (DTI)

	Two dimensions	Three dimensions
Scalar D (same D for all directions)		
Tensor **D** - DTI (D can be different for different directions)		

Diffusion Tensor Imaging (DTI)

Diffusion Tensor Model. In each voxel:

b-value for gradient *j* (known)

Unit vector representing the direction of gradient *j* (known)

$$S_j = S_0 \exp(-b_j \, \boldsymbol{x}_j^T \, \boldsymbol{D} \, \boldsymbol{x}_j)$$

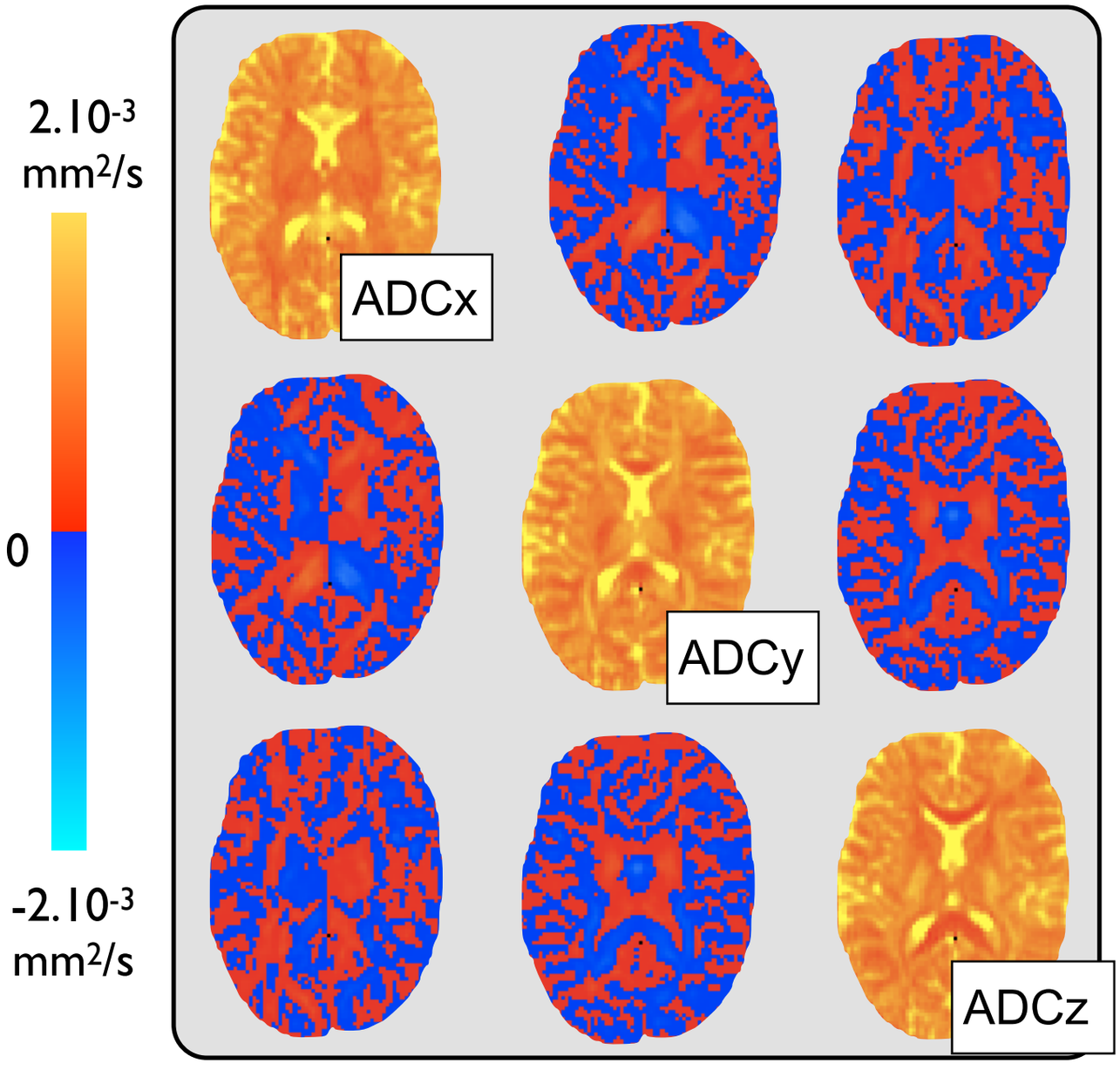
Signal measured after applying a Gradient *j* with direction $\boldsymbol{x}_j$ and b-value b_j (measured)

Signal measured with no diffusion gradient applied (measured)

3x3 Diffusion Tensor (unknown)

[Basser, Biophys J,1994], [Basser et al , J Magn Res, 1994]

The Elements of the Diffusion Tensor



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

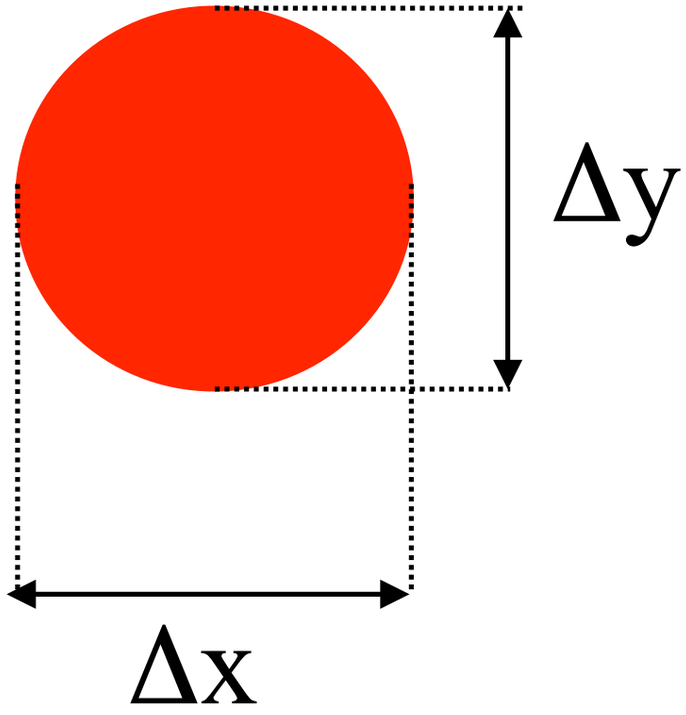
- Tensor is **symmetric** (6 unknowns)

- **Diagonal Elements** are proportional to the diffusion displacement variances (**ADCs**) along the three directions of the experiment coordinate system

-**Off-diagonal Elements** are proportional to the **correlations** (covariances) of displacements along these directions

N_3 (0, 2t**D**)

Why do we need a tensor?



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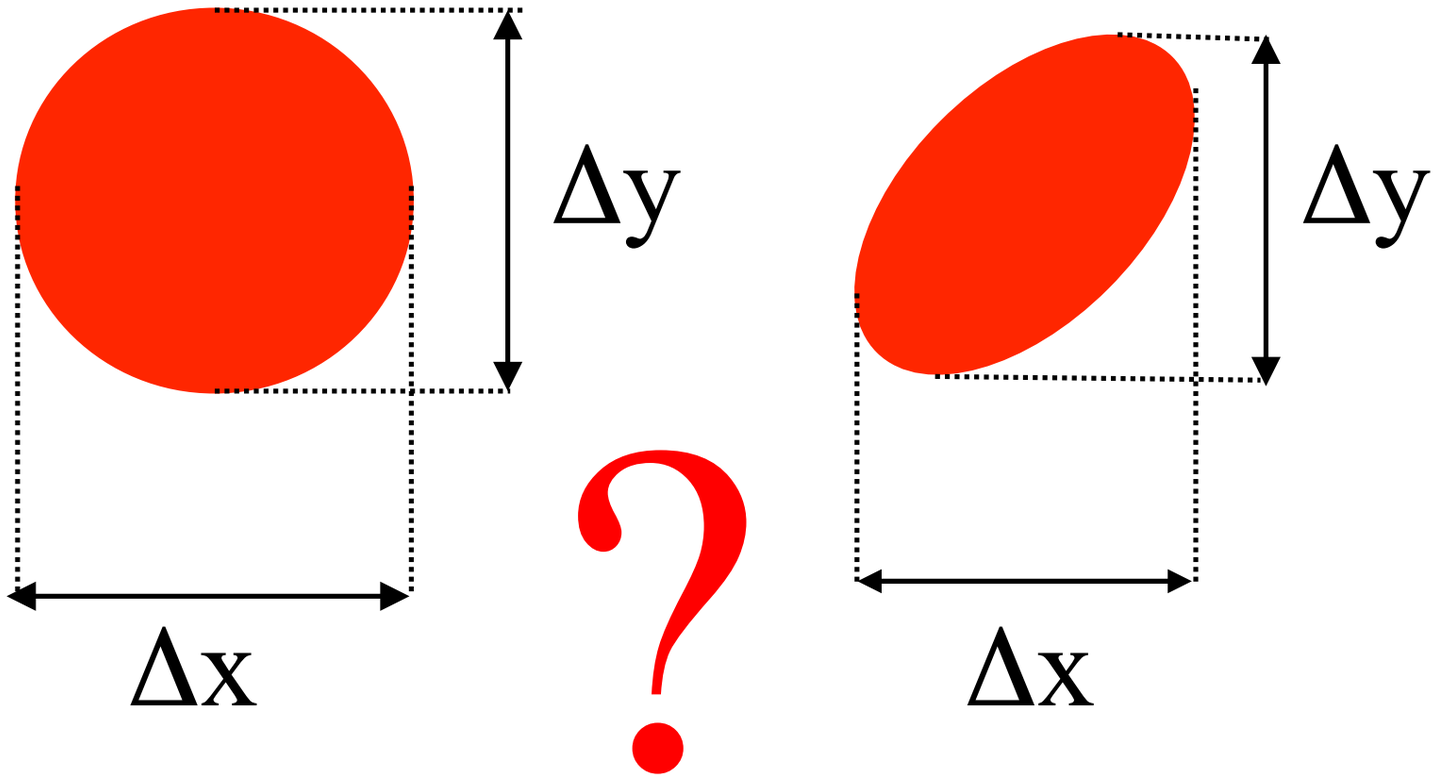

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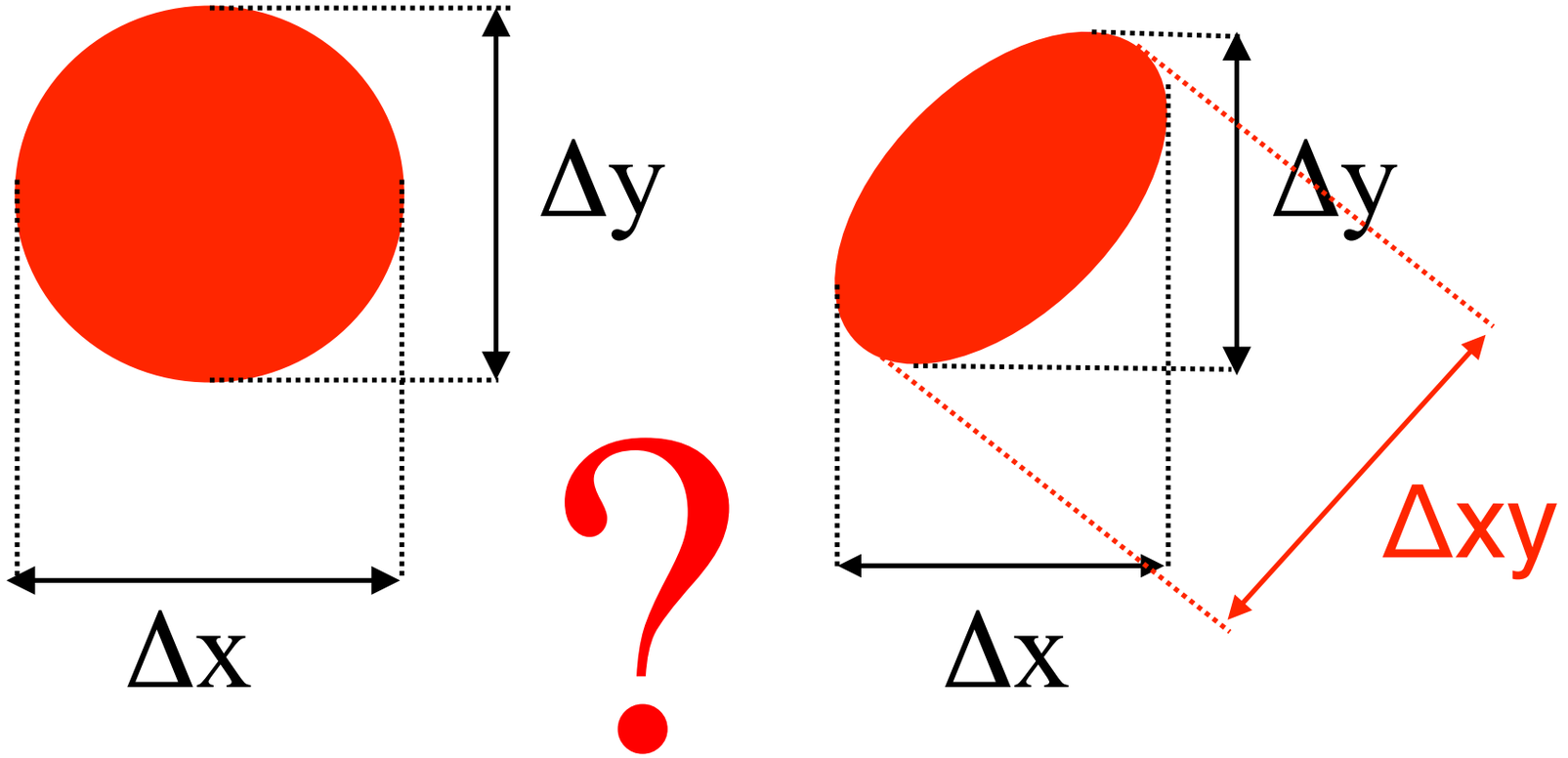
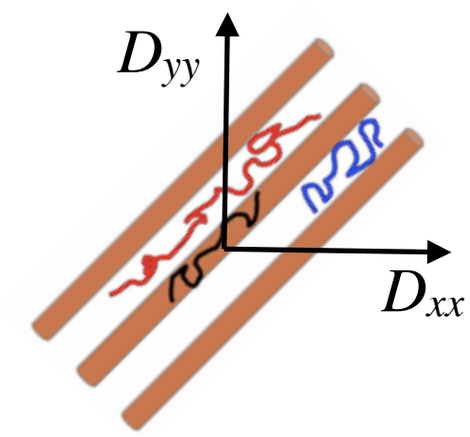


$$\begin{bmatrix} D_x & D_{xy} \\ D_{xy} & D_y \end{bmatrix}$$

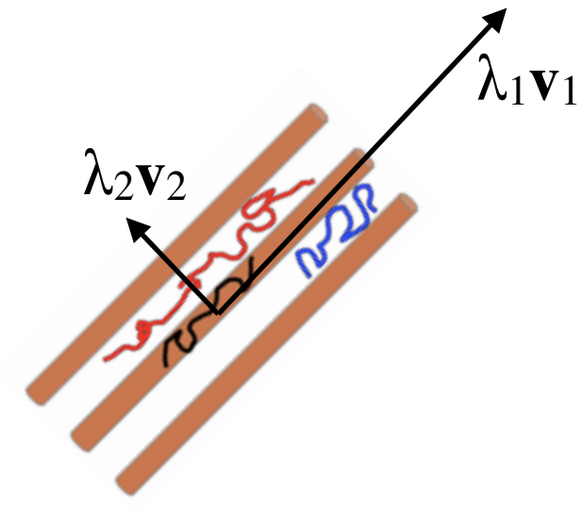
The Diffusion Tensor Eigenspectrum

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



Once D is estimated, we get ADCs along the scanner's coordinate system. But we want ADCs along a local coordinate system in each voxel, determined by the anatomy.

Diagonalize the estimated tensor in each voxel



$$\mathbf{D} = [\mathbf{v_1}|\mathbf{v_2}|\mathbf{v_3}]^{\mathrm{T}} \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix} [\mathbf{v_1}|\mathbf{v_2}|\mathbf{v_3}]$$

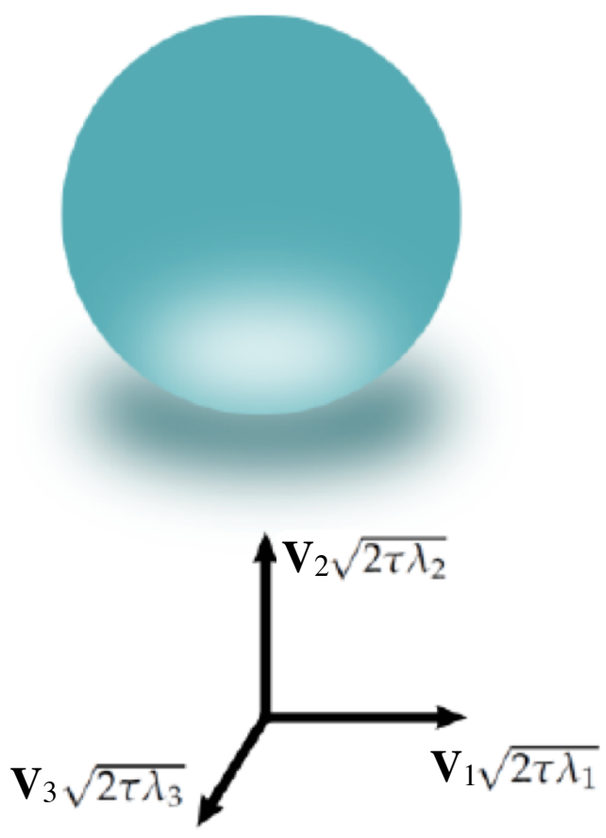
eigenvectors - $\mathbf{v}_1$=direction of max diffusivity

eigenvalues: ADCs along $\mathbf{v}_1$,$\mathbf{v}_2$,$\mathbf{v}_3$

The Diffusion Tensor Ellipsoid

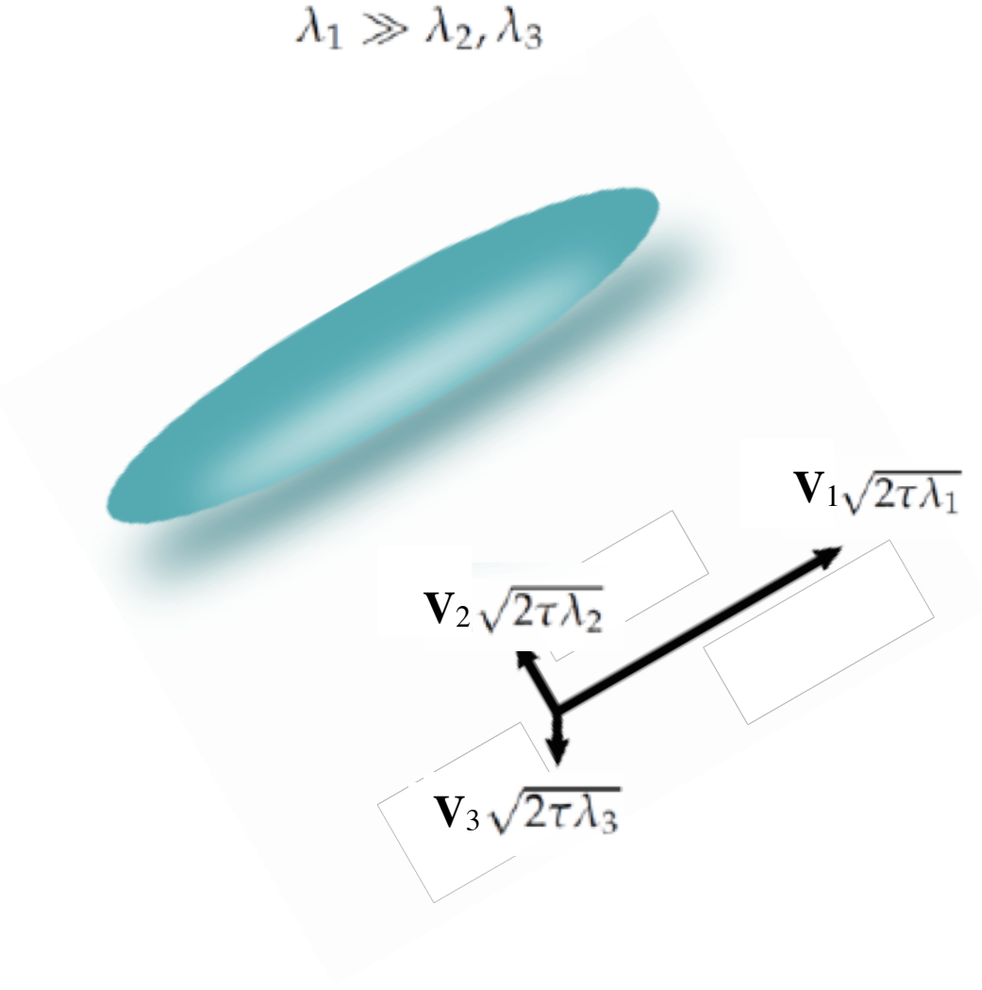
Isotropic voxel

$\lambda_1 \approx \lambda_2 \approx \lambda_3$

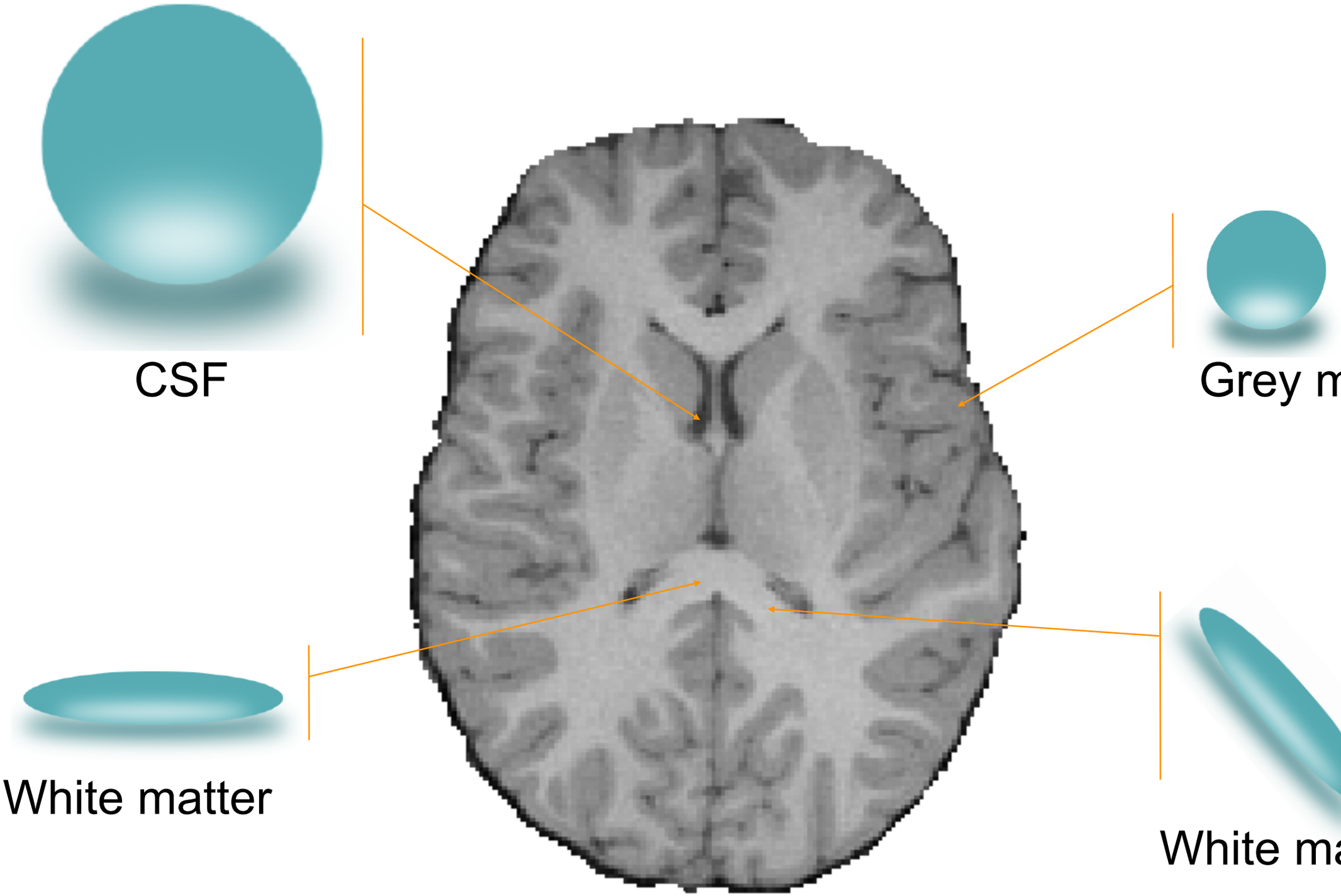


Anisotropic voxel

$\lambda_1 \gg \lambda_2, \lambda_3$



The Diffusion Tensor Ellipsoid



Quantitative Diffusion Maps

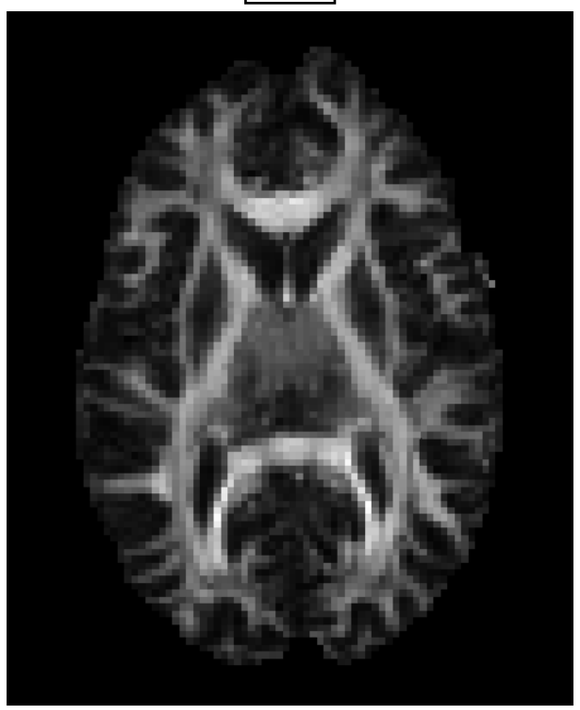
Fractional Anisotropy (FA) ~ Eigenvalues Variance (normalised)
Mean Diffusivity (MD) = Eigenvalues Mean

$$FA = \sqrt{\frac{3\sum_{i=1}^{3}(\lambda_i - \overline{\lambda})^2}{2\sum_{i=1}^{3}\lambda_i^2}}, \qquad FA \text{ in } [0,1]$$

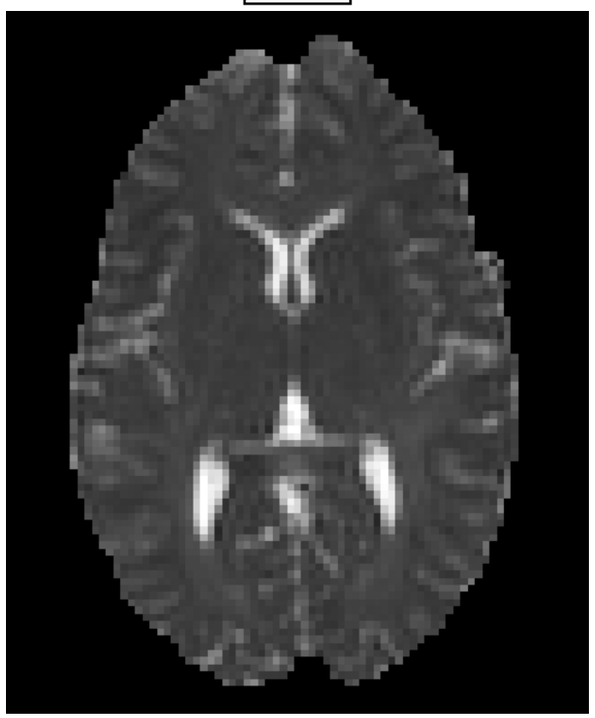
$$MD = \frac{D_{xx} + D_{yy} + D_{zz}}{3} = \frac{\lambda_1 + \lambda_2 + \lambda_3}{3}$$

Quantitative Diffusion Maps

FA

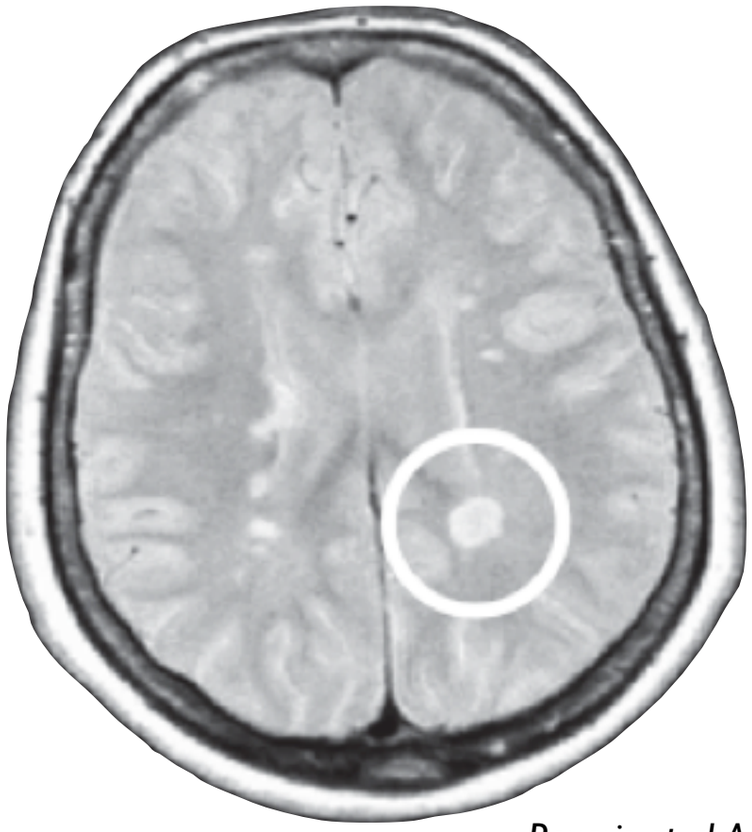


MD

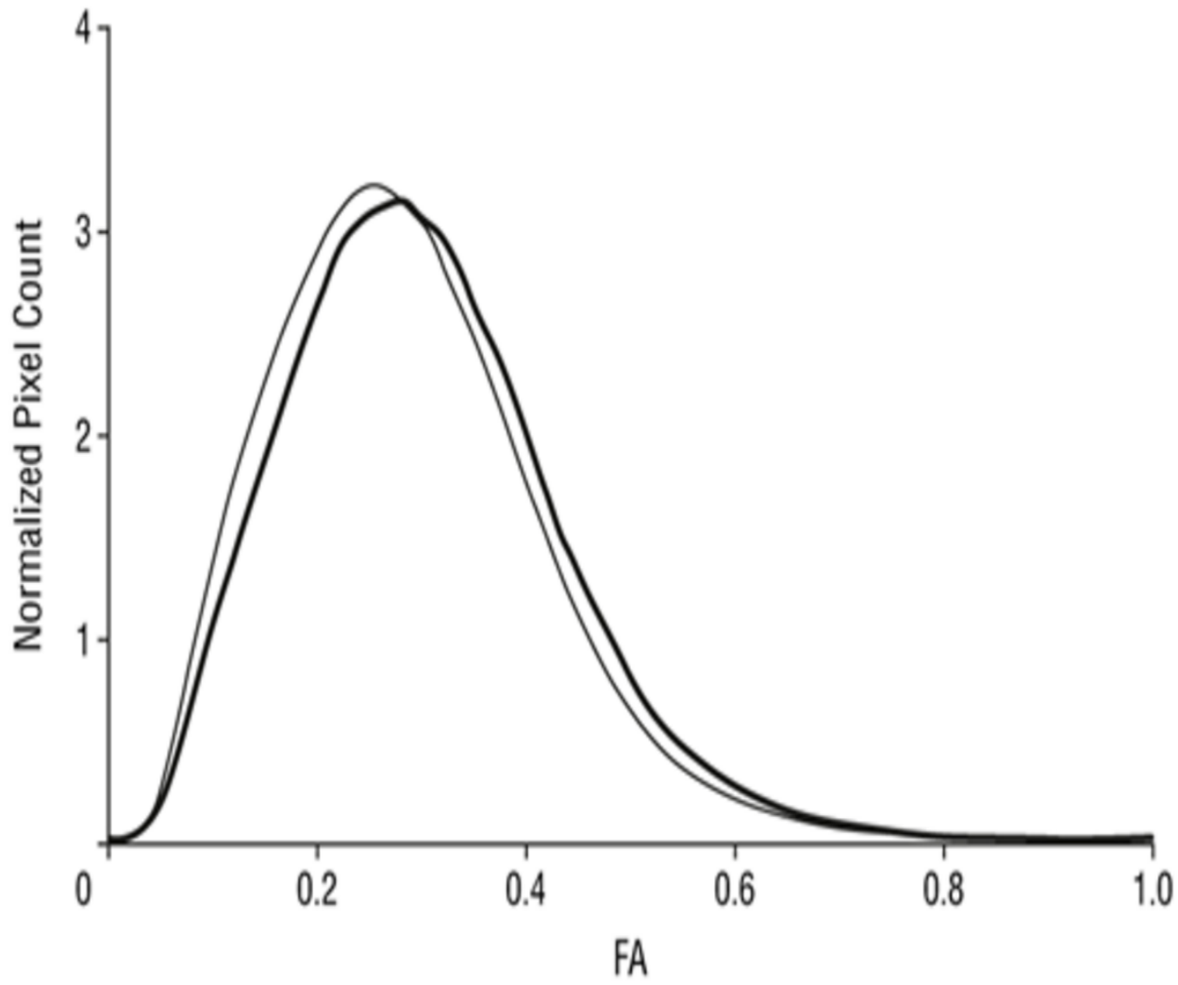


Quantitative Diffusion Maps

FA decrease/ MD increase has been associated in many studies with tissue breakdown (loss of structure).



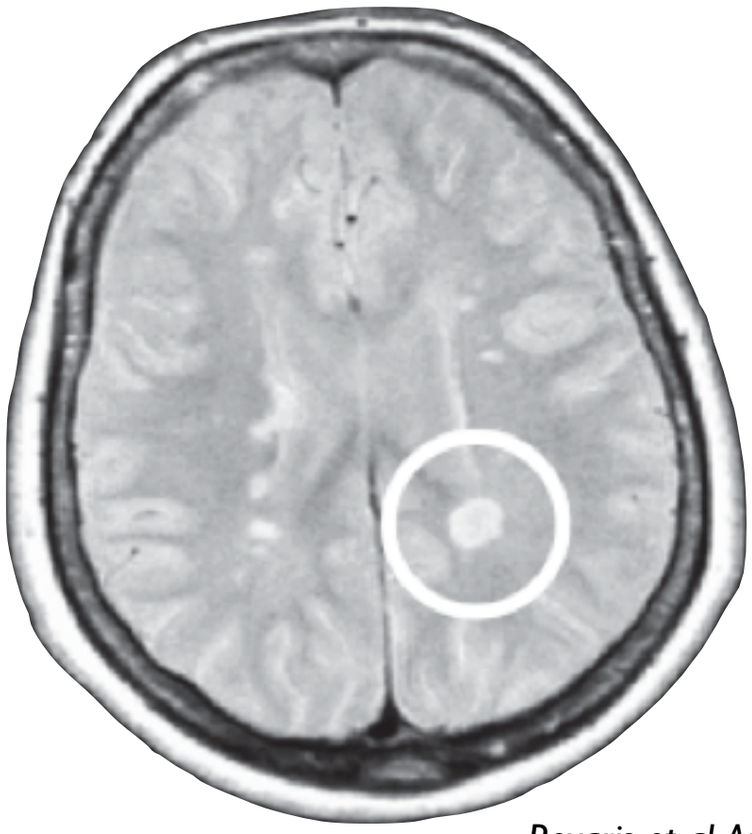
Rovaris et al, Arch Neurol 2002
Gallo et al, Arch Neurol 2005

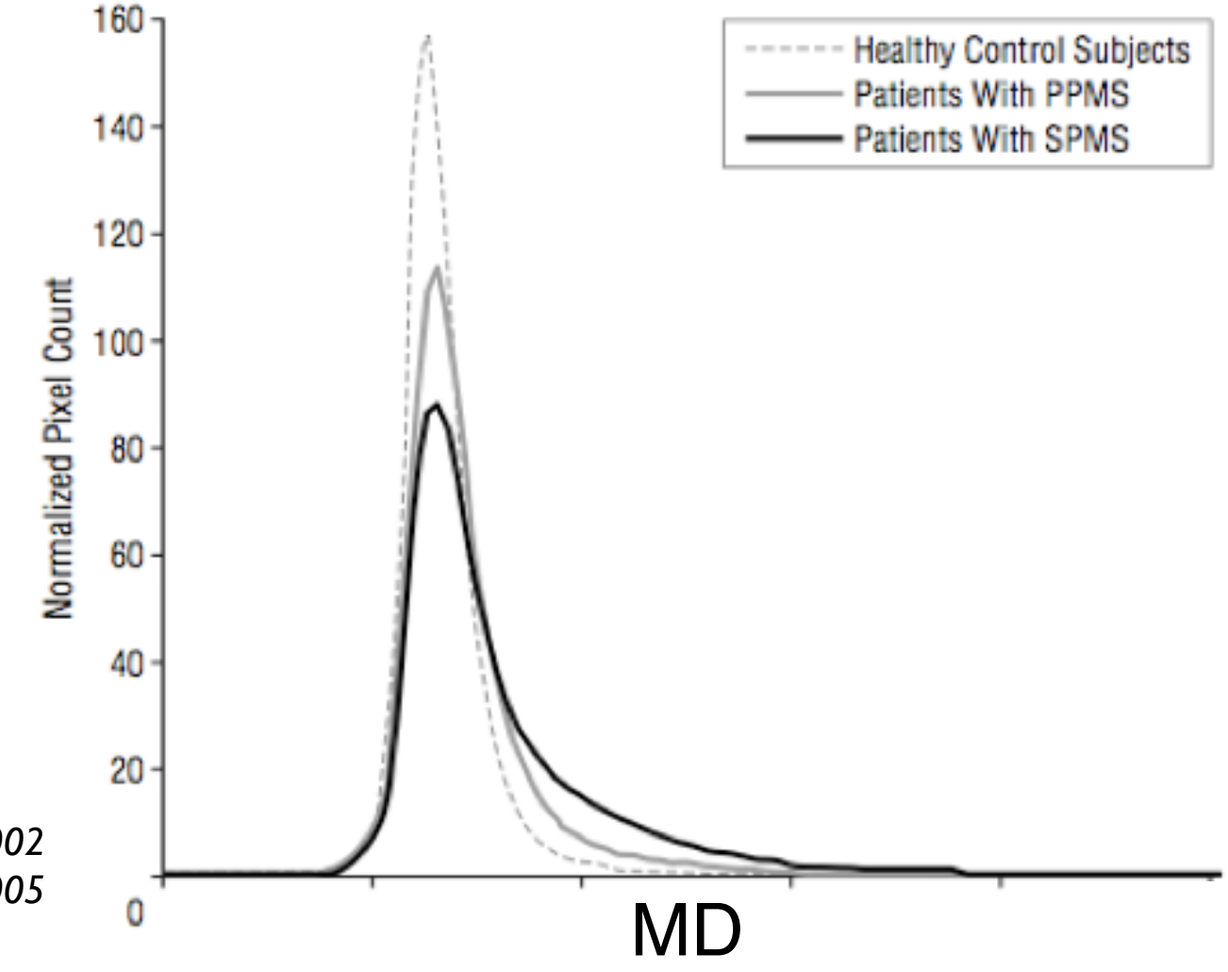


Fractional Anisotropy changes in MS normal appearing white matter

Quantitative Diffusion Maps

FA decrease/ MD increase has been associated in many studies with tissue breakdown (loss of structure).





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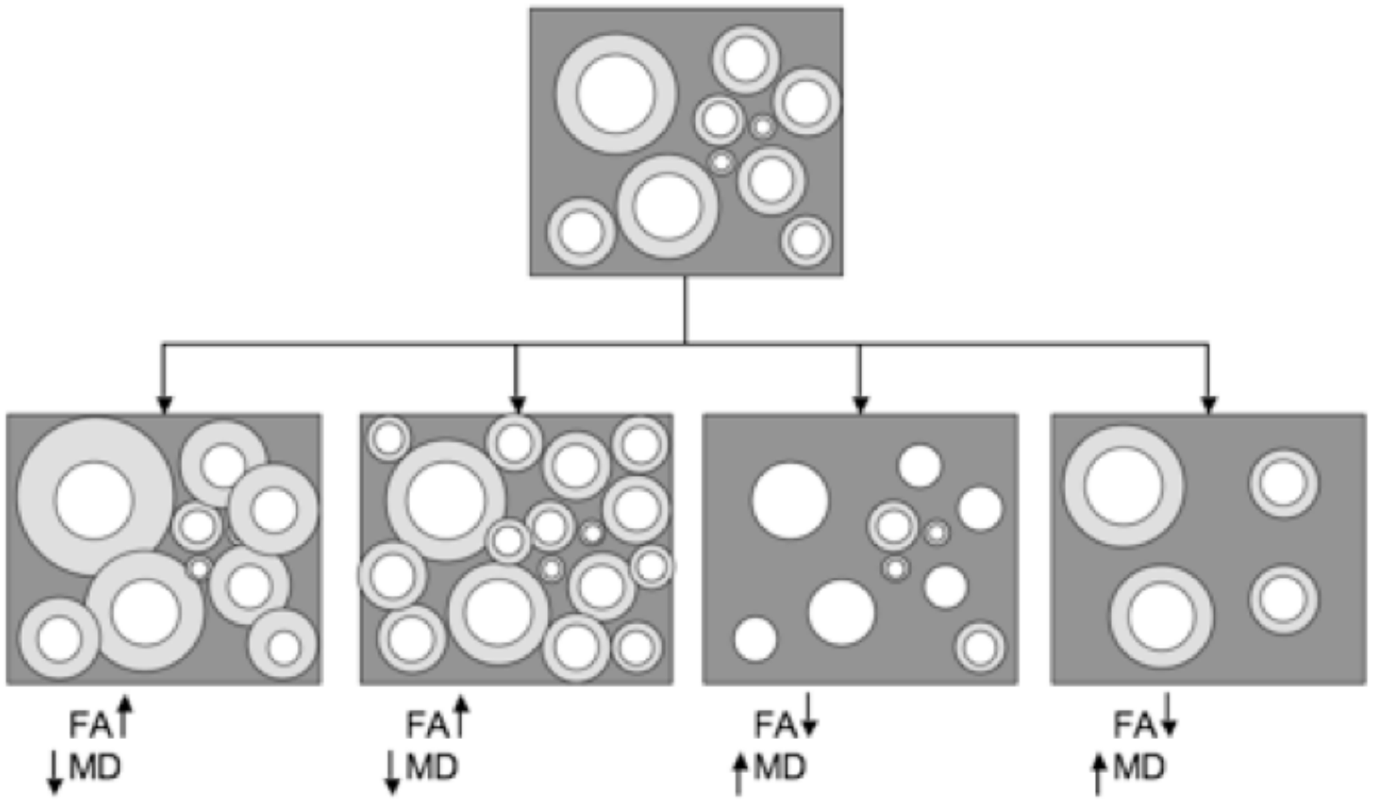
Fractional Anisotropy changes in MS normal appearing white matter

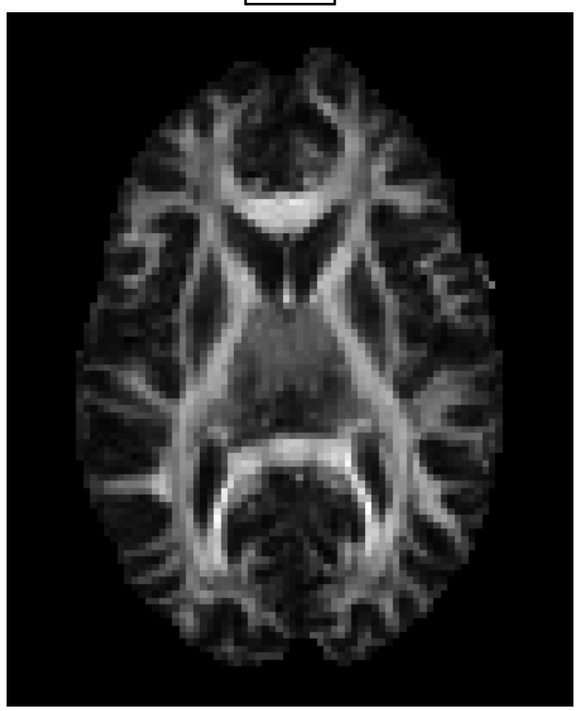
Quantitative Diffusion Maps

Different scenarios can have same effect on FA, MD

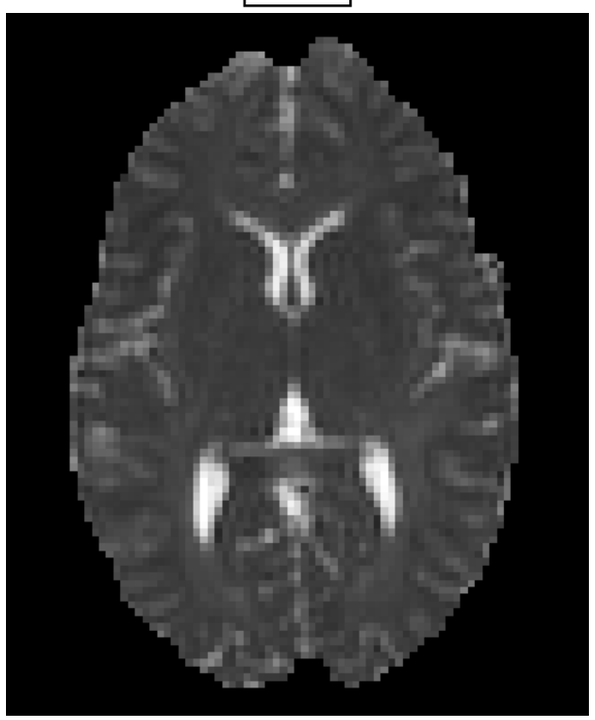


Quantitative Diffusion Maps

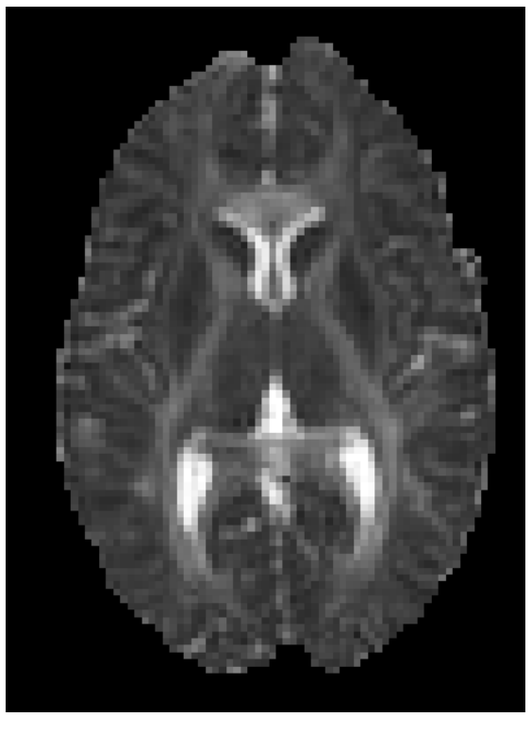
FA



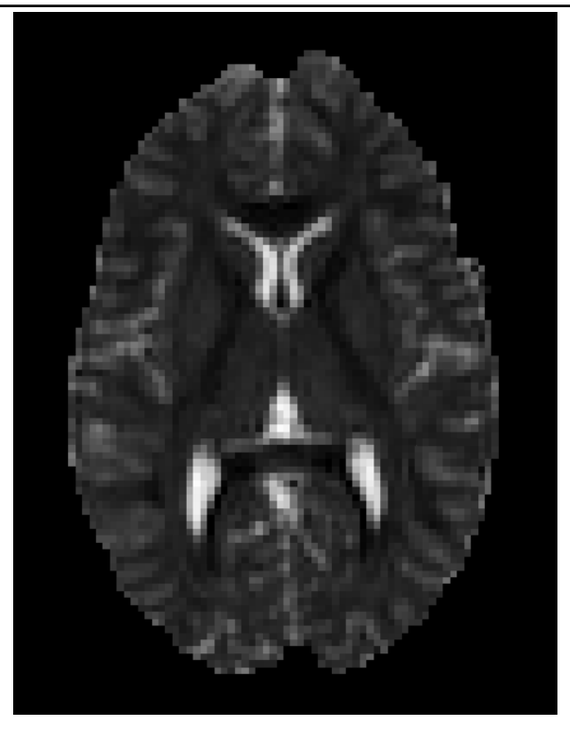
MD



Longitudinal/axial/parallel ADC
(λ_1)



Transverse/radial/perpendicular ADC
($\lambda_2+\lambda_3$)/2



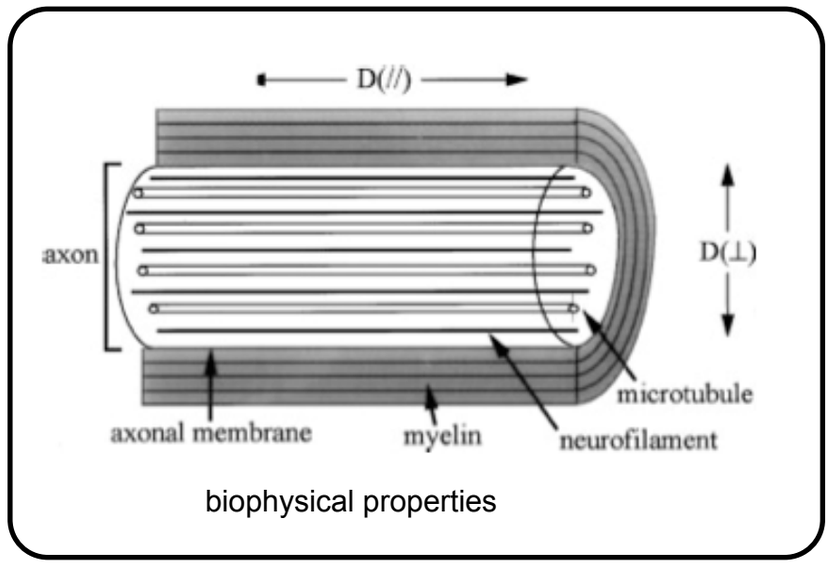
Quantitative Diffusion Maps

FA decrease in WM can be caused:

a) Decrease of longitudinal ADC.
Axonal breakdown?

b) Increase of transverse ADC.
Myelin breakdown?

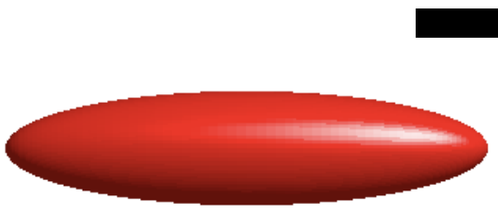
But do not over-interpret your results.
Always keep in mind that the DTI model is an oversimplification of reality



biophysical properties

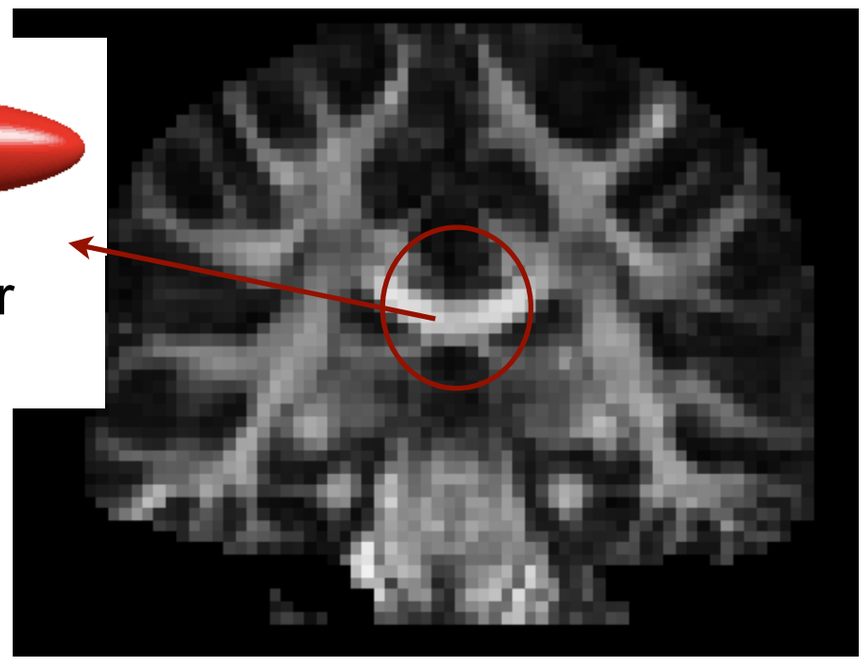
Tensor and FA in Crossing Regions

- In voxels containing two crossing bundles, FA is low and the tensor ellipsoid is pancake-shaped (oblate, planar tensor).



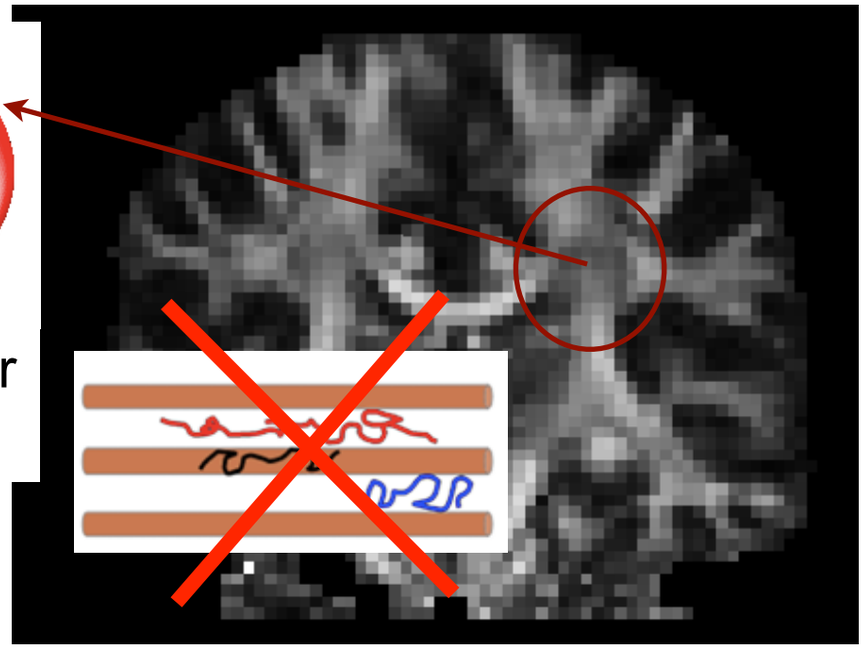
Prolate Tensor

$\lambda_1 >> \lambda_2, \lambda_3$



Oblate Tensor

$\lambda_1 = \lambda_2 >> \lambda_3$

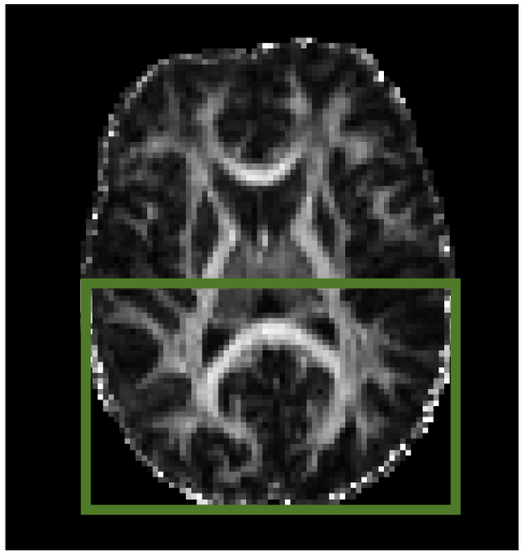


Consequences:

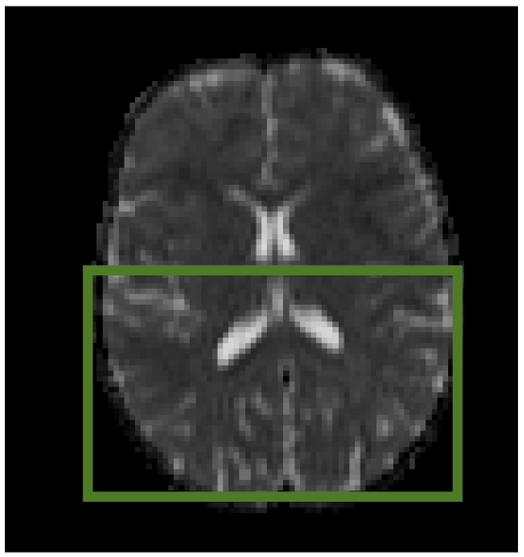
- PDD not necessarily = direction of fibres
- FA changes difficult to interpret

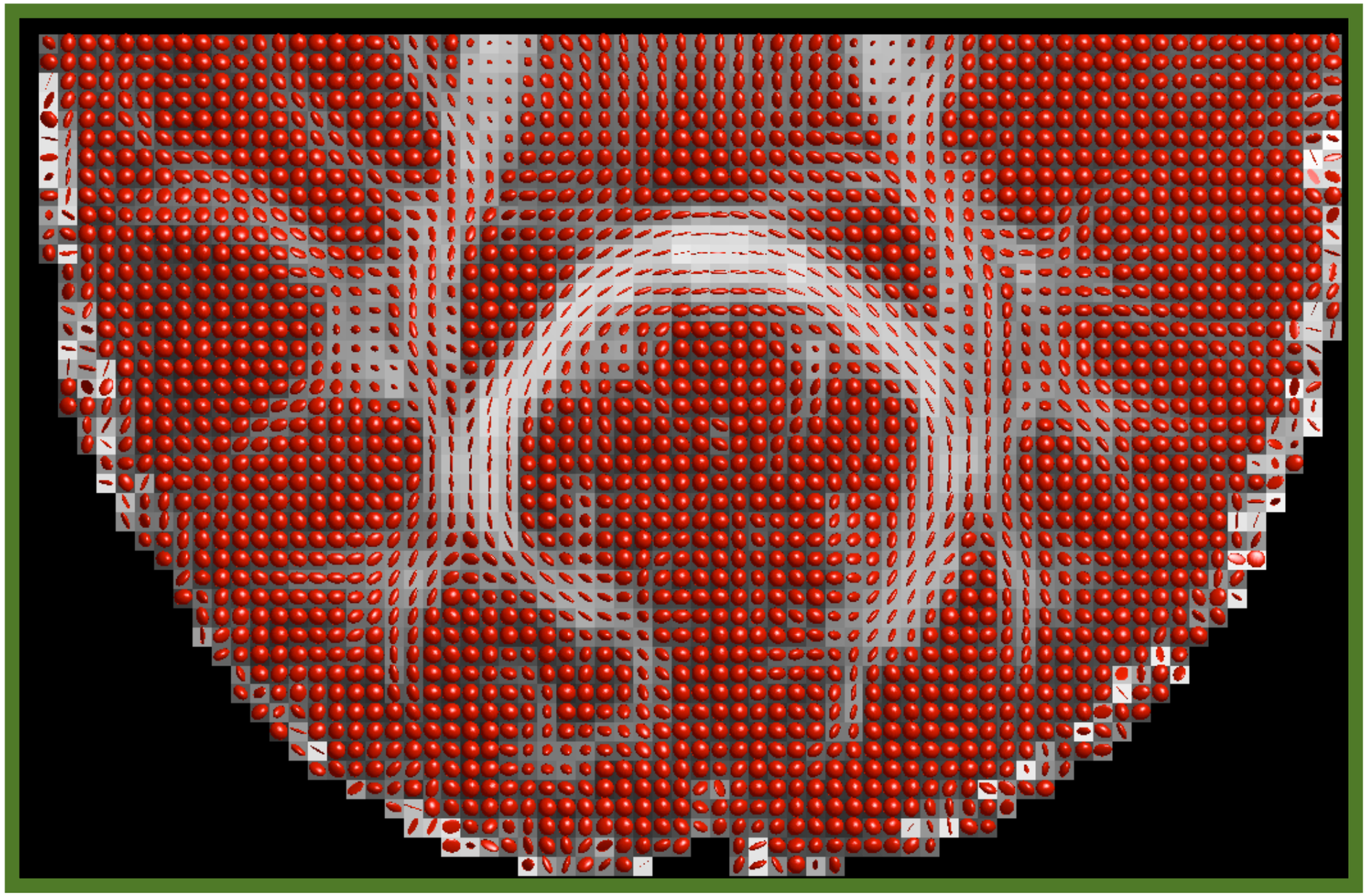
Diffusion Tensor Ellipsoids

Fractional anisotropy



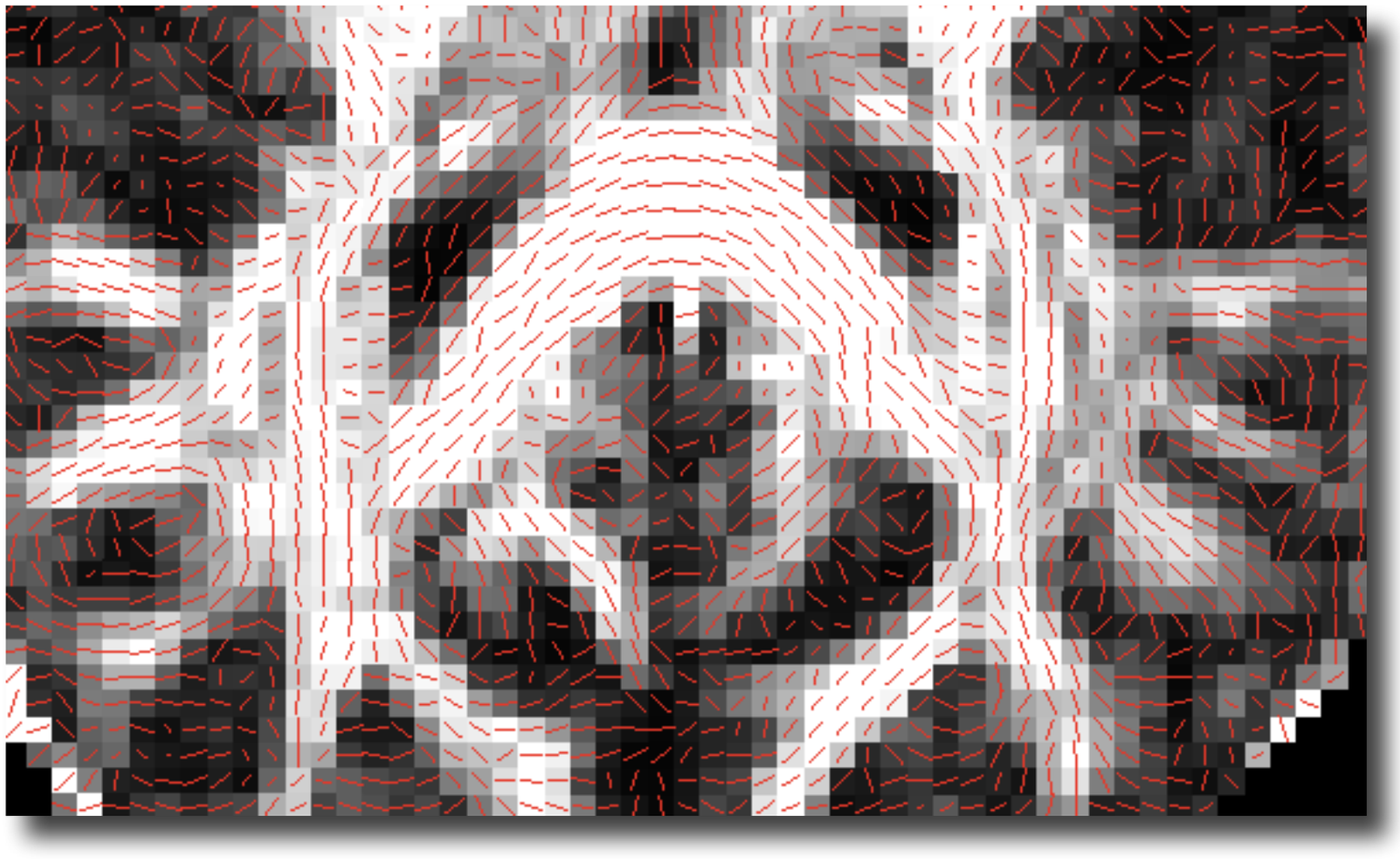
Mean diffusion



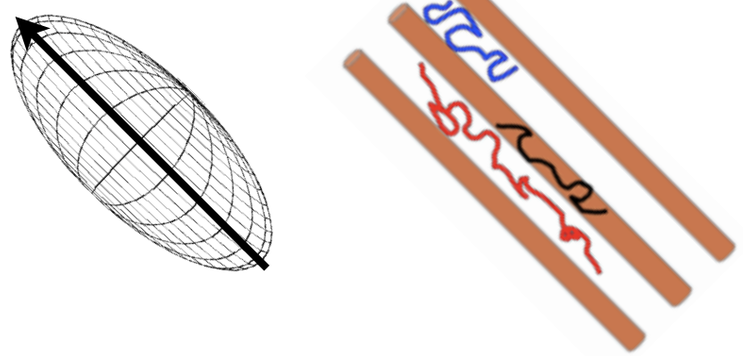


Estimates of Principal Fibre Orientation in WM

$\mathbf{v}_1$ map
Principal Diffusion Direction



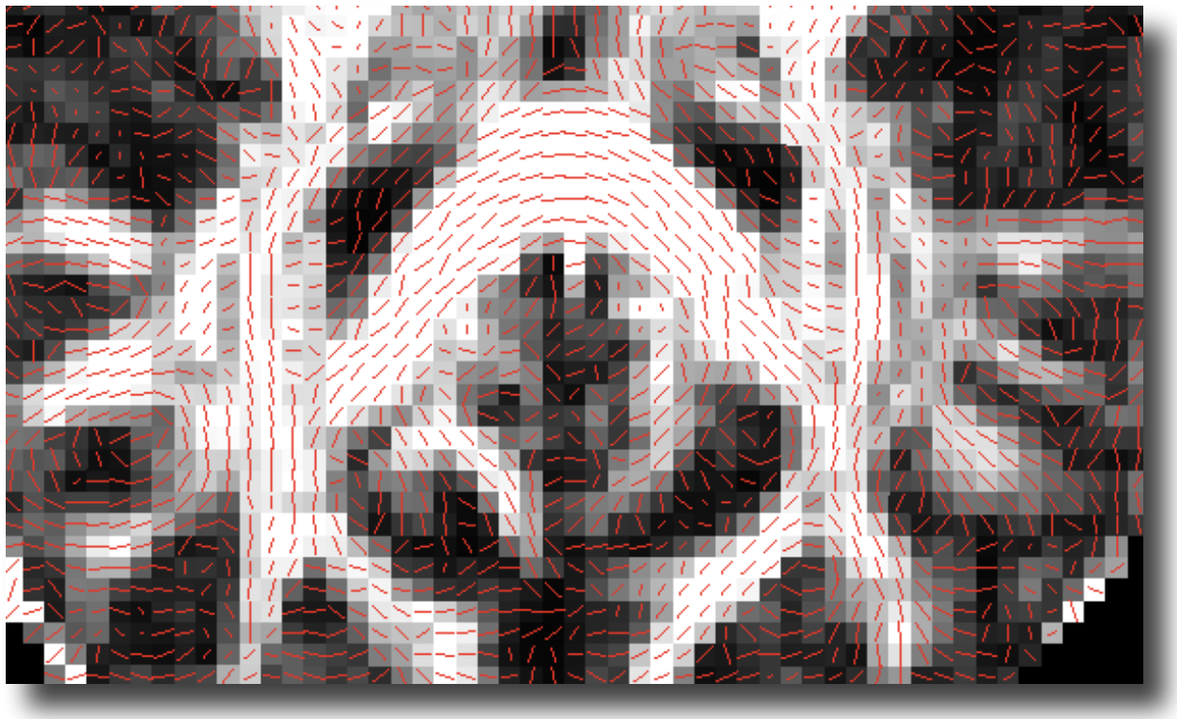
Principal Diffusion Direction

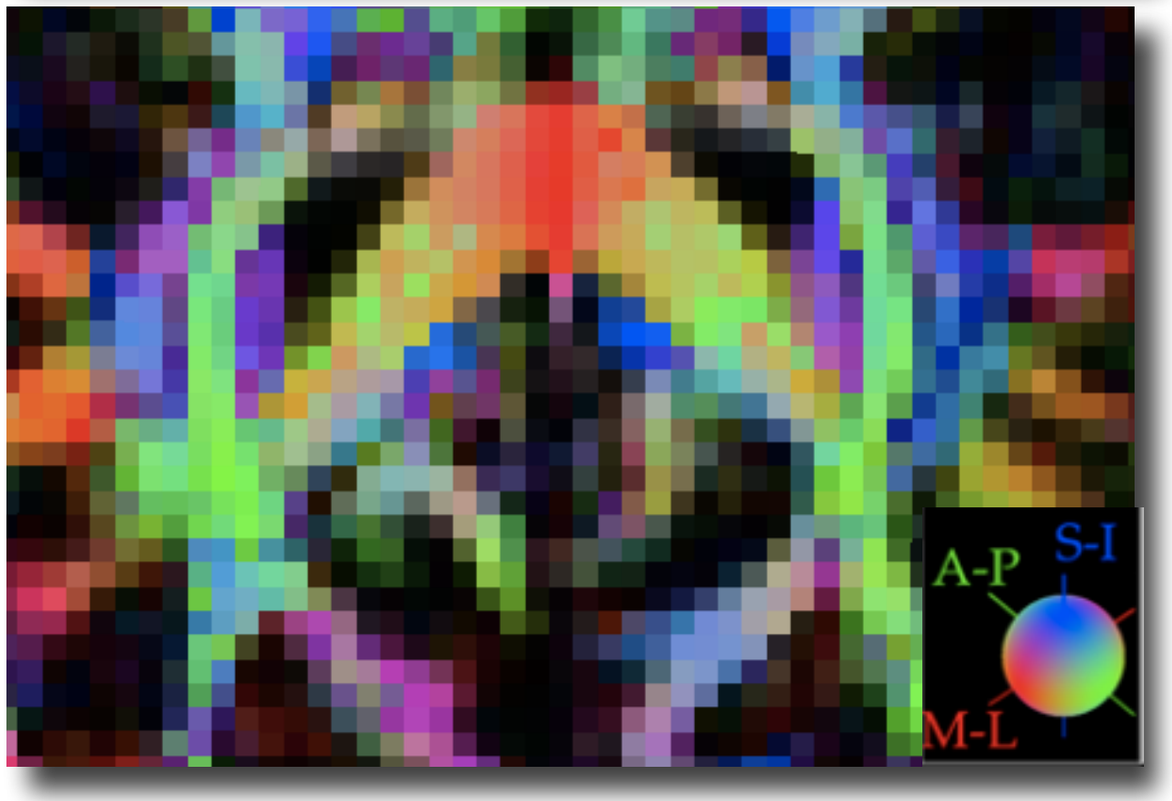


Assumption!!

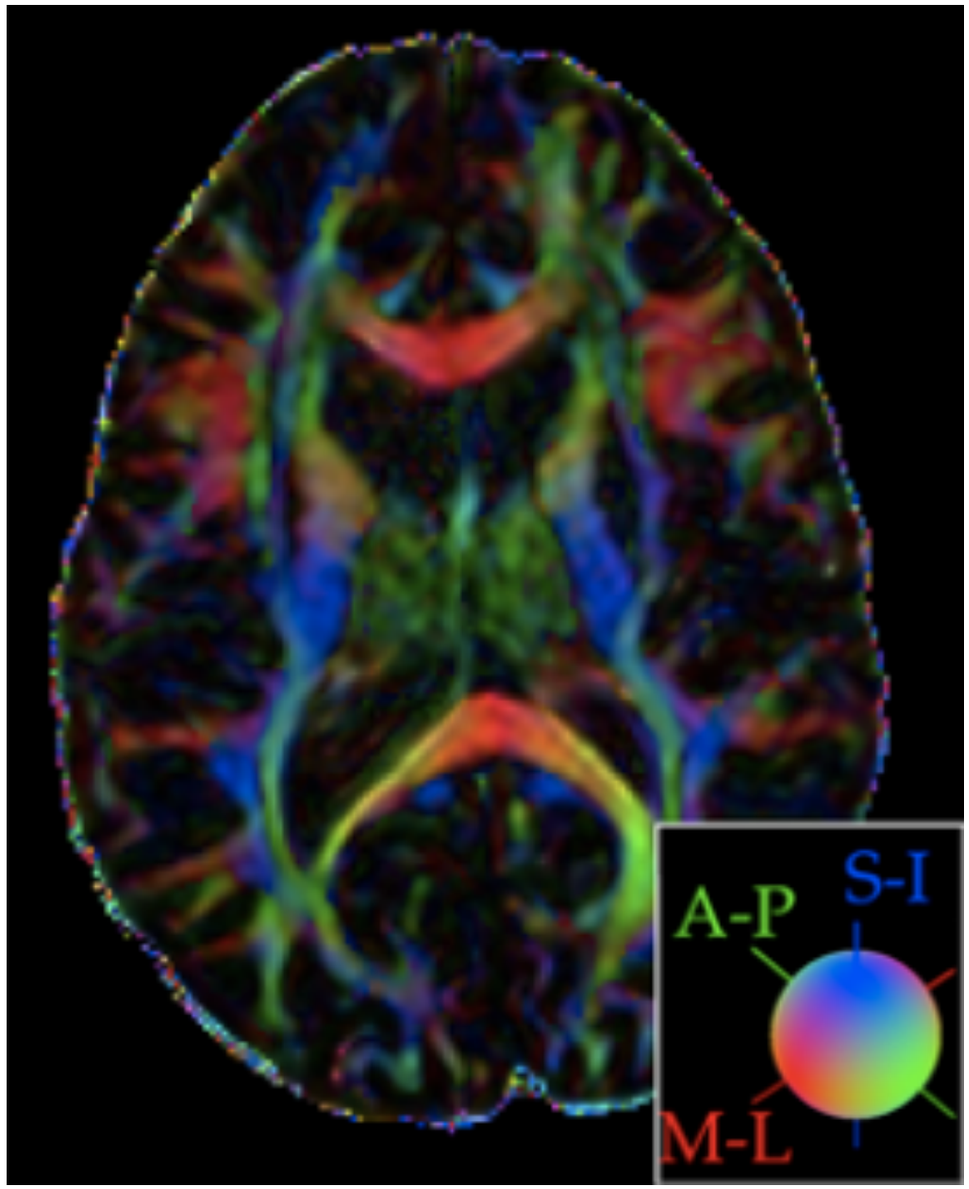
Direction of maximum diffusivity in voxels with anisotropic profile is an **estimate of the major fibre orientation**.

Estimates of Principal Fibre Orientation in WM

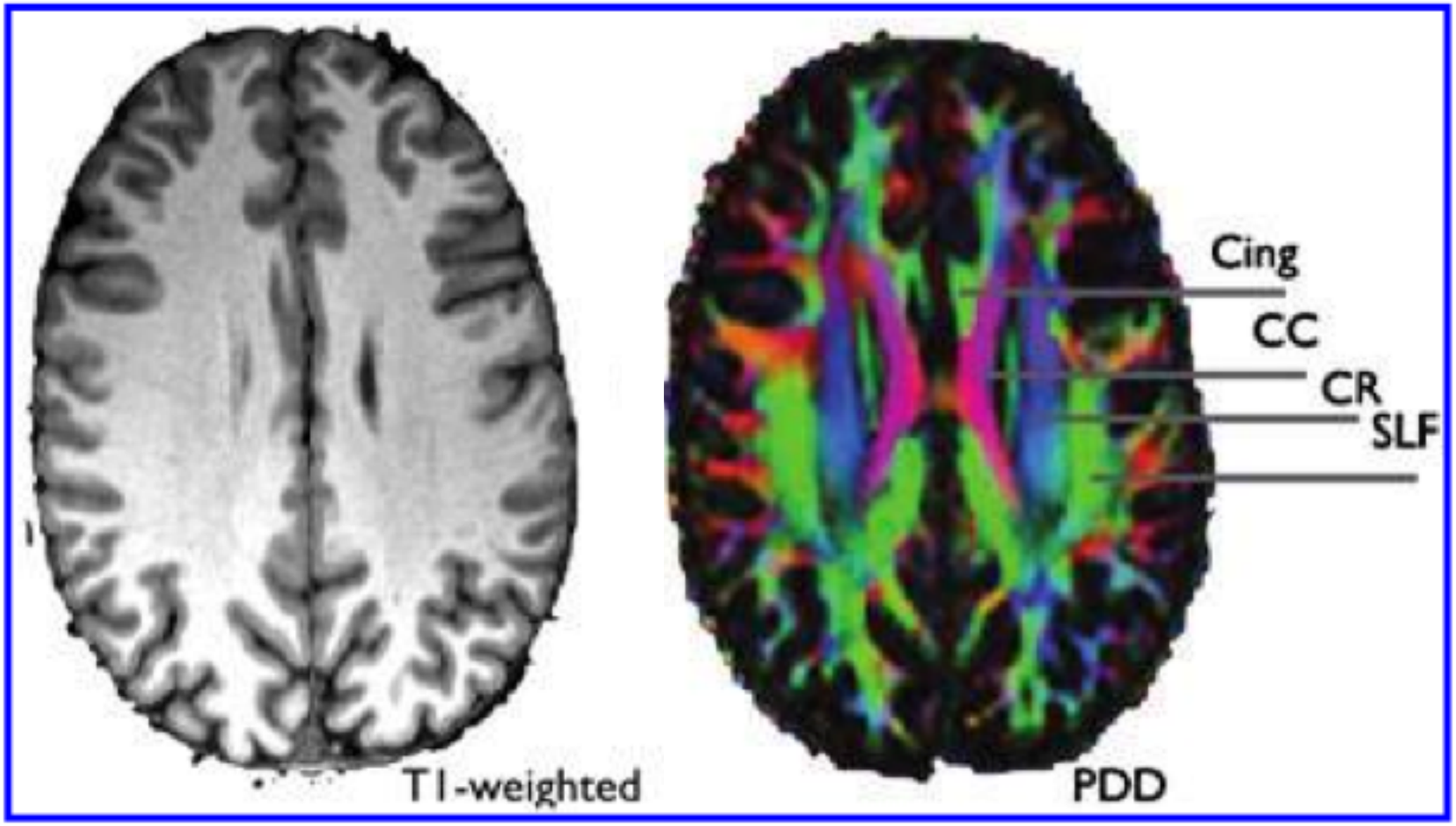




Colour-coded $\mathbf{v}_1$ map

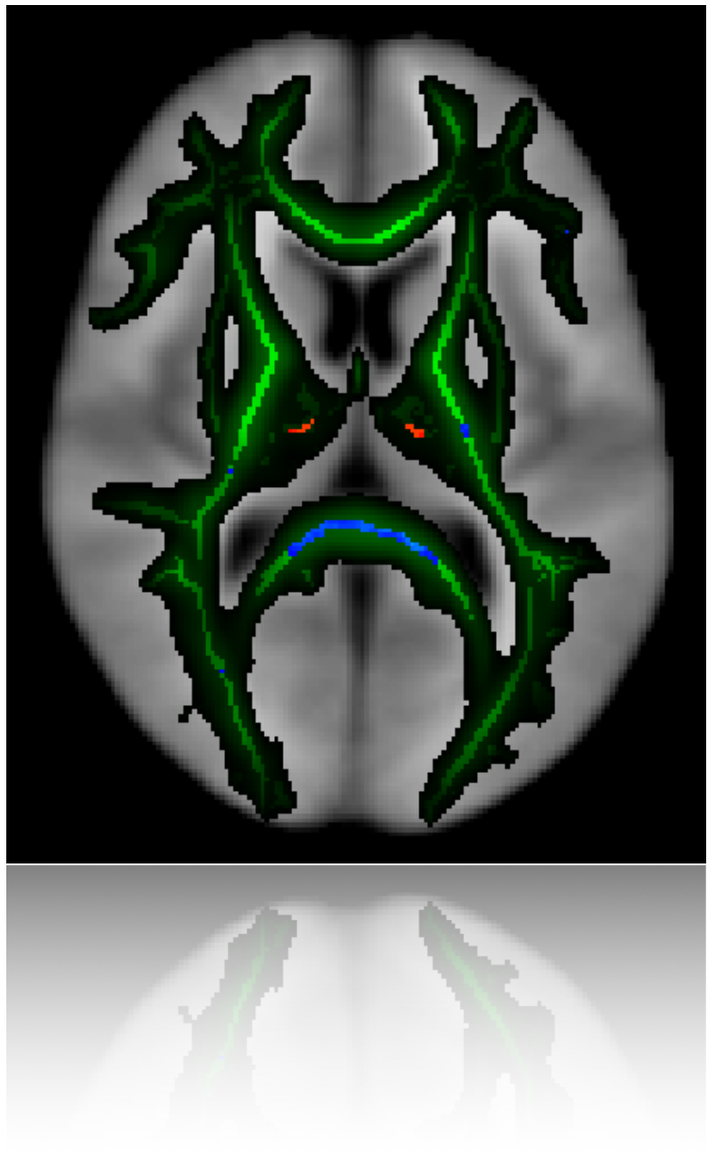


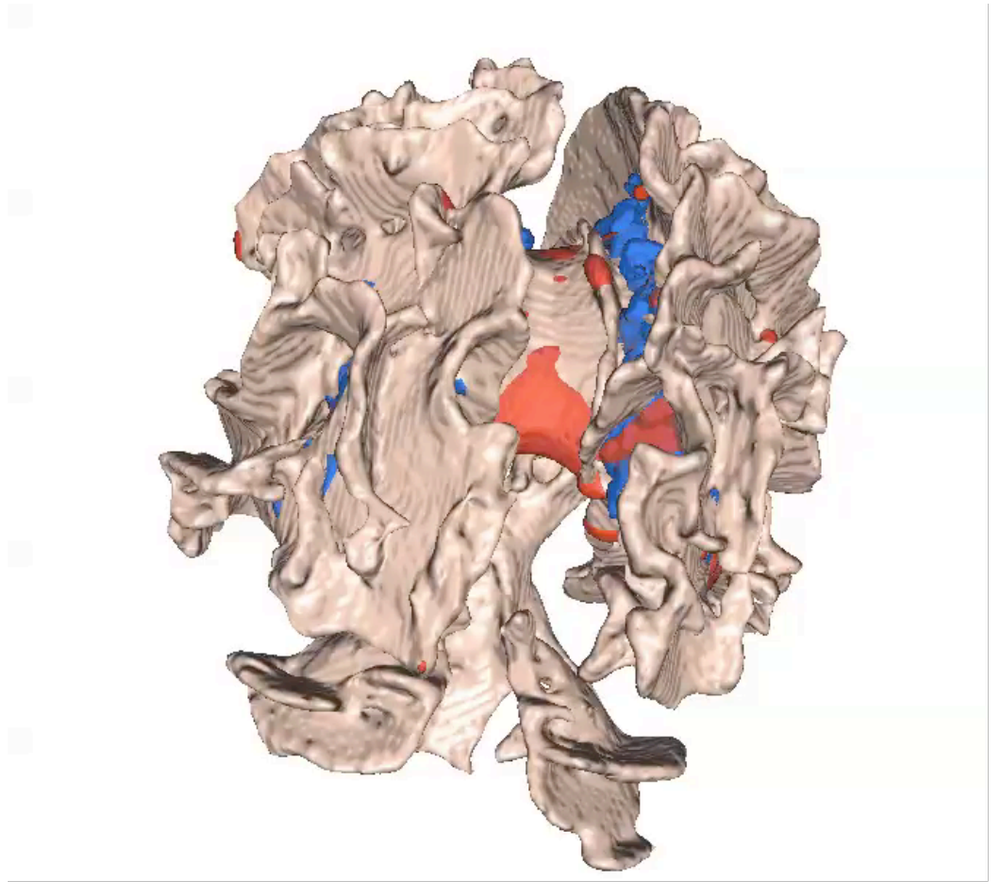
Directional contrast in DTI



TBSS : Tract-Based Spatial Statistics

Robust "voxelwise" cross-subject stats on diffusion-derived measures

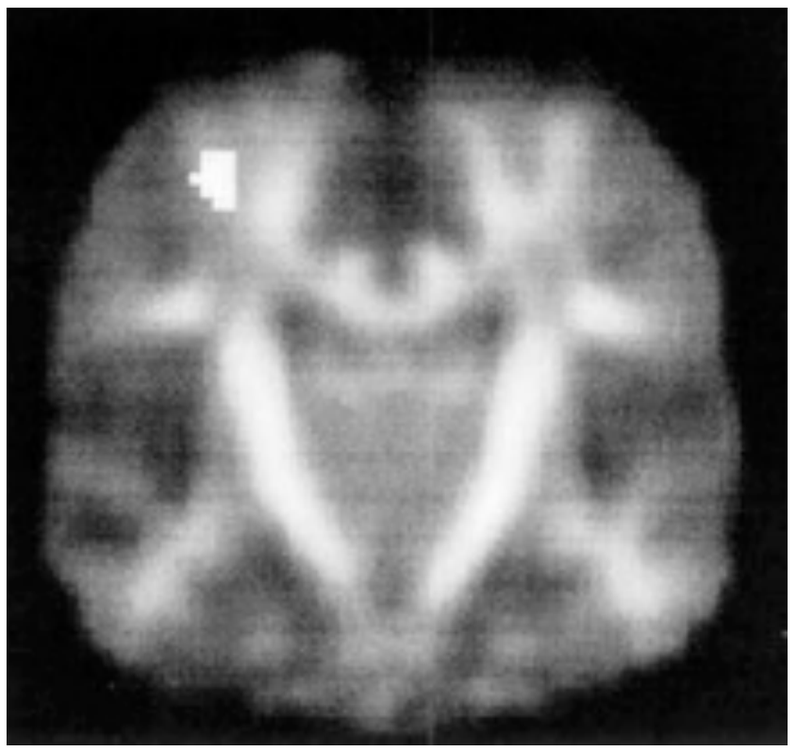


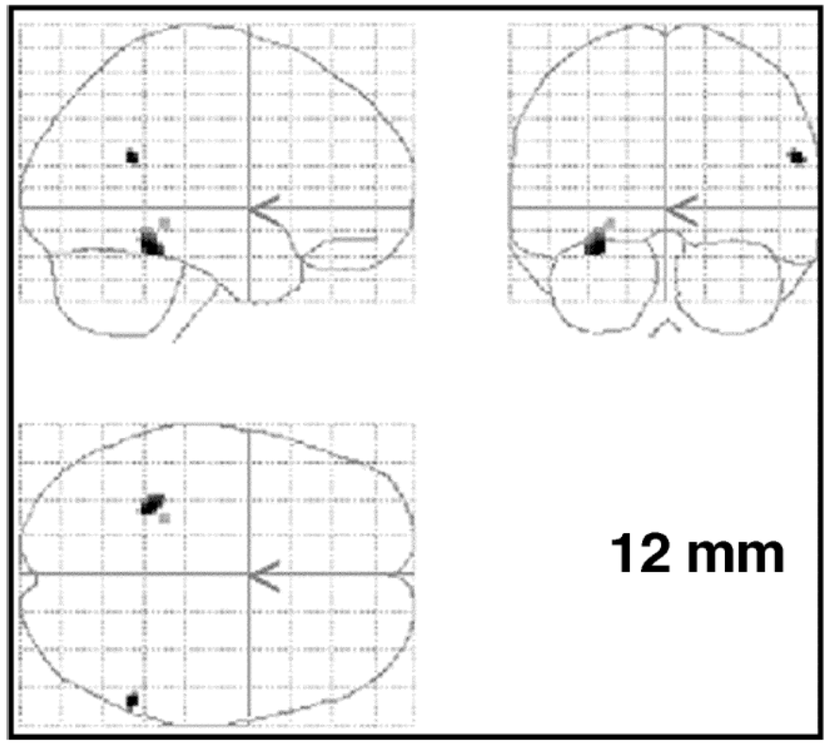


Voxel-wise Analysis of FA

- Compute diffusion tensor
- Align all subjects' data to standard space
  - Diffusion (b0/FA) -> structural -> standard
  - FA -> standard
- Do voxelwise stats (e.g. controls-patients)

Büchel 2004



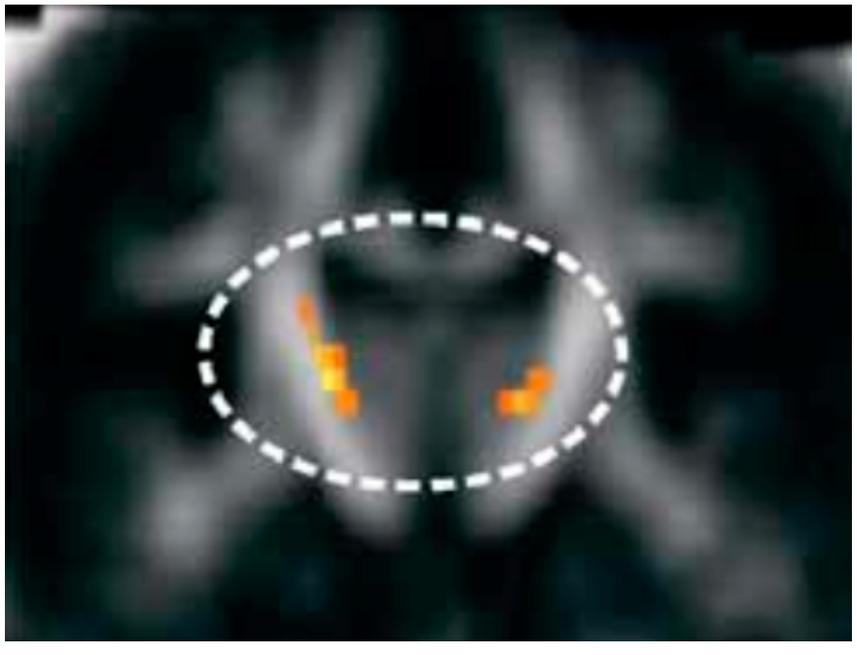
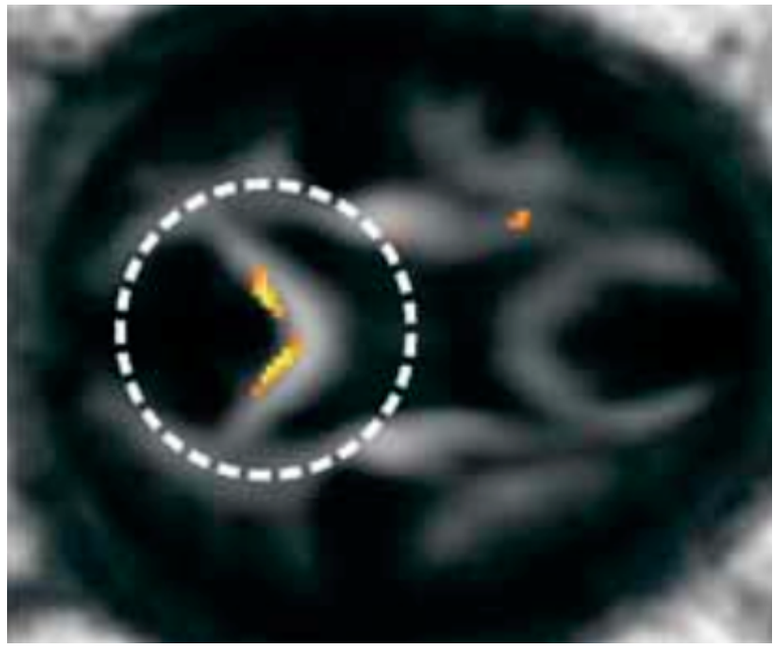
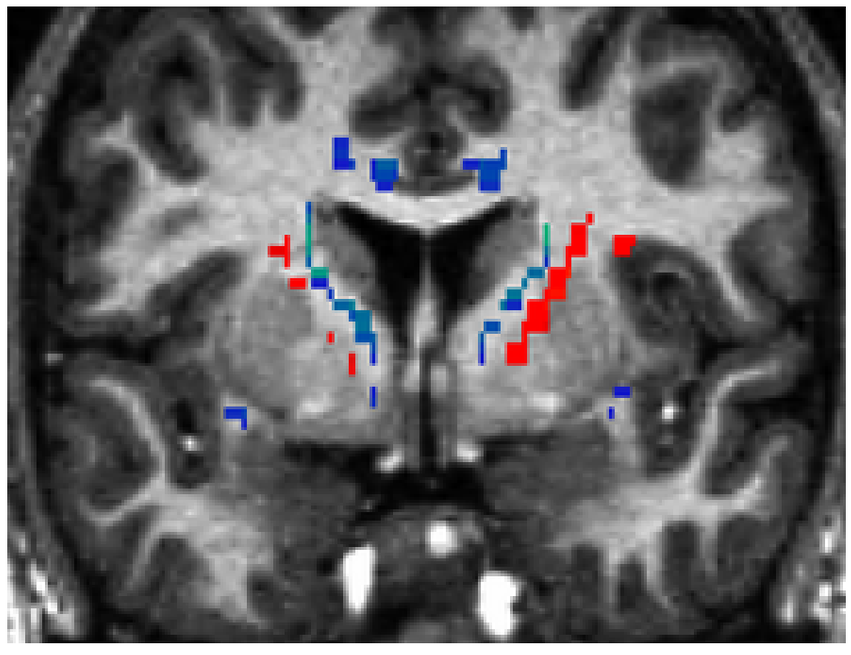


Jones 2005

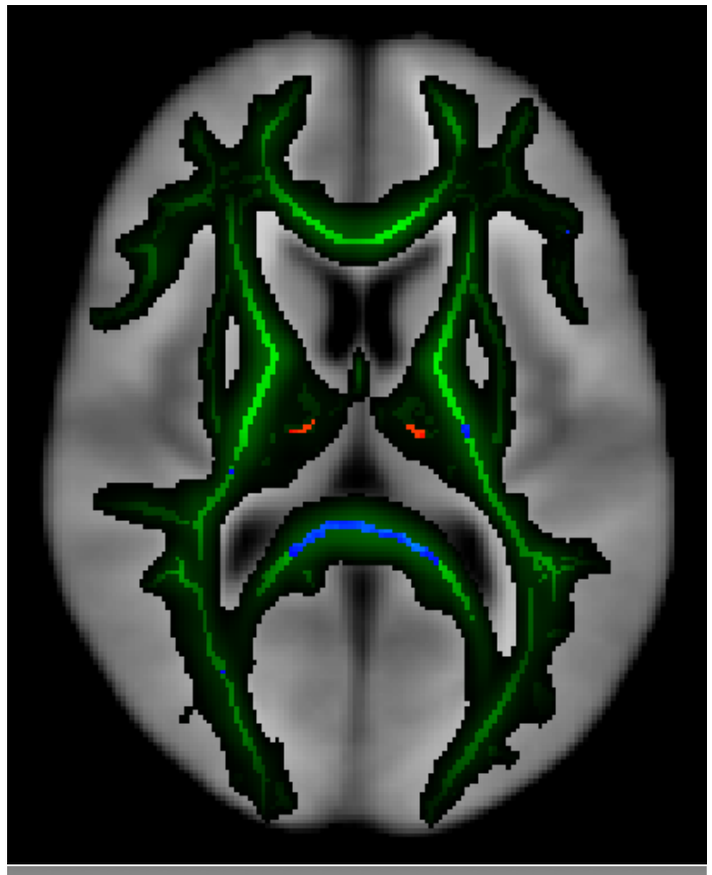
VBM-style Analysis of FA

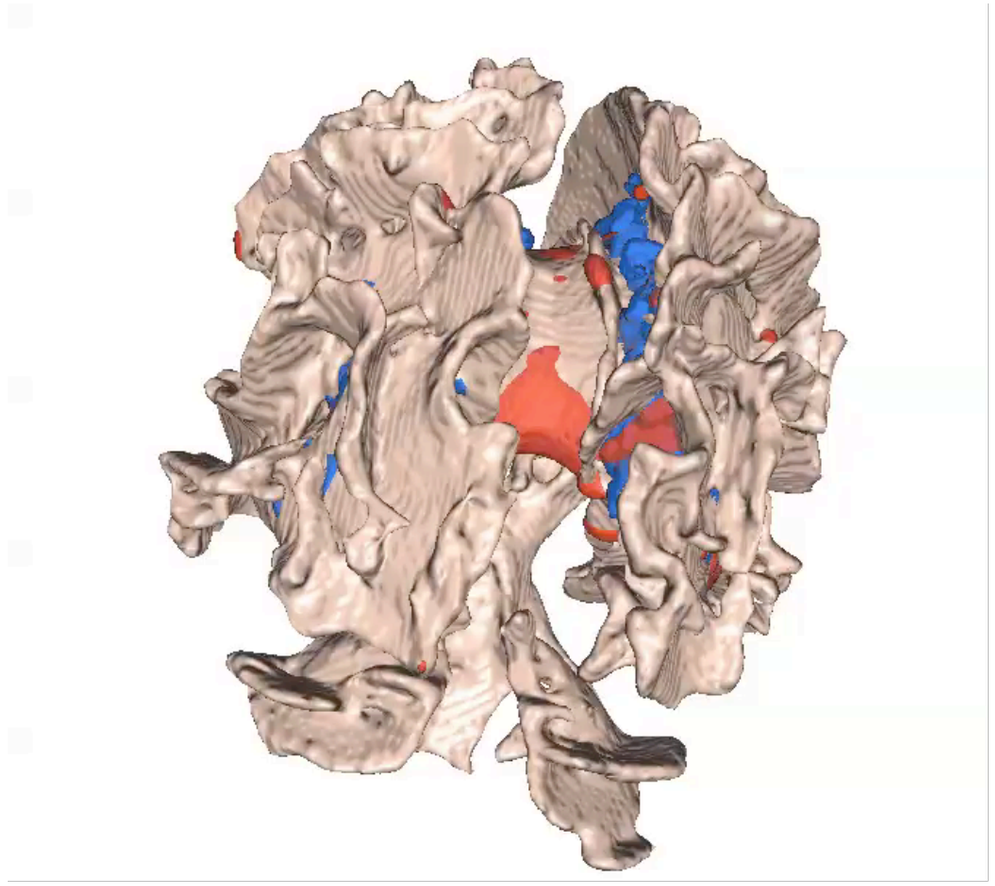
- Strengths
  - Fully automated & quick
  - Investigates whole brain

- Problems [Bookstein 2001, Davatzikos 2004, Jones 2005]
  - Alignment difficult; smallest systematic shifts between groups can be incorrectly interpreted as FA change
  - Needs smoothing to help with registration problems
  - No objective way to choose smoothing extent

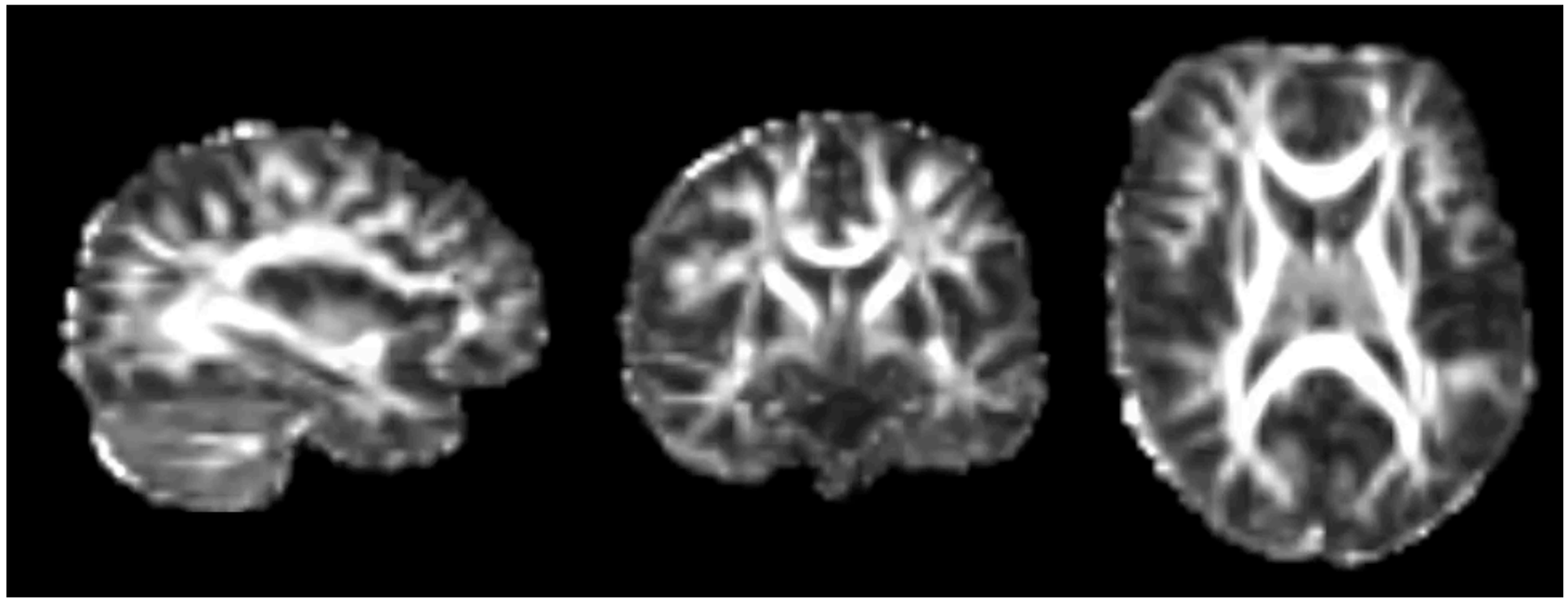
TBSS : Tract-Based Spatial Statistics



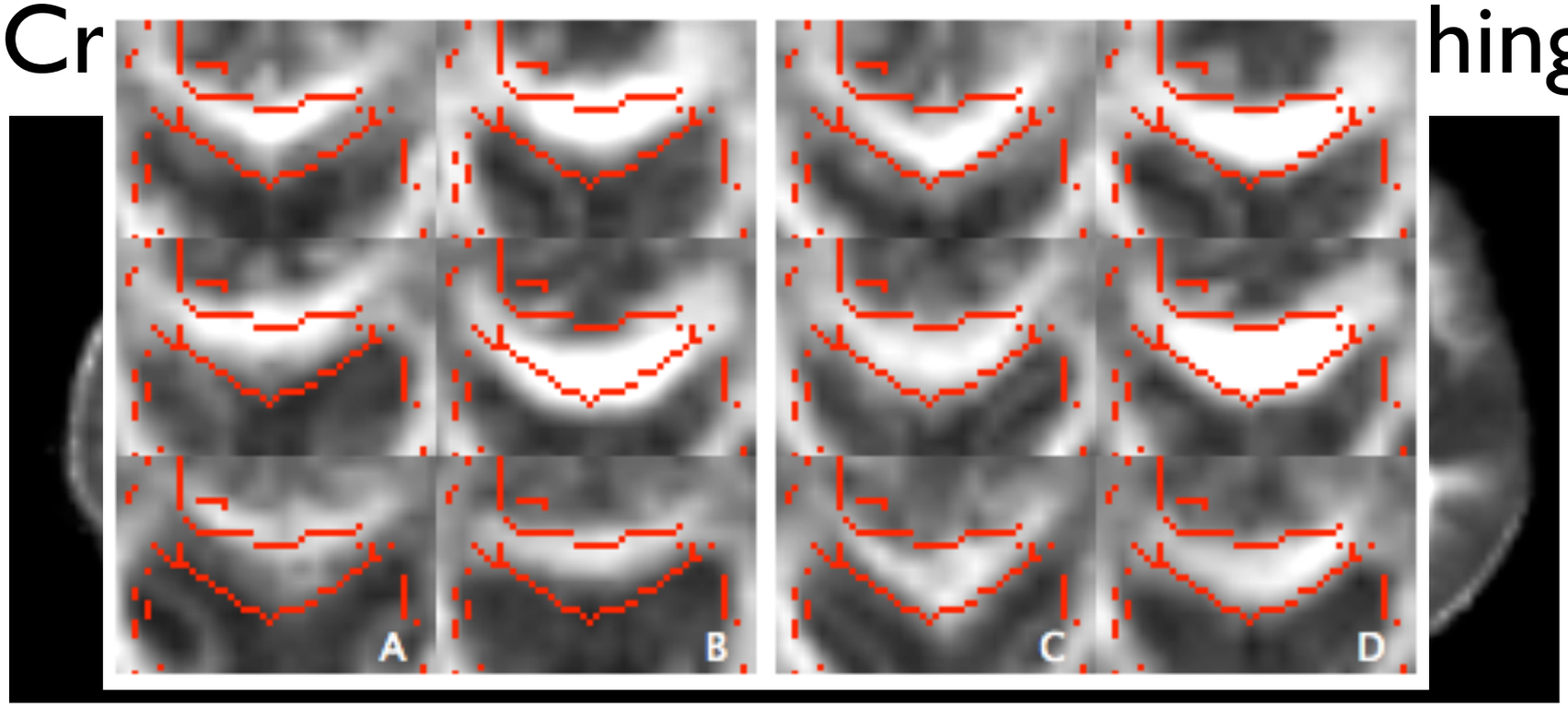


- Need: robust "voxelwise" cross-subject stats on DTI
- Problem: alignment issues confound valid local stats
- TBSS: solve alignment using alignment-invariant features:
- Compare FA taken from tract centres (via skeletonisation)

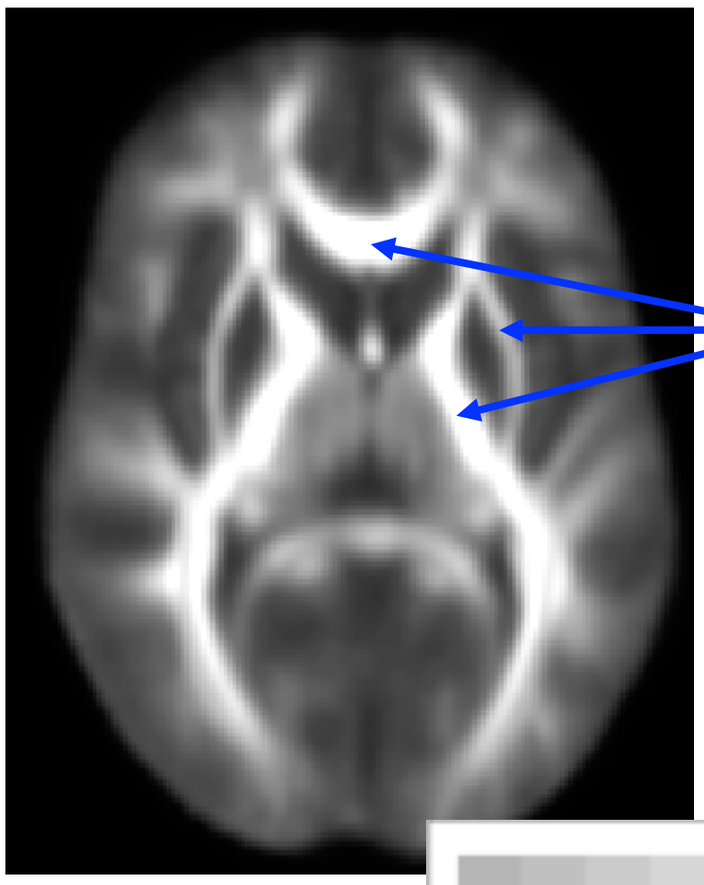
1. Use medium-DoF nonlinear reg to pre-align all subjects' FA
(nonlinear reg: FNIRT)

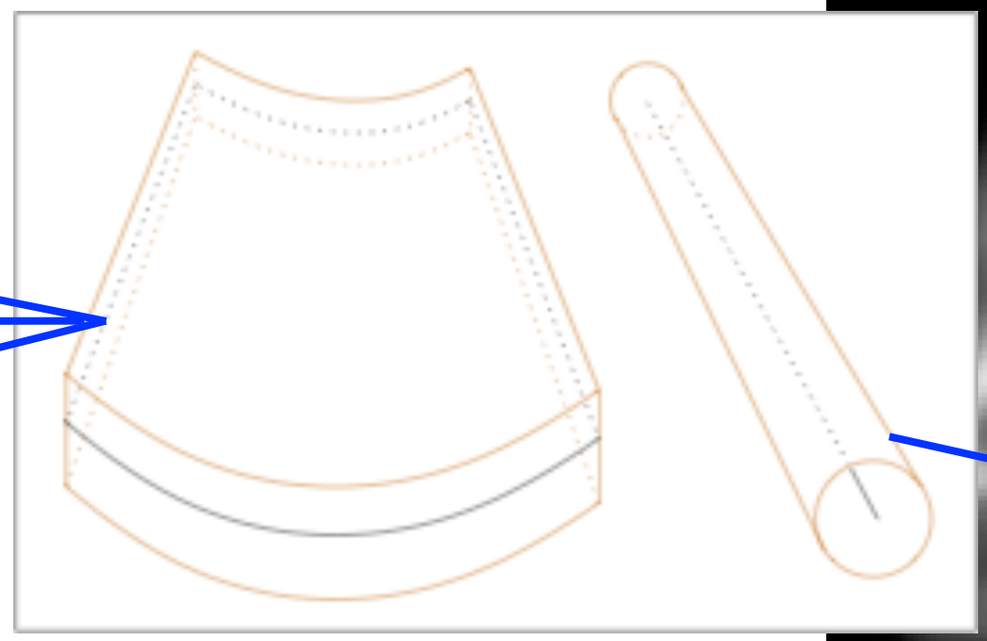


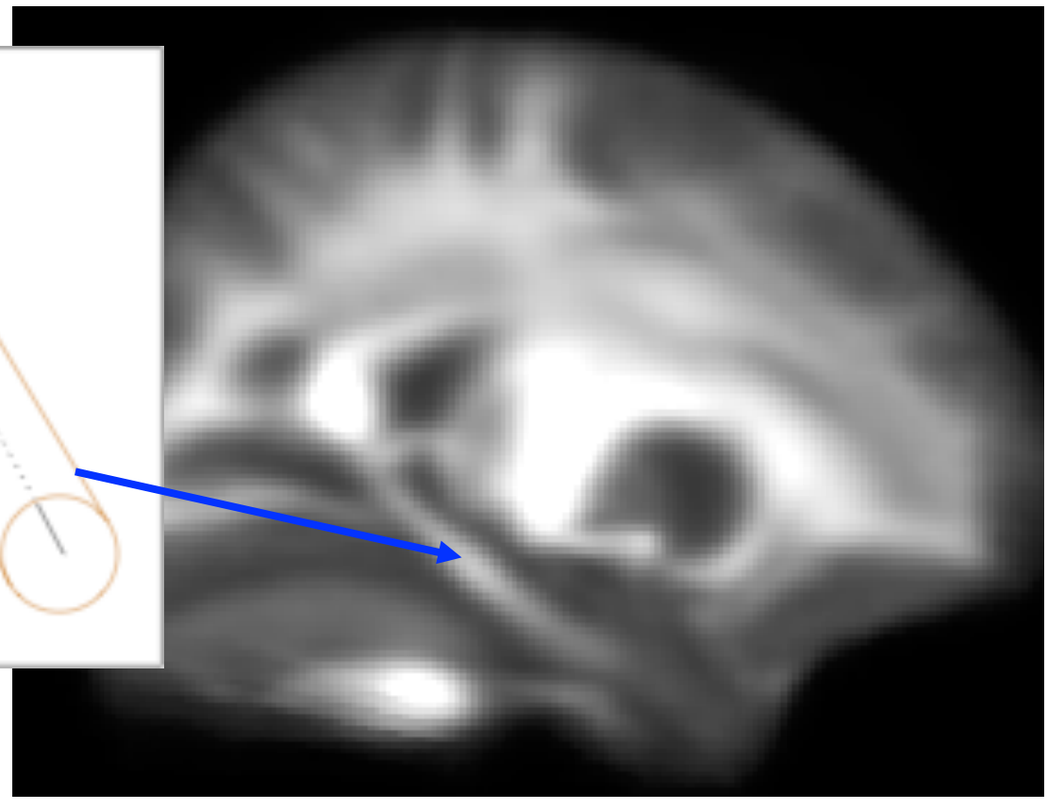
2. Cr hing)

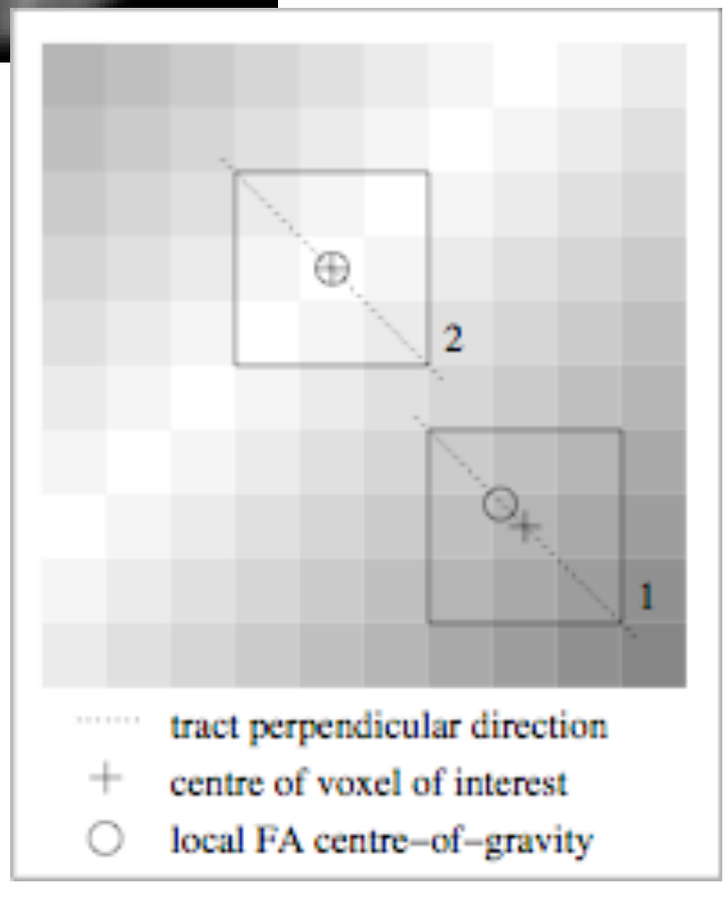


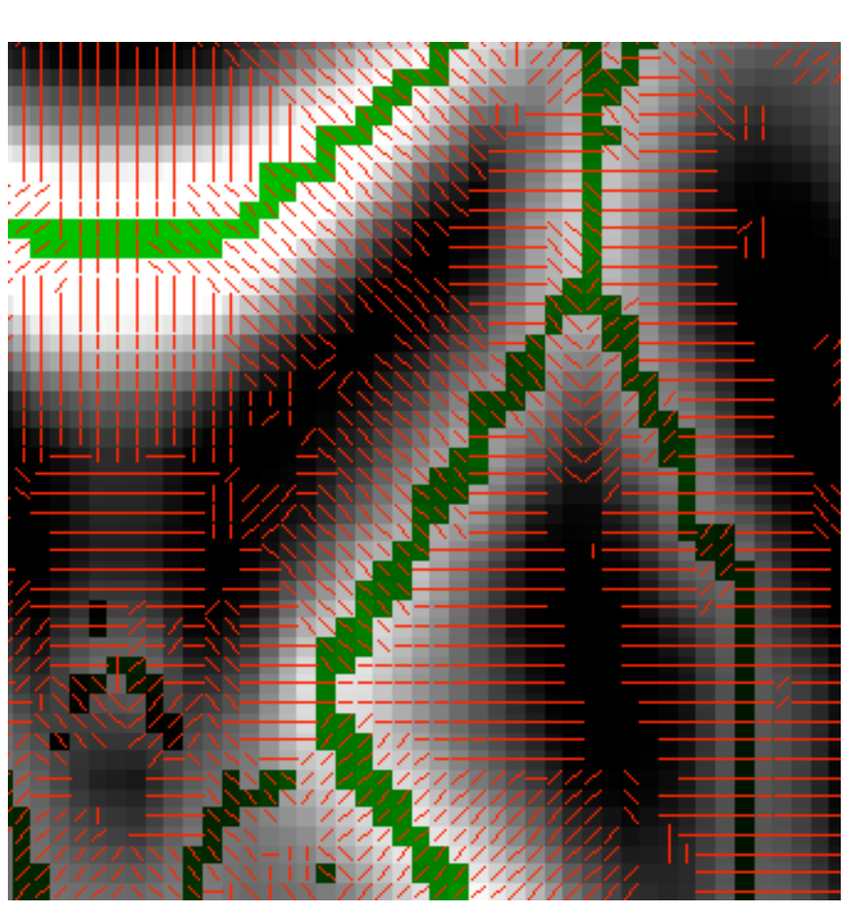
2. “Skeletonise” Mean FA





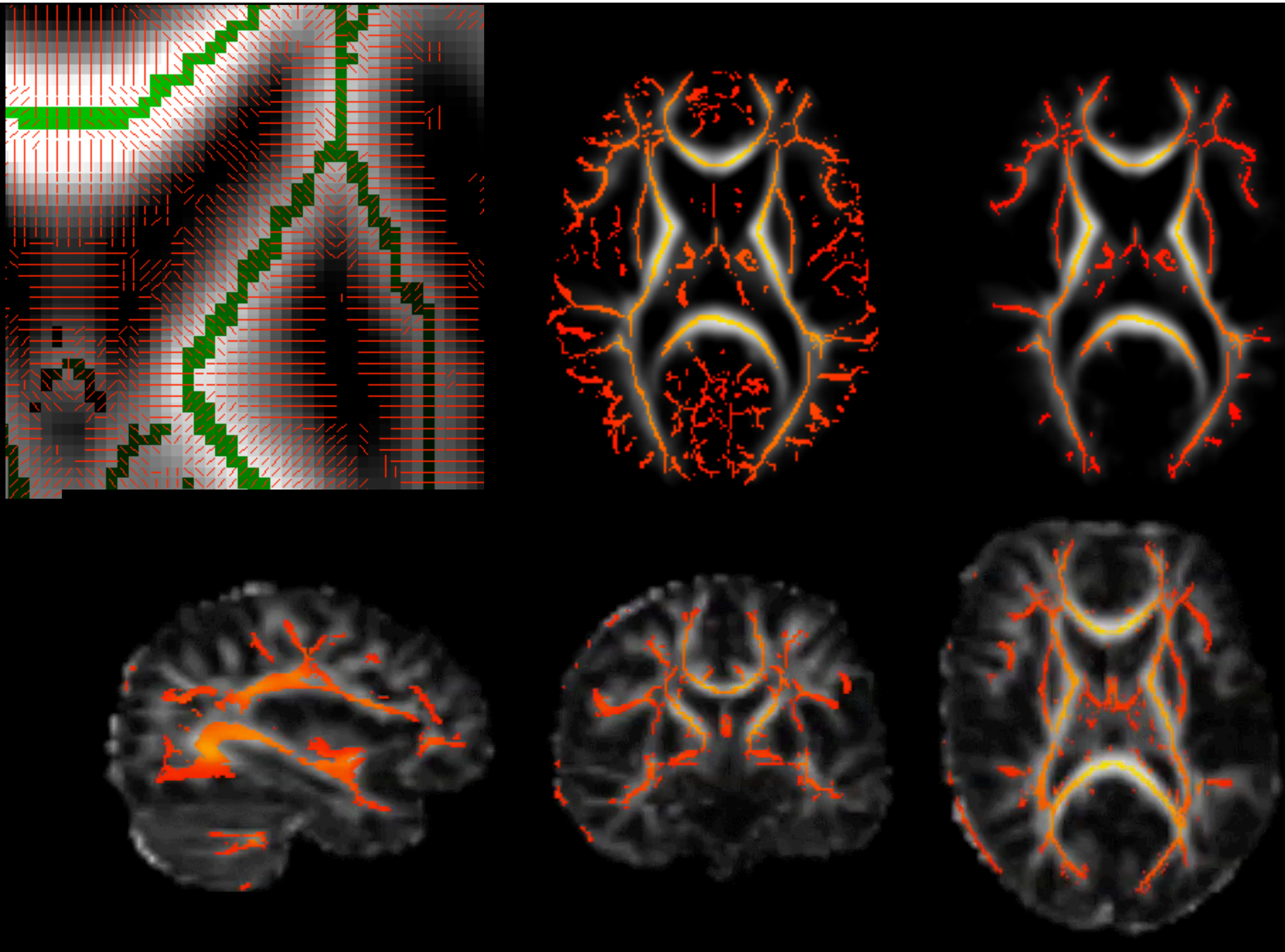






3. Threshold Mean FA Skeleton

giving "objective" tract map



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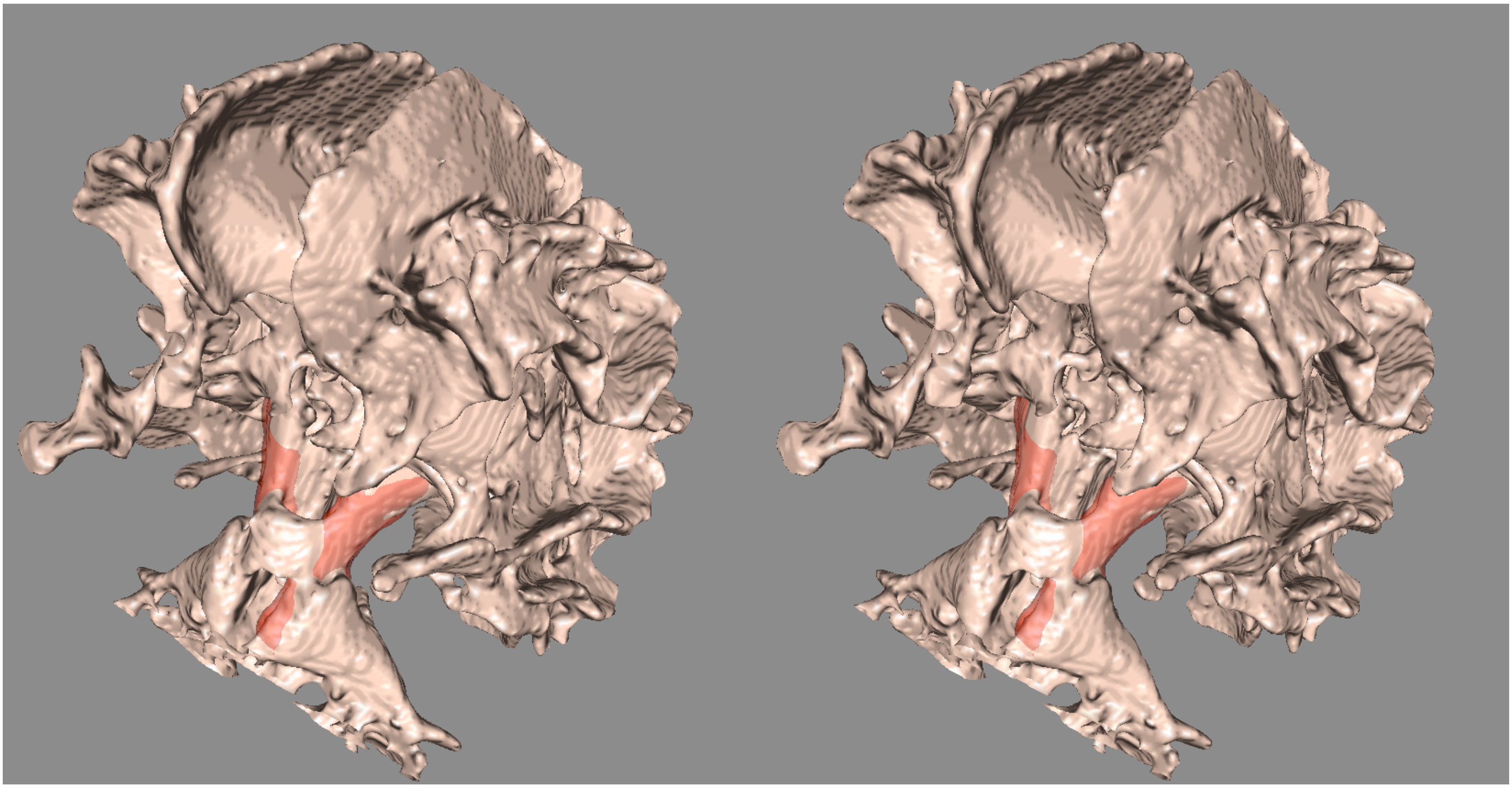
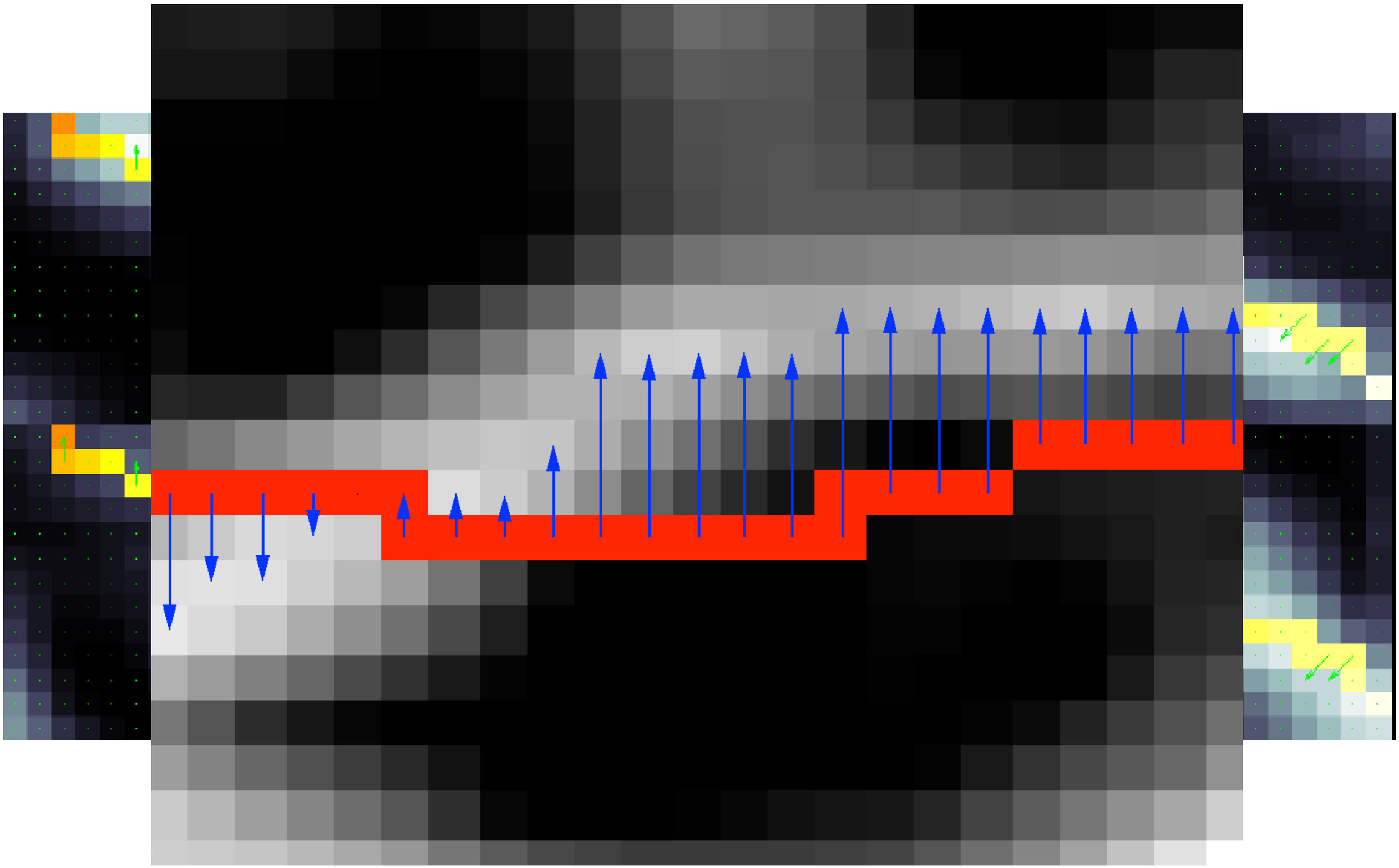
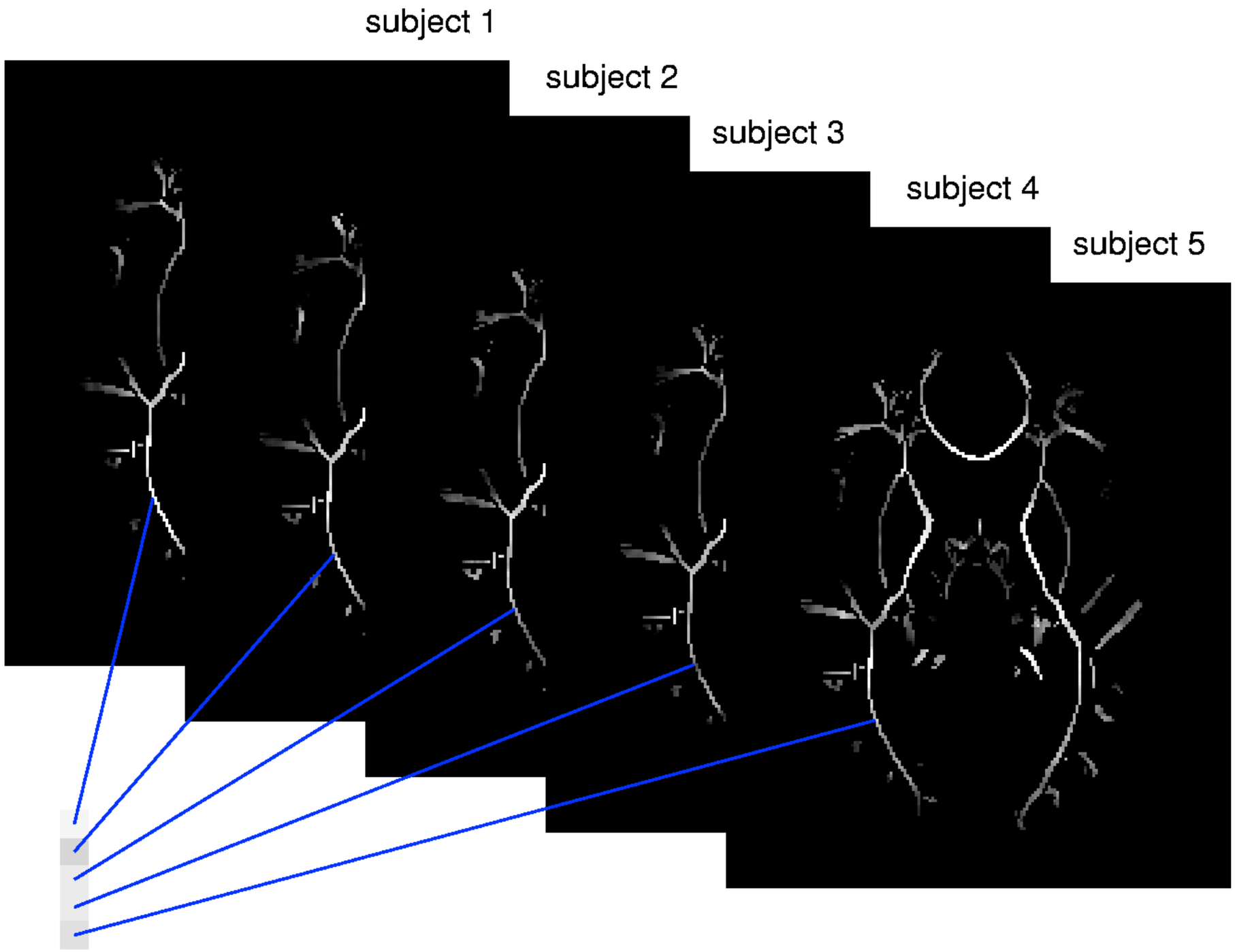


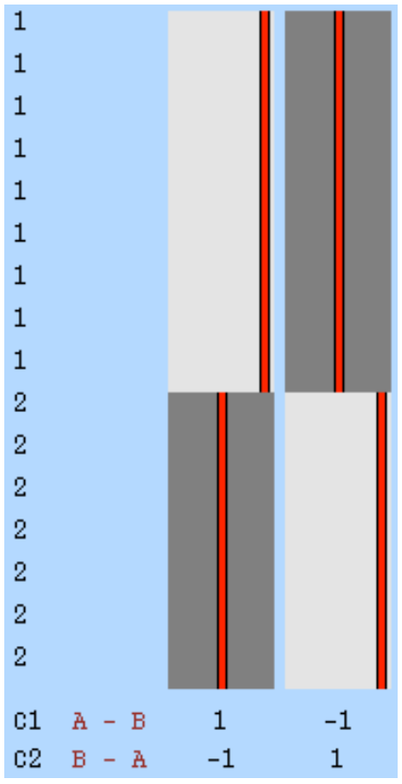
4. For each subject's warped FA, fill each point on the mean-space skeleton with nearest maximum FA value (i.e., from the centre of the subject's nearby tract)

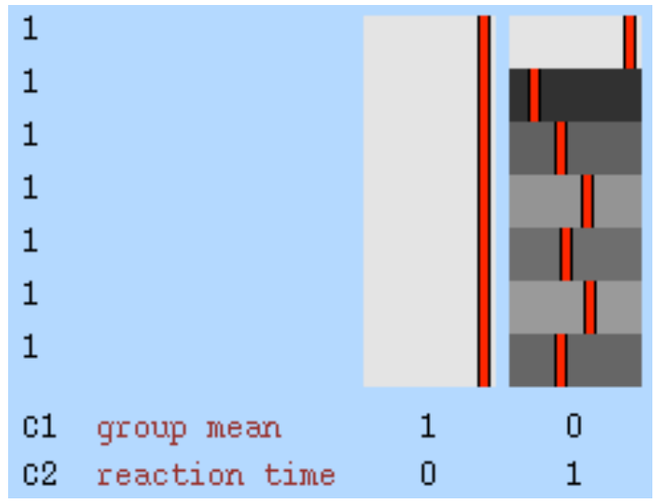


5. Do cross-subject voxelwise stats on skeleton-projected FA and Threshold, (e.g., permutation testing, including multiple comparison correction)



one skeleton voxel's data vector (to be fed into GLM)

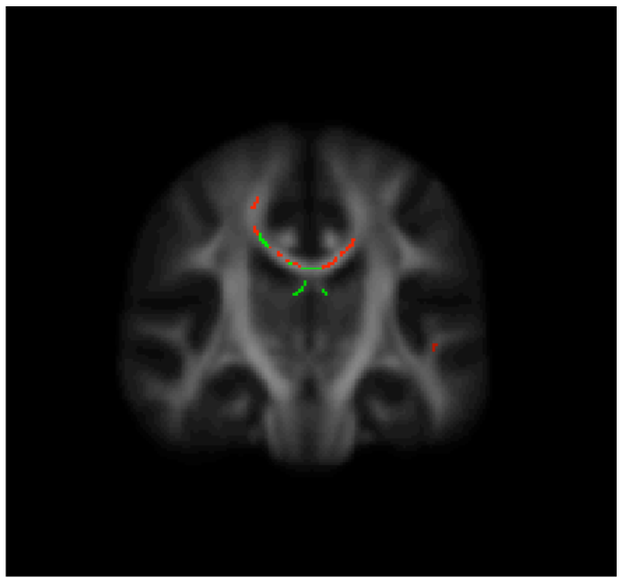


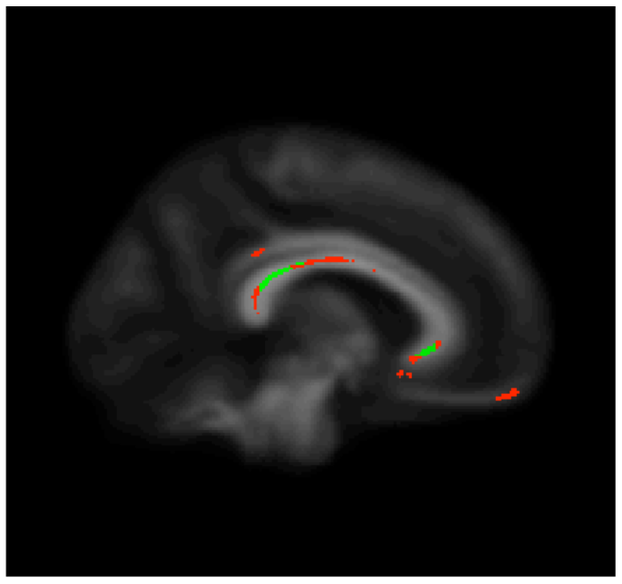


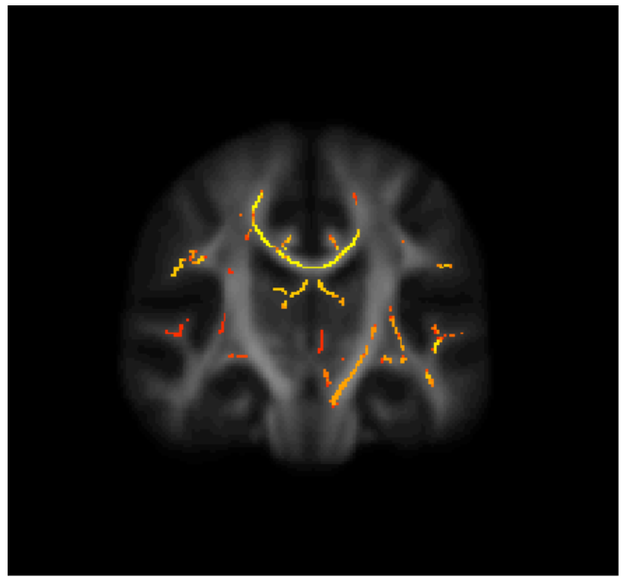
TFCE for TBS

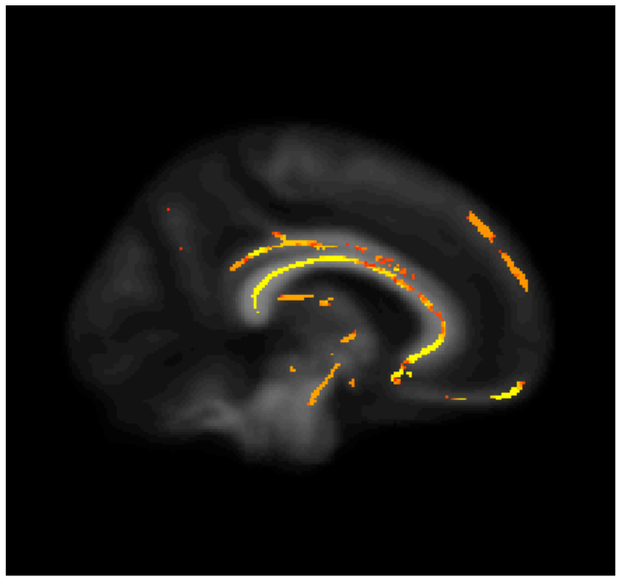
controls > schizophrenics

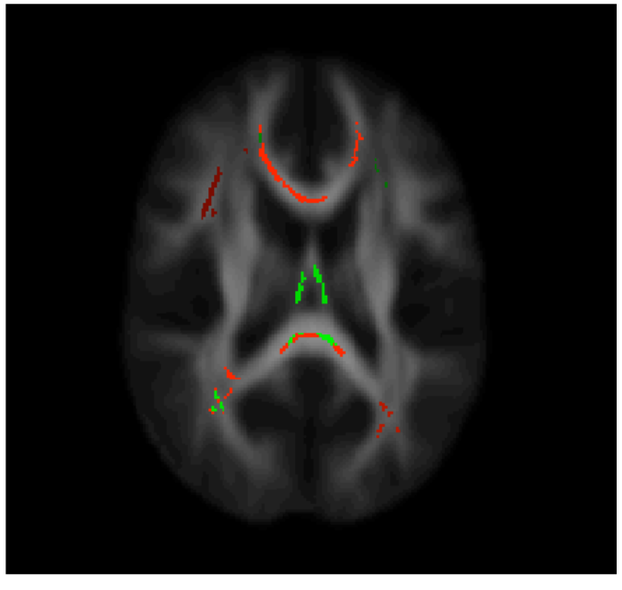
p<0.05 corrected for multiple comparisons across space, using randomise



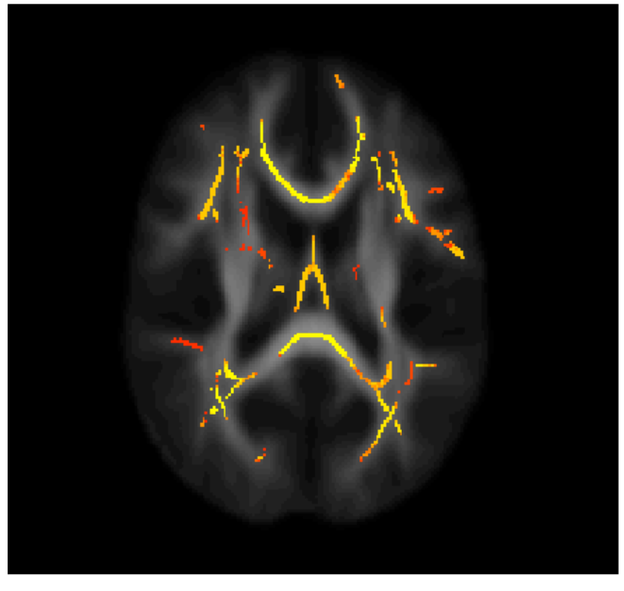








cluster-based:
cluster-forming
threshold =
2 or 3

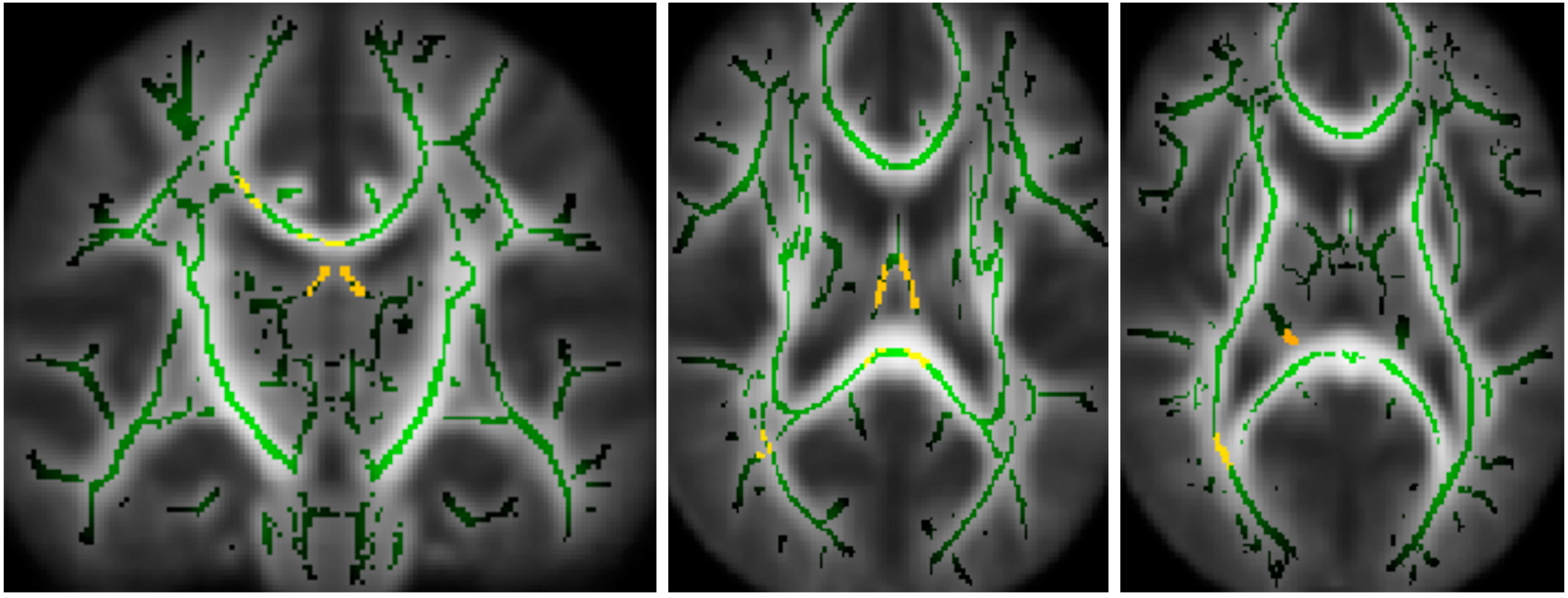


TFCE

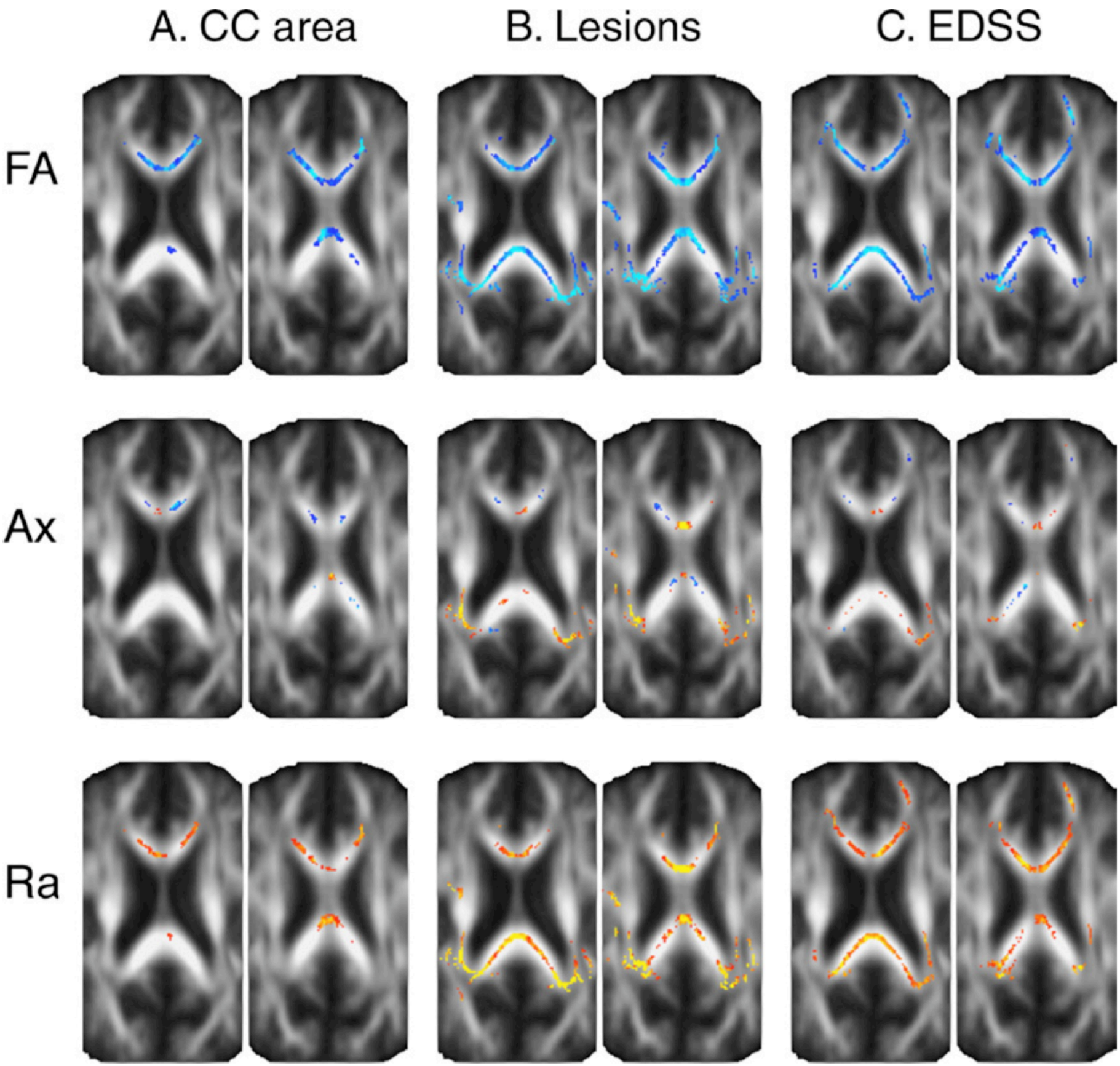
Schizophrenia (Mackay)

TBSS & voxel-wise show reduced FA in corpus callosum & fornix
VBM shows spurious result in thalamus due to increased ventricles in schiz.

TBSS | voxel-wise | mean FA (controls) | mean FA (schiz.)



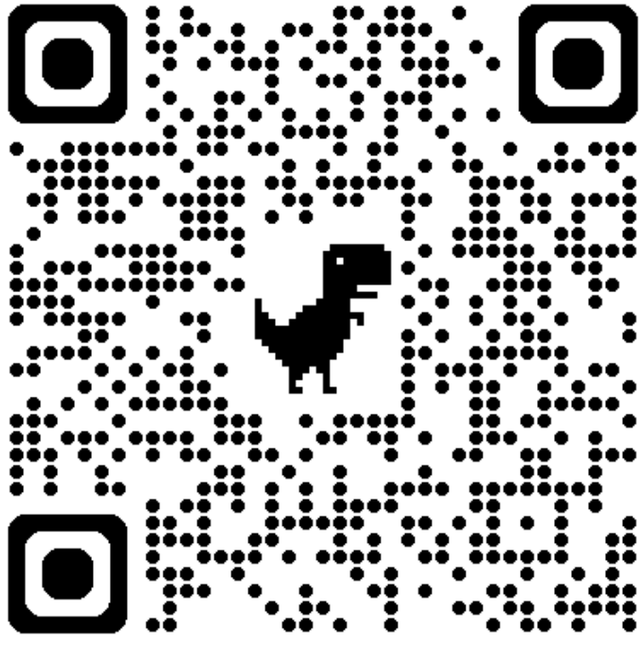
Multiple Sclerosis (Cader, Johansen-Berg & Matthews)

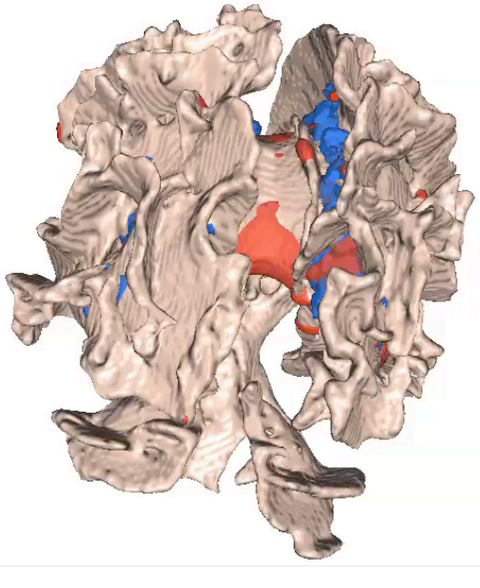


TBSS - Conclusions

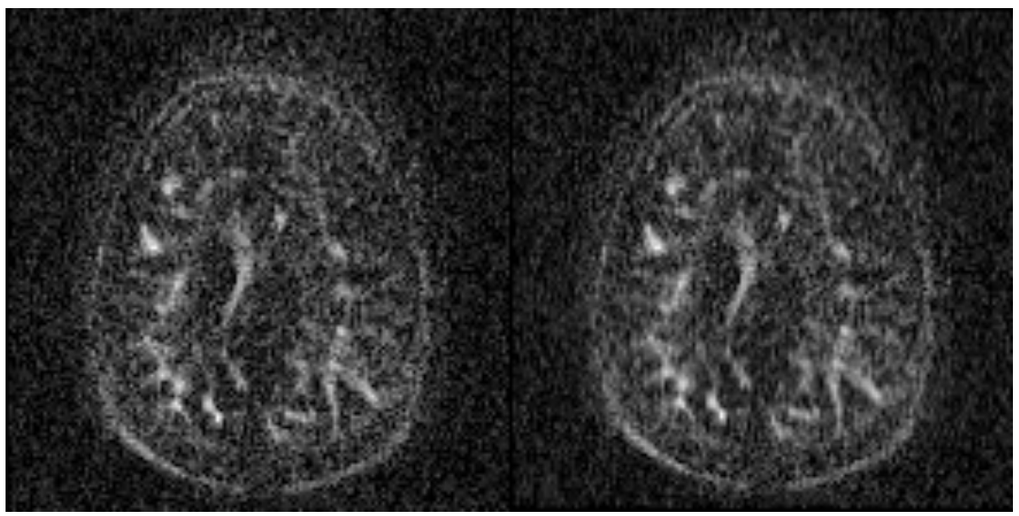
- Diffusion MRI measures direction and size of water diffusion in the brain
- Diffusion tensor (DTI) models this diffusion
- DTI summary measures (FA/MD/axial/radial) can be compared across subjects using TBSS

Submit your questions online





eddy and topup - tools for processing of diffusion data

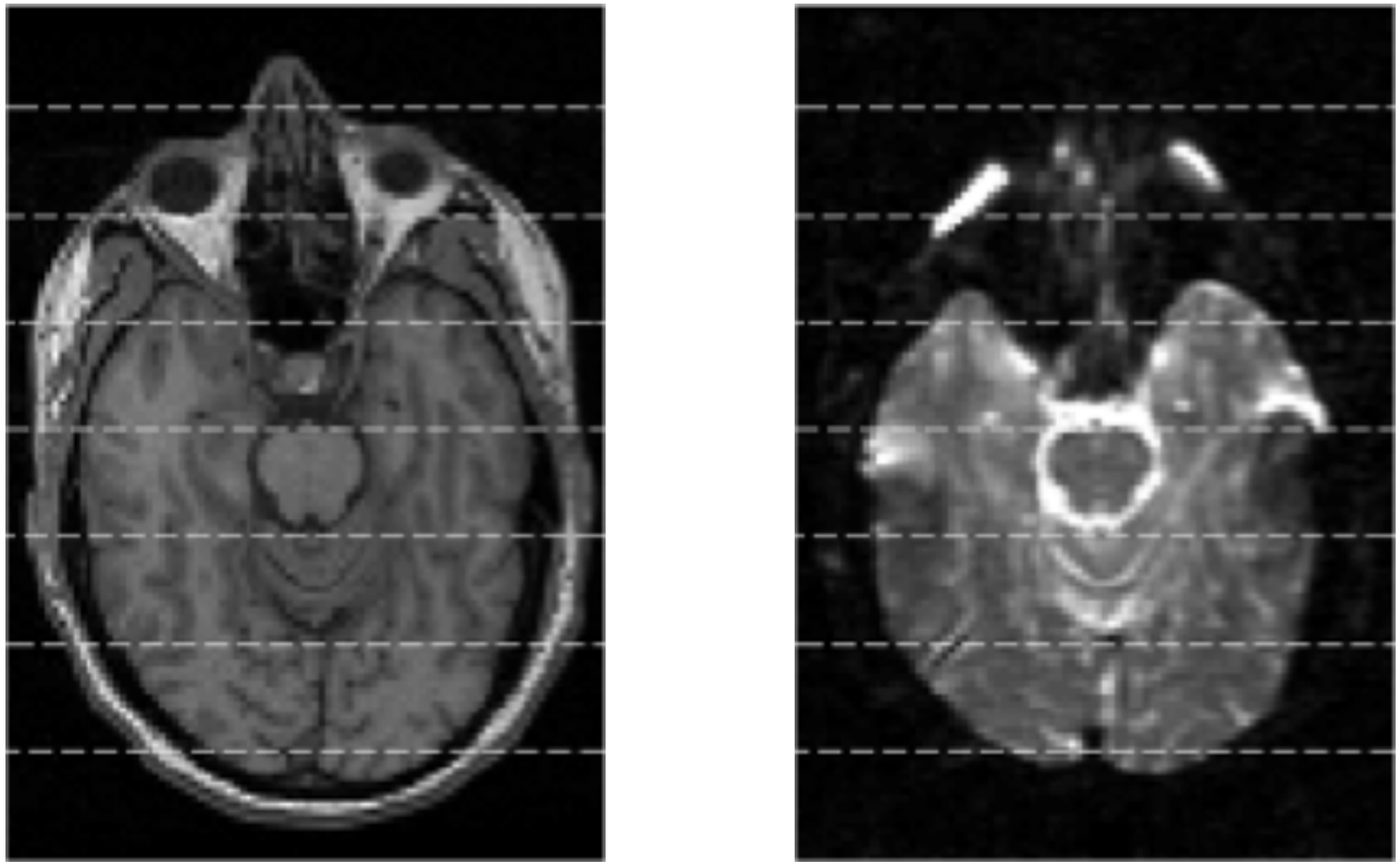


Submit your questions online

Outline of the talk

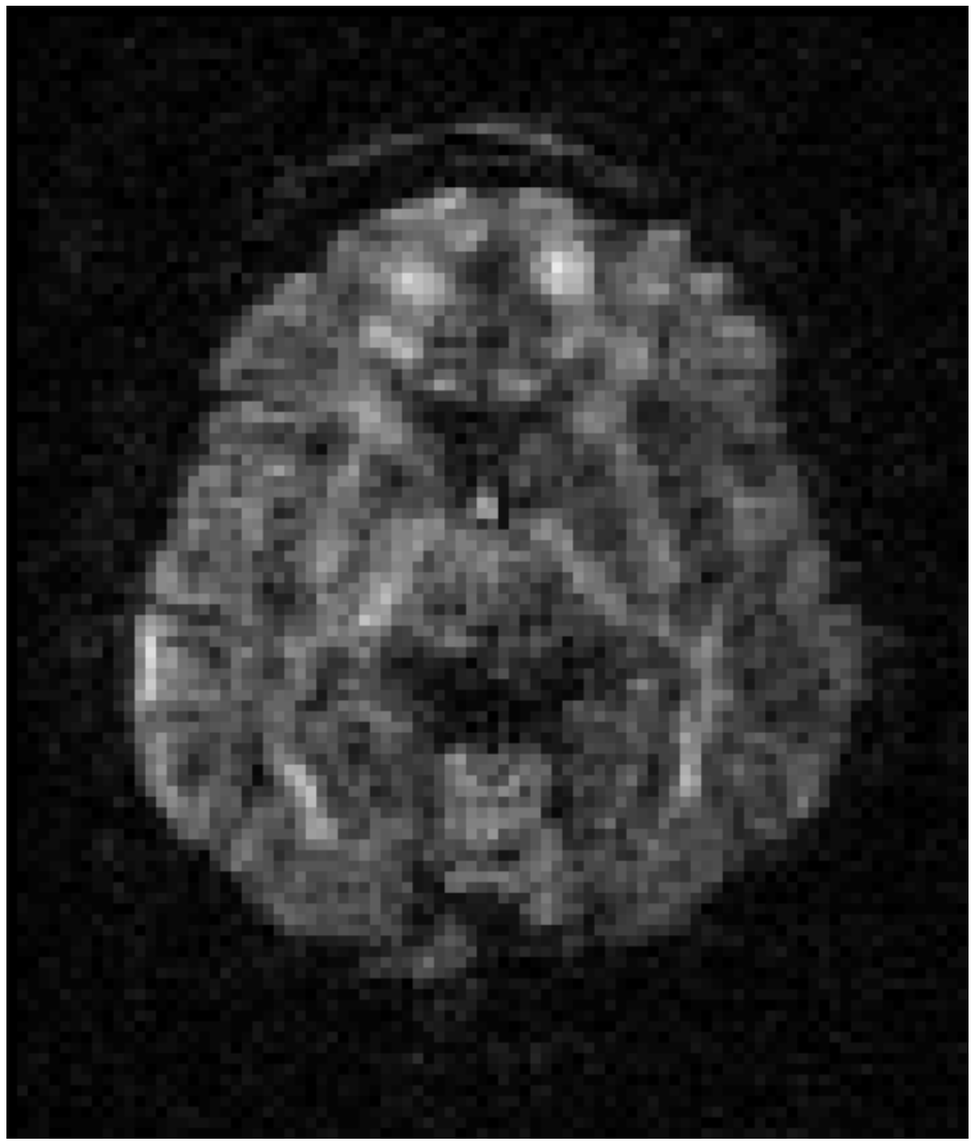
- What is the problem with diffusion data?
- Off-resonance field
  - How does it cause distortions?
  - Where does it come from?
- Registering diffusion data
  - How topup works
  - How eddy works
- Practicalities
- Some results
- Quality control
- New eddy features

What is the problem with diffusion data?



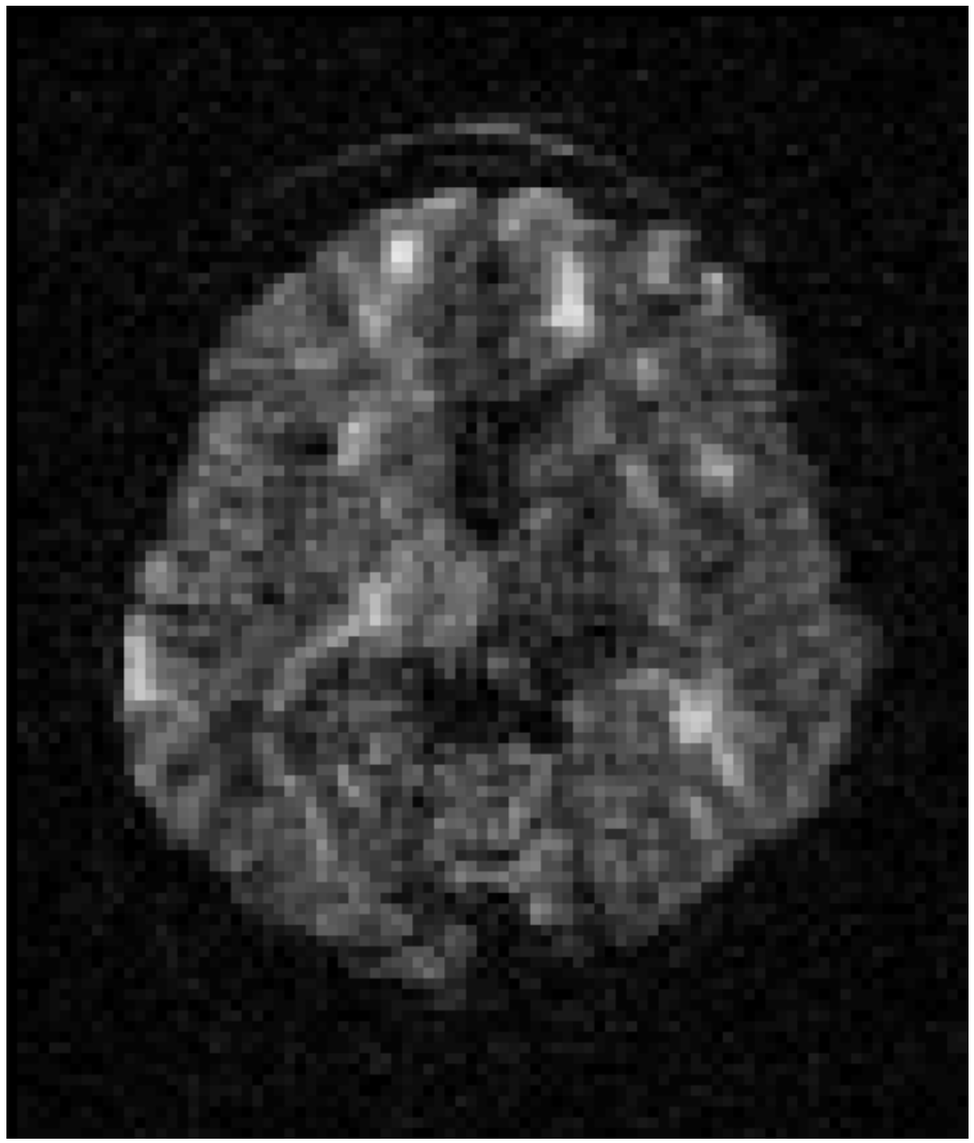
Well, it isn’t very anatomically faithful

What is the problem with diffusion data?



In fact, it isn’t even internally consistent

What is the problem with diffusion data?



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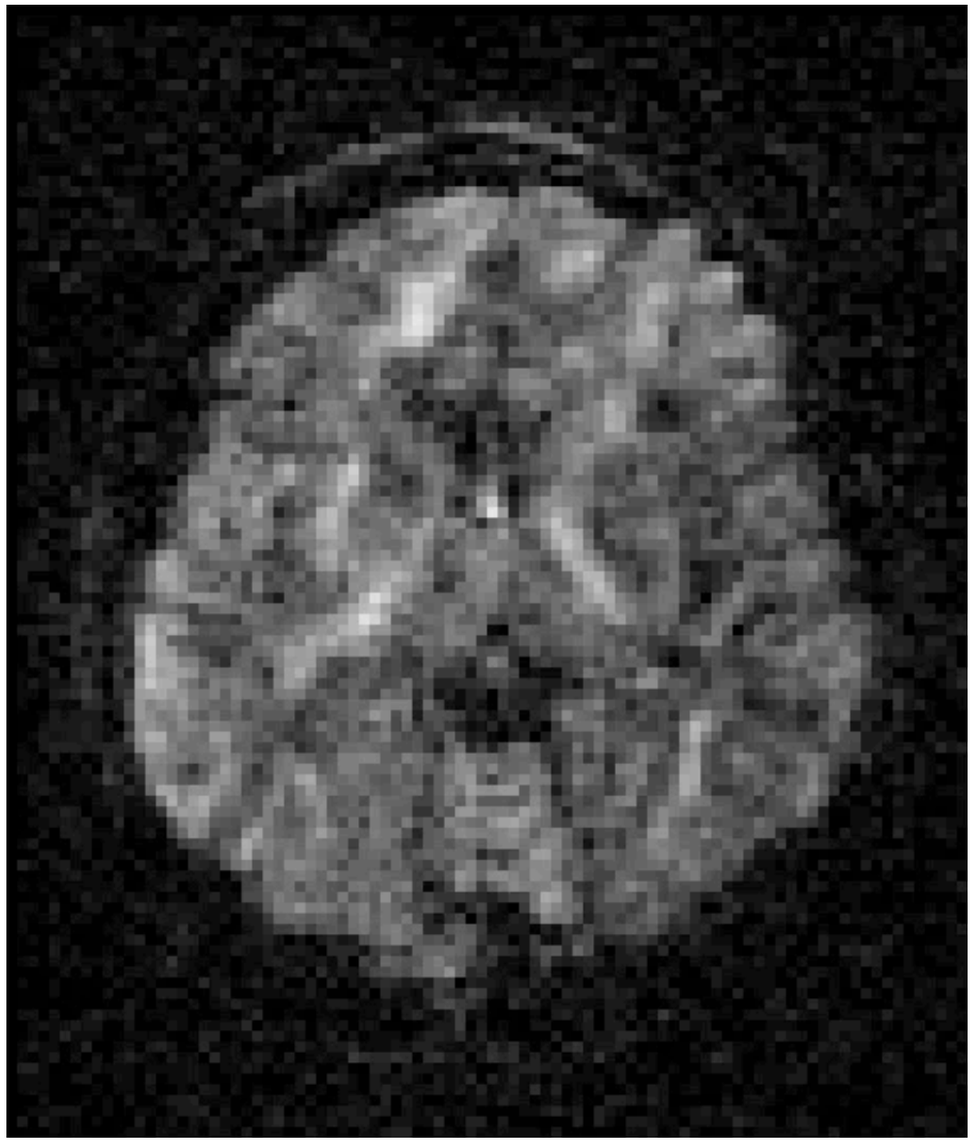

In fact, it isn’t even internally consistent

Outline of the talk

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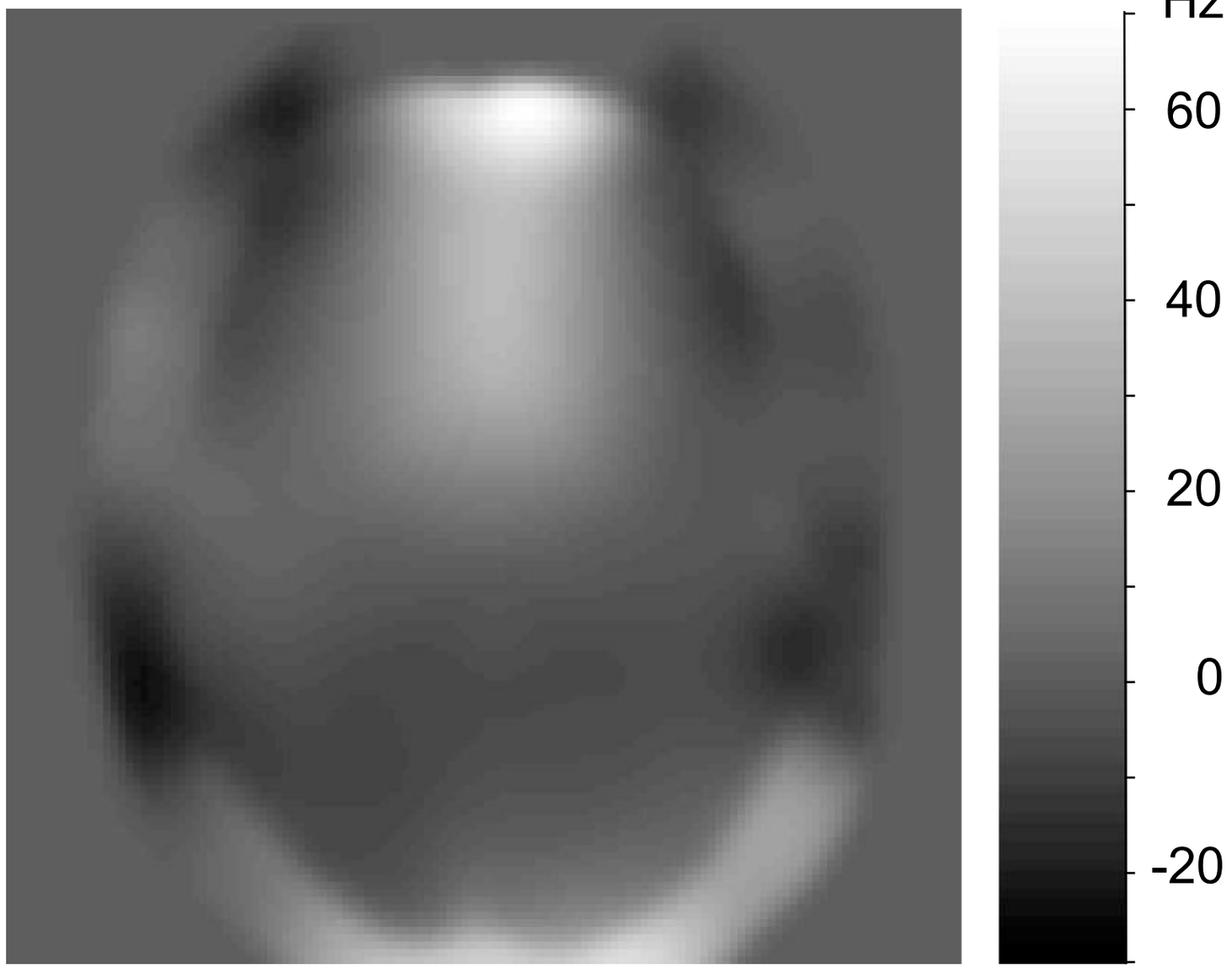
- Some results
- New eddy features

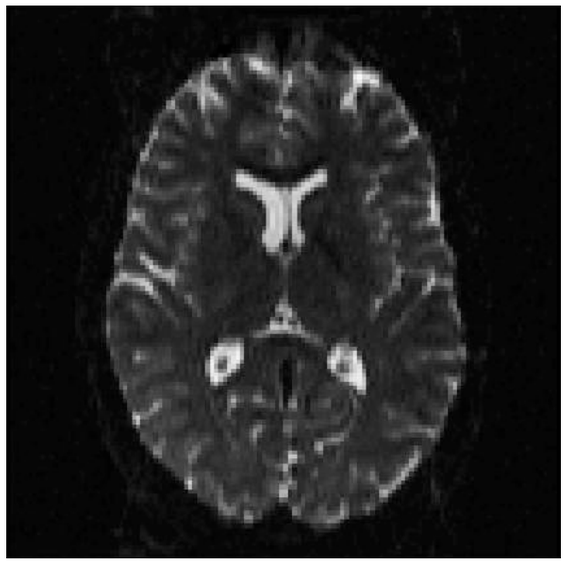
Off-resonance field ⇒ Distortions

An “off-resonance” field is a map of the difference between what we think the field is and what it really is.

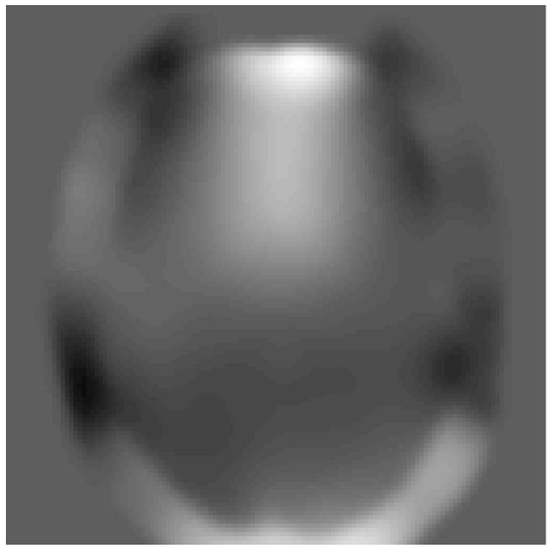


It is all caused by an “off-resonance” field

Off-resonance field ⇒ Distortions



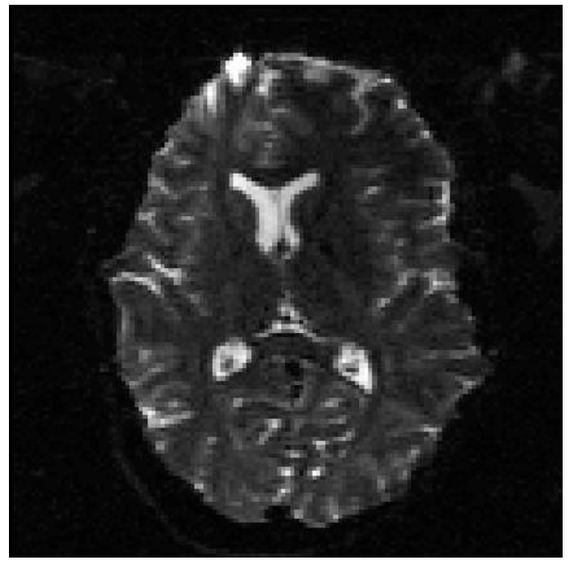
But this object

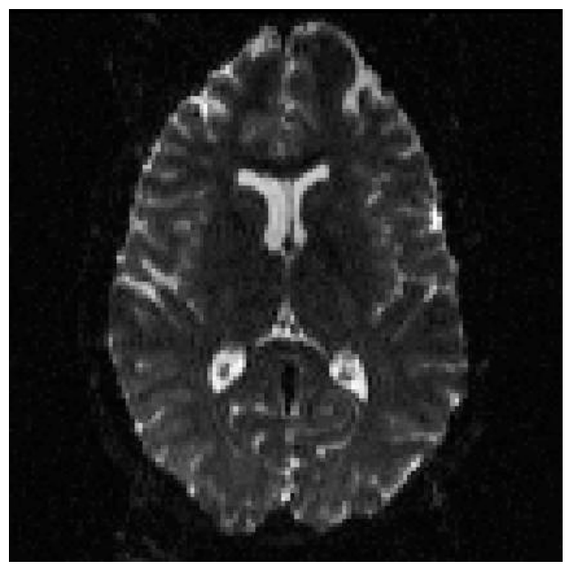


scanned in this field

or this

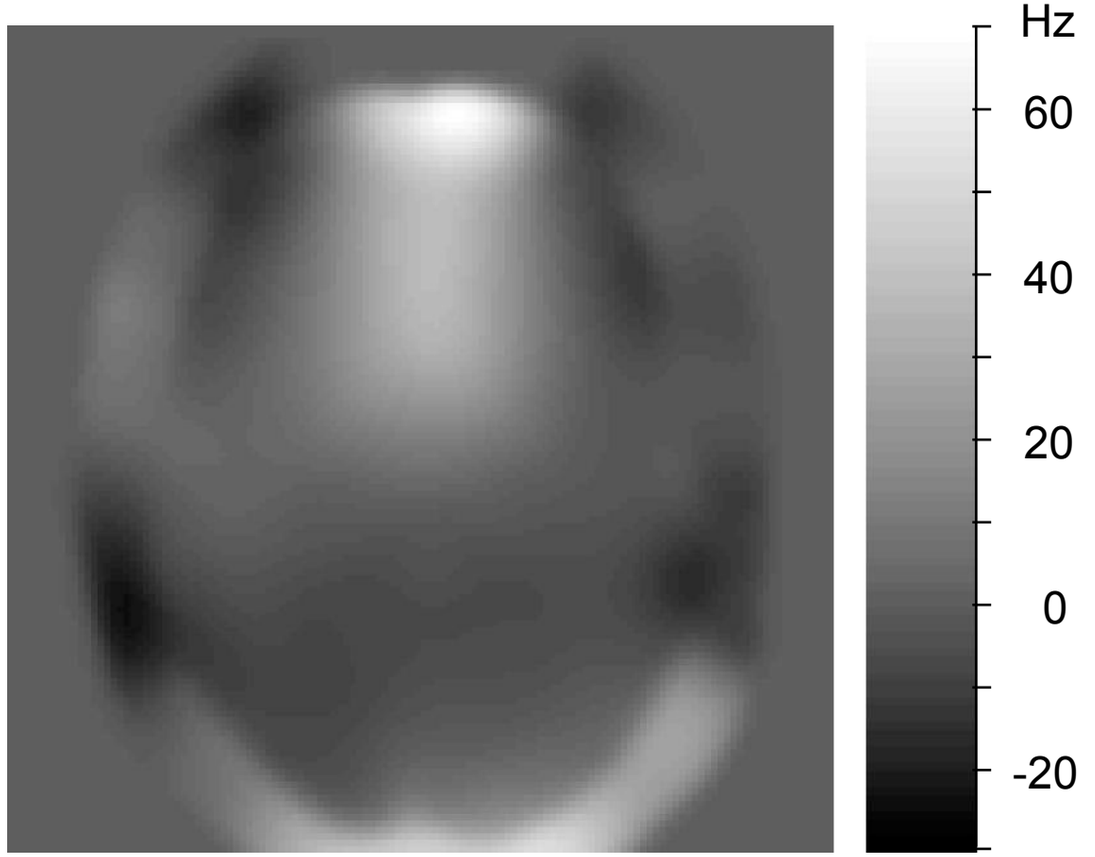
Can yield this





So there is clearly more to this story...

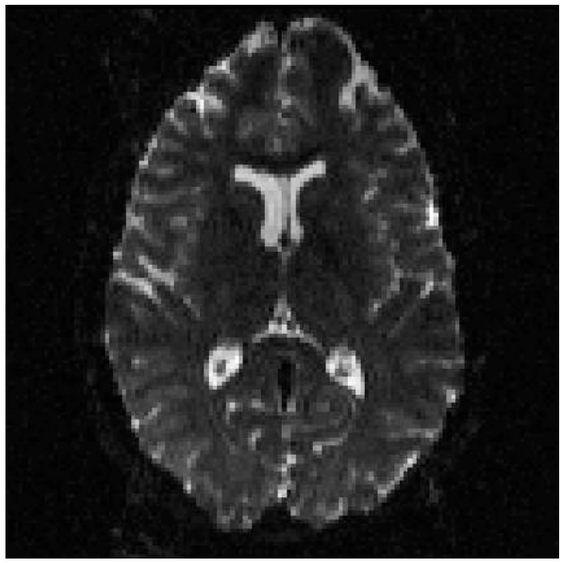
Off-resonance field ⇒ Distortions

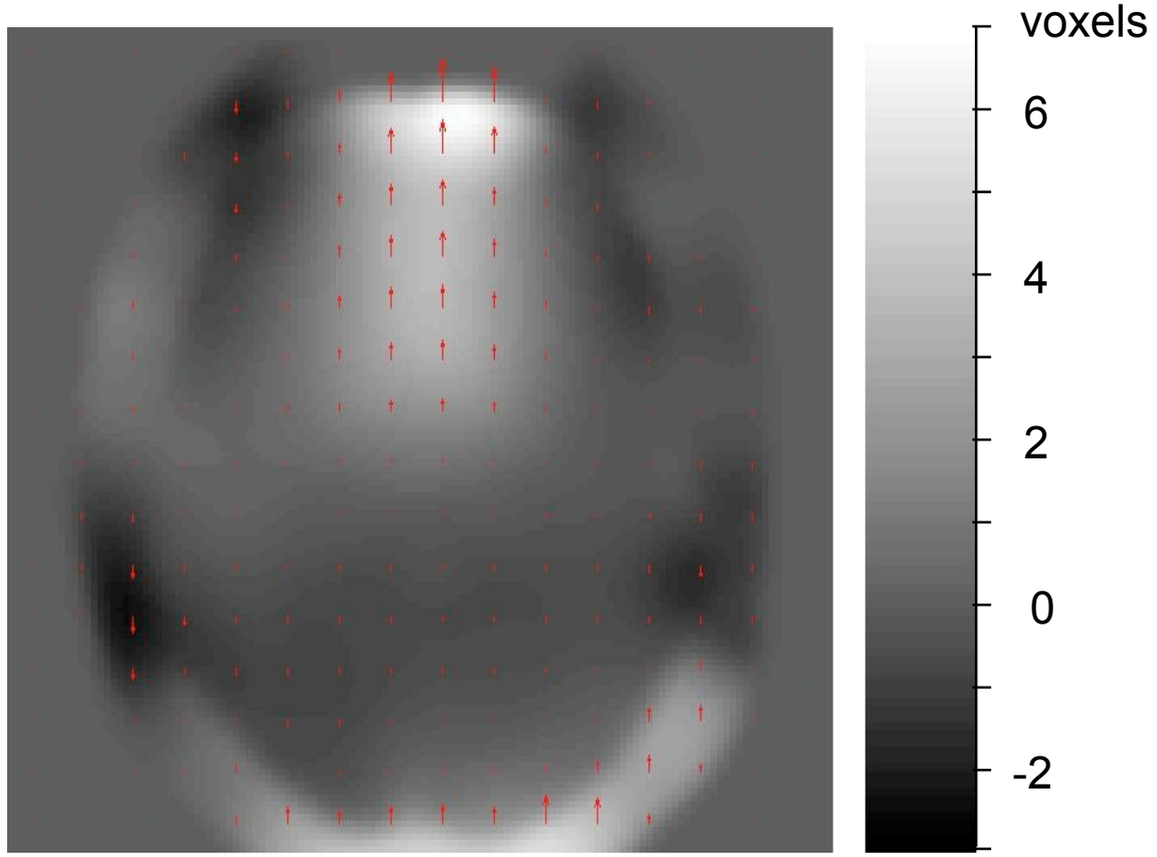


An off-resonance field is effectively a scaled voxel-displacement map.

If we know the imaging parameters we can do the translation.

Off-resonance field ⇒ Distortions





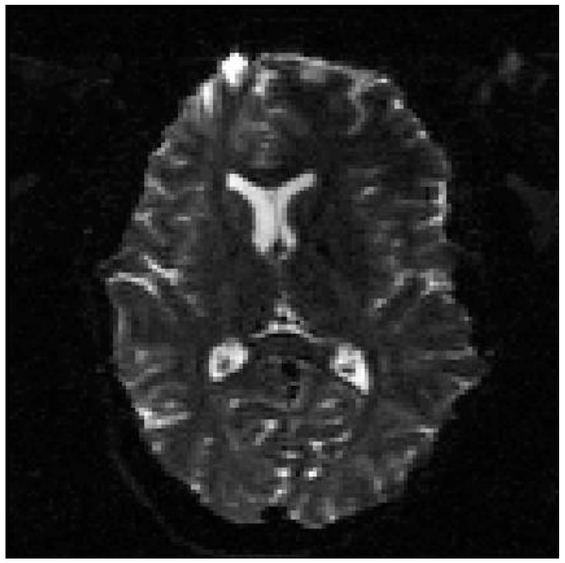
And know what to expect

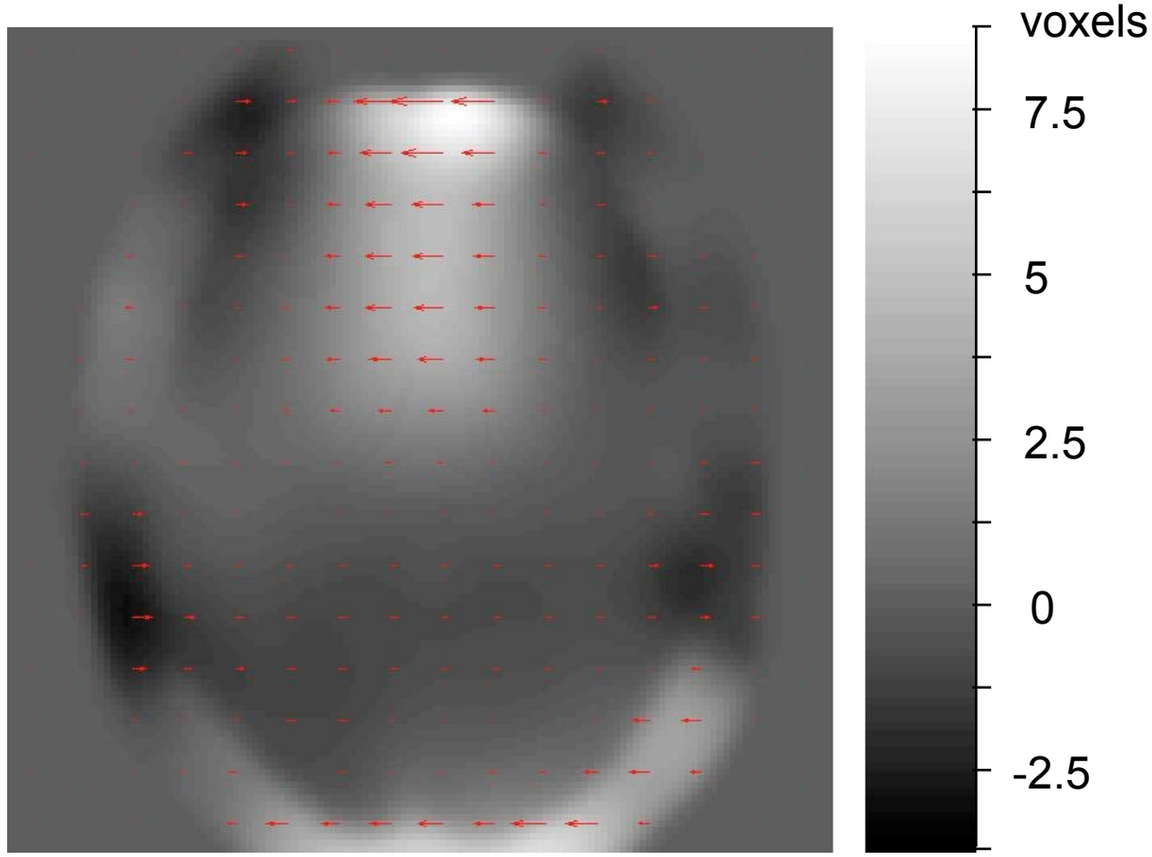
An off-resonance field is effectively a scaled voxel-displacement map.

If we know the imaging parameters we can do the translation.

BW/voxel = 10Hz, **p** = [0 1 0]

Off-resonance field ⇒ Distortions





And know what to expect

So, an off-resonance field is effectively a scaled voxel-displacement map.

And if we know the imaging parameters we can do the translation.

BW/voxel = 8Hz, **p** = [-1 0 0]

Outline of the talk

- What is the problem with diffusion data?
- Off-resonance field
  - How does it cause distortions?
  - Where does it come from?
- Registering diffusion data
  - How topup works
  - How eddy works
- Practicalities
- Some results
- New eddy features

Where does the off-resonance field come from?

- There are two sources
- The first is the object (head) itself.

(CT of) Human head

$B_0 \odot$

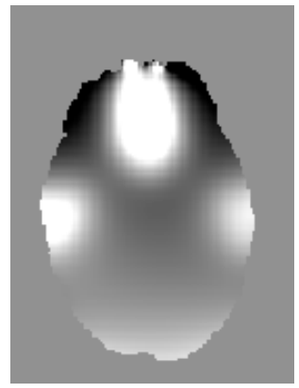
Resulting field

PPMs

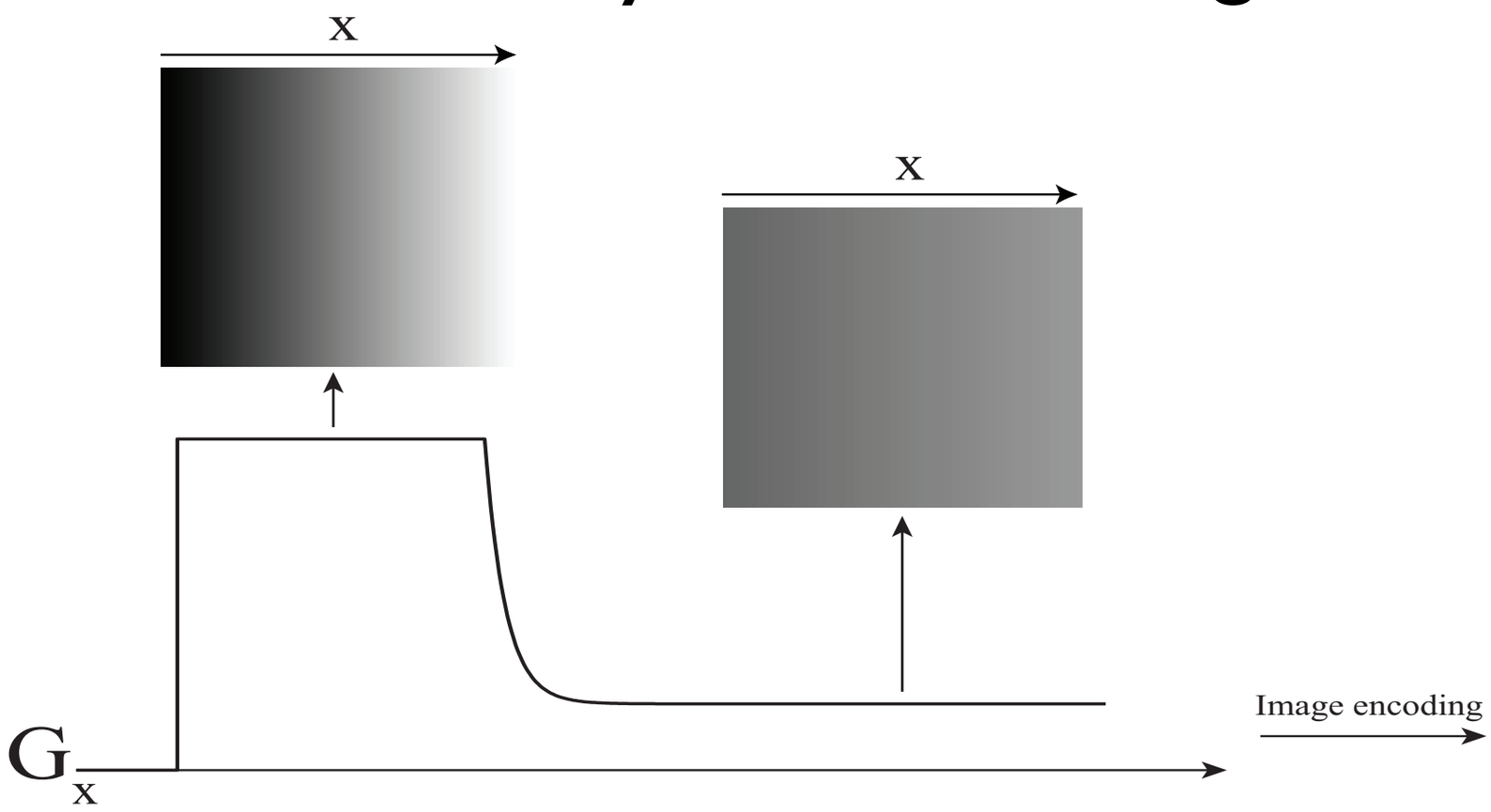
Must fulfil $\begin{cases} \nabla \times \mathbf{H} = 0 \\ \nabla \bullet \mathbf{B} = 0 \end{cases}$ (still)

Where does the off-resonance field come from?

- There are two sources
- The first is the object (head) itself.



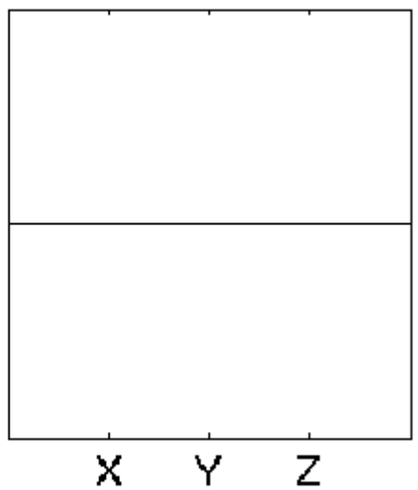
- The second is caused by the diffusion gradient



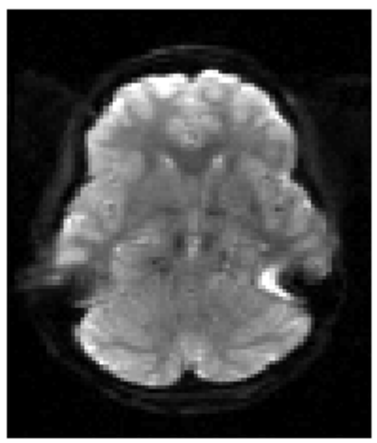
Where does the off-resonance field come from?

So for any diffusion weighted volume the off-resonance field is the sum of these two contributions

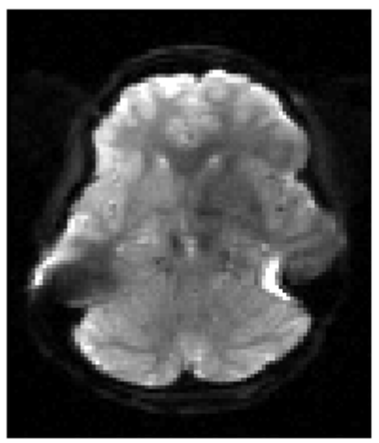
Susceptibility + Eddy currents = Total



Diffusion gradient



"True" object

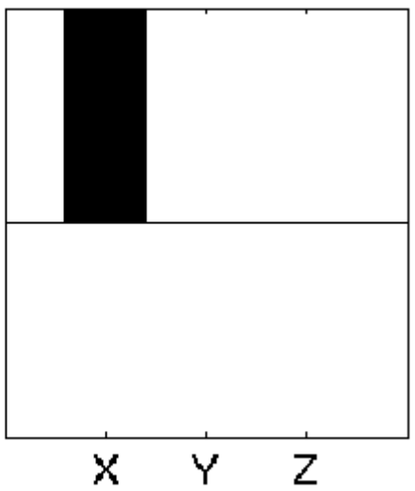


Observed image

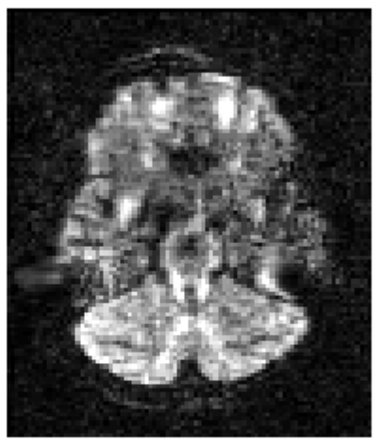
Where does the off-resonance field come from?

So for any diffusion weighted volume the off-resonance field is the sum of these two contributions

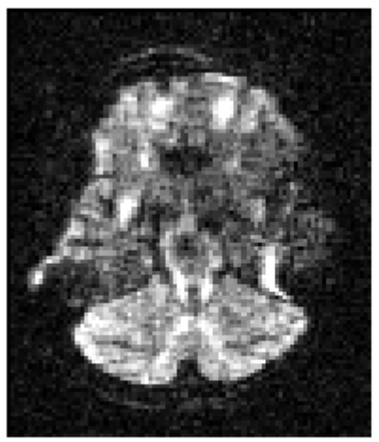
Susceptibility + Eddy currents = Total



Diffusion gradient



"True" object



Observed image

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So for any diffusion weighted volume the off-resonance field is the sum of these two contributions

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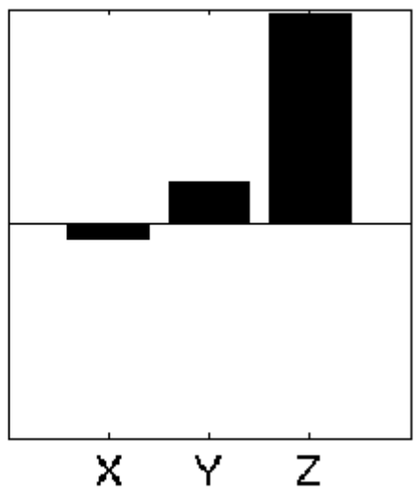
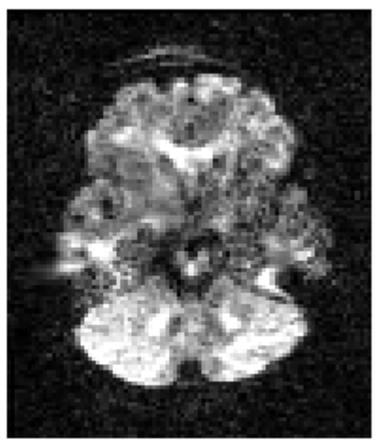
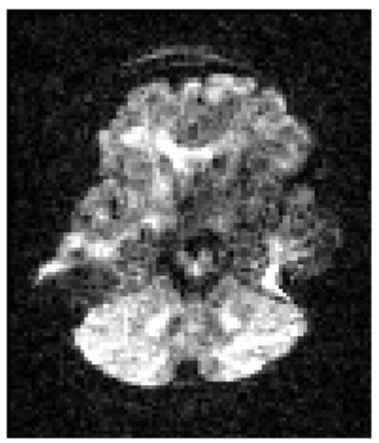


Diffusion gradient



"True" object

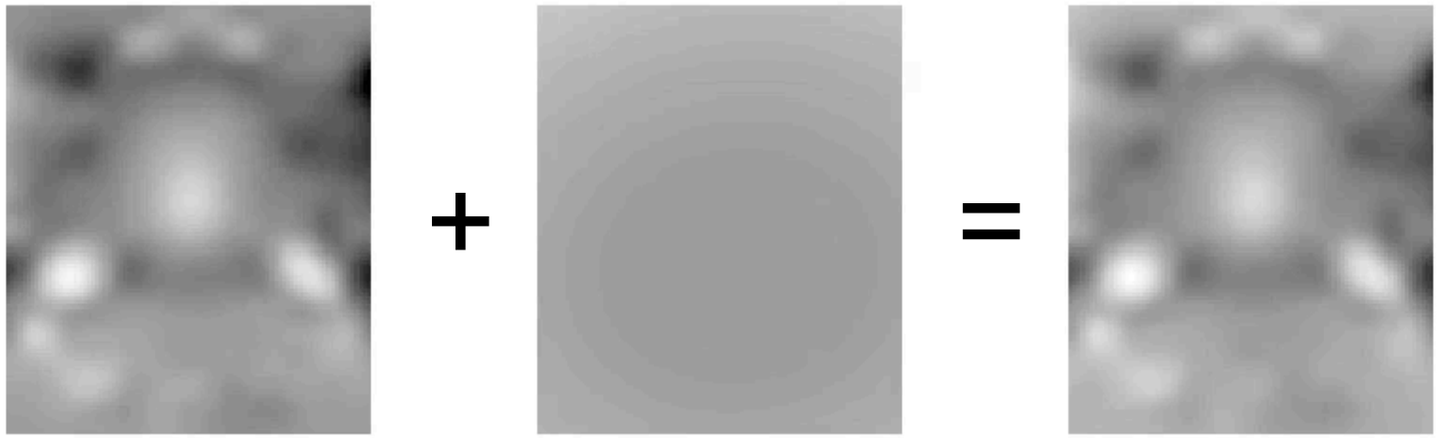


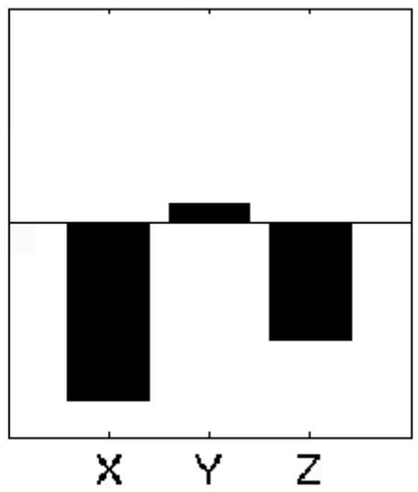
Observed image

Where does the off-resonance field come from?

So for any diffusion weighted volume the off-resonance field is the sum of these two contributions

Susceptibility + Eddy currents = Total





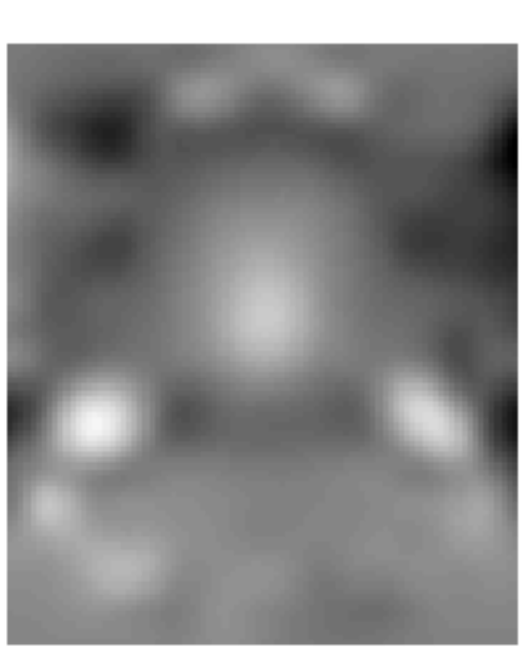
Diffusion gradient

"True" object

Observed image

Separate estimation of susceptibility- and eddy current-fields

So, what we need to estimate is

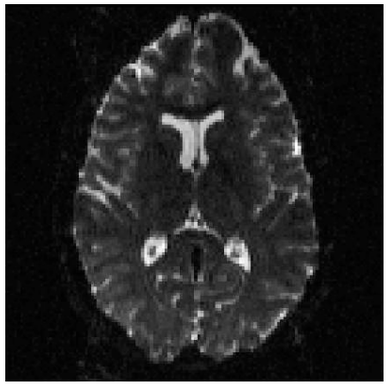
One of these per subject	One of these per volume
	

FSL-tools: topup eddy

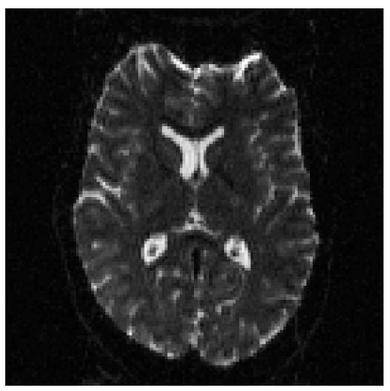
Outline of the talk

- What is the problem with diffusion data?
- Off-resonance field
  - How does it cause distortions?
  - Where does it come from?
- Registering diffusion data
  - How topup works
  - How eddy works
- Practicalities
- Some results
- Quality control
- New eddy features

How topup works (very briefly)



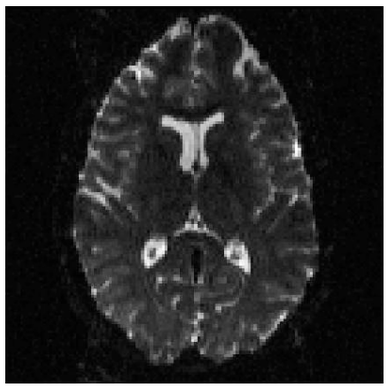
p=[0 1 0]



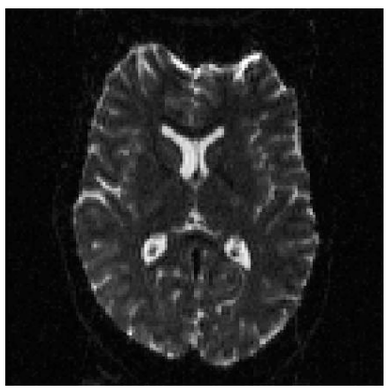
p=[0 -1 0]

Given two images acquired with different phase-encoding

How topup works (very briefly)



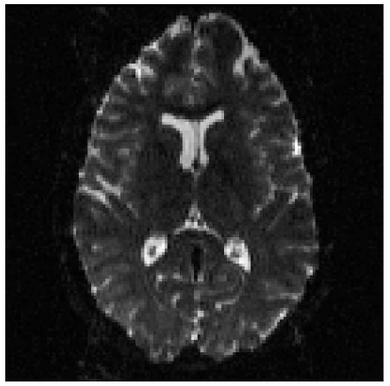
p=[0 1 0]



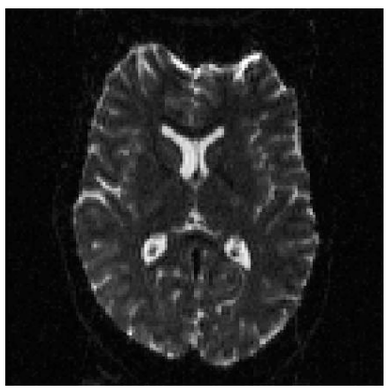
p=[0 -1 0]

topup “guesses” a field...

How topup works (very briefly)



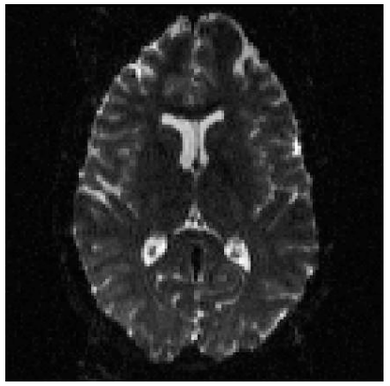
p=[0 1 0]



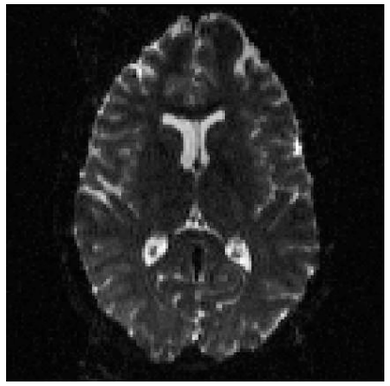
p=[0 -1 0]

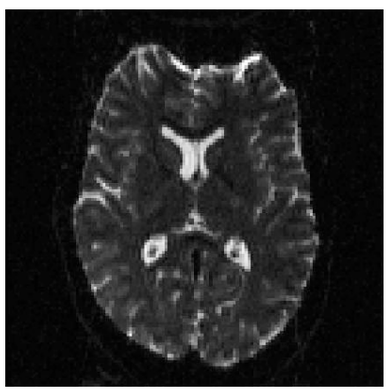
...calculates the displacement maps...

How topup works (very briefly)

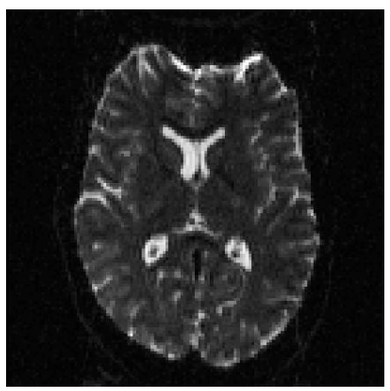


p=[0 1 0]



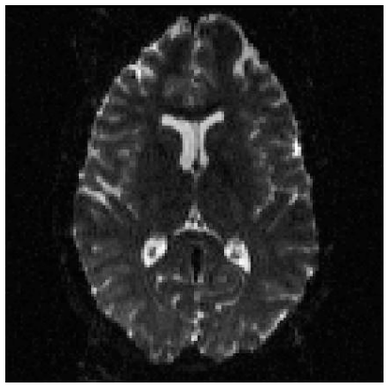


p=[0 -1 0]

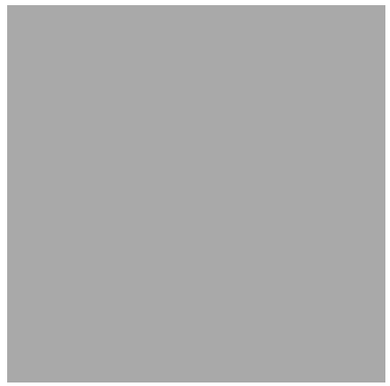


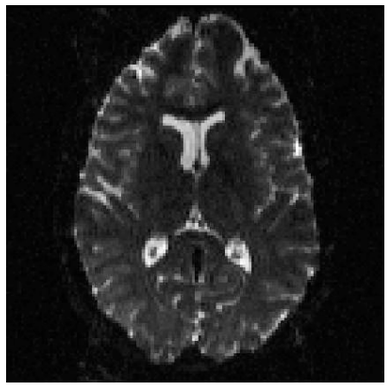
..."corrects" the images...

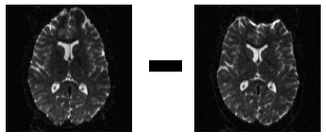
How topup works (very briefly)

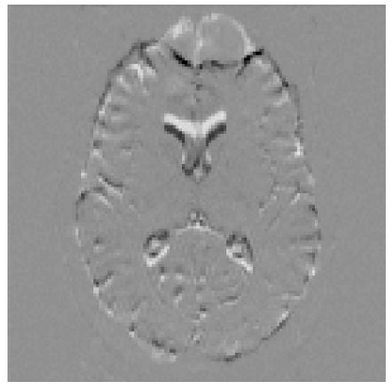


p=[0 1 0]

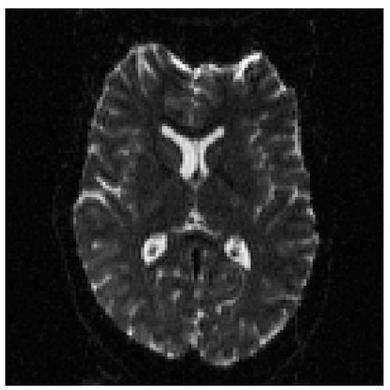




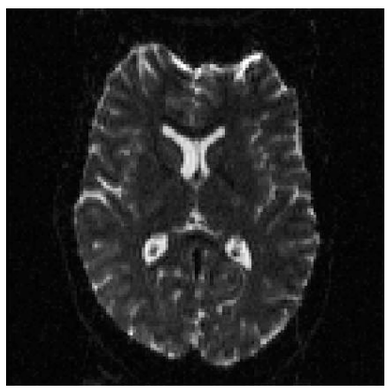




BAD!



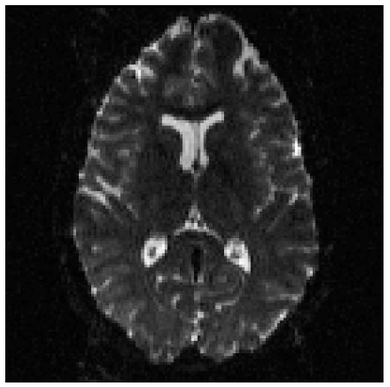
p=[0 -1 0]



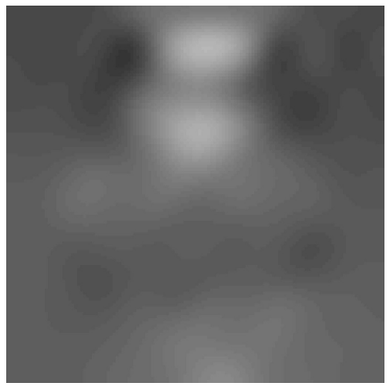
...and evaluates the results...

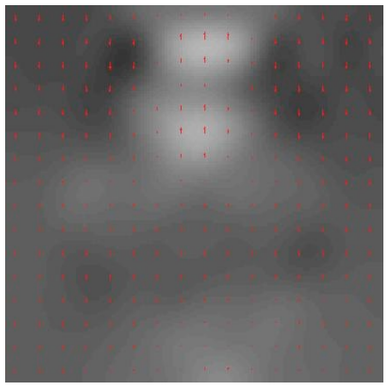
And **this** is the crucial bit.

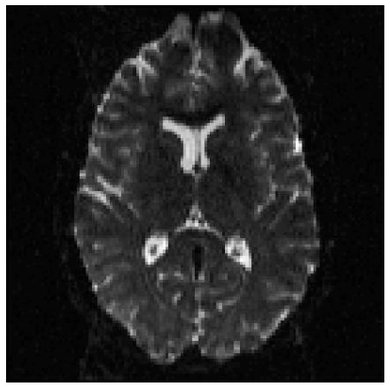
How topup works (very briefly)

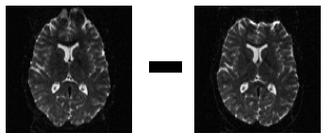


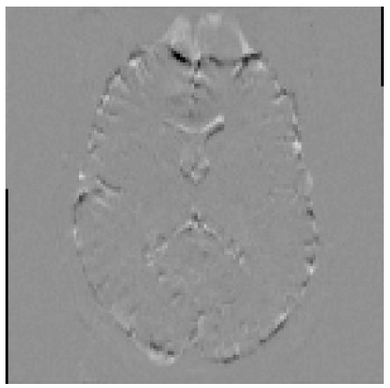
p=[0 1 0]



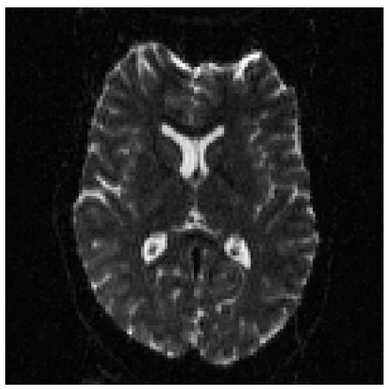




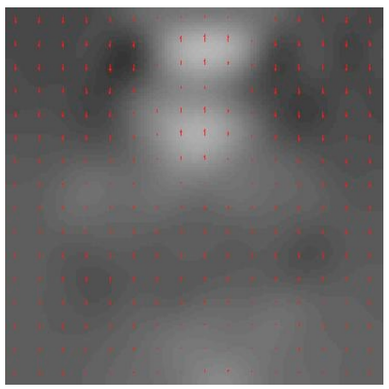


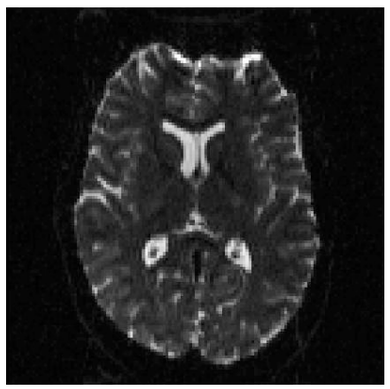


better



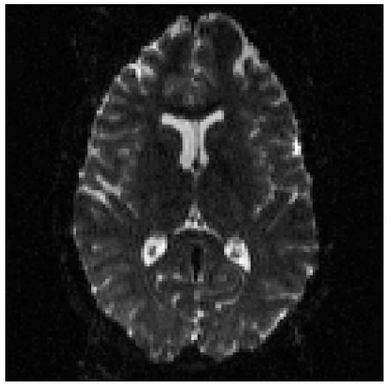
p=[0 -1 0]



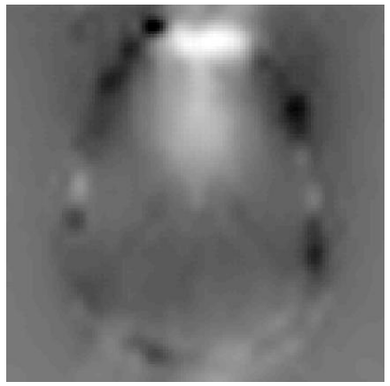


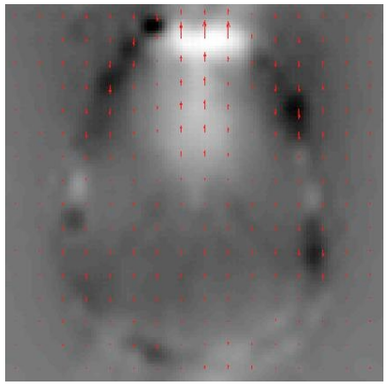
Because topup can then “guess” another field

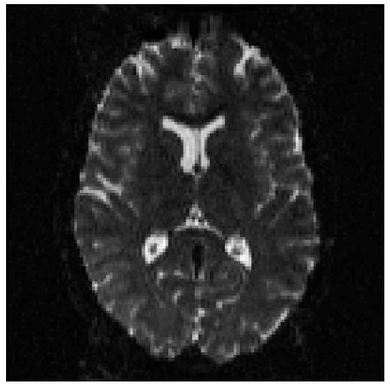
How topup works (very briefly)

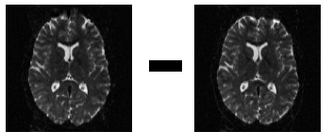


p=[0 1 0]

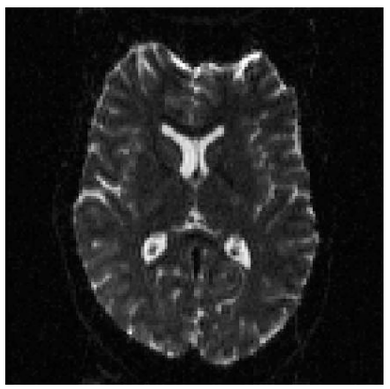




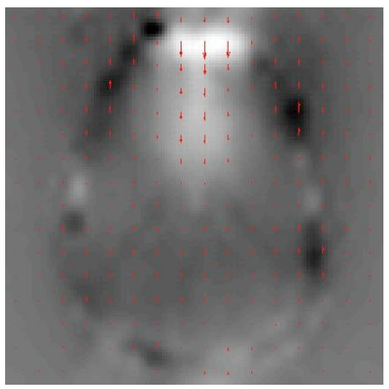


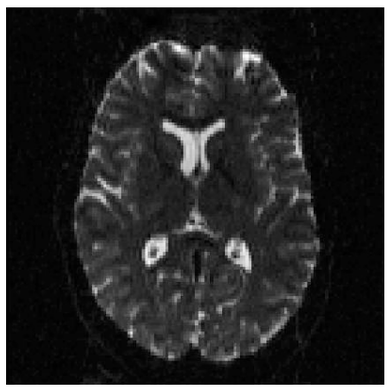


even better



p=[0 -1 0]



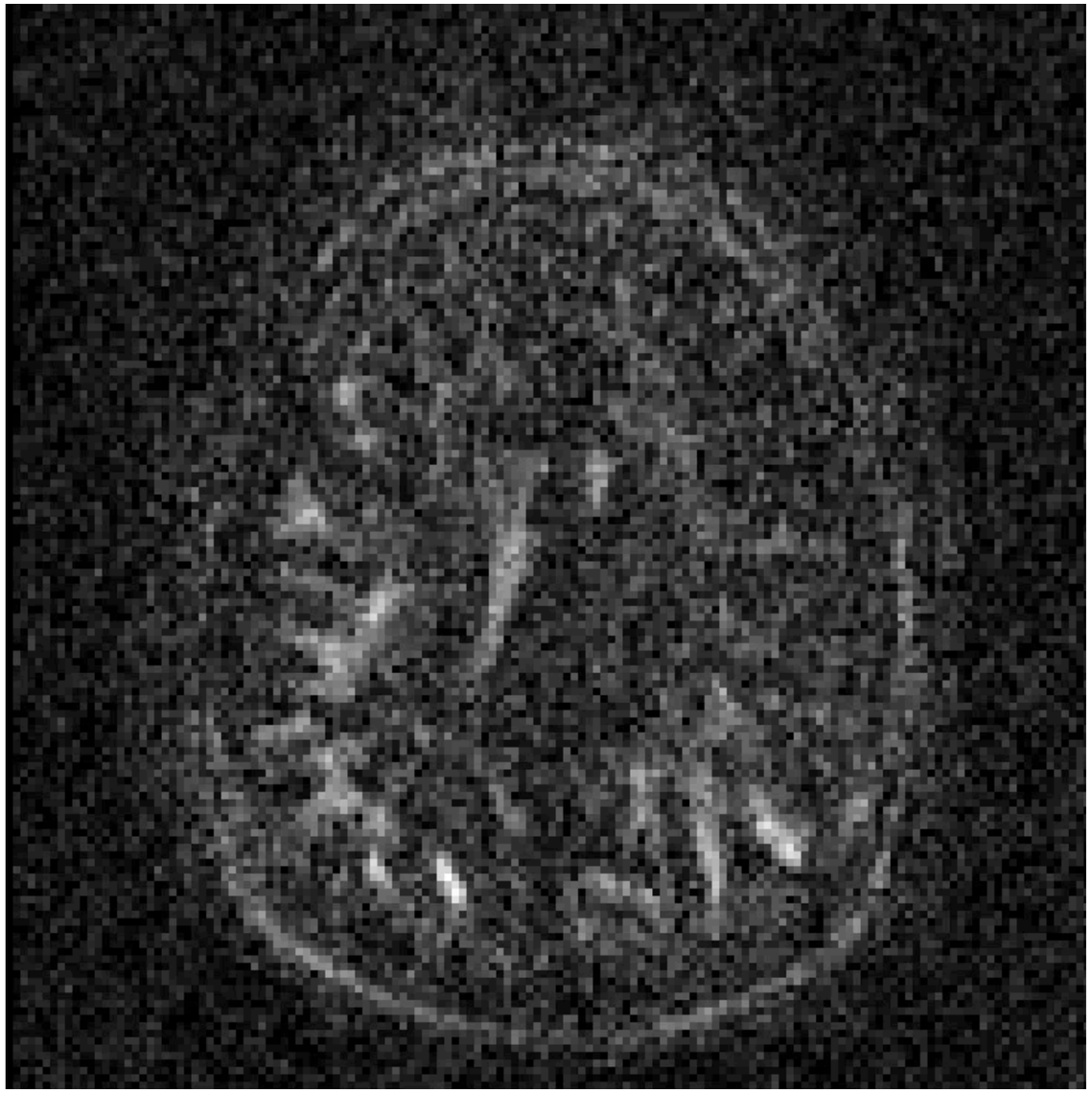


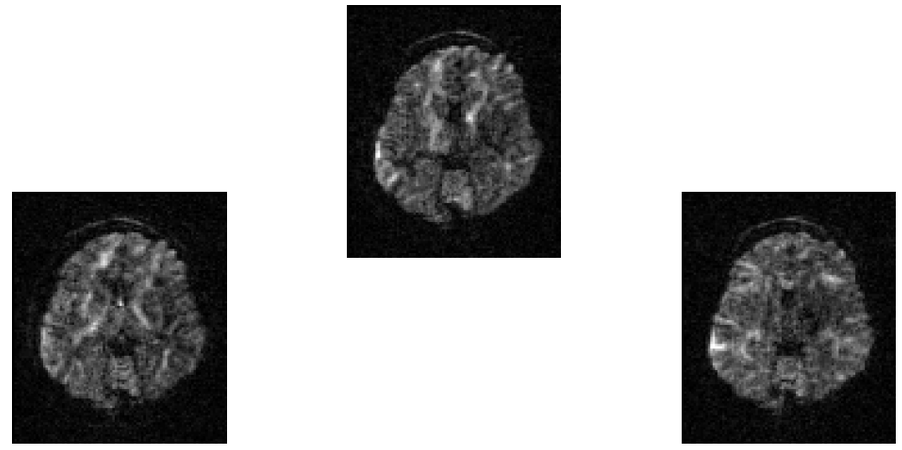
...and another...until it is happy,
and then it “knows” the field

Outline of the talk

- What is the problem with diffusion data?
- Off-resonance field
  - How does it cause distortions?
  - Where does it come from?
- Registering diffusion data
  - How topup works
  - How eddy works
- Practicalities
- Some results
- Quality control
- New eddy features

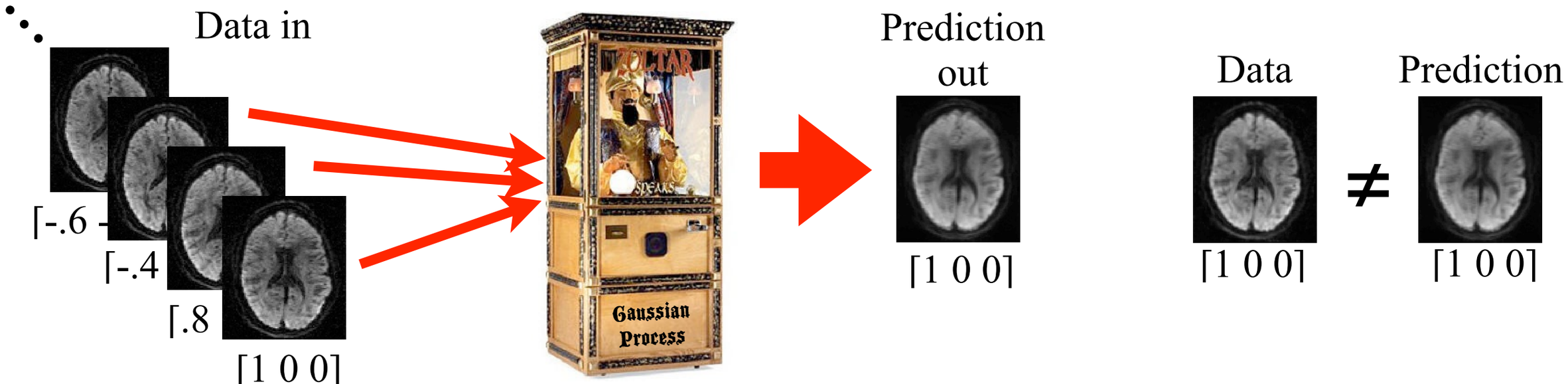
But it is not easy to register diffusion weighted images





- Each image has different distortions -> non-linear registration
- What is the reference image?

Zoltar -- The prediction maker



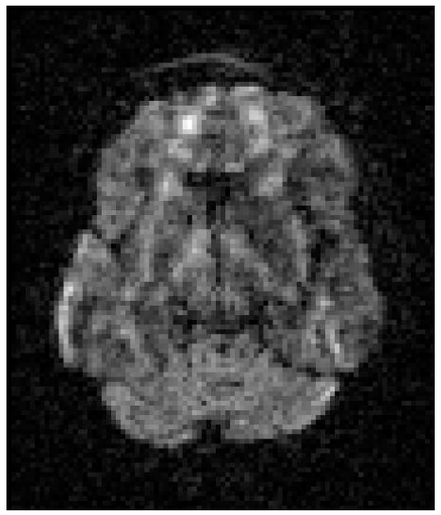
Given some data in, Zoltar will make a prediction what the data “should” be.

The prediction for a given dwi will not be identical to the “input” for that dwi

I know this sounds crazy, but please trust me on this.
(Zoltar is actually a Gaussian Process)

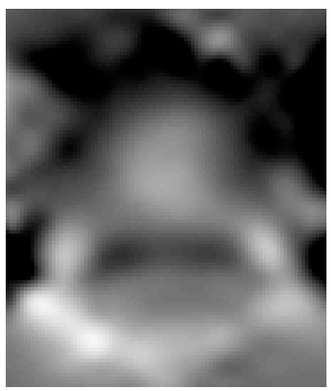
How eddy works: Loading step

Pick the first dwi

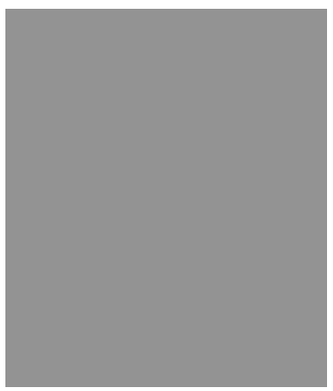


Use current estimates of

Susc



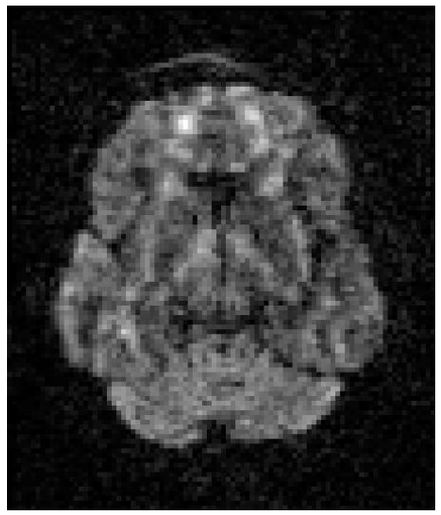
EC



MP

$$\begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

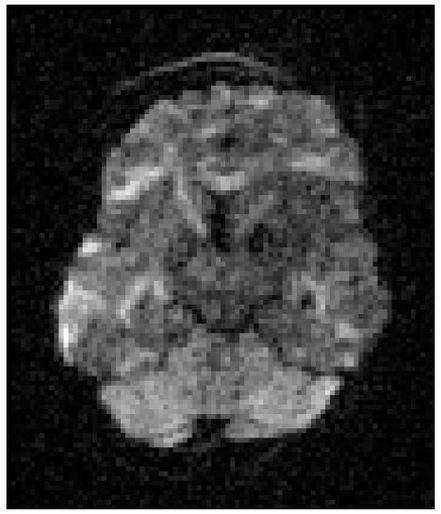
To correct image



And load into prediction maker

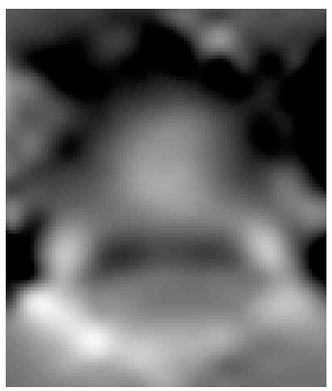
How eddy works: Loading step

then the 2nd dwi

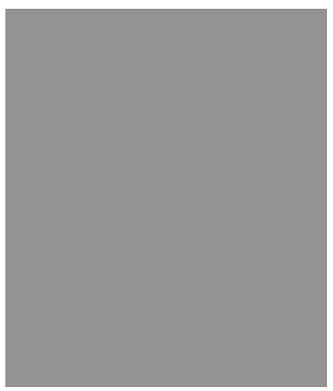


Use current estimates of

Susc



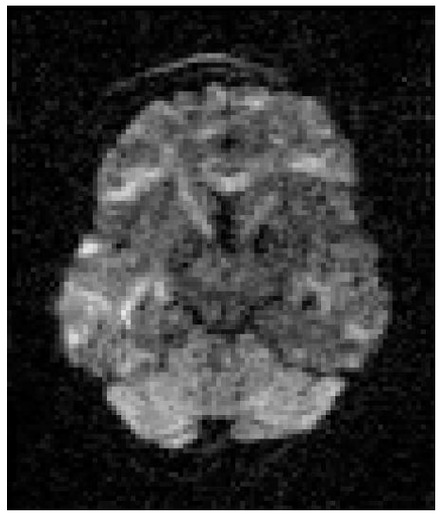
EC



MP

$$\begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

To correct 2nd image

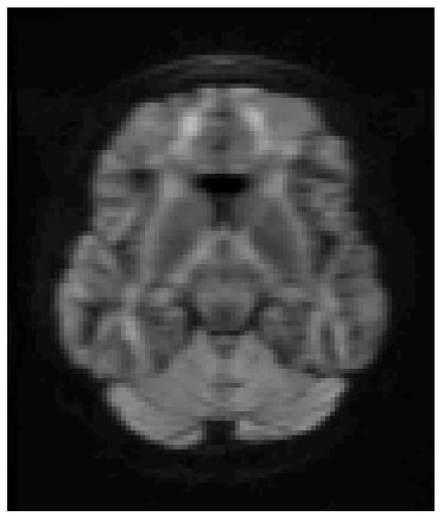


And load into prediction maker

Until we have loaded all dwis

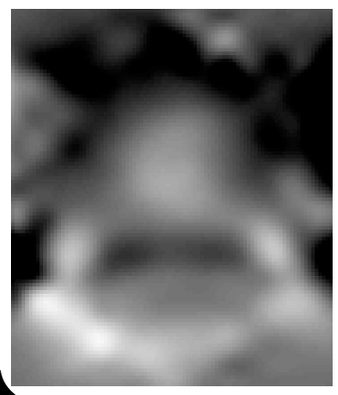
How eddy works: Estimation step

Draw a prediction for first dwi



Use current estimates of

Susc

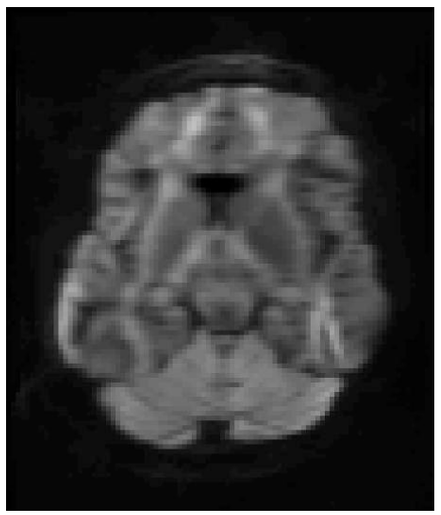


EC

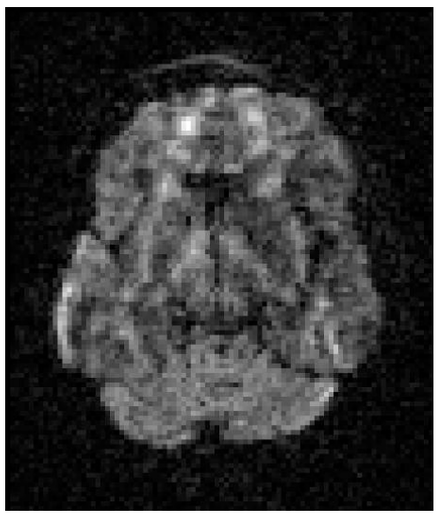
MP

$$\begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

Invert



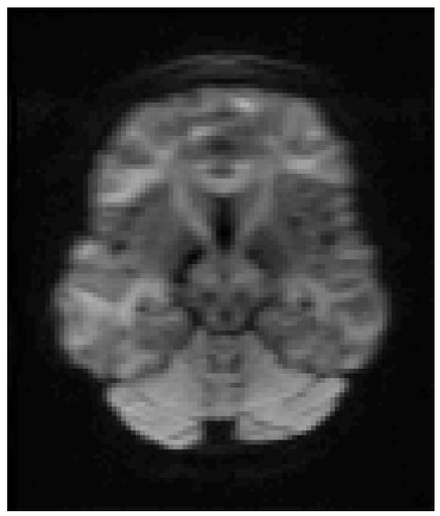
To get prediction in "observation space"



And compare to actual observation

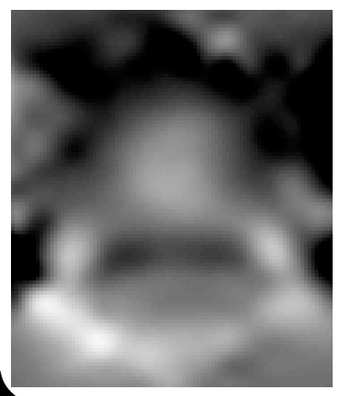
How eddy works: Estimation step

Draw a prediction for 2nd dwi



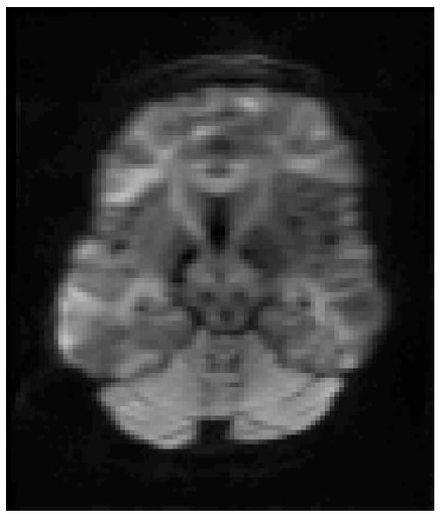
Use current estimates of

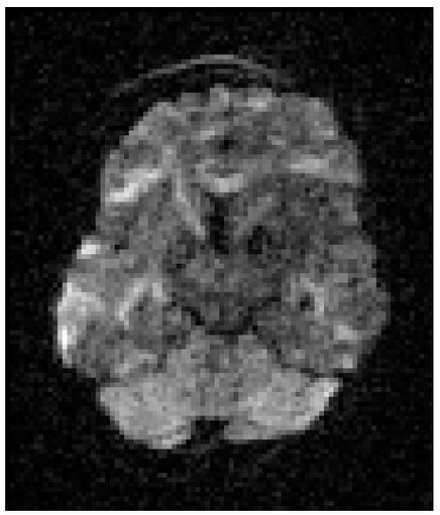
Susc EC MP



$$\begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

Invert



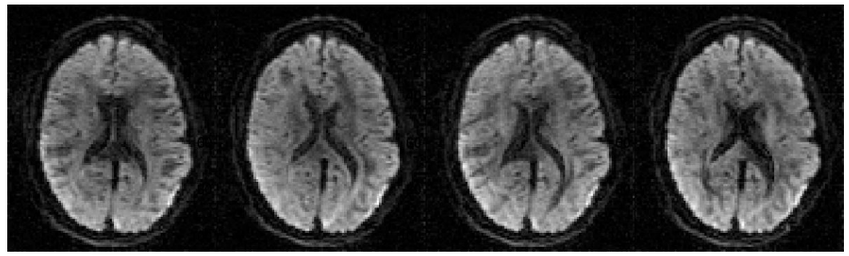


And then we repeat the procedure for the next dwi ...

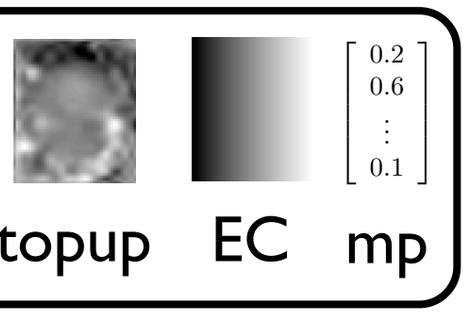
How eddy works

1. For all scans

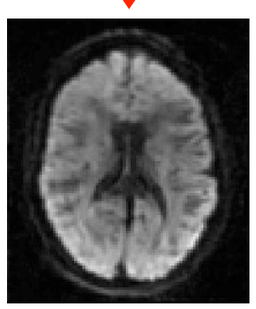
[1 0 0] [.6 -.4 -.7] [.8 .6 0] [-.4 .9 0]



...



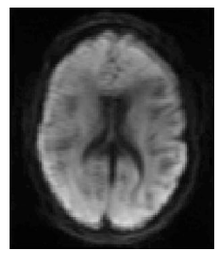
Use susceptibility field and current estimate of EC and movement to "unwarp" scan



Load into prediction maker

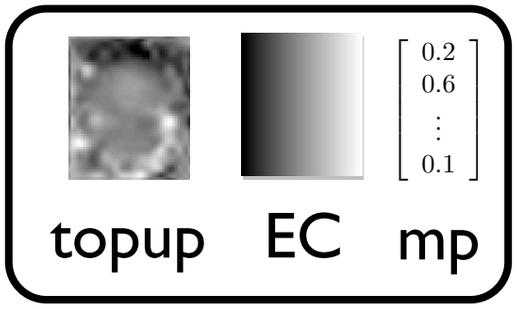
2. For all scans

[1 0 0]



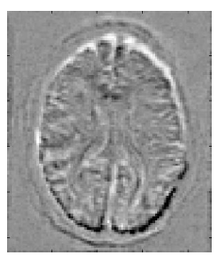
Get prediction

Invert current transform

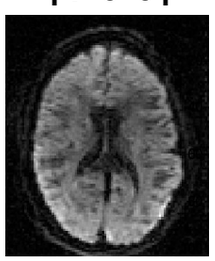


Get prediction in scan space

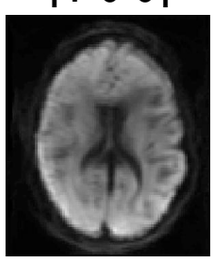
Use difference to update EC and mp



[1 0 0]

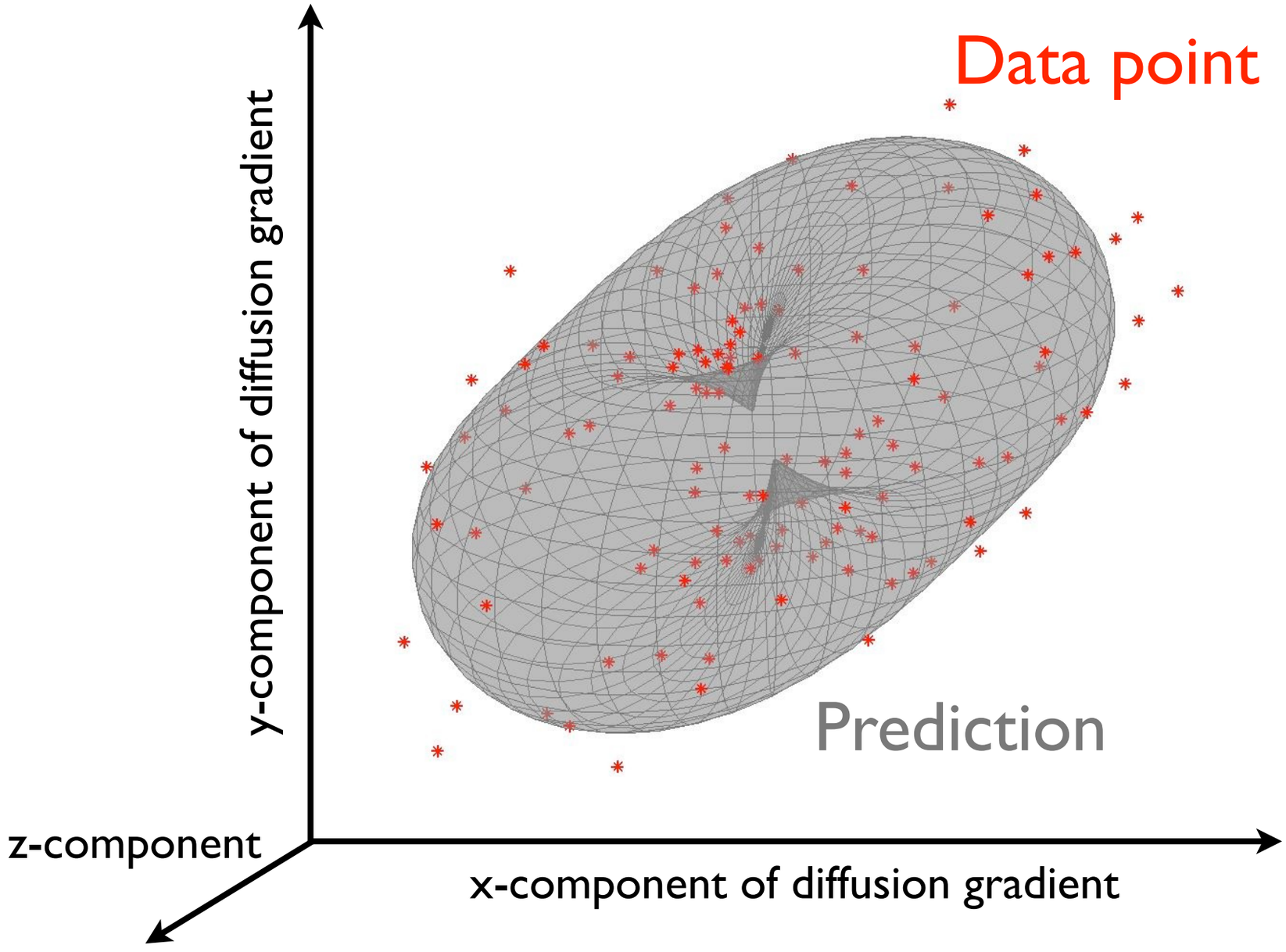


[1 0 0]



Compare to scan

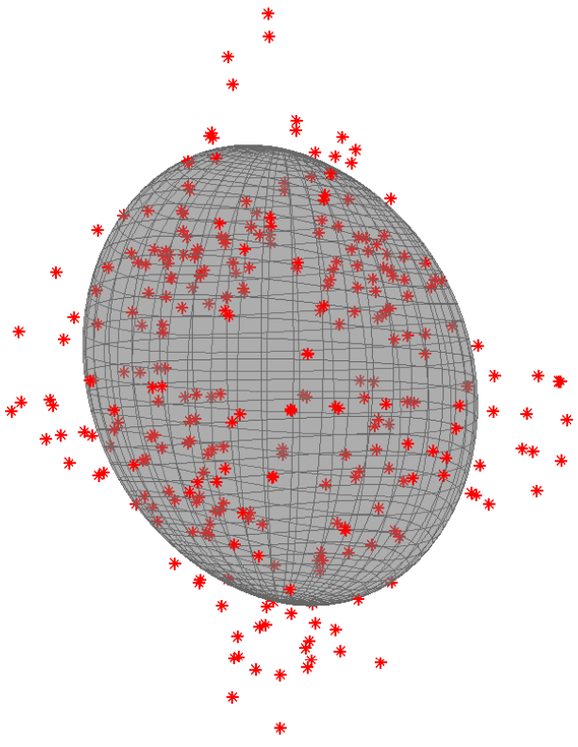
Under the hood of Zoltar



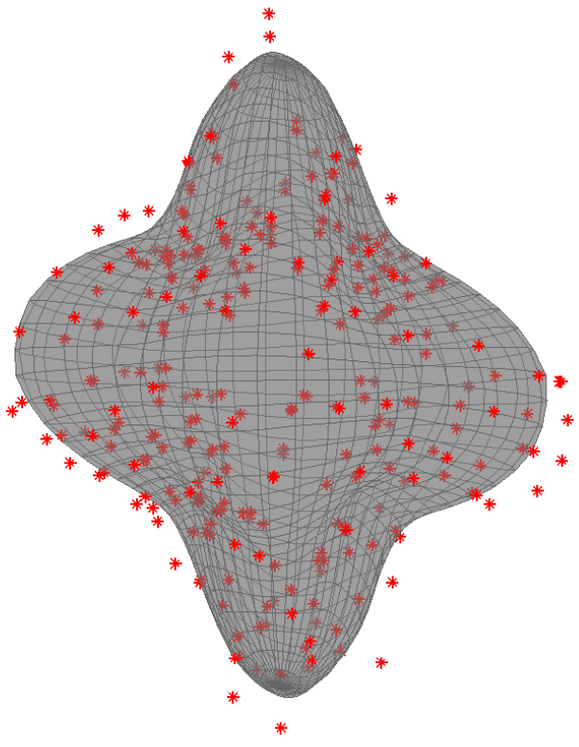
The signal is “modelled” in a data-driven fashion assuming that points close together on the unit sphere have similar signal.

Under the hood of Zoltar

Tensor

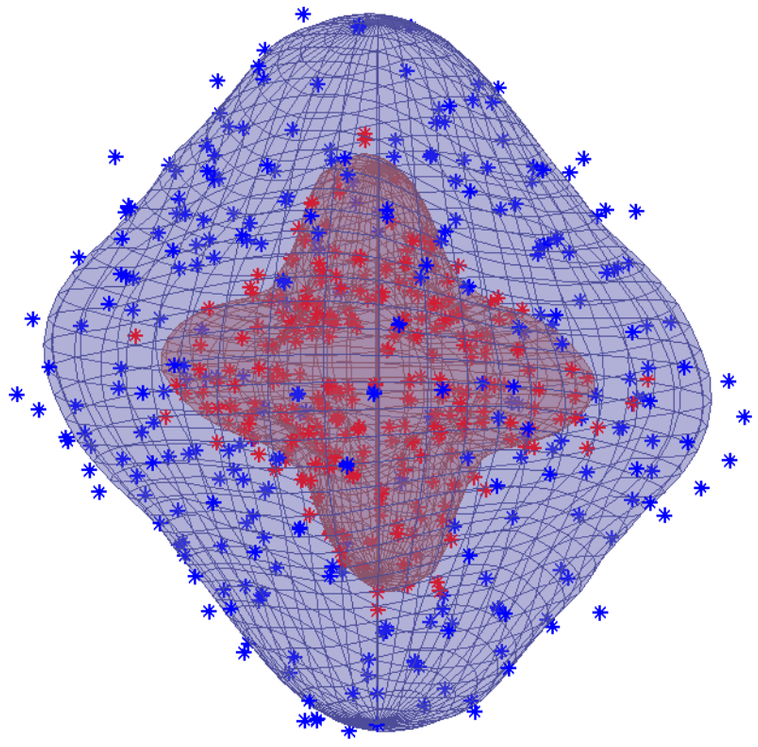


Gaussian Process



The GP can model voxels with complicated anatomy while still being computationally convenient.

Multi-shell predictions

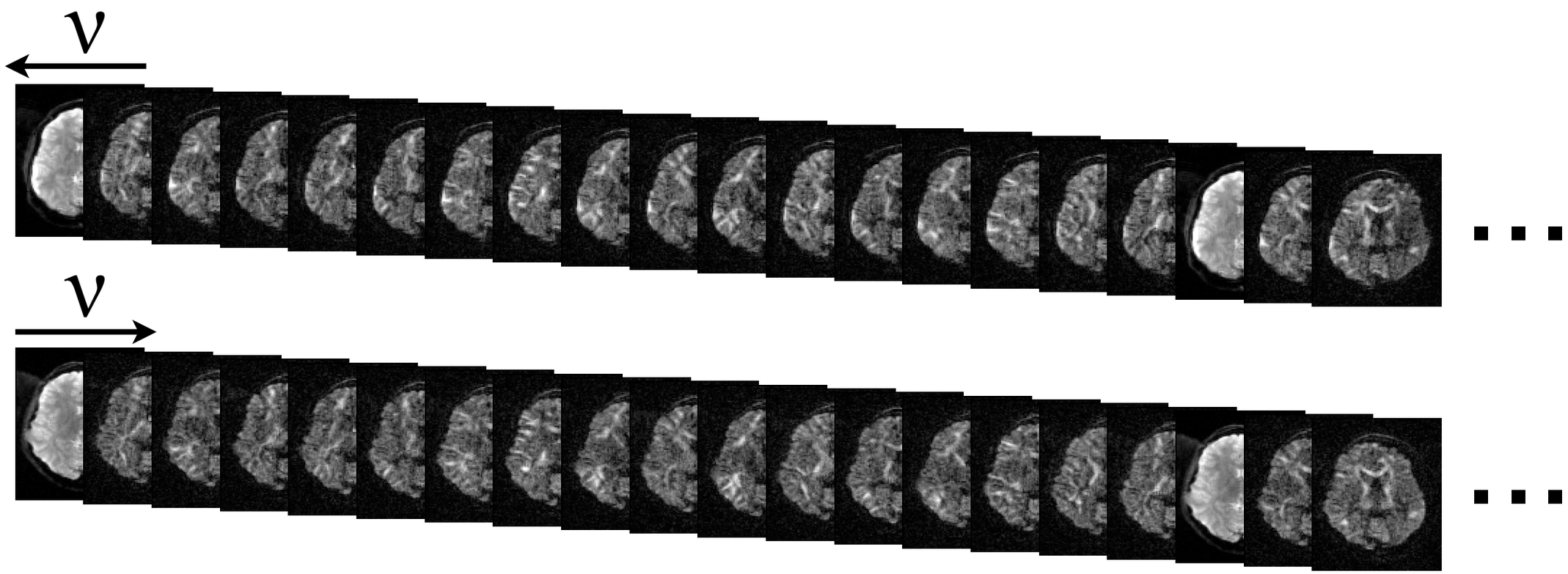


Shells with strong signal can help inform predictions in shells with poor signal

Outline of the talk

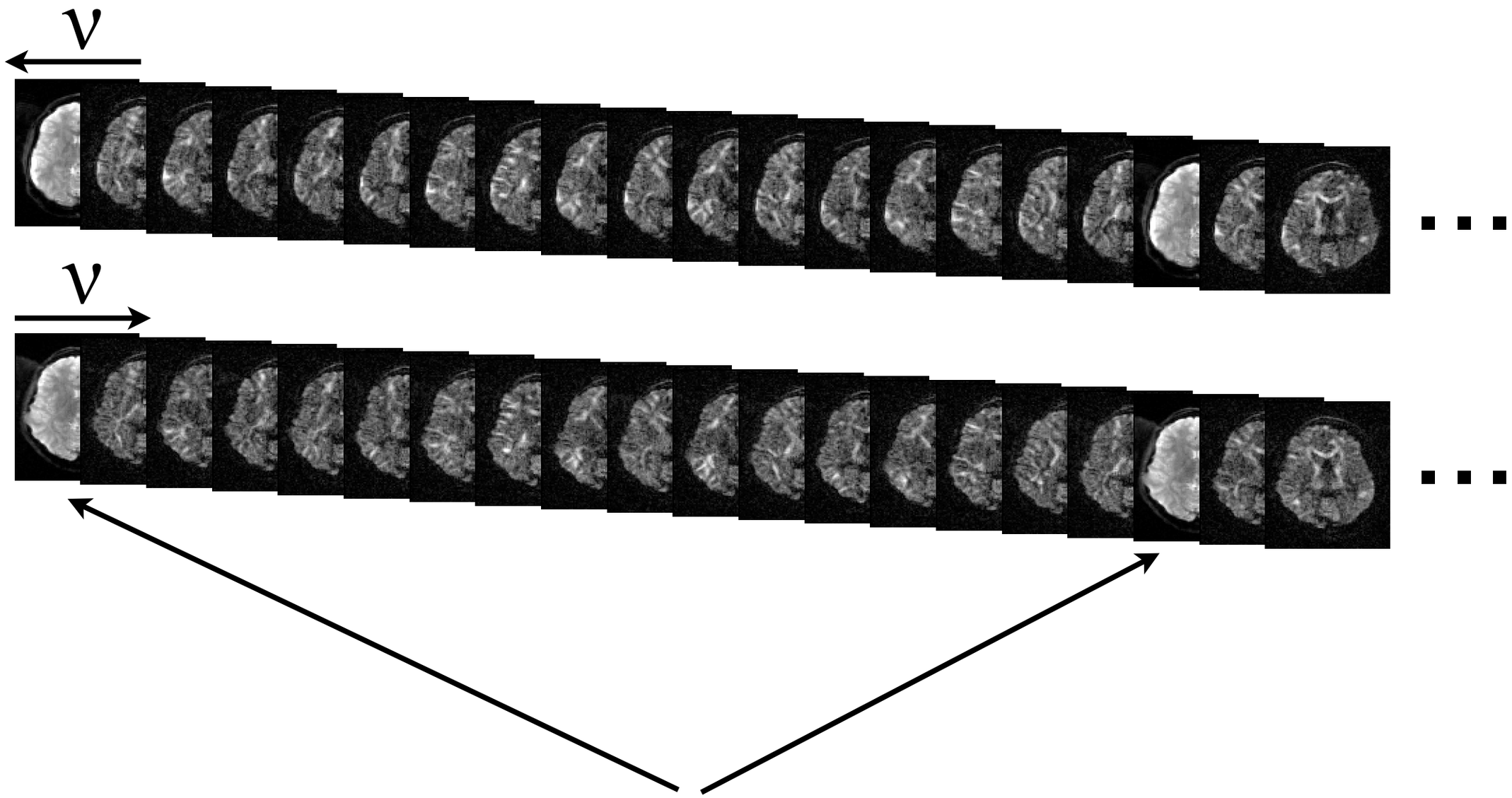
- What is the problem with diffusion data?
- Off-resonance field
  - How does it cause distortions?
  - Where does it come from?
- Registering diffusion data
  - How topup works
  - How eddy works
- Practicalities
- Some results
- Quality control
- New eddy features

Practicalities

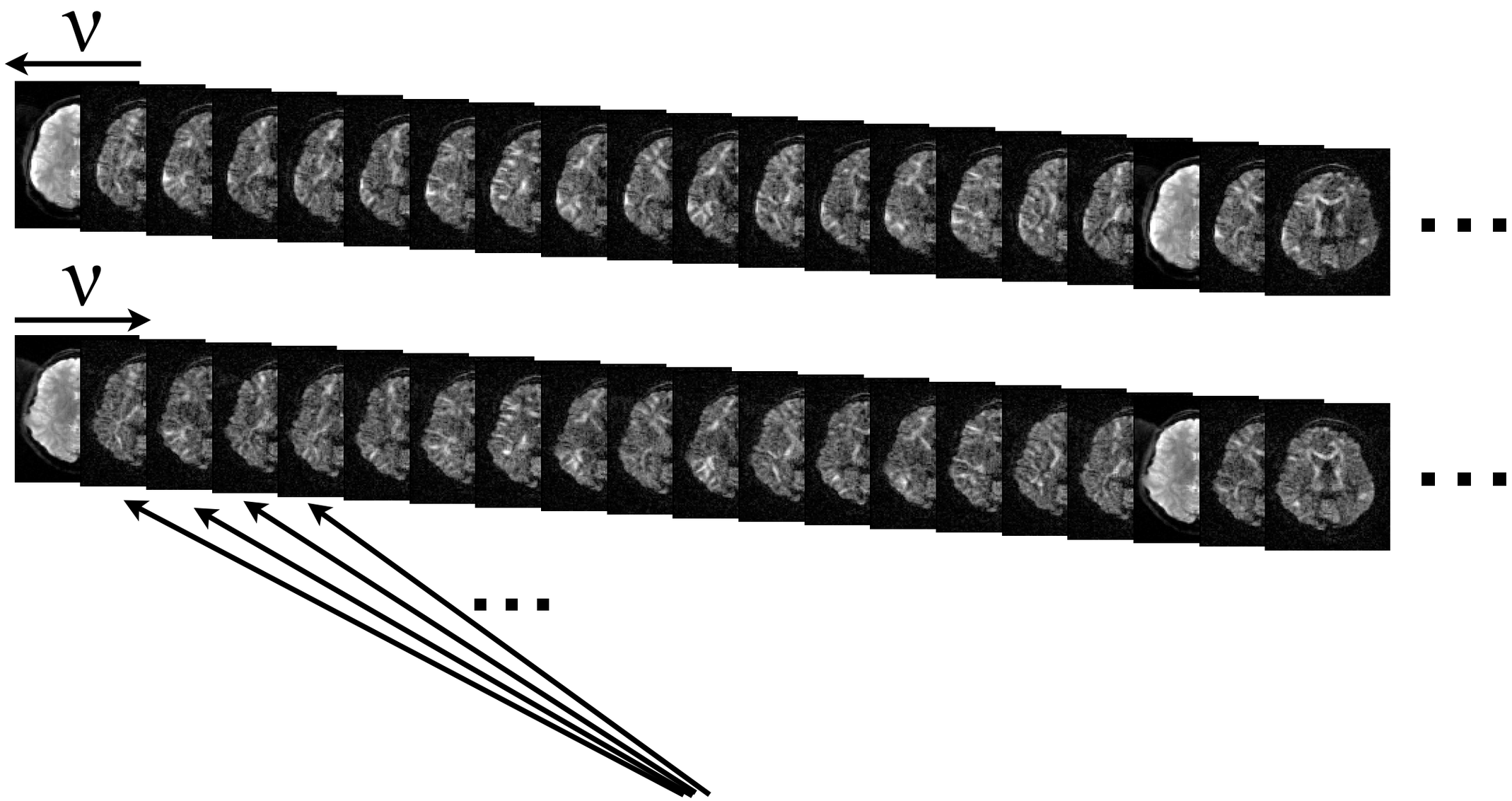


- Our example data consists of:
  - *N* diffusion weighted volumes and *n* *b*=0 volumes
  - *b*=0 volumes interspersed
  - Two repetitions, phase-encode L→R and R→L
  - Same diffusion table for both repetitions

Practicalities



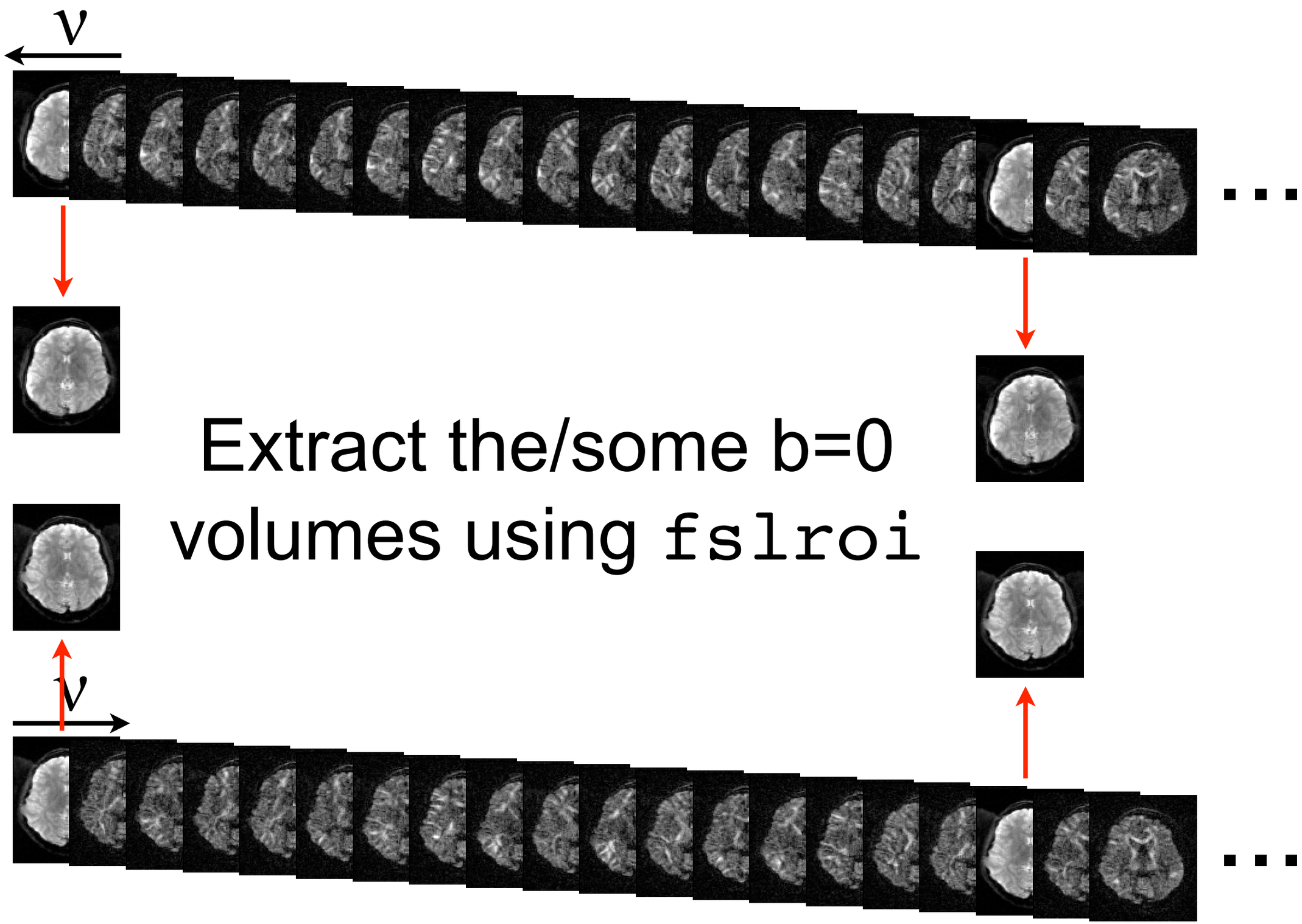
Practicalities



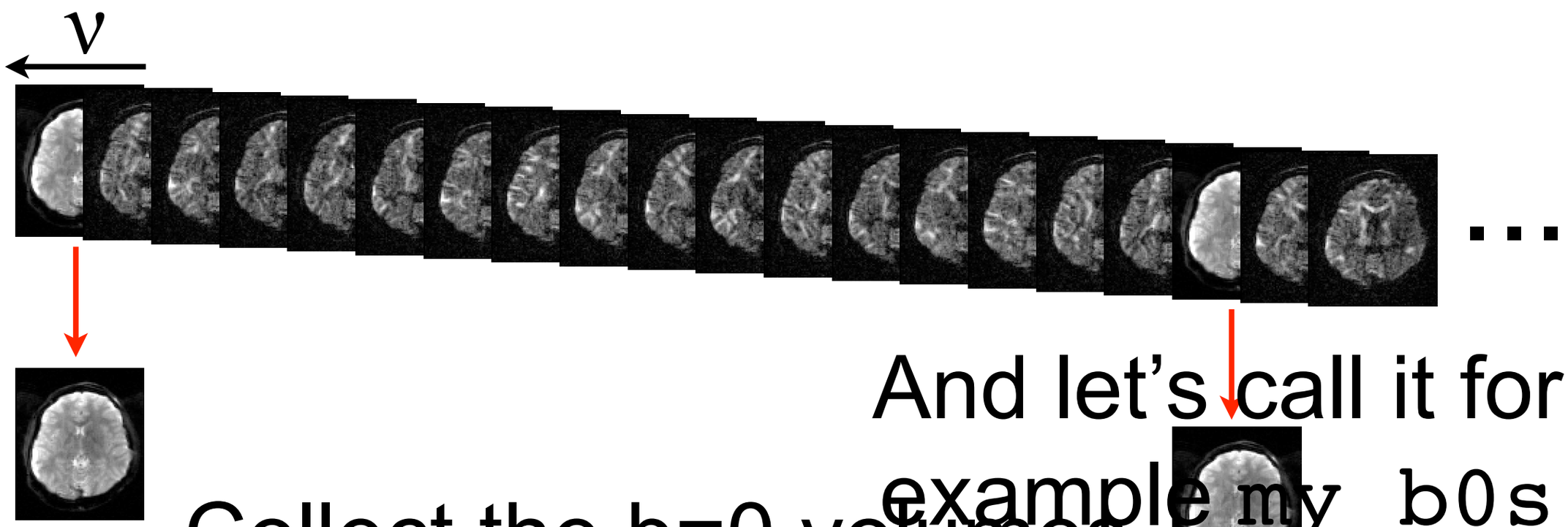
Affected by susceptibility distortions
AND eddy current distortions

And everything is of course affected by subject movement.

So, let's start with susceptibility

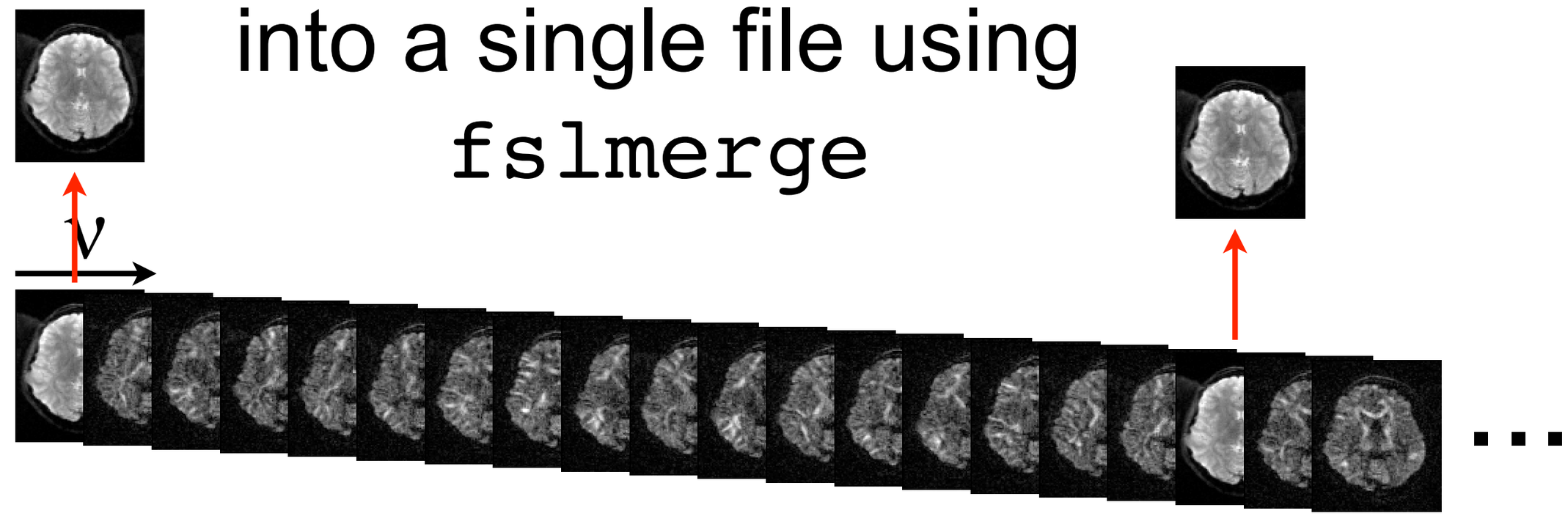


So, let's start with susceptibility



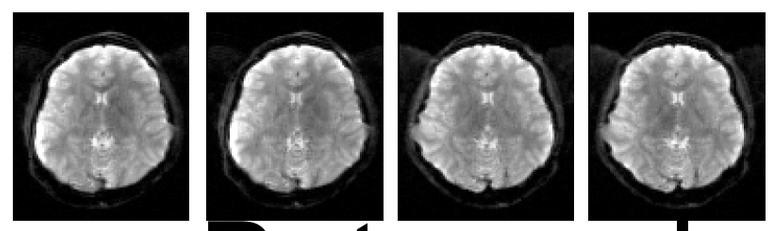
And let's call it for example `my_b0s`

Collect the b=0 volumes into a single file using `fslmerge`



And the tool for that is `topup`

```
topup --imain=my_b0s
```



`my_b0s`

But we also need to inform topup about the acquisition parameters

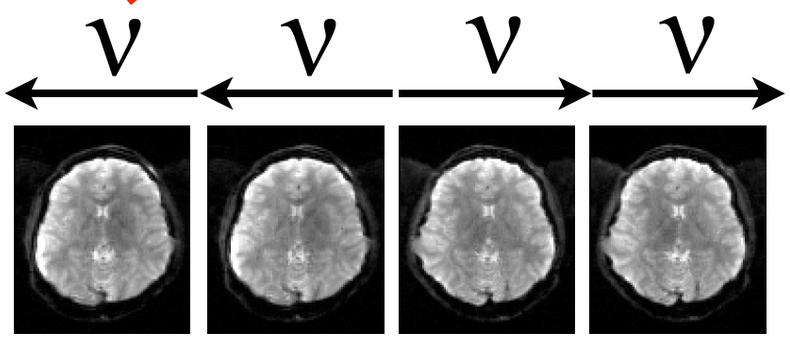
And the tool for that is `topup`

```
topup --imain=my_b0s
```

Means PE in x-direction, L→R

```
-1  0  0  0.051
```

Total readout time (in seconds)



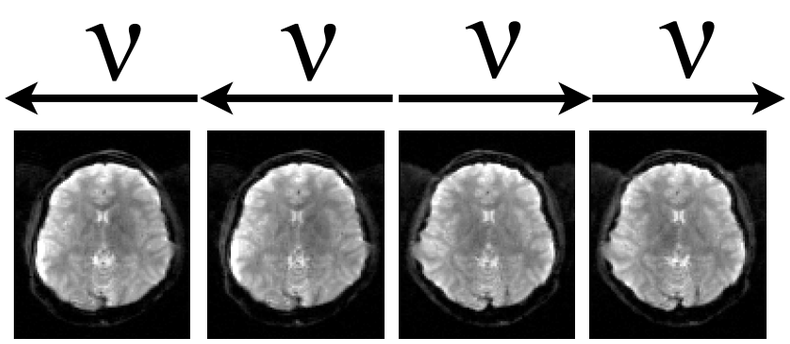
`my_b0s`

And the tool for that is `topup`

```
topup --imain=my_b0s --datain=acqparams.txt
```

```
-1  0  0  0.051
-1  0  0  0.051
1  0  0  0.051
1  0  0  0.051
```

Text file that we can call for example `acqparams.txt`

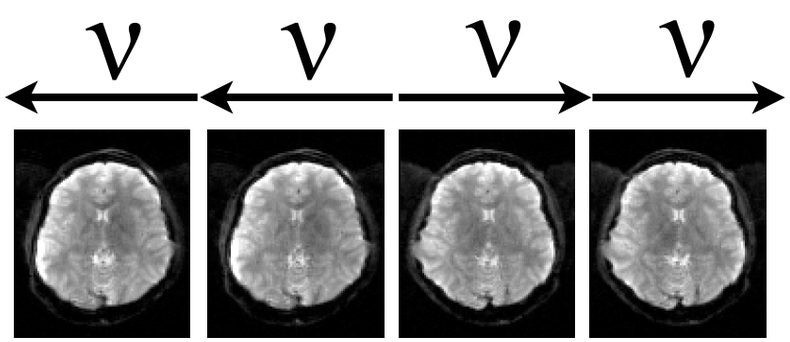


`my_b0s`

And the tool for that is `topup`

```
topup --imain=my_b0s --datain=acqparams.txt --config=b02b0.cnf
```

And then some technical details



`my_b0s`

```
-1  0  0  0.051
-1  0  0  0.051
 1  0  0  0.051
 1  0  0  0.051
```

`acqparams.txt`

And the tool for that is `topup`

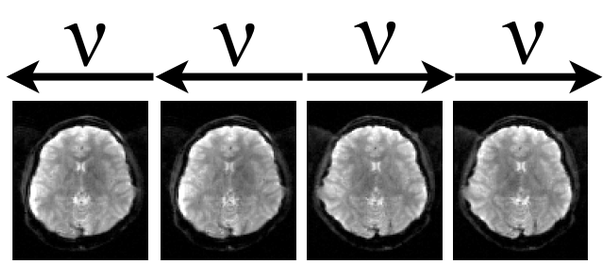
And finally we need to tell it where to put the results

```
topup --imain=my_b0s --datain=acqparams.txt --config=b02b0.cnf --out=my_topup
```

`my_topup_movpar.txt`

Tells position of 2nd b=0 scan relative the first

```
0 0 0 0 0 0
0.72 -0.02 -0.07 0.002 0.000 0.002
0 -0.11 -0.33 0.002 0.013 -0.004
-0.70 -0.12 -0.43 0.002 0.014 -0.004
```



`my_b0s`

```
-1 0 0 0.051
-1 0 0 0.051
1 0 0 0.051
1 0 0 0.051
```

`acqparams.txt`

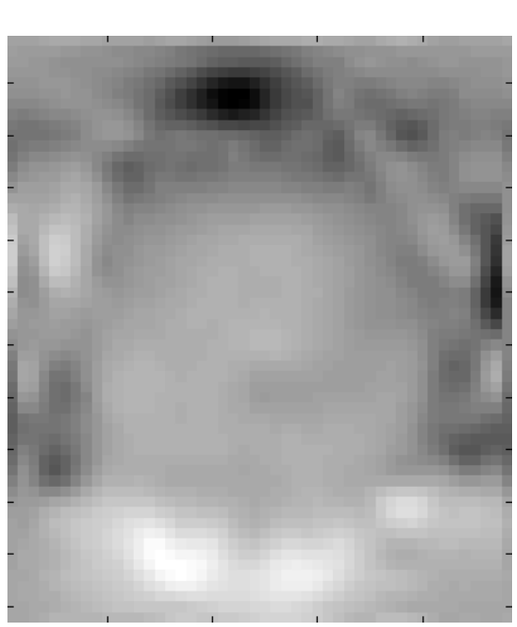
`b02b0.cnf`

And the tool for that is topup

And finally we need to tell it where to put the results

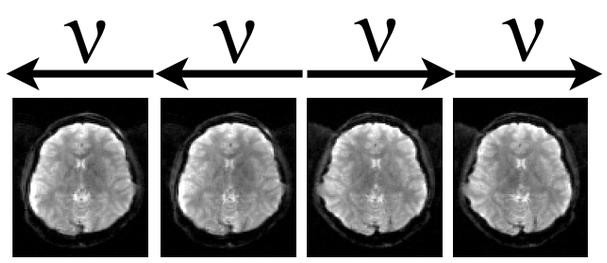
```
topup --imain=my_b0s --datain=acqparams.txt --config=b02b0.cnf --out=my_topup
```

my_topup_fieldcoef.nii



my_topup_movpar.txt

```
0 0 0 0 0 0
0.72 -0.02 -0.07 0.002 0.000 0.002
0 -0.11 -0.33 0.002 0.013 -0.004
-0.70 -0.12 -0.43 0.002 0.014 -0.004
```



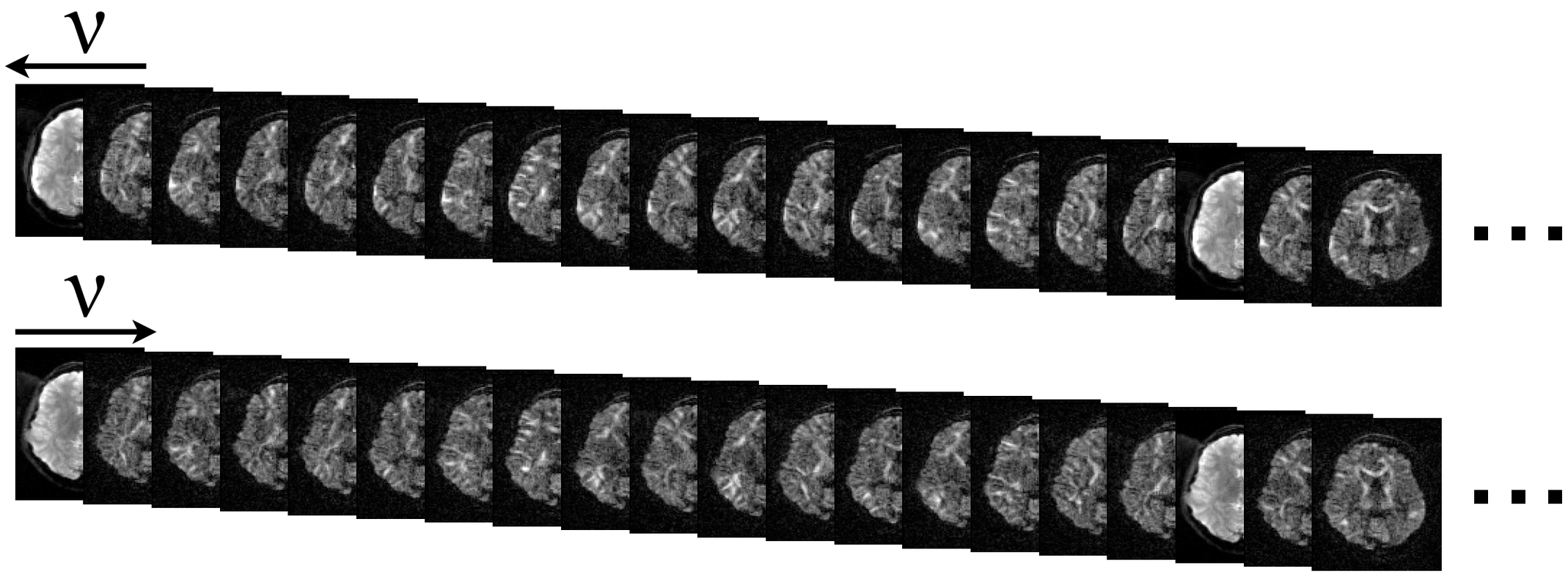
my_b0s

```
-1 0 0 0.051
-1 0 0 0.051
1 0 0 0.051
1 0 0 0.051
```

acqparams.txt

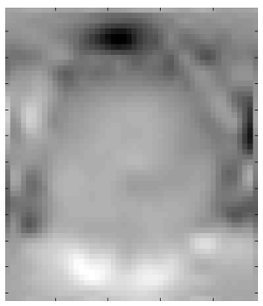
b02b0.cnf

Back to the full data-set



Now we want to correct the eddy current-distortions and subject movement in the whole data set.

my_topup_fieldcoef.nii



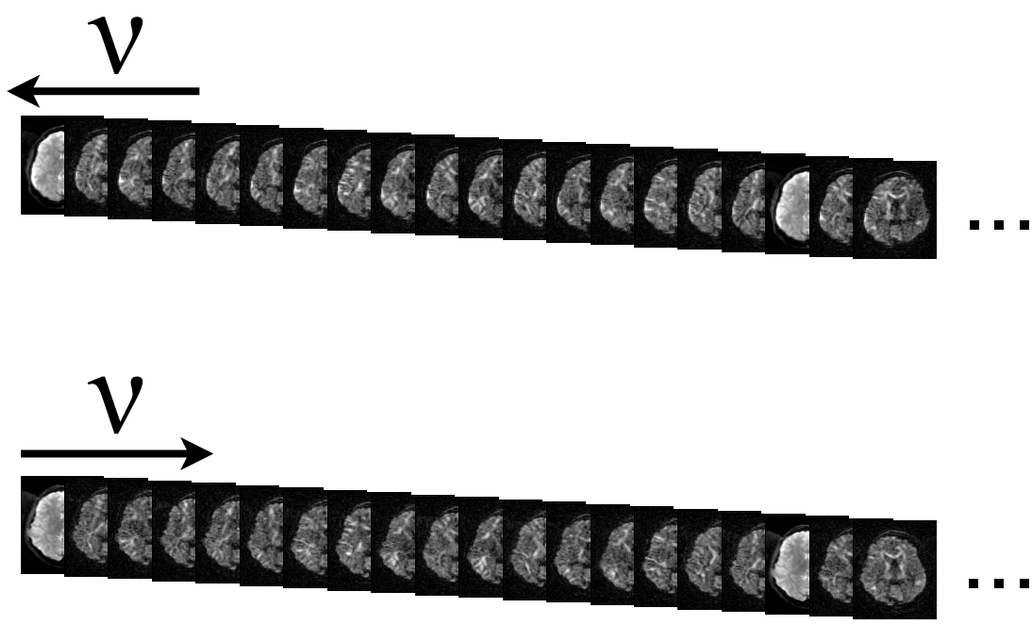
```
-1 0 0 0.051
-1 0 0 0.051
1 0 0 0.051
1 0 0 0.051
```

acqparams.txt

```
0 0 0 0 0 0
0.72 -0.02 -0.07 0.002 0.000 0.002
0 -0.11 -0.33 0.002 0.013 -0.004
-0.70 -0.12 -0.43 0.002 0.014 -0.004
```

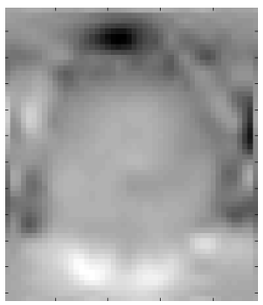
my_topup_movpar.txt

Collect all data in one file



The first thing we do is to collect all data in a single file using `fslmerge` and call it for example `LR_RL`

my_topup_fieldcoef.nii



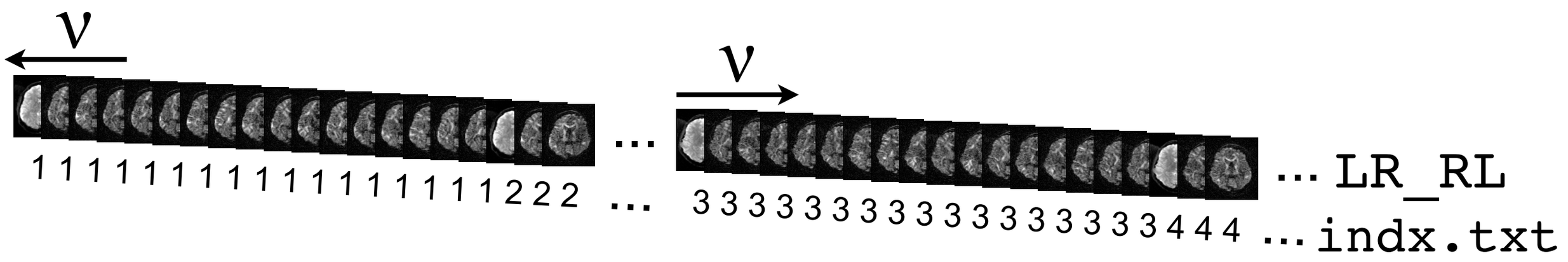
```
-1 0 0 0.051
-1 0 0 0.051
1 0 0 0.051
1 0 0 0.051
```

acqparams.txt

```
0 0 0 0 0 0
0.72 -0.02 -0.07 0.002 0.000 0.002
0 -0.11 -0.33 0.002 0.013 -0.004
-0.70 -0.12 -0.43 0.002 0.014 -0.004
```

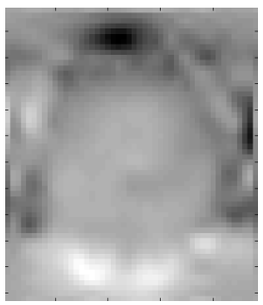
my_topup_movpar.txt

Inform eddy of acquisition parameters



Then we make a text file with one index for each volume, and call it for example `indx.txt`

my_topup_fieldcoef.nii



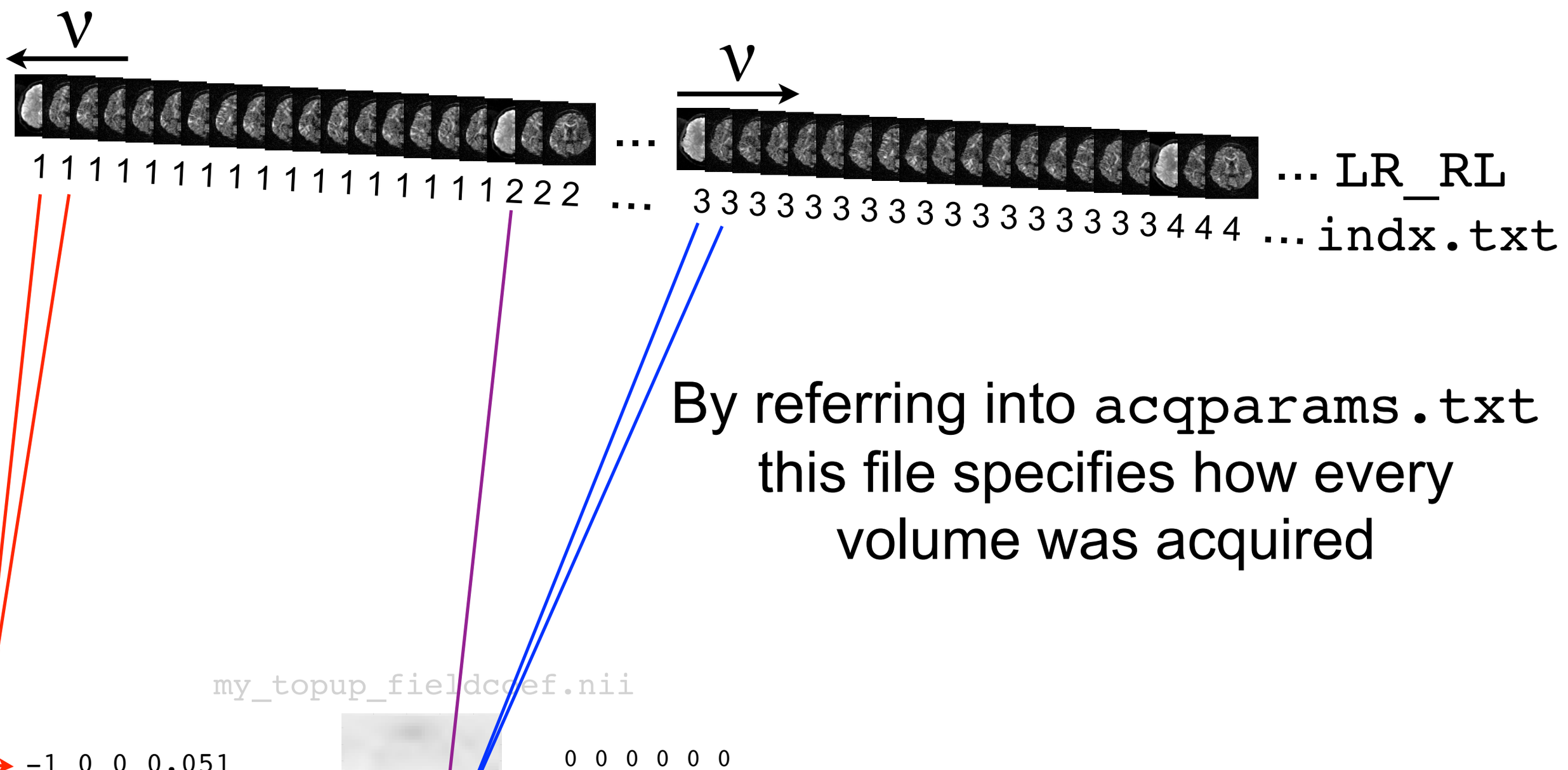
```
-1 0 0 0.051
-1 0 0 0.051
1 0 0 0.051
1 0 0 0.051
```

acqparams.txt

```
0 0 0 0 0 0
0.72 -0.02 -0.07 0.002 0.000 0.002
0 -0.11 -0.33 0.002 0.013 -0.004
-0.70 -0.12 -0.43 0.002 0.014 -0.004
```

my_topup_movpar.txt

Inform eddy of acquisition parameters



By referring into `acqparams.txt` this file specifies how every volume was acquired

my_topup_fieldcoef.nii

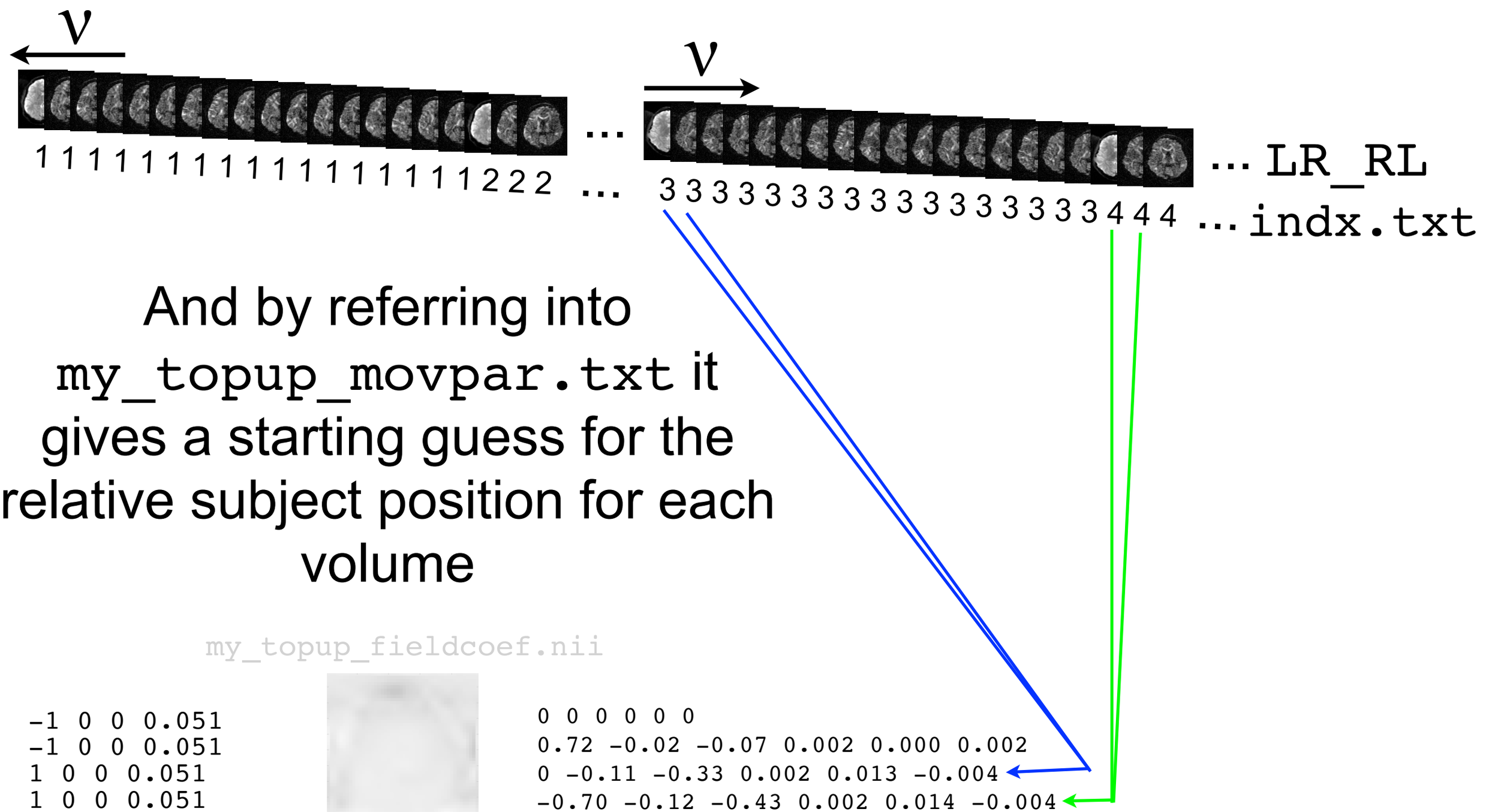
```
-1  0  0  0.051
-1  0  0  0.051
 1  0  0  0.051
 1  0  0  0.051
```

acqparams.txt

```
0 0 0 0 0 0
0.72 -0.02 -0.07 0.002 0.000 0.002
0 -0.11 -0.33 0.002 0.013 -0.004
-0.70 -0.12 -0.43 0.002 0.014 -0.004
```

my_topup_movpar.txt

Inform eddy of acquisition parameters



And by referring into `my_topup_movpar.txt` it gives a starting guess for the relative subject position for each volume

my_topup_fieldcoef.nii

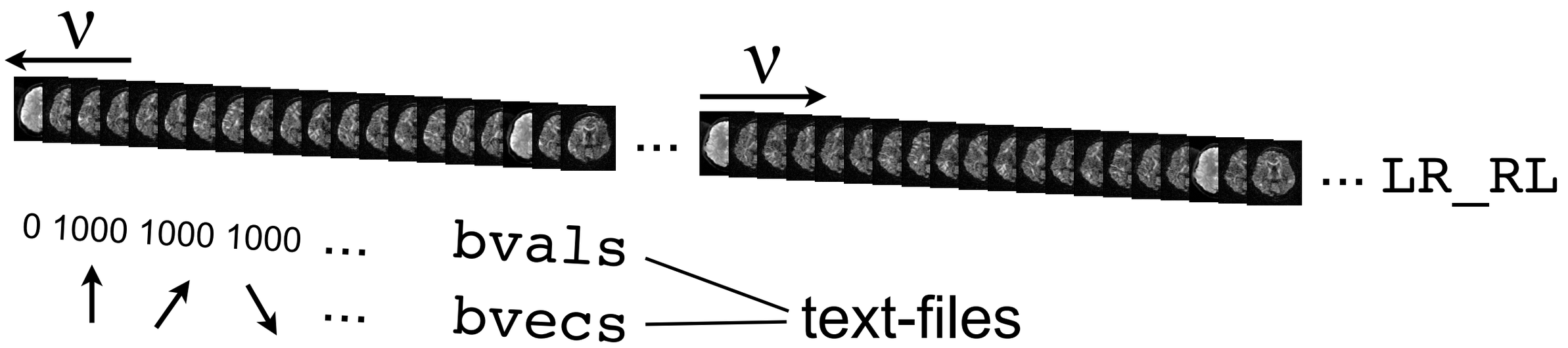

```
-1 0 0 0.051
-1 0 0 0.051
1 0 0 0.051
1 0 0 0.051
```

acqparams.txt

```
0 0 0 0 0 0
0.72 -0.02 -0.07 0.002 0.000 0.002
0 -0.11 -0.33 0.002 0.013 -0.004
-0.70 -0.12 -0.43 0.002 0.014 -0.004
```

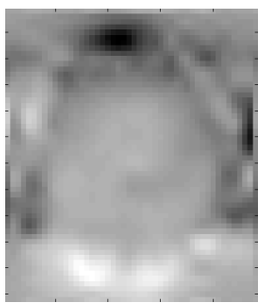
my_topup_movpar.txt

And of diffusion parameters



And we also need to know the b-value and b-vector for each volume (same as for `dtifit` or `bedpost`).

my_topup_fieldcoef.nii

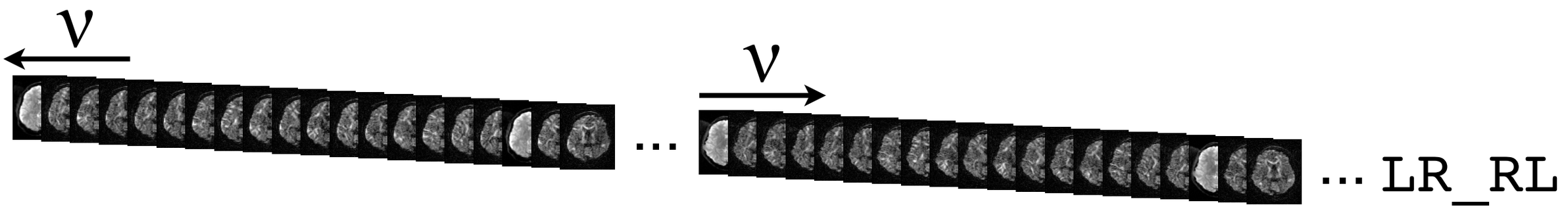


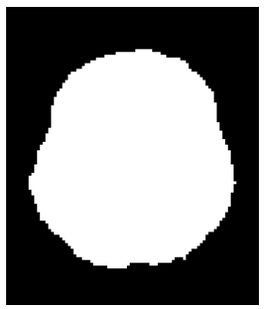
```
-1 0 0 0.051
-1 0 0 0.051
1 0 0 0.051
1 0 0 0.051
```
acqparams.txt

```
0 0 0 0 0 0
0.72 -0.02 -0.07 0.002 0.000 0.002
0 -0.11 -0.33 0.002 0.013 -0.004
-0.70 -0.12 -0.43 0.002 0.014 -0.004
```
my_topup_movpar.txt

```
1111...
```
indx.txt

And where the brain is

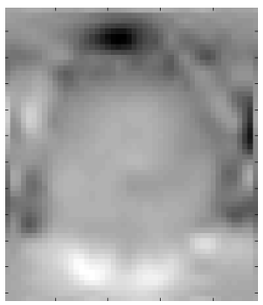




brain_mask.nii

And finally a binary mask that tells eddy which voxels are brain. Also the same that is used for `dtifit/bedpost`.

my_topup_fieldcoef.nii



```
-1 0 0 0.051
-1 0 0 0.051
1 0 0 0.051
1 0 0 0.051
```

acqparams.txt

```
0 0 0 0 0 0
0.72 -0.02 -0.07 0.002 0.000 0.002
0 -0.11 -0.33 0.002 0.013 -0.004
-0.70 -0.12 -0.43 0.002 0.014 -0.004
```

my_topup_movpar.txt

```
1111...
```

indx.txt

```
0 1000 1000 1000 ...
```

bvals

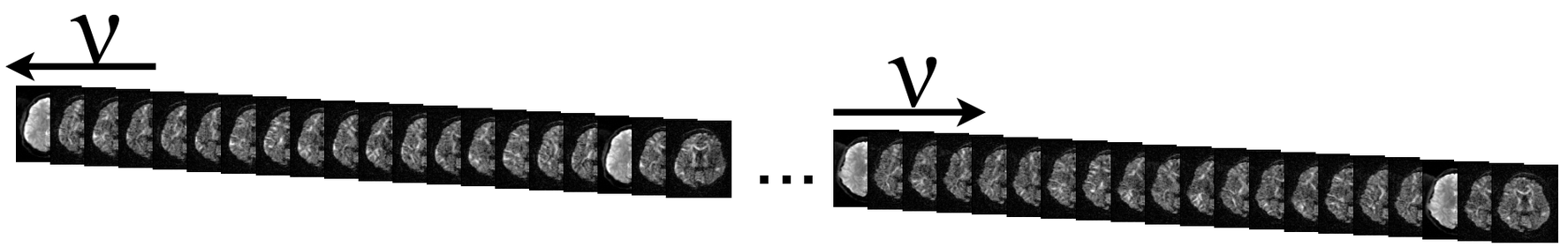
↑ ↗ ↘ ...

bvecs

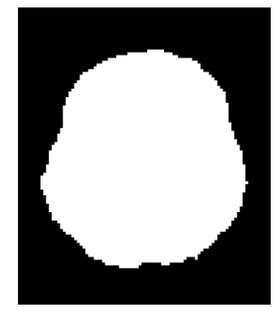
And now we can run eddy

```
eddy --imain=LR_RL --acqp=acqparams.txt
--index=indx.txt --bvecs=bvecs
--bvals=bvals --mask=brain_mask
--topup=my_topup --out=my_eddy
```

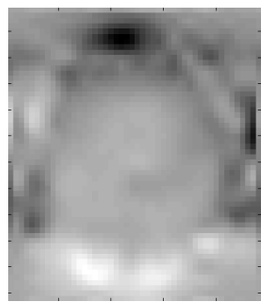
And now we are ready for the most horrible command line in all of `fsl`



brain_mask.nii



my_topup_fieldcoef.nii



```
-1  0  0  0.051
-1  0  0  0.051
 1  0  0  0.051
 1  0  0  0.051
```

acqparams.txt

```
0  0  0  0  0  0
0.72 -0.02 -0.07 0.002 0.000 0.002
0 -0.11 -0.33 0.002 0.013 -0.004
-0.70 -0.12 -0.43 0.002 0.014 -0.004
```

my_topup_movpar.txt

```
1111...
```

indx.txt

```
0 1000 1000 1000 ...
```

bvals

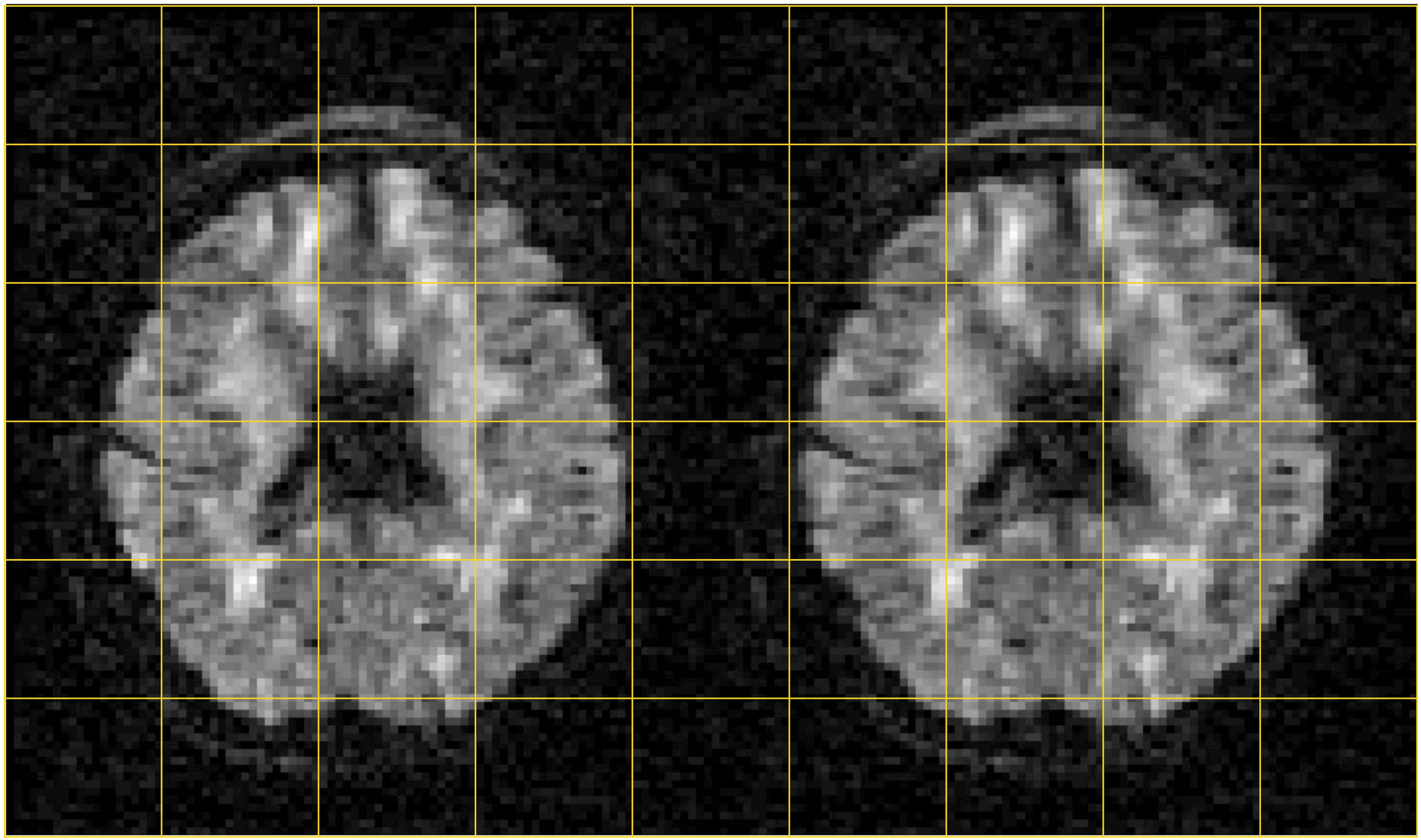
↑ ↗ ↘ ...

bvecs

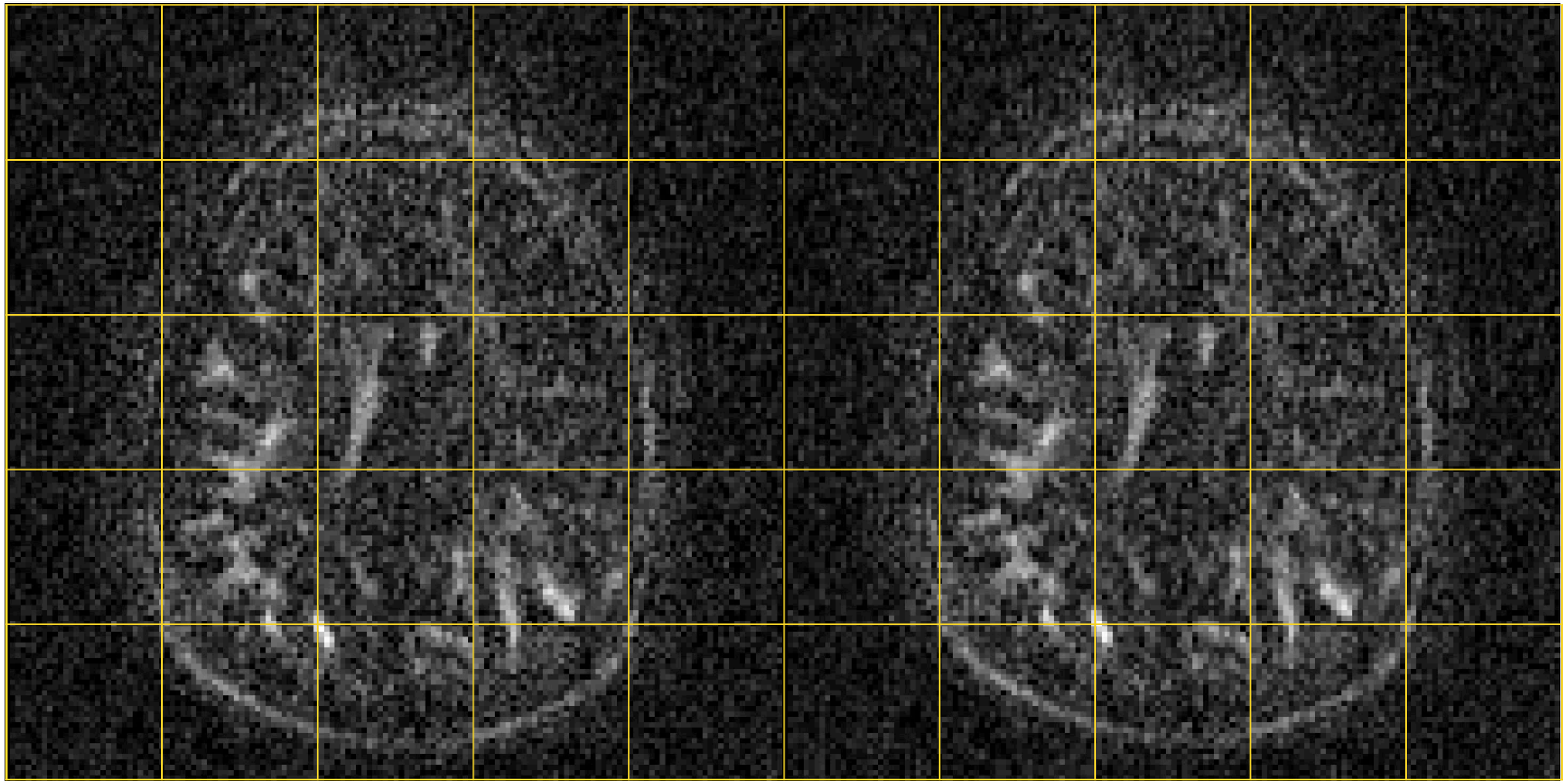
Outline of the talk

- What is the problem with diffusion data?
- Off-resonance field
  - How does it cause distortions?
  - Where does it come from?
- Registering diffusion data
  - How topup works
  - How eddy works
- Practicalities
- Some results
- Quality control
- New eddy features

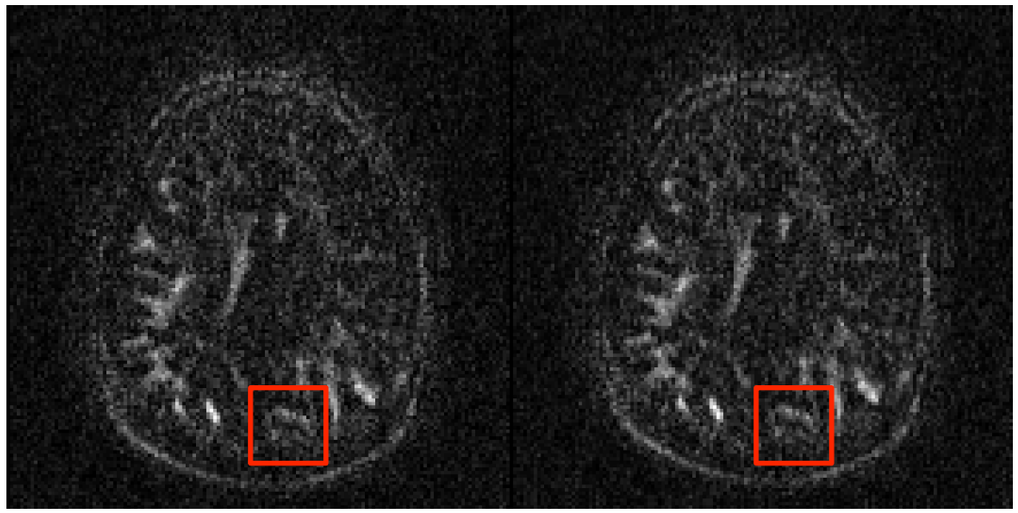
HCP-data, 150 directions, b=3000, blip-up-blip-down

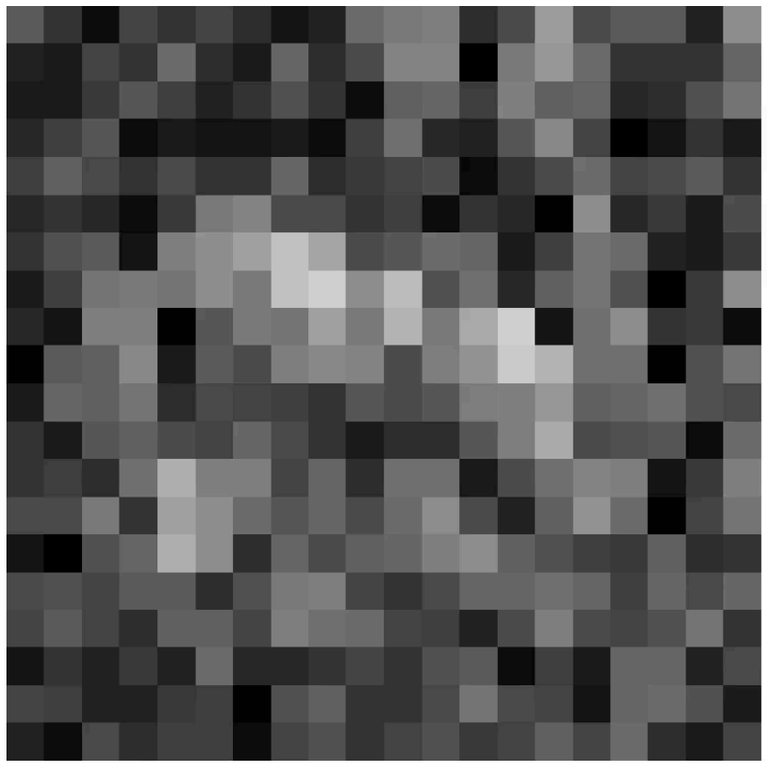


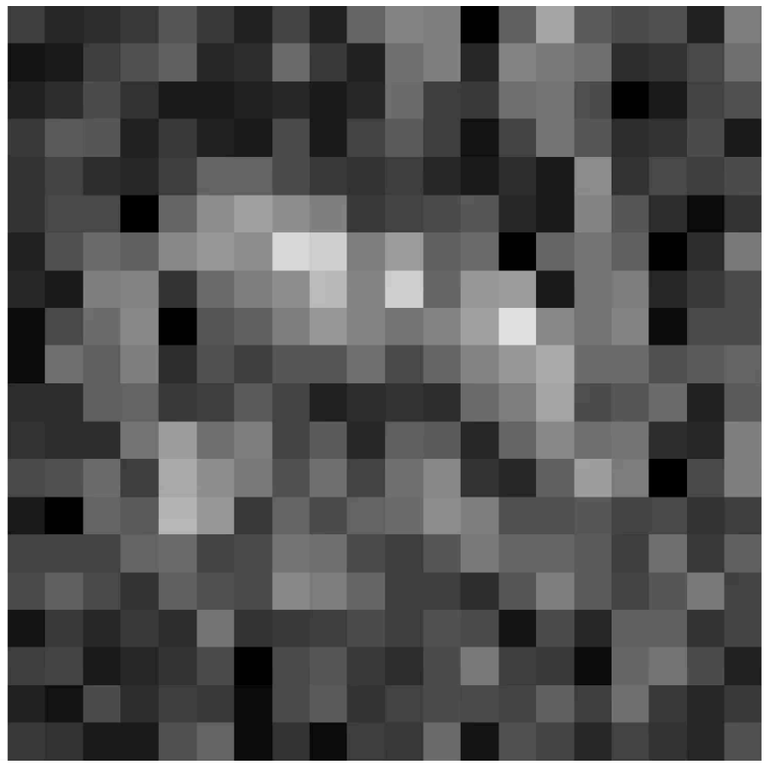
MGH-data, 198 directions, b=10000!



MGH-data, 198 directions, b=10000!







Outline of the talk

- What is the problem with diffusion data?
- Off-resonance field
  - How does it cause distortions?
  - Where does it come from?
- Registering diffusion data
  - How topup works
  - How eddy works
- Practicalities
- Some results
- Quality control
- New eddy features

EDDY QC: data quality summary

QUAD
(subject)

S1/qc.json
S2/qc.json
S3/qc.json
.
.
.
Sn/qc.json

SQUAD
(study)

qc_group.pdf

qc_group.json

P1/qc.json
P2/qc.json
P3/qc.json
...

EDDY QC: single-subject reports

Biobank subject A

Volume-to-volume motion

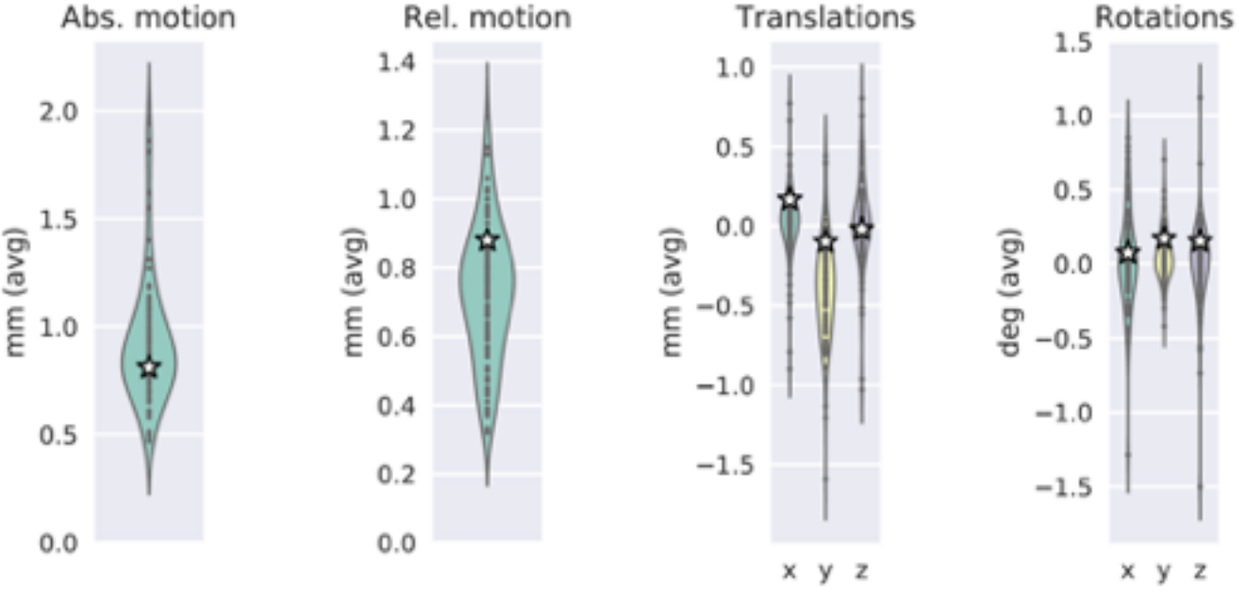
Average abs. motion (mm)	0.81
Average rel. motion (mm)	0.88
Average x translation (mm)	0.17
Average y translation (mm)	-0.10
Average z translation (mm)	-0.02
Average x rotation (deg)	0.07
Average y rotation (deg)	0.17
Average z rotation (deg)	0.15

Within-volume motion

Avg std x translation (mm)	0.02
Avg std y translation (mm)	0.11
Avg std z translation (mm)	0.04
Avg std x rotation (deg)	0.05
Avg std y rotation (deg)	0.05
Avg std z rotation (deg)	0.06

Outliers

Total outliers (%)	0.11
Outliers (b=1000 s/mm^2)	0.22
Outliers (b=2000 s/mm^2)	0.00
Outliers (PE dir=[0. 1. 0.])	0.00
Outliers (PE dir=[0. -1. 0.])	0.11



Biobank subject B

Volume-to-volume motion

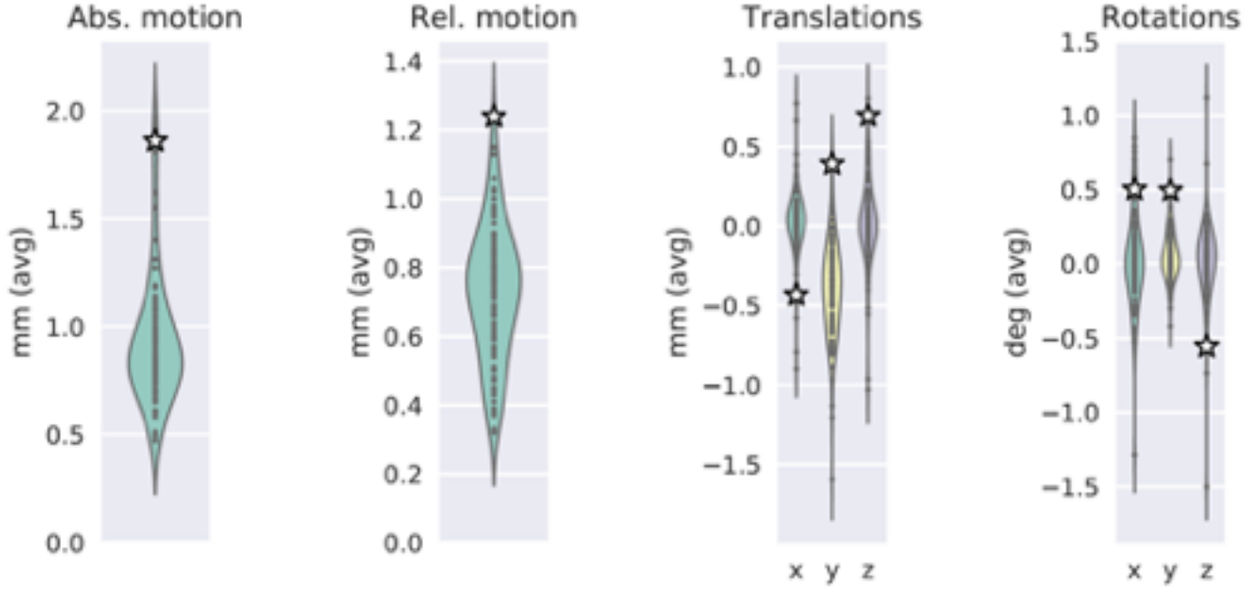
Average abs. motion (mm)	1.86
Average rel. motion (mm)	1.24
Average x translation (mm)	-0.43
Average y translation (mm)	0.39
Average z translation (mm)	0.69
Average x rotation (deg)	0.50
Average y rotation (deg)	0.49
Average z rotation (deg)	-0.55

Within-volume motion

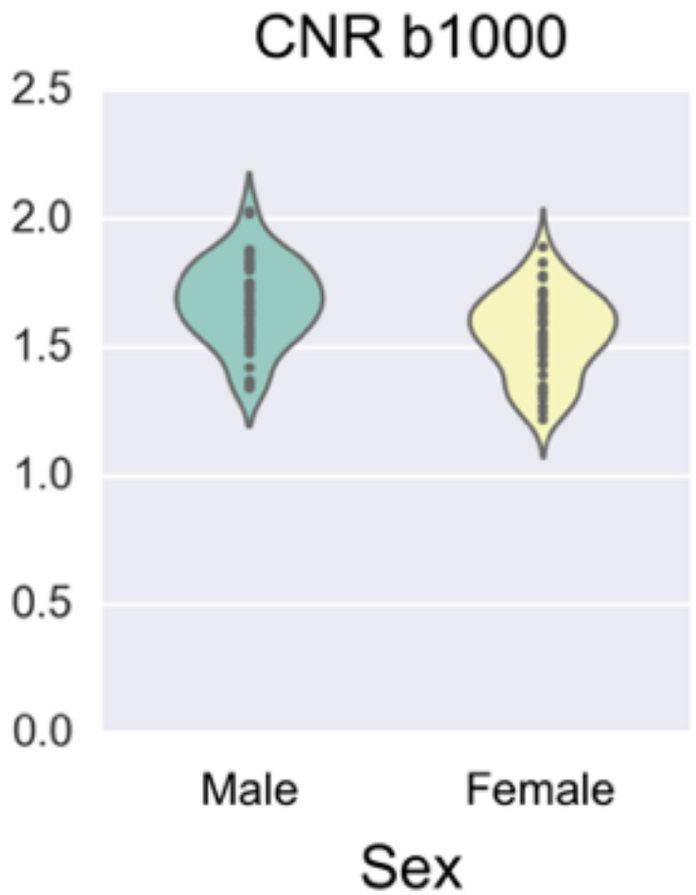
Avg std x translation (mm)	0.08
Avg std y translation (mm)	0.22
Avg std z translation (mm)	0.13
Avg std x rotation (deg)	0.15
Avg std y rotation (deg)	0.09
Avg std z rotation (deg)	0.11

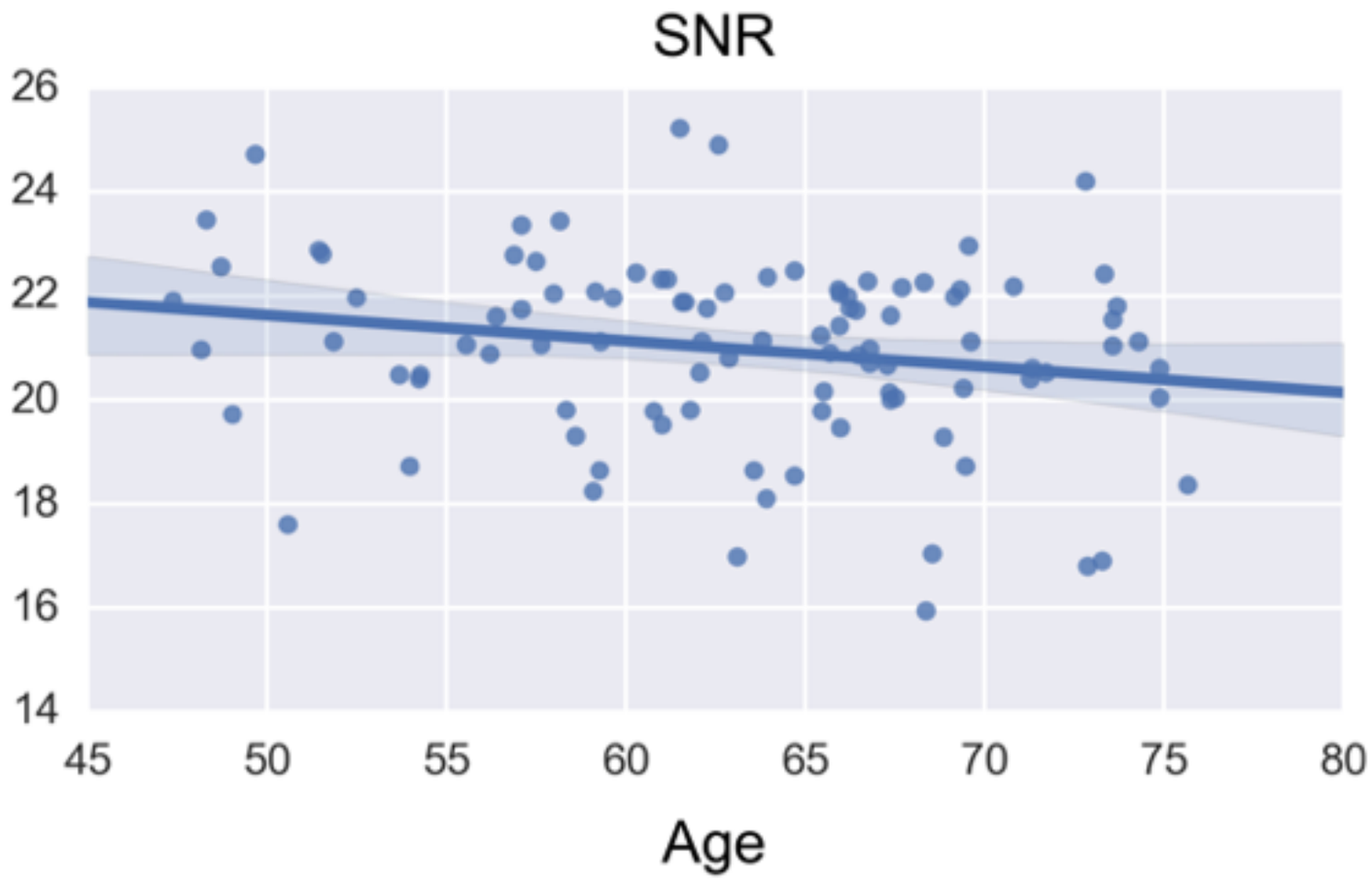
Outliers

Total outliers (%)	2.86
Outliers (b=1000 s/mm^2)	4.69
Outliers (b=2000 s/mm^2)	1.13
Outliers (PE dir=[0. 1. 0.])	2.55
Outliers (PE dir=[0. -1. 0.])	2.66

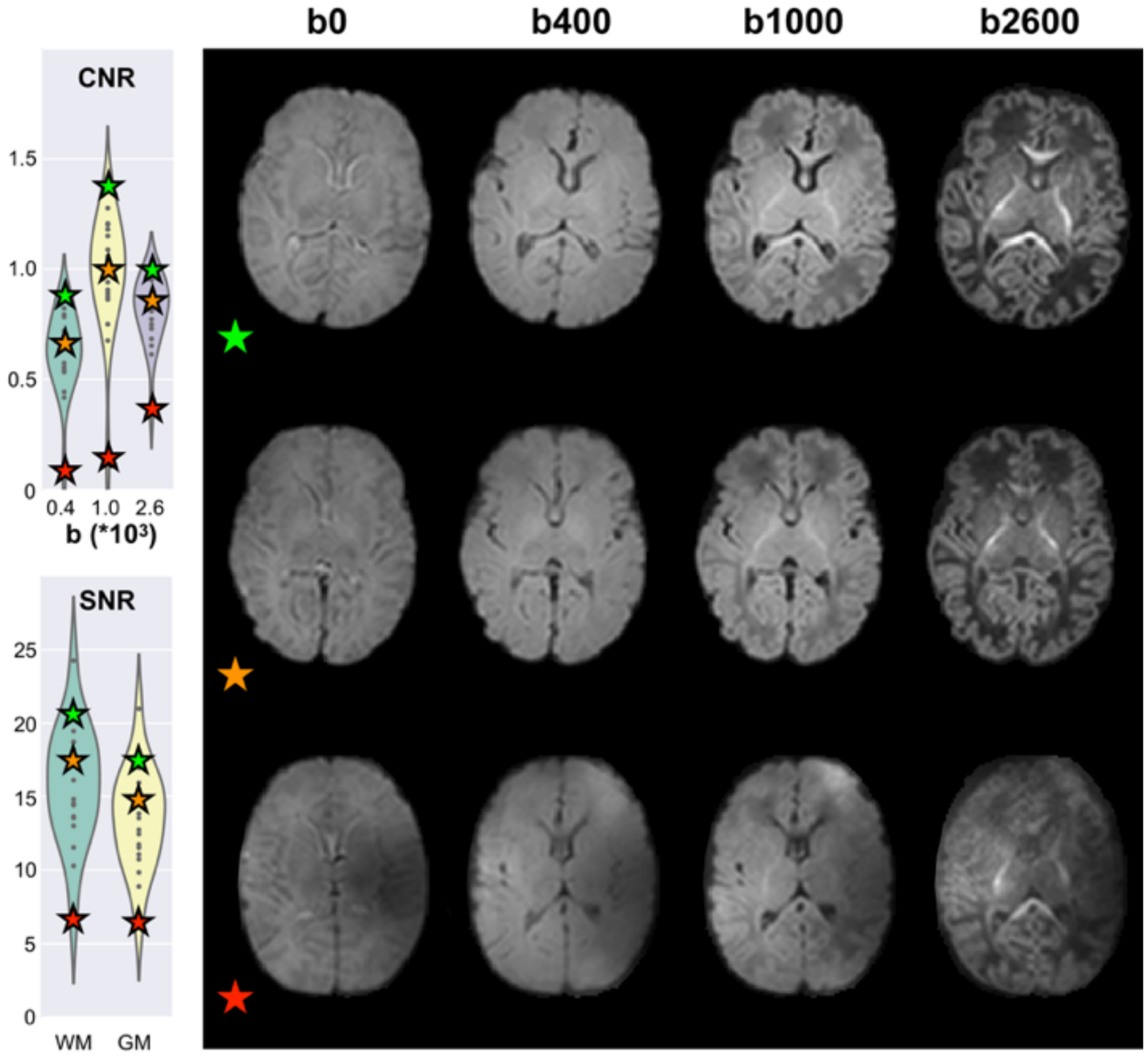


EDDY QC: group report





Data quality illustration



Outline of the talk

- What is the problem with diffusion data?
- Off-resonance field
- Registering diffusion data
- Practicalities
- Some results
- New eddy features
  - Movement-induced dropout
  - Intra-volume motion

Movement induced dropout

Diffusion encoding

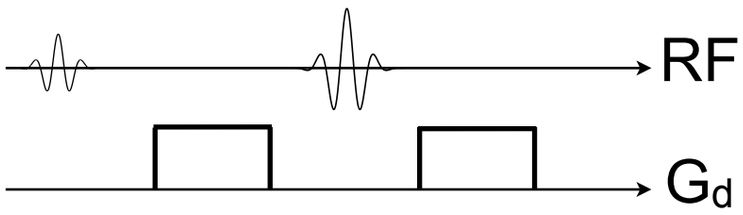
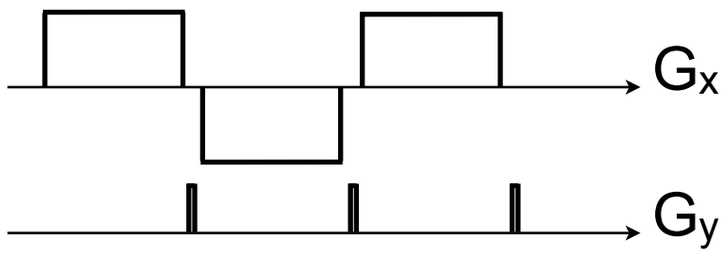
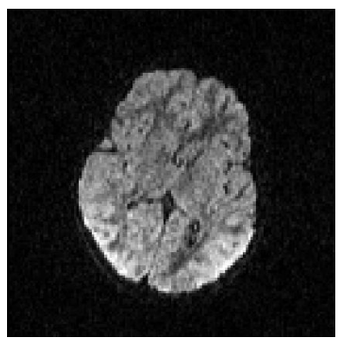


Image encoding

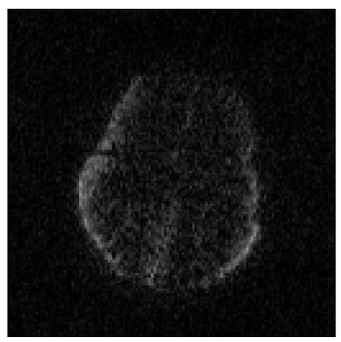


…

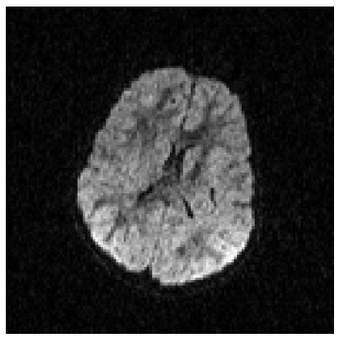
If there is movement during this part…



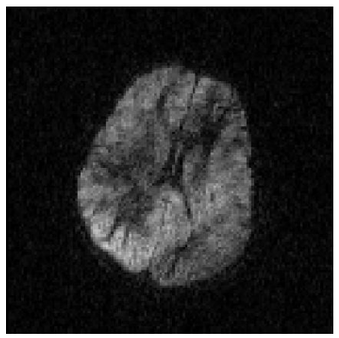
this



can turn to this



or this

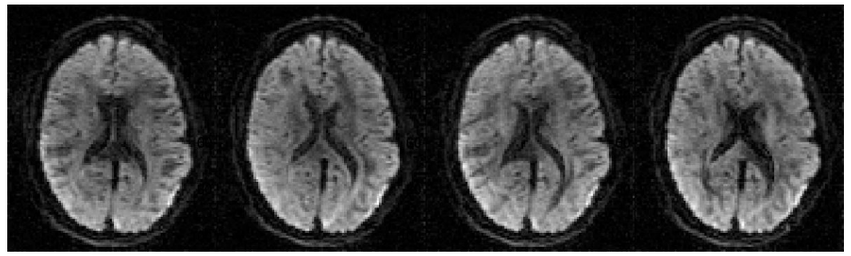


to this

What can eddy do about it?
But first a little recap of eddy

1. **For all scans**

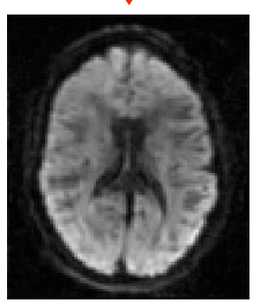
[1 0 0] [.6 -.4 -.7] [.8 .6 0] [-.4 .9 0]



...

topup EC mp $\begin{bmatrix} 0.2 \\ 0.6 \\ \vdots \\ 0.1 \end{bmatrix}$

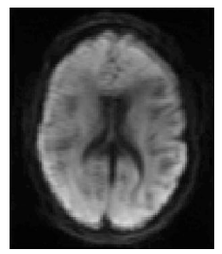
Use susceptibility field and current estimate of EC and movement to "unwarp" scan



Load into prediction maker

2. **For all scans**

[1 0 0]



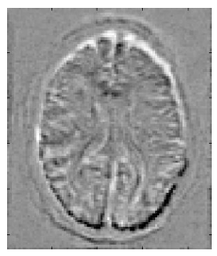
Get prediction

Invert current transform

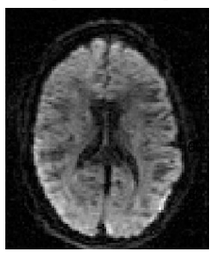
topup EC mp $\begin{bmatrix} 0.2 \\ 0.6 \\ \vdots \\ 0.1 \end{bmatrix}$

Get prediction in scan space

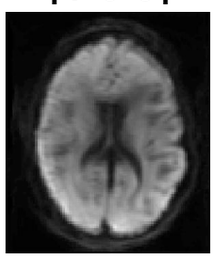
Use difference to update EC and mp



[1 0 0]

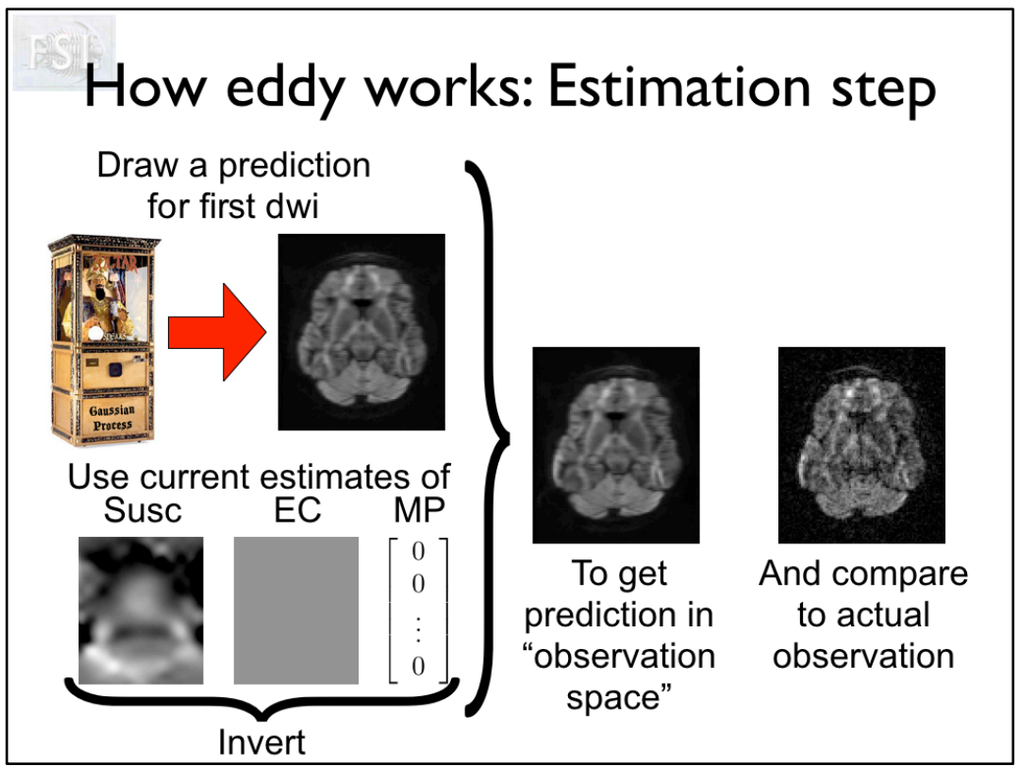


[1 0 0]



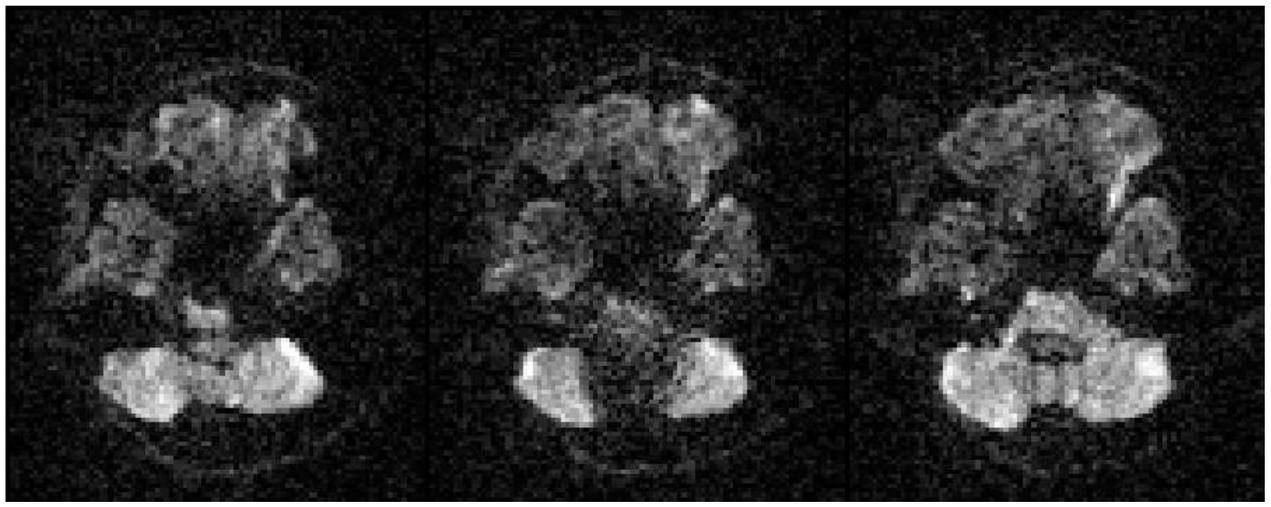
Compare to scan

Outlier detection

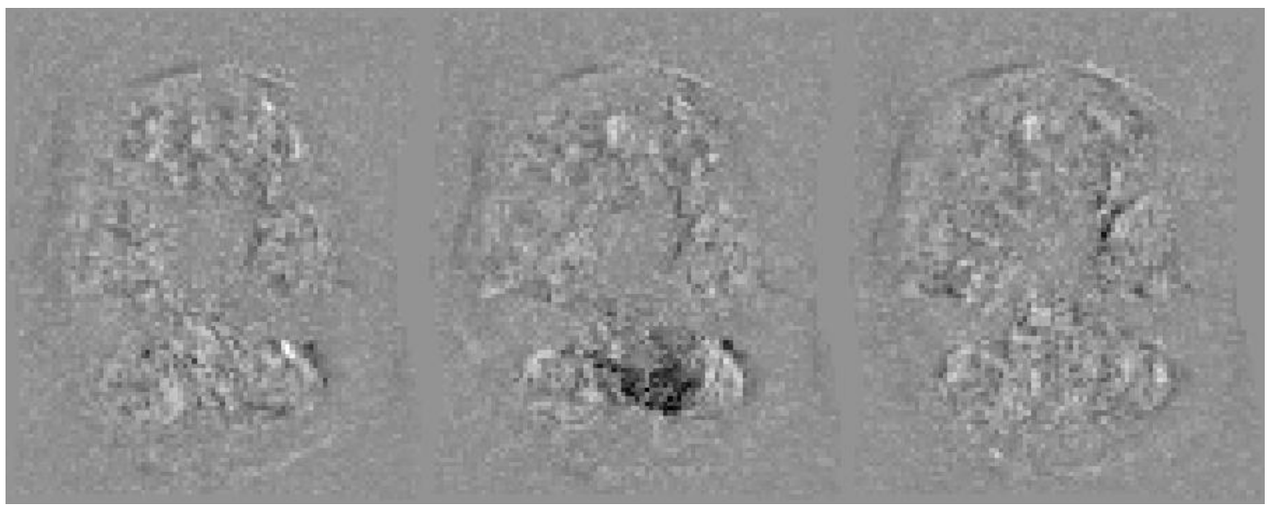


Remember that we do all comparisons in observation space.

Observed data



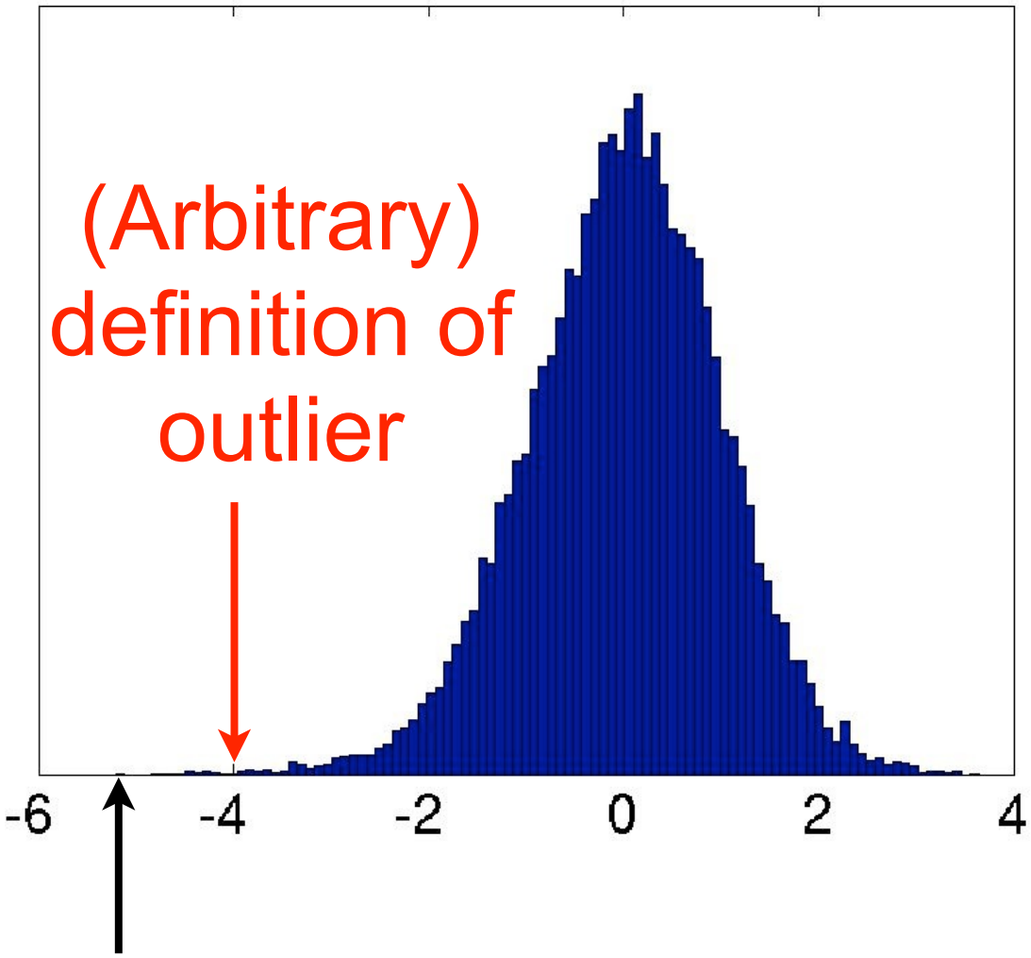
Observed - predicted



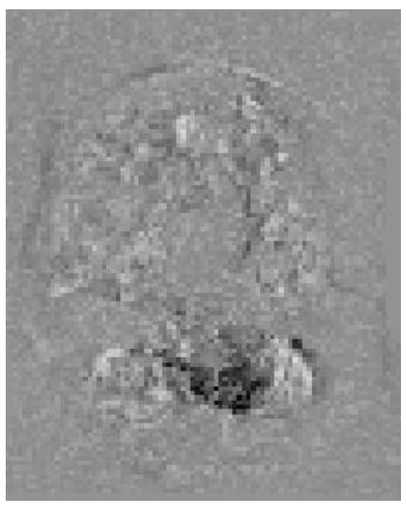
$\overline{x} = 0.084$ $\overline{x} = -0.791$ $\overline{x} = -0.125$

This allows us to calculate the per-slice mean difference between observation and prediction

Outlier detection



We can calculate the mean difference for every slice in every volume and get an empirical distribution that we can convert to z-scores



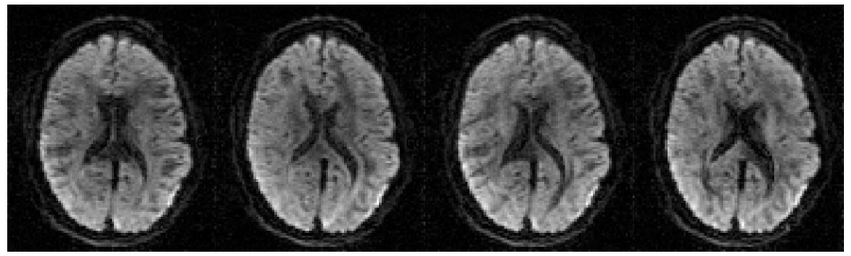
Worst slice

We can define an outlier slice as one with a z-score above an (arbitrary) threshold. We then have a choice of reporting outliers and/or replacing them with their predictions.

eddy revisited

1. For all scans

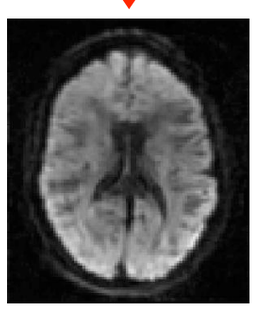
[1 0 0] [.6 -.4 -.7] [.8 .6 0] [-.4 .9 0]



...

topup EC mp $\begin{bmatrix} 0.2 \\ 0.6 \\ \vdots \\ 0.1 \end{bmatrix}$

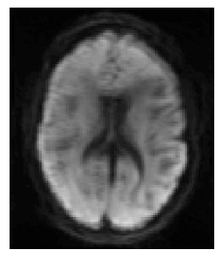
Use susceptibility field and current estimate of EC and movement to "unwarp" scan



Load into prediction maker

2. For all scans

[1 0 0]

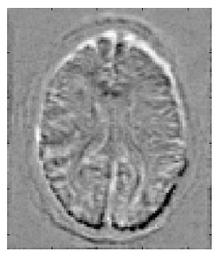


Get prediction

topup EC mp $\begin{bmatrix} 0.2 \\ 0.6 \\ \vdots \\ 0.1 \end{bmatrix}$

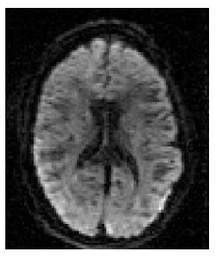
Invert current transform

Use difference to update EC, mp and outlier list

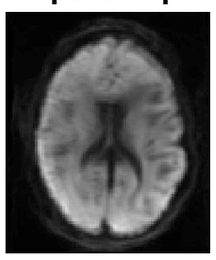


Get prediction in scan space

[1 0 0]

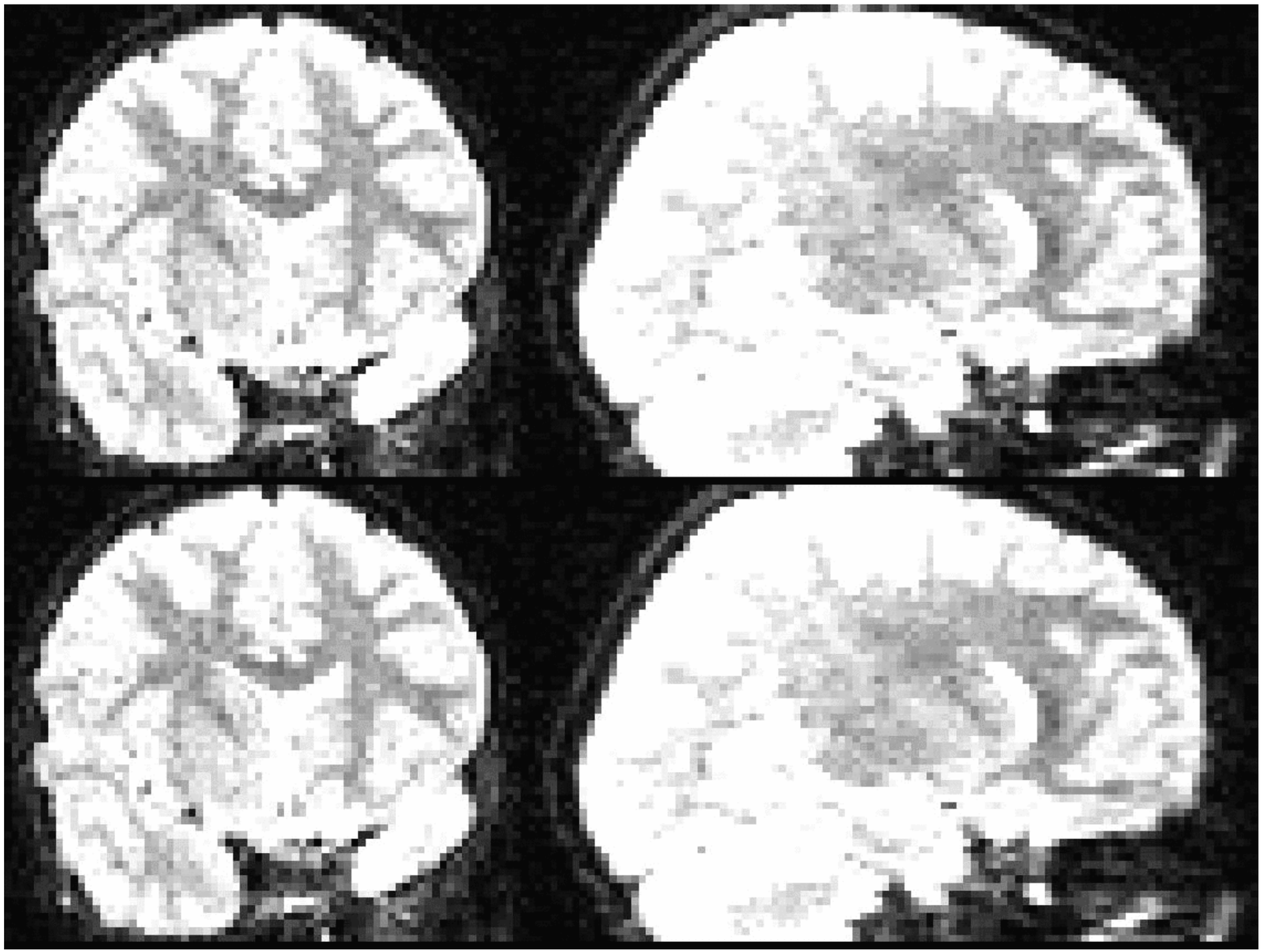


[1 0 0]



Compare to scan

Norwegian data. 32 directions. Hundreds of children.



Eight year old who gets tired towards the end of scanning

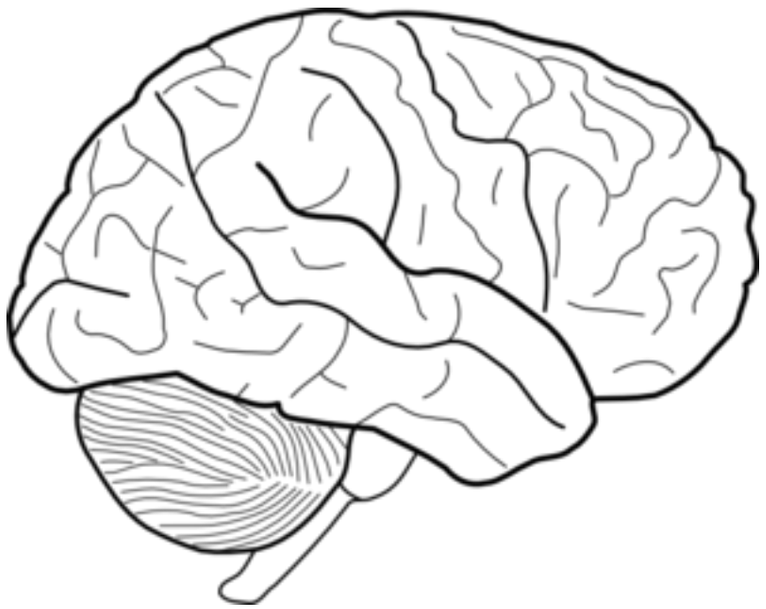
After outlier detection and replacement by eddy

Outline of the talk

- What is the problem with diffusion data?
- Off-resonance field
- Registering diffusion data
- Practicalities
- Some results
- New eddy features
  - Movement-induced dropout
  - Intra-volume motion

Intra-volume movement

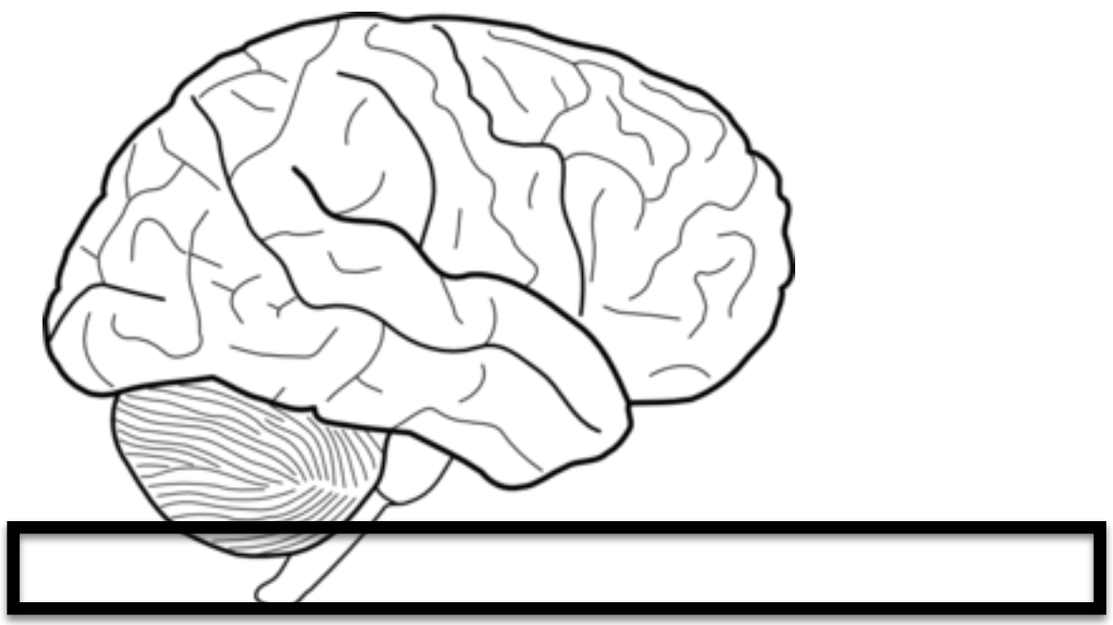
One of the (possibly naive) assumptions of most movement correction is that any movement is instantaneous and occurs between the acquisition of consecutive volumes.



This is the brain we set out to image

Intra-volume movement

One of the (possibly naive) assumptions of most movement correction is that any movement is instantaneous and occurs between the acquisition of consecutive volumes.



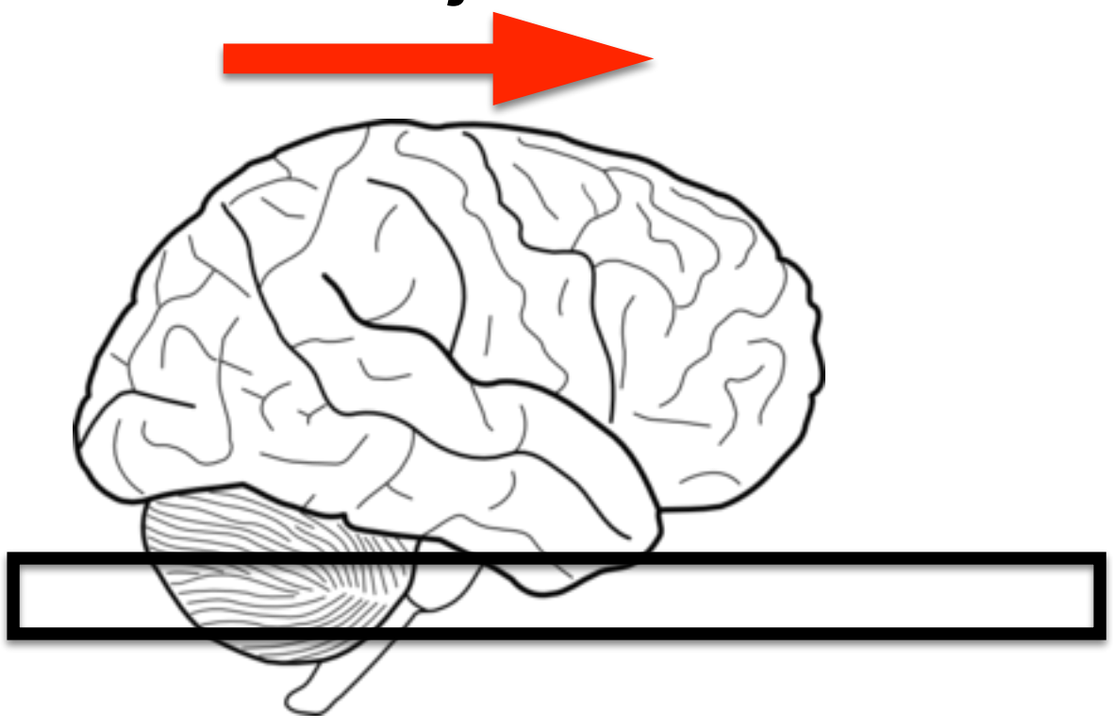
This is the brain we set out to image

And here we have acquired the first slice

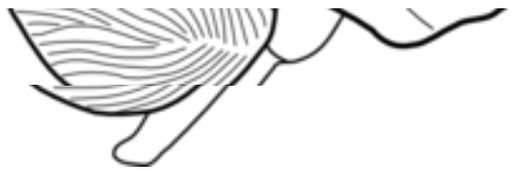
Intra-volume movement

One of the (possibly naive) assumptions of most movement correction is that any movement is instantaneous and occurs between the acquisition of consecutive volumes.

But the subject moves



This is the brain we set out to image

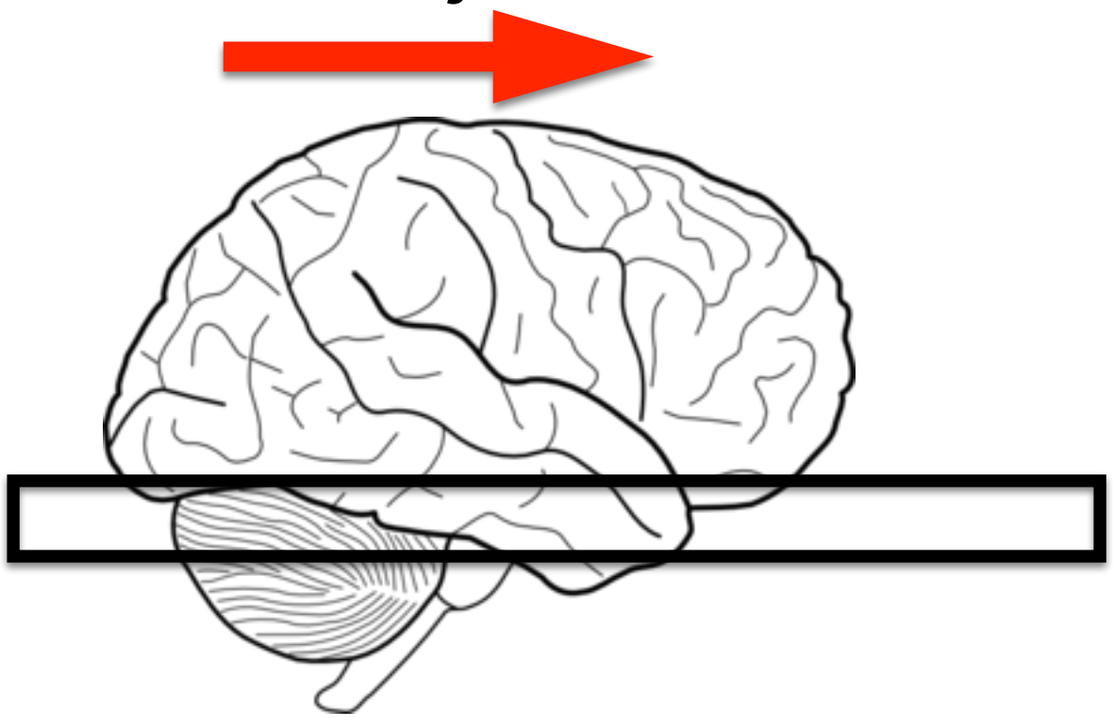


So the brain is offset in the second slice

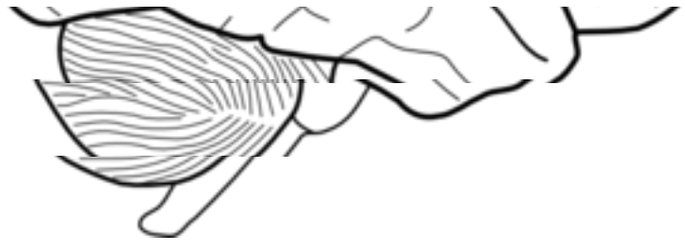
Intra-volume movement

One of the (possibly naive) assumptions of most movement correction is that any movement is instantaneous and occurs between the acquisition of consecutive volumes.

But the subject moves



This is the brain we set out to image

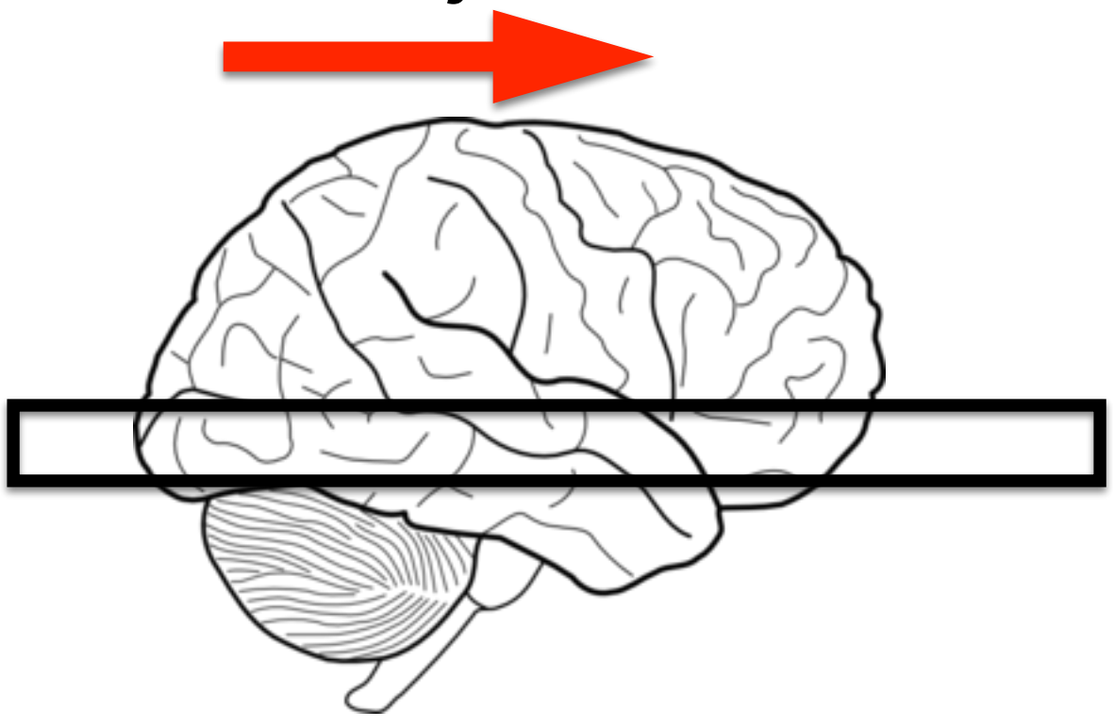


And even more so in the third slice

Intra-volume movement

One of the (possibly naive) assumptions of most movement correction is that any movement is instantaneous and occurs between the acquisition of consecutive volumes.

But the subject moves



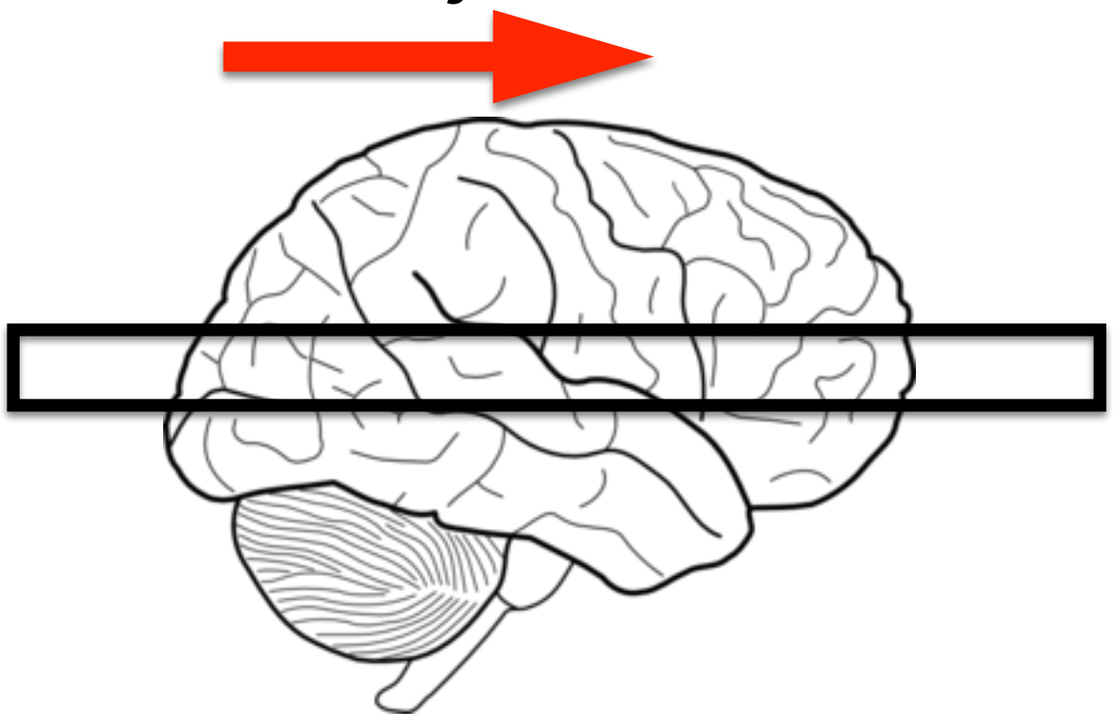
This is the brain we set out to image

And more …

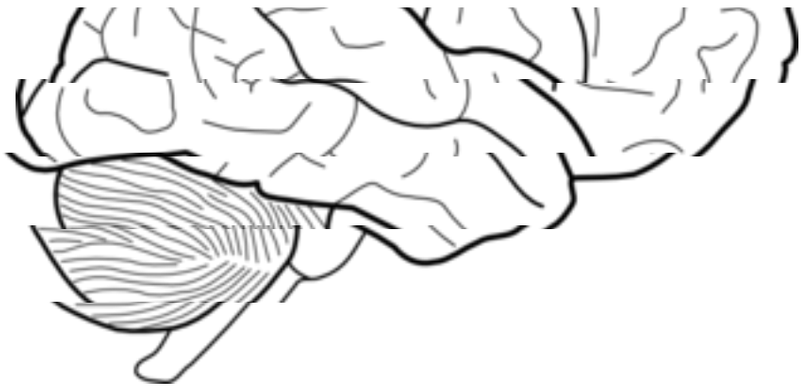
Intra-volume movement

One of the (possibly naive) assumptions of most movement correction is that any movement is instantaneous and occurs between the acquisition of consecutive volumes.

But the subject moves



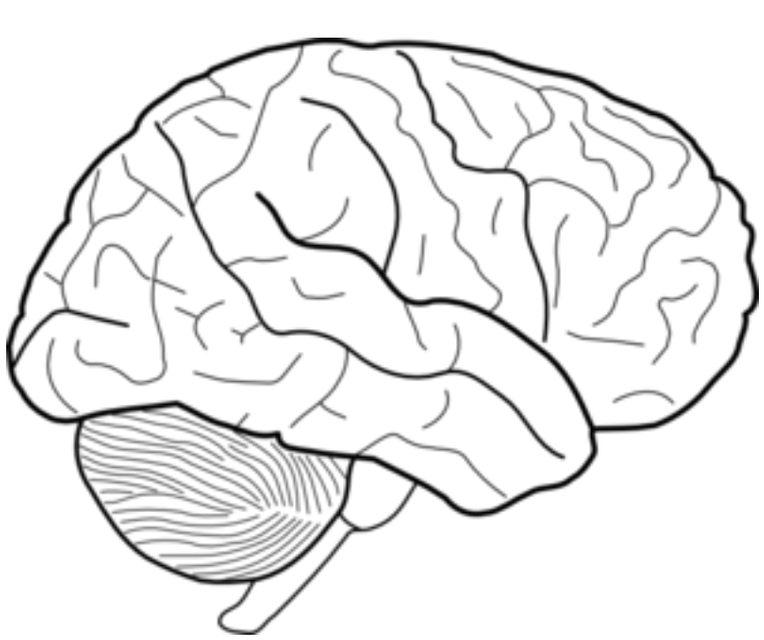
This is the brain we set out to image



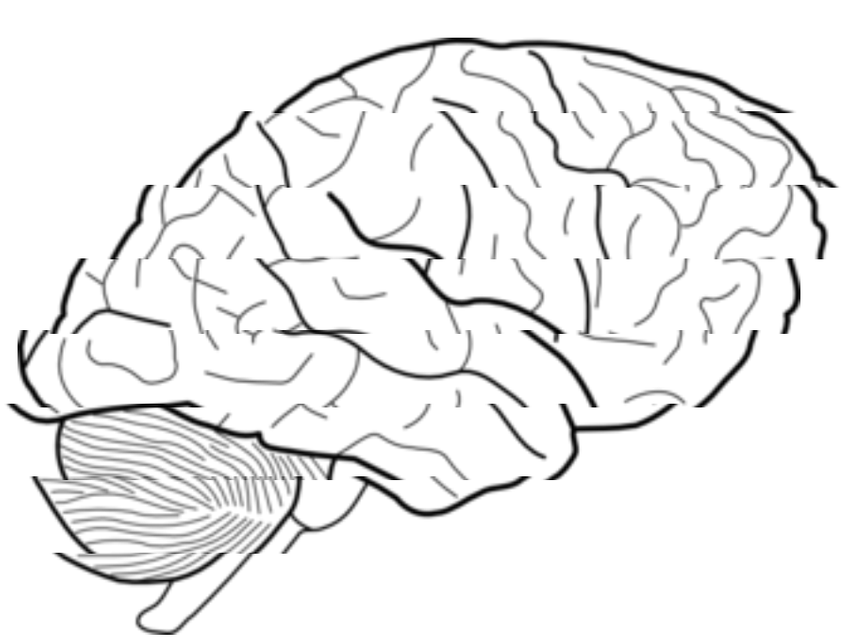
… and more …

Intra-volume movement

One of the (possibly naive) assumptions of most movement correction is that any movement is instantaneous and occurs between the acquisition of consecutive volumes.



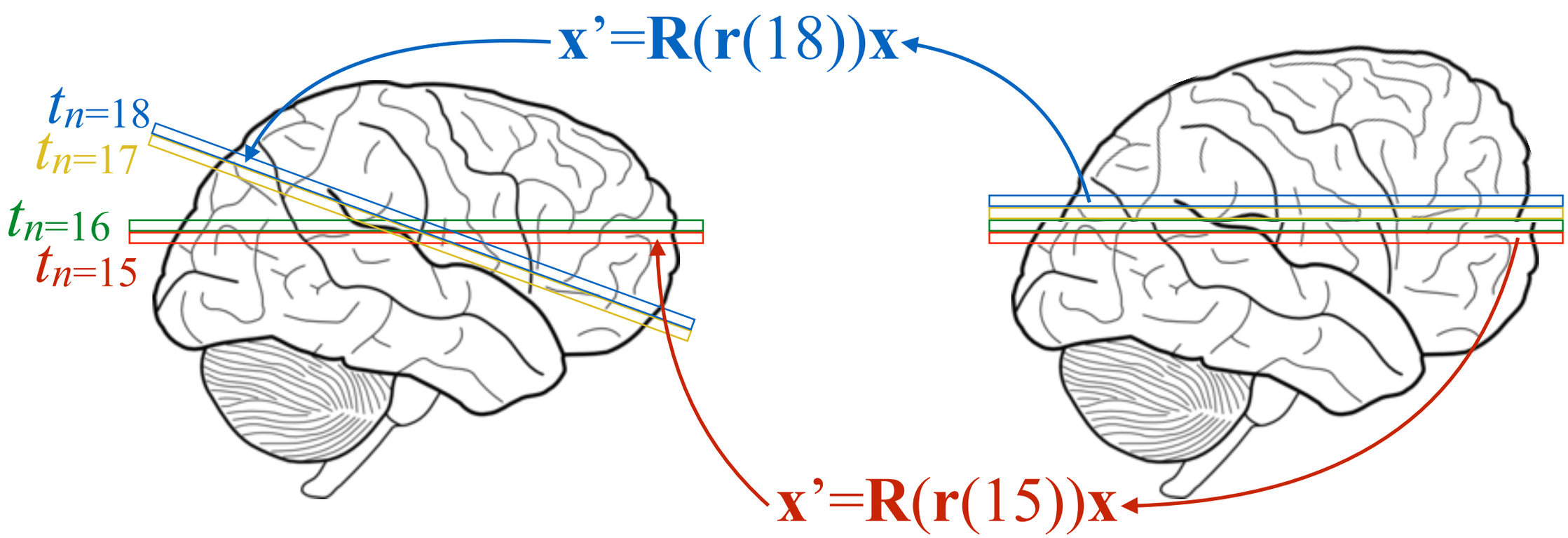
This is the brain we set out to image



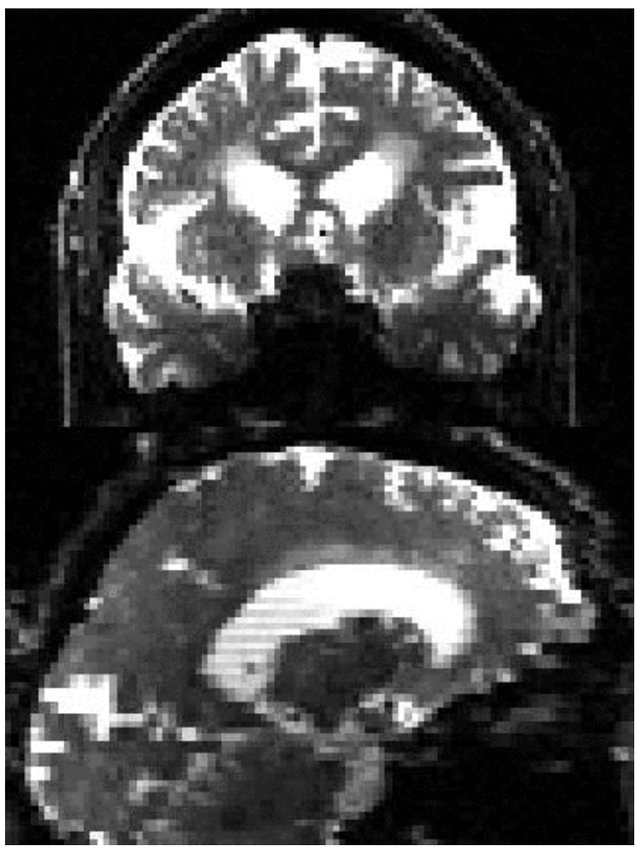
etc.

Intra-volume movement

- This is known as the “slice-to-vol” problem or the “intra-volume movement” problem.
- The new version of `eddy` addresses this problem.
- It estimates the slice wise movement through the same Gaussian Process based forward model.



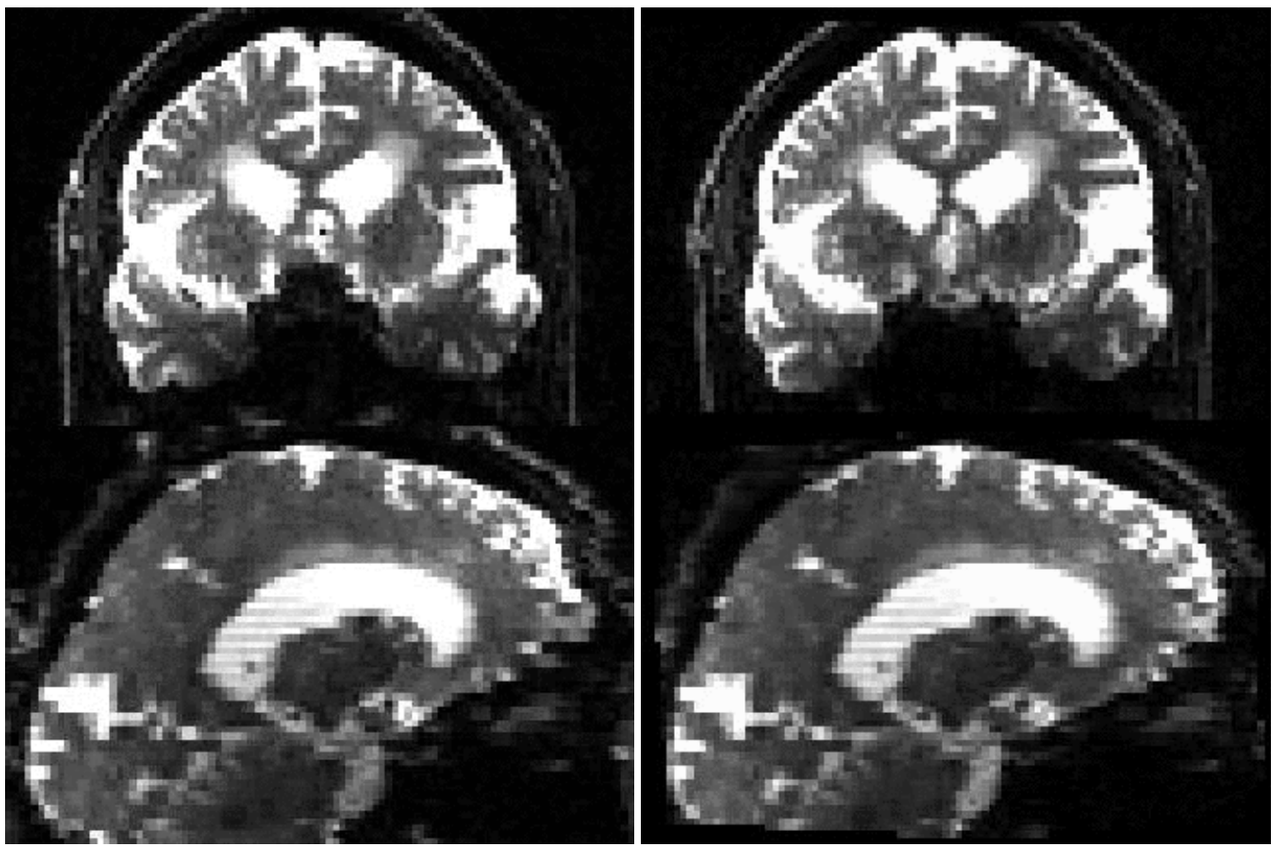
Intra-volume movement



Original data

Problematic elderly subject. Lots of movement induced signal loss and intravolume movement

Intra-volume movement

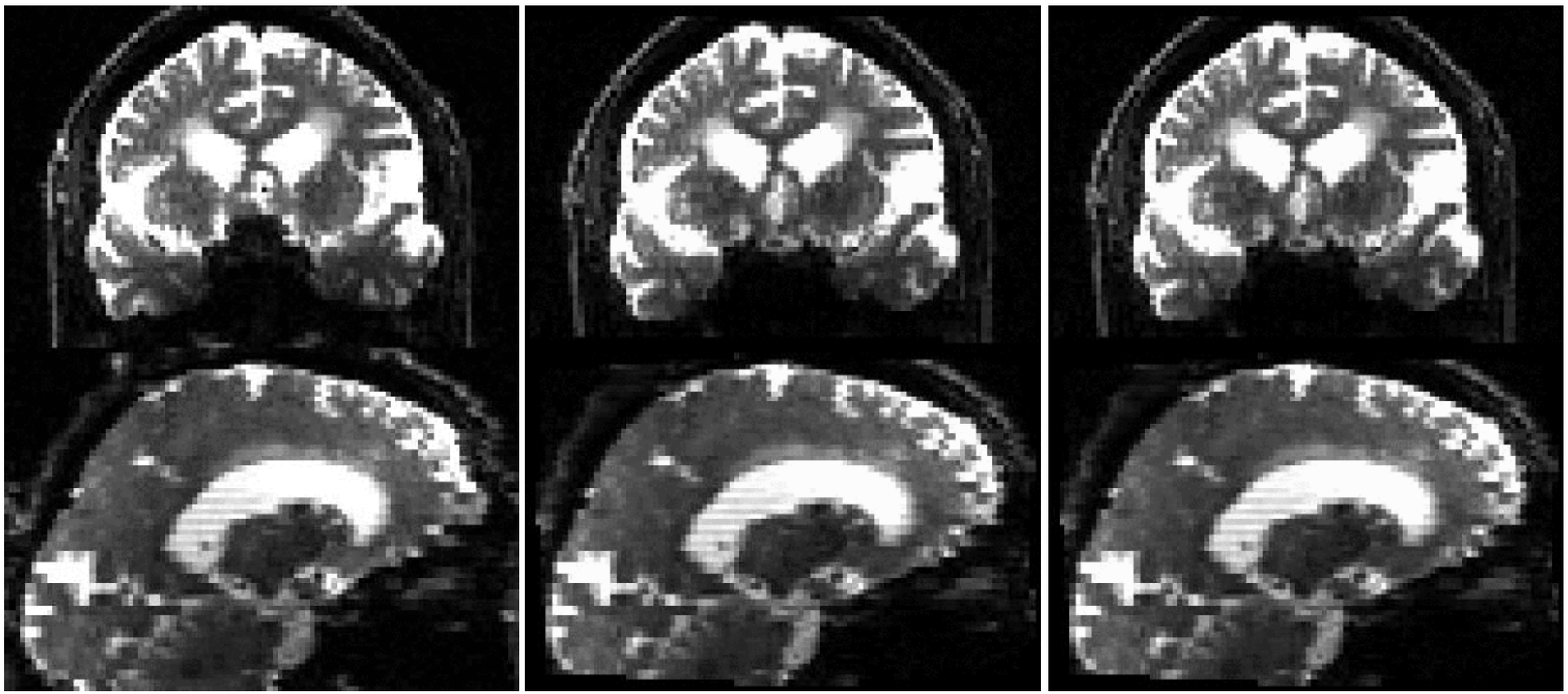


Original data

After correction without outlier correction

Problematic elderly subject. Lots of movement induced signal loss and intravolume movement

Intra-volume movement



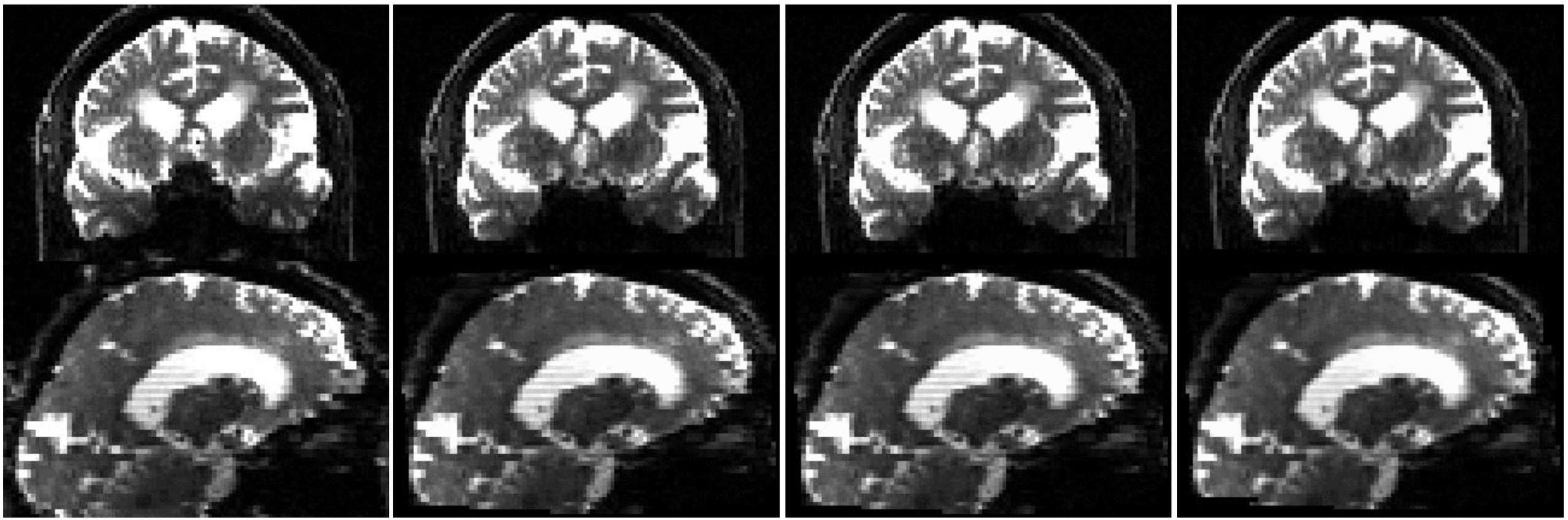
Original data

After correction without outlier correction

After correction with outlier replacement

Problematic elderly subject. Lots of movement induced signal loss and intravolume movement

Intra-volume movement



Original data

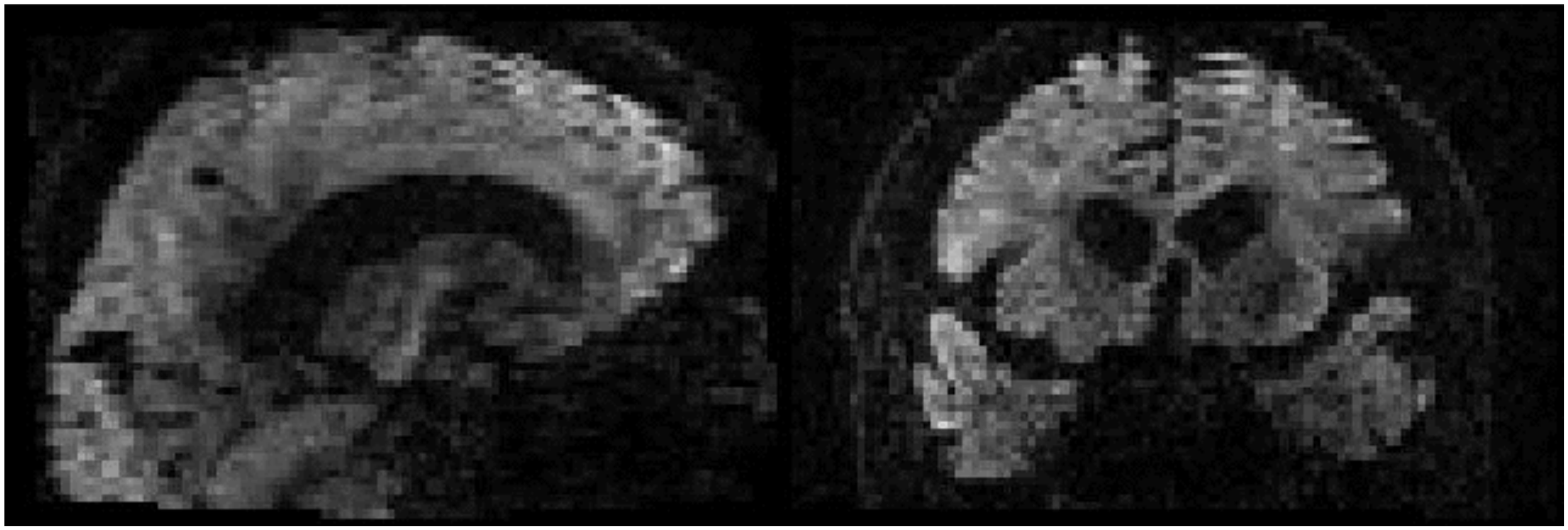
After correction without outlier correction

After correction with outlier replacement

After intravolume movement correction.

Problematic elderly subject. Lots of movement induced signal loss and intravolume movement

Intra-volume movement



Highlighting the difference between just OLR and OLR combined with S2V correction

Problematic elderly subject. Lots of movement induced signal loss and intravolume movement