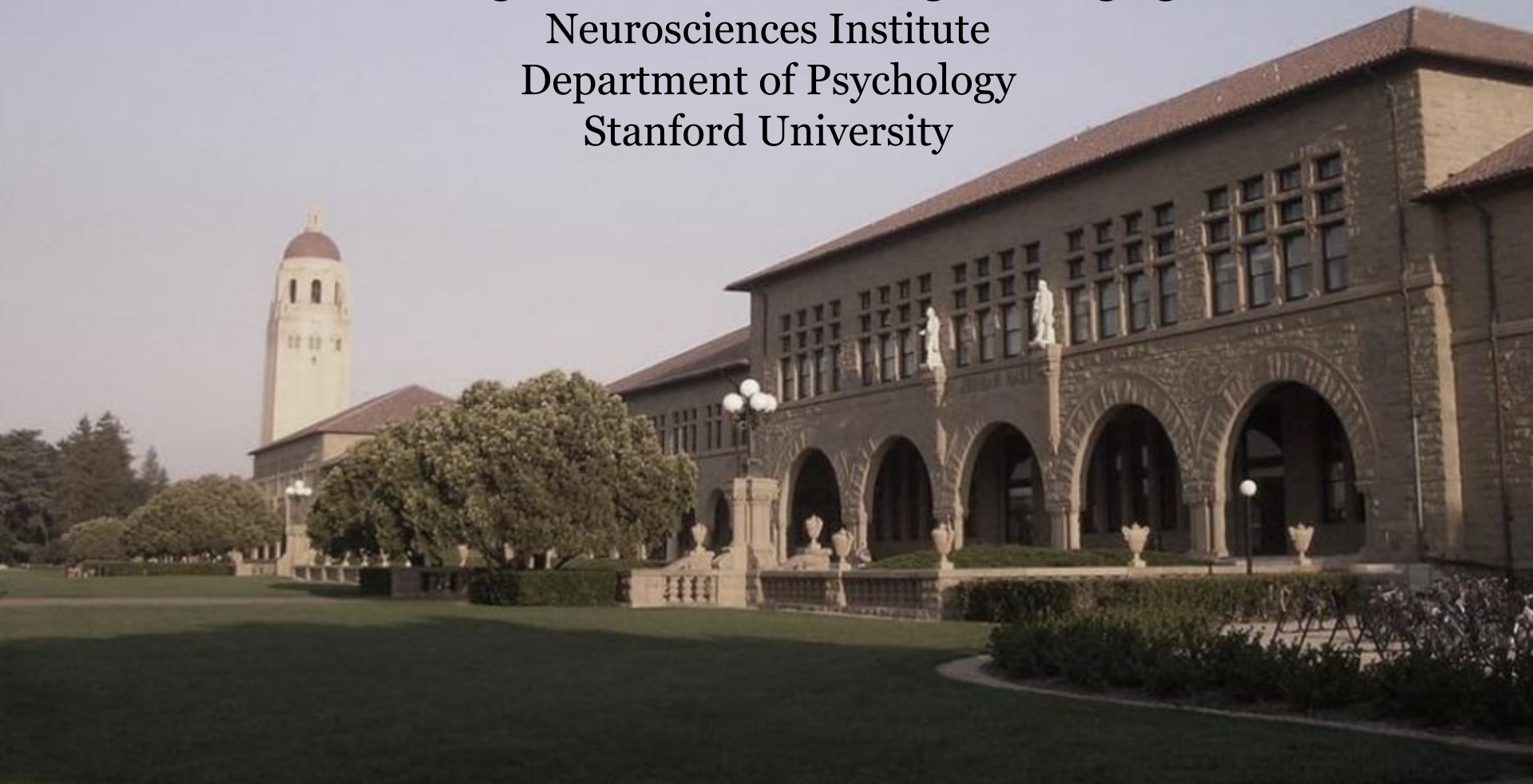


Mostly diffusion and tractography

Professor Brian Wandell
Center for Cognitive and Neurobiological Imaging (CNI)
Neurosciences Institute
Department of Psychology
Stanford University



Neuroscience is broadening its view of key brain functions

Bullock, Bennett, Johnston, Josephson, Marder, Fields
Science, 2005

PERSPECTIVES

NEUROSCIENCE

The Neuron Doctrine, Redux

Theodore H. Bullock, Michael V. L. Bennett, Daniel Johnston,
Robert Josephson, Eve Marder, R. Douglas Fields

After a century, neuroscientists are rethinking the Neuron Doctrine, the fundamental principle of neuroscience. This proposition, developed primarily by the great Spanish anatomist and Nobel laureate Santiago Ramón y Cajal, holds that a neuron is an anatomically and functionally distinct unit that receives

synaptic switch regulating information flow through neural circuits. The synaptic cleft went unseen until a half-century later, when in 1954 the electron microscope provided convincing evidence that essentially refuted the earlier “reticular” view of a nerve fiber web (1).

rather than all-or-nothing electrical spikes that propagate regeneratively (2). It was also determined that evoked electrical responses often occur on a background of spontaneous changes in membrane potential (i.e., produced without input from other neurons) and that some parts of the neuron are incapable of producing all-or-nothing action potentials (3). Today, it is apparent that information processing in the nervous system must operate beyond the limits of the Neuron Doctrine as it was conceived. This has evolved from detailed information gained from techniques devel-

Human fascicles (tracts)

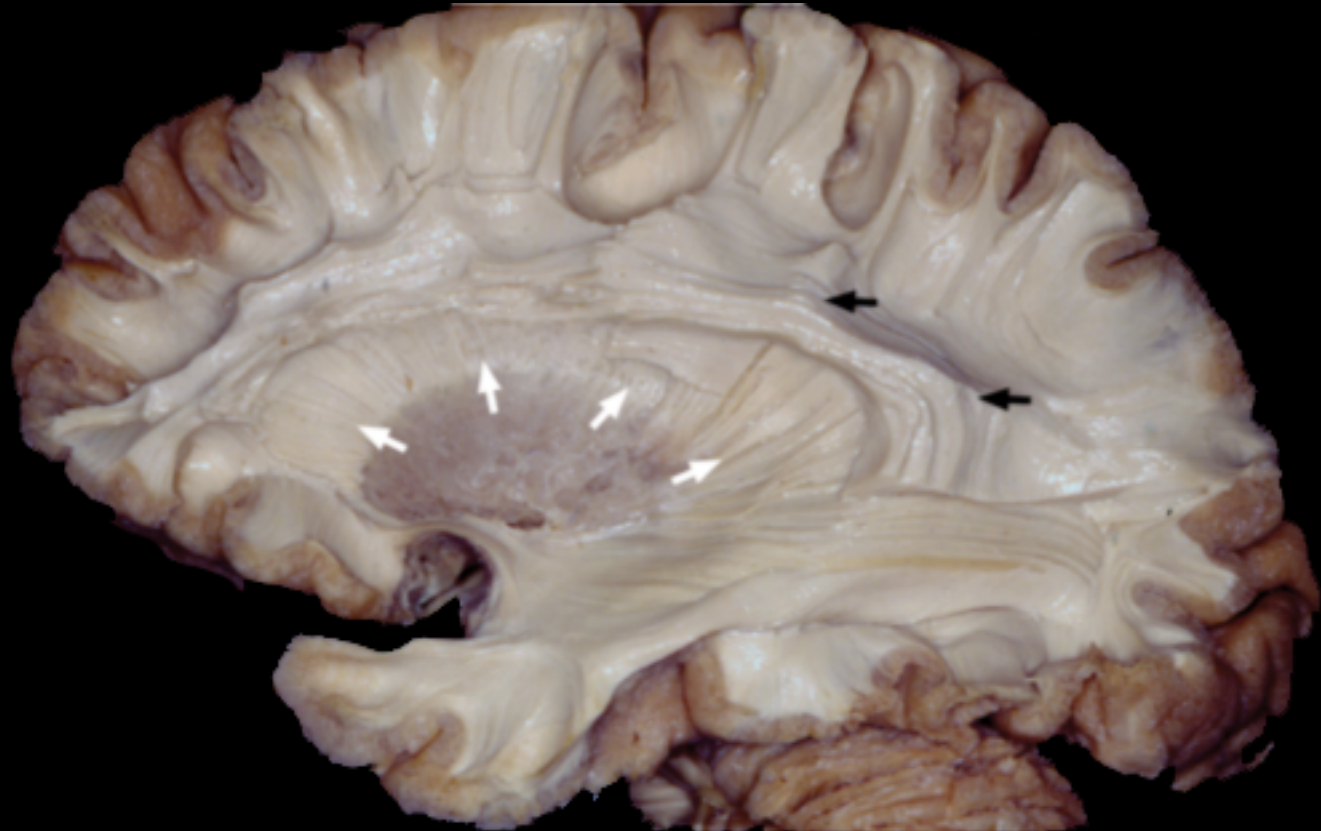
- There are many long-range connections
- These connections are not passive – they change their properties in response to use
- A system with active wires



Courtesy Professor Peggy Mason

Human fascicles (tracts)

- There are many long-range connections
- These connections are not passive – they change their properties in response to use
- A system with active wires



Courtesy Professor Ugur Ture

Types of Glia

Microglia (20%) scavenging for infections, plaques, damaged neurons; regulating healthy neurons

Astrocytes bring nutrients to neurons as well as surround and regulate synapses. (50%)

Oligodendrocytes produce myelin that insulates axons.

Schwann cells perform myelination duties in the body's peripheral nervous system.

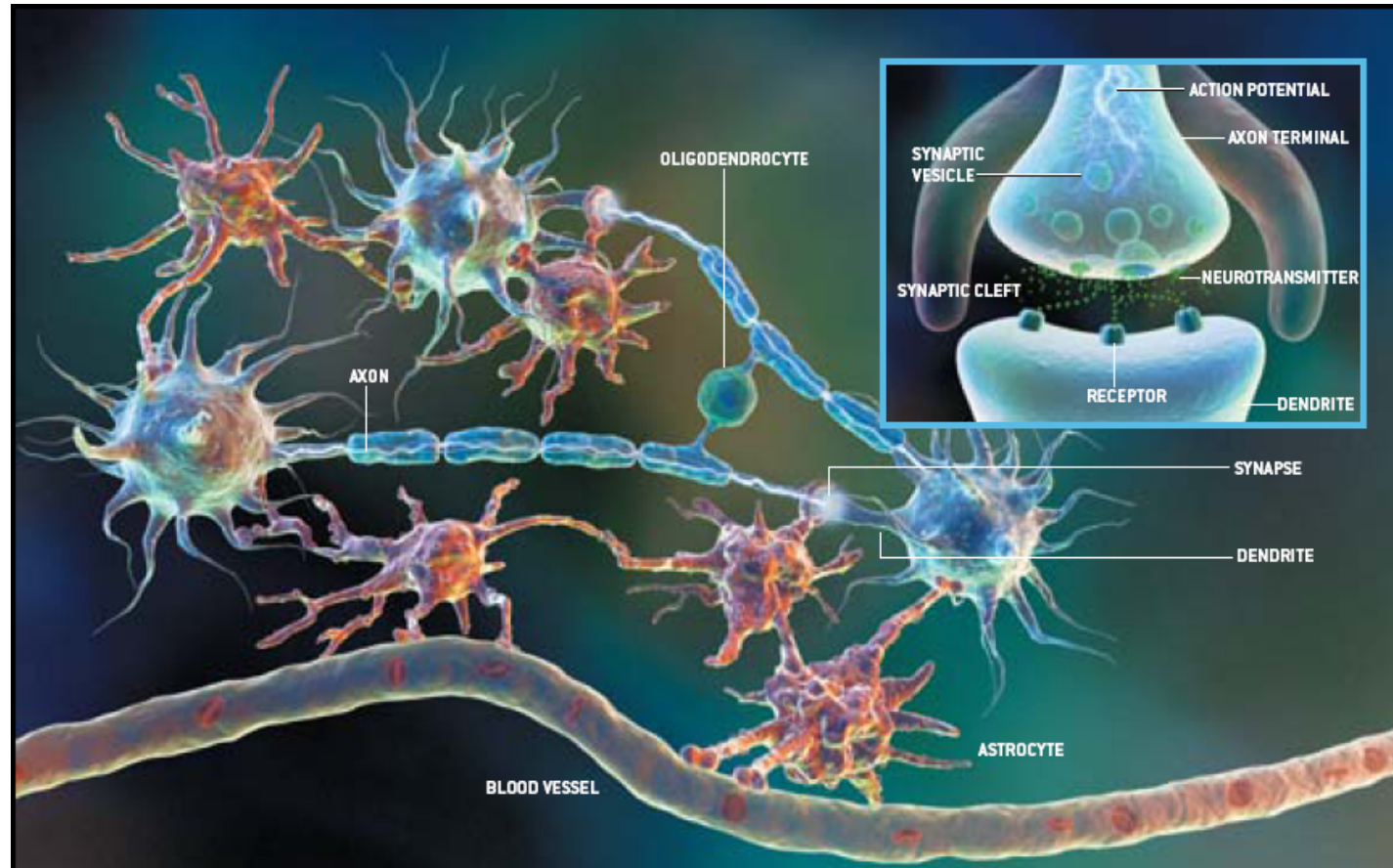
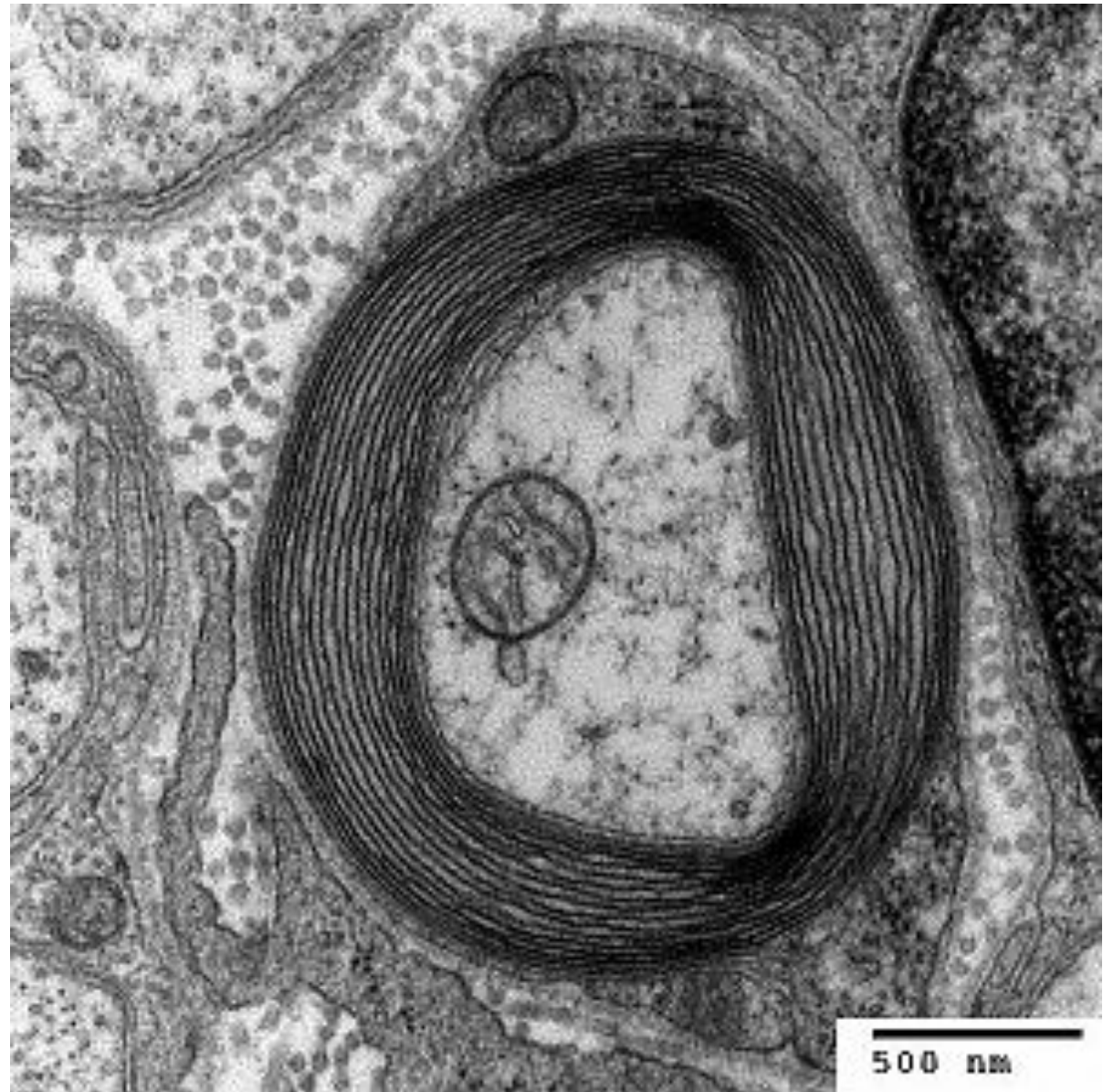


Image from
Wake, et al. Trends in Neurosciences
Volume 36, Issue 4, April 2013

An oligodendrocyte in the white matter

Electron micrograph showing the myelin sheath from an oligodendrocyte wrapping a single axons (cross-section)

Note the scale bar



RESEARCH ARTICLE

SKILL DEVELOPMENT

Motor skill learning requires active central myelination

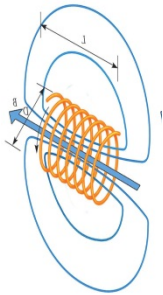
Ian A. McKenzie,^{1*} David Ohayon,^{1*} Huiliang Li,¹ Joana Paes de Faria,^{1†} Ben Emery,² Koujiro Tohyama,³ William D. Richardson^{1‡}

Myelin-forming oligodendrocytes (OLs) are formed continuously in the healthy adult brain. In this work, we study the function of these late-forming cells and the myelin they produce. Learning a new motor skill (such as juggling) alters the structure of the brain's white matter, which contains many OLs, suggesting that late-born OLs might contribute to motor learning. Consistent with this idea, we show that production of newly formed OLs is briefly accelerated in mice that learn a new skill (running on a “complex wheel” with irregularly spaced rungs). By genetically manipulating the transcription factor myelin regulatory factor in OL precursors, we blocked production of new OLs during adulthood without affecting preexisting OLs or myelin. This prevented the mice from mastering the complex wheel. Thus, generation of new OLs and myelin is important for learning motor skills.

Free induction decay

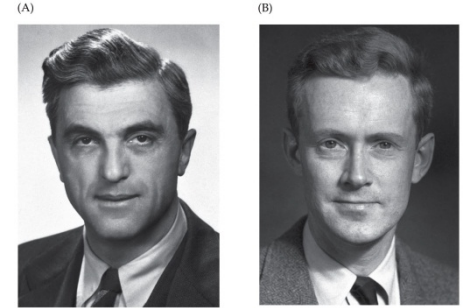


The free induction decay experiment



© 2005 Pearson Education, Inc.

Beaker of water in a perfectly uniform magnetic field



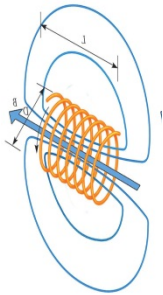
Functional Magnetic Resonance Imaging 2e, Figure 1.10

© 2005 Elsevier Inc.

Bloch

Purcell

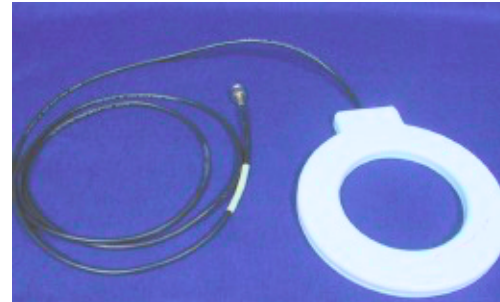
The free induction decay experiment



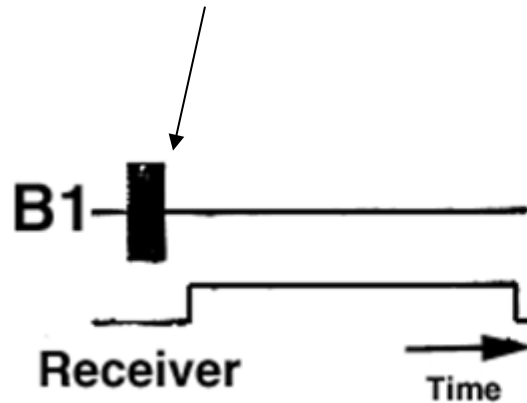
Beaker of water in a perfectly uniform magnetic field



RF signal excites spins



Coil



Functional Magnetic Resonance Imaging 2e, Figure 1.10

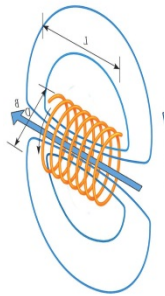
Bloch



© 2009 Elsevier Inc.

Purcell

The free induction decay experiment



Beaker of water in a perfectly uniform magnetic field



RF signal excites spins

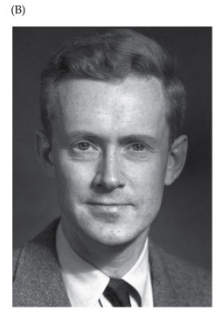


Coil

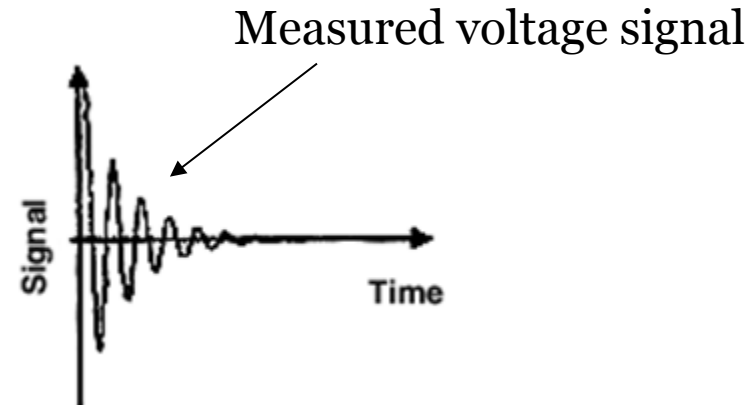
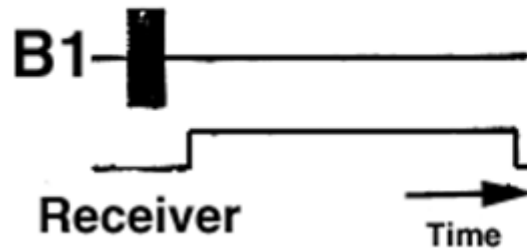


Functional Magnetic Resonance Imaging 2e, Figure 1.10

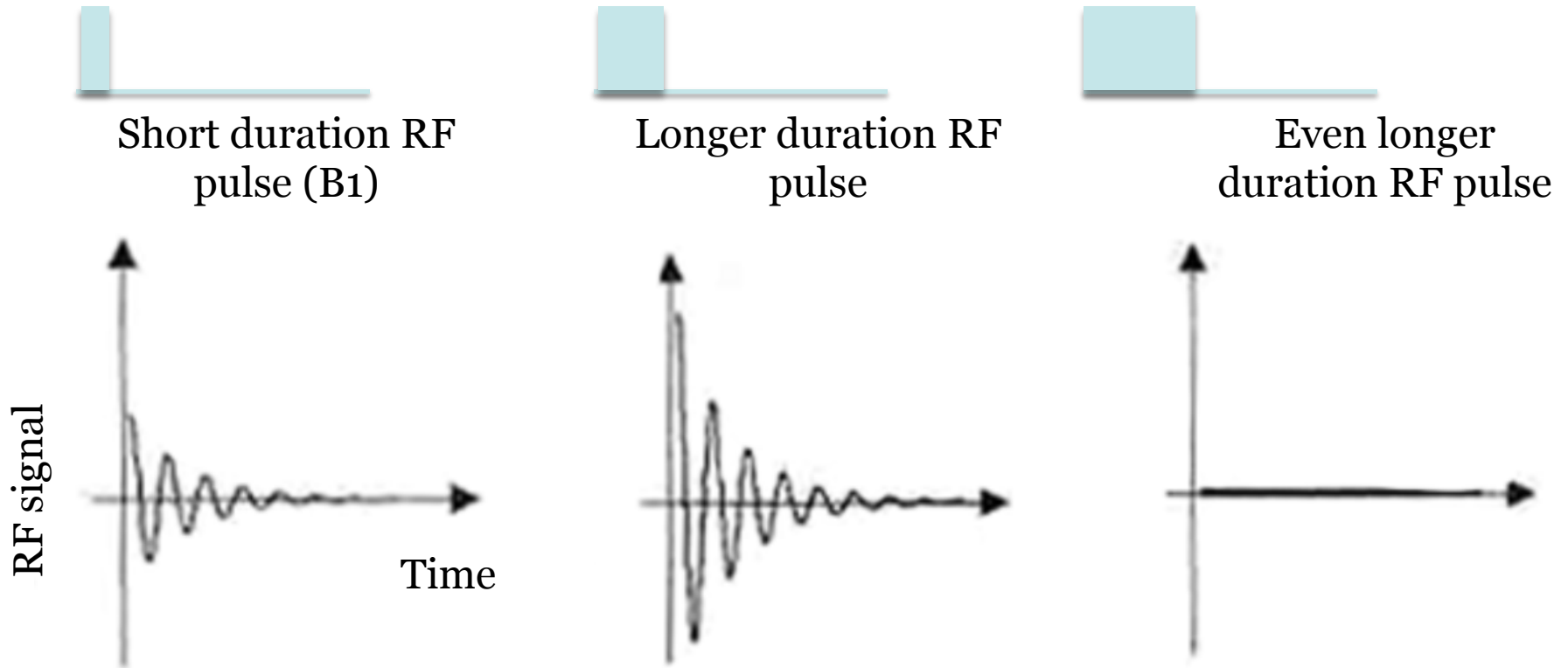
Bloch



Purcell



The FID signal depends on the B1 duration

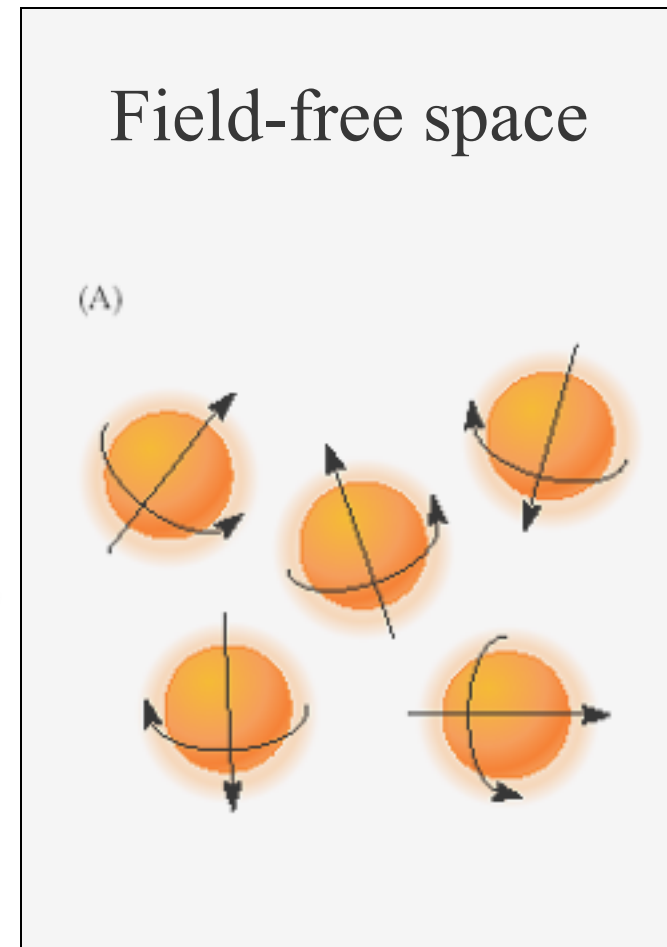
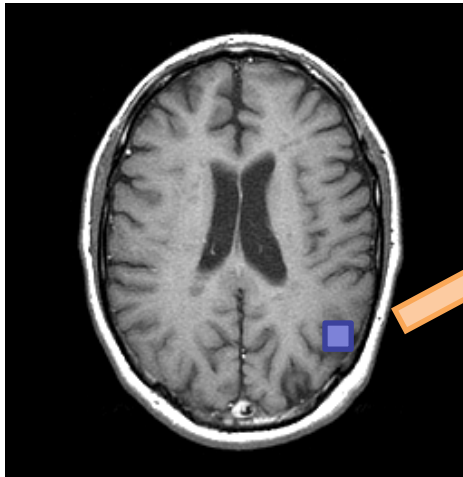


How can we explain this?

Source of the MR signal

Hydrogen nuclei (spins, protons)

An average person who weighs 150 lbs. contains approximately 5×10^{27} hydrogen nuclei (spins);

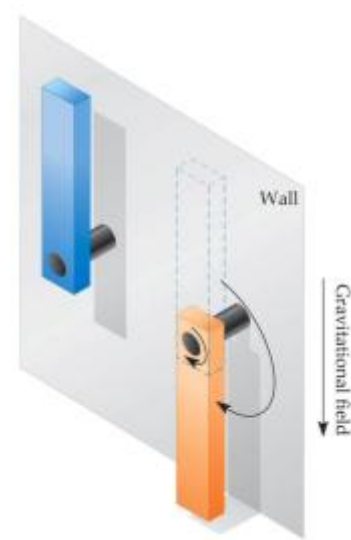
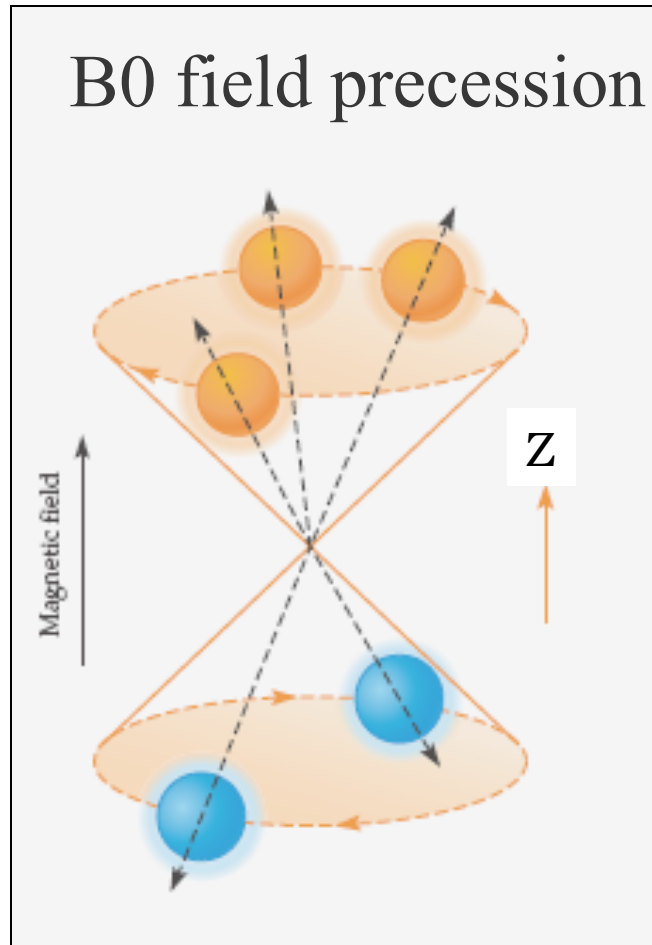


The FID signal: quantal description

In the presence of the B_0 field, the spins generally align with the field (Z-direction)

But they occupy one of two states: Parallel and anti-parallel

(mrTutMR explains how to calculate the percentage in each state)



Parallel

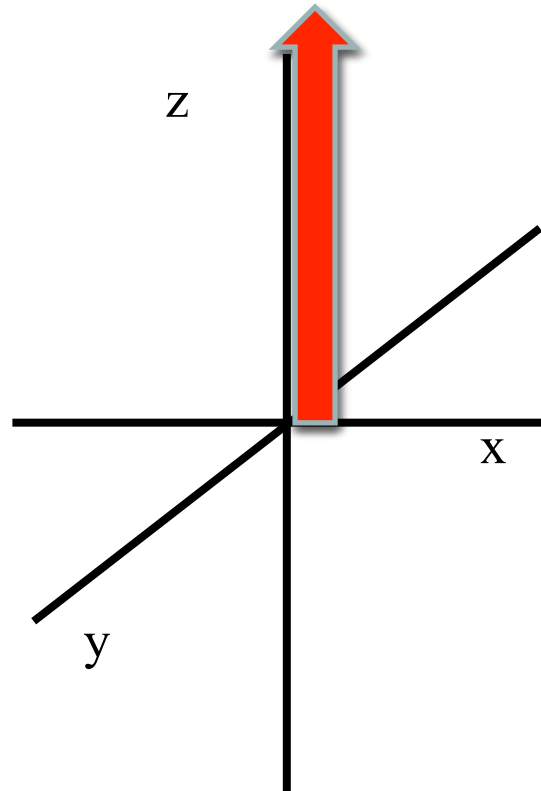
Anti-parallel

The **bulk magnetization** is the sum of the spins

There are lots of spins in each voxel, and we measure the sum of these.

There is no xy-plane direction preference.

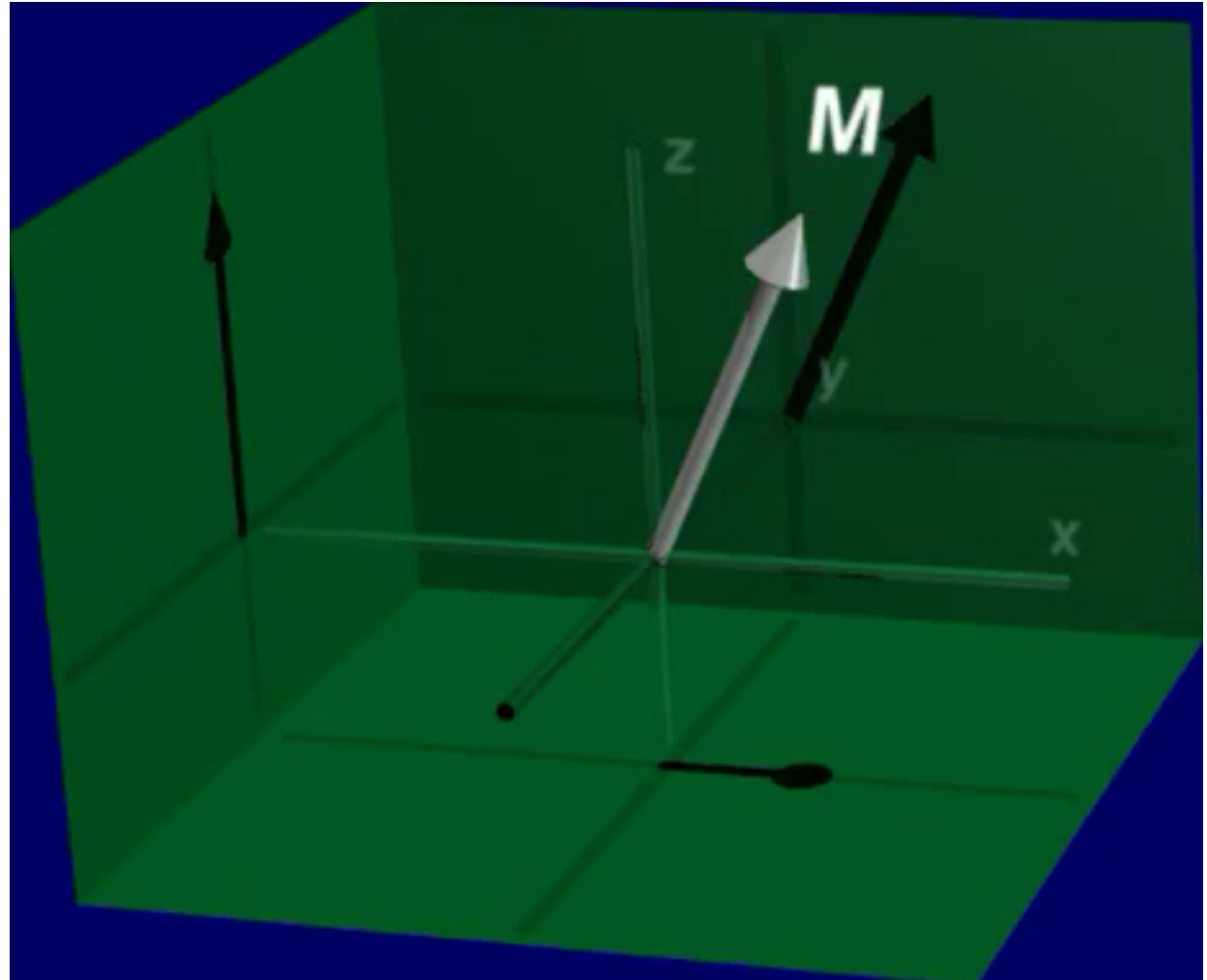
There is a z-direction preference because of the B_0 field.



Precession

When excited by an RF pulse, the bulk magnetization is modeled as spinning around the z-axis, like a top.

It has spin rate (frequency), an angle and a vector length

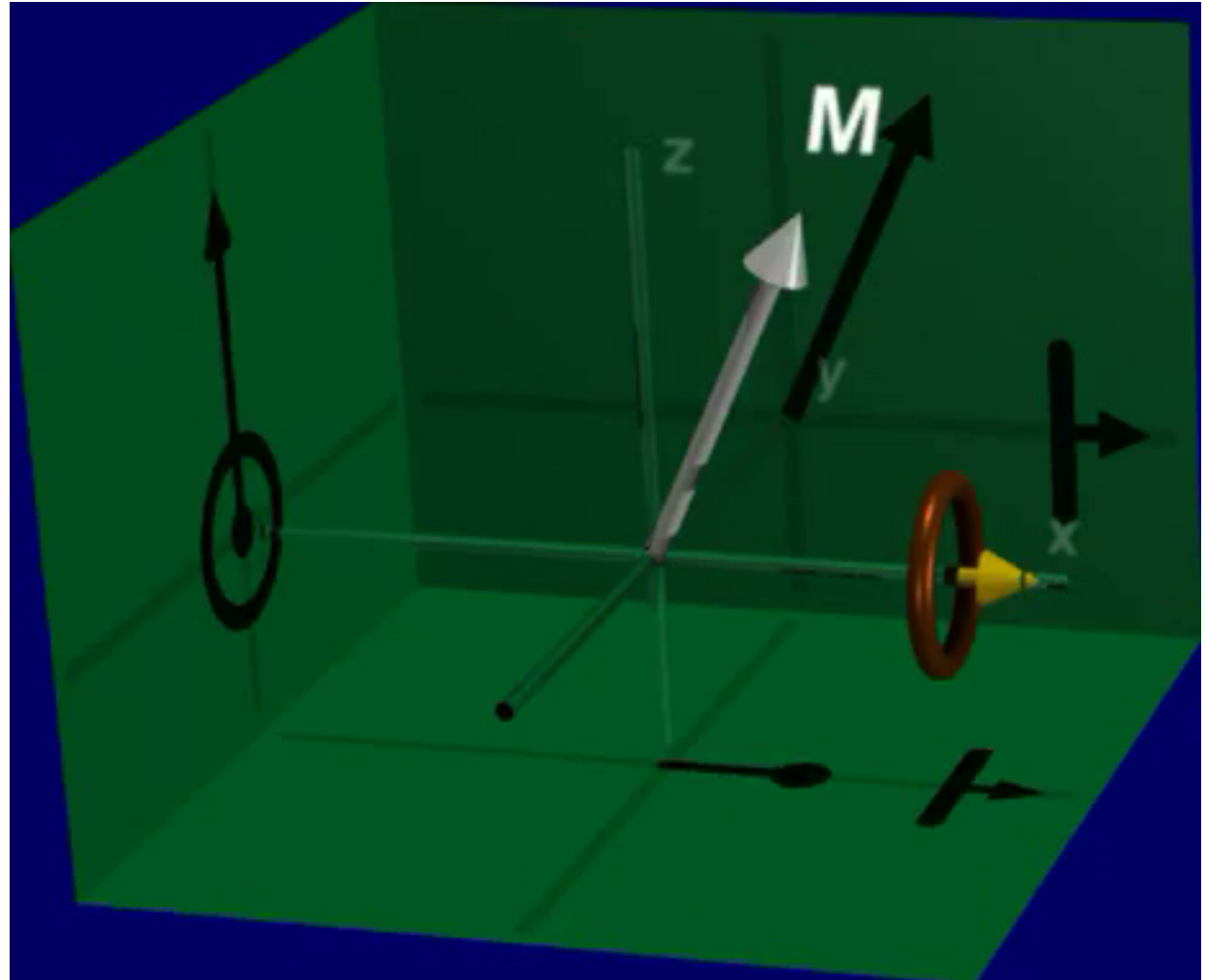


[Play precess.avi](#)

FID: The bulk (net) magnetization metaphor

An RF receive-coil
measures the precessing
bulk magnetization

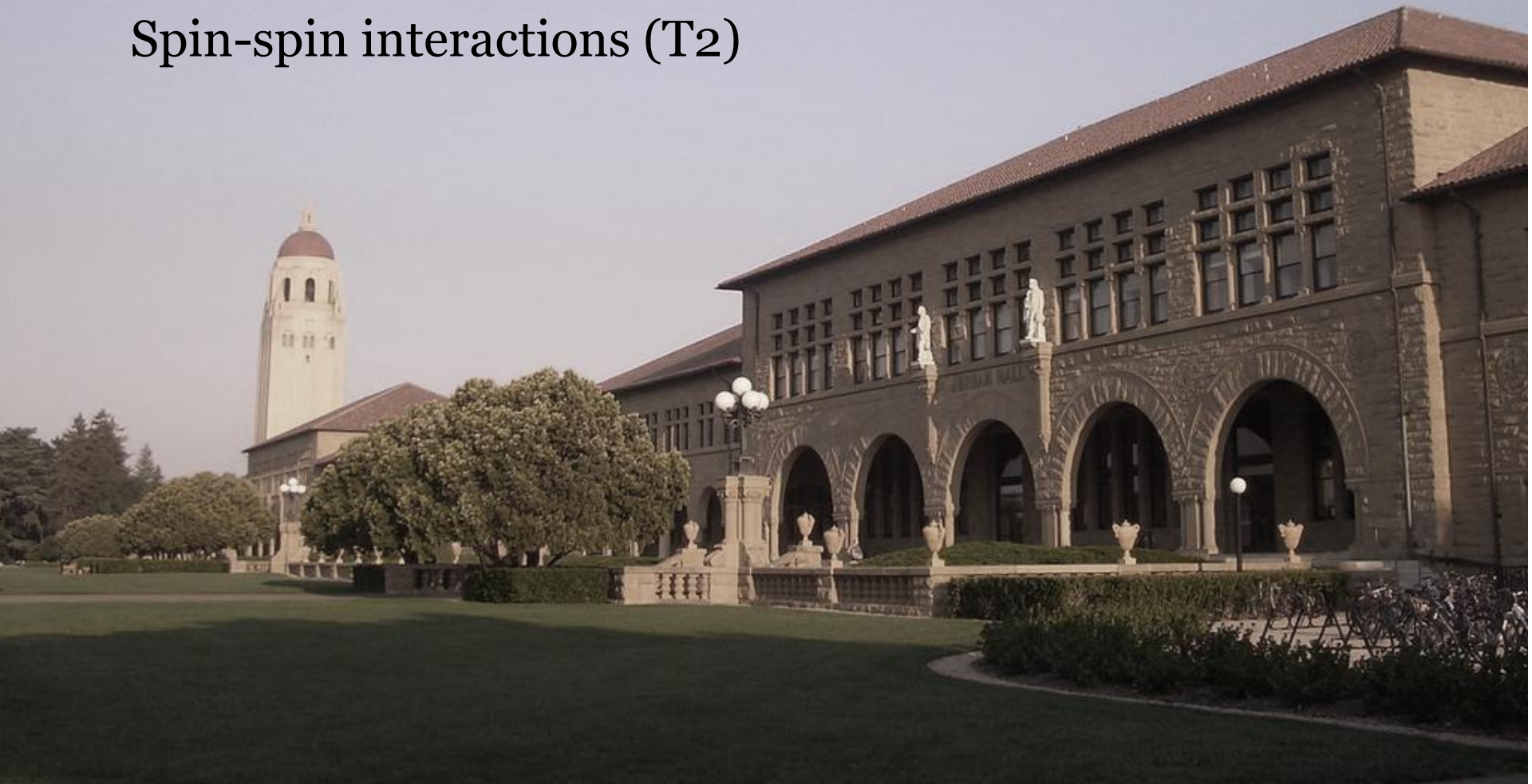
The receive coil can be
the same or different as
the transmit (excite) coil



MR signals

Spin-lattice interactions (T_1)

Spin-spin interactions (T_2)



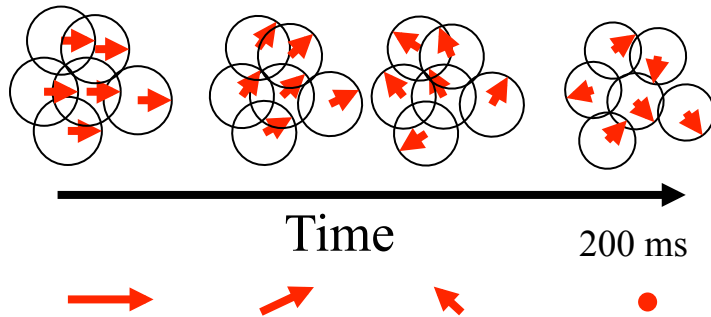
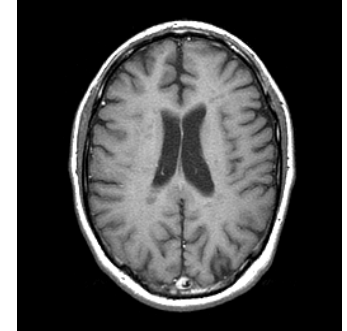
There are multiple mechanisms that can influence the bulk magnetization

High energy

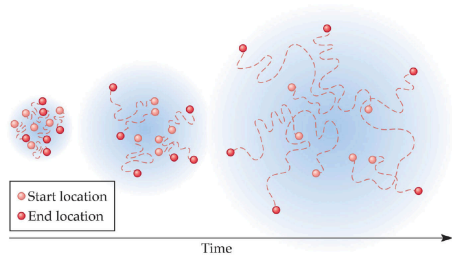
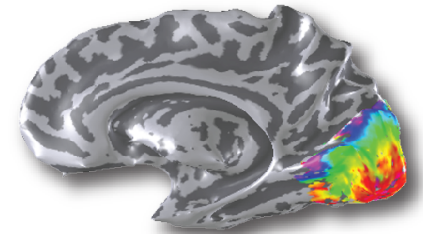
Low energy



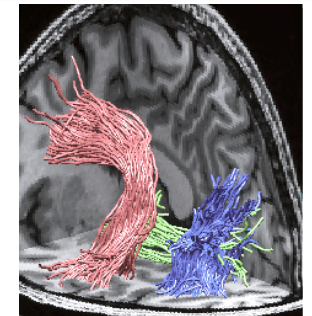
Anti-parallel spins give up energy to macromolecules (lattice) and return to lower parallel state (T1)



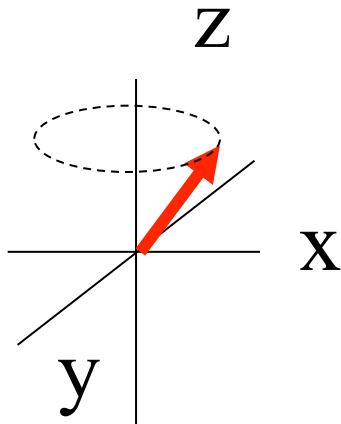
The spins dephase (T2*)



The spins move (diffusion)

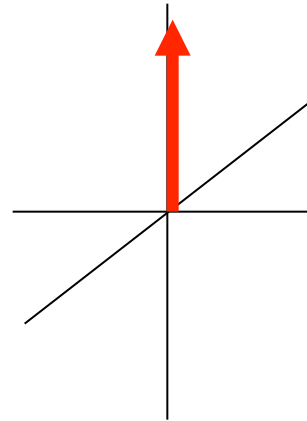


The bulk magnetization is the sum of two components



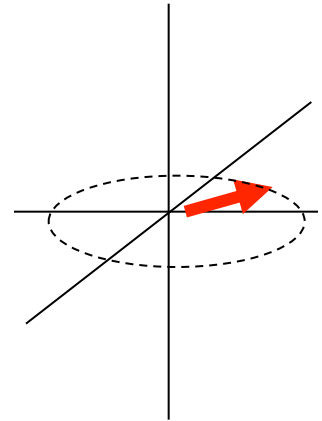
Precessing
spin

=



Longitudinal
component

+

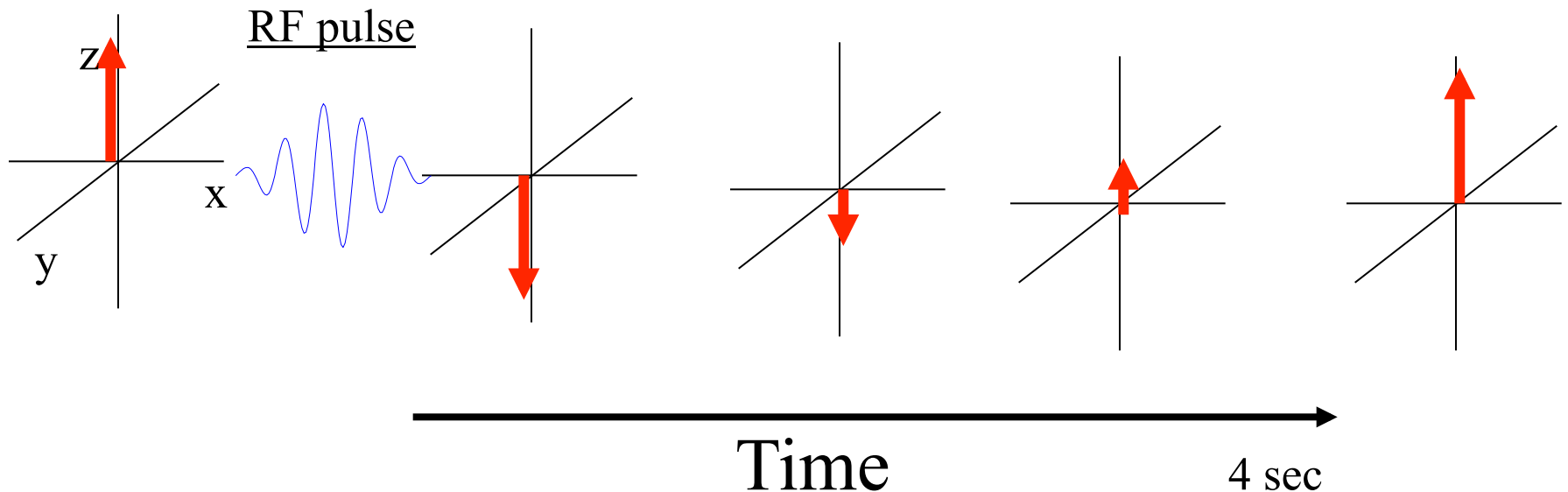


Transverse
component

Longitudinal relaxation (T1)

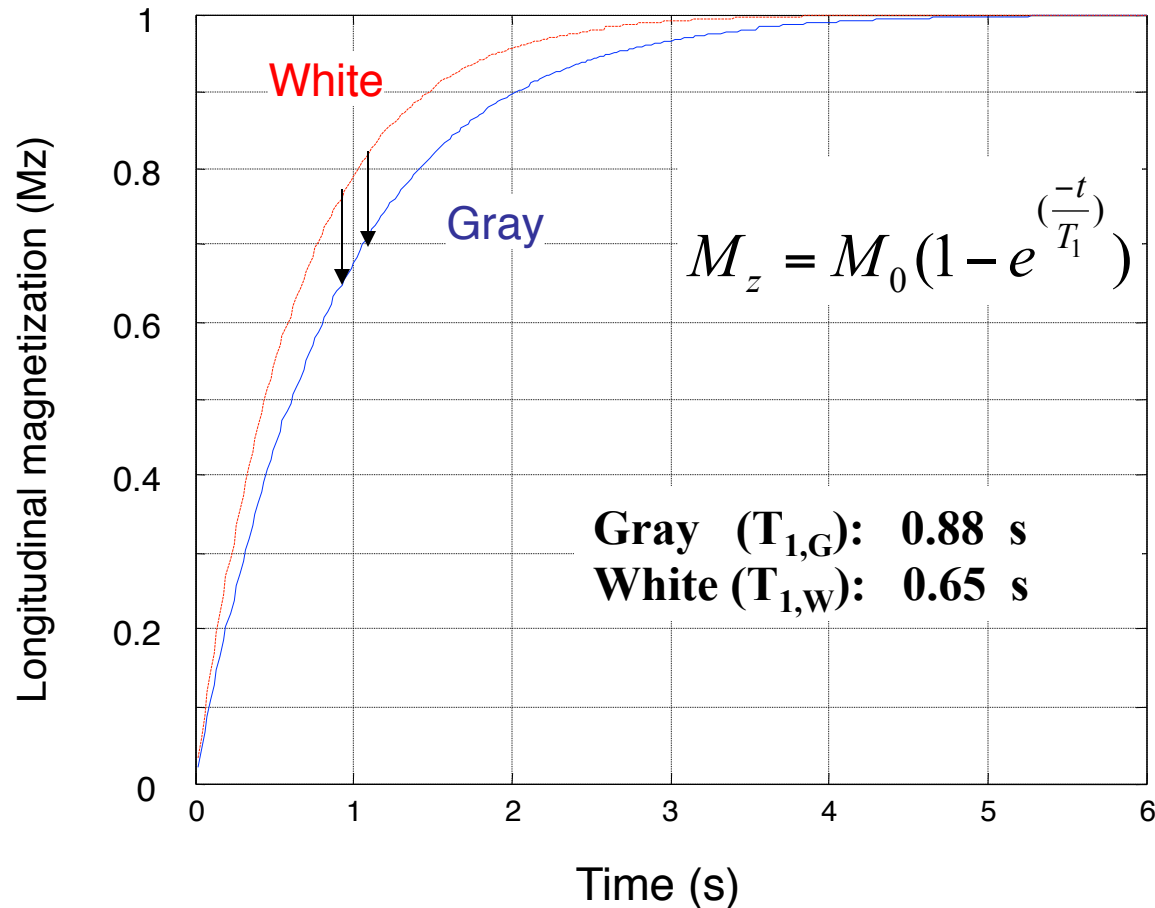
Suppose we apply a pulse that flips the bulk magnetization 180 deg. The longitudinal recovery follows an exponential time course, with a constant called T1

$$M_z = M_0 \left(1 - e^{\left(\frac{-t}{T_1}\right)}\right)$$



Longitudinal relaxation rate depends on your neighborhood

The T1 values of water located in different brain tissue vary.
At 1.5T a good time to measure for contrast is around 0.8-1.2 sec following the RF pulse.

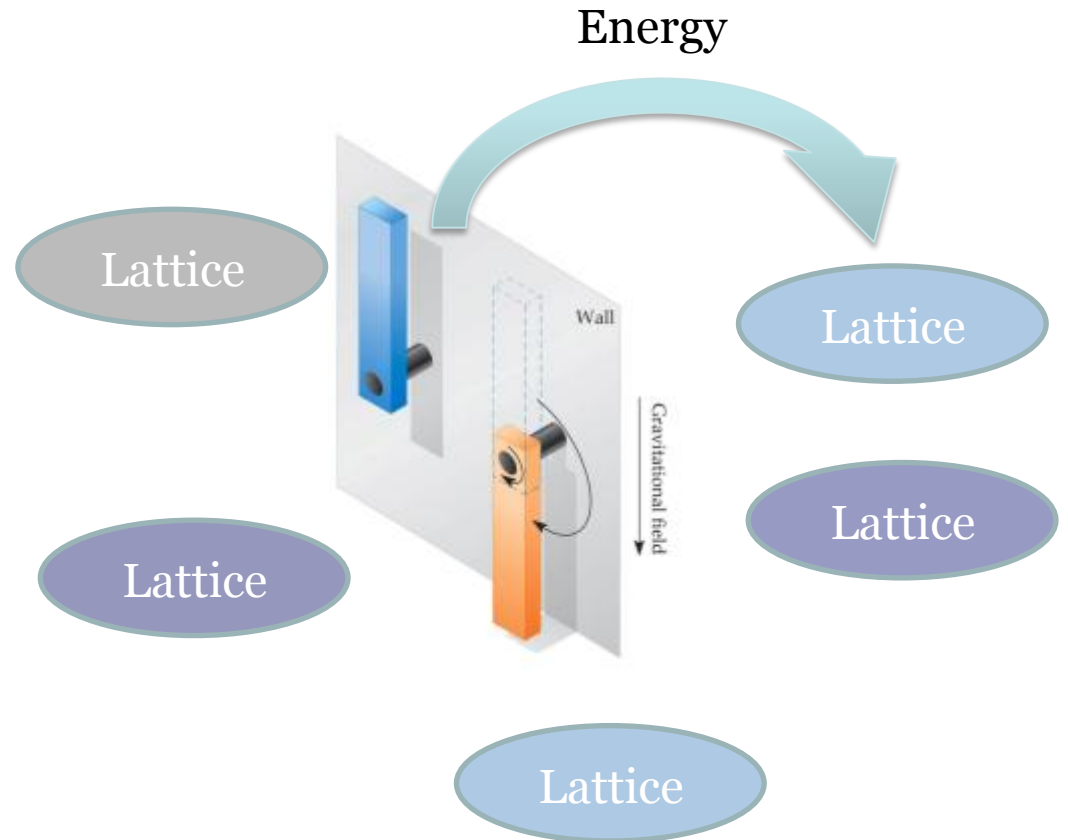


Analyzing spin-lattice exchange (T1)

Energy from anti-parallel spins is absorbed by the macromolecules in the environment (lattice)

How efficient is this energy exchange?

I am glad you asked.



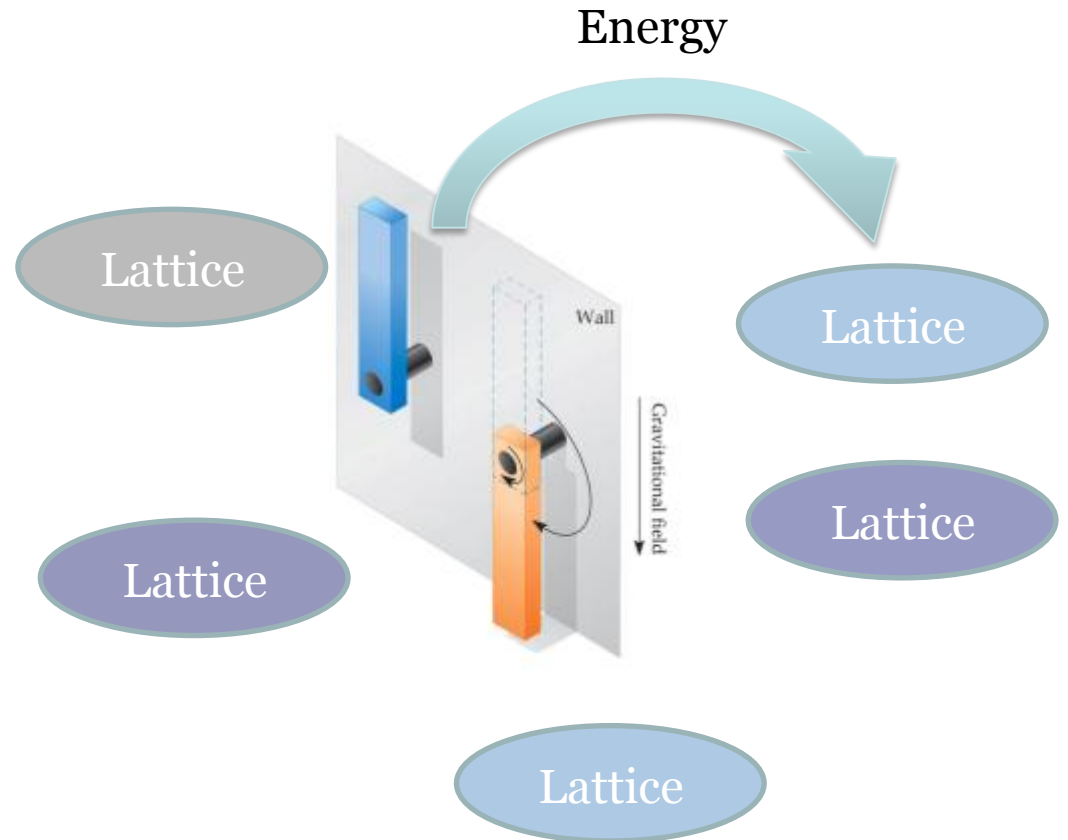
Analyzing spin-lattice exchange (T1)

(Mezer et al., 2014)

Spin-lattice energy exchange rate (T1) depends on

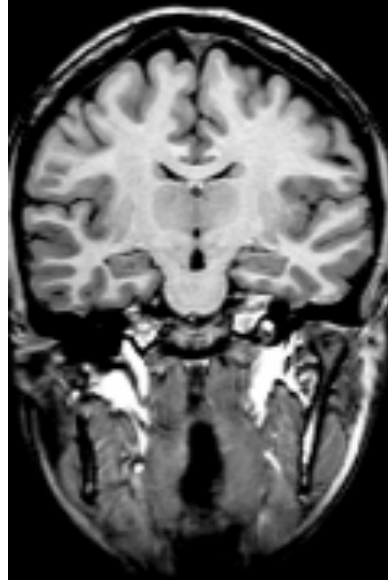
- How many macromolecules are in the lattice
- The type of macromolecules

If you could measure this in the brain, these are pretty good things to know (noninvasively)

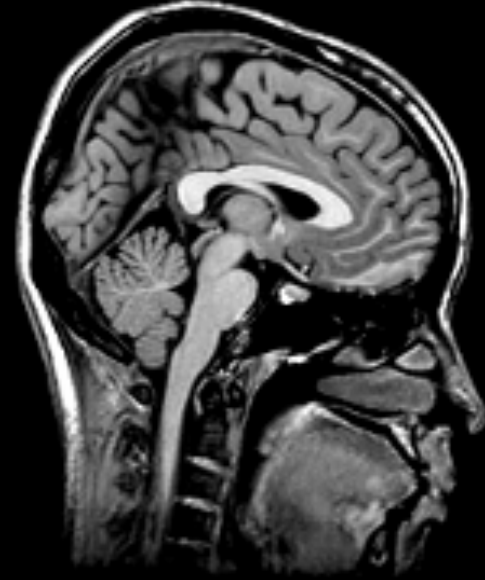


The T1-contrast distinguishes gray and white

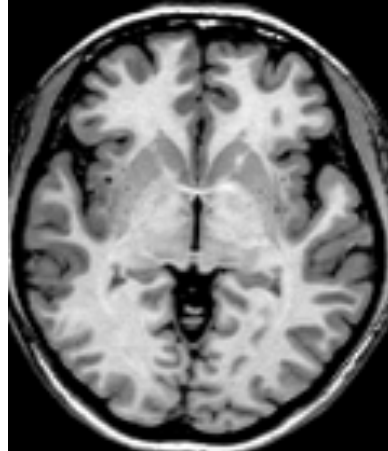
T1-weighted images are typically used for understanding gray matter atrophy, or ventricular enlargement



Coronal



Sagittal



Axial

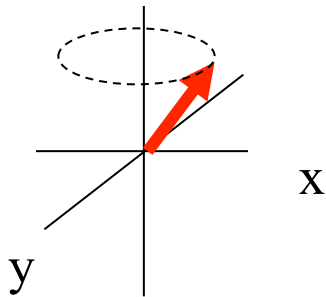
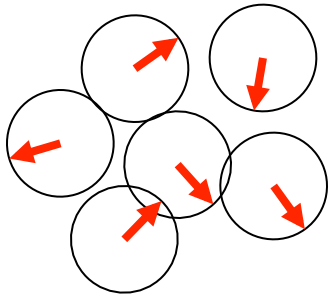
T1 Anatomical

The T_2^* signal and functional MRI Blood Oxygen Level Dependent (BOLD) signals

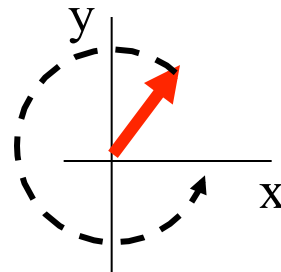
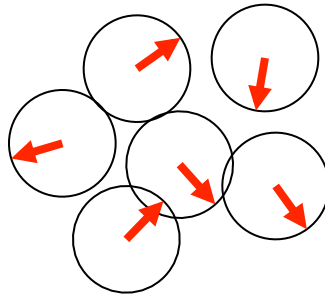


Transverse magnetization

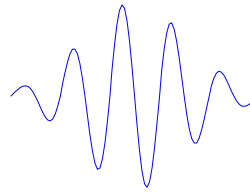
Field-free space



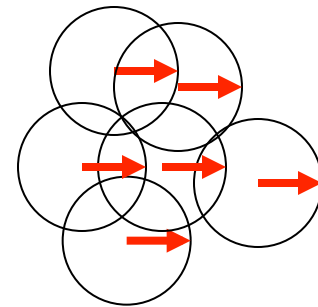
B0 field



RF pulse



Following
RF Pulse



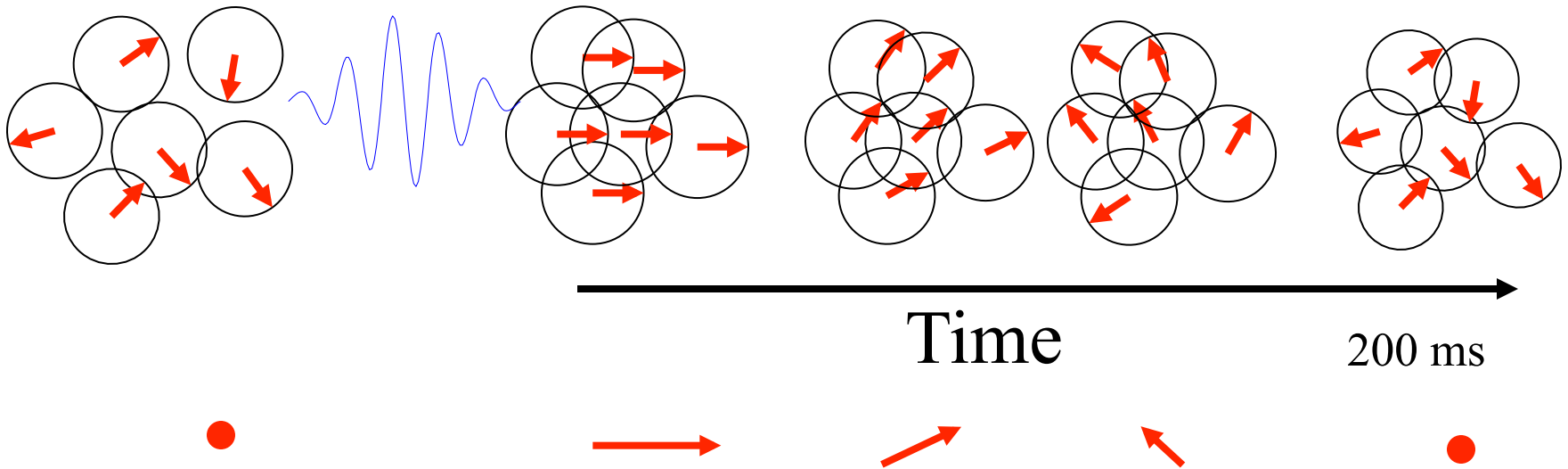
Transverse relaxation: T₂ (and T₂^{*})

Bulk transverse magnetization follows an exponential recovery with a time constant called T₂

$$M_{xy} = M_0 e^{\left(-\frac{t}{T_2}\right)}$$

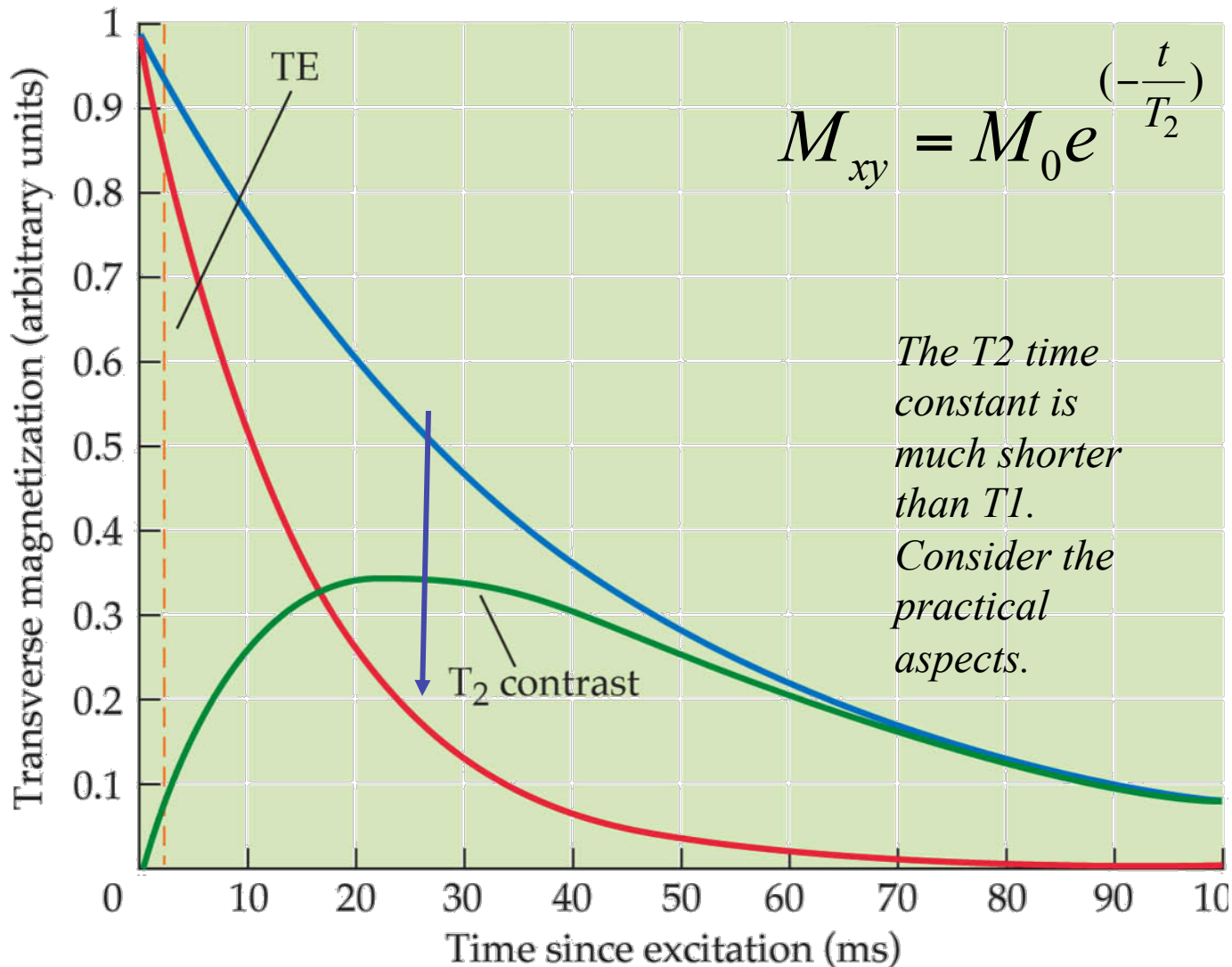
RF pulse

Red arrows denote individual spins

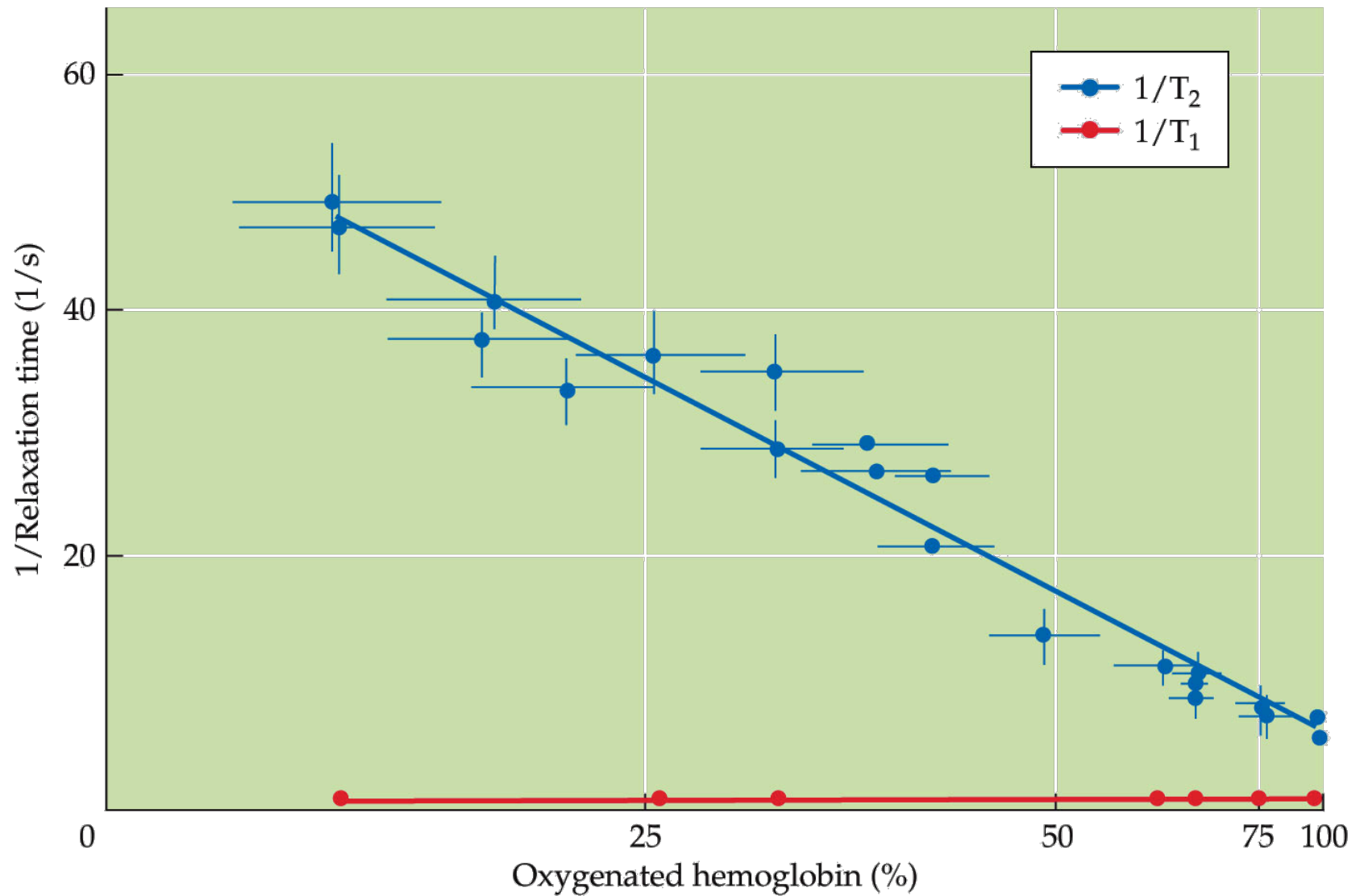


Selection of delay for T2 contrast

(After Huettel et al., Functional Magnetic Resonance Imaging)

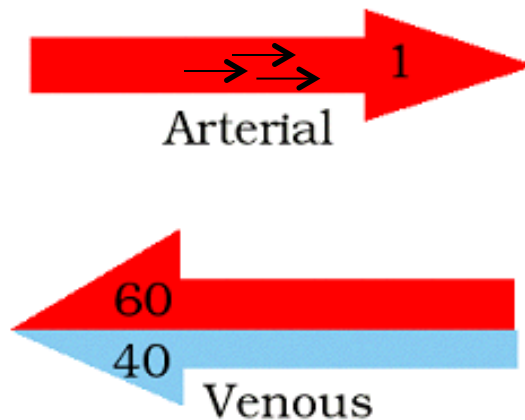
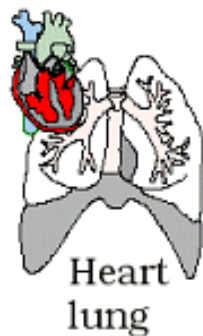


Blood oxygenation effects T2 but not T1

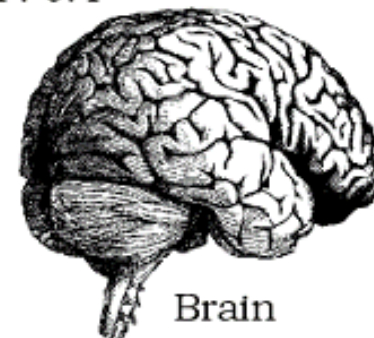


Blood oxygenation increase is localized

Control state

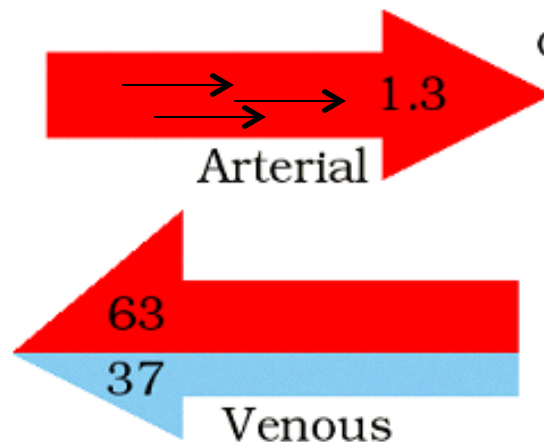
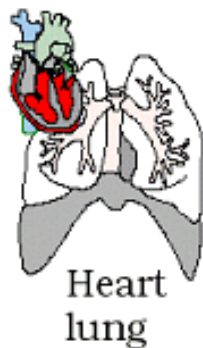


OEF: 0.4

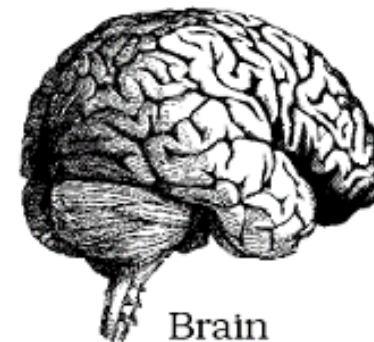


Sokolow
Raichle
Fox

Active state

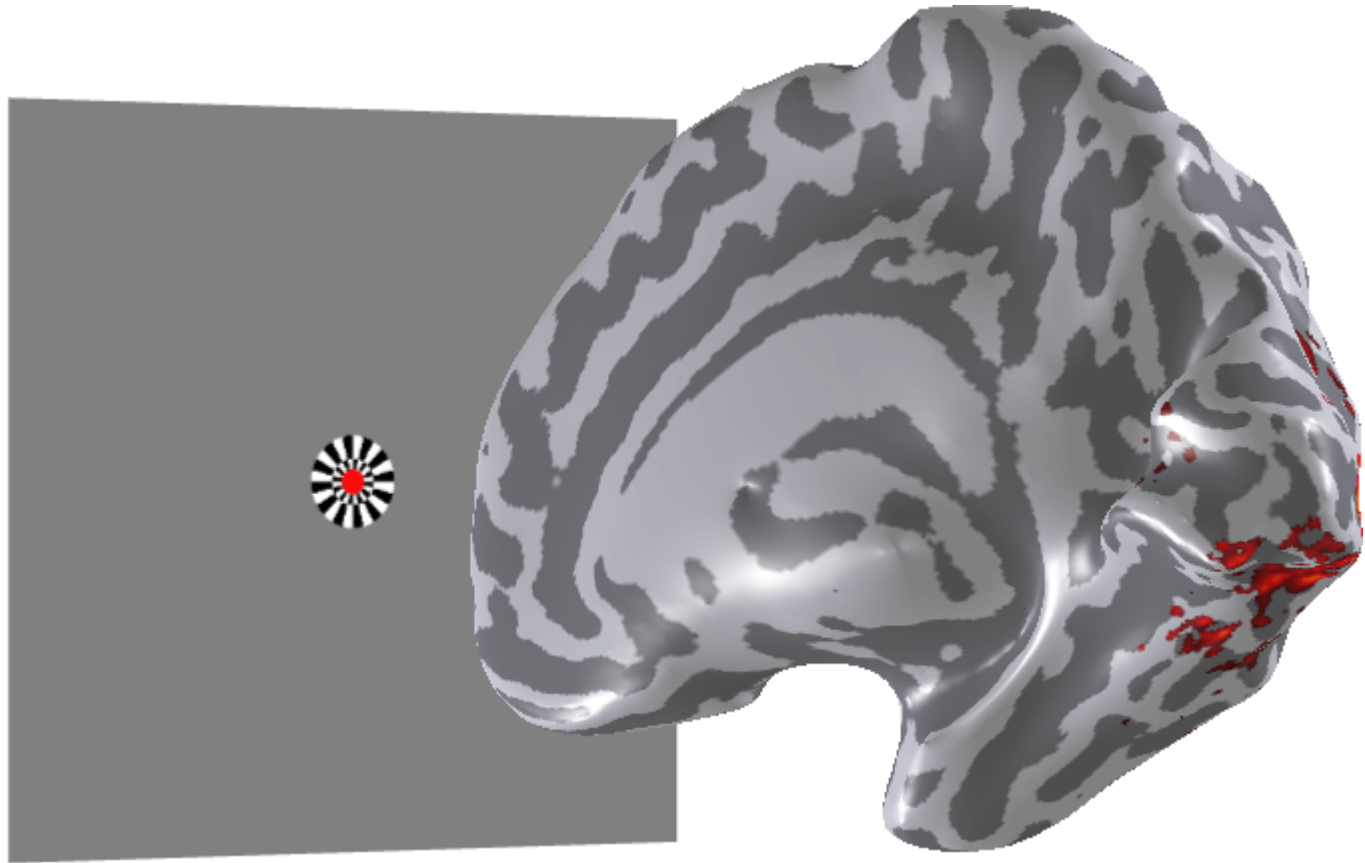


OEF: 0.4/1.2



Human eccentricity mapping with fMRI

(Engel et al., 1994,1997; Sereno; DeYoe; Others)

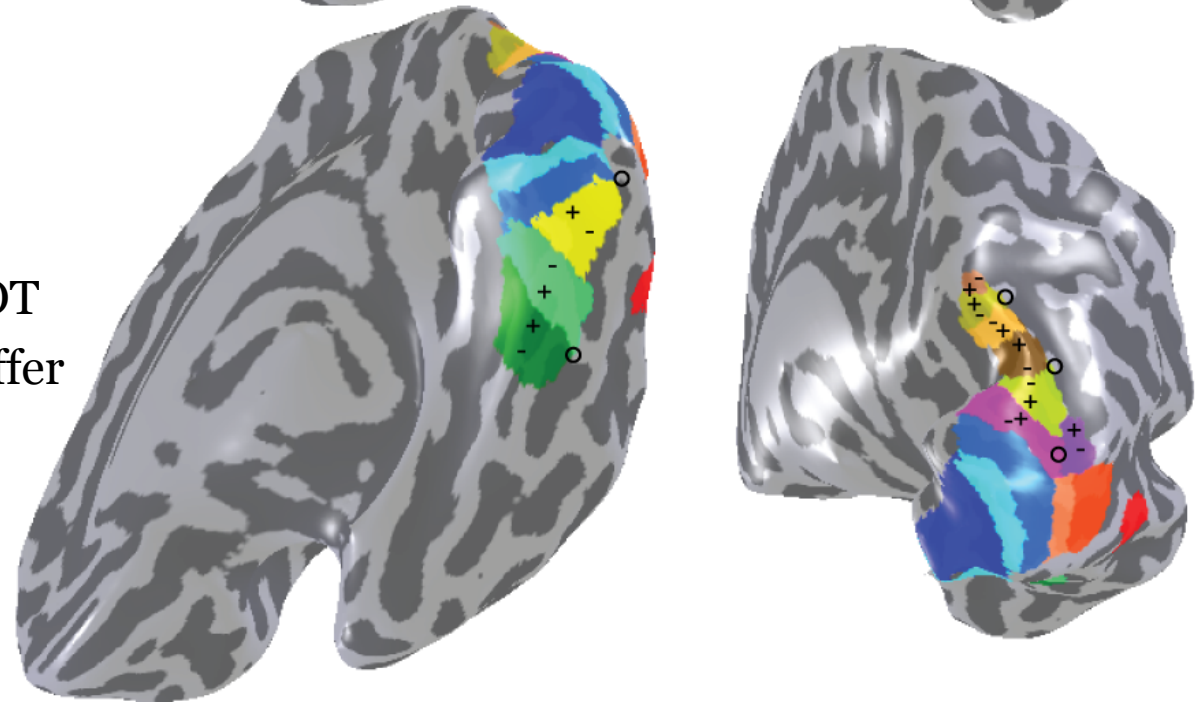
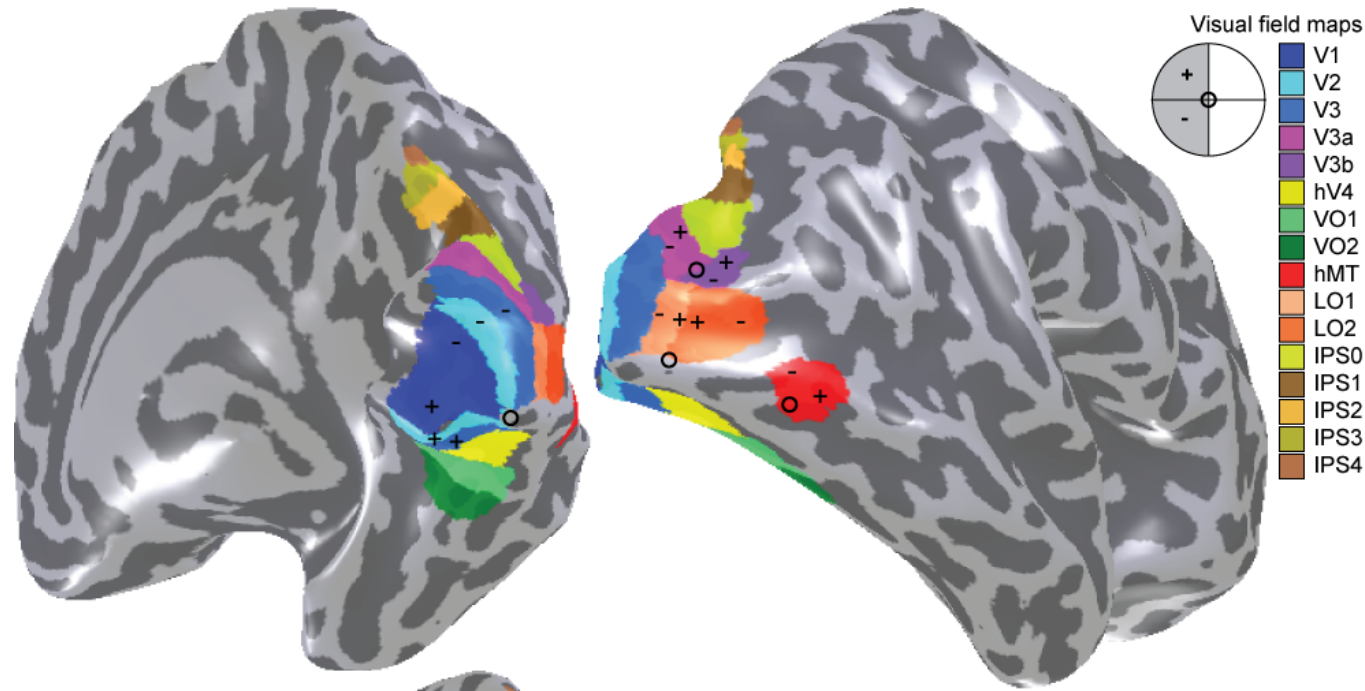


More than twenty visual field maps

Wandell, Dumoulin, Brewer
(2007) **Neuron**

Wandell and Winawer
(2011) **Vision Research**

Wang et al.
(2014) **Cerebral Cortex**



- Tile the occipital lobe
- Extend into IPS and VOT
- Response properties differ

Diffusion weighted imaging tutorial

- Measuring the diffusion signal

Bob
Dougherty

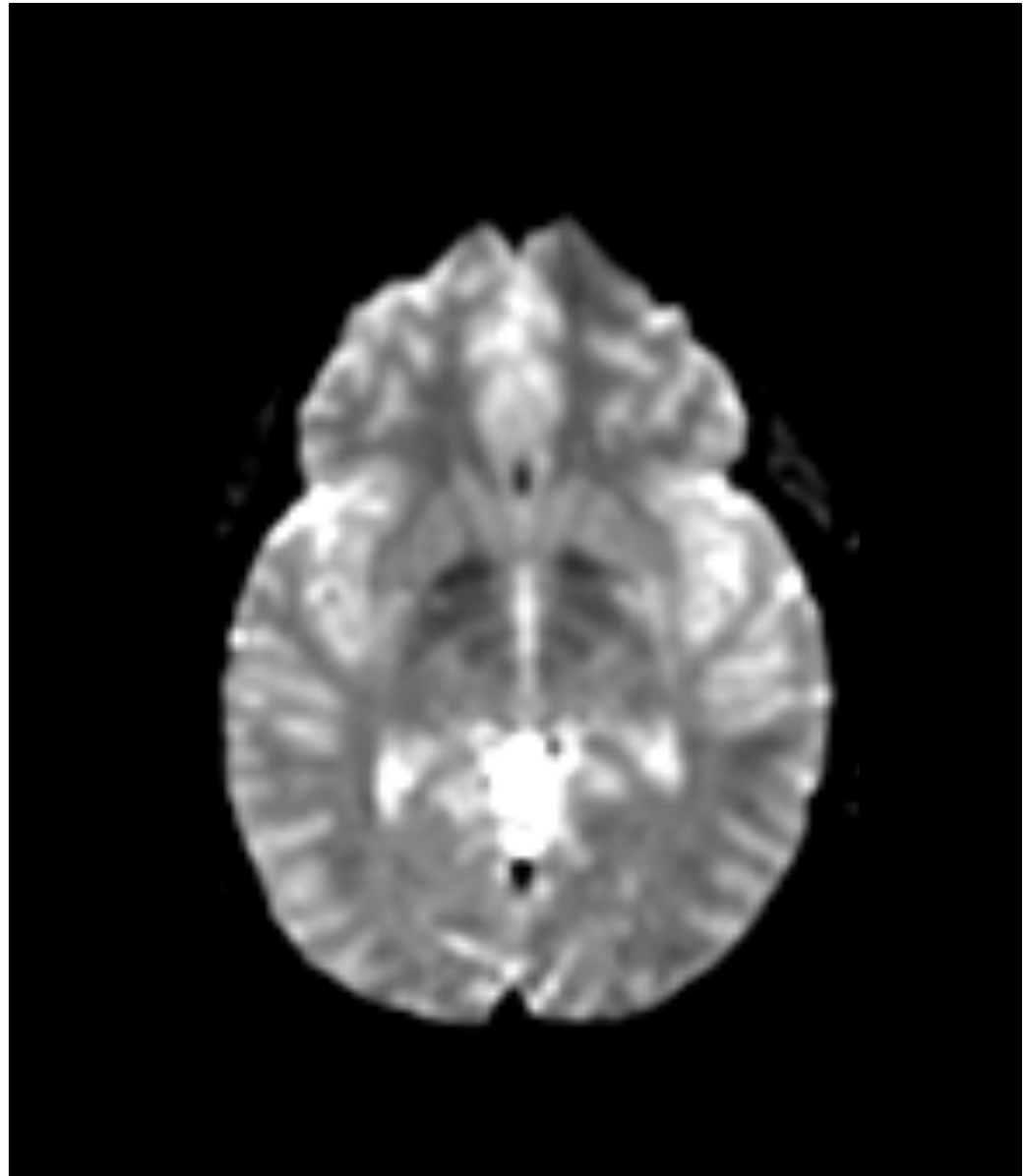


Non-diffusion MR image

Dark means large
signal attenuation
High ADC

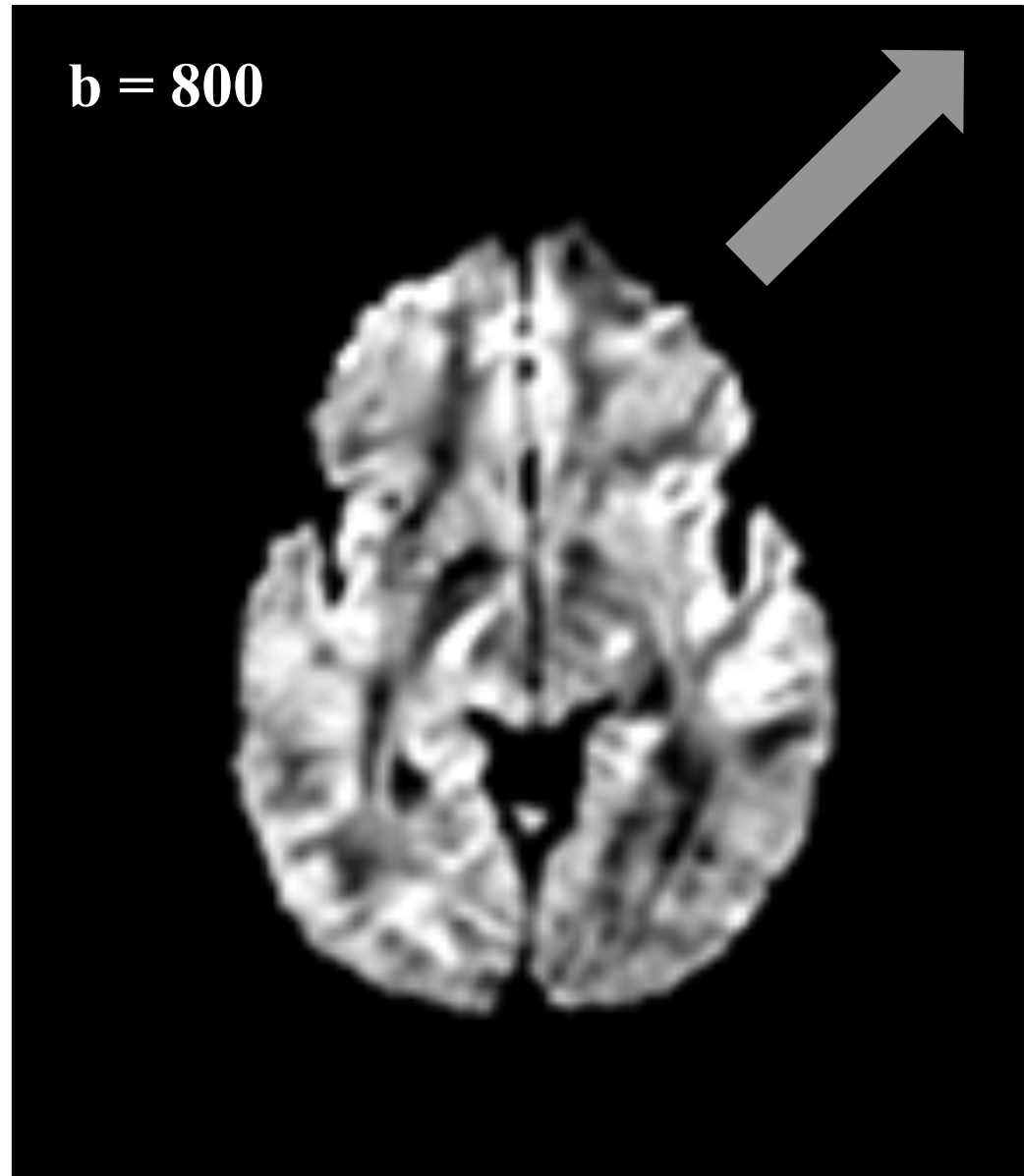
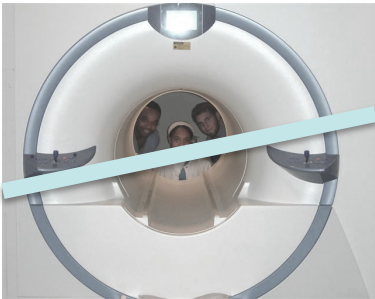


b = 0



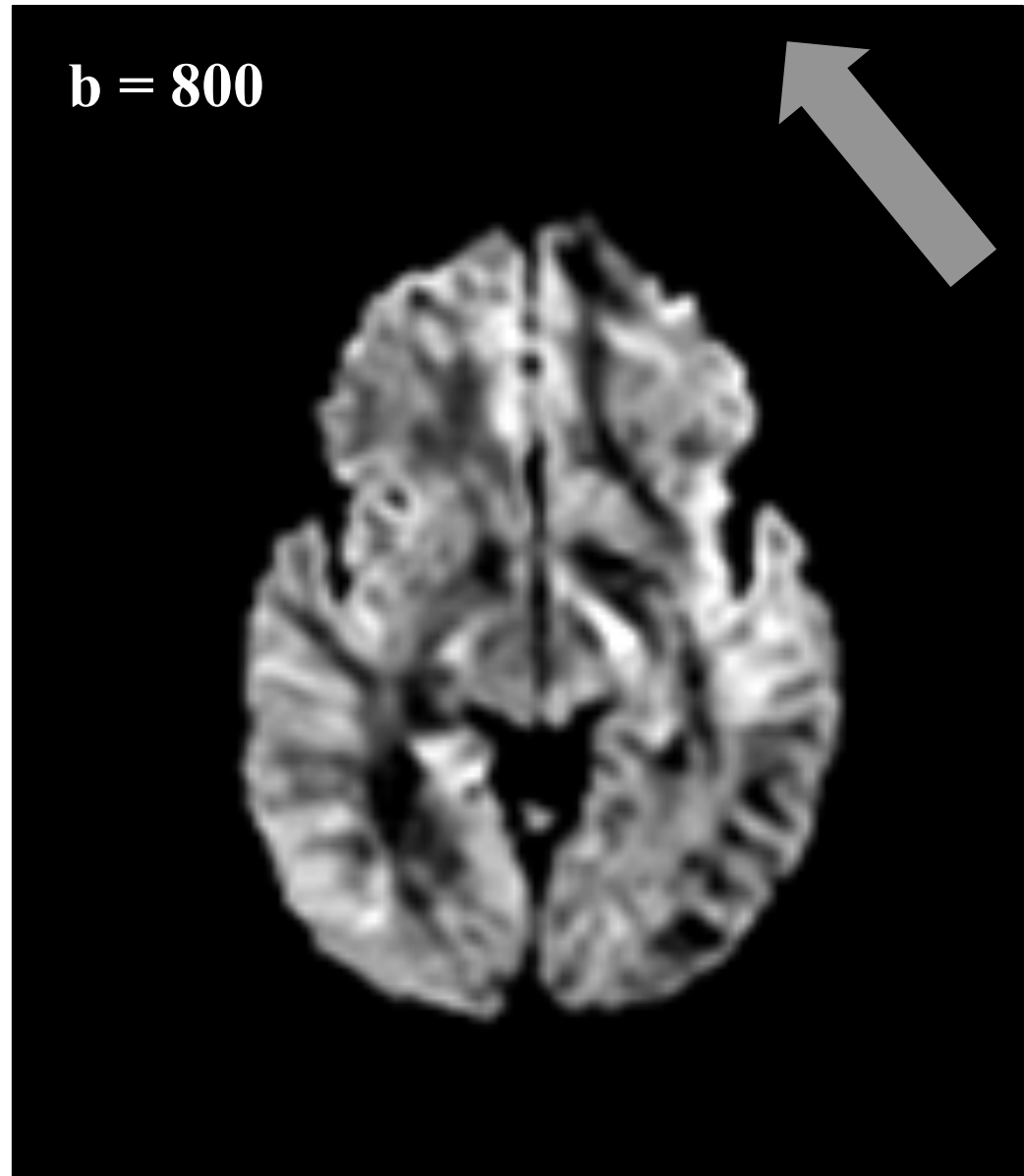
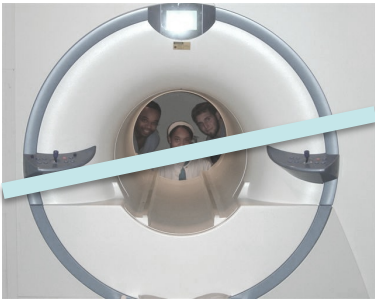
Diffusion weighting: Directions

Dark means large
signal attenuation
High ADC

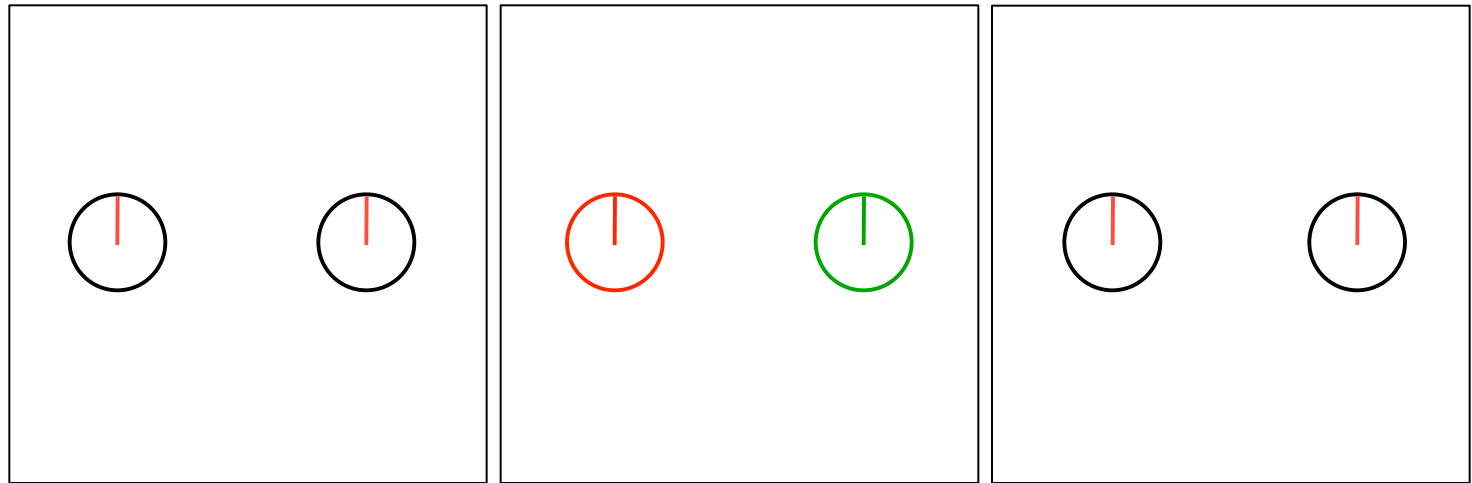


Diffusion weighting: Directions

Dark means large
signal attenuation
High ADC

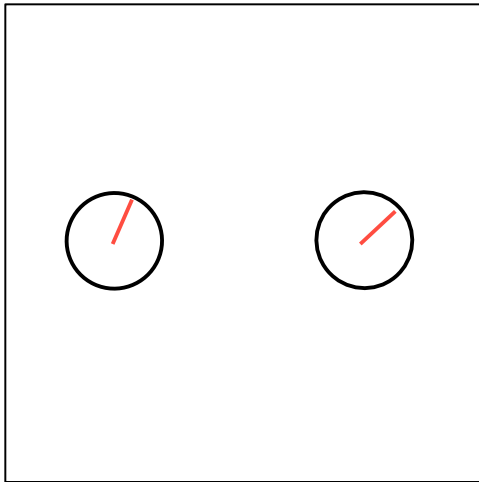
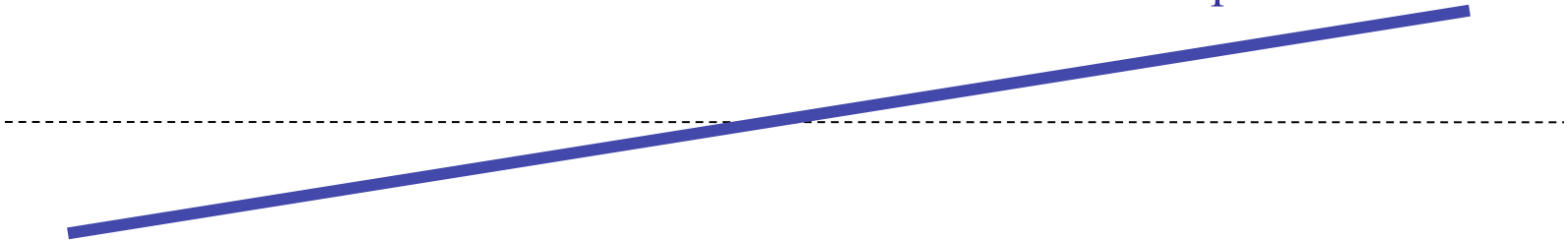


Protons Precessing in Phase

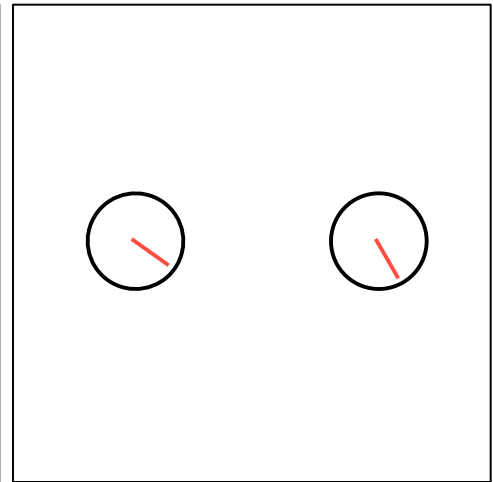
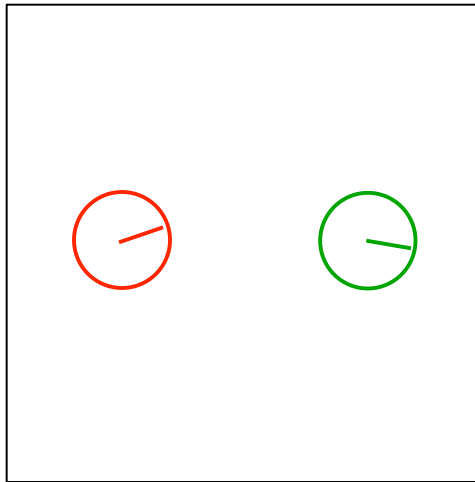


Diffusion Weighting: First Pulse

Gradient over space

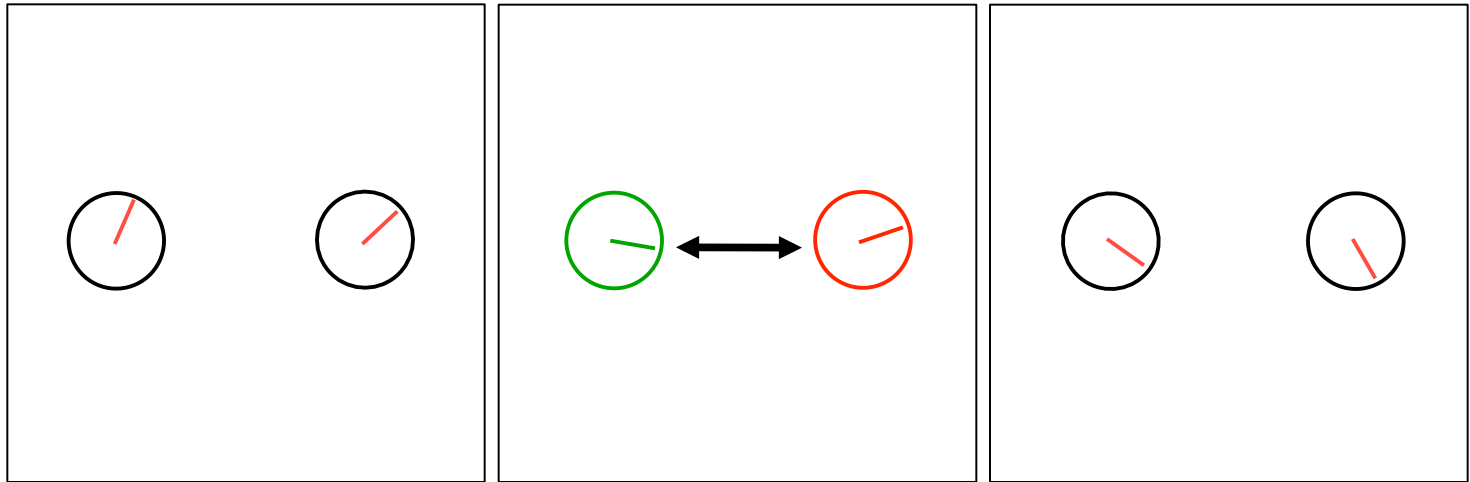


Slower
(local field is lower)



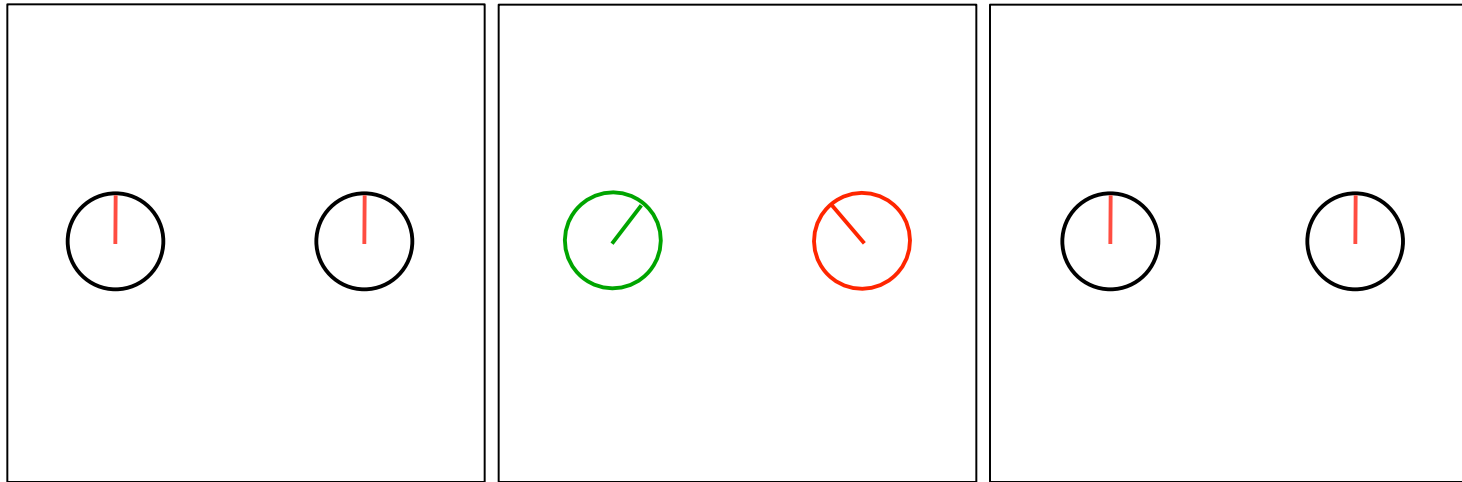
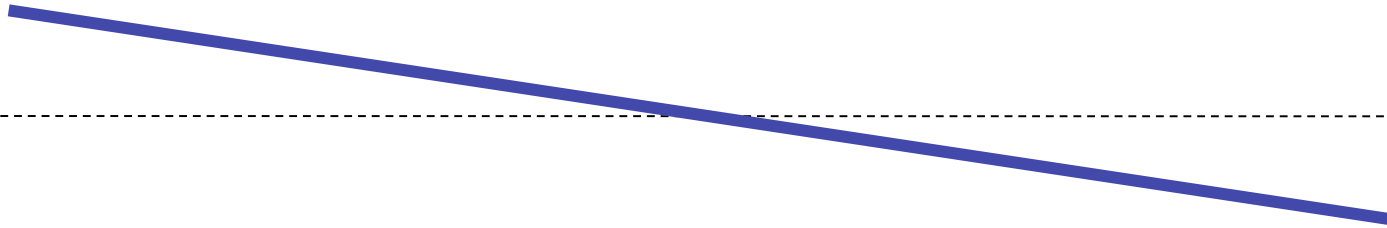
Faster
(local field is higher)

Time to Diffuse



Diffusion Weighting: Second Pulse

Gradient over space



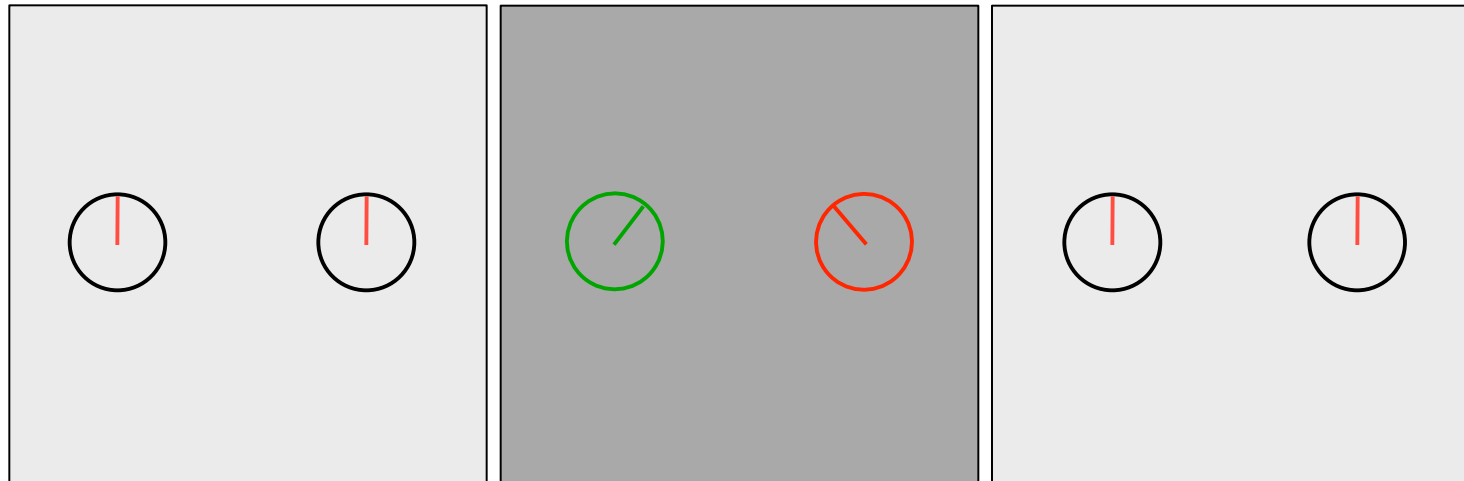
Faster
(local field is higher)

Slower
(local field is lower)

Reduced signal from spin dephasing

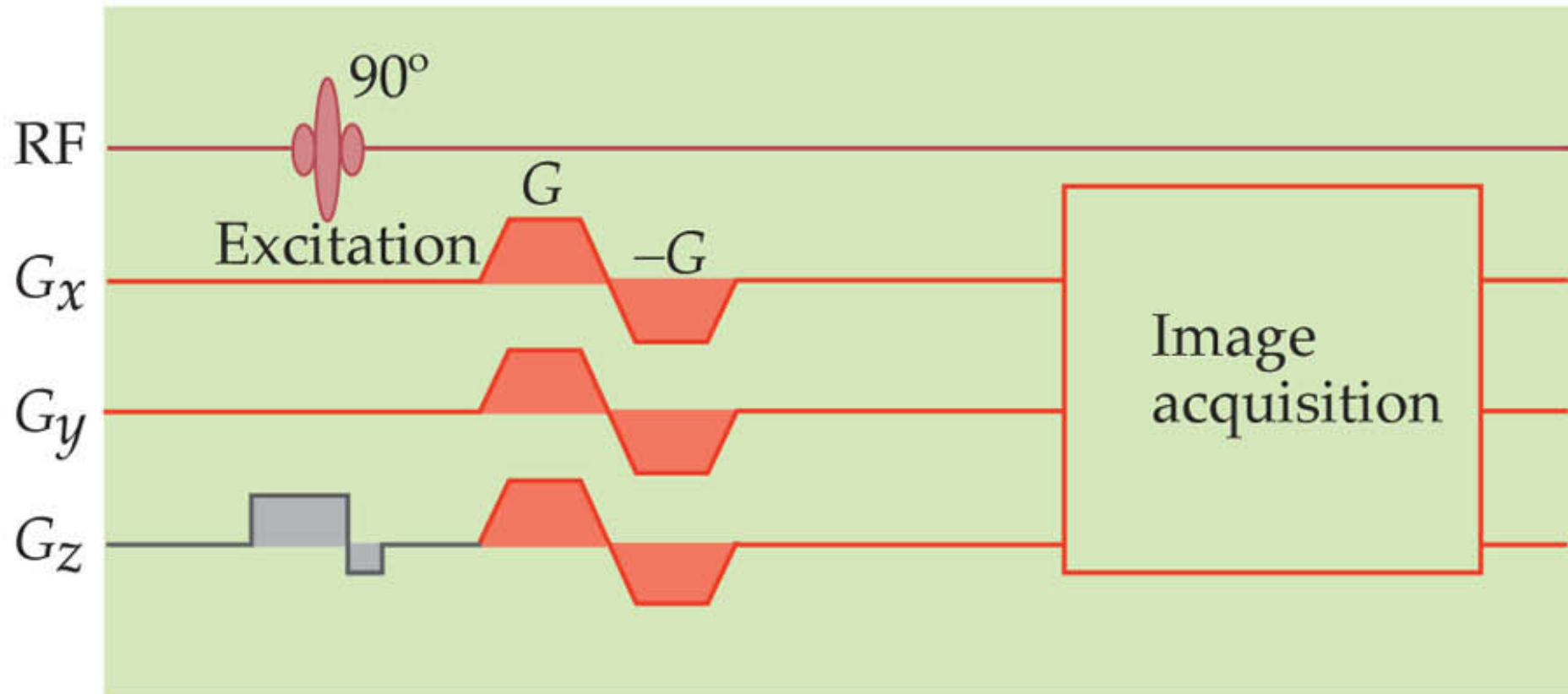
E. O. Stejskal and J. E. Tanner (1965)

$$\text{Signal attenuation} = \exp(-b * \text{ADC})$$



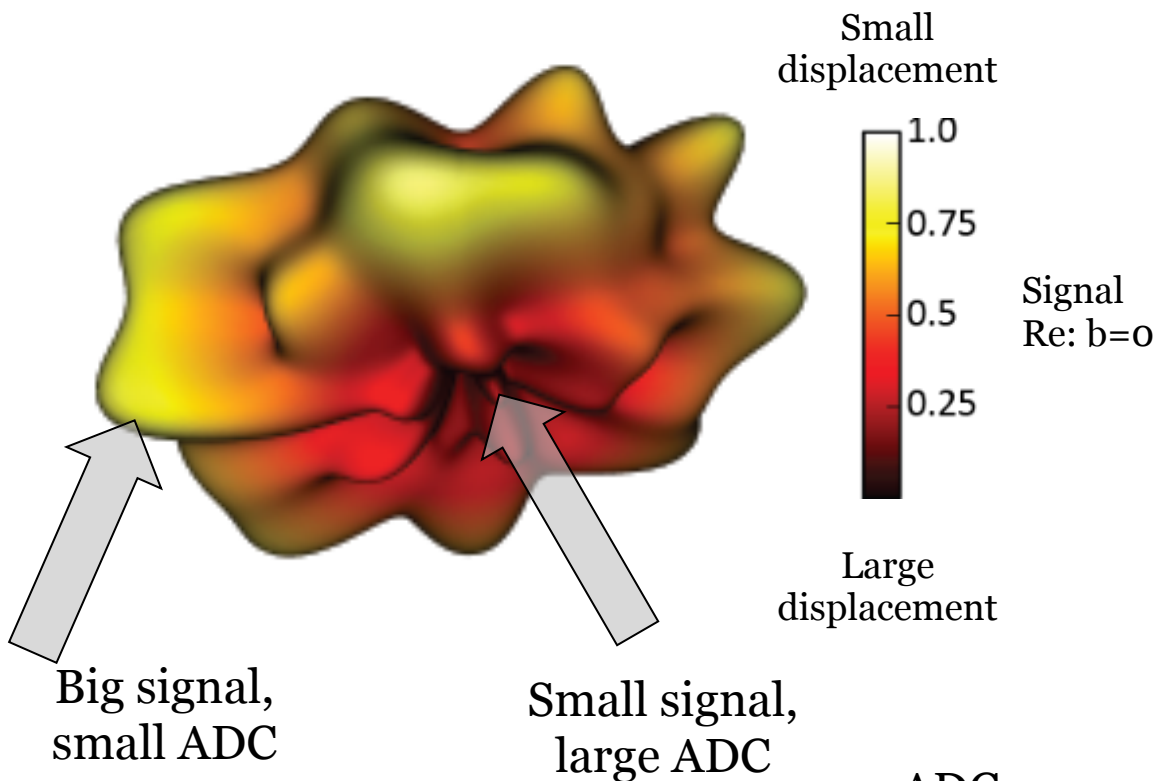
Signal from spins that that
diffused is lower because the
spins are not aligned
(incoherent)

Pulse sequences for diffusion-weighted imaging (Huettel et al.)



Diffusion orientation distribution function (ODF)

$$S(\theta) = S_0 e^{-bD(\theta)}$$



The measured diffusion signal in a direction, θ , is related to the apparent diffusion coefficient in that direction, $D(\theta)$

ADC – apparent diffusion coefficient

Modeling the diffusion signal

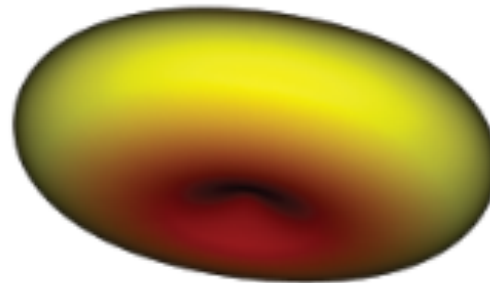
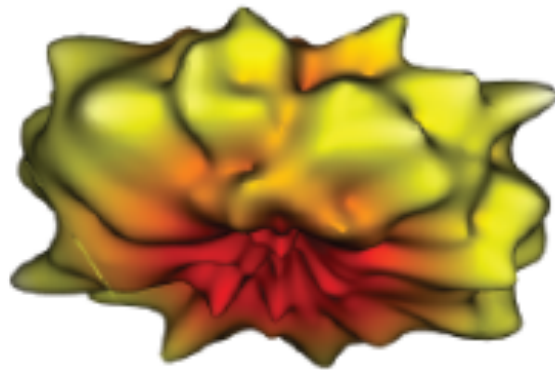
- The diffusion tensor model (DTM)
- The ball-and-stick model (SFM)

Ariel
Rokem



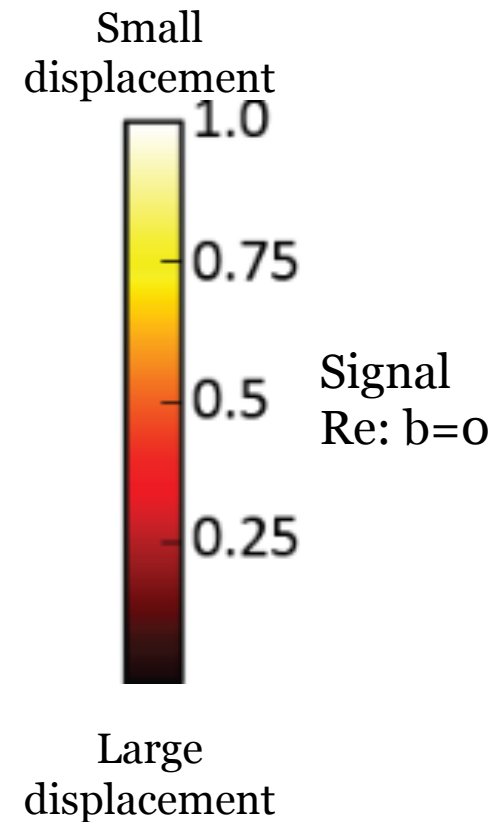
Diffusion tensor model (DTM)

Predicts the **voxel diffusion signal** with a phenomenological equation, motivated by Gaussian diffusion (Basser, Pierpaoli, 1996)



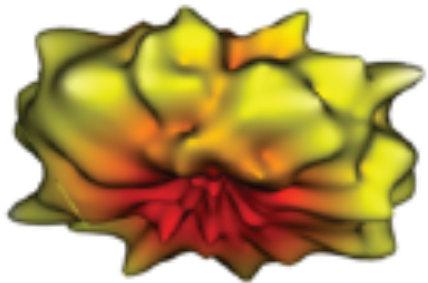
$$S(\theta) = S_0 e^{-bD(\theta)} \leftarrow D(\theta) = \theta^t Q \theta$$

$$Q = A^t A$$



Diffusion tensor model fits

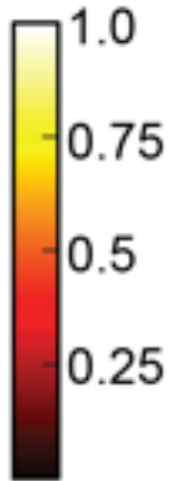
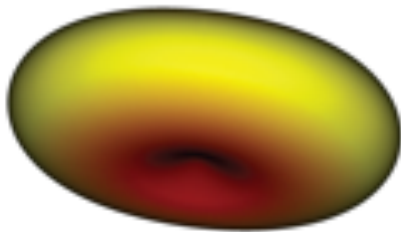
b=1000



b=2000



b=4000



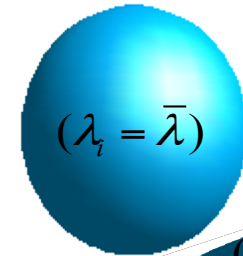
Signal re: b=0

Summary measures of the DTM

(Basser & Pierpaoli, 1996)

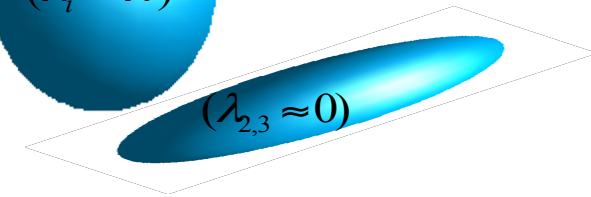
Axial diffusivity (AD)

$$\lambda_1$$



Radial diffusivity (RD)

$$\frac{\lambda_2 + \lambda_3}{2}$$



Mean diffusivity (MD)

$$\bar{\lambda} = \frac{\lambda_1 + \lambda_2 + \lambda_3}{3}$$

Fractional anisotropy
(FA, dimensionless)

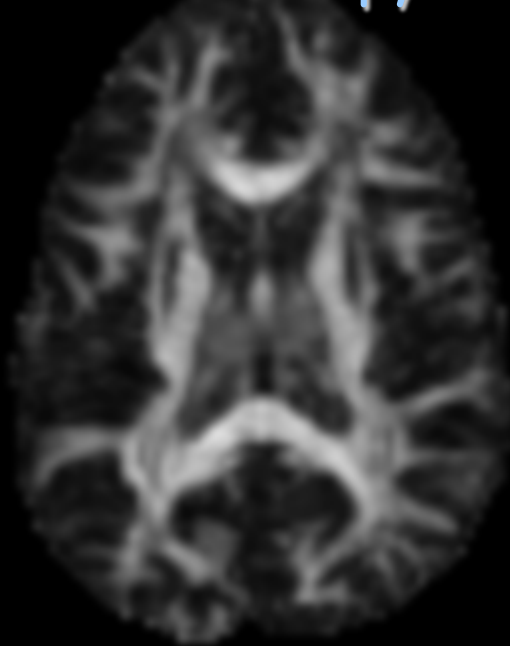
$$\sqrt{\frac{3}{2}} \sqrt{\frac{(\lambda_1 - \bar{\lambda})^2 + (\lambda_2 - \bar{\lambda})^2 + (\lambda_3 - \bar{\lambda})^2}{\lambda_1^2 + \lambda_2^2 + \lambda_3^2}}$$

DTI analyzes white matter structure

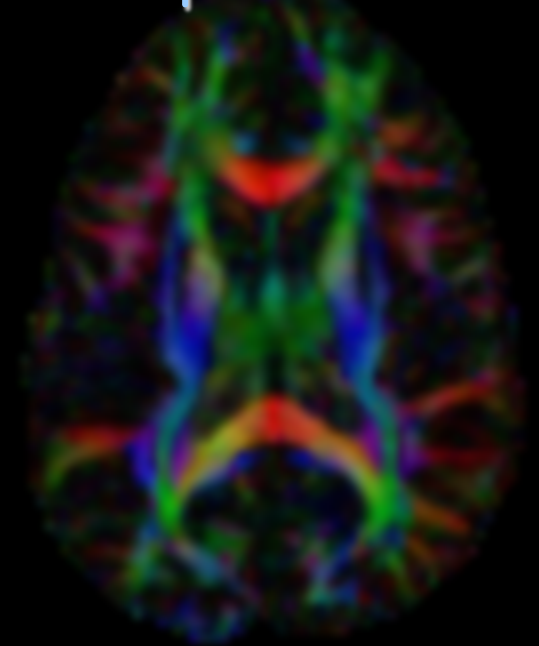
Mean Diffusivity



Anisotropy



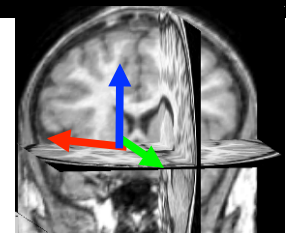
Principal Direction



MD ($\mu\text{m}^2/\text{ms}$)



Fractional anisotropy



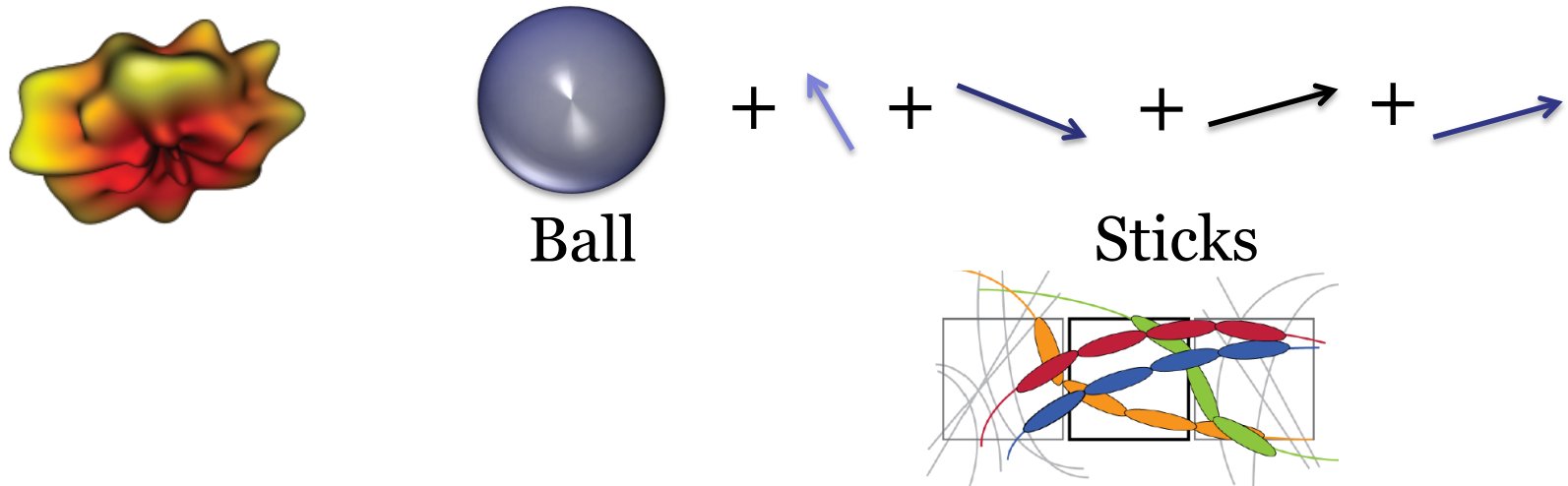
The sparse fascicle model (SFM)

Frank (2002), Behrens et al. (2003)

Predicts the diffusion signal with an isotropic diffusion term (**ball**) plus a weighted sum of anisotropic terms (**sticks**) that are meant to summarize oriented fibers

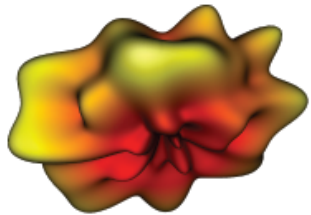
$$S(\theta) = w_0 D_0 + \sum_f w_f e^{-bD_f(\theta)}$$

isotropic weights fascicles

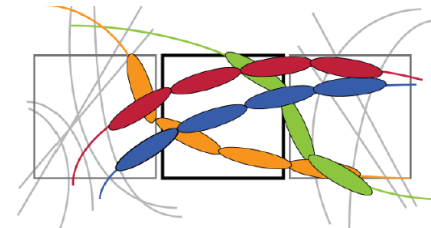
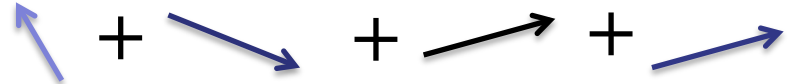


From diffusion data to fiber orientations

Orientation
distribution
function (ODF)



Fiber orientation
distribution
(FOD)



ARD/Probtrackx
(Behrens et al., 2007)

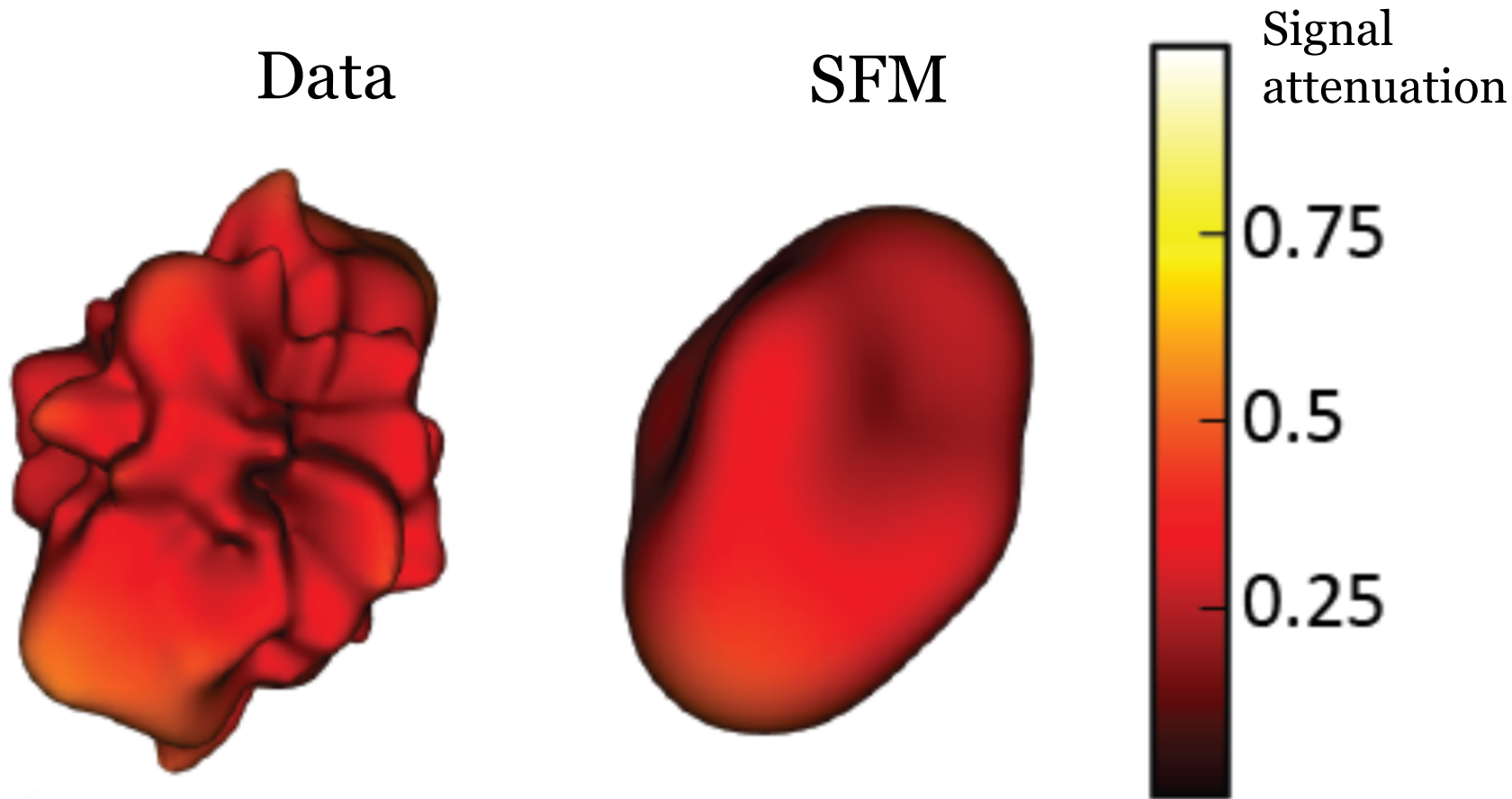
Constrained spherical
deconvolution (CSD)
(Tournier et al., 2007)

Sparse Fascicle Model
(Rokem, 2015)

Others

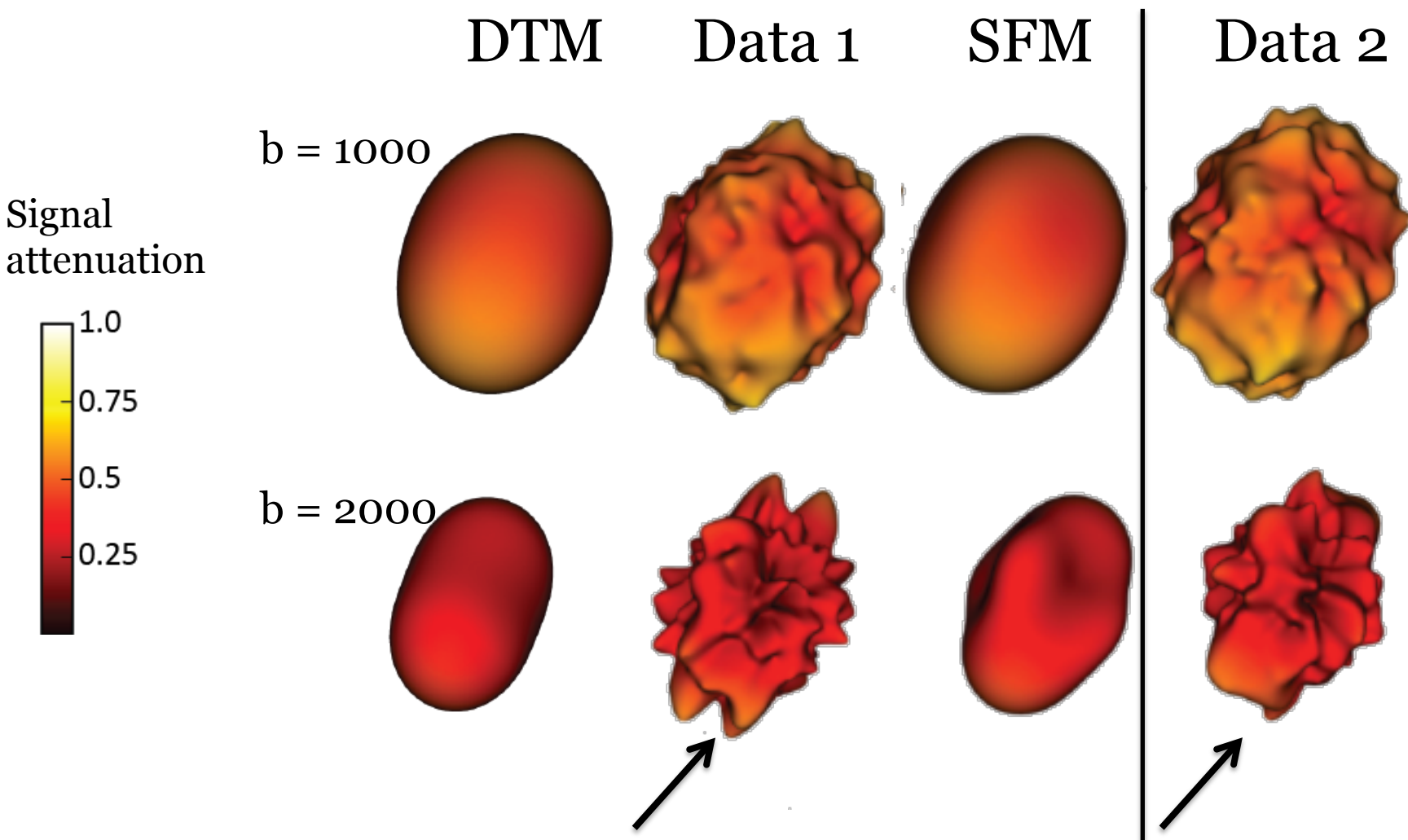
Sparse fascicle model (SFM)

(Rokem et al. 2015)



SFM uses a sparseness constraint on the sticks (fascicles)
Related to mrTrix, but no intermediate spherical harmonics

Evaluating models using cross-validation (Rokem et al., 2015)



Evaluating models using cross-validation (Rokem et al., 2015)

DTM

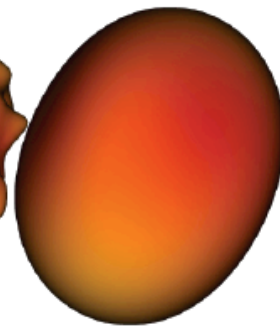
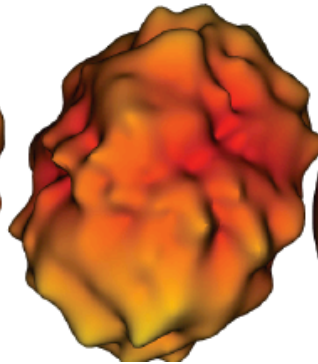
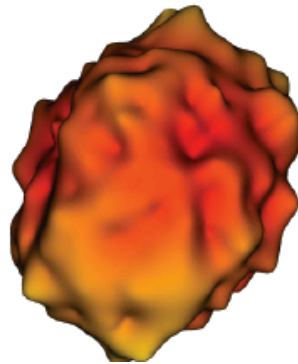
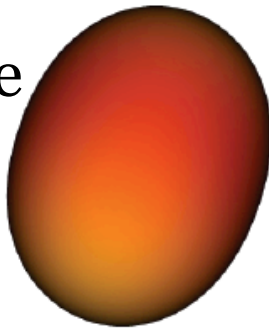
Data 1

Data 2

SFM

Low b-value

b=1000



Evaluating models using cross-validation (Rokem et al., 2015)

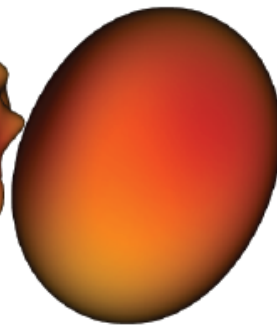
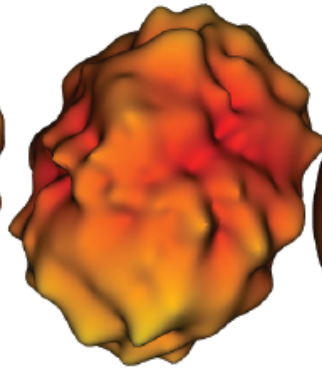
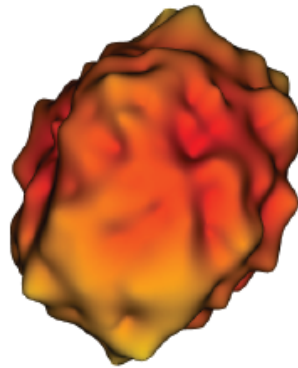
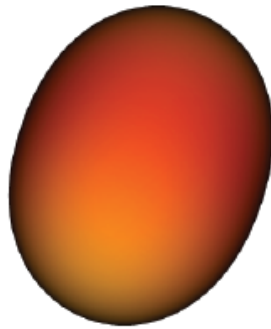
DTM

Data 1

Data 2

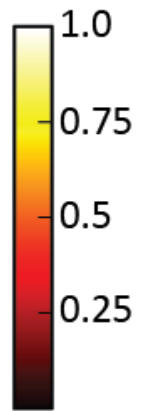
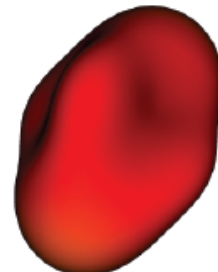
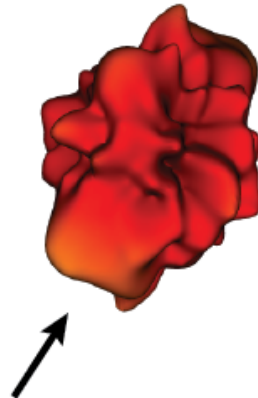
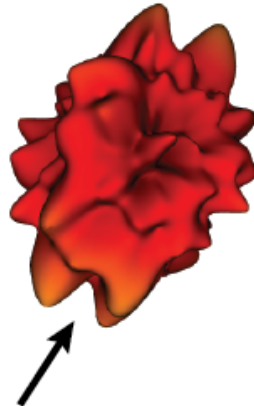
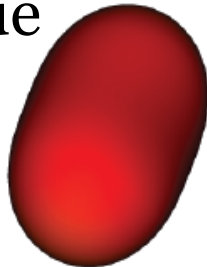
SFM

$b=1000$



Higher b -value

$b=2000$

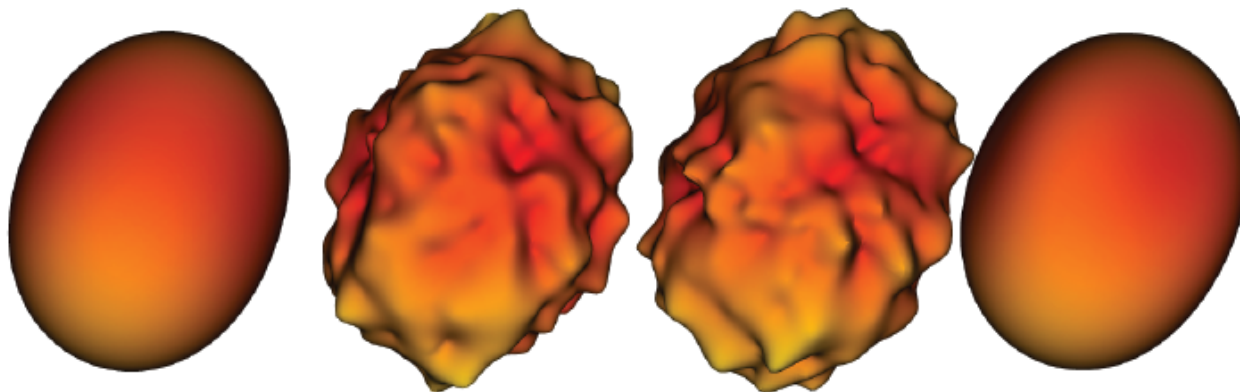
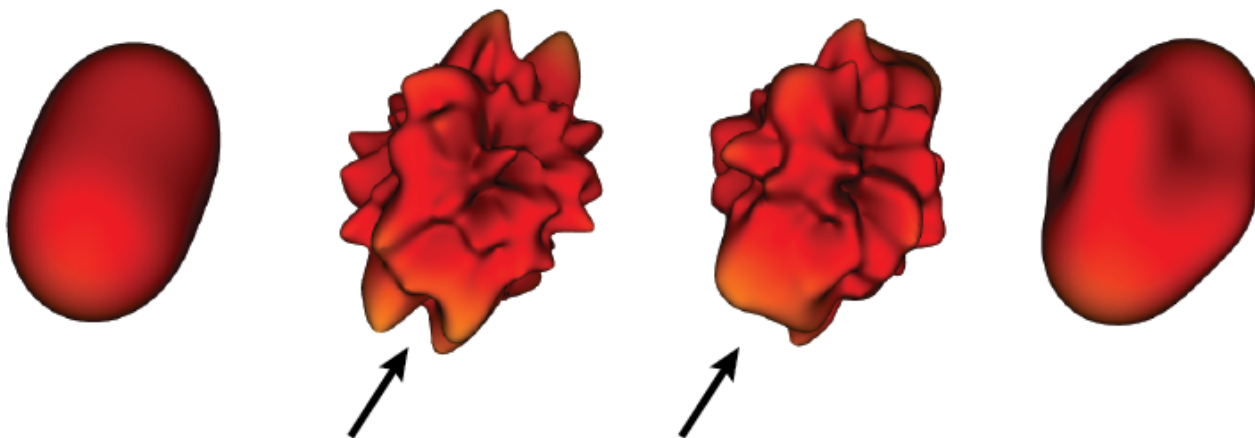
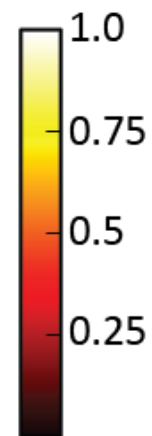
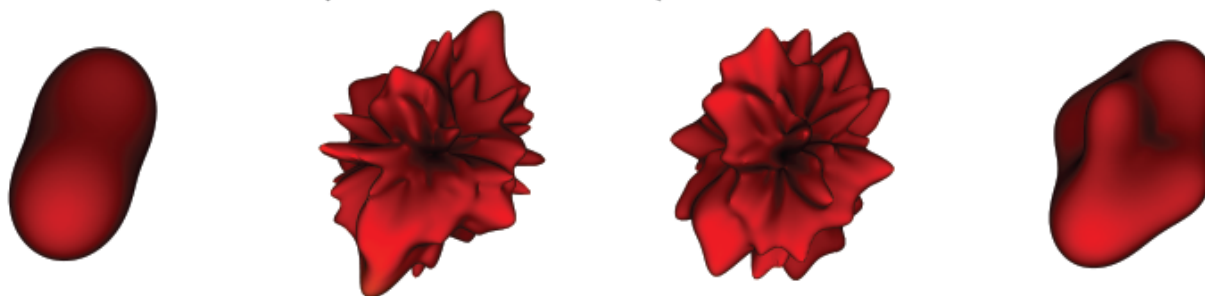


DTM

Data 1

Data 2

SFM

 $b = 1000$  $b = 2000$  $b = 4000$ 

Evaluating models using cross-validation (Rokem et al., 2015)

Two data sets, one b-value, many
directions, same session

Fit the model to these
data

Data set 1

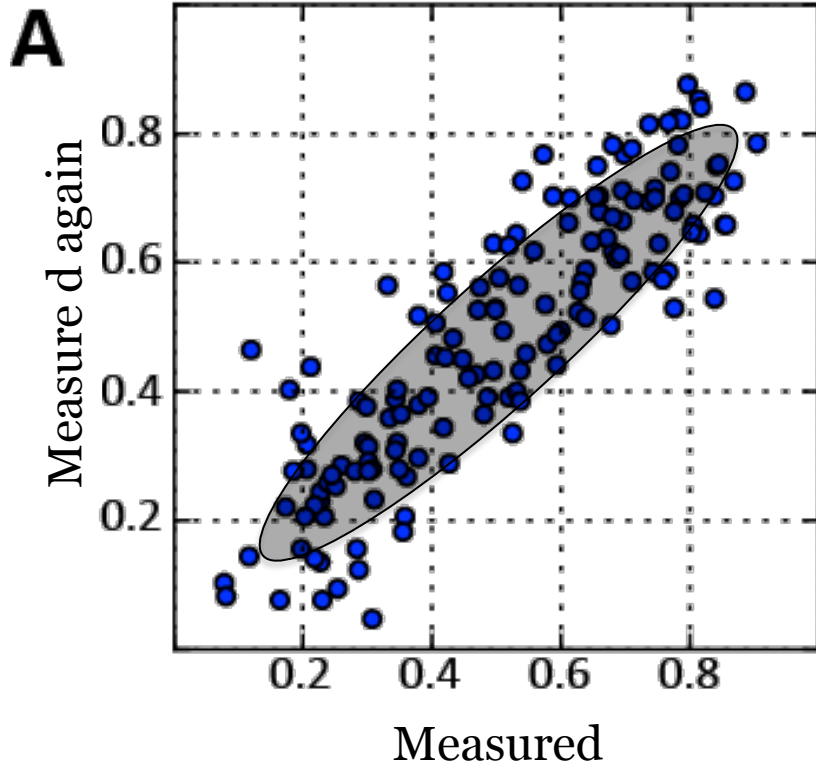
Measure prediction
error with these data

Data set 2

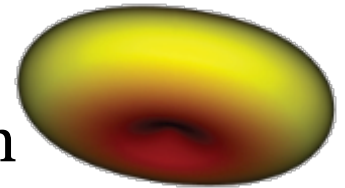
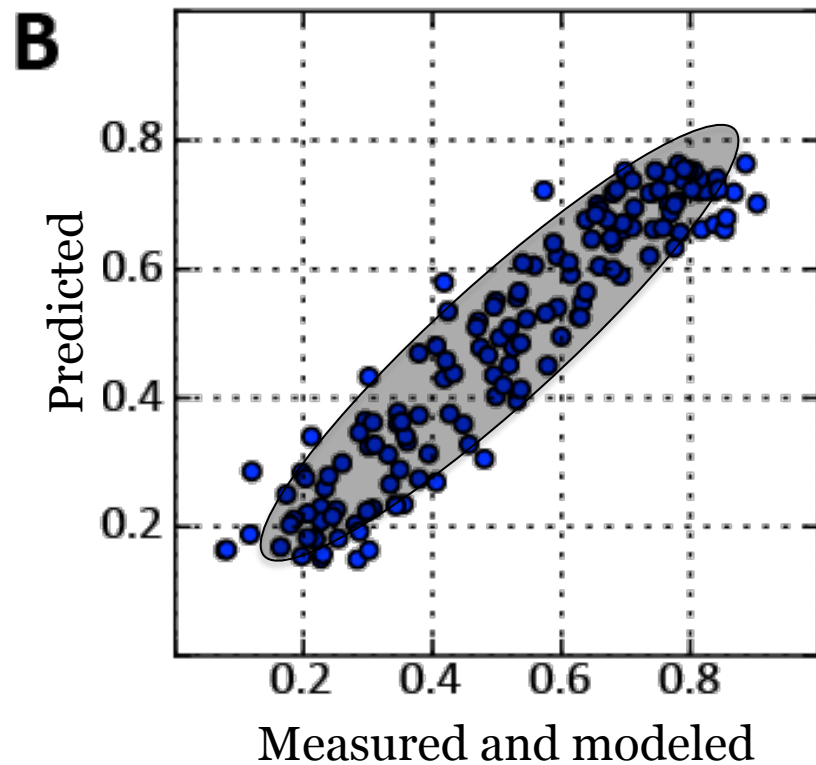
(In the old days, we used to call this testing the
model on an independent data set)

DTM predicts the independent data more accurately than assuming replication

Replication

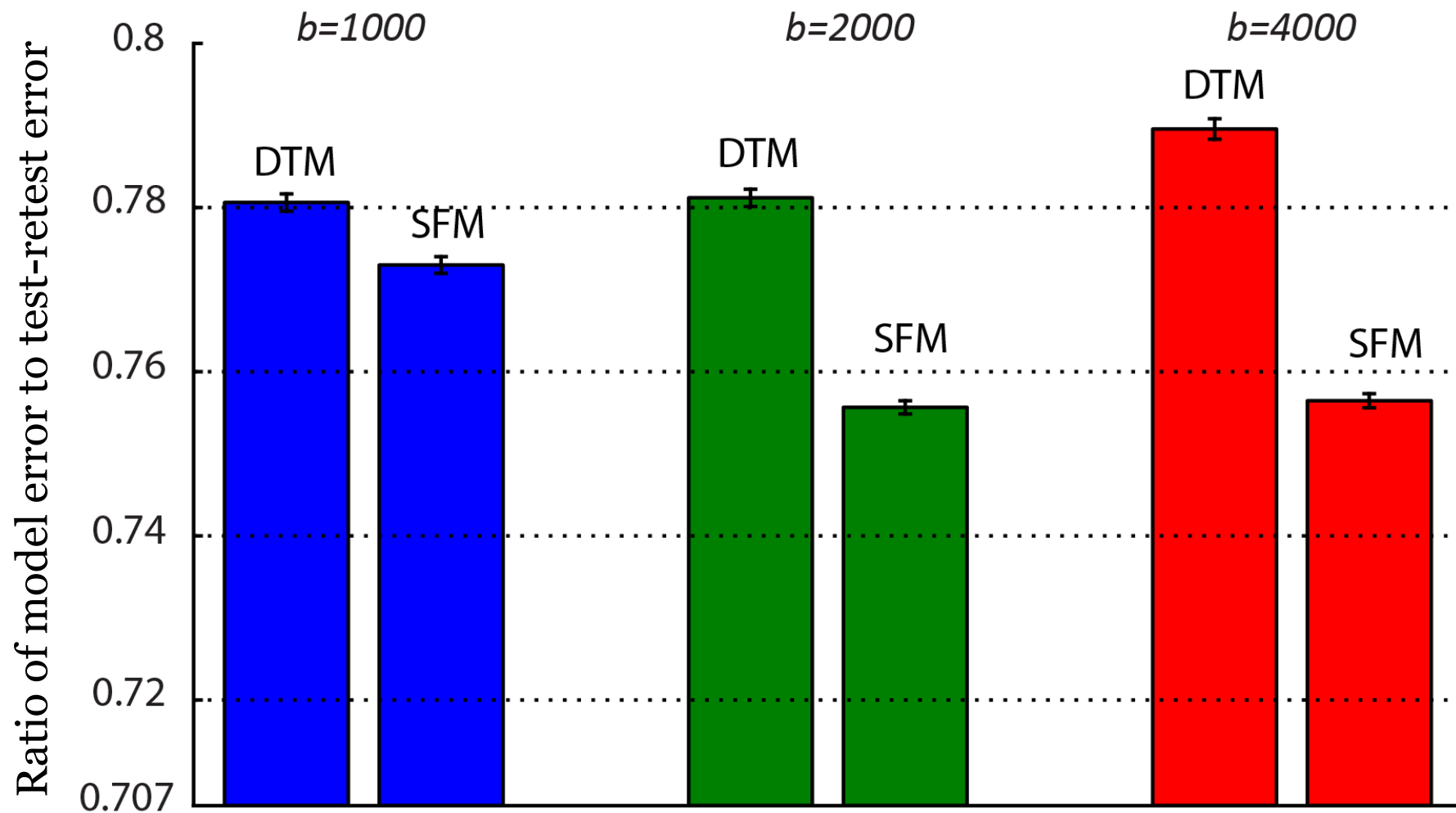


Prediction



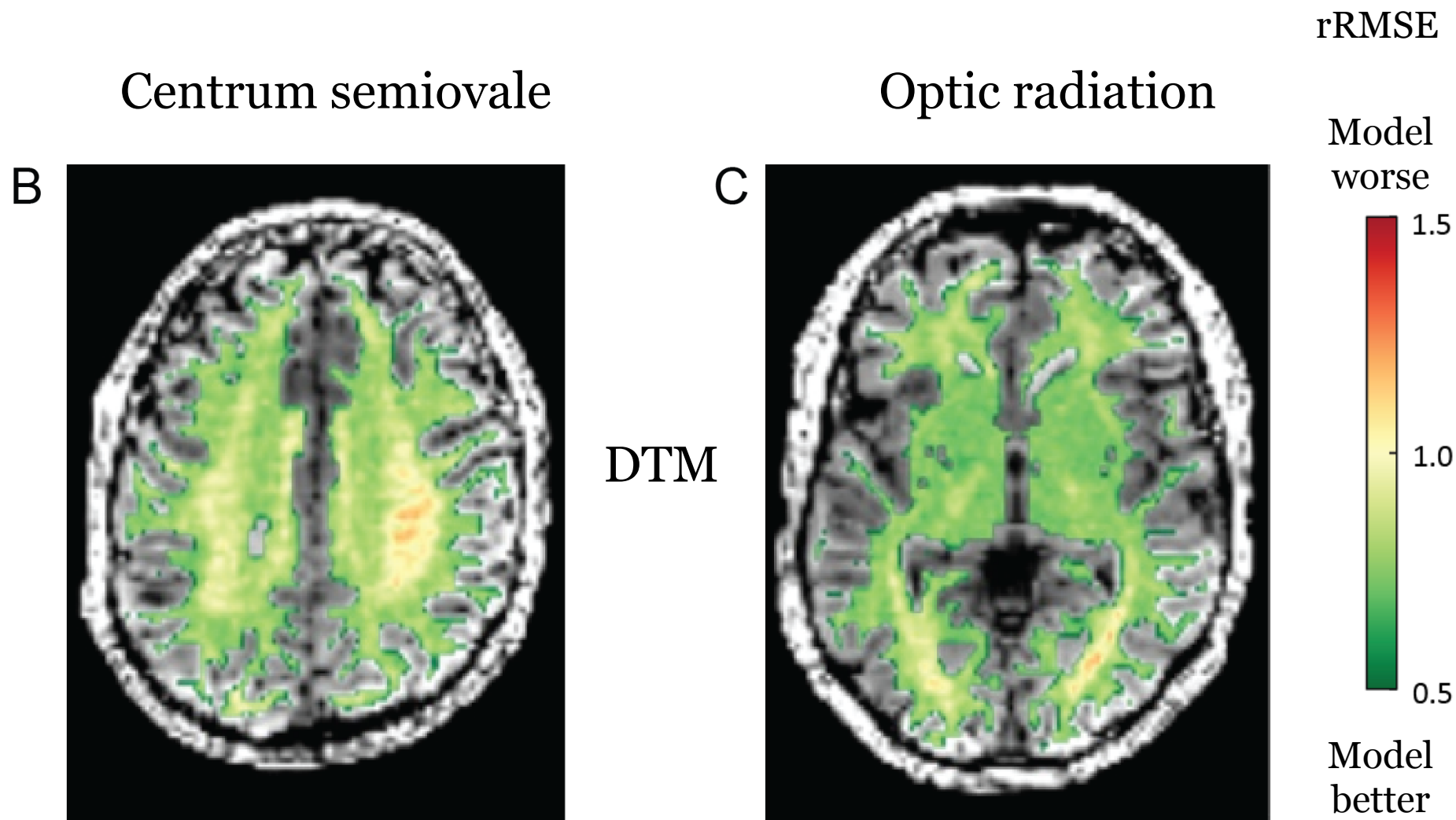
The SFM is slightly better (whole brain analysis)

Both are very good, and just short of best possible performance



Best possible = $1/\sqrt{2}$

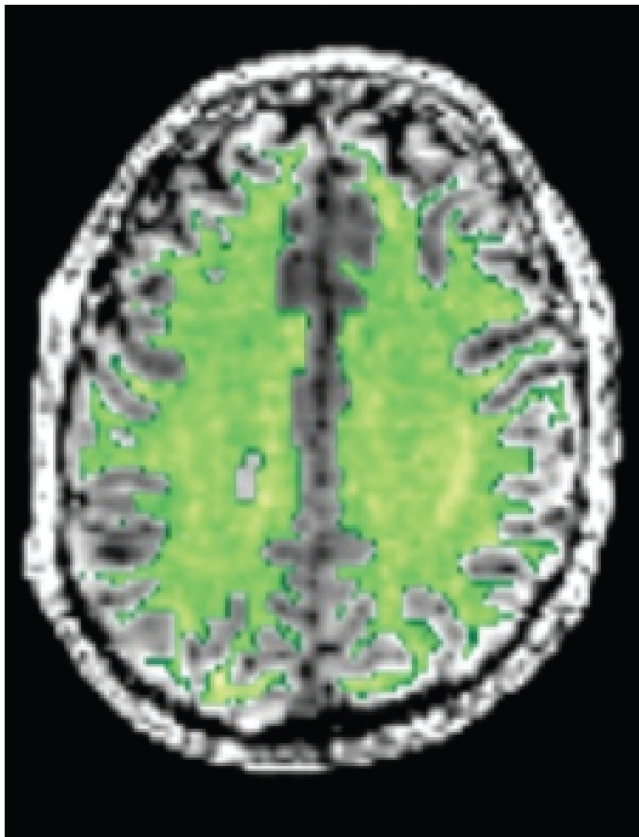
SFM outperforms DTM in $\sim 10\%$ of the voxels ($b = 4000$)



In a few regions, the SFM outperforms DTM ~10% of the voxels
($b = 4000$)

Centrum semiovale

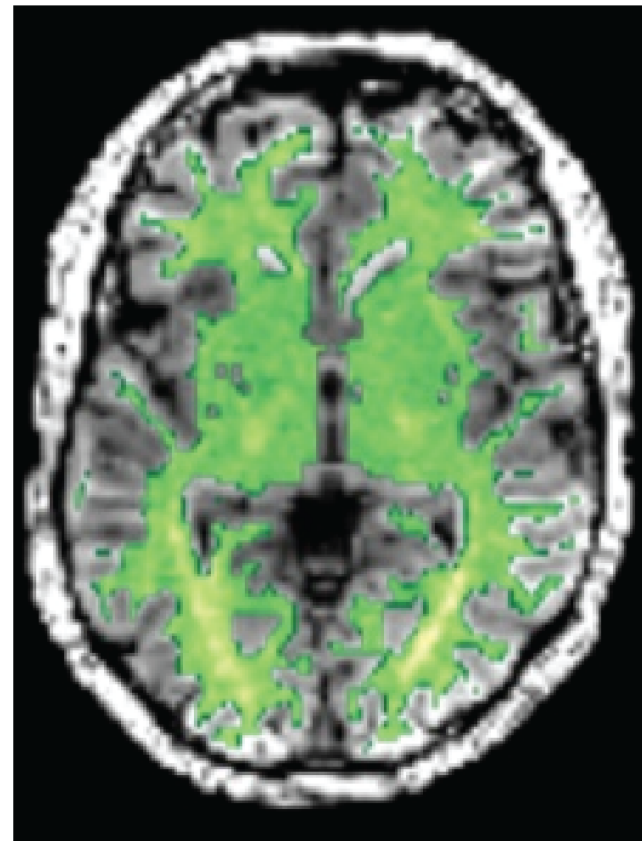
B



SFM

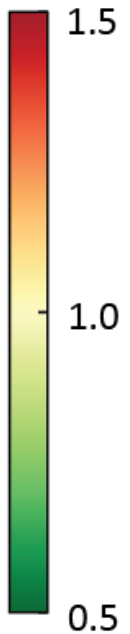
Optic radiation

C



rRMSE

Model
worse



Model
better

Summary

If your goal is to provide a mathematical model of the diffusion signal in each voxel then:

- DTM and SFM are both excellent descriptions of the diffusion data; much better than test-retest reliability
- The summary statistics of the DTM (e.g., FA, RD, AD, MD) are useful for voxel-wise experimental comparisons
- In a few brain regions the SFM is better
- **BUT:** The principal diffusion direction of the DTM is not a good estimate of local axonal direction

References

Moseley, Cohen et al. 1990 Radiology
Origins of white matter diffusion

Le Bihan, Mangin, Poupon et al. 2001 Journal of Magnetic Resonance Imaging
A nice early review

Basser et al., 1994 – Biophysical Journal
Good opening sentence: “This paper describes a new NMR imaging modality-MR diffusion tensor imaging.”

Basser and Pierpaoli – 1996,
Journal of Magnetic Resonance Imaging
Introduces FA and univariate statistics for DTM

Klingberg et al., 2000, Neuron
First application to human cognition

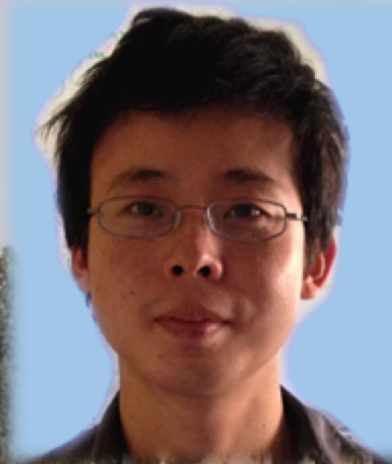
Linear Fascicle Evaluation

- Tractography
- Linear Fascicle Evaluation (LiFE)

Franco Pestilli



Hiromasa
Takemura



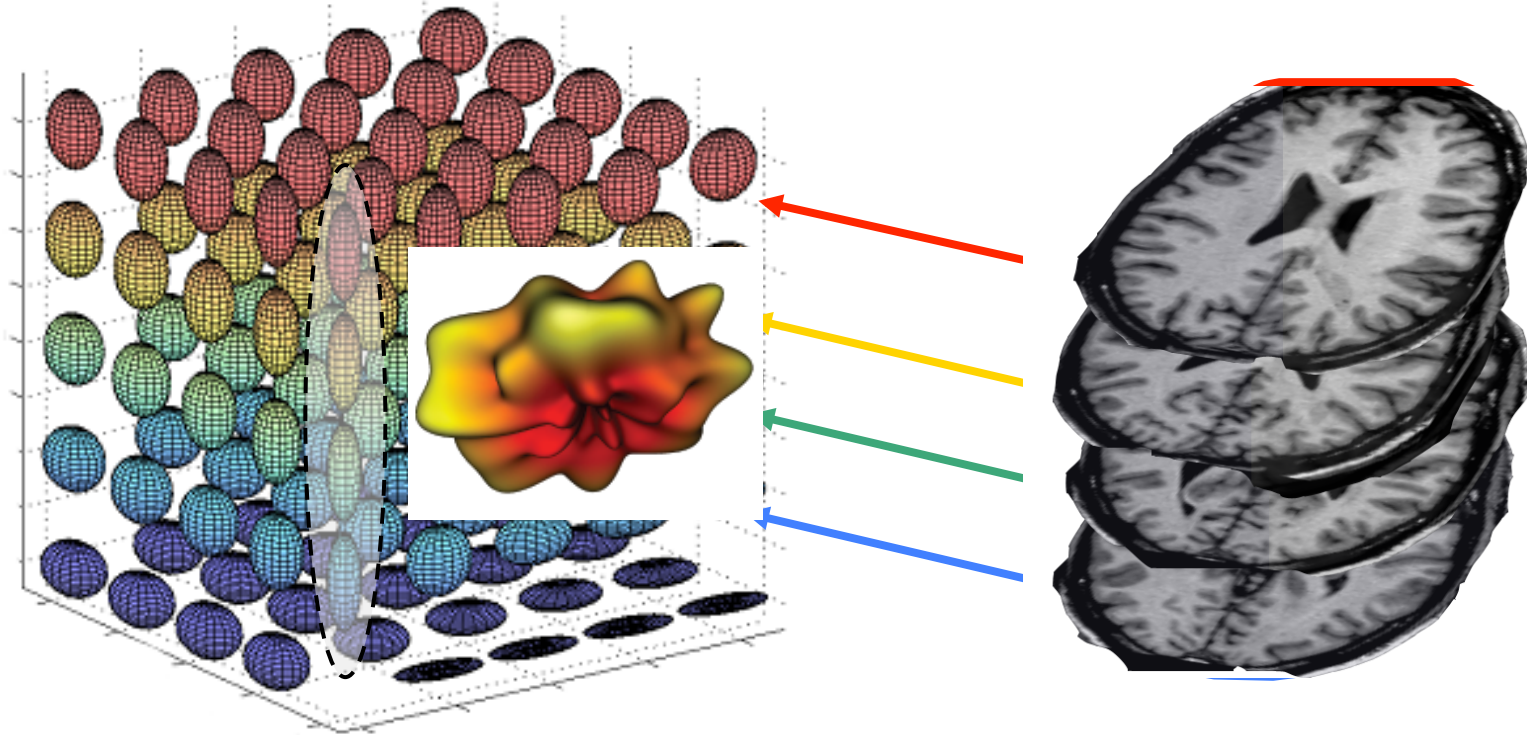
Jason Yeatman



Tractography

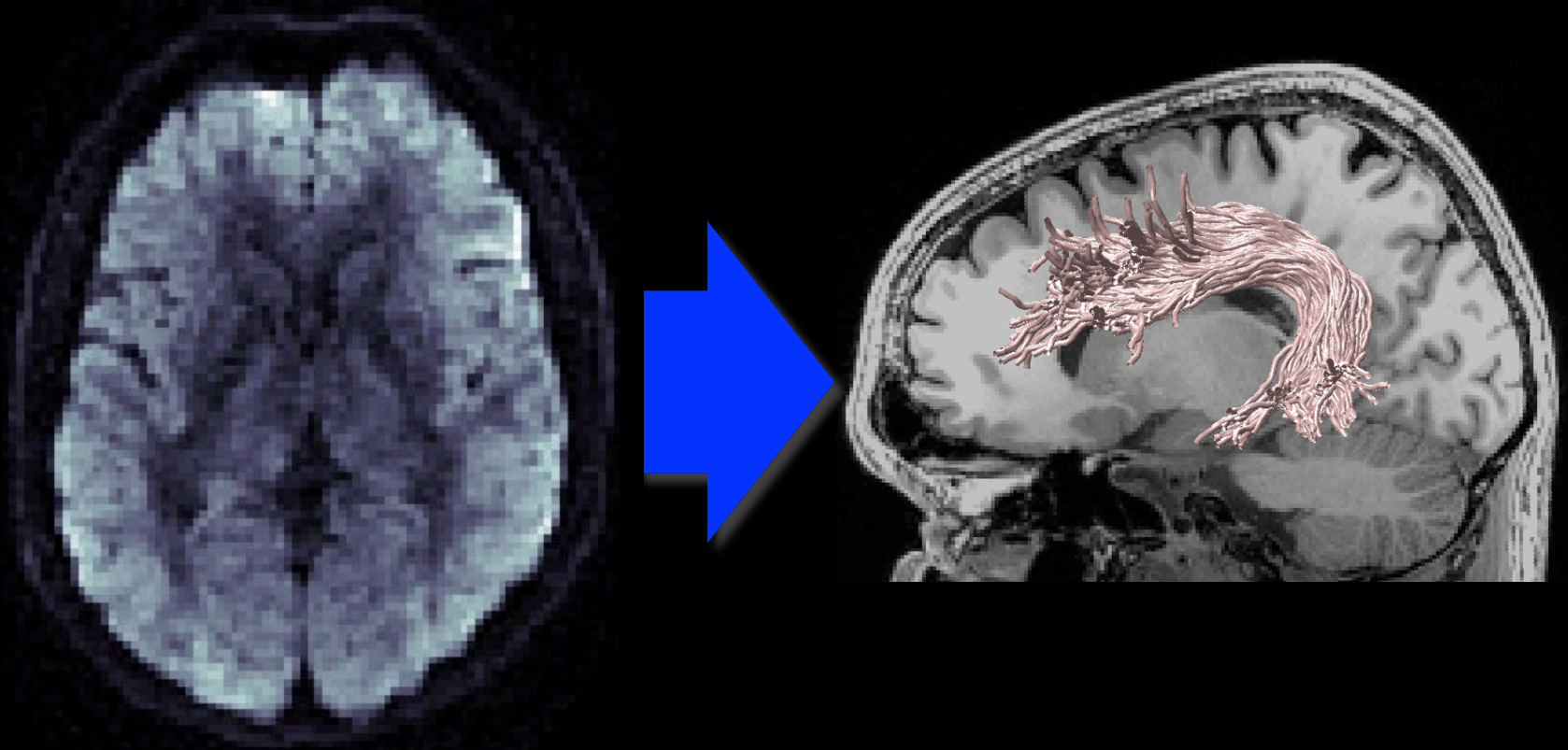
Use the local (voxel) diffusion measurements to estimate white matter tracts

Diffusion data are surfaces

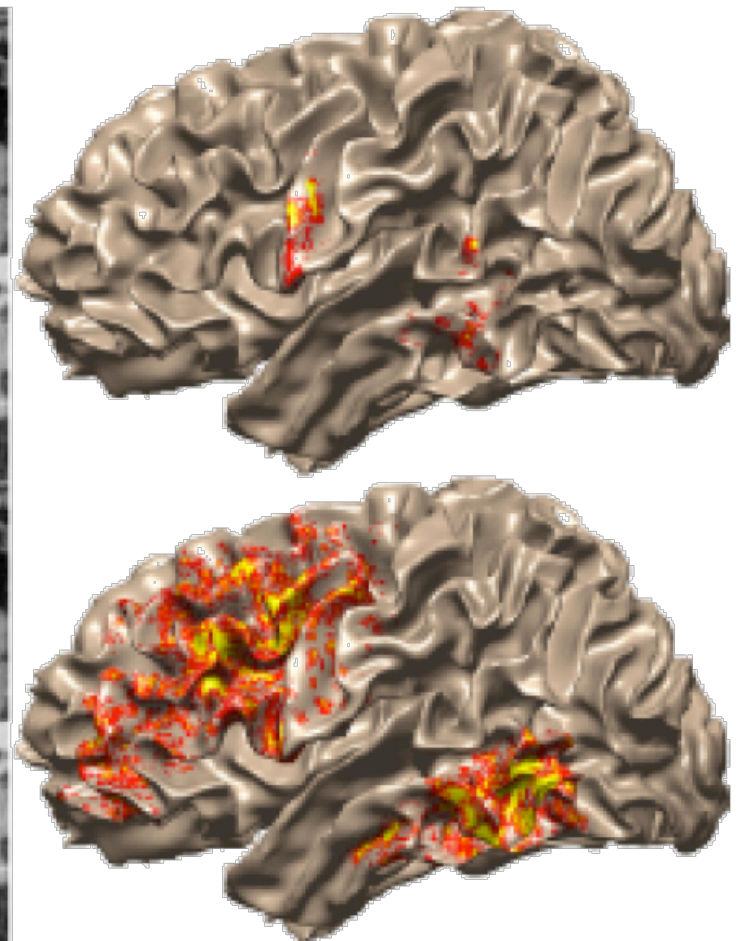
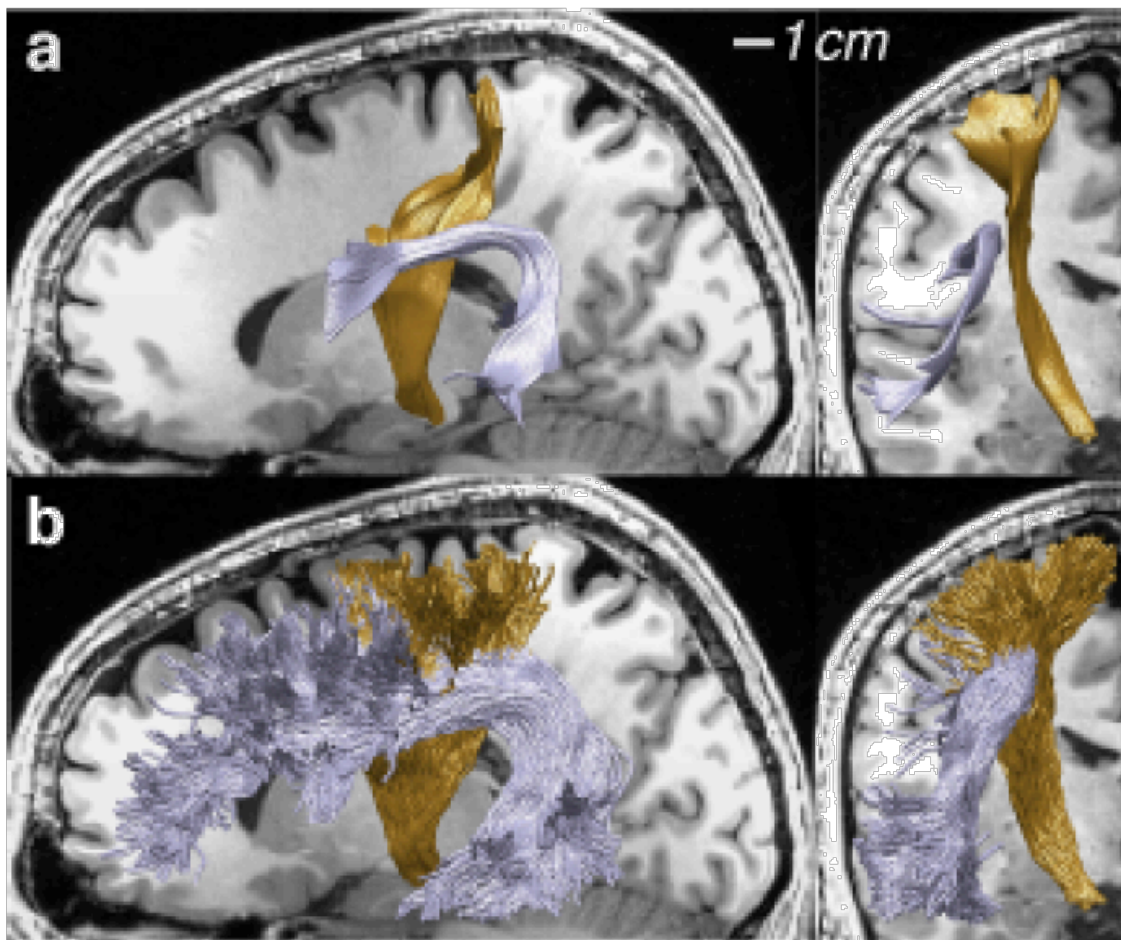


Tractography limitations

Estimate fascicles from diffusion data



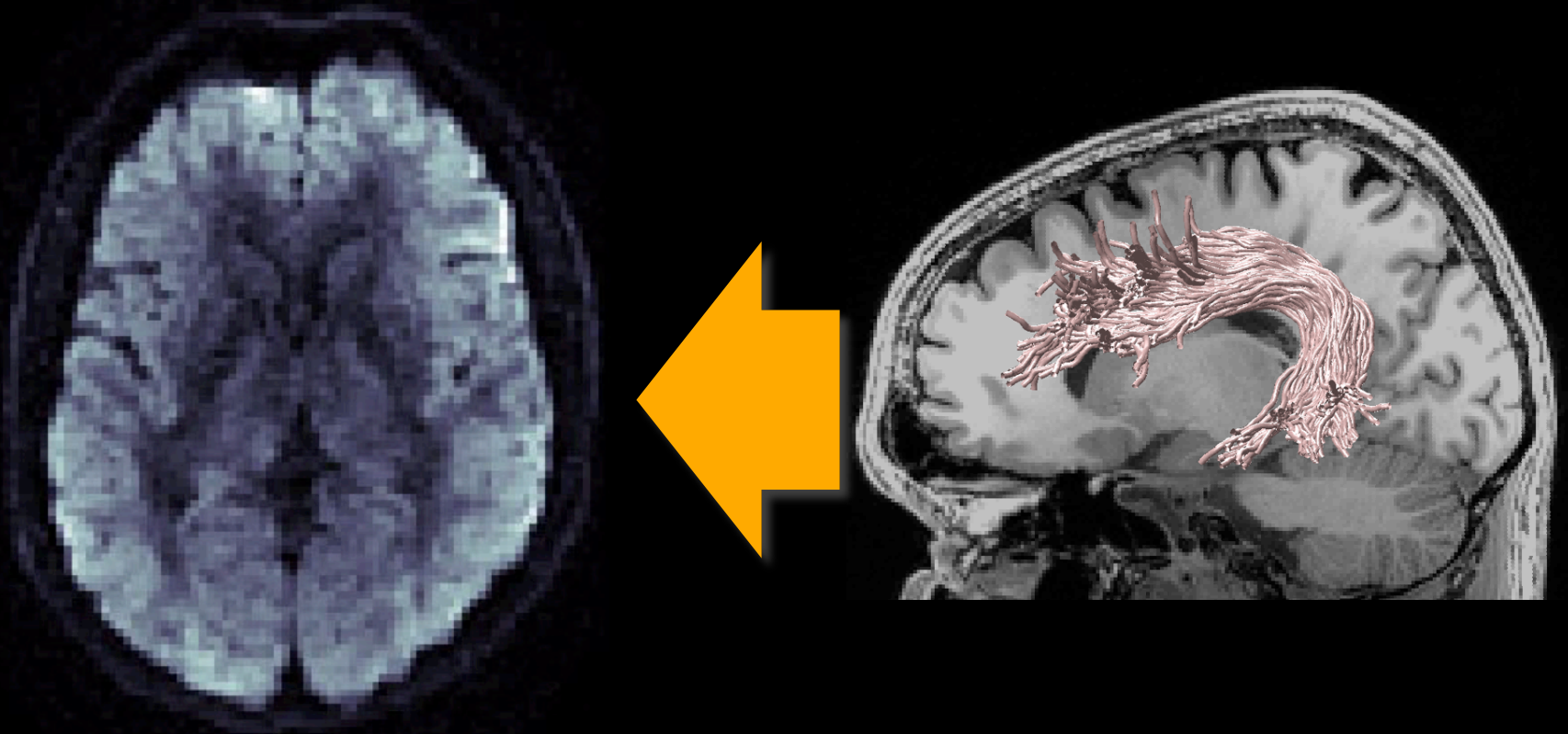
Different tractography methods and parameters make different predictions



Linear Fascicle Evaluation (LiFE)

Predict diffusion data from fascicles

Compare how well different models and algorithms do



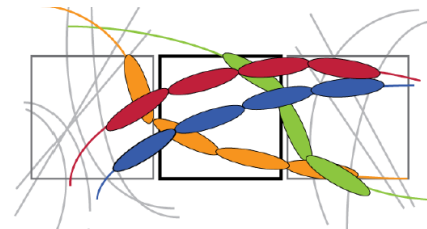
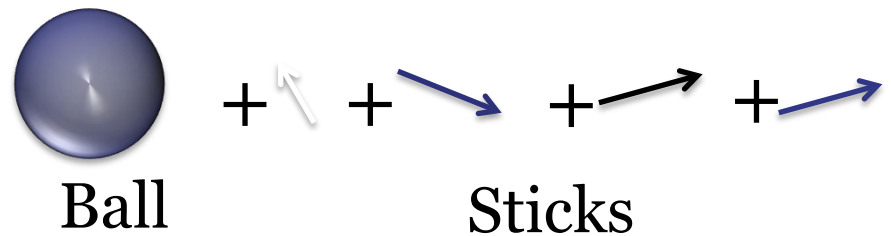
2. Stages of LiFE

Set up diffusion predictions for each voxel

$$S(\theta) = w_0 D_0 + \sum_f w_f e^{-bD_f(\theta)}$$

isotropic weights fascicles

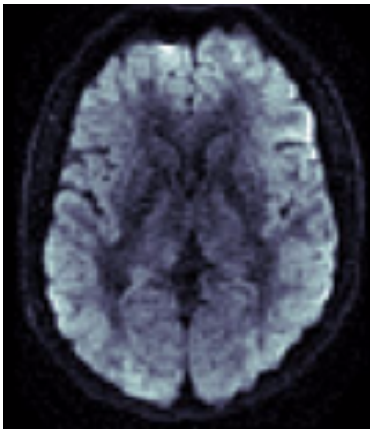
In each voxel use the conventional fascicle diffusion model to predict the diffusion signal from the candidate connectome



3. Stages of Life

Solve for the fascicle weights

Diffusion
signal, $S(\theta)$



$$\begin{matrix} S(\theta) \\ \left[\begin{matrix} v_1 \\ \text{---} \\ v_2 \\ \text{---} \\ \vdots \\ \text{---} \\ v_N \end{matrix} \right] \end{matrix}$$

=

$$\left[\begin{matrix} \text{Each column is the prediction of a fascicle} \\ \text{Each entry is the fascicle contribution for a voxel in a direction} \end{matrix} \right]$$

$$\left[\begin{matrix} w_f \end{matrix} \right]$$

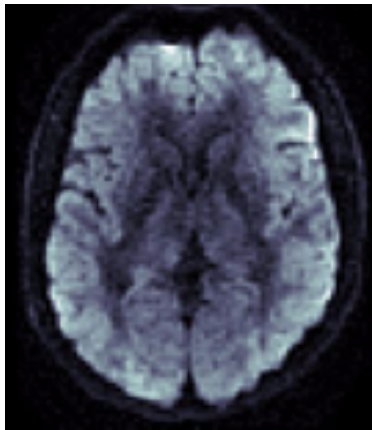
Solve for a non-negative weight for each fascicle (least-squares)

$$10^7 \times 10^6$$

3. Stages of Life

Solve for the fascicle weights

Diffusion
signal, $S(\theta)$



$$\begin{matrix} S(\theta) \\ \left[\begin{matrix} v_1 \\ \text{---} \\ v_2 \\ \text{---} \\ \vdots \\ \text{---} \\ v_N \end{matrix} \right] \end{matrix}$$

=

Each column is
the prediction
of a fascicle

Each entry is
the fascicle
contribution
for a voxel in a
direction

w_f

Depending on
voxel size,
number of
directions, and
so forth, about
80% of typical
tractography
weights are zero.

$10^7 \times 10^6$

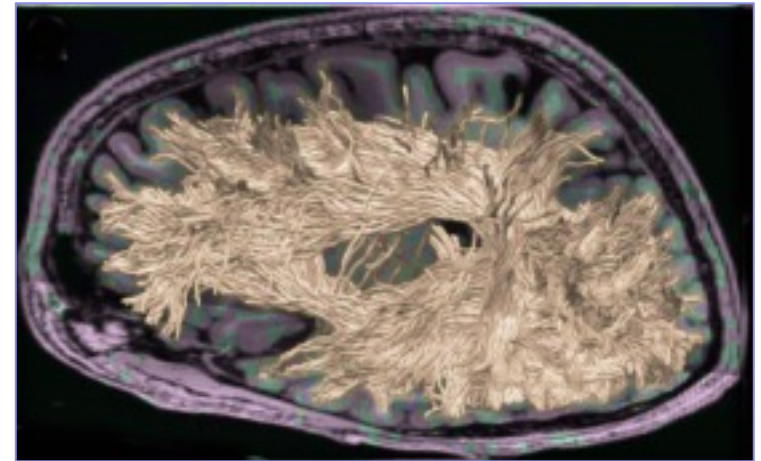
4. Stages of LiFE

Eliminate zero weight fibers (false alarms)

Candidate
connectome



Optimized
connectome

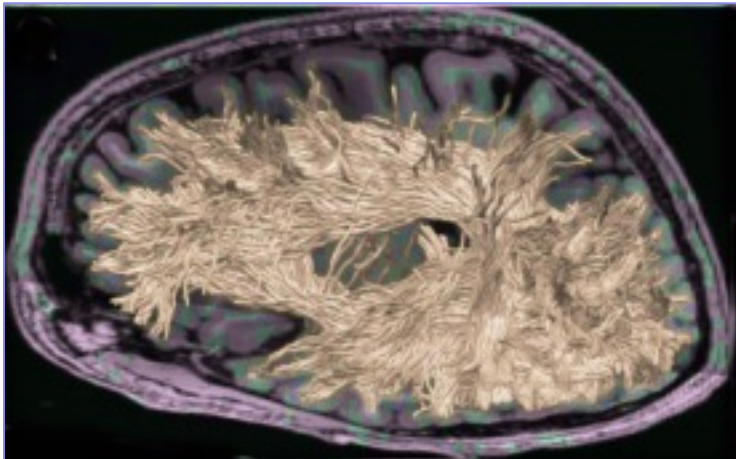


Solving a system of linear equations
(non-negative least-squares)

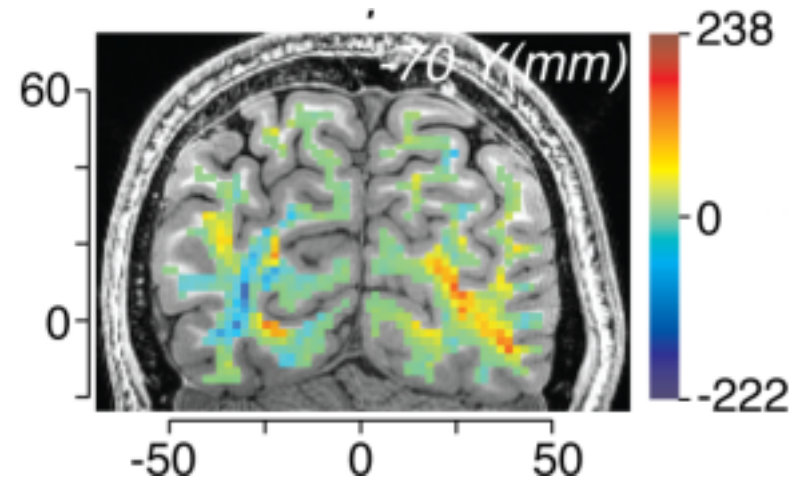
5. Stages of LiFE

Predict diffusion signal

Optimized connectome
and weights



Prediction

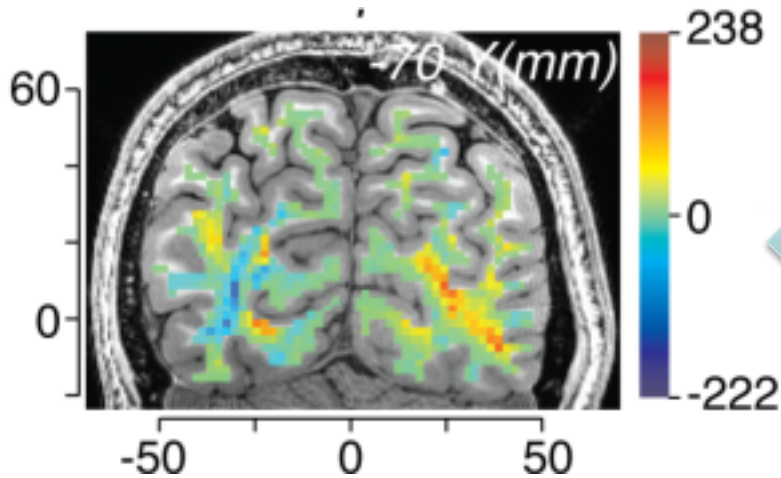


Big matrix multiplication

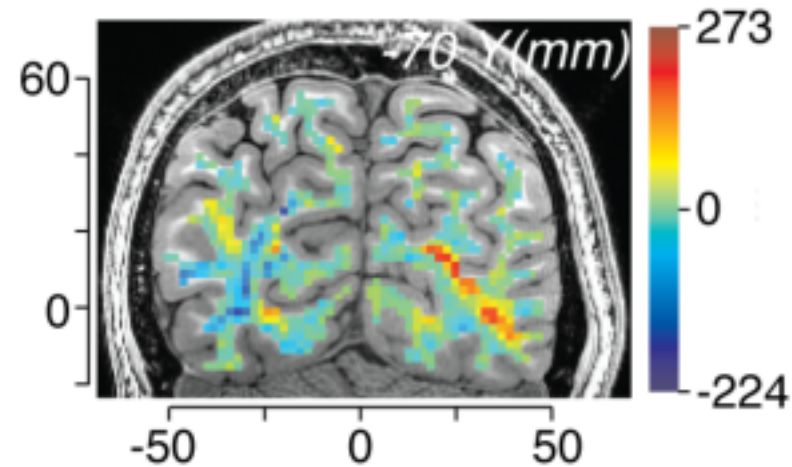
6. Stages of LiFE

Cross-validation error between predicted and 2nd data set

Prediction



Second data set



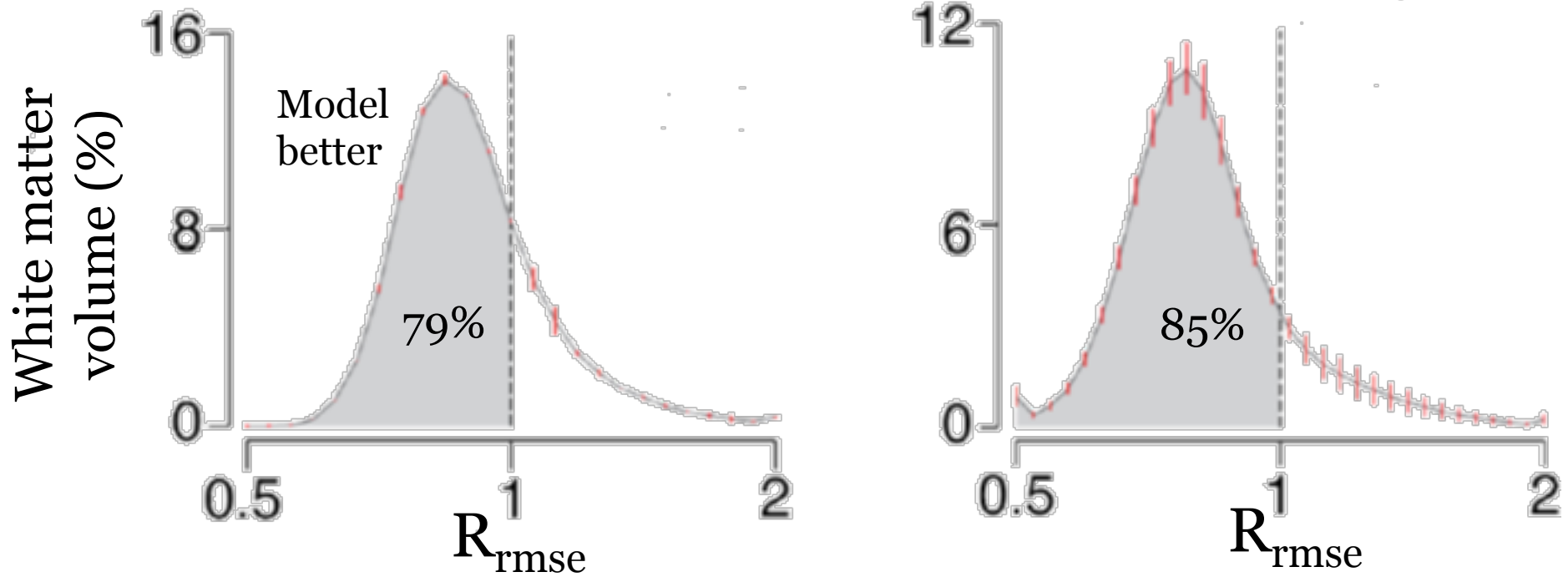
Subtraction and root mean square error

The optimized connectome predicts diffusion data slightly better than test-retest reliability

(b=2000 data shown)

150 directions (N=3)

96 directions (N=6)

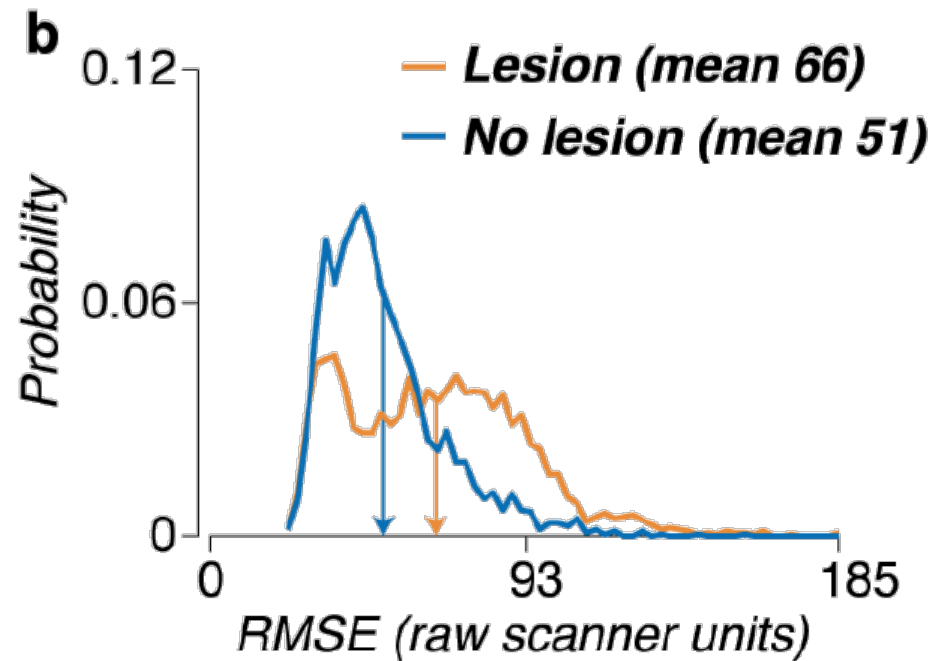
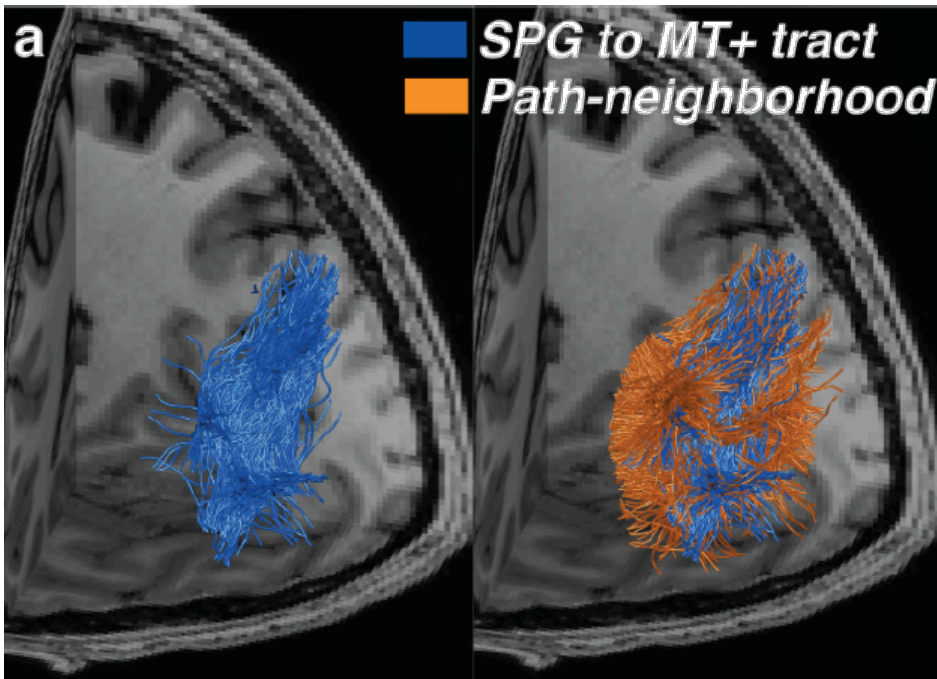


R_{rmse} = Ratio of model error to reliability error

Methods for hypothesis testing

Path-neighborhood (Wedeen)

Earth Mover's Distance on error distribution (Guibas)



Partial list of tractography and visualization software

<http://www.nitrc.org/>

Central source

MRI studio – <http://www.mristudio.org>

FiberTools (Reisert)

FMRIB

- PROBTRACK
http://users.fmrib.ox.ac.uk/~behrens/fdt_docs/fdt_probtrack.html
- Tract Based Spatial Statistics
<http://users.fmrib.ox.ac.uk/fsl/fslwiki/TBSS>

TrackVis - <http://www.trackvis.org>

DSI studio - <http://dsi-studio.labsolver.org/>

MRtrix - <http://brain.org.au/software/mrtrix/>

Exploredti - <http://www.exploredti.com/>

Camino - <http://cmic.cs.ucl.ac.uk/camino/>

mrDiffusion - <https://github.com/vistalab/vistasoft>

Building a model of the circuit for seeing words

- White matter tissue properties predict how well children can quickly recognize words

Michal Ben-Shachar



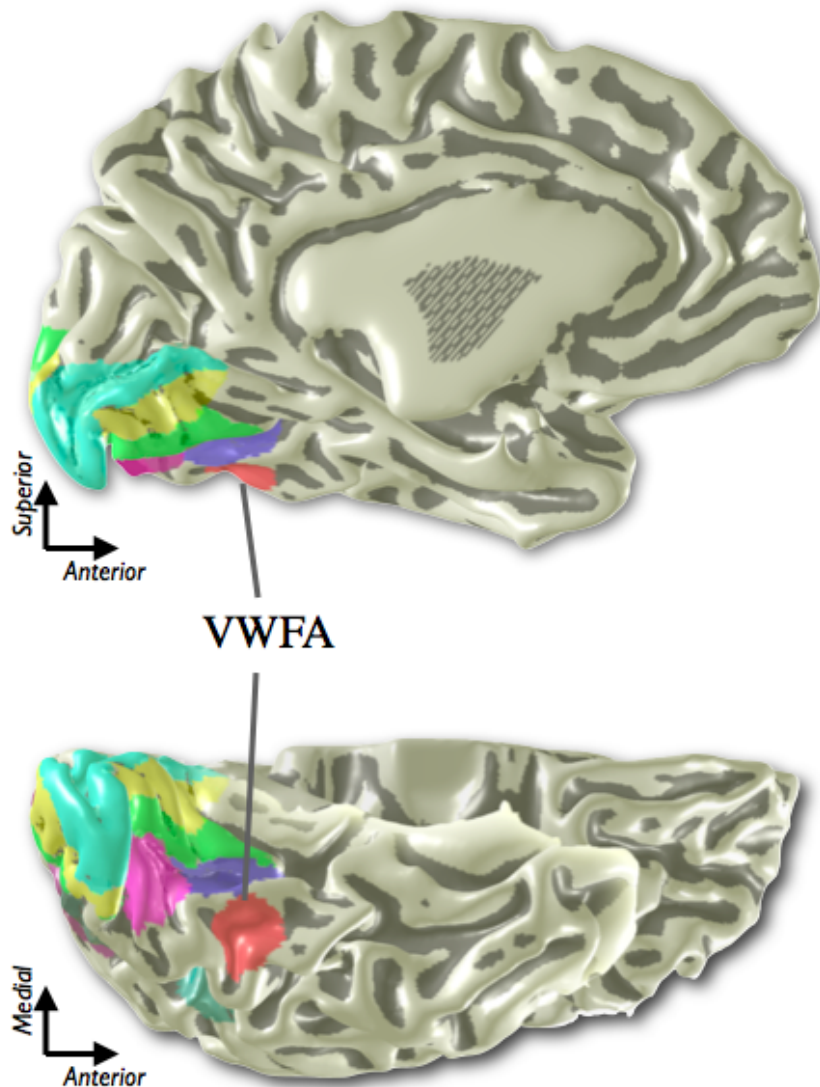
Jason Yeatman



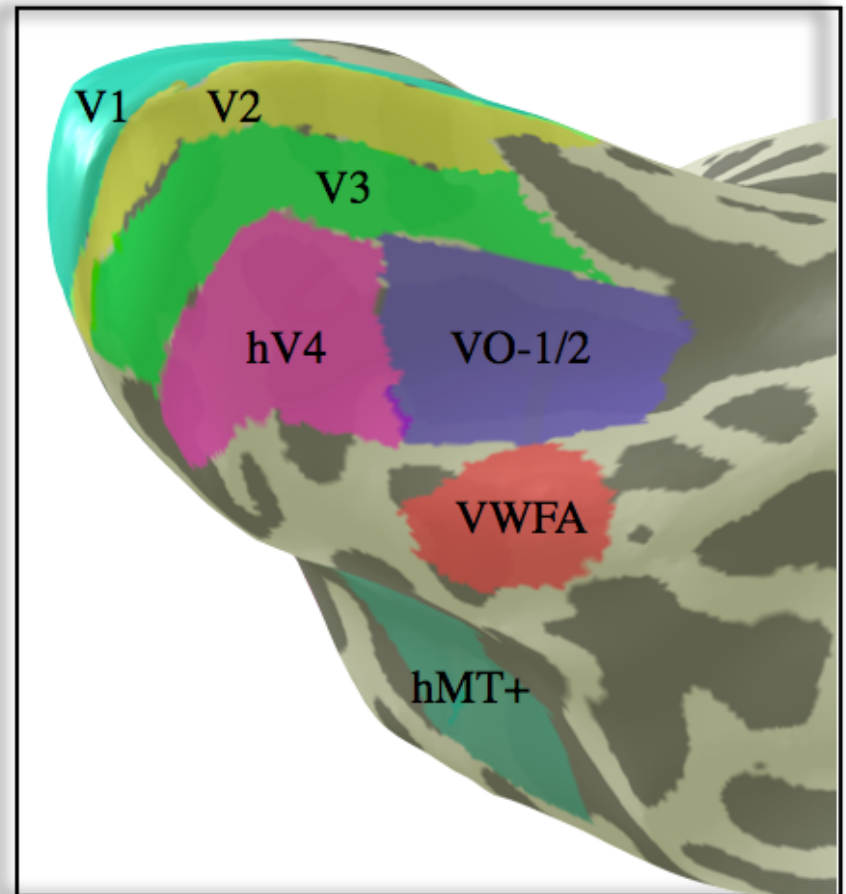
Andreas
Rauschecker

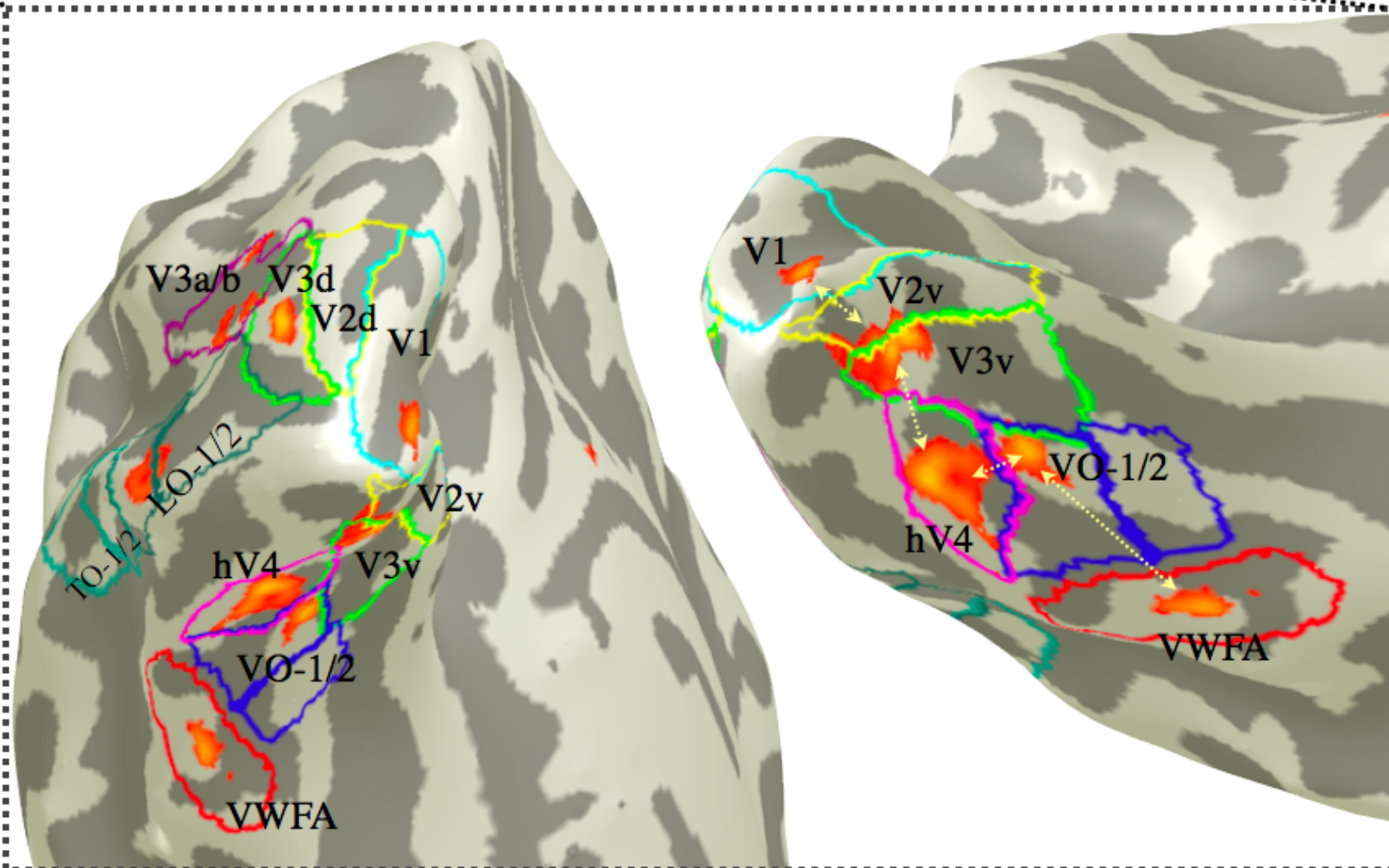
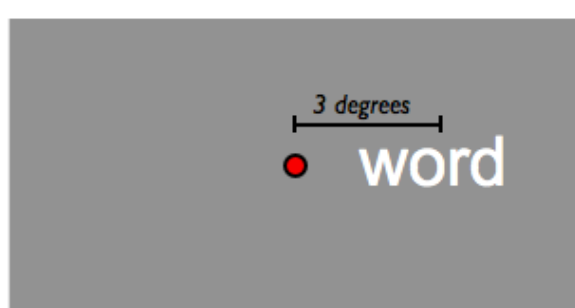
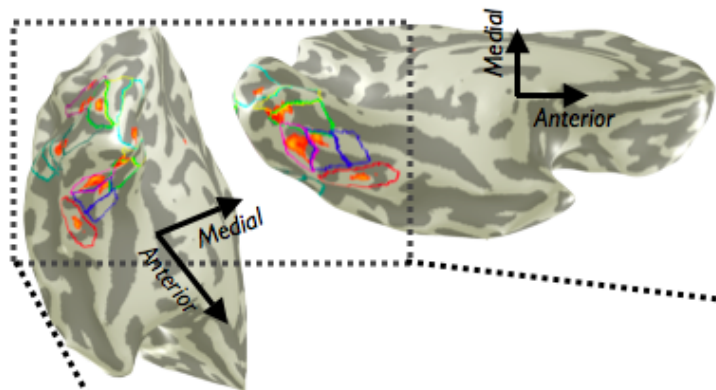


Locating reading circuits and maps



VWFA - essential for reading, but not unique to reading





The cortical reading network

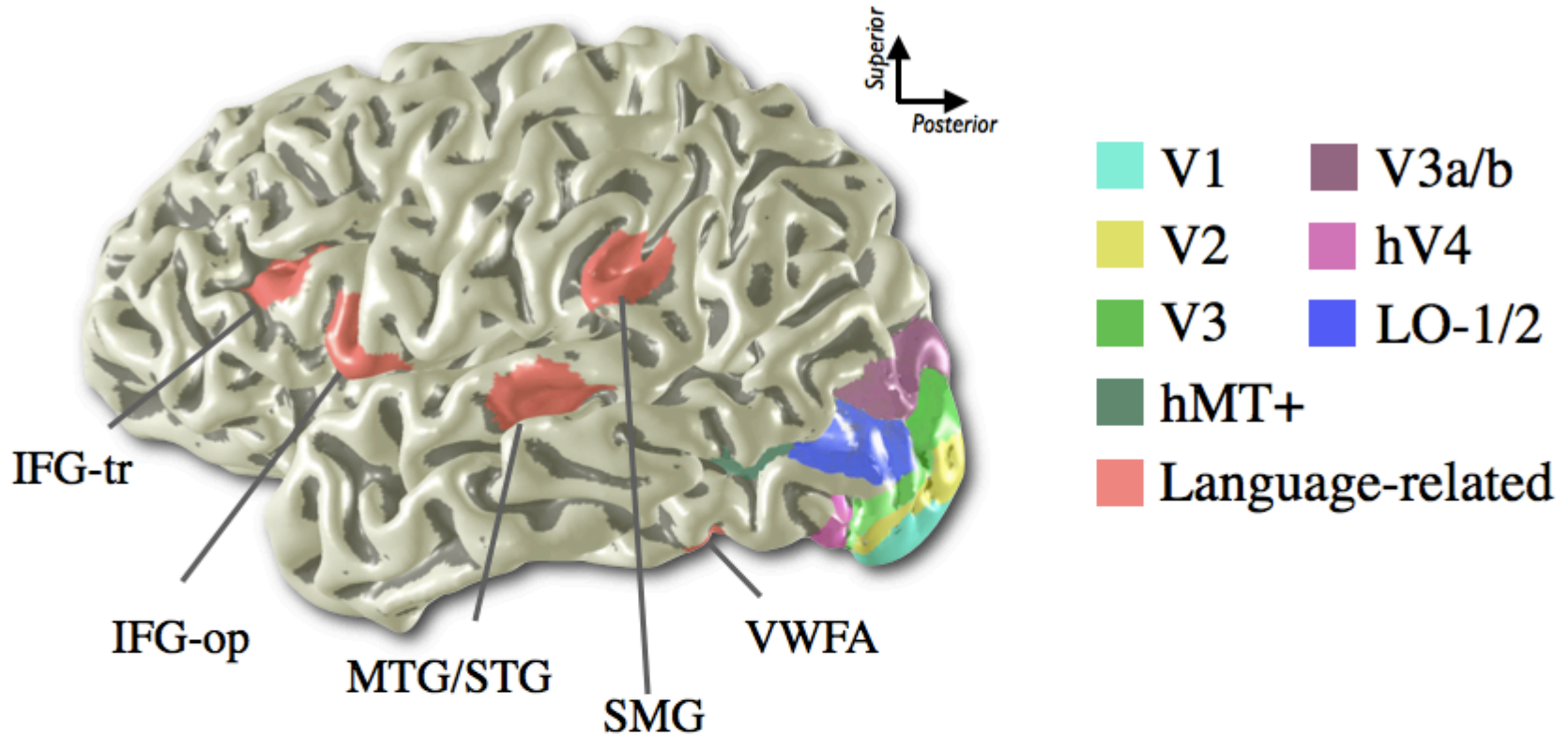
Learning to See Words

B.A. Wandell, A. Rauschecker and

J. Yeatman (2012).

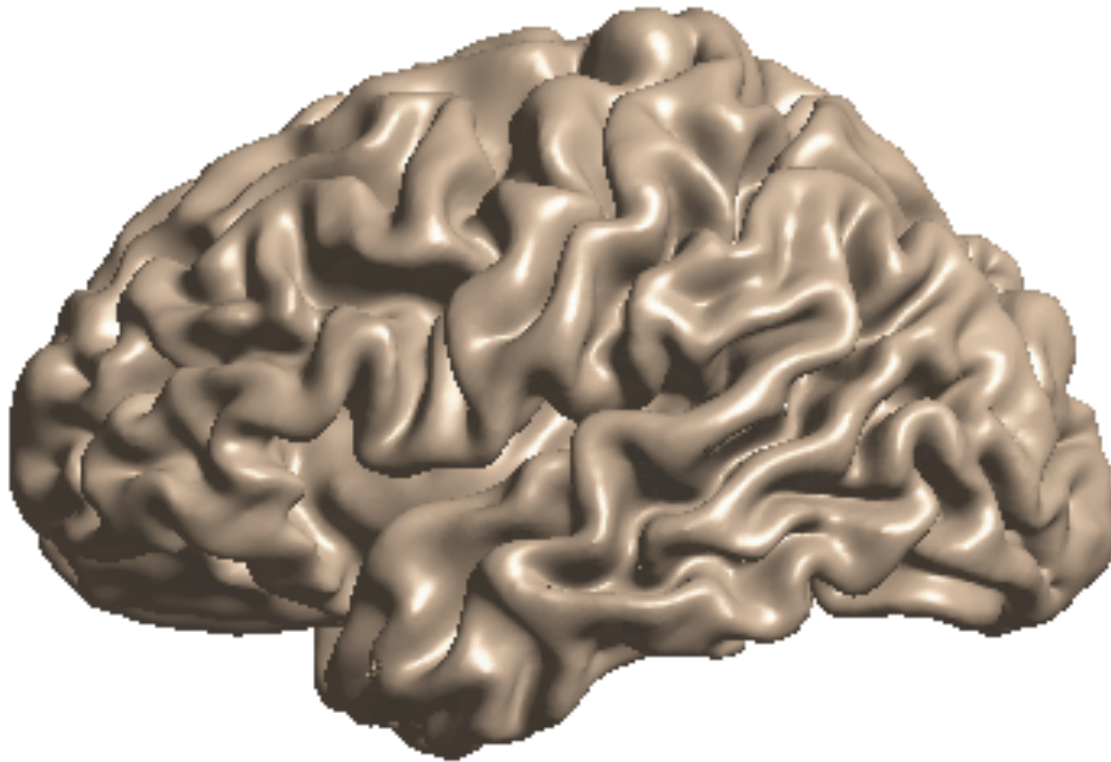
Annual Review of

Psychology Vol. 63, pp.31-53.



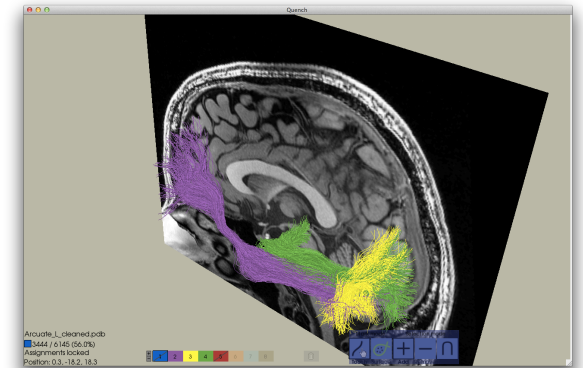
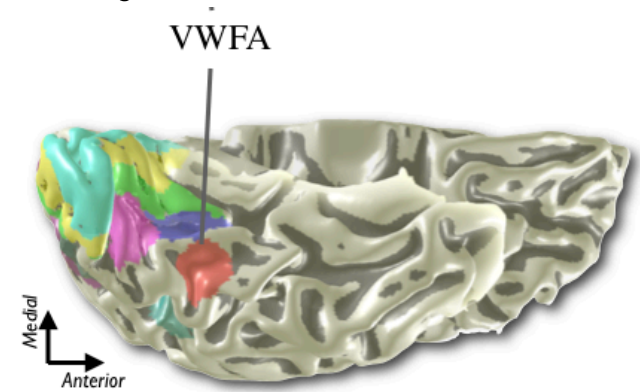
Seeing the white matter reading tracts

(Yeatman et al., 2011)



Intermediate summary

- Reading requires quickly and accurately identifying forms (seeing words)
- The cortex learns to do this using the VWFA, a region located in ventral temporal cortex, amidst a set of visual field maps
- White matter development (arcuate, ILF) predicts reading development



Data management for reproducible research

Prof. Brian Wandell

Director
Stanford Center for Cognitive and
Neurobiological Imaging (CNI)

Deputy Director
Stanford Neurosciences Institute
(SNI)

Gunnar
Schaefer



Bob
Dougherty



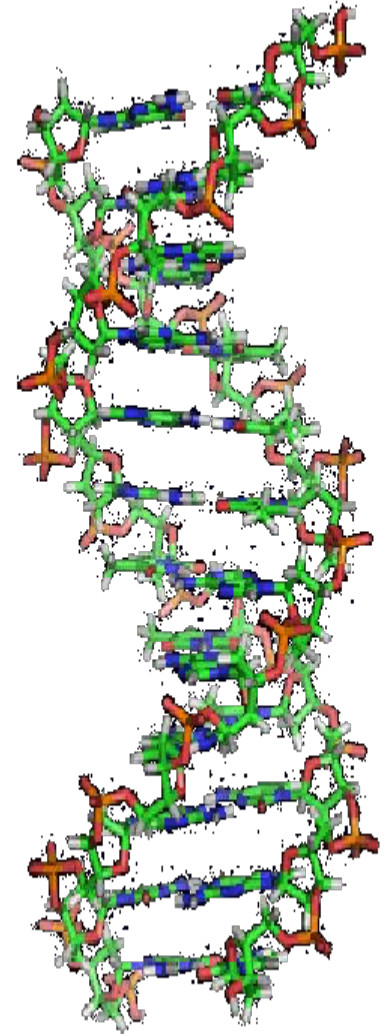
Michael
Perry



Disclosure: [Flywheel.io](https://flywheel.io)

Replication is often impractical

- Neuroscience has entered an era of ‘big science’ in which replication is impractical
 - **Example 1:**
Analyses of 320 subjects with autism, each measured using MRI, at 3 time points over four years
 - **Example 2:**
Structural MRI of 50 illiterate adults flown in from the Amazon rain forest



Reproducible research is within reach

Replication means obtaining the data again, usually by independent investigators using similar methods, equipment and protocols

Many big science experiments are too expensive and time-consuming to replicate

Reproducible means that starting with the data gathered by the scientists, we can confirm the derived results (e.g., statistics, summary curves and images, numerical relationships)

Proper tools enable scientists to achieve reproducibility much more often

Reproducible Research

Computational reproducibility is not an afterthought—it is something that must be designed into a project from the beginning. **One does need to develop a whole set of programming and research disciplines** with the end result in mind and stick with them.



Donoho

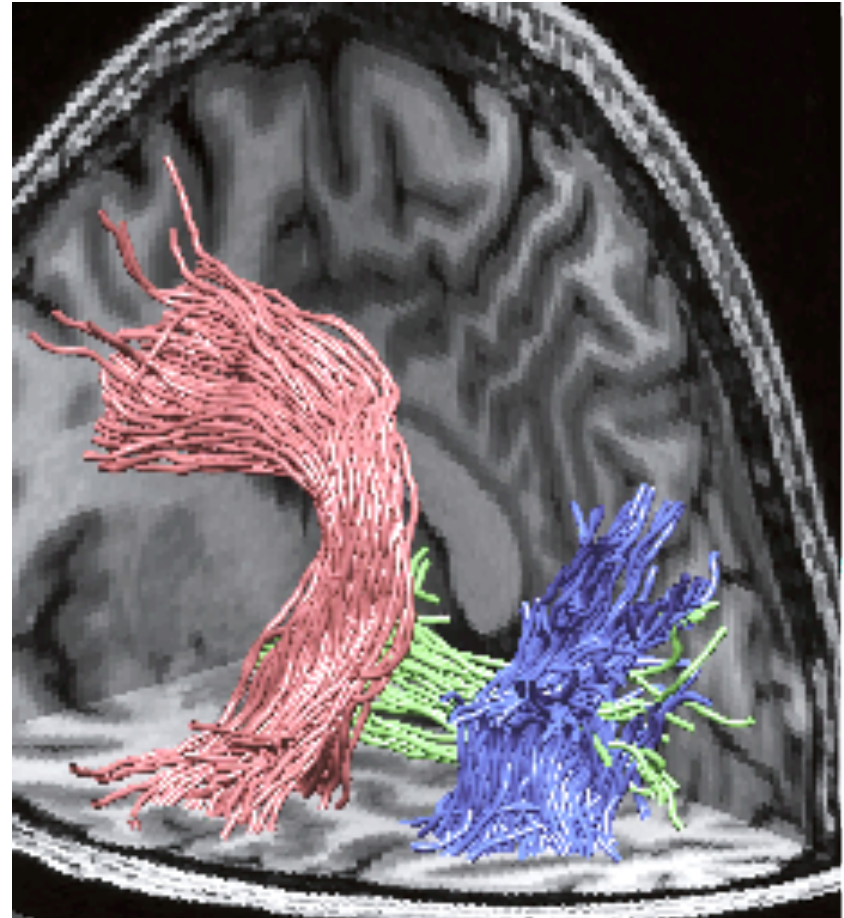
Scientific data management tools

- Reproducible research requires **scientific data management** tools **Disclosure: Flywheel.io**
- These should be an expected part of any important scientific experiment
- For reproducible research the tools should simplify both
 - Data sharing
 - Computational sharing

Scientific goals of the project

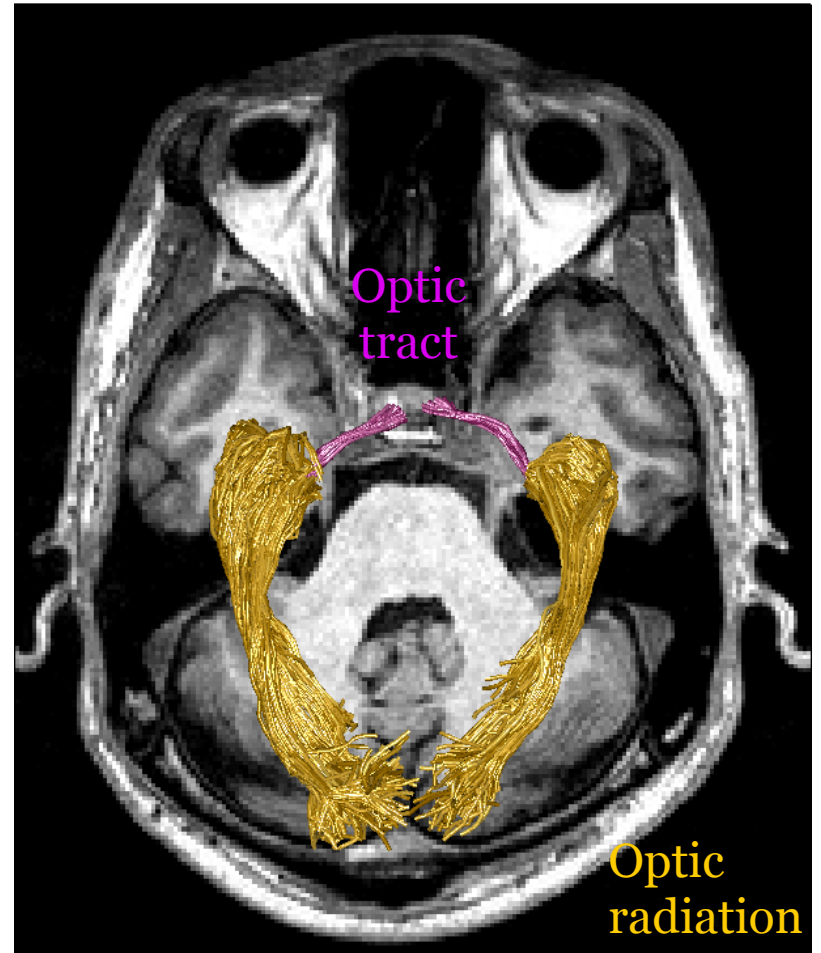
Personalized neuroscience

An opportunity that derives from a combination of data management and the quest for reproducible research



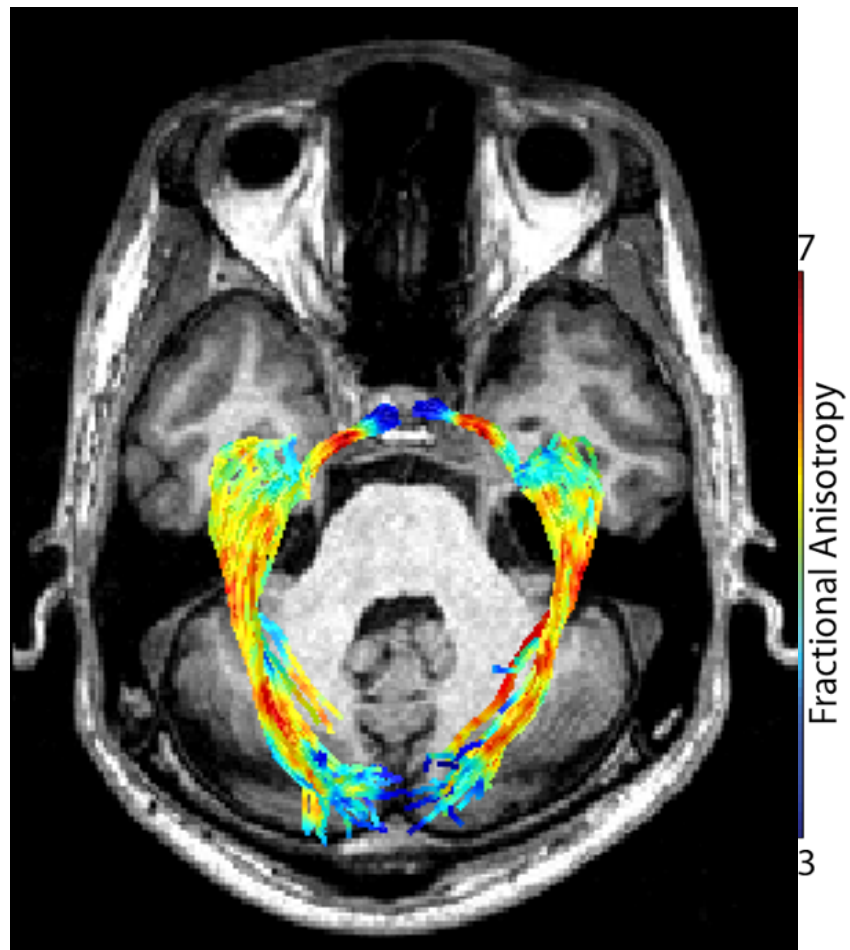
A motivating example

- A subject or patient with a retinal eye disease comes to the lab
- We want to know the consequences of retinal degeneration on cortical structures

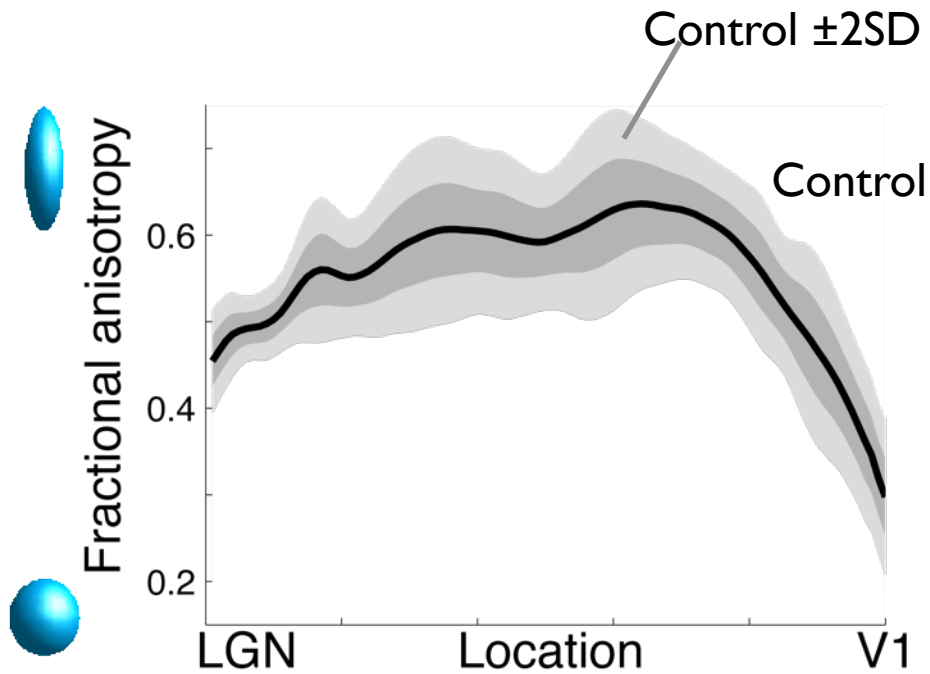


A motivation example

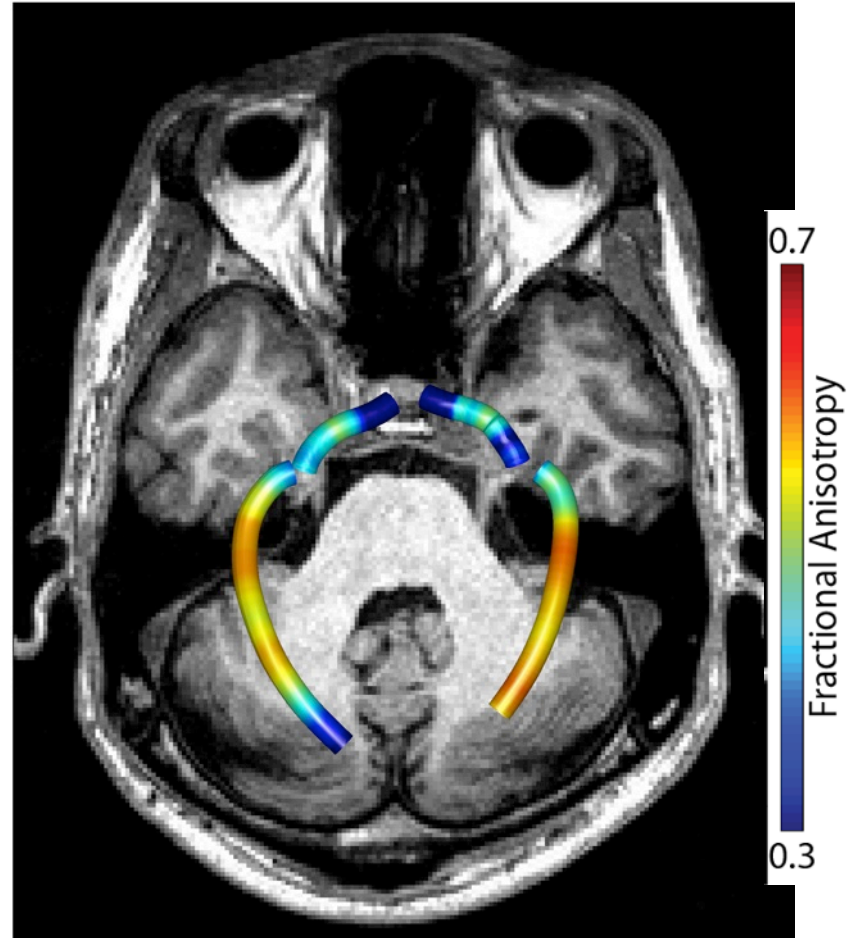
- Measure the subject's visual white matter and secure the data!
- Use validated computational tools for quality assurance
- Use open-source software for tract identification, tissue estimation and comparison with other populations



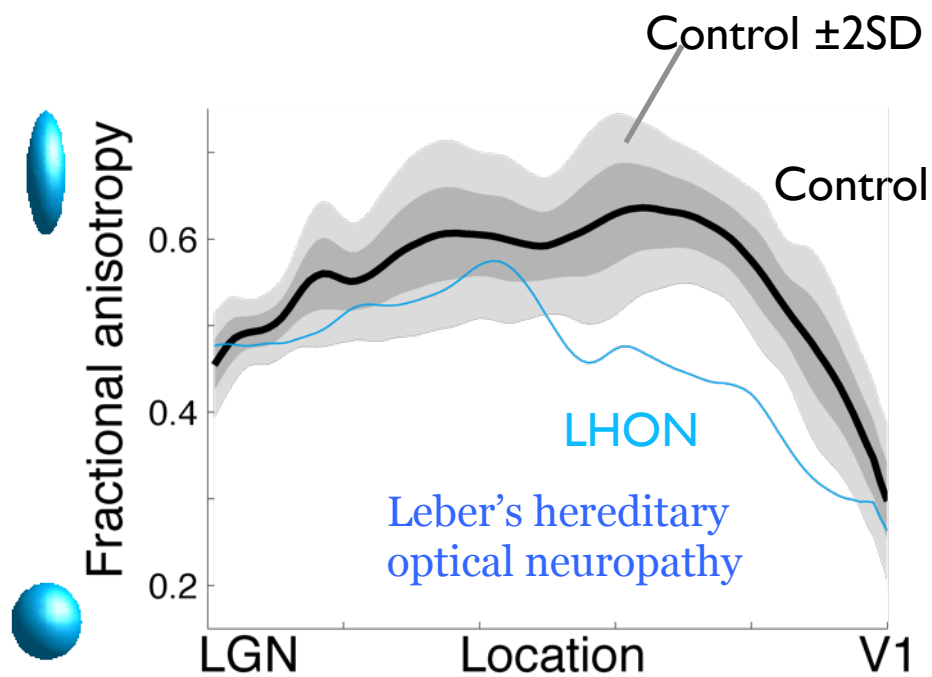
Use databases to find controls



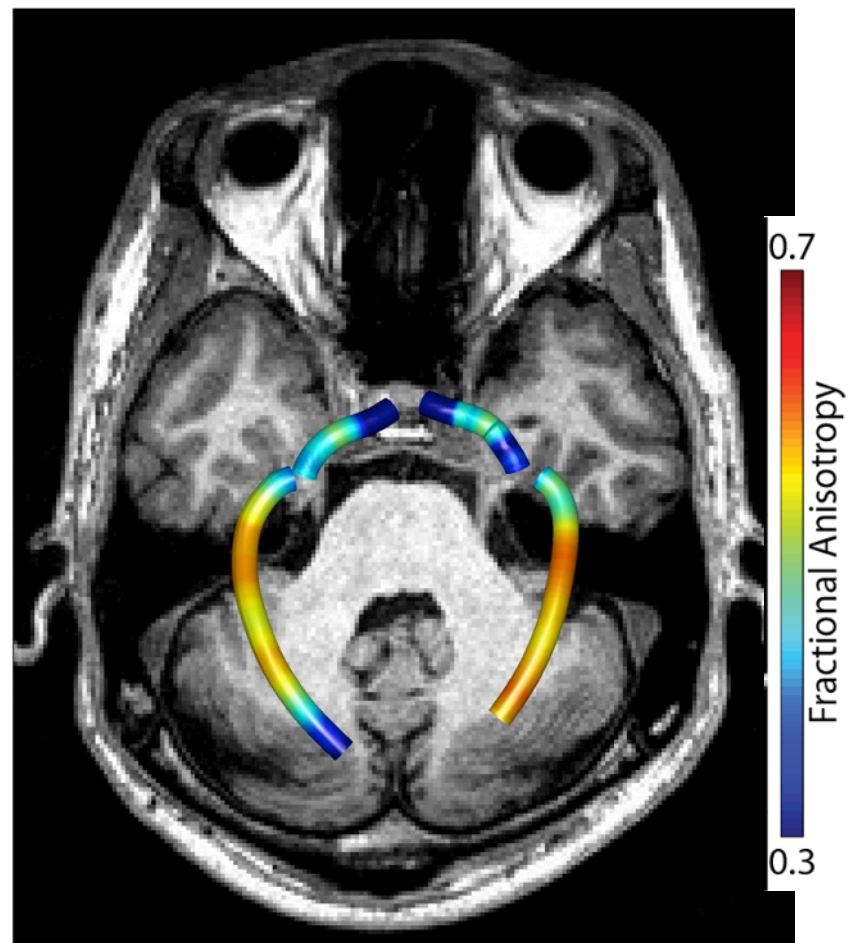
The expectation based on data acquired and stored in the SDM



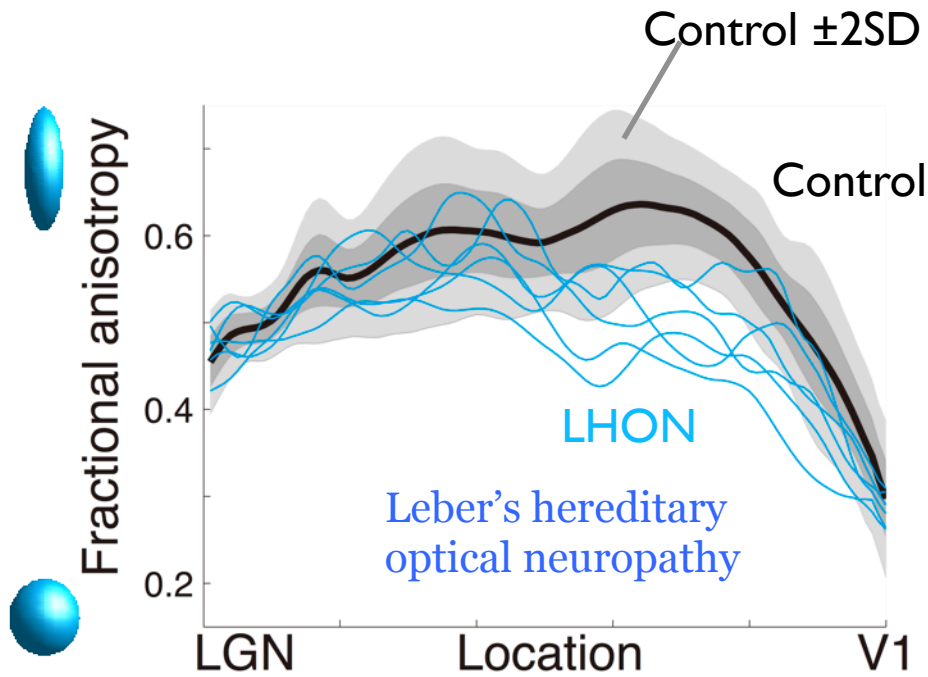
Compare your subject with the distribution and think



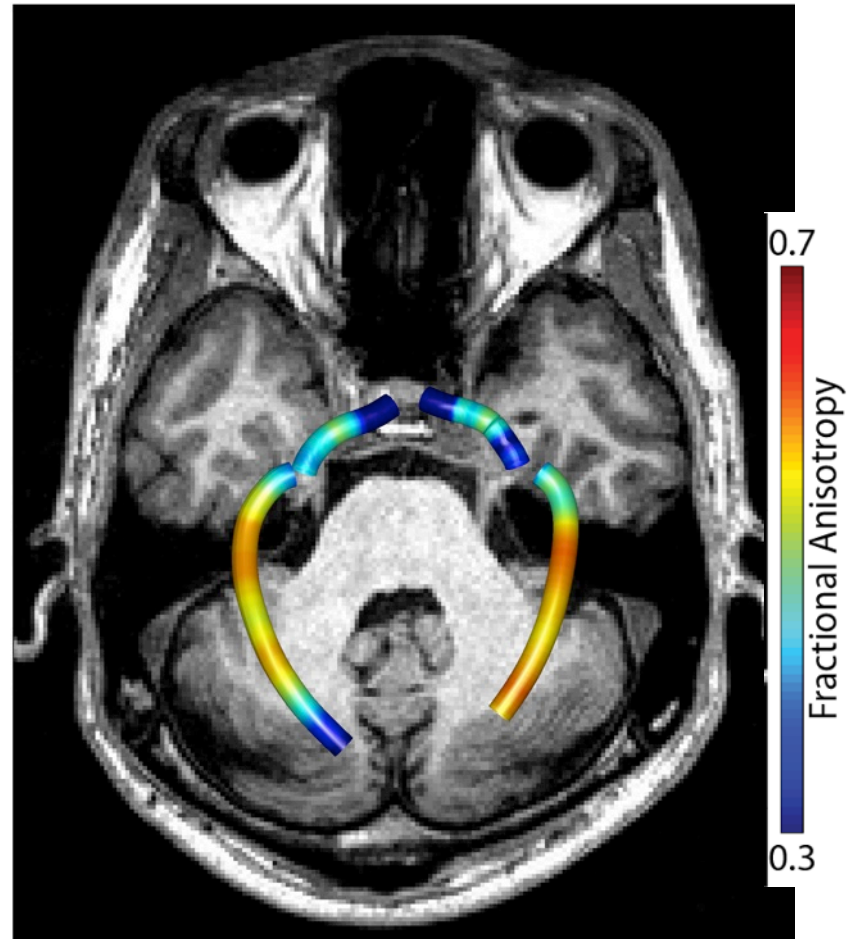
This subject compared to the expectation



Data science and statistics issues

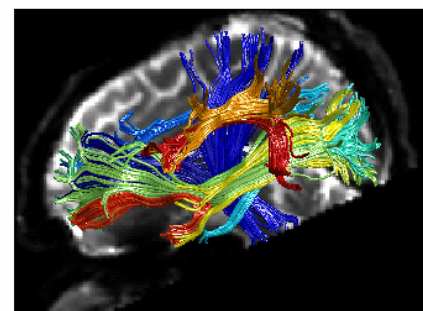


Each subject with the disease has some variation and we would like to know, and track each one over time

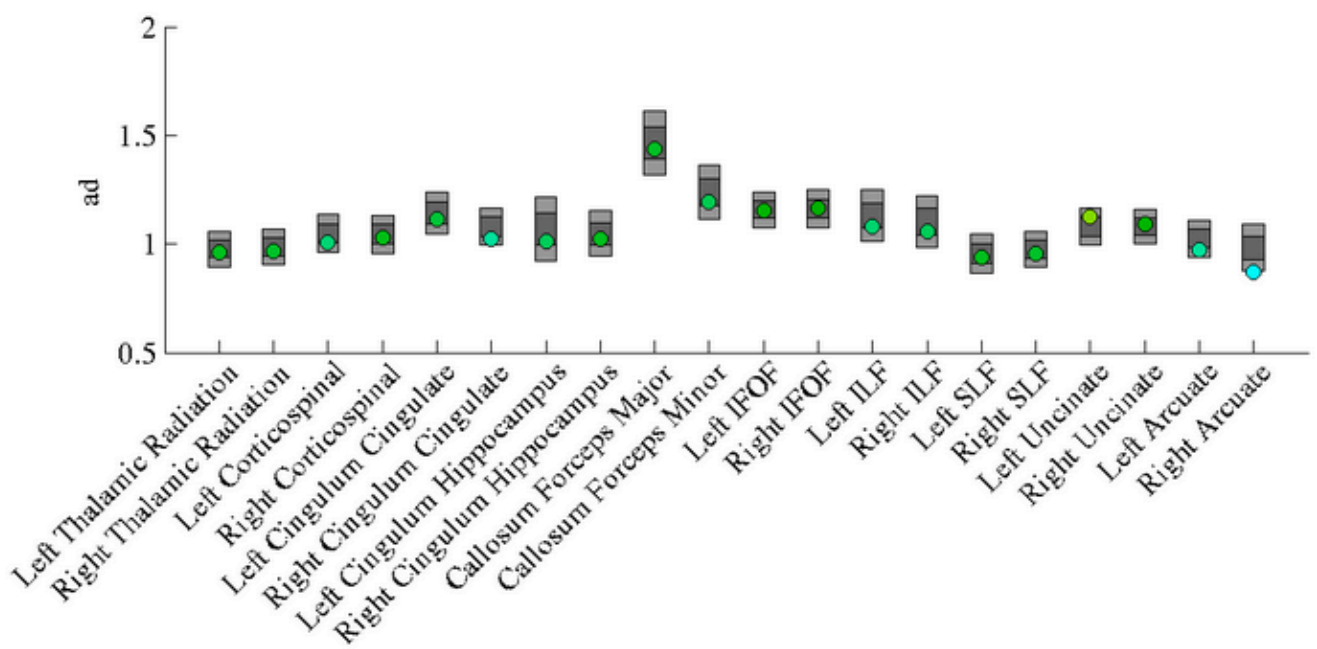


Analysis Summary

LAB
examplelab
DATA IDENTIFIER
exampledata_visual
VIEW RESULTS
Analysis Summary
Axial Diffusivity
Fractional Anisotropy



We are building computational tools that automate the comparison of individual patients with groups of matched controls



Project on Scientific Transparency

Saving Science – Starting with Neuroscience

“ The Project on Scientific Transparency [PoST] is a multi-site collaborative effort that aims to revolutionize the way that neuroscience imaging research is done. By developing simple tools that permit investigators – from many disciplines and institutions – to share data and analytical methods we hope to increase scientific transparency and data exchange.

- Maps and models
- White matter methods
- Reading

Alyssa Brewer

Michal Ben-Shachar

Serge Dumoulin



Bob Dougherty

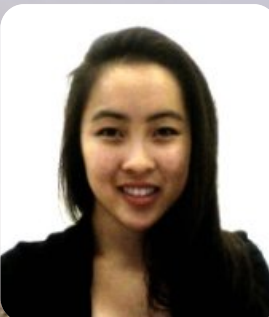


Rosemary Le

Franco Pestilli

Hiromasa Takemura

Jason Yeatman



Andreas Rauschecker



Nathan Witthoft

Kendrick Kay

Jon Winawer

Ariel Rokem



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