# Diffusion Tensor Imaging

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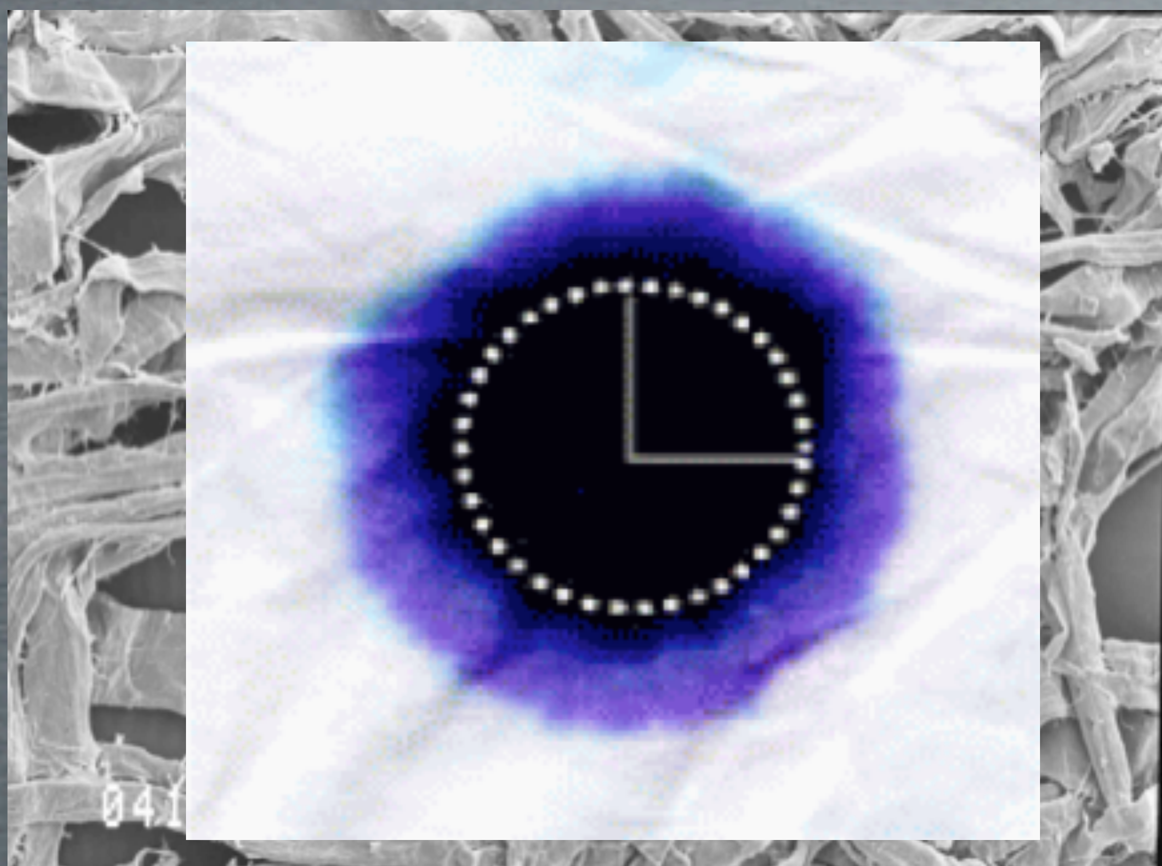
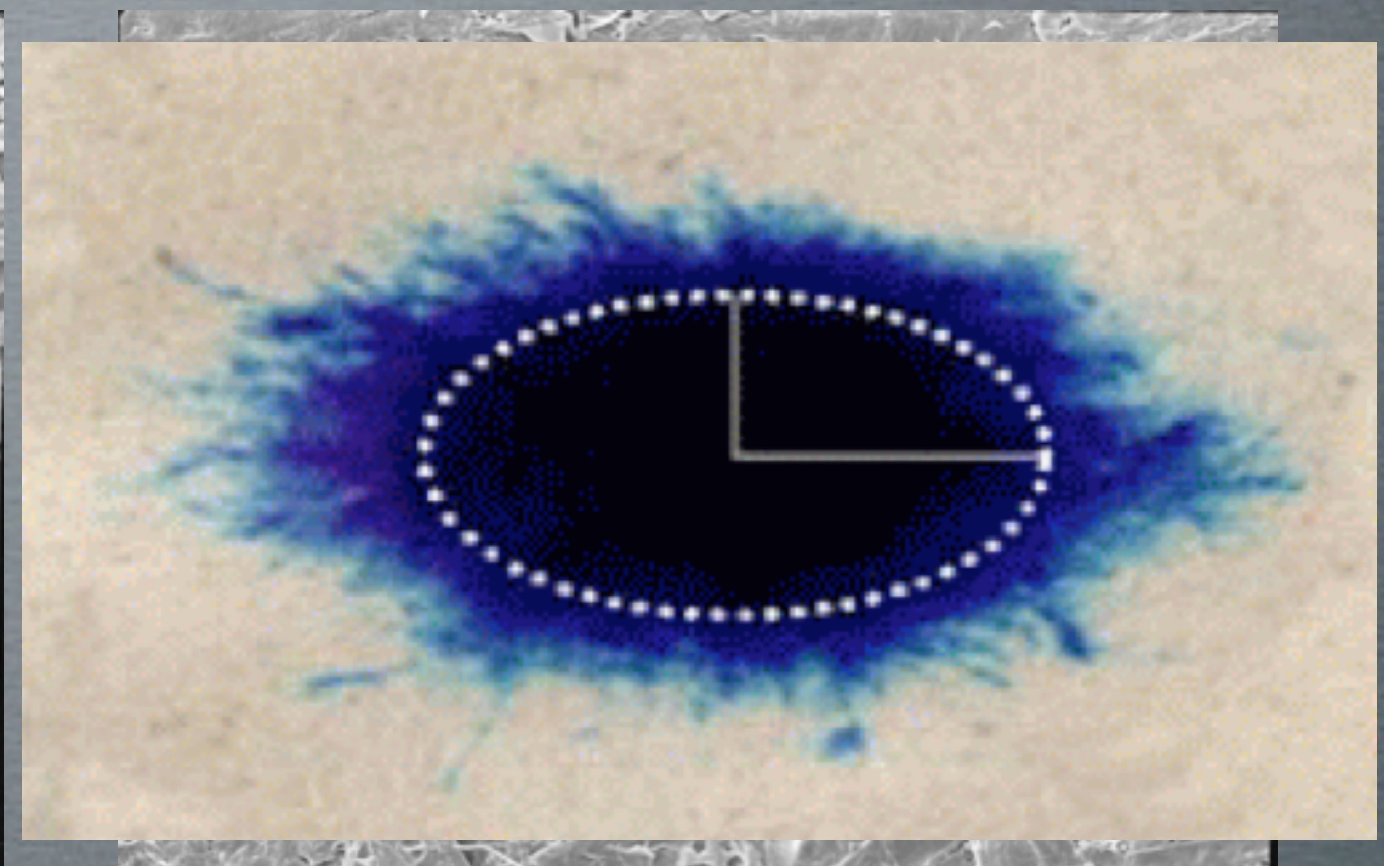
# Macroscopic Information from Microscopic Measurements



tissue paper



newspaper

diffusing ink in paper

# What is diffusion and why do we care about it?

Self-diffusion is the thermally driven random motions of molecules that occurs in the absence of a concentration gradient

The self-diffusion of water is ongoing in the human body and its characteristics depend on the local tissue architecture and physiology

Therefore the ability to measure self-diffusion offers the possibility of non-invasively measuring tissue structure and physiology

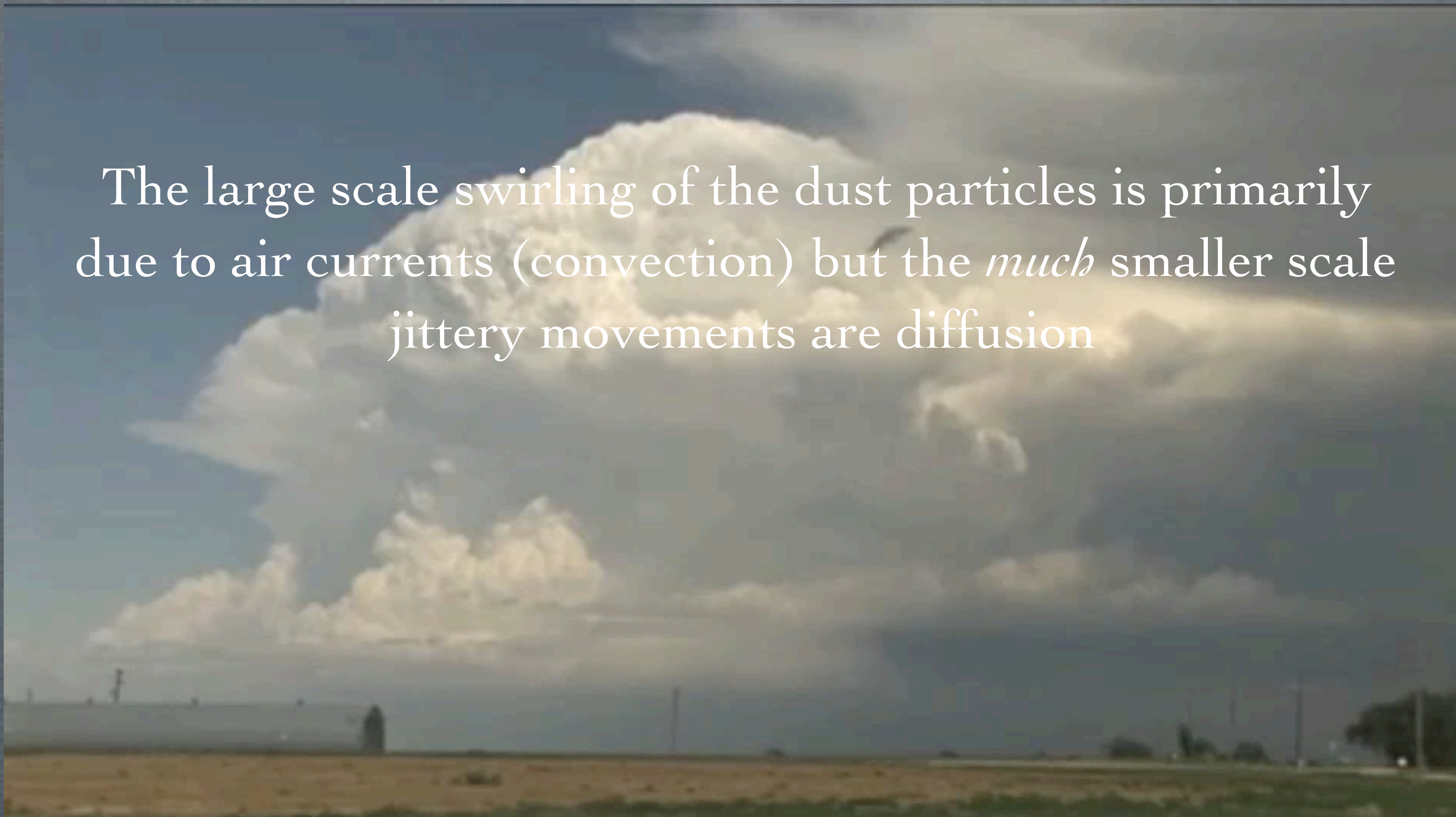
# Inferring the Microscopic from The Macroscopic

Lucretius (99BC-55BC)

Roman philosopher and poet

http://www.youtube.com/eYeFractal

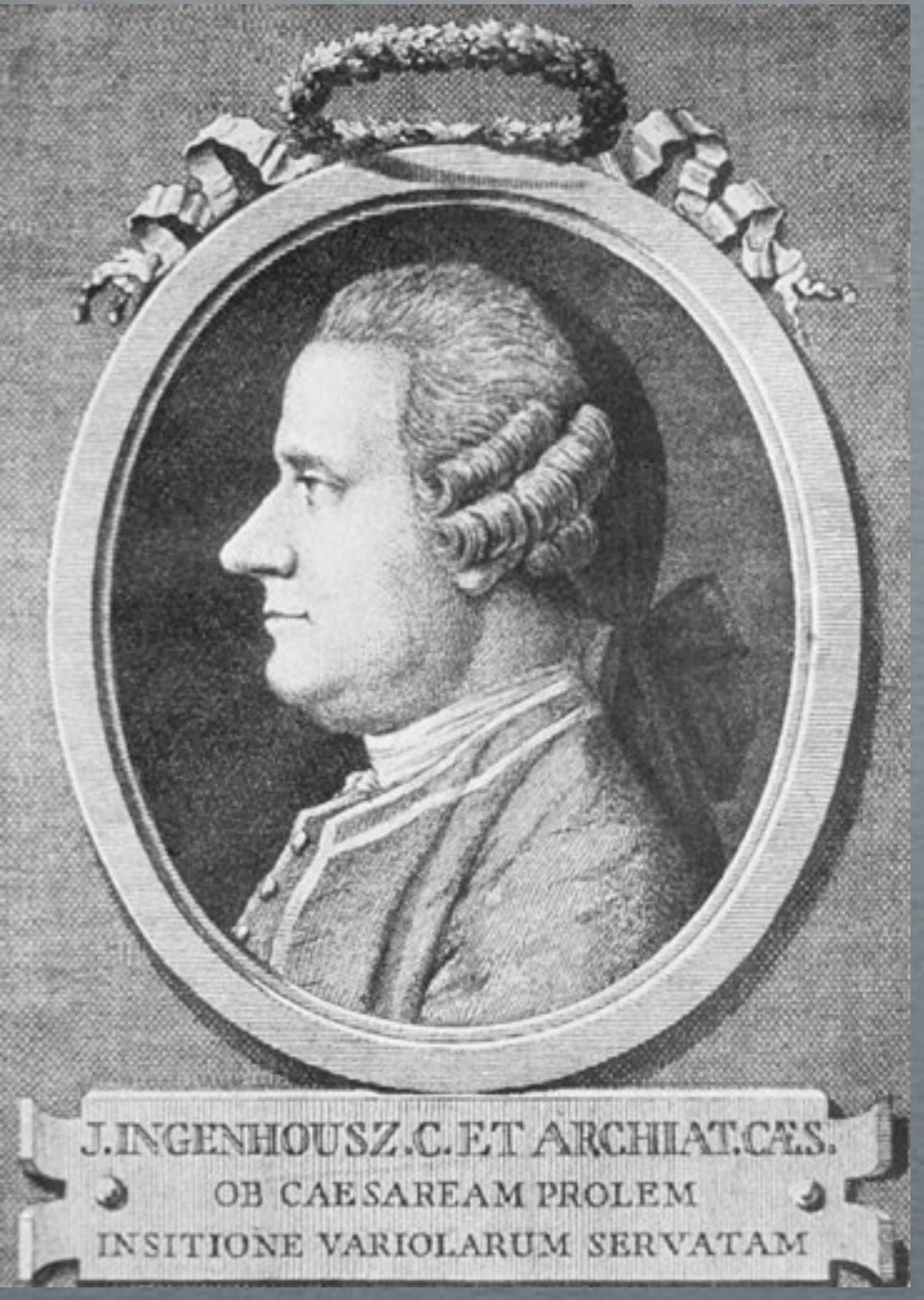
# Convection vs Diffusion
## A Cautionary Note



The large scale swirling of the dust particles is primarily due to air currents (convection) but the *much* smaller scale jittery movements are diffusion

Convection

# A Brief History of Diffusion Measurement

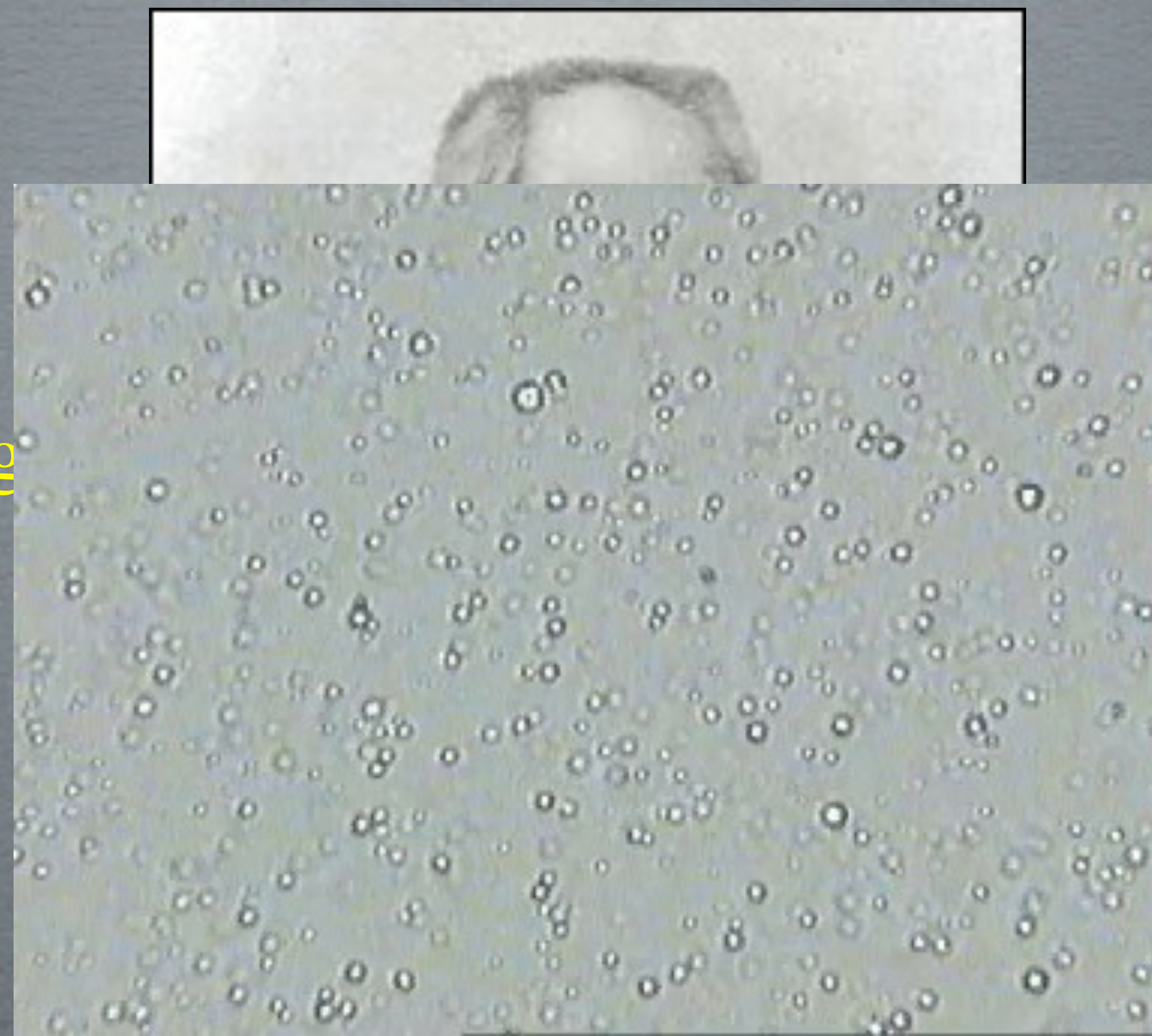



Jan Ingenhousz (1730 – 1799)
Dutch botanist and physiologist

Described the "irregular movements" of coal dust on the surface of alcohol

# A Brief History of Diffusion Measurement

"Brownian Motion"



irreg … ater

Experiment: Repeat pollen experiment using tiny shards of window glass

Robert Brown (1773 – 1858)

British botanist and surgeon

Result: Same!

Conclusion: Not alive

Theory: ???

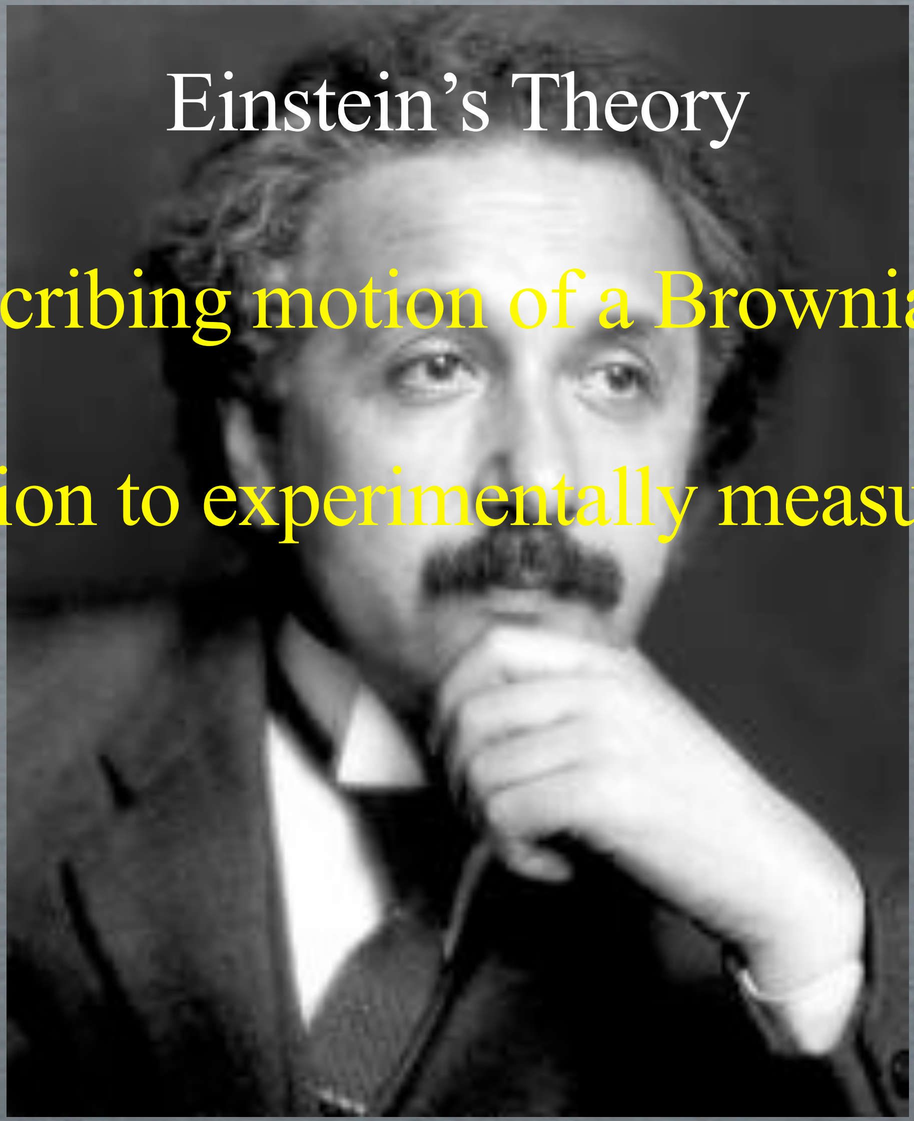
http://www.microscopy-uk.org.uk

# Einstein's Theory of Brownian Motion

Einstein's Theory

Part 1: Equation describing motion of a Brownian particle

Part 2: Relate diffusion to experimentally measurable quantities



Albert Einstein (1879 – 1955)
German patent clerk and physicist

# Einstein Theory of Brownian Motion
# Part I

The particle density $\rho(x,t)$ at a position $x$ at time $t$ obeys

$$\frac{\partial \rho}{\partial t} = D \frac{\partial^2 \rho}{\partial x^2}$$

change with time

diffusion coefficient

change with space

**The Diffusion Equation**

# Einstein Theory of Brownian Motion
## Part I

The solution to the Diffusion Equation
for particles initially at location $x_0$

$$\rho(x,t) = \frac{1}{\sqrt{4\pi D t}}\, e^{-(x-x_0)^2/4Dt}$$

This is a Gaussian (or Normal) distribution
with mean position

$$\bar{x} = x_0$$

and variance in the position

$$\sigma_x^2 = \overline{(x - x_0)^2} = 2Dt$$

# Einstein Theory of Brownian Motion
## Part I

What does this mean?

$$\bar{x} = x_0$$

implies that, on *average*,
the particles do not move from their initial position

$$\sigma_x^2 = 2Dt$$

implies that the *variance* of a Brownian particle's position is proportional to the diffusion coefficient $D$ and time $t$

# Einstein Theory of Brownian Motion
# Part I

Einstein argued that the *displacement* of a Brownian particle is thus the RMS distance

$$\Delta x = \sqrt{\overline{(x - x_0)^2}} = \sqrt{2Dt}$$

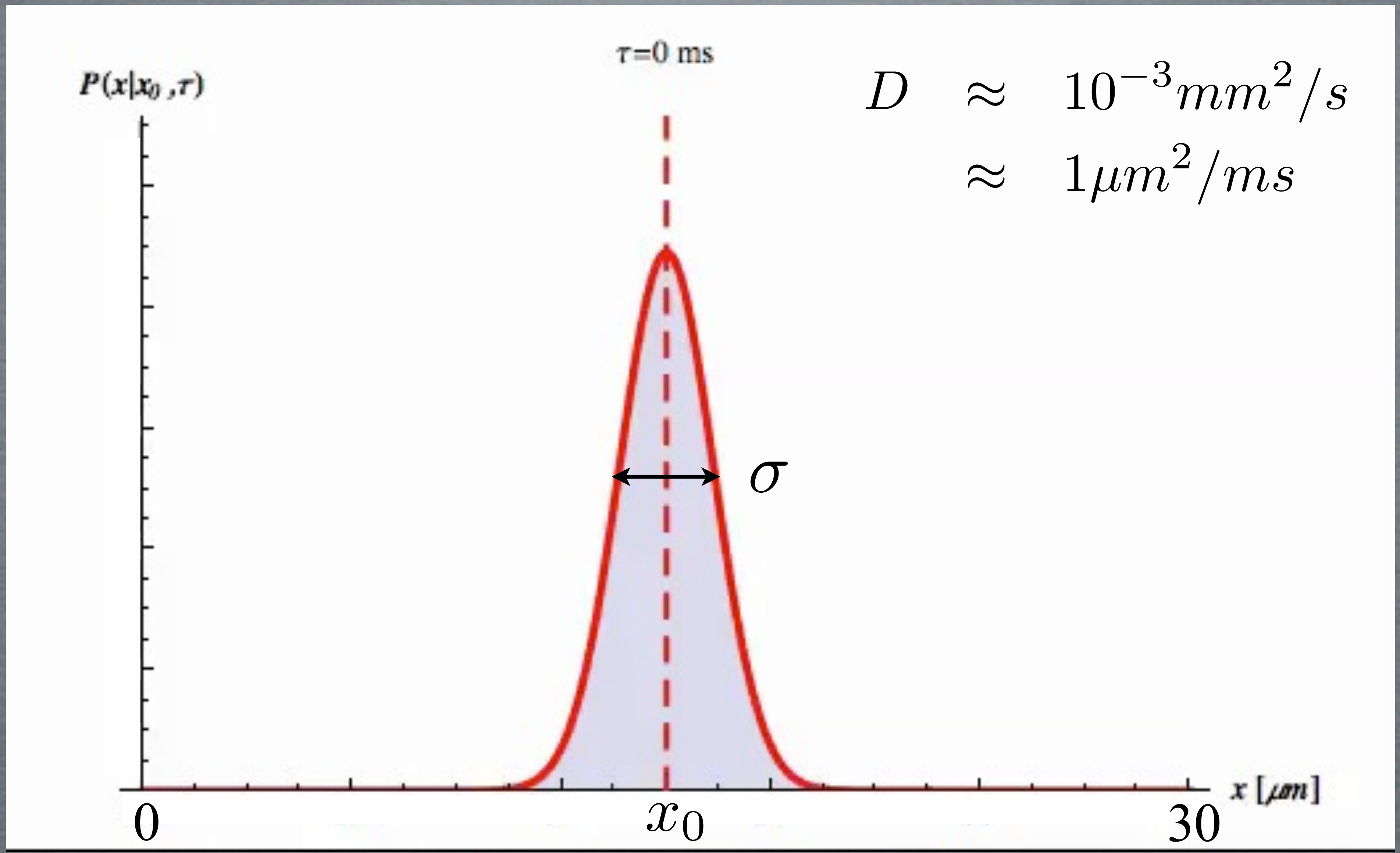
and thus *not* linearly proportional to time (like flow), but to the *square root of time*

Diffusion in Brain Tissue:

D ≅ 1 μ²/ ms = (0.001 mm²/s)

For t=100 msec, Δx ≅ 14 μ

# Gaussian Diffusion




$$P(x|x_o,\tau) = \frac{1}{\sqrt{4\pi D\tau}} e^{-\frac{(x-x_o)^2}{4\pi D\tau}}$$

$$\sigma = \sqrt{2D\tau}$$

# Einstein Theory of Brownian Motion
# Part I

## Diffusion vs Flow

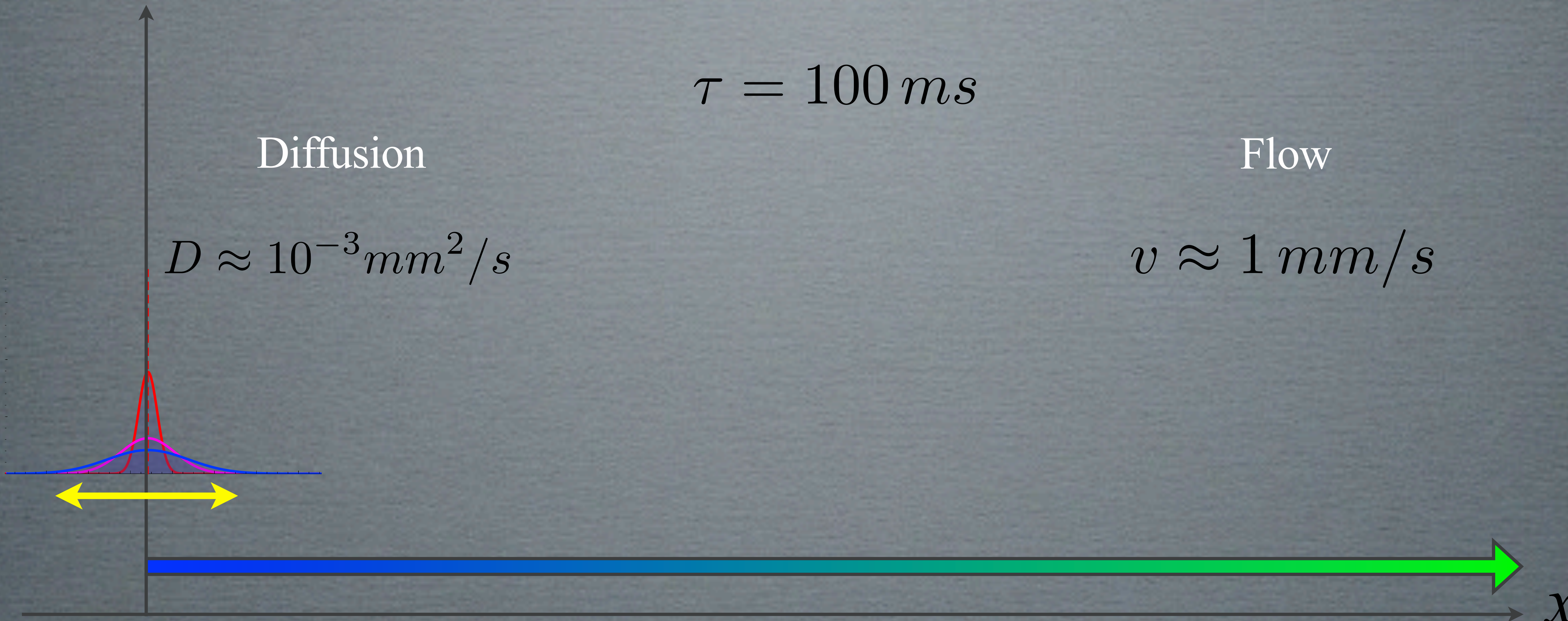
$$\tau = 100\, ms$$

Diffusion

Flow

$D \approx 10^{-3} mm^2/s$

$v \approx 1\, mm/s$




$\Delta x \approx 14\, \mu m$

$\Delta x \approx 100\, \mu m$

# Einstein Theory of Brownian Motion
## Part II

The diffusion coefficient is

$$D = \alpha \frac{T}{\eta r}$$

where

$T$ = temperature

$\eta$ = viscosity

$r$ = particle radius

$\alpha$ = constant = $\frac{R}{6\pi N}$

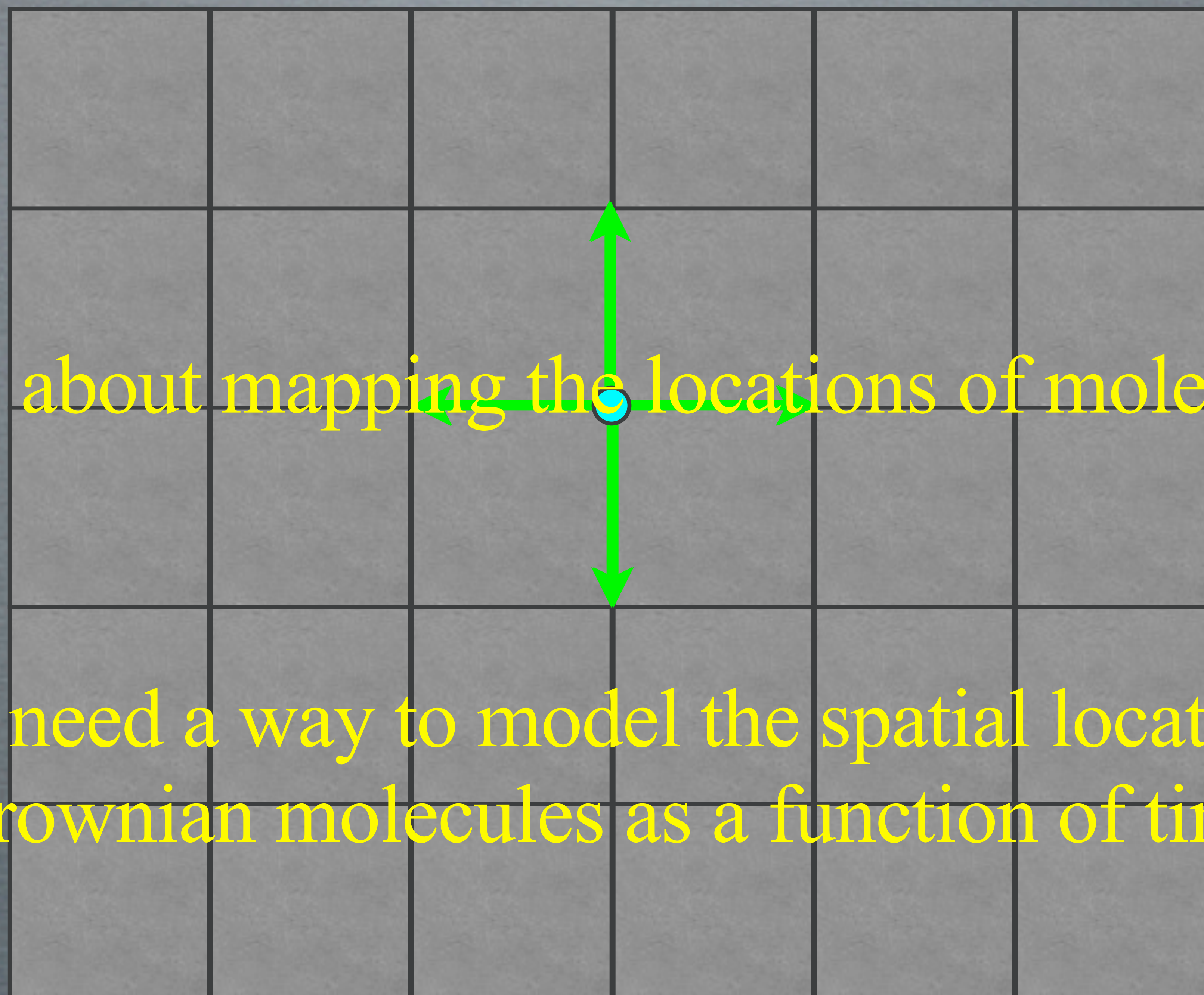
$R$: gas constant

$N$: Avogadro's number

Diffusion coefficient goes up with temperature and down with viscosity and particle radius

*It's sensitive to the local environment!*

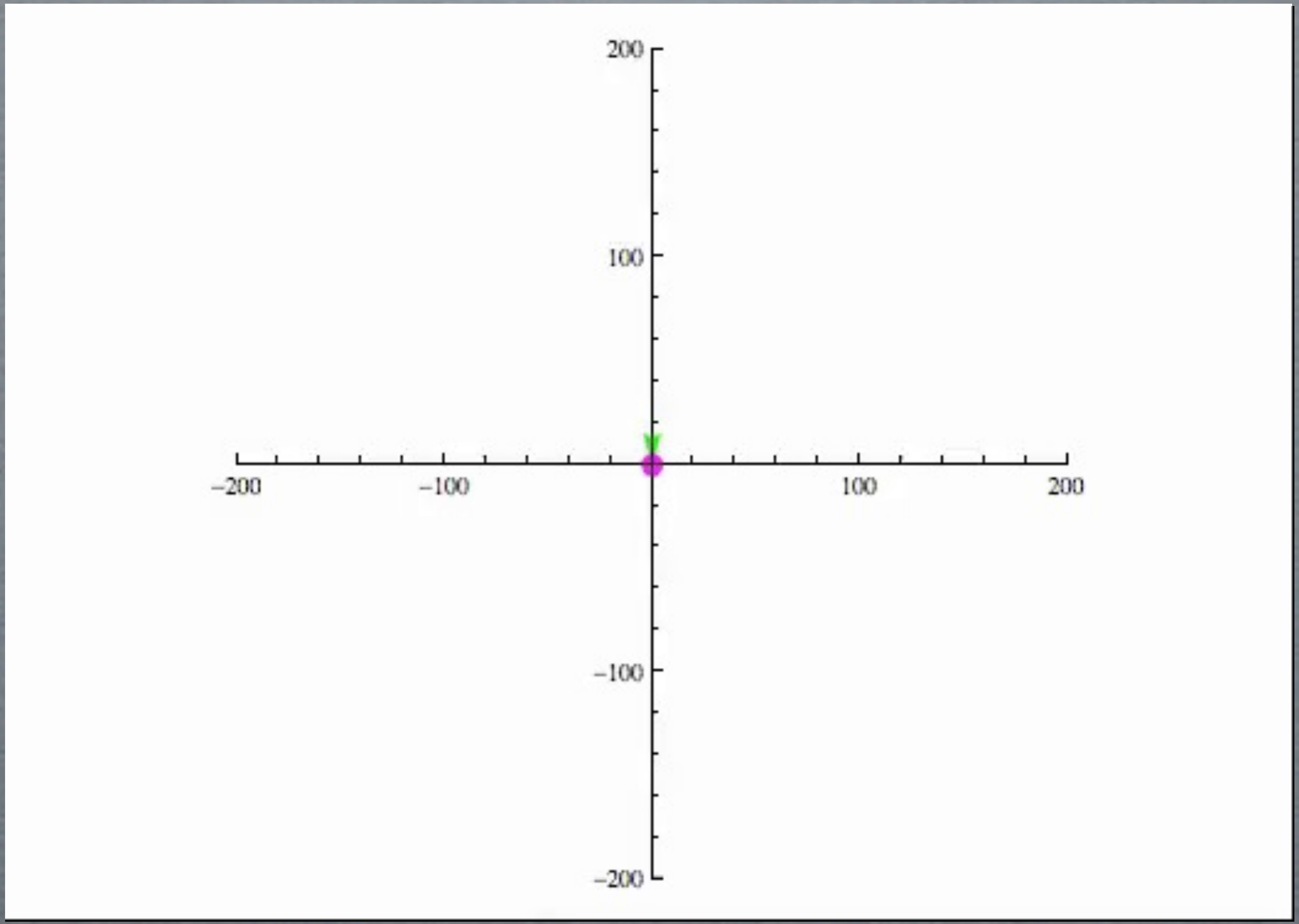
# Modeling diffusion: Random Walk



MRI is all about mapping the locations of molecules ...

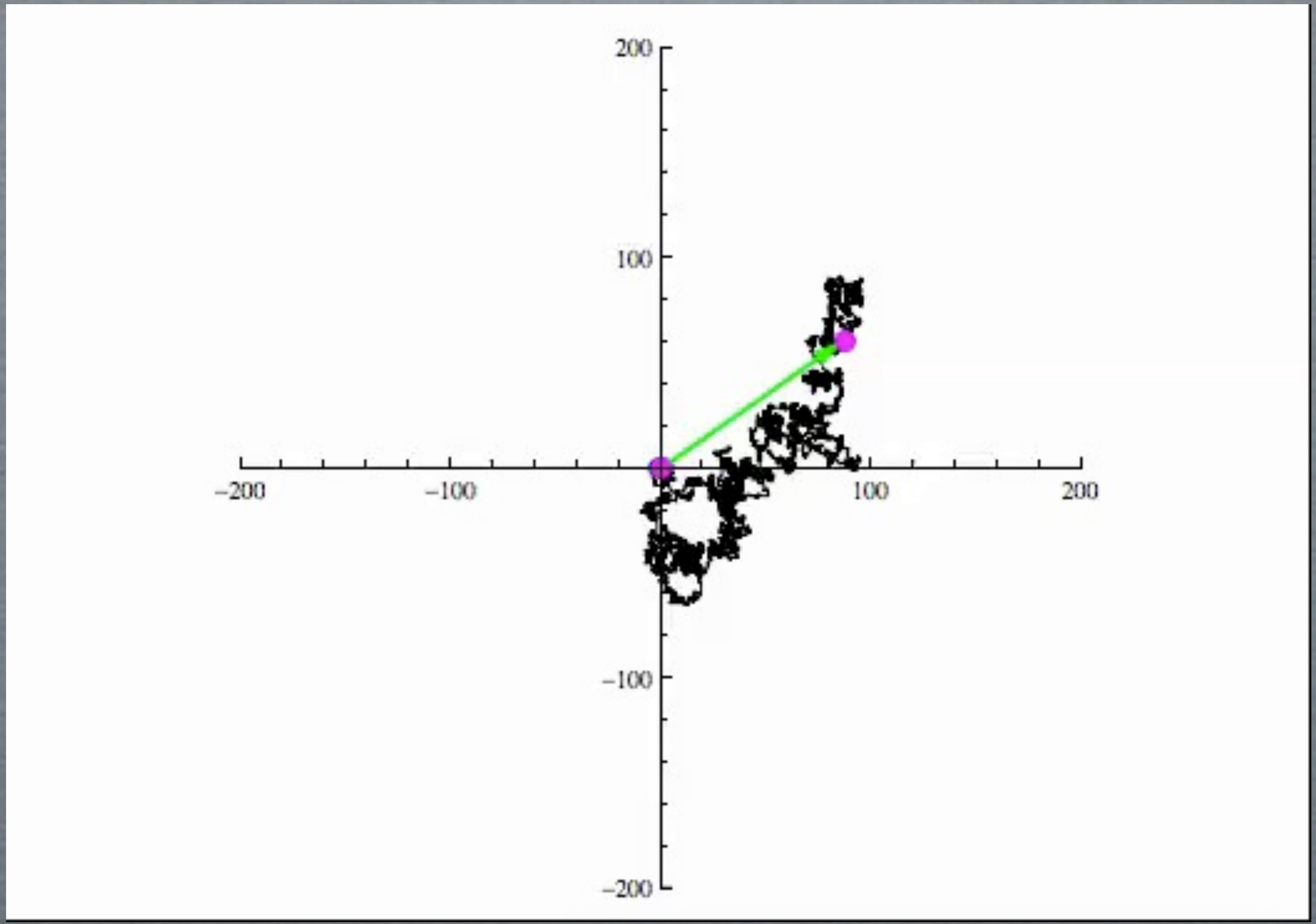
... we need a way to model the spatial locations of Brownian molecules as a function of time

# Modeling diffusion: Random Walk




$$\tau = \text{constant}$$

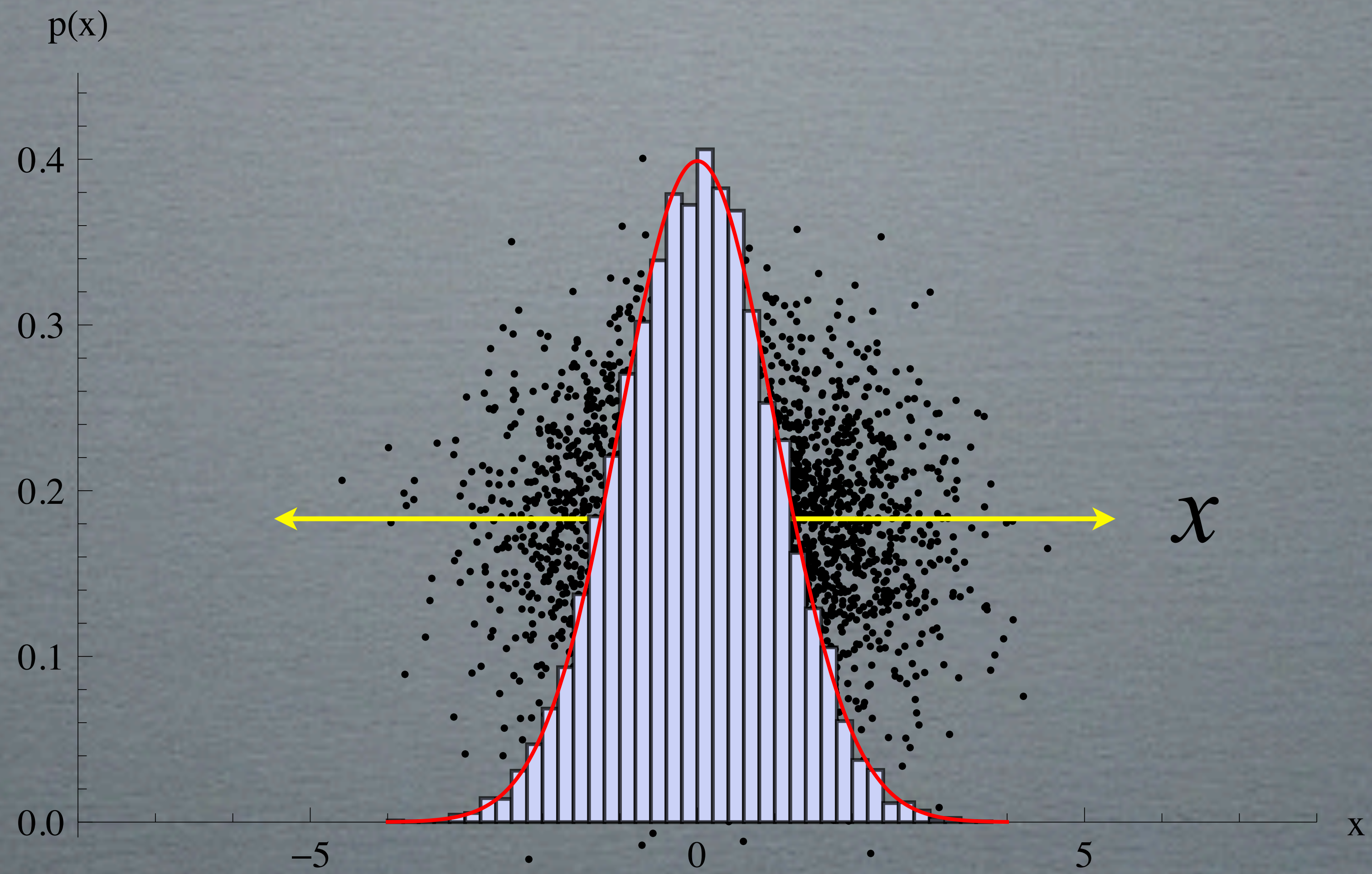
# Modeling diffusion: Random Walk




$$\tau = \text{constant}$$

# Modeling diffusion: Random Walk

## The distribution of particles after a time τ

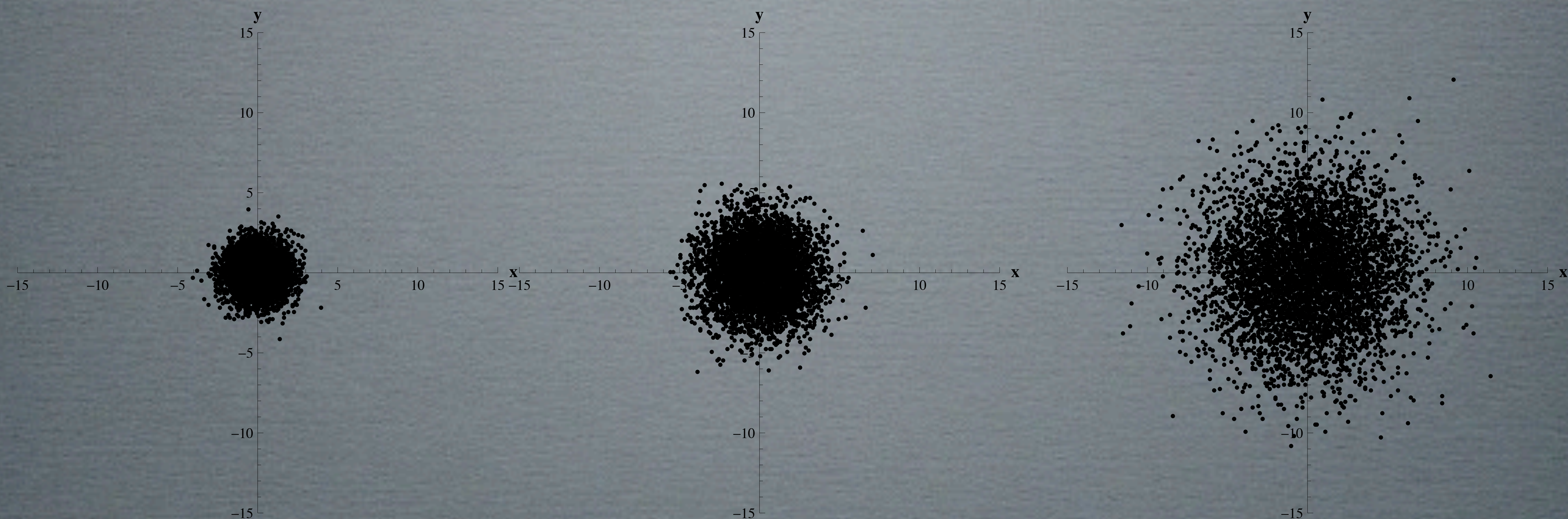



## Gaussian diffusion

$$P(x|x_0,\tau) \simeq N(x_0,\sigma^2)$$

$$= \frac{1}{\sqrt{4\pi D\tau}} e^{-\frac{(x-x_o)^2}{4\pi D\tau}}$$

# ISOTROPIC DIFFUSION IN 2D

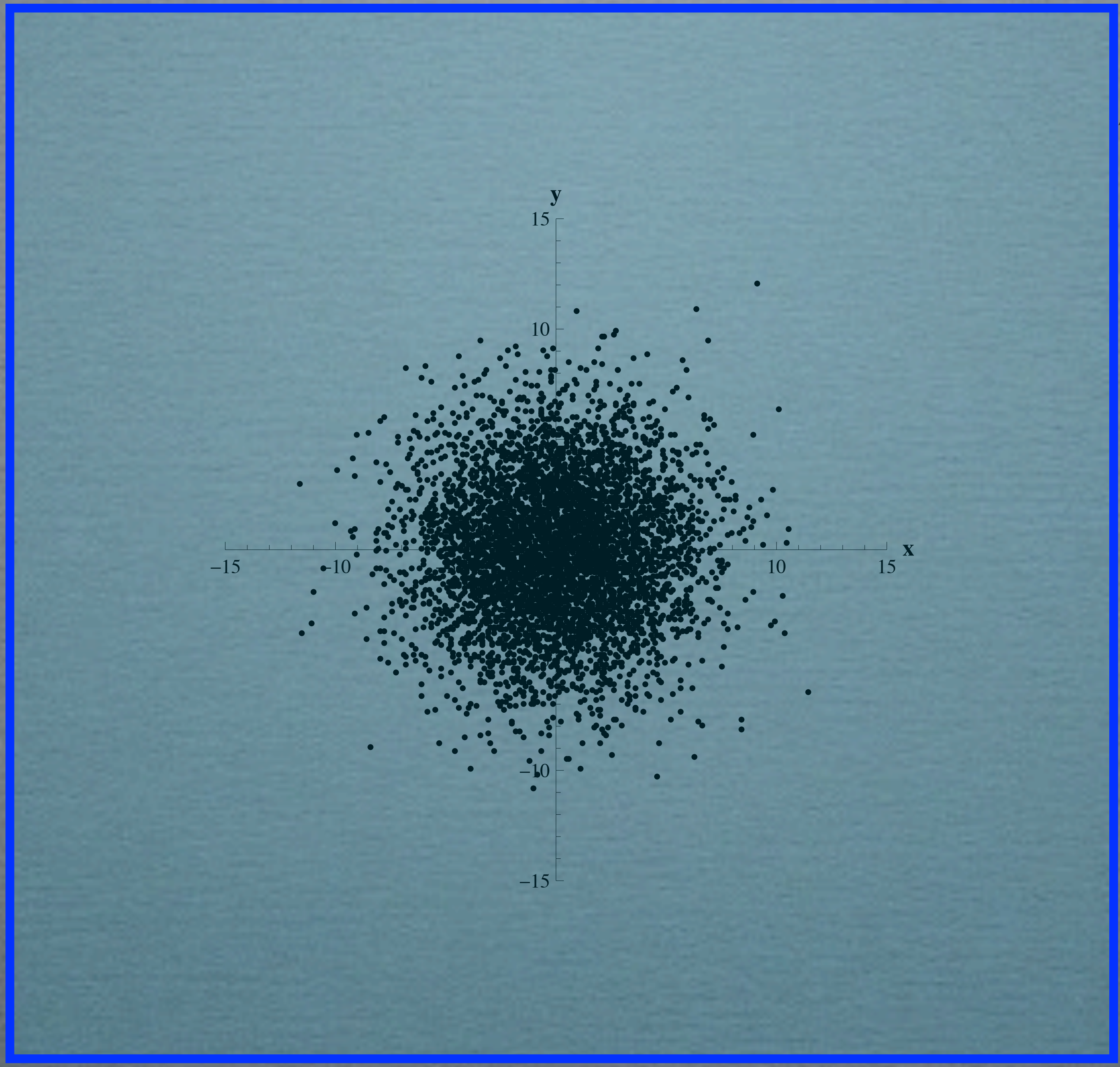



$\tau = 1\, ms$ $\qquad$ $\tau = 10\, ms$ $\qquad$ $\tau = 100\, ms$

# Diffusion Dimensions

voxel

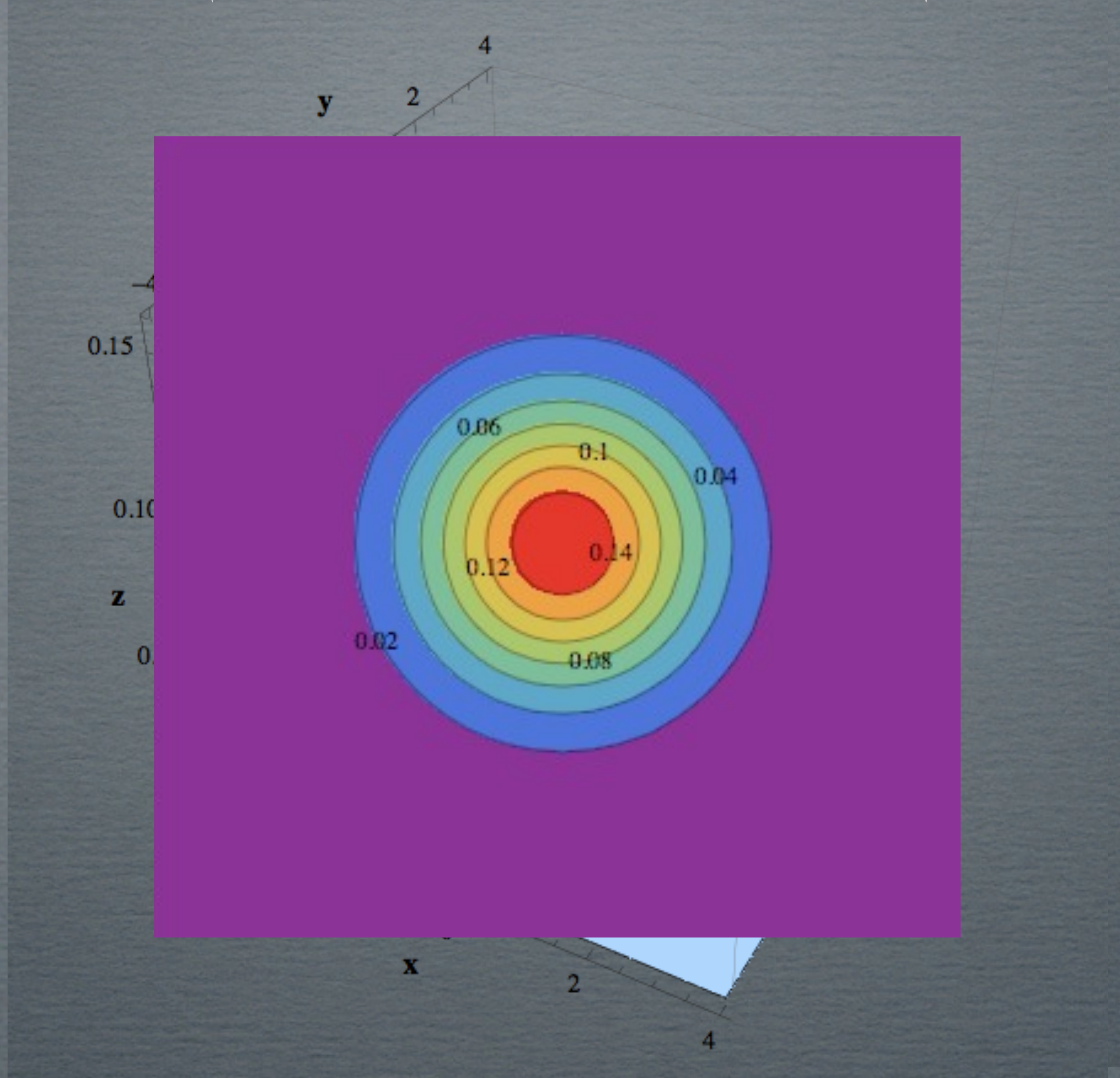
$$\tau = 100\,ms$$



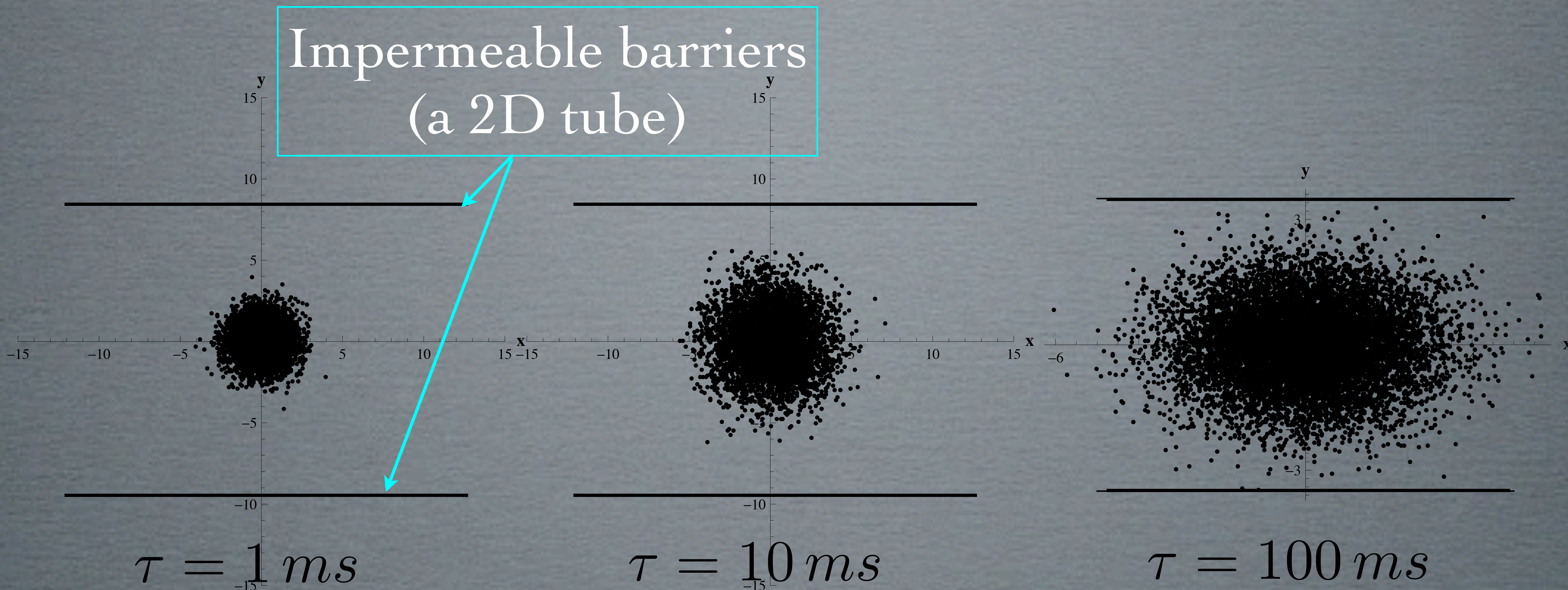

$1.5\,mm$

$$\Delta x \approx \left(\frac{1}{1000}\right) \text{a typical imaging voxel dimension}$$

# Probability Contours (isotropic diffusion)



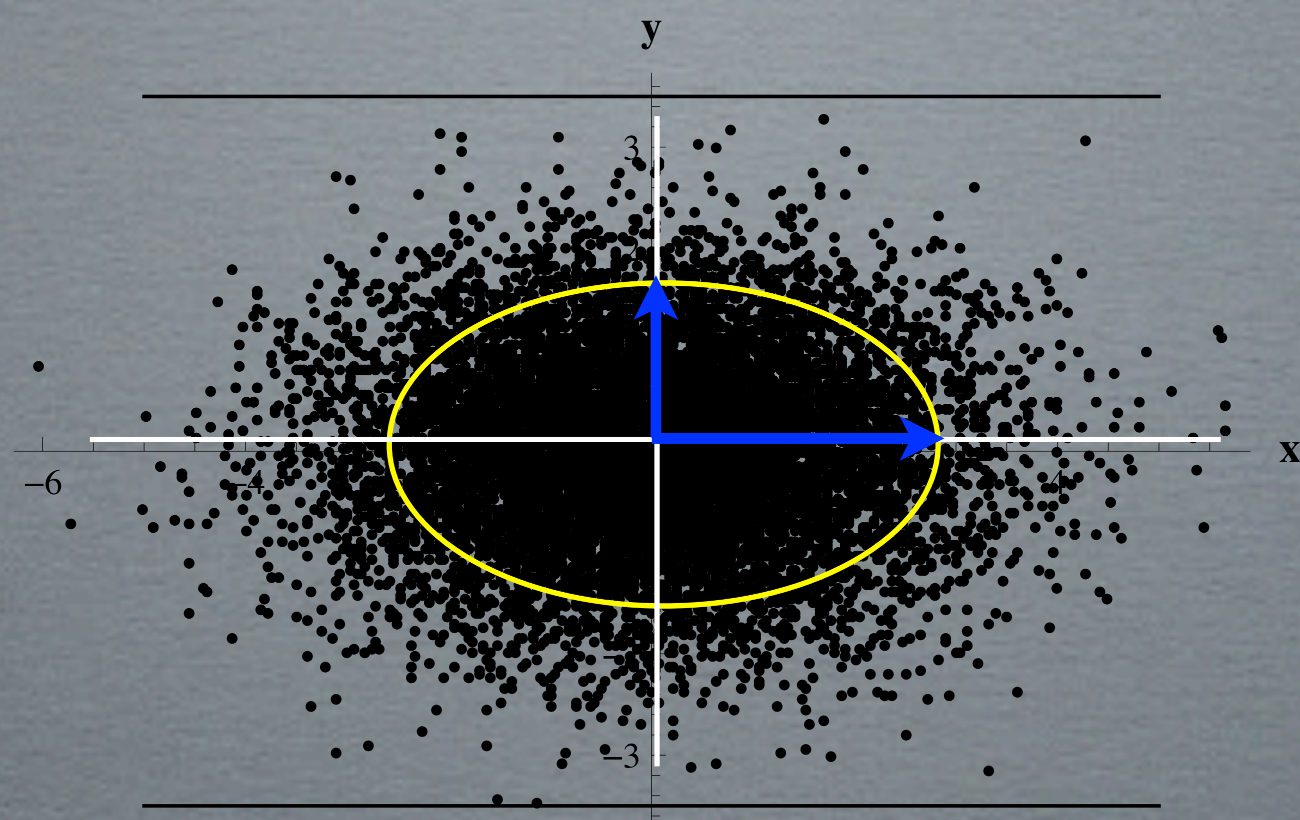
# Anisotropic diffusion in 2D




*Restricted diffusion*

# Anisotropic diffusion in 2D

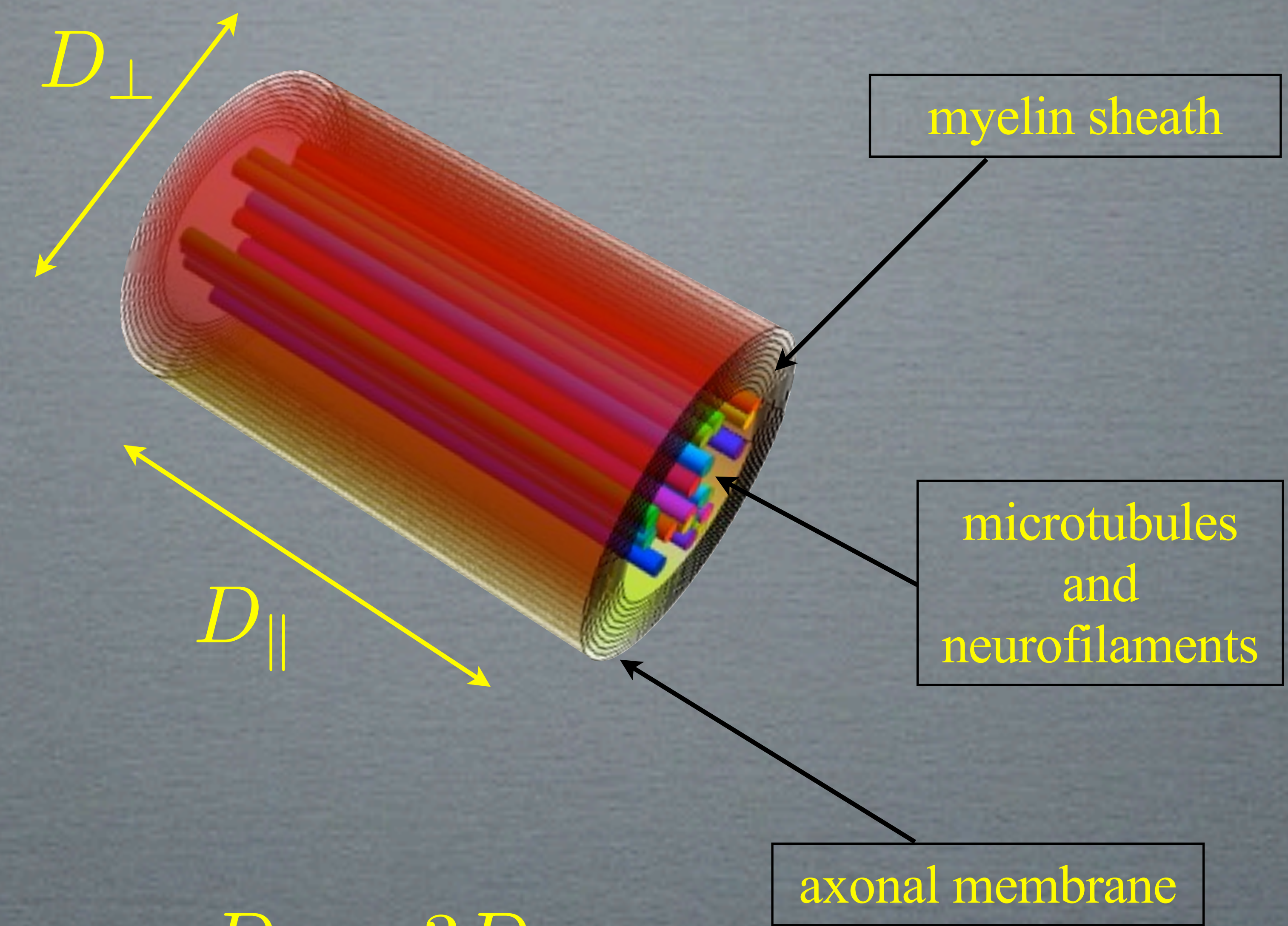
$$P(\boldsymbol{r}|\boldsymbol{r}_0, \tau) \sim N(\boldsymbol{r}_0, \boldsymbol{\Sigma})$$




Covariance matrix

$$\Sigma = \begin{pmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_y^2 \end{pmatrix}$$

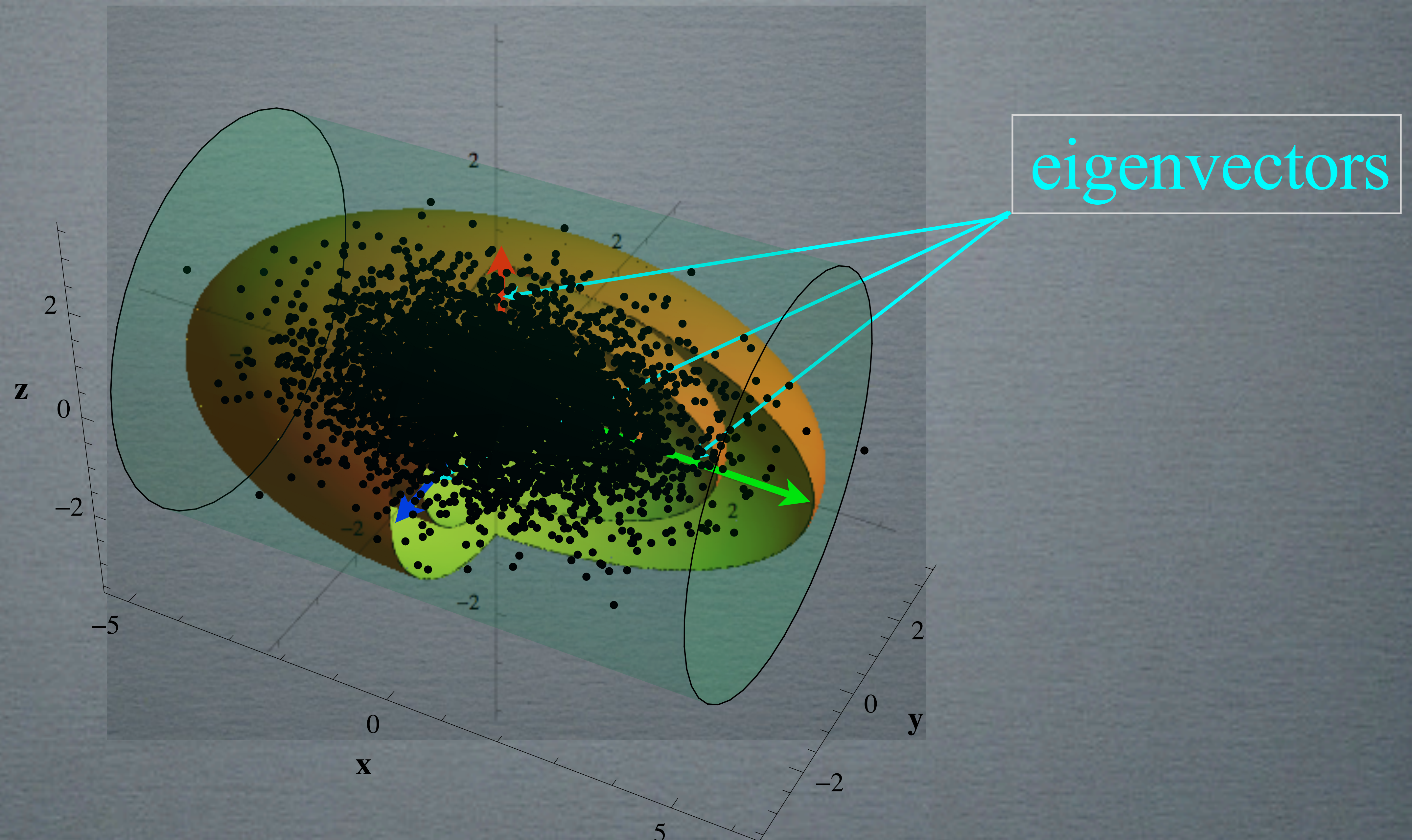
# Diffusion Anisotropy in neural tissues




$$D_\parallel \approx 3D_\perp$$

$$(1.2\mu^2/ms) \qquad (0.4\mu^2/ms)$$

# Diffusion Anisotropy in 3D



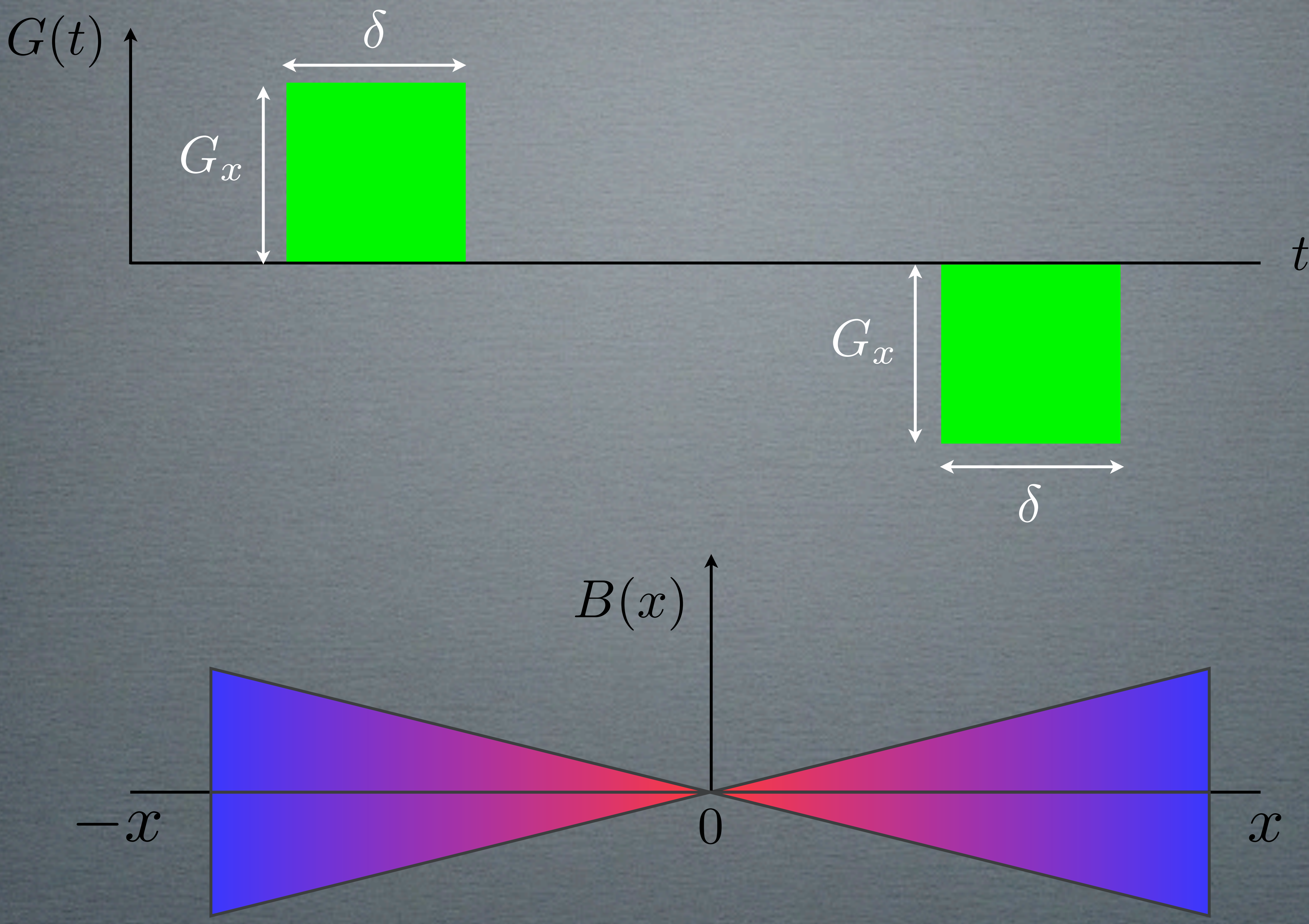

probability contours in 3D

# The Sensitivity of MRI to Diffusion

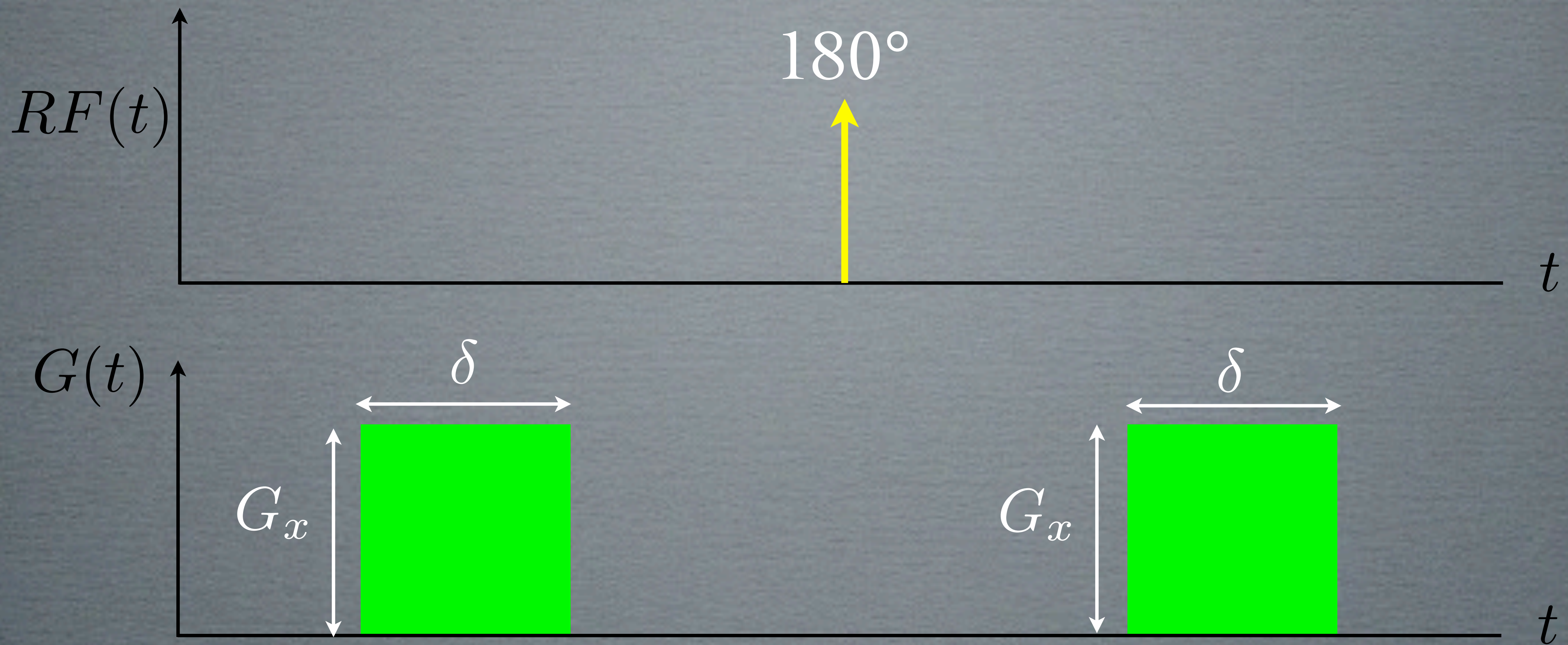
We've described the spatial and Temporal characteristics of the molecules.

What is the influence of this on the MRI signal?

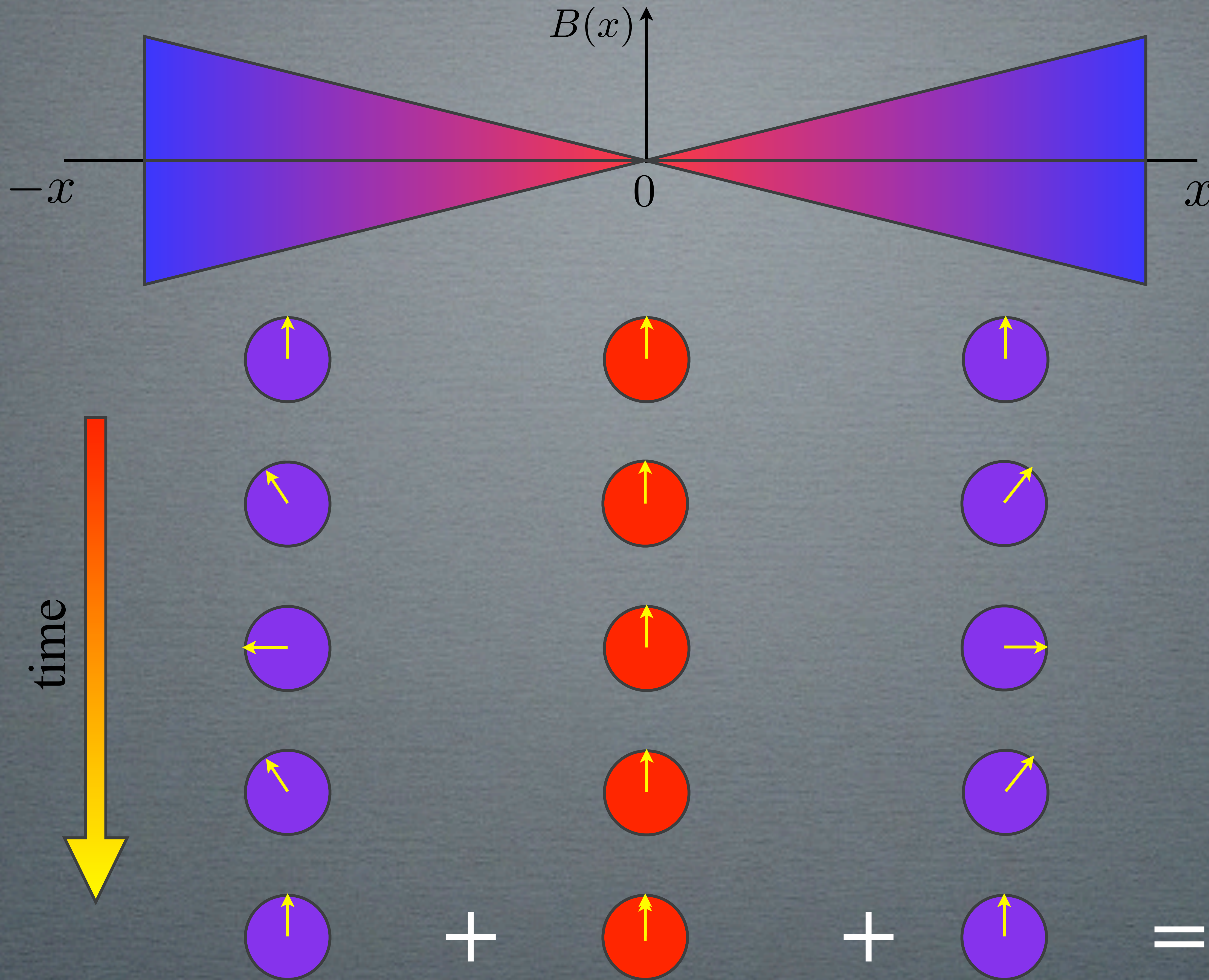
# The Bipolar Gradient Pulse (gradient echo)



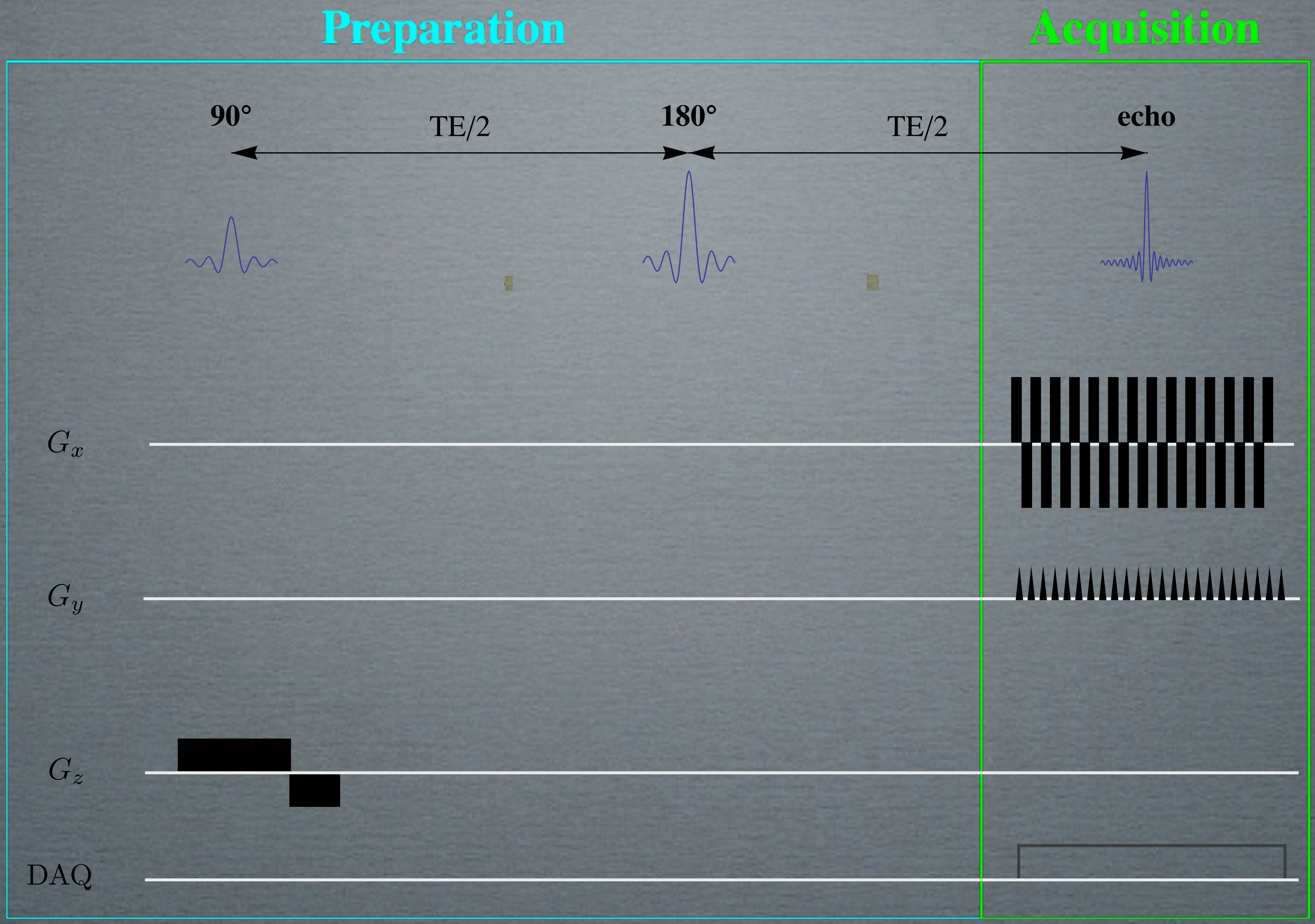
# The Bipolar Gradient Pulse (spin echo)



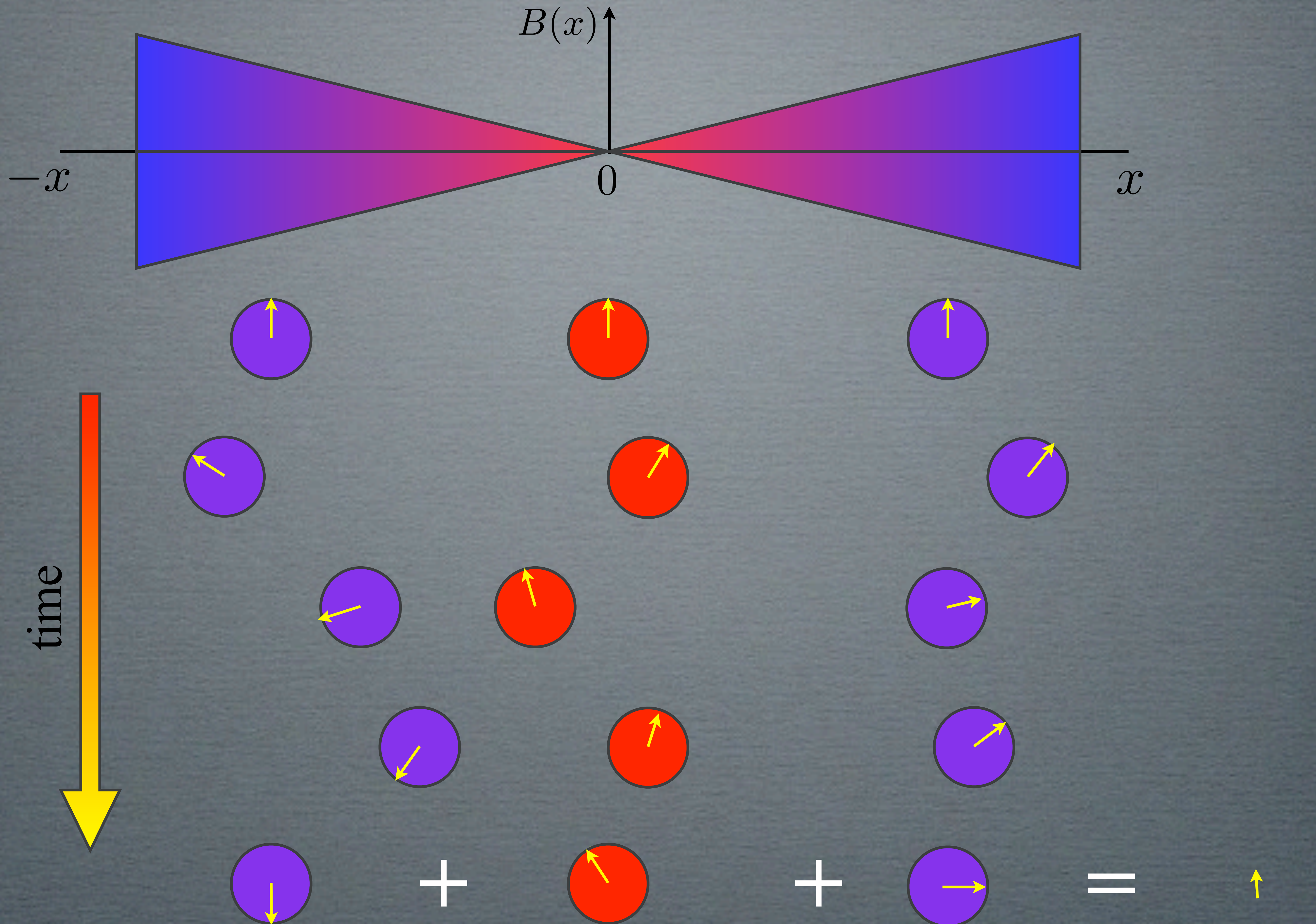
# Stationary Spins in Bipolar Pulse



# Echo-Planar Imaging



# Diffusing Spins in Bipolar Pulse



# Key Fact

Only diffusion along the direction of the applied gradient has an effect

# EARLY NMR MEASUREMENTS OF DIFFUSION

PHYSICAL REVIEW VOLUME 80, NUMBER 4 NOVEMBER 15, 1950

## Spin Echoes*†

E. L. HAHN‡
*Physics Department, University of Illinois, Urbana, Illinois*
(Received May 22, 1950)

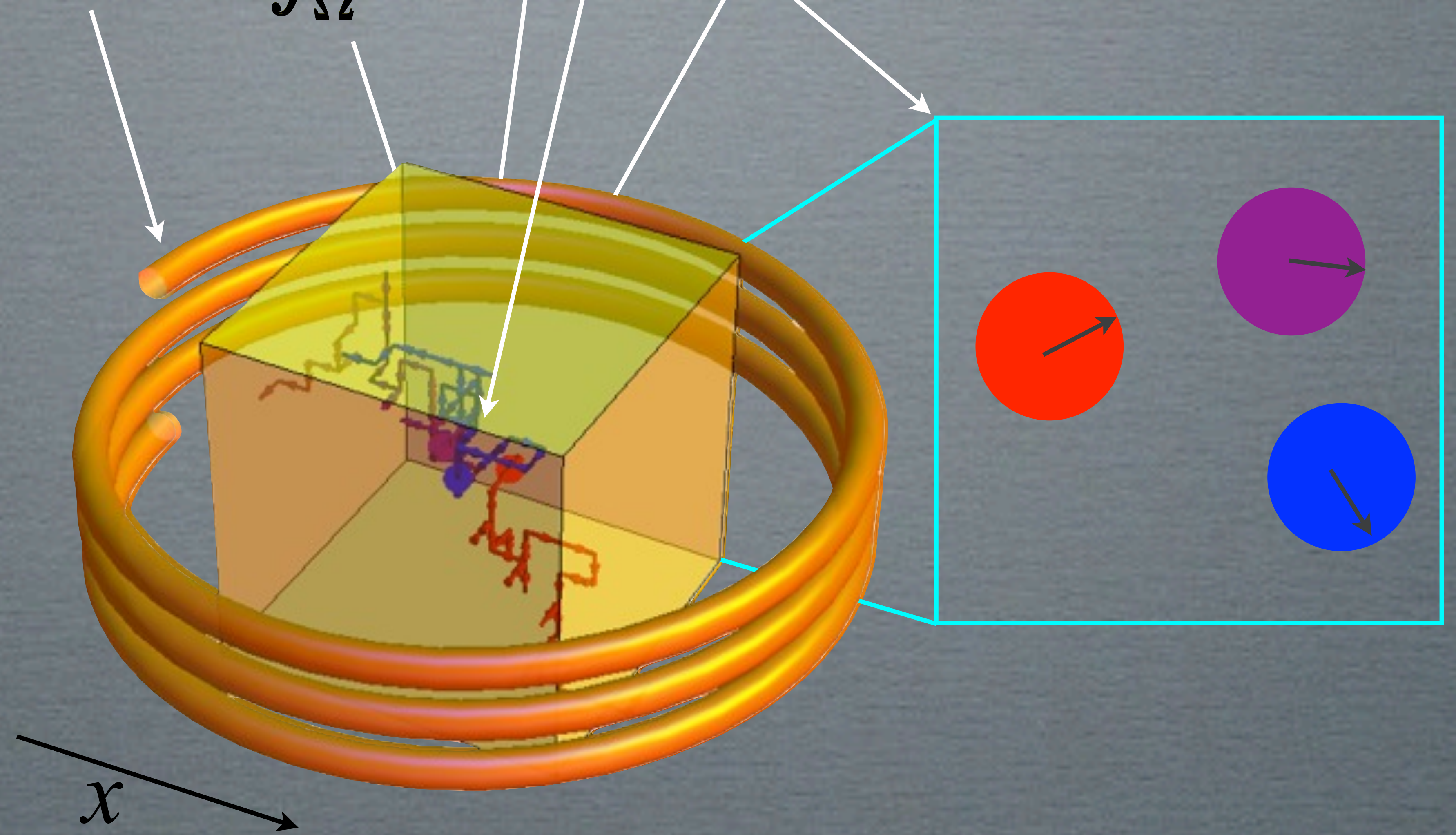
Intense radiofrequency power in the form of pulses is applied to an ensemble of spins in a liquid placed in a large static magnetic field $H_0$. The frequency of the pulsed r-f power satisfies the condition for nuclear magnetic resonance, and the pulses last for times which are short compared with the time in which the nutating macroscopic magnetic moment of the entire spin ensemble can decay. After removal of the pulses a non-equilibrium configuration of isochromatic macroscopic moments remains in which the moment vectors precess freely. Each moment vector has a magnitude at a given precession frequency which is determined by the distribution of Larmor frequencies imposed upon the ensemble by inhomogeneities in $H_0$. At times determined by pulse sequences applied in the past the constructive interference of these moment vectors gives rise to observable spontaneous nuclear induction signals. The properties and underlying principles of these spin echo signals are discussed with use of the Bloch theory. Relaxation times are measured directly and accurately from the measurement of echo amplitudes. An analysis includes the effect on relaxation measurements of the self-diffusion of liquid molecules which contain resonant nuclei. Preliminary studies are made of several effects associated with spin echoes, including the observed shifts in magnetic resonance frequency of spins due to magnetic shielding of nuclei contained in molecules.

Since there is an established gradient of the magnetic field over the volume of the sample, a molecule whose nuclear moment has been flipped initially in a field $H_0$, may, in the course of time $2\tau$, drift by Brownian motion into a randomly differing field $H_0$. Therefore, as $\tau$ is increased, a lesser number of moments participate in the generation of in-phase nuclear radio-frequency signals.

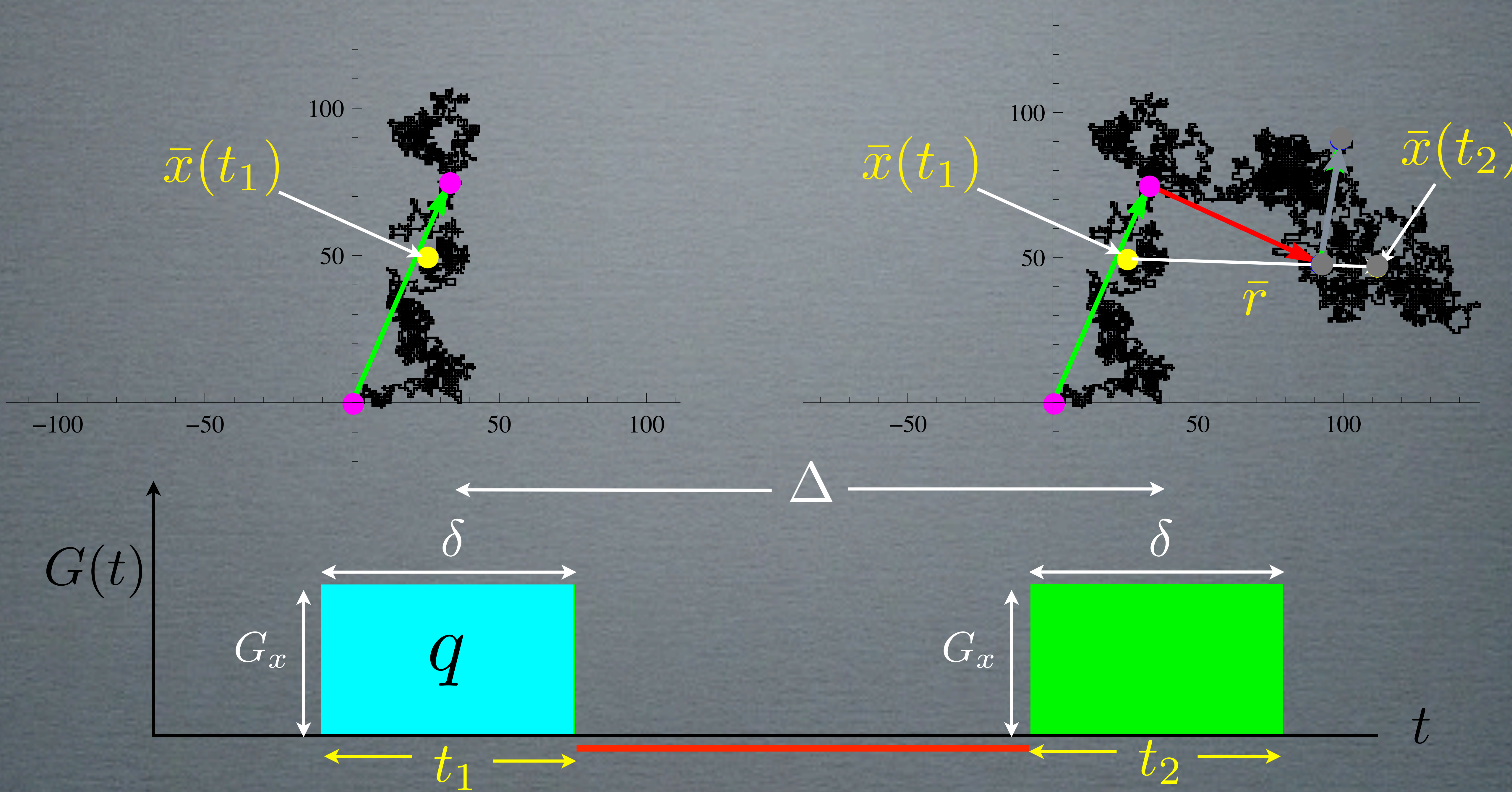
# The MRI Signal

**signal = Sum over all spins**

$$S(\varphi) = \int_{\Omega} dx\, \rho(x,t)\, e^{-i\varphi(x,t)}$$



# Diffusion phase in a Bipolar Pulse




$$\varphi(x,t) = \underbrace{G\delta}_{q} \underbrace{\left[\bar{x}(t_2) - \bar{x}(t_1)\right]}_{\bar{r}} = q\bar{r}$$

# The Diffusion Weighted Signal

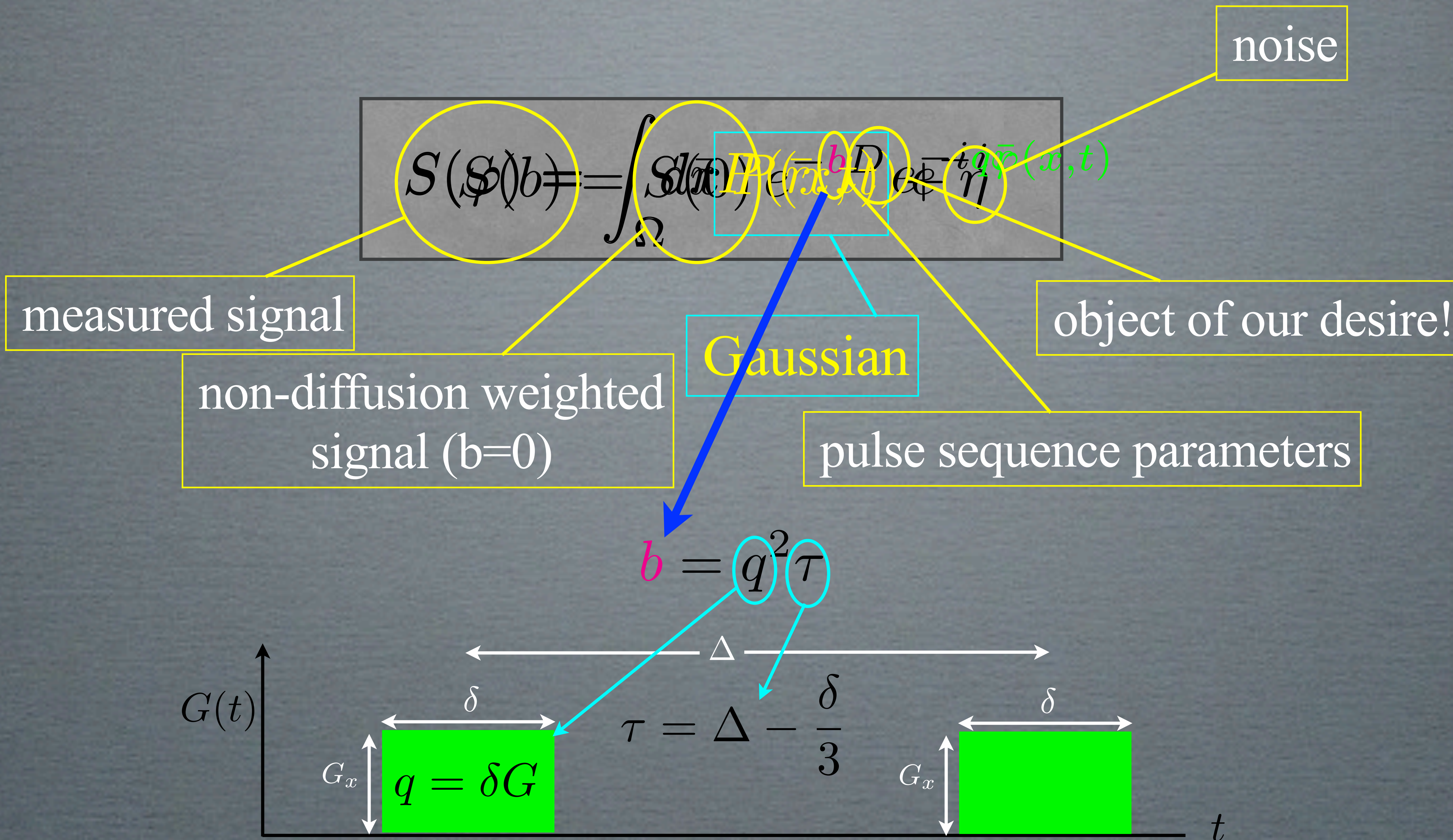
Signal and Distribution are
Fourier Transform pairs

$$\mathfrak{s}(\boldsymbol{q},\tau) = \int P(\bar{\boldsymbol{r}},\tau)e^{-i\boldsymbol{q}\cdot\bar{\boldsymbol{r}}}d\bar{\boldsymbol{r}}$$

$$P(\bar{\boldsymbol{r}},\tau) = \int \mathfrak{s}(\boldsymbol{q},\tau)e^{i\boldsymbol{q}\cdot\bar{\boldsymbol{r}}}dq$$

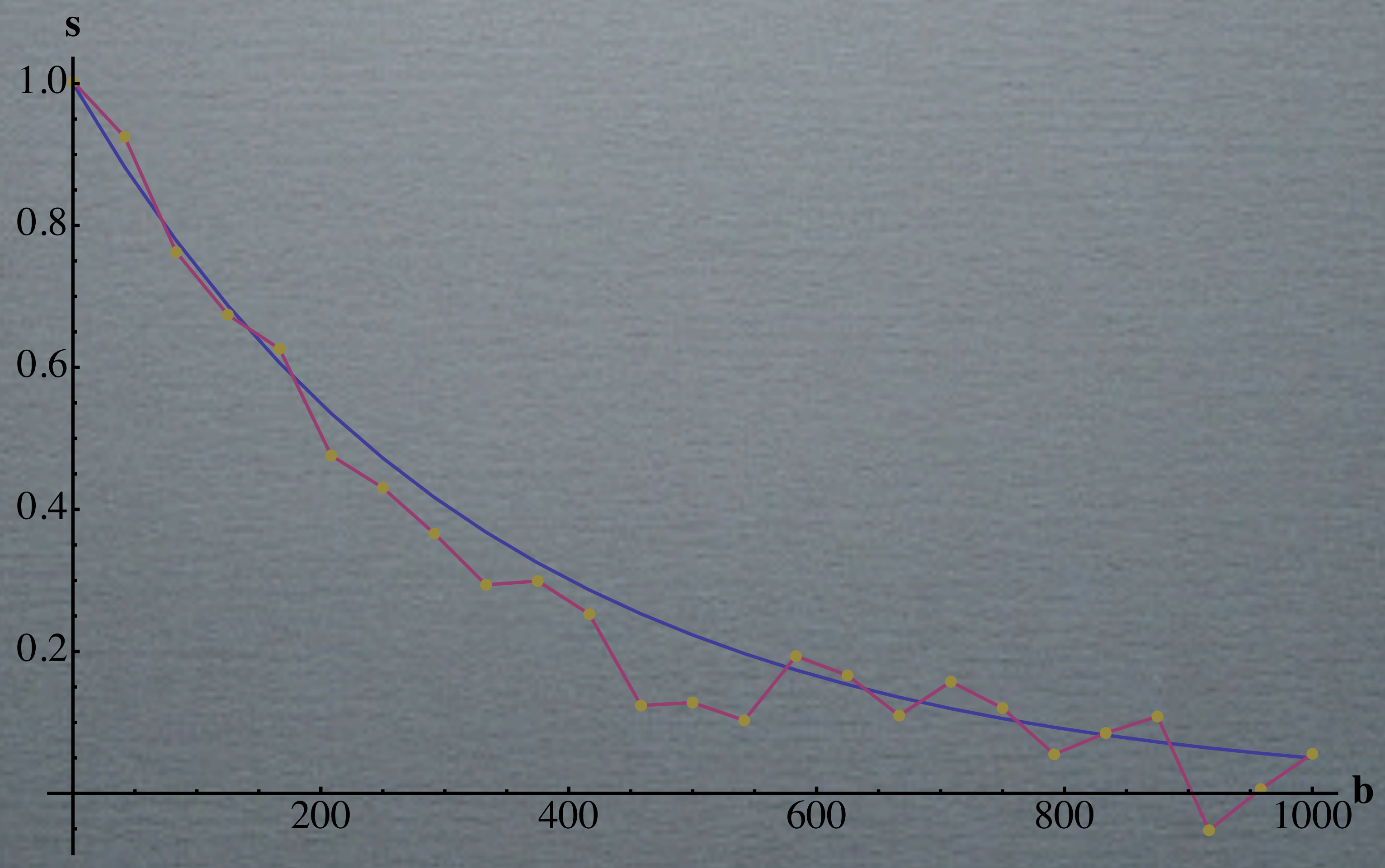
So, in principal, you can measure $P(r,\tau)$ by collecting data throughout $q$-space, just like imaging.
In practice, *very* time consuming

# The Estimation Problem for Gaussian Diffusion

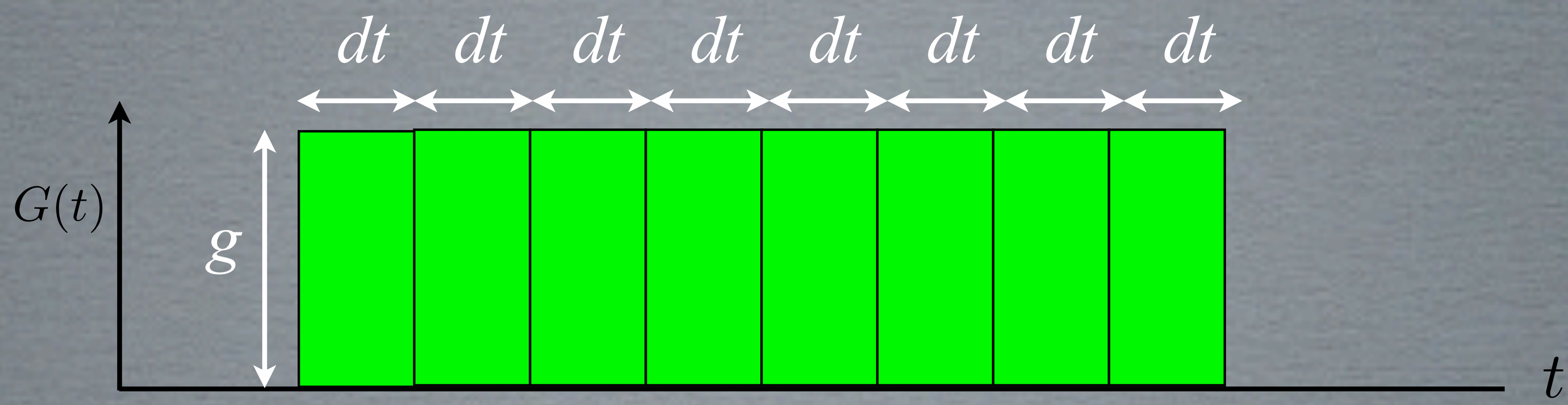


# The signal from Gaussian Diffusion

$$s(b) = s(0)e^{-bD} + \eta(b)$$



# The b-value




attenuation for each little time interval: $A_1 \quad A_2 \quad \cdot \quad \cdot \quad \cdot \quad A_n$

total attenuation $A_\tau = \prod_{i=1}^{n} A_i$ where $A_i = e^{-k^2 D\, dt}$

$$A_\tau = \prod_{i=1}^{n} e^{-k^2 D\, dt} = e^{-D \sum_{i=1}^{n} k^2\, dt} = e^{-D \int k^2\, dt}$$

$dt \to \epsilon$

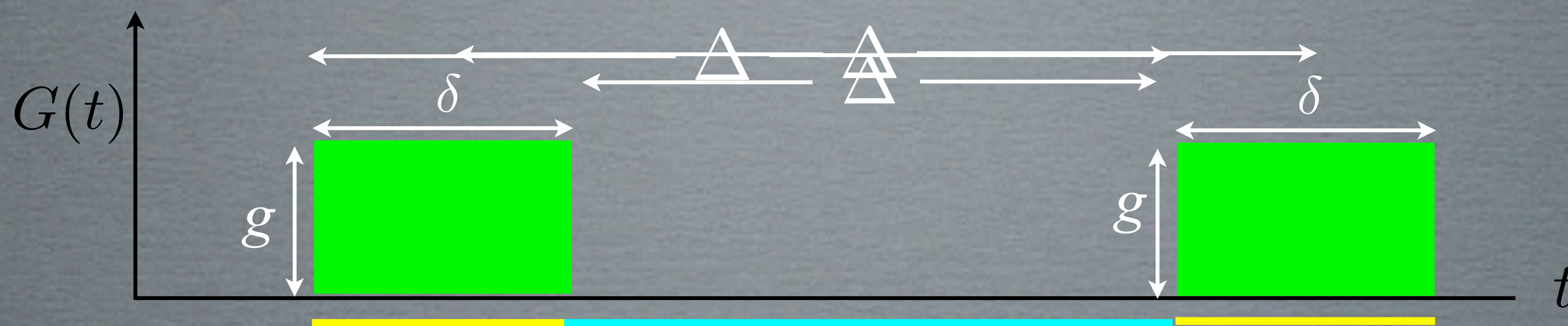
b

$$A_\tau = e^{-D \int k^2\, dt}$$

# The b-value

$$b = g^2\delta^2\left(\Delta - \frac{1}{3}\delta\right)$$

$$b = g^2\delta^2\left(\Delta + \frac{2}{3}\delta\right)$$

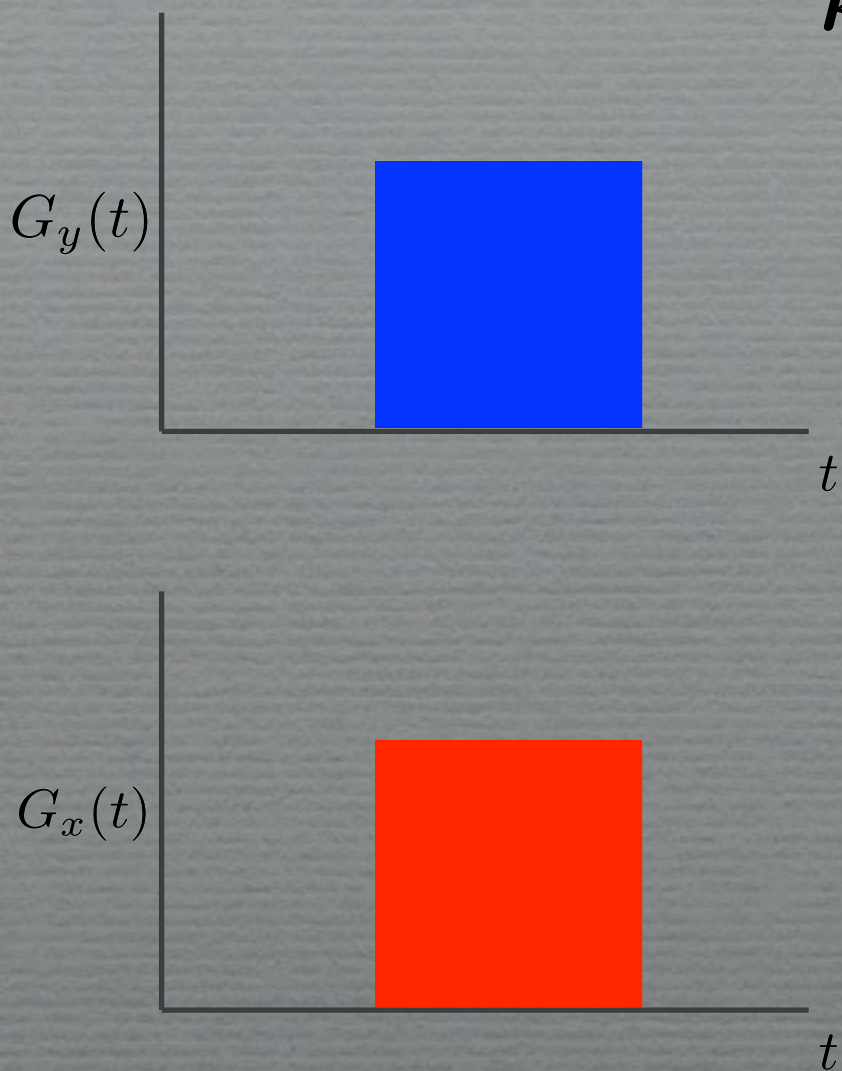


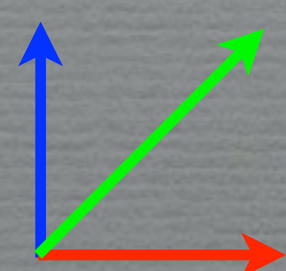

$$\int k^2\,dt = \quad g^2\int_0^{\delta} t^2\,dt \; + \; g^2\delta^2\int_0^{\Delta} dt \; + \; g^2\int_0^{\delta} t^2\,dt$$

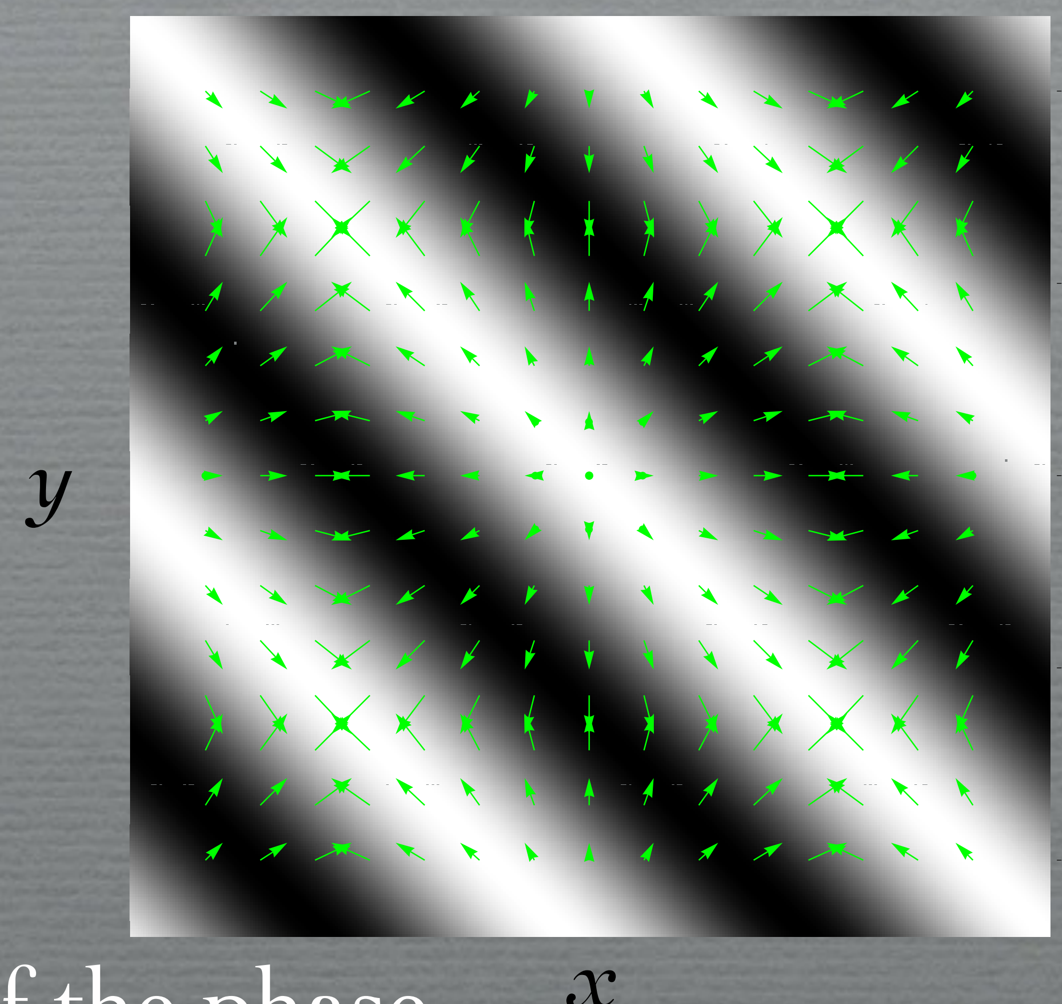
$$b = g^2\frac{\delta^3}{3} + g^2\delta^2\Delta + g^2\frac{\delta^3}{3}$$

# What gradients are doing to k-space

$$\boldsymbol{k} \cdot \boldsymbol{x} = k_x x + k_y y = \gamma G_x t x + \gamma G_y t y$$



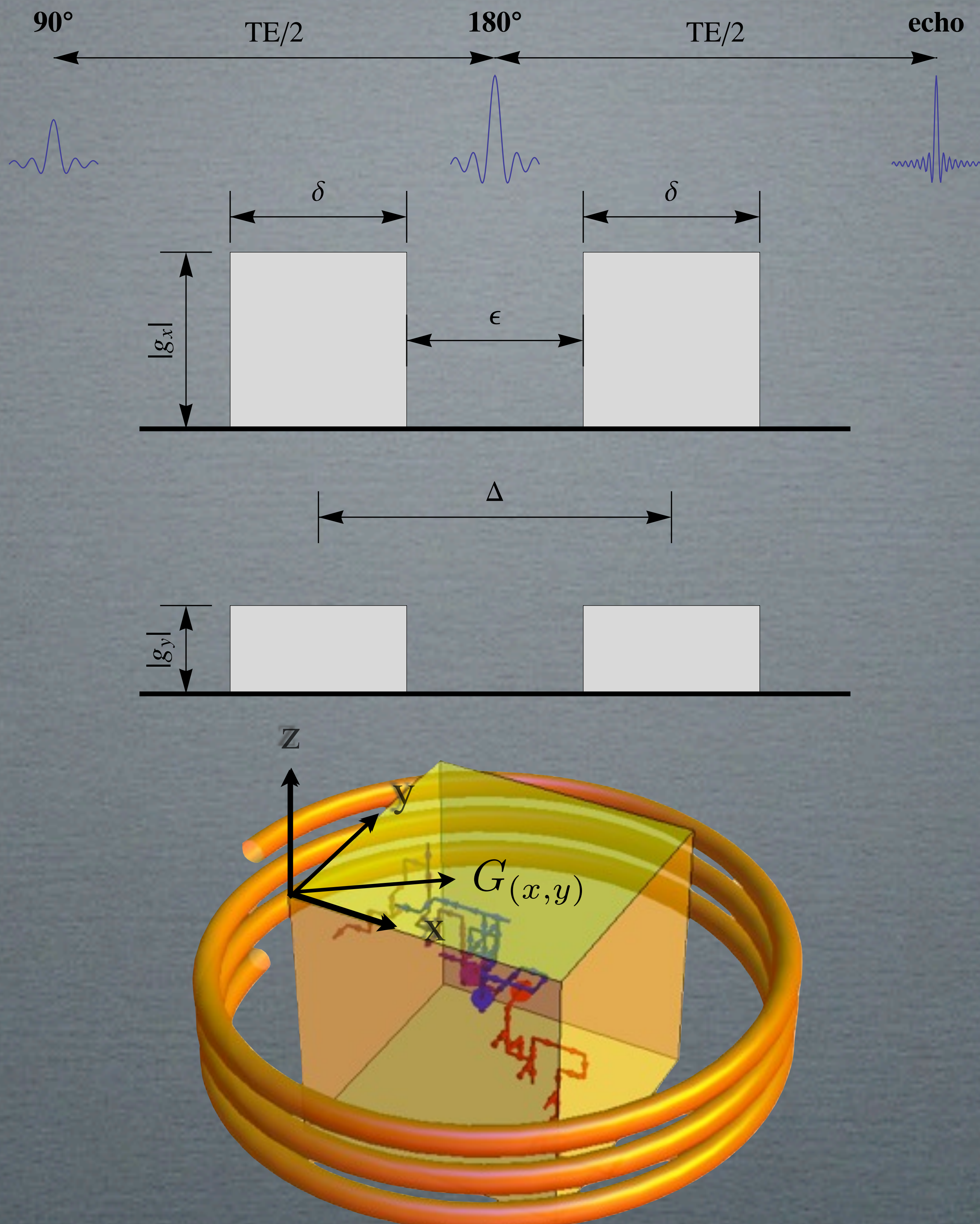






spatial modulation of the phase

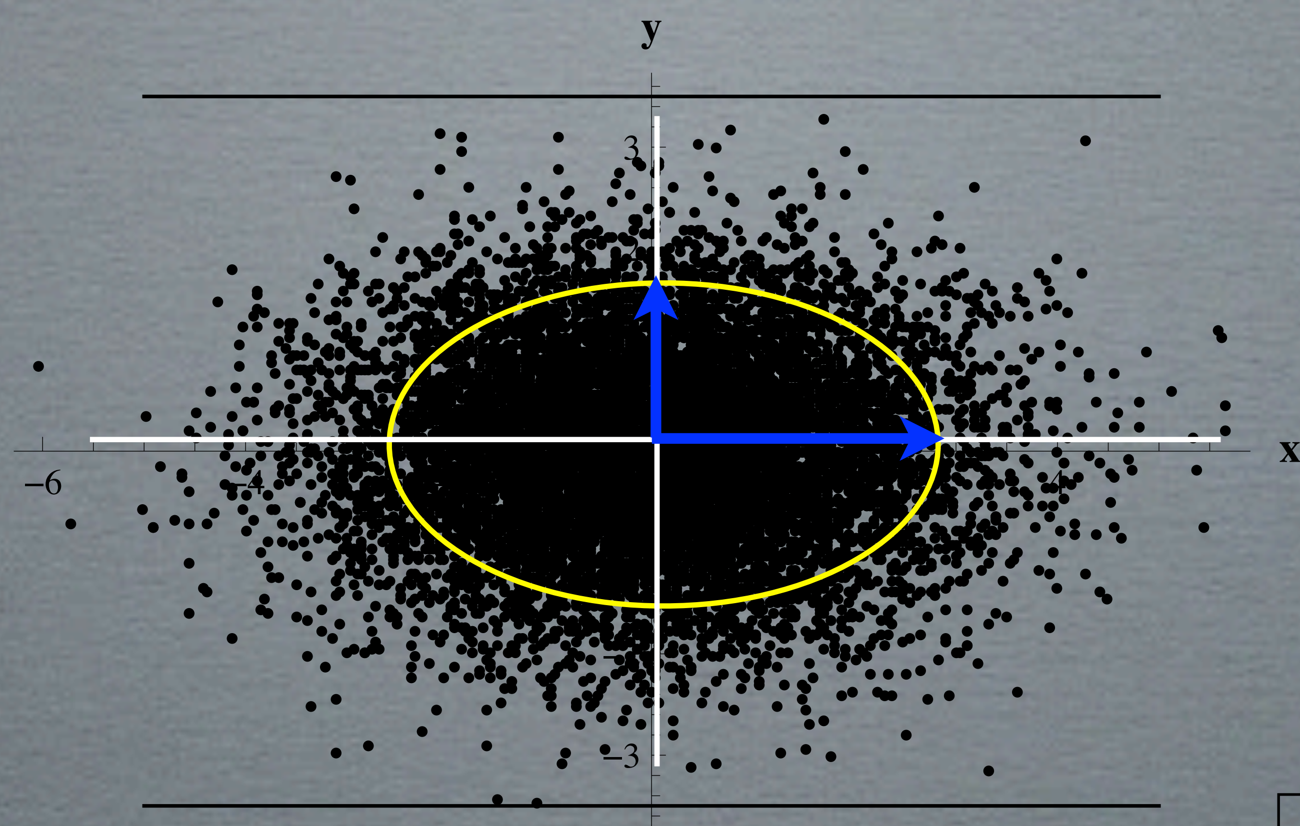
gradients alter the k-space representation of the object

# Directional Diffusion Encoding



# Anisotropic diffusion in 2D

$$P(\boldsymbol{r}|\boldsymbol{r}_0, \tau) \sim N(\boldsymbol{r}_0, \boldsymbol{\Sigma})$$




Covariance matrix

Diffusion Tensor

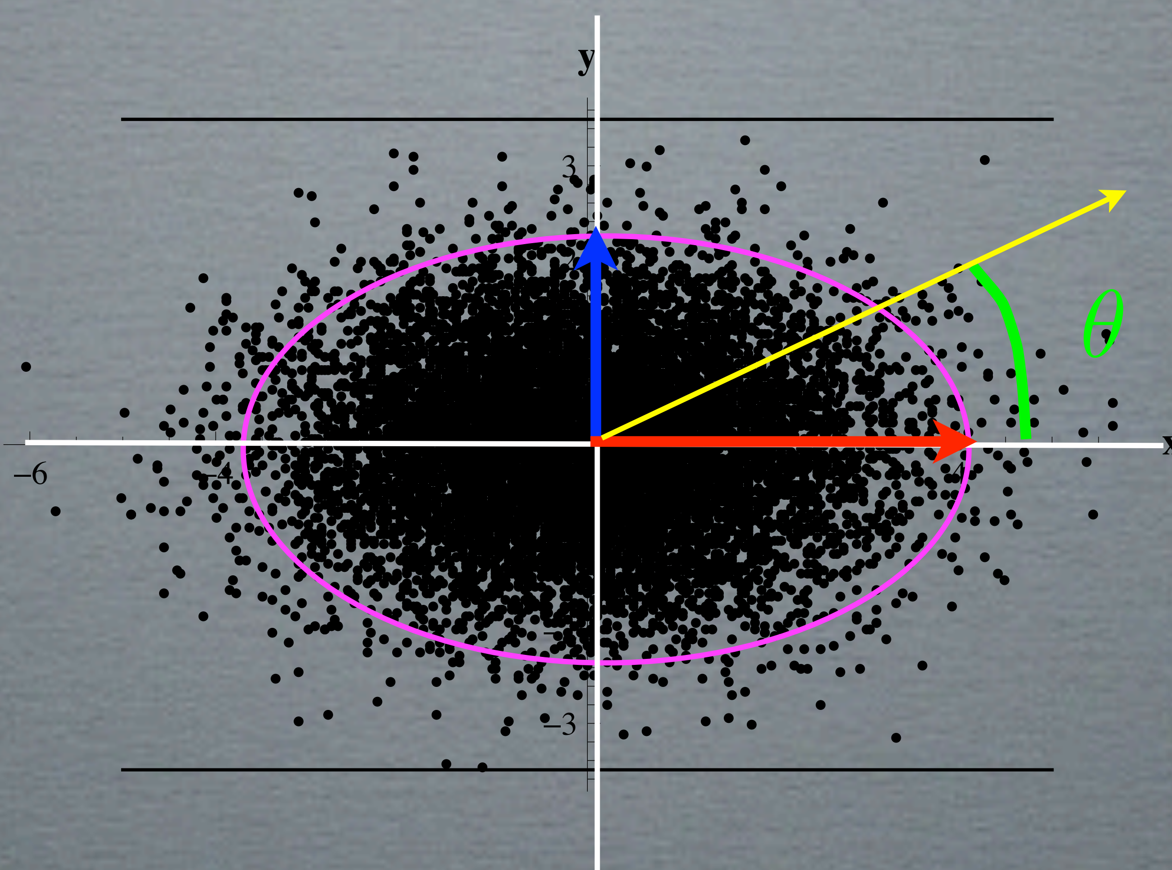
$$\Sigma = \begin{pmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_y^2 \end{pmatrix} = 2\tau \begin{pmatrix} D_x & 0 \\ 0 & D_y \end{pmatrix}$$

$\{D_x, D_y\}$ are the *principal diffusivities*

# Measuring the Diffusion Tensor

$$S(b,\hat{r}) = S(0)e^{-b\tilde{D}} + \eta$$

$$\boldsymbol{D} = \begin{pmatrix} D_x & 0 \\ 0 & D_y \end{pmatrix}$$



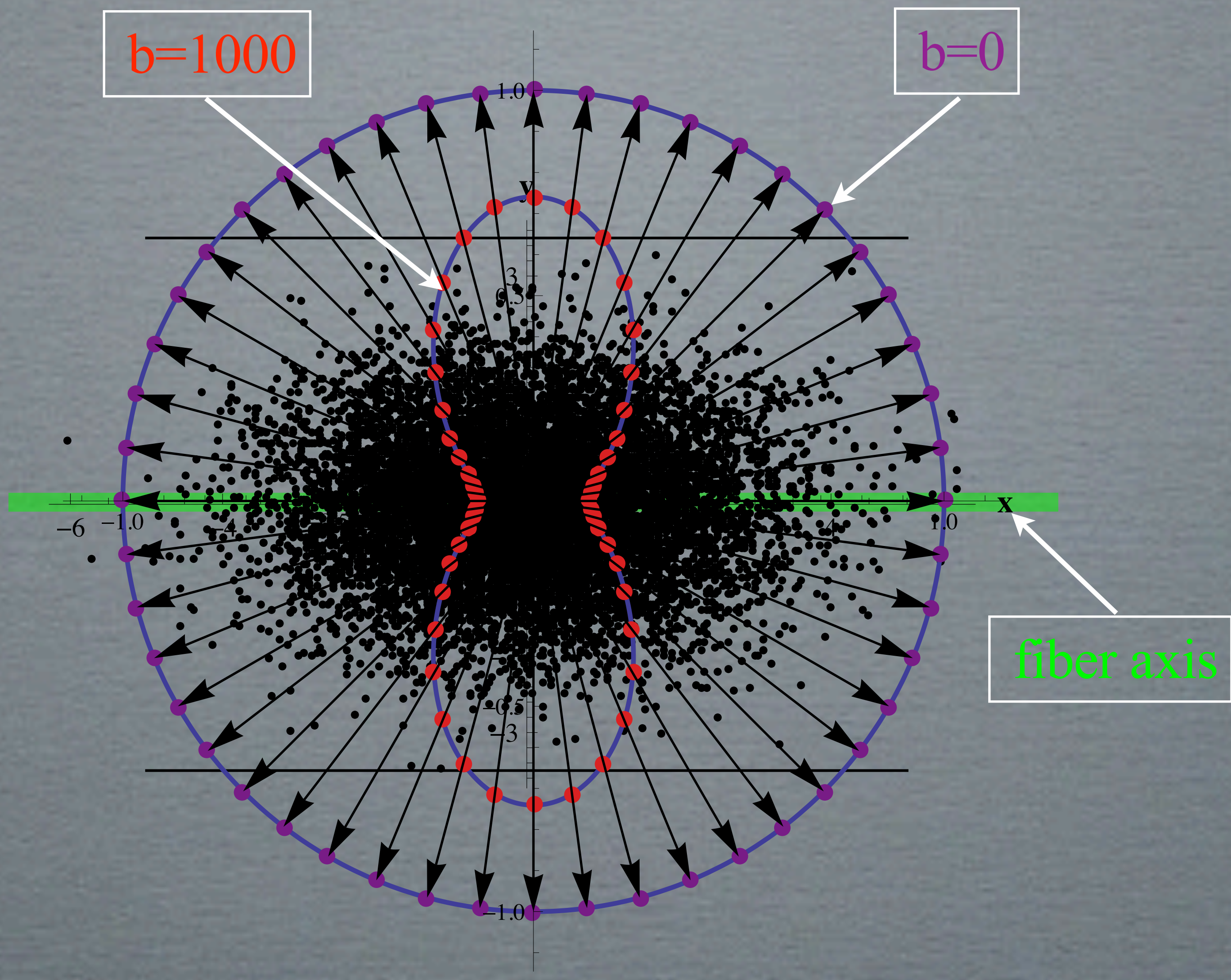

$$\hat{r} = \begin{pmatrix} \cos\theta \\ \sin\theta \end{pmatrix}$$

measurement direction

$$\tilde{D} = \hat{r}^t D \hat{r} = D_x \cos^2\theta + D_y \sin^2\theta$$

projection of an ellipsoid!
not like projection of a vector

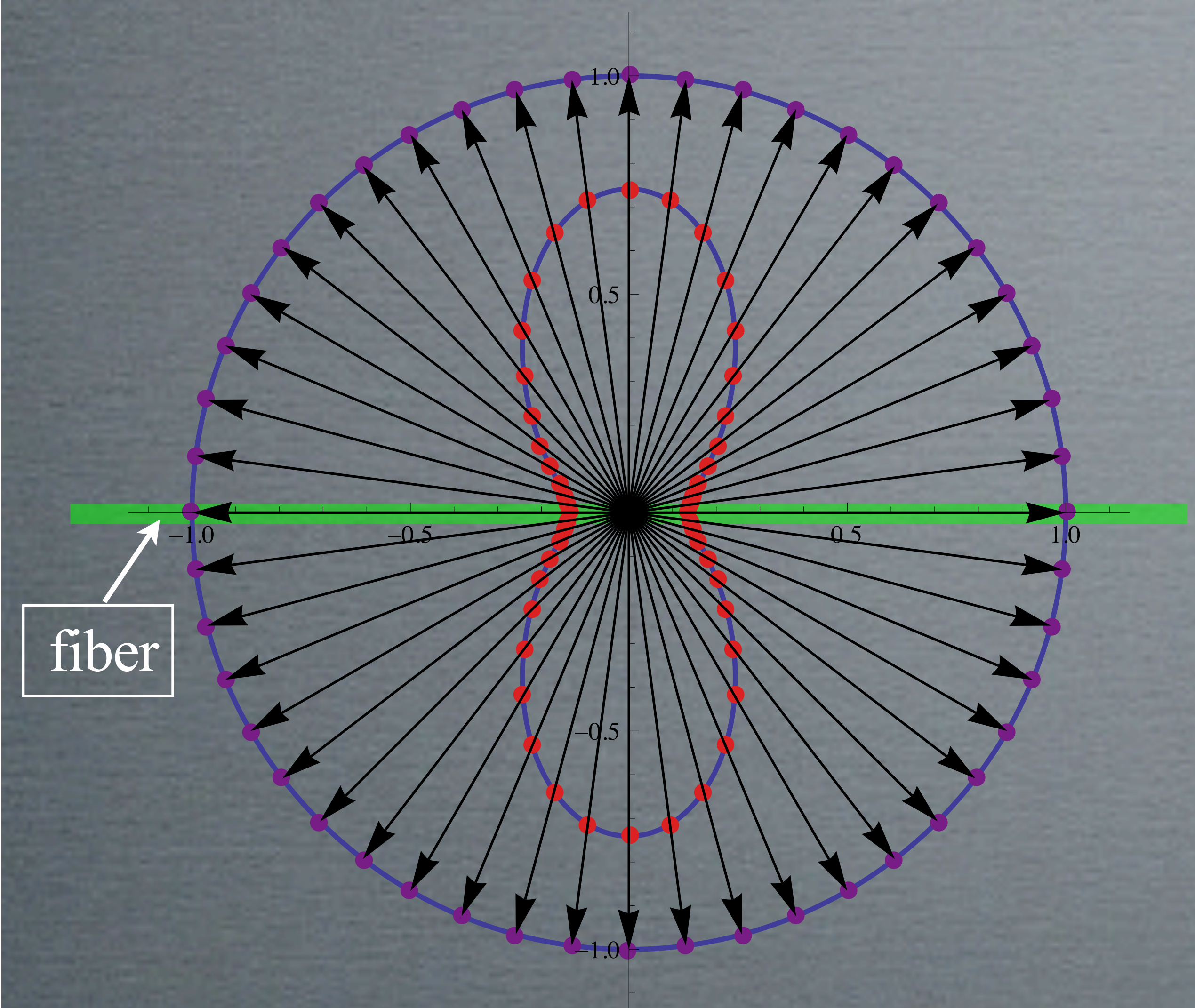
# Measuring the Diffusion Tensor

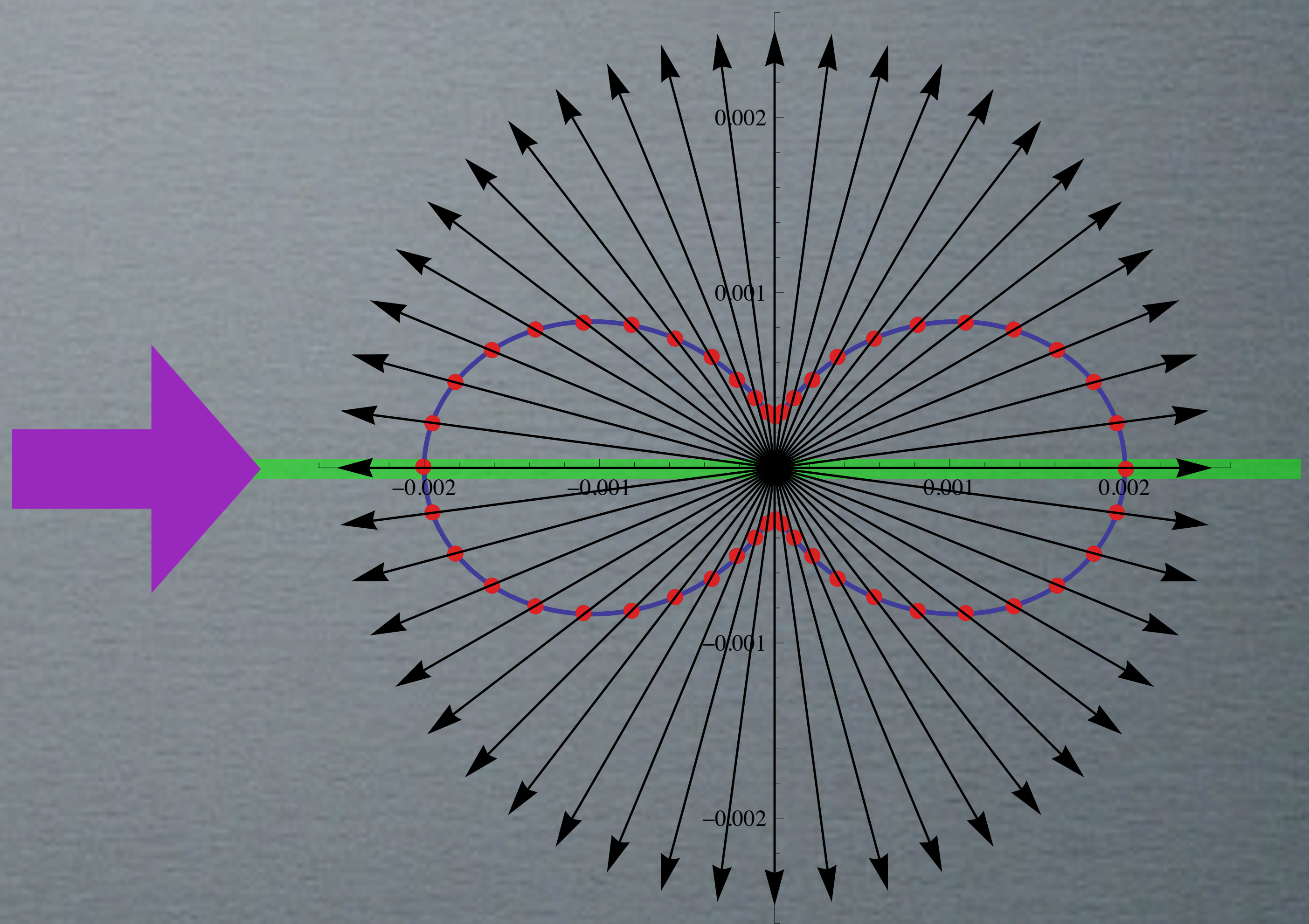



$$S(b,\theta) = S(0)e^{-bD(\theta)} + \eta$$

$$D(\theta) = \lambda_x \cos^2\theta + \lambda_y \sin^2\theta$$

# The Shape of Diffusion

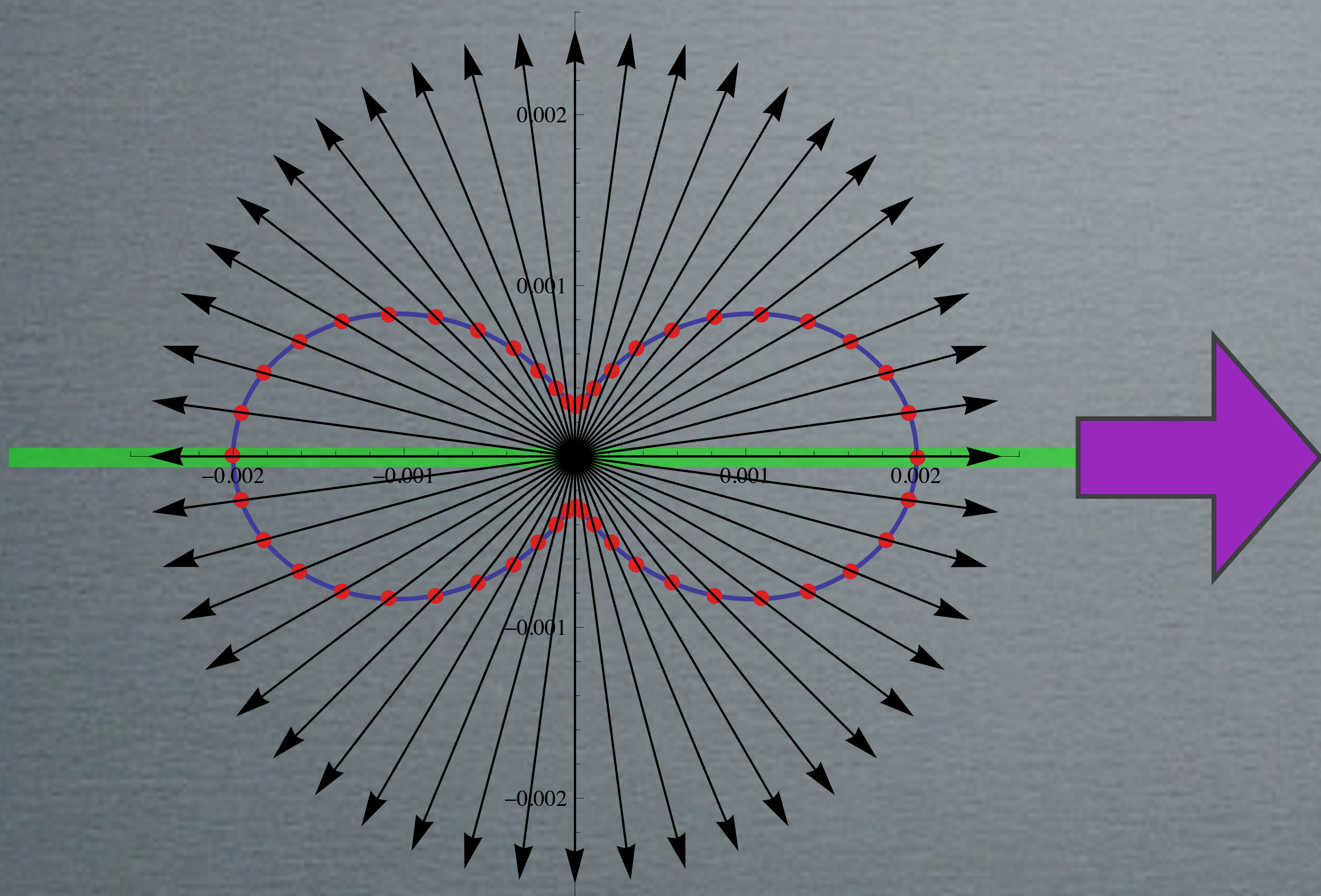


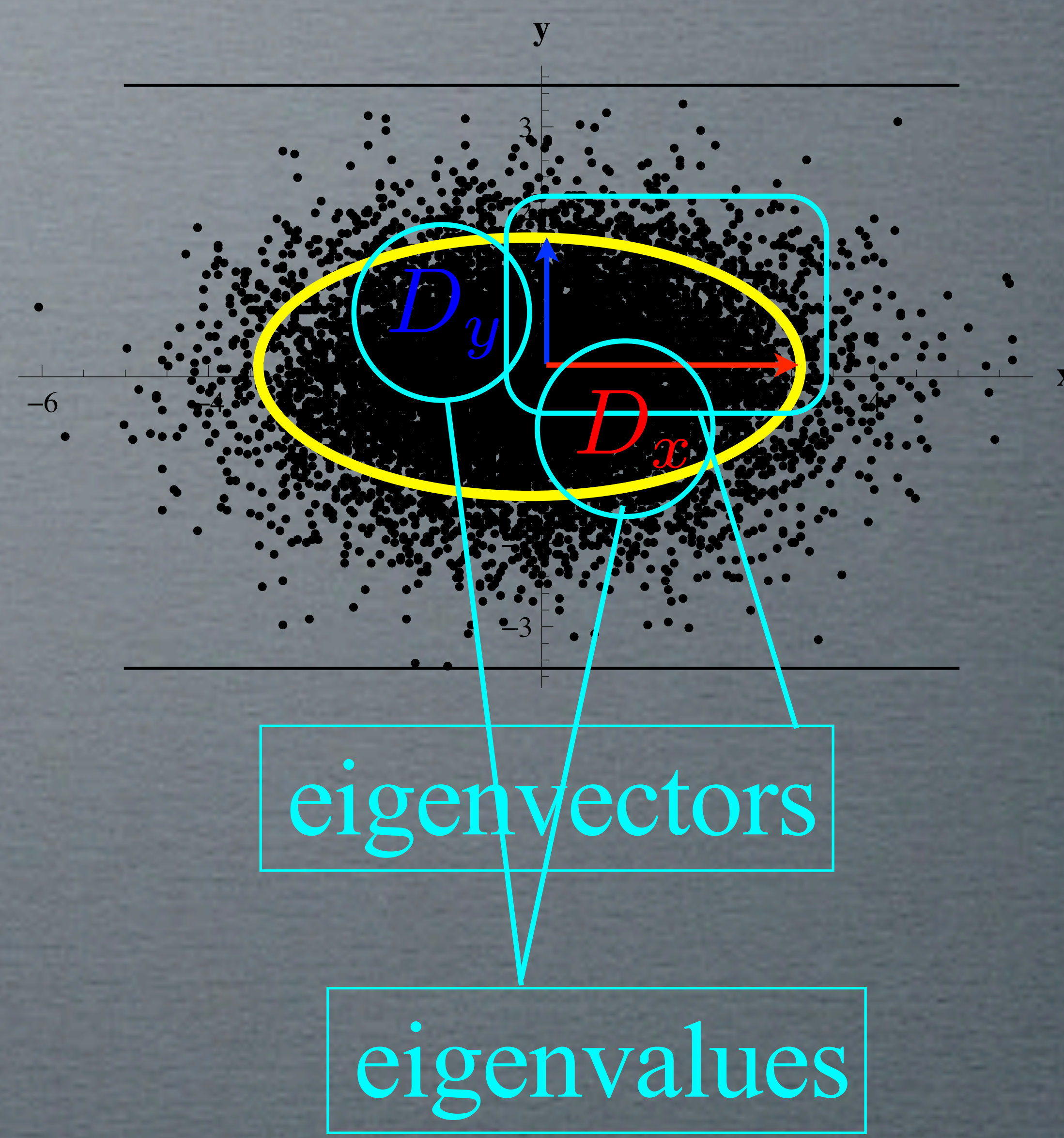

signal $S_b(\theta)$

$$D_{app}(\theta) = -\frac{1}{b}\log\left(\frac{S_b}{S_0}\right)$$

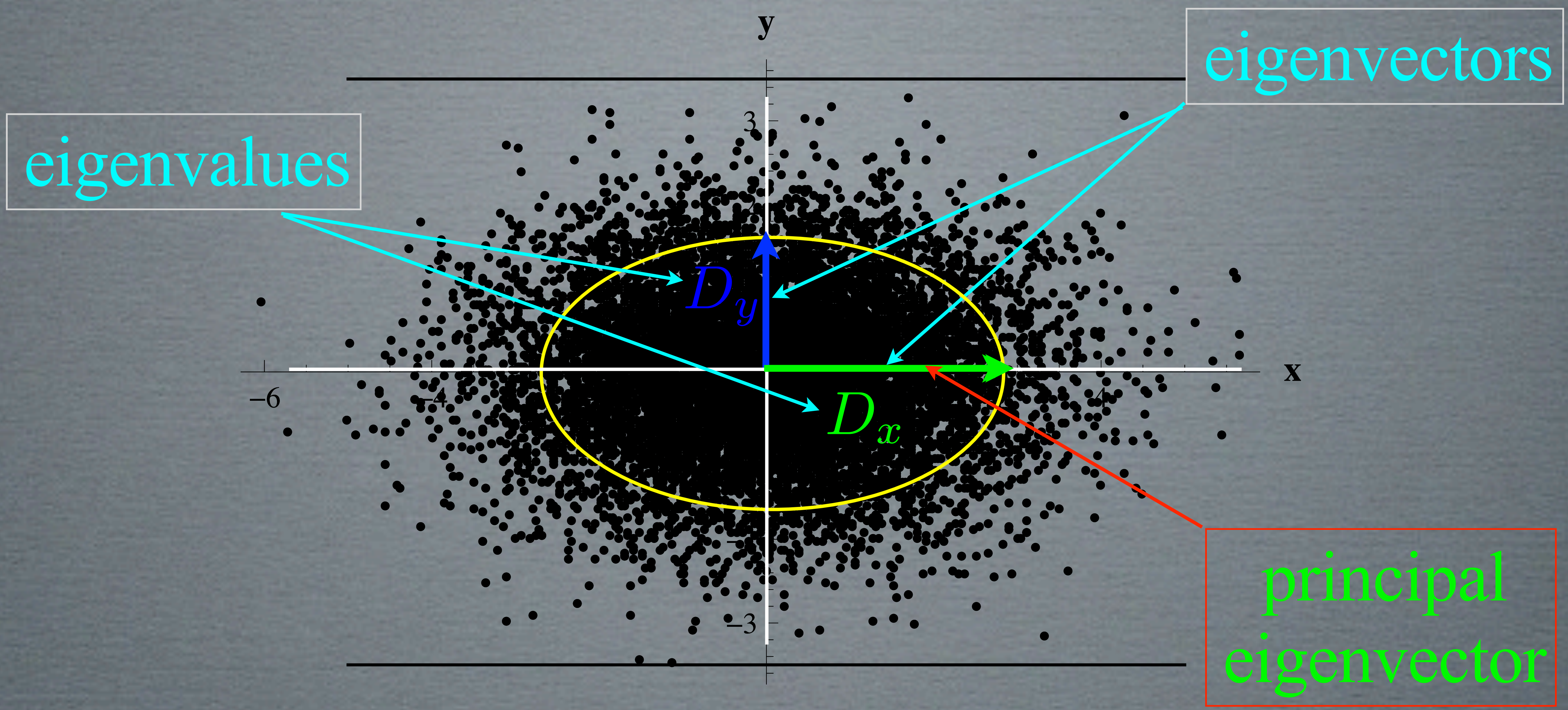
# The Estimation of Diffusion




$$D_{app}(\theta) = -\frac{1}{b}\log\left(\frac{S_b}{S_0}\right)$$



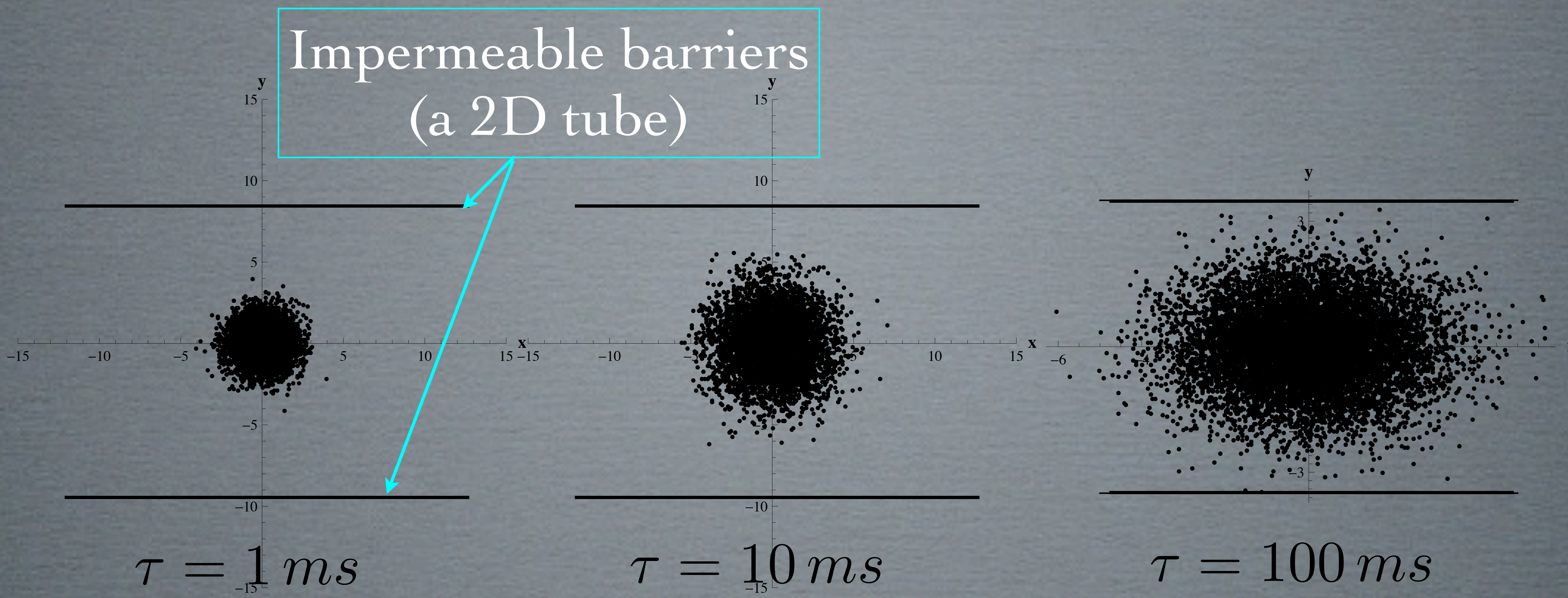
# Anisotropic Gaussian Diffusion




1. The relative dimensions of the contours tells us about local structure

2. The orientation of the eigenvectors is related to the orientation of the structure

# Anisotropic diffusion in 2D

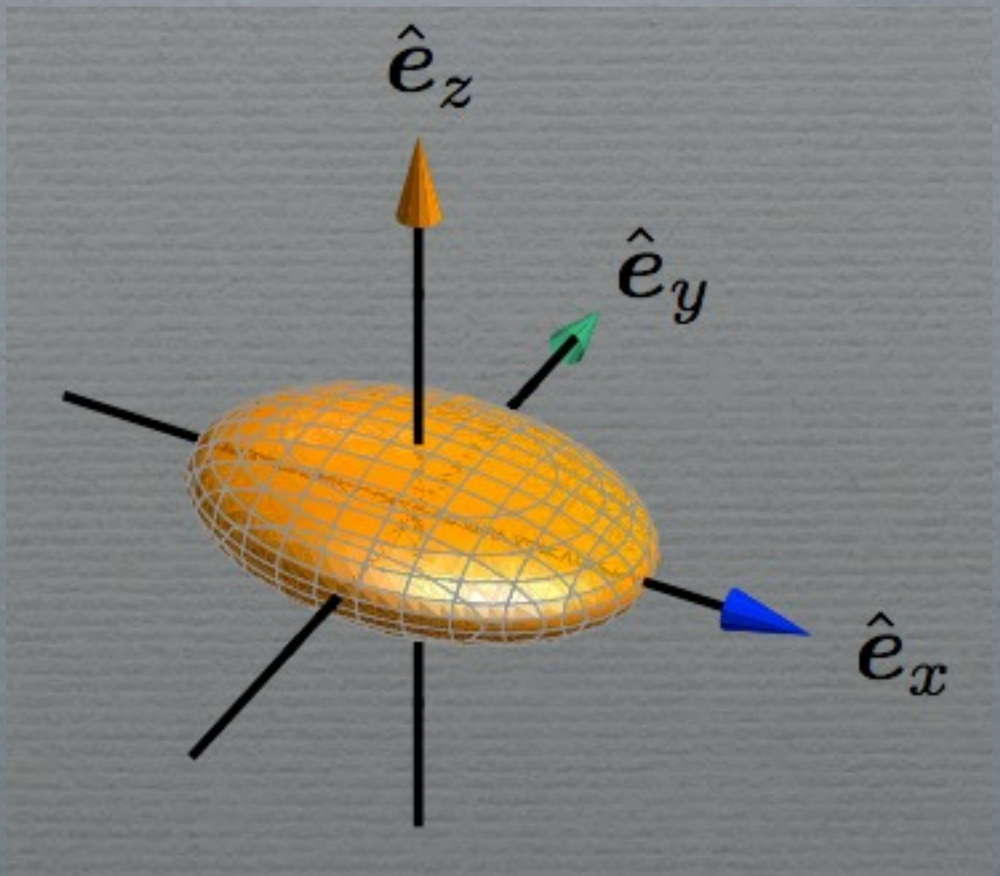



*Restricted diffusion*

1. Anisotropy induced by local geometry
2. Sensitivity to geometry depends upon diffusion time $\tau$
3. While the $D$ of the liquid may be a constant, there is an *apparent diffusion coefficient* (ADC) that varies with direction

# The 3D Gaussian Distribution:

$$P(\boldsymbol{r}|\boldsymbol{r}_0, \tau) \sim N(\boldsymbol{r}_0, \boldsymbol{\Sigma})$$




Covariance matrix

Diffusion Tensor

$$\boldsymbol{\Sigma} = \begin{pmatrix} \sigma_{xx}^2 & 0 & \\ 0 & \sigma_{yy}^2 & 0 \\ 0 & 0 & \sigma_{zz}^2 \end{pmatrix} = 6\tau \begin{pmatrix} D_x & 0 & \\ 0 & D_y & 0 \\ 0 & 0 & D_z \end{pmatrix}$$

# The Diffusion Tensor

The three eigenvectors of ***D***

$$\{\vec{e}_1, \vec{e}_2, \vec{e}_3\}$$

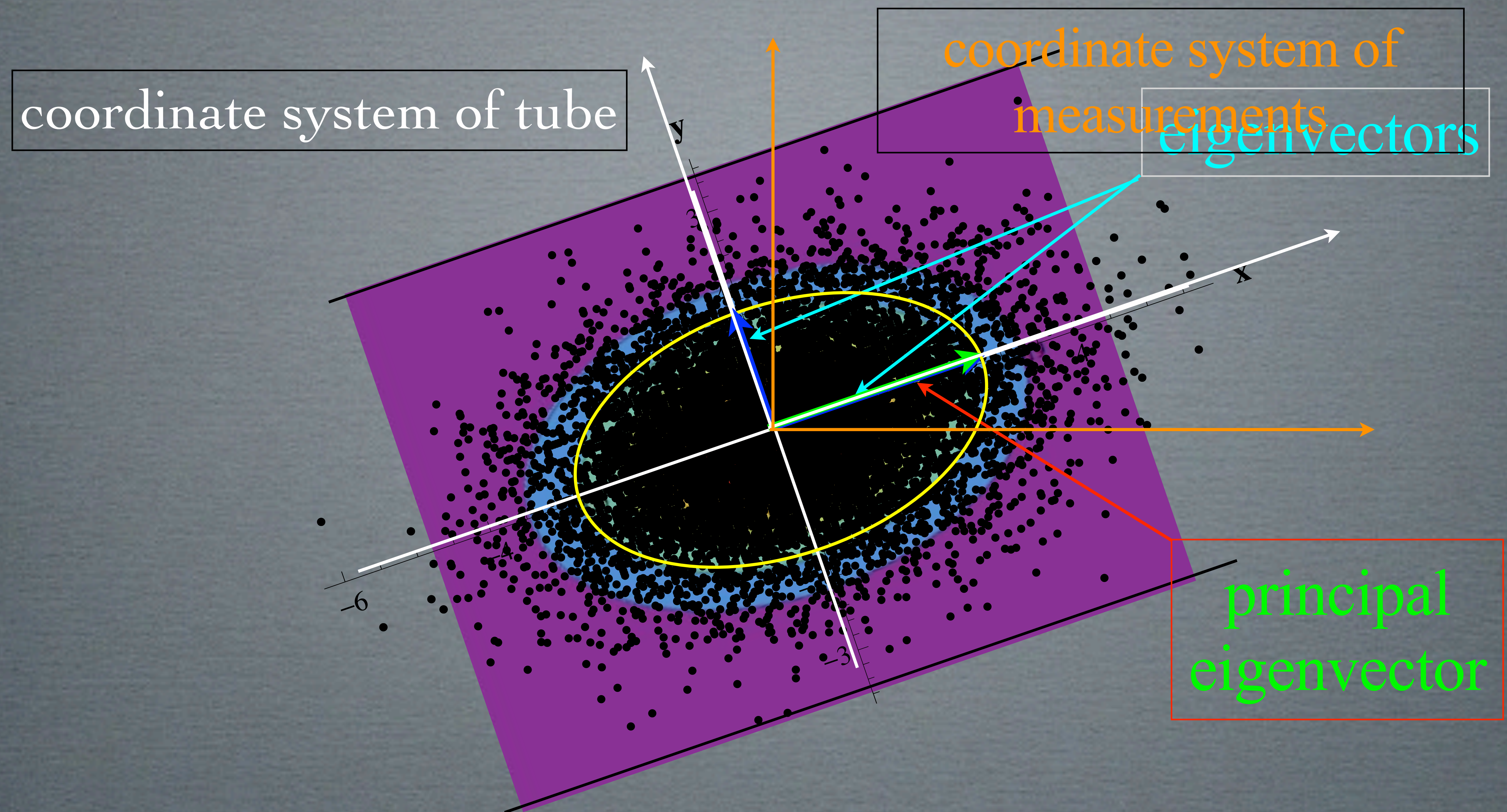
are the three unique directions along which the molecular displacements are uncorrelated

The three eigenvalues of ***D***

$$\{D_x, D_y, D_z\}$$

are the principle diffusivities

# Rotated tube

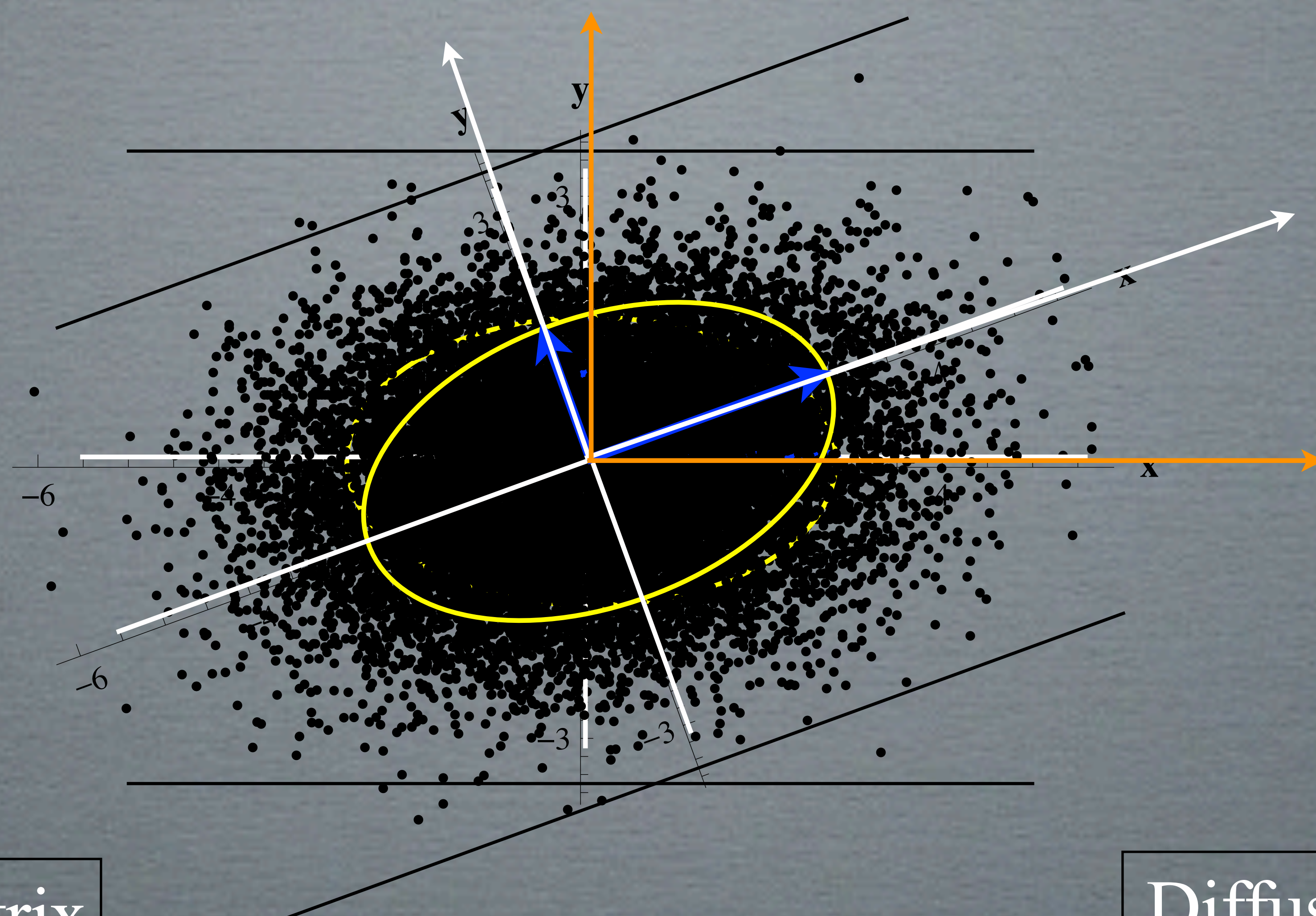



If the tube is not aligned with the coordinate system of the measurements, the diffusion along the measurement axes appears correlated

# The 2D Gaussian Distribution:

$$P(\boldsymbol{r}|\boldsymbol{r}_0,\tau) \sim N(\boldsymbol{r}_0,\boldsymbol{\Sigma})$$

$$\boldsymbol{r} = \{x, y\}$$




Covariance matrix

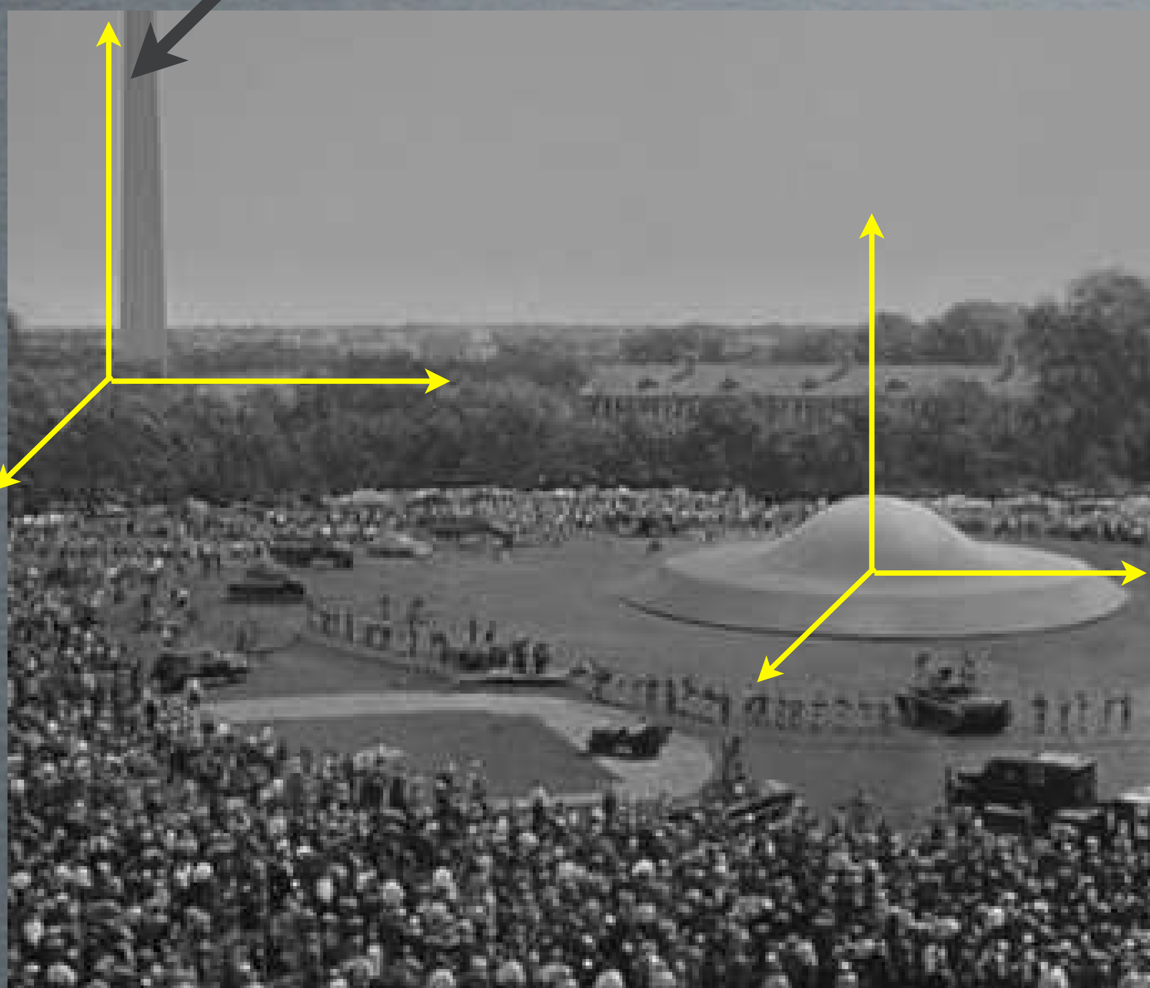
Diffusion Tensor

$$\boldsymbol{\Sigma} = \begin{pmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_y^2 \end{pmatrix} = 4\tau \begin{pmatrix} D_x & 0 \\ 0 & D_y \end{pmatrix}$$

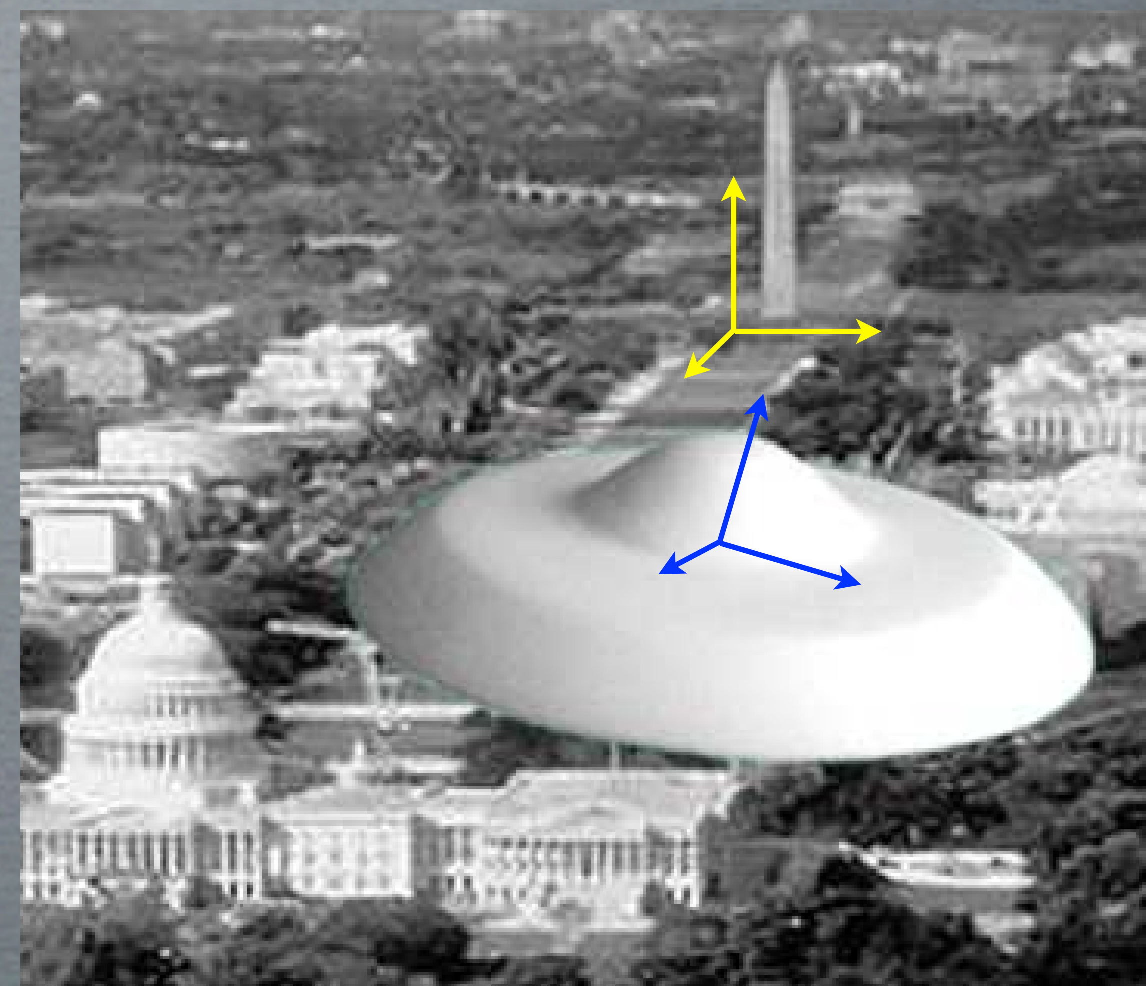
$$\boldsymbol{\Sigma} = \begin{pmatrix} \sigma_{xx}^2 & \sigma_{xy}^2 \\ \sigma_{yx}^2 & \sigma_{yy}^2 \end{pmatrix} = 4\tau \begin{pmatrix} D_{xx} & D_{xy} \\ D_{yx} & D_{yy} \end{pmatrix}$$

# Generally fibers are not aligned along magnet coordinates!

laboratory
coordinate system



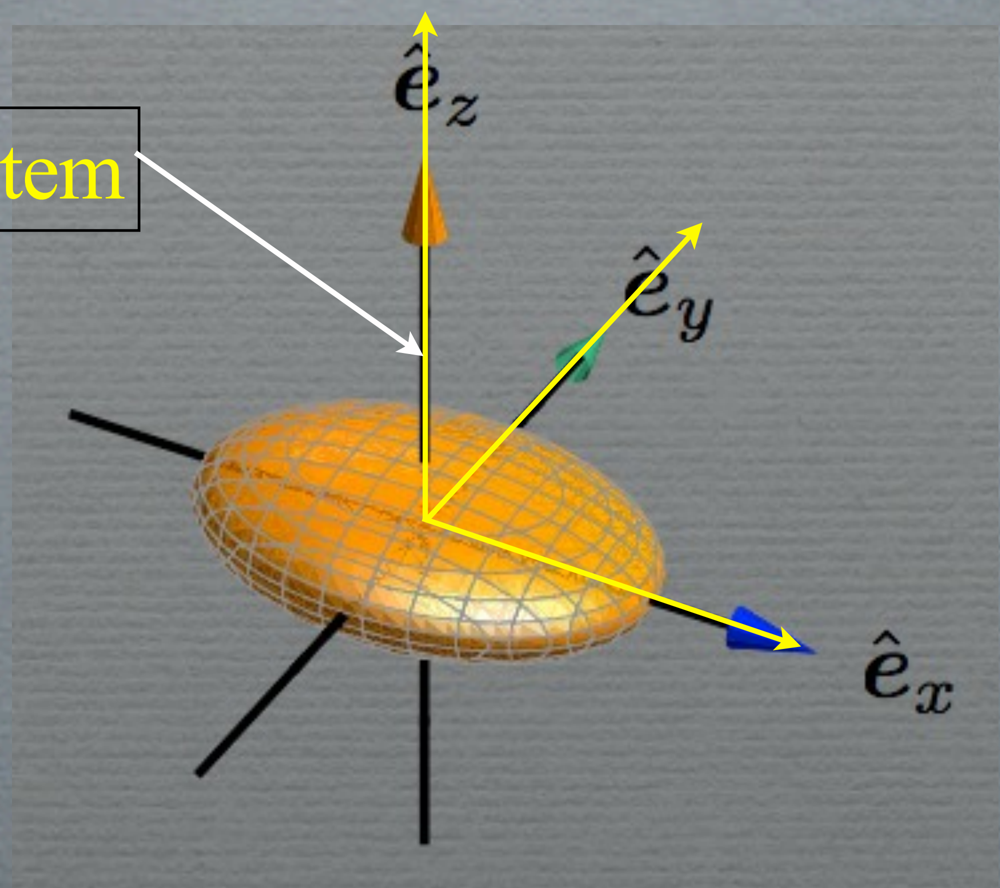
same orientation as laboratory coordinate system



rotated relative to laboratory coordinate system

# The 3D Gaussian Distribution:

$$P(\boldsymbol{r}|\boldsymbol{r}_0, \tau) \sim N(\boldsymbol{r}_0, \boldsymbol{\Sigma})$$




scanner coordinate system

Covariance matrix

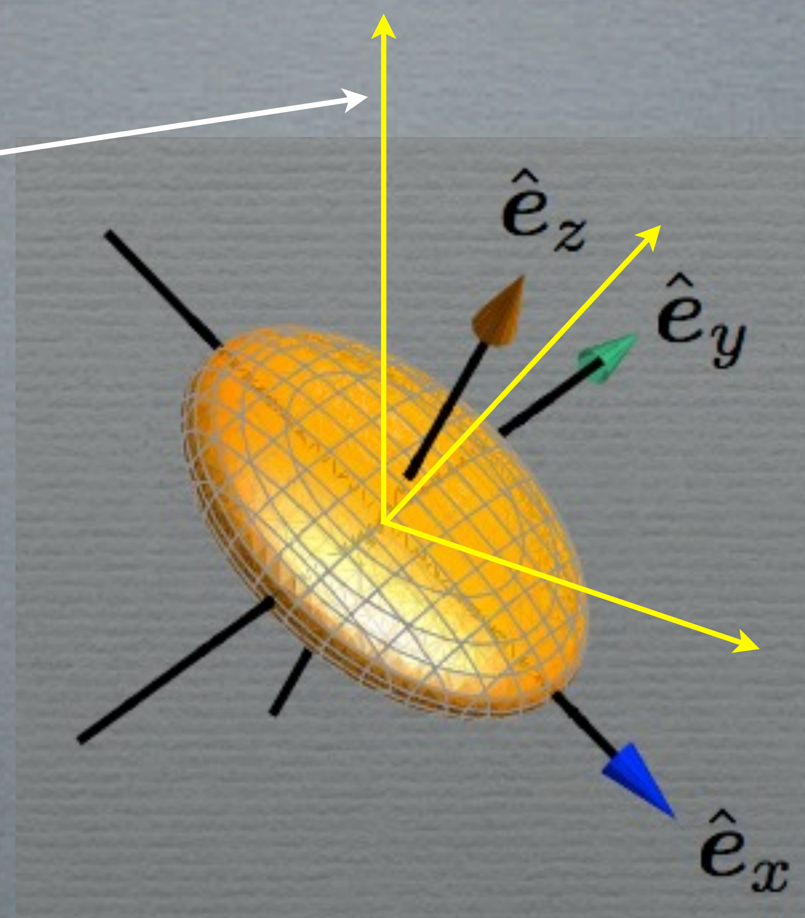
Diffusion Tensor

$$\boldsymbol{\Sigma} = \begin{pmatrix} \sigma_{xx}^2 & 0 & \\ 0 & \sigma_{yy}^2 & 0 \\ 0 & 0 & \sigma_{zz}^2 \end{pmatrix} = 6\tau \begin{pmatrix} D_x & 0 & \\ 0 & D_y & 0 \\ 0 & 0 & D_z \end{pmatrix}$$

# The 3D Gaussian Distribution:

$$P(\boldsymbol{r}|\boldsymbol{r}_0,\tau) \sim N(\boldsymbol{r}_0,\boldsymbol{\Sigma})$$

scanner coordinate system

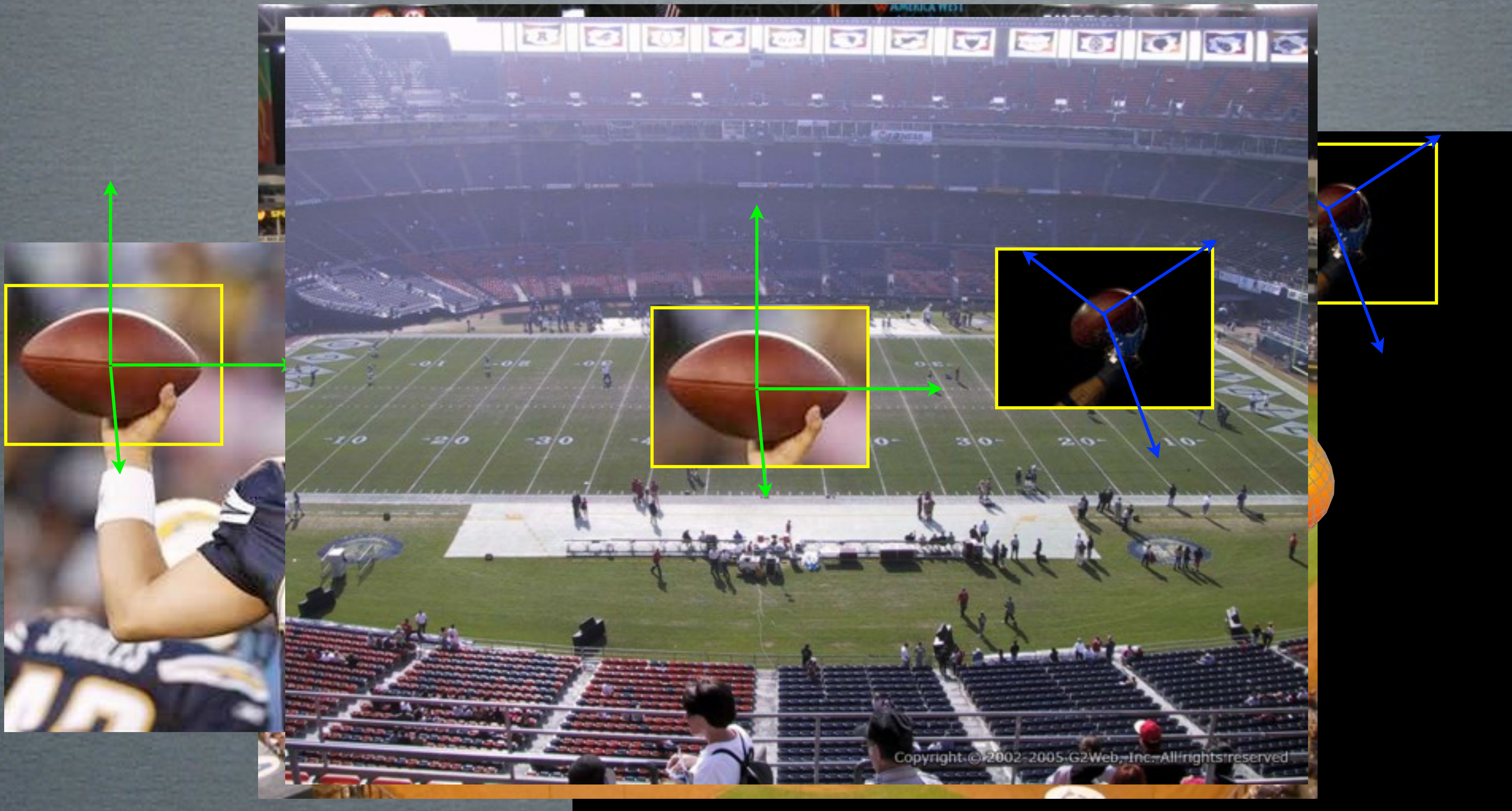



Diffusion Tensor

Covariance matrix

$$\boldsymbol{\Sigma} = \begin{pmatrix} \sigma^2_{xx} & \sigma^2_{xy} & \sigma^2_{xz} \\ \sigma^2_{yx} & \sigma^2_{yy} & \sigma^2_{yz} \\ \sigma^2_{zx} & \sigma^2_{zy} & \sigma^2_{zz} \end{pmatrix} = 6\tau \underbrace{\begin{pmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{yx} & D_{yy} & D_{yz} \\ D_{zx} & D_{zy} & D_{zz} \end{pmatrix}}_{\boldsymbol{D}}$$

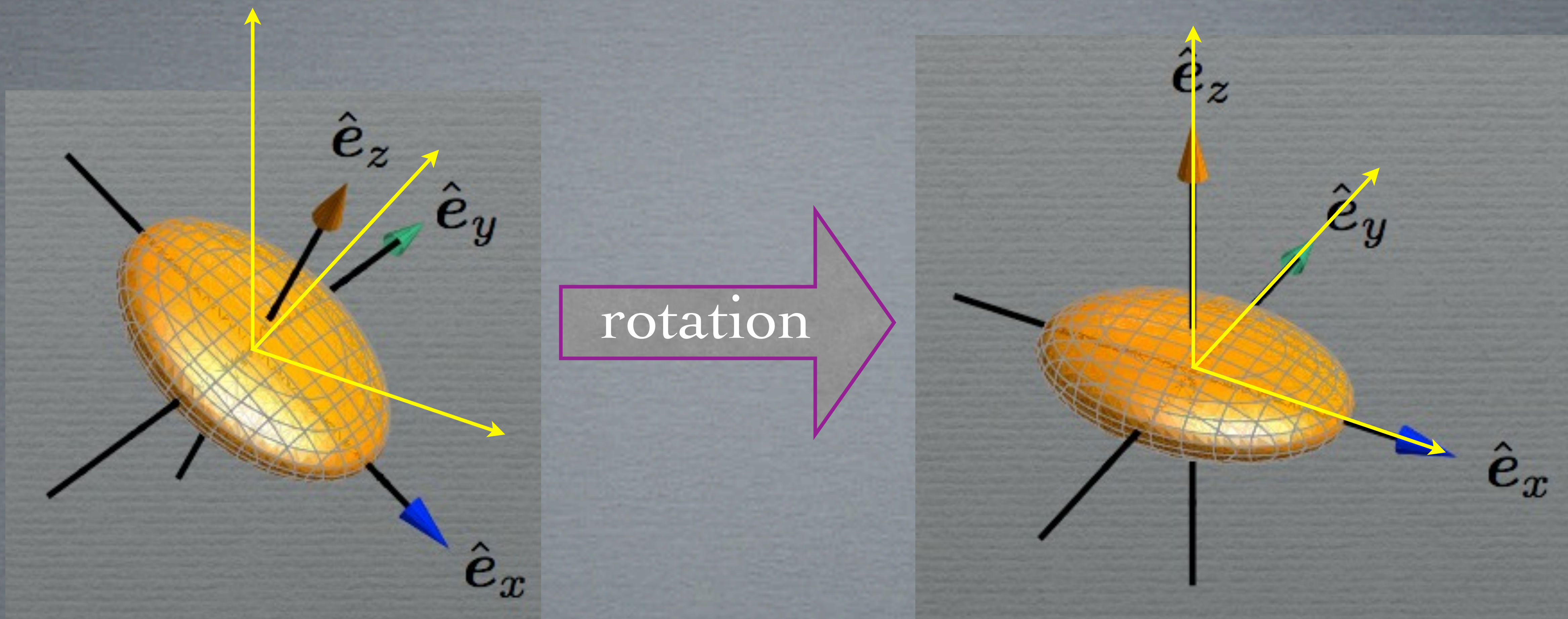
# Tensor Rotations




A baseball is a sphere - it has no sense of orientation

but a football is ellipsoidal, and does!

# What we want




$$\boldsymbol{D} = \begin{pmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{yx} & D_{yy} & D_{yz} \\ D_{zx} & D_{zy} & D_{zz} \end{pmatrix} \xrightarrow{\text{rotation}} \boldsymbol{D} = \begin{pmatrix} D_x & 0 & \\ 0 & D_y & 0 \\ 0 & 0 & D_z \end{pmatrix}$$

This is what eigenvector routines do!

## CAUTION

$$S(b,\hat{r}) = S(0)e^{-bD(\hat{r})} + \eta$$

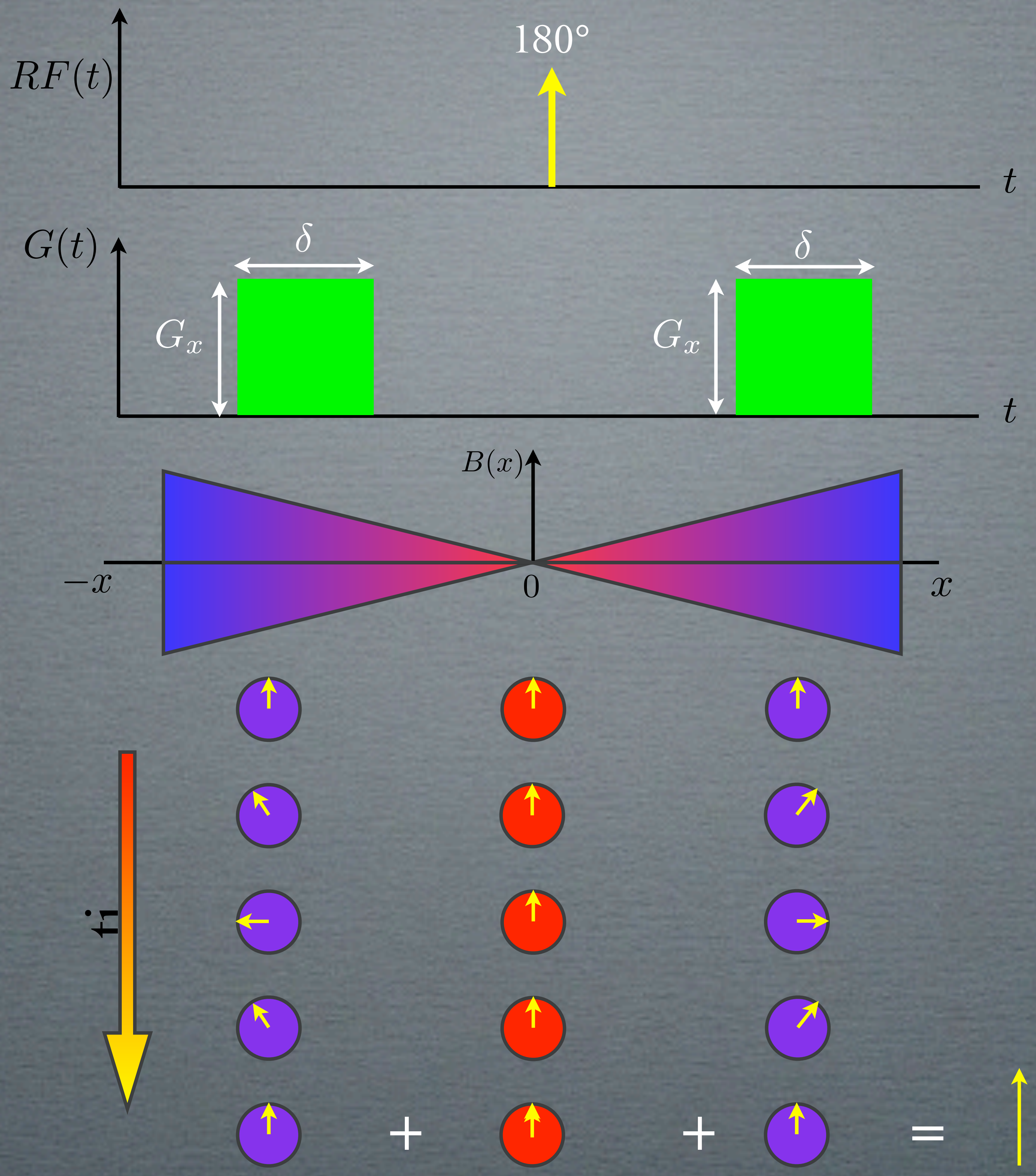
$$D(\hat{r}) = -\frac{1}{b}\log\left(\frac{S(b,\hat{r})}{S(0)} - \eta\right)$$

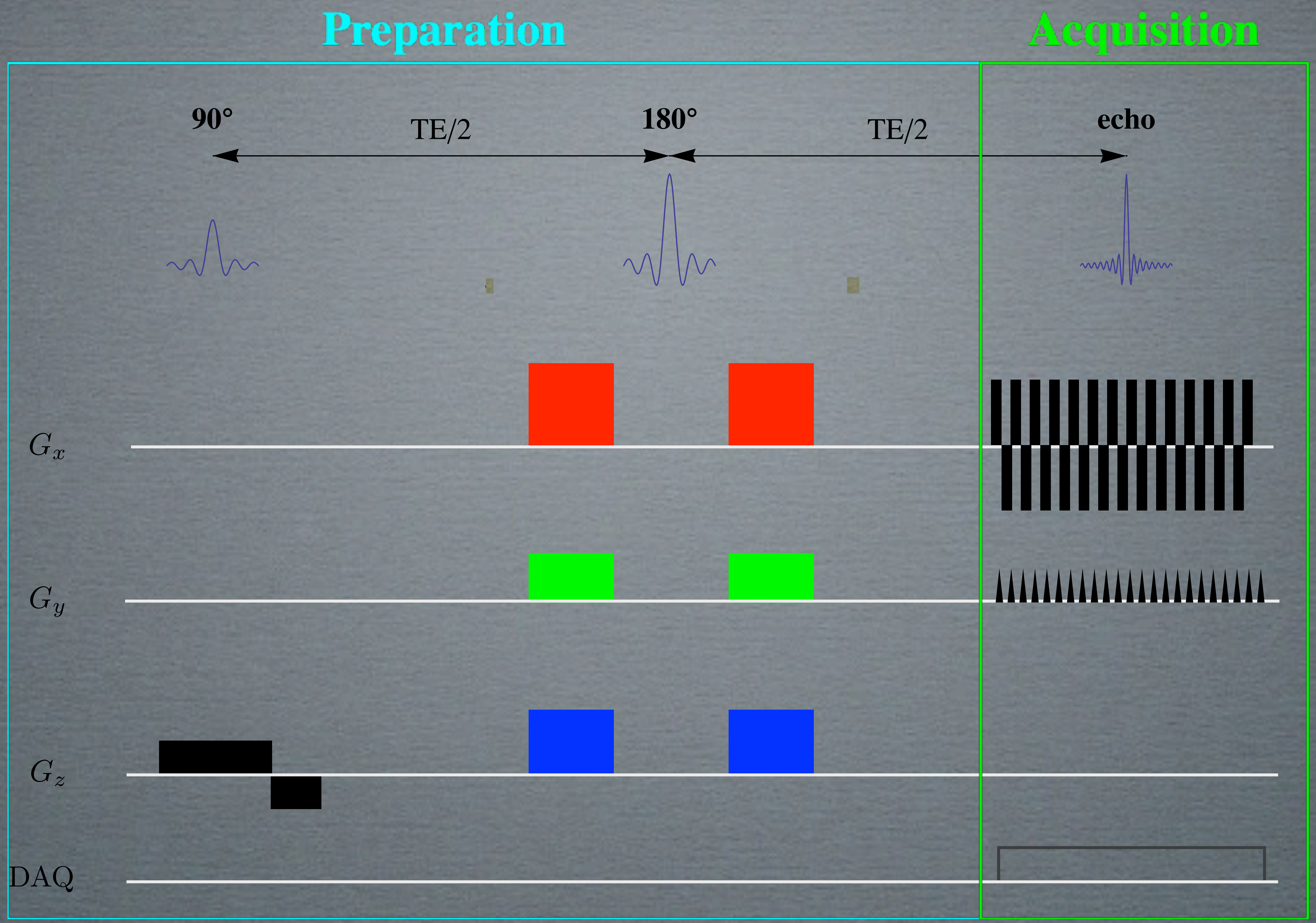
Not additive noise anymore!

# Extension to Imaging

## (Finally!)

# The Bipolar Gradient Pulse (spin echo)

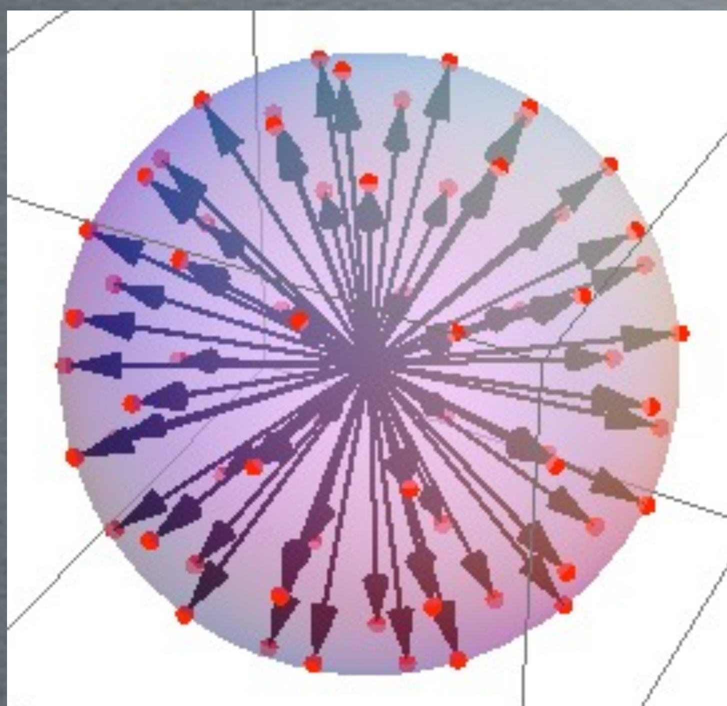


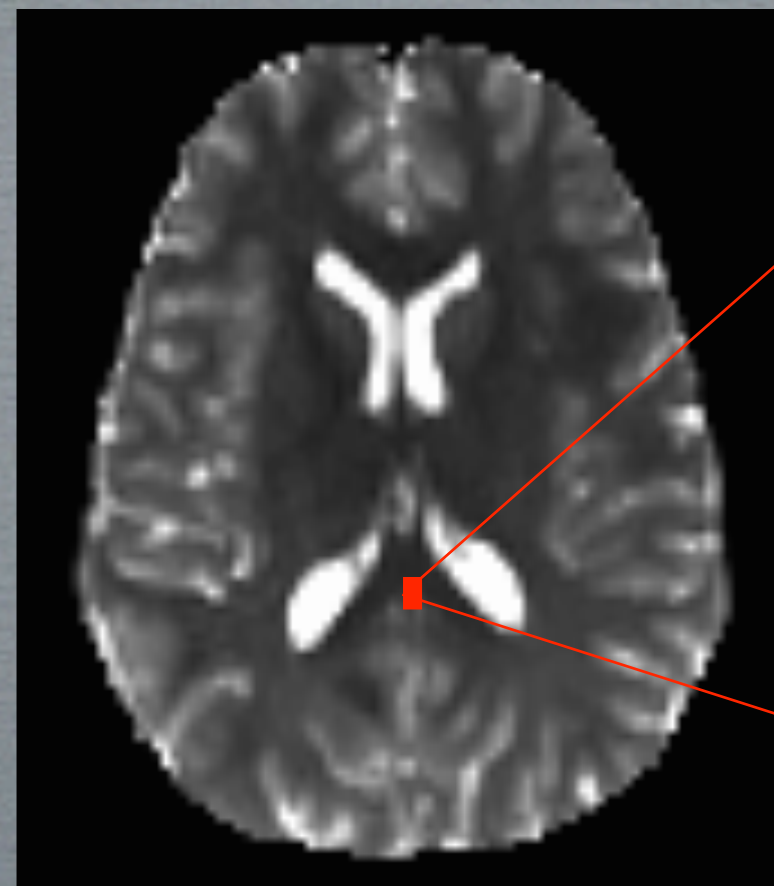


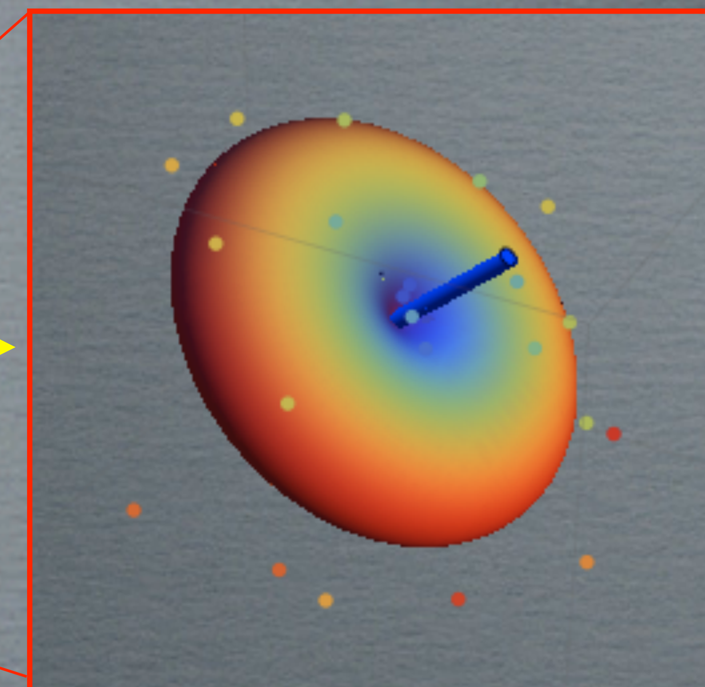

Because the diffusion weighting does not interfere with the stationary tissue signal, we can “insert” it into a standard imaging procedure

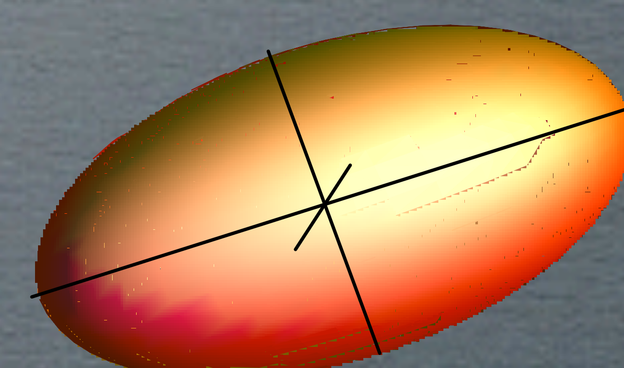
# DTI

voxel signal
from multiple images at
different directions



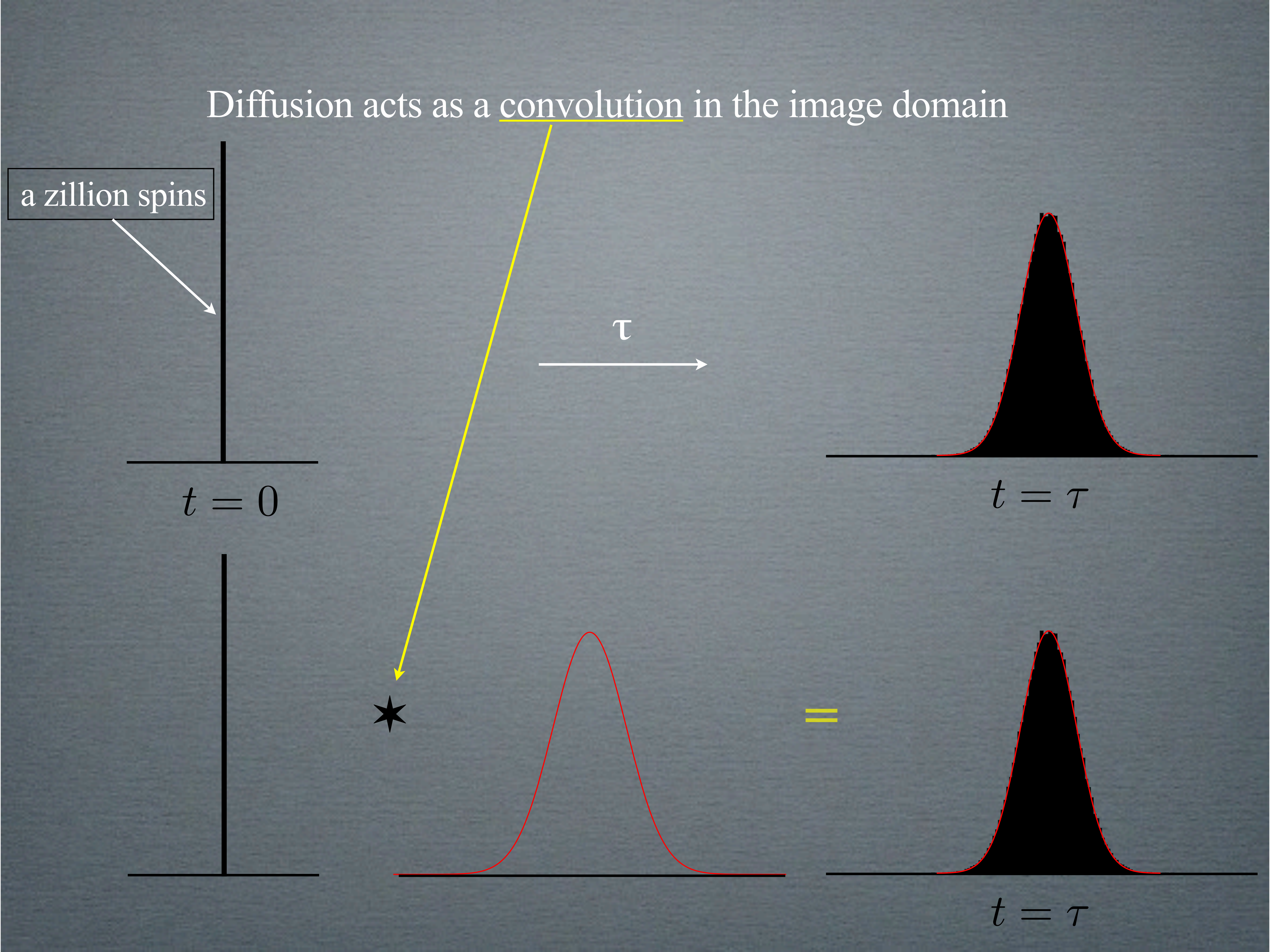




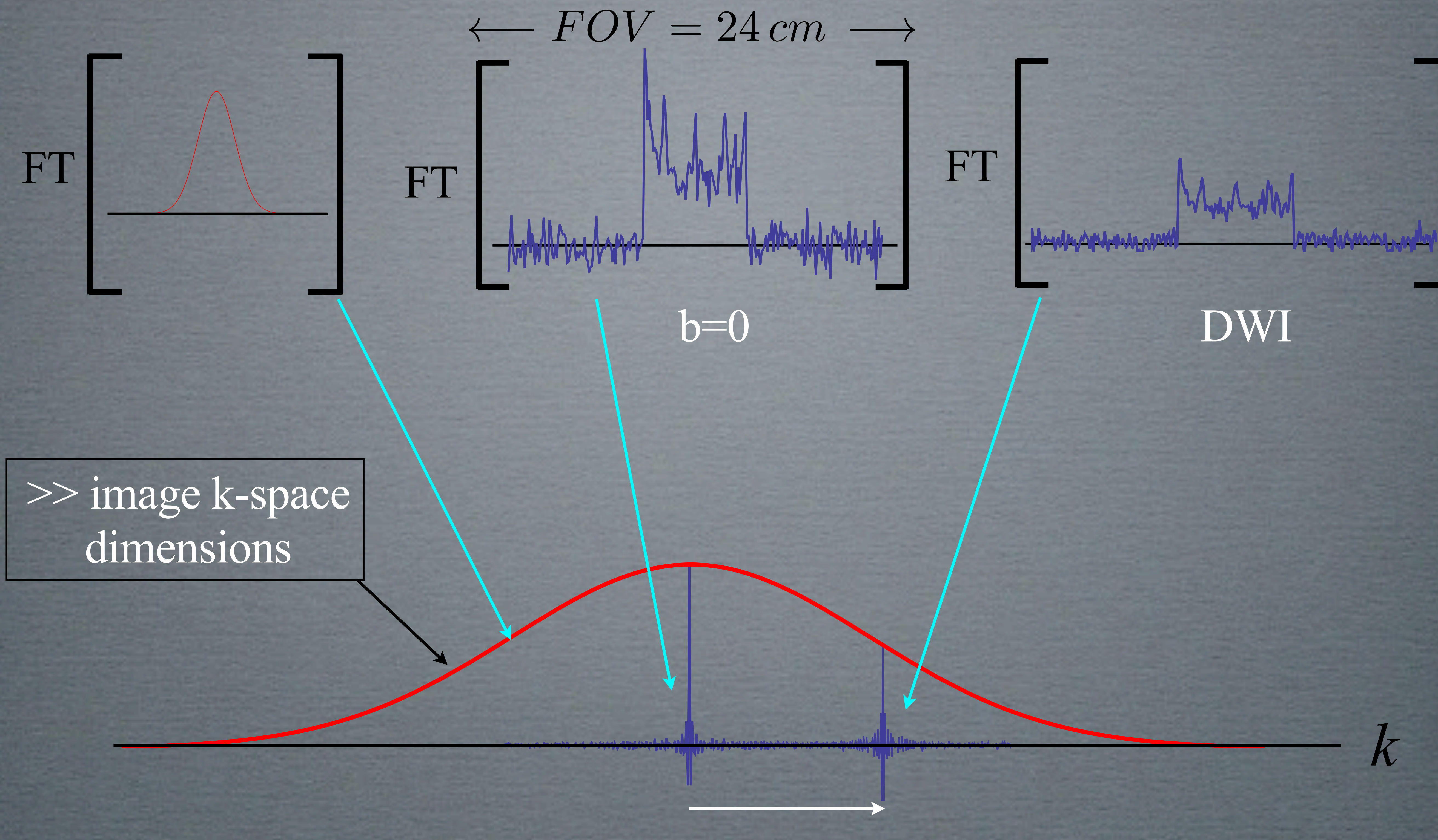


reconstruct **D**
(diffusion ellipsoid)

# Why Does DTI Work at All?

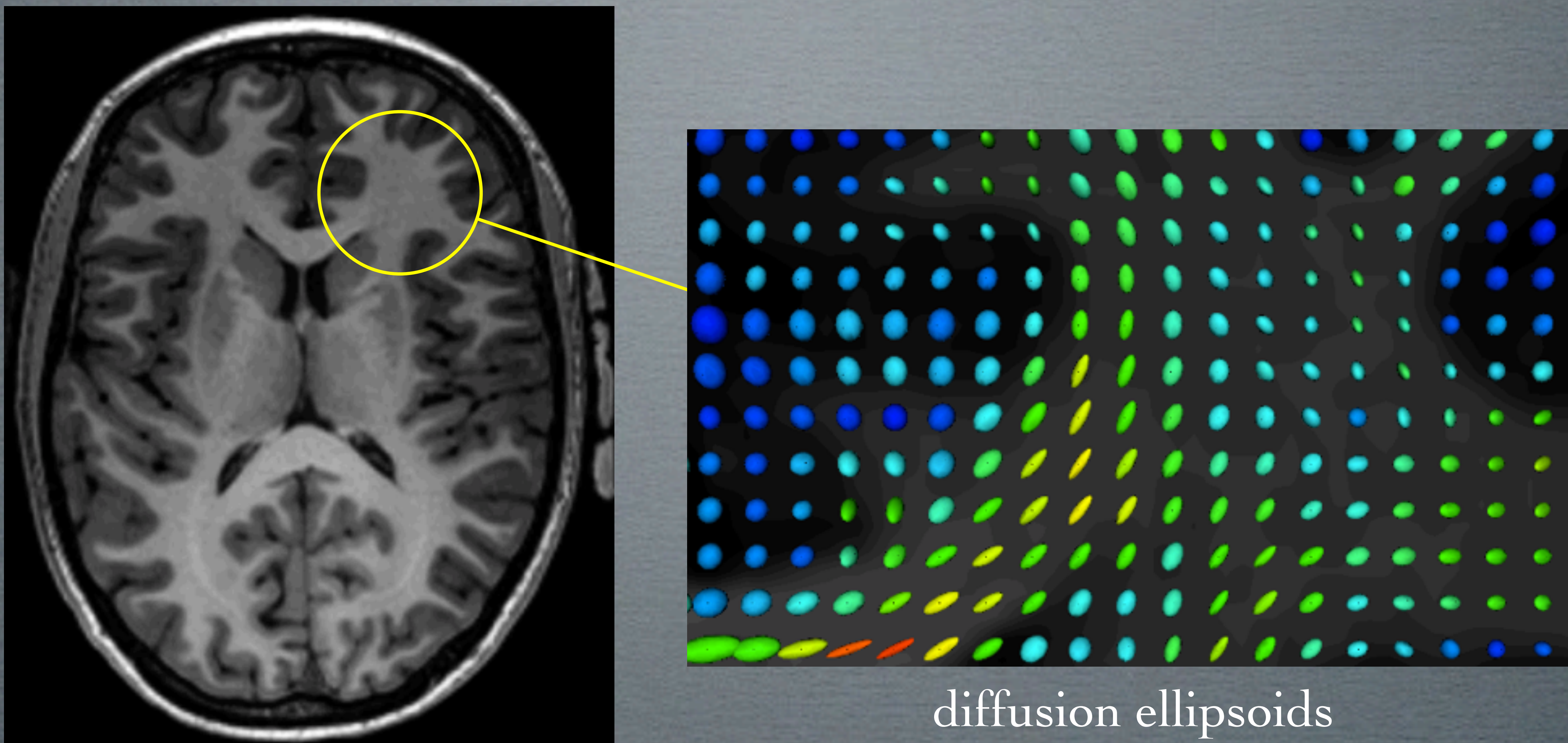

Diffusion acts as a convolution in the image domain
a zillion spins
τ
$t = 0$
$t = \tau$
$t = \tau$

$\sigma \approx 15\mu m \ll$ voxel dimensions




$$e^{-x^2/D\,dt} \Leftrightarrow e^{-k^2\,D\,dt}$$

# Diffusion Ellipsoid



diffusion ellipsoids

# Average Diffusion in a voxel

Three eigenvalues of D are the three principle mean-squared displacements along its three principal directions

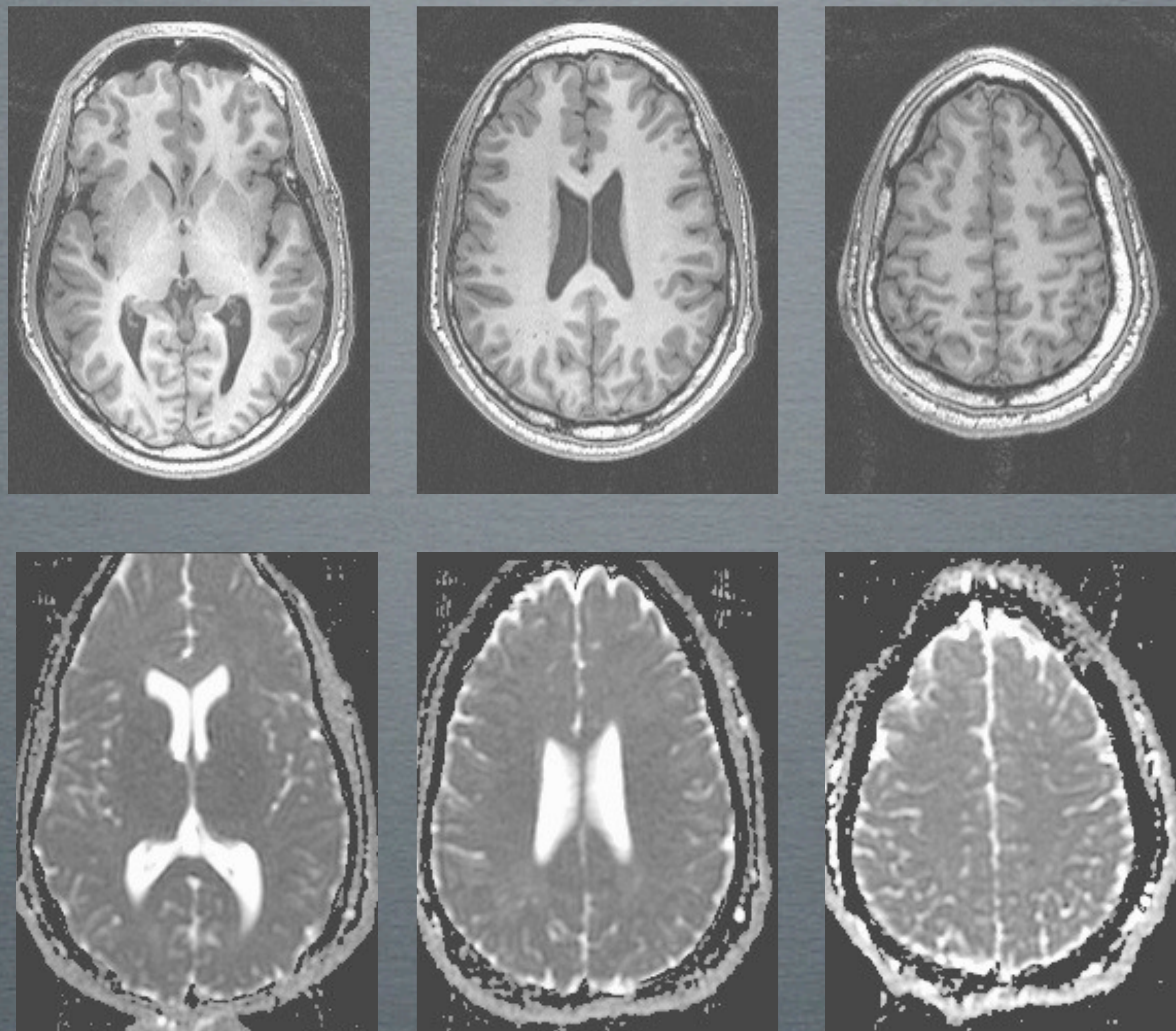
$$D = \begin{pmatrix} \lambda_x & 0 & 0 \\ 0 & \lambda_y & 0 \\ 0 & 0 & \lambda_z \end{pmatrix}$$

$\langle D \rangle = (\lambda_1 + \lambda_2 + \lambda_3)/3 = \langle \lambda \rangle$

$$= \mathrm{Tr}(D)$$

Tr = Trace = sum of diagonal elements

# Average Diffusion in a voxel



# Diffusion Anisotropy in a voxel

One measure of diffusion anisotropy is the variance of the eigenvalues, normalized to the mean-squared eigenvalue

$$\text{anisotropy} \propto \frac{(\lambda_x - \bar{\lambda})^2 + (\lambda_y - \bar{\lambda})^2 + (\lambda_z - \bar{\lambda})^2}{\bar{\lambda}^2}$$

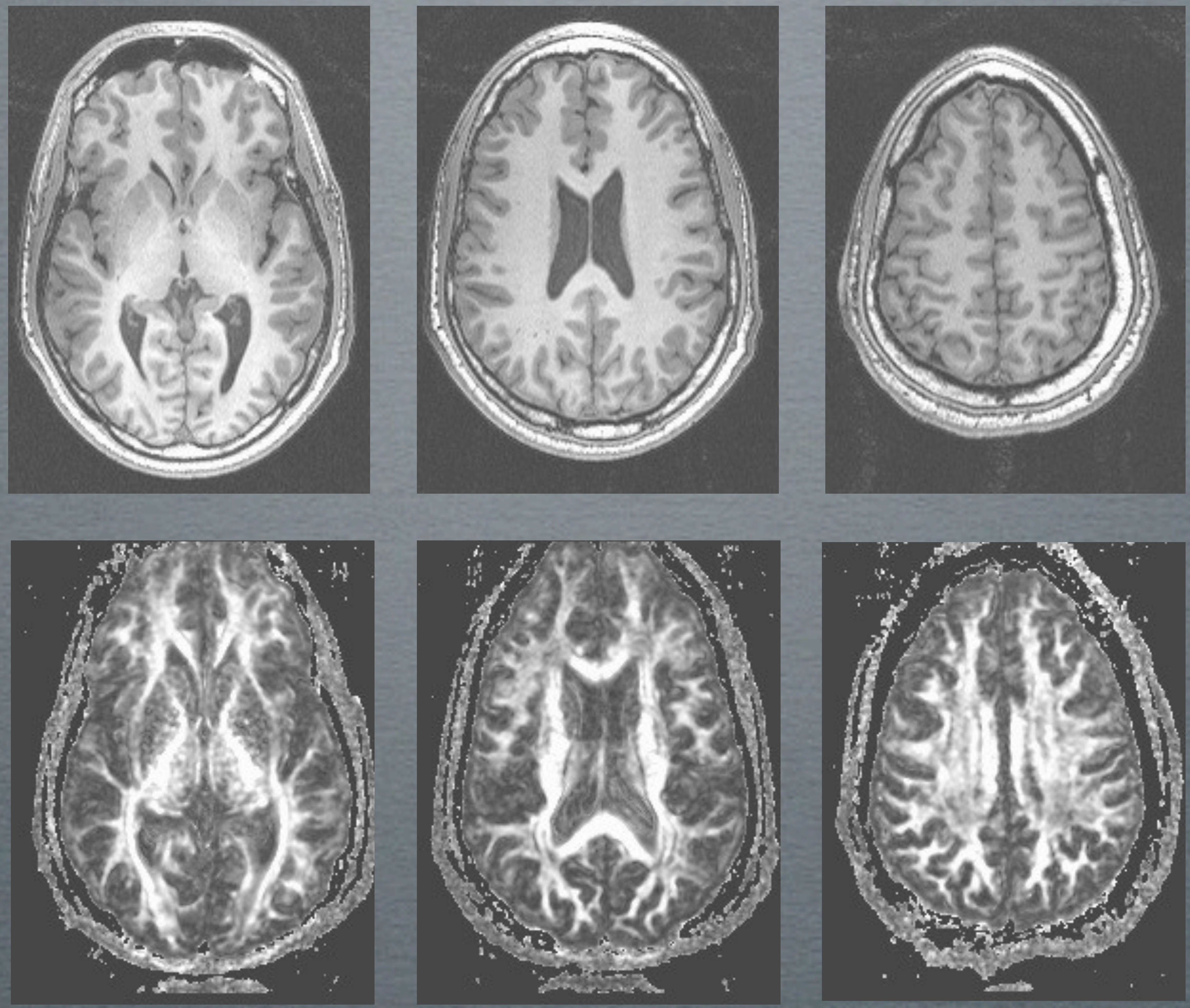
*Fractional Anisotropy*

$$\text{FA} \equiv \sqrt{\frac{3}{2}\frac{\sigma_\lambda^2}{\bar{\lambda}^2}}$$

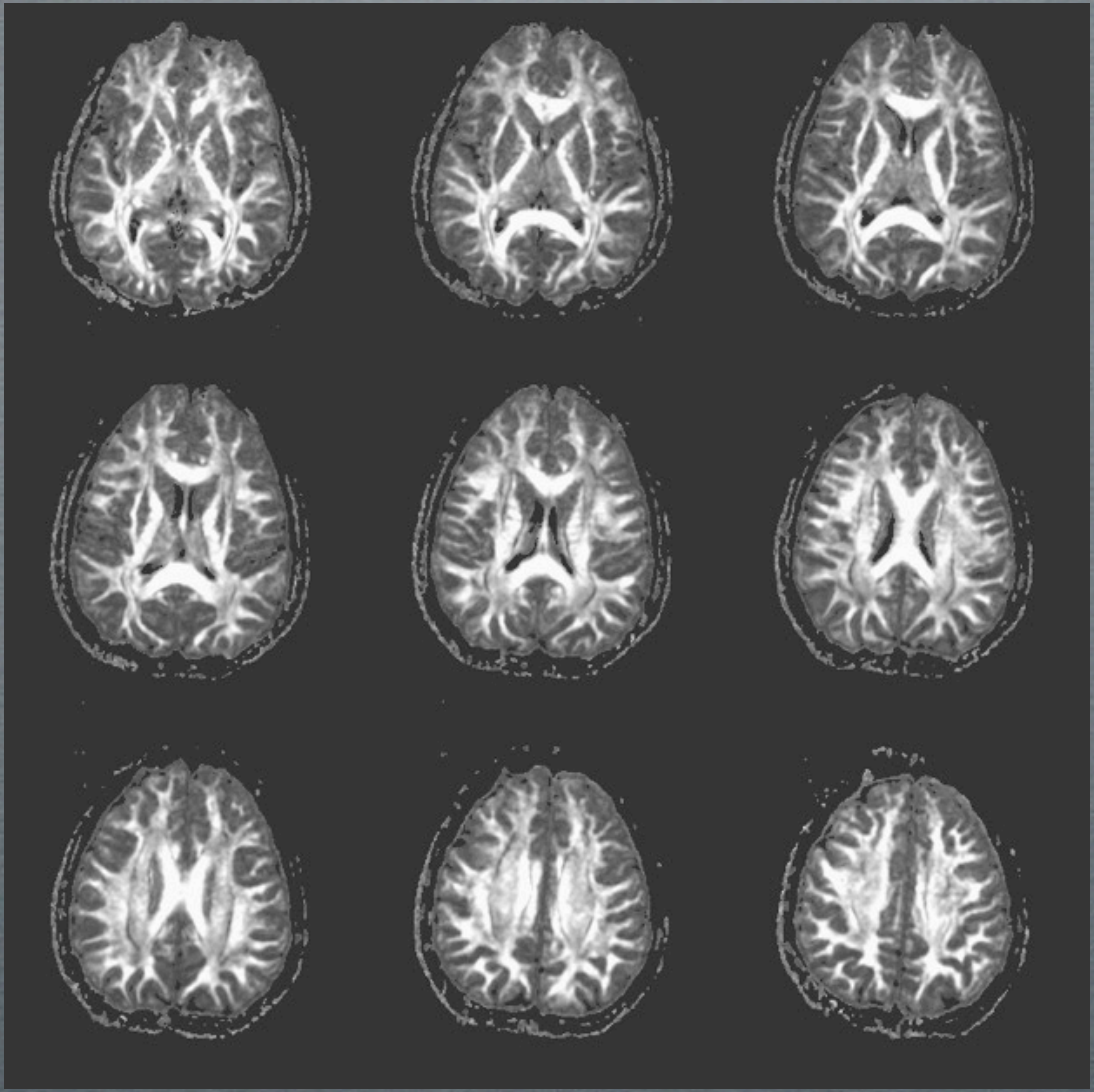
# Diffusion Anisotropy in a voxel

anatomical

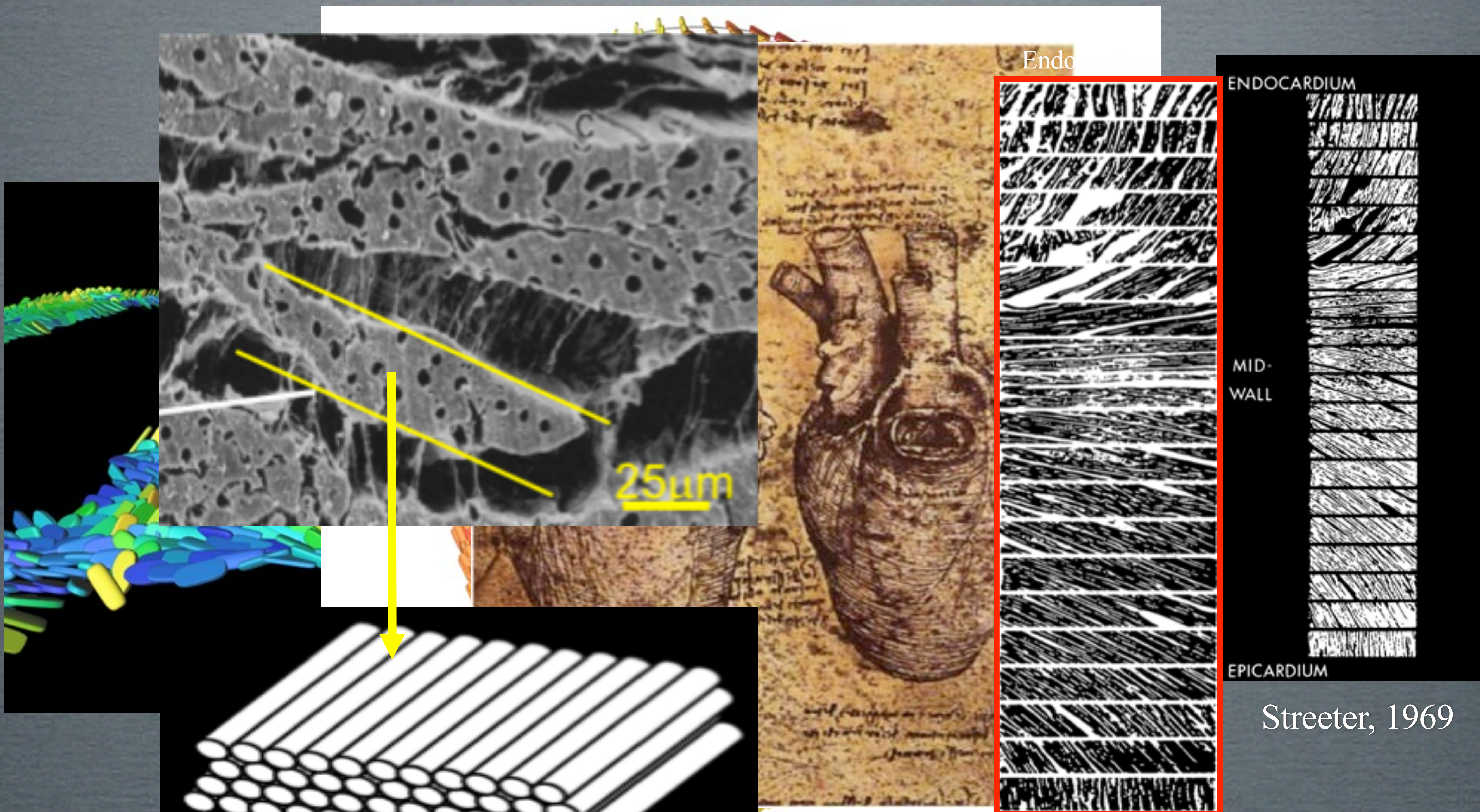
FA



# Diffusion Anisotropy



# The uses of anisotropy: Cardiac Mechanics



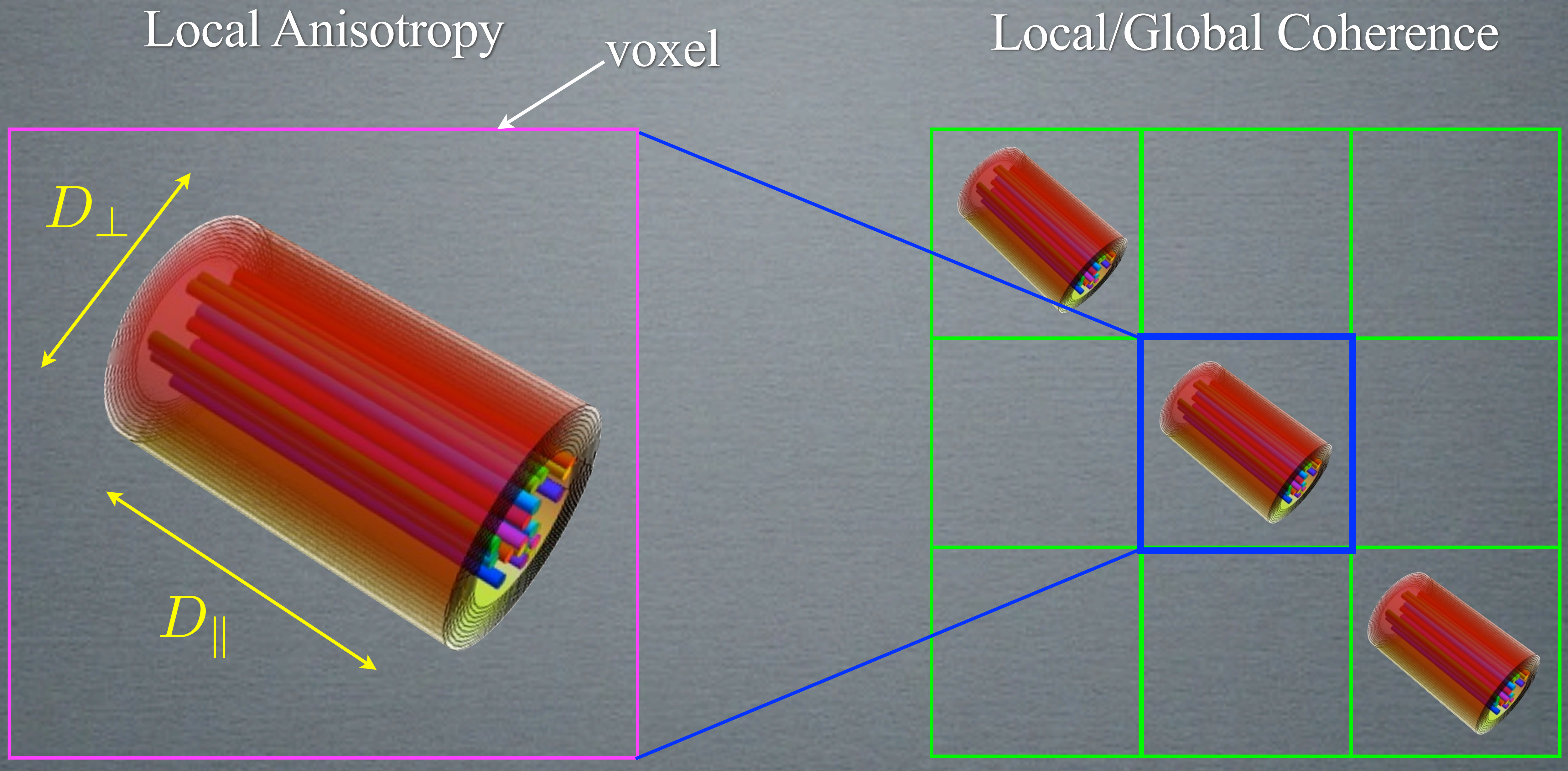

Streeter, 1969

Excised canine heart (Howard, UCSD Cardiac Biomechanics Group 2011) using 3D Spiral FSE DTI sequence (Frank et al, Neuroimage 2010)

Legrice et al. 1994

Our first whole human heart DTI (ex vivo)

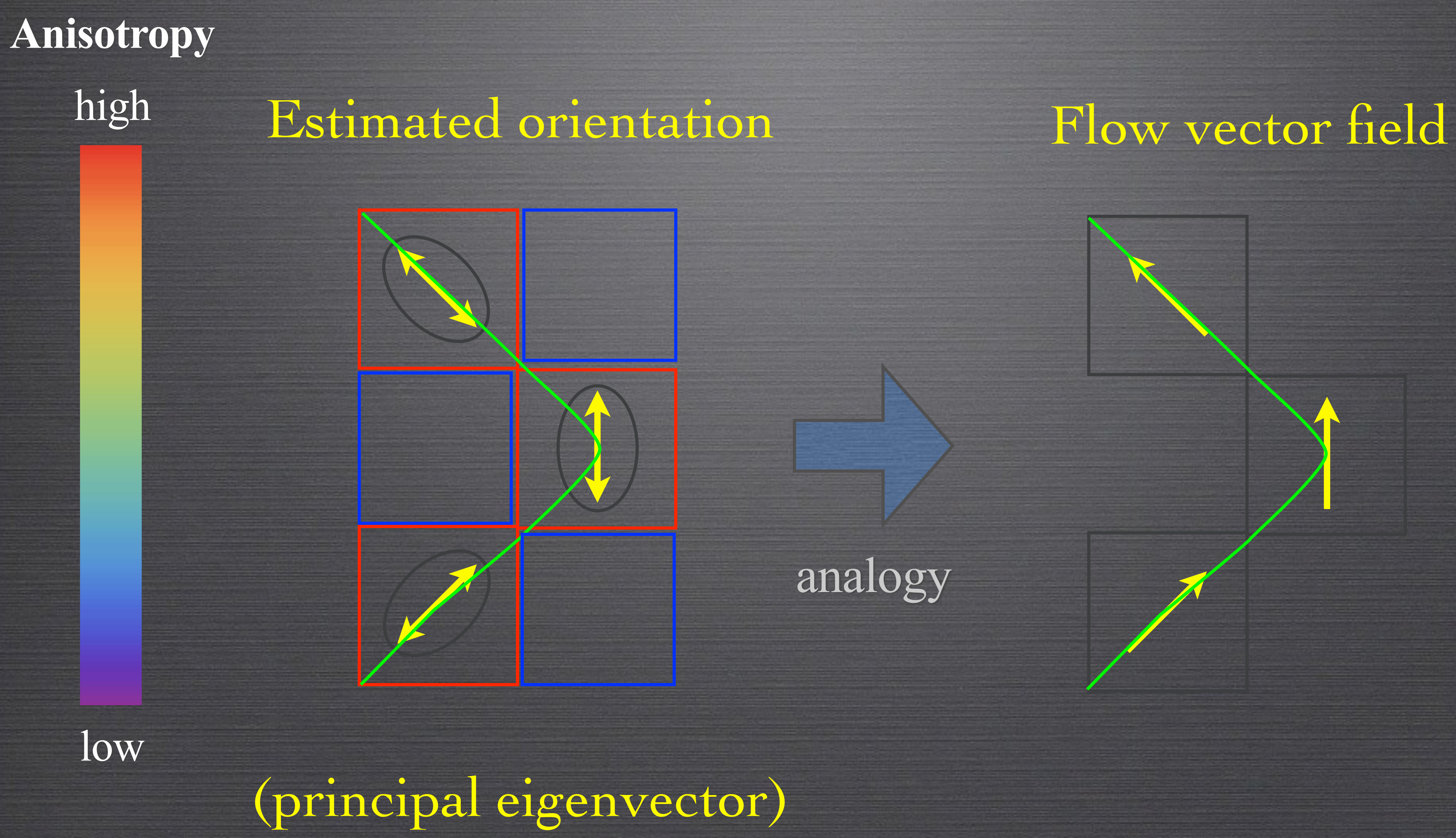
# From local (voxel) anisotropy to extended spatially coherent anisotropy: Tractography




$$D_\parallel \approx 3D_\perp$$

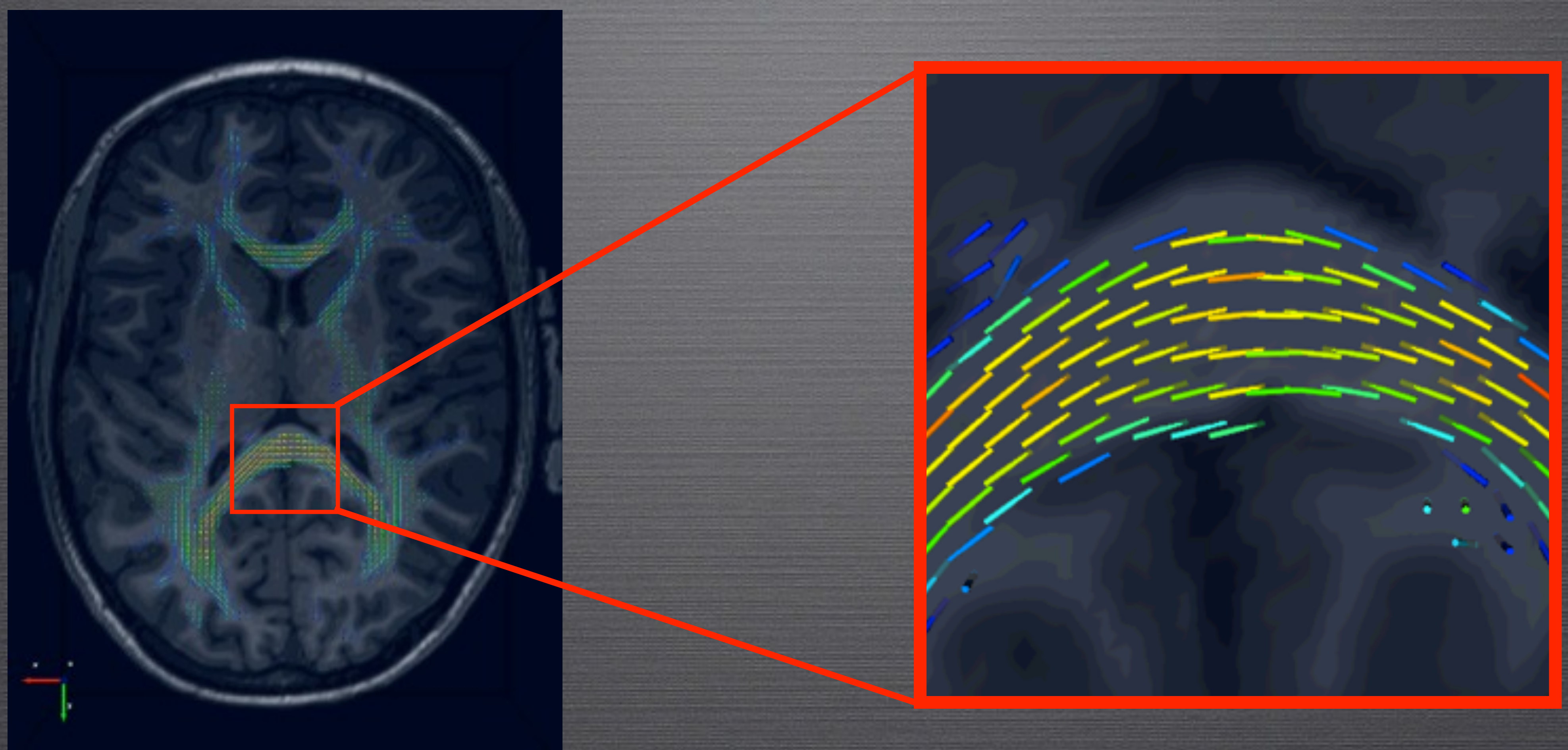
$(1.2\mu^2/ms)$ $(0.4\mu^2/ms)$

# Streamlines



# What we expect of Diffusion Imaging

Some information about the microscopic structure



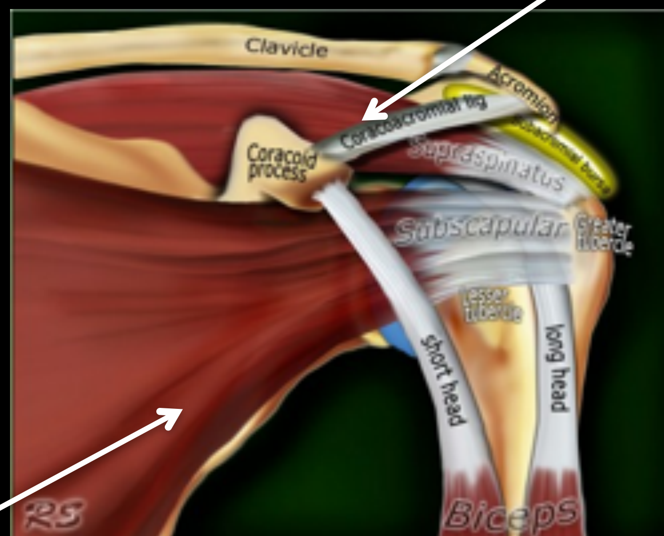
For voxels with aligned fibers (as in the corpus callosum)...

...the primary diffusion direction should be oriented in the same direction as the fiber.

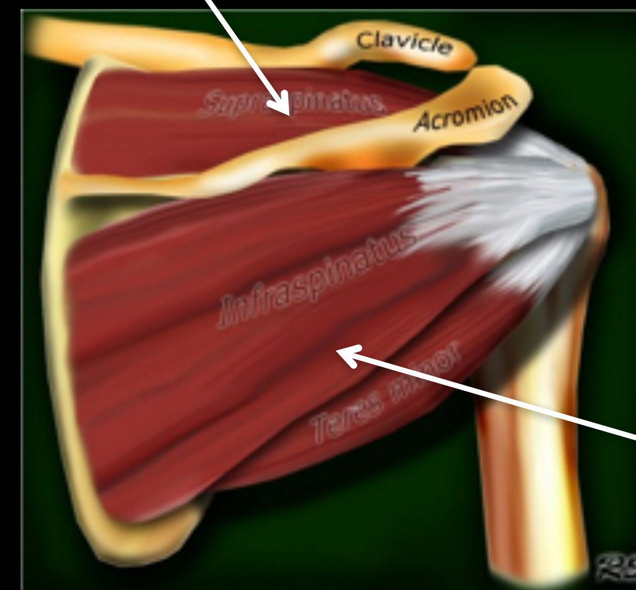
# Supraspinatus DTI

Supraspinatus

Anterior

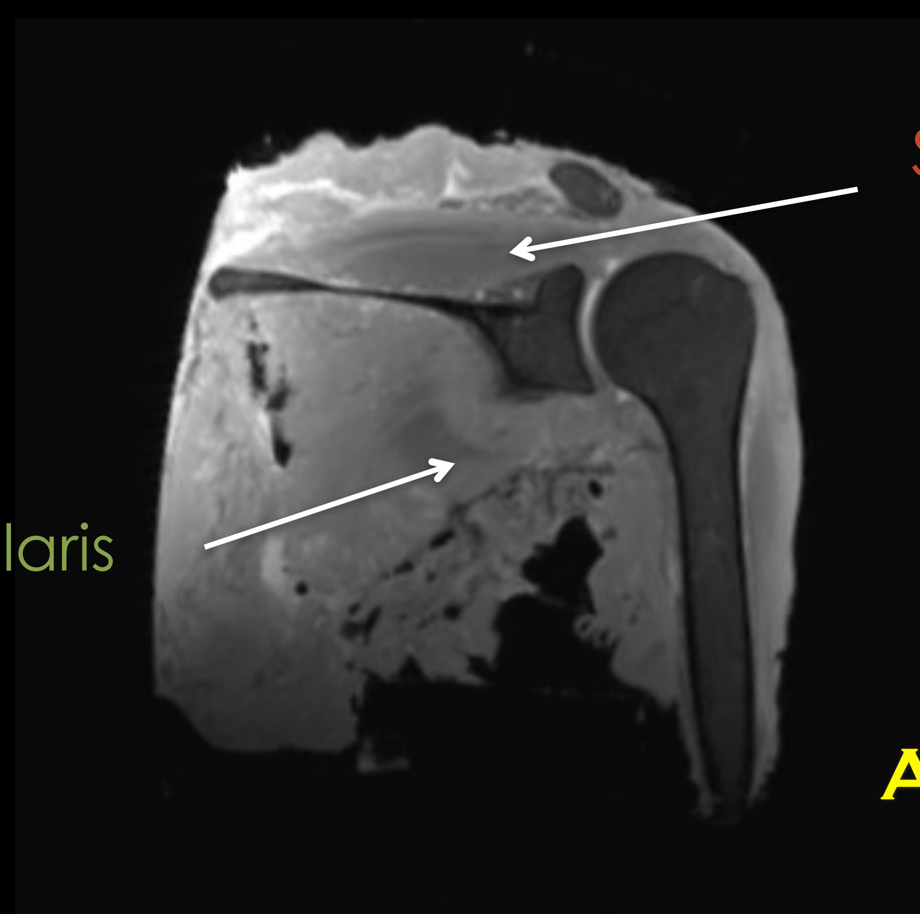



Posterior




Infraspinatus
+ Teres Minor

Subscapularis



Supraspinatus

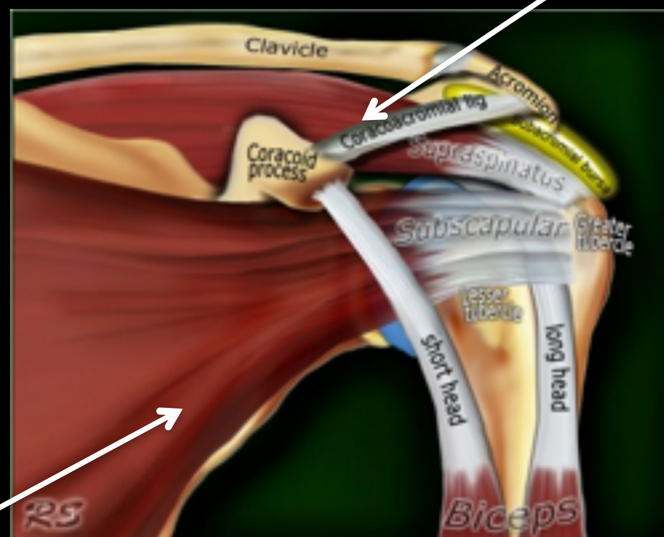
Subscapularis

**A. Rodrigues-Soto, Ward group**

# Supraspinatus DTI

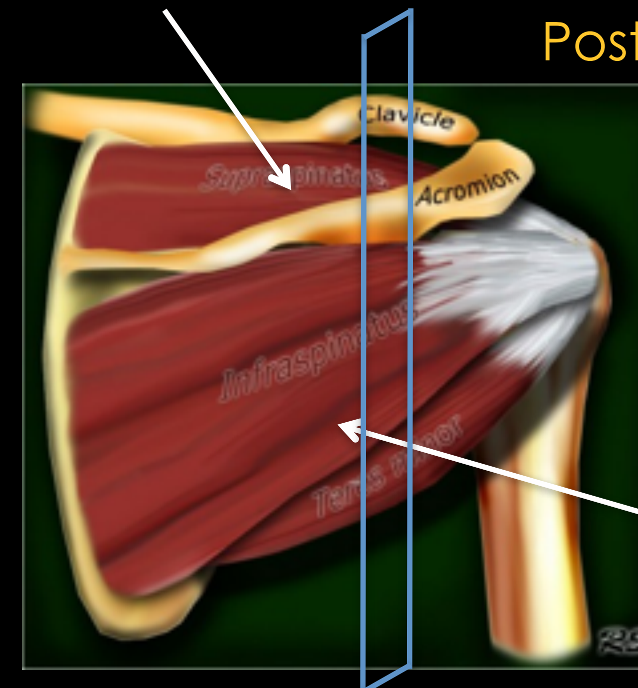
Supraspinatus

Anterior

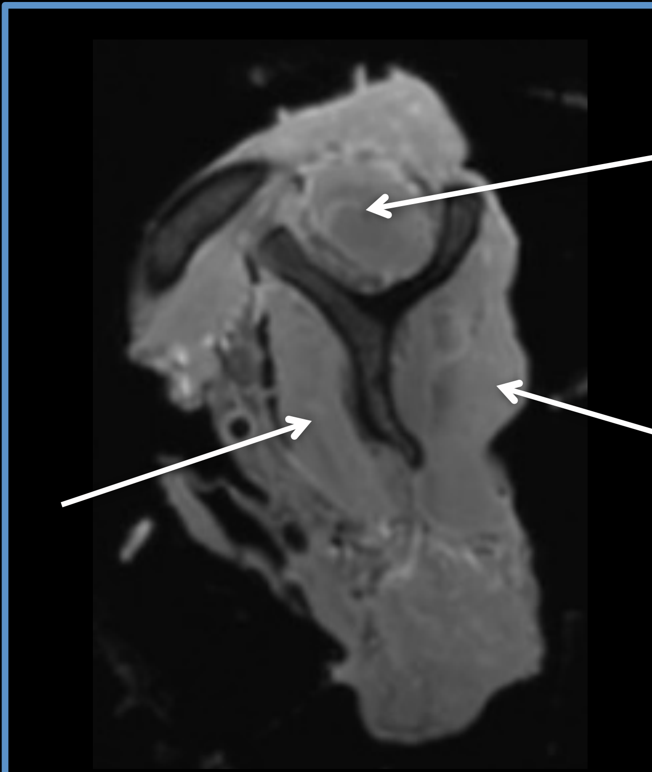



Subscapularis

Posterior




Infraspinatus
+ Teres Minor



Supraspinatus

Subscapularis

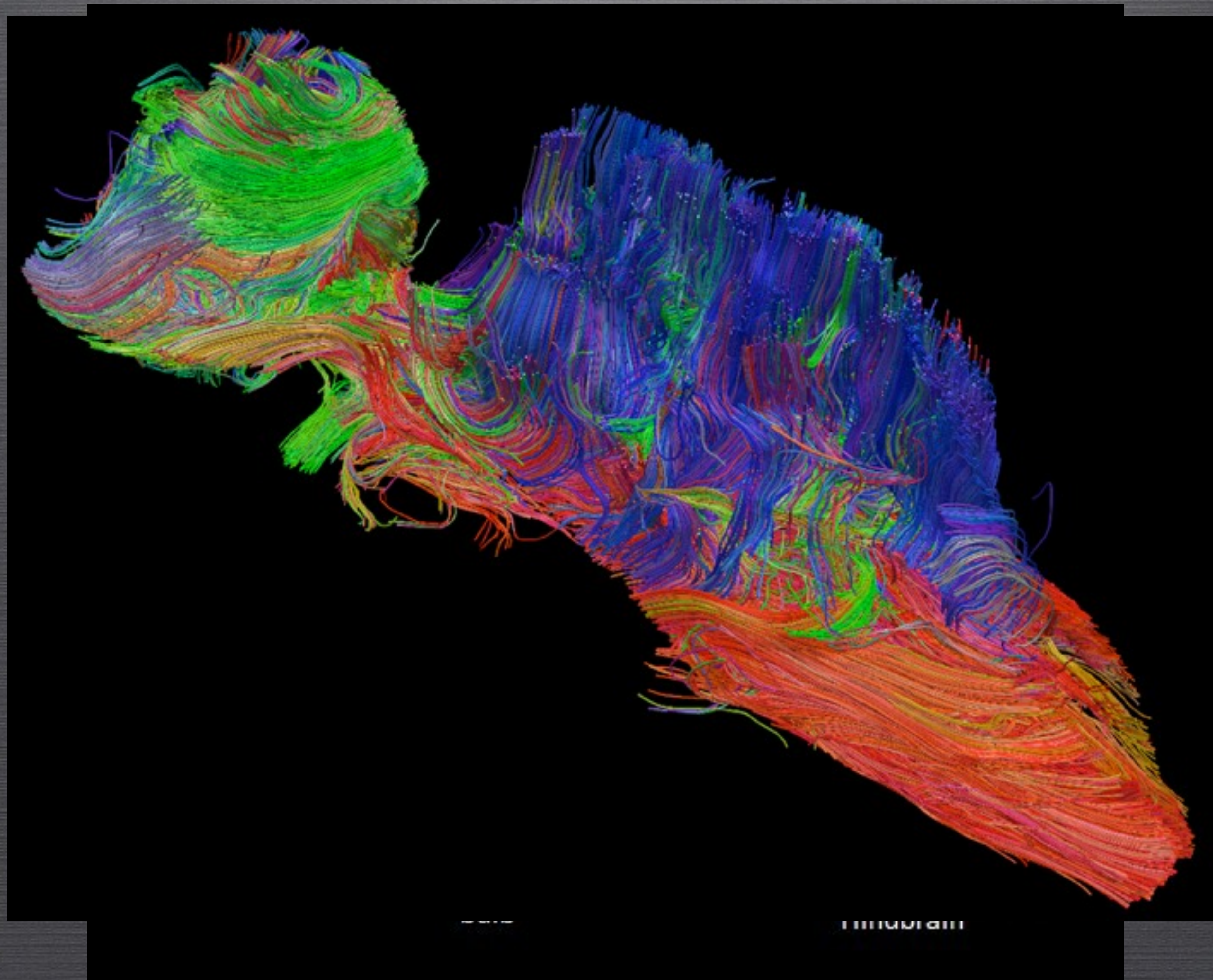
Infraspinatus

**A. Rodrigues-Soto,**
**Ward group**

Supraspinatus Tractography @60 directions


A. Rodrigues-Soto,
Ward group

# What is the Neural Structure of Elasmobranchs?



*Mustelus henlei*

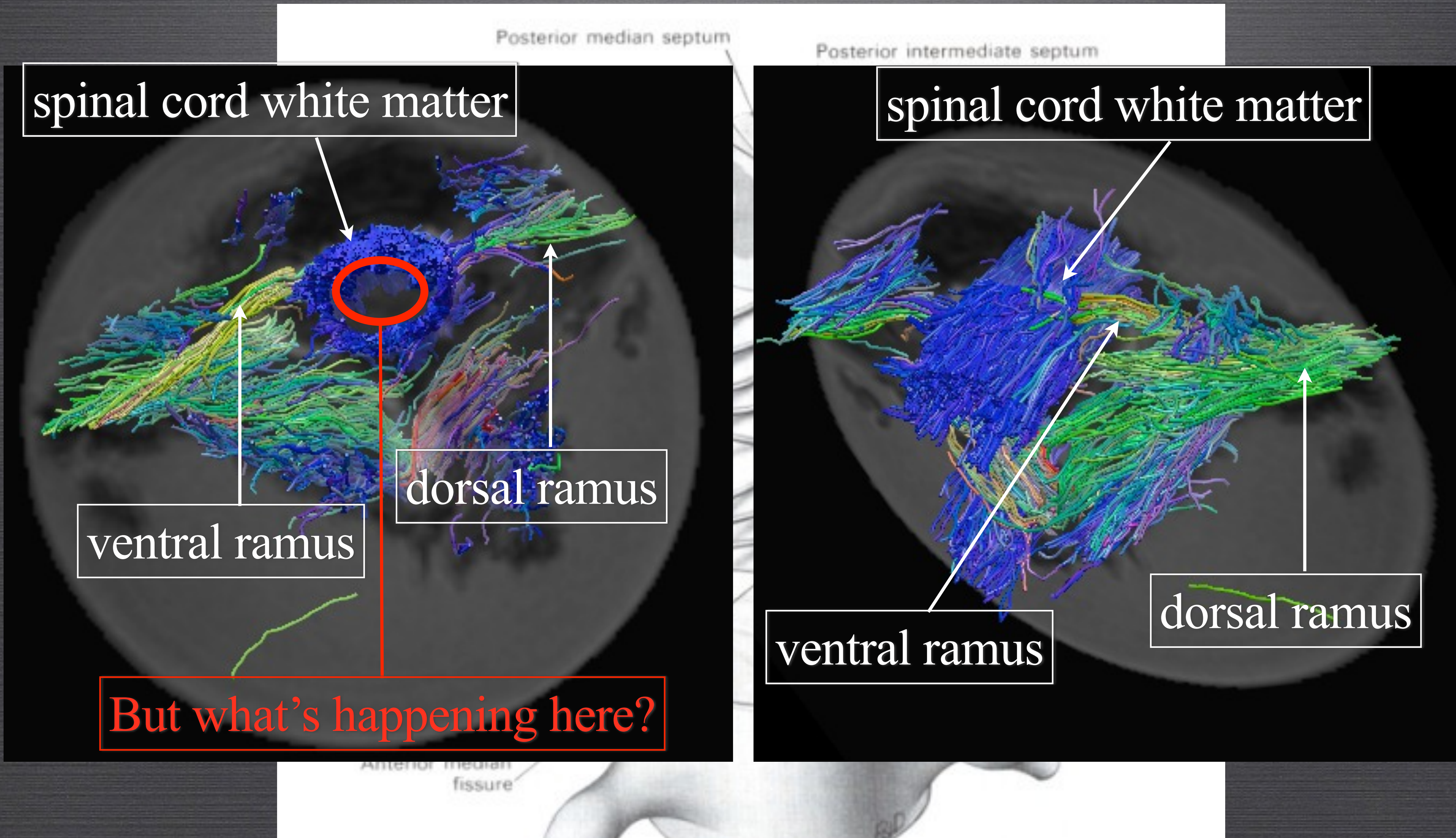
DTI @ 11.7T

Data: M. Tyszka, CalTech

Segmentation: K. Yopak, CSCI

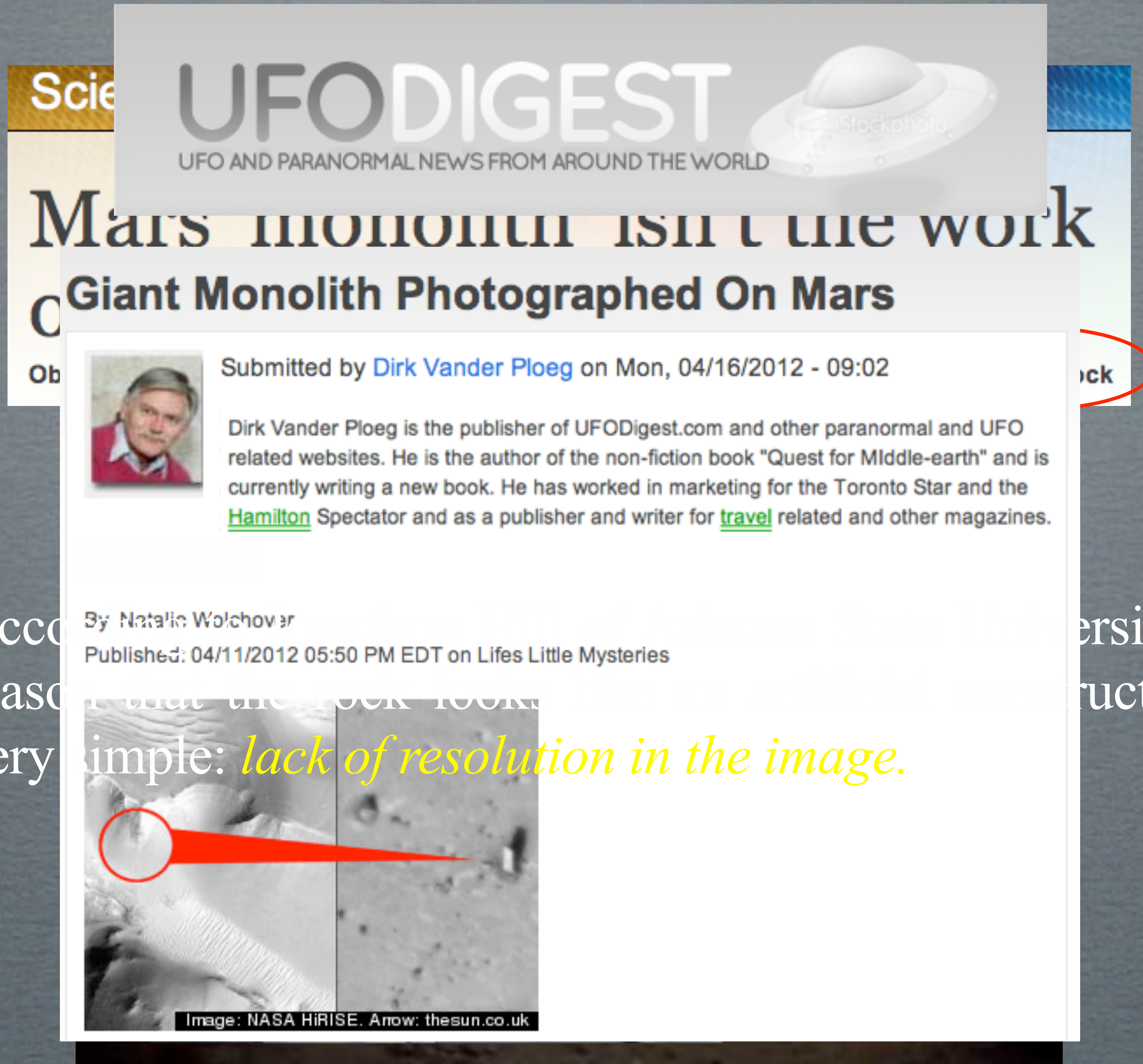
R. Berquist, CSCI

# Spinal Cord Injury (Rat Model at 7T)



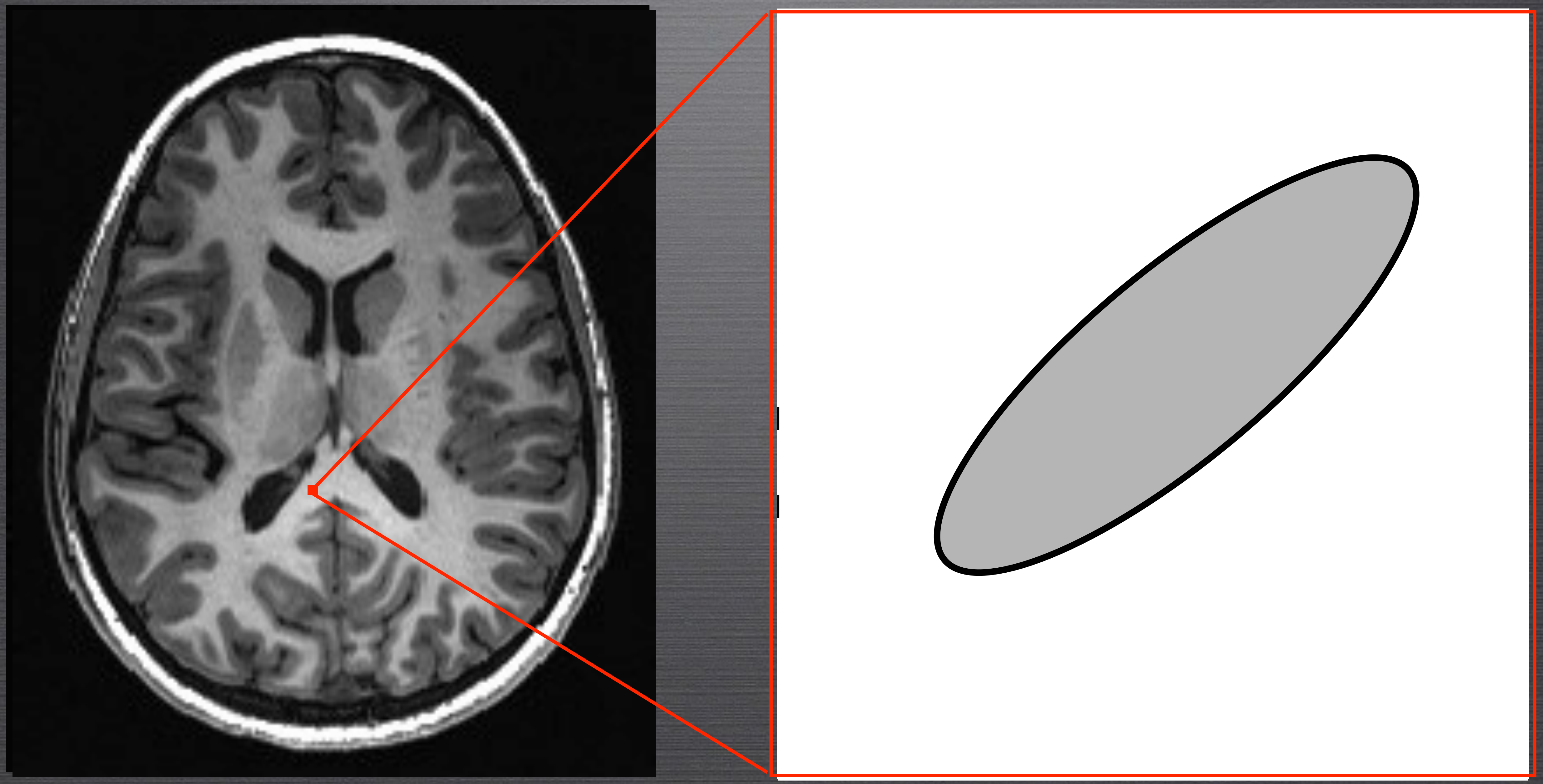

Jacob Koffler, Ph.D.
Mark H. Tuszynski, M.D., Ph.D.
Center for Neural Repair
University of California, San Diego

# How much information can we extract?

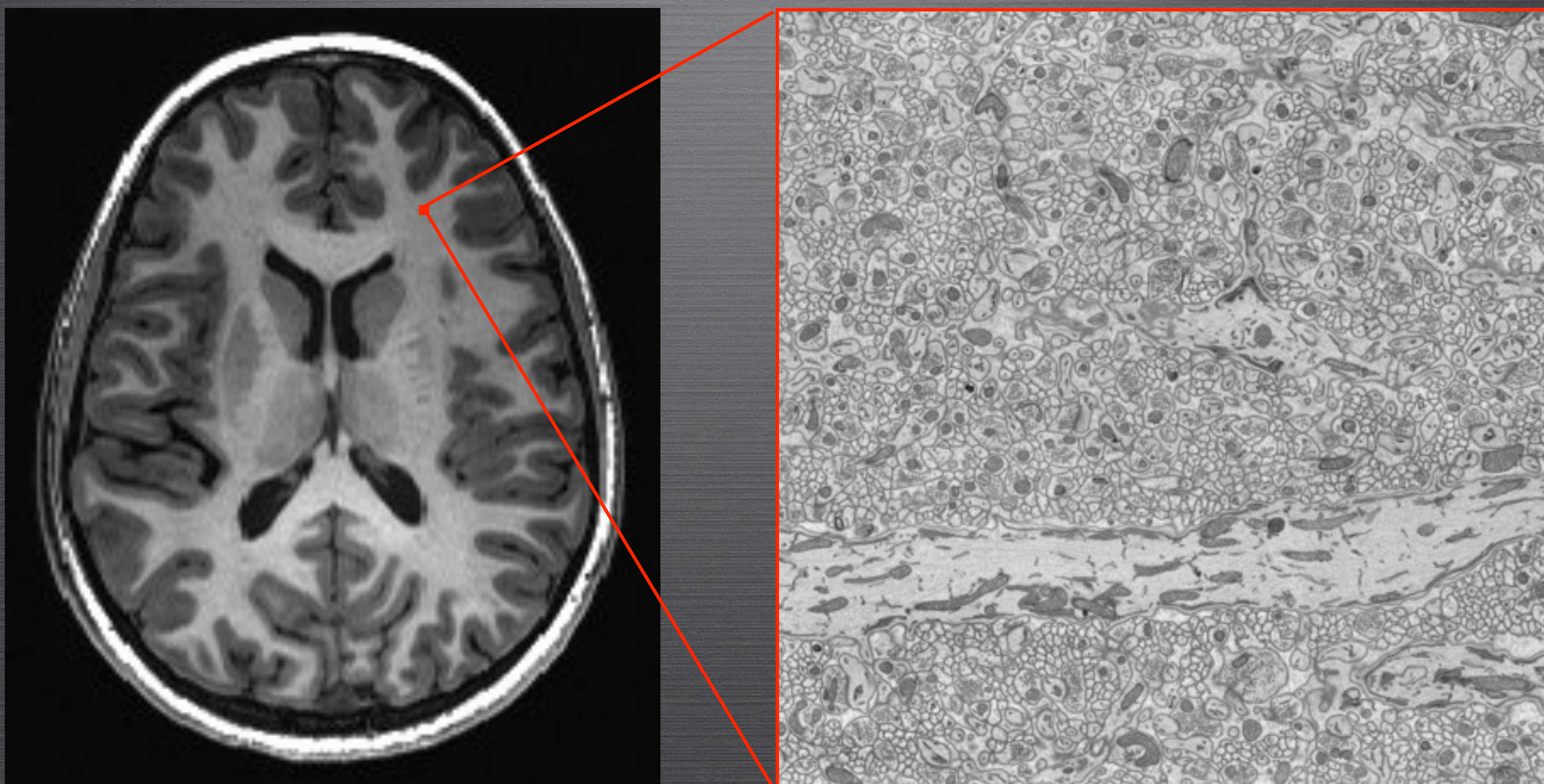



Acc… ersity, the reas… uction is very simple: *lack of resolution in the image.*

# What's the problem?



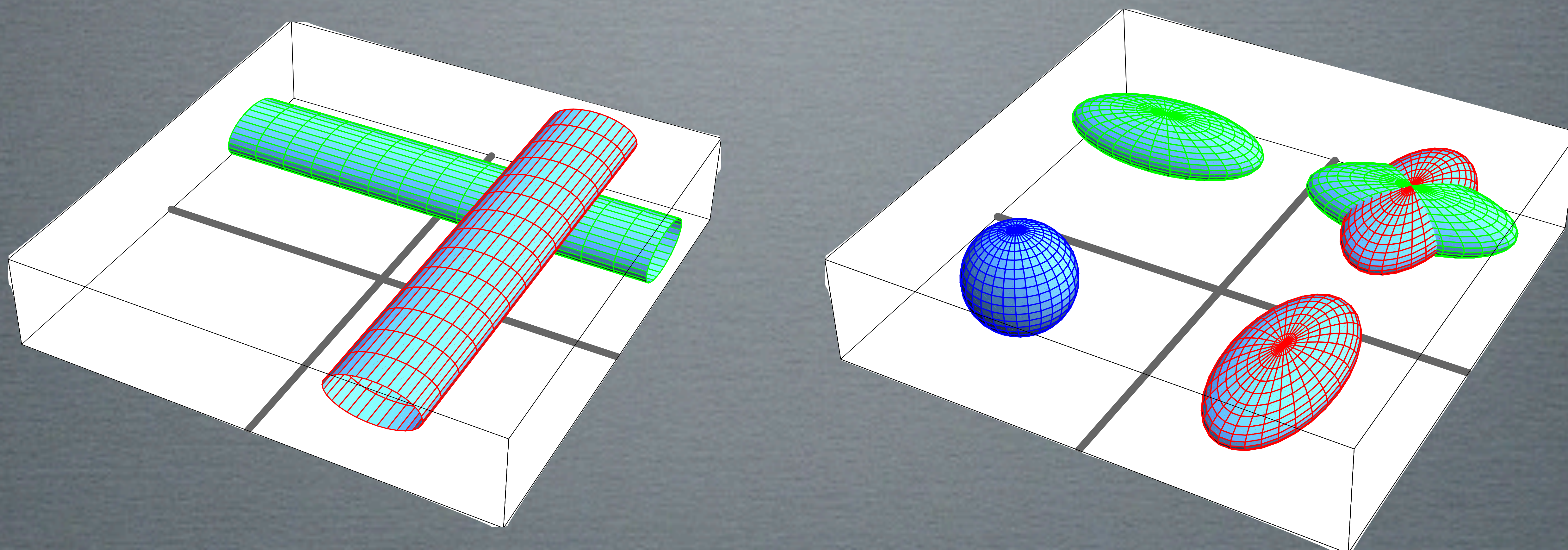
# But we know Neural Tissues aren't that simple



Rat WM electron microscopic image
Courtesy, M. Ellisman, UCSD

# Failure of the standard model

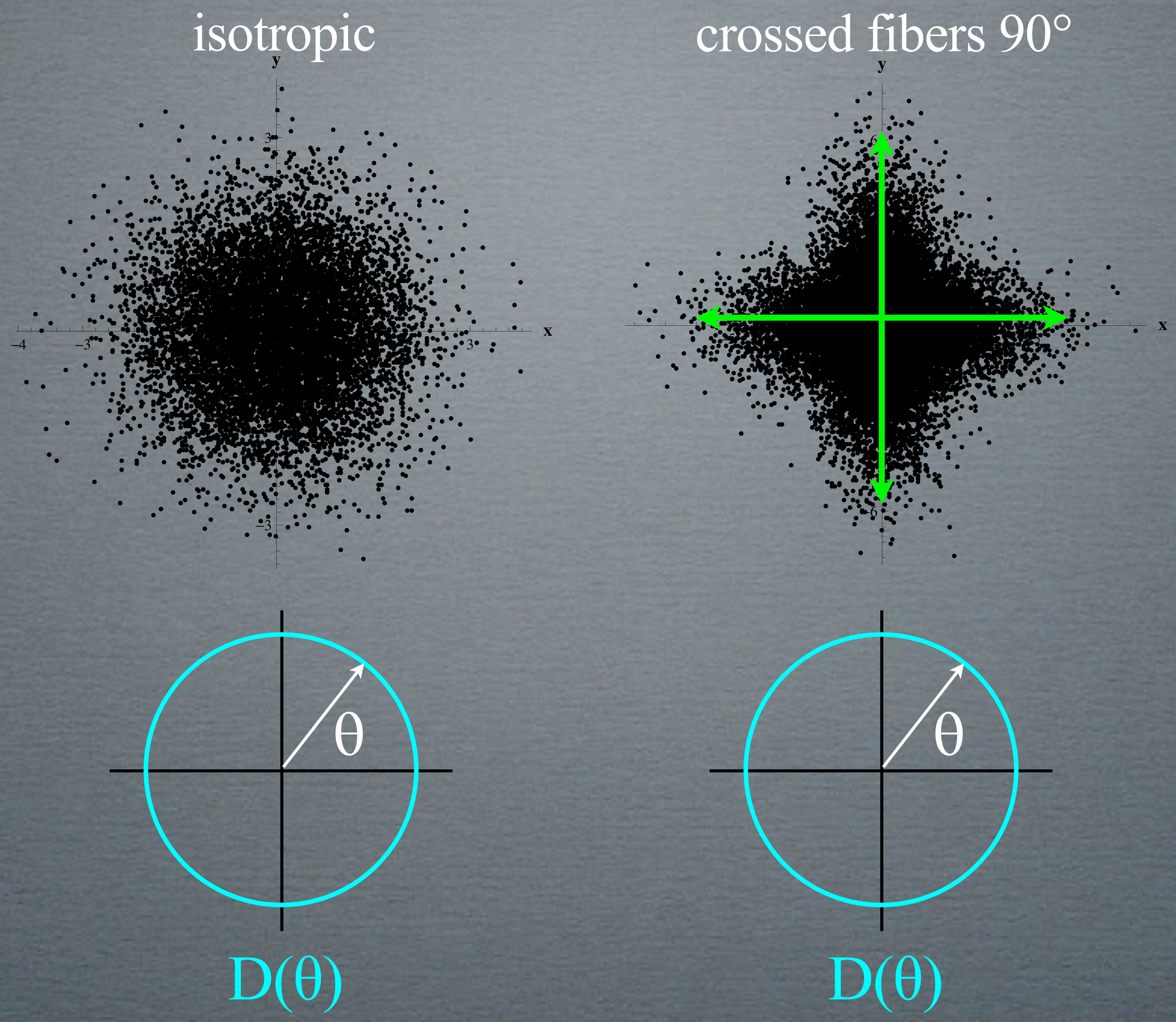
A simple partial-volume model



Two crossing fibers

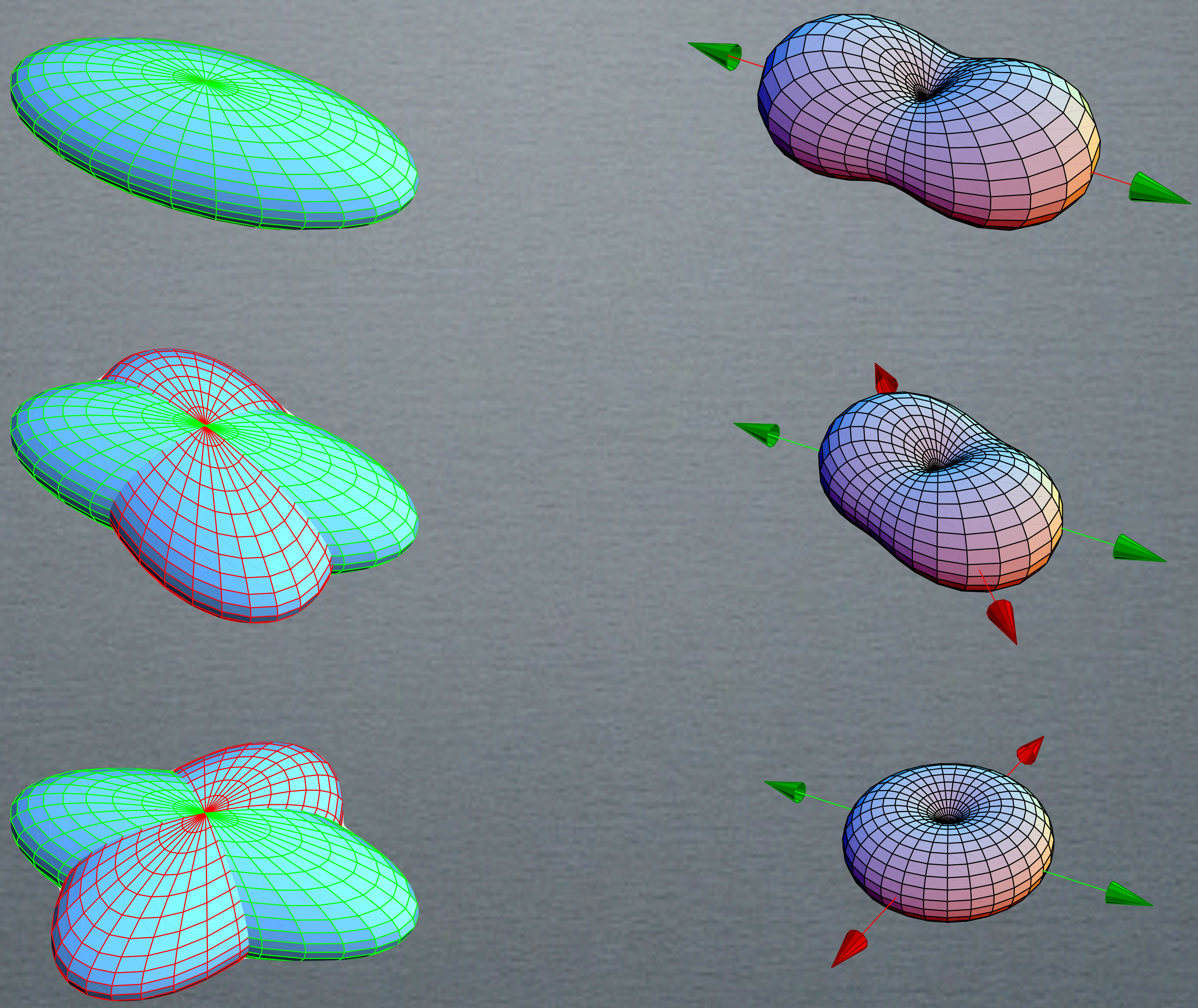
resulting distributions

# Ambiguities in the standard model

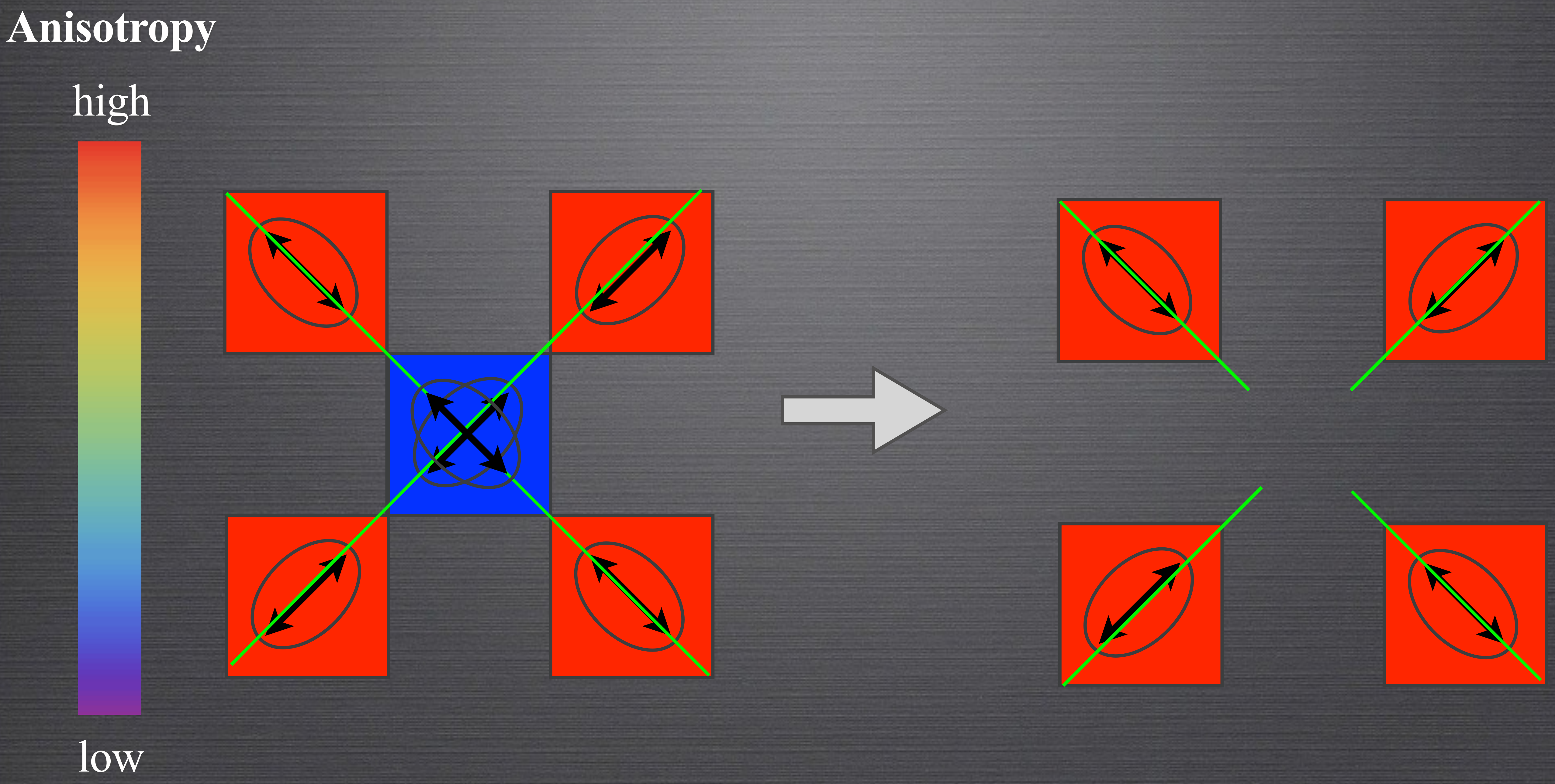


# Failure of the standard model

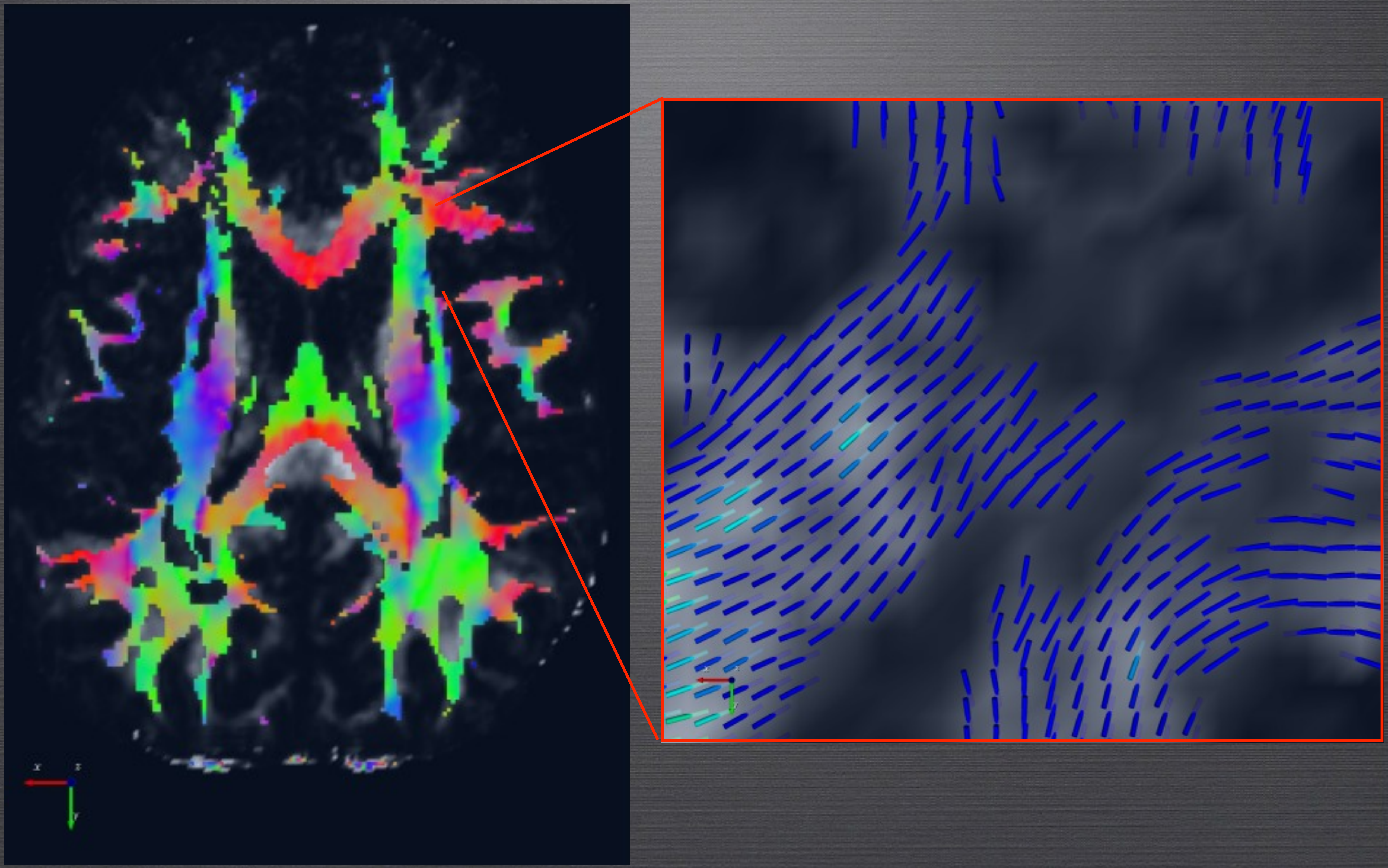
Distribution of spins | Estimated D



# The Major Problem: Heterogeneous Voxels

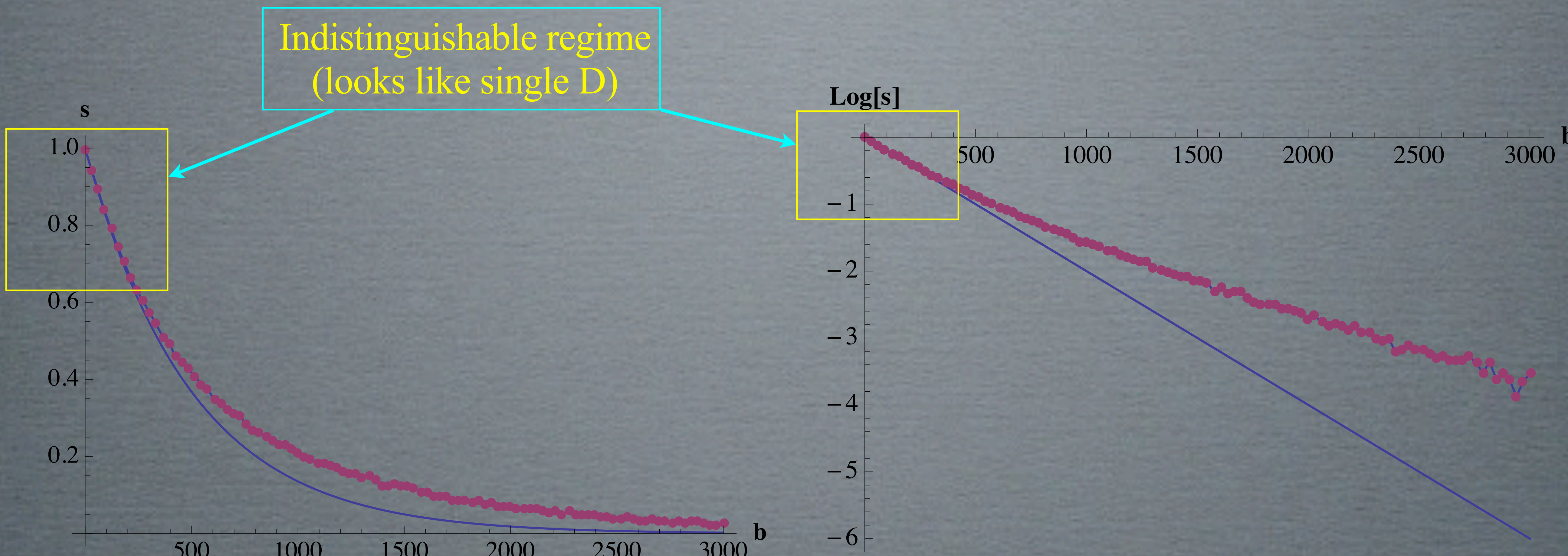


# Tractography Problem



# Failure of the standard model

Not only angular issues, but b-value dependencies as well!

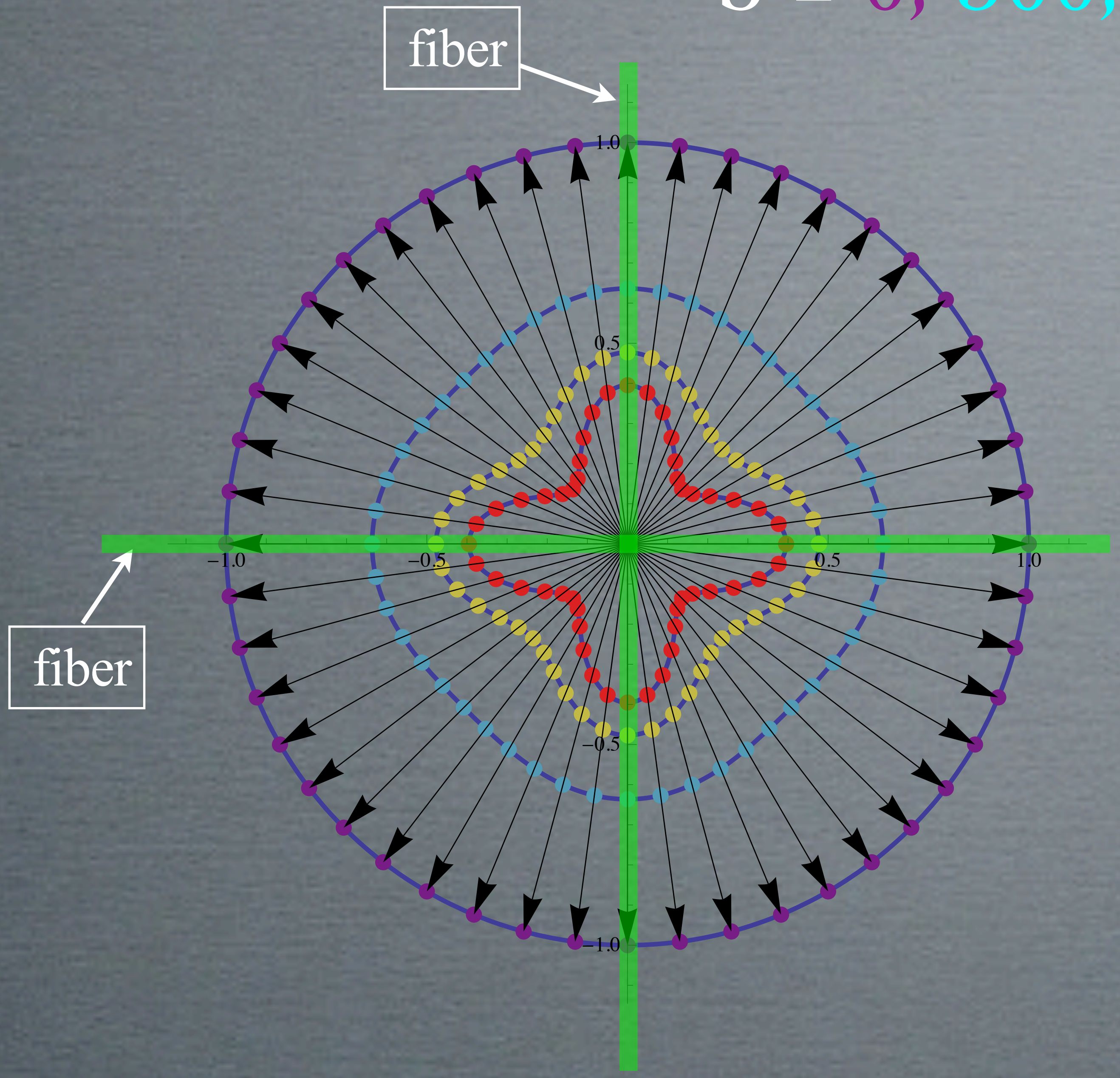



$$\frac{S(b)}{S(0)} = f e^{-bD_1} + (1-f) e^{-bD_2}$$

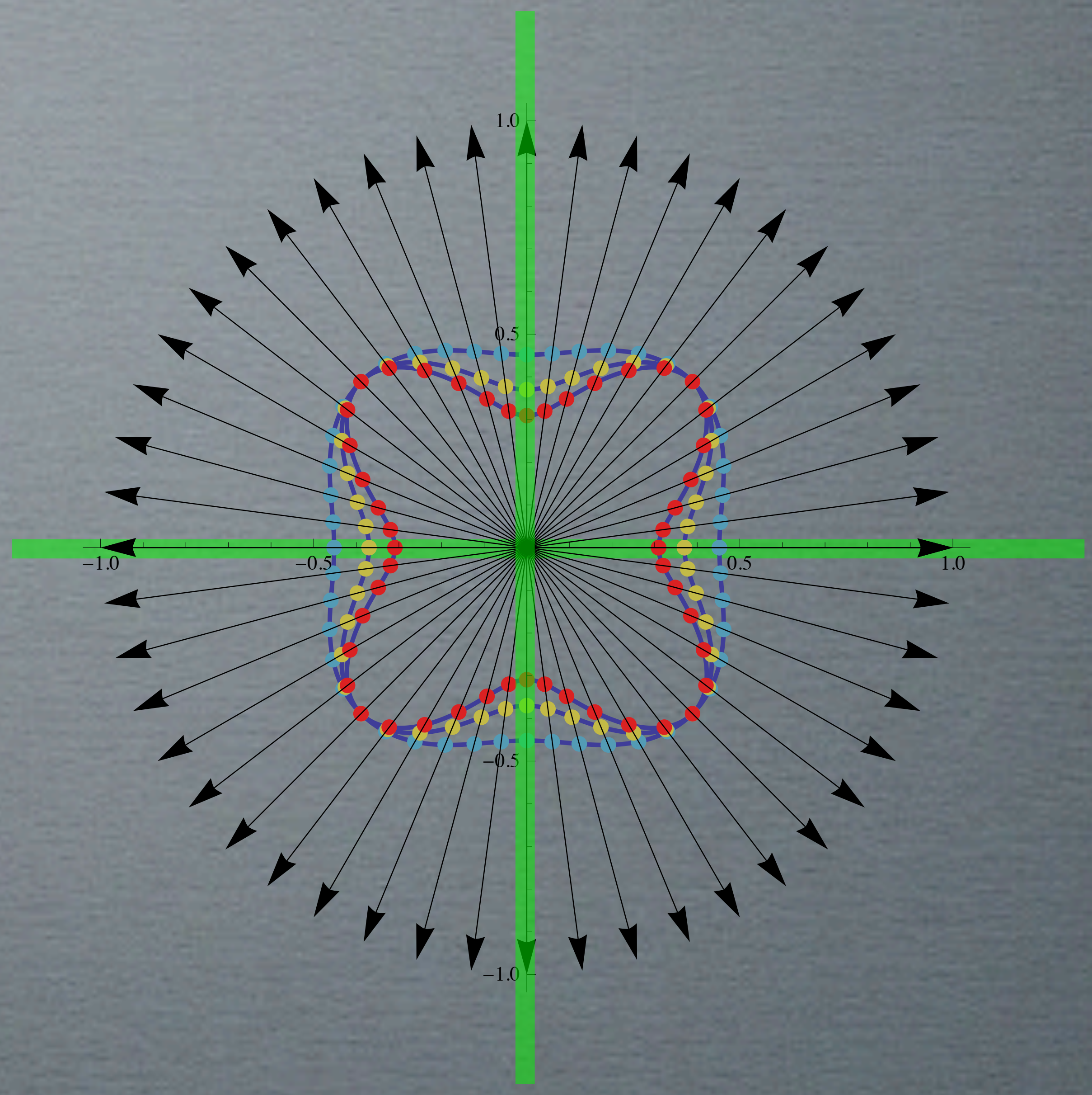
simple two diffusion coefficient model

# High Angular Resolution DTI (HARDI)

b = 0, 500, 1000, 1500



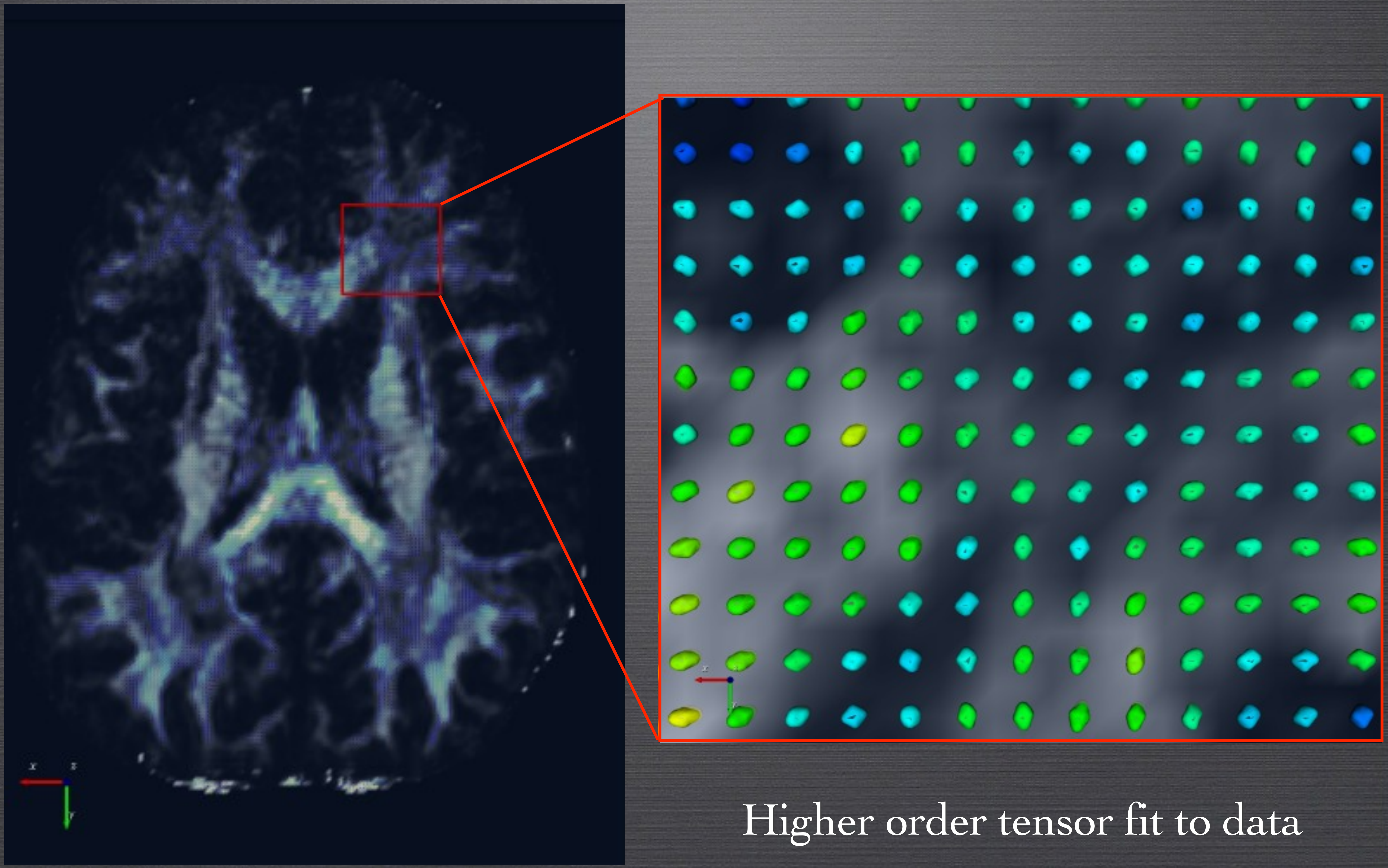

signal




$D_{app}(\theta)$

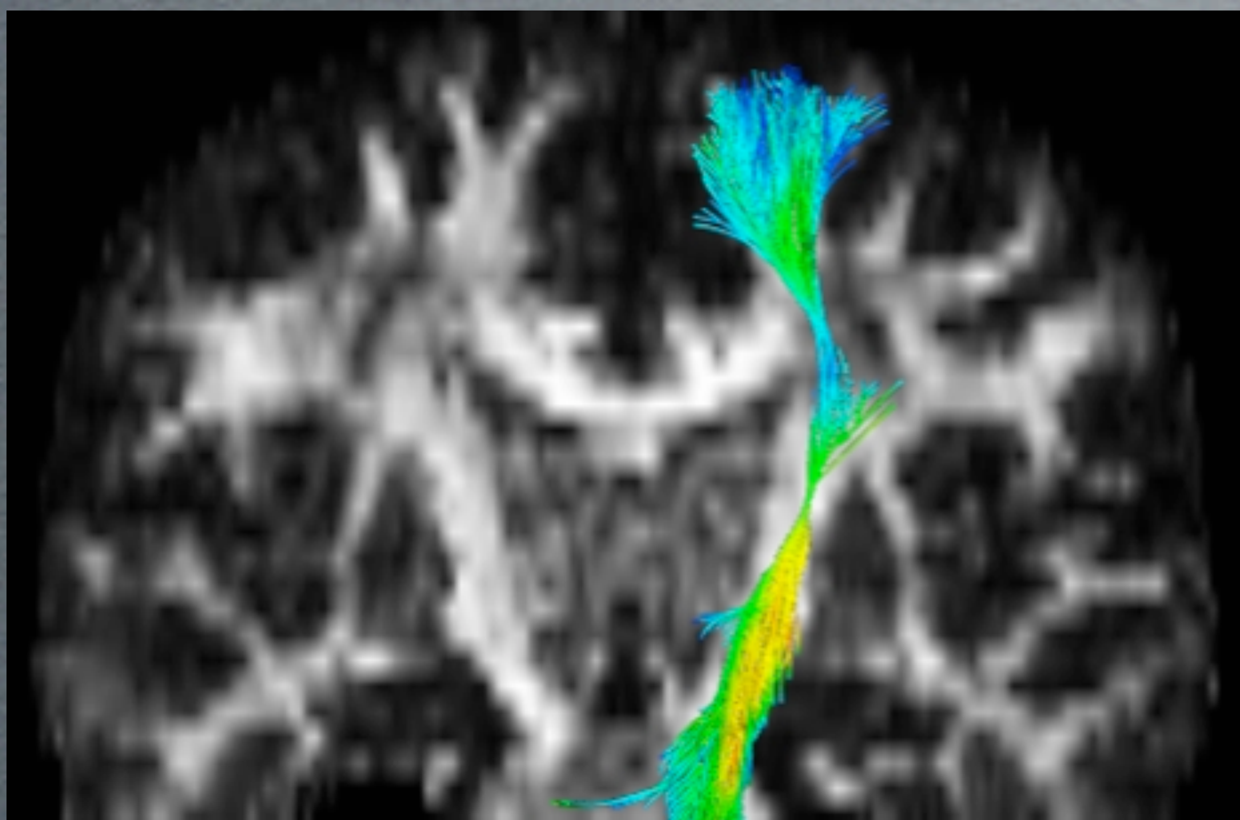
Structure of lobes relative to fiber orientation is “non-intuitive”!

# Tractography Problem, revisited

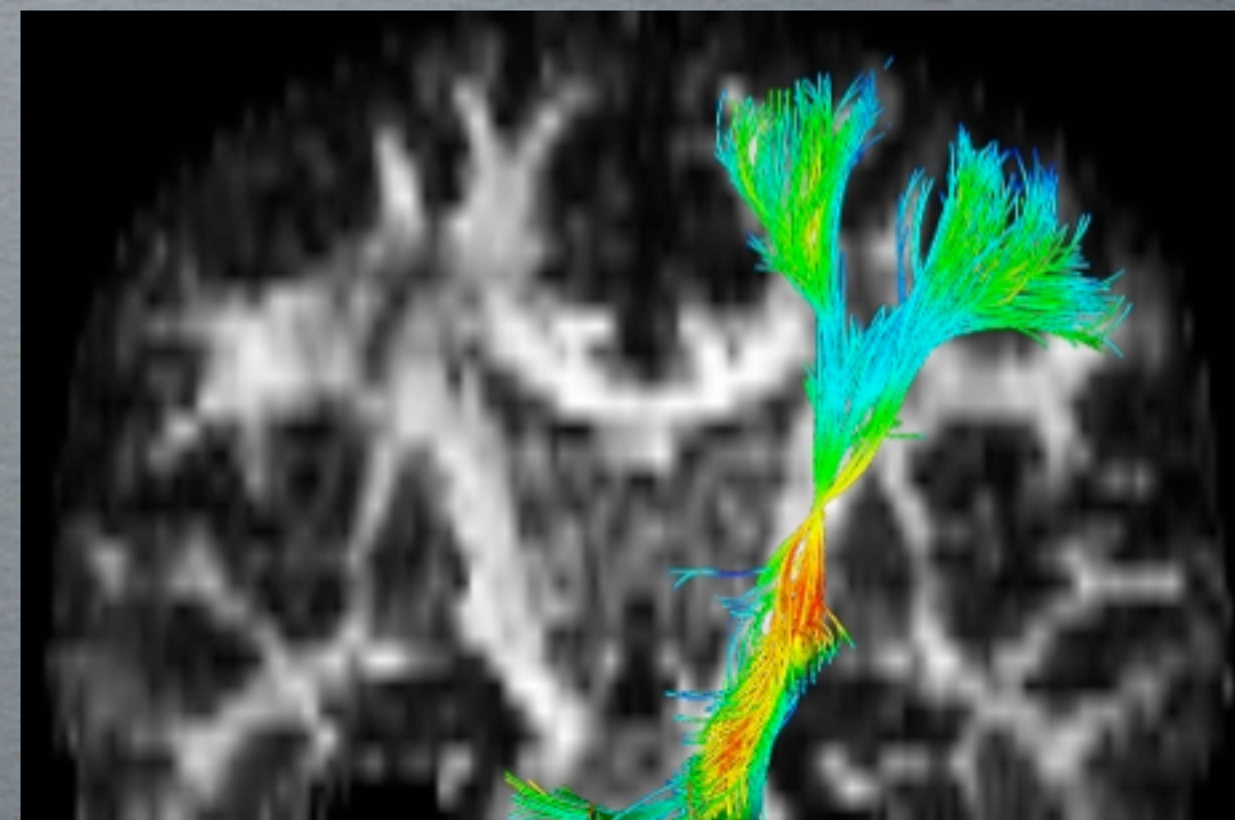


Higher order tensor fit to data

# High Angular Resolution DTI (HARDI)

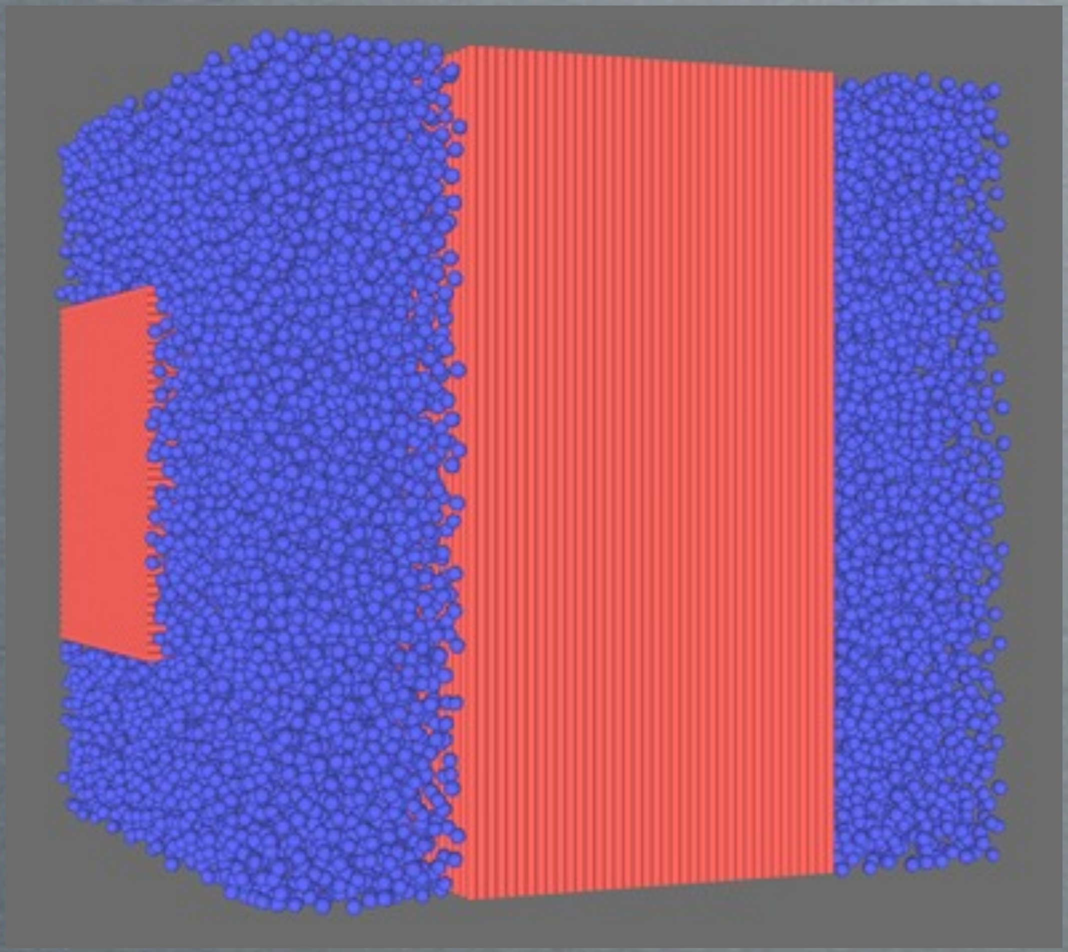


Standard DTI

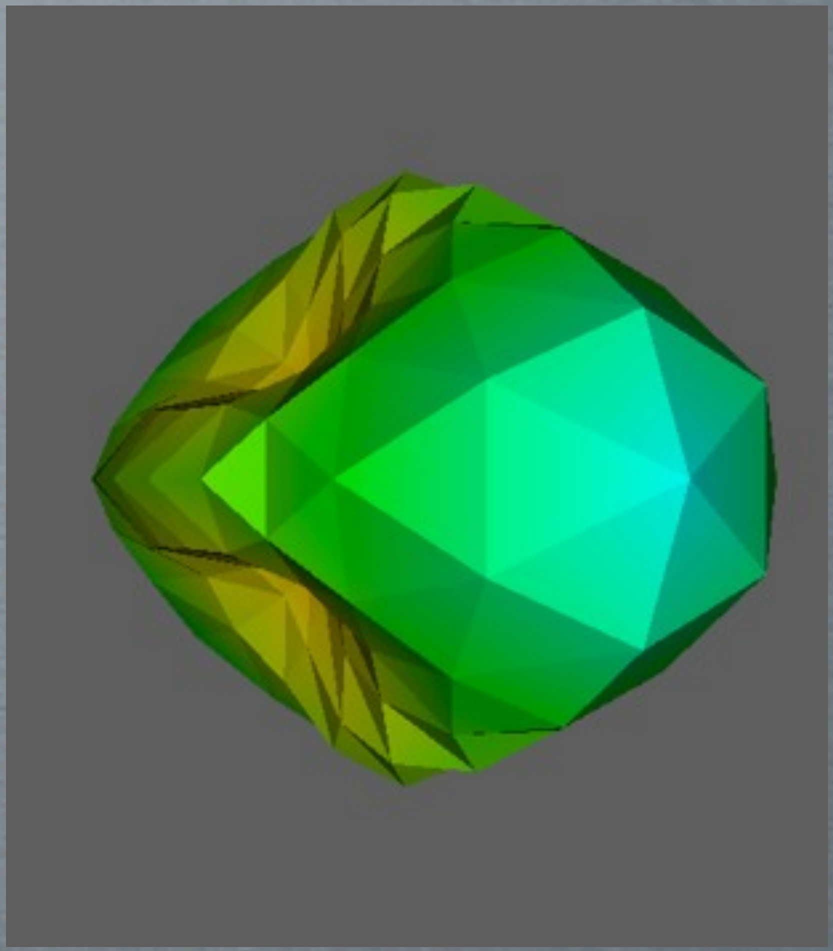


HARDI

# Heterogeneous Voxels and High Angular Resolution Sampling



a voxel with crossing fiber bundles and random spherical cells...



signal from 162 directions

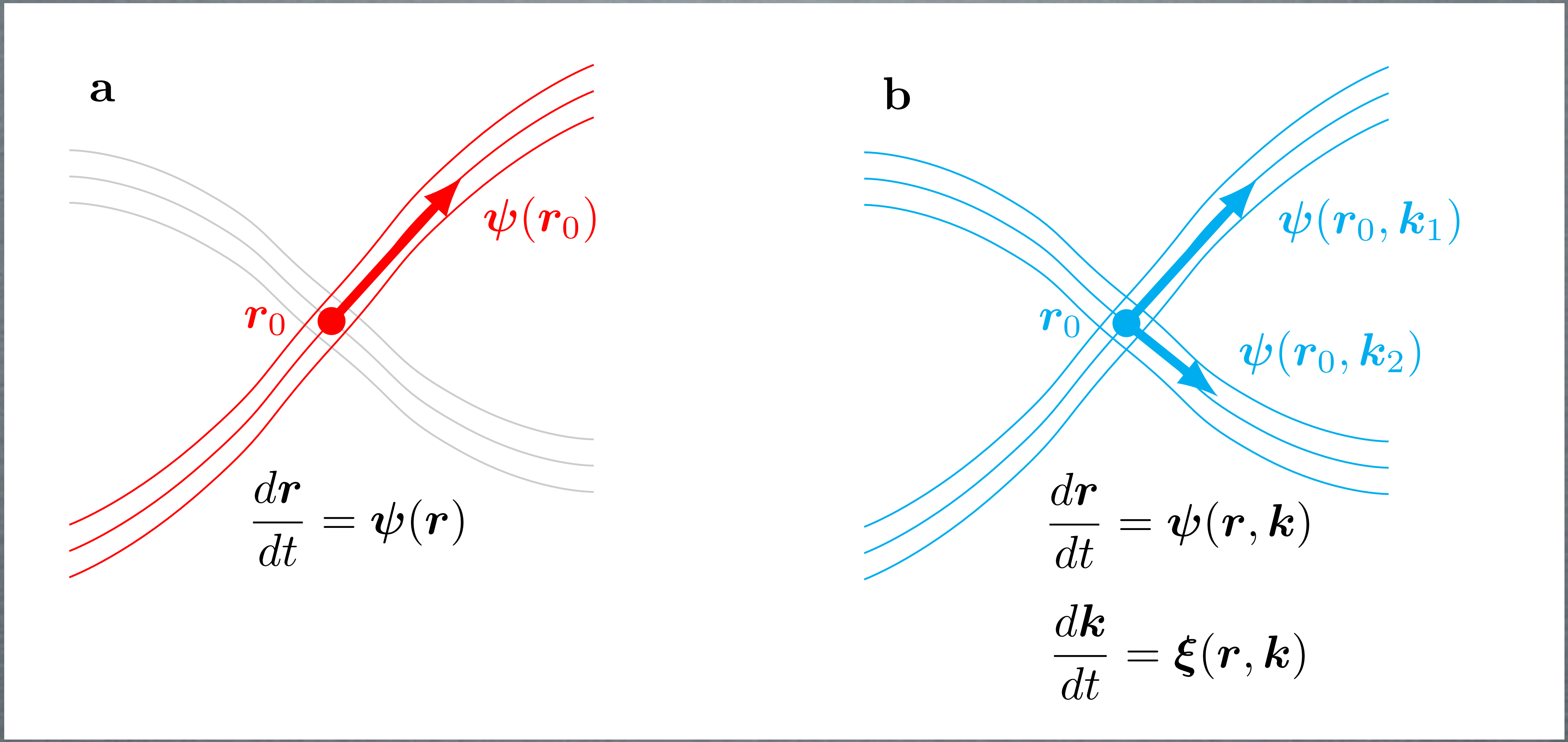
# The Future

IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. XX, NO. X, APRIL 2014

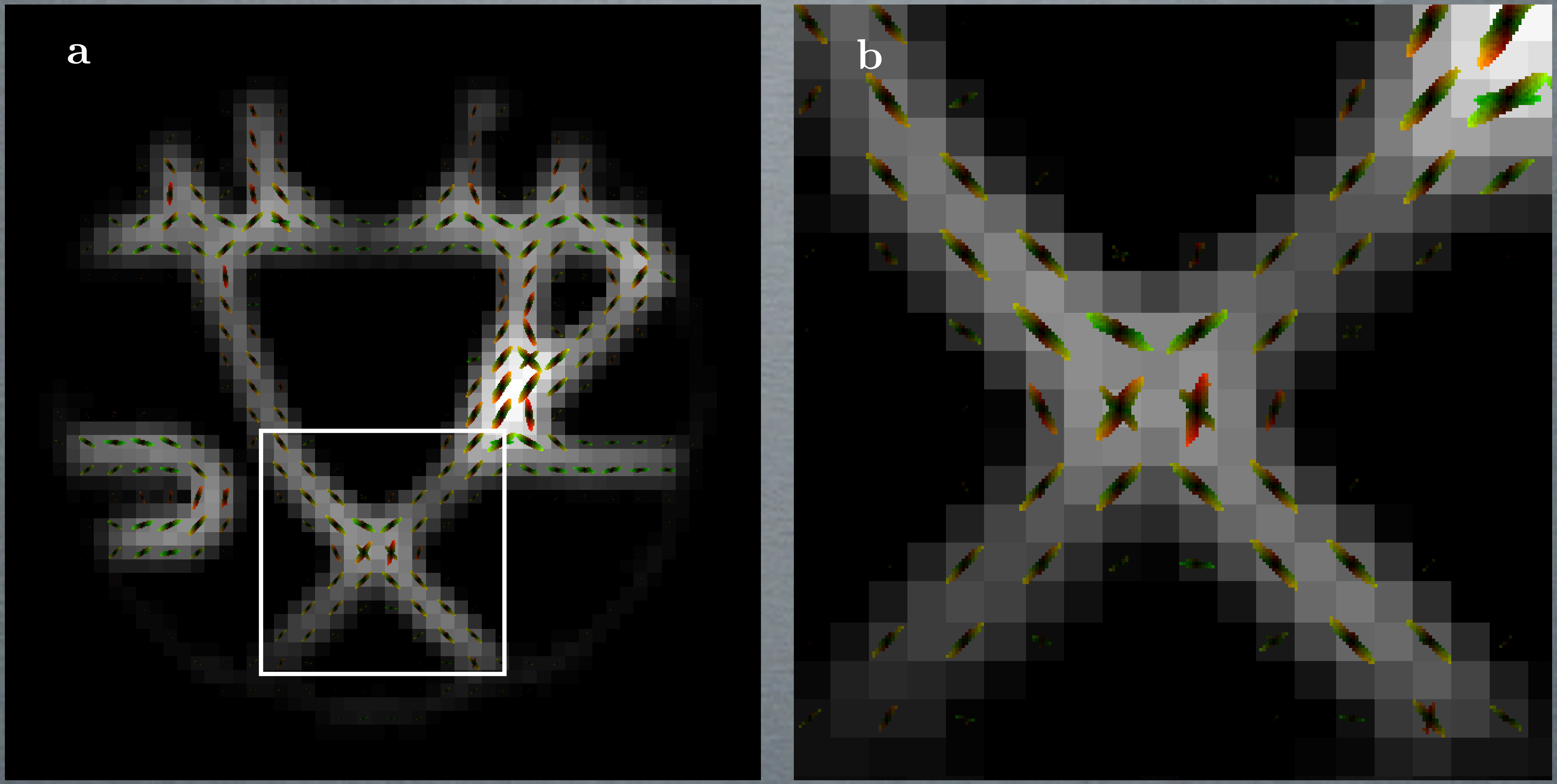
## Simultaneous Multi-Scale Diffusion Estimation and Tractography Guided by Entropy Spectrum Pathways

Vitaly L. Galinsky and Lawrence R. Frank

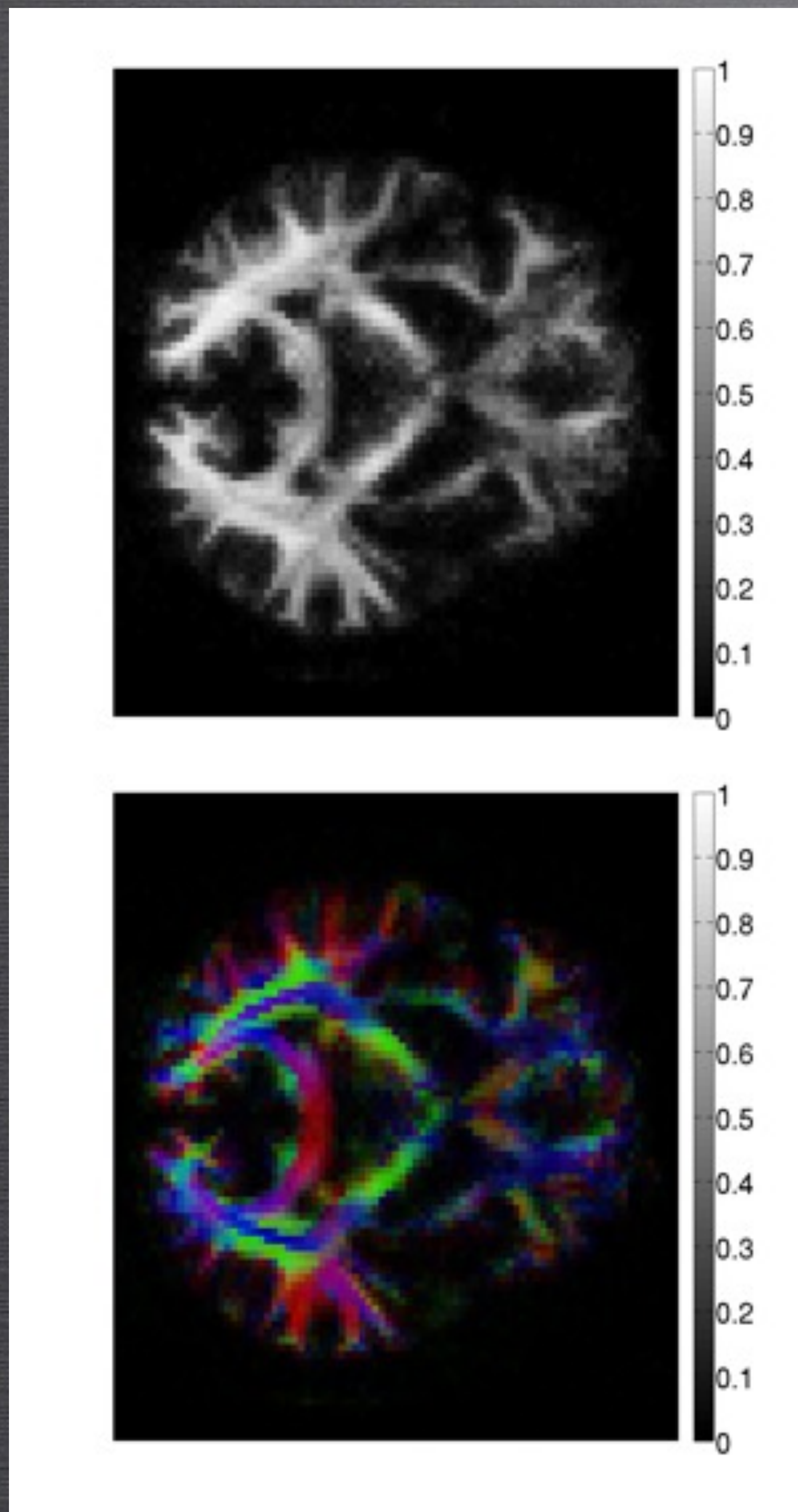
# DWI ESP


a
$\psi(\boldsymbol{r}_0)$
$\boldsymbol{r}_0$
$\frac{d\boldsymbol{r}}{dt} = \psi(\boldsymbol{r})$
b
$\psi(\boldsymbol{r}_0, \boldsymbol{k}_1)$
$\boldsymbol{r}_0$
$\psi(\boldsymbol{r}_0, \boldsymbol{k}_2)$
$\frac{d\boldsymbol{r}}{dt} = \psi(\boldsymbol{r}, \boldsymbol{k})$
$\frac{d\boldsymbol{k}}{dt} = \boldsymbol{\xi}(\boldsymbol{r}, \boldsymbol{k})$

# DWI ESP

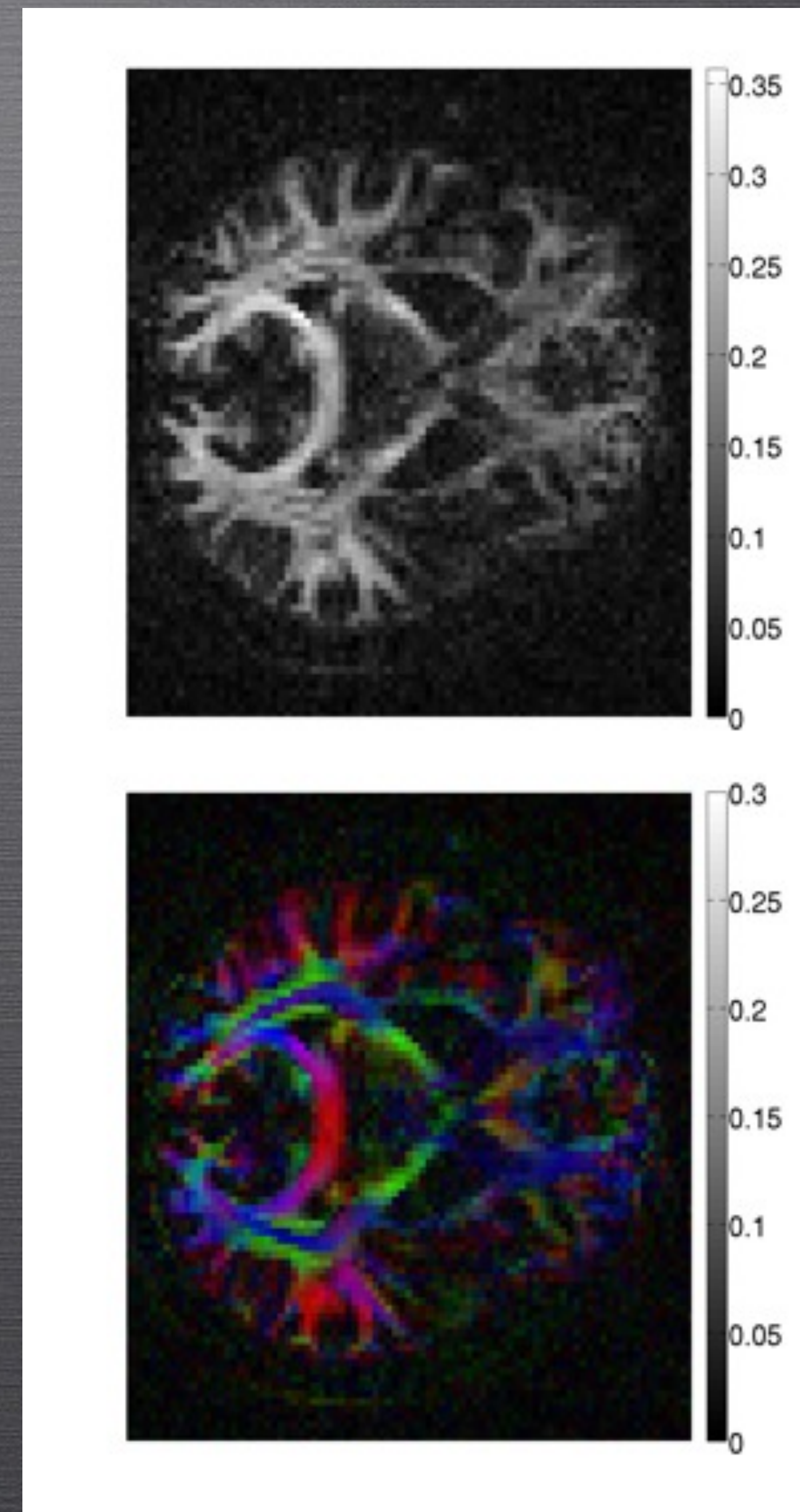


# ESP vs RSI



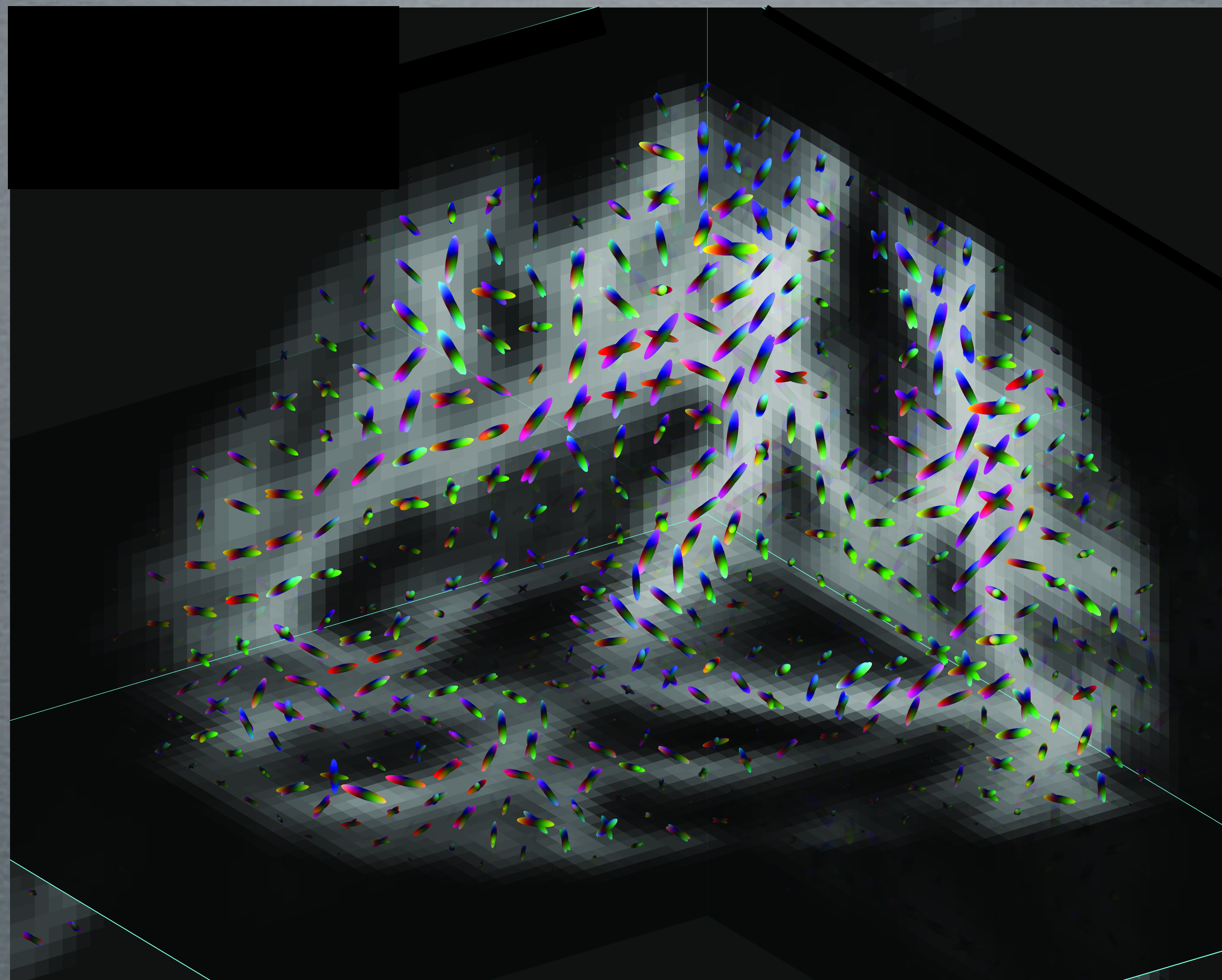

ESP

**FA**

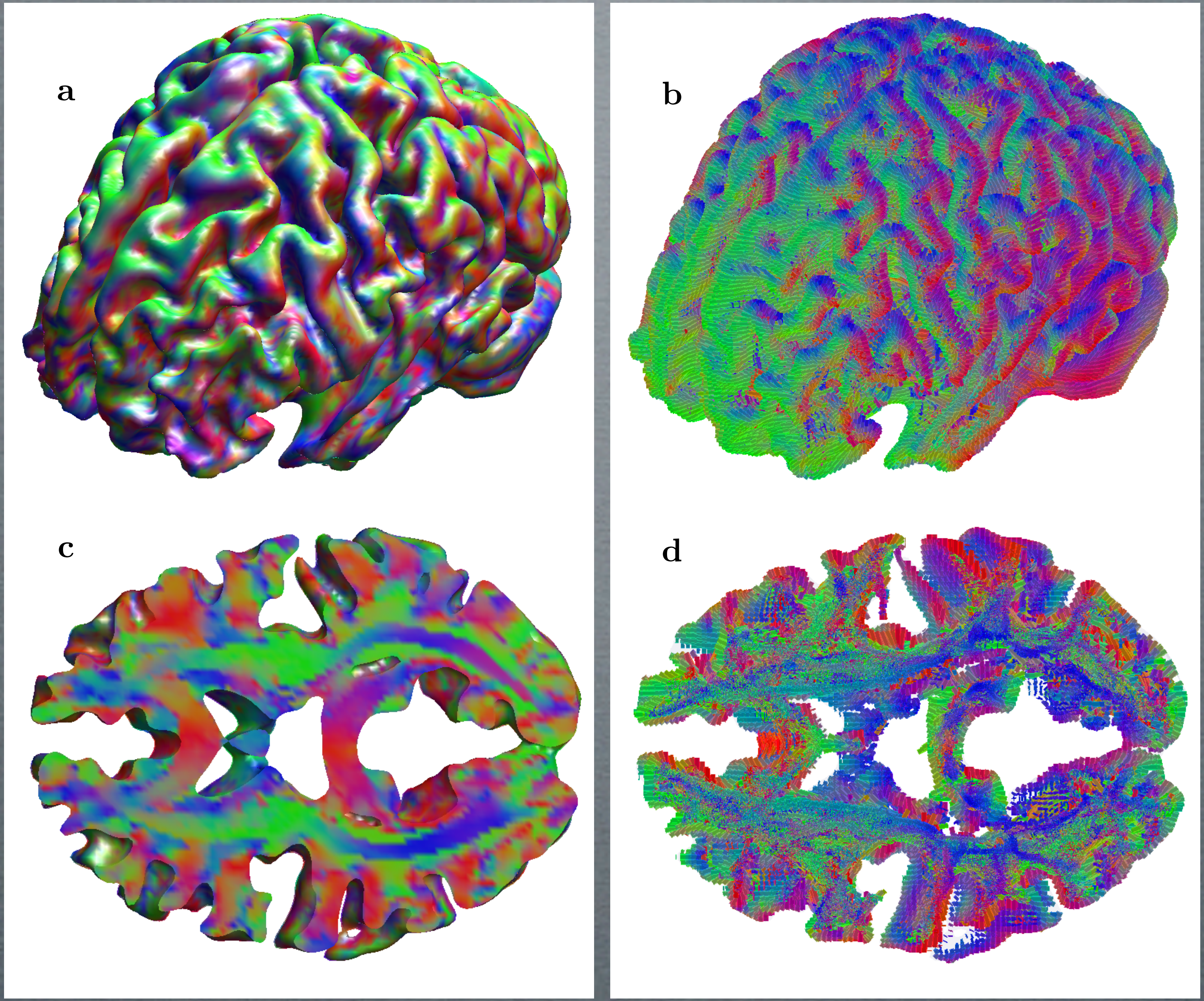



RSI

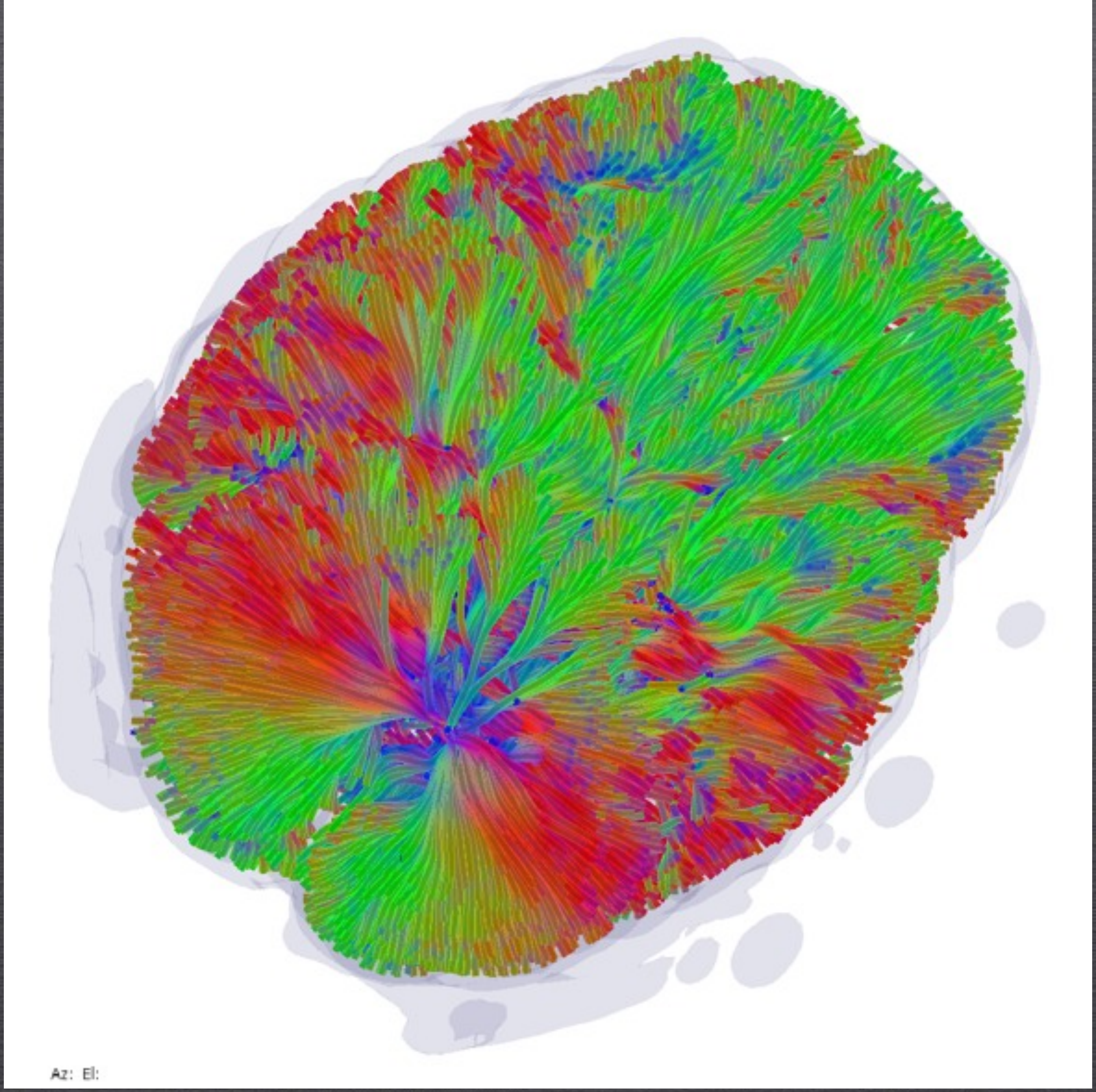
# DWI ESP



# DWI ESP



# ESP full brain tractography



# Conclusion

Diffusion MRI has a unique sensitivity
to tissue architecture and physiology

...and diffusion sensitivity is relatively easy
to incorporate into standard sequences

However ...

- Data artifact correction non-trivial
- Analysis is complicated
- Interpretation is difficult

But it's really cool!

# The End