

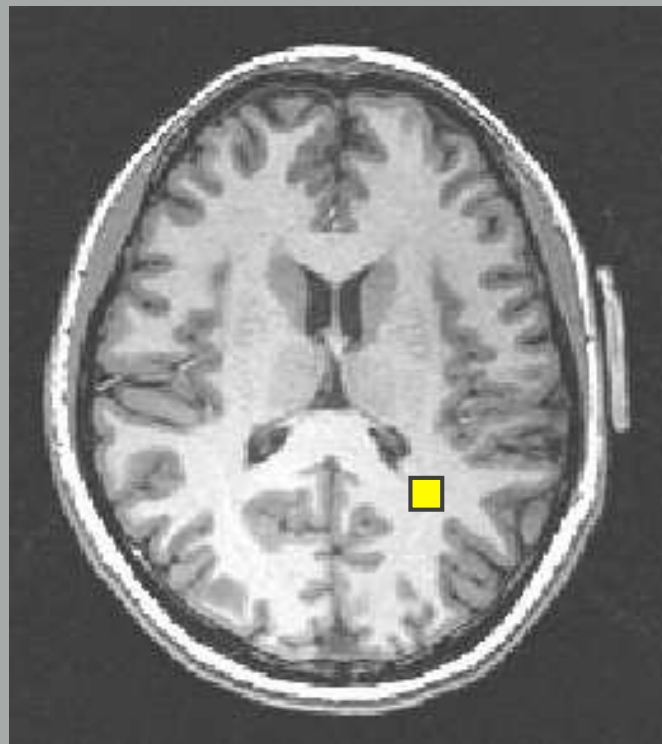
Lecture 8

Analyzing the diffusion weighted signal

Please install AFNI
<http://afni.nimh.nih.gov/afni/>

Next lecture, DTI

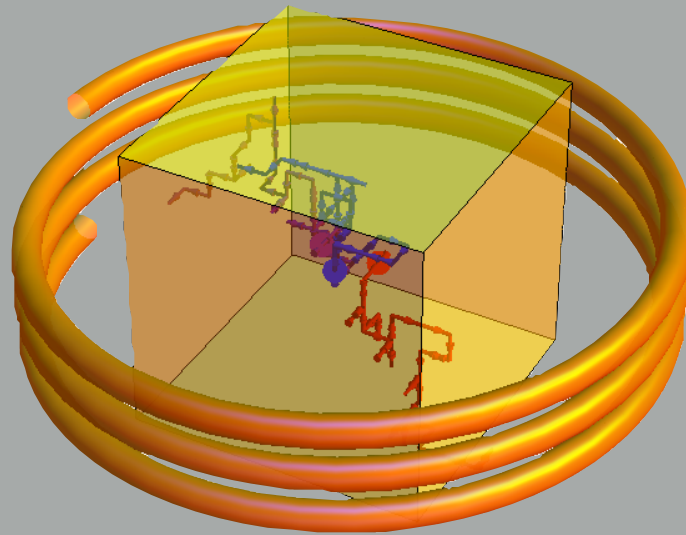
For this lecture, think in terms of a single voxel

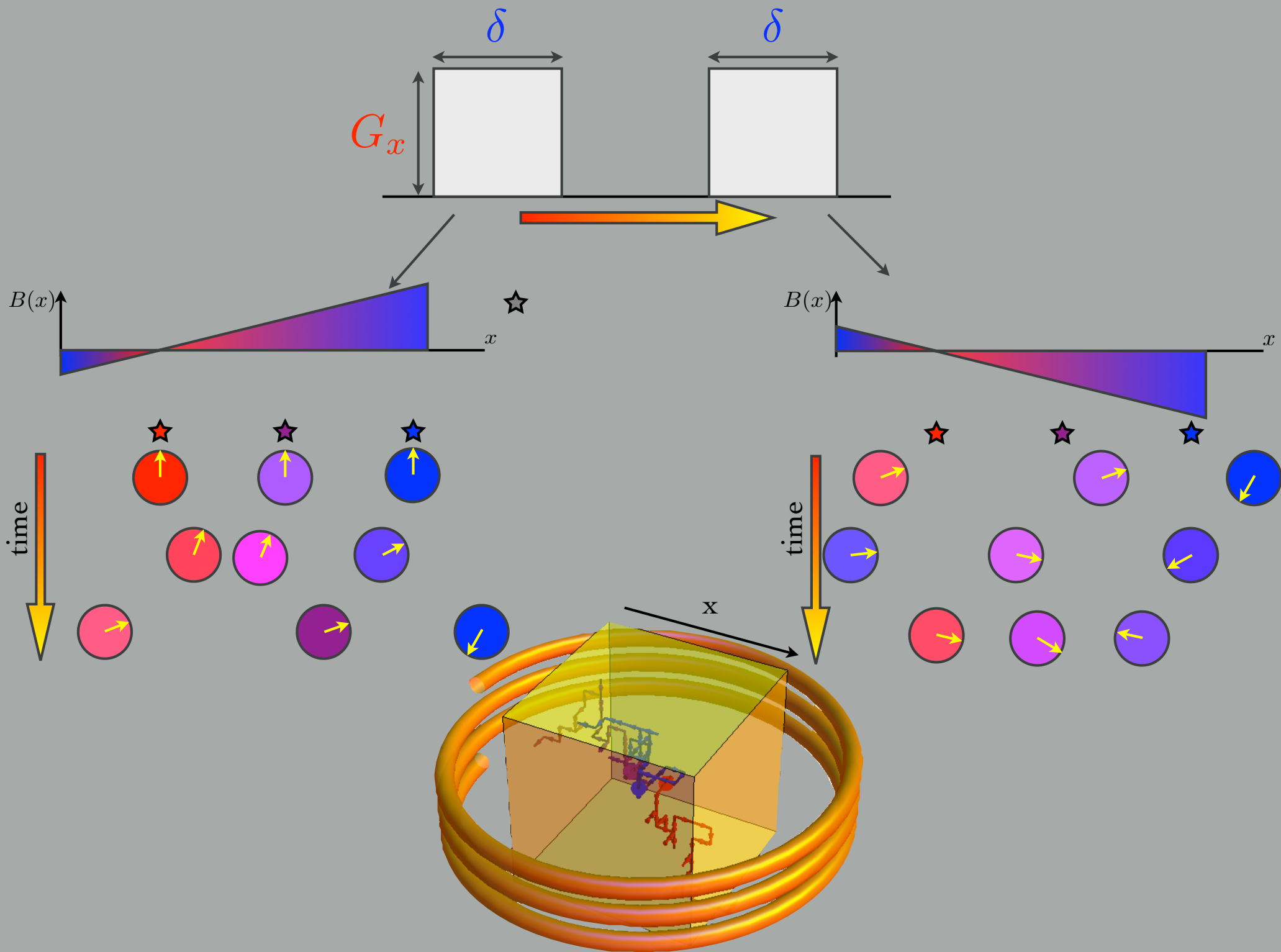


We're still looking only at a single voxel experiment

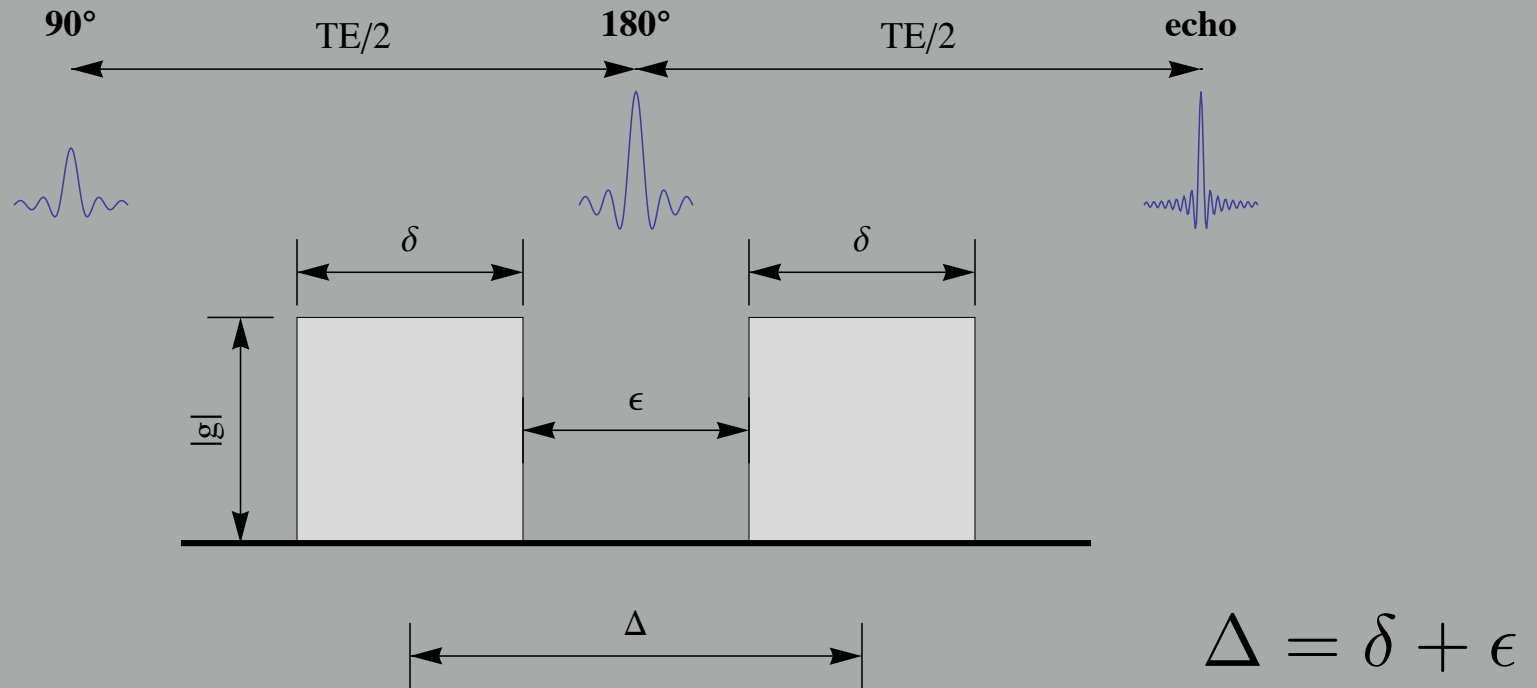
Class Lecture:

Multiple diffusion encoding directions
to estimate a diffusion coefficient D



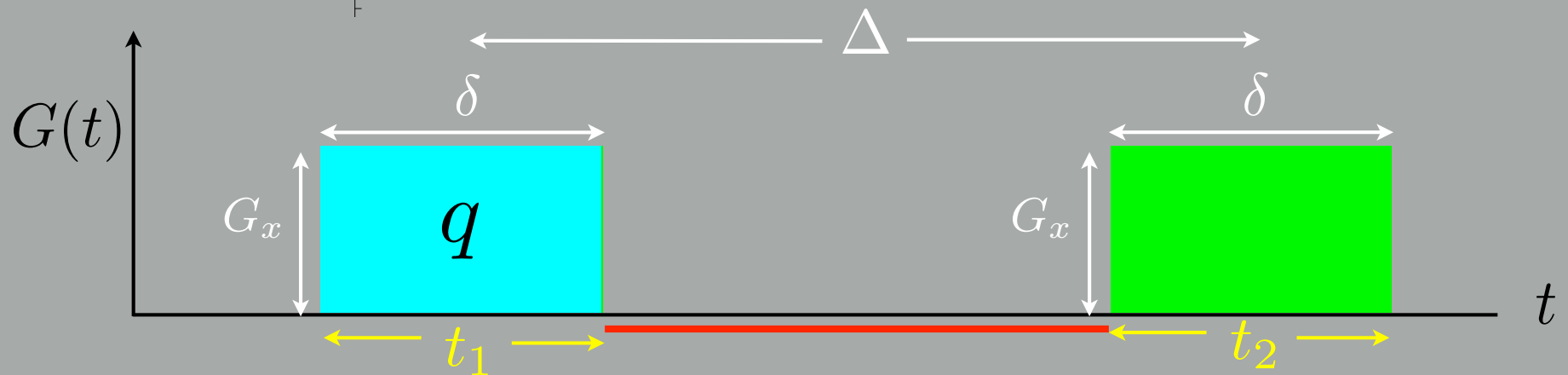
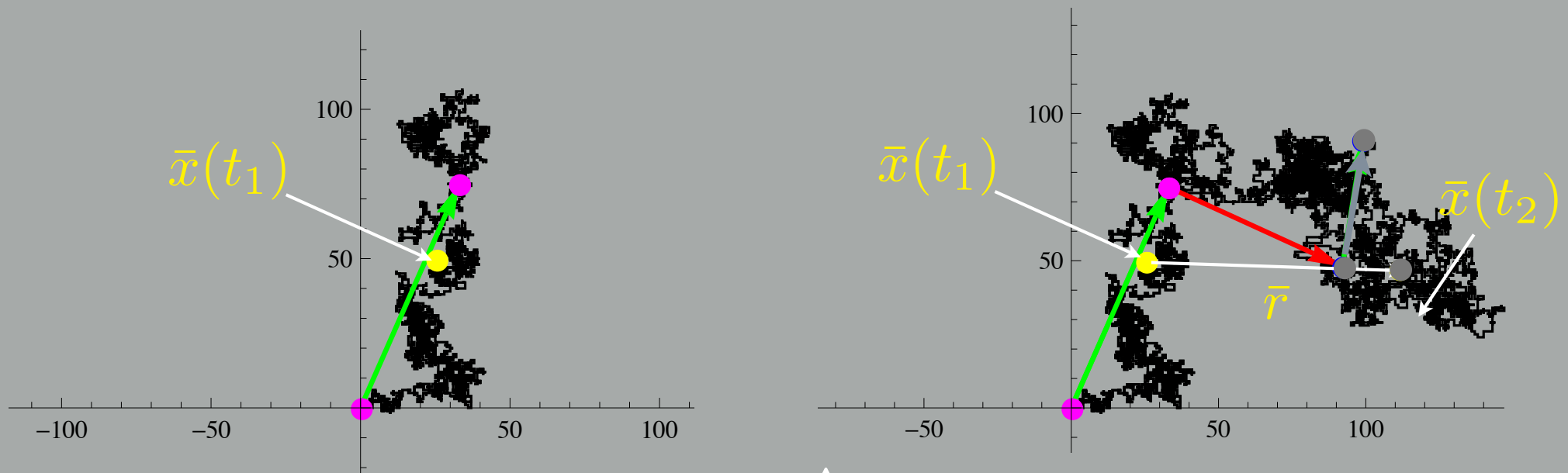


Phases of diffusing spins



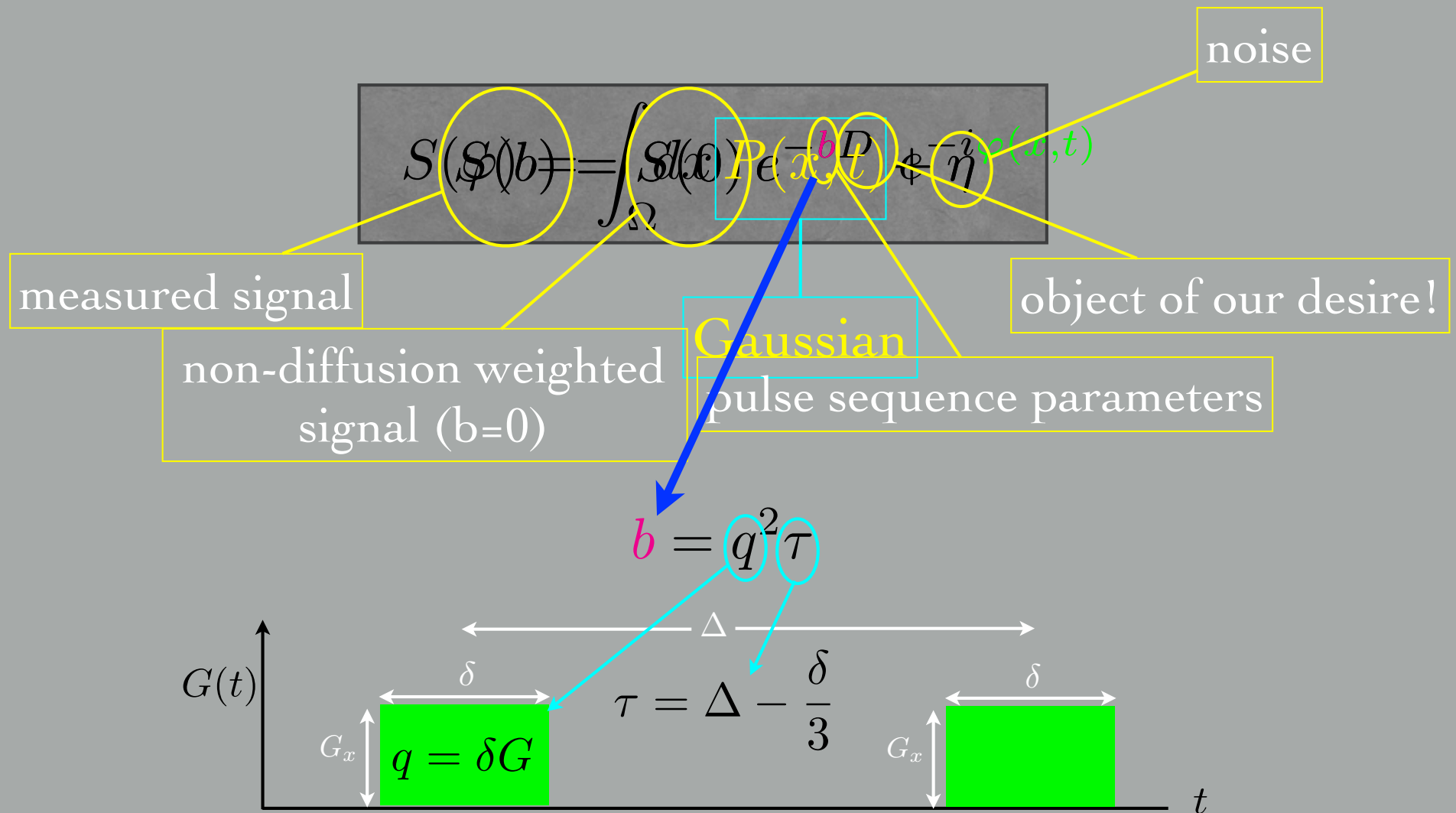
$$\varphi(\tau) = \int_0^\tau G(t)x(t) dt$$

DIFFUSION PHASE IN A BIPOLAR PULSE



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

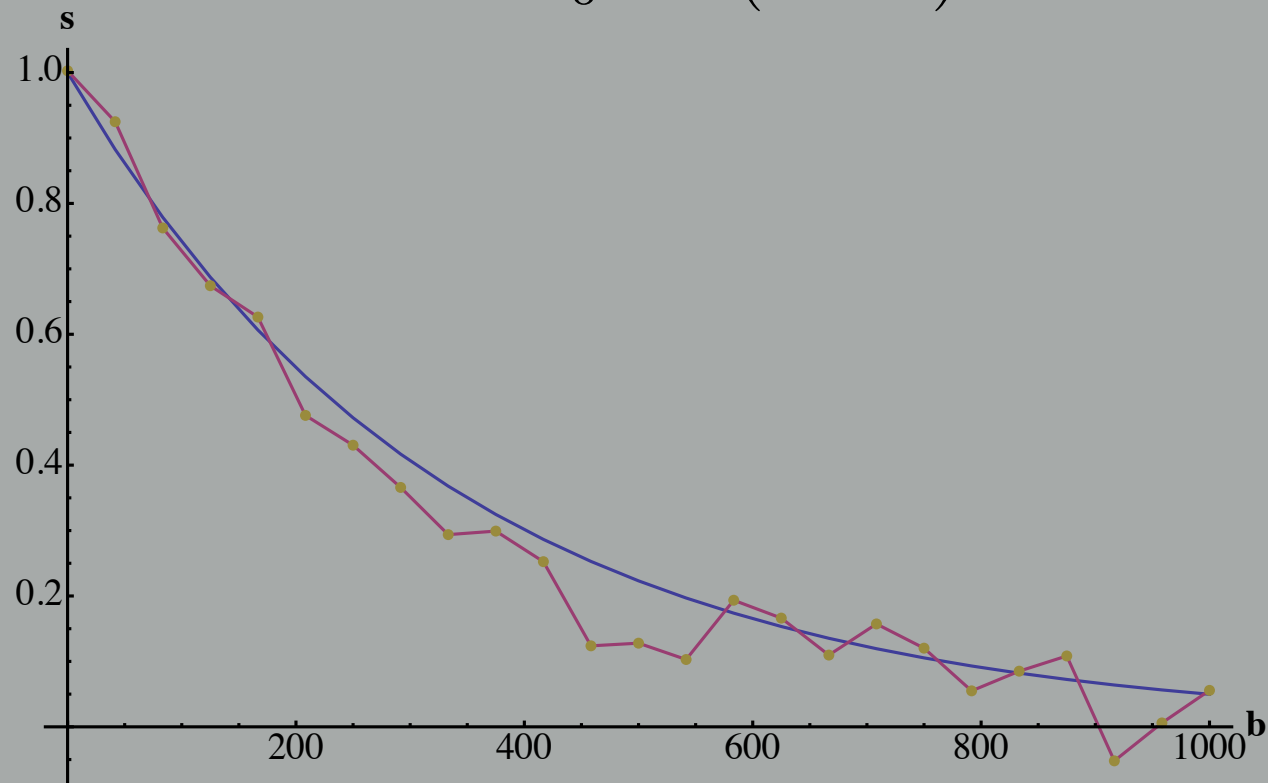
THE ESTIMATION PROBLEM FOR GAUSSIAN DIFFUSION



The signal from 1D Gaussian Diffusion

$$s(b_i) = s_0 e^{-b_i D} + \eta_i$$

where $s_0 \equiv s(b = 0)$



**Consider only two measurements
and write data in vector form**

$$\begin{pmatrix} s(b_1) \\ s(b_2) \end{pmatrix} = s_0 \begin{pmatrix} \exp(-b_1 D) \\ \exp(-b_2 D) \end{pmatrix} + \begin{pmatrix} \eta_1 \\ \eta_2 \end{pmatrix}$$
$$= s_0 \exp \left[- \begin{pmatrix} b_1 D \\ b_2 D \end{pmatrix} \right] + \begin{pmatrix} \eta_1 \\ \eta_2 \end{pmatrix}$$

This clearly generalizes to n measurements

Fit a Single-Term Exponential Model

Generate data with an exponential trend and then fit the data using a single-term exponential. Plot the fit and data.

```
x = (0:0.2:5)';  
y = 2*exp(-0.2*x) + 0.1*randn(size(x));  
f = fit(x,y,'exp1')  
plot(f,x,y)
```

f =

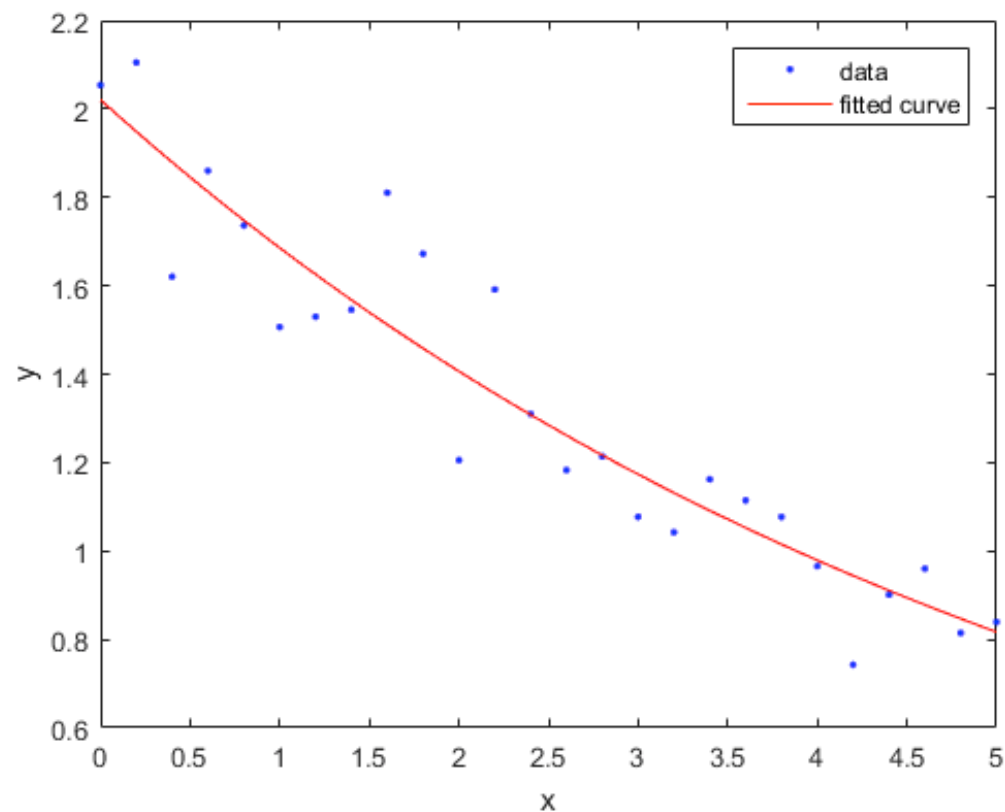
General model Exp1:

$f(x) = a \cdot \exp(b \cdot x)$

Coefficients (with 95% confidence bounds):

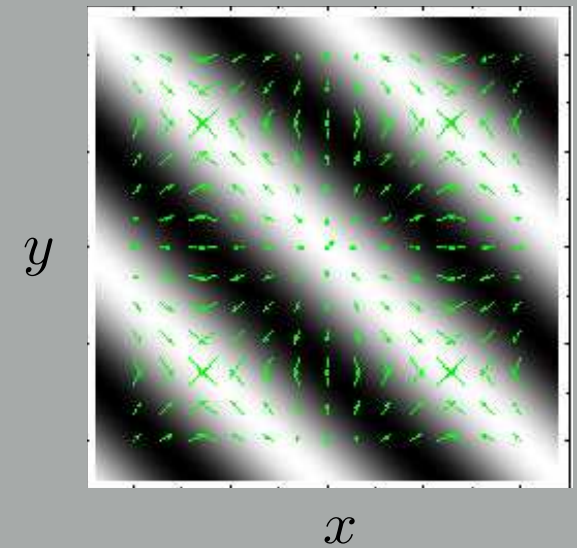
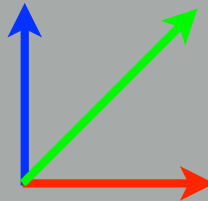
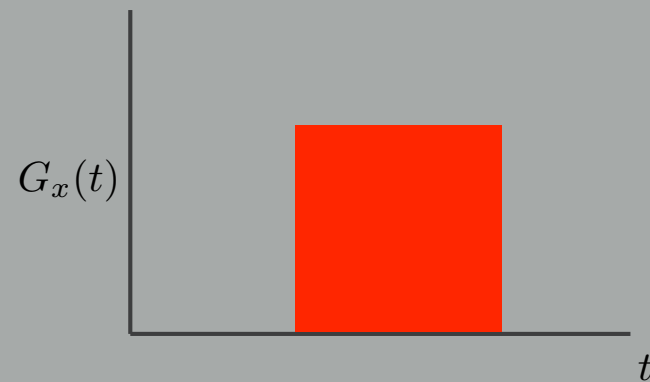
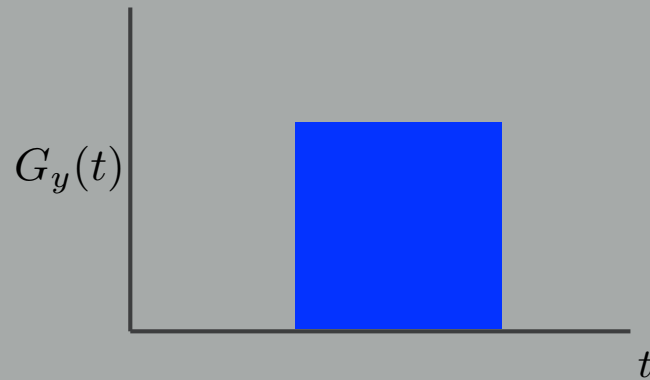
a = 2.021 (1.89, 2.151)

b = -0.1812 (-0.2104, -0.152)



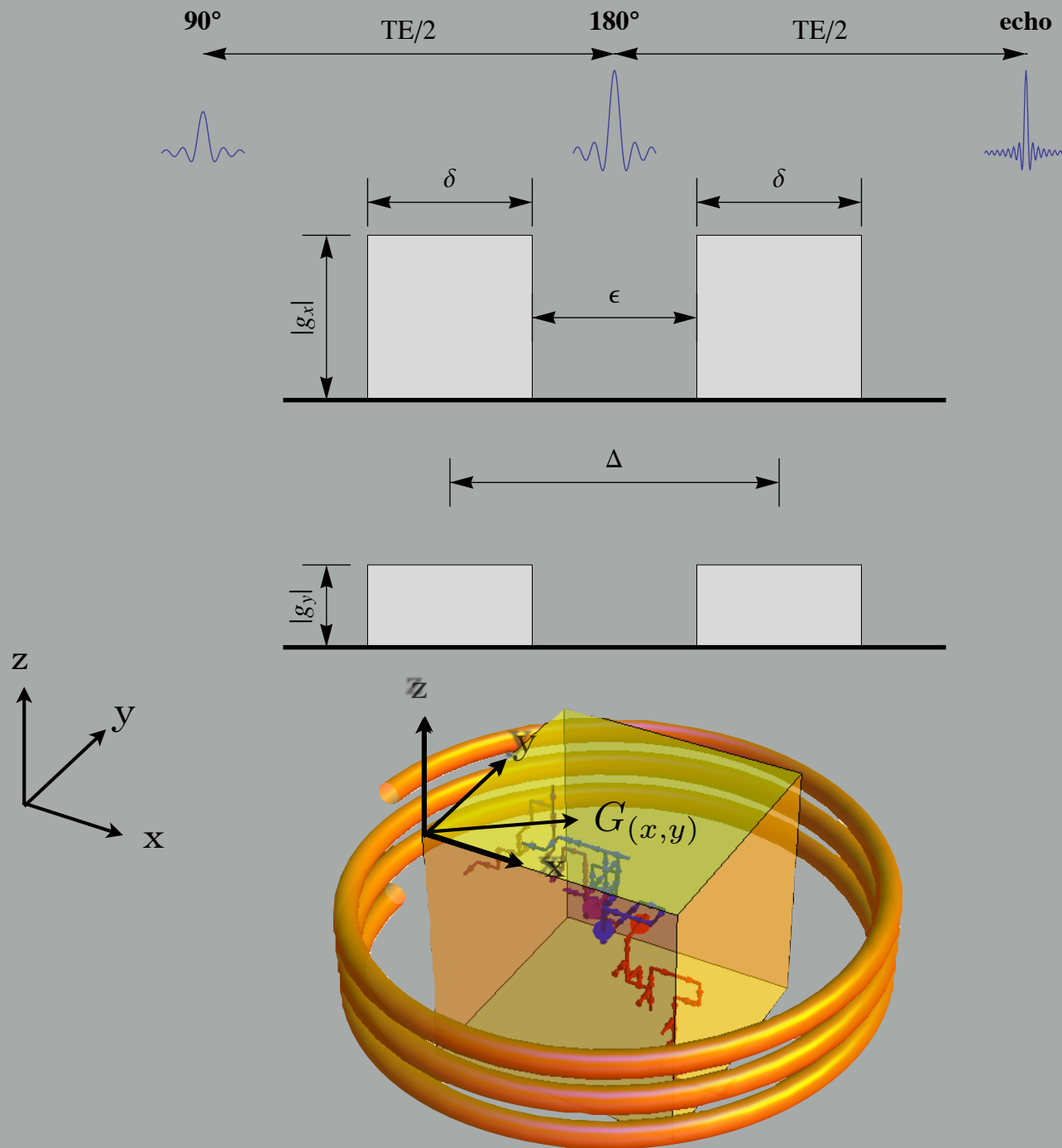
Recall: gradients add like vectors

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

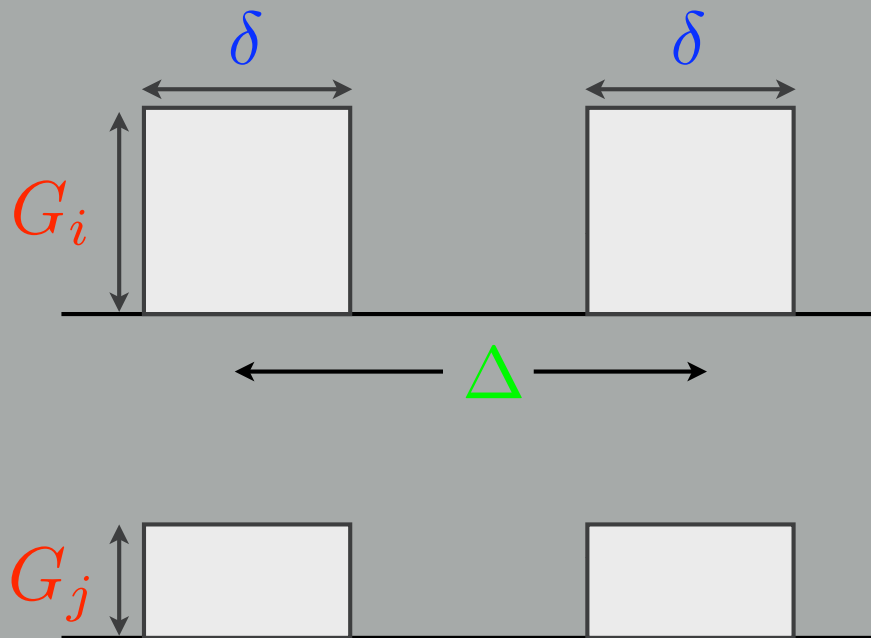


spatial modulation of the phase

DIRECTIONAL DIFFUSION ENCODING

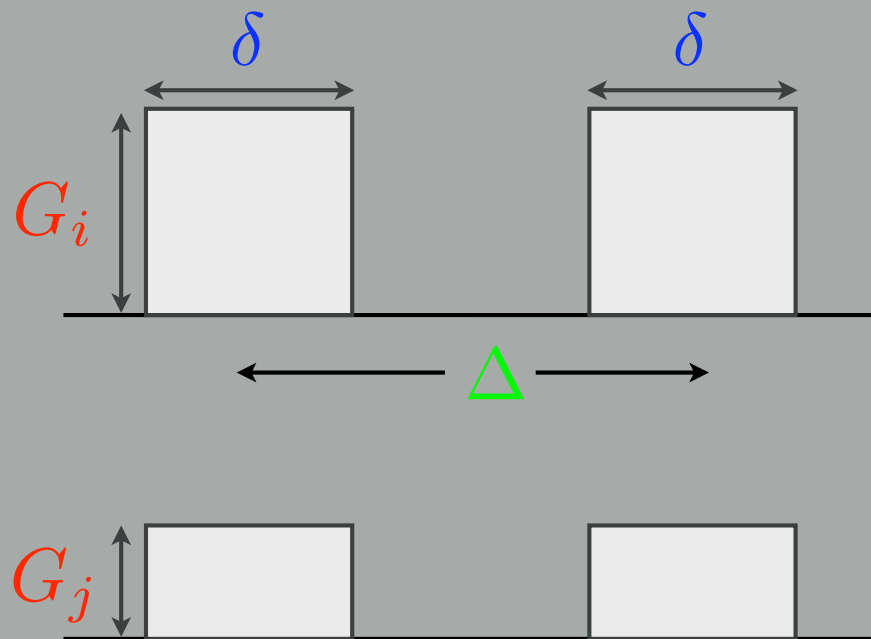


Ideal b-matrix



$$b_{ij} = \underbrace{G_i G_j}_{q_i q_j} \underbrace{\delta^2 (\Delta - \delta/3)}_{\tau} \quad \left\{ \begin{array}{l} q_i = G_i \delta \\ \tau = \Delta - \delta/3 \end{array} \right.$$

Ideal b-matrix



$$b_{ij} = q_i q_j \tau \quad \text{where} \quad \begin{cases} q_i = G_i \delta \\ \tau = \Delta - \delta/3 \end{cases}$$

The b-matrix

$$b_{ij}(\tau) = \int_0^\tau q_i(t)q_j(t)dt \quad i=(x,y,z)$$

where $q = \int g(t) dt$

For constant diffusion gradients

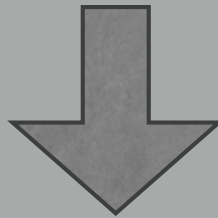
$$b_{ij}(\tau) = q_i q_j \tau$$

The NMR signal for 1D Gaussian diffusion

$$s(q, \tau) = s(0) \int P(\bar{r}, \tau) e^{-iq \cdot \bar{r}} d\bar{r}$$



$$P(\bar{r}, \tau) = \frac{1}{\sqrt{4\pi D\tau}} e^{-\bar{r}^2 / (4D\tau)}$$

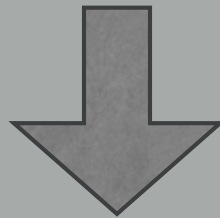


$$s(q, \tau) = s(0) e^{-bD}$$

The NMR signal for 3D Gaussian diffusion

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

$$P(\bar{r}, \tau) = \frac{1}{\sqrt{(4\pi\tau)^3 |D|}} e^{-\bar{r}^t D^{-1} \bar{r} / 4\tau}$$



$$s(q, \tau) = s(0) e^{-bD}$$

b and D

$$\mathbf{b} = \begin{pmatrix} q_x^2 & q_x q_y & q_x q_z \\ q_y q_x & q_y^2 & q_y q_z \\ q_z q_x & q_z q_y & q_z^2 \end{pmatrix} \tau$$

known

$$\mathbf{D} = \begin{pmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{yx} & D_{yy} & D_{yz} \\ D_{zx} & D_{zy} & D_{zz} \end{pmatrix}$$

desired

The NMR signal

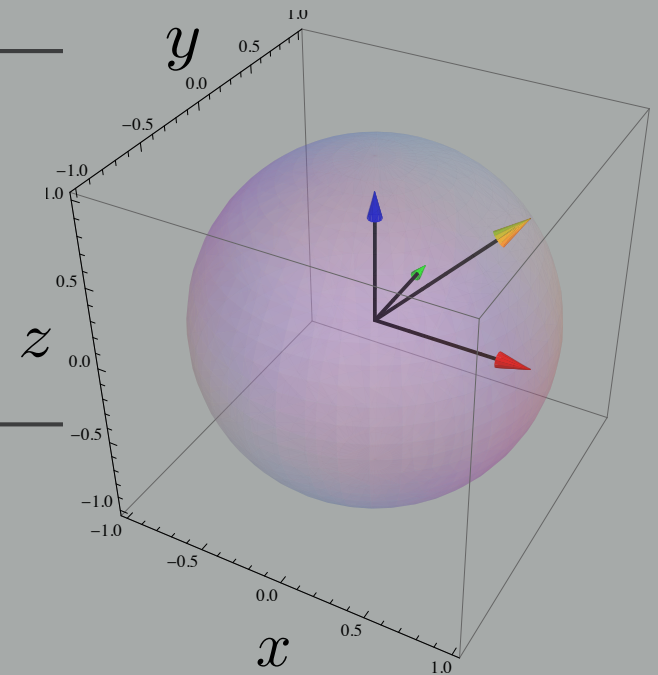
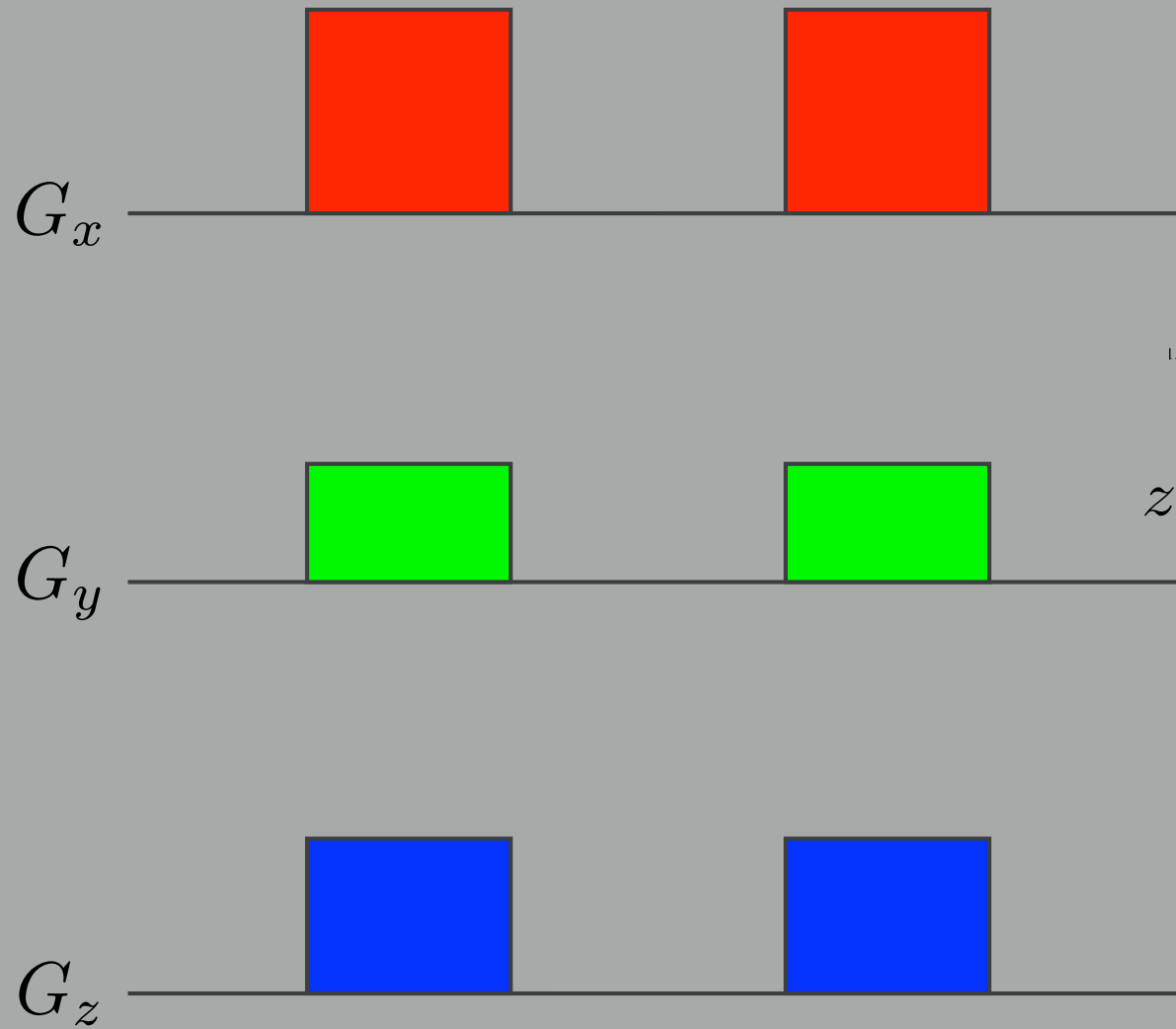
3D Gaussian diffusion

$$s(\mathbf{q}, \tau) = s(0)e^{-\mathbf{b}D}$$

$$s(\mathbf{b}) = s(0) \exp \left(- \sum_i^3 \sum_j^3 b_{ij} D_{ij} \right)$$

$$bD = \tau q^2 D \longrightarrow \mathbf{b}D = \tau \mathbf{q}^t \cdot D \cdot \mathbf{q}$$

A single diffusion-weighting direction



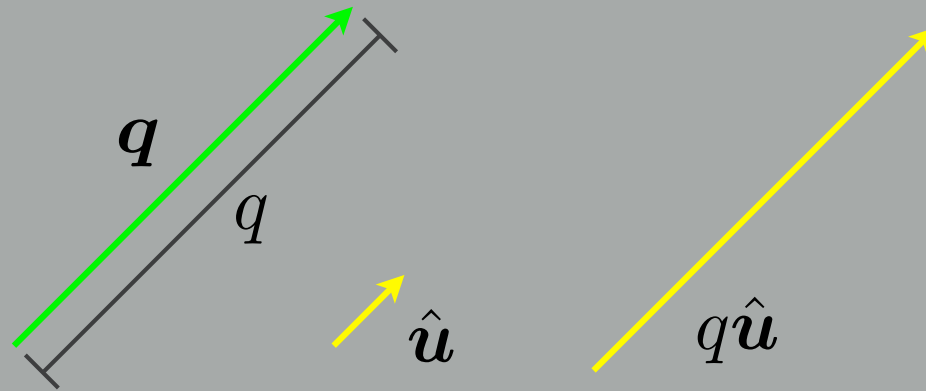
bD

$$\begin{aligned} \frac{1}{\tau} \sum_i \sum_j b_{ij} D_{ij} = & q_x^2 D_{xx} + q_x q_y D_{xy} + q_x q_z D_{xz} + \\ & q_y q_x D_{yx} + q_y^2 D_{yy} + q_y q_z D_{yz} + \\ & q_z q_x D_{zx} + q_z q_y D_{zy} + q_z^2 D_{zz} \end{aligned}$$

Rearranging the directions

$$bD = \tau \mathbf{q}^t \cdot \mathbf{D} \cdot \mathbf{q}$$

$$\mathbf{q} = q \hat{\mathbf{u}} \quad q \equiv |\mathbf{q}|$$



$$bD = q^2 \tau \mathbf{u}^t \cdot \mathbf{D} \cdot \mathbf{u}$$

The NMR signal

$$bD = q^2 \tau \underbrace{u^t \cdot D \cdot u}_{\tilde{D}}$$



$$s(\mathbf{q}, \tau) = s(0) e^{-bD} = e^{-q^2 \tau \tilde{D}}$$



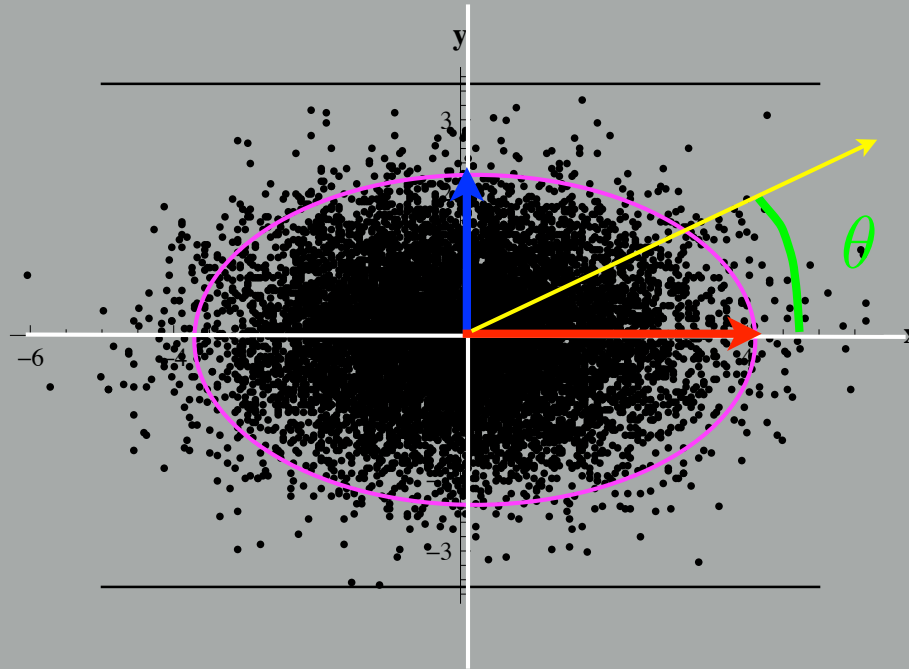
$$s(\mathbf{q}, \tau) = e^{-b\tilde{D}}$$

where $b = q^2 \tau$

MEASURING THE DIFFUSION TENSOR

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

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

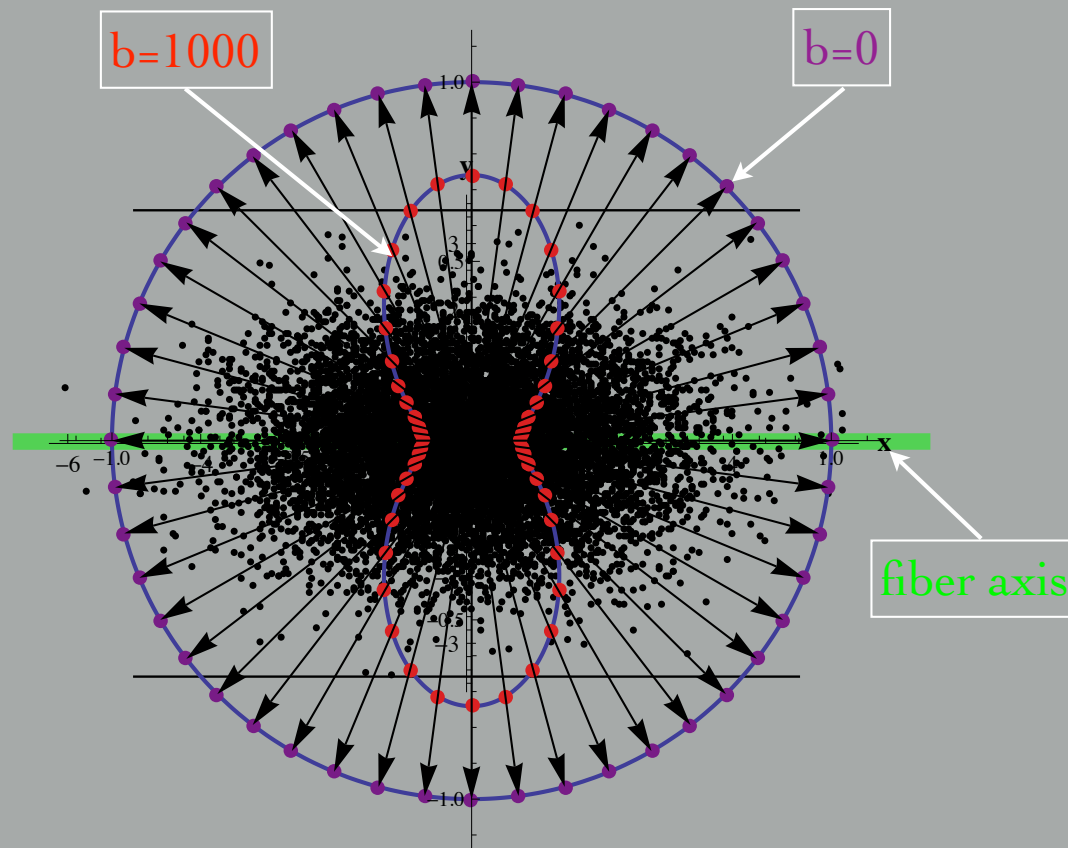


$$\hat{r} = \begin{pmatrix} \cos \theta \\ \sin \theta \end{pmatrix}$$

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

projection of an ellipsoid!
not like projection of a vector

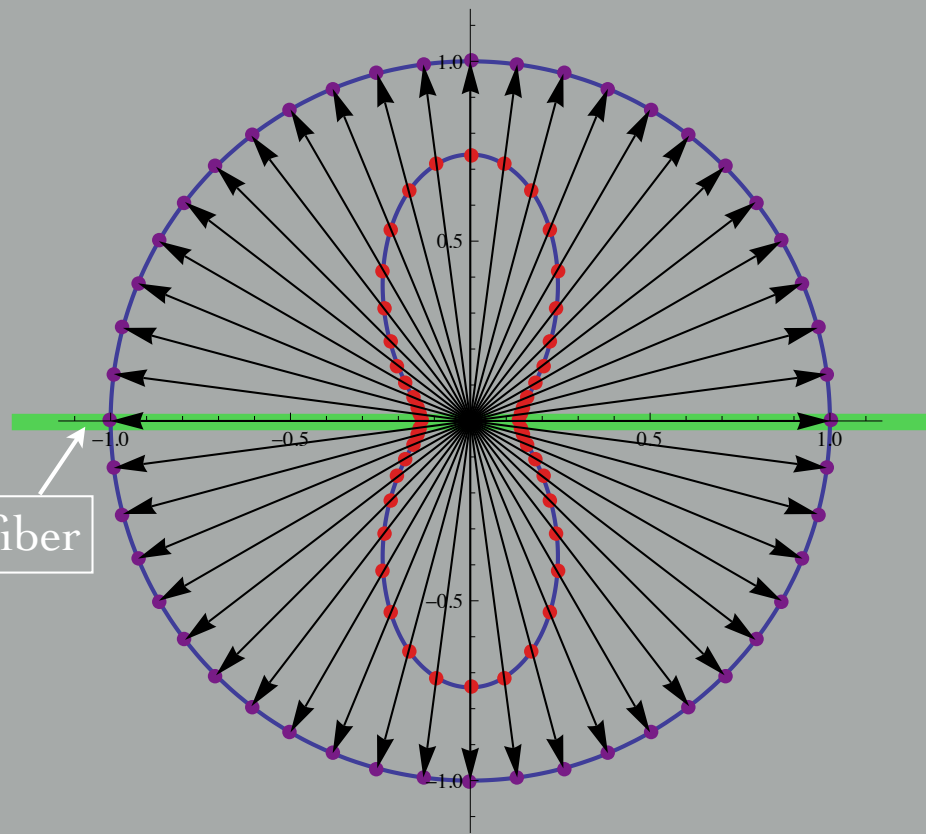
MEASURING THE DIFFUSION TENSOR



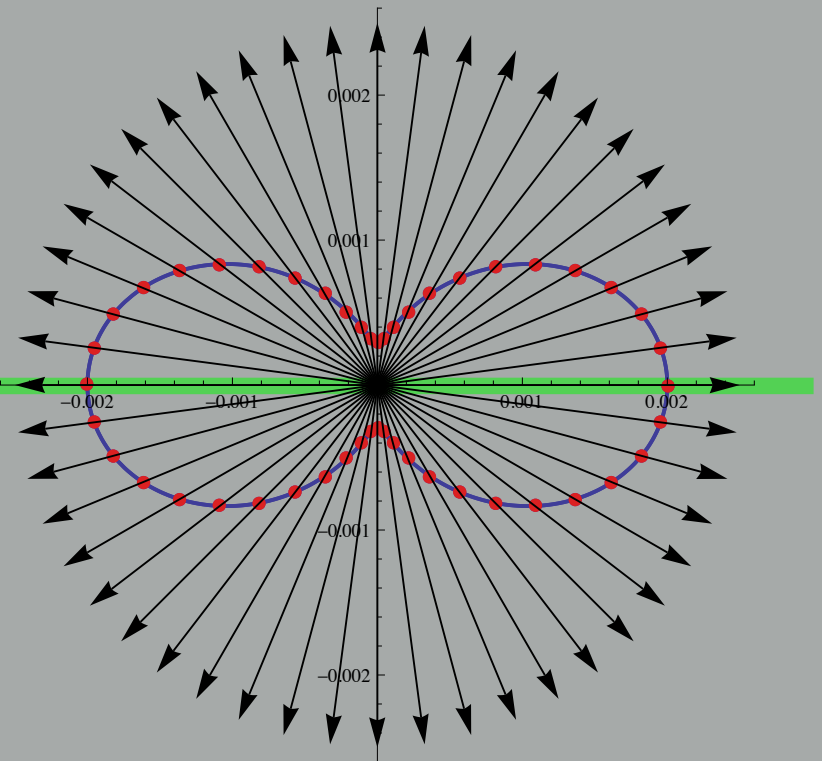
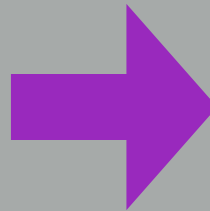
$$S(b, \theta) = S(0)e^{-bD(\theta)} + \eta$$

$$D(\theta) = D_x \cos^2 \theta + D_y \sin^2 \theta$$

THE SHAPE OF DIFFUSION



signal $S_b(\theta)$

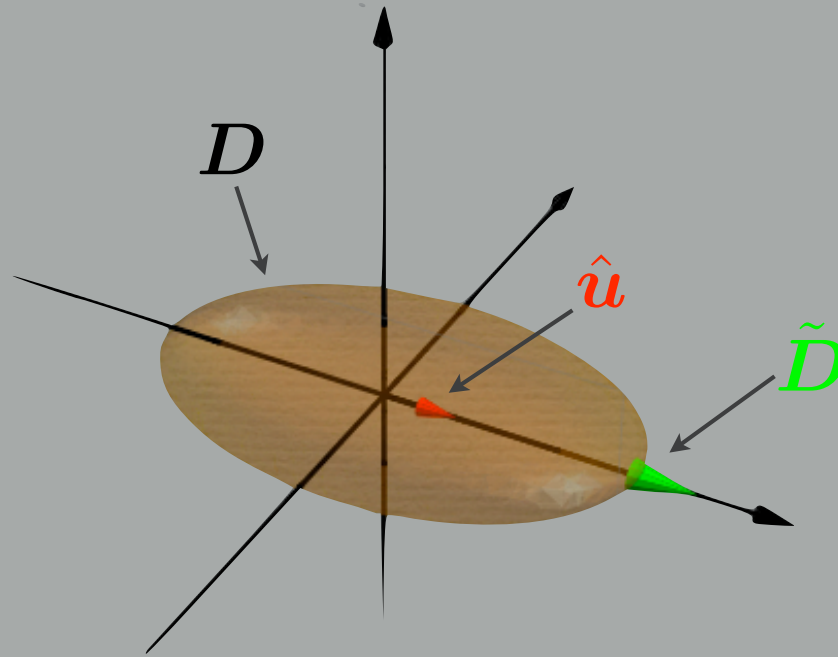


$$D_{app}(\theta) = -\frac{1}{b} \log \left(\frac{S_b}{S_0} \right)$$

What is the meaning of $\tilde{D}$?

$$\tilde{D} \equiv \mathbf{u}^t \cdot \mathbf{D} \cdot \mathbf{u}$$

It is the projection of $\mathbf{D}$ along $\hat{\mathbf{u}}$



Diffusion Tensor is Symmetric

$$\begin{pmatrix} D_{xx} & \boxed{D_{xy}} & \boxed{D_{xz}} \\ \boxed{D_{yx}} & D_{yy} & \boxed{D_{yz}} \\ \boxed{D_{zx}} & \boxed{D_{zy}} & D_{zz} \end{pmatrix} = \begin{pmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{xy} & D_{yy} & D_{yz} \\ D_{xz} & D_{yz} & D_{zz} \end{pmatrix}$$

$$\mathbf{D} = \mathbf{D}^t \quad \text{matrix form}$$

$$D_{ij} = D_{ji} \quad \text{component form}$$

bD

$$\frac{1}{\tau} \sum_i \sum_j b_{ij} D_{ij} = q_x^2 D_{xx} + q_x q_y D_{xy} + q_x q_z D_{xz} +$$

$$q_y q_x D_{yx} + q_y^2 D_{yy} + q_y q_z D_{yz} +$$

$$q_z q_x D_{zx} + q_z q_y D_{zy} + q_z^2 D_{zz}$$

$$\frac{1}{\tau} \sum_i \sum_j b_{ij} D_{ij} = q_x^2 D_{xx} + 2q_x q_y D_{xy} + 2q_x q_z D_{xz} +$$

$$q_y^2 D_{yy} + 2q_y q_z D_{yz} +$$

$$q_z^2 D_{zz}$$

A computational simplification

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

a trick: write $s(0) = e^{\log s(0)}$

$$s(b) = s(0)e^{-bd}$$

Estimating the Diffusion Tensor

$$\mathbf{d} = \begin{pmatrix} D_{xx} \\ D_{yy} \\ D_{zz} \\ D_{xy} \\ D_{xz} \\ D_{yz} \\ -\log s(0) \end{pmatrix}$$

There are 7 unknowns

Estimating the Diffusion Tensor

$$\mathbf{B} = (q_x^2, q_y^2, q_z^2, 2q_xq_y, 2q_xq_z, 2q_yq_z, 1) \tau$$

Estimating the Diffusion Tensor

$$\begin{array}{ccc}
 -\log s(b) & = & \tau(q_x^2, q_y^2, q_z^2, 2q_xq_y, 2q_xq_z, 2q_yq_z, 1) \\
 \mathbf{y} & & \mathbf{B} \qquad \mathbf{D}
 \end{array}
 \begin{pmatrix} D_{xx} \\ D_{yy} \\ D_{zz} \\ D_{xy} \\ D_{xz} \\ D_{yz} \\ -\log s(0) \end{pmatrix}$$

But there are 7 unknowns,
so we need 7 equations to solve for them

Estimating the Diffusion Tensor

$$\mathbf{y} = - \begin{pmatrix} \log s(b_1) \\ \log s(b_2) \\ \vdots \\ \log s(b_n) \end{pmatrix}$$

We make 7 measurements,
each with a different direction

The B-matrix

tensor dimensions $\rightarrow$

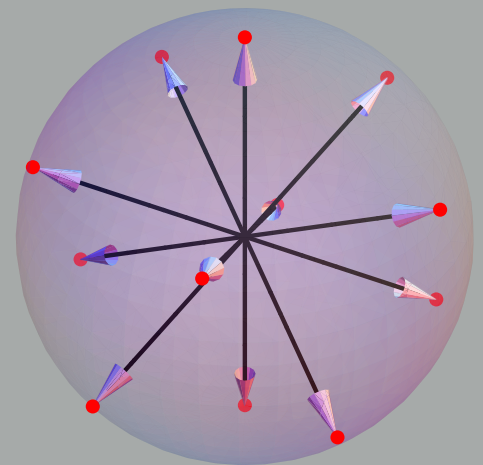
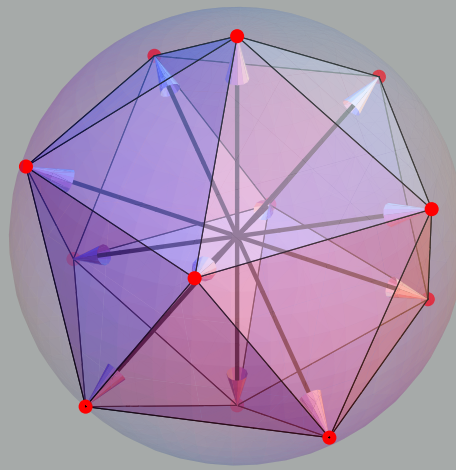
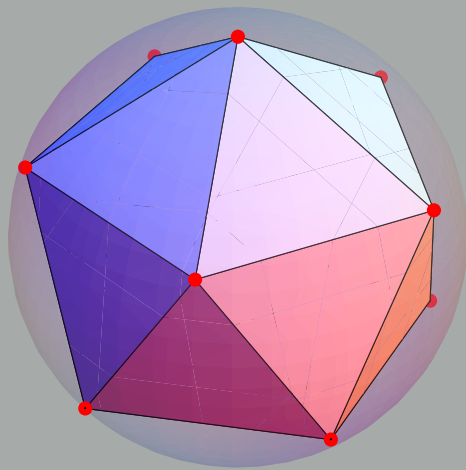
$$B = \begin{pmatrix} \hat{q}_{1,x}^2 & \hat{q}_{1,y}^2 & \hat{q}_{1,z}^2 & \hat{q}_{1,x}\hat{q}_{1,y} & \hat{q}_{1,x}\hat{q}_{1,z} & \hat{q}_{1,y}\hat{q}_{1,z} & 1 \\ \hat{q}_{2,x}^2 & \hat{q}_{2,y}^2 & \hat{q}_{2,z}^2 & \hat{q}_{2,x}\hat{q}_{1,y} & \hat{q}_{2,x}\hat{q}_{2,z} & \hat{q}_{2,y}\hat{q}_{2,z} & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \hat{q}_{n,x}^2 & \hat{q}_{n,y}^2 & \hat{q}_{n,z}^2 & \hat{q}_{n,x}\hat{q}_{1,y} & \hat{q}_{n,x}\hat{q}_{n,z} & \hat{q}_{n,y}\hat{q}_{n,z} & 1 \end{pmatrix}^{\tau}$$

$\uparrow$
gradient directions

$$q_{j,k} = g_k \delta \quad j\text{'th direction}$$

$$\tau = \Delta - \delta/3$$

Angular measurements



Estimating the Diffusion Tensor

$$\begin{array}{ccc}
 - \begin{pmatrix} \log s(b_1) \\ \log s(b_2) \\ \vdots \\ \log s(b_n) \end{pmatrix} & = & \begin{pmatrix} \hat{q}_{1,x}^2 & \hat{q}_{1,y}^2 & \hat{q}_{1,z}^2 & \hat{q}_{1,x}\hat{q}_{1,y} & \hat{q}_{1,x}\hat{q}_{1,z} & \hat{q}_{1,y}\hat{q}_{1,z} & 1 \\ \hat{q}_{2,x}^2 & \hat{q}_{2,y}^2 & \hat{q}_{2,z}^2 & \hat{q}_{2,x}\hat{q}_{1,y} & \hat{q}_{2,x}\hat{q}_{2,z} & \hat{q}_{2,y}\hat{q}_{2,z} & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \hat{q}_{n,x}^2 & \hat{q}_{n,y}^2 & \hat{q}_{n,z}^2 & \hat{q}_{n,x}\hat{q}_{1,y} & \hat{q}_{n,x}\hat{q}_{n,z} & \hat{q}_{n,y}\hat{q}_{n,z} & 1 \end{pmatrix} \begin{pmatrix} D_{xx} \\ D_{yy} \\ D_{zz} \\ D_{xy} \\ D_{xz} \\ D_{yz} \\ -\log s(0) \end{pmatrix} \\
 \boldsymbol{y} & & \boldsymbol{B} \qquad \qquad \qquad \boldsymbol{d}
 \end{array}$$

Least Squares

The matrix equation

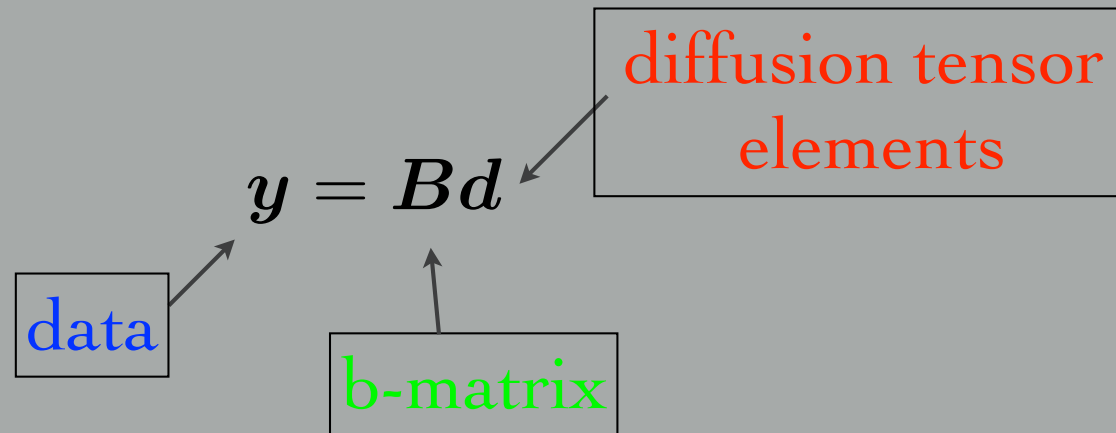
$$\mathbf{y} = \mathbf{B}\mathbf{d}$$

has dimensions

$$[n \times 1] = [n \times m][m \times 1]$$

Estimating the Diffusion Tensor

Solving for the diffusion tensor
is reduced to finding the solution
to the matrix equation



Estimating the Diffusion Tensor

Matrix equation

$$y = B^t d$$

data $\nearrow$ y $\nwarrow$ diffusion tensor elements
 $\nwarrow$ B^t $\nearrow$ b-matrix

Matrix solution

$$d = B^+ y$$

$\nwarrow$ pseudo-inverse

Least Squares

The least-squares solution to the matrix equation

$$\mathbf{y} = \mathbf{A}\mathbf{x}$$

is

$$? \hat{\mathbf{x}} = \mathbf{A}^{-1}\mathbf{y} ?$$

NO!

Least Squares

The least-squares solution to the matrix equation

$$\mathbf{y} = \mathbf{A}\mathbf{x}$$

is

$$\hat{\mathbf{x}} = \mathbf{A}^+ \mathbf{y} \quad (\text{note that } \hat{\mathbf{x}} \neq \mathbf{A}^{-1} \mathbf{y})$$

where

$$\mathbf{A}^+ \equiv (\mathbf{A}^t \mathbf{A})^{-1} \mathbf{A}^t$$

This is called the *pseudo-inverse* of $\mathbf{A}$

Estimating the Diffusion Tensor

In practice

D calculated with 3dDWItoDT (AFNI)

eigensystem calculated by:

$$[\text{evals}, \text{evecs}] = \text{eig}(\mathbf{D})$$