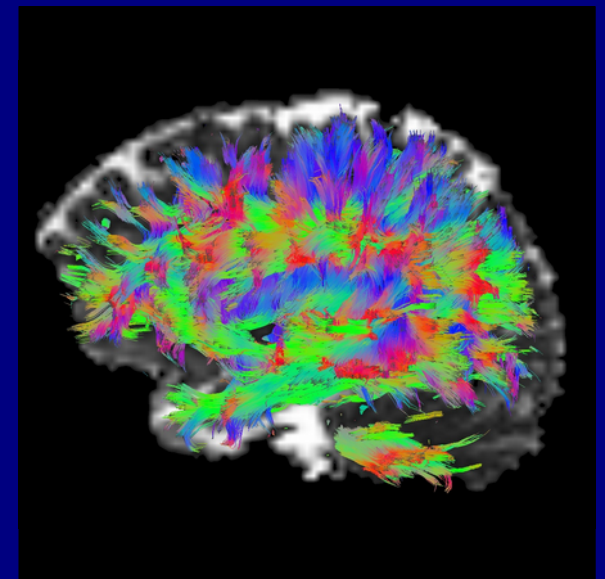


# More about DTI-tracking: Practicalities and programs

AFNI Bootcamp (SSCC, NIMH, NIH)



# Outline

- + Practicalities around tracking with AFNI/FATCAT
- + 3dTrackID's "modes" (a.k.a. styles or types) of tracking
  - and calculating tensor parameter uncertainty
- + Setting up networks of target ROIs with 3dROIMaker
  - examples from anatomical parc/seg and FMRI
- + Checking gradients
- + Additional tracking features

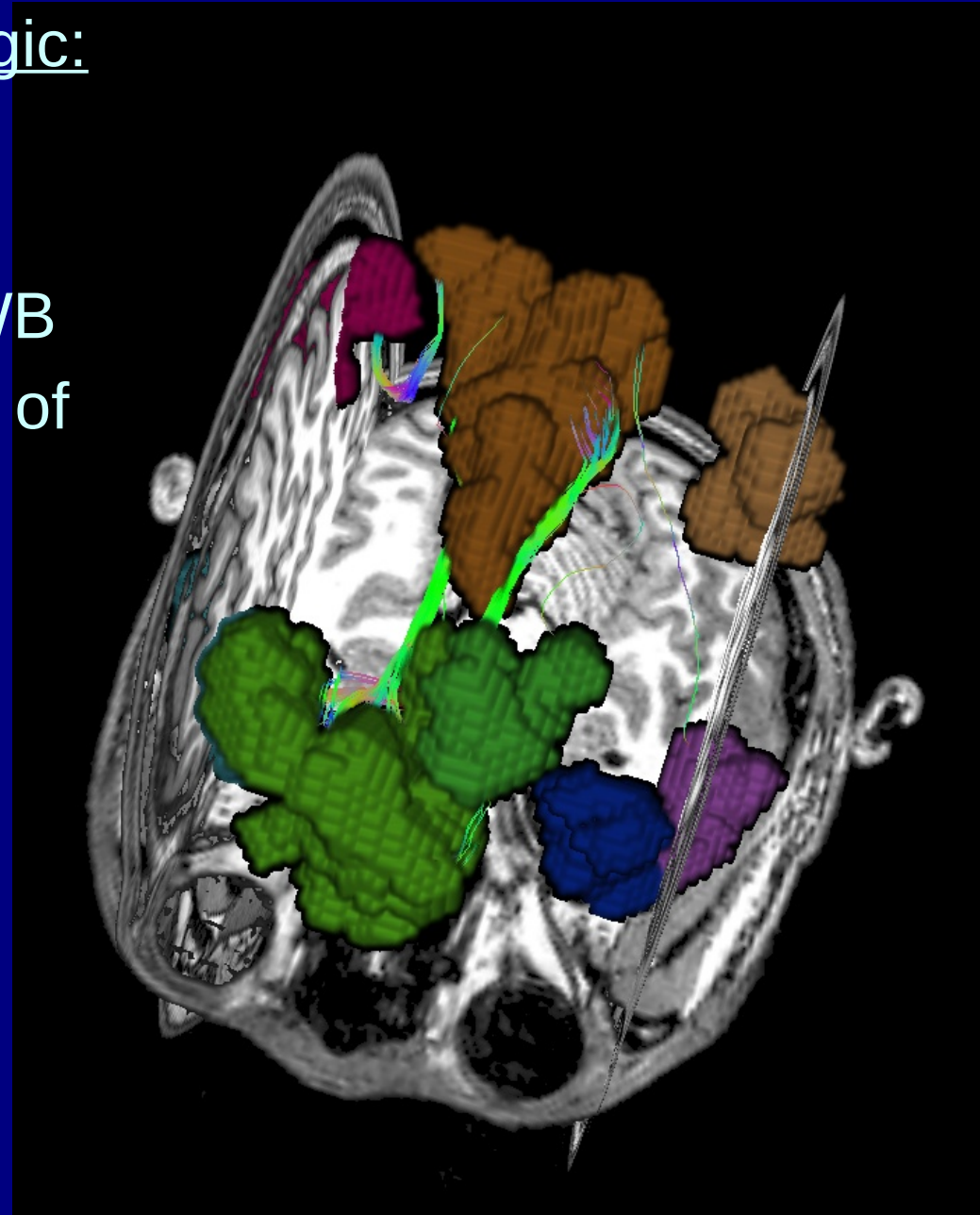
# Network tracking paradigm: recall

Useful generalization of AND-logic:

## “Network tracking”

through several target ROIs simultaneously. Find tracts in WB that go through any pair in a set of targets, where the targets make sense to think about together.

Note that the connections can be “sparse”: not every target is connected to every other target. (Physiologically, we would **not** expect otherwise...)

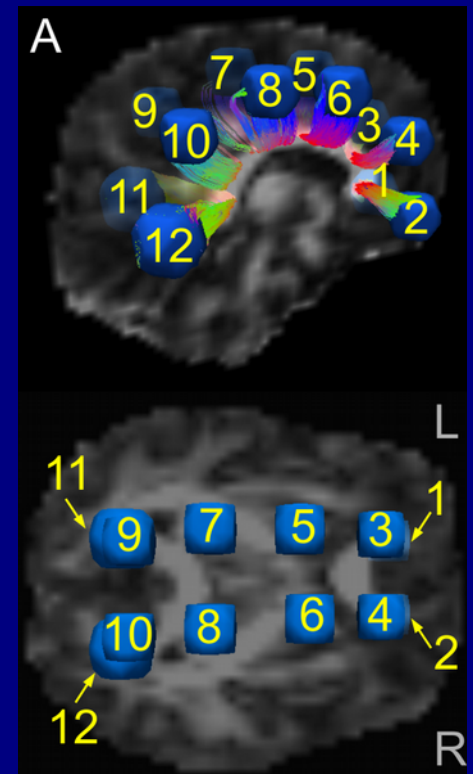
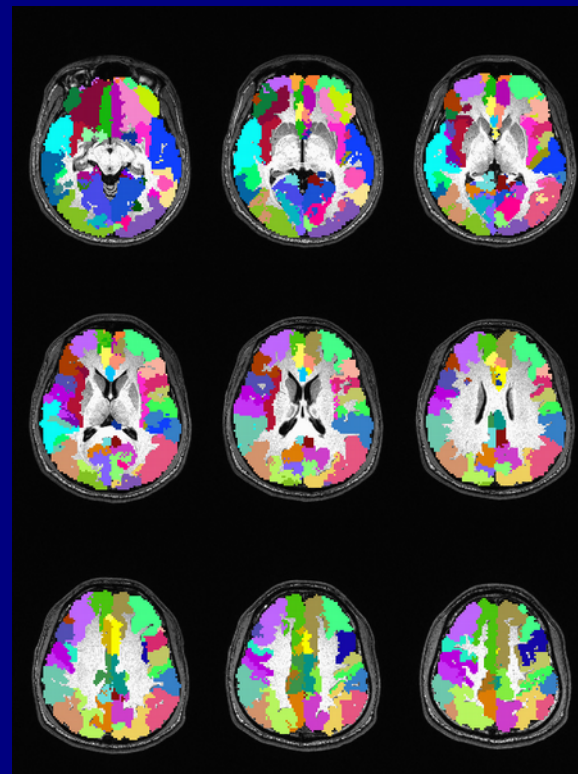
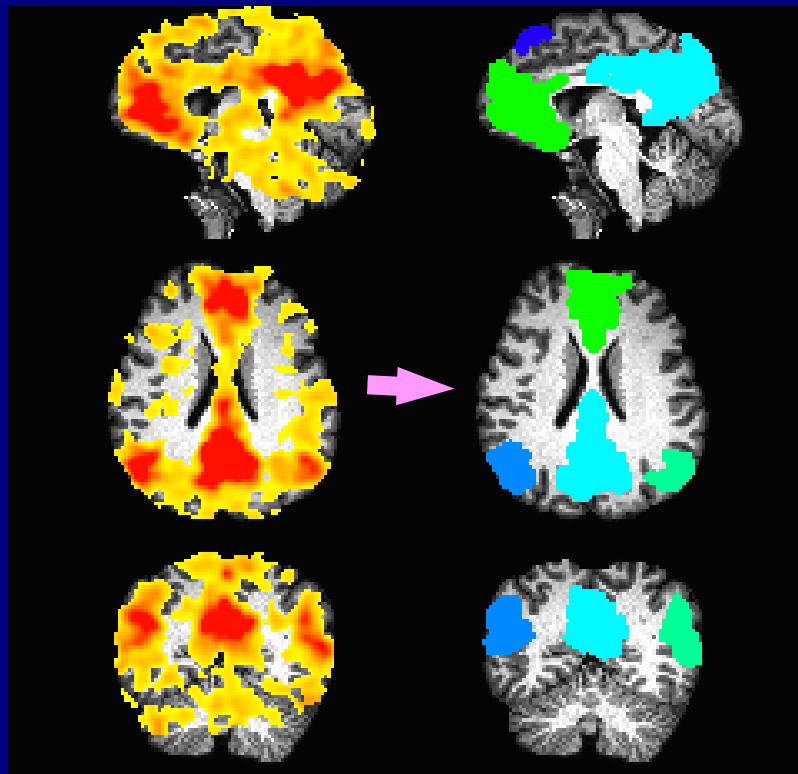


# Network tracking paradigm: recall

FMRI (e.g., thresholded seed-based or ICA maps)

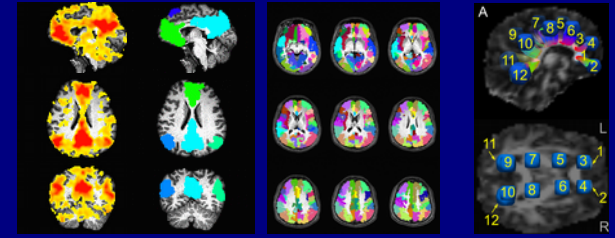
Anatomical parc/seg (e.g., FreeSurfer)

Spheres/simple ROIs (can map across group)





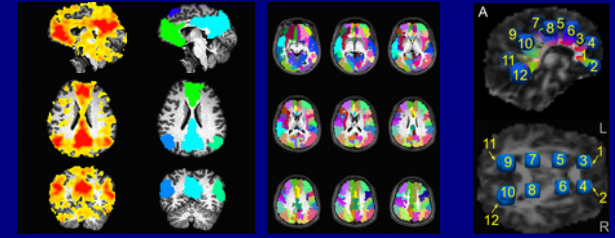
# Network tracking paradigm: points



## Main criteria for making target ROI networks

- + define meaningful regions (-> sensical to be together for hypothesis)
- + make sure targets border on FA-WM
- + for group analysis, create equivalent/consistent regions across group

# Network tracking paradigm: points



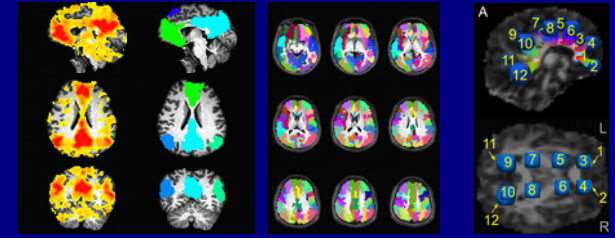
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## ... Then

- + targets can be defined in subject's own DTI space
- + main quantity: **matrix of structural properties** for each network

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## Main criteria for making target ROI networks

- + define meaningful regions (-> sensical to be together for hypothesis)
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- + for group analysis, create equivalent/consistent regions across group

## ... Then

- + targets can be defined in subject's own DTI space
- + main quantity: **matrix of structural properties** for each network

## Different than “voxelwise comparisons”

- + Here, don't need to warp to standard space/WM skeleton
  - > avoid (some) alignment issues/demands
- + Here: calc “network-wide” properties, then zoom in (big -> small)
  - voxelwise comps: calc voxel diffs and build “clusters” (small -> big)
- + Here, WM structure matters; voxelwise comps ignore this.

***Combining FMRI and DTI***  
(much applies to **any** target network)

# Tools for combining FC and SC:

Combining functional and tractographic connectivity will require:

- + determining networks from fMRI, parcellation or other data;
- + finding correlations and local properties of functional networks;
- + turning GM ROIs into targets for tractography;
- + doing reasonable tractography to find WM ROIs;
- + estimating stats on WM ROIs...



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- + estimating stats on WM ROIs...

**FATCAT:** Functional And Tractographic Connectivity Analysis Toolbox  
(Taylor & Saad, 2013, BC; Taylor et al. 2015, BC)

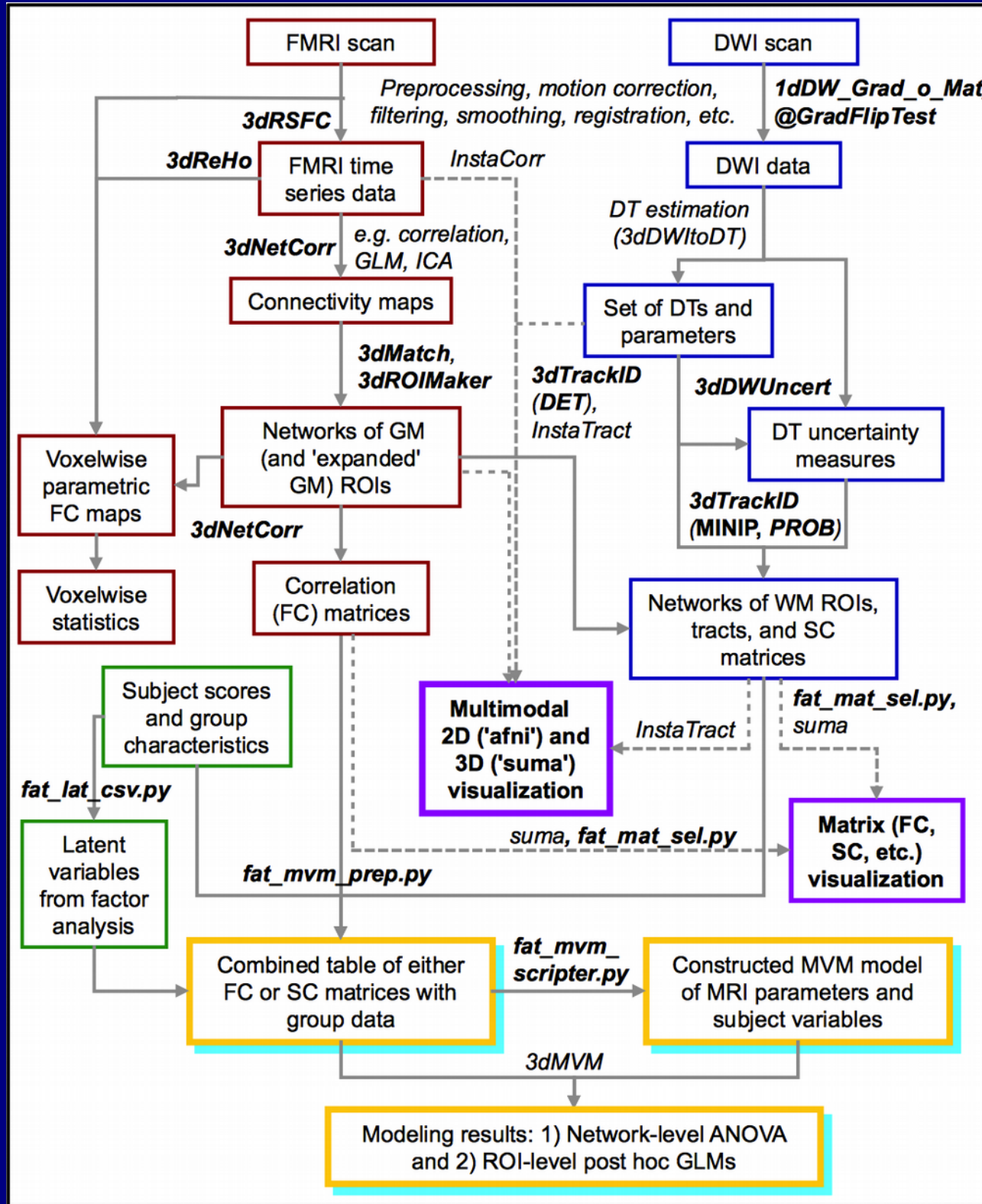
Demos in AFNI: @Install\_FATCAT\_DEMO, @Install\_FATMVM\_DEMO



# Schematic for combining FMRI and DTI-tractography via FATCAT

## FATCAT goals:

- + Do useful tasks
- + Integrate with existing pipelines/software
- + Derive/use information from the data itself
- + Be “simple” to implement
- + Be network-oriented, when possible
- + Be efficient
- + Be flexible and able to grow



(Taylor, Chen, Cox & Saad, 2016)

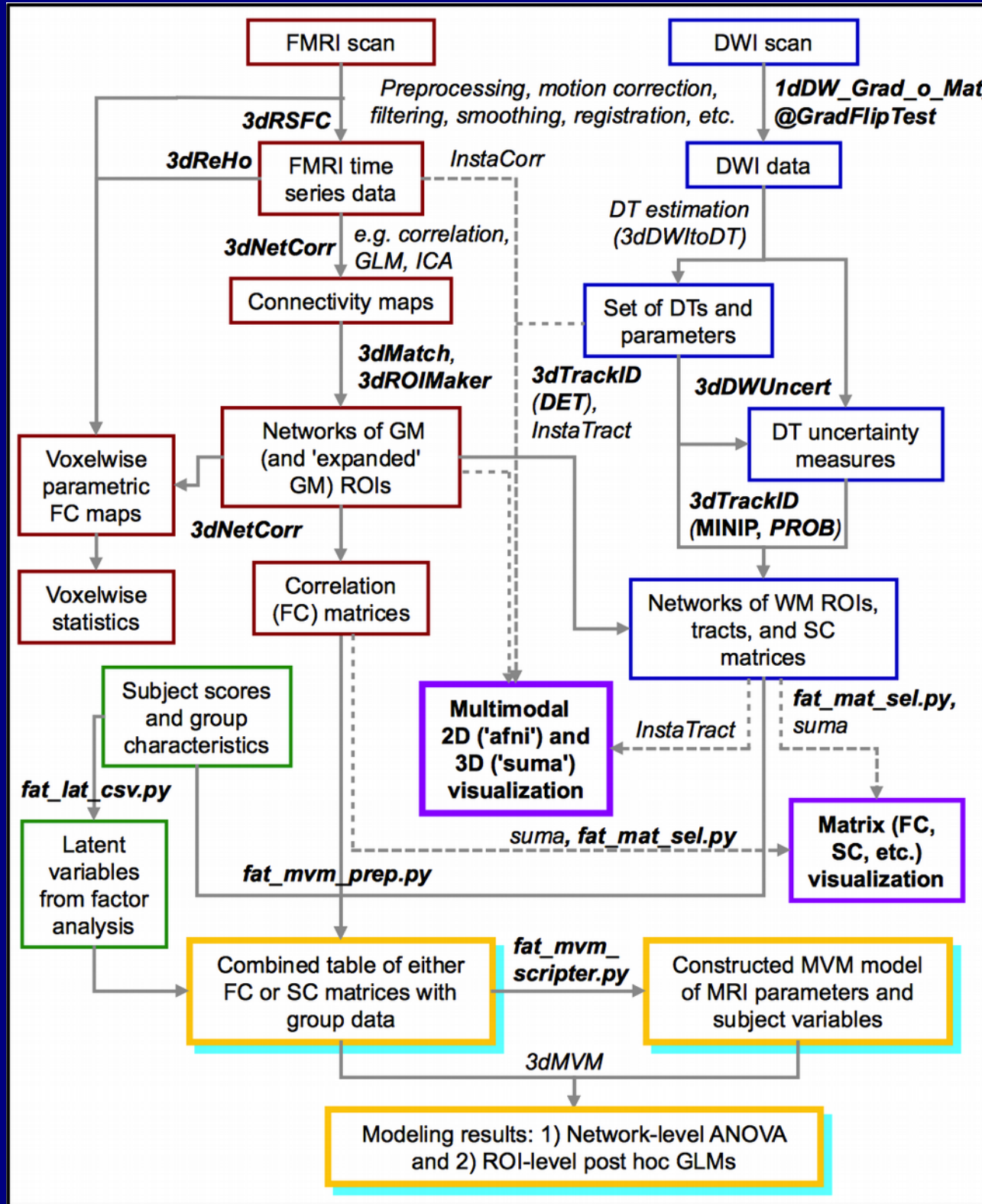
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Main focus today on DTI-tractography, including making ROIs from FMRI

(Taylor, Chen, Cox & Saad, 2016)

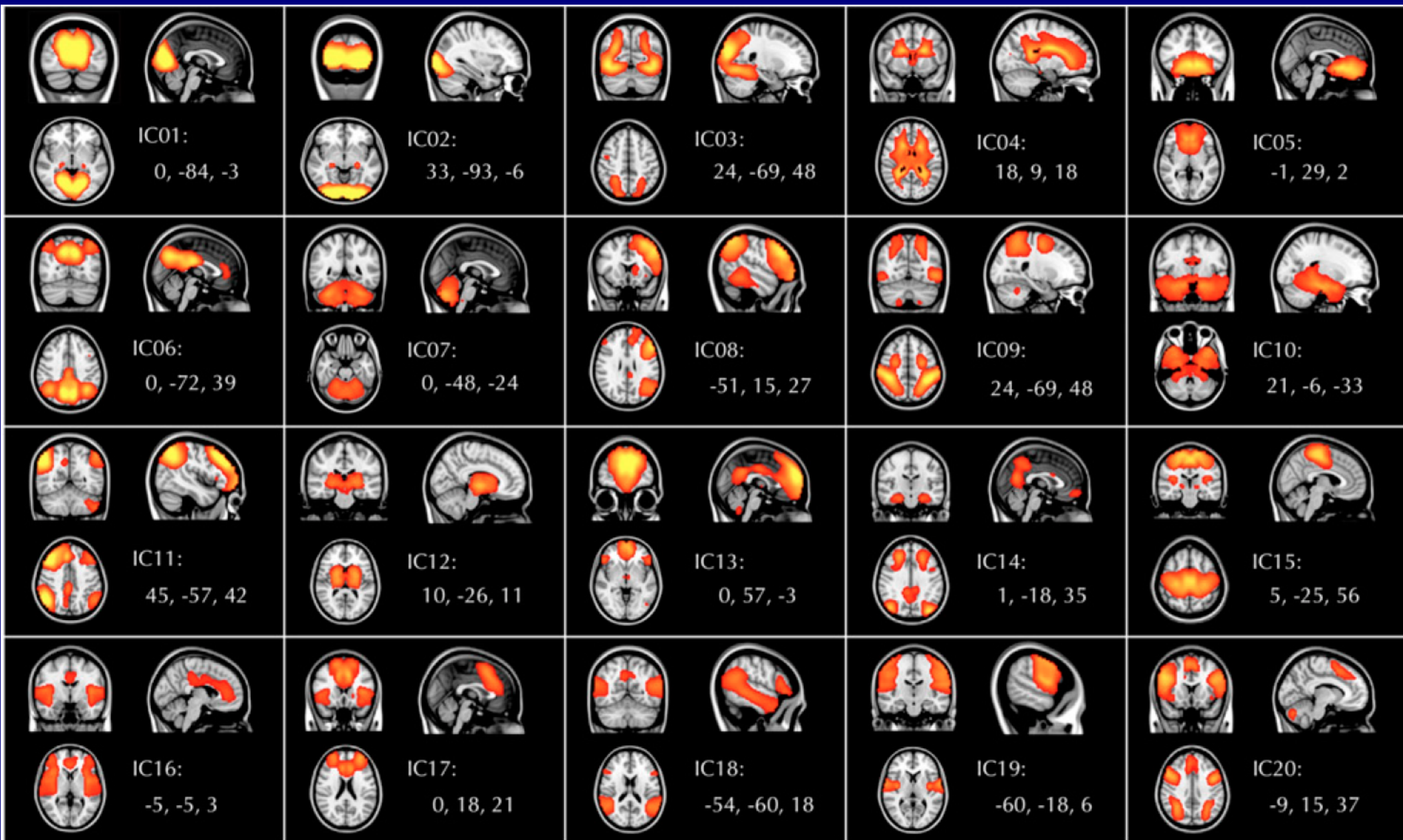


Motivating example

***Network view of both functional  
and structural data***



# FMRI: GM Networks



(Biswal et al., 2010 PNAS)

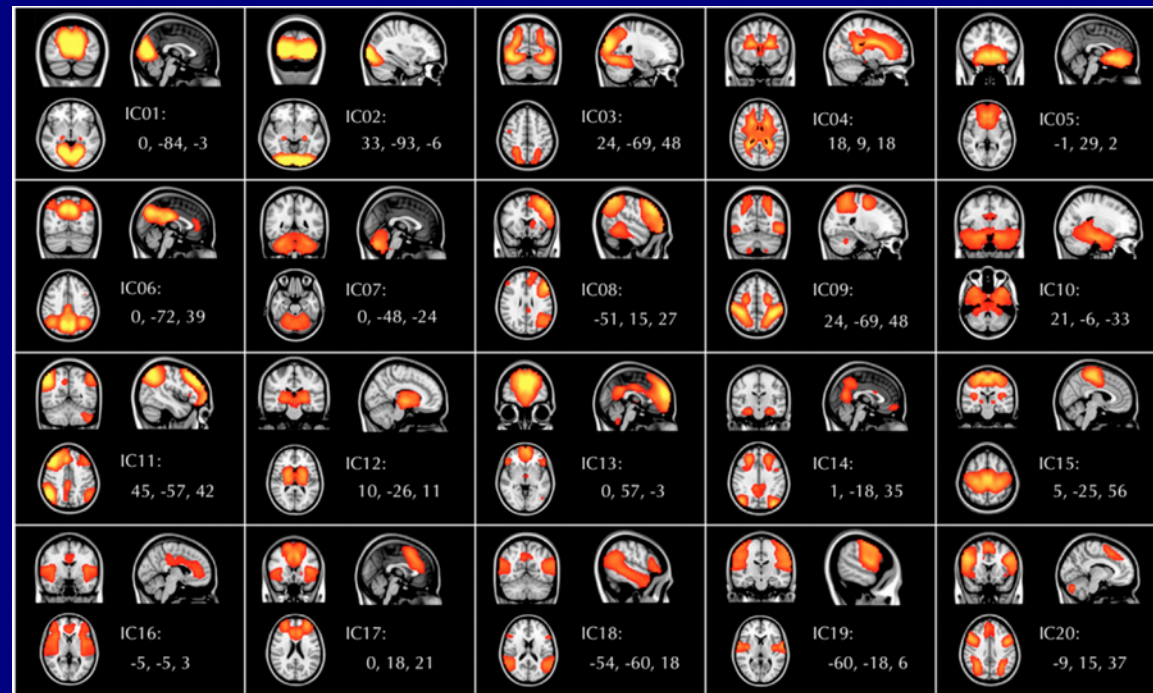


# FMRI: GM Networks

Functional connectivity networks of distinct GM regions, from BOLD time series during task or rest/no task.

+ Quantify GM properties: ALFF, fALFF, RSFA,  $\sigma$ , ReHo, GMV, etc.

+ Quantify network props: seedbased correlation, ICA, graph theoretical measures, etc.



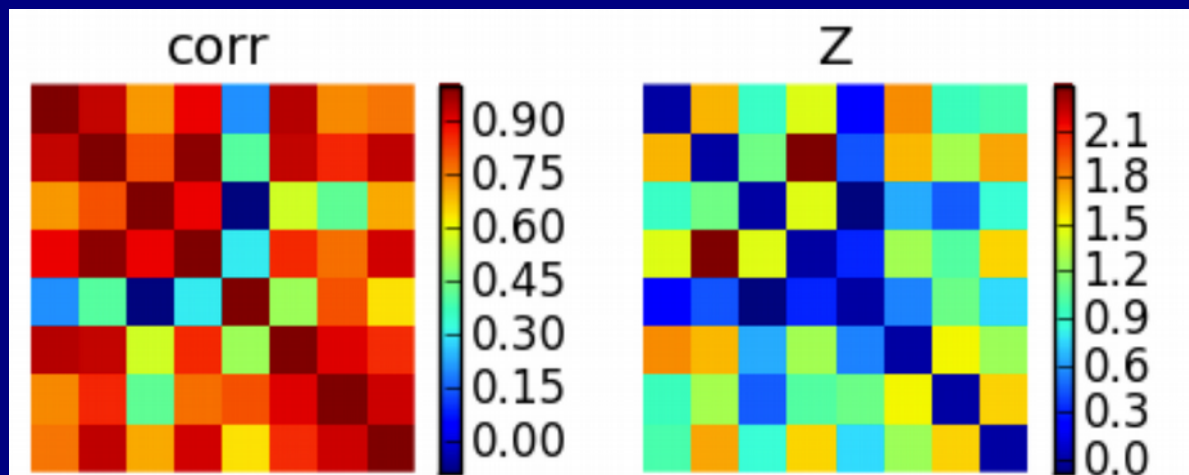
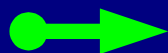
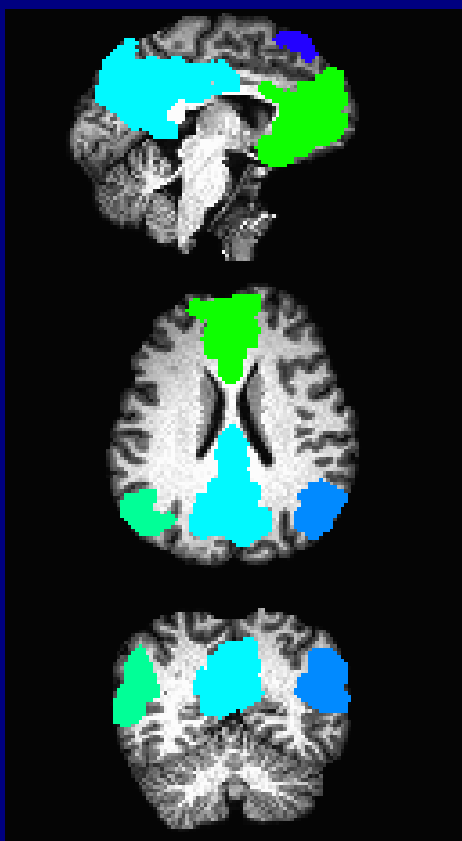
Sidenote:

***Mention of a few of the FMRI tools***

# Functional processing, 3

For {RS- | TB-}fMRI: correlation matrices

- + **3dNetCorr**: calculated post-processing, input time series data + network maps
  - can be multi-brick maps, 1 network per brick
  - calculate average time series per ROI, correlation among network ROIs
  - outputs correlation matrix/matrices, (can also do Fisher-Z transform output)



++ Can also calculate ReHo, ALFF, fALFF, etc. in FATCAT/AFNI.

Applying tractography

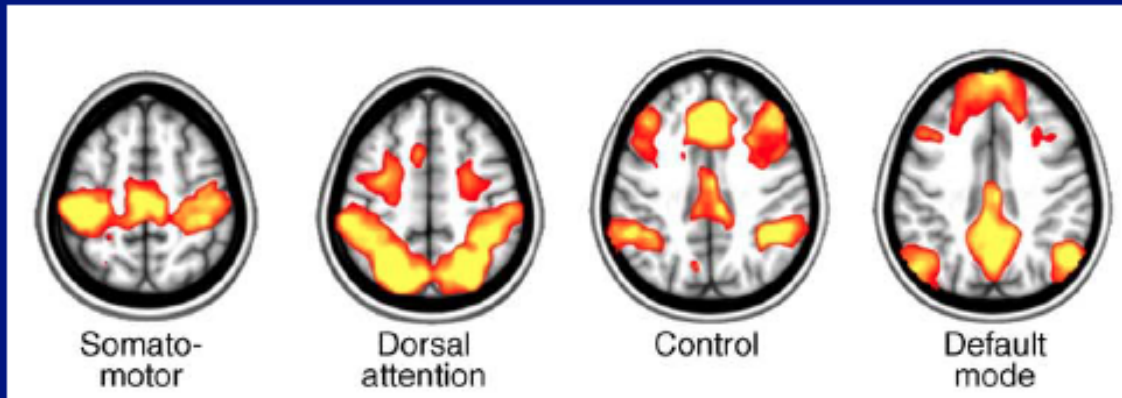
# Structure + Function

Simple example:

**FMRI provides:**

maps of (GM) regions working together

GM ROIs  
network:



*Raichle (2010, TICS)*



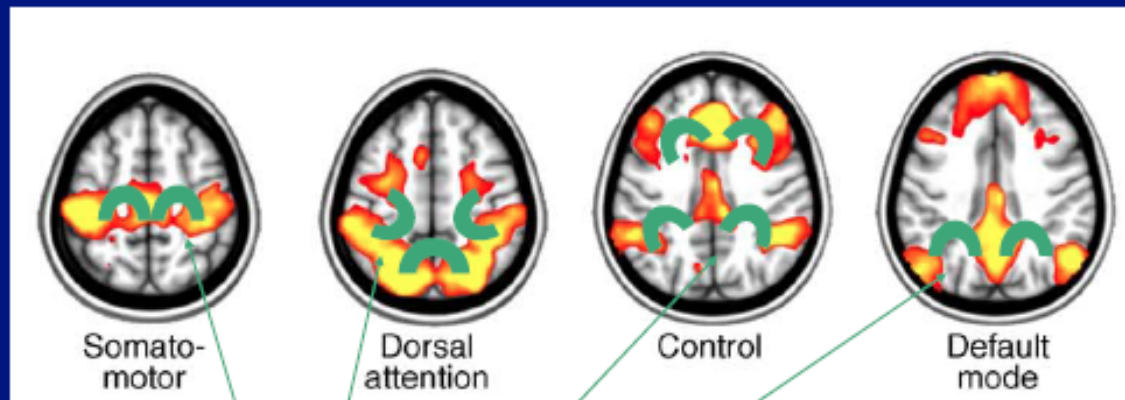
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Associated WM ROIs

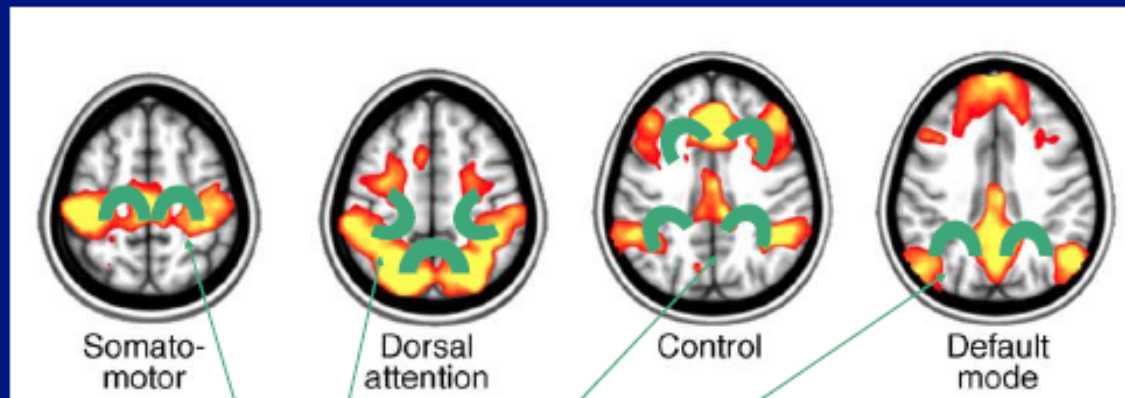
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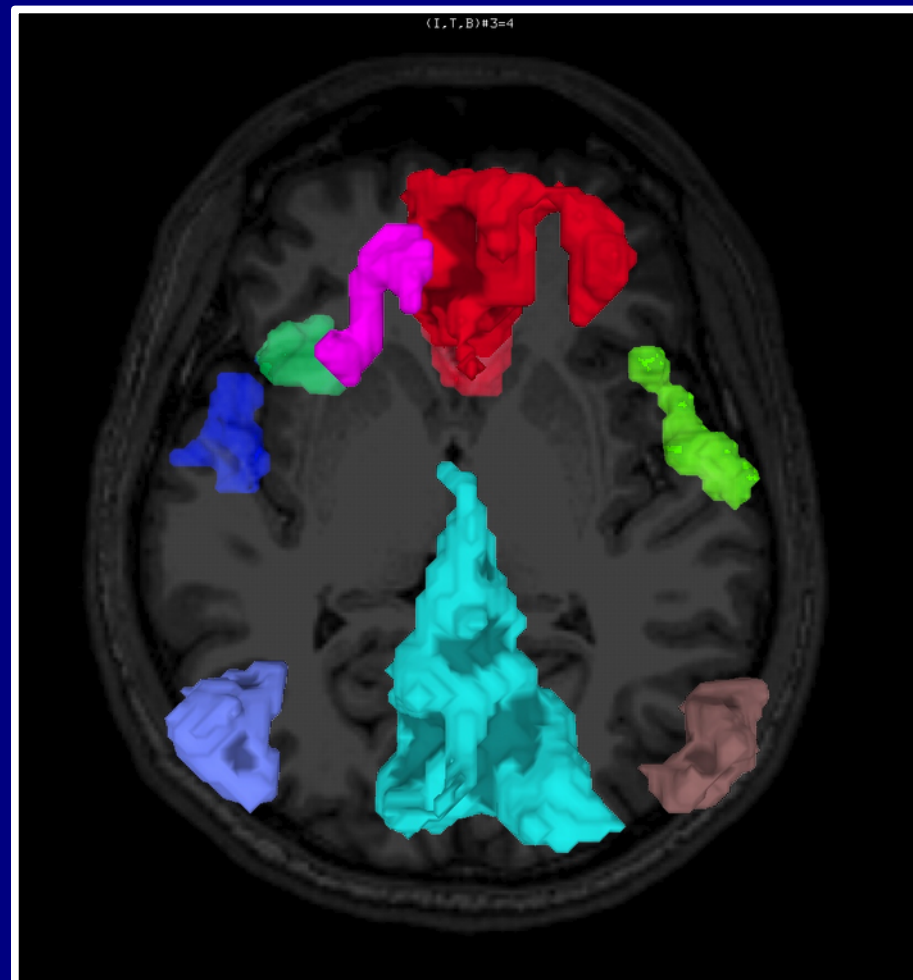
*Raichle (2010, TICS)*

**Associated WM ROIs**

Our goal for tractography->

*estimate likely/probable locations of WM associated with GM,  
and relate ROI quantities with functional/GM properties*

Describing and comparing “modes” of tracking in 3dTrackID,  
with example network of targets:



SUMA view of  
targets from FMRI  
(axial view, S->I)

# Tracking modes: **DET**

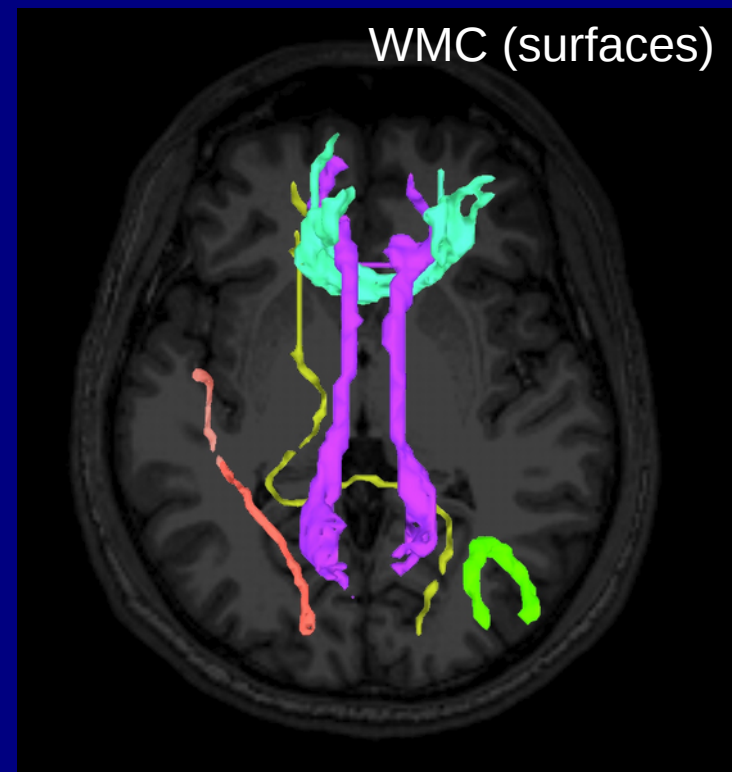
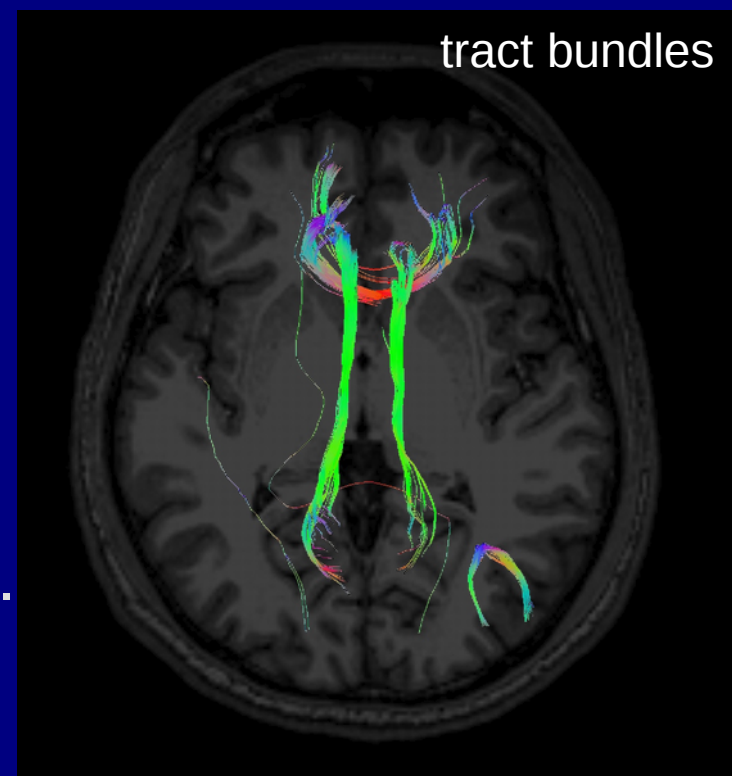
## Deterministic tracking

- + For each FA-WM voxel (e.g.,  $FA > 0.2$ ), place seedpoint(s), track from each until stop criterion reached, and keep tracts through ROIs (AND- or OR-logic).
- + Can delete “bad” bundles with too few tracts.

## + Output:

tract bundles,  
volumetric map of WMCs,  
*and matrix of structural properties.*

- > **DET** is OK for quick testing, QC, general data checking, but does not take into account uncertainty; don't know how reliable or noise-dependent results are. Mostly just used for quick, WB QC.



# Tracking modes: **MINIP**

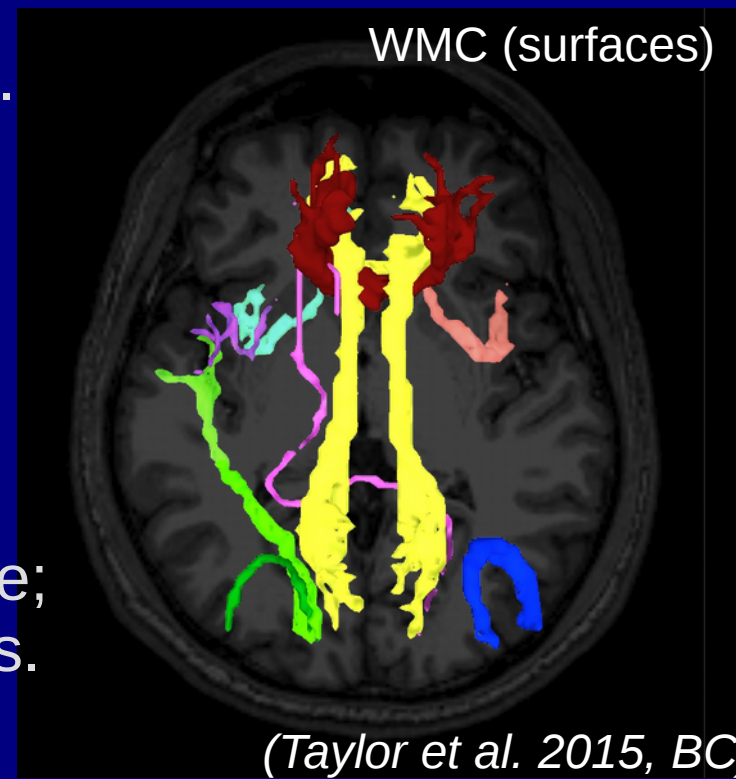
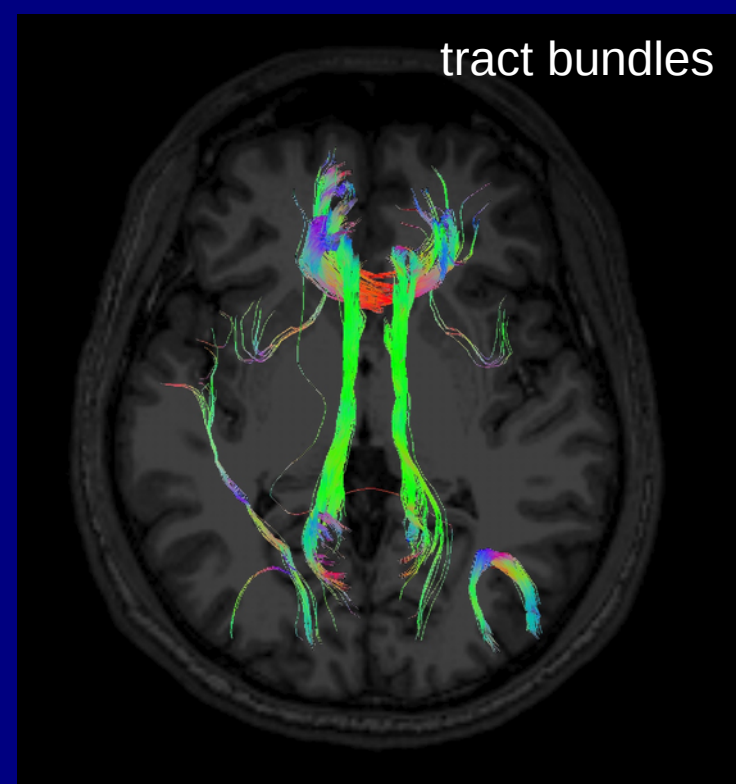
## Mini-probabilistic tracking

- + For each FA-WM voxel (e.g.,  $FA > 0.2$ ), place seedpoint(s), track from each until stop criterion reached, and keep tracts through ROIs (AND- or OR-logic);
- + **Then**, perturb every tensor randomly, according to its estimated uncertainty (-> desc. below), and then do WB tracking. Repeat a few (~5-7) times.
- + Can delete “bad” bundles with too few tracts.

## + Output:

tract bundles,  
volumetric map of WMCs,  
*and matrix of structural properties.*

--> **MINIP** improves on DET: accounts for noise; easier to detect spurious bundles; better vis. than DET. But no voxelwise thresholding...



(Taylor et al. 2015, BC)



# Tracking modes: **PROB**

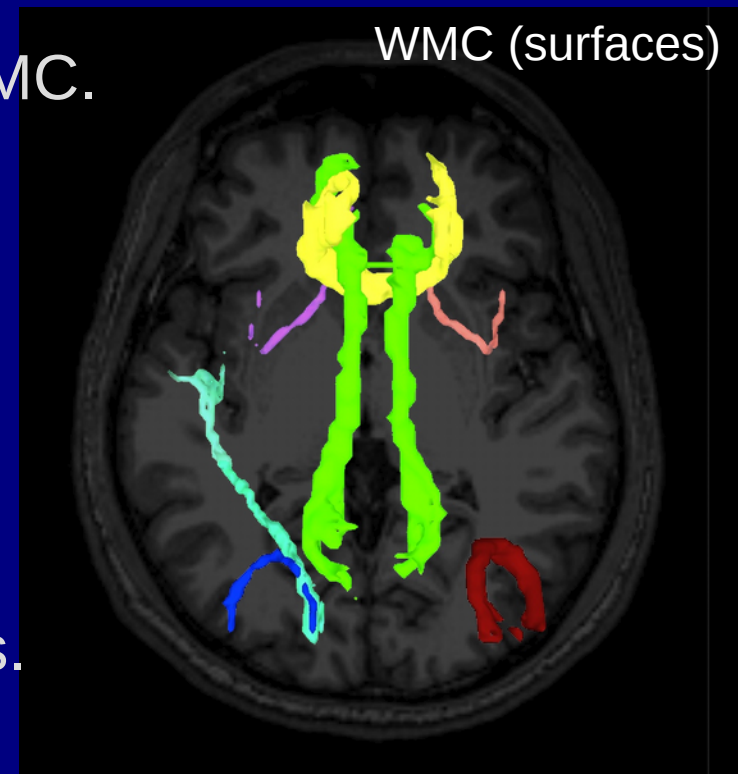
## (full) probabilistic tracking

- + For each FA-WM voxel (e.g.,  $FA > 0.2$ ), place seedpoint(s), track from each until stop criterion reached, and keep tracts through ROIs (AND- or OR-logic);
- + **Then**, perturb every tensor randomly, according to its estimated uncertainty (-> desc. below), and then do WB tracking. Repeat many (~thousands) times.
- + Threshold tract count **per voxel** to make WMC.

+ Output:  
volumetric map of WMCs,  
*and matrix of structural properties.*

--> **PROB** is most robust tracking: noise most strongly accounted for, and each WMC is built with **per voxel** criterion of tract counts. Produces best “likelihood” map of WMC.

*No bundles output  
They are only used  
to build up prob.  
map*



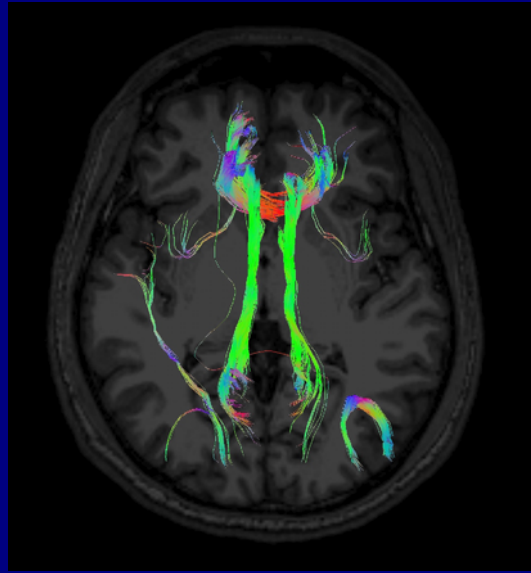
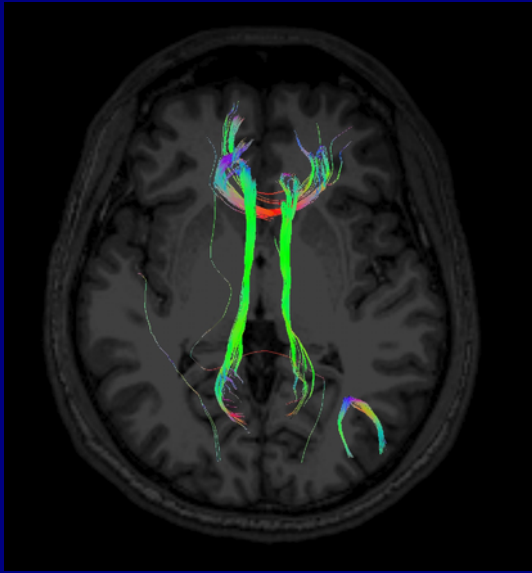
# Bundles/WMCs comparisons per mode

DET

MINIP

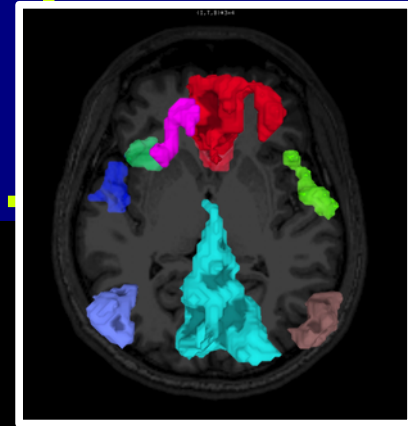
PROB

Tract bundles

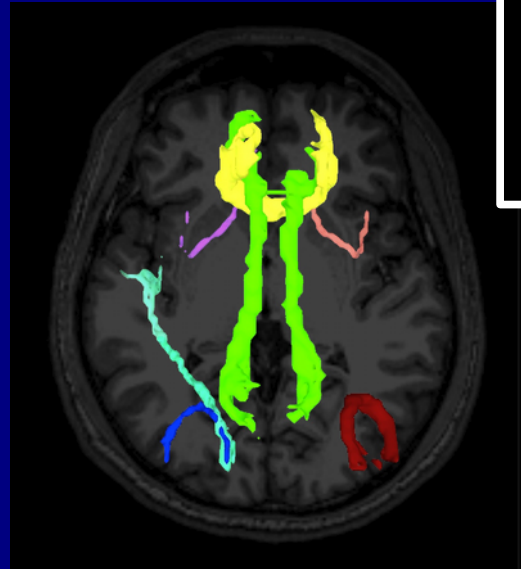
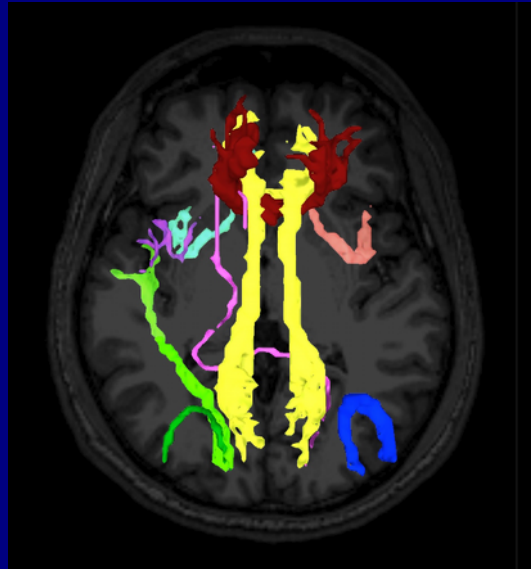
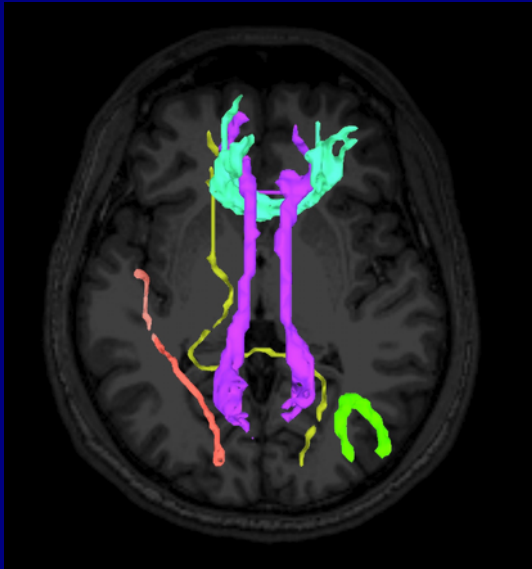


*No bundles output  
They are only used  
to build up prob.  
map*

Target ROIs



WMC surfaces





# 3dTrackID: choosing a “mode”

## DET

- + Initial, quick QC of full DWI data (e.g., WB tracking)
- + Check gradient flip (-> @GradFlipTest)

## MINIP

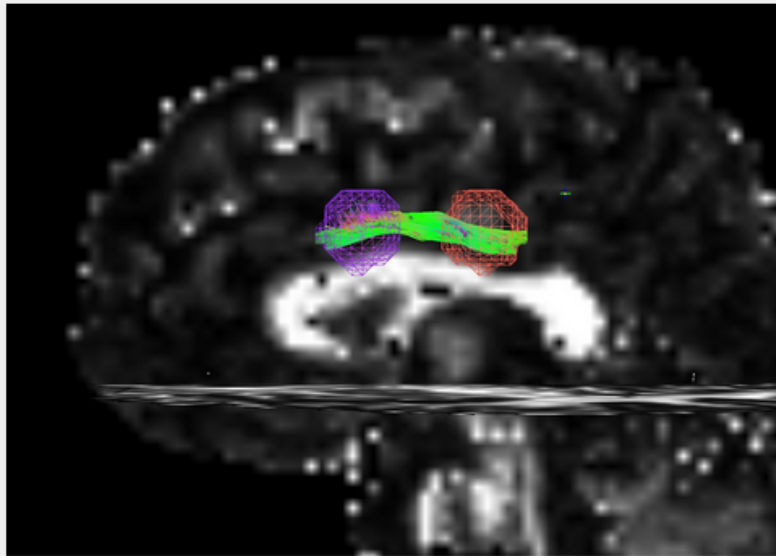
- + Quick network check
- + Visualize tract bundles, esp. for example figure
- + Requires uncert. calc. (3dDWUncert)

## PROB

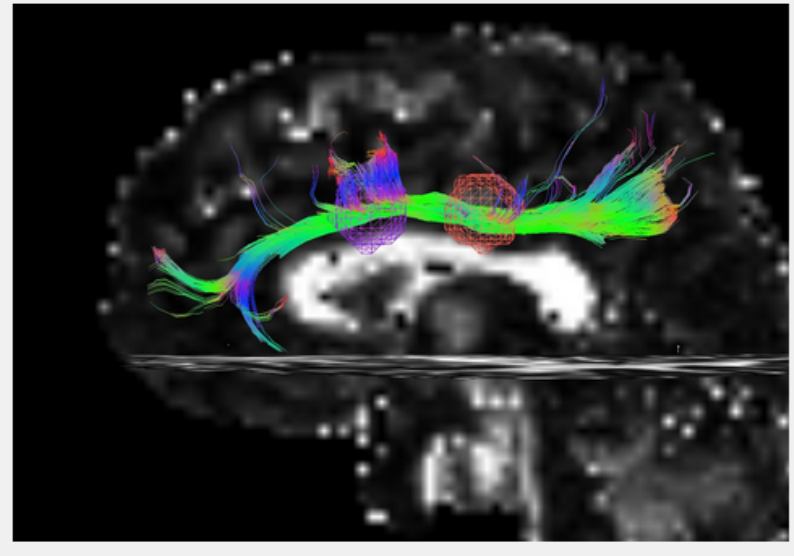
- + **The choice for quantitative work**
- + *Can* also visualize WMCs as RGB or per-bundle coloring
- + Requires uncert. calc. (3dDWUncert)
- + Is slower.... but not too bad.

# 3dTrackID: control tracts at surface boundaries

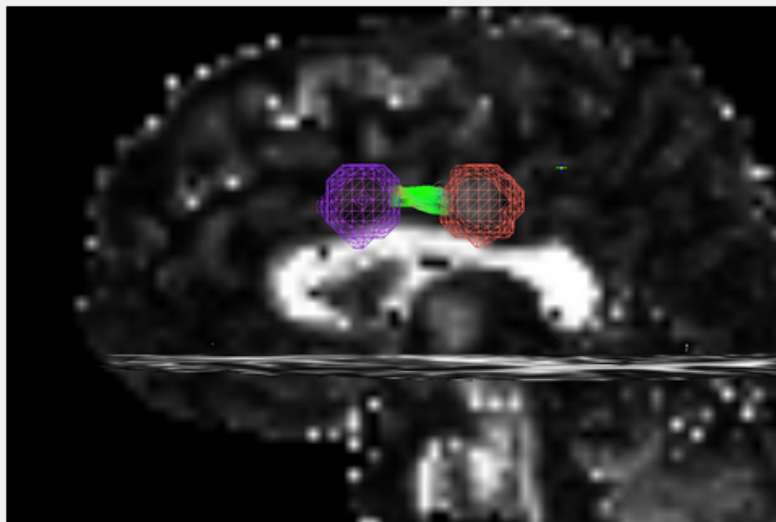
A. Default: between and within target



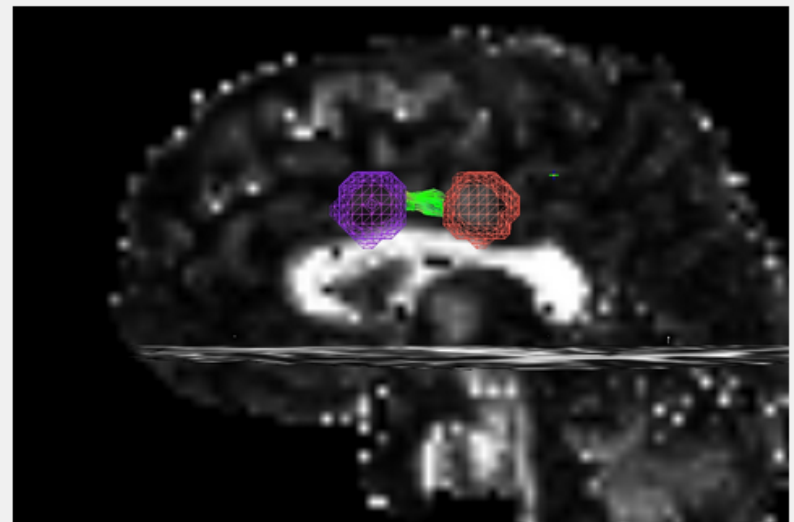
B. `-uncut_at_rois` : no trimming



C. `-targ_surf_stop` : between targets and includes surface



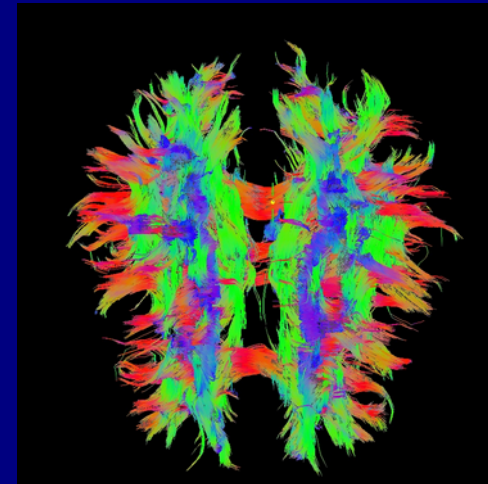
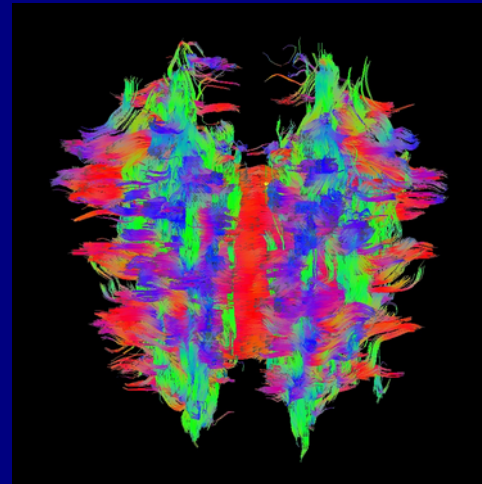
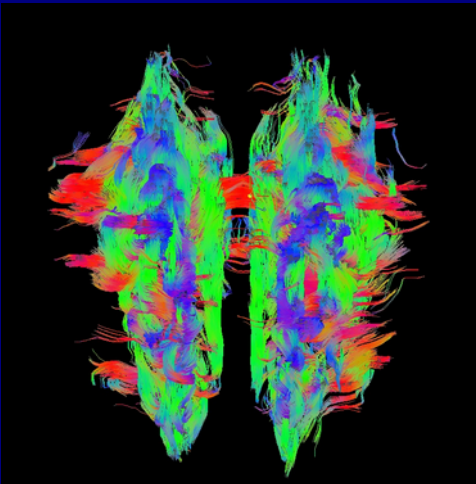
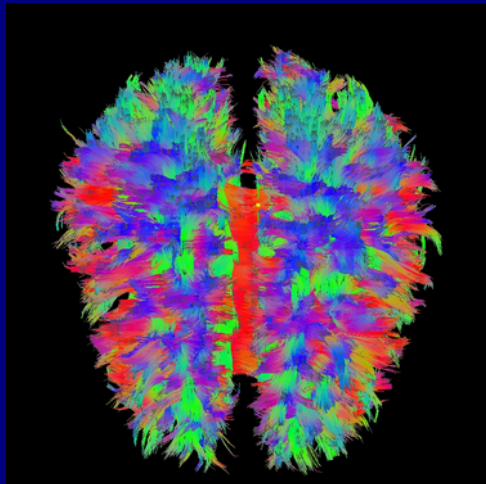
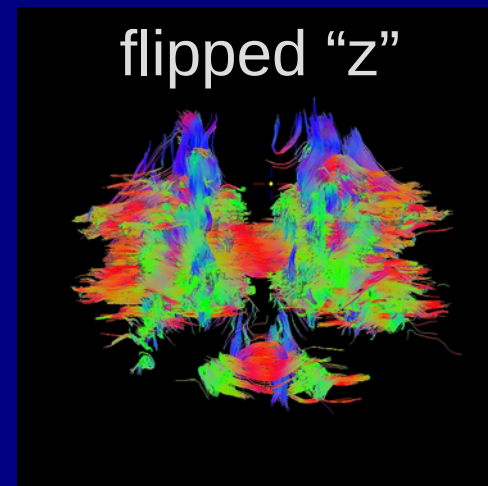
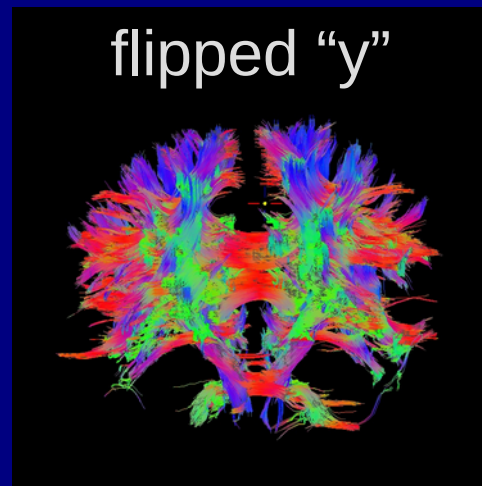
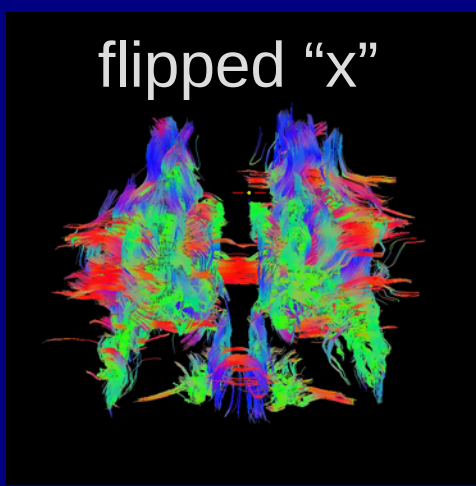
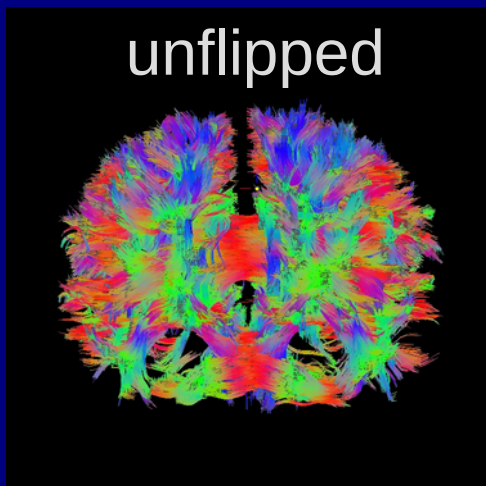
D. `-targ_surf_twixt` : between targets only





# @GradFlipTest: track WB to check grad format

+ Software and scanners have can have different definitions of +/- when interpreting scan directions. So, use WB tracking via **@GradFlipTest** to check and **1dDW\_Grad\_o\_Mat++** to adjust/fix.



<https://afni.nimh.nih.gov/pub/dist/doc/html/doc/FATCAT/GradFlipTest.html>

<https://afni.nimh.nih.gov/pub/dist/doc/html/doc/FATCAT/DealingWithGrads.html>

(Taylor et al. 2015, BC)

Making network of targets for tracking

Ex. 1: from FreeSurfer parc/seg

Ex. 2: from FMRI maps

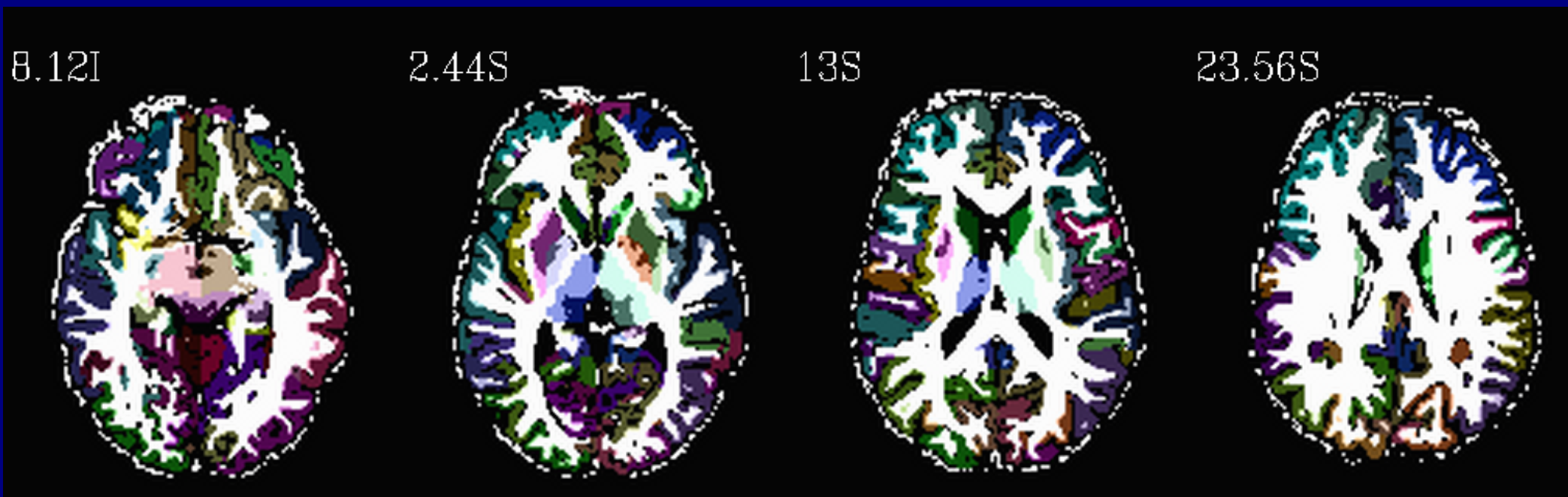


# 3dROIMaker: (controlled) ROI inflation

+ Target ROIs may be slightly “cut off” from the FA-WM masks, due to thresholding (e.g., FMRI) or alignment/resampling (e.g., FS/template or FMRI).

Can use **3dROIMaker** to inflate targets a little to fill in gaps while not overrunning WM or other targets.

**Ex. 1:** **olay:** FS targets **pre-inflation**; **ulay:** FA>0.2 mask



<https://afni.nimh.nih.gov/pub/dist/doc/html/doc/FATCAT/MakingROIs.html>

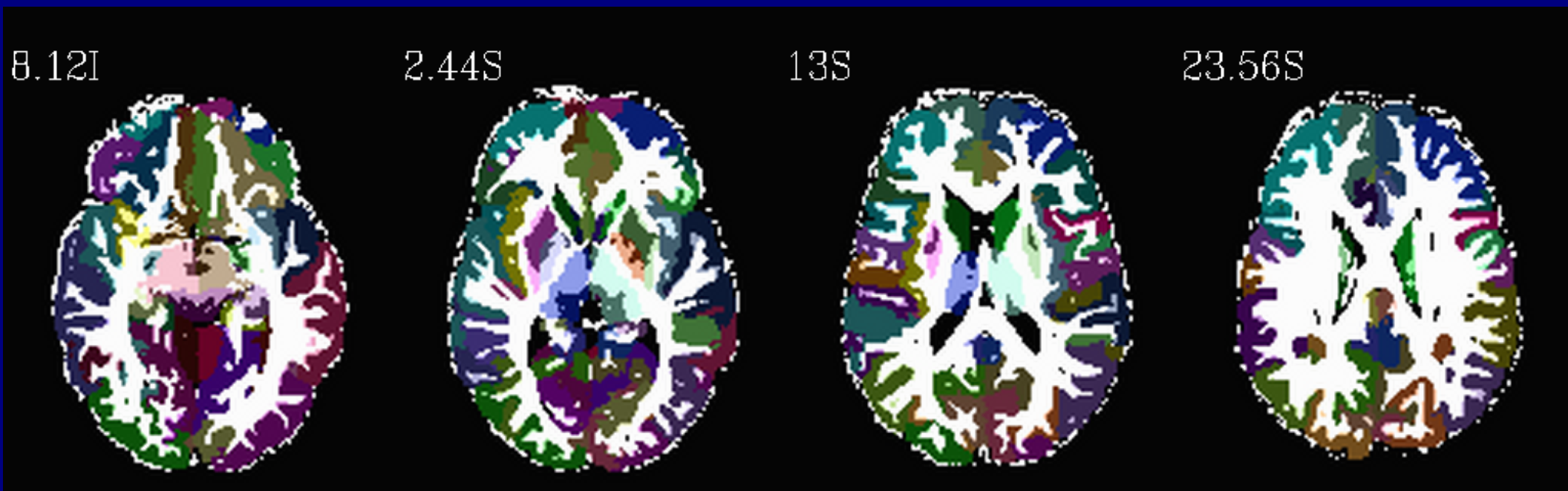
[https://afni.nimh.nih.gov/pub/dist/doc/html/doc/tutorials/fatcat\\_prep/Postprocessing\\_III.html](https://afni.nimh.nih.gov/pub/dist/doc/html/doc/tutorials/fatcat_prep/Postprocessing_III.html)

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[https://afni.nimh.nih.gov/pub/dist/doc/html/doc/tutorials/fatcat\\_prep/Postprocessing\\_III.html](https://afni.nimh.nih.gov/pub/dist/doc/html/doc/tutorials/fatcat_prep/Postprocessing_III.html)

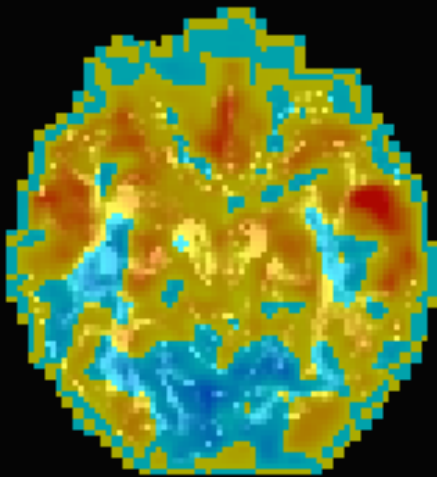
# Ex. 2: FMRI-derived targets

1) Start with some FC map (seed-based correlation, ICA, etc.)

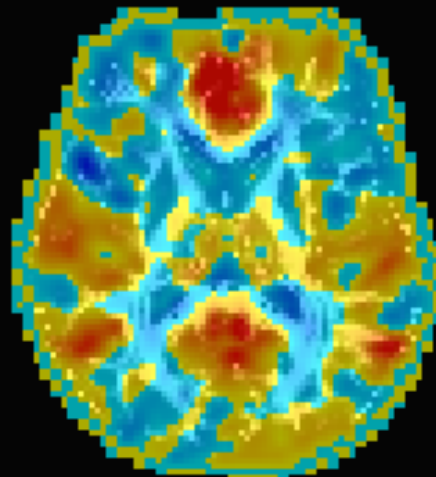
Here:      olay = ICA map (Z-score values)

          ulay = FA map

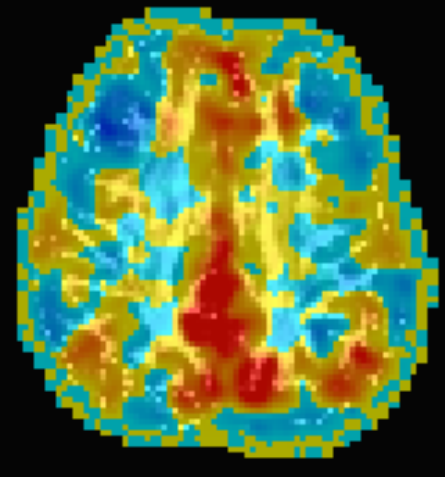
48.71I



26.71I



4.71I



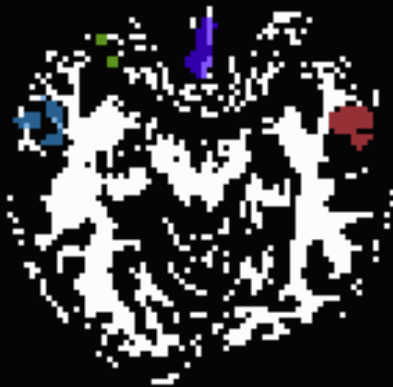
# Ex. 2: FMRI-derived targets

2) Threshold FC map voxelwise and for size of clusters -> isolated ROIs

Here:      olay = map of regions after thresholding

            ulay = mask of  $FA > 0.2$  (-> FA-WM)

48.711



26.711



4.711



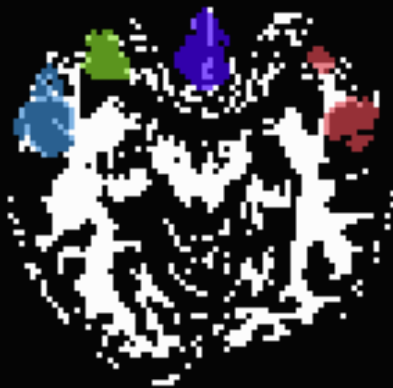
# Ex. 2: FMRI-derived targets

3) Inflate isolated targets a small amount, constrain with FA-WM

Here:       $\text{gray} = \text{inflated ROIs} \rightarrow \text{targets for tracking}$

$\text{white} = \text{mask of } \text{FA} > 0.2 \text{ } (-> \text{FA-WM})$

48.711



26.711



4.711



# 3dROIMaker: additional features

- + Can remove overlap of regions with WM or CSF
- + Inflation options: inflation can stop just before or just after overlapping with FA-WM
- + Select subsets of ROIs with  $N$  highest values
- + Apply a “refset” to have consistent numbering+labelling of ROIs

*How do we estimate tensor parameter  
noise/uncertainty for  
MINIP and PROB tracking?*

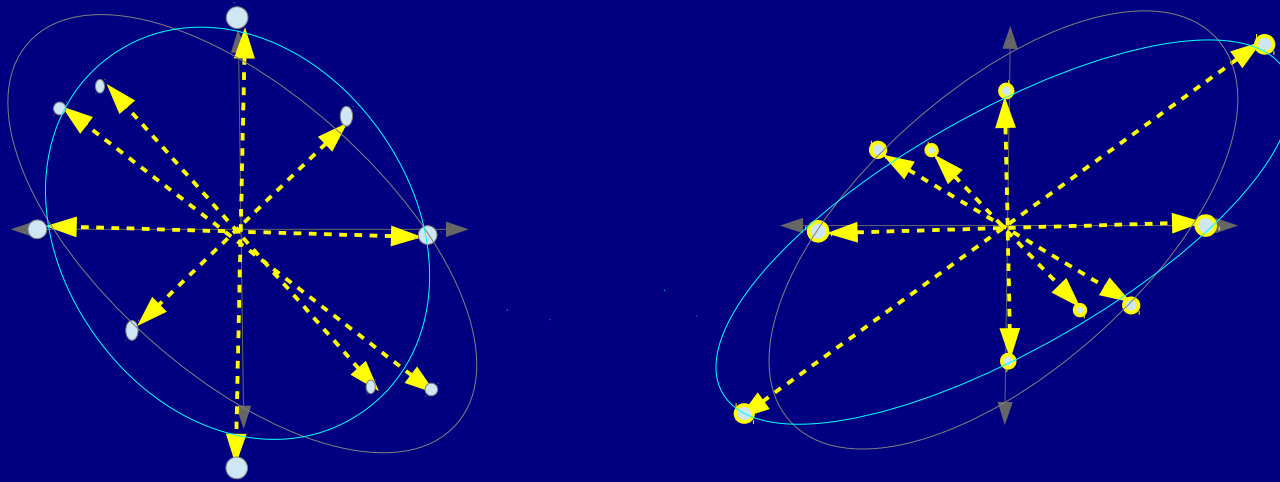


# Recall: noise in DW signals

MRI signals have additive noise

$$S_i = S_0 e^{-b \mathbf{g}_i^T \mathbf{D} \mathbf{g}_i} + \varepsilon,$$

where  $\varepsilon$  is (Rician) noise, with the effect of leading to errors in surface fit, equivalent to **rotations** and **rescalings** of ellipsoids:



'Un-noisy' vs perturbed/noisy fit

EPI distortions, subject motion, et al. also warp ellipsoids.

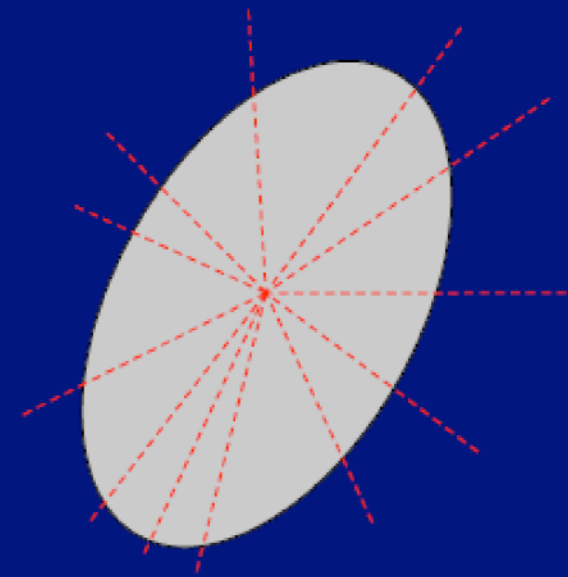
# DTI Uncertainty

- We use jackknife resampling (e.g., Efron 1982)
  - Other studies have used bootstrapping (e.g., Jones 2003), or theoretical estimates (Jeong & Anderson 2008)
  - Jackknifing is efficient (just need one data set unlike bootstrap), simpler than theory, since, e.g., SNR is likely not constant across voxels

# Jackknifing

- Basically, take  $M$  acquisitions

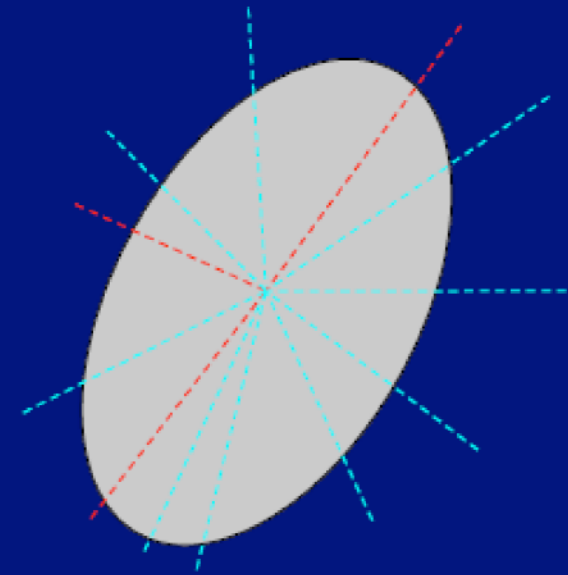
e.g.,  $M=12$



# Jackknifing

- Basically, take  $M$  acquisitions
- Randomly select  $M_J < M$  to use to calculate quantity of interest
  - standard nonlinear fits

e.g.,  $M=12$   
 $M_J=9$

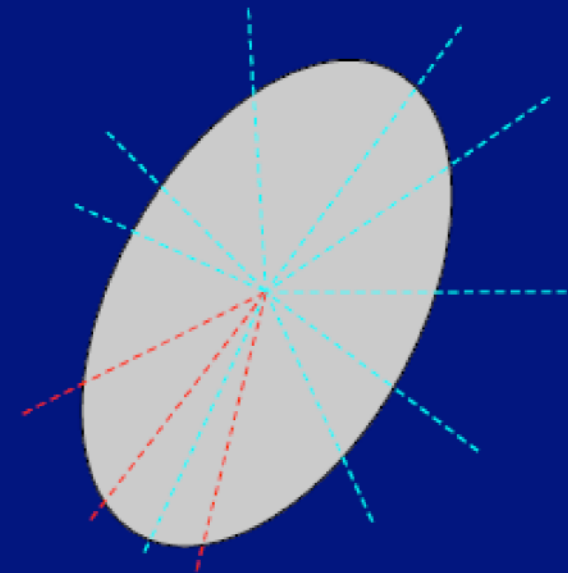


$$[D_{11} \ D_{22} \ D_{33} \ D_{12} \ D_{13} \ D_{23}] = \dots$$

# Jackknifing

- Basically, take  $M$  acquisitions
- Randomly select  $M_J < M$  to use to calculate quantity of interest
  - standard nonlinear fits
- Repeatedly subsample large number ( $\sim 10^3$ - $10^4$  times)

e.g.,  $M=12$   
 $M_J=9$

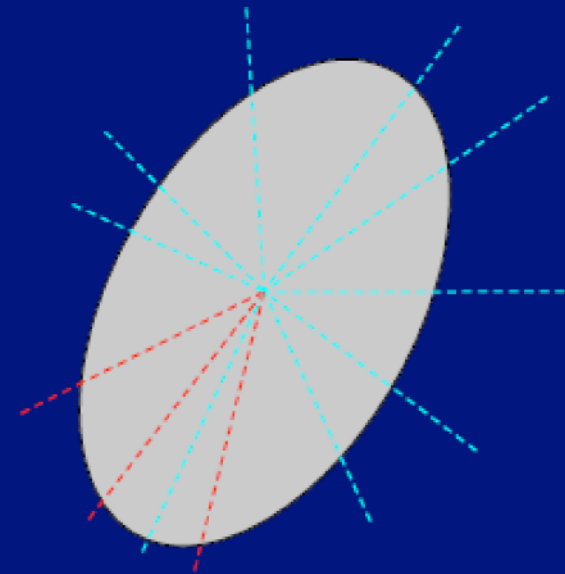


$$\begin{aligned} [D_{11} \ D_{22} \ D_{33} \ D_{12} \ D_{13} \ D_{23}] &= \dots \\ [D_{11} \ D_{22} \ D_{33} \ D_{12} \ D_{13} \ D_{23}] &= \dots \\ [D_{11} \ D_{22} \ D_{33} \ D_{12} \ D_{13} \ D_{23}] &= \dots \\ &\dots \end{aligned}$$

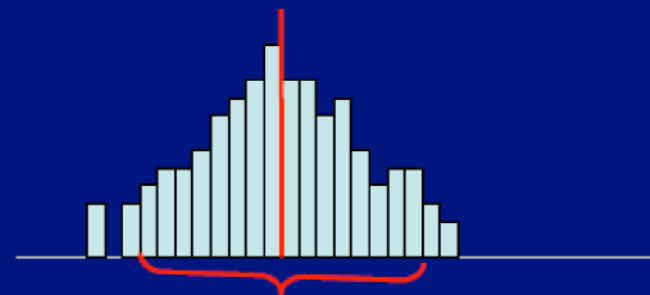
# Jackknifing

- Basically, take  $M$  acquisitions
- Randomly select  $M_J < M$  to use to calculate quantity of interest
  - standard nonlinear fits
- Repeatedly subsample large number ( $\sim 10^3$ - $10^4$  times)
- Analyze distribution of values for estimator (mean) and confidence interval
  - sort/%iles
    - (not so efficient)
  - if Gaussian, e.g.  $\mu \pm 2\sigma$ 
    - simple

e.g.,  $M=12$   
 $M_J=9$



$$\begin{aligned} [D_{11} \ D_{22} \ D_{33} \ D_{12} \ D_{13} \ D_{23}] &= \dots \\ [D_{11} \ D_{22} \ D_{33} \ D_{12} \ D_{13} \ D_{23}] &= \dots \\ [D_{11} \ D_{22} \ D_{33} \ D_{12} \ D_{13} \ D_{23}] &= \dots \\ &\dots \end{aligned}$$

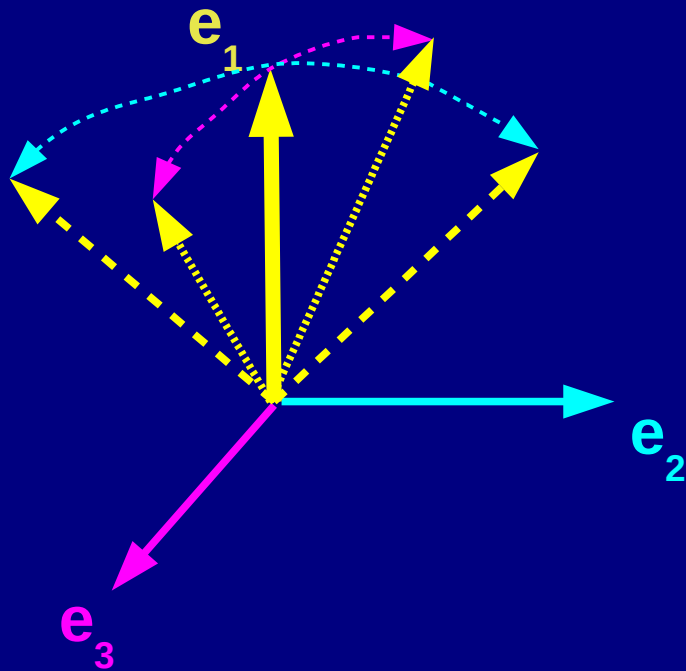




# Uncertainty estimation

+ **3dDWUncert** estimates

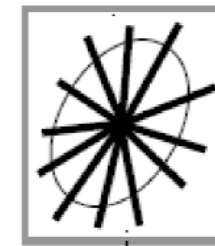
1) bias and  $\sigma$  of the first eigenvector  $e_1$  (main direction of diffusion), for two degrees of freedom: how much it could tip toward either  $e_2$  or  $e_3$ :



2) and the bias and  $\sigma$  of (scalar) FA.

(Taylor & Saad. 2013, BC)

1) Obtain  $M$  DWIs.



1b) Estimate DT and parameters from  $M$  DWIs.

$\hat{D}, \hat{FA}, \dots$

2) Make  $N_j$  subsets of  $M_j$  DWIs.



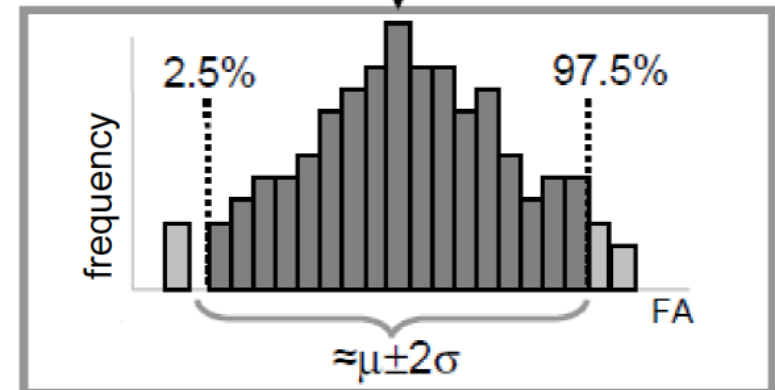
3) Estimate  $N_j$  DTs.

$D_1^*, D_2^*, \dots, D_{N_j}^*$

4) Estimate set of  $N_j$  parameters.

$\{FA_1^*, FA_2^*, \dots, FA_{N_j}^*\}, \{(\Delta e_{1,2})_i\}, \dots$

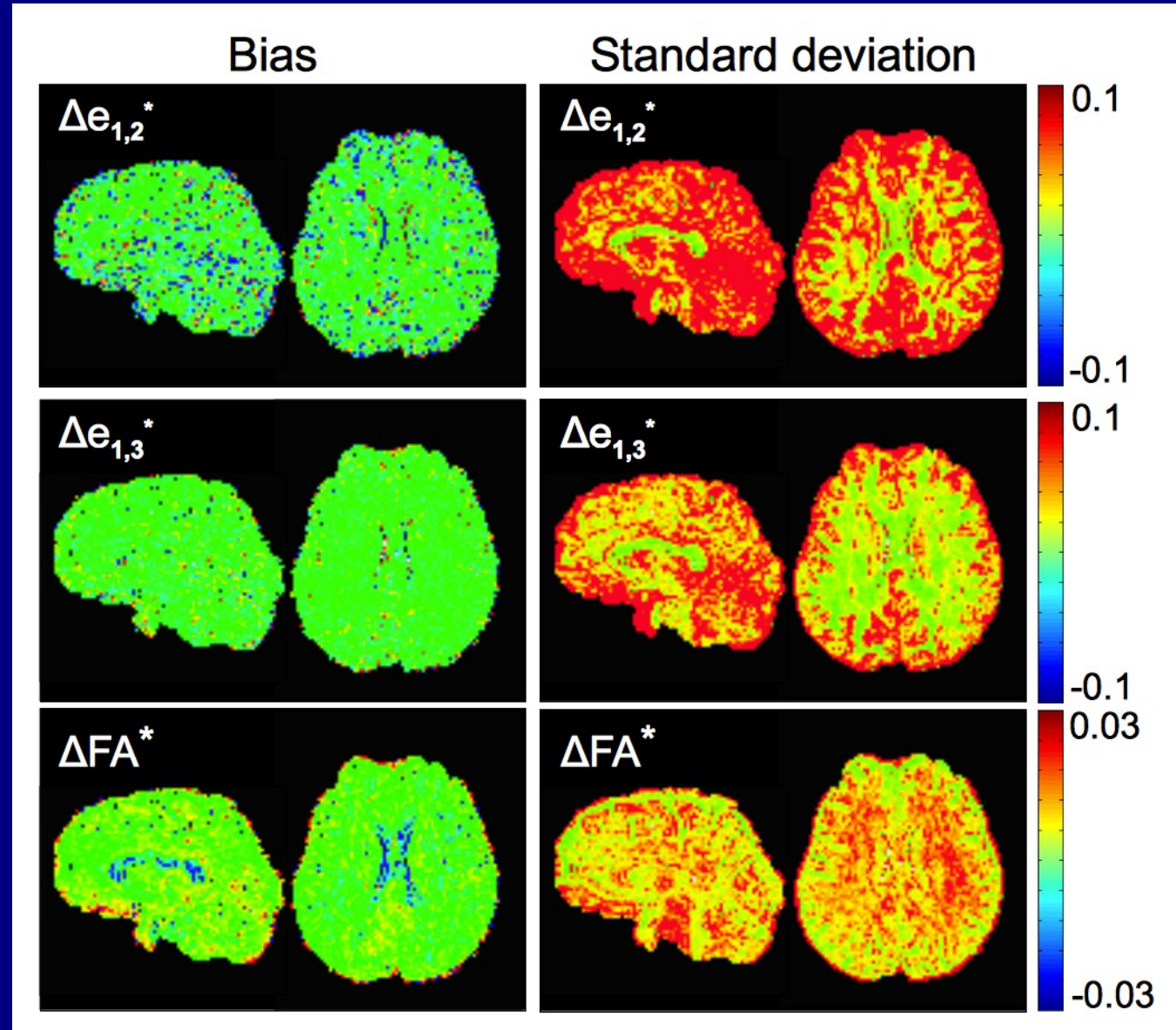
5) Find confidence intervals.



# Uncertainty example

+ Can see difference in  $e_1$  uncertainty along  $e_2$  and  $e_3$  (in rads).

+ Tissue-dependent differences in FA uncertainty.

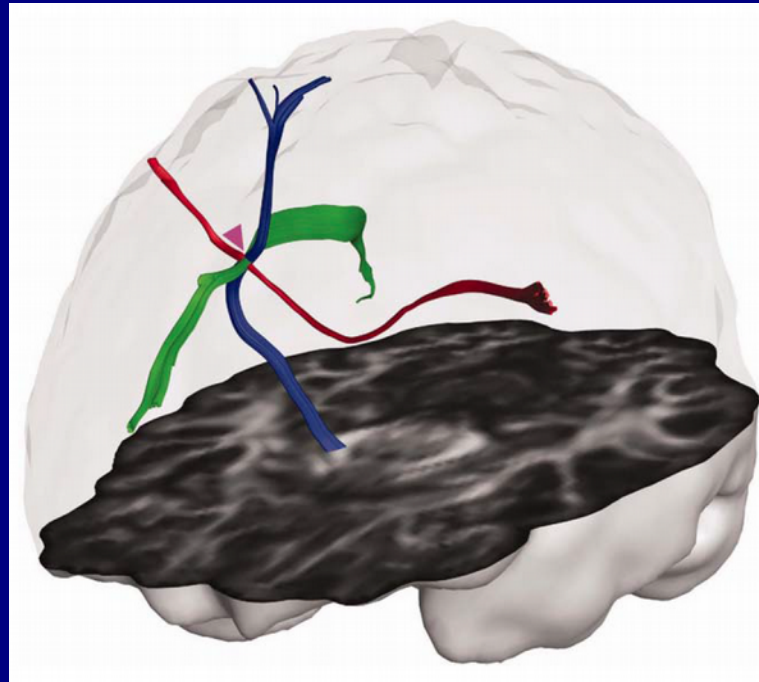


FATCAT addenda:  
*1) HARDI tracking*

# Higher order models

DTI tractography:

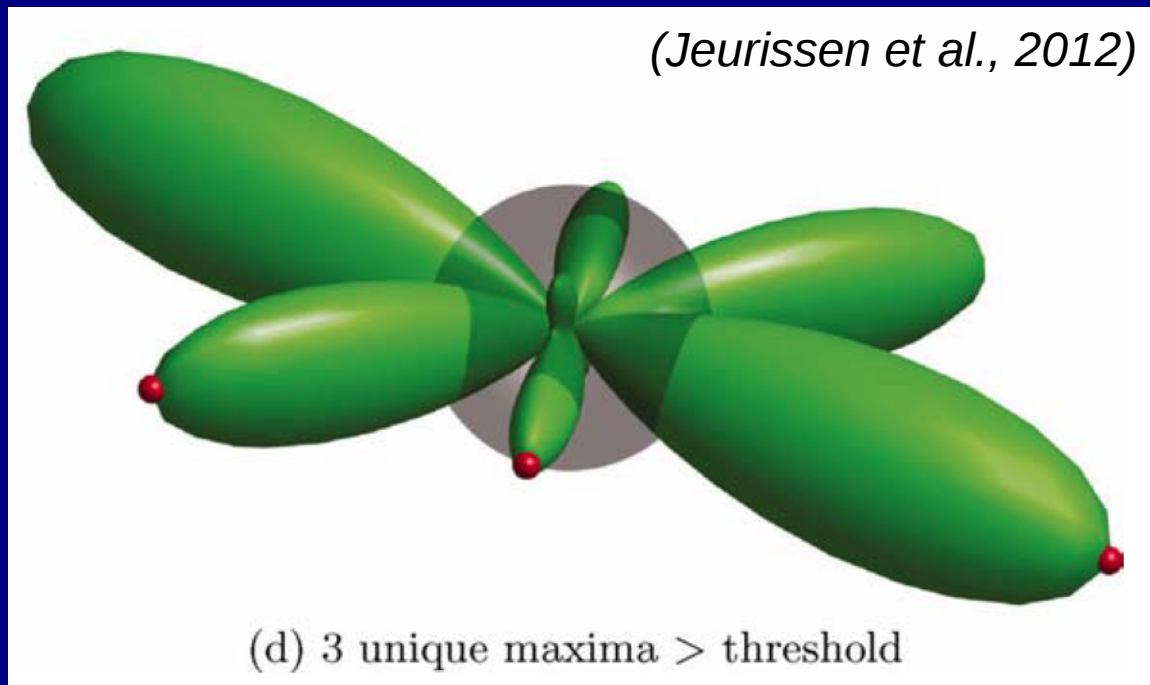
- + susceptible to false negatives, difficulty with long range tracts (noise/error accumulation)
- + Major diffusion can be average of multiple paths
- + Voxels can have low FA from several WM paths, false ending
- + Can't resolve complex underlying architecture
  - Jeurissen et al. (2012, HBM): 60-90% of WM voxels estimated to have multiple fibers



*(Jeurissen et al., 2012)*

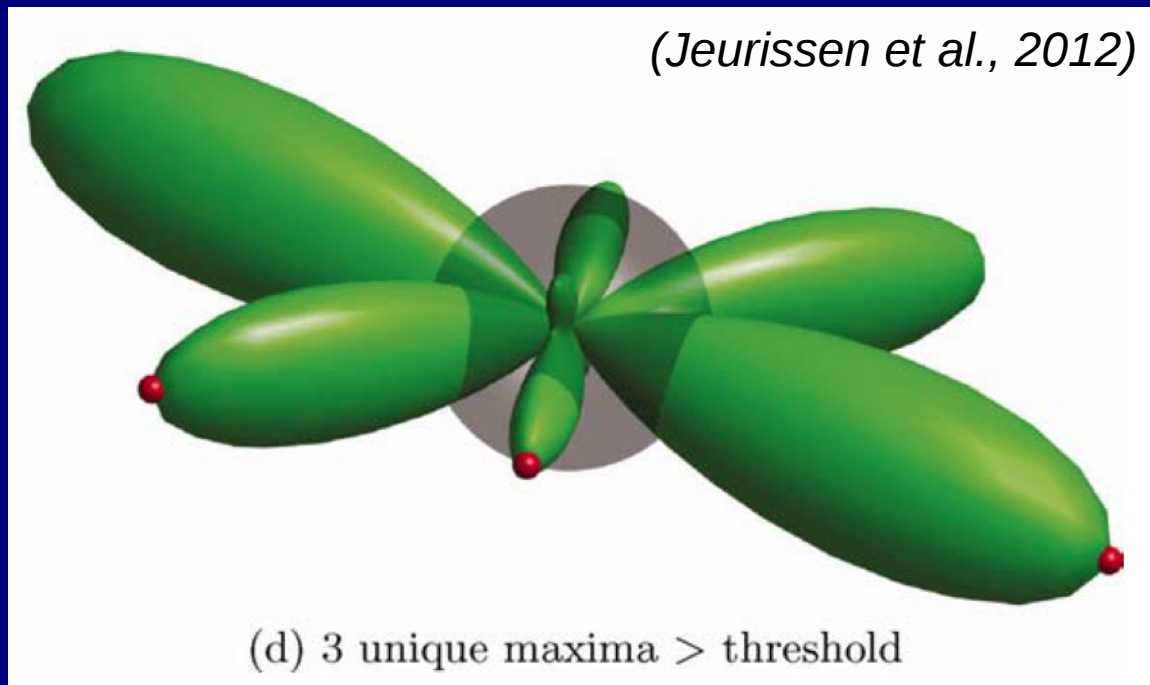
# HARDI

- + High Angular Resolution Diffusion Imaging:
  - DSI, ODF, Qball, FOD...
  - model multiple fiber bundle directions per voxel
  - generally need more scan time and acquisitions and computational power, much higher b-values
  - still can't resolve intravoxel tract behavior (which of multiple paths?)
  - higher DW  $\rightarrow$  lower signal, so susceptible to noise



# HARDI

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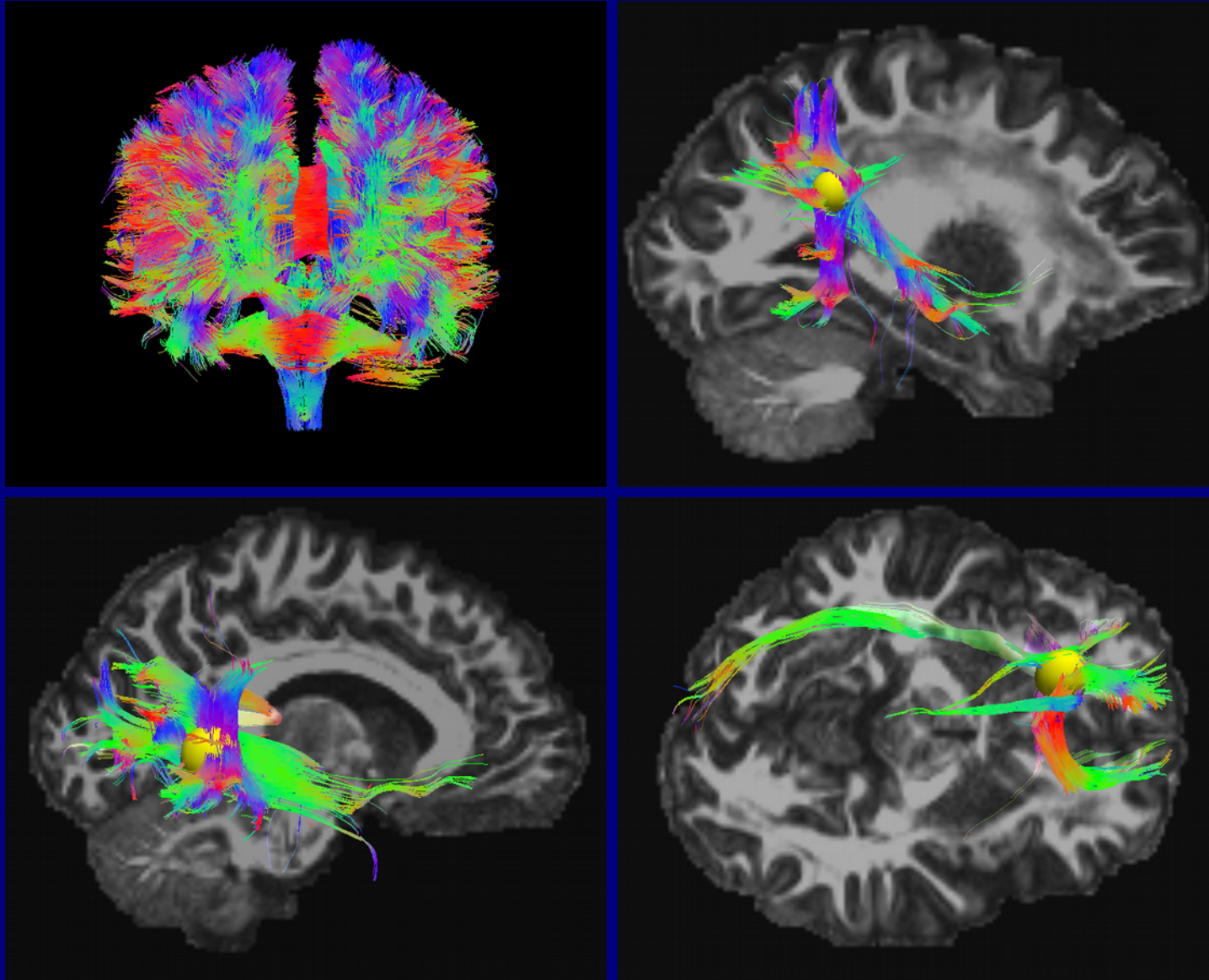
FATCAT can now track through HARDI data

$\rightarrow$  HARDI reconstruction done outside AFNI (e.g., DSI-Studio, Diffusion Toolkit, ...), and outputs tracked in FATCAT.



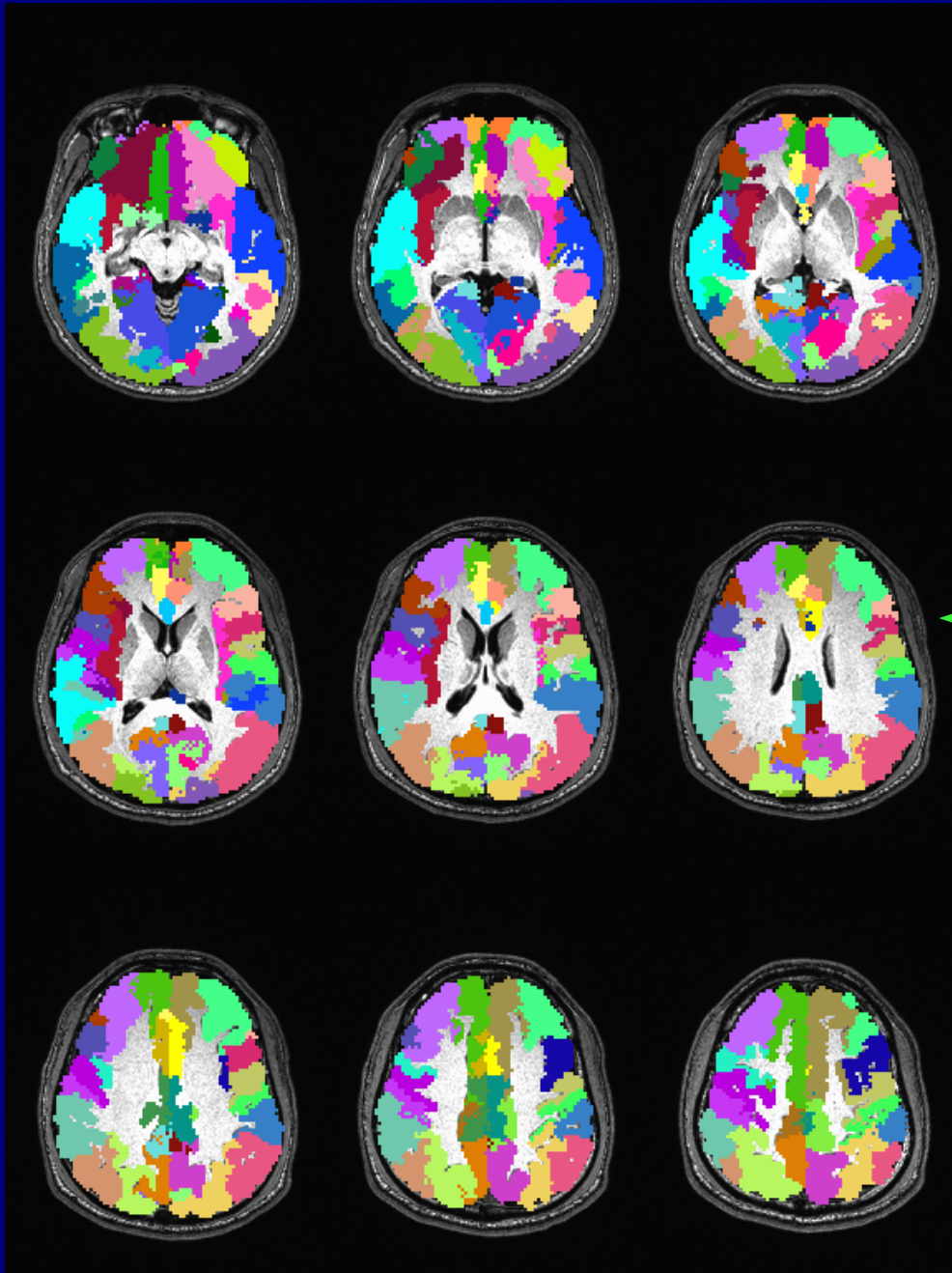
# Example: 3dTrackID on HARDI data

*Ex: Human Connectome Project subject, 288 grads,  
HARDI reconstructed with GQI in DSI-Studio.*



FATCAT addenda:  
2) *'Connectome'-type tracking*

# “Connectome”: parcellation of GM



Example (script available in  
FATCAT\_DEMO):

+ FreeSurfer parcellation into  
>112 ROIs.

+ Selected 80 cortical GM ROIs.

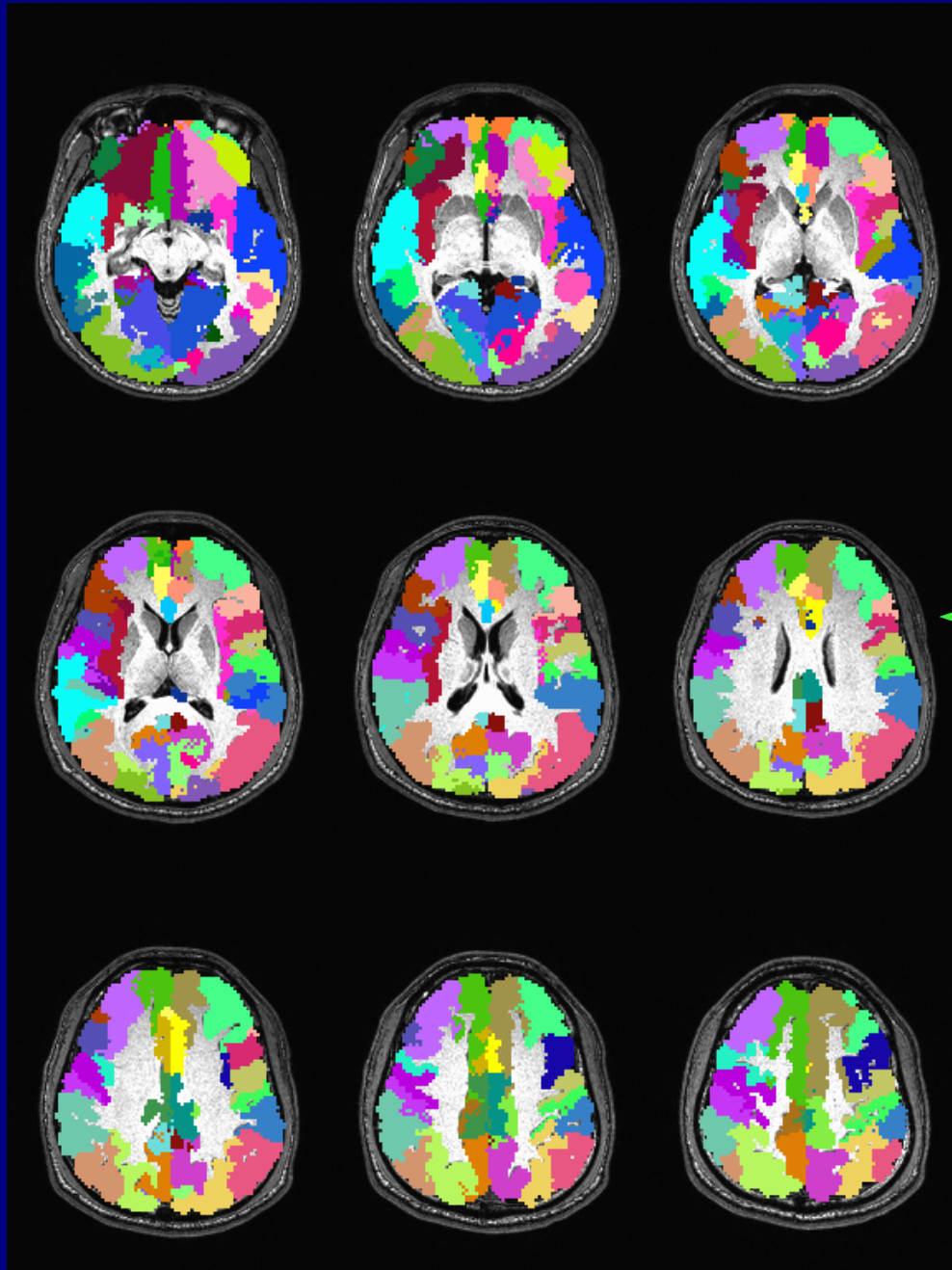
+ Used 3dROIMaker to inflate

← by 1 voxel, up to  $FA > 0.2$ .

(+ *NEW*: keep labeltable labels  
and use them in output.)

+ '3dTrackID' among the regions

# “Connectome”: parcellation of GM



Example (script available in FATCAT\_DEMO):

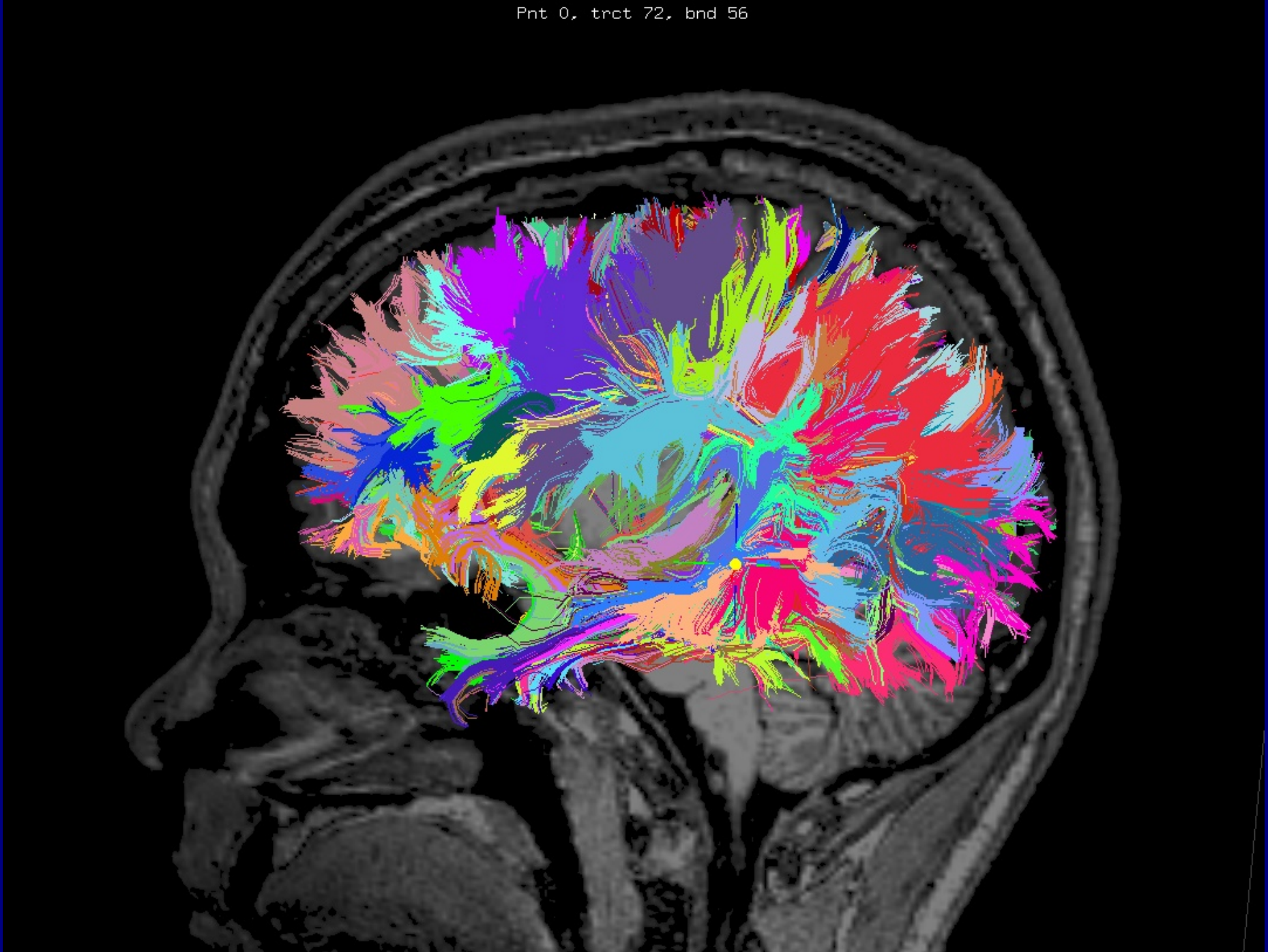
- + FreeSurfer parcellation into >112 ROIs.
  - + Selected 80 cortical GM ROIs.
  - + Used 3dROIMaker to inflate
- ← by 1 voxel, up to  $FA > 0.2$ .  
(+ *NEW*: keep labeltable labels and use them in output.)
- + '3dTrackID' among the regions

and a few seconds later... →



# “Connectome”: tracking

Pnt 0, tract 72, bnd 56



# SUMMARY

- + We motivated using subject data to make networks of targets
  - e.g., fMRI or anatomical parcellation
- + Tracking estimates most likely locations of WMCs
  - Use **PROB** mode in 3dTrackID for best estimation
  - 3dDWUncert to estimate DT parameter uncertainty
- + Quantitative output: matrices of properties in tracked WMCs
- + 3dROIMaker is useful for making target ROIs
- + Checking/fixing grads: @GradFlipTest + 1dDW\_Grad\_o\_Mat
- + 3dTrackID also has HARDI-compatible functionality

