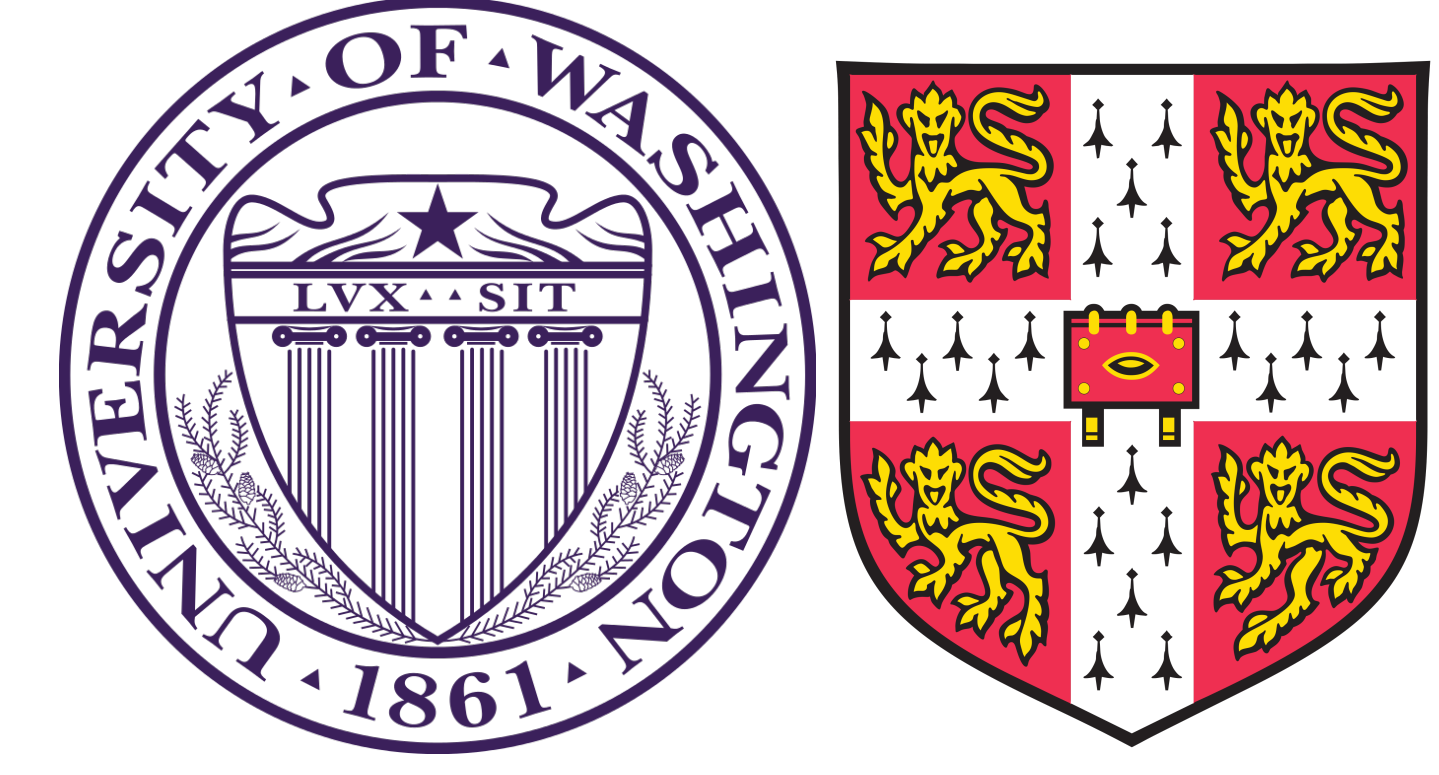


Diffusion Kurtosis Imaging for the Human Connectome Project

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Introduction

The Human Connectome Project

Diffusion MRI (dMRI) measurements provide detailed information about human brain connectivity and microstructure *in vivo*. HCP is measuring high-quality multi-modal MRI data from 1,200 individuals and make these data publicly available [5]. It has already made measurements from approximately 900 subjects available through Amazon's Simple Storage Service (S3).

What model should we use to explain the data?

Diffusion Tensor Imaging (DTI): 6 parameters

Approximates diffusion in every voxel as a Gaussian distribution [1]:

$$S(\theta, b) = S_0 e^{\theta^T \mathbf{Q} \theta}$$

b is the **b-value**,

S_0 is the signal in the absence of diffusion gradient sensitization ($b = 0$)

\mathbf{Q} is a positive-definite quadratic form:

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

Diffusion Kurtosis imaging (DKI): 21 parameters

DKI is an extension of DTI that accounts for non-Gaussian behavior in complex tissue, with many barriers to the diffusion process (cell membranes, myelin sheaths, etc.) [3]:

$$S(\theta, b) = S_0 e^{-bD(\theta) + \frac{1}{6}b^2 D(\theta)^2 K(\theta)}$$

$$D(\theta) = \sum_{i=1}^3 \sum_{j=1}^3 \theta_i \theta_j Q_{ij}$$

$$K(\theta) = \frac{MD^2}{D(\theta)^2} \sum_{i=1}^3 \sum_{j=1}^3 \sum_{k=1}^3 \sum_{l=1}^3 \theta_i \theta_j \theta_k \theta_l W_{ijkl}$$

\mathbf{W} is a rank 4 tensor (3-by-3-by-3-by-3 matrix).

Diffusion Statistics

- Mean diffusivity (MD) characterizes the mean displacement of water molecules within a voxel.
- Fractional anisotropy (FA) characterizes the variance in diffusivity in different directions.

Brain measurements that provide a close tie between brain tissue properties and behavior.

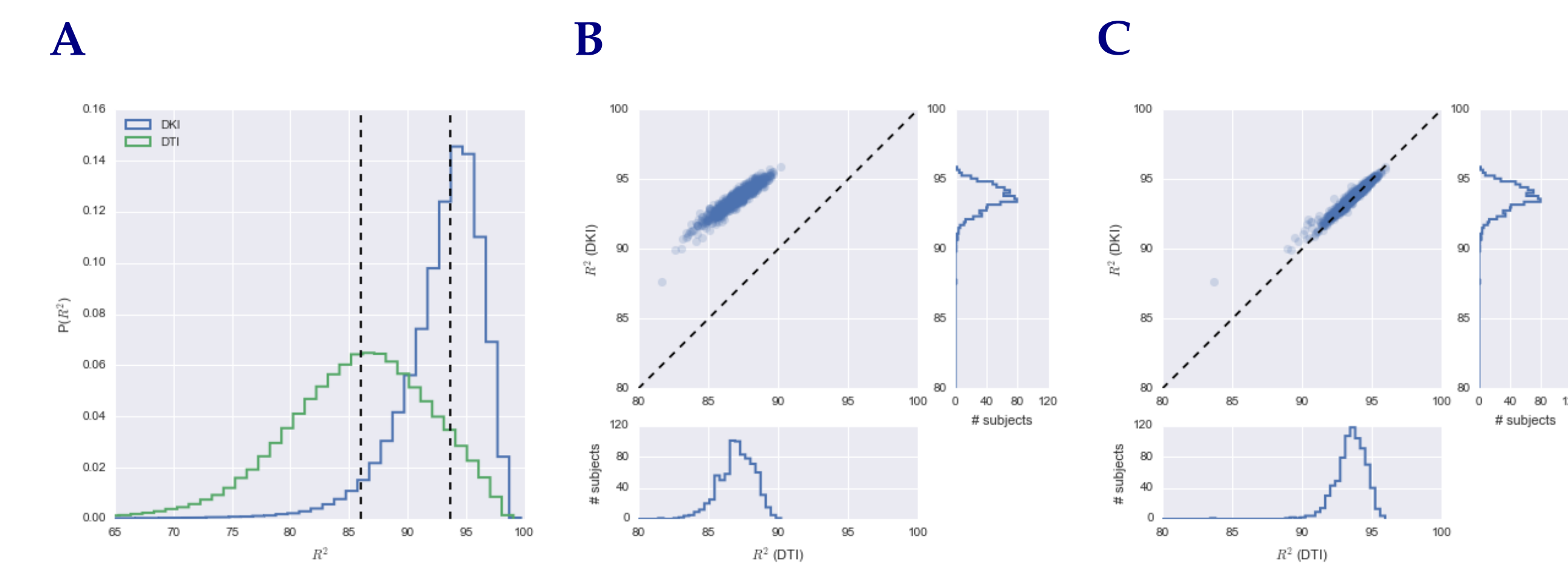
Results

We compared DKI and DTI using *K-fold cross-validation*

We estimated model fit *accuracy* and model parameter *reliability*

Model accuracy

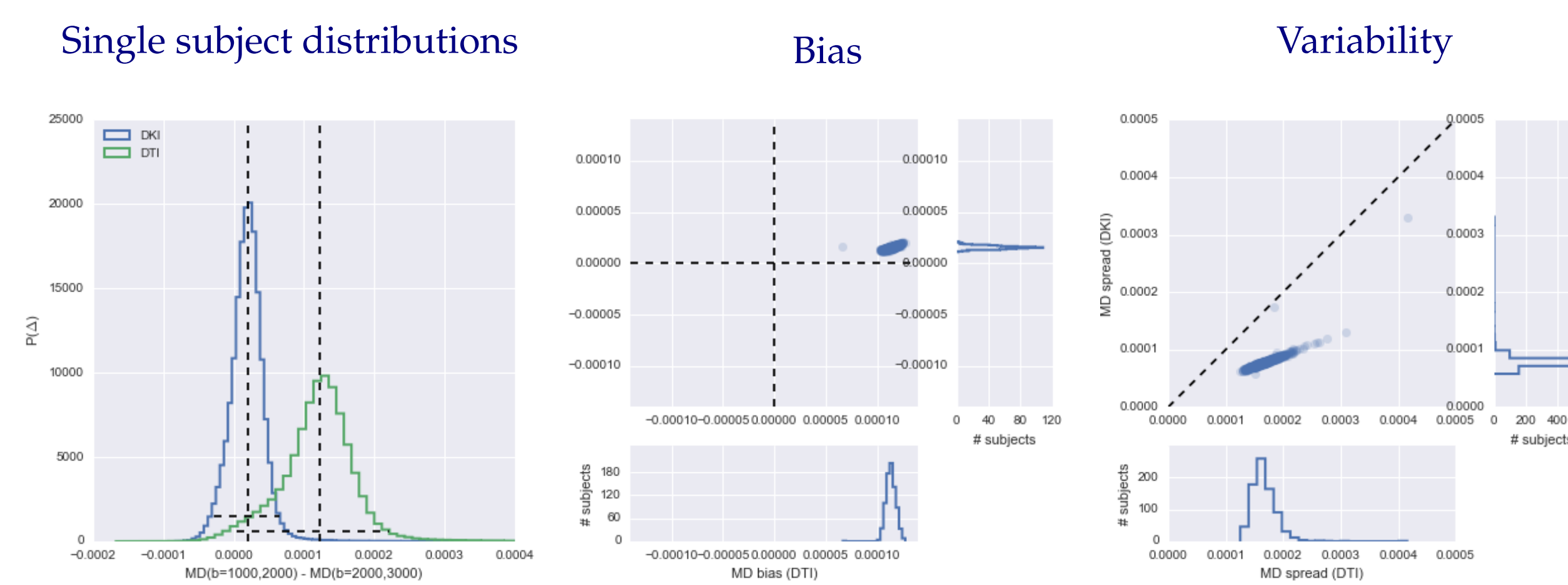
Cross-validated R^2 : **A** Comparison of the full distribution in a single subject, and comparison of the median (dashed line) in all subjects for DKI (all b-values) and DTI (**B** all b-values, **C** only b=1,000 s/mm^2)



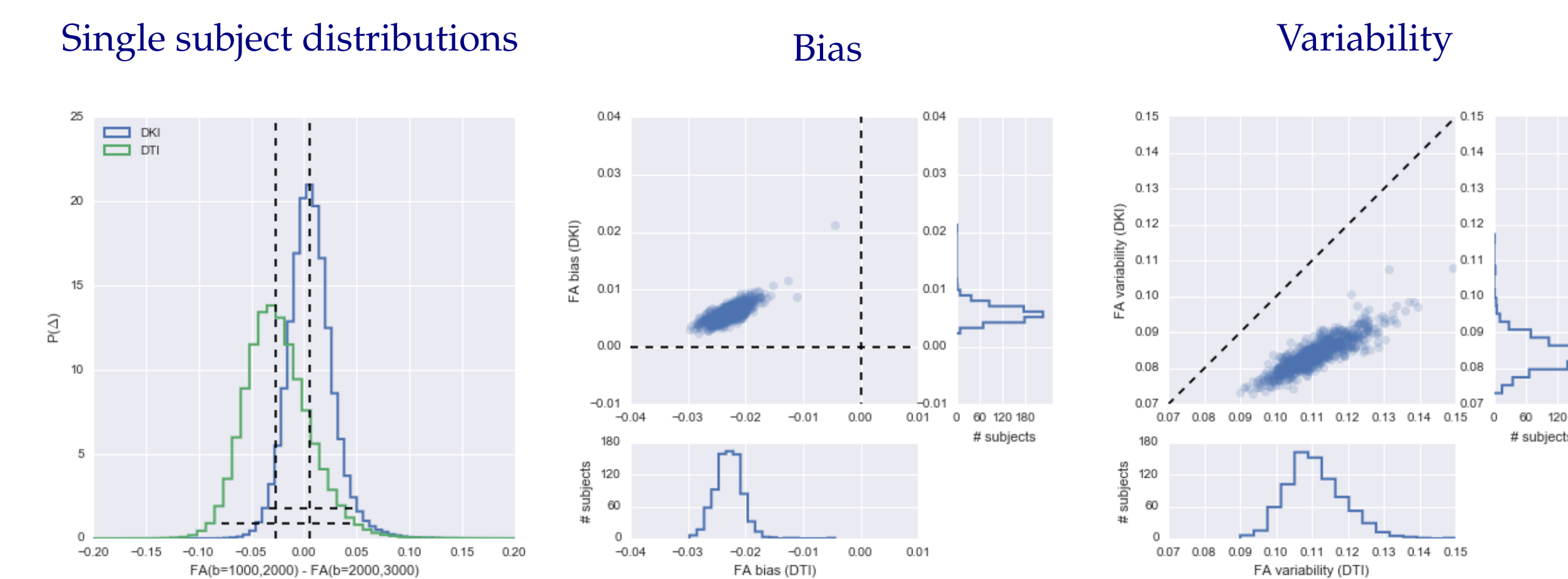
Parameter reliability

Parameter reliability is estimated by comparing diffusion-based statistics based on a difference in FA/MD between b=1000 and b=1000,2000 (DTI) or between b=1000,2000, b=1000,3000 (DKI). BIAS is the median difference between sub-samples VARIABILITY is the spread of differences (central 95% of the distribution)

Mean diffusivity



Fractional anisotropy



Materials and Methods

Data

Measurements were obtained from the WU-Minn Human Connectome Project consortium (<https://www.humanconnectome.org/>) through AWS S3

Of the 900 subjects that are available, 788 subjects have full diffusion measurements: 270 diffusion weighted directions in 3 different b-values (90 directions each): 1,000, 2,000 and 3,000 s/mm^2 , collected at $1.25 \times 1.25 \times 1.25 mm^3$ resolution.

Freesurfer segmentation from a T1-weighted measurement was also we focused our analysis only on the parts of the volume that contained the white matter.

Analysis

We used an Amazon Web Services compute cluster with 36 nodes. AWS *r3.2xlarge* instances were used, optimized for memory-intensive applications: each instance has 8 vCPU, 61 GiB Memory and 160 GB SSD storage.

We used DTI and DKI implementations that are part of the DIPY open-source software library (<http://dipy.org/>) [2]. 5-fold cross-validation was implemented using DIPY's cross-validation module [4]

Computation was distributed using Apache Spark, an open-source parallel processing framework that coordinates computation across distributed clusters (<http://spark.apache.org/>). Because model-fitting requires large amounts of memory, each compute node ran one Spark worker.



Analysis software: <http://github.com/arokem/dki-accuracy-reliability>

Conclusions

- DKI more accurately fits the HCP data than DTI
- DKI statistics are more reliable than DTI statistics
- DKI has the additional benefit that it provides additional parameters that lend themselves to a richer biophysical interpretation of the signal.

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