



Big Data for Reproducible Human Brain Mapping

Standard
Resources
Methodology

Xi-Nian Zuo (左西年)

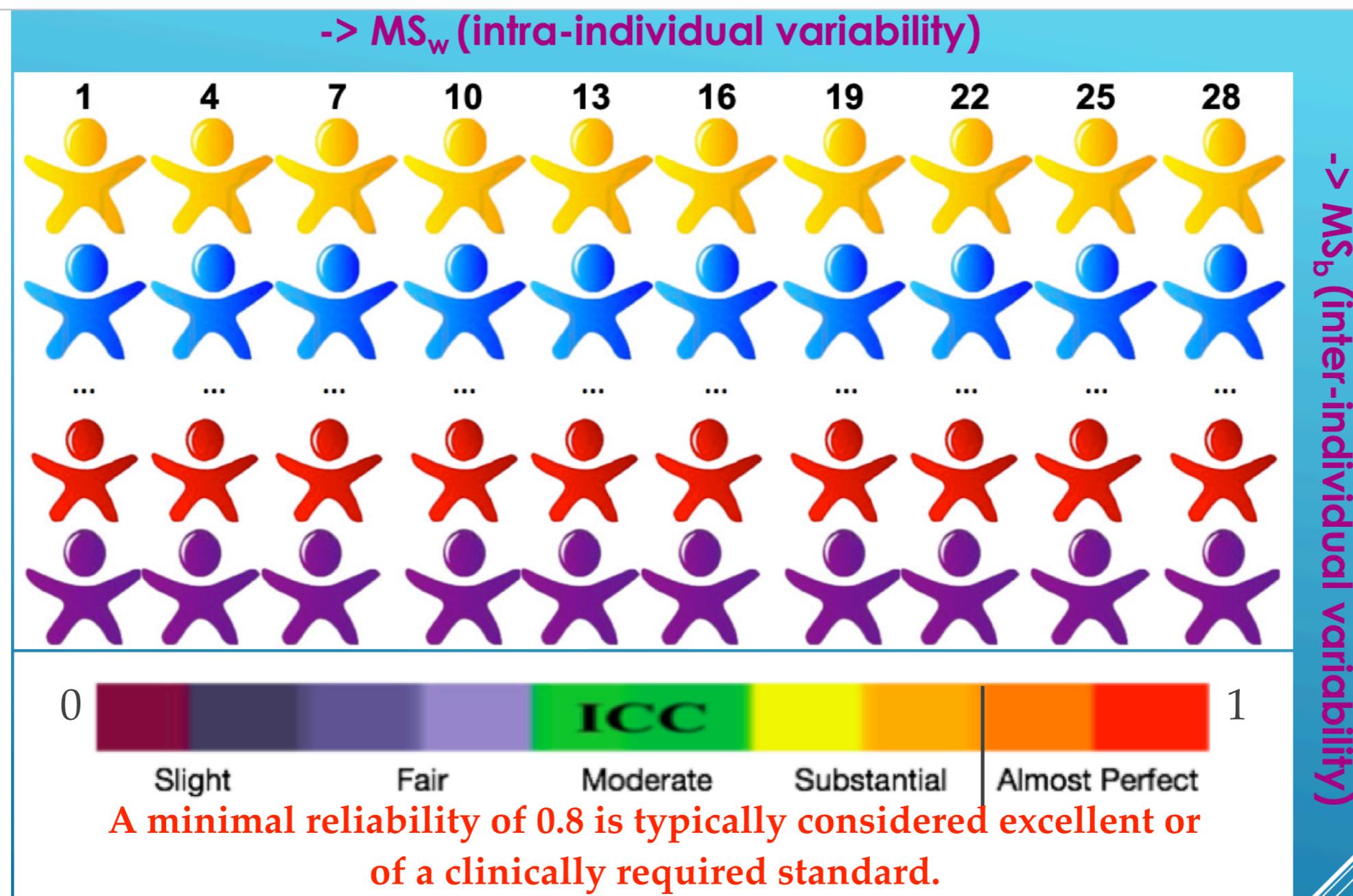
Magnetic Resonance Imaging Research Center
Research Center for Lifespan Development of Mind and Brain (CLIMB)
University of Chinese Academy of Sciences (UCAS) and CAS Institute of Psychology

Standard: Reliability & Validity



$$\text{validity} = V_d/V_s$$
$$\text{reliability} = (V_d + V_c)/V_s$$
$$V_s = V_d + V_c + V_r$$
$$\text{validity} \leq \text{reliability}$$

$$\text{Reliability: } \text{ICC} = (\text{MS}_b - \text{MS}_w) / (\text{MS}_b + \text{MS}_w)$$



Neurosci Biobehav Rev. 2014; 45: 100-18.

PLoS One. 2015; 10: e0144963; Statistical Methods for rates and proportions. 1981.

Reliability: Why Big Data?

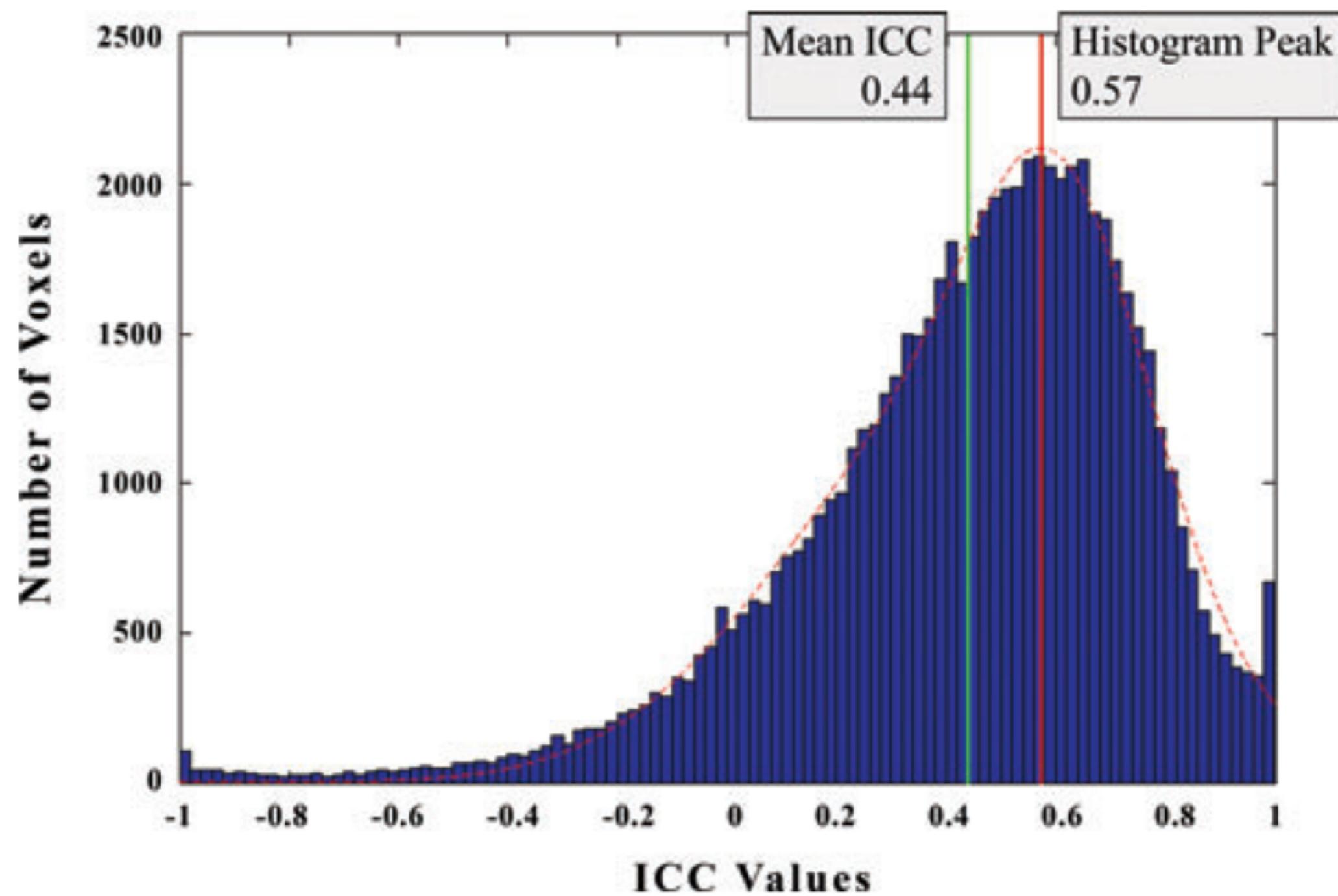
True r	Measure A	Measure B	Observable r	N true	N obs.
.7	.8	.8	.56	13	22
.7	.6	.6	.42	13	42
.7	.4	.7	.37	13	55
.5	.8	.8	.4	29	46
.5	.6	.6	.3	29	84
.5	.4	.7	.26	29	113
.3	.8	.8	.24	84	133
.3	.6	.6	.18	84	239
.3	.4	.7	.16	84	304

$$r(\text{measure } A, \text{ measure } B) = r(\text{true } A, \text{true } B) \sqrt{\text{reliability (Measure } A)\text{reliability(Measure } B)}$$

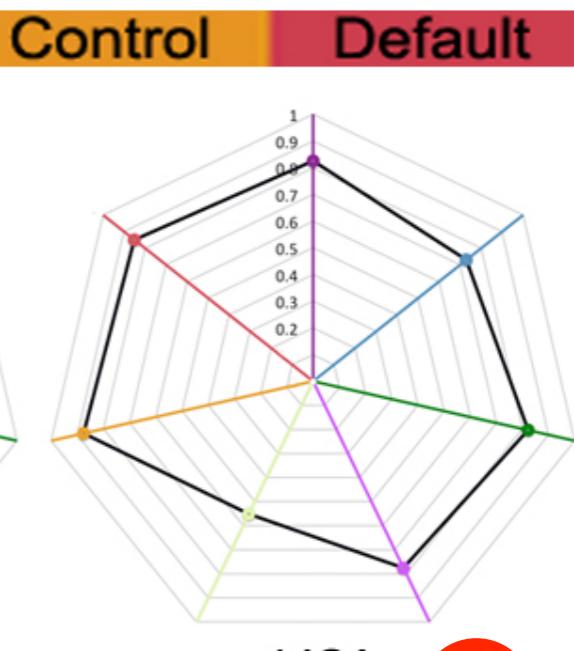
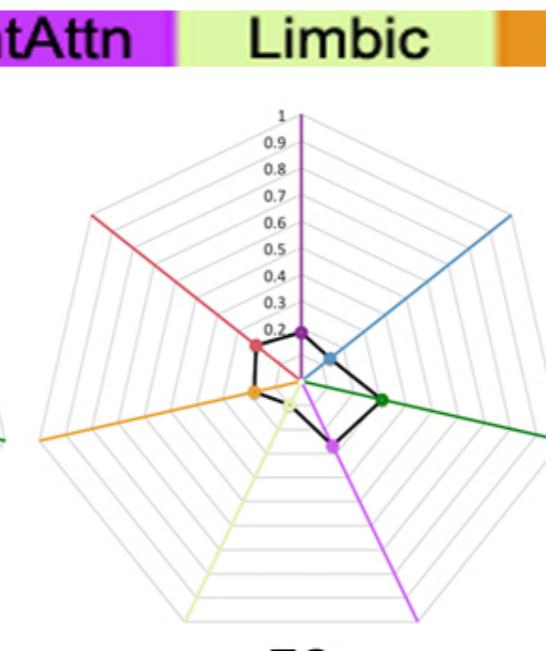
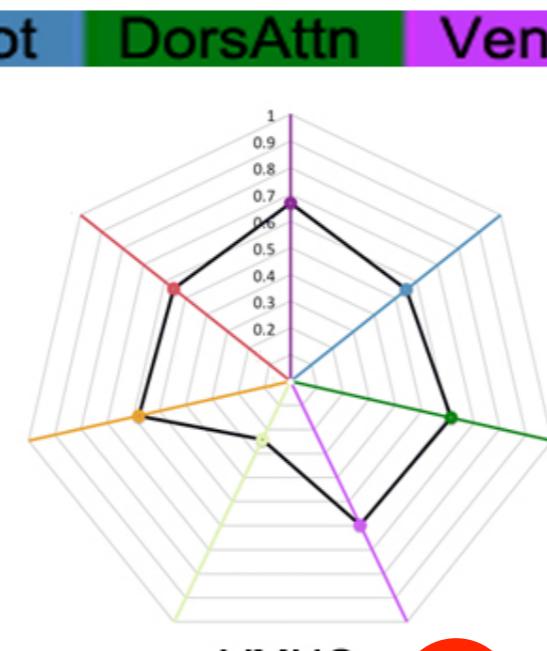
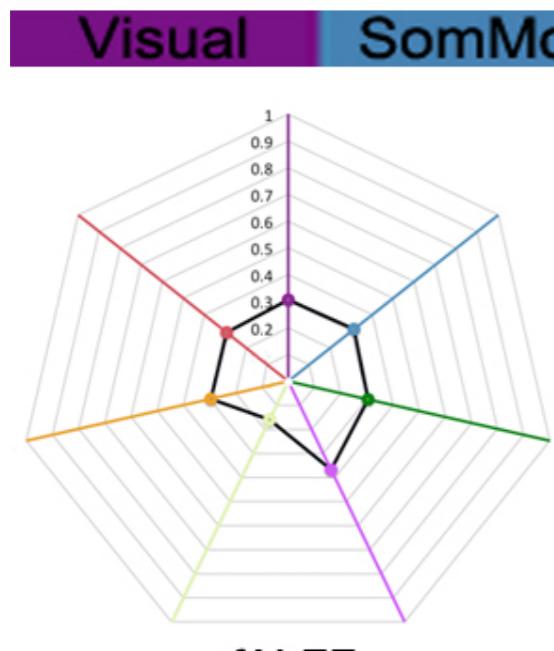
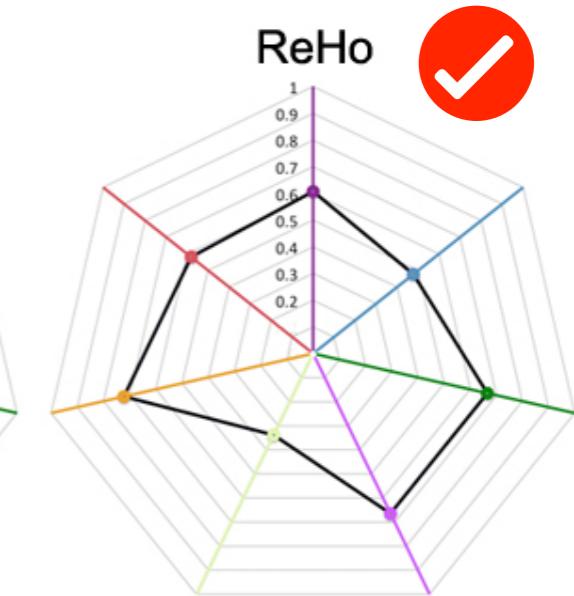
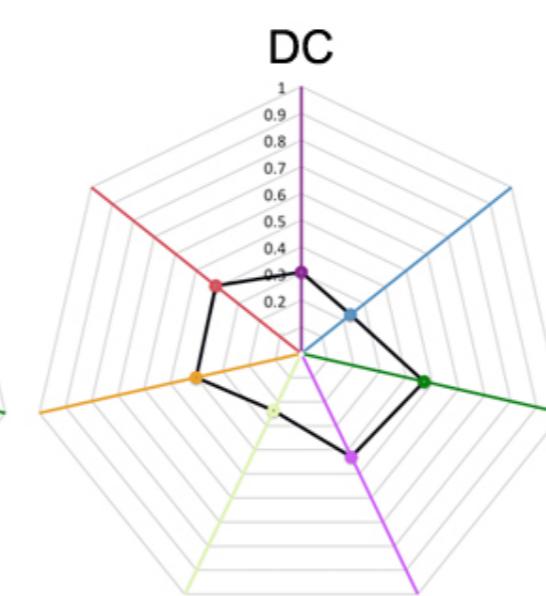
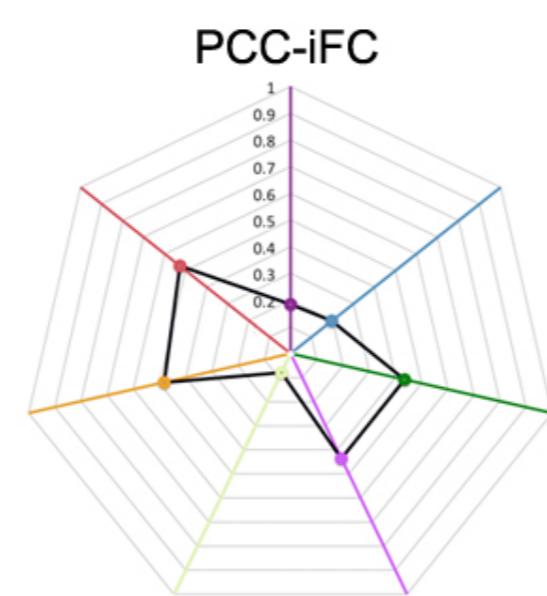
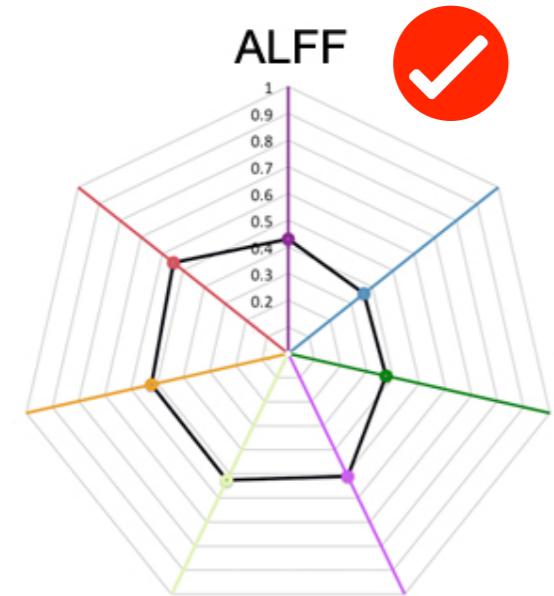
MRI Reliability: State of The Art

Measure	Study 1 CCBD	Study 2 GSP
Thickness (CT)	.816	.890
Gyrification (GI)	.945	.941
<i>Fractal dimensionality</i>		
Dilation filled (FD_f)	.842	.936
Dilation surface	.845	.936
Boxcount filled	.799	.879
Boxcount surface	.769	.849
SPHARM surface	.977	.982

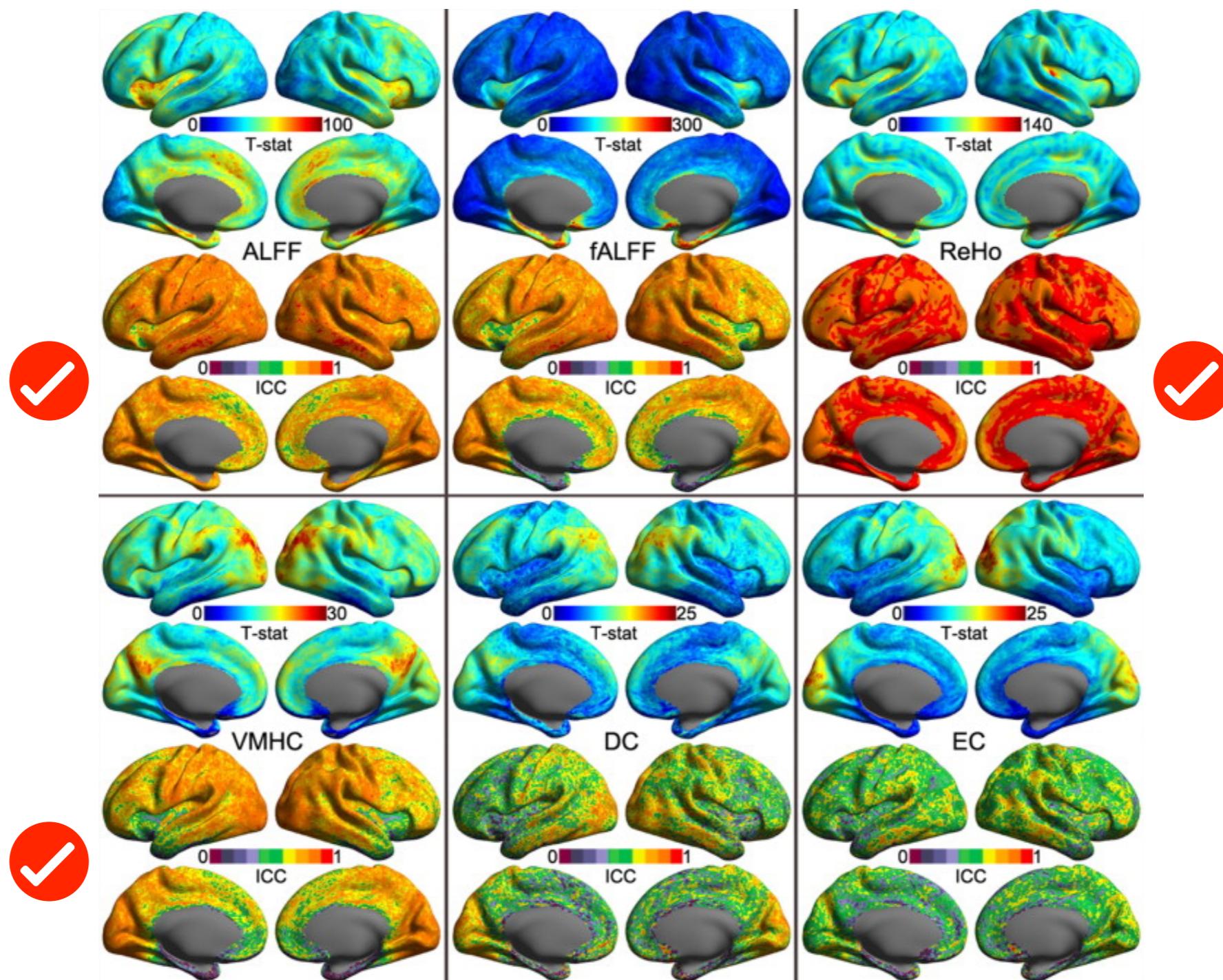
tFMRI Reliability: State of The Art



rFMRI Reliability: State of The Art



rFMRI Reliability: State of The Art



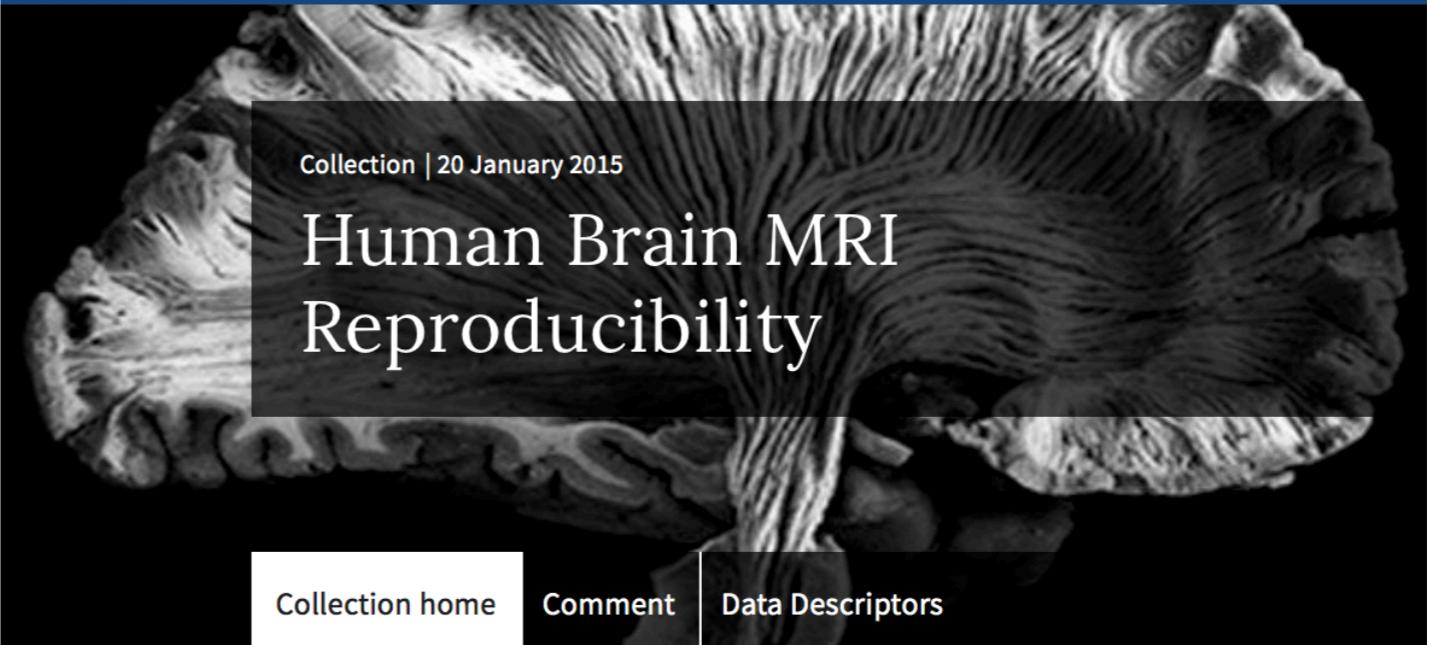
Resources: Big Data for Reliability

An open science resource for establishing reliability and reproducibility in functional connectomics

[Xi-Nian Zuo](#) ✉, [Jeffrey S Anderson](#), [Pierre Bellec](#), [Rasmus M Birn](#), [Bharat B Biswal](#), [Janusch Blautzik](#), [John C.S Breitner](#), [Randy L Buckner](#), [Vince D Calhoun](#), [F. Xavier Castellanos](#), [Antao Chen](#), [Bing Chen](#), [Jiangtao Chen](#), [Xu Chen](#), [Stanley J Colcombe](#), [William Courtney](#), [R Cameron Craddock](#), [Adriana Di Martino](#), [Hao-Ming Dong](#), [Xiaolan Fu](#), [Qiyong Gong](#), [Krzysztof J Gorgolewski](#), [Ying Han](#), [Ye He](#), [Yong He](#), [Erica Ho](#), [Avram Holmes](#), [Xiao-Hui Hou](#), [Jeremy Huckins](#), [Tianzi Jiang](#), [Yi Jiang](#), [William Kelley](#), [Clare Kelly](#), [Margaret King](#), [Stephen M LaConte](#), [Janet E Lainhart](#), [Xu Lei](#), [Hui-Jie Li](#), [Kaiming Li](#), [Kuncheng Li](#), [Qixiang Lin](#), [Dongqiang Liu](#), [Jia Liu](#), [Xun Liu](#), [Yijun Liu](#), [Guangming Lu](#), [Jie Lu](#), [Beatriz Luna](#), [Jing Luo](#), [Daniel Lurie](#), [Ying Mao](#), [Daniel S Margulies](#), [Andrew R Mayer](#), [Thomas Meindl](#), [Mary E Meyerand](#), [Weizhi Nan](#), [Jared A Nielsen](#), [David O'Connor](#), [David Paulsen](#), [Vivek Prabhakaran](#), [Zhigang Qi](#), [Jiang Qiu](#), [Chunhong Shao](#), [Zarrar Shehzad](#), [Weijun Tang](#), [Arno Villringer](#), [Huiling Wang](#), [Kai Wang](#), [Dongtao Wei](#), [Gao-Xia Wei](#), [Xu-Chu Weng](#), [Xuehai Wu](#), [Ting Xu](#), [Ning Yang](#), [Zhi Yang](#), [Yu-Feng Zang](#), [Lei Zhang](#), [Qinglin Zhang](#), [Zhe Zhang](#), [Zhiqiang Zhang](#), [Ke Zhao](#), [Zonglei Zhen](#), [Yuan Zhou](#), [Xing-Ting Zhu](#) & [Michael P Milham](#) ✉ - Show fewer authors

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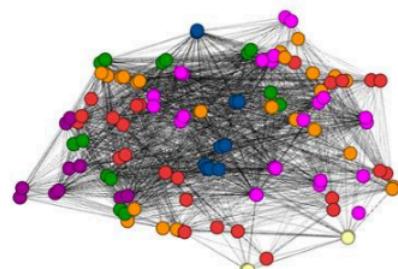
SCIENTIFIC DATA



Collection | 20 January 2015

Human Brain MRI Reproducibility

Collection home Comment Data Descriptors



Research Topic

**Reliability and Reproducibility
in Functional Connectomics**

Comment

1



2



4



2



1



12

CoRR release shared 5093 rFMRI scans of 1629 individuals from 18 international sites

Overview

12
Articles

60
Authors

Impact

1
Comments

VIEWS

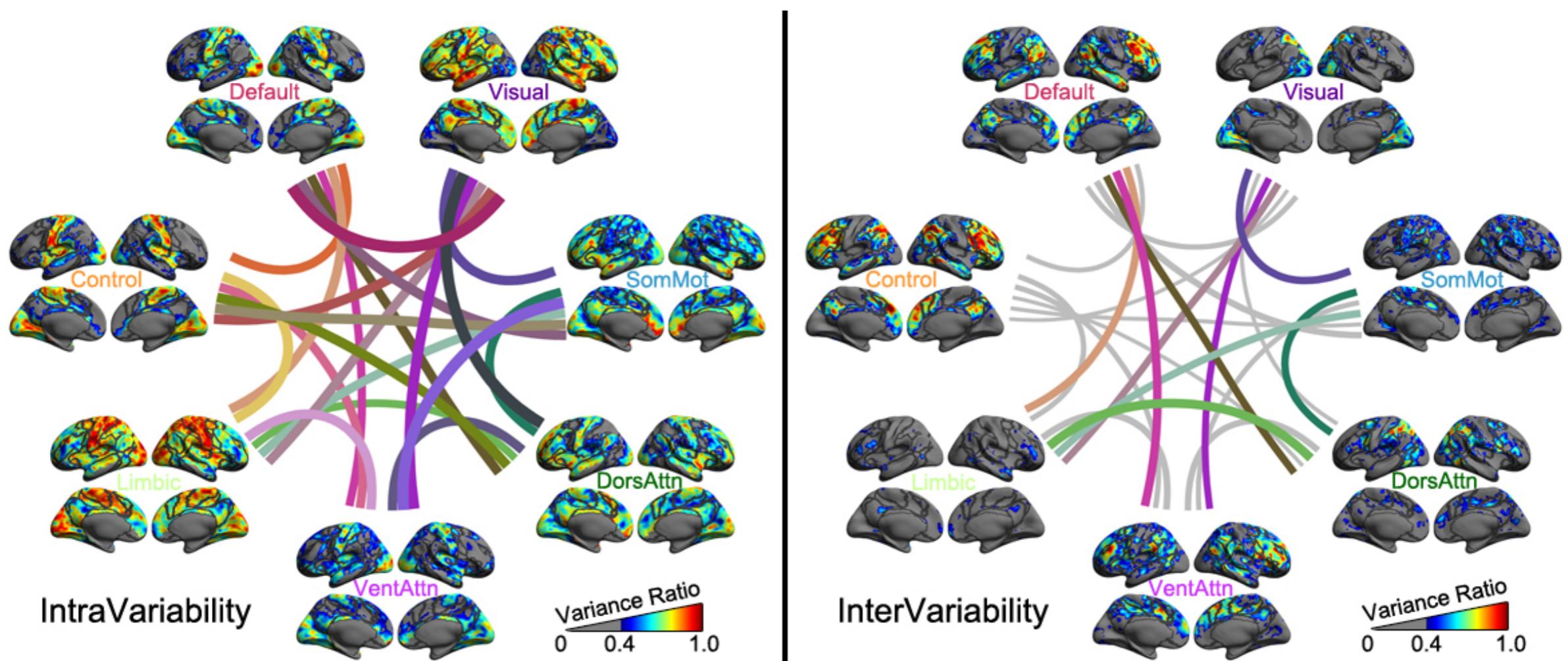
24,876

CoRR - Consortium for Reliability and Reproducibility; Sci Data. 2014; 1: 140049.

Resources: CoRR Use Demos

Individual Variability and Test-Retest Reliability Revealed by Ten Repeated Resting-State Brain Scans over One Month

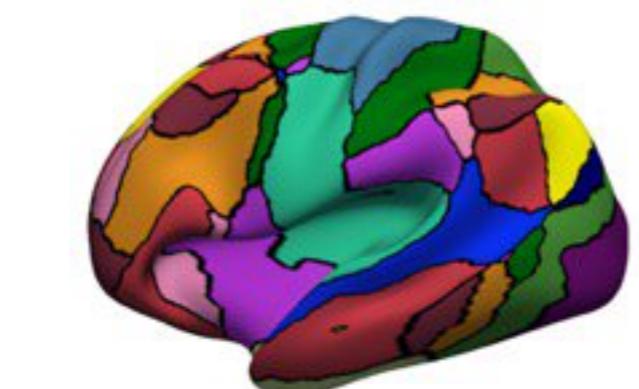
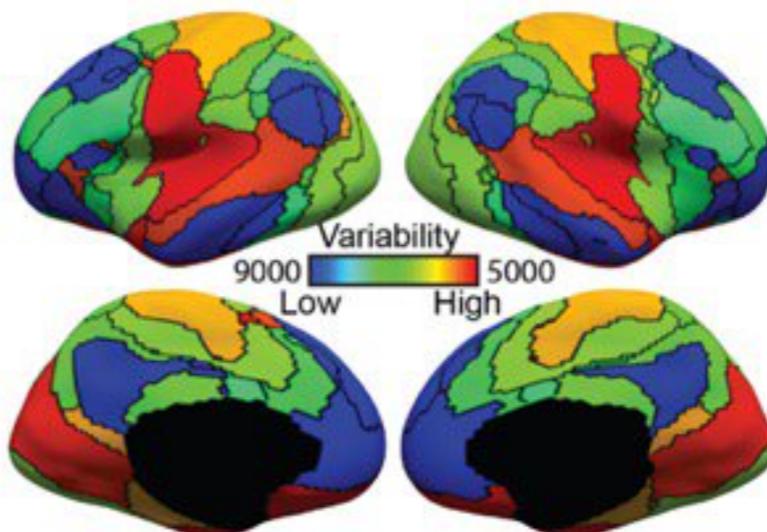
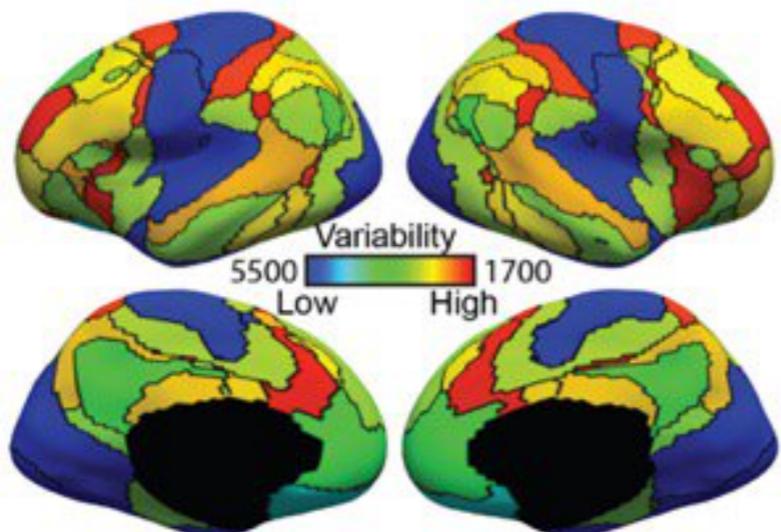
Bing Chen , Ting Xu , Changle Zhou, Luoyu Wang, Ning Yang, Ze Wang, Hao-Ming Dong, Zhi Yang, Yu-Feng Zang, Xi-Nian Zuo , Xu-Chu Weng 



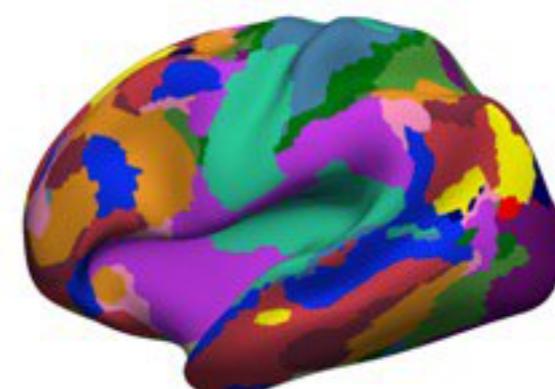
Resources: CoRR Use Demos

Spatial Topography of Individual-Specific Cortical Networks Predicts Human Cognition, Personality, and Emotion.

Kong R¹, Li J¹, Orban C¹, Sabuncu MR², Liu H³, Schaefer A¹, Sun N¹, Zuo XN^{4,5}, Holmes AJ⁶, Eickhoff SB^{7,8}, Yeo BTT^{1,3,9,10}.

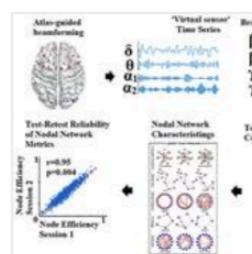


17 resting-state networks
(Yeo et al., J Neurophysiology, 2011)



17 individual-specific networks
(Kong et al., Cerebral Cortex, 2018)

Advances: Special Topic Articles



Reliability of Static and Dynamic Network Metrics in the Resting-State: A MEG-Beamformed Connectivity Analysis

Stavros I. Dimitriadis, Bethany Routley, David E. Linden and Krish D. Singh

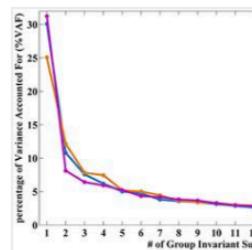
Original Research The resting activity of the brain can be described by so-called intrinsic connectivity networks (ICNs), which consist of spatially and temporally distributed, but functionally connected, nodes. The coordinated activity of the resting state can be ...

Published on 03 August 2018
Front. Neurosci. doi: 10.3389/fnins.2018.00506

2,844 total views



3



Intra- and Inter-scanner Reliability of Scaled Subprofile Model of Principal Component Analysis on ALFF in Resting-State fMRI Under Eyes Open and Closed

Conditions

Li-Xia Yuan, Jian-Bao Wang, Na Zhao, Yuan-Yuan Li, Yilong Ma, Dong-Qiang Liu, Hong-Jian He, Jian-Hui Zhong and Yu-Feng Zang

Topic Editors



Xi-Nian Zuo

Institute of Psychology (CAS)
Beijing, China

107 publications



Bharat B Biswal

University of Medicine and Dentistry of New Jersey
Newark, United States

39 publications



Russell A Poldrack

Stanford University
Stanford, United States

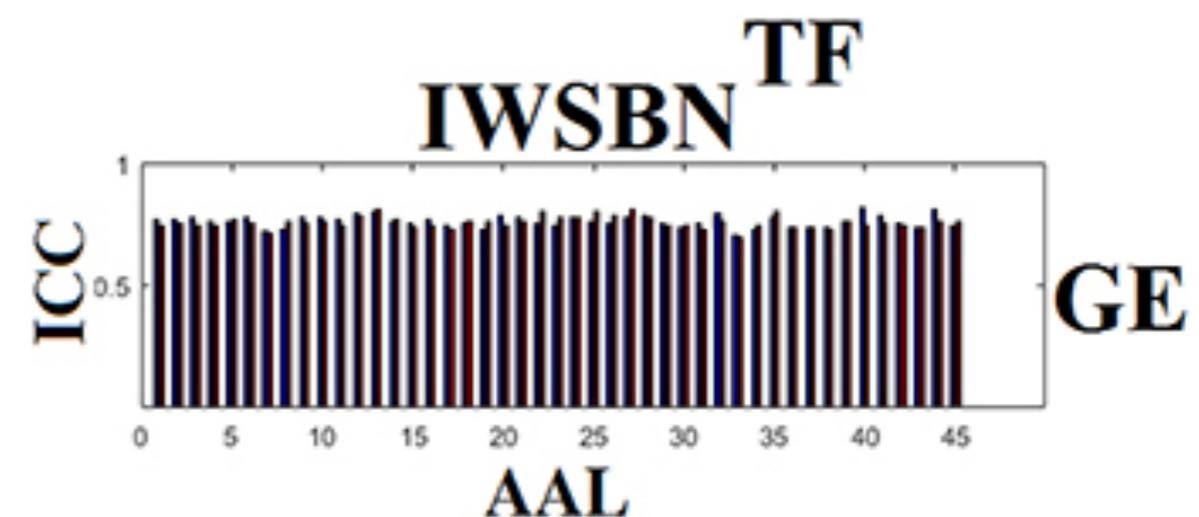
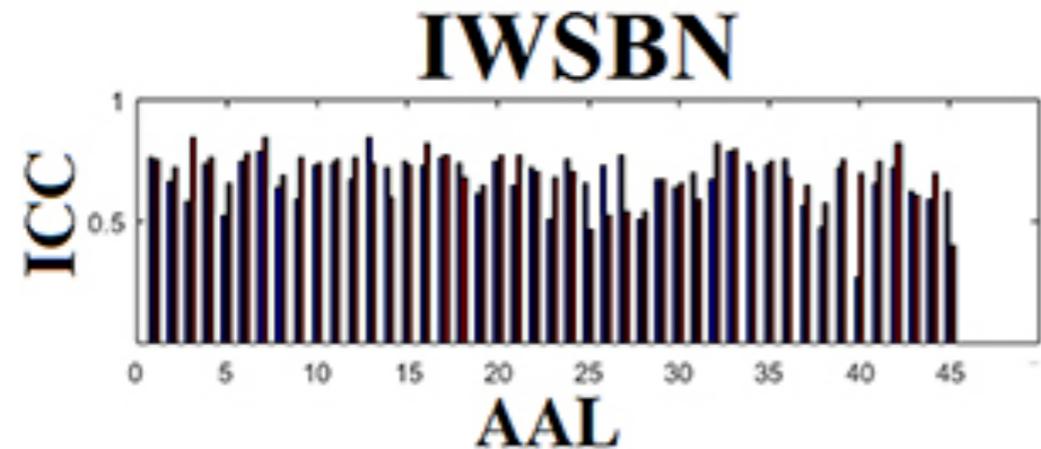
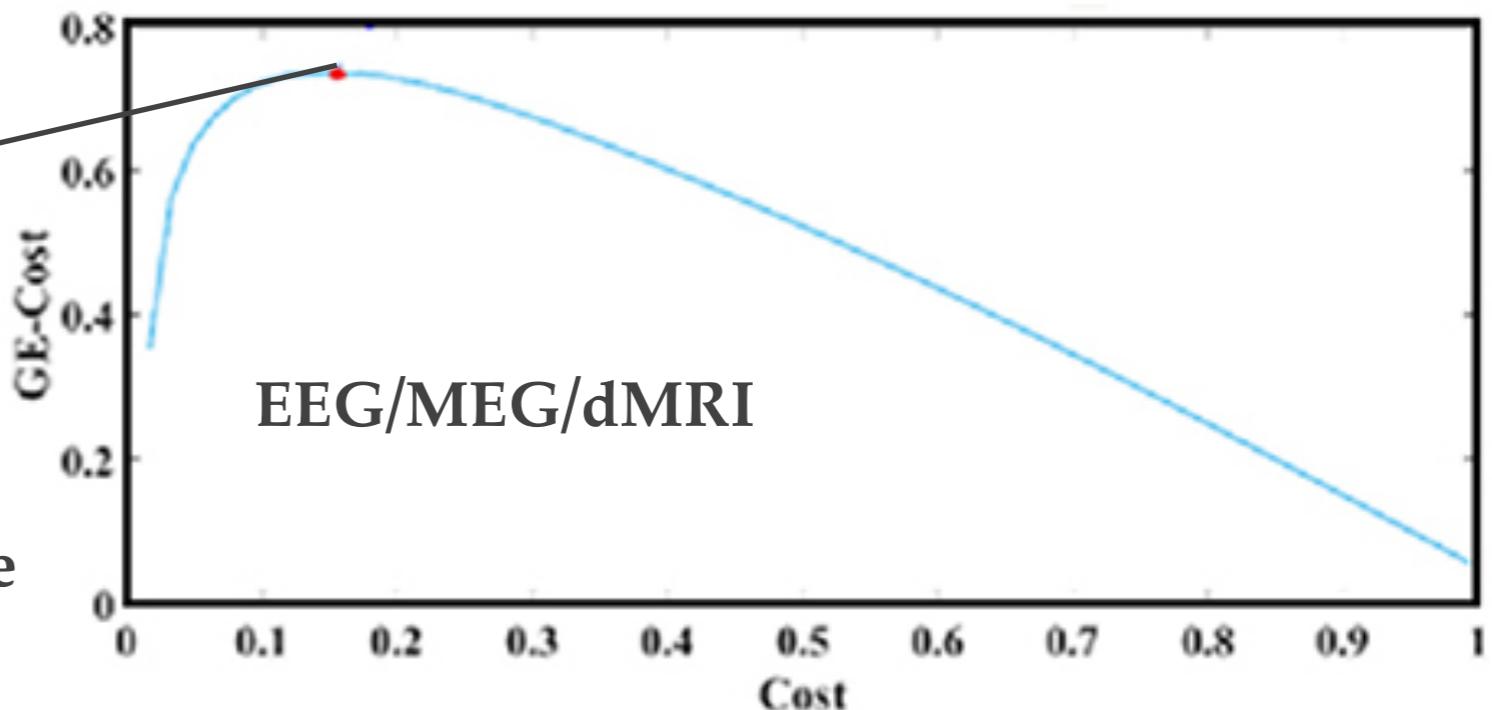
187 publications

Advances: Graph Theory

Individualized Brain Graphs

$$J_{GCE}^{OMSTs} = GE - Cost$$

Orthogonal Minimal Spanning Tree



Resources: R3BRAIN

Data Release Soon ...

Local Travel Project



200 Healthy Subjects
Travel at 3 Local Scanners
with 2-week Retest Design
(1000 scans)

National Travel Project



5 Graduate Students
Travel at 40 National Scanners
(200 scans)

Our Connectomes Project



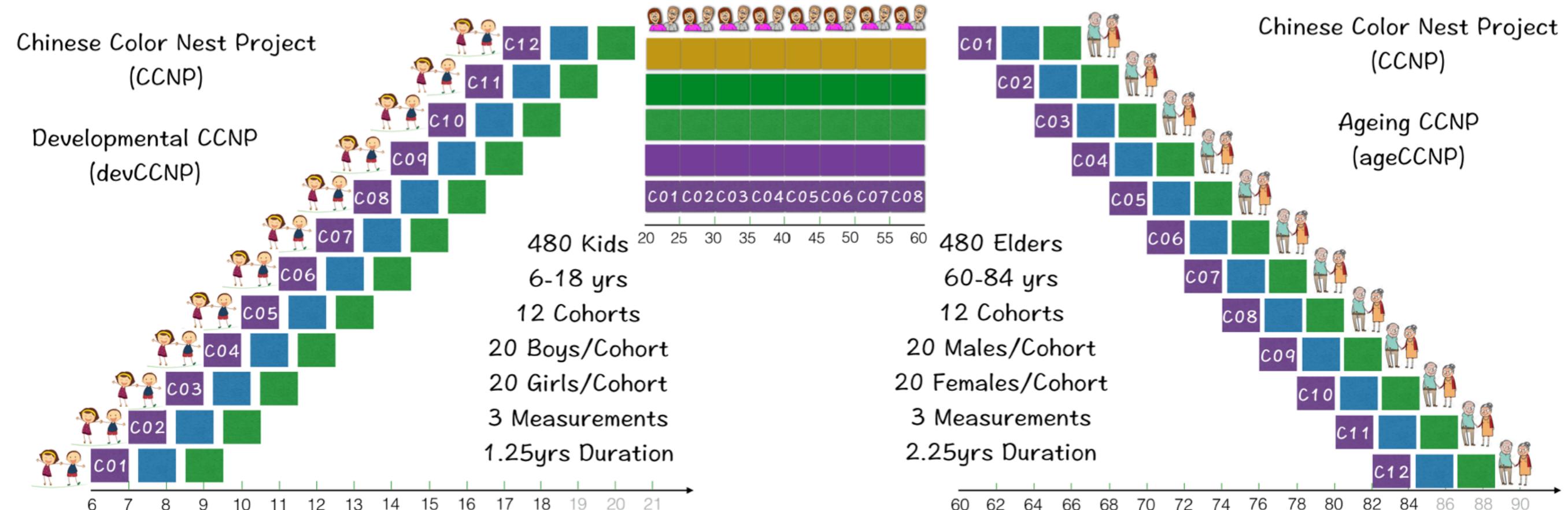
2~3 scans/week



8 Institutional Staffs
Travel at the GE750 Scanner
with 2-year Retest Design
(~1800 scans)

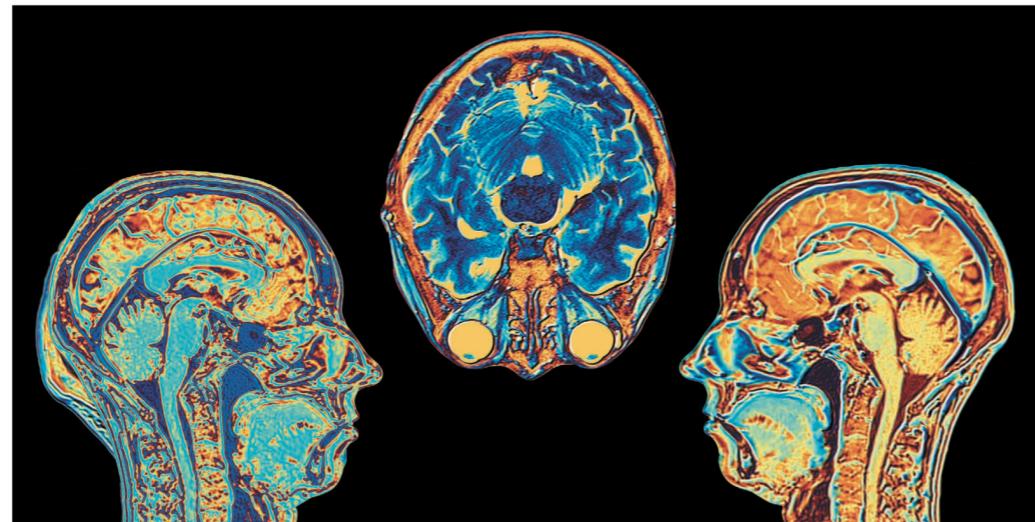
Resources: CCNP

Within-Session Retest Design



Chinese Color Nest Project (CCNP: 2013-2022)
A Lifespan Sample of 1200 People (6-85 yrs)
Total 6000 visits with A Mixed Multicohort Design
<http://zuolab.psych.ac.cn/colornest.html>

Resources: Chinese Twin Brain Project

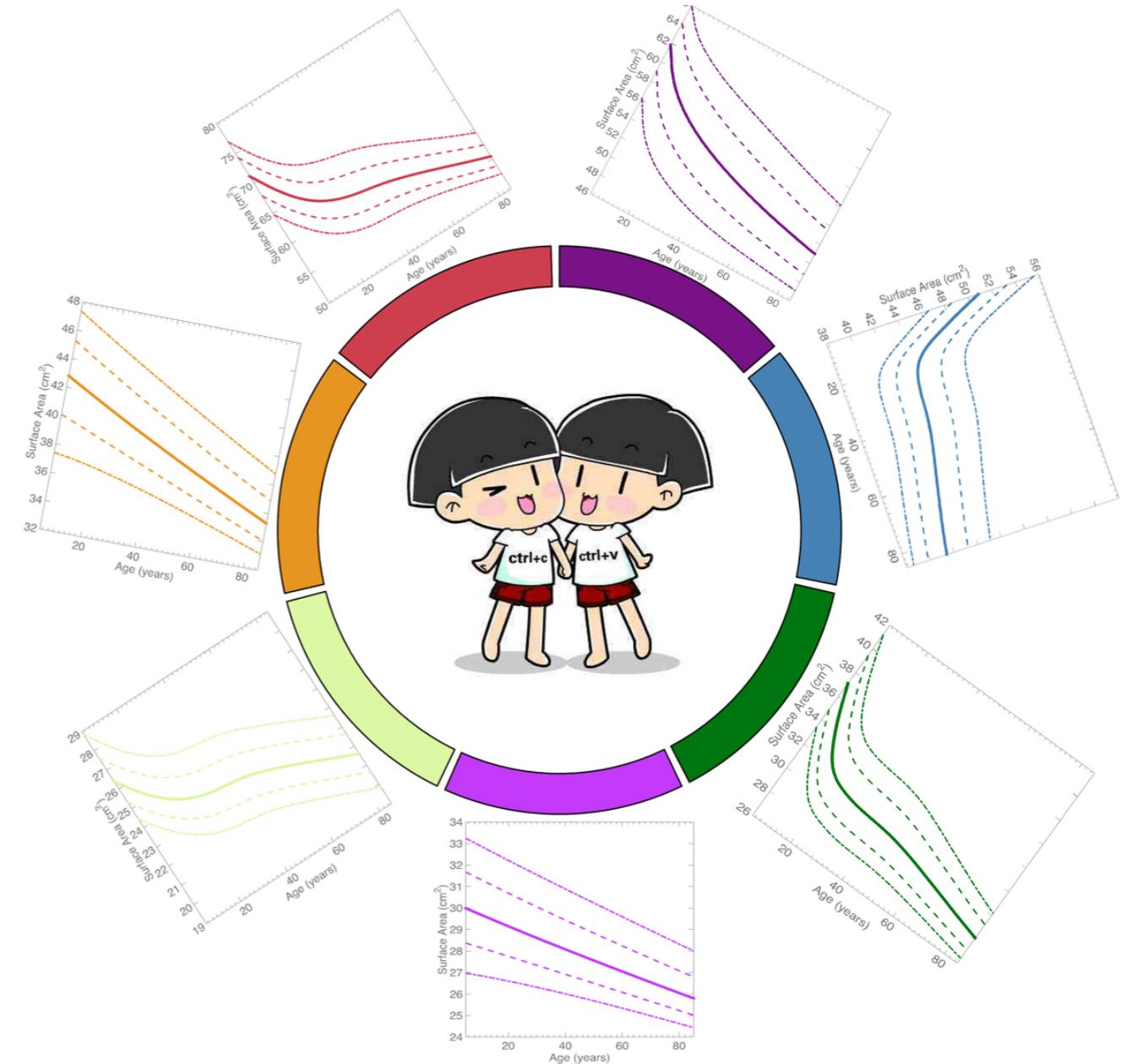
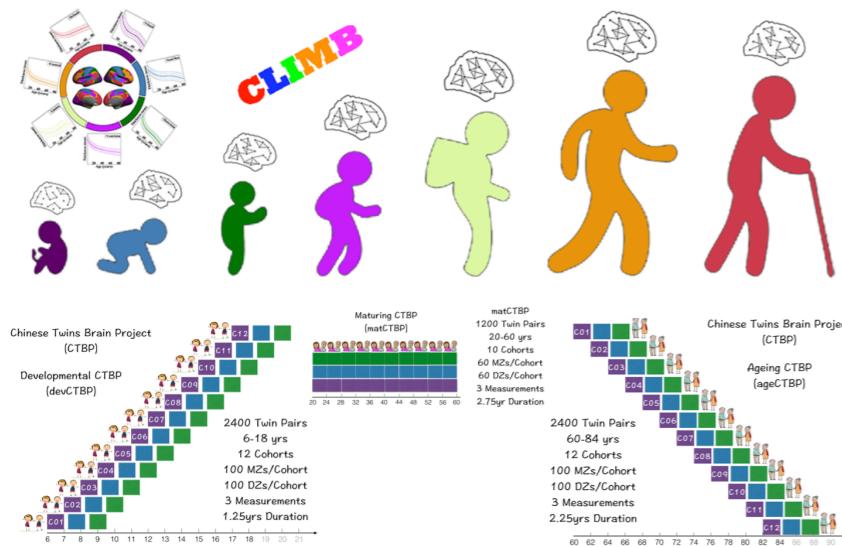


China's new brain-science centre will host some 50 principal investigators and will also support external researchers.

CHINA

Beijing launches pioneering neuroscience centre

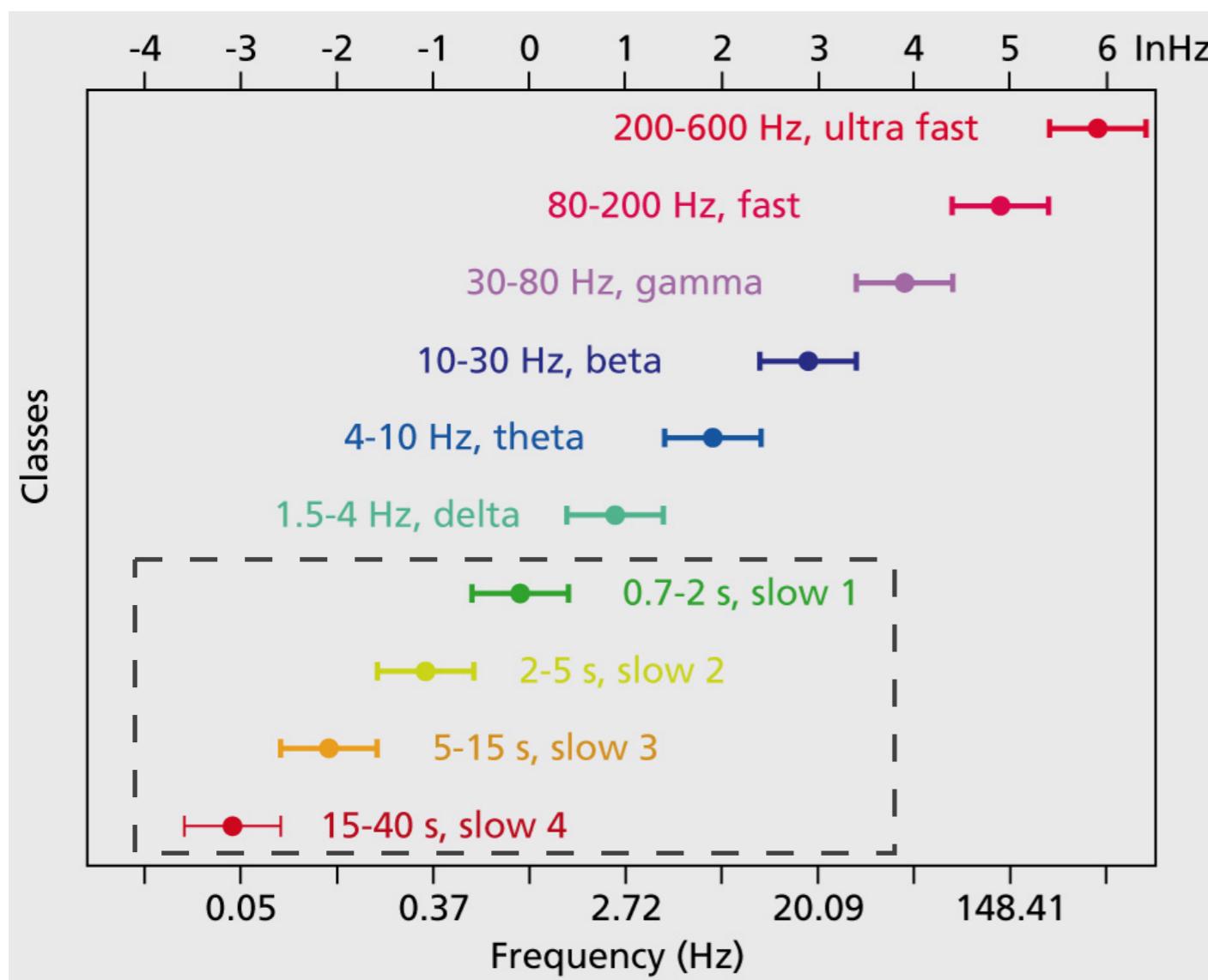
Large research facility will be key part of much-anticipated brain initiative.



Similar Design as CCNP but for 6000 Pairs of Twins across 12 National Sites

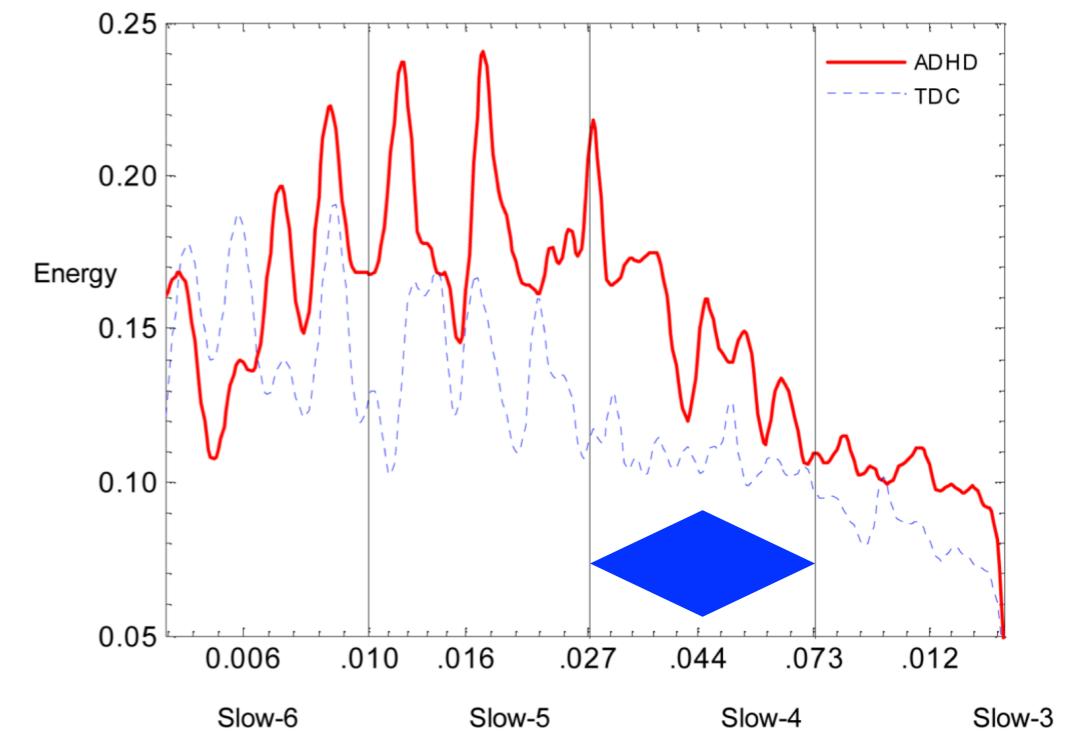
Methodology: Data + Theory

Space and Time in The Brain Rhythms of The Brain



Slow n $\left[e^{0.5-n}, e^{1.5-n} \right]$

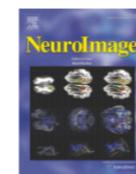
Varies with sampling rates and durations
(TR = 3s, in total 15 mins)



Methodology: Data + Theory

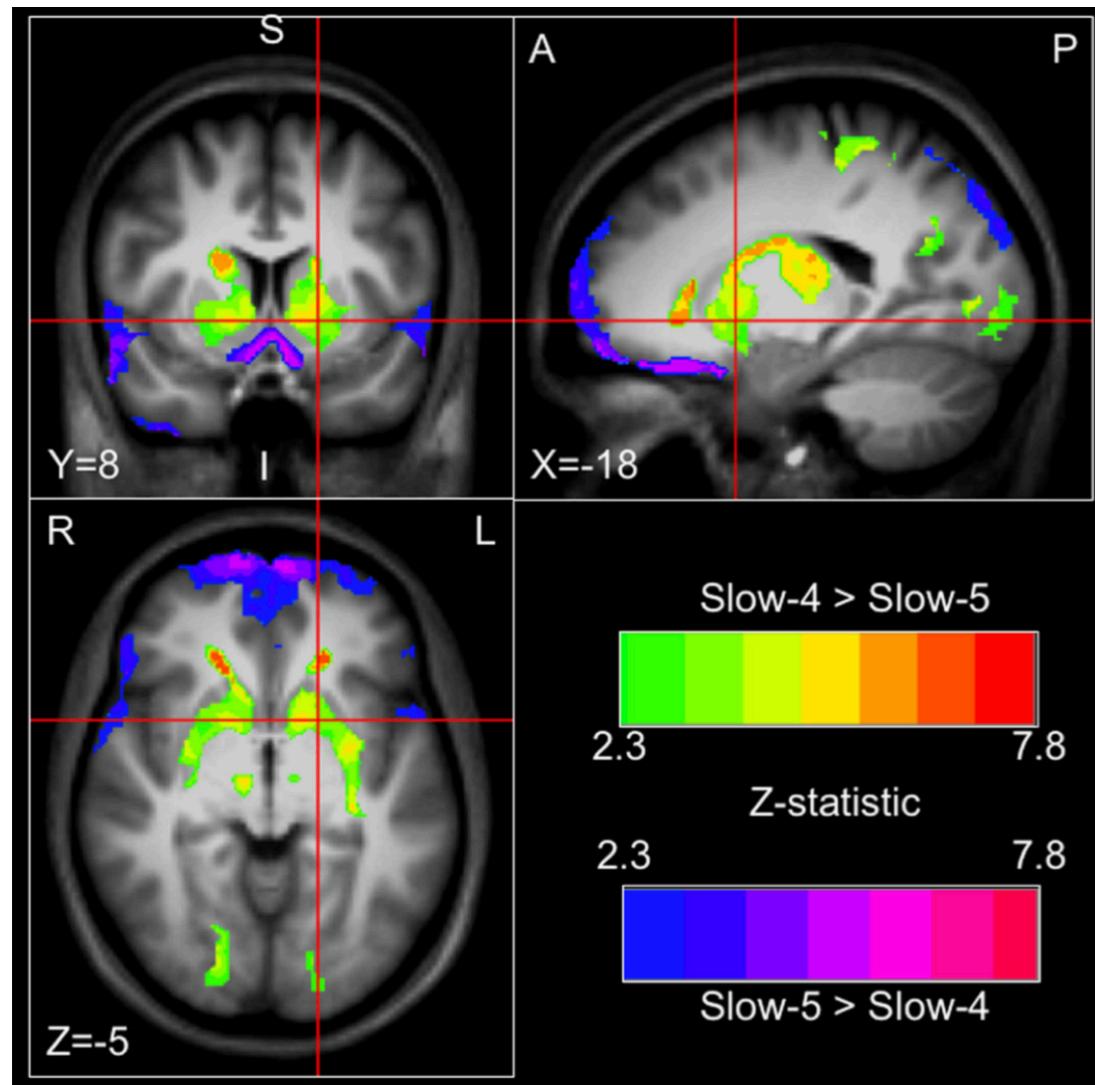


NeuroImage
Volume 49, Issue 2, 15 January 2010, Pages 1432-1445



The oscillating brain: Complex and reliable

Xi-Nian Zuo ^a, Adriana Di Martino ^a, Clare Kelly ^a, Zarrar E. Shehzad ^a, Dylan G. Gee ^a, Donald F. Klein ^{a, b, d}, F. Xavier Castellanos ^{a, b}, Bharat B. Biswal ^{b, c}✉, Michael P. Milham ^a✉



DREAM: A Toolbox to Decode Rhythms of the Brain System

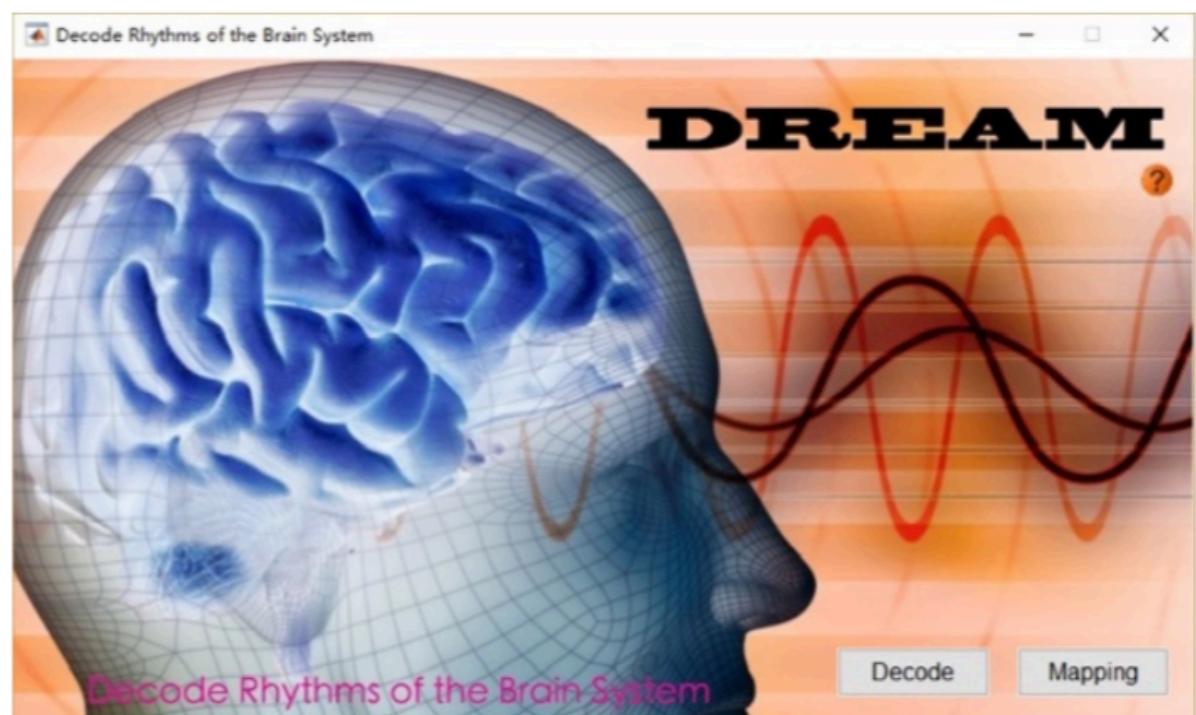


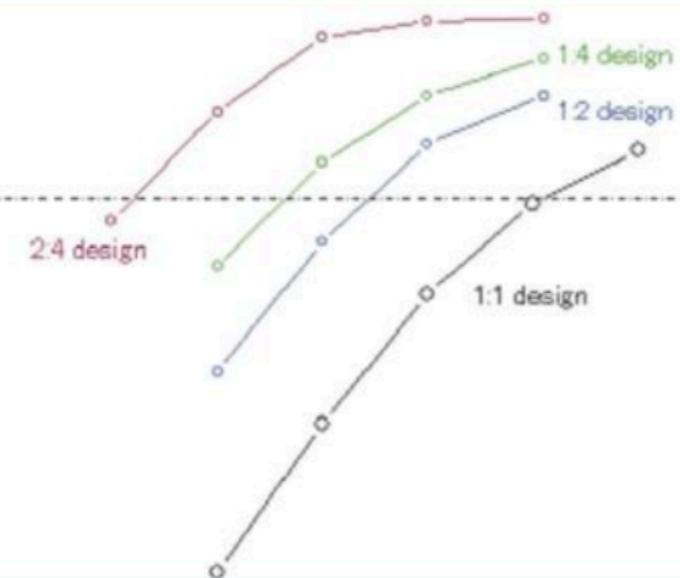
Fig. 1. The graphical user interface of DREAM.



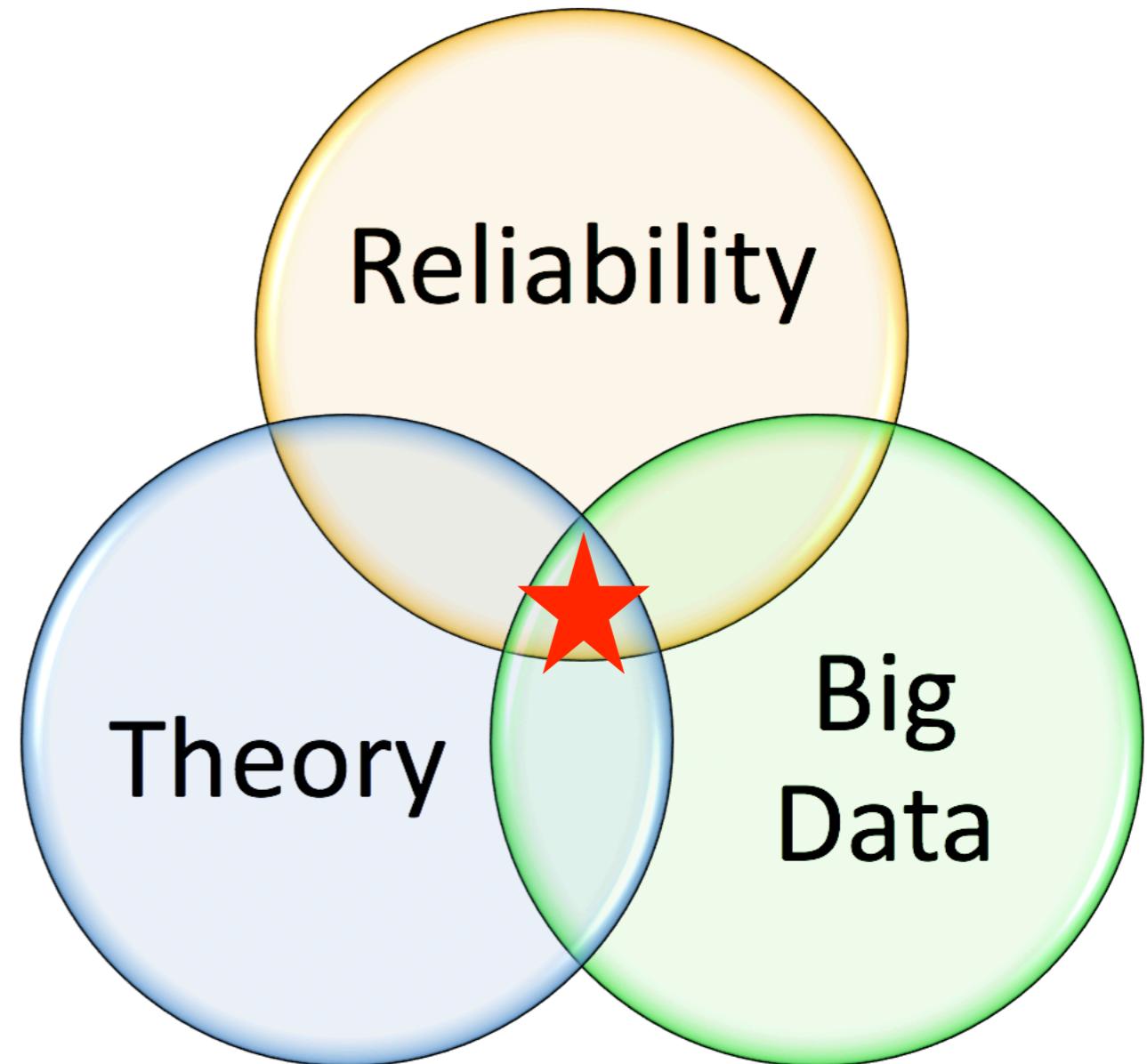
Fig. 2. The mock scanner at CLIMB.

Methodology: Data + Theory

**Repeated Measures
Design with Generalized
Linear Mixed Models
for Randomized
Controlled Trials**



Toshiro Tango



Thank you! Come to Our Posters :)



DREAM: A Toolbox to Decode Rhythms of the Brain System

Zhu-Qing Gong^{1,2,*}, Peng Gao^{3, 2}, Quan Zhou^{1,2}, Hao-Ming Dong⁴, Hai-Fang Li³, Xi-Nian Zuo^{1,2,4,5,*}

¹Department of Psychology, University of Chinese Academy of Sciences (UCAS), Beijing, China; ²CAS Key Laboratory of Behavioral Sciences, Institute of Psychology, Beijing, China; ³College of Information and Computer, Taiyuan University of Technology, Taiyuan; ⁴Magnetic Resonance Imaging Research Center and Research Center for Lifespan Development of Mind and Brain (CLIMB), Institute of Psychology, CAS, Beijing, China; ⁵Key Laboratory for Brain and Education Sciences, Guangxi Teachers Education University, Nanning, Guangxi, China

Introduction

Rhythms of the brain are created by neural oscillations, which are composed of different frequencies. Guided by the multiband frequency theory (i.e., natural log linear law) proposed by Buzsaki [1], these oscillations can be decomposed into bands of different but sequential frequencies underlying distinct physiological mechanism. This multi-band theory has been increasingly applied to study human brain function with functional magnetic resonance imaging (fMRI) [2] and related behavior [3]. For discrete data obtained from MRI scanners, the sampling period and the number of samples determine the number and ranges of decoding frequency bands. In studies published, especially the resting-state fMRI studies, most researchers decoded their data into the multiple frequency bands according to earlier papers on multi-band frequency analysis [2, 3]. However, in most cases, scanning parameters of the fMRI acquisition are different from the reference papers in the studies. One reason for these differences is due to a lack of an easy-to-use toolbox to implement decomposition of the multi-band frequency ranges. Thus, we present DREAM, a MATLAB-based toolbox with a graphical user interface that was developed to achieve the purpose of decoding rhythms of the brain (Figure 1). We demonstrated its function for frequency characteristics on age-related changes of head motion.

Results

Fig. 1. The graphical user interface of DREAM.

Fig. 2. The mock scanner at CLIMB.

Fig. 3. (a) Negative correlations between age and mean FD values of all five frequency bands. (b) Boys moved greater than girls across all bands in an age range of 7-9 years.

Methods

DREAM can output the decoded frequency bands into a text file and provide an example with head motion curves to show the effect of multi-band frequency decoder. To further demonstrate DREAM using real data, we employed the toolbox to decode timeseries of head motion from 84 healthy participants (42 females), aged from 3 to 16 years old. Head motion data were obtained in a mock scanner built by PST (Psychology Software Tools, Inc.) to match the appearance of a GE 750 3.0T scanner with the appearance as close as possible (Figure 2). The data were recorded using MoTrack head motion tracking system (PST - 100722) with an original sampling rate of 103 Hz and an averaging buffer size of 11, which resulted in a recording sampling rate of 9.285 Hz. We first converted original head motion data of six directions (x, y, z, roll, pitch and yaw) into the frame-wise displacement (FD), and then decoded FD with DREAM into multiple independent frequency bands. Correlational analyses between age and the mean FD values were performed for each frequency band whose mean FD values were also compared between males and females. Significance of all the statistical tests were corrected by Bonferroni ($P < 0.05/N = 0.01$) where N is the number of frequency bands.

Conclusion

DREAM decomposed the head motion data into five frequency bands (F1: 0.33323 – 0.0833307 Hz; F2: 0.0833307 – 0.22215 Hz; F3: 0.22215 – 0.80538 Hz; F4: 0.80538 – 1.8495 Hz; F5: 1.8495 – 4.4819 Hz). We detected significant negative correlations between age and mean FD values of all the five frequency bands in both males and females (Figure 3a). Specifically, the correlations in higher frequency bands were stronger than those in lower frequency bands. We also found significant sex differences in mean FD values for the ages from 7 to 9 years old across all the frequency bands that boys moved more than girls (Figure 3b). No such sex-related effects were detectable for other age ranges.

References

- [1] Penttonen, M. and G. Buzsaki. Natural logarithmic relationship between brain oscillators. *Thalamus & Related Systems*. 2003. 2(2): p. 145-152.
- [2] Zuo, X.N., et al., The oscillating brain: Complex and reliable. *NeuroImage*. 2010. 49(2): p. 1432-1445.
- [3] Di Martino, A., et al., Decomposing intra-subject variability in children with attention-deficit/hyperactivity disorder. *Biological Psychiatry*. 2008. 64(7): p. 607-614.
- [4] Power, J.D., Schlaggar, B.L. and Petersen, S.E. Recent progress and outstanding issues in motion correction in resting state fMRI. *NeuroImage*. 2015. 105: p. 536-551.
- [5] Zeng, L.L., et al., Neurophysiological basis of head motion in brain imaging. *Proc Natl Acad Sci U S A*. 2014. 111(16): p.e6058-6062.
- [6] Zhou, Y., et al., Genetic overlap between in-scanner head motion and the default network connectivity. *bioRxiv*. 2016. 087023. doi: <https://doi.org/10.1101/087023>.

Zhu-Qing Gong
17-B

6-B
Peng Gao

The Oscillating Neonatal Brain during Natural Sleep: A Multi-Band Amplitude Analysis

Zhu-Qing Gong^{1,2}, Xi-Nian Zuo^{1,2,3,4,5*}

¹ Department of Psychology, University of Chinese Academy of Sciences (UCAS), Beijing, China; ² Research Center for Lifespan Development of Mind and Brain (CLIMB), Institute of Psychology, CAS, Beijing, China; ³ CAS Key Laboratory of Behavioral Sciences, Institute of Psychology, Beijing, China; ⁴ Magnetic Resonance Imaging Research Center, Institute of Psychology, CAS, Beijing, China; ⁵ Key Laboratory for Brain and Education Sciences, Guangxi Teachers Education University, Nanning, Guangxi, China

Introduction

Most knowledge about the early human connectome has been learnt from models of preterm growth. The Developing Human Connectome Project (dHCP) seeks to collect brain images for the first time in a large sample of fetuses and newborn infants [1]. By sharing these data resource, dHCP will allow the community to explore the neurobiological mechanisms, and genetic and environmental influences, which underpin healthy cognitive development. Here, we presented a multi-band frequency analysis of amplitude of neural oscillations based upon functional MRI recordings of neonatal brains during natural sleep from dHCP.

Methods

The data are obtained from the initial release by dHCP of data from 40 neonatal subjects. All infants were born and imaged at term age (37-44 weeks of age) and were imaged in natural sleep with anatomical (T1w and T2w), resting state functional (rs-fMRI) and diffusion (dMRI) sequences (a total examination time of 63mins). High temporal resolution rs-fMRI developed for neonates used multiband echo-planar imaging and was collected for 15 minutes (TE/TR = 38/392ms, 2300 volumes, 2.15mm isotropic voxels). We employed DREAM (a toolbox to decode rhythms of the brain system) to divide the rs-fMRI data preprocessed by the dHCP minimal pipeline into six frequency bands [2,3]: slow1 (0.0607 – 1.2755 Hz), slow2 (0.229 – 0.6067 Hz), slow3 (0.0821 – 0.2229 Hz), slow4 (0.0299 – 0.0821 Hz), slow5 (0.0111 – 0.0299 Hz), slow6 (0.0067 – 0.0111 Hz). Fractional ALFF (fALFF) maps [4] was then calculated for each frequency band in native space. Multi-scale (whole brain, tissue and region) fALFF features were then extracted to correlate with the post-menstrual age (PMA).

Results

Spatial variability (not mean) of fALFF are highly correlated with PMA across different scales (whole brain, brain tissues and segmented areas). However, such correlations are not happened to all frequencies. Specifically, at whole brain level, the positive correlations between fALFF variability and PMA were detectable for slow4 and slow2 frequencies (Figure 1). Only slow4 showed such correlations for cGM, brainstem, CSF and background tissues (Figure 2). Interestingly, across more detailed level of brain segmentation by DRAW-EM, these two bands came back again with detectable fALFF-PMA correlations for left insula and occipital areas (Figure 3).

Discussion and Conclusions

The first set of observations of multi-band frequency features of amplitudes are provided for sleeping neonates. This may help to derive neural oscillation models of healthy development, providing a vital basis of comparison from which the effects of preterm birth, and neurological conditions of atypical development.

References

- [1] dHCP reference [2] Penttonen, M. and G. Buzsaki. Natural logarithmic relationship between brain oscillators. *Thalamus & Related Systems*. 2003. 2(2): p. 145-152. [3] DREAM abstract [4] Zuo, X.N., et al., The oscillating brain: Complex and reliable. *NeuroImage*. 2010. 49(2): p. 1432-1445.

Fig. 1. The positive correlations between fALFF variability and PMA for slow4 and slow2 frequencies.

Fig. 2. Slow4 showed correlations with cGM, brainstem, CSF and background tissues.

Fig. 3. Slow2 and slow4 showed fALFF-PMA correlations for left insula and occipital areas.