SEW

Resting-state fMRI and data analysis —a brief introduction

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Outline

- Brief history of resting-state and why we should study resting-state?
- Debates in resting-state
- Resting-state **data analysis**
  - Preprocessing
  - ALFF/fALFF
  - ReHo
  - Degree centraility
  - Functional connectivity (network-based statistics)
  - Dynamic functional connectivity
  - Dynamic ICA
  - Graph theory
  - Dynamic graph theory
  - Hidden Markov Model (state)
- Toolboxes
- Recommended papers
- Resting-state predicts human behavior
- Resting-state and task-fMRI

Outline

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- Debates in resting-state
- Resting-state **data analysis** →
  - Preprocessing
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  - Degree centraility
  - Functional connectivity (network-based statistics)
  - Dynamic functional connectivity
  - Dynamic ICA
  - Graph theory
  - Dynamic graph theory
  - Hidden Markov Model (state)
- Toolboxes
- Recommended papers
- Resting-state predicts human behavior (next time)
- Resting-state and task-fMRI (next time)

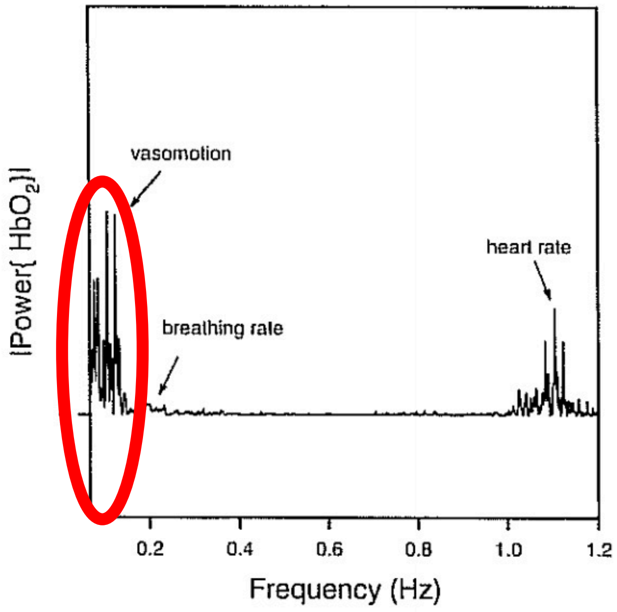
Brief history of resting-state and why we should study resting-state?

Spontaneous BOLD activity

- The brain is always active, even in the absence of explicit input or output
  - task-related changes in neuronal metabolism are only about 5% of brain's total energy consumption

- What is the "noise" in standard activation studies?
  - faster frequencies related to respiratory and cardiac activities
  - spontaneous, neuronal oscillations between 0.01 – 0.10 Hz

< 0.10 Hz

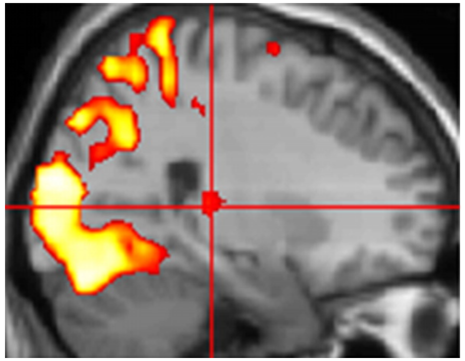


Brief history of resting-state and why we should study resting-state?

Two fundamental properties of brain architecture

Functional Segregation ↔ **Functional Integration**

What is the neural correlate of… ?



How do cortical areas interact … ?

'Connectivity' analysis

Brief history of resting-state and why we should study resting-state?

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Distinguished Professor, Bio-Medical Engineering
biswal@njit.edu
(973) 596-8380 619 Fenster Hall

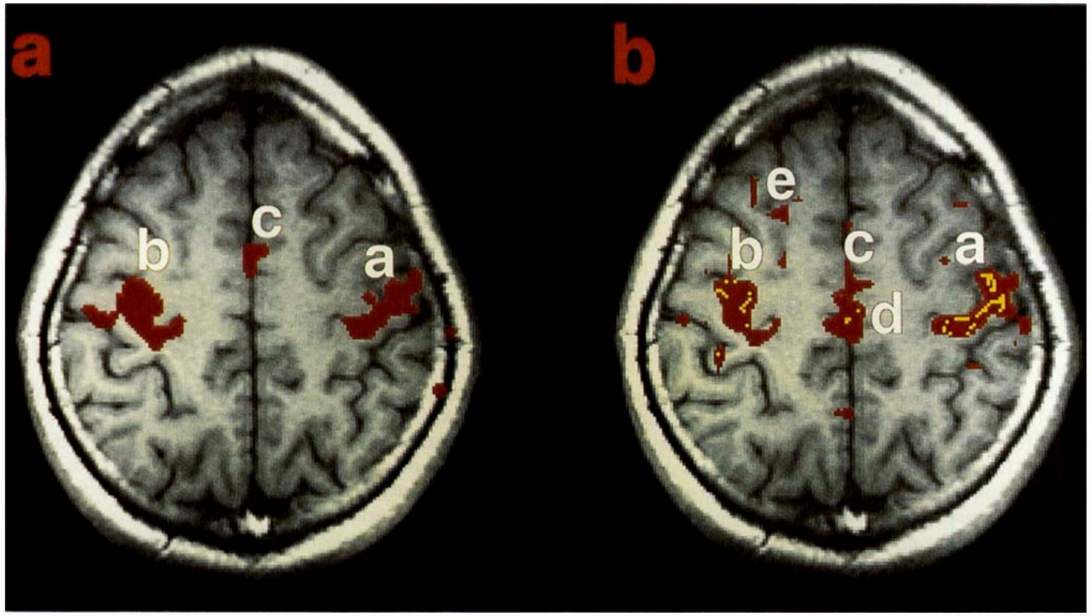
First resting-state paper!

Functional Connectivity in the Motor Cortex of Resting Human Brain Using Echo-Planar MRI

Bharat Biswal, F. Zerrin Yetkin, Victor M. Haughton, James S. Hyde

An MRI time course of 512 echo-planar images (EPI) in resting human brain obtained every 250 ms reveals fluctuations in signal intensity in each pixel that have a physiologic origin. Regions of the sensorimotor cortex that were activated secondary to hand movement were identified using functional MRI methodology (FMRI). Time courses of low frequency (<0.1 Hz) fluctuations in resting brain were observed to have a high degree of temporal correlation ($P < 10^{-3}$) within these regions and also with time courses in several other regions that can be associated with motor function. It is concluded that correlation of low frequency fluctuations, which may arise from fluctuations in blood oxygenation or flow, is a manifestation of functional connectivity of the brain.

Key words: functional connectivity; motor cortex; fMRI; EPI.



Brief history of resting-state and why we should study resting-state?

www.pnas.org › content · 翻译此页

A default mode of brain function | PNAS

作者： ME Raichle · 2001 · 被引用次数： 11575 — We used quantitative metabolic and circulatory measurements from positron-emission tomography to obtain the OEF regionally throughout the brain. ... These decreases suggest the existence of an organized, baseline default mode of brain function that is suspended during specific goal-directed behaviors.

Marcus E Raichle, MD

Alan A. & Edith L. Wolff Distinguished Professor in Medicine

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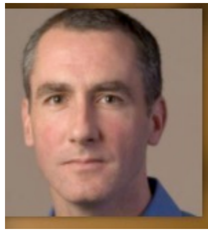
www.pnas.org › content · 翻译此页

Functional connectivity in the resting brain: A network analysis ...

作者： MD Greicius · 2003 · 被引用次数： 6233 — Taken together, our results demonstrate that a distinct set of brain regions, whose activity decreases during cognitive tasks compared with baseline states, shows significant functional connectivity during the resting state, thus providing the most compelling evidence to date for the existence of a cohesive, tonically ...



Michael Greicius, MD, MPH

ASSOCIATE PROFESSOR OF NEUROLOGY AND, BY COURTESY, OF PSYCHIATRY AND BEHAVIORAL SCIENCES

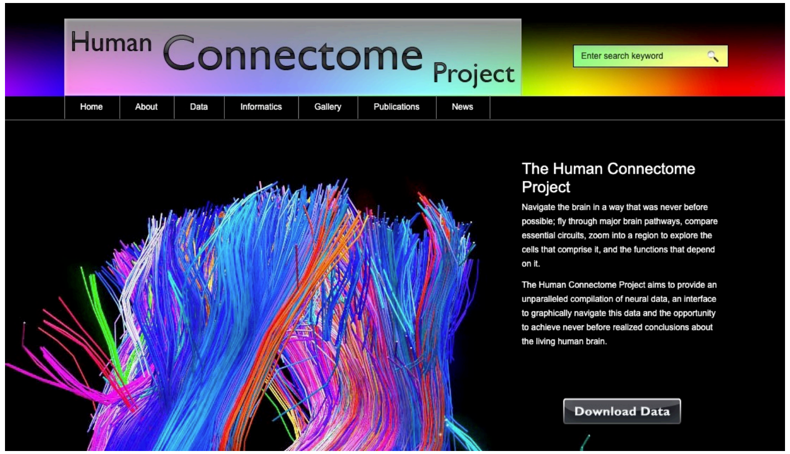
Neurology & Neurological Sciences

Practices at Stanford Hospital and Clinics

Brief history of resting-state and why we should study resting-state?

Main advantages of resting-state fMRI

1. **Patients** (especially mental disorder patients) **, children, old people**
2. **Allows researchers to observe many networks at once**
3. **It easier for researchers to replicate each other's experiments and compare results.**



In 2010, the NIH launched the Human Connectome Project: aimed to map the brain networks of more than 1,000 people

Debates about resting-state fMRI

Debates #1: **Resting-state BOLD signals result from physiological processes, like respiratory and cardiac oscillations ?**

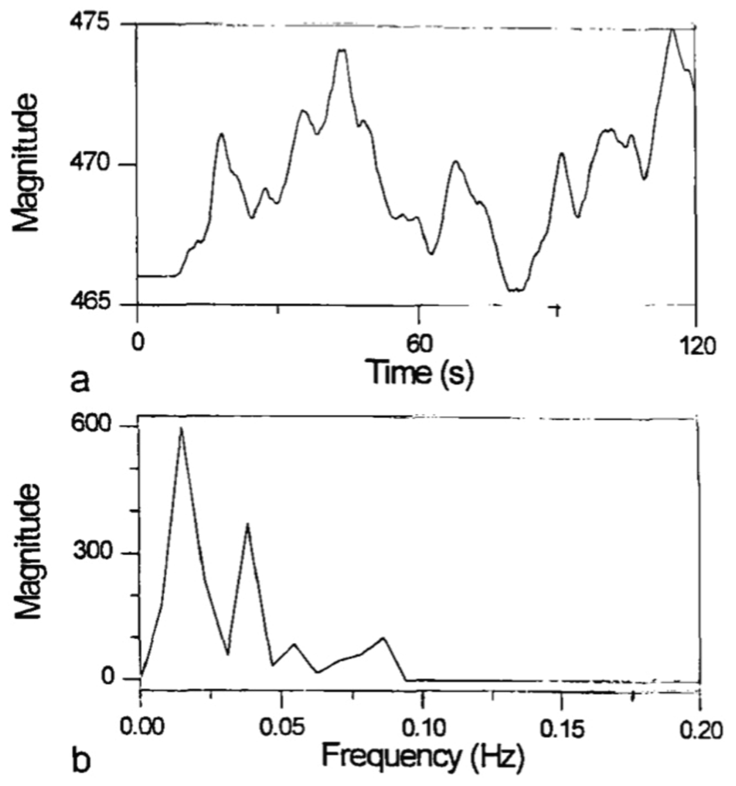


FIG. 1. (a) Representative time course of motor cortex physiological fluctuations after FIR filtering that passes frequencies <0.08 Hz. (b) Fourier transform of the time course.

Biswal et al., 1995

fMRI protocols have a low temporal resolution (common acquisition rate of 2–3 s per scan, i.e. 0.5 Hz), causing high frequent respiratory and cardiac oscillations to be aliased back into the lower resting- state frequencies (0.01–0.1 Hz).
these higher frequent cardiac and respiratory patterns might shape the BOLD time-series of anatomically separate brain regions in a similar way, introducing artificial correlations between the time-series of these regions

Debates about resting-state fMRI

Debates #1: Resting-state BOLD signals result from physiological processes, like respiratory and cardiac oscillations ?

Argue back 1: Most of the resting-state patters tend to occur between brain regions that overlap in both function and neuroanatomy

Argue back 2: Cardiac and respiratory oscillations have been reported to have a different frequency pattern and therefore a different frequency related influence on resting-state correlations than the low frequencies of interest in (0.01– 0.1 Hz)
respiratory (0.1–0.5 Hz) and cardiovascular (0.6–1.2 Hz) signal frequencies

Debates about resting-state fMRI

Debates #1: Resting-state BOLD signals result from physiological processes, like respiratory and cardiac oscillations ?

ARTICLES

nature neuroscience

Argue back 3: A strong association between spontaneous BOLD fluctuations and simultaneous measured fluctuations in neuronal spiking

Interhemispheric correlations of slow spontaneous neuronal fluctuations revealed in human sensory cortex

Yuval Nir[1], Roy Mukamel[2], Ilan Dinstein[3], Eran Privman[4], Michal Harel[1], Lior Fisch[1], Hagar Gelbard-Sagiv[1], Svetlana Kipervasser[5,6], Fani Andelman[7], Miri Y Neufeld[5,6], Uri Kramer[5,7], Amos Arieli[1], Itzhak Fried[2,5,7] & Rafael Malach[1]

Animal studies have shown robust electrophysiological activity in the sensory cortex in the absence of stimuli or tasks. Similarly, recent human functional magnetic resonance imaging (fMRI) revealed widespread, spontaneously emerging cortical fluctuations. However, it is unknown what neuronal dynamics underlie this spontaneous activity in the human brain. Here we studied this issue by combining bilateral single-unit, local field potentials (LFPs) and intracranial electrocorticography (ECoG) recordings in individuals undergoing clinical monitoring. We found slow (< 0.1 Hz, following 1/*f*-like profiles) spontaneous fluctuations of neuronal activity with significant interhemispheric correlations. These fluctuations were evident mainly in neuronal firing rates and in gamma (40–100 Hz) LFP power modulations. Notably, the interhemispheric correlations were enhanced during rapid eye movement and stage 2 sleep. Multiple intracranial ECoG recordings revealed clear selectivity for functional networks in the spontaneous gamma LFP power modulations. Our results point to slow spontaneous modulations in firing rate and gamma LFP as the likely correlates of spontaneous fMRI fluctuations in the human sensory cortex.

Debates about resting-state fMRI

Debates #2: , eyes closed (EC), eyes open (EO), or eyes fixated on an object (EO-F)?

Resting state connectivity differences in eyes open versus eyes closed conditions

Oktay Agcaoglu[1] | Tony W. Wilson[2] | Yu-Ping Wang[3,4] | Julia Stephen[1] | Vince D. Calhoun[1,5]

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Abstract

Functional magnetic resonance imaging data are commonly collected during the resting state. Resting state functional magnetic resonance imaging (rs-fMRI) is very practical and applicable for a wide range of study populations. Rs-fMRI is usually collected in at least one of three different conditions/tasks, eyes closed (EC), eyes open (EO), or eyes fixated on an object (EO-F). Several studies have shown that there are significant condition-related differences in the acquired data. In this study, we compared the functional network connectivity (FNC) differences assessed via group independent component analysis on a large rs-fMRI dataset collected in both EC and EO-F conditions, and also investigated the effect of covariates (e.g., age, gender, and social status score). Our results indicated that task condition significantly affected a wide range of networks; connectivity of visual networks to themselves and other networks was increased during EO-F, while EC was associated with increased connectivity of auditory and sensorimotor networks to other networks. In addition, the association of FNC with age, gender, and social status was observed to be significant only in the EO-F condition (though limited as well). However, statistical analysis did not reveal any significant effect of interaction between eyes status and covariates. These results indicate that resting-state condition is an important variable that may limit the generalizability of clinical findings using rs-fMRI.

KEYWORDS

eyes closed, eyes open, functional network connectivity, independent component analysis, resting state fMRI

Data analysis-preprocessing

- Quality control
- Convert DICOM files to NIFTI images
- Remove First 10 Time Points
- Slice Timing
- Realign
- Normalize
- Smooth (optional)
- Detrend (optional)
- Nuisance covariates regression
- Filter
- Calculate ALFF and fALFF
- Calculate ReHo/Degree centrality (without smooth in preprocessing)
- Calculate Functional Connectivity

Data analysis-preprocessing

How to deal with head motion?

Rigid body 6
Friston 24 (Friston et al., 1996)
Power framewise displacement

Framewise Displacement of a time series is defined as the sum of the absolute values of the derivatives of the six realignment parameters. Rotational displacements are converted from degrees to millimeters by calculating displacement on the surface of a sphere of radius 50 mm.

$$\Delta d_{ix} = d_{(i-1)x} - d_{ix}$$

$$FD_i = |\Delta d_{ix}| + |\Delta d_{iy}| + |\Delta d_{iz}| + |\Delta \alpha_i| + |\Delta \beta_i| + |\Delta \gamma_i|$$

Data analysis-preprocessing

Recommend papers:

NeuroImage 76 (2013) 183–201

Contents lists available at SciVerse ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/ynimg

A comprehensive assessment of regional variation in the impact of head micromovements on functional connectomics

Chao-Gan Yan [a,b,c], Brian Cheung [b], Clare Kelly [c], Stan Colcombe [a], R. Cameron Craddock [b,d], Adriana Di Martino [c], Qingyang Li [b], Xi-Nian Zuo [e], F. Xavier Castellanos [a,c], Michael P. Milham [a,b,*]

[a] Nathan Kline Institute for Psychiatric Research, Orangeburg, NY, USA
[b] Center for the Developing Brain, Child Mind Institute, New York, NY, USA
[c] The Phyllis Green and Randolph Cowen Institute for Pediatric Neuroscience, New York University Child Study Center, New York, NY, USA
[d] Virginia Tech Carilion Research Institute, Roanoke, VA, USA
[e] Key Laboratory of Behavioral Science, Laboratory for Functional Connectome and Development, Magnetic Resonance Imaging Research Center, Institute of Psychology, Chinese Academy of Sciences, Beijing, China

Objective	Analytic method	Data employed	Key novel findings
1. Demonstrate Regional Variation in the Impact of Motion on the BOLD Signal (Figures 1, 2, S1, S2, S3)	• Calculate the correlation between BOLD signal and voxel-specific head motion and then perform one-sample t-test.	All datasets	• High motion datasets exhibited more pronounced negative motion-BOLD relationships (esp. prefrontal areas). • Low motion datasets exhibited more pronounced positive motion-BOLD relationships (esp. primary and supplementary motor areas).
2. Evaluate the Ability of Motion Correction Strategies to Decrease the Impact of Motion on the BOLD Signal at Individual-Level (Figures 3, 4, S4)	• After applying the individual-level motion correction strategies on the functional data (after realignment), calculate the correlation between corrected BOLD signal and voxel-specific head motion. • Calculate the mean positive correlation and mean negative correlation as summary measures for each participant, and then perform paired t-test to compare strategies.	Cambridge Adults (n= 158; 18 participants removed due to motion)	• Only 'scrubbing' (FD < 0.2mm) removed negative motion-BOLD relationships. • Positive motion-BOLD relationships tended to cluster in primary and supplementary motor areas and remained even after scrubbing, thus may reflect to motion-related neural activity.
3. Evaluate the Ability of Motion Correction Strategies to Decrease Residual Relationships Between Motion and R-fMRI Metrics at Group-Level (Figures 5, 6, S5-S10)	• Calculate R-fMRI metrics after motion correction strategies, and then evaluate their correlation with motion across participants. • Wilcoxon signed-rank test were used to test the distribution of residual motion effects (absolute correlation) across motion correction strategies.	Cambridge Adults (n= 158)	• None of the individual-level motion correction approaches successfully bypass the need for group-level correction for inter-individual differences in R-fMRI related to motion. • Z-standardization on subject-level maps reduced relationships between motion and inter-individual differences.
4. Examine the Influence of Global Signal Regression (GSR) on the Impact of Motion on the BOLD signal and R-fMRI metrics (Figures 7, S11)	• Repeat the analyses in objective 2 and 3, taking in account GSR as well as WM/CSF signal regression.	Cambridge Adults (n= 158)	• GSR introduced negative motion-BOLD relationships at individual level. • However, GSR was highly effective in removing inter-individual differences related to motion.
5. Examine the Impact of Motion and Motion Correction Strategies on Test-Retest Reliability (Figures 8, S12)	• Calculate R-fMRI metrics after motion correction strategies, then evaluate the test-retest reliability via intra-class correlation (ICC). • Wilcoxon signed-rank test were employed to compare the reliability across motion correction strategies.	NYU TRT (high motion dataset [n= 11] vs. low motion dataset [n= 11])	• Motion appears to reduce test-retest reliability for correlation-based metrics. • Motion did artifactually increase the reliability of frequency-based metrics (ALFF >> fALFF); correction approaches reduced these increases.
6. Compare Framewise Displacement (FD) Metrics (Figure 9)	• Plot the difference between FD_{vol} and $mean_{sp}$ FD_{vox} as a function of $mean_{sp}$ FD_{vox} for all time points and all participants. • Plot the temporal mean of FD_{vol} (mean FD_{vol}) and temporal mean of $mean_{sp}$ FD_{vox} (mean	Cambridge Adults (N = 176)	• Overall, there was high concordance among volume-based metrics of FD. • Failure to account for rotation can lead to substantial underestimation of FD.

Data analysis-preprocessing

Recommend papers:

nature methods

ARTICLES

https://doi.org/10.1038/s41592-018-0235-4

fMRIPrep: a robust preprocessing pipeline for functional MRI

Oscar Esteban[1*], Christopher J. Markiewicz[1], Ross W. Blair[1], Craig A. Moodie[1], A. Ilkay Isik[2], Asier Erramuzpe[3], James D. Kent[4], Mathias Goncalves[5], Elizabeth DuPre[6], Madeleine Snyder[7], Hiroyuki Oya[8], Satrajit S. Ghosh[5,9], Jessey Wright[1], Joke Durnez[1], Russell A. Poldrack[1,10] and Krzysztof J. Gorgolewski[1,10*]

Data analysis-ALFF

https://pubmed.ncbi.nlm.nih.gov › ...

Altered baseline brain activity in children with ... - Pub Med

by YF Zang · 2007 · Cited by 1851 — As a result, we found that patients with **ADHD** ha
decreased ALFF in the right inferior frontal cortex, [corrected] and bilateral cerebellum a
vermis as well as increased ALFF in the right anterior cingulated cortex, left sensorimot
and bilateral brainstem.

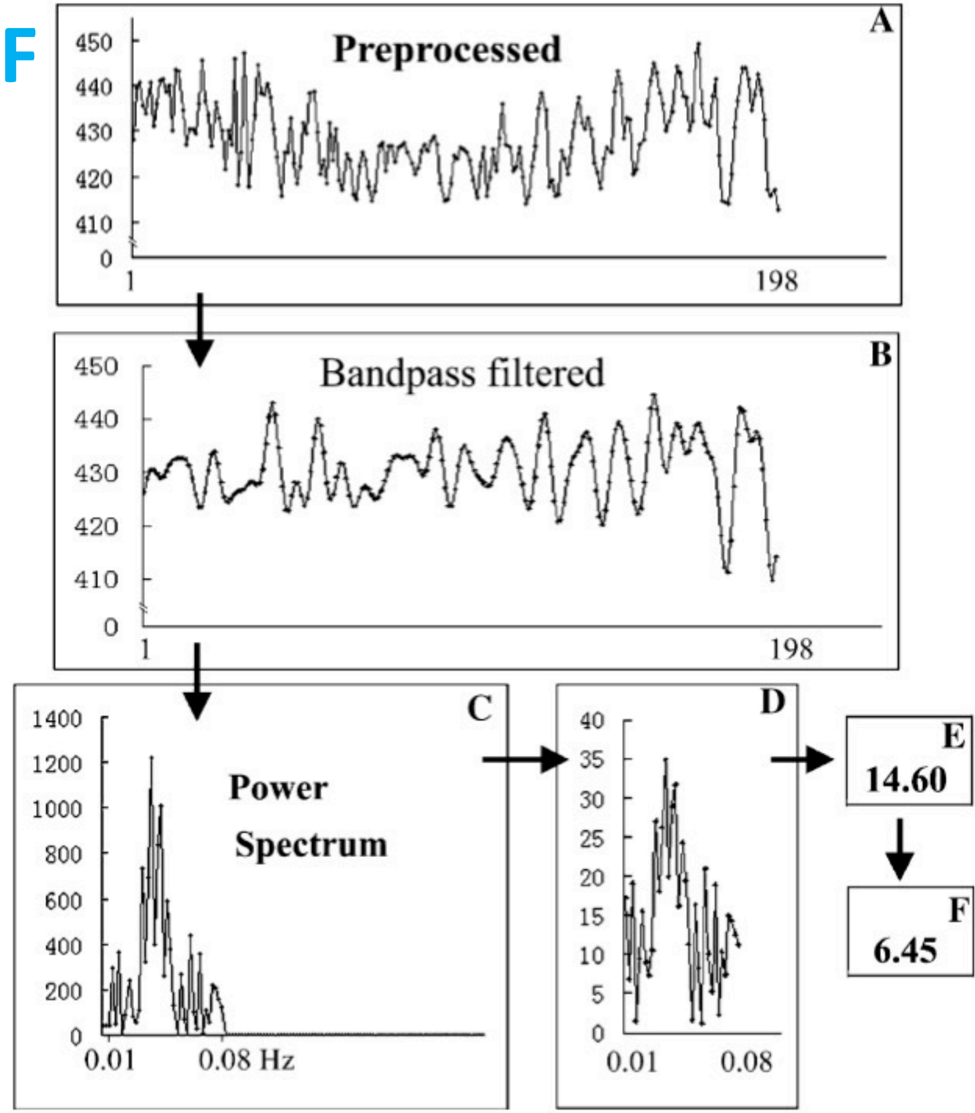


Fig. 1. Schematic illustration of the current ALFF analysis. The signal intensity is measured in arbitrary units. (A) The time course after preprocessing. (B) Band-filtered (0.01–0.08 Hz) time course. (C) Power spectrum using fast Fourier transformation. (D) Square root of the power spectrum between 0.01 and 0.08 Hz, i.e., ALFF. (E) Averaged ALFF across 0.01–0.08 Hz (14.60), the global mean ALFF (2.26) and the standardized ALFF (6.45).

Amplitude of Low Frequency Fluctuation (ALFF)
(Biswal et al., 1995; Zang et al., 2007)

Data analysis-fALFF

https://pubmed.ncbi.nlm.nih.gov › ...

An improved approach to detection of amplitude of low ...

by QH Zou · 2008 · Cited by 1134 — The current study proposed a frac **approach**, i.e., the ratio of power spectrum of **low-frequency** (0.01-0.0 **frequency** range and this **approach** was tested in two groups of restin

The square root was calculated at each frequency of the power spectrum. The sum of amplitude across 0.01–0.08 Hz was divided by that across the entire frequency range, i.e., 0–0.25 Hz

Fractional ALFF (fALFF)= inclusion of information in frequencies outside of the normal range

(Zou et al., 2008)

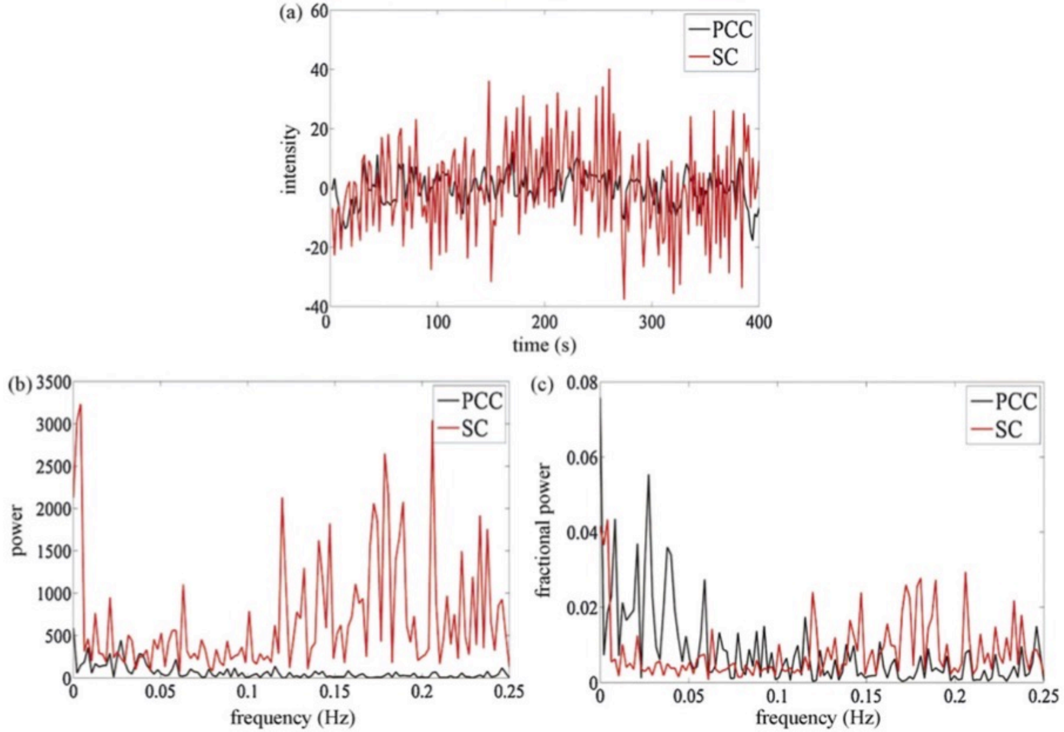


Fig. 2.
Illustration of the improvement of ALFF approach. (a) The time series (without filtering) from a typical voxel in the suprasellar cistern (SC) (–1, –2, –18) and the posterior cingulate cortex (PCC) (–4, –56, 25) of an individual. (b) The power in the SC is higher than that in PCC at almost every frequency. (c) The ratio of the power at each frequency to the integrate power of the entire frequency range indicates that the power in the low-frequency range (0.01–0.08 Hz) is significantly suppressed in the SC.

Data analysis-Regional homogeneity (ReHo)

https://pubmed.ncbi.nlm.nih.gov › ...

Regional homogeneity approach to fMRI data analysis

by Y Zang · 2004 · Cited by 1713 — **2004** May;22(1):394-400. doi: 10.1016/j.neuroimage.2003.12.030. Authors. Yufeng **Zang** ...

- Calculate the Kendall coefficient of concordance
- Similarity or synchronization of time courses within a cluster (i.e., neighboring voxels)

$$W = \frac{\Sigma(R_i)^2 - n(\overline{R})^2}{\frac{1}{12}K^2(n^3 - n)}$$

R_i is the sum rank of the *i*th time point

$\overline{R}$ = (n+1)K/2

K is the number of time series within a measured cluster

n is the number of ranks (here n = 78).

Data analysis- Degree centraliy (DC)

Cerebral Cortex Advance Access published October 12, 2011

Cerebral Cortex
doi:10.1093/cercor/bhr269

Network Centrality in the Human Functional Connectome

Xi-Nian Zuo[1,2], Ross Ehmke[3], Maarten Mennes[2], Davide Imperati[2], F. Xavier Castellanos[2,4], Olaf Sporns[3] and Michael P. Milham[4,5]

[1]Laboratory for Functional Connectome and Development, Key Laboratory of Behavioural Science, Institute of Psychology, Chinese Academy of Sciences, Beijing 100101, China, [2]Phyllis Green and Randolph Cōwen Institute for Pediatric Neuroscience, New York University Langone Medical Center, New York, NY 10016, USA, [3]Department of Psychological and Brain Sciences, Indiana University, Bloomington, IN 47405, USA, [4]Nathan Kline Institute for Psychiatric Research, Orangeburg, NY 10962, USA and [5]Center for the Developing Brain, Child Mind Institute, New York, NY 10022, USA

Address correspondence to Dr Xi-Nian Zuo, Laboratory for Functional Connectome and Development, Key Laboratory of Behavioural Science, Institute of Psychology, Chinese Academy of Sciences, 4A Datun Road, Chaoyang District, Beijing 100101, China. Email: zuoxn@psych.ac.cn or zuoxinian@gmail.com.

Degree Centrality

For a binary graph, degree centrality (DC) is the number of edges connecting to a node. For a weighted graph, it is defined as the sum of weights from edges connecting to a node (also sometimes referred to as the node strength). According to the adjacency matrix of a graph, DC can be computed as in equation (3). It represents the most local and directly quantifiable centrality measure. This measure has been widely used to examine node characteristics of ICNs (Buckner et al. 2009; Bullmore and Sporns 2009; He et al. 2009; Cole, Pathak, et al. 2010; Wang et al. 2010; Fransson et al. 2011).

$$\mathrm{DC}(i)=\sum_{j=1}^{N} a_{ij}. \tag{3}$$

Data analysis- Functional connectivity(model-based)

- **Model-dependent methods**
  - Seed-based correlation analysis (SCA) (e.g., Biswal et al., 1995)
    - Whole-brain, voxel-wise functional connectivity maps of covariance with the seed region
  - Structural equation modeling
    - Doesn't take into account features of fMRI (e.g., temporal variations in connections)
  - Granger causality (Roebreck et al., 2005; Sridharan et al., 2008)
  - Dynamic causal modeling (DCM) (Friston et al., 2014)

  (If interested in effective connectivity, recommend reading Cole et al., 2010 & Ramsey et al., 2010)

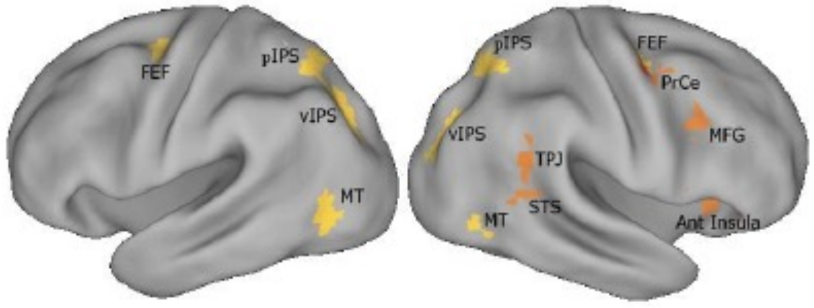
!! Be mindful of you select ROIs

Surface-based parcellations, atlases, subject-specific maps, coordinates from previous work

Data analysis- Functional connectivity(model-based)

Seed-based FC

Seed-based functional connectivity analysis

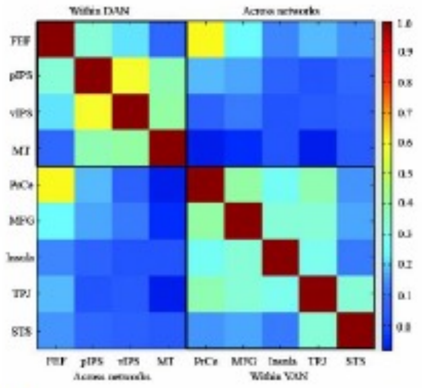


Definition of the regions of interest (ROIs) -> seeds

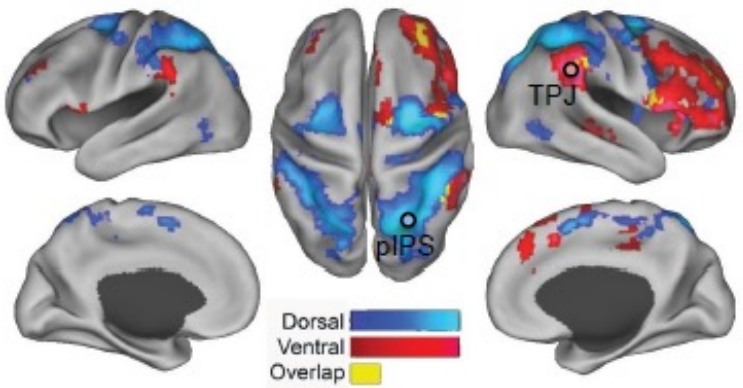
He et al., 2007

seed-to-brain connectivity maps

seed-to-seed connectivity matrix



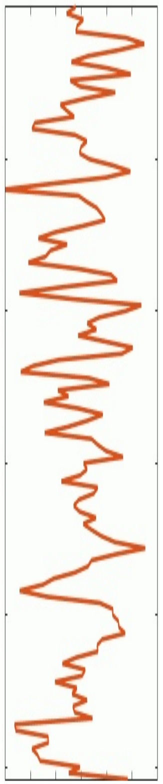
He et al. 2007



Fox et al., 2006

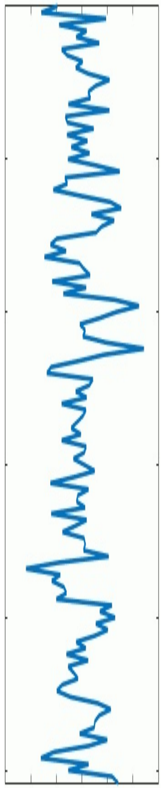
Data analysis- Functional connectivity(model-based)

Seed-based FC



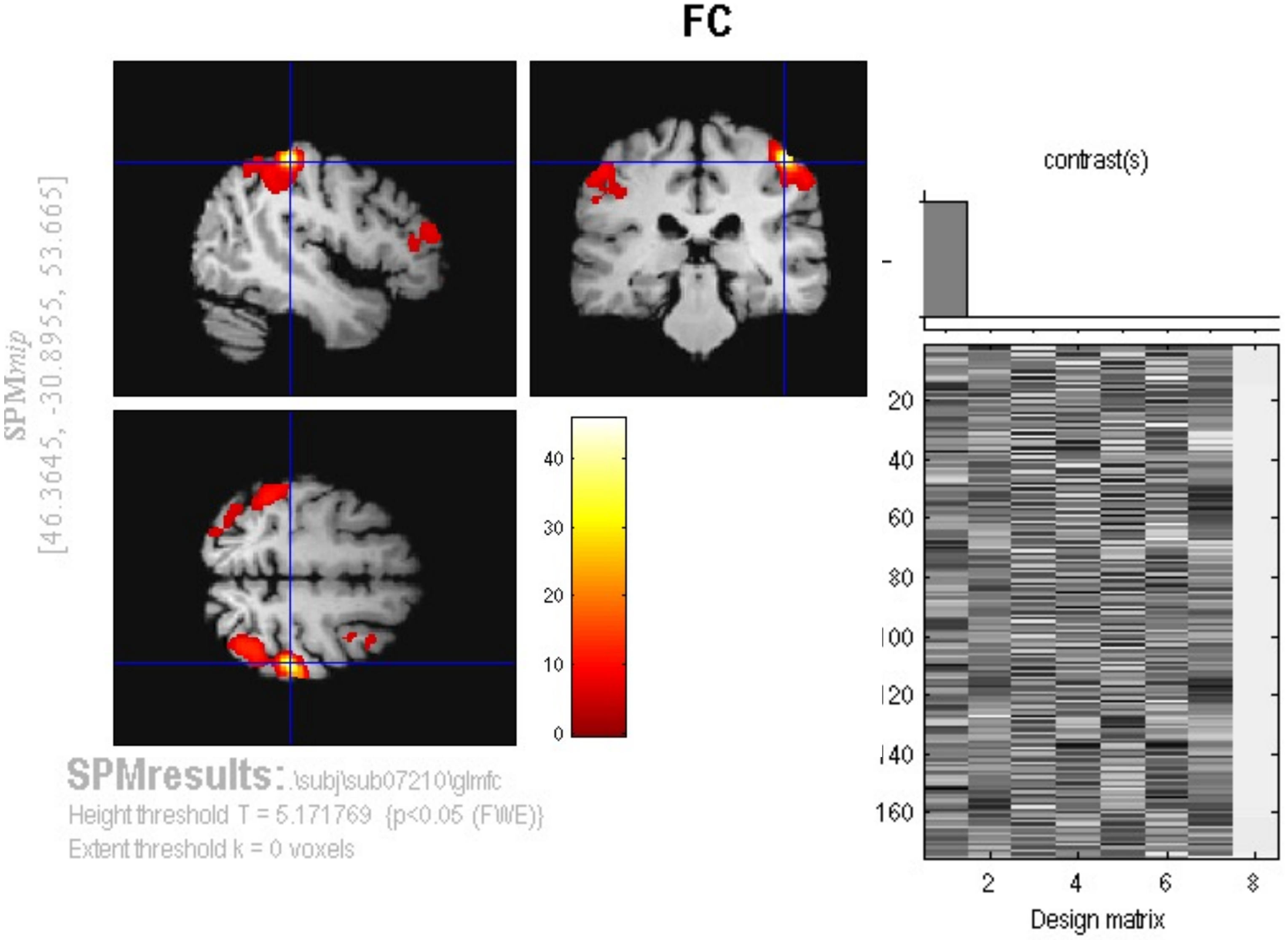
Voxel

$$=$$



Seed

$$*\beta$$



Data analysis- Functional connectivity(model-based)

ROI-wised/network-wised FC

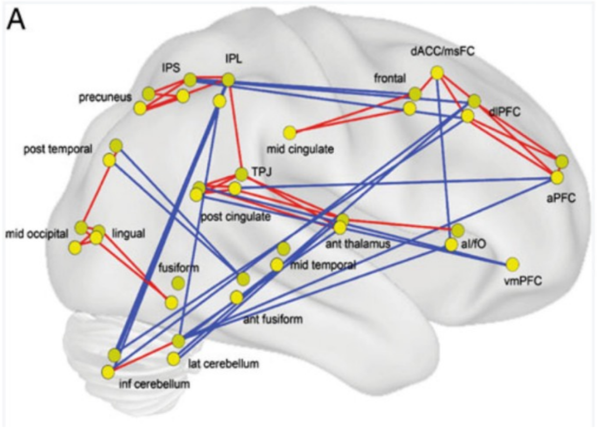


Figure is adopted from Vogel et al., 2010

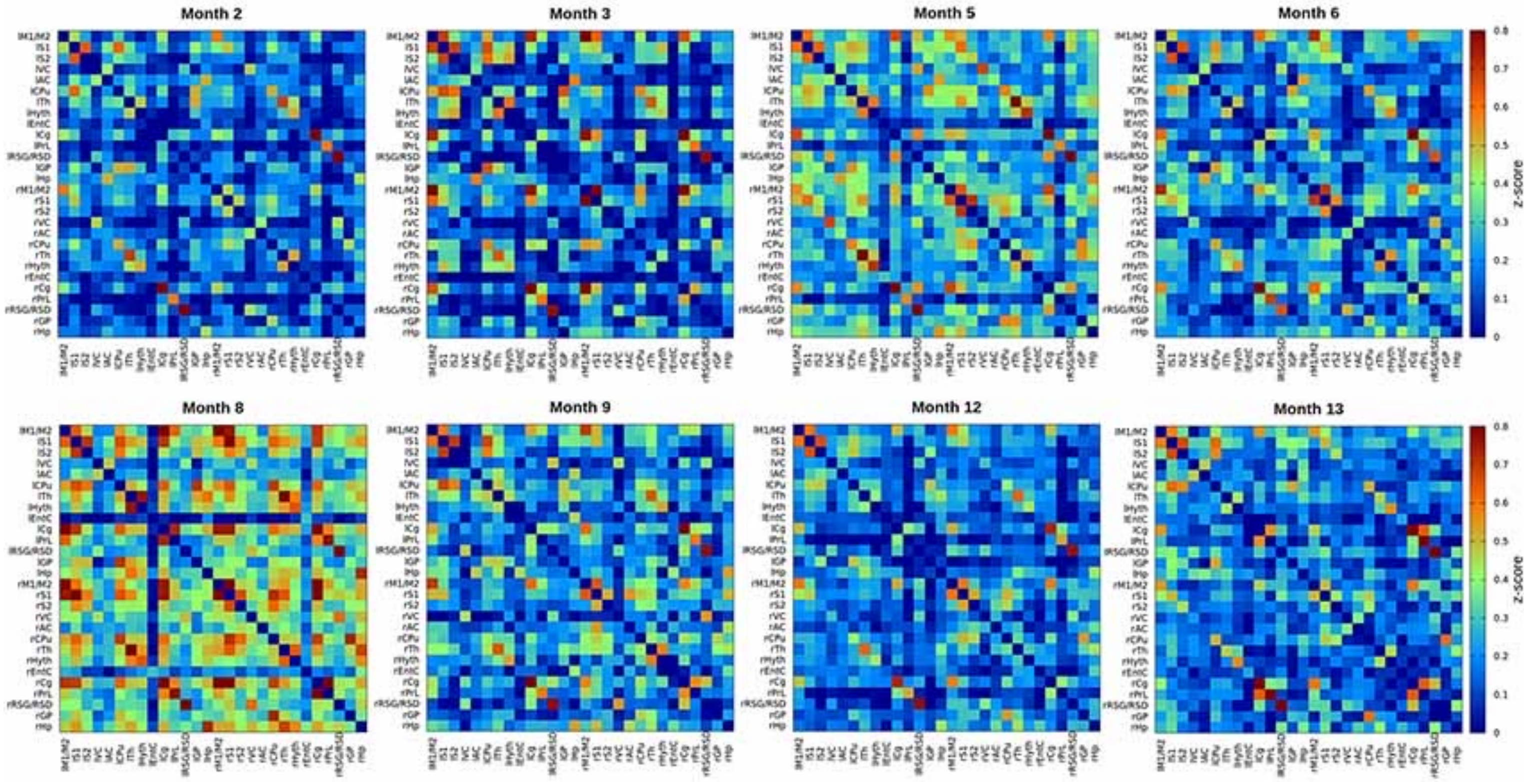
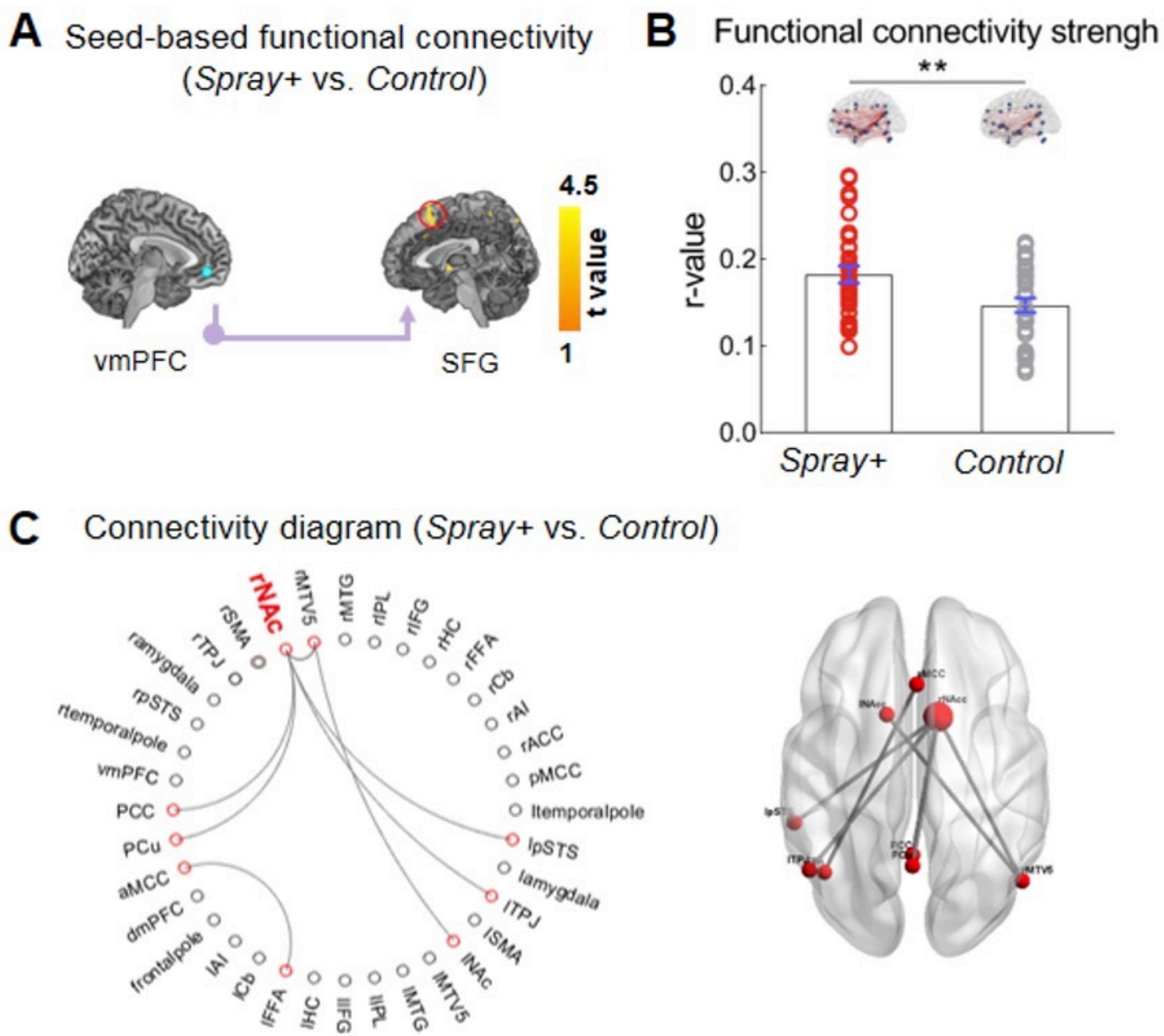


Figure is adopted from Egimendia et al., 2019
(rodents' resting-state, 9.7T scanner)

Data analysis- Functional connectivity(model-based)

Network-based statistics



By Xinyuan Yan
(unpublished figure)

Network-Based Statistic (NBS)

Visit Website

Matlab toolbox for testing hypotheses about the human connectome. NBS has been widely used to identify connections and networks comprising the connectome that are associated with an experimental effect or a between-group difference. User provides a series of connectivity matrices from different cohorts, or from the same subject during different conditions. Connectivity matrices are inferred from neuroimaging data using packages that, for example, count the number of tractography streamlines that interconnect each pair of regions (diffusion-MRI), or measure the extent of correlation in BOLD response (fMRI). User specifies hypothesis with the GLM. Features include: graphical user interface; NBSview, a basic network viewer modeled on SPMresults; exchange blocks for repeated measures. Developed by Zalesky, Fornito, Cocchi & Bullmore.

- NBS extension for directed networks by Max von Gellhorn (NBSDirected.zip).

- R package for NBS by Zeus Gracia-Tabuenca: https://cran.r-project.org/web/packages/...

https://www.nitrc.org/projects/nbs/

Data analysis- Dynamic functional connectivity (model-based)

https://pubmed.ncbi.nlm.nih.gov › ...

Tracking whole-brain connectivity dynamics in the resting state

by EA Allen · 2014 · Cited by 1662 — In this work, we describe an approach to assess **whole-brain** FC **dynamics** based on spatial independent component analysis, sliding time window correlation, and k-means clustering of windowed correlation matrices. The method is applied to **resting-state** data from a large sample (n = 405) of young adults.

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DOI: 10.1002/hbm.23890

RESEARCH ARTICLE

WILEY

Chronnectome fingerprinting: Identifying individuals and predicting higher cognitive functions using dynamic brain connectivity patterns

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2.4 | Dynamic characteristic measurements

To quantitatively describe the time-varying characteristics of the functional connectivities, we calculated three measurements, including DFC mean strength (DFC-Str), DFC stability (DFC-Sta) and DFC variability (DFC-Var), for each functional connectivity as follows:

$$\text{DFC-Str}\ (i,j)=\frac{1}{T}\sum_{t=1}^{T} r_{(i,j)t} \tag{1}$$

$$\text{DFC-Sta}\ (i,j)=1-\frac{1}{(T-1)}\sum_{t=1}^{T-1}\frac{|r_{(i,j)(t+1)}-r_{(i,j)t}|}{2} \tag{2}$$

$$\text{DFC-Var}\ (i,j)=\frac{1}{F}\sum_{F_i=1}^{F} A_{f(i,j)} \tag{3}$$

Data analysis- Dynamic functional connectivity (model-based)

Sliding window

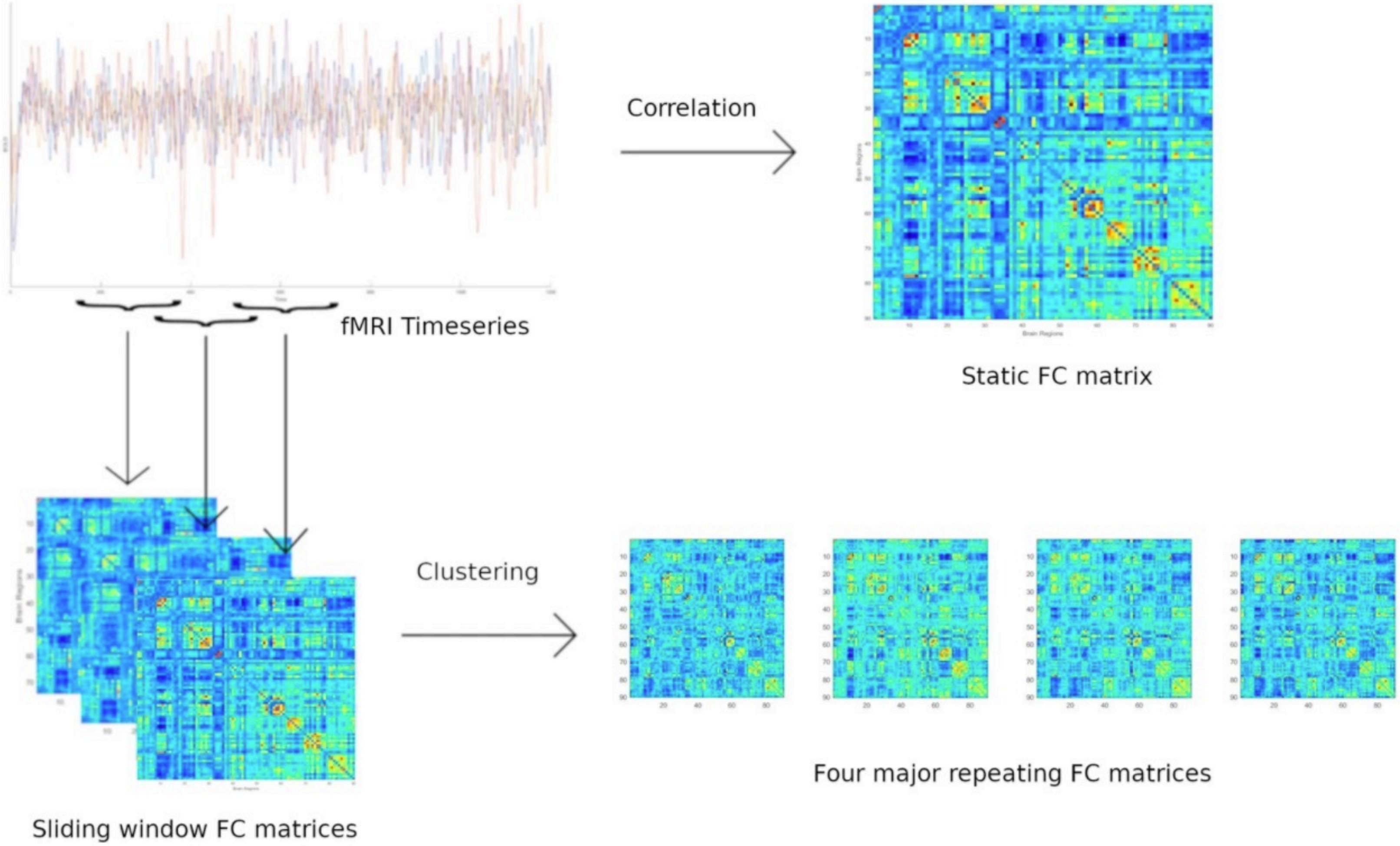
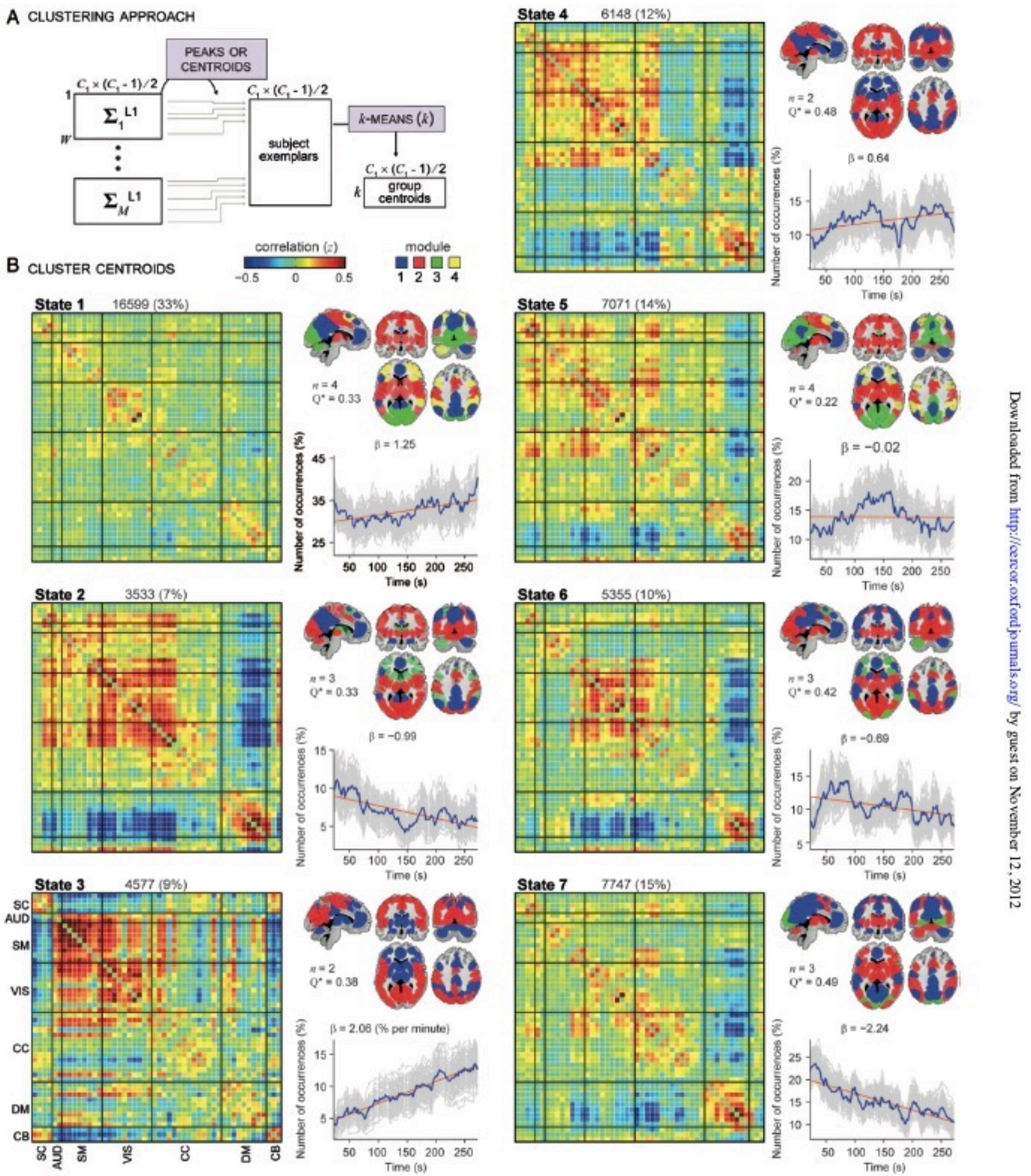


Figure is adopted from Menon et al., 2019

Data analysis- Dynamic functional connectivity (model-based)



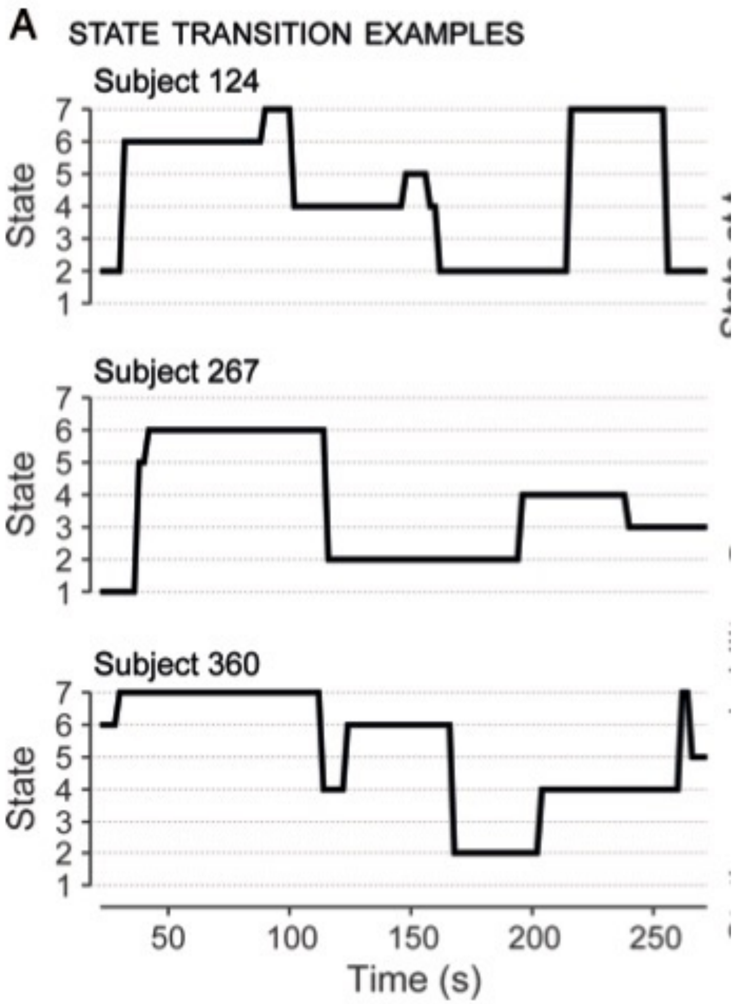


Figure is adopted from Allen et al., 2014

Data analysis- ICA (Independent component analysis; model-free)

https://onlinelibrary.wiley.com › doi › full › hbm

A method for making group inferences from functional MRI ...

by VD Calhoun · 2001 · Cited by 2451 — Abstract Independent component analysis (**ICA**) is a promising analysis ... are met [**Calhoun et al., 2001b**; McKeown and Sejnowski, 1998].

INTRODUCTION · THEORETICAL... · EXPERIMENTS AND... · DISCUSSION

ICA methods are designed to search for a mixture of underlying sources that can explain the resting- state patterns

Looking for the existence of spatial sources of resting-state signals that are maximally independent from each other.

Tools (recommended)
Group ICA of fMRI ToolBox; GIFT (https://www.nitrc.org/projects/gift)

Data analysis- ICA (Independent component analysis; model-free)

https://pubmed.ncbi.nlm.nih.gov › ...

Tracking whole-brain connectivity dynamics in the resting state

by EA Allen · 2014 · Cited by 1662 — In this work, we describe an approach to assess **whole-brain** FC **dynamics** based on spatial inde
correlation, and k-means clustering of winc
resting-state data from a large sample (n
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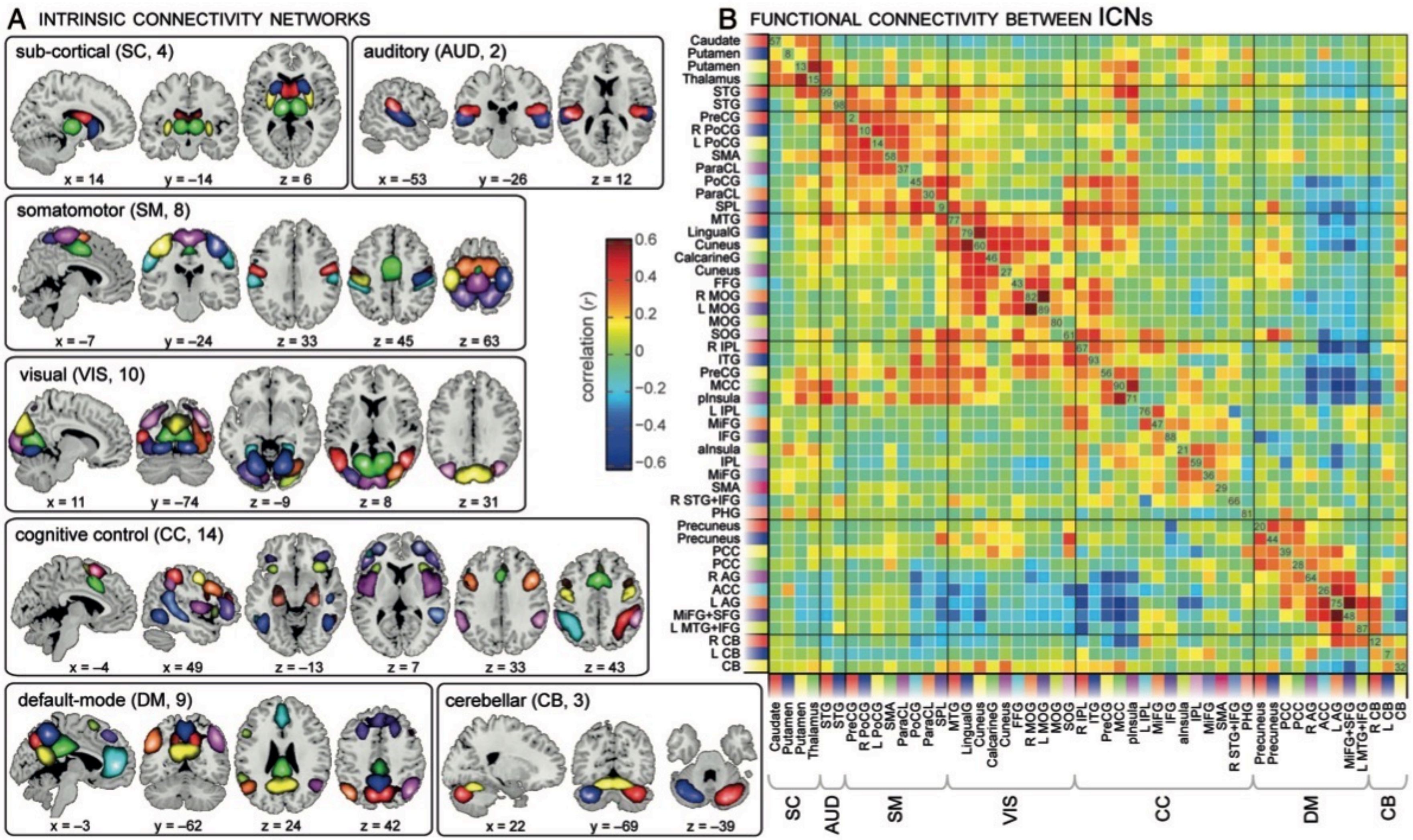


Figure is adopted from Allen et al., 2014

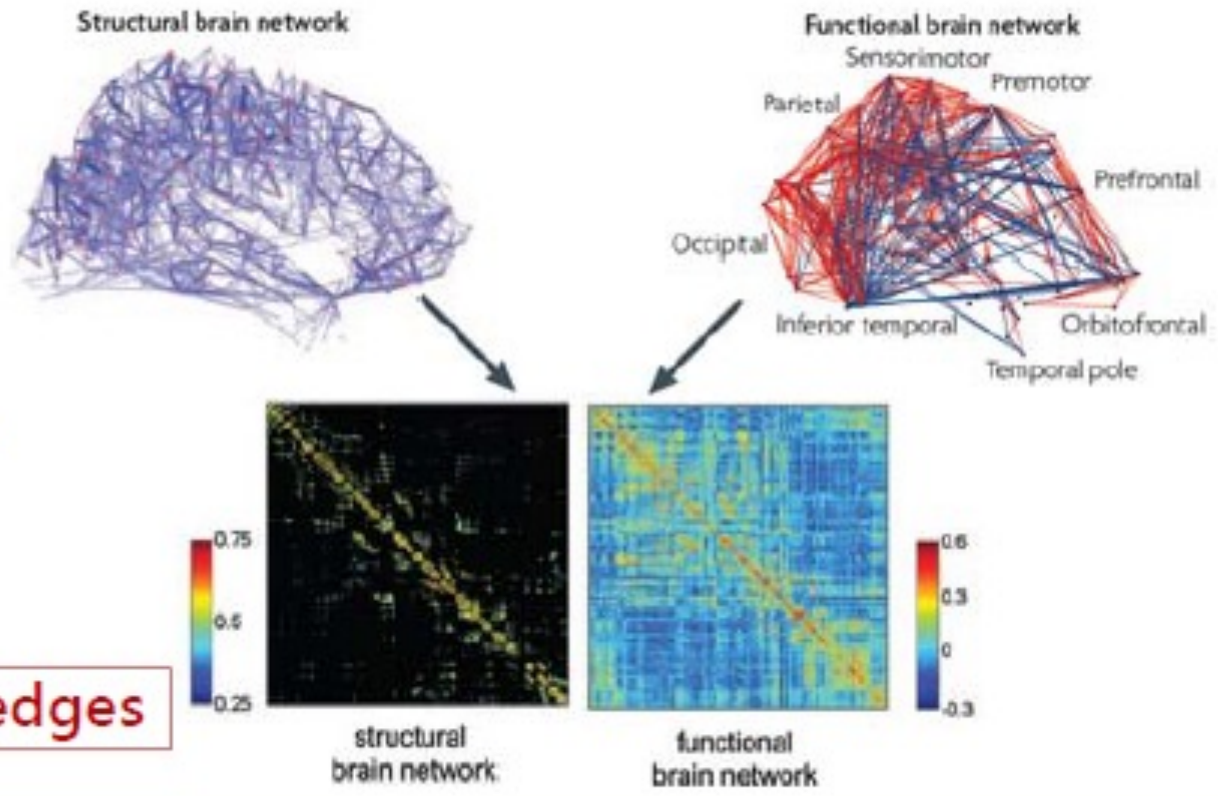
Data analysis-graph theory

Graph theory based network analysis:

Nodes
- Cortical regions

Edges
- Cortical thickness correlations
- Fiber connections
  - DSI, DTI, transneuronal tracers
- Functional connectivity
  - fMRI, EEG, MEG

Network = nodes + edges



Data analysis-graph theory

https://www.sciencedirect.com › science › article › pii

Complex network measures of brain connectivity: Uses and ...

by M Rubinov · 2010 · Cited by 7396 — We describe **measures** that variously detect functional integration and segregation, quantify centrality of individual **brain** regions or pathways, characterize patterns of local anatomical circuitry, and test resilience of **networks** to insult.

Table A1
Mathematical definitions of complex network measures (see supplementary information for a self-contained version of this table).

Measure	Binary and undirected definitions	Weighted and directed definitions
Basic concepts and measures		
Basic concepts and notation	N is the set of all nodes in the network, and n is the number of nodes. L is the set of all links in the network, and l is number of links. (i, j) is a link between nodes i and j, $(i, j \in N)$. a_{ij} is the connection status between i and j: $a_{ij} = 1$ when link (i, j) exists (when i and j are neighbors); $a_{ij} = 0$ otherwise ($a_{ii} = 0$ for all i). We compute the number of links as $l = \sum_{i,j \in N} a_{ij}$ (to avoid ambiguity with directed links we count each undirected link twice, as a_{ij} and as a_{ji}).	Links (i, j) are associated with connection weights w_{ij}. Henceforth, we assume that weights are normalized, such that $0 \le w_{ij} \le 1$ for all i and j. l^w is the sum of all weights in the network, computed as $l^w = \sum_{i,j \in N} w_{ij}$. Directed links (i, j) are ordered from i to j. Consequently, in directed networks a_{ij} does not necessarily equal a_{ji}.
Degree: number of links connected to a node	Degree of a node i, $$k_i = \sum_{j \in N} a_{ij}.$$	Weighted degree of i, $k_i^w = \sum_{j \in N} w_{ij}$. (Directed) out-degree of i, $k_i^{out} = \sum_{j \in N} a_{ij}$. (Directed) in-degree of i, $k_i^{in} = \sum_{j \in N} a_{ji}$.
Shortest path length: a basis for measuring integration	Shortest path length (distance), between nodes i and j, $$d_{ij} = \sum_{a_{uv} \in g_{i \leftrightarrow j}} a_{uv},$$ where $g_{i \leftrightarrow j}$ is the shortest path (geodesic) between i and j. Note that $d_{ij} = \infty$ for all disconnected pairs i, j.	Shortest weighted path length between i and j, $d_{ij}^w = \sum_{a_{uv} \in g_{i \overset{w}{\leftrightarrow} j}} f(w_{uv})$, where f is a map (e.g., an inverse) from weight to length and $g_{i \overset{w}{\leftrightarrow} j}$ is the shortest weighted path between i and j. Shortest directed path length from i to j, $d_{ij}^{\rightarrow} = \sum_{a_{ij} \in g_{i \rightarrow j}} a_{ij}$, where $g_{i \rightarrow j}$ is the directed shortest path from i to j.
Number of triangles: a basis for measuring segregation	Number of triangles around a node i, $$t_i = \frac{1}{2} \sum_{j,h \in N} a_{ij} a_{ih} a_{jh}.$$	(Weighted) geometric mean of triangles around i, $t_i^w = \frac{1}{2} \sum_{j,h \in N} (w_{ij} w_{ih} w_{jh})^{1/3}$. Number of directed triangles around i, $t_i^{\rightarrow} = \frac{1}{2} \sum_{j,h \in N} (a_{ij} + a_{ji})(a_{ih} + a_{hi})(a_{jh} + a_{hj})$.
Measures of integration		
Characteristic path length	Characteristic path length of the network (e.g., Watts and Strogatz, 1998), $$L = \frac{1}{n} \sum_{i \in N} L_i = \frac{1}{n} \sum_{i \in N} \frac{\sum_{j \in N, j \ne i} d_{ij}}{n - 1},$$	Weighted characteristic path length, $L^w = \frac{1}{n} \sum_{i \in N} \frac{\sum_{j \in N, j \ne i} d_{ij}^w}{n - 1}$. Directed characteristic path length, $L^{\rightarrow} = \frac{1}{n} \sum_{i \in N} \frac{\sum_{j \in N, j \ne i} d_{ij}^{\rightarrow}}{n - 1}$.

Data analysis-graph theory

Brain Connectivity Toolbox

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Navigation

- **Home**
  - **Getting started**
  - Latest releases
  - All functions
  - All help headers
- **Network construction**
- **Network measures**
  - List of measures
- **Network models**
- **Network comparison**
  - Network Based Statistic Toolbox
- **Network visualization**
- **Datasets and demos**

About the Brain Connectivity Toolbox

The Brain Connectivity Toolbox (brain-connectivity-toolbox.net) is a MATLAB toolbox for complex-network (graph) analysis of structural and functional brain-connectivity data sets. Several people have contributed to the toolbox and users are welcome to contribute new functions with due acknowledgement.

All efforts have been made to avoid errors, but users are strongly urged to independently verify the accuracy and suitability of individual toolbox functions. Please report bugs or substantial improvements to Olaf Sporns or to Mika Rubinov.

Toolbox contributors

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Andrea Avena-Koenigsberger	AA	
Danielle Bassett	DB	
Richard Betzel	RB	
Nicolas Crossley	NC	

https://sites.google.com/site/bctnet/Home/help

Data analysis-graph theory

Basic Measures

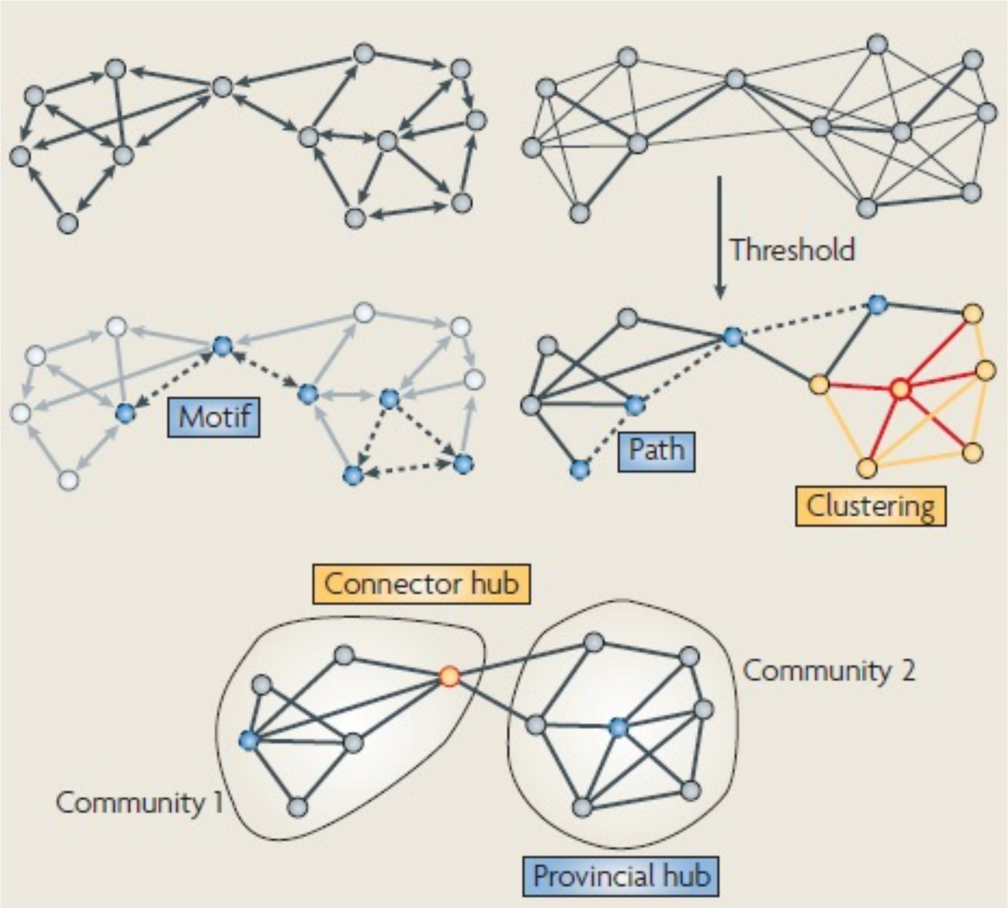
- degree, strength, shortest path length

Measures of integration

- global efficiency

Measures of segregation

- Clustering coefficient, local efficiency, modularity



Data analysis-graph theory

Measures of centrality

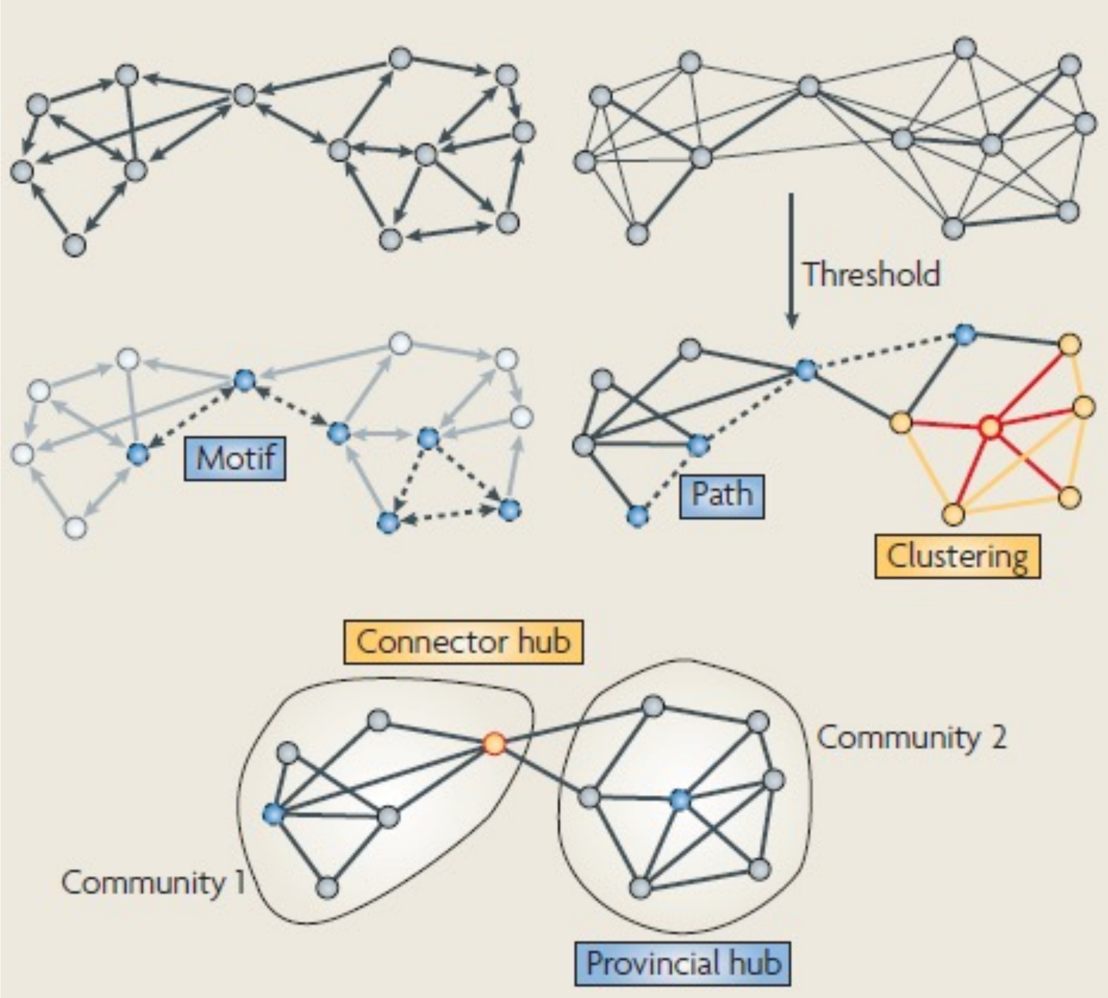
- Betweenness, within-module degree, participation coefficient

Network motifs

Measures of resilience

- Degree distribution, neighbor degree, assortativity coefficient

Network small-worldness



Data analysis-dynamic graph theory

NeuroImage 180 (2018) 417–427

Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/neuroimage

ELSEVIER

Dynamic graph metrics: Tutorial, toolbox, and tale

CrossMark

Ann E. Sizemore [a], Danielle S. Bassett [a,b,*]

[a] Department of Bioengineering, University of Pennsylvania, Philadelphia, PA, 19104, USA

[b] Department of Electrical and Systems Engineering, University of Pennsylvania, Philadelphia, PA, 19104, USA

Data analysis-dynamic graph theory

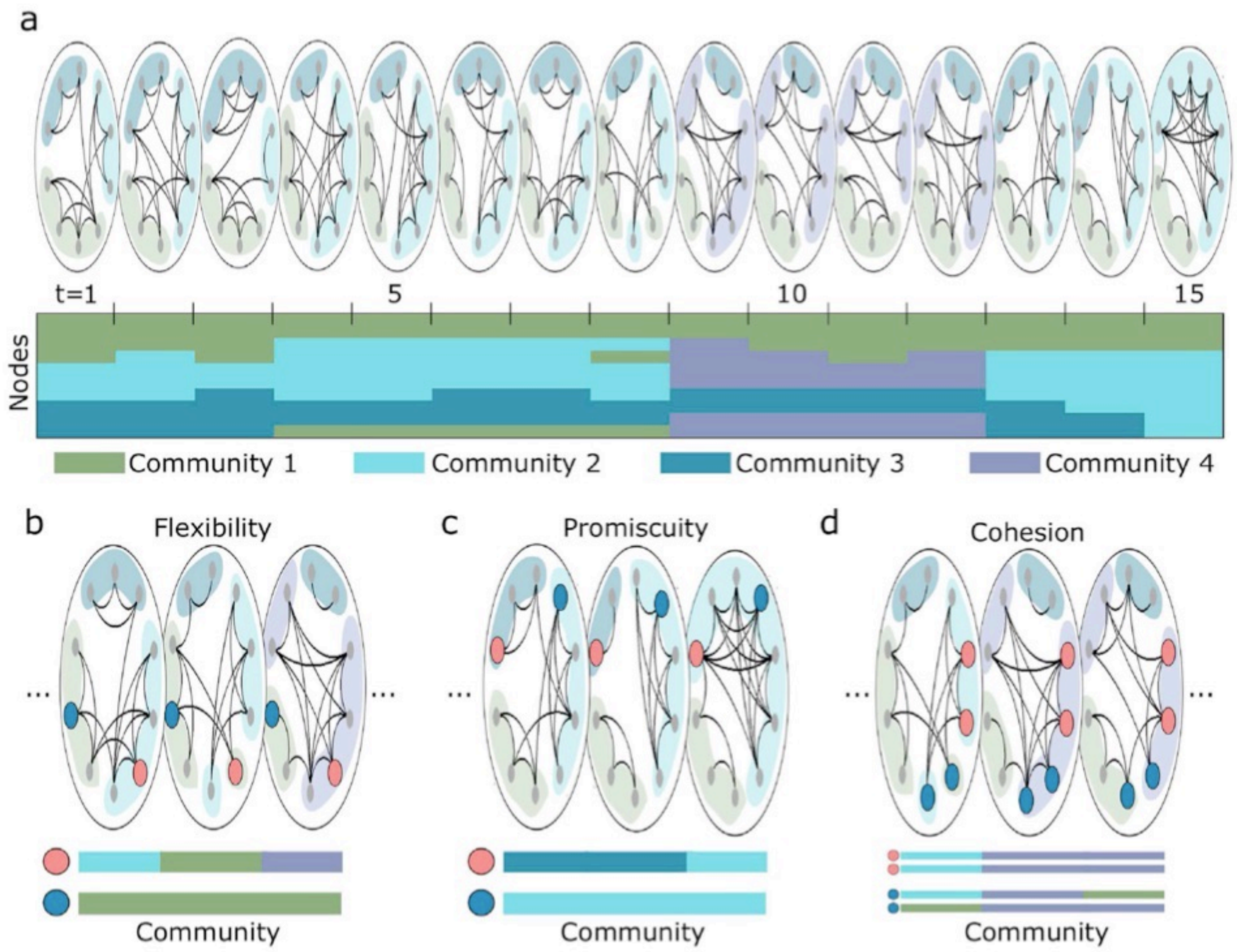


Fig. 5. Measures associated with dynamic community structure. *(a)* Example dynamic network with a community partition: an assignment of nodes to communities (densely intra-connected groups of nodes) as a function of time. Node community assignments are shown both within a sequence of graphs (top), and as a heatmap (bottom). Examples of nodes with high (orange) and low (blue) values for associated metrics: *(b)* flexibility, *(c)* promiscuity, and *(d)* cohesion.

Data analysis-dynamic graph theory

Peter Mucha
https://mucha.web.unc.edu/category/collaborations/

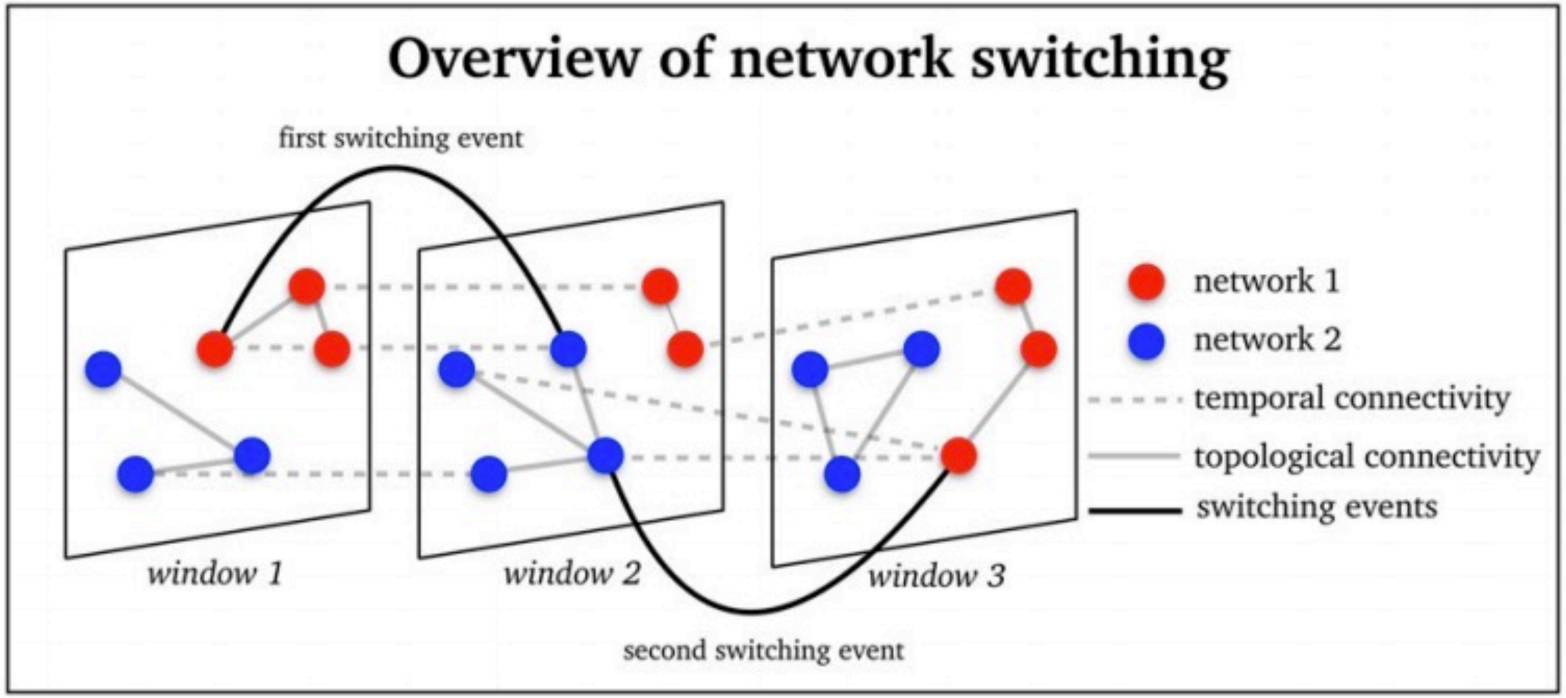
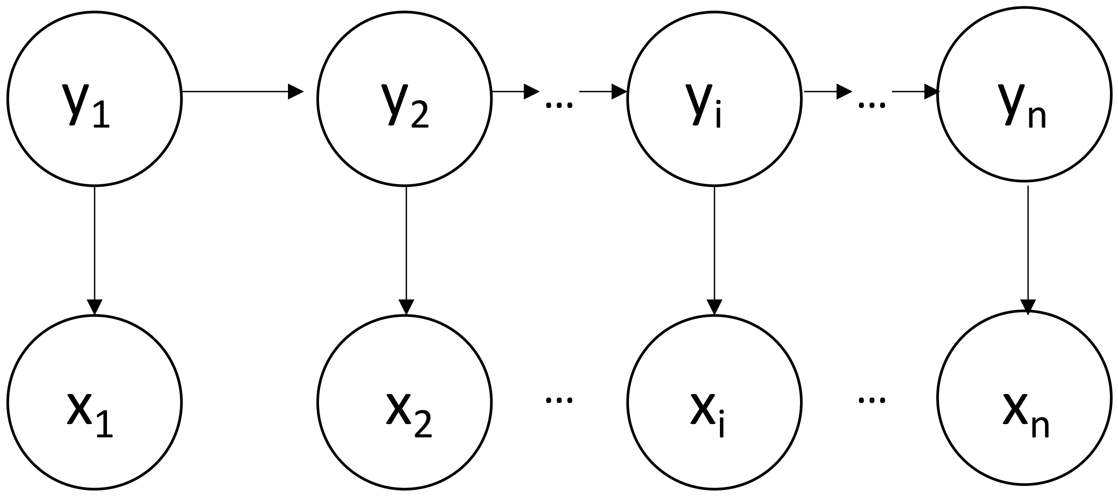


Fig. 1. An overview of network switching within a multilayer modularity network with six nodes and three time windows (window 1, window 2, and window 3) and two modularity partitions (red = network 1; blue = network 2). This example shows two switching events exemplified when node changes between red and blue colors between time points (solid black line between time points). Solid gray lines correspond to within-layer, or topological, connectivity. Dashed gray lines correspond to between layer, or temporal, connectivity.

Pedersen et al., 2018, PNAS

Data analysis-Hidden markov model

Let us define HMM first



Joint distribution

$P(x_1,y_1,\ldots,x_n,y_n) = P(y_1)P(x_1|y_1)\prod_{i=2}^{n} P(y_i|y_{i-1})P(x_i|y_i)$

Details see *simple_HMM.md*

Data analysis-Hidden markov model

SEE COMMENTARY

Check for updates

Brain network dynamics are hierarchically organized in time

Diego Vidaurre[a,1], Stephen M. Smith[b], and Mark W. Woolrich[a,b]

[a]Oxford Centre for Human Brain Activity (OHBA), Wellcome Centre for Integrative Neuroimaging, Department of Psychiatry, University of Oxford, Oxford OX3 7JX, United Kingdom; and [b]Oxford Centre for Functional MRI of the Brain (FMRIB), Wellcome Centre for Integrative Neuroimaging, Nuffield Department of Clinical Neurosciences, University of Oxford, Oxford OX3 9DU, United Kingdom

Edited by Marcus E. Raichle, Washington University in St. Louis, St. Louis, MO, and approved September 28, 2017 (received for review April 3, 2017)

https://www.pnas.org › content

Brain network dynamics are hierarchically organized in time ...

by D Vidaurre · 2017 · Cited by 259 — We find that the transitions between networks are nonrandom, with certain networks more likely to occur after others. Further, this nonrandom sequencing is itself **hierarchically organized**, revealing two distinct sets of networks, or metastates, that the **brain** has a tendency to cycle within.

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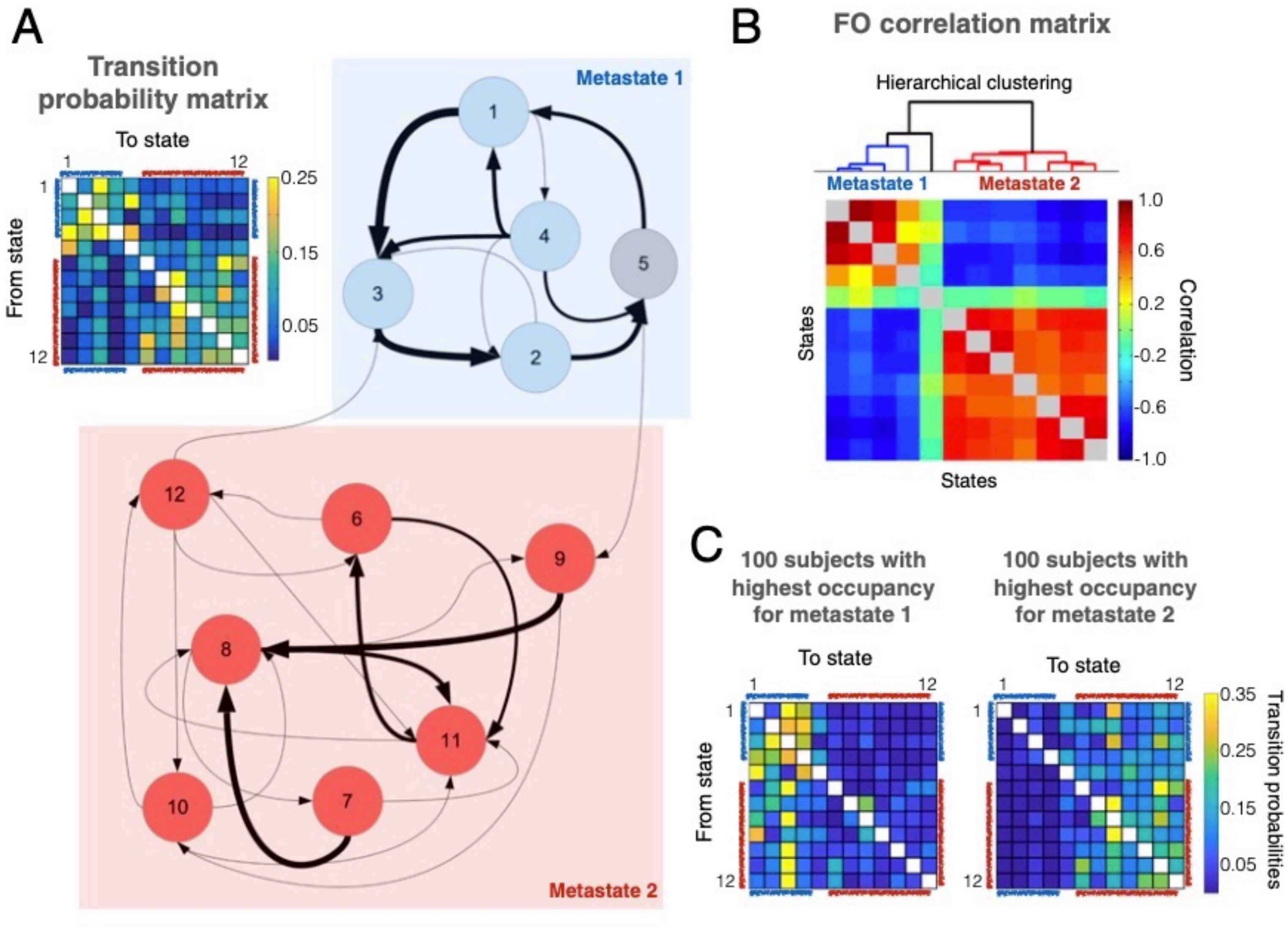
Data analysis-Hidden markov model



Vidaurre et al., 2017, PNAS

Data analysis-Hidden markov model

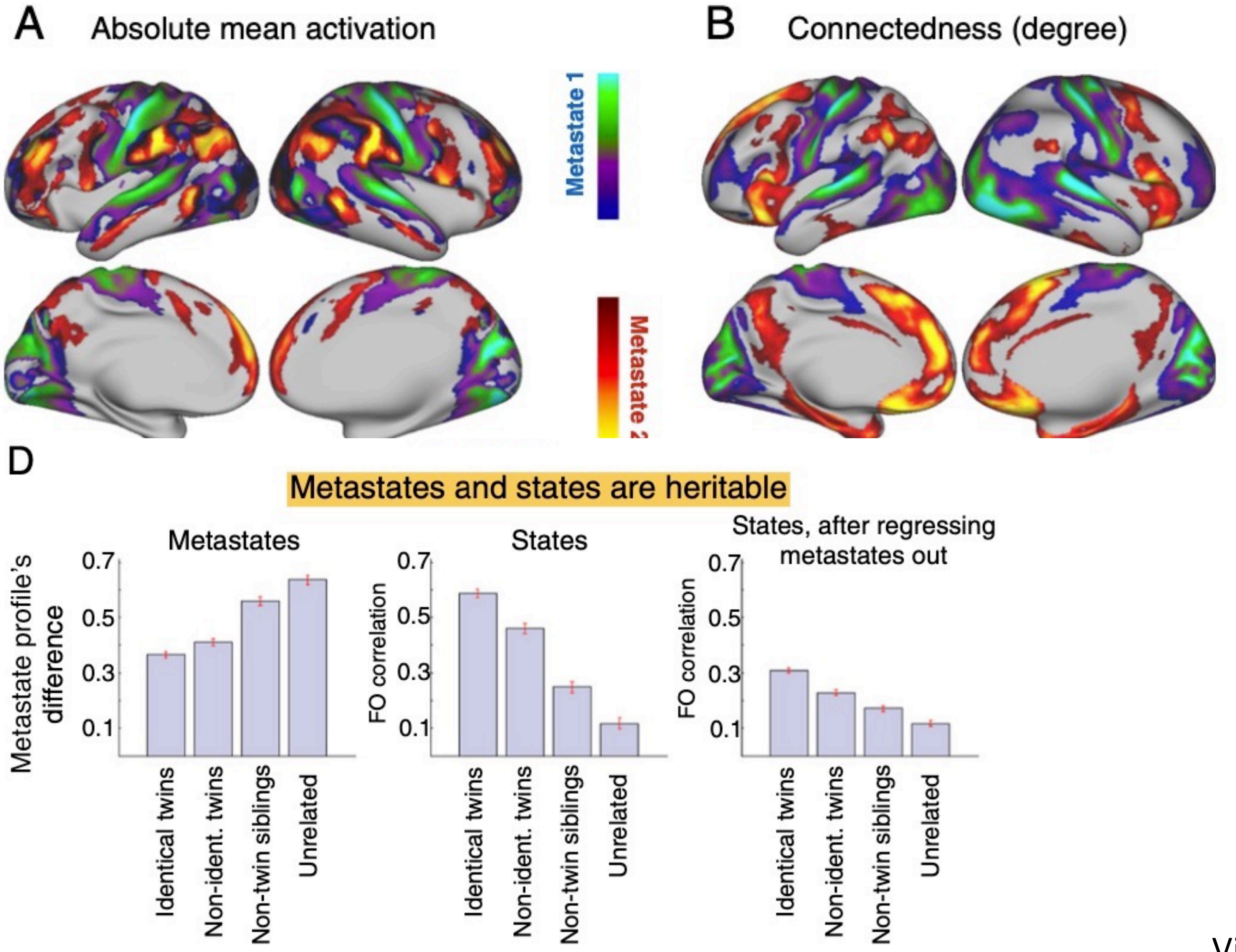
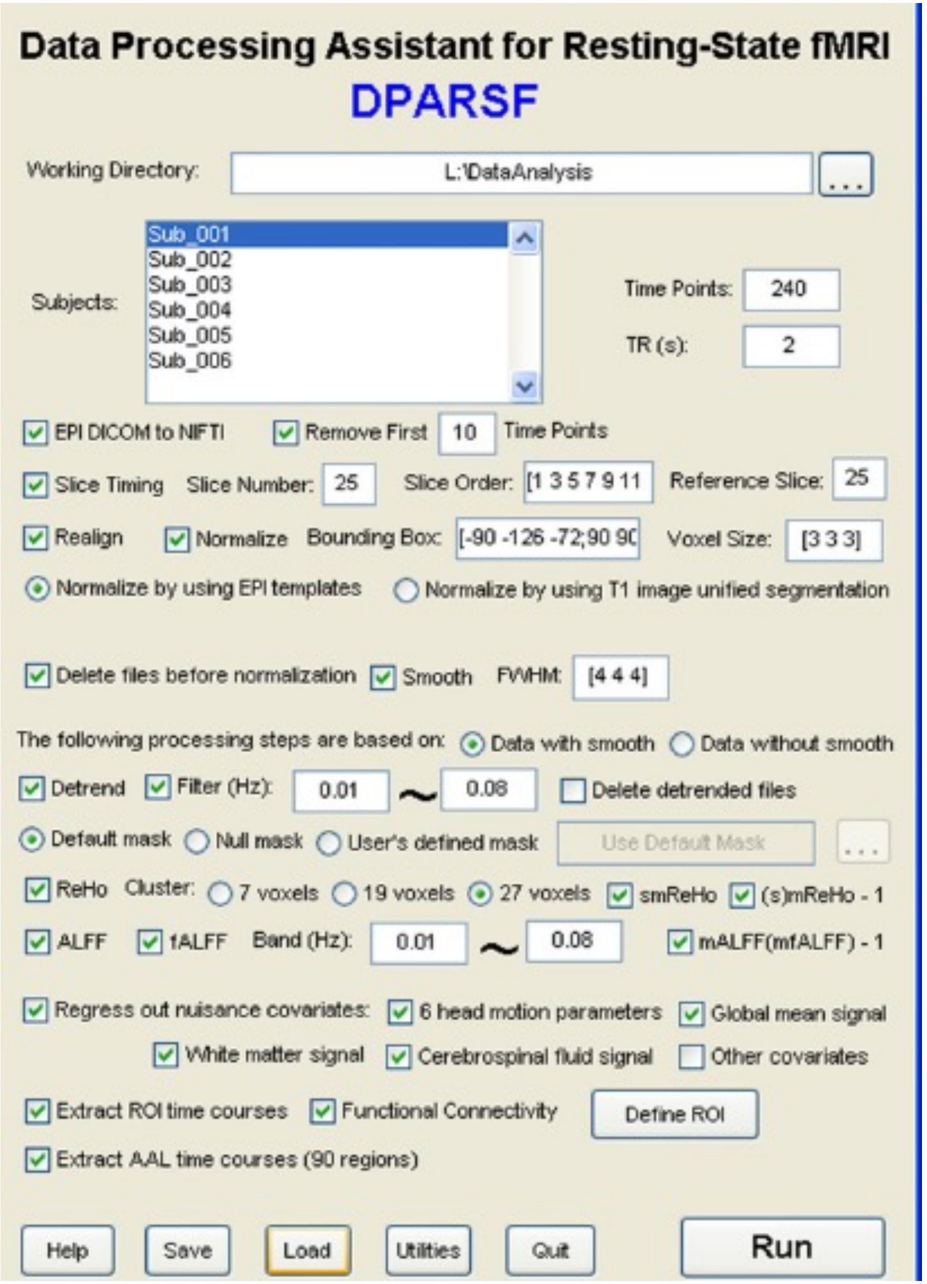


Fig. 3. Two metastates contain distinctive functional areas. Whereas the first metastate is associated with sensory (somatic, visual, and auditory) and motor regions, the second metastate involves areas related to higher order cognition (including regions of the DMN, language, and extensive prefrontal areas). This is apparent in both the activation level and connectivity. (*A*) In the first case, we look at the average absolute amplitude of each region within the metastate, which can be interpreted as a measure of the amount of deviation from average activity levels. (*B*) In the second case, we compute the connectedness, or degree, defined as the sum of functional connectivity of each region with the rest of the brain.

Vidaurre et al., 2017, PNAS

Toolboxes

Toolbox-preprocessing



Toolbox-Functional connectivity & visualization

Conn: A Functional Connectivity Toolbox for Correlated and Anticorrelated Brain Networks

S Whitfield-Gabrieli, A Nieto-Castanon - Brain connectivity, 2012 - online.liebertpub.com

Abstract Resting state functional connectivity reveals intrinsic, spontaneous networks that elucidate the functional architecture of the human brain. However, valid statistical analysis used to identify such networks must address sources of noise in order to avoid possible confounds such as spurious correlations based on non-neuronal sources. We have developed a functional connectivity toolbox Conn (www. nitrc. org/projects/conn) that implements the component-based noise correction method (CompCor) strategy for

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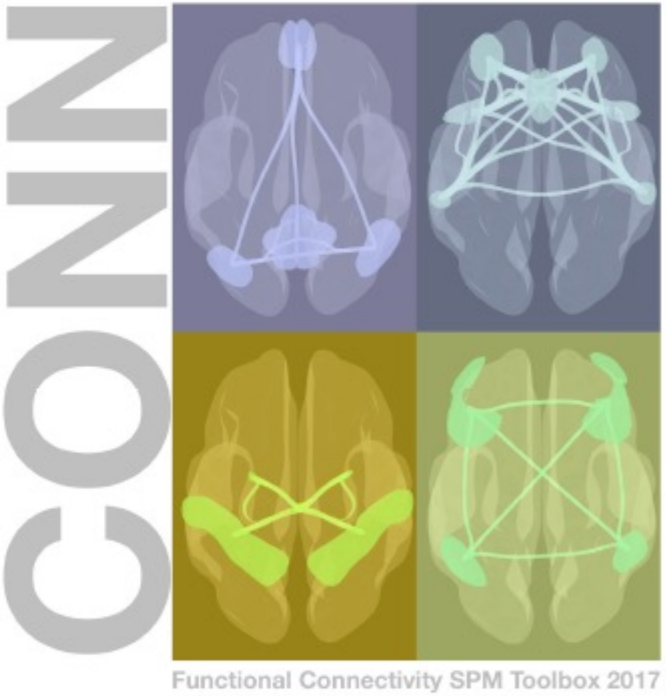
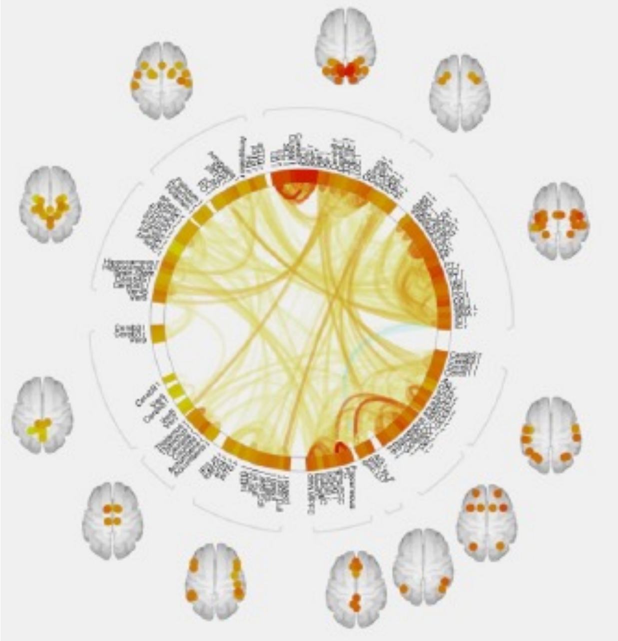
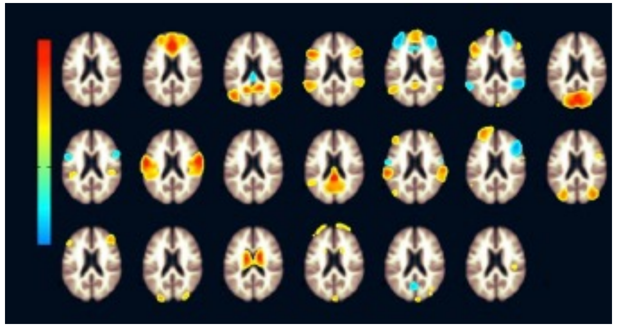


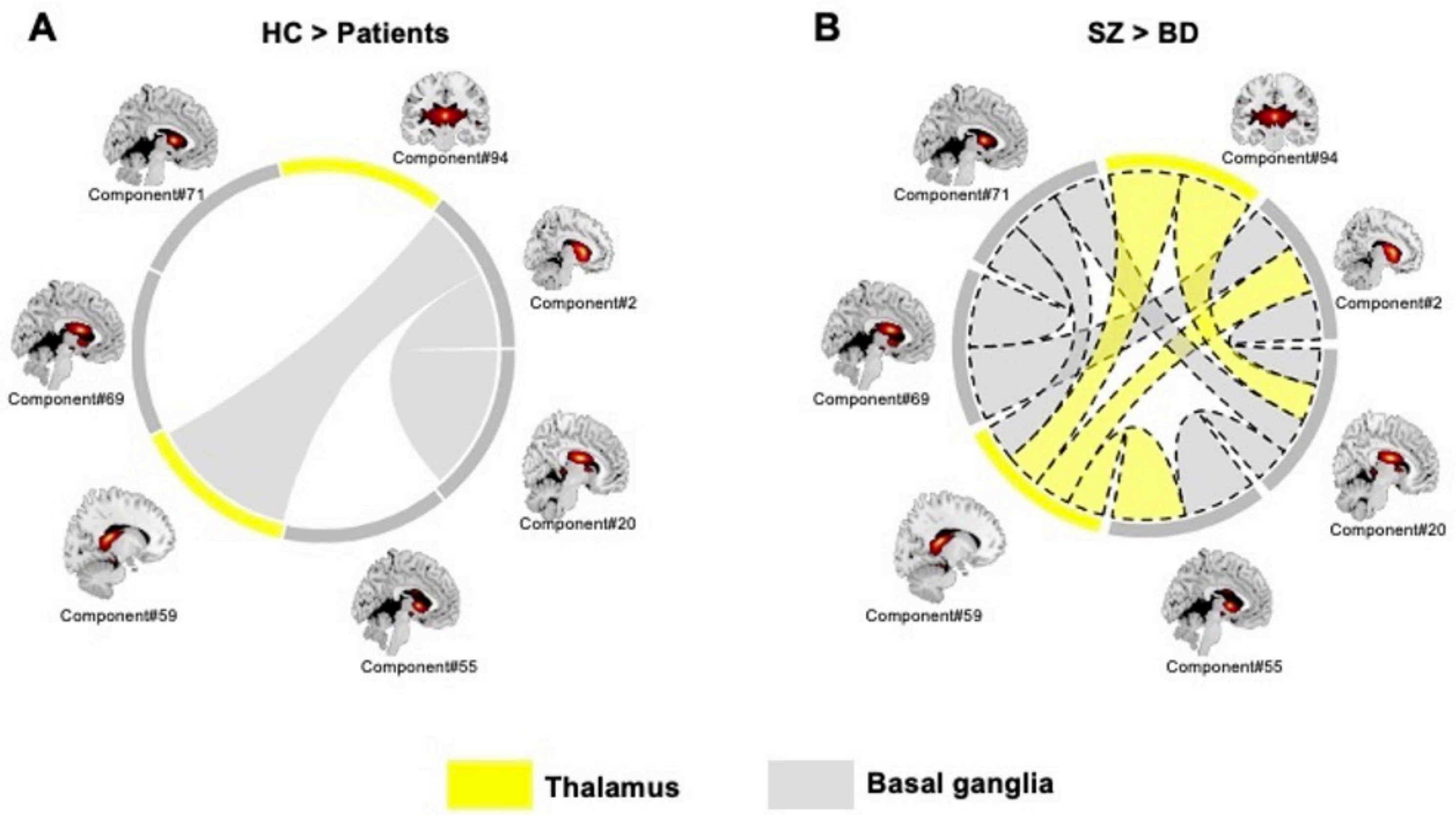
Toolbox-Functional connectivity & visualization





Toolbox-Functional connectivity & visualization

R package *circlize* (https://github.com/jokergoo/circlize)



By Xinyuan Yan
(unpublished figure)

Toolbox-Network Based Statistic Toolbox

https://sites.google.com/site/bctnet/comparison/nbs

Toolbox-graph theory

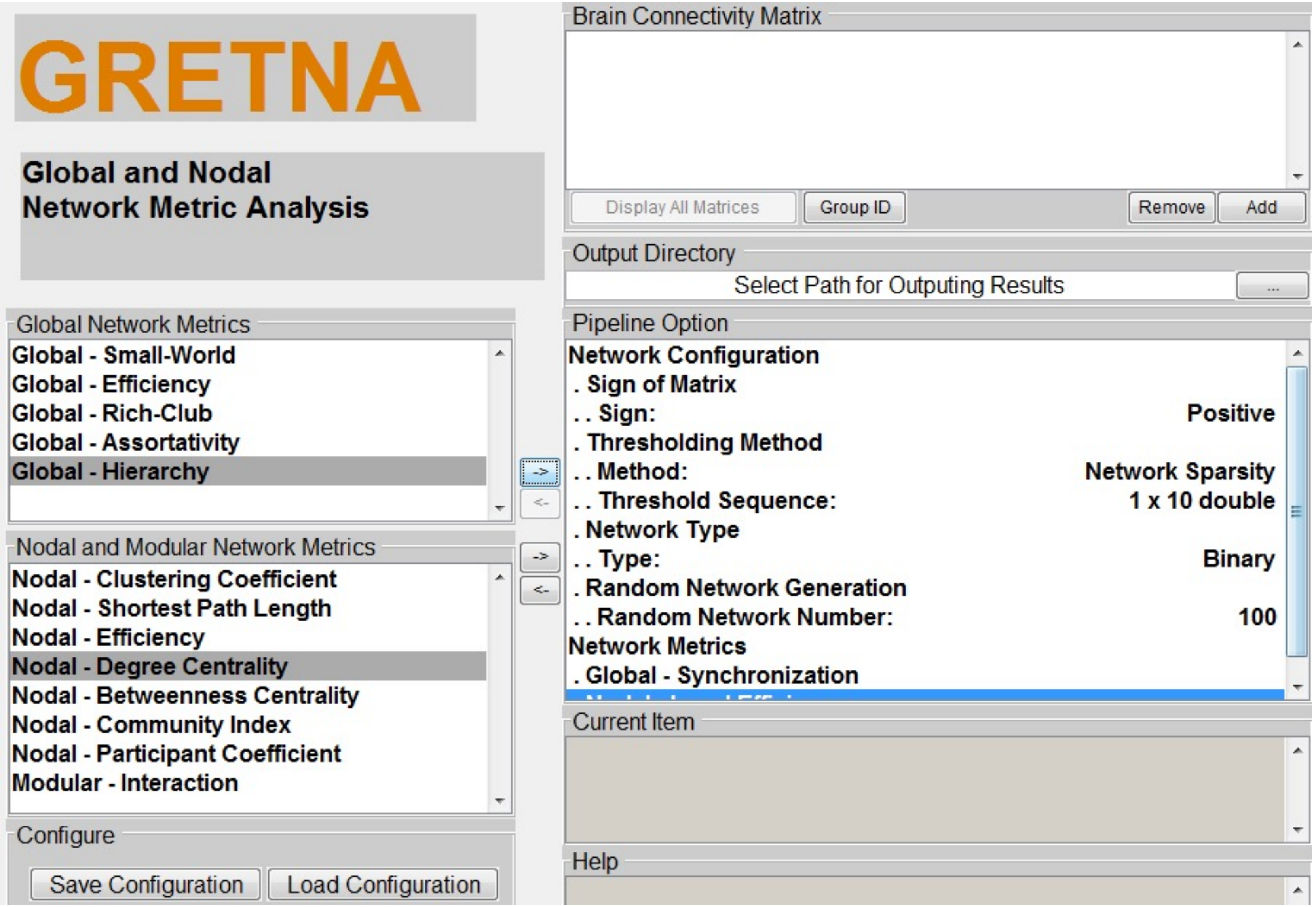
BCT toolbox (http://www.brain-connectivity-toolbox.net)

Complex network measures of brain connectivity: uses and interpretations

M Rubinov, O Sporns - Neuroimage, 2010 - Elsevier

Brain connectivity datasets comprise networks of brain regions connected by anatomical tracts or by functional associations. Complex network analysis—a new multidisciplinary approach to the study of complex systems—aims to characterize these brain networks with a small number of neurobiologically meaningful and easily computable measures. In this article, we discuss construction of brain networks from connectivity data and describe the most commonly used network measures of structural and functional connectivity. We

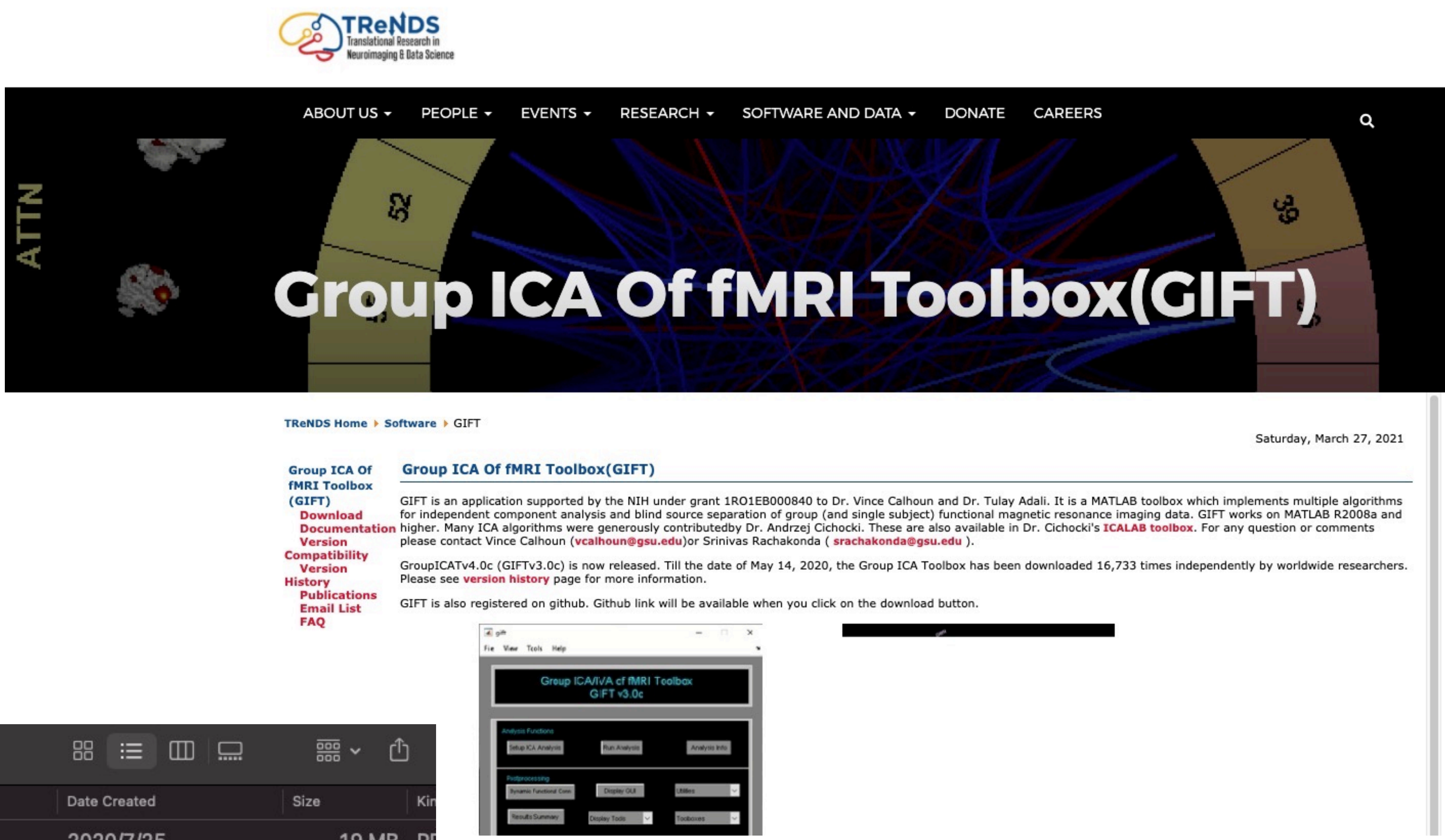
Toolbox-graph theory

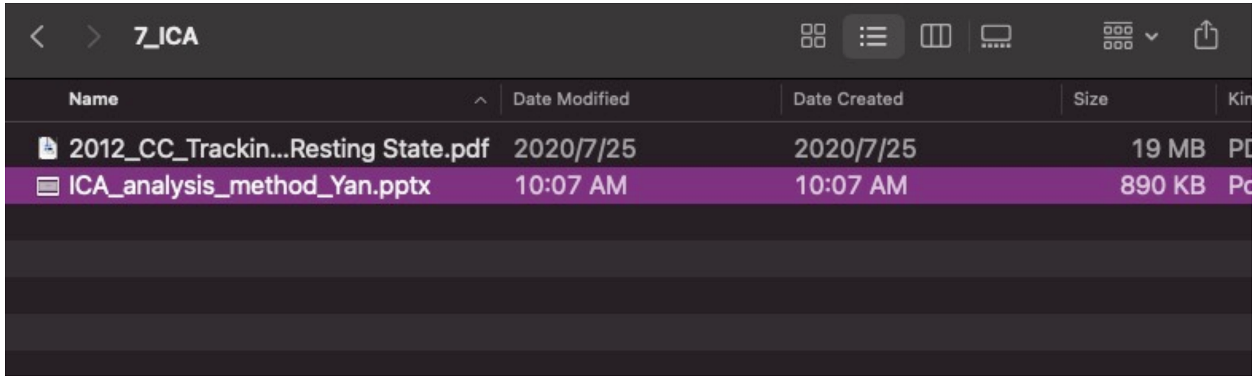


Toolbox-dynamic graph theory

https://github.com/asizemore/Dynamic-Graph-Metrics

Toolbox-ICA and dynamic ICA





https://trendscenter.org/software/gift/

Toolbox-HMM

https://github.com/OHBA-analysis/HMM-MAR

Recommended papers to read

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0_general_resting-state	Yesterday	Yesterday	Zero bytes	Folder
1_preprocessing	Yesterday	Yesterday	6.2 MB	Folder
2_ReHo	Yesterday	Yesterday	1.9 MB	Folder
3_DegreeCentraliy	Yesterday	Yesterday	3.6 MB	Folder
4_ALFF_fALFF	Yesterday	Yesterday	1.7 MB	Folder
5_FC	Yesterday	Yesterday	6 KB	Folder
6_dynamic_FC	9:57 AM	Yesterday	21.5 MB	Folder
7_ICA	10:07 AM	Yesterday	19.9 MB	Folder
8_graph_theory	Yesterday	Yesterday	1.5 MB	Folder
9_dynamic_graphtheory	Yesterday	Yesterday	2.9 MB	Folder
10_HMM	9:57 AM	Yesterday	3.7 MB	Folder

SEW

Thanks for your listening!

Xinyuan Yan

xinyuanyan2016@gmail.com

https://twitter.com/XinyuanYan