# Network Analysis

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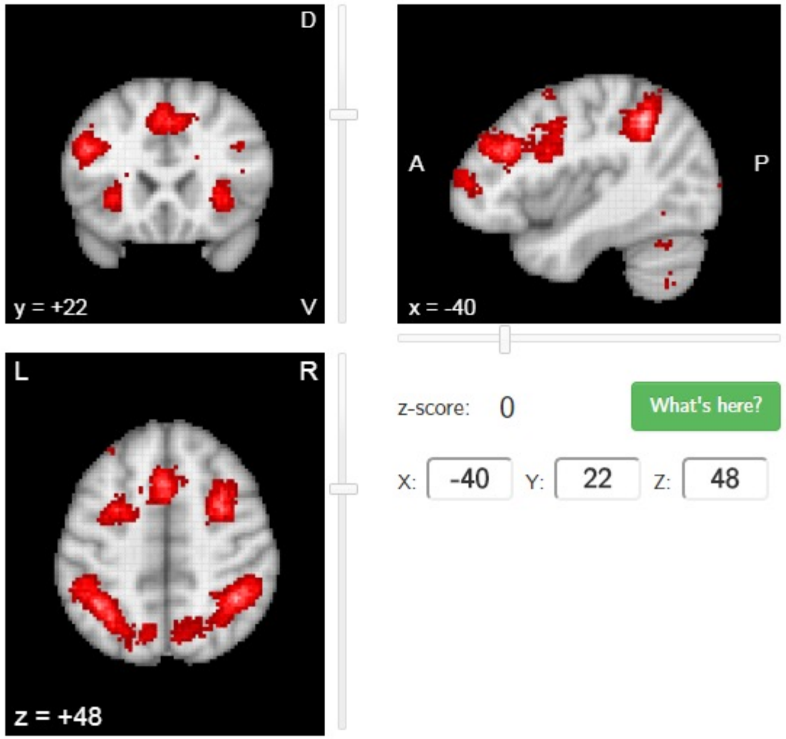
# From brain regions to brain graphs

**Neurosynth – “*working memory*”** → **Network organization of brain areas**

Automated meta-analysis of 901 studies




## The Graph-theoretic Approach

- enables characterization of the brain’s connectivity structure
- derives measures that assess **global** and **local** features that may be important for network function

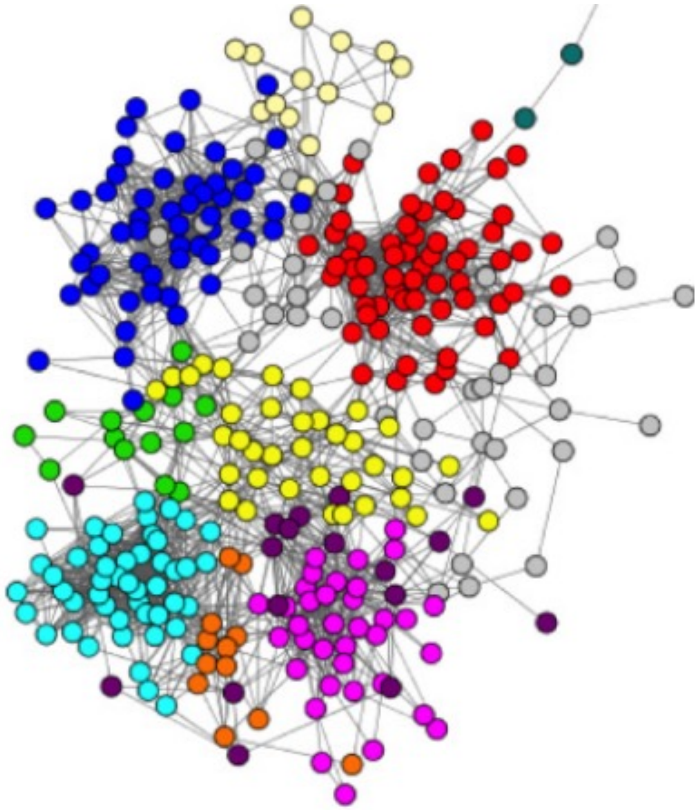
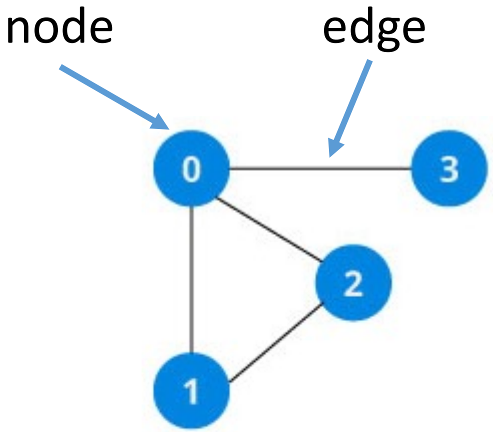


Image: Wig, 2017

# What is a graph?




adjacency matrix

| | 0 | 1 | 2 | 3 |
|---|---|---|---|---|
| 0 | 0 | 1 | 1 | 1 |
| 1 | 1 | 0 | 1 | 0 |
| 2 | 1 | 1 | 0 | 0 |
| 3 | 1 | 0 | 0 | 0 |

- undirected graph –> symmetric matrix
- unweighted graph –> binary matrix
- diagonal is zero

➢ Any network can be represented as a collection of nodes connected by edges.

image: programiz.com

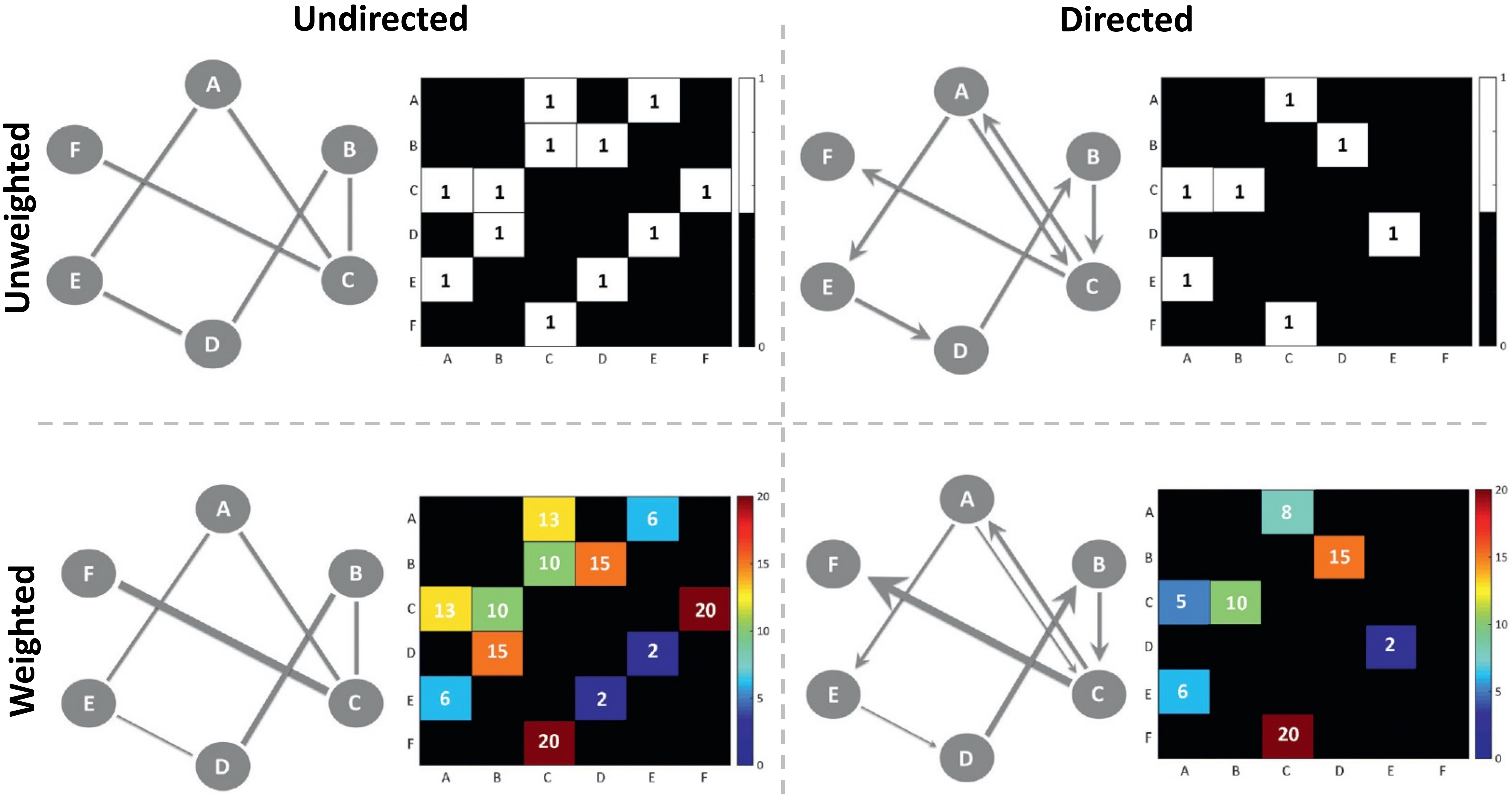
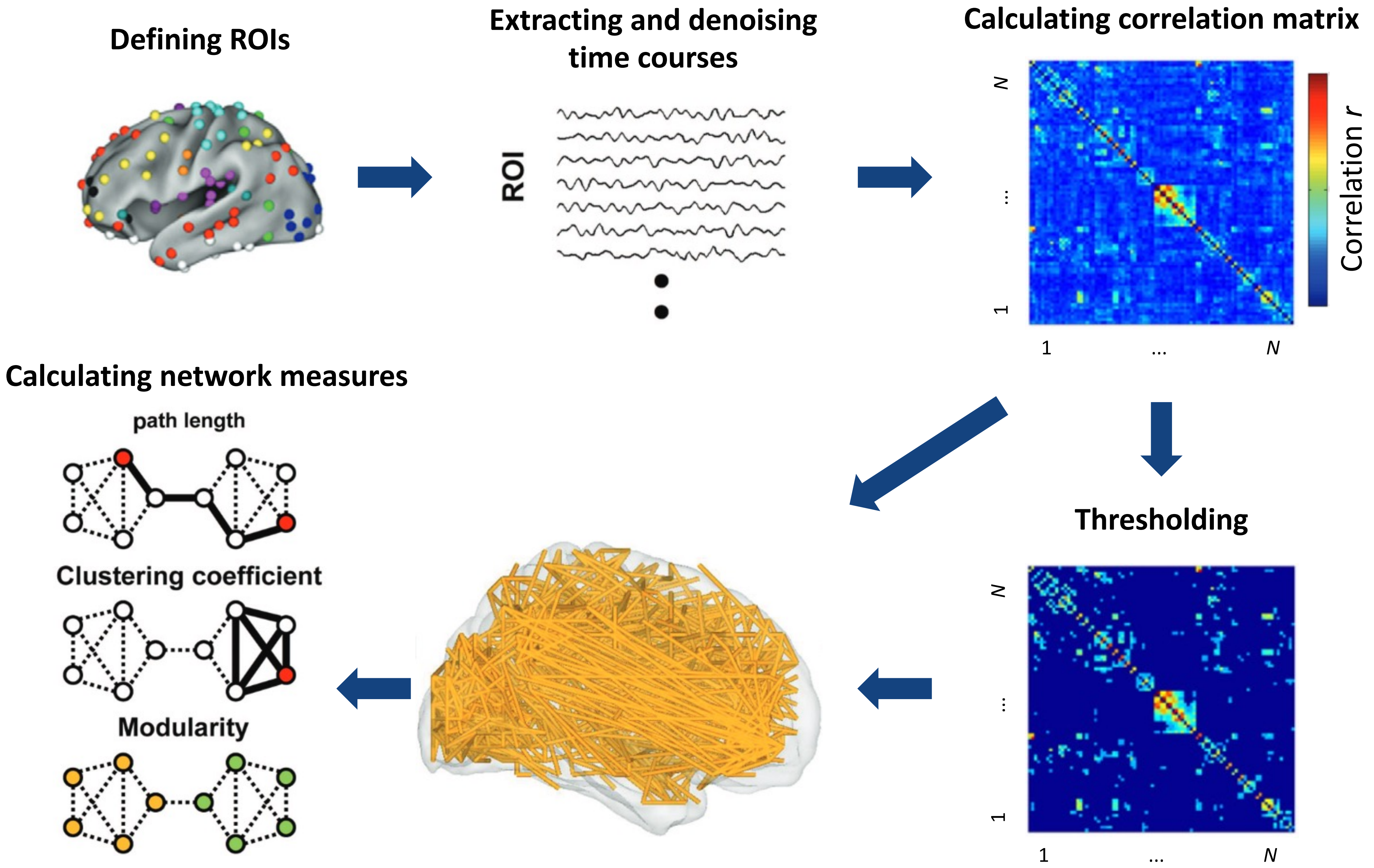



image: Fornito et al., 2016

# Procedure

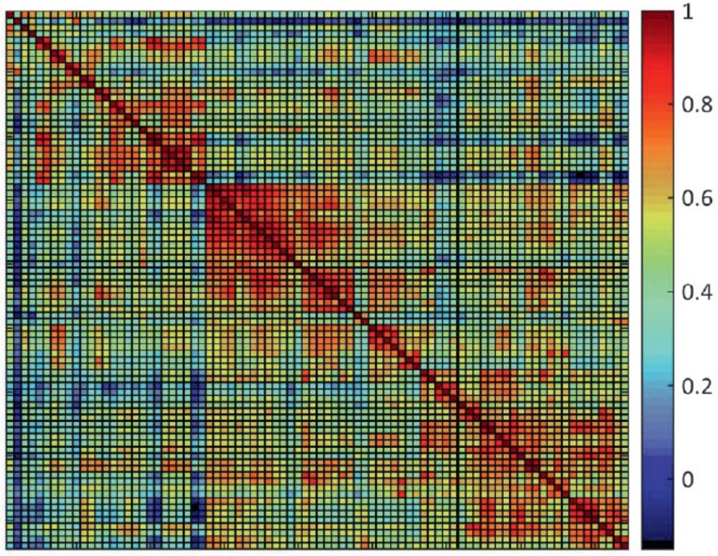



images: Uehara et al., 2013; Taya et al., 2016; Power et al., 2013

# Thresholding and binarizing an adjacency matrix

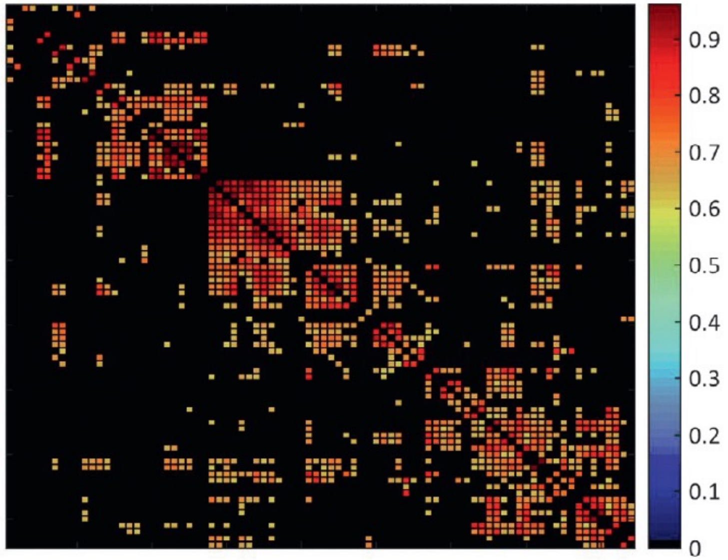
E.g., functional connectivity connectivity data

### Unthresholded



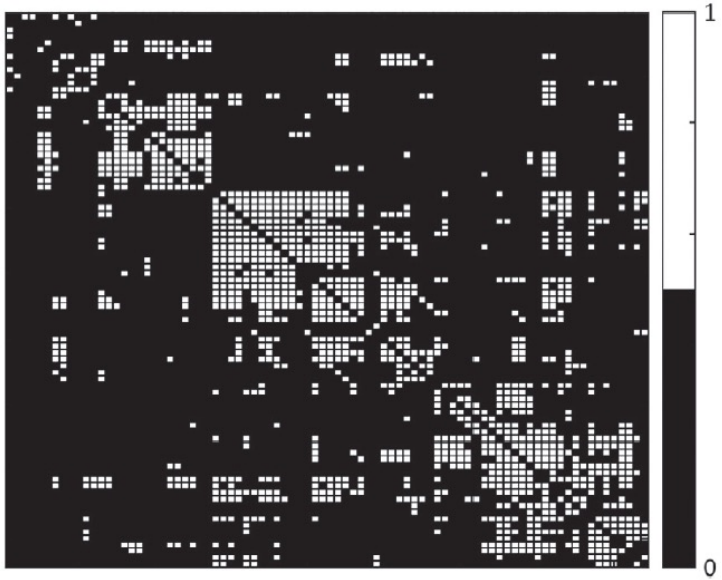

$$C_{ij} = \begin{bmatrix} C_{11} & {\color{red}C_{12}} & {\color{red}\cdots} & {\color{red}C_{1N}} \\ {\color{blue}C_{21}} & C_{22} & & {\color{red}C_{2N}} \\ {\color{blue}\vdots} & & \ddots & {\color{red}\vdots} \\ {\color{blue}C_{N1}} & {\color{blue}C_{N2}} & {\color{blue}\cdots} & C_{NN} \end{bmatrix}$$

### Thresholded




$$A_{ij} = \begin{cases} C_{ij} & \text{if } C_{ij} > \tau, \\ 0 & \text{otherwise} \end{cases}.$$

### Binarized



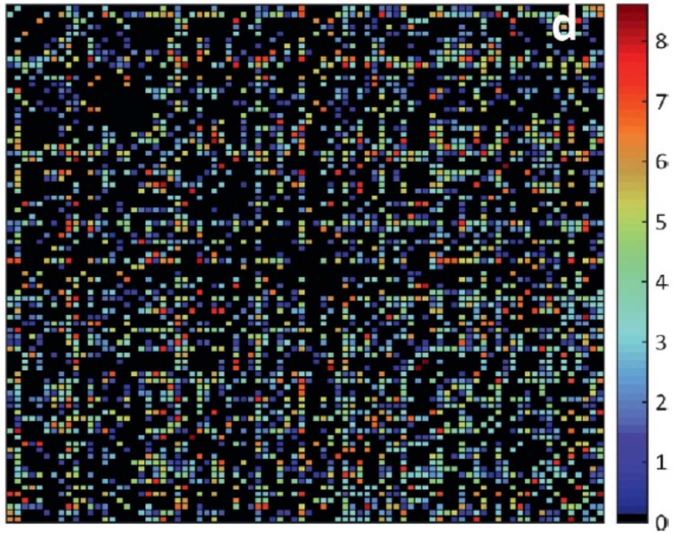

$$A_{ij} = \begin{cases} 1 & \text{if } C_{ij} > \tau, \\ 0 & \text{otherwise} \end{cases}.$$

image: Fornito et al., 2016

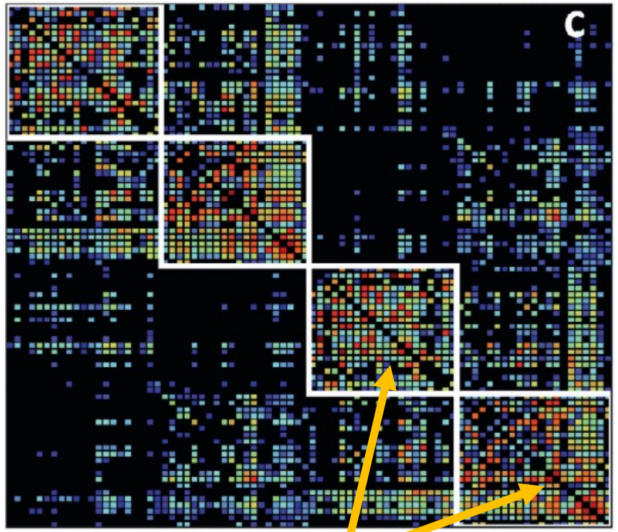
# Visualizing adjacency matrices

E.g., structural connectivity data

Random order

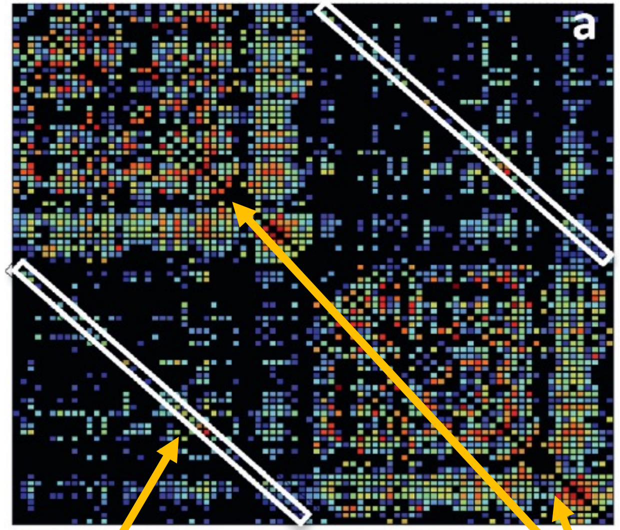



Modular structure




Modules

L vs R hemisphere




Intra-hemispheric connectivity

Connectivity of each region with homologue in the other hemisphere

Anatomical projection

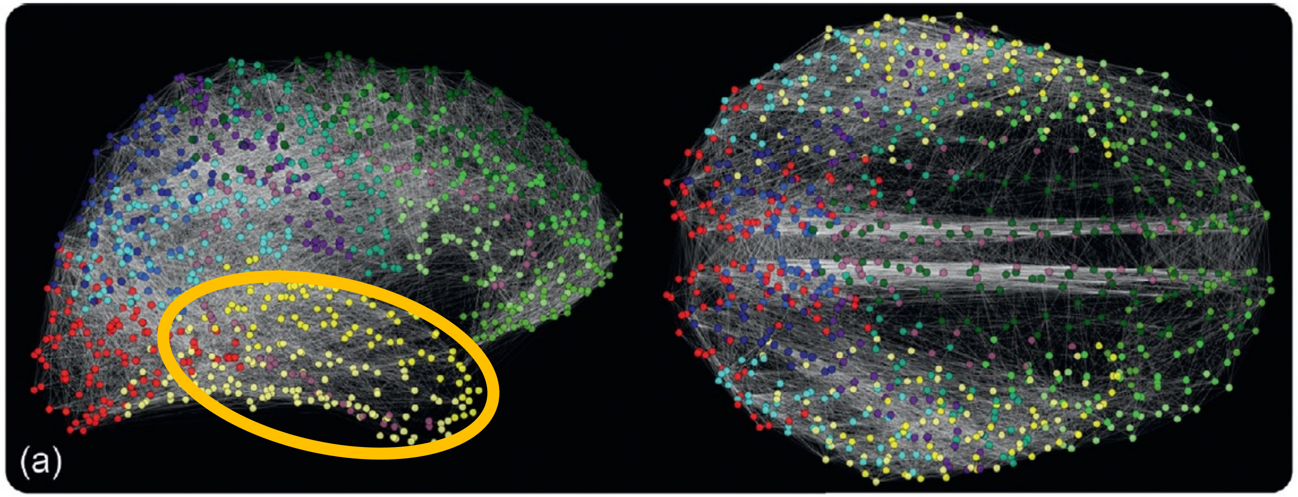
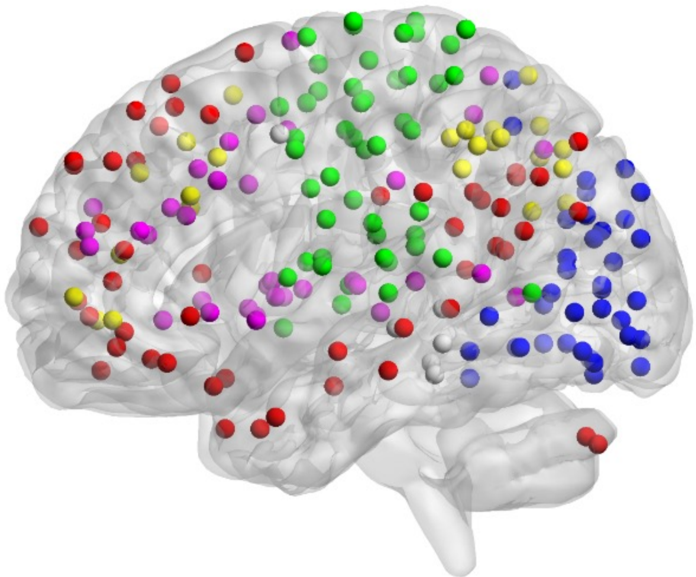


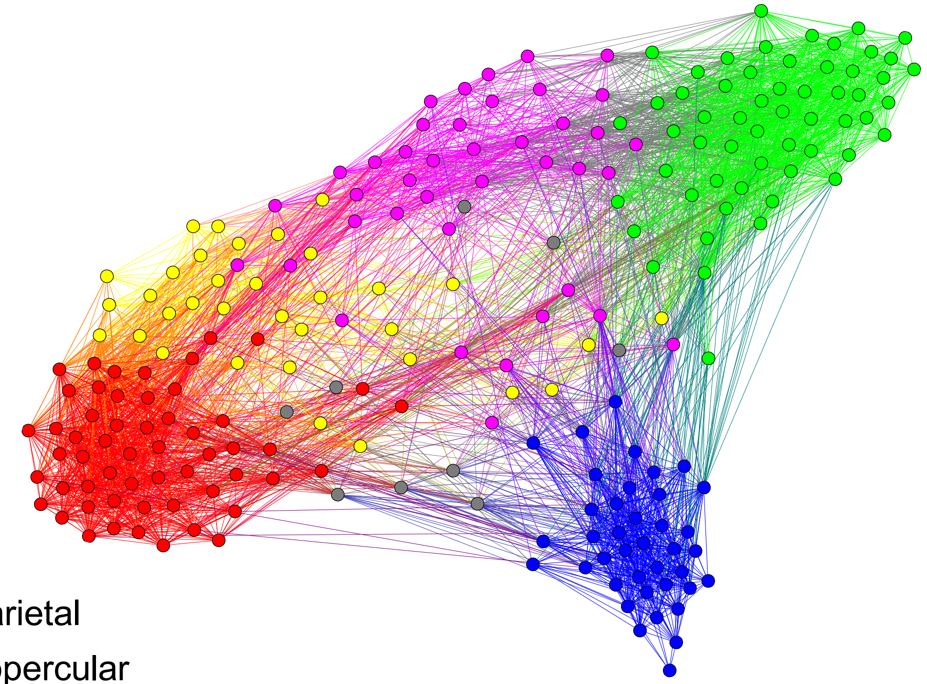

image: Fornito et al., 2016

# Common types of visualizations

## Anatomical projection

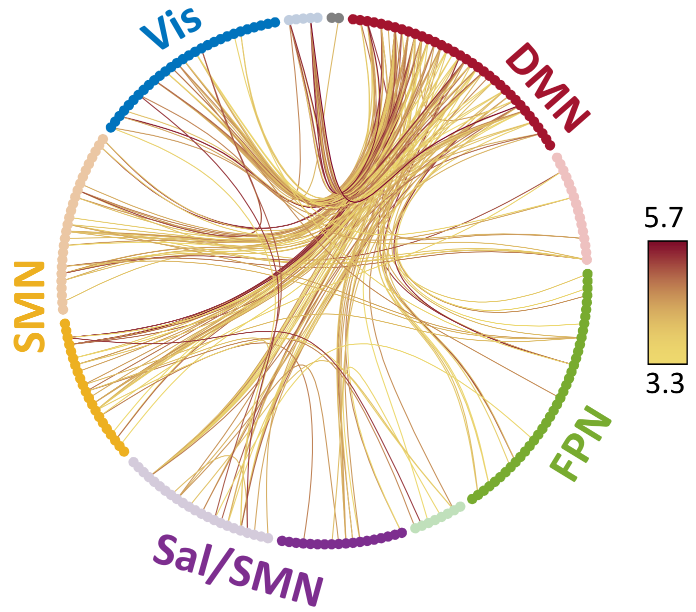


## Force-directed projection



Fronto-parietal
Cingulo-opercular
Default-mode
Visual
Sensorimotor

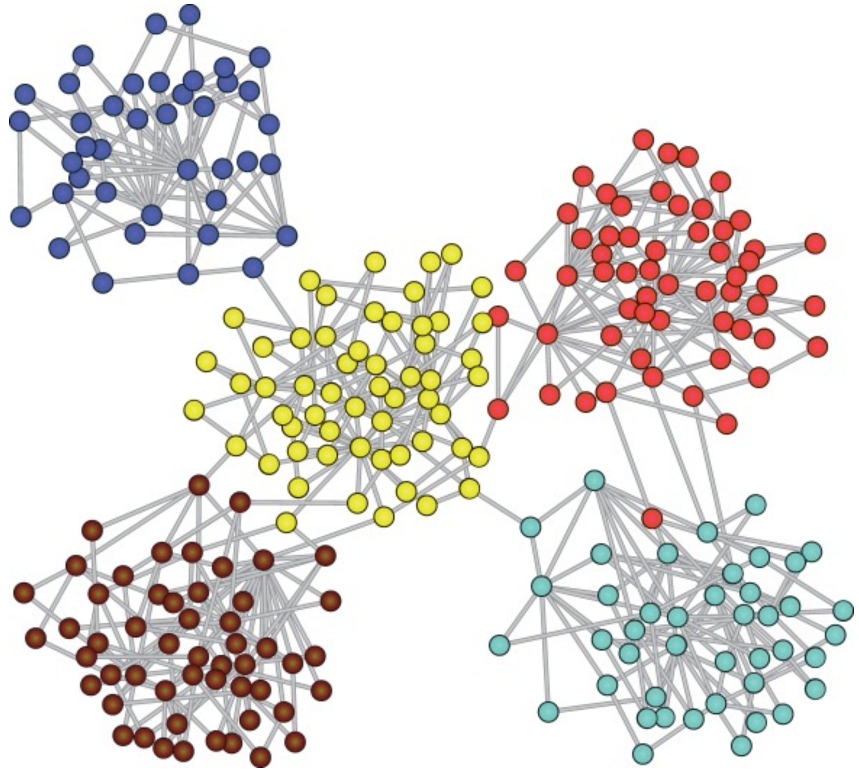
## Circular projection/ connectogram



# Modularity – Key topological property

## Description (Newman & Girvan, 2004)

- Nodes cluster into highly cohesive modules.
- Degree of intramodule connectivity is greater than expected by chance (i.e., in a random network).



## Quantification – *Modularity Index*

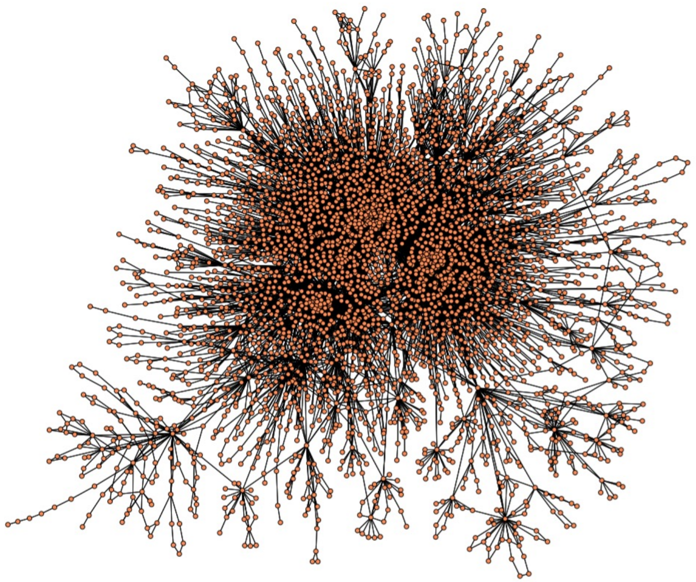
$$Q = \frac{1}{2E}\sum_{ij}[A_{ij} - \gamma e_{ij}]\delta(m_i, m_j)$$

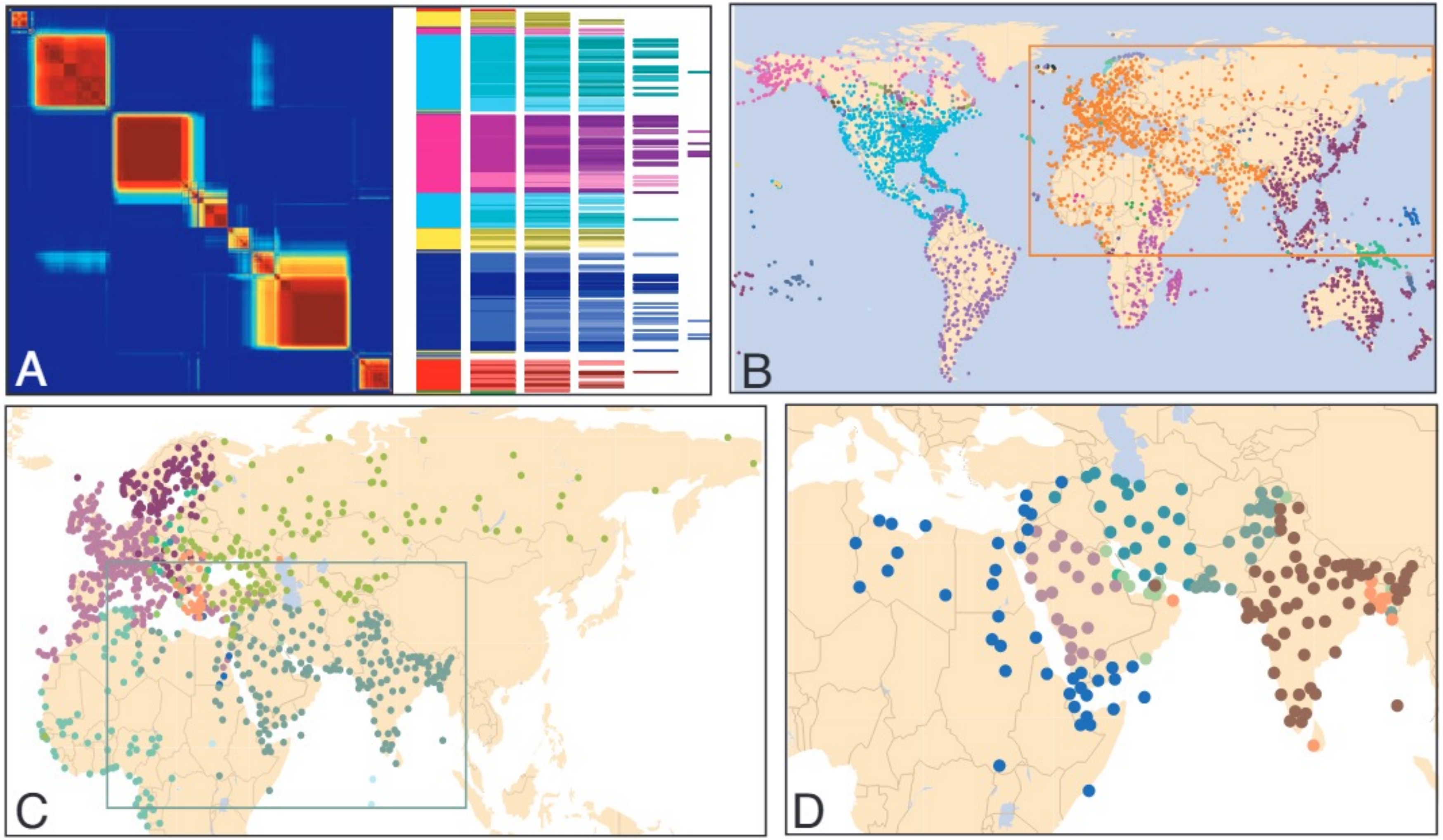
## Detection

- community detection algorithms

image: Muller-Linow et al., 2008

# Example - Air Transportation Network
(3,618 nodes; 28,287 edges)






Sales-Pardo et al., 2007

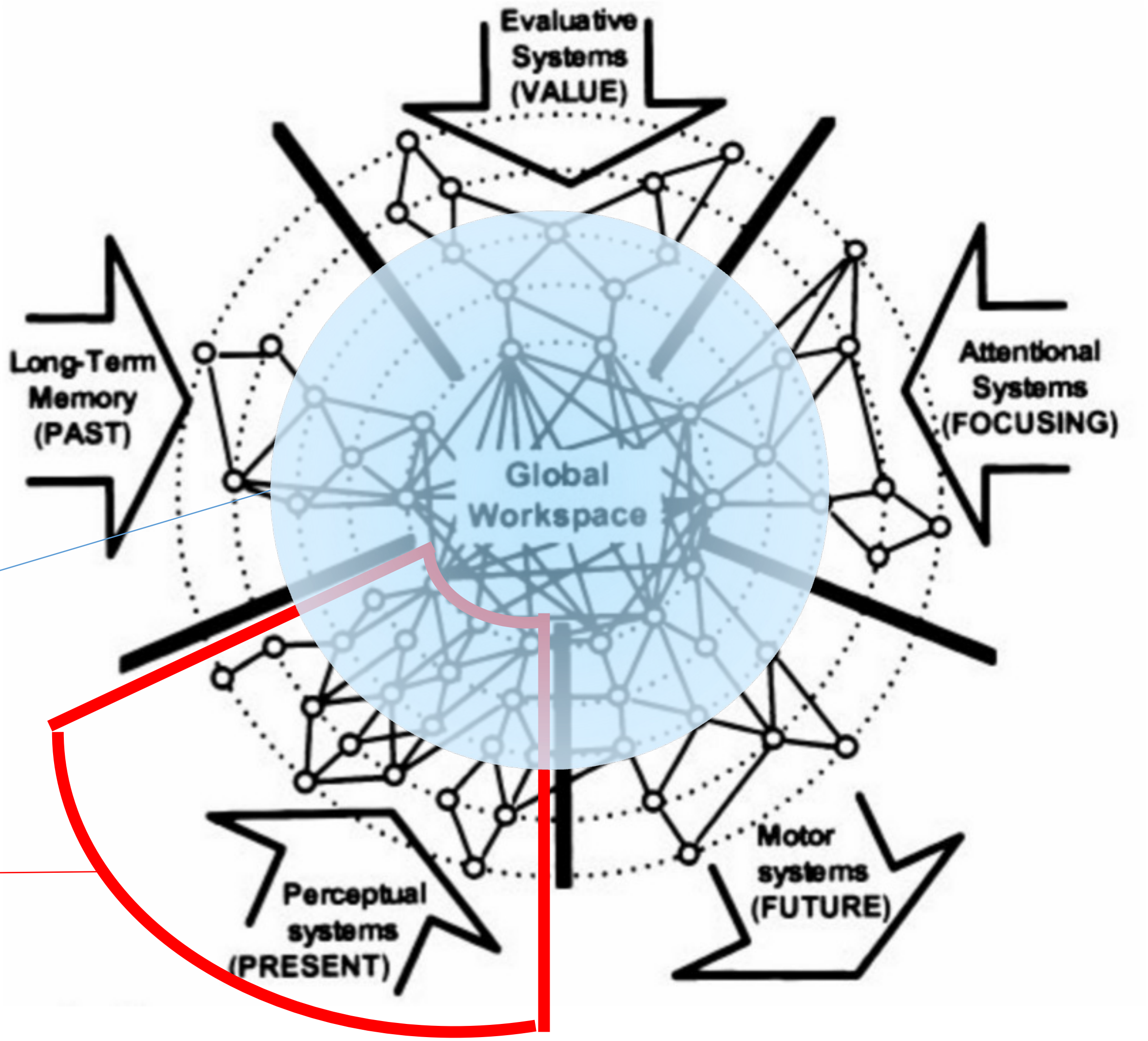
# Cognitive modules and global workspace

*Modularity of mind* (Fodor, 1983)

Functional segregation & integration

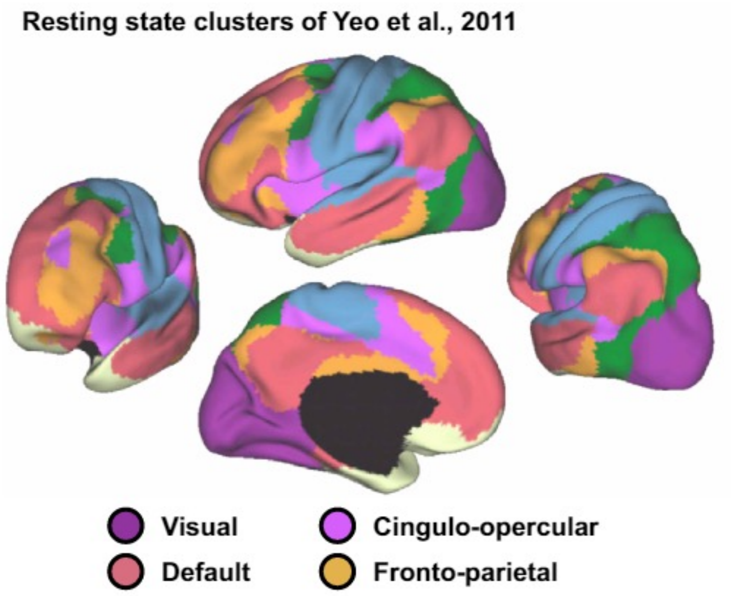
*High-level* cognitive functions (eg. WM) - rely more on a ***global workspace*** than on segregated modular functions.

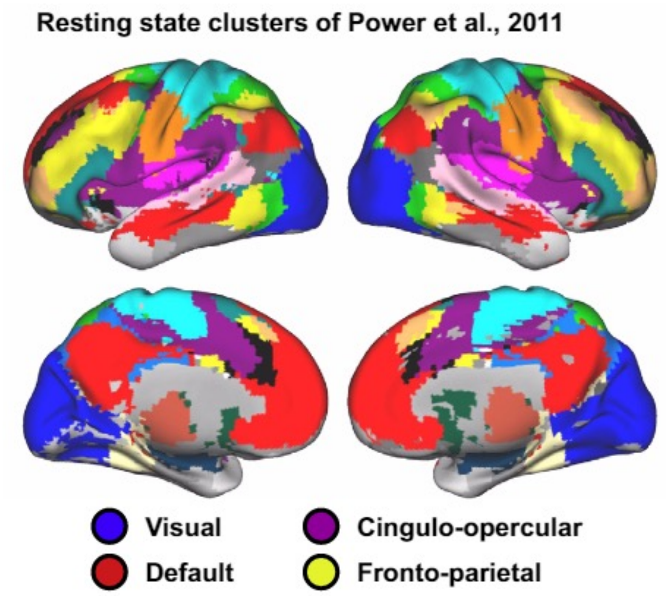
***Modules*** - spatially localized and include specialized brain areas (visual, auditory, motor ...)

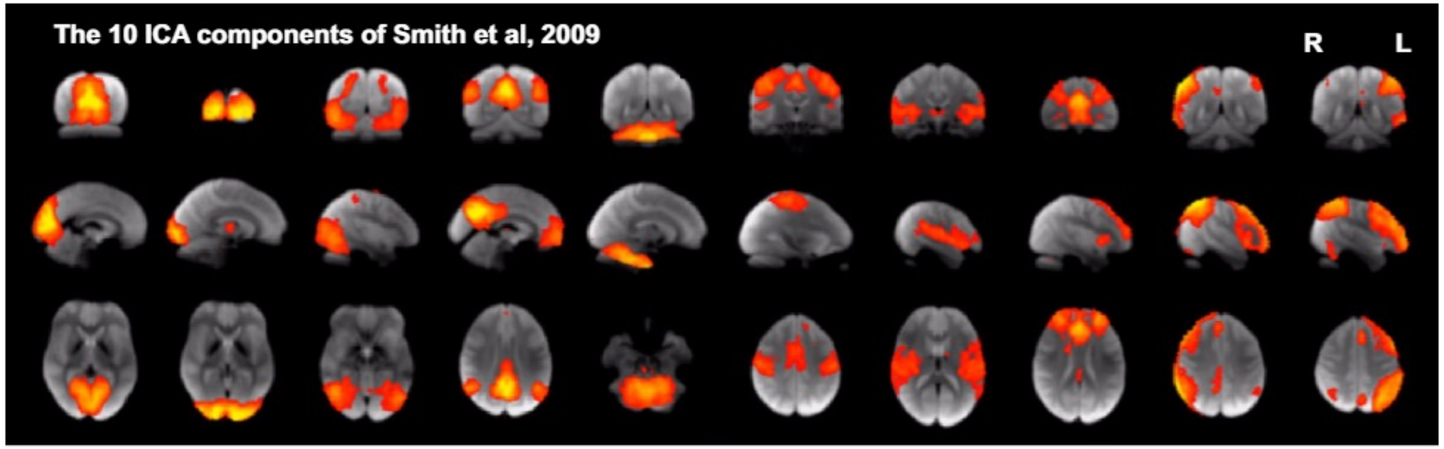



Dehaene et al., 1998

# Large-scale functional organization of the brain

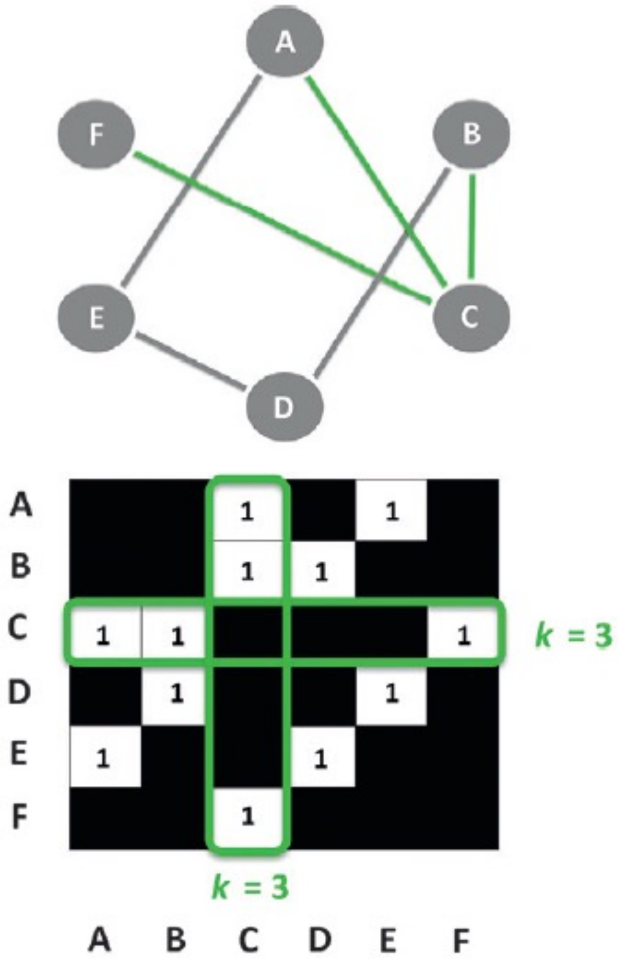



Power et al., 2014

# Node degree & strength




- Binary undirected network
  - Degree of node i:
    - # of edges connecting node i with all other nodes
  - Mean degree of an undirected network:
    - mean of all node degrees

$$k_i = \sum_{j \neq i} A_{ij}.$$

$$\langle k \rangle = \frac{1}{N} \sum_{i=1}^{N} k_i.$$

- Weighted undirected network
  - Strength of node *i*:
    - sum of weights of edges attached to node *i*
  - Positive vs. negative node strength
    - signed weighted networks (e.g., correlation)

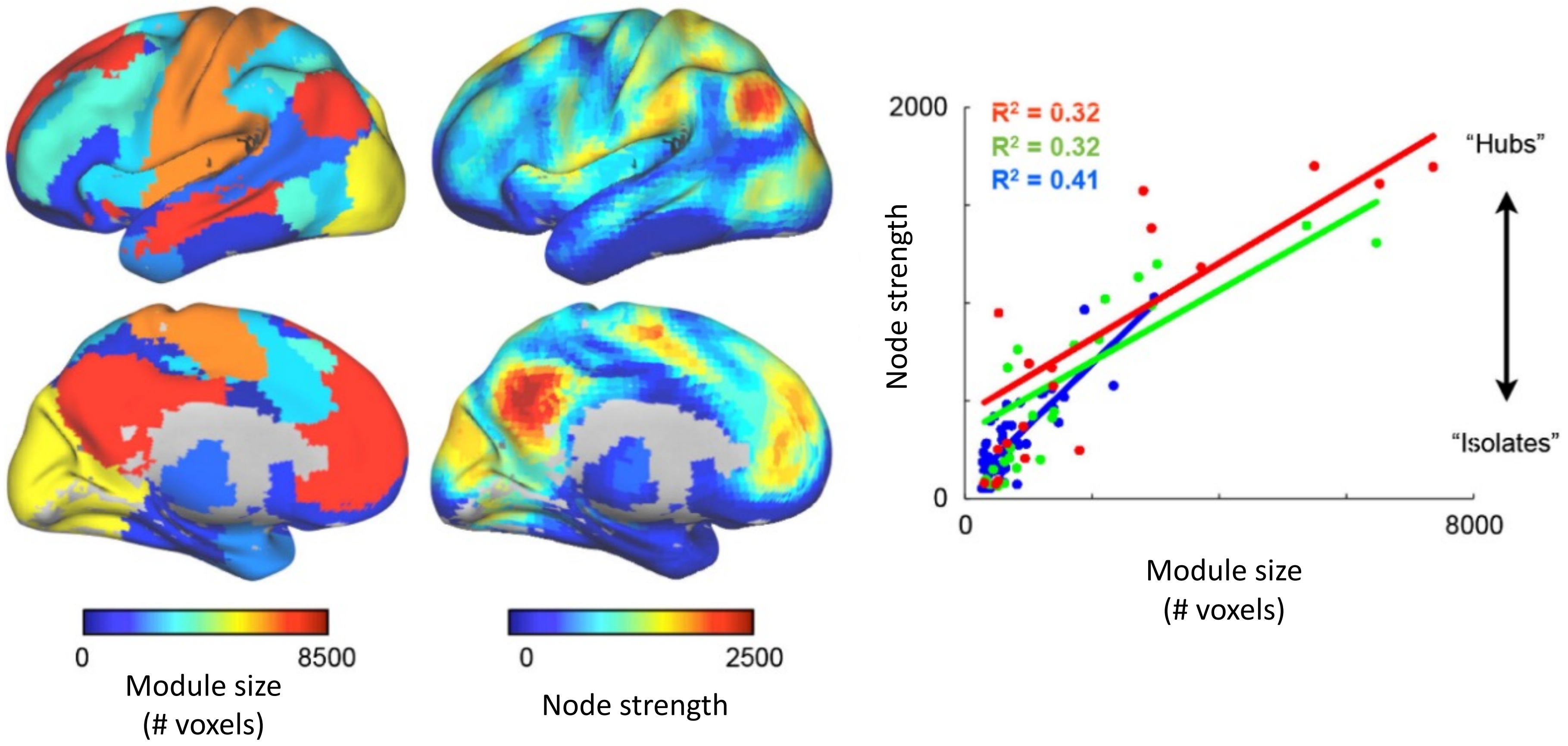
$$s_i = \sum_{j \neq i} w_{ij}$$

$$s_i^+ = \sum_{j \neq i} w_{ij}^+, \quad \text{and} \quad s_i^- = -\sum_{j \neq i} w_{ij}^- .$$

Fornito et al., 2016

# Node roles: Hubs

Caution: Association between node strength and module size in correlation-based FC




Power et al., 2013

# Node roles

- **Within-module degree z-score**

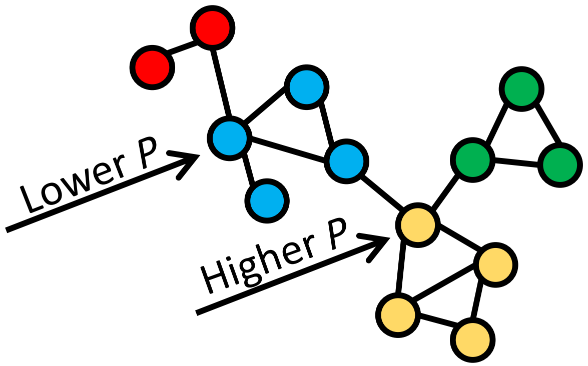
$$z_i = \frac{k_i(m_i) - \bar{k}(m_i)}{\sigma_{k(m_i)}}$$

  - Difference between
    - Within-module degree for node *i* (# connections linking node *i* to other nodes in the same module *m*)
    - Mean within-module degree of nodes in the same module as node *i*
  - Divided by standard deviation of $k(m)$ values across all nodes in module *m*

- **Participation coefficient**

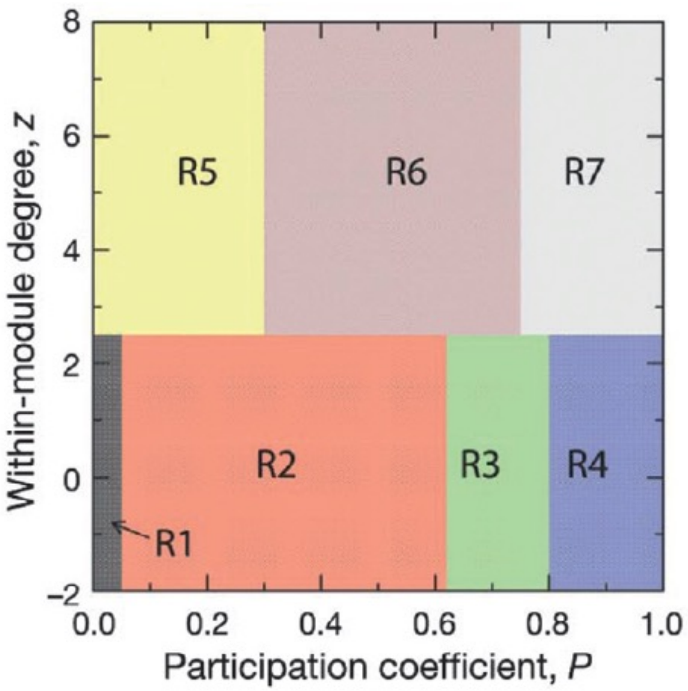
$$P_i = 1 - \sum_{m=1}^{M} \left( \frac{k_i(m)}{k_i} \right)^2$$

  - How a node's links are distributed across different modules



## Topological Roles for Network Nodes

Guimera & Amaral,  2005

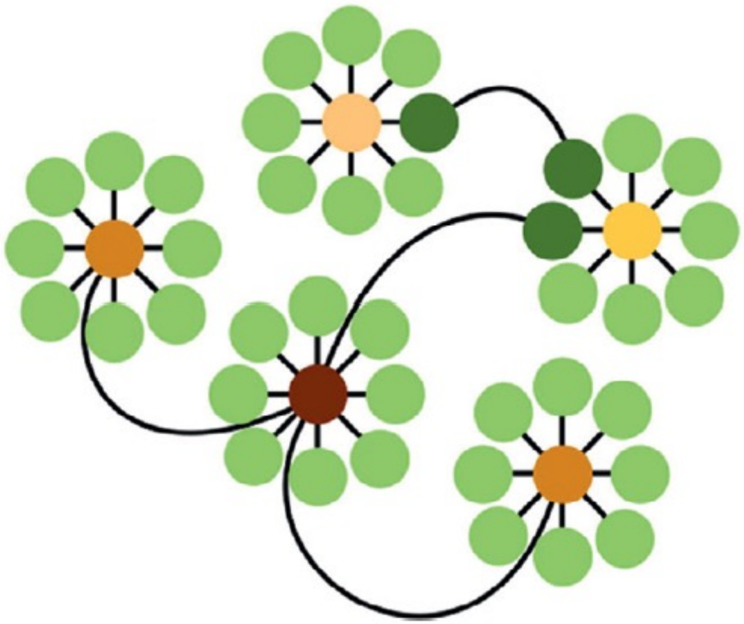


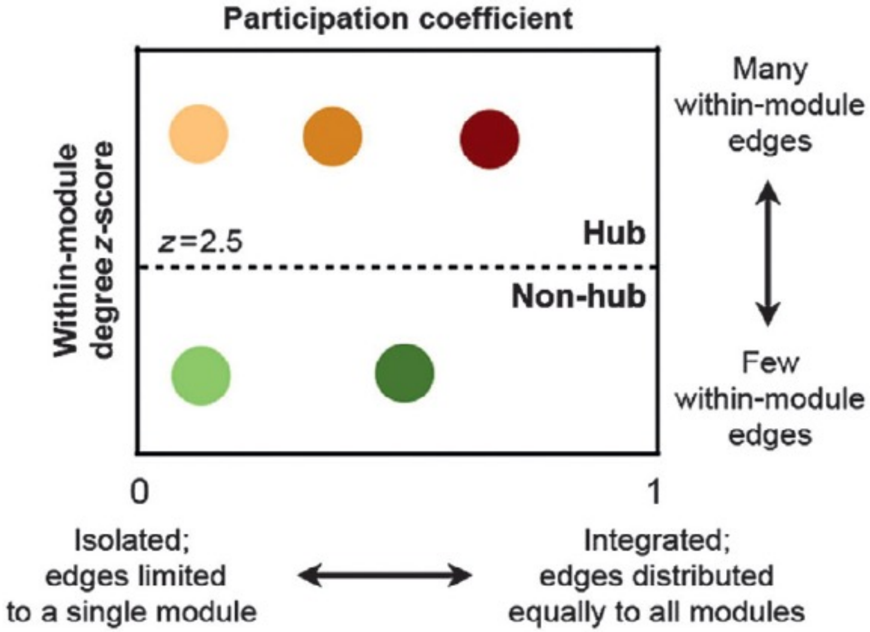

R5, provincial hub
R6, connector hub
R7, kinless hub

R1, ultra-peripheral
R2, peripheral
R3, nonhub connector
R4, nonhub kinless

## Node role distinctions in brain imaging

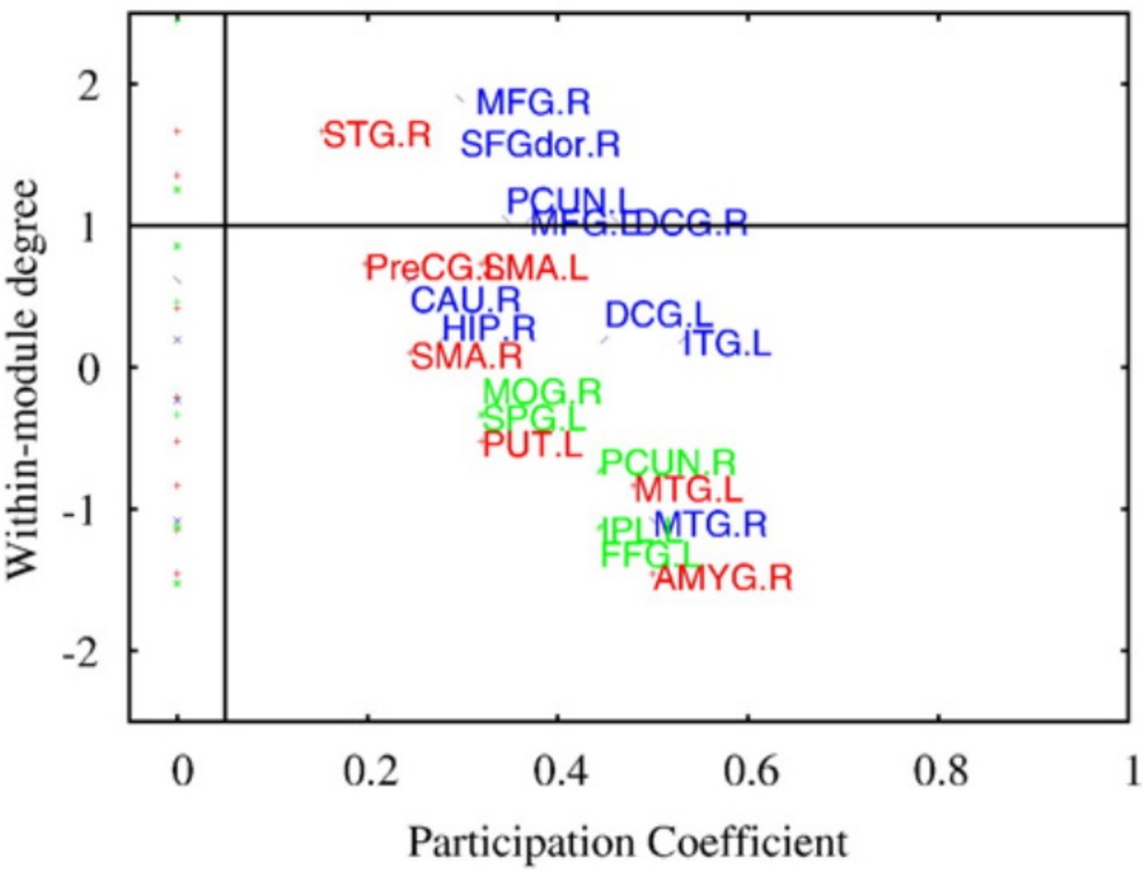
Power et al., 2013

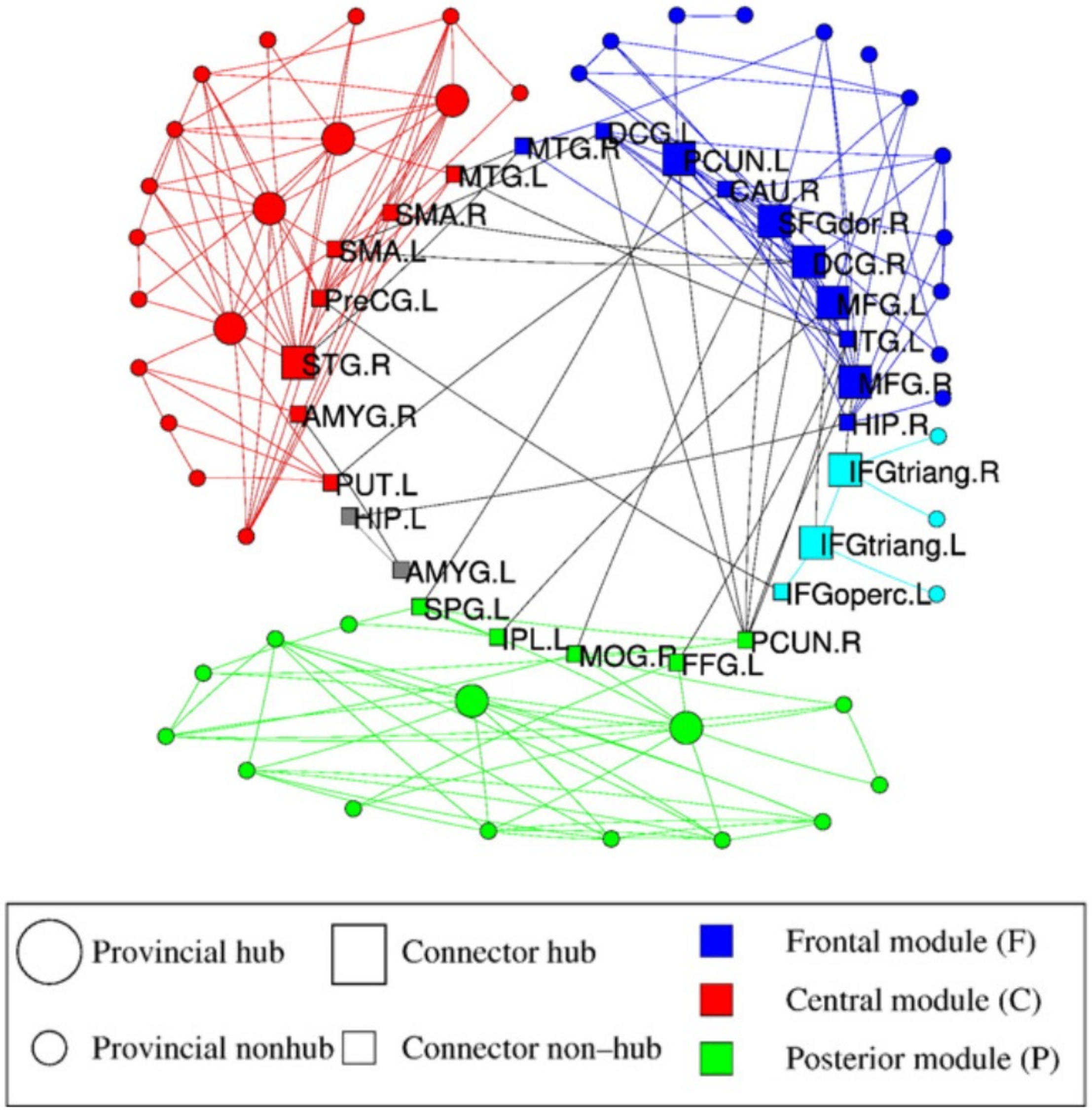




# Brain modules and regional node roles

Resting state data, 90 anatomically defined brain regions

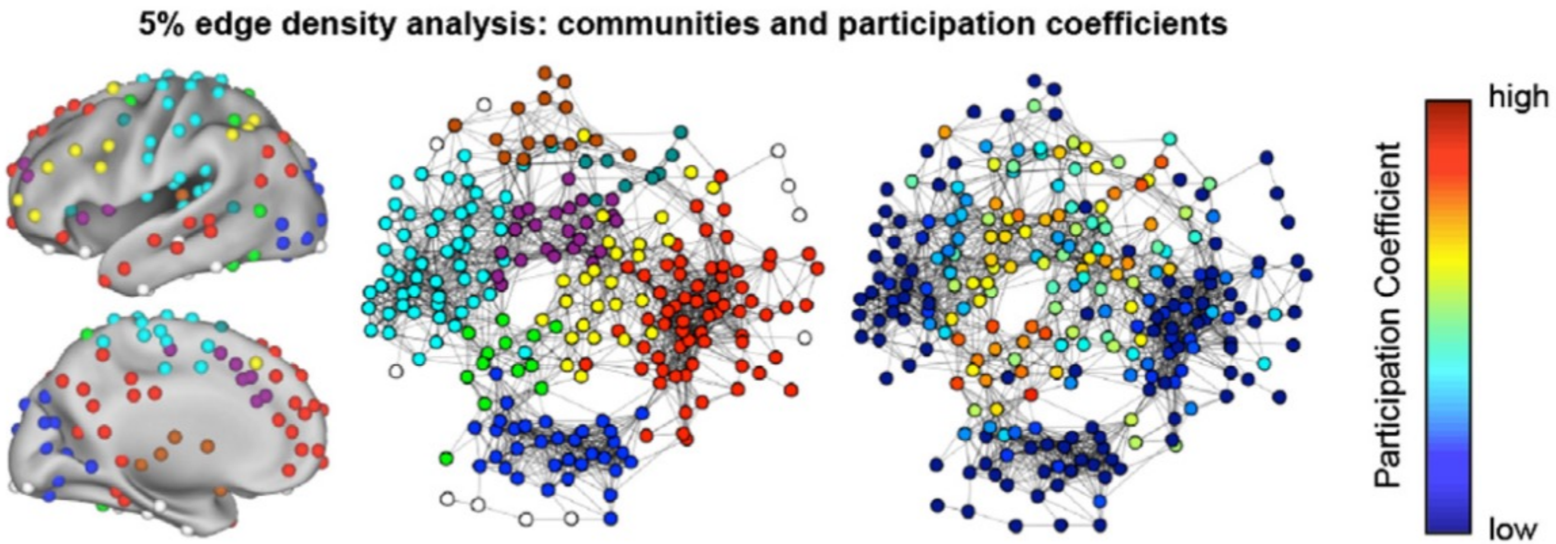



Meunier et al., 2009

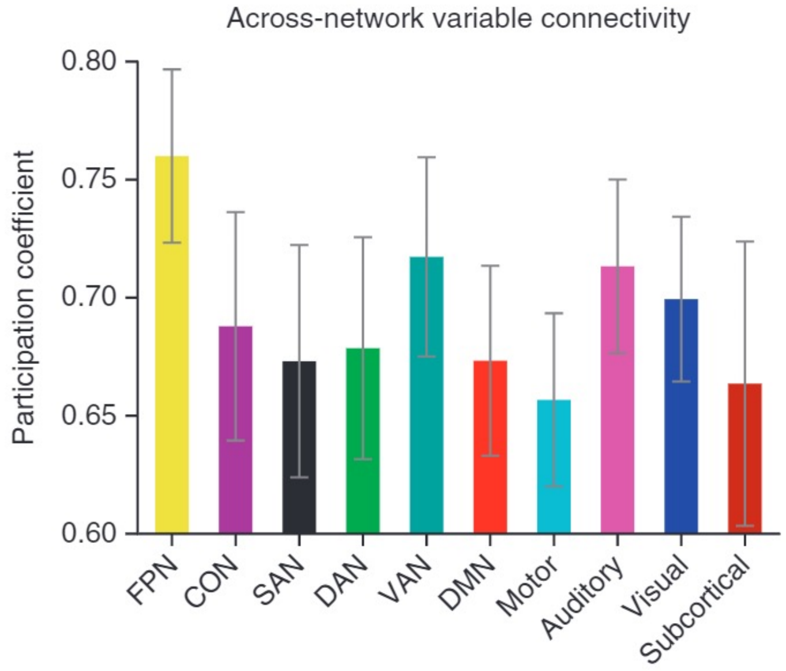
# Variation of participation coefficient across the brain

**During resting-state**



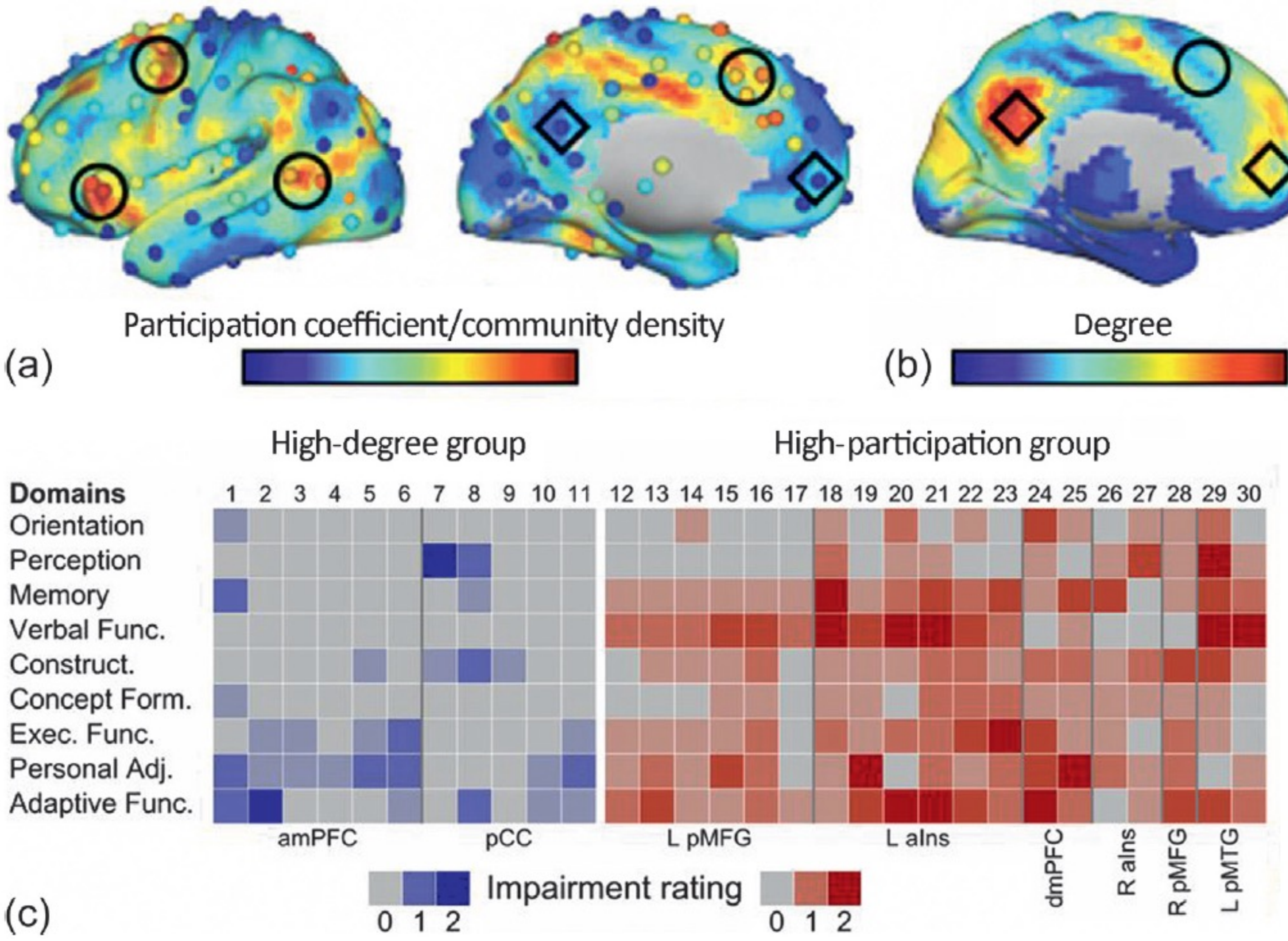

Power et al., 2013

**Across tasks**

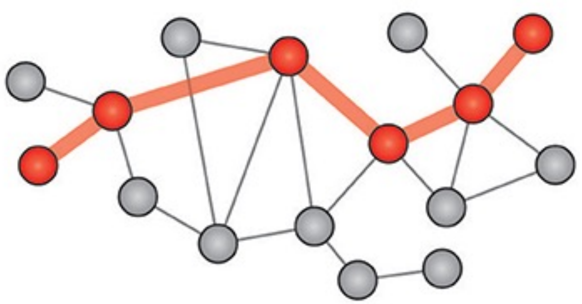



Cole et al., 2013

Experimental evidence: Neuropsychological deficits are more consistent and widespread in patients with lesions to areas with high community participation.




Warren et al., 2014; image: Fornito et al., 2016




# Efficiency

- Global efficiency

$$E_{\text{glob}} = \frac{1}{L'} = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{l_{ij}}.$$

  - Efficiency of information exchange in a parallel system

- Nodal efficiency

$$E_{\text{nodal}}(j) = \frac{1}{N-1} \sum_{i} \frac{1}{l_{ij}}.$$

  - Measures node integration within network

- Local efficiency

$$E_{\text{loc}}(i) = \frac{1}{N_{G_i}(N_{G_i}-1)} \sum_{j,\, h \in G_i} \frac{1}{l_{jh}},$$

  - Measures integration between the immediate neighbors of a given node

image: Farahani et al., 2019

# Network measures interpretation

- ***Modularity*** -> network distinctiveness,
  functional segregation

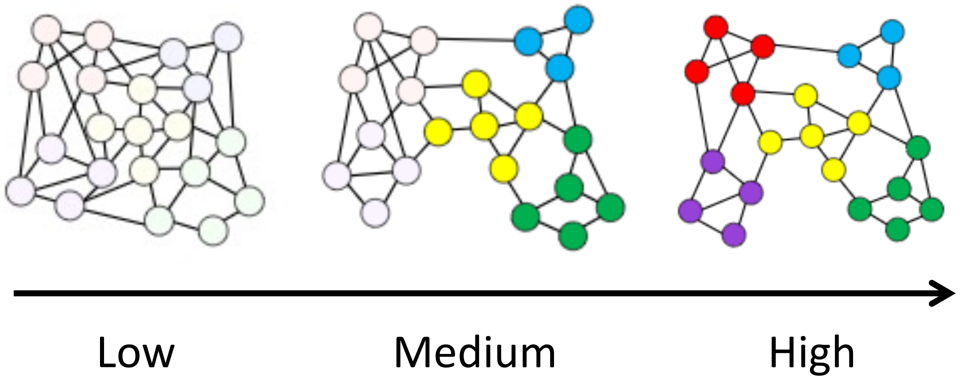
$$Q = \frac{1}{2E}\sum_{ij}[A_{ij} - \gamma e_{ij}]\delta(m_i, m_j)$$

- ***Global efficiency*** -> graph-wide integration,
  rapid information exchange

$$E_{glob} = \frac{1}{N(N-1)}\sum_{i \neq j}\frac{1}{L_{ij}}$$

- ***Local efficiency*** -> regional integration,
  fault tolerance

$$E_{loc}(i) = \frac{1}{N_{G_i}(N_{G_i} - 1)}\sum_{j,h \in G_i}\frac{1}{L_{jh}}$$




Wig, 2017

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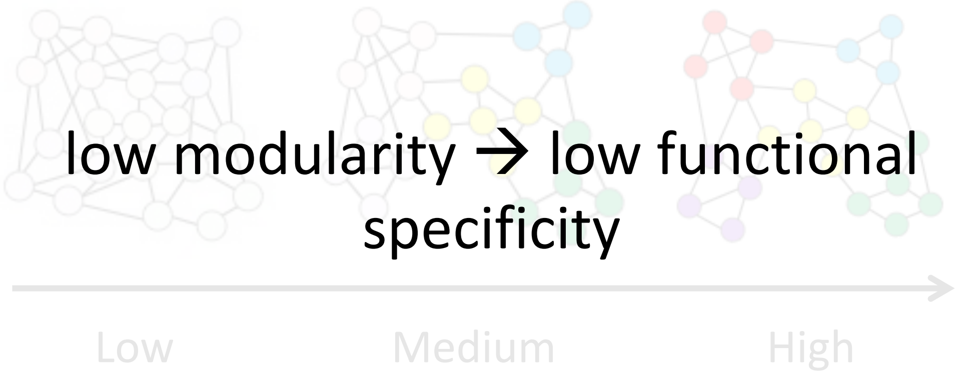


low modularity → low functional specificity

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Wig, 2017

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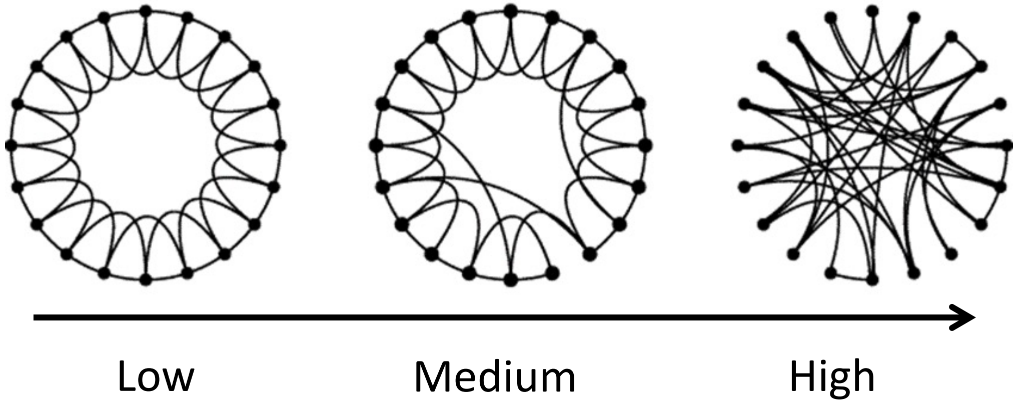


Watts & Strogatz, 1998

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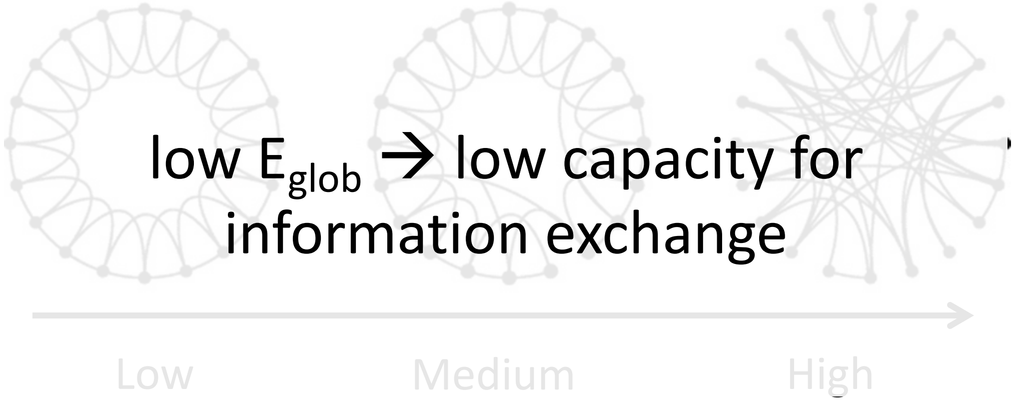


low $E_{glob}$ → low capacity for information exchange

Watts & Strogatz, 1998

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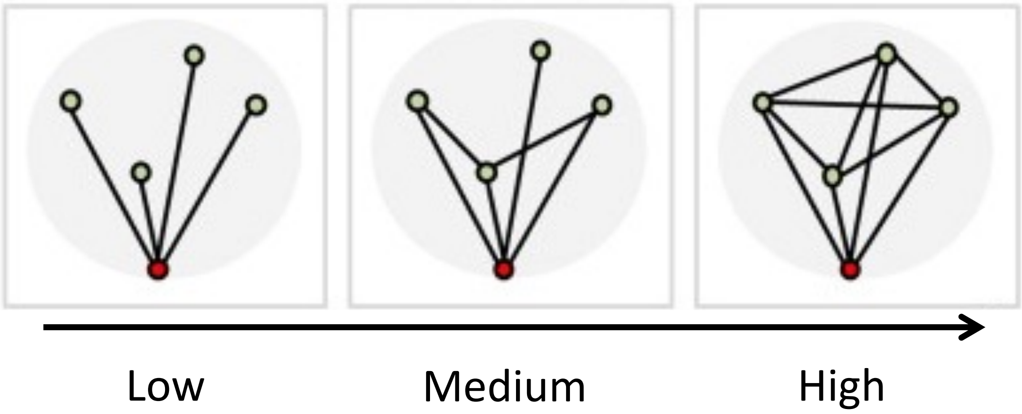


Onoda & Yamaguchi, 2015

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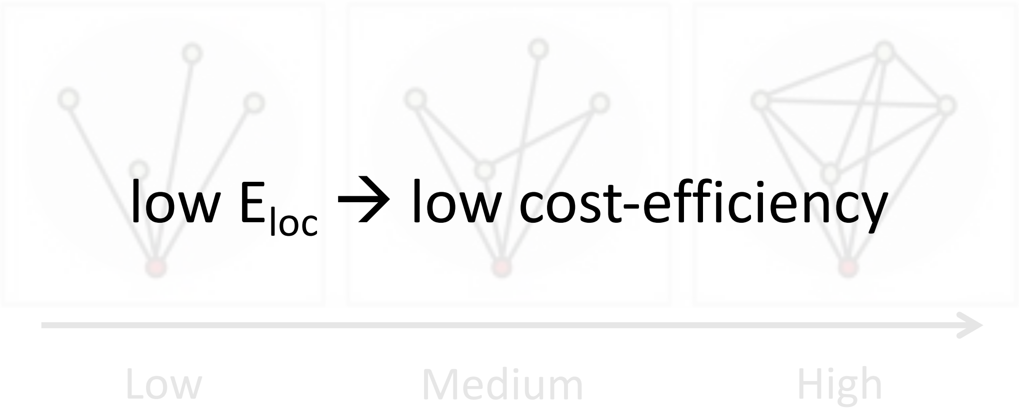



low $E_{loc}$ → low cost-efficiency

Onoda & Yamaguchi, 2015

# Comparing partitions

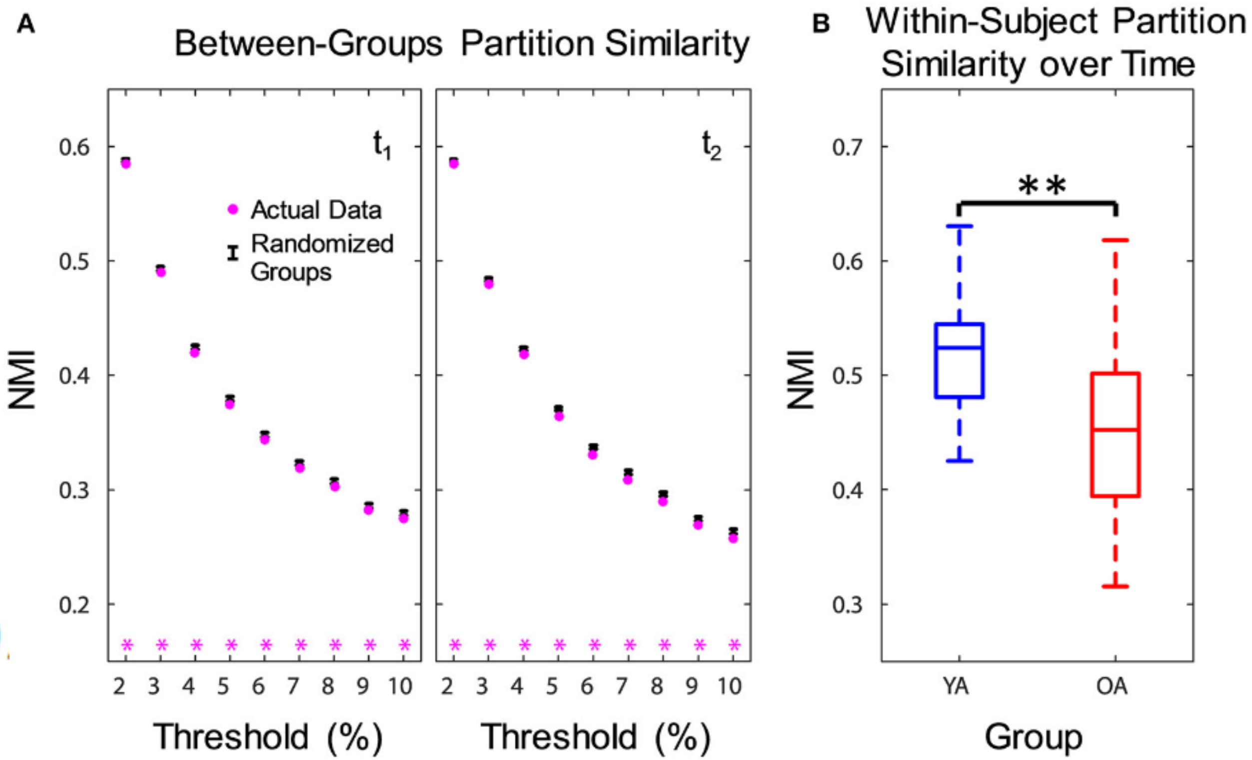
- **Mutual information**: degree to which knowing the community assignment of a node in partition Y reduces uncertainty about that node's community assignment in partition X

  - Normalized mutual information

$$MI'(X,Y) = \frac{2\mathrm{MI}(X,Y)}{H(X)+H(Y)}.$$

  - Variation of information (metric of partition distance)

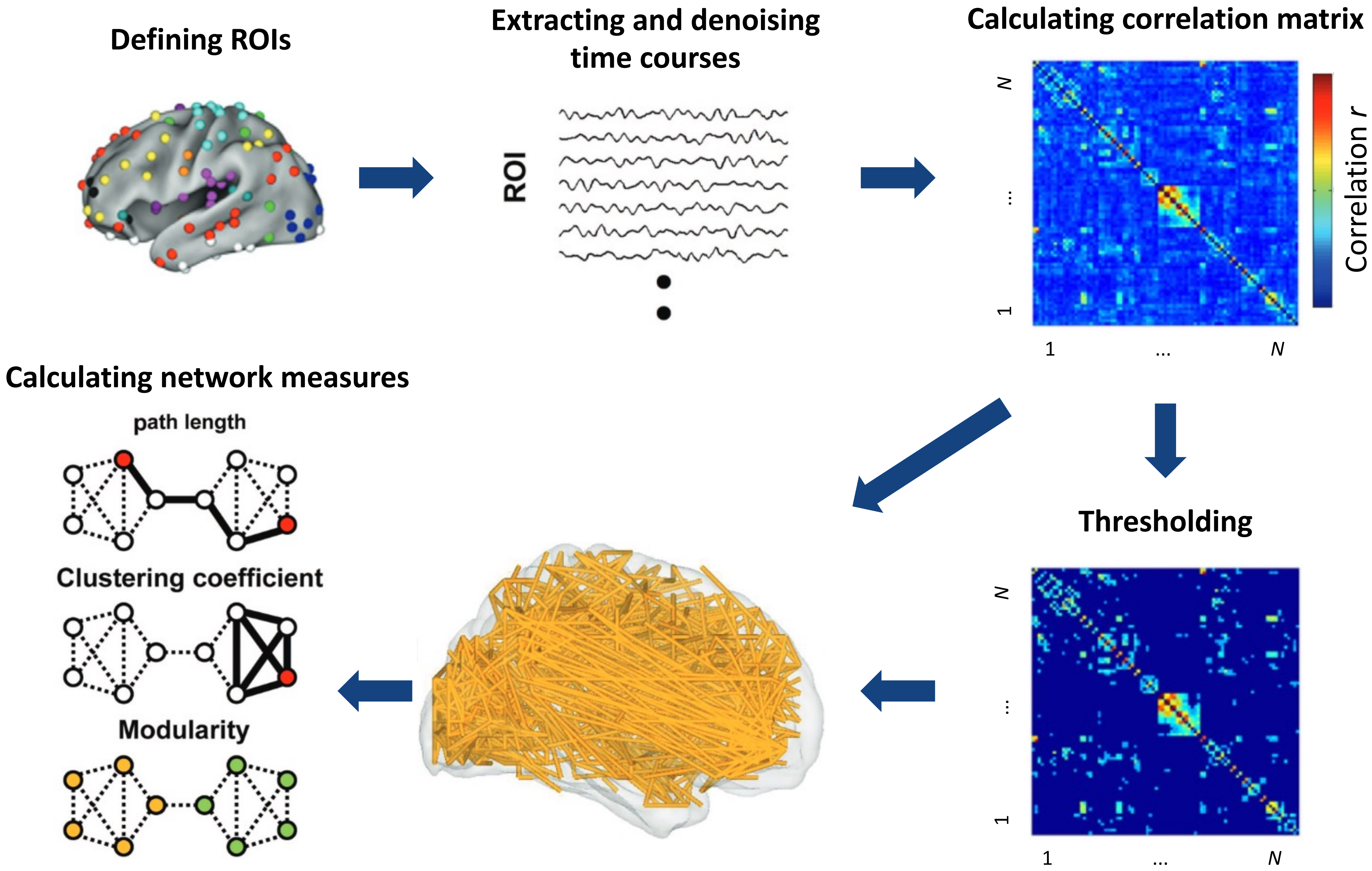
$$VI(X,Y) = H(X) + H(Y) - 2MI(X,Y)$$




Iordan et al., 2018

# Methodological issues

# Procedure

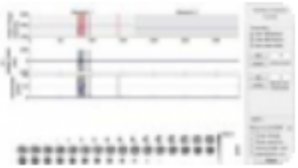



images: Uehara et al., 2013; Taya et al., 2016; Power et al., 2013

# Tools

NITRC
The source for neuroinformatics tools & resources
Neuroimaging data repository
Cloud computing environment

## Artifact Detection Tools (ART)



Toolbox for post-processing fMRI data. Includes software for comprehensive analysis of sources of artifacts in timeseries data including spiking and motion. Most compatible with SPM processing, but adaptable for FSL as well.

## CONN : functional connectivity toolbox

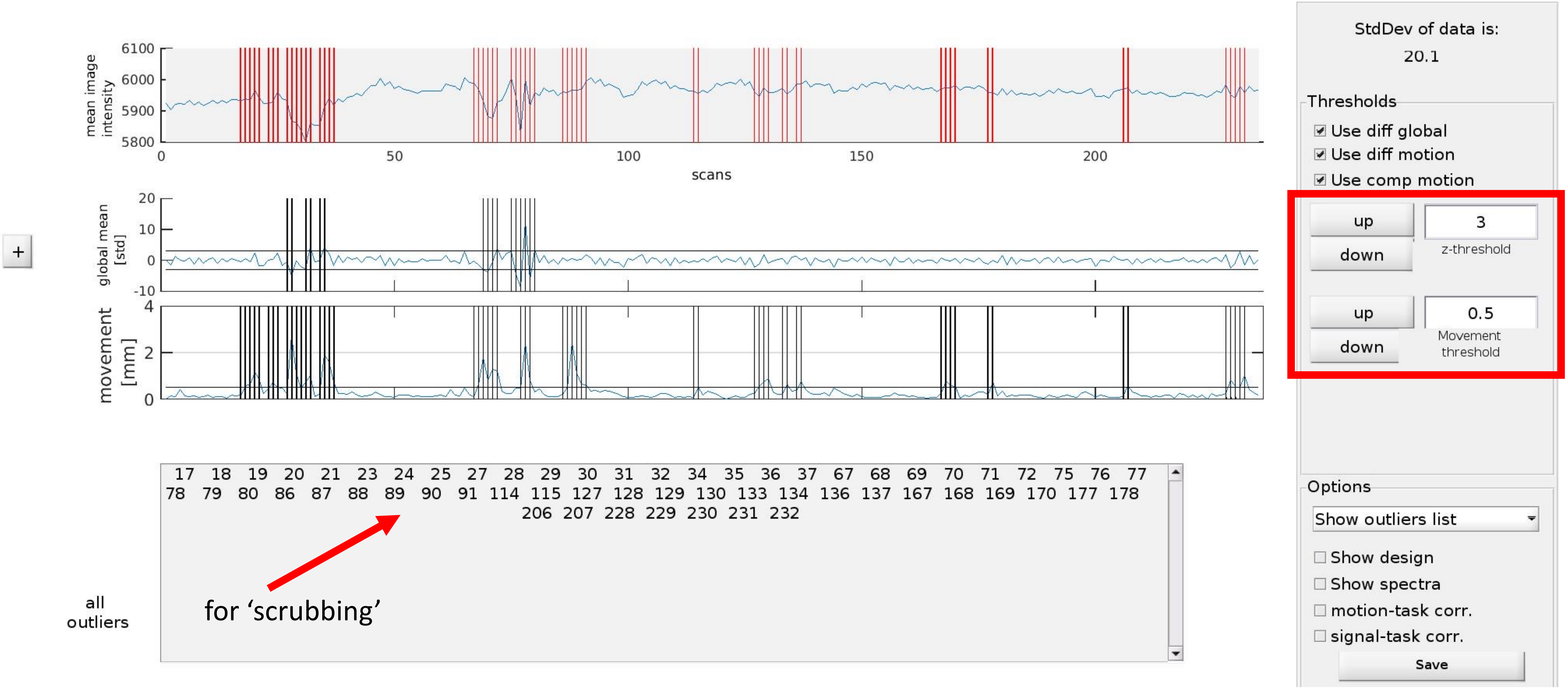

CONN is a Matlab-based cross-platform software for the computation, display, and analysis of functional connectivity in fMRI (fcMRI).

CONN includes a rich set of connectivity analyses (seed-based correlations, ROI-to-ROI graph analyses, group ICA, masked ICA, generalized PPI, ALFF, ICC, GCOR, LCOR, etc.) in a simple-to-use and powerful software package

## Brain Connectivity Toolbox

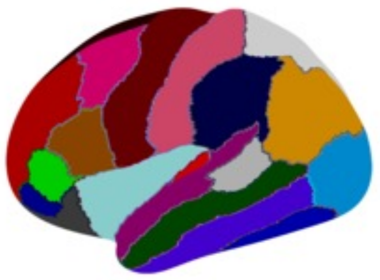
The Brain Connectivity Toolbox (brain-connectivity-toolbox.net) is a MATLAB toolbox for complex-network (graph) analysis of structural and functional brain-connectivity data sets. Several people have contributed to the toolbox and users are welcome to contribute new functions with due acknowledgement.

# Identifying outlier volumes (ART)



# Choosing ROI atlas

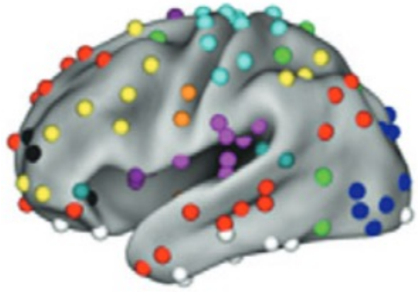
**Anatomical**



Tzurio-Mazoyer et al., 2002
Desikan et al., 2006

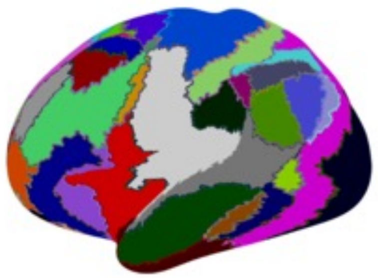
**Functional**

Meta-analytical



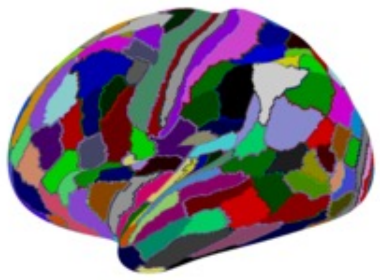
Dosenbach et al., 2010
Power et al., 2011

Data-driven



Yeo et al., 2011
Craddock et al., 2012

**Multi-modal**

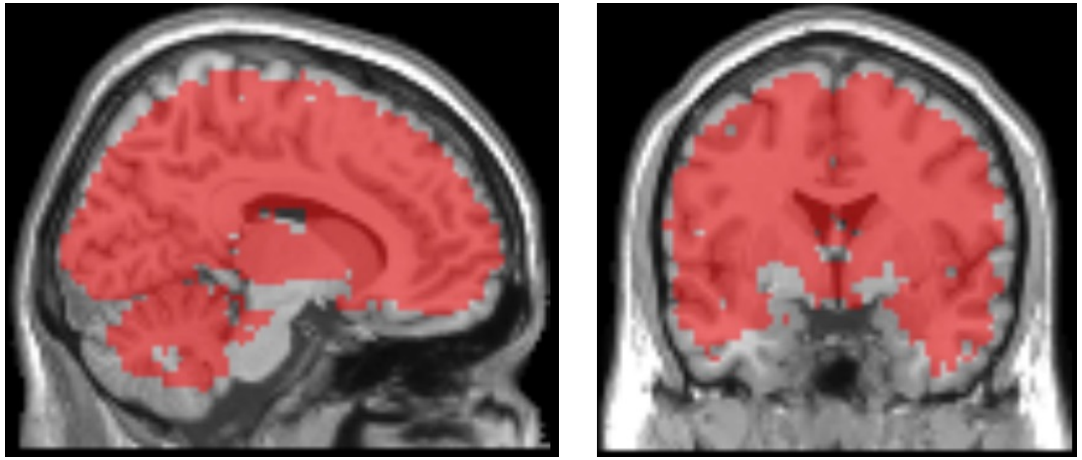


Glasser et al., 2016

images: biomedia.doc.ic.ac.uk; Power et al., (2013)

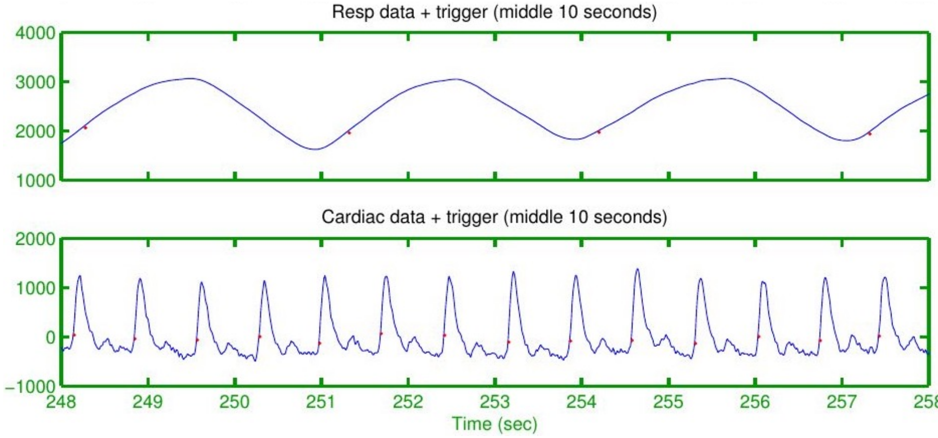
# Signal vs. Noise

## Signal Intensity Mask

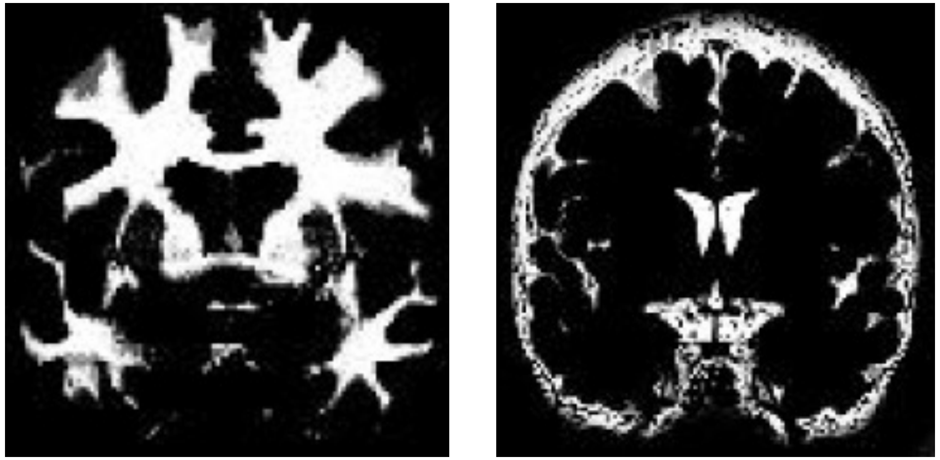


Excluding ROIs that lack good coverage.

## Physiological noise




## WM and CSF Masks

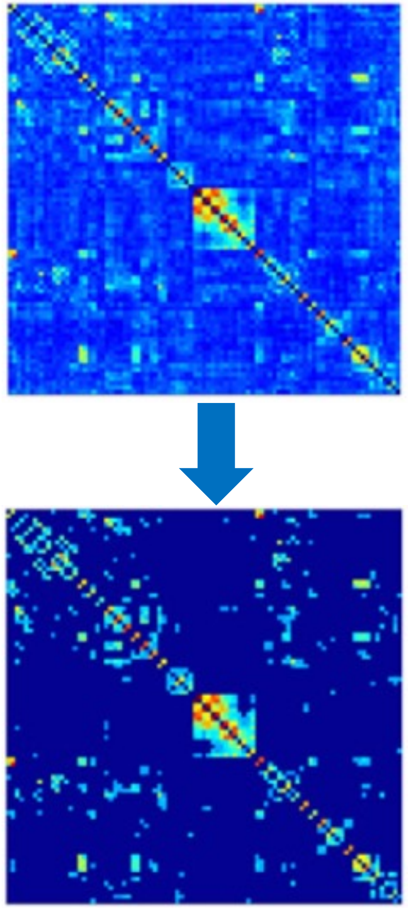


# Removing physiological and other sources of noise

- aCompCor (Behzadi et al., 2007) temporal covariates:
  - signal extracted from noise ROIs (white matter, CSF) (PCA)
  - motion parameters (+ derivatives)
  - regressors for outlier volumes (‘scrubbing’)
- band-pass filtering – e.g. [.01 .1]
- detrending
- despiking

# Issues re: Thresholding

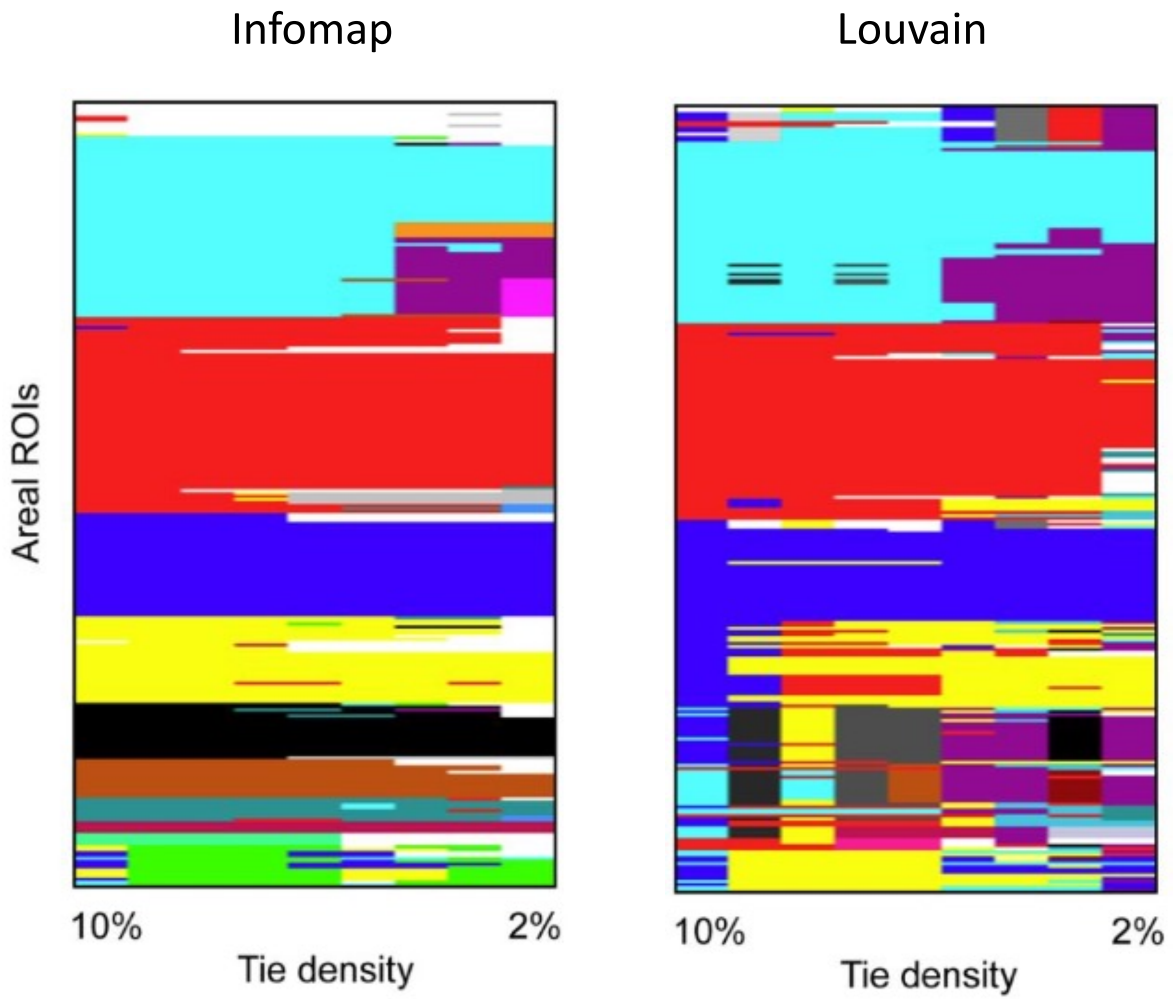
- Is it necessary to threshold or binarize?
- Comparing partitions between 2 groups:
  - Weight-based/absolute thresholding
    - Measures may be influenced by trivial differences in the number of edges.
  - Density/'cost'-based thresholding
    - Adequate if groups are matched in edge weight-distribution.
    - Otherwise, may be influenced by spurious edges.
- Use stringent thresholds
  - False positives are more detrimental than false negatives!



Zalesky, OHBM, 2017; Zalesky et al., 2016; image: Taya et al., 2016

# Community detection

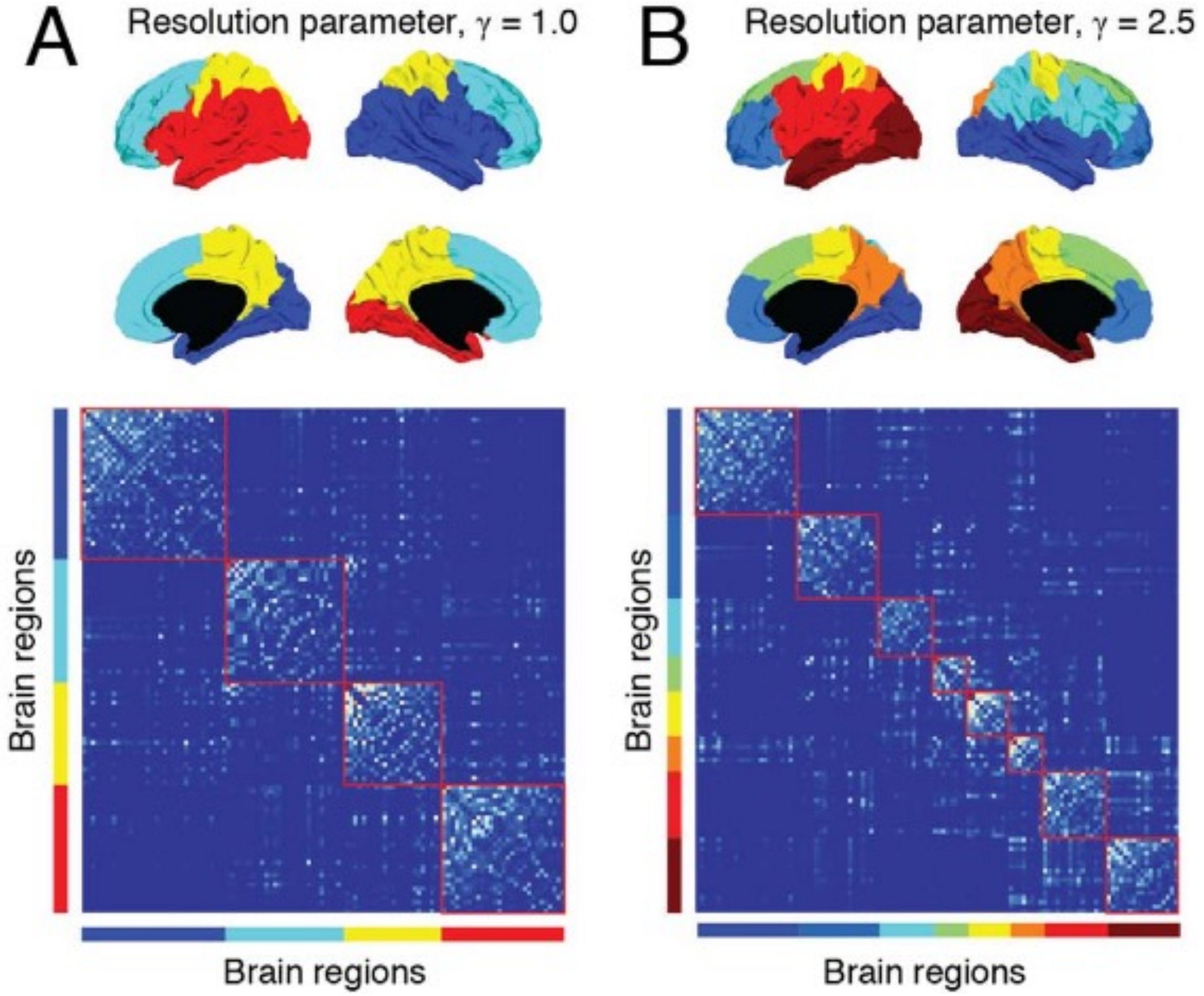
- Algorithms
  - 'Louvain' (Blondel et al., 2008)
  - 'Infomap' (Rosvall & Bergstrom, 2008)
  - …
- Resolution
- Degeneracy
- Consensus clustering




Power et al., 2011

# Community detection

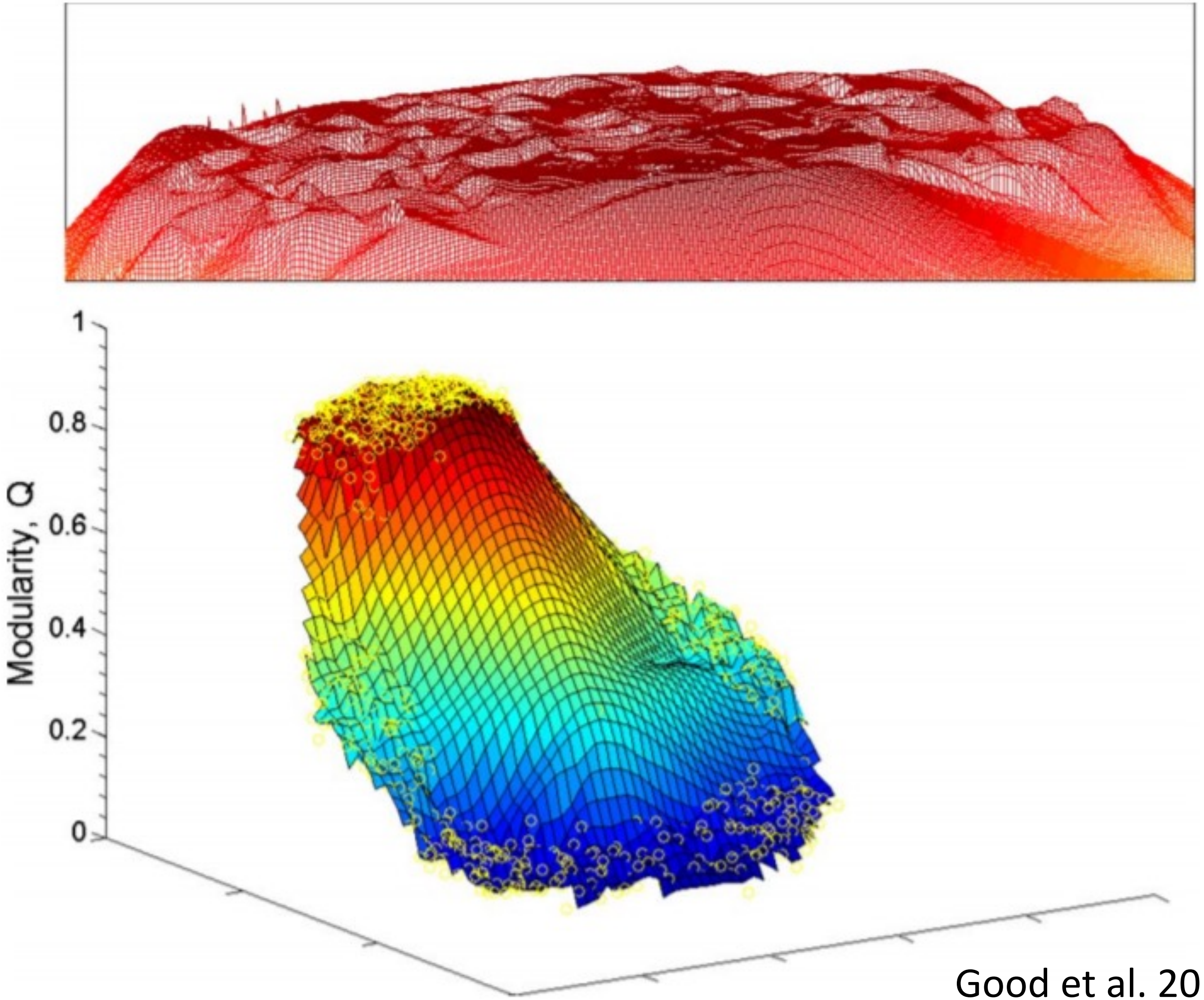
- Algorithms
- Resolution
  - Multi-scale community detection
- Degeneracy
- Consensus clustering




Betzel & Bassett, 2016

# Community detection

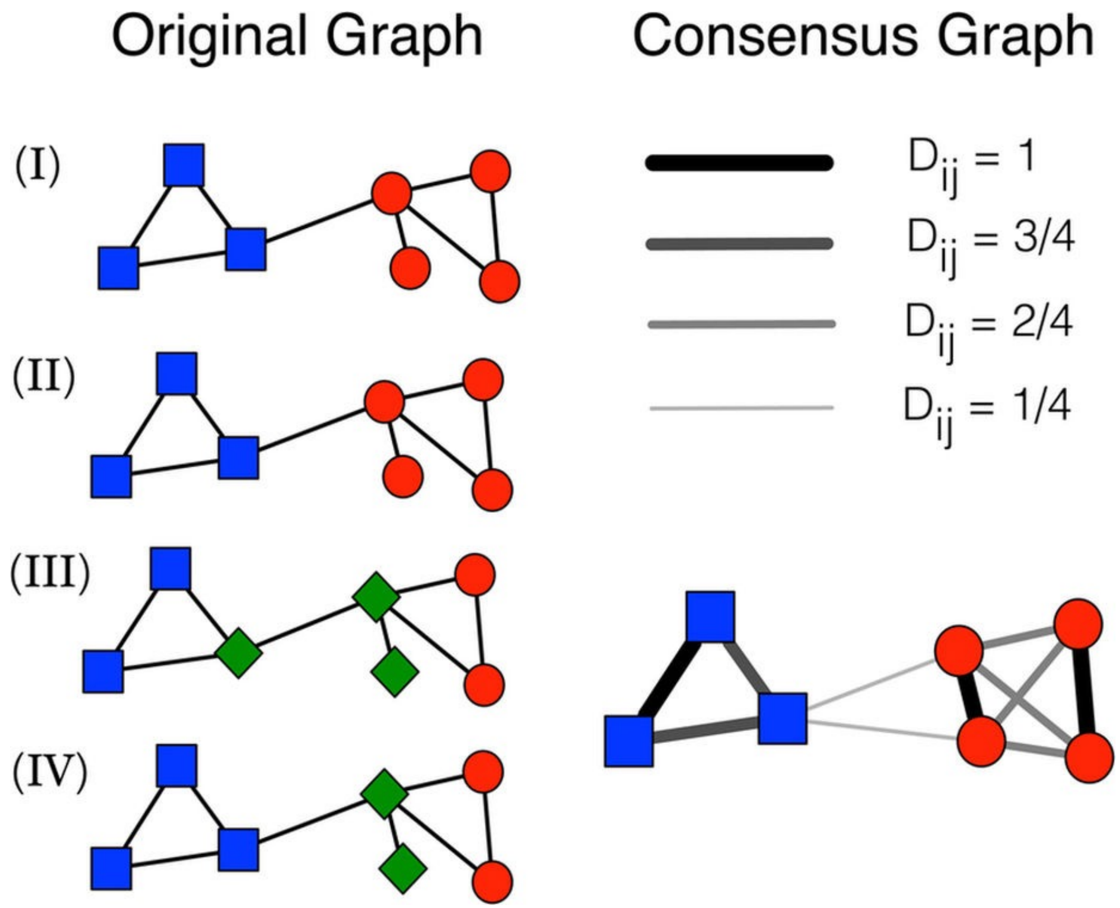
- Algorithms
- Resolution
- Degeneracy
  - There is no clear maximum modularity
- Consensus clustering




Good et al. 2010

# Community detection

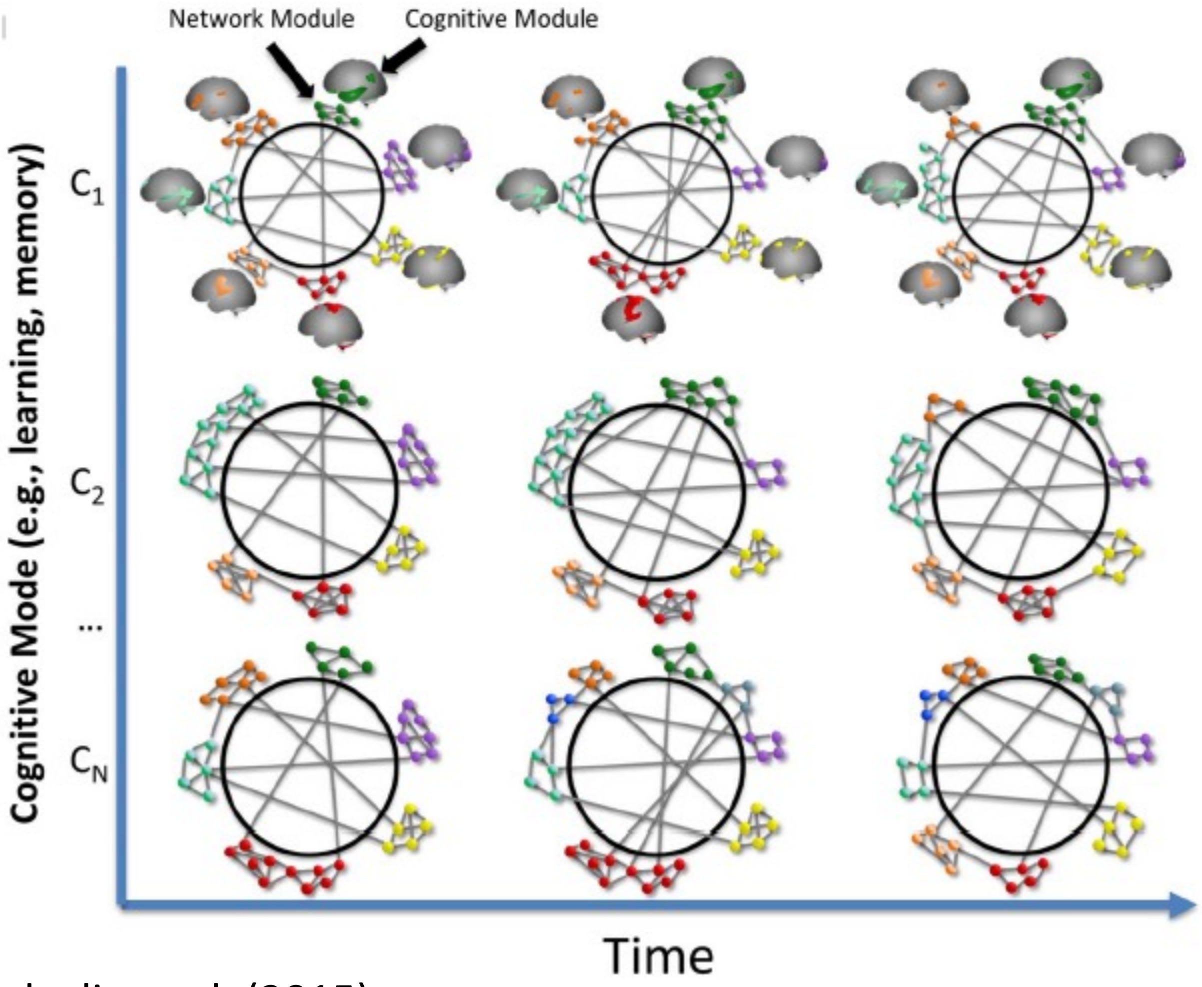
- Algorithms
- Resolution
- Degeneracy
- Consensus clustering
  - Building a representative partition




Lancichinetti & Fortunato, 2012

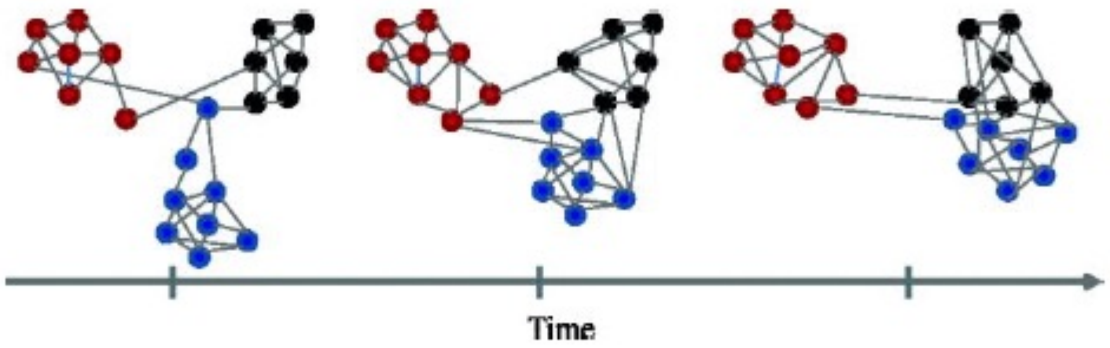
# Dynamic Networks

Cognitive Processes are Dynamic



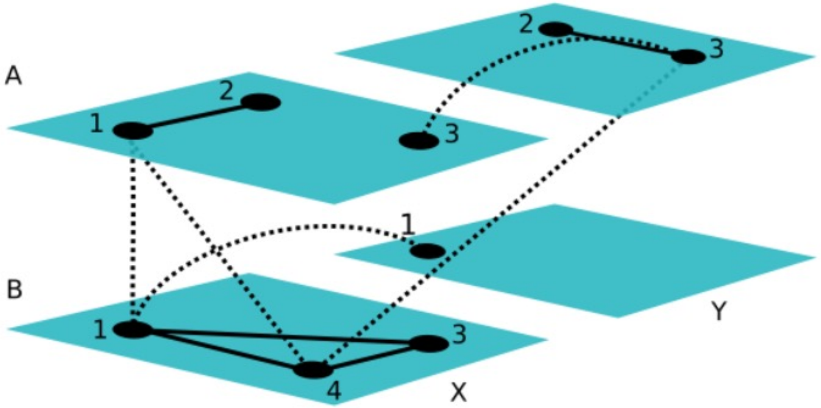

Medaglia et al. (2015)

Network Structure Changes over Time

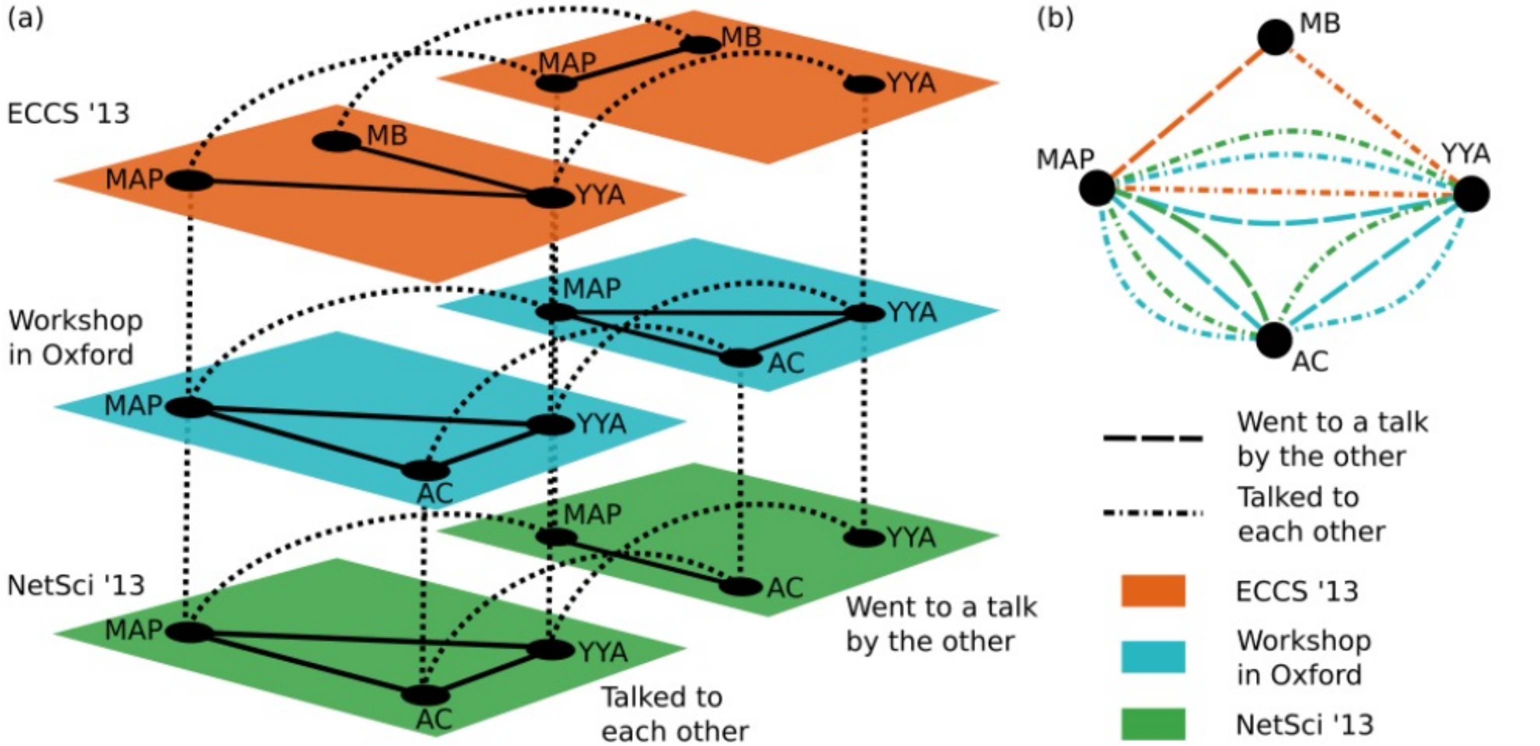



Bassett et al. (2013)

# Multilayer Networks

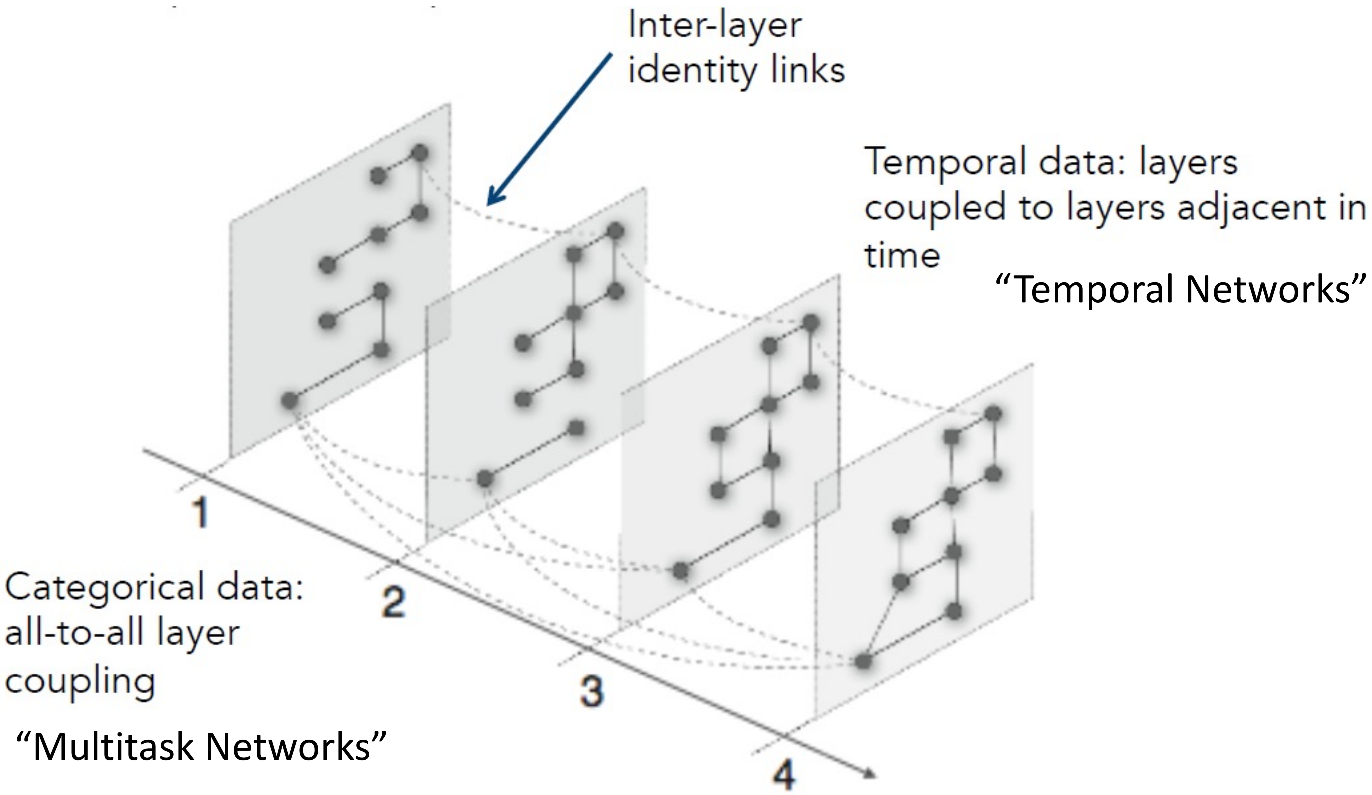



- 4 nodes
- 2 layers (A, B)
- 2 aspects (X, Y)




Kivela et al. (2014)

# Multilayer Modularity




"Temporal Networks"

"Multitask Networks"

Coupling within layer

Coupling between layers

Resolution Parameter For Module Size

Adjacency Matrix

For i and j in same community

Community i in time slice l

$$Q = \frac{1}{2\mu} \sum_{ijlr} \left\{ \left( A_{ijl} - \gamma_l P_{ijl} \right) \delta_{lr} + \delta_{ij} \omega_{jlr} \right\} \delta(g_{il}, g_{jr}) \, ,$$

Null Model Adjacency Matrix

Resolution Parameter for Module Dynamics

Community j in time slice r

Mucha et al. (2010); Basset et al. (2013)

# Application

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RESEARCH ARTICLE

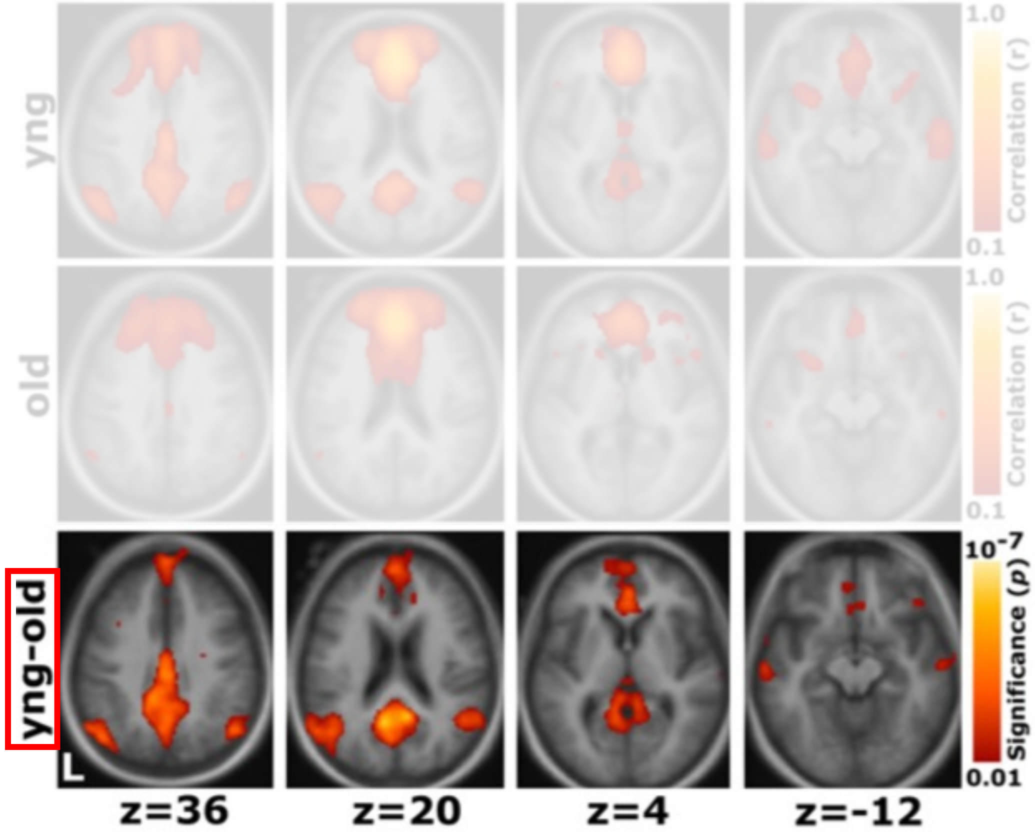
WILEY

## Age differences in functional network reconfiguration with working memory training

Alexandru D. Iordan[1] | Kyle D. Moored[2] | Benjamin Katz[3] | Katherine A. Cooke[1] | Martin Buschkuehl[4] | Susanne M. Jaeggi[5] | Thad A. Polk[1] | Scott J. Peltier[6,7] | John Jonides[1] | Patricia A. Reuter-Lorenz[1]

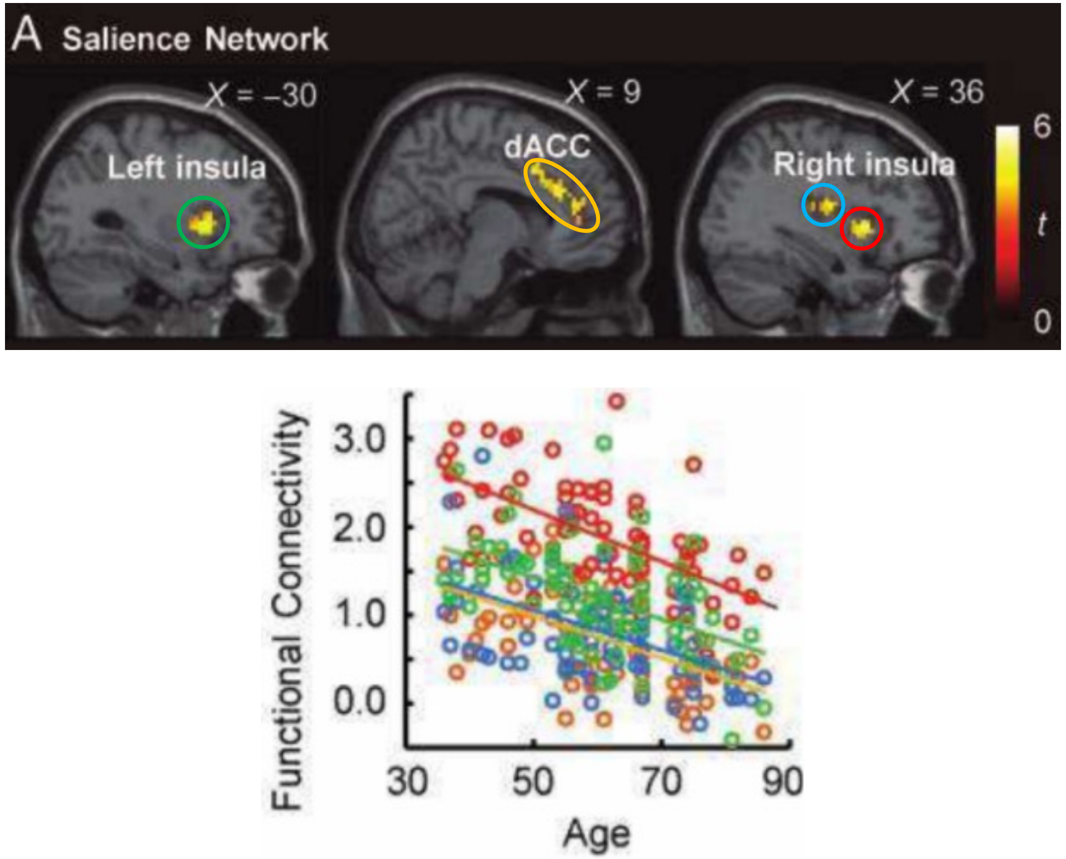
# Aging influences the functional organization of the brain

Default-mode Network




Andrews-Hanna et al., 2007

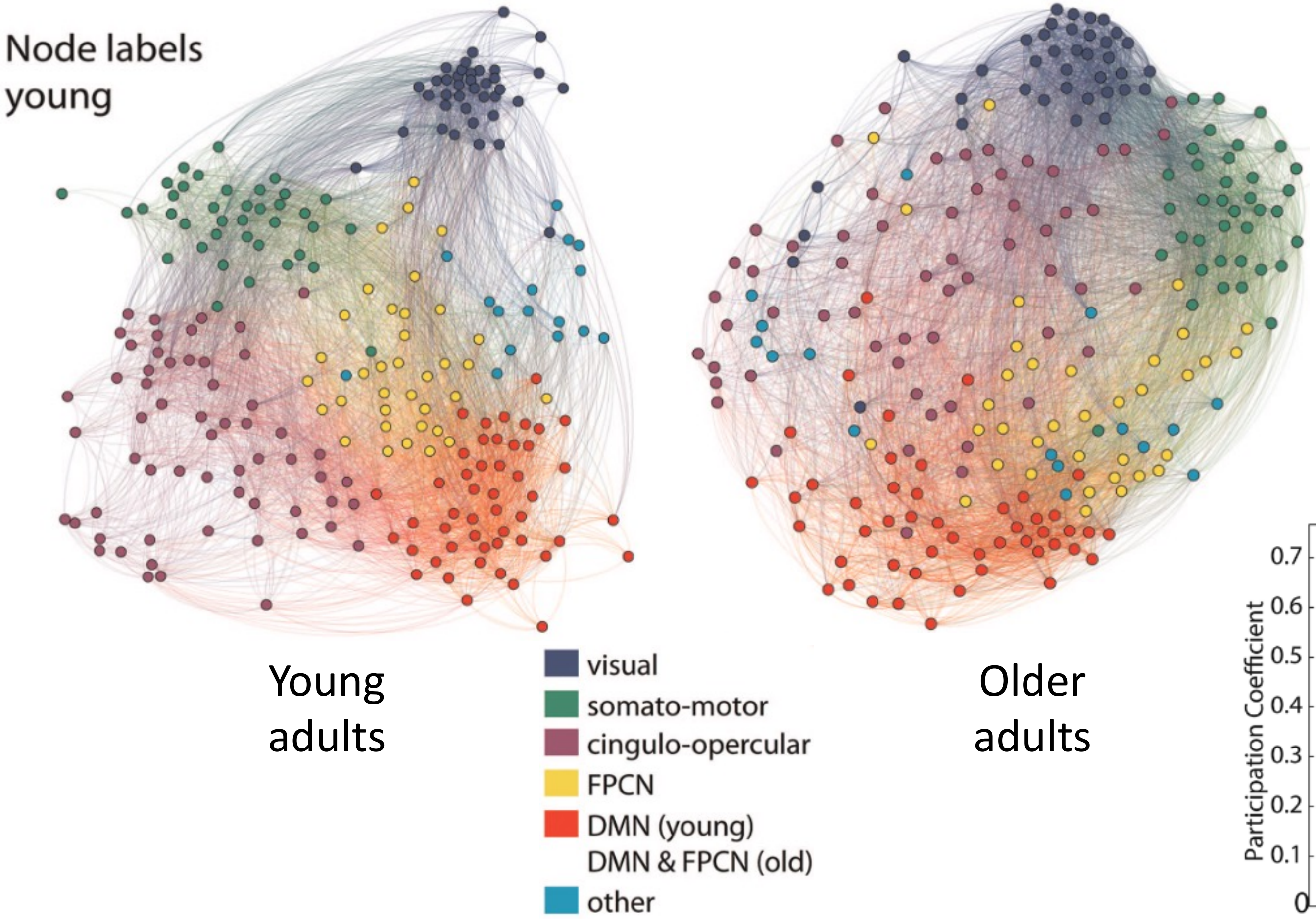
Salience/Cingulo-Opercular Network



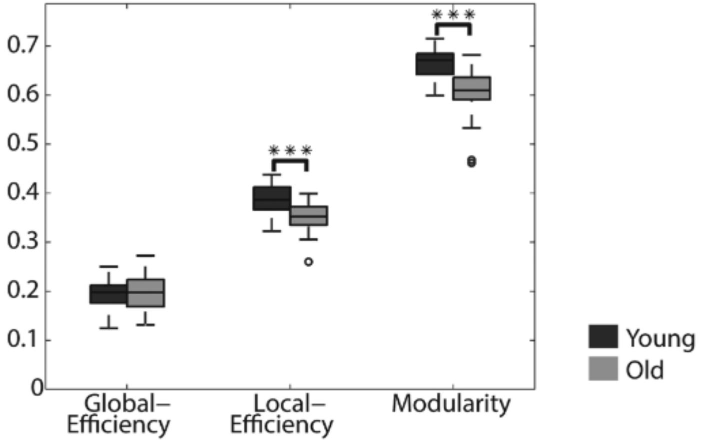

Onoda et al., 2012

# Evidence for network differences between young and older adults

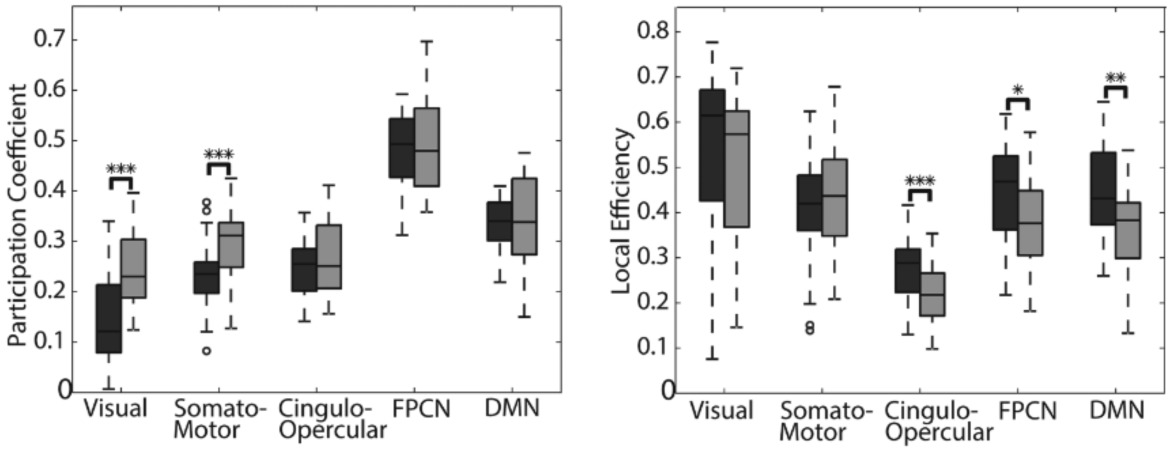
**Differences in community structure**




**Differences in brain-wide network measures**

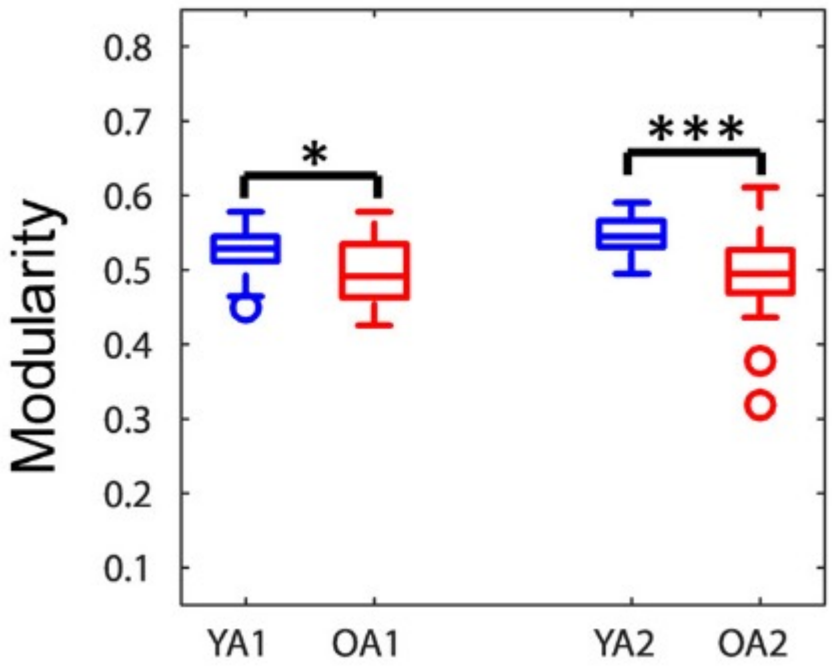


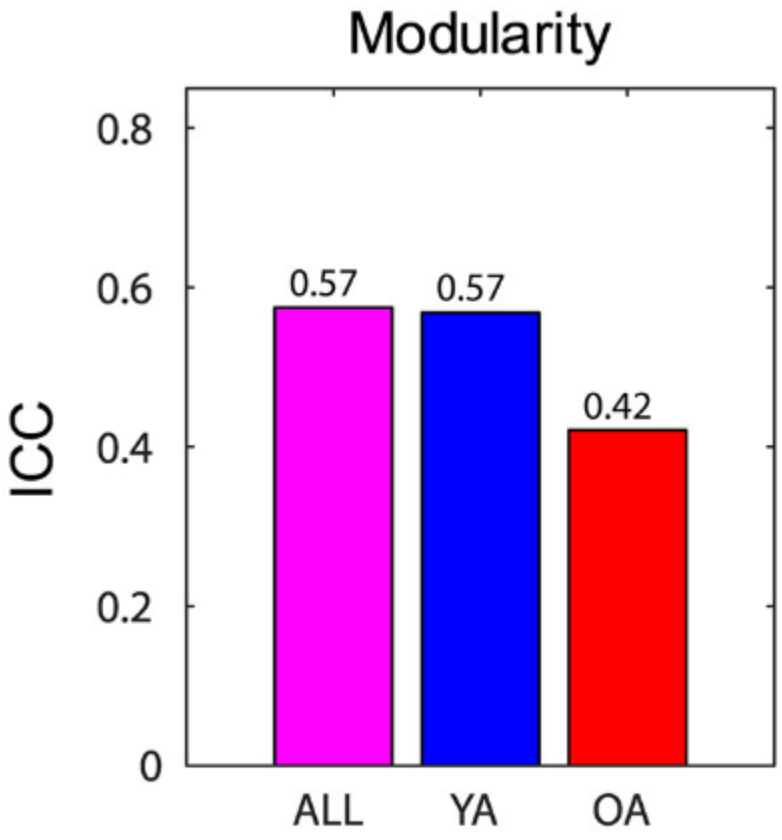

**Differences in individual network measures**




Geerligs et al., 2015

# Modularity decreases with aging



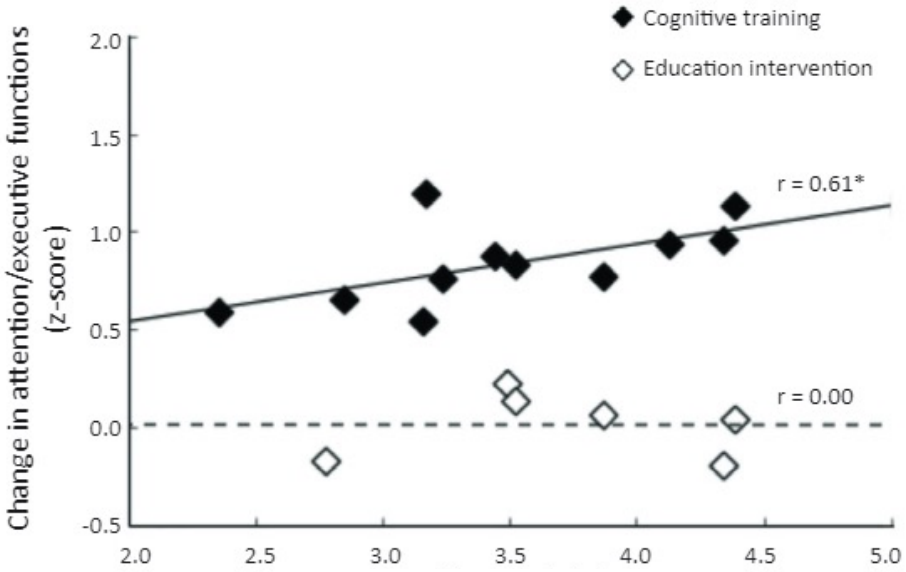

Similar results:
Betzel et al., 2014; Cao et al., 2014; Chan et al., 2014; Gallen et al., 2016;
Geerligs et al., 2015; Onoda & Yamaguchi, 2013; Song et al., 2014

Iordan et al., 2018

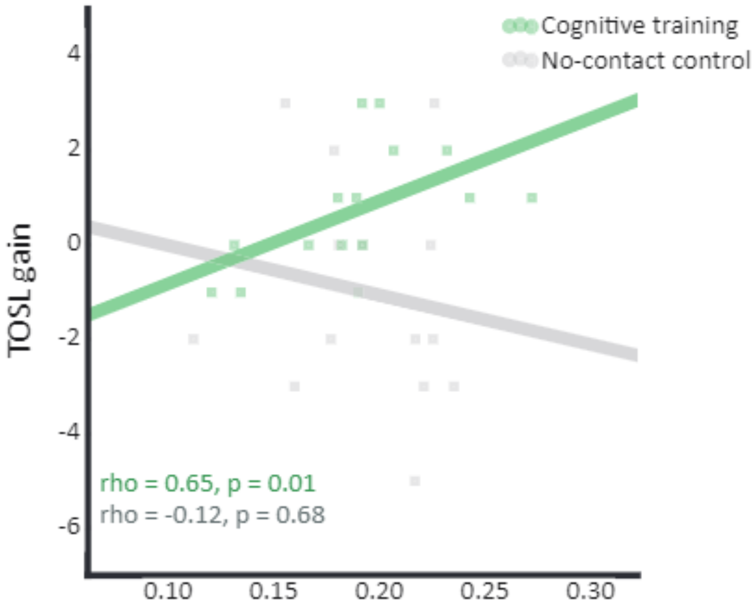
# Modularity Predicts Training-related Cognitive Gains

Patients with
acquired brain injury

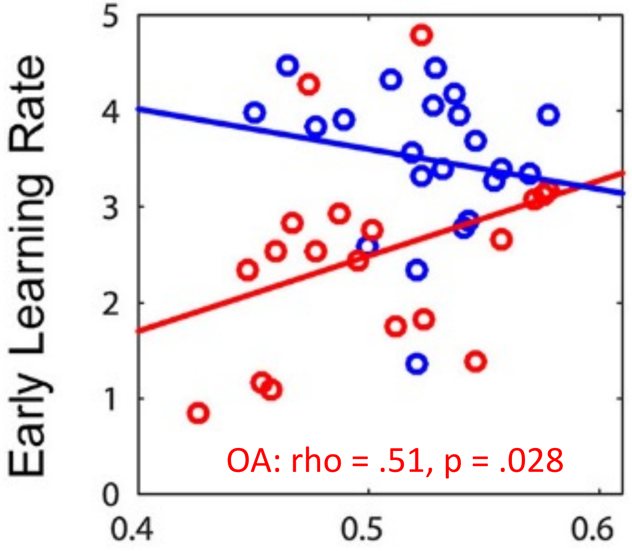
Healthy older adults




Baseline modularity




Baseline modularity




Baseline modularity

Arneman et al., 2015

Gallen et al., 2016

Iordan et al., 2018

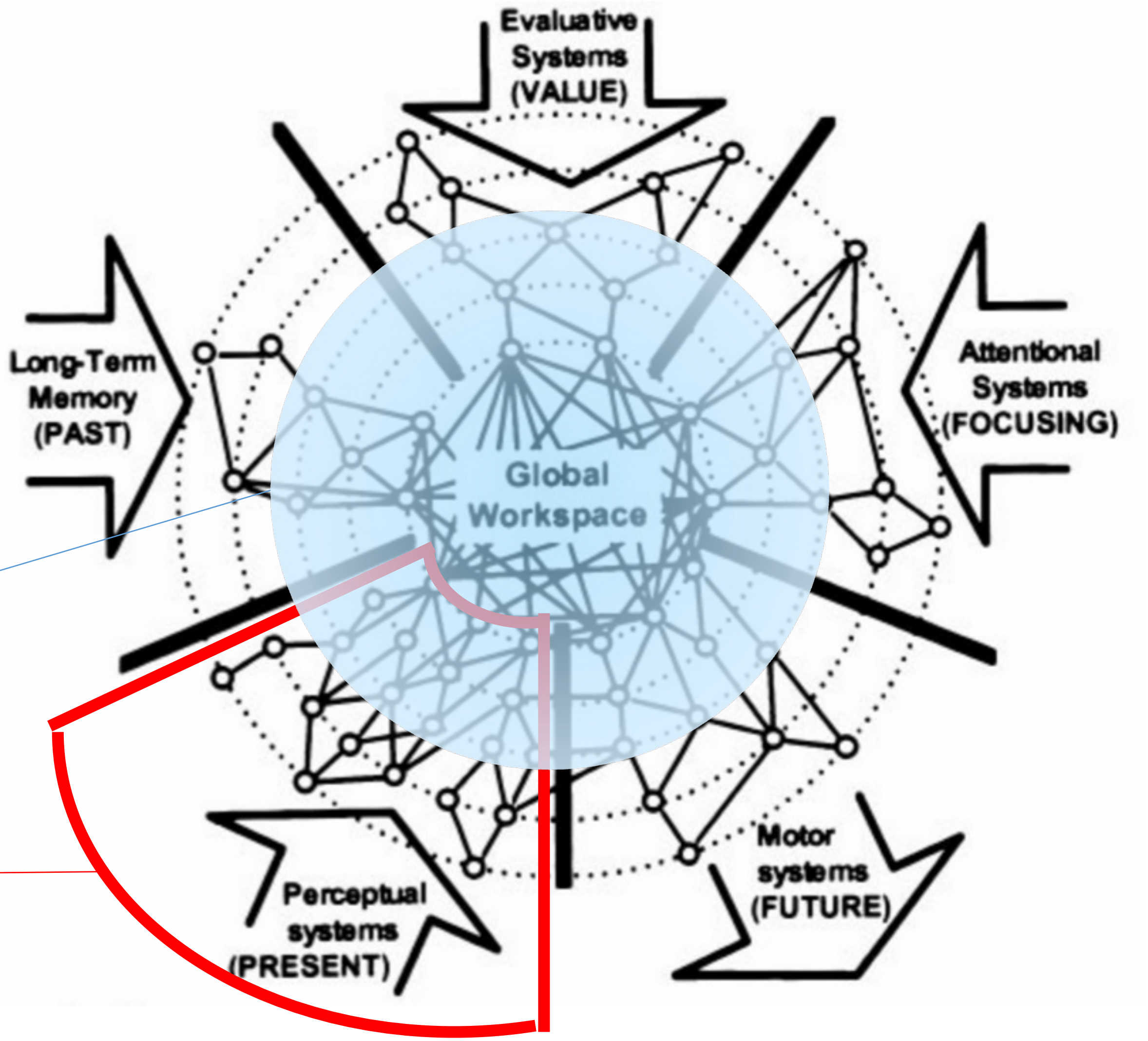
# Cognitive modules and global workspace

- *Modularity of mind* (Fodor, 1983)

- Functional segregation & integration

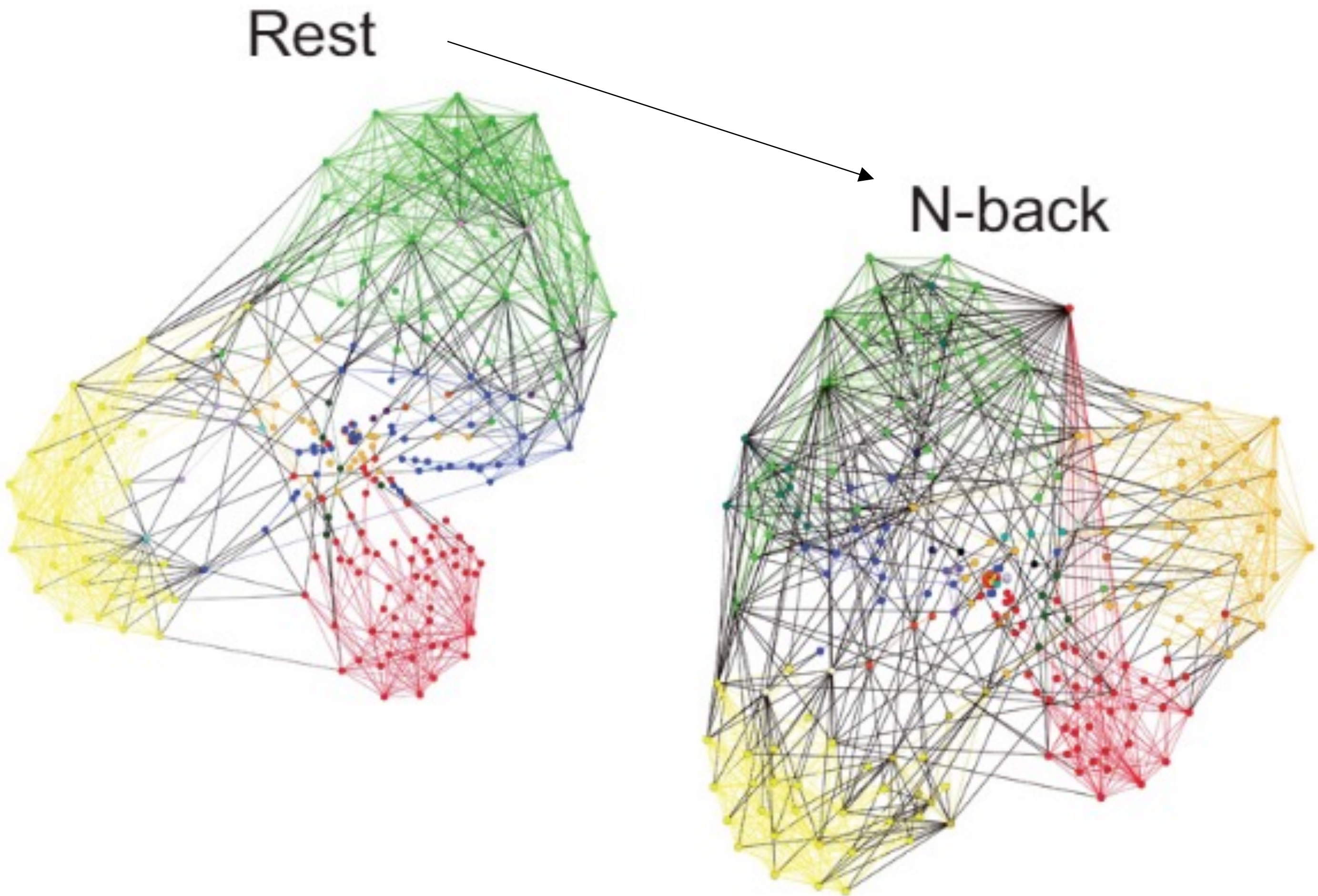
*High-level* cognitive functions (eg. WM) - rely more on a ***global workspace*** than on segregated modular functions.

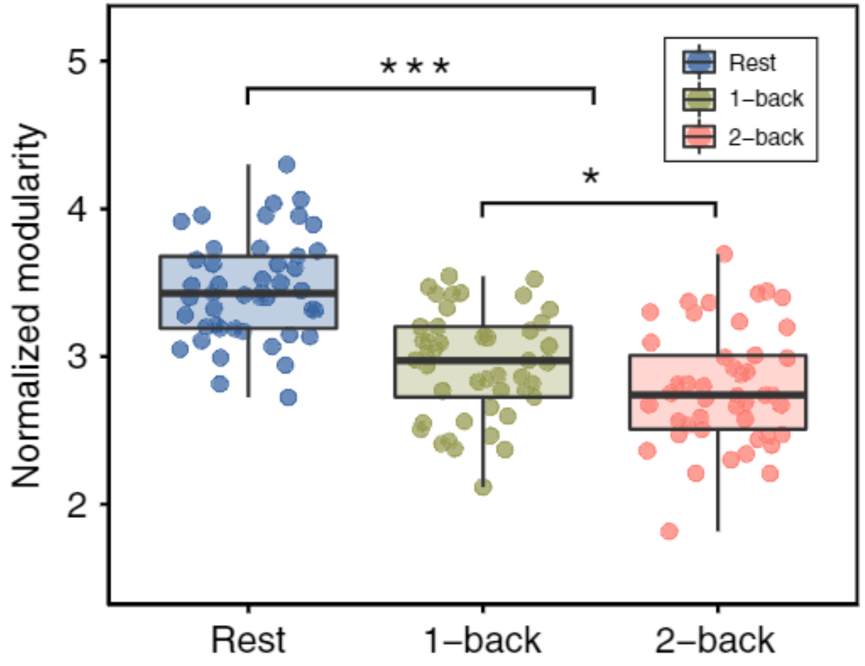
***Modules*** - spatially localized and include specialized brain areas (visual, auditory, motor ...)




Dehaene et al., 1998

# Modularity decreases with increasing cognitive demand

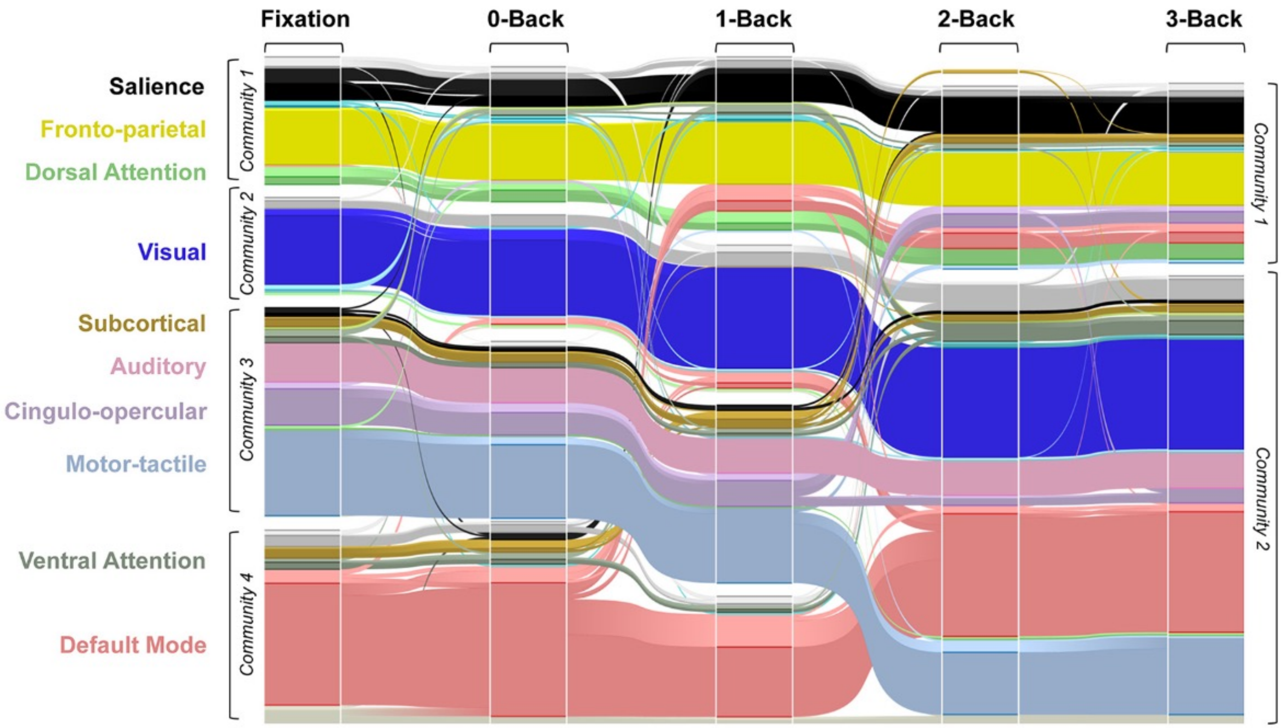


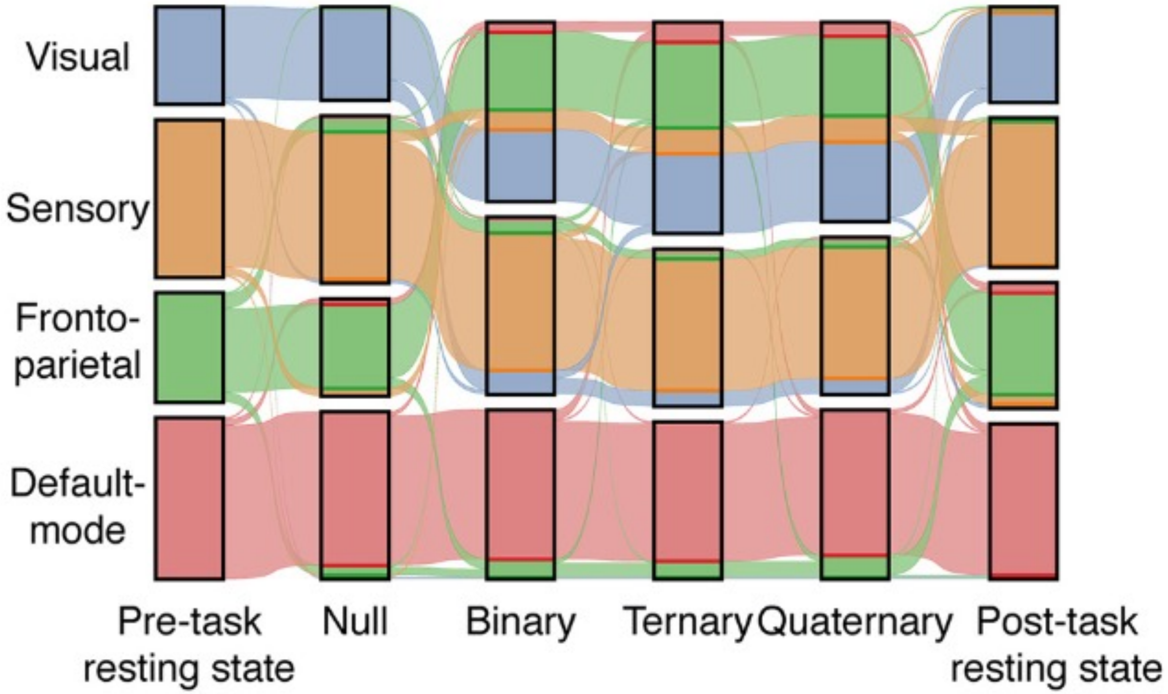

Cohen & D'Esposito, 2016

Finc et al., 2020

# Community structure is influenced by (large shifts in) cognitive demand

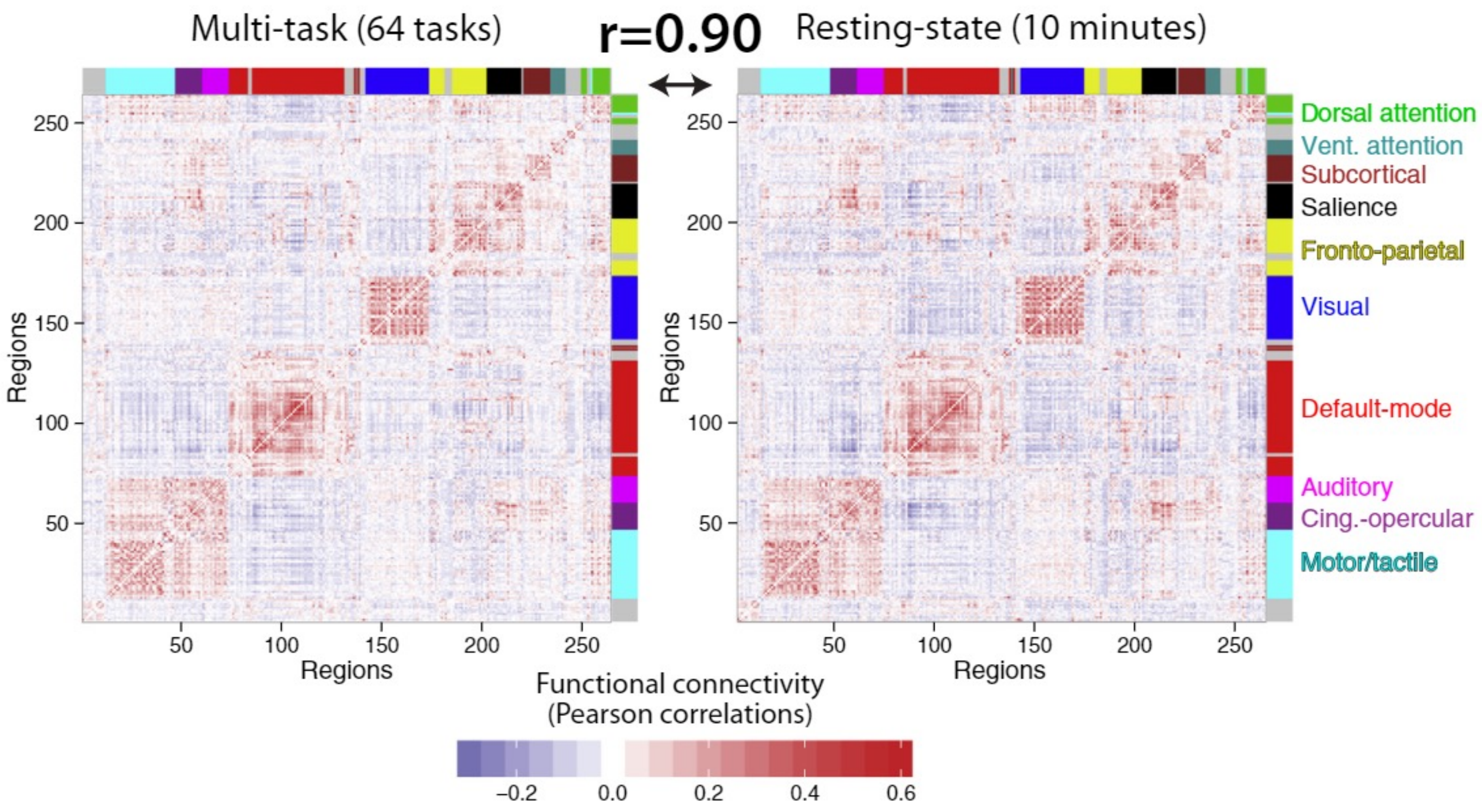



Vatansever et al., 2015




Hearne et al., 2016

# Task-related reconfigurations are “relatively small”



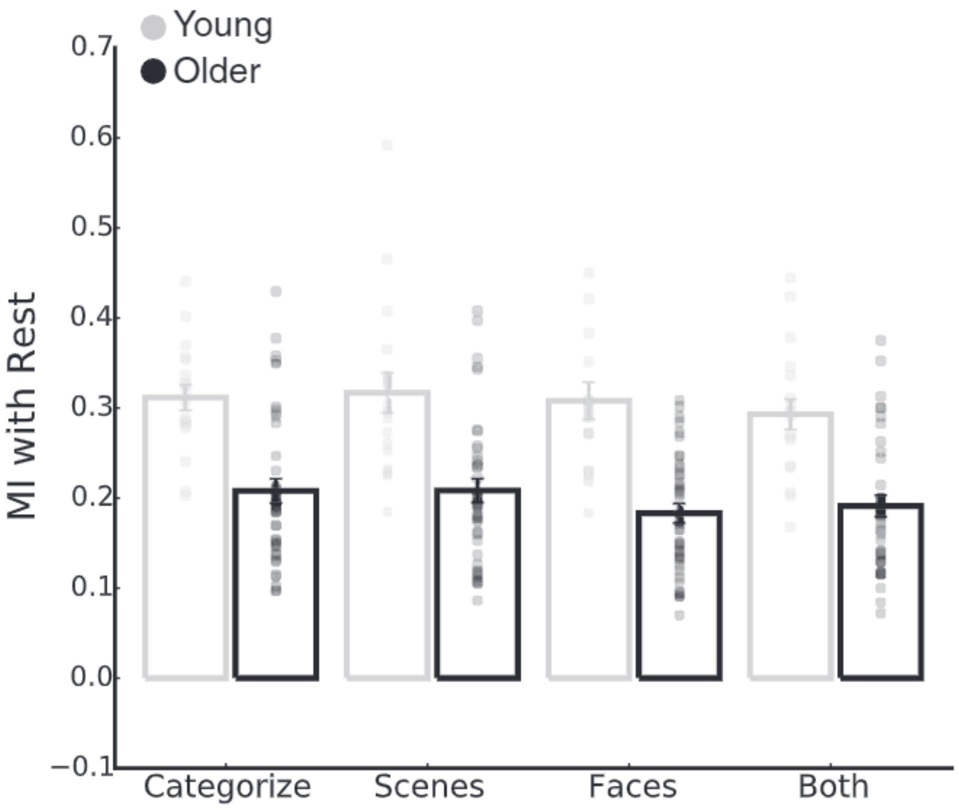

Cole et al., 2014

# Questions

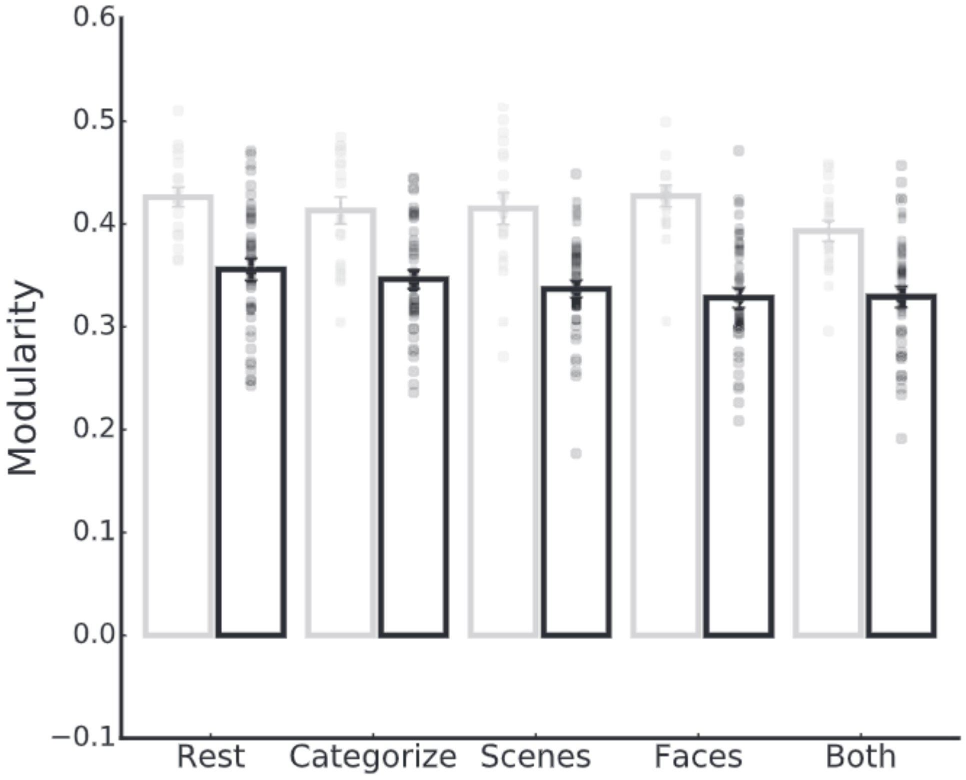
- How does aging affect brain network reconfigurations elicited by demanding cognitive tasks?

- Can these be influenced by cognitive training?

## Greater rest-to-task reconfiguration in OA than YA

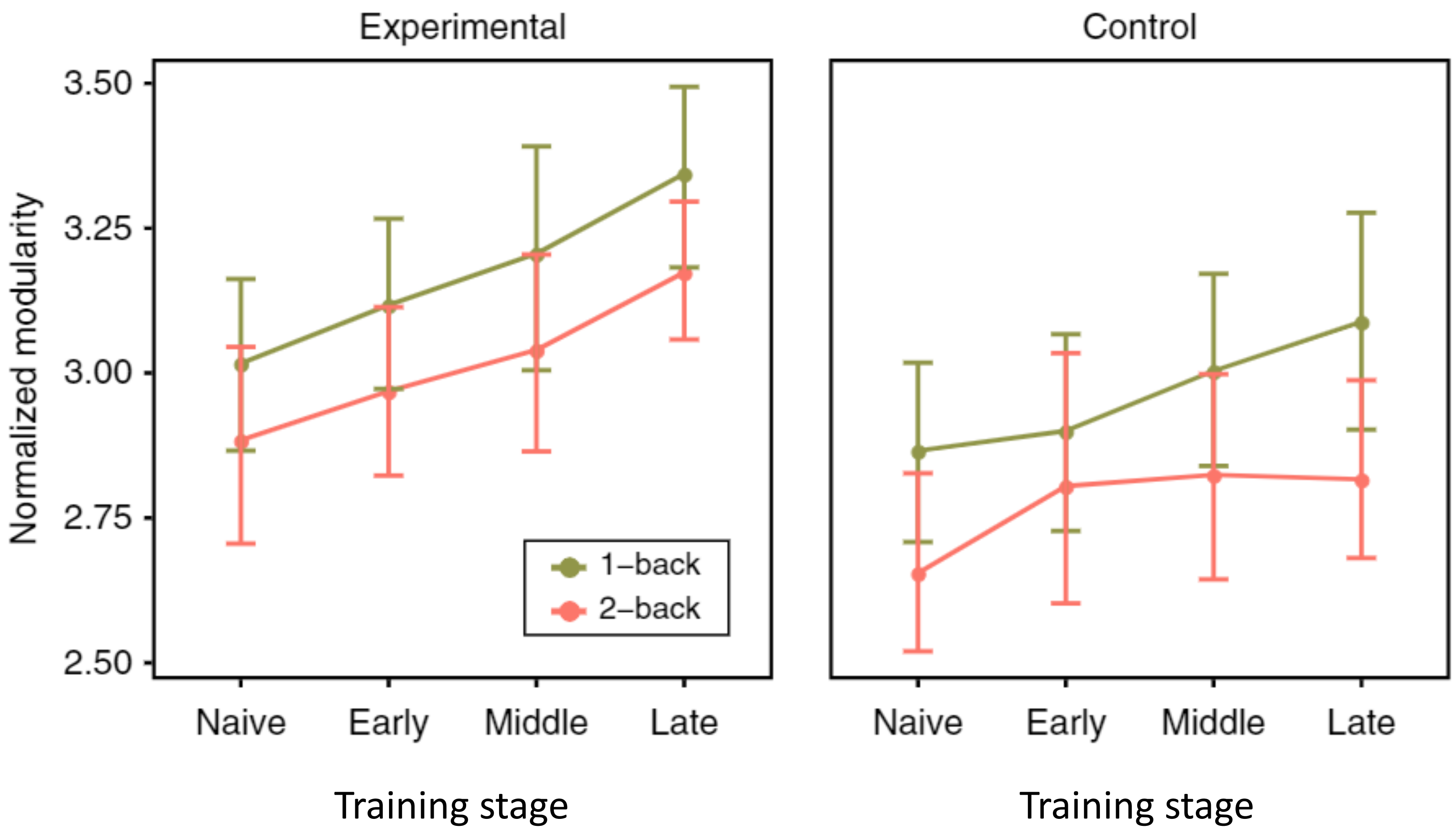



## Lower overall modularity in OA than YA




Gallen et al., 2016

# Modularity increases with training in YA




Finc et al., 2020

# How does aging affect brain network reconfigurations elicited by demanding cognitive tasks?

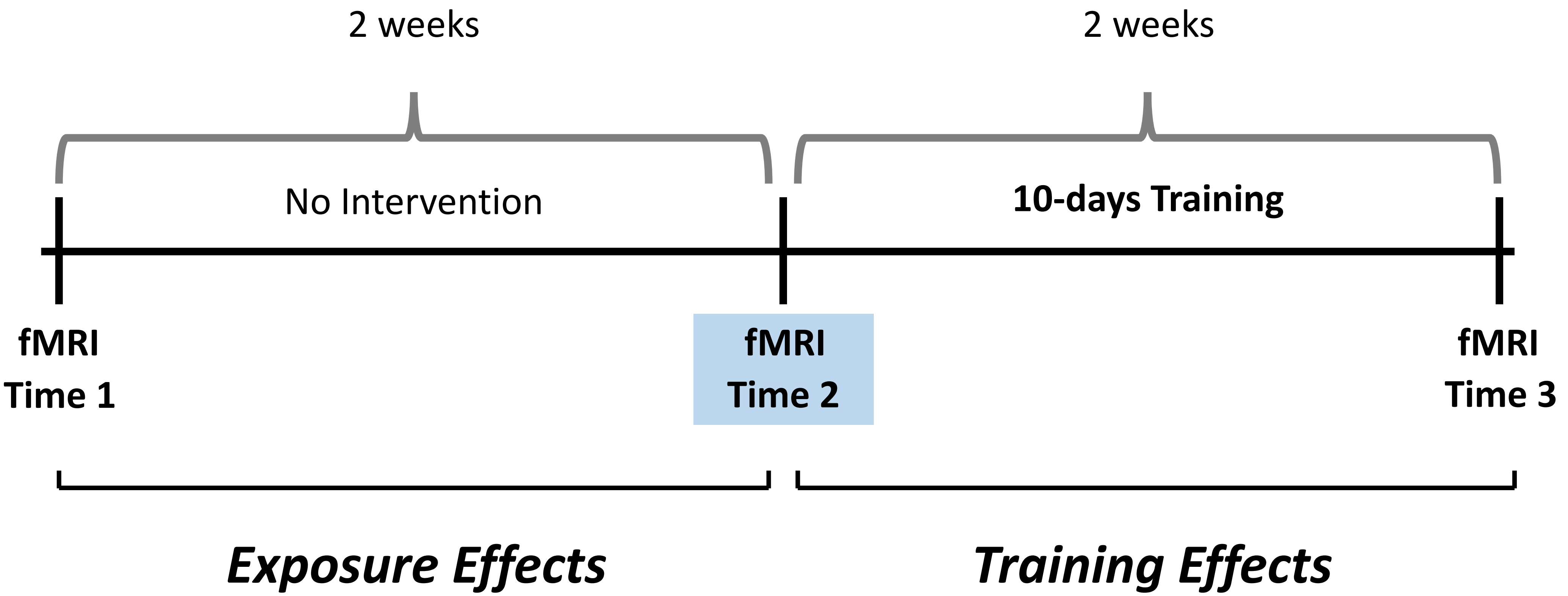
- We expect:
  - Overall lower modularity in older compared to younger adults
  - Lower modularity during task performance compared to resting-state
  - Progressively lower modularity with increasing WM load

- Open questions OA vs. YA
  - Greater decrease in modularity when shifting from resting-state to task mode?
  - Steeper decrease in modularity with increasing task load?

# What is the influence of cognitive training?

- We expect:
  - network reorganization elicited by *training* not *task-exposure*
  - task-related FC more sensitive to training than resting-state
- Open question:
  - Greater modularity enhancement with training in YA vs. OA?
- Brain networks level:
  - Training reconfigures primarily associative brain networks (FPN and DMN)

# Present study: Design



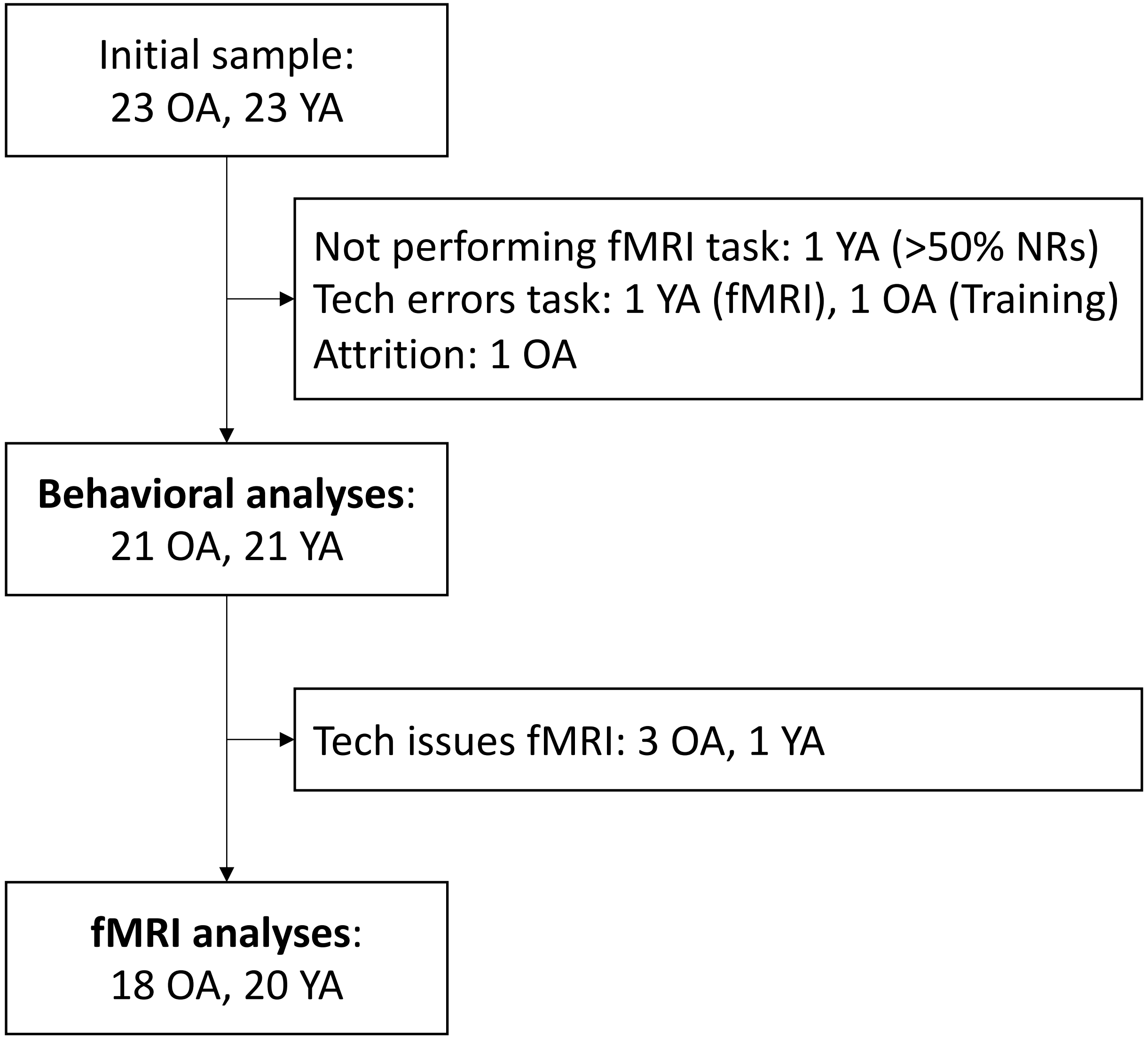

Neuropsychological testing was performed at each time point (Not discussed here).

# Participants

**Power analysis**: 20 OA and 20 YA, 94% power (two-tailed $\alpha$=.05; $\Delta_{\text{MR signal}} \geq .015$), based on Cappell et al., 2010

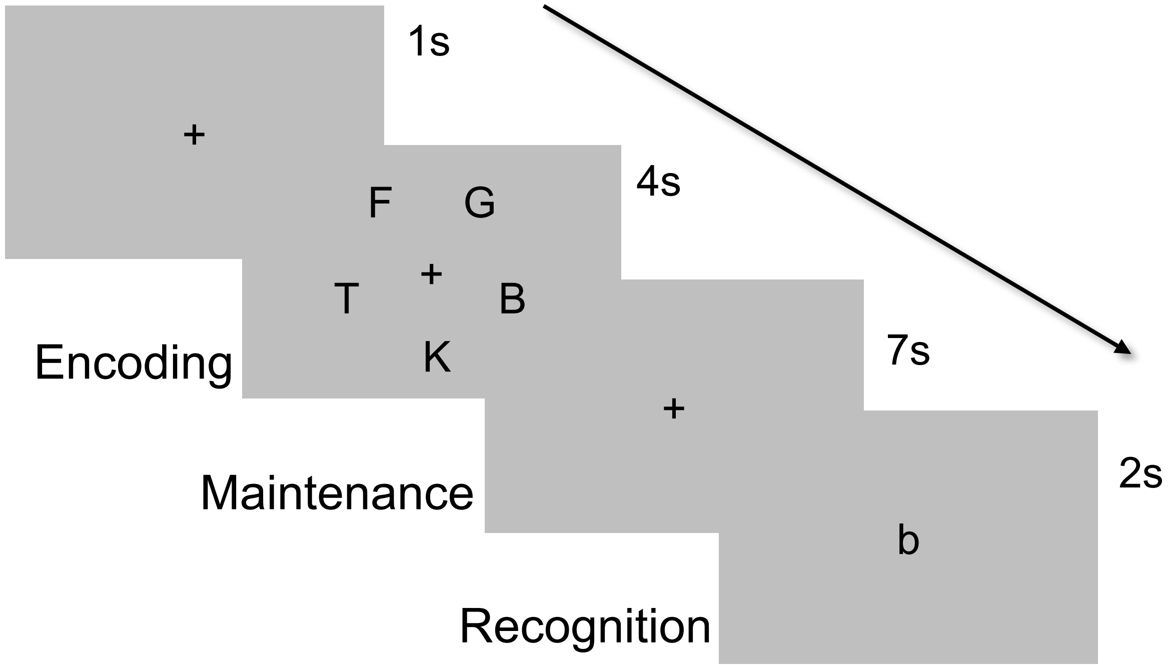
| | **OA** (N = 21) | **YA** (N = 21) |
|---|---|---|
| % Female | 48 | 57 |
| Age (S.D.) | 67.81 (3.31) | 21.33 (2.65) |
| Edu (S.D.)$^{***}$ | 17.05 (1.63) | 14.81 (1.75) |
| MoCA (S.D.) | 28.24 (1.61) | 28.48 (1.50) |

$^{***}$*p*<.001




MoCA, Montreal Cognitive Assessment

# fMRI & Training Tasks:
# Verbal WM (Sternberg) tasks with varying Load



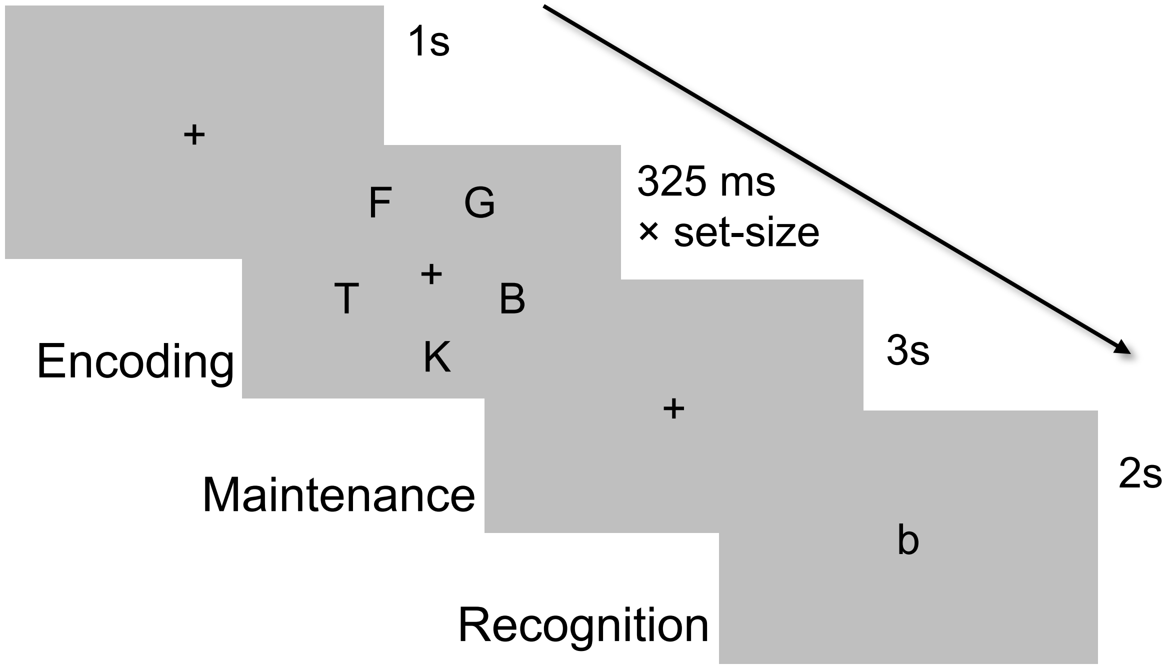

***fMRI (Criterion) Task:***

OA: loads 1 (task mode), 4-8

YA: loads 1 (task mode), 5-9

- Set-size was randomized (6 blocks of 24 trials)

# fMRI & Training Tasks: Verbal WM (Sternberg) tasks with varying Load




***fMRI (Criterion) Task:***

OA: loads 1 (Baseline), 4-8

YA: loads 1 (Baseline), 5-9

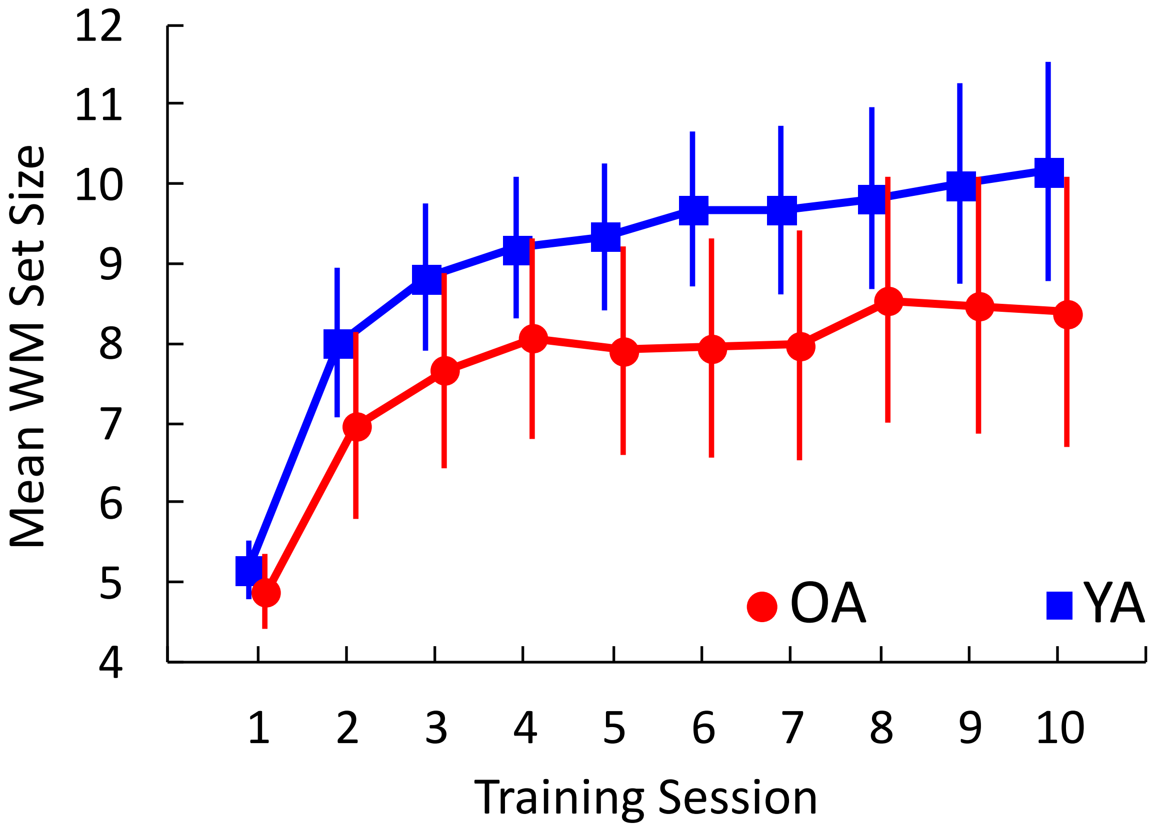
- Set-size was randomized (6 blocks of 24 trials)

***Adaptive Training Task:***

Initial set size = 3 letters

- Set-size was blocked: increased if accuracy >86%, decreased if <72% (6 blocks of 14 trials/sess)

# Adaptive Training Task Results

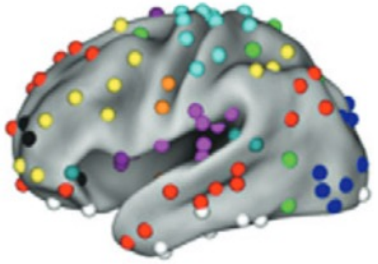



Both groups improved in WM performance across the course of training, $F_{9,378}$=103.9, $p$<.001, $\eta_p^2$=.712

YA improved more than OA, $F_{1,378}$=15.7, $p$<.001, $\eta_p^2$=.40

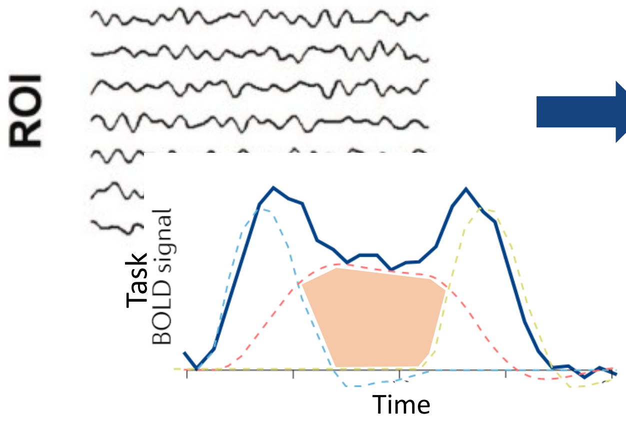
# Procedure
# "Background connectivity"

**Defining ROIs**

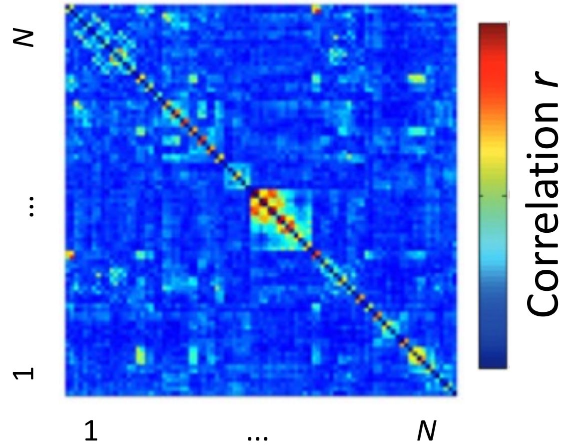


Power et al., 2011

**Extracting and de-noising time courses**

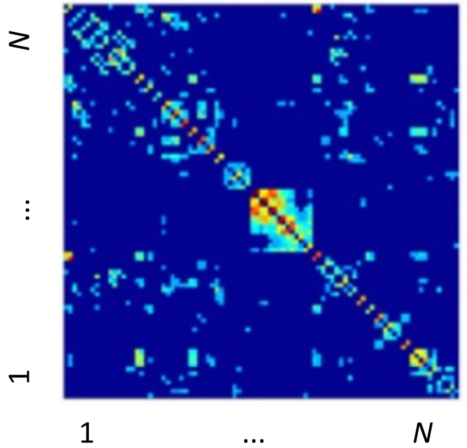



**Calculating correlation matrix**

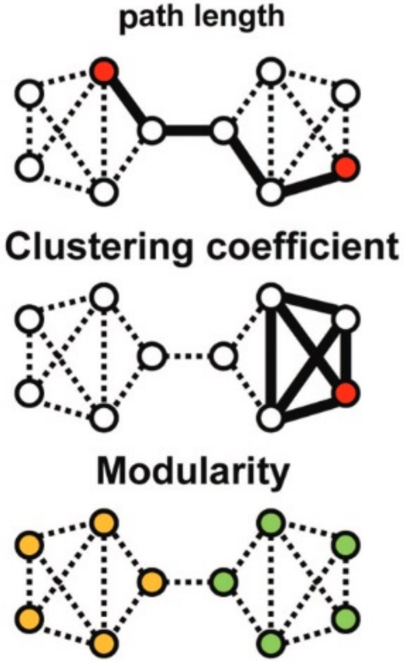



Fisher-*z* transform

**Thresholding**
10-30%, weighted



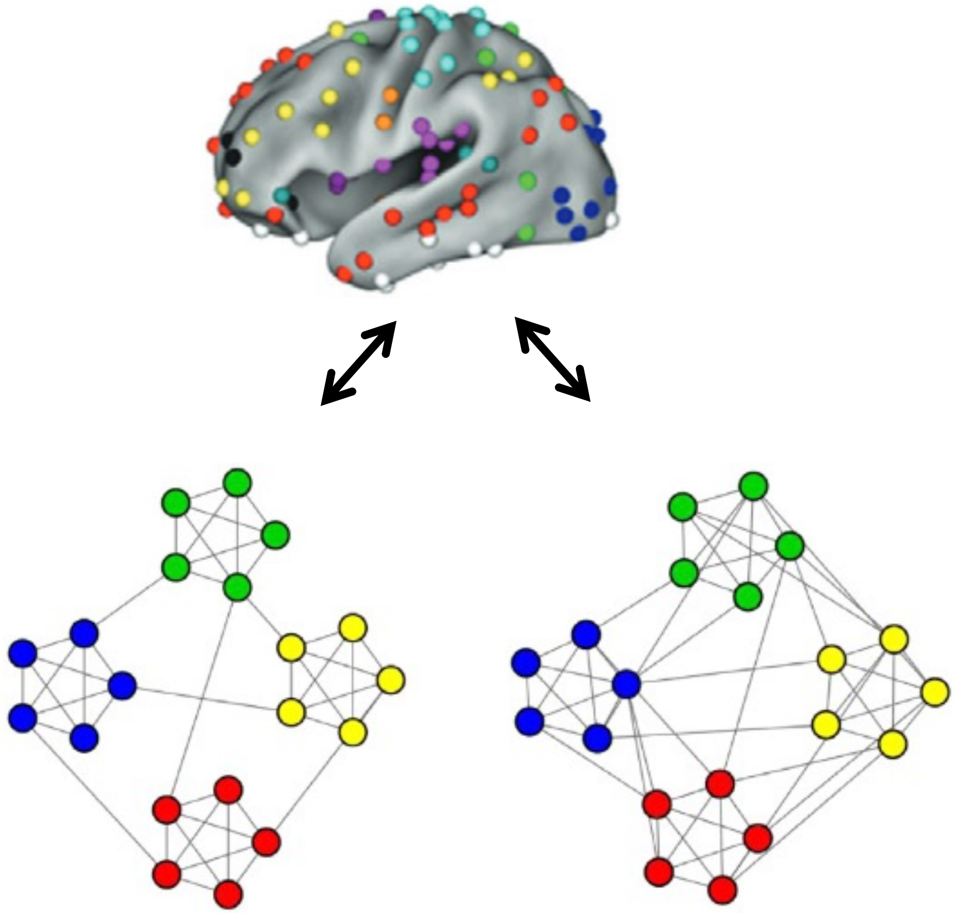

**Calculating network measures**




images: Uehara et al., 2013; Taya et al., 2016; Power et al., 2013; Sreenivasan & D'Esposito, 2019

# 3 levels of analysis

- Whole brain
  - Segregation/integration
- Individual networks
  - Within-network communication
  - Between-network communication
- Network components (sub-network)
  - Pairwise relations between brain regions

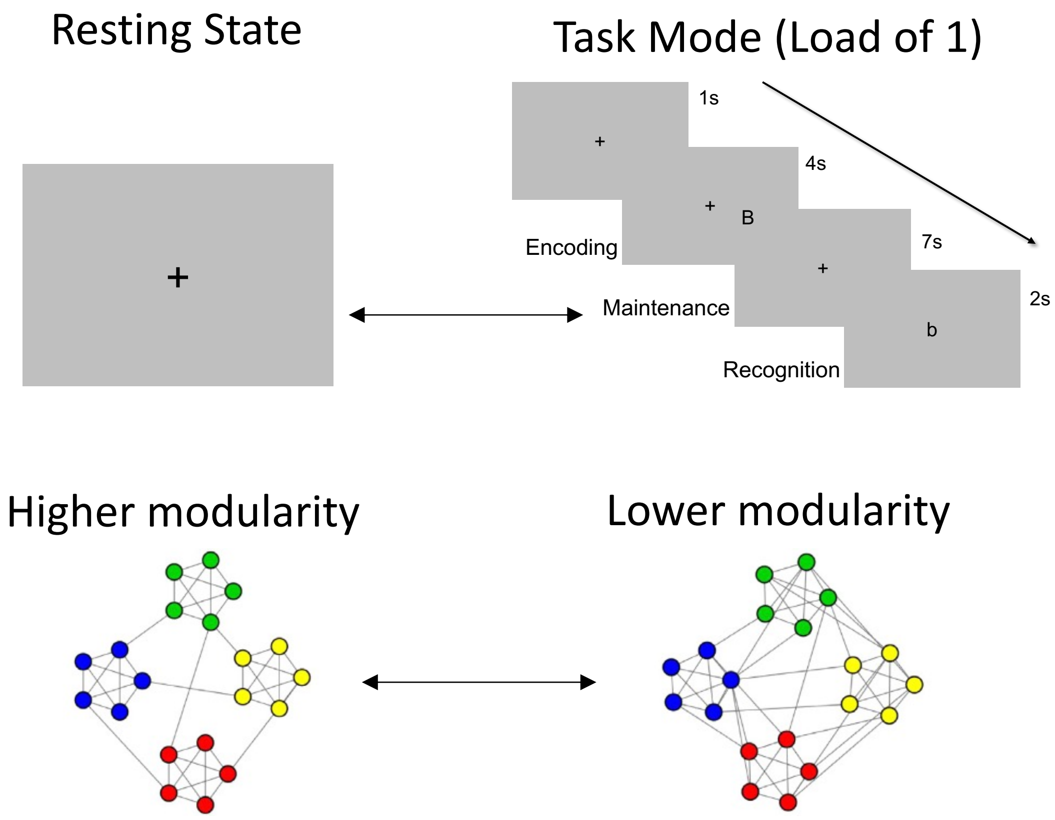


Images: Power et al., 2013; Wig, 2017

# 1. Whole-Brain Results

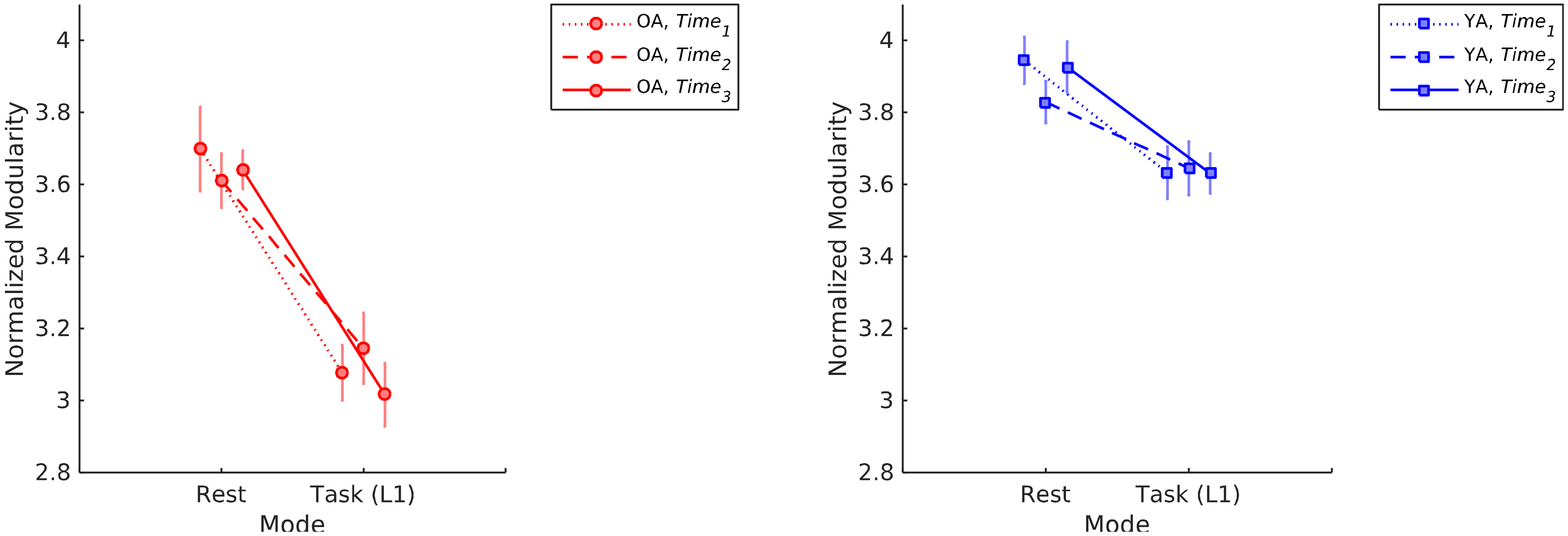
## Modularity: Whole-brain segregation/integration

- **Rest-to-task shift**
  - Lower modularity in OA than YA
  - Lower modularity during task than during rest
  - Greater modularity decrement with rest-to-task shift in OA than YA?
  - Minimal effect of training



# 1. Whole-Brain Results: Modularity

**Lower modularity and greater decrement with rest-to-task shift in OA**

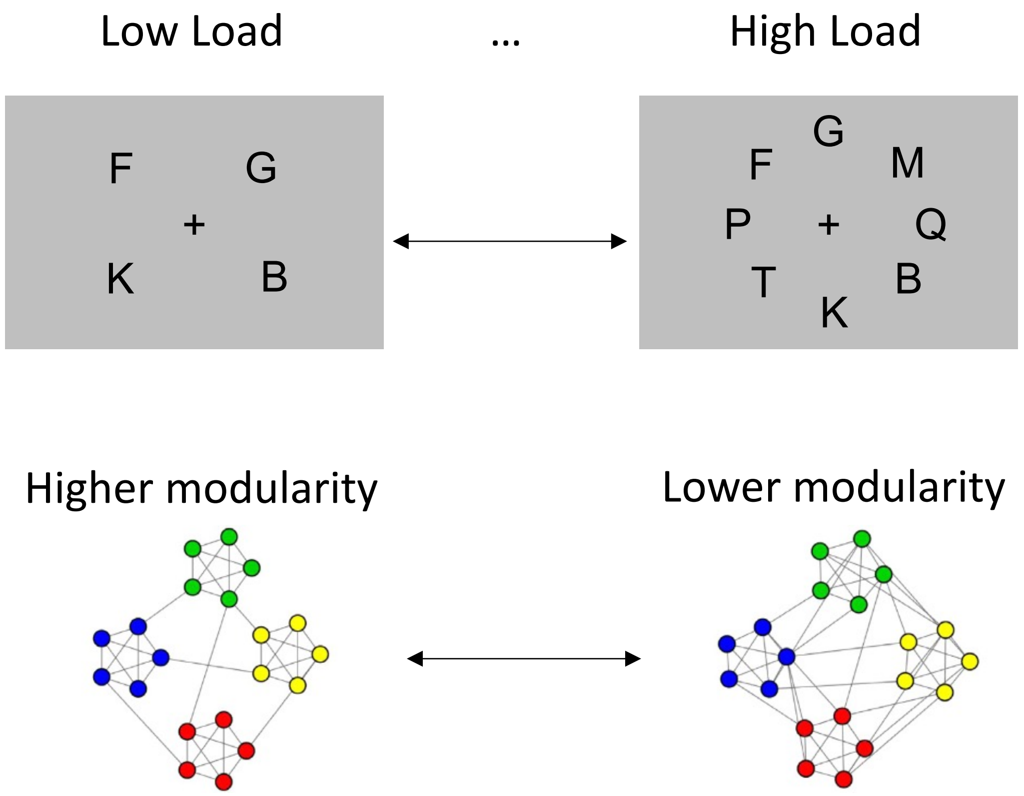



- Lower overall modularity in OA vs. YA. Group: $F_{1,36}$=31.99, $p$<0.001, $\eta_p^2$=0.47
- Lower modularity during task than rest. Mode: $F_{1,36}$=141.51, $p$<0.001, $\eta_p^2$=0.8
- Greater modularity decrement with rest-to-task shift in OA. Group×Mode: $F_{1,36}$=19.14, $p$<0.001, $\eta_p^2$=0.35

# 1. Whole-Brain Results

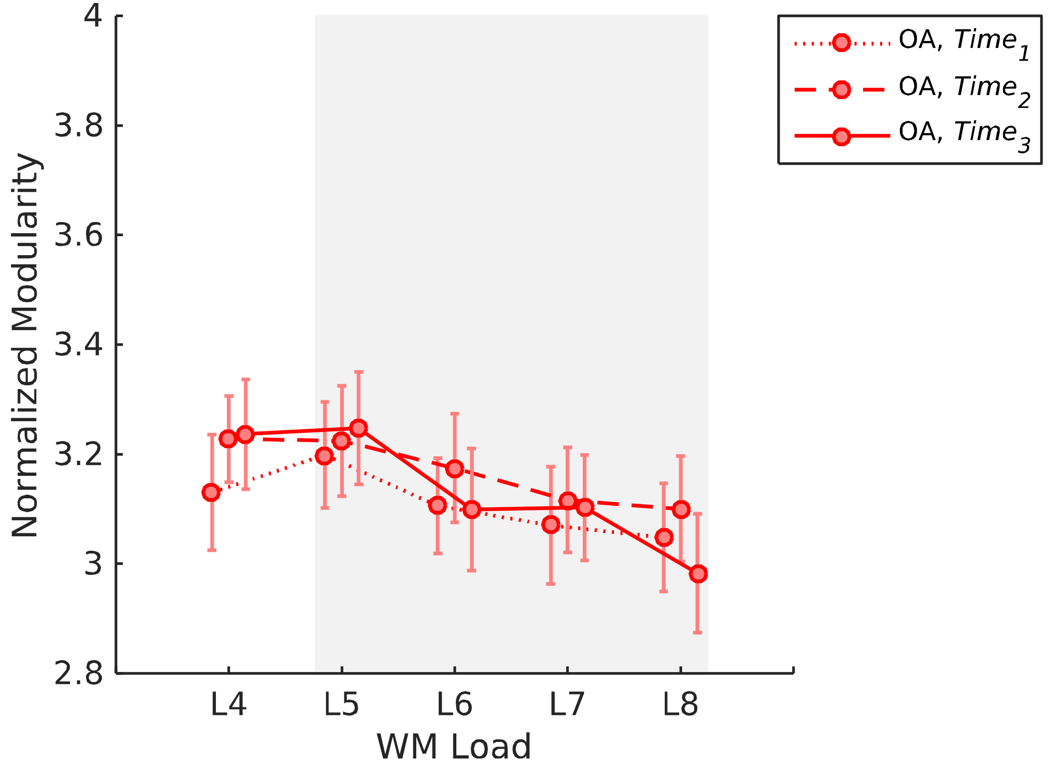
## **Modularity: Whole-brain segregation/integration**

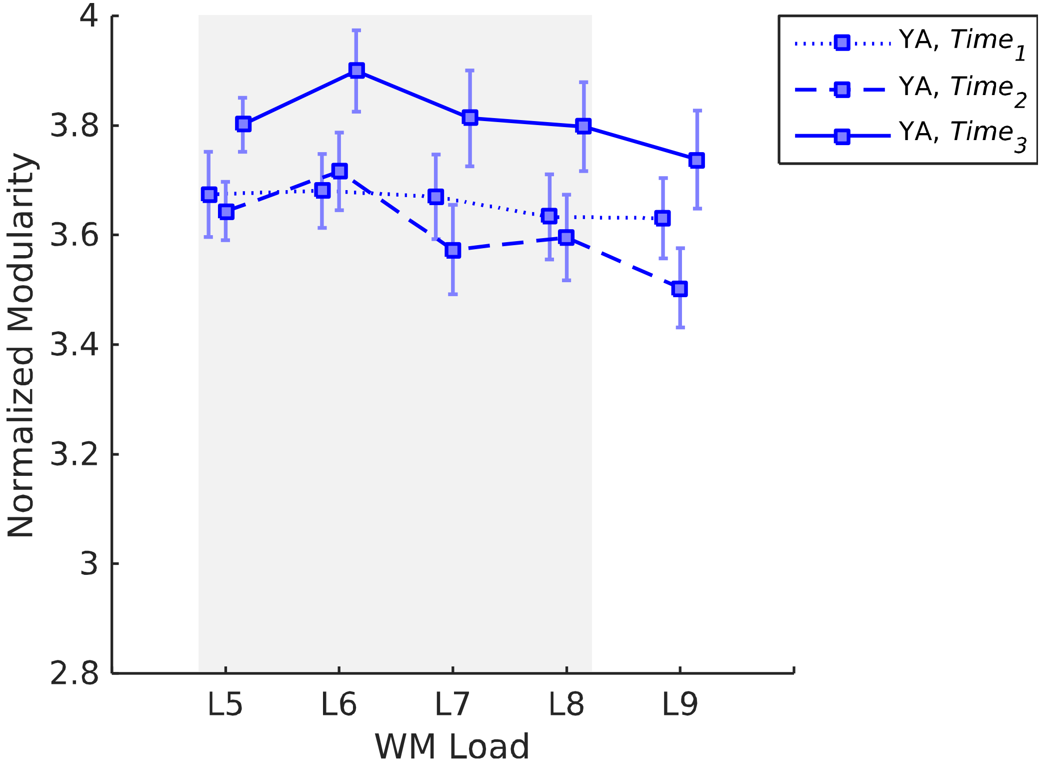
- **Increasing task demand**
  - Lower modularity in OA than YA
  - Lower modularity with increasing load
  - Steeper modularity decrement in OA than YA?
  - Changes with *training*, not simple *task-exposure*
  - Greater modularity with training in YA than OA?



# 1. Whole-Brain Results: Modularity

## Increased task-related modularity with training in YA



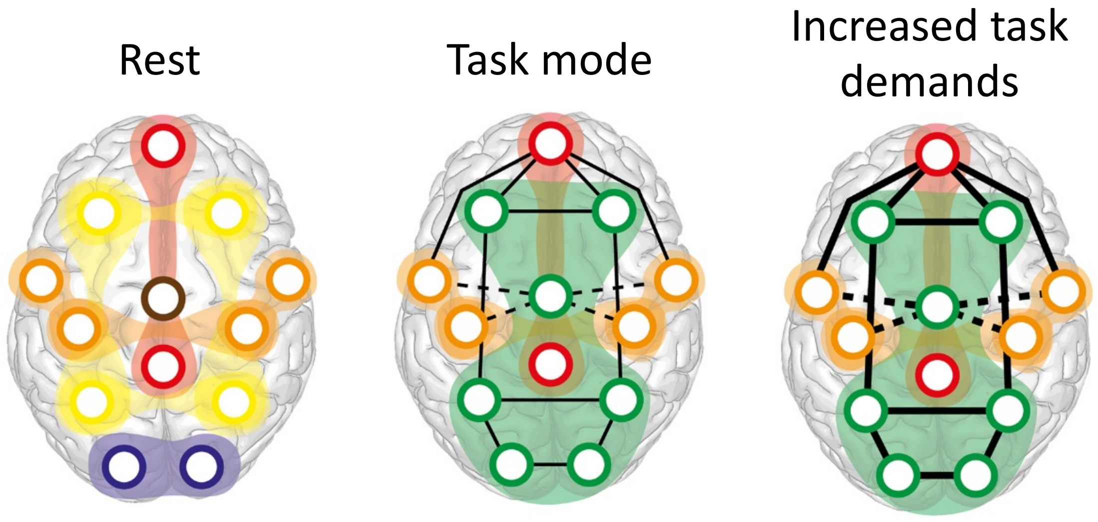



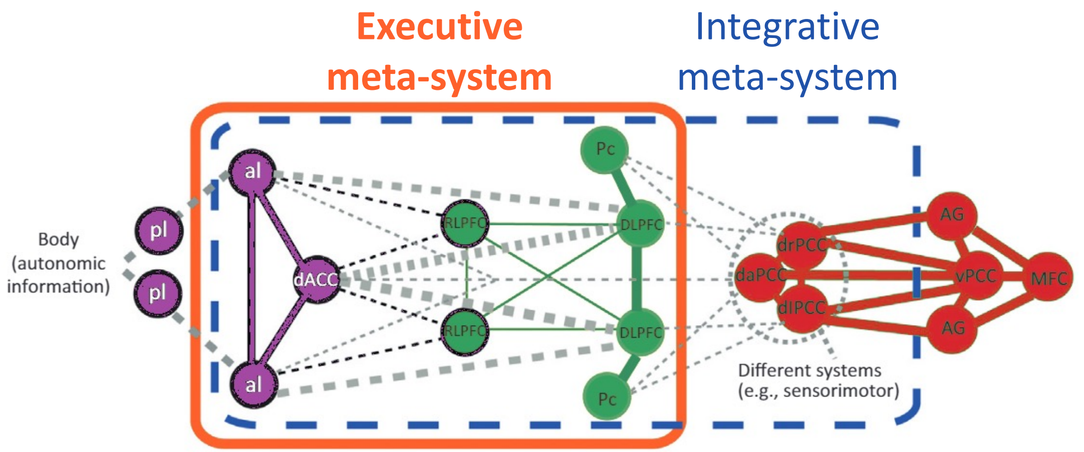

- Lower overall modularity in OA vs. YA. Group: $F_{1,36}$=37.38, $p$<0.001, $\eta_p^2$=0.51
- Lower modularity with increasing load. Load: $F_{3,108}$=5.89, $p$=0.001, $\eta_p^2$=0.14, linear trend p<0.001;
- Steeper modularity decrement in OA vs YA. Group×Load: $F_{3,108}$=3.21, $p$=0.026, $\eta_p^2$=0.08
- Group×Time interaction. $F_{2,72}$=4.64, $p$=0.013, $\eta_p^2$=0.11
  - OA: No *task exposure* or training effects
  - YA: No *task exposure* but significant *training* effect, Time: $F_{1,19}$=25.88, $p$<0.001, $\eta_p^2$=0.58

# 1. Whole-Brain Results

## Community structure: Network/module composition

- **Demand and training effects**
  - Change from rest to task
  - Greater reorganization in OA than YA?
  - Less change with increasing demand
    - Integrative -> Executive meta-system
  - Effect of training?

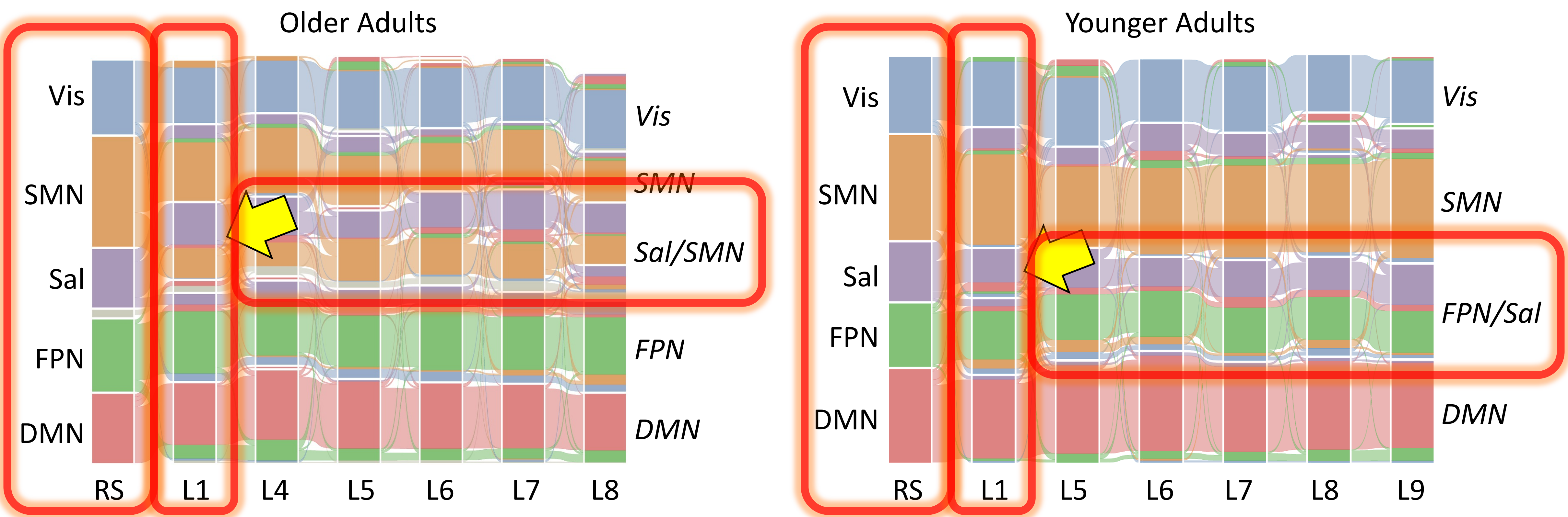



Images: Hearne et al., 2017; Cocchi et al., 2013

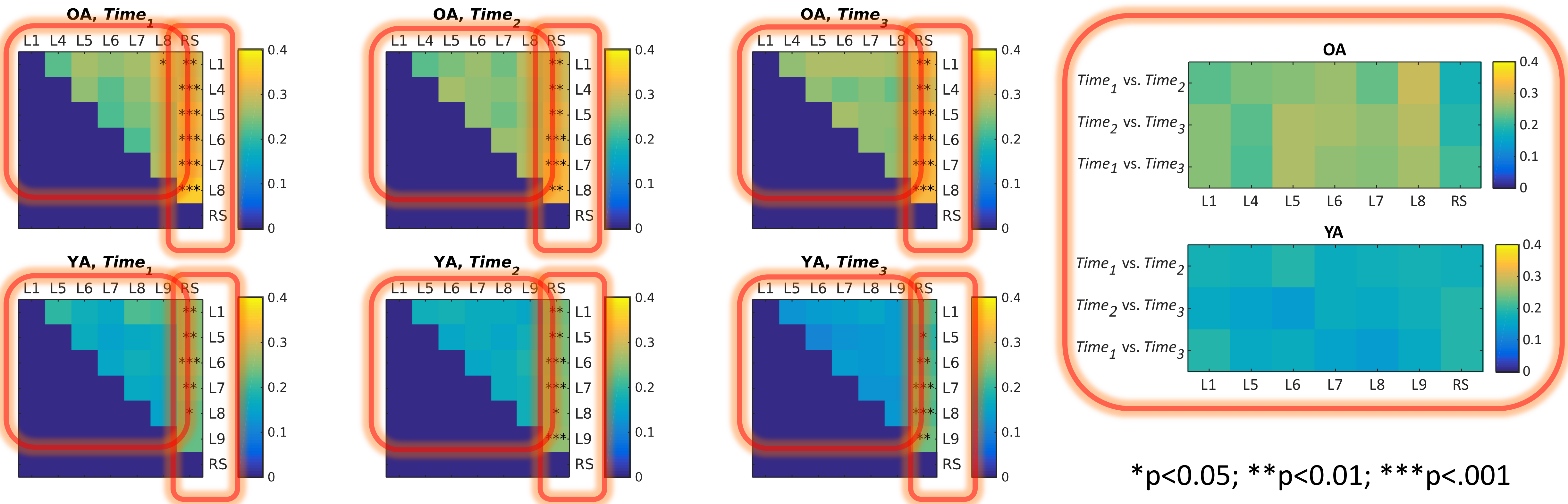
# 1. Whole-Brain Results: Community Structure

**Node-module assignments across rest and task loads at Time1**




- OA and YA show 5 main modules at rest
- Switching from rest (RS) to task (L1) leads to different configurations
  - OA: emergence of *salience/sensorimotor module* (Sal/SMN)
  - YA: relatively less reorganization; Group×Time ANOVA on VIn, Group: $F_{1,36}$=75.89, $p$<0.001, $\eta_p^2$=0.68
- Increasing WM load
  - OA: Task community structure largely preserved
  - YA: emergence of *fronto-parietal/salience module* (FPN/Sal)

# Rest-to-task differences in community structure

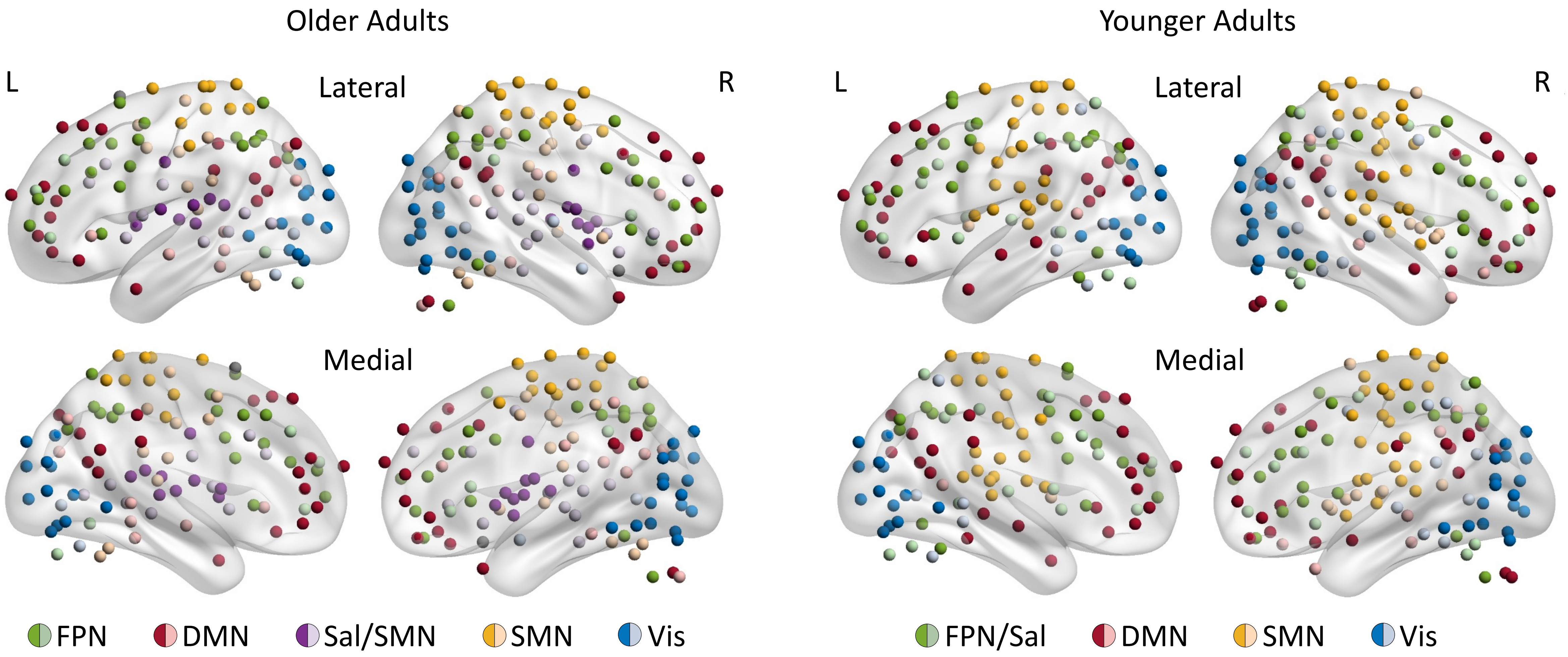



*p<0.05; **p<0.01; ***p<.001

- Community structure is different for rest compared to WM loads
- No (consistent) differences in community structure between loads
- No differences in community structure across time

# 2. Individual Networks Results

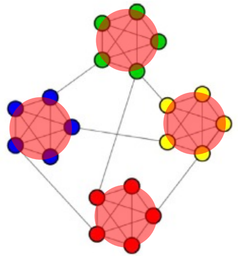
**Node-module assignments across loads at Time1**

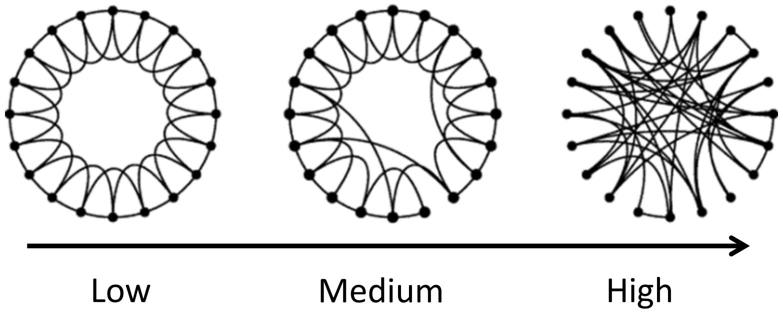


# 2. Individual Networks Results

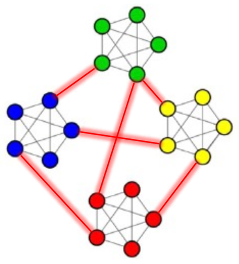
## Primary targets: FPN and DMN

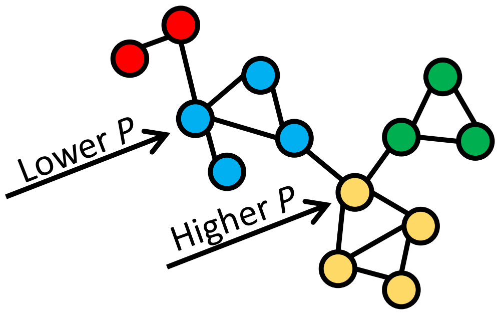
- **Within-network communication: Global Efficiency**
  - Parallel information transfer, integrated processing






- **Between-network communication: Participation Coefficient**
  - Distribution of node connections across modules

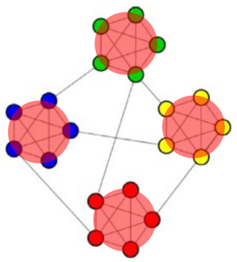


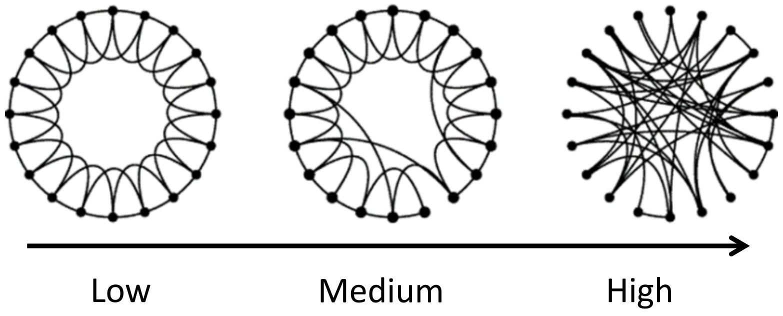


# 2. Individual Networks Results

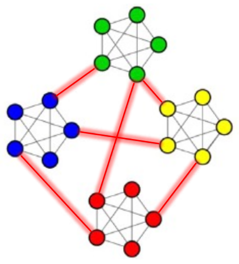
## Outcomes:

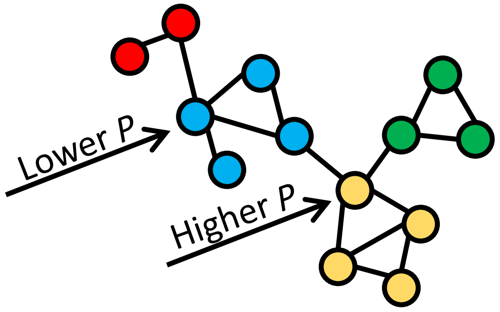
- **Within-network communication: Global Efficiency**
  - ↗Training: Greater increase = more efficient processing
  - ↘Load: Less decrease = better coping with demand





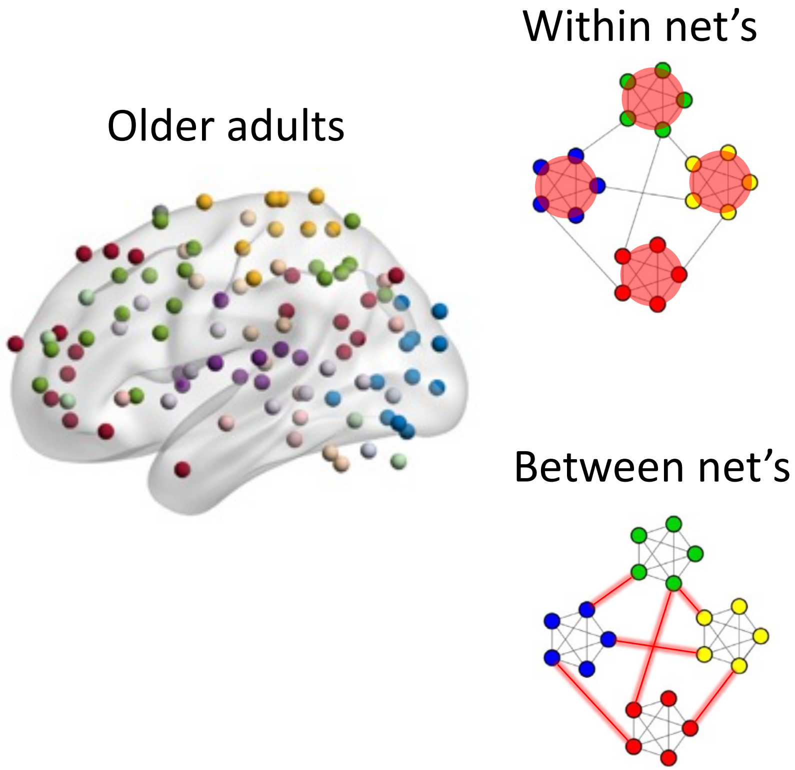

- **Between-network communication: Participation Coefficient**
  - ↘Training: Greater decrease = more automatic processing (less integration required)
  - ↗Load: Less increase = better coping with demand (less integration required)

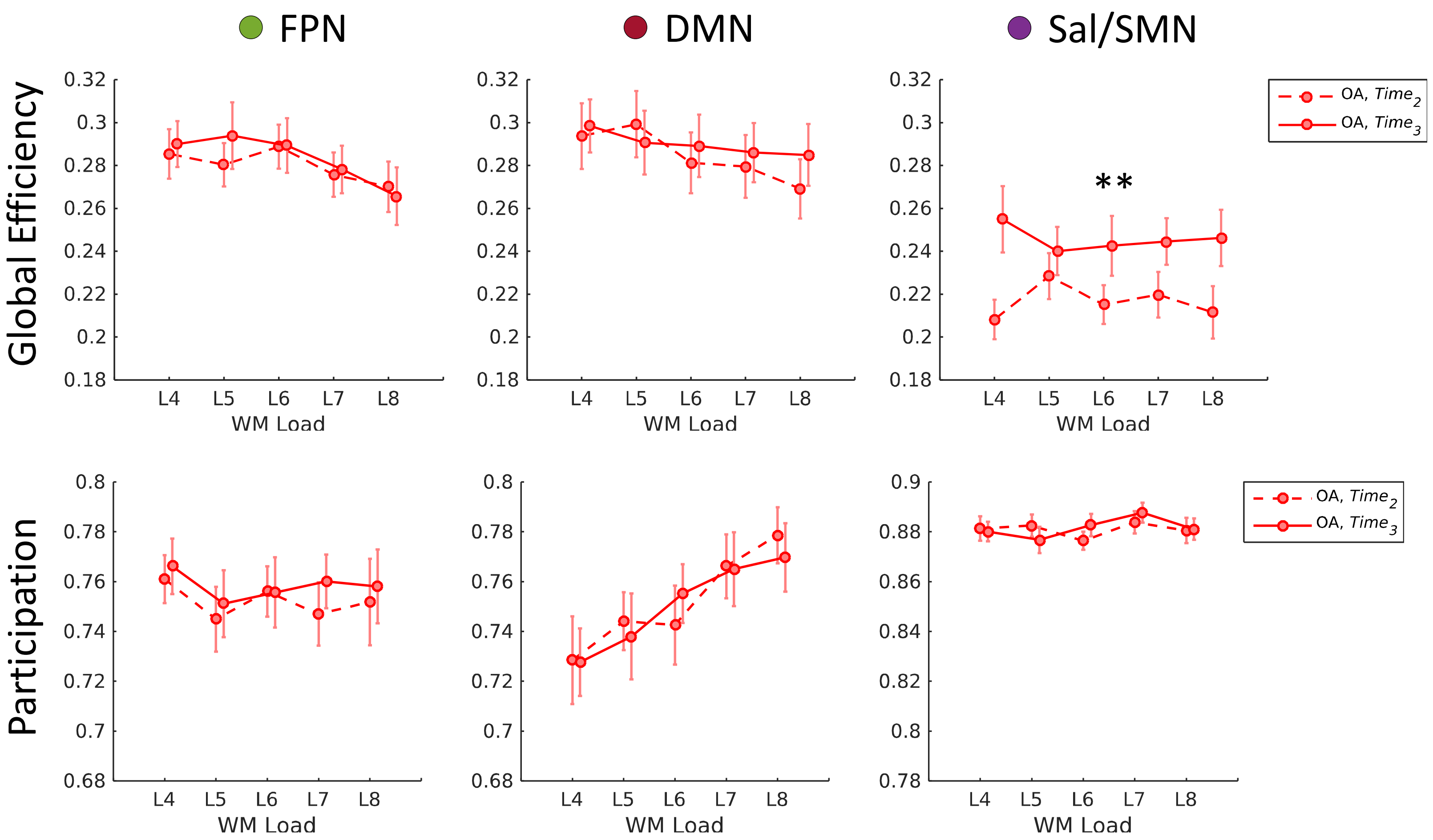




# 2. Individual Networks Results

## OA: Increased global efficiency within Sal/SMN with training

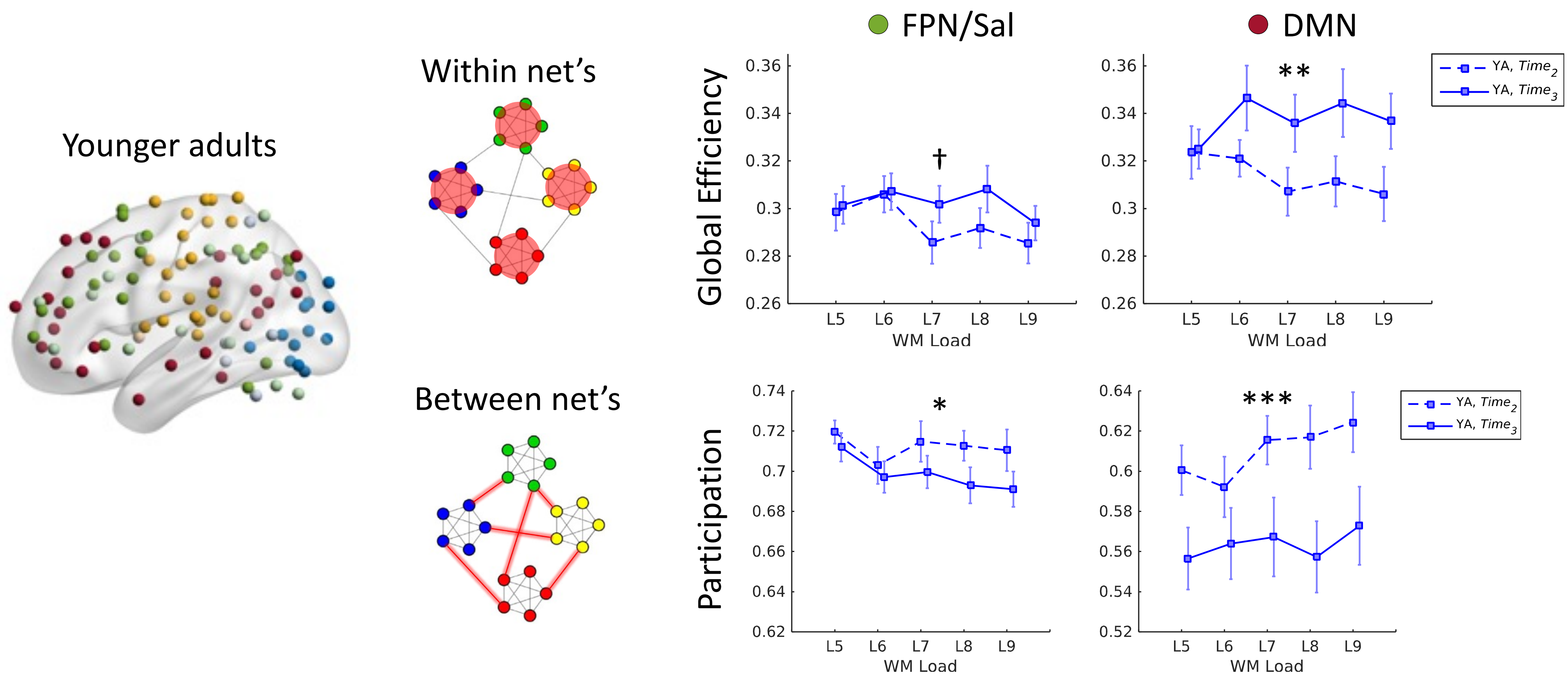



- **Training effect** on Sal/SMN global efficiency ($p$=0.008)
- **Load effects** on FPN ($p$=0.01) and DMN global efficiency ($p$=0.029), and DMN participation ($p$<0.001).

# 2. Individual Networks Results

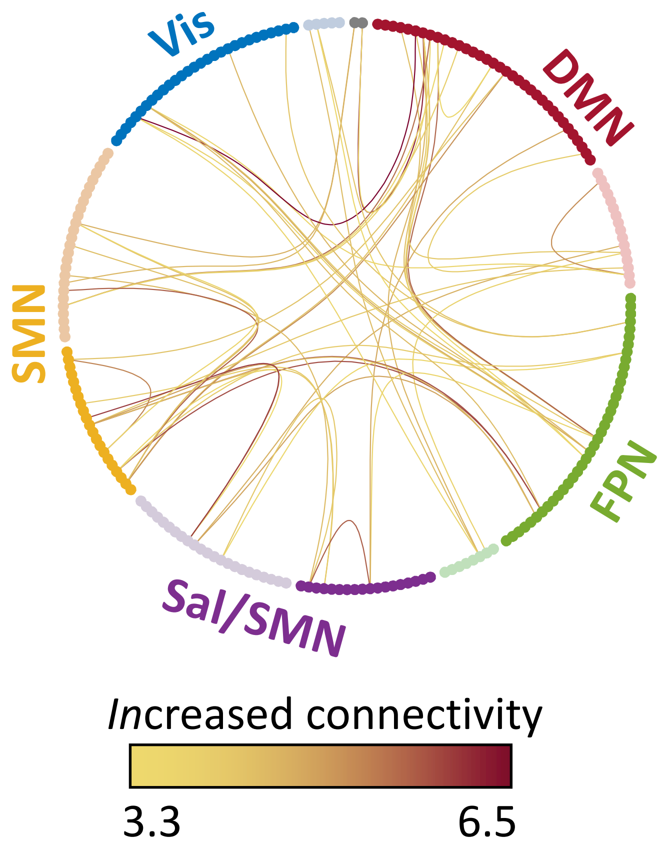
## YA: Increased global efficiency within and lower participation of FPN/Sal and DMN with training



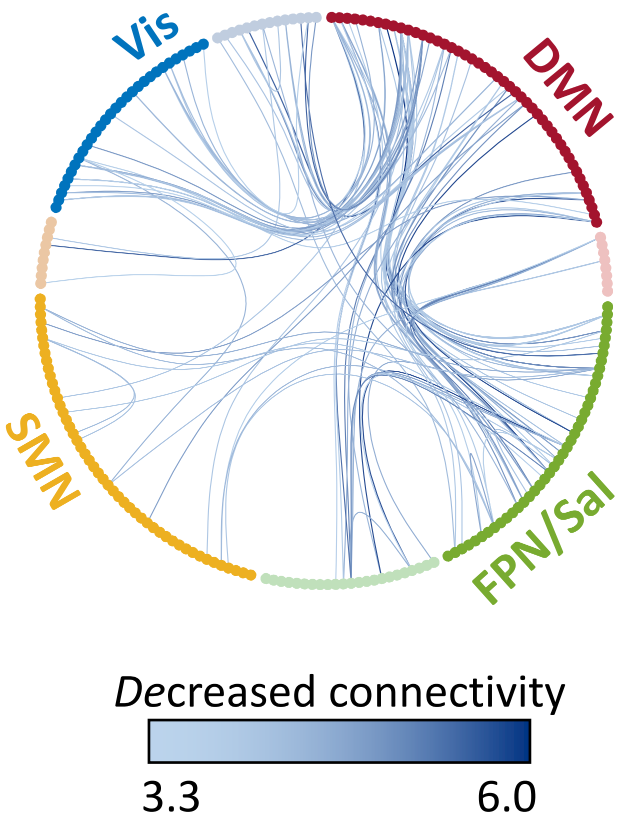

- **Training effects** on:
  - Global efficiency of FPN/Sal ($p$=0.076) and DMN ($p$=0.003).
  - Participation of FPN/Sal ($p$=0.012) and DMN ($p$<0.001).

# 3. Pairwise Connectivity Results: Training Effects

**OA: Diffusely increased between-network connectivity with training**



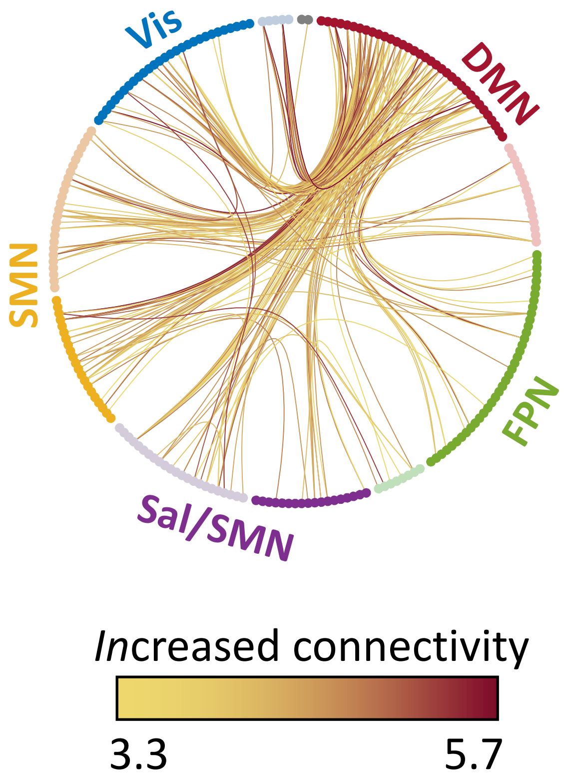

**YA: Increased DMN segregation from FPN/Sal and Vis with training**

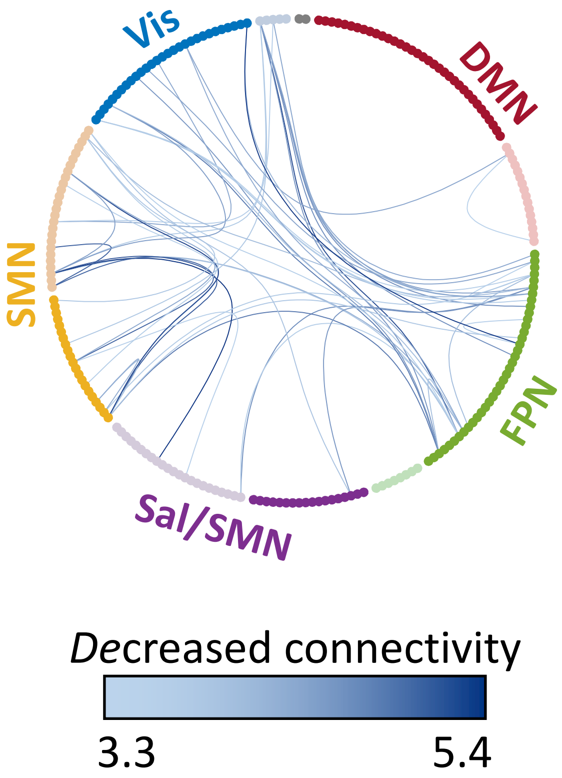



*Legend: t*-values

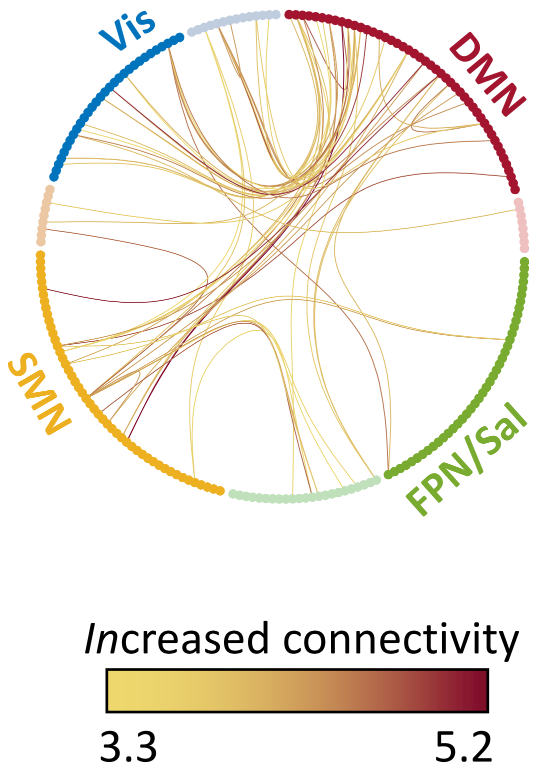
# 3. Pairwise Connectivity Results: Load Effects

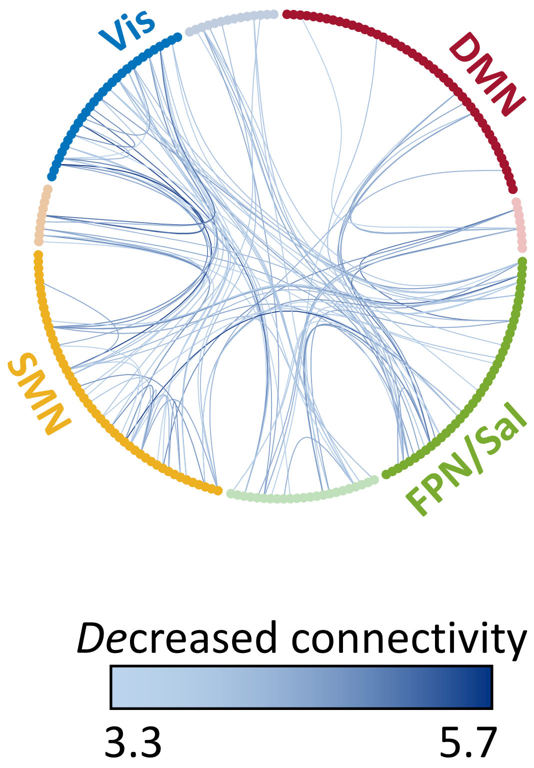
**OA: Increased integration of DMN with other networks**




**YA: Increased segregation of FPN/Sal from sensory networks**




*Legend: t*-values

# Conclusions

- Despite behavioral gains in both age groups, younger and older brains responded differently to WM training.
- Younger adults increase network segregation with training, suggesting more automated processing with enhanced expertise.
- Older adults maintain, and potentially amplify, a more integrated global workspace, which may enhance capacity for network engagement.
- In sum, WM training promotes different trajectories in functional network reconfiguration for younger and older adults.

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

# Brain Connectivity Toolbox

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- Datasets and demos

## Home

Download the Toolbox

Getting started

The Brain Connectivity Toolbox (brain-connectivity-toolbox.net) is a MATLAB toolbox for complex-network analysis of structural and functional brain-connectivity data sets.

**Reference and citation**

Complex network measures of brain connectivity: Uses and interpretations.
Rubinov M, Sporns O (2010) NeuroImage 52:1059-69.