FUNCTIONAL CONNECTOME: PROBING THE COMPLEXITY OF THE WORKING BRAIN

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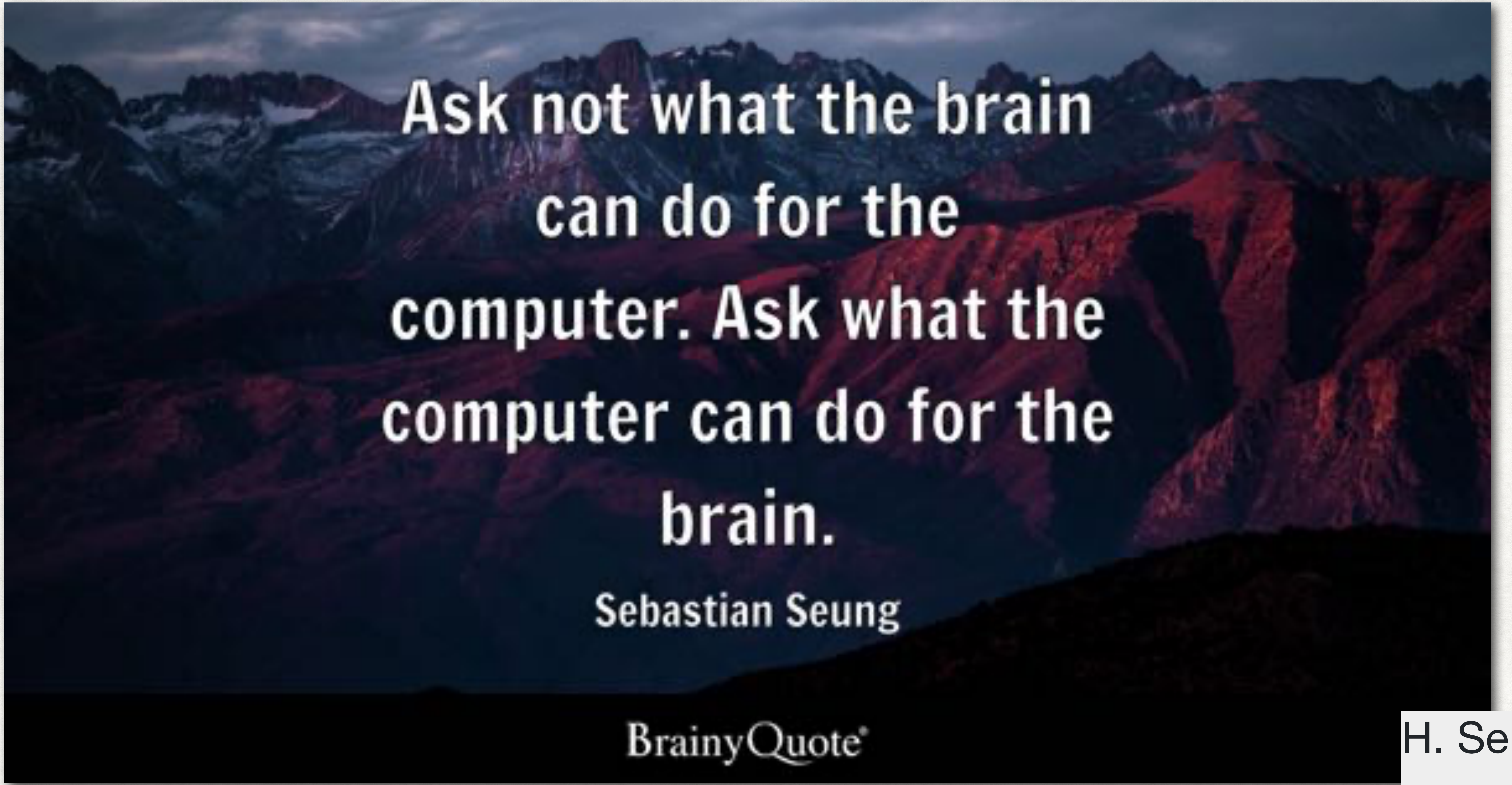

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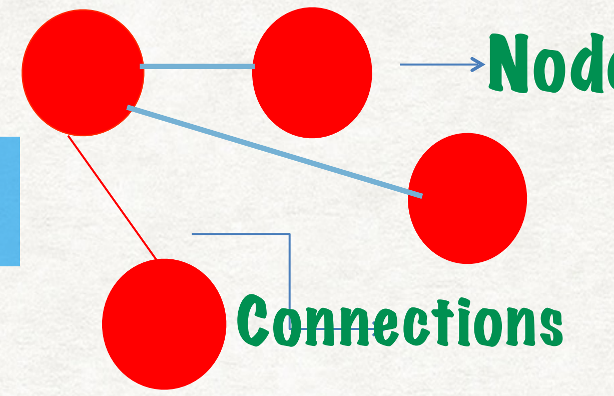
Princeton Neuroscience Institute
Ph.D., Harvard University

Networks

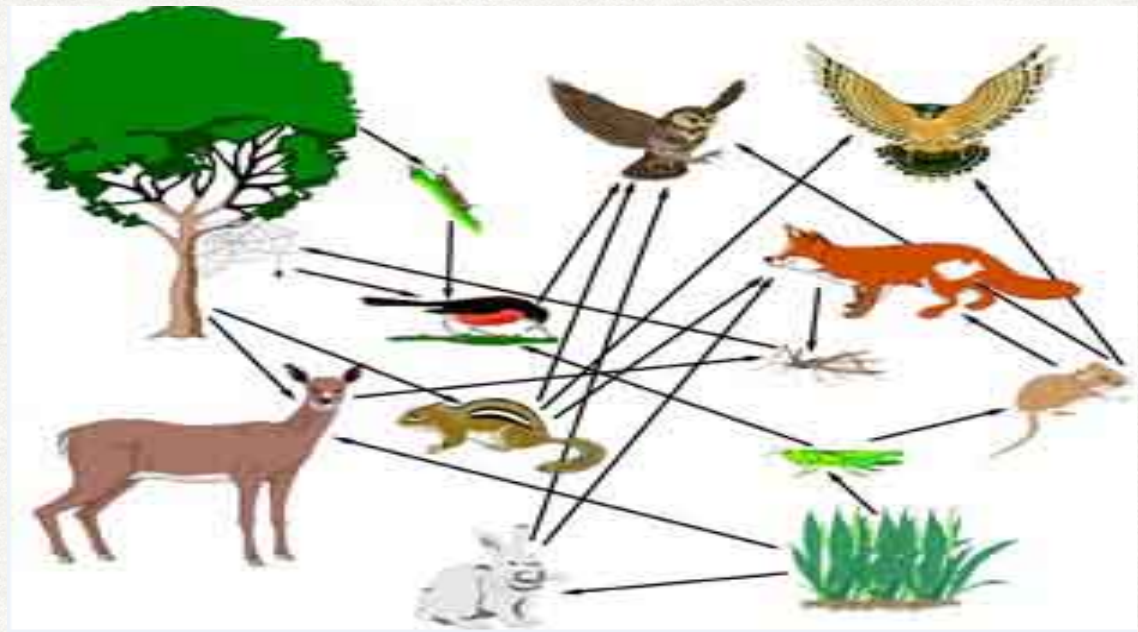
A network is mainly a collection of nodes/vertices and edges/connections



Schematic of a small Network

Nothing exists in isolation—network are everywhere

(1)

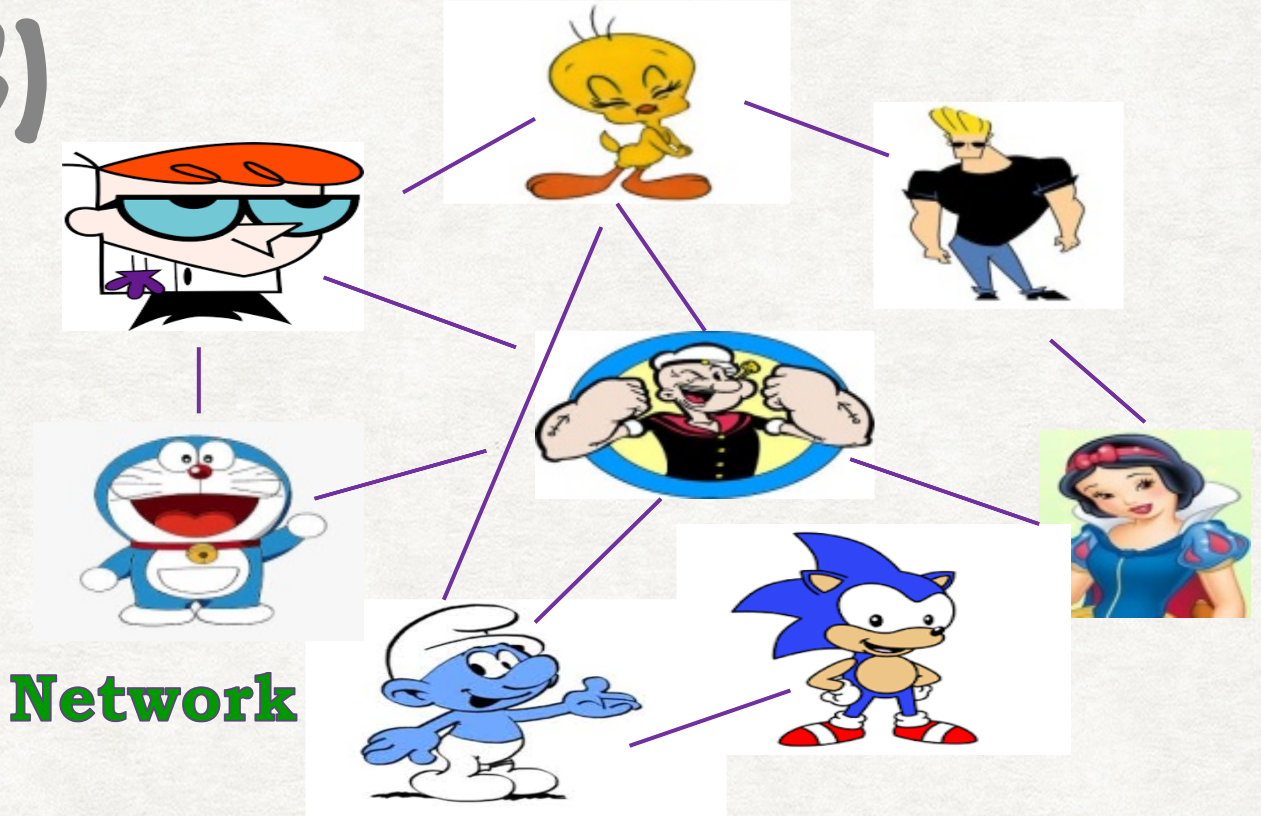


Ecological Networks

(2)

Transport Networks

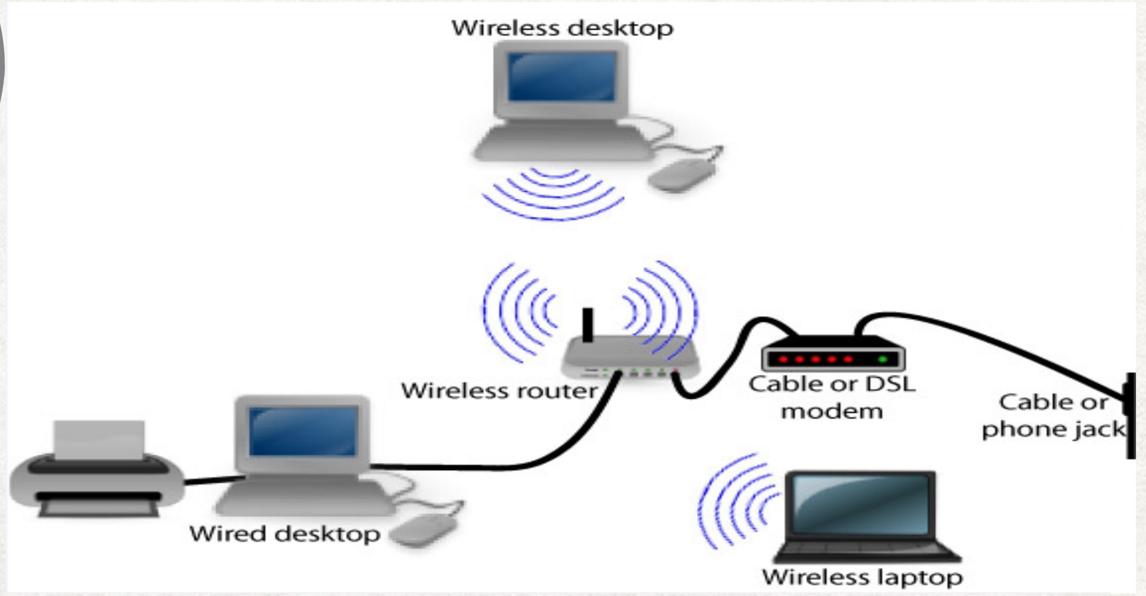
(3)



Social Network

We all are connected
May be @

(4)



Internet Networks

(5)

Brain Networks

Other examples:

6. Power-grid

7. Gene regulatory networks

Could you think of something else?

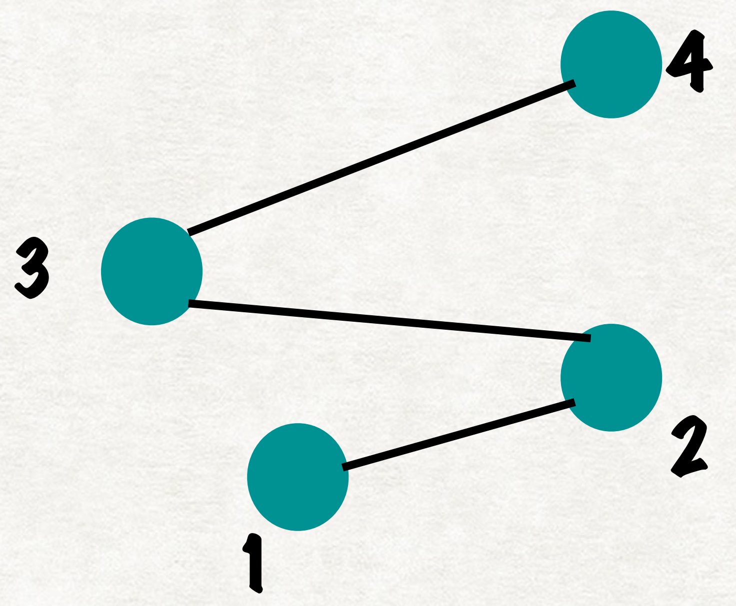
Figs are taken from the wiki and other different resources on internet

NETWORKS: ADJACENCY MATRIX

$A_{ij} = w_{ij}$, if i and j have a link,
A_{ij} = 0, otherwise,
w_{ij} = weight of link betw i and j

Binary undirected network

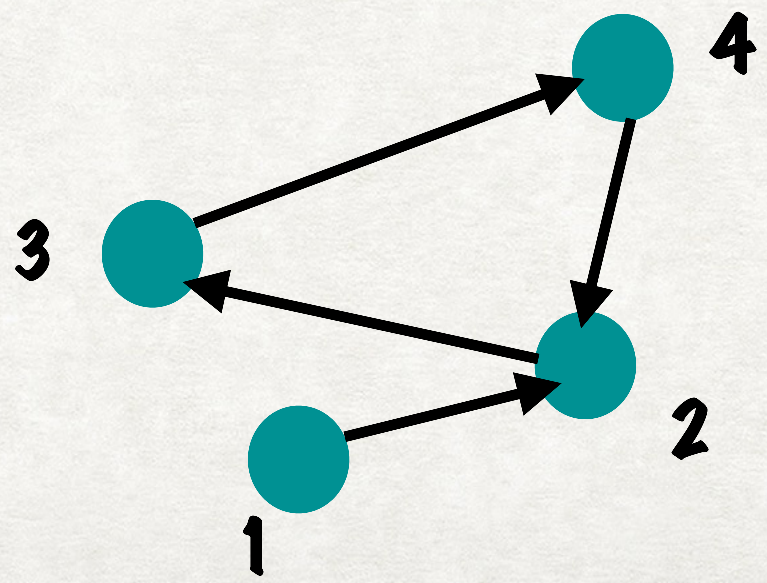
$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$



$$A_{ij} = A_{ji} = 1$$

Binary directed network

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$



CONNECTOME

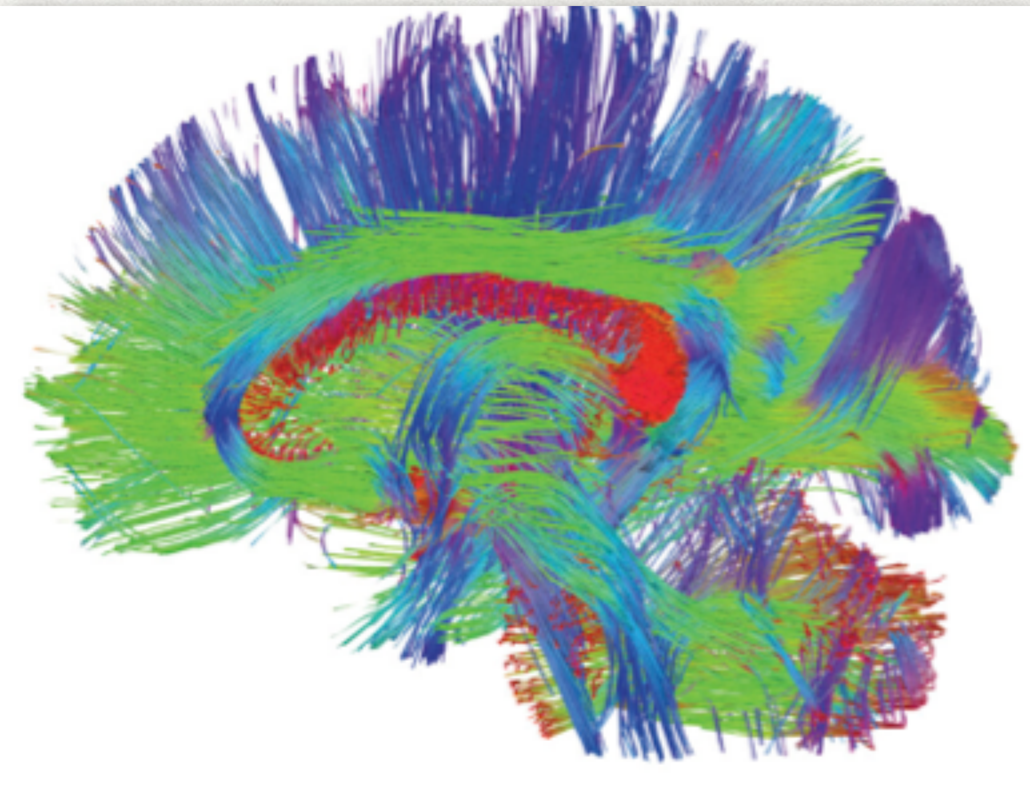
The connectome is the complete description of the structural connectivity (the physical wiring) of an organism's nervous system.

Olaf Sporns (2010)

1 Structural Connectome

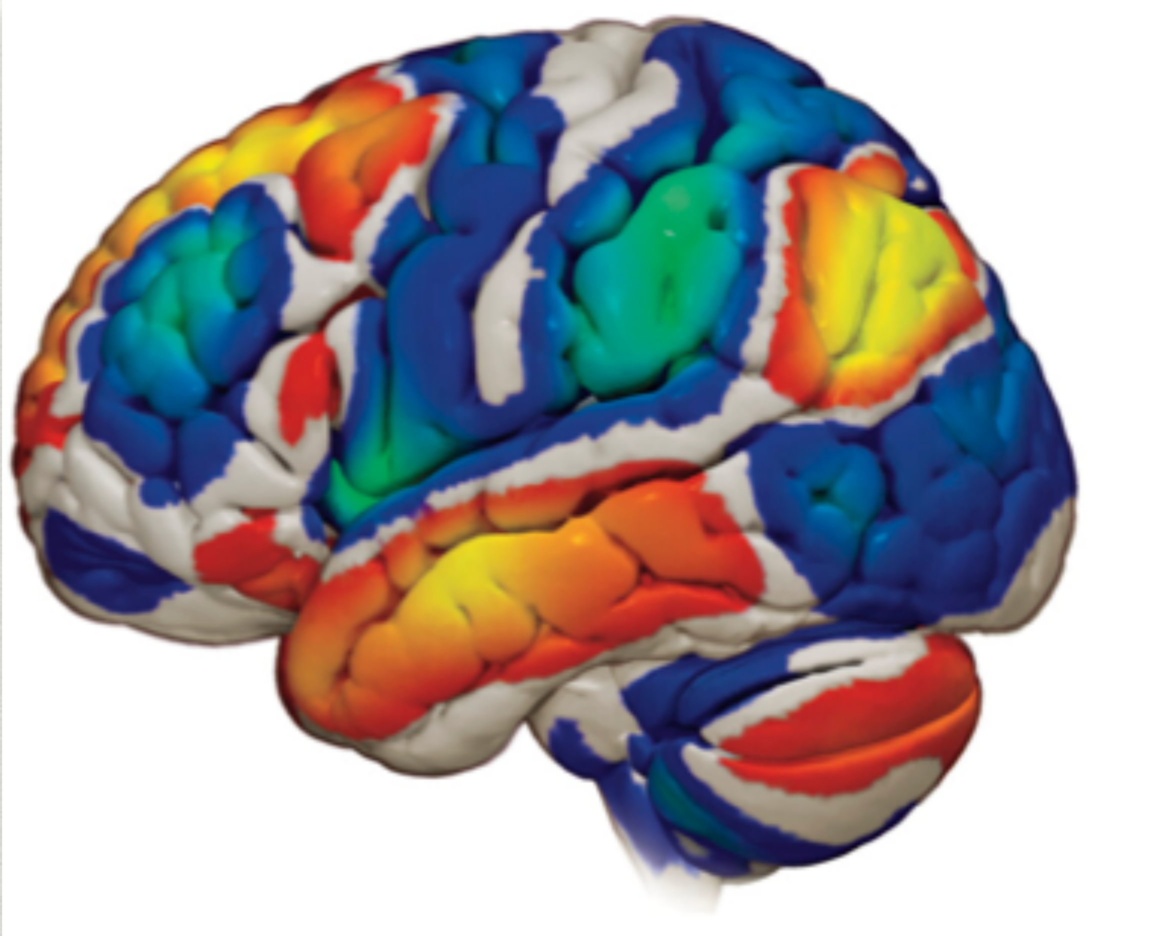
Maps of anatomical connectivity based on isolate specific fiber tracts.

Methods: Parcellation of the brain volume or DTI



2 Functional Connectome

Maps of functional connectivity can be used to identify brain regions with spontaneous activity that is positively correlated (yellow or red) or negatively correlated (blue or green) with any other region.



Methods: Neuroimaging toolkits, mainly on the basis of time series obtained from the functional magnetic resonance imaging (fMRI), electroencephalogram (EEG), magnetoencephalogram (MEG), positron emission tomography (PET) .

Ref. Frontiers in Medicine, Mapping Symptoms to Brain Networks with the Human Connectome

FUNCTIONAL CONNECTOME: TIME SERIES

✱ The time series recorded in electroencephalography (EEG) or magnetoencephalography (MRI) represents the activity of neurons

✱When a neuron is activated or "fires," an electrical current cascades down the cell

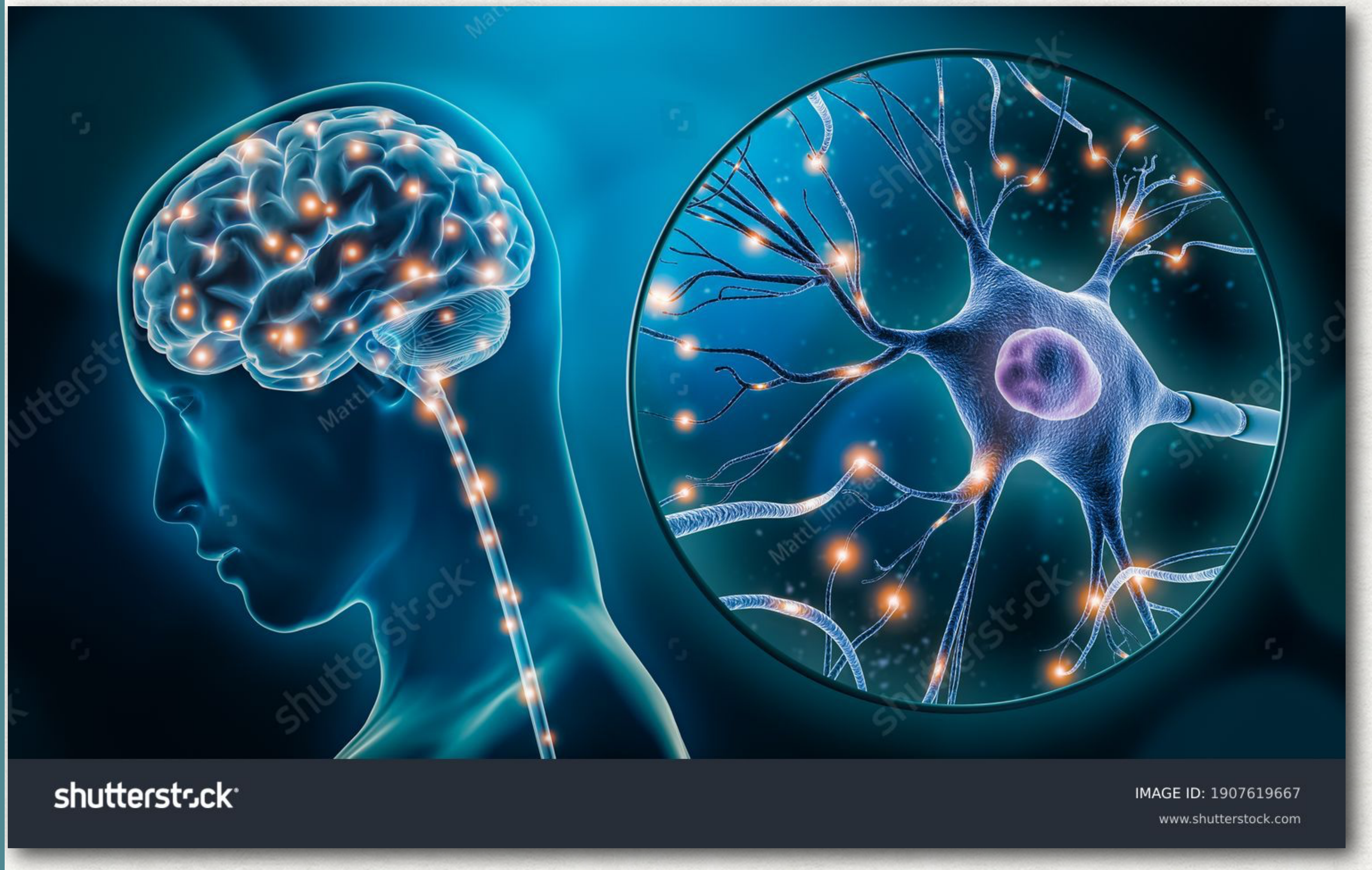
✱When numerous neurons fire simultaneously, sensors on the scalp can perceive this voltage shift—a mechanism that underpins(EEG). The range of this voltage signals is in the order of micro Volts. They are often referred to as “brain waves”

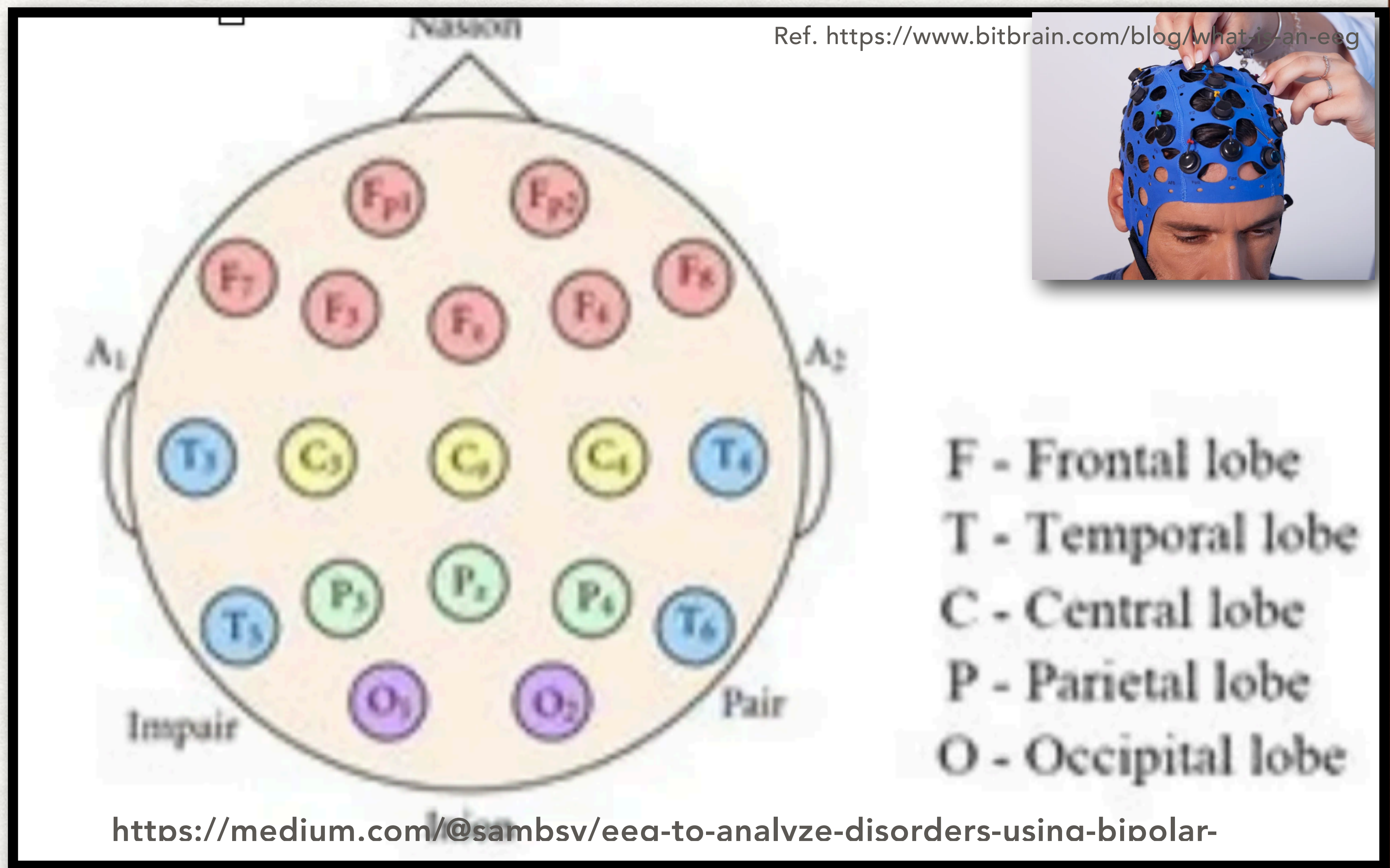
✱Also changes in blood oxygenation level-dependent (BOLD) responses occurred is measured via functional Magnetic Resonance Imaging (fMRI)

✱fMRI has good spatial resolution but lacks in the time resolution

✱ EEG lacks in spatial resolution but has good time resolution

Refs. [1] Ogawa S., Lee T. M., Kay A. R., Tank D. W. (1990). Brain magnetic resonance imaging with contrast dependent on blood oxygenation. Proc. Natl. Acad. Sci. U.S.A. 87, 9868–9872. [2] Front. Neurosci., 05 June 2019 Sec. Neural Technology Volume 13 - 2019 | https://doi.org/10.3389/fnins.2019.00585 [3] https://www.bitbrain.com/blog/what-is-an-eeg

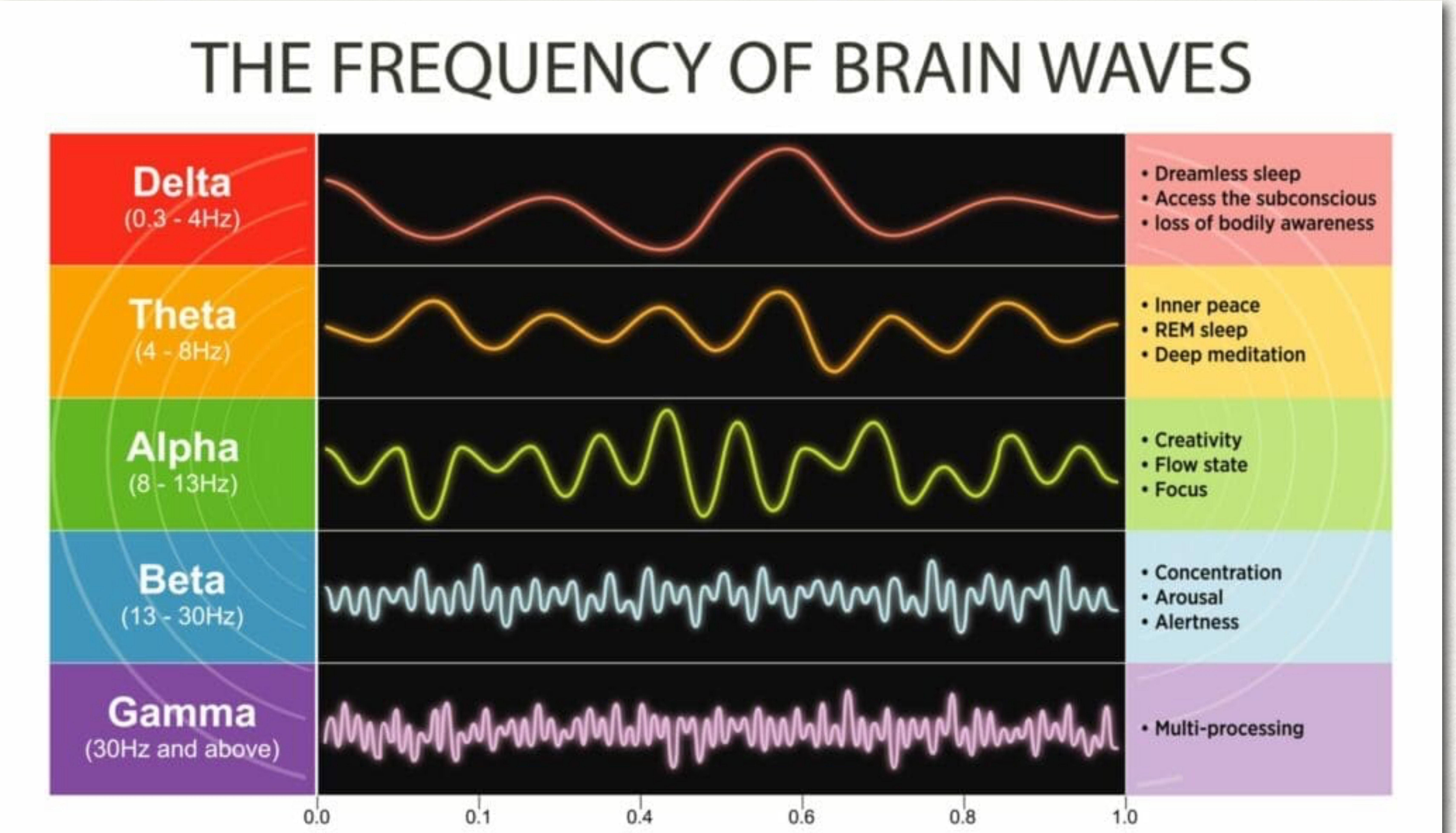




16 Electrode montage covering different ROIs.

Functional Connectome: Time series

Brain wave patterns include: delta (0.5-4 hz), theta (4-8hz), alpha (8-12 hz), beta (12-35 hz), and gamma (32-100 hz) waves



From: https://greymatters.studio/anxiety-brain-mental-health-stress/

Why Functional Connectome?

- The network-based evaluation of functional brain networks can can reveal specific spatial changes in brain activity during neurological disorders like epilepsy.
- Network analysis can be used as an adjunct to clinical diagnosis and as a screening tool for therapeutic trials.
-

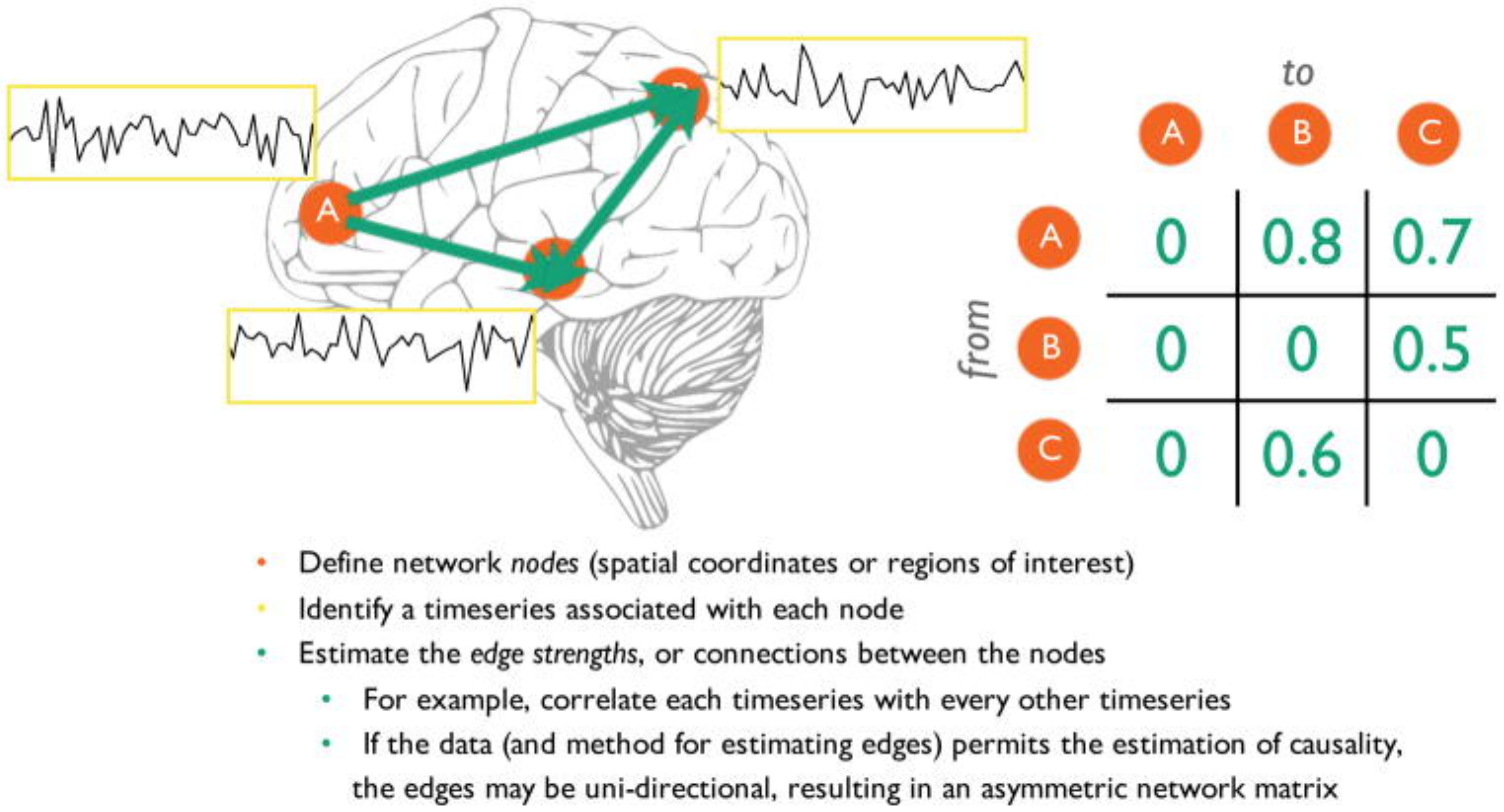
  Functional Connectome could also be useful in understanding the underlying mechanism for the decision making and the memory formation in brain

https://onlinelibrary.wiley.com/doi/10.1684/epd.2020.1203

FUNCTIONAL CONNECTOME (FC)

* Nodes: Different Brain Regions (ROI)

* Connections: Functional correlation/coherence between the brain regions



Ref. The brain as a complex network: assessment of EEG-based functional connectivity patterns in patients with childhood

→ Network Analysis

* Brain connectivity patterns from fMRI/EEG data are classified as statistical dependencies (coupling/functional connectivity) or causal interactions (effective connectivity) among various neural units.

Ref. [1] Hlinka, J., *et al* (2011). Functional connectivity in resting-state fMRI: is linear correlation sufficient? NeuroImage, 54(3), 2218–25. doi:10.1016/j.neuroimage.2010.08.042; [2] Giovanni Chiarion *et al.* Connectivity Analysis in EEG Data: A Tutorial Review of the State of the Art and Emerging Trends

Connections in FC

(1)**Correlation:** (Most traditional method for testing functional connectivity, which is defined by measuring the the Pearson's correlation, Time domain, coupling, Undirected FC)

$$r_{xy} = \frac{\sum_{t=1}^{T}(x_t - \bar{x})(y_t - \bar{y})}{\sqrt{\sum_{t=1}^{T}(x_t - \bar{x})^2}\sqrt{\sum_{t=1}^{T}(y_t - \bar{y})^2}}$$

(2) **Mutual information** (Quantifies the shared information (undirected) between two random variables, time/frequency domain, coupling, Undirected FC). For two discrete random variables X and Y, their mutual information takes the following form:

$$\mathrm{MI}(X,Y) = \sum_{x\in S_x}\sum_{y\in S_y} p(x,y)\ \log\left(\frac{p(x,y)}{p(x)\,p(y)}\right),$$

where S_x and S_y are possible values of X and Y, $p(x, y)$ is the probability that the pair (X, Y) takes values x in S_x and y in S_y, and $p(x)$ and $p(y)$ are two marginal probabilities of X and Y.

Ref. [1] Hlinka, J., *et al* (2011). Functional connectivity in resting-state fMRI: is linear correlation sufficient? NeuroImage, 54(3), 2218–25. doi:10.1016/j.neuroimage.2010.08.042; [2] Giovanni Chiarion *et al.* Connectivity Analysis in EEG Data: A Tutorial Review of the State of the Art and Emerging Trends

Connections in FC

(3) <u>Phase Synchronization Index</u> : (Coupling, undirected FC) Given time-series $x(t)$ and y(t) the Phase Locking Value (PLV) is defined as follows:

$$PLV = \left| E\left[e^{i(\Phi_x(t)-\Phi_y(t))}\right] \right|,$$

Where,

$$\Phi_x(t) = \arctan \frac{\tilde{x}(t)}{x(t)},$$

$\tilde{x}(t)$ is the Hilbert Transform of x(t), similarly phase of y(t) can be defined.

(4) **Coherence** (Spectral representation of correlation in the frequency domain, It captures how strongly two signals co-vary at each frequency, coupling, could be directed or undirected)

(5) Granger causality: (causality, Directed FC)

(6) Transfer entropy: (causality, Directed FC)

Ref. [1] Hlinka, J., *et al* (2011). Functional connectivity in resting-state fMRI: is linear correlation sufficient? NeuroImage, 54(3), 2218–25. doi:10.1016/j.neuroimage.2010.08.042; [2] Giovanni Chiarion *et al.* Connectivity Analysis in EEG Data: A Tutorial Review of the State of the Art and Emerging Trends; https://pmc.ncbi.nlm.nih.gov/articles/PMC8928656/; https://pmc.ncbi.nlm.nih.gov/articles/PMC6217888/

Methods…

Which method is best?

- Wei Zhang et al reported that Mutual Information Better Quantifies Brain Network Architecture in Children with Epilepsy, Comput Math Methods Med. 2018 Oct 22;2018:6142898. doi: 10.1155/2018/6142898
- However, in most cases simple linear correlation is enough (Hlinka, J., et al)

  - The connectivity measures are in general affected by the volume-conduction effect.

    - ☆ In practice, an appropriate threshold can give a correct/meaningful connectivity.

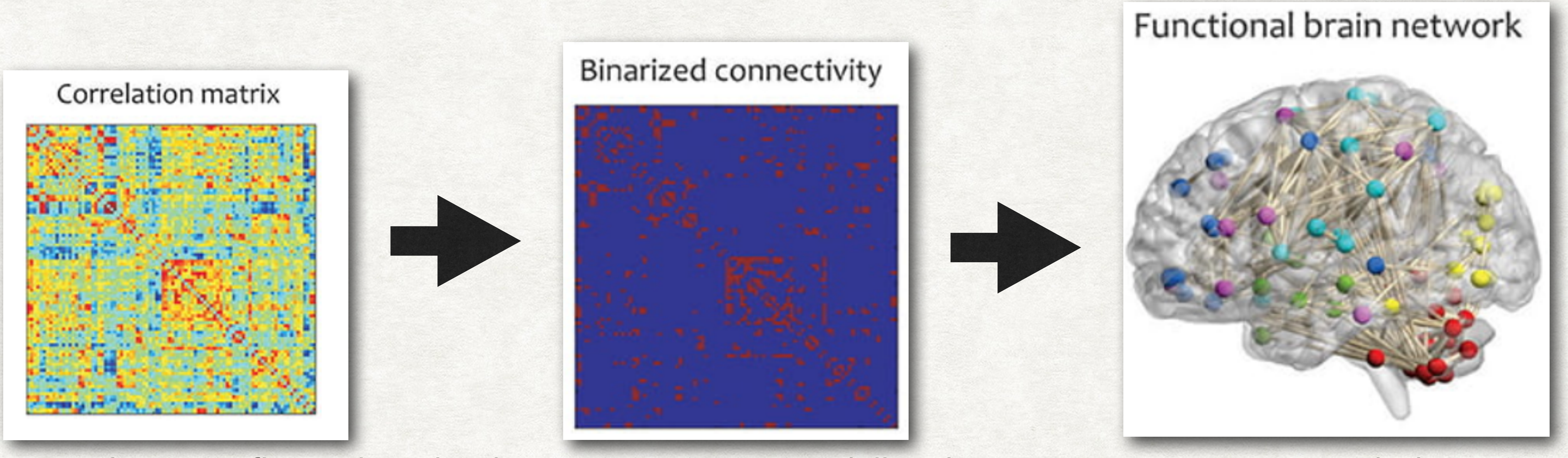


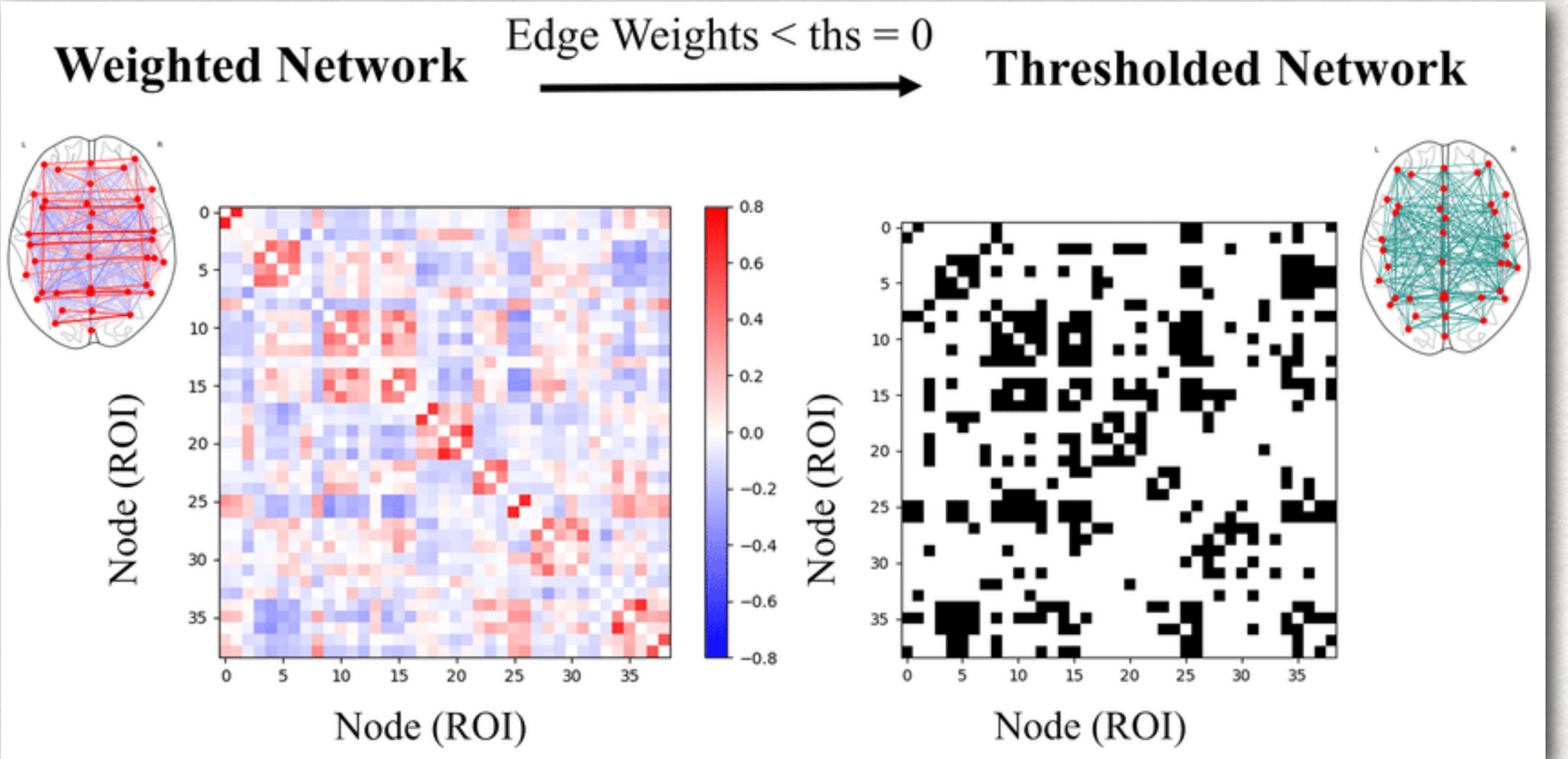
Fig. From https://reflect.ucl.ac.uk/ad-veturi/2021/06/08/modelling-brain-connectivity-using-graph-theory/

Ref: Front. Comput. Neurosci., 11 May 2017 Volume 11 - 2017 | https://doi.org/10.3389/fncom.2017.00036,; Hlinka, J., et al (2011). Functional connectivity in resting-state fMRI: is linear correlation sufficient? NeuroImage, 54(3), 2218–25. doi:10.1016/j.neuroimage.2010.08.042; Giovanni Chiarion *et al.* Connectivity Analysis in EEG Data: A Tutorial Review of the State of the Art and Emerging Trends

Thresholding methods:

<u>(1) Absolute Thresholding:</u> Simplest method bested considering the connections based on a threshold value (say ths).

$$A_{ij} = \begin{cases} 1 & \text{if } w_{ij} \gtrsim \text{ths} \\ 0 & \text{otherwise} \end{cases}$$



From: [Esfahlani, F.Z., Sayama, H. (2018). A Percolation-Based Thresholding Method with Applications in Functional Connectivity Analysis. In: Cornelius, S., Coronges, K., Gonçalves, B., Sinatra, R., Vespignani, A. (eds) Complex Networks IX. CompleNet 2018. Springer Proceedings in Complexity. Springer, Cham. https://doi.org/10.1007/978-3-319-73198-8_19].

<u>(2) Largest connected component: Percolation-based Thresholding Method</u>

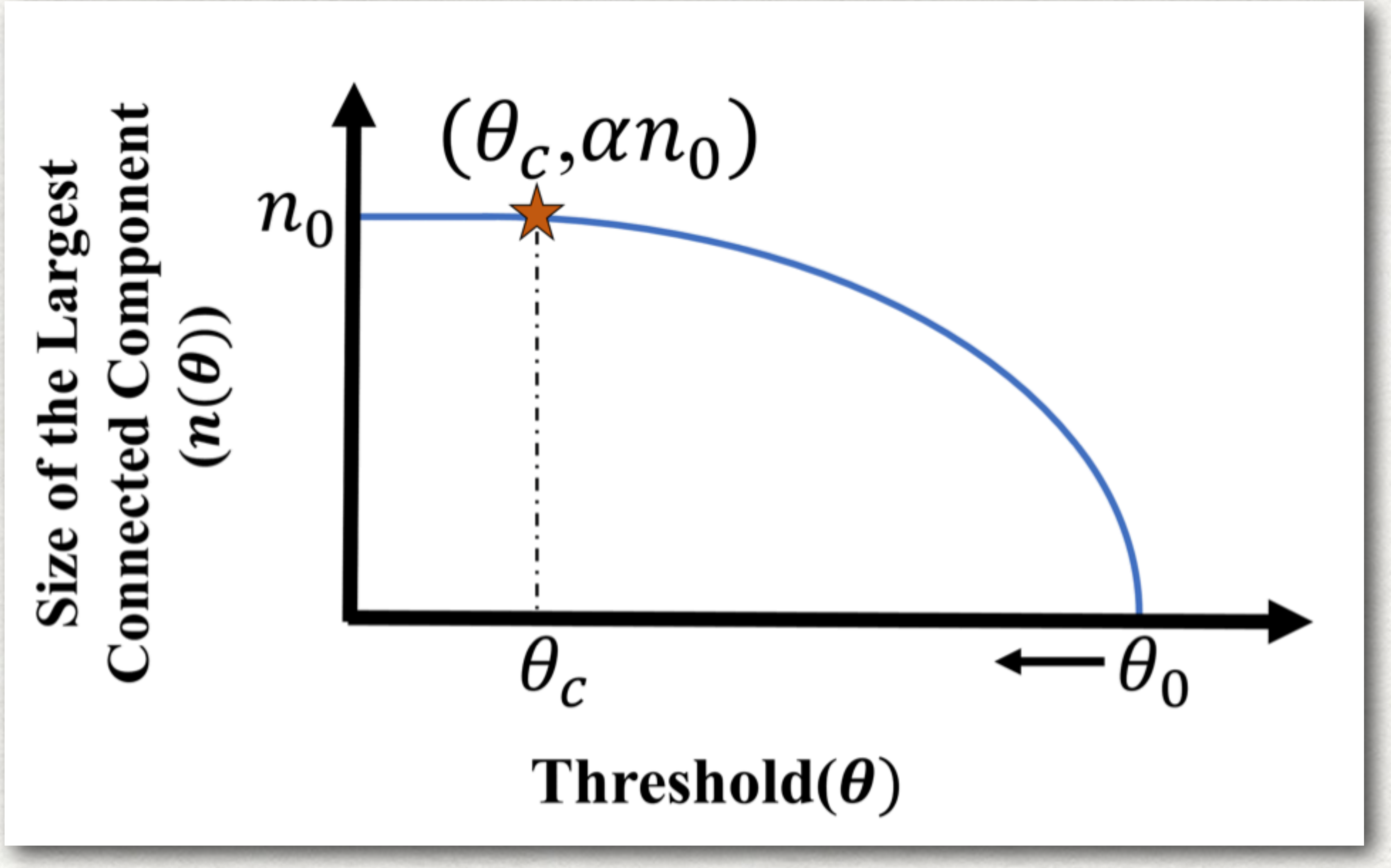


Fig. A schematic illustration of the percolation-based thresholding method. The basic idea of the percolation-based thresholding method is to identify the minimum number of edges that maintain the giant component identified in the original weighted network [Esfahlani, F.Z., Sayama, H. (2018). A Percolation-Based Thresholding Method with Applications in Functional Connectivity Analysis. In: Cornelius, S., Coronges, K., Gonçalves, B., Sinatra, R., Vespignani, A. (eds) Complex Networks IX. CompleNet 2018. Springer Proceedings in Complexity. Springer, Cham. https://doi.org/10.1007/978-3-319-73198-8_19].

Ref. Thresholding functional connectomes by means of mixture modeling, 2018 May 1;171:402–414. doi: 10.1016/j.neuroimage.2018.01.003

Thresholding methods..

<u>(3) Proportional thresholding (Density Thresholding):</u> A top percentage of all partial correlation values in a subject-specific functional connectome is selected. The main aim of this approach is to keep the number of connections fixed for all the individuals in order to eliminate the impact of network density on the comparison of graph metrics across groups. This method for sparsifying functional connectomes is currently the most popular approach in the field, which might be due to its simplicity. Good for comparison.

<u>(4) Minimum spanning tree (MST): backbone of the functional brain network:</u>

$N =$ number of the nodes

$M = N - 1$ (no. of connections)

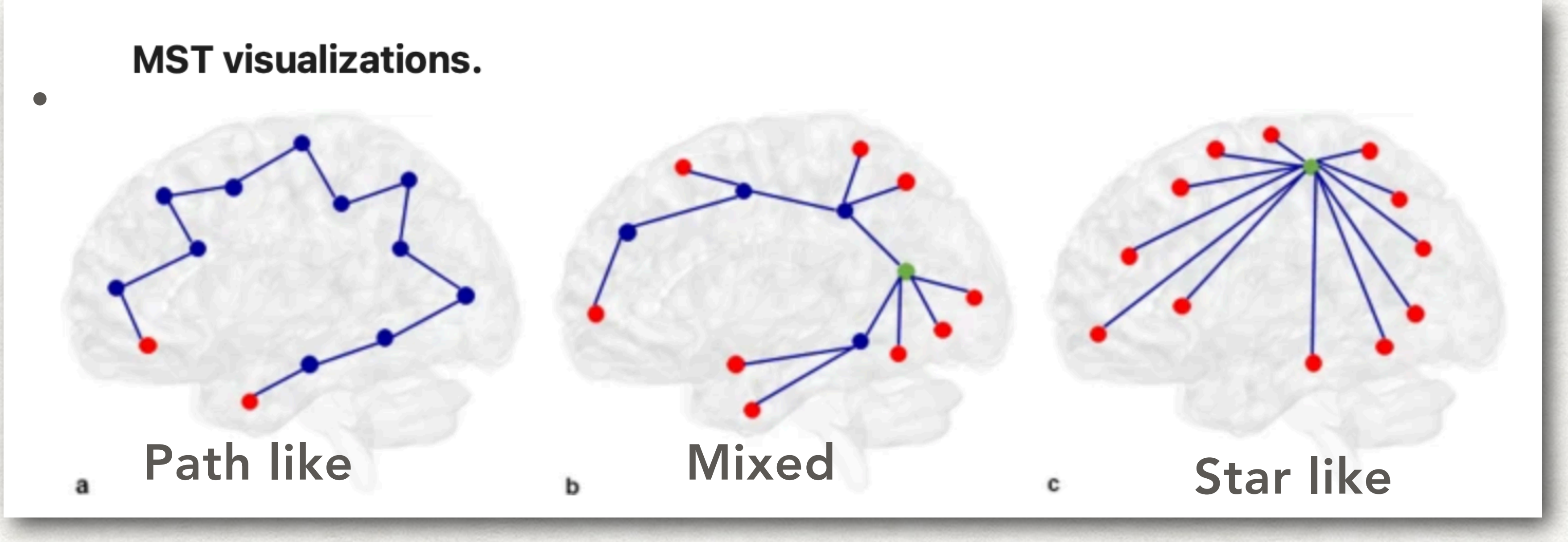


Fig. Different types of MST. Ref. "Functional brain networks in the schizophrenia spectrum and bipolar disorder with psychosis, <u>npj Schizophrenia</u> volume 6, Article number: 22 (2020)"

(5) Permutation testing: A null distribution of connections estimated from time series with shuffled subject labels (confidence levels computed on the population level). The correlation matrix is then thresholded at a chosen significance level in the light of this null distribution, for each connection independently

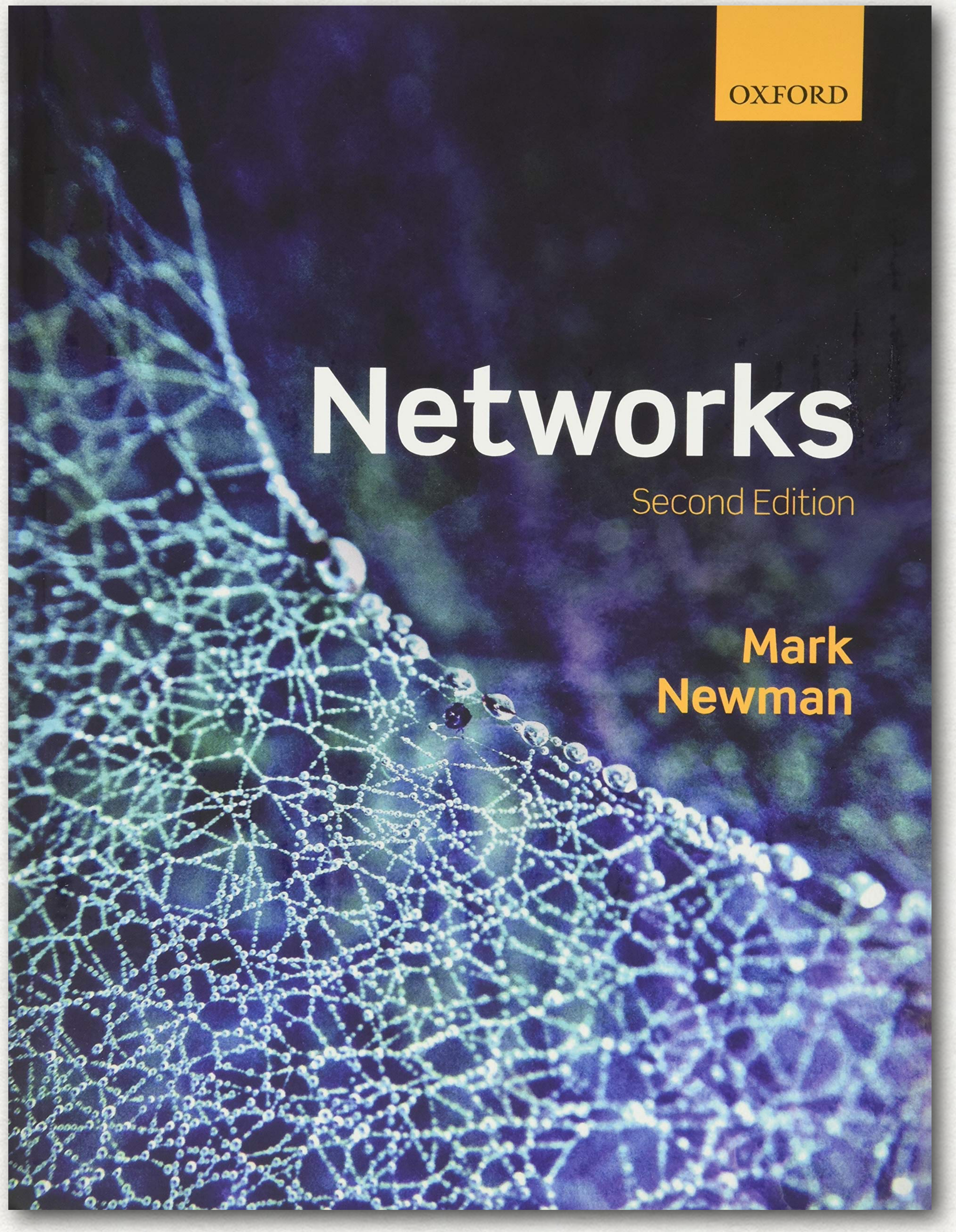
Ref. Farahani F V, *et al.* Application of GraphTheoryforIdentifying ConnectivityPatternsinHumanBrain Networks:ASystematicReview. Front.Neurosci.13:585. doi:10.3389/fnins.2019.00585

Fig. From https://reflect.ucl.ac.uk/ad-veturi/2021/06/08/modelling-brain-connectivity-using-graph-theory/

MNE

MEG + EEG ANALYSIS & VISUALIZATION

Open-source Python package for exploring, visualizing, and analyzing human neurophysiological data: MEG, EEG and more. https://mne.tools/mne-connectivity/stable/index.html

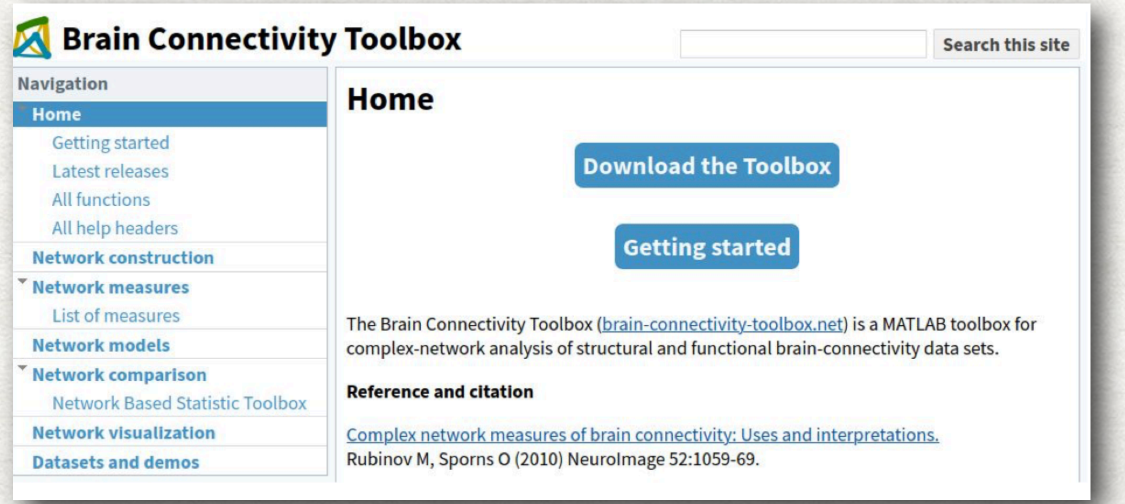


NetworkX

Network Analysis in Python

Or

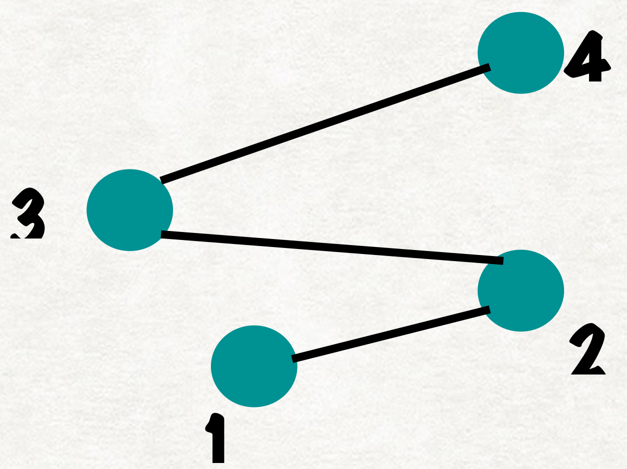
MATLAB



Complex Network Measures: Network's perspective to study brain

Node Degree

k_i = **Number of links node i has**



$$k_1 = 1 \text{ and } k_2 = 2$$

$$k_i = \sum_j A_{ij}$$

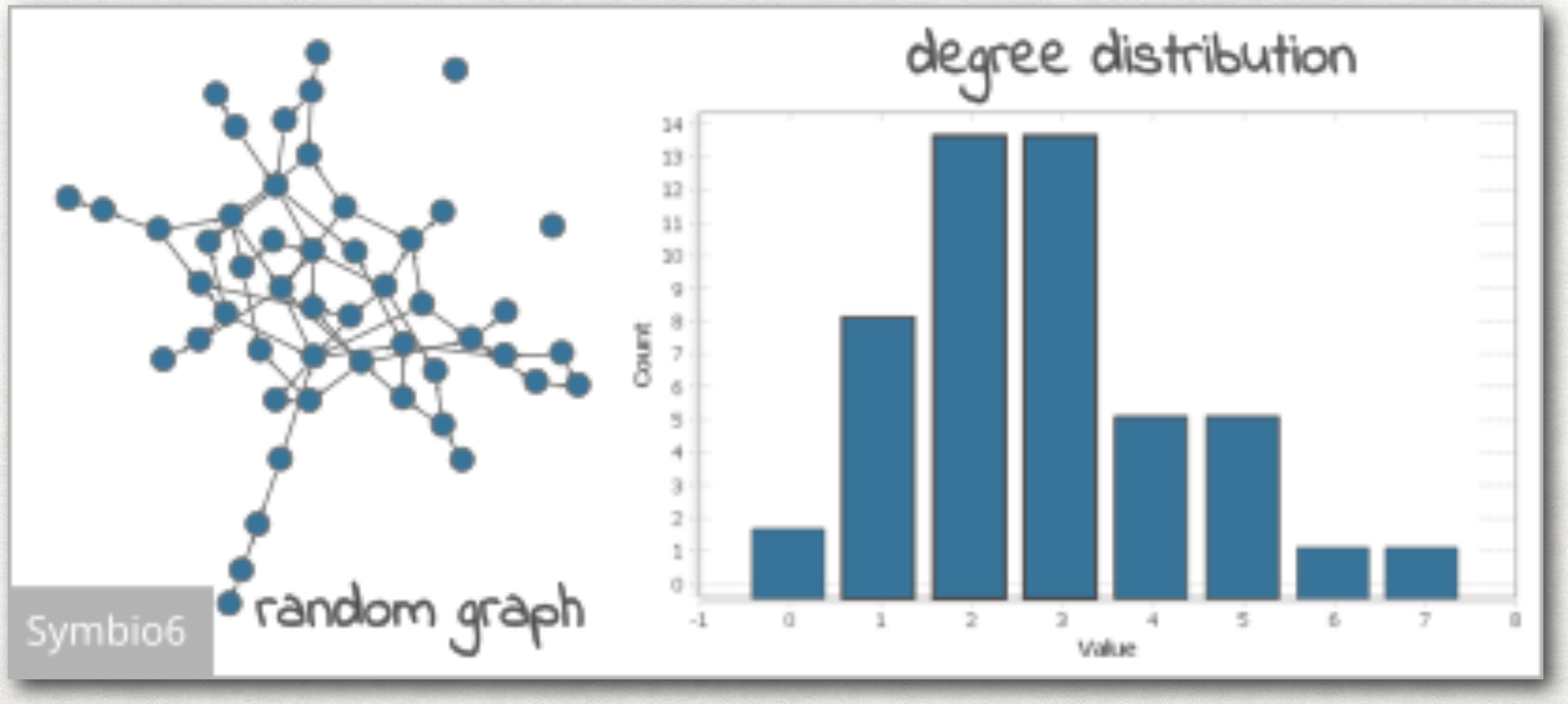
Number of links $L = \frac{\sum_i k_i}{2}$

Average degree $\langle k \rangle = \frac{k_i}{N} = \frac{2L}{N}$

$$\langle k \rangle_{max} = N - 1$$

Degree Distribution

https://symbio6.nl/en/blog/theory/definition/degree-distribution



Complex Network Measures: Network's perspective to study brain

Finding Important Nodes: Centrality

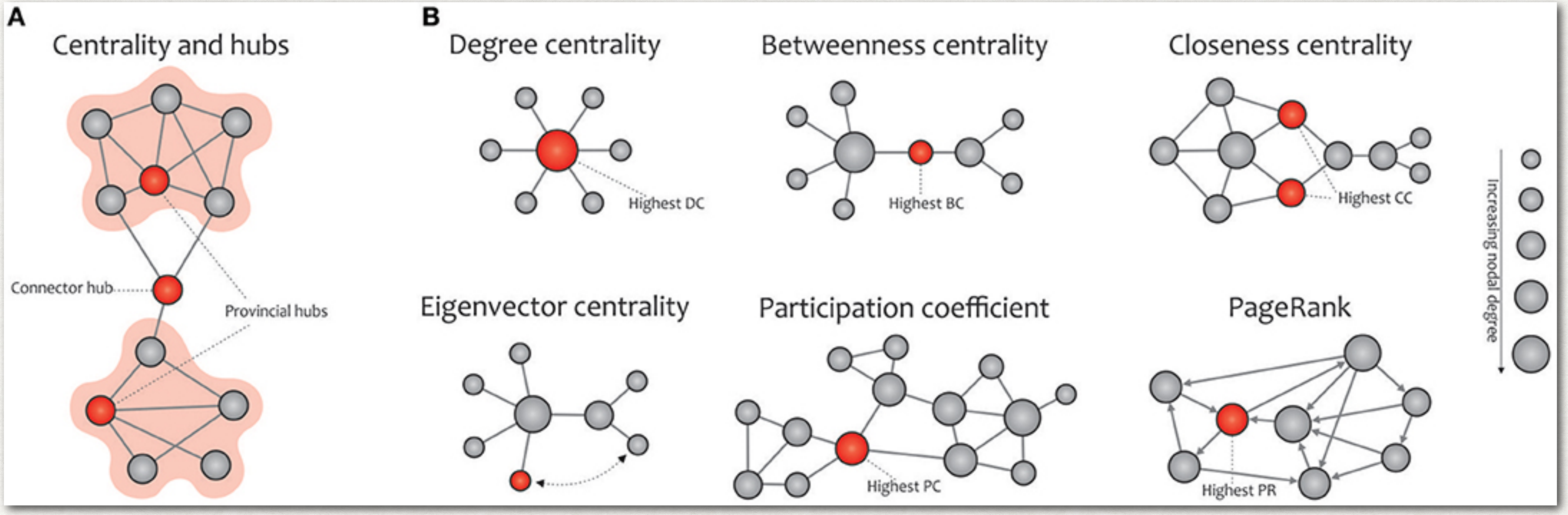


Fig. Basic concept of network centralities. (A) Hubs (connector or provincial) refer to nodes with a high nodal centrality, which can be identified using different measures. (B) The degree centrality is defined as the number of node's neighbors. The betweenness centrality measures the node's role in acting as a bridge between separate clusters by computing the ratio of all shortest paths in the network that contain a given node. The closeness centrality quantifies how fast a given node in a connected graph can access all other nodes, hence the more central a node is, the closer it is to all other nodes. The eigenvector centrality is a self-referential measure of centrality that considers the quality of a link, so that being connected to a central node increases one's centrality in turn; the red colored node is more central than the gray colored node, although their degrees are equal. The participation coefficient of a node represents the distribution of its connections among separate modules. PageRank is a variant of eigenvector centrality, used by Google Search to determine a page's importance; the PageRank of an undirected graph is statistically similar to the degree centrality, but they are generally distinct. Note that the size of the nodes in all cases is proportional to the node degree, and the red nodes (except in the eigenvalue centrality) are the most central with respect to the corresponding definition of centrality, even though their degree are low.

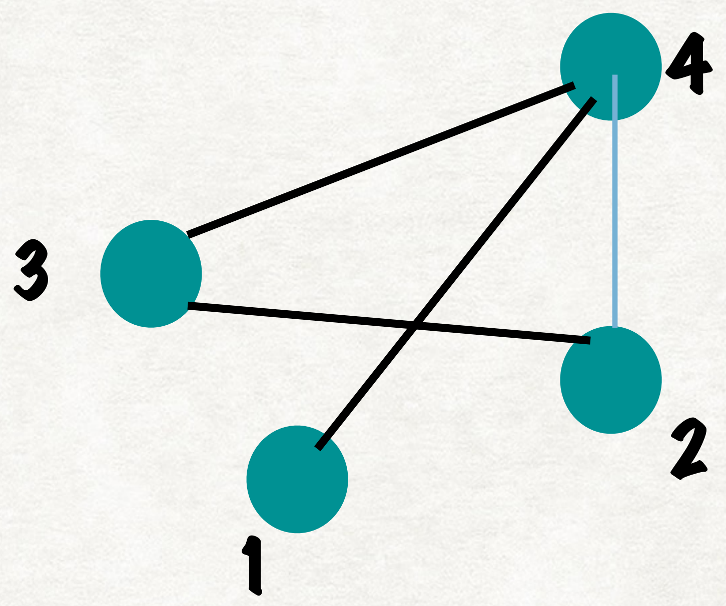
Complex Network Measures: Network's perspective to study brain

Clustering

The clustering coefficient is a measure of the degree to which nodes in a network tend to cluster together.

Global Clustering:

$$C_\Delta = \frac{3n_\Delta}{N_\Delta}$$



$n_\Delta =$ Number of existing triangles

$N_\Delta =$ Number of possible triangles

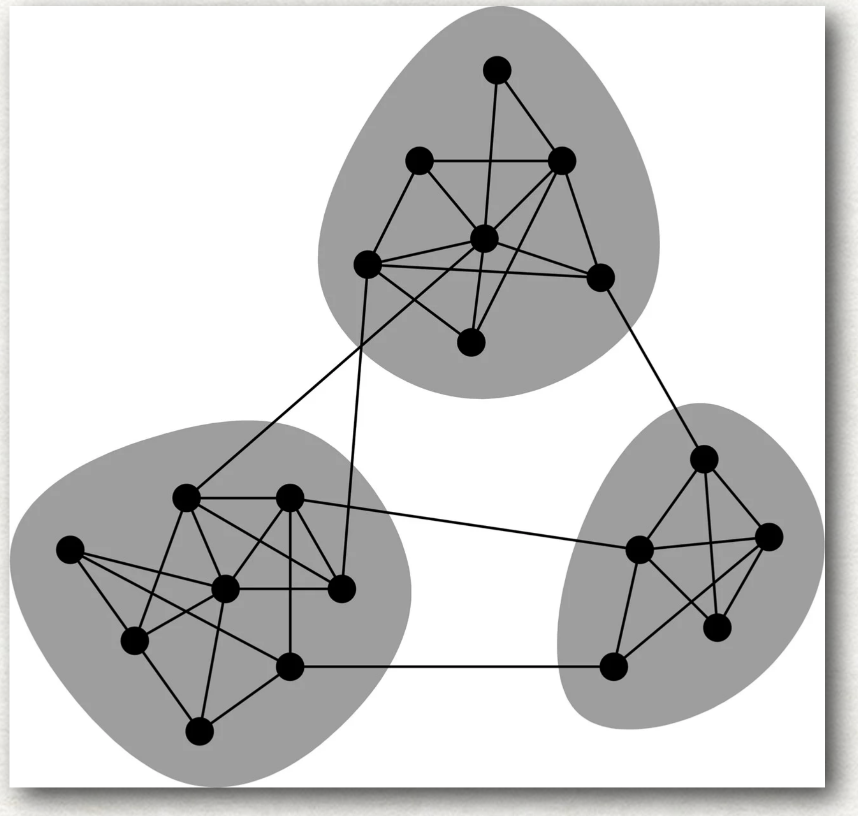
C_Δ is often called ratio of transitive triplets

The clustering coefficient of a graph is closely related to the transitivity of a graph, as both measure the relative frequency of triangles.

Modularity

Modular Networks have denser connections in modules & sparser connections between modules.
Modularity (Q) is then defined as the fraction of edges that fall within groups, minus the expected number of edges within groups for a random graph with the same node degree distribution as the given network, given as follows for a partition p:

$$Q(p) = \sum_{i=1}^{N_m} \left[\frac{w_i}{W} - \left(\frac{W_i}{2W} \right)^2 \right]$$



Modularity and community structure in networks
M. E. J. Newman

where N_m is the number of modules, W is the total weight of the network, w_i is the sum of the connectional weights between all nodes in module i and W_i is the sum of the all regional functional connection strengths in module i. $Q_{\max}$ is the largest network modularity resulting from a specific partition p [https://pmc.ncbi.nlm.nih.gov/articles/PMC6987957/]

Path-length & Efficiency

The distance between two nodes (path-length, L_{ij}) is the number of the edges along the shortest path connecting them.

Example: $L_{12} = 1,\ L_{13} = 2,\ L_{24} = 1$

For $L_{ij} = 1$, $A_{ij} = 1$

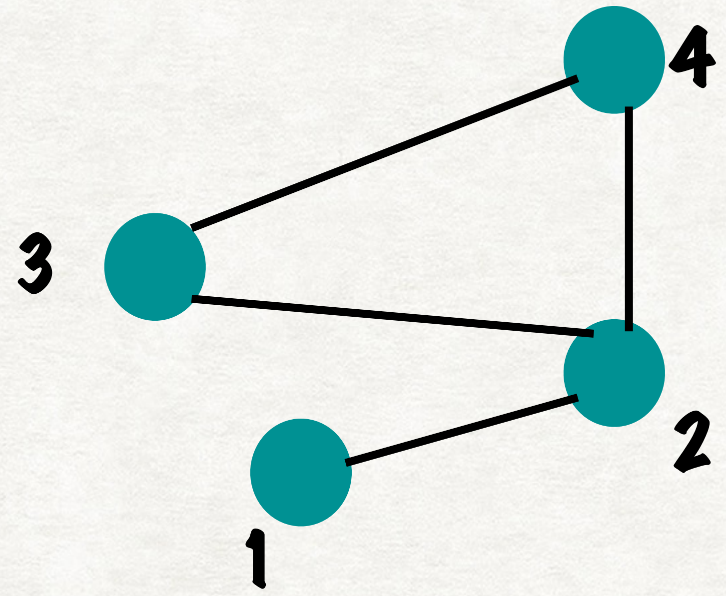
For $L_{ij} = 2$, $A_{ik} * A_{kj} = 1$

*
*

For $L_{ij} = n$, $A_{ik} * A_{kl} * \ldots * A_{lj} = 1$

No. Of paths of length 2 i.e. $L_{ij}^2 = \sum_{k=1}^{N} A_{ik} * A_{kj} = B_{ij}$, where, $B = A^2$

No. Of paths of length n i.e. $L_{ij}^n = (A^n)_{ij}$



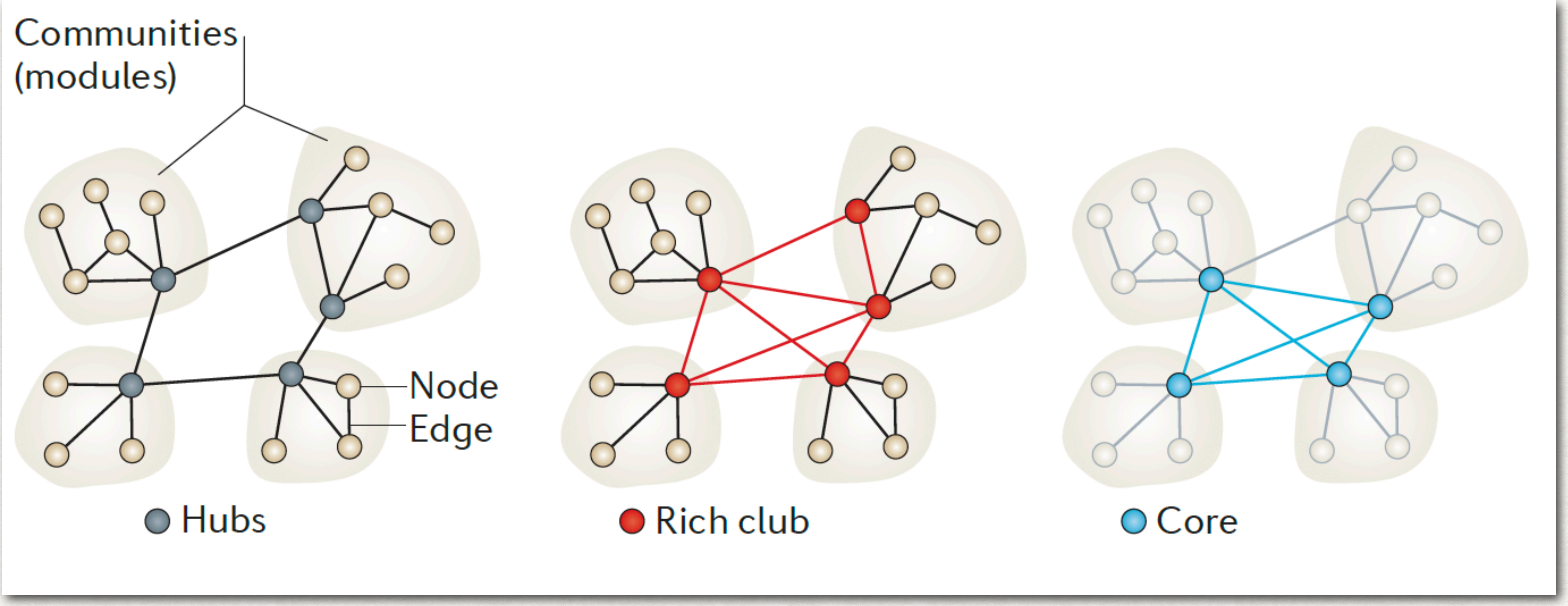
If two nodes are disconnected the pathlength between them will be infinite

Diameter: Largest path length between any pair of nodes in a network

The efficiency of a network is the summation of inverse of the all the shortest pathlengths

$$E = \sum_{ij} \frac{1}{N(N-1)} * \frac{1}{d_{ij}}$$

Rich-club and core:



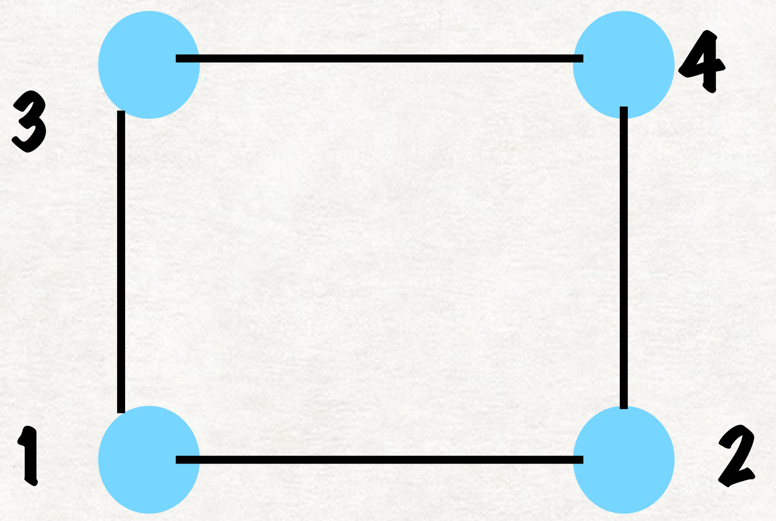
Core act as a crucial hub that integrates the more loosely connected peripheral nodes, ensuring efficient network functionality

Bullmore, E., & Sporns, O. (2012). The economy of brain network organization. Nature reviews. Neuroscience, 13(5), 336–49

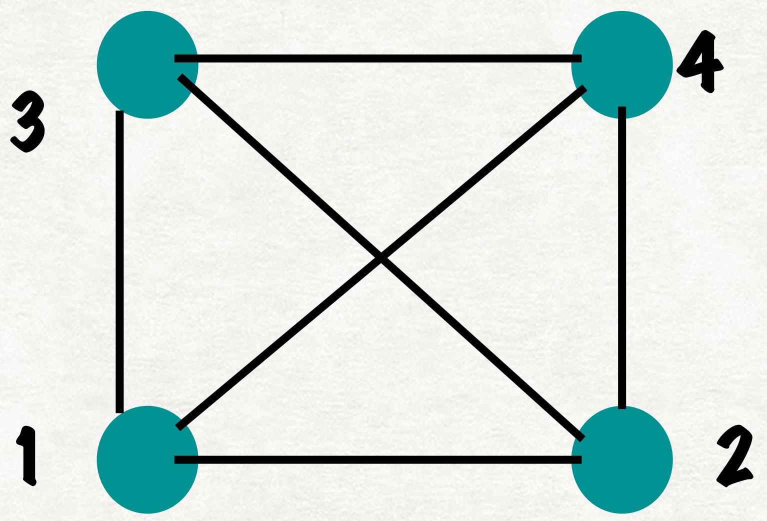
NULL MODELS FOR STATISTICAL VALIDATIONS

Regular Networks

Lattice



Globally connected network



Random Networks

Erdős Pál Alfréd Rényi

A mathematician is a device for turning coffee into theorems
Alfred Renyi

Each pair of nodes is connected with probability p

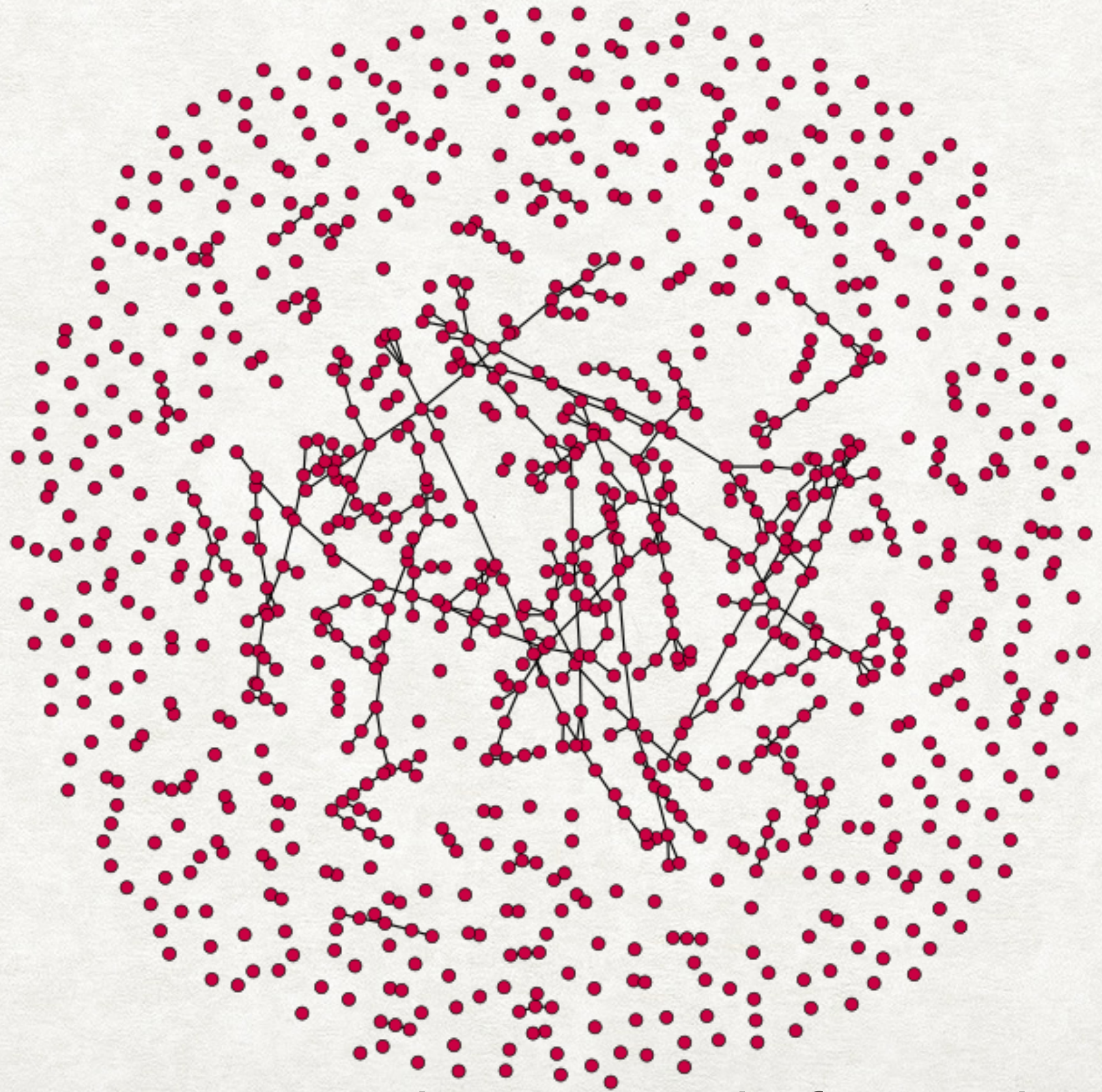


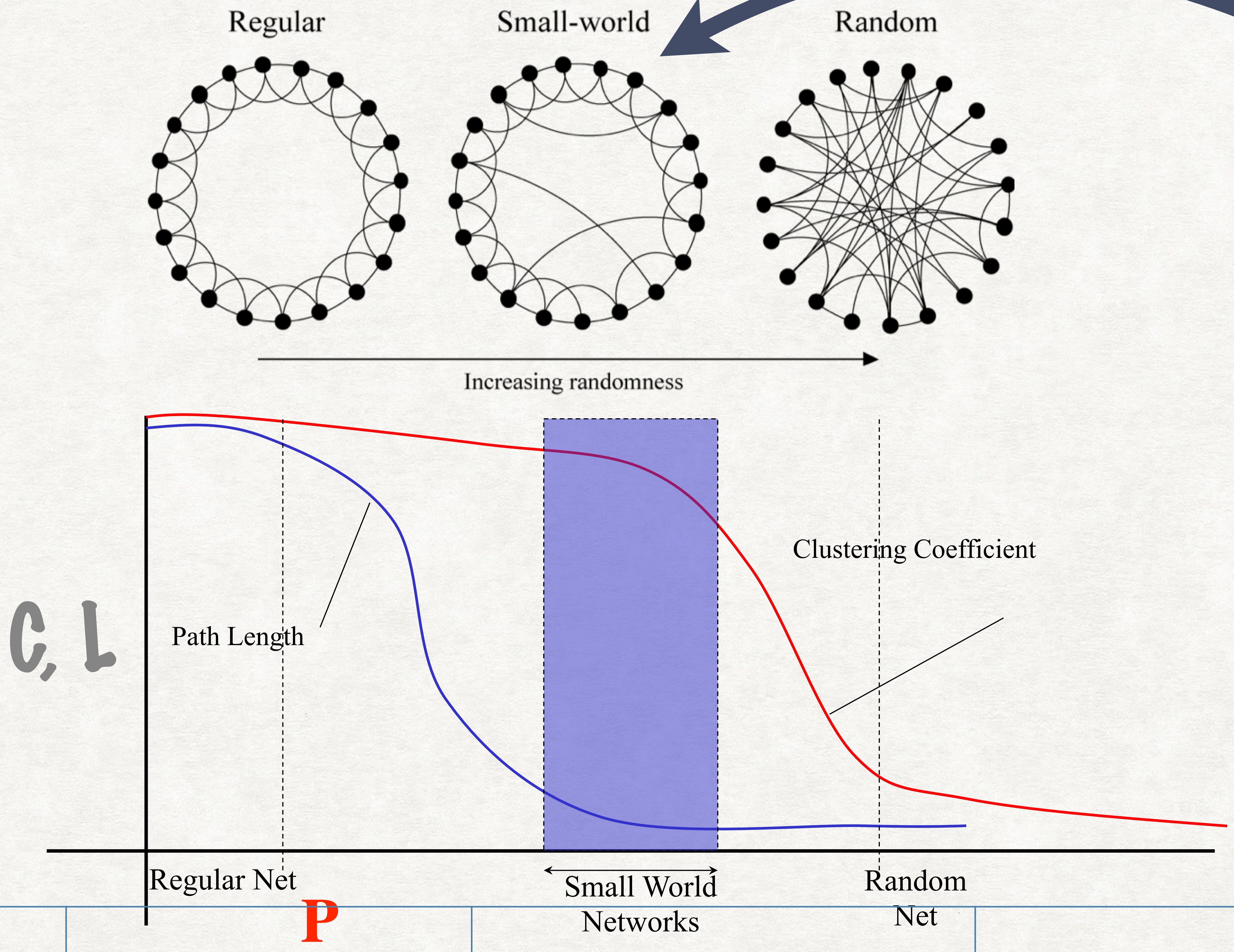
Fig. A random network, from wiki

NULL MODELS FOR STATISTICAL VALIDATIONS

Small-world networks

Watts and Strogatz, Nature 1998

Regular + Random

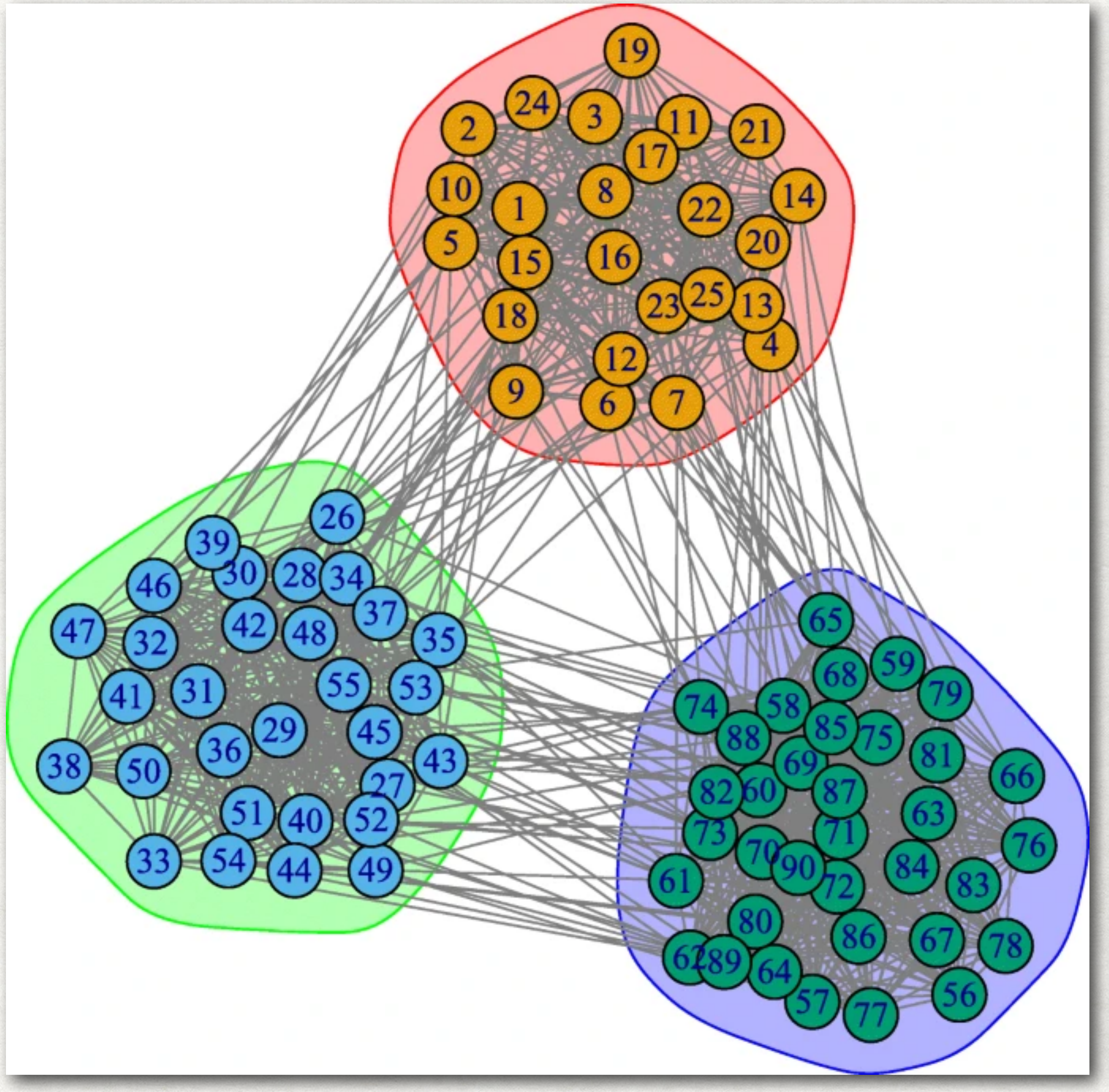


P = probability of long-range connections (Randomness)

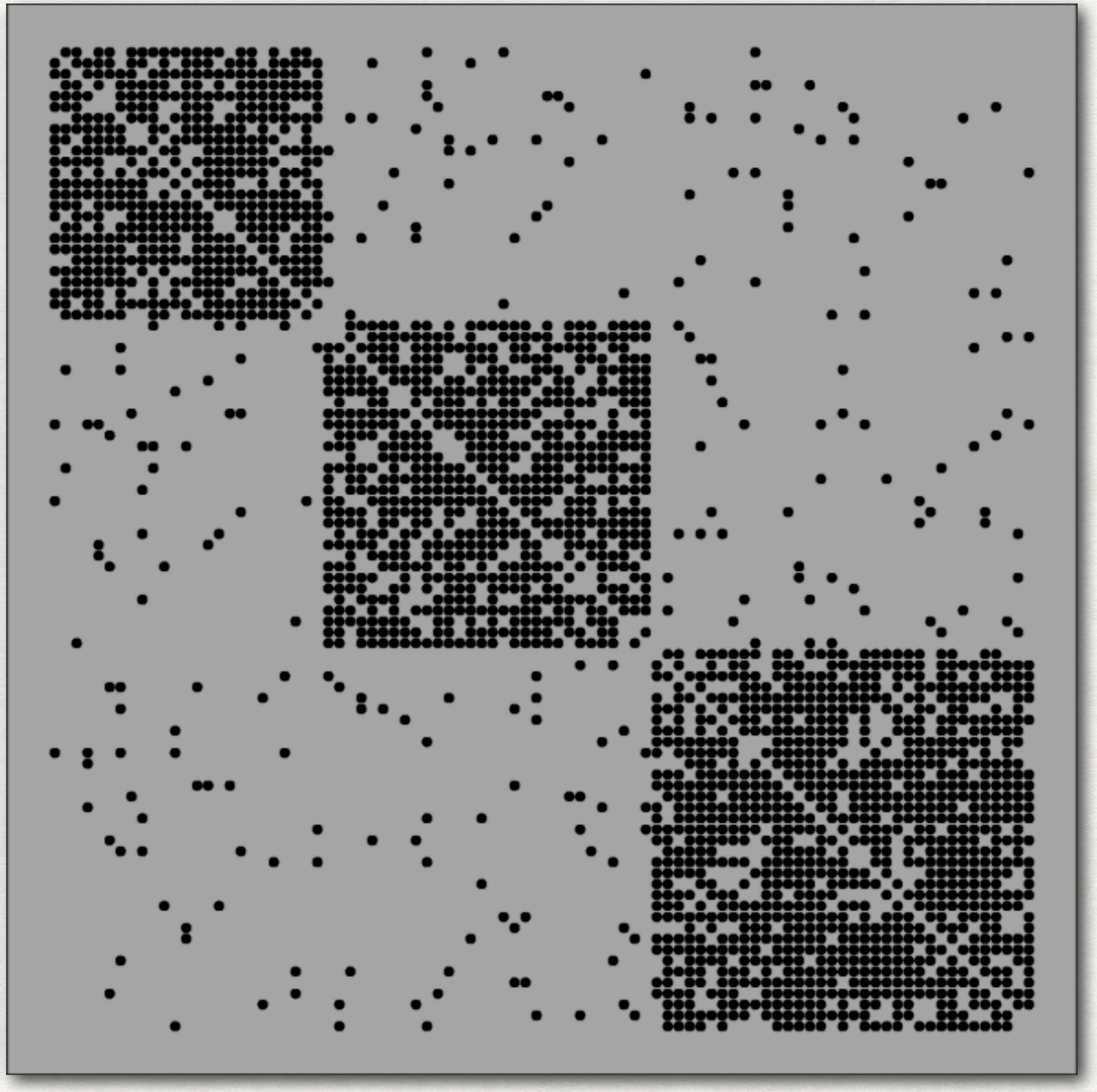
Randomness	Type of Graph	Clustering	Path Length
$p=0$	Regular	Highly clustered:	High diameter: $L_{max} \simeq \frac{N}{\langle k \rangle}$
$p=1$	Random (~Erdos-Renyi)	Low clustering: $C \approx <k>/N$	Low diameter : $L_{max} \simeq \frac{ln(N)}{lnk}$

From: Chih-Ling Hsu 2020

Modular networks: Stochastic Block Methods (SBMs)



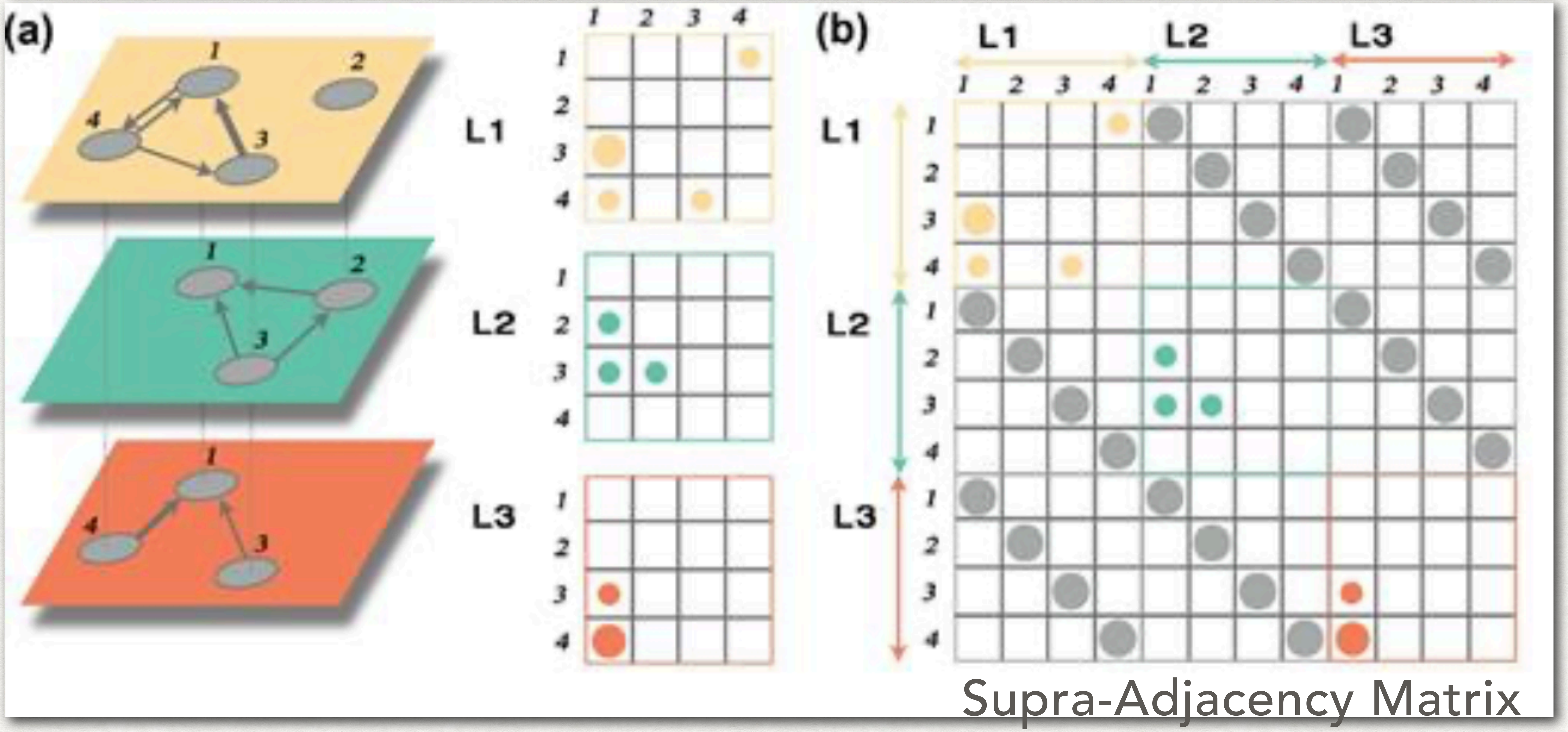
Network of 90 nodes



Adjacency matrix

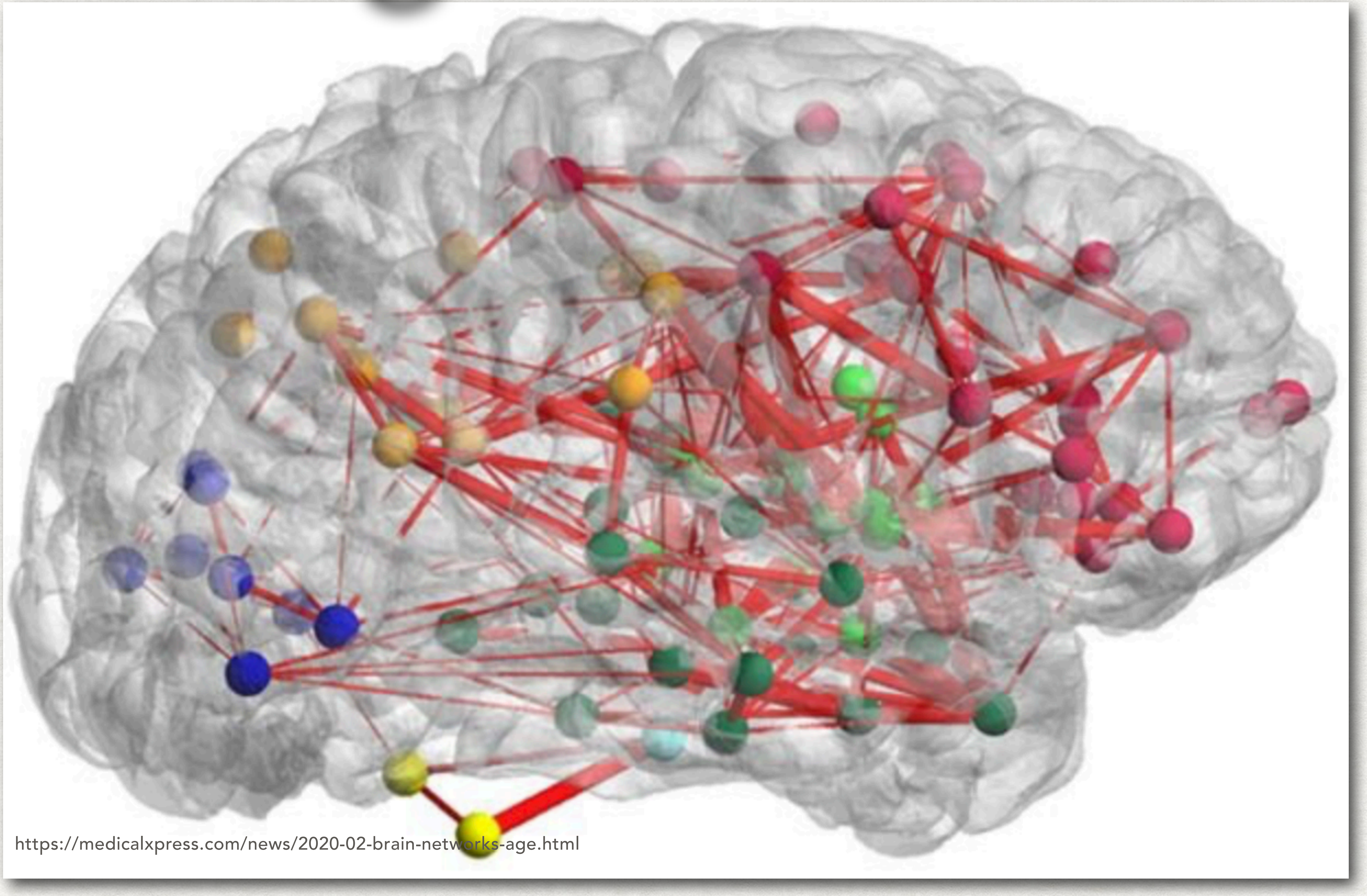
Ref. A review of stochastic block models and extensions for graph clustering Applied Network Science volume **4**, 122 (2019)

Multilayer Networks



(a) A multilayer network consists of different networks encoded by layers, each one represented by a (possibly directed and weighted) adjacency matrix. (b) The rank-4 multilayer adjacency tensor, representing intra- and inter-layer connectivity, is generally flattened by matricization to a rank-2 tensor, generally known as supra-adjacency matrix, without loss of information. Manlio De Domenico GigaScience, Volume 6, Issue 5, May 2017, gix004, https://doi.org/10.1093/gigascience/gix004

Understanding


https://medicalxpress.com/news/2020-02-brain-networks-age.html

Brain Networks are highly clustered

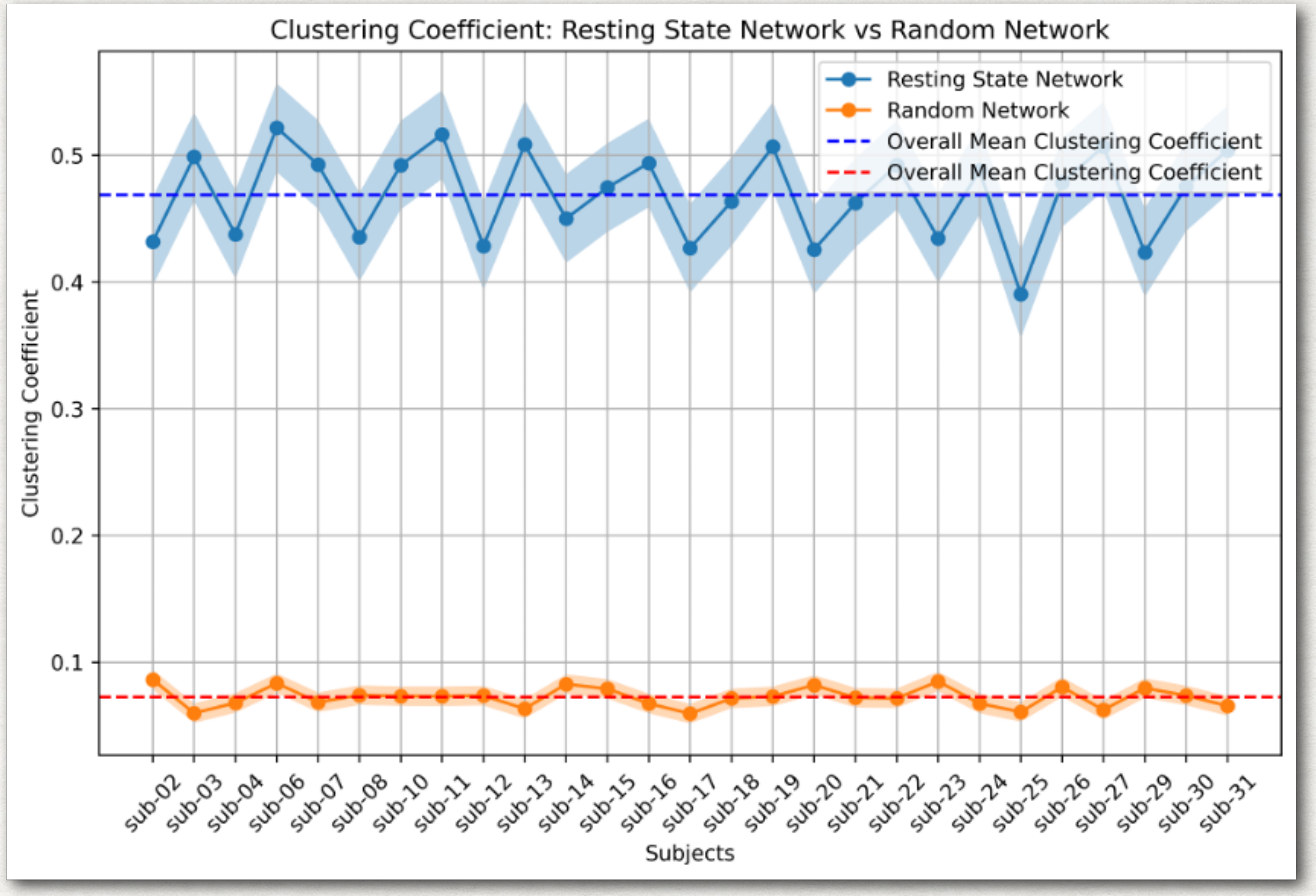
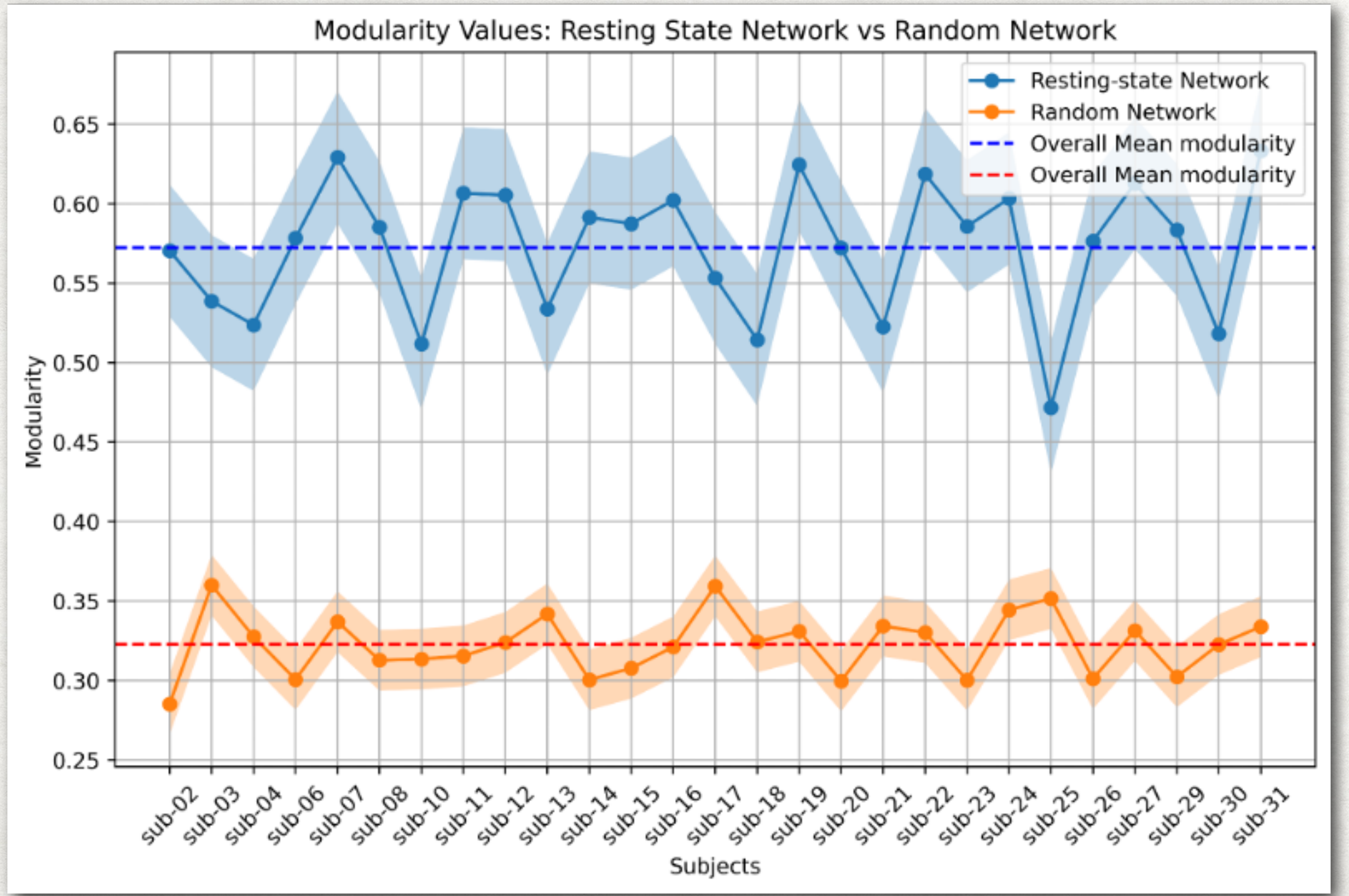


Fig. Global clustering in the resting state networks compared to the corresponding random networks.

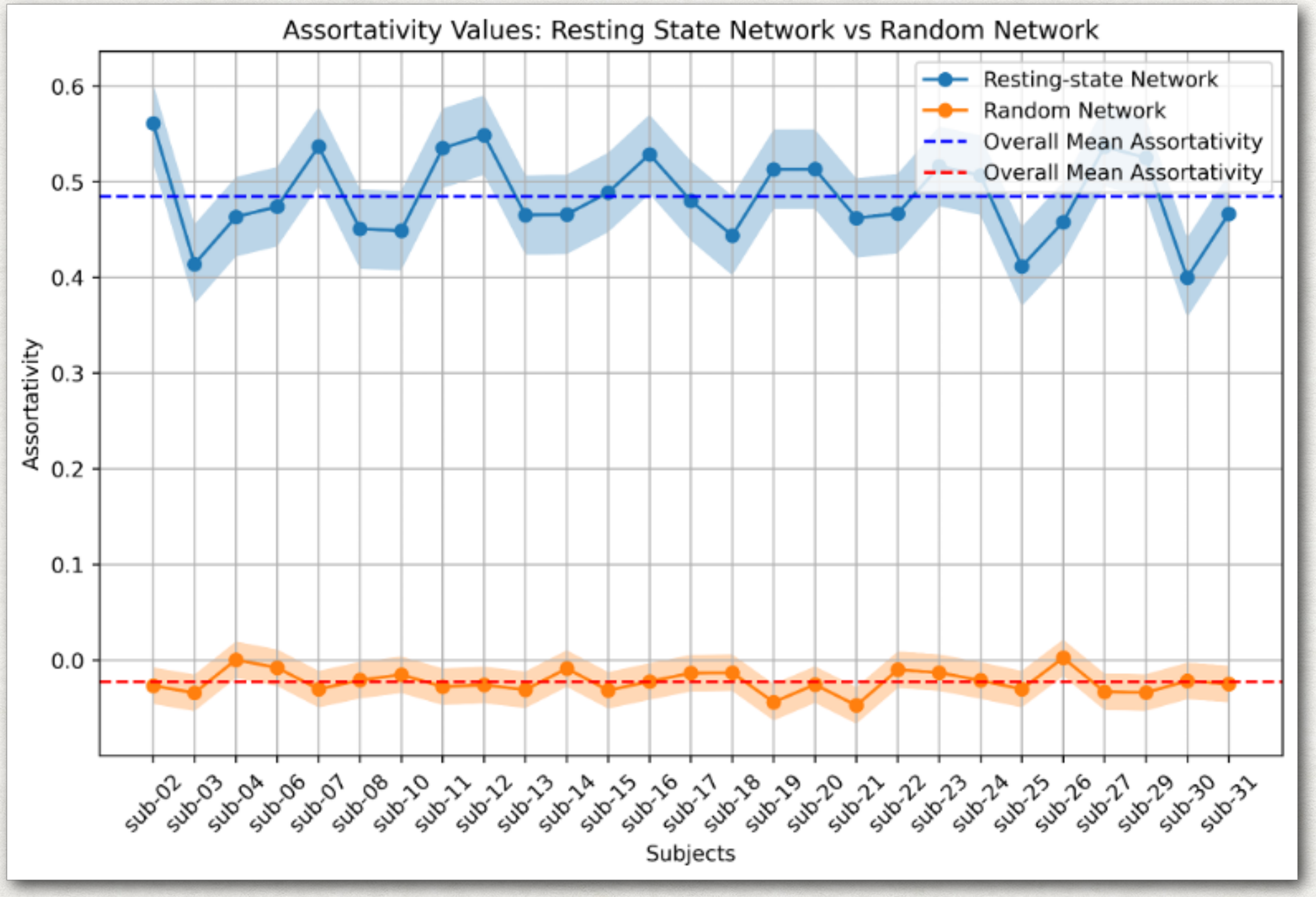
Fig. Modularity in the resting state networks compared to the corresponding random networks for the EEG data with 101 ROIs



A. Singh*, Lakshana Balaji & Mitanshu Sukhvani

Brain Networks: Has hubs and are Homophilic

Fig. Assortativity in the resting state networks compared to the corresponding random networks for the resting state EEG data with 101 ROIs.



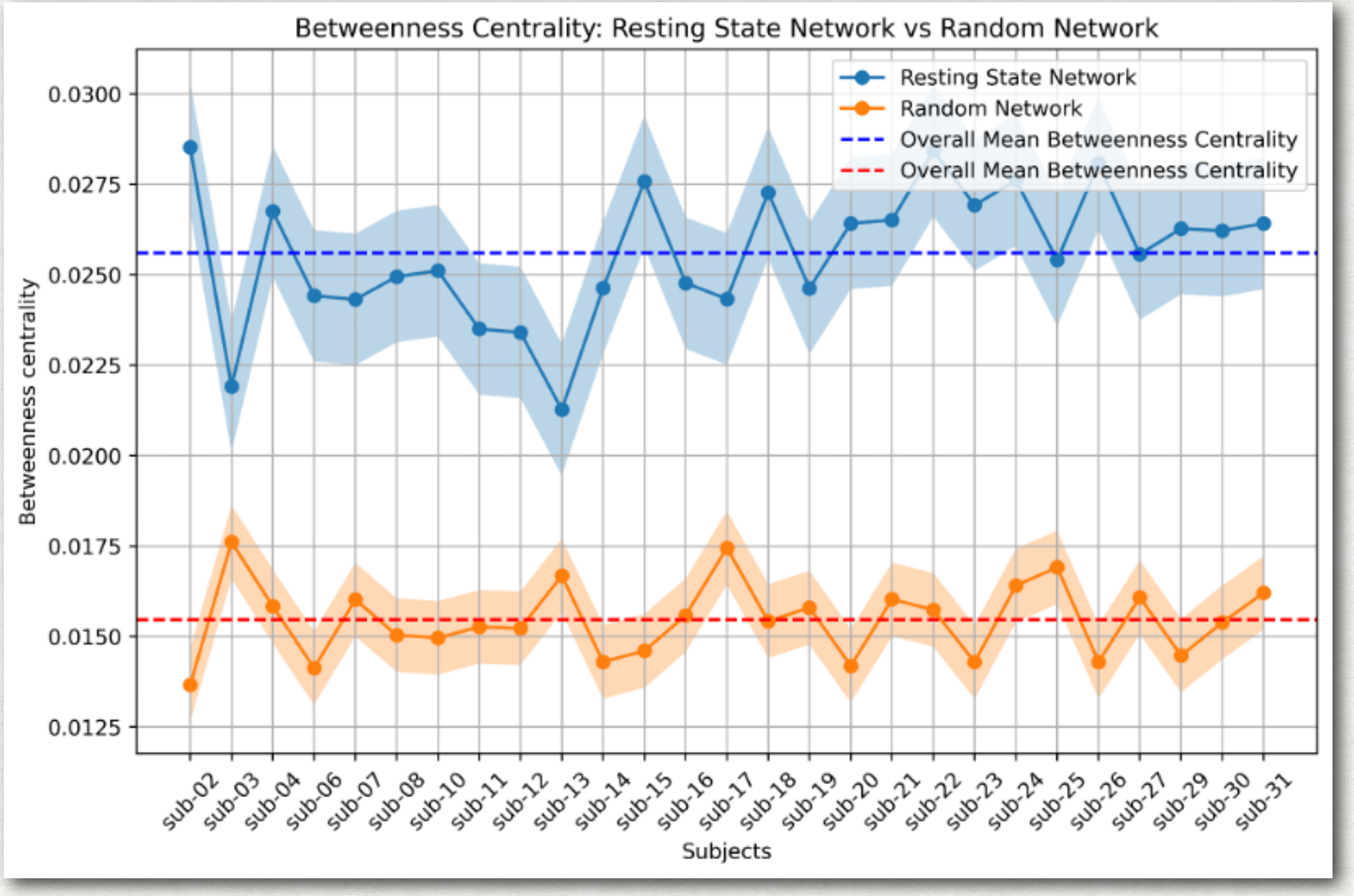


Fig. Average betweenness centrality in the resting state networks compared to the corresponding random networks for the resting state EEG data with 101 ROIs.

A. Singh*, Lakshana Balaji & Mitanshu Sukhvani

It's a small-world

SEGREGATION:

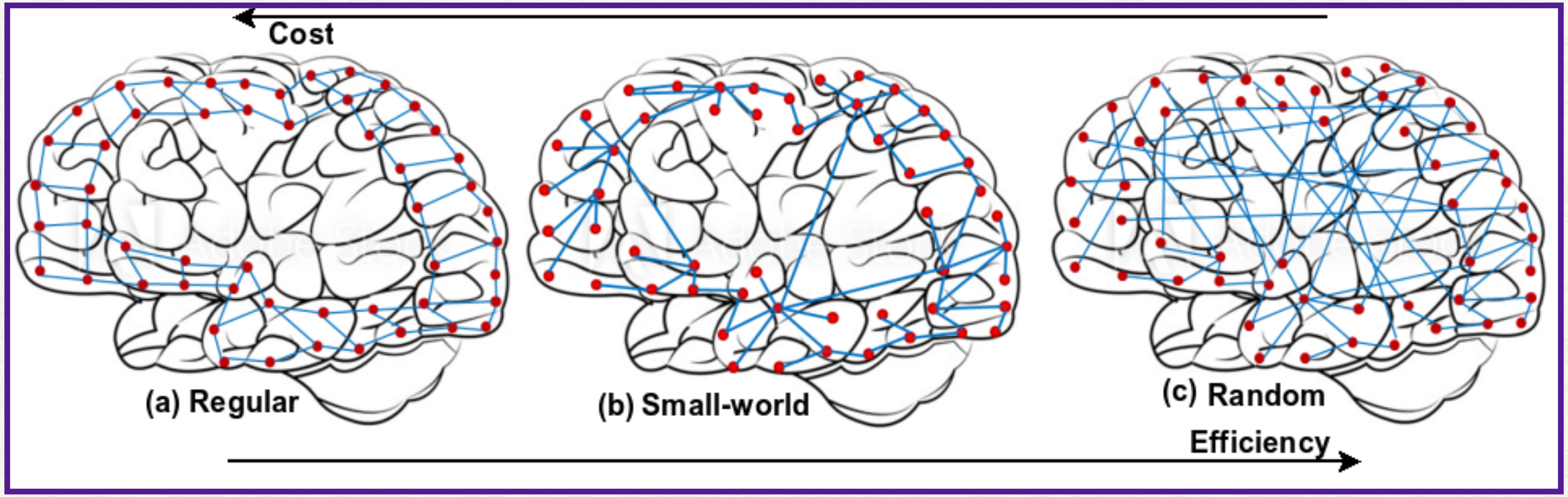
Clustering, Motifs, Modularity

+

Most Efficient

INTEGRATION:

Distance, Path length, Efficiency



The spatial organization of brain networks. (a) Localized network, in which nodes link based on spatial proximity; (b) Small-world network, a coexistence of a majority local and a small fraction of long range connections; (c) Random connectivity. These structural patterns represent a trade-off between cost and efficiency: localized is cost-effective but inefficient in terms of information dissemination, random exhibits maximum efficiency, but at a high cost, small-world optimally balances the two.

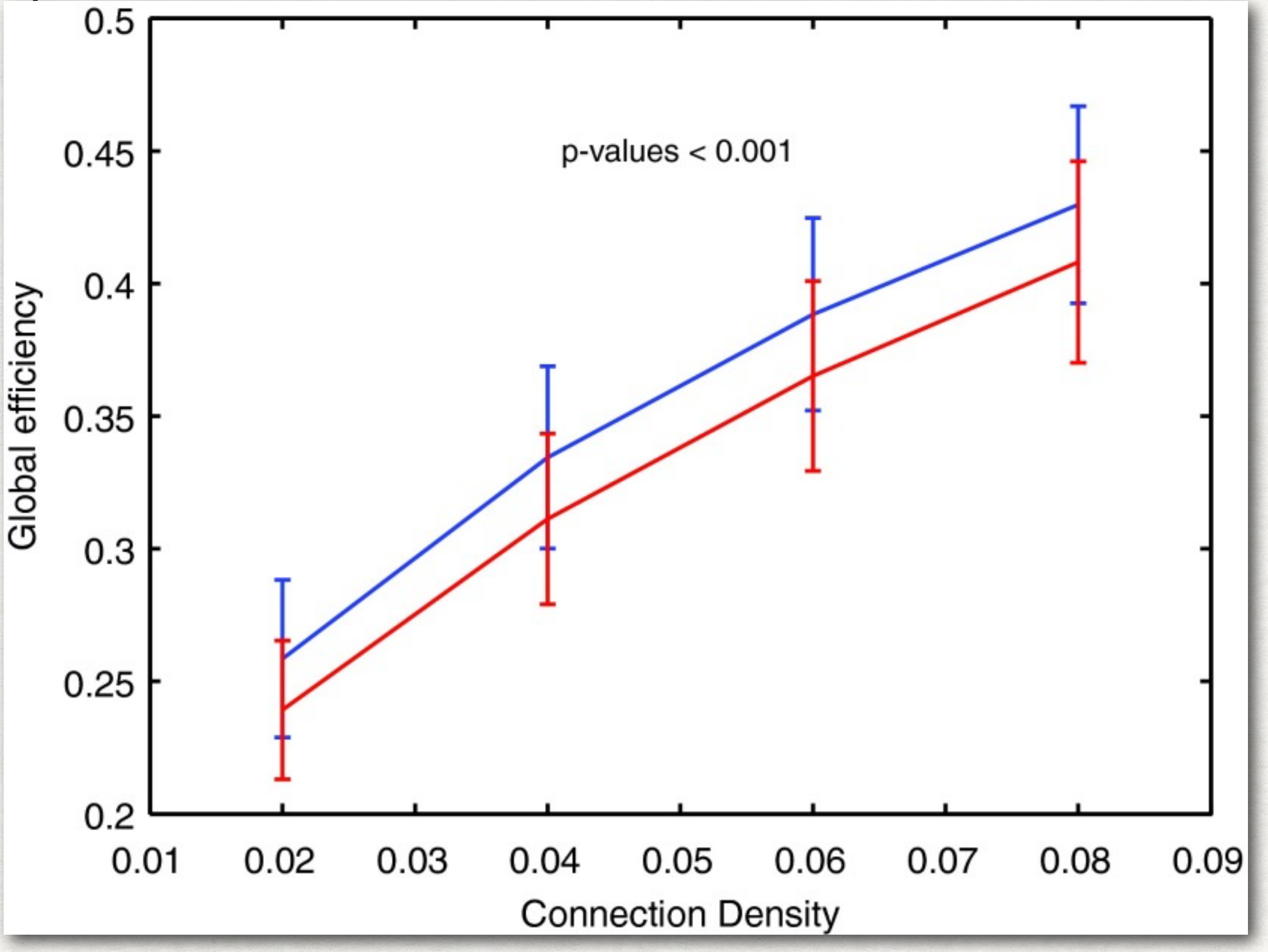
⭐Replicating the structural behavior the functional connectome has also been found to show the small-world phenomenon [https://www.sciencedirect.com/science/article/pii/S1389945718308967#sec3]

Brain Diseases and Network topology

Disrupted Brain Functional Organization in Epilepsy Revealed by Graph Theory Analysis

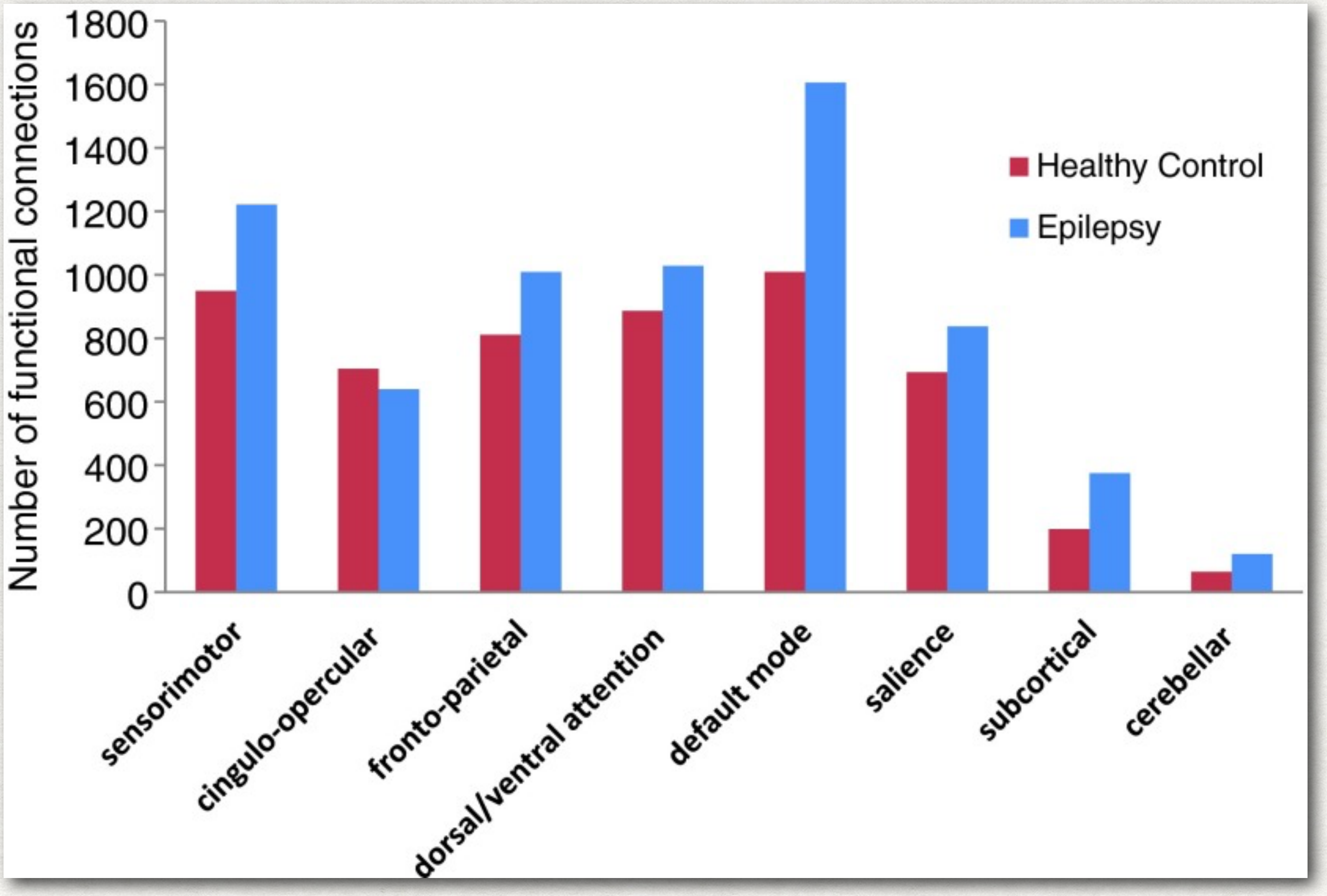
Jie Song, Veena A Nair, Wolfgang Gaggl, Vivek Prabhakaran

(1) Global efficiency is significantly increased in the epilepsy group across a range of different connection densities



Overall global efficiency is higher for the Epileptic patients. Whereas, the medial temporal lobe and PCG show decreased global efficiency, and PCC, angular gyrus, thalamus, and cerebellar vermis show increased global efficiency.

(2) Increased number of functional connections in the epilepsy patients.



Brain Connect. 2015 Jun 1;5(5):276–283. doi: 10.1089/brain.2014.0308

Default Mode Network (DMN) and Brain related diseases

- DMN is a large-scale distributed brain network which plays a critical role in cognition, including episodic memory formation and monitoring internal thoughts

- DMN impairments are prominent in psychiatric disorders.

- DMN is also found particularly sensitive to Alzheimer's disease pathology and the ensuing loss of episodic memory and related cognitive functions.

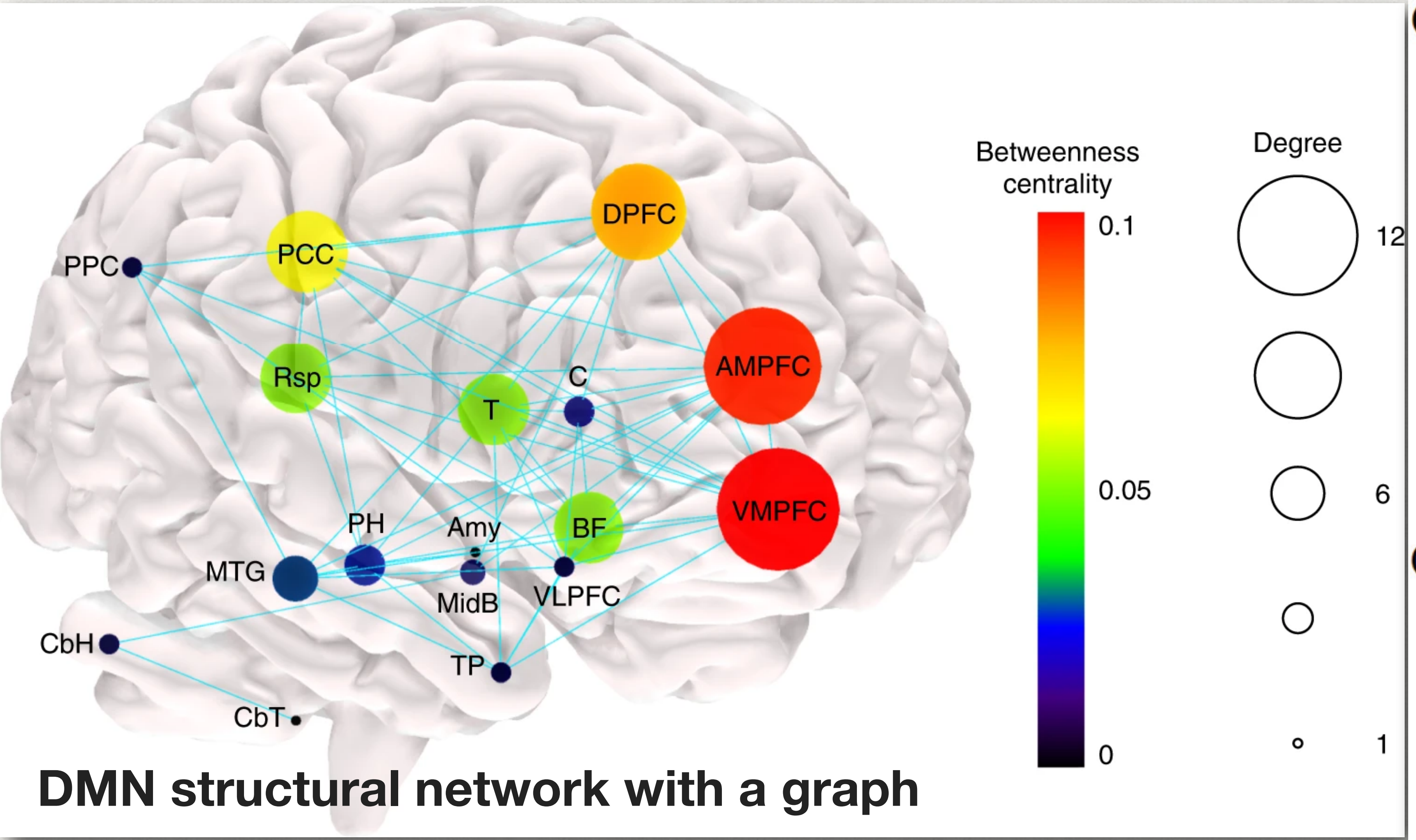
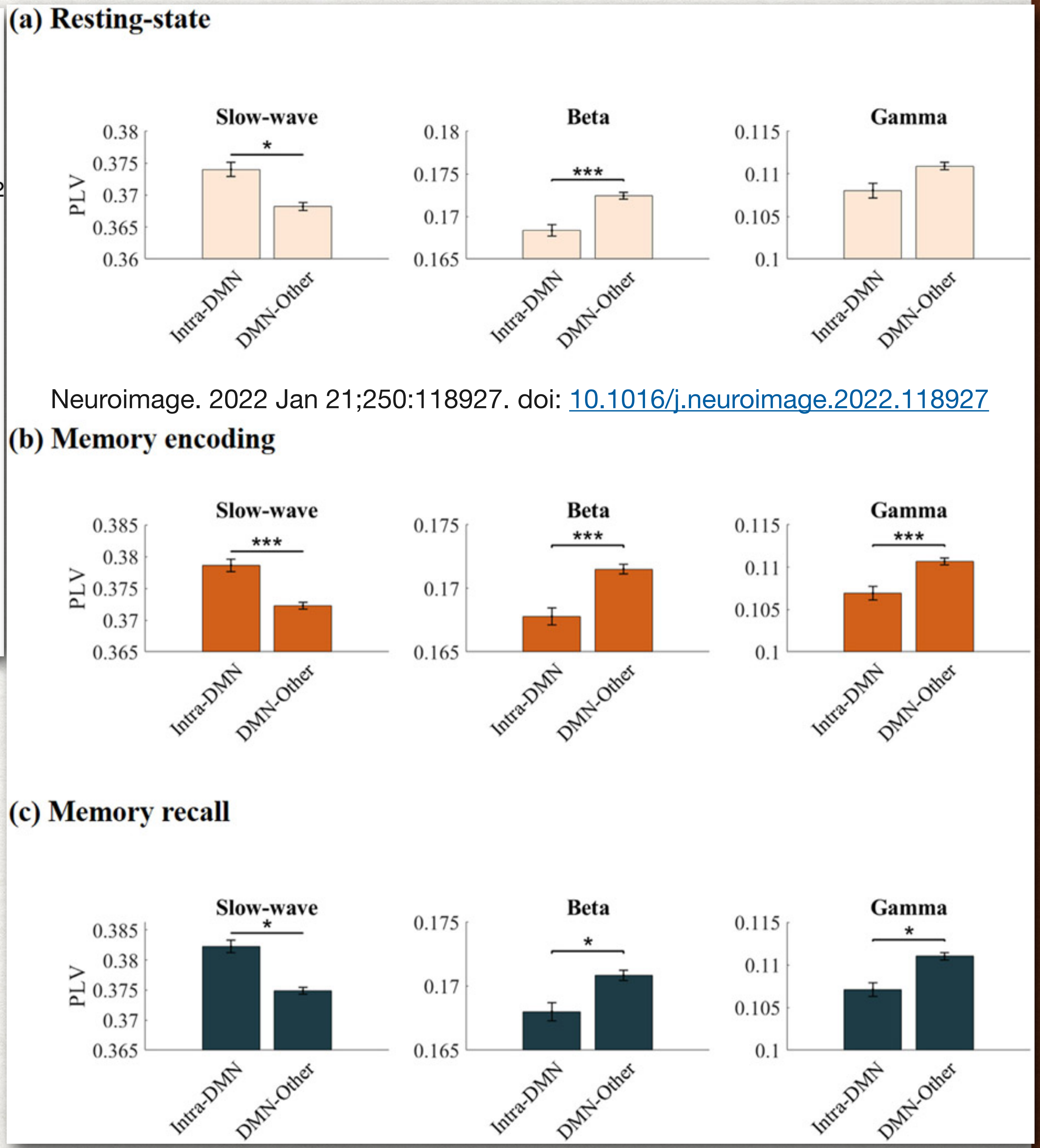


Fig. DMN. (DPFC) dorsal prefrontal cortex, PPC posterior parietal cortex, VLPFC ventrolateral prefrontal cortex, Rsp retrosplenial cortex, MTG middle temporal gyrus, PCC posterior cingulate cortex, C caudate, DPFC dorsal prefrontal cortex, AMPFC antero-median prefrontal cortex, VMPFC ventro-median prefrontal cortex, TP temporal pole, BF basal forebrain, T thalamus, PH parahippocampal region, CbH cerebellar hemisphere, CbT cerebellar tonsil, Amy amygdala, MidB midbrain. $n = 20$ participants Communications Biology volume **2**, 370 (2019)



Neuroimage. 2022 Jan 21;250:118927. doi: 10.1016/j.neuroimage.2022.118927

Network based understanding of progression of the Alzheimer's Disease (AD)

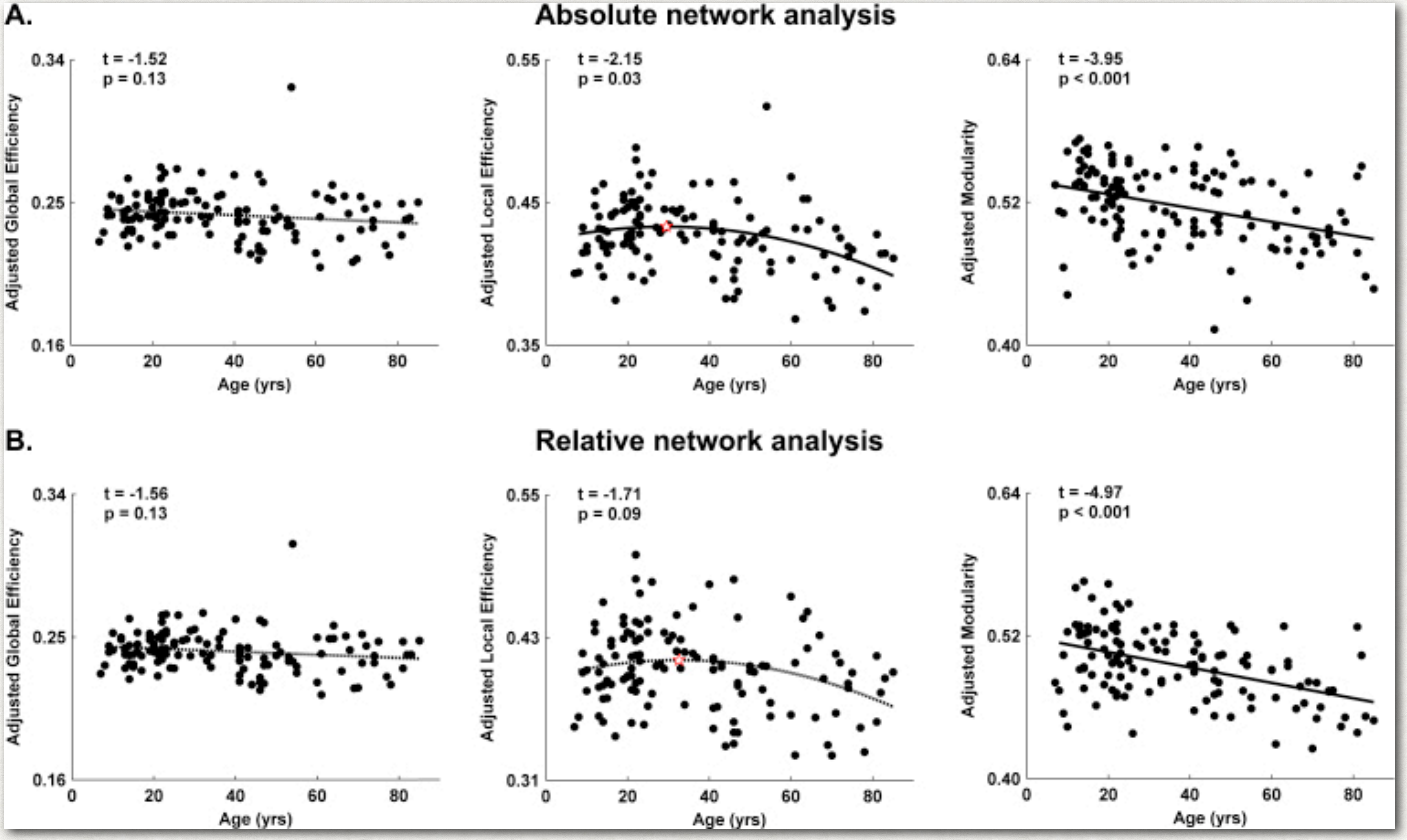
Individuals with AD exhibited degeneration of specific brain hubs, reduced clustering coefficients and path lengths very close to the values of random networks (Supekar et al., 2008; Sanz-Arigita et al., 2010; Dai et al., 2015; delEtoile and Adeli, 2017),

The cognitive impairment in the AD was associated with a weakness in modular interconnectivity and hubs destruction (Brier et al., 2014) and significant alterations within the default network (Toussaint et al., 2014; Zhong et al.,2014).

These findings were in parallel with a global decrease in long-distance functional connections especially between frontal and caudal brain regions (Sanz-Arigita et al., 2010).

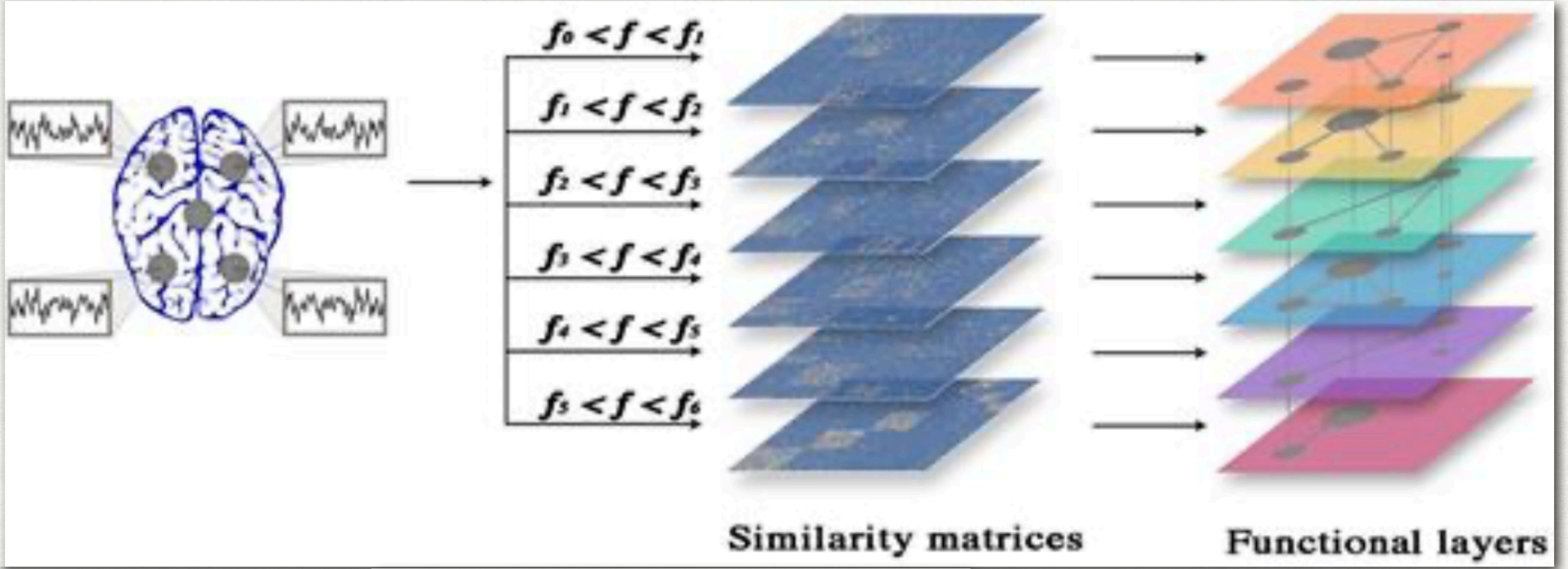
Ref. Farahani F V, *et al.* Application of GraphTheoryforIdentifying ConnectivityPatternsinHumanBrain Networks:ASystematicReview. Front.Neurosci.13:585. doi:10.3389/fnins.2019.00585

AGING AND THE BRAIN NETWORK



The lifespan trajectories of functional network efficiency and modularity. Absolute network properties based on the correlation thresholding method, and relative network properties are based on density thresholding networks [Dev Cogn Neurosci. 2013 Nov 28;7:76–93. doi: 10.1016/j.dcn.2013.11.004]

Multilayer Brain Networks: Frequency-based decomposition



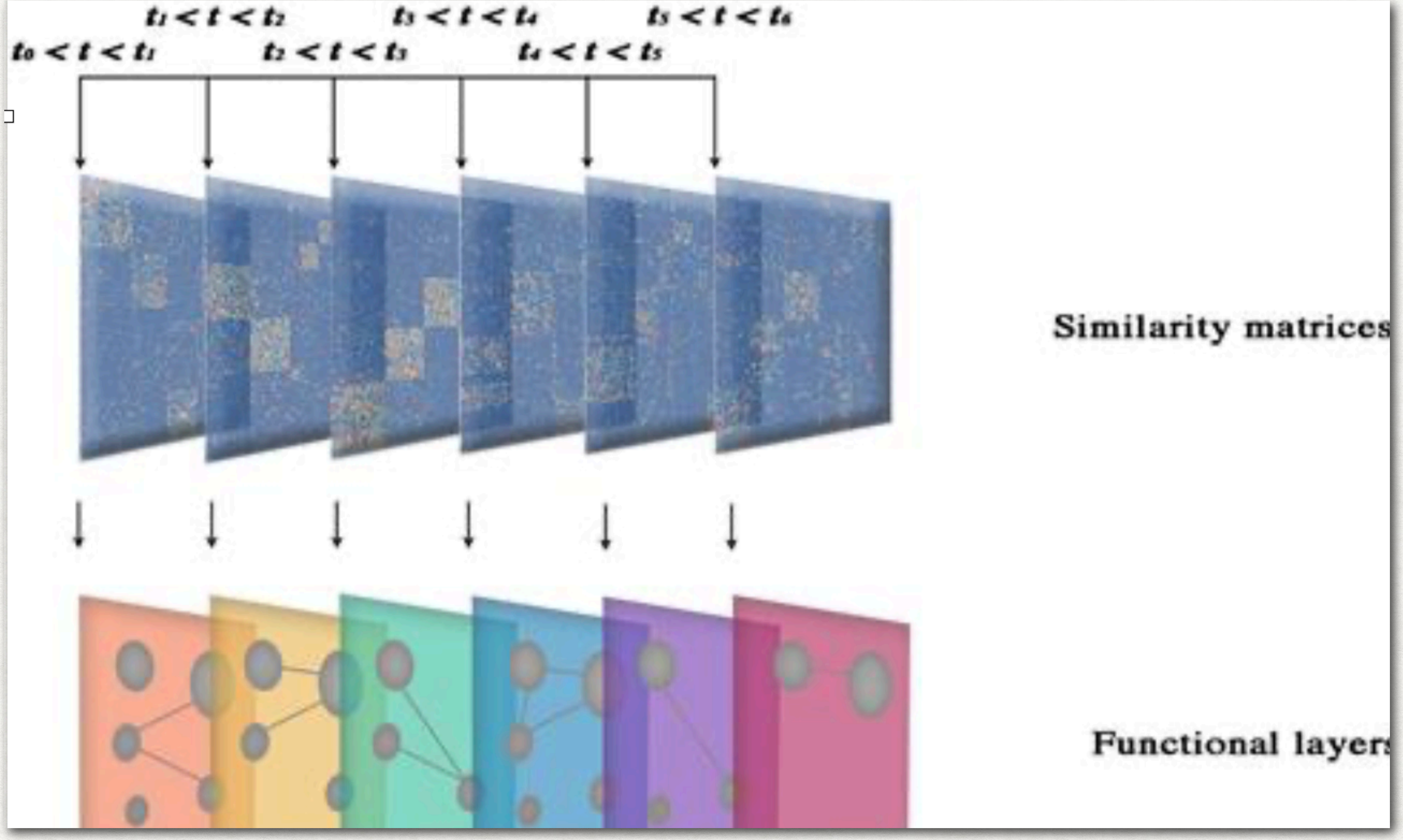
Supra-adjacency matrix element

$$M_{ij}^{\alpha\beta} = \begin{cases} A_{ij}^{[\alpha]}, & \text{if } \alpha = \beta \\ D \cdot \delta_{ij}, & \text{if } \alpha \neq \beta \\ 0, & \text{otherwise} \end{cases}$$

α and β correspond to different layers and i, j are nodes in a layer

Manlio De Domenico GigaScience, Volume 6, Issue 5, May 2017, gix004, https://doi.org/10.1093/gigascience/gix004

Multilayer Brain Networks: Time based decomposition



Manlio De Domenico GigaScience, Volume 6, Issue 5, May 2017, gix004, https://doi.org/10.1093/gigascience/gix004

Multilayer functional brain networks are more informative than the monolayer networks

- De Domenico et al. also calculated centrality measures (i.e., measures of the importance of network components; Newman, 2010) on the frequency-based multiplex networks to demonstrate the existence of hubs that had not been classified previously as important brain regions for functional integration.

- Hubs of the control group were located in anterior cingulate, superior frontal, insula, and superior temporal cortices; however, hubs for schizophrenic patients were distributed over frontal, parietal, and occipital cortices.

- The accuracy of the classification using the network features among the healthy and schizophrenic patients had better accuracy in multilayer frame than the monolayer.

- These results revealed that frequency-based multiplex networks include relevant information about the functional organization of brain networks that is not captured by using a classical monolayer approach.

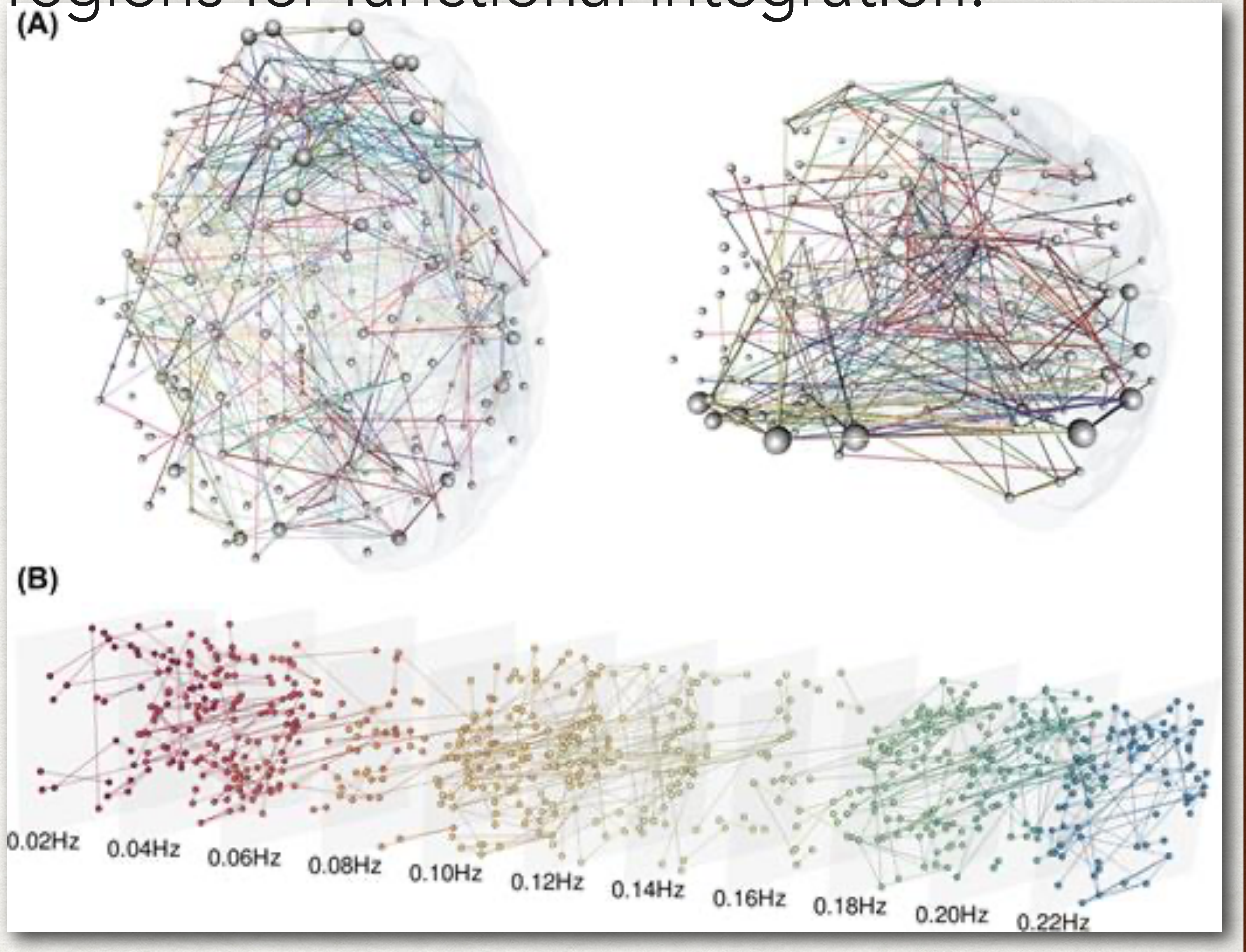


Fig. Visualizing the multilayer functional brain. Three-dimensional representations of the multilayer functional brain of a schizophrenic subject, based on frequency decomposition

Manlio De Domenico GigaScience, Volume 6, Issue 5, May 2017, gix004, https://doi.org/10.1093/gigascience/gix004

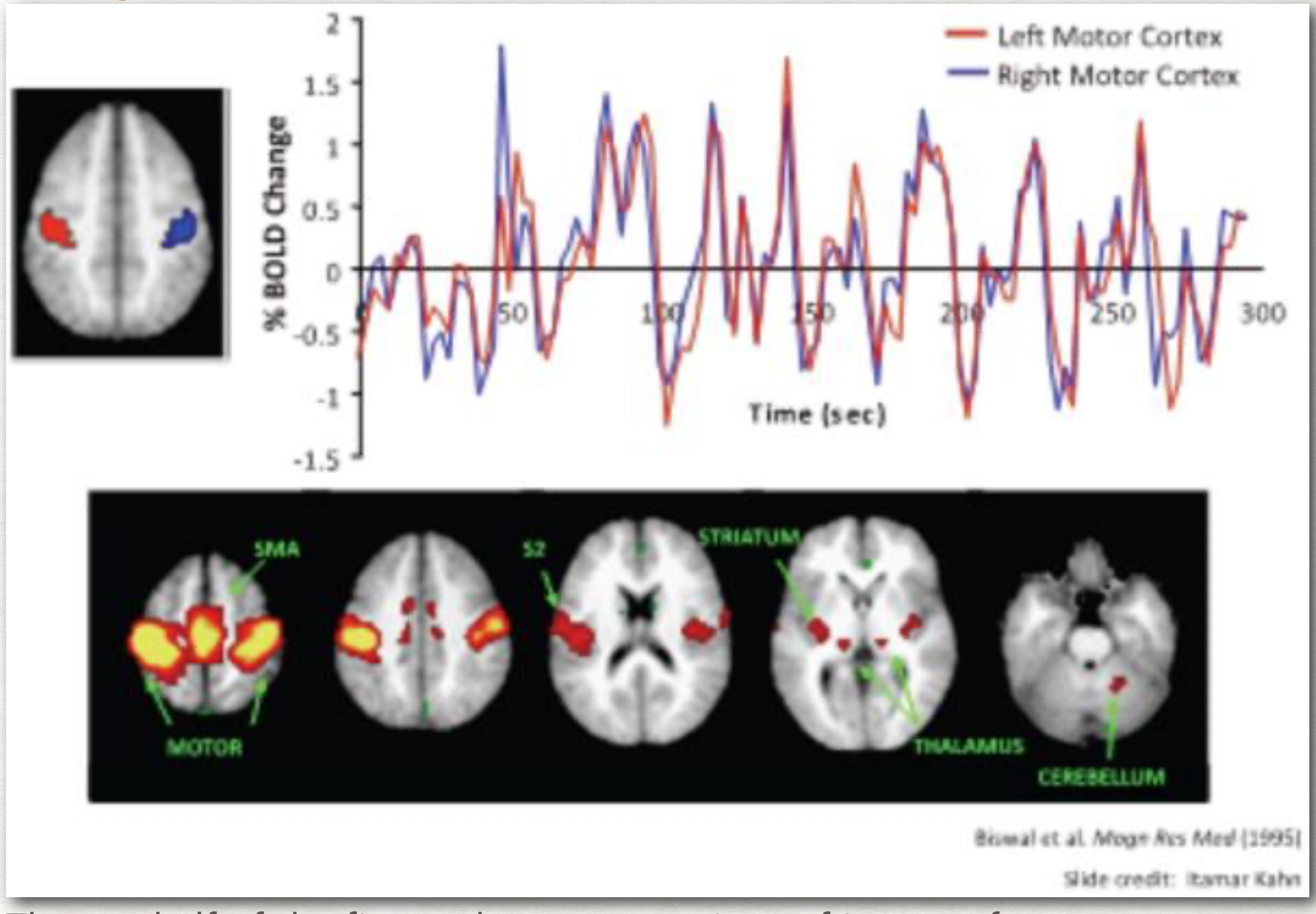
Is the Functional Connectome a Reflection of Anatomical Brain Connectivity?

* Functional correlations can be found between left motor cortex and right cerebellum (Buckner et al., The organization of the human cerebellum estimated by intrinsic functional connectivity 2011), two structures that are multiple steps away from one another in anatomical terms (figure).

* The eccentric representations of primary visual cortex in left and right hemispheres correlate, without the presence of direct anatomical connections (Vincent et al., 2007 10.1038/nature05758.).

No *one*-to-*one* mapping between Structural and functional connectome

Understanding brain networks and brain organization, Luiz Pessoa



The top half of the figure shows two regions of interest from motor cortex in red and blue on a brain image. On the right are resting time courses from these two regions showing high correlation across several minutes. This is resting state functional correlation (RSFC). The bottom panel shows regions of the brain that have high correlation with the red ROI from above. Each of these regions is nominally related to motor and somatosensory processing suggesting that RSFC illuminates regions that are functionally related.

From: Brain Networks and Cognitive Architectures, Steven E Petersen, Olaf Sporns.

Future scope and Challenges

- **<u>Generalizable patterns/reliability:</u>** Functional networks differ across individuals due to genetics, development, learning, or even moment-to-moment variability. Therefore, it is hard to consider FC a robust and actionable clinical tool.

- **<u>Uncertainty in Predicting Brain Waves:</u>** In adults, brain waves can often be associated with specific cognitive functions. However, in a developing brain, interpreting brain waves and understanding their correlations is more challenging.

- **<u>A Field in Fast Transition:</u>** While the functional connectome provides insights into cognition, the emergence of improved experimental techniques and analytical methods is likely to reshape our understanding of the brain.

⭐This continual evolution makes it a long-lasting and vital field in neuroscience.

Acknowledgement

The organizers of the “ Brains, Dynamics & Computation”
Shakti N Menon (IMSc Chennai)
Prof. Sitabhra Sinha (IMSc Chennai)

Funding Agency:
DST
IISER Tirupati

All the group members of Complex Systems Lab @ IISER Tirupati

Clockwise from left: Prateek Yadav (iPhD), Kartik Dahake (PhD), Amod Rai (PhD), Ritish Khetrapal (DST-Project associate-I), Sheksha (Project student)


https://www.timeshighereducation.com/features/when-will-neuroscience-blow-our-minds

Thanks!