Advances in Network Neuroscience

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About this Topic: https://github.com/donghui1119/Network-Neuroscience

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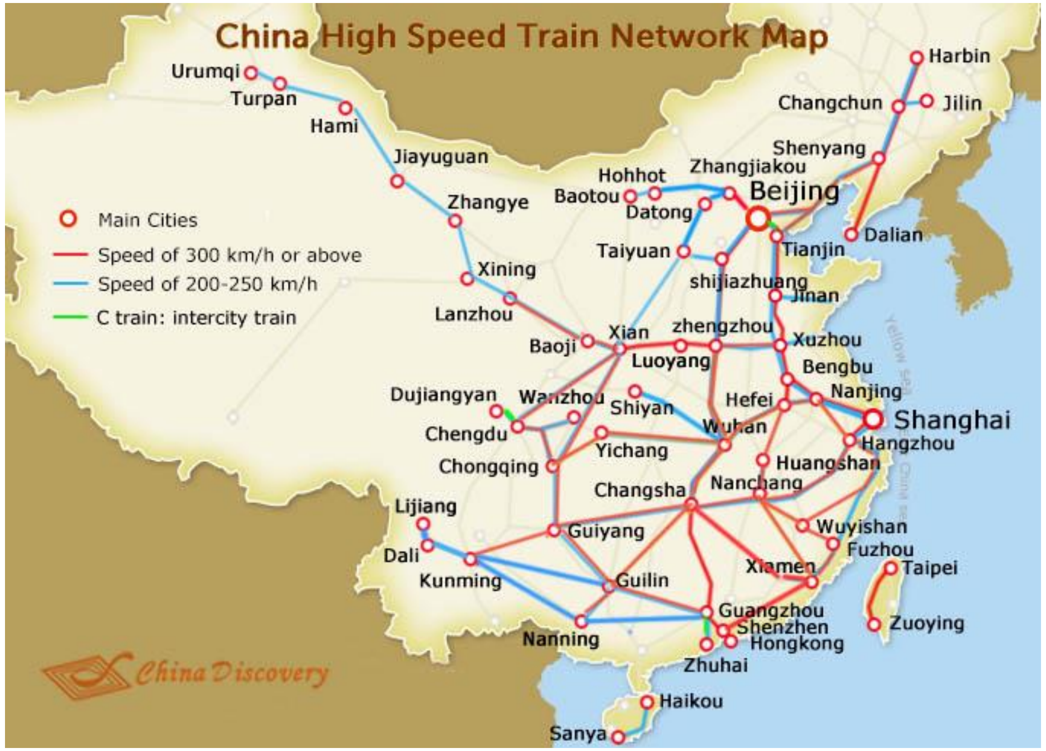
Oct 27, 2021

Network in Daily life



China High Speed Train Network

(https://en.imsilkroad.com/p/314370.html)

Six degrees of separation

Social Network

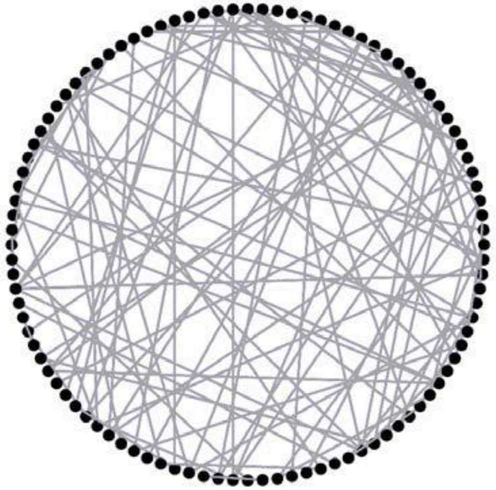
(https://towardsdatascience.com/how-to-visualize-social-network-with-graph-theory-4b2dc0c8a99f)

A Brief History of Graph Theory

Leonhard Euler (1707-1783)

Seven Bridges of Königsberg

Paul Erdős (1913-1996)

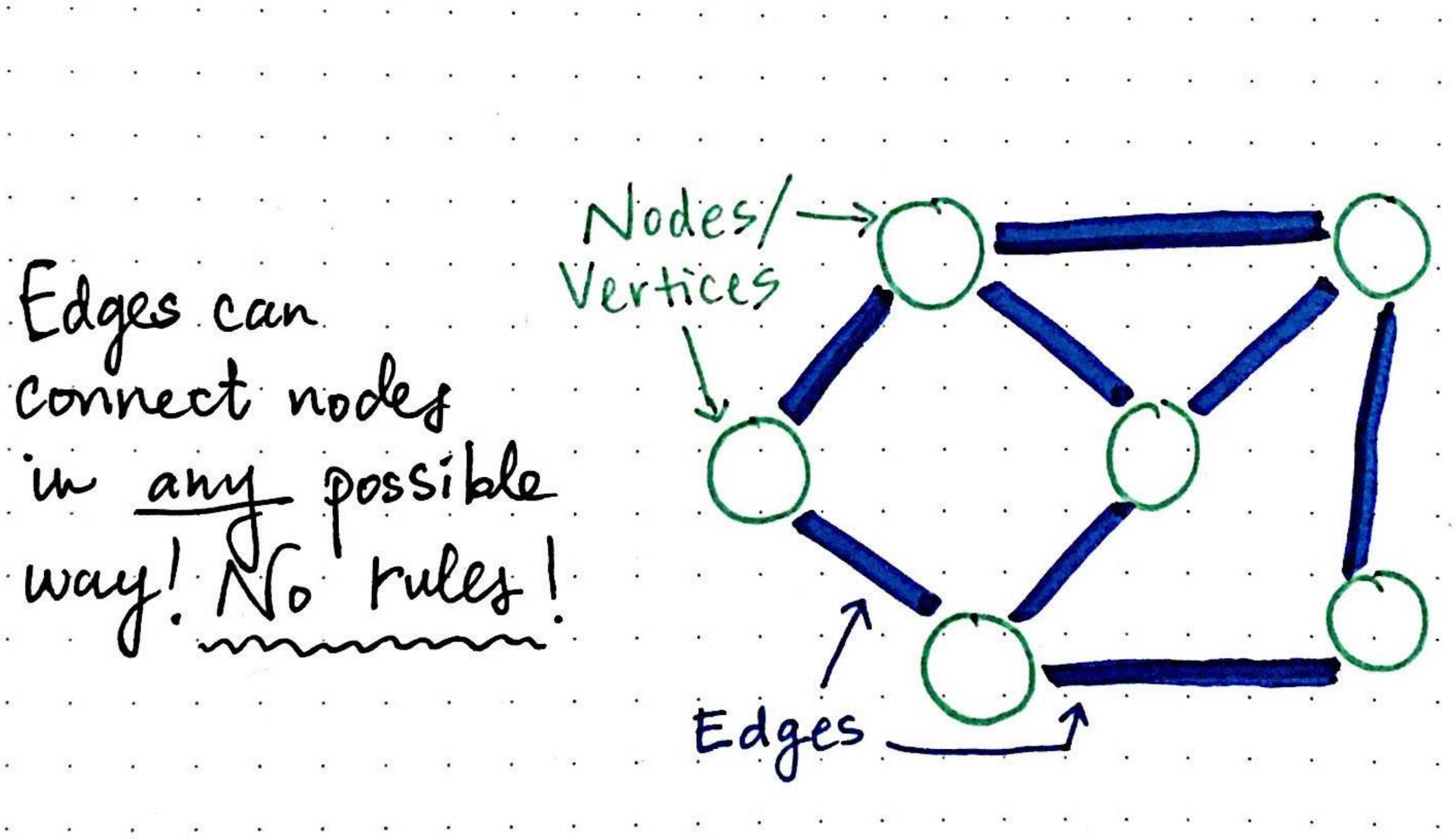


Random Graph

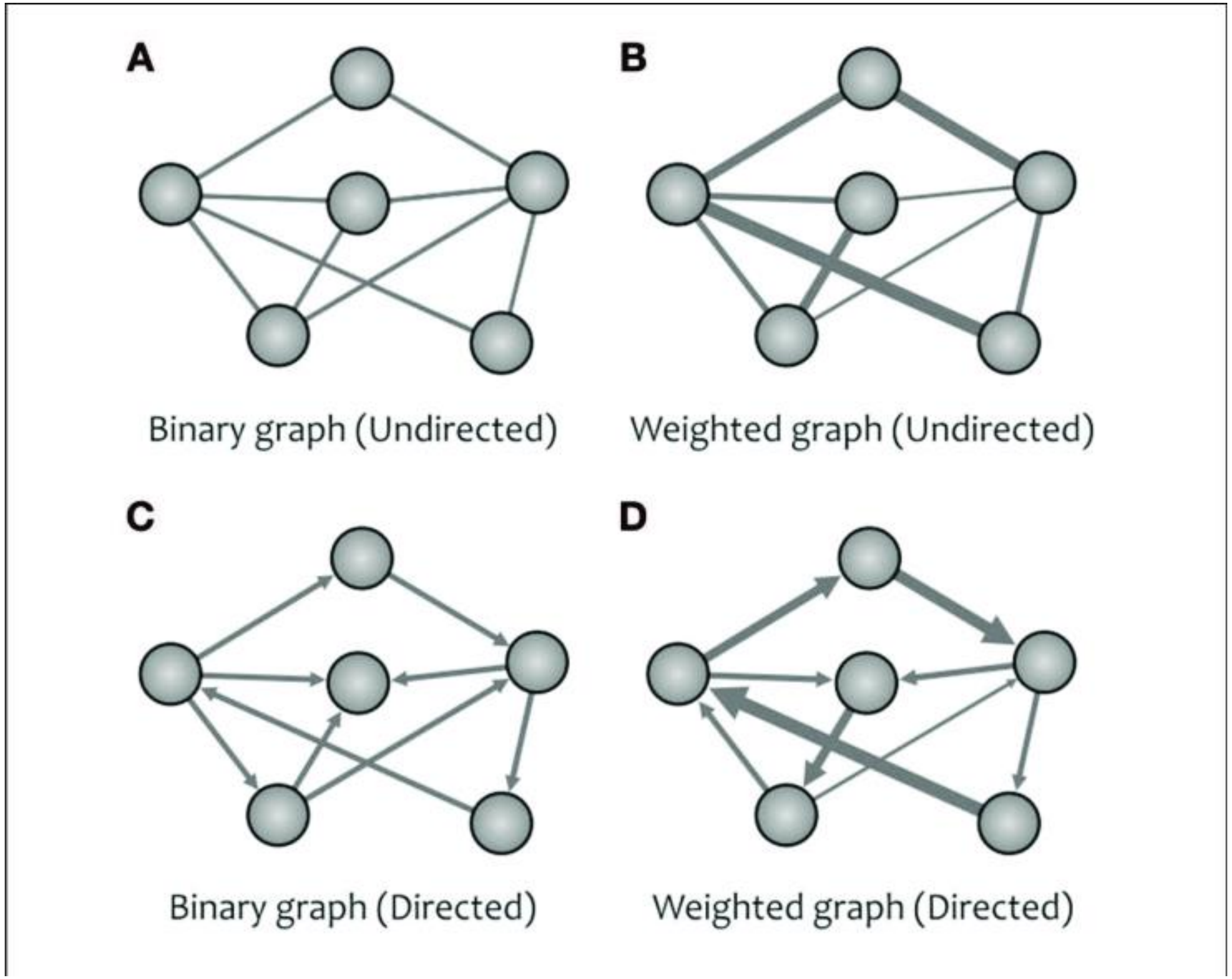
Alfréd Rényi （1921-1970）

Node (Vertex) + Edge = Graph

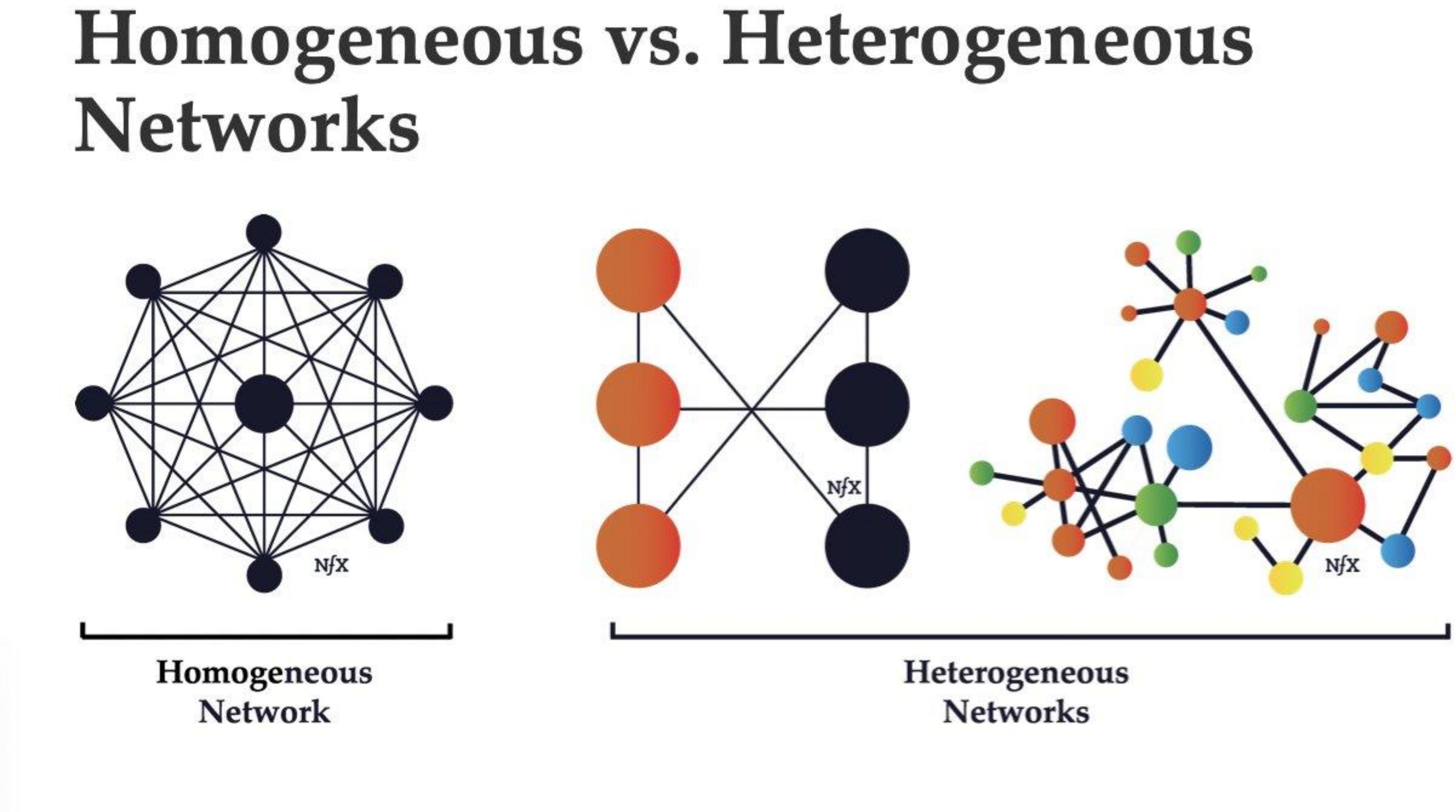
Node is the fundamental unit of which graphs are formed;
Edge is one of the two basic units out of which graphs are constructed;



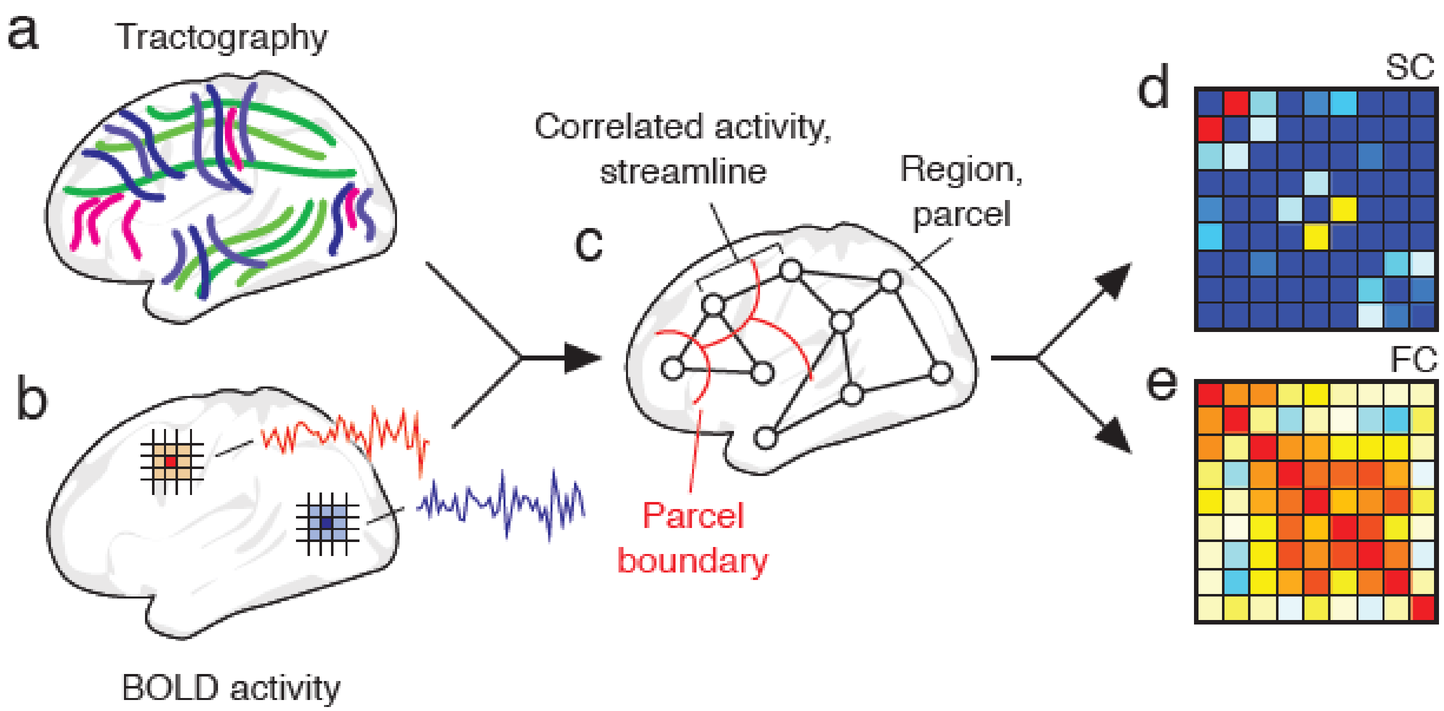
Different Graphs



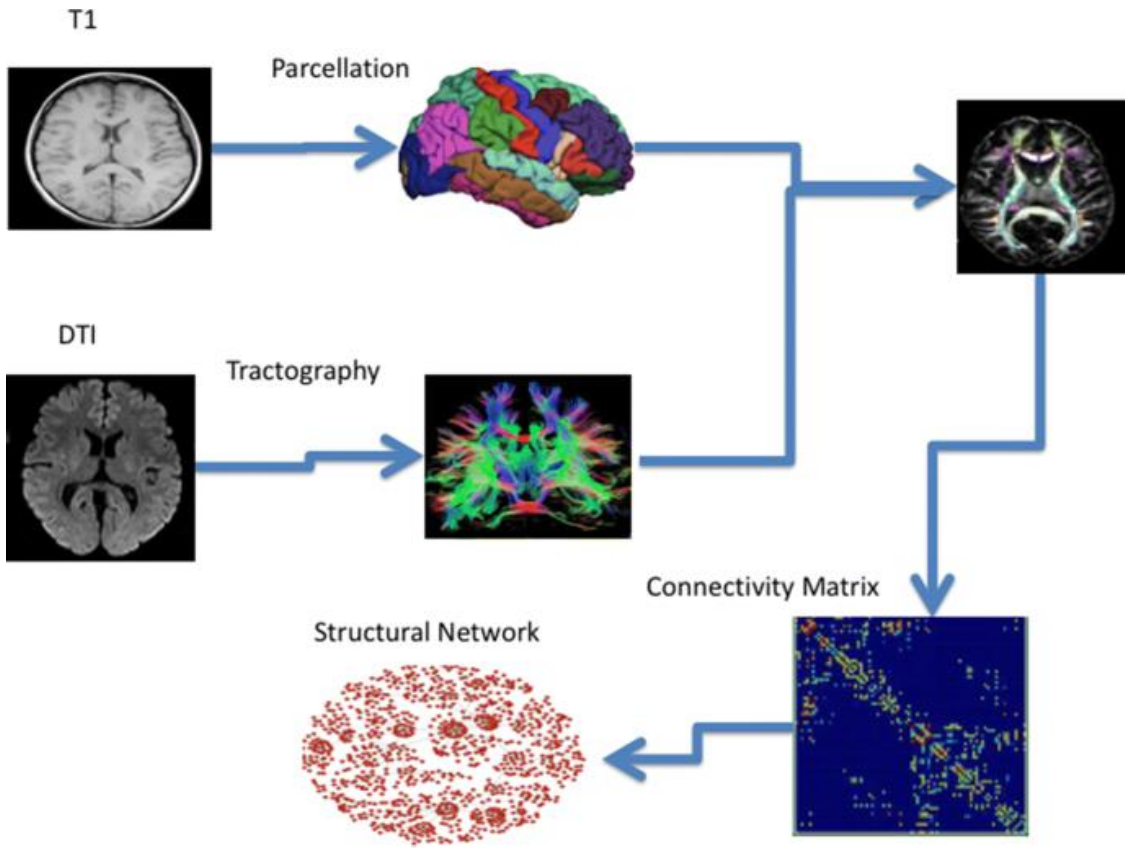
Different Graphs

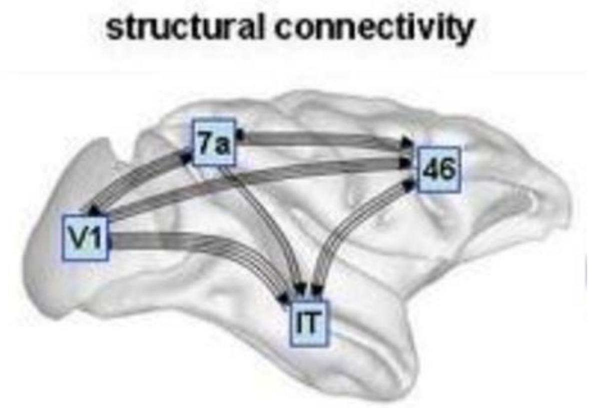


Brain Network Construction in Human Brain



Structural Connectivity

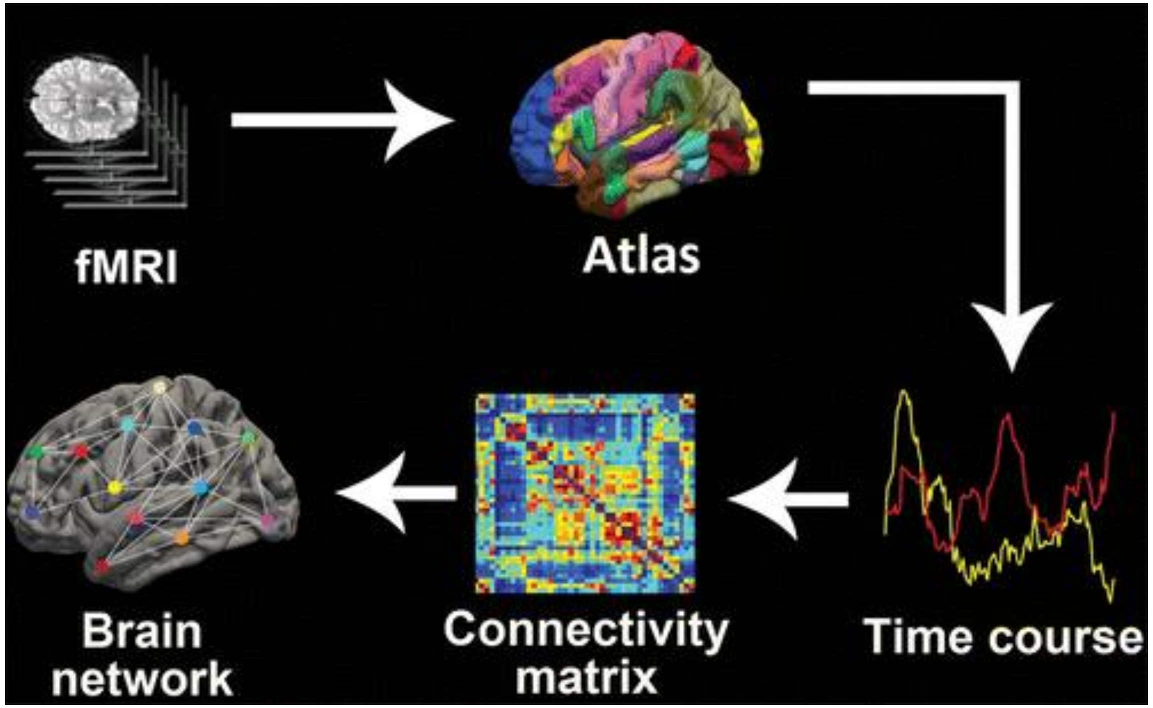




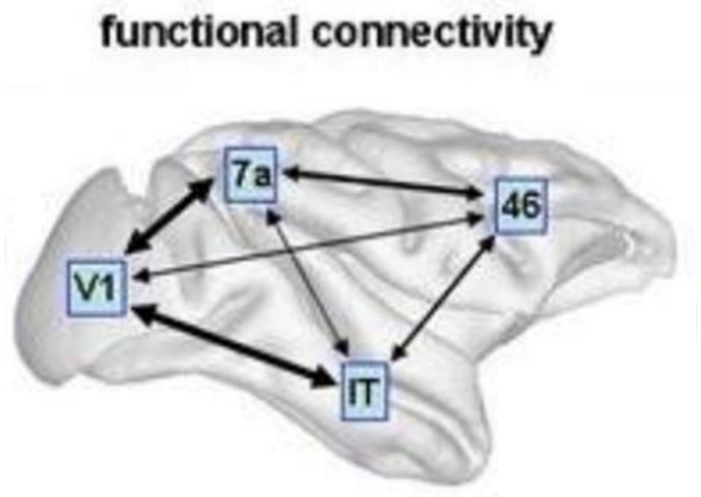
Sporns, 2007, scholarpedia

Marianna Milano, 2019, Network Modeling Analysis in Health Informatics and Bioinformatics

Functional connectivity

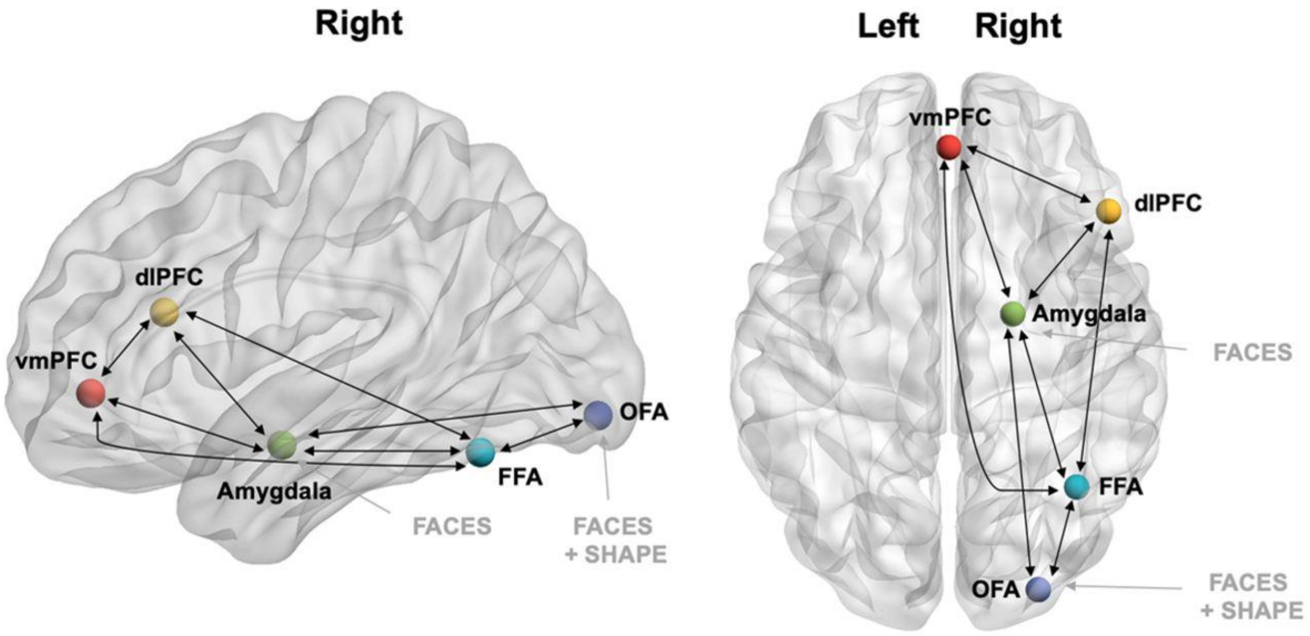


Anand J. C. Eijlers, 2019, Radiology

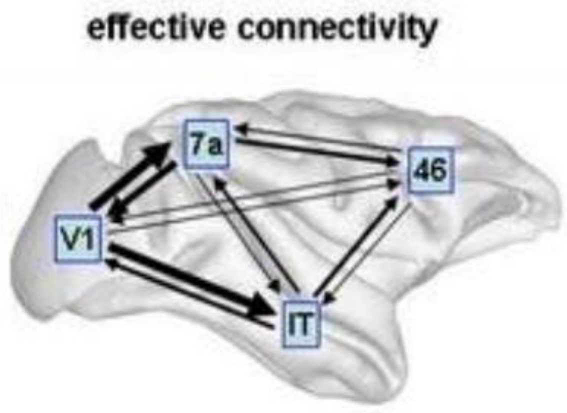


Sporns, 2007, scholarpedia

Effective connectivity



Alec J. Jamieson,et al 2021 eNeuro

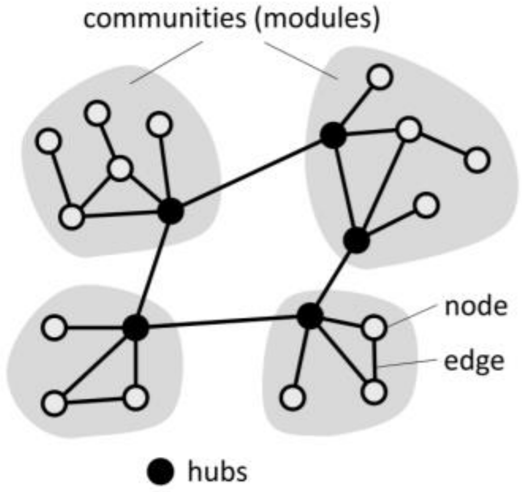


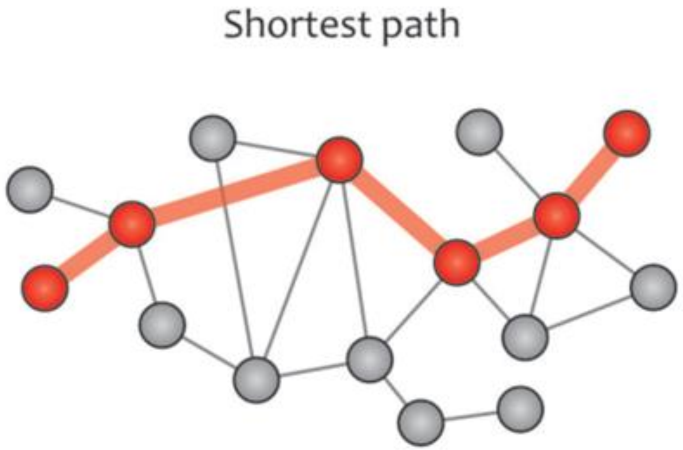
Sporns 2007, Scholarpedia

Analysis of network

Node's Degree： counts the number of incoming and outgoing connections that the node makes.

Shortest path: a path between two nodes in a graph such that the sum of the weights of its constituent edges is minimized.





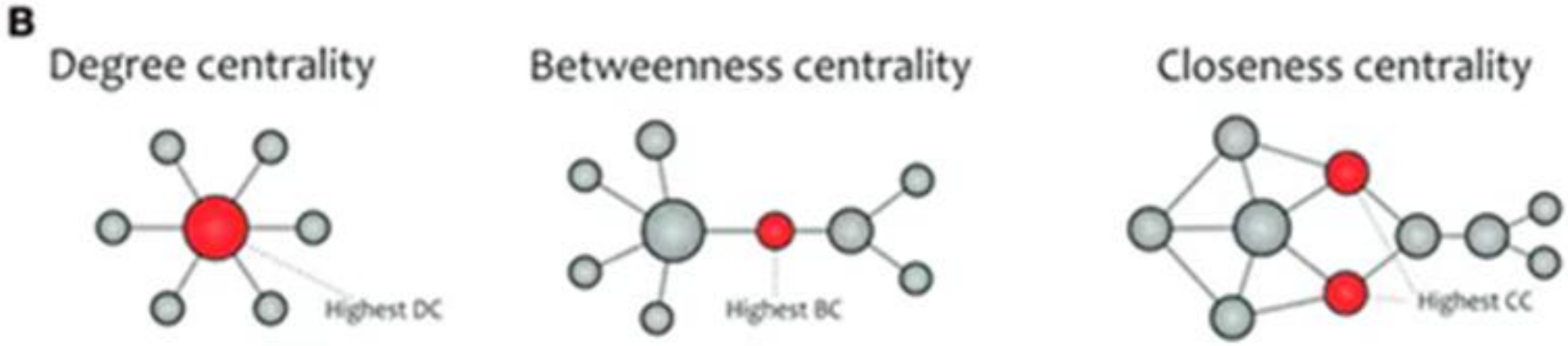
Analysis of network

Centrality measures quantify the importance of a node or an edge with respect to dynamical process taking place on a network or to other structural features of a network.

Degree centrality : the number of links incident upon a node.

Betweenness centrality: the number of shortest paths between pairs of nodes that include a given node.

Closeness centrality: the inverse of the sum of all shortest paths to other nodes.

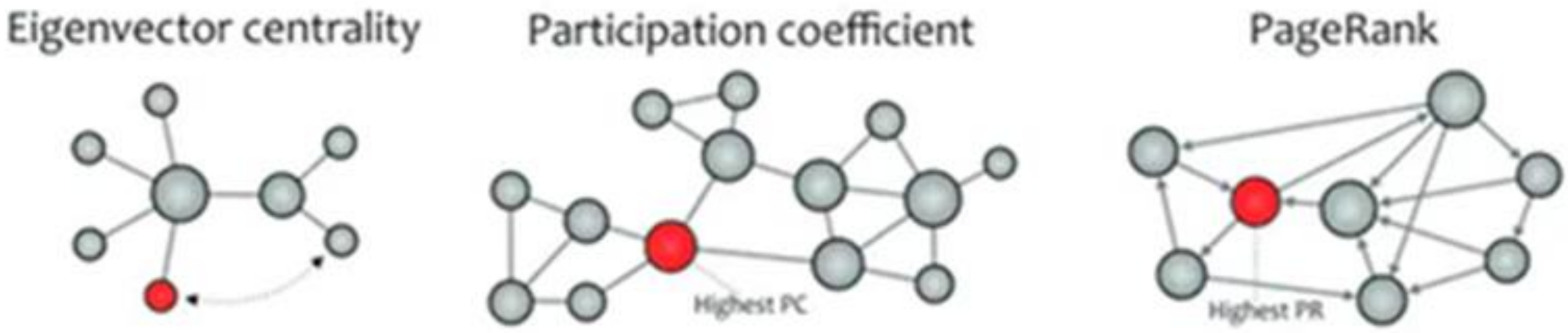


Analysis of network

Eigenvector centrality: Relative scores are assigned to all nodes in the network based on the concept that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes. A high eigenvector score means that a node is connected to many nodes who themselves have high scores.

Participation coefficient: the distribution of a node's edges among the communities of a graph.

PageRank: Counting the number and quality of links to a page to determine a rough estimate of how important the website is. The underlying assumption is that more important websites are likely to receive more links from other website.



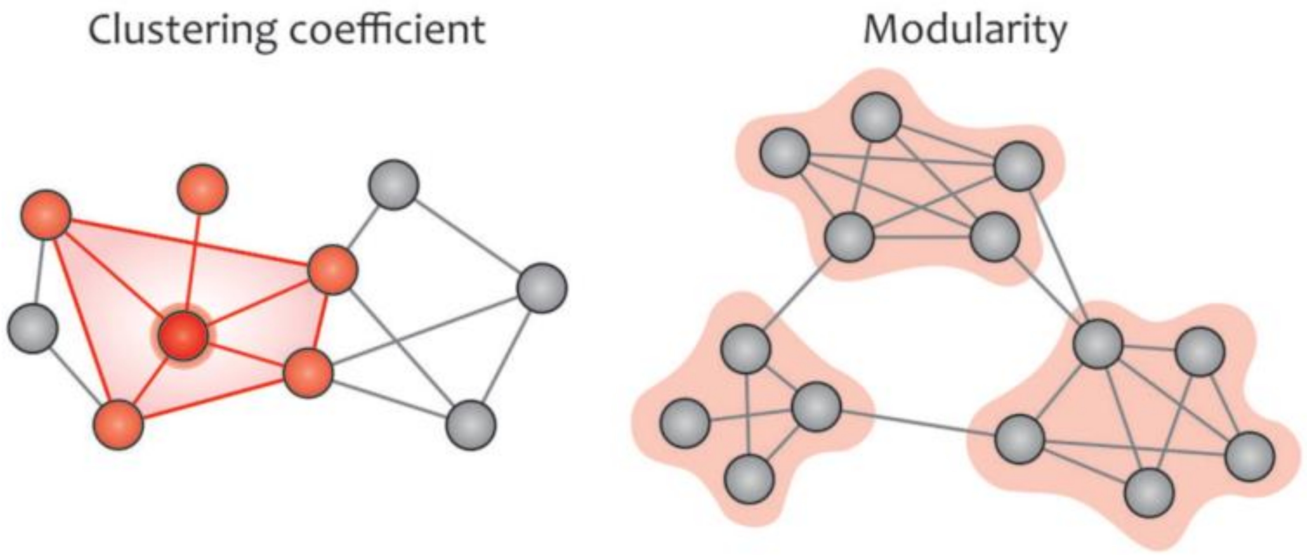
Analysis of network

Characteristic path length: the average number of edges in the shortest paths between all node pairs.

Efficiency is equal to the average reciprocal shortest path length (1 divided by the length of the shortest path).

Clustering coefficient : the degree to which nodes in a graph tend to cluster together.

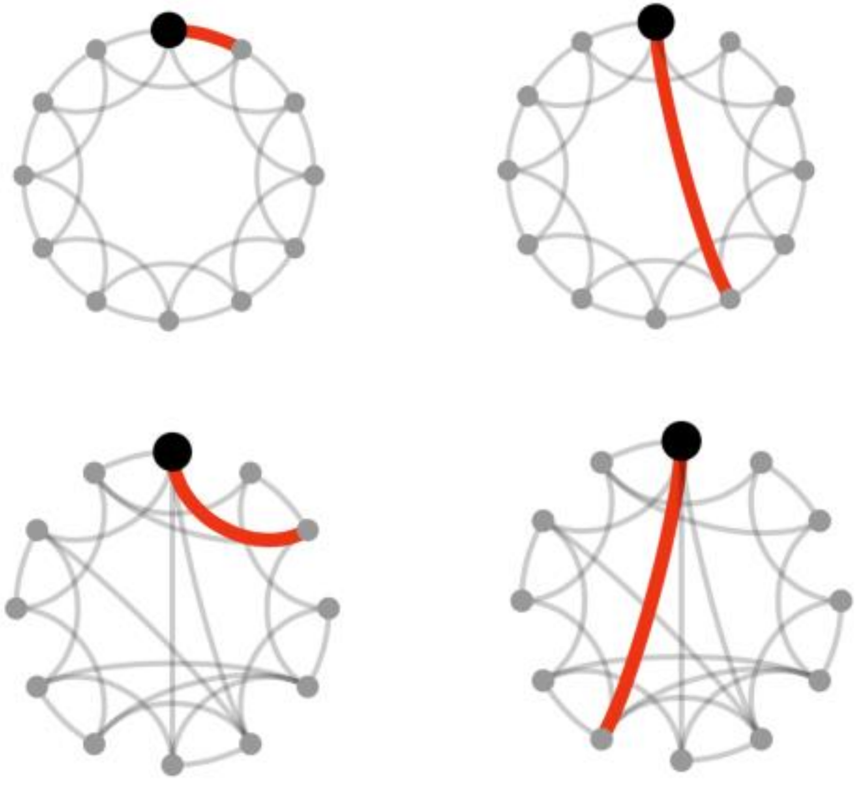
Modularity: the structure of networks or graphs which measures the strength of division of a network into modules



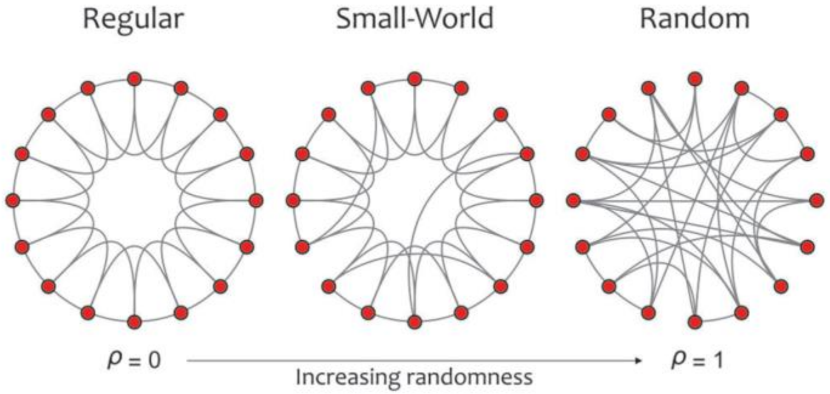
Analysis of network

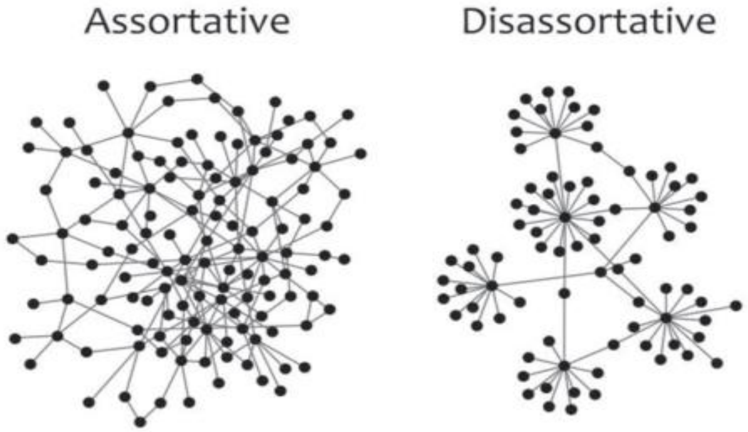
Small-world Network: Most nodes are not neighbors of one another, but the neighbors of any given node are likely to be neighbors of each other and most nodes can be reached from every other node by a small number of hops or steps.

Assortative: a network's nodes to attach to others that are similar in some way.



From regular to random





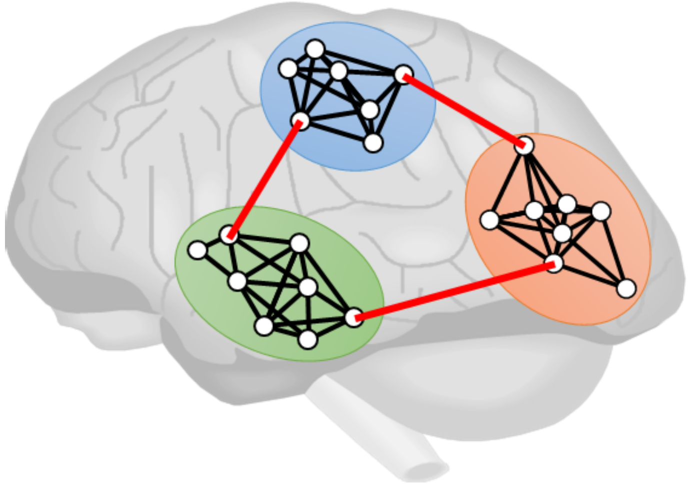
Important discovers from network neuroscience

Small-world architecture

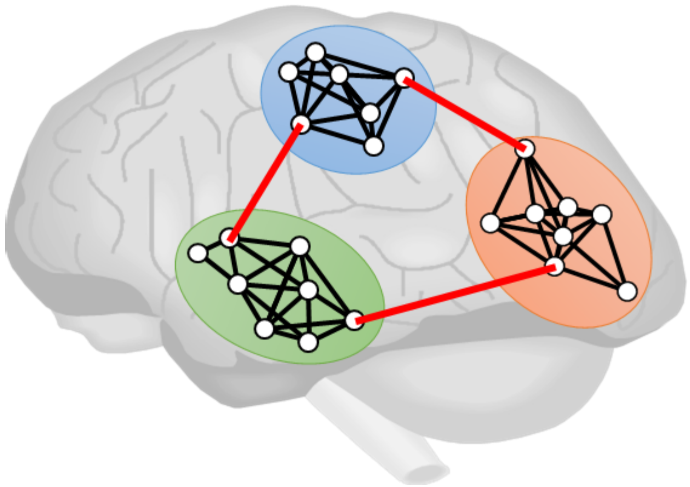
meaning that they have high levels of local clustering to support specialized processing but also topological “shortcuts" to reduce the average length of shortest paths, supporting rapid transmission of information across the brain.

Heterogeneous degree distributions

a small number of brain regions make many more connections than others, forming a so-called “rich-club” of highly-influential brain regions. Rich club nodes are distributed throughout the brain's functional systems



Modular structure of real-world structural and functional brain networks



Why is modular organization?

The autonomy of modules enables them to develop specialized cognitive and psychological functions;

The autonomy of modules from one another also has implications for network robustness;

It helps reduce total cost of wiring and supports a rich repertoire of dynamics and leads to reductions in wiring cost.

Modular structure of real-world structural and functional brain networks

1. The brain exhibits modular structure comes from the analysis of resting-state functional imaging data using clustering algorithm like as Infomap and K-means;

2. The boundaries of modules at rest circumscribed the activation patterns, suggesting that the brain’s modular structure subtends the same systems that support active cognitive processing;

3. Many studies have reported that the brain's modular structure is hierarchical, with smaller communities nested inside of larger communities;

4. Brain's modular structure reconfigured when the brain is engaged in cognitively demanding tasks. task-evoked modular structure is that modules exhibit increased integration and reduced segregation relative to rest.

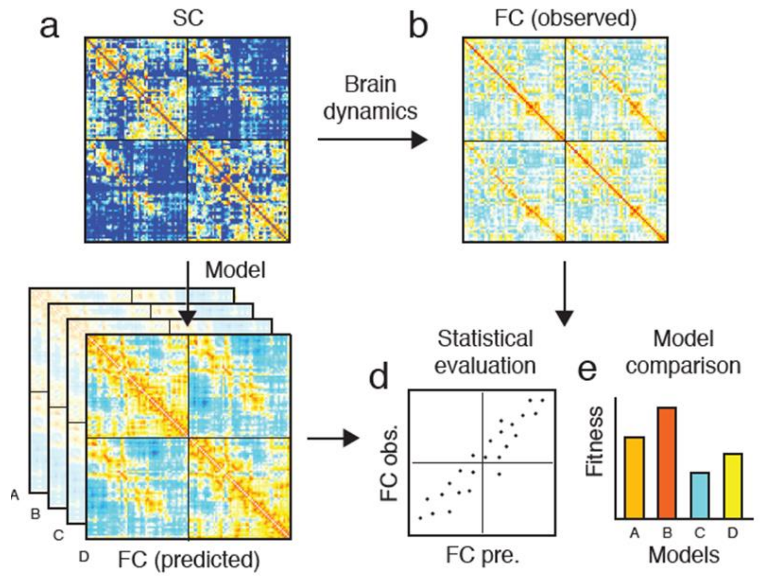
Structural basis of activity and connectivity

How does the anatomical structure shape patterns of functional coupling between distant sites?

SC is causally related to patterns of functional coupling.

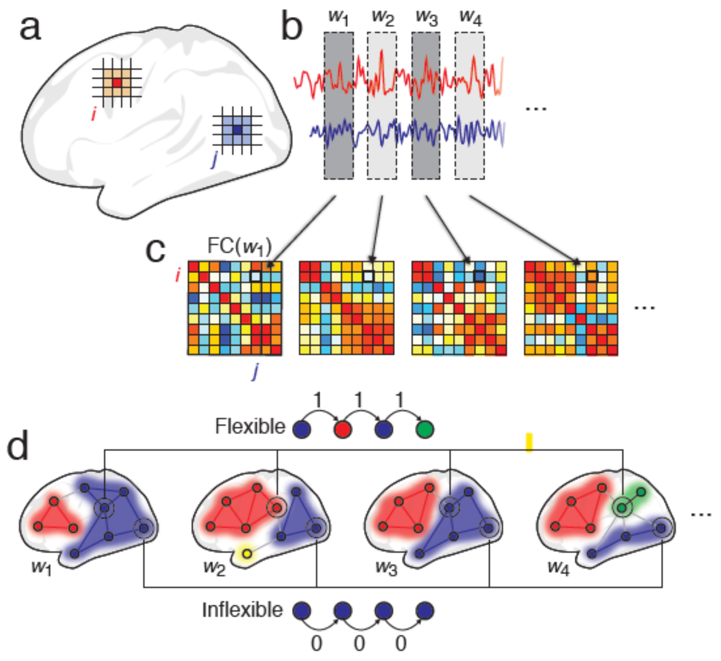
Lesion studies indicated direct structural insults lead to acute changes in FC. Such as macaque monkeys before and after surgically removal the colossal fibers, resting state FC was changed.

SC shapes functional coupling, SC is considered part of a networked dynamical system.



Connectome Dynamics

Brains are never quiet, even during cognitive rest, the human brain is in constant transit, traversing a high-dimensional landscape of activity and connectivity patterns over time.



In the future

1. Generative Modeling

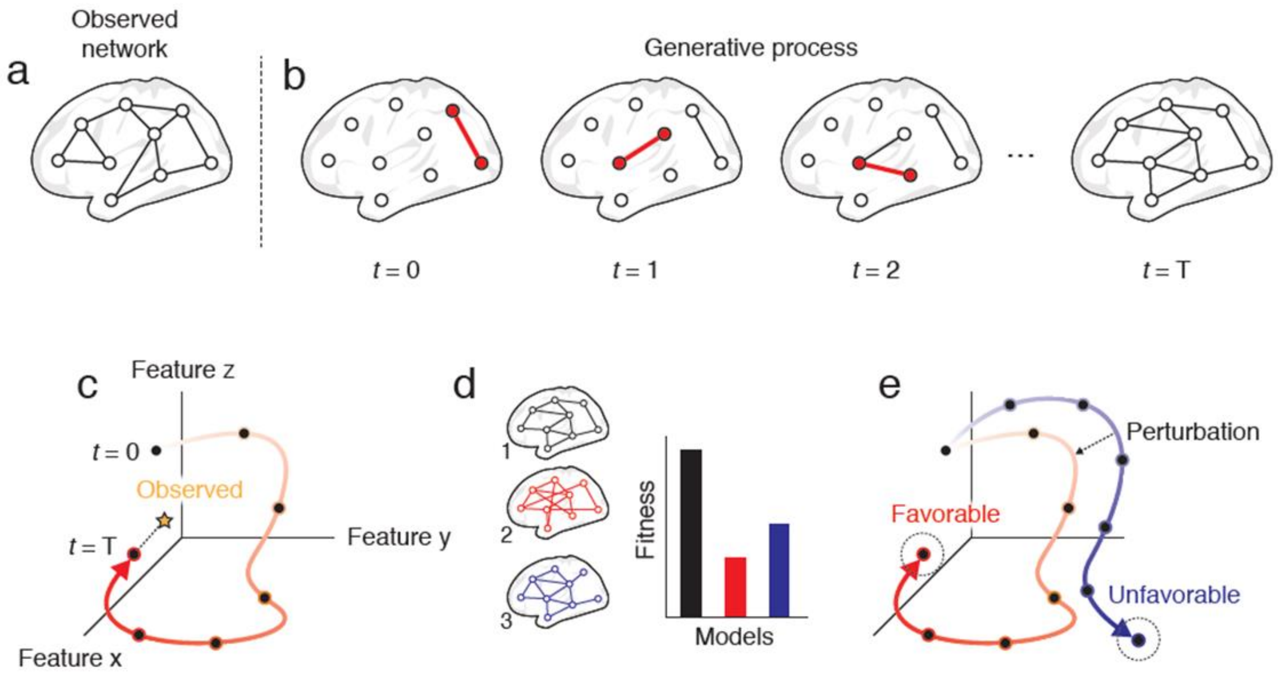
2. Network Control

3. Edge-Centric Connectomics

4. Multilayer Networks

Generative Modeling

Generative models work by identifying a desired set of properties for a network to have, and work backwards to identify the processes that yields networks with those properties.

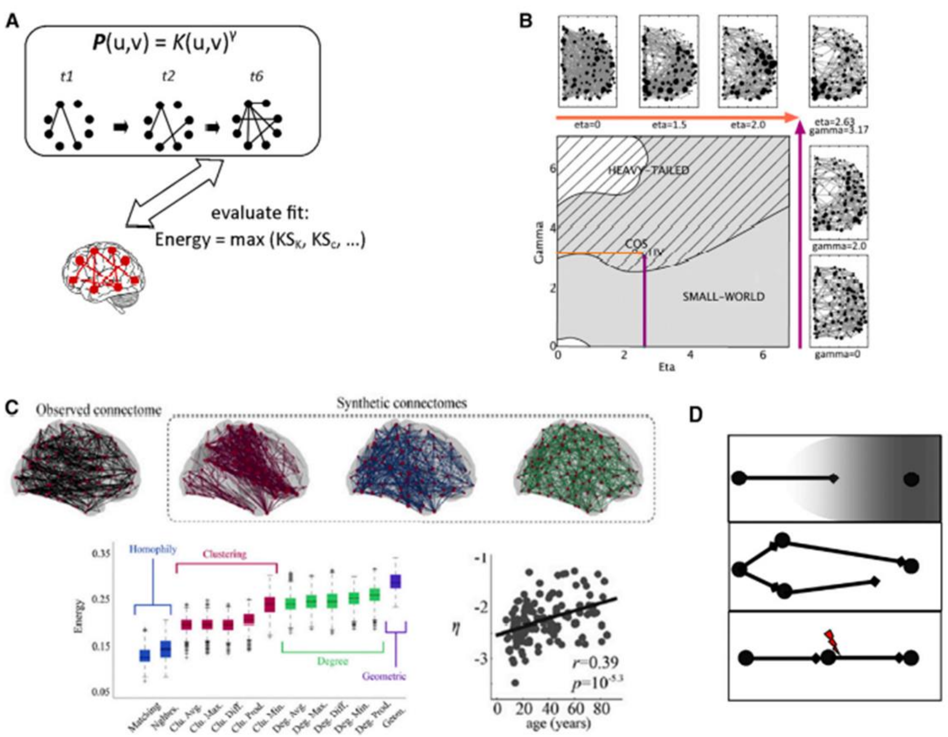


Generative Modeling

1.Generative models help discover the drivers of network organization, which helps refocus attention onto those features and away from “spandrels“;

2.Generative models can be fit to subject-specific data and their parameters used to study individual differences;

3. Generative models can provide insight into human development by incorporating additional neurobiological and developmental details into their wiring rules.

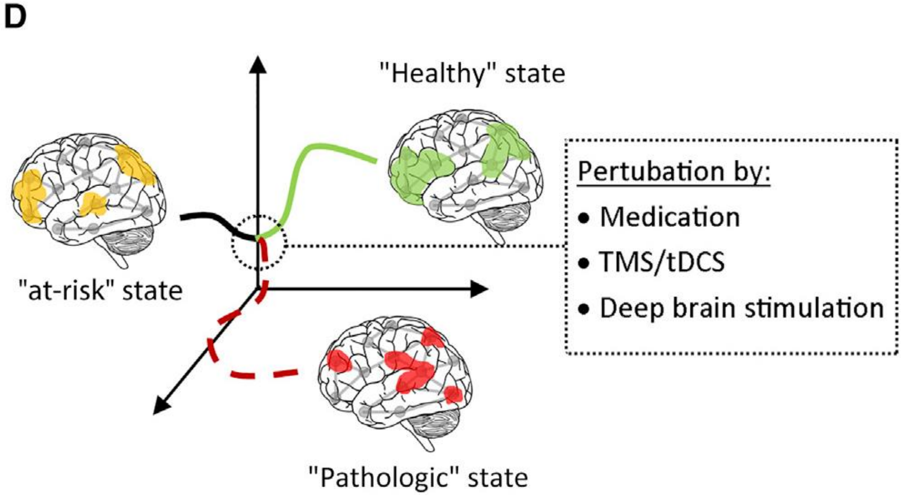


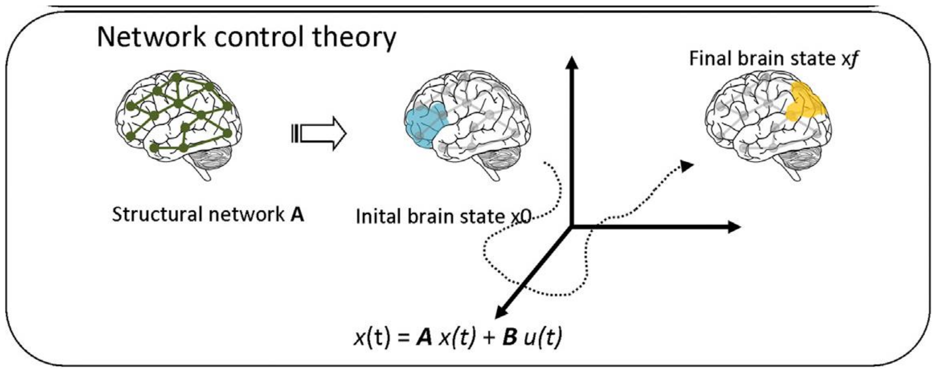
Network Control

In order to meet ongoing cognitive demands, the human brain must seamlessly transition from one brain state to another in order. How does the brain accomplish this? How are these transitions supported by the underlying anatomical connectivity?

Network Control Framework

the brain is a networked dynamical system and that, in the absence of any intervention, the activity of each brain region evolves over time according to its own state and the states of connected neighbors, tracing out a trajectory over time.

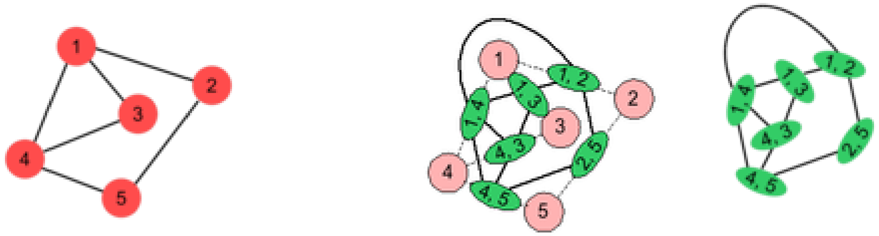




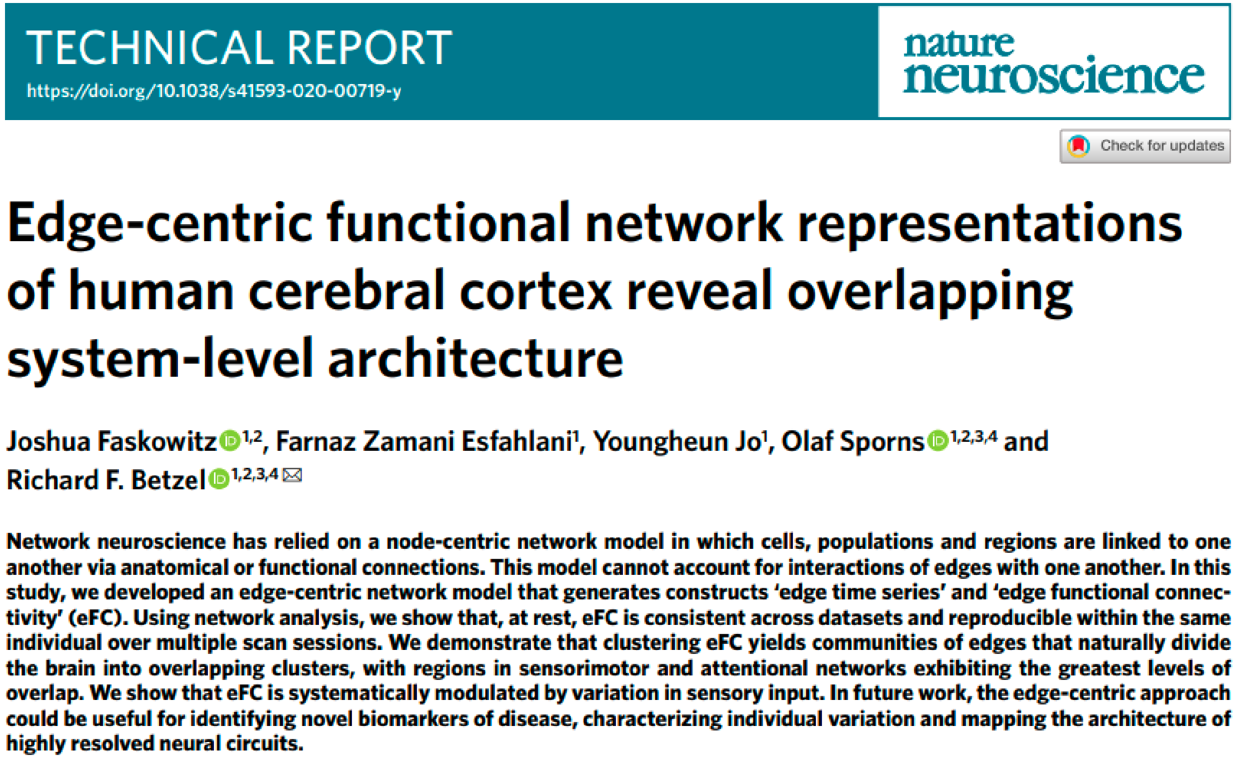
Edge-centric Connectomics

Quantify how strongly pairs of edges in the network interact with one another.

Interestingly, the highest levels of overlap were observed in sensorimotor and attentional networks, suggesting that these regions may play a previously undisclosed role in supporting a wide range of cognitive functions.



Line graph



TECHNICAL REPORT
https://doi.org/10.1038/s41593-020-00719-y
nature neuroscience

Edge-centric functional network representations of human cerebral cortex reveal overlapping system-level architecture

Joshua Faskowitz[1,2], Farnaz Zamani Esfahlani[1], Youngheun Jo[1], Olaf Sporns[1,2,3,4] and Richard F. Betzel[1,2,3,4]

Network neuroscience has relied on a node-centric network model in which cells, populations and regions are linked to one another via anatomical or functional connections. This model cannot account for interactions of edges with one another. In this study, we developed an edge-centric network model that generates constructs 'edge time series' and 'edge functional connectivity' (eFC). Using network analysis, we show that, at rest, eFC is consistent across datasets and reproducible within the same individual over multiple scan sessions. We demonstrate that clustering eFC yields communities of edges that naturally divide the brain into overlapping clusters, with regions in sensorimotor and attentional networks exhibiting the greatest levels of overlap. We show that eFC is systematically modulated by variation in sensory input. In future work, the edge-centric approach could be useful for identifying novel biomarkers of disease, characterizing individual variation and mapping the architecture of highly resolved neural circuits.

Edge-centric Connectomics

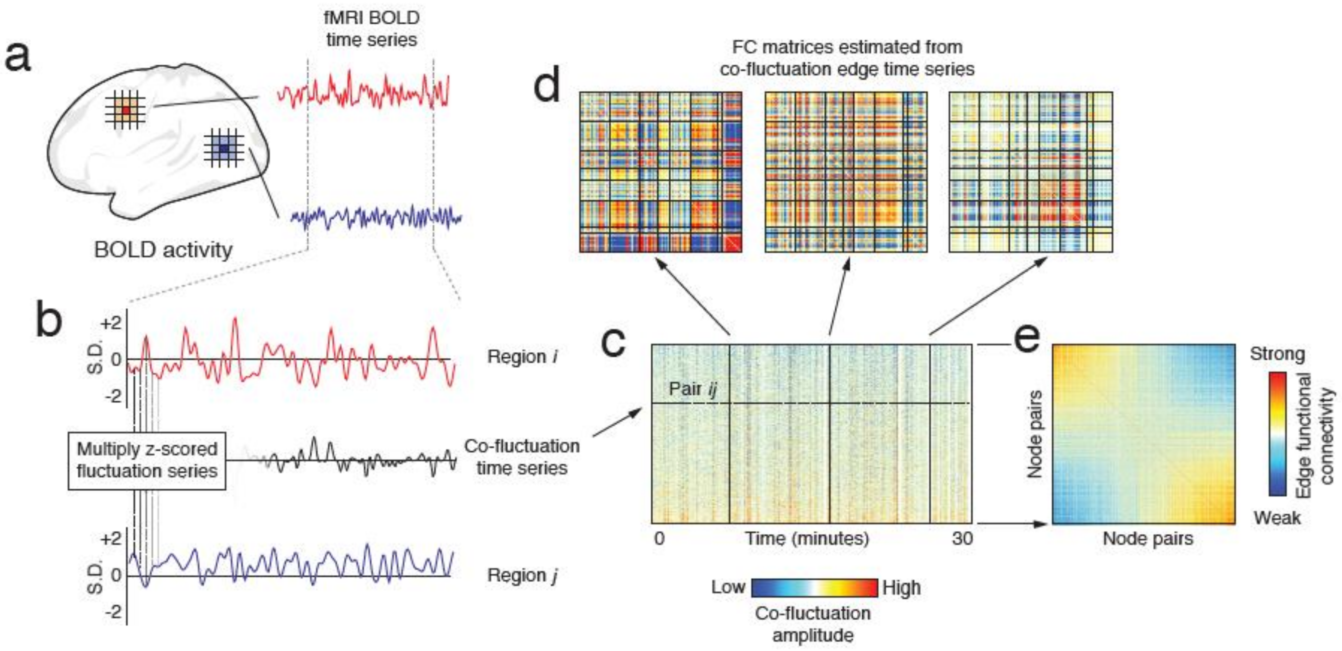
$$x_i = [x_i(1),\ldots,x_i(T)]$$
$$x_j = [x_j(1),\ldots,x_j(T)]$$

$$z_i = \frac{x_i - \mu_i}{\sigma_i}$$

$$r_{ij} = \frac{1}{T-1}\sum\left[z_i(t)\cdot z_j(t)\right]$$

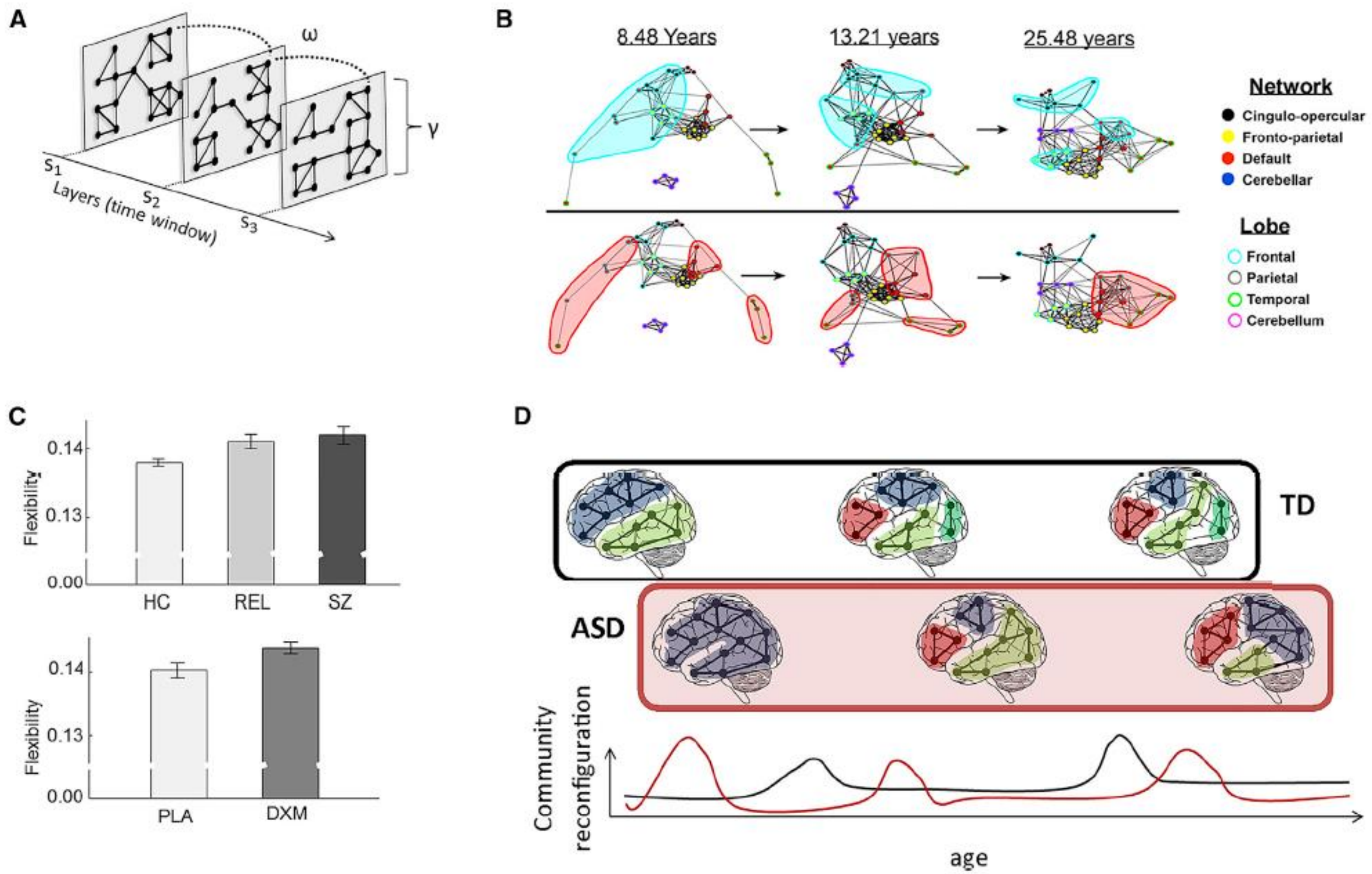
$$c_{ij} = [z_i(1)\cdot z_j(1),\ldots,z_i(T)\cdot z_j(T)]$$
$$c_{uv} = [z_u(1)\cdot z_v(1),\ldots,z_u(T)\cdot z_v(T)]$$

$$eFC_{ij,uv} = \frac{\sum_t c_{ij}(t)\cdot c_{uv}(t)}{\sqrt{\sum_t c_{ij}(t)^2}\sqrt{\sum_t c_{uv}(t)^2}}$$



Multilayer Networks

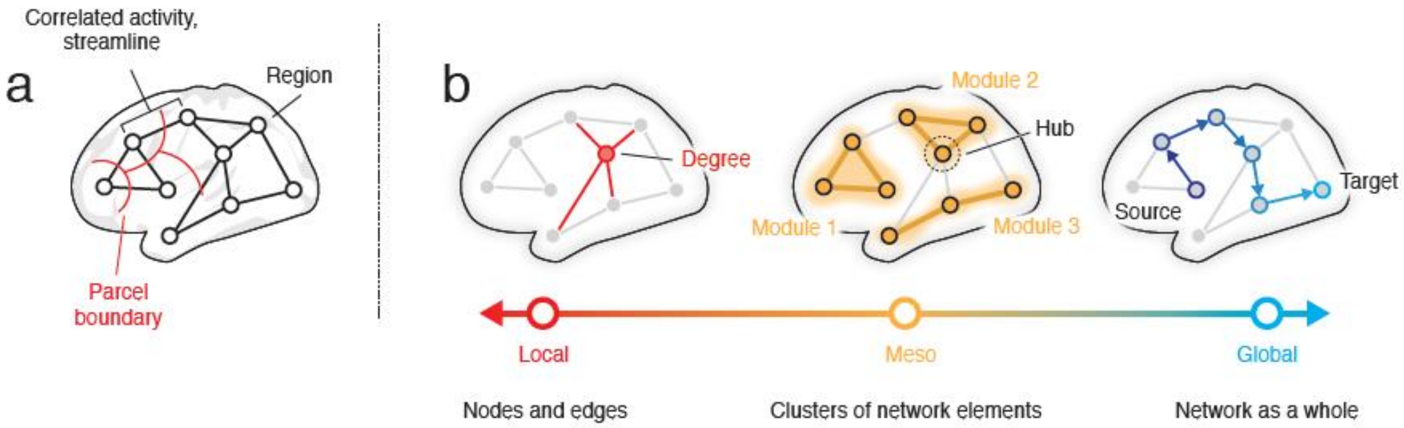
Connectivity matrices representing either the state of the network at a particular time point or different connectivity modalities can be linked together by connecting each node in one layer to itself in a different layer.

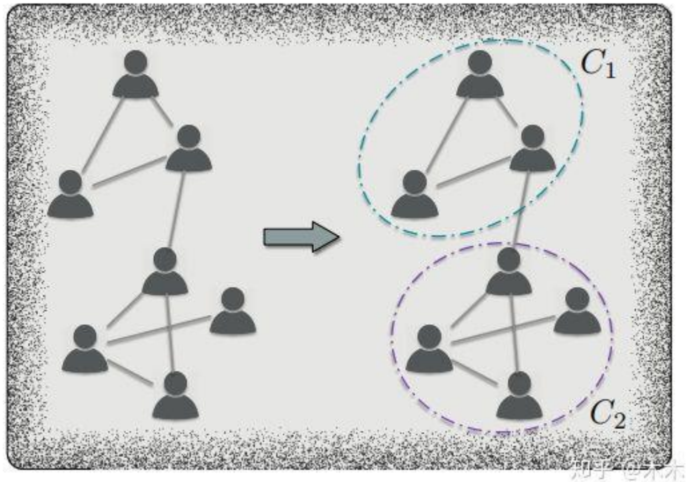


Community Detection

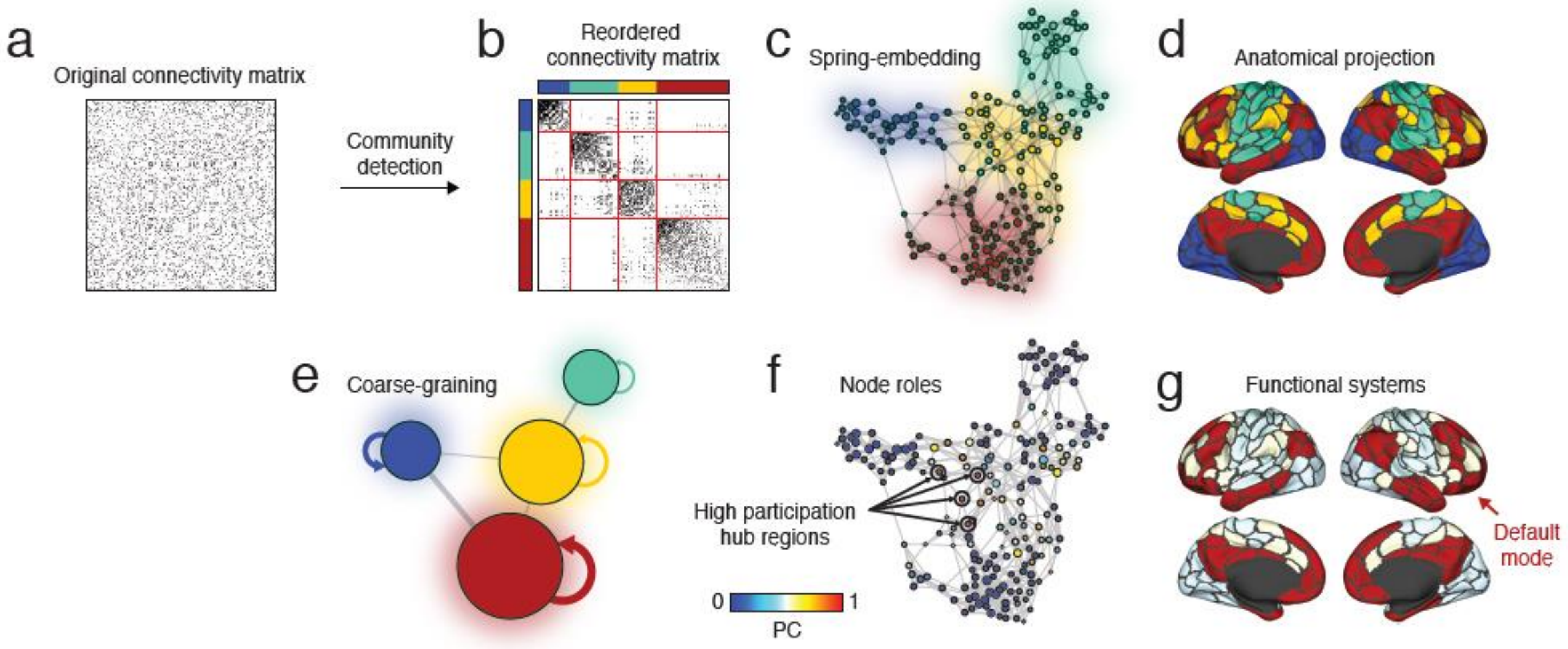
Communities refer to meaningful sub-networks, also referred as modules or clusters embedded within a larger global network.

Modular structure has been observed in empirical brain network data, both in structural and functional brain networks reconstructed from virtually all imaging and recording modalities and across every spatial scale.





The Space of Community Detection Methods



Choosing an Algorithm

Different algorithms dene communities in different ways and can yield dissimilar estimates of your network's community structure.

1. Every algorithm operates according to a different definition of what it means for a group of nodes or edges to form a community.

2. Some algorithms require first transforming your network in some way, e.g. by discarding or rectifying negative connection weights.

3. Algorithms encode a set of assumptions about how your network was generated and what its communities look like.

Infomap

Infomap define communities to be collections of nodes that constrain the probabilistic flow of a random walker moving over the network.

Infomap detects communities that are “assortative" with connection density concentrated within communities compared to between.

However, because Infomap is based on random walks which are only defined for networks with positively-weighted edges, all negative weights must be first thresholded.

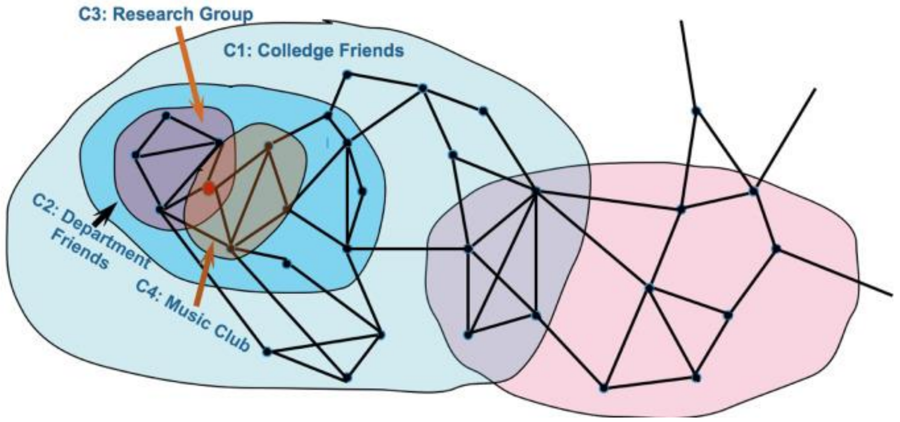
Stochastic Blockmodels

Stochastic Blockmodels use statistical inference to recover the parameters (including community labels) of the generative model that gave rise to an observed network.

Every node belongs to a community and edges are generated stochastically based on some underlying distribution that depends only on the community to which an edge's stub nodes belong.

Blockmodels can detect more general classes of communities; including core-periphery and disassortative configurations.

In many real-world networks nodes belong to multiple communities, but both Infomap and the stochastic blockmodel assign nodes to non-overlapping communities, meaning that each node is assigned to one community and one community only.



Link communities

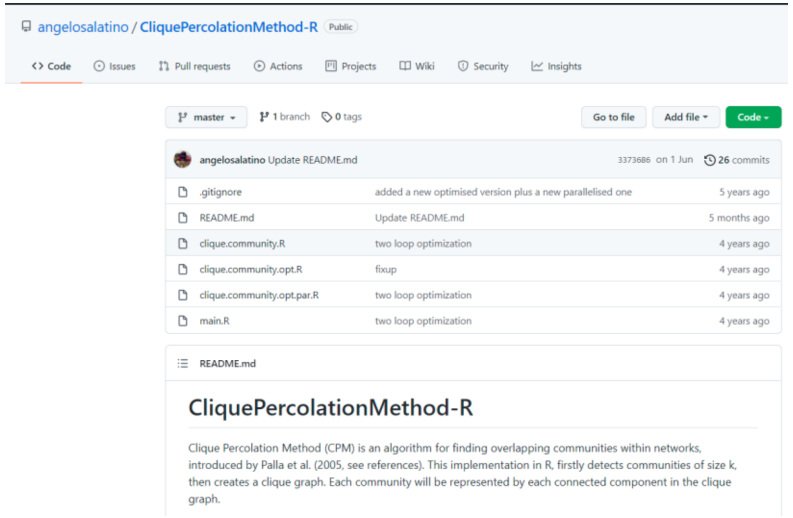
linkcomm: an R package for the generation, visualization, and analysis of link communities in networks of arbitrary size and type

Alex T. Kalinka, Pavel Tomancak   Author Notes

Bioinformatics, Volume 27, Issue 14, 15 July 2011, Pages 2011–2012,
https://doi.org/10.1093/bioinformatics/btr311
Published: 19 May 2011   **Article history** ▾

https://academic.oup.com/bioinformatics/article/27/14/2011/194743?login=true

Clique percolation



Line graph clustering

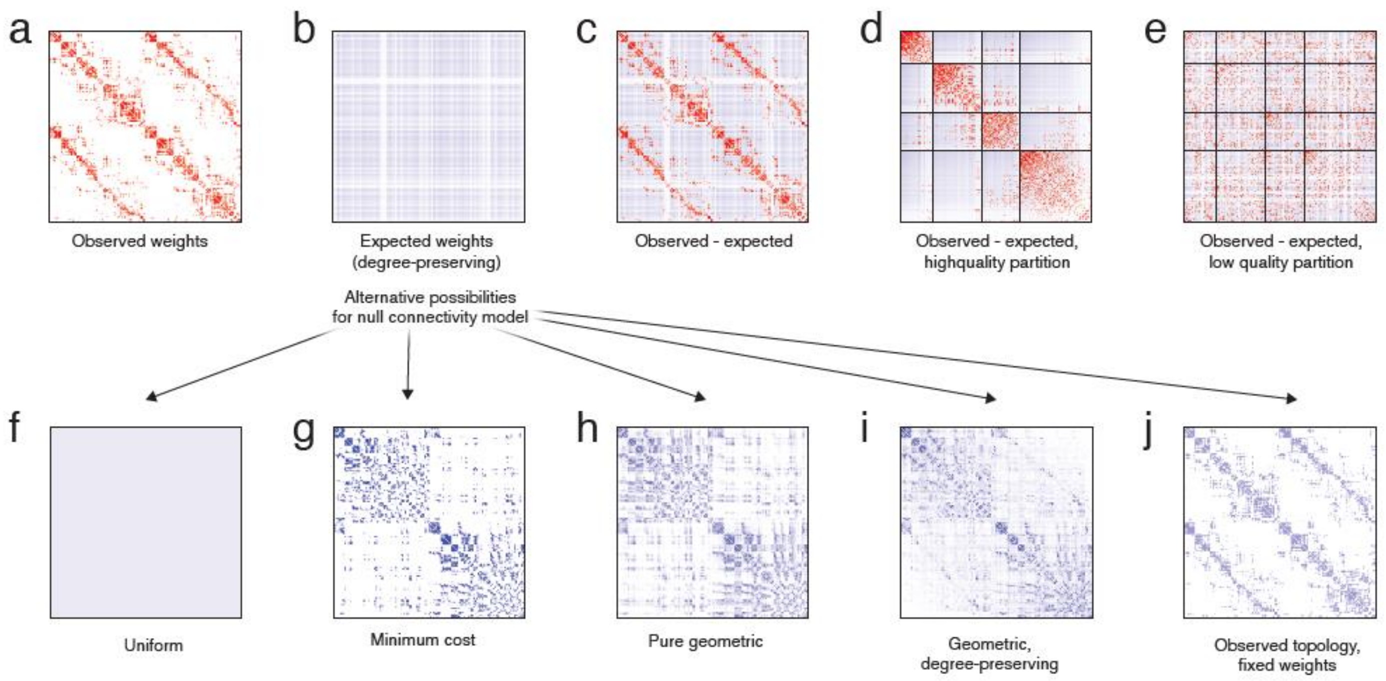
https://github.com/angelosalatino/CliquePercolationMethod-R

Modularity maximization

Modularity defines communities to be groups of nodes more densely connected to one another than would be expected had the network been generated by a random null model.

Q is calculated by comparing your real network with the network you would expect given some a null connectivity model.

The choice of null model is critical and should be motivated by research question and properties of your network.



Algorithms for optimizing Q

In general, Q measures the quality of a modular partition, partitions corresponding to larger values of Q are generally considered better.

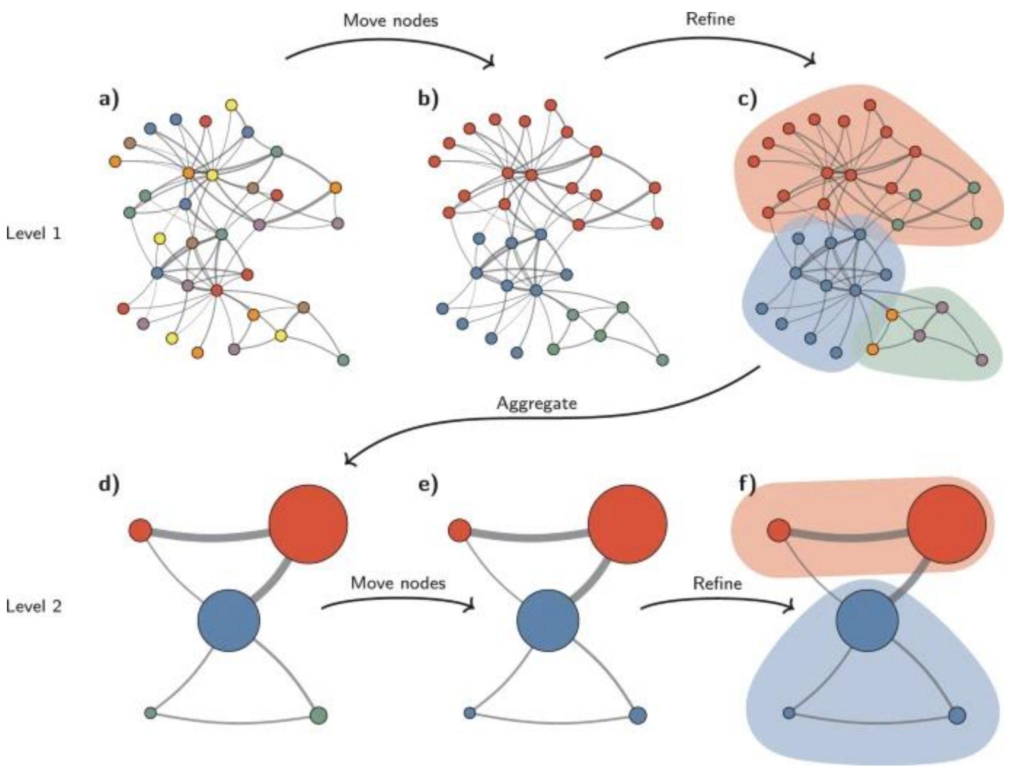
Louvain algorithm

The Louvain algorithm is a greedy, two-stage algorithm that scores well on benchmark tests and, in most practical contexts, runs exceptionally fast.

The Louvain algorithm is initialized with each node assigned to its own; if a network has N nodes, then the number of communities at this stage is equal to N.

Leiden algorithm

guarantees well-connected communities while preserving the speed and parsimony of the original Louvain algorithm.



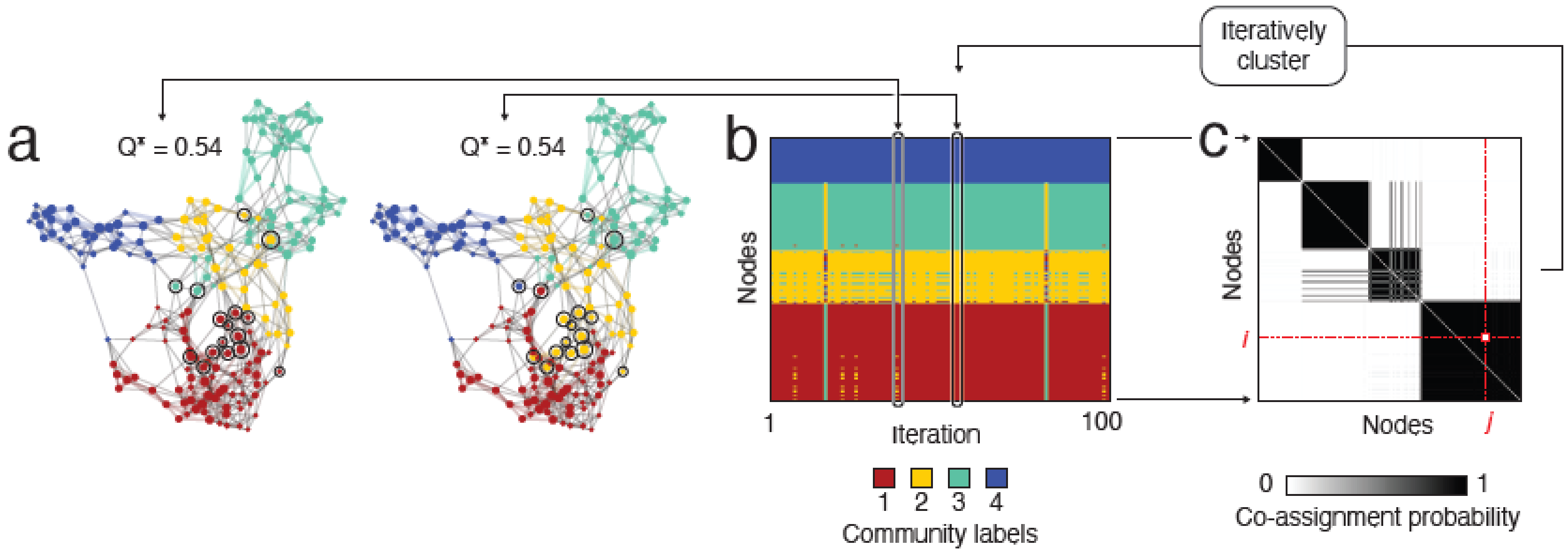
https://www.nature.com/articles/s41598-019-41695-z

Algorithms for optimizing Q

Louvain algorithm is a greedy and stochastic algorithm, which means that successive runs of the algorithm can result in different estimates of the optimal partition.

Consensus Clustering

Iteratively clustering a co-assignment matrix until convergence,it assumes that there is a single representative set of communities for a network,every node must be assigned to a cluster.



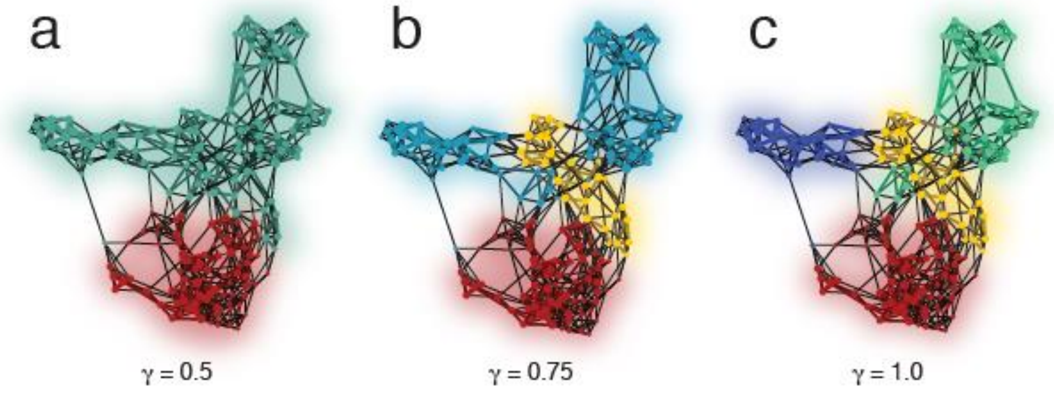
Multi-scale extensions

Resolution Limit

For a network of given density, modularity maximization will be unable to detect communities below a certain scale, even if they are unambiguously defined perfect cliques.

Resolution Parameter γ

Incorporating the resolution parameter into modularity maximization makes it possible to change its value and detect communities that might have been undetectable otherwise.
Resolution parameter enables user to detect multi-scale or hierarchical communities.



Node Roles

Participation Coefficient

Participation coefficients measure the distribution of a node's edges among the communities of a graph, it quantifies whether a node's connections are distributed uniformly across many modules (high participation) or concentrated within a relatively small number (low participation).

Module Degree-z-score

Within-module degree-z-score is a complementary method, and describes how strongly a node is connected to its own module relative the other nodes within its module. Nodes with larger values are generally considered more influential among their neighbors.

Limitations

1. The modularity function and how to interpret Q;

2. The lack of a unique solution;

3. Lack of correspondence between ground truth community structure and the community structure detected based on network topology;

4. Modularity maximization forces every node to have a community assignment, a requirement that, in general, real-world networks are not subjected to.

Future directions and alternative approaches

“vanilla" modularity maximization is to extend it to multi-layer networks

Infomap

Stochastic blockmodels

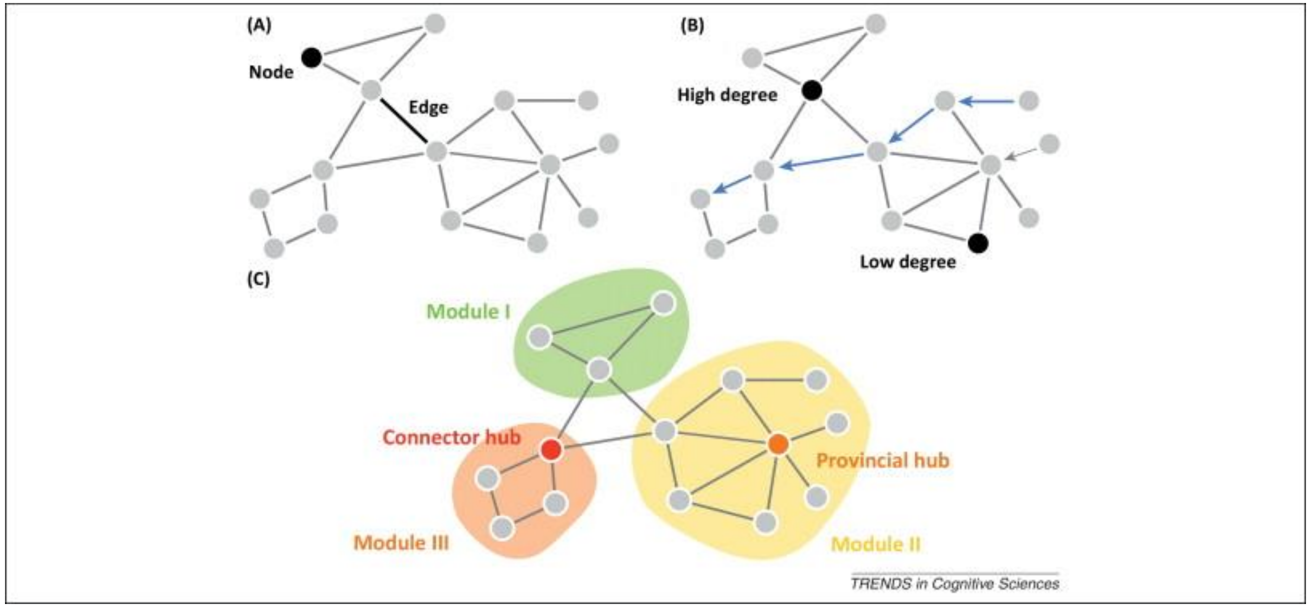
Edge-centric methods

From Description to Prediction: Multi-dimensional Network Neuroscience

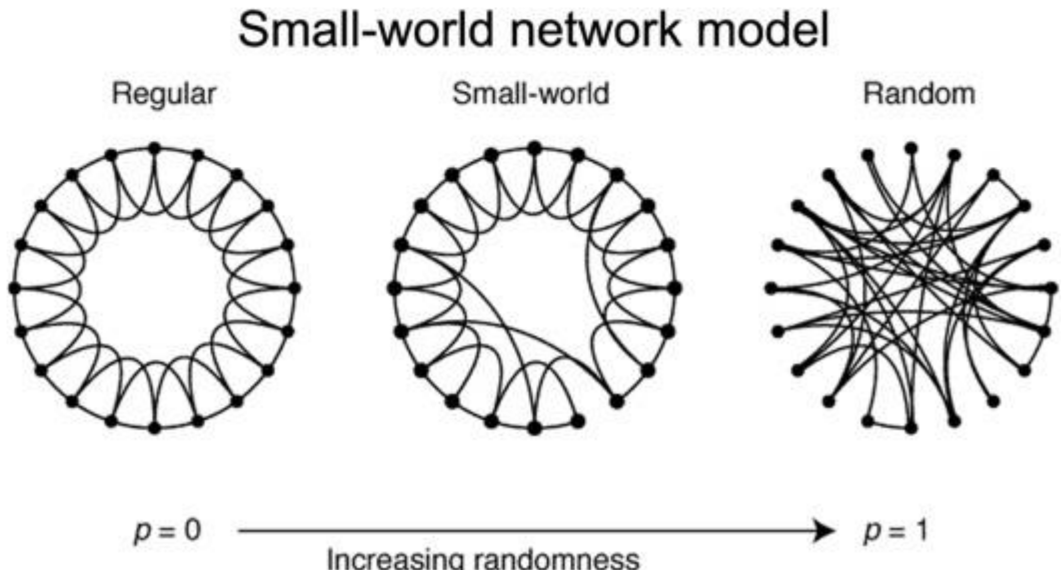
Rich-hubs

Modular Organization

Small-world Architecture



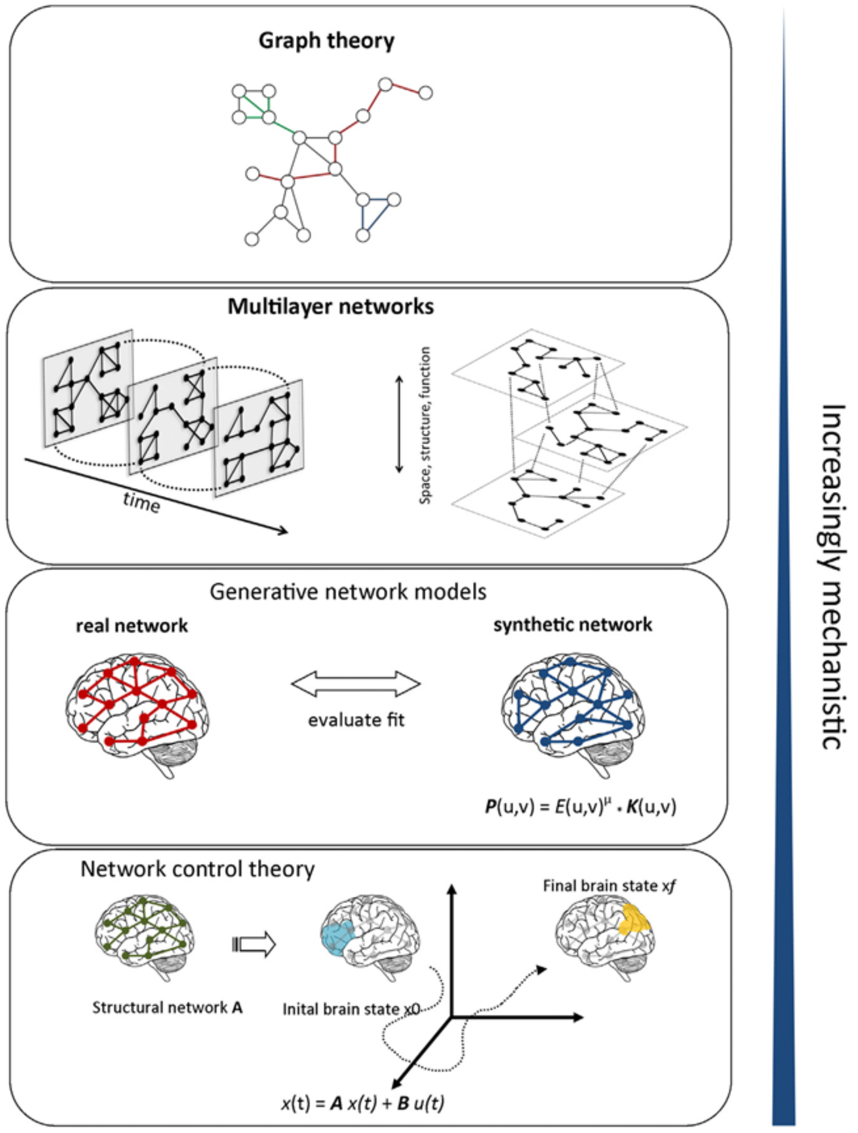
https://www.cell.com/trends/cognitive-sciences/fulltext/S1364-6613(13)00216-7



From Description to Prediction: Multi-dimensional Network Neuroscience

Network model results are derived from statistical differences in graph theoretical parameters or from correlations between parameters and empirically measured estimates of behavior, cognition, or disease.

Parameters do not equate to mechanisms and correlations do not equate to causal drivers.



SOFTWARE

1. Brain Connectivity Toolbox (`https://sites.google.com/site/bctnet/`):
   - `community_louvain.m`: Implements Louvain algorithm for optimizing Q.
   - `consensus_und.m`: Runs threshold-based consensus clustering.
   - `participation_coef.m` and `participation_coef_sign.m`: calculates nodal participation coefficient for networks with positive and signed connections, respectively.
   - `module_degree_zscore.m`: calculates nodal module-degree-zscore.
2. NetWiki (`http://netwiki.amath.unc.edu/GenLouvain/GenLouvain`): Includes function for running a generalized Louvain algorithm (`genlouvain.m`). This function allows the user to flexibly define their own modularity functions by changing null models and resolution parameters. Includes tutorials for implementing multi-layer and multi-resolution network models.
3. Network Community Toolbox (requires `genlouvain.m` function; `http://commdetect.weebly.com/`): Suite of functions for optimizing modularity, null models for significance testing, and for further characterizing single communities and entire partitions. Also includes flexibility coefficient.

graph theory/network science

Newman (2010) Networks: An introduction.

Newman (2003) SIAM Rev.

Albert & Barabasi (2002) Rev Modern Physics

graph theory and the brain

Sporns (2011) Networks of the brain.

Sporns (2012) Discovering the human connectome.

Bullmore & Sporns (2009) Nat Rev Neurosci.

Bullmore & Bassett (2011) Annu Rev Clin Psychol.

Fornito, Zalesky & Breakspear (2013) NeuroImage.

software

Brain connectivity toolbox:

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

Graph analysis toolbox:

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

Network-based statistic:

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

Task-related functional connectivity (cPPI):

http://www.nitrc.org/projects/cppi_toolbox/

Network visualization

http://immersive.erc.monash.edu.au/neuromarvl/