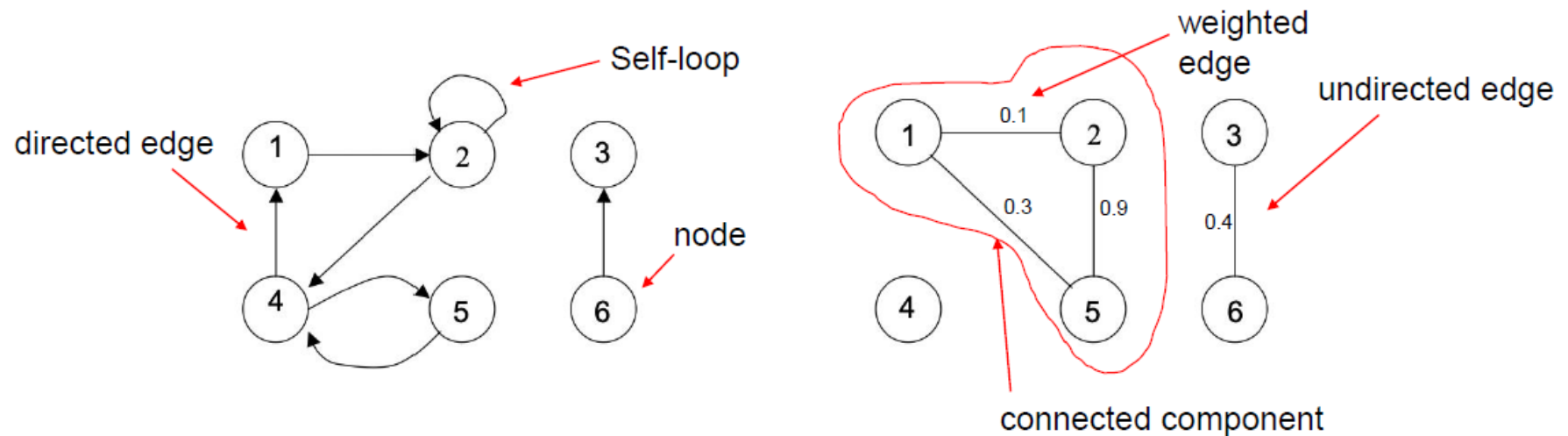# Brain Network Analysis

Rik Henson (based on slides by Isaac Sebenius)

MRC CBU, Cambridge
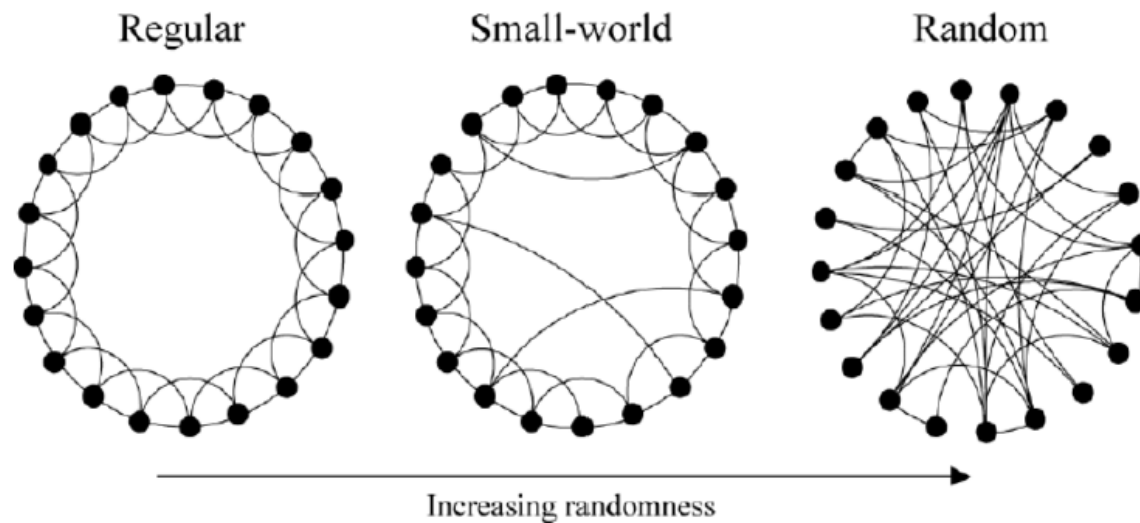
What is a network?

- **Network = Graph**

- **A graph/network is simply a set of nodes (a.k.a vertices) and edges**
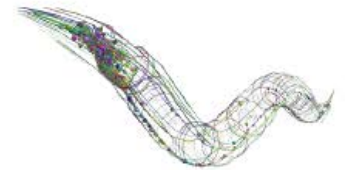
Sample networks: transportation

The cost-efficiency tradeoff of 'small-world' brain networks
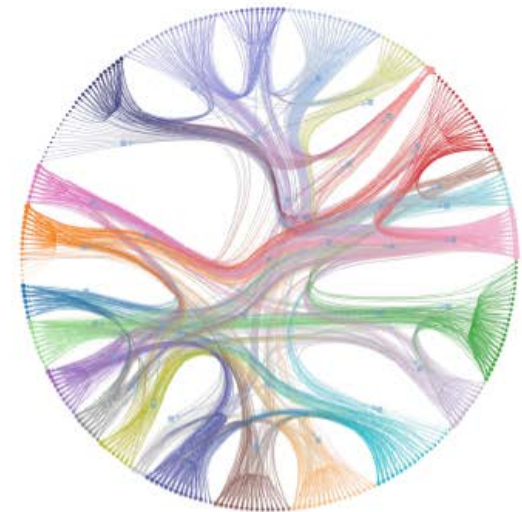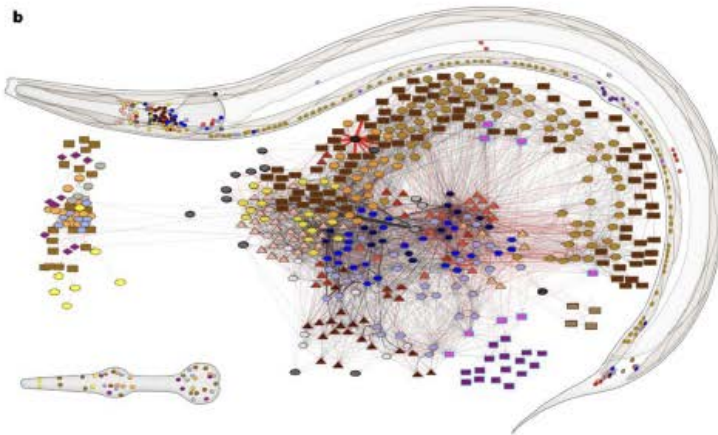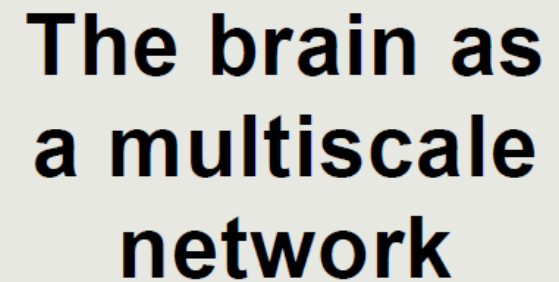

Watts & Strogatz, Nature (1998)

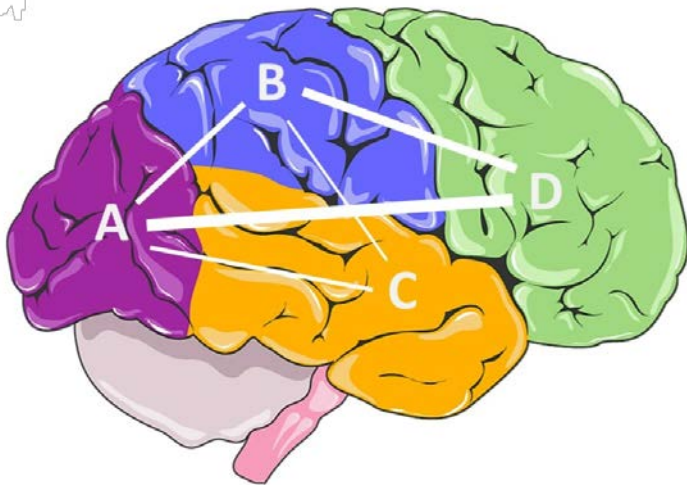# The complete c. Elegans synaptic connectome

Synaptic connectome

The brain as a multiscale network

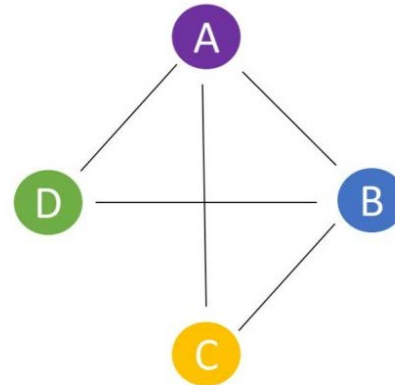**Brain networks can be studies at various:**

> **Temporal scales**
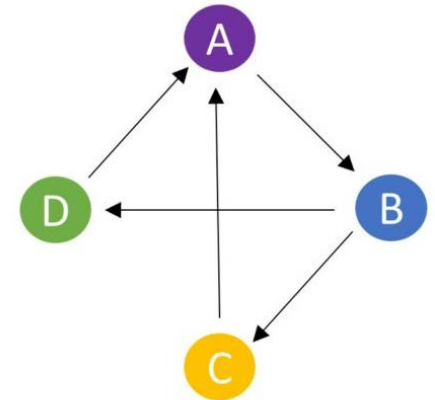> **Spatial scales**
> **Topological scales**

(And even within the same scale, multiple types of connections can be considered!)

Binary / Undirected

Binary / Directed

Weighted / Undirected
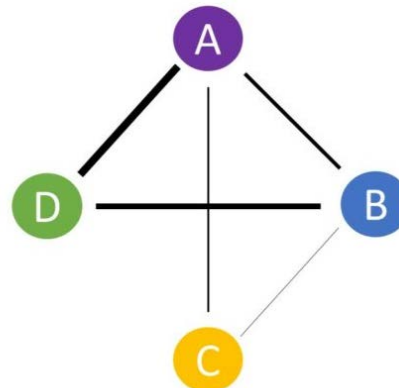
Weighted / Directed
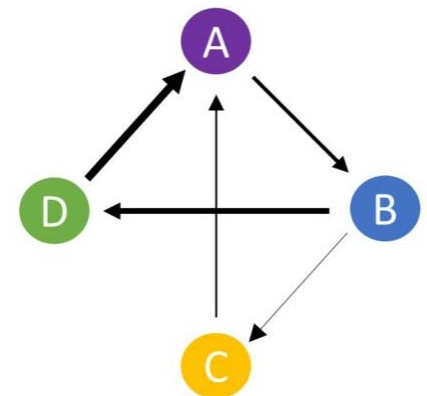
	A	B	C	D
A		0.5	0.4	0.8
B	0.5		0.2	0.6
C	0.4	0.2		
D	0.8	0.6		
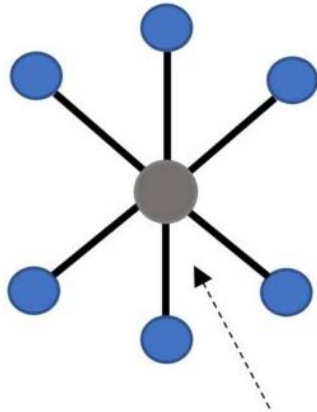
Highest Degree Centrality
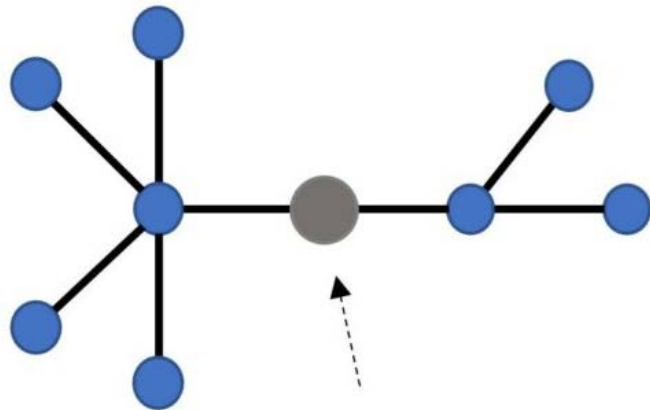
Highest Betweenness Centrality

Module 1

Module 2

Connector Hub

Provincial hub
(and Highest Clustering Coefficient)

https://github.com/RikHenson/PythonNeuroimagingCourse/blob/main/Notebooks/nb10_network_analysis.ipynb
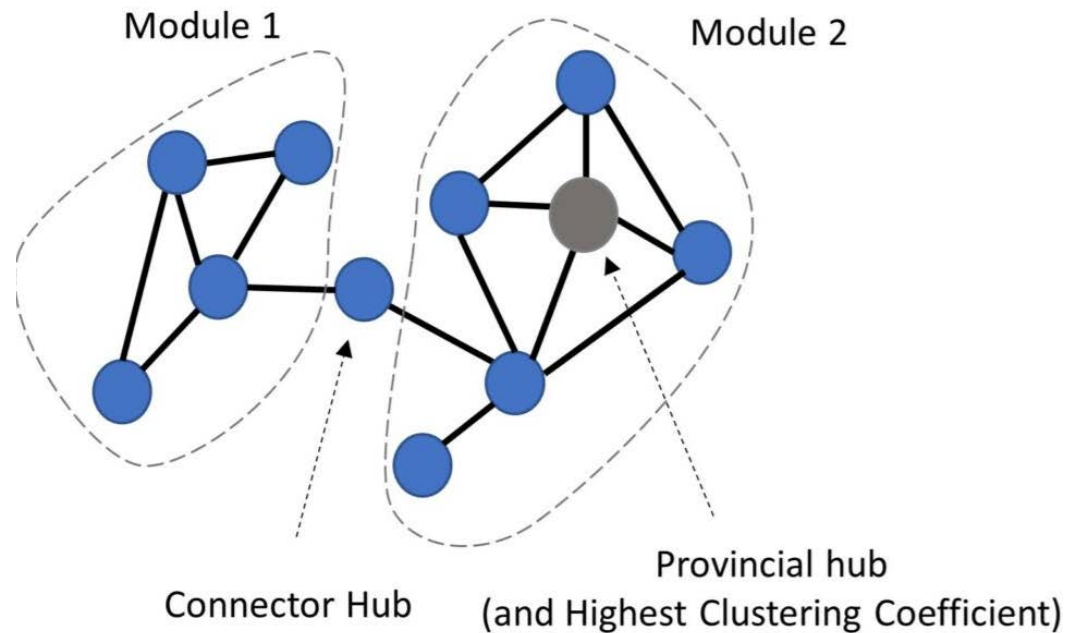
Shortest Path:
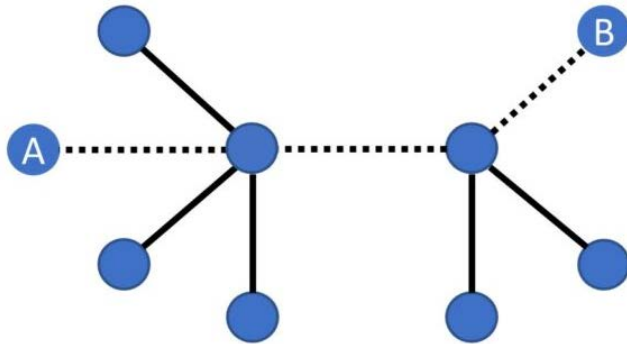
Minimum Spanning Tree:
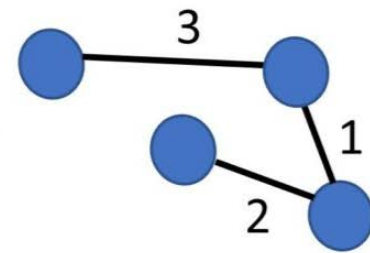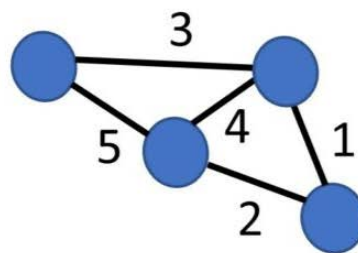
Tree with the Lowest Sum of Distances

https://github.com/RikHenson/PythonNeuroimagingCourse/blob/main/Notebooks/nb10_network_analysis.ipynb

Brain networks: brief discussion

Let's say you are interested in studying a brain, parcellated into a set of regions of interest.

How would we turn it into a brain network? What could be the edges?

What are some justifications for turning it into a 'connectome'?

➢ **Communication between regions across white matter tracts.**

➢ **Harmonized activity patterns between distant regions suggest network-structure of activity.**

➢ **Developmental coordination across different areas of the brain.**

➢ **Strong genetic and phenotypic covariance between different brain regions.**
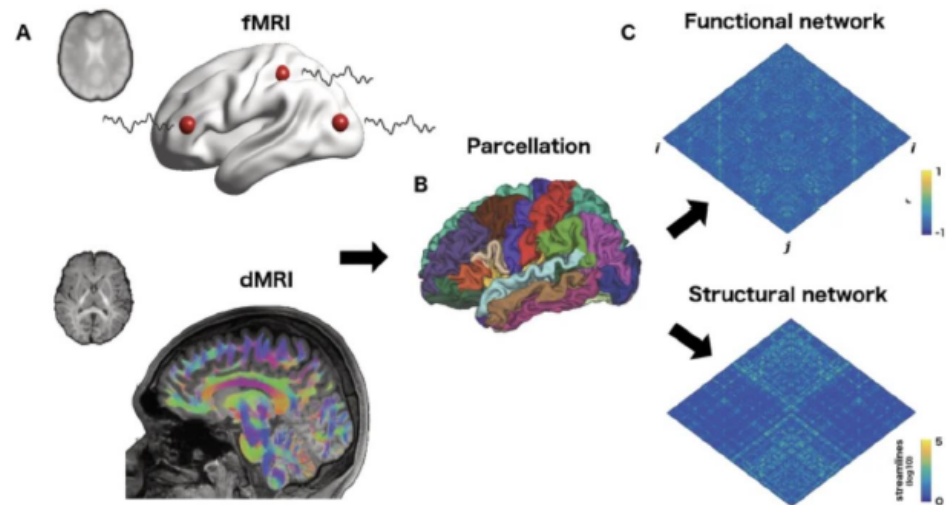
➢ **More???**

Classic views on human brain networks

Steps:

1. **Parcellate brain into regions (ROIs)**
2. **Define pairwise metric of connectivity**
3. **Calculate it for all pairs of ROIs**

Common types of brain connectivity:

1. **fMRI-derived estimates of functional connectivity**
2. **dMRI-derived estimates of structural connectivity.**

correlated gene expression · receptor similarity · laminar similarity · metabolic connectivity · haemodynamic connectivity · electrophysiological connectivity · temporal similarity
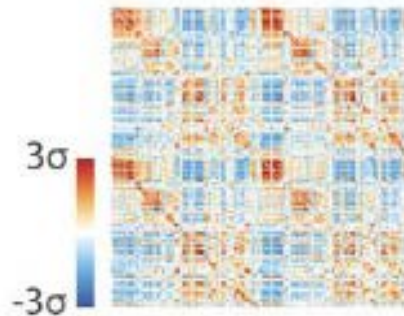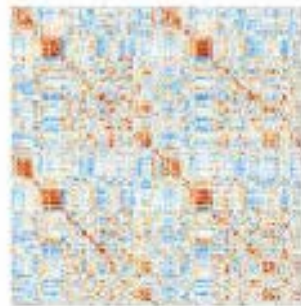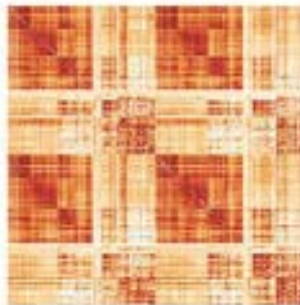
Hansen et al., PloS Biology (2023)
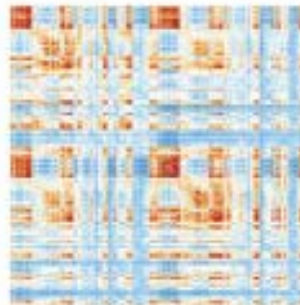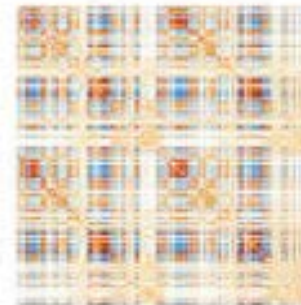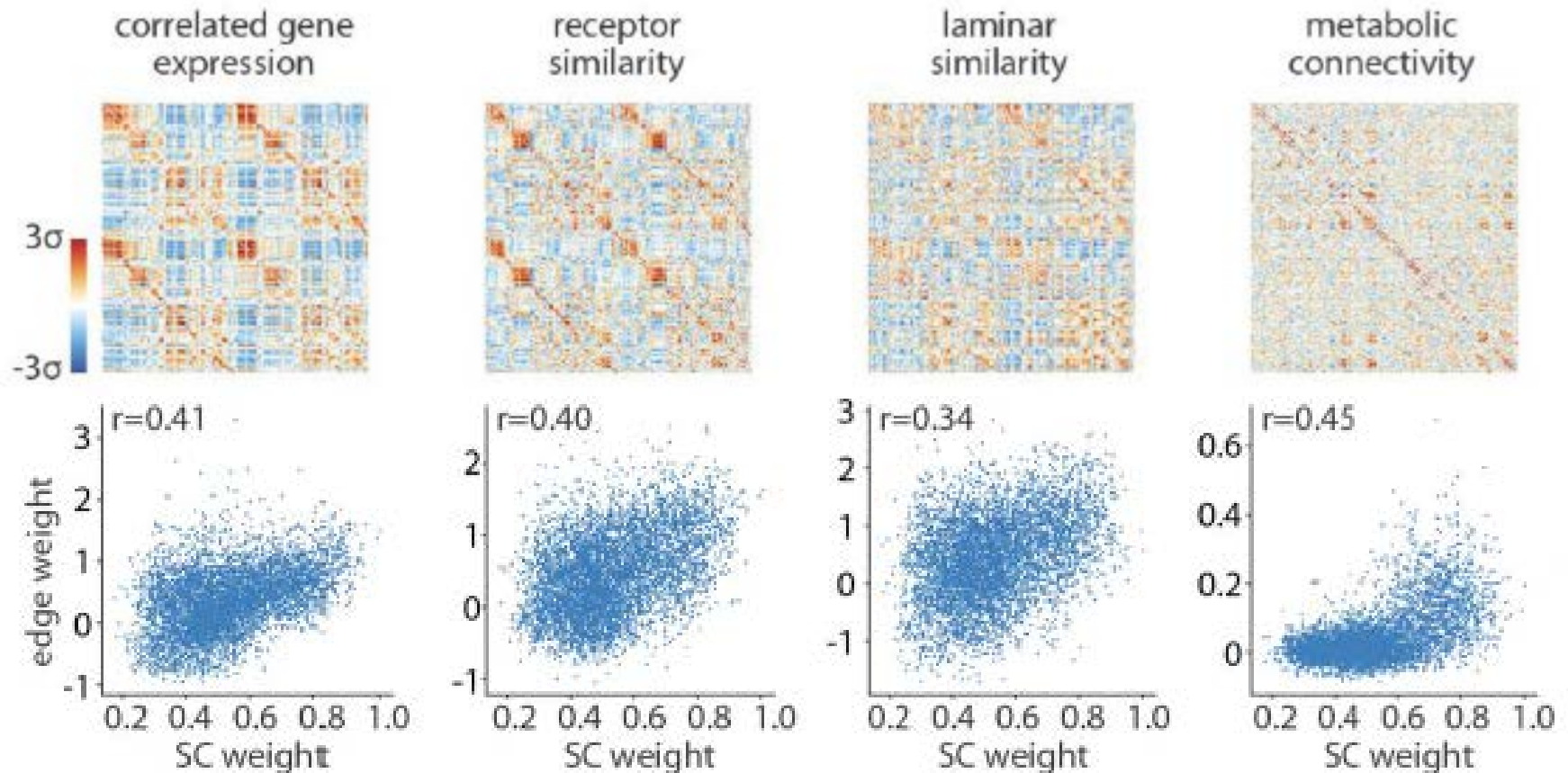
Axonally-connected brain regions tend to be more similar across a wide range of definitions of biological similarity

$r = 0.76$, $P_{spin} < 0.001$

MIND network edges

Gene co-expression network edges
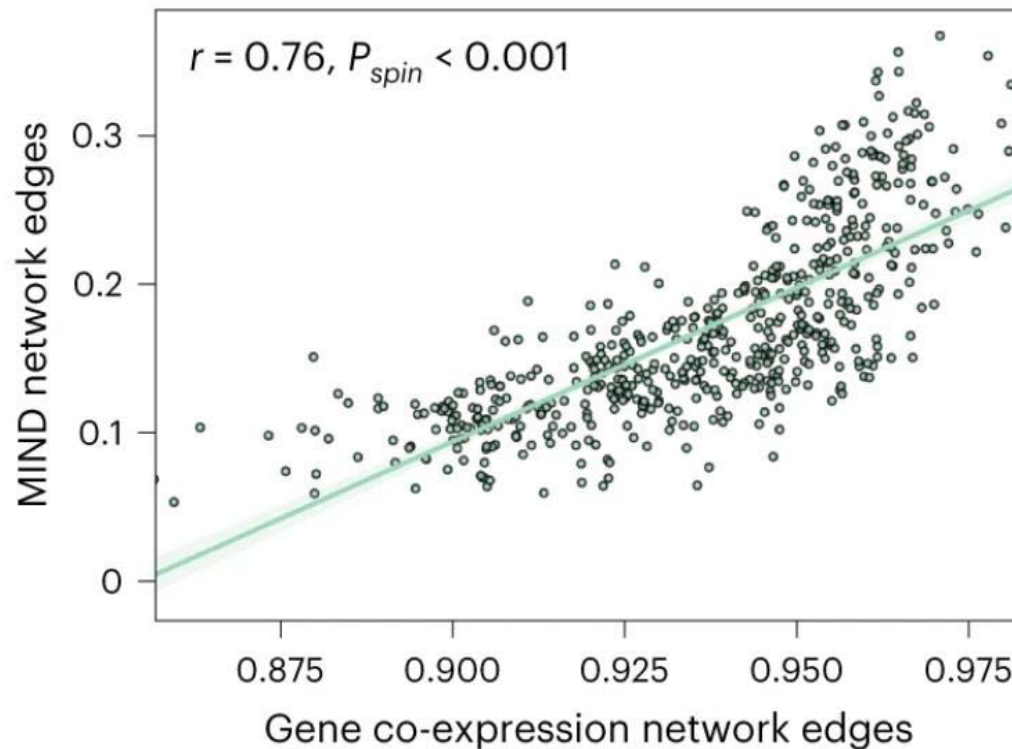
Sebenius et al., Nat. Neuro

Brain regions with similar gene expression have similar structure, tend to be more connected by white matter, and are more likely to be functionally connected

a Syndrome-specific grey-matter atrophy

AD   bvFTD   SD   LIFG   PNFA   CBS   RPMC

RANG   RFI   LTPL
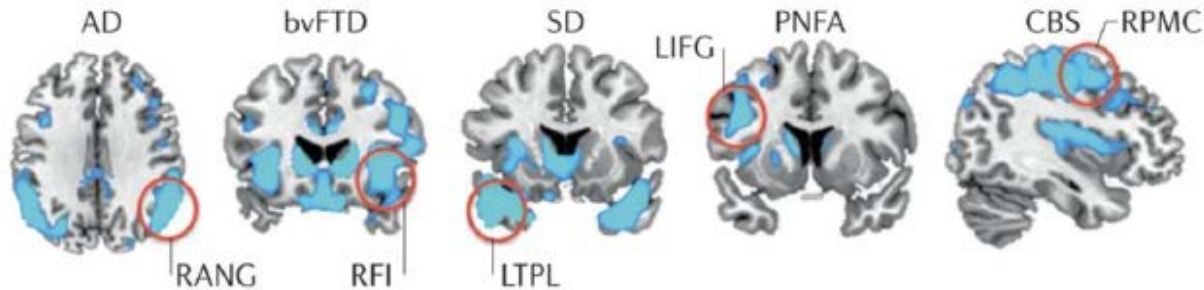
b Spontaneous functional connectivity in controls

c Structural covariance in controls

Seeley et al., Neuron (2009)

Brain networks constrain patterns of degeneration in psychiatric and neurodegenerative diseases

Special properties of nodes:

- Spatially-embedded

- Nodes are not interchangeable

- Tend to be fully-connected (thresholding often must therefore often be applied).
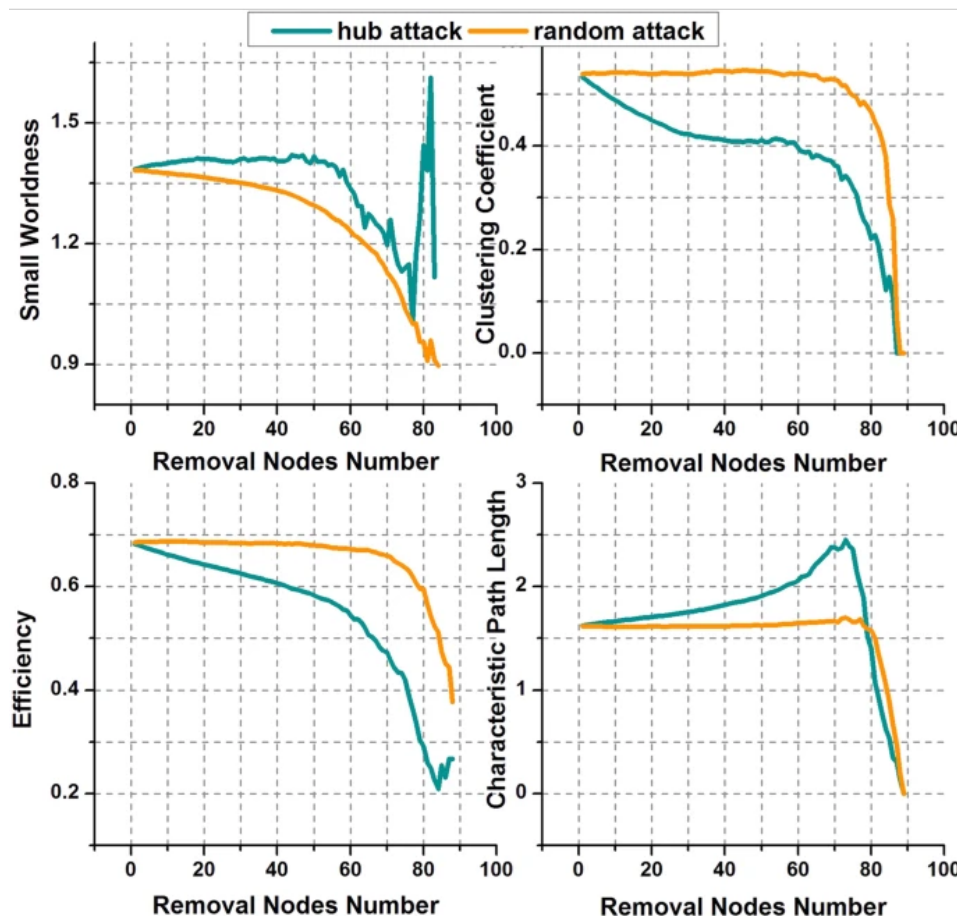
Generative Models

Rather than using graph theory to *describe* networks, we can play with wiring rules in order to simulate processes like neuro-degeneration or brain development, and match to graph-metrics, in order to understand *mechanisms*
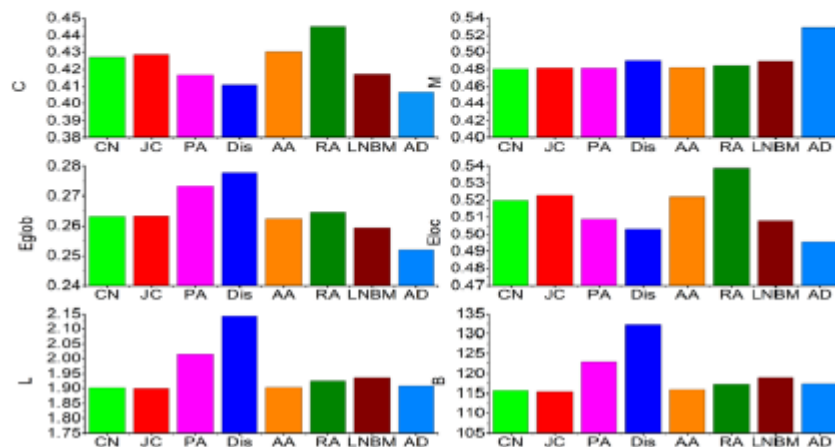
Brain Degeneration

(a) real initial network (b) synthetic network (c) real target network

LNBM

clustering efficiency modularity

Network Modeling   Evaluation

| Link prediction index	Index abbreviation	Mathematical definition
Common neighbor	CN	$S_{(u,v)}^{CN} = |\Gamma(u) \cap \Gamma(v)|$
Jaccard	JC	$S_{(u,v)}^{JC} = \dfrac{|\Gamma(u) \cap \Gamma(v)|}{|\Gamma(u) \cup \Gamma(v)|}$
Preferential attachment	PA	$S_{(u,v)}^{PA} = |\Gamma(u)| \times |\Gamma(v)|$
Adamic-Adar	AA	$S_{(u,v)}^{AA} = \sum_{\xi \in |\Gamma(u) \cap \Gamma(v)|} \dfrac{1}{\log |\xi|}$
Resource allocation	RA	$S_{(u,v)}^{RA} = \sum_{\xi \in |\Gamma(u) \cap \Gamma(v)|} \dfrac{1}{|\xi|}$

$\Gamma(u)$ represents the neighbor set of node u; $|\Gamma(u)|$ represents the number of neighbors of node u.

Shuai-Zong et al (2019) Neural Reg Res
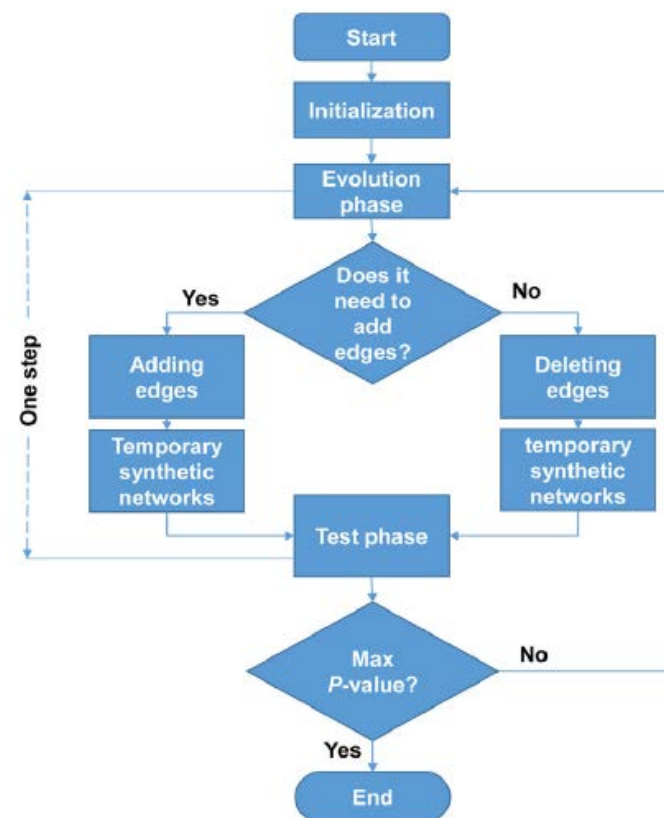
Brain Development

$$P_{i,j} \propto (D_{i,j})^{\eta}(K_{i,j})^{\gamma}$$

$D_{i,j}$ represents the Euclidean distance between nodes i and j (i.e., "costs")

$K_{i,j}$ reflects the value (i.e., "attractiveness") in forming a connection
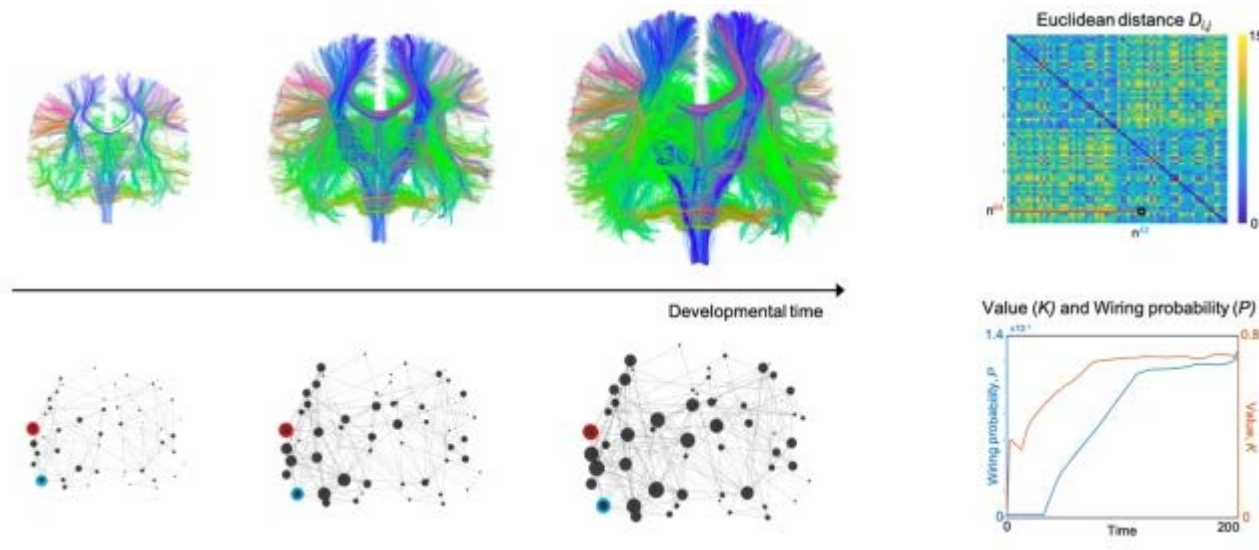
- Attractiveness could be similarity of neighbours ("homophily")

- Simulations of development show that D_{ij} dominates early, but K_{ij} becomes more important over time

Akarca et al (2021) Nature Comms

https://github.com/RikHenson/PythonNeuroimagingCourse/blob/main/Notebooks/nb10_network_analysis.ipynb