EDUCATIONAL WORKSHOP
fNIRS CONFERENCE 2026

Advanced Topics in Functional Connectivity with fNIRS

From isolated to integrated approaches

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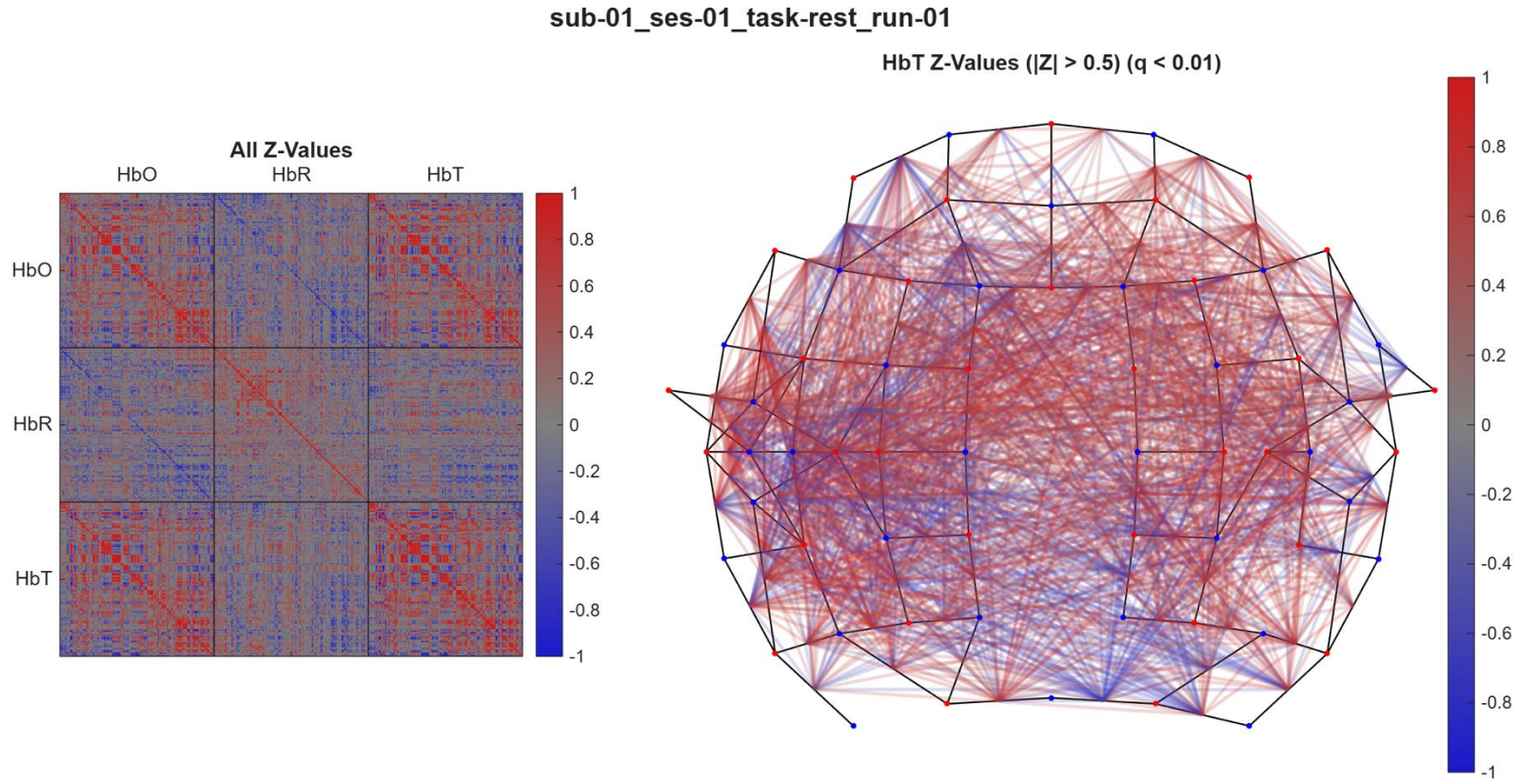
Output from preprocessing



What's next?

Overview

1 The brain as a complex system

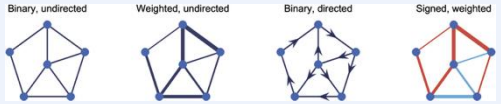
Why graphs? Scales, proxies and assumptions



Hands-on #1

2 From matrix to graph

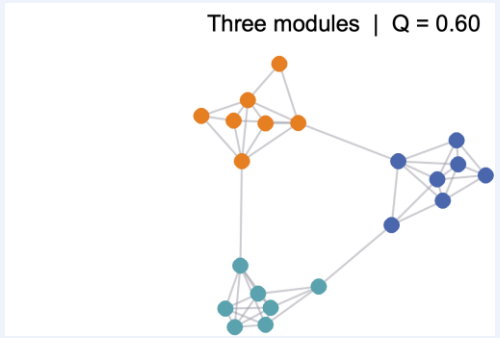
Nodes, edges, negatives, thresholds



Hands-on #2

3 What graphs tell us

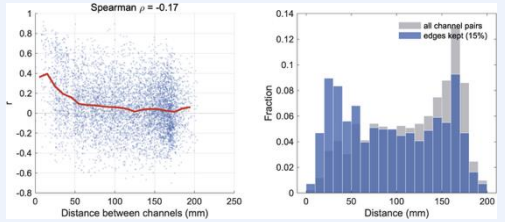
Integration, segregation, hubs, modules, resilience



Hands-on #3

4 fNIRS caveats & good practice

Distance, preprocessing, reliability, reporting



Hands-on #4

Running example for the hands-on

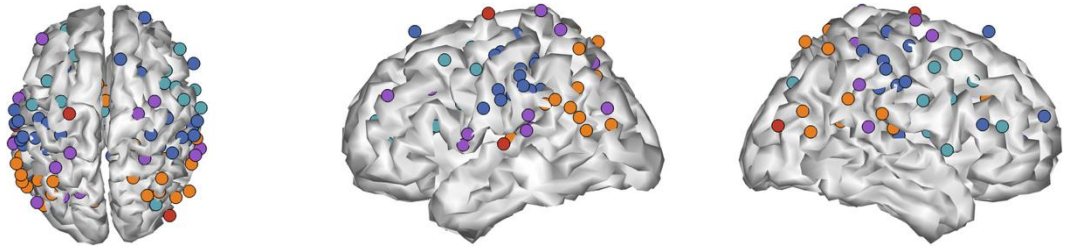
Raw → QC + motion → SCI / PSP → Segment & prune → OD → TDDR → Wavelet → MBLL → Band-pass 0.009–0.08 Hz → Short-ch. regression → HbT → Connectivity

8 min
resting state (eyes open)

121
long channels, whole head

115
nodes after QC (6 flagged)

8
short channels regressed



- **Starting Output:**

  r and Fisher-z matrices for HbO, HbR, HbT;

  2D/3D channel positions;

  approximate AAL region per channel

- **Interactive hands-on:**

  https://rcmesquita.info/fnirs-graphs

  no toolbox required

SECTION 1

The brain as a complex system

Moving from pairs of channels to the organisation of the whole

1. Brain as a complex system

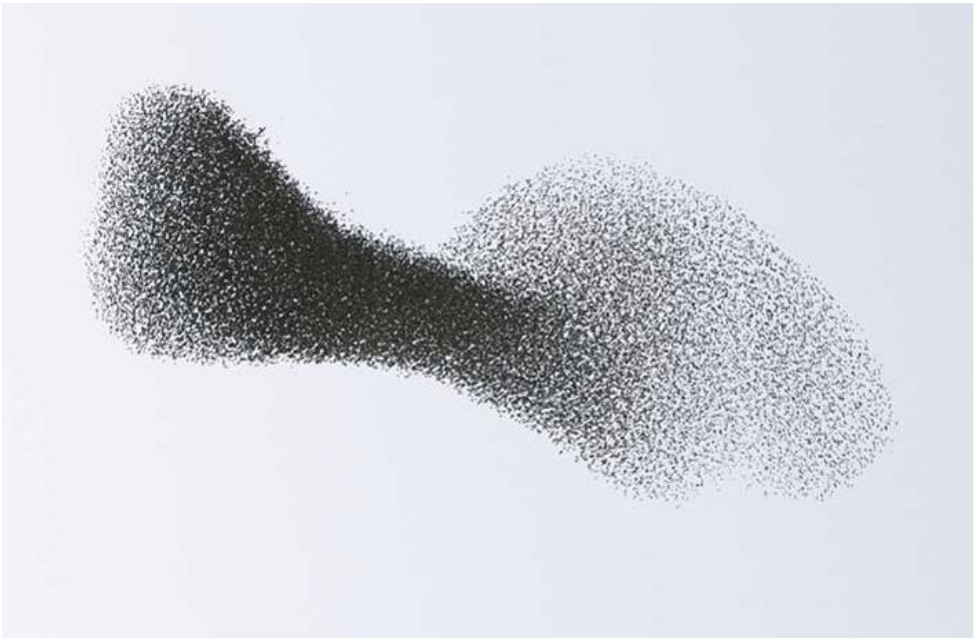
2. From matrix to graph

3. What graphs tell us

4. fNIRS caveats & practice

Complicated is not the same as complex





COMPLICATED

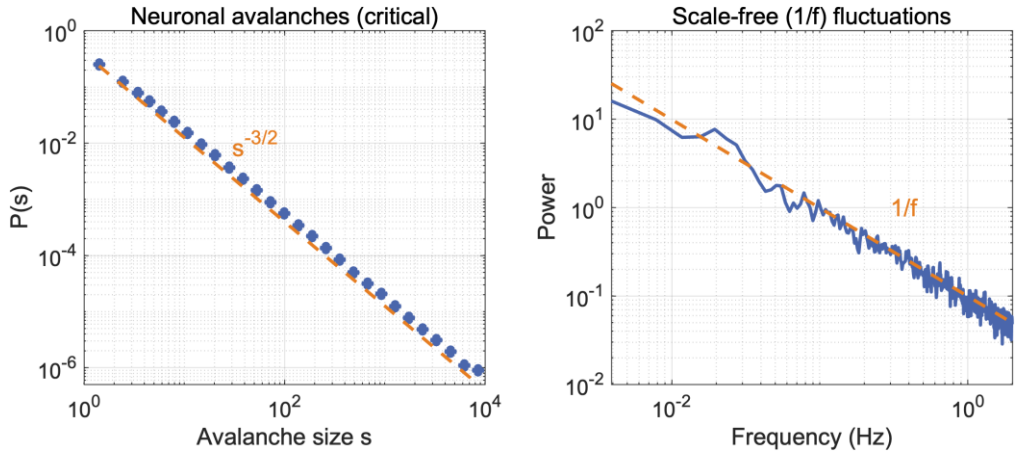
- Many parts, designed interactions
- The whole is predictable from the parts
- Remove a part → a specific, foreseeable failure

COMPLEX

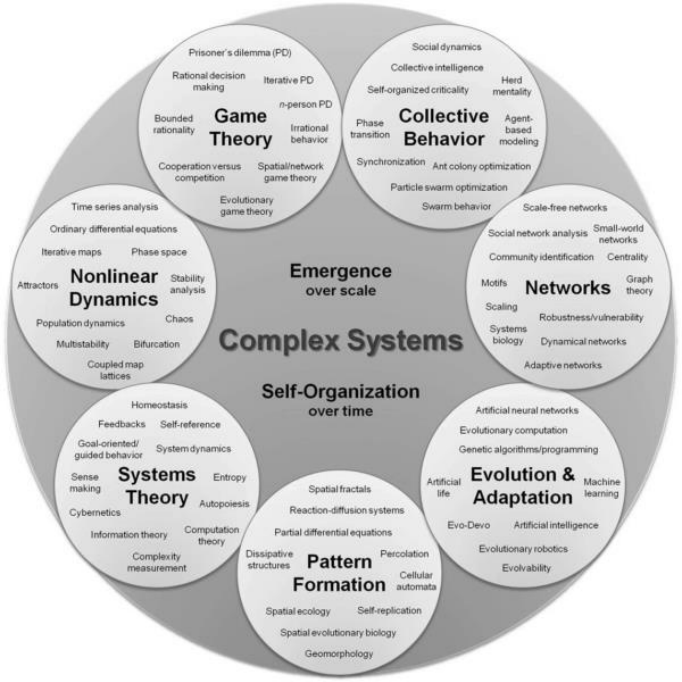
- Many simple units, local interactions
- Collective behaviour emerges (“more is different”)
- The function lives in the organisation of the links

Anderson, Science (1972); Bullmore & Sporns, Nat. Rev. Neurosci. (2009)

Is the brain a complex system?



Simulated illustrations: a critical branching process and 1/f noise



Many scales

10^{11} neurons and ~10^{14} synapses; organisation from µm to 10 cm and from ms to years

Scale-free dynamics

Neuronal avalanches with power-law sizes; 1/f, long-range temporal correlations in slow brain activity

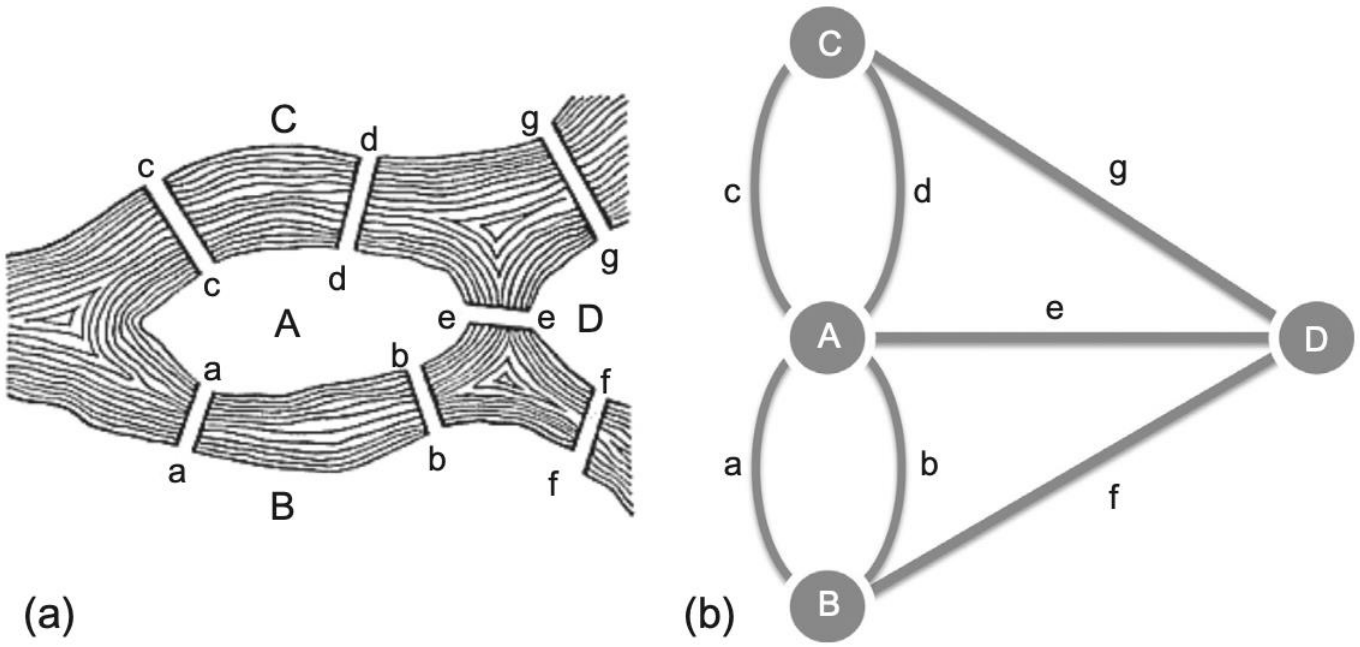
Distributed function

Focal lesions alter remote regions (diaschisis); consciousness tracks integration across systems

Graphs are a lens to see that complexity in the pattern of interactions.

Beggs & Plenz, J. Neurosci. (2003); Linkenkaer-Hansen et al., J. Neurosci. (2001); He et al., Neuron (2010); Carrera & Tononi, Brain (2014); Luppi et al., Nat. Commun. (2019)

What is a graph?



Can you walk through Königsberg crossing each of the seven bridges exactly once?

Euler (1736)

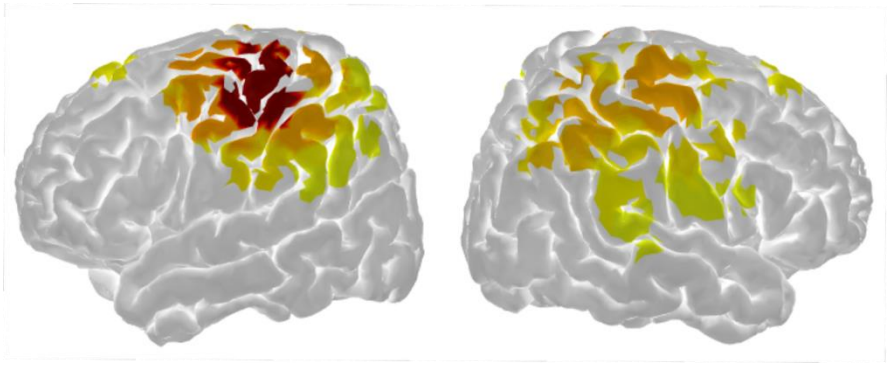
- The answer does not depend on bridge lengths or positions
- It depends only on how land masses (nodes) are linked by bridges (edges)
- Topological properties survive any spatial deformation of the system
- **Graph G = (V, E): a (non-empty) set of vertices (nodes) V, and a set of edges (links) E between them that is a subset of the set V x V**

$$V = \{a, b, c, d\}$$
$$E = \{(a, b), (a, c), (a, d), (b, d), (c, d)\}$$

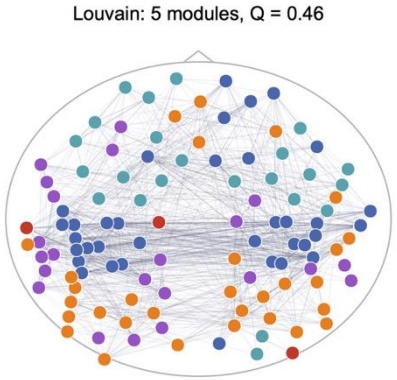
What do graphs add to the correlation matrix?

A graph adds no new information to the matrix.

But it changes the question: from properties of pairs to properties of the pattern.



Pairs: which channels correlate with this seed?



Pattern: how is the whole set organised?

1 Many-node structure

Paths, triangles, modules involve 3+ nodes at once

2 A reference

Compare with random or lattice graphs of the same size

3 System properties

Integration, segregation, robustness of the whole

4 Compact descriptors

A few numbers to compare subjects and groups

Bullmore & Sporns, Nat. Rev. Neurosci. (2009); Rubinov & Sporns, NeuroImage (2010)

Graph representation in fNIRS

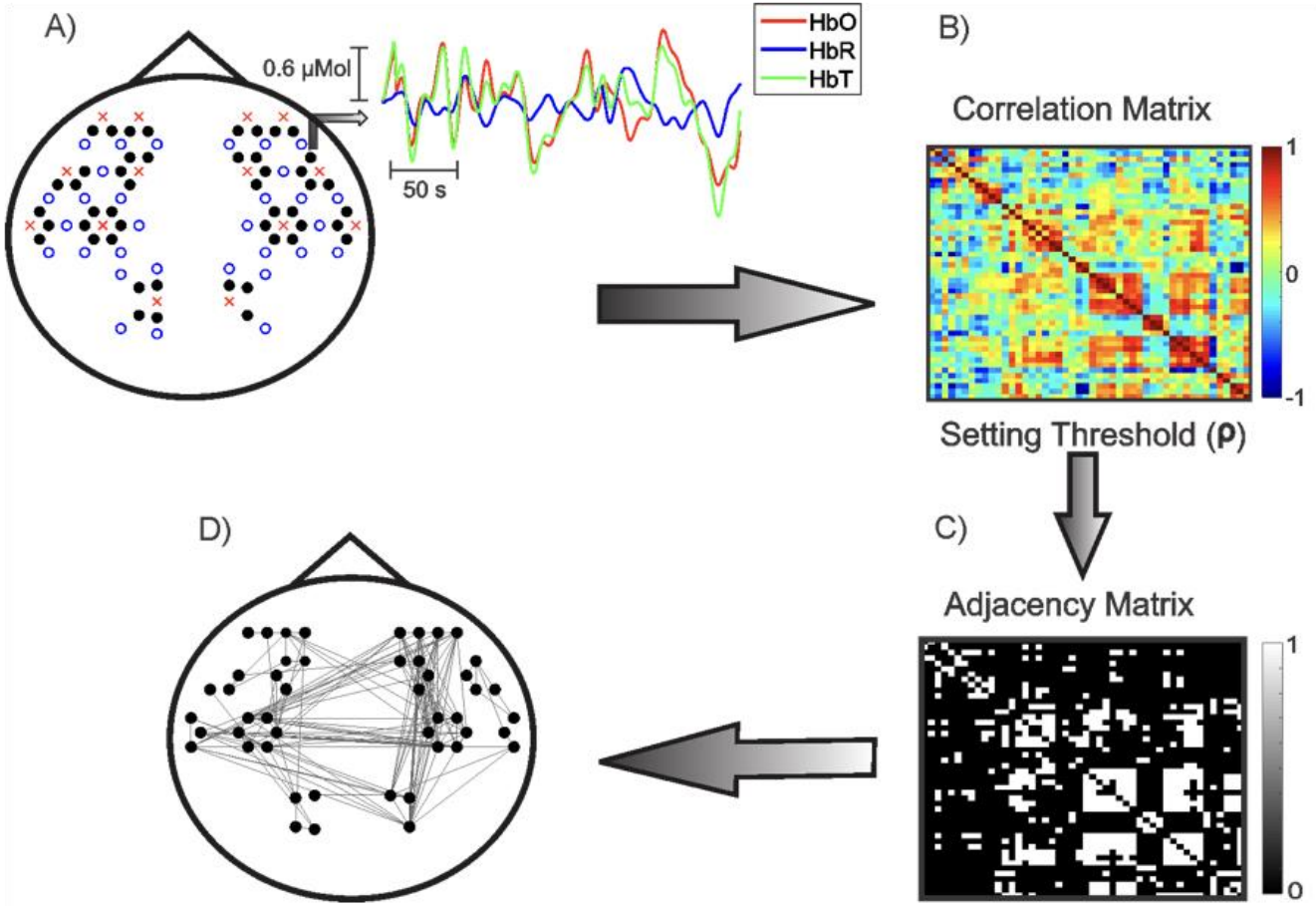
Nodes

- The parts of the system we have information from
- Here: channels (or ROIs, or cortical parcels after image reconstruction)

Links (edges)

- Something that represents the interaction of two nodes
- Here: Pearson correlation of HbO, HbR or HbT
- Other possibilities: Mutual information, correntropy, coherence, WTC

Functional links are statistical, undirected and not anatomical.



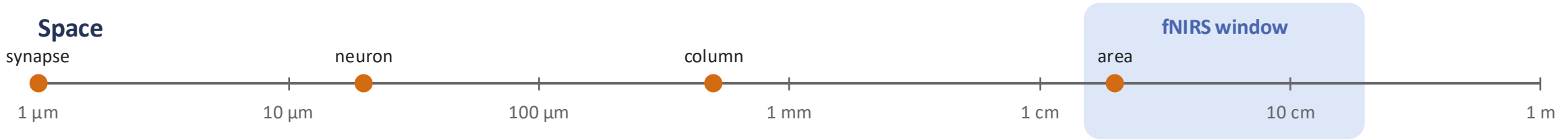
Novi, Rodrigues & Mesquita, Biomed. Opt. Express (2016)

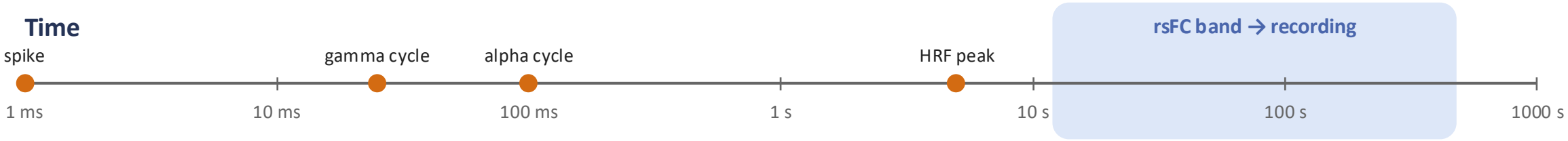
Haemodynamic organisation as a proxy for neural organisation

temporal low-pass filter *spatial blur + extracerebral signals*

Neural activity	Neurovascular coupling	Haemodynamics	Optical measurement	Graph
ms · µm–mm	HRF peak ≈ 5 s	HbO · HbR · HbT	cm · superficial · scalp	0.01–0.1 Hz · ~100 nodes

An fNIRS graph describes a filtered view of neural organisation: infra-slow, centimetre-scale haemodynamic coordination.





Consequences

- About one decade in space and in time: power laws and “scale-free” claims cannot be tested
- Patterns that arise across orders of magnitude are outside the window
- **For graphs to make sense in fNIRS, the theory has to be assumed; it cannot be shown**

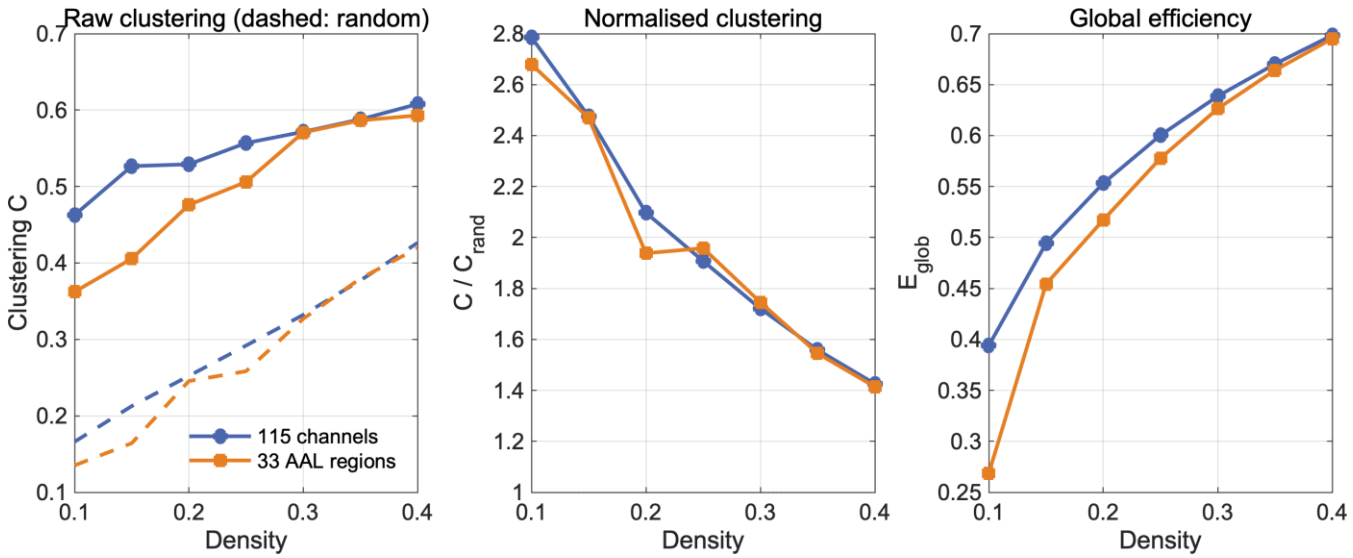
Working assumptions

1. **Coarse-graining:** Organisation partly survives averaging over cm and seconds
2. **Haemodynamic proxy:** Infra-slow haemodynamic coupling reflects neural coupling
3. **Channels as units:** Each channel is a separate part of the system
4. **Stationarity:** The organisation is stable over the recording

Consequence of coarse-graining

$$C_{rand} \approx \frac{\langle k \rangle}{N} \qquad L_{rand} \approx \frac{\ln N}{\ln \langle k \rangle}$$

Raw metrics depend on the number of nodes N and the mean degree ⟨k⟩, so they change whenever the node set changes.



Running Example:

115 channels → 33 AAL regions (15% density)

`raw C: 0.53 → 0.41`

`C/C_rand: 2.48 → 2.47`

Compare normalised metrics, and compare only graphs built at the same scale.

Zalesky et al., NeuroImage (2010); van Wijk, Stam & Daffertshofer, PLoS One (2010)

SECTION 2

From the connectivity matrix to a graph

Every choice along the way changes the graph you will analyse

1. Brain as a complex system

2. From matrix to graph

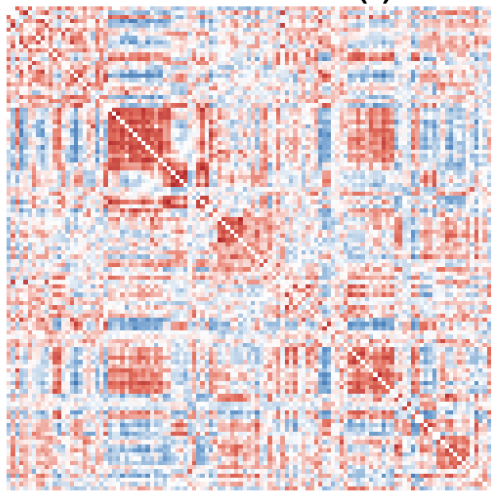
3. What graphs tell us

4. fNIRS caveats & practice

Building a graph is a sequence of choices

Nodes	Edges	Negatives	Threshold	Metrics	Reference	Statistics
channels, ROIs?	r, coherence, chromophore?	drop, |r|, signed?	absolute, proportional, none?	binary or weighted?	null models	single subject, group

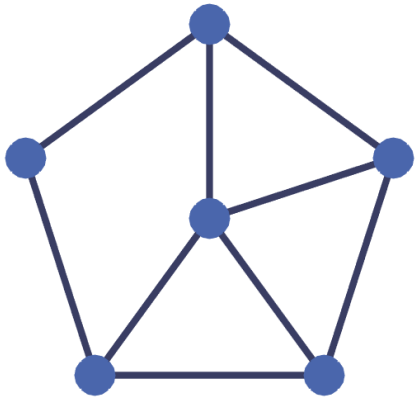
1. Correlation (r)



There is no single graph “hidden” in a correlation matrix.

Types of graphs

Binary, undirected



Binary, undirected

Edge present or absent. Simplest; needs a threshold.

Weighted, undirected

Keeps edge strength (e.g., r). Less information discarded.

Directed

Needs a directed measure (e.g., Granger, effective connectivity). Not correlation.

Signed

Positive (red) and negative (blue) edges. Few metrics are defined for signs.

Rubinov & Sporns, NeuroImage (2010); Fornito, Zalesky & Bullmore, Fundamentals of Brain Network Analysis (2016)

Choice 1 – Nodes: what counts as a part of the system?

The same brain parcellated at different resolutions yields different properties

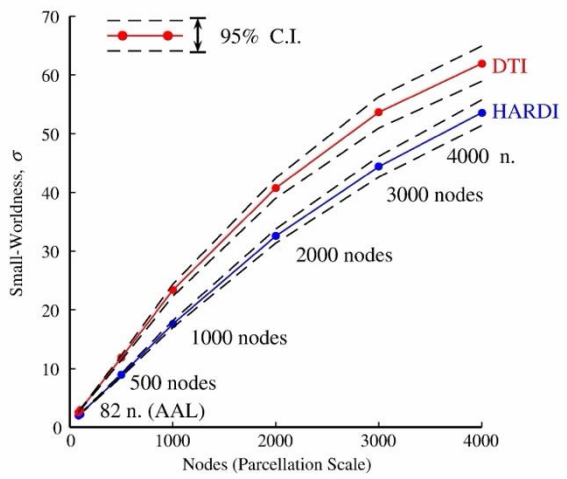
Options in fNIRS

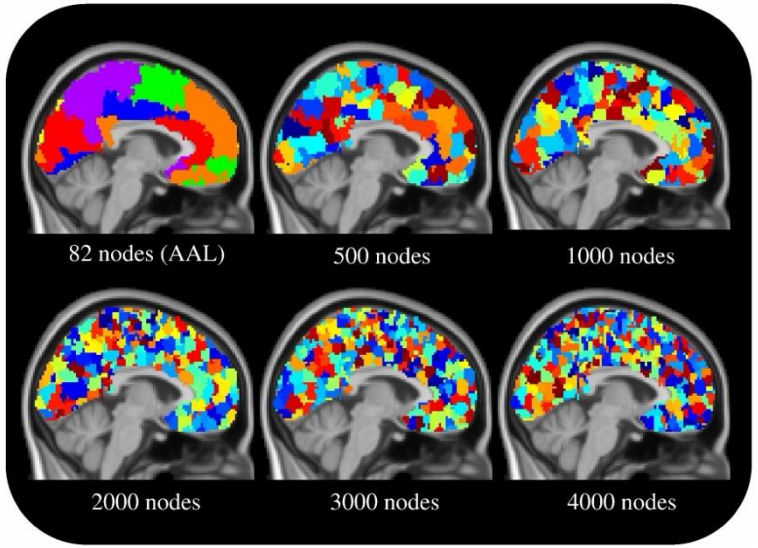
- Channels (most common)
- Anatomical ROIs: average channels per region
- Cortical parcels after image reconstruction (HD-DOT)

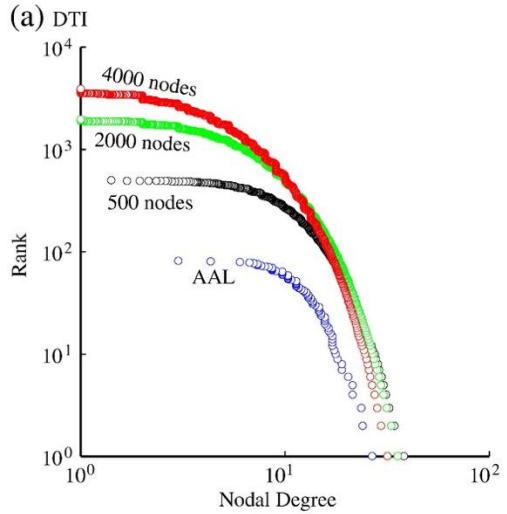
Flexibility has consequences

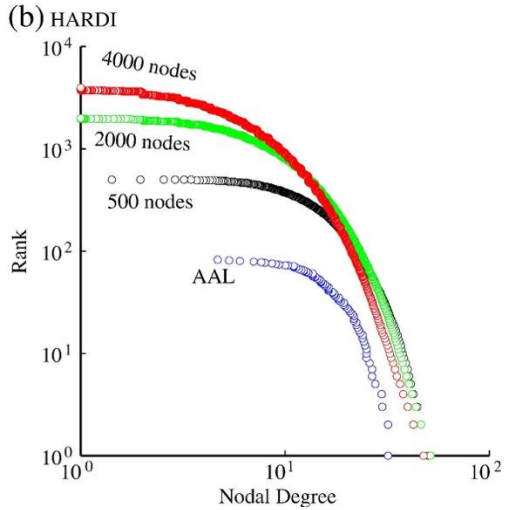
- Metrics scale with the number of nodes N and mean degree
- Pruning bad channels changes N, and differently in each subject
- **Group comparisons need a common node set**

Compare graphs only when they have comparable nodes.



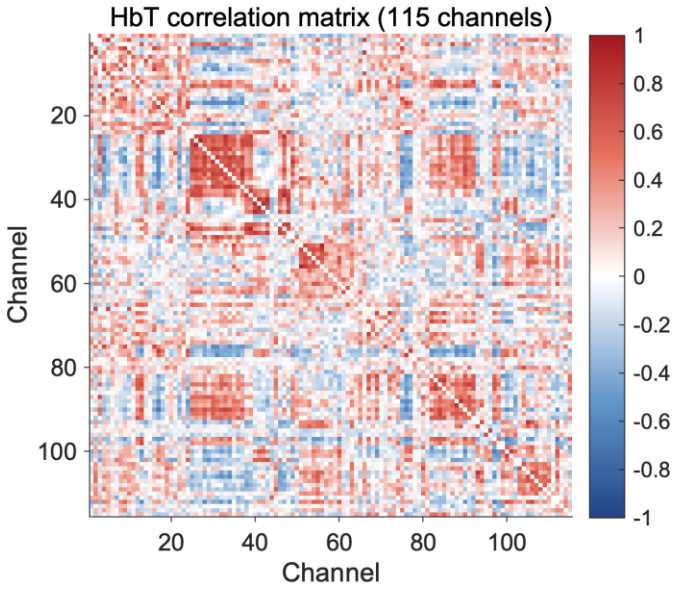


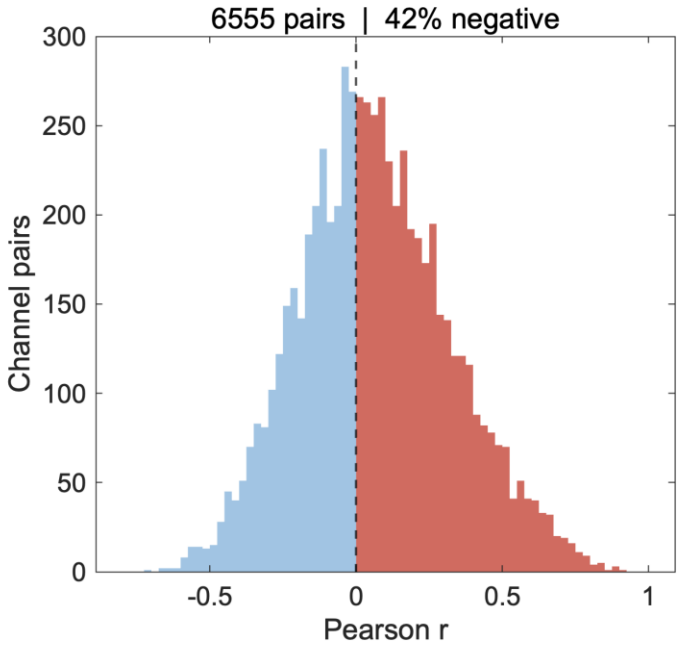




Zalesky et al., NeuroImage (2010)

Choice 2 – Edges: which measure, which chromophore?





Common edge measures

- Pearson correlation (Part 1)
- Partial correlation
- Coherence / wavelet coherence
- Mutual information
- Correntropy

$$z = \operatorname{atanh}(r) = \frac{1}{2} \ln \frac{1+r}{1-r}$$

Fisher's transform makes r approximately normal, so it can be averaged across runs and subjects.

Chromophore

- HbO: largest SNR, most systemic contamination
- HbR: more specific, noisier
- HbT: common in rsFC; our example

Significance and autocorrelation

Can we keep only the “significant” edges?

- Neighbouring fNIRS samples are not independent: the signal is band-limited (0.009–0.08 Hz) and autocorrelated, so the effective degrees of freedom are much lower than the number of samples.
- **Consequence:** p-value thresholds give dense, nearly complete graphs that reflect sampling rate and run length, not the brain.
- **Options:** prewhitening, corrected degrees of freedom, phase-randomised surrogates, or density-based thresholds

85%

of pairs with $p < 0.05$ (uncorrected)

68%

still significant after Bonferroni (6555 tests)

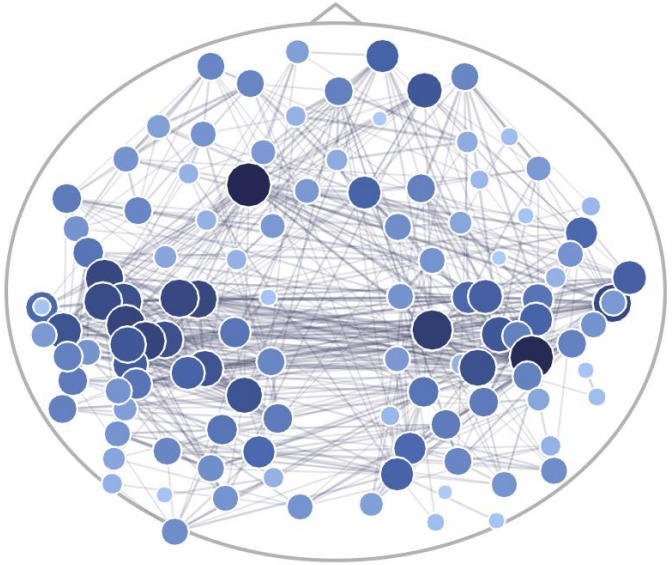
1794

degrees of freedom assumed: ~4 Hz × 8 min

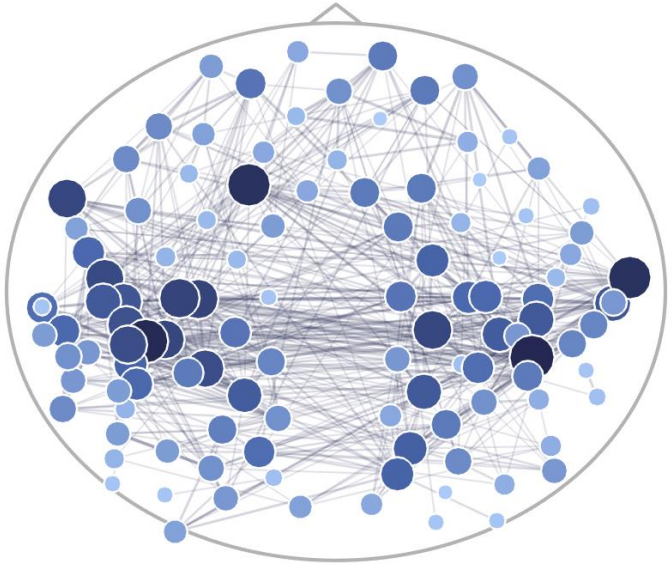
Santosa et al., Neurophotonics (2017); Barker et al., Biomed. Opt. Express (2013)

Choice 3 – What to do with negative correlations?

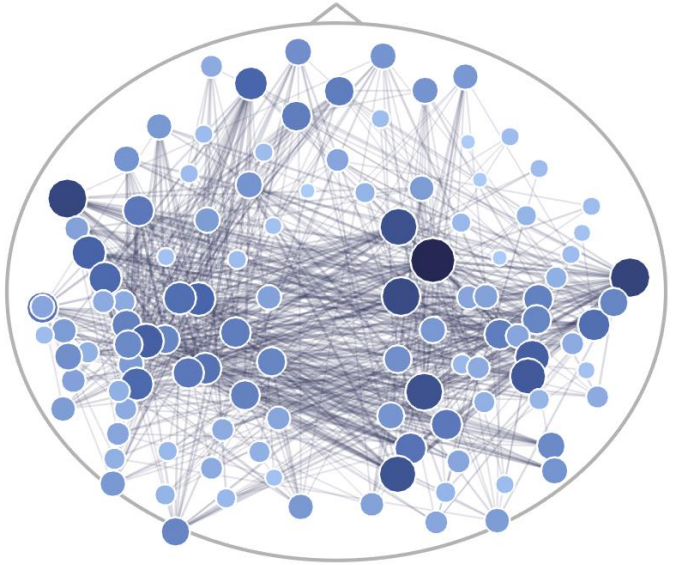
Positive only



Absolute value |r|



Negative only (|r|, r<0)



Positive only
Most common. Interpretable, but discards information

Absolute value
Treats anticorrelation as coupling. Mixes two phenomena

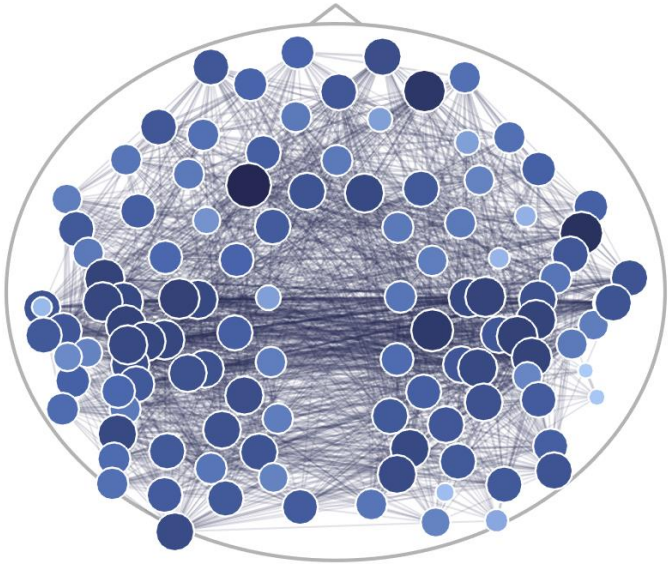
Separate graphs
Positive and negative graphs analysed side by side

Signed metrics
Weight-conserving measures for signed graphs

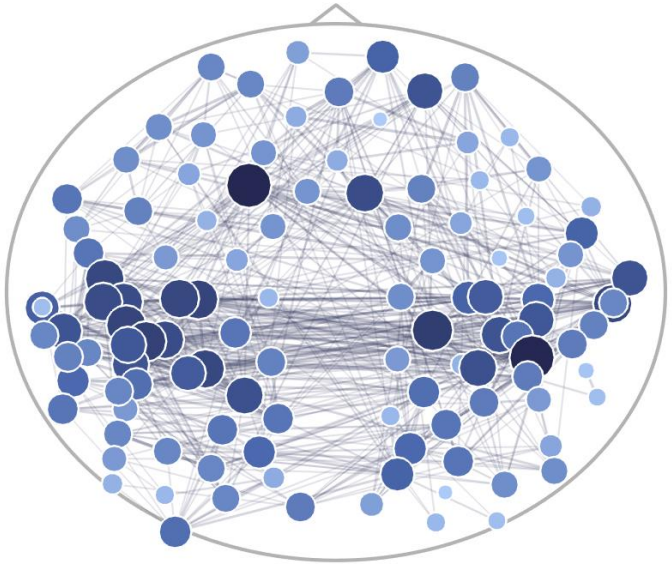
Murphy et al., NeuroImage (2009); Rubinov & Sporns, NeuroImage (2011)

Choice 4 – Thresholding: absolute threshold

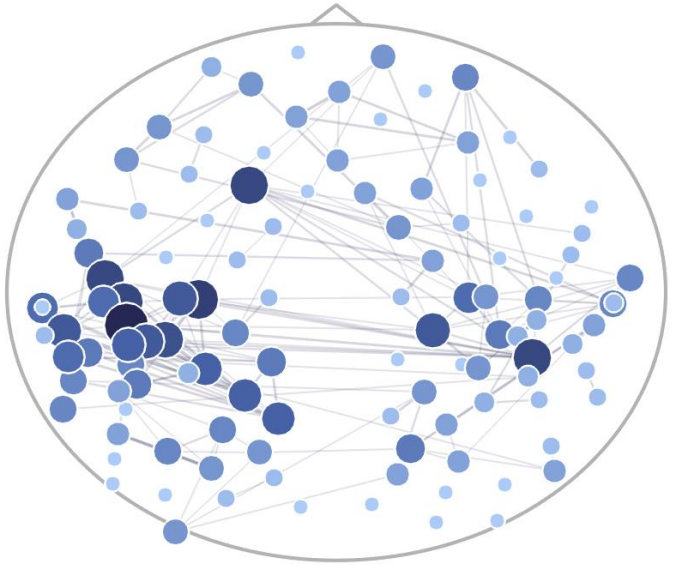
$r \geq 0.2$ | density 29% | 1 comp.



$r \geq 0.4$ | density 11% | 3 comp.



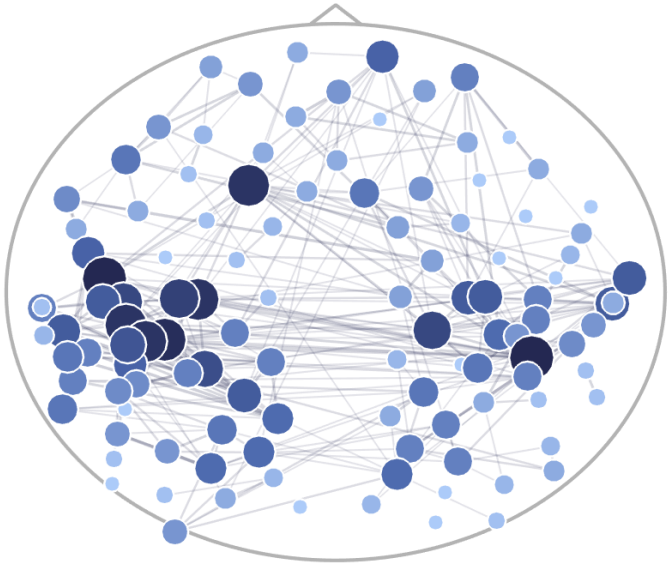
$r \geq 0.6$ | density 3% | 34 comp.



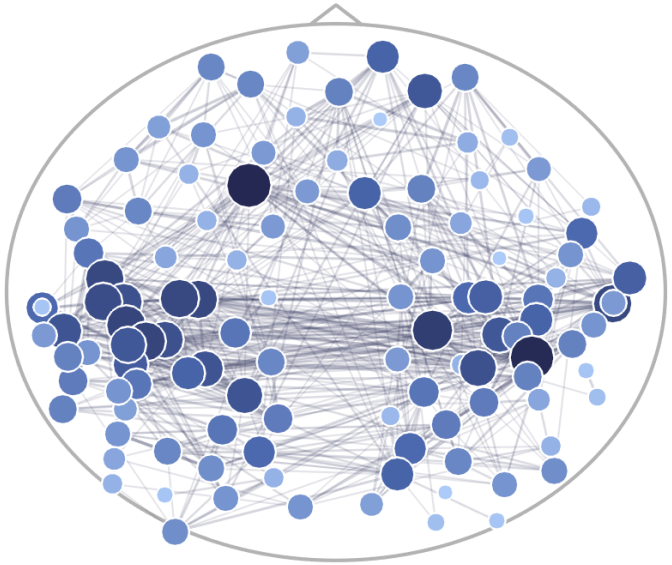
Keep edges with r ≥ τ. Same meaning of an edge across subjects, but the number of edges (density) varies with overall connectivity, and high τ fragments the graph.

Choice 4 – Thresholding: proportional threshold (density)

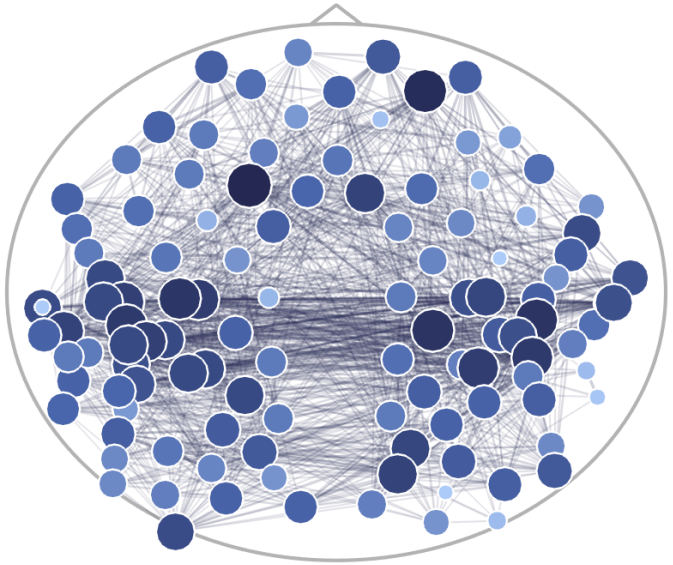
5% density | $r \geq 0.52$ | 17 comp.



10% density | $r \geq 0.41$ | 5 comp.



20% density | $r \geq 0.28$ | 1 comp.



Keep the strongest X% of edges. Same density for everyone, which makes topologies comparable. But the meaning of an edge changes between subjects, and weak graphs gain noisy edges.

Hands-on #1

Scan, or open in any browser

rcmesquita.info/fnirs-graphs/handson1.html

≈ 25 min · in pairs

From a connectivity matrix to a graph

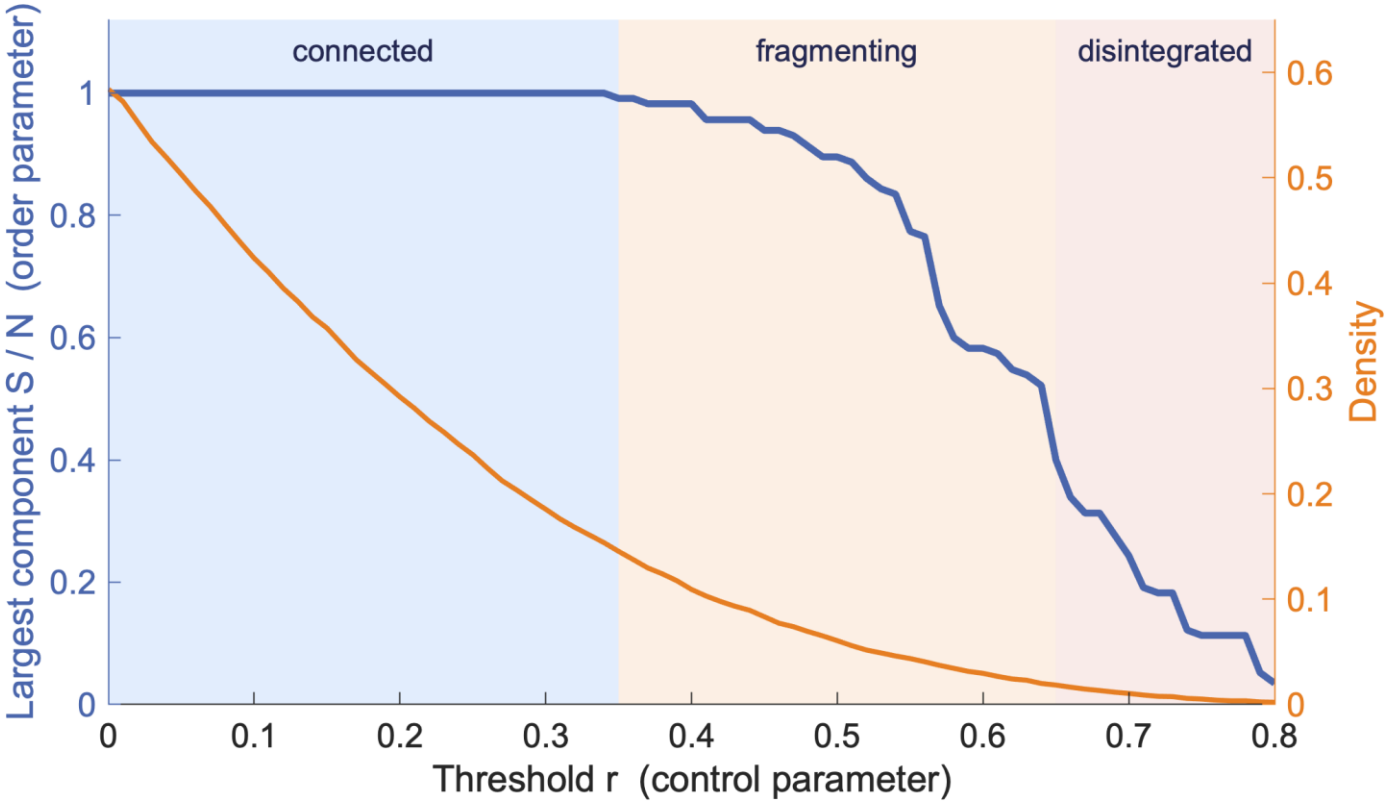
WHAT TO DO · follow the numbered steps on the page

1. Look at the matrix and the distribution of r; switch HbO / HbR / HbT
2. How many edges are “significant”? Move the degrees-of-freedom slider
3. Compare positive, absolute and negative-only graphs
4. Absolute vs proportional threshold
5. Binary vs weighted measures
6. Follow the largest component as the threshold rises

DISCUSS WITH YOUR PAIR

- Is the correlation matrix already a graph?
- Why does almost every edge look “significant”?
- Before the next slide: which threshold is correct? Write down one number and your reason.

Which threshold is correct?



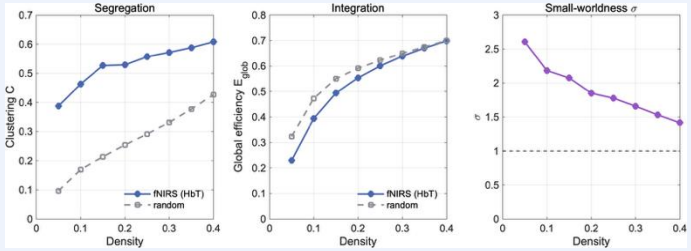
- **Control parameter:** threshold r (or density)
- **Order parameter:** largest component S/N
- **Three regimes:** connected → fragmenting → disintegrated
- **Finite size:** ~100 nodes give a smooth crossover, not a sharp transition
- **Metrics change most** near the transition, so a single threshold there is fragile

In this subject: the graph stays fully connected up to r = 0.35, which is exactly 15% density, the sparsest graph that keeps every channel connected.

Gallos, Makse & Sigman, PNAS (2012); Bordier, Nicolini & Bifone, Front. Neurosci. (2017)

So which number? Three potential strategies

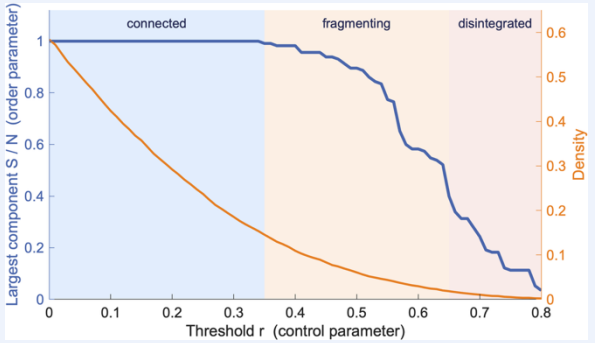
1 Sweep the control parameter



Report metric curves across the connected regime, e.g. 5–40% density.

van Wijk et al. (2010); Garrison et al. (2015)

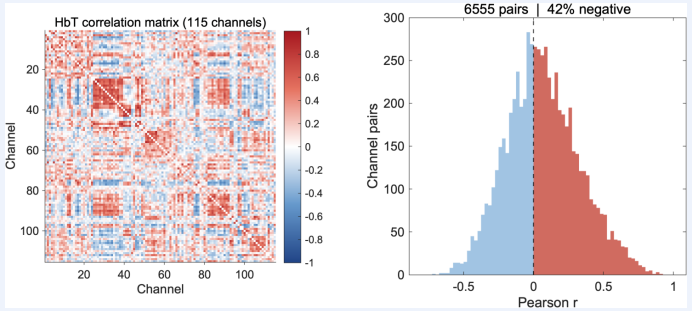
2 Percolation-based threshold



Per subject, the sparsest graph that is still connected: a data-driven reference point.

Gallos et al. (2012); Bordier et al. (2017)

3 No threshold at all



Fully weighted metrics: no control parameter, no binarisation. Negatives still need a decision.

Rubinov & Sporns (2010, 2011)

Whatever the strategy: normalise by null models at the same density and degree.

SECTION 3

What graphs tell us about the system

Integration, segregation, hubs, modules and resilience

1. Brain as a complex system
2. From matrix to graph
3. What graphs tell us
4. fNIRS caveats & practice

Groups of graph measures by the question they answer

1	**Connectivity**	*How connected is each node?*	degree, strength, density, degree distribution
2	**Segregation**	*Are there densely interconnected groups?*	clustering coefficient, local efficiency, modularity
3	**Integration**	*How easily does information combine across the graph?*	characteristic path length, global efficiency
4	**Centrality**	*Which nodes are most important for the graph?*	betweenness, eigenvector, participation, hubs
5	**Resilience**	*How does the graph tolerate damage?*	targeted and random node removal

Rubinov & Sporns, NeuroImage (2010); Bullmore & Sporns, Nat. Rev. Neurosci. (2009)

Derived measures: balance segregation vs. integration

Segregation

Specialised processing within densely connected groups of regions

Graph measures: *clustering, modularity*

Integration

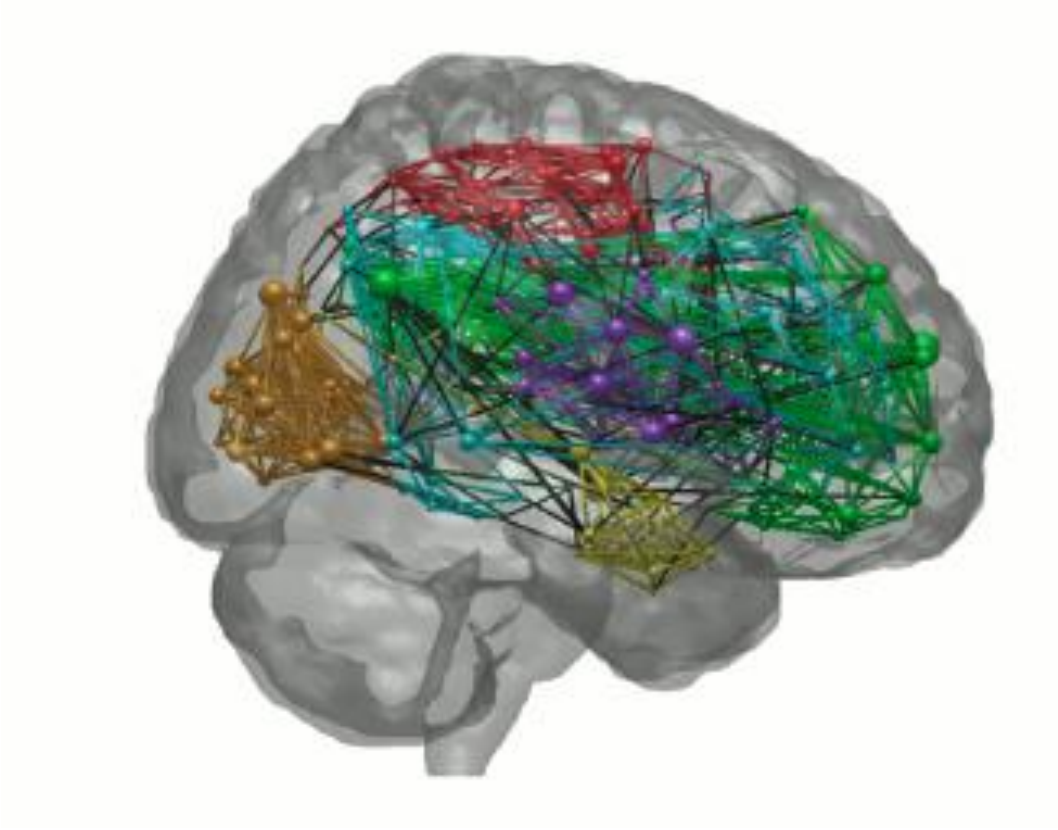
Fast combination of information across distant groups

Graph measures: *path length, efficiency*

Balance

Complexity is high when both coexist; too much of one is pathological

Graph measures: *small-worldness, hubs*

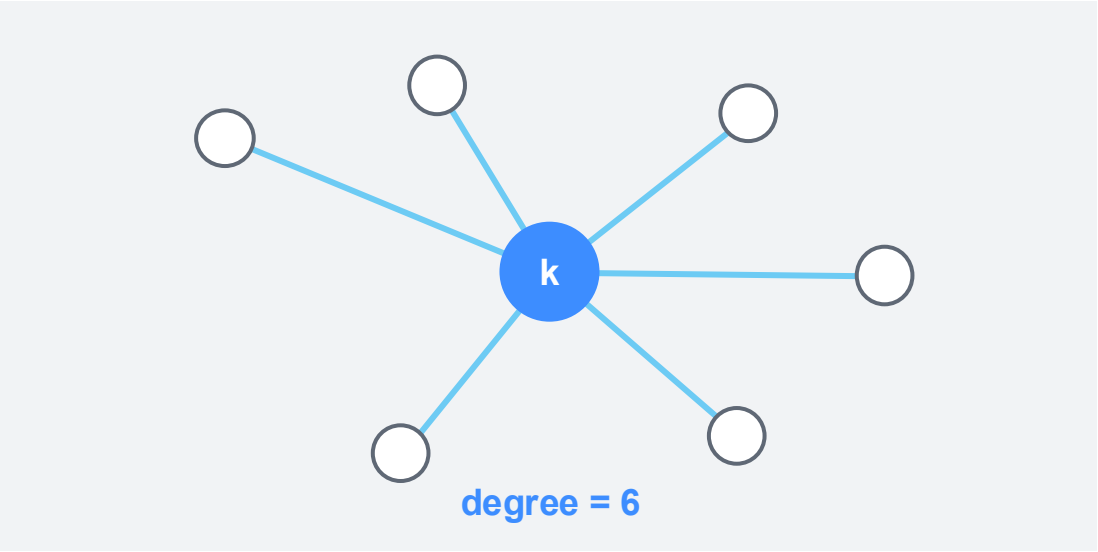


Tononi, Sporns & Edelman, PNAS (1994); Sporns, Dialogues Clin. Neurosci. (2013); Rubinov & Sporns, NeuroImage (2010)

Connectivity: degree and connected components

DEGREE (CENTRALITY)

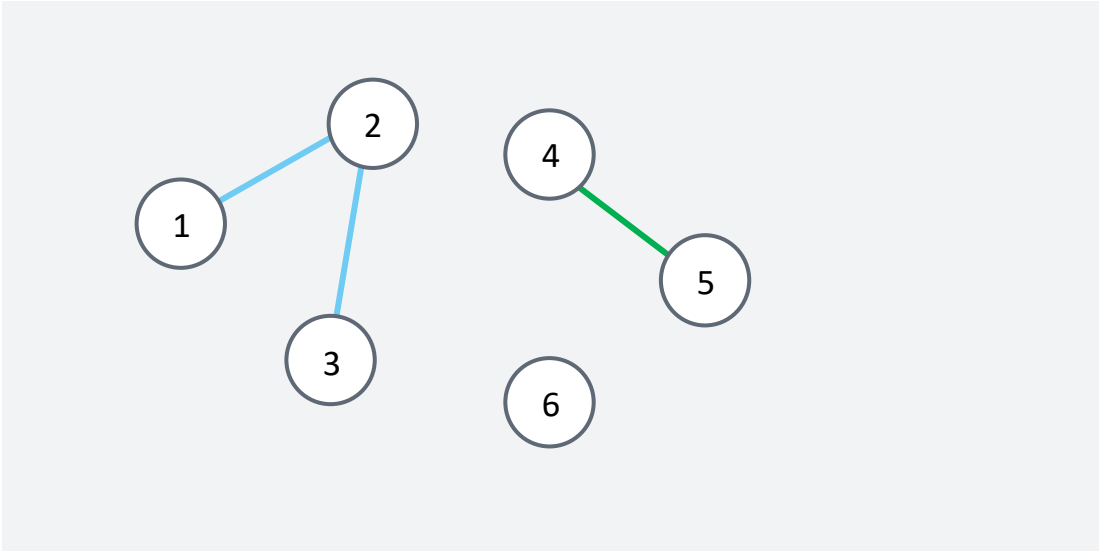
How many direct connections does this node have?



Degree is the number of direct edges attached to a node; high-degree channels are **locally** well connected.

CONNECTED COMPONENTS

Is every node reachable from every other?

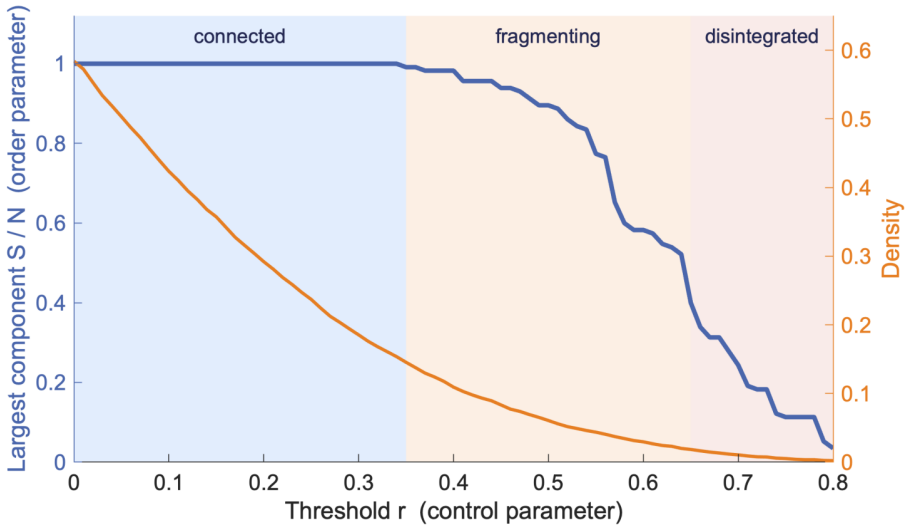


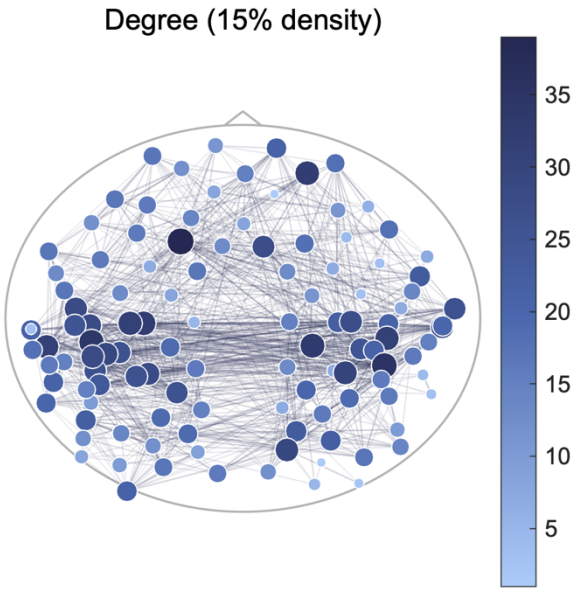
Connected component: maximal set of nodes in which every pair is linked by at least one path.

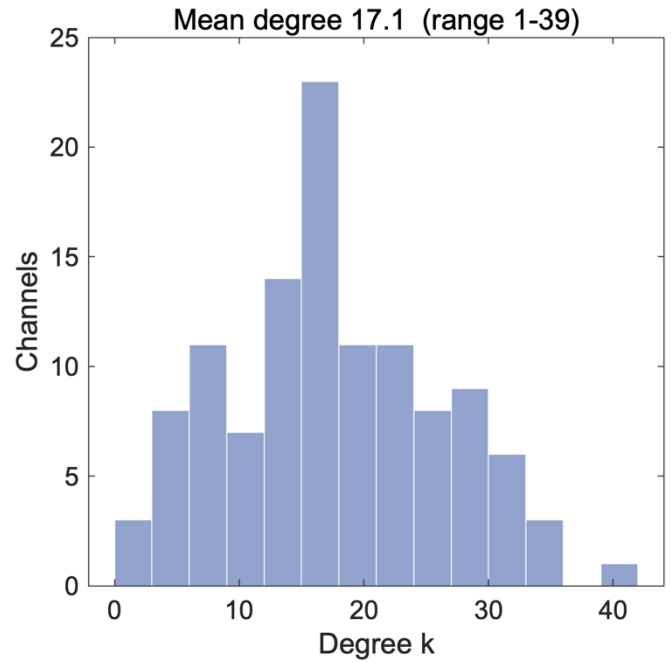
- Components: {1, 2, 3}, {4, 5}, {6}
- Sizes: 3, 2, 1
- Largest component has 3 nodes, so S/N = 3/6 = 0.5

Gupta (2024), Wang, Zuo & He (2010). Original diagrams

Degree in our running data: who is well connected?







In our data at 15% density: one component, S/N = 1. It is the sparsest density that keeps every channel connected.

Reading the degree distribution

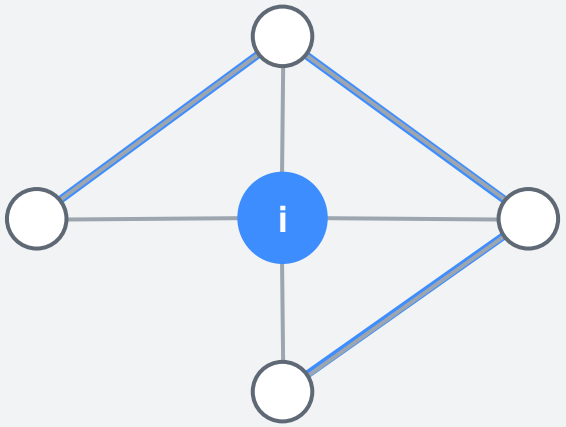
- Random graphs: narrow, Poisson-like. Many real networks: heavy tails (hubs)
- With ~100 nodes, claims about power laws or "scale-free" graphs cannot be tested reliably
- **In fNIRS, high degree can also reflect strong residual systemic signal**

- Mean degree 17 (range 1–39)
- Strongest nodes: bilateral postcentral / supramarginal, left superior frontal
- Dense interhemispheric (homologous) links

Segregation: clustering and local efficiency

CLUSTERING COEFFICIENT

How tightly connected are this node's neighbours?

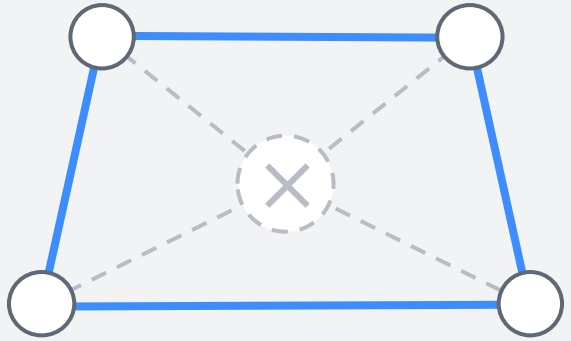


$C_i = 3 / 6 = 0.50$

Clustering coefficient is the fraction of possible links that actually exist among a node's neighbours.

LOCAL EFFICIENCY

Can the neighbours still communicate if this node fails?

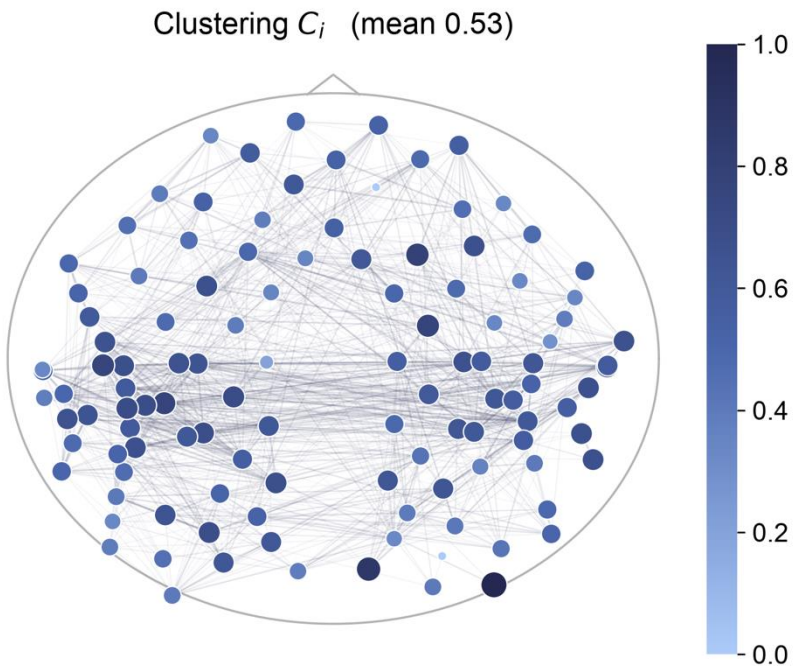


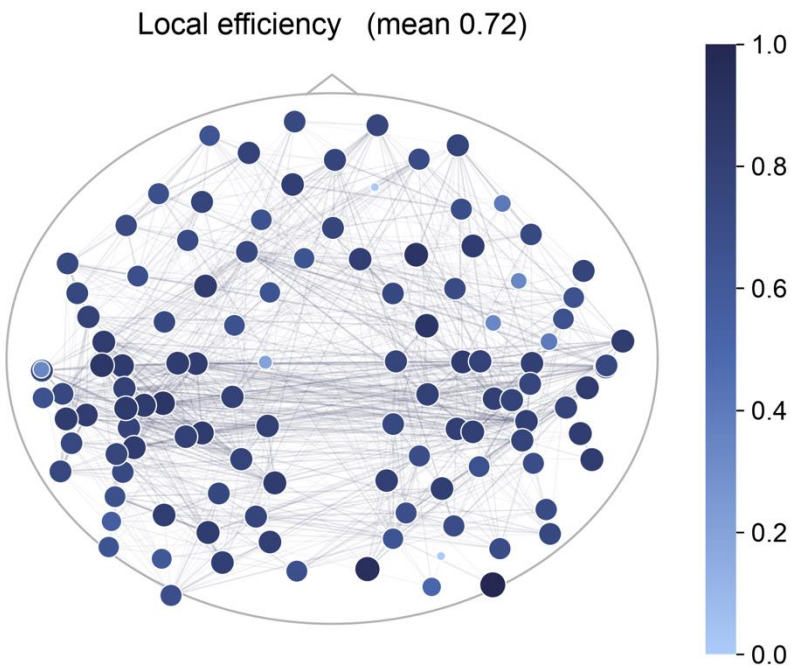
routes persist

Local efficiency measures how efficiently a node's neighbours communicate after that node is removed; higher values imply **fault tolerance**.

Gupta (2024); Wang, Zuo & He (2010); Niu et al. (2013). Original diagrams.

Clustering and local efficiency in our running data





In this example participant

C = 0.53

mean clustering (binary); 0.29 weighted

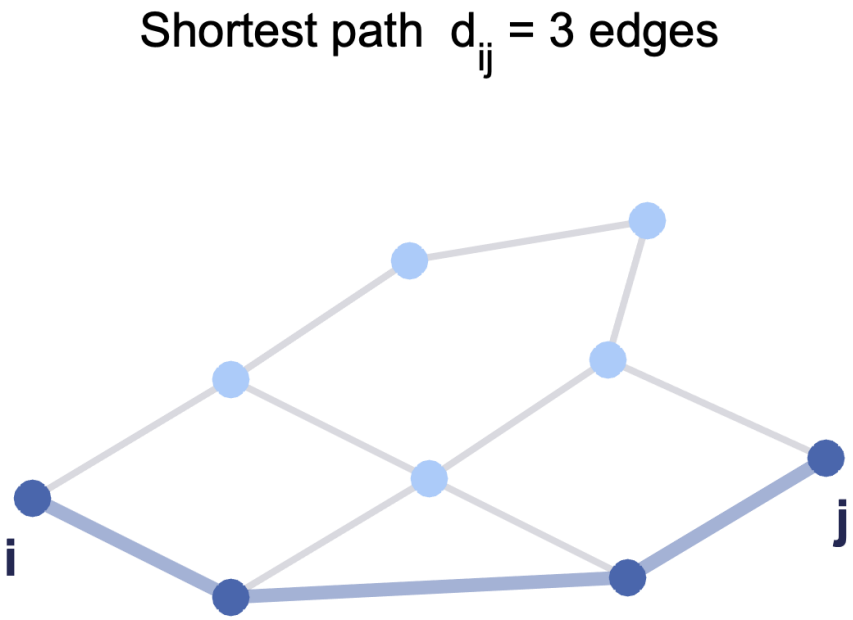
0.72

mean local efficiency

Reading it

- Most channels sit in tightly knit neighbourhoods: their neighbours are also connected to each other
- Is 0.53 high? A random graph with the same degrees has C ≈ 0.22: we need a reference (null models, next)
- **fNIRS: neighbouring channels share optodes and scalp: short-range edges inflate local measures**

Integration: path length and global efficiency



$$L = \frac{1}{N(N-1)} \sum_{i \neq j} d_{ij}$$

Characteristic path length: average shortest distance0 (measured in units of edges)

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

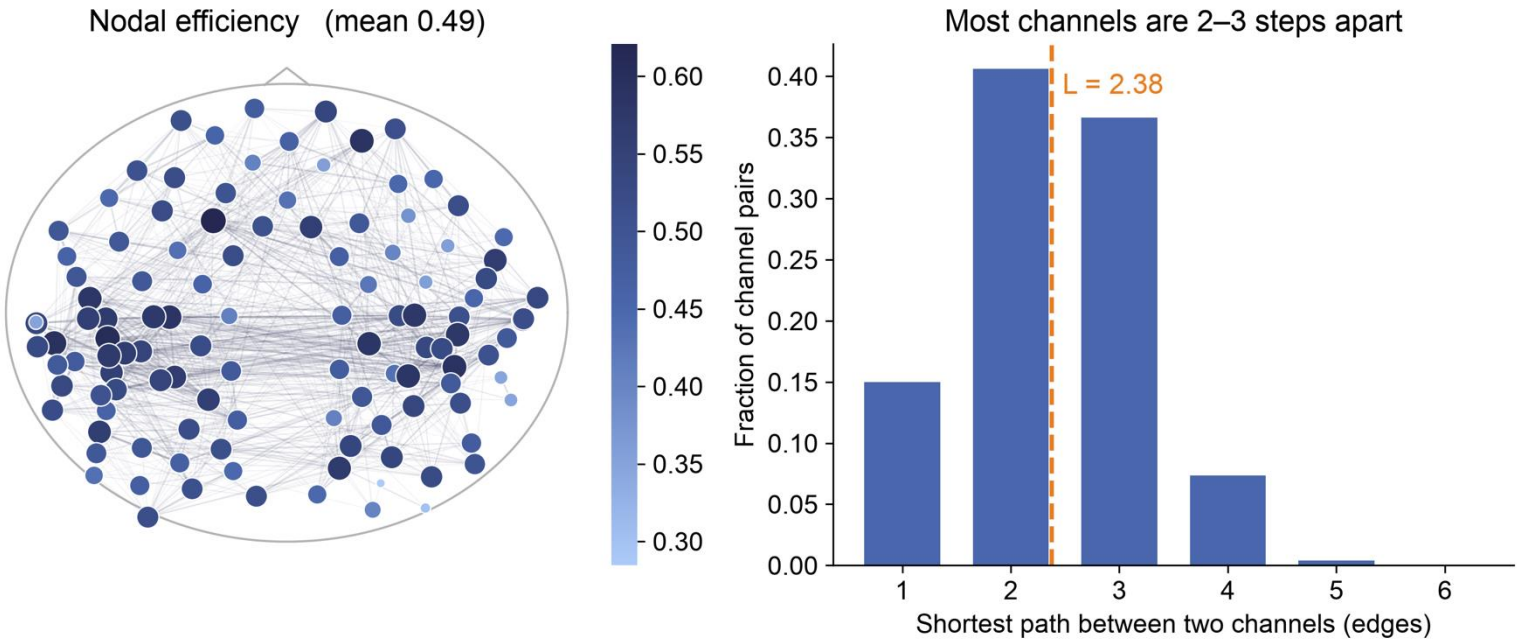
Global efficiency: average inverse distance

$$\ell_{ij} = 1/w_{ij}$$ weighted graphs: strong edge = short edge

Short paths / high efficiency → information from distant parts of the system can be combined in a few steps. With fNIRS (and most neuroimaging), a "path" is a chain of statistical dependencies between hemodynamic signals.

Watts & Strogatz, Nature (1998); Latora & Marchiori, Phys. Rev. Lett. (2001); Achard & Bullmore, PLoS Comput. Biol. (2007)

Integration in our running data



In this example participant

L = 2.38

steps on average (connected graph)

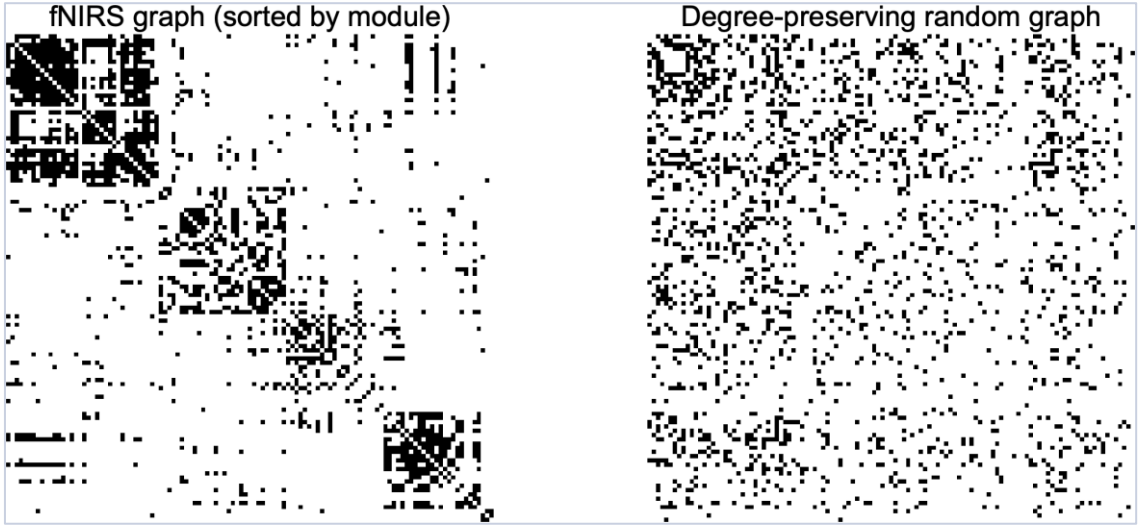
E = 0.49

global efficiency; 0.26 weighted

Reading it

- **Nodal efficiency:** mean inverse distance from each channel to all others
- 77% of channel pairs are 2–3 steps apart; none is more than 6
- The graph is connected at this density, so L is defined; if it fragments, use efficiency ($1/\infty = 0$)

Numbers mean nothing if not compared to null models



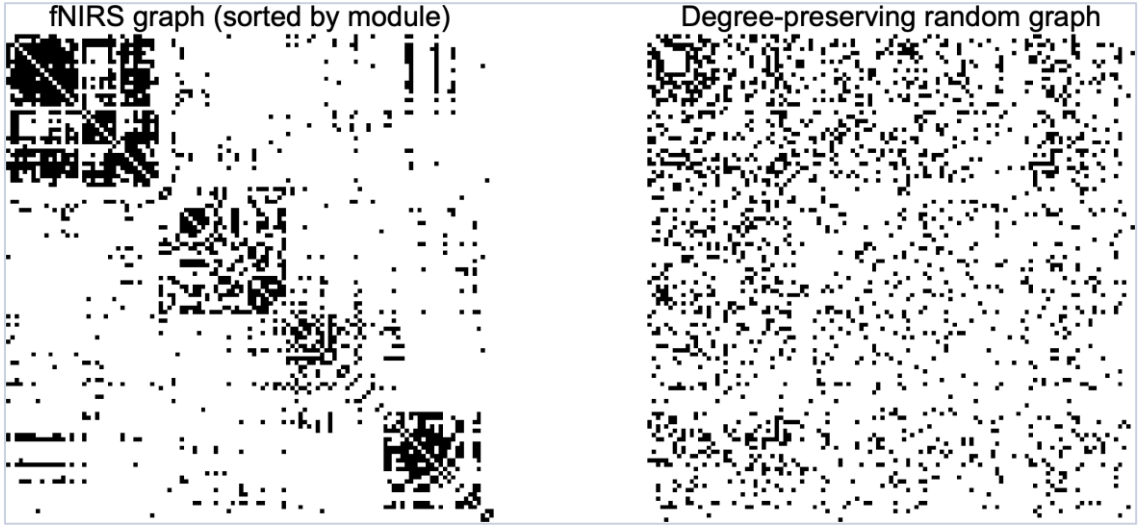
Common null models

- **Erdős–Rényi:** same N and number of edges
- **Degree-preserving rewiring:** same degree of every node (Maslov–Sneppen)
- **Lattice:** same degrees, maximal clustering
- **Correlation-based nulls:** random matrices with the same mean and variance of r

Normalised measures: $\gamma = C/C_{rand}$, $\lambda = L/L_{rand}$.

Average over many random graphs.

Numbers mean nothing if not compared to null models



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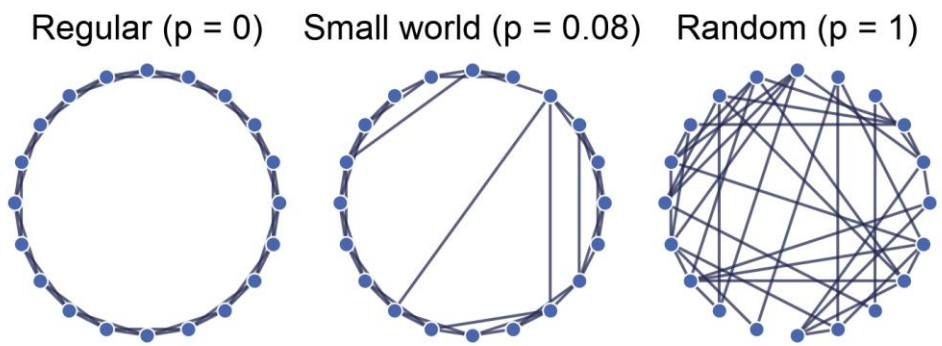
Normalised measures: γ = C/C_rand, λ = L/L_rand.

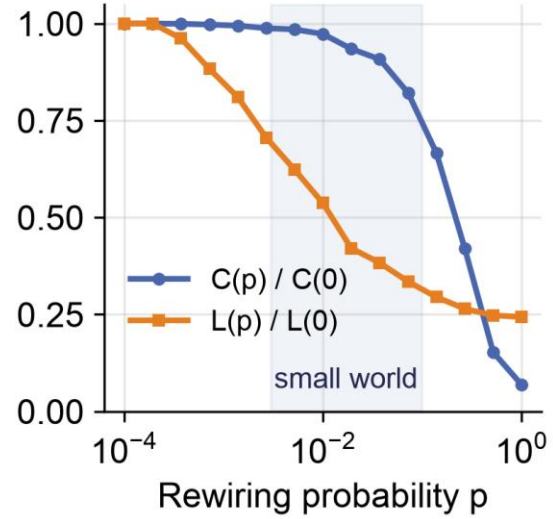
Average over many random graphs.

Watts and Strogatz generative model

- **Rewiring a ring lattice with probability p**
- A few random shortcuts collapse the path length while clustering stays high: **this property sits between order and randomness**

$$\sigma = \frac{C / C_{rand}}{L / L_{rand}}$$

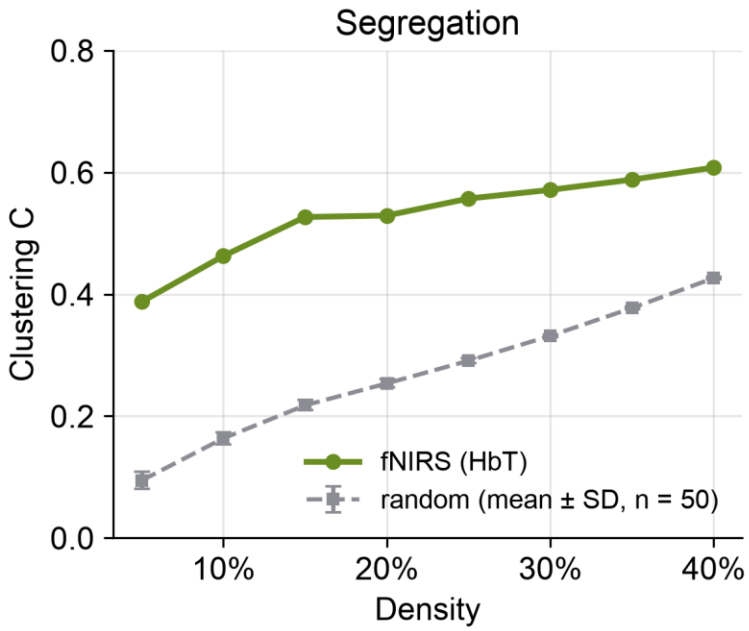


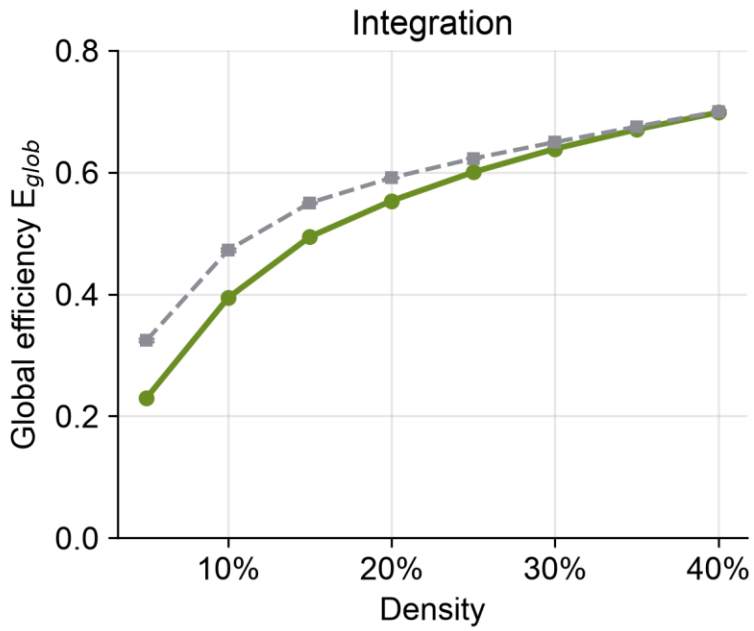


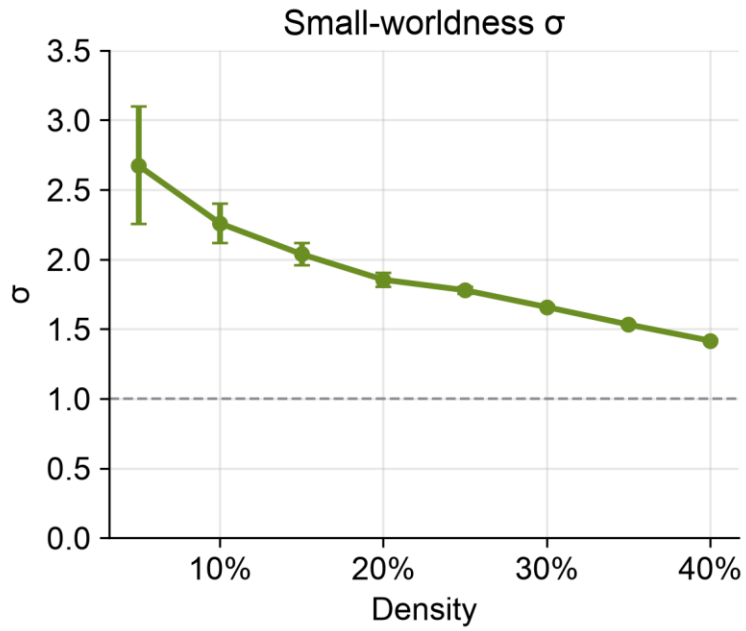
Small world = clustering much higher than random (C/C_rand ≫ 1) with path length close to random (L/L_rand ≈ 1) → σ > 1

Maslov & Sneppen, Science (2002); Zalesky, Fornito & Bullmore, NeuroImage (2012); Watts & Strogatz, Nature (1998); Humphries & Gurney, PLoS One (2008); Telesford et al., Brain Connect. (2011)

Our example: segregation and integration over a density range







2.4×

C / C_rand at 15% density (± 0.09)

1.19

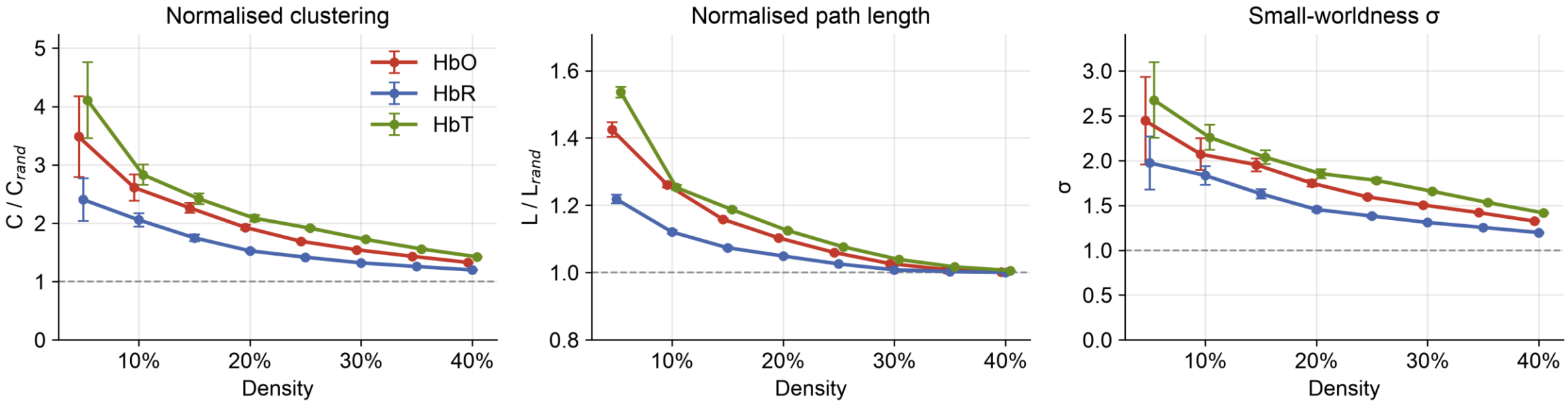
L / L_rand at 15% density (± 0.005)

σ = 2.0

small-worldness at 15% (± 0.08)

Niu et al., PLoS One (2012); Novi, Rodrigues & Mesquita, Biomed. Opt. Express (2016)

HbO, HbR and HbT yield different properties but similar behaviour



- HbR stays closest to random (σ = 1.63 vs 1.95 HbO, 2.04 HbT at 15%)
- HbT ≈ HbO: larger amplitude dominates
- All three are small-world (σ > 1) at every density; differences decrease as density grows

Good practice

- Report more than one chromophore
- Do not mix chromophores across subjects or groups

Hands-on #2

Scan, or open in any browser

rcmesquita.info/fnirs-graphs/handson2.html

≈ 20 min · in pairs

Integration, segregation and small worlds

WHAT TO DO · follow the numbered steps on the page

1. Clustering, path length and efficiency (binary and weighted)
2. Compare with degree-preserving random graphs
3. Small-worldness across densities
4. Compare HbO, HbR and HbT
5. Watts–Strogatz: rewire a ring lattice
6. Coarse-grain channels into AAL regions

DISCUSS WITH YOUR PAIR

- Is C = 0.5 high? Compared to what?
- Does σ > 1 tell us something about the brain, or about correlation matrices?
- Which single number would you use to compare two groups?

Groups of graph measures by the question they answer

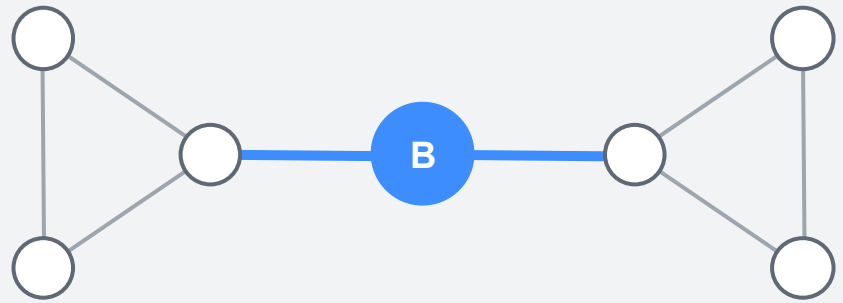
1	**Connectivity**	*How connected is each node?*	degree, strength, density, degree distribution
2	**Segregation**	*Are there densely interconnected groups?*	clustering coefficient, local efficiency, modularity
3	**Integration**	*How easily does information combine across the graph?*	characteristic path length, global efficiency
4	**Centrality**	*Which nodes are most important for the graph?*	betweenness, eigenvector, participation, hubs
5	**Resilience**	*How does the graph tolerate damage?*	targeted and random node removal

Rubinov & Sporns, NeuroImage (2010); Bullmore & Sporns, Nat. Rev. Neurosci. (2009)

Centrality: which nodes matter most for the graph?

BETWEENNESS CENTRALITY

Which node bridges the shortest routes between communities?



bridge node

Betweenness centrality is the fraction of shortest paths that pass through a node; high values identify **network bridges**.

OTHER WAYS TO BE IMPORTANT

Degree / strength: many direct edges, or strong ones

Betweenness: lies on many shortest paths: a bridge

Eigenvector: connected to other well-connected nodes

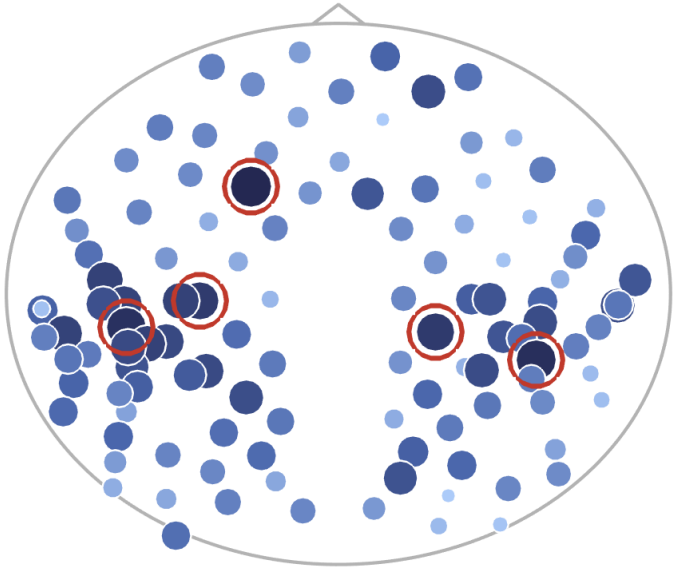
Closeness: few steps from every other node

Each measure answers a different question, so each can pick different hubs.

Gupta (2024), Niu et al. (2013). Original diagrams.

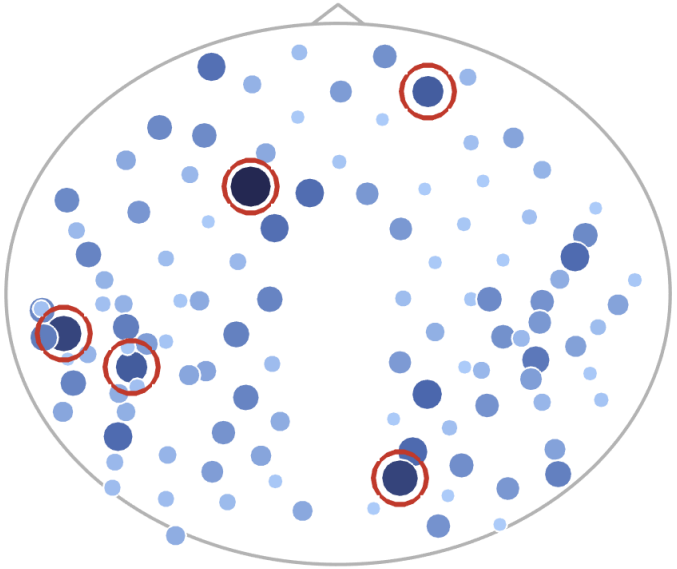
Hubs: which channels are central?

Strength



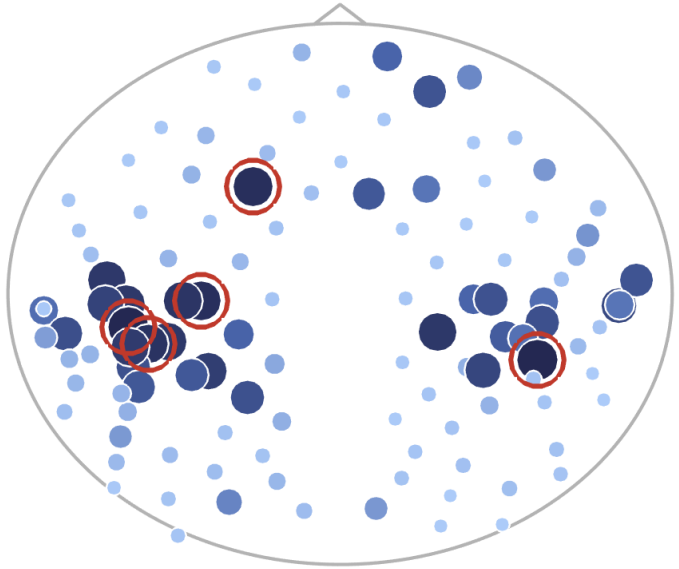
Strength
Sum of edge weights: locally well connected

Betweenness



Betweenness
Lies on many shortest paths: a bridge

Eigenvector

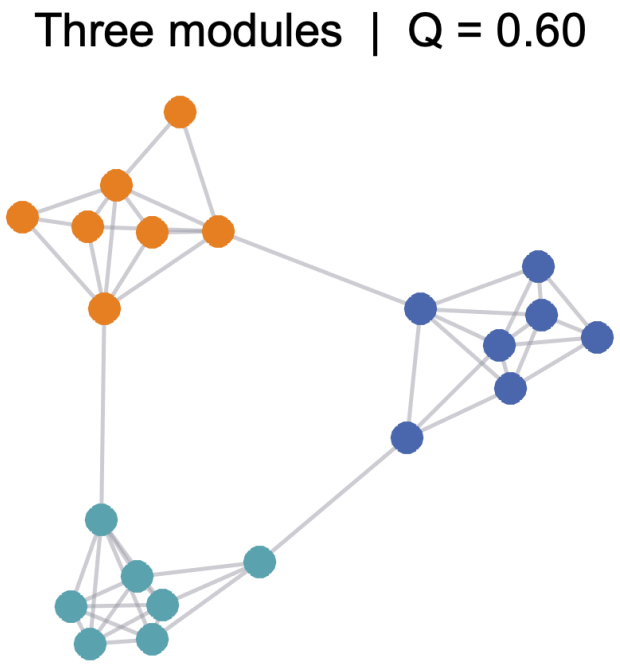


Eigenvector
Connected to other well-connected nodes

Rank correlation with strength: eigenvector 0.79, betweenness 0.44.

A “hub” depends on the measure.

Modules: communities within the graph



Compares the weight inside modules with the weight expected by chance for the same node strengths.

$Q > 0$: **community structure**

$$Q = \frac{1}{2m} \sum_{ij} \left[w_{ij} - \gamma \frac{s_i \, s_j}{2m} \right] \delta(M_i, M_j)$$

w_{ij}: edge weight; s_i: node strength; m: total weight

$\delta(M_i, M_j) = 1$ if i and j are in the same module

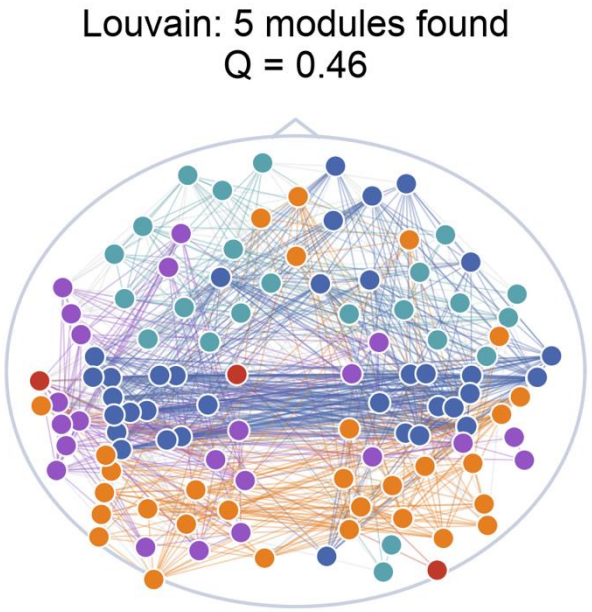
γ: resolution ($\gamma > 1 \rightarrow$ more, smaller modules)

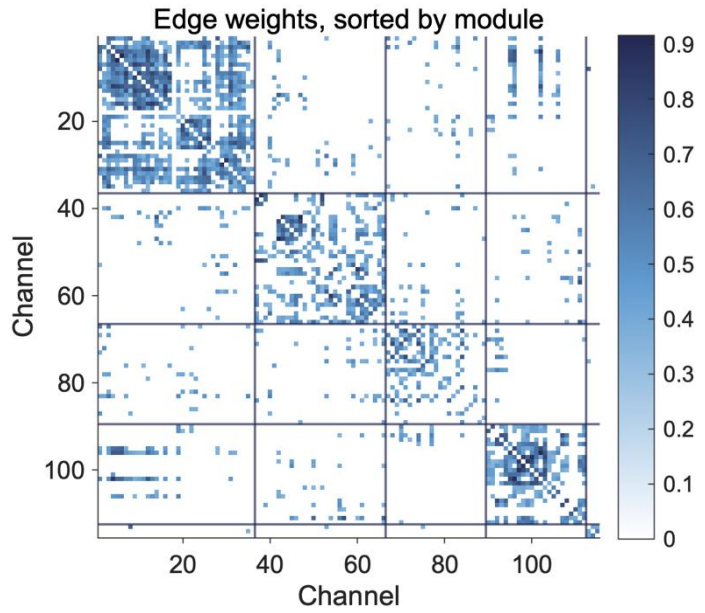
In practice

- Louvain (Blondel et al. 2008): greedy, fast, stochastic. Keep the best of many runs, or a consensus partition
- Many near-optimal partitions exist (degeneracy): check how stable the modules are

Newman, PNAS (2006); Blondel et al., J. Stat. Mech. (2008); Good, de Montjoye & Clauset, Phys. Rev. E (2010)

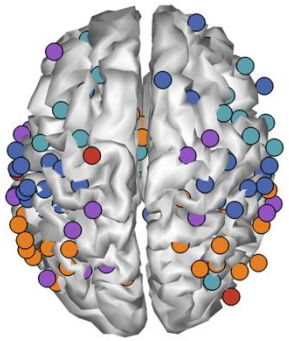
Modules in our example data: Louvain algorithm

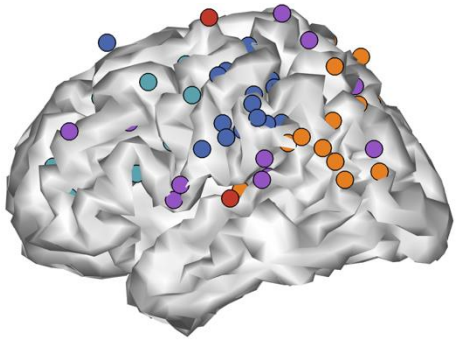


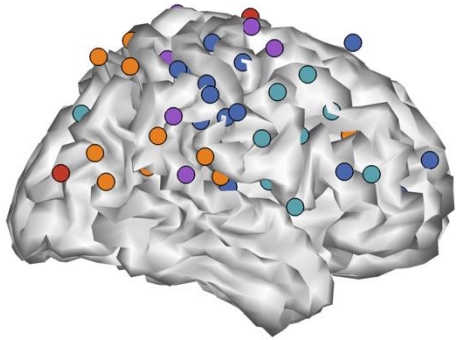


Q = 0.46, 5 modules

- **M1** bilateral parietal / sensorimotor (23 of 36)
- **M2** mixed parietal, temporal, occipital
- **M3** frontal (18 of 23)
- **M4** left temporal / frontal (17 of 23 left)
- **M5** 3 channels







Anatomy, or geometry of the cap?

Neighbouring channels share optodes and scalp, so spatially compact modules are expected for both reasons.

Many ways to find modules

Method	What it maximises (or minimises)	Number of modules	Good to know
Louvain	Modularity Q (greedy)	**found**	Fast, stochastic; tune with γ. Used on the previous slide
Leiden	Modularity Q (greedy + refinement)	**found**	Fixes Louvain's occasionally disconnected modules
Leading eigenvector	Modularity Q (spectral)	**found**	Deterministic; splits the graph in two, repeatedly
Infomap	Compression of a random walk	**found**	Modules = where flow gets trapped
Spectral clustering	Normalised cut (k-means on eigenvectors)	**chosen (k)**	You ask for k modules and get k
Hierarchical clustering	Linkage distance (e.g. 1 − r)	**chosen (cut)**	A whole tree; the cut sets the number
Stochastic block model	Likelihood of a generative model	**either**	Also finds non-assortative blocks
Consensus clustering	Agreement across many partitions	**found**	Stabilises stochastic methods

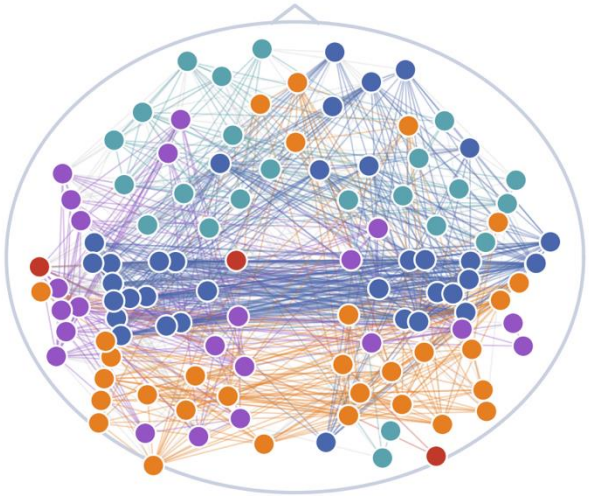
Main difference for the user: what is optimised, and is the number of modules **found** or **chosen**?

Choosing k imposes structure, i.e., you get k modules whether or not they are there.

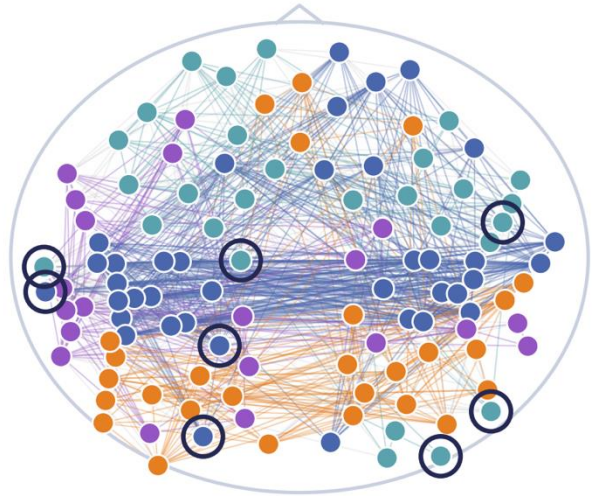
Blondel et al. (2008); Traag, Waltman & van Eck (2019); Newman (2006); Rosvall & Bergstrom (2008); Ng, Jordan & Weiss (2002); Lancichinetti & Fortunato (2012); Fortunato, Phys. Rep. (2010)

Louvain vs spectral clutering in the example data

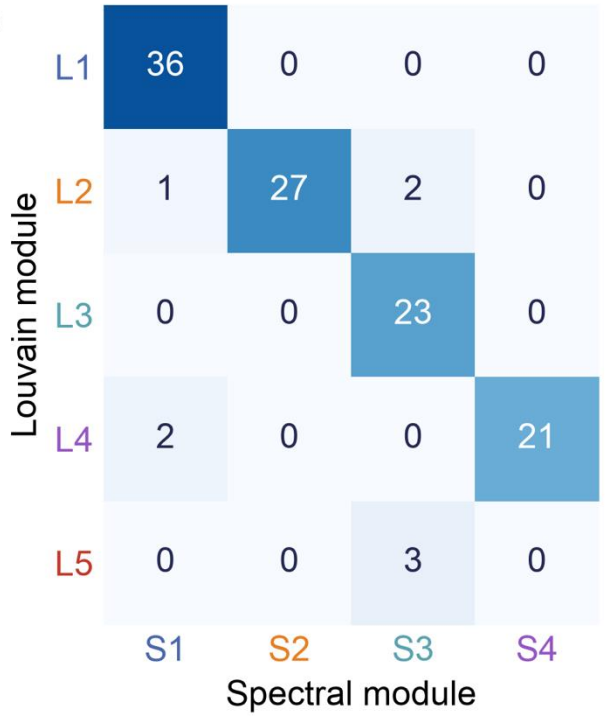
Louvain: 5 modules found
Q = 0.46



Spectral clustering: k = 4 chosen
Q = 0.45 (circled: 8 channels that switch)

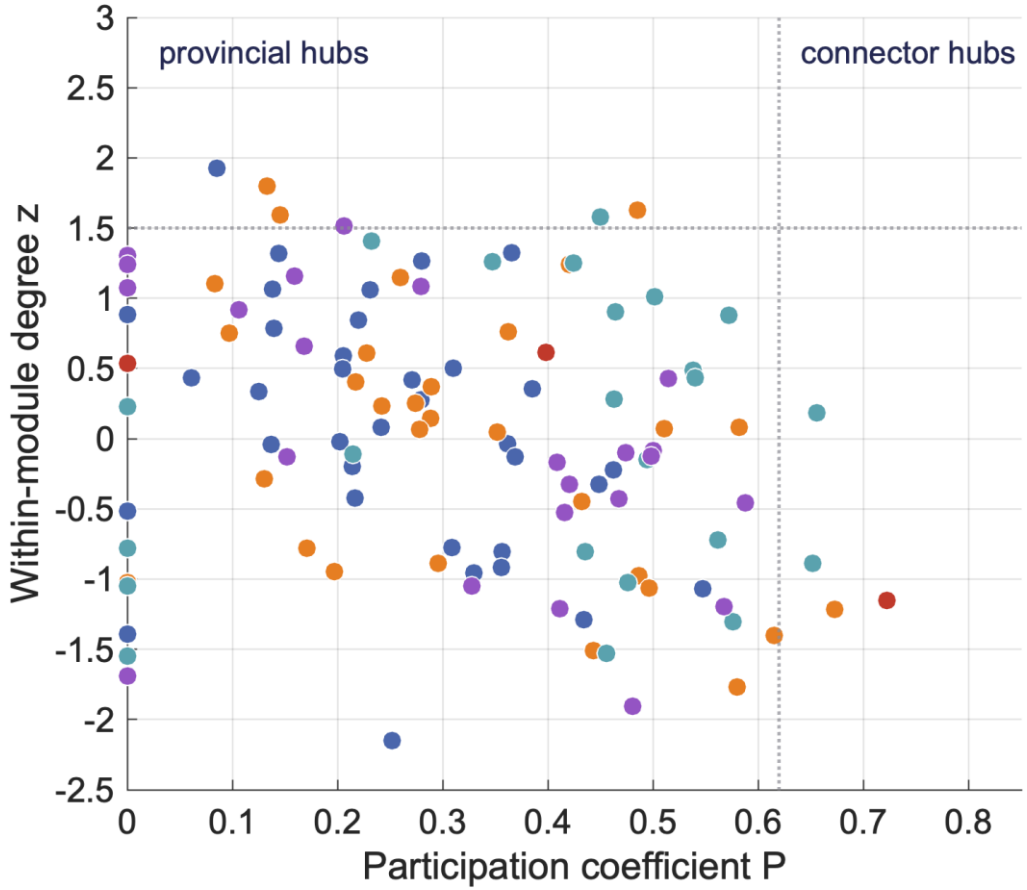


Channels in each pair of modules
NMI = 0.85, ARI = 0.85



- **Agree on the large modules** (parietal/sensorimotor, posterior, frontal, left temporal/frontal): 107 of 115 channels keep their module.
- **Differ at the edges:** Louvain's 3-channel module L5 is absorbed when k = 4; Q barely changes (0.46 vs 0.45).
- **Louvain is not stable either:** 200 single runs gave 4, 5 or 6 modules (18%, 75%, 7%). Report the method, its settings and the stability.

Node roles: provincial and connector hubs



Participation coefficient measures how evenly a node's edges are spread across modules:

$$P_i = 1 - \sum_s \left(\frac{k_{is}}{k_i} \right)^2$$

- **P ≈ 0:** all edges inside the node's own module
- **P ≈ 1:** edges spread evenly across modules
- **z:** within-module degree, z-scored within each module

In this subject (15% density)

- 6 provincial hubs, 0 connector hubs
- **fNIRS**: connector hubs are edges are mostly local (few channels link modules)

Guimerà & Amaral, Nature (2005); Power et al., Neuron (2013)

Resilience (robustness): how does a network cope with losing nodes?

Resilience in graphs

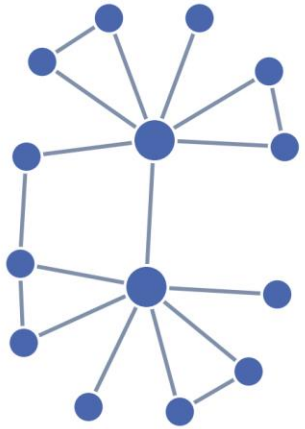
- The ability to stay connected and keep short paths when nodes are lost
- A property of the whole system: no single node can show it

How we measure it

- Remove nodes one at a time: at random (failure) or with a specific strategy (e.g., most connected first, a.k.a. attack)
- Recompute global efficiency and the size of the largest connected piece

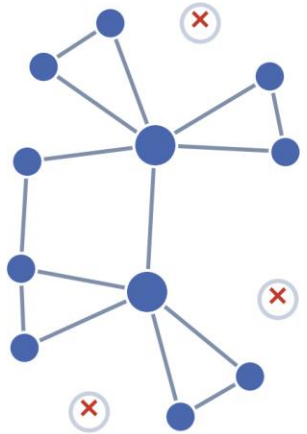
- **Brain**: resting networks resist random failure; lesions and many disorders hit hubs
- **fNIRS**: how much do results depend on losing channels (poor contact, a loose holder)?

Intact network
two hubs (large nodes)



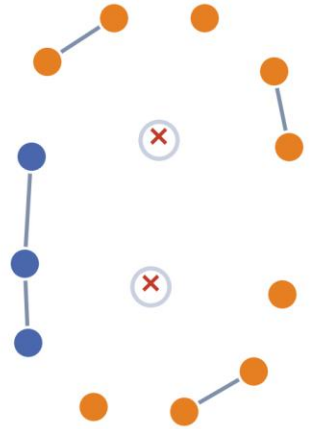
1 piece · largest holds 14 of 14 nodes

Random failure
3 random nodes removed



1 piece · largest holds 11 of 11 nodes

Targeted attack
the 2 hubs removed



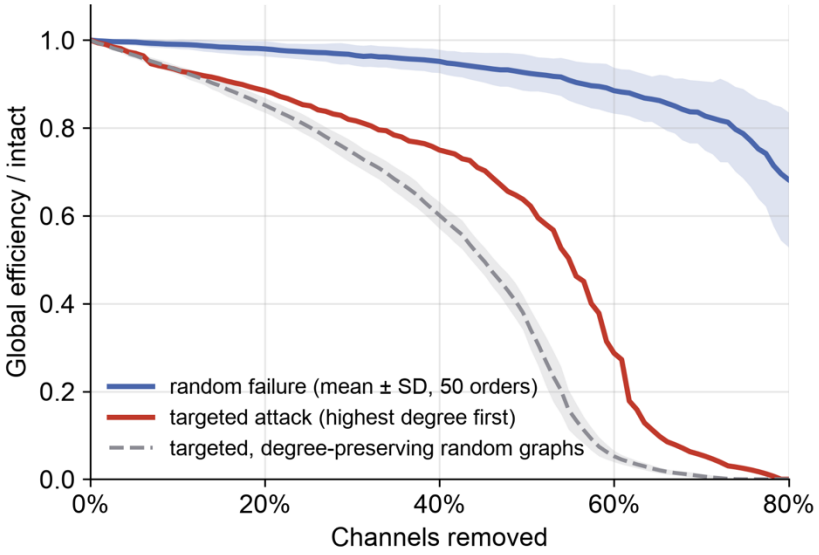
7 pieces · largest holds 3 of 12 nodes

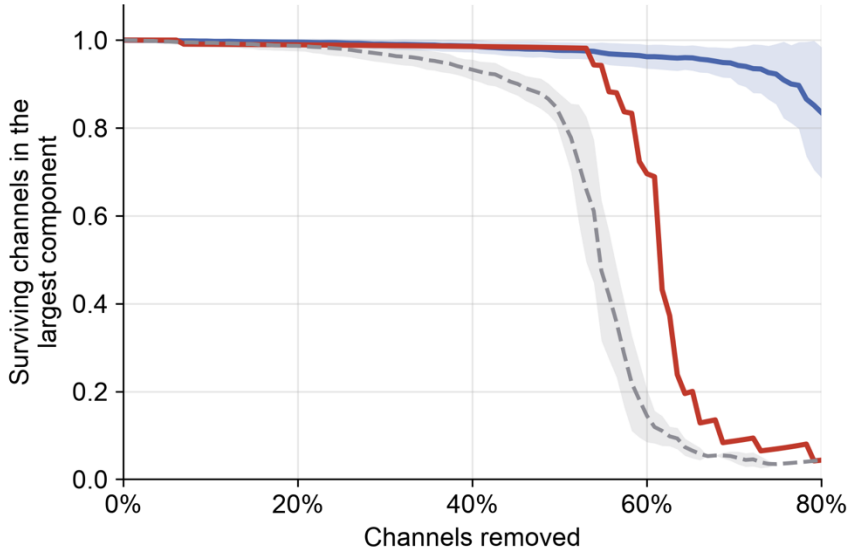
blue: largest connected piece · orange: cut off

Albert, Jeong & Barabási, Nature (2000); Achard et al., J. Neurosci. (2006); Crossley et al., Brain (2014)

Resilience in our running example

Example participant · HbT · 15% density · binary graph · 115 channels · removing channels one by one





0.88

efficiency left after removing 60% at random (± 0.05)

0.29

… after removing the 60% most connected channels first

0.05

… same attack on random graphs with the same degrees

- **Robust to random failure:** after losing 60% of channels at random, 88% of the efficiency remains and the graph stays essentially in one piece.
- **Vulnerable to losing hubs:** removing the most connected channels first leaves 29% at 60%; the first channels are cut off after only 8 removals.
- **More resilient than a random graph with the same degrees:** dense local clustering gives detours around the hubs. Part of that redundancy comes from neighbouring channels sharing tissue.

Hands-on #3



Scan, or open in any browser

rcmesquita.info/fnirs-graphs/handson3.html

≈ 30 min · in pairs

Hubs, modules and resilience

WHAT TO DO · follow the numbered steps on the page

1. Degree and its distribution
2. Strength, betweenness and eigenvector centrality
3. Modules: Louvain (number found) vs spectral clustering (k chosen)
4. Node roles: provincial and connector hubs
5. Resilience: random failure vs targeted attack

DISCUSS WITH YOUR PAIR

- Are the same channels hubs for every measure?
- Run Louvain again, or change k. Same modules? Do they follow anatomy or the probe?
- Why are targeted attacks more damaging?

SECTION 4

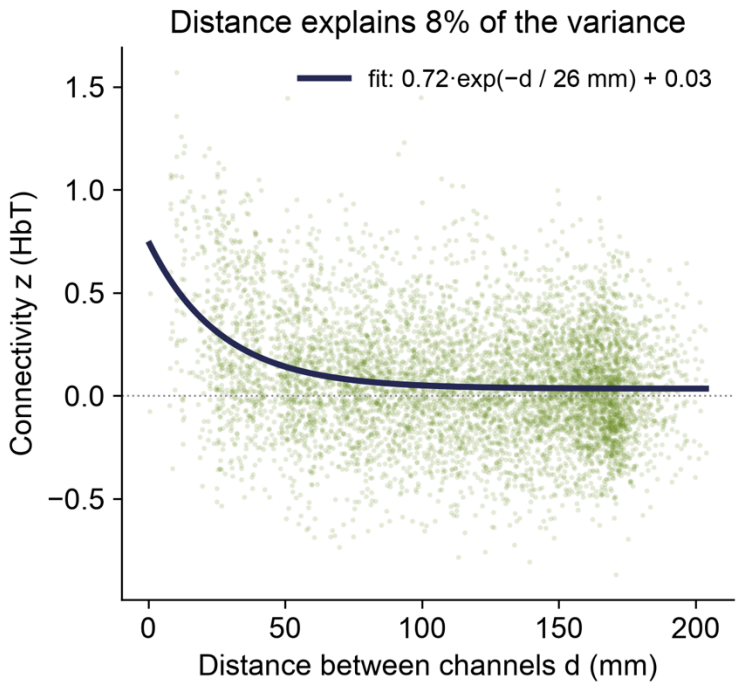
Caveats and good practice for fNIRS graphs

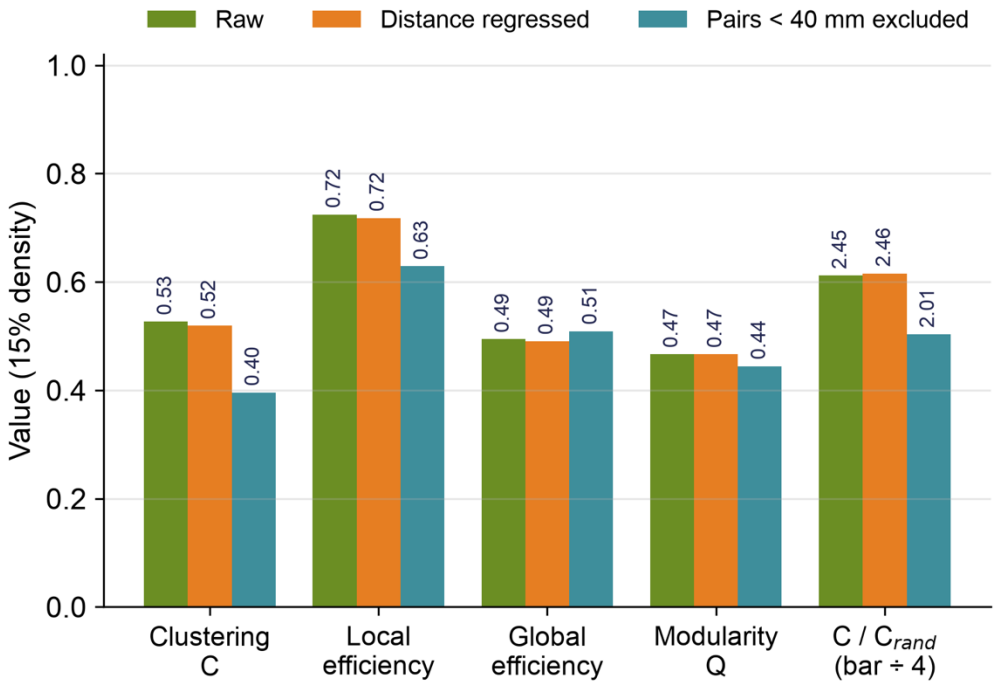
Separating the brain from the measurement

1. Brain as a complex system
2. From matrix to graph
3. What graphs tell us
4. **fNIRS caveats & practice**

Caveat 1 – Neighbouring channels share optodes and scalp

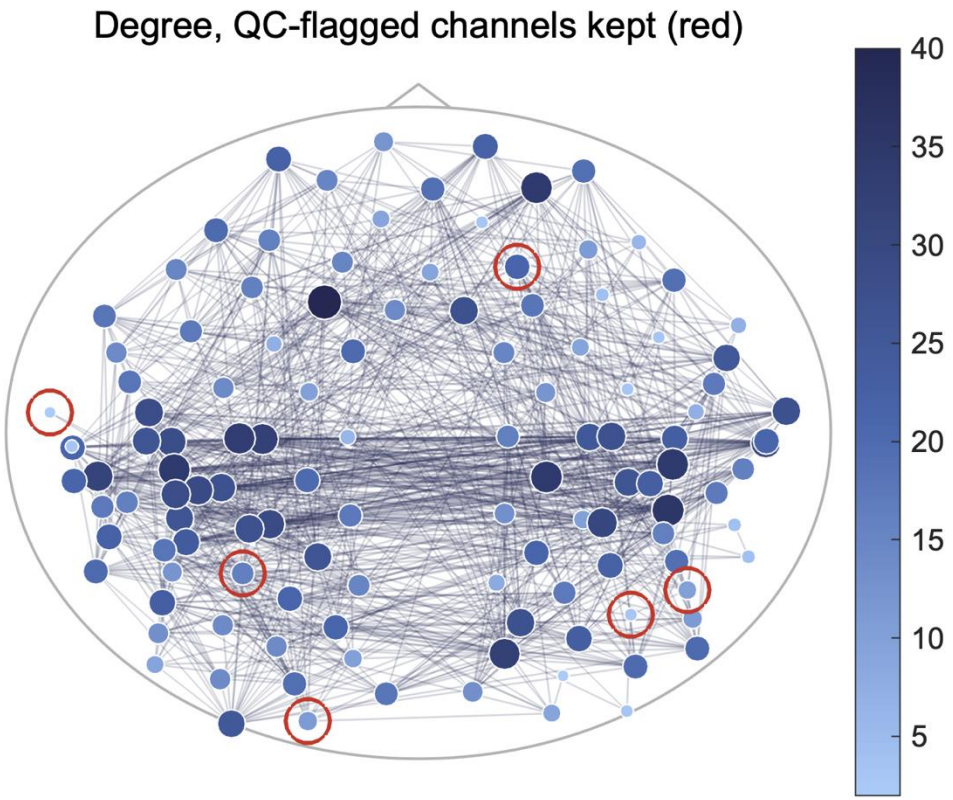
Connectivity follows (physical) distance between channels





- **Report short-range edges:** 23% of edges are < 40 mm (vs 9% of pairs). Without them, local measures drop (clustering −25%, local efficiency −13%); global ones do not.
- **Regressing distance is a gentle correction:** $\tilde{z}$ = z − f(d) keeps connectivity beyond what distance predicts. Here distance explains < 10% of the variance and the graph barely changes.
- **Clustering is not only geometry:** C/C_rand stays ≈ 2 without short pairs.

Caveat 2 – Channel quality and preprocessing shape the graph



QC-flagged channels (red) have half the degree of good ones (10.5 vs 18.4)

Channel quality

- Bad channels look like peripheral, poorly connected nodes
- Pruning changes N, and differently per subject
- Report the exclusion criteria and the final number of nodes

Systemic physiology

- Shared scalp/systemic signals raise all correlations: dense, highly clustered graphs with 'hubs' where scalp flow is strongest
- Short-channel / physiological regression changes topology, not just the maps
- **Graph metrics are only as clean as the matrix they come from**

Abdalmalak, Novi et al., Front. Neurosci. (2022); Novi, Rodrigues & Mesquita, Biomed. Opt. Express (2016)

From one subject to a study: reliability and group comparisons

1 Reliability

- fNIRS: most global metrics and nodal degree / efficiency show fair to excellent test–retest reliability
- Nodal betweenness is less reliable
- Reliability depends on threshold and chromophore

2 Group statistics

- Same nodes, same density range for everyone
- Metric curves or AUC across densities
- Permutation tests; FDR across nodes
- Network-based statistic for edges

3 Avoid

- Different thresholds per group
- Raw metrics with different N or density
- Interpreting nodes as regions without registration

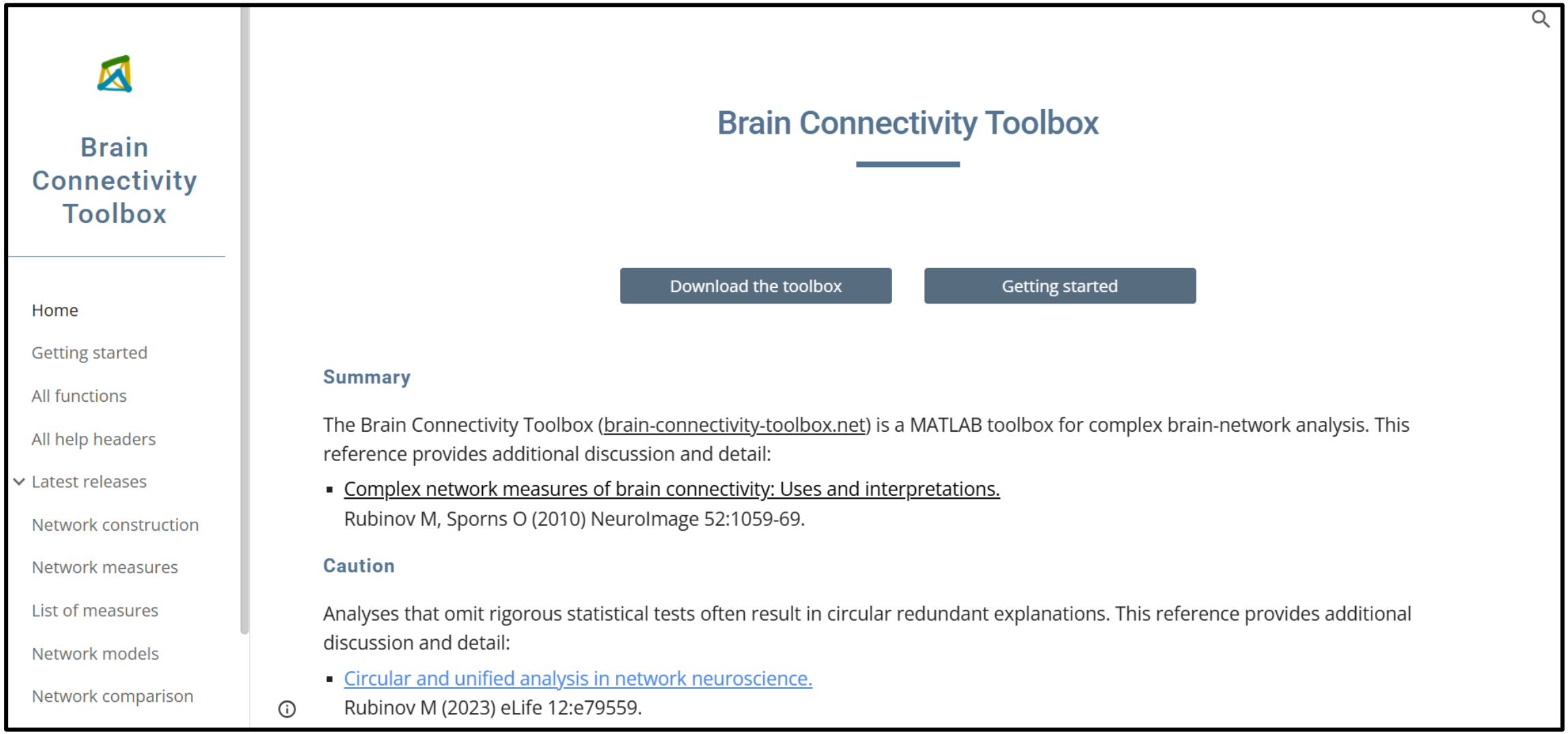
Single-subject graphs are descriptive; inference needs a sample, a common node set and a null model.

Niu et al., PLoS One (2013); Zalesky, Fornito & Bullmore, NeuroImage (2010); van Wijk et al., PLoS One (2010)

Reporting checklist for fNIRS graph analysis

- ✓ **Nodes**
  channels / ROIs / parcels; number per subject; exclusion criteria
- ✓ **Signal**
  chromophore; full preprocessing (systemic correction, prewhitening)
- ✓ **Edges**
  measure (Pearson, coherence…); Fisher z; time window length
- ✓ **Negatives**
  removed, absolute value, or signed analysis
- ✓ **Threshold**
  absolute or proportional; range of densities; connectedness
- ✓ **Weights**
  binary or weighted metrics; weight normalisation
- ✓ **Null model**
  type (random, lattice, correlation-based); number of nulls
- ✓ **Software**
  toolbox and version; random seeds for stochastic steps

Brain Connectivity Toolbox



Hands-on #4

Scan, or open in any browser

rcmesquita.info/fnirs-graphs/handson4.html

≈ 20 min · in pairs

fNIRS caveats: brain or measurement?

WHAT TO DO · follow the numbered steps on the page

1. Plot connectivity against the distance between channels
2. Regress distance, or exclude short pairs, and recompute
3. Keep the QC-flagged channels and look at their degree

DISCUSS WITH YOUR PAIR

- How much of the clustering is explained by distance?
- Why does regression change so little, while excluding short pairs changes more?
- What would you report in a paper?

Beyond static, single-layer graphs

1

Dynamic graphs

Sliding-window or time-resolved connectivity: how topology changes over minutes

2

Multilayer graphs

HbO and HbR (or frequency bands) as coupled layers of one network

3

Hyperscanning

Inter-brain graphs: edges between two people’s channels

4

Directed graphs

Effective connectivity or Granger causality: who drives whom

Take-home messages

1

Graphs re-describe the matrix to show the system

No new information, but properties of the whole pattern: integration, segregation, hubs, modules, resilience.

2

Construction is part of the result

The threshold is a control parameter: sweep it, use percolation, or stay weighted; report every choice.

3

Always compare with a reference

Sweep densities and normalise by null models; remember that correlation graphs are clustered by construction.

4

fNIRS sees one coarse window of a multiscale system

About one decade in space and time, through a haemodynamic filter: graphs need assumptions, and metrics depend on N.

5

Clean matrices make meaningful graphs

The preprocessing of Part 1 propagates directly into every graph metric.

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Thank you for your attention!

Any questions?

THE CHANNELS ARE OPEN.

