

# NACS 645 – Connections

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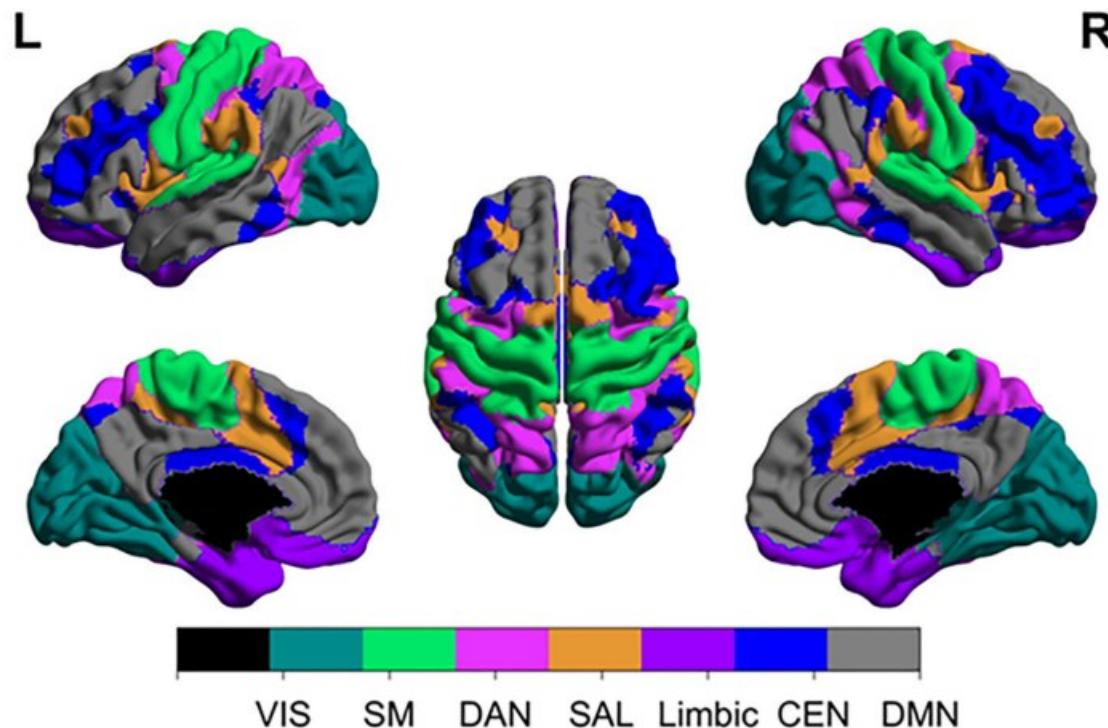
DEPARTMENT OF  
PSYCHOLOGY



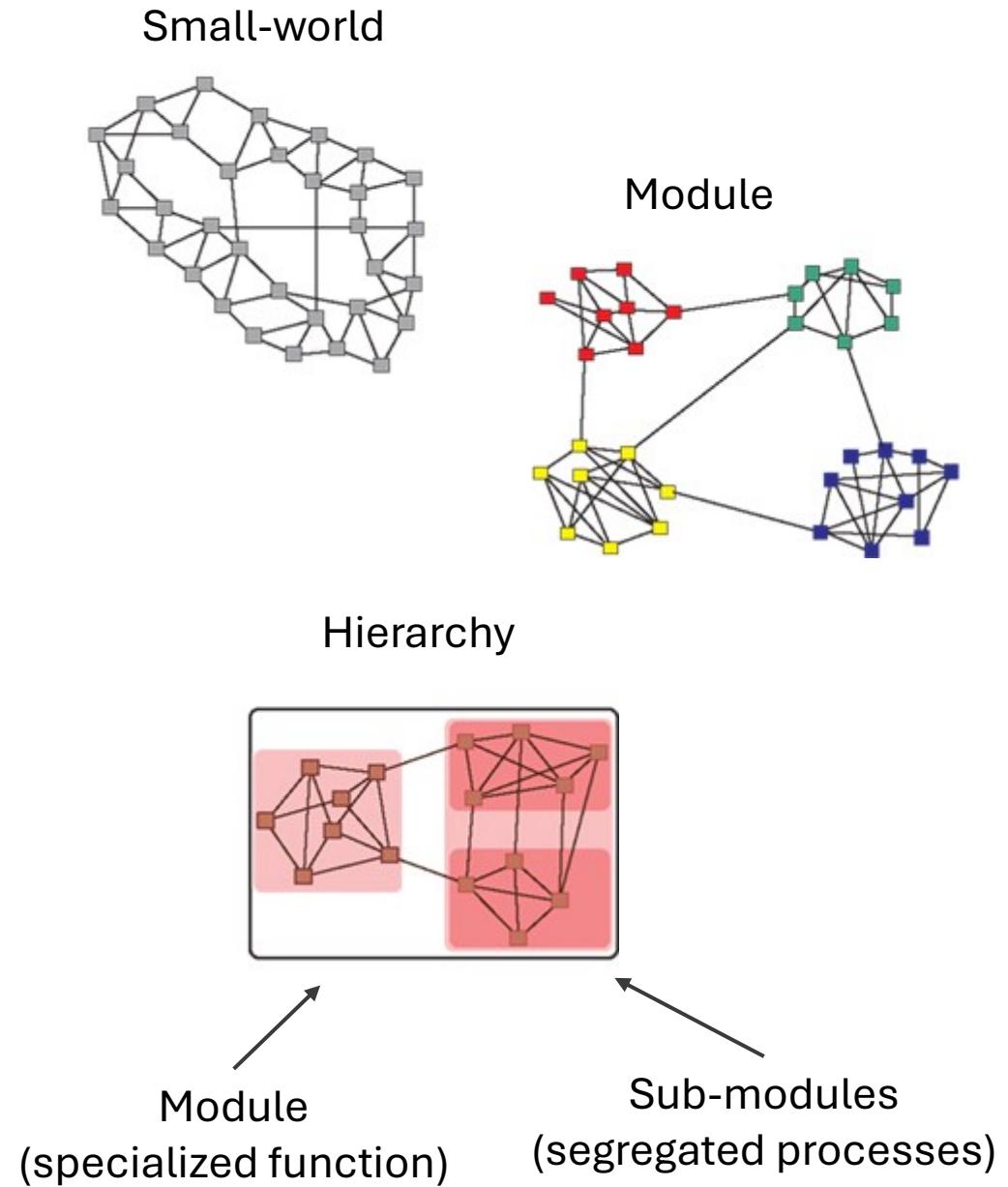
PROGRAM IN  
NEUROSCIENCE &  
COGNITIVE SCIENCE

# Topological Modularity: Early networks

The brain is hierarchically modular, with  
**modules and sub-modules.**



Boerger et al., 2023.  
*Frontiers in Human Neuroscience*



# Topological Modularity: Modularity of anatomy and functions

Meunier, Lambiotte et Bullmore, 2010. *Frontiers in Neuroscience*  
Seguin, Sporns et Zalesky, 2023. *Nature reviews neuroscience*

## Cognitive modularity

- Modularity is a property of brain regions
  - Mind organized into **modules**: specialized systems for processing certain inputs (vision, language)
  - Modules defined by: **domain specificity** (operate only on certain inputs), **encapsulation** (insulated from other knowledge), **automaticity** (mandatory operations), relatively **fixed neural architecture**
  - *Psychological-level* definition: modules are computational “boxes” in the mind

## Network modularity (predictive coding -compatible)

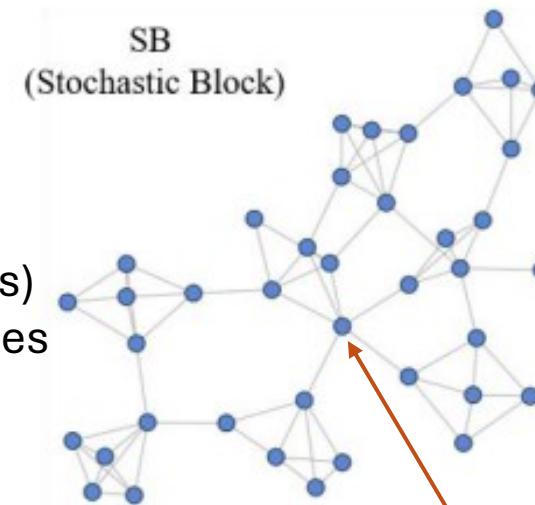
- Modularity is a property of networks that optimizes information communication
  - A module is a cluster of brain regions with **dense internal connectivity, sparse external connectivity and recursivity**
  - Brain networks are **hierarchically modular**: large modules (e.g., visual network) subdivided into smaller submodules (ventral vs. dorsal visual pathways) subdivided into smaller submodules
  - Modularity provides **computational advantages**: efficiency, robustness, balance between segregation (specialization) and integration (coordination)
  - Modules forward information with **dedicated paths and diffusion processes** to achieve *optimal signalling delay*

# Why are brain networks expected to be modular?

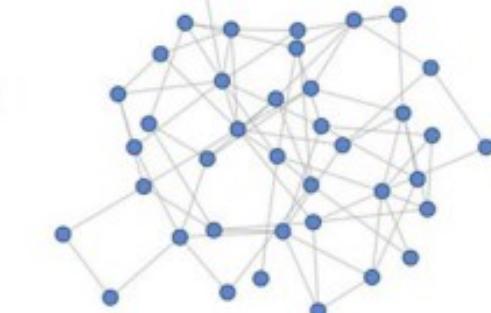
- **Small-world design:** high clustering within modules supports **locally segregated processing** (e.g., visual motion detection) at low wiring cost, while short path lengths **enable global integration** for generic functions (e.g., working memory)
- **Rich non-linear dynamic behaviors:** Modularity supports **fast intra-modular and slower inter-modular processes**; neural activity can remain **locally encapsulated**; **neural activity is balanced**: *activity doesn't die, doesn't spread network-wise*; **redundancy of signal**; **flexibility and stability** by allowing modules and submodules **reconfiguration**
- **Origins:** Modular networks arise naturally when structure and dynamics co-evolve. Connections between regions that tend to synchronize are reinforced; weak or unsynchronized links are pruned. Specialized submodules can be reused

# Network structures in the nature

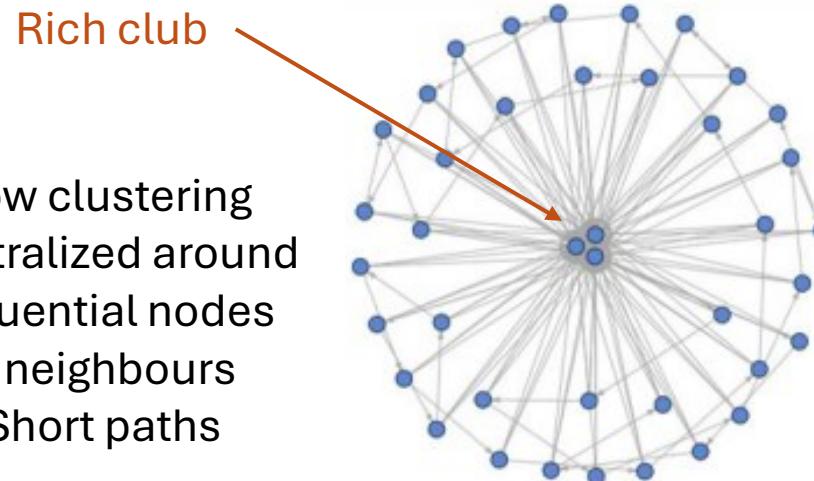
- High clustering  
(connection with similar nodes)
- Centralized around communities
  - 4 neighbours
  - Long paths



ER  
(Erdős-Renyi)

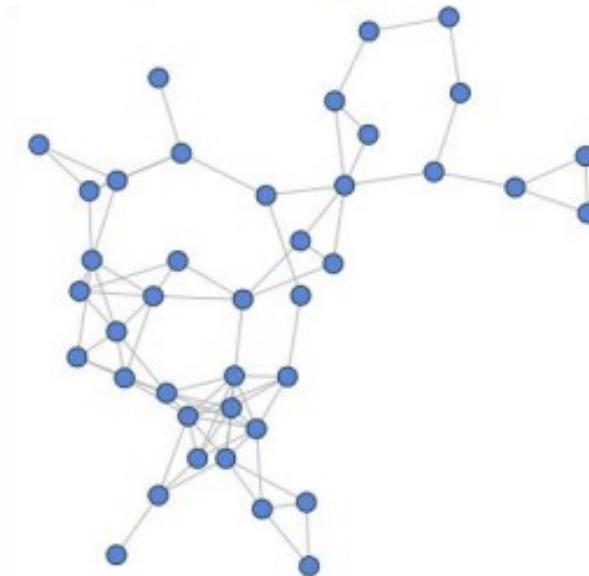


- Mid clustering
- Decentralized
- 2.5 neighbours
- Mid paths



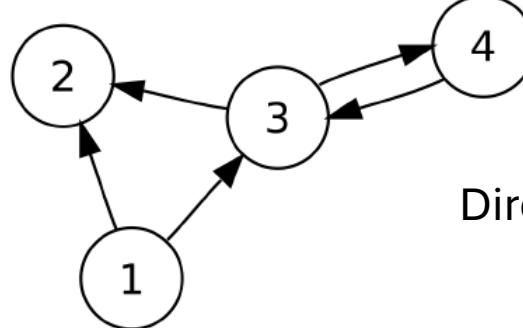
Hub

- Low clustering
- Centralized around influential nodes
- 2 neighbours
- Short paths

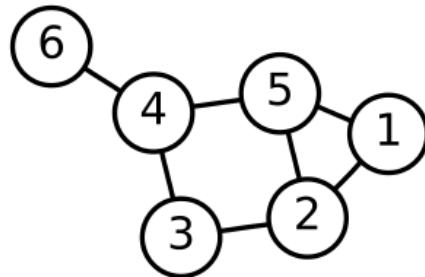


- Mid clustering
- Decentralized
- 2 neighbours
- Long paths

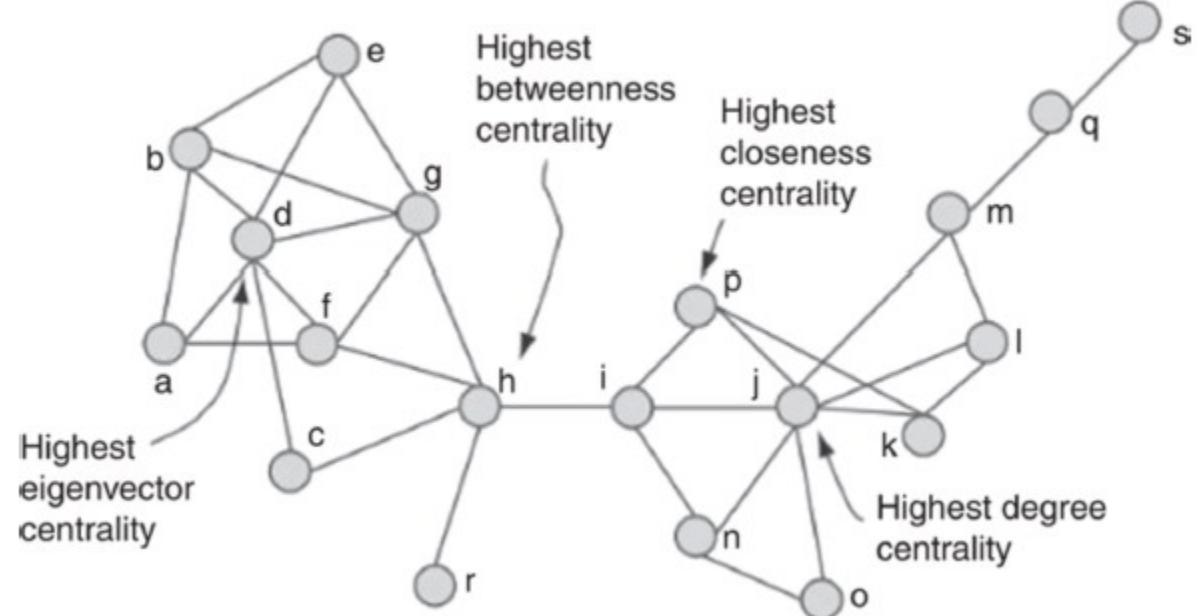
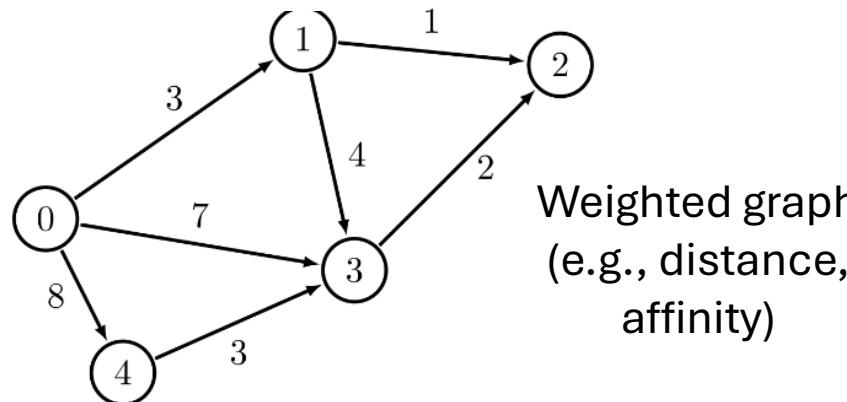
# Network graphs



Directed graph



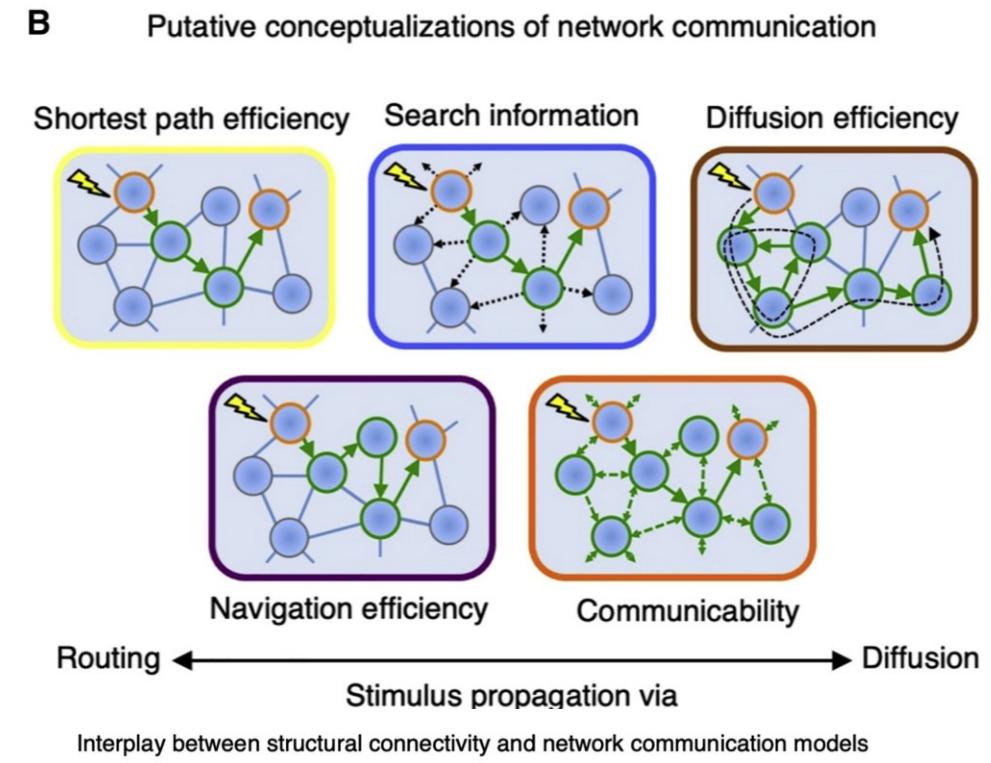
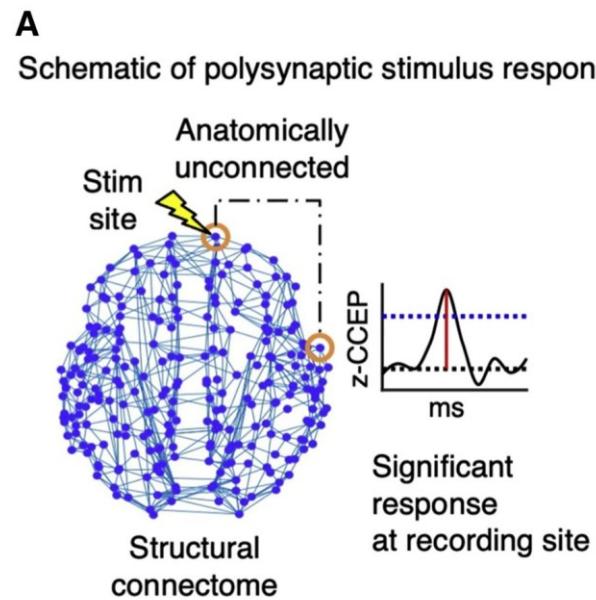
Undirected graph



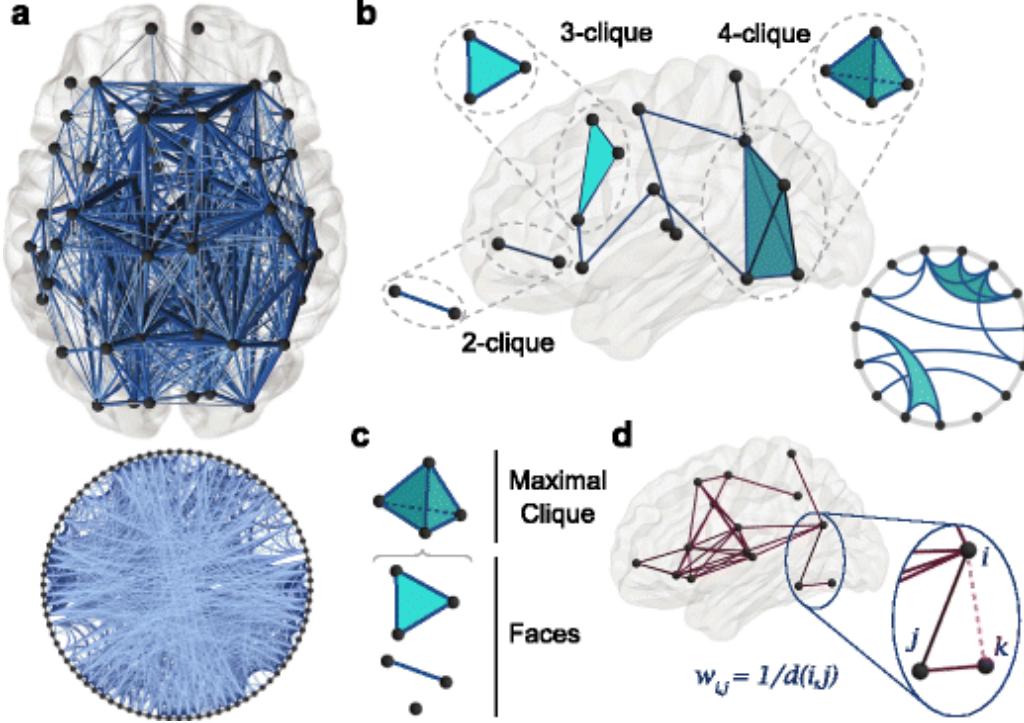
- **Degree Centrality:** number of incident edge on the node (in-degree vs out-degree)
- **Closeness Centrality:** how quickly/efficiently the node can reach the rest of the network
- **Betweenness Centrality:** how a node finds itself along the shortest path between other pairs of nodes in the graph
- **Eigenvector Centrality:** the node is linked both to many nodes and to other important nodes

# Signal propagation

- Structural connectivity alone doesn't fully predict how stimulation or neural signals propagate
- Information travels via short path, long paths, polysynaptic (multiple indirect) paths, broadcasting via multiple routes, random walks, etc.
- The mode of propagation is not fixed by the wiring, but constrained by task demands, network topology, physiological state, trade-offs

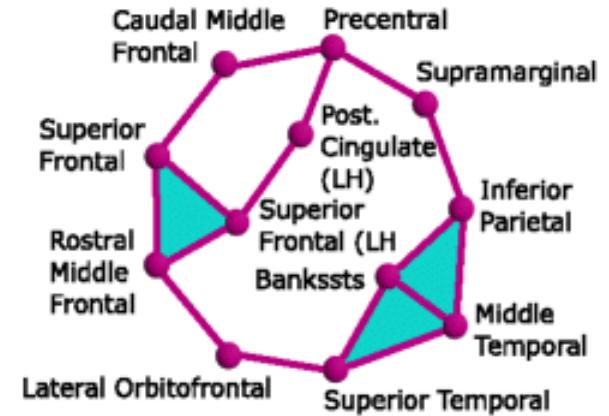
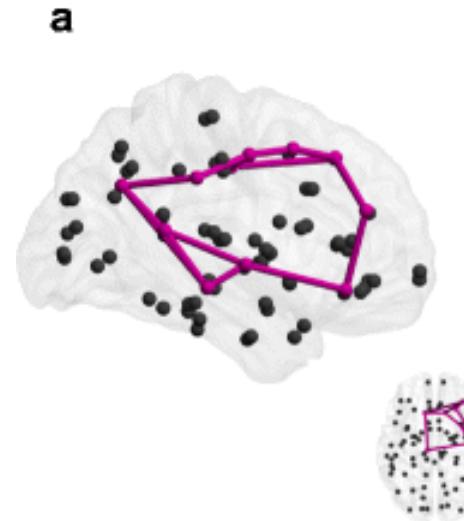
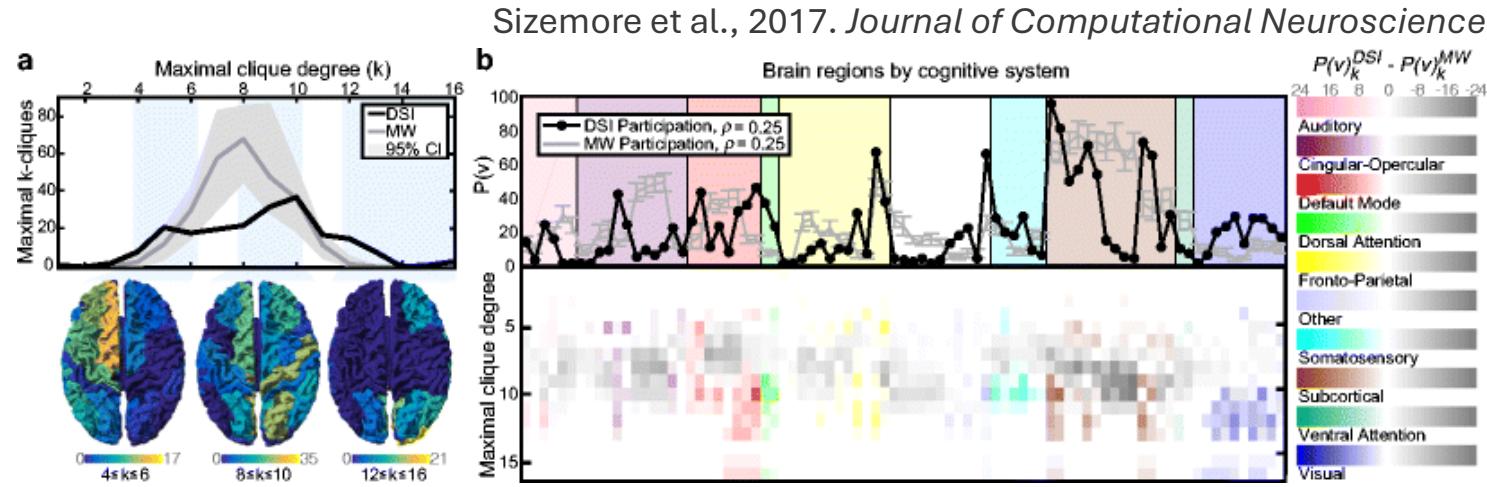


# Structures of cliques and cavities



Cliques: local neighborhoods in structural brain networks; a single neuron can join multiple cliques

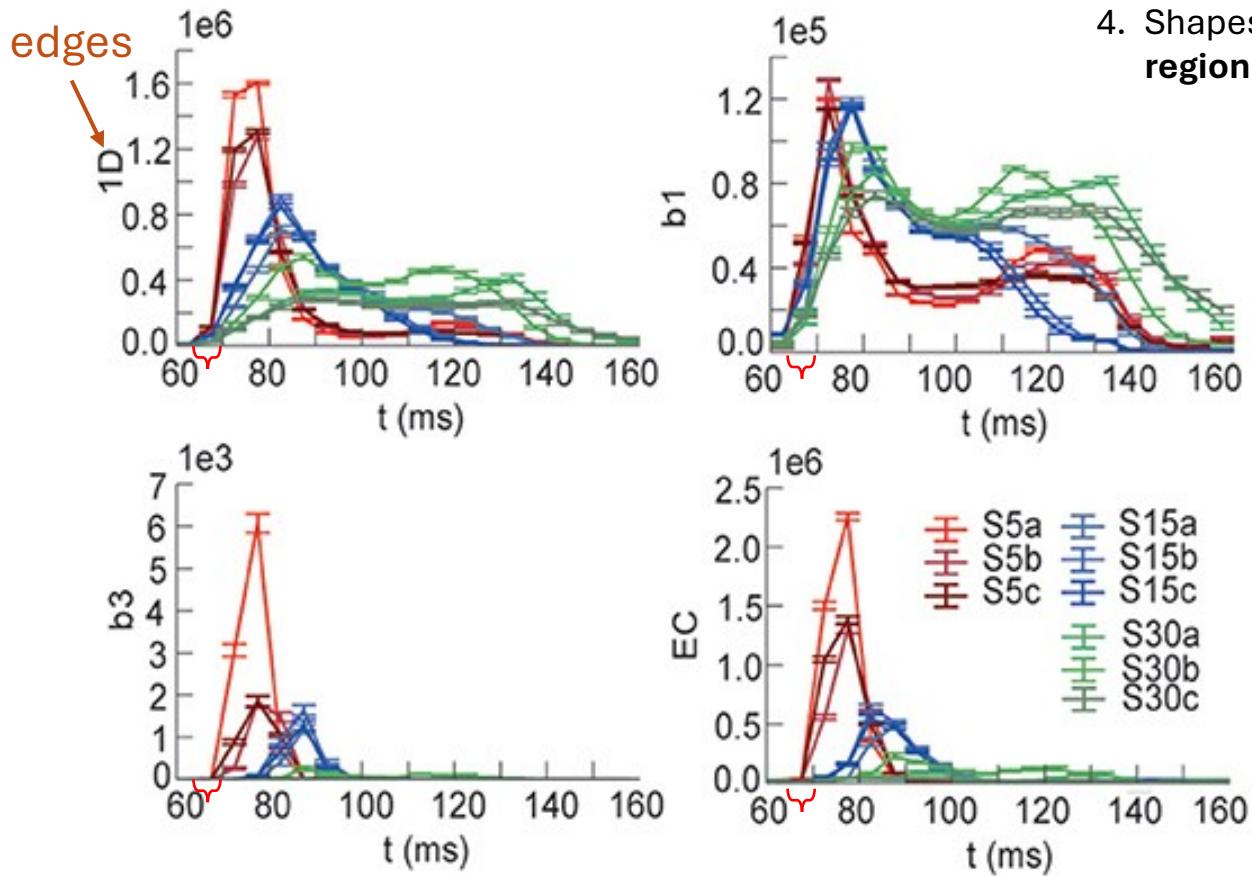
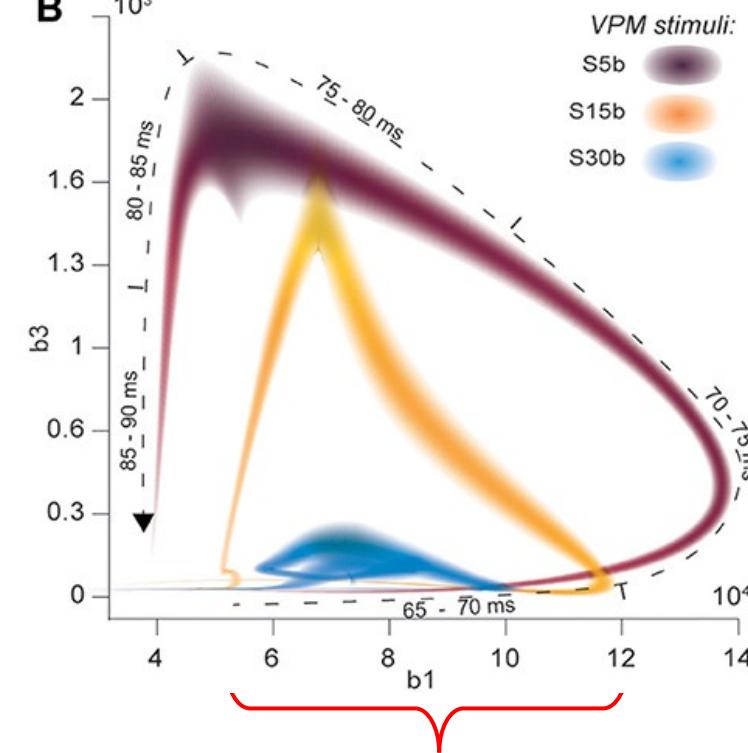
Long-lived cavities show that the connectome is organized in a multi-scale, higher-order way, rather than just edges and triangles.



Cavities: joints of cliques; appear [void enclosed by simplices (2+ cliques)] then disappear as we add more simplices

# Dynamics of cliques and cavities

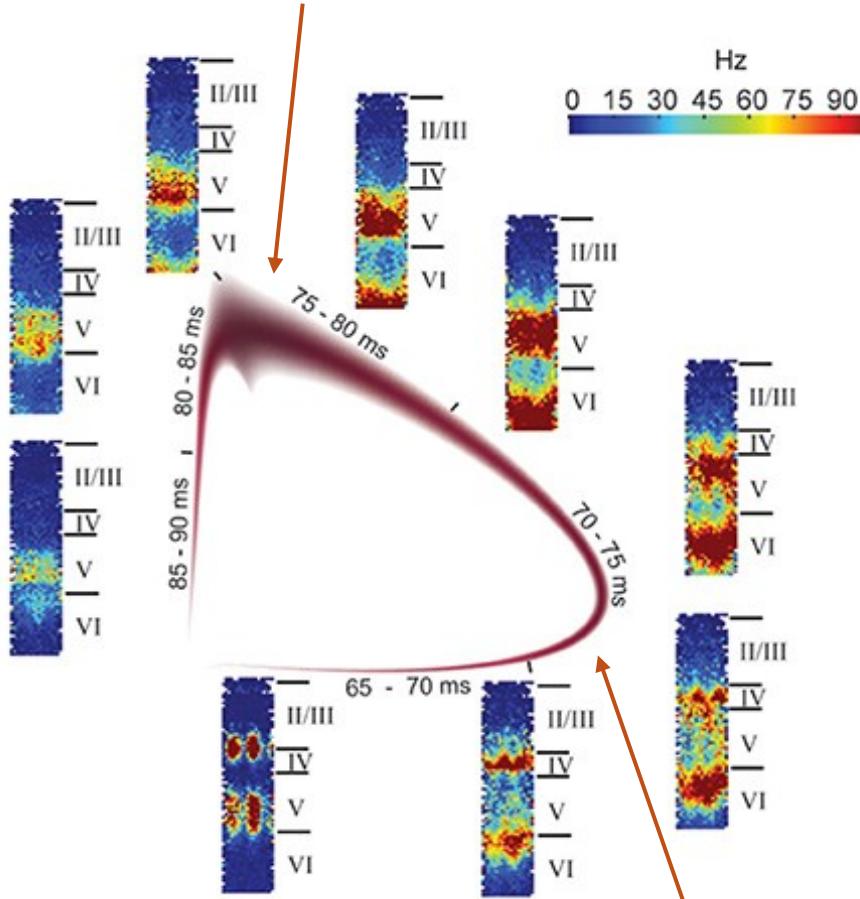
- As activity propagates, **small groups of neurons fire together and form fully connected cliques** (simplices)
- When **these cliques overlap, they bound a cavity** (a higher-dimensional void).
- As additional neurons are recruited, **more cliques form and eventually fill in the cavity**
- Shapes fill-in then fill-out. **This process repeats across time and across regions:** “rain of high-dimensional cavities”

**A****B**

# Dynamics of cliques and cavities

High  $\beta_3$ : cavities bounded by higher-order cliques

C



High  $\beta_1$ : edges connect neurons such that we obtain loops (with hole)

- **Cliques** show **feedforward local motifs**: *neurons are tightly connected*
- **Cavities** show how local **cliques are organized in relation to each other**: *many tightly connected groups are arranged together such that it leaves a gap*
- **High  $\beta_1$**  (many 1D cavities / loops)
  - Activity has spread such that it generates many separate cycles
  - This reflects a **more distributed pattern**
- **High  $\beta_3$**  (many 3D cavities / voids bounded by tetrahedra)
  - Activity has escalated into *cohesive, high-order cliques* (4+ neurons, fully interconnected, overlapping)
  - This reflects **stronger coordination**, where many neurons fire together in structured ensembles
- Tracking **cliques** show **local motifs of information flow**
- Tracking **cavities** show **global scaffolding of information flow**