UNDERSTANDING NETWORK STRUCTURE & FUNCTION IN THE HUMAN BRAIN

SIAM
PORTLAND, OR
JULY 12, 2018

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BRAIN NETWORKS THAT LEARN & THE NETWORKS THAT THEY LEARN

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From Dewey's Democracy and Education (NY: Simon & Brown, 2011):

"…[K]nowledge is a perception of those connections of an object which determine its applicability in a given situation. [...] Thus, we get at a new event indirectly instead of immediately - by invention, ingenuity, resourcefulness. An ideally perfect knowledge would represent such a network of interconnections that any past experience would offer a point of advantage from which to get at the problem presented in a new experience" (185).

How do we gain this knowledge network?

1. **Curiosity**. "Curiosity is not an accidental isolated possession; it is a necessary consequence of the fact that an experience is a moving, changing thing, involving all kinds of connections with other things. Curiosity is but the tendency to make these conditions perceptible" (116).

2. **Example**.

Learning knowledge networks by example

Roger Deakin: English writer and documentary-maker on water(ways).

"I stared dedicatedly at my shoes, embarrassed that my friend was failing to perform in front of my academic peers. It was only later that I realized it wasn't a failure to perform, but a refusal to conform. Cambridge seminars expect rigor and logic from their speakers: a braced subtlety of exposition and explanation, tested proofs of cause and consequence. But water doesn't do rigor in that sense, and neither did Roger, though his writing was often magnificently precise in its poetry (precision being, to my mind, preferable to rigor – the former being exhilaratingly exact and the latter grimly exacting). For Roger, water flowed fast and wildly through culture: it was protean, it was `slip-shape' – to borrow Alice Oswald's portmanteau from her river poem, Dart – and so that was how he followed it, slipshod and shipshape at once, moving from a word here to an idea there, pursuing water's influence, too fast for his notes or audience to keep up with, joining his archipelago of watery subjects by means of an invisible network of tunnels and drains."

Waterways of the UK.

Macfarlane, *Landmarks*

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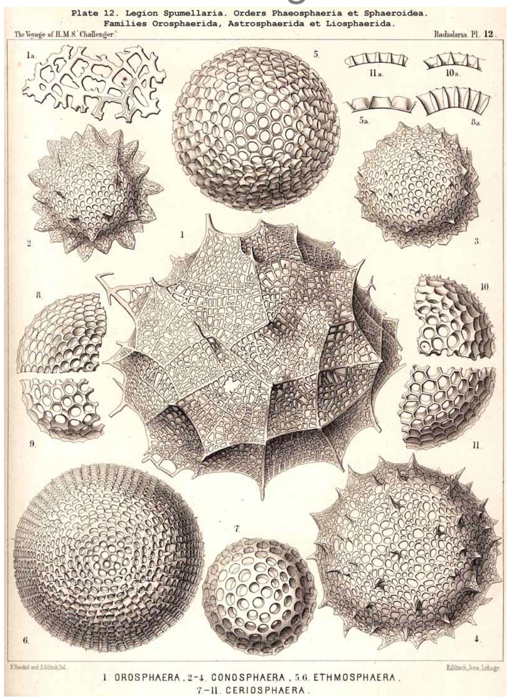
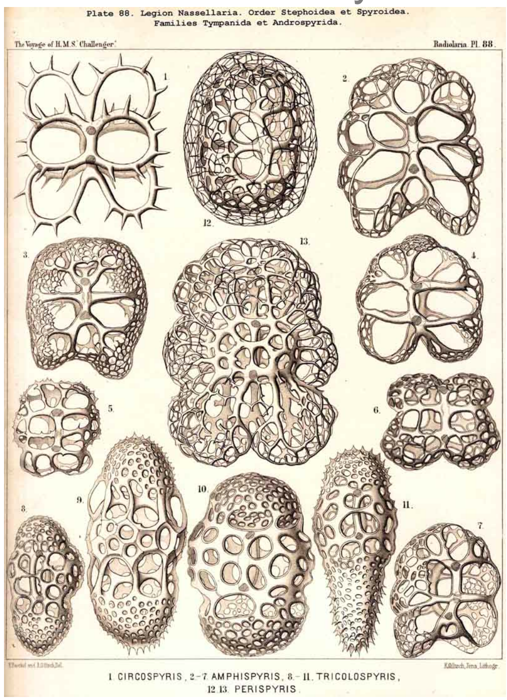
The lecture as a walk through a network

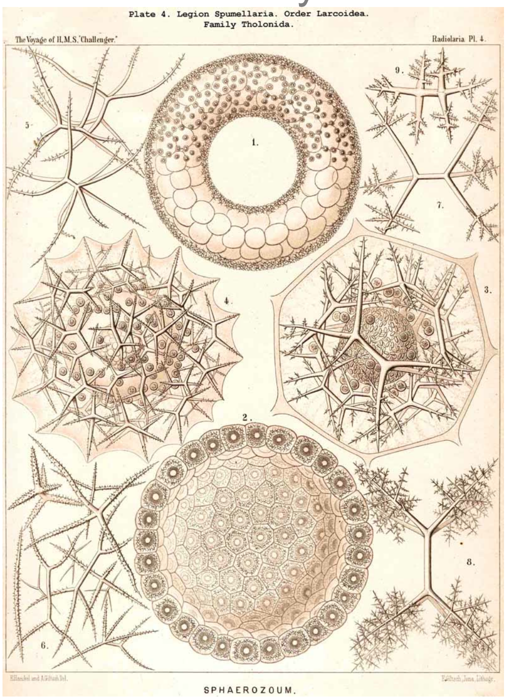
Linear algebra



UK Waterways



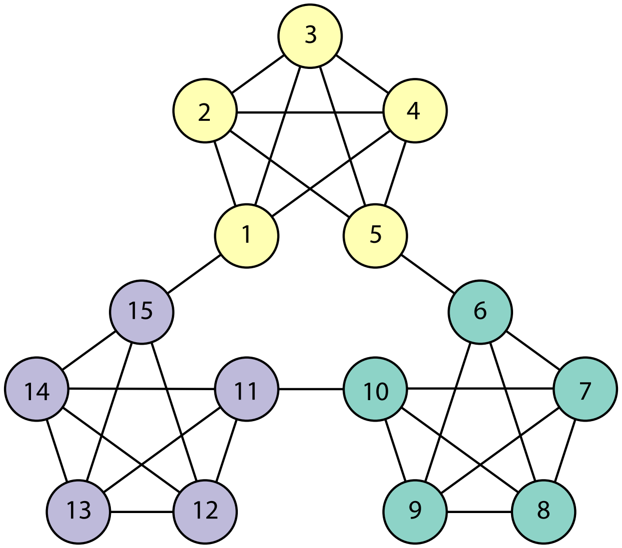
History



- What is the network structure of different areas of the knowledge space?
- Is there a good (or useful or even optimal) way of walking through that network in lectures, books, papers, etc.?

Ernst Haeckel, *Radiolaria,* microscopic sea organisms

Lectures, Papers, Books: Walks through networks



Let's suppose I have 15 ideas to translate in a class.

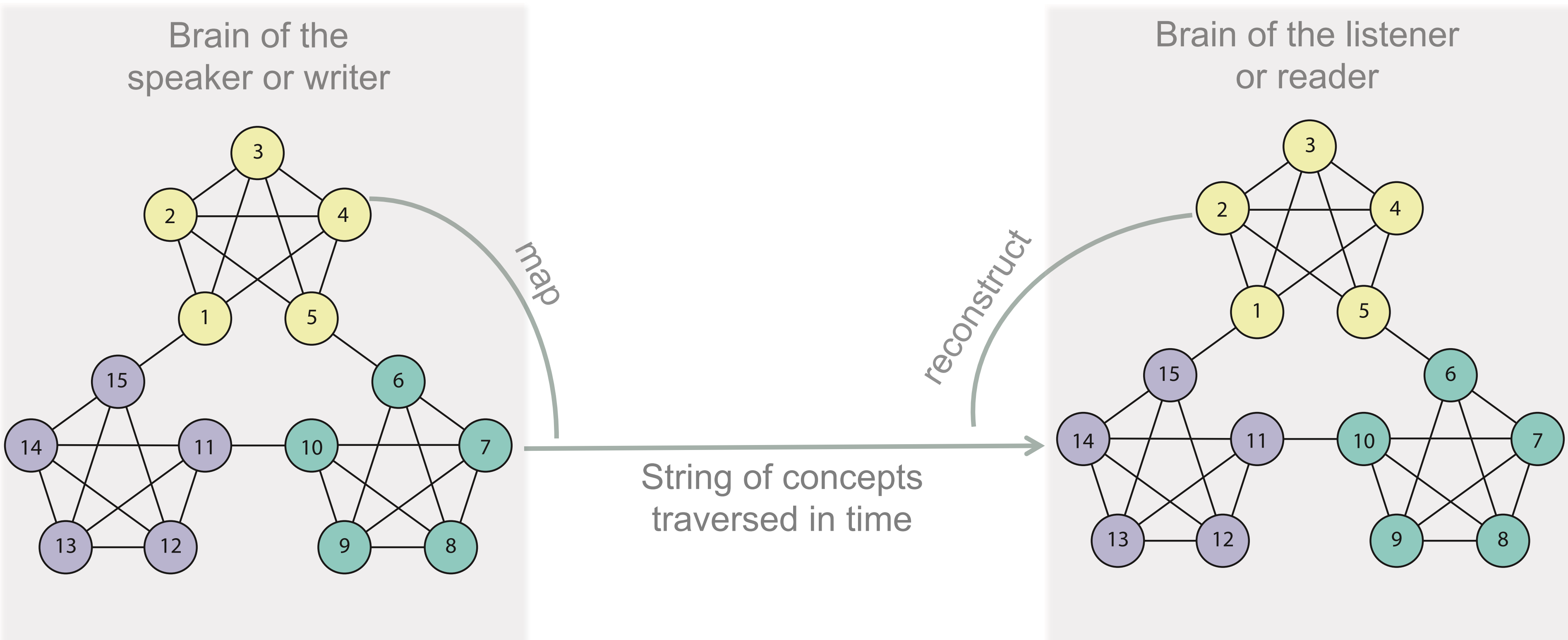
Those 15 ideas are related to one another in a heterogeneous manner, making a network like this ←

But I have to translate that information linearly, because time is one-dimensional and uni-directional.

How should I do it in a way that maximizes learning?

A “good walk” minimizes reconstruction error

and maximizes perception of the network’s topology



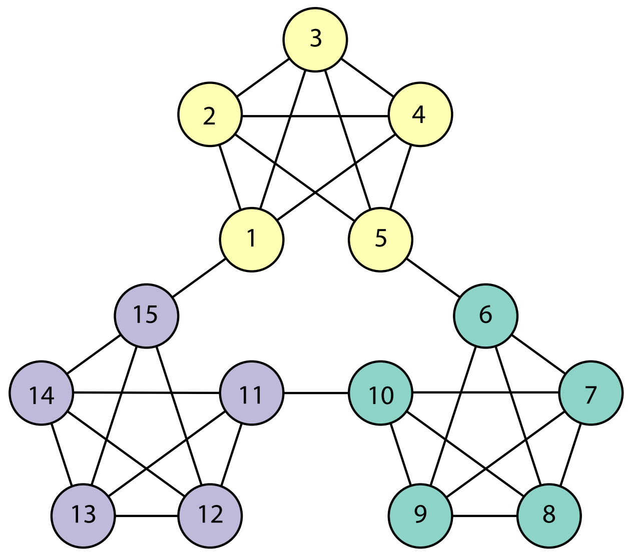
One word after another ….
One line after another …

Can we measure perception of network topology

in a continuous stream of stimuli?

Let each specific stimuli (word, image, or movement) be a ***node in a graph***.

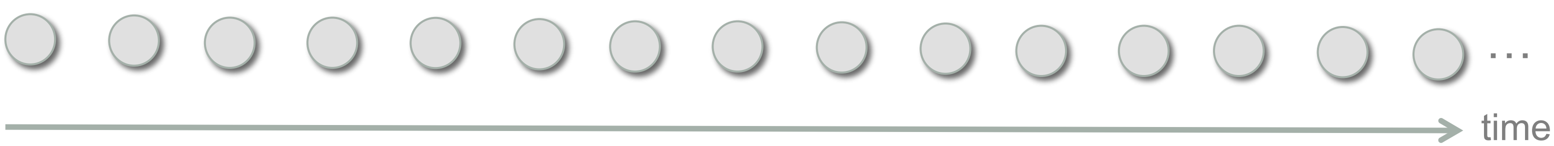
Let each ***edge in the graph*** indicate an allowable transition between nodes.



Choose ***a k-regular graph*** so that local transition probabilities are flat.

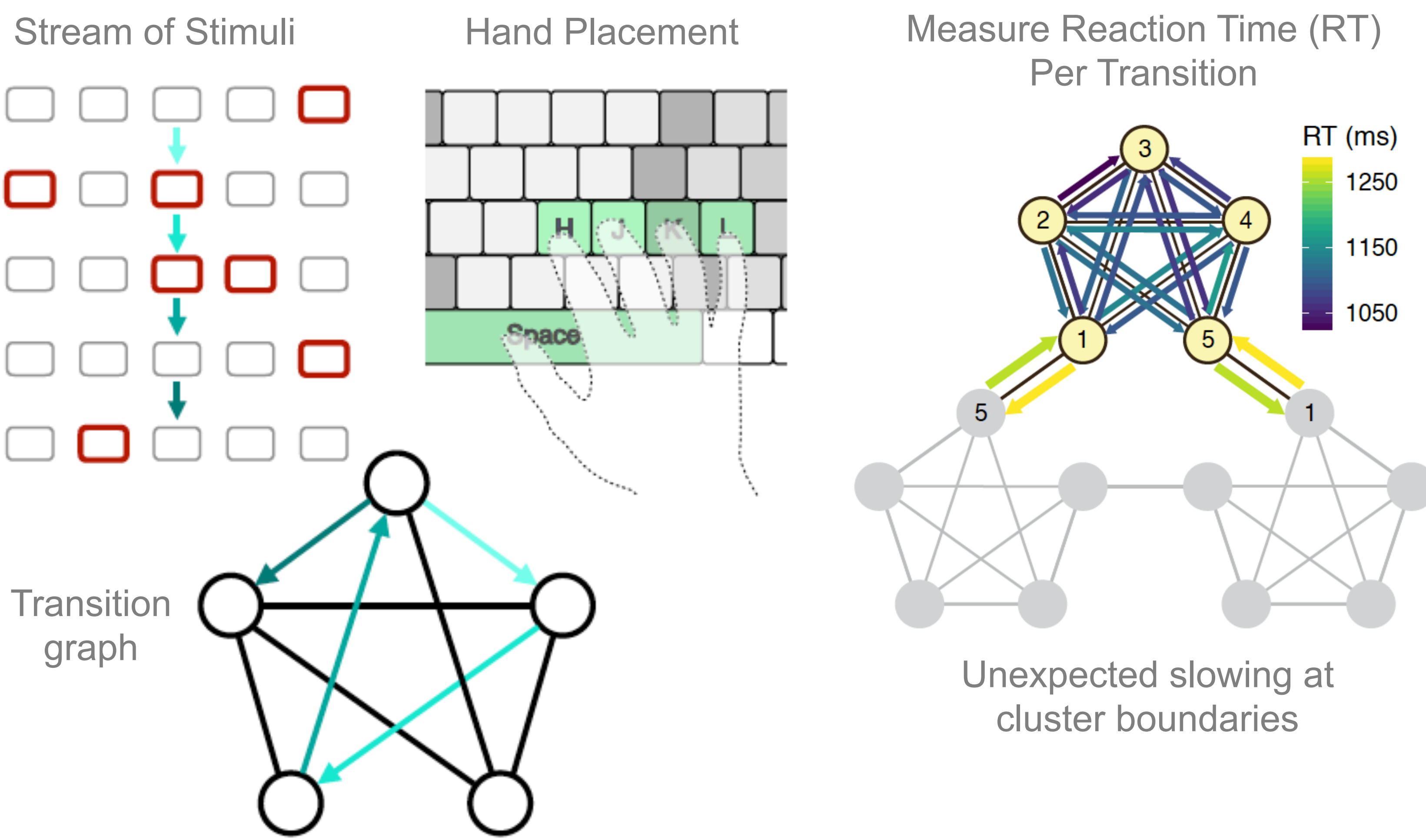
Randomly assign stimuli to nodes so the graph is the only salient structure.

Construct a sequence of stimuli by a random (Eulerian, Hamiltonian) walk on the graph.



At each stimuli, require the participant to perform a task, so that their time-to-react can be used as a measure of how well that edge in the graph was learned.

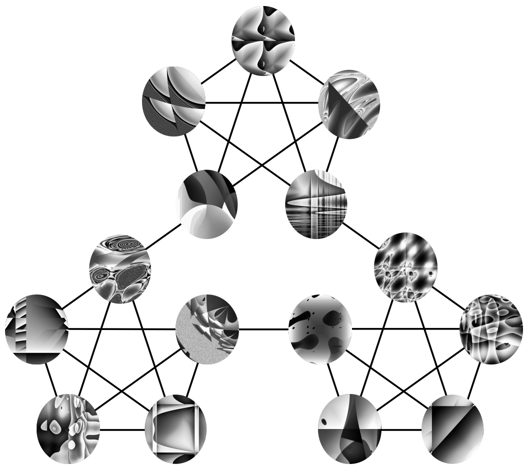
Example experimental setup: I

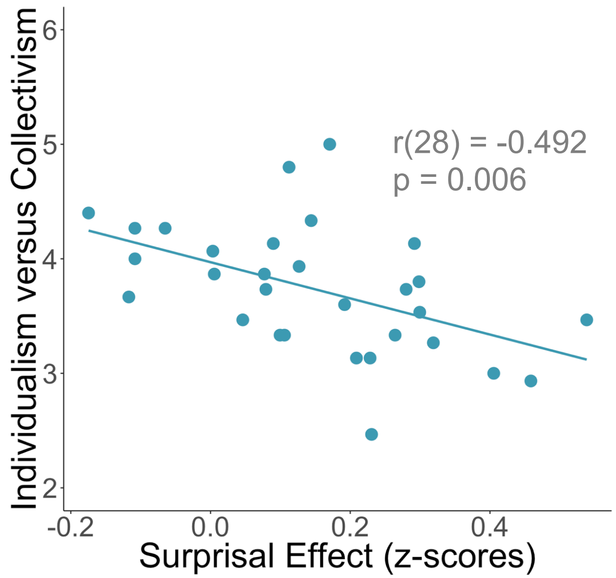


Kahn et al. 2018 In Revision at *Nature Human Behavior*

Example experimental setup: II

Tell the participants that each fractal is actually an online avatar for a real person.
35 min of exposure; 1.5 s per image; task - detect image rotation





Participants who reported greater collectivistic (versus individualistic) cultural values learned social networks better.

This type of learning may be important for understanding how humans learn about the social networks around them, … and why some people understand their surrounding social networks better than others.

Tompson et al. 2017 JEP: LCM

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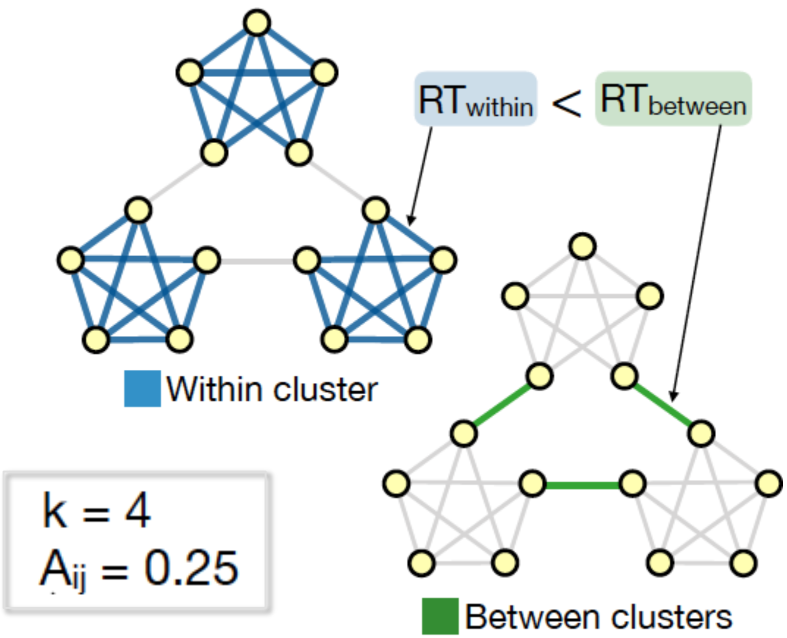
Perception of higher-order network structure

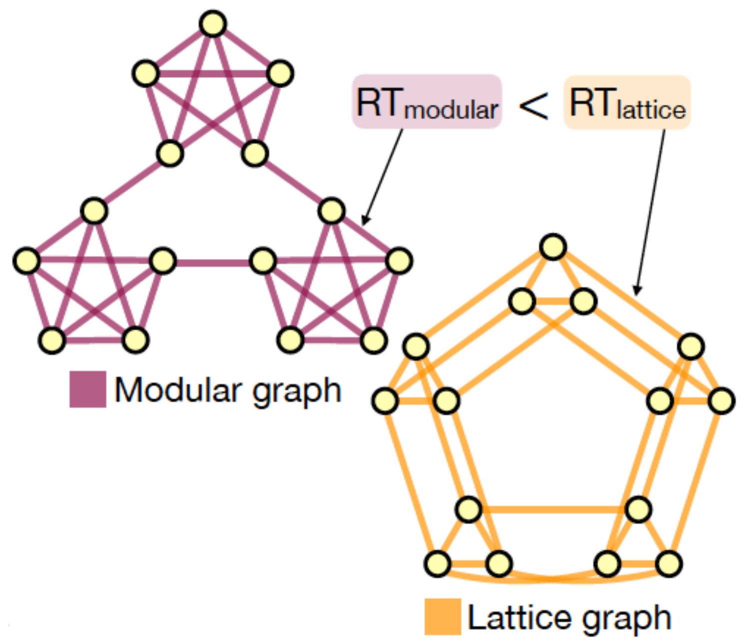
in continuous streams of stimuli

Cross-cluster surprisal



Robustly observed for different node types and task types.

Modular-lattice effect



Cannot be explained by local transition probabilities.

What are they thinking?

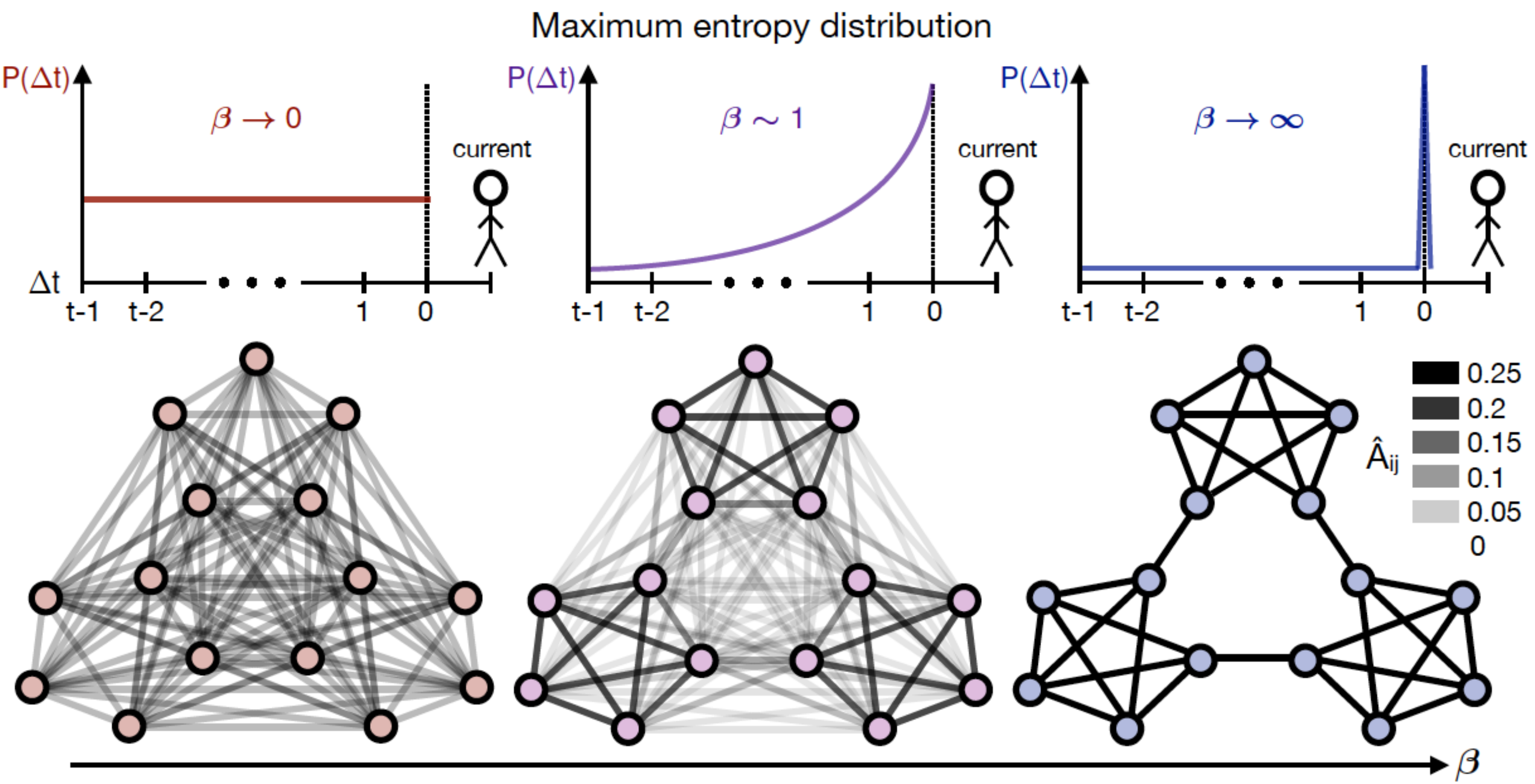
We build expectations about a network structure with a counts matrix n_{ij}

Probability of recalling $x_{t-\Delta t}$ rather than x_t.

We call on the free energy principle to suggest that the brain minimizes (i) errors and (ii) computational resources.

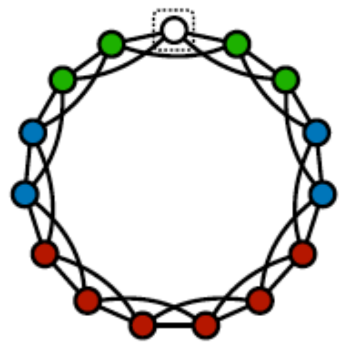
This gives us the Boltzmann distribution with an inverse temperature parameter: $P(\Delta t) = \frac{1}{Z} e^{-\beta \Delta t}$

Each human has a unique temperature



The effects of network violations

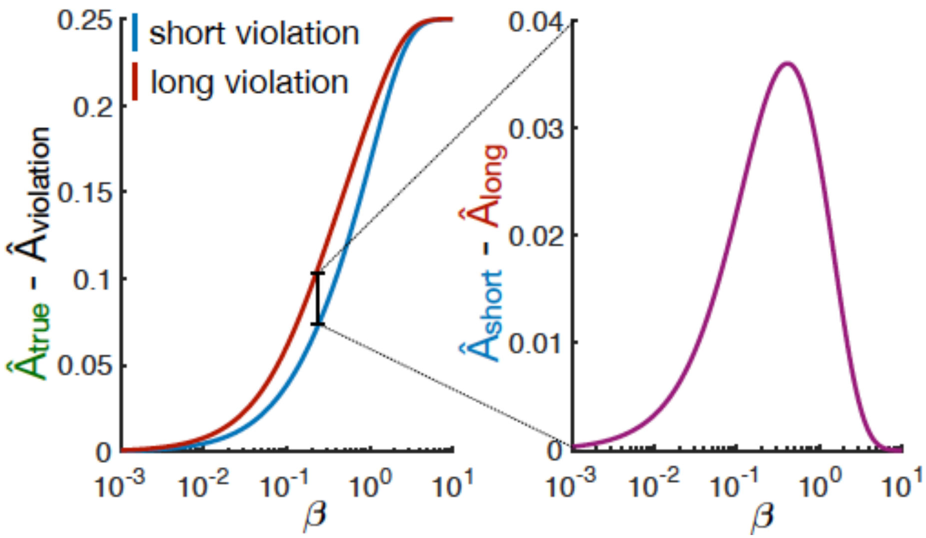
- Ring graph:



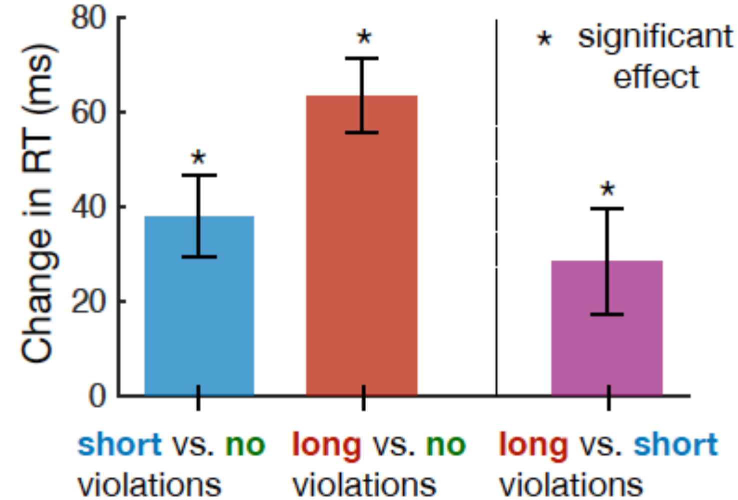
Topological distance:

- 0 (current node)
- 2 (short violation)
- 1 (no violation)
- 3,4 (long violation)

- Analytic predictions:



- Empirical results:



Humans are more surprised by stimuli from farther away on the ring than closer, indicating their implicit perception of the network topology.

Searching for design rules

Which nodes are easiest to learn? Could we built a network with more of those types of nodes to enhance learnability?

What is the optimally learnable graph? Does it differ across humans? Does it have a topology that is common in language or nature?

Can we use the optimally learnable graph to enhance performance in clinical populations with learning deficits?

Dr. Lizz Karuza,
Soon to be Asst. Prof of Psychology at PSU

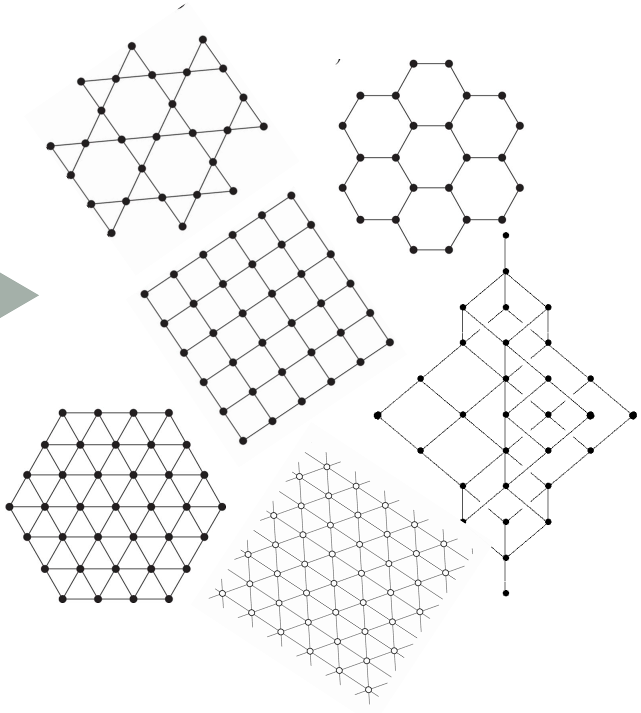
Ari Kahn,
Graduate Student in Neuroscience

Chris Lynn,
Graduate Student in Physics

There’s some Peculiar in each leaf and grain,
Some unmark’d fibre, or some varying vein;
Shall only Man be taken in the gross?
Grant but as many sorts of Mind as Moss.

Alexander Pope, *Epistle I: To Richard Temple, Viscount Cobham* (1730-33; publ. 1734)

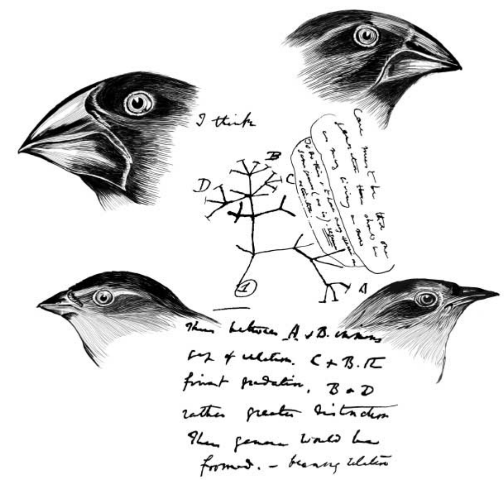
Brain networks may support learning



What features of the brain might support the learning of graphs?
Might differences in those features explain differences in the ability to learn?

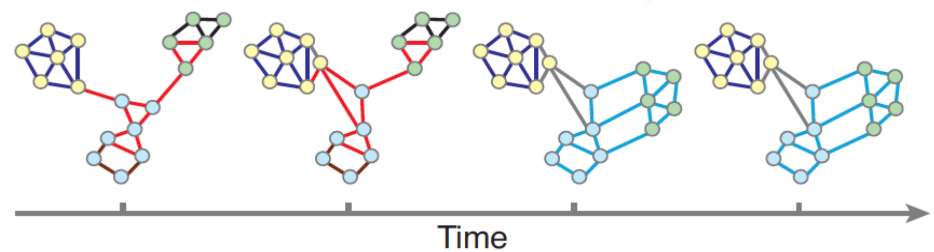
Network substrates for adaptation & learning

Modularity of structure
& morphology



Modularity of mind

Modularity of networks



- Are brain networks modular? Does modularity help us to understand large-scale neural signatures of adaptation and learning?

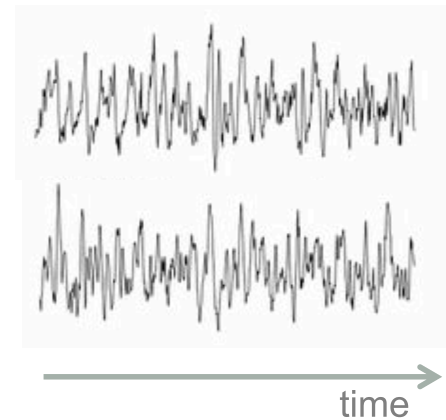
1

2

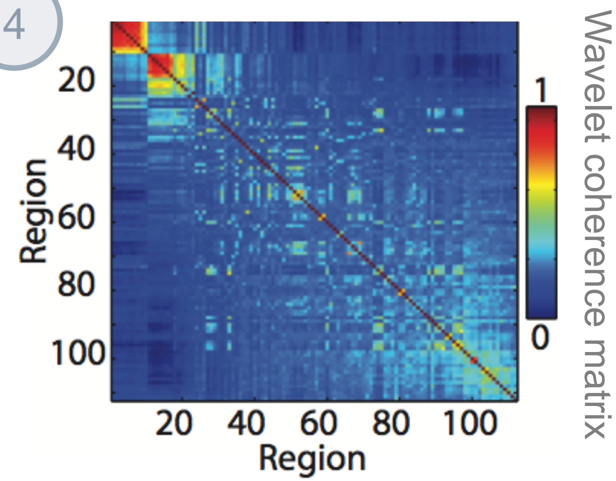
Parcellate into
200-1000 regions

3

Regional activity time series

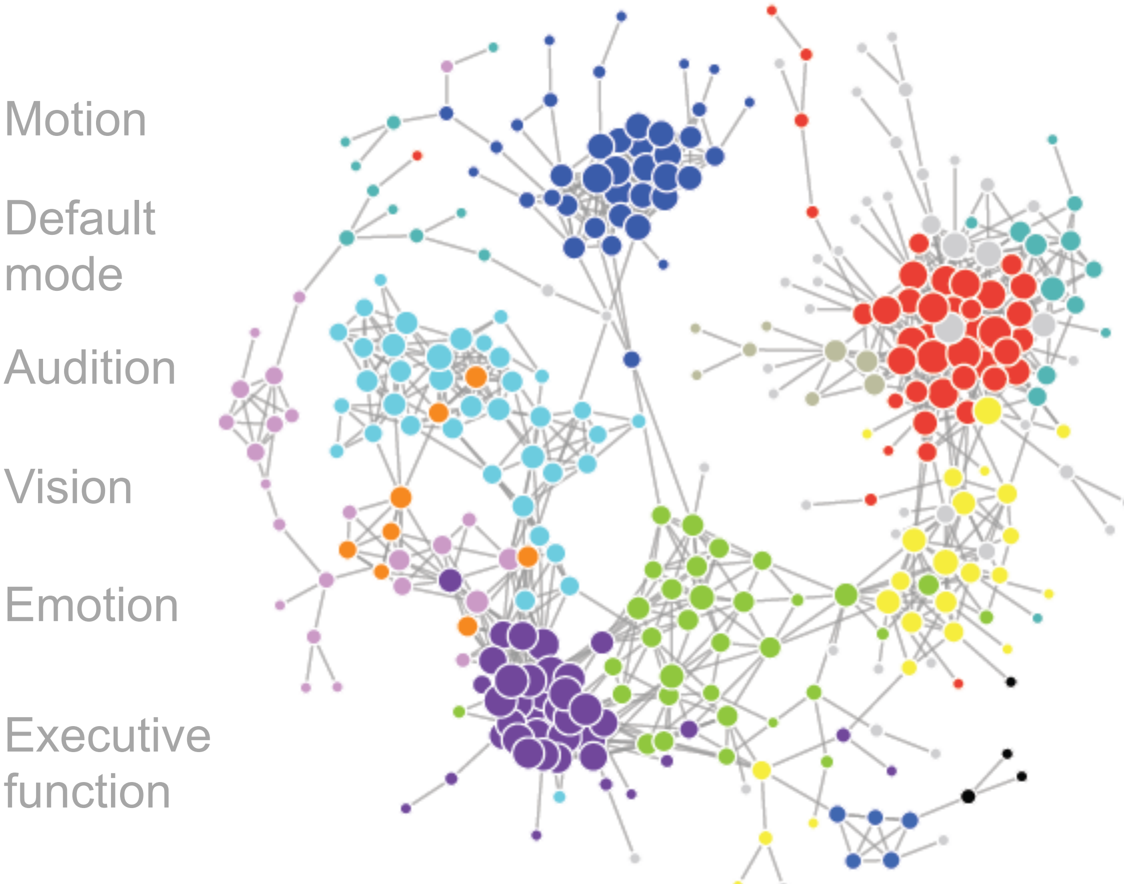


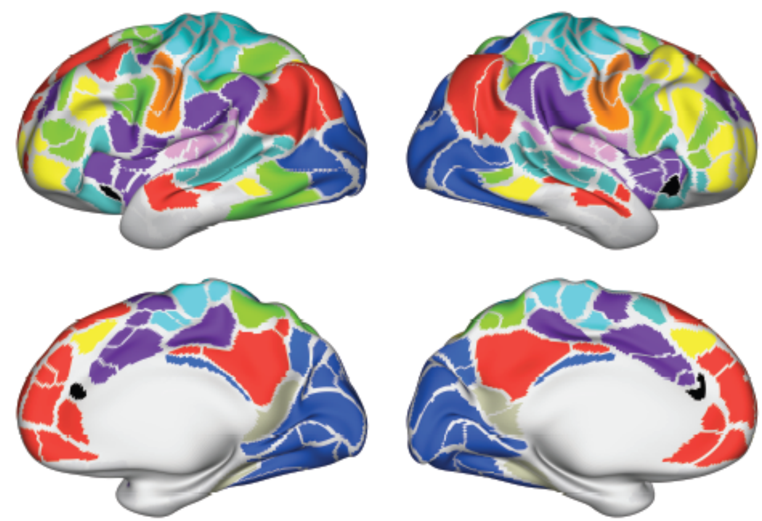
4



We build a functional brain network by acquiring time-varying images of brain activity in an MRI scanner.

Modularity in functional brain networks

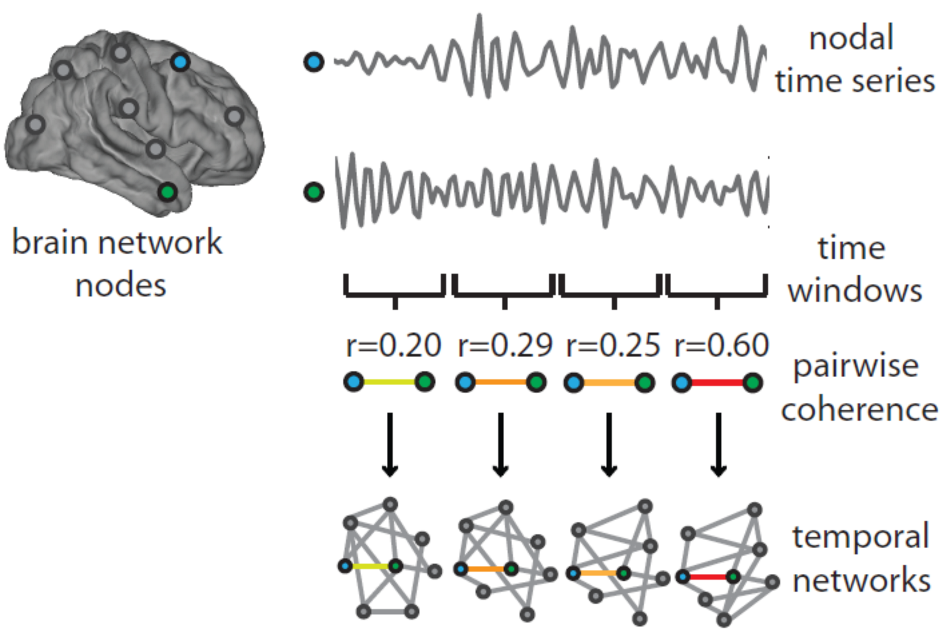




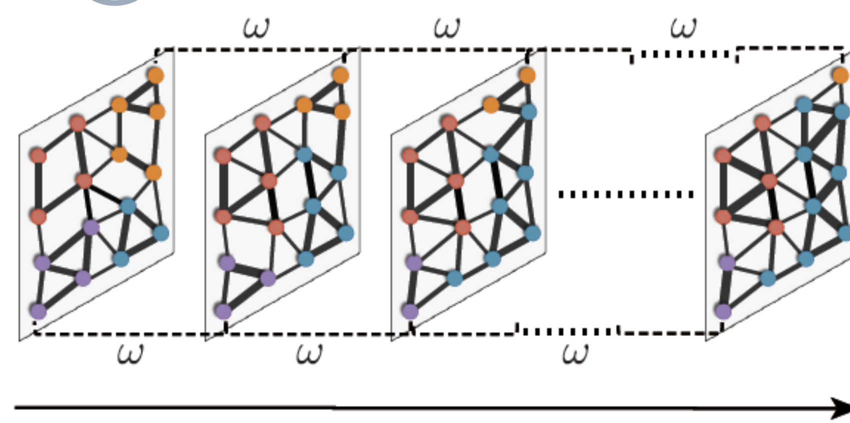
Modularity in networks can be detected algorithmically using community detection approaches.

Dynamic Networks in the Brain

1 Construct a temporally ordered ensemble of graphs

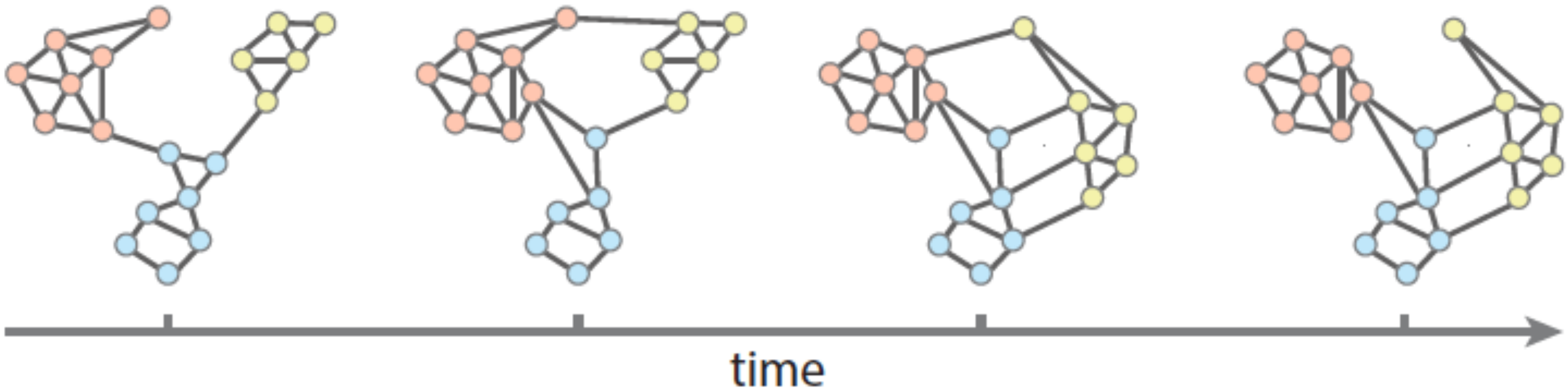


2 Build a multilayer network



3 Maximize multilayer modularity quality function

Flexibility accompanies cognitive function

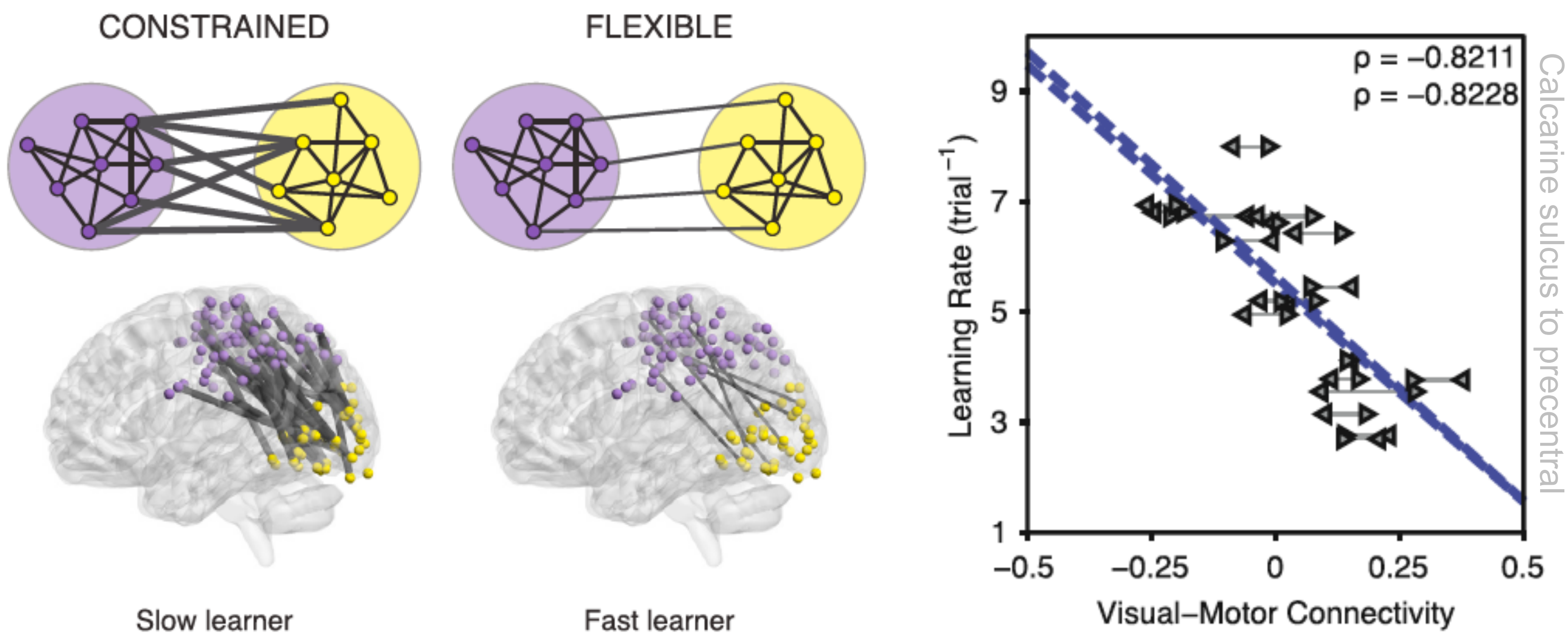


Flexibility in network modules is predicts individual differences in:

- **Visuo-motor learning** (Bassett et al. 2011 *PNAS*; Bassett et al. 2015 *Nature Neuroscience*)
- **Cognitive flexibility** (Braun et al. 2015 *PNAS*)
- **Working memory** (Braun et al. 2015 *PNAS*)
- **Reinforcement learning rate** (Gerraty … Shohamy, 2018, *J Neurosci*)
- **Positive mood** (Betzel et al. 2017 *Sci Rep*)

Predicting future learning from 5’ data before learning

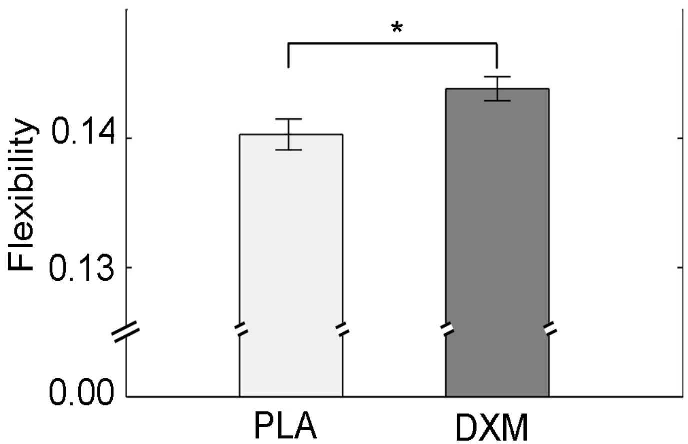
Hypothesis: Networks that can flexibly adapt are those with greater modularity.



In resting state MRI scan prior to any training, visual motor connectivity predicts future learning rate of the next 6 weeks of training on a new visual-motor skill.

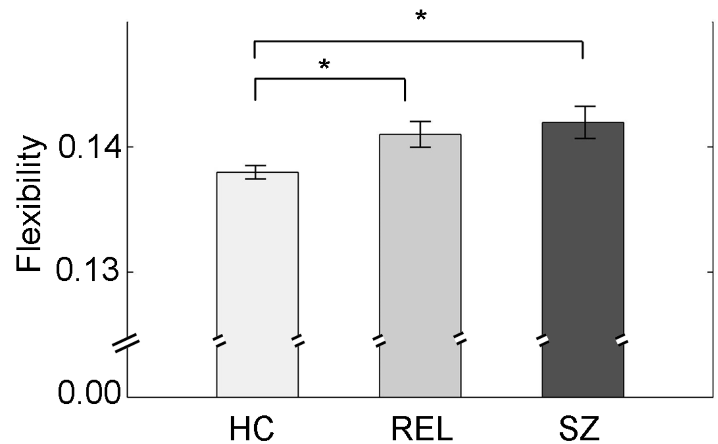
Drivers of a Flexible Brain

Flexibility may be driven by excitatory/inhibitory balance.



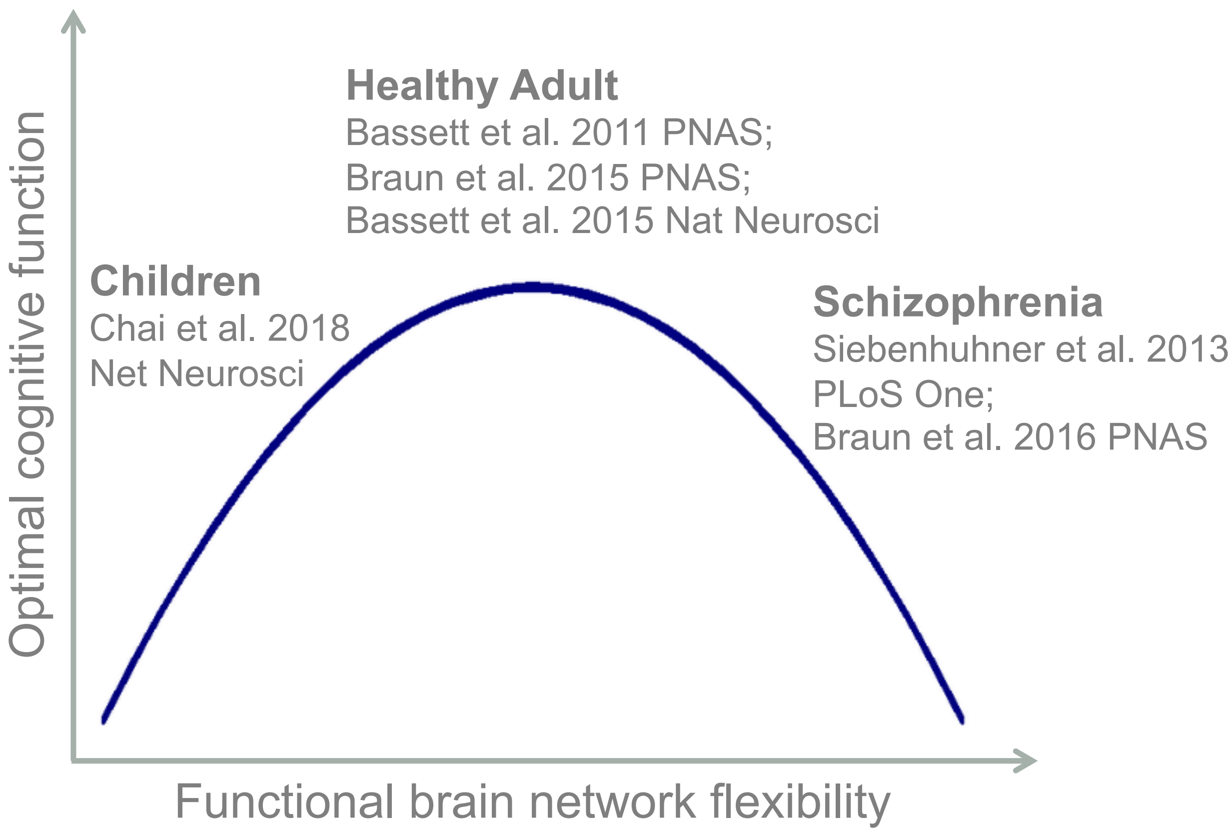
41 healthy subjects taking an NMDA receptor antagonist: Dextromethorphan.

Increased flexibility in people with schizophrenia.



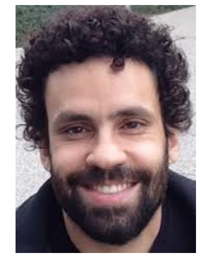
Brain network flexibility in an intermediate phenotype for schizophrenia.

Searching for a conceptual model




Urs Braun


Mason Porter


Marcelo Mattar


Peter Mucha


Rick F. Betzel


Scott Grafton


Raphael Gerraty

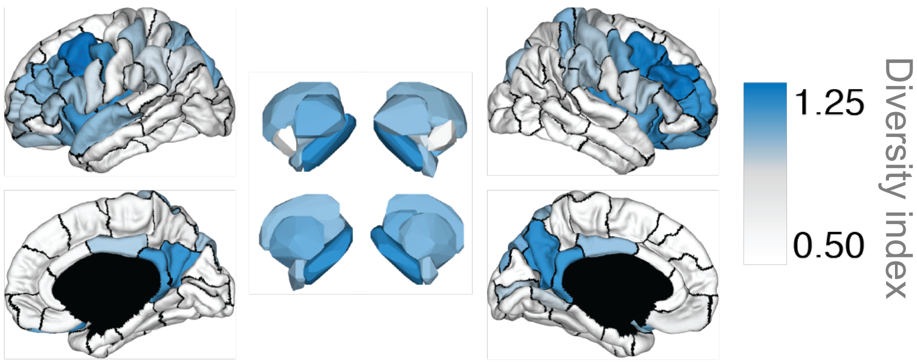

Daphna Shohamy

One should be able to prove, for example, that the introduction of a small perturbation in the dynamical problem leads to additional terms for the energy (...) of the type of the ones found by Kramers and Born.

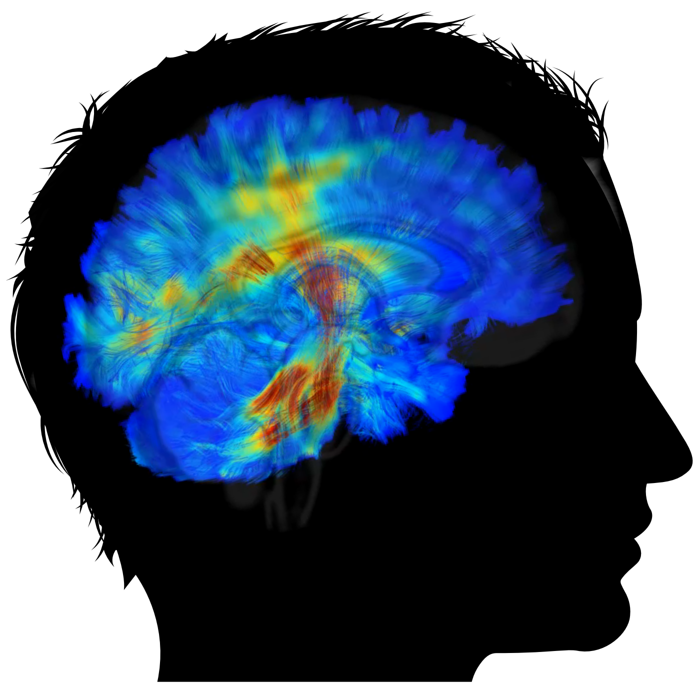
Heisenberg, 1925

Cognitive control

In human neuroimaging studies, fronto-parietal regions are activated when the brain needs to **switch between different states**.



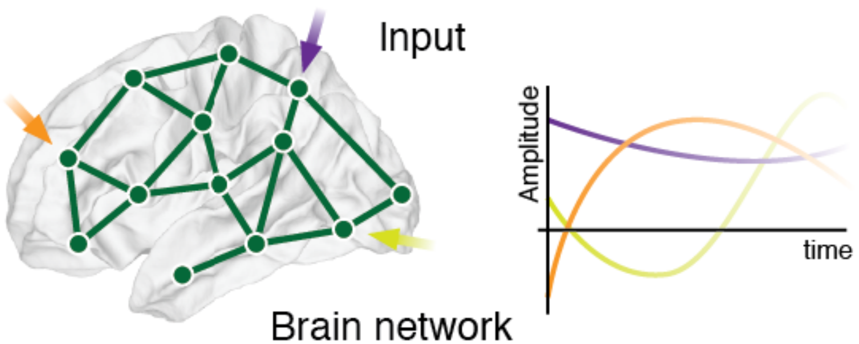
Using weighted stochastic block models, we know that these regions also participate in the most diverse sets of assortative communities, disassortative communities, and core-periphery structures.

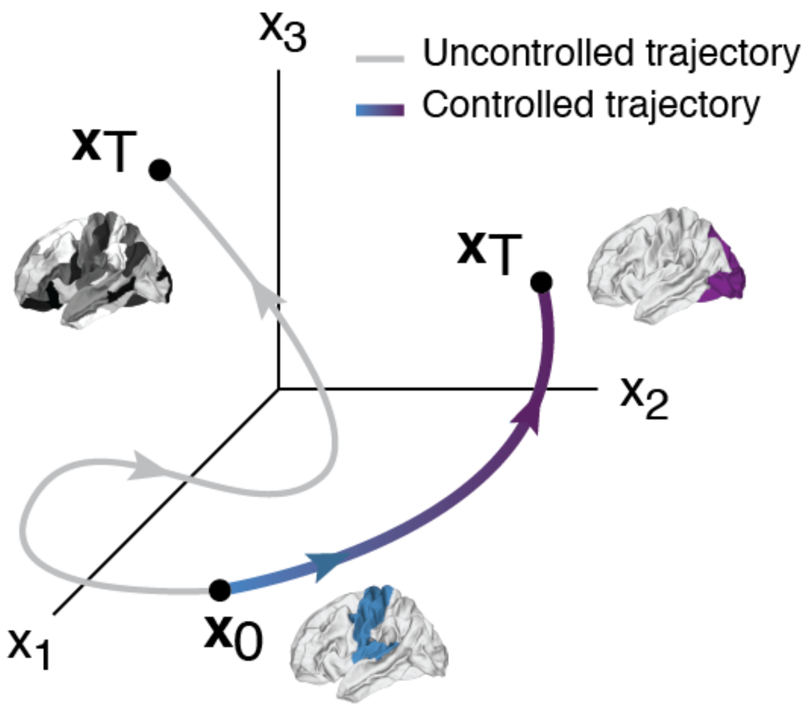


Diffusion MRI estimates the locations of structural wires

Cognitive Control as Network Control

Could cognitive control be understood as a network control process facilitating learning?





Theory (Kim et al. 2018 *Nature Physics*)

Comparing to random graphs (Wu-Yan et al. (2018) *J Nonlinear Science*), linking to ***nonlinear models*** of brain dynamics (Muldoon et al. 2016 *PLoS Comp Biol*), and extending to ***cellular circuits*** (Wiles et al. 2017 *Scientific Reports*); ***Control trajectories at rest*** (Betzel et al. 2016 *Scientific Reports*); Alterations in ***control trajectories after traumatic brain injury*** (Gu et al. 2017 *Neuroimage*)

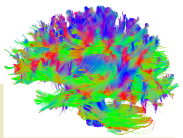
Network control in human brain

Number of regions being controlled

$$x(t+1) = Ax(t) + B_{\mathcal{K}} u_{\mathcal{K}}(t)$$

State of brain regions over time

Weighted adjacency matrix



Control energy

T-steps controllability Gramian:

$$W_{\mathcal{K},T} = \sum_{\tau=0}^{T-1} A^{\tau} B_{\mathcal{K}} B_{\mathcal{K}}^{\top} (A^{\top})^{\tau}$$

Average: Trace(W_K^{-1}))

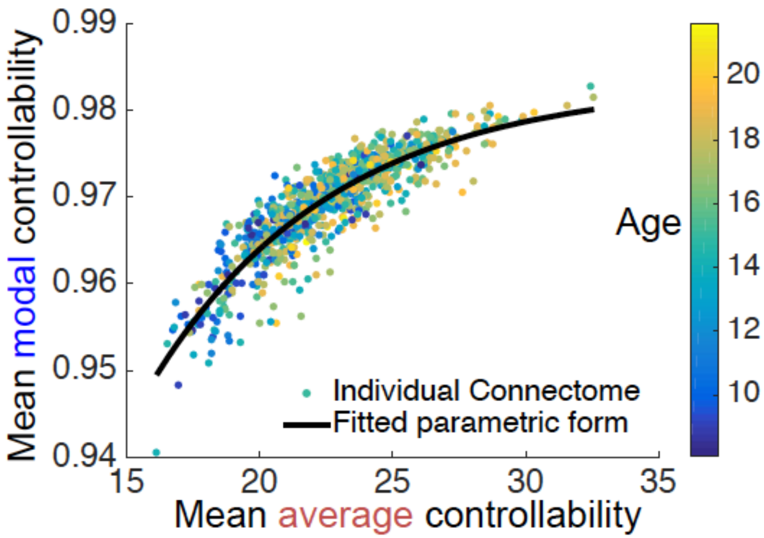
Modal: Let v_j be the j^{th} eigenvector of A with eigenvalue λ_j. Then if v_{ij} is small, then the j^{th} mode is poorly controllable from node i. Define $\phi_i = \sum_{j=1}^{N} (1 - \lambda_j^2(A)) v_{ij}^2$ as a scaled measure of controllability of all N modes from region i.)

Predicts ease of state transitions based on (i) ***white matter connectivity***, and (ii) a model of neural dynamics.

Network control as cognitive control

Three pieces of evidence:

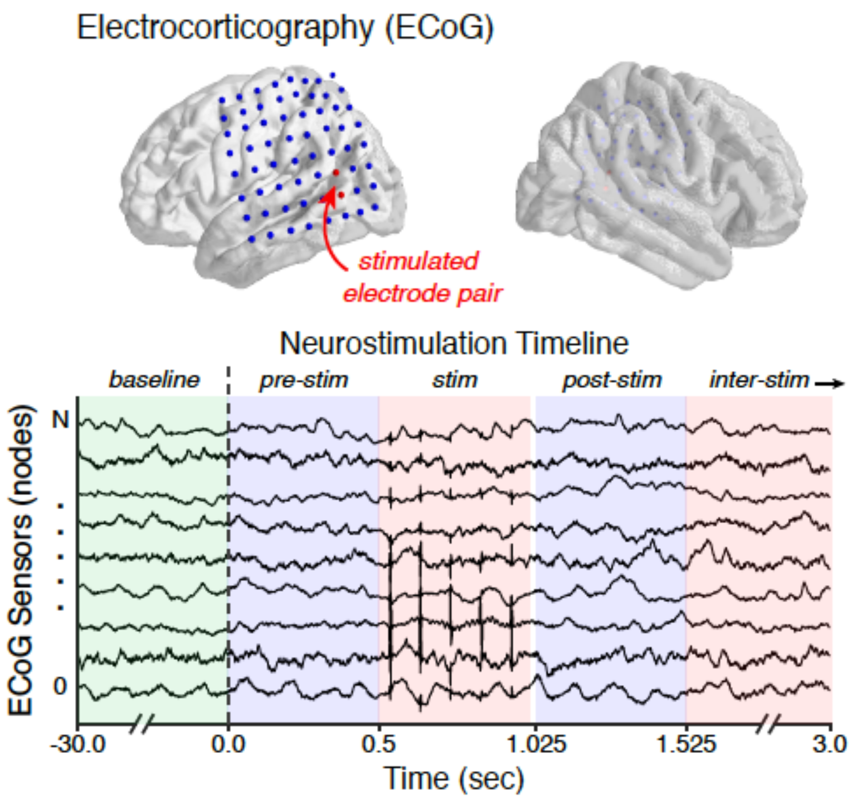
- Cognitive control areas show high predicted levels of network control (Gu et al. 2015 *Nature Communications*)
- Network control grows as children develop cognitive control (Tang et al. 2017 *Nature Communications*)
- Individual differences in network control predict individual differences in executive function in youth (Cornblath et al. 2017 *arXiv*:1801.04623)

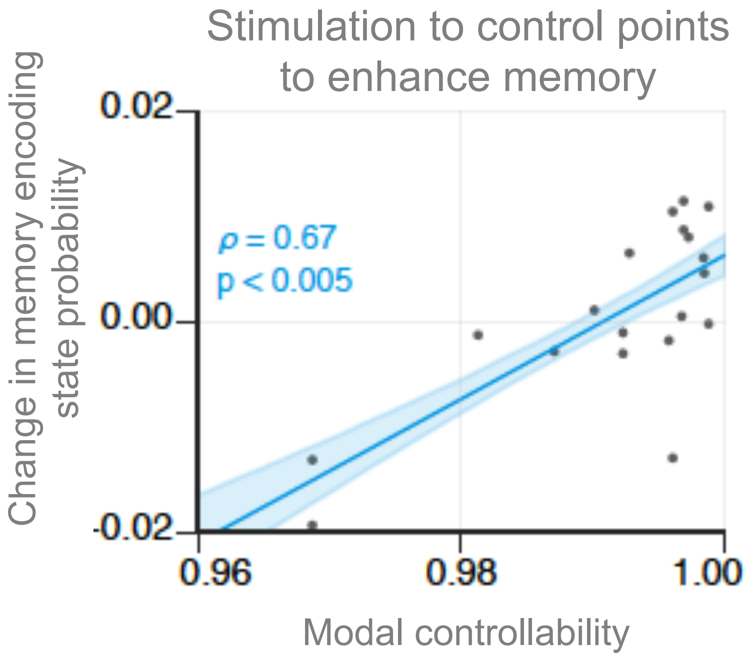


Suggests that cognitive control can be thought of as a network-level control process, whose function is strongly constrained by the pattern of white matter connections between large-scale brain areas.

Grid stimulation to modal controllers

Preliminary work actively testing whether (and how) stimulation to modal controllers can alter cognitive control.





Searching for optimal stimulation

Network control has direct implications for open-loop and closed-loop control.

1. Validating utility of network control theory in predicting power changes in response to grid stimulation in ECoG data

2. Understanding time scales of control, and frequency specificity of control

3. Determining the relative role of white matter connectivity vs. effective connectivity in predicting effects of stimulation

*Fundamentally, we are seeking generalizable first-principles theories that tell us not just that control **can** work, but exactly **how** and **why** it works.*


Fabio Pasqualetti

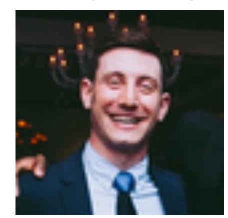

Jason Z. Kim


Ankit Khambhati


Shi Gu

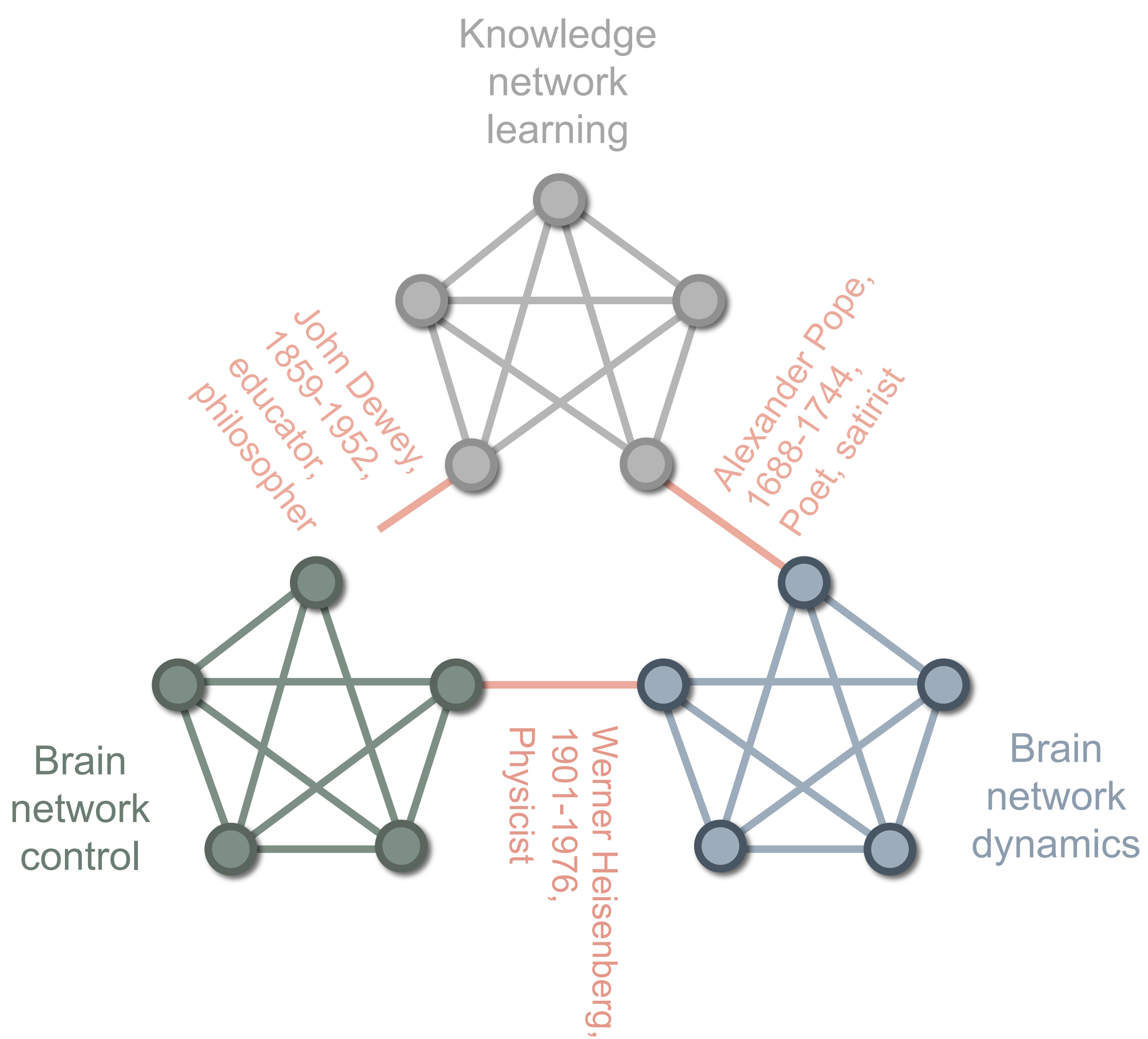

Evelyn Tang


Rick F. Betzel

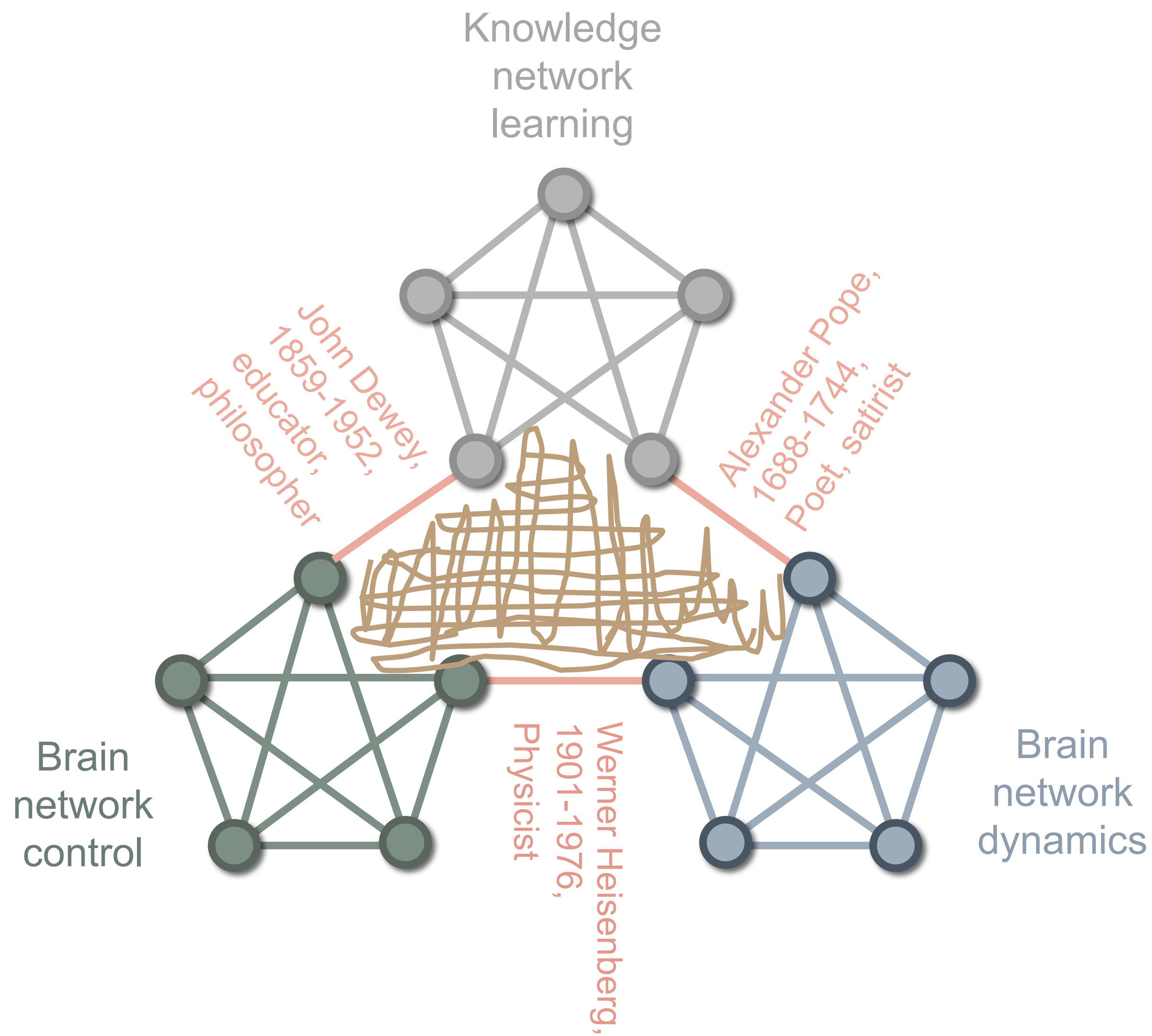

Eli Cornblath


Jeni Stiso

Network wanderings



Network wanderings



To do for next time:

... take a random walk

... somehow link Dewey with brain network control

... pull in algebraic topology to fill in the central cavity, like toddlers fill in knowledge gaps in language (Sizemore et al. arXiv:1709.00133)

... till next time!

Acknowledgments

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Past trainees now faculty:


Sarah Muldoon


Shi Gu


John Medaglia


Ralf Schmaezle


Chad Giusti

Current trainees about to be faculty:


Lizz Karuza


Evelyn Tang


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Faculty collaborators:


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Network wanderings