



Informational and topological signatures of individuality and age

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The Sense 23/11/2023



Network Science Institute
at Northeastern University





Higher-order signatures of individuality and age

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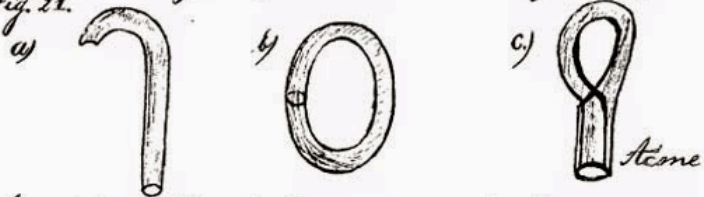
Network Science Institute
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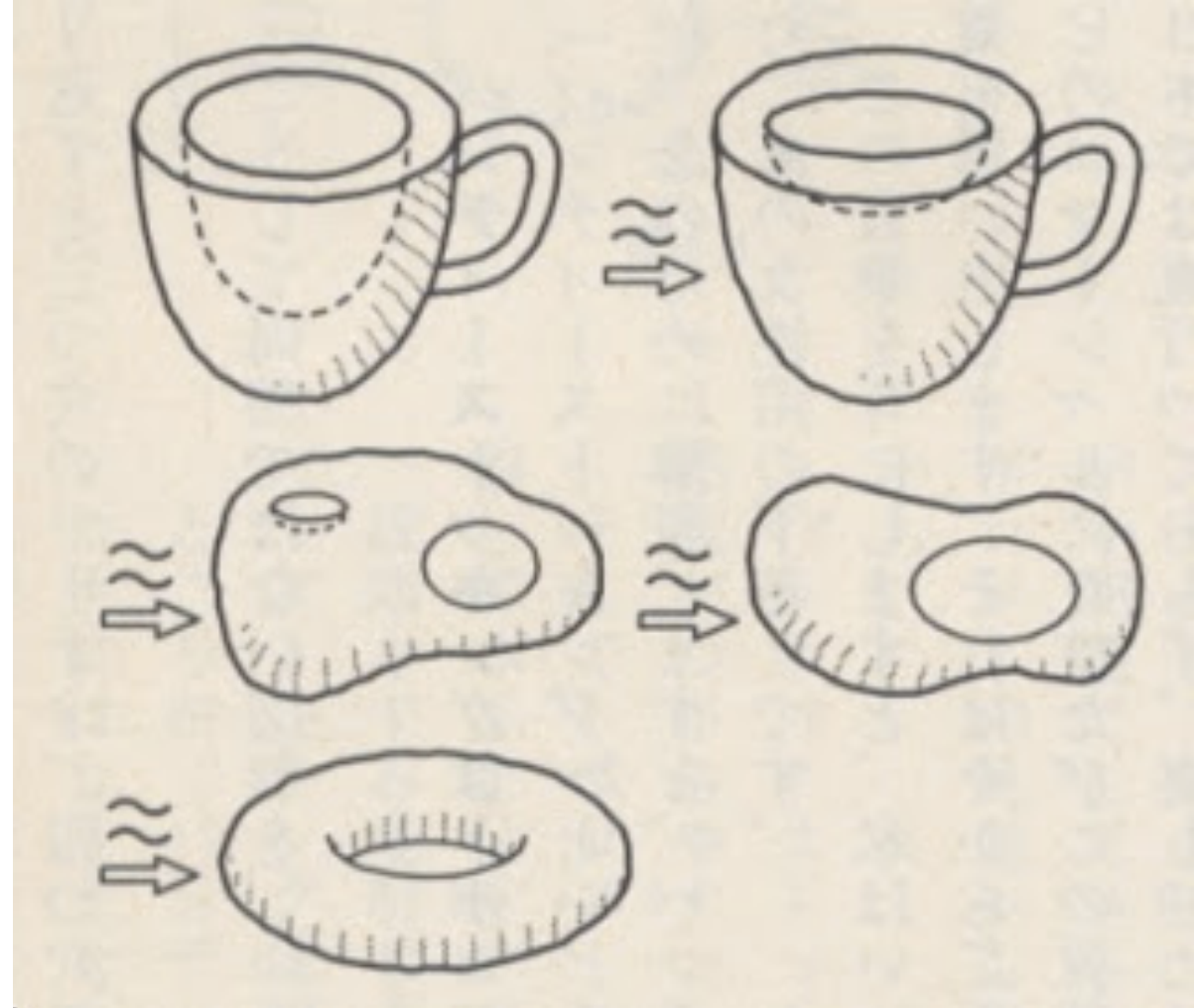
What is topology?

- 102 -

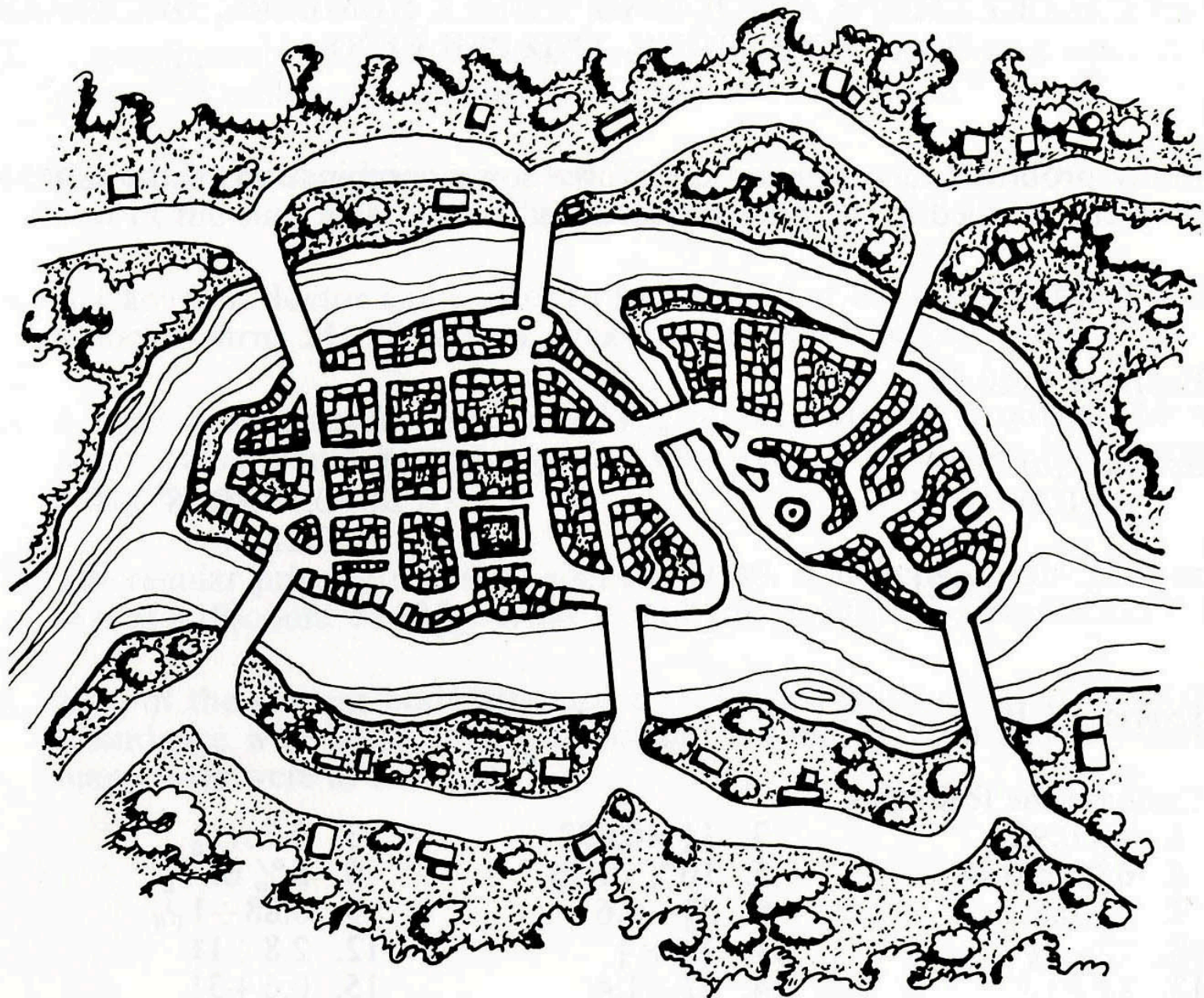
auf die fläche geseht, sich nur entlang der fläche bewegen kann, so kann dasselbe, wenn es einmal an der Außenseite sich befindet, wie es sich auch bewegen mag, niemals an die Innenseite gelangen und umgekehrt. Ebenso kann man entweder die Außenseite oder die Innenseite der fläche für sich mit farbe anstreichen. Doch nun kann man den schlduch noch in ganz anderer weise zusammenbewegen, indem man nämlich das eine ende nach innen umstülpt, das andere dagegen durch die wandung in das innere hineinleitet und dann mit dem umgestülpten ende vereinigt. v. Gay. 21. c. Fig. 21.



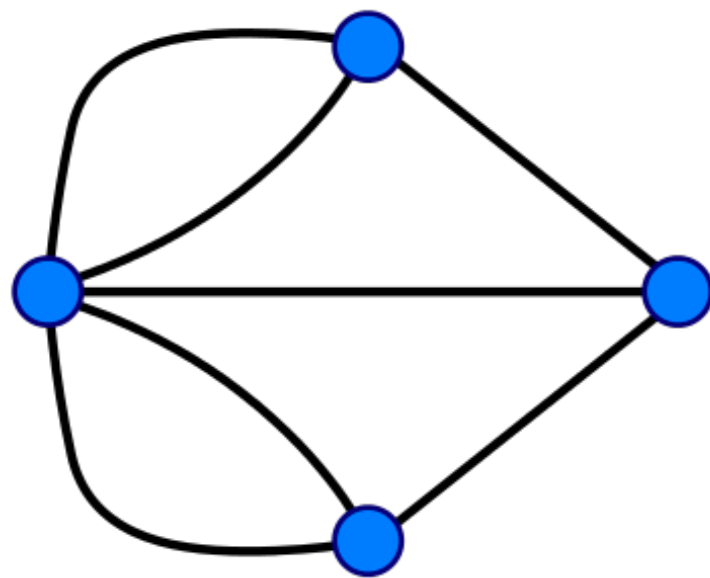
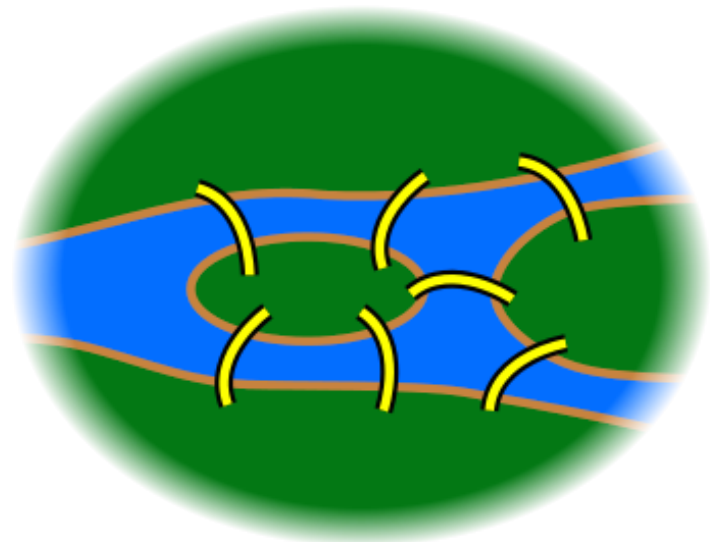
Stemediere weise haben wir eine durchaus zusammenhängende doppel fläche gewonnen, bei welcher eine innern- und außenseite etwa durch besondern farbigen anstrich nicht mehr zu unterscheiden ist. Denken wir uns auf dieser fläche ein zweidimensionales wesen, so wird dies, indem es an seinen früheren ort zurückgelangt, dabei sein eigener antipode werden können, und es muß zwei mal herumkröchen, ehe es in die ausgangslage zurück-



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Why topology?

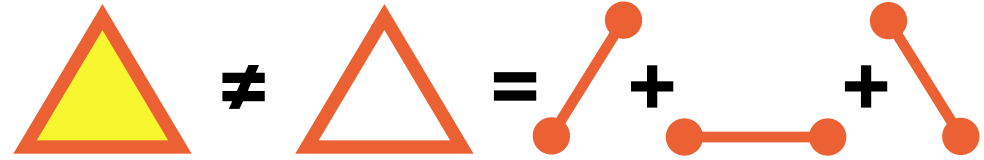
DOT
= 0-simplex



EDGE =
1-simplex



TRIANGLE
= 2-simplex



Definition of k-simplex

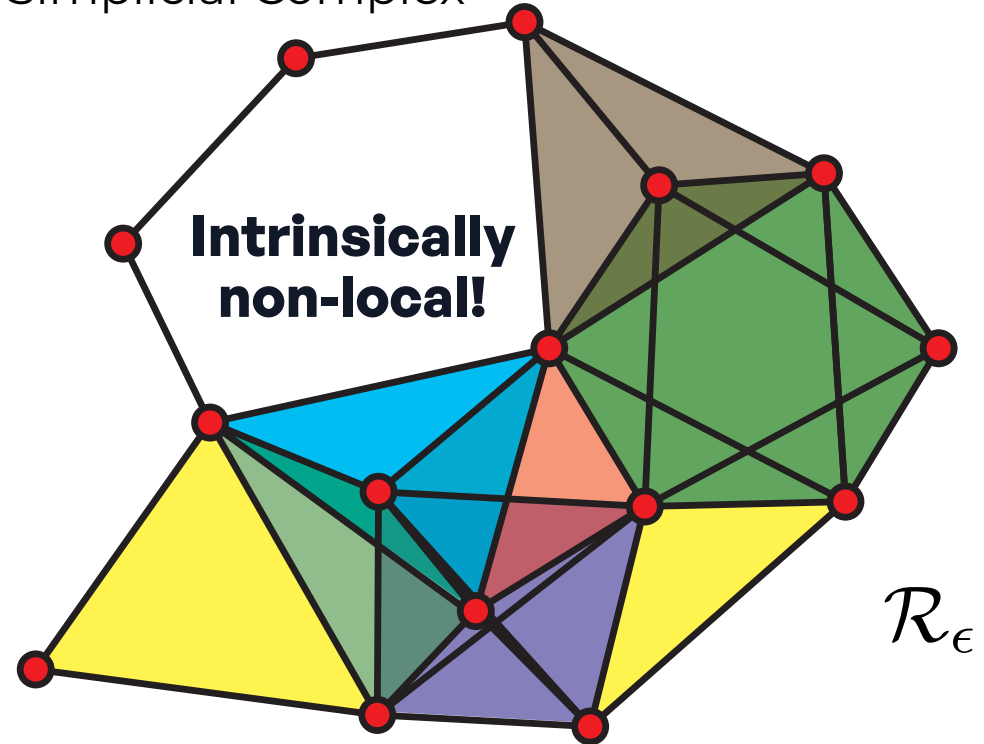
$$\sigma = [p_0, p_1, p_2, \dots, p_{k-1}]$$

Multivariate information

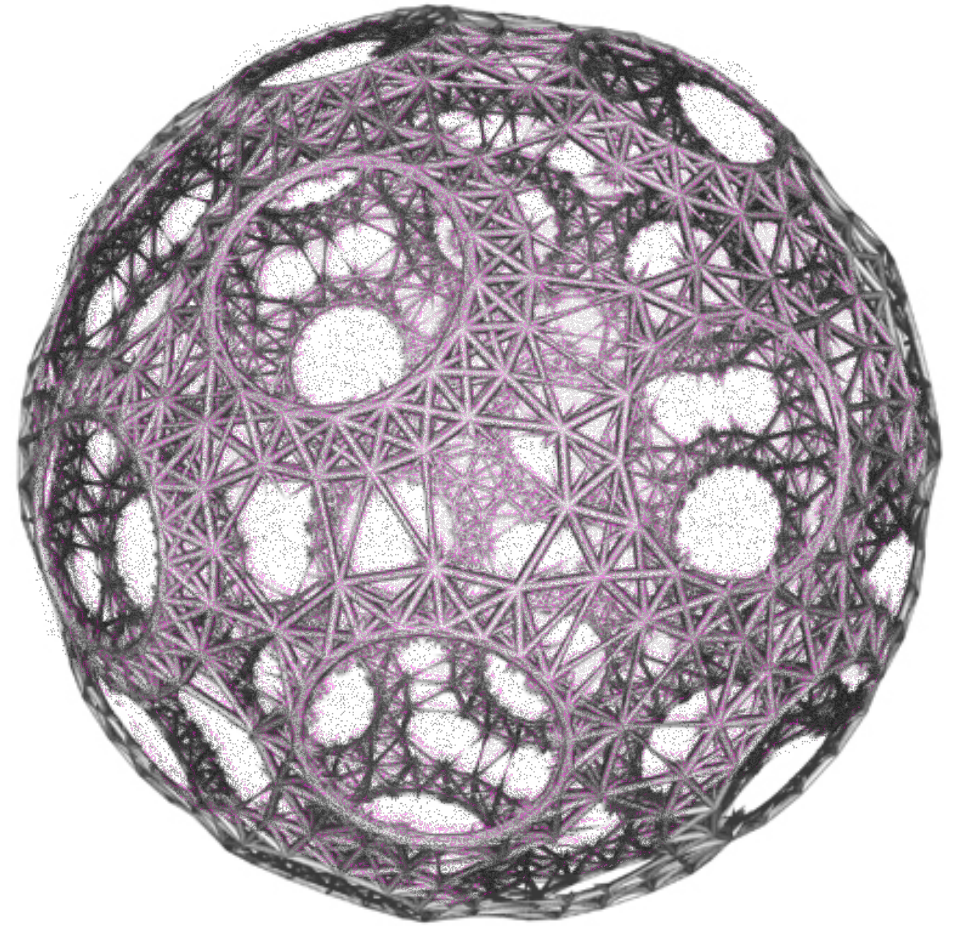
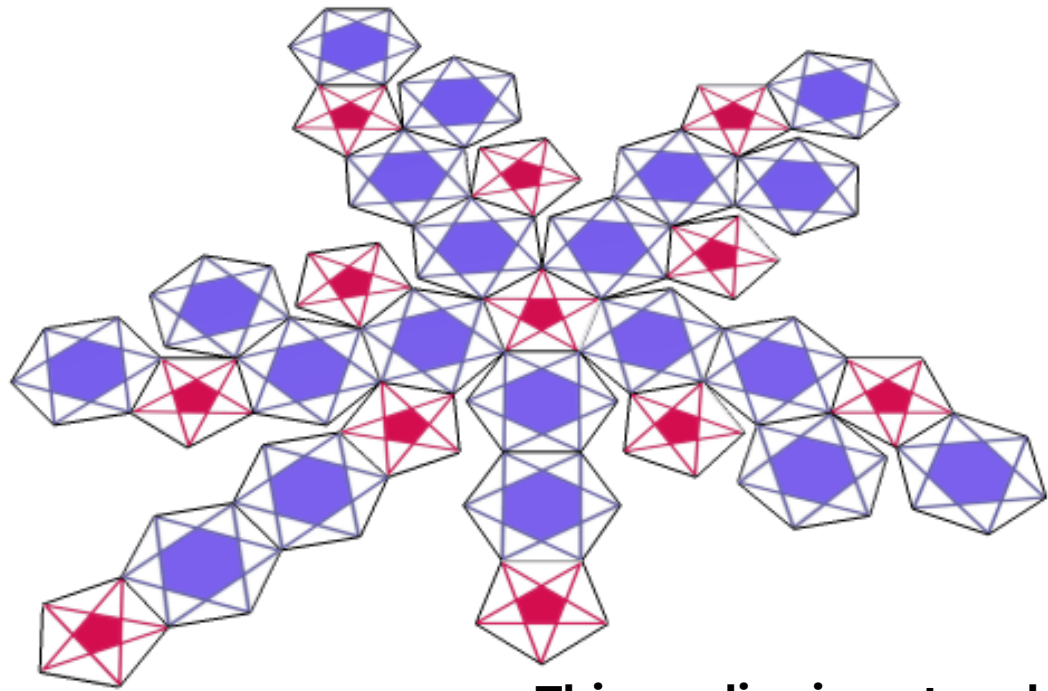
$$P(\mathbf{X}) = P(X_0, X_1, X_2, \dots, X_{k-1})$$

**Intrinsically
higher-order!**

Simplicial Complex



Topology in the wild

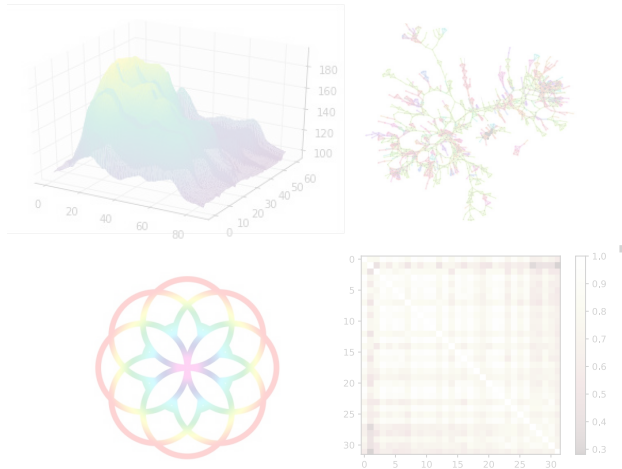


This applies in networks as well as to data spaces

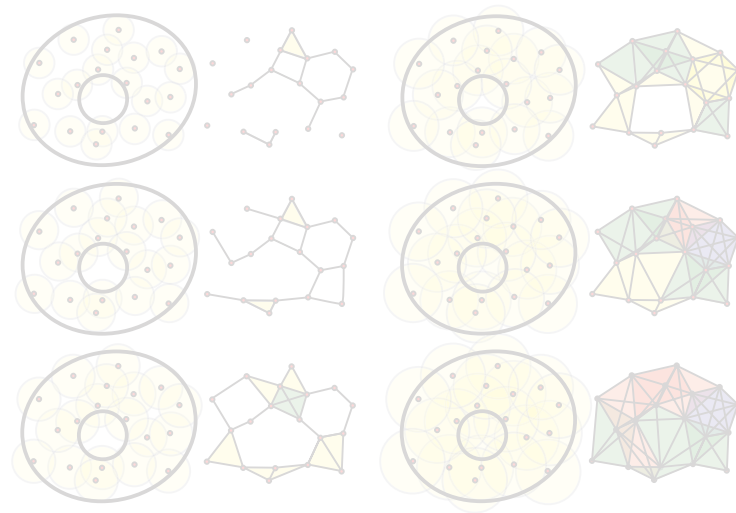
What does it mean in practice?

Persistent homology pipeline (Christ 2008)

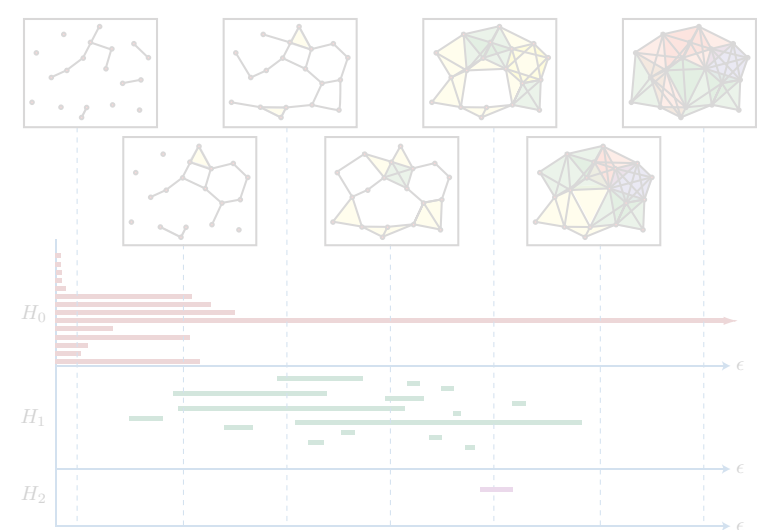
Data of sorts



Filtration over distance/density/weights



Homological properties

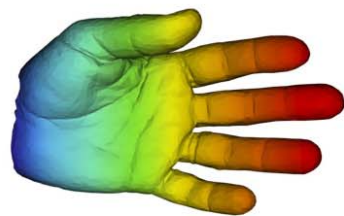


Mapper Pipeline (Singh et al 2007)

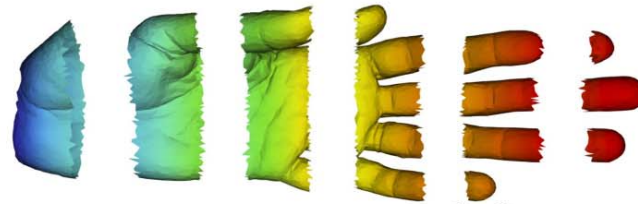
Point cloud



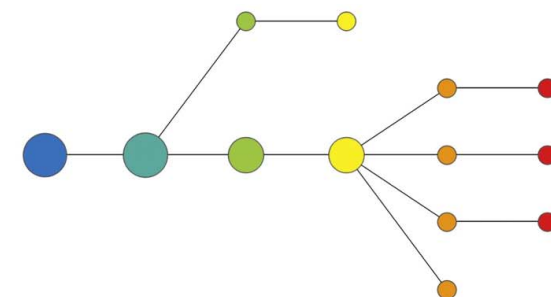
colouring (projecting) using geometric filters



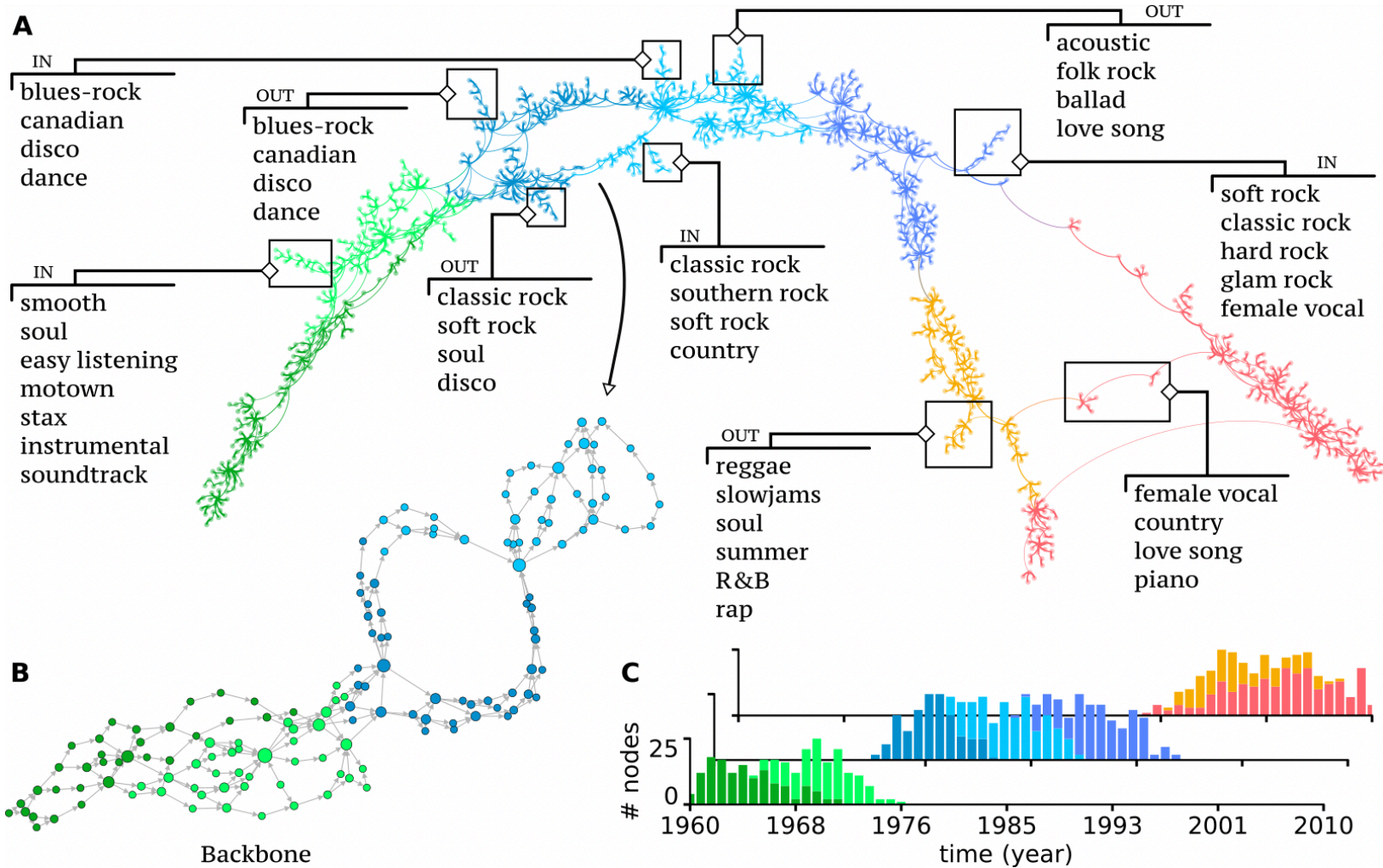
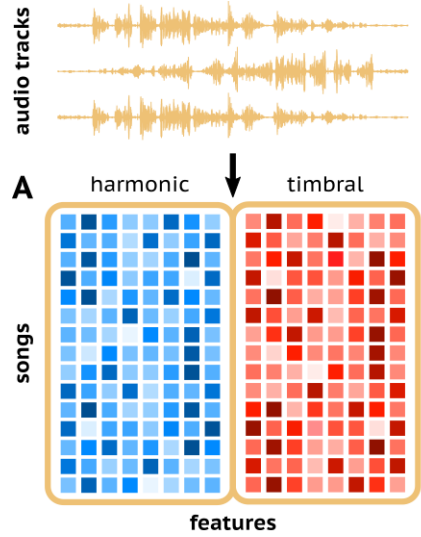
overlapped binning



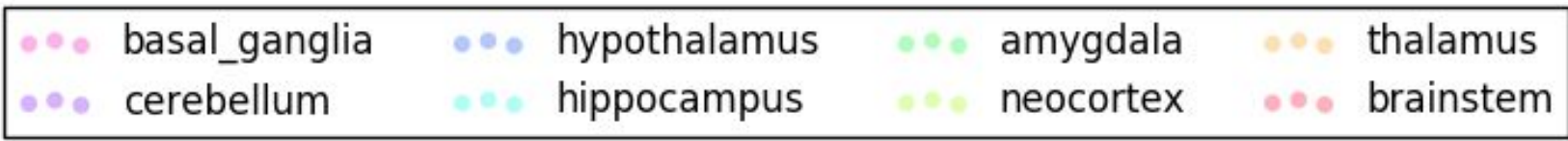
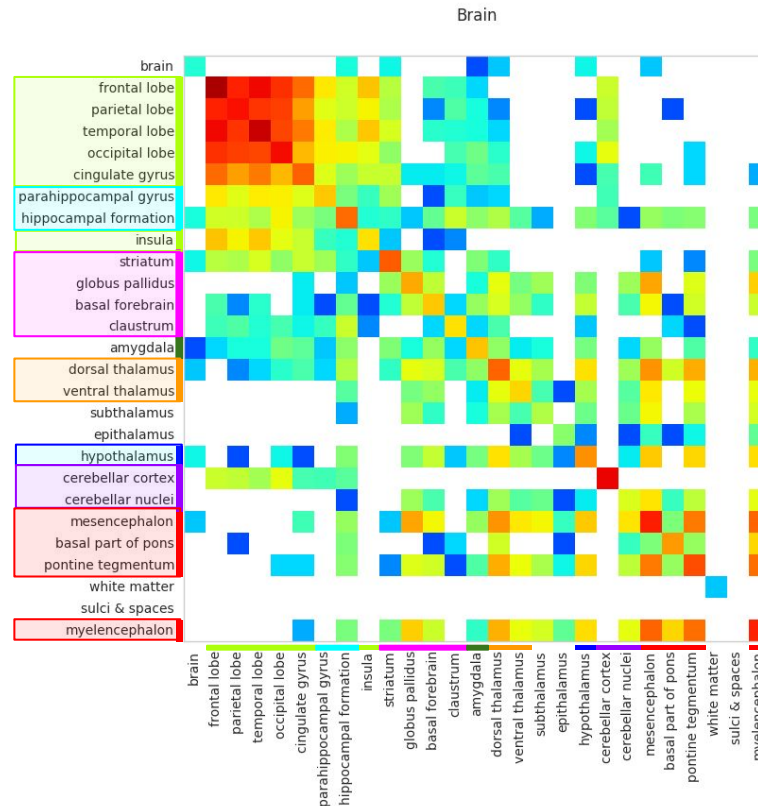
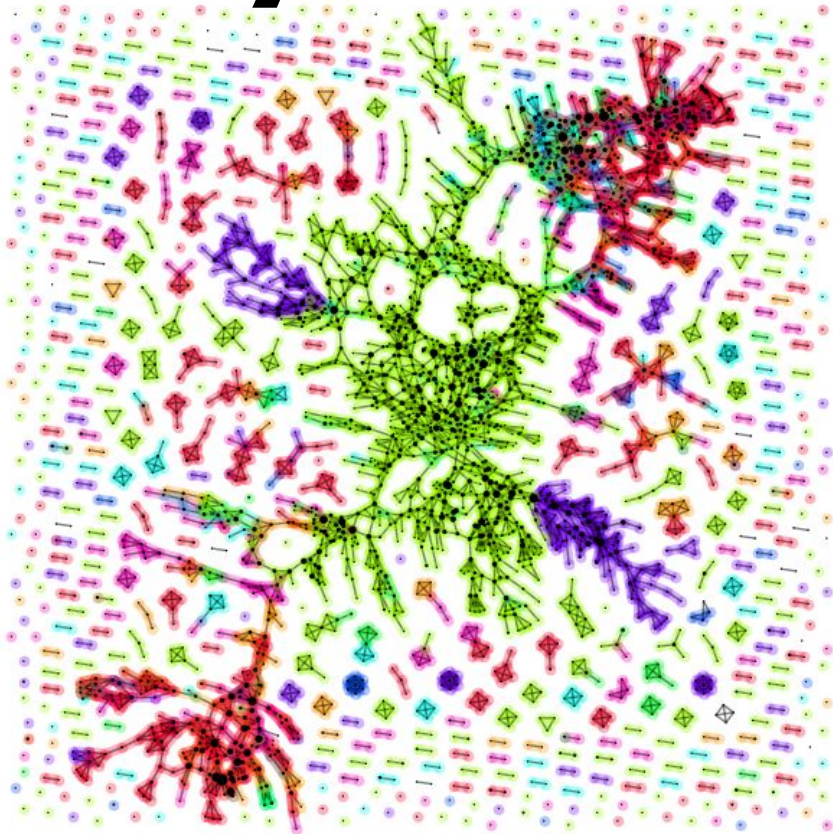
Clustering and network construction binning



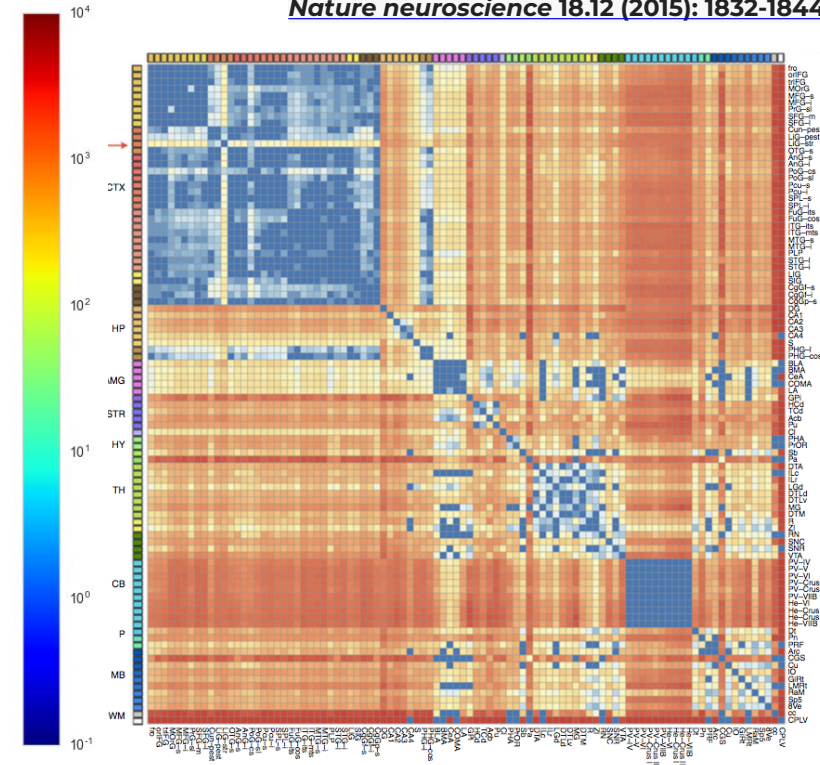
What does it mean in practice?



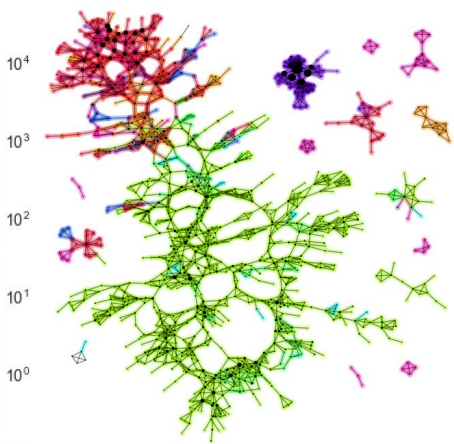
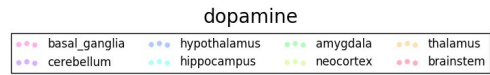
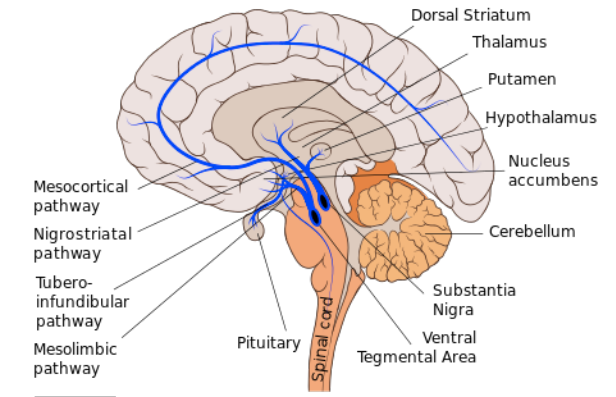
Do topological gene-backbones carry information?



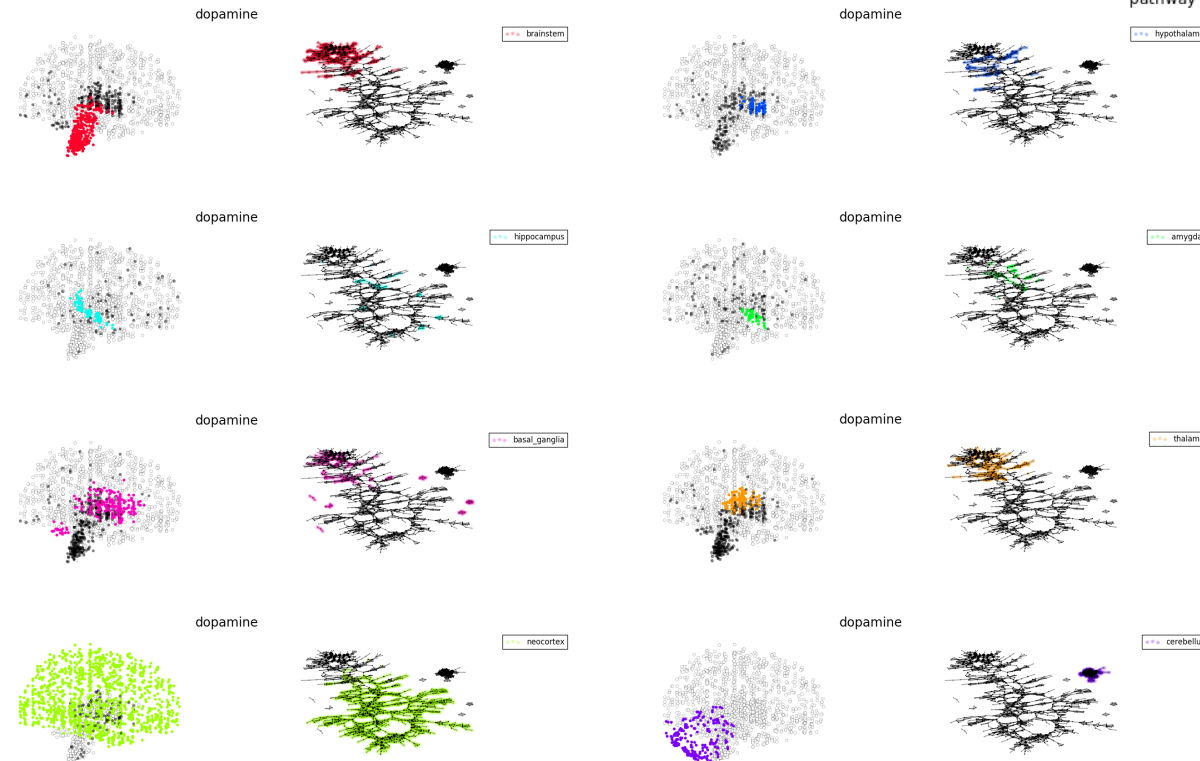
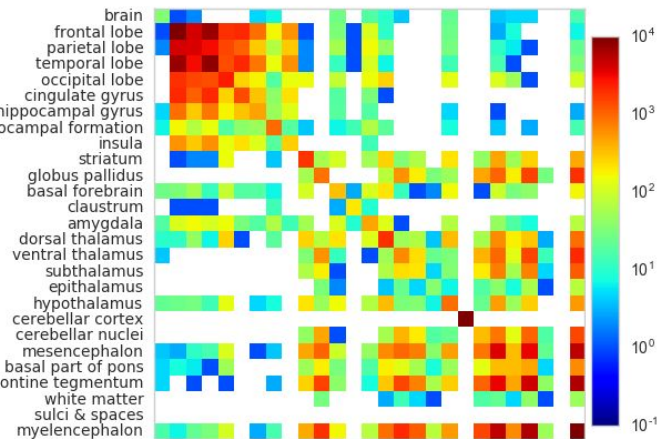
Hawrylycz, Michael, et al. "Canonical genetic signatures of the adult human brain." *Nature neuroscience* 18.12 (2015): 1832-1844.



Do topological gene-backbones carry information?



Dopamine



Patania, A., Solvaggi, P., Veronese, M., Dipasquale, O., Expert, P., & Petri, G. (2019). Topological gene-expression networks recapitulate brain anatomy and function. *Network Neuroscience*. Advance publication. https://doi.org/10.1162/netn_a_00094

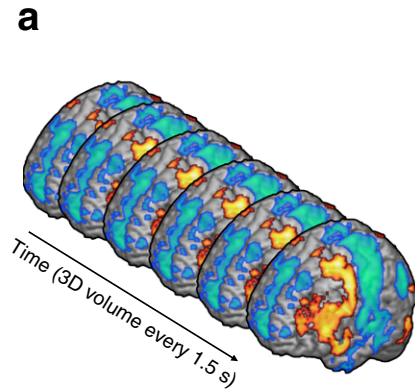
Topological gene-expression networks recapitulate brain anatomy and function

Alice Patania¹, Pierluigi Solvaggi², Mattia Veronese², Ottavia Dipasquale², Paul Expert^{2,3,4} and Giovanni Petri^{1,5,6}

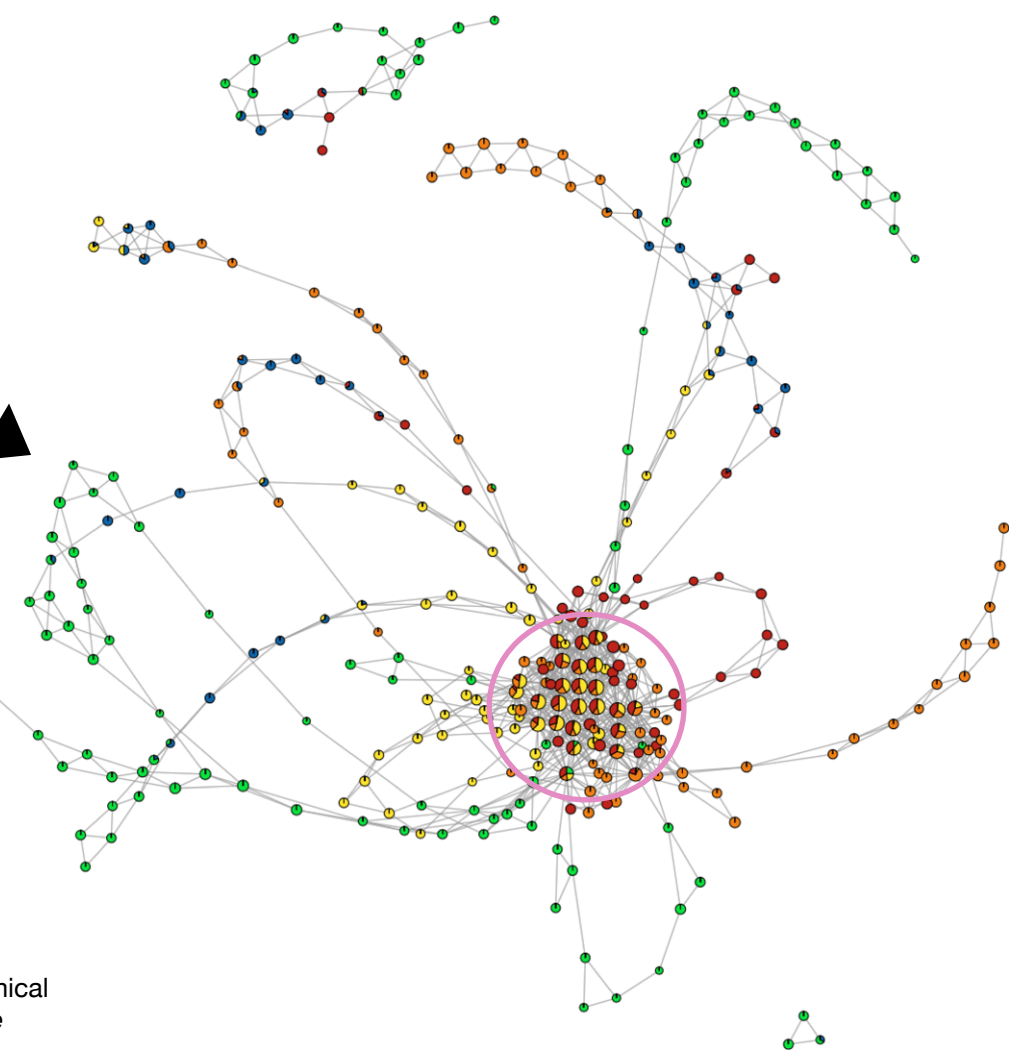
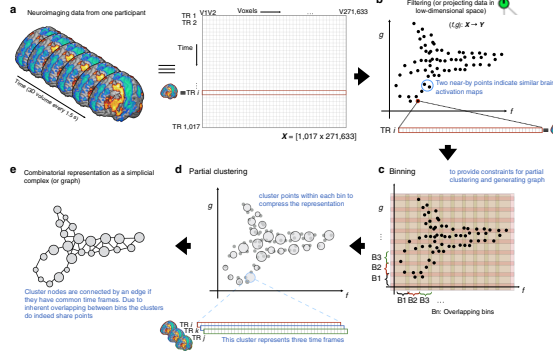
¹Network Science Institute, Indiana University, Bloomington, USA
²Department of Neuroimaging, Institute of Psychiatry, Psychology and Neuroscience, King's College London, London, UK
³Department of Mathematics, Imperial College London, London, UK
⁴EPiRC Centre for Mathematics of Precision Healthcare, Imperial College London, London, UK

Approximate activity landscapes using topology

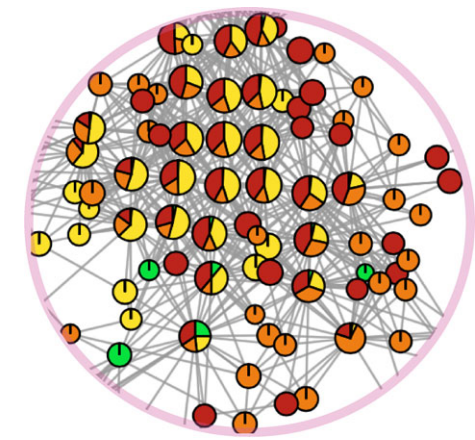
Task brain activation data



Task-fMRI dataset from one CMP participant S₀₁



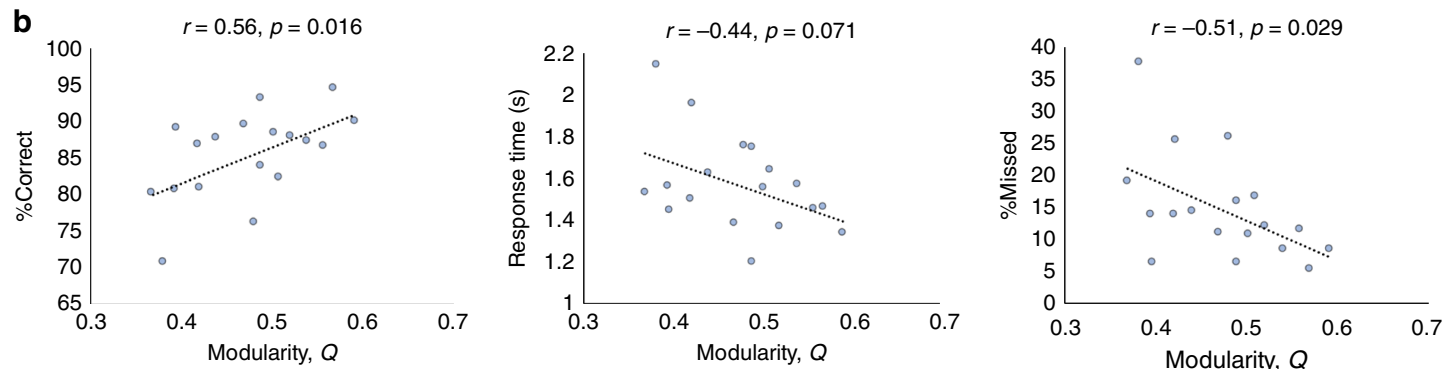
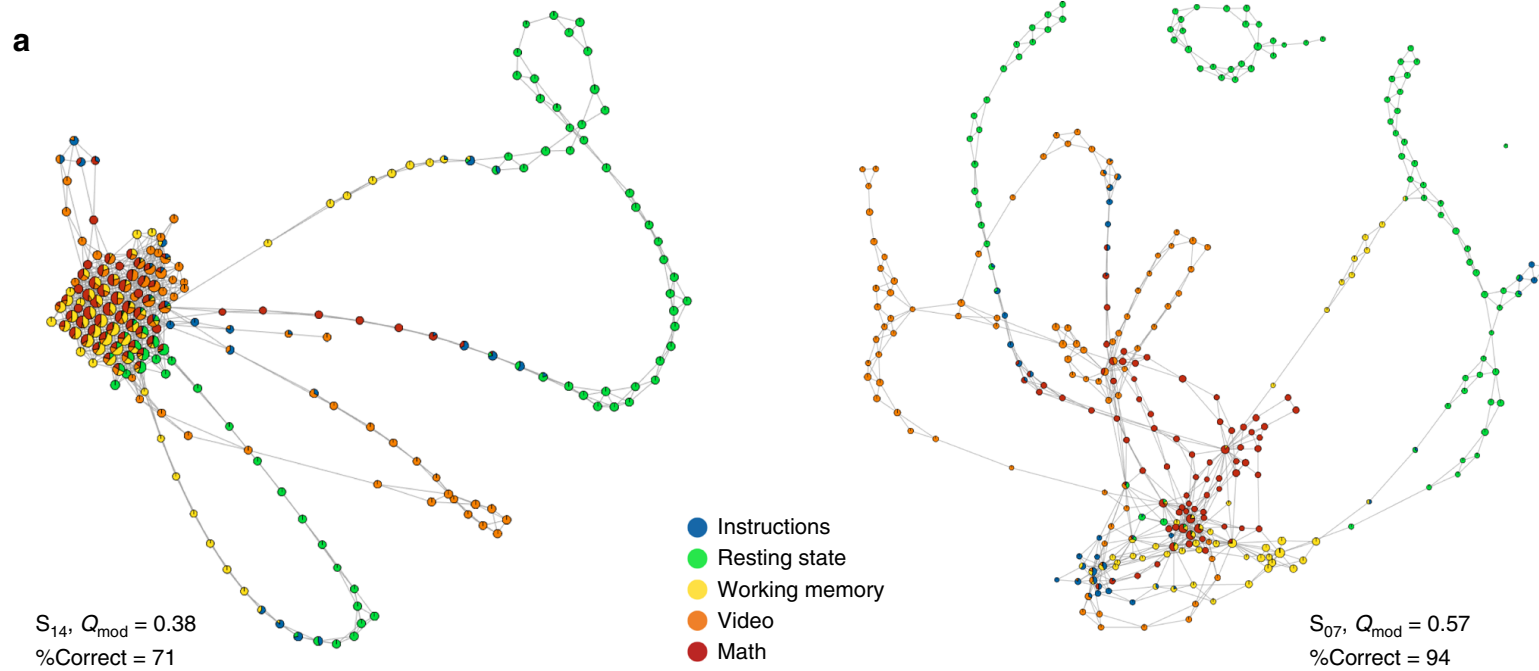
b



- Instructions
- Resting state
- Working memory
- Video
- Math

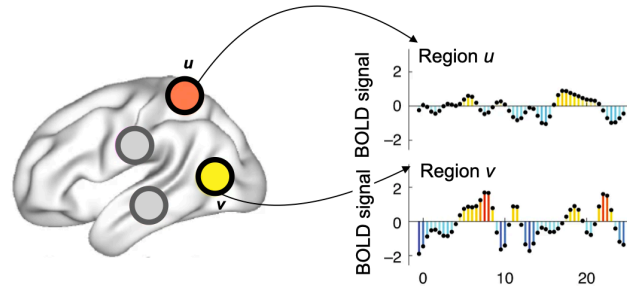
Saggar, Manish, et al. "Towards a new approach to reveal dynamical organization of the brain using topological data analysis." *Nature communications* 9.1 (2018): 1399.

Approximate activity landscapes using topology

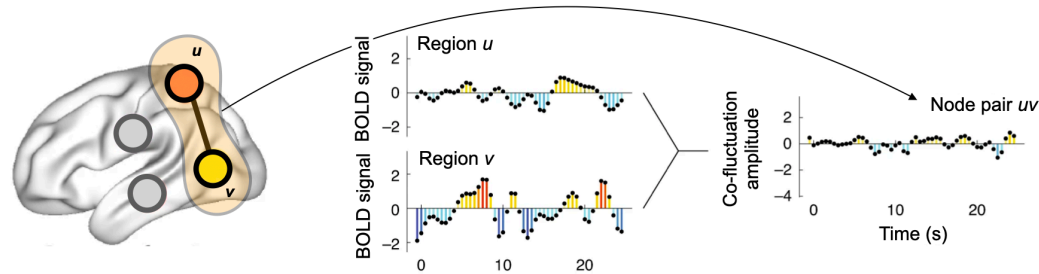


Approximate activity landscapes using topology

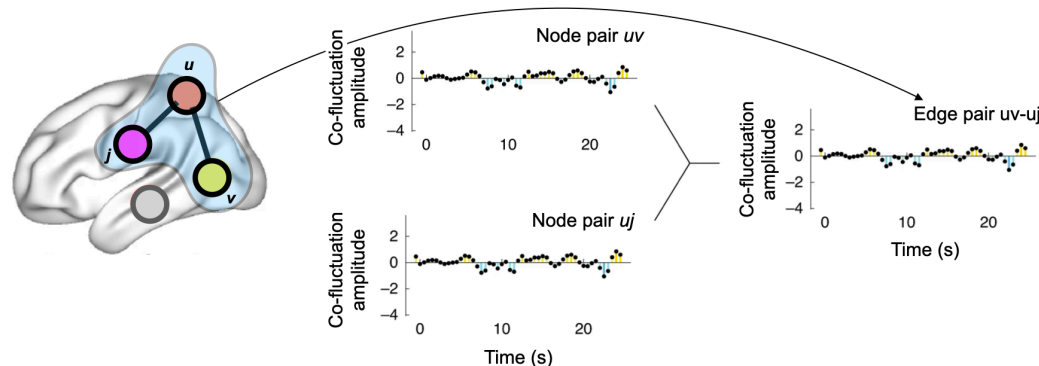
1st order
(activation)



2nd order
(Edge-
timeseries)

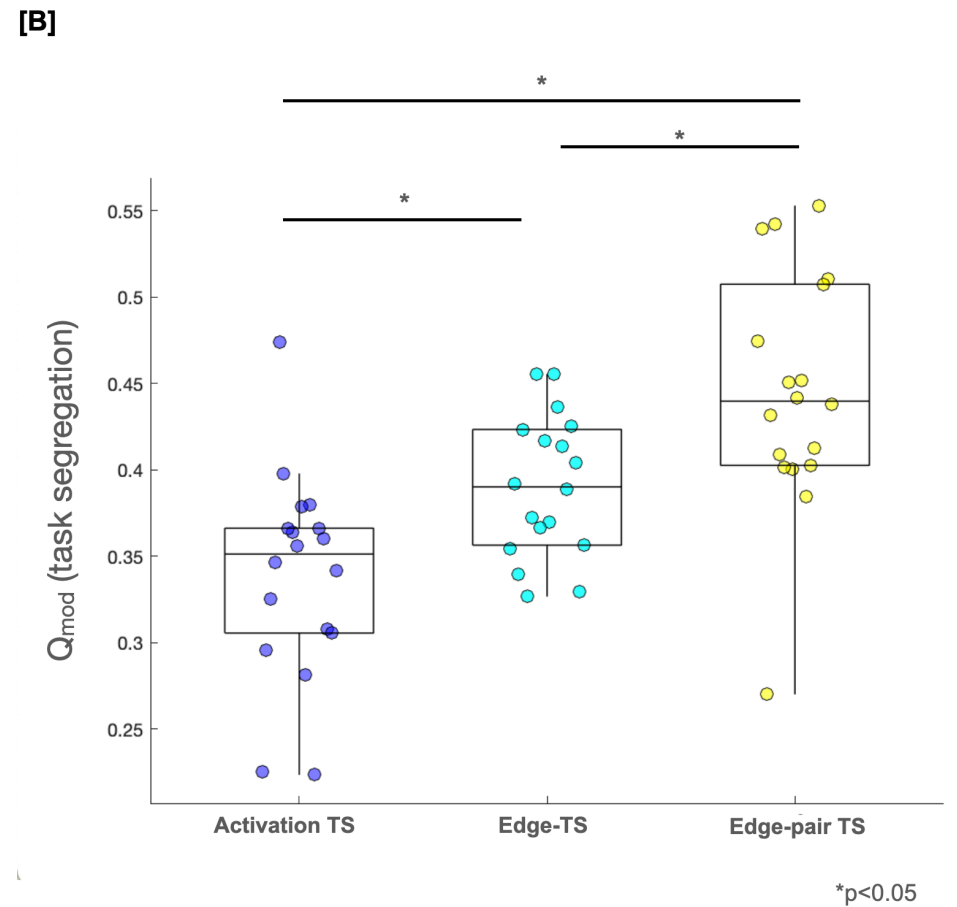
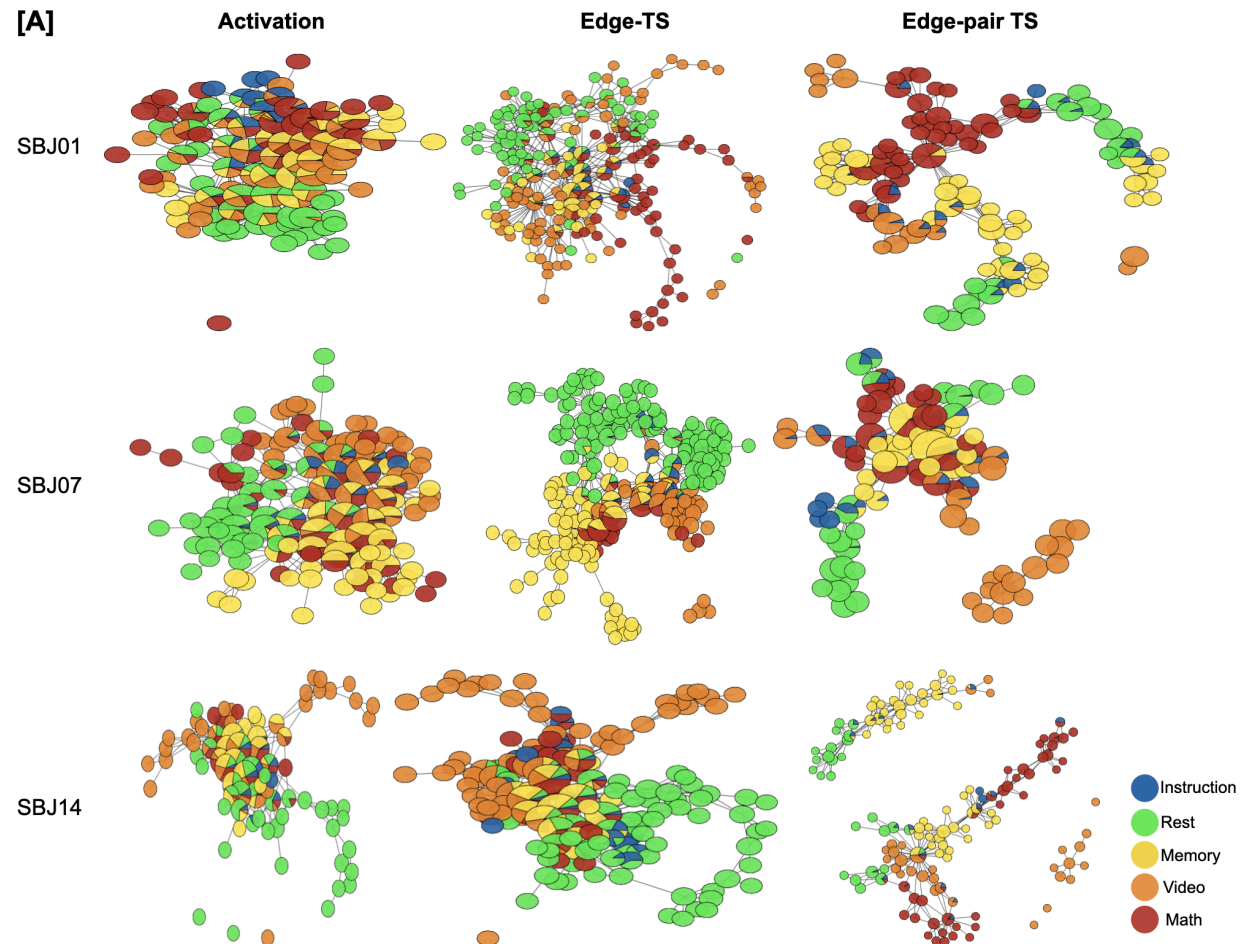


3rd order
(Edge-pair
timeseries)



...

Approximate activity landscapes using topology

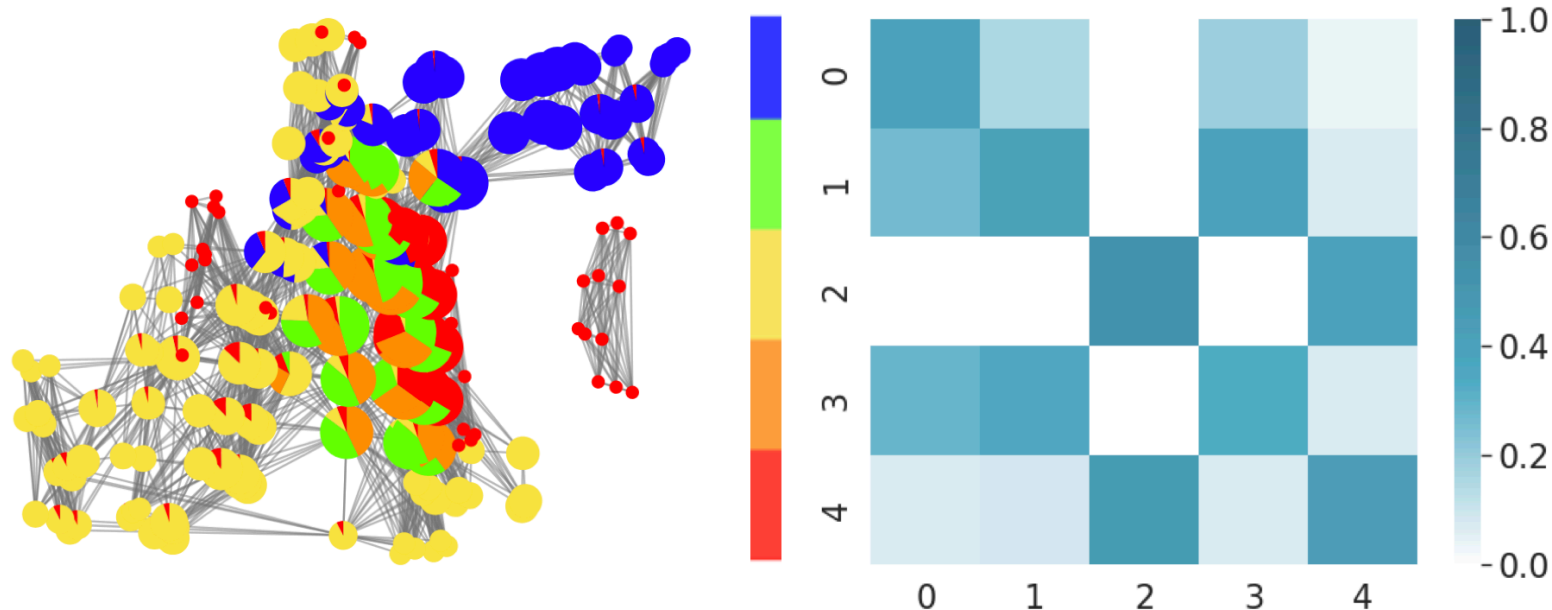


Topological fingerprinting (in general)

Def. Connectivity Mixing Matrix. Given C the number of classes:

$$\mathbf{C} = (c_{ij})_{i,j=1}^C \quad c_{ij} = \sum_{t_i \in i} \sum_{t_j \in j} \chi_{t_i, t_j}$$

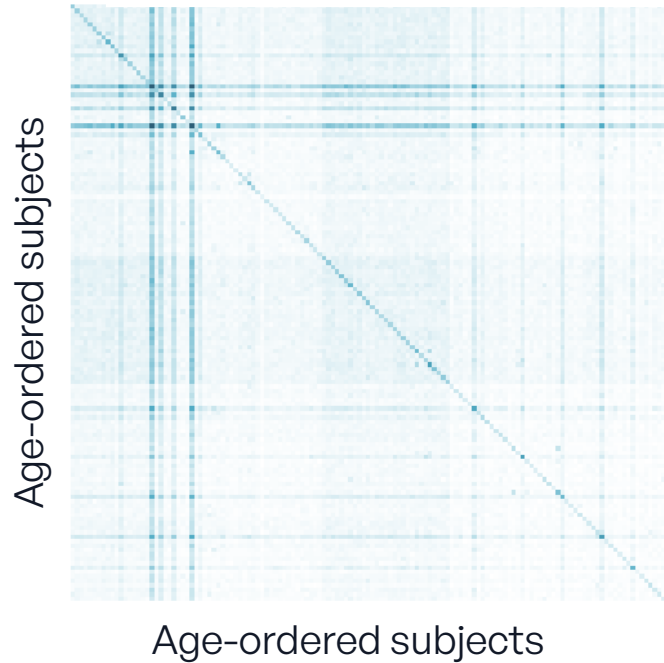
where $\chi_{t_i, t_j} = \begin{cases} 1 & \text{if } \text{node}_{t_i} = \text{node}_{t_j} \text{ or } \exists \text{ edge}(\text{node}_{t_i}, \text{node}_{t_j}) \\ 0 & \text{otherwise} \end{cases}$.



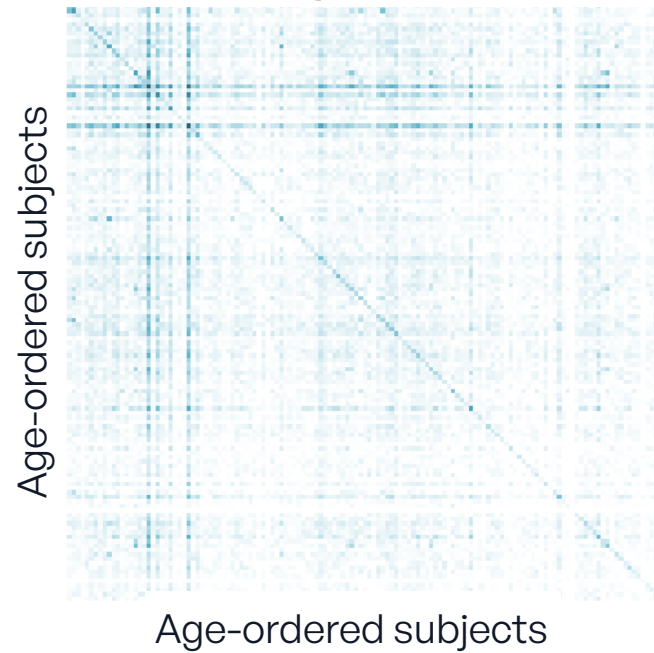
Topological brain fingerprinting

Is the signal strong enough across subjects?

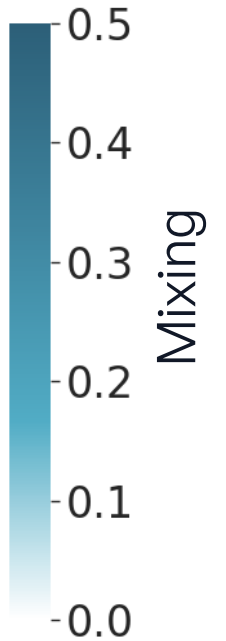
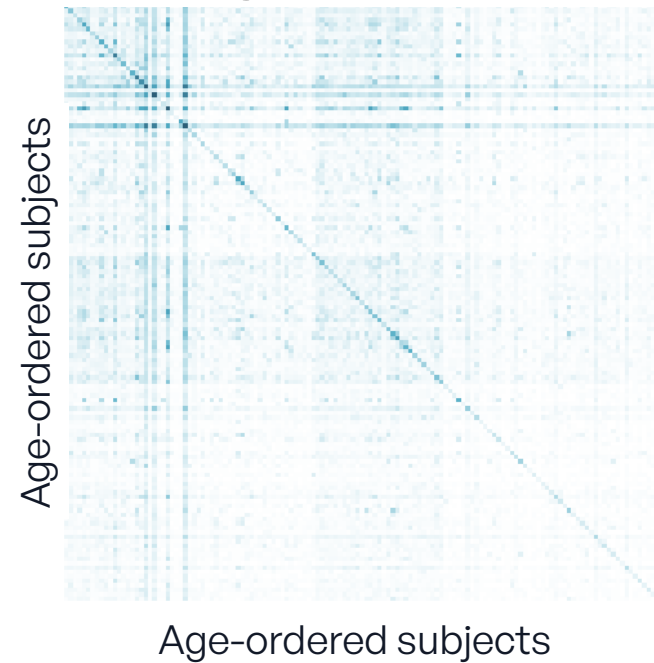
Activation TS



Edge TS



Edge-Pair TS



Topological brain fingerprinting

Is the signal strong enough across subjects?

—Intensive—

Def. Mixing Matrix. Given the classes $1, \dots, C$, assigned to each node, be M_{ij} the number of links between nodes from class i to class j . The mixing matrix of the network is

$$e = \frac{\mathbf{M}}{E},$$

where E is the total number of ordered links.

Def. Attribute assortativity coefficient. Assigned every node to a class:

$$r = \frac{\text{Tr}(e) - \|e^2\|_2}{1 - \|e^2\|_2}.$$

Def. Modularity. Assigned a class c_i to each node i :

$$Q = \frac{1}{2L} \sum_{i,j=1}^N \left(a_{ij} - \frac{k_i k_j}{2L} \right) f(c_i, c_j).$$

$$f(c_i, c_j) = D_{JS}(c_i || c_j)$$

Jensen-Shannon divergence

—Discriminative—

Def. Self-identifiability. Given C the number of classes and \mathbf{C} the CMM:

$$I_{self}(i) = c_{ii}$$

Def. Others-identifiability. Given C the number of classes and \mathbf{C} the CMM:

$$I_{others}(i) = \frac{1}{2} \sum_{j \neq i} (c_{ij} + c_{ji}).$$

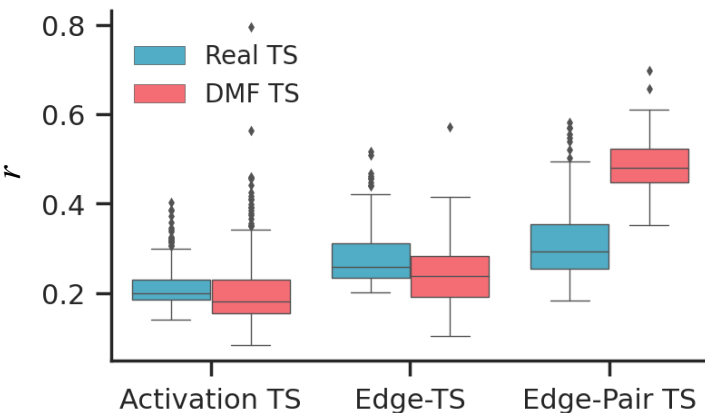
Def. Topological fingerprint. Given C the number of classes and \mathbf{C} the CMM:

$$\langle I_{diff} \rangle = \frac{\langle I_{self} \rangle - \langle I_{others} \rangle}{\langle I_{self} \rangle},$$

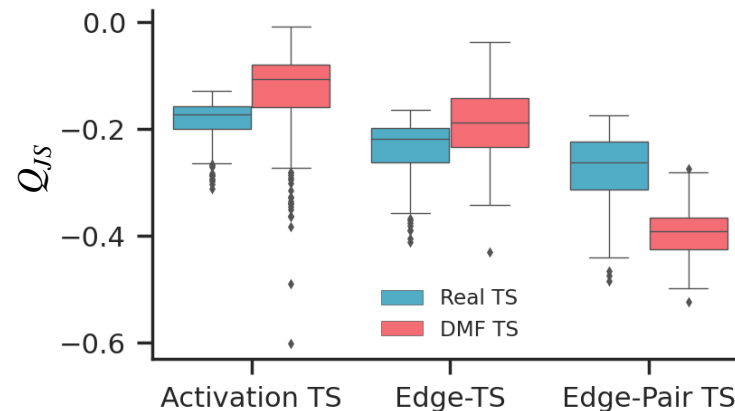
where $\langle I_{self} \rangle$ and $\langle I_{others} \rangle$ are the average self and others identifiability.

Van De Ville, Dimitri, et al. "When makes you unique: temporality of the human brain fingerprint." *Science advances* 7.42 (2021): eabj0751.

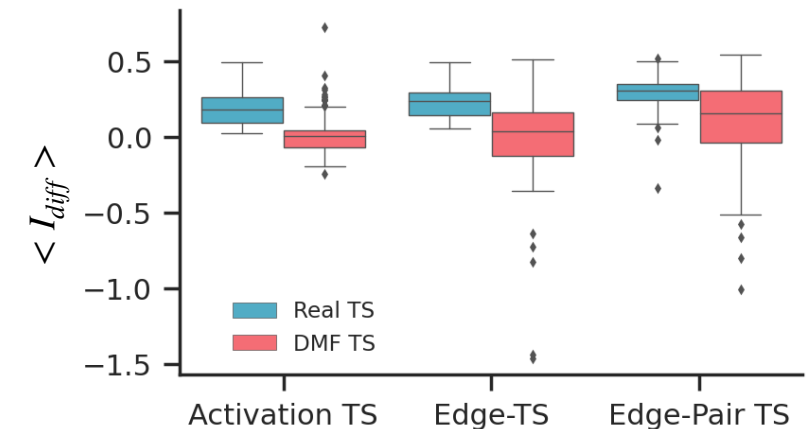
Attribute Assortativity Coefficient



JS-modularity



Topological Fingerprint



Topo+Info brain fingerprinting

Def. Shannon Entropy. Expected surprise of a random discrete variable X , distributed according to $p : \mathcal{X} \rightarrow [0,1]$:

$$H(X) = - \sum_{x \in \mathcal{X}} p(x) \log(p(x)).$$

Def. Joint Entropy. Expected surprise of a set of random discrete variables $\mathbf{X} = X_1, X_2, \dots, X_n$, distributed according to $p_i : \mathcal{X}_i \rightarrow [0,1], i = 1, \dots, n$:

$$H(\mathbf{X}) = H(X_1, \dots, X_n) = - \sum_{x_i \in \mathcal{X}_i, i=1, \dots, n} p(x_1, \dots, x_n) \log(p(x_1, \dots, x_n)).$$

Def. Ω -information.

$$\Omega(\mathbf{X}) = \Omega(X_1, \dots, X_n) = (n - 2)H(\mathbf{X}) - \sum_{i=1}^n (H(X_i) - H(\mathbf{X}_{-i})).$$

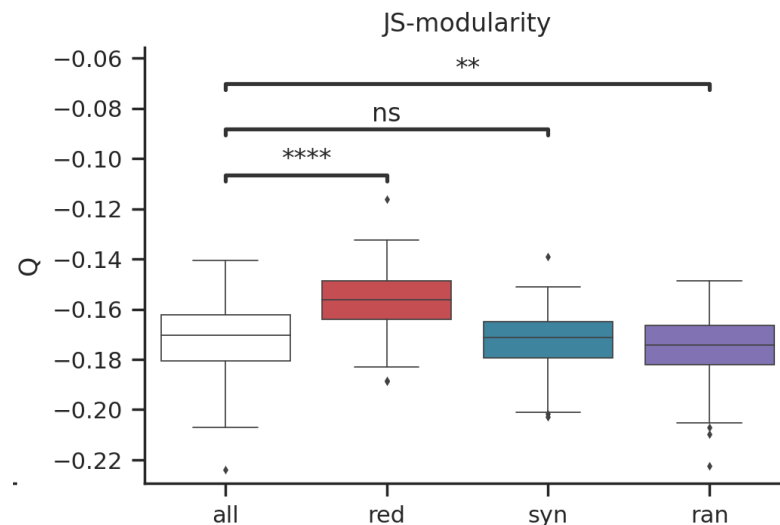
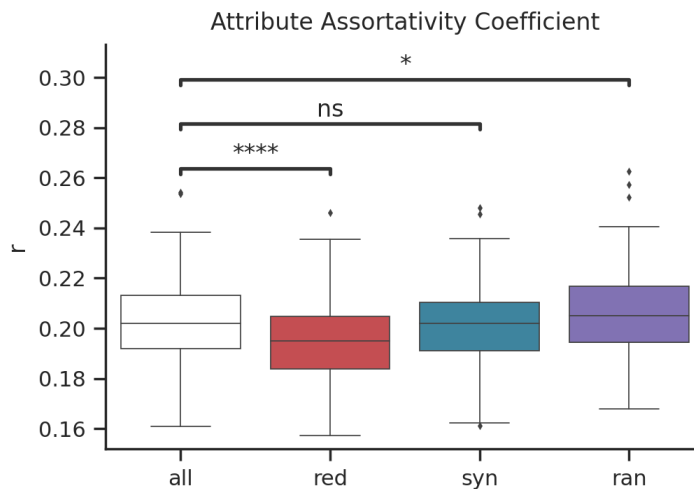
$\Omega(\mathbf{X}) > 0$

REDUNDANCY

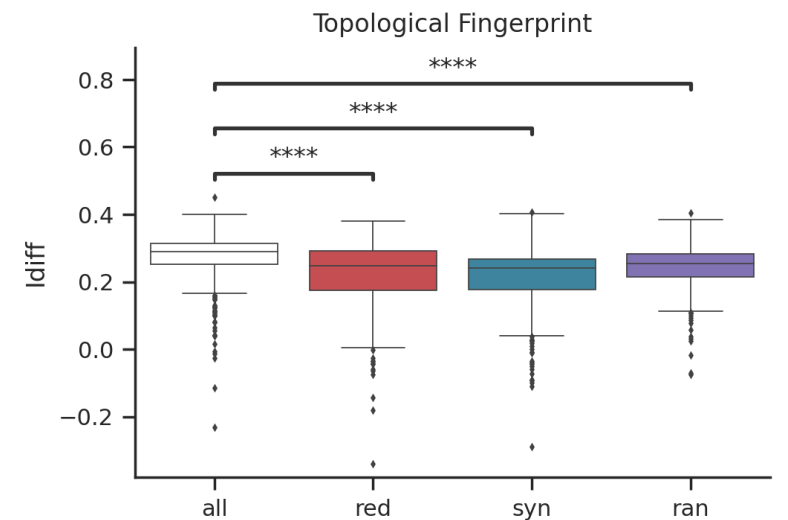
$\Omega(\mathbf{X}) < 0$

SYNERGY

—Intensive—




—Discriminative—



Topo+Info brain fingerprinting

Summing up

- Topological information (simplification) discriminates well across individuals
- Stronger effect for higher-order timeseries
- Global markers, but no relation to the actual synergy/redundancy patterns



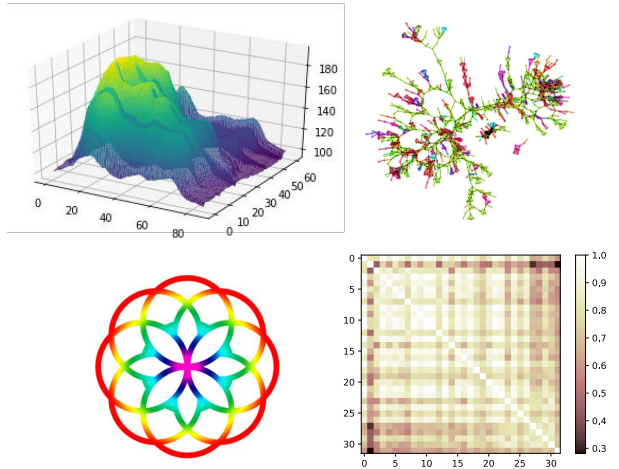
**Can topology
quantify
local shapes?**

Functional, structural, you name it...

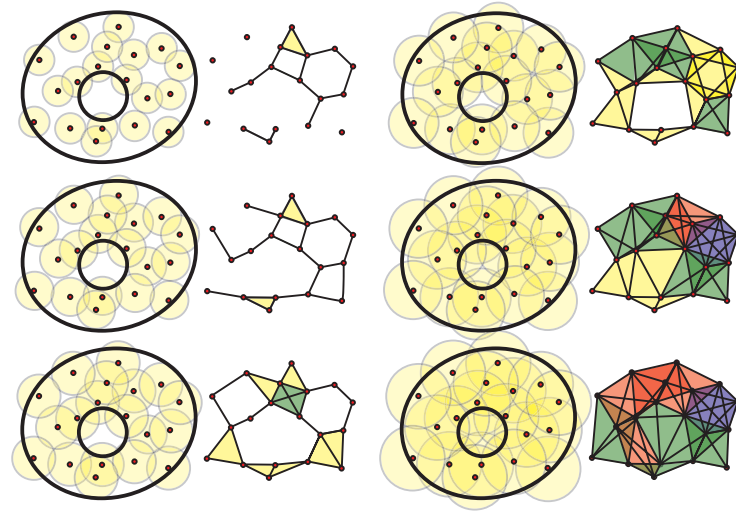
What does it mean in practice?

Persistent homology pipeline (Christ 2008)

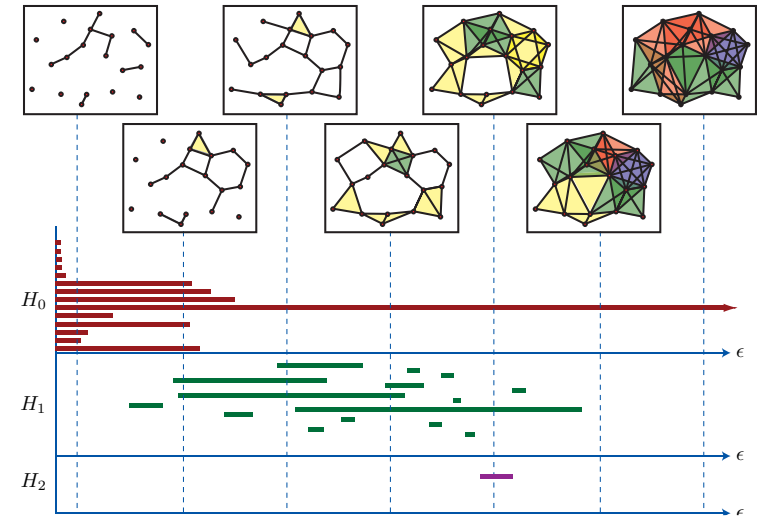
Data of sorts



Filtration over distance/density/weights



Homological properties



Mapper Pipeline (Singh et al 2007)

Point cloud



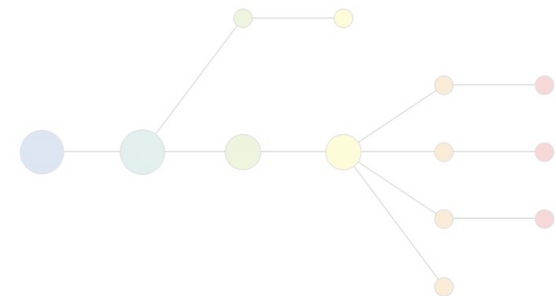
colouring (projecting)
using geometric filters



overlapped
binning



Clustering and
network construction binning



From data to simplices

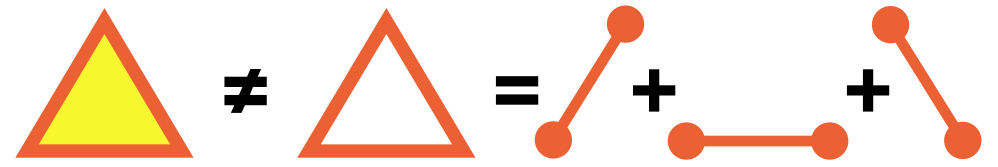
DOT
= 0-simplex



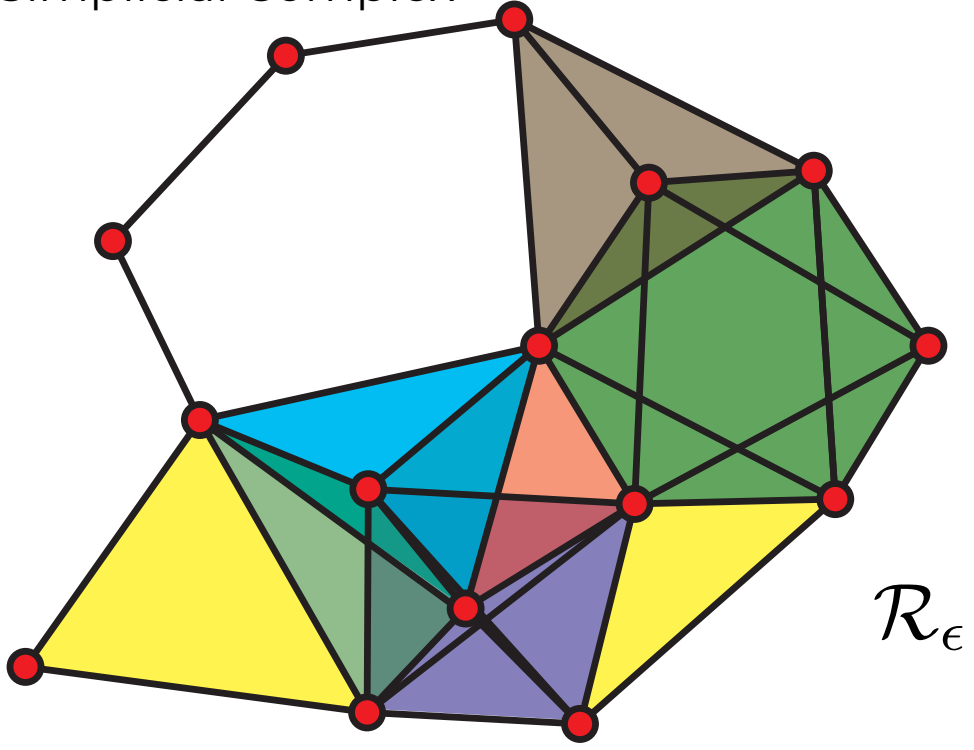
EDGE =
1-simplex



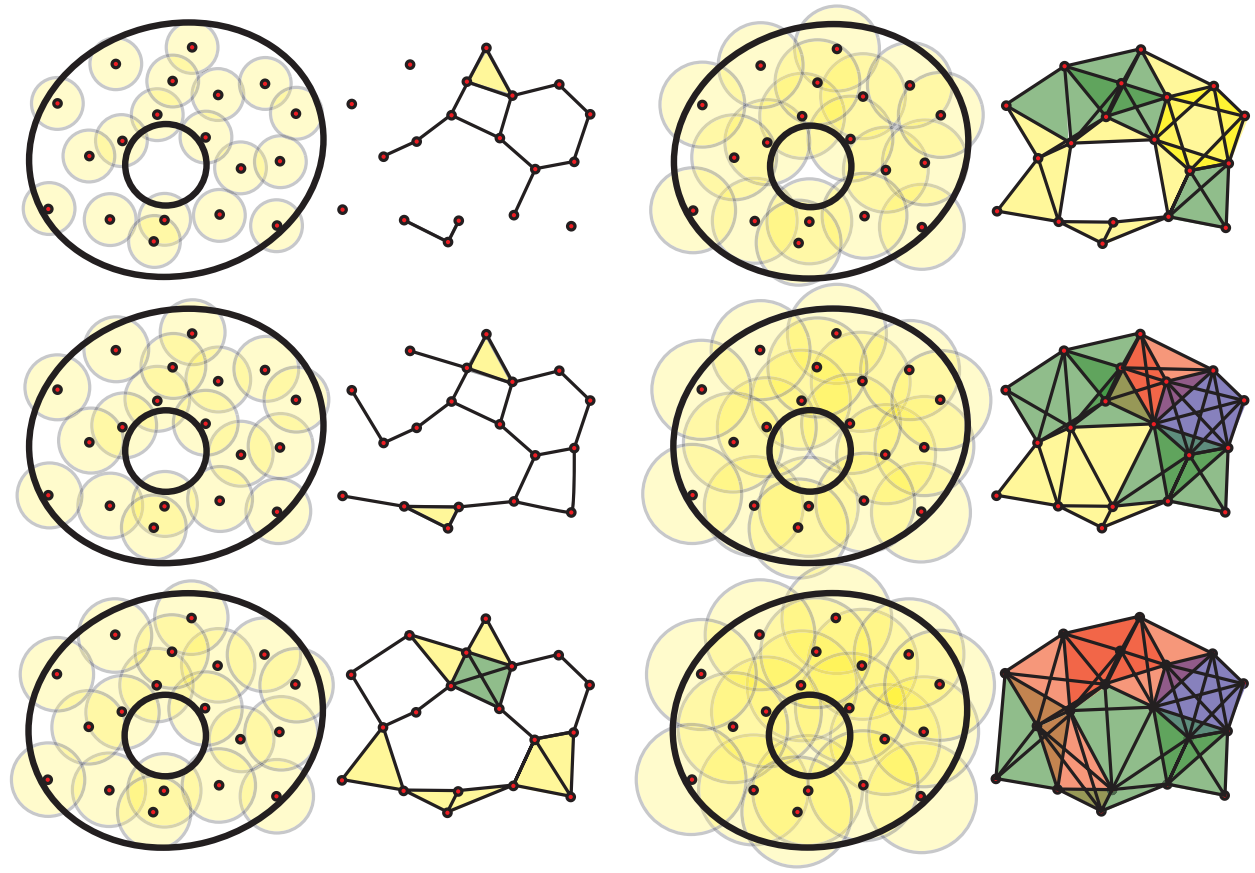
TRIANGLE
= 2-simplex



Simplicial Complex



\mathcal{R}_ϵ



From data to simplices

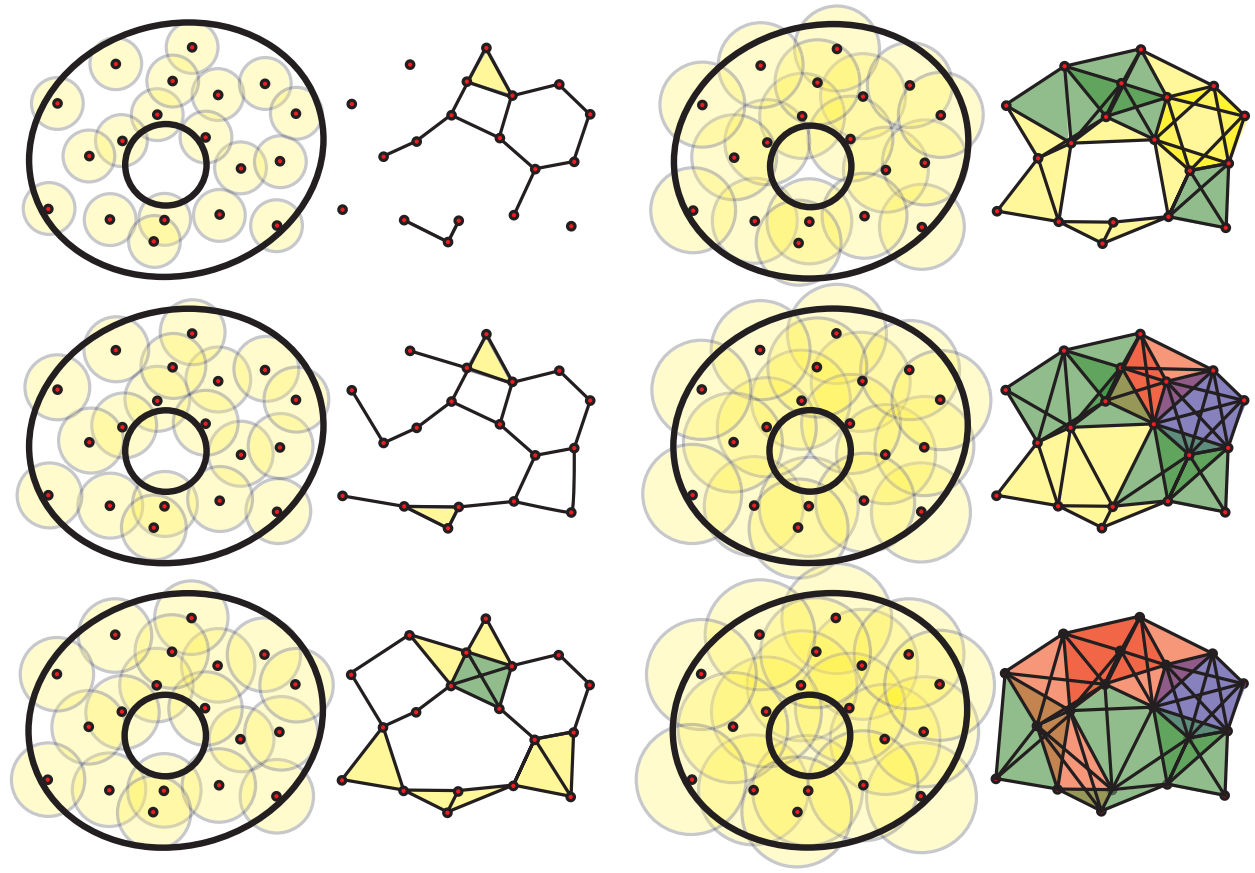
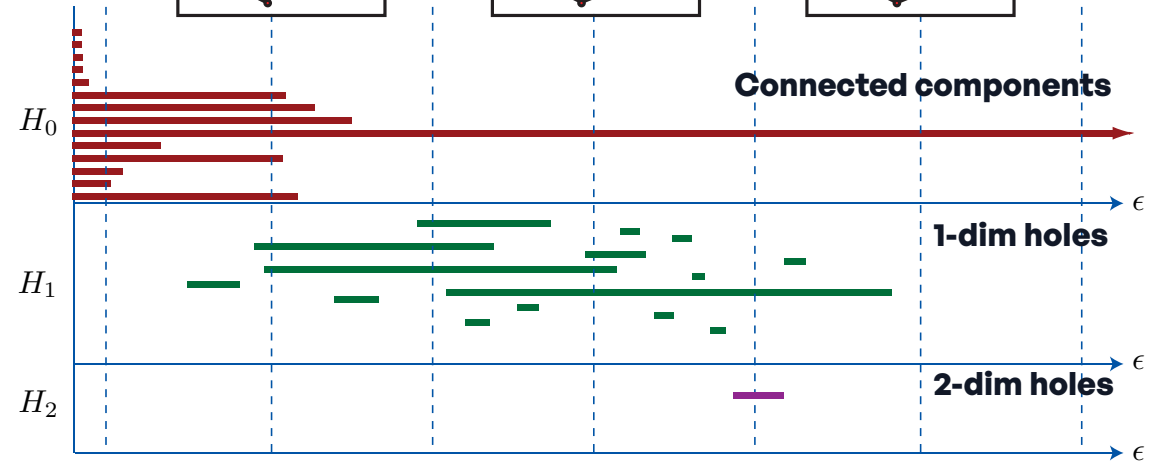
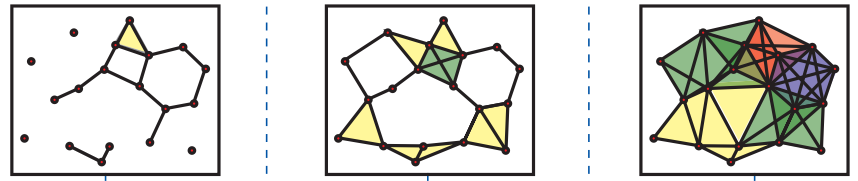
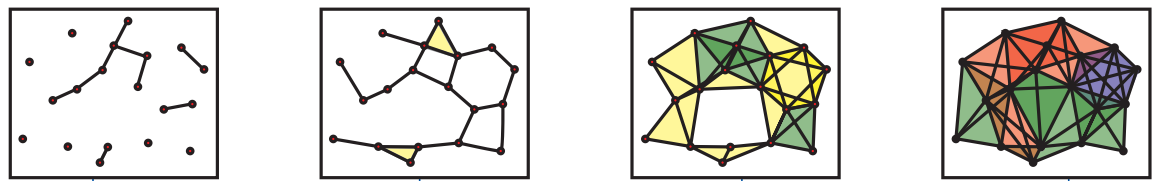
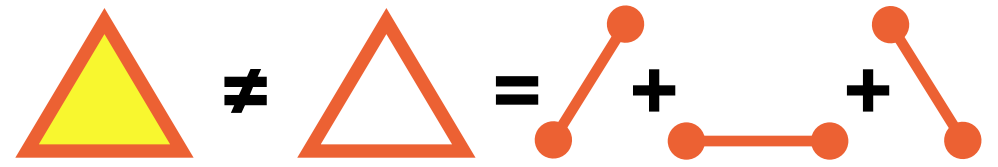
DOT
= 0-simplex



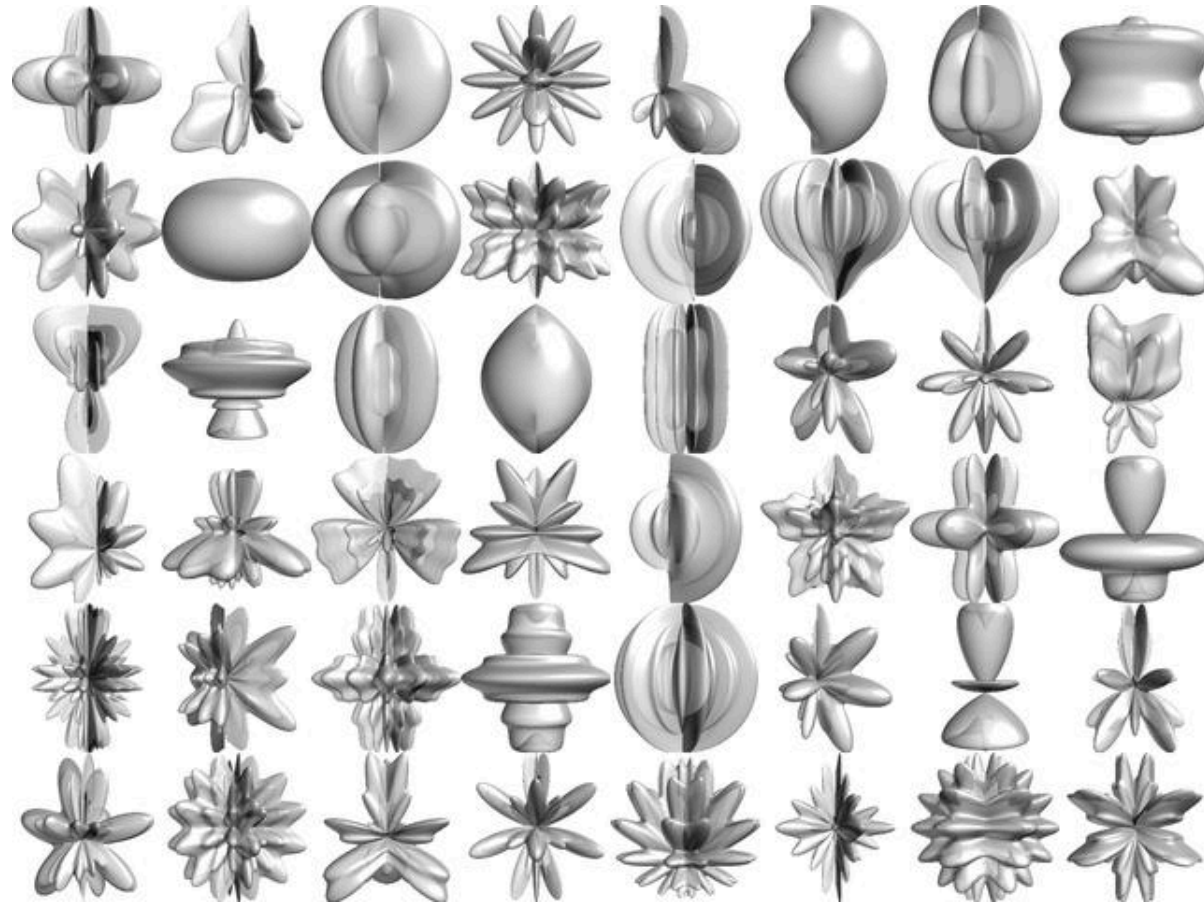
EDGE =
1-simplex



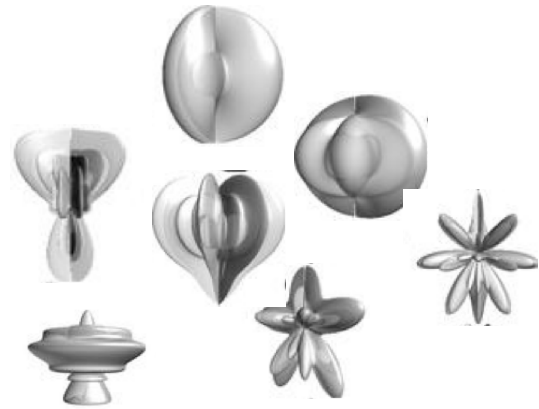
TRIANGLE
= 2-simplex



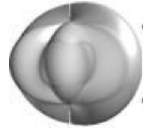
Quantitative topological comparison



Quantitative topological comparison



Quantitative topological comparison



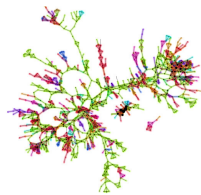
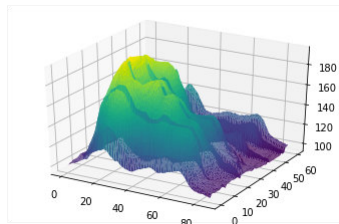
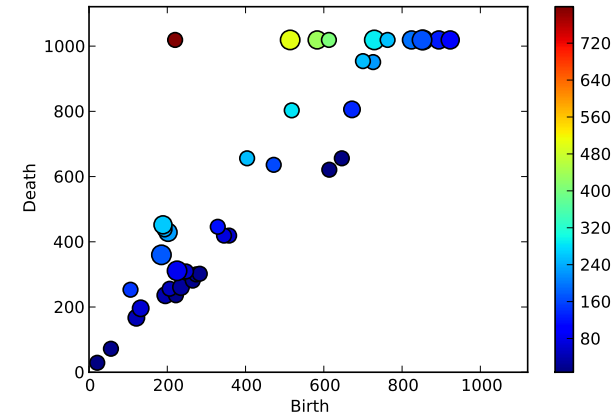
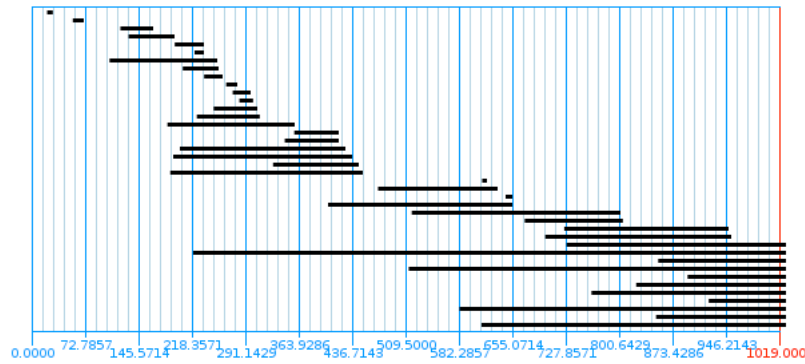
Aktas, Mehmet E., Esra Akbas, and Ahmed El Fatmaoui. "Persistence homology of networks: methods and applications." *Applied Network Science* 4.1 (2019): 1-28.

Fasy, Brittany, et al. "Comparing distance metrics on vectorized persistence summaries." *TDA & Beyond*. 2020.

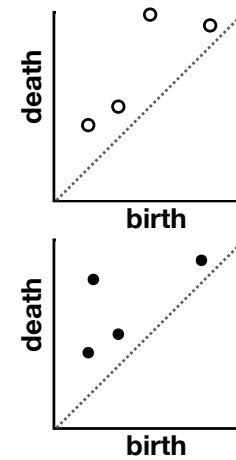
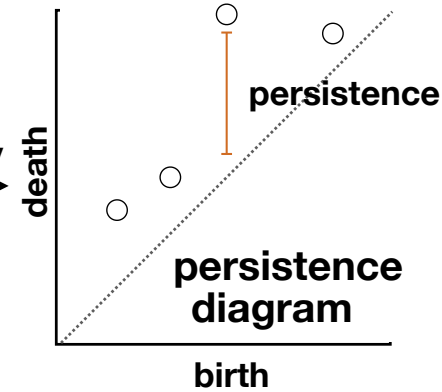
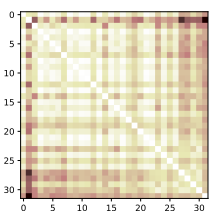
Chung, Moo K., et al. "Topological distances between brain networks." *Connectomics in Neuroimaging: First International Workshop, CNI 2017, Held in Conjunction with MICCAI 2017, Quebec City, QC, Canada, September 14, 2017, Proceedings 1*. Springer International Publishing, 2017.



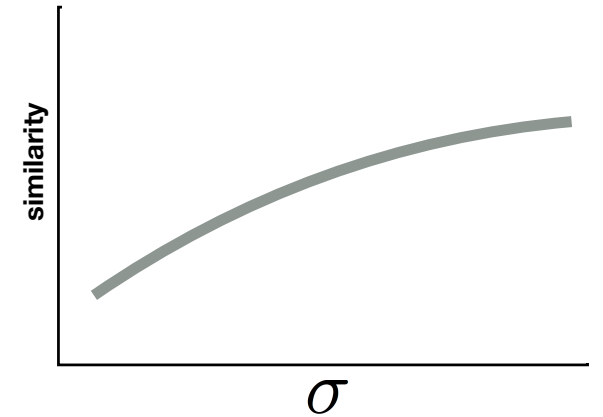
Quantitative topological comparison



topology



Wasserstein distance



BrainZ

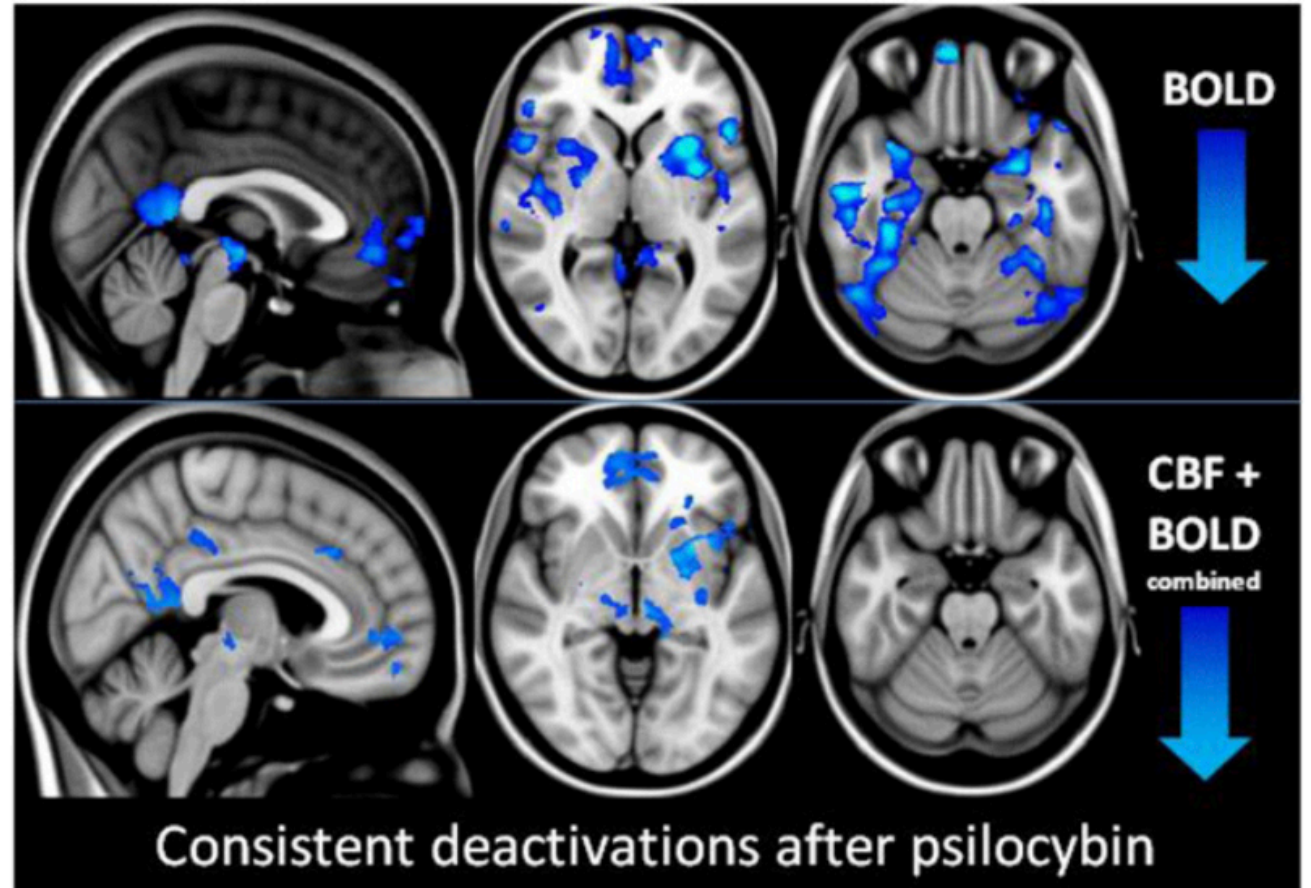


Altered functional topology



rs-fMRI
15 subjects, 2 sessions
1 recording condition

Carhart-Harris, Robin L., et al. "Neural correlates of the psychedelic state as determined by fMRI studies with psilocybin." *Proceedings of the National Academy of Sciences* 109.6 (2012): 2138-2143.

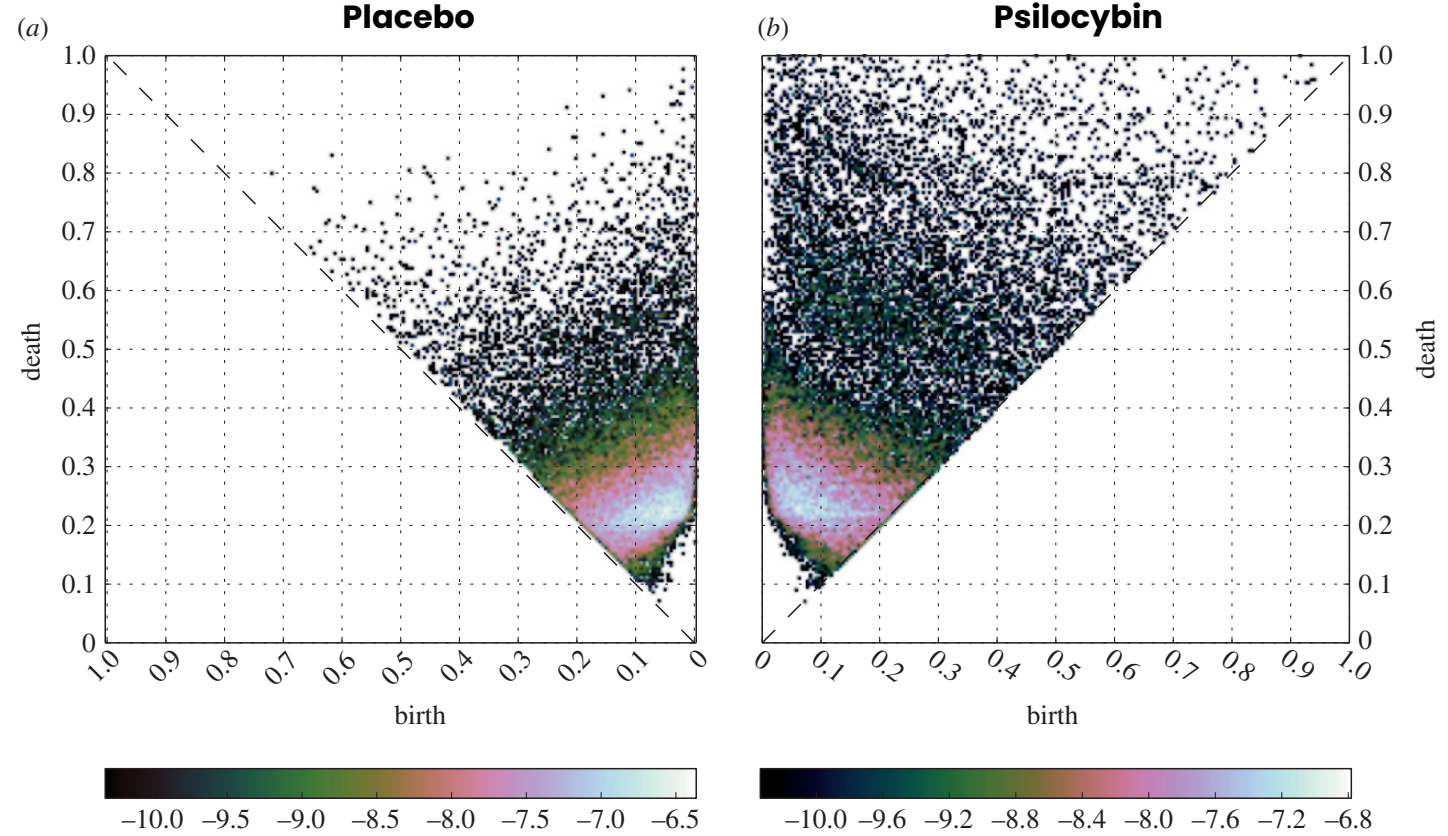
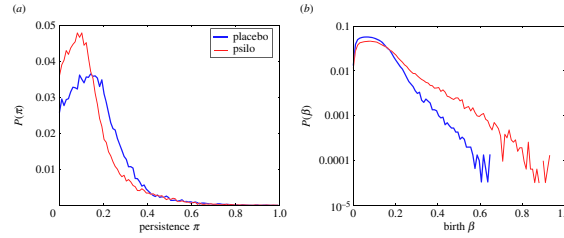


Altered functional topology



rs-fMRI
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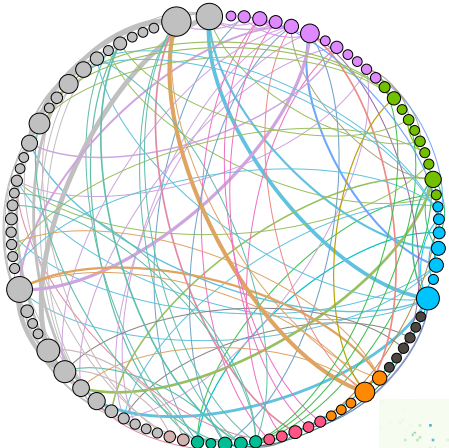
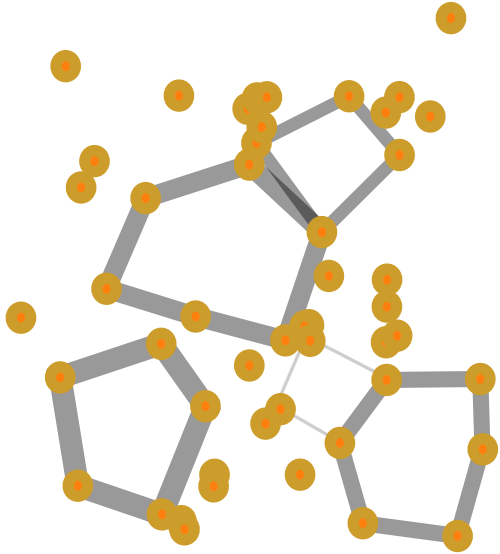
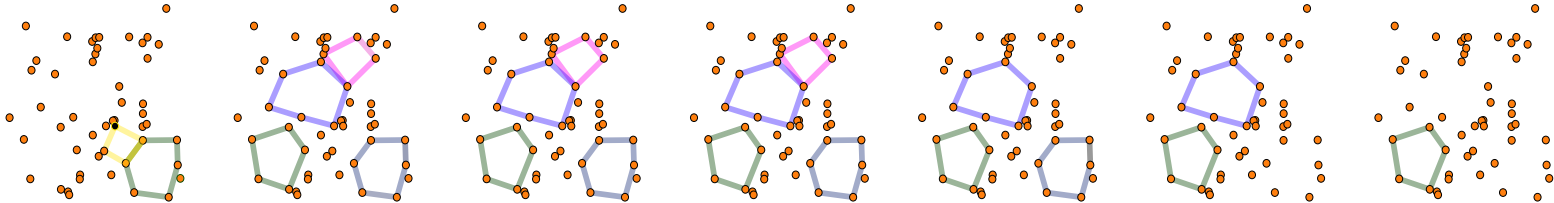
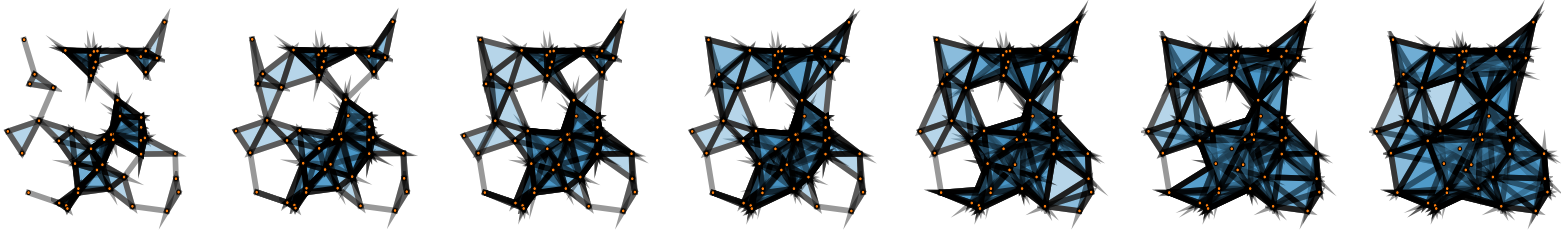


Group level persistence diagrams

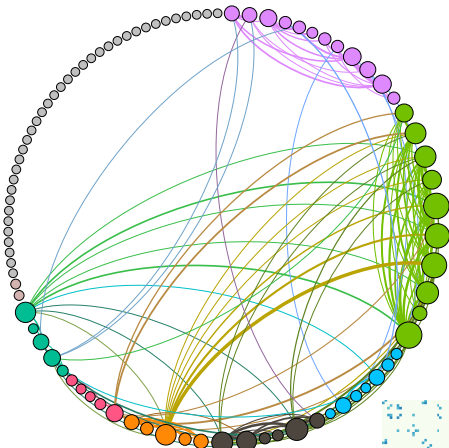
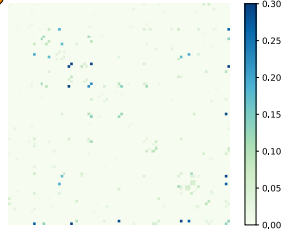
Localisation of information?

Petri, Giovanni, et al. "Homological scaffolds of brain functional networks." *Journal of The Royal Society Interface* 11.101 (2014): 20140873.

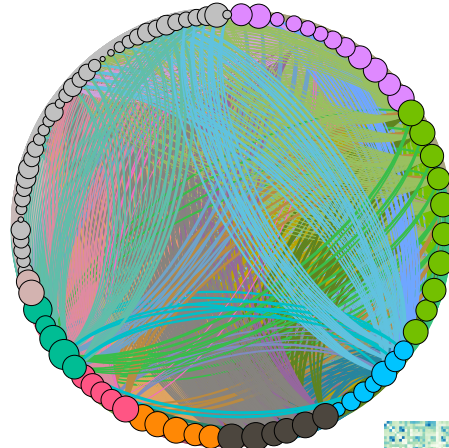
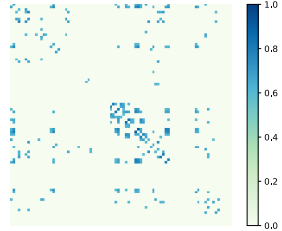
Scaffolds in one slide



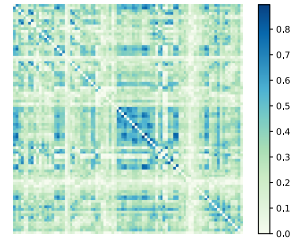
Scaffold



Diluted FC



Min-weight FC

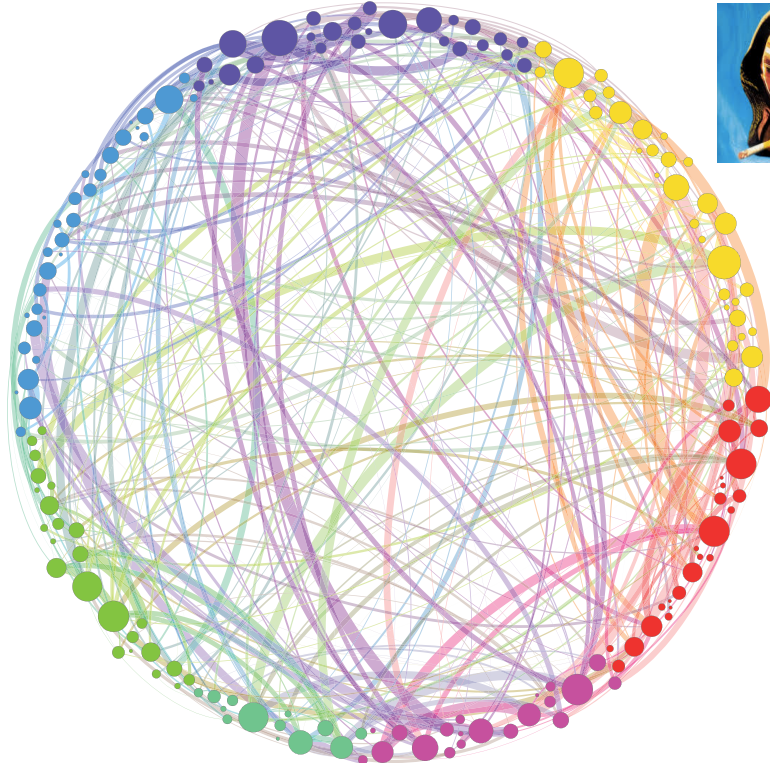


Brain scaffolds: local alterations

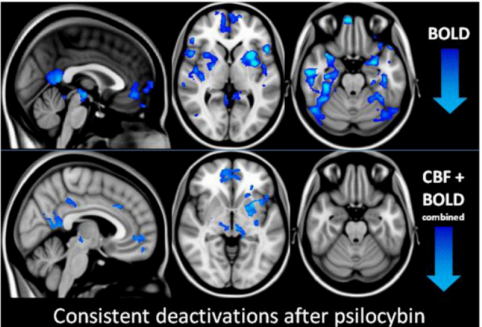
distributed



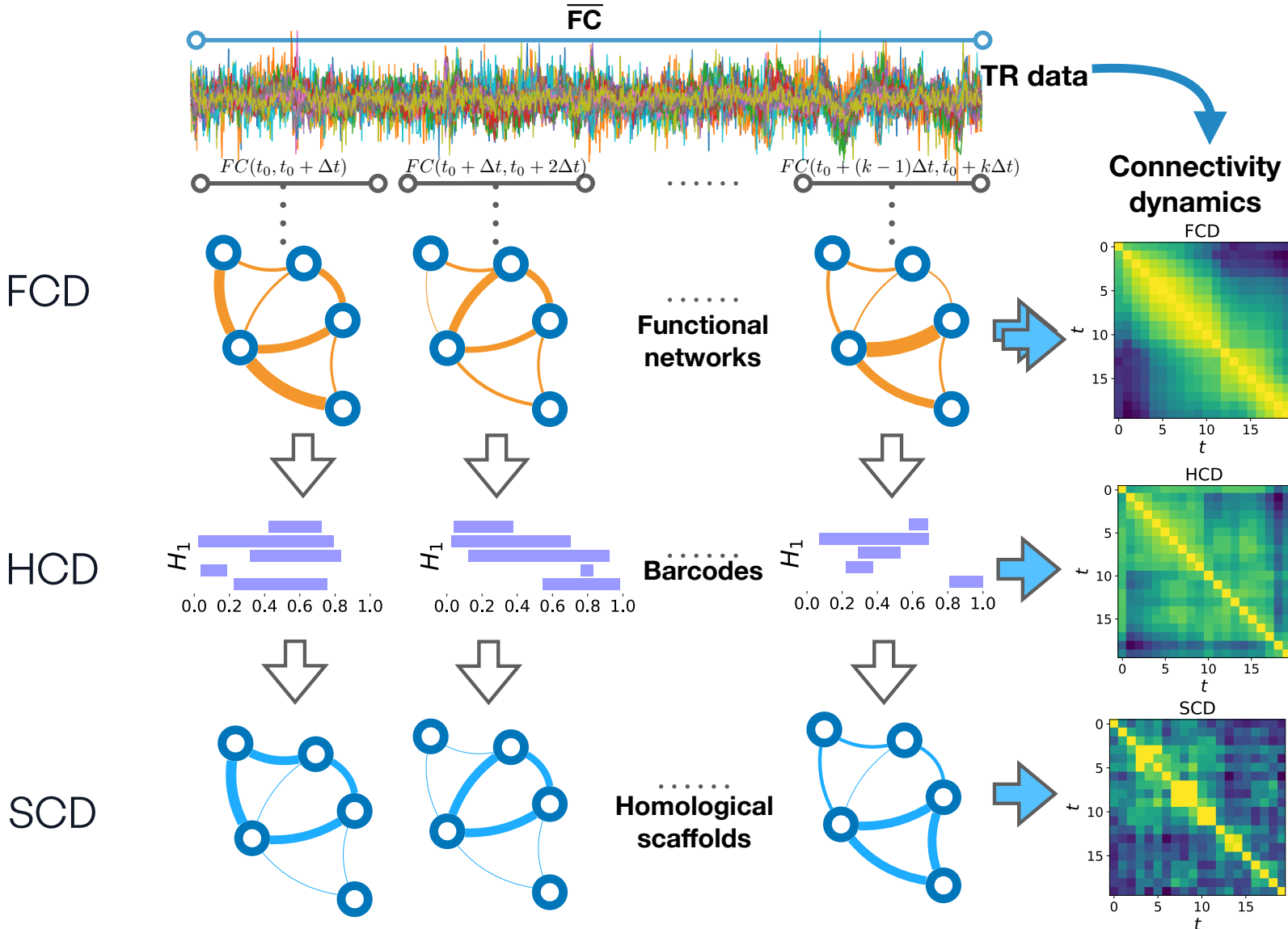
(b)



Distributed reorganisation of the hierarchy of functional circuits

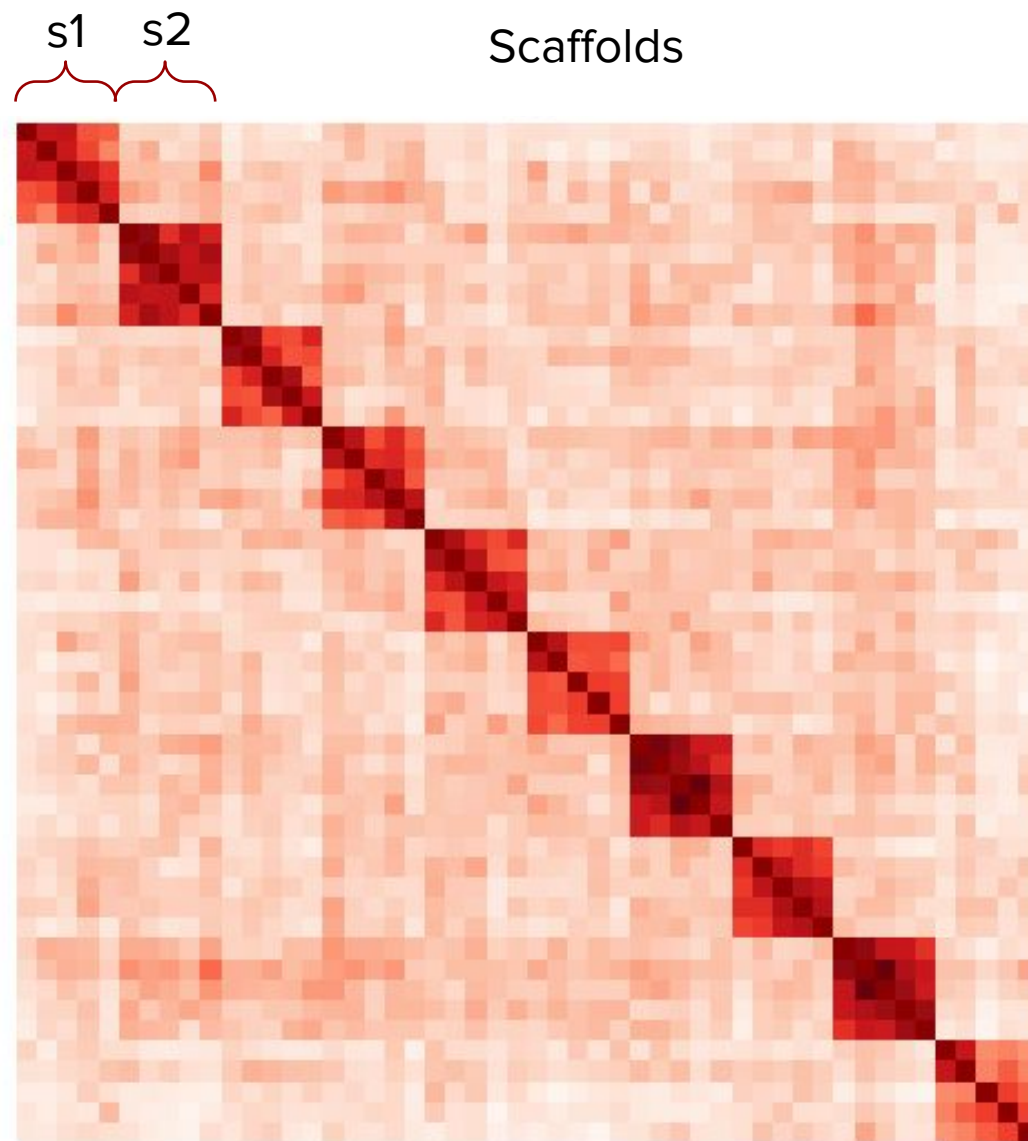
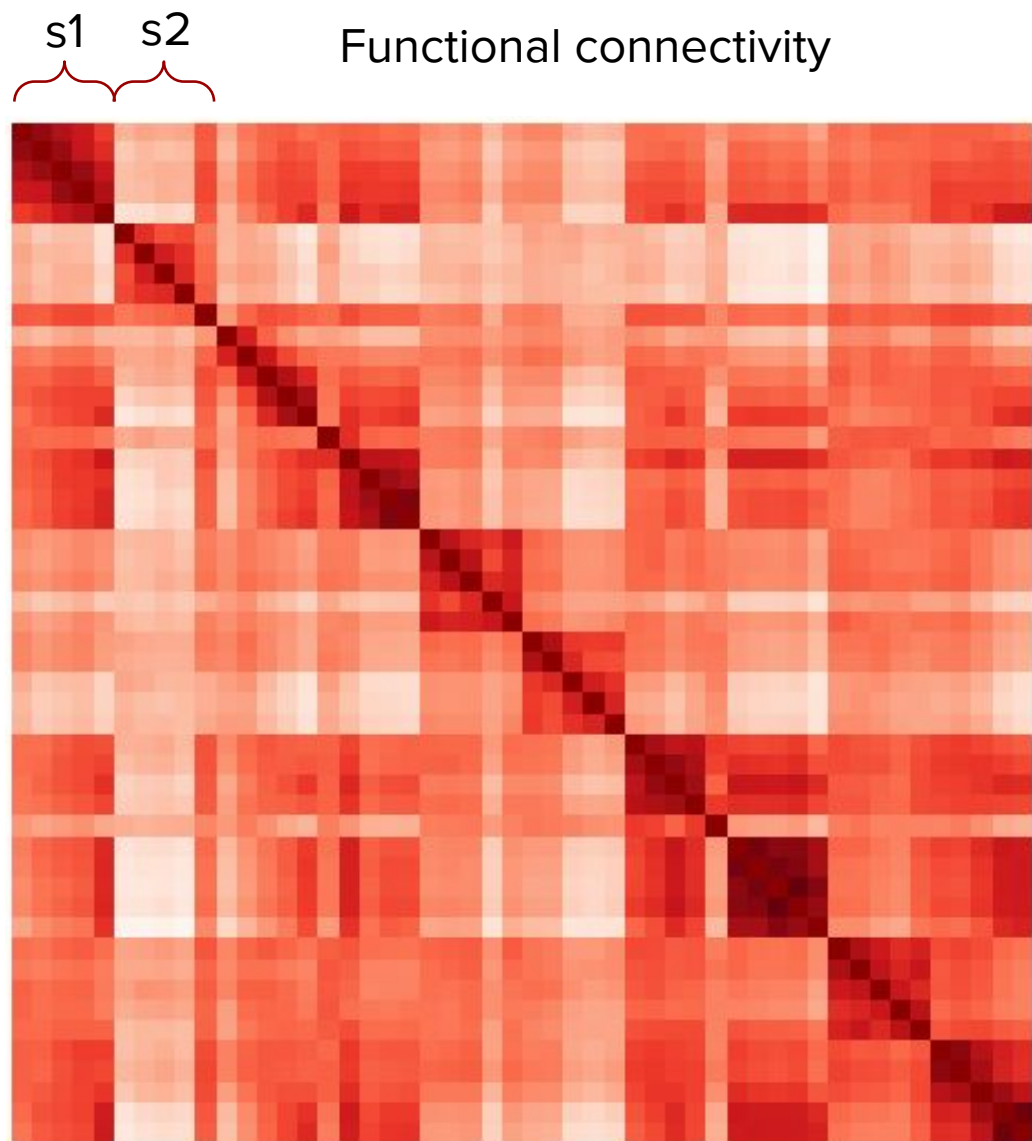


Scaffold fingerprinting



Scaffold fingerprinting

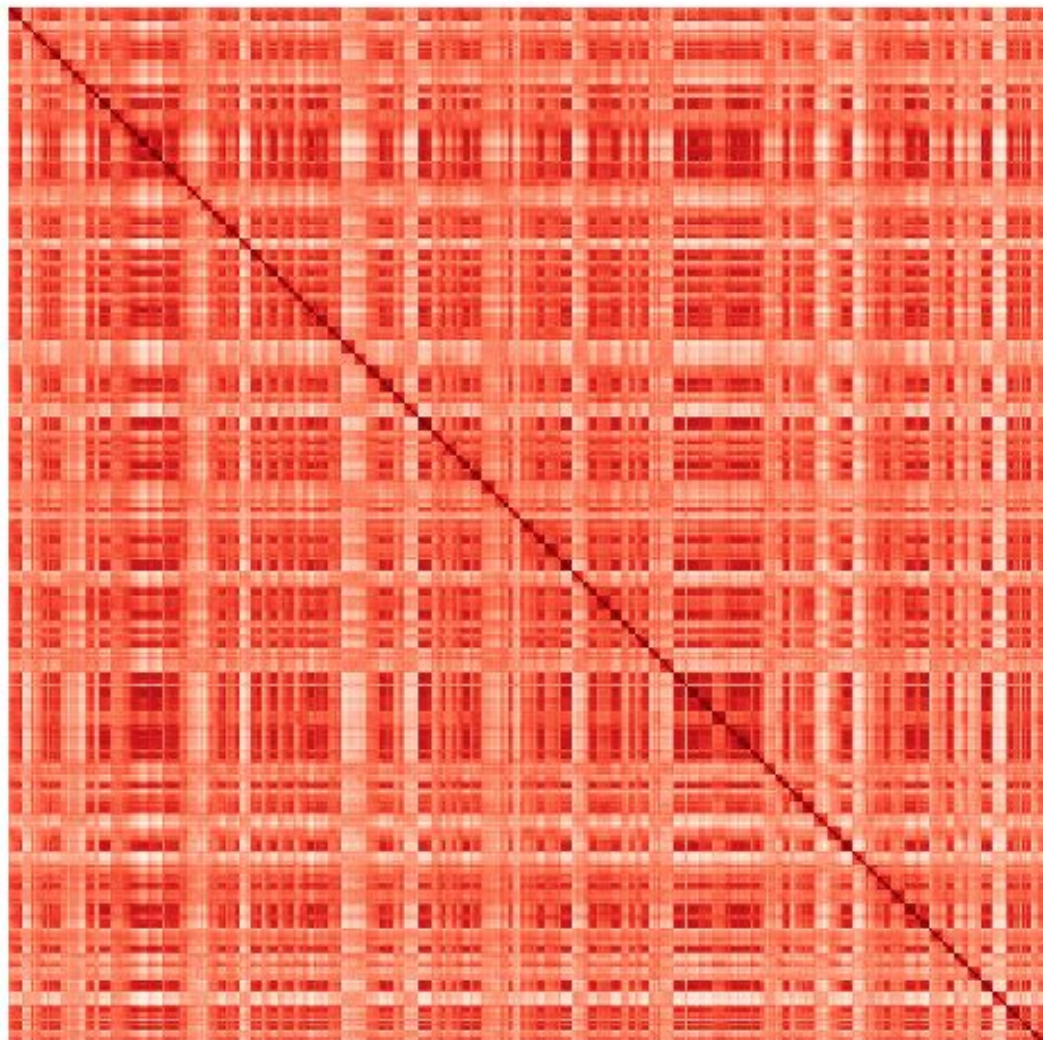
100 subjects (HCP), rs-fMRI, test+retest



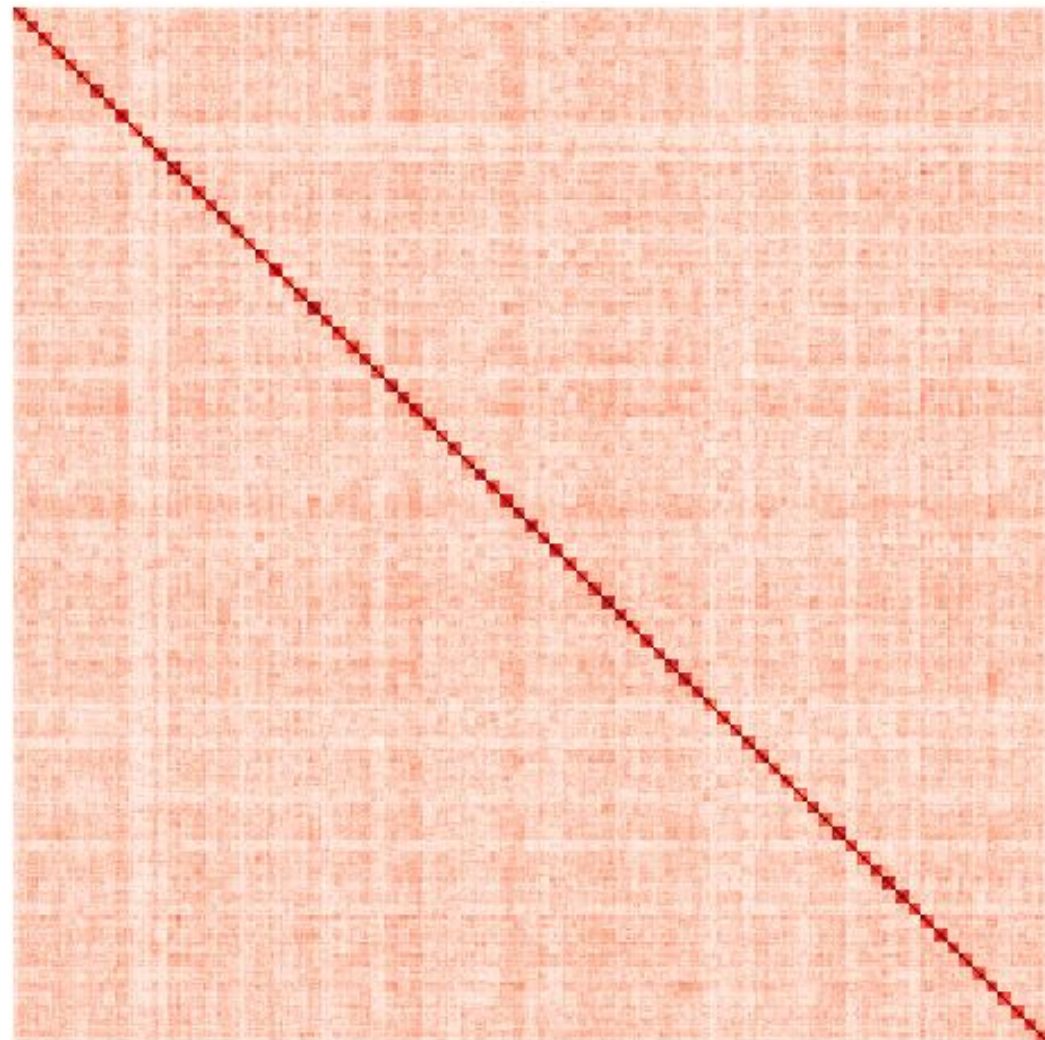
Scaffold fingerprinting

100 subjects (HCP), rs-fMRI, test+retest

Functional connectivity

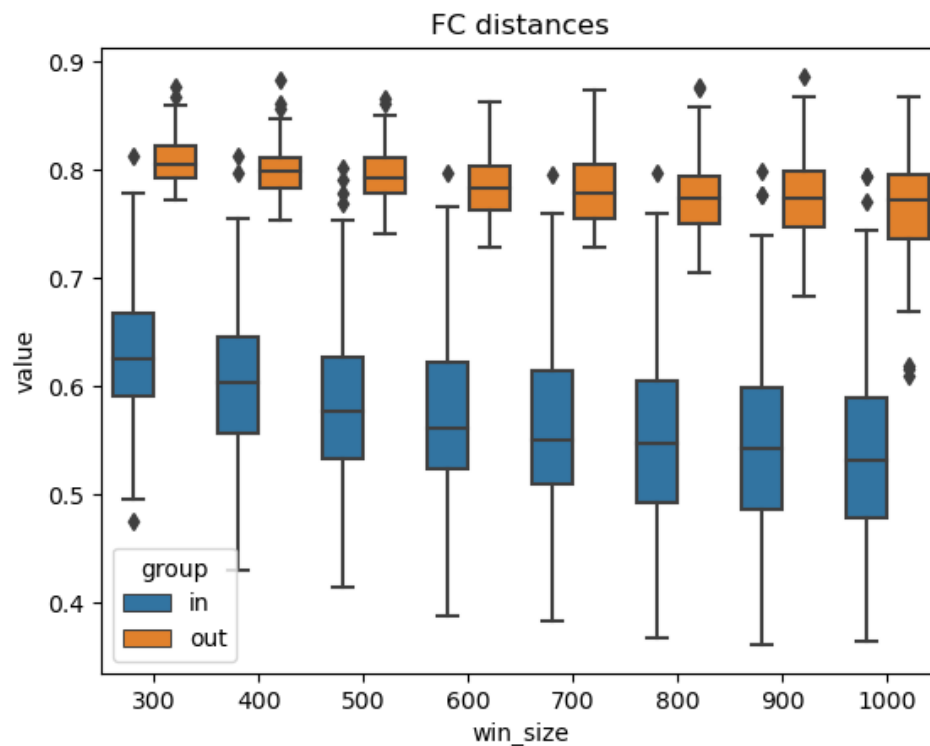
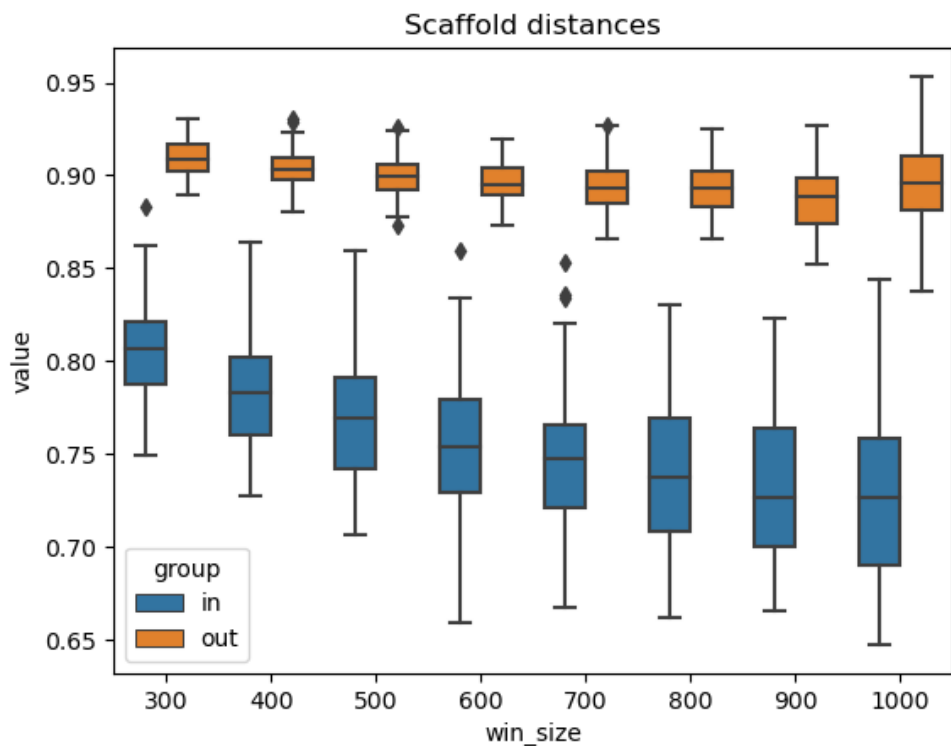


Scaffolds



Scaffold fingerprinting

100 subjects (HCP), rs-fMRI, test+retest



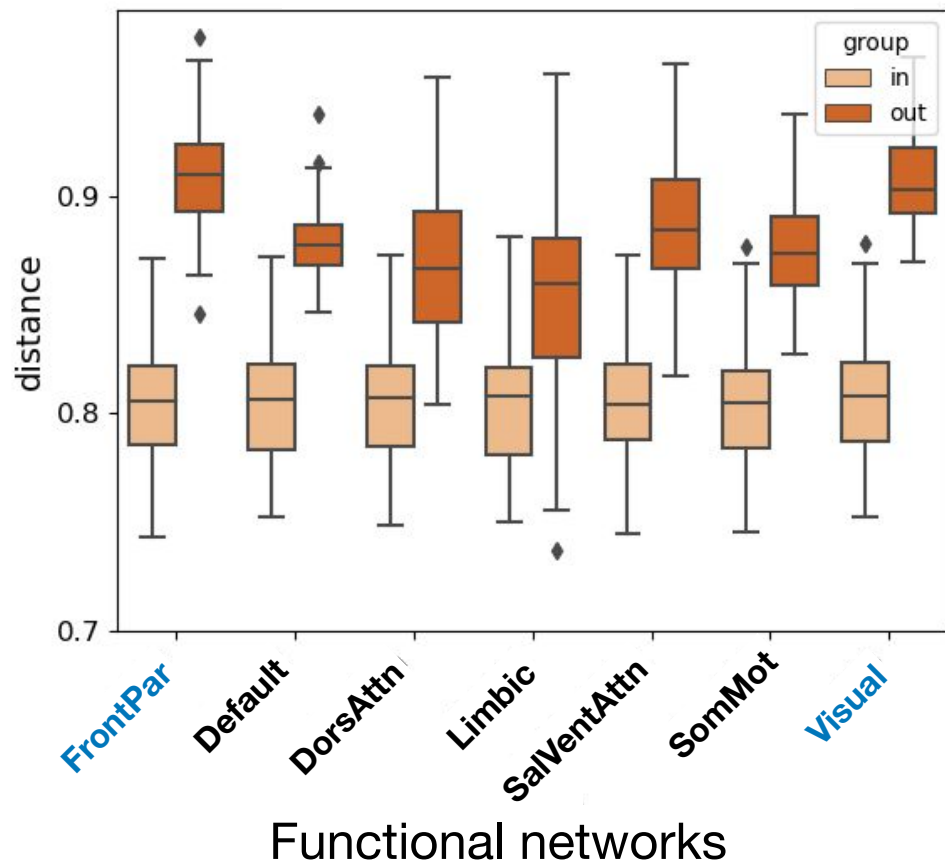
Incredible
fingerprinting
capacity!

QUASI idea on
the origin!

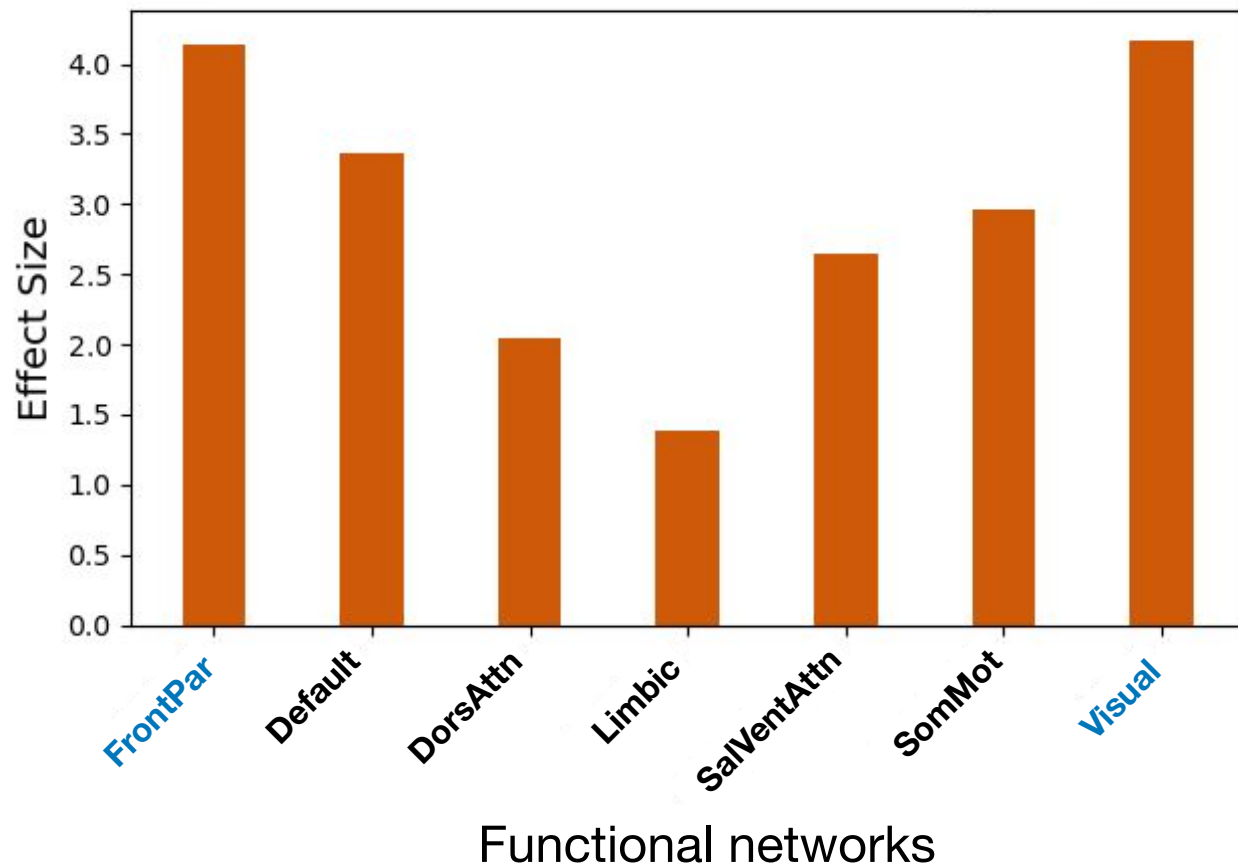
Scaffold fingerprinting

100 subjects (HCP), rs-fMRI, test+retest

Scaffold distances



Effect sizes

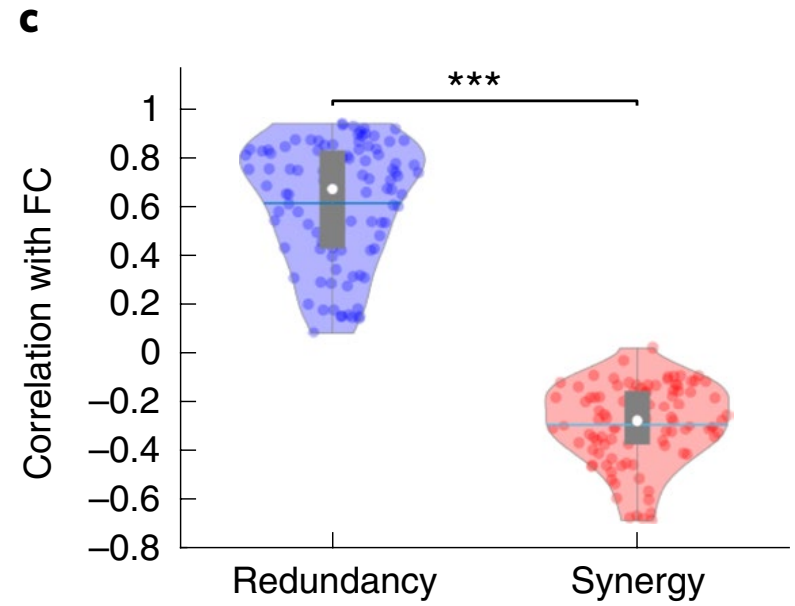
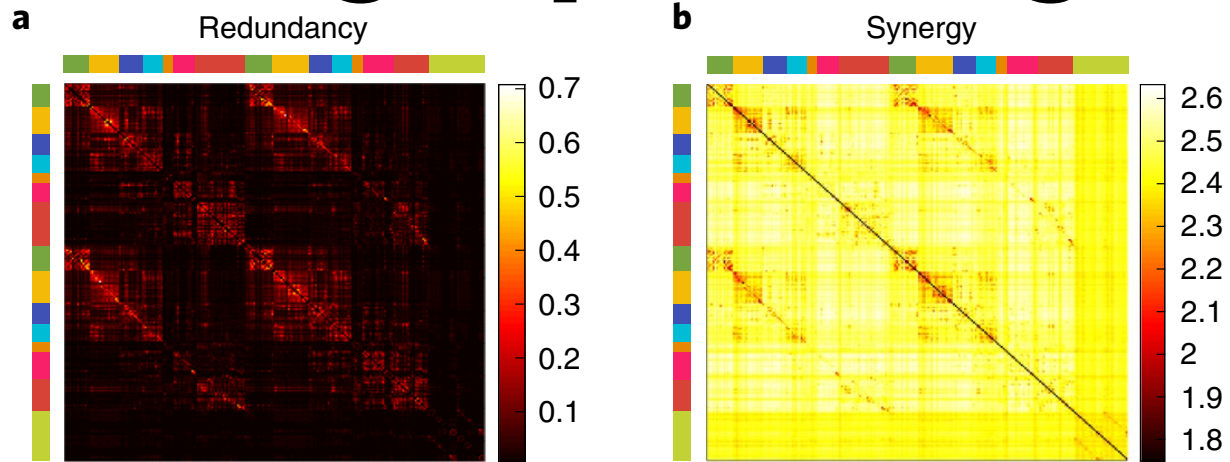
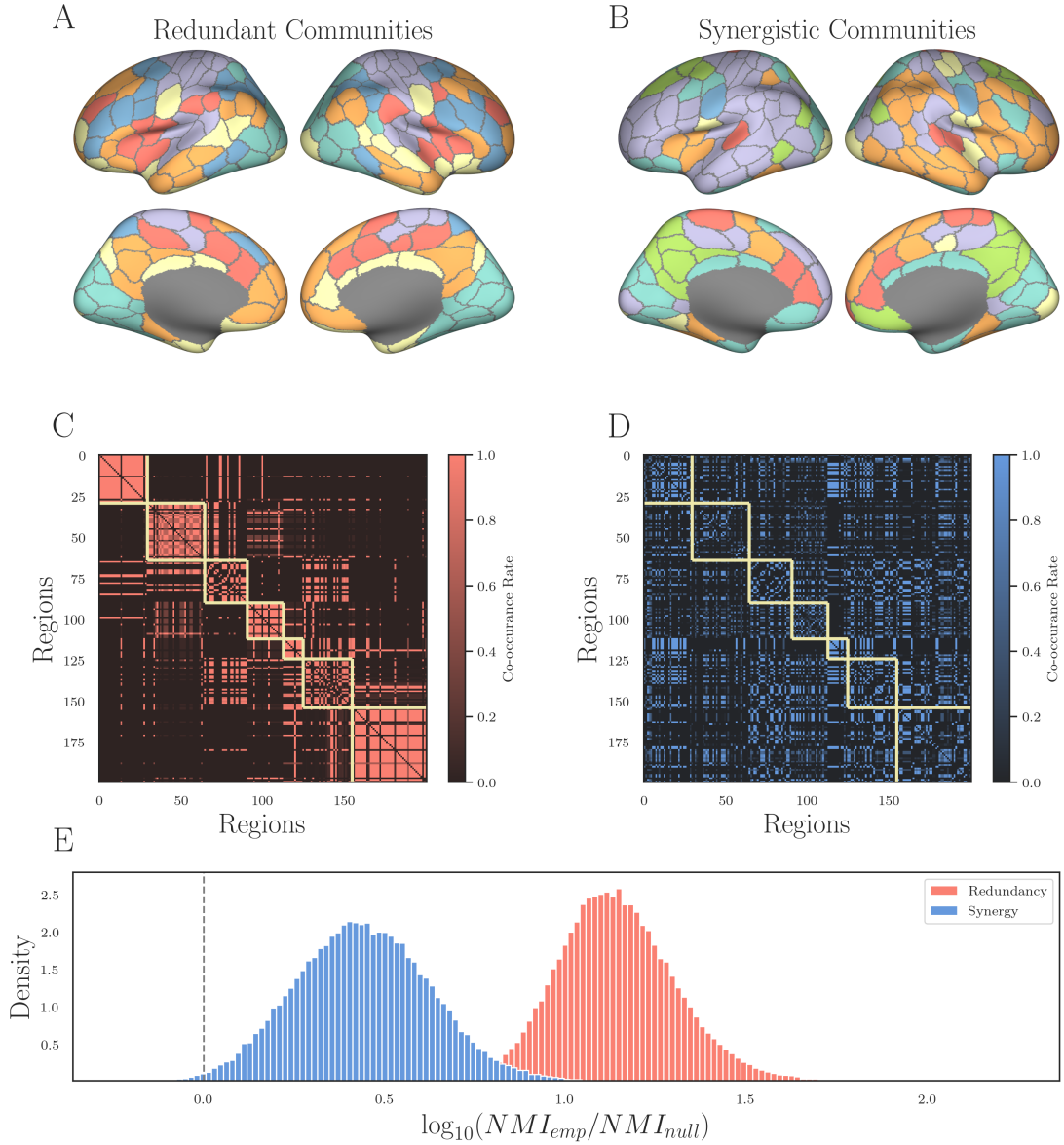


Scaffold fingerprinting

Summing up

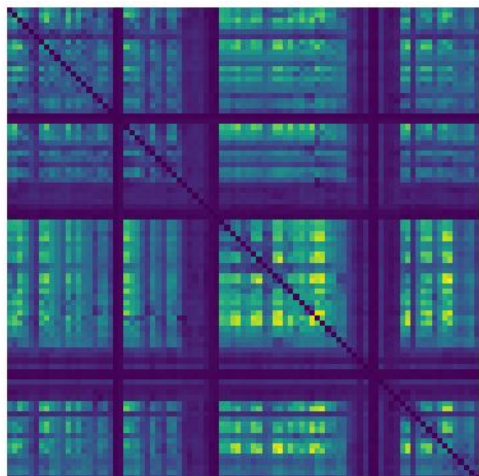
- Consistently better
- Works for the short windows
- Sparse representation
- Ok, but why?

Brain informational fingerprinting

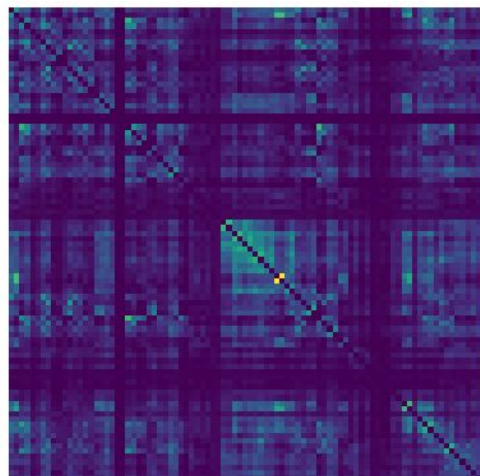


Topo+Info brain fingerprinting

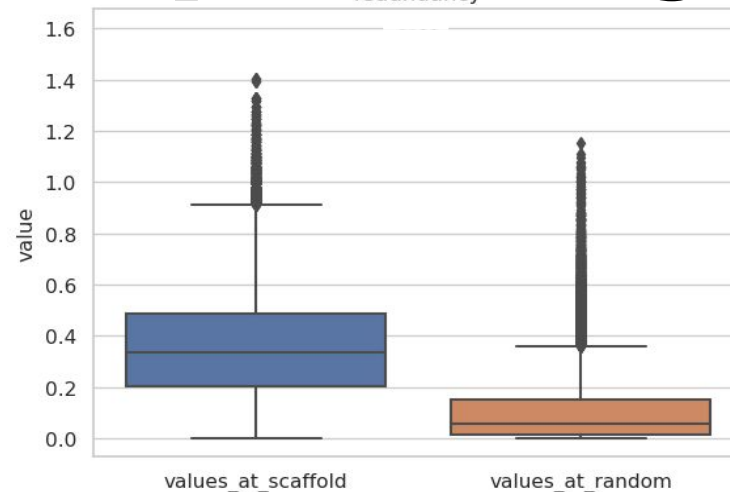
Synergy



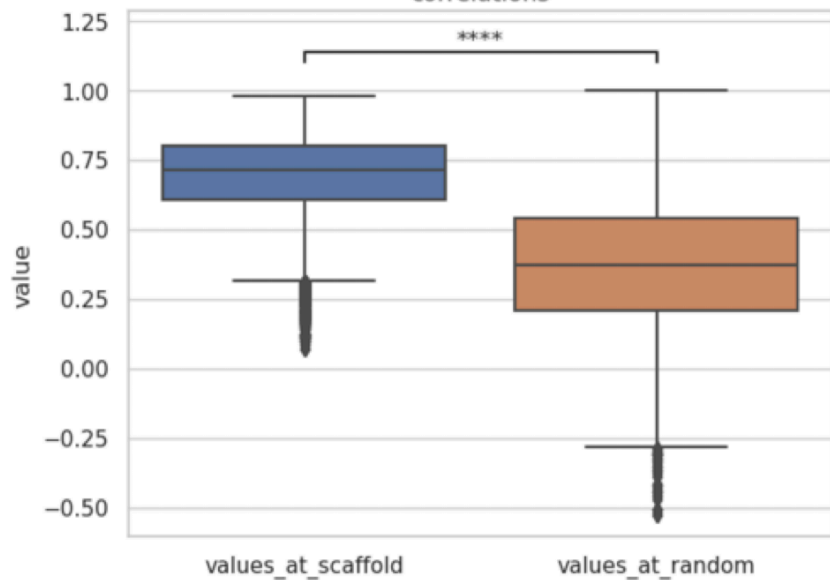
Redundancy



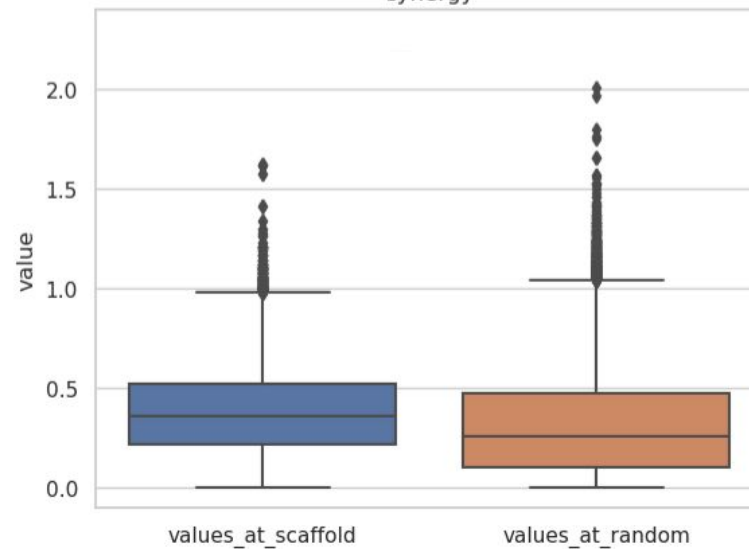
redundancy



correlations



synergy



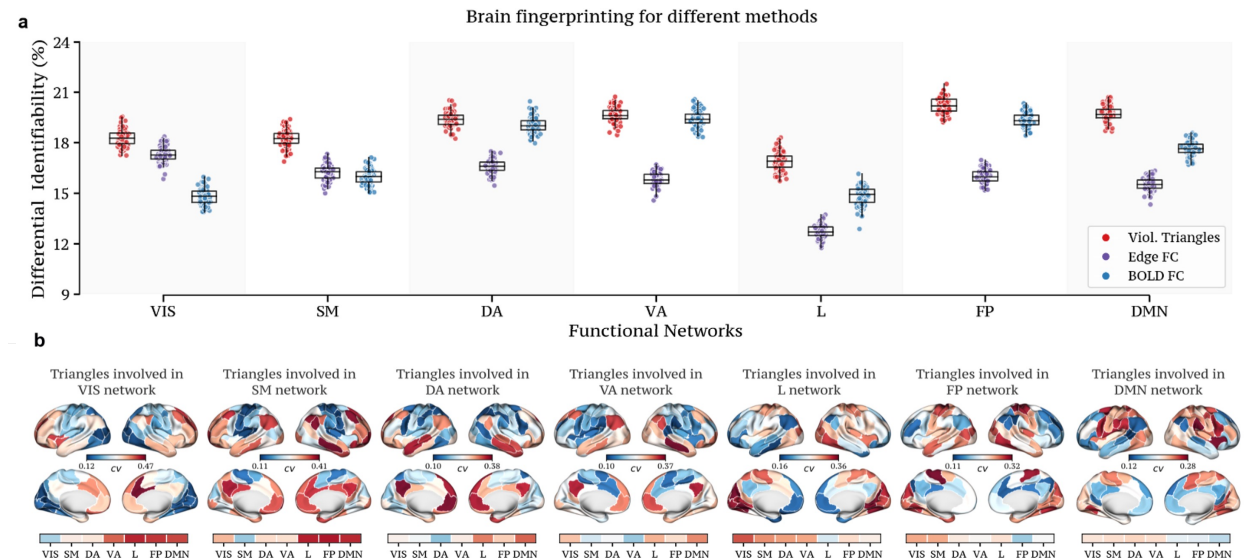
Topo+Info brain fingerprinting

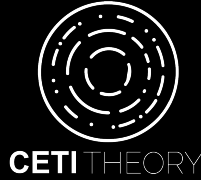
Summing up

- Topological information (simplification) discriminates well across individuals
- Stronger effect for higher-order timeseries
- Global markers (Mapper) powerful
 - no relation to the actual synergy/ redundancy patterns
- Local markers (scaffold) even more powerful.
 - Related to local HOI info-theory, but not sufficient to explain

To do

- Time-resolved (a la Santoro, Andrea, et al. Nat. Phys. (2023))
- Distinguish by functional subnetwork
- Generative models of target topology





Network Science Institute at Northeastern University

We are hiring Phds+postdocs (in London!)

nature
physics

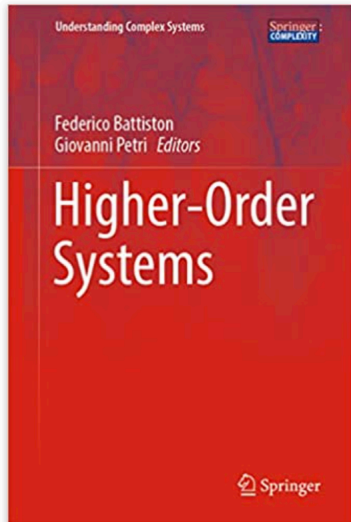
PERSPECTIVE

<https://doi.org/10.1038/s41567-021-01371-4>



The physics of higher-order interactions in complex systems

Federico Battiston¹✉, Enrico Amico^{2,3}, Alain Barrat^{4,5}, Ginestra Bianconi^{6,7},
Guilherme Ferraz de Arruda⁸, Benedetta Franceschiello^{9,10}, Iacopo Iacopini¹, Sonia Kéfi^{11,12},
Vito Latora^{6,13,14,15}, Yamir Moreno^{8,15,16,17}, Micah M. Murray^{9,10,18}, Tiago P. Peixoto^{1,19},
Francesco Vaccarino^{10,20} and Giovanni Petri^{10,21}✉



Understanding Complex Systems

Book Series

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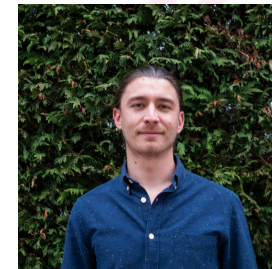
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Manish Saggarr



Simone Poetto



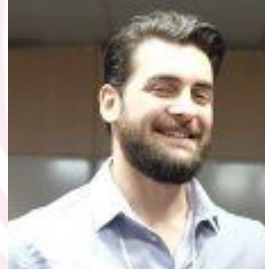
Francesco Vaccarino



Demian Battaglia



Giovanni Rabuffo



Thanks!

Slides here:

