Informational and topological signatures of individuality and age

G. Petri

The Sense 23/11/2023

Network Science Institute
at Northeastern University

PROJECT CETI

CENTAI

Higher-order signatures of individuality and age

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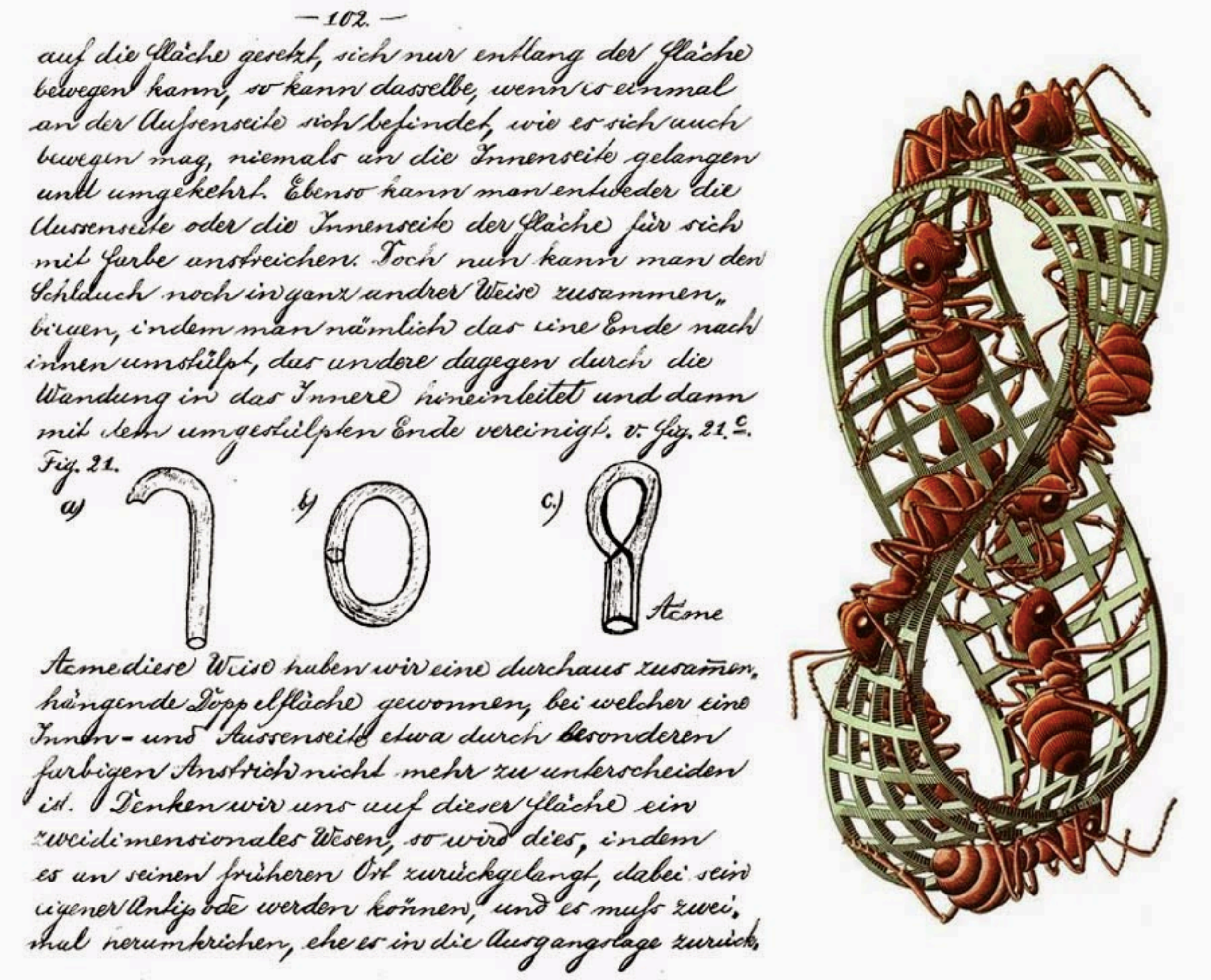
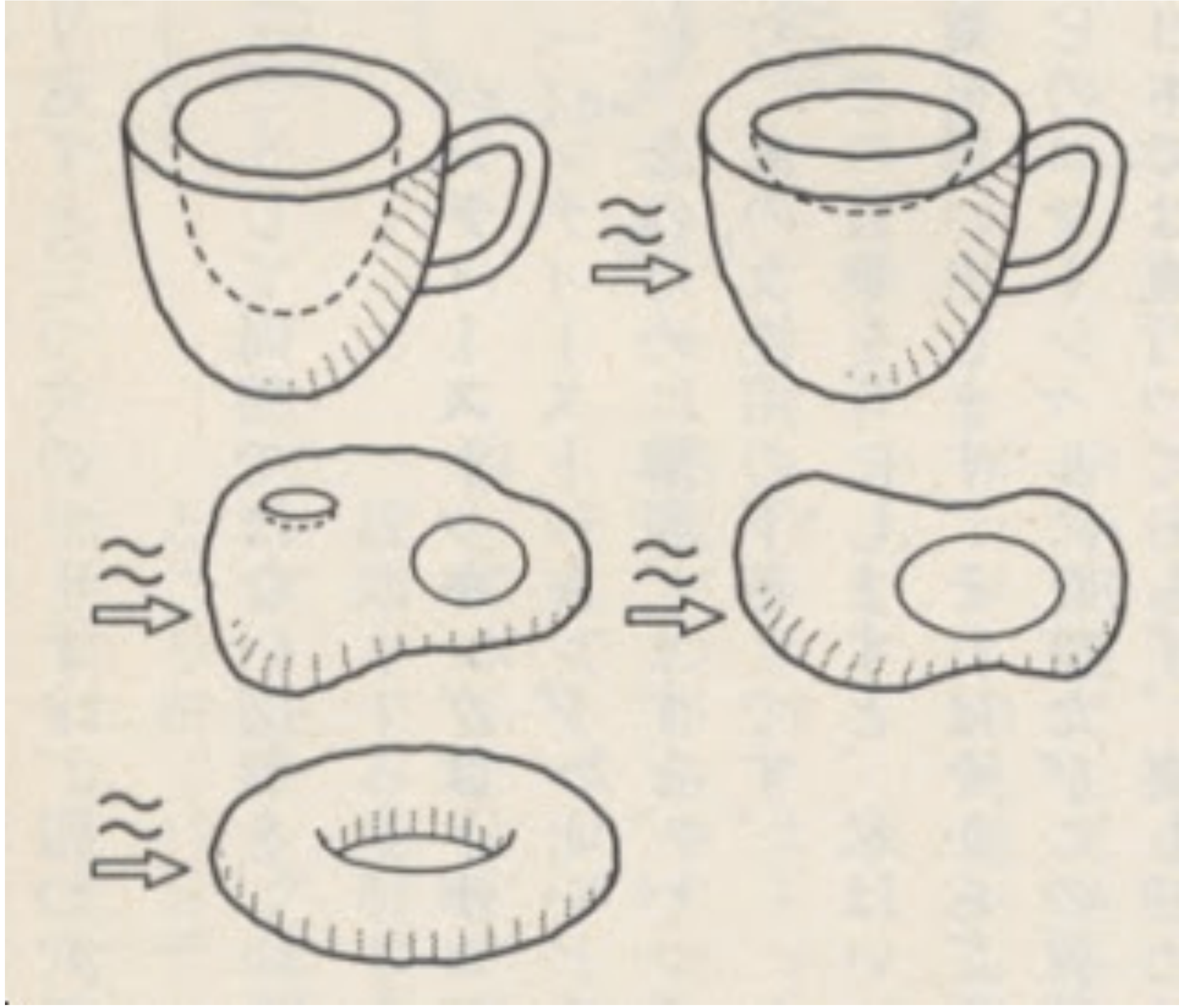
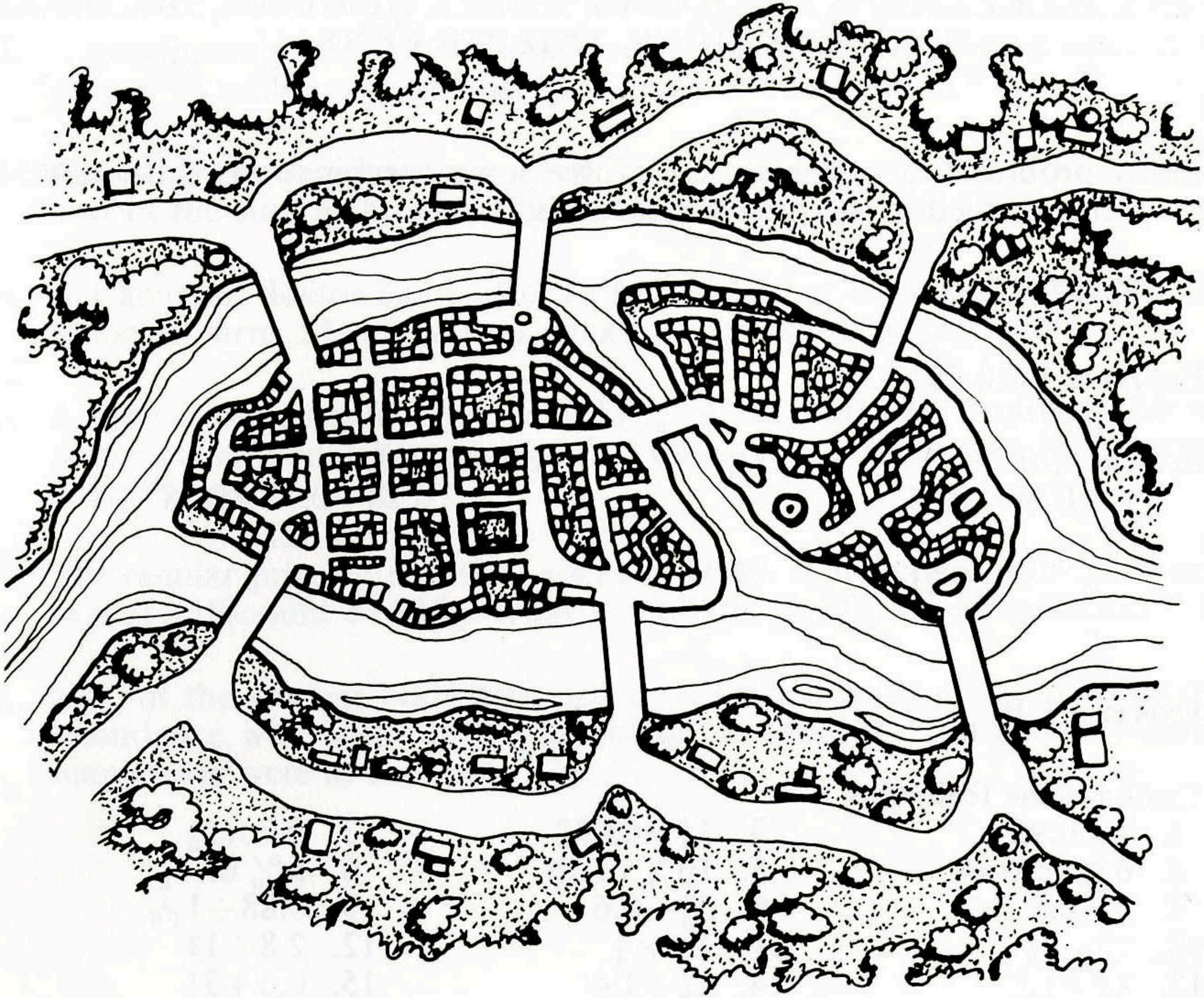
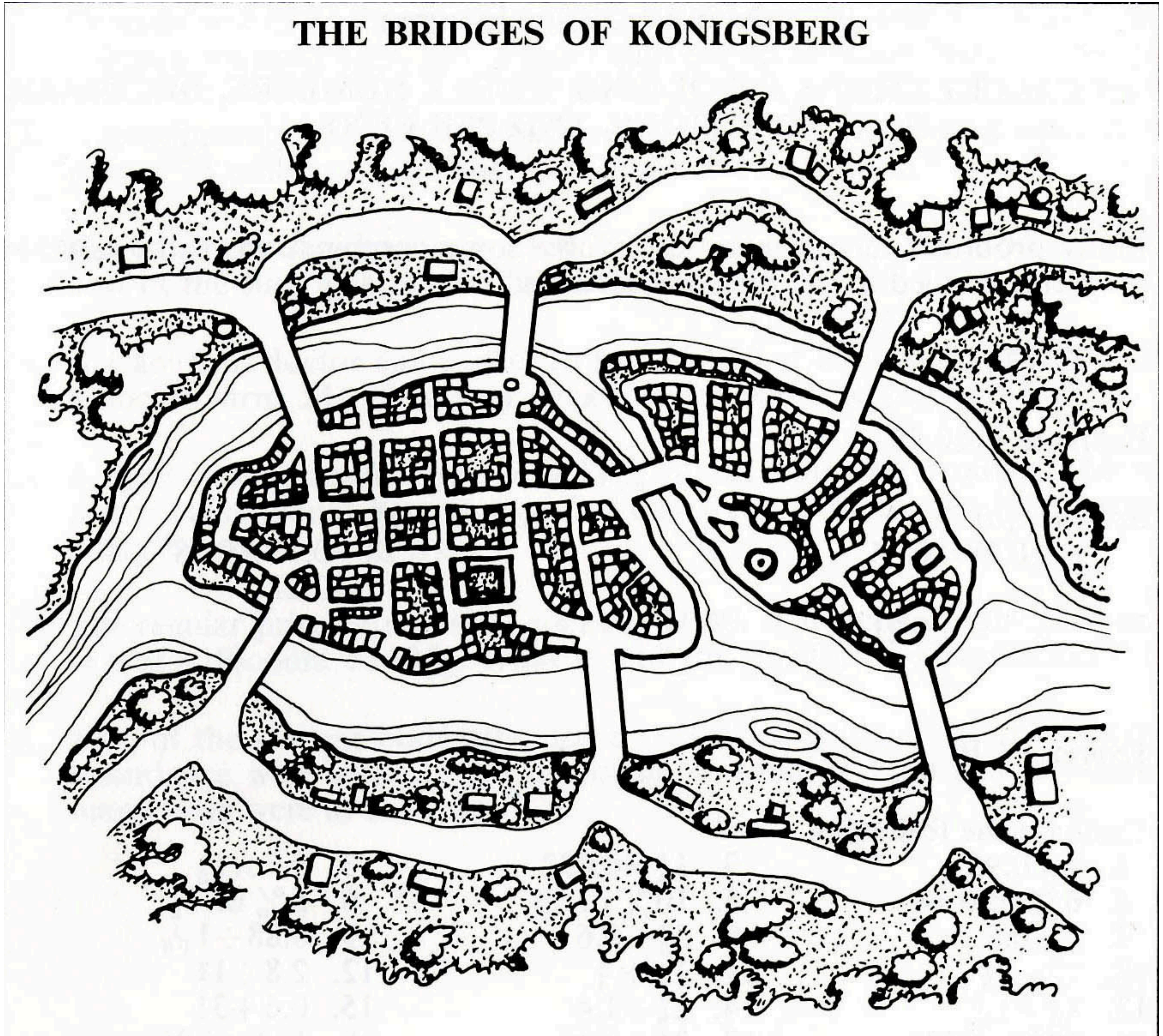
What is topology?





THE BRIDGES OF KONIGSBERG

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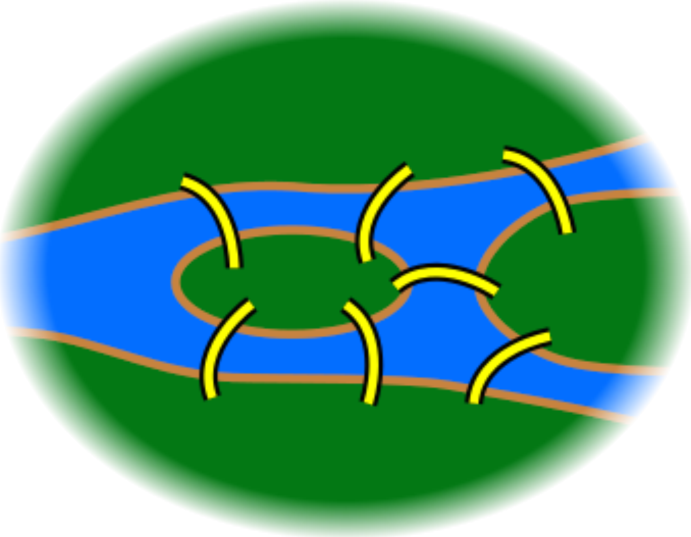

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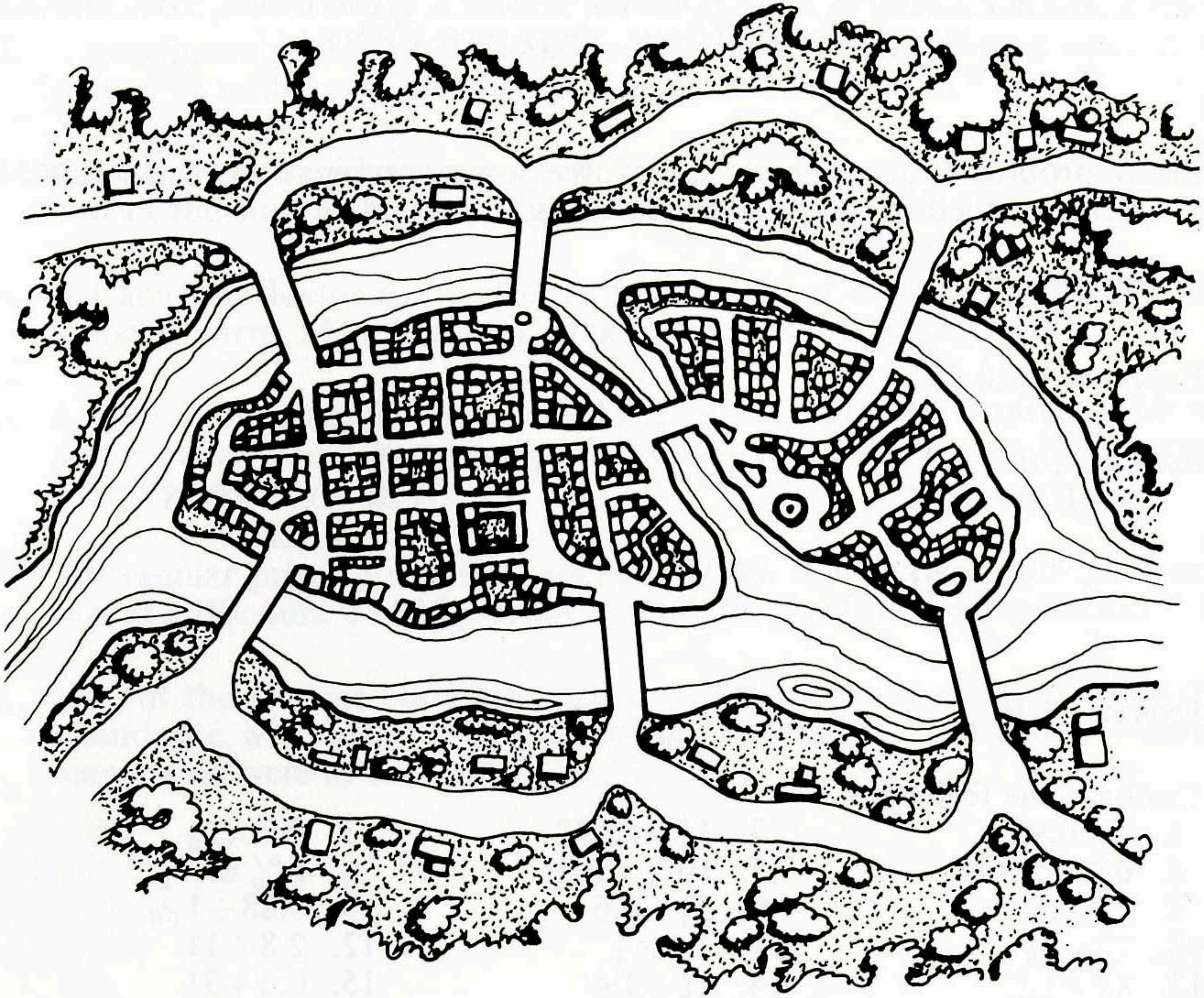

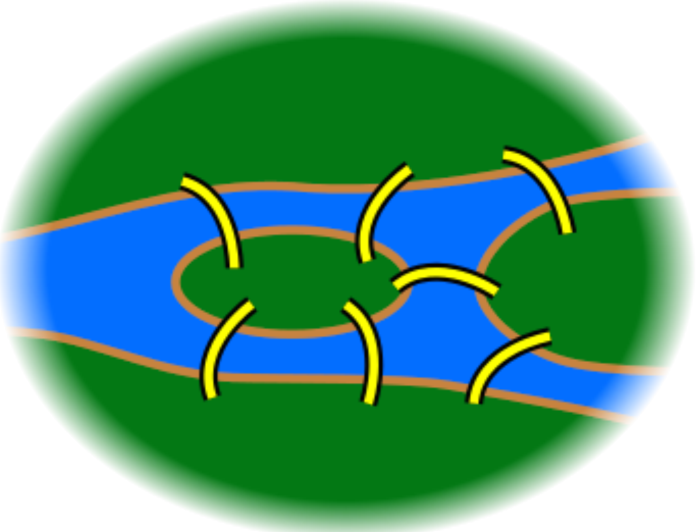

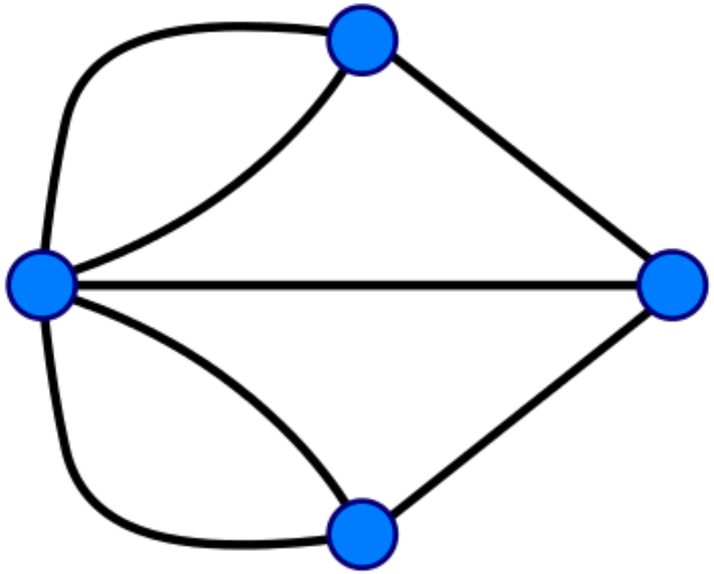

Why topology?

DOT
= 0-simplex

EDGE =
1-simplex

Ghrist, R. (2008). Barcodes: The persistent topology of data. *Bulletin-American Mathematical Society*, *45*(1), 61.

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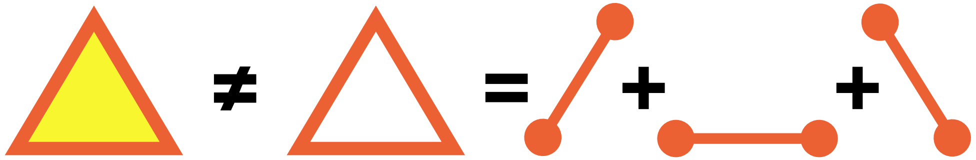

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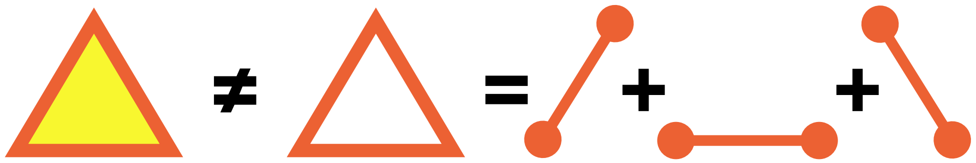

Definition of k-simplex

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

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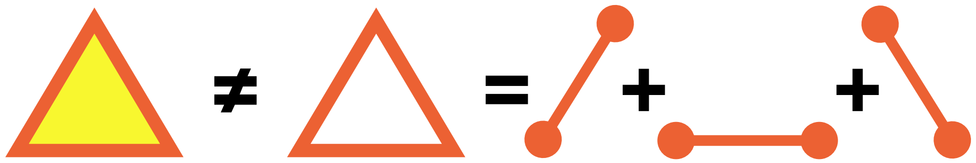

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$$P(\mathbf{X}) = P(X_0, X_1, X_2, \ldots, X_{k-1})$$

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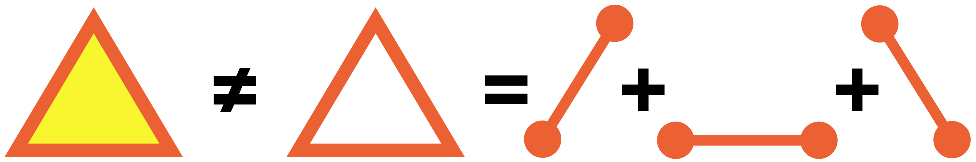

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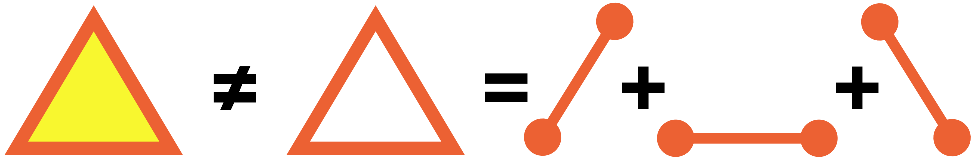

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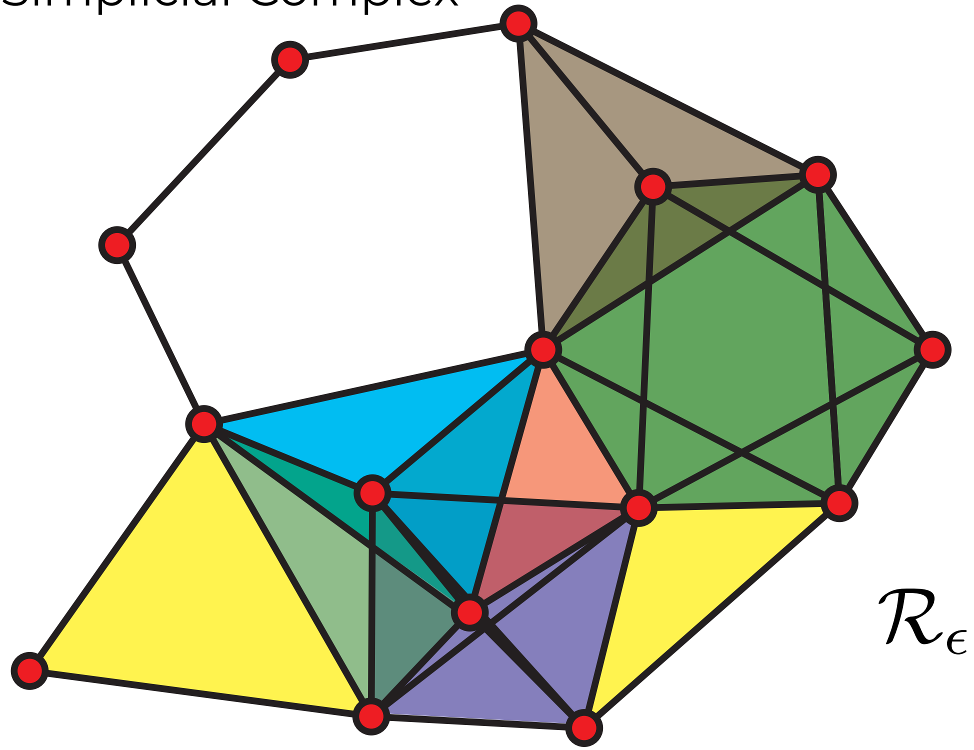

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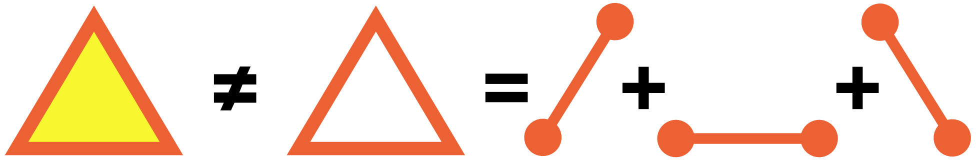

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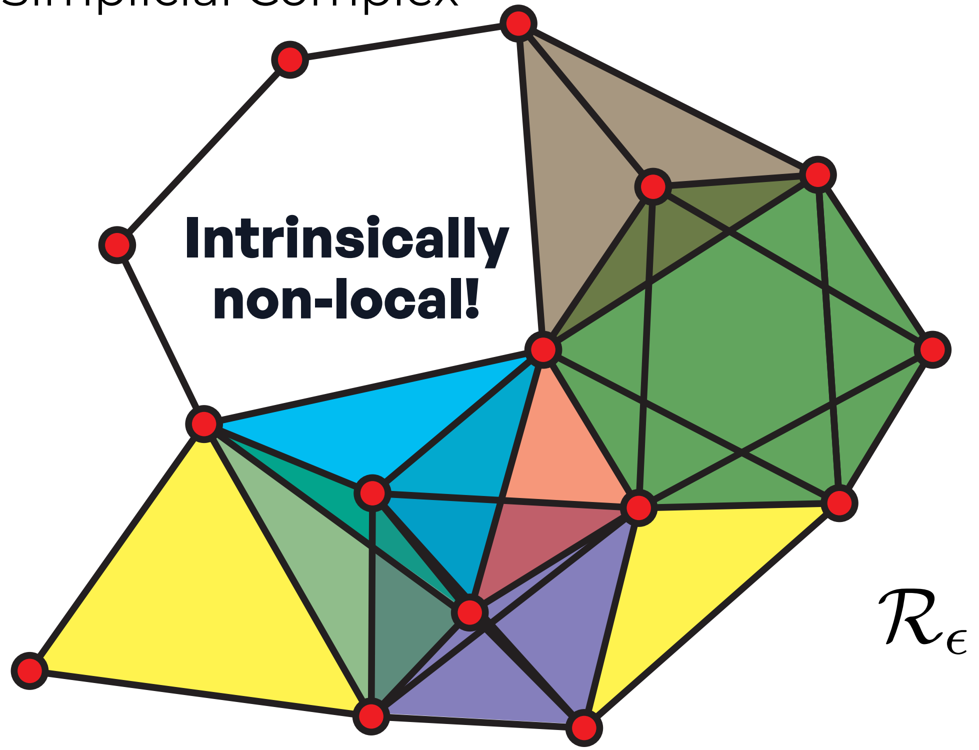

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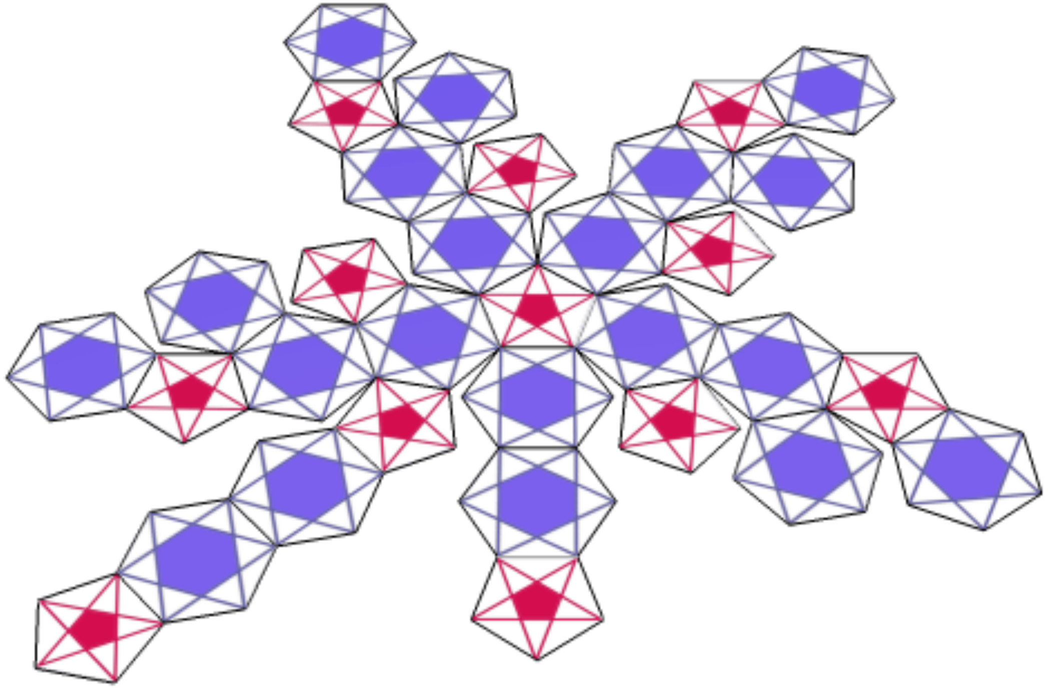

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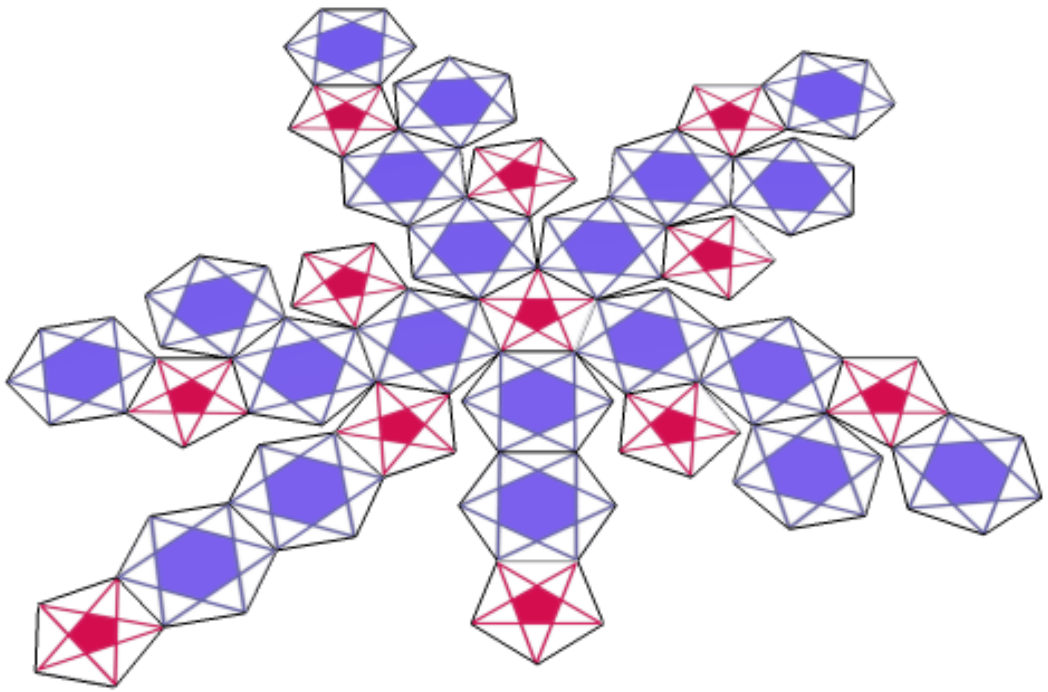

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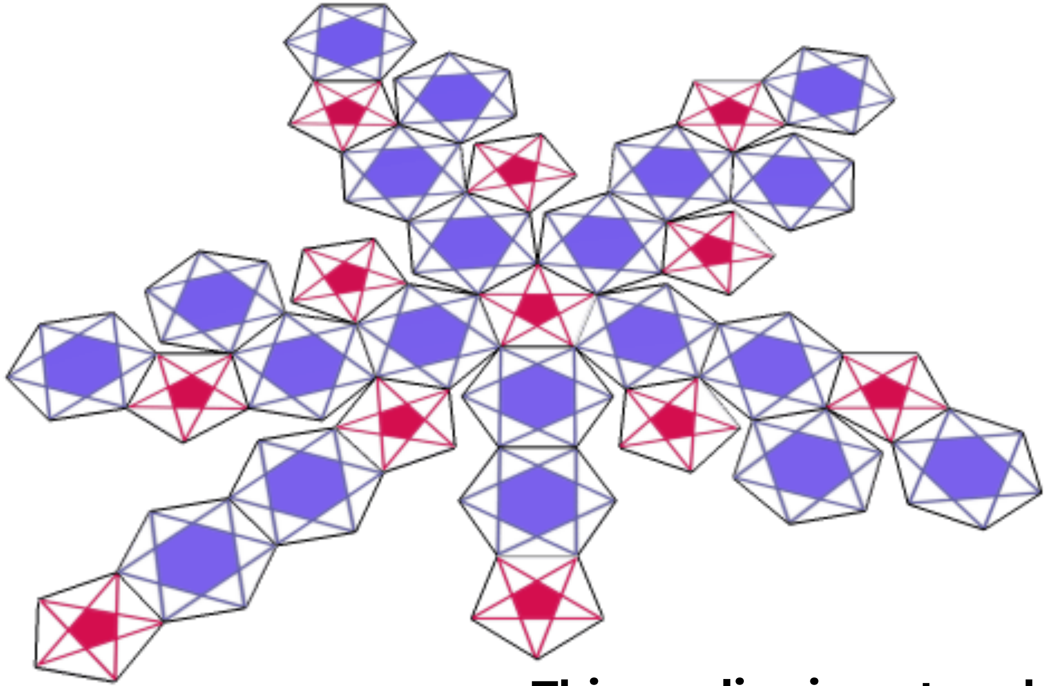

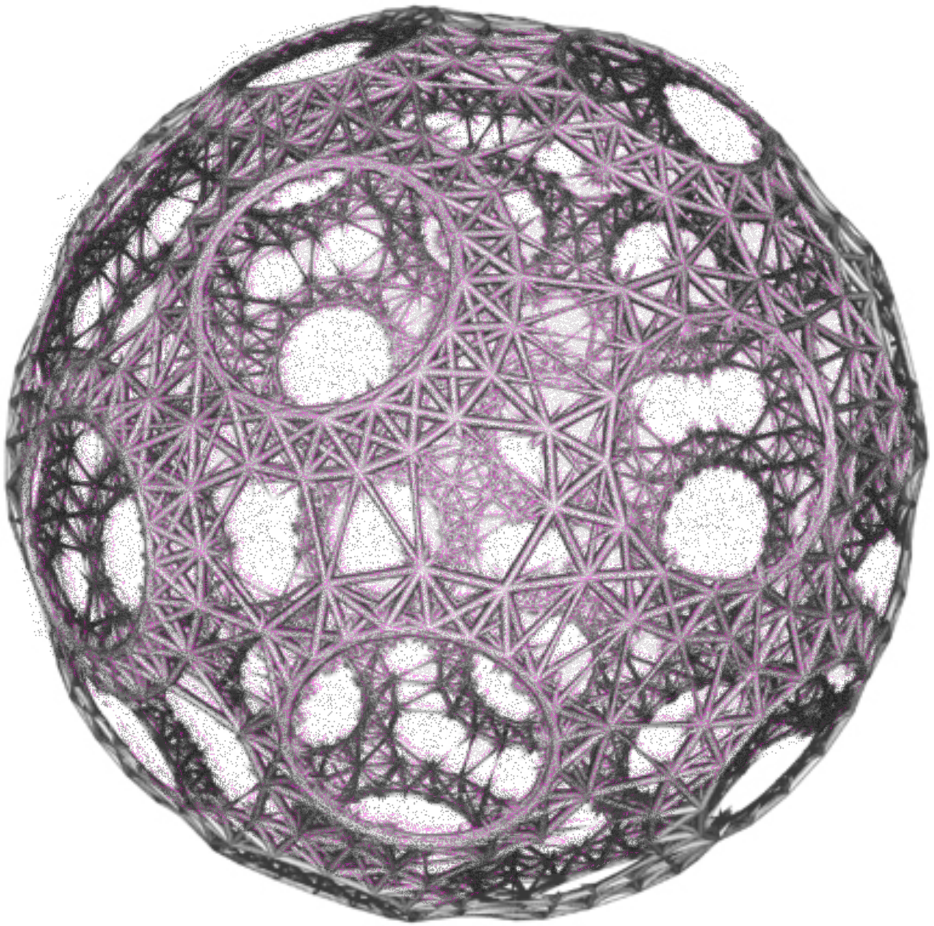

This applies in networks as well as to data spaces

What does it mean in practice?

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Persistent homology pipeline (Ghrist 2008)

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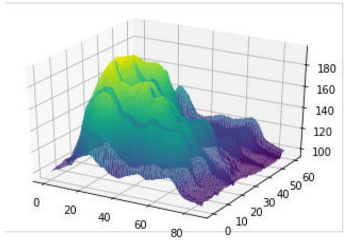
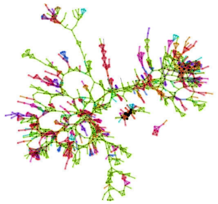
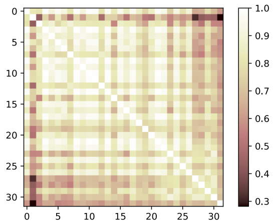
Data of sorts







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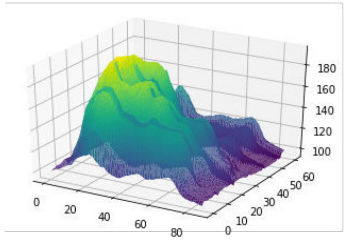
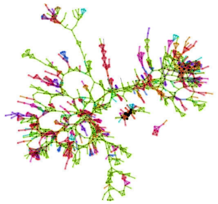
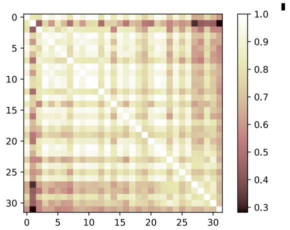
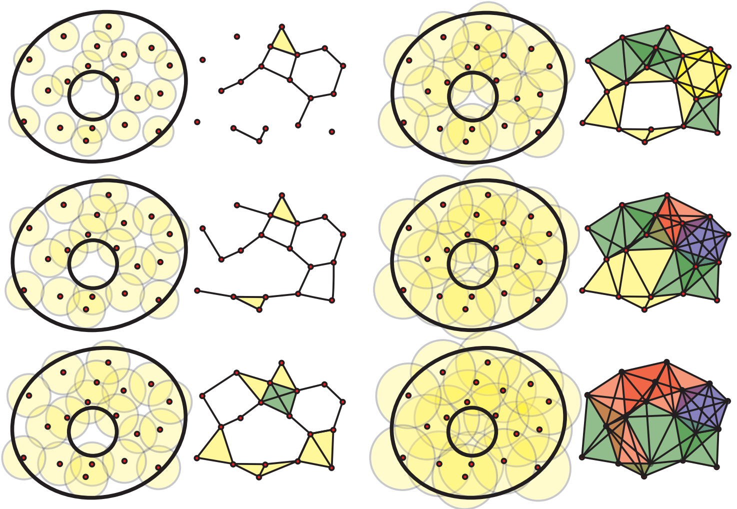






Filtration over distance/density/weights



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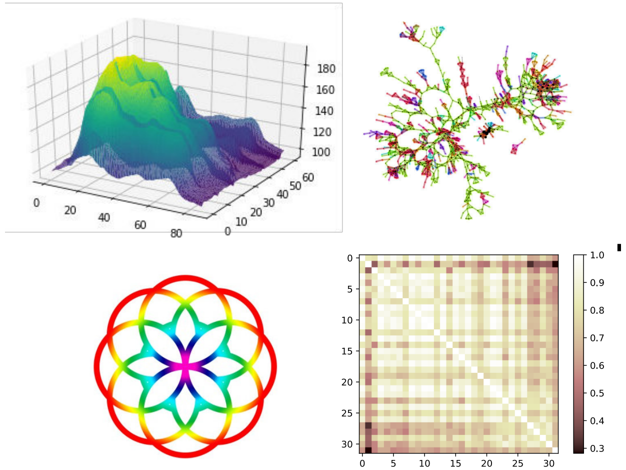

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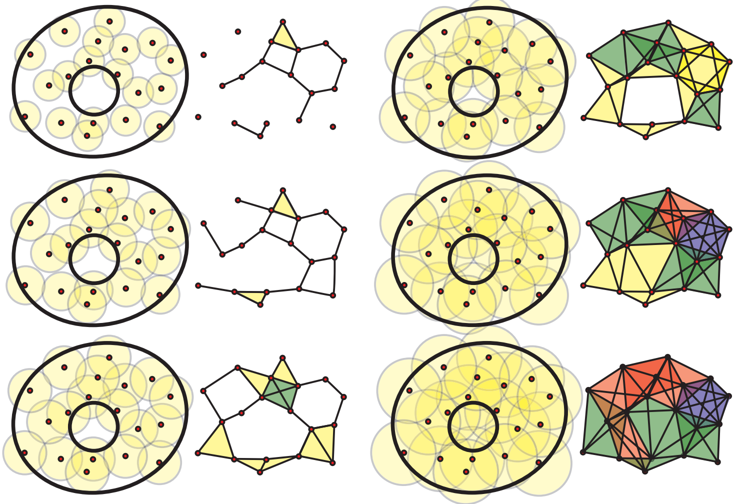
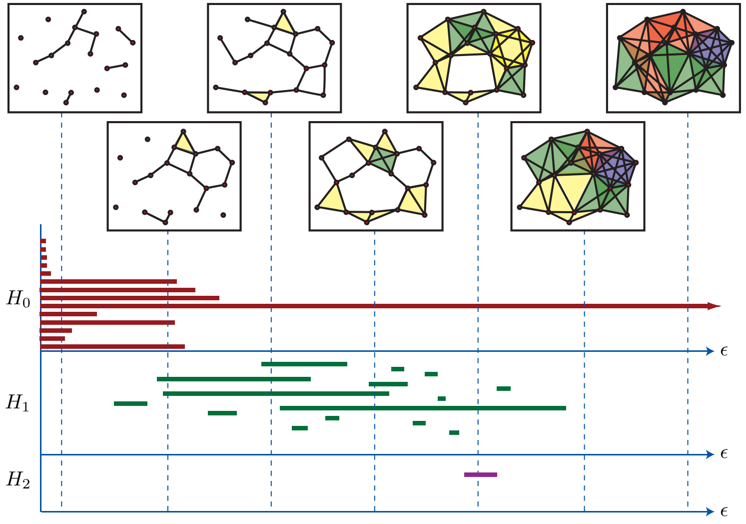


Homological properties



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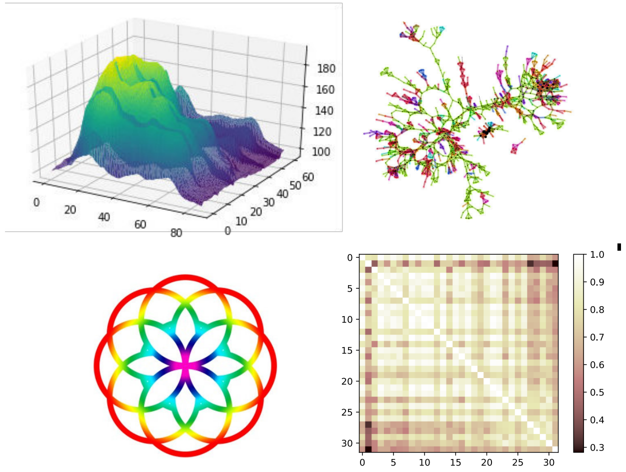

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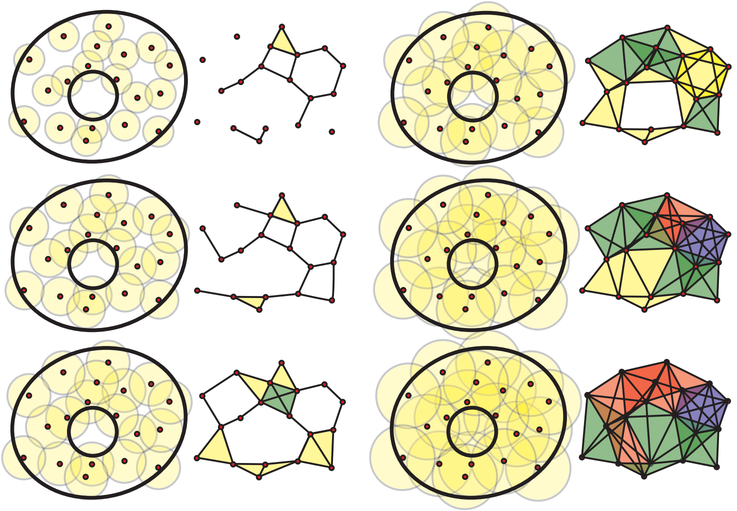

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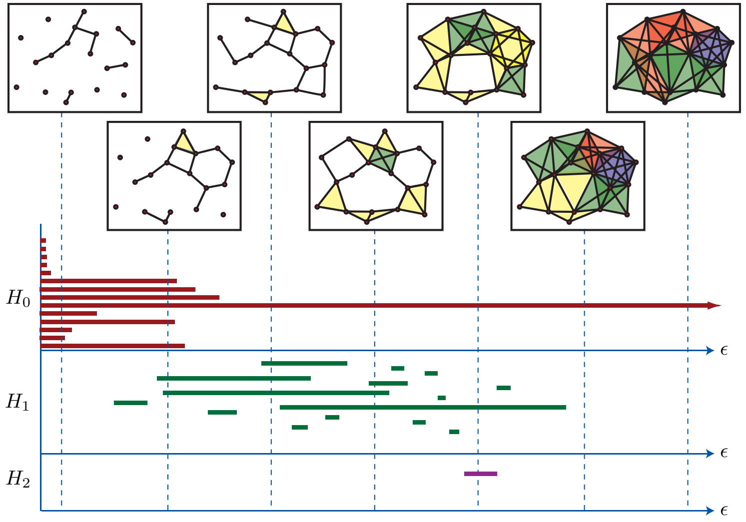

Mapper Pipeline (Singh et al 2007)

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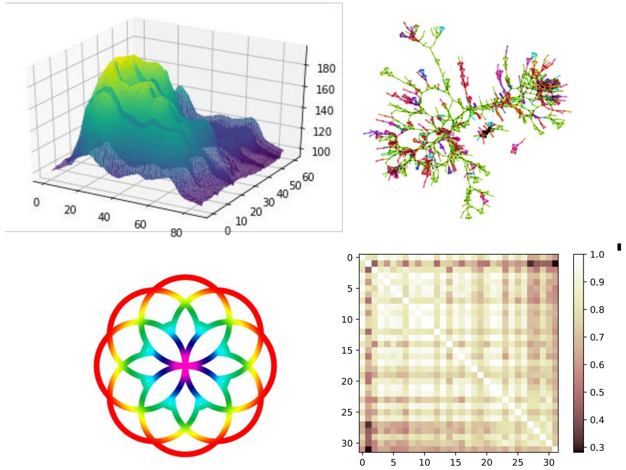

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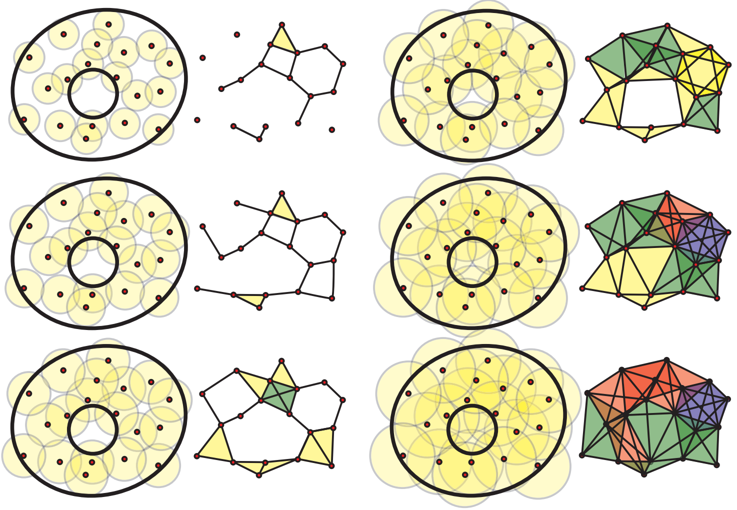

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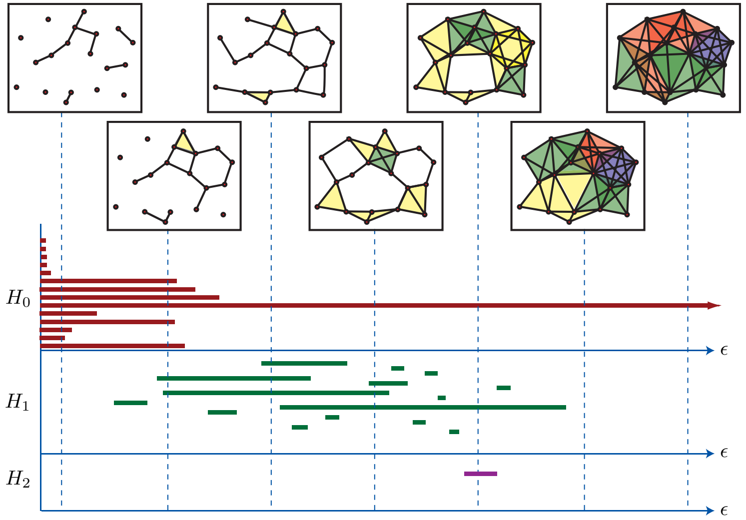

Mapper Pipeline (Singh et al 2007)

Point cloud

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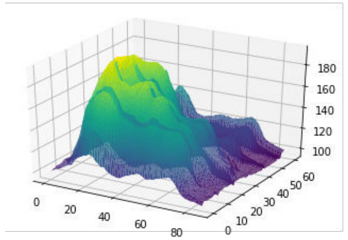
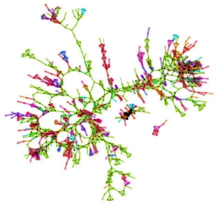

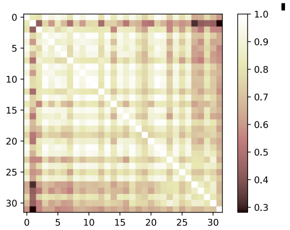

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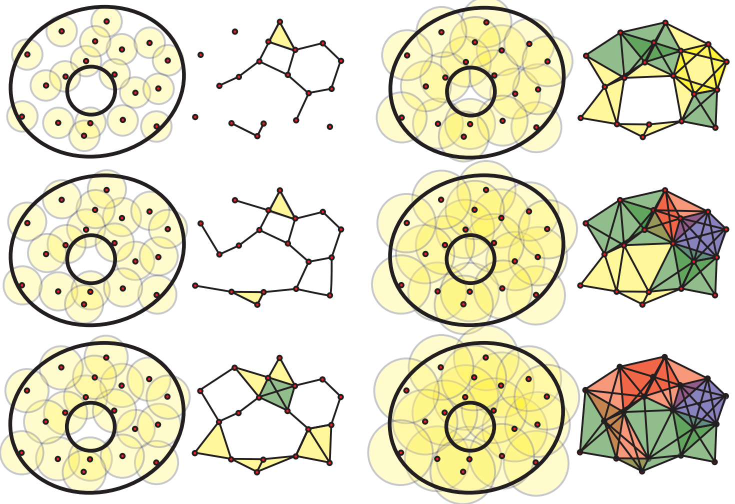

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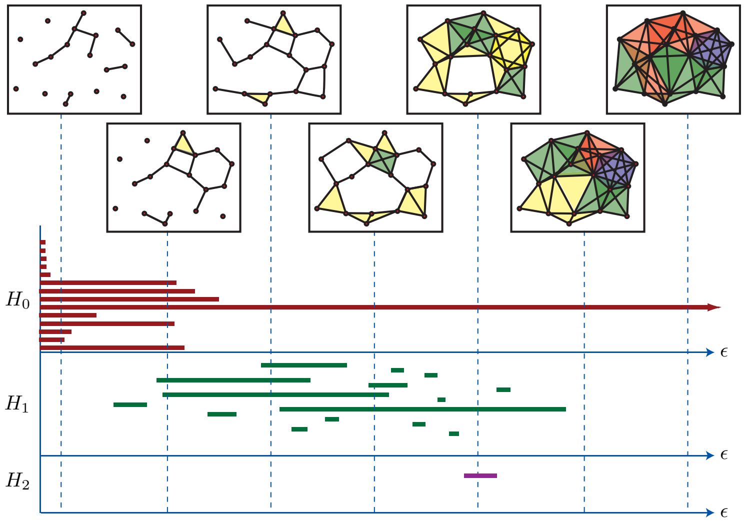

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colouring (projecting)
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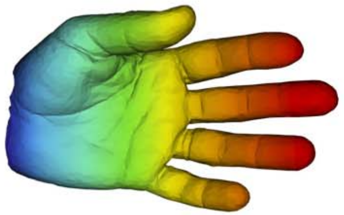

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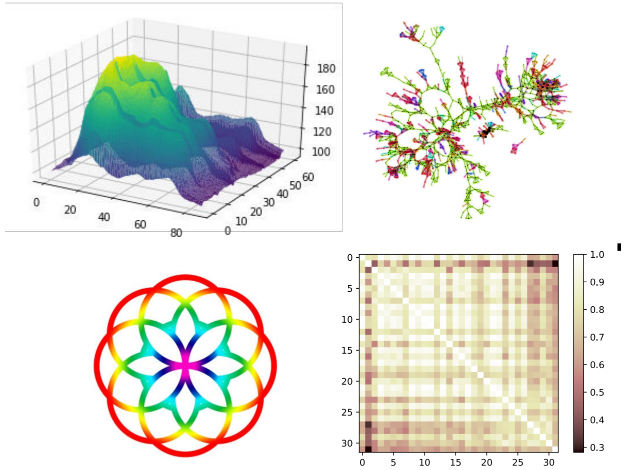

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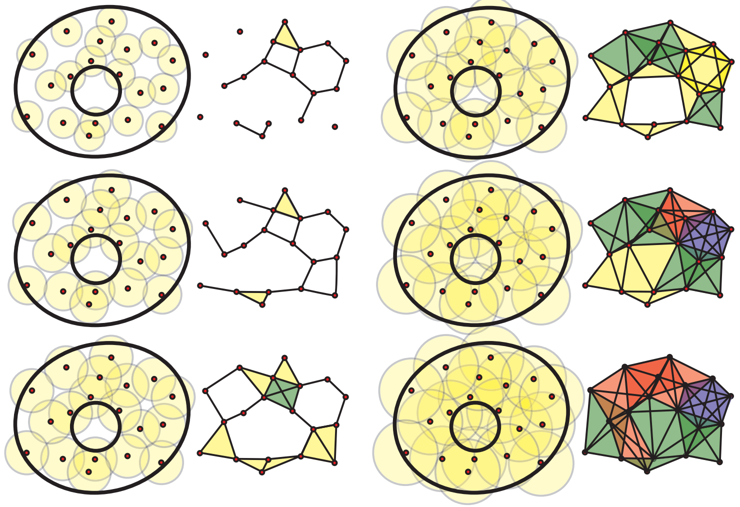

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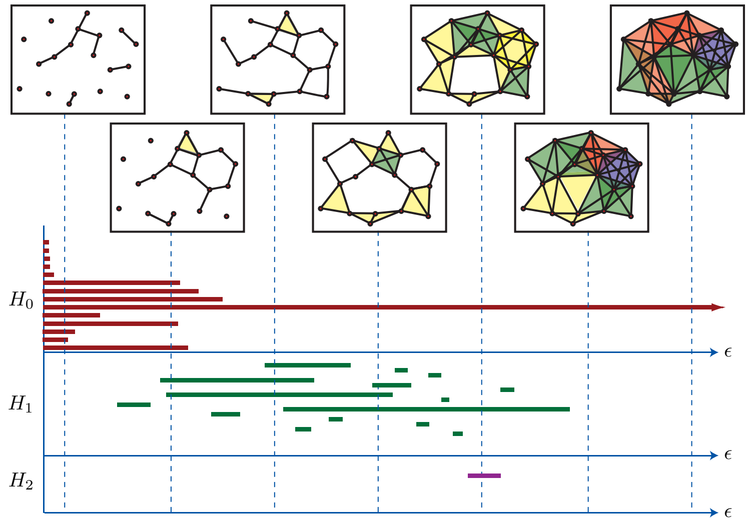

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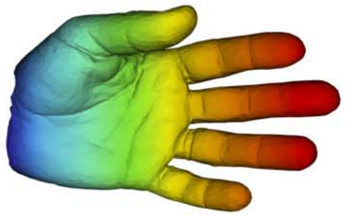
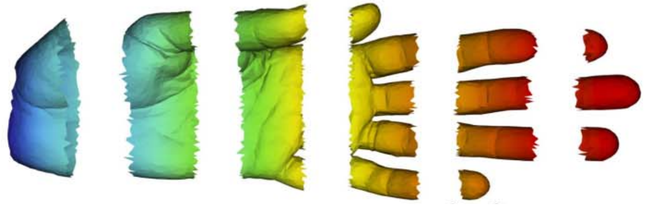


overlapped
binning



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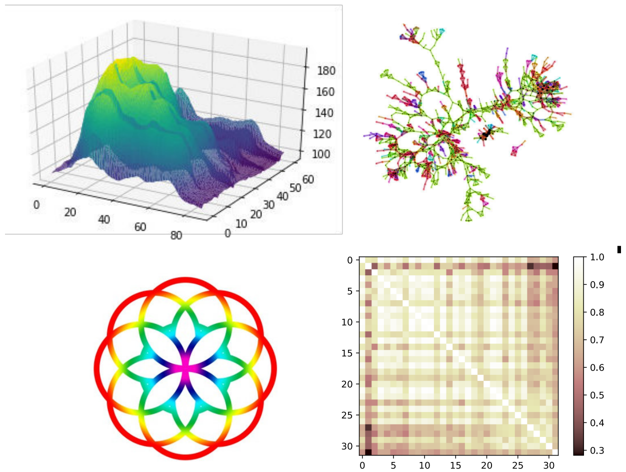

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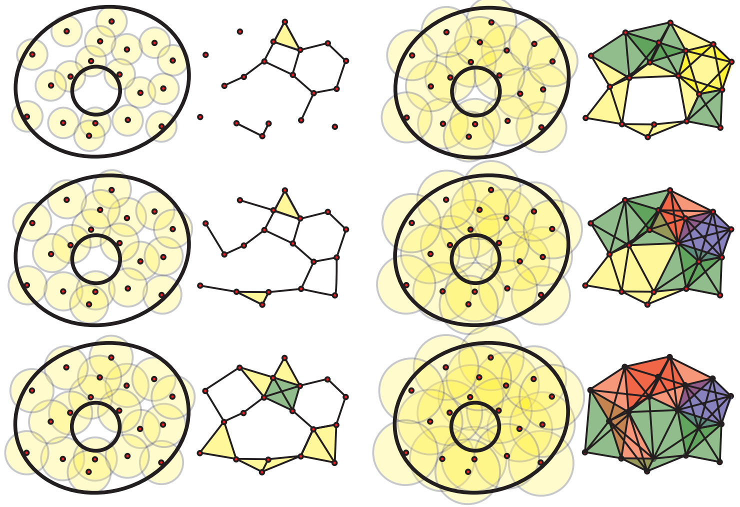

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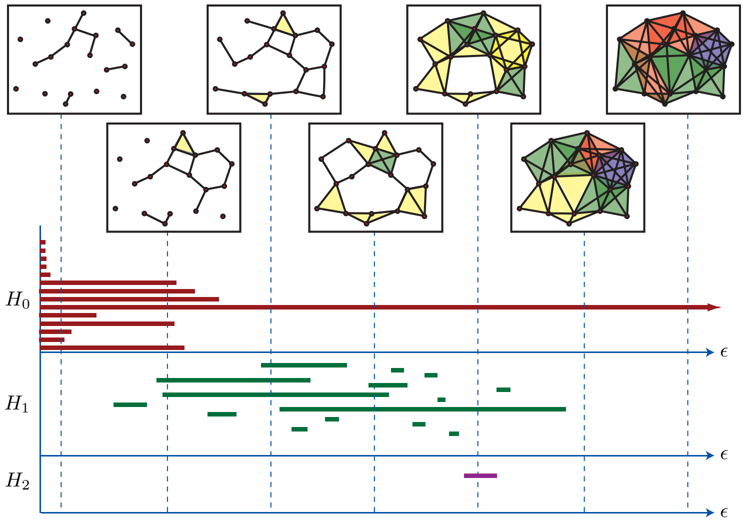

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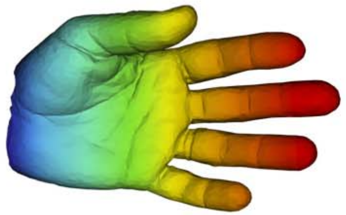

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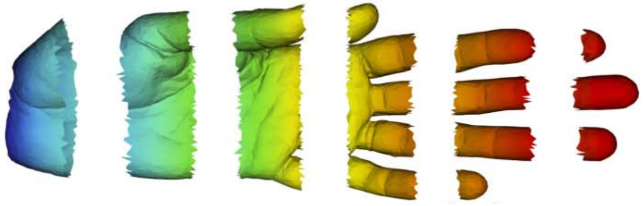
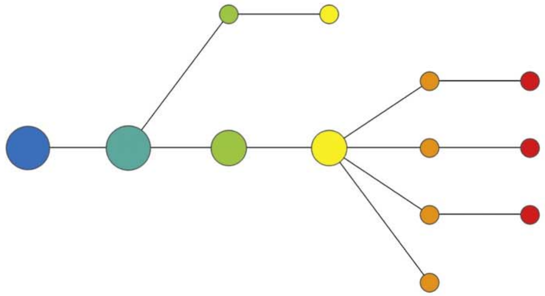


Clustering and
network construction binning



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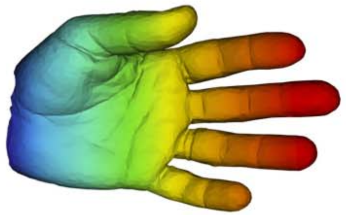

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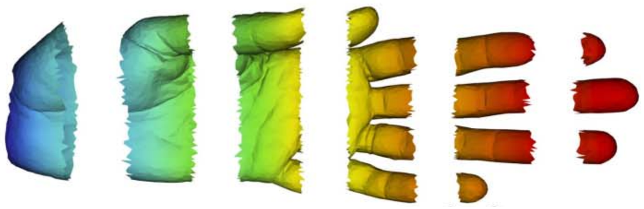

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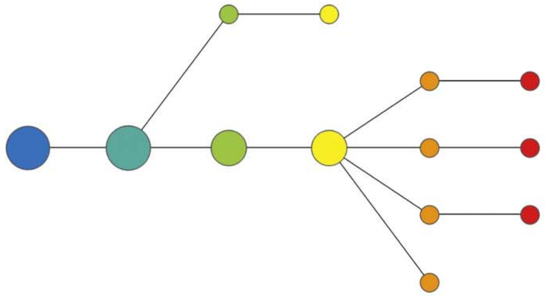

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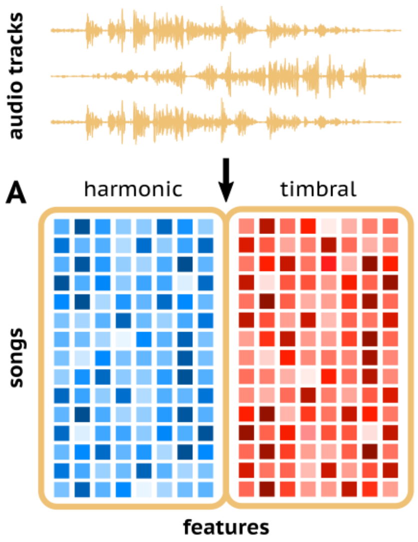

Iacopini, Petri, Latora, (2020) in eternal preparation

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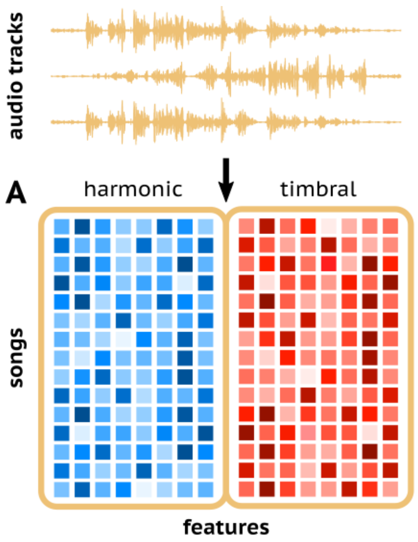

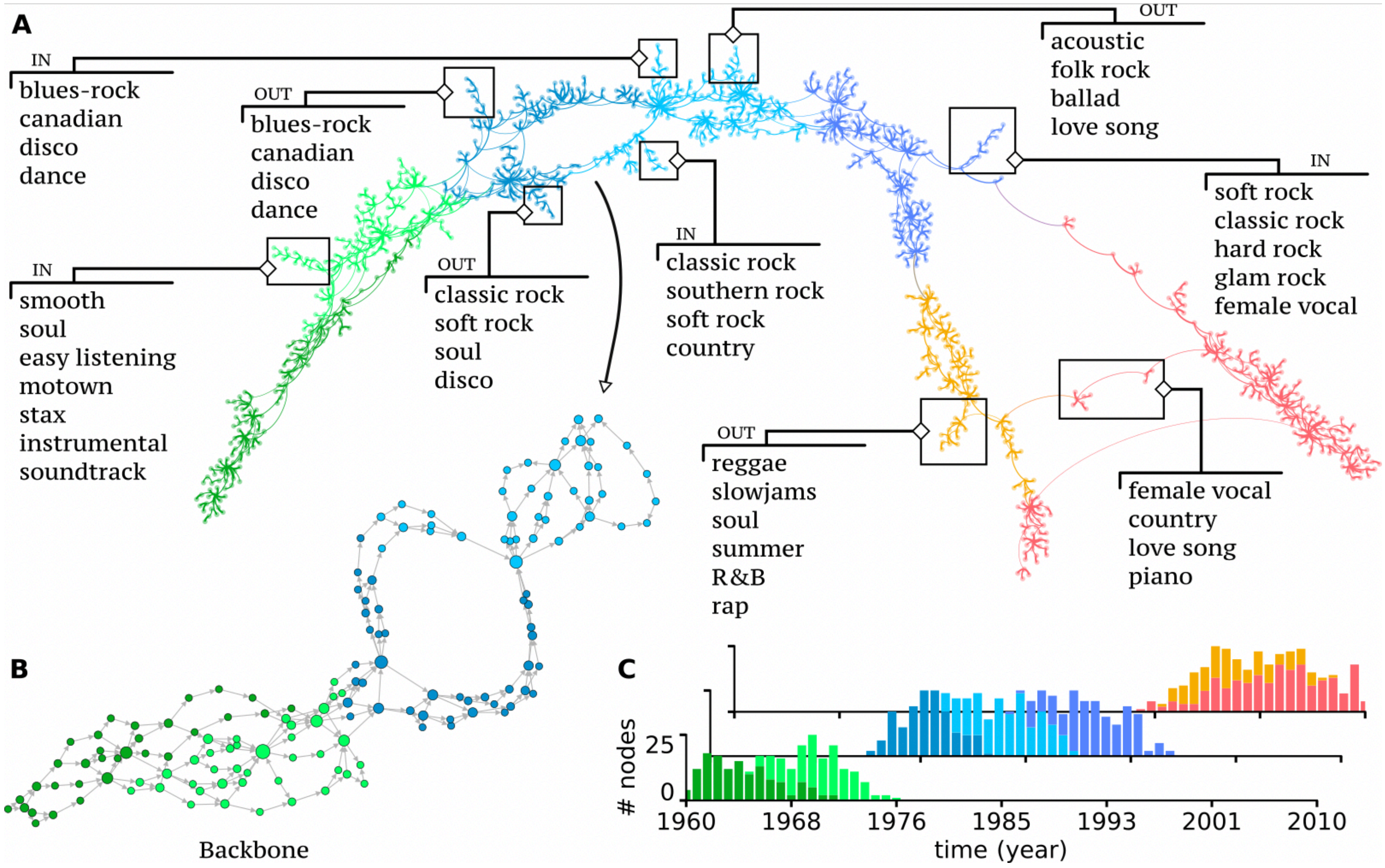

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Do topological gene-backbones carry information?

Patania, Selvaggi, di Pasquale, Veronese, Expert, Petri, Net. Neuroscience 2019

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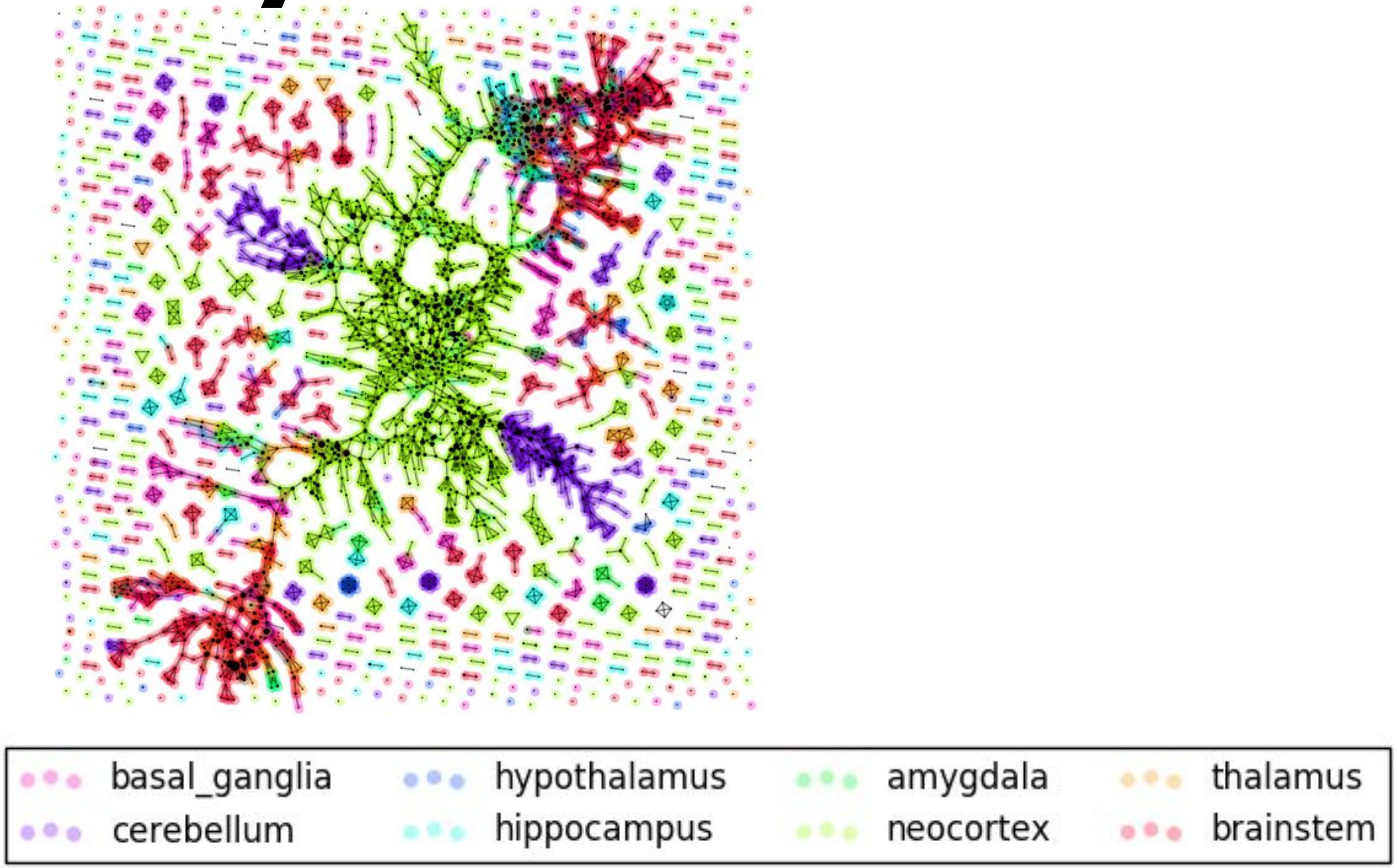
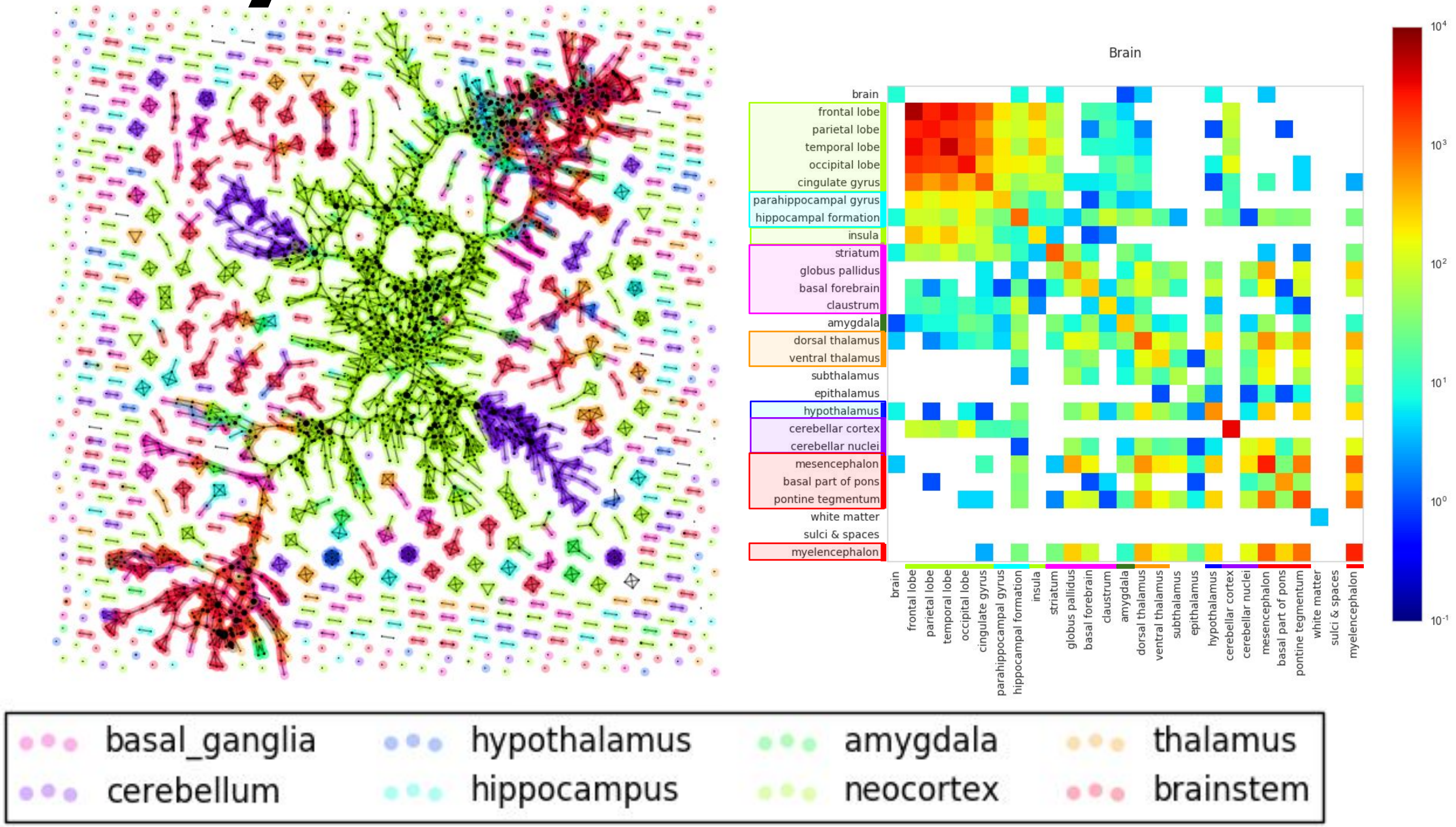


Patania, Selvaggi, di Pasquale, Veronese, Expert, Petri, Net. Neuroscience 2019

Do topological gene-backbones carry information?



Patania, Selvaggi, di Pasquale, Veronese, Expert, Petri, Net. Neuroscience 2019

ALLEN INSTITUTE for BRAIN SCIENCE

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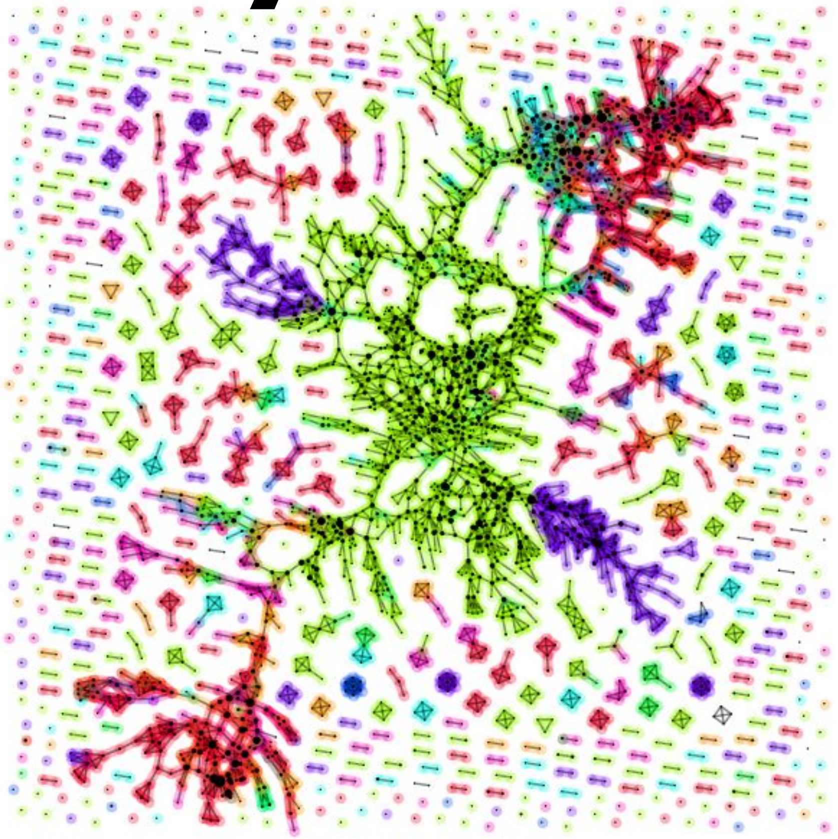
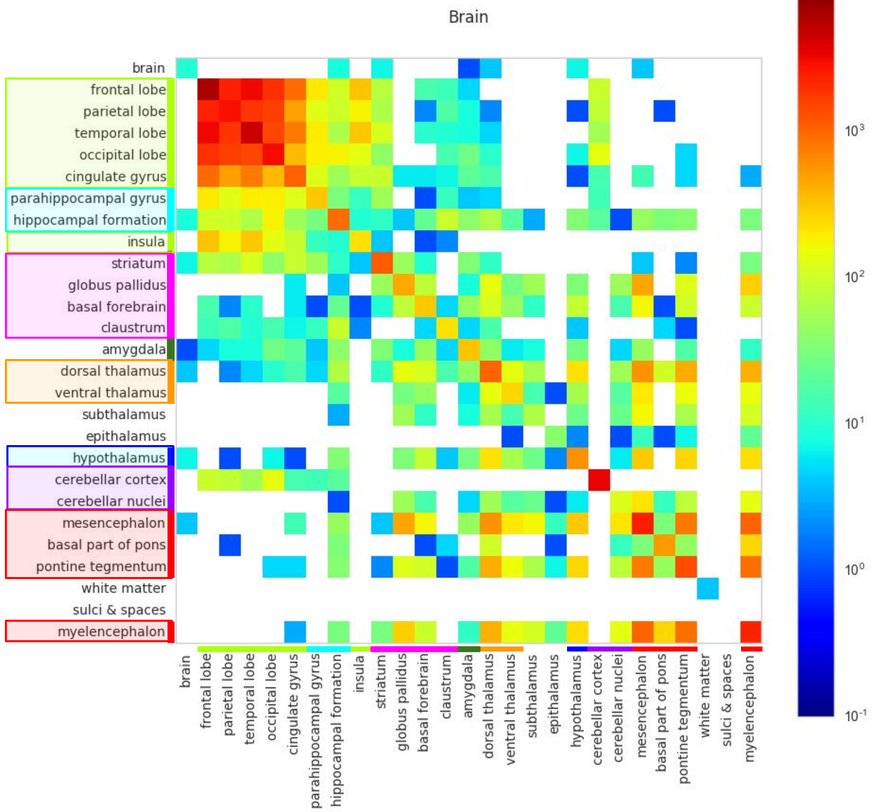
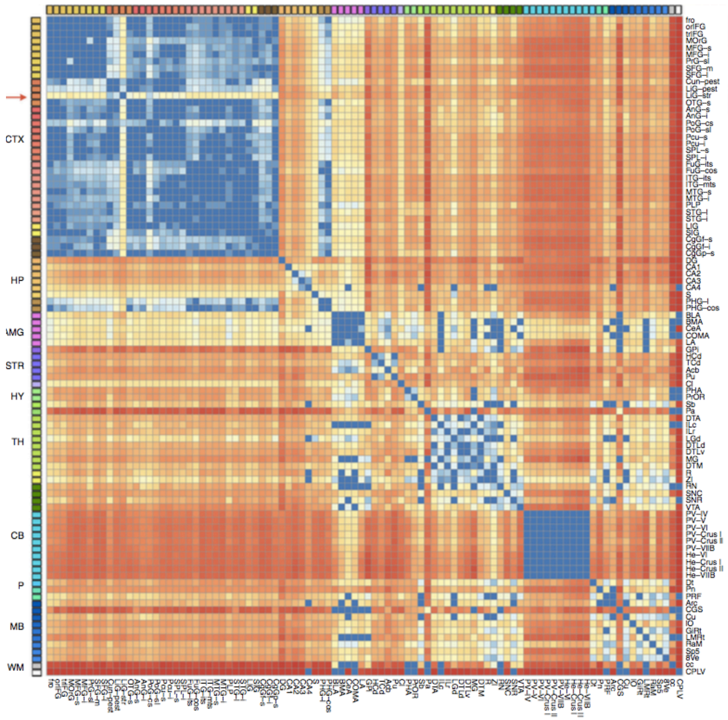




[Hawrylycz, Michael, et al. "Canonical genetic signatures of the adult human brain." *Nature neuroscience* 18.12 (2015): 1832-1844.]



basal_ganglia	hypothalamus	amygdala	thalamus
cerebellum	hippocampus	neocortex	brainstem

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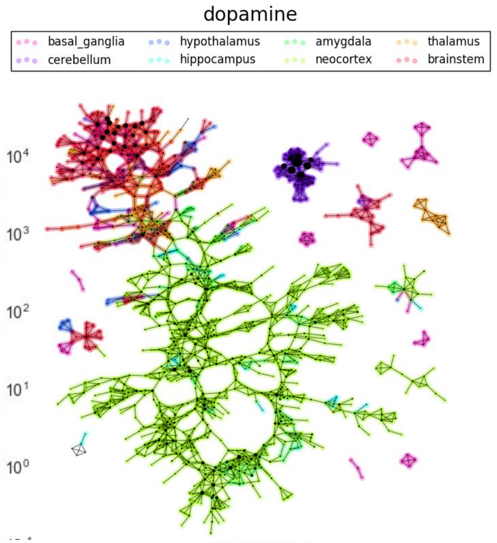

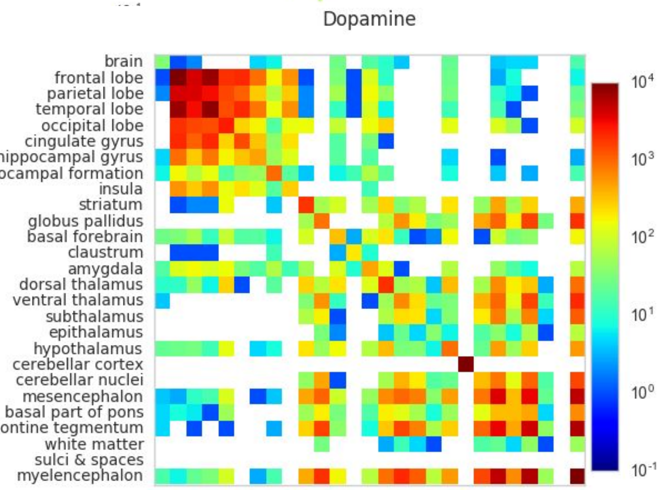

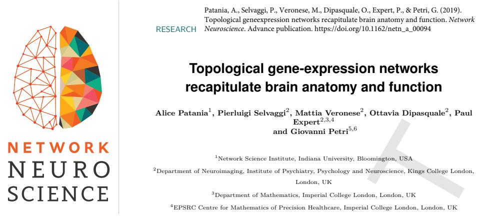

NETWORK NEURO SCIENCE

RESEARCH

Patania, A., Selvaggi, P., Veronese, M., Dipasquale, O., Expert, P., & Petri, G. (2019). Topological geneexpression 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 Patania[1], Pierluigi Selvaggi[2], Mattia Veronese[2], Ottavia Dipasquale[2], Paul Expert[2,3,4] and Giovanni Petri[5,6]

[1]Network Science Institute, Indiana University, Bloomington, USA

[2]Department of Neuroimaging, Institute of Psychiatry, Psychology and Neuroscience, Kings College London, London, UK

[3]Department of Mathematics, Imperial College London, London, UK

[4]EPSRC Centre for Mathematics of Precision Healthcare, Imperial College London, London, UK

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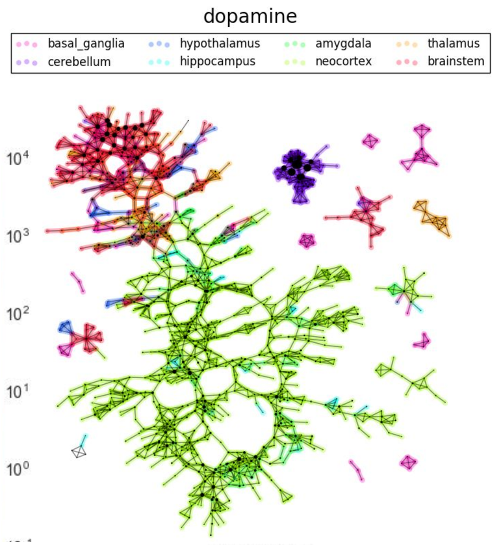

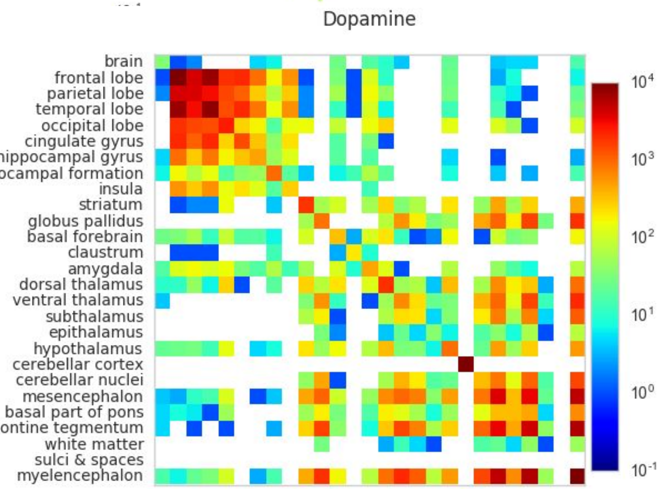

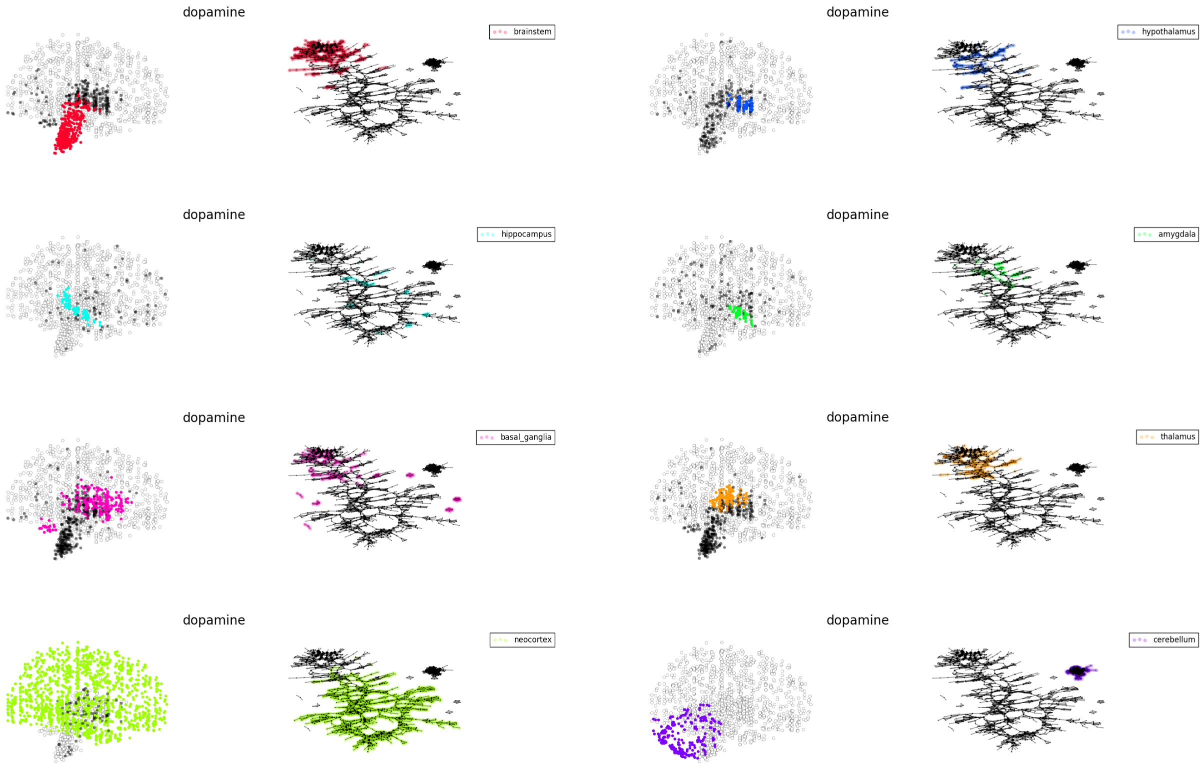

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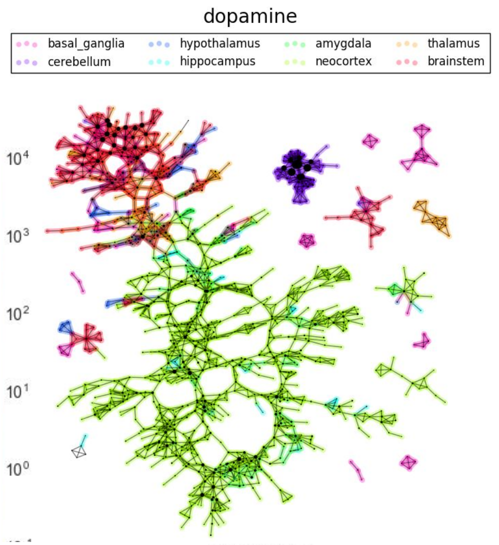
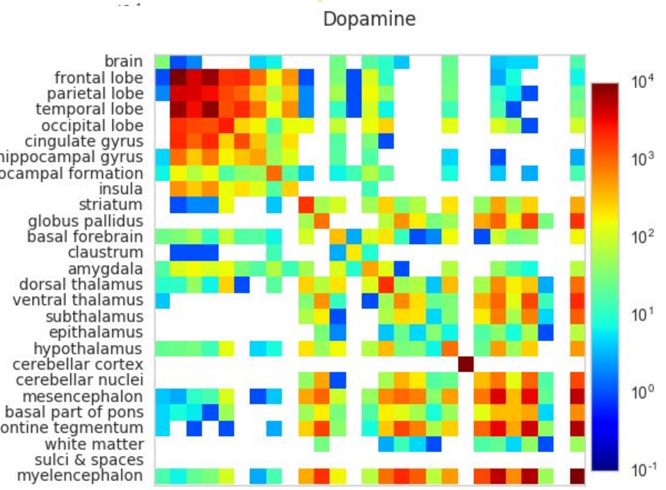
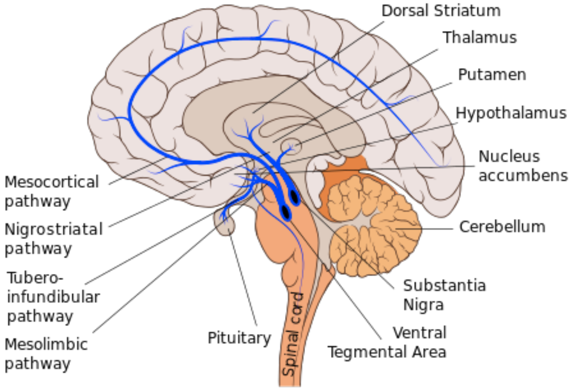
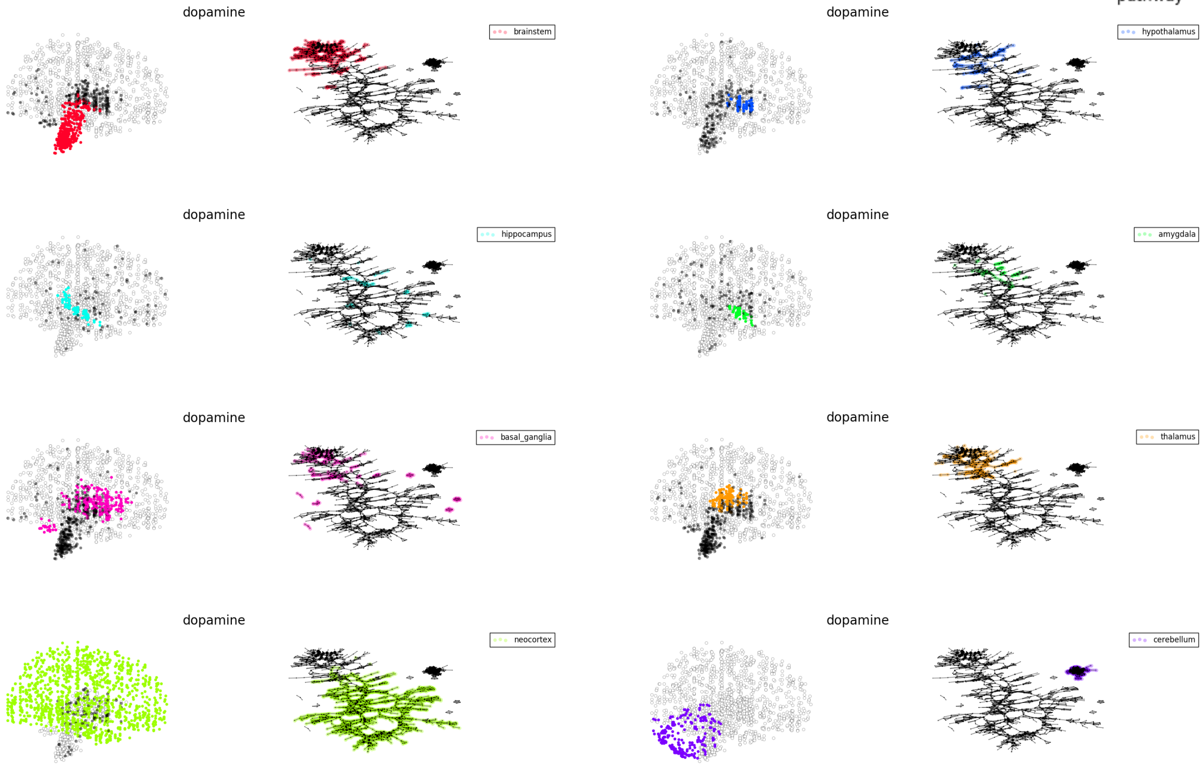
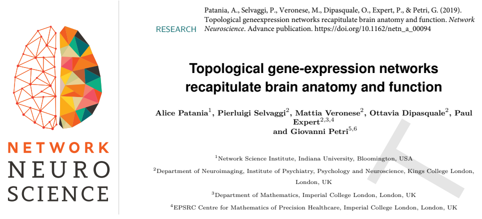










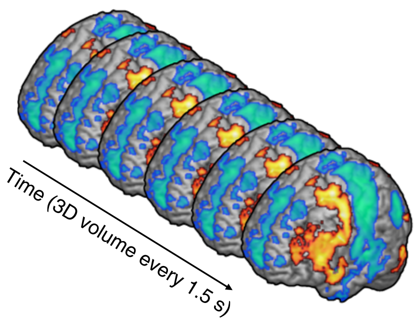
Approximate activity landscapes using topology

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

a

Task brain activation data



Task-fMRI dataset from one CMP participant S_{01}

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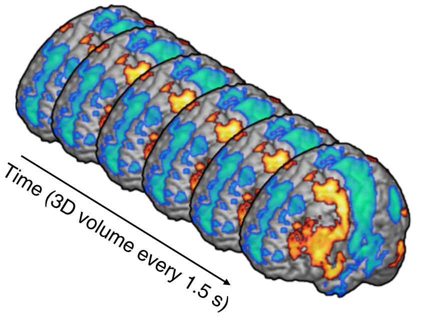

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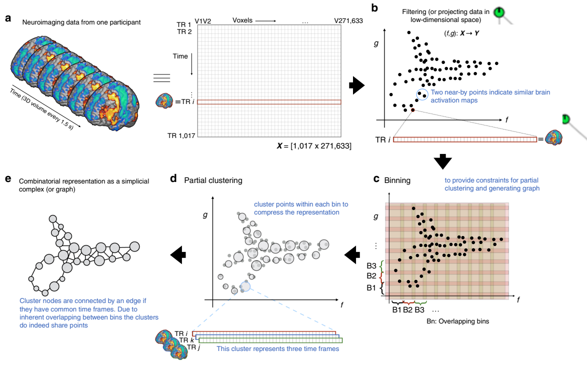

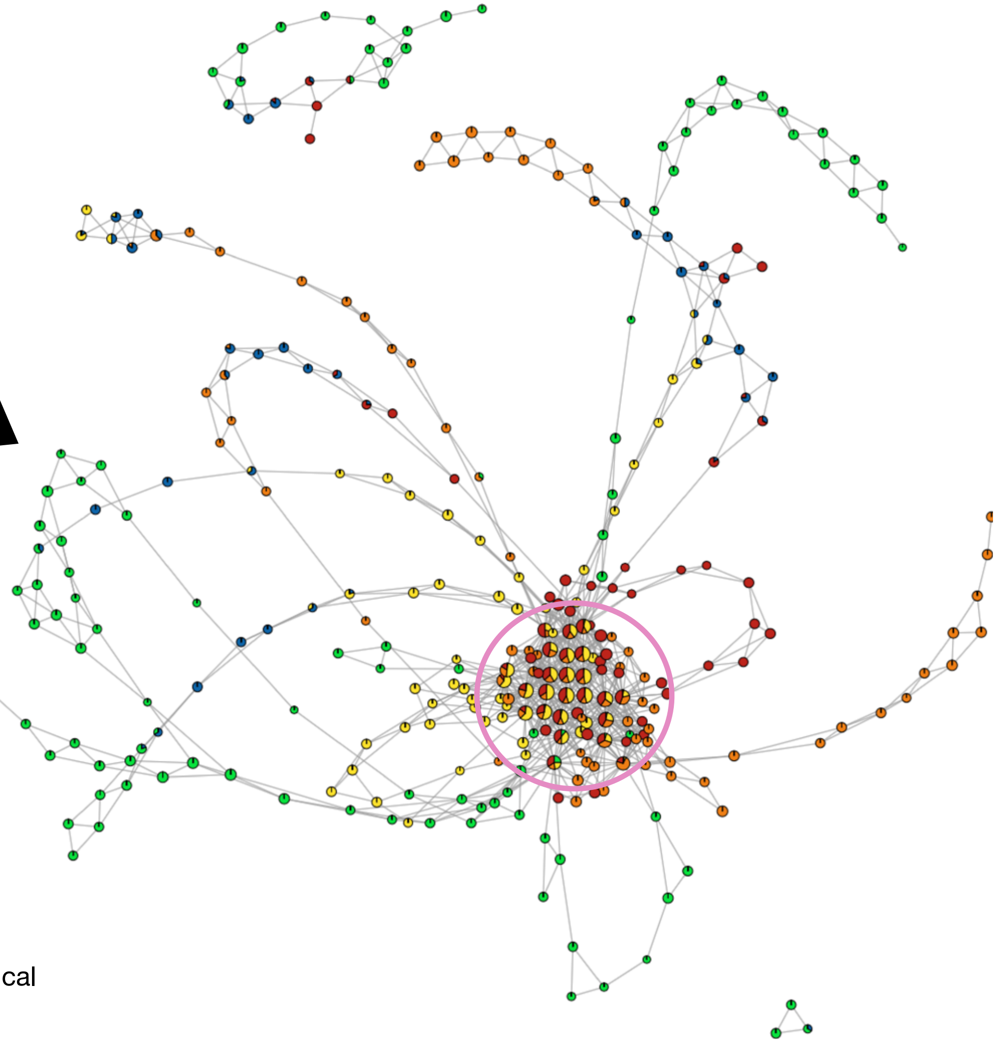

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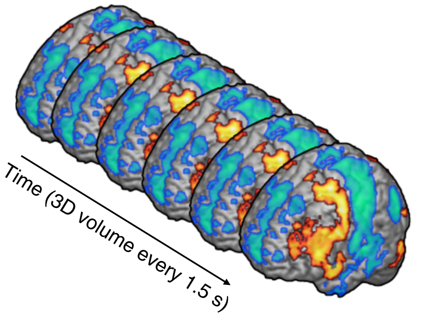

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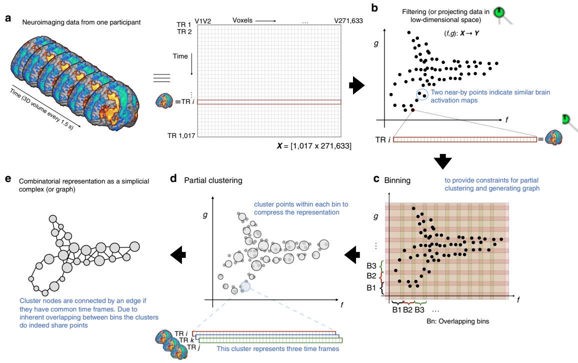
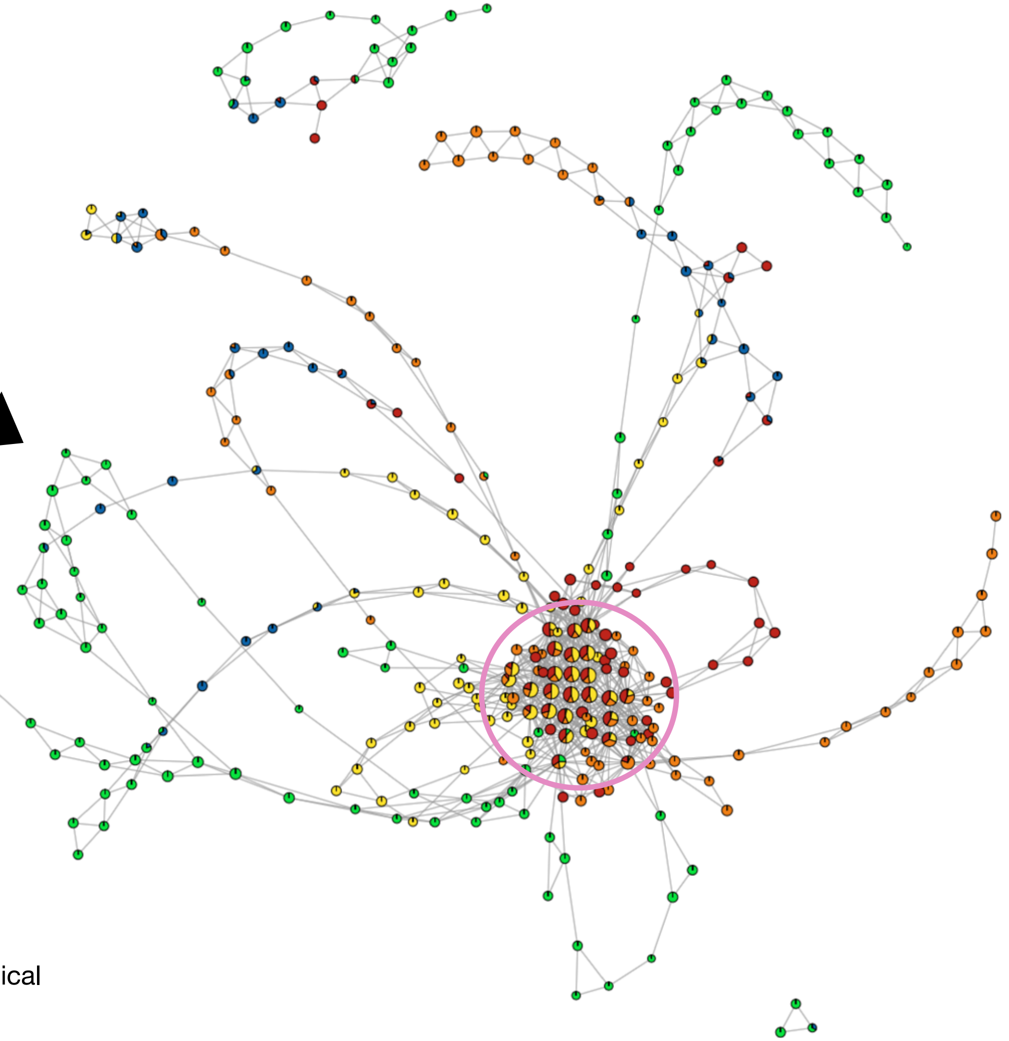
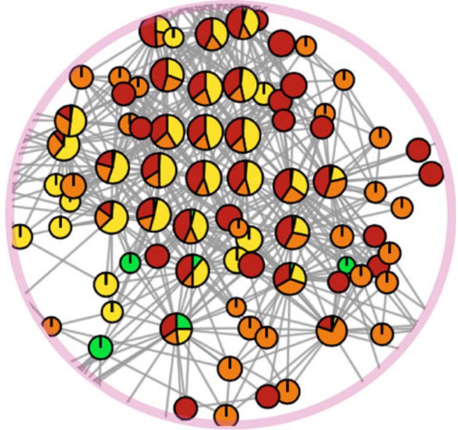




b



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

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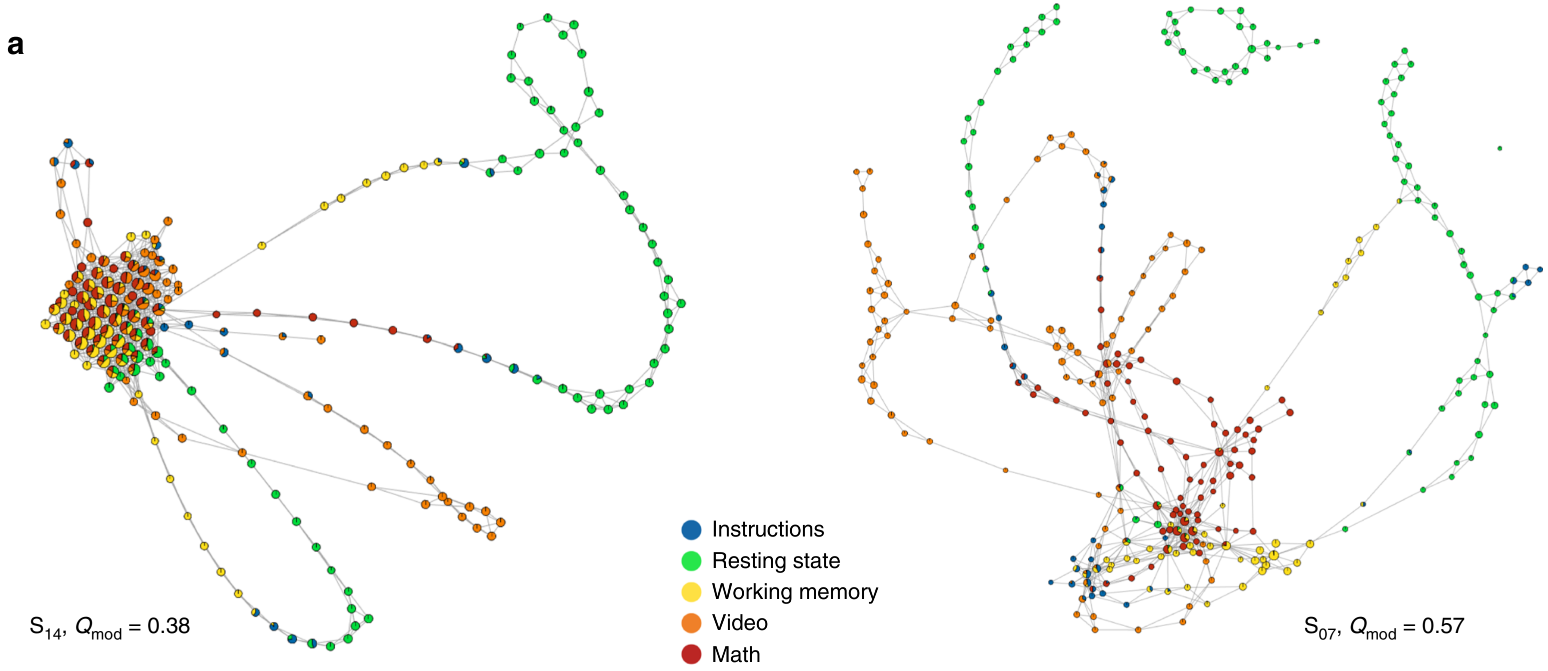

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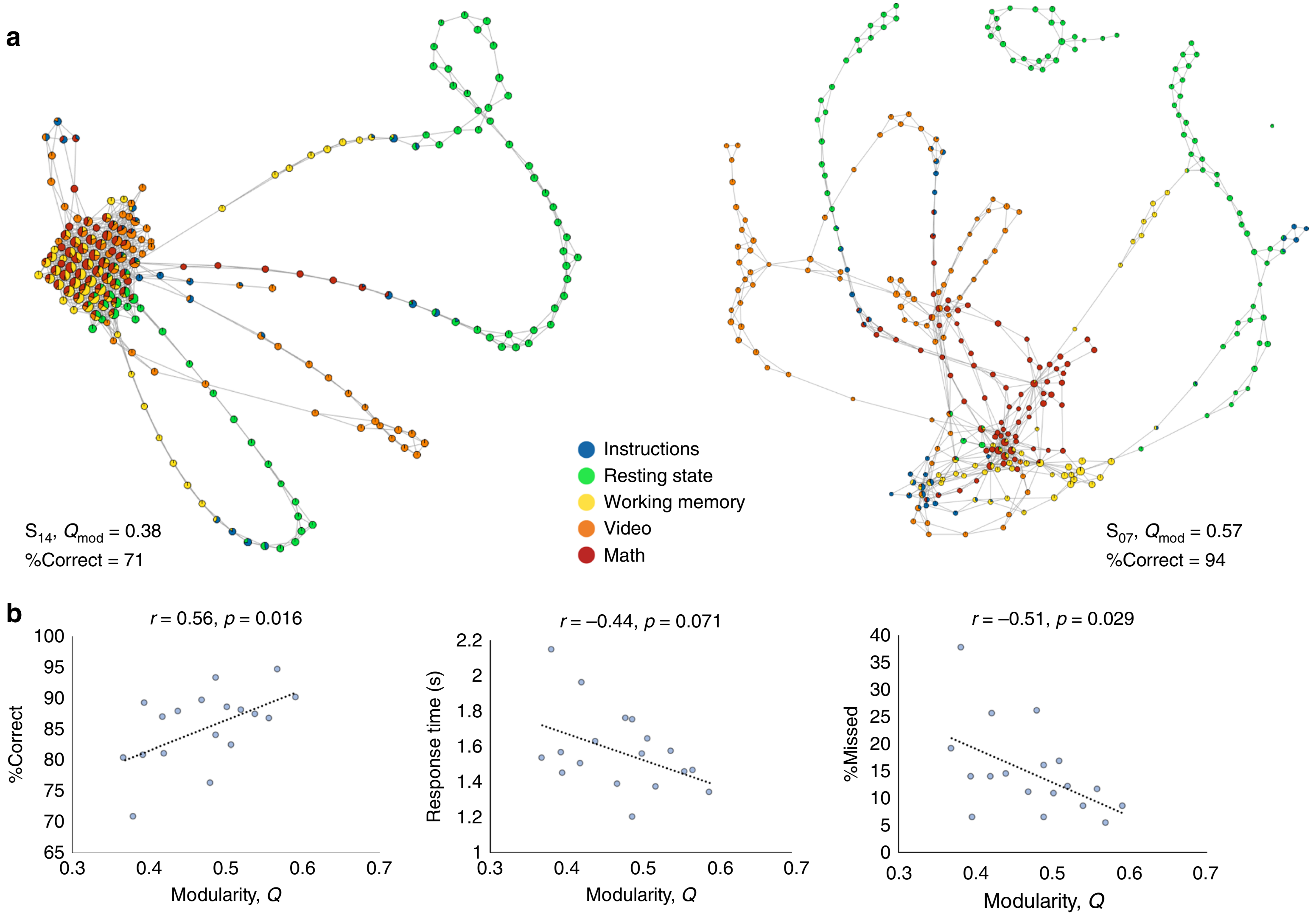

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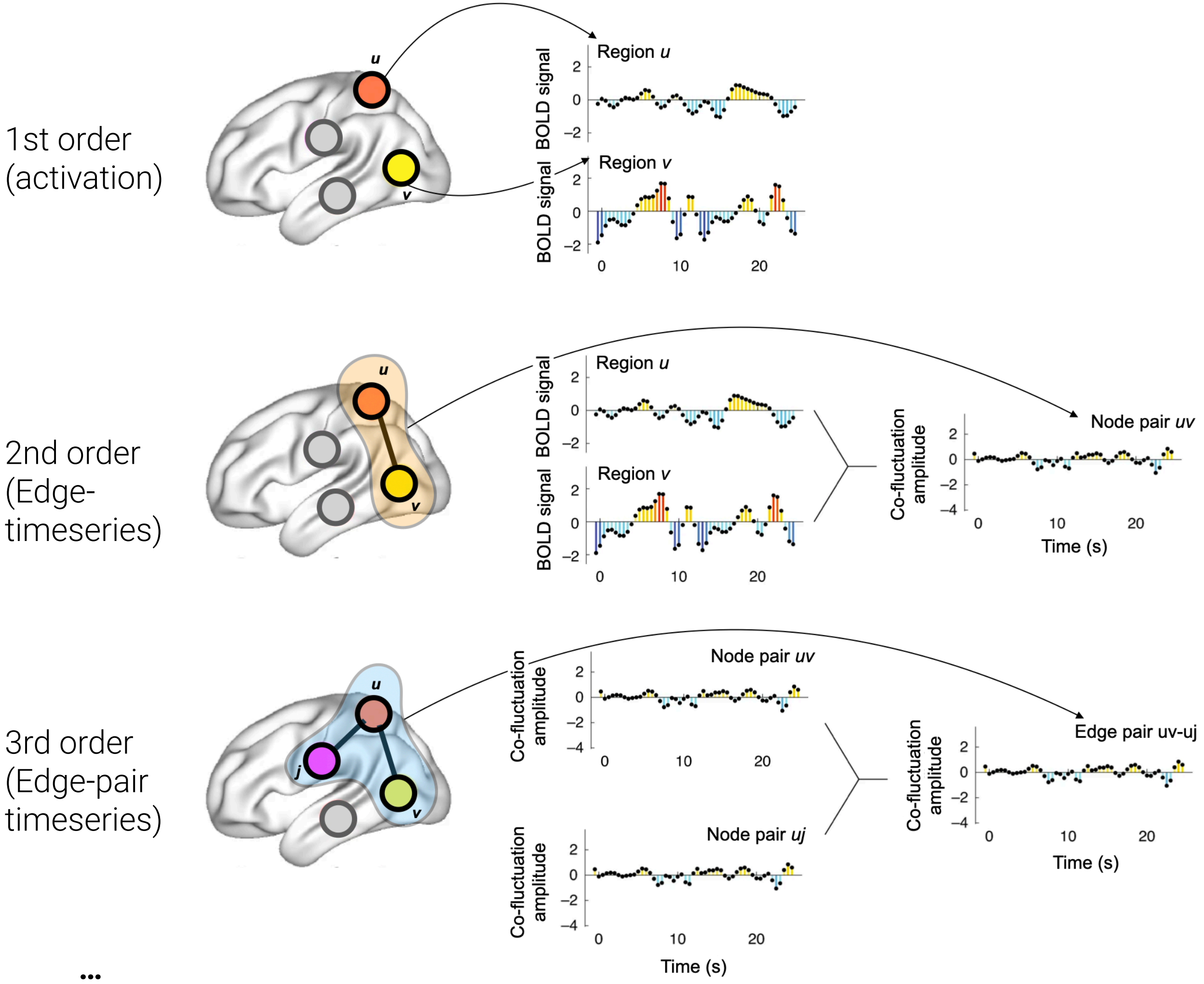
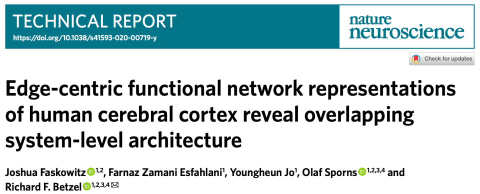




TECHNICAL REPORT

https://doi.org/10.1038/s41593-020-00719-y

nature neuroscience

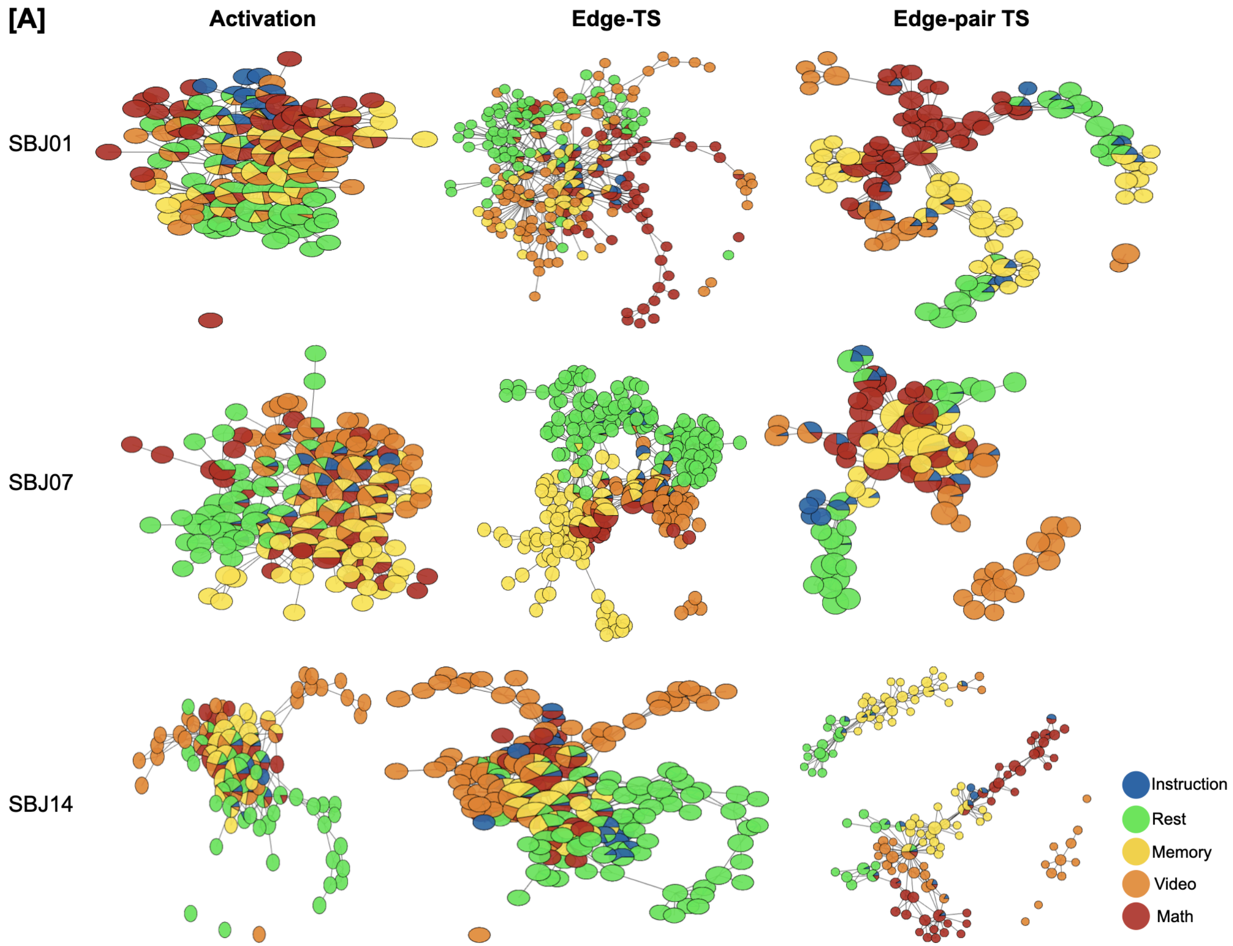
Check for updates

Edge-centric functional network representations of human cerebral cortex reveal overlapping system-level architecture

Joshua Faskowitz[1,2], Farnaz Zamani Esfahlani[1], Youngheun Jo[1], Olaf Sporns[1,2,3,4] and Richard F. Betzel[1,2,3,4]

...

Approximate activity landscapes using topology



Morandini, Petri, Saggar, in prep

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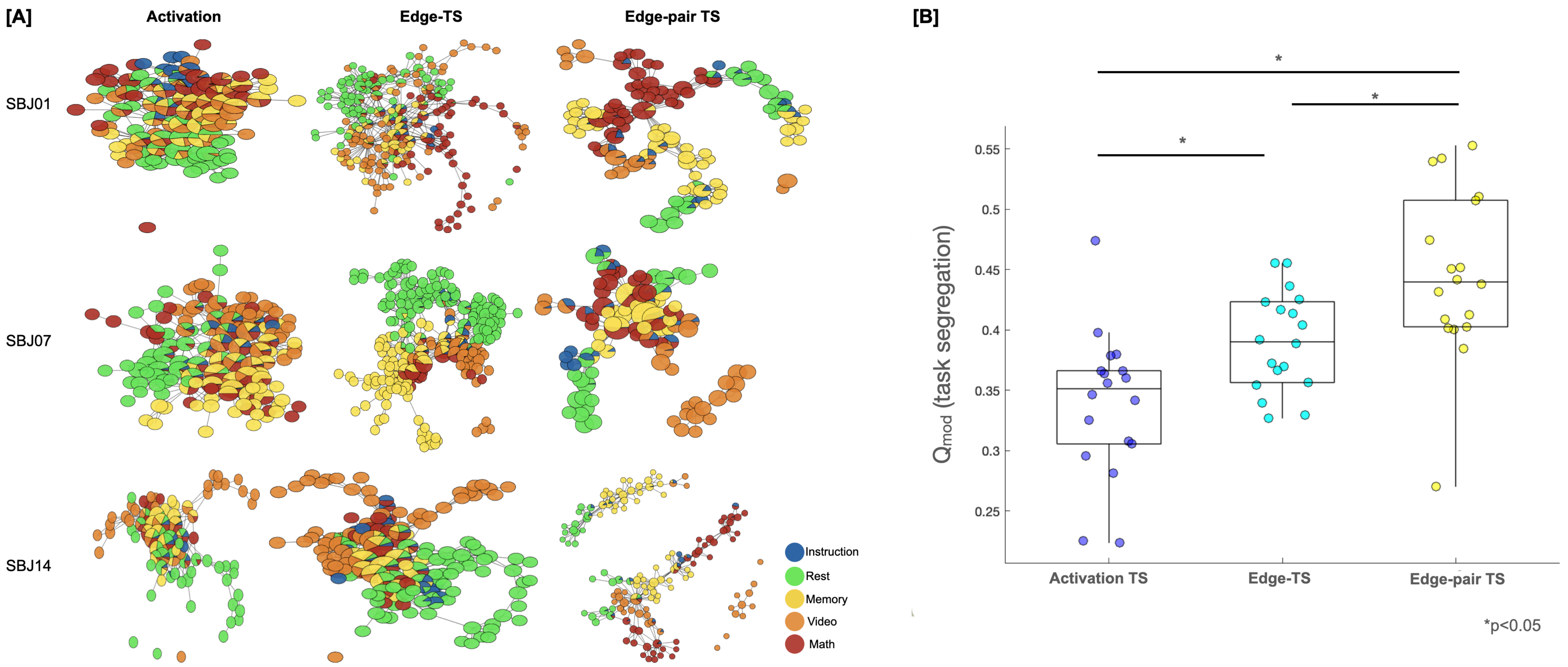


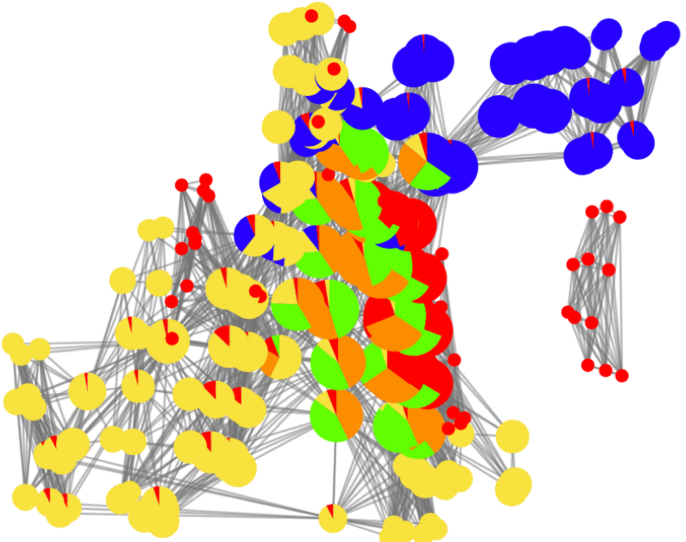
Morandini, Petri, Saggar, in prep

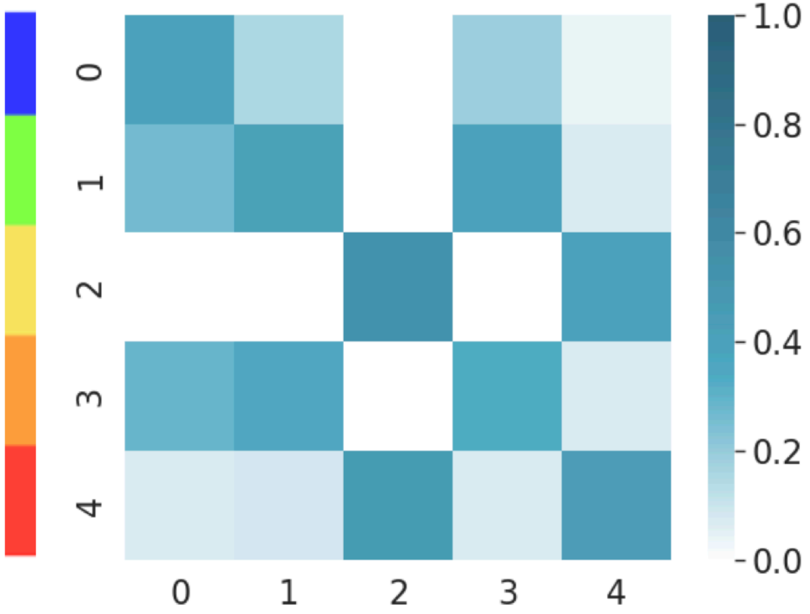
Topological fingerprinting (in general)

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

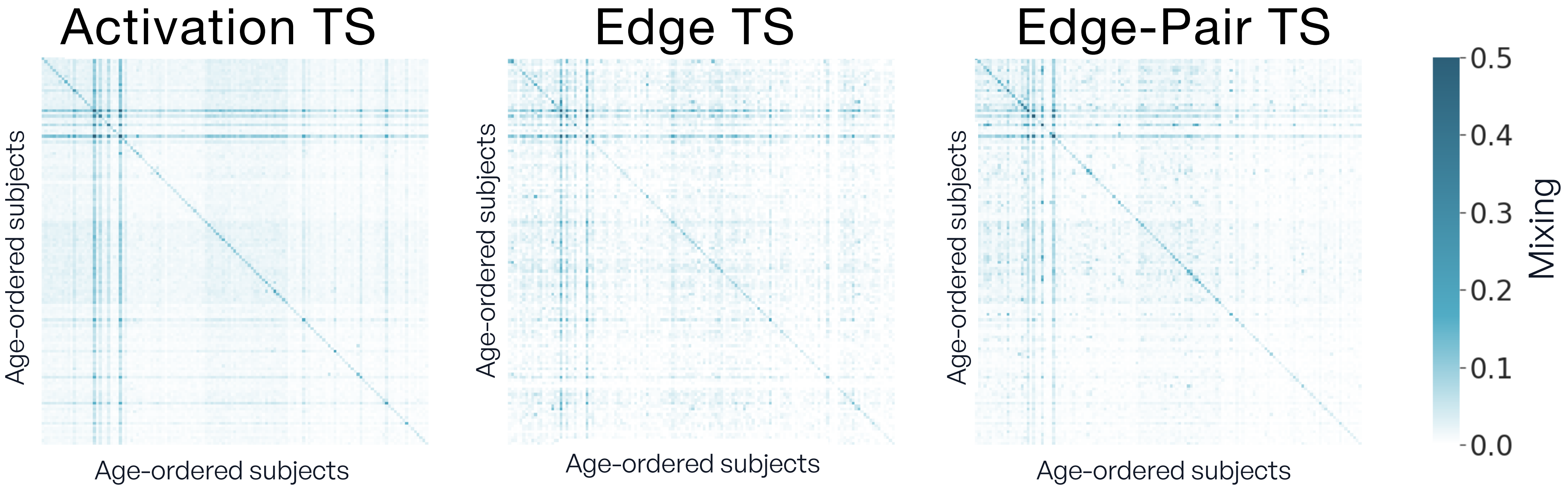




Morandini, Petri, Saggar, in prep

Topological brain fingerprinting

Is the signal strong enough across subjects?



Morandini, Petri, Saggar, in prep

Topological brain fingerprinting

Is the signal strong enough across subjects?

Morandini, Petri, Saggar, in prep

Topological brain fingerprinting

Is the signal strong enough across subjects?

Intensive

Def. Mixing Matrix. Given the classes $1,\ldots,C$, 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:

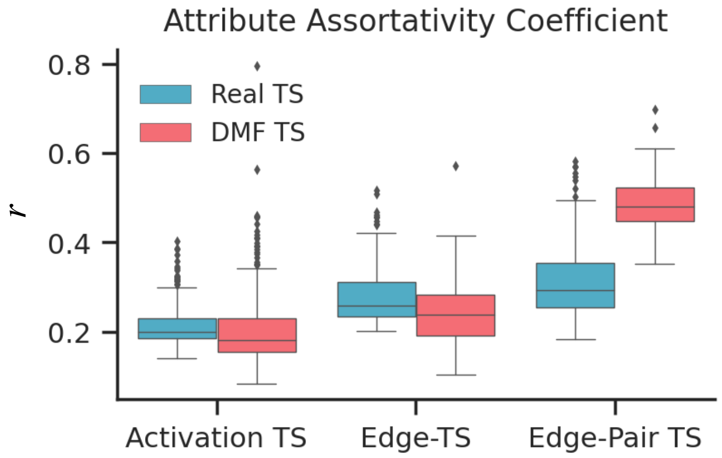
$$r = \frac{Tr(e) - ||e^2||_2}{1 - ||e^2||_2}.$$

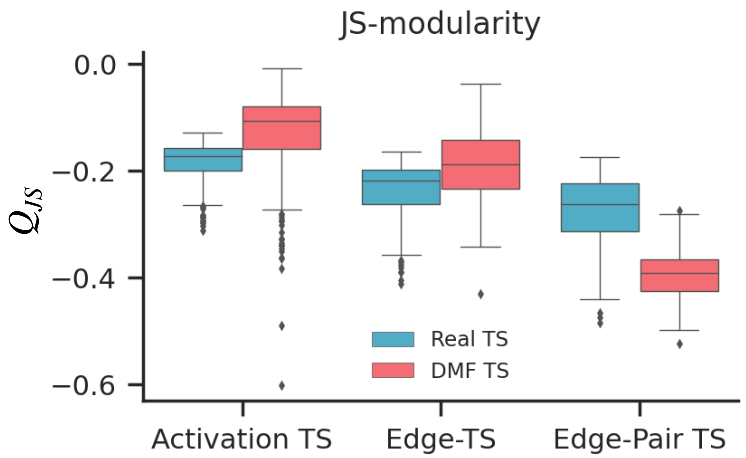
Def. Modularity. Assigned a class c_i to each node i:

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

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

Jensen-Shannon divergence





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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:

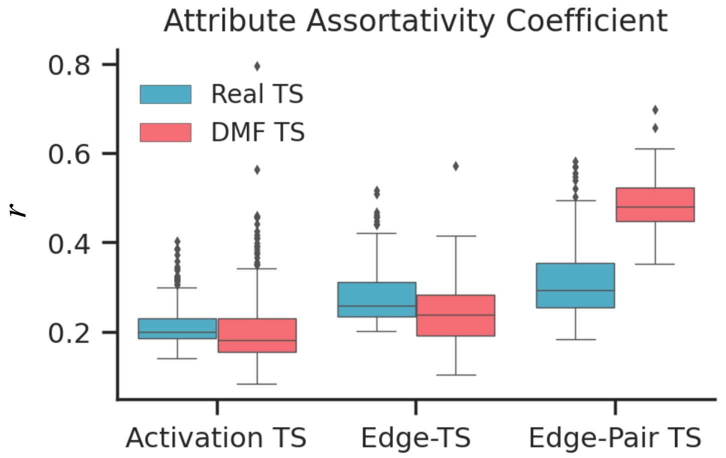
$$I_{others}(i) = \frac{1}{2}\sum_{j\neq i}(c_{ij} + c_{ji}).$$

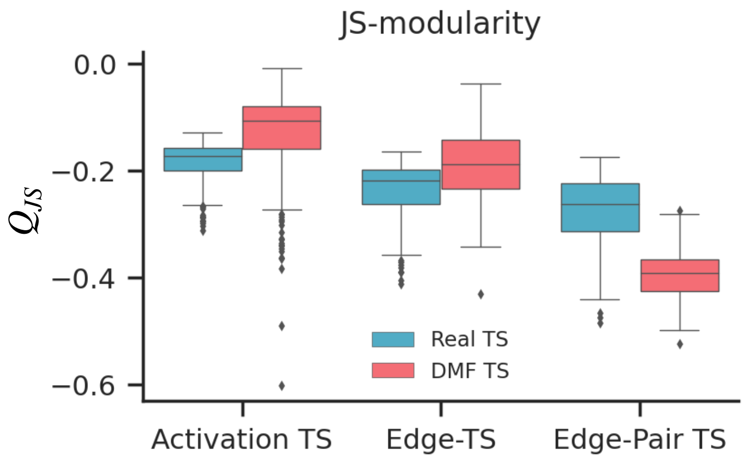
Def. Topological fingerprint. Given C the number of classes and $\mathbf{C}$ the CMM:

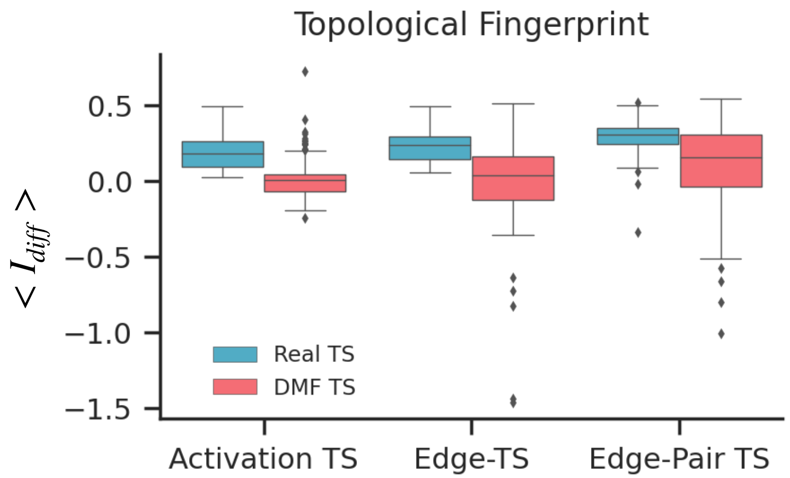
$$< I_{diff} > = \frac{< I_{self} > - < I_{others} >}{< I_{self} >},$$

where $< I_{self} >$ and $< I_{others} >$ 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.







Morandini, Petri, Saggar, in prep

Topo+Info brain fingerprinting

Morandini, Petri, Saggar, in prep

Topo+Info brain fingerprinting

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

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

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

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

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Def. Ω-information.

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

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

REDUNDANCY

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

SYNERGY

Morandini, Petri, Saggar, in prep

Topo+Info brain fingerprinting

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

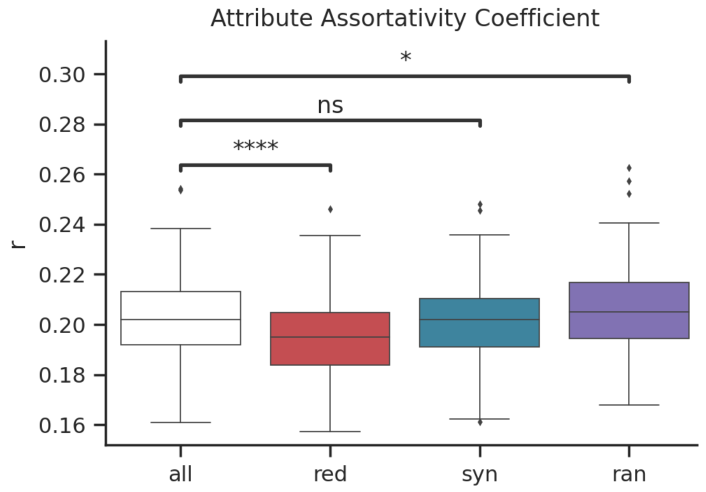
REDUNDANCY

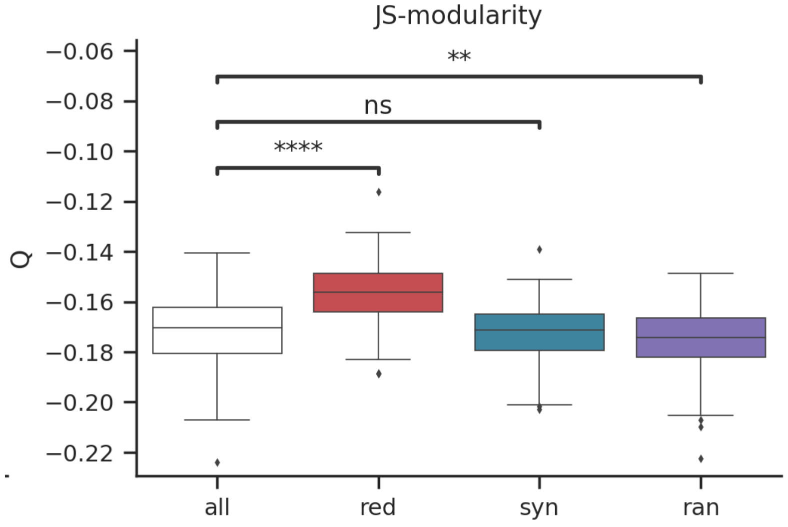
$\Omega(\mathbf{X}) < 0$

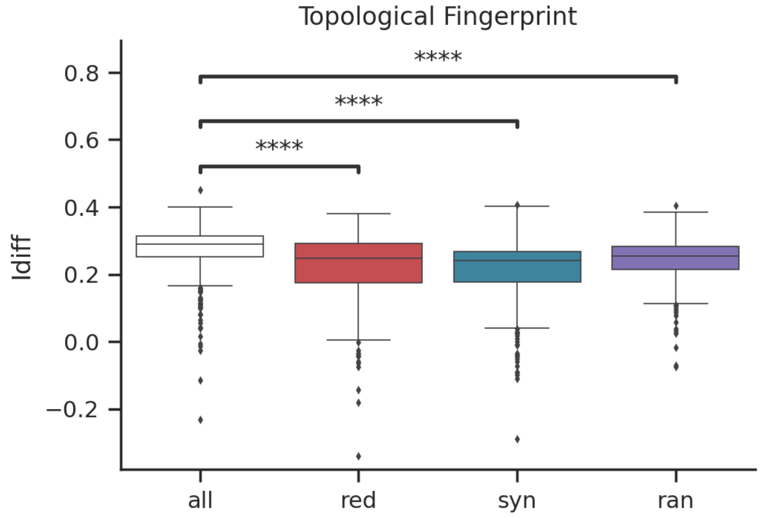
SYNERGY

Intensive

Discriminative







Morandini, Petri, Saggar, in prep

Topo+Info brain fingerprinting

Summing up

Topo+Info brain fingerprinting

Summing up

- Topological information (simplification) discriminates well across individuals

Topo+Info brain fingerprinting

Summing up

- Topological information (simplification) discriminates well across individuals

- Stronger effect for higher-order timeseries

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…

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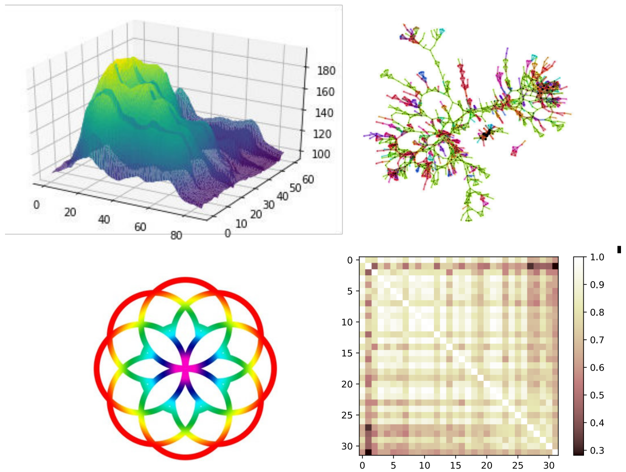
Functional, structural, you name it…

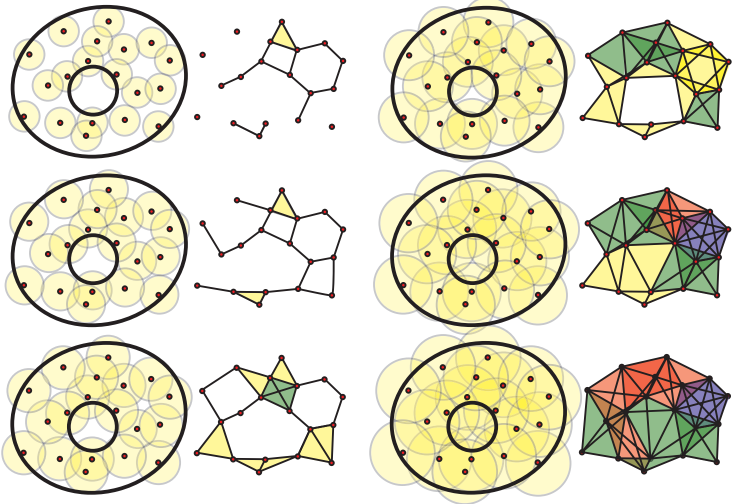
What does it mean in practice?

Persistent homology pipeline (Ghrist 2008)

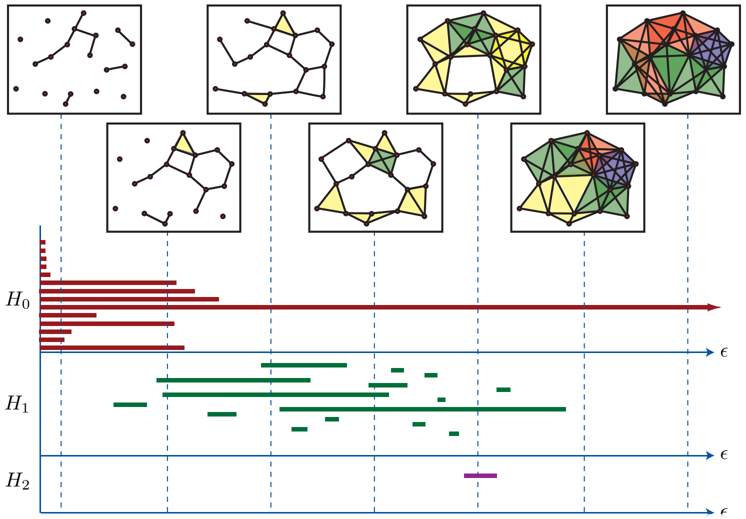
Data of sorts



Filtration over distance/density/weights



Homological properties



Mapper Pipeline (Singh et al 2007)

Point cloud

colouring (projecting) using geometric filters

overlapped binning

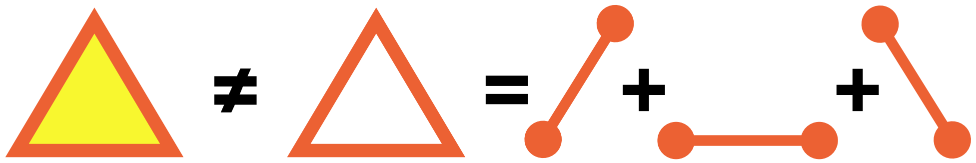
Clustering and network construction binning

From data to simplices

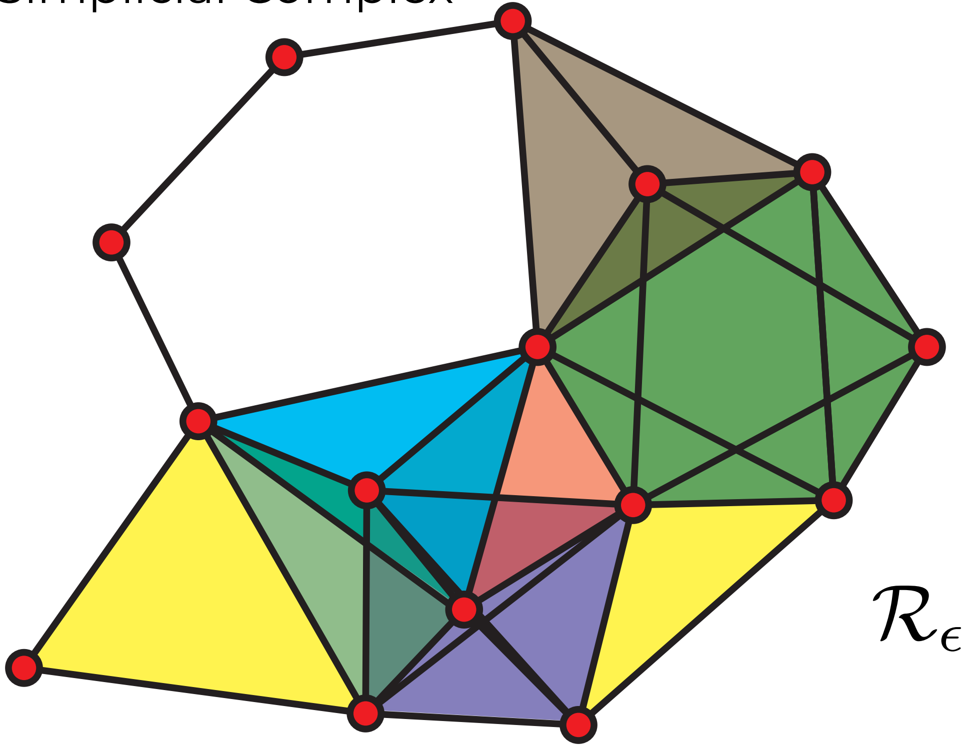
DOT
= 0-simplex

EDGE =
1-simplex

TRIANGLE
= 2-simplex



Simplicial Complex



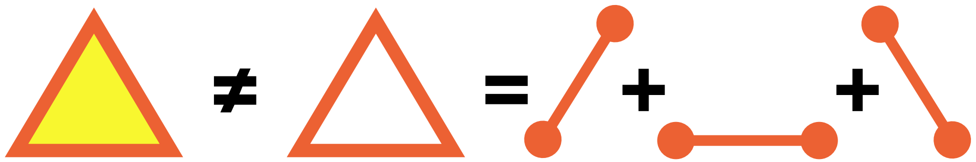
Ghrist, R. (2008). Barcodes: The persistent topology of data. *Bulletin-American Mathematical Society*, *45*(1), 61.

From data to simplices

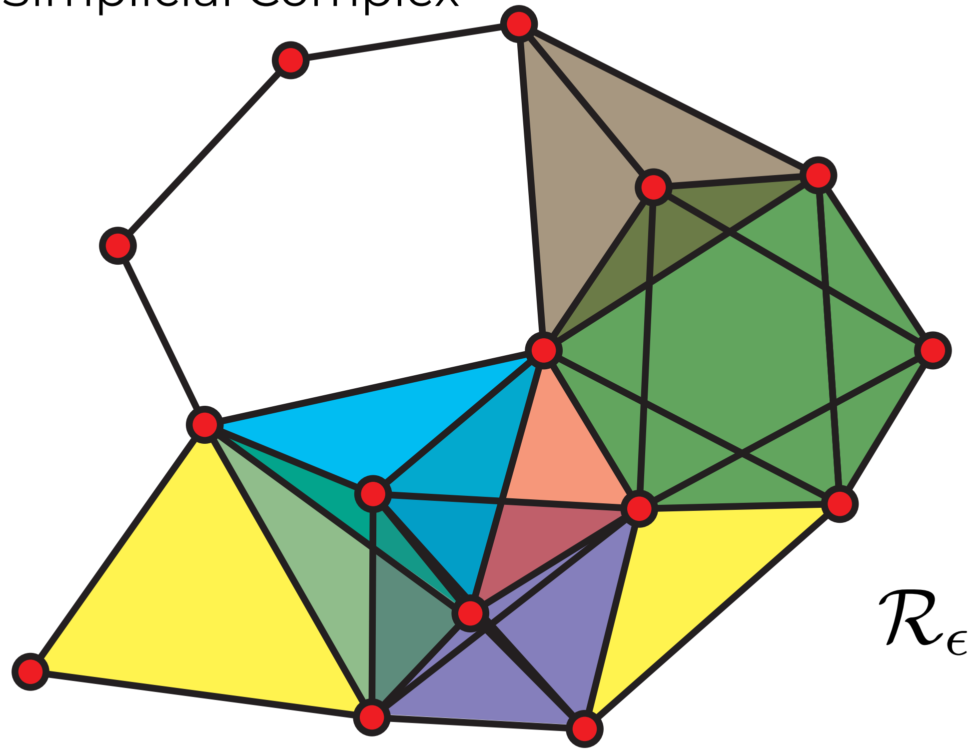
DOT
= 0-simplex

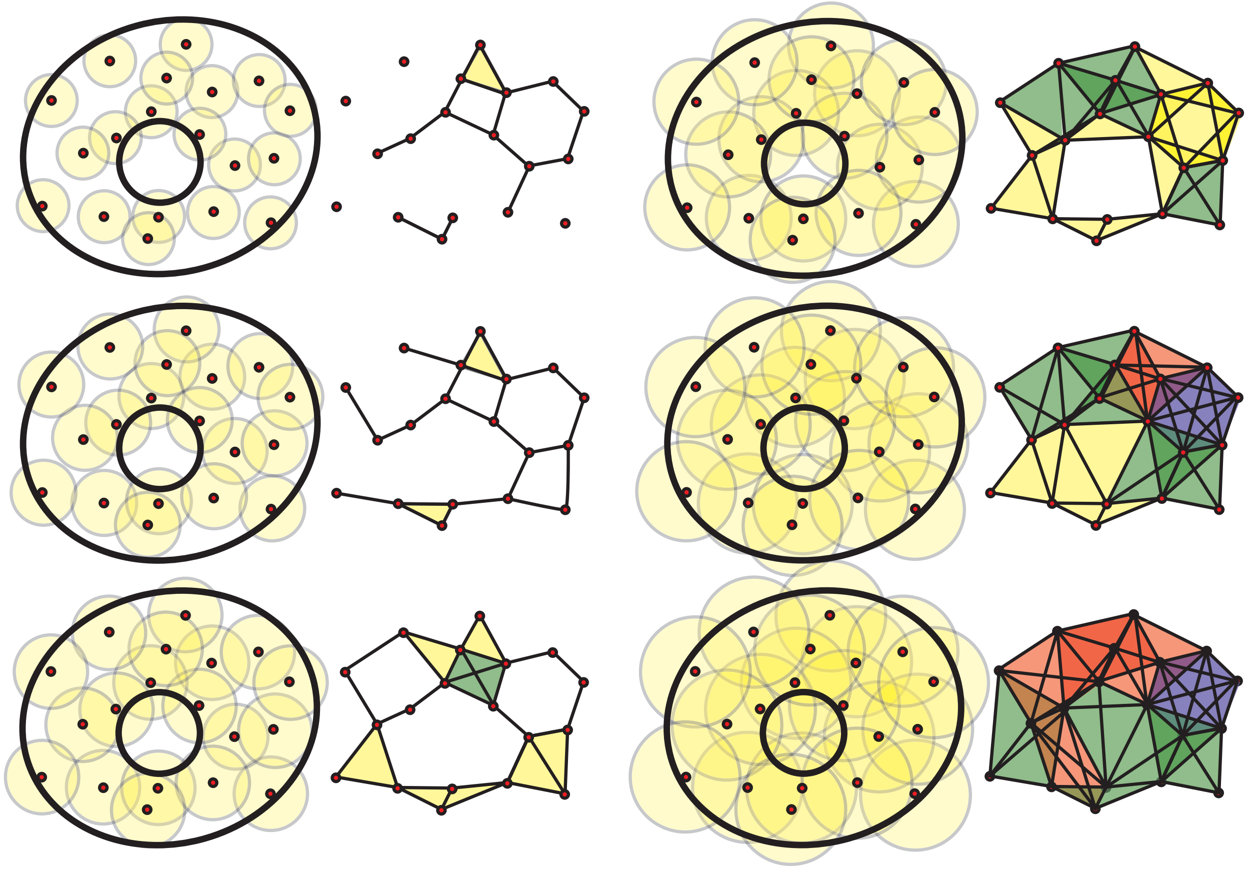
EDGE =
1-simplex

TRIANGLE
= 2-simplex



Simplicial Complex





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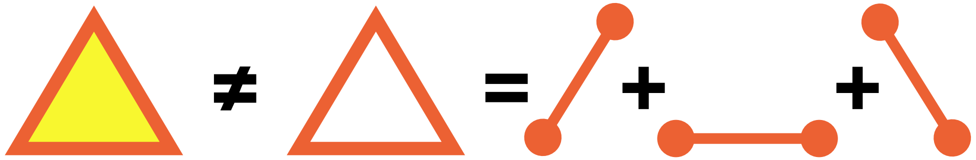

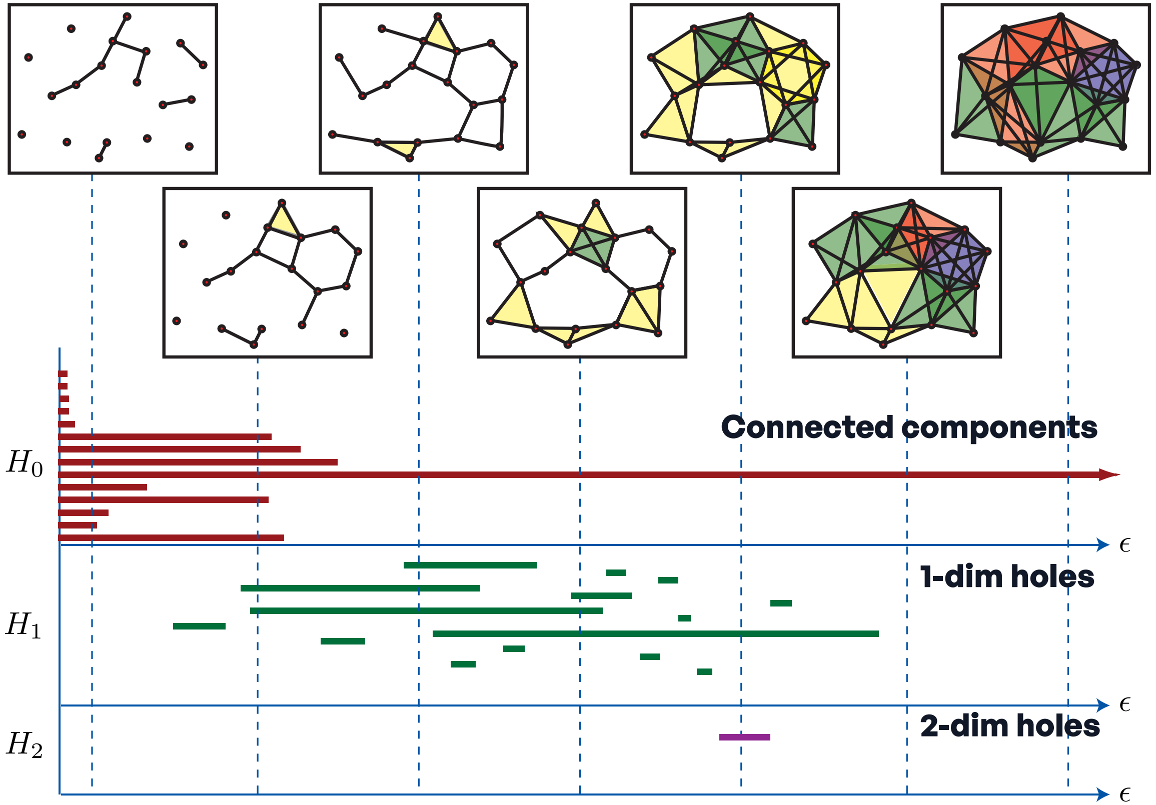

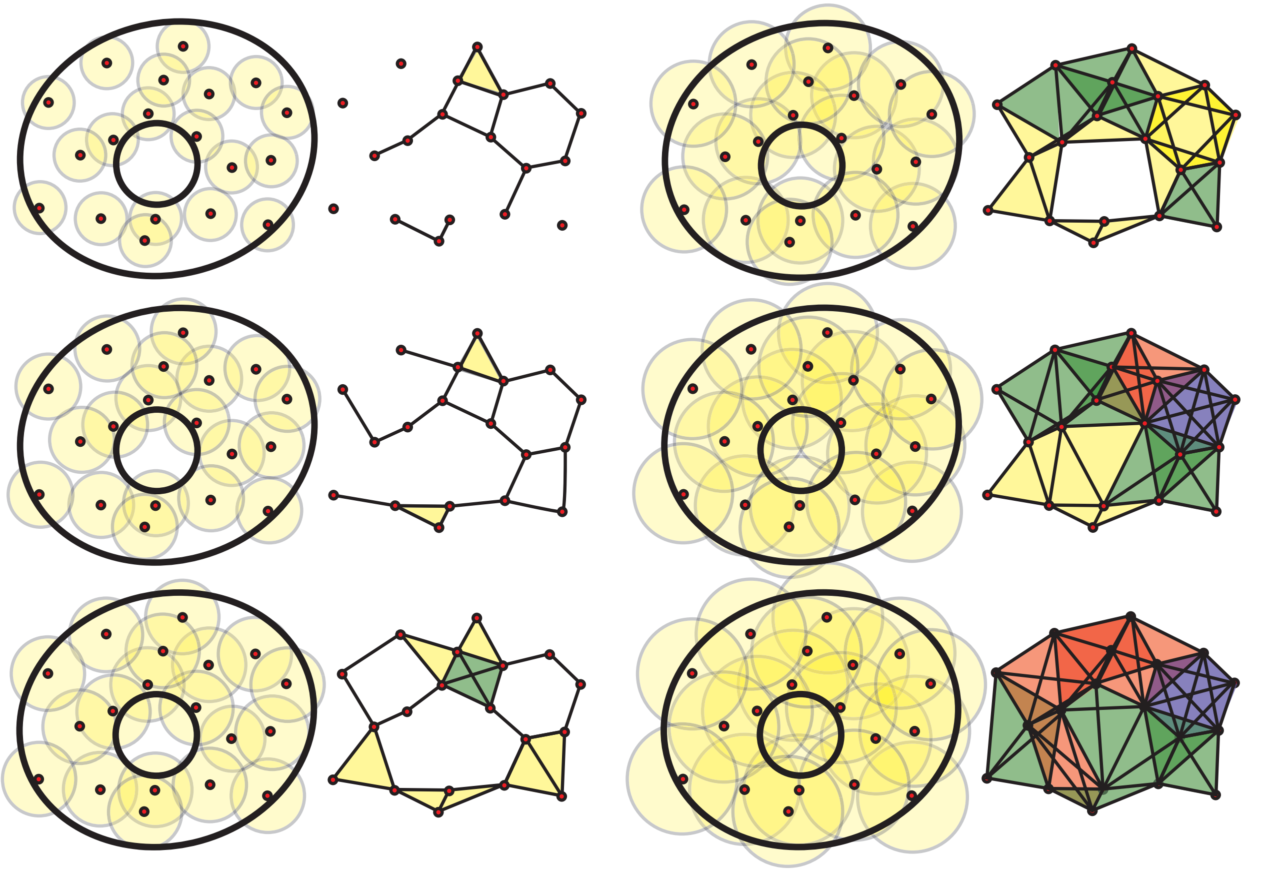

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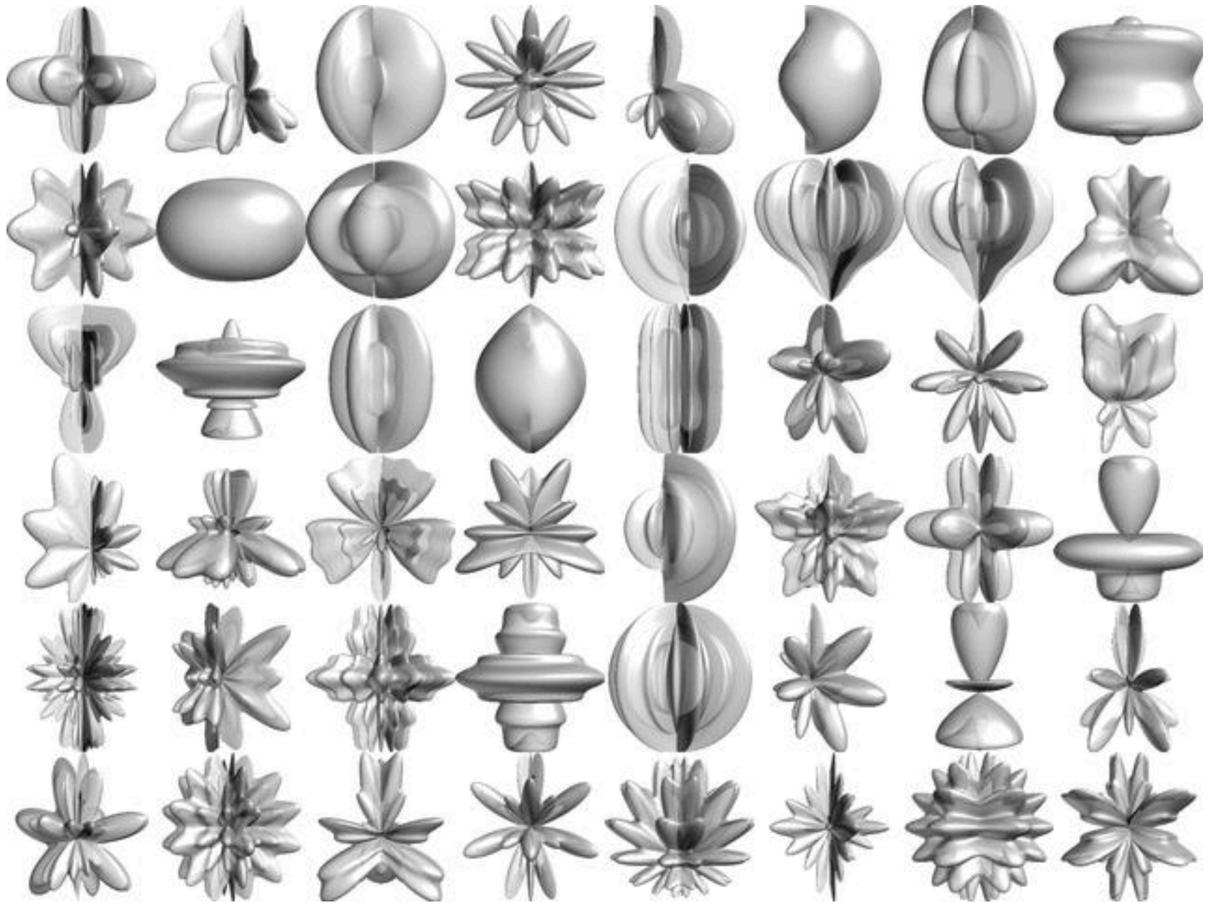
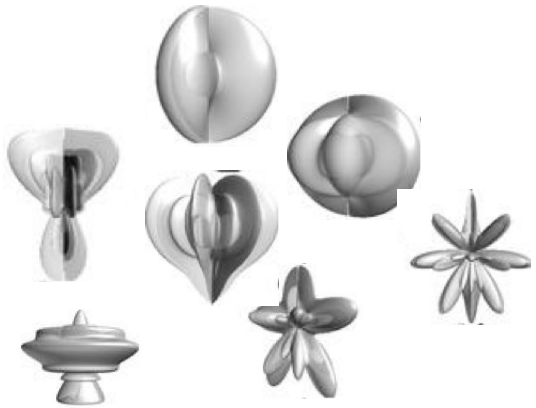
Quantitative topological comparison



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

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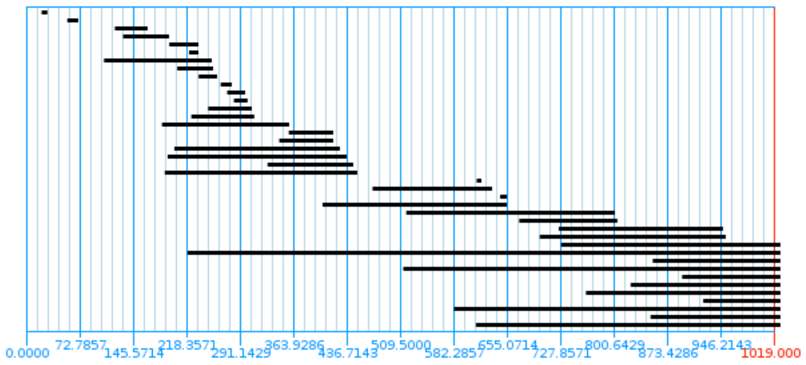
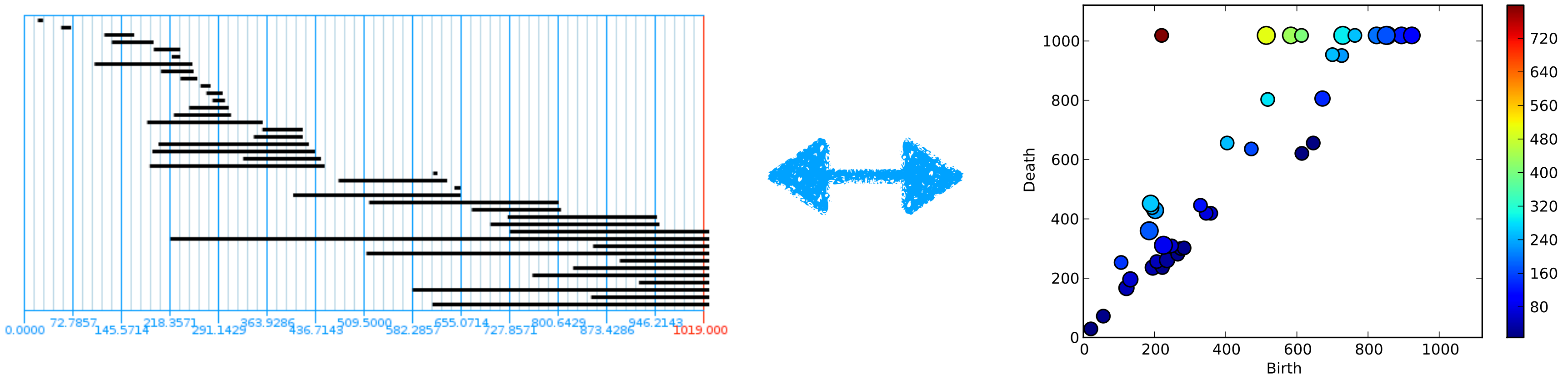
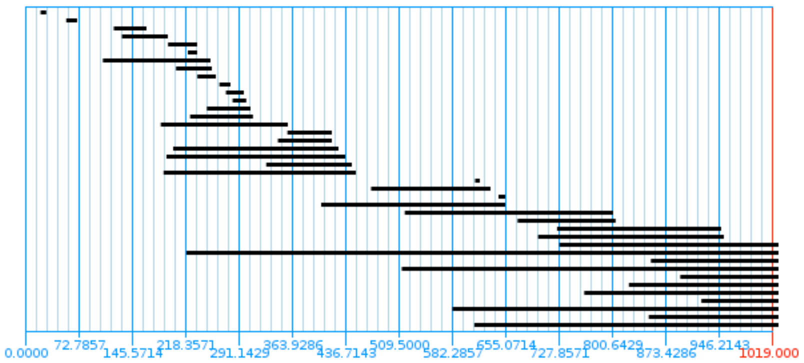
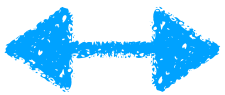


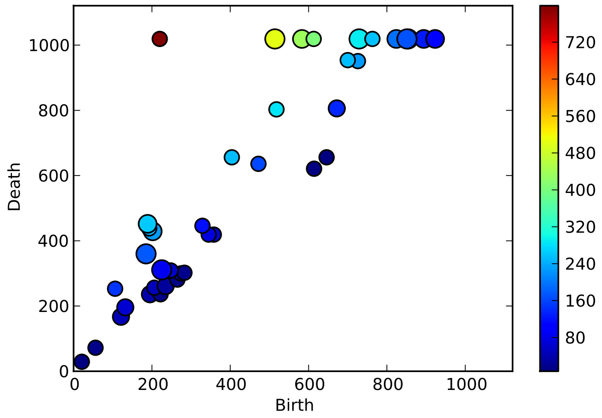
Quantitative topological comparison

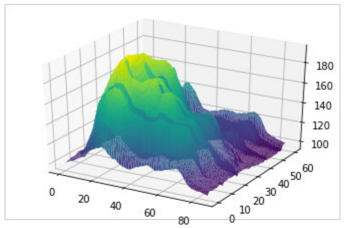


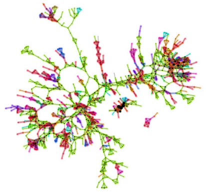
Quantitative topological comparison

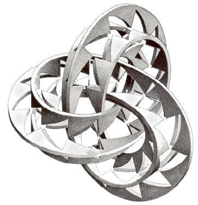


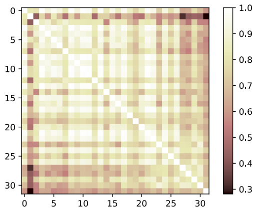




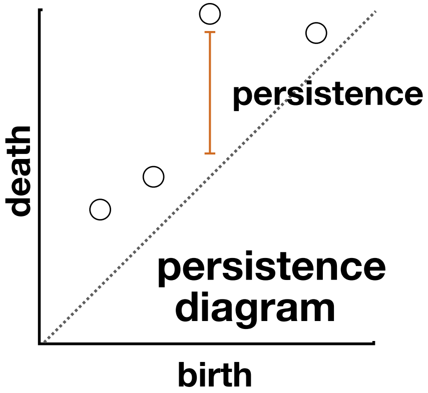


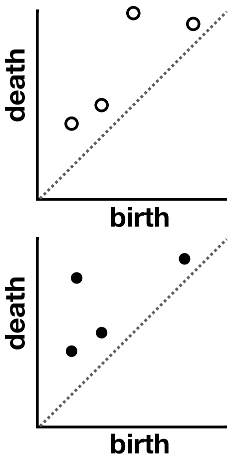






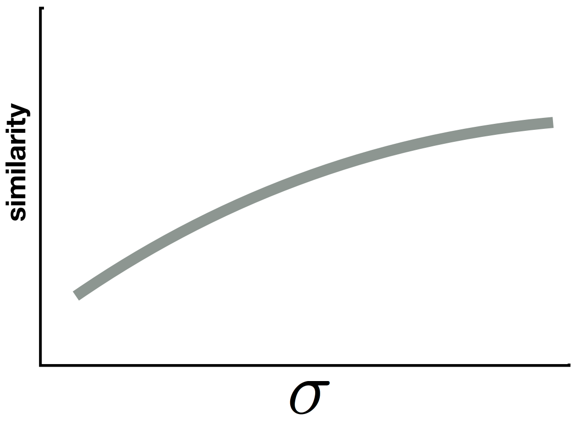
topology





persistence kernel

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.

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

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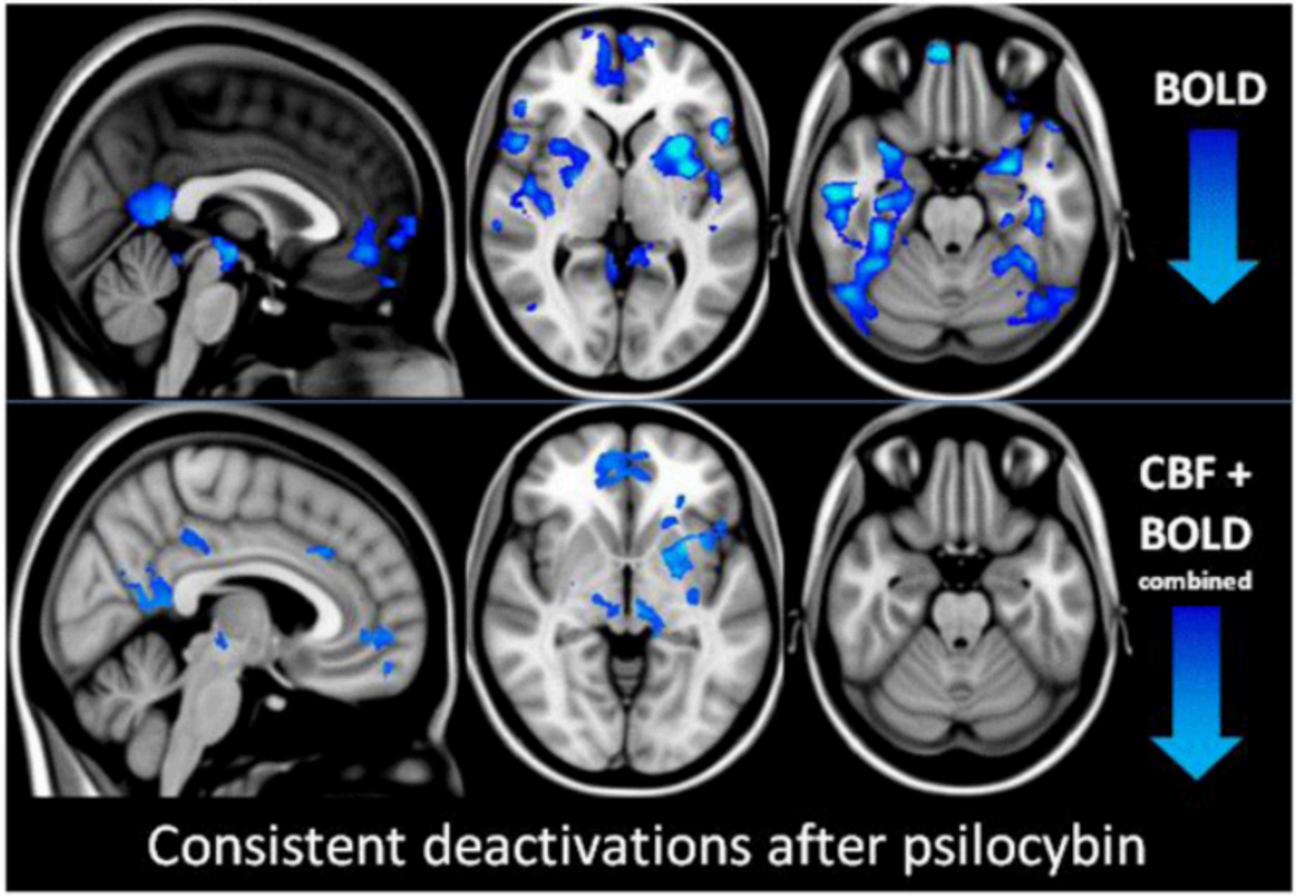

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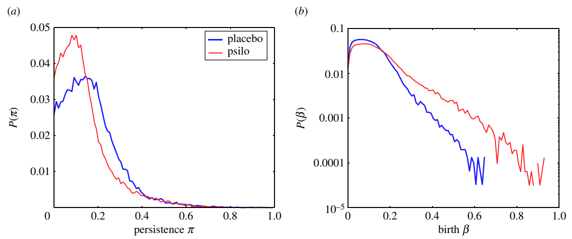

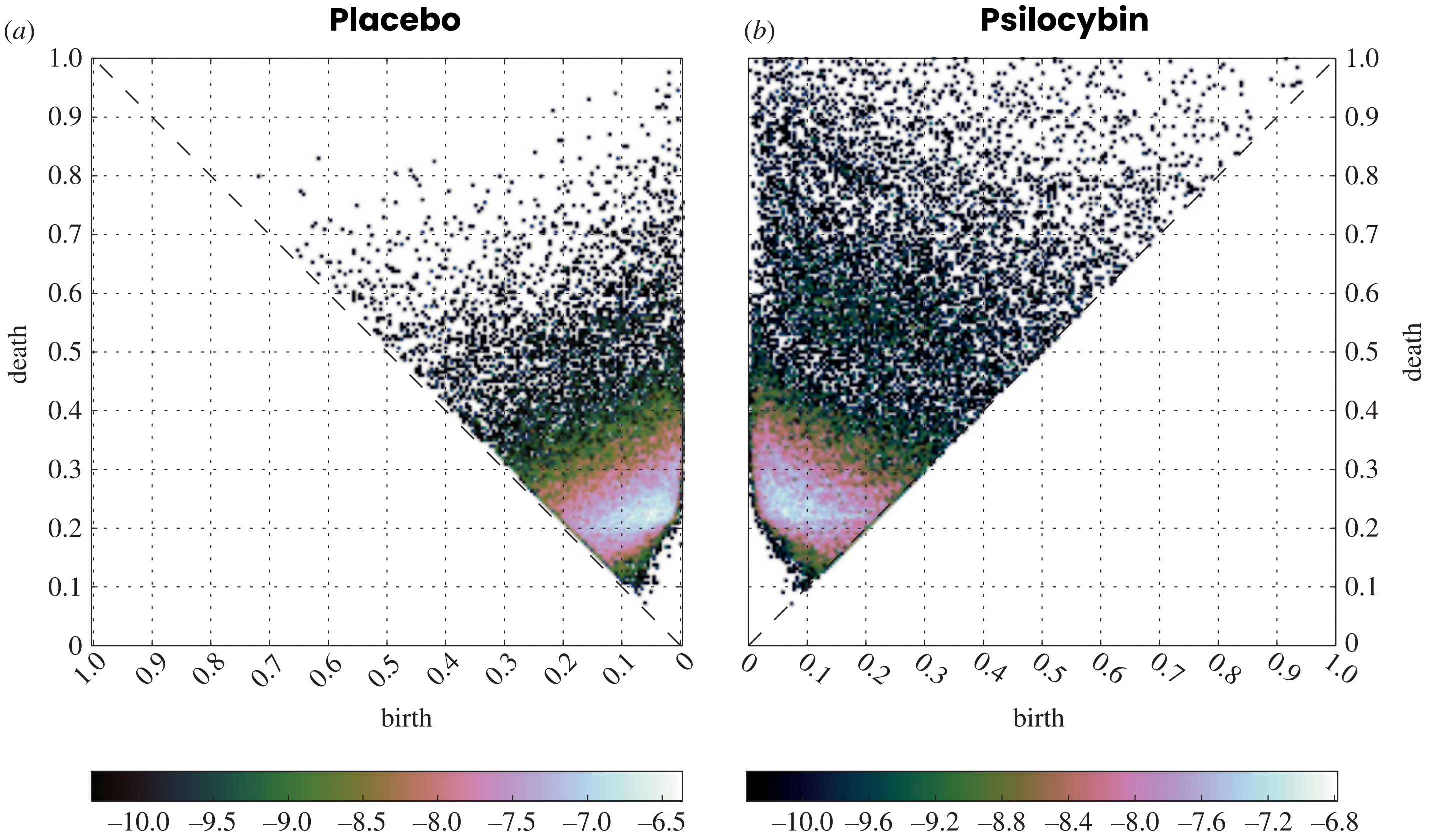

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Group level persistence diagrams

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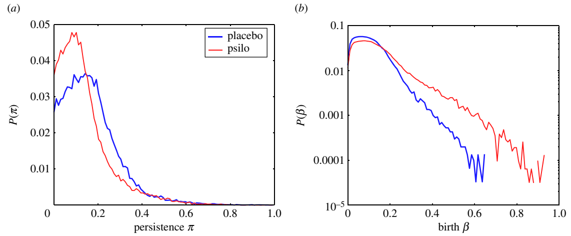

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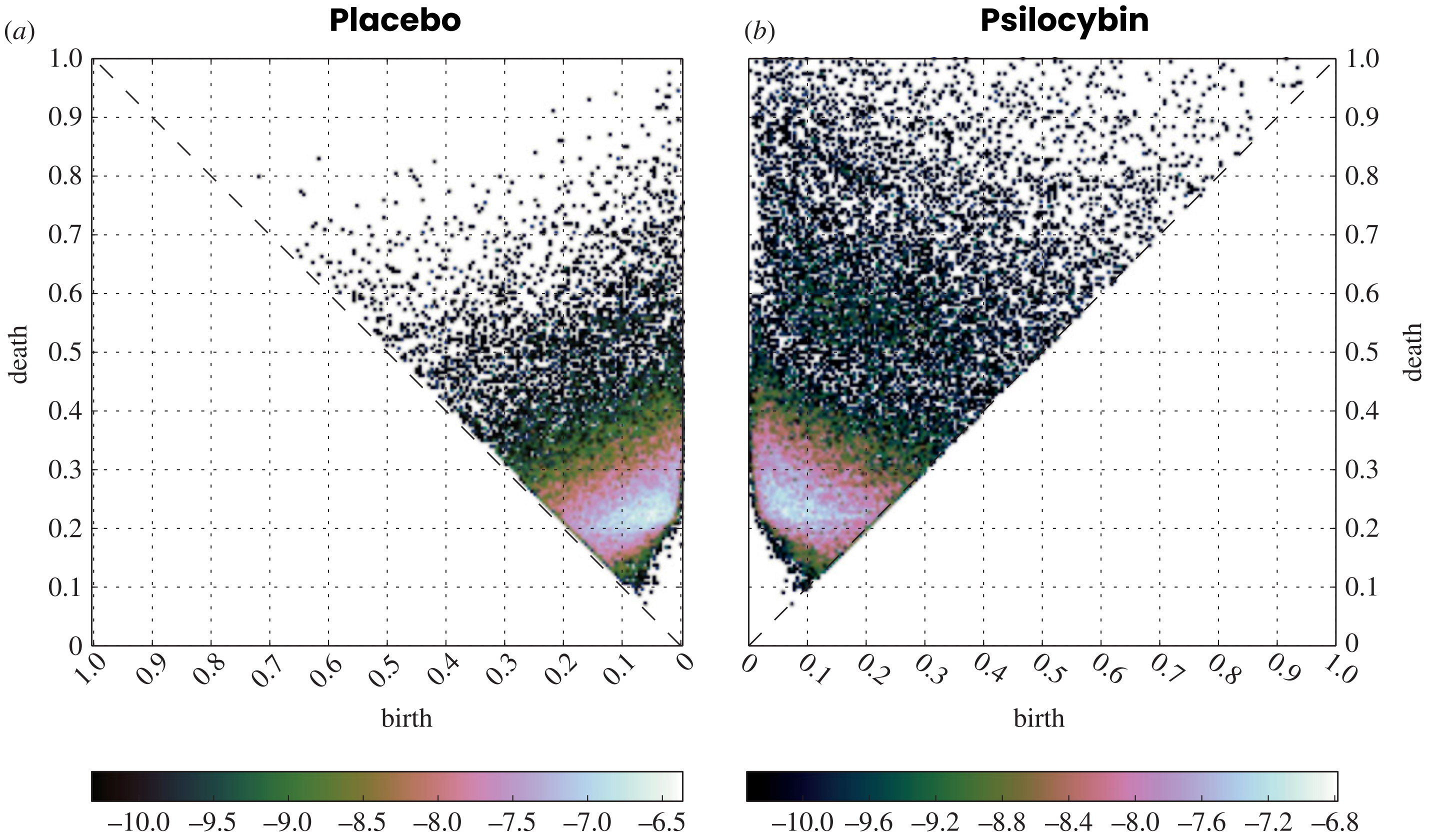


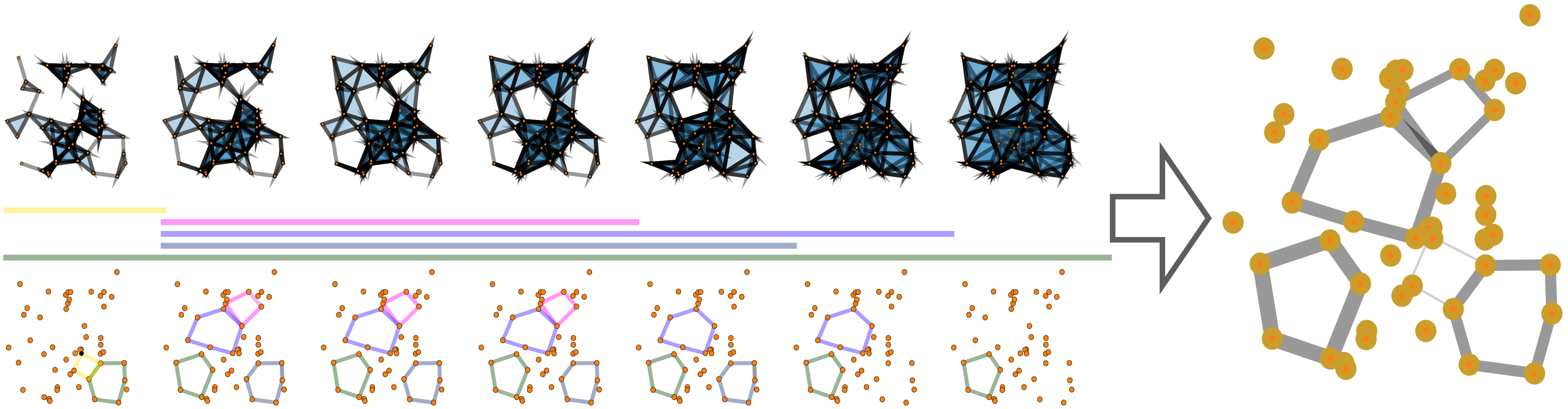
Group level persistence diagrams

Localisation of information?

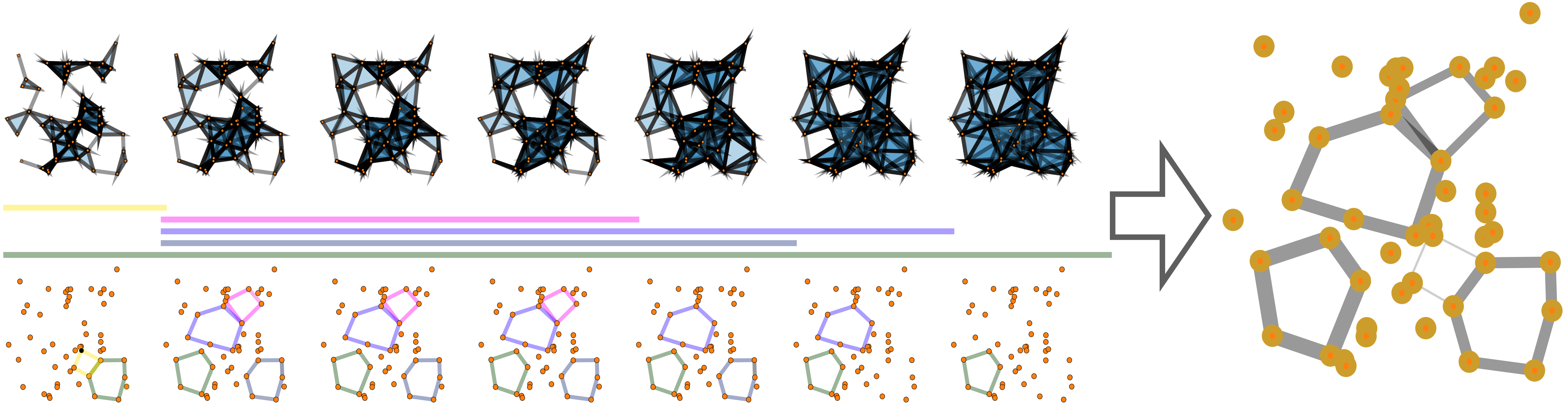
Petri, Giovanni, et al. "Homological scaffolds of brain functional networks." *Journal of The Royal Society Interface* 11.101 (2014): 20140873.

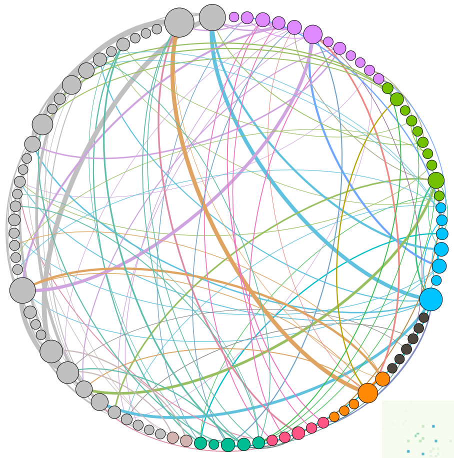
Scaffolds in one slide

Scaffolds in one slide



Scaffolds
in one slide





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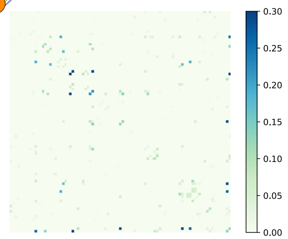
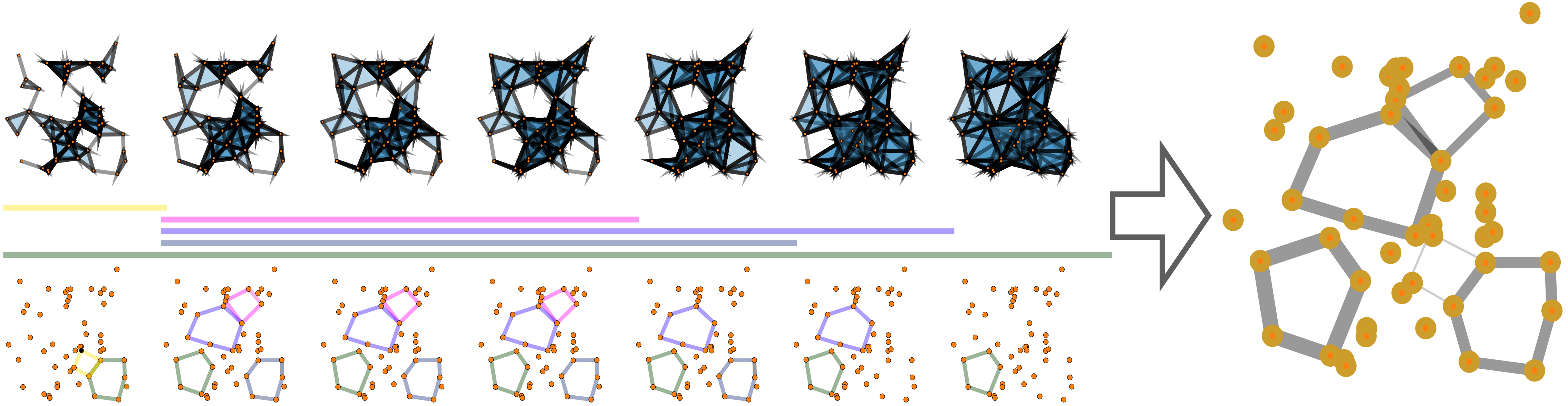
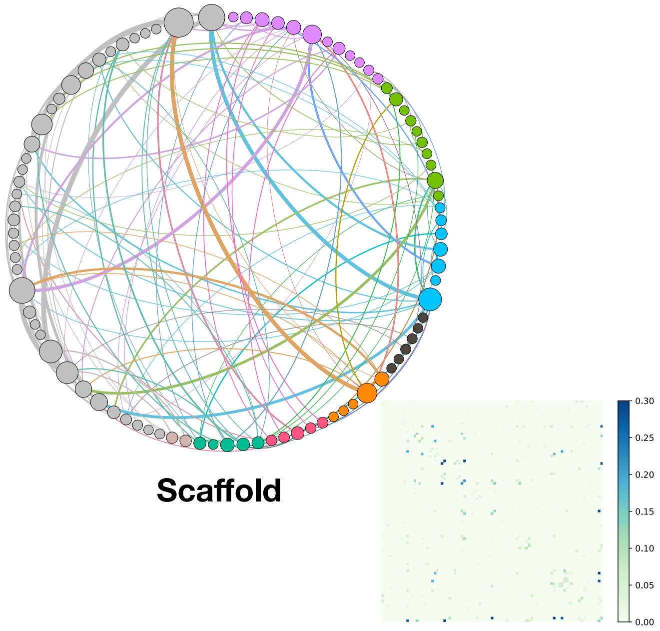
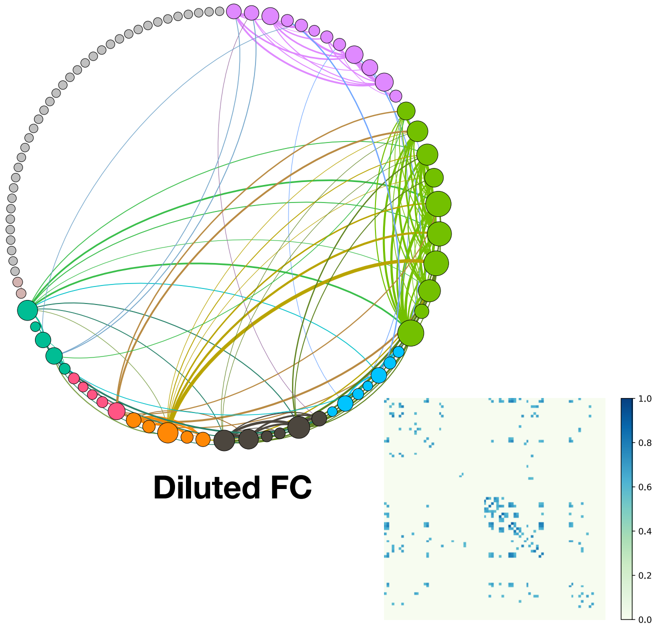


Scaffolds in one slide







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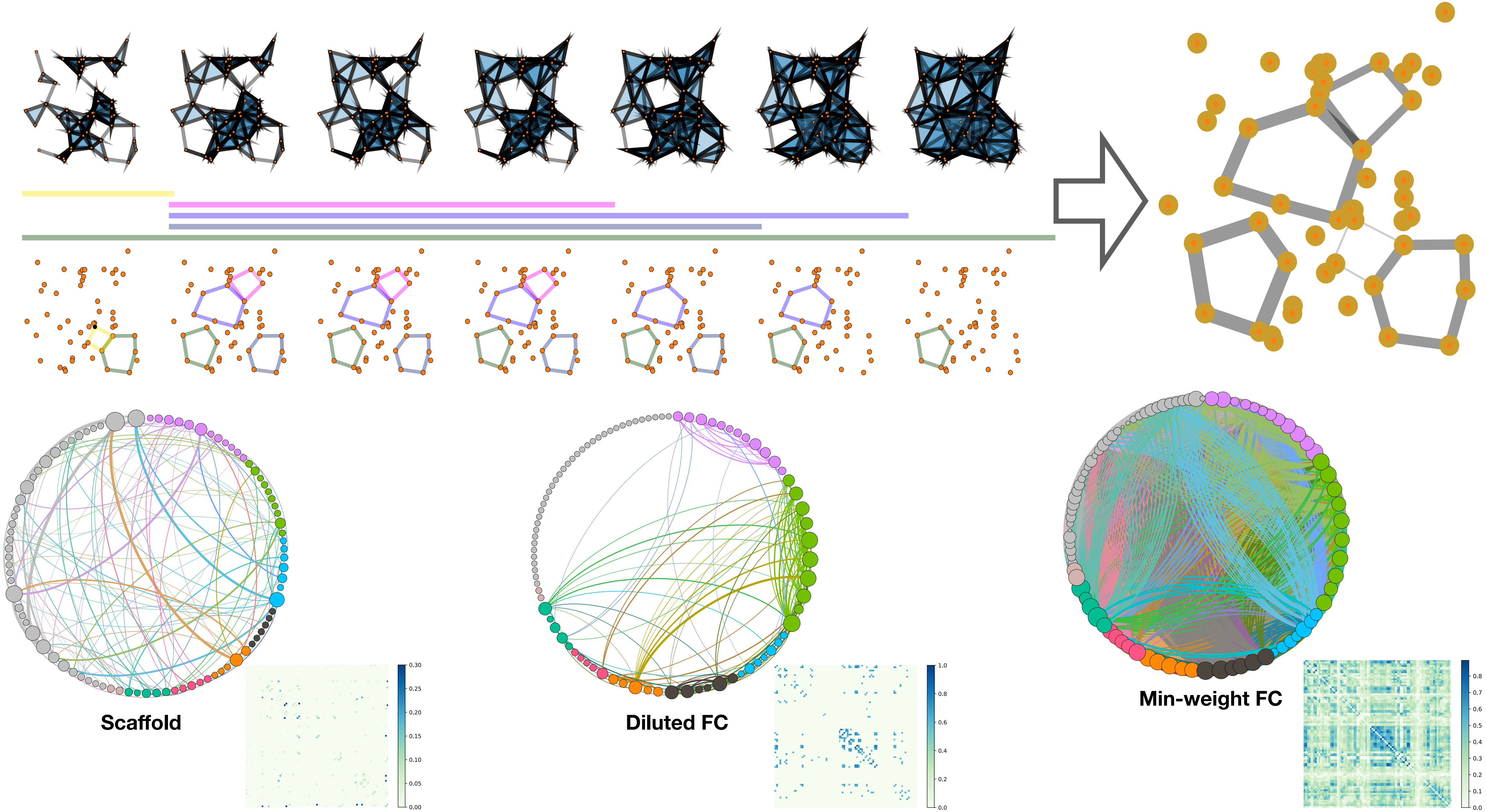
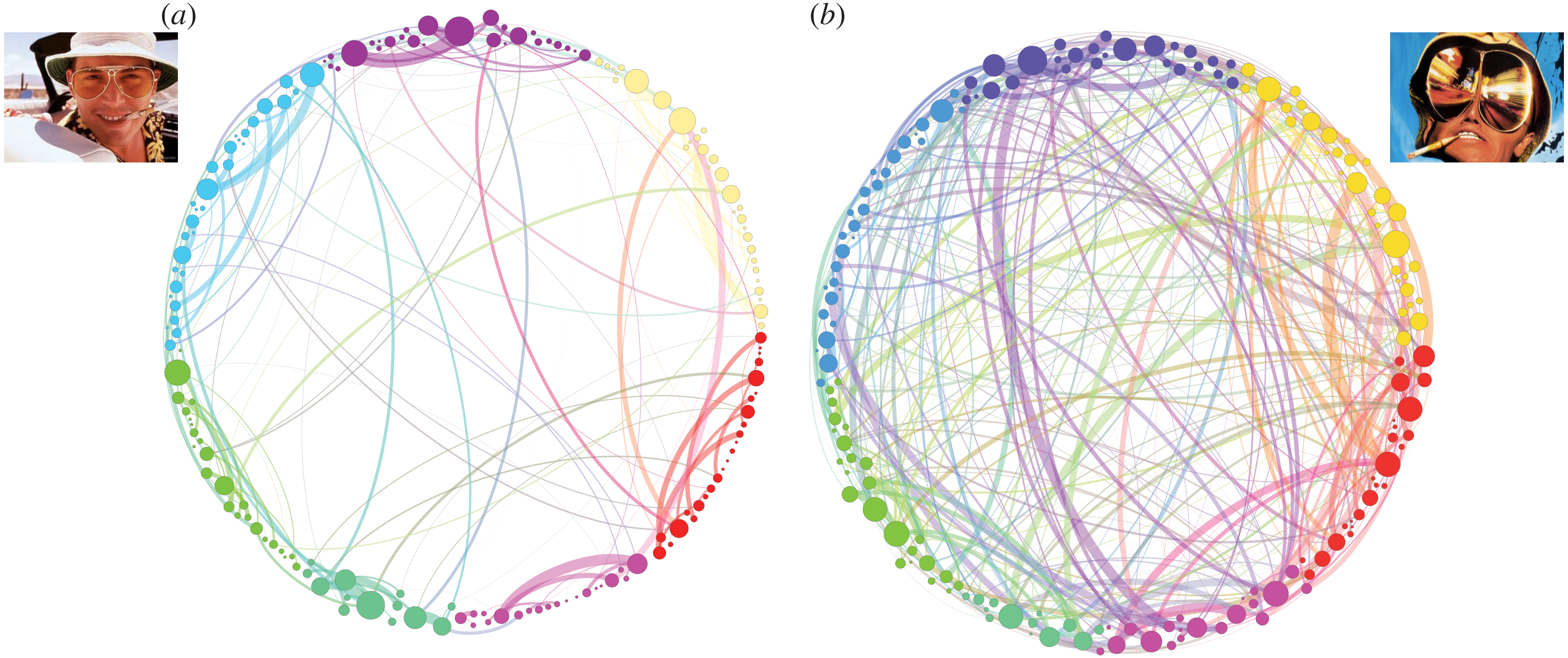


Brain scaffolds: local alterations

distributed



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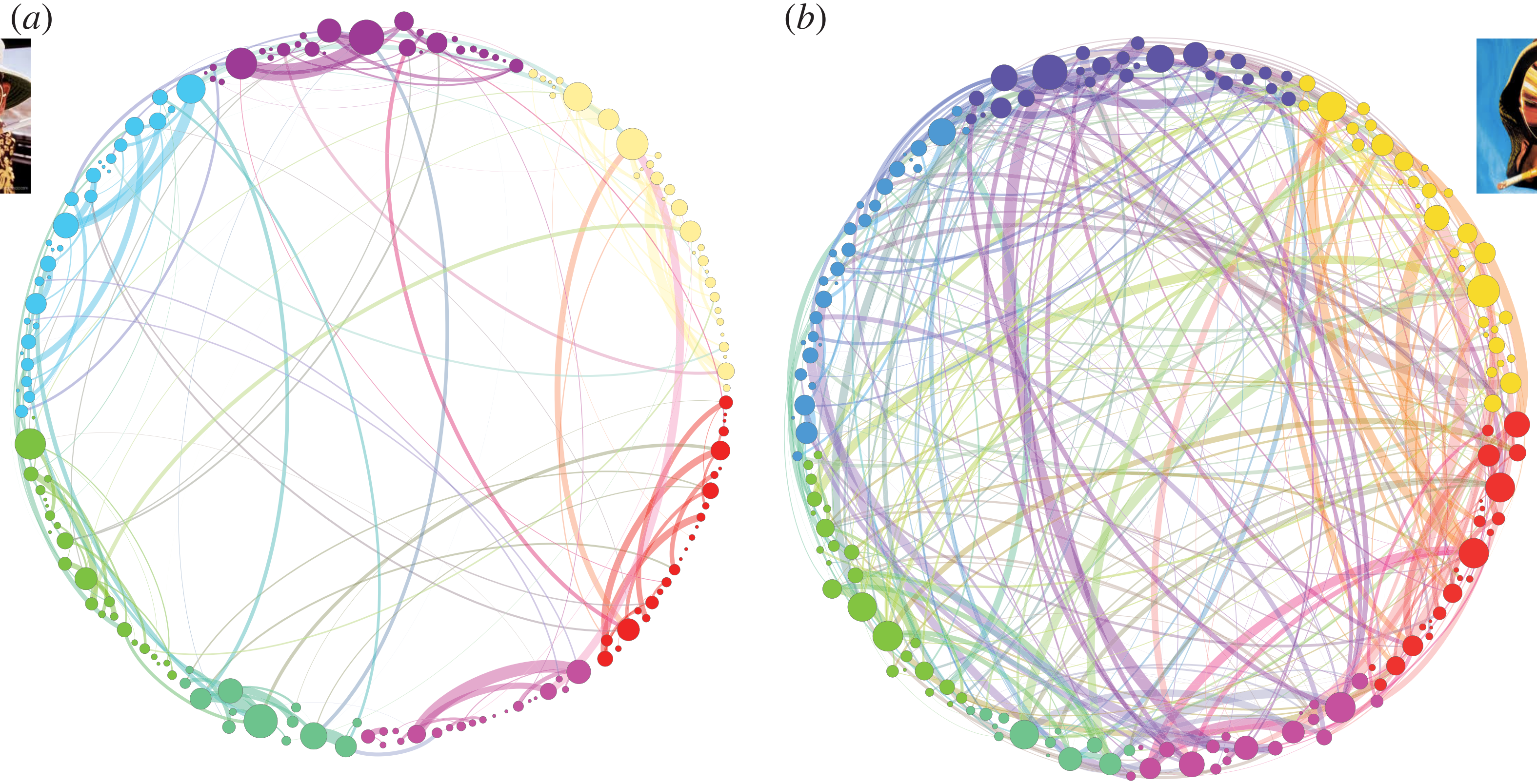

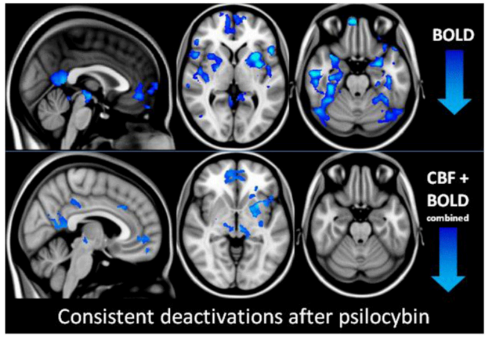

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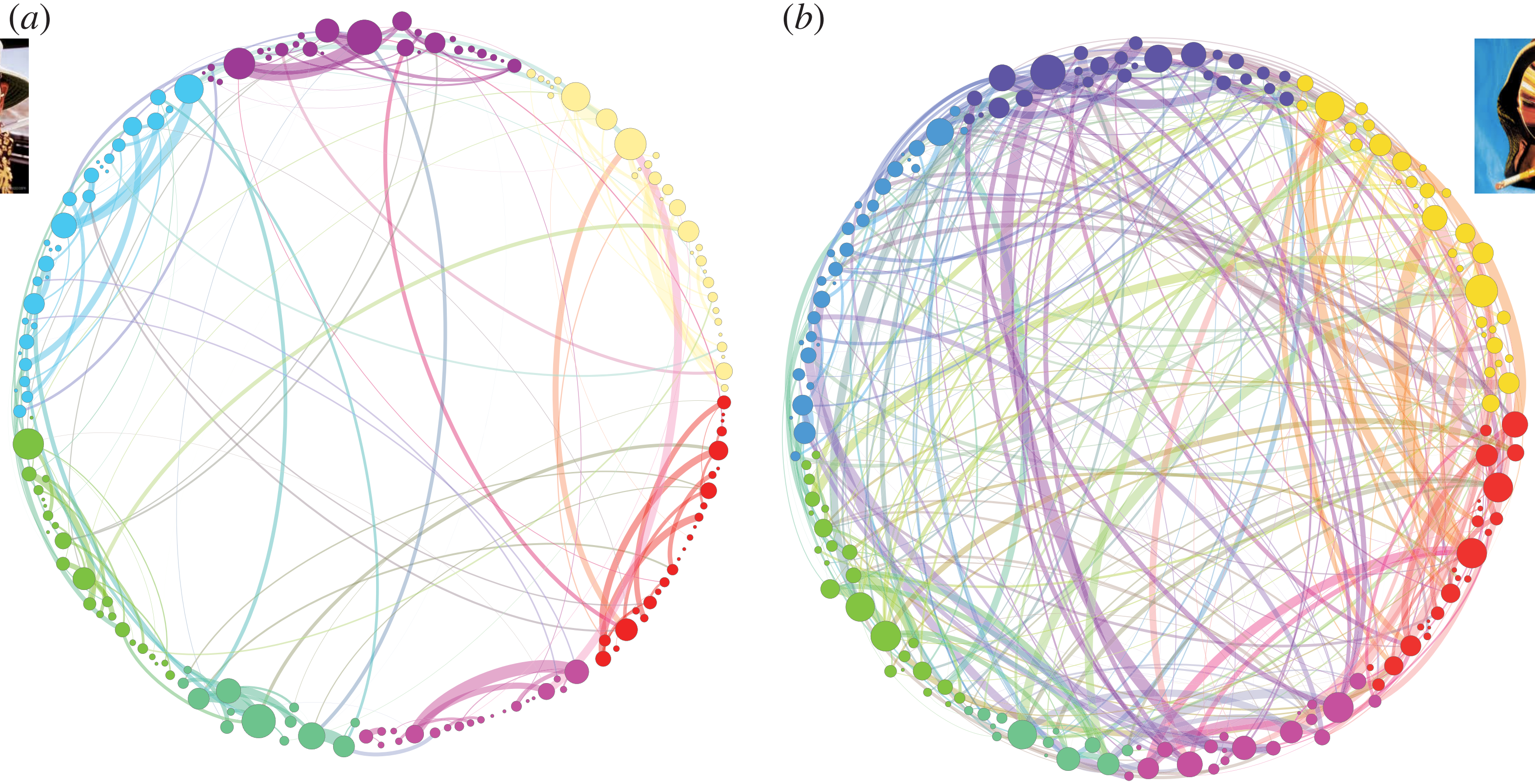
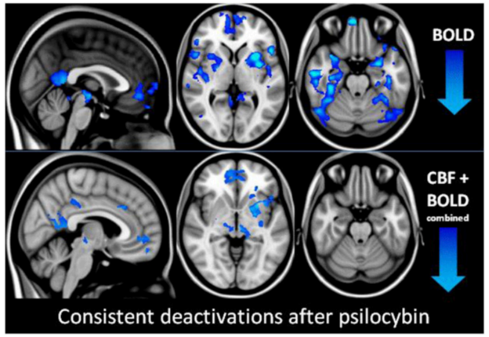
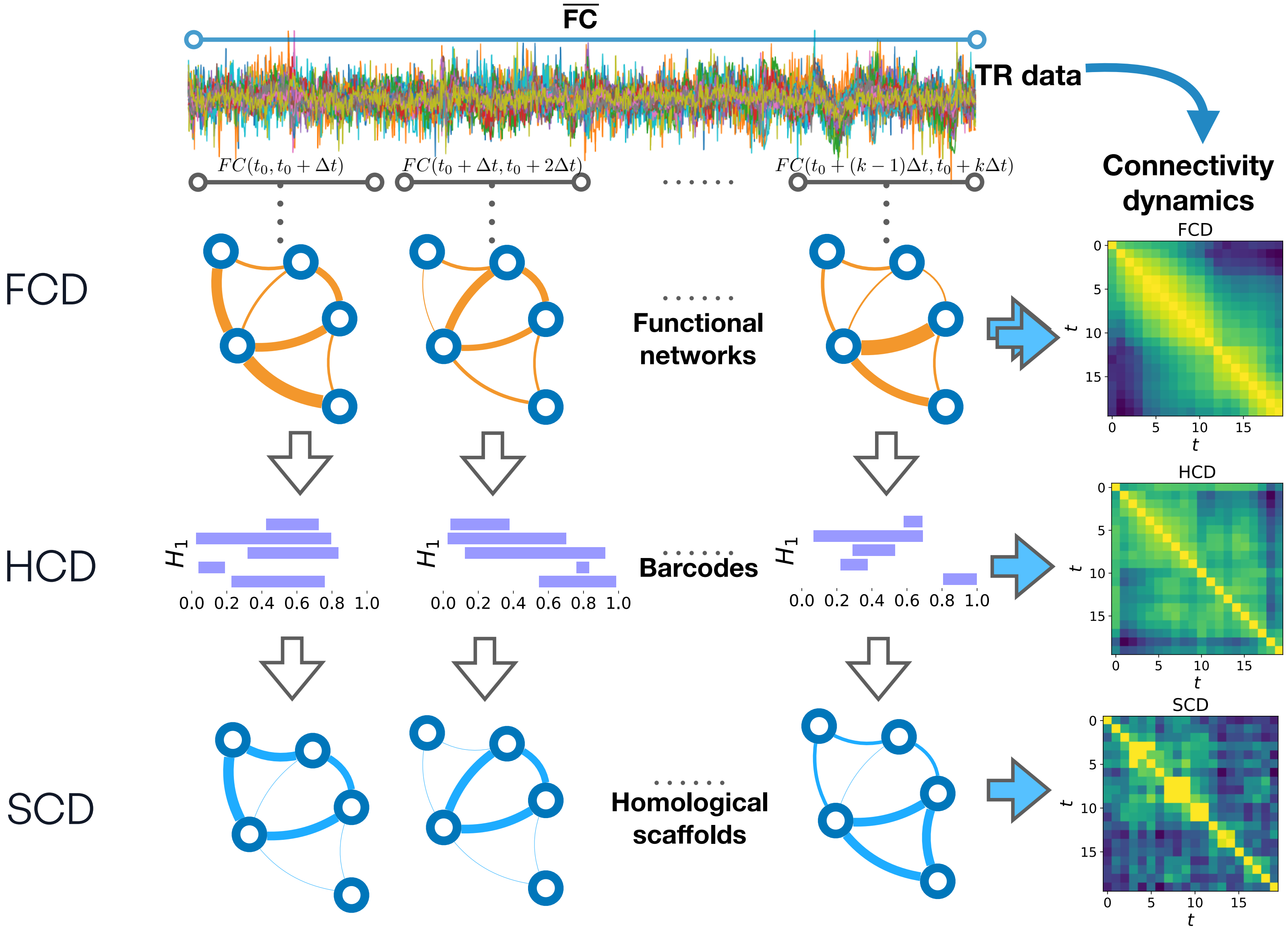




Distributed reorganisation of the hierarchy of functional circuits

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

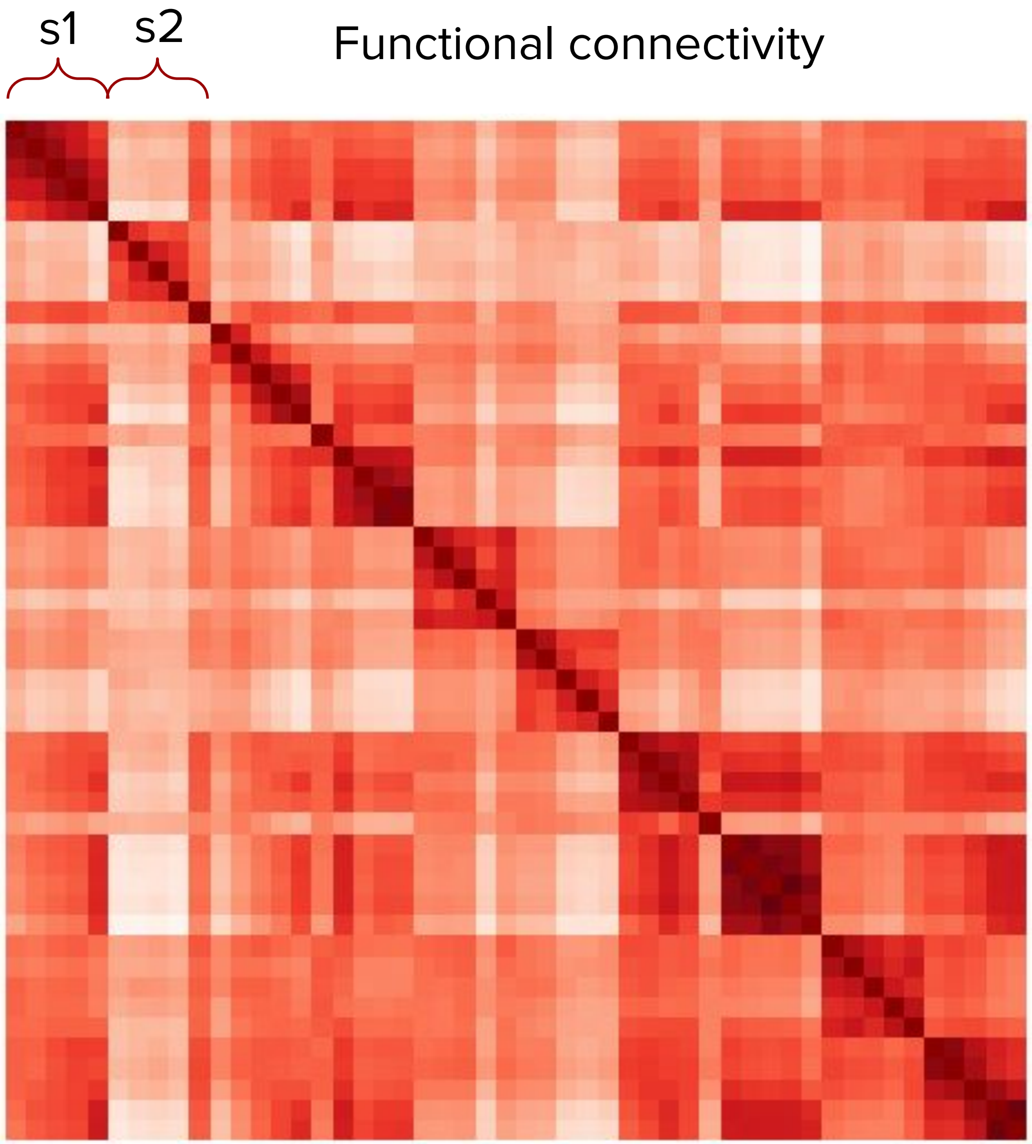
Scaffold fingerprinting

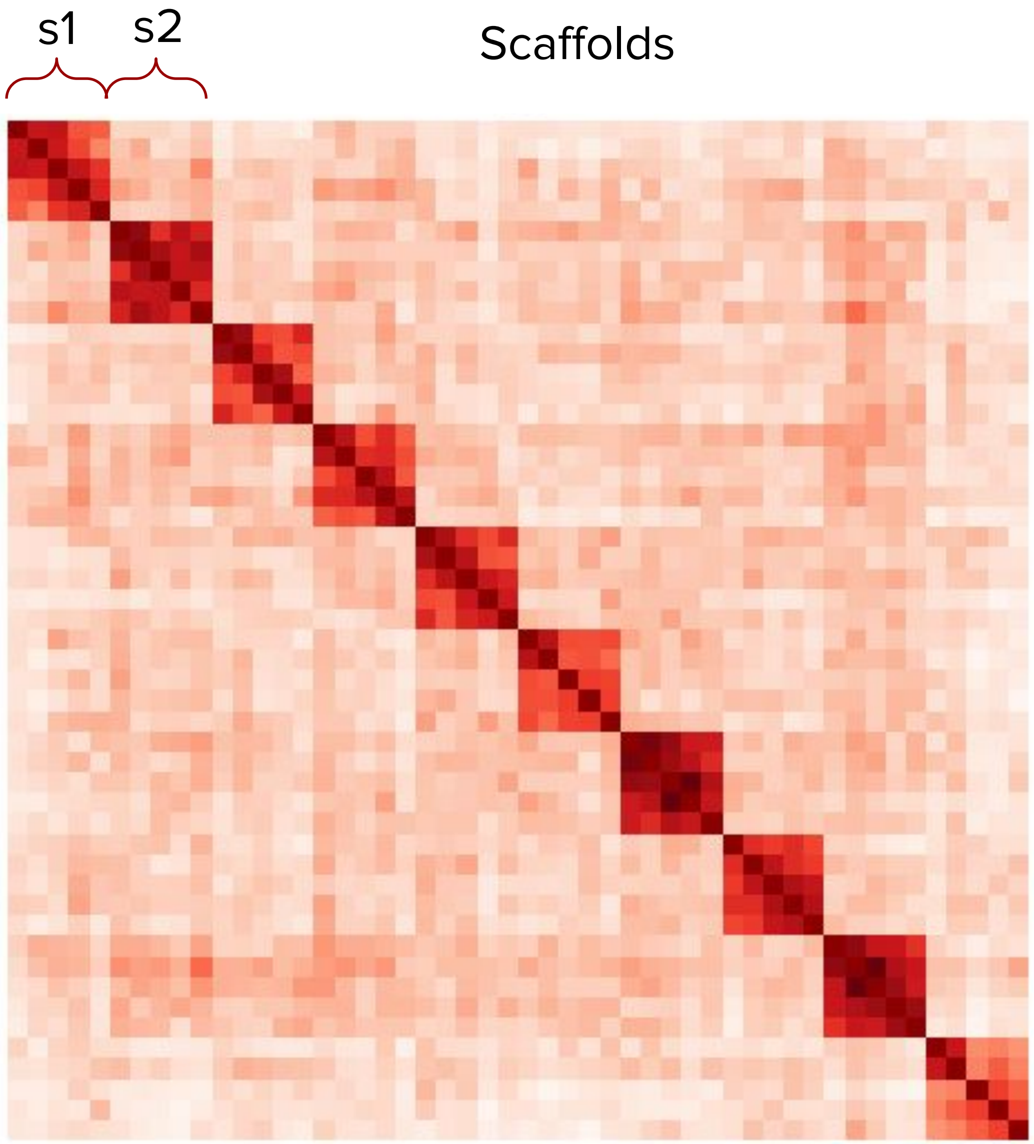


Poetto, Saggar, Battaglia, Vaccarino, Rabuffo, Petri in prep

Scaffold fingerprinting

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





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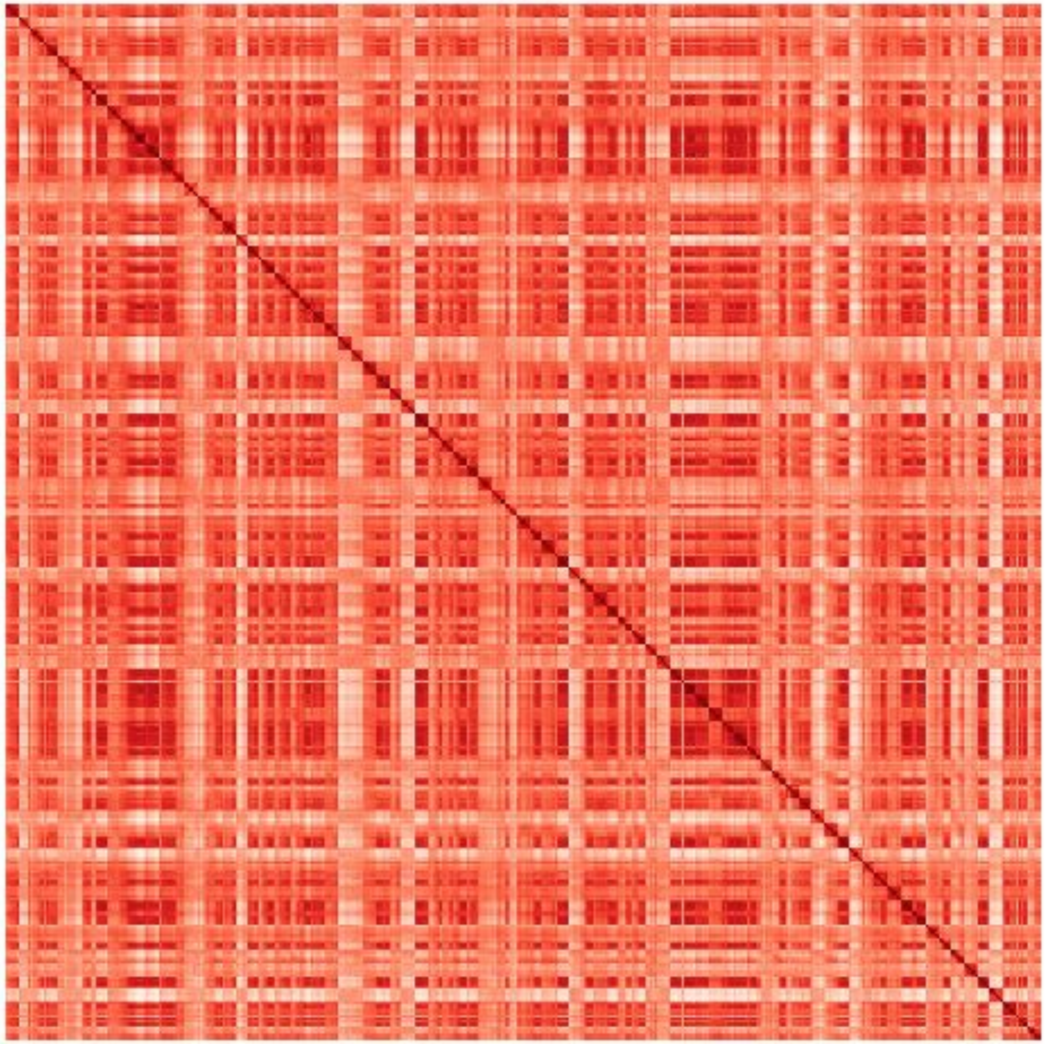
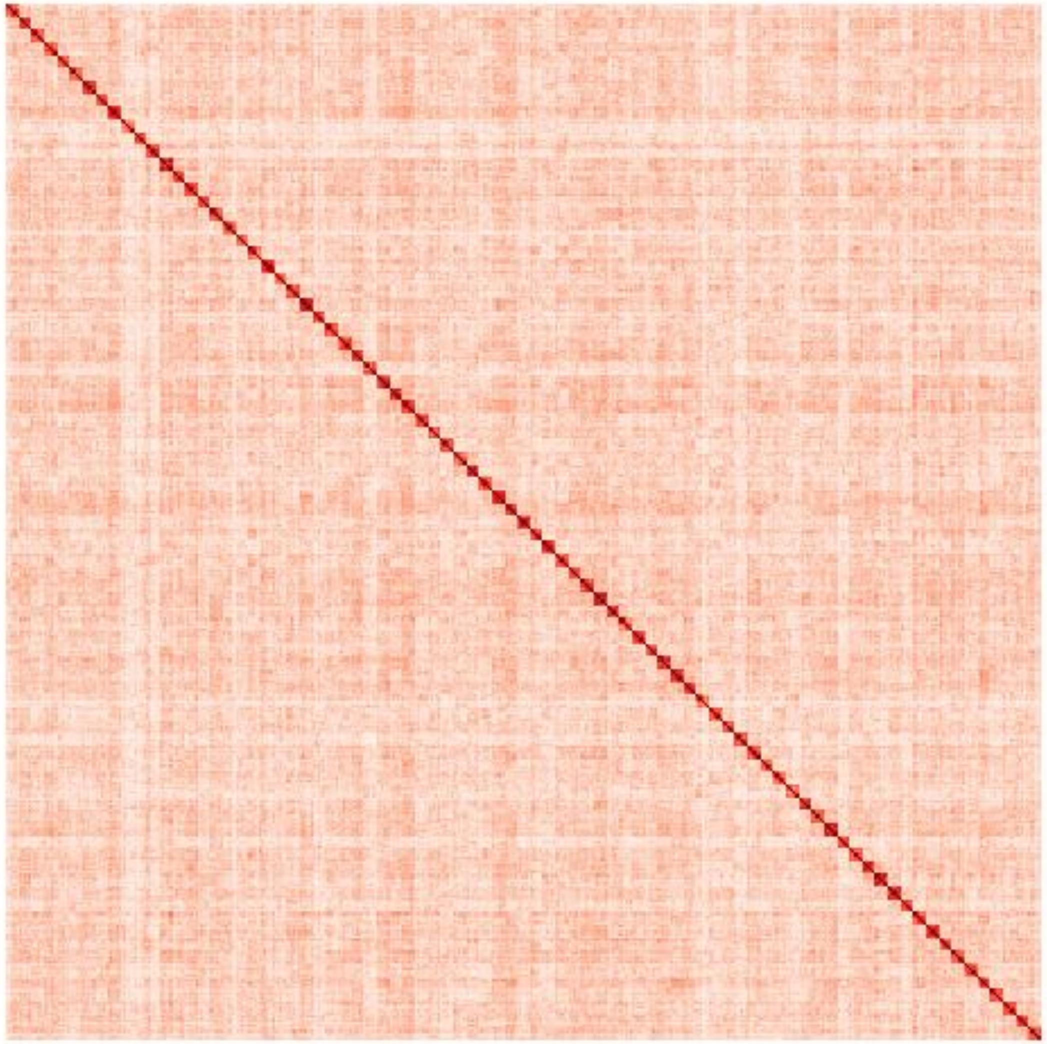
Functional connectivity



Scaffolds



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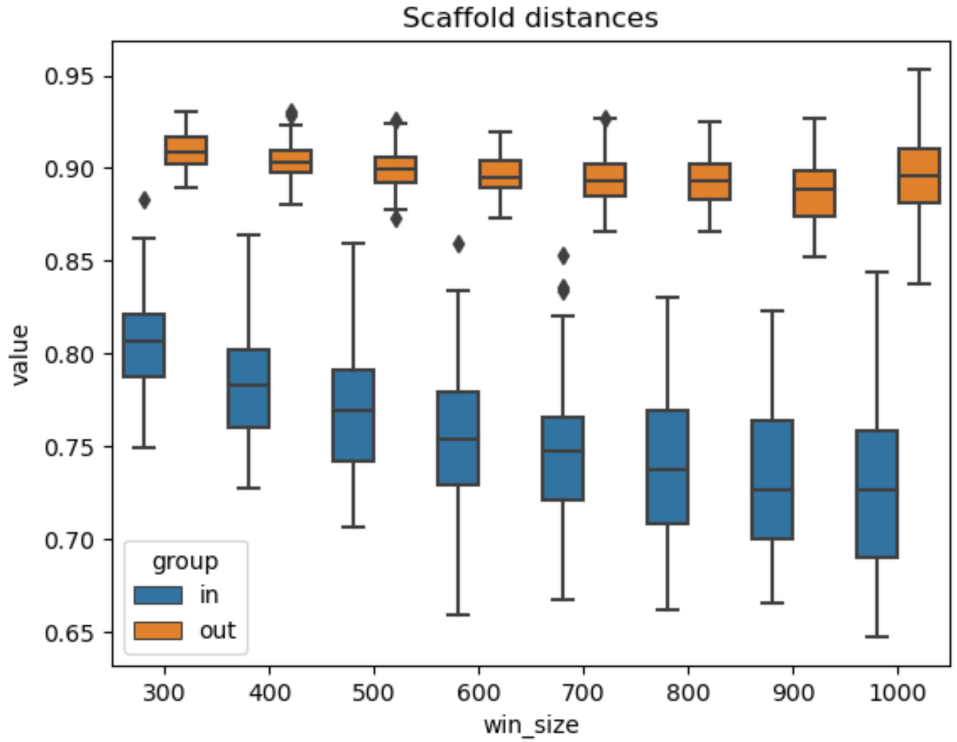

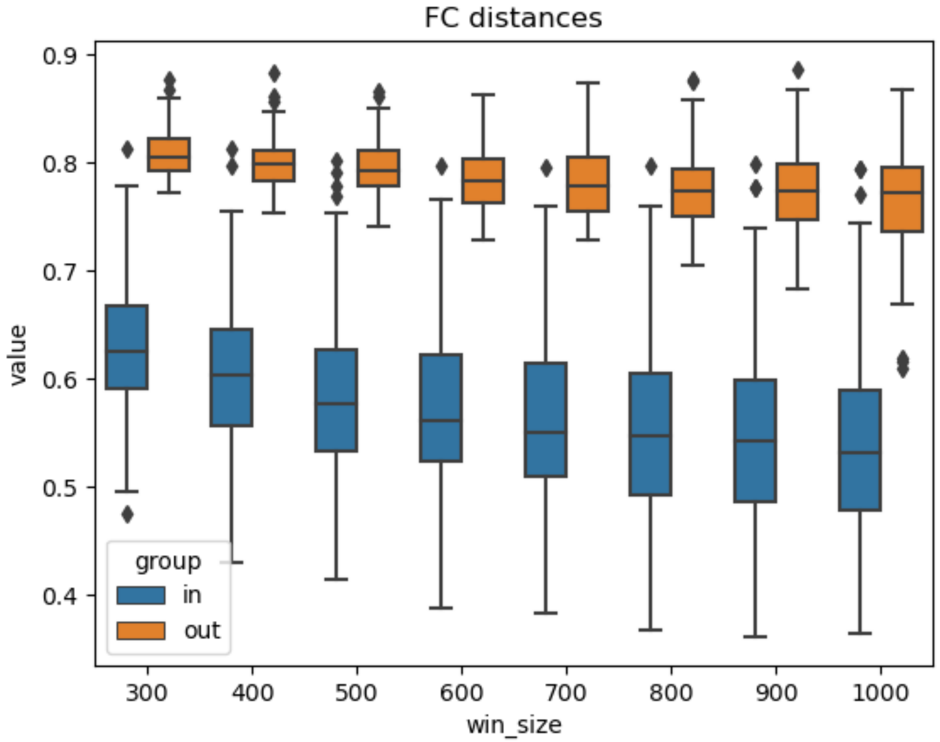

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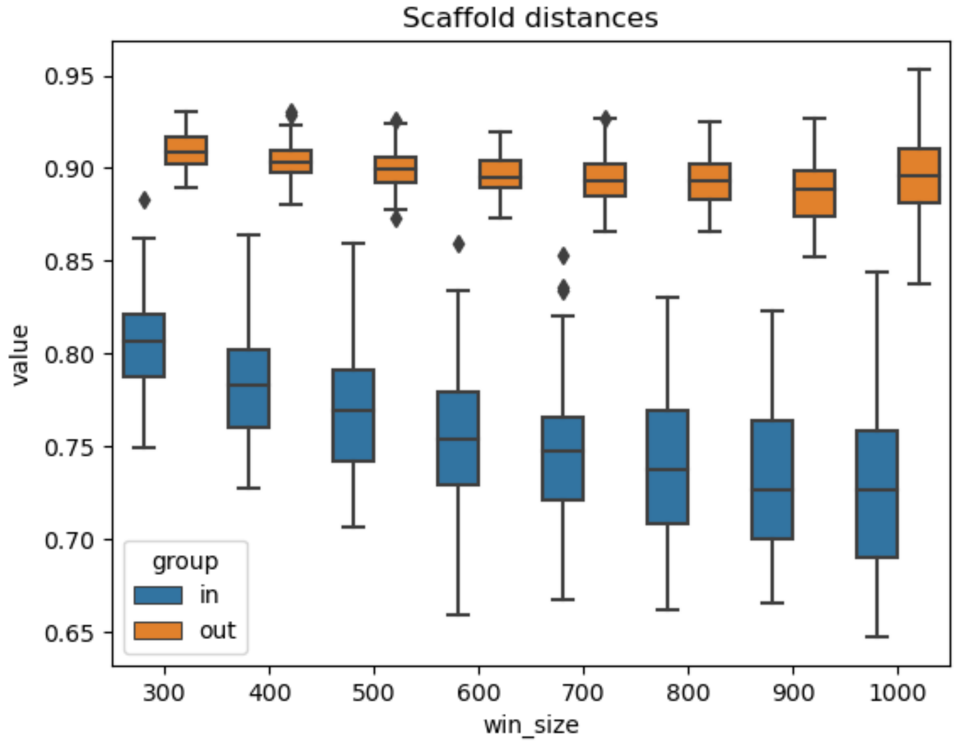
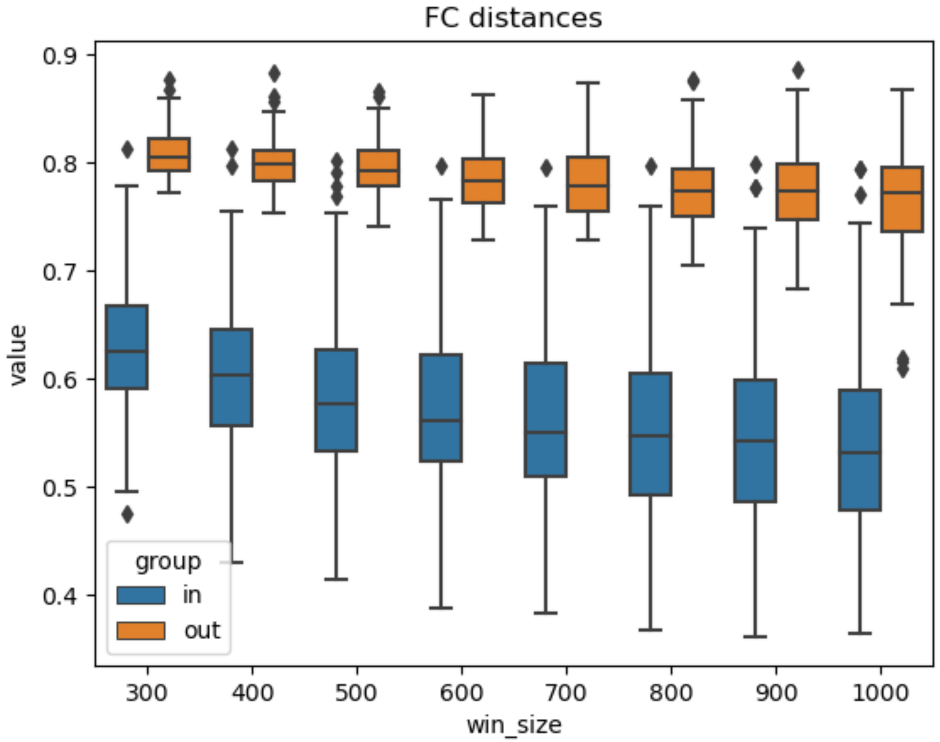




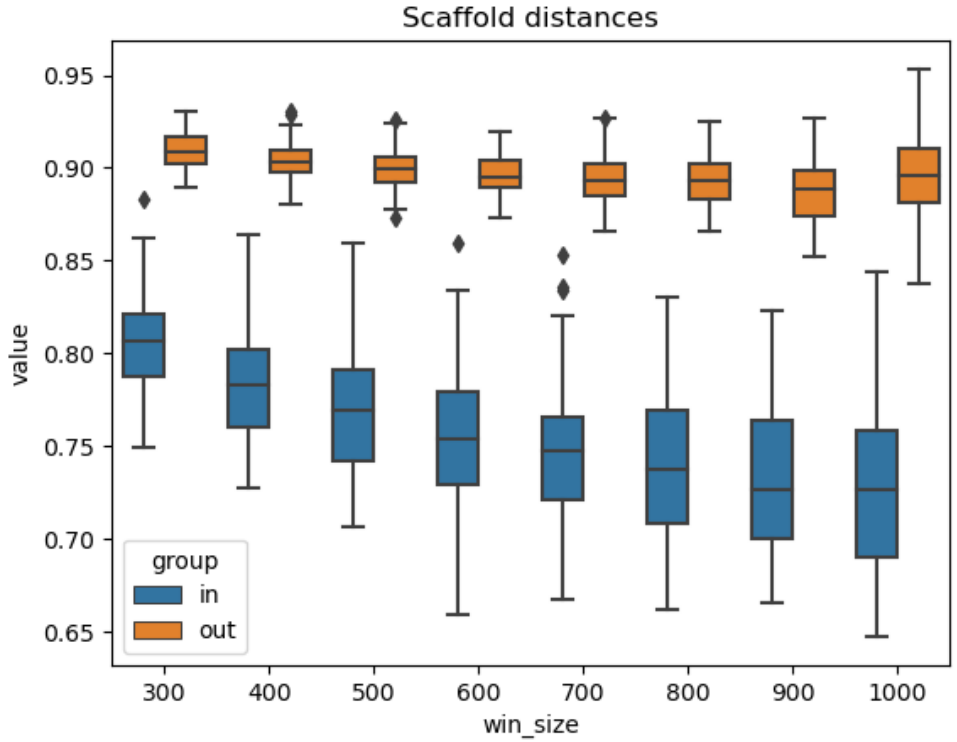
Incredibile fingerprinting capacity!

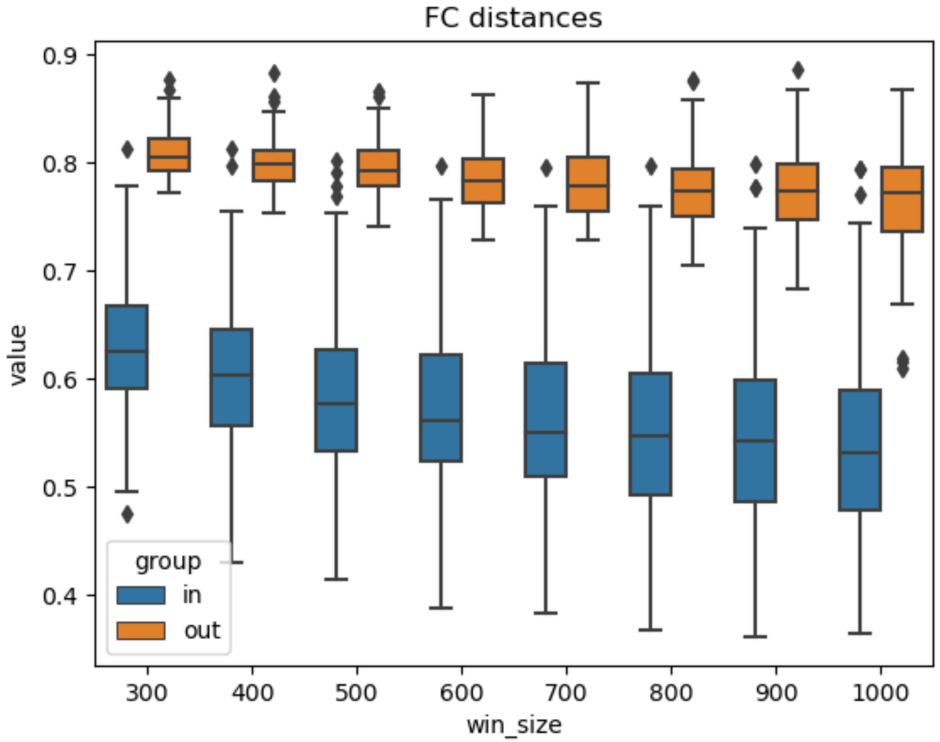
No idea on the origin!

Poetto, Saggar, Battaglia, Vaccarino, Rabuffo, Petri in prep

Scaffold fingerprinting

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





Incredibile fingerprinting capacity!

QUASI idea on the origin!

Poetto, Saggar, Battaglia, Vaccarino, Rabuffo, Petri in prep

Scaffold fingerprinting

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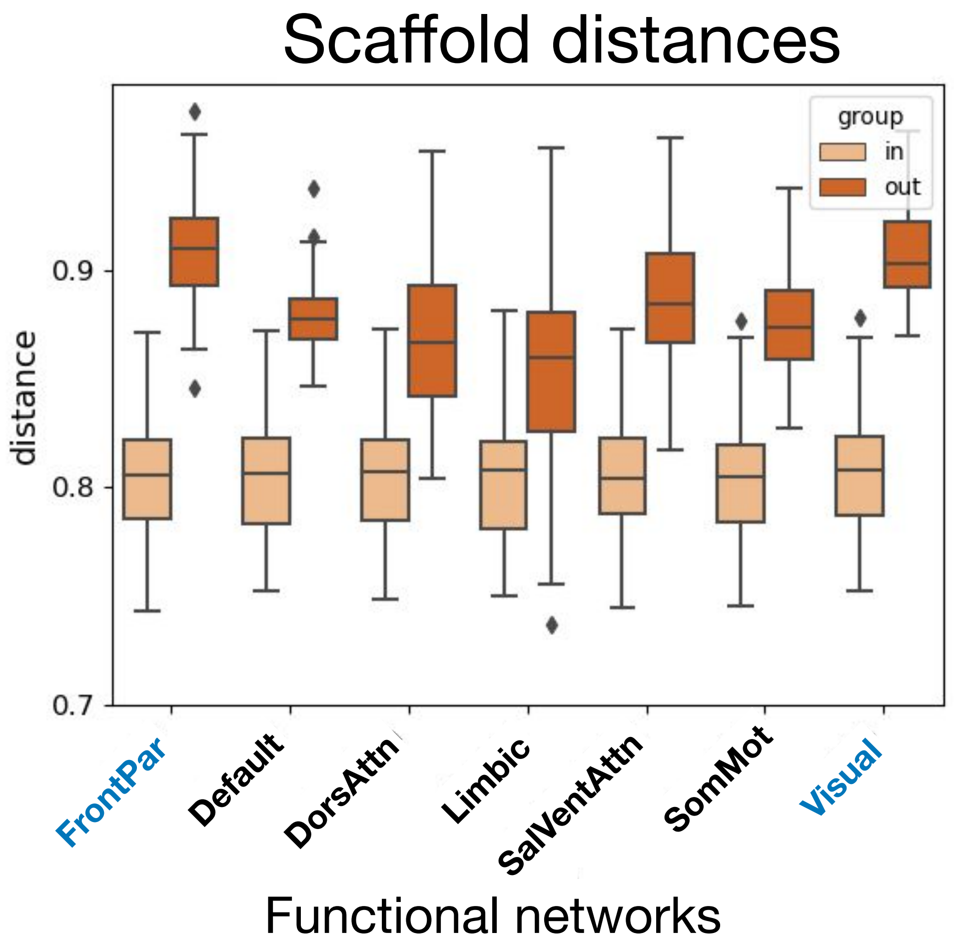

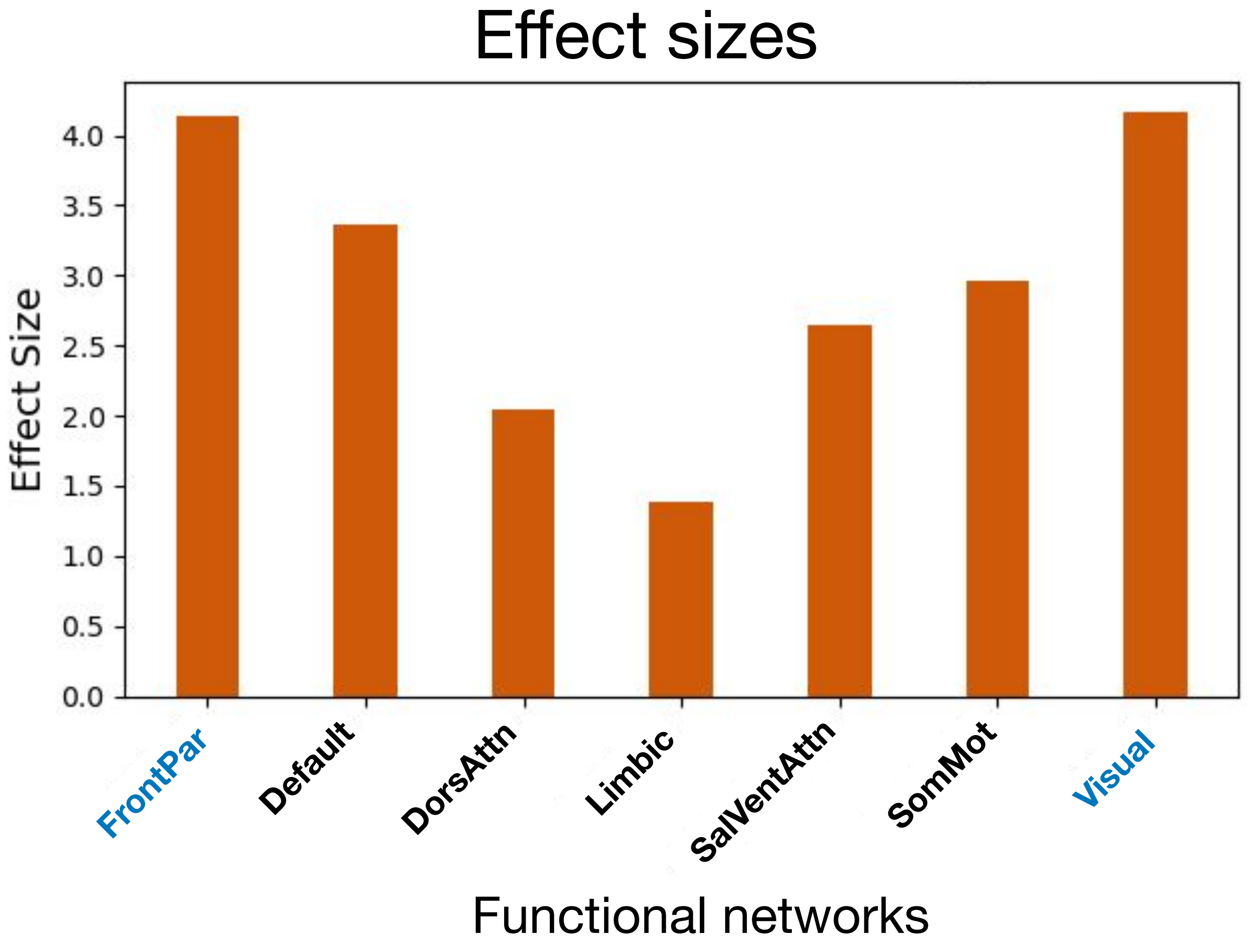

Poetto, Saggar, Battaglia, Vaccarino, Rabuffo, Petri in prep

Scaffold fingerprinting

Summing up

Scaffold fingerprinting

Summing up

- Consistently better

Scaffold fingerprinting

Summing up

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Scaffold fingerprinting

Summing up

- Consistently better
- Works for the short windows

Scaffold fingerprinting

Summing up

- Consistently better
- Works for the short windows

Scaffold fingerprinting

Summing up

- Consistently better
- Works for the short windows
- Sparse representation

Scaffold fingerprinting

Summing up

- Consistently better
- Works for the short windows
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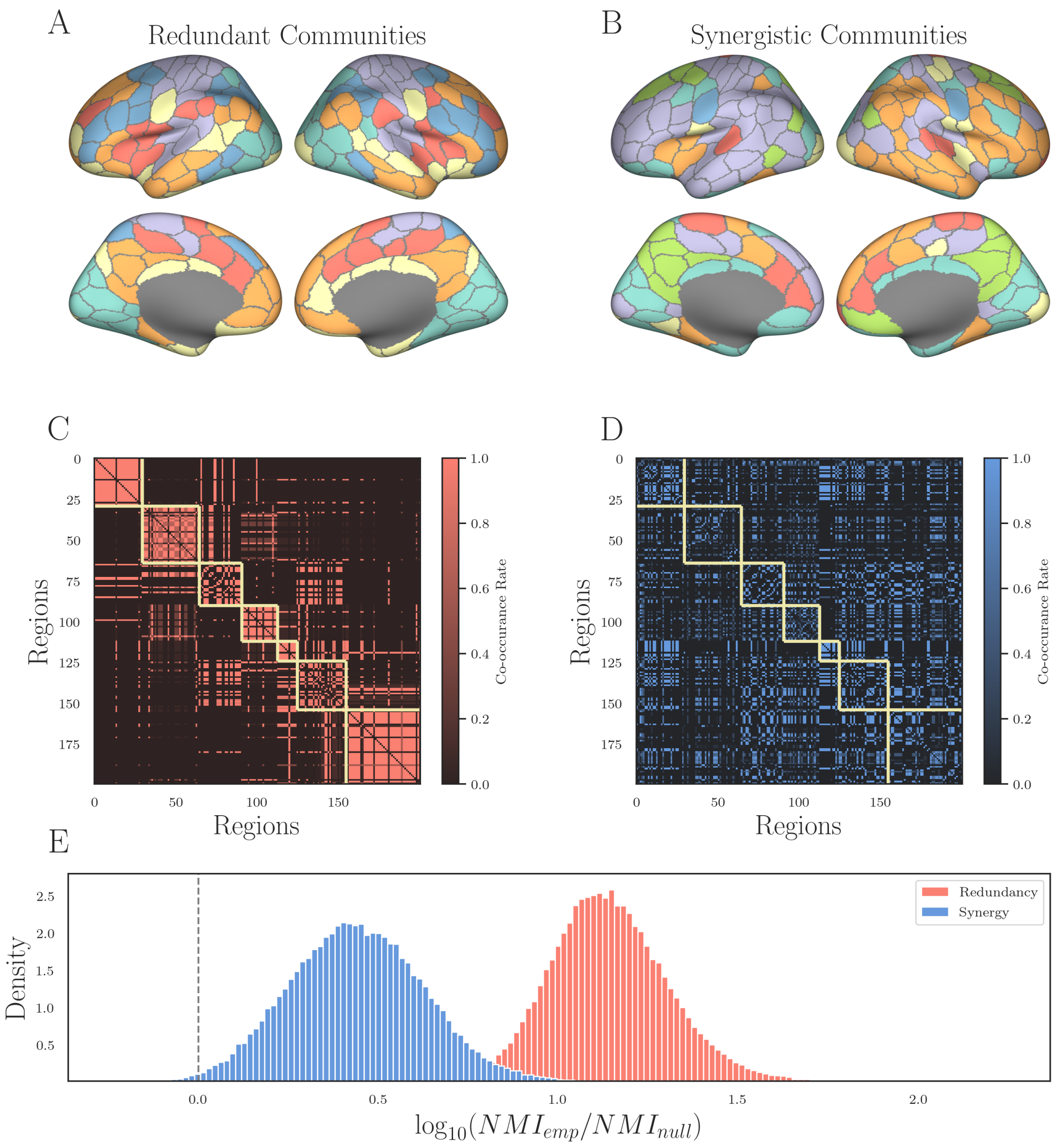
Scaffold fingerprinting

Summing up

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

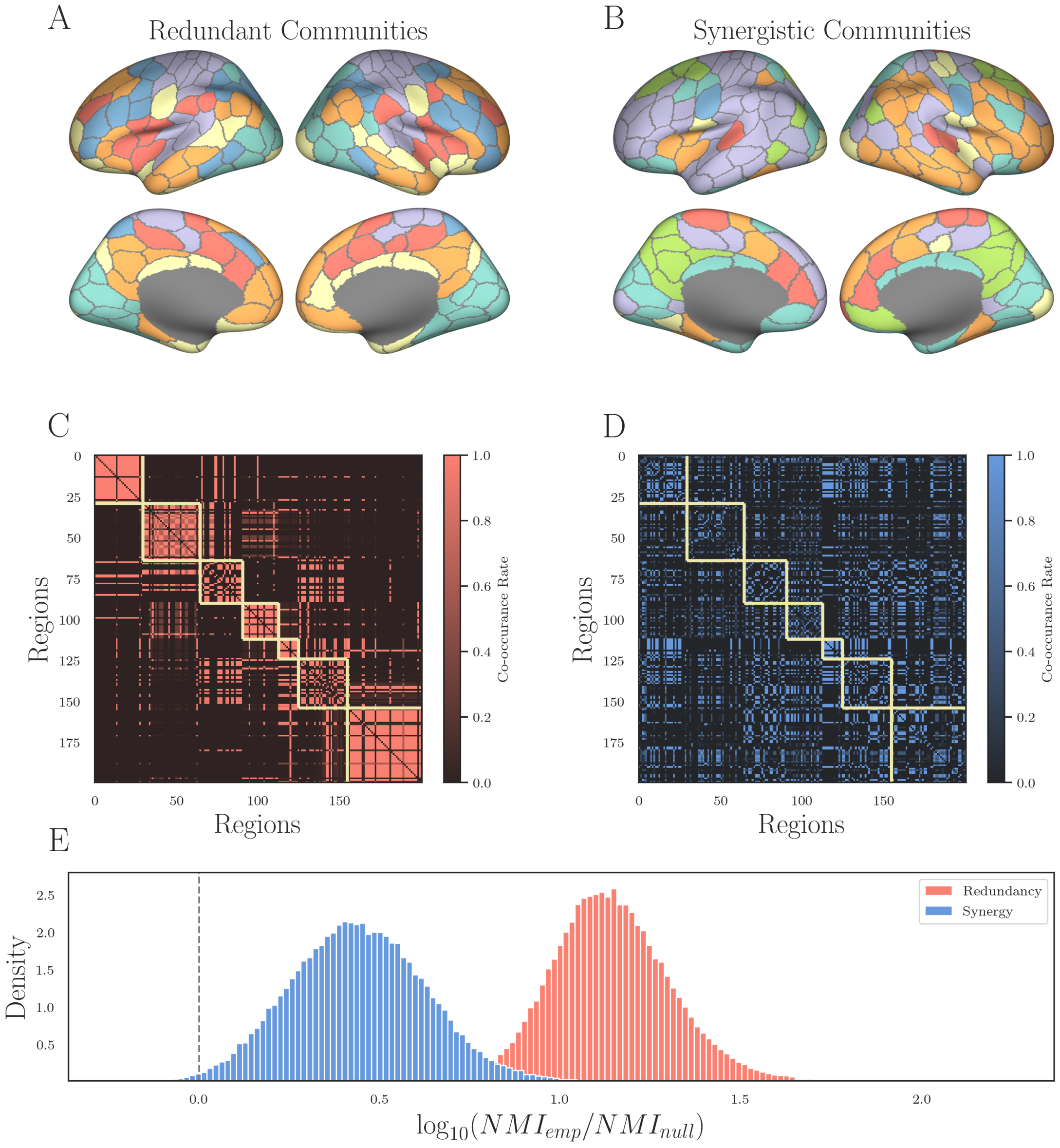
Brain informational fingerprinting

Brain informational fingerprinting



Varley, Thomas F., et al. *arXiv preprint arXiv:2301.05307* (2023).

Brain informational fingerprinting



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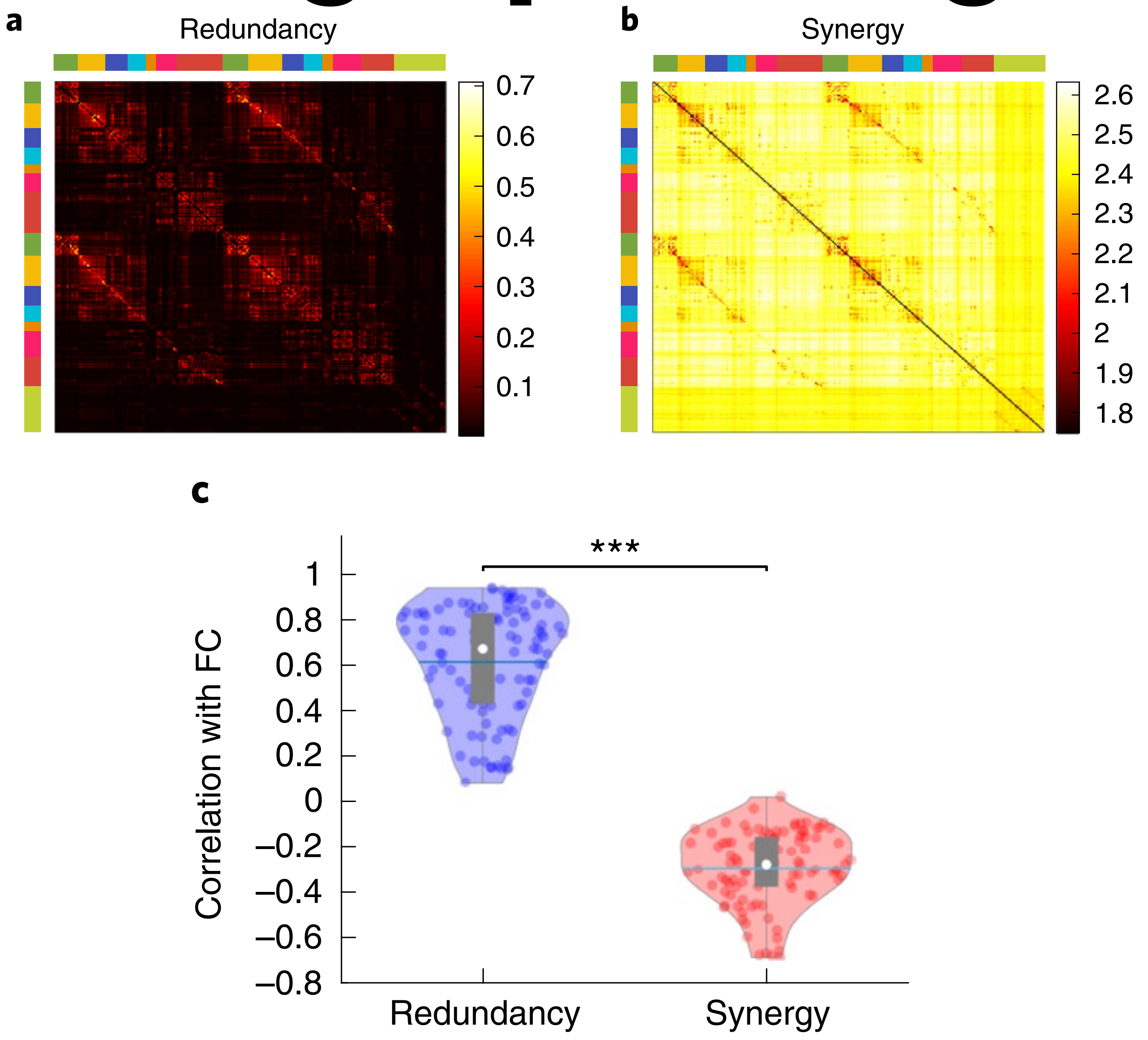
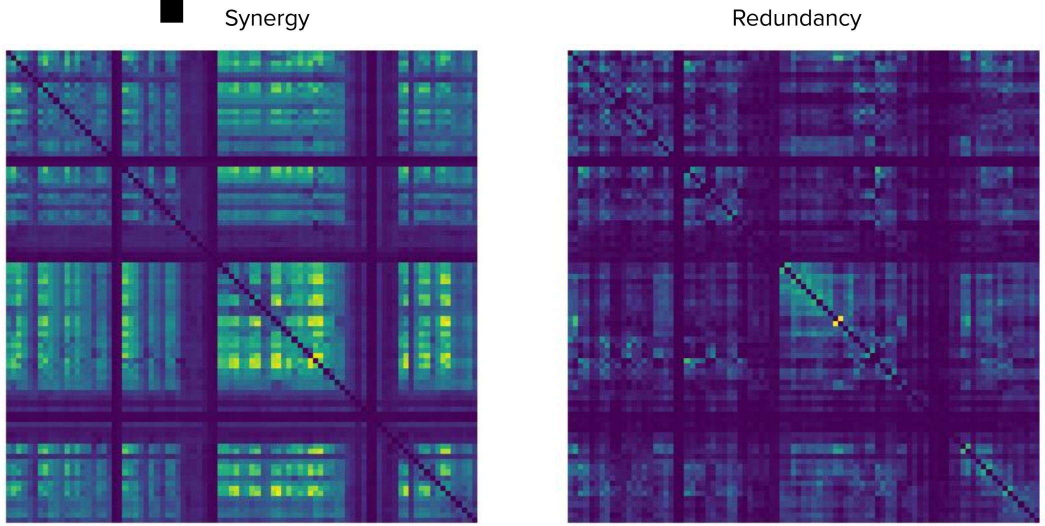


Luppi, Andrea I., et al. *Nature Neuroscience* 25.6 (2022): 771-782.

Topo+Info brain fingerprinting

Poetto, Saggar, Battaglia, Vaccarino, Rabuffo, Petri in prep

Topo+Info brain fingerprinting



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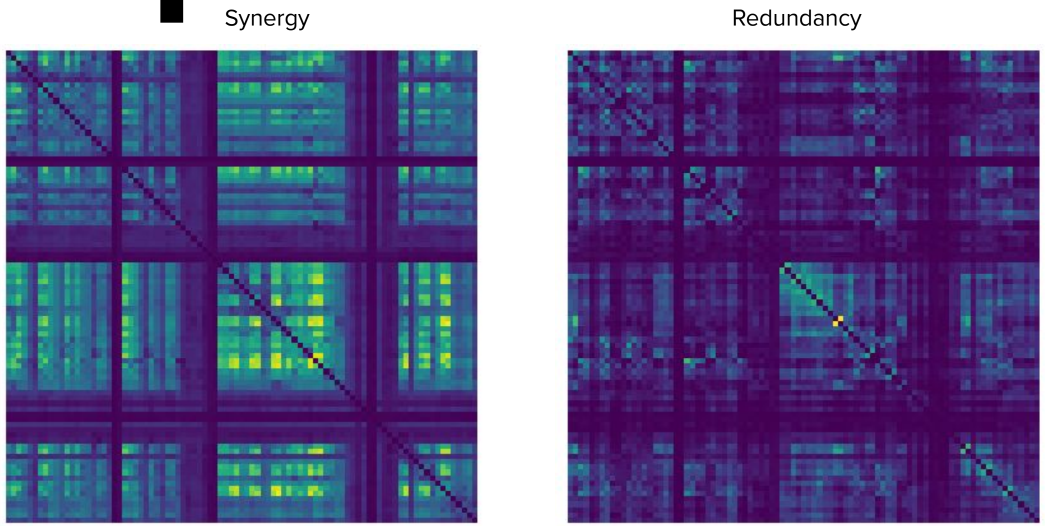
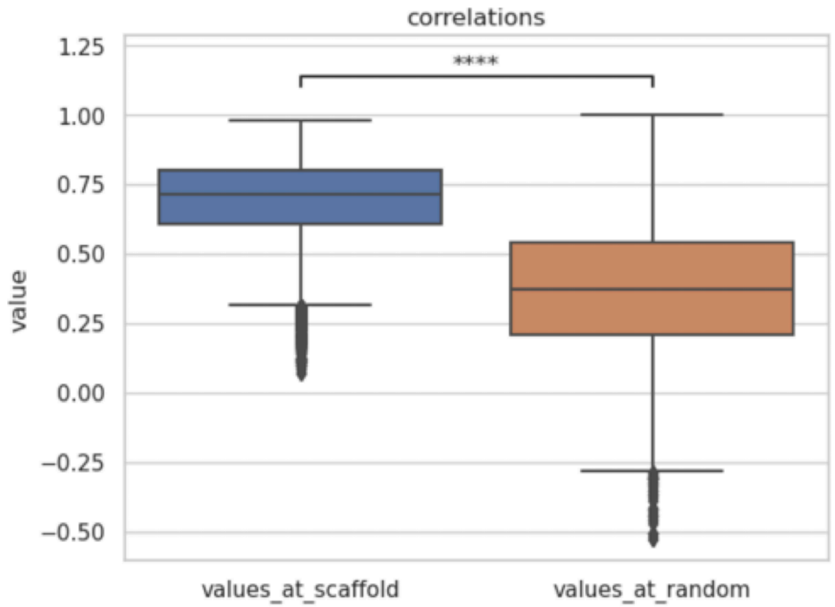
Topo+Info brain fingerprinting





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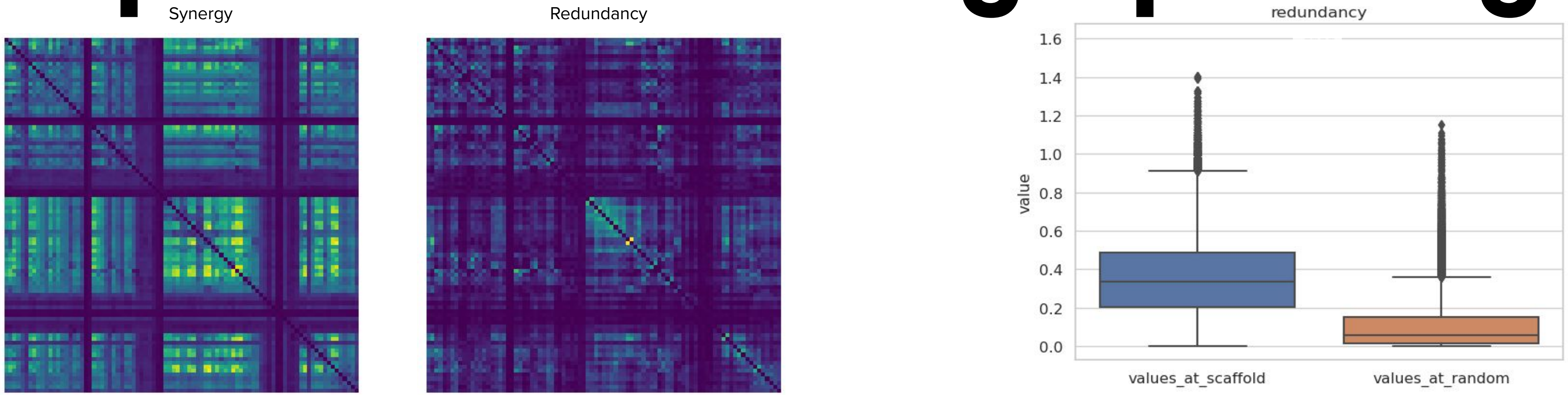

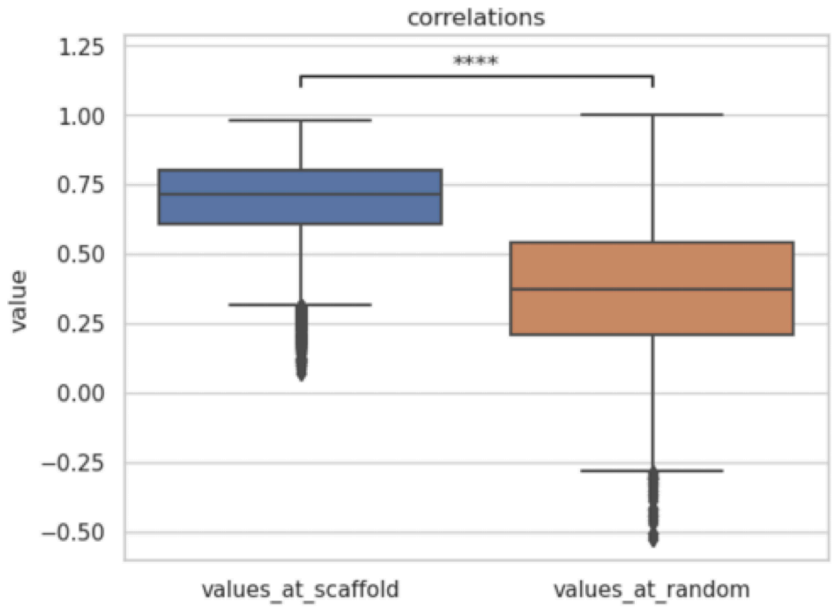

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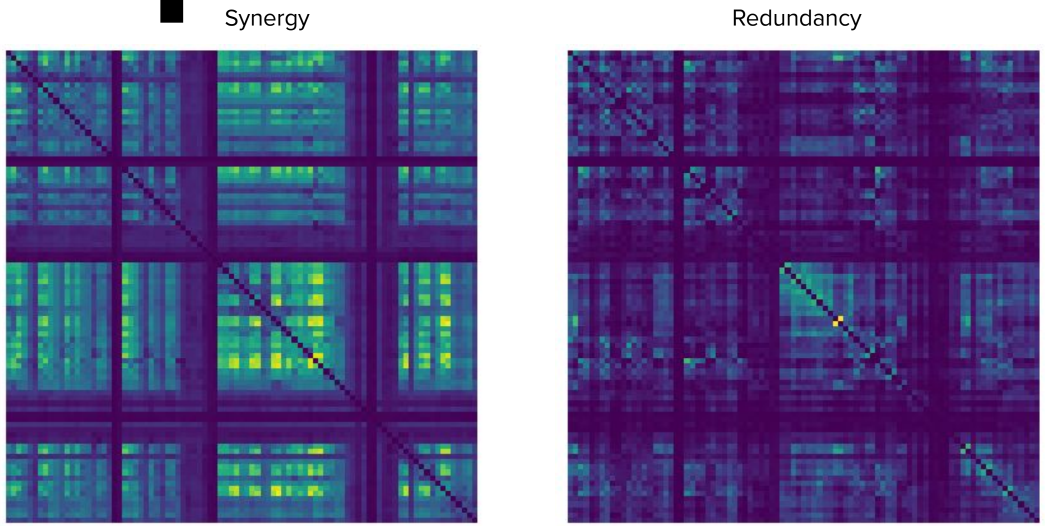

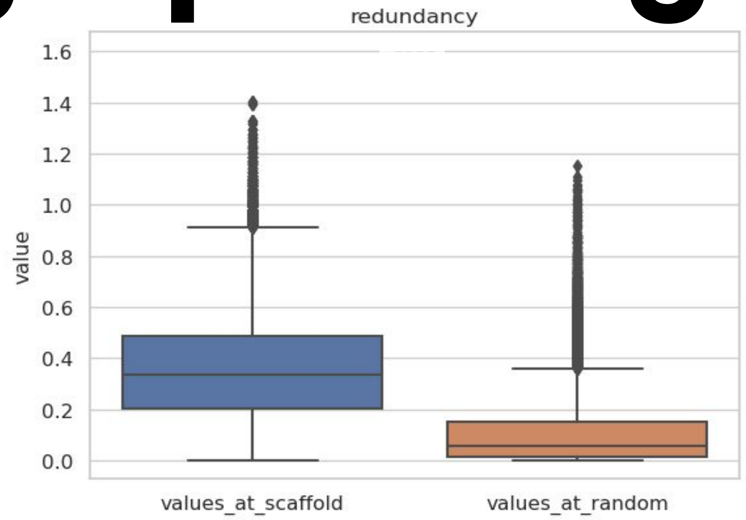

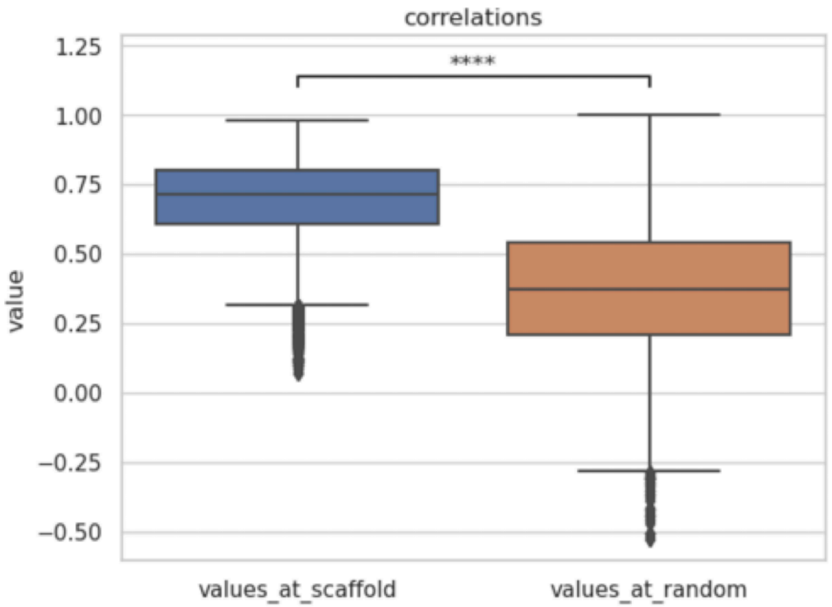

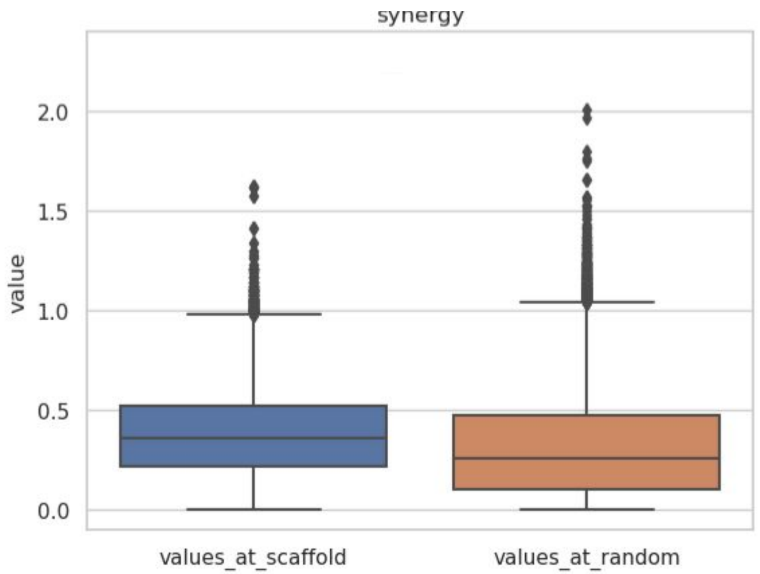

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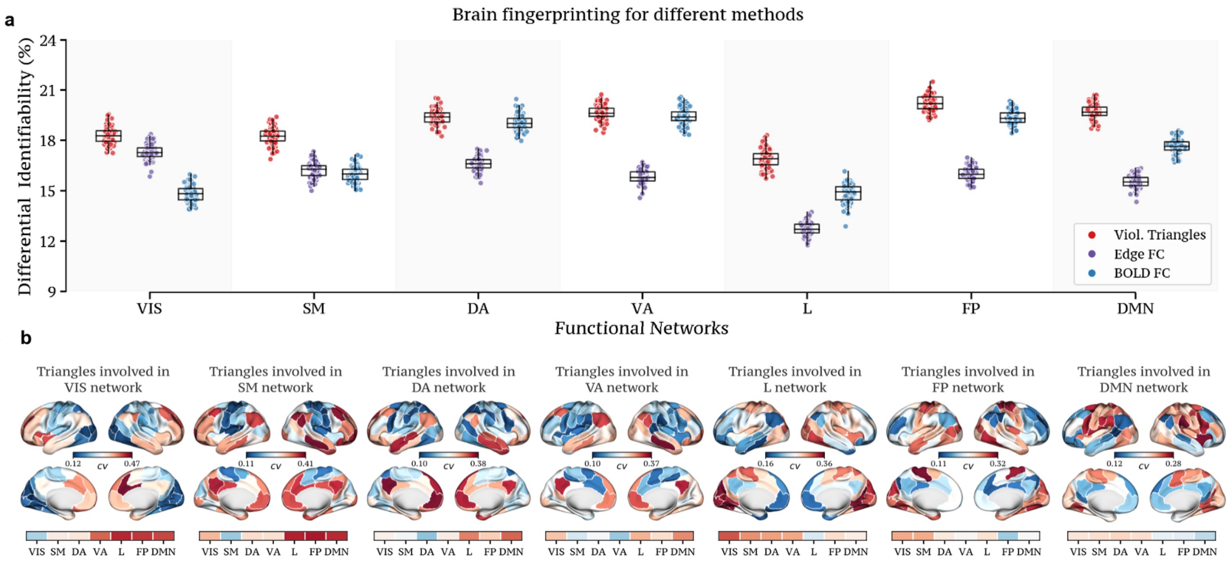

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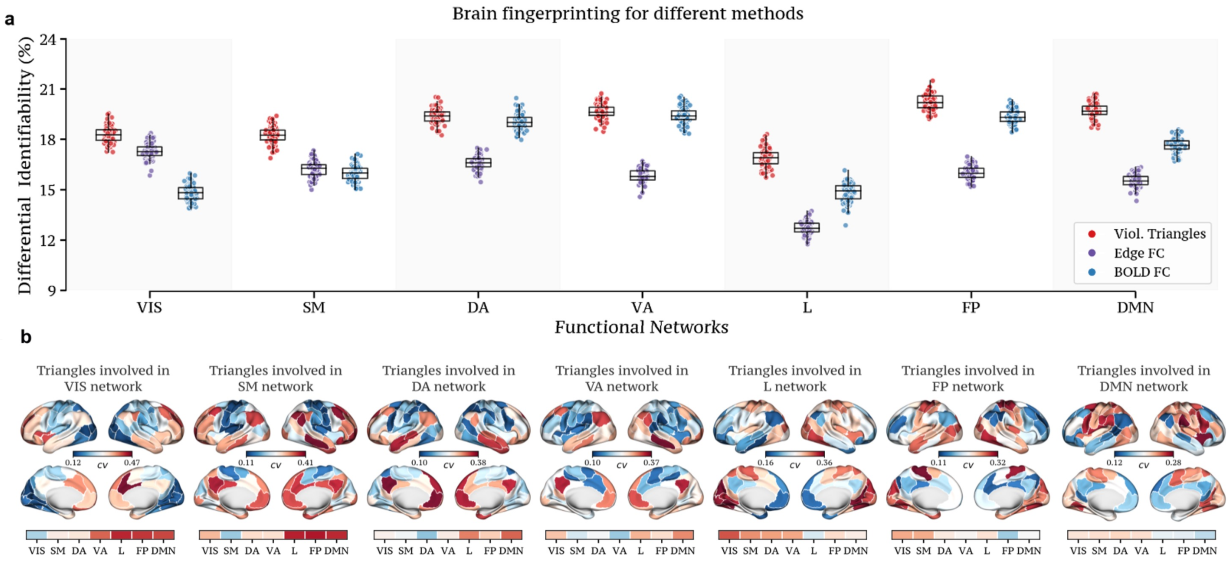

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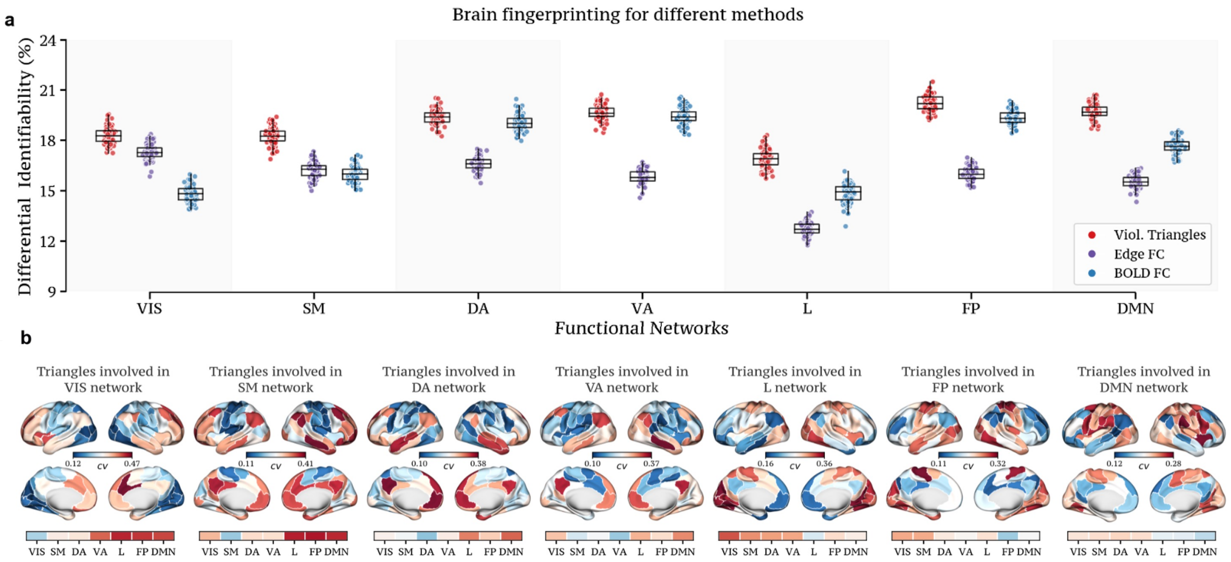

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NPL RESEARCH

CETI THEORY

nature physics

PERSPECTIVE

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

Check for updates

The physics of higher-order interactions in complex systems

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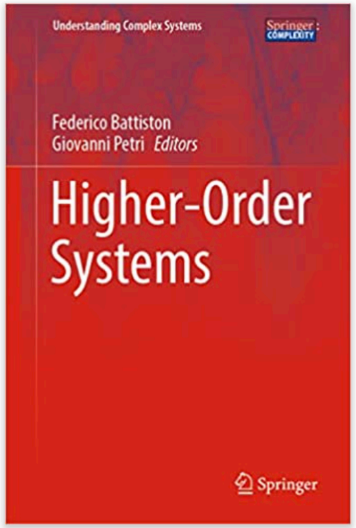

Understanding Complex Systems

Book Series

There are 141 volumes in this series

Published 2004 - 2021

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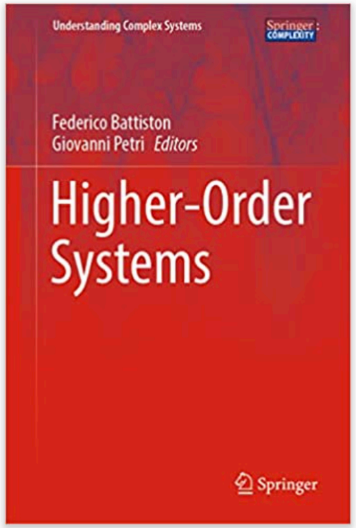

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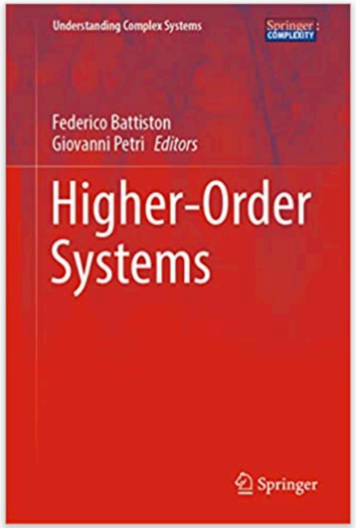

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Thanks!

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