

Localising Shapes in Neuroimaging Data

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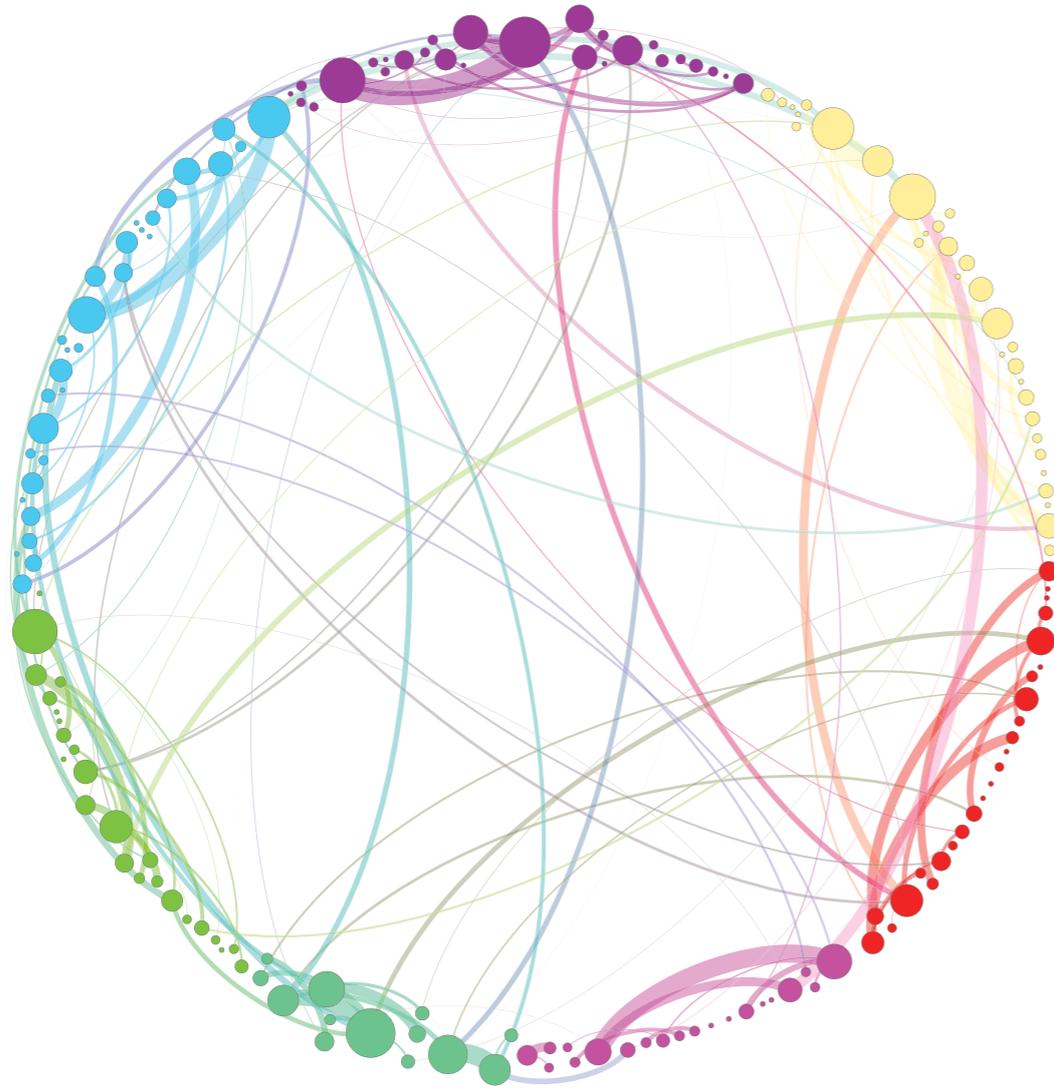
Developments in Healthcare Imaging – Connecting with Academia
Isaac Newton Institute, Cambridge

Old question: how to reduce the dimensionality of a large dataset to extract salient features?

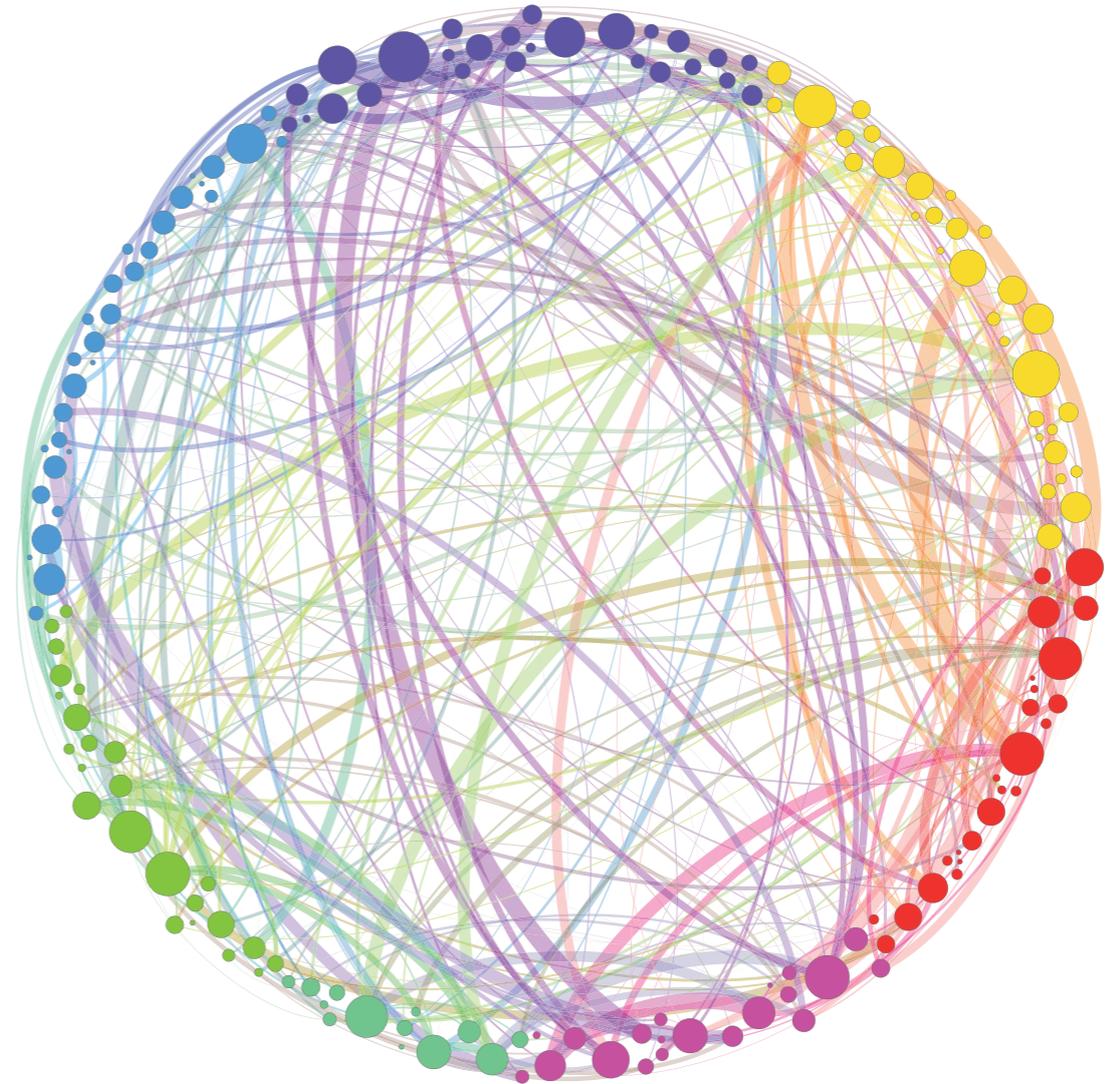
One possible answer is: look at its shape!
and where it is ...

Key words: topological data analysis, persistent homology,
localisation

Quantify functional differences

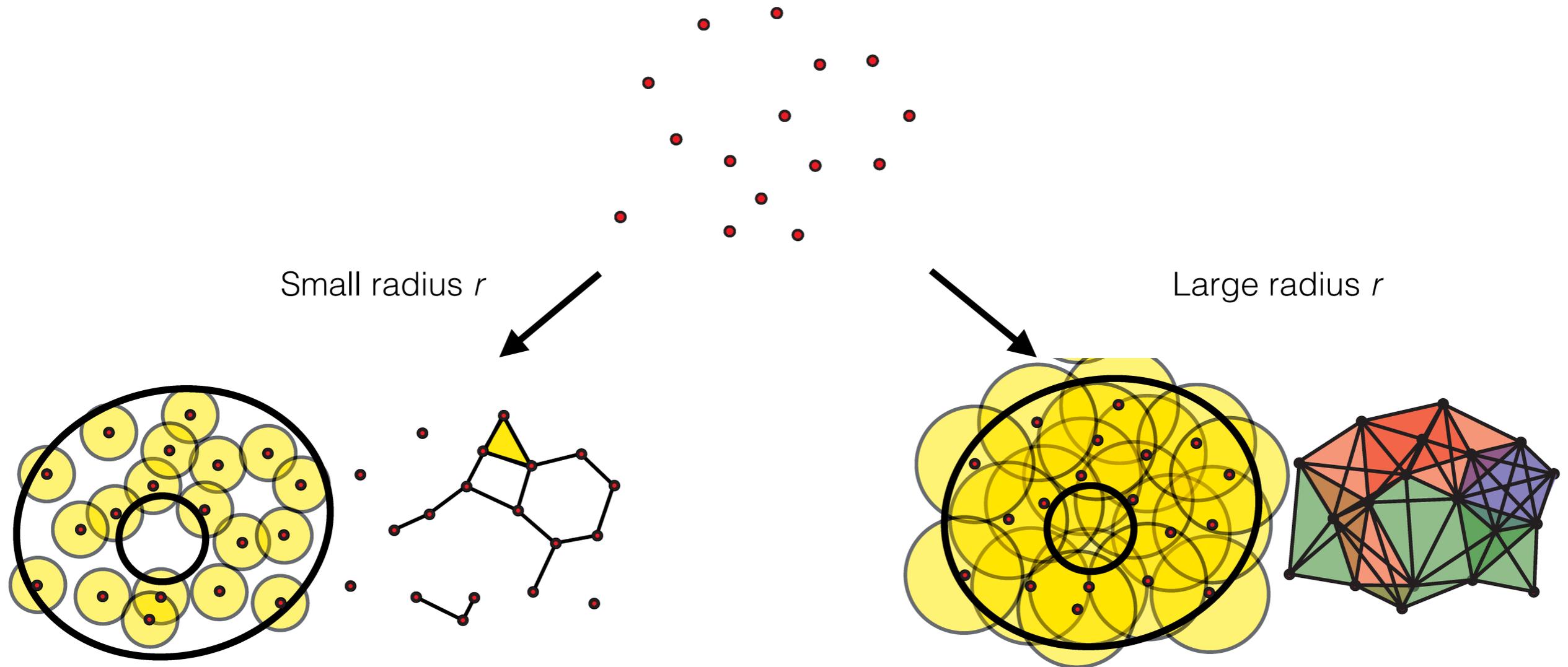


Placebo



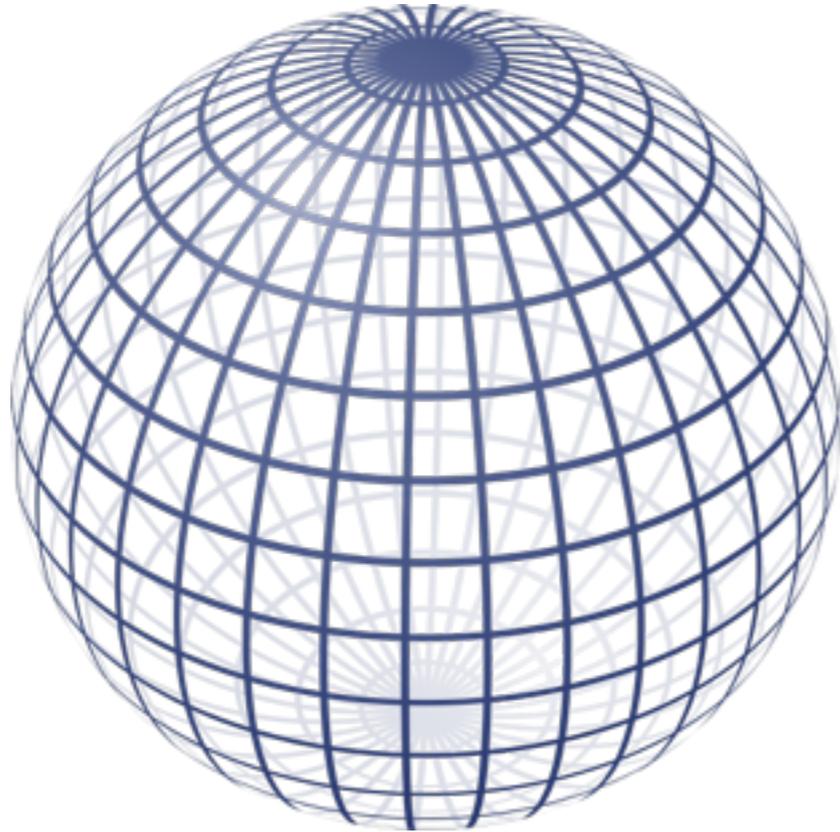
Psilocybin

From a *cloud of points*, create a *simplicial complex*

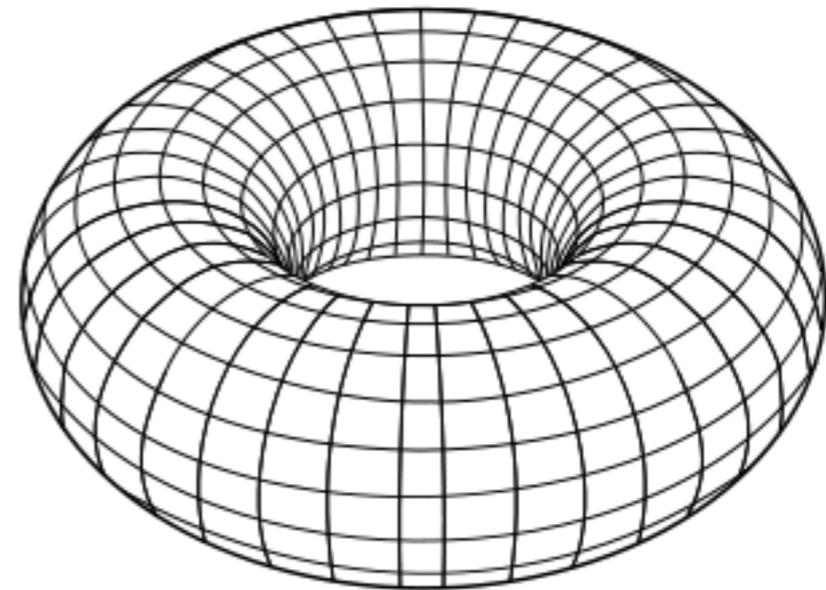


and compute its *homology*

Homology



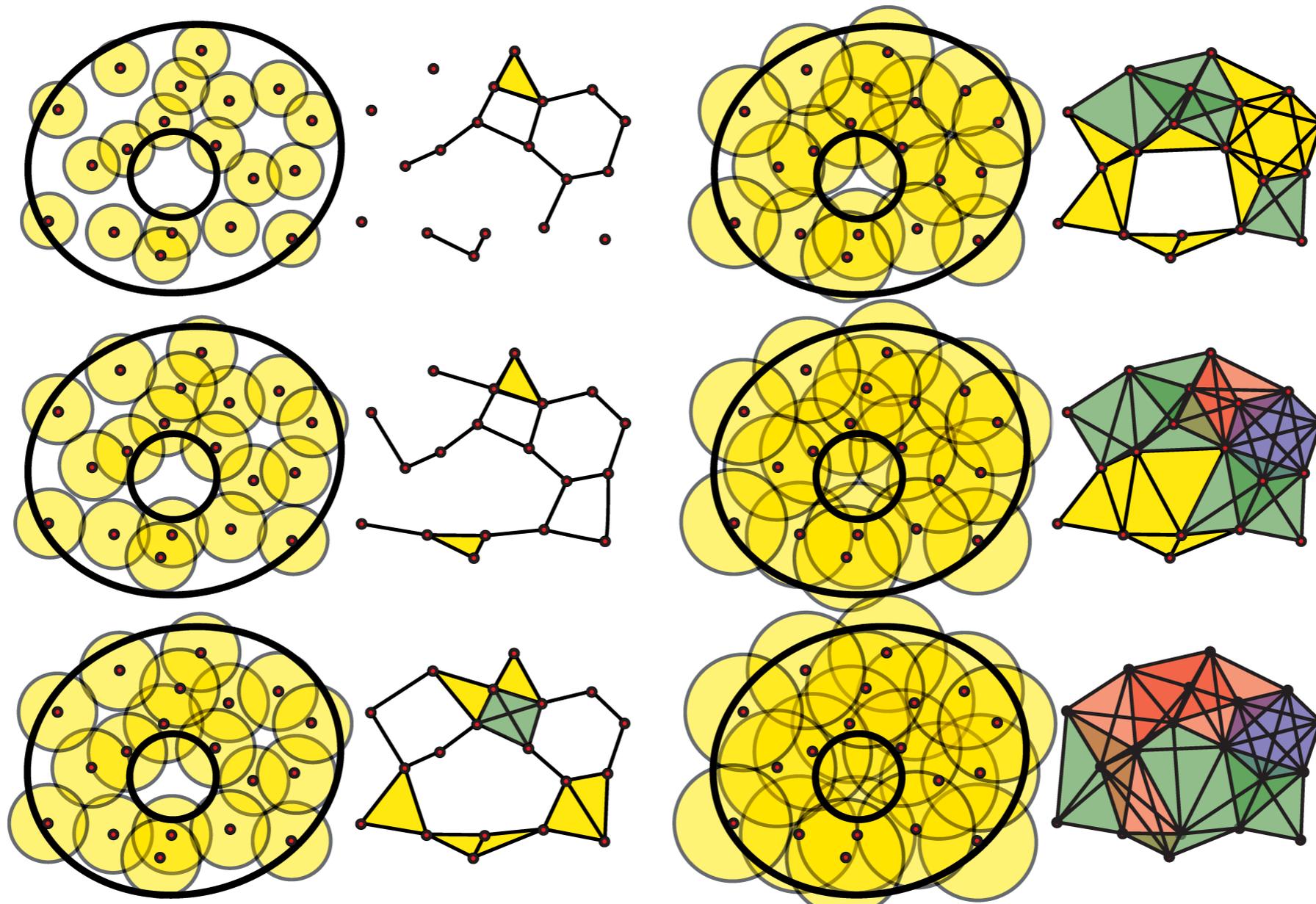
One 2d hole



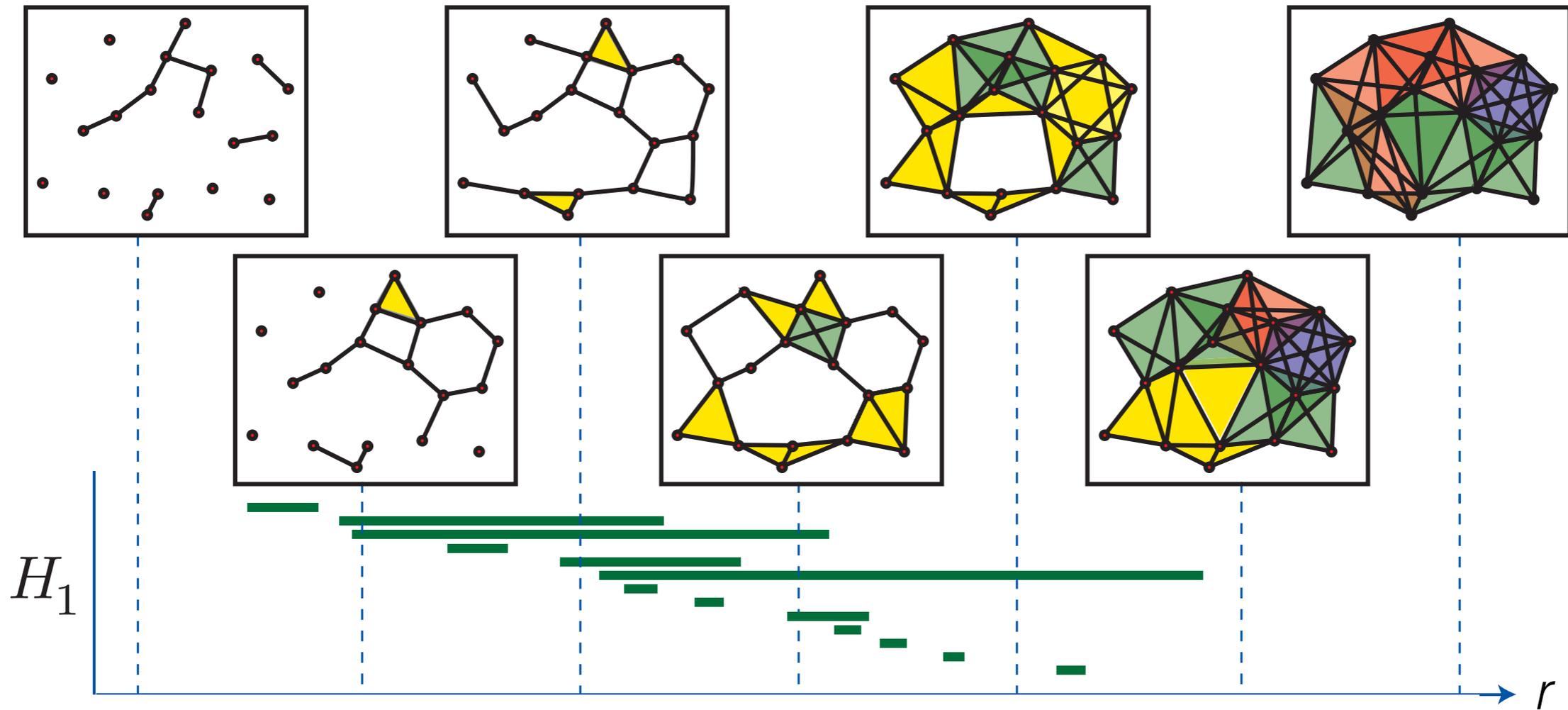
One 2d hole and two 1d holes

Characterise a simplicial complex by
its *holes* and their *dimensions*

We perform a parameter sweep and generate a *filtration*.

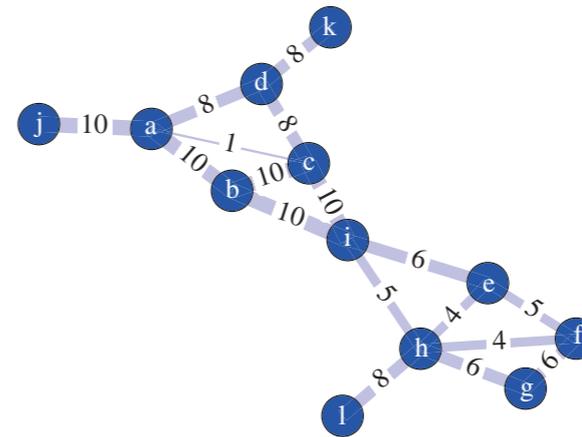
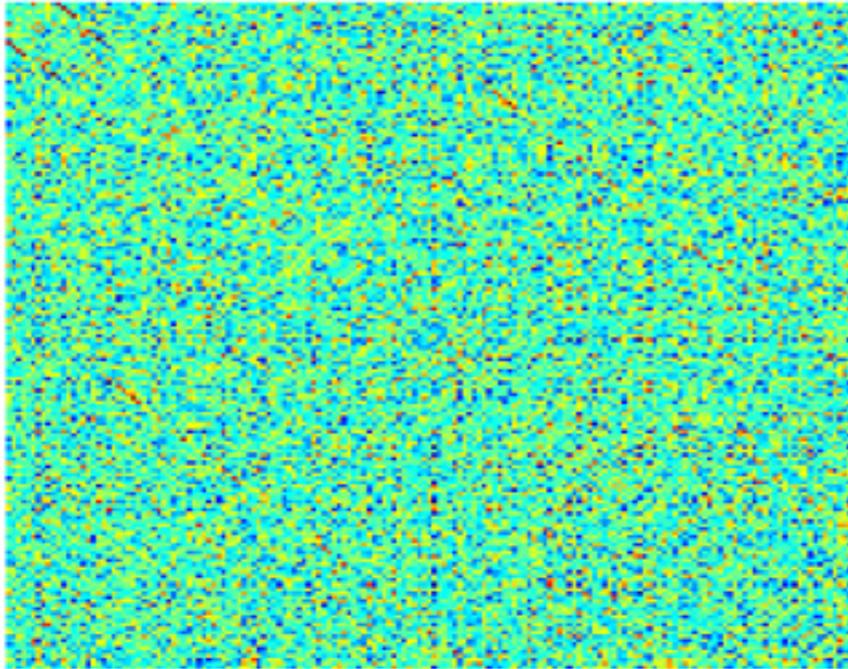


Persistent homology

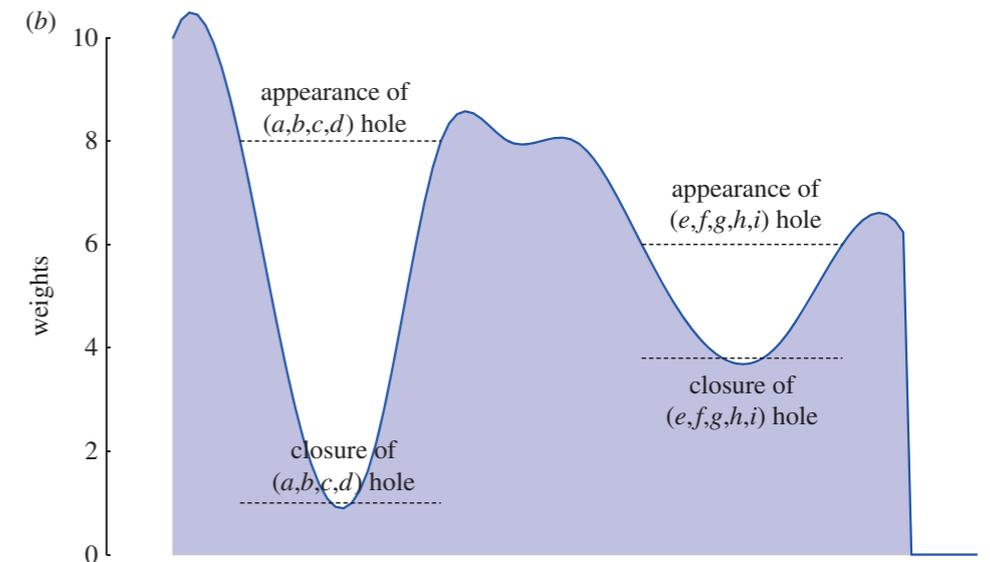


Barcodes

Functional neuroimaging yields time series

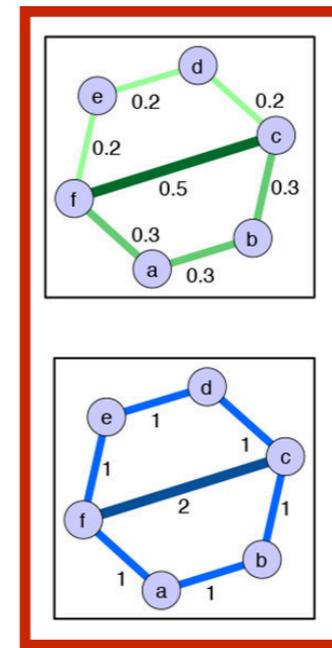
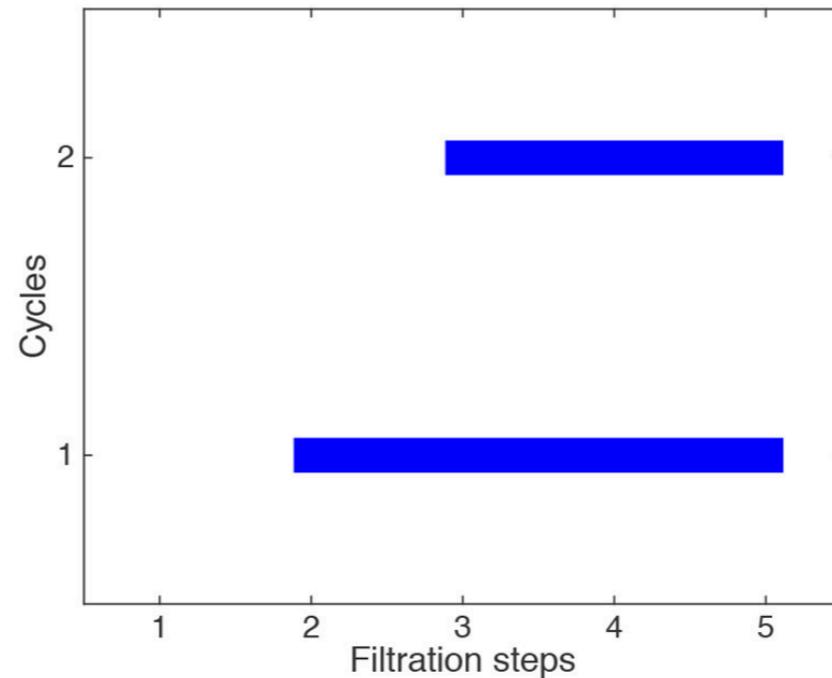
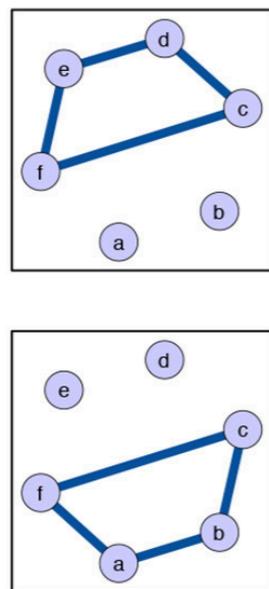
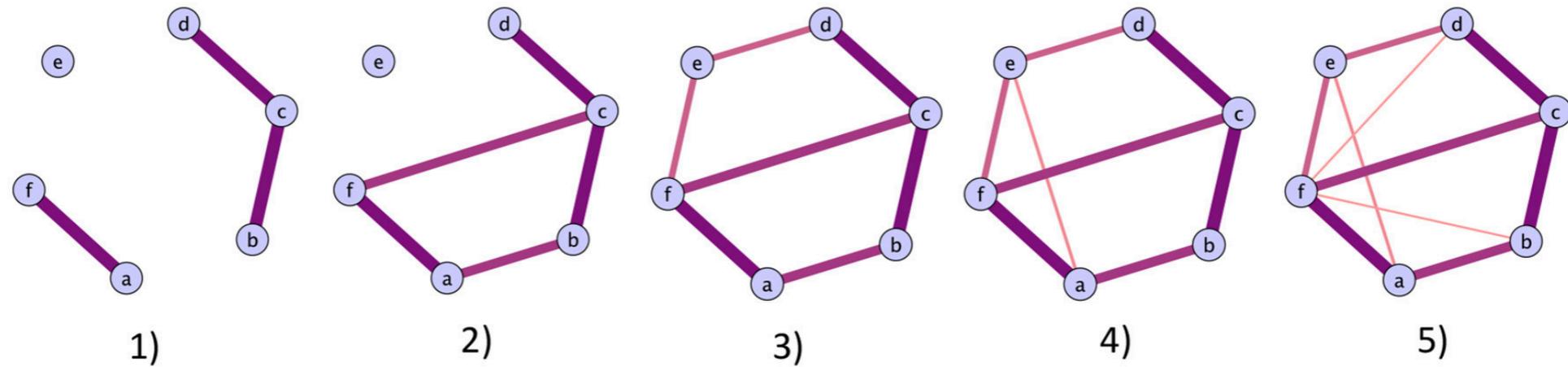


Sweeps through the correlations:
weight rank clique filtration



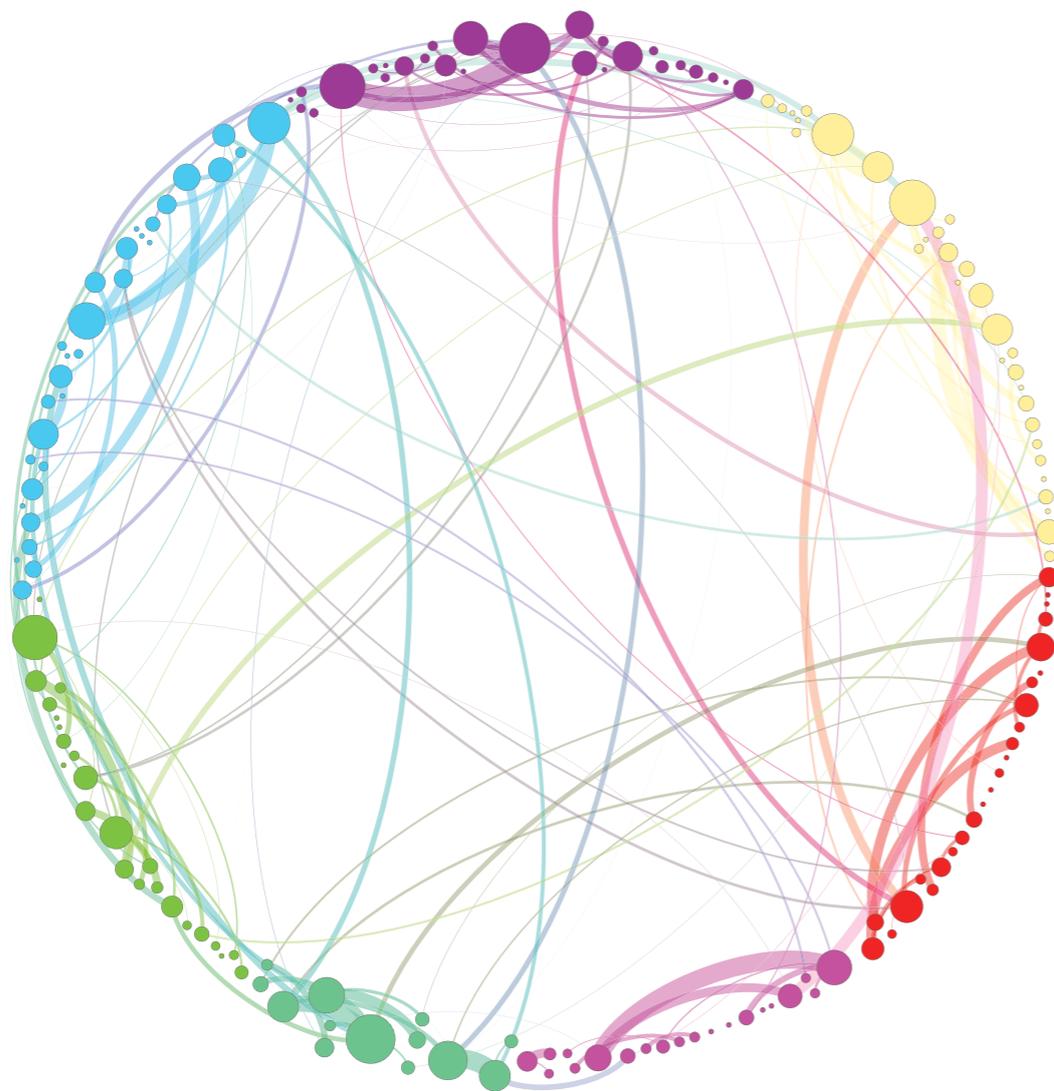
No thresholding, all the information is used.

Localising the holes

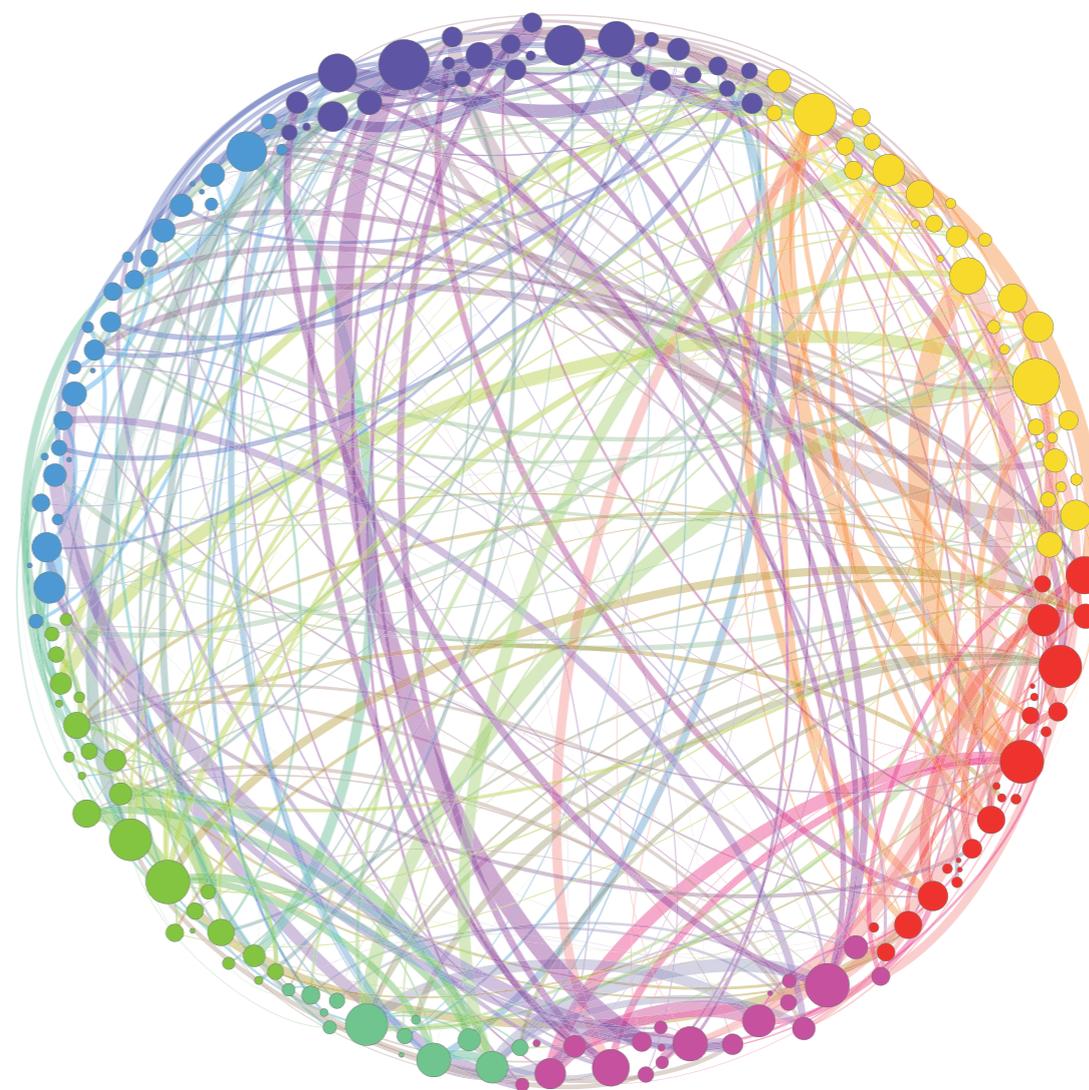


Persistence and frequency *homological scaffolds*

Persistence scaffolds



Placebo



Psilocybin

Take home messages

Persistent homology can be used to *characterise* and *differentiate* datasets.

Advantages over traditional network analysis methods.

Localising the homology is crucial for the *interpretation* of the holes and differences.

G. Petri, P. Expert, *et al.*, Jour. Royal Soc. Inter. 11, (2014).

L.-D. Lord, P. Expert, *et al.*, Front. Syst. Neurosci. 10, (2016).