COMMUNITY DETECTION IN BRAIN FUNCTIONAL NETWORKS BEYOND THE RESOLUTION LIMIT

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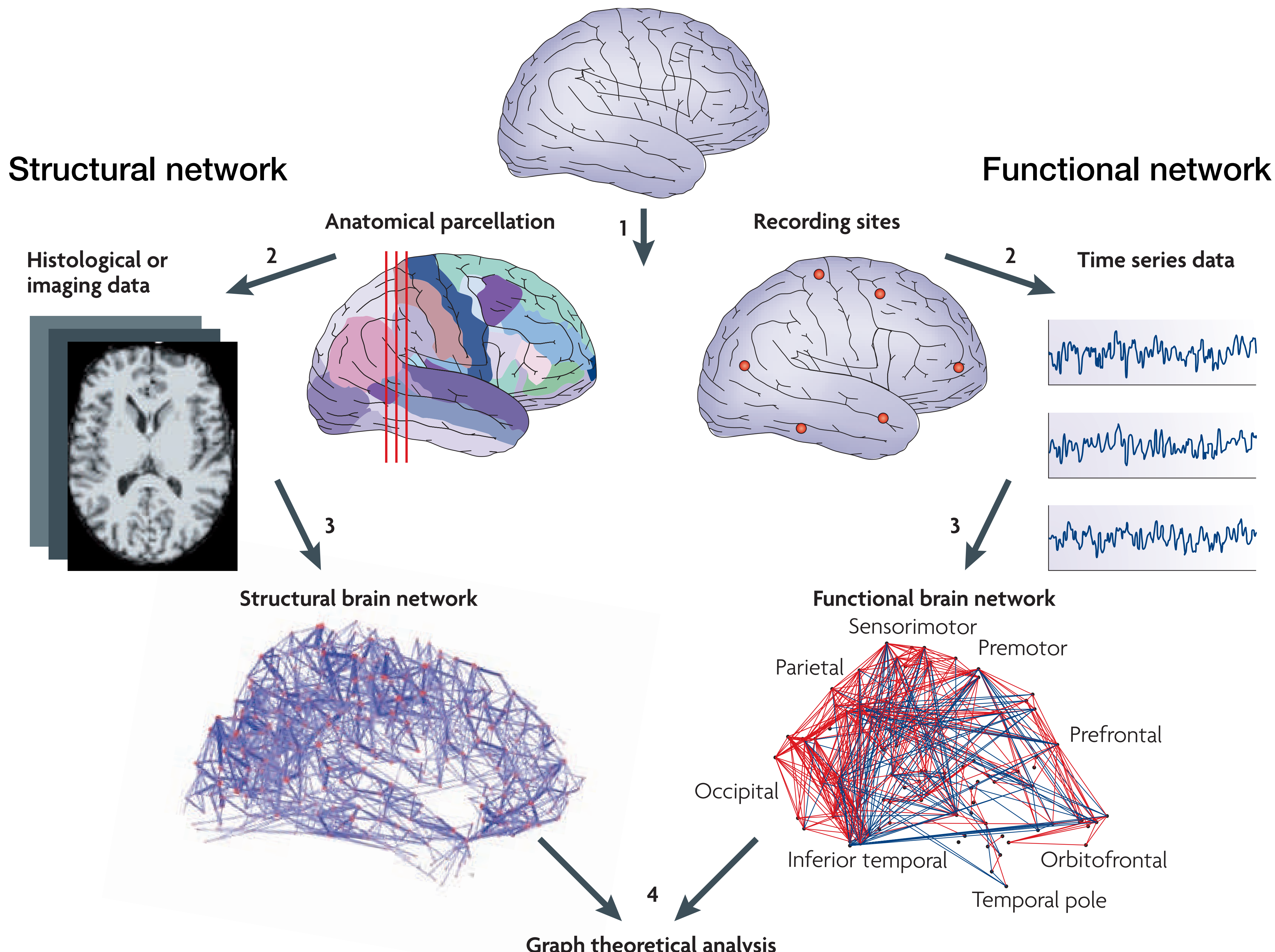
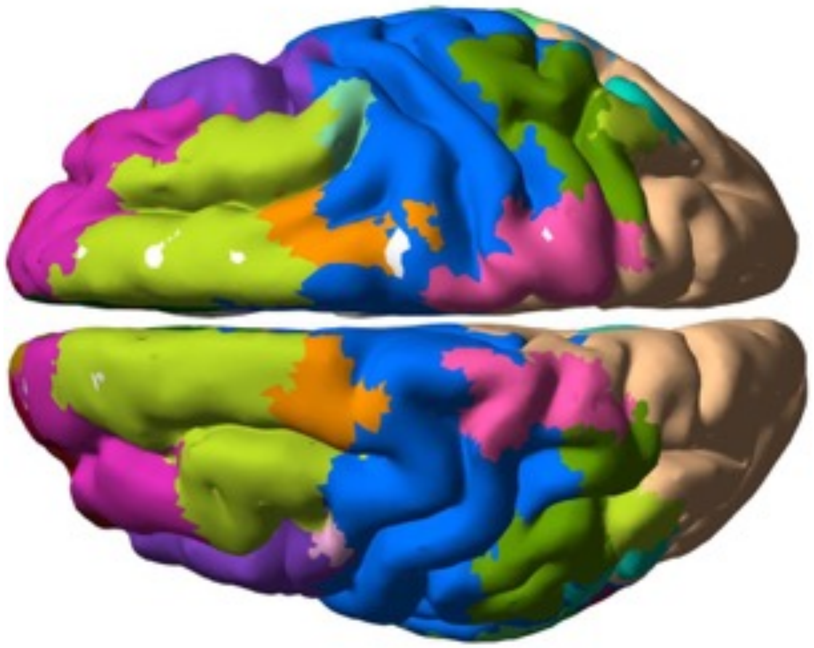
GRAPH THEORY FOR BRAIN NETWORKS



Bullmore, Nat.Rev.Neuro. 2009

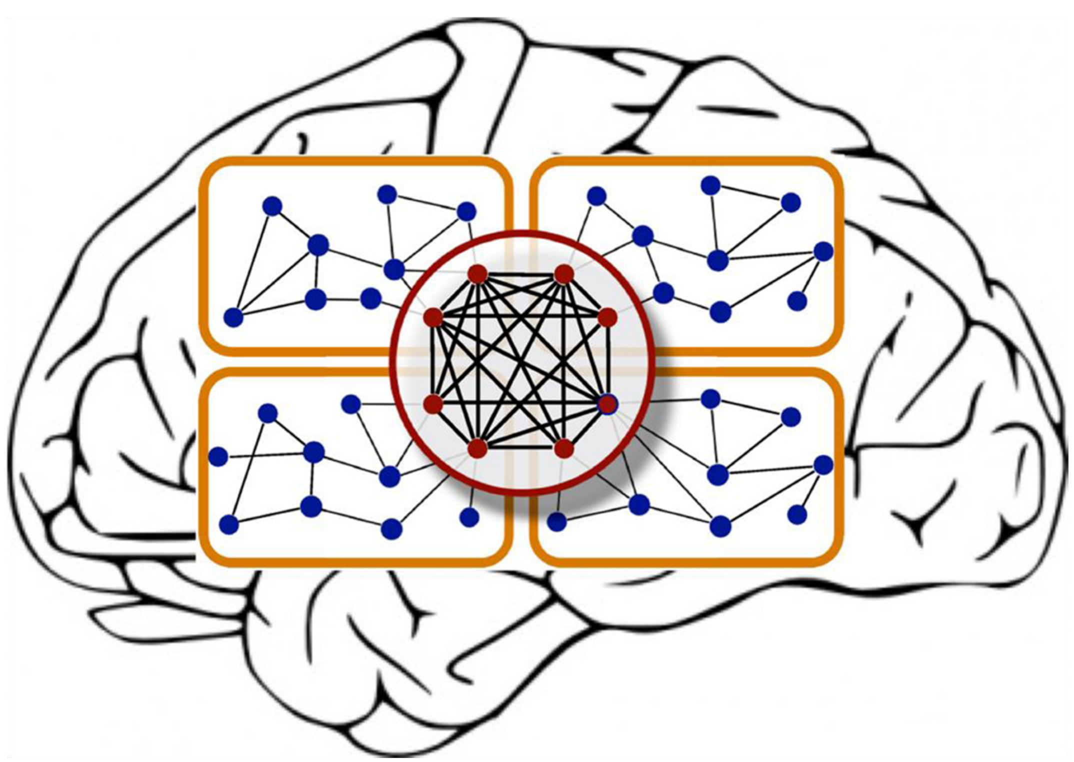
FUNCTIONAL BRAIN NETWORKS

- A mirror over the living brain.
- Clinically important biomarker.
- Aberrant connectivity is observed in many diseases.
- Modular structure of FC connectivity.
- Graph theoretical community detection unveils the mesoscopic organization of functional connectivity.



WHY LOOKING FOR MODULES IN THE BRAIN?

- "Nearly decomposable systems" are faster to adapt and evolve in a changing environment [Simon 1962].
- Confers stability against abrupt external changes (lesions).
- Allows for functional segregation and integration.
- Coevolution of structural and functional connectivity.



Kaiser, Front.Neuroinf. [2010]

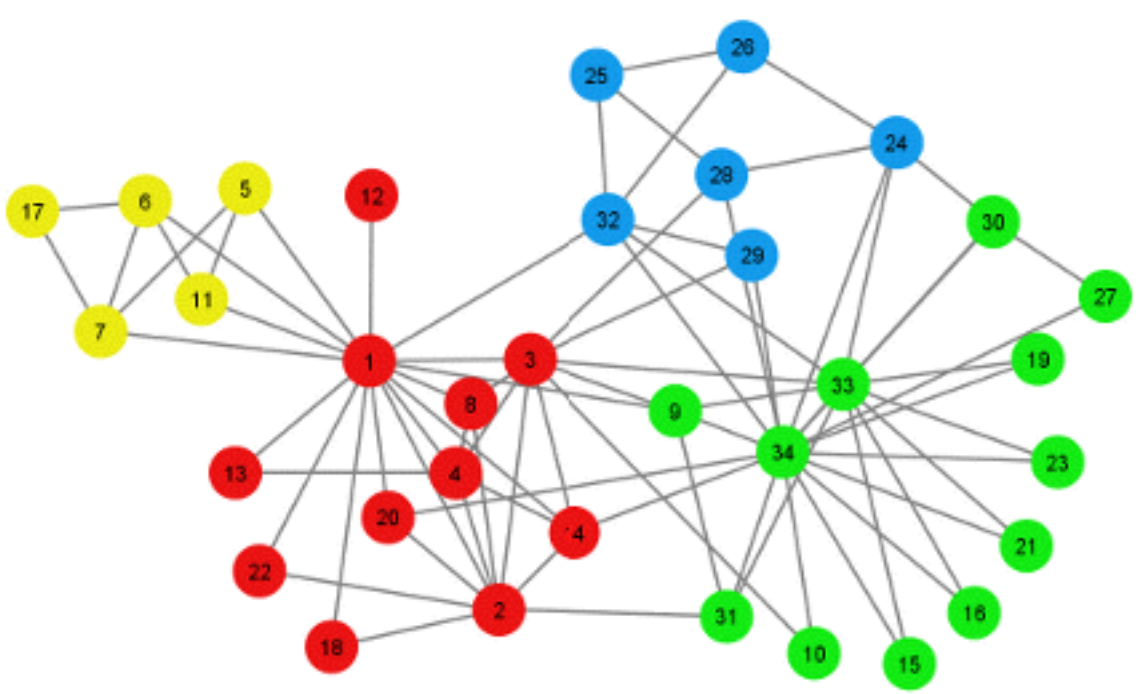
NEWMAN-GIRVAN MODULARITY

$$Q = \frac{1}{2m}\sum_{ij}\left[\boxed{A_{ij}} - \boxed{\frac{k_i k_j}{2m}}\right]\delta(\sigma_i, \sigma_j)$$

1 if node i and node j in the same community

Observed fraction intracluster edges

Expected fraction of intracluster edges



- Based on a **null configuration model**
- Same degree sequence
- Randomly rewired

Newman, 2006

Zachary, 1977

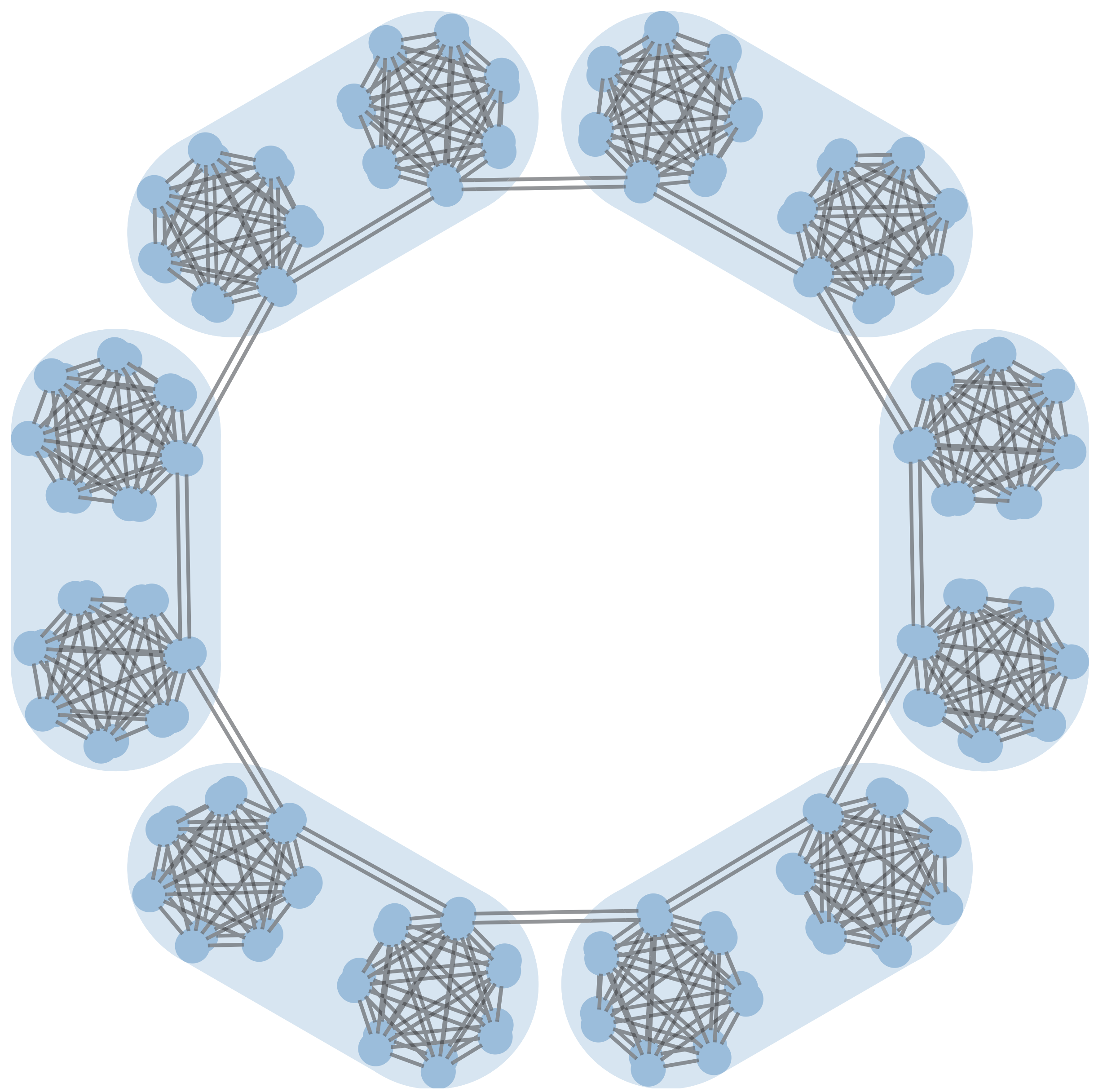
MOST USED QUALITY FUNCTION FOR COMMUNITY DETECTION

But it has some problems:

- **Resolution limit:**
  Inability to detect communities smaller than a certain scale.
- **Degeneracy:**
  Many high Q solutions are different.

Good et al, PRE, 2010

RESOLUTION LIMIT: AN EXAMPLE



Original network

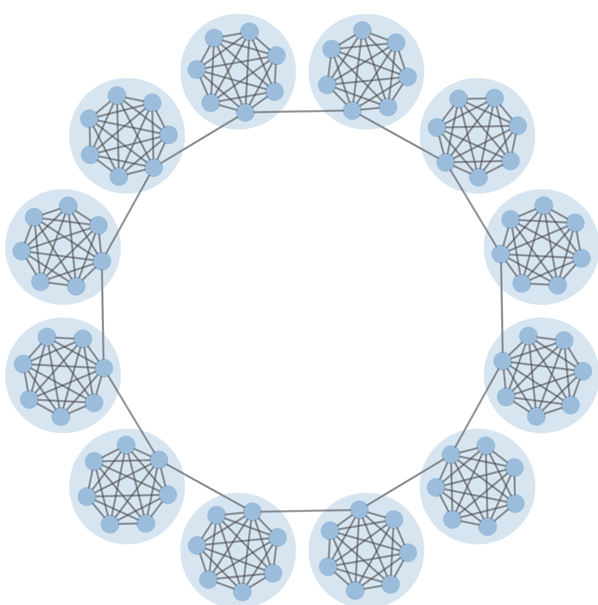
Maximum modularity partition

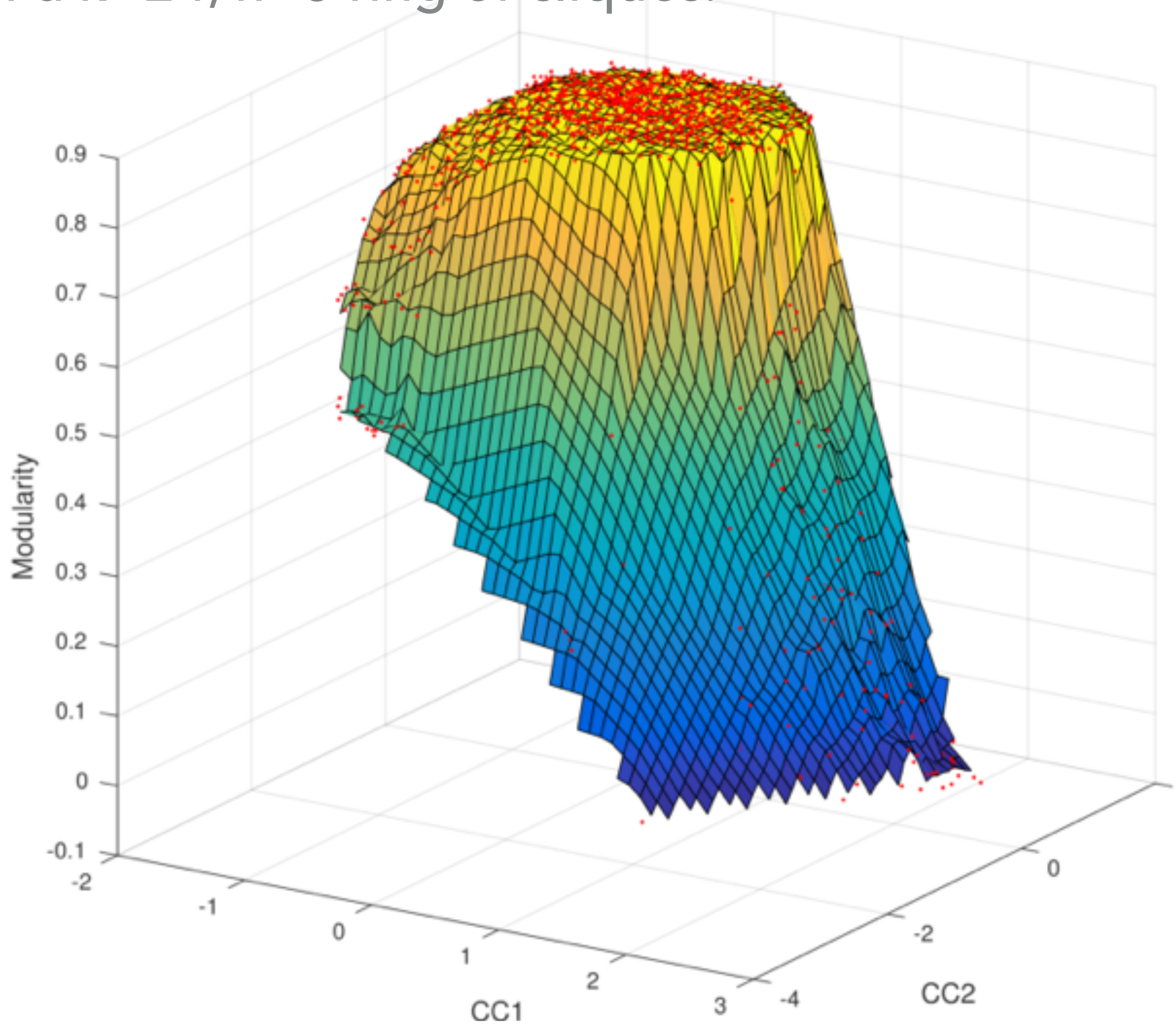
Ground truth

Adapted from Traag, 2011

DEGENERACY

- Degeneracy landscape of a k=24, n=5 ring of cliques.
- Curvilinear components analysis.
- Red points are solutions.
- Distance embedding.





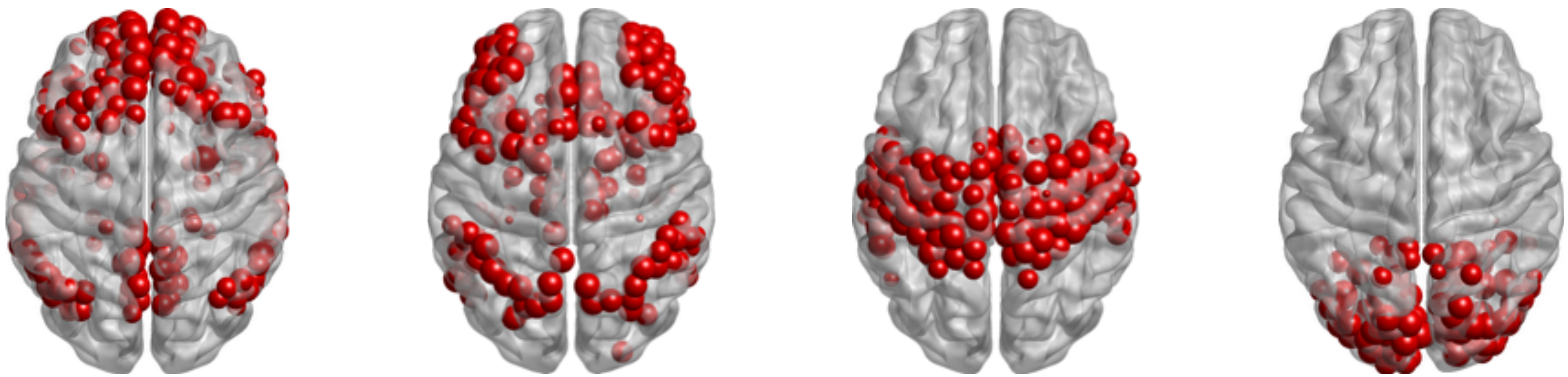
Adapted from Good et al. (2008)

RESOLUTION LIMIT

Resolution limit is an almost ubiquitous phenomenon:

- Resolution parameter γ [Arenas 2008, Reichardt 2006] only shifts the problem at different scales.
- It depends on Modularity, not on the heuristic.
- In Infomap depends on intercluster edges [Kawamoto 2015].
- Global parameters? Resolution limit kicks in [Fortunato 2016].

REAL WORLD EFFECTS OF RESOLUTION LIMIT



- Resting state group average over 27 healthy subjects.
- 4 modules found by modularity maximization.

$$m_c \geq \sqrt{\frac{m}{2}}$$

We need to move this limit away.

Crossley, 2013

SURPRISE

$$S = -\log_{10} \sum_{i=m_\zeta}^{m} \frac{\binom{p_\zeta}{i}\binom{p-p_\zeta}{m-i}}{\binom{p}{m}}$$

- p-value of a Fisher exact test based on urn model.
- Measures how surprising is to observe that the intracluster density is the same as graph density.
- The higher Surprise, the better the clustering.
- Attention to the statistical significance of the partitioning.

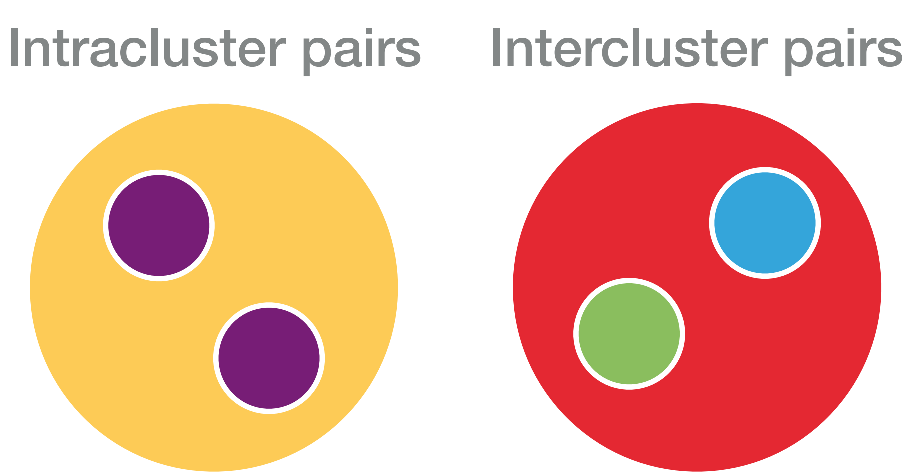
Aldecoa, Sci.Rep. 2011

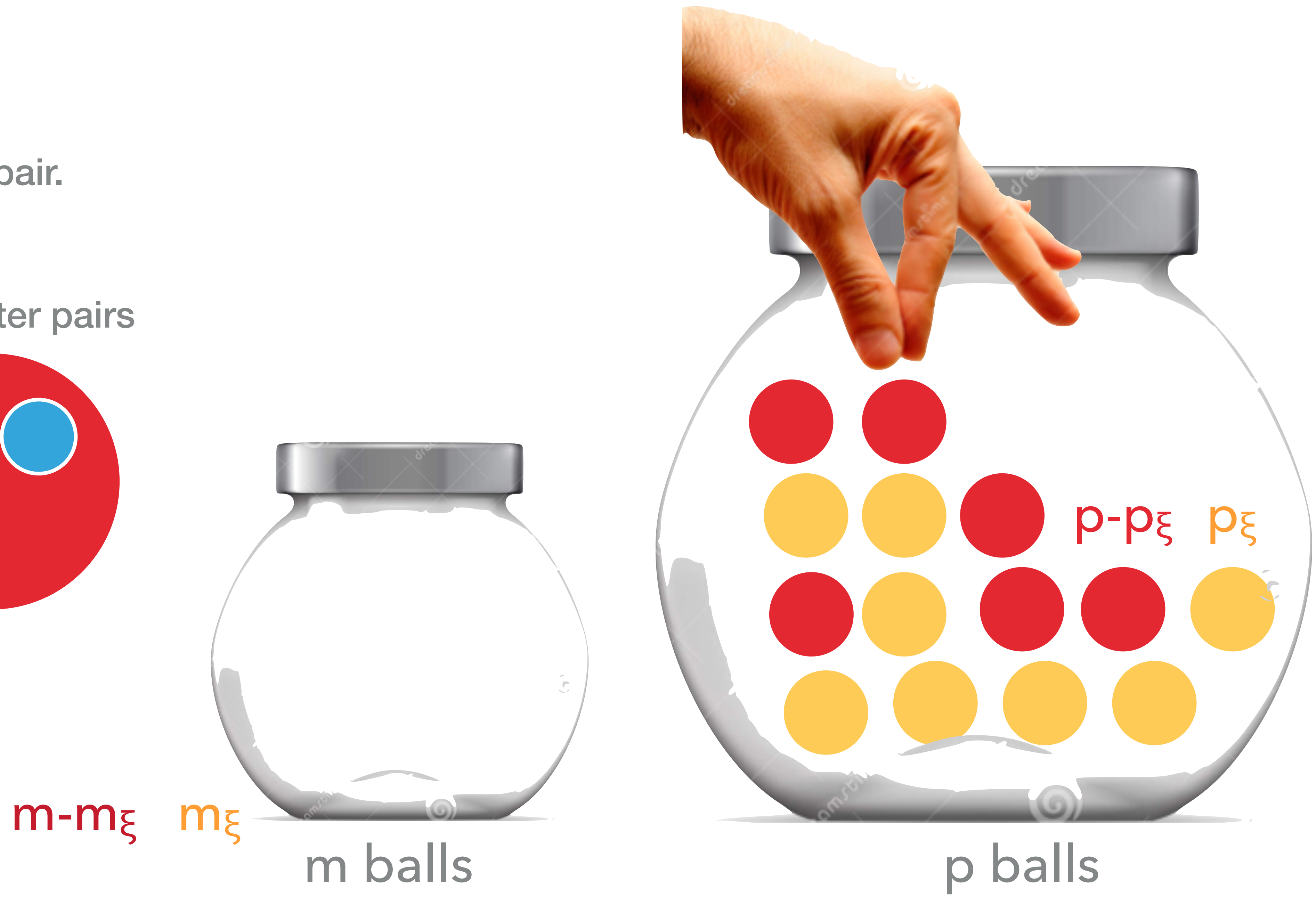
URN MODEL

p total balls, p_ξ yellow and $p-p_\xi$ red.

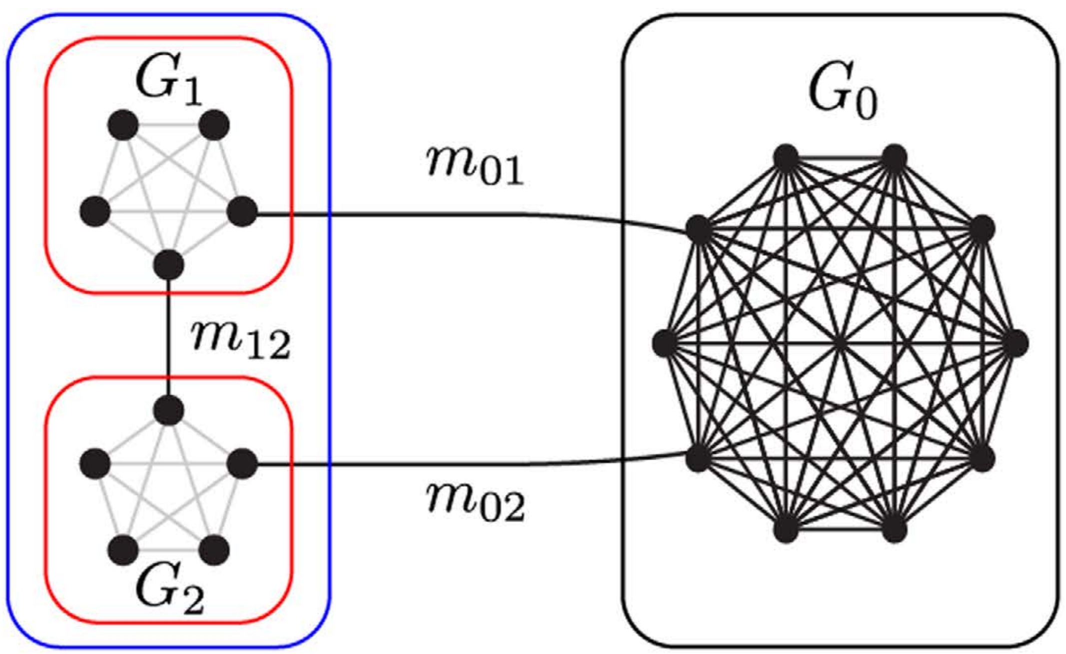
Pick m marbles, randomly, what is the probability of having at least m_ξ yellow balls?

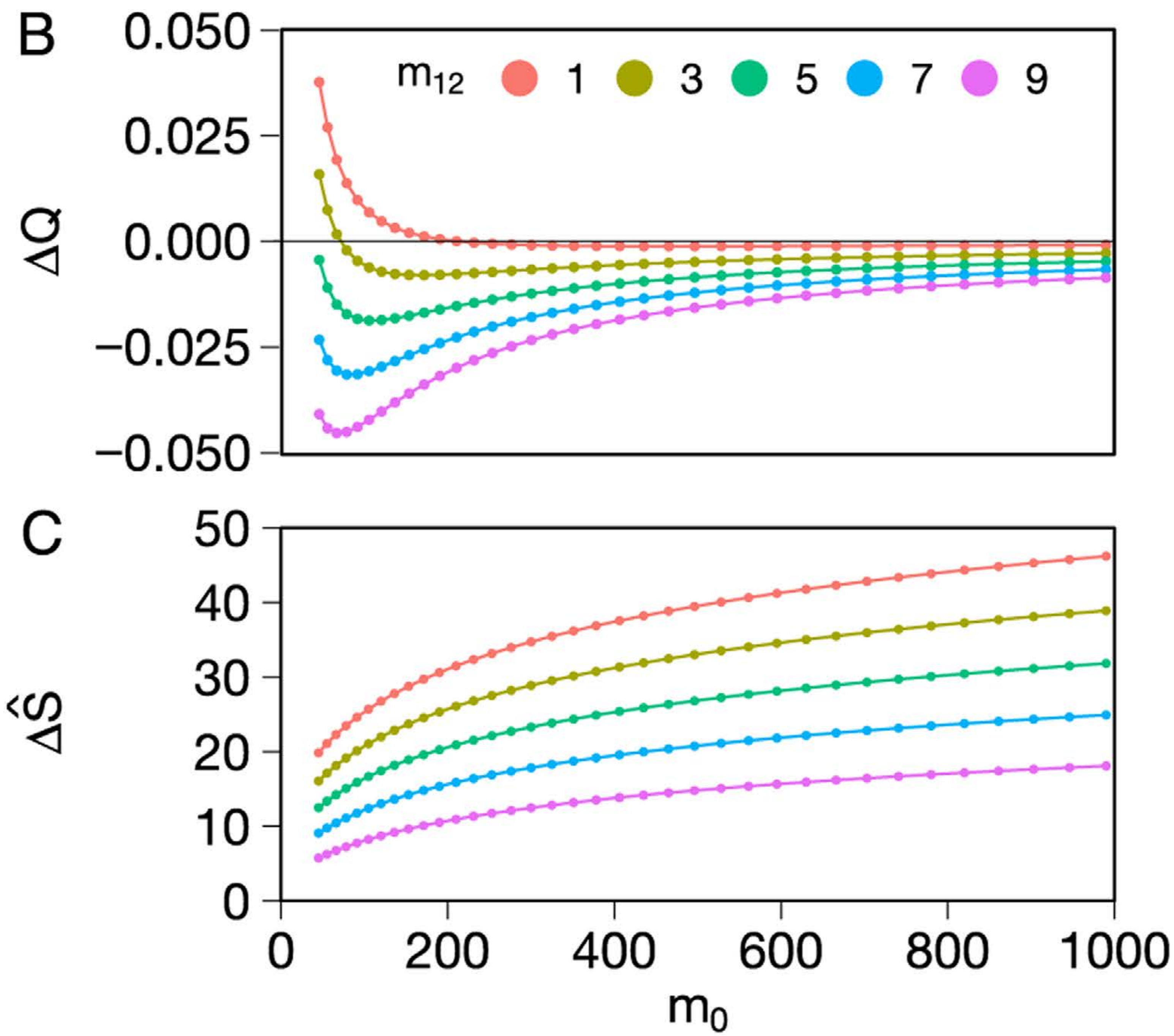
Every marble is a node pair.





RESOLUTION LIMIT AND SURPRISE





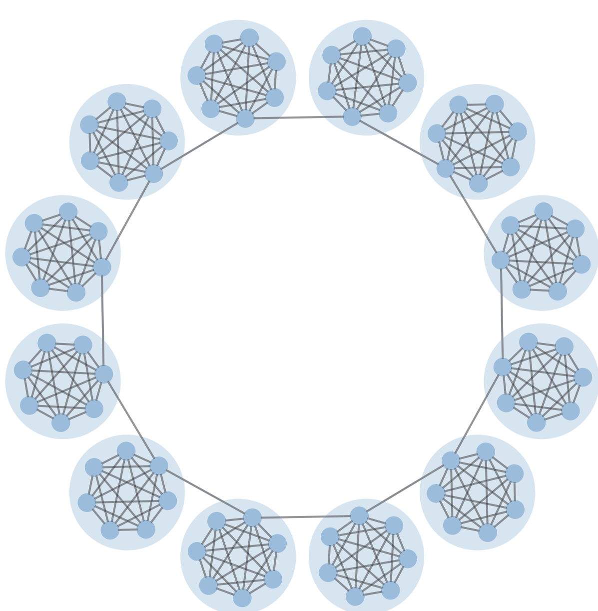
$$\Delta Q = Q_A - Q_B$$

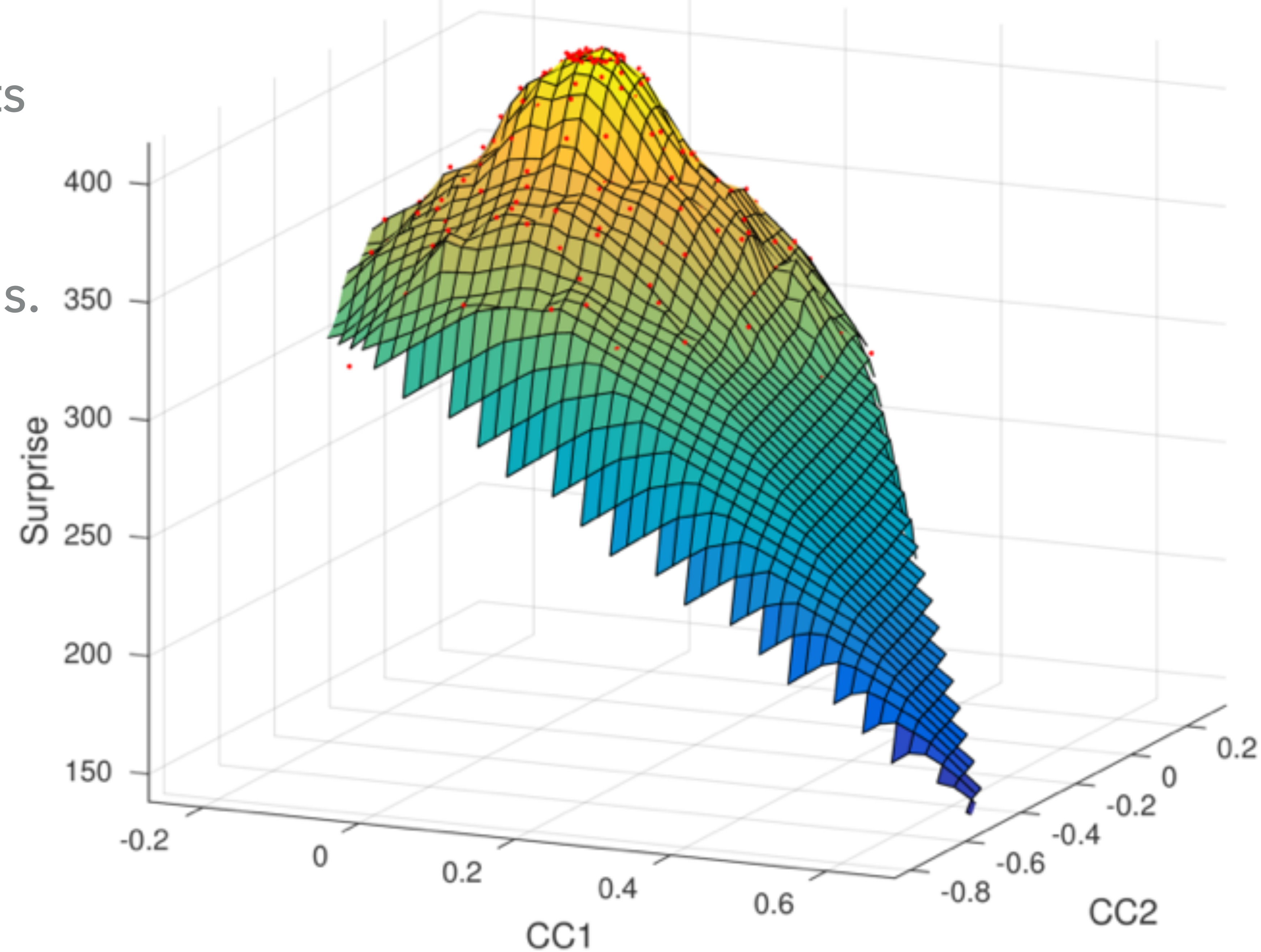
$$\Delta S = S_A - S_B$$

Nicolini, 2016a

NO DEGENERACY

- Degeneracy landscape of a k=24, n=5 ring of cliques.
- Curvilinear components analysis.
- Red points are solutions.
- Distance embedding.

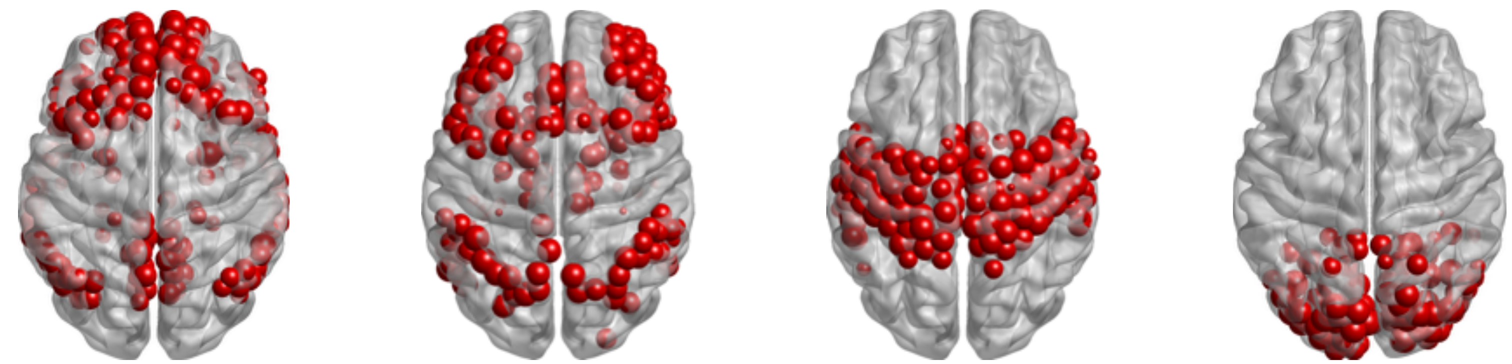




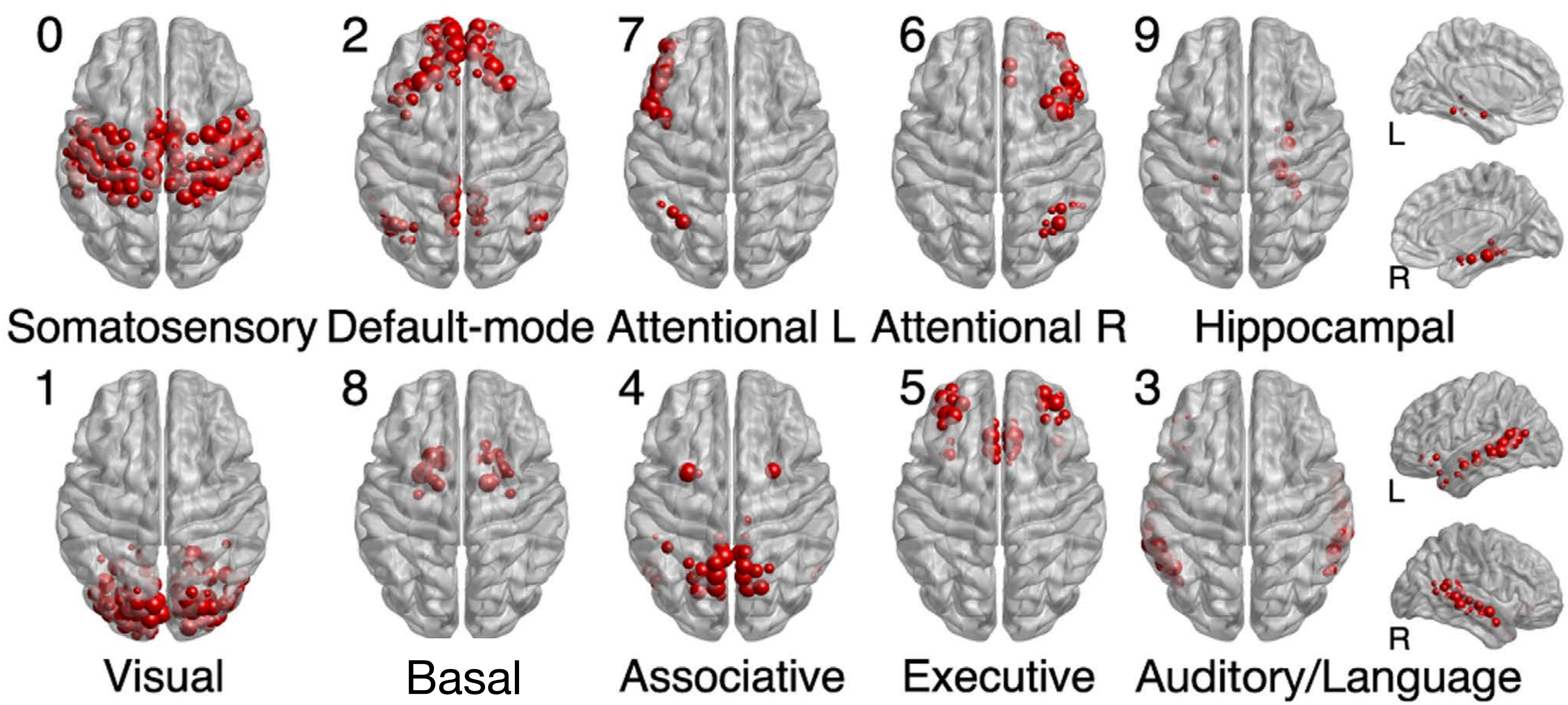
Nicolini, ArXiv 2016

APPLICATION OF SURPRISE OPTIMIZATION

Modularity



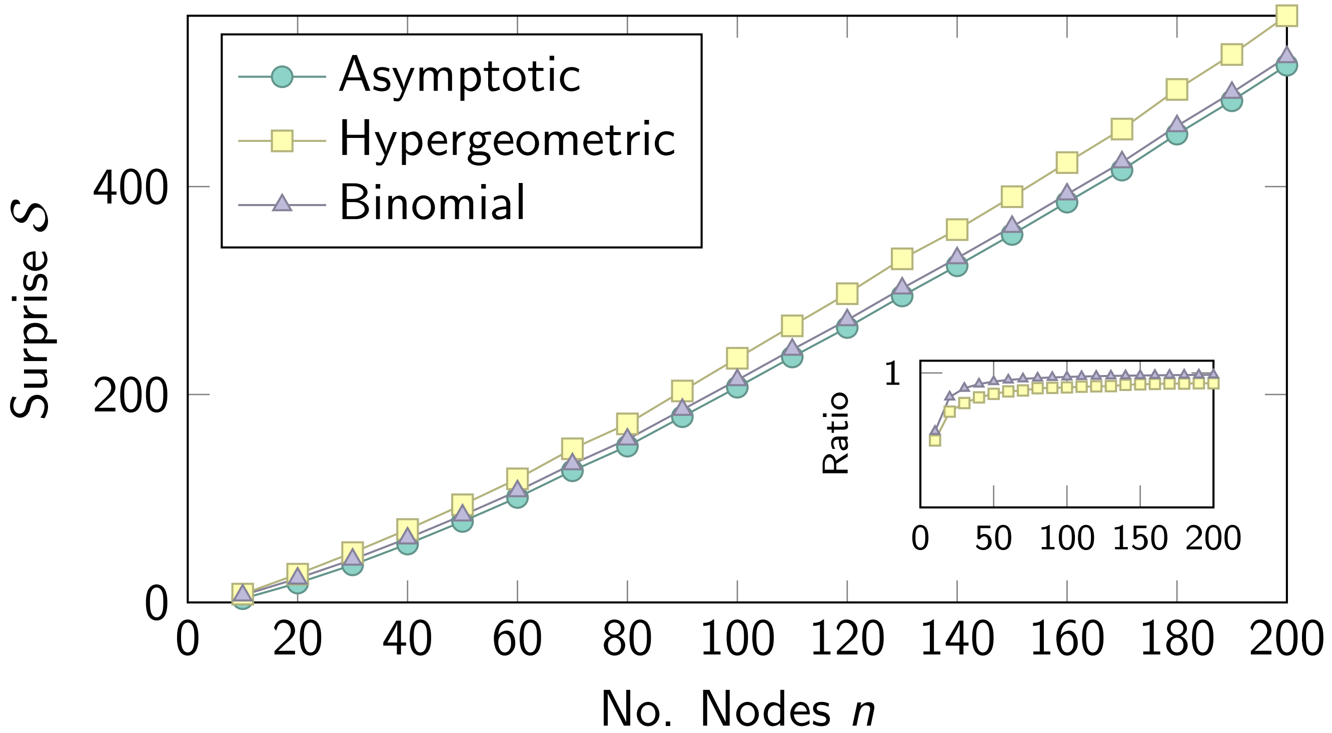
Surprise



ASYMPTOTICAL SURPRISE

$$S_a = mD_{\mathrm{KL}}\left(\frac{m_\zeta}{m} \middle\| \frac{p_\zeta}{p}\right)$$

- Asymptotical approximation valid for large n.
- Information theoretic distributions pseudo-distance.
- Information gained.
- Supports weighted graphs.

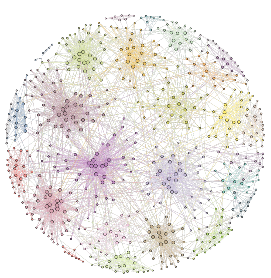


Traag, 2015

COMPARING ASYMPTOTICAL SURPRISE WITH OTHER METHODS

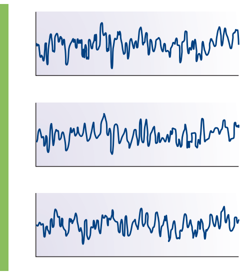
How to make fair comparison on brain networks if we don't have the brain networks community structure?

COMPUTE THE NEAREST POSITIVE DEFINITE MATRIX



GENERATE A NETWORK WITH GIVEN COMMUNITY STRUCTURE

SIMULATE RS BOLD SIGNALS FOR MANY VIRTUAL SUBJECTS



LFR Model

neuroSim R package

Rician distribution

Fisher Transformation

Surprise, Infomap, Modularity

NMI

GET PARTITION SIMILARITY WITH THE PLANTED ONE

INJECT CORRELATION INTO SYNTHETIC TIME SERIES

RUN COMMUNITY DETECTION TO ASSESS EFFECTS OF NOISE

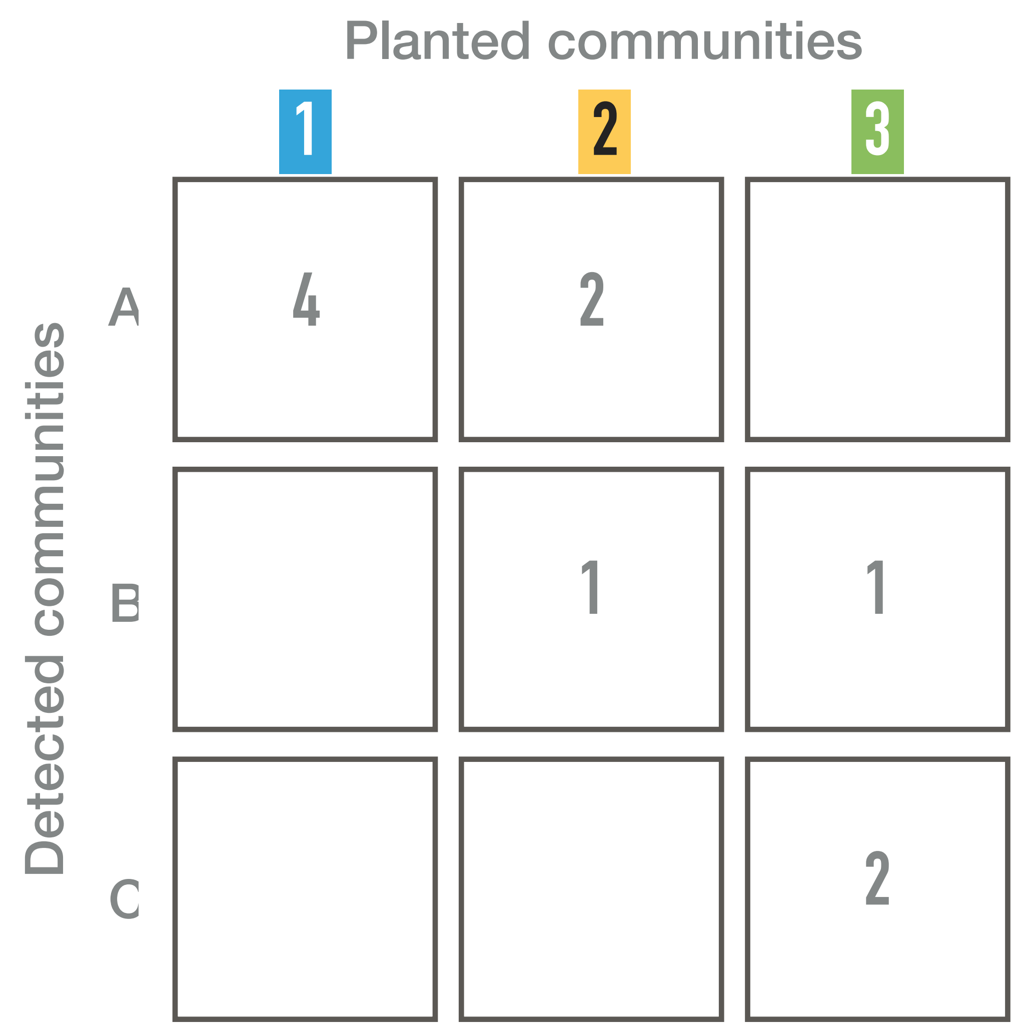
ADD REALISTIC NOISE TO TIME SERIES

GRAPH CREATION

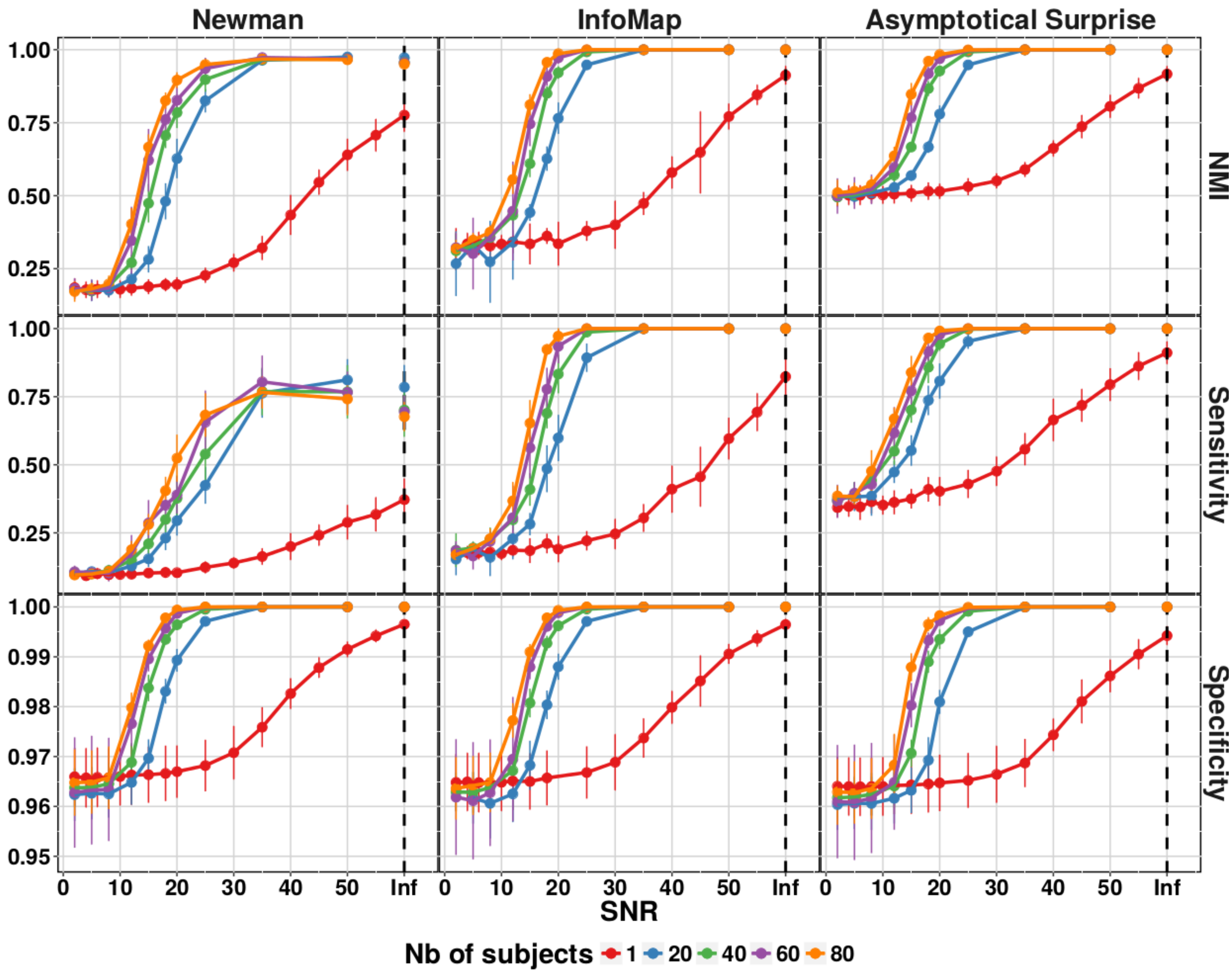
COMPARING COMMUNITY DETECTION ON BRAIN NETWORKS

- Varied SNR=$\langle S \rangle / \sigma_n$ and number of subjects.
- Normalized Mutual Information (NMI)
- Matrix C_{ij} is the number of nodes in the planted community-i appearing in the detected community-j.
- Sensitivity (Recall) = TP/(TP + FN)
- Specificity = TN/(TN + FP)

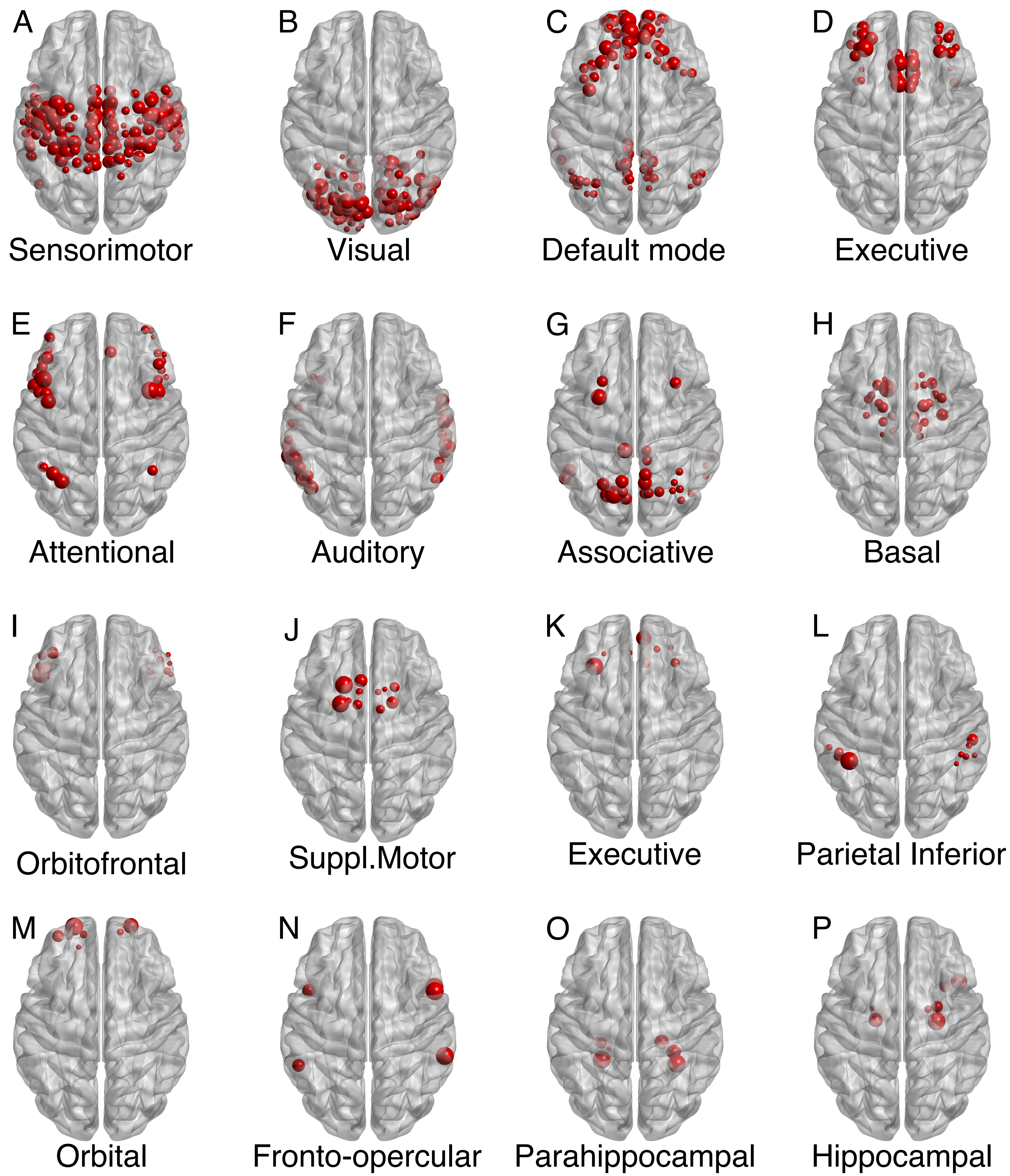
TP	FN
FP	TN



RESULTS


Newman
InfoMap
Asymptotical Surprise
NMI
Sensitivity
Specificity
1.00
0.75
0.50
0.25
0.99
0.98
0.97
0.96
0.95
0 10 20 30 40 50 Inf
SNR
Nb of subjects 1 20 40 60 80

HUMAN RESTING STATE DATE



CONCLUSIONS

- Functional connectivity can be studied with graph-theoretical approaches.
- Resolution limit hindered detection of functional modules.
- Coarse resolution hides small details and differences between groups.
- Asymptotical Surprise can identify neurofunctionally plausible and anatomically well-defined substructures.

But …

- It may overfit the community structure due to its improved sensitivity.

THANK YOU!

github.com/carlonicolini
brainetlab.github.io

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Cecile Bordier

REFERENCES

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Nicolini C., Bordier C., Bifone A. Arvix 1609.04316 arvix.org/1609.04316