COMMUNITY DETECTION IN BRAIN FUNCTIONAL NETWORKS BEYOND THE RESOLUTION LIMIT

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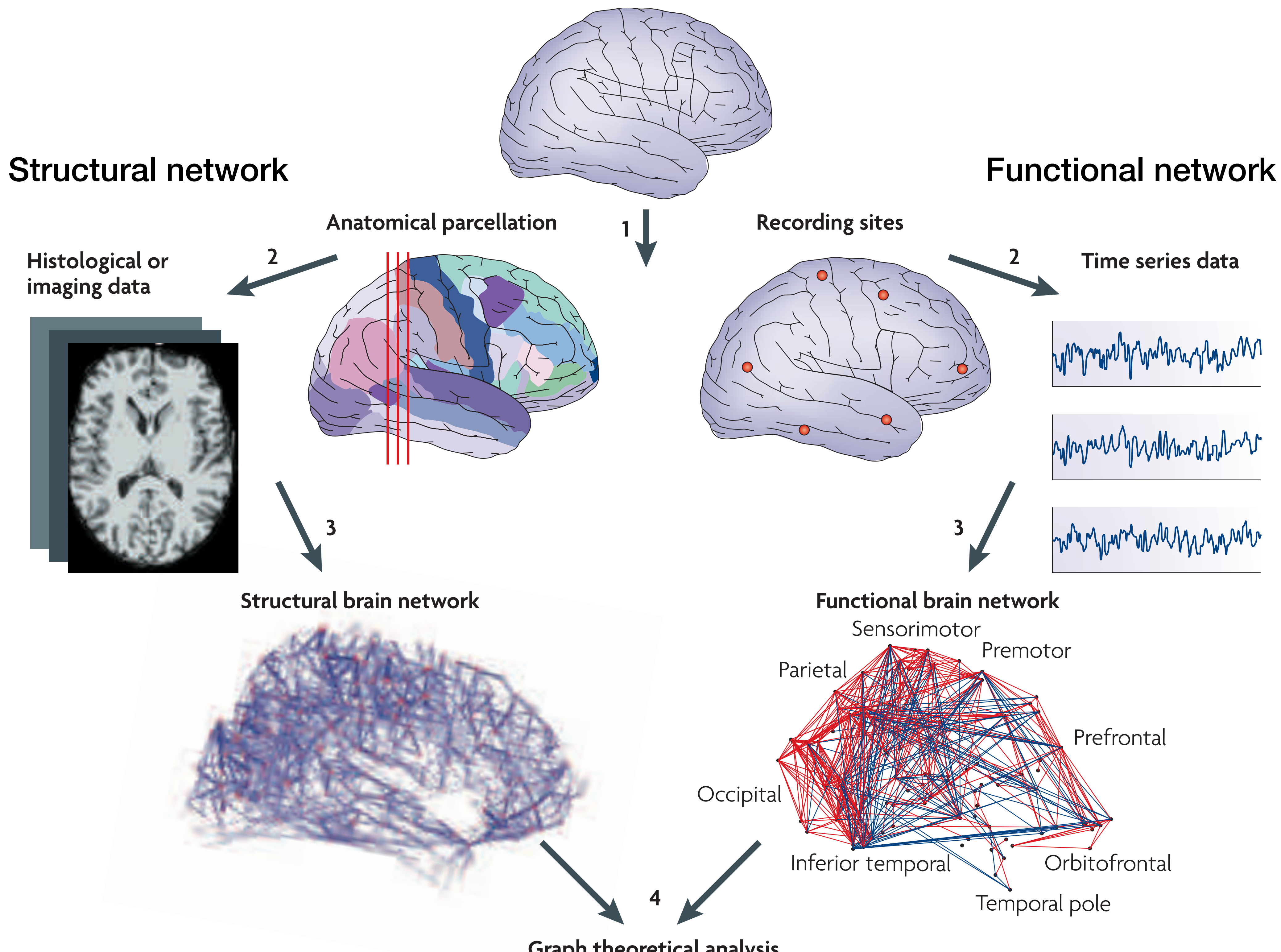
brainetlab.github.io

arvix.org/1609.04316

GRAPH THEORY FOR BRAIN NETWORKS



Bullmore, Nat.Rev.Neuro. 2009

FUNCTIONAL BRAIN NETWORKS

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- A mirror over the living brain.

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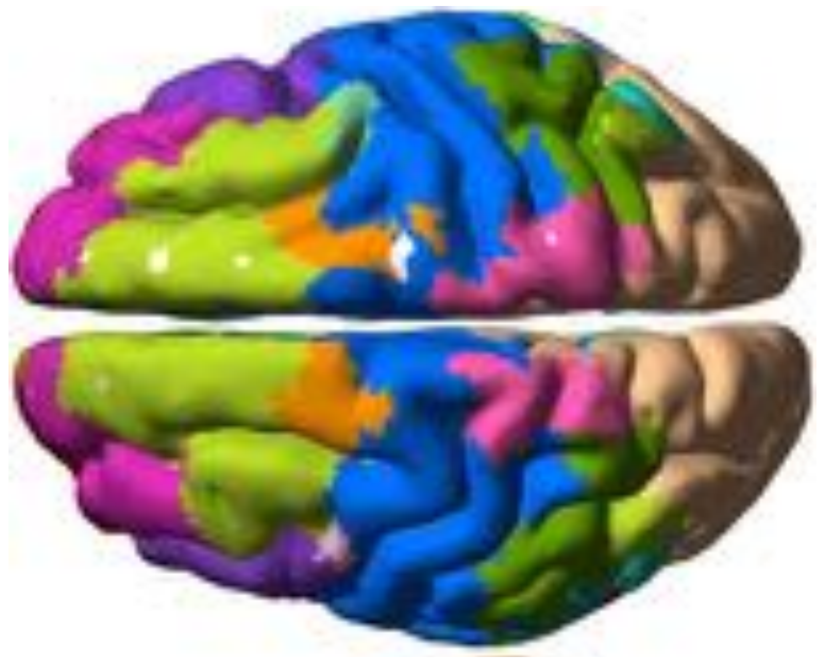
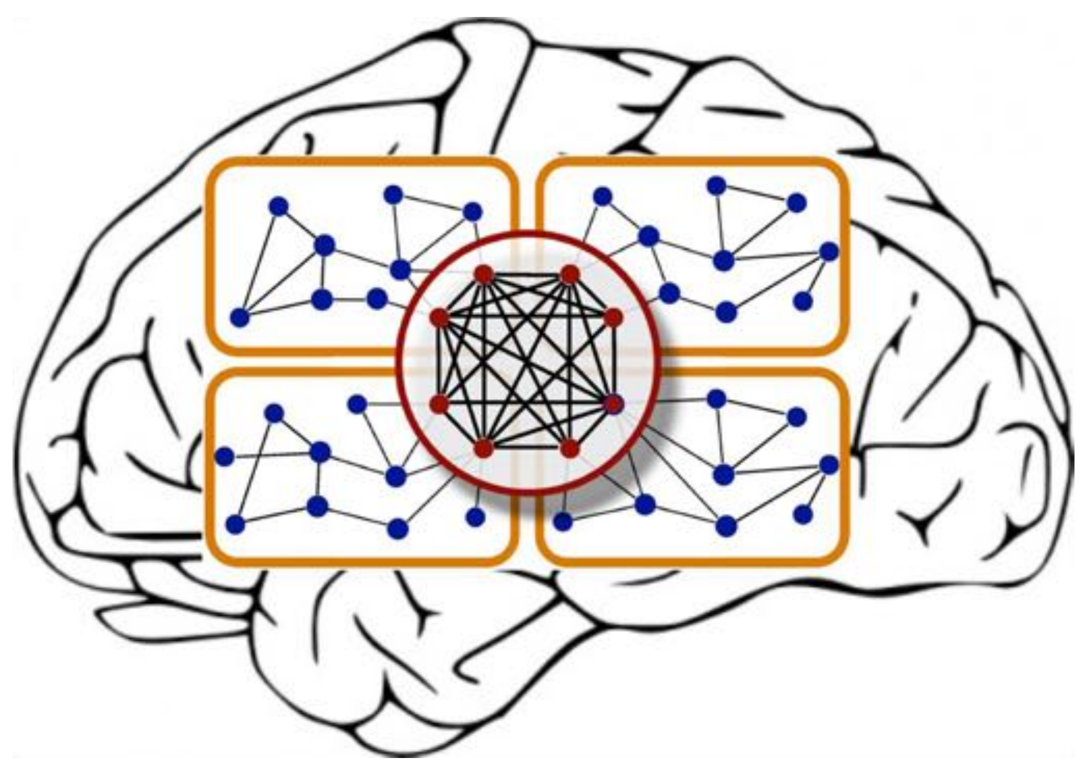
- Modular structure of FC connectivity.
- Graph theoretical community detection unveils the mesoscopic organization of functional connectivity.



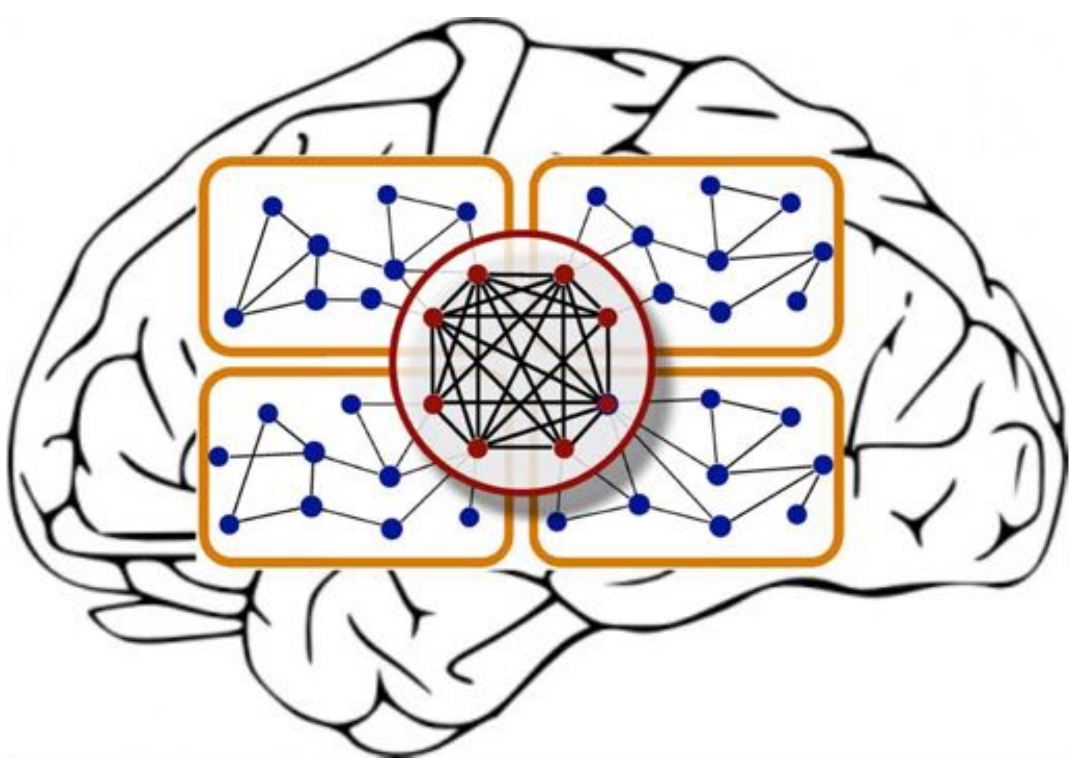
WHY LOOKING FOR MODULES IN THE BRAIN?



Kaiser, Front.Neuroinf. [2010]

WHY LOOKING FOR MODULES IN THE BRAIN?

- "Nearly decomposable systems" are faster to adapt and evolve in a changing environment [Simon 1962].



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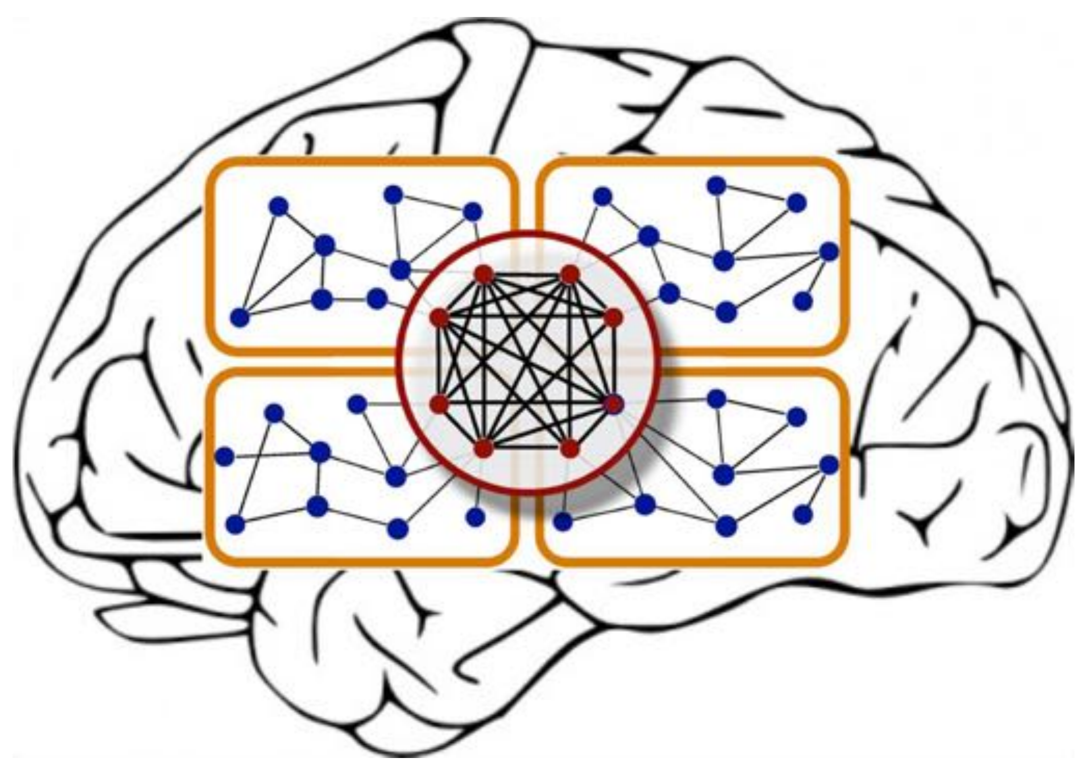

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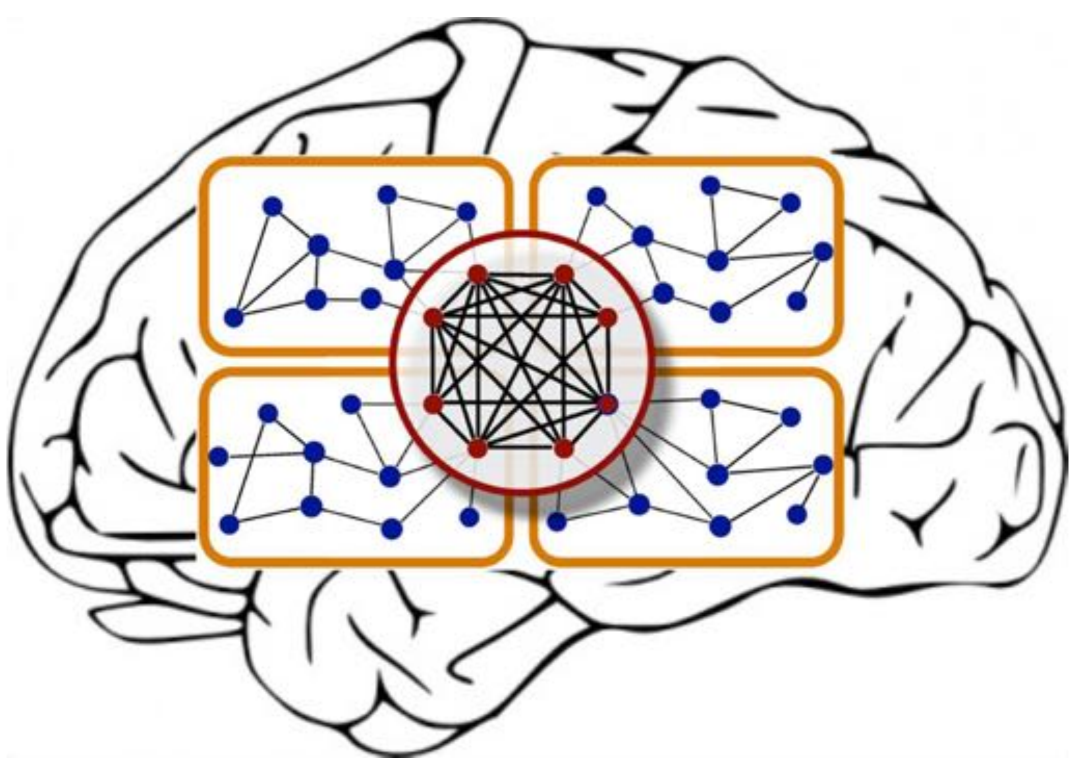

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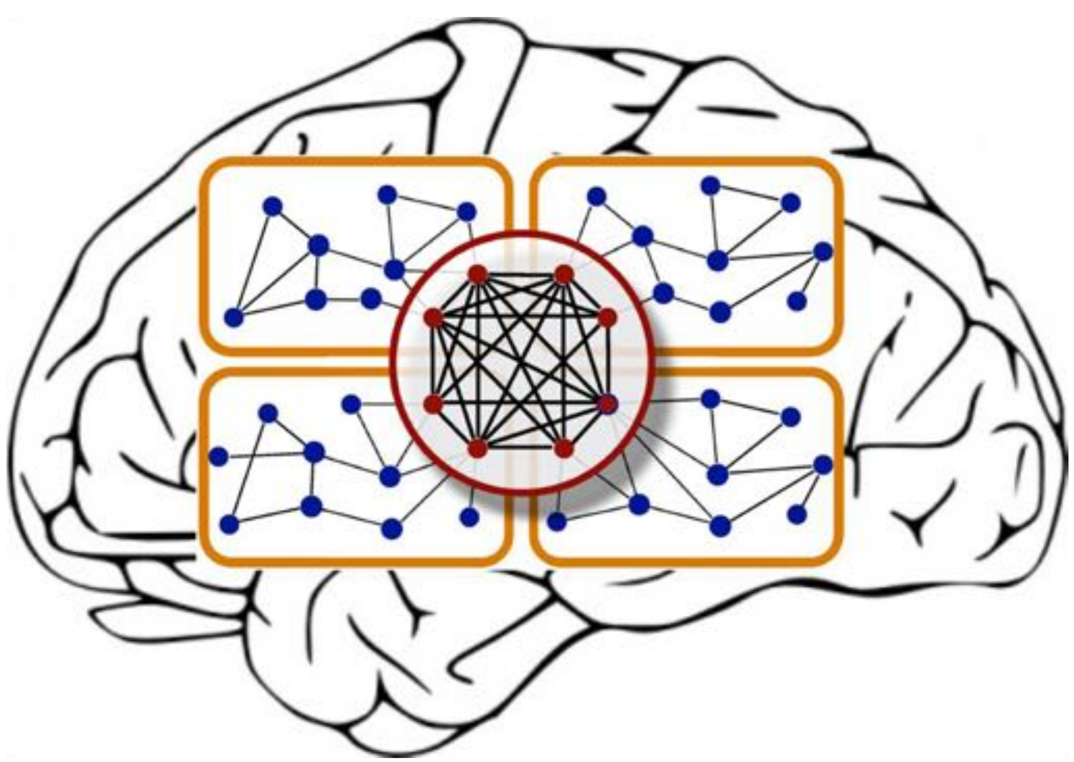
- Allows for functional segregation and integration.
- Coevolution of structural and functional connectivity.



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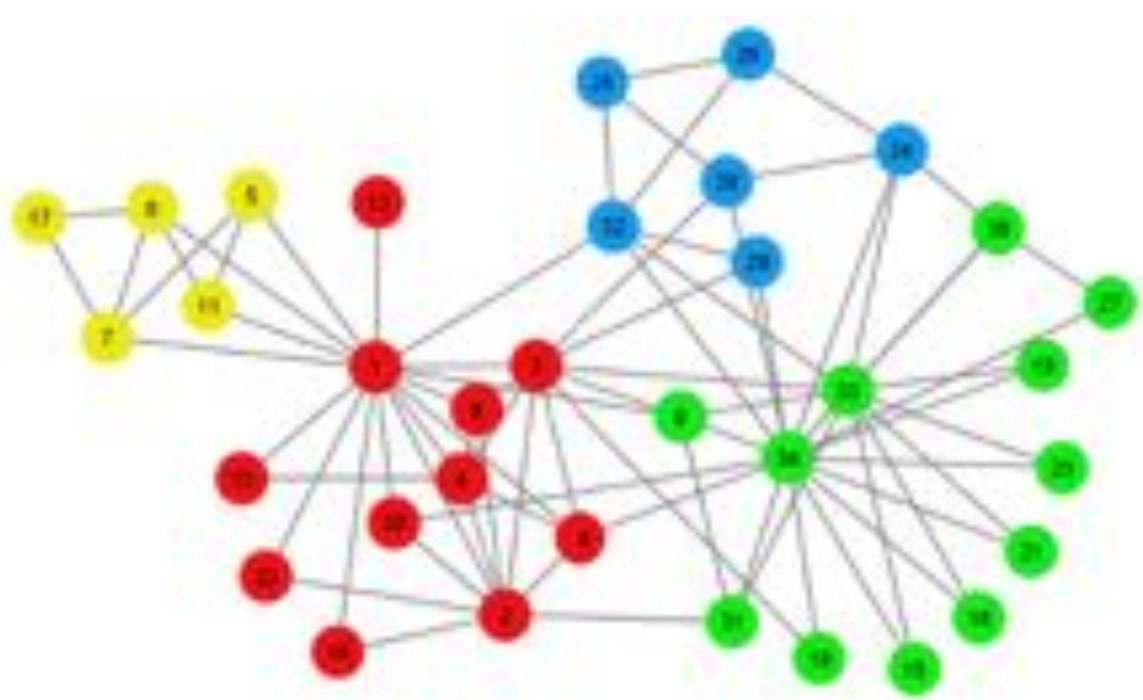
NEWMAN-GIRVAN MODULARITY

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

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

Good et al, PRE, 2010

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But it has some problems:

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- **Resolution limit:**
  Inability to detect communities smaller than a certain scale.

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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

Adapted from Traag, 2011

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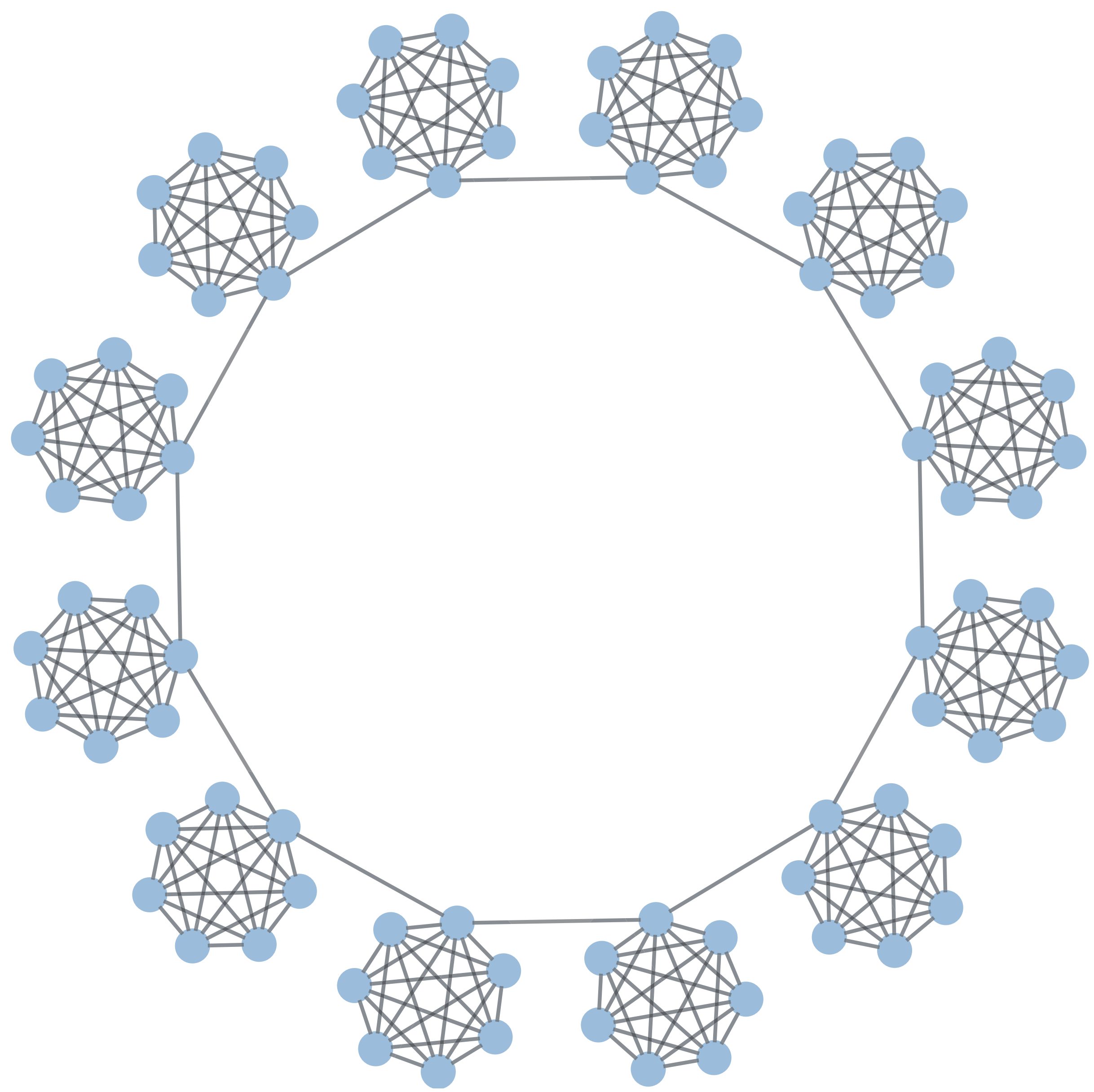

Original network

Adapted from Traag, 2011

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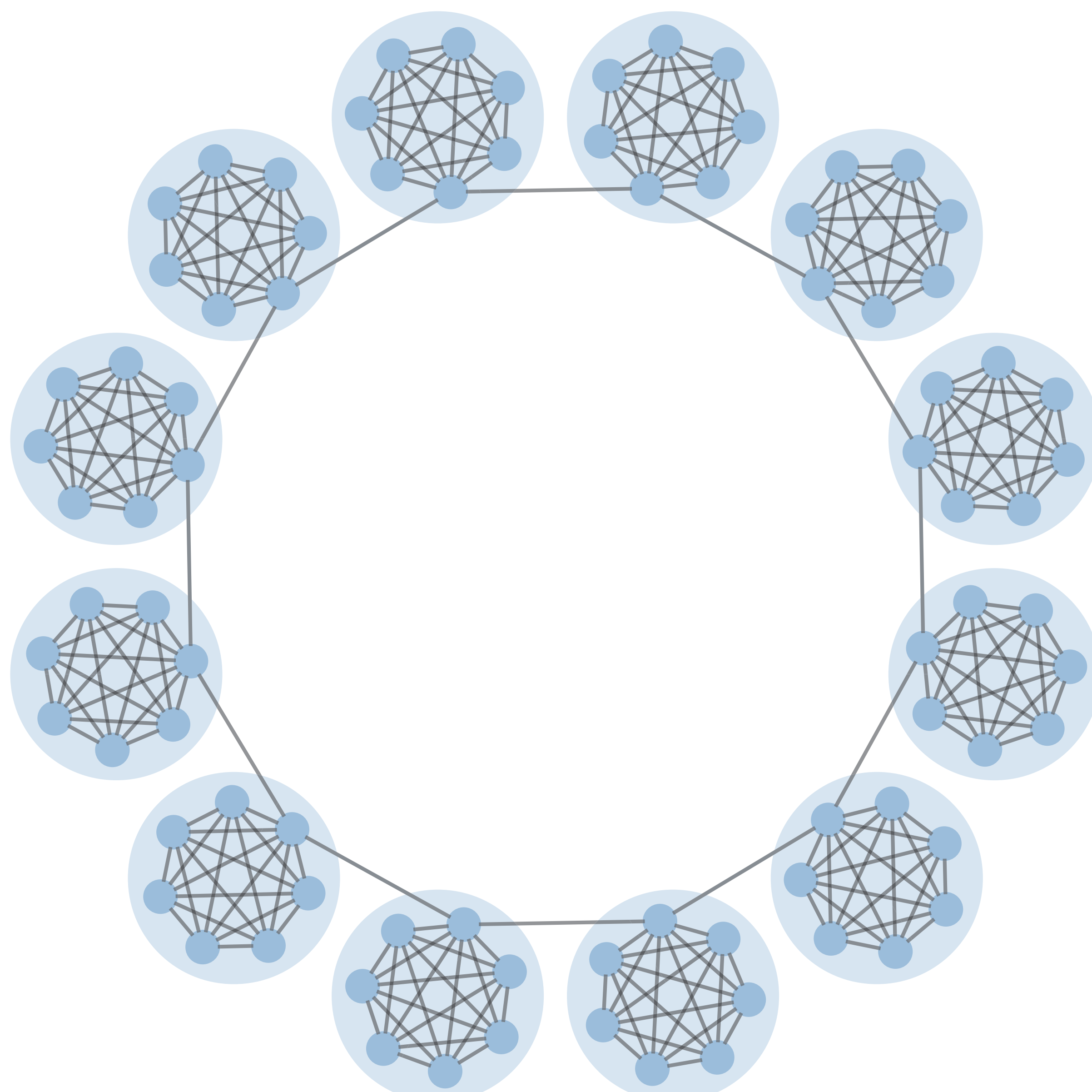
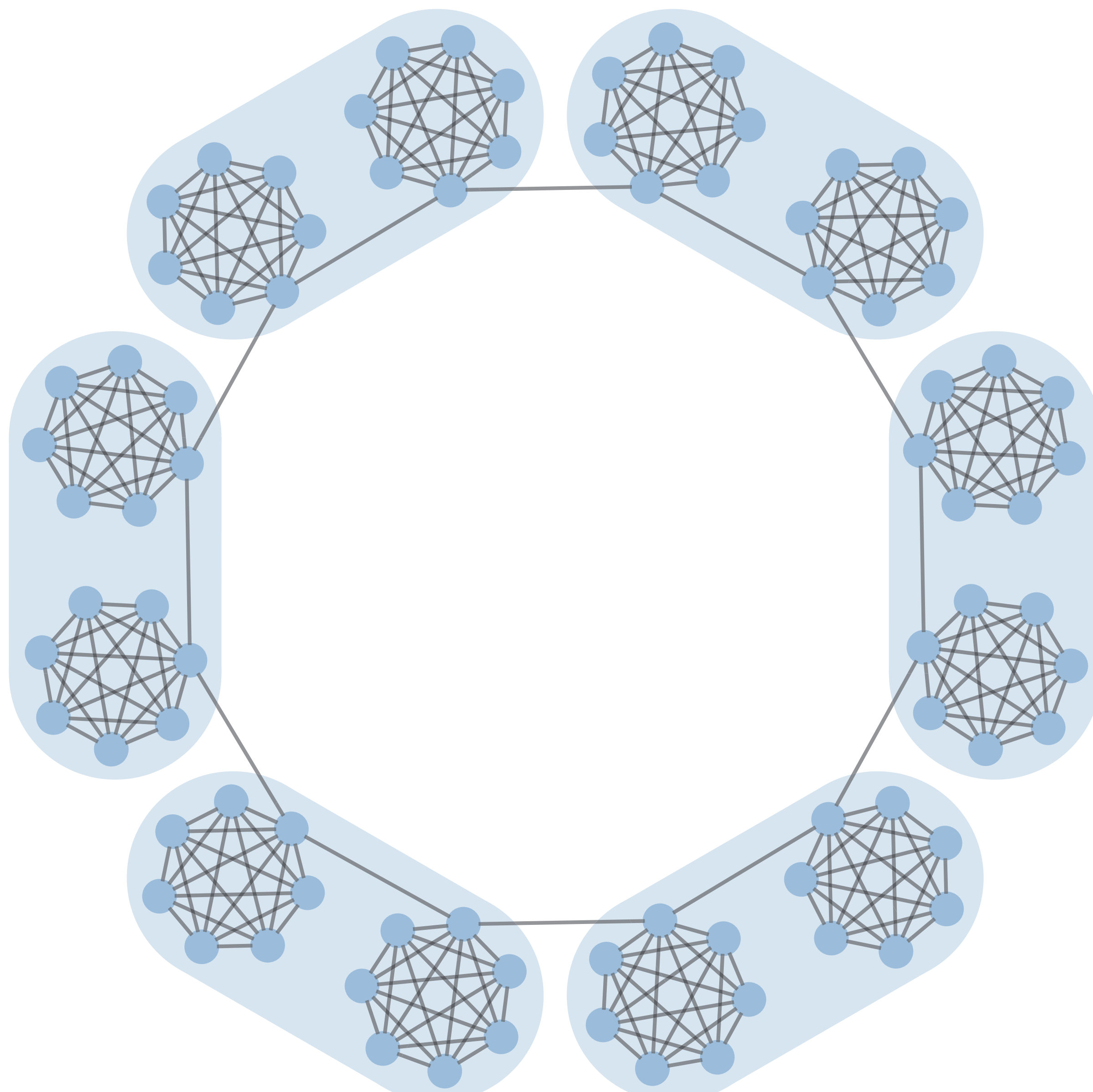


Ground truth partition

Adapted from Traag, 2011

RESOLUTION LIMIT: AN EXAMPLE

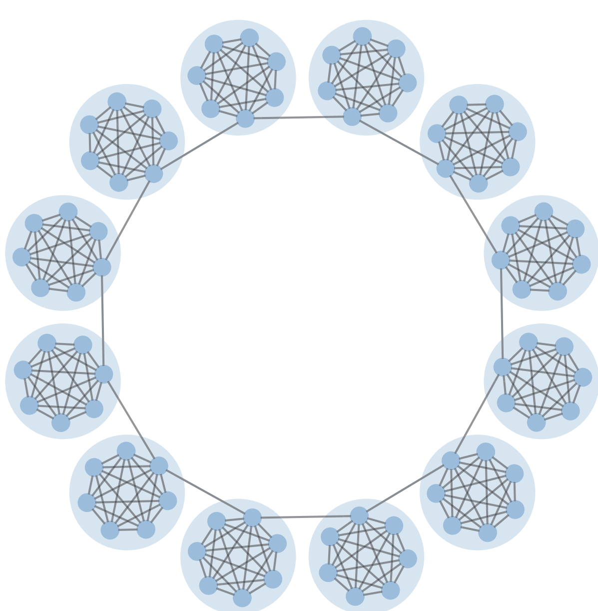


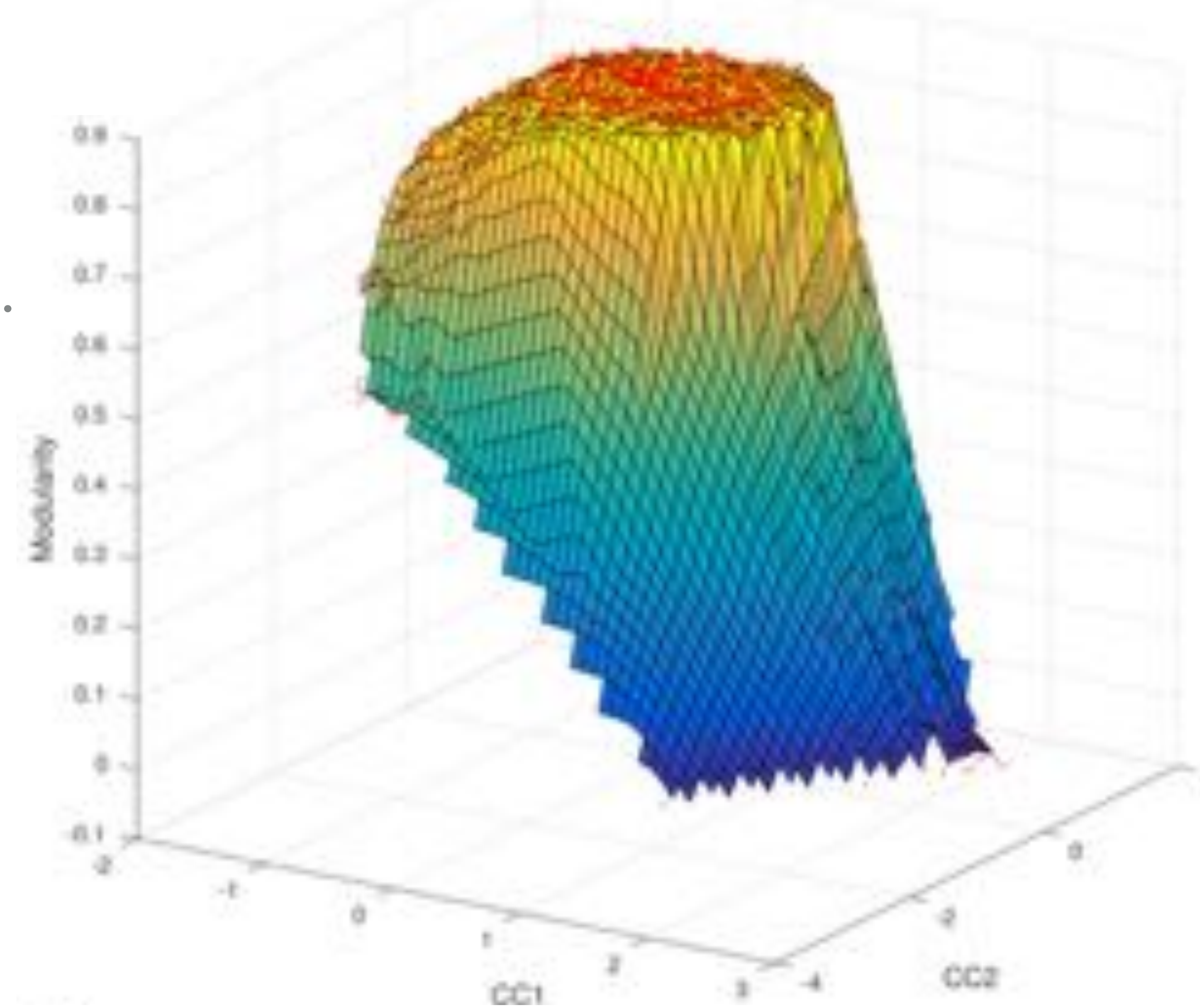
Maximum modularity partition

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.





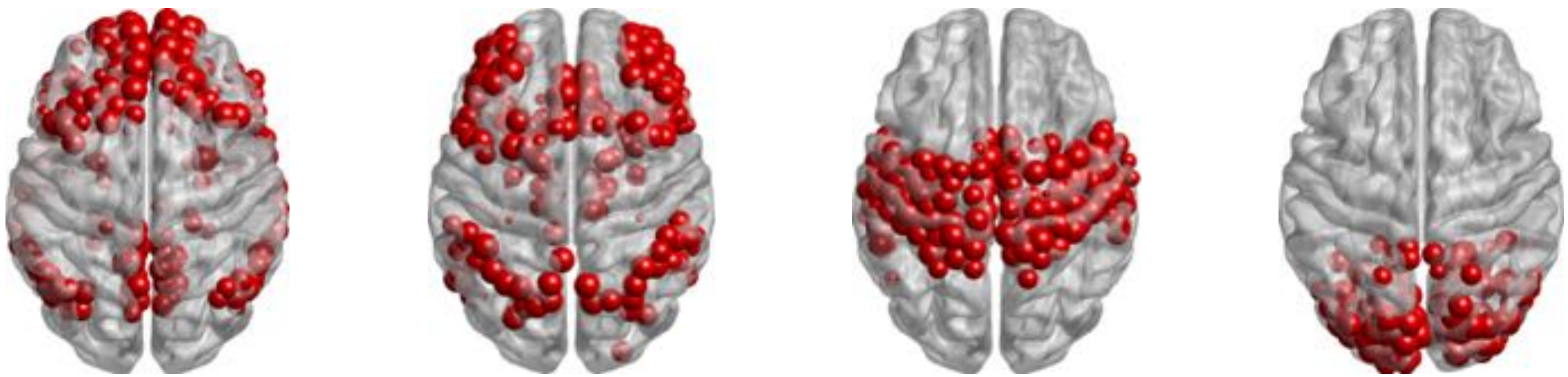
Adapted from Good et al. (2008)

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

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

Aldecoa, Sci.Rep. 2011

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- The higher Surprise, the better the clustering.
- Attention to the statistical significance of the partitioning.

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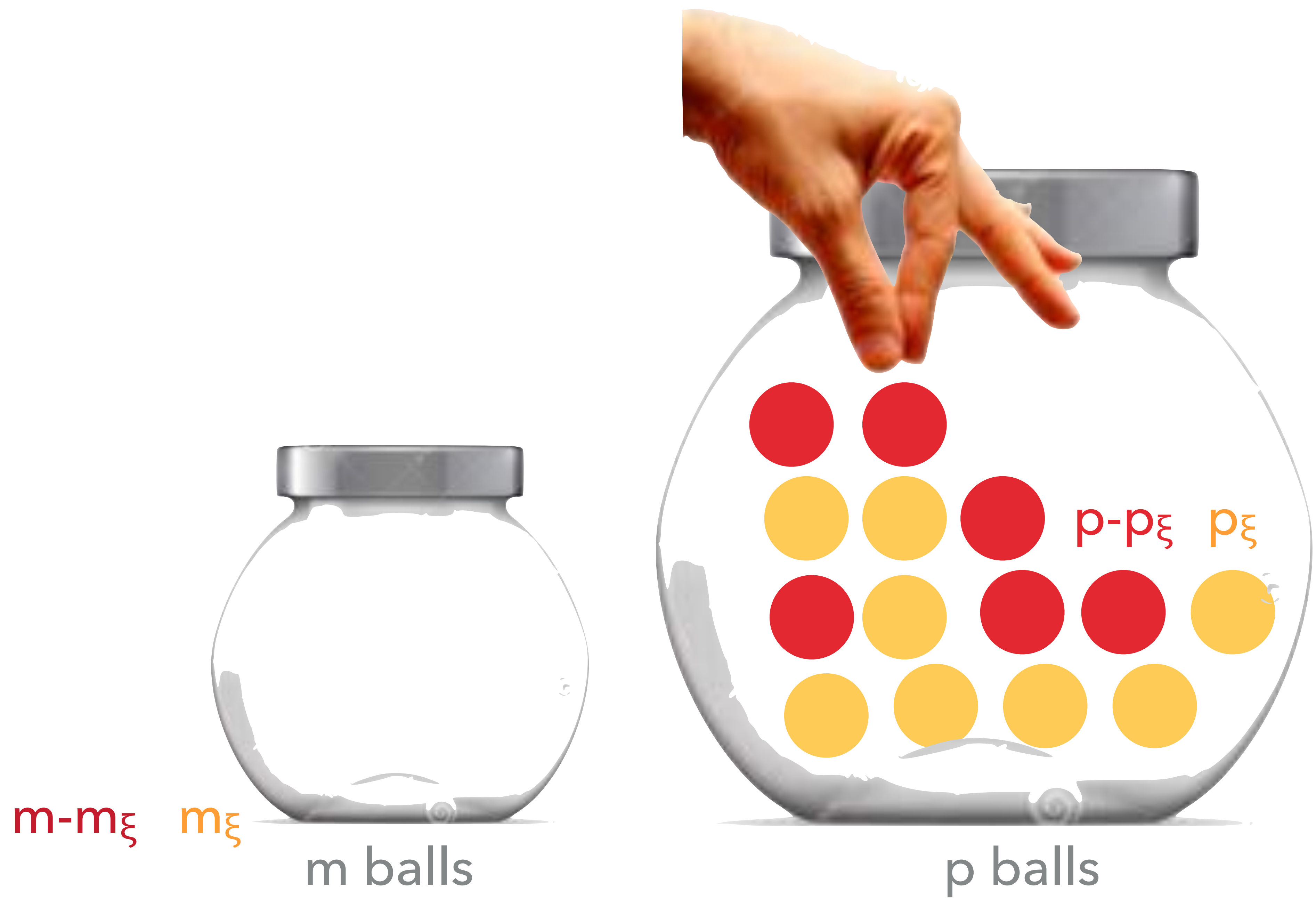
URN MODEL

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?



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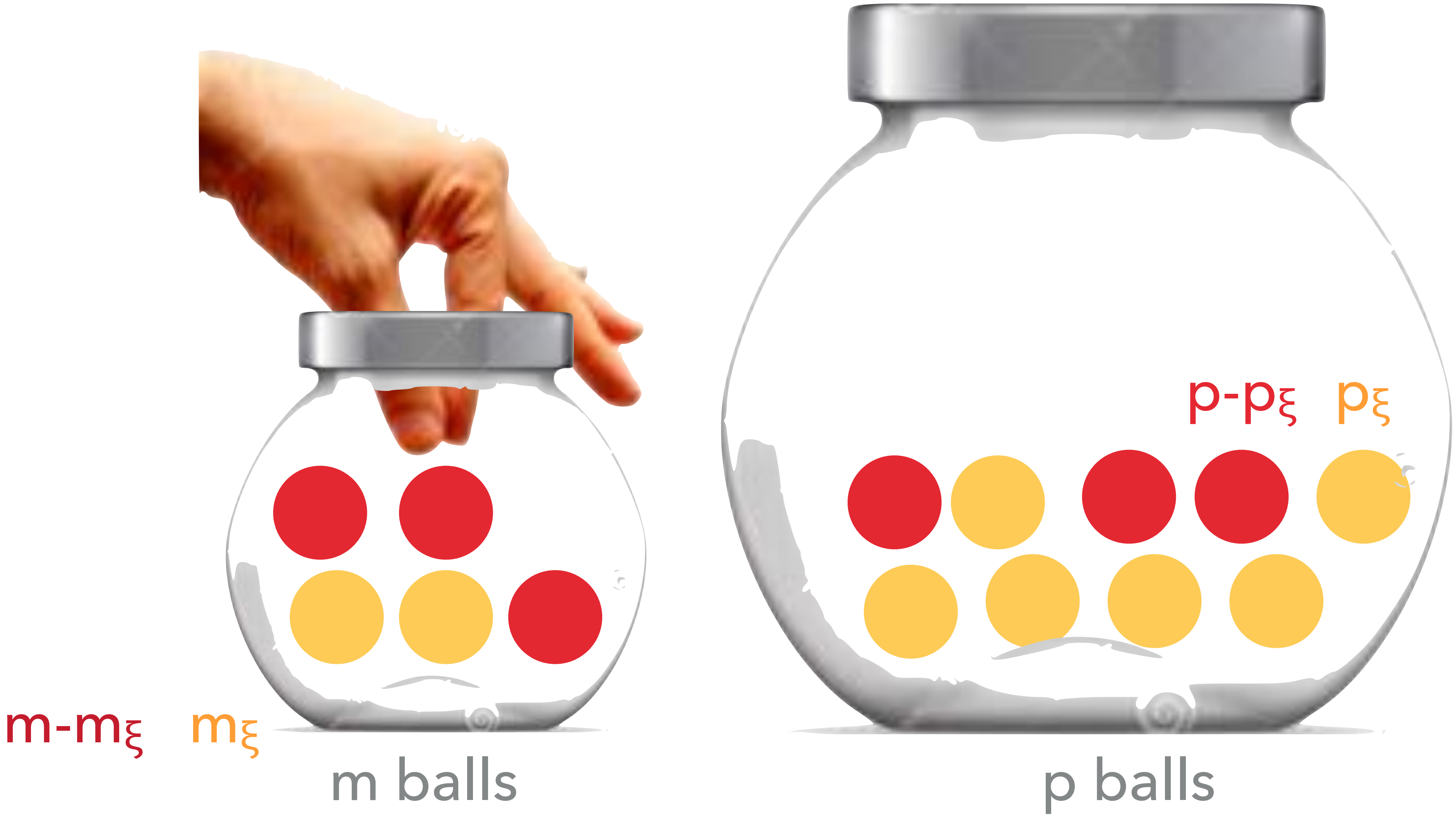

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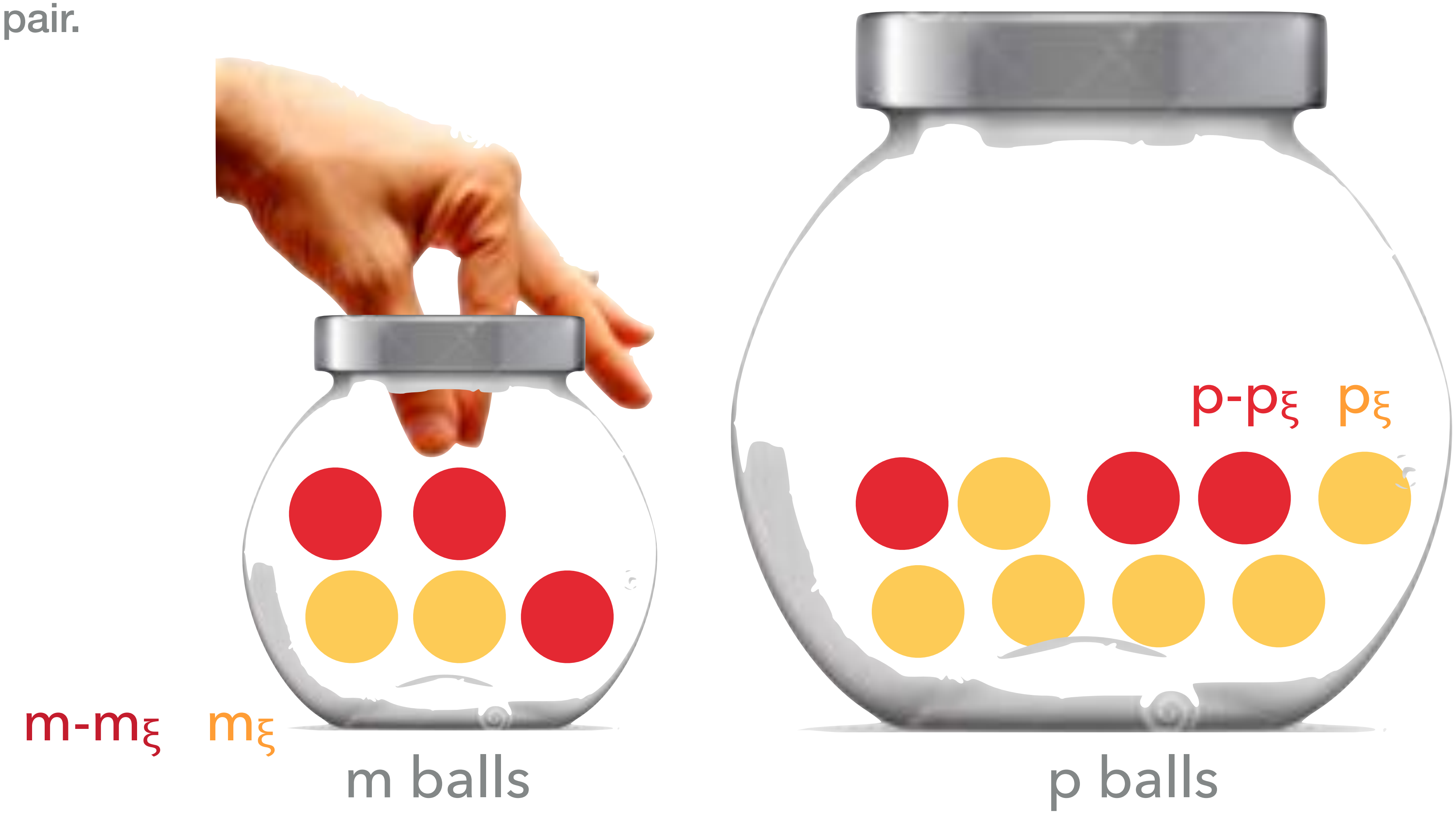

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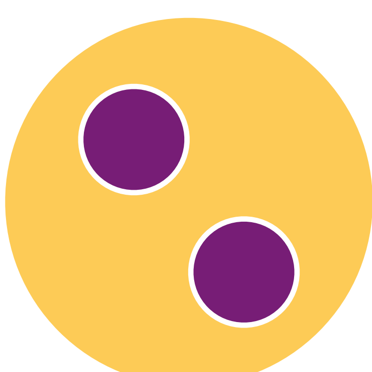

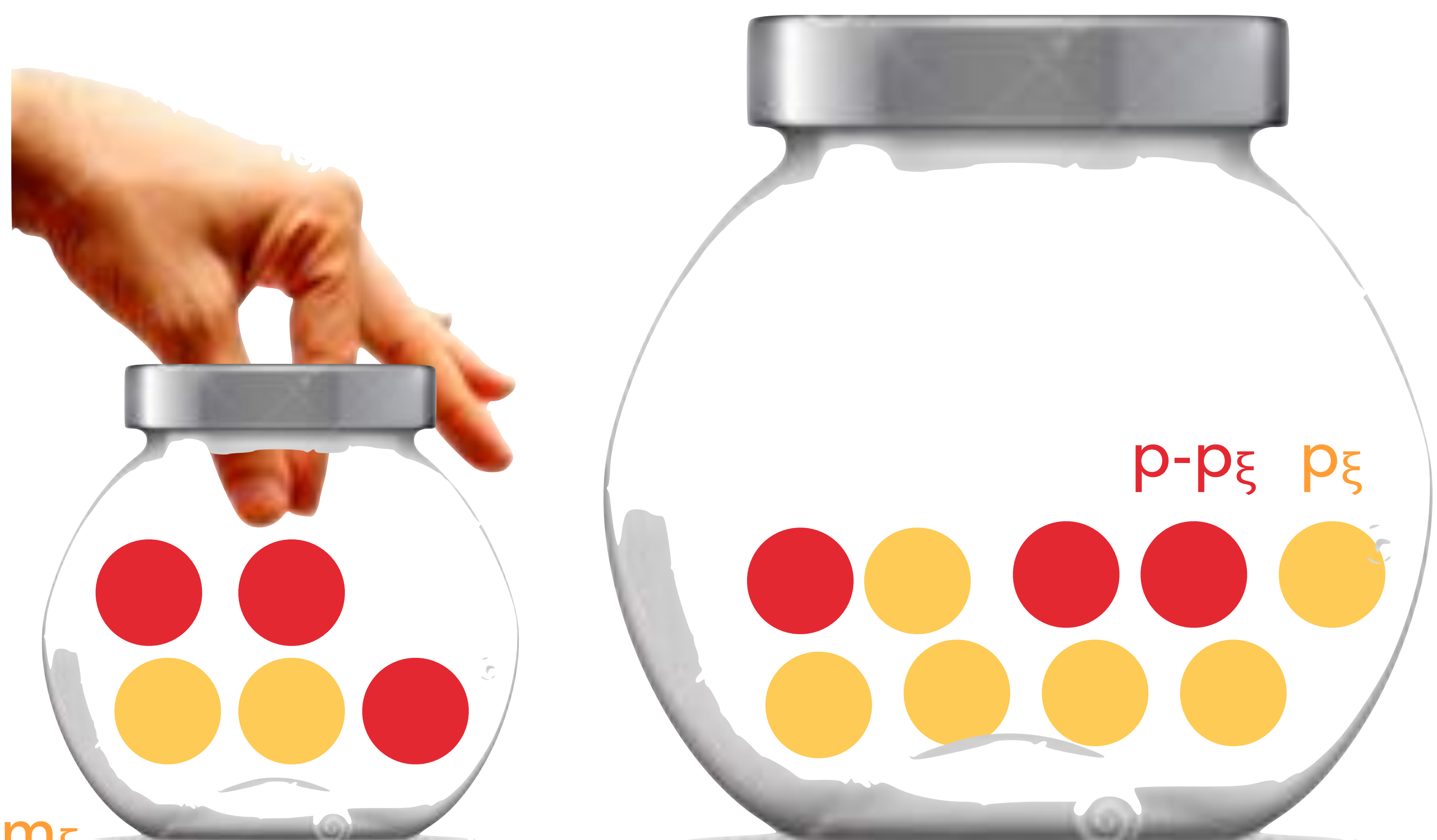

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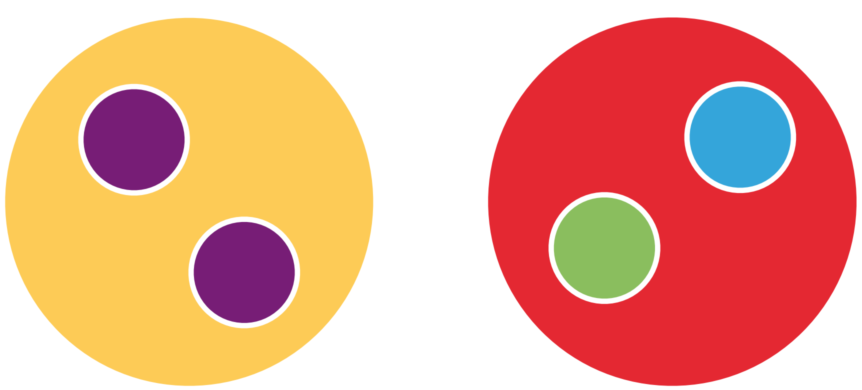
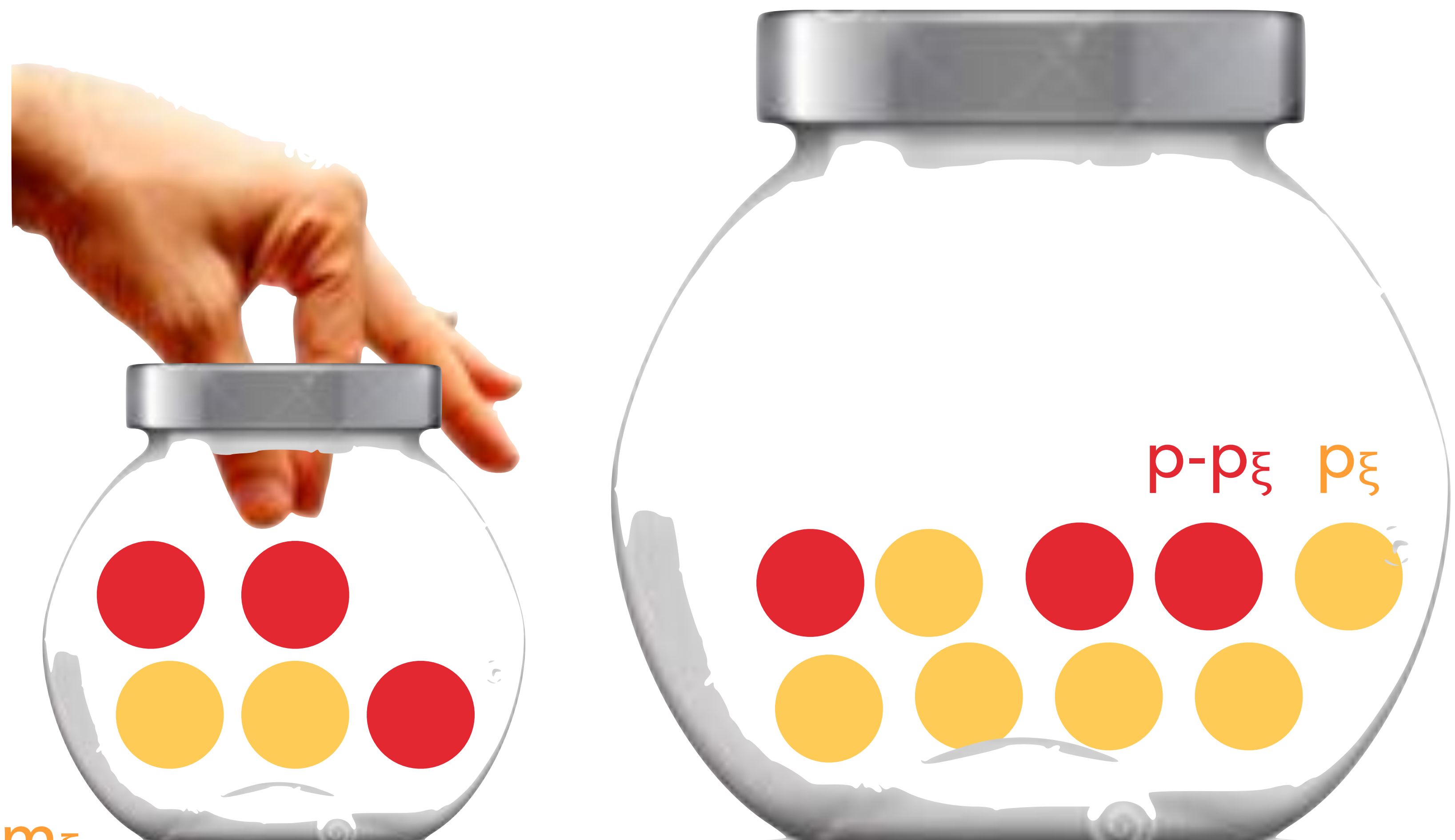
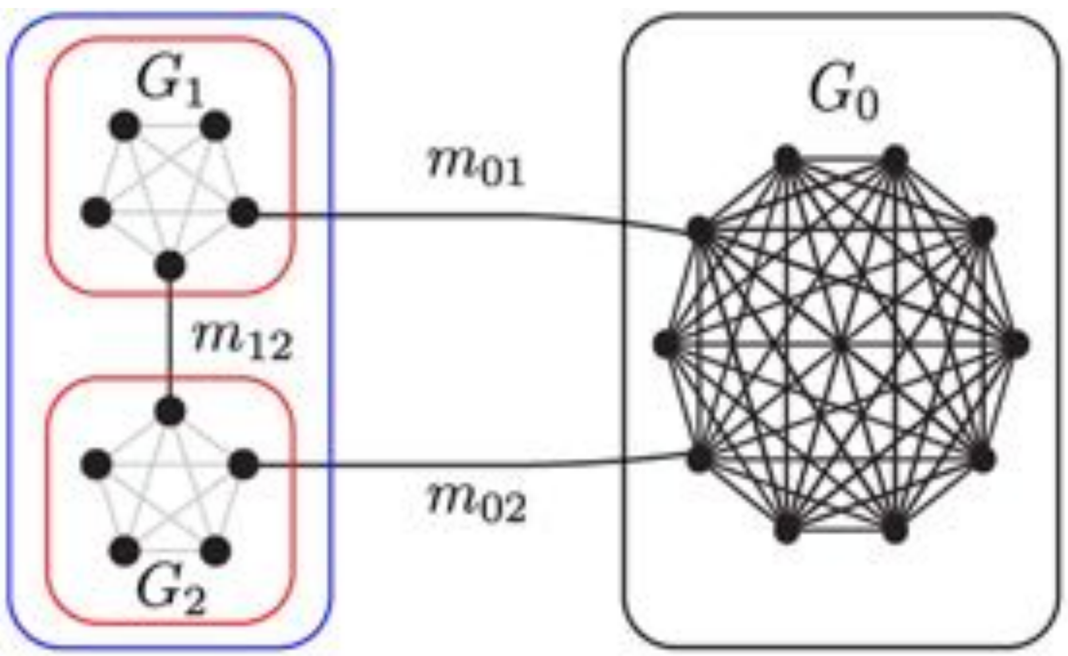
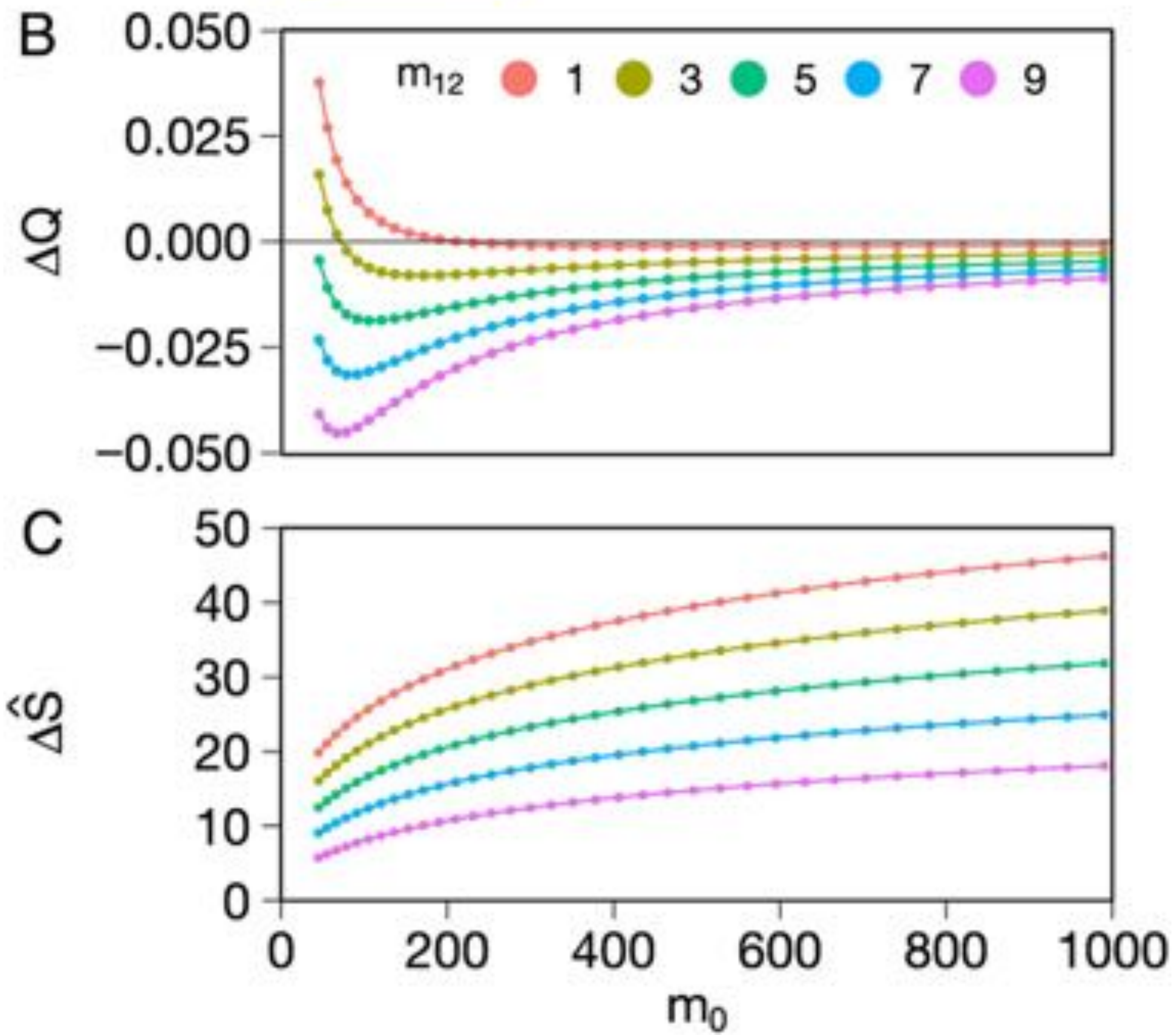
Intracluster pairs Intercluster pairs





RESOLUTION LIMIT AND SURPRISE





$$\Delta Q = Q_A - Q_B$$

$$\Delta S = S_A - S_B$$

Nicolini, 2016a

NO DEGENERACY

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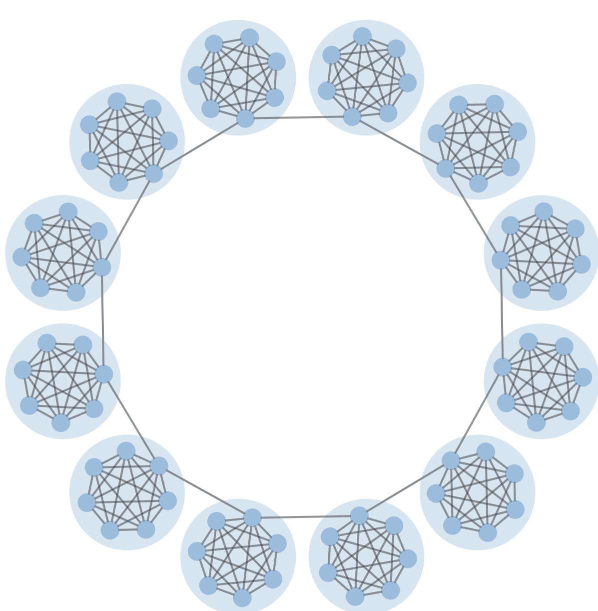
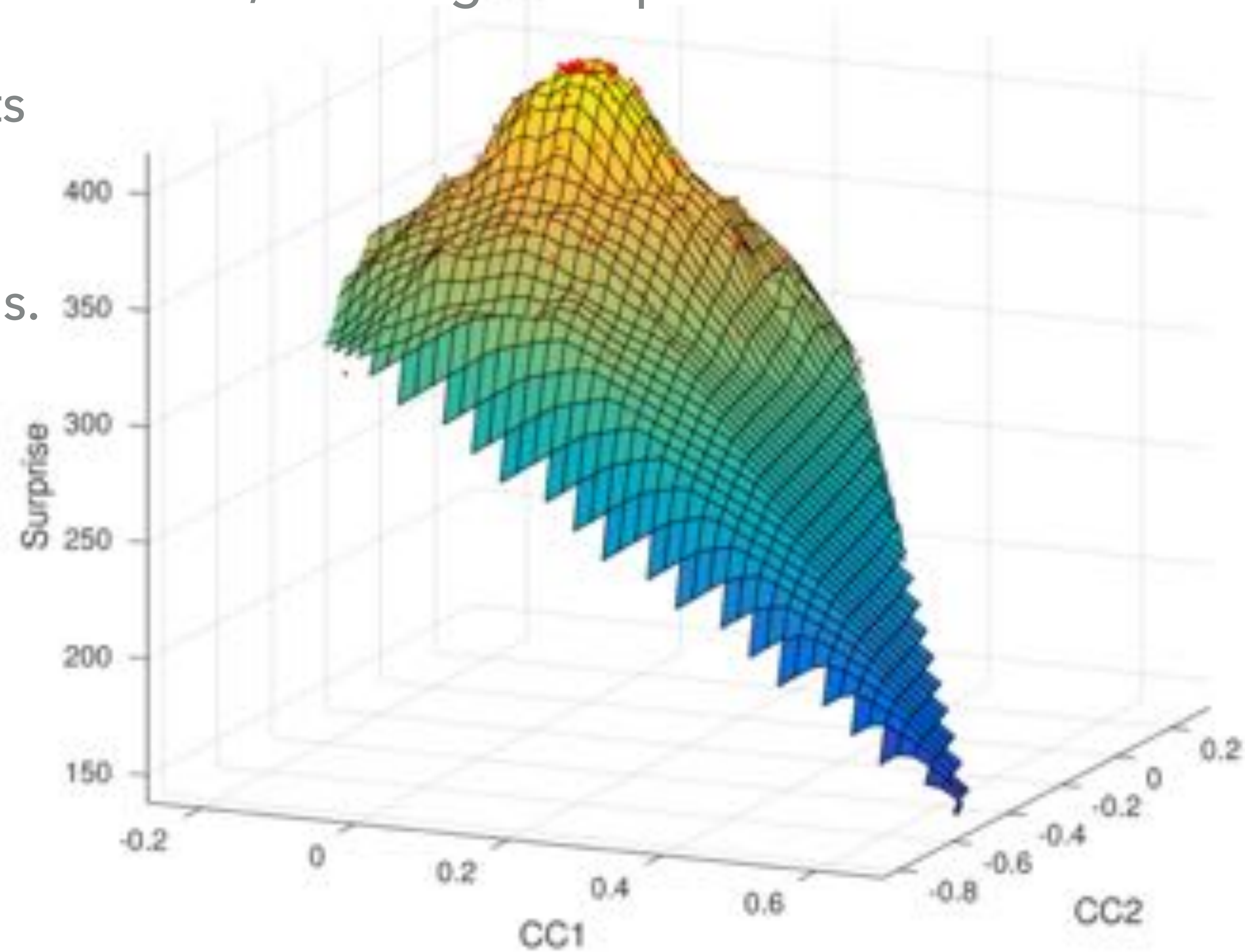
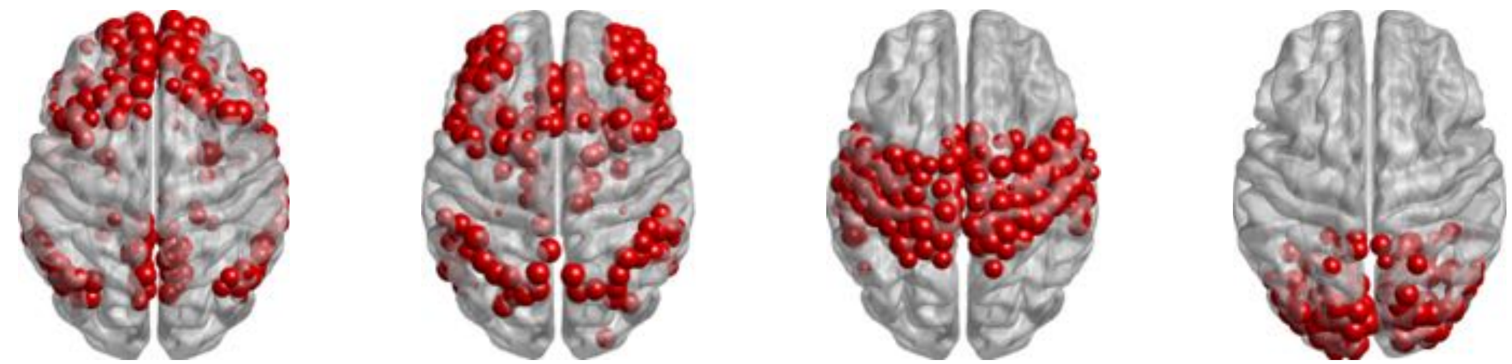




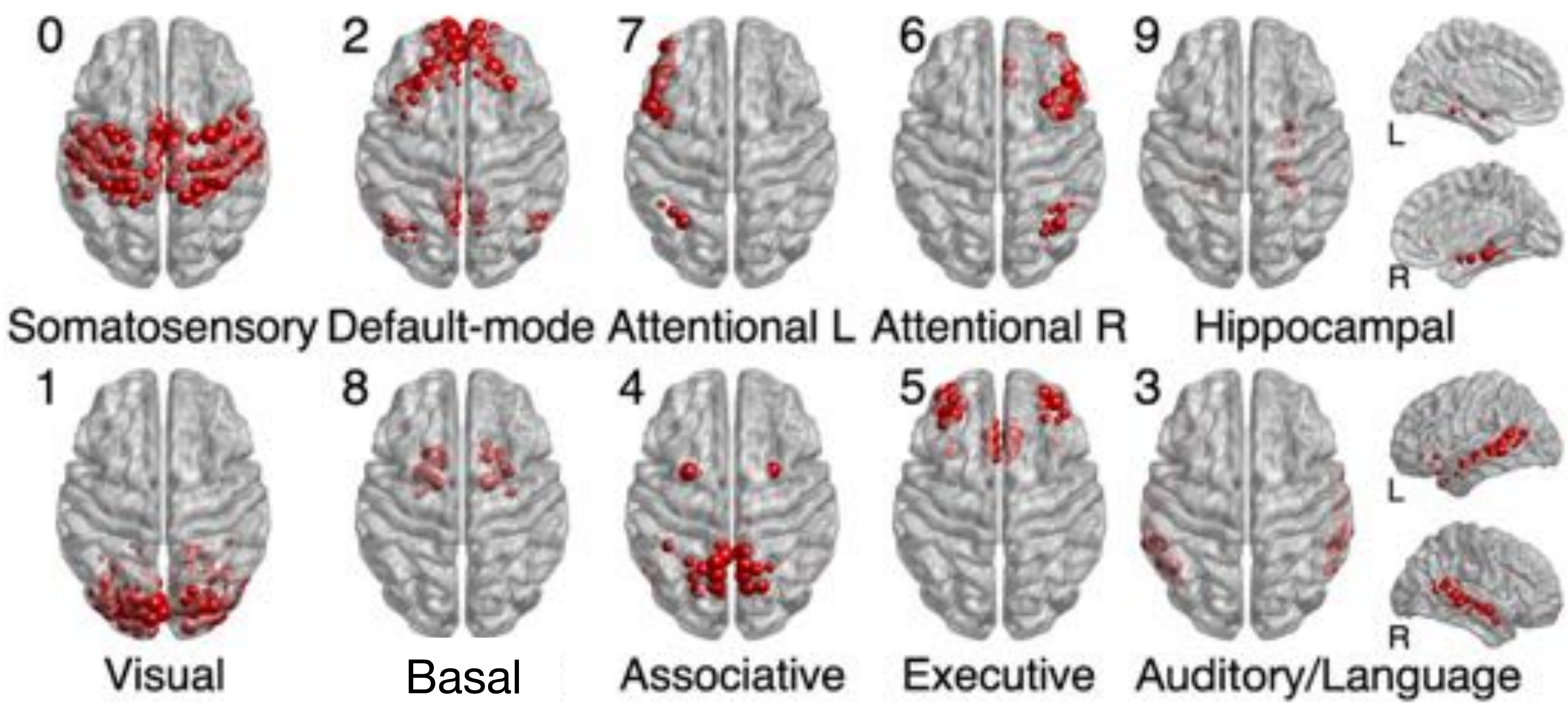
Nicolini, ArXiv 2016

APPLICATION OF SURPRISE OPTIMIZATION

Modularity



Surprise



ASYMPTOTICAL SURPRISE

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

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

Traag, 2015

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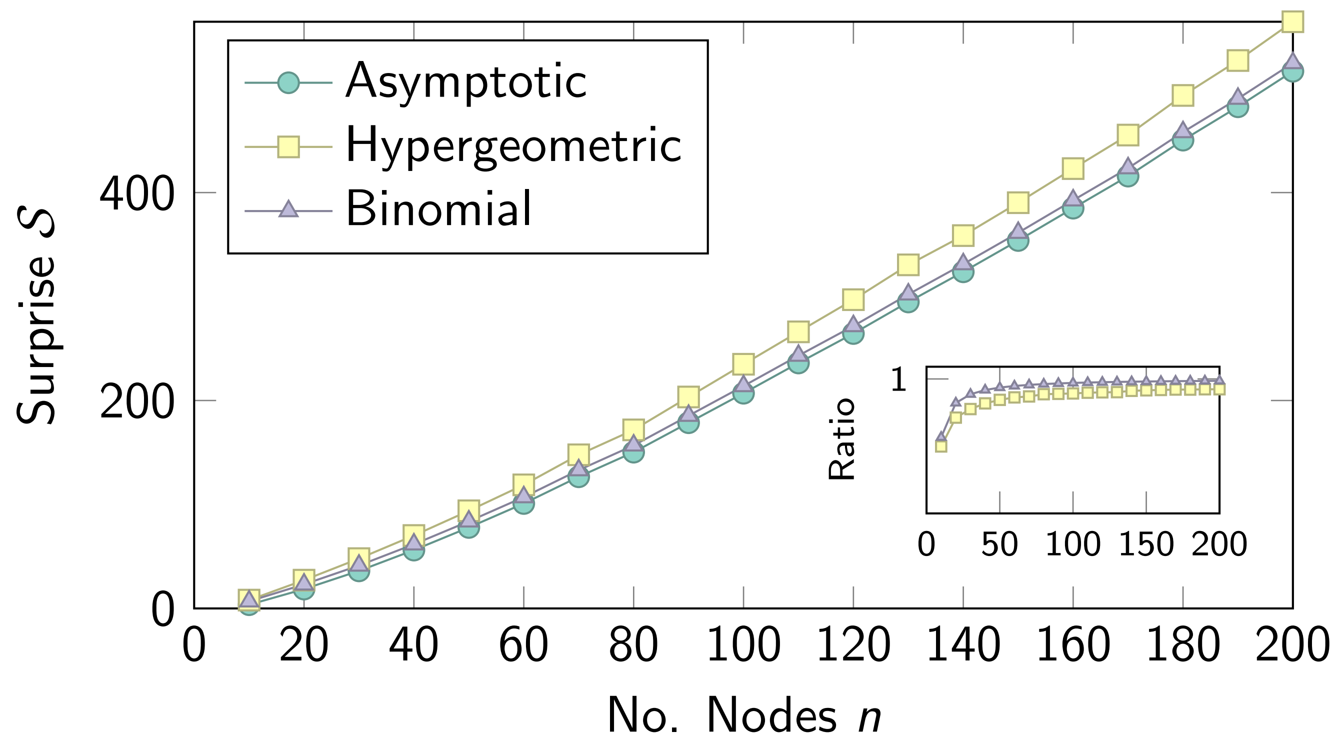

Traag, 2015

COMPARING ASYMPTOTICAL SURPRISE WITH OTHER METHODS

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

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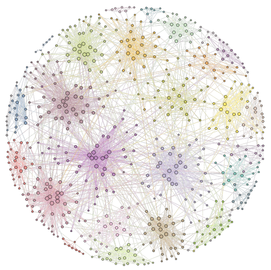

GENERATE A NETWORK WITH GIVEN COMMUNITY STRUCTURE

LFR Model

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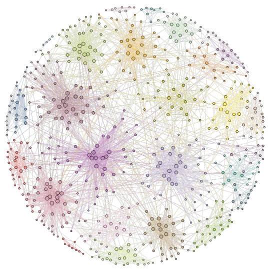

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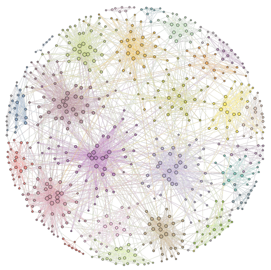

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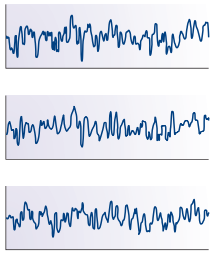
neuroSim R package

SIMULATE RS BOLD SIGNALS FOR MANY VIRTUAL SUBJECTS



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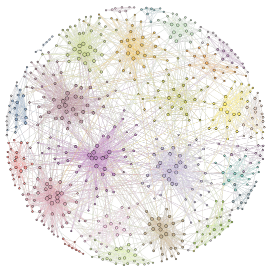

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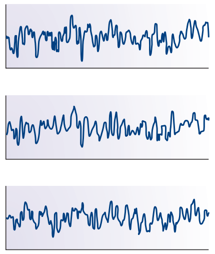

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INJECT CORRELATION INTO SYNTHETIC TIME SERIES

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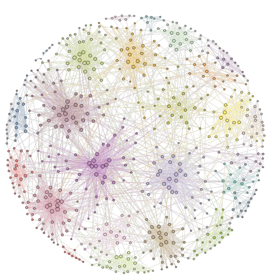

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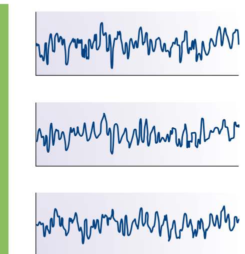

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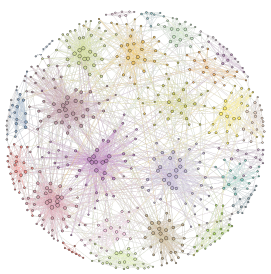

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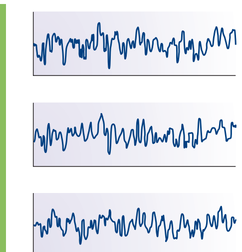

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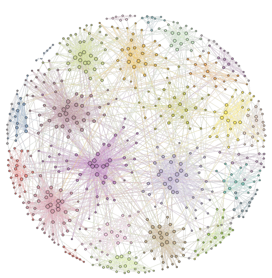

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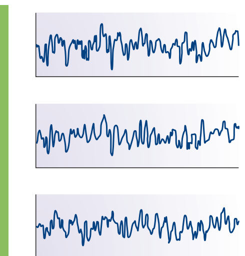

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Surprise, Infomap, Modularity

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RUN COMMUNITY DETECTION TO ASSESS EFFECTS OF NOISE

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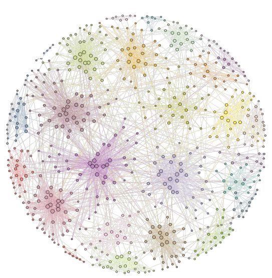

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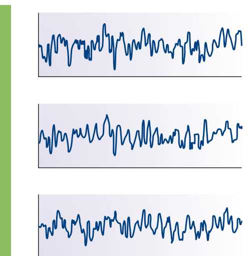

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NMI

GET PARTITION SIMILARITY WITH THE PLANTED ONE

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COMPARING COMMUNITY DETECTION ON BRAIN NETWORKS

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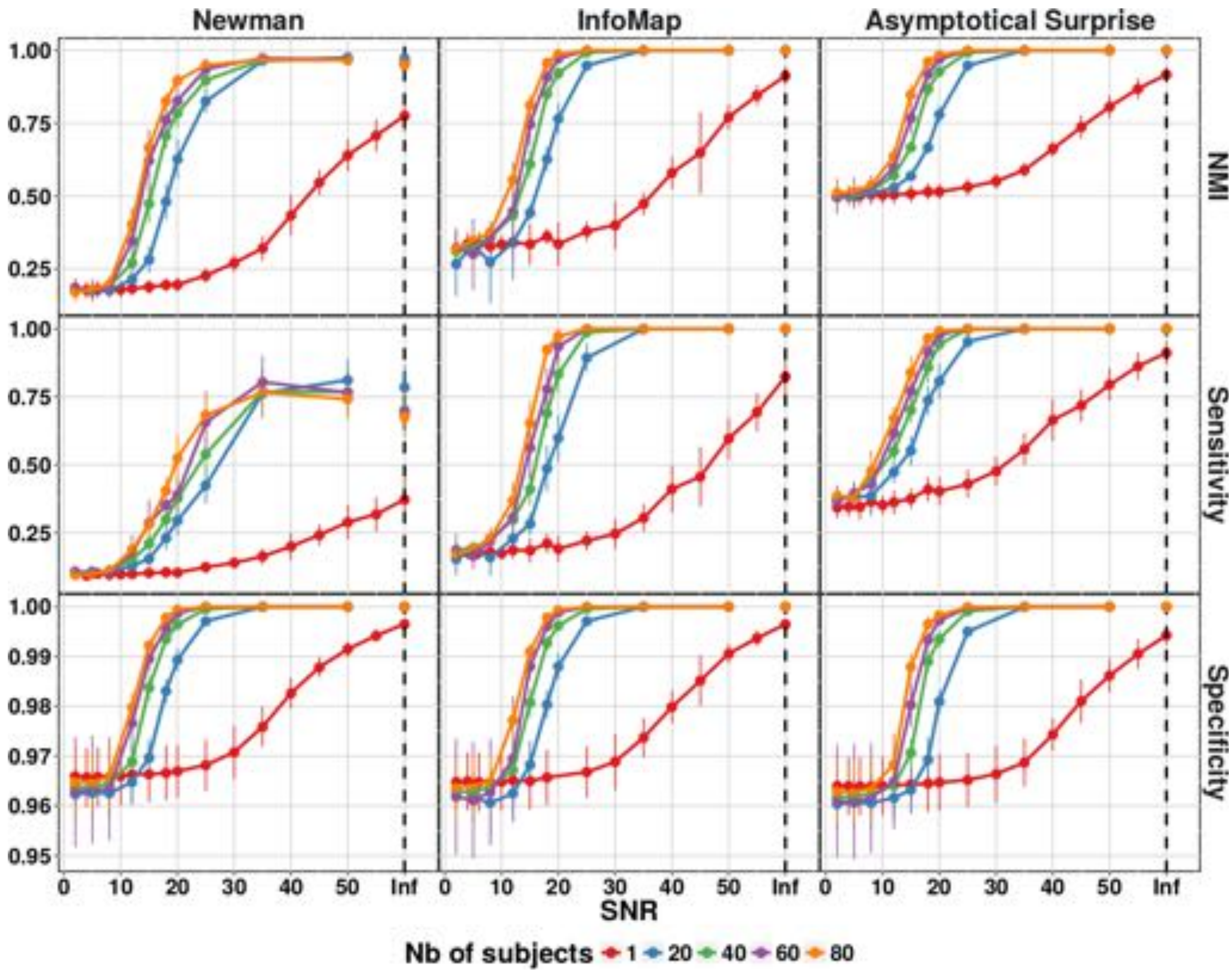
TP	FN
FP	TN

Planted communities

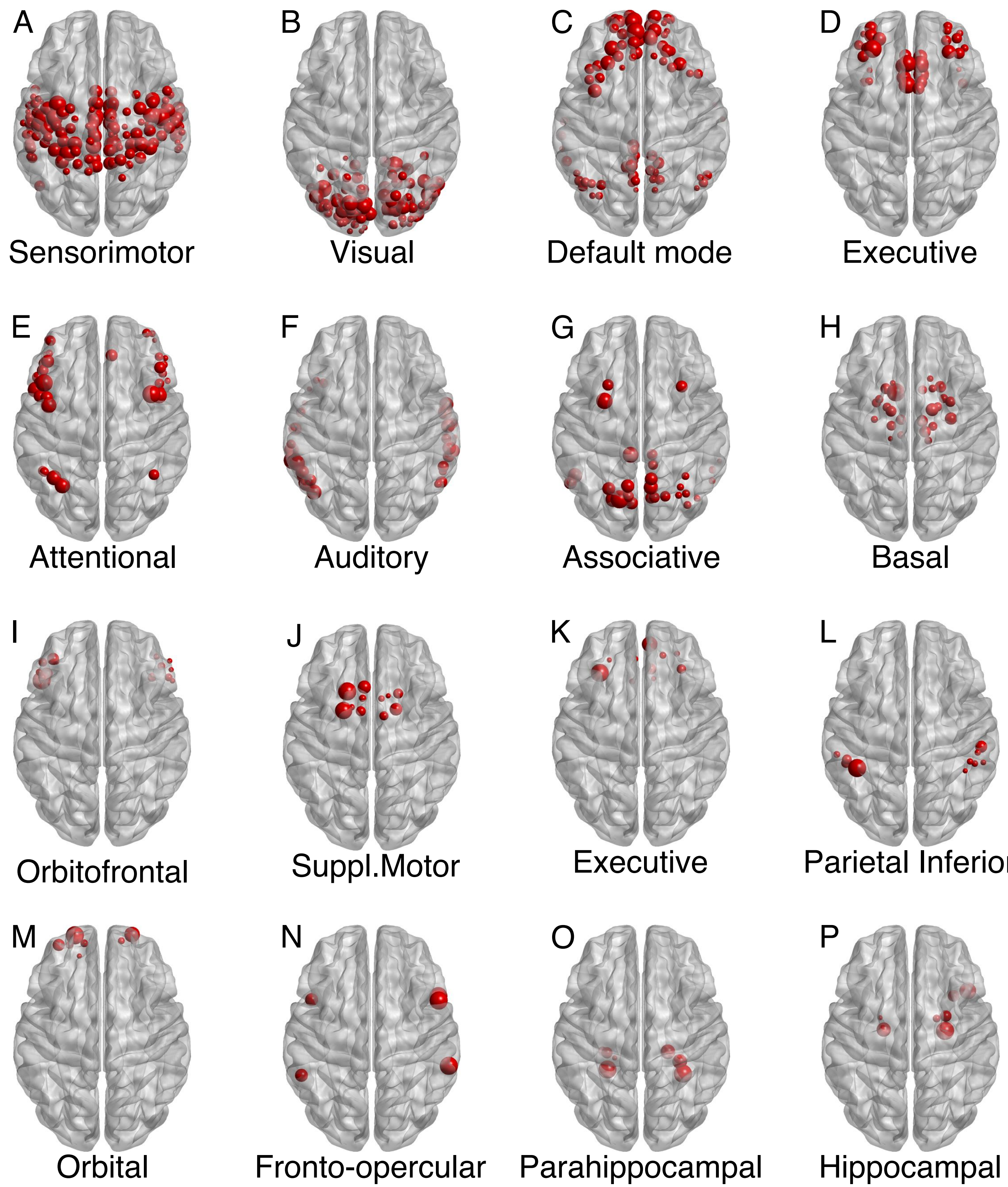
Detected communities	1	2	3
A	4	2	
B		1	1
C			2

RESULTS

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.

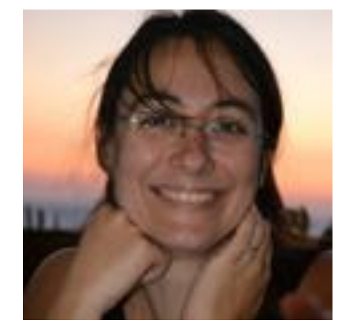
But …

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

THANK YOU!

Angelo Bifone

github.com/carlonicolini
brainetlab.github.io



Cecile Bordier

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