Statistical inference links data and theory in network science

Leto Peel
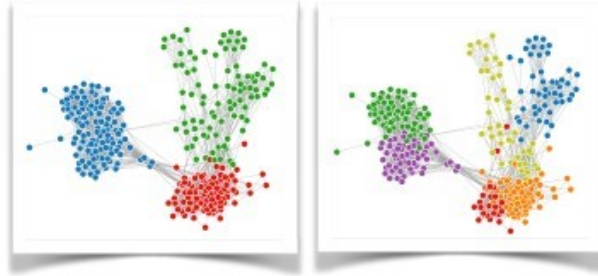Maastricht University
@PiratePeel
l.peel@maastrichtuniversity.nl

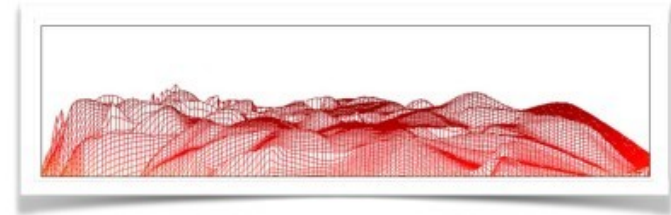# SINM 1st edition

Opportunities:

1. Model selection

2. Tradeoffs between general and specific models

3. Dynamics

4. Computational challenges

Trade-offs between general and specific models

general ←——————————————————————→ specific

Trade-offs between general and specific models

general ←——————————————→ specific

More likely to get a science/nature paper
Good to raise awareness of Network Science
Doesn't really solve any actual problems

Trade-offs between general and specific models

general ←——————————————————→ specific

More likely to get a "high-impact" paper
Good to raise awareness of Network Science
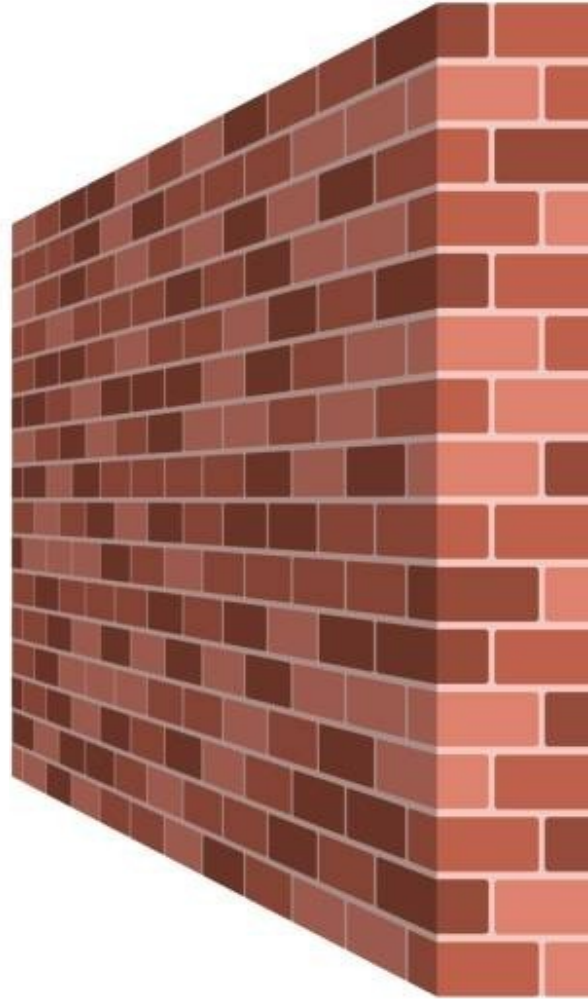Doesn't really solve any actual problems

We need to be going more in this direction
This is where the real heroes will be

Network Science

Network science allows us to analyse systems as a whole!
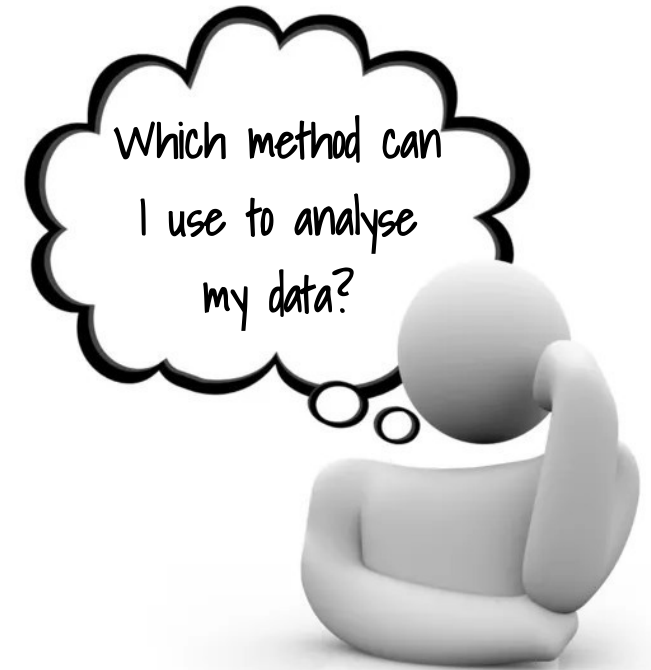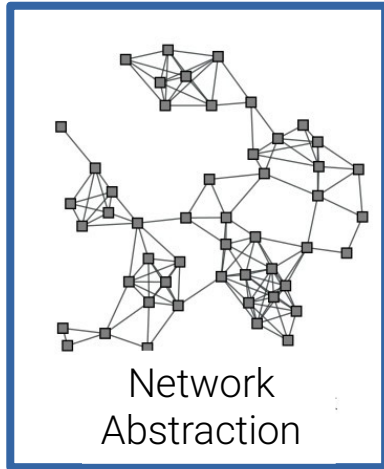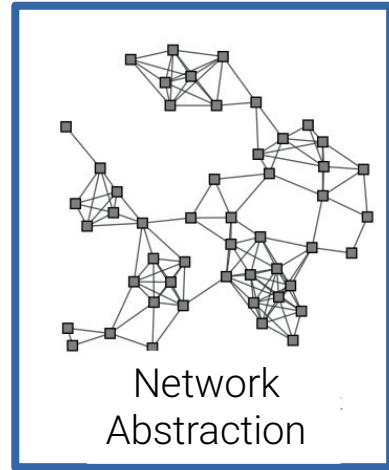
Network
Abstraction

What we'd like to know

Measurement

Network
Abstraction

What we'd like to know

Measurement

Errors and Omissions

Network
Abstraction

What we'd like to know

Network Abstraction
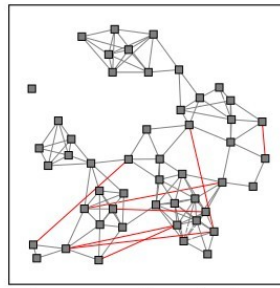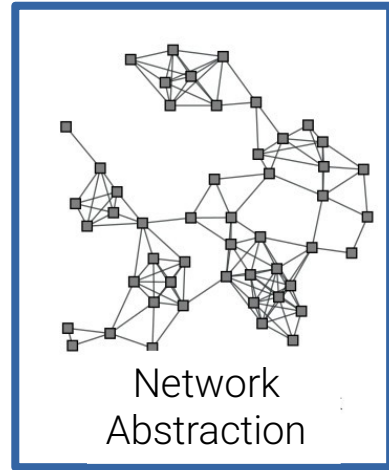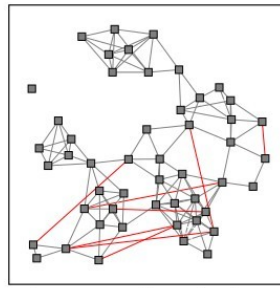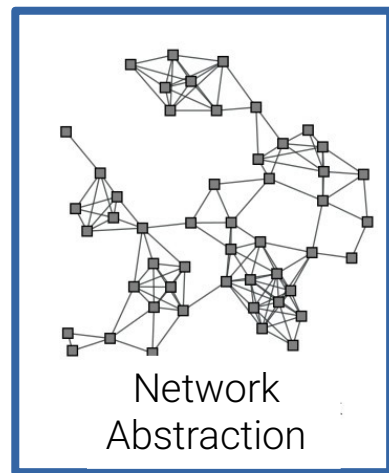
What we'd like to know

Measurement

Measurement

Measurement

Errors and omissions

Node states

Time
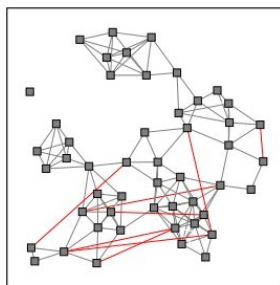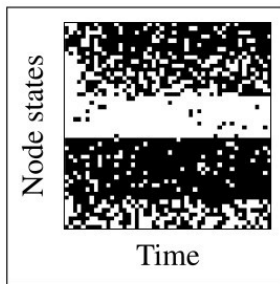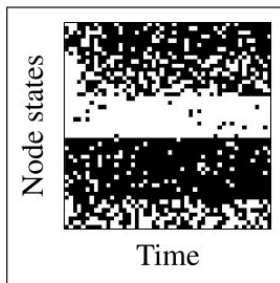
Dynamics
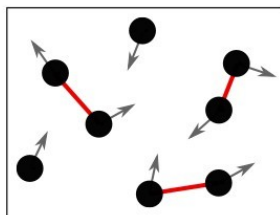
Proximity events

What we observe
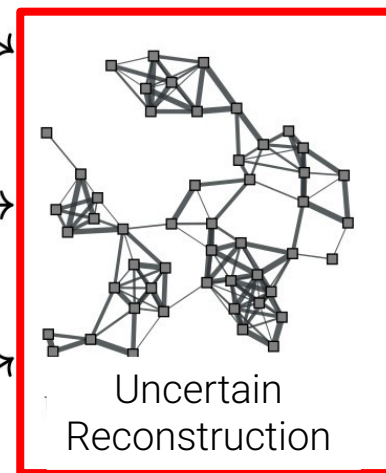
Errors and Omissions

Indirect observations

Thresholds and approximations

Network
Abstraction

Errors and omissions

Node states

Time

Dynamics

Proximity events

Measurement

Measurement

Measurement

Inference

Inference

Inference

Uncertain
Reconstruction

What we'd like to know

What we observe

What we can infer

Errors and omissions

Node states

Time

Dynamics

Proximity events

Network Abstraction

Uncertain Reconstruction

Measurement

Measurement

Measurement

Inference

Inference

Inference

What we'd like to know
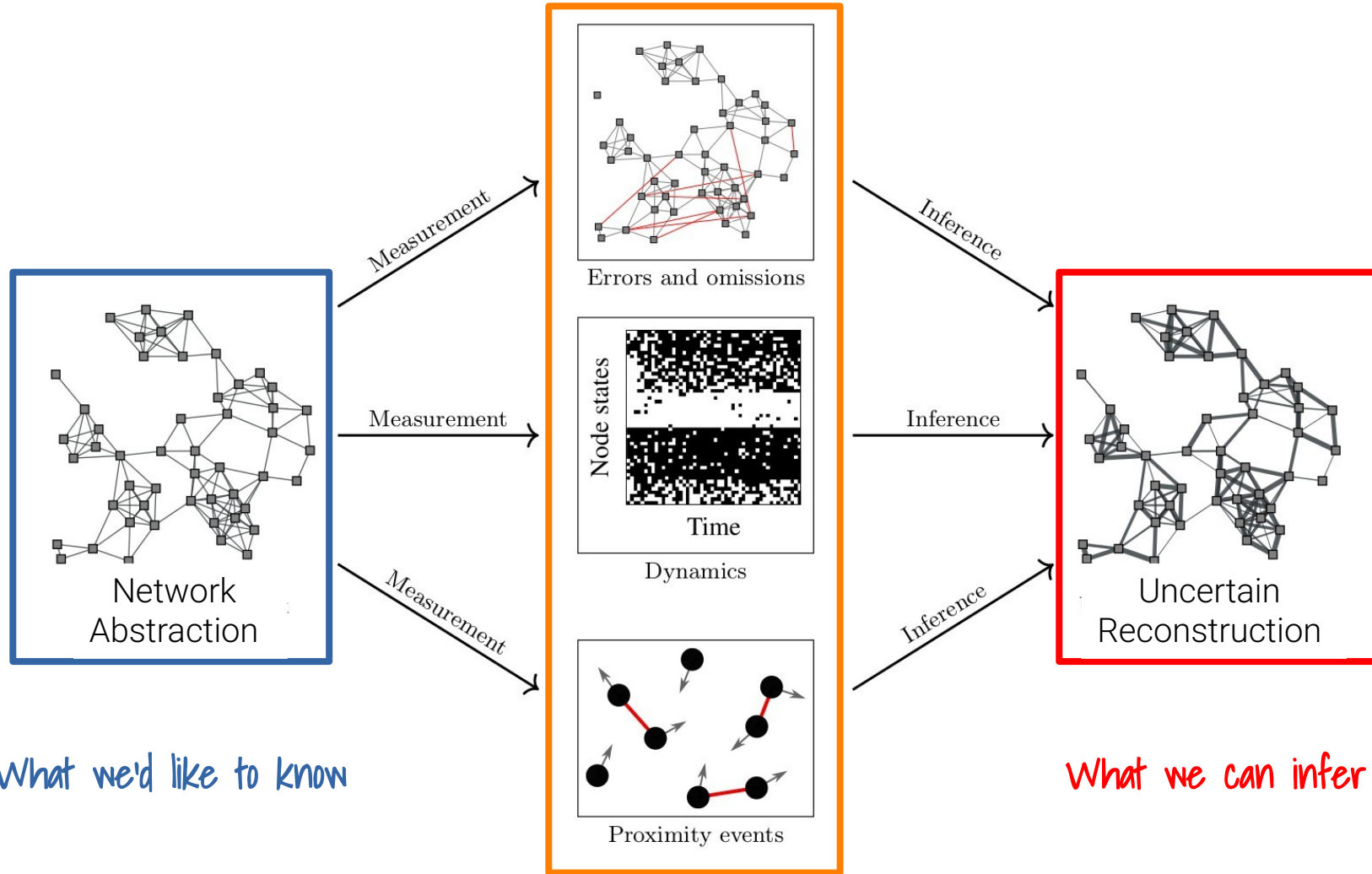
What we can infer

$$\underset{\text{Unknown parameter}}{\boxed{\boldsymbol{A}}} \rightarrow \underset{\text{Generative process}}{\boxed{P(\boldsymbol{D}|\boldsymbol{A})}} \rightarrow \underset{\text{Data}}{\boxed{\boldsymbol{D}}} \rightarrow \underset{\text{Posterior distribution}}{\boxed{P(\boldsymbol{A}|\boldsymbol{D})}} \rightarrow \underset{\text{Estimate}}{\boxed{\hat{\boldsymbol{A}}}}$$

Three Zachary Karate club club trophy winners enter a Zoom...

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This scene never actually happened, its a reconstruction!

Network science in 3 easy steps...
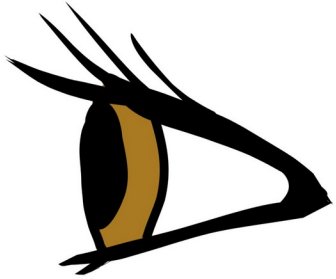
1. Observations/
measurements

Network science in 3 easy steps...

1. Observations/measurements
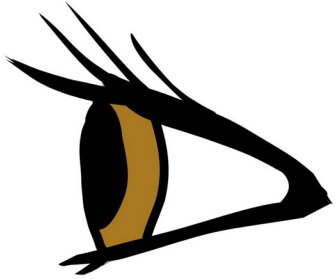
2. Network representation

Network science in 3 easy steps...
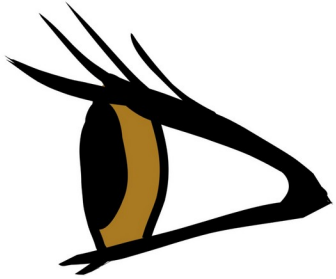
1. Observations/ measurements

2. Network representation
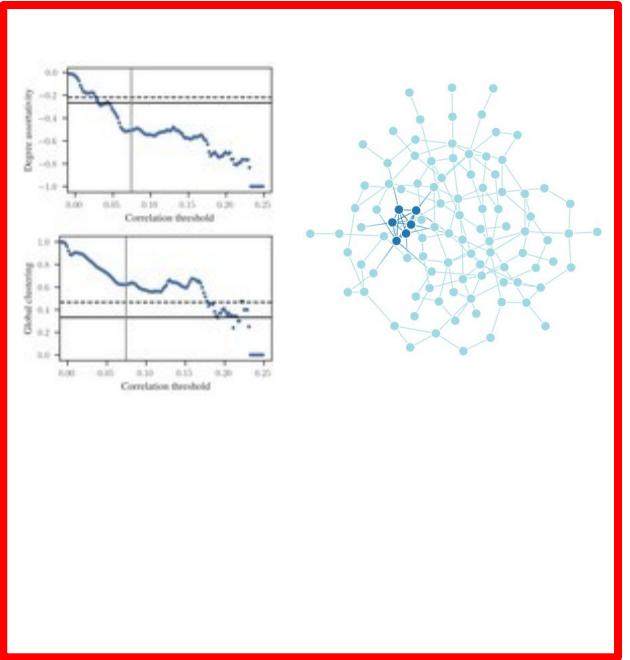
3. Network analysis

Network science in 3 easy steps...

1. Observations/measurements
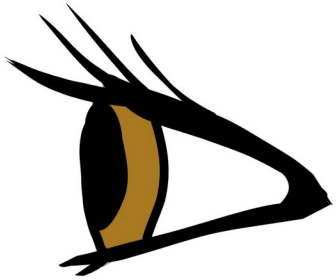
Obscured quality of data

2. Network representation
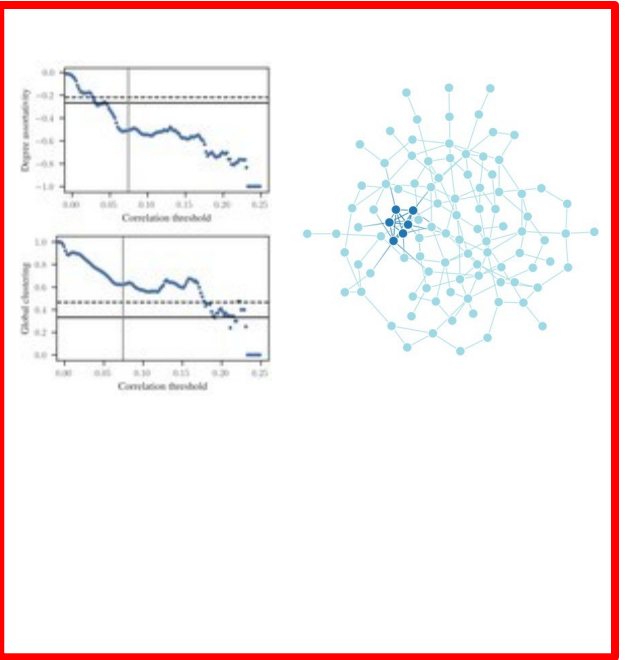
3. Network analysis

Network science in 3 easy steps...

1. *Observations/ measurements*
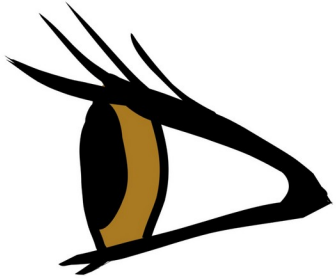
Obscured quality of data

2. *Network representation*
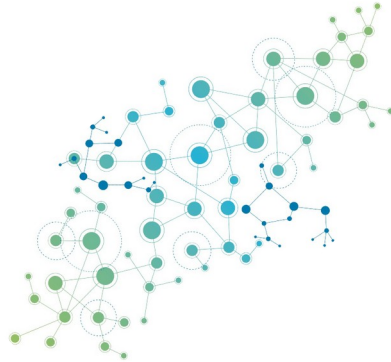
Choice of representation

3. *Network analysis*

Network science in 3 easy steps...

1. Observations/measurements

2. Network representation

3. Network analysis

Obscured quality of data

Choice of representation

Suitability of the methods

1. Obscured quality of data

Zachary's Karate Club
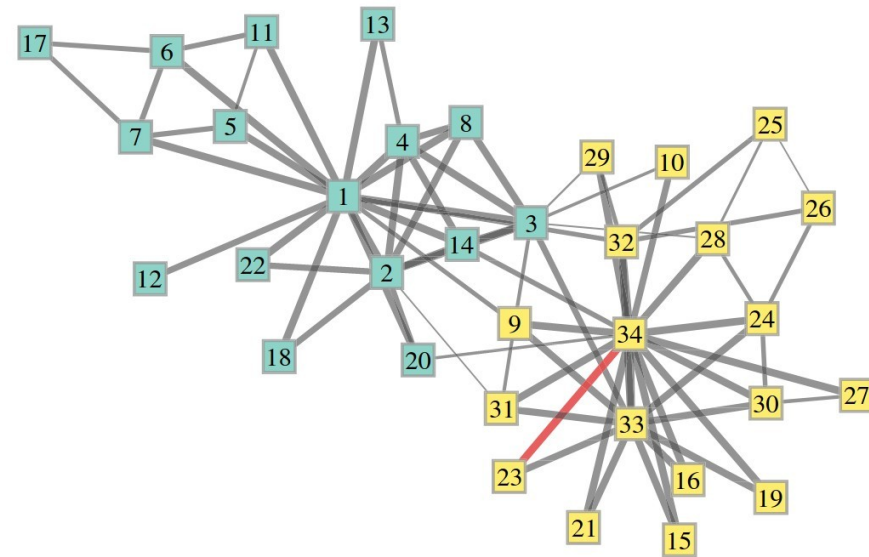
Zachary's Karate Club

Individual Number

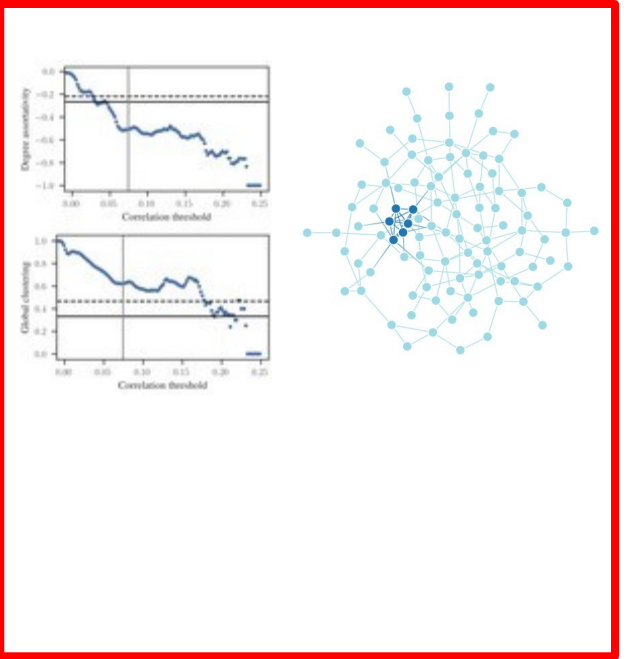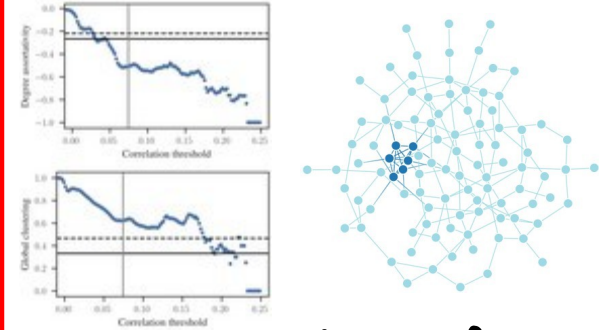|	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
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Zachary, W. W. An Information Flow Model for Conflict and Fission in Small Groups. J. Anthropological Res. 33, 452-473 (1977).

Zachary's Karate Club

Individual Number

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33	0	0	2	0	0	0	0	0	3	0	0	0	0	0	3	3	0	0	1	0	3	0	0	0	0	0	4	3	4	0	5			
34	0	0	0	0	0	0	0	4	2	0	0	0	3	2	4	0	0	2	1	1	**3**	0	0	2	4	2	2	3	4	5	0			

Does this edge exist?

Zachary, W. W. An Information Flow Model for Conflict and Fission in Small Groups. J. Anthropological Res. 33, 452-473 (1977).

Assessing experimentally derived interactions in a small world

Debra S. Goldberg and Frederick P. Roth*

Department of Biological Chemistry and Molecular Pharmacology, Harvard Medical School, Boston, MA 02115

Experimentally determined networks are susceptible to errors, yet important inferences can still be drawn from them. Many real networks have also been shown to have the small-world
negative errors (24, 25). Here we consider in detail a network of protein–protein interactions derived from high-throughput, error-prone yeast two-hybrid (Y2H) studies (26, 27). These data
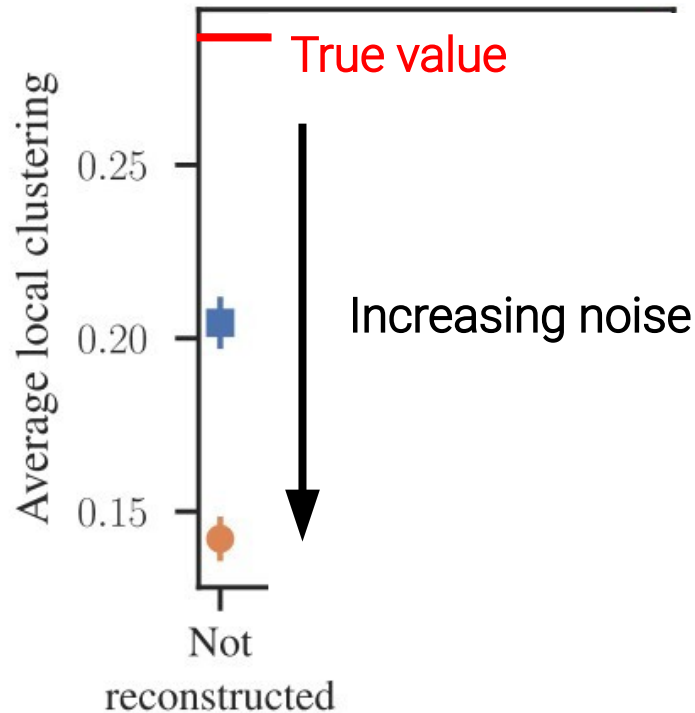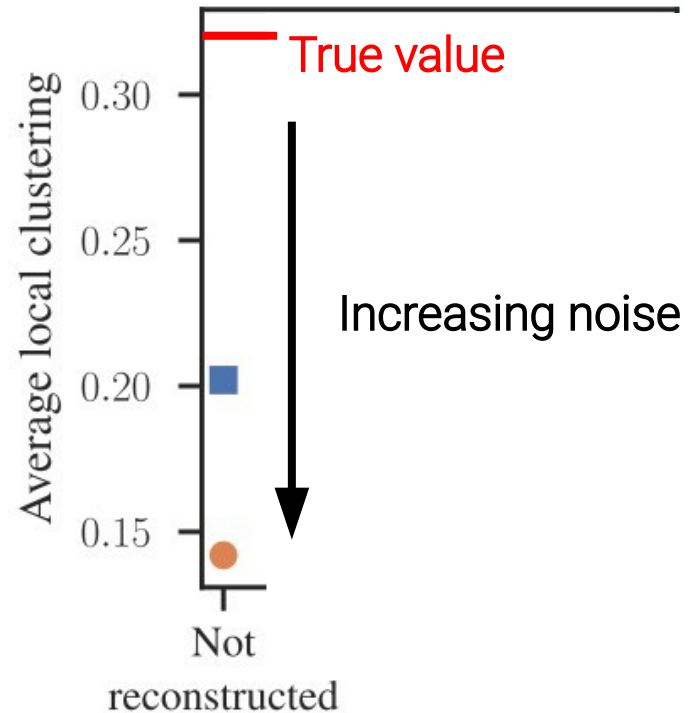
Assessing experimentally derived interactions in a small world

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Experimentally determined networks are susceptible to errors, yet important inferences can still be drawn from them. Many real networks have also been shown to have the small-world negative errors (24, 25). Here we consider in detail a network of protein–protein interactions derived from high-throughput, error-prone yeast two-hybrid (Y2H) studies (26, 27). These data
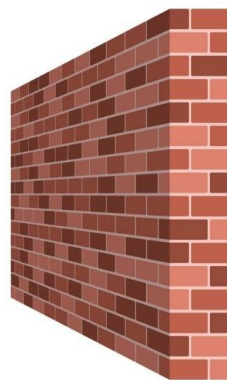
Link prediction   Rest of network science

Errors in network data create systematic biases...

Errors in network data create systematic biases...
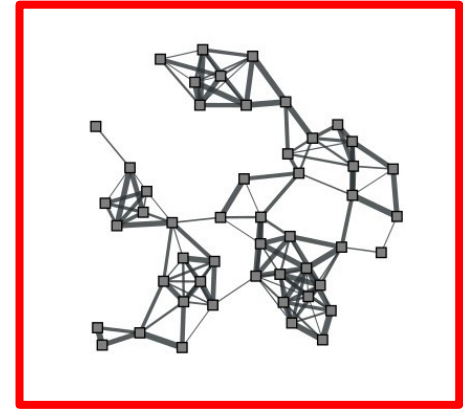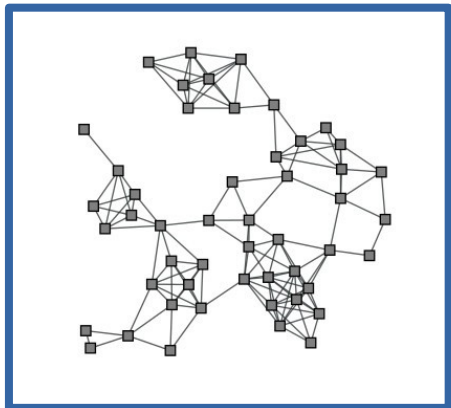

(a) High-school friendships

(b) Political blogs

Average local clustering

Average local clustering

True value

True value

Increasing noise

Increasing noise

0.25

0.20

0.15

0.30

0.25

0.20

0.15

Not reconstructed

Not reconstructed

$p = 0.1$

$p = 0.2$
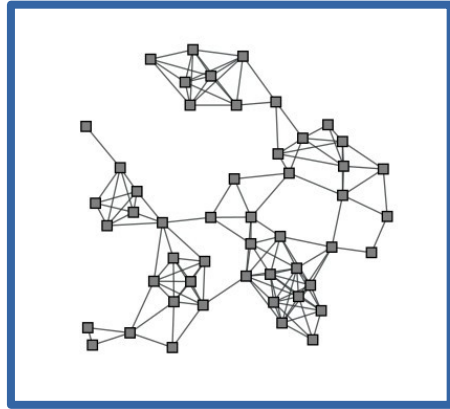
True Network

Reconstructed Network

We don't know if the network represents the system

$$P(\boldsymbol{A}|\boldsymbol{D}) = \frac{P(\boldsymbol{D}|\boldsymbol{A})P(\boldsymbol{A})}{P(\boldsymbol{D})} \; .$$
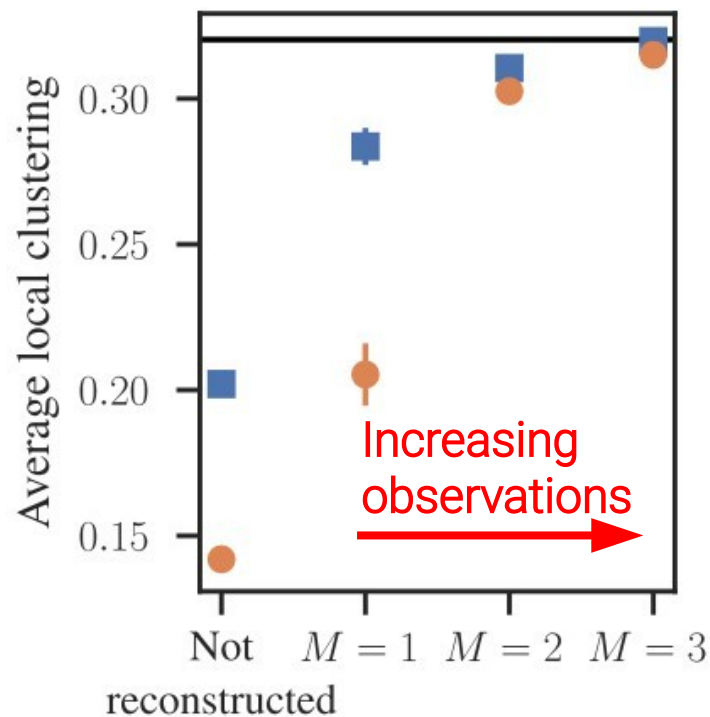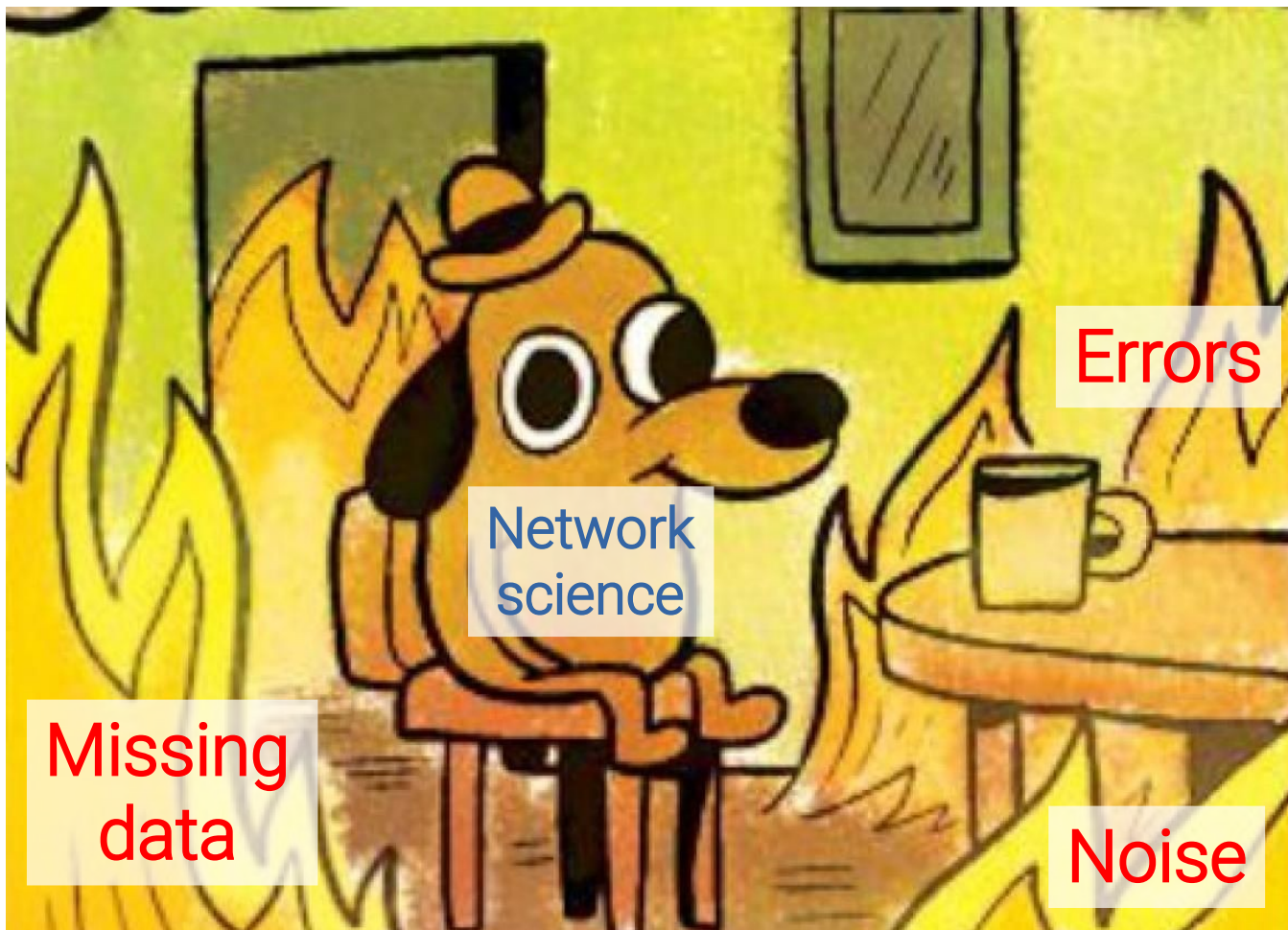
Bayesian inference

True Network
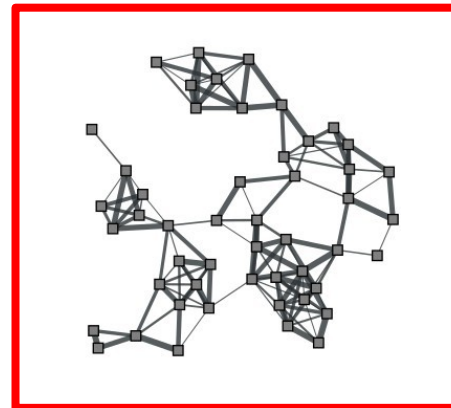
Reconstructed Network

(a) High-school friendships

(b) Political blogs

Average local clustering

Increasing observations

Not reconstructed $M = 1$ $M = 2$ $M = 3$
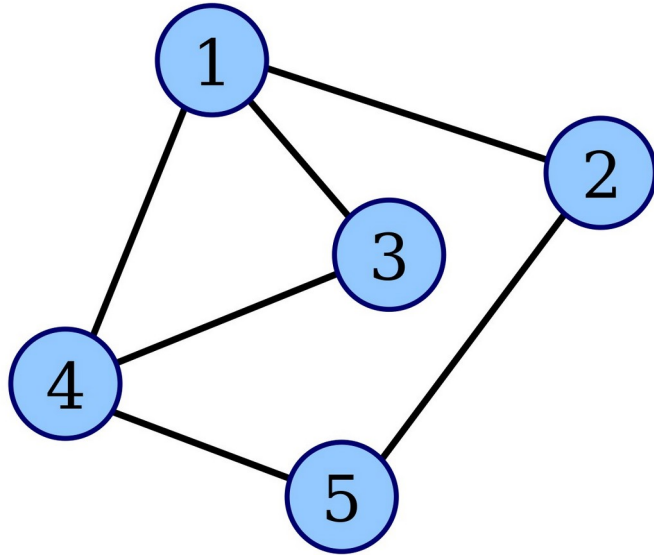
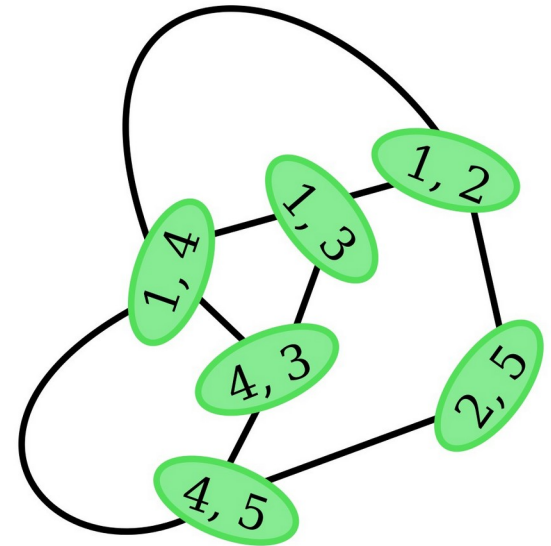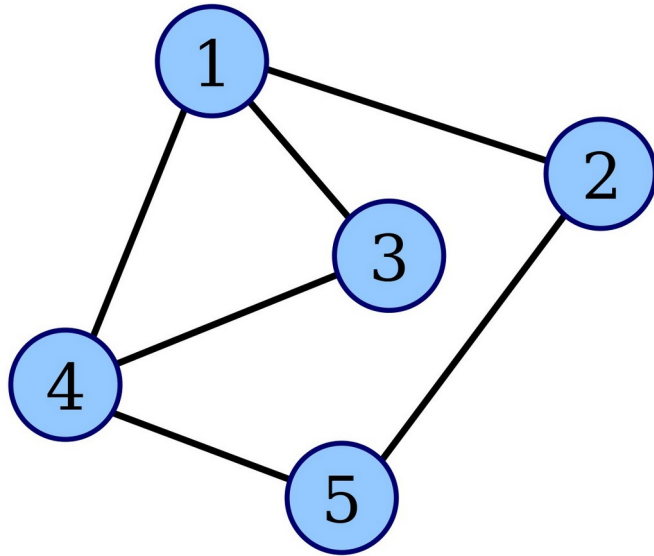$p = 0.1$
$p = 0.2$
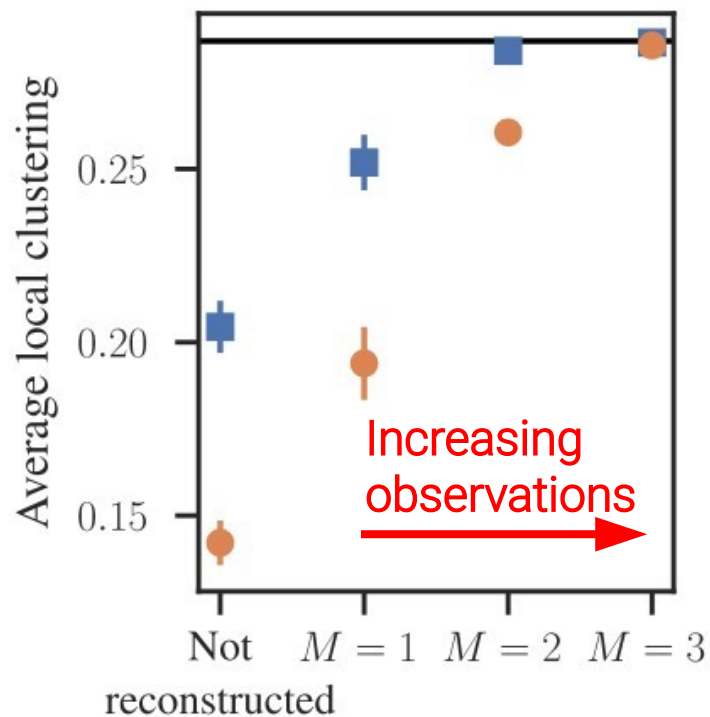
This is NOT fine

II. Choice of representation
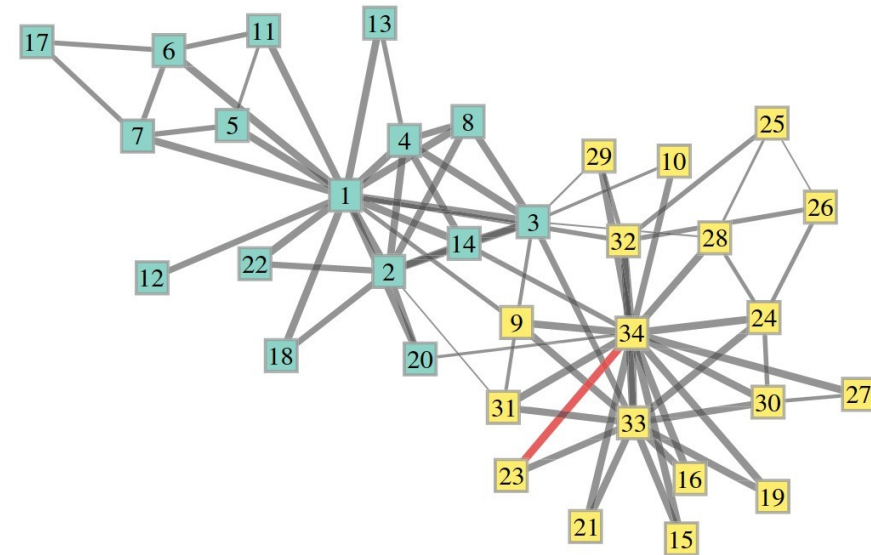
What are the nodes and what are the edges?

What are the nodes and what are the edges?

Zachary's Karate Club

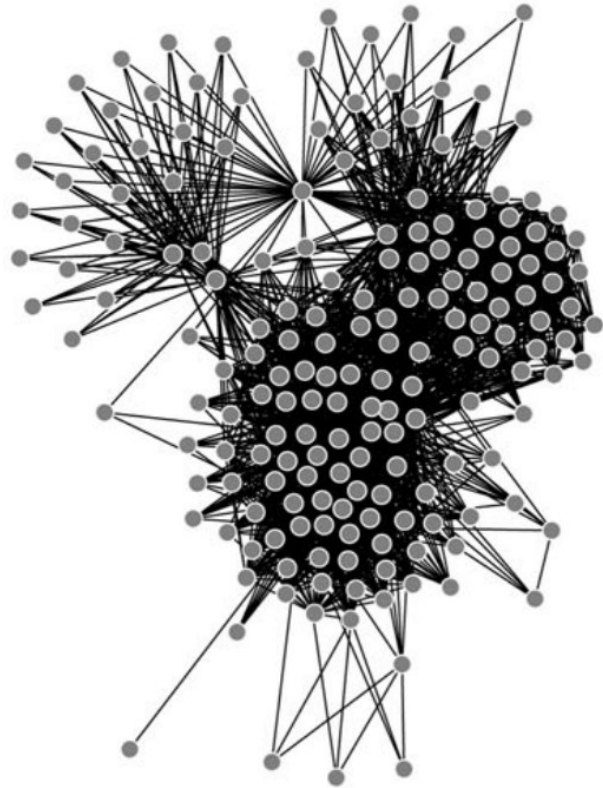What about the raw data?

Individual Number

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
1	0	4	5	3	3	3	3	2	2	0	2	3	2	3	0	0	0	2	0	2	0	2	0	0	0	0	0	0	0	0	0	2	0	0
2	4	0	6	3	0	0	0	4	0	0	0	0	0	5	0	0	0	1	0	2	0	2	0	0	0	0	0	0	0	0	0	2	0	0
3	5	6	0	3	0	0	0	4	5	1	0	0	0	3	0	0	0	0	0	0	0	0	2	2	0	0	0	0	0	3	0			
4	3	3	3	0	0	0	0	3	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	3	0	0	0	0	0	2	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	3	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0
7	3	0	0	0	2	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0
8	2	4	4	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	2	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	4	3	
10	0	0	1	0																								0	0	0	0	0	0	2
11	2	0	0	0																								0	0	0	0	0	0	0
12	3	0	0	0																								0	0	0	0	0	0	0
13	1	0	0	3																								0	0	0	0	0	0	0
14	3	5	3	3																								0	0	0	0	0	0	3
15	0	0	0	0																								0	0	0	0	0	3	2
16	0	0	0	0																								0	0	0	0	0	3	4
17	0	0	0	0																								0	0	0	0	0	0	0
18	2	1	0	0																								0	0	0	0	0	0	0
19	0	0	0	0																								0	0	0	0	0	1	2
20	2	2	0	0																								0	0	0	0	0	0	1
21	0	0	0	0																								0	0	0	0	0	3	1
22	2	2	0	0																								0	0	0	0	0	0	0
23	0	0	0	0																								0	0	0	0	2	0	
24	0	0	0	0																					0	4	0	2	0	0	5	4		
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	3	0	0	0	2	0	0		
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	2	0	0	0	0	7	0	0		
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	2	
28	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	3	0	0	0	0	0	0	0	4	
29	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2		
30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	4	0	0	0	0	0	3	2	
31	0	2	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	3	
32	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	7	0	0	2	0	0	0	0	4	4	
33	0	0	2	0	0	0	0	3	0	0	0	0	3	3	0	1	0	3	0	2	5	0	0	0	0	0	4	3	4	0	5			
34	0	0	0	0	0	0	0	4	2	0	0	0	3	2	4	0	2	1	1	0	3	4	0	0	2	4	2	2	3	4	5	0		

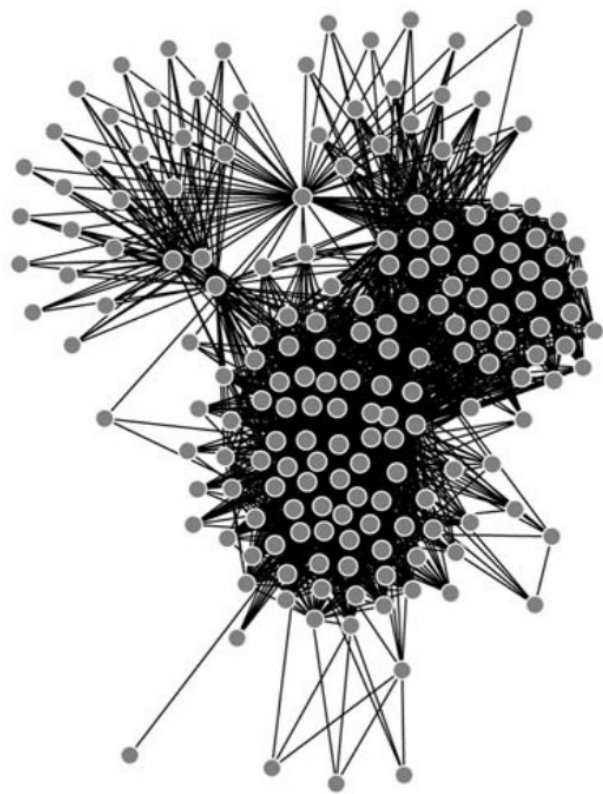Zachary, W. W. An Information Flow Model for Conflict and Fission in Small Groups. J. Anthropological Res. 33, 452-473 (1977).
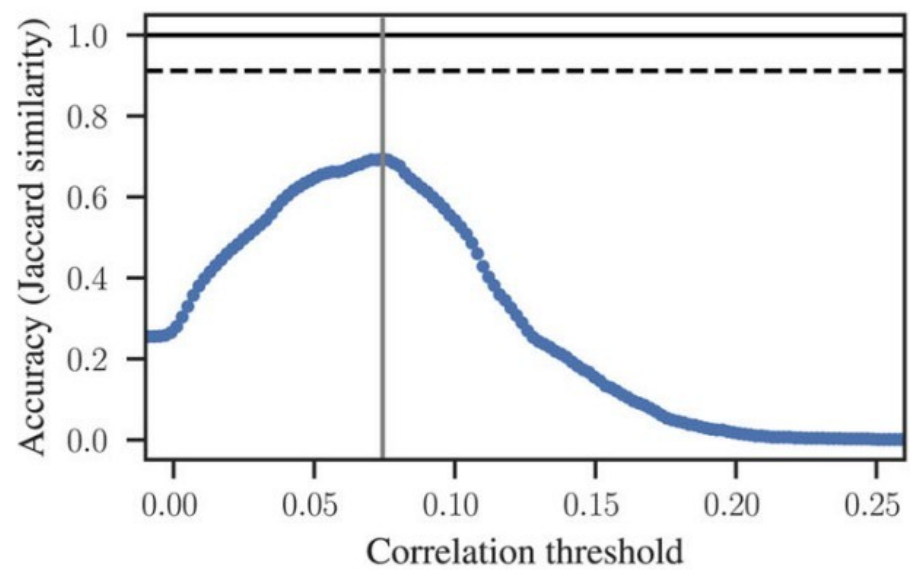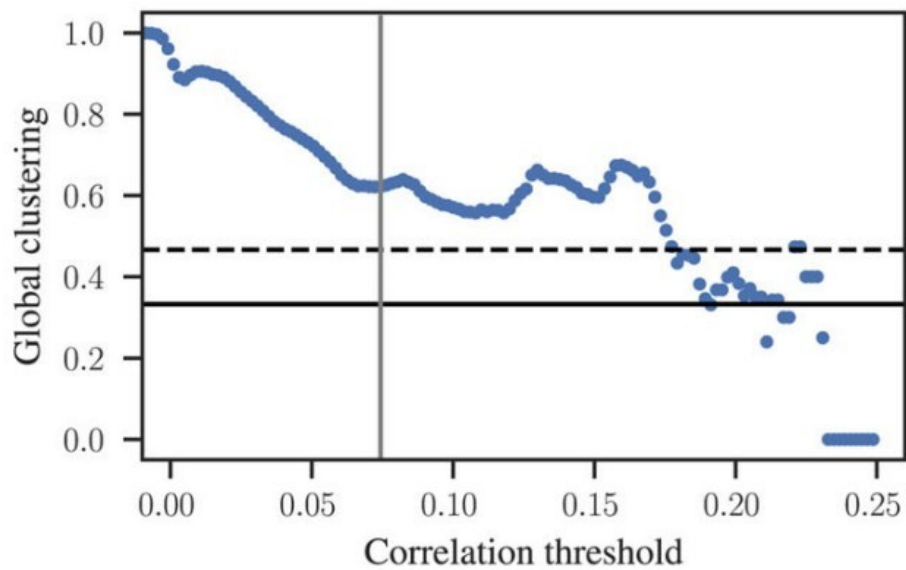
How does the network generate data?

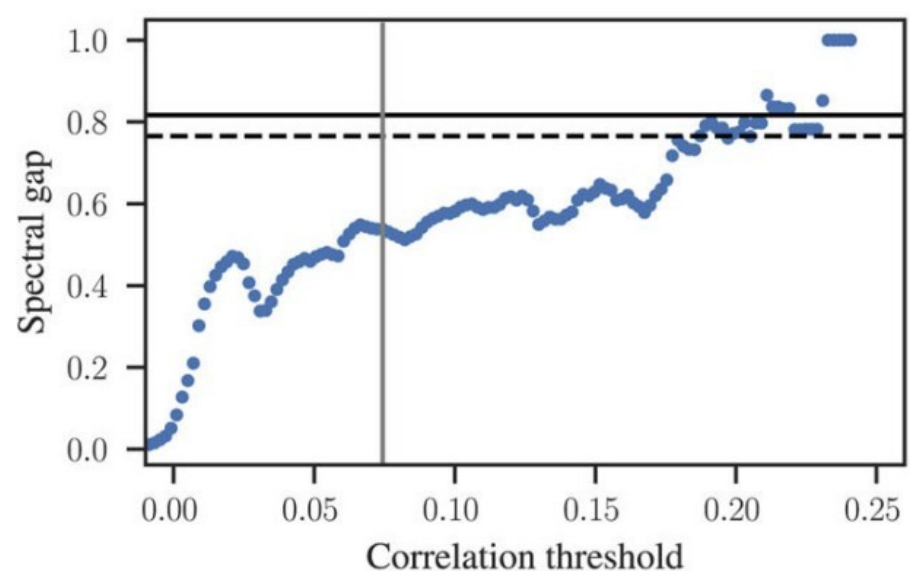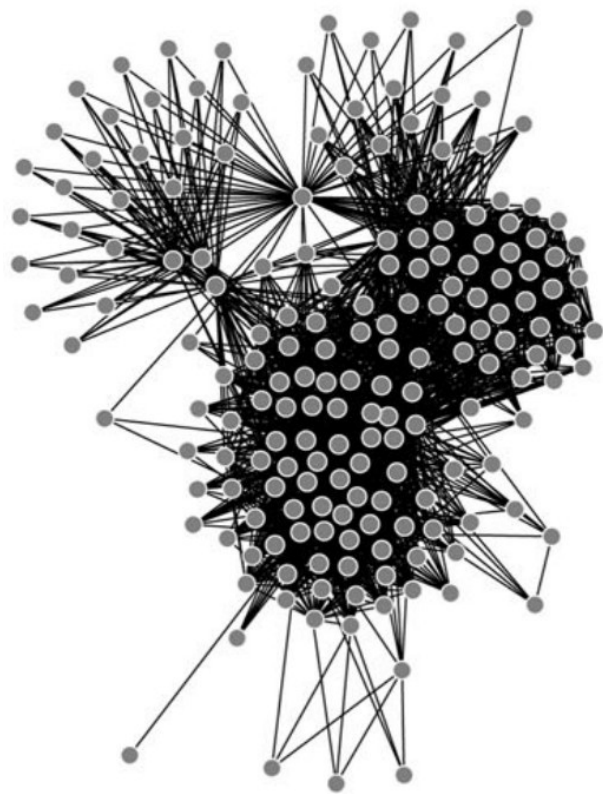
(a) True network

Correlation "networks"

(a) True network
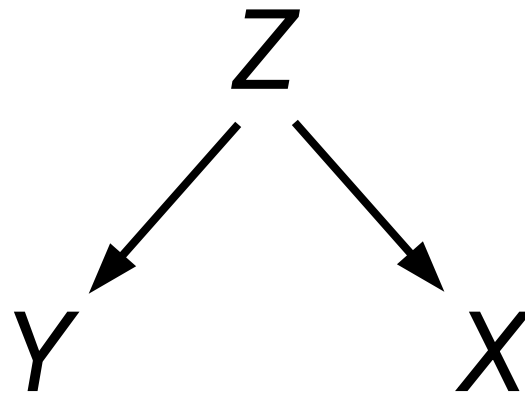
$t = 0.005$ $t = 0.01$ $t = 0.02$

$t = 0.03$ $t = 0.05$ $t = 0.075$

$t = 0.09$ $t = 0.12$ $t = 0.15$

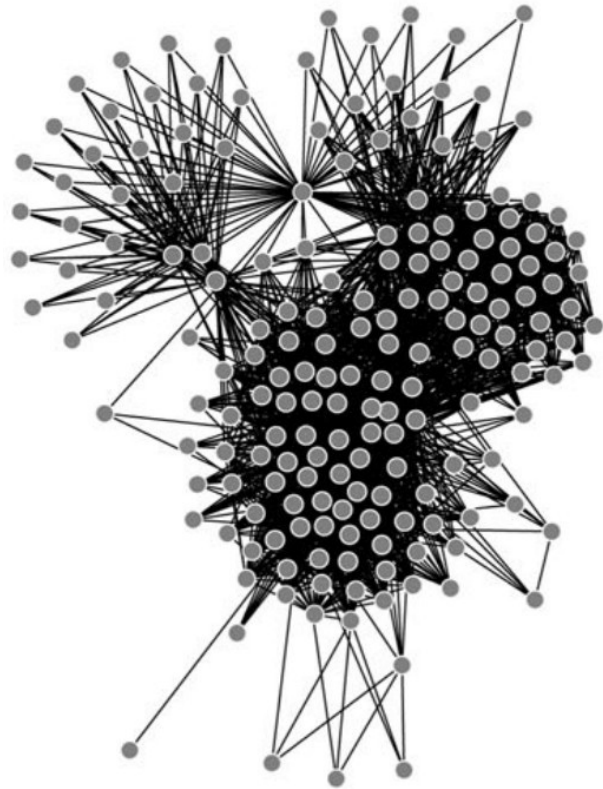# Correlation "networks"

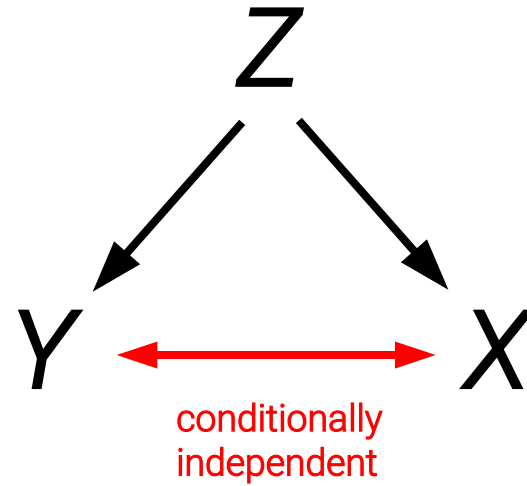(a) True network

$$Z$$

$$Y \qquad\qquad X$$
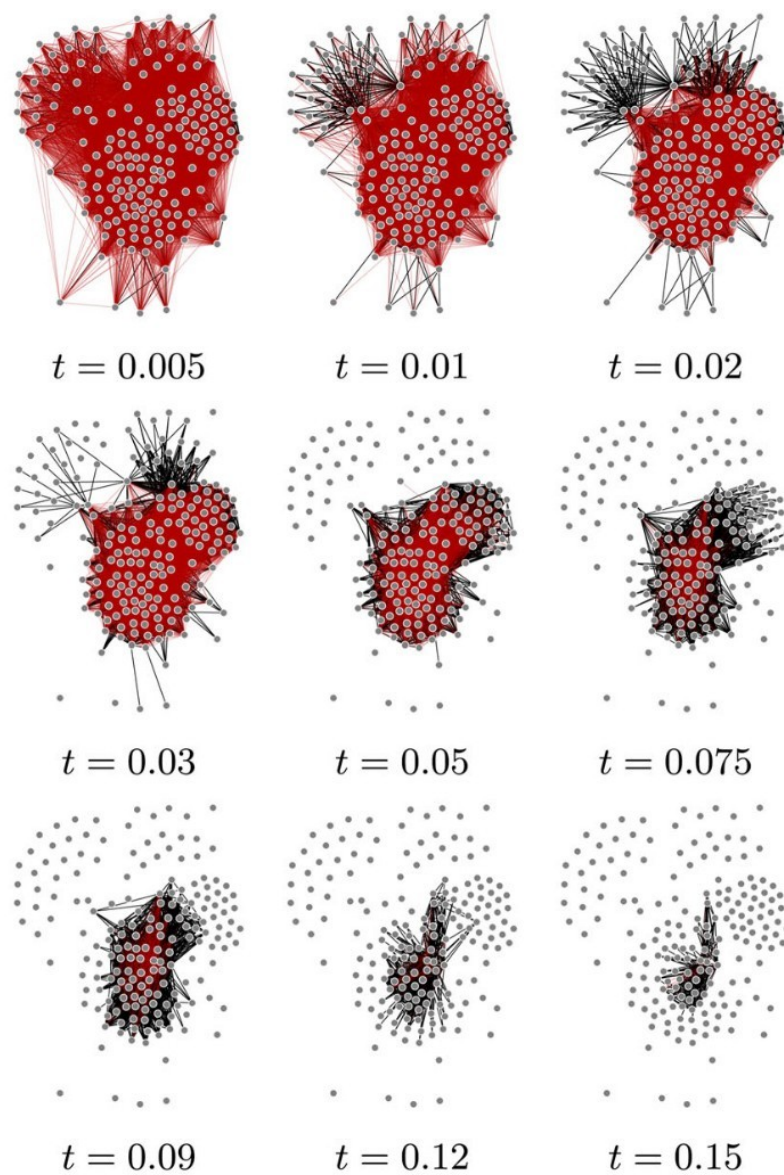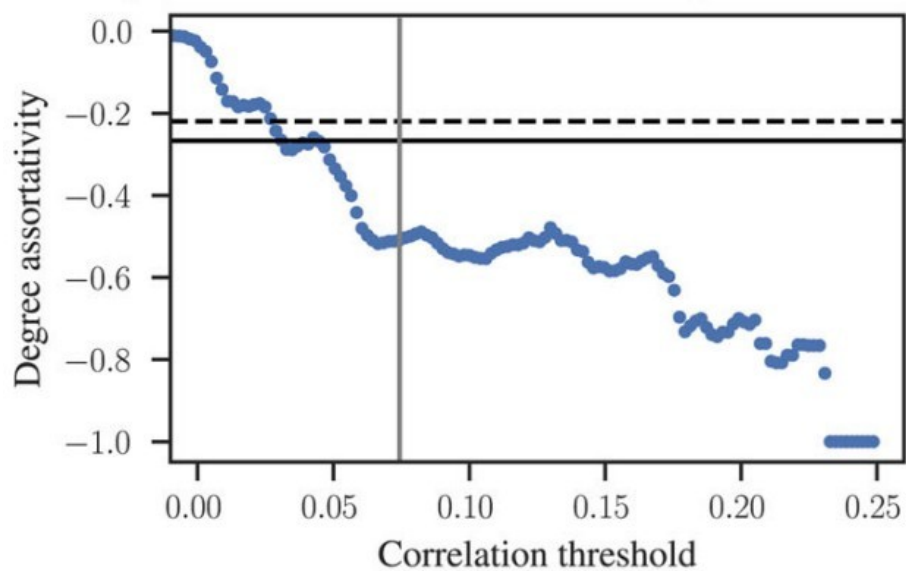
$$X(t) \;=\; Z(t) + \epsilon_1$$
$$Y(t) \;=\; Z(t) + \epsilon_2,$$

Correlation "networks"

(a) True network

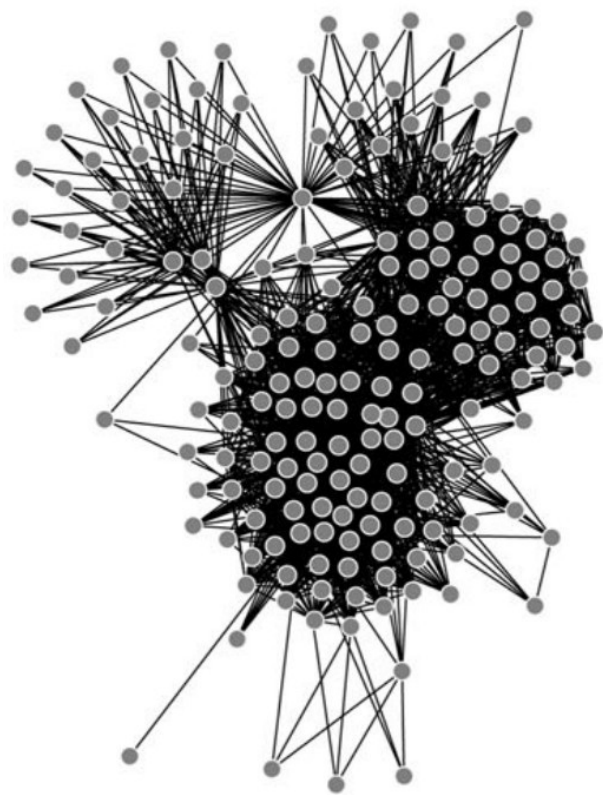$$X(t) = Z(t) + \epsilon_1$$

$$Y(t) = Z(t) + \epsilon_2,$$

conditionally independent

Dempster, A. P. Covariance selection. Biometrics 157-175 (1972)
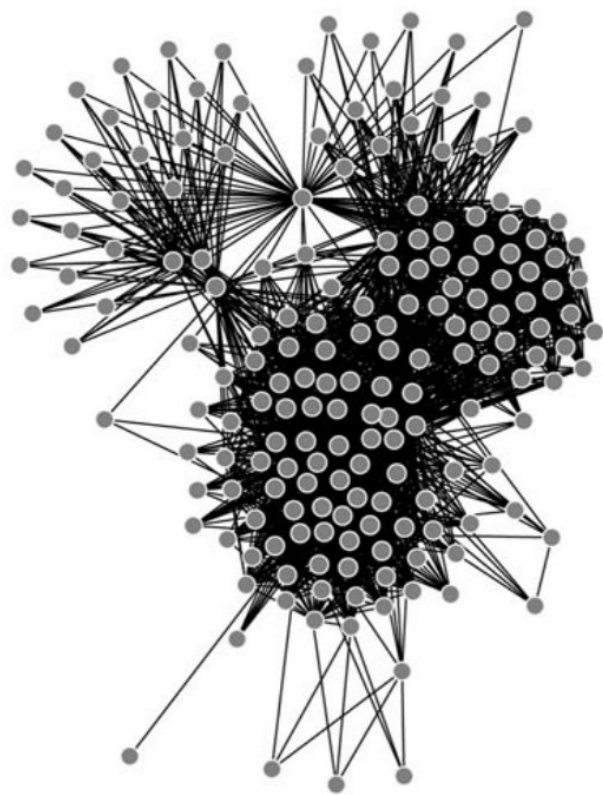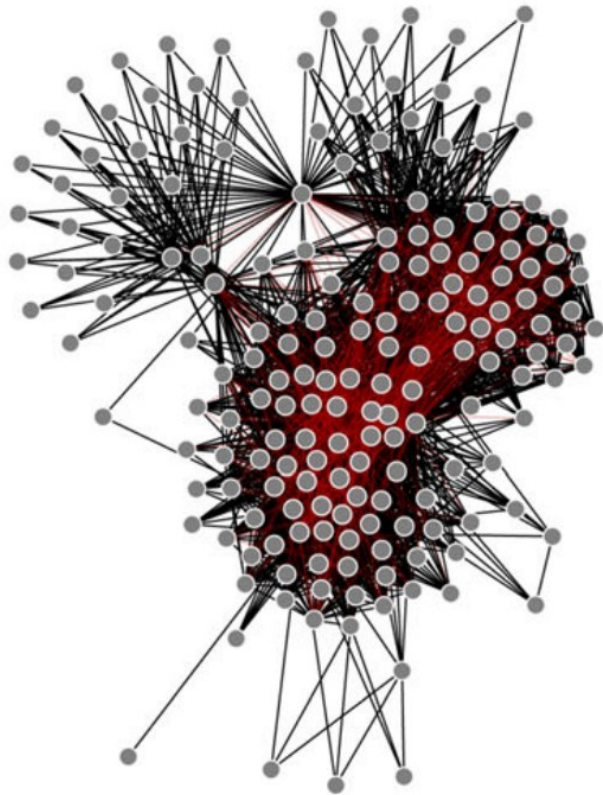
(a) True network   (b) Graphical LASSO

Friedman, J., Hastie, T. & Tibshirani, R. Sparse inverse covariance estimation with the graphical lasso. Biostatistics 9, 432-441 (2008).
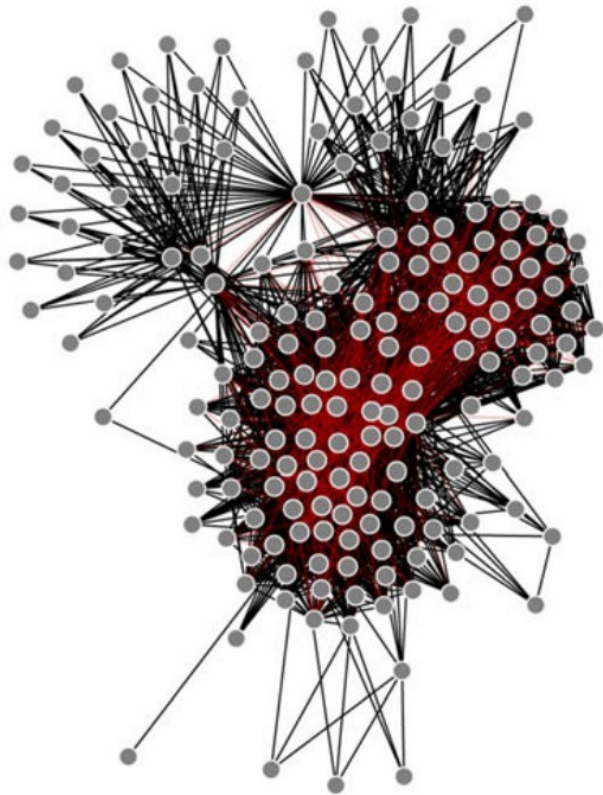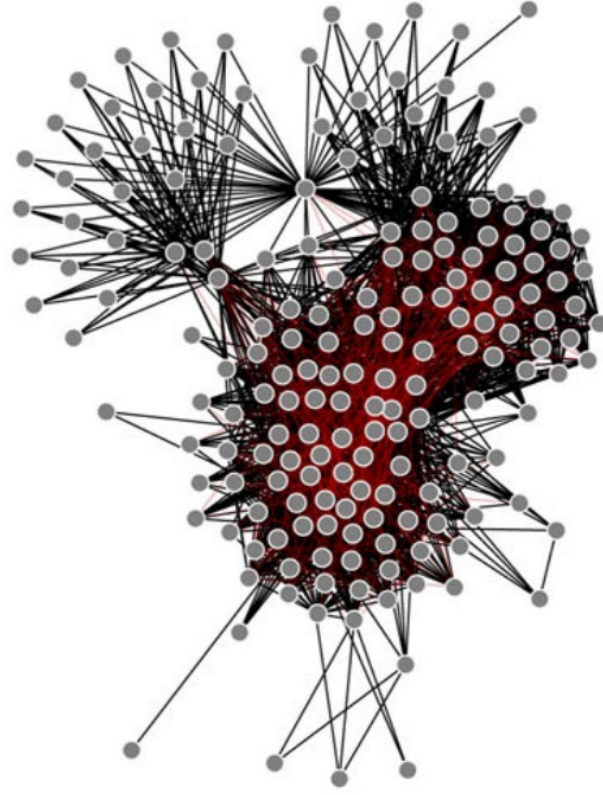
(a) True network (b) Graphical LASSO (c) Bayesian inference

"I see networks!"

III. Suitability of the methods

Summary descriptors used out of context
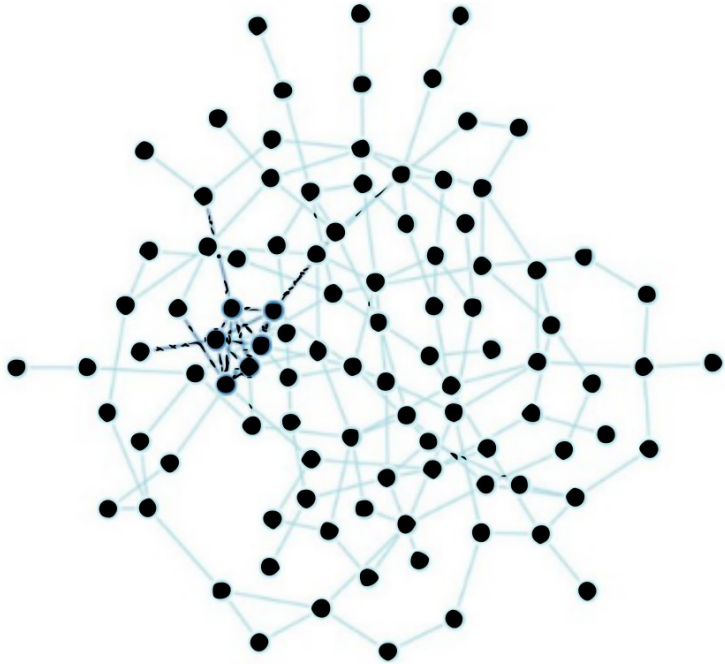
Shortest path of a correlation network?

Maximum modularity of a network?

What to vary, what to keep the same?

What to vary, what to keep the same?
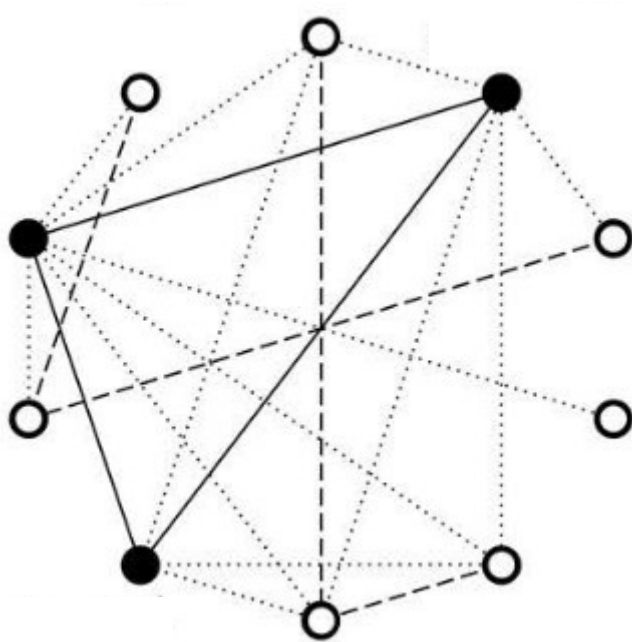
Assortativity of node labels for different null models

Cinelli, M., Peel, L., Iovanella, A. & Delvenne, J.-C. Network constraints on the mixing patterns of binary node metadata. Phys. Rev. E. 102, 062310 (2020).

What to vary, what to keep the same?

Assortativity of node labels for different null models

Edge rewiring + label permutation

Edge rewiring

Label permutation

mgs

gs

Cinelli, M., Peel, L., Iovanella, A. & Delvenne, J.-C. Network constraints on the mixing patterns of binary node metadata. Phys. Rev. E. 102, 062310 (2020).
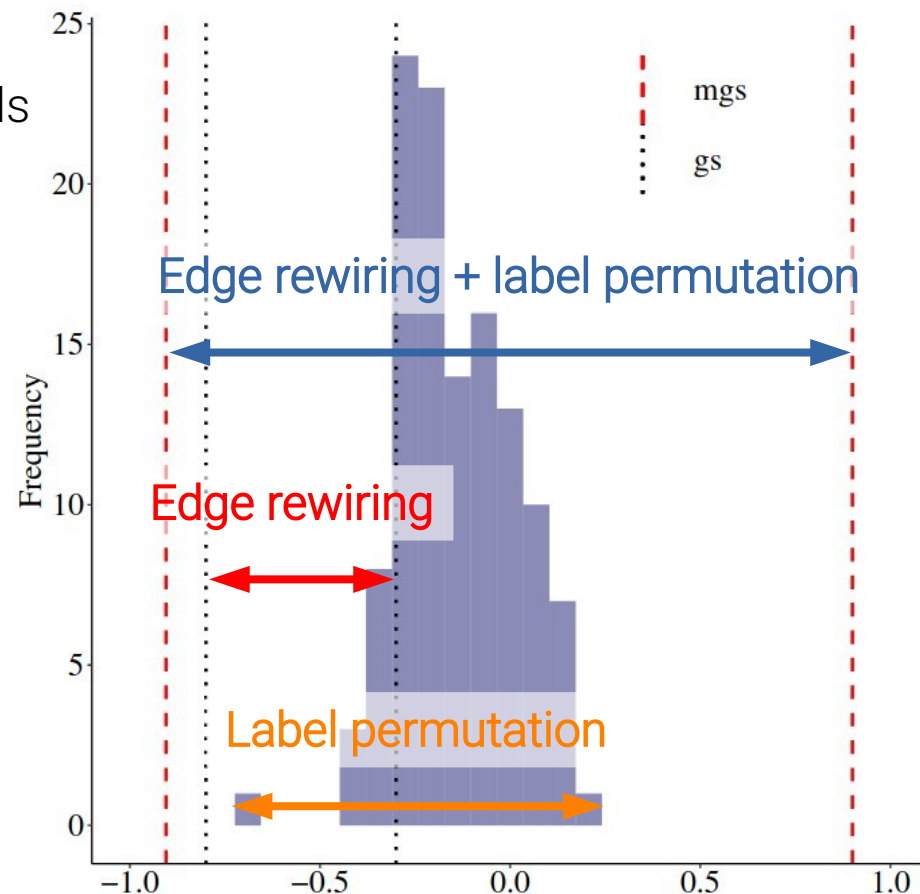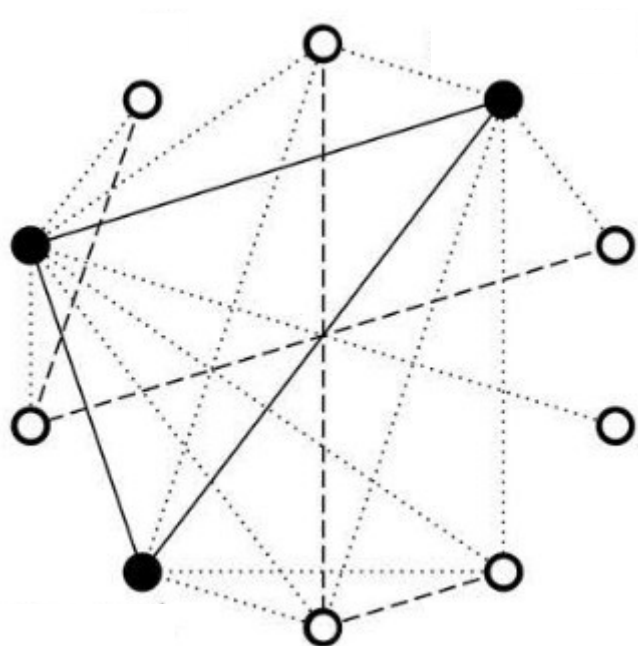
Null models and testing hypotheses
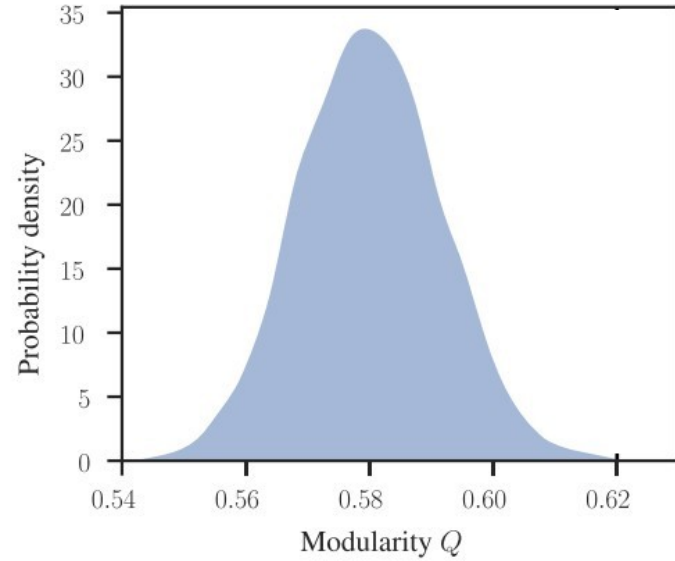
Null models and testing hypotheses

Reject the null hypothesis
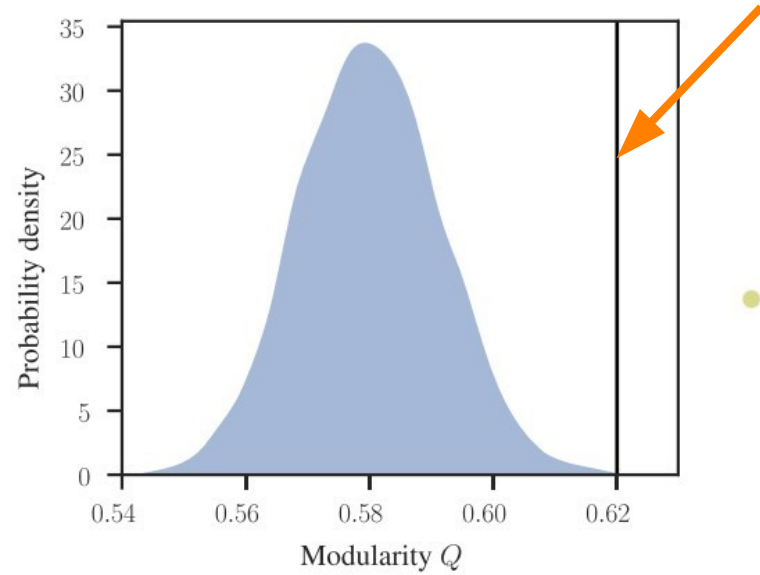
Rejecting the null hypothesis does not test the alternative...
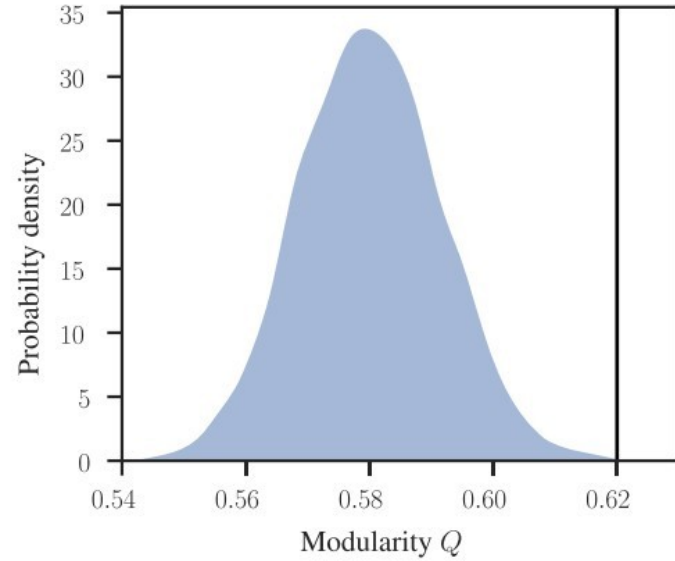
Accounting for reconstruction uncertainty

Original (unknown) Network

Observable

Observable
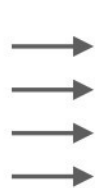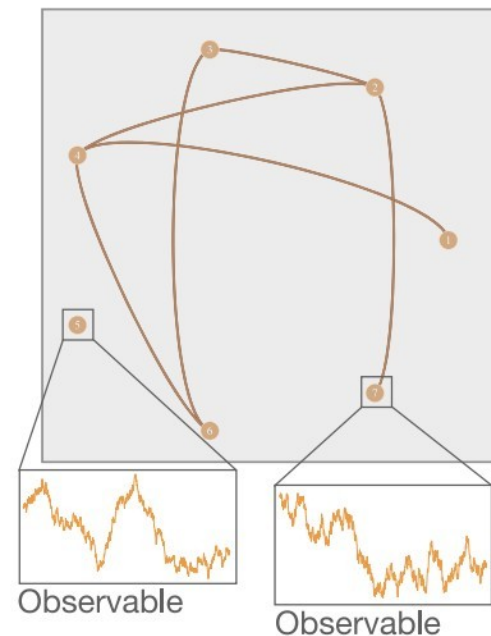
Network Reconstruction Method

Probabilistic Network Model

Low — High

Probability of link presence
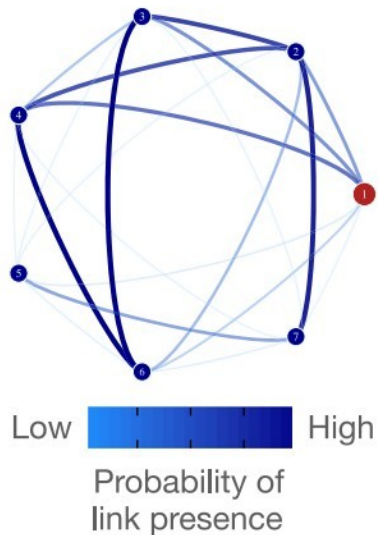
Descriptors Inference

Degree — Probability

Transitivity — Probability
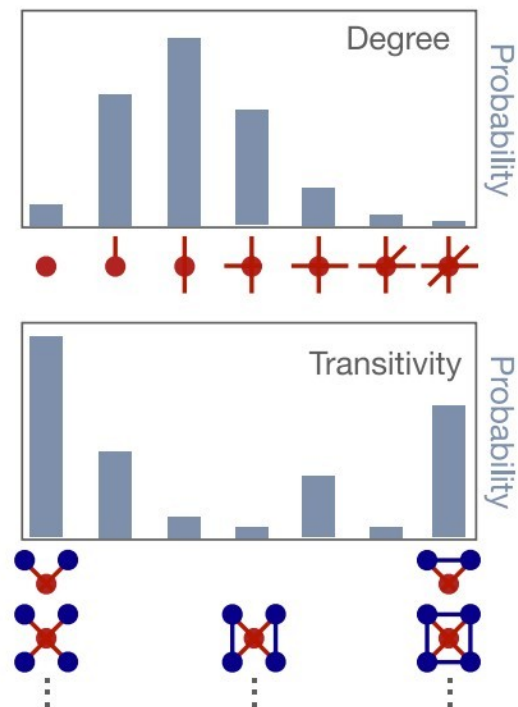
IV. Outlook

Looking forwards...

Looking forwards...

Eat our own dog food. More focus on collaborations, less on individuals

Looking forwards...

Eat our own dog food. More focus on collaborations, less on individuals

Break down walls. Strengthen the link between theory and application.

Looking forwards...

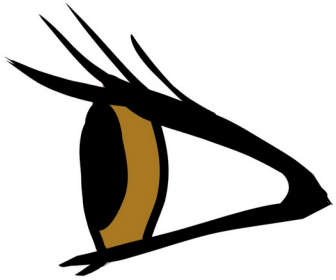**Eat our own dog food.** More focus on collaborations, less on individuals

Break down walls. Strengthen the link between theory and application.

Better modelling. Generative models + statistical inference. Focus on more specific models. Solve real problems.
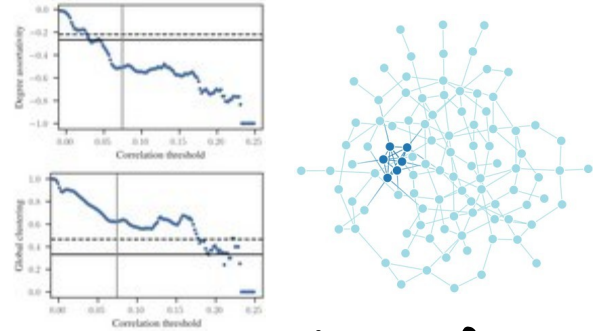
Observations/
measurements

Network representation
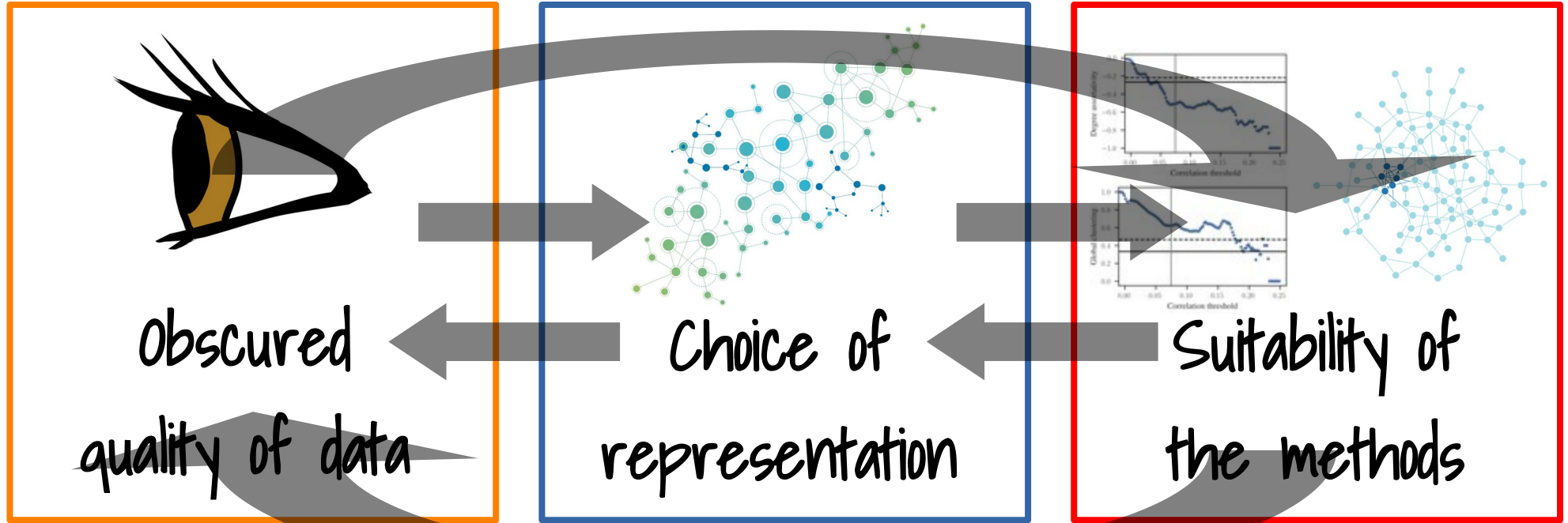
Network analysis

Obscured
quality of data

Choice of
representation

Suitability of
the methods

These steps are interdependent

Observations/measurements

Network representation

Network analysis

Obscured quality of data

Choice of representation

Suitability of the methods
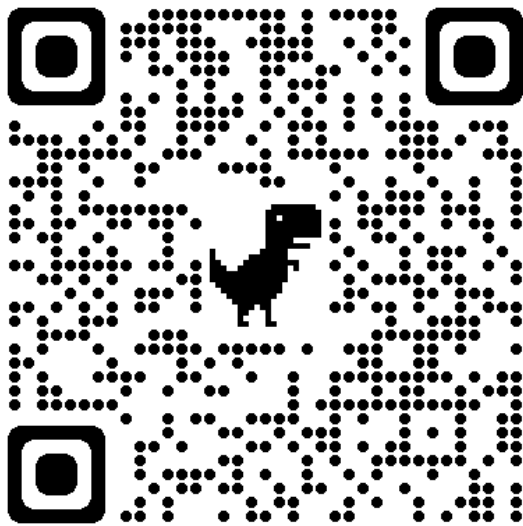
Download the paper!

Peel, L., Peixoto, T.P. & De Domenico, M. Statistical inference links data and theory in network science. *Nat Commun* **13**, 6794 (2022).

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l.peel@maastrichtuniversity.nl

Joint work with...

Tiago P. Peixoto

Manlio De Domenico