

# Network Science

## #16 Other approaches to community detection

© 2020 T. Erseghe

# Authority shift

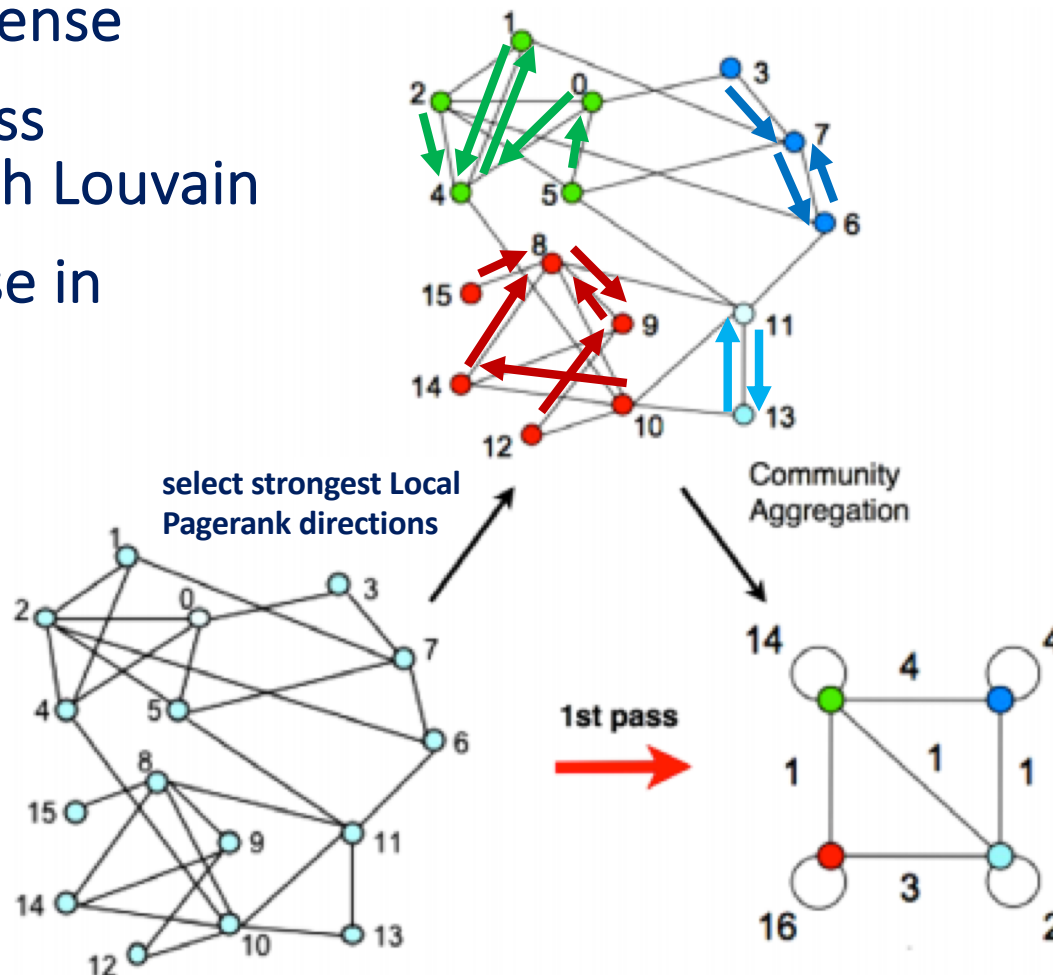
Cho & MuLee (2010)

Authority-shift clustering: Hierarchical clustering by authority seeking on graphs  
<https://ieeexplore.ieee.org/abstract/document/5540081>

# Authority shift

## Idea

- ❑ Connect a node towards the strongest direction in the **Local PageRank** sense
- ❑ Iterate the process recursively as with Louvain
- ❑ Stop if no increase in **modularity**



# Characteristics

- ❑ Implements modularity optimization
- ❑ Scalable (low complexity)
- ❑ Effective
- ❑ Local PageRank can be efficiently calculated
- ❑ Not a greedy technique
- ❑ Easily extendable to networks with signs
- ❑ No parameters to be set

# Brain Network Example

AUD = auditory

CCN = cognitive control

CON = cingulo-opercular

DAN = dorsal attention

DMN = default mode

FPN = fronto-parietal

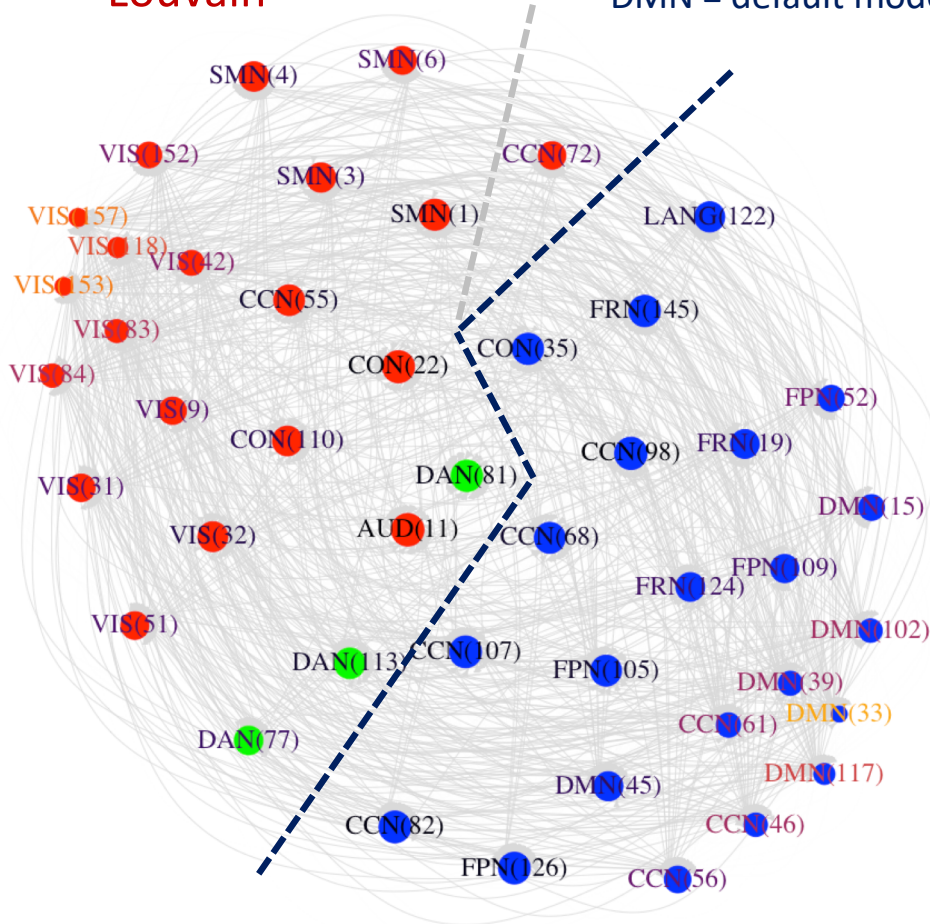
FRN = feedback-related negativity

LANG = language

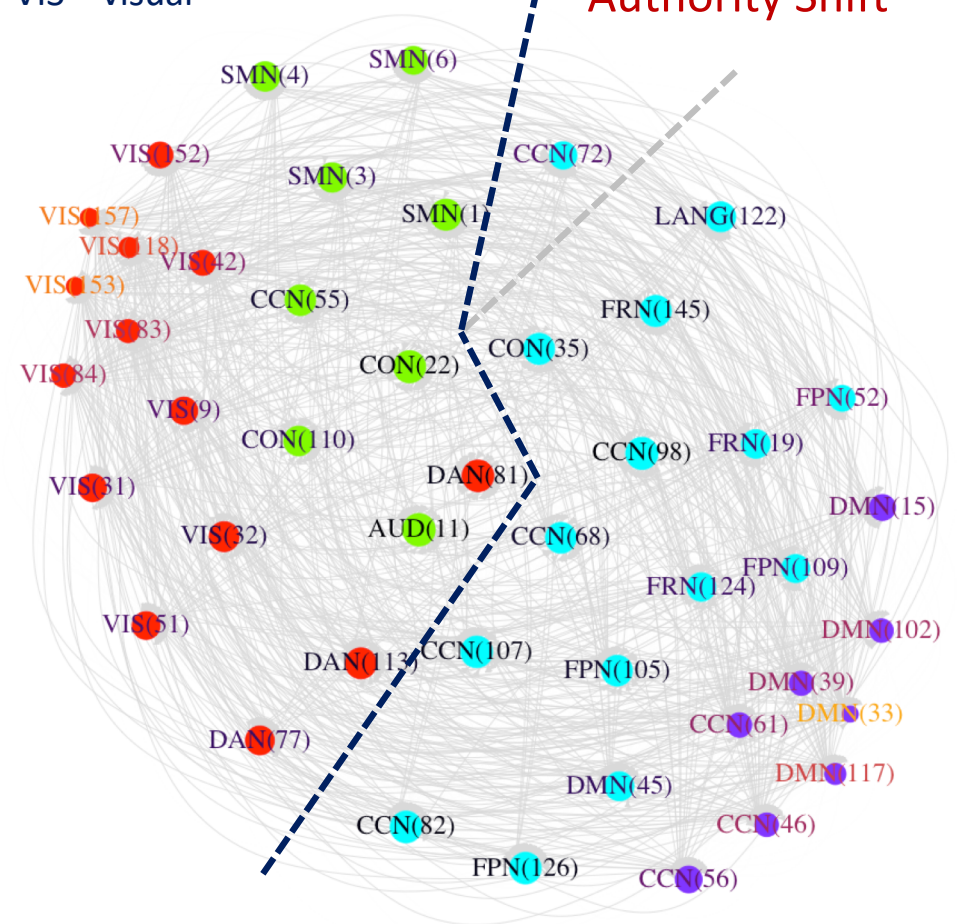
SMN = somato-motor

VIS = visual

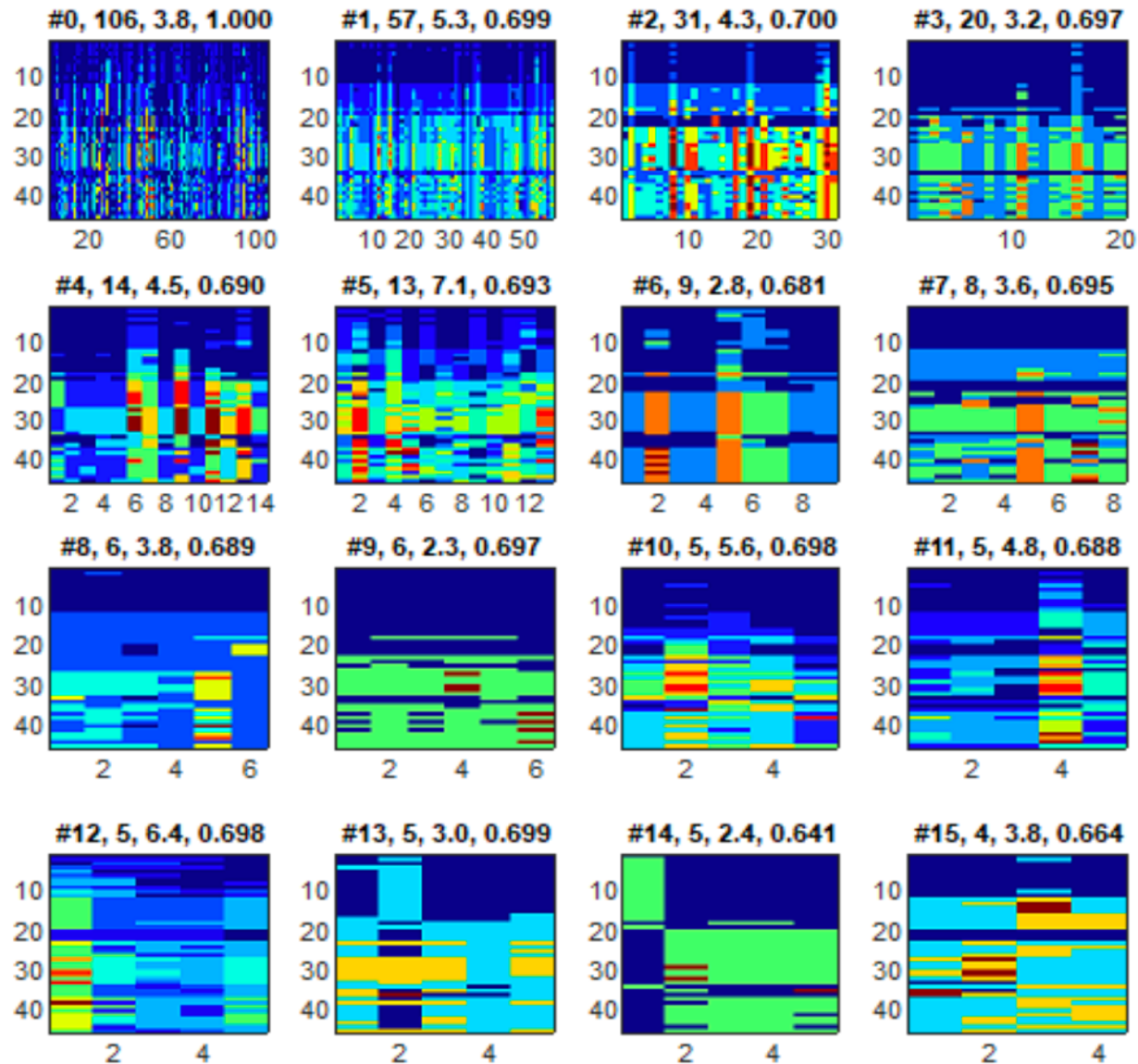
Louvain



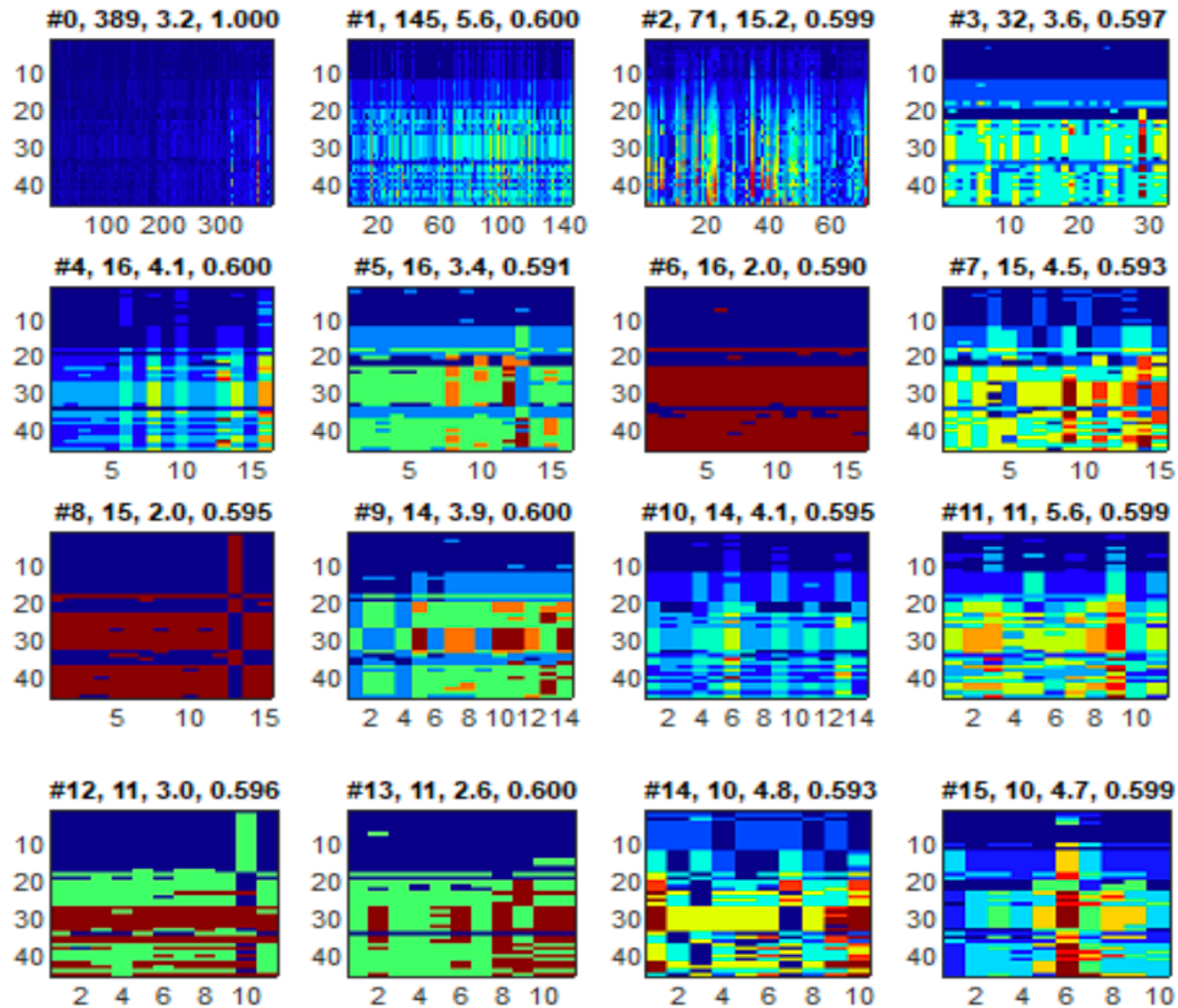
Authority Shift



# Authority Shift – Subjects Clusters



# Louvain – Subject Clusters



# Clique percolation



# Clique percolation

## Idea

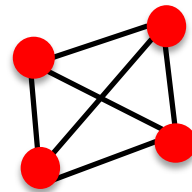
- Two nodes belong to the same community if they can be connected through **adjacent  $k$  cliques**

## $k$ clique

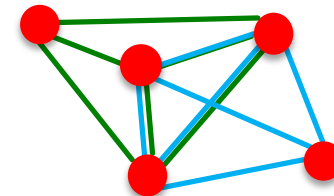
- Fully connected graph of  $k$  nodes

## Adjacent $k$ cliques

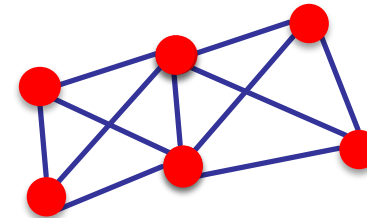
- Overlap in  $k-1$  nodes



4-clique



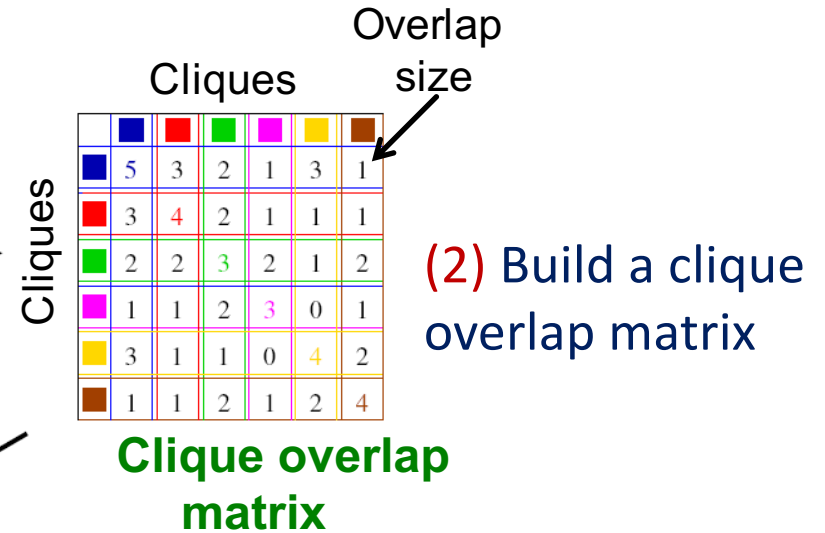
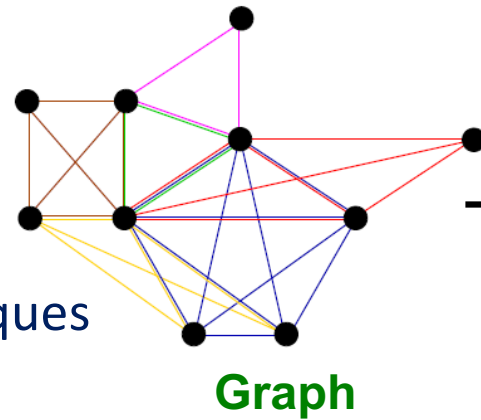
Adjacent 4-cliques



Non-adjacent 4-cliques

# Clique percolation

(1) identify cliques

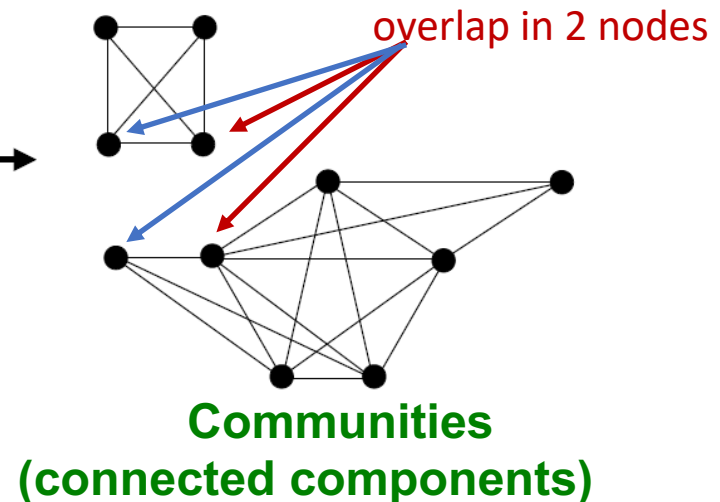


$k=4$

(3) Set a threshold  
(the one providing the richest community structure = most widely distributed cluster sizes)

	Blue	Red	Green	Magenta	Yellow	Brown
Blue	1	1	0	0	1	0
Red	1	1	0	0	0	0
Green	0	0	0	0	0	0
Magenta	0	0	0	0	0	0
Yellow	1	0	0	0	1	0
Brown	0	0	0	0	0	1

Thresholded matrix at 3



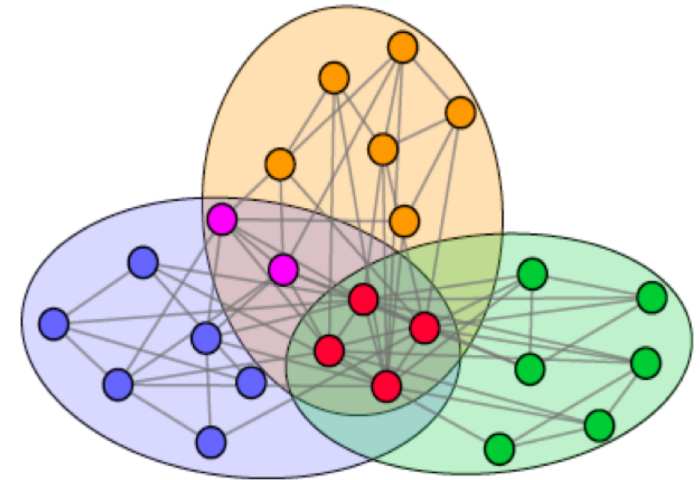
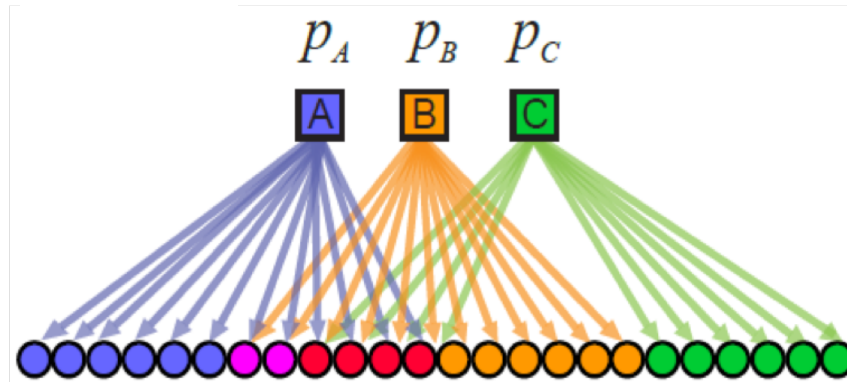
# Big CLAM

Yang & Leskovec (2013)

Overlapping community detection at scale: a nonnegative matrix factorization approach

[https://dl.acm.org/doi/pdf/10.1145/2433396.2433471?casa\\_token=ENfVUy8WEaUAAAAA:DDh024Jw5wchw69gYXm3BR3NRKDBjiDNz0pXRoJAWTKQD6HyT1iMRvc64WcclS7GLAAj30I-6Kiu](https://dl.acm.org/doi/pdf/10.1145/2433396.2433471?casa_token=ENfVUy8WEaUAAAAA:DDh024Jw5wchw69gYXm3BR3NRKDBjiDNz0pXRoJAWTKQD6HyT1iMRvc64WcclS7GLAAj30I-6Kiu)

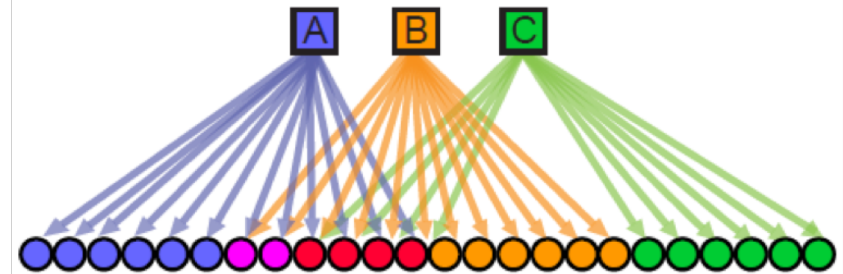
# BigCLAM



## Affiliation graph model (AGM)

- ❑ Nodes  $N$
- ❑ Communities  $C$
- ❑ Membership matrix  $M$ , binary  $|N| \times |C|$  matrix
- ❑ Probability  $p = [p_c]$  that a connection is active
- ❑ Probability that edge  $(i,j)$  is not active  $Q_{ij} = \prod_{c \in M_i \cap M_j} (1-p_c)$
- ❑  $Q = \exp(-M \text{diag}(q) M^T)$ ,  $q = -\log(1-p) > 0$

# BigCLAM



Target function

$$f = \prod_{(i,j) \in \mathcal{E}} (1-Q_{ij}) \prod_{(i,j) \notin \mathcal{E}} Q_{ij}$$

active edges  $\mathcal{E}$  is a  
known data

Recall that  $Q = \exp(-M \text{diag}(\mathbf{q}) M^T)$

Want to **maximize**  $f$  w.r.t.  $M$  binary and  $\mathbf{q} > 0$

- ❑ This is a **maximum likelihood** estimator (best fit in probability)
- ❑ Needs to know in advance the # of communities  $|C|$
- ❑ Very difficult to solve exactly – **NP-complex**

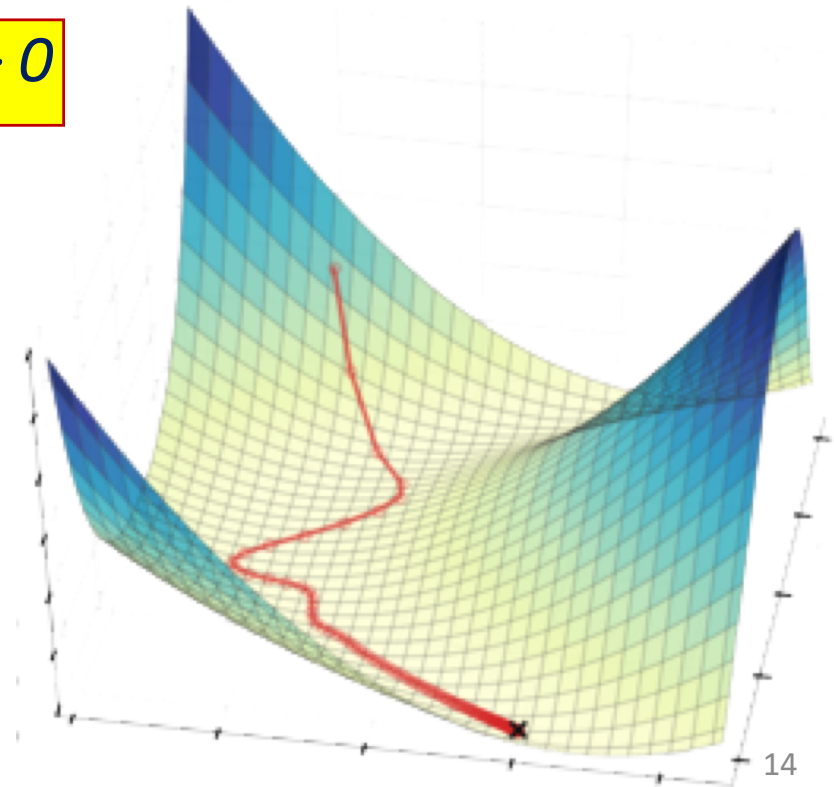
# BigCLAM

**Idea:** give membership  $M$  a strength = relaxation !!!

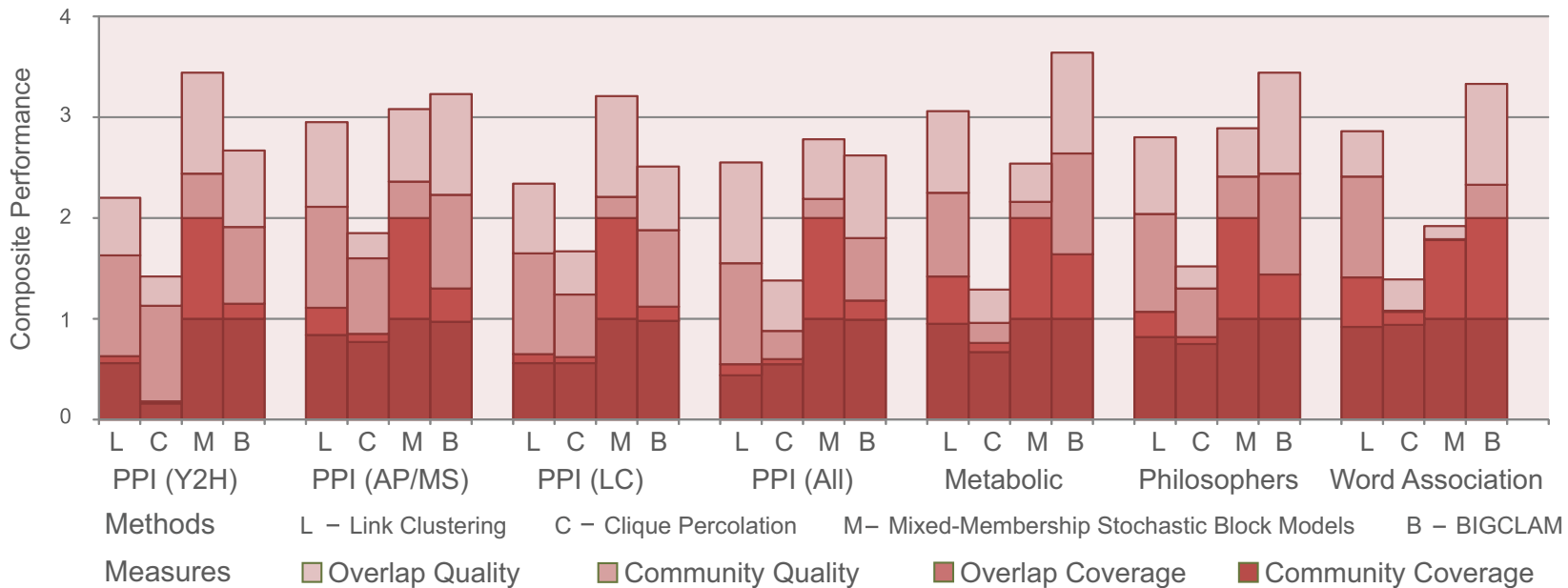
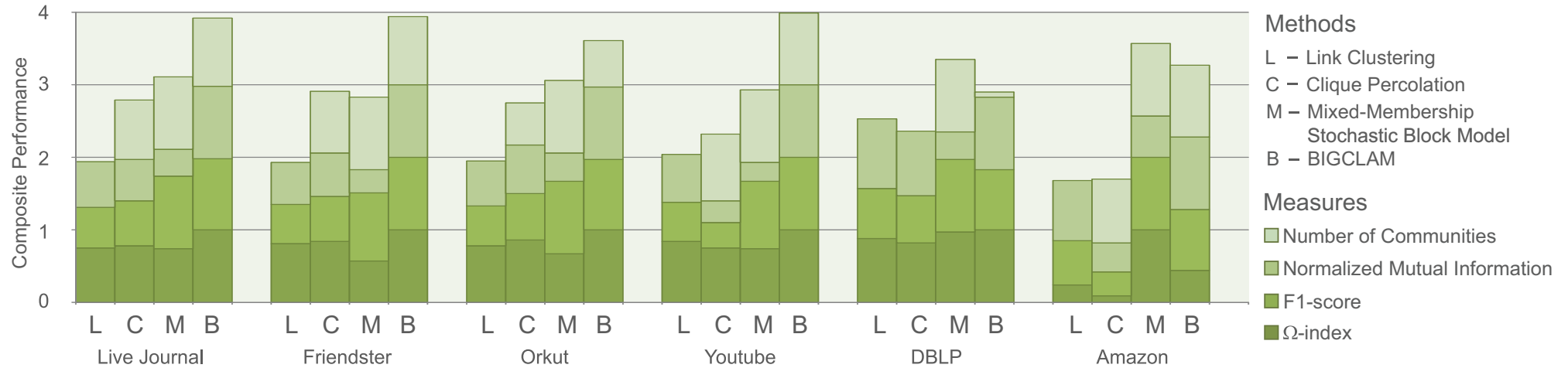
Target function  $f = \prod_{(i,j) \in \mathcal{E}} (1-Q_{ij}) \prod_{(i,j) \notin \mathcal{E}} Q_{ij}$

s. to  $Q = \exp(-M M^T)$  and  $M > 0$

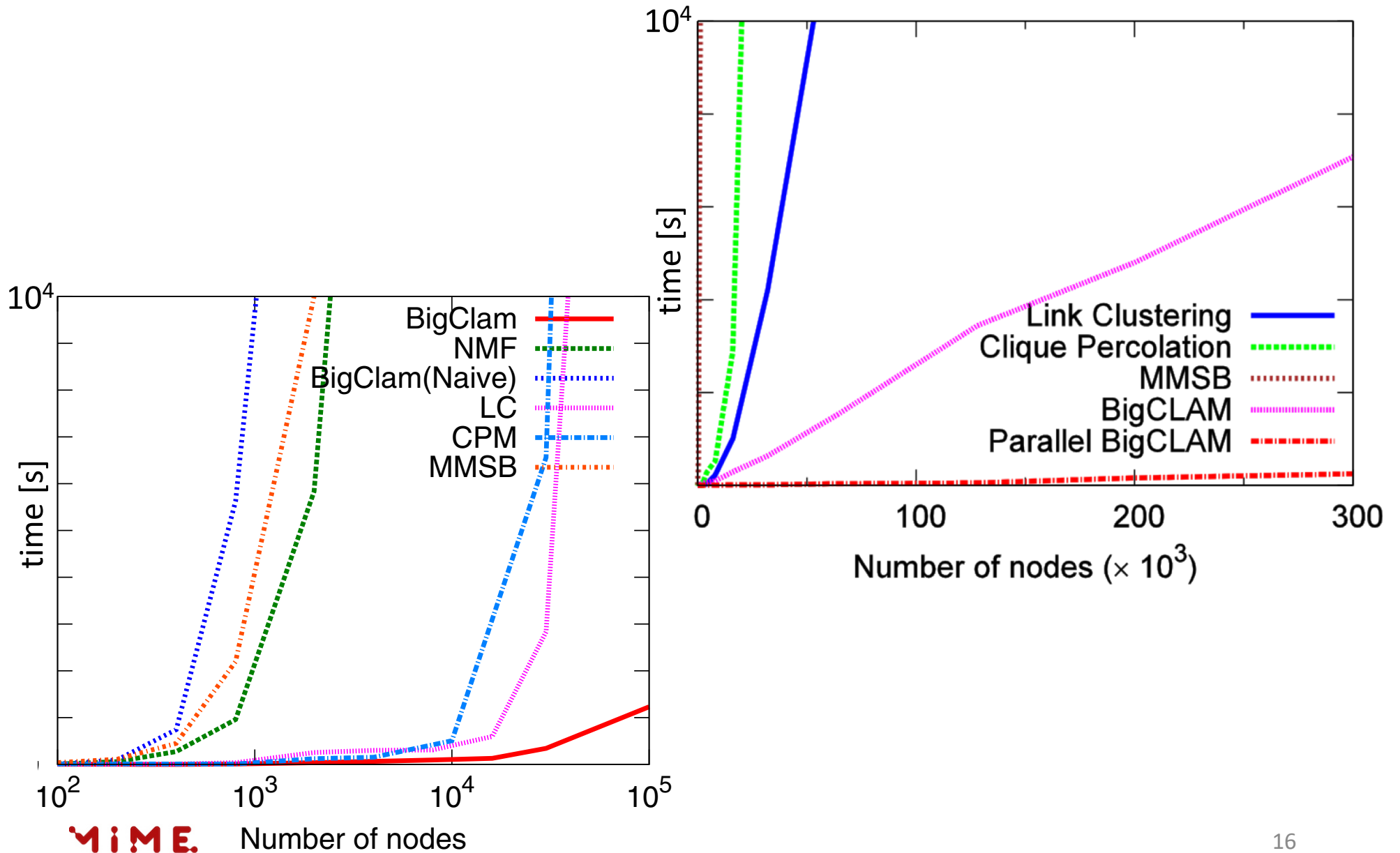
Can be solved using  
gradient descent methods



# Performance



# Performance





# Questions ?

