

Community detection in growing networks with aging

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Introduction to community detection

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 - Some nodes are densely connected with each other (community)
 - Communities in social networks can be due to language, age, race, ...

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“As long as there will be networks, there will be people looking for communities in them.”

— Fortunato and Hric, 2016

Introduction to community detection

- We focus on growing networks in particular: information and social networks, for example
- Detecting communities in such systems can help to understand:
 1. Group formation
 2. Opinion polarization
 3. Spreading of misinformation
 4. ...

Network modularity (static)

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in the same community

↓

number of links connected or not link expectation

Growing networks with community structure

- Modeling growing networks (Medo *et al.*, 2011):

$$P(i|j, t) \sim \underbrace{k_i(t)}_{\text{degree}} \times \underbrace{f_i}_{\text{fitness}} \times \underbrace{D(t)}_{\text{aging}}$$

- Preferential attachment and node fitness are optional
- Node aging: timescale Θ

Growing networks with community structure

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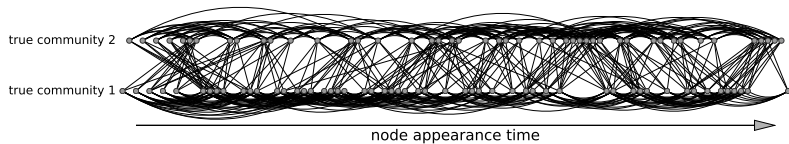
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- Preferential attachment and node fitness are optional
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- Community structure can be easily introduced
 - Assign each node to a ground-truth community C
 - Multiply $P(i|j, t)$ with

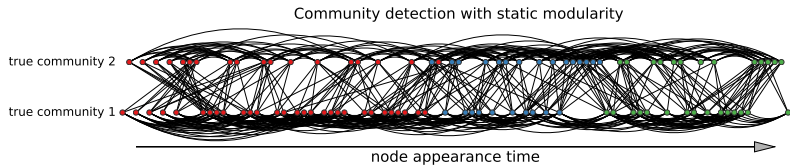
$$\mu[1 - \delta(C_i, C_j)] + (1 - \mu)\delta(C_i, C_j)$$

- $\mu = 0$: only nodes from the same community can connect

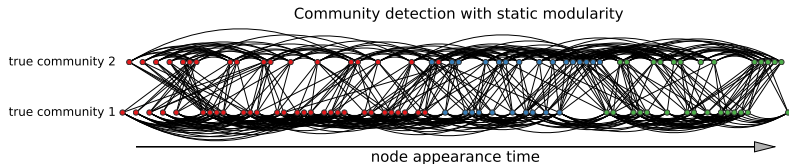
The problem in growing networks



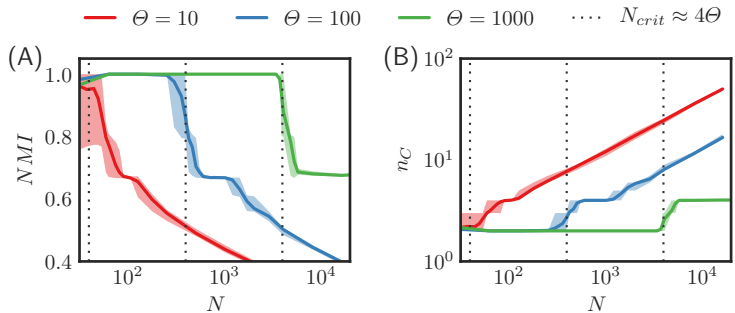
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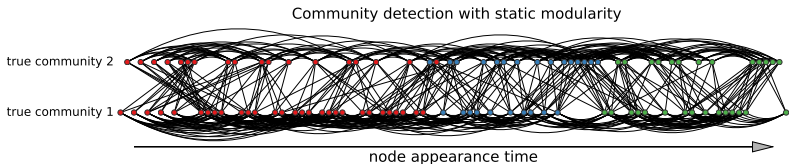
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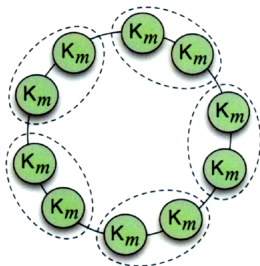
Problem even when $\mu = 0$



The problem in growing networks



Opposite to the well-known “resolution limit” of modularity



Fortunato & Barthélemy, 2007

Modularity for growing networks (to be submitted)

- **The reason of failure:**

If time matters, the link expectation term is wrong

$$Q = \frac{1}{m} \sum_{i,j} \left(A_{ij} - \frac{k_i^{\text{out}} k_j^{\text{in}}}{m} \right) \delta(c_i, c_j)$$

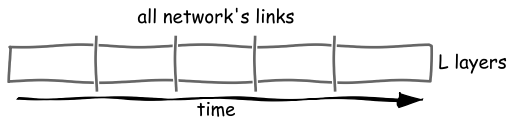
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- Dynamic Configuration Model (Ren *et al.*, 2018?):



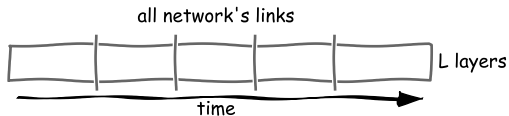
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- Dynamic Configuration Model (Ren et al., 2018?):



Temporal modularity computes link expectation from L layers

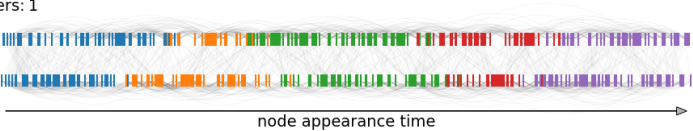
$$Q_T(L) = \frac{1}{m} \sum_{i,j} \left(A_{ij} - \sum_{l=1}^L \frac{\Delta k_{i,l}^{\text{out}} \Delta k_{j,l}^{\text{in}}}{m_l} \right) \delta(c_i, c_j)$$

Temporal modularity in action

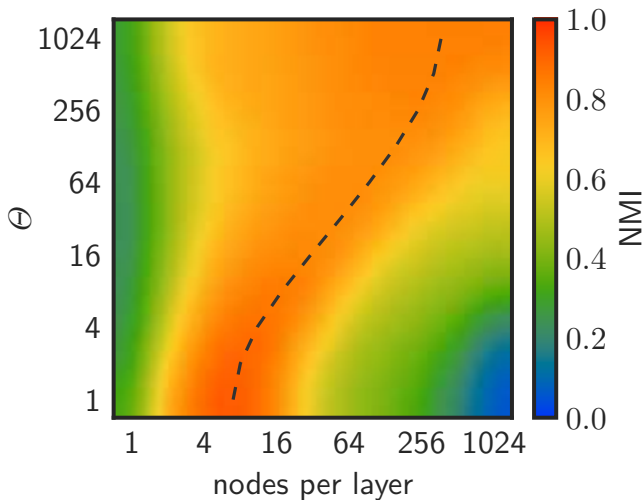
number of layers: 1

true community 2

true community 1



Temporal modularity in action



Dashed line corresponds to choosing L by the median link span

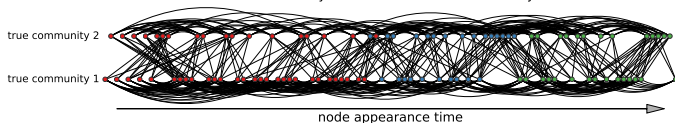
- Two real datasets
 1. Subsets of the APS citation data from years 1893–2013 corresponding to the second level in the PACS classification (e.g., 89.75.* = “Complex systems”)
 2. Subsets of a news citation dataset (Spitz and Gertz, 2015) corresponding to individual newspapers

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- But... How to evaluate network partitions in real data without the ground truth?

Custom-made evaluation metric

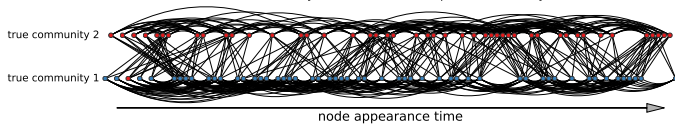
bad

Community detection with static modularity



good

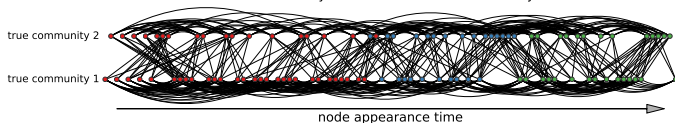
Community detection with temporal modularity



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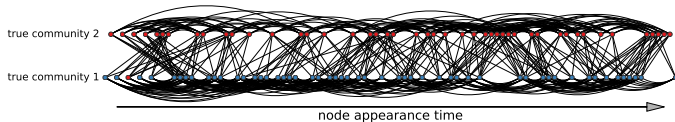
bad

Community detection with static modularity



good

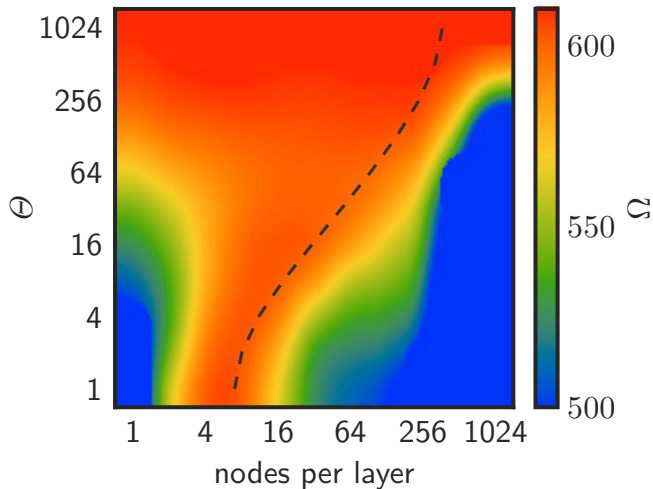
Community detection with temporal modularity



New metric: **average community span** * Ω

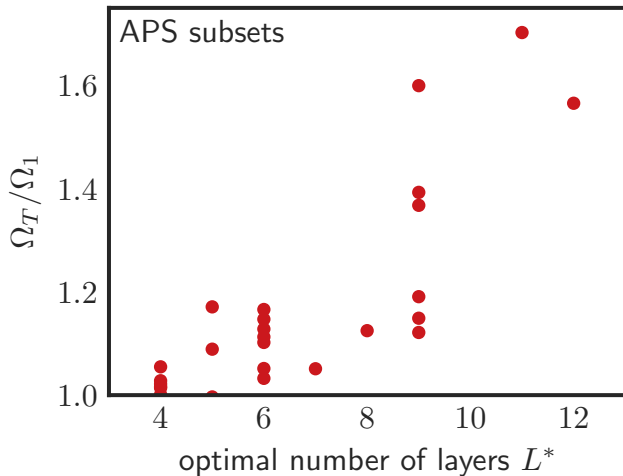
*: Span of a community is the difference between the 20th and 80th percentile of node IDs in the community, and the average is weighted by community size.

Custom-made evaluation metric

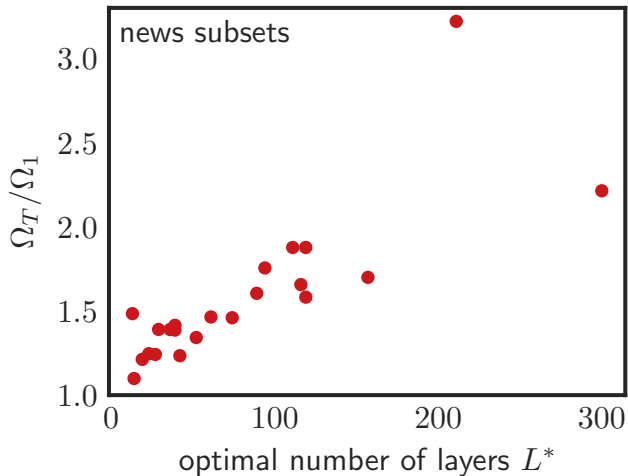


Look back at the model data

Real data results



Real data results



Take-home message



1. Static modularity fails when aging is fast, temporal modularity just works
2. Models help you assess old tools and devise new ones
3. In many systems, taking time into account improves the results

Further related work:

1. H. Liao, M. S. Mariani, M. Medo, Y.-C. Zhang, M.-Y. Zhou, Ranking in evolving complex networks, *Physics Reports* 689, 1-54, 2017
2. Z.-M. Ren, M. S. Mariani, Y.-C. Zhang, M. Medo, Randomizing growing networks with a time-respecting null model arXiv:1703.07656
3. G. Vaccario, M. Medo, N. Wider, M. S. Mariani, Quantifying and suppressing ranking bias in a large citation network, *Journal of Informetrics* 11, 766-782, 2017
4. M. Medo, G. Cimini, Model-based evaluation of scientific impact indicators, *Physical Review E* 94, 032312, 2016
5. A. Vidmer, M. Medo, The essential role of time in network-based recommendation, *EPL* 116, 30007, 2016
6. M. Medo, M. S. Mariani, A. Zeng, Y.-C. Zhang, Identification and modeling of discoverers in online social systems, *Scientific Reports* 6, 34218, 2016

Web site: www.ddp.fmph.uniba.sk/~medo/physics/



Manuel Mariani



Zhuo-Ming Ren



An Zeng



Yi-Cheng Zhang

Thank you for your attention!

Questions?