

# Community Extraction for Social Networks

Yunpeng Zhao

Department of Statistics, University of Michigan, Ann Arbor, MI 48109, USA

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Advisor: Liza Levina and Ji Zhu

- Review of community detection
- Community extraction
- Asymptotic consistency
- Simulation study
- Real data analysis

Network analysis has been a focus of attention in different fields.

- Social science: friendship networks
- Internet: WWW, hyper-links
- Biology: food webs, gene regulatory networks

# Community detection

- Communities: Networks consist of communities, or clusters, with many connections within a community and few connections between communities.
- Community detection problem: For an undirected network  $N = (V, E)$ , the community detection problem is typically formulated as finding a **partition**  $V = V_1 \cup \dots \cup V_K$  which gives “tight” communities in some suitable sense.

# Community detection problem

Existing community detection methods: minimizing links between communities while maximizing links within communities (see Newman (2004) for a review).

For simplicity, we consider the case of partitioning the network into two communities  $V_1$  and  $V_2$ .

To minimize

$$R = \sum_{i \in V_1, j \in V_2} A_{ij} .$$

However, min-cut always yields a trivial solution of  $V_1 = V$  or  $V_2 = V$ .

$$\min R/(|V_1| \cdot |V_2|),$$

where  $|V_1|$  and  $|V_2|$  represent the sizes of two groups respectively.

Ratio-cut can avoid trivial solutions because the maximizer of  $|V_1| \cdot |V_2|$  is achieved at  $|V_1| = |V_2| = |V|/2$ .

$$\min \frac{R}{\text{assoc}(V_1, V)} + \frac{R}{\text{assoc}(V_2, V)},$$

where  $\text{assoc}(V_k, V) = \sum_{i \in V_k, j \in V} A_{ij}$  for  $k = 1, 2$ .

Normalized-cut can avoid trivial solutions because an extremely small group  $V_k$  may have a large ratio  $R/\text{assoc}(V_k, V)$ .



To maximize

$$Q = \sum_{k=1}^2 \left[ \frac{O_{kk}}{L} - \left( \frac{D_k}{L} \right)^2 \right],$$

where  $O_{kk} = \sum_{i \in V_k, j \in V_k} A_{ij}$ ,  $D_k = \sum_{i \in V_k, j \in V} A_{ij}$ ,  $L = \sum_{k=1}^2 D_k$ .

$Q$  represents the fraction of edges that fall within communities, minus the “average” value of the same quantity if edges fall at random given the degree of each node.

- ✓ Review of community detection
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# Community extraction

- Most networks consist of a number (not known a priori) of **communities**, with relatively tight links within each community and sparse links to the outside, and **“background” nodes** that only have sparse links to other nodes.
- We propose a method that **extracts communities** sequentially: at each step, the tightest is extracted from the network until no more meaningful communities exist.

- Extract one community at a time by looking for a set of nodes with a large number of links within itself and a small number of links to the rest of the network.
- The links within the complement of this set do not matter.

To maximize

$$W(S) = \frac{I(S)}{k^2} - \frac{B(S)}{k(n-k)},$$

where

$$I(S) = \sum_{i,j \in S} A_{ij}, \quad B(S) = \sum_{i \in S, j \in S^c} A_{ij}, \quad k = |S|.$$

# Adjusted criterion

- Empirically, the previous criterion performs well for **dense** networks. However, it always finds very small communities for **sparse** networks.
- To avoid small communities, we also propose

To maximize

$$W_a(S) = k(n-k) \left( \frac{I(S)}{k^2} - \frac{B(S)}{k(n-k)} \right).$$

The factor  $k(n-k)$  penalizes communities with  $k$  close to 1 or  $n$  and encourages more balanced solutions.

- Tabu Search (Glover, 1986; Glover and Laguna, 1997): a local optimization technique based on label switching
- Run the algorithm for many randomly ordered nodes

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  - *Asymptotic consistency*
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  - Future work

# Block models

Asymptotic consistency can be established under the assumption of block models.

## General block models

- 1 Each node is assigned to a block independently of other nodes, with probability  $\pi_k$  for block  $k$ ,  $1 \leq k \leq K$ ,  $\sum_{k=1}^K \pi_k = 1$ .
- 2 Given that node  $i$  belongs to block  $a$  and node  $j$  belongs to block  $b$ ,  $P[A_{ij} = 1] = p_{ab}$ , and all edges are independent.

## Block models for networks with background

- We can define the last block as background, by assuming  $p_{aK} < p_{bb}$  for all  $a = 1, \dots, K$ , and all  $b = 1, \dots, K - 1$ .



# Asymptotic consistency

- For simplicity, assume there is only one community and background in the network ( $K = 2$  with parameters  $p_{11}, p_{12}, p_{22}, \pi$  and  $1 - \pi$ ).
- Let  $\mathbf{c}$  denote the true community labels,  $\hat{\mathbf{c}}^{(n)}$  denote the estimated labels, based on Bickel and Chen (2010), we proved

## Theorem

For any  $0 < \pi < 1$ , if  $p_{11} > p_{12}$ ,  $p_{11} > p_{22}$  and  $p_{11} + p_{22} > 2p_{12}$ , the maximizer  $\hat{\mathbf{c}}^{(n)}$  of both *unadjusted* and *adjusted* criteria satisfies

$$P[\hat{\mathbf{c}}^{(n)} = \mathbf{c}] \rightarrow 1 \quad \text{as } n \rightarrow \infty.$$

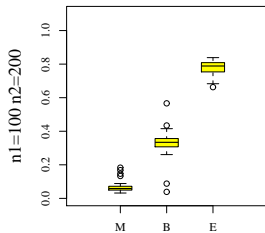
- ✓ Review of community detection
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- ✓ Asymptotic consistency
- [Simulation study](#)
- Real data analysis

# Simulation I

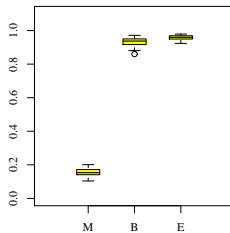
- Two communities with background (block model)
- $n = 1000$
- $n_1 = 100, 200, n_2 = 100$
- $p_{12} = p_{23} = p_{13} = p_{33} = 0.05$
- $p_{11} = 0.05i, p_{22} = 0.04i, i = 3, 4$
- Rand index

# Results for simulation I

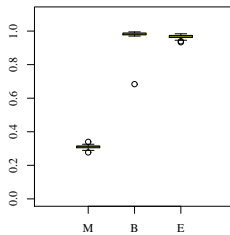
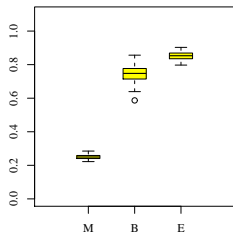
p11=0.15 p22=0.12



p11=0.2 p22=0.16



n1=200 n2=200

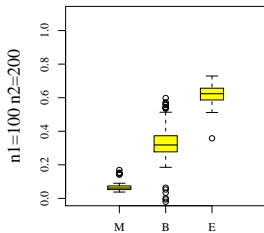


# Simulation II

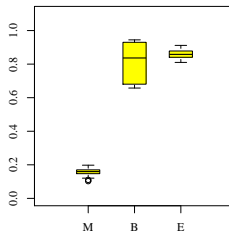
- Two communities with background
- $n = 1000$
- $n_1 = 100, 200, n_2 = 100$
- $p_{12} = p_{23} = p_{13} = p_{33} = 0.05$
- $p_{11} = 0.05i, p_{22} = 0.04i, i = 3, 4$
- Doubling the degree for 10 highest degree nodes

# Results for simulation II

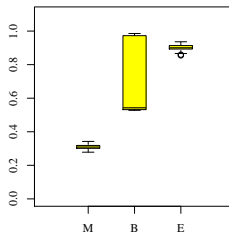
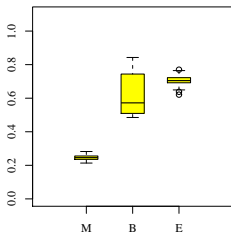
$p_{11}=0.15$   $p_{22}=0.12$



$p_{11}=0.2$   $p_{22}=0.16$



$n_1=200$   $n_2=200$



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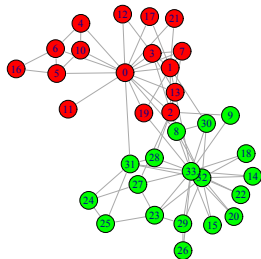
# Karate club network

- Friendships between 34 members of a karate club (Zachary, 1977).
- This club has subsequently split into two parts following a disagreement between an instructor (node 0) and an administrator (node 33).

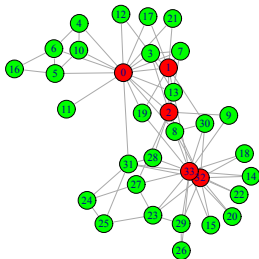


# Karate club network

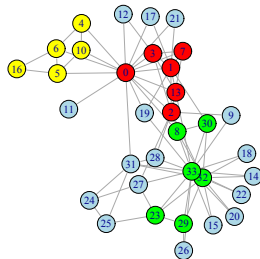
(a) Modularity



(b) Block model



(c) Extraction



# Political books network

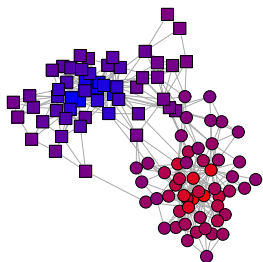
Links in the political books network (Newman, 2006) represent pairs of books frequently bought together on amazon.com.

**Blue:** liberal

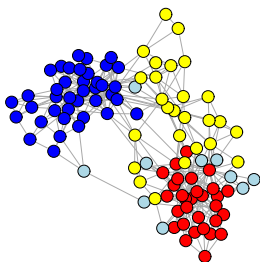
**Red:** conservative

# Political books network

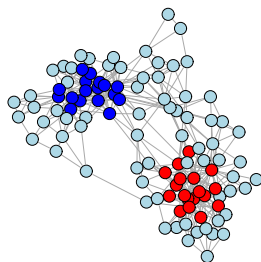
(a) Modularity



(b) Block model



(c) Extraction



# Acknowledgment

- Thank my advisors: Elizaveta Levina and Ji Zhu
- Thank Professor Mark Newman for constructive suggestion and sharing his code
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