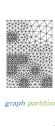
network blockmodeling

introduction to network analysis (ina)

Lovro Šubelj University of Ljubljana spring 2024/25

blockmodeling overview





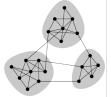




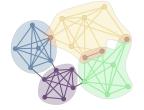
graph partitioning [KL70, Fie73]

blockmodeling [LW71, WR83]

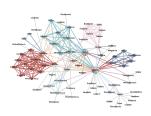
stochastic block model [Pei15]







overlapping communities [PDFV05]



link communities [EL09, ABL10]

 $^{^{*}}$ assortative & disassortative equivalence blockmodeling

blockmodeling equivalence

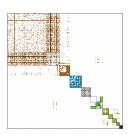
- standard equivalence blockmodeling [DBF05]
 - define node similarity as (structural) equivalence

$$\sigma_{ij} \sim |\Gamma_i \cap \Gamma_j|$$

- 1. blockmodeling by (hierarchical) clustering $O(n^2)$
- 2. return block model at desired clustering resolution



javax adjacency matrix



javax block model

[‡]javax.swing, javax.management, javax.naming, javax.print, javax.xml, javax.lang etc.

blockmodeling structural

similar nodes have same neighbors

— standard structural equivalence [LW71] of i and j is

$$\sigma_{ij} = \sum_{x} A_{ix} A_{xj} = |\Gamma_i \cap \Gamma_j|$$

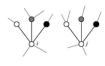
- Salton structural equivalence [SM83] of i and j is
 - θ_{ij} is angle between neighborhoods A_i and A_j

$$\sigma_{ij} = \cos \theta_{ij} = \frac{\sum_{\mathbf{x}} A_{i\mathbf{x}} A_{\mathbf{x}j}}{\sqrt{\sum_{\mathbf{x}} A_{i\mathbf{x}}^2} \sqrt{\sum_{\mathbf{x}} A_{j\mathbf{x}}^2}} = \frac{|\Gamma_i \cap \Gamma_j|}{\sqrt{k_i k_j}}$$

— Leicht structural equivalence [LHN06] of i and j is $\sigma_{ij} = \frac{|\Gamma_i \cap \Gamma_j|}{k_i k_j / n}$



structural



regular equivalence

blockmodeling regular

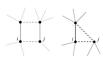
similar nodes have equivalent neighbors

- standard regular equivalence [WR83] of i and j is $-\alpha < \lambda^{-1} \text{ is positive constant and } \lambda \text{ leading eigenvalue of } A$ $\sigma_{ij} = \alpha \sum_{xy} A_{ix} A_{jy} \sigma_{xy} + \delta_{ij} = \alpha \sum_{x \in \Gamma_i} \sum_{y \in \Gamma_j} \sigma_{xy} + \delta_{ij}$ $\sigma = \alpha A \sigma A + I \text{ and thus } \sigma^{(0)} = 0, \ \sigma^{(1)} = I, \ \sigma^{(2)} = \alpha A^2 + I, \ \sigma^{(3)} = \alpha^2 A^4 + \alpha A^2 + I \text{ etc.}$
- Katz regular equivalence [Kat53] of i and j is

$$\begin{split} \sigma_{ij} &= \alpha \sum_{\mathbf{X}} A_{i\mathbf{X}} \sigma_{\mathbf{X}j} + \delta_{ij} = \alpha \sum_{\mathbf{X} \in \mathbf{\Gamma}_i} \sigma_{\mathbf{X}j} + \delta_{ij} \\ \sigma &= \alpha A \sigma + I \text{ and thus } \sigma^{(0)} = \mathbf{0}, \ \sigma^{(1)} = I, \ \sigma^{(2)} = \alpha A + I, \ \sigma^{(3)} = \alpha^2 A^2 + \alpha A + I \text{ etc.} \end{split}$$







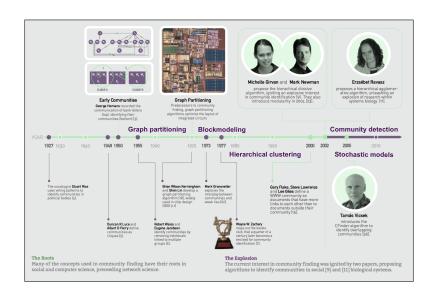
structural

regular equivalence

standard k

Katz

blockmodeling *history*



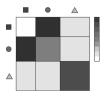
stochastic models

introduction to network analysis (ina)

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stochastic models

- random graph model G(n, m) for network links m [ER59]
- configuration model $G(\{k\})$ for node degrees $\{k\}$ [NSW01]
- exponential p^* -model $G(n, \{\langle x \rangle\})$ for any expectations $\{\langle x \rangle\}$
- stochastic block model $G(\{C\})$ for node clusters $\{C\}$ [HLL83]





^{*} assortative & disassortative stochastic block models

stochastic $G(\{C\})$ model

- $G(\{C\}, \{p\})$ stochastic block model [HLL83]
- link between i and j placed with probability $p_{c_ic_i}$
 - m_{cici} is number of links between C_i and C_i

$$\begin{array}{l} - \ \textit{M}_{c_i c_j} \text{ is } \textit{maximum } \textit{m}_{c_i c_j} \text{ hence } \textit{n}_i \textit{n}_j \text{ or } \binom{n_i}{2} \\ P(\textit{A}|\{\textit{C}\},\{\textit{p}\}) = \prod_{i \leq j} \textit{p}_{c_i c_j}^{\textit{A}_{ij}} (1 - \textit{p}_{c_i c_j})^{1 - \textit{A}_{ij}} = \prod_{c_i \leq c_j} \textit{p}_{c_i c_j}^{\textit{m}_{c_i c_j}} (1 - \textit{p}_{c_i c_j})^{\textit{M}_{c_i c_j} - \textit{m}_{c_i c_j}} \end{array}$$

— maximum likelihood $G(\{C\})$ block model

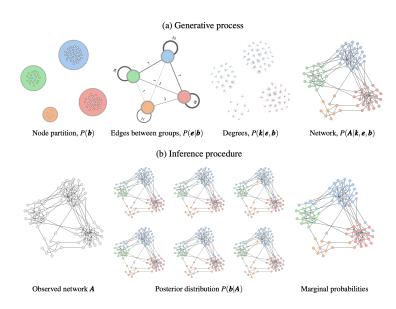
$$-\frac{\frac{m_{c_ic_j}}{M_{c_ic_j}} \text{ is } \max \text{imum likelihood estimate for } p_{c_ic_j} \\ \mathcal{L}(A|\{C\}) = \log P(A|\{C\}) = \sum_{c_i \leq c_j} m_{c_ic_j} \log \frac{m_{c_ic_j}}{M_{c_ic_i} - m_{c_ic_j}} + M_{c_ic_j} \log \frac{M_{c_ic_j} - m_{c_ic_j}}{M_{c_ic_i}}$$



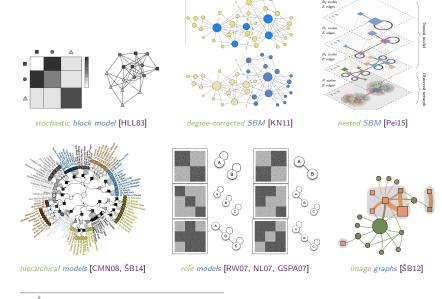


see graph-tool implementation

stochastic process



stochastic overview



Toverlapping & corrected models also known as mixture & mixed membership models



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