

Estimation II

Notations

- Observed collection of networks: $\mathcal{A} = \{A^{(m)}, m = 1, \dots, M\}$
- Latent variables: $\mathcal{U} = (U_1, \dots, U_M)$, $\mathcal{Z} = \{\mathbf{Z}^{(m)}, m = 1, \dots, M\}$
- Model parameters: $\theta = ((p_1, \dots, p_C), (\pi^{(c)}, \gamma^{(c)})_{c=1, \dots, C})$

Integrated classification likelihood (ICL)

- Bayesian approach: put a prior $p(\theta)$ on the parameters θ
- Likelihood of complete data (Biernacki et al., 2000):

$$\text{ICL}(\mathcal{U}, \mathcal{Z}; \mathcal{A}) = \log(p(\mathcal{U}, \mathcal{Z}, \mathcal{A})) = \log \left(\int p(\mathcal{U}, \mathcal{Z}, \mathcal{A} | \theta) p(\theta) d\theta \right)$$

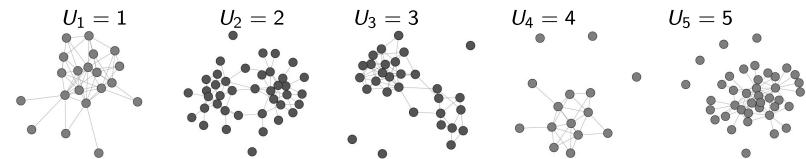
- Estimates of \mathcal{U} and \mathcal{Z} (Côme and Latouche, 2015):

$$(\hat{\mathcal{U}}, \hat{\mathcal{Z}}) = \arg \max_{\mathcal{U}, \mathcal{Z}} \text{ICL}(\mathcal{U}, \mathcal{Z}; \mathcal{A})$$

- With an appropriate prior $p(\theta)$, the ICL has closed-form expression
- Discrete optimization

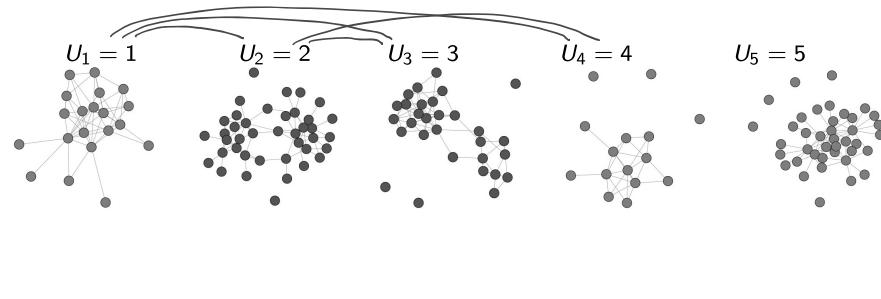
Estimation III

Agglomerative algorithm



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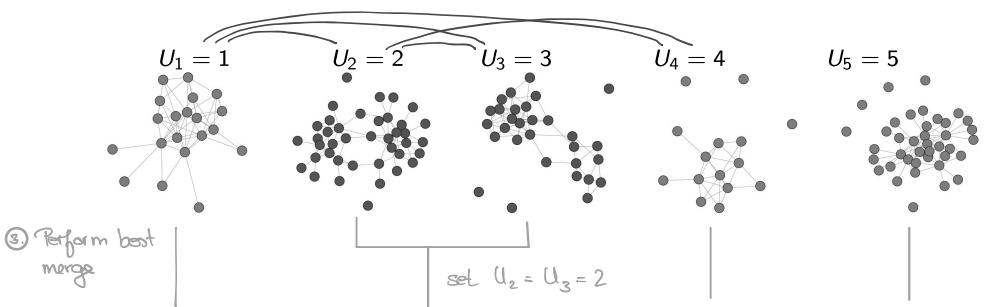


① Compute $\text{ICL}(u)$ for initial u

② Compute $\text{ICL}(u_{\text{cuc}}) \forall (c,c')$

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③ Perform best merge

① Compute $\text{ICL}(u)$ for initial u

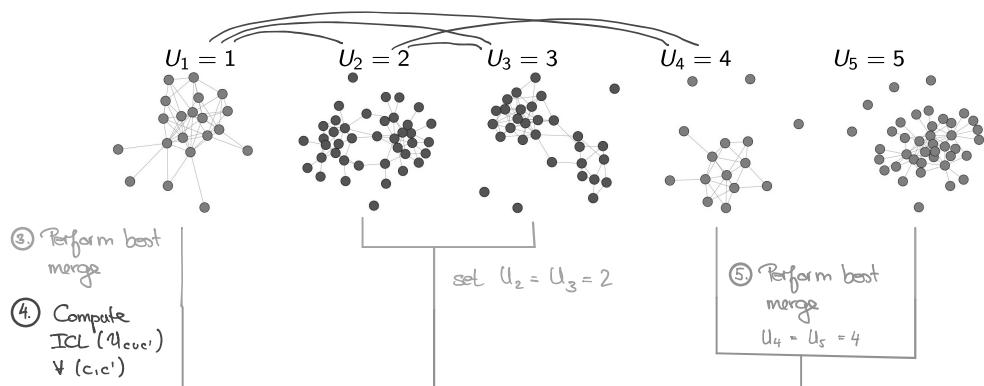
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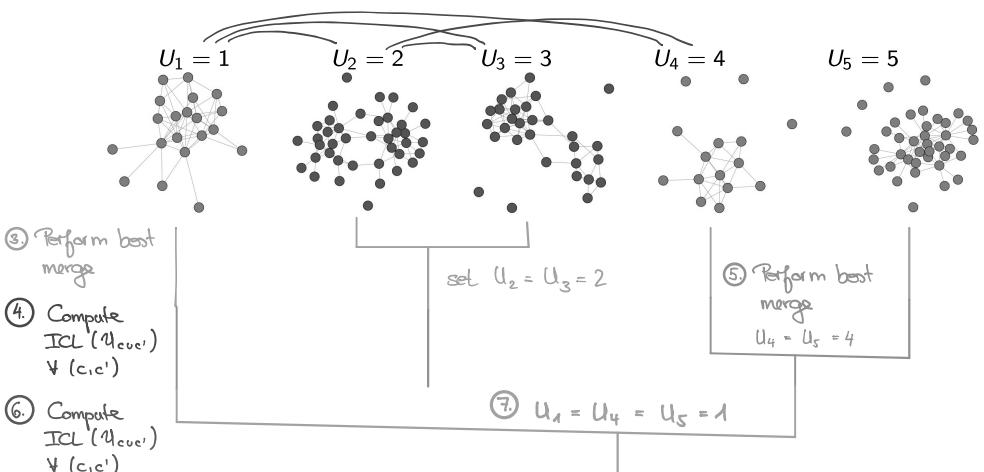


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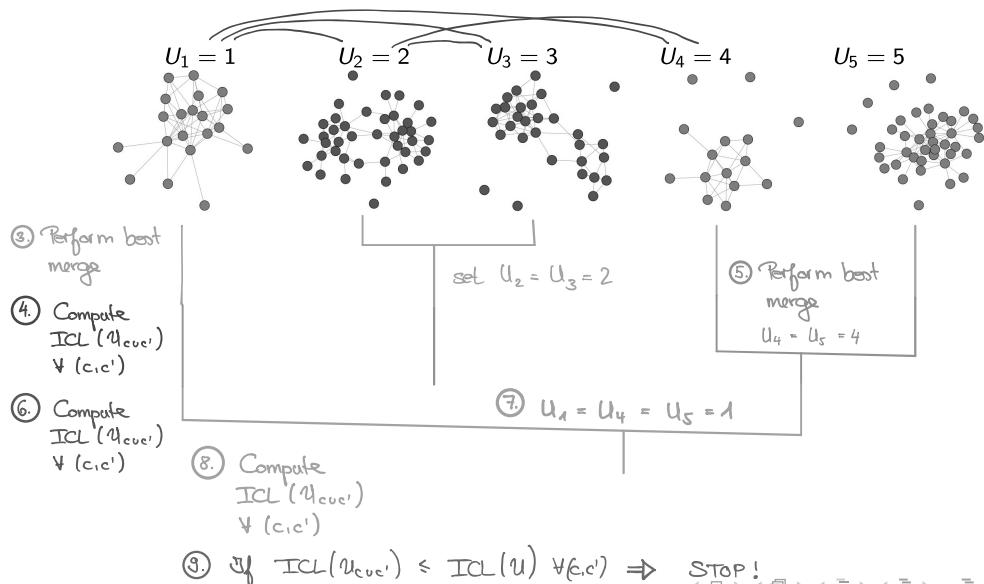


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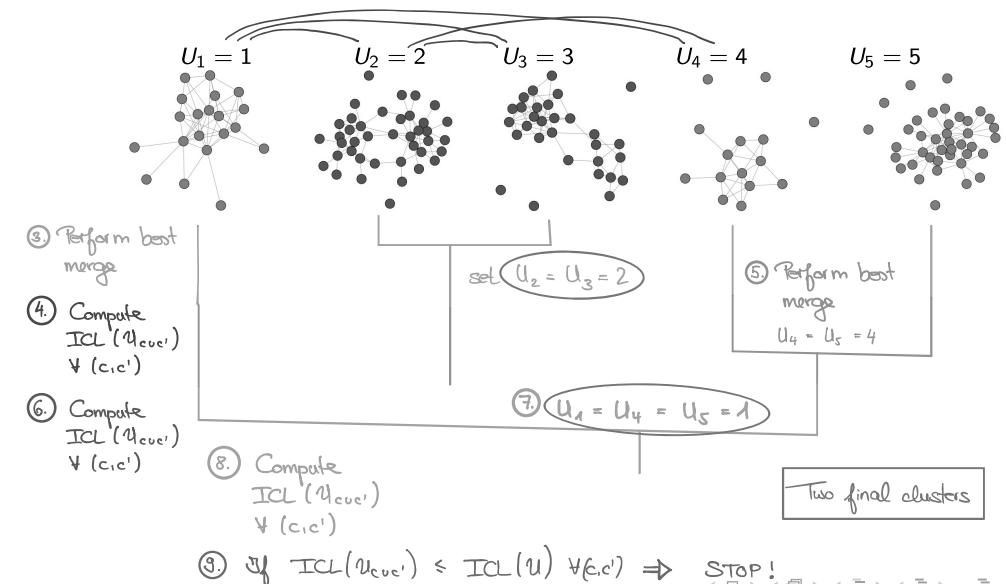


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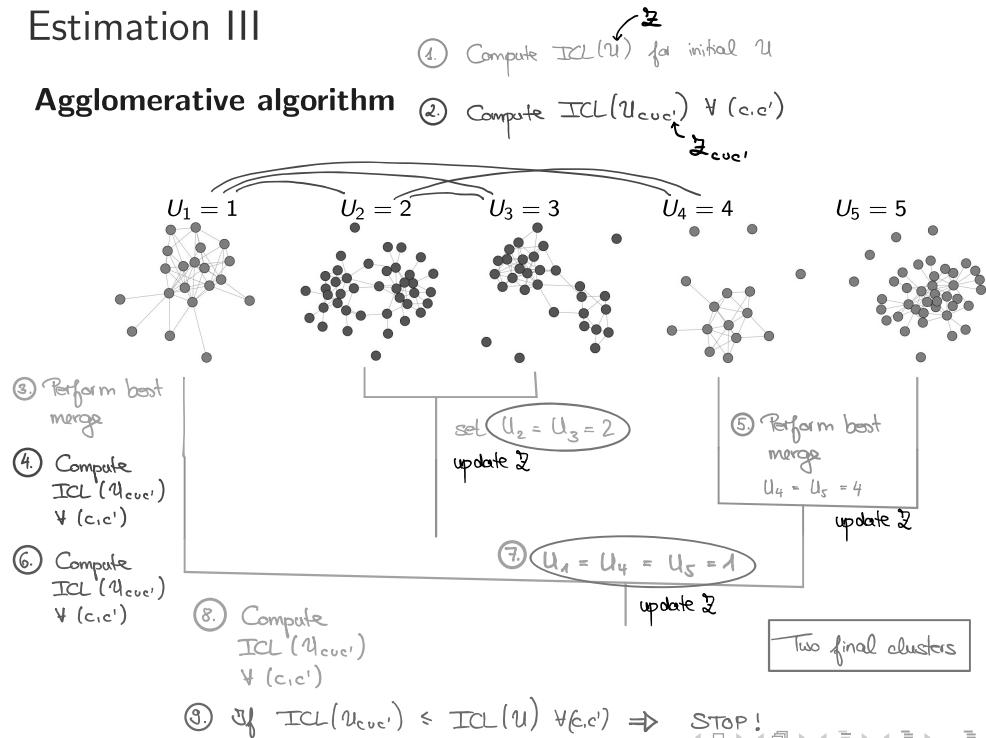
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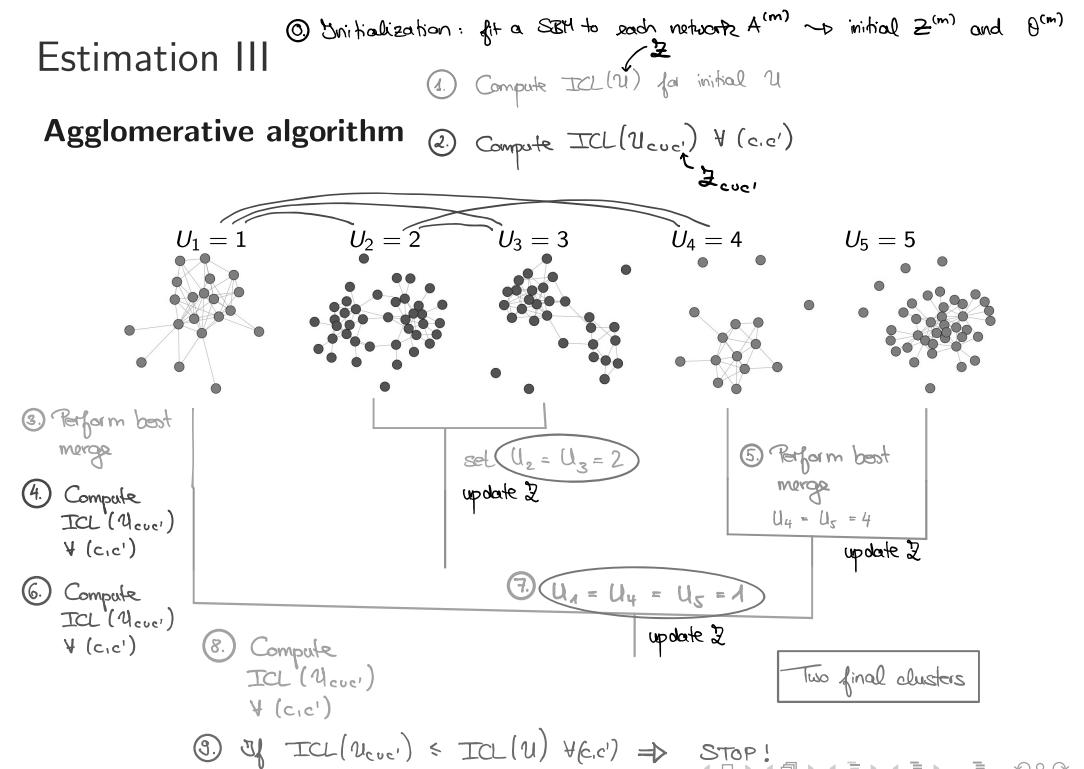
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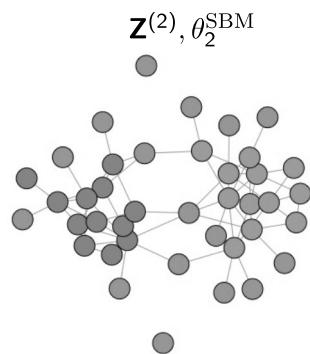


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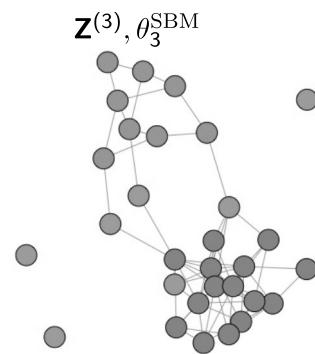
Agglomerative algorithm



Fusion of two clusters I



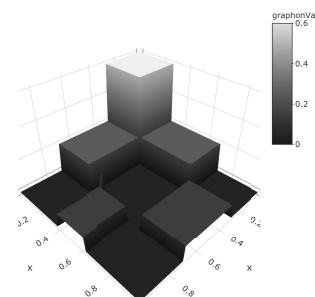
Label-switching problem in the SBM



Fusion of two clusters II

$$\pi = (0.3, 0.4, 0.3)$$

$$\gamma = \begin{pmatrix} 0.6 & 0.2 & 0 \\ 0.2 & 0 & 0.1 \\ 0 & 0.1 & 0 \end{pmatrix}$$



Graphon of a SBM

- $g(u, v) = \gamma_{k,l}$ for all $u \in I_k, v \in I_l$
- intervals $I_k = \left(\sum_{s=1}^{k-1} \pi_s, \sum_{s=1}^k \pi_s\right]$
- piecewise constant function
- Graphon g depends on the block labelling!

(Lovász, 2012)

Fusion of two clusters III

- Consider L^2 -distance of two graphons:

$$\|g_{\theta_1} - g_{\theta_2}\|_2 = \left(\int_{[0,1]^2} (g_{\theta_1}(u, v) - g_{\theta_2}(u, v))^2 d(u, v) \right)^{\frac{1}{2}}$$

Matching blocks of two SBMs

Search the best permutations of block labels by

$$(\hat{\sigma}_1, \hat{\sigma}_2) \in \arg \min_{\sigma_1 \in \mathfrak{S}_{K_1}, \sigma_2 \in \mathfrak{S}_{K_2}} \|g_{\sigma_1(\theta_1)} - g_{\sigma_2(\theta_2)}\|_2,$$

where \mathfrak{S}_K denotes the set of all permutations of $\{1, \dots, K\}$ and
 $\sigma(\theta) = ((\pi_{\sigma(1)}, \dots, \pi_{\sigma(K)}), (\gamma_{\sigma(k), \sigma(l)})_{k,l})$.

- does not depend on the clusterings, the data, the number of networks or the number nodes
- works also for $K_1 \neq K_2$