

Supplement to “Consistency of community detection in networks under degree-corrected stochastic block models”

Yunpeng Zhao¹, Elizaveta Levina², and Ji Zhu²

¹Department of Statistics, George Mason University, Fairfax, VA 22030

²Department of Statistics, University of Michigan, Ann Arbor, MI 48109

This supplement contains the proofs of Lemma A.1 and Lemma A.2 stated in the Appendix of [3].

Lemma A.1. *Let $\|X\|_\infty = \max_{kl} |X_{kl}|$ and $|\mathbf{e} - \mathbf{c}| = \sum_{i=1}^n I(e_i \neq c_i)$. Then*

$$\mathbb{P}(\max_{\mathbf{e}} \|X(\mathbf{e})\|_\infty \geq \epsilon) \leq 2K^{n+2} \exp\left(-\frac{1}{8C}\epsilon^2\mu_n\right), \quad (1)$$

for $\epsilon < 3C$, where $C = \max\{x_u x_v P_{ab}\}$.

$$\mathbb{P}(\max_{|\mathbf{e}-\mathbf{c}|\leq m} \|X(\mathbf{e}) - X(\mathbf{c})\|_\infty \geq \epsilon) \leq 2\binom{n}{m} K^{m+2} \exp\left(-\frac{3}{8}\epsilon\mu_n\right), \quad (2)$$

for $\epsilon \geq 6Cm/n$.

$$\mathbb{P}(\max_{|\mathbf{e}-\mathbf{c}|\leq m} \|X(\mathbf{e}) - X(\mathbf{c})\|_\infty \geq \epsilon) \leq 2\binom{n}{m} K^{m+2} \exp\left(-\frac{n}{16mC}\epsilon^2\mu_n\right), \quad (3)$$

for $\epsilon < 6Cm/n$.

Proof. This lemma is similar to Lemma 1.1 of [1], but since the proof in [1] contains some relatively minor errors, we give a full proof here for completeness. First note that in order to prove (1), it is sufficient to show

$$\mathbb{P}(|X_{kl}(\mathbf{e})| \geq \epsilon | \mathbf{c}, \boldsymbol{\theta}) \leq 2 \exp\left(-\frac{1}{8C}\epsilon^2\mu_n\right), \quad (4)$$

where

$$\begin{aligned} X_{kl}(\mathbf{e}) &= \frac{1}{\mu_n} [O_{kl}(\mathbf{e}) - \mathbb{E}(O_{kl}(\mathbf{e}) | \mathbf{c}, \boldsymbol{\theta})], \\ O_{kl}(\mathbf{e}) &= \sum_{i=1}^n A_{ii} I(e_i = k, e_j = l) + 2 \sum_{i < j}^n A_{ij} I(e_i = k, e_j = l). \end{aligned}$$

The proof relies on Bernstein's inequality (see e.g., [2]): If Y_i are independent, $|Y_i| \leq M$, $EY_i = 0$, $S_I = \sum_{i=1}^I Y_i$, then

$$\mathbb{P}(|S_I| \geq w) \leq 2 \exp\left(-\frac{w^2/2}{\text{Var}(S_I) + Bw/3}\right). \quad (5)$$

Note that conditioning on $\mathbf{c}, \boldsymbol{\theta}$, A_{ij} are independent and $|A_{ij}| \leq 1$. Let $B = 2$, and then (5) becomes

$$\mathbb{P}(|\mu_n X_{kl}(\mathbf{e})| \geq w | \mathbf{c}, \boldsymbol{\theta}) \leq 2 \exp\left(-\frac{w^2/2}{\text{Var}(O_{kl} | \mathbf{c}, \boldsymbol{\theta}) + 2w/3}\right). \quad (6)$$

In order to compare two terms in the denominator, we need to evaluate $\text{Var}(O_{kl} | \mathbf{c}, \boldsymbol{\theta})$:

$$\begin{aligned} \text{Var}(A_{ij} | \mathbf{c}, \boldsymbol{\theta}) &= \rho_n \theta_i \theta_j P_{c_i c_j} - (\rho_n \theta_i \theta_j P_{c_i c_j})^2 \leq \rho_n C, \\ \text{Var}(O_{kl} | \mathbf{c}, \boldsymbol{\theta}) &\leq (n + 4(n-1)n/2) \rho_n C \leq 2n^2 \rho_n C. \end{aligned}$$

Let $w = \epsilon \mu_n = \epsilon n^2 \rho_n$, for $\epsilon < 3C$,

$$\begin{aligned} \mathbb{P}(|X_{kl}(\mathbf{e})| \geq \epsilon | \mathbf{c}, \boldsymbol{\theta}) &\leq 2 \exp\left(-\frac{w^2/2}{\text{Var}(O_{kl} | \mathbf{c}, \boldsymbol{\theta}) + 2w/3}\right) \\ &\leq 2 \exp\left(-\frac{\epsilon^2 n^4 \rho_n^2}{8n^2 \rho_n C}\right) = 2 \exp\left(-\frac{1}{8C} \epsilon^2 \mu_n\right). \end{aligned}$$

We now prove (2) and (3). If $e_{m+1} = c_{m+1}, \dots, e_n = c_n$,

$$\begin{aligned} O_{kl}(\mathbf{e}) - O_{kl}(\mathbf{c}) &= \sum_{i=1}^m (A_{ii} I(e_i = k, e_i = l) - A_{ii} I(c_i = k, c_i = l)) \\ &\quad + 2 \sum_{i < j}^m (A_{ij} I(e_i = k, e_j = l) - A_{ij} I(c_i = k, c_j = l)) \\ &\quad + 2 \sum_{i=1}^m \sum_{j=m+1}^n (A_{ij} I(e_i = k, e_j = l) - A_{ij} I(c_i = k, c_j = l)). \end{aligned}$$

$$\text{var}(O_{kl}(\mathbf{e}) - O_{kl}(\mathbf{c}) | \mathbf{c}, \boldsymbol{\theta}) \leq [m + 4(m(m-1)/2 + m(n-m))] \rho_n C \leq 4mn \rho_n C.$$

We again apply (5). For $|\mathbf{e} - \mathbf{c}| \leq m$, $\epsilon \geq 6Cm/n$,

$$\begin{aligned} \mathbb{P}(|X_{kl}(\mathbf{e}) - X_{kl}(\mathbf{c})| \geq \epsilon | \mathbf{c}, \boldsymbol{\theta}) &\leq 2 \exp\left(-\frac{(\epsilon n^2 \rho_n)^2/2}{4mn \rho_n C + 2\epsilon n^2 \rho_n/3}\right) \\ &\leq 2 \exp\left(-\frac{3}{8} \epsilon \mu_n\right). \end{aligned}$$

For $\epsilon < 6Cm/n$,

$$\begin{aligned} \mathbb{P}(|X_{kl}(\mathbf{e}) - X_{kl}(\mathbf{c})| \geq \epsilon | \mathbf{c}, \boldsymbol{\theta}) &\leq 2 \exp\left(-\frac{(\epsilon n^2 \rho_n)^2/2}{4mn \rho_n C + 2\epsilon n^2 \rho_n/3}\right) \\ &\leq 2 \exp\left(-\frac{n}{16mC} \epsilon^2 \mu_n\right). \end{aligned}$$

□

Lemma A.2. Let g, P, S be $K \times K$ matrices with nonnegative entries. Assume that

- a) P and g are symmetric;
- b) P does not have two identical columns;
- c) there exists at least one nonzero entry in each column of S ;
- d) for $1 \leq k, l, a, b \leq K$, $g_{kl} = P_{ab}$ whenever $S_{ka}S_{lb} > 0$.

Then S is a diagonal matrix or a row/column permutation of a diagonal matrix.

Proof. The proof is similar to Lemma 3.2 [1].

1) If there exists a permutation of the rows and columns of S such that its diagonals are all positive after permutation, i.e., $S_{bb} > 0$ for $b = 1, \dots, K$. If S is not diagonal, there exists $k \neq a$ such that $S_{ka} > 0$. For $b = 1, \dots, K$,

$$\begin{aligned} S_{ka}S_{bb} > 0 &\Rightarrow g_{kb} = P_{ab}, \\ S_{kk}S_{bb} > 0 &\Rightarrow g_{kb} = P_{kb}, \\ &\Rightarrow P_{ab} = P_{kb}. \end{aligned}$$

This contradicts with b).

2) If there does not exist such a permutation, then we can always permute row and columns of S , such that for some $m \geq 1$, $S_{ij} = 0$ for $1 \leq i, j \leq m$, and $S_{bb} > 0$ for $b = m + 1, \dots, K$. By c), there exists $S_{k_i i} > 0$ for $i = 1, \dots, m$ and some $k_i \in \{m + 1, \dots, K\}$. Then

$$\begin{aligned} S_{k_i i}S_{k_1 1} > 0 &\Rightarrow g_{k_i k_1} = P_{i1} = P_{1i}, \text{ for } i = 1, \dots, m. \\ S_{k_i i}S_{k_1 k_1} > 0 &\Rightarrow g_{k_i k_1} = P_{ik_1} = P_{k_1 i}, \text{ for } i = 1, \dots, m. \\ &\Rightarrow P_{1i} = P_{k_1 i}, \text{ for } i = 1, \dots, m. \end{aligned} \tag{7}$$

$$\begin{aligned} S_{k_1 1}S_{bb} > 0 &\Rightarrow g_{k_1 b} = P_{1b}, \text{ for } b = m + 1, \dots, K. \\ S_{k_1 k_1}S_{bb} > 0 &\Rightarrow g_{k_1 b} = P_{k_1 b}, \text{ for } b = m + 1, \dots, K. \\ &\Rightarrow P_{1b} = P_{k_1 b}, \text{ for } b = m + 1, \dots, K. \end{aligned} \tag{8}$$

(7) and (8) contradict with b). □

References

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