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immediate

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Introduction

n individuals K communities Each individual belongs to exactly one community Denote by A the (n, K) membership matrix, i.e $A_{i,j} = 1$ if the i-th individual belongs to the j-th community (and 0 otherwise), for $1 \leq i \leq n$ and $1 \leq j \leq K$. Denote by X the (n, n) connectivity matrix. We use the SBM model : SBM assumes that for each $1 \leq i, j \leq n$, $X_{i,j}$ follows a Bernoulli law whose parameter only depends on $g(i)$ and $g(j)$, the respective groups of i and j. Furthermore, it assumes that the coordinates of the matrix X are all independent. Letting C be the (K, K) matrix such that $C_{i,j}$ is the parameter of connectivity between groups i and j, one can write $E[X] = ACA^T - diag(ACA^t)$. In what follows we write $X = ACA^t + \mathcal{E} - D$, where $\mathcal{E} = X - E[X]$ is a zero-mean matrix and $D = diag(ACA^t)$. The objective is to recover the membership matrix A, up to a permutation, given one realization of X, i.e given one instance of connections between the n individuals. Note that the membership matrix can be represented equivalently by the "normalized" membership (n, n) matrix $B*$ defined as follows : $B_{i,j} = \frac{1}{|G_k|}$ if $i$and j both belong to group k and $B_{i,j} = 0$ otherwise. Following the notations of [2], we now write $X = ZA^t + E$, where $Z = AC$ and $E = \mathcal{E} - D$. In doing so we can see the SBM model as a special instance of the G-latent models defined in [2]. This paper shows that the main guarantees and results of [2] can be successfully adapted to the SBM model. Denoting $\Delta(C) = \min_{j<k}(C_{kk} + C_{jj} - 2C_{jk})$, namely we show that under some conditions on $\Delta(C)$, one can recover the exact matrix $B*$ by solving a convex optimization problem : Let

$$\mathcal{C} = \left\{ \begin{array}{c} B \succeq 0 \\ \Sigma_a B_{ab} = 1, \forall b \\ B_{ab} \geq 0, \forall a, b \\ \mathrm{tr}(B) = K \end{array} \right\} \subset \mathbb{R}^{p \times p}$$

Let $\widehat{\Sigma} = X^t X$. PECOK algorithm :
1/ Estimate B^* by $\widehat{B} = \mathrm{argmax}_{B \in \mathcal{C}} \langle \widehat{\Sigma}, B \rangle$
2/ Estimate G^* by applying a clustering algorithm to the columns of $\widehat{B}$.

In this paper, we develop suficient conditions on the SBM model, via the quantity $\Delta(C)$, so that the PECOK algorithm above recovers B^*, and hence G^*, exactly with high probability.

Our investigation follows the outline of [2], as its main arguments can be adapted to our case. Lemma 1 p.6 and its proof p.16 remain valid and so is Lemma 3 p.16. So we only need to prove that $\langle \widehat{\Sigma}, B^* - B \rangle \geq 0$ for all $B \in \mathcal{C}$ such that $\mathrm{supp}(B) \nsubseteq \mathrm{supp}(B^*)$, with high probability. Following the decomposition (46) we write similarly $W = W_1 + W_2 + E^2$.

[1] Lei, Rinaldo. Consistency of spectral clustering in stochastic block models.

[2] PECOK : a convex optimization approach to variable clustering.

Lemma 1:

with probability larger than $1 - \frac{2}{n}$ it holds that :

$$|\langle W_2, B^* - B\rangle| \leq \Sigma_{j\neq k}(4(\ln n + |D|_\infty)|Z_{:j} - Z_{:k}|_\infty + \sqrt{6.\ln n.(V_j + V_k)}|Z_{:j} - Z_{:k}|_2)|B_{G_j G_k}|_1$$

$$\text{where } V_j = max_{c\in\{1..n\}} Z_{cj}(1 - Z_{cj})$$

Proof:

Condsider any a and b in $[n]$ and let j and k be such that $a \in G_j$ and $b \in G_k$. If $j = k$, $(W_2)_{ab} = 0$. if $j \neq k$, then we have :

$$\begin{aligned}(W_2)_{ab} &= [E_{b:} - E_{a:}].[Z_{:j} - Z_{:k}]\\ &= \sum_{c\neq a, c\neq b} (\mathcal{E}_{bc} - \mathcal{E}_{ac}).(Z_{cj} - Z_{ck}) + \mathcal{E}_{ab}(Z_{aj} + Z_{bk} - Z_{bj} - Z_{ak}) - D_{bb}.(Z_{bj} - Z_{bk}) - D_{aa}.(Z_{aj} - Z_{ak}).\end{aligned}$$

Hence $\mathbb{E}[(W_2)_{ab}] = -D_{bb}.(Z_{bj} - Z_{bk}) - D_{aa}.(Z_{aj} - Z_{ak})$.

Note that the sum above is a sum of centered independent variables, as $\mathcal{E}_{de}$ is independent of all other variables $\mathcal{E}_{fg}$ but $\mathcal{E}_{ed}$. Thus we can apply Bernstein's inequality :

$$\mathbb{P}(|(W_2)_{ab} - \mathbb{E}[(W_2)_{ab}]| > t) \leq 2exp(-\frac{\frac{1}{2}t^2}{Var((W_2)_{ab}) + \frac{2}{3}|Z_{:j} - Z_{:k}|_\infty t}),$$

as $|\mathcal{E}_{de}| \leq 1$ for all d, e.

Hence with probability less than $\frac{2}{n^3}$, it holds that :

$$|(W_2)_{ab} - \mathbb{E}[(W_2)_{ab}]| > 4.\ln n|Z_{:j} - Z_{:k}|_\infty + \sqrt{6.\ln n.Var((W_2)_{ab})}$$

Now

$$\begin{aligned}Var((W_2)_{ab}) &= \sum_{c\neq a, c\neq b} (Var(\mathcal{E}_{bc}) + Var(\mathcal{E}_{ac})).(Z_{cj} - Z_{ck})^2 + Var(\mathcal{E}_{ab})(Z_{aj} + Z_{bk} - Z_{bj} - Z_{ak})^2\\ &= \sum_{c\neq a, c\neq b} (Z_{ck}(1 - Z_{ck}) + Z_{cj}(1 - Z_{cj})).(Z_{cj} - Z_{ck})^2\\ &+ \frac{Z_{ak}(1 - Z_{ak}) + Z_{bj}(1 - Z_{bj})}{2}(Z_{aj} + Z_{bk} - Z_{bj} - Z_{ak})^2\end{aligned}$$

Hence $Var((W_2)_{ab}) \leq (V_j + V_k)|Z_{:j} - Z_{:k}|_2^2$.
By a union bound we have the inequality required.

Lemma 2:

With probability larger than $1-\frac{2}{n}$ it holds that

$$|\langle E^2, B^* - B\rangle| \leq (7.(C^2+1).[\sum_{j\neq k}|B_{G_jG_k}|_1].\tfrac{d}{\sqrt{m}})$$

With $d = \max(n.\max_{i,j}C_{ij}, \ln n)$

Proof:

if we do the same of (58) we have :

$$|\langle E^2, B^* - B\rangle| \leq 2.[\sum_{j\neq k}|B_{G_jG_k}|_1](3.|B^*E^2|_\infty + \frac{||E^2||_{op}}{2m})$$

$$||E^2||_{op} = ||E||_{op}^2 \leq 2.(||\mathcal{E}||_{op}^2 + |D|_\infty^2)$$

for all a in G_k:

$$\begin{aligned}|[B^*E^2]_{a:}|_\infty &= \frac{1}{|G_k|}|[E^2.1_{G_k}]|_\infty \\ &\leq \frac{1}{|G_k|}||[E^2.1_{G_k}]||_2 \leq \frac{1}{|G_k|}||E^2||_{op}||1_{G_k}||_2 \\ &\leq \frac{1}{\sqrt{m}}||E^2||_{op}\end{aligned}$$

And :

$$\begin{aligned}|B^*E^2|_\infty &= \max_a|[B^*E^2]_{a:}|_\infty \\ &\leq \frac{1}{\sqrt{m}}||E^2||_{op}\end{aligned}$$

Hence :

$$|\langle E^2, B^* - B\rangle| \leq 7.[\sum_{j\neq k}|B_{G_jG_k}|_1].\frac{||\mathcal{E}||_{op}^2 + |D|_\infty^2}{\sqrt{m}}$$

We use the Theorem 5.1 With probability $1-\frac{2}{n}$

$$||\mathcal{E}||_{op} \leq C\sqrt{d}$$

And : $|D|_\infty^2 \leq d$
So :

$$|\langle E^2, B^* - B\rangle| \leq 7.(C^2+1).[\sum_{j\neq k}|B_{G_jG_k}|_1].\frac{d}{\sqrt{m}}$$

Condition :

if :

$$\frac{1}{2}|Z_{:j} - Z_{:k}|_2^2 \geq (4(\ln n + |D|_\infty)|Z_{:j} - Z_{:k}|_\infty + \sqrt{6.\ln n.(V_j + V_k)}|Z_{:j} - Z_{:k}|_2 + 7.(C^2+1).\frac{d}{\sqrt{m}}$$

then with probability $1 - \frac{4}{n}$, $B^* = \text{argmax}_{B \in \mathcal{C}} \langle X^T X, B \rangle$