Proof for ARE Theory

Runze

June 10, 2015

1 Problem Description

Under the stochastic block model with parameters (B, ρ), we have $X_i \overset{iid}{\sim} \sum_{k=1}^{K} \rho_k \delta_{\nu_k}$, where $\nu = [\nu_1, \cdots, \nu_K]^T$ satisfies $B = \nu^T \nu$. Define the block assignment τ such that $\tau_i = k$ if and only if $X_i = \nu_k$. Let $P = XX^T$ where $X = [X_1, \cdots, X_n]^T$.

First draw τ from the multinomial distribution with parameter ρ. Then we are going to sample m conditionally i.i.d. graphs $A^{(1)}, \cdots, A^{(m)}$ such that $A_{ij}^{(k)} \overset{ind}{\sim} Bern(P_{ij})$ for each $1 \leq k \leq m$, $1 \leq i, j \leq n$.

Define $\bar{A} = \frac{1}{m} \sum_{k=1}^{m} A^{(k)}$. Let USU^T be the rank-d decomposition of $\bar{A}$, then we define $\hat{X} = US^{1/2}$.

We would like to know either $\bar{A}$ or $\hat{P} = \hat{X}\hat{X}^T$ is a better estimation of P.

2 Proofs

2.1 $\bar{A}$

Since $\bar{A}_{ij}$ is the mean of m i.i.d. Bernoulli random variables with parameter P_{ij}, we have $E[\bar{A}_{ij}] = P_{ij}$ and $Var(\bar{A}_{ij}) = \frac{1}{m} P_{ij}(1 - P_{ij})$.

2.2 $\hat{P}$

First, we need to prove $\lim_{n\to\infty} E[\hat{X}_i] = X_i$.

$$\text{ARE} = \lim_{n\to\infty} \frac{Var(\hat{P}_{ij})}{Var(\bar{A}_{ij})} = \lim_{n\to\infty} \frac{E[(\hat{P}_{ij} - P_{ij})^2]}{E[(\bar{A}_{ij} - P_{ij})^2]}$$

DLS: Explain & give context to this displayed eq

In Athreya et al. (2013), Theorem 4.8 states that conditioned on $X_i = \nu_k$, $P\left(\sqrt{n}(\hat{X}_i - \nu_k) \leq z | X_i = \nu_k\right) \to \phi(z, \Sigma(x_i))$, where $\Phi(z, \Sigma)$ denotes the cumulative distribution function for the multivariate normal, with mean zero and covariance matrix Σ, evaluated at z. So conditioned on $X_i = \nu_k$, we have

DLS: ϕ vs Φ? converges how?

- $\lim_{n\to\infty} E[\hat{X}_i] = \nu_k$;
- $\lim_{n\to\infty} n\text{Cov}(\hat{X}_i, \hat{X}_i) = \Sigma(\nu_k)$, where $\Sigma(x) = \Delta^{-1} E[X_j X_j^T (x^T X_j)(1 - x^T X_j)] \Delta^{-1}$ and $\Delta = E[X_1 X_1^T]$.

DLS: Define Σ before this.

Here the setting is a little different from Avanti's CLT theorem. We have m i.i.d. graph, so $\bar{A}$ is closer to P than A_i with a scale m. Thus the new version is: conditioned on $X_i = \nu_k$, we have

DLS: More detail here?

- $\lim_{n\to\infty} E[\hat{X}_i] = \nu_k$;
- $\lim_{n\to\infty} n\mathrm{Cov}(\hat{X}_i, \hat{X}_i) = \Sigma(\nu_k)/m$.

In Athreya et al. (2013), Corollary 4.11 says $\hat{X}_i$ and $\hat{X}_j$ are asymptotically independent. Since $\hat{P}_{ij} = \hat{X}_i^T \hat{X}_j$ is a noisy version of the dot product of $\nu_s^T \nu_t$, by Equation 5 in Brown and Rutemiller (1977), combined with asymptotic independence between $\hat{X}_i$ and $\hat{X}_j$ and $E[\hat{X}_i] = \nu_s$ when conditioning on $X_i = \nu_s$ and $X_j = \nu_t$, when n is large enough, we have

$$E[(\hat{P}_{ij} - P_{ij})^2] \approx \frac{1}{mn}\left(\nu_s^T \Sigma(\nu_t)\nu_s + \nu_t^T \Sigma(\nu_s)\nu_t^T\right) + \frac{1}{m^2 n^2}\left(tr(\Sigma(\nu_s)\Sigma(\nu_t))\right). \quad (1)$$

Lemma 2.1 $\nu_s^T \Sigma(\nu_t)\nu_s = \frac{1}{\rho_s}\nu_s^T \nu_t (1 - \nu_s^T \nu_t)$.

Proof: Under the stochastic block model with parameters (B, ρ), we have $X_i \stackrel{iid}{\sim} \sum_{k=1}^K \rho_k \delta_{\nu_k}$, where $\nu = [\nu_1, \cdots, \nu_K]^T$ satisfies $B = \nu^T \nu$. Without loss of generality, we could assume that $\nu = US$ where $U = [u_1, \cdots, u_K]^T$ is orthonormal in columns and S is a diagonal matrix. Here we can conclude that $\nu_s^T = u_s^T S$. Also define $R = \mathrm{diag}(\rho_1, \cdots, \rho_K)$, then we have

$$\Delta = E[X_1 X_1^T] = \sum_{k=1}^K \rho_k \nu_k \nu_k^T = \nu^T R \nu = SU^T RUS.$$

Thus

$$\begin{aligned}
\nu_s^T \Sigma(\nu_t)\nu_s =& \nu_s^T \Delta^{-1} \sum_{k=1}^K \rho_k \nu_k \nu_k^T (\nu_t^T \nu_k)(1 - \nu_t^T \nu_k)\Delta^{-1}\nu_s \\
=& \sum_{k=1}^K \rho_k (\nu_s^T \Delta^{-1}\nu_k)(\nu_k^T \Delta^{-1}\nu_s)(\nu_t^T \nu_k)(1 - \nu_t^T \nu_k) \\
=& \sum_{k=1}^K \rho_k (u_s^T U^T R^{-1} U u_k)^2 (\nu_t^T \nu_k)(1 - \nu_t^T \nu_k) \\
=& \sum_{k=1}^K \rho_k (e_s^T R^{-1} e_k)^2 (\nu_t^T \nu_k)(1 - \nu_t^T \nu_k) \\
=& \sum_{k=1}^K \rho_k \delta_{sk} \rho_s^{-2} (\nu_t^T \nu_k)(1 - \nu_t^T \nu_k) \\
=& \frac{1}{\rho_s} \nu_t^T \nu_s (1 - \nu_t^T \nu_s)
\end{aligned}$$

■

Lemma 2.2 $tr(\Sigma(\nu_s)\Sigma(\nu_t)) = \sum_{k,l=1}^K u_k^T S^{-2} U_l \nu_t^T \nu_k (1 - \nu_t^T \nu_k)\nu_s^T \nu_l (1 - \nu_s^T \nu_l)$.

DLS: Why do we need this lemma? We just need its bounded

Proof: Same as proof for Lemma 2.1. ■

By Lemma 2.1 and Lemma 2.2, as $n \to \infty$, Equation 1 can be written as:

$$E[(\hat{P}_{ij} - P_{ij})^2] \approx \frac{1}{mn} \left(\nu_{\tau_i}^T \Sigma(\nu_{\tau_j}) \nu_{\tau_i} + \nu_{\tau_j}^T \Sigma(\nu_{\tau_i}) \nu_{\tau_j}^T \right) + o(\frac{1}{mn}) \tag{2}$$

$$\approx \frac{1}{mn} \left(\frac{1}{\rho_{\tau_i}} + \frac{1}{\rho_{\tau_j}} \right) \nu_{\tau_i}^T \nu_{\tau_j} (1 - \nu_{\tau_i}^T \nu_{\tau_j}) \tag{3}$$

$$= \frac{1}{mn} \left(\frac{1}{\rho_{\tau_i}} + \frac{1}{\rho_{\tau_j}} \right) P_{ij}(1 - P_{ij}) \tag{4}$$

So

DLS: I would state this as nARE $\to$ ...

$$\begin{aligned} \text{ARE} = \lim_{n\to\infty} \frac{Var(\hat{P}_{ij})}{Var(\bar{A}_{ij})} &= \lim_{n\to\infty} \frac{E[(\hat{P}_{ij} - P_{ij})^2]}{Var(\bar{A}_{ij})} \\ &= \lim_{n\to\infty} \frac{\left(1/\rho_{\tau_i} + 1/\rho_{\tau_j}\right) P_{ij}(1 - P_{ij})/mn}{P_{ij}(1 - P_{ij})/m} \\ &= \lim_{n\to\infty} \left(\rho_{\tau_i}^{-1} + \rho_{\tau_j}^{-1} \right) /n \\ &= 0 \end{aligned}$$

And the relative efficiency could be approximated by $\left(\rho_{\tau_i}^{-1} + \rho_{\tau_j}^{-1} \right) /n$ when n is large enough.

DLS: Now you should explain what this means? Describe in words how the the theory implies what Ketcha's plots show.