

1 Supplementary materials for RSC

Proof of Lemma 3.2:

Proof. Recall that $\mathcal{D}_{ii} = \theta_i [D_B]_{z_i}$ and $[\Theta_\tau]_{ii} = \theta_i \frac{\mathcal{D}_{ii}}{\mathcal{D}_{ii} + \tau}$. The ij 'th element of \mathcal{L}_τ :

$$[\mathcal{L}_\tau]_{ij} = \frac{\mathcal{A}_{ij}}{\sqrt{(\mathcal{D}_{ii} + \tau)(\mathcal{D}_{jj} + \tau)}} = \frac{\theta_i \theta_j B_{z_i z_j}}{\sqrt{\mathcal{D}_{ii} \mathcal{D}_{jj}}} \sqrt{\frac{\mathcal{D}_{ii}}{\mathcal{D}_{ii} + \tau} \frac{\mathcal{D}_{jj}}{\mathcal{D}_{jj} + \tau}} = \frac{B_{z_i z_j}}{\sqrt{[D_B]_{z_i} [D_B]_{z_j}}} * \sqrt{[\Theta_\tau]_{ii} [\Theta_\tau]_{jj}}.$$

Hence,

$$\mathcal{L}_\tau = \Theta_\tau^{\frac{1}{2}} Z B_L Z^T \Theta_\tau^{\frac{1}{2}}.$$

□

Proof of Lemma 3.3:

Proof. Let $C = (Z^T \Theta_\tau Z)^{1/2} B_L (Z^T \Theta_\tau Z)^{1/2}$. If $\theta_i > 0, i = 1, \dots, N$, then $C \succ 0$ since $B \succ 0$ by assumption. Let $\lambda_1 \geq \dots \geq \lambda_K > 0$ be the eigenvalues of C . Let $\Lambda \in \mathcal{R}^{K \times K}$ be a diagonal matrix with its s 'th element to be λ_s . Let $U \in \mathcal{R}^{K \times K}$ be an orthogonal matrix where its s 'th column is the eigenvector of C corresponding $\lambda_s, s = 1, \dots, K$. By eigen-decomposition, we have $C = U \Lambda U^T$. Define $\mathcal{X}_\tau = \Theta_\tau^{\frac{1}{2}} Z (Z^T \Theta_\tau Z)^{-1/2} U$, then

$$\mathcal{X}_\tau^T \mathcal{X}_\tau = U^T (Z^T \Theta_\tau Z)^{-1/2} (Z^T \Theta_\tau Z) (Z^T \Theta_\tau Z)^{-1/2} U = U^T U = I.$$

On the other hand,

$$\mathcal{X}_\tau^T \Lambda \mathcal{X}_\tau^T = \Theta_\tau^{\frac{1}{2}} Z (Z^T \Theta_\tau Z)^{-1/2} C (Z^T \Theta_\tau Z)^{-1/2} Z^T \Theta_\tau^{\frac{1}{2}} = \Theta_\tau^{\frac{1}{2}} Z B_L Z^T \Theta_\tau^{\frac{1}{2}} = \mathcal{L}_\tau.$$

Hence, $\lambda_s, s = 1, \dots, K$ are \mathcal{L}_τ 's positive eigenvalues and \mathcal{X}_τ contains \mathcal{L}_τ 's eigenvectors corresponding to its nonzero eigenvalues. For part 2, notice that $\|\mathcal{X}_\tau^i\|_2 = \left(\frac{[\Theta_\tau]_{ii}}{[Z^T \Theta_\tau Z]_{z_i z_i}} \right)^{1/2}$, then

$$[\mathcal{X}_\tau^*]^i = \frac{\mathcal{X}_\tau^i}{\|\mathcal{X}_\tau^i\|_2} = \frac{\left(\frac{[\Theta_\tau]_{ii}}{[Z^T \Theta_\tau Z]_{z_i z_i}} \right)^{1/2} Z_i U}{\left(\frac{[\Theta_\tau]_{ii}}{[Z^T \Theta_\tau Z]_{z_i z_i}} \right)^{1/2}} = Z_i U.$$

Therefore, $\mathcal{X}_\tau^* = ZU$.

□

Proof of Theorem 4.1:

Proof. We extend the proof of Theorem 2 in Chung and Radcliffe [1] to the case of regularized graph laplacian. Let $H = \mathcal{D}_\tau^{-1/2} A \mathcal{D}_\tau^{-1/2}$. Then $\|L_\tau - \mathcal{L}_\tau\| \leq \|H - \mathcal{L}_\tau\| + \|L_\tau - H\|$. We bound the two terms separately.

For the first term, we apply the concentration inequality for matrix:

Lemma 1.1. *Let X_1, X_2, \dots, X_m be independent random $N \times N$ Hermitian matrices. Moreover, assume that $\|X_i - \mathbb{E}(X_i)\| \leq M$ for all i , and put $v^2 = \|\sum \text{var}(X_i)\|$. Let $X = \sum X_i$. Then for any $a > 0$,*

$$\text{pr}(\|X - \mathbb{E}(X)\| \geq a) \leq 2N \exp\left(-\frac{a^2}{2v^2 + 2Ma/3}\right).$$

Notice that $\|H - \mathcal{L}_\tau\| = \mathcal{D}_\tau^{-1/2} (A - \mathcal{A}) \mathcal{D}_\tau^{-1/2}$. Let $E^{ij} \in \mathcal{R}^{N \times N}$ be the matrix with 1 in the ij and ji 'th positions and 0 everywhere else. Let

$$\begin{aligned} X_{ij} &= \mathcal{D}_\tau^{-1/2} ((A_{ij} - p_{ij}) E^{ij}) \mathcal{D}_\tau^{-1/2} \\ &= \frac{A_{ij} - p_{ij}}{\sqrt{(\mathcal{D}_{ii} + \tau)(\mathcal{D}_{jj} + \tau)}} E^{ij}. \end{aligned}$$

$H - \mathcal{L}_\tau = \sum X_{ij}$. Then we can apply the matrix concentration theorem on $\{X_{ij}\}$. By similar argument as in [1], we have

$$\|X_{ij}\| \leq [(\mathcal{D}_{ii} + \tau)(\mathcal{D}_{jj} + \tau)]^{-1/2} \leq \frac{1}{\delta + \tau}, \quad v^2 = \|\sum E(X_{ij}^2)\| \leq \frac{1}{\delta + \tau}.$$

Take $a = \sqrt{\frac{3 \ln(4N/\epsilon)}{\delta + \tau}}$. By assumption $\delta + \tau > 3 \ln N + 3 \ln(4/\epsilon)$, it implies $a < 1$. Applying Lemma 1.1, we have

$$\begin{aligned} \text{pr}(\|H - \mathcal{L}_\tau\| \geq a) &\leq 2N \exp\left(-\frac{\frac{3 \ln(4N/\epsilon)}{\delta + \tau}}{2/(\delta + \tau) + 2a/[3(\delta + \tau)]}\right) \\ &\leq 2N \exp\left(-\frac{3 \ln(4N/\epsilon)}{3}\right) \\ &\leq \epsilon/2. \end{aligned}$$

For the second term, first we apply the two sided concentration inequality for each i , (see for example Chung and Lu [2, chap. 2])

$$\text{pr}(|D_{ii} - \mathcal{D}_{ii}| \geq \lambda) \leq \exp\left\{-\frac{\lambda^2}{2\mathcal{D}_{ii}}\right\} + \exp\left\{-\frac{\lambda^2}{2\mathcal{D}_{ii} + \frac{2}{3}\lambda}\right\}$$

Let $\lambda = a(\mathcal{D}_{ii} + \tau)$, where a is the same as in the first part.

$$\begin{aligned} \text{pr}(|D_{ii} - \mathcal{D}_{ii}| \geq a(\mathcal{D}_{ii} + \tau)) &\leq \exp\left\{-\frac{a^2(\mathcal{D}_{ii} + \tau)^2}{2\mathcal{D}_{ii}}\right\} + \exp\left\{-\frac{a^2(\mathcal{D}_{ii} + \tau)^2}{2\mathcal{D}_{ii} + \frac{2}{3}a(\mathcal{D}_{ii} + \tau)}\right\} \\ &\leq 2 \exp\left\{-\frac{a^2(\mathcal{D}_{ii} + \tau)^2}{(2 + \frac{2}{3}a)(\mathcal{D}_{ii} + \tau)}\right\} \\ &\leq 2 \exp\left\{-\frac{a^2(\mathcal{D}_{ii} + \tau)}{3}\right\} \\ &\leq 2 \exp\left\{-\ln(4N/\epsilon) \frac{(\mathcal{D}_{ii} + \tau)}{\delta + \tau}\right\} \\ &\leq 2 \exp\{-\ln(4N/\epsilon)\} \\ &\leq \epsilon/2N. \end{aligned}$$

$$\|\mathcal{D}_\tau^{-1/2} D_\tau^{1/2} - I\| = \max_i \left| \sqrt{\frac{D_{ii} + \tau}{\mathcal{D}_{ii} + \tau}} - 1 \right| \leq \max_i \left| \frac{D_{ii} + \tau}{\mathcal{D}_{ii} + \tau} - 1 \right|.$$

$$\begin{aligned} \text{pr}(\|\mathcal{D}_\tau^{-1/2} D_\tau^{1/2} - I\| \geq a) &\leq \text{pr}(\max_i \left| \frac{D_{ii} + \tau}{\mathcal{D}_{ii} + \tau} - 1 \right| \geq a) \\ &\leq \text{pr}(\cup_i \{|(D_{ii} + \tau) - (\mathcal{D}_{ii} + \tau)| \geq b(\mathcal{D}_{ii} + \tau)\}) \\ &\leq \epsilon/2. \end{aligned}$$

Note that $\|L_\tau\| \leq 1$, therefore, with probability at least $1 - \epsilon/2$, we have

$$\begin{aligned} \|L_\tau - H\| &= \|D_\tau^{-1/2} A D_\tau^{-1/2} - \mathcal{D}_\tau^{-1/2} A \mathcal{D}_\tau^{-1/2}\| \\ &= \|L_\tau - \mathcal{D}_\tau^{-1/2} D_\tau^{1/2} L_\tau D_\tau^{1/2} \mathcal{D}_\tau^{-1/2}\| \\ &= \|(I - \mathcal{D}_\tau^{-1/2} D_\tau^{1/2}) L_\tau D_\tau^{1/2} \mathcal{D}_\tau^{-1/2} + L_\tau (I - D_\tau^{1/2} \mathcal{D}_\tau^{-1/2})\| \\ &\leq \|\mathcal{D}_\tau^{-1/2} D_\tau^{1/2} - I\| \|\mathcal{D}_\tau^{-1/2} D_\tau^{1/2}\| + \|\mathcal{D}_\tau^{-1/2} D_\tau^{1/2} - I\| \\ &\leq a^2 + 2a. \end{aligned}$$

Combining the two part, we have that with probability at least $1 - \epsilon$,

$$\|L_\tau - \mathcal{L}_\tau\| \leq a^2 + 3a \leq 4a,$$

where $a = \sqrt{\frac{3 \ln(4N/\epsilon)}{\delta + \tau}}$. □

Proof of Theorem 4.2:

Proof. First we apply a lemma from McSherry [3]:

Lemma 1.2. *For any matrix A , let P_A denotes the projection onto the span of A 's first K left sigular vectors. Then P_AA is the optimal rank K approximation to A in the following sense. For any rank K matrix X , $\|A - P_AA\| \leq \|L - X\|$. Further, for any rank K matrix B ,*

$$\|P_AA - B\|_F^2 \leq 8K\|A - B\|^2. \quad (1)$$

Let $W \in \mathcal{R}^{K \times K}$ be a diagonal matrix that contains the K largest eigenvalues of L_τ , $w_1 \geq w_2 \geq \dots \geq w_K$. Let $\Lambda \in \mathcal{R}^{K \times K}$ be the diagonal matrix that contains all positive eigenvalues of \mathcal{L}_τ . Take $A = L_\tau$ and $B = \mathcal{L}_\tau$ in Lemma 1.2. then $P_{L_\tau}L_\tau = X_\tau W X_\tau^T$ and the previous inequality can be rewritten as

$$\|P_{L_\tau}L_\tau - \mathcal{L}_\tau\|_F^2 = \|X_\tau W X_\tau^T - \mathcal{X}_\tau \Lambda \mathcal{X}_\tau^T\|_F^2 \leq 8K\|L_\tau - \mathcal{L}_\tau\|^2.$$

Then we apply a modified version of the Davis-Kahan theorem (Rohe et al. [4]) to \mathcal{L}_τ .

Proposition 1.3. *Let $S \subset \mathcal{R}$ be an interval. Denote \mathcal{X}_τ as an orthonormal matrix whose column space is equal to the eigenspace of \mathcal{L}_τ corresponding to the eigenvalues in $\lambda_S(\mathcal{L}_\tau)$ (more formally, the column space of \mathcal{X}_τ is the image of the spectral projection of \mathcal{L}_τ induced by $\lambda_S(\mathcal{L}_\tau)$). Denote by X_τ the analogous quantity for $P_{L_\tau}L_\tau$. Define the distance between S and the spectrum of \mathcal{L}_τ outside of S as*

$$\Delta = \min\{|\lambda - s|; \lambda \text{ eigenvalue of } \mathcal{L}_\tau, \lambda \notin S, s \in S\}.$$

if \mathcal{X}_τ and X_τ are of the same dimension, then there is an orthogonal matrix \mathcal{O} , that depends on \mathcal{X}_τ and X_τ , such that

$$\|X_\tau - \mathcal{X}_\tau \mathcal{O}\|_F^2 \leq \frac{2\|P_{L_\tau}L_\tau - \mathcal{L}_\tau\|_F^2}{\Delta^2}.$$

Take $S = (\lambda_K/2, 2)$, then $\Delta = \lambda_K/2$. By assumption (a) $\sqrt{\frac{K \ln(4N/\epsilon)}{\delta + \tau}} \leq \frac{1}{8\sqrt{3}}\lambda_K$, we have that when N is sufficiently large, with probability at least $1 - \epsilon$,

$$|\lambda_K - w_K| \leq \|L_\tau - \mathcal{L}_\tau\| \leq 4\sqrt{\frac{3 \ln(4N/\epsilon)}{\delta + \tau}} \leq \lambda_K/2.$$

Hence $w_K \in S$. X and \mathcal{X} are of the same dimension.

$$\begin{aligned} \|X_\tau - \mathcal{X}_\tau \mathcal{O}\|_F &\leq \frac{\sqrt{2}\|P_{L_\tau}L_\tau - \mathcal{L}_\tau\|_F}{\Delta} \leq \frac{2\sqrt{2}\|P_{L_\tau}L_\tau - \mathcal{L}_\tau\|_F}{\lambda_K} \\ &\leq \frac{8\sqrt{K}\|L_\tau - \mathcal{L}_\tau\|}{\lambda_K} \\ &\leq \frac{C}{\lambda_K} \sqrt{\frac{K \ln(4N/\epsilon)}{\delta + \tau}}. \end{aligned}$$

holds for $C = 32\sqrt{3}$ with probability at least $1 - \epsilon$.

For part 2, note that for any i ,

$$\|[X_\tau^*]^i - [\mathcal{X}_\tau^*]^i \mathcal{O}\|_2 \leq \frac{\|X_\tau^i - \mathcal{X}_\tau^i \mathcal{O}\|_2}{\min\{\|X_\tau^i\|_2, \|\mathcal{X}_\tau^i\|_2\}},$$

We have that

$$\|X_\tau^* - \mathcal{X}_\tau^* \mathcal{O}\|_F \leq \frac{\|X_\tau - \mathcal{X}_\tau \mathcal{O}\|_F}{m},$$

where $m = \min_i \{\min\{\|X_\tau^i\|_2, \|\mathcal{X}_\tau^i\|_2\}\}$. □

Proof of Main Theorem

Proof. Recall that the set of misclustered nodes is defined as:

$$\mathcal{M} = \{i : \exists j \neq i, \text{s.t. } \|C_i \mathcal{O}^T - C_i\|_2 > \|C_i \mathcal{O}^T - C_j\|_2\}.$$

Note that Lemma 3.3 implies that the population centroid corresponding to i 'th row of \mathcal{X}_τ^*

$$C_i = Z_i U.$$

Since all population centroids are of unit length and are orthogonal to each other, a simple calculation gives a sufficient condition for one observed centroid to be closest to the population centroid:

$$\|C_i \mathcal{O}^T - C_i\|_2 < 1/\sqrt{2} \Rightarrow \|C_i \mathcal{O}^T - C_i\|_2 < \|C_i \mathcal{O}^T - C_j\|_2 \quad \forall Z_j \neq Z_i.$$

Define the following set of nodes that do not satisfy the sufficient condition,

$$\mathcal{U} = \{i : \|C_i \mathcal{O}^T - C_i\|_2 \geq 1/\sqrt{2}\}.$$

The mis-clustered nodes $\mathcal{M} \in \mathcal{U}$.

Define $Q \in \mathcal{R}^{N \times K}$, where the i 'th row of Q is C_i , the observed centroid of node i from k-means. By definition of k-means, we have

$$\|X_\tau^* - Q\|_2 \leq \|X_\tau^* - \mathcal{X}_\tau^* \mathcal{O}\|_2.$$

By triangle inequality,

$$\|Q - ZU\mathcal{O}\|_2 = \|Q - \mathcal{X}_\tau^* \mathcal{O}\|_2 \leq \|X_\tau^* - Q\|_2 + \|X_\tau^* - \mathcal{X}_\tau^* \mathcal{O}\|_2 \leq 2\|X_\tau^* - \mathcal{X}_\tau^* \mathcal{O}\|_2.$$

We have with probability at least $1 - \epsilon$,

$$\begin{aligned} \frac{|\mathcal{M}|}{N} &\leq \frac{|\mathcal{U}|}{N} = \frac{1}{N} \sum_{i \in \mathcal{U}} 1 \\ &\leq \frac{2}{N} \sum_{i \in \mathcal{U}} \|C_i \mathcal{O}^T - C_i\|_2^2 \\ &= \frac{2}{N} \sum_{i \in \mathcal{U}} \|C_i - Z_i U \mathcal{O}\|_2^2 \\ &\leq \frac{2}{N} \|Q - ZU\mathcal{O}\|_F^2 \\ &\leq \frac{8}{N} \|X_\tau^* - \mathcal{X}_\tau^* \mathcal{O}\|_F^2 \\ &\leq c_1 \frac{K \ln(N/\epsilon)}{Nm^2(\delta + \tau)\lambda_K^2}. \end{aligned}$$

□

References

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