Graphic Lasso: Estimation Error

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1 Estimation Error

The precision model is stated as

$$\mathbb{E}[S^k] = \Omega^k = \sum_{l=1}^{r} u_{kl}\Theta^l, \quad k \in [K].$$

Consider the following penalized optimization problem

$$\max_{\boldsymbol{U},\Theta^l} \mathcal{L}_S(\boldsymbol{U},\Theta^l) = -\sum_{k=1}^{K} \operatorname{tr}(S^k\Omega^k) + \log\det(\Omega^k) + \lambda \left\|\Omega^k\right\|,$$

where $\boldsymbol{U}$ is a membership matrix, and $\{\Theta^l\}$ are irreducible and invertible.

Notations.

1. $I'_l = \{k : u'_{kl} \neq 0\}$ is the index set for the l-th group based on the membership $\boldsymbol{U}'$.
2. δ be the minimal gap between Θ^l. That is

$$\min_{k,l\in[r]} \left\|\Theta^l - \Theta^k\right\|_F^2 = \delta^2.$$

3. Let $l(\boldsymbol{U},\Theta^l)$ be the population-based loss function. That is

$$l(\boldsymbol{U},\Theta^l) = \mathbb{E}_S[\mathcal{L}_S(\boldsymbol{U},\Theta^l)] = -\sum_{k=1}^{K} \operatorname{tr}(\Sigma^k\Omega^k) + \log\det(\Omega^k) - \lambda\sum_{k=1}^{K} \left\|\Omega^k\right\|_1.$$

4. Given the membership $\boldsymbol{U}'$, let $\hat{\Theta}^l(\boldsymbol{U}') = \arg\max_{\Theta^l} \mathcal{L}_S(\boldsymbol{U}',\Theta)$. Particularly, for each $l \in [r]$, we have

$$\hat{\Theta}^l(\boldsymbol{U}') = \arg\max_{\Theta} -\sum_{k\in I'_l} \langle S^k,\Theta\rangle + |I'_l| \log\det(\Theta) - \lambda|I'_l| \left\|\Theta\right\|_1,$$

5. Given the membership $\boldsymbol{U}'$, let $\tilde{\Theta}^l(\boldsymbol{U}') = \arg\max_{\boldsymbol{U}',\Theta^l}$. Particularly, for each $l \in [r]$, we have

$$\tilde{\Theta}^l(\boldsymbol{U}') = \arg\max_{\Theta} -\sum_{k\in I'_l} \langle \Sigma^k,\Theta\rangle + |I'_l| \log\det(\Theta) - \lambda|I'_l| \left\|\Theta\right\|_1.$$

6. Define functions

$$F(\boldsymbol{U}') = \mathcal{L}_S(\boldsymbol{U}',\hat{\Theta}^l(\boldsymbol{U}')), \quad G(\boldsymbol{U}') = l(\boldsymbol{U}',\tilde{\Theta}^l(\boldsymbol{U}')).$$

Upper bound of lambda —> required by clustering accuracy —> low lambda is good for accuracy, whereas high lambda is bad (think about why).

Lower bound of lambda —> required by selection consistency (the second results in Guo el al)—> low lambda is bad for selection accuracy, whereas low lambda is good (think about why.)

7. τ be the maximal singular value of the true precision matrix, i.e., $\tau = \max_{l\in[r]} \varphi_{\max}(\Theta^l)$.

Lemma 1 (Estimation error)**.** *Given a membership $\boldsymbol{U}'$, assume $\lambda \leq \mathcal{O}(n^{-1/2})$. With high probability, we have the following probability*

use Taylor expansion around (lambda,t) = (0,0) to show a(lambda,t)~(t/Kp^2\tau ^2)

$$p(t) = \mathbb{P}\left(|F(\boldsymbol{U}') - G(\boldsymbol{U}')| \geq t\right) \leq C_1 \exp\left[-C_2 n a(\lambda, t)^2\right],$$

where $a(\lambda,t) = \frac{-(2\lambda+1)+\sqrt{(2\lambda+1)^2-4(2\lambda^2-t/Kp^2\tau^2)}}{2}$, C_1, C_2 are two constants, and $p(t) \to 0$ as $t \to \infty$.

Proof. With given membership $\boldsymbol{U}'$, we have estimations $\hat{\Theta}^l(\boldsymbol{U}')$ and $\tilde{\Theta}^l(\boldsymbol{U}')$, which we use $\hat{\Theta}^l$ and $\tilde{\Theta}^l$ refer to them for simplicity, respectively. By the definition, we have

Combine with your earlier self-consistency results. What conclusion do we have?

$$\begin{aligned}|F(\boldsymbol{U}') - G(\boldsymbol{U}')| &= |\mathcal{L}_S(\boldsymbol{U}', \hat{\Theta}^l) - l(\boldsymbol{U}', \tilde{\Theta}^l)| \\ &\leq \sum_{l=1}^{r} |f^l(\hat{\Theta}^l) - g^l(\tilde{\Theta}^l)|,\end{aligned}$$

where

$$f^l(\Theta) = -\sum_{k\in I_l'} \langle S^k, \Theta\rangle + |I_l'| \log\det(\Theta) - \lambda |I_l'| \, \|\Theta\|_1,$$

and

$$g^l(\Theta) = -\sum_{k\in I_l'} \langle \Sigma^k, \Theta\rangle + |I_l'| \log\det(\Theta) - \lambda |I_l'| \, \|\Theta\|_1.$$

Note that the functions $f^l(\cdot)$ and $g^l(\cdot)$ for $l \in [r]$ depends on the membership $\boldsymbol{U}'$, and $\hat{\Theta}^l, \tilde{\Theta}^l$ are unique maximizers for $f^l(\Theta), g^l(\Theta)$, respectively.

Next, for an arbitrary $l \in [r]$, we try to find the upper bound for $|f^l(\hat{\Theta}^l) - g^l(\tilde{\Theta}^l)|$. For simplicity, we use $f, g, \hat{\Theta}, \tilde{\Theta}$ denote $f^l, g^l, \hat{\Theta}^l$ and $\tilde{\Theta}^l$. Consider a new estimation $\breve{\Theta}$ such that

$$\breve{\Theta} = \arg\max_{\Theta} -\sum_{k\in I_l'} \langle \Sigma^k, \Theta\rangle + |I_l'| \log\det(\Theta).$$

By a straight calculation, we have the closed form of $\breve{\Theta}$, which is equal to

$$\breve{\Theta} = \left(\frac{\sum_{k\in I_l'} \Sigma^k}{|I_l'|}\right)^{-1}.$$

Then, we have

$$\begin{aligned}|f(\hat{\Theta}) - g(\tilde{\Theta})| &\leq |f(\hat{\Theta}) - f(\breve{\Theta})| + |f(\breve{\Theta}) - g(\breve{\Theta})| + |g(\breve{\Theta}) - g(\tilde{\Theta})| \\ &= M_1 + M_2 + M_3.\end{aligned}$$

1. **For** M_1, we have

$$f(\hat{\Theta}) - f(\breve{\Theta}) = \sum_{k\in I_l'} \langle S^k, \breve{\Theta} - \hat{\Theta}\rangle + |I_l'| \left(\log\det(\hat{\Theta}) - \log\det(\breve{\Theta})\right) - \lambda |I_l'| \left(\left\|\hat{\Theta}\right\|_1 - \|\breve{\Theta}\|_1\right).$$

Define $\Delta_1 = \hat{\Theta} - \check{\Theta}$ and consider the function $m(t) = \log\det(\check{\Theta} + t\Delta_1)$. By Taylor expansion, we have

$$\begin{aligned}
\log\det(\hat{\Theta}) - \log\det(\check{\Theta}) &= m(1) - m(0) \\
&= \langle \check{\Theta}^{-1}, \Delta_1 \rangle - \mathrm{vec}(\Delta_1)^T \int_0^1 (1-v)(\check{\Theta} + v\Delta_1)^{-1} \otimes (\check{\Theta} + v\Delta_1)^{-1} dv \mathrm{vec}(\Delta_1) \\
&\leq \langle \check{\Theta}^{-1}, \Delta_1 \rangle - \frac{1}{4\tau^2} \|\Delta_1\|_F^2,
\end{aligned}$$

where the first inequality follows by the proof of Theorem 1 in A.J. Rothman et al. (inequality (18)). Note that $f(\hat{\Theta}) - f(\check{\Theta}) \geq 0$, we have

$$\begin{aligned}
|f(\hat{\Theta}) - f(\check{\Theta})| &\leq \sum_{k \in I_l'} \langle S^k - \Sigma^k, \Delta_1 \rangle - \frac{1}{4\tau^2} |I_l'| \|\Delta_1\|_F^2 + \lambda |I_l'| \|\Delta_1\|_1 \\
&\leq |I_l'| \max_{(i,j), k \in I_l'} |S_{ij}^k - \Sigma_{ij}^k| \|\Delta_1\|_1 - \frac{1}{4\tau^2} |I_l'| \|\Delta_1\|_F^2 + \lambda |I_l'| \|\Delta_1\|_1 \\
&\leq |I_l'| \left(-\frac{1}{4\tau^2} \|\Delta_1\|_F^2 + (\lambda + \max_{(i,j), k \in I_l'} |S_{ij}^k - \Sigma_{ij}^k|) p \|\Delta_1\|_F \right), \\
&\leq |I_l'| \tau^2 p^2 (\lambda + \max_{(i,j), k \in I_l'} |S_{ij}^k - \Sigma_{ij}^k|)^2
\end{aligned}$$

where the third inequality follows by the fact the $\|\Delta\|_1 \leq p \|\Delta\|_F$, and the last inequality follows by the property of quadratic function.

2. **For** M_2, we have

$$\begin{aligned}
|f(\check{\Theta}) - g(\check{\Theta})| &= |\sum_{k \in I_l'} \langle S^k - \Sigma^k, \check{\Theta} \rangle| \\
&\leq |I_l'| \left\| S^k - \Sigma^k \right\|_2 \|\check{\Theta}\|_2 \\
&\leq p^2 \tau^2 |I_l'| \max_{(i,j), k \in I_l'} |S_{ij}^k - \Sigma_{ij}^k|.
\end{aligned}$$

3. **For** M_3, we have

$$g(\check{\Theta}) - g(\tilde{\Theta}) = \sum_{k \in I_l'} \langle \Sigma^k, \tilde{\Theta} - \check{\Theta} \rangle + |I_l'| \left(\log\det(\check{\Theta}) - \log\det(\tilde{\Theta}) \right) - \lambda |I_l'| (\|\check{\Theta}\|_1 - \left\|\tilde{\Theta}\right\|_1).$$

Let $\Delta_2 = \tilde{\Theta} - \check{\Theta}$. By Taylor Expansion and similar procedures for M_1, we have

$$\log\det(\tilde{\Theta}) - \log\det(\check{\Theta}) \leq \langle \check{\Theta}^{-1}, \Delta_2 \rangle - \frac{1}{4\tau^2} \|\Delta_2\|_F^2.$$

Then, we have

$$\begin{aligned}
g(\check{\Theta}) - g(\tilde{\Theta}) &\geq \sum_{k \in I_l'} \langle \Sigma^k, \Delta_2 \rangle - |I_l'| (\langle \check{\Theta}^{-1}, \Delta_2 \rangle - \frac{1}{4\tau^2} \|\Delta_2\|_F^2) - \lambda |I_l'| \|\Delta_2\|_1 \\
&= \frac{1}{4\tau^2} |I_l'| \|\Delta_2\|_F^2 - \lambda |I_l'| \|\Delta_2\|_1.
\end{aligned}$$

Since $g(\breve{\Theta}) - g(\tilde{\Theta}) \le 0$, we have

$$\begin{aligned}
|g(\breve{\Theta}) - g(\tilde{\Theta})| &\le -\frac{1}{4\tau^2}|I_l'| \, \|\Delta_2\|_F^2 + \lambda |I_l'| \, \|\Delta_2\|_1 \\
&\le -\frac{1}{4\tau^2}|I_l'| \, \|\Delta_2\|_F^2 + \lambda |I_l'| p \, \|\Delta_2\|_F \\
&\le \tau^2 \lambda^2 p^2 |I_l'|
\end{aligned}$$

Therefore, we have the upper bound

$$\begin{aligned}
|f(\hat{\Theta}) - g(\tilde{\Theta})| &\le M_1 + M_2 + M_3 \\
&\le |I_l'| p^2 \tau^2 \left[(\lambda + \max_{(i,j),k \in I_l'} |S_{ij}^k - \Sigma_{ij}^k|)^2 + \max_{(i,j),k \in I_l'} |S_{ij}^k - \Sigma_{ij}^k| + \lambda^2 \right],
\end{aligned}$$

and thus we have

$$\begin{aligned}
|F(\boldsymbol{U}') - G(\boldsymbol{U}')| &\le \sum_{l=1}^{r} |f^l(\hat{\Theta}^l) - g^l(\tilde{\Theta}^l)| \\
&\le K p^2 \tau^2 \left[(\lambda + \max_{(i,j),k \in K} |S_{ij}^k - \Sigma_{ij}^k|)^2 + \max_{(i,j),k \in K} |S_{ij}^k - \Sigma_{ij}^k| + \lambda^2 \right].
\end{aligned}$$

Intuitively, if λ tends to 0, the error only related to the gap between population and sample $\max_{(i,j),k\in K} |S_{ij}^k - \Sigma_{ij}^k|$.

Last, we obtain the probability

$$\begin{aligned}
\mathbb{P}(|F(\boldsymbol{U}') - G(\boldsymbol{U}')| \ge t) &\le \mathbb{P}\left((\lambda + \max_{(i,j),k \in K} |S_{ij}^k - \Sigma_{ij}^k|)^2 + \max_{(i,j),k \in K} |S_{ij}^k - \Sigma_{ij}^k| + \lambda^2 \ge \frac{t}{Kp^2\tau^2} \right) \\
&= \mathbb{P}\left(\max_{(i,j),k \in K} |S_{ij}^k - \Sigma_{ij}^k|^2 + (2\lambda + 1) \max_{(i,j),k \in K} |S_{ij}^k - \Sigma_{ij}^k| + 2\lambda^2 - \frac{t}{Kp^2\tau^2} \ge 0 \right) \\
&= \mathbb{P}\left(\max_{(i,j),k \in K} |S_{ij}^k - \Sigma_{ij}^k| \ge \frac{-(2\lambda+1) + \sqrt{(2\lambda+1)^2 - 4(2\lambda^2 - t/Kp^2\tau^2)}}{2} \right).
\end{aligned}$$

Let $a(\lambda, t) = \frac{-(2\lambda+1)+\sqrt{(2\lambda+1)^2-4(2\lambda^2-t/Kp^2\tau^2)}}{2}$. Note that $\lim_{\lambda \to 0} a(\lambda, t) = \frac{-1+\sqrt{1+4t/Kp^2\tau^2}}{2}$ is an increasing function along with t. By the Lemma 2, we have

also expand around t~0?

linear

$$p(t) = \mathbb{P}(|F(\boldsymbol{U}') - G(\boldsymbol{U}')| \ge t) \ge \mathbb{P}\left(\max_{(i,j),k \in K} |S_{ij}^k - \Sigma_{ij}^k| \ge a(\lambda, t) \right) \le C_1 \exp\left\{ -C_2 n a(\lambda, t)^2 \right\}.$$

To ensure $p(t)$ decreases as $n \to \infty$, we need $\lambda \le \mathcal{O}(n^{-1/2})$ since $a(\lambda, t) = \mathcal{O}(\lambda)$.

□

Remark 1. In non-penalized case, it is easy to measure the distance between $\hat{\Theta}$ and $\tilde{\Theta}$, since both of them have closed form and can be represented by the gap between sample and population $|S - \Sigma|$ and the properties of the true Θ. But in our case, both $\hat{\Theta}$ and $\tilde{\Theta}$ do not have closed form and thus it is hard to describe $\left\| \hat{\Theta} - \tilde{\Theta} \right\|$. Therefore, I introduce a new estimation $\breve{\Theta}$ which is the estimate without the penalty and is a combination of true precision matrices. Then, taking the advantage of the optimization properties of $\hat{\Theta}, \tilde{\Theta}$, we find the bound.

Lemma 2. *Let $Z_i \sim_{i.i.d.} \mathcal{N}(0, \Sigma)$ and $\varphi_{max}(\Sigma) \leq \tau < \infty$. Let $\Sigma = [\![\Sigma_{ij}]\!]$, then*

$$P\left(\left|\sum_{i=1}^{n} Z_{ij}Z_{ik} - n\Sigma_{jk}\right| \geq n\nu\right) \leq c_1 e^{-c_2 n\nu^2}, \quad \textit{for} \quad |\nu| \leq \delta,$$

where c_1, c_2, δ depends on τ only.