Graphic Lasso: Possible Accuracy

Jiaxin Hu

January 5, 2021

1 Optimization with 1/2 norm

Let $Q(\Omega) = \operatorname{tr}(S\Omega) - \log |\Omega|$. Consider the primal minimization problem

$$\min_{\Omega = \llbracket \omega_{j,j'} \rrbracket} Q(\Omega),$$

$$s.t. \sum_{j \neq j'} |\omega_{j,j'}|^{1/2} \leq C.$$

For simplicity, let $|\Omega|^{1/2} = \sum_{j \neq j'} |\omega_{j,j'}|^{1/2}$, T denote the set of indices of non-zero off-diagonal elements, and q = |T|. We assume following assumptions.

- 1. There exist two constants τ_1, τ_2 such that $0 < \tau_1 < \phi_{\min}(\Omega_0) \le \phi_{\max}(\Omega_0) < \tau_2 < \infty$, for all $p \ge 1, k = 1, ..., K$, where $\phi_{\min}(\cdot), \phi_{\max(\cdot)}$ denote the minimal and maximal eigenvalues, respectively.
- 2. There exists a constant $\tau_3 > 0$ such that $\min_{(i,j') \in T} |\omega_{0,i,j'}| \ge \tau_3$.

Theorem 1.1 (Consistency (Preliminary)). Suppose two assumptions hold and C is a positive constant. Let Ω denote the true precision matrix. There exists a local minimizer $\hat{\Omega}$ such that $Q(\hat{\Omega}) \leq Q(\Omega)$ and $|\hat{\Omega}|^{1/2} \leq C$, and the following accuracy bound holds with probability tending to 1.

$$\left\| \hat{\Omega} - \Omega \right\|_F = O_p \left[\left\{ \frac{(p+q)\log p}{n} \right\}^{1/4} \right].$$

Proof follows tensor paper

Proof. Consider the following decomposition

$$G(\Delta) = \operatorname{tr}(S(\Omega + \Delta)) - \operatorname{tr}(\Omega) - \log |\Omega + \Delta| + \log |\Omega| = I_1 + I_2$$

where

$$I_1 = \operatorname{tr}((S - \Sigma)\Delta), \quad I_2 = (\tilde{\Delta})^T \int_0^1 (1 - v)(\Omega + v\Delta)^{-1} \otimes (\Omega + v\Delta)^{-1} dv\tilde{\Delta}.$$

Suppose $\hat{\Omega} = \Omega + \Delta$ has larger or equal likelihood value than the true precision matrix Ω . Then, we have $G(\Delta) \leq 0$, i.e.,

$$I_2 \le -I_1 \le |I_1|. \tag{1}$$

Note that

$$|I_1| \le C_1 \left(\frac{\log p}{n}\right)^{1/2} \left(|\Delta_T^-|_1 + |\Delta_{T^c}^-|_1\right) + C_2 \left(\frac{p \log p}{n}\right)^{1/2} \left\|\Delta^+\right\|_F, \quad I_2 \ge \frac{1}{4\tau_2^2} \left\|\Delta\right\|_F^2,$$

 $|\Delta_T^-|_1 \le q^{1/2} \|\Delta\|_F$, and $|\Delta_{T^c}^-|_1 \le C$. To satisfy the inequality (1), we have

$$\frac{1}{4\tau_2^2} \|\Delta\|_F^2 \le (C_1 + C_2) \left(\frac{(p+q)\log p}{n}\right)^{1/2} \|\Delta\|_F + C_1 \left(\frac{(p+q)\log p}{n}\right)^{1/2} C. \tag{2}$$

Consider the equation

$$0 = -\frac{1}{4\tau_2^2}x^2 + (C_1 + C_2)\left(\frac{(p+q)\log p}{n}\right)^{1/2}x + C_1\left(\frac{(p+q)\log p}{n}\right)^{1/2}C.$$
 (3)

The solutions to the equation (3) are

$$x^* = 2\tau_2^2 \left\{ (C_1 + C_2) \left(\frac{(p+q)\log p}{n} \right)^{1/2} \pm \sqrt{(C_1 + C_2)^2 \left(\frac{(p+q)\log p}{n} \right) + C_1 C \left(\frac{(p+q)\log p}{n} \right)^{1/2} / \tau_2^2} \right\}$$

$$= \mathcal{O} \left[\left(\frac{(p+q)\log p}{n} \right)^{1/4} \right],$$

$$(4)$$

where the second equality follows by the fact that the term $\sqrt{C_1 C \left(\frac{(p+q)\log p}{n}\right)^{1/2}/\tau_2^2}$ dominates the solution. Therefore, to satisfy the inequality (2), we have

$$\left\|\hat{\Omega} - \Omega\right\|_F = \left\|\Delta\right\|_F = \mathcal{O}\left[\left(\frac{(p+q)\log p}{n}\right)^{1/4}\right].$$

We could still improve to the root-n convergence, at a cost of an additional F(p,q) factor.

Proof follows Guo's paper

Proof. Let $\mathcal{A} = \left\{ \|\Delta\|_F \leq M\left(\frac{(p+q)\log p}{n}\right)^{1/4}, |\Omega + \Delta|^{1/2} \leq C \right\}$. Define $G(\Delta)$, I_1 , and I_2 same as above proof. We know that

$$G(\Delta) \ge I_2 - |I_1|$$

$$\ge \frac{1}{4\tau_2^2} \|\Delta\|_F^2 - \left(\frac{(p+q)\log p}{n}\right)^{1/2} \|\Delta\|_F - C_1 \left(\frac{(p+q)\log p}{n}\right)^{1/2} C.$$

By the solution (4), we have $G(\Delta) > 0$ for all $\Delta \in \partial \mathcal{A}$ with M large enough. Therefore, there exists a local minimizer inside \mathcal{A} and thus $\left\|\hat{\Omega} - \Omega\right\|_F = \mathcal{O}\left[\left(\frac{(p+q)\log p}{n}\right)^{1/4}\right]$

2 Different constrains

1. We change the constrain as

$$\frac{|\Omega + \Delta|_1}{\|\Omega + \Delta\|_F} < C.$$

Then we have

$$|\Delta_{T^c}^-|_1 < C \|\Omega + \Delta\|_F.$$

However, the relationship between $\|\Omega + \Delta\|_F$ and $\|\Delta\|_F$ is uncertain. We only have

$$\|\Omega + \Delta\|_F \le \|\Delta\|_F + \|\Omega\|_F = \|\Delta\|_F + C'.$$

The solutions x^* are still dominated by the $\left(\frac{(p+q)\log p}{n}\right)^{1/4}$ term.

2. We change the constrain as

$$|\Omega + \Delta|_0 < s$$
.

Note that $|\Omega + \Delta|_0 = |\Omega_T + \Delta_T|_0 + |\Delta_{T^c}|_0 < s$. We have

$$|\Delta_{T^c}^-|_1 < |\Delta_{T^c}^-|_0 \|\Delta\|_{\max} \le s \|\Delta\|_F.$$
 (5)

Plugging (5) into the inequality (1), we have inequality 1: $G(\Delta) < 0$.

$$\frac{1}{4\tau_2^2} \|\Delta\|_F^2 \le (C_1 + C_2) \left(\frac{(p+q)\log p}{n}\right)^{1/2} \|\Delta\|_F + C_1 \left(\frac{\log p}{n}\right)^{1/2} s \|\Delta\|_F,$$

and thus we have

$$\left\| \hat{\Omega} - \Omega \right\|_F = \left\| \Delta \right\|_F = \mathcal{O} \left[\left(\frac{(p+q)\log p}{n} \right)^{1/2} \right]. \tag{6}$$

Remark. The above accuracy (6) holds when q is fixed. Since the true Ω should satisfy the constrain, we need $|\Omega|_0 = q < s$. Therefore, when q is not a fixed number, let s = Mq for some constant M. The accuracy is of order $\mathcal{O}\left\{q\left(\frac{\log p}{n}\right)^{1/2}\right\}$.

3 Optimization without constrain

Consider the problem

$$\min_{\Omega = \llbracket \omega_{i,i'} \rrbracket} Q(\Omega).$$

Theorem 3.1. Suppose two assumptions hold. For estimation $\hat{\Omega}$ such that $Q(\hat{\Omega}) \leq Q(\Omega)$, we have following accuracy bound with probability tending to 1.

$$\left\| \hat{\Omega} - \Omega \right\|_F = O_p \left[p \left\{ \frac{\log p}{n} \right\}^{1/2} \right].$$

Proof. Define $G(\Delta)$, I_1 , and I_2 same as above proofs. Unlike above proofs, we have

$$|I_{1}| \leq C_{1} \left(\frac{\log p}{n}\right)^{1/2} |\Delta|_{1} + C_{2} \left(\frac{p \log p}{n}\right)^{1/2} \|\Delta^{+}\|_{F}$$

$$\leq \left\{ C_{1} p \left(\frac{\log p}{n}\right)^{1/2} + C_{2} \left(\frac{p \log p}{n}\right)^{1/2} \right\} \|\Delta\|_{F},$$

where the second inequality follows by the fact that $|\Delta|_1 \leq p \|\Delta\|_F$. Then, to let $G(\Delta) \neq 0$, we need $I_2 \leq |I_1|$, i.e.,

$$\frac{1}{4\tau_2^2} \|\Delta\|_F^2 \le C' p \left(\frac{\log p}{n}\right)^{1/2} \|\Delta\|_F,$$

which implies that

$$\left\| \hat{\Omega} - \Omega \right\|_F = \left\| \Delta \right\|_F = O_p \left[p \left\{ \frac{\log p}{n} \right\}^{1/2} \right].$$

This result makes sense. The degree of freedom for the dense model is p^2 while for sparse model is p+q. Compared with the accuracy with constrain, the optimization without constrain corresponds to the dense model, and the p+q part in the accuracy is replaced by p^2 .

Add a paragraph:

Which is better, L0 or L1, in the case of growing (p,n), but fixed q. Does it intuitively make sense?

Next, back to our multi-layer model. Two questions before next meeting.

- 1. What constraints should we put in order for identifiability?
- 2. Any thoughts on convergence rate?