Graphic Lasso: two precision matrices

Jiaxin Hu

January 17, 2021

1 Consistency

Suppose K categories are clustered by two groups with precision matrices Θ_1, Θ_2 . The model becomes

$$\Omega^k = \mathbf{I}_k \Theta_1 + (1 - \mathbf{I}_k) \Theta_2, \quad k = 1, ..., K,$$

where $I_k = I(k$ -th category belongs to group 1) are indicator functions. The model is identifiable since the indicator functions can be replaced by a membership matrix. Consider the optimization problem

$$\min_{\Theta_1,\Theta_2,\boldsymbol{I}_k} \quad \sum_{k=1}^K \operatorname{tr}(S^k \Omega^k) - \log |\Omega^k|$$

$$s.t. \quad \Omega^k = \boldsymbol{I}_k \Theta_1 + (1 - \boldsymbol{I}_k) \Theta_2, \quad k = 1, ..., K,$$

$$\|\Theta_i\|_0 \le b, \quad i = 1, 2.$$

Theorem 1.1. Let $(\Theta_1, \Theta_2, \mathbf{I}_k)$ be the true precision matrices and the membership. Suppose $0 < \tau_1 < \phi_{min}(\Theta_i) \le \phi_{max}(\Theta_0) < \tau_2 < \infty$, where i = 1, 2 and τ_1, τ_2 are positive constants. For the estimation $(\hat{\Theta}_1, \hat{\Theta}_2, \hat{I}_k)$ such that $\sum_{k=1}^K tr(S^k \hat{\Omega}^k) - \log |\hat{\Omega}^k| \le \sum_{k=1}^K tr(S^k \Omega^k) - \log |\Omega^k|$, we have the following accuracy with probability tending to 1

$$\sum_{k=1}^{K} \left\| \hat{\Omega}^k - \Omega^k \right\| \le 2\sqrt{2K}C'' \left[C\sqrt{\frac{b\log p}{n}} + C'\sqrt{\frac{p\log p}{n}} \right]. \tag{1}$$

Proof. Let Σ^1, Σ^2 denote the true covariance matrices. Define the sets $A_{11} = \{k : \hat{I}_k = I_k = 1\}$, $A_{12} = \{k : \hat{I}_k = 1, I_k = 0\}$, $A_{21} = \{k : \hat{I}_k = 0, I_k = 1\}$ and $A_{22} = \{k : \hat{I}_k = I_k = 0\}$. Correspondingly, we define $\Delta_{11} = \hat{\Theta}_1 - \Theta_1$, $\Delta_{12} = \hat{\Theta}_1 - \Theta_2$, $\Delta_{21} = \hat{\Theta}_2 - \Theta_1$, and $\Delta_{22} = \hat{\Theta}_2 - \Theta_2$. Let $\Delta^k = \hat{\Omega}^k - \Omega \in \{\Delta_{11}, \Delta_{12}, \Delta_{21}, \Delta_{22}\}$. The value of Δ^k depends on the true and estimated membership of k. Consider the function

$$G(\Delta_{11}, \Delta_{12}, \Delta_{21}, \Delta_{22}) = I_1 + I_2,$$

where

$$I_1 = \sum_{k \in A_{11}} \operatorname{tr}((S^k - \Sigma^1)\Delta_{11}) + \sum_{k \in A_{12}} \operatorname{tr}((S^k - \Sigma^2)\Delta_{12}) + \sum_{k \in A_{21}} \operatorname{tr}((S^k - \Sigma^1)\Delta_{21}) + \sum_{k \in A_{22}} \operatorname{tr}((S^k - \Sigma^2)\Delta_{22})$$

$$=I_{11}+I_{12}+I_{21}+I_{22},$$

and

$$I_2 = |A_{11}|f(\Delta_{11}, \Theta_1) + |A_{12}|f(\Delta_{12}, \Theta_2) + |A_{21}|f(\Delta_{21}, \Theta_1) + |A_{22}|f(\Delta_{22}, \Theta_2),$$

with
$$f(\Delta, \Theta) = (\tilde{\Delta})^T \int_0^1 (1 - v)(\Theta + v\Delta)^{-1} \otimes (\Theta + v\Delta)^{-1} dv \tilde{\Delta}$$
.

Recall the result in the common precision matrix case. For each I_{ij} , i, j = 1, 2, we have

$$\frac{1}{|A_{ij}|}|I_{ij}| = \operatorname{tr}\left(\left(\frac{1}{|A_{ij}|}\sum_{k \in A_{ij}} S^k - \Sigma^j\right) \Delta_{ij}\right) \le C_{ij} \sqrt{\frac{\log p}{n|A_{ij}|}} |\Delta_{ij}^-|_1 + C'_{ij} \sqrt{\frac{p \log p}{n|A_{ij}|}} \|\Delta_{ij}\|_F.$$

Let $T_j = \{(k,l) : \Theta_{j,kl} \neq 0\}, j = 1,2$. We have $|\Delta_{ij}^-|_1 = |\Delta_{T_j,ij}^-|_1 + |\Delta_{T_j^c,ij}^-|_1$. Note that $|\Delta_{T_j,ij}^-|_0, |\Delta_{T_j^c,ij}^-|_0 \leq b$ and $|\Delta_{T_j,ij}^-|_1, |\Delta_{T_j^c,ij}^-|_1 \leq \sqrt{b} \|\Delta_{ij}\|_F$. Then, we have

$$|I_{ij}| \le \sqrt{|A_{ij}|} \left[C_{ij} \sqrt{\frac{b \log p}{n}} + C'_{ij} \sqrt{\frac{p \log p}{n}} \right] \|\Delta_{ij}\|_F.$$

On the other hand, the lower bound for I_2 is

$$I_2 \ge \frac{1}{4\tau_2^2} \sum_{ij} |A_{ij}| \|\Delta_{ij}\|_F^2.$$

To let $G \leq 0$, we have $I_2 \leq |I_1| \leq \sum_{ij} |I_{ij}|$. Plug the upper bound for $|I_{ij}|$ and the lower bound for I_2 , we have

$$\frac{1}{4\tau_2^2} \sum_{ij} |A_{ij}| \|\Delta_{ij}\|_F^2 \le \left[C\sqrt{\frac{b \log p}{n}} + C'\sqrt{\frac{p \log p}{n}} \right] \sum_{ij} \sqrt{|A_{ij}|} \|\Delta_{ij}\|_F.$$

By Cauchy Schwartz inequality, we have

$$\sum_{ij} |A_{ij}| \|\Delta_{ij}\|_F^2 \ge \frac{1}{4} \left(\sum_{ij} \sqrt{|A_{ij}|} \|\Delta_{ij}\|_F \right)^2.$$
 (2)

Thus, we have

$$\sum_{ij} \sqrt{|A_{ij}|} \|\Delta_{ij}\|_F \le 4C'' \left[C\sqrt{\frac{b \log p}{n}} + C'\sqrt{\frac{p \log p}{n}} \right].$$

Multiply max $\sqrt{|A_{ij}|}$ on both sides. We obtain the accuracy

$$\sum_{k=1}^{K} \left\| \hat{\Omega}^k - \Omega^k \right\|_F = \sum_{ij} |A_{ij}| \left\| \Delta_{ij} \right\|_F$$

$$\leq \max \sqrt{|A_{ij}|} \sum_{ij} \sqrt{|A_{ij}|} \left\| \Delta_{ij} \right\|_F$$

$$\leq 4 \max \sqrt{|A_{ij}|} C'' \left[C \sqrt{\frac{b \log p}{n}} + C' \sqrt{\frac{p \log p}{n}} \right]. \tag{3}$$

Remark 1. In two group case with equal group size, we have $\max \sqrt{|A_{ij}|} \leq \sqrt{\frac{K}{2}}$. Then, we obtain the accuracy (1) in Theorem 1.1. If we have r groups and each group has equal number of categories, the number 4 should be replaced by r(r-1) and $\max \sqrt{|A_{ij}|} \leq \sqrt{\frac{K}{r}}$. Thus the accuracy is of order $\mathcal{O}(\sqrt{K}r^{3/2})$.

2 Discussion

What's the difference between known I_k and unknown I_k ?

In two group case with equal sample size, if the membership I_k is already known, we only need to consider A_{11} and A_{22} because $A_{12} = A_{21} = \emptyset$. Then, by Cauchy Schwartz, the inequality (2) becomes

$$\sum_{ij} |A_{ij}| \|\Delta_{ij}\|_F^2 \ge \frac{1}{2} \left(\sum_{ij} \sqrt{|A_{ij}|} \|\Delta_{ij}\|_F \right)^2,$$

 $\max \sqrt{|A_{ij}|} = \sqrt{\frac{K}{2}}$, and thus

$$\sum_{k=1}^K \left\| \hat{\Omega}^k - \Omega^k \right\|_F \leq \sqrt{2K} C'' \left[C \sqrt{\frac{b \log p}{n}} + C' \sqrt{\frac{p \log p}{n}} \right].$$

Further, consider the r group case with equal sample size. If the membership is known, the number 4 in accuracy (3) becomes r and $\max \sqrt{|A_{ij}|} = \sqrt{\frac{K}{r}}$. The accuracy in this case is of order $\mathcal{O}(\sqrt{Kr})$, which is better than the unknown membership case with accuracy of order $\mathcal{O}(\sqrt{Kr})$.

How the rate affected by the clustering result?

Let $a = |\{(i, j) : A_{ij} \neq \emptyset\}|$, which is the number of non-empty A_{ij} . The inequality (2) becomes

$$\sum_{ij} |A_{ij}| \|\Delta_{ij}\|_F^2 \ge \frac{1}{a} \left(\sum_{ij} \sqrt{|A_{ij}|} \|\Delta_{ij}\|_F \right)^2.$$

Thus, the accuracy will be of order $\mathcal{O}(a \max \sqrt{|A_{ij}|}) = \mathcal{O}(aK^{1/2}r^{-1/2})$. The number $a \in [r, r(r-1)]$, and the small a implies a more accurate clustering. Therefore, the accuracy of clustering will affect the estimation accuracy through the factor a(r).

On the other hand, the accuracy of clustering will also affect estimation accuracy through factor $\max \sqrt{|A_{ij}|}$. Consider r group with equal group size. The worst estimation leads to $|A_{i1}| = \cdots = |A_{ir}| = \frac{K}{r^2}$, for all i = 1, ..., r. However, the accuracy under the worst case is of $\mathcal{O}(r\sqrt{K})$, which is not the worst accuracy $\mathcal{O}(\sqrt{K}r^{3/2})$. Need to figure out this problem next.

What is the accuracy of $\hat{\Theta}_1, \hat{\Theta}_2$ and \hat{I}_k ?

Note that

$$\begin{split} \|\Delta_{11}\|_{F} &= \left\| \hat{\Theta}_{1} - \Theta_{1} \right\|_{F}, \quad \|\Delta_{21}\|_{F} \leq \left\| \hat{\Theta}_{1} - \Theta_{1} \right\|_{F} + \left\| \hat{\Theta}_{1} - \hat{\Theta}_{2} \right\|_{F} \\ \|\Delta_{22}\|_{F} &= \left\| \hat{\Theta}_{2} - \Theta_{2} \right\|_{F}, \quad \|\Delta_{12}\|_{F} \leq \left\| \hat{\Theta}_{2} - \Theta_{2} \right\|_{F} + \left\| \hat{\Theta}_{1} - \hat{\Theta}_{2} \right\|_{F} \end{split}$$