

# Graphic Lasso: Clustering accuracy for precision matrix model

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## 1 Accuracy

Consider the optimization problem.

$$\begin{aligned} \min_{\mathbf{U}, \{\Theta^l\}} \quad & Q(\mathbf{U}, \{\Theta^l\}) = \sum_{k=1}^K \text{tr}(S^k \Omega^k) - \log |\Omega^k|, \\ \text{s.t.} \quad & \Omega^k = \sum_{l=1}^r u_{kl} \Theta^l, \\ & \mathbf{U} \in \{0, 1\}^{K \times r} \text{ is a membership matrix,} \\ & \{\Theta^l\} \text{ are irreducible and invertible.} \end{aligned}$$

*Proof.* Recall the objective function

$$Q(\mathbf{U}, \{\Theta^l\}) = \sum_{k=1}^K \text{tr}(S^k \Omega^k) - \log |\Omega^k| = \sum_{k=1}^K \langle S^k, \Omega^k \rangle - \log |\Omega^k|.$$

The deviation between the true parameters  $\{\mathbf{U}, \{\Theta^l\}\}$  and estimations  $\{\hat{\mathbf{U}}, \{\hat{\Theta}^l\}\}$  comes from two aspects: the estimation of  $\{\Theta^l\}$  and the misclassification (estimation of  $\mathbf{U}$ ). We tease apart these two parts.

1. First, we suppose the membership  $\mathbf{U}$  is given. We now assess the stochastic error due to the estimation of  $\{\Theta^l\}$ , conditional on  $\mathbf{U}$ . Define the index sets  $I_l = \{k : u_{kl} = 1\}$  for  $l = 1, \dots, r$ . Note that the objective function is convex. The optimal  $\{\Theta^l\}$  satisfies the first order condition.

$$\frac{\partial Q}{\partial \Theta_{ij}^l} = \sum_{k \in I_l} S_{ij}^k - |I_l| \frac{C(\Theta^l)_{ij}}{|\Theta^l|} = 0,$$

where  $C(A)_{ij}$  is the cofactor of matrix  $A$  corresponding to the element  $A_{ij}$ . Note that  $\Theta^l$  should be a symmetric matrix. The cofactor matrix  $C(\Theta^l) = C^T(\Theta^l)$ . Then, the derivation of the matrix  $\Theta^l$  is equal to

$$\frac{\partial Q}{\partial \Theta^l} = \sum_{k \in I_l} S^k - |I_l| \frac{C^T(\Theta^l)}{|\Theta^l|} = 0,$$

which implies that

$$\hat{\Theta}^l = \left( \frac{\sum_{k \in I_l} S^k}{|I_l|} \right)^{-1}, \quad \text{for } l \in [r].$$

Therefore, the estimation of  $\{\Theta^l\}$  is a function of  $\mathbf{U}$ . Consider the function  $F(\mathbf{U}) = Q(\mathbf{U}, \{\hat{\Theta}^l\})$ . By a straightforward calculation, we have

$$\begin{aligned} F(\mathbf{U}) &= \sum_{l=1}^r \sum_{k \in I_l} \langle S^k, \left( \frac{\sum_{k \in I_l} S^k}{|I_l|} \right)^{-1} \rangle - |I_l| \log \left| \left( \frac{\sum_{k \in I_l} S^k}{|I_l|} \right)^{-1} \right| \\ &= \sum_{l=1}^r \langle \sum_{k \in I_l} S^k, \left( \frac{\sum_{k \in I_l} S^k}{|I_l|} \right)^{-1} \rangle - |I_l| \log \left| \left( \frac{\sum_{k \in I_l} S^k}{|I_l|} \right)^{-1} \right| \\ &= \sum_{l=1}^r |I_l| p - |I_l| \log \left| \left( \frac{\sum_{k \in I_l} S^k}{|I_l|} \right)^{-1} \right|. \end{aligned}$$

Note that  $\sum_{l=1}^r |I_l| p = Kp$  is independent with the membership. We only need to consider the second term. For simplicity, we define

$$F(\mathbf{U}) = \sum_{l=1}^r |I_l| \log \left| \left( \frac{\sum_{k \in I_l} S^k}{|I_l|} \right)^{-1} \right|.$$

Correspondingly, we define the population version of  $F(\mathbf{U})$  as following.

$$G(\mathbf{U}) = \sum_{l=1}^r |I_l| \log \left| \left( \frac{\sum_{k \in I_l} \Sigma^k}{|I_l|} \right)^{-1} \right|,$$

where  $\Sigma^k = \mathbb{E}[S^k]$  is the true covariance matrices. Therefore, the deviation  $F(\mathbf{U}) - G(\mathbf{U})$  quantifies the stochastic error due to the estimation of  $\{\Theta^l\}$ .

2. Next, we free  $\mathbf{U}$  and quantify the total deviation. Considering the maximizer,

$$\hat{\mathbf{U}} = \arg \max_{\mathbf{U}} F(\mathbf{U}).$$

The corresponding  $G(\hat{\mathbf{U}})$  is

$$G(\hat{\mathbf{U}}) = \sum_{l=1}^r |\hat{I}_l| \log \left| \left( \frac{\sum_{k \in \hat{I}_l} \Sigma^k}{|\hat{I}_l|} \right)^{-1} \right|,$$

and the function  $G(\mathbf{U})$  with true membership is

$$G(\mathbf{U}) = \sum_{l=1}^r |I_l| \log \left| \left( \frac{\sum_{k \in I_l} \Sigma^k}{|I_l|} \right)^{-1} \right| = \sum_{l=1}^r |I_l| \log |\Theta^l|.$$

Then, the deviation  $G(\hat{\mathbf{U}}) - G(\mathbf{U})$  measures the stochastic error of the misclassification. □

**Lemma 1.** Suppose the misclassification rate  $MCR(\hat{\mathbf{U}}, \mathbf{U}) = \max_{l, a \neq a' \in [r]} \min\{D_{al}, D(a'l)\} \geq \epsilon$ .

$$G(\hat{\mathbf{U}}) - G(\mathbf{U}) \leq$$

*Proof.* Recall the definition of confusion matrix  $D_{ll'} = \sum_{k=1}^K \mathbf{I}\{u_{kl} = 1, \hat{u}_{kl'} = 1\}$ . Since  $MCR(\hat{\mathbf{U}}, \mathbf{U}) \geq \epsilon$ , without the loss of generality, let  $D_{11}$  be the largest element in the first column of  $D$ ,  $D_{12}$  be the second largest element in the column, and  $D_{21} \geq \epsilon$ . □