Graphic Lasso: Expectation Issue

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1 Outside Expectation

Suppose $\mathcal{Y}$ is a binary tensor, where $\mathcal{Y}_{i_1,\ldots,i_K} \sim Ber(c_{r_1,\ldots,r_K})$ independently.

1.1 Least squared

Suppose the objective function is the least squared function. With given membership $\{\boldsymbol{M}_k\}$, the estimation of core tensor is

$$\hat{c}_{r_1,\ldots,r_K} = \frac{1}{d_1 \ldots d_K p_{r_1}^{(1)} \cdots p_{r_K}^{(K)}} [\mathcal{Y} \times_1 \boldsymbol{M}_1^T \times_2 \cdots \times_K^T \boldsymbol{M}_K]_{r_1,\ldots,r_K}.$$

The function $F(\boldsymbol{M}_k)$ and $G(\boldsymbol{M}_k)$ are defined as following.

$$F(\boldsymbol{M}_k) = \sum_{r_1,\ldots,r_K} \prod_k p_{r_k}^{(k)} \hat{c}_{r_1,\ldots,r_K}^2, \quad G(\boldsymbol{M}_k) = \mathbb{E}[F(\boldsymbol{M}_k)] = \sum_{r_1,\ldots,r_K} \prod_k p_{r_k}^{(k)} \mathbb{E}(\hat{c}_{r_1,\ldots,r_K}^2). \tag{1}$$

Let $\mu_{r_1,\ldots,r_K} = \mathbb{E}[\hat{c}_{r_1,\ldots,r_K}]$. We have

$$\mu_{r_1,\ldots,r_K} = \mathbb{E}[\hat{c}_{r_1,\ldots,r_K}] = \frac{1}{\prod_k p_{r_k}^{(k)}} [\mathcal{C} \times_1 \boldsymbol{D}^{(1),T} \times_2 \cdots \times_K \boldsymbol{D}^{(K),T}]_{r_1,\ldots,r_K}.$$

Note that $\text{Var}(\mathcal{Y}) = V(\mathcal{C}) \times_1 \boldsymbol{M}_1 \times_2 \cdots \times_K \boldsymbol{M}_K$, where $V(c_{r_1,\ldots,r_K}) = c_{r_1,\ldots,r_K}(1 - c_{r_1,\ldots,r_K})$. Therefore, we have

$$\begin{aligned} \mathbb{E}[\hat{c}_{r_1,\ldots,r_K}^2] &= \text{Var}(\hat{c}_{r_1,\ldots,r_K}) + [\mathbb{E}(\hat{c}_{r_1,\ldots,r_K})]^2 \\ &= \frac{1}{[\prod_k d_k][\prod_k p_{r_k}^{(k)}]^2} [V(\mathcal{C}) \times_1 \boldsymbol{D}^{(1),T} \times_2 \cdots \times_K \boldsymbol{D}^{(K),T}]_{r_1,\ldots,r_K} + \mu_{r_1,\ldots,r_K}^2. \end{aligned} \tag{2}$$

Plugging the equation (2) into the definition of $G(\boldsymbol{M}_k)$ (1), we have

$$G(\boldsymbol{M}_k) = \sum_{r_1,\ldots,r_K} \prod_k p_{r_k}^{(k)} \mu_{r_1,\ldots,r_K}^2 + \sum_{r_1,\ldots,r_K} \frac{1}{[\prod_k d_k][\prod_k p_{r_k}^{(k)}]} [V(\mathcal{C}) \times_1 \boldsymbol{D}^{(1),T} \times_2 \cdots \times_K \boldsymbol{D}^{(K),T}]_{r_1,\ldots,r_K}.$$

Since the estimation of the core tensor $\mathcal{C}$ is related to both the mean of $\mathcal{Y}$ but also the variance of $\mathcal{Y}$, the error for misclassification can be separated into two parts.

Suppose we have the true membership, the first term $I_1 = \sum_{r_1,\ldots,r_K} \prod_k p_{r_k}^{(k)} \mu_{r_1,\ldots,r_K}^2$ is maximized with true membership. the However, the variance term $I_2 = \sum_{r_1,\ldots,r_K} \frac{1}{[\prod_k d_k][\prod_k p_{r_k}^{(k)}]} [V(\mathcal{C}) \times_1$

$\boldsymbol{D}^{(1),T} \times_2 \cdots \times_K \boldsymbol{D}^{(K),T}]_{r_1,\ldots,r_K}$ may not achieve the maxima with the true membership. Here is a couter-example.

Counter Example

Let $\{\boldsymbol{M}_k\}$ denote the true membership, and $\{\hat{\boldsymbol{M}}_k\}$ denote the estimation of the membership. Then we have

$$I_2(\boldsymbol{M}_k) = \sum_{r_1,\ldots,r_K} \frac{1}{\prod_k d_k} V(\mathcal{C})_{r_1,\ldots,r_K},$$

and

$$I_2(\hat{\boldsymbol{M}}_k) = \sum_{r_1,\ldots,r_K} \frac{1}{[\prod_k d_k][\prod_k \hat{p}^{(k)}_{r_k}]} [V(\mathcal{C}) \times_1 \boldsymbol{D}^{(1),T} \times_2 \cdots \times_K \boldsymbol{D}^{(K),T}]_{r_1,\ldots,r_K}.$$

Consider a special case. Suppose $\hat{\boldsymbol{M}}_k = \boldsymbol{M}_k$ for $k = 2, \ldots, K$. Then $\boldsymbol{D}^{(k)}$ are diagonal matrices and $\hat{p}^{(k)}_{r_k} = p^{(k)}_{r_k}$ for $k = 2, \ldots, K$. Since the misclassification happens only on the first mode, let $MCR(\hat{\boldsymbol{M}}_1, \boldsymbol{M}_1) = \epsilon$. Fixed $r_2, \ldots, r_K$, assume the misclassification happens only between blocks $(r_1, r_2, \ldots, r_K)$ and $(r'_1, r_2, \ldots, r_K)$, keeping the cluster proportions the same as true proportion $\hat{p}^{(1)}_{r_1} = p^{(1)}_{r_1}, \hat{p}^{(1)}_{r'_1} = p^{(1)}_{r'_1}$. This setting describes the case that $d_1\epsilon$ elements are switched from block r_1 to r'_1, where other membership on mode 1 are correct. For simplicity, let $V(\mathcal{C})_{r_1,\ldots,r_K} = V(c)$ and $V(\mathcal{C})_{r'_1,\ldots,r_K} = V(c')$. Therefore, we only need to compare

$$\tilde{I}_2(\boldsymbol{M}_k) = V(c) + V(c'),$$

and

$$\tilde{I}_2(\hat{\boldsymbol{M}}_k) = \frac{d_1 D^{(1)}_{r_1,r_1} V(c) + d_1\epsilon V(c')}{d_1 p^{(1)}_{r_1}} + \frac{d_1 D^{(0)}_{r'_1,r'_1} V(c') + d_1\epsilon V(c)}{d_1 p^{(1)}_{r'_1}},$$

where $D^{(1)}_{r_1,r_1} + \epsilon = p^{(1)}_{r_1}$ and $D^{(0)}_{r'_1,r'_1} + \epsilon = p^{(1)}_{r'_1}$.

By a straight forward calculation, we have

$$\tilde{I}_2(\hat{\boldsymbol{M}}_k) - \tilde{I}_2(\boldsymbol{M}_k) = \left(\frac{\epsilon}{p^{(1)}_{r'_1}} - \frac{\epsilon}{p^{(1)}_{r_1}} \right) V(c) + \left(\frac{\epsilon}{p^{(1)}_{r_1}} - \frac{\epsilon}{p^{(1)}_{r'_1}} \right) V(c').$$

Note that the proportion of cluster and the magnitude of variance are independent. Let $p^{(1)}_{r_1} < p^{(1)}_{r'_1}$. The subtraction $\tilde{I}_2(\hat{\boldsymbol{M}}_k) - \tilde{I}_2(\boldsymbol{M}_k) < 0$ when $V(c) > V(c')$, and $\tilde{I}_2(\hat{\boldsymbol{M}}_k) - \tilde{I}_2(\boldsymbol{M}_k) > 0$ when $V(c) < V(c')$. This implies that the term I_2 may not achieve the maxima with true membership.