

**Week 11**  
Spring 2009

**Lecture 21. Estimation of Large Covariance Matrices: Lower bound (II)**

Observe

$\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_n$  i.i.d. from a  $p$ -variate Gaussian distribution,  $N(\mu, \Sigma_{p \times p})$ .

We assume that the covariance matrix  $\Sigma_{p \times p} = (\sigma_{ij})_{1 \leq i, j \leq p}$  is contained in the following parameter space,

$$\mathcal{F}(\alpha, \varepsilon, M) = \left\{ \Sigma : |\sigma_{ij}| \leq M |i - j|^{-(\alpha+1)} \text{ for all } i \neq j \text{ and } \lambda_{\min}(\Sigma) \leq 1/\varepsilon \right\} \quad (1)$$

**Theorem 1** Under the assumption (1), we have

$$\inf_{\Sigma} \sup_{\mathcal{F}} \mathbb{E} \left\| \tilde{\Sigma} - \Sigma \right\|^2 \geq c n^{-\frac{1}{\alpha+1}} + c \frac{\log p}{n}. \quad (2)$$

Last time we have shown

$$\inf_{\Sigma} \sup_{\mathcal{F}} \mathbb{E} \left\| \tilde{\Sigma} - \Sigma \right\|^2 \geq c \frac{\log p}{n}.$$

In this lecture we will show

$$\inf_{\Sigma} \sup_{\mathcal{F}} \mathbb{E} \left\| \tilde{\Sigma} - \Sigma \right\|^2 \geq c n^{-\frac{1}{\alpha+1}}$$

by the Assouad's lemma.

We shall now define a parameter space that is appropriate for the minimax lower bound argument. For given positive integers  $k$  and  $m$  with  $2k \leq p$  and  $1 \leq m \leq k$ , define the  $p \times p$  matrix  $B(m, k) = (b_{ij})_{p \times p}$  with

$$b_{ij} = I \{i = m \text{ and } m + 1 \leq j \leq 2k, \text{ or } j = m \text{ and } m + 1 \leq i \leq 2k\}.$$

Set  $k = n^{\frac{1}{\alpha+1}}$  and  $\alpha = k^{-(\alpha+1)}$ . We then define the collection of  $2^k$  covariance matrices as

$$\mathcal{H} = \left\{ \Sigma(\theta) : \Sigma(\theta) = I_p + \tau \alpha \sum_{m=1}^k \theta_m B(m, k), \quad \theta = (\theta_m) \in \{0, 1\}^k \right\} \quad (3)$$

where  $I_p$  is the  $p \times p$  identity matrix and  $\tau$  is a constant. It is easy to check that as long as  $0 < \tau < \min\{M, (1-\varepsilon)/2\}$  the collection  $\mathcal{H} \subset \mathcal{F}_\alpha(\varepsilon, M)$ . We will show

$$\inf_{\Sigma} \sup_{\mathcal{H}} \mathbb{E} \left\| \tilde{\Sigma} - \Sigma \right\|^2 \geq c n^{-\frac{1}{\alpha+1}} \quad (4)$$

**A Lower bound by the Assouad's Lemma**

We first prove equation (4). Let  $\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_n$  be i.i.d.  $N(0, \Sigma(\theta))$  with  $\Sigma(\theta) \in \mathcal{H}$ . Denote the joint distribution by  $P_\theta$ . We apply Assouad's Lemma to the parameter space  $\mathcal{H}$ ,

$$\max_{\theta \in \mathcal{H}} 2^2 E_\theta \left\| \bar{\Sigma} - \Sigma(\theta) \right\|^2 \geq \min_{H(\theta, \theta') \geq 1} \frac{\|\Sigma(\theta) - \Sigma(\theta')\|^2}{H(\theta, \theta')} \frac{k}{2} \min_{H(\theta, \theta') = 1} \|P_\theta \wedge P_{\theta'}\|$$

From Lemma 2 we have

$$\min_{H(\theta, \theta') \geq 1} \frac{\|\Sigma(\theta) - \Sigma(\theta')\|^2}{H(\theta, \theta')} \geq cka^2$$

and from Lemma 3,

$$\min_{H(\theta, \theta') = 1} \|P_\theta \wedge P_{\theta'}\| \geq c > 0$$

thus

$$\max_{\theta \in \mathcal{F}_{11}} 2^2 E_\theta \left\| \bar{\Sigma} - \Sigma(\theta) \right\|^2 \geq \frac{c^2}{2} k^2 a^2 \geq c_1 n^{-\frac{2}{k+1}}.$$

Now we give proofs of auxiliary lemmas.

**Lemma 2** For  $\Sigma(\theta)$  defined in (8) we have

$$\min_{H(\theta, \theta') \geq 1} \frac{\|\Sigma(\theta) - \Sigma(\theta')\|^2}{H(\theta, \theta')} \geq cka^2.$$

Proof of Lemma 2: We define  $v = (1_{\{k \leq i \leq 2k\}})$ . Let

$$[\Sigma(\theta) - \Sigma(\theta')] v = (w_i).$$

There are exactly  $H(\theta, \theta')$  number of  $w_i$  such that  $|w_i| = ka$  (just consider upper half of the matrix), which implies

$$\|[\Sigma(\theta) - \Sigma(\theta')] v\|_2^2 \geq H(\theta, \theta') \cdot (ka)^2$$

and so  $\|\Sigma(\theta) - \Sigma(\theta')\|^2 \geq H(\theta, \theta') \cdot (ka)^2 / k \geq cka^2$ .

**Lemma 3** Let  $P_\theta$  be the joint distribution of  $n$  i.i.d.  $\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_n$  with  $\mathbf{X}_1 \sim N(0, \Sigma(\theta))$  and  $\Sigma(\theta) \in \mathcal{F}_{11}$ . Then for some  $c_1 > 0$  we have

$$\min_{H(\theta, \theta') = 1} \|P_\theta \wedge P_{\theta'}\| \geq c_1.$$

Proof of Lemma 3: When  $H(\theta, \theta') = 1$ , we will show

$$\begin{aligned} \|P_{\theta'} - P_\theta\|_1^2 &\leq 2K(P_{\theta'} | P_\theta) = 2n \left[ \frac{1}{2} \text{tr}(\Sigma(\theta') \Sigma^{-1}(\theta)) - \frac{1}{2} \log \det(\Sigma(\theta') \Sigma^{-1}(\theta)) - \frac{p}{2} \right] \\ &\leq n \cdot cka^2 \end{aligned}$$

for some small  $c > 0$ , where  $K(\cdot|\cdot)$  is the Kullback–Leibler divergence and the first inequality follows from the well known Pinsker’s inequality (see, e.g., Csizsar (1967)). This immediately implies the  $L_1$  distance between two measures is bounded away from 1, and then the lemma follows. Write

$$\Sigma(\theta') = D_1 + \Sigma(\theta).$$

Then

$$\frac{1}{2} \text{tr}(\Sigma(\theta') \Sigma^{-1}(\theta)) - \frac{p}{2} = \frac{1}{2} \text{tr}(D_1 \Sigma^{-1}(\theta)).$$

Let  $\lambda_i$  be the eigenvalues of  $D_1 \Sigma^{-1}(\theta)$ . Since  $D_1 \Sigma^{-1}(\theta)$  is similar to the symmetric matrix  $\Sigma^{-1/2}(\theta) D_1 \Sigma^{-1/2}(\theta)$ , and

$$\left\| \Sigma^{-1/2}(\theta) D_1 \Sigma^{-1/2}(\theta) \right\| \leq \left\| \Sigma^{-1/2}(\theta) \right\| \|D_1\| \left\| \Sigma^{-1/2}(\theta) \right\| \leq c_1 \|D_1\| \leq c_1 \|D_1\|_1 \leq c_2 k \alpha,$$

then all eigenvalues  $\lambda_i$ ’s are real and in the interval  $[-c_2 k \alpha, c_2 k \alpha]$ , where  $k \alpha = k \cdot k^{-(\alpha+1)} = k^{-\alpha} \rightarrow 0$ . Note that the Taylor expansion yields

$$\log \det(\Sigma(\theta') \Sigma^{-1}(\theta)) = \log \det(I + D_1 \Sigma^{-1}(\theta)) = \text{tr}(D_1 \Sigma^{-1}(\theta)) - R_2$$

where

$$R_2 \leq c_3 \sum_{i=1}^p \lambda_i^2 \text{ for some } c_3 > 0.$$

Write  $\Sigma^{-1/2}(\theta) = UV^{1/2}U^T$ , where  $UU^T = I$  and  $V$  is a diagonal matrix. It follows from the fact that the Frobenius norm of a matrix remains the same after an orthogonal transformation that

$$\sum_{i=1}^p \lambda_i^2 = \left\| \Sigma^{-1/2}(\theta) D_1 \Sigma^{-1/2}(\theta) \right\|_F^2 \leq \|V\|^2 \cdot \|U^T D_1 U\|_F^2 = \|\Sigma^{-1}(\theta)\|_F^2 \cdot \|D_1\|_F^2 \leq c_4 k \alpha^2. \quad \blacksquare$$