

## Lecture: Apr 26

Lecturer: Xianyang Zhang

theorem

## 1 Theorem

Let  $Y \sim N_p(\mu, \sigma^2 \mathbf{I}_p)$  and recall from the previous lecture that the ideal risk is given by

$$R^I(\mu) = \sum_{i=1}^p \min(\mu_i^2, \sigma^2).$$

Let  $\hat{\mu}$  be hard-thresholding or soft-thresholding estimator, that is  $\hat{\mu} = \eta_S(Y, \lambda)$  or  $\hat{\mu} = \eta_H(Y, \lambda)$  with  $\lambda = \sigma\sqrt{2 \log p}$ . Then

$$\mathbb{E}\|\hat{\mu} - \mu\|^2 \leq (2 \log p + \delta) (\sigma^2 + R^I(\mu)),$$

where

$$\delta = \begin{cases} 1.0 & \text{for soft-thresholding,} \\ 1.2 & \text{for hard-thresholding.} \end{cases}$$

## 2 Proof

We shall give the proof of the theorem for soft-thresholding estimator and the case of hard-thresholding estimator can be derived in a similar fashion.

WLOG, we let  $\sigma = 1$ . The risk for each coordinate is

$$r_s(\lambda, \mu) = \mathbb{E}(\eta_S(Y, \lambda) - \mu)^2, \quad Y \sim N(\mu, 1).$$

**Claim 1**

$$r_s(\lambda, \mu) \leq \min(r_s(\lambda, 0) + \mu^2, 1 + \lambda^2) \leq r_s(\lambda, 0) + \min(\mu^2, 1 + \lambda^2).$$

**Proof of Claim 1:** The second inequality follows easily. Here we shall show the steps to derive the first inequality. Note

$$\begin{aligned} r_s(\lambda, \mu) &= \int_{\lambda}^{\infty} (y - \lambda - \mu)^2 \phi(y - \mu) dy + \int_{-\infty}^{-\lambda} (y + \lambda - \mu)^2 \phi(y - \mu) dy + \mu^2 \mathbb{P}(-\lambda - \mu \leq Z \leq \lambda - \mu) \\ &= \int_{\lambda - \mu}^{\infty} (u - \lambda)^2 \phi(u) du + \int_{-\infty}^{-\lambda - \mu} (u + \lambda)^2 \phi(u) du + \mu^2 \mathbb{P}(-\lambda - \mu \leq Z \leq \lambda - \mu) \end{aligned}$$

where  $u = y - \mu$  and  $Z \sim N(0, 1)$ . Thus we get

$$0 \leq \frac{\partial r_s(\lambda, \mu)}{\partial \mu} = 2\mu \mathbb{P}(-\lambda - \mu \leq Z \leq \lambda - \mu) \leq 2\mu$$

which implies that

$$r_s(\lambda, \mu) \leq \lim_{\mu \rightarrow \infty} r_s(\lambda, \mu) = 1 + \lambda^2.$$

Also, note that

$$r_s(\lambda, \mu) - r_s(\lambda, 0) = \int_0^\mu \frac{\partial r_s(\lambda, u)}{\partial u} du \leq \int_0^\mu 2u du = \mu^2$$

which indicates that  $r_s(\lambda, \mu) \leq r_s(\lambda, 0) + \mu^2$ .

**Claim 2:**

$$r_s(\lambda, 0) \leq \frac{2\phi(\lambda)}{\lambda}.$$

**Proof of Claim 2:**

$$\begin{aligned} r_s(\lambda, 0) &= 2 \int_\lambda^\infty (y - \lambda)^2 \phi(y) dy \\ &= 2\lambda^2 \mathbb{P}(Z > \lambda) + 2 \int_\lambda^\infty y^2 \phi(y) dy - 4\lambda \int_\lambda^\infty y \phi(y) dy. \end{aligned}$$

As  $\phi'(y) = -y\phi(y)$ , we have

$$\lambda \int_\lambda^\infty y \phi(y) dy = -\lambda \int_\lambda^\infty d\phi(y) = \lambda \phi(\lambda).$$

Moreover using integration by parts, we have

$$\begin{aligned} \int_\lambda^\infty y^2 \phi(y) dy &= - \int_\lambda^\infty y d\phi(y) \\ &= \lambda \phi(\lambda) + \int_\lambda^\infty \phi(y) dy \\ &= \lambda \phi(\lambda) + \mathbb{P}(Z > \lambda). \end{aligned}$$

Also,

$$\mathbb{P}(Z > \lambda) = \mathbb{E}[\mathbf{1}\{Z > \lambda\}] \leq \mathbb{E}\left[\frac{Z}{\lambda} \mathbf{1}\{Z > \lambda\}\right] = \frac{1}{\lambda} \int_\lambda^\infty y \phi(y) dy = \frac{\phi(\lambda)}{\lambda}.$$

Then,

$$r_s(\lambda, 0) = 2(1 + \lambda^2) \mathbb{P}(Z > \lambda) - 2\lambda \phi(\lambda) \leq 2(1 + \lambda^2) \frac{\phi(\lambda)}{\lambda} - 2\lambda \phi(\lambda) = \frac{2\phi(\lambda)}{\lambda}.$$

## 2.1 Back to main proof

Putting  $\lambda = \sqrt{2 \log p}$ , we have:

$$r_s(\lambda, 0) \leq 2 \frac{1}{\sqrt{2 \log p}} \frac{1}{\sqrt{2\pi}} \frac{1}{p} = \frac{1}{p \sqrt{\pi \log p}} \leq \frac{2 \log p + 1}{p}.$$

Now,

$$\begin{aligned} \mathbb{E}\|\hat{\mu} - \mu\|^2 &= \sum_{i=1}^p \mathbb{E}(\hat{\mu}_i - \mu_i)^2 \\ &\leq p r_s(\lambda, 0) + \sum_{i=1}^p \min(\mu_i^2, \lambda^2 + 1) \\ &\leq (2 \log p + 1) + \sum_{i=1}^p \min(\mu_i^2, 2 \log p + 1) \\ &\leq (2 \log p + 1) (1 + R^I(\mu)). \end{aligned}$$

### 3 Risk inflation

Foster and George (1994) proved that

$$\inf_{\hat{\mu}} \sup_{\mu} \frac{R(\mu, \hat{\mu})}{\sigma^2 + R^I(\mu)} \geq 2 \log p (1 + o(1))$$

where the infimum is over all hard-thresholding estimators:

$$\hat{\mu}_i^{HT} = \begin{cases} Y_i & \text{if } |Y_i| \geq \lambda, \\ 0 & \text{if } |Y_i| < \lambda. \end{cases}$$

Assuming  $\sigma = 1$ , then for  $k$ -sparse  $\mu$ , we have

$$R^I(\mu) = \sum_{i=1}^p \min(\mu_i^2, 1) \leq k \implies \frac{1}{1+k} \leq \frac{1}{1+R^I(\mu)}.$$

It is enough to show that  $\forall \lambda \geq 0$ ,

$$RI(\lambda) = \max_k \sup_{\|\mu\|_0=k} \frac{R(\mu, \hat{\mu})}{1+k} \geq 2 \log p (1 + o(1)).$$

To this end, we note that

$$\begin{aligned} r_H(\lambda, \mu) &= \mathbb{E} \left[ (Y - \mu)^2 \mathbf{1}\{|Y| \geq \lambda\} + \mu^2 \mathbf{1}\{|Y| < \lambda\} \right] \\ &= \mathbb{E} \left[ Z^2 \mathbf{1}\{|Z + \mu| \geq \lambda\} + \mu^2 \mathbf{1}\{|Z + \mu| < \lambda\} \right] \\ &= \mathbb{E} \left[ Z^2 \mathbf{1}\{|Z + \mu| \geq \lambda\} \right] + \mu^2 \mathbb{P}(|Z + \mu| < \lambda) \\ &\geq \mu^2 \mathbb{P}(\mu + Z \leq \lambda) \end{aligned}$$

where  $Z \sim N(0, 1)$  and  $Y \sim N(\mu, 1)$ . For  $k$ -sparse  $\mu$ , we let

$$f(k) = \sup_{\|\mu\|_0=k} R(\mu, \hat{\mu}) = (p-k) r_H(\lambda, 0) + k \sup_{\mu} r_H(\lambda, \mu).$$

Then we have

$$RI(\lambda) = \max_{0 \leq k \leq p} \frac{f(k)}{1+k} \geq \max \left( f(0), \frac{f(p)}{1+p} \right) = \max \left( p r_H(\lambda, 0), \frac{p}{1+p} \sup_{\mu} r_H(\lambda, \mu) \right).$$

Now,

$$r_H(\lambda, 0) = \mathbb{E} \left[ Z^2 \mathbf{1}\{|Z| > \lambda\} \right] = 2 \mathbb{E} \left[ Z^2 \mathbf{1}\{Z > \lambda\} \right] = 2 \int_{\lambda}^{\infty} y^2 \phi(y) dy \approx 2 \lambda \phi(\lambda),$$

where  $\lambda = \sqrt{2 \log p}$ . Recall from the above that

$$\sup_{\mu} r_H(\lambda, \mu) \geq \sup_{\mu} \mu^2 \mathbb{P}(\mu + Z \leq \lambda).$$

Then

$$\begin{aligned} \sup_{\mu} r_H(\lambda, \mu) &\geq \sup_{\mu} \mu^2 \mathbb{P}(\mu + Z \leq \lambda) \\ &= \sup_{\mu} \mu^2 \Phi(\lambda - \mu) \\ &\geq \sup_{0 \leq u \leq \lambda} (\lambda - u)^2 \Phi(u), \text{ where } u = \lambda - \mu \\ &= \sup_{0 \leq u \leq \lambda} \left[ \lambda^2 \Phi(u) + u^2 \Phi(u) - 2 \lambda u \Phi(u) \right] \\ &\geq \lambda^2 - 4 \lambda \sqrt{\log \lambda} + o(\lambda \sqrt{\log \lambda}), \end{aligned}$$

where we set  $u = \sqrt{2 \log \lambda^2}$  to get the last inequality. Finally, we get

$$RI(\lambda) \underset{\sim}{\geq} \max(2p\lambda\phi(\lambda), \lambda^2) \sim 2 \log p(1 + o(1)).$$