

## Math 6266. Fall 2017. Midterm 2.

**Exercise 1** (The James-Stein estimator). Let  $X \sim \mathcal{N}(\theta, \sigma^2 \mathbf{I}_p)$  for some  $\sigma^2 > 0$ ,  $\theta \in \mathbf{R}^p$ ; dimension  $p \geq 3$ ;  $\theta$  is an unknown true parameter. Denote the quadratic risk function as  $R(\delta, \theta) = \mathbf{E}_\theta(\|\delta - \theta\|^2)$ , where  $\delta = \delta(X)$  is some estimator of  $\theta$ , and  $\|\cdot\|$  is the  $\ell_2$ -norm in  $\mathbf{R}^p$ .

1. Calculate the quadratic risk for  $\delta = X$ .
2. Let  $\hat{R} \stackrel{\text{def}}{=} p\sigma^2 + \|h(X)\|^2 - 2\sigma^2 \text{trace}(Dh(X))$ , where  $h = (h_1, \dots, h_p)^\top : \mathbf{R}^p \mapsto \mathbf{R}^p$  is a differentiable function, s.t. all necessary moments exist.  $Dh(x)$  is a  $p \times p$  matrix of partial derivatives:  $\{Dh(x)\}_{i,j} = \frac{\partial}{\partial x_j} h_i(x)$ .

Show that  $\hat{R}$  is an unbiased risk estimator for  $\delta(X) = X - h(X)$ , i.e.

$$R(\theta, X - h(X)) = \mathbf{E}_\theta \hat{R}.$$

(Hint: use Stein's identity)

3. Consider

$$h(X) = \frac{(p-2)\sigma^2}{\|X\|^2} X$$

and the James-Stein estimator

$$\hat{\theta}_{JS} = X - h(X).$$

Show that  $R(\theta, \hat{\theta}_{JS}) < R(\theta, X)$  for all  $\theta \in \mathbf{R}^p$ .

4. Now consider an i.i.d. sample  $Y_1, \dots, Y_n$ , where  $Y_i \sim \mathcal{N}(\theta, \sigma^2 \mathbf{I}_p)$ . Denote  $\bar{Y} \stackrel{\text{def}}{=} n^{-1} \sum_{i=1}^n Y_i$ . Calculate the risk  $R(\theta, \bar{Y})$ .
5. Consider the estimator

$$\tilde{\theta}_{JS} = \bar{Y} - \frac{(p-2)\sigma^2/n}{\|\bar{Y}\|^2} \bar{Y}.$$

Show that  $R(\theta, \tilde{\theta}_{JS}) < R(\theta, \bar{Y})$  for all  $\theta \in \mathbf{R}^p$ .

(Hint: Use that  $\bar{Y} \sim \mathcal{N}(\theta, \sigma^2 n^{-1} \mathbf{I}_p)$ )

## References:

- Lecture note “The James-Stein Phenomenon” by Prof. Michael Jordan:  
[https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&cad=rja&uact=8&ved=0ahUKEwjv58a-80LXAhXGZCYKHaX3Bc8QFggmMAA&url=https%3A%2F%2Fpiazza.com%2Fclass\\_profile%2Fget\\_resource%2Fhzdbtb6jdr56q1%2Fi2kz4qj4x102b1&usg=AOvVaw3i8Zmw8Sq6oU](https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&cad=rja&uact=8&ved=0ahUKEwjv58a-80LXAhXGZCYKHaX3Bc8QFggmMAA&url=https%3A%2F%2Fpiazza.com%2Fclass_profile%2Fget_resource%2Fhzdbtb6jdr56q1%2Fi2kz4qj4x102b1&usg=AOvVaw3i8Zmw8Sq6oU)
- A “non-technical” introduction with a real data example by Prof. Richard J. Samworth:  
<https://pdfs.semanticscholar.org/7eeb/d55f569395544f2b5d367d6aee614901d2c1.pdf>

**Exercise 2.** Consider the linear regression model  $Y_i = X_i^\top \theta^* + \varepsilon_i$ ,  $i = 1, \dots, n$  the errors  $\varepsilon_i$  are i.i.d,  $\mathbf{E}\varepsilon_i = 0$ ,  $\text{Var} \varepsilon_i = \sigma^2 > 0$ . The unknown true parameter  $\theta^* \in \mathbf{R}^p$ . Assume that matrix  $XX^\top = \sum_{i=1}^n X_i X_i^\top$  is not invertible, i.e. some of its eigenvalues equal to zero.

Derive the spectral representation of the model  $Y = X^\top \theta^* + \varepsilon$  (this was done at a lecture), i.e. show that for some  $Z, \xi, \eta^* \in \mathbf{R}^p$  the model is equivalent to

$$Z = \Lambda \eta^* + \xi,$$

where  $\Lambda = \text{diag}\{\lambda_1, \dots, \lambda_p\}$  and  $\lambda_1 \geq \dots \geq \lambda_p \geq 0$  are eigenvalues of  $XX^\top$ .

Let  $A \stackrel{\text{def}}{=} \text{diag}\{\alpha_1, \dots, \alpha_p\}$  for some numbers  $\alpha_1, \dots, \alpha_p \in [0, 1]$ . Let  $\hat{\eta}_A = (\hat{\eta}_{A,1}, \dots, \hat{\eta}_{A,p})^\top$  be a shrinkage estimator of  $\eta^* = (\eta_1^*, \dots, \eta_p^*)^\top$ :

$$\hat{\eta}_{A,j} = \begin{cases} \alpha_j \lambda_j^{-1} z_j, & \text{if } \lambda_j \neq 0, \\ 0, & \text{otherwise.} \end{cases}$$

Find bias, variance and the quadratic risk of  $\hat{\eta}_A$ :  $R(\eta^*, \hat{\eta}_A) = \mathbf{E}(\|\hat{\eta}_A - \eta^*\|^2)$ .

Reference: Chapters 4.2.4, 4.7, 4.8 in the textbook <https://link.springer.com/book/10.1007/978-3-642-39909-1>

**Exercise 3.** Let  $X_1, \dots, X_n$  be real valued i.i.d. random variables. Assume  $\mathbf{E}(|X_i|^M) < \infty$  for some  $M \geq 2$ . Let  $X_1^*, \dots, X_n^*$  be a bootstrap sample based on the original data  $X_1, \dots, X_n$  and obtained by the Efron's bootstrap procedure, i.e.

$$\mathbf{P}(X_j^* = X_i \mid \{X_i\}_{i=1}^n) = 1/n \quad \forall j = 1, \dots, n.$$

Show that for all integer  $m \in [0, M]$

$$\mathbf{E}(X_j^{*m} \mid \{X_i\}_{i=1}^n) \xrightarrow{\mathbf{P}} \mathbf{E}(X_1^m) \text{ for } n \rightarrow \infty.$$

Show also that

$$\text{Var}(X_j^* \mid \{X_i\}_{i=1}^n) \xrightarrow{\mathbf{P}} \text{Var}(X_1) \text{ for } n \rightarrow \infty.$$

(Hint 1: use the Weak Law of Large Numbers.)

(Hint 2: the 1-st bootstrap moment of  $X_j^*$  equals to  $\mathbf{E}(X_j^* \mid \{X_i\}_{i=1}^n) = \sum_{i=1}^n X_i/n$ .)

References:

- A concise introductory text:  
<http://galton.uchicago.edu/~eichler/stat24600/Handouts/bootstrap.pdf>
- Lecture notes by Prof. Peter Hall:  
<http://anson.ucdavis.edu/~peterh/sta251/bootstrap-lectures-to-may-16.pdf>