

University of California, Los Angeles
Department of Statistics

Statistics 100B

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Homework 7

Answer the following questions:

- a. Suppose Y_1, Y_2, \dots, Y_n follow multivariate normal with mean $\mu \mathbf{1}$ and variance covariance matrix $\sigma^2 \mathbf{V}$, where \mathbf{V} is an $n \times n$ symmetric matrix of known constants. Show that the maximum likelihood estimates of μ and σ^2 are $\hat{\mu} = \frac{\mathbf{1}' \mathbf{V}^{-1} \mathbf{Y}}{\mathbf{1}' \mathbf{V}^{-1} \mathbf{1}}$ and $\hat{\sigma}^2 = \frac{(\mathbf{Y} - \hat{\mu} \mathbf{1})' \mathbf{V}^{-1} (\mathbf{Y} - \hat{\mu} \mathbf{1})}{n}$.
- b. Refer to question (a). Find $E(\hat{\mu})$ and $E(\hat{\sigma}^2)$.
- c. Refer to question (a). Find the Fisher information matrix $\mathbf{I}(\theta)$, where $\theta = (\mu, \sigma^2)'$. Is $\hat{\mu}$ an efficient estimator of μ ?
- d. Let Y_1, Y_2, \dots, Y_n independent random variables, and let $Y_i \sim N(i\theta, i\sigma)$, i.e. $E(Y_i) = i\theta$ and $\text{var}(Y_i) = i^2 \sigma^2$, for $i = 1, 2, \dots, n$. Find the maximum likelihood estimator of θ . Is this estimator efficient estimator of θ ?
- e. Suppose that the radius of a circle is measured with an error $\epsilon \sim N(0, \sigma)$. If n independent measurements are made find an unbiased estimator of the area of the circle.
- f. Let Y_1, \dots, Y_n be i.i.d. random variables from the Weibull distribution $f(y|\theta) = \left(\frac{2y}{\theta}\right) \exp\left(-\frac{y^2}{\theta}\right), y > 0$. Show that $\hat{\theta} = \frac{\sum_{i=1}^n Y_i^2}{n}$ is unbiased estimator of θ . Is $\hat{\theta}$ an efficient estimator of θ ?
- g. Let X_1, \dots, X_n be i.i.d. $N(\theta, \theta), \theta > 0$. For this model both \bar{X} and cS are unbiased estimators of θ , where $c = \frac{\sqrt{n-1}\Gamma(\frac{n-1}{2})}{\sqrt{2}\Gamma(\frac{n}{2})}$. Define the estimator $T = \alpha_1 \bar{X} + \alpha_2 (cS)$, where we do not assume that $\alpha_1 + \alpha_2 = 1$. Find the estimator that minimizes $E(T - \theta)^2$.

$$a. f(\mathbf{Y}) = \frac{1}{(2\pi)^{\frac{n}{2}}} |\Sigma|^{-\frac{1}{2}} \cdot e^{-\frac{1}{2}(\mathbf{Y} - \mu \mathbf{1})' \Sigma^{-1} (\mathbf{Y} - \mu \mathbf{1})}$$

$$\ln L = -\frac{n}{2} \ln 2\pi - \frac{1}{2} \ln |\sigma^2 \mathbf{V}| - \frac{1}{2} (\mathbf{Y} - \mu \mathbf{1})' (\sigma^2 \mathbf{V})^{-1} (\mathbf{Y} - \mu \mathbf{1})$$

$$= -\frac{n}{2} \ln 2\pi - \frac{1}{2} \ln(\sigma^2)^n - \frac{1}{2} \ln |\mathbf{V}| - \frac{1}{2} \cdot \frac{1}{\sigma^2} \cdot (\mathbf{Y}' - \mu \mathbf{1}') \mathbf{V}^{-1} (\mathbf{Y} - \mu \mathbf{1})$$

$$- \frac{1}{2} \cdot \frac{1}{\sigma^2} (\mathbf{Y}' \mathbf{V}^{-1} \mathbf{Y} - \mu \mathbf{1}' \mathbf{V}^{-1} \mathbf{Y} - \mu \mathbf{1}' \mathbf{V}^{-1} \mathbf{Y} + \mu^2 \mathbf{1}' \mathbf{V}^{-1} \mathbf{1})$$

$$\frac{\partial \ln L}{\partial \mu} = -\frac{1}{2\sigma^2} \left[\underbrace{-\mathbf{Y}' \mathbf{V}^{-1} \mathbf{1}}_{1 \times n \text{ } n \times n} - \underbrace{\mathbf{1}' \mathbf{V}^{-1} \mathbf{Y}}_{n \times n \text{ } n \times 1} + 2\mu \mathbf{1}' \mathbf{V}^{-1} \mathbf{1} \right] = 0$$

$$\therefore \hat{\mu} = \frac{\mathbf{1}' \mathbf{V}^{-1} \mathbf{Y}}{\mathbf{1}' \mathbf{V}^{-1} \mathbf{1}}$$

$$\frac{\partial \ln L}{\partial \sigma^2} = -\frac{n}{2} \cdot \frac{1}{\sigma^2} - \frac{1}{2} \cdot \frac{-2}{\sigma^4} (Y - \mu \mathbf{1})' V^{-1} (Y - \mu \mathbf{1}) = 0$$

$$\therefore \sigma^2 = \frac{(Y - \mu \mathbf{1})' V^{-1} (Y - \mu \mathbf{1})}{n}$$

$$\therefore \hat{\sigma}^2 = \frac{(Y - \hat{\mu} \mathbf{1})' V^{-1} (Y - \hat{\mu} \mathbf{1})}{n}$$

$$b. E(\hat{\mu}) = E\left(\frac{\mathbf{1}' V^{-1} Y}{\mathbf{1}' V^{-1} \mathbf{1}}\right) = \frac{1}{\mathbf{1}' V^{-1} \mathbf{1}} \cdot \mathbf{1}' V^{-1} E(Y) = \frac{1}{\mathbf{1}' V^{-1} \mathbf{1}} \cdot \mathbf{1}' V^{-1} \cdot \mu \mathbf{1} = \mu$$

$$E(\hat{\mu}^2) = E\left(\frac{(\mathbf{1}' V^{-1} Y)^2}{(\mathbf{1}' V^{-1} \mathbf{1})^2}\right)$$

$$E(\hat{\sigma}^2) = \frac{1}{n} E\left(Y' V^{-1} Y - \hat{\mu} Y' V^{-1} \mathbf{1} - \hat{\mu} \mathbf{1}' V^{-1} Y + \hat{\mu}^2 \mathbf{1}' V^{-1} \mathbf{1}\right)$$

$$E(\hat{\sigma}^2) = \frac{1}{n} E\left((Y - \hat{\mu} \mathbf{1})' V^{-1} (Y - \hat{\mu} \mathbf{1})\right)$$

$$= \frac{1}{n} E\left[\text{tr}\left((Y - \hat{\mu} \mathbf{1})' V^{-1} (Y - \hat{\mu} \mathbf{1})\right)\right]$$

$$= \frac{1}{n} \text{tr} E\left(V^{-1} (Y - \hat{\mu} \mathbf{1}) (Y - \hat{\mu} \mathbf{1})'\right)$$

$$= \frac{1}{n} \text{tr} V^{-1} E\left((Y - \hat{\mu} \mathbf{1}) (Y - \hat{\mu} \mathbf{1})'\right)$$

$$= \frac{1}{n} \text{tr} V^{-1} \left[\underbrace{\text{var}(Y - \hat{\mu} \mathbf{1})}_{\mathbf{0}} + \underbrace{E(Y - \hat{\mu} \mathbf{1}) E(Y - \hat{\mu} \mathbf{1})'}_{\mathbf{0}} \right]$$

$$= \frac{1}{n} \text{tr} V^{-1} \text{var}(Y - \hat{\mu} \mathbf{1})$$

$$\text{var}(Y - \mu \mathbf{1}) = \text{var}\left(Y - \frac{\mathbf{1} \mathbf{1}' V^{-1} Y}{\mathbf{1}' V^{-1} \mathbf{1}}\right)$$

$$= \text{var}\left(\left(I - \frac{\mathbf{1} \mathbf{1}' V^{-1}}{\mathbf{1}' V^{-1} \mathbf{1}}\right) Y\right)$$

$$= \left(I - \frac{\mathbf{1} \mathbf{1}' V^{-1}}{\mathbf{1}' V^{-1} \mathbf{1}}\right) \sigma^2 \left(I - \frac{\mathbf{1} \mathbf{1}' V^{-1}}{\mathbf{1}' V^{-1} \mathbf{1}}\right)'$$

$$= \sigma^2 \left(V - \frac{11'}{1'V^{-1}1} \right)$$

$$\therefore E(\hat{\sigma}^2) = \frac{1}{n} \text{tr } V^{-1} \left(\sigma^2 \left(V - \frac{11'}{1'V^{-1}1} \right) \right)$$

$$= \frac{1}{n} \sigma^2 \left[\text{tr } V^{-1}V - \text{tr } \frac{V^{-1}11'}{1'V^{-1}1} \right]$$

$$= \frac{1}{n} \sigma^2 \left(n - \text{tr } \frac{1'V^{-1}1}{1'V^{-1}1} \right)$$

$$= \frac{n-1}{n} \sigma^2$$

$$C. I(\theta) = \begin{pmatrix} \frac{\partial^2 \ln L}{\partial \mu^2} & \frac{\partial^2 \ln L}{\partial \mu \partial \sigma^2} \\ \frac{\partial^2 \ln L}{\partial \sigma^2 \partial \mu} & \frac{\partial^2 \ln L}{\partial \sigma^2 \partial \sigma^2} \end{pmatrix}$$

$$\frac{\partial^2 \ln L}{\partial \mu^2} = - \frac{1' V^{-1} 1}{\sigma^2}$$

$$\frac{\partial^2 \ln L}{\partial \mu \partial \sigma^2} = \frac{1}{2\sigma^4} [2\mu 1' V^{-1} 1 - 2 1' V^{-1} Y] = \frac{1}{\sigma^4} [1' V^{-1} 1 \mu - 1' V^{-1} Y]$$

$$\frac{\partial \ln L}{\partial \sigma^2} = -\frac{n}{2} \cdot \frac{1}{\sigma^2} + \frac{1}{2} \cdot \frac{1}{\sigma^4} [(Y - \mu 1)' V^{-1} (Y - \mu 1)]$$

$$\frac{\partial^2 \ln L}{\partial \sigma^2 \partial \sigma^2} = \frac{n}{2} \cdot \frac{1}{\sigma^4} - \frac{1}{\sigma^6} (Y - \mu 1)' V^{-1} (Y - \mu 1)$$

$$I^{-1}(\mu) = \begin{pmatrix} \frac{\sigma^2}{1' V^{-1} 1} & 0 \\ 0 & \frac{2\sigma^4}{n} \end{pmatrix}$$

$$- \frac{1' V^{-1} 1}{\sigma^2} \neq 0 \text{ when } n \rightarrow \infty \quad \therefore \hat{\mu} \text{ is not efficient}$$

$$E(\hat{\mu}) = \mu$$

$$\text{var}(\hat{\mu}) = \text{var}\left(\frac{1' V^{-1} Y}{1' V^{-1} 1}\right) = \sigma^2 \frac{1' V^{-1} V V^{-1} 1}{(1' V^{-1} 1)^2} = \frac{\sigma^2}{1' V^{-1} 1}$$

$$d. \quad f(y_i) = \frac{1}{\sqrt{2\pi} i \sigma} \cdot e^{-\frac{(y_i - i\theta)^2}{2(i\sigma)^2}} \quad (2\pi)^{-\frac{1}{2}}$$

$$L = \prod_{i=1}^n f(y_i) = (2\pi)^{-\frac{n}{2}} \cdot \prod_{i=1}^n i \cdot \sigma^{-n} \cdot e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n \left(\frac{y_i - i\theta}{i}\right)^2}$$

$$\ln L = -\frac{n}{2} \ln 2\pi + \sum_{i=1}^n \ln i - n \ln \sigma - \frac{1}{2\sigma^2} \sum_{i=1}^n \left(\theta - \frac{y_i}{i}\right)^2$$

$$\frac{\partial \ln L}{\partial \theta} = -\frac{1}{2\sigma^2} \sum_{i=1}^n 2\left(\theta - \frac{y_i}{i}\right) = 0$$

$$\therefore \hat{\theta} = \frac{1}{n} \sum_{i=1}^n \frac{y_i}{i}$$

$$E(\hat{\theta}) = \frac{1}{n} \sum_{i=1}^n E\left(\frac{y_i}{i}\right) = \frac{1}{n} \cdot \sum_{i=1}^n \frac{E(y_i)}{i} = \frac{1}{n} \cdot n \theta = \theta.$$

$$\text{var}(\hat{\theta}) = \frac{1}{n^2} \sum_{i=1}^n \text{var}\left(\frac{y_i}{i}\right) = \frac{1}{n^2} \sum_{i=1}^n \frac{\text{var}(y_i)}{i^2} = \frac{1}{n^2} \sum_{i=1}^n \frac{i^2 \sigma^2}{i^2} = \frac{\sigma^2}{n} \rightarrow 0$$

when $n \rightarrow \infty$

$\therefore \hat{\theta}$ is efficient

Q. Suppose the radius equals R .

$$R_i = R + \epsilon_i$$

$$E(\bar{R}) = \frac{1}{n} \sum_{i=1}^n E(R + \epsilon_i) = R.$$

$$E(\bar{R}^2) = \text{var}(\bar{R}) + E^2(\bar{R}) = \frac{1}{n^2} \sum_{i=1}^n \text{var}(R + \epsilon_i) + R^2 = \frac{\sigma^2}{n} + R^2$$

$$\hat{R} = \bar{R}^2 - \frac{\sigma^2}{n}$$

$$\therefore \hat{S} = \pi \left(\bar{R}^2 - \frac{\sigma^2}{n} \right)$$

$$f. \quad f(y|\theta) = \frac{2y}{\theta} e^{-\frac{y^2}{\theta}}$$

$$X = Y^2$$

$$X \sim \exp\left(\frac{1}{\theta}\right)$$

$$\hat{\theta} = \frac{1}{n} \sum_{i=1}^n Y_i^2$$

$$E(Y_i^2) = \int_0^{+\infty} y^2 \cdot \frac{2y}{\theta} \cdot e^{-\frac{y^2}{\theta}} dy$$

$$= \theta \int_0^{+\infty} \frac{y^2}{\theta} \cdot e^{-\frac{y^2}{\theta}} d\left(\frac{y^2}{\theta}\right)$$

$$t = \frac{y^2}{\theta} = \theta \int_0^{+\infty} t e^{-t} dt$$

$$= \theta \cdot \left[-t e^{-t} \Big|_0^{+\infty} - \int_0^{+\infty} -e^{-t} dt \right]$$

$$= \theta \left[- \int_0^{+\infty} e^{-t} d(-t) \right]$$

$$= \theta$$

$$\therefore E(\hat{\theta}) = \frac{1}{n} \sum_{i=1}^n E(Y_i^2) = \frac{1}{n} \cdot n\theta = \theta$$

$$E(Y_i^4) = \int_0^{+\infty} y^4 \cdot \frac{2y}{\theta} e^{-\frac{y^2}{\theta}} dy \quad \text{or} \quad \frac{y^4}{\theta^2} e^{-\frac{y^2}{\theta}} d\frac{y^2}{\theta}$$

$$= \theta^2 \int_0^{+\infty} \left(\frac{y^2}{\theta}\right)^2 e^{-\frac{y^2}{\theta}} d\left(\frac{y^2}{\theta}\right)$$

$$t = \frac{y^2}{\theta} = \theta^2 \int_0^{+\infty} t^2 e^{-t} dt$$

$$= \theta^2 \left[-t^2 e^{-t} \Big|_0^{+\infty} - \int_0^{+\infty} 2t (-e^{-t}) dt \right]$$

$$= \theta^2 \cdot \left[2 \int_0^{+\infty} t e^{-t} dt \right]$$

$$= 2\theta^2$$

$$\therefore \text{var}(\hat{\theta}) = \frac{1}{n^2} \sum_{i=1}^n \text{var}(Y_i^2)$$

$$= \frac{1}{n^2} \sum_{i=1}^n [E(Y_i^2) - E^2(Y_i^2)]$$

$$= \frac{1}{n^2} \sum_{i=1}^n [2\theta^2 - \theta^2]$$

$$= \frac{\theta^2}{n} \rightarrow 0 \text{ when } n \rightarrow \infty$$

$\therefore \hat{\theta}$ is efficient

$$g. E(T-\theta)^2 = \text{var}(T) + B^2$$

$$\text{var}(T) = \text{var}(\alpha_1 \bar{X} + \alpha_2 cS)$$

$$= \alpha_1^2 \text{var}(\bar{X}) + \alpha_2^2 \text{var}(cS)$$

$$= \alpha_1^2 \frac{\theta^2}{n} + \alpha_2^2 (c^2-1)\theta^2$$

$$B = E(T) - \theta = (\alpha_1 + \alpha_2 - 1)\theta$$

$$\begin{aligned} \text{var}(cS) &= E(c^2 Y^2) - E^2(cS) \\ &= (c^2-1)\theta^2 \end{aligned}$$

$$\therefore E(T-\theta)^2 = \frac{\alpha_1^2}{n} \theta^2 + \alpha_2^2 (c^2-1)\theta^2 + (\alpha_1 + \alpha_2 - 1)^2 \theta^2$$

$$= \left[\frac{\alpha_1^2}{n} + (c^2-1)\alpha_2^2 + (\alpha_1 + \alpha_2 - 1)^2 \right] \theta^2$$

$$\begin{cases} \frac{\partial f}{\partial \alpha_1} = \frac{2\alpha_1}{n} + 2(\alpha_1 + \alpha_2 - 1) = 0 \\ \frac{\partial f}{\partial \alpha_2} = 2(c^2-1)\alpha_2 + 2(\alpha_1 + \alpha_2 - 1) = 0 \end{cases} \Rightarrow \begin{cases} \alpha_1 = \frac{n(c^2-1)}{(n+1)(c^2-1)+1} \\ \alpha_2 = \frac{1}{(n+1)(c^2-1)+1} \end{cases}$$

$$A = \frac{\partial^2 f}{\partial \alpha_1^2} = \frac{2}{n} + 2, \quad B = \frac{\partial^2 f}{\partial \alpha_1 \partial \alpha_2} = 2, \quad C = \frac{\partial^2 f}{\partial \alpha_2^2} = 2(c^2-1) + 2 = 2c^2$$

$$A > 0, \quad B^2 - AC = 4 - \left(\frac{2}{n} + 2\right)(2c^2) = 4 - 4\left(\frac{1}{n} + 1\right)c^2$$

$$4 \left[1 - \left(\frac{1}{n} + 1 \right) \cdot C^2 \right]$$

$$1 - \frac{n+1}{n} \cdot \frac{n-1}{2} \cdot \frac{\Gamma^2\left(\frac{n-1}{2}\right)}{\Gamma^2\left(\frac{n}{2}\right)}$$