

UNIVERSITY OF MASSACHUSETTS
Department of Mathematics and Statistics
Basic Exam - Statistics
Monday, August 31, 2015

Work all problems. 60 points are needed to pass at the Masters Level and 75 to pass at the Ph.D. level.

1. Let X_1, \dots, X_n be a random sample from a Bernoulli distribution with parameter θ .
 - (a) Find the maximum likelihood estimator and the moment estimator of θ .
 - (b) Compare the mean squared errors (MSEs) of the above two estimators.
 - (c) Find the Fisher information for θ and the Cramer-Rao lower bound for estimating θ .
 - (d) Describe how to construct the $100(1 - \alpha)\%$ likelihood-based interval for θ .

For the following parts (e), (f), (g), consider the flat prior distribution for θ , $f(\theta) = 1$.

- (e) Find the posterior distribution of θ . Note that a random variable Y with a Beta distribution with parameters α and β , denoted by $Y \sim \text{Beta}(\alpha, \beta)$, has the mean $\frac{\alpha}{\alpha + \beta}$ and the mode $\frac{\alpha - 1}{\alpha + \beta - 2}$, and the pdf as follows:

$$f(y) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)}(1 - y)^{\beta - 1}y^{\alpha - 1} \quad y \in [0, 1].$$

- (f) Find the posterior mode of θ .
 - (g) Describe how to construct the $100(1 - \alpha)\%$ Highest Posterior Density (HPD) interval for θ .
2. Assume that the n pairs of observations, $\left[\begin{pmatrix} X_1 \\ Y_1 \end{pmatrix}, \begin{pmatrix} X_2 \\ Y_2 \end{pmatrix}, \dots, \begin{pmatrix} X_n \\ Y_n \end{pmatrix} \right]$, are independently sampled from a bivariate normal distribution with mean vector $(\mu_X, \mu_Y)'$ and covariance matrix $\begin{pmatrix} \sigma_X^2 & \rho\sigma_X\sigma_Y \\ \rho\sigma_X\sigma_Y & \sigma_Y^2 \end{pmatrix}$ where $-\infty < \mu_X = E(X_i), \mu_Y = E(Y_i) < \infty$, $0 < \sigma_X^2 = \text{Var}(X_i), \sigma_Y^2 = \text{Var}(Y_i) < \infty$ and $-1 < \rho = \text{Corr}(X_i, Y_i) < 1$ is the correlation between X_i and Y_i . The maximum likelihood estimator (MLE) of ρ is the sample coefficient of correlation,

$$\hat{\rho} = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2 \sum_{i=1}^n (Y_i - \bar{Y})^2}},$$

where $\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$, $\bar{Y} = \frac{1}{n} \sum_{i=1}^n Y_i$, and $\hat{\rho}$ is a consistent estimator of ρ .

- (a) The asymptotic distribution of $\hat{\rho}$ is $\sqrt{n}(\hat{\rho} - \rho) \xrightarrow{D} N(0, (1 - \rho^2)^2)$. Derive the approximate $100(1 - \alpha)\%$ confidence interval of ρ .

Consider the following transformation $g(\rho) = \frac{1}{2} \log \frac{1+\rho}{1-\rho}$ for the next three questions, (b), (c) and (d).

- (b) What is the MLE of $g(\rho)$?
 (c) Derive the asymptotic distribution of the MLE of $g(\rho)$.
 (d) Construct the approximate $100(1 - \alpha)\%$ confidence interval of ρ using the transformation $g(\rho)$ and its asymptotic distribution derived in (c).

- (e) The bivariate normal pdf is given by

$$f(x, y | \mu_X, \mu_Y, \sigma_X^2, \sigma_Y^2, \rho) = \{2\pi\sigma_X\sigma_Y\sqrt{(1 - \rho^2)}\}^{-1} \exp \left\{ -\frac{1}{2(1 - \rho^2)} \left[\frac{(x - \mu_X)^2}{\sigma_X^2} + \frac{(y - \mu_Y)^2}{\sigma_Y^2} - \frac{2\rho(x - \mu_X)(y - \mu_Y)}{\sigma_X\sigma_Y} \right] \right\}$$

Write out the joint likelihood $L(\mu_X, \mu_Y, \sigma_X^2, \sigma_Y^2, \rho)$ of the observations $\left[\begin{pmatrix} X_1 \\ Y_1 \end{pmatrix}, \dots, \begin{pmatrix} X_n \\ Y_n \end{pmatrix} \right]$.

- (f) It is known that the maximum likelihood estimators (MLEs) of the parameters $\mu_X, \mu_Y, \sigma_X^2, \sigma_Y^2$, and ρ are respectively $\hat{\mu}_X = \bar{X}, \hat{\mu}_Y = \bar{Y}, \hat{\sigma}_X^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2, \hat{\sigma}_Y^2 = \frac{1}{n} \sum_{i=1}^n (Y_i - \bar{Y})^2$, and $\hat{\rho}$. Plug in these MLEs to the joint likelihood and show that the maximized likelihood is

$$\begin{aligned} \max_{\mu_X, \mu_Y, \sigma_X^2, \sigma_Y^2, \rho} L(\mu_X, \mu_Y, \sigma_X^2, \sigma_Y^2, \rho) &= L(\hat{\mu}_X, \hat{\mu}_Y, \hat{\sigma}_X^2, \hat{\sigma}_Y^2, \hat{\rho}) \\ &= \{2\pi\hat{\sigma}_X\hat{\sigma}_Y\sqrt{(1 - \hat{\rho}^2)}\}^{-n} \exp\{-n\}. \end{aligned}$$

- (g) For the hypothesis

$$H_0 : \rho = 0 \text{ vs } H_1 : \rho \neq 0,$$

Show that the likelihood ratio test is equivalent to

$$\text{Reject } H_0 \text{ if and only if } (1 - \hat{\rho}^2)^{n/2} < k$$

for some constant k .

- (h) Let $T = \frac{\hat{\rho}\sqrt{n-2}}{\sqrt{1-\hat{\rho}^2}}$. It is known that the above likelihood ratio test is equivalent to

$$\text{Reject } H_0 \text{ if and only if } |T| > c$$

for some constant c . It is also known that T has the Student's t distribution with $n - 2$ degrees of freedom when $\rho = 0$. Find the value c to make the likelihood ratio test a level α test.

3. Suppose we conduct an experiment by giving rats one of five possible doses of a drug, denoted by $Y_1 < Y_2 < \dots < Y_5$. For each dose level Y_i , n rats are used and the number of dead rats, denoted by X_i , is observed. Here we have five independent binomial random variables, that is X_i has a binomial distribution with the probability of death, p_i ($X_i \sim \text{Binom}(n, p_i)$) where $i = 1, \dots, 5$ and $p_1 \leq p_2 \leq \dots \leq p_5$. The main interest in this experiment is to estimate the dose at which the rats have a 50 percent chance of dying: $\theta = \min\{i : p_i \geq 0.5\}$, which is a function of p_1, \dots, p_5 . We decide to take a Bayesian approach by using a flat prior distribution truncated over the parameter space, $H = \{(p_1, \dots, p_5) : p_1 \leq p_2 \leq \dots \leq p_5\}$.

- (a) Write the joint likelihood $L(p_1, \dots, p_5)$.
- (b) Describe how to estimate the posterior mean of θ ,

$$E(\theta \mid X_1, \dots, X_5) = \int \cdots \int_H \theta f(p_1, \dots, p_5 \mid X_1, \dots, X_5) dp_1 \cdots dp_5.$$