

Southern University of Science and Technology
Department of Mathematics

MA204: Mathematical Statistics

Tutorial 3: Examples/Solutions

A. Order Statistics

A.1 Definition

Let X_1, \dots, X_n be a random sample from a population with cdf $F(\cdot)$ and pdf $f(\cdot)$. Then, $X_{(1)} \leq \dots \leq X_{(n)}$ are called the *order statistics*.

How to understand $X_{(1)} = \min(X_1, \dots, X_n)$?

> x <- rnorm(4, mean=2, sd=0.2)	min(x)
Sample 1: 1.792966 1.935051 2.205505 1.717259	1.717259
Sample 2: 1.736903 2.092398 1.955097 2.292306	1.736903
Sample 3: 3.100611 2.144726 1.855688 1.862706	1.855688
Sample 4: 2.087154 1.733278 2.185363 1.823968	1.733278
Sample 5: 1.821756 1.861677 1.785434 1.997736	1.785434
Sample 6: 2.209436 1.836078 2.413644 1.998032	1.836078
Sample 7: 1.862467 1.938282 2.011536 2.223131	1.862467
Sample 8: 1.927599 2.012464 2.003386 1.899905	1.899905

A.2 Single order statistic

Let $G_r(x)$ and $g_r(x)$ be the cdf and pdf of the r -th order statistic $X_{(r)}$, respectively. Then

$$\begin{aligned} G_r(x) &= \sum_{i=r}^n \binom{n}{i} F^i(x) [1 - F(x)]^{n-i} \\ &= \frac{1}{B(r, n-r+1)} \int_0^{F(x)} t^{r-1} (1-t)^{n-r} dt, \\ g_r(x) &= \frac{n!}{(r-1)!(n-r)!} f(x) F^{r-1}(x) [1 - F(x)]^{n-r}. \end{aligned}$$

A.3 Multiple order statistics

Let $g_{r_1, \dots, r_k}(x_1, \dots, x_k)$ be the joint pdf of $X_{(r_1)}, \dots, X_{(r_k)}$ ($1 \leq r_1 \leq \dots \leq r_k \leq n$; $1 \leq k \leq n$),

$$g_{r_1, \dots, r_k}(x_1, \dots, x_k) = n! \left[\prod_{i=1}^k f(x_i) \right] \cdot \prod_{i=0}^k \left\{ \frac{[F(x_{i+1}) - F(x_i)]^{r_{i+1} - r_i - 1}}{(r_{i+1} - r_i - 1)!} \right\},$$

$$g_{1, \dots, r}(x_1, \dots, x_r) = \frac{n!}{(n-r)!} f(x_1) \cdots f(x_r) [1 - F(x_r)]^{n-r},$$

$$g_{r,s}(x, y) = \frac{n!}{(r-1)!(s-r-1)!(n-s)!} f(x)f(y) \times F^{r-1}(x)[F(y) - F(x)]^{s-r-1}[1 - F(y)]^{n-s}.$$

Example T3.1: Let X_1, \dots, X_n be independent exponential r.v.'s and $X_i \sim \text{Exponential}(\lambda_i)$.

Show that

- (i) $Y = \min(X_1, \dots, X_n)$ is also an exponential r.v. with parameter $\lambda_1 + \dots + \lambda_n$.
- (ii) For a fixed i , $\Pr(Y = X_i) = \Pr(X_i \leq X_j, \forall j = 1, \dots, n; j \neq i) = \frac{\lambda_i}{\lambda_1 + \dots + \lambda_n}$.

Solution: (i) Although X_1, \dots, X_n are independent, they have different distributions, the formula $G_1(\cdot)$ on page 51 of Lecture Notes cannot be applied. Since

$$F_{X_i}(x) = (1 - e^{-\lambda_i x}) \cdot I_{(0, \infty)}(x),$$

we have

$$\begin{aligned} \Pr(Y \leq y) &= 1 - \Pr(Y > y) \\ &= 1 - \Pr(\text{all } X_i > y) \\ &= 1 - \prod_{i=1}^n \Pr(X_i > y) \quad (\text{since all } X_i \text{ are independent}) \\ &= 1 - \prod_{i=1}^n [1 - \Pr(X_i \leq y)] \\ &= 1 - \prod_{i=1}^n [1 - F_{X_i}(y)] \\ &= 1 - e^{-(\sum_{i=1}^n \lambda_i)y}. \end{aligned}$$

Thus, $Y \sim \text{Exponential}(\lambda_1 + \dots + \lambda_n)$.

(ii) Let $Y_i = \min(X_1, \dots, X_{i-1}, X_{i+1}, \dots, X_n)$, $\lambda_{-i} = \sum_{j=1, j \neq i}^n \lambda_j$, and $Z_i = X_i - Y_i$, we have

$$\Pr(Y = X_i) = \Pr(X_i \leq X_j, \forall j \neq i) = \Pr(X_i \leq Y_i) = \Pr(Z_i \leq 0),$$

and

$$\begin{aligned} F_{Z_i}(z) &= \Pr(X_i - Y_i \leq z) \\ &= \int_0^\infty \int_{x-z}^\infty f_{X_i, Y_i}(x, y) dy dx \quad (x - y \leq z \Rightarrow x - z \leq y) \\ &= \int_0^\infty \int_{x-z}^\infty f_{X_i}(x) f_{Y_i}(y) dy dx \quad (\text{since } X_i \text{ and } Y_i \text{ are independent}) \\ &= - \int_0^\infty \int_z^{-\infty} f_{X_i}(x) f_{Y_i}(x - u) du dx \quad (\text{let } y = x - u) \\ &= \int_{-\infty}^z \int_0^\infty f_{X_i}(x) f_{Y_i}(x - u) dx du \\ &= \int_{-\infty}^z \int_0^\infty \lambda_i e^{-\lambda_i x} \lambda_{-i} e^{-\lambda_{-i}(x-u)} dx du \\ &= \int_{-\infty}^z \frac{\lambda_i \lambda_{-i}}{\lambda_1 + \dots + \lambda_n} e^{\lambda_{-i} u} du \\ &= \left[\frac{\lambda_i}{\lambda_1 + \dots + \lambda_n} e^{\lambda_{-i} u} \right] \Big|_{-\infty}^z \\ &= \frac{\lambda_i}{\lambda_1 + \dots + \lambda_n} e^{\lambda_{-i} z}. \end{aligned}$$

Therefore, $\Pr(Y = X_i) = \Pr(Z_i \leq 0) = F_{Z_i}(0) = \frac{\lambda_i}{\lambda_1 + \dots + \lambda_n}$. ||

B. Convergence in Distribution

B.1 [Definition](#)

Let the distribution function $F_n(x)$ of the r.v. X_n depends upon n ($n = 1, 2, \dots$). If $F(x)$ is a distribution function of a r.v. X and

$$\lim_{n \rightarrow \infty} F_n(x) = F(x), \quad \forall x \text{ s.t. } F(x) \text{ is continuous,}$$

then the sequence of r.v.'s X_1, X_2, \dots converge in distribution to X and denote as $X_n \xrightarrow{L} X$.

B.2 [Theorem](#)

Let X_n , $n = 1, 2, \dots$ have a moment generating function $M(t; n)$, $t \in (-h, h)$. If there exists a moment generating function $M(t)$ with respect to the distribution function $F(x)$ such that

$$M(t) = \lim_{n \rightarrow \infty} M(t; n), \quad \forall t \in (-h, h),$$

then $X_n \xrightarrow{L} X$.

Example T3.2: Let the sequence of r.v. $X_n \sim N(0, \frac{1}{n})$. Show that $X_n \xrightarrow{L} X$, where the cdf of X is $F(x) = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{if } x < 0 \\ \frac{1}{2}, & \text{if } x = 0 \end{cases}$.

Solution: Let $\phi(s) = \exp(-s^2/2)/\sqrt{2\pi}$ denote the pdf of $N(0, 1)$, then the cdf of X_n is

$$F_n(x) = \int_{-\infty}^x \frac{1}{\sqrt{2\pi/n}} e^{-\frac{t^2}{2/n}} dt = \int_{-\infty}^{\sqrt{n}x} \phi(s) ds \quad (\text{let } s = \sqrt{n}t).$$

so that $\lim_{n \rightarrow \infty} F_n(x) = \lim_{n \rightarrow \infty} \int_{-\infty}^{\sqrt{n}x} \phi(s) ds$

$$\begin{aligned} &= \int_{-\infty}^{\lim_{n \rightarrow \infty} \sqrt{n}x} \phi(s) ds \\ &= \begin{cases} \int_{-\infty}^{\infty} \phi(s) ds = 1, & \text{if } x > 0, \\ \int_{-\infty}^{-\infty} \phi(s) ds = 0, & \text{if } x < 0, \\ \int_{-\infty}^0 \phi(s) ds = \frac{1}{2}, & \text{if } x = 0 \end{cases} \\ &= F(x). \end{aligned}$$

Therefore, $X_n \xrightarrow{L} X$. ||

C. Central Limit Theorem (CLT)

If X_1, \dots, X_n be a sequence of i.i.d. r.v.'s with the mean μ and the variance σ^2 , then the r.v. $\sqrt{n}(\bar{X}_n - \mu)/\sigma$ has a standard normal limiting distribution, where $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$.

$$\text{i.e., } \sqrt{n}(\bar{X}_n - \mu)/\sigma \xrightarrow{L} N(0, 1).$$

Example T3.3: Let X follow a negative binomial distribution, denoted by $X \sim \text{NBinomial}(20, 0.7)$. (i) Exactly calculate the value of $\Pr(X = 12)$. (ii) Approximately calculate $\Pr(X = 12)$ by the Central Limit Theorem.

Solution: (i) The pmf of $X \sim \text{NBinomial}(r, p)$ is

$$\Pr(X = x) = \binom{x+r-1}{x} p^r (1-p)^x, \quad x = 0, 1, 2, \dots$$

where $E(X) = r(1-p)/p$ and $\text{Var}(X) = r(1-p)/p^2$. We directly compute

$$\Pr(X = 12) = \binom{12+20-1}{12} \times 0.7^{20} \times 0.3^{12} = 0.0598.$$

(ii) Now,

$$E(X) = \frac{20 \times (1-0.7)}{0.7} = 8.5714 \quad \text{and} \quad \text{Var}(X) = \frac{20 \times (1-0.7)}{0.7^2} = 12.2449.$$

By CLT,

$$\frac{X - E(X)}{\sqrt{\text{Var}(X)}} \xrightarrow{L} Z \sim N(0, 1).$$

We obtain

$$\begin{aligned} \Pr(X = 12) &= P(12 - 0.5 < X < 12 + 0.5) \\ &= \Pr\left(\frac{11.5 - 8.5714}{\sqrt{12.2449}} < \frac{X - 8.5714}{\sqrt{12.2449}} < \frac{12.5 - 8.5714}{\sqrt{12.2449}}\right) \\ &= \Pr(0.8369 < Z < 1.1227) \\ &= \Phi(1.1227) - \Phi(0.8369) \\ &= 0.8692 - 0.7987 = 0.0705. \end{aligned}$$

The error is $0.0705 - 0.0598 = 0.0107$. And the percentage error is

$$\frac{0.0107}{0.0598} = 17.87\%. \quad \parallel$$

Example T3.4: Let $X_i \stackrel{\text{i.i.d.}}{\sim} \text{Poisson}(0.03)$, $i = 1, \dots, 50$ and $Y = \sum_{i=1}^{50} X_i$. Calculate $\Pr(Y \geq 3)$.

Solution: $E(X_i) = 0.03$ and $\text{Var}(X_i) = 0.03$. By CLT,

$$\begin{aligned} Z &= \sqrt{n} \cdot \frac{\bar{X} - E(X_i)}{\sqrt{\text{Var}(X_i)}} \\ &= \sqrt{50} \cdot \frac{Y/50 - 0.03}{\sqrt{0.03}} \\ &= \frac{Y - 50 \times 0.03}{\sqrt{50 \times 0.03}} \\ &= \frac{Y - 1.5}{\sqrt{1.5}} \xrightarrow{L} N(0, 1). \end{aligned}$$

Therefore,

$$\begin{aligned} \Pr(Y \geq 3) &= \Pr\left(Z = \frac{Y - 1.5}{\sqrt{1.5}} \geq \frac{3 - 1.5}{\sqrt{1.5}}\right) \\ &= 1 - \Pr(Z < 1.224745) \\ &= 1 - \Phi(1.224745) \\ &= 1 - 0.8896643 \\ &= 0.1103357. \end{aligned}$$

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