

Theory of Probability Lecture Notes: 6.6-6.7

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Lecture Video Notes

Order Statistics

Let X_1, \dots, X_n be independent and identically distributed continuous random variables.

Let $X_{(1)}$ = smallest X_1, \dots, X_n

$X_{(2)}$ = the next smallest X_1, \dots, X_n

...

$X_{(n)}$ = the largest X_1, \dots, X_n

$\implies X_{(1)} \leq X_{(2)} \leq \dots \leq X_{(n)}$ which is the order statistics of X_1, \dots, X_n .

What is the probability distribution function?

$X_{(1)} \leq X_{(2)} \leq \dots \leq X_{(n)}$ take on the values $X_1 \leq X_2 \leq \dots \leq X_n$ if and only if:

$X_1 = X_{i_1}$

$X_2 = X_{i_2}$

...

$X_n = X_{i_n}$ for some permutation (i_1, i_2, \dots, i_n) of $(1, 2, \dots, n)$.

So in the terms of X_1, \dots, X_n :

$P[x_{i_1} - \frac{\epsilon}{2} \leq X_1 \leq x_{i_1} + \frac{\epsilon}{2}, \dots, x_{i_n} - \frac{\epsilon}{2} \leq X_n \leq x_{i_n} + \frac{\epsilon}{2}]$

$= \epsilon^n f_{x_1 x_2 \dots x_n}(x_{i_1}, \dots, x_{i_n})$

$= \epsilon^n f_{x_1}(x_{i_1}) \dots f_{x_n}(x_{i_n})$

Now since there are $n!$ permutations of $(1, 2, \dots, n)$ we have that:

$P[x_{i_1} - \frac{\epsilon}{2} \leq X_1 \leq x_{i_1} + \frac{\epsilon}{2}, \dots, x_{i_n} - \frac{\epsilon}{2} \leq X_n \leq x_{i_n} + \frac{\epsilon}{2}] \approx n! \epsilon^n f(x_1) \dots f(x_n) \implies$

$f_{x_{(1)} \dots x_{(n)}}(X_1, \dots, X_n) = n! f(x_1) \dots f(x_n)$ for $x_1 \leq x_2 \leq x_3 \dots \leq x_n$ since it does not matter which $x_i = x_1$ etc.

Joint Distributions of Functions of Several Random Variables

Goal: Given joint probability distribution function $f = f(x_1, x_2)$ for X_1, X_2 , and if $Y_1 = g_1(X_1, X_2), Y_2 = g_2(X_1, X_2)$ what is the probability distribution function of Y_1, Y_2 ?

We need two assumptions:

1. The mapping $\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \rightarrow \begin{pmatrix} g_1(x_1, x_2) \\ g_2(x_1, x_2) \end{pmatrix} = \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}$ is uniquely invertible, with $x_1 = h_1(y_1, y_2)$, $x_2 = h_2(y_1, y_2)$

2. g_1, g_2 are continuously differential, and that:

$$J(x_1, x_2) = \begin{vmatrix} \frac{\partial g_1}{\partial x_1} & \frac{\partial g_1}{\partial x_2} \\ \frac{\partial g_2}{\partial x_1} & \frac{\partial g_2}{\partial x_2} \end{vmatrix} = \frac{\partial g_1}{\partial x_1} \frac{\partial g_2}{\partial x_2} - \frac{\partial g_1}{\partial x_2} \frac{\partial g_2}{\partial x_1} \neq 0.$$

Under these two assumptions we have that $f_{x_1, x_2}(h_1(y_1, y_2), h_2(y_1, y_2)) \frac{1}{|J(h_1(y_1, y_2), h_2(y_1, y_2))|}$

$$\text{The idea is: } P[Y_1 \leq y_1, Y_2 \leq y_2] = P[g_1(x_1, x_2) \leq y_1, g_2(x_1, x_2) \leq y_2] = \int \int_{g_1(x_1, x_2) \leq y_1, g_2(x_1, x_2) \leq y_2} f_{x_1 x_2}(x_1, x_2) dx_1 dx_2$$

Make the following change of variables: $x_1 = h_1(y_1, y_2), x_2 = h_2(y_1, y_2) \implies f \rightarrow f(h_1, h_2)$

$$dx_1 dx_2 = \begin{vmatrix} h_{1,1} & h_{1,2} \\ h_{2,1} & h_{2,2} \end{vmatrix} dy_1 dy_2$$

If we insert back into the integral we obtain that the integrand is:
 $f_{x_1 x_2}(h_1, h_2) \frac{1}{|J(h_1, h_2)|} = f_{Y_1, Y_2}(y_1, y_2)$.

Zoom notes

Order Statistics

Let X_1, \dots, X_n (has density $f(x)$) be independent and identically distributed continuous random variables.

Let X_1, X_2, X_3, \dots
 $\Leftrightarrow X_1 \leq X_2 \leq X_3 \leq \dots$

$X_1 = \min(X_1, \dots, X_n)$

$X_2 = \text{next smallest}$

$\Rightarrow f_{X_1, X_2, \dots, X_n}(x_1, \dots, x_n) = n! f(x_1) f(x_2) \dots f(x_n)$ on the set $x_1 < x_2 < x_3 \dots < x_n$

Example:

$X_1, X_2, X_3 \sim U(0, 1)$

$x_1 < x_2 < x_3$ be the order statistics

$f(x) = 1$ on $x \in (0, 1)$

$\Rightarrow f_{X_1, X_2, X_3}(x_1, x_2, x_3) = 3!$ on the set $0 < x_1 < x_2 < x_3 < 1$.

Check that this is indeed a probability density.

$$\begin{aligned} \iiint_{0 < x_1 < x_2 < x_3 < 1} 3! dx_1 dx_2 dx_3 &= \int_0^1 \int_0^{x_3} \int_0^{x_2} 3! dx_1 dx_2 dx_3 \\ &= \int_0^1 \int_0^{x_3} 6x_1 \Big|_0^{x_2} dx_2 dx_3 \\ &= \int_0^1 \int_0^{x_3} 6x_2 dx_2 dx_3 \\ &= \int_0^1 3x_3^2 \Big|_0^{x_3} dx_3 \end{aligned}$$

$$= \int_0^1 3x_3^2 dx_3$$

$$= x_3^3 \Big|_0^1 = 1$$

Ex: $E[X_1] = \int_{-\infty}^{\infty} \int_{-\infty}^{x_n} \dots \int_{-\infty}^{x_2} x_1 n! f(x_1) \dots f(x_n) dx_1 \dots dx_n$

Functions of Several Random Variables

Change of Variables in multiple integrals: $\int \int f(x, y) dx dy$ change to polar coordinates :

$$x = r \cos \theta$$

$$y = r \sin \theta$$

$$dx dy = J dr d\theta$$

$$= \begin{vmatrix} \frac{\partial x}{\partial r} & \frac{\partial x}{\partial \theta} \\ \frac{\partial y}{\partial r} & \frac{\partial y}{\partial \theta} \end{vmatrix} dr d\theta$$

$$dx dy = \left(\frac{\partial x}{\partial r} \frac{\partial y}{\partial \theta} - \frac{\partial x}{\partial \theta} \frac{\partial y}{\partial r} \right) dr d\theta$$

$$= (\cos \theta r \cos \theta + r \sin \theta \sin \theta) dr d\theta$$

$$= (r \cos^2 \theta + r \sin^2 \theta) dr d\theta = r dr d\theta \int \int f(x, y) dx dy = \int \int f(r \cos \theta, r \sin \theta) r dr d\theta$$

If X_1, X_2 are continuous random variables with joint probability distribution function $f(x_1, x_2)$, and if:

the mapping (have to be continuously differentiable and uniquely invertible)

$$Y_1 = g_1(x_1, x_2) \mid x_1 \rightarrow g_1(x_1, x_2) = Y_1$$

$$Y_2 = g_2(x_1, x_2) \mid x_2 \rightarrow g_2(x_1, x_2) = Y_2$$

Then what is the joint probability distribution function of Y_1, Y_2 ?

Start with the distribution function:

$$P[Y_1 \leq y_1, Y_2 \leq y_2] = P[g_1(X_1, X_2) \leq y_1, g_2(X_1, X_2) \leq y_2]$$

$$= \int \int f(x_1, x_2) dx_1 dx_2$$

Change variables:

$$u = g_1(x_1, x_2)$$

$$v = g_2(x_1, x_2)$$

Defines "some" region of integration:

$$g_1(x_1, x_2) \leq y_1 \Rightarrow u \leq y_1$$

$$g_2(x_1, x_2) \leq y_2 \Rightarrow v \leq y_2$$

$$du dv = \begin{vmatrix} \frac{\partial g_1}{\partial x_1} & \frac{\partial g_1}{\partial x_2} \\ \frac{\partial g_2}{\partial x_1} & \frac{\partial g_2}{\partial x_2} \end{vmatrix} dx_1 dx_2 \text{ (matrix=J)}$$

$$x_1 = h_1(u, v)$$

$$x_2 = h_2(u, v)$$

$$\Rightarrow dx_1 dx_2 = \frac{1}{J} du dv$$

$$\Rightarrow \int_{-\infty}^{y_2} \int_{-\infty}^{y_1} f[h_1(u, v), h_2(u, v)] \frac{1}{J} du dv = F_{Y_1 Y_2}(y_1, y_2)$$

$$\Rightarrow f_{Y_1, Y_2}(y_1, y_2) = \frac{\partial^2 F_{Y_1, Y_2}}{\partial y_1 \partial y_2}$$

$$= f[h_1(y_1, y_2), h_2(y_1, y_2)] \frac{1}{J}$$

extra exercises

1. theoretical exercise 6.32 let $X_{(1)} \leq X_{(2)} \leq \dots \leq X_{(n)}$ be the ordered values of n independent uniform $(0,1)$ random variables. prove that for $1 \leq k \leq n+1$,

$$P\{X_{(k)} - X_{(k-1)} > t\} = (1-t)^n$$

where $X_{(0)} \equiv 0, X_{(n+1)} \equiv 1$, and $0 < t < 1$

since the random variables are uniform distribution, meaning that $f(x) = \frac{1}{b-a} = \frac{1}{1-0} = \frac{1}{1} = 1$

$$F(y) = \int_0^y f(x) dx = \int_0^y 1 dx = y$$

for $X_{(k)} - X_{(k-1)} > t$ means that $X_{(k)} > t$ which should also be true for $i > k$ and $X_{(k-1)} \leq 1-t$ which should also be true for $i < k-1$, otherwise it's impossible.

$$P(X_{(k)} - X_{(k-1)} > t) = P(x_{(1)} \leq 1-t, \dots, X_{(k-1)} \leq 1-t, X_{(k)} > t, \dots, x_{(n)} > t)$$

$$= P(X \leq 1-t)^{k-1} P(X > t)^{n-(k-1)}$$

$$= (1-t)^{k-1} (1-t)^{n-(k-1)}$$

$$= (1-t)^{n-(k-1)+(k-1)}$$

$$= (1-t)^n$$

2. theoretical exercise 6.36 if X and Y are independent standard normal random variable, determine the joint density function of

$$U = X \quad V = \frac{X}{Y}$$

then use your result to show that $\frac{X}{Y}$ has a Cauchy distribution

for normal variable we have $f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-\mu)^2/2\sigma^2}$ since X and Y are standard normal variable, meaning that $\mu = 0, \sigma = 1$

sub that in we get

$$f_X(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

$$f_Y(y) = \frac{1}{\sqrt{2\pi}} e^{-y^2/2}$$

since we know X and Y are independent we get the joint probability density function:

$$f_{X,Y}(x,y) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2} \frac{1}{\sqrt{2\pi}} e^{-y^2/2}$$

$$= \frac{1}{2\pi} e^{-x^2/2} e^{-y^2/2}$$

from $U=X$ and $V=\frac{X}{Y}$ we can get $x = U$ and $Y = \frac{U}{V}$

use that we get

$$J = \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix}$$

$$= \begin{vmatrix} 1 & 0 \\ \frac{1}{v} & -\frac{u}{v^2} \end{vmatrix} \\ = -\frac{u}{v^2} - 0 = -\frac{u}{v^2}$$

$$f_{UV}(u, v) = f_{X,Y}(u, u/v)|J|^{-1} = \frac{v^2}{|u|} \frac{1}{2\pi} e^{-u^2/2} e^{-(u/v)^2/2} \\ = \frac{v^2}{|u|2\pi} e^{-u^2(1+1/v^2)/2}$$

we can find the distribution of V by integrating the joint pdf of UV over U

$$f_v(v) = \int_{-\infty}^{\infty} f_{UV}(u, v) du \\ = \int_{-\infty}^{\infty} \frac{v^2}{|u|2\pi} e^{-u^2(1+1/v^2)/2} \text{ since } f(-u)=f(u) \text{ for all } u \\ = 2 \int_0^{\infty} \frac{v^2}{u2\pi} e^{-u^2(1+1/v^2)/2} \\ \text{let } w = u^2(1+1/v^2)/2 \text{ so that } dw = u(1+1/v^2) du \text{ we sub that in and get} \\ 2 \int_0^{\infty} \frac{v^2}{u2\pi} e^{-w} \frac{1}{u(1+1/v^2)} dw \\ 2 \int_0^{\infty} \frac{v^2}{u^2 2\pi(1+1/v^2)} e^{-w} dw \\ \frac{v^2}{u^2 \pi(1+1/v^2)} \int_0^{\infty} e^{-w} dw \\ = \frac{v^2}{u^2 \pi(1+1/v^2)} (0 + 1) \\ = \frac{v^2}{u^2 \pi(1+1/v^2)} = \frac{v^4}{u^2 \pi(v^2+1)} \text{ thus } X/Y \text{ is a cauchy distribution..}$$