

Joint, Marginal, and Conditional Densities

Rice 3.1-3.5, Blitzstein 7.1

2/5/2025

Discrete

Joint CDF:

$$F_{X,Y}(x, y) = P(X \leq x, Y \leq y)$$

Joint PMF:

$$p_{X,Y}(x, y) = P(X = x, Y = y).$$

Such that

$$\sum_x \sum_y P(X = x, Y = y) = 1.$$

Marginal PMF:

$$P(X = x) = \sum_y P(X = x, Y = y).$$

Conditional PMF:

$$P(Y = y | X = x) = \frac{P(X = x, Y = y)}{P(X = x)}.$$

Continuous

Joint CDF:

$$F_{X,Y}(x, y) = P(X \leq x, Y \leq y)$$

Joint PDF:

$$f_{X,Y}(x, y) = \frac{\partial^2}{\partial x \partial y} F_{X,Y}(x, y).$$

Such that

$$f_{X,Y}(x, y) \geq 0, \text{ and } \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(x, y) dx dy = 1.$$

Marginal PDF:

$$f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x, y) dy.$$

Conditional PDF:

$$f_{Y|X}(y|x) = \frac{f_{X,Y}(x, y)}{f_X(x)},$$

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- b) As an example, suppose X and Y have joint pdf $f_{xy}(x, y) = \lambda^2 e^{-\lambda y} I_{(0 < x < y)}$. Show that the marginal distributions are $X \sim \text{Exponential}(\lambda)$ and $Y \sim \text{Gamma}(2, \lambda)$.

$$f_{xy}(x, y) = \lambda^2 e^{-\lambda y} I_{(0 < x < y)}$$

→ so to find marg dist of Y , fix y and integrate over all possible values of x

Marginal density found by integrating wrt opposite variable

$$f_x(x) = \int_{-\infty}^{\infty} f(x, y) dy \quad f_y(y) = \int_{-\infty}^{\infty} f(x, y) dx$$

$$f_x(x) = \int_x^{\infty} \lambda^2 e^{-\lambda y} dy \quad \text{bounds determined by indicator (y must be greater than x)}$$

$$f_x(x) = \lambda^2 \int_x^{\infty} e^{-\lambda y} dy$$

$$f_x(x) = \lambda^2 \left[\frac{-e^{-\lambda y}}{\lambda} \right]_x^{\infty} = \lambda e^{-\lambda x} I_{(x > 0)} \quad \text{marginal pdf shows } X \sim \text{Expo}(\lambda)$$

$$f_y(y) = \int_0^y \lambda^2 e^{-\lambda y} dx = y \lambda^2 e^{-\lambda y} I_{(0 < x < y)} \quad \text{marg pdf shows } Y \sim \text{Gamma}(2, \lambda)$$

- c) Show that $Y|X = x$ is a translated Exponential, and $X|Y = y$ is Uniform.

$$f_{y|x}(y|x) = \frac{f_{xy}(x, y)}{f_x(x)} = \frac{\lambda^2 e^{-\lambda y} I_{(0 < x < y)}}{\lambda e^{-\lambda x} I_{(0 < x)}}$$

$$= \frac{\lambda e^{-\lambda y}}{e^{-\lambda x}}$$

$$= \lambda e^{-\lambda y + \lambda x}$$

$$= \lambda e^{-\lambda(y-x)} I_{(x < y)}$$

↳ exponential pdf shifted along x-axis by x

$$f_{x|y}(x|y) = \frac{f_{xy}(x, y)}{f_y(y)} = \frac{\lambda^2 e^{-\lambda y}}{y \lambda^2 e^{-\lambda y}}$$

$$= \frac{1}{y} e^{-\lambda y + \lambda y}$$

$$= \frac{1}{y} I_{(0 < x < y)}$$

↳ uniform pdf for interval $(0, y)$

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- d) Review the factorization theorem for independence. Show that X and Y are not independent, but that X and $Y - X$ are independent.

factorization theorem for independence:

X, Y independent iff $f_{xy}(x, y) = g_1(x)g_2(y)$

in other words, joint PDF factors into product of marginal PDFs or joint PMF factors into product of marginal PMFs that depend on one variable only

$$f_{xy}(x, y) = \lambda^2 e^{-\lambda y} \mathbb{I}_{(0 < x < y)}$$

intuitively indicator shows not independent
range changes based on both variables

$$f_x(x) = \lambda e^{-\lambda x} \mathbb{I}_{(x > 0)}$$

$$f_y(y) = y \lambda^2 e^{-\lambda y} \mathbb{I}_{(0 < x < y)}$$

$$f_x(x) \neq g_1(x)$$

$$f_y(y) \neq g_2(y)$$

Show that X and $Y - X$ are independent:

$$\begin{aligned} X_1 &= X & \Rightarrow & X = X_1 \\ X_2 &= Y - X & Y &= X_1 + X_2 \end{aligned}$$

change of variables $\rightarrow f(x, y) = f(\tau(u, v)) | \det DT(u, v) |$

$$\frac{\partial(x, y)}{\partial(x_1, x_2)} = \begin{bmatrix} \frac{\partial x}{\partial x_1} & \frac{\partial x}{\partial x_2} \\ \frac{\partial y}{\partial x_1} & \frac{\partial y}{\partial x_2} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}$$

$$|J| = 1$$

↳ Jacobian is the determinant of a 2×2 matrix

$$\begin{aligned} f_{x_1, x_2}(x_1, x_2) &= f_{xy}(x_1, x_1 + x_2) \cdot 1 \\ f_{x_1, x_2}(x_1, x_2) &= \lambda^2 e^{-\lambda(x_1 + x_2)} \mathbb{I}_{(x_1 > 0, x_2 > 0)} \end{aligned}$$

$$f_{x_1, x_2}(x_1, x_2) = (\lambda e^{-\lambda x_1} \mathbb{I}_{(x_1 > 0)}) (\lambda e^{-\lambda x_2} \mathbb{I}_{(x_2 > 0)})$$

since $f_{x_1, x_2}(x_1, x_2)$ is able to be factored into factors containing only x_1 or x_2 , x_1 and x_2 are independent, so X and $Y - X$ are independent

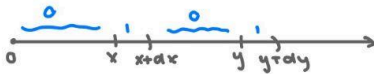
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- e) A bivariate differential argument approximates $P(X \in [x, x+dx], Y \in [y, y+dy])$ by $f_{xy}(x, y)dx dy$. Use this approach to show that this is the joint pdf for the time of the first event (x) and the time of the second event (y) for a Poisson process with rate λ events per unit time. Show this agrees with what you find setting $X = X_1$ and $Y = X_1 + X_2$, for $X_1, X_2 \stackrel{i.i.d.}{\sim} \text{Exponential}(\lambda)$.

first event at time x
second event at time y



$$f_{xy}(x, y) dx dy \approx P(X \in [x, x+dx], Y \in [y, y+dy]) \\ = F_{xy}(x+dx, y+dy) - F_{xy}(x, y)$$

$\rightarrow \approx P(0 \text{ events in time } x, 1 \text{ event in time } dx, 0 \text{ events in time } y-(x+dx), 1 \text{ event in time } (y+dy)-y)$

Poisson process tells us each event is independent so total prob = product of individual probs

$$f_{xy}(x, y) dx dy \approx \left(\frac{(\lambda x)^0 e^{-\lambda x}}{0!} \right) \left(\frac{(\lambda dx)^1 e^{-\lambda dx}}{1!} \right) \left(\frac{(\lambda (y-(x+dx)))^0 e^{-\lambda (y-(x+dx))}}{0!} \right) \\ \times \left(\frac{(\lambda dy)^1 e^{-\lambda dy}}{1!} \right)$$

simplify

$$f_{xy}(x, y) dx dy = e^{-\lambda x} \lambda dx e^{-\lambda dx} e^{-\lambda y + \lambda x + \lambda dx} \lambda dy e^{-\lambda dy}$$

$$f_{xy}(x, y) dx dy = \lambda^2 dx dy e^{-\lambda y} e^{-\lambda dx}$$

$$f_{xy}(x, y) = \lambda^2 e^{-\lambda y} \mathbb{I}_{(0 < x < y)}$$

this is the same joint pdf as the one we found when

$$X = X_1,$$

$$Y = X_1 + X_2$$

for $X_1, X_2 \stackrel{i.i.d.}{\sim} \text{Exp}(\lambda)$