

Marginal and conditional distributions

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Outline

- 1 Marginal probability distributions
- 2 Conditional probability distributions
- 3 Independent random variables
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Marginal probability distributions

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The function p_X , defined for all possible values of X , is called the **marginal probability distribution** of X . Analogously, the function p_Y , defined for all possible values of Y , is called the **marginal probability distribution** of Y , where

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The PDFs in (1) correspond to the basic PDFs of the univariate random variables X and Y , respectively. For example,

$$\begin{aligned}\mathbb{P}(c \leq X \leq d) &= \mathbb{P}(c \leq X \leq d, -\infty \leq Y \leq +\infty) \\ &= \int_c^d \int_{-\infty}^{+\infty} f(x, y) dy dx \\ &= \int_c^d f_X(x) dx.\end{aligned}$$



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Note that,

$$\begin{aligned} p(x, y) &= p_X(x) \times p_{Y|X}(y|x) \\ &= p_Y(y) \times p_{X|Y}(x|y), \end{aligned}$$

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Observation

Marginal or conditional PMFs and PDFs do not always have a closed-form expression.



Marginal and conditional probability distributions

Example 4. Let $Y|X = x \sim \text{Rayleigh}(x)$ and $X \sim \text{log-normal}(\mu, \sigma^2)$, where $\mu > 0$ and $\sigma^2 > 0$. That is,

$$f_{Y|X}(y|x) = \frac{y}{x^2} \exp \left\{ -\frac{1}{2} \left(\frac{y}{x} \right)^2 \right\} \mathbb{I}_{(0,\infty)}(y),$$

$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma x}} \exp \left\{ -\frac{1}{2} \left(\frac{\log x - \mu}{\sigma} \right)^2 \right\} \mathbb{I}_{(0,\infty)}(x).$$

Obtain the marginal PDF of Y .



Marginal and conditional probability distributions

The joint PDF of $(X, Y)^T$ is given by

$$\begin{aligned} f(x, y) &= f_{Y|X}(y|x) \times f_X(x) \\ &= \frac{y}{\sqrt{2\pi}\sigma x^3} \exp \left\{ -\frac{1}{2} \left[\left(\frac{\log x - \mu}{\sigma} \right)^2 + \left(\frac{y}{x} \right)^2 \right] \right\} \mathbb{I}_{(0,\infty)}(x) \mathbb{I}_{(0,\infty)}(y). \end{aligned}$$



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The marginal PDF of Y is obtained as follows:

$$\begin{aligned}f_Y(y) &= \int_{-\infty}^{+\infty} f(x, y) dx \\&= \int_{-\infty}^{+\infty} \frac{y}{\sqrt{2\pi}\sigma x^3} \exp \left\{ -\frac{1}{2} \left[\left(\frac{\log x - \mu}{\sigma} \right)^2 + \left(\frac{y}{x} \right)^2 \right] \right\} \mathbb{I}_{(0, \infty)}(x) \mathbb{I}_{(0, \infty)}(y) dx \\&= \frac{y}{\sqrt{2\pi}\sigma} \int_0^{+\infty} \frac{1}{x^3} \exp \left\{ -\frac{1}{2} \left[\left(\frac{\log x - \mu}{\sigma} \right)^2 + \left(\frac{y}{x} \right)^2 \right] \right\} dx \mathbb{I}_{(0, \infty)}(y). \quad (3)\end{aligned}$$



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The integral in (3) does not have a closed-form expression. Therefore, (3) gives the marginal PDF of Y .

Result

When $Y|X = x \sim \text{Rayleigh}(x)$ and $X \sim \text{log-normal}(\mu, \sigma^2)$, the marginal distribution of Y is known as the Suzuki distribution (Suzuki, 1977), with parameters μ and σ^2 .



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Suzuki, H. (1977). A statistical model for urban radio propagation. *IEEE Transactions on Communications*, 25(7):673–680.



Thank you!

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