

Example. If X and Y have a joint pdf

$$f(x, y) = \frac{2}{(1+x+y)^3}$$

examine whether it's a joint pdf.

for $0 \leq x, y < \infty$, then

$$f_X(x) = \int_0^\infty f(x, y) dy = -\frac{1}{(1+x+y)^2} \Big|_0^\infty = \frac{1}{(1+x)^2}$$

for $0 \leq x < \infty$. So,

$$f_{Y|X}(y|x) = \frac{f(x, y)}{f_X(x)} = \frac{2(1+x)^2}{(1+x+y)^3}$$

fixed random

and, $P(Y > c | X = x) = \int_c^\infty \frac{2(1+x)^2}{(1+x+y)^3} dy$

$$= -\frac{(1+x)^2}{(1+x+y)^2} \Big|_{y=c}^\infty = \frac{(1+x)^2}{(1+x+c)^2}$$

a function of x

joint marginal

$X \in x \pm \frac{\Delta x}{2}$

Mixed Joint Distribution: Definition of conditional distribution can be similarly generalized to the case in which some random variables are discrete and the others continuous (see a later example).

Recall. The 3 laws in LNp. 4-11~13. $P(A_1 \cap \dots \cap A_n) = P(A_1) \cdot P(A_2 | A_1) \cdot \dots \cdot P(A_n | A_1 \cap \dots \cap A_{n-1})$

Theorem (Multiplication Law). Let \mathbf{X} and \mathbf{Y} be random vectors and (\mathbf{X}, \mathbf{Y}) have a joint pdf $f_{\mathbf{X}, \mathbf{Y}}(\mathbf{x}, \mathbf{y})$ /pmf $p_{\mathbf{X}, \mathbf{Y}}(\mathbf{x}, \mathbf{y})$, then

$$p_{\mathbf{X}, \mathbf{Y}}(\mathbf{x}, \mathbf{y}) \stackrel{\text{cf. independent}}{=} p_{\mathbf{Y}|\mathbf{X}}(\mathbf{y}|\mathbf{x}) \times p_{\mathbf{X}}(\mathbf{x}) \quad \text{or} \quad P_{x_1, \dots, x_n}(x_1, \dots, x_n) = P_{x_1}(x_1) \times P_{x_2|x_1}(x_2|x_1) \times \dots \times P_{x_n|x_1, \dots, x_{n-1}}(x_n|x_1, \dots, x_{n-1})$$

similar extension

Proof. By the definition of conditional distribution. $P(B) = \sum_i P(B|A_i)P(A_i)$

Theorem (Law of Total Probability). Let \mathbf{X} and \mathbf{Y} be random vectors and (\mathbf{X}, \mathbf{Y}) have a joint pdf $f_{\mathbf{X}, \mathbf{Y}}(\mathbf{x}, \mathbf{y})$ /pmf $p_{\mathbf{X}, \mathbf{Y}}(\mathbf{x}, \mathbf{y})$, then

$$\sum_{\mathbf{x} \in \mathcal{X}} p_{\mathbf{X}, \mathbf{Y}}(\mathbf{x}, \mathbf{y}) = p_{\mathbf{Y}}(\mathbf{y}) = \sum_{\mathbf{x} \in \mathcal{X}} p_{\mathbf{Y}|\mathbf{X}}(\mathbf{y}|\mathbf{x}) p_{\mathbf{X}}(\mathbf{x})$$

or

$$f_{\mathbf{Y}}(\mathbf{y}) = \int_{\mathbb{R}^n} f_{\mathbf{Y}|\mathbf{X}}(\mathbf{y}|\mathbf{x}) f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x}$$

joint pmf

Proof. By the definition of marginal distribution and the multiplication law.

Theorem (Bayes Theorem). Let \mathbf{X} and \mathbf{Y} be random vectors and (\mathbf{X}, \mathbf{Y}) have a joint pdf $f_{\mathbf{X}, \mathbf{Y}}(\mathbf{x}, \mathbf{y})$ /pmf $p_{\mathbf{X}, \mathbf{Y}}(\mathbf{x}, \mathbf{y})$, then

$$p_{\mathbf{X}|\mathbf{Y}}(\mathbf{x}|\mathbf{y}) = \frac{p_{\mathbf{X}, \mathbf{Y}}(\mathbf{x}, \mathbf{y})}{p_{\mathbf{Y}}(\mathbf{y})} = \frac{p_{\mathbf{Y}|\mathbf{X}}(\mathbf{y}|\mathbf{x}) p_{\mathbf{X}}(\mathbf{x})}{\sum_{\mathbf{x} \in \mathcal{X}} p_{\mathbf{Y}|\mathbf{X}}(\mathbf{y}|\mathbf{x}) p_{\mathbf{X}}(\mathbf{x})}$$

or

$$f_{\mathbf{X}|\mathbf{Y}}(\mathbf{x}|\mathbf{y}) = \frac{f_{\mathbf{X}, \mathbf{Y}}(\mathbf{x}, \mathbf{y})}{\int_{-\infty}^{\infty} f_{\mathbf{X}, \mathbf{Y}}(\mathbf{x}, \mathbf{y}) d\mathbf{x}}$$

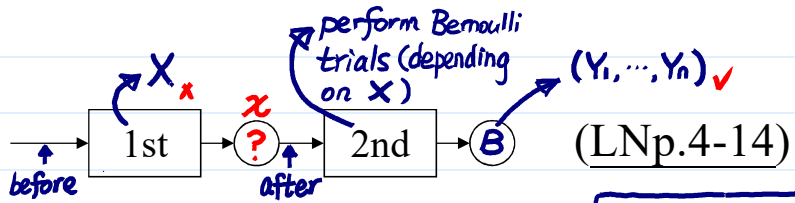
meaning

Proof. By the definition of conditional distribution, multiplication law, and the law of total probability.

Example.

Bayesian estimation

Gold coins example in LNp.4-29



(Y_1, \dots, Y_n)
(LNp.4-14)

Note

X : continuous
 Y_1, \dots, Y_n : discrete

Suppose that $X \sim \text{Uniform}(0, 1)$, and $(Y_1, \dots, Y_n | X=x)$ are i.i.d. with Bernoulli(x), i.e.,

$$p_{Y|X}(y_1, \dots, y_n | x) = x^{y_1 + \dots + y_n} (1-x)^{n - (y_1 + \dots + y_n)}$$

for $y_1, \dots, y_n \in \{0, 1\}$.

Q: Y_1, \dots, Y_n indep.?
NO
after 1st stage
before 1st stage

joint dist.: a mix of pmf & pdf

By the multiplication law, for $y_1, \dots, y_n \in \{0, 1\}$ and $0 < x < 1$,
 $p_{Y,X}(y_1, \dots, y_n, x) = x^{y_1 + \dots + y_n} (1-x)^{n - (y_1 + \dots + y_n)} \times \Delta x$

Intuition. What values of x are more probable?

Suppose that we observed $Y_1=1, \dots, Y_n=1$. (or $Y_i=y_1, \dots, Y_n=y_n$)

By the law of total probability,

$$P(Y_1 = 1, \dots, Y_n = 1) = p_Y(1, \dots, 1)$$

$$= \int_0^1 p_{Y|X}(1, \dots, 1 | x) f_X(x) dx$$

$$= \int_0^1 x^n dx = \frac{1}{n+1} x^{n+1} \Big|_0^1 = \frac{1}{n+1}$$

marginal dist. of Y_1, \dots, Y_n

$$P_Y(y_1, \dots, y_n) = \frac{\Gamma(n+1) \Gamma(k+1) \Gamma(n-k+1)}{\Gamma(n+1)} = \frac{k! (n-k)!}{(n+1)!}$$

$$= \frac{(\sum_{i=1}^n y_i)! (n - \sum_{i=1}^n y_i)!}{(n+1)!}$$

$k = \sum_{i=1}^n y_i$

And, by Bayes' Theorem,

joint marginal

$$f_{X|Y}(x | Y_1 = 1, \dots, Y_n = 1) = \frac{p_{Y|X}(1, \dots, 1 | x) f_X(x)}{p_Y(1, \dots, 1)} = \frac{\frac{\Gamma(n+1) \Gamma(1) x^{(n+1)-1} (1-x)^{1-1}}{\Gamma(n+1) \Gamma(1)} x^n}{\frac{1}{n+1}}$$

$$E(X | Y_1=1, \dots, Y_n=1) = \frac{n+1}{n+2}$$

for $0 < x < 1$, i.e., $(X | Y_1=1, \dots, Y_n=1) \sim \text{Beta}(n+1, 1)$.

Why is X still random?

(cf., marginal distribution of $X \sim \text{Uniform}(0, 1) = \text{Beta}(1, 1)$.)

If there were an $(n+1)^{\text{st}}$ Bernoulli trial Y_{n+1} ,

probability of getting "1" after we know $Y_1=Y_2=\dots=Y_n=1$

$Y_{n+1} | Y_1=y_1, \dots, Y_n=y_n \sim \text{Bernoulli}(\frac{\sum y_i + 1}{n+2})$
 $Y_{n+1} \sim \text{Bernoulli}(\frac{1}{2})$

$$P(Y_{n+1} = 1 | Y_1 = 1, \dots, Y_n = 1) = \frac{P(Y_1 = 1, \dots, Y_{n+1} = 1)}{P(Y_1 = 1, \dots, Y_n = 1)} = \frac{1/(n+2)}{1/(n+1)} = \frac{n+1}{n+2}$$

(exercise) In general, it can be shown that

Why not x ?

$(X | Y_1=y_1, \dots, Y_n=y_n) \sim \text{Beta}((y_1 + \dots + y_n) + 1, n - (y_1 + \dots + y_n) + 1)$.

$E(X | Y_1=y_1, \dots, Y_n=y_n) = (\sum_{i=1}^n y_i + 1) / (n+2)$ ← a Bayesian estimator of x .

Theorem (Conditional Distribution & Independent). Let X and Y be random vectors and (X, Y) have a joint pdf $f_{X,Y}(x, y)$ /pmf $p_{X,Y}(x, y)$. Then, X and Y are independent, i.e.,

$$P_{Y|X}(y|x) \cdot P_X(x) = p_{X,Y}(x,y) = p_X(x) \times p_Y(y), \text{ or}$$

$$f_{X,Y}(x,y) = f_X(x) \times f_Y(y),$$

if and only if

$$\frac{P_{X,Y}(x,y)}{P_X(x)} = \frac{p_{Y|X}(y|x)}{p_Y(y)} = p_Y(y), \text{ or}$$

$$f_{Y|X}(y|x) = f_Y(y).$$

use the concept to examine whether the (Y_1, \dots, Y_n) in LNp 7-58 are indep.?

Proof. By the definition of conditional distribution.

➤ Intuition.

- The 2 graphs about the joint pmf/pdf of independent r.v.'s in LNp.7-27
- $p_{Y|X}(y|x)$ or $f_{Y|X}(y|x)$ offers information about the distribution of Y when X=x.

$p_Y(y)$ or $f_Y(y)$ offers information about the distribution of Y when X not observed. cf.

❖ Reading: textbook, Sec 6.4, 6.5

