

➤ 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 (exercise)

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

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

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

a function of x

joint
marginal

• 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

$$p_{\mathbf{X}, \mathbf{Y}}(\mathbf{x}, \mathbf{y}) = p_{\mathbf{Y}|\mathbf{X}}(\mathbf{y}|\mathbf{x}) \times p_{\mathbf{X}}(\mathbf{x}), \quad \text{or} \quad p_{\mathbf{X}, \mathbf{Y}}(\mathbf{x}, \mathbf{y}) = p_{\mathbf{X}|\mathbf{Y}}(\mathbf{x}|\mathbf{y}) \times p_{\mathbf{Y}}(\mathbf{y}).$$

cf. independent similar extension

Proof. By the definition of conditional distribution.

pmf (Lnp. 7-51), pdf (Lnp. 7-53)

• 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

$$\sum_{\mathbf{x} \in \mathcal{X}} p_{\mathbf{X}, \mathbf{Y}}(\mathbf{x}, \mathbf{y}) = p_{\mathbf{Y}}(\mathbf{y}) = \sum_{\mathbf{x} \in \mathcal{X}} p_{\mathbf{Y}|\mathbf{X}}(\mathbf{y}|\mathbf{x}) p_{\mathbf{X}}(\mathbf{x}), \quad \text{or} \quad p_{\mathbf{Y}}(\mathbf{y}) = \int_{\mathbb{R}^n} f_{\mathbf{Y}|\mathbf{X}}(\mathbf{y}|\mathbf{x}) f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x}.$$

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

$$p_{\mathbf{X}|\mathbf{Y}}(\mathbf{x}|\mathbf{y}) = \frac{p_{\mathbf{X}, \mathbf{Y}}(\mathbf{x}, \mathbf{y})}{p_{\mathbf{Y}}(\mathbf{y})} = \frac{p_{\mathbf{Y}|\mathbf{X}}(\mathbf{y}|\mathbf{x}) p_{\mathbf{X}}(\mathbf{x})}{\sum_{\mathbf{x}' \in \mathcal{X}} p_{\mathbf{Y}|\mathbf{X}}(\mathbf{y}|\mathbf{x}') p_{\mathbf{X}}(\mathbf{x}')}, \quad \text{or} \quad p_{\mathbf{X}|\mathbf{Y}}(\mathbf{x}|\mathbf{y}) = \frac{f_{\mathbf{Y}|\mathbf{X}}(\mathbf{y}|\mathbf{x}) f_{\mathbf{X}}(\mathbf{x})}{\int_{\mathbb{R}^n} f_{\mathbf{Y}|\mathbf{X}}(\mathbf{y}|\mathbf{x}') f_{\mathbf{X}}(\mathbf{x}') d\mathbf{x}'}$$

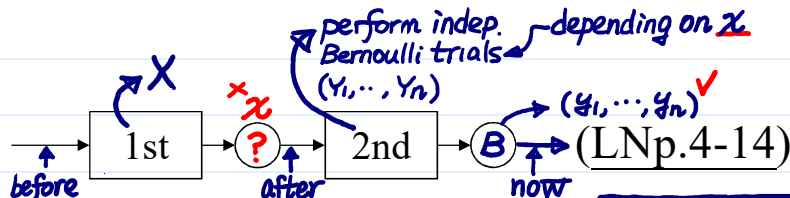
joint pmf

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

Example.

Bayesian estimation

Gold coins example in LNp.4-29



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

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 $Y_1, \dots, Y_n$

$$P_Y(y_1, \dots, y_n) = \frac{\Gamma(n+1) \Gamma(n-k+1)}{\Gamma(n+2)} = \frac{k! (n-k)!}{(n+1)!}$$

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

And, by Bayes' Theorem,

$$f_{X|Y}(x | Y_1 = 1, \dots, Y_n = 1) = \frac{p_{Y|X}(1, \dots, 1 | x) f_X(x)}{p_Y(1, \dots, 1)} = \frac{\frac{\Gamma(n+2)}{\Gamma(n+1)\Gamma(1)} x^{(n+1)-1} (1-x)^{1-1}}{(n+1)x^n}.$$

$$= \frac{p_{Y|X}(1, \dots, 1 | x) f_X(x)}{p_Y(1, \dots, 1)} = \frac{\frac{\Gamma(n+2)}{\Gamma(n+1)\Gamma(1)} x^{(n+1)-1} (1-x)^{1-1}}{(n+1)x^n}.$$

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} ,

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

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

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

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

Why not x ?

(exercise) In general, it can be shown that

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

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

- Theorem (Conditional Distribution & Independent). 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, $\mathbf{X}$ and $\mathbf{Y}$ are independent, i.e.,

$$p_{Y|X}(y|x) \cdot p_X(x) = p_{X,Y}(x,y) = p_X(x) \times p_Y(y), \quad \text{or} \\ f_{X,Y}(x,y) = f_X(x) \times f_Y(y),$$

if and only if

$$\frac{p_{X,Y}(x,y)}{p_X(x)} = \frac{p_{Y|X}(y|x)}{p_Y(y)} = \frac{p_Y(y)}{f_Y(y)}, \quad \text{or} \\ \frac{f_{X,Y}(x,y)}{f_X(x)} = \frac{f_{Y|X}(y|x)}{f_Y(y)} = \frac{f_Y(y)}{f_Y(y)}.$$

use the concept to
examine whether the
(Y₁, ..., Y_n) in LNp.7-58
are indep.?

Proof. By the definition of conditional distribution.

➤ Intuition.

conditionally indep: Y₁, ..., Y_n | X=x indep. ∀x

mutually indep: Y₁, ..., Y_n indep. ← X

- 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