

Probability and statistics

Lecture notes from March 6.

Definition 1. The function $f(x, y)$ is called the density function(density) of the 2-dimensional random variable (X, Y) iff

1. $f(x, y) \geq 0$, for $(x, y) \in \mathbb{R}^2$,
2. $\int_{\mathbb{R}} \int_{\mathbb{R}} f(x, y) dy dx = 1$.

For the discrete case, the function $p(i, j)$ is called the density (probability) iff

1. $P(X = x_i, Y = y_j) = p_{ij} \geq 0$, for $(i, j) \in \mathbb{N}^2$,
2. $\sum_{i \in \mathbb{N}} \sum_{j \in \mathbb{N}} p_{ij} = 1$.

Definition 2. The marginal density function of a random variable (X, Y) with density $f(x, y)$ are the functions $f_1(x) = \int_{\mathbb{R}} f(x, y) dy$ and $f_2(y) = \int_{\mathbb{R}} f(x, y) dx$.

For the discrete case, we use the symbols: $p_{i\bullet} = \sum_{j \in \mathbb{N}} p_{ij}$ and $p_{\bullet j} = \sum_{i \in \mathbb{N}} p_{ij}$.

Definition 3.

- The moment of the order of k (k -th moment) of the random variable X is $m_k = E(X^k)$.
- The central moment of the order k (k -th central moment) is equal to $\mu_k = E[(X - EX)^k]$.
- For a 2-dimensional random variable (X, Y) , the mixed moment of the order (k, l) is $m_{kl} = E(X^k Y^l)$ and $\mu_{kl} = E[(X - EX)^k \cdot (Y - EY)^l]$.

Comments

Continuous distribution	Discrete distribution
$m_k = \int_{\mathbb{R}} x^k f(x) dx$	$m_k = \sum_{i \in \mathbb{N}} x_i^k p_i$
$\mu_k = \int_{\mathbb{R}} (x - EX)^k f(x) dx$	$\mu_k = \sum_{i \in \mathbb{N}} (x_i - EX)^k p_i$
$m_{kl} = \int_{\mathbb{R}} \int_{\mathbb{R}} x^k y^l f(x, y) dy dx$	$m_{kl} = \sum_{i, j \in \mathbb{N}} x_i^k y_j^l p_{ij}$

The expected value EX is m_1 , the variance VX is μ_2 , the mixed moment m_{11} is the covariance of the variables X, Y , also denoted as $\text{Cov}(X, Y)$. The symbols EX , $E(X)$ mean the same (expected value). Similarly, the symbols VX , $V(X)$ mean variance. For distinction: $E(X^2)$ is the expected value of the variable X^2 , while $E^2(X)$ or $[EX]^2$ - the square of the expected value of the variable X .

Definition 4. Let (X, Y) be a 2-dimensional random variable. Variables (1-dimensional) X, Y are called independent iff

- $\forall x, y \in \mathbb{R} \quad f(x, y) = f_1(x) \cdot f_2(y)$ (vide def. 2), or
- $\forall i, j \in \mathbb{N} \quad p_{ij} = p_{i\bullet} \cdot p_{\bullet j}$.

Example:

(i) We consider the function $f(x, y) = \frac{3xy}{16}$ defined in the area bounded by the straight lines $y = 0$, $x = 2$ and the curve $y = x^2$. Immediately we obtain

$$\int_0^2 \int_0^{x^2} x \cdot y \, dy \, dx = \frac{16}{3}, \quad (1)$$

i.e. the non-negative function $f(x, y)$ in the selected area can be considered as density. The equation (1) should be written as

$$\int_{\mathbb{R}} \int_{\mathbb{R}} f(x, y) \, dy \, dx = 1,$$

where by default, we assume that $f(x, y) = 0$ anywhere outside the defined area.

(ii) The 2-dimensional cumulative distribution $F(s, t) \equiv F_{XY}(x, y) = \int_{-\infty}^s \int_{-\infty}^t f(x, y) \, dy \, dx$.

(iii) Let us determine the marginal densities:

$$\begin{aligned} f_1(x) \equiv f_X(x) &= \int_{\mathbb{R}} \frac{3xy}{16} \, dy = \int_0^{x^2} \frac{3xy}{16} \, dy = \frac{3x^5}{32}, \quad x \in [0, 2], \\ f_2(y) \equiv f_Y(y) &= \int_{\mathbb{R}} \frac{3xy}{16} \, dx = \int_{\sqrt{y}}^2 \frac{3xy}{16} \, dx = \frac{3(4-y)y}{32}, \quad y \in [0, 4]. \end{aligned}$$

Note (in the first equation) that, $y \in [0, x^2]$ for the variable x . Similarly, $x \in [\sqrt{y}, 2]$ for the variable y . In addition, $f_1(x), f_2(x)$ can be considered as densities because they are non-negative (in the defined area) and

$$\int_0^2 f_1(x) \, dx = \int_0^2 \frac{3x^5}{32} \, dx = 1, \quad \int_0^4 f_2(y) \, dy = \int_0^4 \frac{3(4-y)y}{32} \, dy = 1.$$

Subsequent integrals give the results: $EX = \int_0^2 x \cdot f_1(x) \, dx = \frac{12}{7}$ and $EY = \int_0^4 y \cdot f_2(y) \, dy = 2$
(but it is such addition).

Let's check if the variables X, Y are independent. Let's consider $(x, y) = (1, 1.5)$. Then

$$0 = f(1, 1.5) \neq f_1(1) \cdot f_2(1.5) = \frac{3}{32} \cdot \frac{45}{128}.$$

This means that the variables X, Y are not independent (In short: they are dependent).

Example:

The next example shows that it is much simpler for the discrete variables. Also **for this reason** (there are other reasons) we will pay less attention to these variables. (i) We define the

random variable (X, Y) as follows:

	y_1	y_2	y_3	
$(X, Y) =$	x_1	p_{11}	p_{12}	p_{13}
	x_2	p_{21}	p_{12}	p_{23}
	x_3	p_{31}	p_{32}	p_{33}
	x_4	p_{41}	p_{42}	p_{43}

In the above formula, $p_{ij} \geq 0$ and $\sum_{i,j} p_{ij} = 1$, i.e. for example:

	X/Y	2	3	5
$(X, Y) =$	-2	0.10	0.05	0.07
	0	0.05	0.03	0.08
	1	0.01	0.07	0.15
	$\sqrt{2}$	0.38	0.00	0.01

(ii) Distribution $F(s, t) = \sum_{x_i \leq s, y_j \leq t} p_{ij}$.

(iii) Marginal density:

	X/Y	2	3	5	$p_{1\bullet}$
$(X, Y) =$	-2	0.10	0.05	0.07	0.22
	0	0.05	0.03	0.08	0.16
	1	0.01	0.07	0.15	0.23
	$\sqrt{2}$	0.38	0.00	0.01	0.39
	$p_{\bullet j}$	0.54	0.15	0.31	1.00

Therefore, the variables X, Y have the marginal distributions:

$X =$	$\frac{x_i}{p_{i\bullet}}$	-2	0	1	$\sqrt{2}$
		0.22	0.16	0.23	0.39
$Y =$	$\frac{y_j}{p_{\bullet j}}$	2	3	5	
		0.54	0.15	0.31	

(iv) Independence of the variables X, Y : The variables are dependent because

$$0.01 = p_{31} = P(X = 1, Y = 2) \neq P(X = 1) \cdot P(Y = 2) = p_{3\bullet} \cdot p_{\bullet 1} = 0.23 \cdot 0.54.$$

Polski	Angielski
dystybuanta	cdf (cummulative distribution function)
gęstość	density (pdf)
gęstość brzegowa	marginal density
gęstość warunkowa	conditional density
i.i.d. ¹	i.i.d. ²
kowariancja	covariance
rozkład	distribution
rozkład ciągły	continuous distribution

¹(zmienne) niezależne o tym samym rozkładzie

²independent and of identical distribution (variables)

Polski	Angielski
rozkład dyskretny	discrete distribution
wariancja	variance
wartość oczekiwana	expected value
zmienna losowa	random variable
zmienne niezależne	independent variables

Z poważaniem,
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