Lecture 7 Multivariate Distributions

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Multivariate distribution

In many practical cases, it is possible, and often desirable, to take more than one measurement of a random observation. Moreover, we sometimes want to use these measurements to predict a third one. For example, we measure the GPA and extracurriculum activities of a student, and we give each of them a comprehensive evaluation score.

Definition: Let X and Y be two discrete random variables. Let S denote the two-dimensional space of X and Y. The probability that X = x and Y = y is denoted by f(x, y) = P(X = x, Y = y). The function f(x, y) is called the joint probability mass function.

Joint probability mass function

Example: Roll a pair of fair dice. For each of the 36 sampling points with probability 1/36, let X denote the smaller and Y the larger outcome on the dice. For example, if the outcome is (3,2), then the observed values are X=2, Y=3. What is the joint PMF of X and Y?

The event X=2, Y=3 can happen in one of two ways (2,3) or (3,2). So its probability is 2/36. However, for event such as X=2, Y=2, it can only happen in one way. Thus, in general, the joint probability mass function is

$$f(x,y) = \begin{cases} \frac{1}{36} & x = y \\ \frac{1}{18} & x \neq y \end{cases}$$

Multinomial distribution

Suppose we have three mutually exclusive and exhaustive ways for an experiment to end: perfect, seconds, and defective. We repeat the experiment n independent times and the probability p_X , p_Y , $1-p_X-p_Y$ of the three type of results. Let X and Y be the number of perfect and seconds. What is the joint probability mass function of X and Y?

The probability of having x perfects, y seconds, and n - x - y defective is

$$p_X^x p_Y^y (1 - p_X - p_Y)^{n-x-y}$$

And it can be achieved in

$$\mathbf{C}_{n}^{x}\mathbf{C}_{n-x}^{y} = \frac{n!}{x!(n-x)!} \frac{(n-x)!}{y!(n-x-y)!} = \frac{n!}{x!y!(n-x-y)!}$$

Thus, the joint PMF is

$$f(x,y) = \frac{n!}{x!y!(n-x-y)!} p_X^x p_Y^y (1 - p_X - p_Y)^{n-x-y}$$

Marginal probability mass function

Let X and Y have the joint probability mass function f(x, y) with space S. The probability mass function of X alone is called the marginal probability mass function of X and is defined by

$$f_X(x) = \sum_y f(x, y) \ x \in S_X$$

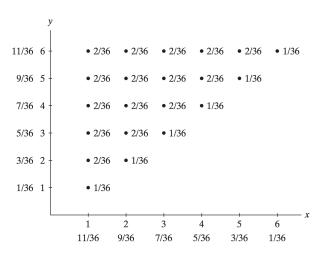
The random variables X and Y are independent if and only if, for every $x \in S_X$ and $y \in S_Y$,

$$f(x,y)=f_X(x)f_Y(y)$$

Otherwise, *X* ad *Y* are said to be dependent.

Marginal probability mass function

Example: In the dice rolling example mentioned above, what is the marginal probability mass function of *X* and *Y*? Are *X* and *Y* independent?



Marginal probability mass function

If X and Y has a multinomial distribution, are they independent?

It is easy to see by logic that X and Y both have a binomial distribution.

$$f_X(x) = \mathbf{C}_n^x p_X^x (1 - p_X)^{n-x}$$

$$f_Y(y) = \mathbf{C}_n^y p_Y^y (1 - p_Y)^{n-y}$$

Therefore,

$$f_X(x)f_Y(y) = \mathbf{C}_n^x \mathbf{C}_n^y p_X^x (1 - p_X)^{n-x} p_Y^y (1 - p_Y)^{n-y} \neq f(xy)$$

Thus, X and Y are not indepenent.

Mathematical expectation

Let X_1 and X_2 be random variables of the discrete type with the joint PMF $f(x_1, x_2)$ on the space S. If $u(X_1, X_2)$ is a function of these two random variables, then

$$E[u(X_1, X_2)] = \sum_{(x_1, x_2) \in S} u(x_1, x_2) f(x_1, x_2)$$

if it exists, is called the mathematical expectation of $u(X_1, X_2)$.

If
$$u(X_1, X_2) = X_i$$
, then $E[u(X_1, X_2)] = E(X_i) = \mu_i$; if $u(X_1, X_2) = (X_i - \mu_i)^2$, then $E[u(X_1, X_2)] = E[(X_i - \mu_i)^2] = Var(X_i)$

Mathematical expectation

Example: There are eight chips in a bow: three marked (0,0), two marked (1,0), two marked (0,1), and one marked (1,1). A player selects a chip at random and is given the sum of the two coordinates in dollars as a prize. What is the expected prize money a play can get?

Let X_1 and X_2 denote the two coordinates. Their joint PMF is

$$f(x,y) = \frac{3 - x_1 - x_2}{8}, x_1 = 0, 1 \text{ and } x_2 = 0, 1$$

Thus,

$$E(X_1 + X_2) = \sum_{x_2=0}^{1} \sum_{x_1=0}^{1} (x_1 + x_2) \frac{3 - x_1 - x_2}{8}$$
$$= (0)(\frac{3}{8}) + (1)(\frac{2}{8}) + (1)(\frac{2}{8}) + (2)(\frac{1}{8}) = \frac{3}{4}$$

Let $u(X, Y) = (X - \mu_X)(Y - \mu_Y)$, then

$$E[u(X,Y)] = E[(X - \mu_X)(Y - \mu_Y)] = Cov(X,Y) = \sigma_{XY}$$

is called the covariance of *X* and *Y*.

$$\rho = \frac{Cov(X, Y)}{\sigma_X \sigma_Y} = \frac{\sigma_{XY}}{\sigma_X \sigma_Y}$$

is called the correlation coefficient of *X* and *Y*.

A commonly used formula to calculate covariance:

$$Cov(X, Y) = E[(X - \mu_X)(Y - \mu_Y)]$$

$$= E(XY - \mu_X Y - \mu_Y X + \mu_X \mu_Y)$$

$$= E(XY) - \mu_X E(Y) - \mu_Y E(X) + \mu_X \mu_Y$$

$$= E(XY) - \mu_X \mu_Y$$

Example: Let *X* and *Y* have the joint PMF

$$f(x,y) = \frac{x+2y}{18}$$
, $x = 1,2$ and $y = 1,2$

What is the correlation coefficient of *X* and *Y*?

The marginal PMF are respectively

$$f_X(x) = \sum_{y=1}^{2} \frac{x+2y}{18} = \frac{x+3}{9}$$
$$f_Y(y) = \sum_{y=1}^{2} \frac{x+2y}{18} = \frac{3+4y}{18}$$

The mean and variance of X are

$$\mu_X = \sum_{x=1}^2 x \frac{x+3}{9} = (1)\frac{4}{9} + (2)\frac{5}{9} = \frac{14}{9}$$

$$\sigma_X^2 = E(X^2) - \mu_X^2 = \sum_{x=1}^2 x^2 \frac{x+3}{9} - \left(\frac{14}{9}\right)^2 = \frac{20}{81}$$

Similarly, we get the mean and variance of Y

$$\mu_{Y} = \frac{29}{18} \ \sigma_{Y}^{2} = \frac{77}{324}$$

The covariance of X and Y

$$Cov(X, Y) = \sum_{x=1}^{2} \sum_{y=1}^{2} xy \frac{x+2y}{18} - \frac{14}{9} \frac{29}{18}$$

$$= (1)(1) \frac{3}{18} + (2)(1) \frac{4}{18} + (1)(2) \frac{5}{18} + (2)(2) \frac{6}{18} - \frac{14}{9} \frac{29}{18}$$

$$= -\frac{1}{162}$$

$$\rho = \frac{Cov(X, Y)}{\sigma_X \sigma_Y} = -0.025$$

Proposition: If *X* and *Y* are independent, Cov(X, Y) = 0.

$$E(XY) = \sum_{S_X} \sum_{S_Y} xyf(x, y)$$

$$= \sum_{S_X} \sum_{S_Y} xyf_X(x)f_Y(y)$$

$$= \sum_{S_X} xf_X(x) \sum_{S_Y} yf_Y(y)$$

$$= \mu_X \mu_Y$$

Thus, we have

$$Cov(X, Y) = E(XY) - \mu_X \mu_Y = 0$$

If Cov(X, Y) = 0, are X and Y necessarily independent?

Example: Let *X* and *Y* have the joint PMF

$$f(x,y) = \frac{1}{3}, \quad (x,y) = (0,1), (1,0), (2,1).$$

It is easy to get the marginal PMF of X and Y:

$$f_X(x) = \frac{1}{3}, \ x = 0, 1, 2; \quad f_Y(y) = \begin{cases} \frac{1}{3}, \ y = 0 \\ \frac{2}{3}, \ y = 1 \end{cases}$$

Thus, $\mu_X = 1$ amd $\mu_Y = 2/3$. Then

$$Cov(X, Y) = E(XY) - \mu_X \mu_Y$$

$$= (0)(1)\frac{1}{3} + (1)(0)\frac{1}{3} + (2)(1)\frac{1}{3} - (1)\frac{2}{3}$$

$$= 0$$

It is obvious that $f(x, y) \neq f_X(x)f_Y(y)$. Thus, X and Y are dependent.