Stat 230 Introductory Statistics Joint Distribution

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Joint Distributions

- So far, we have mostly looked at univariate probability.
- ► That is, distributions of a single random variable.
- Now we jump into multiple variables (two to start) .

Discrete: Joint

Definition 5.1 (Joint Probability Mass Function)

Let X and Y be discrete random variables. The joint PMF of X and Y describes how much mass is placed on each possible pair of values (x, y).

$$p(x,y) = P([X=x] \cap [Y=y])$$

Definition 5.2 (Joint Probability Function)

Let A be a set consisting of (x, y) pairs. Then the probability that a random pair (X, Y) lies in A is obtained by

$$P[(X,Y) \in A] = \sum_{(x,y) \in A} p(x,y)$$

Discrete: Joint

Definition 5.3 (Marginal Pability Mass Function)

The marginal PMFs of X and Y, called $p_X(x)$ and $p_Y(y)$, can be found by

$$p_X(x) = \sum_{y} p(x, y)$$
 $p_Y(y) = \sum_{x} p(x, y)$

Theorem 5.4 (Joint Probability Mass Function)

For p(x,y) to be a joint PMF, then $p(x,y) \geq 0$ and $\sum_{x} \sum_{y} p(x,y) = 1$ must hold.

Discrete: Joint PMF

Example 5.1

Suppose that the random variable X can take only the values 1,2 and 3; that the random variable Y can take only the value 1,2,3 and 4; that the joint pmf of X and Y is as specified in the follow table:

		Y			
		1	2	3	4
	1	0.1	0	0.1	0
Χ	2	0.3	0	0.1	0.2
	3	0	0 0 0.2	0	0

Find the value below:

- 1. p(X = 1, Y = 3)
- **2.** $P((X,Y) \in \{(X,Y)|X \le 2, Y \ge 3\})$
- **3.** P(X = 1)
- **4.** List probability distribution of X
- **5.** $P((X, Y) \in \{(X, Y) | X \le 2, Y \ge 3 \text{ and } X + Y = 5\})$

Discrete: Joint PMF

Definition 5.5

Let X and Y be continuous random variables. The joint PDF for X and Y for any two-dimensional set A is f(x,y) if for any two-dimensional set A

$$P[(X,Y) \in A] = \int_A \int f(x,y) dxdy$$

▶ If A is a rectangle, $\{(x, y) \mid a \le x \le b, c \le y \le d\}$

$$P[(X,Y) \in A] = P(a \le X \le b, c \le Y \le d) = \int_a^b \int_c^d f(x,y) dy dx$$

► From textbook...

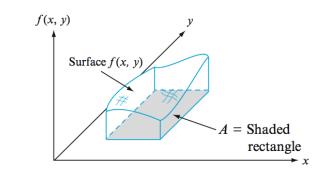


Figure 5.1 $P[(X, Y) \in A] = \text{volume under density surface above } A$

Definition 5.6

Marginal PDFs of X and Y, denoted $f_X(x)$ and $f_Y(y)$, can be found by

$$f_X(x) = \int_{-\infty}^{\infty} f(x, y) dy$$
 $f_Y(y) = \int_{-\infty}^{\infty} f(x, y) dx$

Example 5.2

Let X and Y be two continuous random variables defined over the unit square and with joint PDF $f(x,y)=c(x^2+y^2)$.

- **1.** Find *c*.
- **2.** Find the marginal PDF of X.

Independence

- ► We have discussed independence of events.
- ▶ We learned, for instance, that if A and B are independent events, then $P(A \cap B) = P(A)P(B)$.
- Let's now extend this idea to independence among probability distributions.

Independence

► The random variables X and Y are said to be independent if for any two sets of real numbers A and B,

$$P(X \in A, Y \in B) = P\{X \in A\}P\{Y \in B\}$$

▶ In other words, X and Y are independent if , for all A and B, the events $E_A = \{X \in A\}$ and $F_B = \{Y \in B\}$ are independent.

Independence

Theorem 5.7

When X and Y are two discrete random variables, the condition of independence is equivalent to

$$p(x,y) = p_X(x)p_Y(y)$$

In the jointly continuous case the condition of independent is equibalent to

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

for all x, y

▶ If these properties do not hold, then X and Y are dependent.

Examples

Example 5.3

Let X and Y be two continuous random variables defined over the unit square and with joint PDF $f(x,y)=\frac{3}{2}(x^2+y^2)$. Are X and Y independent?

Example 5.4

Let X and Y be two discrete random variables with the following joint probability distribution:

$$p(x,y) = \begin{cases} \frac{3^{x}2^{y}e^{-5}}{x!y!} & x = 0,1,... & y = 0,1,... \\ 0 & \text{otherwise} \end{cases}$$

Are X and Y independent?

Expected Values for Joint variables

Definition 5.8 (Joint Distribution)

When h is a function of two variables

▶ If X and Y are discrete random variables with joint probability mass function p(x, y), then

$$\mathbb{E}[h(X,Y)] = \sum_{x} \sum_{y} h(x,y) p(x,y)$$

If X and Y are continuous random variables with joint probability density function f(x, y), then

$$\mathbb{E}[h(X,Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(x,y)f(x,y)dxdy$$

Expected Values for Joint variables

Example 5.5

Consider X and Y are discrete random variables with joint distribution p(x,y). If X and Y are independent, find $\mathbb{E}[XY]$.

Covariance

Definition 5.9

The covariance between random variables X and Y is defined by

$$Cov(X, Y) = \mathbb{E}[(X - \mu_x)(Y - \mu_y)] = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y]$$

- It is a measure of how linearly associated two variables are. Negative covariance means that an increase in one variable results in a decrease of the other. Positive covariance means that the variables increase/decrease together.
- ▶ If X and Y are independent, this implies Cov(X, Y) = 0. THE REVERSE IS NOT NECESSARILY TRUE!

Variance

Theorem 5.10

Let a, b and c be constants, then:

$$Var[X + Y] = Var[X] + Var[Y] + 2Cov(X, Y)$$
$$Var[X - Y] = Var[X] + Var[Y] - 2Cov(X, Y)$$

Theorem 5.11

If X and Y are independent then Cov(X, Y) = 0 and so

$$\mathbb{V}$$
ar[$X \pm Y$] = \mathbb{V} ar[X] + \mathbb{V} ar[Y].

Covariance

Theorem 5.12

for a and b constants:

$$Cov(aX + bY, Z) = aCov(X, Z) + bCov(Y, Z)$$

- Note: covariance needs context. If you measure a covariance of -150,348, is this a strong negative relationship?
- ▶ That will depend on the scales of X and Y...
- Hence, more often we would like correlation, which is a standardized measure.

Correlation

► The correlation between two random variables X and Y is

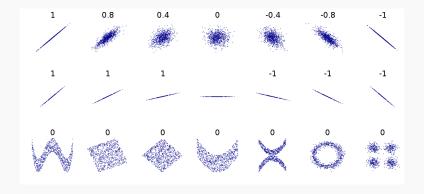
$$\rho = \frac{\mathsf{Cov}(X, Y)}{\sigma_X \sigma_Y}$$

Correlation is bounded:

$$-1 \le \rho \le 1$$

▶ If X and Y independent, then $\rho = 0$. THE REVERSE IS NOT NECESSARILY TRUE!

Correlation



upload.wikimedia.org/wikipedia/commons/d/d4/Correlation_examples2.svg