Chapter 5 Joint Probability Distributions and Random Samples:

5.1 Jointly Distributed RVs:

Two discrete random variables.

Let X and Y be two discrete RVs on the same sample space S.

The joint probability mass function (pmf) p(x,y) is defined

$$p(x,y) = P(X = x \text{ and } Y = y)$$

Like before, $p(x,y) \ge 0$, and $\mathcal{E} \mathcal{E} p(x,y) = 1$.

Example 1: Let X be the number of cats at a randomly selected

residence in a particular city. Let Y be the number of dogs at a

randomly selected residence in that city. The joint pmf is given in the

table:

			y		
P(x,y)		0	l	2	$P_{\times}(x)$
*	0	.3	. 05	.1	,45
	l	. 15	. 1	٠١	. 35
	2	.05	.05	.05	.15
	3	.05	0	0	.05
Py (7)		.55	.2	. 25	-

Find
$$P(X=| and Y=2) = 1$$

 $P(X=Y) = .3 + .1 + .05 = [.45]$ $(P(X=Y=0) + P(X=Y=1) + P(X=Y=2))$
 $P(X=0) = .3 + .05 + .1 = [.45]$ $(P(X=0 \text{ and } Y=0) + P(X=0 \text{ and } Y=1) + P(X=0 \text{ and } Y=2))$

The marginal probability mass function (pmf) of X, $P_X(x)$ is given by

$$p_X(x) = \sum_{y: p(x,y) > 0} p(x,y)$$
 for each possible x.

(add row or column)

Similarly, the marginal pmf of Y is

$$P_{y}(y) = \sum_{x: p(x,y) > 0} P(x,y)$$
 for each possible y.

Example 2: Find the marginal pmfs for Example 1.

Two Continuous RUs:

Let X and Y be continuous RVs. A joint probability density function (pdf) is a function f(x,y) such that for any two-dimensional set A, $P((X,Y) \in A) = \iint\limits_A f(x,y) \ dx dy$

In particular $P(a \le X \le b \text{ and } c \le Y \le d) = \int_{a}^{b} \int_{c}^{d} f(x,y) dy dx$

As before, $f(x,y) \ge 0$ for all x,y and $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y) dx dy = 1$

Example 3: Let X and Y have joint pdf $f(x,y) = \begin{cases} xy, & 0 < x < 1 \text{ and } 0 < y < 2 \\ 0, & \text{otherwise} \end{cases}$

Find $P(\frac{1}{4} \le X \le \frac{1}{2} \text{ and } Y \le 1)$.

 $P(\frac{1}{4} \leq X \leq \frac{1}{4} \text{ and } Y \leq 1) = \int_{0}^{1} \int_{\frac{1}{4}}^{\frac{1}{4}} xy \, dx \, dy$

 $= \int_{0}^{1} \frac{1}{2} y x^{2} \Big|_{X=\frac{1}{4}}^{X=\frac{1}{2}} dy = \int_{0}^{1} \left(\frac{1}{8} y - \frac{1}{32} y\right) dy = \int_{0}^{1} \frac{3}{32} y dy$ $= \frac{3}{32} \cdot \frac{1}{2} y^{2} \Big|_{0}^{1} = \frac{3}{32} \cdot \frac{1}{2} = \left[\frac{3}{64}\right]$

The marginal probability density functions of X and Y are

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

Example 4: Let X and Y have joint pdf $f(x,y) = \begin{cases} xy, & 0 < x < 1 \text{ and } 0 < y < 2 \\ 0, & \text{otherwise} \end{cases}$

Find the marginal pdfs $f_X(x)$ and $f_Y(y)$

$$f_{x}(x) = \int_{0}^{2} xy \, dy = x \cdot \frac{y^{2}}{2} \Big|_{y=0}^{y=2} = x \cdot \frac{2^{2}}{2} - x \cdot \frac{0^{2}}{2} = 2x, \quad 0 < x < 1$$

$$f_{y}(y) = \int_{0}^{1} xy \, dx = y \cdot \frac{x^{2}}{2} \Big|_{x=0}^{x=1} = y \cdot \frac{1}{2} - 0 = \frac{y}{2}, \quad 0 < y < 2$$

iterated integral

Independent Random Variables

If X, Y are discrete RVs, then X and Y are independent if and only if $p(x,y) = p_X(x) \cdot p_Y(y) \qquad \text{for all } x,y.$

If X, Y are continuous, then X and Y are independent if and only if $f(x,y) = f_X(x) \cdot f_Y(y) \quad \text{for all } x,y.$

If X, Y are not independent, then they are dependent.

Example 5: Are X and Y in example 1 independent or dependent? Why?

Dependent since $P(x,y) \neq P_{\times}(x) \cdot P_{Y}(y)$. For example $P(X=3,Y=2) = 0 \quad \text{but}$ $P(X=3) \cdot P(Y=2) = (0.05)(0.25)$ So $P(3,2) \neq P_{\times}(3) \cdot P_{Y}(2)$.

Example 6: Let $X \sim Exp(5)$ and $Y \sim Exp(2)$ be independent.

What is their joint pdf f(x,y)?

What is P(X < 3 and Y > 4)?

$$f_X(x) = 5e^{-5x}$$
, x=0

$$f_{y}(y) = 2e^{-2y}, \quad y \ge 0$$

OR

$$f(x,y) = f_X(x) \cdot f_Y(y) = 10e^{-5x-2y}$$
 $x \ge 0$ and $y \ge 0$

$$P(X < 3 \text{ and } Y > 4) = \int_{4}^{\infty} \int_{0}^{3} 10e^{-5x} e^{-2y} dx dy = \dots$$

 $P(X < 3 \text{ and } Y > Y) = P(X < 3) \cdot P(Y > Y) = F_X(3) \cdot (1 - F_Y(Y))$ independent $(1 - 5 \cdot 3) - 2 \cdot 3$

$$= (1 - e^{-5.3}) \cdot e^{-2.4}$$

$$= (1 - e^{-15}) \cdot e^{-8} \approx 0.000335$$

More than 2 RVs:

These ideas also work if we have several RVs.

If X1, ..., Xn are discrete, their joint pmf is

$$p(x_1, ..., x_n) = P(X_1 = x_1, ..., X_n = x_n)$$

If $X_1, ..., X_n$ are jointly continuous with pdf $f(x_1, ..., x_n)$ then

$$P(a_i \in X_i \subseteq b_1, \dots, a_n \subseteq X_n \subseteq b_n) = \int_{a_i}^{b_i} \dots \int_{a_n}^{b_n} f(x_i, \dots, x_n) dx_n \dots dx_1$$

The RVs $X_1,...,X_n$ are all independent if and only if for every subset of them (every pair, every triple, ...) the joint pmf/pdf is the product of the marginal pmfs/pdfs.

The Multinomial Distribution

Review: If X is a Binomial RV with parameters n and p, this means n trials with probability of success p X is counting the number of successes.

For the multinomial distribution, we have n independent trials, each of which has r possible outcomes (e.g. r colors). Each trial has the same probabilities: p_1 to be type 1, p_2 to be type 2, ... p_r to be type r. $p_1 + p_2 + ... + p_r = 1$ We count how many of each type we get.

$$\rho(x_1, x_2, ..., x_r) = \frac{n!}{x_1! x_2! \dots x_r!} \rho_1^{x_1} \cdot \rho_2^{x_2} \dots \rho_r^{x_r}$$

multinomial coefficient

Example 7: A grab-bag contains 10 small candies of 3 different types A, B, C.

Each candy has a 40% chance to be type A, a 50% chance to be type B, and a 10% chance to be type C.

What is the probability a randomly selected bag has 3 As, 5 Bs, and 2 Cs?

$$\frac{10!}{3! \ 5! \ 2!} \cdot (.4)^{3} (.5)^{5} (.1)^{2}$$

5.2 Expected Values, Covariance, and Correlation:

In Chapters 3-4, we saw how to calculate E[h(X)] for functions h. We can do similar calculations with multiple RVs.

Let X,y be discrete with joint pmf p(x,y). Then

$$\mathbb{E}\big[h(X,y)\big] = \sum_{x} \sum_{y} h(x,y) \cdot \rho(x,y).$$

If instead X,y are jointly continuous with joint pdf f(x,y), then $\mathbb{E}[h(X,Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(x,y) f(x,y) dx dy.$

Example 1: Two friends play a game. Each takes a turn and scores either

O, I, or 2 points. Let X be the points scored by the first friend and Y be the points scored by the second friend. The joint pmf for X, Y is given in

$$E[|X-Y|] = O(0.1) + I(0.05) + 2(0.15) + ... + O(0.15)$$

$$= O(0.1+0.1+0.15) + I(.2+.15+.05+.1) + 2(0+0.15)$$

$$= O+0.5+0.3 = \boxed{0.8}$$

Example 2: On a certain exam, two subscores are given.

For a randomly selected test-taker, let X and Y be the subscores they receive.

The joint pdf for X, Y is $f(x,y) = \begin{cases} 4xy, & 0 < x < 1, & 0 < y < 1 \\ 0, & otherwise \end{cases}$

What is E[XY]? $E[XY] = \int_0^1 \int_0^1 xy \cdot 4xy \, dx \, dy$ $= 4 \int_0^1 y^2 \int_0^1 x^2 \, dx \, dy = 4 \int_0^1 x^2 \, dx \cdot \int_0^1 y^2 \, dy = 4 \cdot \frac{1}{3} \cdot \frac{1}{3} = \frac{4}{9}$ Covariance: When we have multiple RVs, we might wonder how strongly related they are.

If X,Y are RUs with means μ_X and μ_Y , then the Covariance of X and Y is

$$Cov(X,Y) = E[(X-\mu_x)(Y-\mu_y)]$$

$$\underline{\text{Note}}: \quad \text{Cov}(X,X) = E\Big[\big(X-\mu_X\big)\cdot \big(X-\mu_X\big)\Big] = E\Big[\big(X-\mu_X\big)^2\Big] = \text{Var}(X)$$

Like with variance, there is a shortcut formula for covariance

$$Cov(X,Y) = E[XY] - E[X]E[Y]$$

Most of the time this is easier to use.

Example 3: Let X, y be as in Example 1: Find Cov(X, Y)

$$Cov(X,Y) = E[XY] - E[X] \cdot E[Y]$$

marginal pmf for y E[XY] = 0.0.0.1 + 0.1.0.05 + 0.2.0.15 + 1.0.0.2 + 2.0.0+ 1-1.0.1 + 1.2.0.1 + 2.1.0.15 + 2.2.0.15

$$= 0.1 + 0.2 + 0.3 + 0.6 = 1.2$$

$$E[X] = 0.0.3 + 1.0.4 + 2.0.3 = 1$$

 $E[Y] = 0.0.3 + 1.0.3 + 2.0.4 = 1.1$

$$C_{ov}(X, Y) = E[XY] - E[X]E[Y]$$

= 1.2 - 1(1.1) = [0.1]

Example 4: Let X, Y be as in Example 2. Find Cov (X, Y).

The joint pdf for X, Y is $f(x,y) = \begin{cases} 4xy, & 0 < x < 1, & 0 < y < 1 \\ 0, & \text{otherwise} \end{cases}$

We found $E[XY] = \frac{4}{9}$.

 $Cov(X,Y) = E[XY] - E[X] \cdot E[Y]$

$$E[X] = \int_{0}^{1} \int_{0}^{1} x \cdot 4xy \, dx \, dy$$

$$E[X] = \int_0^1 \int_0^1 x \cdot 4xy \, dx \, dy$$

$$E[XY] = \int_0^1 \int_0^1 xy \cdot 4xy \, dx \, dy = \frac{4}{9}$$

$$= \int_{0}^{1} \frac{4y}{3} \cdot \frac{x^{3}}{3} \Big|_{x=0}^{x=1} dy = \int_{0}^{1} \frac{4y}{3} \cdot \frac{1}{3} dy = \frac{4}{3} \cdot \frac{4y}{3} = \frac{4}{3} \cdot \frac{1}{3} = \frac{4}{3} \cdot \frac{1}{3} = \frac{2}{3}$$

 $E[Y] = \int_{0}^{1} \int_{1}^{1} y \cdot 4xy \, dy \, dx = \frac{2}{3}$. $Cov(X, Y) = \frac{4}{9} - \frac{2}{3} \cdot \frac{2}{3} = 0$

Correlation

Covariance helps us understand how two random variables are related, but the covariance value depends greatly on the units of measurement.

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

To address this, we use correlation instead.

The correlation coefficient of X and Y is

$$Corr(X,Y) = \rho_{X,Y} = \frac{Cov(X,Y)}{\sigma_X \cdot \sigma_Y}$$

Example 5: Say X and Y are RVs with these properties:

$$E[X] = 4 \qquad Var(X) = 25 = \overline{U_X}^2 \qquad \overline{U_X} = 5$$

$$E[Y] = -2 \qquad Var(Y) = 9 = \overline{U_Y}^2 \qquad \overline{U_Y} = 3$$

$$E[XY] = -1$$

What is
$$Corr(X,Y)$$
? $Cov(X,Y) = E[XY] - E[X]E[Y]$

$$Corr(X,Y) = \frac{Cov(X,Y)}{\nabla x \cdot \nabla y} = \frac{-1 - (-2)(4)}{5 \cdot 3} = \frac{7}{15}$$

Some Correlation Facts:

- If a and c are both positive or both negative, then Corr(aX+b, cY+d) = Corr(X, Y)
- For any RVs X, y (where E[x], E[Y], E[XY] exist and are finite), $-| \leq \rho_{X,Y} \leq | .$
- * X and Y are uncorrelated if $p_{x,y} = 0$.
- If X,Y are independent, then $P_{X,Y} = 0$. But $P_{X,Y} = 0$ does not imply X,Y are independent.
- $\rho = 1$ or -1 if and only if Y = aX + b for real numbers a and b with $a \neq 0$