Sets 18 and 19: Section 5.4 (discrete parts only!) Jointly distributed random variables

Joint probability distributions associated with a vector rv  $(X_1, \ldots, X_k)$ .

Example: a trivariate discrete distribution described by the pmf p(x, y, z)

	X=1	X=2	X=3	
Y=1	0.10	0.20	0.00	Z=5
Y=2	0.00	0.05	0.05	

The marginal pmf  $p(x) = \Sigma_{y,z} p(x, y, z)$ 

The concept of independence applies to rv's.

Definition: Random variables are independent if their joint pmfs factor into their marginal pmfs.

Example: Consider the bivariate pmf given by

$$\begin{array}{c|cccc} & X=1 & X=2 \\ \hline Y=1 & 0.4 & 0.2 \\ \hline Y=2 & 0.1 & 0.3 \\ \end{array}$$

(a) Obtain the marginal pmf for X.

- (b) Obtain the marginal pmf for Y.
- (c) Are X and Y independent?

Proposition: In the discrete case,

$$E[g(X_1,\ldots,X_k)] = \sum_{x_1} \cdots \sum_{x_k} g(x_1,\ldots x_k) p(x_1,\ldots x_k)$$

Example: An instructor gives a quiz with two parts. For a randomly selected student, let X and Y be the scores obtained on the two parts respectively. The joint pmf p(x,y) of X and Y:

p(x,y)	y=0	y=5	y=10	y=15
x=0	0.02	0.06	0.02	0.10
x=5	0.04	0.15	0.20	0.10
x=10	0.01	0.15	0.14	0.01

- (a) What is the expected total score E(X + Y)?
- (b) What is the expected maximum score from the two parts?
- (c) Are X and Y independent?
- (d) Obtain  $P(Y = 10 | X \ge 5)$ .

Example: We return to the discrete distribution described by the pmf p(x,y,z)

	X=1	X=2	X=3	
Y=1	0.10	0.20	0.00	Z=5
Y=2	0.00	0.05	0.05	

Obtain E(g) where g(x, y, z) = xz.

Problem: The number of customers waiting for the gift-wrap service at department store is a rv X taking possible values 0, 1, 2, 3 and 4 with corresponding probabilities 0.10, 0.20, 0.30, 0.25 and 0.15. A random customer has 1, 2 or 3 packages for wrapping with probabilities 0.6, 0.3 and 0.1 respectively. Let Y be the total number of packages to be wrapped by customers waiting in line.

- (a) **Determine** P(X = 3, Y = 3).
- (b) Determine P(X = 4, Y = 11).

Omit this example

Definition: The *covariance* between the rvs X and Y is given by

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

## Interpretation:

- positive covariance
  - large x's occur with large y's
  - small x's occur with small y's
- negative covariance
  - large x's occur with small y's
  - small x's occur with large y's

Correlation is the scaled and preferred version of covariance.

Definition: The *correlation* between the rvs X and Y is given by

$$\rho = \operatorname{Corr}(X, Y) = \frac{\operatorname{Cov}(X, Y)}{\sqrt{\operatorname{Var}(X)}\sqrt{\operatorname{Var}(Y)}}$$

Notes:

- $-1 \leq \operatorname{Corr}(X, Y) \leq 1$
- $\rho$  is the population analogue of r
- if a > 0, then Corr(X, aX + b) = 1
- if a < 0, then Corr(X, aX + b) = -1

Example: Obtain the correlation between X and Y where the joint pmf of X and Y is:

	X=1	X=2	X=3
Y=1	0.1	0.2	0.3
Y=2	0.0	0.2	0.2

Proposition: If X and Y are independent, then

$$Cov(X, Y) = 0$$

In addition, Corr(X, Y) = 0 provided Var(X) and Var(Y) are nonzero. The converse is not true.

Recall that correlation does not imply causation.

**Proposition:** Var(X + Y) = Var(X) + Var(Y) + 2Cov(X, Y)

Proposition: More generally,

$$Var(aX + bY + c) = a^{2}Var(X) + b^{2}Var(Y) + 2abCov(X, Y)$$

Proposition: Even more generally,

$$\operatorname{Var}\left(\sum_{i=1}^{n} a_{i}X_{i} + c\right) = \sum_{i=1}^{n} a_{i}^{2}\operatorname{Var}(X_{i}) + 2\sum_{i < j} a_{i}a_{j}\operatorname{Cov}(X_{i}, X_{j})$$
$$\operatorname{E}\left(\sum_{i=1}^{n} a_{i}X_{i} + c\right)c \Rightarrow \sum_{i=1}^{n} a_{i}\operatorname{E}(X_{i})$$

Here is a useful result.

Corollary: Suppose that the rv's  $X_1, \ldots, X_n$  are a *random sample*. In other words, the X's are independent and arise from a common distribution with mean  $\mu$  and variance  $\sigma^2$ . Then the sample mean has the following properties:

- $E(\bar{X}) = \mu$
- $\operatorname{Var}(\bar{X}) = \sigma^2/n$