Conditional Expectations (Section 5.11)

Conditional distributions can be used in the same way unconditional distributions are used. For example, conditional distributions may be used to compute conditional expectations.

Definition 5.13: Conditional Expectations

If Y_1 and Y_2 are two random variables and $g(Y_1)$ is a function of Y_1 , then the **conditional** expectation of $g(Y_1)$ given that $Y_2 = y_2$ is:

$$E[|g(Y_1)|| Y_2 = y_2] = \begin{cases} \sum_{\substack{all \ y_1}} g(y_1) \times p(y_1|y_2) & \text{; if } Y_1 \text{ and } Y_2 \text{ are DISCRETE} \\ \int_{-\infty}^{\infty} g(y_1) \times f(y_1|y_2) dy_1 & \text{; if } Y_1 \text{ and } Y_2 \text{ are CONTINUOUS} \end{cases}$$

In particular, the **conditional mean** of Y_1 given that $Y_2 = y_2$ is denoted by and computed using

$$\mu_{Y_1|Y_2} = E(Y_1|Y_2 = y_2)$$

and the **conditional variance** of Y_1 given that $Y_2 = y_2$ is denoted by and computed as

$$Var(Y_1| Y_2 = y_2) = E[(Y_1 - \mu_{Y_1|Y_2})^2| Y_2 = y_2]$$

Further, the shortcut formula for $Var(Y_1|Y_2=y_2)$:

$$Var[Y_1 \mid Y_2 = y_2] = E[Y_1^2 \mid Y_2 = y_2] - (\mu_{Y_1 \mid Y_2})^2$$

Example 7: Consider the joint pdf

$$f_{Y_1,Y_2}(y_1,y_2) = e^{-y_2}$$
; $0 < y_1 < y_2 < \infty$

Previously, we showed the conditional distribution of $Y_1 \mid Y_2$ is

Find
$$E(Y_1 | Y_2 = y_2)$$
.

Example 6 Contd.: Let Y_1 denote the number of luxury cars sold on a given day and let Y_2 denote the number of extended warranties sold.

Find the expected number of warranties sold if only 1 car was sold on a given day. That is, find

In example 6, we found that conditional pmf of $Y_2 | Y_1 = 1$ is given by

Example 8: Let Y_1 and Y_2 have the following joint pmf.

$$p_{Y_1,Y_2}(y_1,y_2) = \frac{y_1 + y_2}{32}$$
 ; $y_1 = 1,2$; $y_2 = 1,2,3,4$

Find $E(Y_2^2 | Y_1)$.

Conditional expectations lend themselves to other useful results, such as finding the expected values and variances of univariate random variables.

Theorem 5.14:

If Y_1 and Y_2 are two random variables, then

$$E(Y_1) = E[E(Y_1 | Y_2)]$$
 and $E(Y_2) = E[E(Y_2 | Y_1)]$

Proof:

Let Y_1 and Y_2 be jointly distributed **discrete** random variables.

Example 7 Continued: Consider the joint pdf

$$f_{Y_1,Y_2}(y_1,y_2) = e^{-y_2}$$
; $0 < y_1 < y_2 < \infty$

Previously, we mentioned that $f_2(y_2) =$

Also, we showed, $E(Y_1|Y_2=y_2) =$

Compute $E(Y_1)$ using $E(Y_1|Y_2=y_2)$.

Example 5 Continued: Consider the joint pmf

$$p_{Y_1,Y_2}(y_1,y_2) = {y_2 \choose y_1} p^{y_1} (1-p)^{(y_2-y_1)} \left(\frac{e^{-\lambda} \lambda^{y_2}}{y_2!}\right) ; y_2 = 0,1,...; y_1 = 0,1,...,y_2$$

Find $E(Y_1)$ using $E[E(Y_1 | Y_2)]$?

Theorem 5.15:

If Y_1 and Y_2 are two random variables, then

$$E[Var(Y_1 | Y_2)] + Var[E(Y_1 | Y_2)] = Var(Y_1)$$

Proof:

Example 9 : (Problem 5.153) Suppose the (Y_1) number of eggs laid by a certain insect has a Poisson distribution with mean λ . The probability that any one egg hatches is p . Assume the eggs hatch independently of one another. What do we know?
Let $Y_2 =$ the number of eggs that hatch. Then $Y_2 \mid Y_1$
(a) Find the expected value of Y_2 , the total number of eggs that hatch.
(b) Find the variance of Y_2 .

Covariance and Correlation (Sections 5.7 & 5.8)

If two random variables are not independent, we are often interested in finding their conditional distributions. However, we are often also interested in quantifying the strength of the relationship between them.

For example, we could quantify the strength of the relationship between a randomly chosen person's height and weight or the strength of the relationship between a randomly chosen person's height and GPA.

We would expect the relationship between a randomly chosen person's **height and weight** would be much _____ than that between a randomly chosen person's **height and GPA**. Covariance and correlation are two commonly used numerical measures of a <u>linear</u> relationship between two random variables.

- Covariance described only the <u>nature (or direction)</u> of a <u>linear</u> relationship between two random variables.
- Correlation describes both nature and strength of a linear relationship between two random variables.

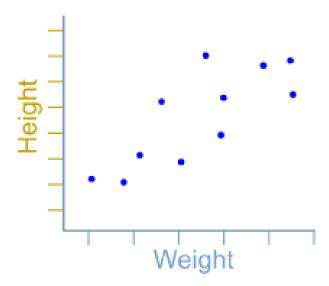
Definition 5.10 and Theorem 5.10: (Covariance)

Let Y_1 and Y_2 be jointly distributed random variables such that $E(Y_1) = \mu_{Y_1}$, $Var(Y_1) = \sigma_{Y_1}^2$,

$$E(Y_2) = \mu_{Y_2}$$
, and $Var(Y_2) = \sigma_{Y_2}^2$.

The **covariance** between Y_1 and Y_2 is

$$Cov(Y_1, Y_2) = E[(Y_1 - \mu_{Y_1})(Y_2 - \mu_{Y_2})] = E(Y_1Y_2) - [E(Y_1)E(Y_2)]$$



Correlation:

$$Corr(Y_1, Y_2) = \rho_{Y_1Y_2} = \frac{Cov(Y_1, Y_2)}{\sigma_{Y_1}\sigma_{Y_2}}$$

Note: $-1 \le \rho_{Y_1Y_2} \le 1$

Note: $Cov(Y_1, Y_2) = Cov(Y_2, Y_1).$

What is $Cov(Y_1, Y_1)$?

Theorem 5.11:

If Y_1 and Y_2 are independent random variables, then

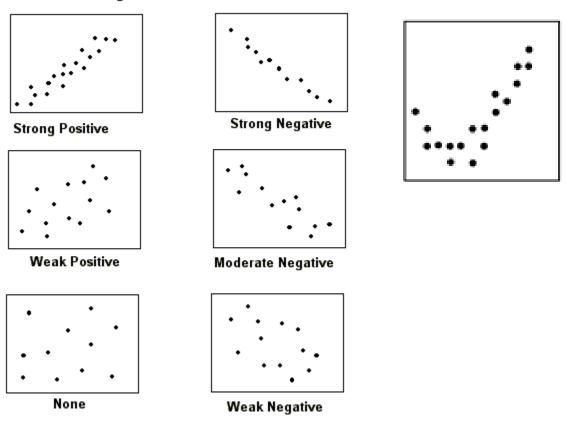
$$Cov(Y_1, Y_2) = 0$$

because $E(Y_1Y_2) - [E(Y_1) E(Y_2)] = E(Y_1) E(Y_2) - [E(Y_1) E(Y_2)]$

Thus, independent random variables must be uncorrelated.

However, the **converse** is **not** true. That is, **if the covariance** between two random variables **is zero**, **this does necessarily imply they are independent**.

Degree of Correlation



Covariance is also useful when calculating the variance of linear functions of random variables.

Theorem 5.12:

If Y_1 and Y_2 are jointly distributed random variables, then

$$E(aY_1 + bY_2) = a E(Y_1) + b E(Y_2)$$

$$Var(aY_1 + bY_2) = a^2 Var(Y_1) + b^2 Var(Y_2) + 2ab Cov (Y_1, Y_2)$$

If Y_1 and Y_2 are independent random variables, then

$$Var(aY_1 + bY_2) = a^2 Var(Y_1) + b^2 Var(Y_2)$$

Proof:

Suppose Y_1 and Y_2 are jointly distributed random variables such that $E(Y_1)=\mu_{Y_1}$, $Var(Y_1)=\sigma_{Y_1}^2$, $E(Y_2)=\mu_{Y_2}$, and $Var(Y_2)=\sigma_{Y_2}^2$.

Example 5 Continued: Consider the joint pmf

$$p_{Y_1,Y_2}(y_1,y_2) = {y_2 \choose y_1} p^{y_1} (1-p)^{(y_2-y_1)} \left(\frac{e^{-\lambda}\lambda^{y_2}}{y_2!}\right) ; y_2 = 0,1,...; y_1 = 0,1,...,y_2$$

- (a) Find $Corr(Y_1, Y_2)$.
- (b) Find $E(3Y_1 4Y_2)$
- (c) Find $Var(3Y_1 4Y_2)$

What do we know?

Example 11: (Problem 5.102) A firm purchases two types of chemicals. Type I chemical costs \$3 per gallon, whereas type II costs \$5 per gallon.

Let Y_1 be the number of gallons purchased from type I chemical.

The mean and variance for this are 40 and 4, respectively.

Let Y_2 be the number of gallons purchased from type II chemical.

The mean and variance for this are 65 and 8, respectively.

Assume that Y_1 and Y_2 are independent.

Find the mean and standard deviation of total amount of money spent on the two chemicals.

Example 12: (Problem 5.138) Assume that Y denotes the number of bacteria per cubic centimeter in a particular liquid and that Y has a Poisson distribution with parameter λ for a given location.

Further, assume that λ varies from location to location and has a gamma distribution with parameters α and β , where α is a positive integer.

If we randomly select a location, what is the

- (a) expected number of bacteria per cubic centimeter?
- (b) standard deviation of the number of bacteria per cubic centimeter?