

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:

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

This is a function of ONLY Y_2

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

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

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

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

Recall: If Y is a random variable with mean μ and variance σ^2
 $\mu = E(Y)$ and $\sigma^2 = \text{Var}(Y) = E[(Y - \mu)^2] = E(Y^2) - \mu^2$

Example 7: Consider the joint pdf

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

Previously, we showed the conditional distribution of $Y_1 | Y_2$ is $f(y_1 | y_2) = \begin{cases} \frac{1}{y_2} & ; 0 < y_1 < y_2 \\ 0 & ; \text{otherwise} \end{cases}$

Find $E(Y_1 | (Y_2 = y_2))$. Here Y_1 is a function only of y_1 .

$$\begin{aligned} E(Y_1 | (Y_2 = y_2)) &= \int_{-\infty}^{\infty} y_1 f(y_1 | y_2) dy_1 \\ &= \int_0^{y_2} y_1 \left(\frac{1}{y_2}\right) dy_1 = \underline{\underline{\frac{y_2}{2}}} \end{aligned}$$

$$\Rightarrow E(Y_1 | Y_2 = 5) = \underline{\underline{\frac{5}{2}}}$$

$$\text{Let } E(Y_1^2 | (Y_2 = y_2)) = \int_{-\infty}^{\infty} y_1^2 f(y_1 | y_2) dy_1$$

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.

$$Y_1 = 1$$

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

$$E[Y_2 | (Y_1=1)]$$

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

$$p(Y_2 | (Y_1=1)) = \begin{cases} \frac{1}{3} & ; Y_2=0 \\ \frac{2}{3} & ; Y_2=1 \\ 0 & ; \text{otherwise} \end{cases}$$

$$\begin{aligned} E(Y_2 | (Y_1=1)) &= \sum_{\text{all } Y_2} [Y_2 p(Y_2 | Y_1=1)] \\ &= (0 \times \frac{1}{3}) + (1 \times \frac{2}{3}) \\ &= \underline{\underline{\frac{2}{3}}} \end{aligned}$$

Y_1	Y_2
0	0 1 2
1	X2 1/6 0
2	

Note that when Y_1 is 1, Y_2 can be 0 or 1. Therefore, $0 < E[Y_2 | Y_1=1] < 1$.

$$E[Y_2^2 | (Y_1=1)] = \sum_{\text{all } Y_2} [Y_2^2 p(Y_2 | Y_1=1)] = (0^2 \times \frac{1}{3}) + (1^2 \times \frac{2}{3}) = \underline{\underline{\frac{2}{3}}}$$

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

$$p_{Y_1, Y_2}(y_1, y_2) = \begin{cases} \frac{y_1 + y_2}{32} & ; y_1 = 1, 2 ; y_2 = 1, 2, 3, 4 \\ 0 & ; \text{otherwise} \end{cases}$$

Find $E(Y_2^2 | Y_1)$. $E[Y_2^2 | Y_1] = \sum_{\text{all } Y_2} [Y_2^2 p(Y_2 | Y_1)]$

These are two Discrete random variables and hence use Σ

First, need to find $p(Y_2 | Y_1) = \frac{p(Y_1, Y_2)}{p(Y_1)}$

Therefore, need to find $p_i(Y_1) = \sum_{\text{all } Y_2} p(Y_1, Y_2) = \sum_{y_2=1}^4 \left(\frac{y_1+y_2}{32} \right) = \frac{4(y_1+10)}{32}$

Then $p(Y_2 | Y_1) = \frac{p(Y_1, Y_2)}{p_i(Y_1)} = \frac{\frac{y_1+y_2}{32}}{\frac{4(y_1+10)}{32}} = \frac{y_1+y_2}{4y_1+10} ; y_1=1, 2, y_2=1, 2, 3, 4$

Finally,

$$E(Y_2^2 | Y_1) = \sum_{y_2=1}^4 \left[Y_2^2 \left(\frac{y_1+y_2}{4y_1+10} \right) \right] = \frac{30y_1+100}{4y_1+10} = \underline{\underline{\frac{15y_1+50}{2y_1+5}}}$$

This must be a function of only Y_1 .

In general, $E[g(X_1)] = E[E(g(X_1)|X_2)]$ and $E[g(X_2)] = E[E(g(X_2)|X_1)]$

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

Theorem 5.14: This is true for both Discrete and Continuous variables.

If Y_1 and Y_2 are two random variables, then

$$E(Y_1) = E[E(Y_1|Y_2)] \quad \text{and} \quad E(Y_2) = E[E(Y_2|Y_1)]$$

Proof:

Let Y_1 and Y_2 be jointly distributed discrete random variables.

$$\begin{aligned} E(Y_2) &= \sum_{\text{all } y_1} \sum_{\text{all } y_2} y_2 p(y_1, y_2) \quad \text{by definition of } E[g(Y_2)] \\ &= \sum_{\text{all } y_1} \sum_{\text{all } y_2} [y_2 [P(Y_2|y_1) \times P(y_1)]] \\ &= \sum_{\text{all } y_1} \left\{ P(y_1) \sum_{\text{all } y_2} [y_2 P(Y_2|y_1)] \right\} \\ &= \sum_{\text{all } y_1} [P(y_1) E(Y_2|y_1)] \\ &= E[E(Y_2|Y_1)]. \end{aligned}$$

* Note that $E(Y_2|Y_1)$ is a function of ONLY y_1 . Therefore, $g(y_1) = E(Y_2|Y_1)$.

Example 7 Continued: Consider the joint pdf

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

Previously, we mentioned that $f_2(y_2) = y_2 \bar{e}^{y_2}; \quad 0 < y_2 < \infty$ and zero otherwise

$$\text{Also, we showed, } E(Y_1|Y_2=y_2) = \frac{y_2}{2}$$

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

$$\text{From Theorem 5.14, } E(Y_1) = E[E(Y_1|Y_2)]$$

$$\begin{aligned} &= E\left[\frac{y_2}{2}\right] \\ &= \frac{1}{2} E(Y_2) \\ &= \frac{1}{2} \int_{-\infty}^{\infty} y_2 f_2(y_2) dy_2 \end{aligned}$$

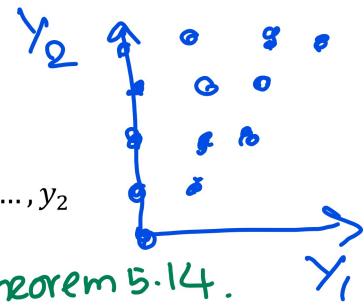
$$= \frac{1}{2} \int_0^{\infty} y_2 (y_2 \bar{e}^{y_2}) dy_2$$

$$\stackrel{?}{=} 1$$

Recall:
For any constant k ,
 $E(kY) = kE(Y)$.

To confirm this answer,
do $E(Y_1) = \int_{-\infty}^{\infty} y_1 f_1(y_1) dy_1$,

$$\text{where } f_1(y_1) = \bar{e}^{y_1}; \quad 0 < y_1 < \infty.$$



Example 5 Continued: Consider the joint pmf

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

Find $E(Y_1)$ using $E[E(Y_1 | Y_2)]$? $E(Y_1) = E[E(Y_1 | Y_2)]$ from Theorem 5.14.
Since we previously found $Y_1 | Y_2$ has a Binomial (y_2, p) we know $E(Y_1 | Y_2) = y_2 p$.

Therefore, $E(Y_1) = E(y_2 p)$
 $= p E(Y_2)$ because p is a constant

Since we previously found Y_2 has a Poisson (λ) we know $E(Y_2) = \lambda$.

Therefore, $E(Y_1) = p \lambda$.

If you did not know specific distribution of $X_1 | Y_2$ and Y_2 , compute $E(Y_1 | Y_2) = \sum_{all y_1} [y_1 p(y_1 | Y_2)] = y_2 p$ and then

$$\begin{aligned} E(Y_1) &= E[E(Y_1 | Y_2)] \\ &= E(Y_2 p) = p E(Y_2) = p \sum_{all y_2} [y_2 p(y_2)] = p \lambda \end{aligned}$$

Theorem 5.15: This is true for both Discrete and Continuous Variables

If Y_1 and Y_2 are two random variables, then

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

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

Proof:

From Theorem 5.14, $E(Y_1) = E[E(Y_1 | Y_2)]$ (1)

Similarly, $E(Y_1^2) = E[E(Y_1^2 | Y_2)]$ (2)

By definition, $Var(Y) = E(Y^2) - [E(Y)]^2$

similarly, $Var(Y_1 | Y_2) = E(Y_1^2 | Y_2) - [E(Y_1 | Y_2)]^2$

Take expected value on both sides,

$$\begin{aligned} E[Var(Y_1 | Y_2)] &= E\{E(Y_1^2 | Y_2) - [E(Y_1 | Y_2)]^2\} \\ &= E[E(Y_1^2 | Y_2)] - E[E(Y_1 | Y_2)]^2 \end{aligned} \quad (3)$$

Again, apply the definition of variance to $E(Y_1|Y_2)$,

$$\text{Var}[E(Y_1|Y_2)] = E[(E(Y_1|Y_2))^2] - [E[E(Y_1|Y_2)]]^2 \quad (4)$$

Now add equations ③ and ④,

$$\begin{aligned} E[\text{Var}(Y_1|Y_2)] + \text{Var}[E(Y_1|Y_2)] &= E[E(Y^2|Y_2)] - [E[E(Y_1|Y_2)]]^2 \\ &= E(Y_1^2) - [E(Y_1)]^2 \quad \text{substitute from equations ① and ②} \\ &= \text{Var}(Y_1) \end{aligned}$$

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 $Y_2 | Y_1$

(a) Find the expected value of Y_2 , the total number of eggs that hatch.

(b) Find the variance of Y_2 .