

Frequently Asked Questions

1. Write conditional mean of a continuous function $g(X, Y)$ of discrete bivariate random variable.

Answer:

Conditional mean value or expectation of a continuous function $g(X, Y)$ given that $Y=y_j$, is defined by

$$\begin{aligned} E[g(X, Y) | Y = y_j] &= \sum_{i=1}^{\infty} g(x_i, y_j) P(X = x_i | Y = y_j) \\ &= \frac{\sum_{i=1}^{\infty} g(x_i, y_j) P(X = x_i \cap Y = y_j)}{P(Y = y_j)} \end{aligned}$$

2. Define Expectation of Discrete random variable.

Answer:

The conditional expectation of discrete random variable X given $Y=y_j$ is given by,

$$E[X | Y = y_j] = \sum_{i=1}^{\infty} x_i P(X = x_i | Y = y_j)$$

The conditional expectation of discrete random variable Y given $X=x_i$ is given by,

$$E[Y | X = x_i] = \sum_{j=1}^{\infty} y_j P(Y = y_j | X = x_i)$$

3. Give the conditional variance of discrete bivariate random variable.

Answer:

The conditional variance of X given $Y=y_j$ is given by,

$$V[X | Y = y_j] = E[\{X - E(X | Y = y_j)\}^2 | Y = y_j] \text{ and}$$

Conditional variance of Y given $X=x_i$ can be written as

$$V[Y | X = x_i] = E[\{Y - E(Y | X = x_i)\}^2 | X = x_i]$$

4. Write conditional mean of a continuous function $g(X, Y)$ of discrete bivariate random variable.

Answer:

Conditional mean value or expectation of a continuous function $g(X, Y)$ given $Y=y$ is given by,

$$E[g(X, Y) | Y = y] = \int_{-\infty}^{\infty} g(x, y) f_{X|Y}(x | y) dx = \frac{\int_{-\infty}^{\infty} g(x, y) f_{XY}(xy) dx}{f_Y(y)}$$

5. Write the conditional mean of continuous bivariate random variable.

Answer:

The conditional mean of X given $Y=y$ is defined by,

$$E[X | Y = y] = \frac{\int_{-\infty}^{\infty} x f_{XY}(xy) dx}{f_Y(y)} \text{ and } E[Y | X = x] = \frac{\int_{-\infty}^{\infty} y f_{XY}(x, y) dy}{f_X(x)}$$

6. Give conditional variance of continuous bivariate random variable.

Answer:

The conditional variance of X may be defined as,

$$V(X|Y=y) = E\{[X - E(X|Y=y)]^2 | Y=y\}$$

Similarly, the conditional variance of Y is,

$$V(Y|X=x) = E\{[Y - E(Y|X=x)]^2 | X=x\}$$

7. The expected value of X is equal to the expectation of the conditional expectation of X given Y. Symbolically, $E(X) = E\{E(X|Y)\}$ for discrete bivariate random variables.

Answer:

Consider, $E\{E(X|Y)\} = E\{\sum_i x_i P(X=x_i|Y=y_j)\}$

$$\begin{aligned} &= E\left\{\sum_i x_i \frac{P(X = x_i \cap Y = y_j)}{P(Y = y_j)}\right\} = \sum_j \left[\sum_i \left\{ x_i \frac{P(X = x_i \cap Y = y_j)}{P(Y = y_j)} \right\} P(Y = y_j) \right] \\ &= \sum_i \sum_j x_i P(X = x_i \cap Y = y_j) = \sum_i \left[x_i \left\{ \sum_j P(X = x_i \cap Y = y_j) \right\} \right] \\ &= \sum_i x_i P(X = x_i) = E(X) \end{aligned}$$

8. The expected value of X is equal to the expectation of the conditional expectation of X given Y. Symbolically, $E(X) = E\{E(X|Y)\}$ for discrete bivariate random variables.

Answer:

Consider

$$\begin{aligned} E\{E(X|Y)\} &= E\left\{\int_{-\infty}^{\infty} x f(x|y) dx\right\} = E\left\{\int_{-\infty}^{\infty} x \frac{f(x,y)}{f_y(y)} dx\right\} \\ &= \int_{-\infty}^{\infty} \left\{ \int_{-\infty}^{\infty} x \frac{f(x,y)}{f_y(y)} dx \right\} f_y(y) dy = \int_{-\infty}^{\infty} x \left\{ \int_{-\infty}^{\infty} f(x,y) dy \right\} dx \\ &= \int_{-\infty}^{\infty} x f_x(x) dx = E(X) \end{aligned}$$

9. The variance of X can be regarded as consisting of two parts, the expectation of the conditional variance and the variance of the conditional expectation. Symbolically, $V(X) = E[V(X|Y)] + V[E(X|Y)]$

Answer:

Consider $E[V(X|Y)] + V[E(X|Y)]$

$$\begin{aligned} &= E[E(X^2|Y) - \{E(X|Y)\}^2] + E[\{E(X|Y)\}^2] - [E\{E(X|Y)\}]^2 \\ &= E[E(X^2|Y)] - E\{E(X|Y)\}^2 + E\{E(X|Y)\}^2 - [E\{E(X|Y)\}]^2 \\ &= E[E(X^2|Y)] - \{E(X)\}^2 \\ &= E\left\{\sum_i x_i^2 P(X = x_i | Y = y_j)\right\} - \{E(X)\}^2 \\ &= \sum_j \left[\left\{ \sum_i x_i^2 \frac{P(X = x_i \cap Y = y_j)}{P(Y = y_j)} \right\} P(Y = y_j) \right] - \{E(X)\}^2 \\ &= \sum_i \left\{ x_i^2 \sum_j P(X = x_i \cap Y = y_j) \right\} - \{E(X)\}^2 = \sum_i x_i^2 P(X = x_i) - \{E(X)\}^2 \\ &= E(X^2) - \{E(X)\}^2 = V(X). \end{aligned}$$

Hence, the theorem.

10. Let A and B be two mutually exclusive events, then

$$E(X | A \cup B) = \frac{P(A)E(X | A) + P(B)E(X | B)}{P(A \cup B)} \quad \text{Where by definition}$$

$$E(X | A) = \frac{1}{P(A)} \sum_{x_i \in A} x_i P(X = x_i)$$

Answer:

$$E(X | A \cup B) = \frac{1}{P(A \cup B)} \sum_{x_i \in A \cup B} x_i P(X = x_i)$$

Since A and B are mutually exclusive events,

$$\sum_{x_i \in A \cup B} x_i P(X = x_i) = \sum_{x_i \in A} x_i P(X = x_i) + \sum_{x_i \in B} x_i P(X = x_i)$$

$$\therefore E(X | A \cup B) = \frac{1}{P(A \cup B)} [P(A)E(X | A) + P(B)E(X | B)]$$

11. Show that $E(X) = P(A)E(X | A) + P(\bar{A})E(X | \bar{A})$

Answer:

We know that,

$$\therefore E(X | A \cup B) = \frac{1}{P(A \cup B)} [P(A)E(X | A) + P(B)E(X | B)]$$

If we put $B = \bar{A}$ in the above theorem, we get,

$$E(X | A \cup \bar{A}) = \frac{1}{P(A \cup \bar{A})} [P(A)E(X | A) + P(\bar{A})E(X | \bar{A})]$$

$$\Rightarrow E(X) = P(A)E(X | A) + P(\bar{A})E(X | \bar{A})$$

12. Given two variables X and Y with joint density function $f(x,y)$, prove that conditional mean of Y given X coincide with unconditional mean only if X and Y are independent.

Answer:

Conditional mean of Y given X is given by,

$$E(Y | X) = \int_{-\infty}^{\infty} y f(y | x) dy, \text{ where } f(y|x) \text{ is conditional pdf of } Y \text{ given } X=x, \text{ which is given by, } f(y|x) = f(x,y)/f(x)$$

$$\text{Hence, } E(Y | X) = \int_{-\infty}^{\infty} y \left[\frac{f(x,y)}{f(x)} \right] dy \text{ ----- (1)}$$

Unconditional mean of Y is given by,

$$E(Y) = \int_{-\infty}^{\infty} y f(y) dy \text{ ----- (2)}$$

From (1) and (2) we conclude that the conditional mean of Y given X will coincide with unconditional mean of Y only if

$$\frac{f(x,y)}{f(x)} = f(y) \Rightarrow f(x,y) = f(x)f(y).$$

i.e., X and Y are independent.

13. Let $f(x, y) = 8xy$, $0 < x < y < 1$; and zero elsewhere. Find $E(Y|X=x)$, $E(XY|X=x)$, $V(Y|X=x)$.

Answer:

First let us find the marginal pdf of given distribution of X

$$f_x(x) = \int_x^1 f(x, y) dy = 8x \int_x^1 y dy = 4x(1 - x), 0 < x < 1$$

Conditional pdf of Y given X is given by,

$$f_{y|x}(y | x) = \frac{f(x, y)}{f_x(x)} = \frac{2y}{1 - x^2}; 0 < x < y < 1$$

$$E(Y | X = x) = \int_x^1 y \left[\frac{2y}{1 - x^2} \right] dy = \frac{2}{3} \left[\frac{1 - x^3}{1 - x^2} \right] = \frac{2}{3} \left[\frac{1 + x + x^2}{1 + x} \right]$$

$$E(XY | X = x) = xE(Y | X = x) = \frac{2}{3} \frac{x(1 + x + x^2)}{1 + x}$$

To find $V(Y|X=x)$, first let us find the $E(Y^2|X=x)$.

$$E(Y^2 | X = x) = \int_x^1 y^2 \left[\frac{2y}{1 - x^2} \right] dy = \frac{1}{2} \left[\frac{1 - x^4}{1 - x^2} \right] = \frac{1 + x^2}{2}$$

$$\begin{aligned} \therefore V(Y | X = x) &= E(Y^2 | X = x) - [E(Y | X = x)]^2 \\ &= \frac{1 + x^2}{2} - \frac{4}{9} \frac{(1 + x + x^2)^2}{(1 + x)^2} \end{aligned}$$

14. Let $f(x, y) = 21x^2y^3$, $0 < x < y < 1$ and zero elsewhere be the joint pdf of X and Y. Find the conditional mean and variance of X given $Y=y$, $0 < y < 1$.

Answer:

Given $f(x, y) = 21x^2y^3$, $0 < x < y < 1$ and zero elsewhere. Marginal pdf of Y is given by,

$$f_y(y) = \int_0^y f(x, y) dx = 21y^3 \int_0^y x^2 dx = 7y^6$$

Therefore, the conditional pdf of X given Y is given by,

$$f(x | y) = \frac{f(x, y)}{f_y(y)} = \frac{21x^2y^3}{7y^6} = 3 \frac{x^2}{y^3}; 0 < x < y; 0 < y < 1$$

Conditional mean of X is,

$$E(X | Y = y) = \int_0^y xf(x | y) dx = \frac{3}{y^3} \int_0^y x^3 dx = \frac{3y}{4}; 0 < y < 1$$

To find variance, let us find,

$$E(X^2 | Y = y) = \int_0^y x^2 f(x | y) dx = \frac{3}{y^3} \int_0^y x^4 dx = \frac{3}{y^3} \frac{y^5}{5} = \frac{3}{5} y^2; 0 < y < 1$$

$$\therefore V(X|Y=y) = E(X^2|Y=y) - [E(X|Y=y)]^2 = \frac{3}{5} y^2 - \frac{9}{16} y^2 = \frac{3}{80} y^2; 0 < y < 1$$

15. Let X and Y be two random variable each taking three values -1, 0, 1 and having the following joint probability distribution, find $V(Y|X=-1)$

Y \ X	-1	0	1	Total
-1	0	0.1	0.1	0.2
0	0.2	0.2	0.2	0.6
1	0	0.1	0.1	0.2
Total	0.2	0.4	0.4	1.0

Answer:

We know that,

$$V(Y|X=-1) = E(Y^2|X=-1) - [E(Y|X=-1)]^2$$

$$E(Y|X=-1) = \sum_y yP(Y=y, X=-1) = (-1)0 + 0(0.2) + 1(0) = 0$$

$$E(Y^2|X=-1) = \sum_y y^2P(Y=y, X=-1) = (-1)^2 0 + 0^2(0.2) + 1^2(0) = 0$$

$$\therefore V(Y|X=-1) = 0$$