Conditional distributions and expectations

- Suppose that X and Y are discrete random variables.
 - For y such that P(Y = y) > 0, the conditional expectation of g(X, Y) given Y = y, denoted by E(g(X, Y)|Y = y), is defined by

$$E(g(X,Y)|Y=y) = \sum_{x:P(X=x|Y=y)>0} g(x,y)P(X=x|Y=y).$$

- For y such that P(Y = y) > 0, let $p_{X|Y=y}$ be a function defined by $p_{X|Y=y}(x) = P(X = x|Y = y)$ for all $x \in R$, then $p_{X|Y=y}$ is called the conditional PMF of X given Y = y, then

$$E(g(X,Y)|Y=y) = \sum_{x:p_X|Y=y}(x)>0} g(x,y)p_{X|Y=y}(x).$$

That is, E(g(X,Y)|Y = y) is the expectation with respect to the conditional PMF $p_{X|Y=y}$.

- For y such that P(Y = y) > 0, Var(X|Y = y) is the variance with respect to the conditional PMF $p_{X|Y=y}$, that is,

$$Var(X|Y = y) = E[(X - E(X|Y = y))^2|Y = y]$$

- Let h(y) = E(g(X, Y)|Y = y) for $y \in \{y : P(Y = y) > 0\}$, then h(Y) is the conditional expectation of g(X, Y) given Y, denoted by E(g(X, Y)|Y).
- $Var(X|Y) = E[(X E(X|Y))^2|Y].$
- Example 1. Suppose that (X, Y) is a discrete random vector with joint PMF $p_{X,Y}$, where

$$p_{X,Y}(x,y) = \begin{cases} 0.4 & \text{if } (x,y) = (0,2); \\ 0.4 & \text{if } (x,y) = (1,2); \\ 0.2 & \text{if } (x,y) = (4,3); \\ 0 & \text{otherwise.} \end{cases}$$

Find E(X|Y = 2), E(X|Y = 3), Var(X|Y = 2), Var(X|Y = 3), E(X|Y)and Var(X|Y).

Ans. E(X|Y = 2) = 0.5, E(X|Y = 3) = 4, Var(X|Y = 2) = 0.25, Var(X|Y = 3) = 0.

$$E(X|Y) = \begin{cases} 0.5 & \text{if } Y = 2; \\ 4 & \text{if } Y = 3, \\ = & 0.5I_{\{2\}}(Y) + 4I_{\{3\}}(Y). \end{cases}$$

and

$$Var(X|Y) = 0.25I_{\{2\}}(Y).$$

- Suppose that X and Y are random vectors of dimensions k and m respectively. Suppose that (X, Y) has a joint PDF.
 - Suppose that f_Y is a PDF of Y and $R_Y = \{y \in \mathbb{R}^m : f_Y(y) > 0\}$, and for $y \in \mathbb{R}_Y$, h_y is a nonnegative function defined on \mathbb{R}^k such that $\int_{\mathbb{R}^k} h_y(x) dx = 1$, and

$$P((X,Y) \in A \times B) = \int_{A \times B} f_Y(y) h_y(x) d(x,y)$$

for $A \in \mathcal{B}(\mathbb{R}^k)$, $B \in \mathcal{B}(\mathbb{R}^m)$, then we say that $\{h_y : y \in \mathbb{R}_Y\}$ is a version of the conditional PDF of X given Y.

– Suppose that $f_{X,Y}$ is a PDF of (X,Y). For $y \in \mathbb{R}^m$, define

$$f_Y(y) = \int_{R^k} f_{X,Y}(x,y) dx.$$

Let $R_Y = \{y \in R^m : f_Y(y) > 0\}$ and for $y \in R_Y$, define

$$f_{X|Y=y}(x) = \frac{f_{X,Y}(x,y)}{f_Y(y)}$$
(1)

for $x \in \mathbb{R}^k$. Then $\{f_{X|Y=y} : y \in \mathbb{R}_Y\}$ is a version of conditional PDF of X given Y.

– Suppose that $\{f_{X|Y=y} : y \in R_Y\}$ is a version of conditional PDF of X given Y. Then

$$E(g(X,Y)|Y) = \int_{\mathbb{R}^k} g(x,y) f_{X|Y=y}(x) dx \Big|_{y=Y}$$

and $Var(X|Y) = E[(X - E(X|Y))^2|Y].$

- Some properties of conditional expectation. Suppose that g(X, Y), $g_1(X, Y)$, $g_2(X, Y)$ and $g_1(Y)g_2(X, Y)$ are integrable. Then we have
 - E(E[g(X,Y)|Y]) = E(g(X,Y)). $- E[(g_1(X,Y) + g_2(X,Y))|Y] = E[g_1(X,Y)|Y] + E[g_2(X,Y)|Y].$ $- E[g_1(Y)g_2(X,Y)|Y] = g_1(Y)E[g_2(X,Y)|Y].$ - E[1|Y] = 1.
- Example 2. Suppose that (X, Y) has a joint PDF $f_{X,Y}$, where

$$f_{X,Y}(x,y) = \begin{cases} 2xy + 2(1-x)(1-y) & \text{if } (x,y) \in (0,1) \times (0,1); \\ 0 & \text{otherwise.} \end{cases}$$

Find E(X|Y).

Sol. Compute $f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dx$, then

$$f_Y(y) = \begin{cases} \int_0^1 (2xy + 2(1-x)(1-y))dx = 1 & \text{if } y \in (0,1); \\ 0 & \text{if } y \notin (0,1), \end{cases}$$

and the set $\{y : f_Y(y) > 0\}$ is (0, 1). For $y \in (0, 1)$,

$$\begin{aligned} \int_{-\infty}^{\infty} x \cdot \frac{f_{X,Y}(x,y)}{f_Y(y)} dx &= \int_{-\infty}^{\infty} x f_{X,Y}(x,y) dx \\ &= \int_{0}^{1} x [2xy + 2(1-x)(1-y)] dx \\ &= \frac{2y}{3} + \frac{1-y}{3} = \frac{1+y}{3}, \end{aligned}$$

 \mathbf{SO}

$$E(X|Y) = \frac{1+y}{3}\Big|_{y=Y} = \frac{1+Y}{3}.$$

• Fact 1 Suppose that $E(X^2) < \infty$. Then for u(Y) such that $E[u^2(Y)] < \infty$,

$$E[(X - E(X|Y))u(Y)] = 0$$

and for h(Y) such that $E[h^2(Y)] < \infty$,

$$E[(X - h(Y))^{2}] = E[(X - E(X|Y))^{2}] + E[(E(X|Y) - h(Y))^{2}].$$
 (2)

Remarks.

- When predicting X using a function of Y, the best choice is E(X|Y) in the sense that $E(X h(Y))^2 \ge E(X E(X|Y))^2$, which is implied by (2).
- Take h(Y) = E(X) in (2), then we have $Var(X) \ge Var(E(X|Y))$.
- $E[(X E(X|Y))^{2}] = E(Var(X|Y)).$
- Fact 2 Suppose that X and Y are random vectors of dimensions k and m respectively, and (X, Y) has a PDF. Suppose that $\{f_{X|Y=y}: y \in R_Y\}$ is a version of the conditional PDF of X given Y, and f_Y is a PDF of Y. Let

$$g(x,y) = f_{X|Y=y}(x)f_Y(y)I_{R_Y}(y)$$

for $x \in \mathbb{R}^k$ and $y \in \mathbb{R}^m$, then g is a PDF of (X, Y).

• Example 3. Suppose that X and Y are random variables, $f_Y(y) = 2yI_{(0,1)}(y)$ for $y \in R$ and f_Y is a PDF of Y. Suppose that for $y \in (0,1)$,

$$f_{X|Y=y}(x) = \left(\frac{1}{2y}\right) I_{(-y,y)}(x)$$

for $x \in R$, and $\{f_{X|Y=y} : y \in (0,1)\}$ is a version of the conditional PDF of X given Y Find a PDF of X.

Sol. For $(x, y) \in \mathbb{R}^2$, let

$$g(x,y) = f_{X|Y=y}(x)f_Y(y)I_{(0,1)}(y) = \left(\frac{1}{2y}\right)I_{(-y,y)}(x)2yI_{(0,1)}(y),$$

then g is a PDF of (X, Y). Let

$$f_X(x) = \int_{-\infty}^{\infty} g(x, y) dy$$

for $x \in R$, then f_X is a PDF of X. The expression of $f_X(x)$ can be simplified to

$$f_X(x) = (1 - |x|)I_{(-1,1)}(x)$$

for $x \in R$.