

Math 3501 - Probability and Statistics I

4.3 - Conditional distributions

Motivation

Let X and Y have joint discrete distribution with pmf $f(x, y)$ on the space S , and marginal pmfs $f_X(x)$ and $f_Y(y)$ with spaces S_X and S_Y , respectively.

Define the events

$$\underline{A} = \{X = x\} \quad \text{and} \quad \underline{B} = \{Y = y\}, \quad (x, y) \in S$$

and note that

$$\underline{A} \cap \underline{B} = \{X = x, Y = y\}.$$

Since

$$\underline{P(A \cap B)} = P(X = x, Y = y) = f(x, y)$$

and

$$\underline{P(B)} = P(Y = y) = f_Y(y) > 0 \quad (\text{because } y \in S_Y),$$

the conditional probability of A given B is

$$P(\underline{\underline{X=x}} | \underline{\underline{Y=y}}) = \underline{\underline{P(A|B)}} = \frac{P(A \cap B)}{P(B)} = \frac{f(x, y)}{f_Y(y)}. \quad \begin{matrix} \text{conditional pmf of } X \\ \text{given } Y=y \end{matrix}$$

Chp 1

Conditional probability mass function

Definition (Conditional probability mass function)

Let \underline{X} and \underline{Y} have joint discrete distribution with pmf $f(x, y)$ on the space S , and marginal pmfs $f_X(x)$ and $f_Y(y)$ with spaces S_X and S_Y , respectively.

- (a) The *conditional probability mass function of X , given that $\underline{Y} = y$* , is given by

$$g(x | y) = \frac{f(x, y)}{f_Y(y)}, \quad \text{provided that } f_Y(y) > 0.$$

- (b) The *conditional probability mass function of Y , given that $\underline{X} = x$* , is given by

$$h(y | x) = \frac{f(x, y)}{f_X(x)}, \quad \text{provided that } f_X(x) > 0.$$

Example

Let X and Y have the joint pmf

$$f(x,y) = \frac{x+y}{21}, \quad x = 1, 2, 3, \quad y = 1, 2.$$

Determine:

- the conditional probability mass function of X , given that $Y = y$.
- the conditional probability mass function of Y , given that $X = x$.

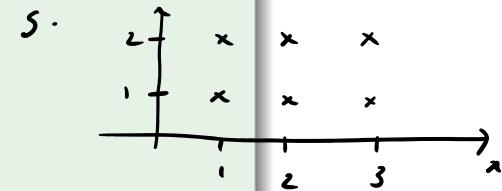
We start by determining the marginal pmfs for X and Y :

$$f_X(x) = \sum_{y \in S_Y} f(x,y) = \sum_{y=1}^2 \frac{x+y}{21} = \frac{x+1}{21} + \frac{x+2}{21} = \frac{2x+3}{21}, \quad x = 1, 2, 3$$

$$f_Y(y) = \sum_{x \in S_X} f(x,y) = \sum_{x=1}^3 \frac{x+y}{21} = \frac{1+y}{21} + \frac{2+y}{21} + \frac{3+y}{21} = \frac{6+3y}{21}, \quad y = 1, 2$$

conditional pmf of X given $Y = y$ is $g(x|y) = \frac{f(x,y)}{f_Y(y)} = \frac{\frac{x+y}{21}}{\frac{6+3y}{21}} = \frac{x+y}{6+3y}$ for $x = 1, 2, 3$

we have two functions of x : $g(x|1)$ and $g(x|2)$



$$S_X = \{1, 2, 3\}$$

$$S_Y = \{1, 2\}$$

$$\left. \begin{array}{l} f(x,y) = P(X=x, Y=y) \\ f_y(y) = P(Y=y) \end{array} \right\} \Rightarrow g(x|y) = \frac{f(x,y)}{f_y(y)} = \frac{P(X=x \text{ and } Y=y)}{P(Y=y)}$$

$\longrightarrow = P(X=x | Y=y)$

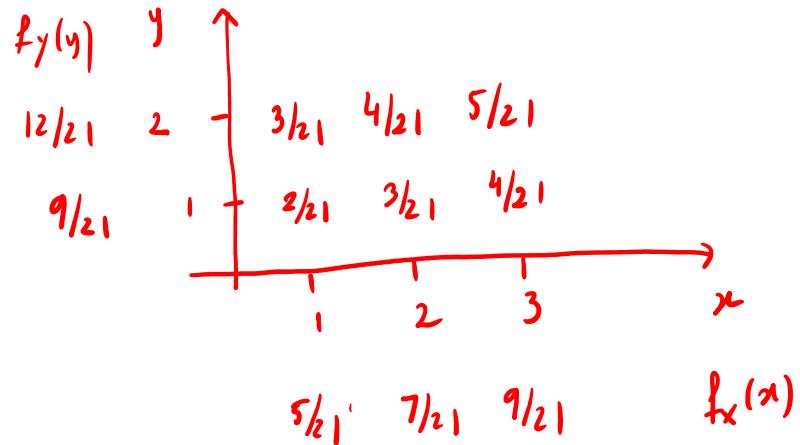
Conditional pmf of Y given $X=x$

$$h(y|x) = \frac{f(x,y)}{f_x(x)} = \frac{\frac{x+y}{21}}{\frac{2x+3}{21}} = \frac{x+y}{2x+3} \quad \text{for } y=1,2 \quad \text{for each } x=1,2,3$$

↑

This represents three functions of y : $h(y|1)$, $h(y|2)$, $h(y|3)$

Alternative approach



$$f_x(x) = \begin{cases} \frac{5}{12}, & \text{if } x=1 \\ \frac{7}{12}, & \text{if } x=2 \\ \frac{9}{12}, & \text{if } x=3 \end{cases}$$

$$f_y(y) = \begin{cases} \frac{9}{12}, & \text{if } y=1 \\ \frac{12}{12}, & \text{if } y=2 \end{cases}$$

$$g(x|y) = \frac{f(x,y)}{f_y(y)}$$

$$g(x|1) = \frac{\frac{2}{12}}{\frac{9}{12}} = \frac{2}{9}$$

$$g(x|2) = \frac{\frac{3}{12}}{\frac{12}{12}} = \frac{3}{12}$$

$$g(x|3) = \frac{\frac{4}{12}}{\frac{12}{12}} = \frac{4}{12}$$

$$h(y|x) = \frac{f(x,y)}{f_x(x)}$$

$$h(1|x) = \frac{\frac{2}{12}}{\frac{5}{12}} = \frac{2}{5}$$

$$h(2|x) = \frac{\frac{3}{12}}{\frac{7}{12}} = \frac{3}{7}$$

$$h(3|x) = \frac{\frac{4}{12}}{\frac{9}{12}} = \frac{4}{9}$$

Note: the conditional probability mass functions $g(x | y)$ and $h(y | x)$ satisfy the conditions of a probability mass function.

The claim above follows from observing that $0 \leq h(y | x)$ and

$$\sum_y h(y | x) = \sum_y \frac{f(x, y)}{f_X(x)} = \frac{f_X(x)}{f_X(x)} = 1 ,$$

with a similar reasoning applying to $g(x | y)$.

Consequence: we can compute conditional probabilities such as

$$\underbrace{P(a < Y < b | X = x)}_{\text{red underline}} = \sum_{\{y: a < y < b\}} \underbrace{h(y | x)}_{\text{red underline}}$$

and conditional expectations such as

$$\underbrace{E[u(Y) | X = x]}_{\text{red underline}} = \sum_y u(y) \underbrace{h(y | x)}_{\text{red underline}}$$

as done with unconditional probabilities and expectations.

EXAMPLE (previous example continued).

For the r.v.s X, Y with joint p.m.f $f(x,y) = \frac{x+y}{21}$, $x=1,2,3$ and $y=1,2$

Compute

$$\begin{aligned} P(X \leq 2 | Y=2) &= \sum_{x \leq 2} g(x|2) = \sum_{x=1}^2 g(x|2) \\ &= \frac{3}{12} + \frac{4}{12} = \frac{7}{12} \end{aligned}$$

Conditional mean and conditional variance

The conditional mean of X , given that $\underline{Y = y}$, is defined as

$$\mu_{X|y} = \underline{E[X | y]} = \sum_x \underline{xg(x | y)},$$

and the conditional variance of X , given that $\underline{Y = y}$, is defined as

$$\sigma_{X|y}^2 = \text{Var}(X | y) = \underline{E[(X - E[X | y])^2 | y]} = \sum_x (x - E[X | y])^2 g(x | y).$$

The latter may be computed using

$$\sigma_{X|y}^2 = \underline{E[X^2 | y]} - \underline{(E[X | y])^2}.$$

analogue to

$$\text{Var}(x) = E[x^2] - (E[x])^2$$

Similarly, the conditional mean of Y , given that $X = x$, is defined as

$$\underline{\mu_{Y|x}} = \underline{E[Y|x]} = \sum_y \underline{yh(y|x)},$$

and the conditional variance of Y , given that $X = x$, is defined as

$$\sigma_{Y|x}^2 = \underline{\text{Var}(Y|x)} = E[(\underline{Y} - \underline{\mu_{Y|x}})^2 | x] = \sum_y (y - \underline{\mu_{Y|x}})^2 \underline{h(y|x)}.$$

The latter may be computed using

$$\sigma_{Y|x}^2 = E[\underline{Y^2} | x] - (\underline{E[Y|x]})^2.$$

Example (Previous example continued)

Let X and Y have the joint pmf

$$f(x, y) = \frac{x+y}{21}, \quad x = 1, 2, 3, \quad y = 1, 2.$$

conditioning on $x=a$

Determine:

- $E[Y | x]$ for $x = \underline{1}, \underline{2}, \underline{3}$

$$\left\{ \begin{array}{l} E[Y | x=1] = \sum_{y \in S_Y} y \cdot h(y|1) = 1 \cdot h(1|1) + 2 \cdot h(2|1) = 1 \cdot \frac{2}{5} + 2 \cdot \frac{3}{5} = \frac{8}{5} \\ E[Y | x=2] = \sum_{y \in S_Y} y \cdot h(y|2) = 1 \cdot h(1|2) + 2 \cdot h(2|2) = 1 \cdot \frac{3}{7} + 2 \cdot \frac{4}{7} = \frac{11}{7} \\ E[Y | x=3] = \sum_{y \in S_Y} y \cdot h(y|3) = 1 \cdot h(1|3) + 2 \cdot h(2|3) = 1 \cdot \frac{4}{9} + 2 \cdot \frac{5}{9} = \frac{14}{9} \end{array} \right.$$

X because
we don't
yet know
which values
 X will
take

Note: $E[Y | X]$ is the random variable taking the values $E[Y | x]$ for $x \in S_X$,
with probabilities given by the marginal pmf of X .

- Recall previous example!

↳ $E[Y | X]$ takes the values:

$$E[Y | x] = \begin{cases} E[Y | x=1] = \frac{8}{5} \text{ with probability } f_X(1) = \frac{5}{21} \\ E[Y | x=2] = \frac{11}{7} \text{ with probability } f_X(2) = \frac{7}{21} \\ E[Y | x=3] = \frac{14}{9} \text{ with probability } f_X(3) = \frac{9}{21} \end{cases}$$

Consequence: Because $E[Y | X]$ is a random variable, its expectation may exist,
in which case it is given by

$$\underline{E[E[Y | X]]} = \sum_x \underbrace{E[Y | x]}_{x} \underbrace{f_X(x)}_{x} .$$

$$\begin{aligned} E[E[Y | X]] &= \frac{8}{5} \cdot \frac{5}{21} + \frac{11}{7} \cdot \frac{7}{21} + \frac{14}{9} \cdot \frac{9}{21} = \frac{8}{21} + \frac{11}{21} + \frac{14}{21} \\ &= \frac{33}{21} = E[Y] \end{aligned}$$

Law of total probability for expectation

Theorem

Let X and Y be random variables such that $E(Y)$ exists. It holds that

$$E[E[Y | X]] = E[Y].$$

Example (Previous example continued)

Let X and Y have the joint pmf

$$f(x, y) = \frac{x+y}{21}, \quad x = 1, 2, 3, \quad y = 1, 2.$$

Determine:

- $\text{Var}(Y | x)$ for $x = 1, 2, 3$

$$E[Y^2 | X=1] = \sum_{y \in S_y} y^2 \cdot h(y|1) = 1^2 \cdot h(1|1) + 2^2 \cdot h(2|1) = 1 \cdot \frac{2}{5} + 4 \cdot \frac{3}{5} = \frac{14}{5}$$

$$E[Y^2 | X=2] = \sum_{y \in S_y} y^2 \cdot h(y|2) = 1^2 \cdot h(1|2) + 2^2 \cdot h(2|2) = 1 \cdot \frac{3}{7} + 4 \cdot \frac{4}{7} = \frac{19}{7}$$

$$E[Y^2 | X=3] = \sum_{y \in S_y} y^2 \cdot h(y|3) = 1^2 \cdot h(1|3) + 2^2 \cdot h(2|3) = 1 \cdot \frac{4}{9} + 4 \cdot \frac{5}{9} = \frac{24}{9}$$

$$\text{Var}(Y|X=1) = E[Y^2|X=1] - (E[Y|X=1])^2 = \frac{14}{5} - \left(\frac{8}{5}\right)^2 = \frac{6}{25}$$

$$\text{Var}(Y|X=2) = E[Y^2|X=2] - (E[Y|X=2])^2 = \frac{19}{7} - \left(\frac{11}{7}\right)^2 = \frac{12}{49}$$

$$\text{Var}(Y|X=3) = E[Y^2|X=3] - (E[Y|X=3])^2 = \frac{24}{9} - \left(\frac{14}{9}\right)^2 = \frac{20}{81}$$

Note: $\text{Var}(Y | X)$ is the random variable taking the values $\text{Var}(Y | x)$ for $x \in S_X$, with probabilities given by the marginal pmf of X .

- Recall previous example!

$$\text{Var}(Y|X) = \begin{cases} \text{Var}(Y|x=1) &= \frac{6}{25} \quad \text{with probability } f_X(1) = \frac{5}{21}, \\ \text{Var}(Y|x=2) &= \frac{12}{49} \quad " " \quad f_X(2) = \frac{7}{21}, \\ \text{Var}(Y|x=3) &= \frac{20}{81} \quad " " \quad f_X(3) = \frac{9}{21} \end{cases}$$

Consequence: Because $\text{Var}(Y | X)$ is a random variable, its expectation may also exist, in which case it is given by

$$E[\text{Var}(Y | X)] = \sum_x \text{Var}(Y | x) f_X(x).$$

$$E[\text{Var}(Y | X)] = \frac{6}{25} \cdot \frac{5}{21} + \frac{12}{49} \cdot \frac{7}{21} + \frac{20}{81} \cdot \frac{9}{21} = \dots$$

calculation

Law of total probability for variances

Theorem

If X and Y are random variables, then

$$E[\text{Var}(Y | X)] + \text{Var}(E[Y | X]) = \text{Var}(Y)$$

provided that all of the expectations and variances exist.

Example

Let \underline{X} have a Poisson distribution with mean 4, and let \underline{Y} be a random variable whose conditional distribution, given that $\underline{X} = \underline{x}$, is binomial with sample size $n = \underline{x} + 1$ and probability of success p .

Determine $E[Y]$ and $\text{Var}(Y)$.

We know : $\underline{X} \sim \text{Poisson}(4)$ and $\underline{Y} | \underline{X} = \underline{x} \sim \text{Binomial}(\overset{\sim}{\underline{x}+1}, p)$

$\lambda = 4$

We will use the laws of total probability to determine $E[Y]$ and $\text{Var}(Y)$:

$$E[Y] = E[\underbrace{E[Y|X]}_{\text{Since } Y|X \sim \text{Binomial}(x+1, p) \text{ then } E[Y|X] = (x+1) \cdot p}] = E[(x+1)p] = p E[x+1] = p(\overset{\sim}{E[X]} + 1) = p(4+1) = 5p$$

$$\text{Var}(Y) = E[\underbrace{\text{Var}(Y|X)}_{(x+1)p} + \text{Var}(\underbrace{E[Y|X]}_{(x+1)p})] = E[(x+1) \cdot p \cdot (1-p)] + \text{Var}((x+1) \cdot p) = p(1-p) E[x+1] + p^2 \text{Var}(x+1)$$

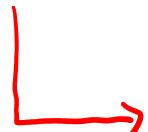
$$= p(1-p) \cdot (E[X] + 1) + p^2 \text{Var}(X)$$

$$= p(1-p) (4+1) + p^2 \cdot 4 \quad \begin{matrix} \text{if } X \sim \text{Poisson}(\lambda) \\ E[X] = \text{Var}(X) = \lambda \end{matrix} \leftarrow \begin{matrix} \text{from} \\ \text{formula} \\ \text{sheet} \end{matrix}$$

$$= 5p(1-p) + 4p^2 = 5p - p^2$$

Math 3501 - Probability and Statistics I

4.4 - Bivariate distributions of the continuous type

 extends the concepts introduced in secs 4.1, 4.2, and 4.3
to the case of continuous-type r.v.s.

Joint probability density function

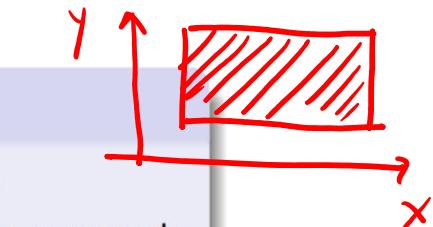
Definition (Joint probability density function)

Let X and Y be two continuous random variables, and let S denote the corresponding two-dimensional space of X and Y (also referred to as the support of X and Y).

The joint probability density function (abbreviated joint pdf) of X and Y is an integrable real-valued function $f(x, y)$ with the following properties:

(a) $f(x, y) \geq 0$ for all $(x, y) \in \mathbb{R}^2$ with $f(x, y) = 0$ when $(x, y) \notin S$.

(b) $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) dx dy = 1.$ $\Leftrightarrow \iint_S f(x, y) dx dy = 1$



$f(x, y)$ is only positive on the support S of X and Y

(c) $P[(X, Y) \in A] = \iint_A f(x, y) dx dy$ where $A \subset \mathbb{R}^2$.

Example

Determine the constant c that makes the function

$$f(x, y) = c, \quad 0 < x < y < 1$$

into a joint pdf of two continuous random variables X and Y .

First identify the support of X and Y

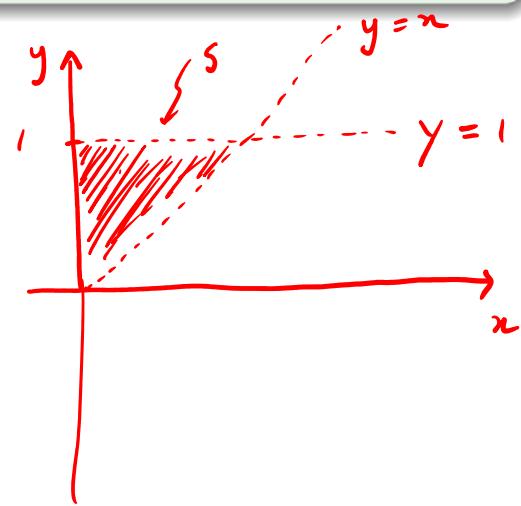
$$S = \{(x, y) \in \mathbb{R}^2 : 0 < x < y < 1\}$$

It is helpful to sketch S

We must have

$$i) c > 0$$

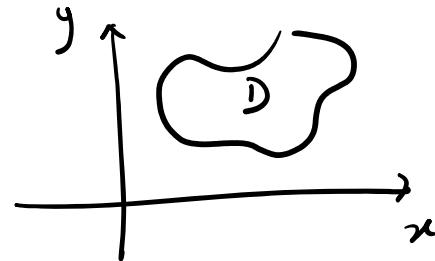
$$ii) \iint_S f(x, y) dxdy = 1 \Leftrightarrow \iint_S c dxdy = 1 \Leftrightarrow c \underbrace{\iint_S 1 dxdy}_{\text{Area of } S} = 1 \Leftrightarrow c \cdot \frac{1}{2} = 1 \Leftrightarrow c = 2$$



Recall for a region D on the plane

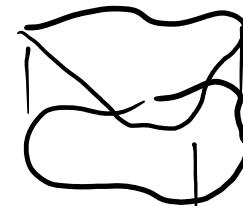
$$\text{Area}(D) = \iint_D 1 \, dx \, dy$$

which also happens to be equal to
the volume of the cylinder of height 1
and base D



$$\text{Volume} = \text{Area}(S)$$

↓



$$\text{Volume} = \text{Area}(S) \times \underbrace{\text{height}}_{=1} = \text{Area}(S)$$

Example (Continued)

Let X and Y have the joint pdf

$$f(x, y) = 2, \quad 0 < x < y < 1.$$

Determine $P(X \leq 1/2)$.

$$\begin{aligned} P(X \leq 1/2) &= \\ &= \int_0^{1/2} \int_x^1 f(x, y) dy dx \\ &= \int_0^{1/2} \int_x^1 2 dy dx = \int_0^{1/2} [2y]_{y=x}^{y=1} dx \\ &= \int_0^{1/2} 2 - 2x dx = [2x - x^2]_{x=0}^{x=1/2} = 1 - \frac{1}{4} = \frac{3}{4} \end{aligned}$$

