

Conditional Distributions

- X, Y discrete: the **conditional pmf** of X given $Y = y$ is defined to be

$$p_{X|Y}(x|y) = \frac{\mathbb{P}(X = x, Y = y)}{\mathbb{P}(Y = y)} = \frac{p(x, y)}{p_Y(y)}, \quad p_Y(y) > 0.$$

- Given $Y = y$, the randomness of X is described by $p(x, y)$ but $p(x, y)$ is NOT a pmf wrt^a x since $\sum_{\text{all } x} p(x, y) \neq 1$. We need this normalizing constant $p_Y(y)$ to make it a valid pmf.

^awrt = with respect to

- X, Y continuous: the **conditional pdf** of X given $Y = y$ is defined to be

$$f_{X|Y}(x|y) = \frac{f(x, y)}{f_Y(y)}, \quad f_Y(y) > 0.$$

- Given $Y = y$, $f(x, y)$ is NOT a pdf wrt x , since $\int f(x, y)dx = f_Y(y) \neq 1$. So we need $f_Y(y)$ in the denominator to make it a legit pdf.

Check the [Wolfram Demo](#).

- If X and Y independent,

$$\begin{aligned} f_{X|Y}(x|y) &= \frac{f(x, y)}{f_Y(y)} \\ &= \frac{f_X(x)f_Y(y)}{f_Y(y)} && \text{due to independence} \\ &= f_X(x) \end{aligned}$$

$$p_{X|Y}(x|y) = p_X(x)$$

- In general, X and Y are dependent and then $f_{X|Y}(x|y) \neq f_X(x)$:
Given the extra information that $Y = y$, the distribution of X is no longer the same as the marginal $f_X(x)$.

Example 1 (2.1.1 on p.74, Revisit)

X / Y	0	1	2	3	$p_X(x)$
0	1/8	1/8	0	0	2/8
1	0	2/8	2/8	0	4/8
2	0	0	1/8	1/8	2/8
$p_Y(y)$	1/8	3/8	3/8	1/8	

a)] Find the conditional pmf $p_{Y|X}(y|x)$, conditional expectation $\mathbb{E}(Y|X = x)$ and conditional variance $\text{Var}(Y | X = x)$.

	0	1	2	3	$\mathbb{E}(Y X = x)$	$\text{Var}(Y X = x)$
$p_{Y X}(y 0)$	0.5	0.5	0	0	0.5	1/4
$p_{Y X}(y 1)$	0	0.5	0.5	0	1.5	1/4
$p_{Y X}(y 2)$	0	0	0.5	0.5	2.5	1/4

Conditional Expectations

$$\mathbb{E}(X|Y = y) = \sum_x x \cdot \mathbb{P}(X = x|Y = y) = \sum_x x \cdot p_{X|Y}(x|y).$$

$$\mathbb{E}(X|Y = y) = \int x \cdot f_{X|Y}(x|y) dx$$

What does the symbol $\mathbb{E}(X | Y)$ mean? You can view it as a function of Y , i.e., $\mathbb{E}(X | Y) = g(Y)$ with its value at $Y = y$ given by

$$g(y) = \mathbb{E}(X | Y = y).$$

Therefore $\mathbb{E}(X | Y)$ is a random variable. We can talk about its distribution (HW1, p7) and compute its mean and variance.

Example 1 (2.1.1 on p.74, Revisit)

$\mathbb{E}(Y|X)$ is a r.v., which equals $\mathbb{E}(Y|X = x)$ with probability $p_X(x)$.

That is,

$$\mathbb{E}(Y|X) = 0.5 \quad \text{with prob} \quad p_X(0) = 1/4,$$

$$\mathbb{E}(Y|X) = 1.5 \quad \text{with prob} \quad p_X(1) = 1/2,$$

$$\mathbb{E}(Y|X) = 2.5 \quad \text{with prob} \quad p_X(2) = 1/4.$$

What's the expectation of the r.v. $\mathbb{E}(Y|X)$?

$$\mathbb{E}[\mathbb{E}(Y|X)] = (0.5)\frac{1}{4} + (1.5)\frac{1}{2} + (2.5)\frac{1}{4} = \frac{0.5 + (1.5)(2) + 2.5}{4} = \frac{6}{4} = 1.5$$

which is the same as

$$\mathbb{E}Y = (0)\frac{1}{8} + (1)\frac{3}{8} + (2)\frac{3}{8} + (3)\frac{1}{8} = \frac{12}{8} = 1.5.$$

This is true for any joint dist, $\mathbb{E}[\mathbb{E}(Y|X)] = \mathbb{E}Y$, due to the iterative rule for expectation.

Iterative Rule $\mathbb{E}[\mathbb{E}(X | Y)] = \mathbb{E}X^{\text{a}}$.

$$\begin{aligned}\mathbb{E}[\mathbb{E}(X | Y)] &= \int [\mathbb{E}(X | Y = y)] f_Y(y) dy \\ &= \int \left[\int x \cdot f_{X|Y}(x|y) dx \right] f_Y(y) dy = \int \left[\int x \cdot \frac{f(x, y)}{f_Y(y)} dx \right] f_Y(y) dy \\ &= \iint x \cdot \frac{f(x, y)}{f_Y(y)} f_Y(y) dx dy = \iint x \cdot f(x, y) dx dy \\ &= \iint x \cdot f(x, y) dy dx = \int x \left[\int f(x, y) dy \right] dx \\ &= \int x f_X(x) dx = \mathbb{E}X.\end{aligned}$$

Similarly we have $\mathbb{E}[\mathbb{E}(g(X)|Y)] = \mathbb{E}[g(X)]$.

^aWhat's more useful is $\mathbb{E}_X[X] = \mathbb{E}_Y[\mathbb{E}(X | Y)]$.

- Sometimes, I'll write the conditional expectation $\mathbb{E}[\cdot | Y]$ as $\mathbb{E}_{X|Y}[\cdot]$ especially when $[\cdot]$ has a lengthy expression, where $\mathbb{E}_{X|Y}$ just means that taking expectation of X with respect to the conditional distribution of X given Y ^a.
- I also use notations like \mathbb{E}_Y in the slides, to remind you that this expectation is over Y only, wrt the marginal distribution $f_Y(y)$. Similarly, \mathbb{E}_X refers to the expectation over X wrt $f_X(x)$
- Usually the meaning of expectation is clear from the context, e.g., $\mathbb{E}g(X)$ must be $\mathbb{E}_X g(X)$, so you don't need to write subscripts in your homework/exam.

^aNote that $\mathbb{E}_{X|Y}$ would only average over X but treat Y as a constant.

The general Iterative Rule

$$\mathbb{E}g(X, Y) = \mathbb{E}_Y \mathbb{E}_{X|Y} [g(X, Y)]$$

$$\text{LHS} = \mathbb{E}g(X, Y) = \iint f(x, y)g(x, y)dx dy$$

$$\begin{aligned} \text{RHS} &= \mathbb{E}_Y [\mathbb{E}_{X|Y} g(X, Y)] \\ &= \int f_Y(y) \left[\int f_{X|Y}(x|y)g(x, y)dx \right] dy \\ &= \iint f_Y(y) \frac{f(x, y)}{f_Y(y)} g(x, y) dx dy \\ &= \iint f(x, y)g(x, y) dx dy \end{aligned}$$

This is essentially the same as the **Chain Rule** of probability.

Useful Properties

- Linearity

$$\mathbb{E}(aX_1 + bX_2|Y) = a\mathbb{E}(X_1|Y) + b\mathbb{E}(X_2|Y)$$

- Take constants outside an expectation

$$\mathbb{E}[g(Y)|Y] = g(Y), \quad \mathbb{E}[g(Y)X|Y] = g(Y)\mathbb{E}(X|Y)$$

In particular, $\mathbb{E}[\mathbb{E}(X|Y)|Y] = \mathbb{E}(X|Y)$

- Iterative rule

$$\mathbb{E}_Y [\mathbb{E}(X|Y)] = \mathbb{E}(X), \quad \mathbb{E}_Y [\mathbb{E}(g(X)|Y)] = \mathbb{E}[g(X)]$$

- $\mathbb{E} \left[(X - \mathbb{E}(X|Y))g(Y) \right] = 0$

$$\begin{aligned} \mathbb{E}_Y \left[\mathbb{E}_{X|Y} (X - \mathbb{E}(X|Y))g(Y) \right] &= \mathbb{E}_Y g(Y) \left[\mathbb{E}_{X|Y} (X - \mathbb{E}(X|Y)) \right] \\ &= \mathbb{E}_Y g(Y) \left[\mathbb{E}(X|Y) - \mathbb{E}(X|Y) \right] \end{aligned}$$

Similarly, we can define conditional variance $\text{Var}(X|Y)$ that is the variance of r.v. $g(Y) = \mathbb{E}(X | Y)$ (check the calculation for Example 1).

$$\begin{aligned}\text{Var}(X|Y) &= \mathbb{E}\left[(X - \mathbb{E}(X|Y))^2|Y\right] \\ &= \mathbb{E}\left[X^2 - 2X \cdot \mathbb{E}(X|Y) + \mathbb{E}(X|Y)^2|Y\right] \\ &= \mathbb{E}[X^2|Y] - 2\mathbb{E}[X \cdot \mathbb{E}(X|Y)|Y] + \mathbb{E}[\mathbb{E}(X|Y)^2|Y] \\ &= \mathbb{E}[X^2|Y] - 2\mathbb{E}(X|Y)\mathbb{E}(X|Y) + \mathbb{E}(X|Y)^2 \\ &= \mathbb{E}(X^2|Y) - [\mathbb{E}(X|Y)]^2 \\ &= (\text{Conditional 2nd Moment}) - (\text{Conditional Mean})^2.\end{aligned}$$

Note that (shown on the next slide)

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

$$\begin{aligned}
\text{Var}(X) &= \mathbb{E}(X - \mu_X)^2 = \mathbb{E}(X - \mathbb{E}(X|Y) + \mathbb{E}(X|Y) - \mu_X)^2 \\
&= \mathbb{E}[X - \mathbb{E}(X|Y)]^2 + \mathbb{E}[\mathbb{E}(X|Y) - \mu_X]^2 \\
&\quad + 2\mathbb{E}[(X - \mathbb{E}(X|Y))(\mathbb{E}(X|Y) - \mu_X)] \\
&= \mathbb{E}_Y \left\{ \mathbb{E}_{X|Y} [X - \mathbb{E}(X|Y)]^2 \right\} + \mathbb{E}_Y \mathbb{E}_{X|Y} [\mathbb{E}(X|Y) - \mu_X]^2 \\
&\quad + 2\mathbb{E}_Y \left\{ \mathbb{E}_{X|Y} [(X - \mathbb{E}(X|Y))(\mathbb{E}(X|Y) - \mu_X)] \right\} \\
&= \mathbb{E}(\text{Var}(X|Y)) + \text{Var}(\mathbb{E}(X|Y))
\end{aligned}$$

You may get confused with the expression $\mathbb{E}(X|Y)$ on the previous slide. Let's go through the proof again with notation $g(Y) = \mathbb{E}(X|Y)$ and note that $\mathbb{E}g(Y) = \mathbb{E}X = \mu_X$.

$$\begin{aligned}\text{Var}(X) &= \mathbb{E}(X - \mu_X)^2 = \mathbb{E}(X - g(Y) + g(Y) - \mu_X)^2 \\ &= \mathbb{E}_{X,Y} [X - g(Y)]^2 + \mathbb{E}_Y [g(Y) - \mu_X]^2 \\ &\quad + 2\mathbb{E}_{X,Y} [(X - g(Y))(g(Y) - \mu_X)] \\ &= \mathbb{E}_Y \left\{ \mathbb{E}_{X|Y} [X - g(Y)]^2 \right\} + \mathbb{E} [g(Y) - \mu_X]^2 \\ &\quad + 2\mathbb{E}_Y \left\{ \mathbb{E}_{X|Y} [(X - g(Y))(g(Y) - \mu_X)] \right\} \\ &= \mathbb{E}(\text{Var}(X|Y)) + \text{Var}(\mathbb{E}(X|Y))\end{aligned}$$

How to understand

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

Let X denote the height of a randomly chosen student from stat410.

Suppose students can be divided into several sub-populations (r.v. Y).

The height (r.v. X) variation comes from two sources:

- Variation within each sub-population (variation of X given Y)
- Variation among the mean height for each sub-population
(variation of $\mathbb{E}(X | Y)$)

The total variation is the sum of these two.

Example 2: The joint pdf is

$$f(x, y) = 60x^2y, \quad 0 \leq x, y \leq 1, \quad x + y \leq 1, \quad \text{zero, elsewhere.}$$

(JointDistributions.pdf, ConditionalDistributions.pdf)

We have computed the marginal pdf

$$f_X(x) = 30x^2(1-x)^2, \quad 0 < x < 1, \quad \mathbb{E}(X) = \frac{1}{2},$$

$$f_Y(y) = 20y(1-y)^3, \quad 0 < y < 1, \quad \mathbb{E}(Y) = \frac{1}{3}.$$

a) Find the conditional pdf $f_{X|Y}(x|y)$ of X given $Y = y$, $0 < y < 1$.

$$f_{X|Y}(x|y) = \frac{f(x, y)}{f_Y(y)} = \frac{3x^2}{(1-y)^3}, \quad 0 < x < 1-y.$$

Check $f_{X|Y}(x|y)$ is a valid pdf wrt x : apparently $f_{X|Y}(x|y) \geq 0$,

$$\int f_{X|Y}(x|y) dx = \int_0^{1-y} 3x^2 / (1-y)^3 dx = 1.$$

b) Find $\mathbb{P}(X > \frac{1}{2} | Y = \frac{1}{3})$.

Calculate this conditional probability using conditional pdf:

$$f_{X|Y}(x | 1/3) = \frac{3x^2}{(1 - 1/3)^3} = \frac{3x^2}{(2/3)^3}, \quad 0 < x < 2/3.$$

$$\begin{aligned} \mathbb{P}\left(X > \frac{1}{2} \mid Y = \frac{1}{3}\right) &= \int_{1/2}^{2/3} \frac{3x^2}{(2/3)^3} dx = \frac{x^3}{(2/3)^3} \Big|_{1/2}^{2/3} \\ &= 1 - \frac{27}{64} = \frac{37}{64}. \end{aligned}$$

How to use conditional pmf/pdf to evaluate $\mathbb{P}(a < X < b \mid Y = y)$?

- For discrete rvs, you can either use conditional pmf

$$\sum_{a < x < b} p_{X|Y}(x \mid y) = \sum_{a < x < b} \frac{p(x, y)}{p_Y(y)} = \frac{\sum_{a < x < b} p(x, y)}{p_Y(y)},$$

or just follow the definition of conditional probability

$$\frac{\mathbb{P}(a < X < b, Y = y)}{\mathbb{P}(Y = y)} = \frac{\sum_{a < x < b} p(x, y)}{\sum_{\text{all } x} p(x, y)}.$$

- For **continuous** rvs, we **CANNOT** evaluate this probability via $\mathbb{P}(a < X < b, Y = y)/\mathbb{P}(Y = y)$ as in the discrete case, since $\mathbb{P}(Y = y) = 0$, instead we need to use conditional pdf

$$\mathbb{P}(a < X < b \mid Y = y) = \int_a^b f_{X|Y}(x|y) dx.$$

Go through other examples from `ConditionalDistributions.pdf`