

Section 4.3. Conditional Distributions

- Q • How does the distribution of a RV, say X , change given information of another RV, say Y ?
- How to systematically work with such "conditional distributions"?

□ Conditional PMFs

DEF Suppose X & Y have a joint PMF. Then the conditional PMF of X given $Y=y$ is defined by

$$P_{X|Y}(x|y) := P(X=x | Y=y) = \frac{P_{X,Y}(x,y)}{P_Y(y)}, \quad \text{why?}$$

provided $P_Y(y) > 0$.

Ex 1 Let X & Y have the joint PMF:

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

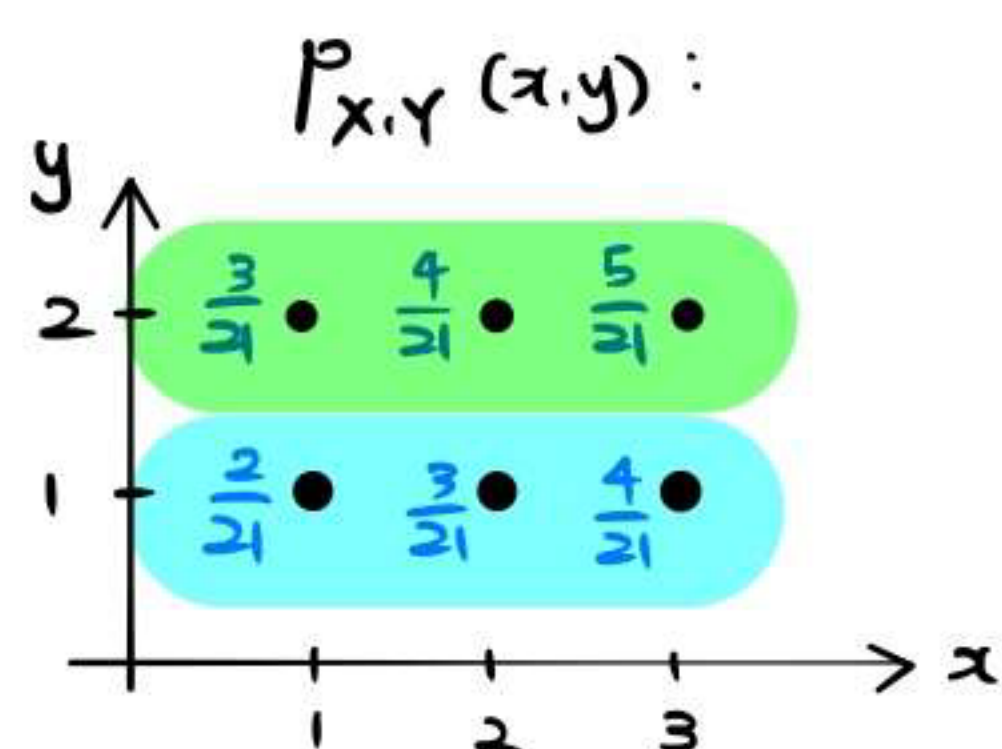
Then the marginal PMF $P_Y(y)$ is

$$P_Y(y) = \sum_{x=1}^3 P_{X,Y}(x,y) = \sum_{x=1}^3 \frac{x+y}{21} = \frac{6+3x}{21}, \quad y = 1, 2.$$

So the conditional PMF of X given $Y=y$, for $y = 1, 2$, is

$$P_{X|Y}(x|y) = \frac{P_{X,Y}(x,y)}{P_Y(y)} = \frac{(x+y)/21}{(3y+6)/21} = \frac{x+y}{3y+6}, \quad x = 1, 2, 3.$$

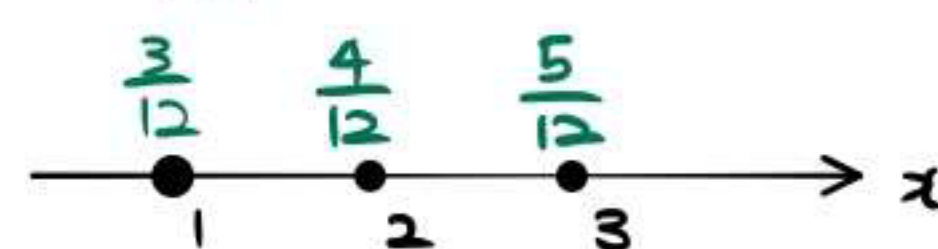
Visually,



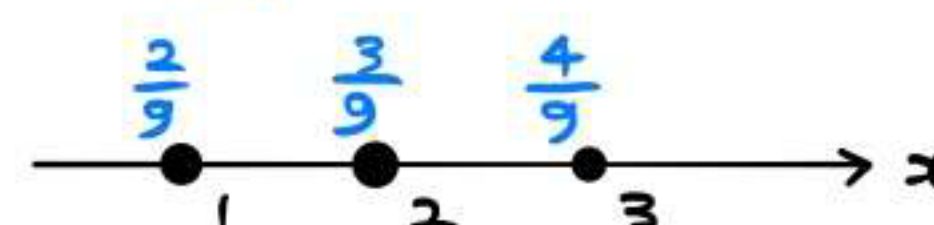
given $Y=2$

given $Y=1$

$P_{X|Y}(x|2):$



$P_{X|Y}(x|1):$



For instance,

$$P(X=2 | Y=1) = P_{X|Y}(2|1) = \frac{3}{9} = \frac{1}{3}.$$

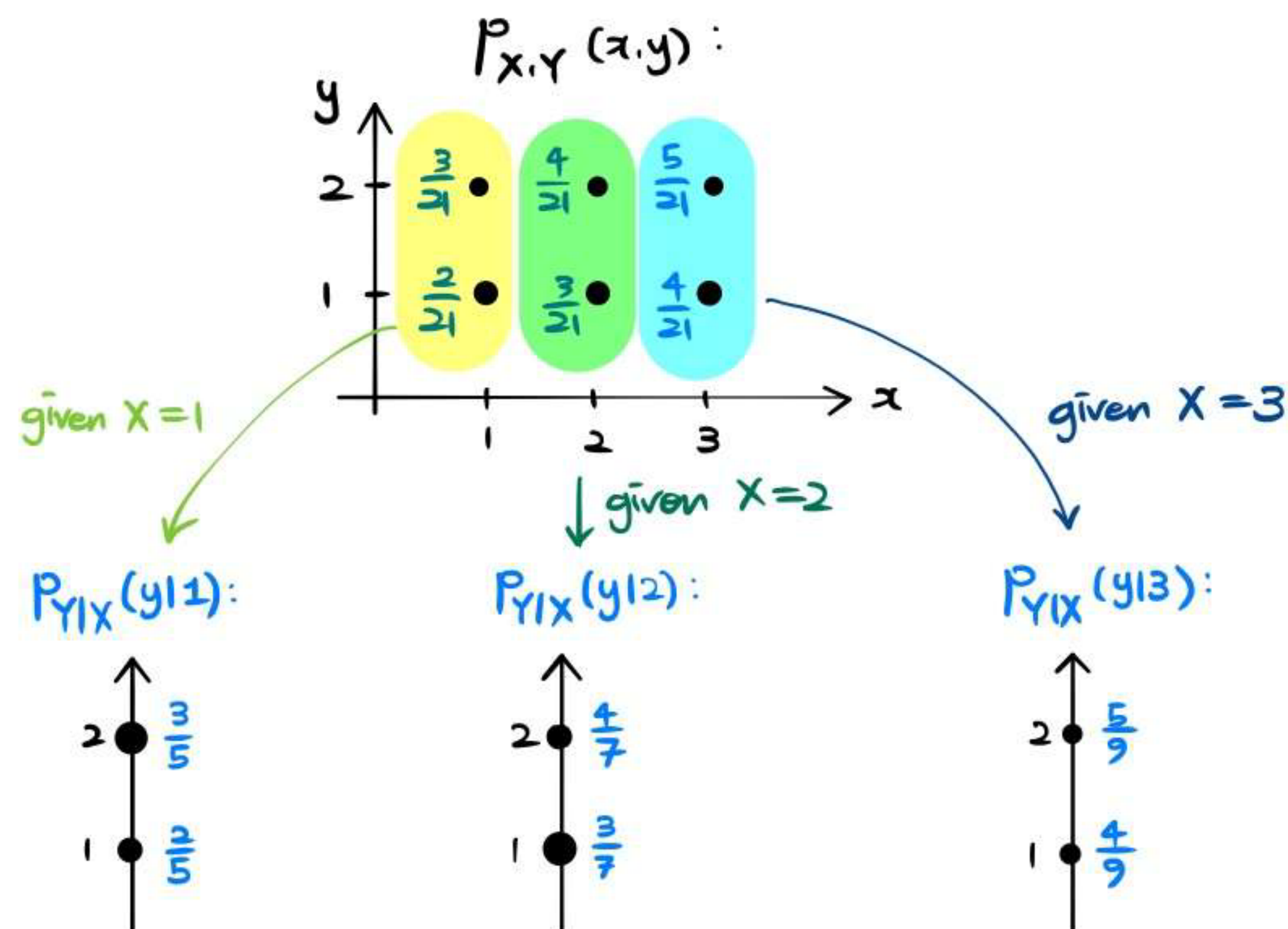
Similarly, $P_{Y|X}(y|x)$ can be computed as

$$\begin{aligned} P_{Y|X}(y|x) &= P(Y=y | X=x) = \frac{P_{X,Y}(x,y)}{P_X(x)} \\ &= \frac{(x+y)/21}{(2x+3)/21} = \frac{x+y}{2x+3}, \quad y=1,2, \quad \text{when } x=1,2,3. \end{aligned}$$

For example,

$$P(Y=1 | X=3) = P_{Y|X}(1|3) = \frac{4}{9}.$$

Visually,



NOTE Each conditional PMF is a PMF. Indeed, given $P_X(x) > 0$,

(a) $0 \leq P_{Y|X}(y|x) \leq 1$ for any y ,

(b) $\sum_y P_{Y|X}(y|x) = \sum_y \frac{P_{X,Y}(x,y)}{P_X(x)} = \frac{1}{P_X(x)} \underbrace{\sum_y P_{X,Y}(x,y)}_{= P_X(x)} = 1$

- The previous observation tells that we can compute

$$P(Y \in A | X=x) = \sum_{y \in A} P_{Y|X}(y|x).$$

2 Conditional Expectation given $X=x$.

- We have learned that :
 - $P_{Y|X}(y|x)$ describes the dist. of Y , given $X=x$.
 - Conditional prob. of events in terms of Y , given $X=x$, can be computed by $P_{Y|X}(y|x)$.
- This suggests : We may consider the expected value of $u(Y)$ given $X=x$. Indeed, we define the **conditional expectation** as :

$$E[u(Y) | X=x] = \sum_y u(y) P_{Y|X}(y|x).$$

- Two special cases :
 - the **conditional mean** of Y , given $X=x$, is

$$E(Y | X=x) = \sum_y y P_{Y|X}(y|x).$$

- the **conditional variance** of Y , given X , is

$$\begin{aligned} \text{Var}(Y | X=x) &:= E[(Y - E(Y | X=x))^2 | X=x] \\ &= E(Y^2 | X=x) - E(Y | X=x)^2. \end{aligned}$$

Ex 1 (continued) Recall $P_{Y|X}(y|x) = \frac{x+y}{2y+3}$, $x=1,2,3$, $y=1,2$. Then

$$E(Y | X=2) = \sum_{y=1}^2 y P_{Y|X}(y|2) = (1) \cdot \left(\frac{3}{7}\right) + (2) \cdot \left(\frac{4}{7}\right) = \frac{11}{7}$$

and

$$E(Y^2 | X=2) = \sum_{y=1}^2 y^2 \cdot P_{Y|X}(y|2) = (1)^2 \cdot \left(\frac{3}{7}\right) + (2)^2 \cdot \left(\frac{4}{7}\right) = \frac{19}{7}$$

So we get

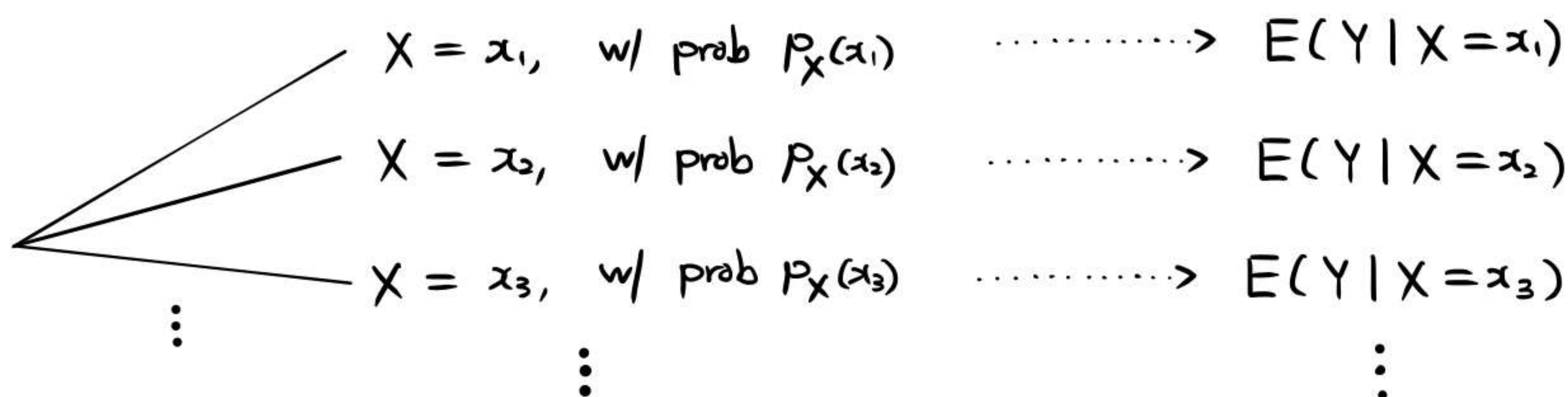
$$\begin{aligned}\text{Var}(Y|X=2) &= E(Y^2|X=2) - E(Y|X=2)^2 \\ &= \frac{19}{7} - \left(\frac{11}{7}\right)^2 = \frac{12}{49}.\end{aligned}$$

[3] Conditional Expectation as Random Variable

- We may think of $E(Y|X=x)$ as "expectation of Y , knowing that $X=x$ is observed".

$$X = \boxed{?} \xrightarrow[\text{X is observed}]{} X = \boxed{x} \xrightarrow{} [\text{cond. exp. of } Y] = E(Y|X=x).$$

- Then it makes sense to consider "expectation of Y given X , before X is observed". Then



So, what we get is a random variable that takes the value $E(Y|X=x)$ with when $X=x$ occurs.

DEF The conditional expectation of Y given X , denoted by

$$E(Y|X),$$

is the random variable such that:

$$E(Y|X) = E(Y|X=x) \quad \text{whenever } X=x \text{ occurs.}$$

Note $E(Y|X)$ is always a function of X .

Ex 1 (continued) Recall that $P_{Y|X}(y|x) = \frac{x+y}{2y+3}$, $y = 1, 2$ when $x = 1, 2, 3$.

Then $E(Y|X)$ is the random variable taking values:

$$\begin{cases} E(Y|X=1) = \frac{8}{5} & \text{w/ prob. } P_X(1) = \frac{5}{21} \\ E(Y|X=2) = \frac{11}{7} & \text{w/ prob. } P_X(2) = \frac{7}{21} \\ E(Y|X=3) = \frac{14}{9} & \text{w/ prob. } P_X(3) = \frac{9}{21} \end{cases}$$

- There are two useful theorems involving conditional expectations:

THM 1 (Law of Total Expectation)

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

$$\begin{aligned} \text{Pf)} \quad E[E(Y|X)] &= \sum_x E(Y|X=x) P_X(x) && \text{(from the def. of } E(Y|X)) \\ &= \sum_x \left(\sum_y y P_{Y|X}(y|x) \right) P_X(x) && \text{(from the def. of } E(Y|X=x)) \\ &= \sum_{x,y} y \underbrace{P_{Y|X}(y|x) P_X(x)}_{= P_{X,Y}(x,y)} && \text{(from the def. of } P_{Y|X}(y|x)) \\ &= \sum_{x,y} y P_{X,Y}(x,y) \\ &= E(Y). \end{aligned}$$

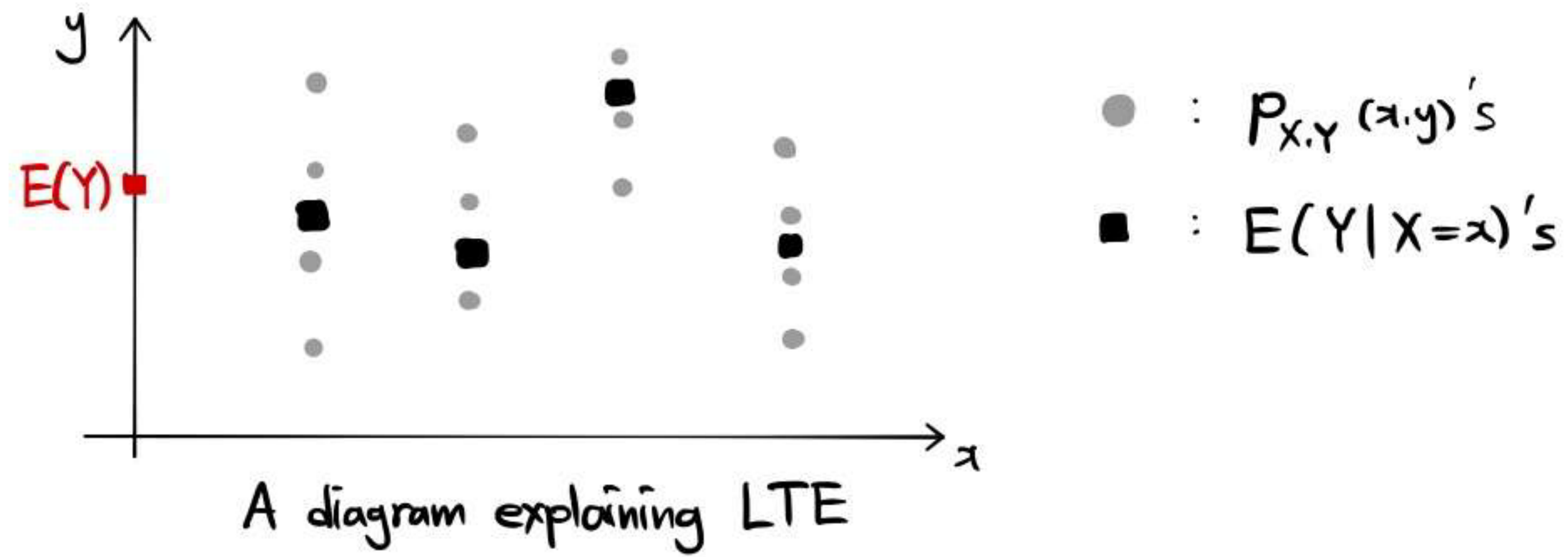
□

Note The proof suggests another way of stating LTE:

$$E(Y) = \sum_x E(Y|X=x) P(X=x).$$

Compare this with the Law of Total Probability!

Figure



DEF The conditional variance of Y given X , denoted by $\text{Var}(Y|X)$

is the random variable such that:

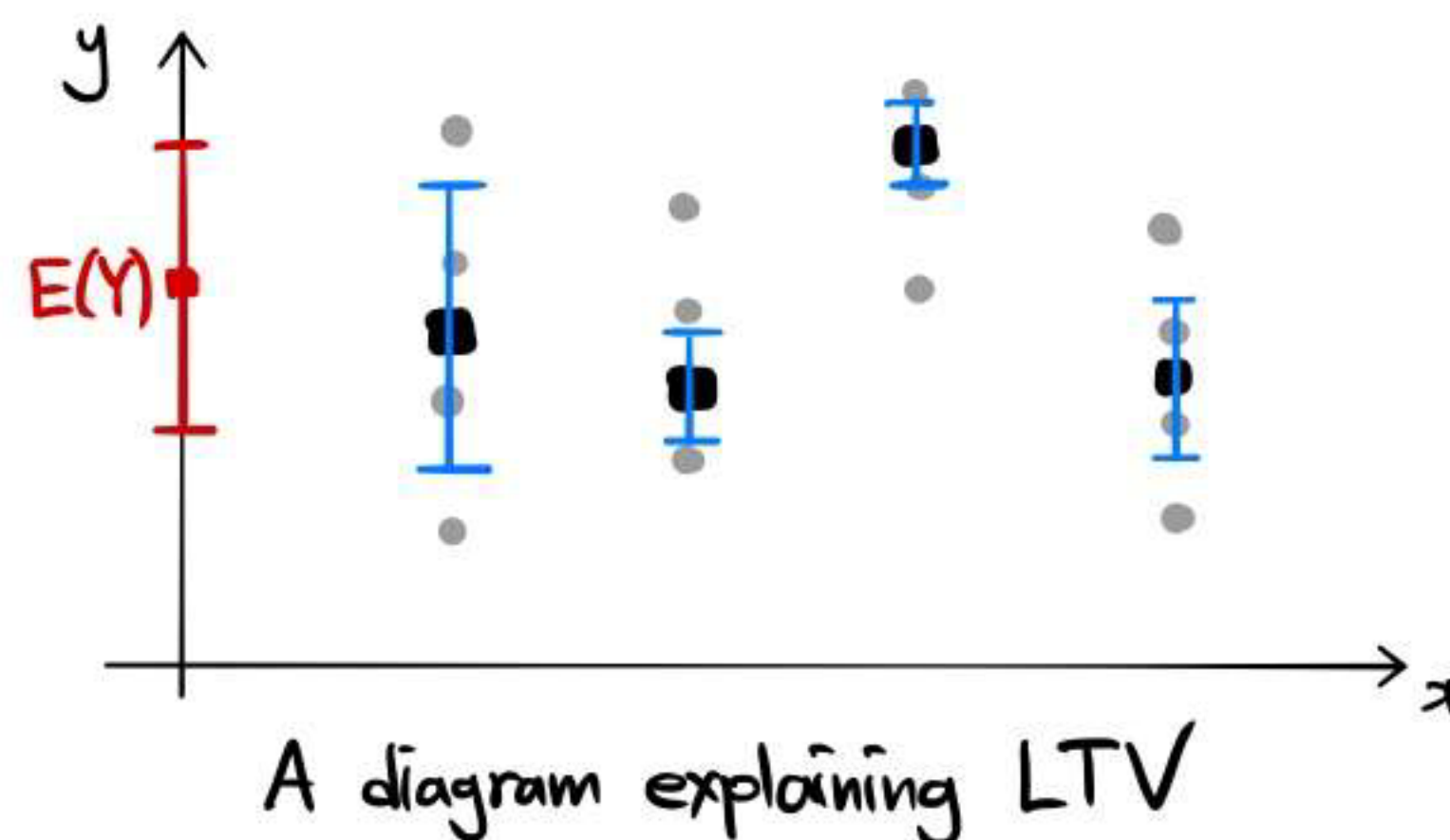
$$\text{Var}(Y|X) = \text{Var}(Y|X=x) \quad \text{whenever } X=x.$$

THM 2 (Law of Total Variance)

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

- The proof can be done in a similar spirit.

Figure



$$\text{Var}(Y) = [\text{mean of cond. vars } \textcolor{blue}{I}] + [\text{var. of cond. exps } \blacksquare]$$

Ex 2 Roll a fair die and let X be the outcome. Then flip a biased coin (with H's appearing w/ prob. p) X times and let

$$Y = [\# \text{ of H's}].$$

Then the conditional dist. of Y given X is $b(X, p)$, and so,

$$\begin{aligned} E(Y) &= E(E(Y|X)) \\ &= E(Xp) \\ &= \frac{7}{2}p. \end{aligned} \quad (\because E(X) = \frac{7}{2})$$

Moreover,

$$\begin{aligned} \text{Var}(Y) &= E(\text{Var}(Y|X)) + \text{Var}(E(Y|X)) \\ &= E(Xp(1-p)) + \text{Var}(Xp) \\ &= \frac{7}{2}p(1-p) + \frac{35}{12}p^2 \end{aligned} \quad (\because \text{Var}(X) = \frac{35}{12})$$

□

THM 3 (Pulling out what is known)

$$E[u(X)Y|X] = u(X)E(Y|X).$$

Pf) Given $X=x$, we know $u(X) = u(x)$. So, whenever $X=x$ is observed,

$$E[u(X)Y|X=x] = E[\overset{\text{truly a constant!}}{u(x)}Y|X=x] = u(x)E(Y|X=x). \quad \square$$

Ex 2 (continued)

$$\begin{aligned} E(XY) &= E[E(XY|X)] = E[XE(Y|X)] \\ &= E[X \cdot Xp] = \frac{91}{6}p \end{aligned} \quad (\because E(X^2) = \frac{91}{6})$$