## Conditional PMFs

- · Say we have a pair of discrete random variables X and Y described by joint PMF Px, v(x, y).
  - → Observe that Y=y.
  - + How can we update the joint PMF to include this?
- · By conditioning on  $\{Y=y\}$ , we restrict the joint PMF to pairs where Y=y and rescale by dividing by  $P_{\nu}(y)$ .
- . The conditional PMF PXIY(X|y) of X given Y is

$$P_{x|y}(x|y) = \begin{cases} \frac{P_{x,y}(x,y)}{P_{y}(y)} & (x,y) \in R_{x,y} \\ P_{y}(y) & \text{otherwise} \end{cases}$$

· Similarly, the conditional PMF PyIX(yIX) of Y given X is

$$P_{Y|X}(y|x) = \begin{cases} \frac{P_{x,y}(x,y)}{P_{x}(x)} & (x,y) \in R_{x,y} \\ 0 & \text{otherwise} \end{cases}$$

· Why? Let B = {x}.

$$P_{Y|x}(y|x) = P_{Y|B}(y) = P[\{Y=y\} \mid \{X \in B\}]$$

$$= P[\{Y=y\} \mid \{X=x\}]$$

$$= \frac{P[\{Y=y\} \cap \{X=x\}]}{P[\{X=x\}]} \quad P[\{X=x\}]$$
otherwise

1P[{x = x}] > 0

Positive if and only if if 
$$(x,y) \in R_{x,y}$$
, which  $= \left(\begin{array}{c} P_{x,y}(x,y) \\ P_{x}(x) \end{array}\right)$   $= \left(\begin{array}{c} P_{x,y}(x,y) \\ P_{x}(x) \end{array}\right)$   $= \left(\begin{array}{c} P_{x,y}(x,y) \\ P_{x,y}(x,y) \end{array}\right)$  Holds if and only if also guarantees  $x \in R_{x}$ .

- · The conditional PMF satisfies the basic PMF properties:
- > Non-negativity: PxIY(x|y) > 0, PyIX(y|x) > 0
- -> Normalization:  $\sum_{x \in R_x} P_{x|x}(x|y) = 1, \sum_{y \in R_y} P_{Y|x}(y|x) = 1$
- -) additivity: IP[{x \in B} | {Y = y}] = \( \sum\_{x \in B} P\_{x | Y} (x | y) \)

$$P[\{Y \in B\} \mid \{X = x\}] = \sum_{y \in B} P_{Y|x}(y|x)$$

- · Conditional probability techniques also apply:
- -> Multiplication Rule: Px, y(x,y) = Px y (x | y) Py(y) = Py x (y | x) Px(x)
- Law of Total Probability:  $P_{x}(x) = \sum_{y \in R_{x}} P_{x|y}(x|y) P_{y}(y)$   $P_{y}(y) = \sum_{x \in R_{x}} P_{y|x}(y|x) P_{x}(x)$
- Bayes' Rule:  $P_{x|y}(x|y) = P_{y|x}(y|x)P_{x(x)}$   $P_{y|x}(y|x) = P_{x|y}(x|y)P_{y(y)}$   $P_{y(y)}$

## Joint PMF

| · Example: Pxx(x,y) |   |   | ×   |    |   |
|---------------------|---|---|-----|----|---|
|                     |   |   | 1   | 2  | 3 |
|                     |   | 1 | 1/3 | 0  | 0 |
|                     | y | 2 | 16  | 16 | 3 |

Sum over Columns  $\begin{array}{c}
PY(y) = \\
\frac{1}{3} & y = 1 \\
\frac{2}{3} & y = 2
\end{array}$ 

Sum over rows

$$P_{\times}(\times) = \begin{cases} \frac{1}{2} & x = 1 \\ \frac{1}{6} & x = 2 \end{cases}$$
of  $\times$ 
of  $\times$ 

$$\frac{1}{3} & x = 3$$

Normalization: Rows sum to 1.

| D (1)     |   | , , , | ×                     |                                 |                                 |  |  |  |
|-----------|---|-------|-----------------------|---------------------------------|---------------------------------|--|--|--|
| Pxix(xly) |   |       | 1                     | 2                               | 3                               |  |  |  |
|           | У | ı     | $\frac{1/3}{1/3} = 1$ | 0 = 0                           | 0 = 0                           |  |  |  |
|           |   | 2     | 1/6<br>2/3 = 4        | $\frac{1/6}{2/3} = \frac{1}{4}$ | $\frac{1/3}{2/3} = \frac{1}{2}$ |  |  |  |

Calculate Px14(xly) and Px1x(ylx).

$$P_{x|y}(x|y) = \frac{P_{x,y}(x,y)}{P_{y}(y)} \quad P_{y|x}(y|x) = \frac{P_{x,y}(x,y)}{P_{x}(x)}$$

Normalization: Columns sum to 1.

Unless tenominator is 0, then conditional PMF is 0 too.

| Pylx(ylx) |       | ×                               |         |                       |  |
|-----------|-------|---------------------------------|---------|-----------------------|--|
| אוץי      | (AIX) | 1                               | 2       | 3                     |  |
| .,        | ı     | $\frac{1/3}{1/2} = \frac{2}{3}$ | 0       | 0                     |  |
| y         | 2     | $\frac{1/6}{1/2} = \frac{1}{3}$ | 1/6 = 1 | $\frac{1/3}{1/3} = 1$ |  |

- The conditional PMF can be used to express hierarchical probability models. For instance, we can write  $P_{Y|X}(y|x)$  using a family of random variables where the parameters are a function of x, which is generated using  $P_{x}(x)$ .
- Example: Model the number of photons Y observed at a detector as Poisson (>) where  $\lambda = g(x)$ .
  - $\Rightarrow$  X is 0 if sample is absent, 1 if sample is present. Sample present with probability  $\frac{1}{3}$ .  $\Rightarrow$  X is Bernoulli( $\frac{1}{3}$ ).
  - Average # photons is 2 when sample absent, 4 when present. Model by  $\lambda = g(x) = (2 \times 0) = (4 \times 0)$

 $\Rightarrow$  Y given X = x is Poisson(g(x)).

$$P_{Y|X}(y|x) = \begin{cases} \frac{(q(x))^{y}}{y!} e^{-g(x)} & x=0,1\\ y=0,1,2,...\\ 0 & \text{otherwise} \end{cases} = \begin{cases} \frac{2^{y}}{y!} e^{-2} & x=0,\\ y=0,1,2,...\\ \frac{4^{y}}{y!} e^{-4} & x=1,\\ y=0,1,2,...\\ 0 & \text{otherwise} \end{cases}$$
Sample

Sample

On therwise

Example: 
$$P_{Y|X}(y|x) = \begin{pmatrix} \frac{2y}{y!} & e^{-2} & x=0, \\ \frac{4y}{y!} & e^{-4} & y=0,1,2,... \\ 0 & \text{otherwise} \end{pmatrix}$$

• Example: 
$$P_{Y|X}(y|x) = \begin{pmatrix} \frac{2y}{y!} & e^{-2} & x=0, \\ \frac{y}{y!} & e^{-2} & y=0,1,2,... \end{pmatrix}$$
 Sample Absent Sample  $P_{X}(x) = \begin{pmatrix} \frac{2}{3} & x=0 \\ \frac{1}{3} & x=1 \end{pmatrix}$  otherwise

$$P[Y=3|X=1] = P_{Y|X}(3|1) = \frac{4^3}{3!}e^{-4} = \frac{64}{6}e^{-4} = \frac{32}{3}e^{-4}$$

$$P[Y=3, X=1] = P_{x,y}(1,3) = P_{y|x}(3|1) P_{x}(1) = \frac{32}{3}e^{-4} \cdot \frac{1}{3} = \frac{32}{9}e^{-4}$$

Comma means "and" Multiplication Rule

$$|P[Y=0] = P_{Y}(0) = \sum_{x \in R_{X}} P_{Y|X}(0|x) P_{X}(x) \\
 = P_{Y|X}(0|0) P_{X}(0) + P_{Y|X}(0|1) P_{X}(1) \\
 = \frac{2^{\circ}}{0!} e^{-2} \cdot \frac{2}{3} + \frac{4^{\circ}}{0!} e^{-4} \cdot \frac{1}{3} \\
 = \frac{2e^{-2} + e^{-4}}{3}$$