

Expected Value of a Function of Two Random Variables

- While the joint PMF or PDF provides a full characterization of a pair of random variables X and Y , we are sometimes more interested in the average (or expected) value of a function $W = g(X, Y)$.
- One approach is to first determine the distribution of $W = g(X, Y)$ and then its expected value $E[W]$. However, determining the PMF (or PDF) of W can be quite challenging and is actually unnecessary.
See lecture notes for examples.
- The expected value $E[g(X, Y)]$ of a function $g(X, Y)$ is

$$\text{Discrete: } E[g(X, Y)] = \sum_{x \in R_X} \sum_{y \in R_Y} g(x, y) P_{X, Y}(x, y)$$

$$\text{Continuous: } E[g(X, Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) f_{X, Y}(x, y) dx dy$$

- Linearity of Expectation: For any functions $g_1(x, y), \dots, g_n(x, y)$ and constants a_1, \dots, a_n ,

$$\mathbb{E}[a_1 g_1(x, y) + \dots + a_n g_n(x, y)] = a_1 \mathbb{E}[g_1(x, y)] + \dots + a_n \mathbb{E}[g_n(x, y)]$$

→ Why?

$$\sum_{x \in R_x} \sum_{y \in R_y} (a_1 g_1(x, y) + \dots + a_n g_n(x, y)) P_{x, y}(x, y) = a_1 \sum_{x \in R_x} \sum_{y \in R_y} g_1(x, y) P_{x, y}(x, y) + \dots + a_n \sum_{x \in R_x} \sum_{y \in R_y} g_n(x, y) P_{x, y}(x, y)$$

Same argument for continuous case.

- Special Cases: $\mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y]$
 $\mathbb{E}[aX + bY + c] = a \mathbb{E}[X] + b \mathbb{E}[Y] + c$

• Linearity of Expectation **always holds!**
Does not require independence of X and Y!

- Expectation of Products: If X and Y are independent, then for any functions $g(x)$ and $h(y)$

$$\mathbb{E}[g(x)h(y)] = \mathbb{E}[g(x)] \mathbb{E}[h(y)]$$

→ Why?

$$\sum_{x \in R_x} \sum_{y \in R_y} g(x)h(y) P_{X,Y}(x,y) \stackrel{\text{independence}}{=} \sum_{x \in R_x} \sum_{y \in R_y} g(x)h(y) P_x(x) P_y(y)$$

Change sums to integrals for continuous case.

$$= \sum_{x \in R_x} g(x) P_x(x) \sum_{y \in R_y} h(y) P_y(y)$$

- Caveats: → Does not hold in general for dependent X, Y .

→ But even if $\mathbb{E}[g(x)h(y)] = \mathbb{E}[g(x)] \mathbb{E}[h(y)]$ for a particular example, X and Y might be dependent!

• Example: $P_{X,Y}(x,y)$

		x		
		-1	+1	+2
y	-1	$\frac{1}{3}$	0	$\frac{1}{12}$
	+2	$\frac{1}{6}$	$\frac{1}{4}$	$\frac{1}{6}$

→ Add up each row →

Marginal PMF of Y

$$P_Y(y) = \begin{cases} \frac{5}{12} & y = -1 \\ \frac{7}{12} & y = +2 \end{cases}$$

→ Calculate $E[Y^2]$. Can work with the joint PMF directly.

$$\begin{aligned} E[Y^2] &= \sum_{x \in R_X} \sum_{y \in R_Y} y^2 P_{X,Y}(x,y) \\ &= (-1)^2 (P_{X,Y}(-1,-1) + P_{X,Y}(+1,-1) + P_{X,Y}(+2,-1)) \\ &\quad + (+2)^2 (P_{X,Y}(-1,+2) + P_{X,Y}(+1,+2) + P_{X,Y}(+2,+2)) \\ &= \frac{1}{3} + 0 + \frac{1}{12} + 4 \cdot \left(\frac{1}{6} + \frac{1}{4} + \frac{1}{6} \right) = \frac{4 + 1 + 8 + 12 + 8}{12} = \frac{33}{12} = \frac{11}{4} \end{aligned}$$

→ Double check calculation using marginal.

$$E[Y^2] = \sum_{y \in R_Y} y^2 P_Y(y) = (-1)^2 \frac{5}{12} + (+2)^2 \frac{7}{12} = \frac{5}{12} + \frac{28}{12} = \frac{33}{12} = \frac{11}{4} \quad \checkmark$$

• Example:

$P_{X,Y}(x,y)$		X		
		-1	+1	+2
Y	-1	$\frac{1}{3}$	0	$\frac{1}{12}$
	+2	$\frac{1}{6}$	$\frac{1}{4}$	$\frac{1}{6}$

→ Calculate $\mathbb{E}[X^2 Y]$.

$$\mathbb{E}[X^2 Y] = \sum_{x \in R_x} \sum_{y \in R_y} x^2 y P_{X,Y}(x,y)$$

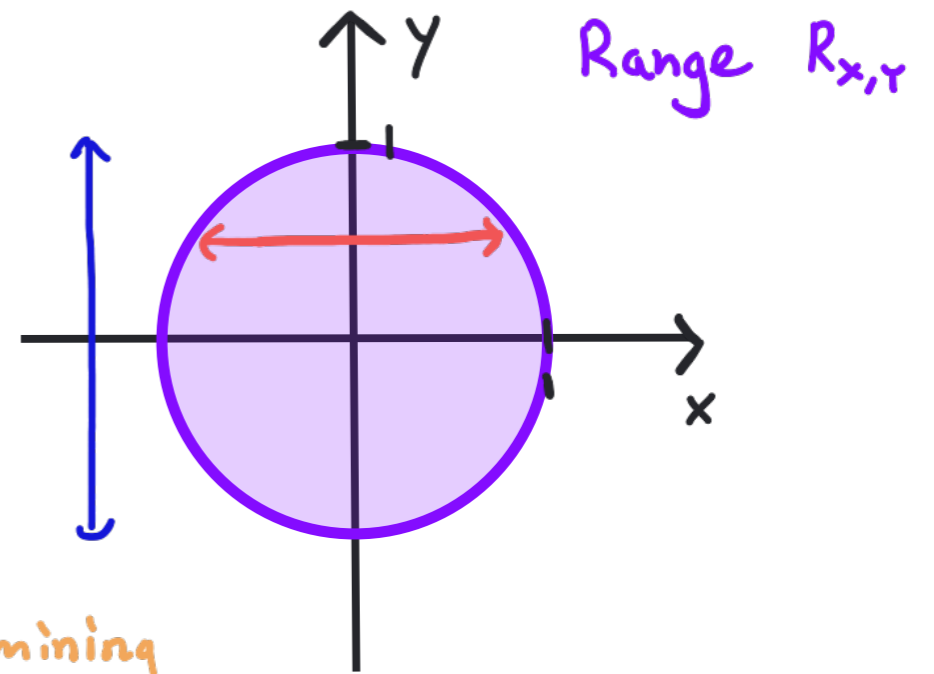
$$\begin{aligned} &= (-1)^2 \cdot (-1) P_{X,Y}(-1,-1) + (+1)^2 \cdot (-1) P_{X,Y}(+1,-1) + (+2)^2 \cdot (-1) P_{X,Y}(+2,-1) \\ &+ (-1)^2 \cdot (+2) P_{X,Y}(-1,+2) + (+1)^2 \cdot (+2) P_{X,Y}(+1,+2) + (+2)^2 \cdot (+2) P_{X,Y}(+2,+2) \\ &= (-1) \cdot \frac{1}{3} + (-1) \cdot 0 + (-4) \cdot \frac{1}{12} + (+2) \cdot \frac{1}{6} + (+2) \cdot \frac{1}{4} + (+8) \cdot \frac{1}{6} \\ &= \frac{-4 - 4 + 4 + 6 + 16}{12} = \frac{18}{12} = \frac{3}{2} \end{aligned}$$

→ Calculate $\mathbb{E}[4X^2 Y - Y^2]$.

$$\mathbb{E}[4X^2 Y - Y^2] = 4 \mathbb{E}[X^2 Y] - \mathbb{E}[Y^2] = 4 \cdot \frac{3}{2} - \frac{11}{4} = \frac{24 - 11}{4} = \frac{13}{4}$$

↑
Linearity of Expectation

• Example: $f_{x,y}(x,y) = \begin{cases} \frac{1}{\pi} & x^2 + y^2 \leq 1 \\ 0 & \text{otherwise} \end{cases}$



→ Calculate $E[X]$ and $E[Y]$.

$$E[X] = \iint_{R_{x,y}} x f_{x,y}(x,y) dx dy \quad \leftarrow \text{Direct calculation instead of determining } f_x(x) \text{ first.}$$

$$= \int_{-1}^1 \int_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} x \frac{1}{\pi} dx dy$$

$$= \frac{1}{\pi} \int_{-1}^1 \left(\frac{1}{2} x^2 \right) \Big|_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} dy = \frac{1}{\pi} \int_{-1}^1 \frac{1}{2} (1-y^2) - \frac{1}{2} (1-y^2) dy = 0 \stackrel{\text{symmetry}}{=} E[Y]$$

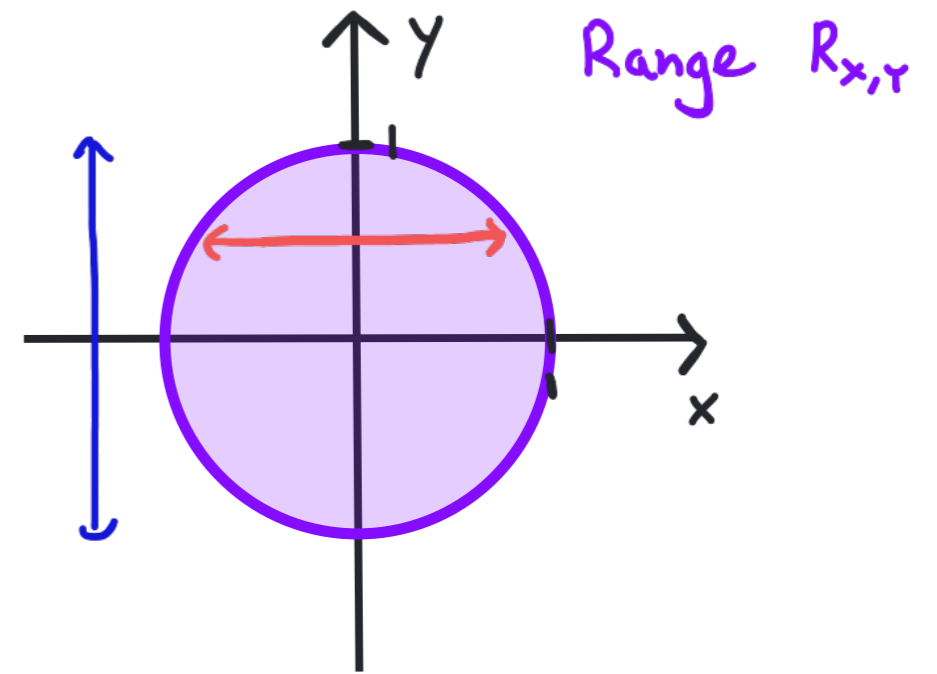
→ Calculate $E[XY]$. From range, X and Y are dependent.

$$E[XY] = \iint_{R_{x,y}} xy f_{x,y}(x,y) dx dy = \int_{-1}^1 \int_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} xy \frac{1}{\pi} dx dy = \int_{-1}^1 \left(\frac{1}{2} x^2 \right) \Big|_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} y \frac{1}{\pi} dy$$

$$= \int_{-1}^1 \left(\frac{1}{2} (1-y^2) - \frac{1}{2} (1-y^2) \right) y \frac{1}{\pi} dy = 0 = E[X] E[Y]$$

But x, y dependent!

• Example: $f_{x,y}(x,y) = \begin{cases} \frac{1}{\pi} & x^2 + y^2 \leq 1 \\ 0 & \text{otherwise} \end{cases}$



→ Calculate $E[X^2]$ and $E[Y^2]$.

$$\begin{aligned} E[X^2] &= \int_{-1}^1 \int_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} x^2 \frac{1}{\pi} dx dy \\ &= \int_{-1}^1 \left(\frac{1}{3} x^3 \right) \Big|_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} \frac{1}{\pi} dy = \int_{-1}^1 \left(\frac{1}{3} (1-y^2)^{\frac{3}{2}} - (-1) \frac{1}{3} (1-y^2)^{\frac{3}{2}} \right) \frac{1}{\pi} dy \\ &= \int_{-1}^1 \frac{2}{3\pi} (1-y^2)^{\frac{3}{2}} dy \stackrel{\text{Computer}}{=} \frac{1}{4} \stackrel{\text{Symmetry}}{=} E[Y^2] \end{aligned}$$

→ Calculate $E[X^2 Y^2]$.

$$E[X^2 Y^2] = \int_{-1}^1 \int_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} x^2 y^2 \frac{1}{\pi} dx dy \stackrel{\text{Computer}}{=} \frac{1}{24} \neq \frac{1}{4} \cdot \frac{1}{4} = E[X^2] E[Y^2]$$

For this choice of function, there was no factorization.