

§5.2 Expected Values, Covariance, Correlation

Expected Values for joint p.m.f. are defined as usual

• $E[X] = \sum_{x,y} x \cdot p(x,y)$ *This is a double sum*

" μ_X " $= \sum_x x \cdot P_X(x) = \sum_x x \sum_y p(x,y)$

• $E[Y] = \sum_{x,y} y \cdot p(x,y)$

" μ_Y " $= \sum_y y \cdot P_Y(y)$

• More generally, if $h(x,y)$ is any function, then

$$E[h(X,Y)] = \sum_{x,y} h(x,y) \cdot p(x,y)$$

Examples:

- $E[X \cdot Y] = \sum_{x,y} x \cdot y \cdot p(x,y)$
- $E[X+Y] = \sum_{x,y} (x+y) \cdot p(x,y)$
- $E[\max(X,Y)] = \sum_{x,y} \max(x,y) \cdot p(x,y)$

If X & Y are continuous then sums (\sum) are replaced by integrals ($\iint \dots dA$)

We can compute Variance with joint r.v. also

• $\text{Var}[X] = E[(X - \mu_X)^2]$ *"spread in x direction"*

" σ_X^2 " $= E[X^2] - (E[X])^2$

These can be computed using the marginal pmf f_X also...

• $\text{Var}[Y] = E[(Y - \mu_Y)^2]$ *"spread in y direction"*

" σ_Y^2 " $= E[Y^2] - (E[Y])^2$

These can be computed using the marginal pmf f_Y also...

Note:

- $E[X+Y] = E[X] + E[Y]$

More generally

$$E[aX + bY] = aE[X] + bE[Y]$$

What about $\text{Var}[X+Y]$?

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

$$\begin{aligned}
 \text{Var}[X+Y] &= E[(X+Y)^2] - (E[X+Y])^2 \\
 &= E[X^2 + 2XY + Y^2] - (E[X] + E[Y])^2 \\
 &= E[X^2] - (E[X])^2 + 2E[XY] - 2E[X] \cdot E[Y] + E[Y^2] - (E[Y])^2 \\
 &\quad \text{Var}[X] \qquad \qquad \qquad \text{Var}[Y]
 \end{aligned}$$

Name the extra term above "Covariance":

Def: Covariance of X & Y is

$$\begin{aligned}
 \text{Cov}[X, Y] &= E[X \cdot Y - \mu_X \cdot \mu_Y] \\
 &= E[X \cdot Y] - E[X] \cdot E[Y]
 \end{aligned}$$

"Cov" \nearrow

Note: If X & Y are independent, then

$$P(x, y) = P_X(x) \cdot P_Y(y)$$

$$\begin{aligned}
 E[X \cdot Y] &= \sum_x \sum_y x \cdot y \cdot P(x, y) \\
 &= \sum_x \sum_y x \cdot y \cdot P_X(x) \cdot P_Y(y) \\
 &= \left(\sum_x x \cdot P_X(x) \right) \left(\sum_y y \cdot P_Y(y) \right) \\
 &= E[X] \cdot E[Y]
 \end{aligned}$$

Thm: If X & Y are independent then

- $\text{Cov}[X, Y] = 0$
- $\text{Var}[X+Y] = \text{Var}[X] + \text{Var}[Y]$

\curvearrowright This probably will not happen if X & Y not indep.

Thm: If X & Y are not independent then

- $\text{Var}[X+Y] = \text{Var}[X] + \text{Var}[Y] + 2 \cdot \text{Cov}[X, Y]$

More generally

$$\begin{aligned}
 \text{Var}[aX + bY] &= a^2 \text{Var}[X] + b^2 \text{Var}[Y] \\
 &\quad + 2ab \text{Cov}[X, Y]
 \end{aligned}$$

Note: $\text{Cov}[X, a] = 0$

$\text{Cov}[X, X] = \text{Var}[X]$

$\text{Cov}[aX, bY] = ab \cdot \text{Cov}[X, Y]$

Idea: $\text{Cov}[X, Y]$ is "spread in diagonal (x+y) direction"

Variance gives Standard Deviation

$$\sigma_X^2 = \text{Var}[X] \implies \sigma_X = \sqrt{\text{Var}[X]}$$

"Standard Deviation"

→ Standard Deviation scales with X:

$$\sqrt{\text{Var}[aX]} = \sqrt{a^2 \text{Var}[X]}$$

$$\sigma_{aX} = |a| \cdot \sigma_X$$

"(Standard Deviation of aX) = a · (Standard Dev. of X)"

Covariance gives Correlation

$$\text{Cov}[X, Y] \implies \rho = \frac{\text{Cov}[X, Y]}{\sigma_X \cdot \sigma_Y}$$

Sometimes we will write " ρ_{XY} " to make it look more like σ_X & σ_Y

"Correlation": Greek letter "rho"

- "rho" for "relation"
- letter before σ in Greek alphabet
- looks like sideways σ "sigma"

→ Correlation is "unit free":

$$\frac{\text{Cov}[aX, bY]}{\sigma_{aX} \cdot \sigma_{bY}} = \frac{ab \text{Cov}[X, Y]}{(a\sigma_X) \cdot (b\sigma_Y)} = \frac{\text{Cov}[X, Y]}{\sigma_X \cdot \sigma_Y}$$

Correlation Facts:

- $-1 \leq \rho \leq 1$
- X & Y independent $\implies \rho = 0$
- $Y = aX$ (completely dependent) $\implies \rho = \pm 1$

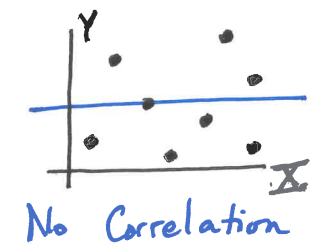
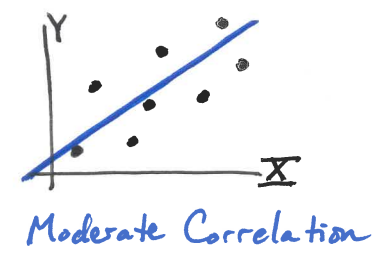
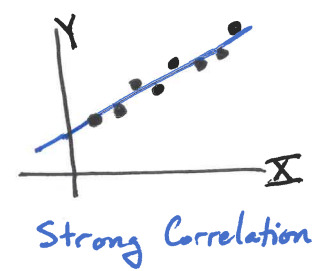
same sign as a

Idea: ρ measures how close the relationship between X & Y is to linear.

$|\rho| \geq .8$ "Strong Correlation"

$.5 < |\rho| < .8$ "Moderate Correlation"

$|\rho| \leq .5$ "Weak Correlation"



Example. Suppose X & Y have joint p.m.f.

		X			
	$p(x, y)$	-1	0	1	$P_Y(y)$
Y	2	$2/15$	$2/15$	$1/15$	$5/15$
	1	$2/15$	$3/15$	$2/15$	$7/15$
	0	$1/15$	$1/15$	$1/15$	$3/15$
	$P_X(x)$	$5/15$	$6/15$	$4/15$	

$$I) E[X] = \sum_{x,y} x \cdot p(x,y)$$

$$= (-1) \left[\frac{2}{15} + \frac{2}{15} + \frac{1}{15} \right] \leftarrow \begin{matrix} 2^{nd} \text{ column} \\ x = -1 \end{matrix}$$

$$+ (0) \left[\frac{2}{15} + \frac{3}{15} + \frac{1}{15} \right] \leftarrow \begin{matrix} 2^{nd} \text{ column} \\ x = 0 \end{matrix}$$

$$+ (1) \left[\frac{1}{15} + \frac{2}{15} + \frac{1}{15} \right] \leftarrow \begin{matrix} 3^{rd} \text{ column} \\ x = 1 \end{matrix}$$

$$= (-1) \frac{5}{15} + (0) \frac{6}{15} + (1) \frac{4}{15}$$

$$= -1/15$$

$$E[Y] = \sum_y y \cdot P_Y(y) \leftarrow \begin{matrix} \text{Let's just use the} \\ \text{marginal pmf this time} \end{matrix}$$

$$= 0 \cdot \frac{3}{15} + 1 \cdot \frac{7}{15} + 2 \cdot \frac{5}{15}$$

$$= \frac{17}{15}$$

$$E[X^2] = \sum_x x^2 \cdot P_X(x)$$

$$= (-1)^2 \cdot \frac{5}{15} + 0^2 \cdot \frac{6}{15} + 1^2 \cdot \frac{4}{15}$$

$$= \frac{9}{15}$$

$$E[Y^2] = \sum_y y^2 P_Y(y)$$

$$= 0^2 \cdot \frac{3}{15} + 1^2 \cdot \frac{7}{15} + 2^2 \cdot \frac{5}{15}$$

$$= \frac{27}{15}$$

$$E[XY] = \sum_{x,y} x \cdot y \cdot p(x,y) \leftarrow \begin{matrix} \text{cannot use marginals here...} \\ \leftarrow = 0 \end{matrix}$$

$$= (-1)(2) \cdot \frac{2}{15} + \cancel{(0)(2) \cdot \frac{2}{15}} + (1)(2) \frac{1}{15}$$

$$+ (-1)(1) \cdot \frac{2}{15} + \cancel{(0)(1) \cdot \frac{2}{15}} + (1)(1) \frac{2}{15}$$

$$+ \cancel{(-1)(0) \cdot \frac{1}{15}} + \cancel{(0)(0) \cdot \frac{1}{15}} + \cancel{(1)(0) \cdot \frac{1}{15}} \leftarrow = 0$$

$$= -4/15 + 2/15 - 2/15 + 2/15 = -2/15$$

$$E[X+Y] = E[X] + E[Y]$$

$$= -1/15 + 17/15 = 16/15$$

Continuing Example

cannot use marginals here (or any other short-cut)

$$E[\min(X, Y)] = \sum_{x,y} \min(x,y) \cdot p(x,y)$$

$$\begin{aligned}
&= (-1) \cdot \frac{2}{15} + \cancel{0 \cdot \frac{2}{15}} + 1 \cdot \frac{1}{15} \\
&+ (-1) \cdot \frac{3}{15} + \cancel{0 \cdot \frac{3}{15}} + 1 \cdot \frac{3}{15} \\
&+ (-1) \cdot \frac{4}{15} + \cancel{0 \cdot \frac{4}{15}} + \cancel{0 \cdot \frac{4}{15}} \\
&= -\frac{2}{15}
\end{aligned}$$

The "dot product" of the "matrices" $\min(x,y)$ and $p(x,y)$

		X		
		-1	0	1
Y	2	-1	0	1
	1	-1	0	1
	0	-1	0	0

		X		
		-1	0	1
Y	2	2/15	3/15	1/15
	1	2/15	3/15	2/15
	0	4/15	1/15	1/15

$\min(x,y)$ = smaller # of x & y

probabilities.

II) Compute Variance and Covariance

$$\begin{aligned}
\text{Var}[X] &= E[X^2] - (E[X])^2 \\
&= 9/15 - (-1/15)^2 = \frac{134}{15^2} = \frac{134}{225}
\end{aligned}$$

But 15² is better in denom...

$$\begin{aligned}
\text{Var}[Y] &= E[Y^2] - (E[Y])^2 \\
&= 27/15 - (17/15)^2 = \frac{27(15) - 17^2}{15^2} \\
&= \frac{116}{15^2} = \frac{116}{225}
\end{aligned}$$

But 15² is better...

$$\begin{aligned}
\text{Cov}[X, Y] &= E[X \cdot Y] - E[X] \cdot E[Y] \\
&= -2/15 - (-1/15)(17/15) = \frac{-13}{15^2}
\end{aligned}$$

III) Compute Standard Deviation & Correlation

$$\sigma_X = \sqrt{\text{Var}[X]} = \sqrt{\frac{134}{15^2}} = \frac{\sqrt{134}}{15}$$

$$\sigma_Y = \sqrt{\text{Var}[Y]} = \sqrt{\frac{116}{15^2}} = \frac{\sqrt{116}}{15}$$

$$\rho = \frac{\text{Cov}[X, Y]}{\sigma_X \cdot \sigma_Y} = \frac{-13/15^2}{\frac{\sqrt{134}}{15} \cdot \frac{\sqrt{116}}{15}} = -\frac{13}{\sqrt{134} \sqrt{116}}$$

IV) $\text{Var}[3X + Y] = 9\text{Var}[X] + \text{Var}[Y] + 6\text{Cov}[X, Y]$

$$= 9 \cdot \frac{134}{15^2} + \frac{116}{15^2} + 6 \left(\frac{-13}{15^2} \right)$$