

MULTIVARIATE DISTRIBUTIONS

Covariances and correlations

Covariances of random variables

- The **covariance** between two random variables is a measure of how much the two tend to vary together.
- **Note:** Covariance is concerned only with “linear” variation.
- **Definition 6:** If Y_1 and Y_2 are random variables with means μ_1 and μ_2 , respectively, then the **COVARIANCE** of Y_1 and Y_2 is:

$$\text{Cov}(Y_1, Y_2) = E[(Y_1 - \mu_1)(Y_2 - \mu_2)]$$

$$\begin{aligned}E[Y_1] &= \mu_1 \\E[Y_2] &= \mu_2\end{aligned}$$

Positive covariance, negative covariance, no covariance

- If $Cov(Y_1, Y_2) > 0$ then the variables are positively (linearly) related (Large values of Y_1 are associated with large values of Y_2).
- If $Cov(Y_1, Y_2) < 0$ then the variables are negatively (linearly) related (Large values of Y_1 are associated with small values of Y_2 and vice-versa).
- If $Cov(Y_1, Y_2) = 0$ then there is no (linear) association between Y_1 and Y_2 .
- Q: What is $Cov(\underline{Y_1}, \underline{Y_1})$?

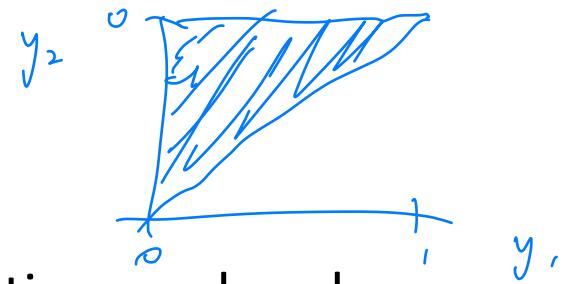
$$\begin{aligned} E[(Y_1 - \mu_1)(Y_1 - \mu_1)] &= E[(Y_1 - \mu_1)^2] \\ &= \text{Var}(Y_1) \end{aligned}$$

$$V_Y(Y) = E(Y^2) - (E[Y])^2$$

Covariances of random variables: An alternative expression

- Theorem 10: For any random variables Y_1 and Y_2 ,

$$Cov(Y_1, Y_2) = \underbrace{E[Y_1 Y_2]}_{\text{ }} - \underbrace{E[Y_1]}_{\text{ }} \underbrace{E[Y_2]}_{\text{ }}$$



Example 7 re-revisited: Y_1 and Y_2 are both proportions and we know that $Y_1 < Y_2$. If their joint pdf is $f(y_1, y_2) = 6y_1$ for $0 < y_1 < y_2 < 1$ (and zero otherwise), find $\text{Cov}(Y_1, Y_2)$.

$$E[Y_1] = \int_0^1 \int_0^{y_2} y_1 6y_1 dy_1 dy_2 = \frac{1}{2}$$

$$E[Y_2] = \int_0^1 \int_0^{y_2} y_2 6y_1 dy_1 dy_2 = \frac{3}{4}$$

$$E[Y_1 Y_2] = \int_0^1 \int_0^{y_2} y_1 y_2 6y_1 dy_1 dy_2 = \int_0^1 \int_0^{y_2} 6y_1^2 y_2 dy_1 dy_2$$

$$= \int_0^1 y_2 \left(2y_1^3 \right) \Big|_0^{y_2} dy_2 = \int_0^1 y_2 2y_2^3 dy_2 = \int_0^1 2y_2^4 dy_2 = \frac{2}{5} y_2^5 \Big|_0^1$$

$$\text{Cov}(Y_1, Y_2) = \frac{2}{5} - \frac{1}{2} \cdot \frac{3}{4} = \frac{2}{5} - \frac{3}{8} = \frac{16 - 15}{40} = \frac{1}{40} = \frac{1}{40}$$

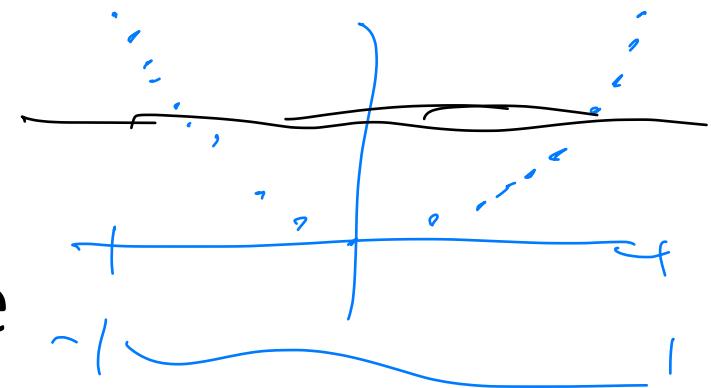
Independence and covariance

- Theorem 11 (independence and covariance): If Y_1 and Y_2 are independent random variables, then $\text{Cov}(Y_1, Y_2) = 0$.

$$\begin{aligned}\text{Cov}(Y_1, Y_2) &= \overbrace{E[Y_1 Y_2] - E[Y_1]E[Y_2]}^{\neq} \\ &= \overbrace{E[Y_1]E[Y_2]}^{\cancel{\text{because}} \atop \cancel{\text{indep.}}} - \overbrace{E[Y_1]E[Y_2]}^{\cancel{\text{because}} \atop \cancel{\text{indep.}}} = 0\end{aligned}$$

$\boxed{Y_1 \text{ \& } Y_2 \text{ are indep.} \Rightarrow \text{Cov}(Y_1, Y_2) = 0}$

$\text{Cov}(Y_1, Y_2) = 0 \not\Rightarrow Y_1 \text{ \& } Y_2 \text{ indep. ?}$



Covariance and independence

$$f_Y(y) = \begin{cases} \frac{1}{2} & -1 \leq y \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

- Note: The converse (of the previous theorem) is not true!
- Example 10: $\underline{Y_1 \sim U(-1, 1)}$ and $\underline{Y_2 = Y_1^2}$. Find $\text{Cov}(Y_1, Y_2)$ and determine whether $\underline{Y_1}$ and $\underline{Y_2}$ are independent.

$$\text{Cov}(Y_1, Y_2) = \underline{E[Y_1 Y_2]} - \underline{E[Y_1] E[Y_2]}$$

$$E[Y_1 Y_2] = \underline{E[Y_1 \cdot Y_1^2]} = E[Y_1^3] = \int_{-1}^1 y_1^3 \frac{1}{2} dy_1 = \frac{1}{8} y_1^4 \Big|_{-1}^1 = \frac{1}{8} (1 - 1) = 0$$

$$E[Y_1] = \int_{-1}^1 y_1 \frac{1}{2} dy_1 = \frac{1}{4} y_1^2 \Big|_{-1}^1 = \frac{1}{4} (1 - 1) = 0$$

$$\frac{1}{8} (1 - 1) = 0$$

$$\text{Cov}(Y_1, Y_2) = 0 - 0 E[Y_2] = 0$$

Correlations of random variables

- The covariance will change if either Y_1 or Y_2 is expressed in different units.
(Check this on your own.)
- Definition 7: For two random variables Y_1 and Y_2 , the CORRELATION COEFFICIENT between Y_1 and Y_2 is

$$\text{Corr}(Y_1, Y_2) = \rho_{Y_1, Y_2} = \frac{\text{Cov}(Y_1, Y_2)}{\sqrt{\text{Var}(Y_1) \text{Var}(Y_2)}}$$

- Theorem 12: For any random variables Y_1 and Y_2 ,
$$-1 \leq \text{Corr}(Y_1, Y_2) \leq 1$$
- A correlation near 1 means a strong positive (linear) relationship between Y_1 and Y_2 ; near -1 means a strong negative (linear) relationship.

“Perfect” correlations

- Theorem 13: For random variables Y_1 and Y_2 , $|Corr(Y_1, Y_2)| = 1$ if and only if there are numbers $a \neq 0$ and b such that $Y_2 = aY_1 + b$. If $a > 0$ then $Corr(Y_1, Y_2) = 1$; if $a < 0$ then $Corr(Y_1, Y_2) = -1$.

Linear functions of random variables

- In statistical analysis, we often use statistics that are linear functions of multiple random variables (data) Y_1, Y_2, \dots, Y_n , i.e., functions that can be expressed as $\sum_{i=1}^n a_i Y_i = a_1 Y_1 + a_2 Y_2 + \dots + a_n Y_n$ for constants a_1, a_2, \dots, a_n .

Linear functions of random variables

- Theorem 14: Given sequences of random variables X_1, X_2, \dots, X_m and Y_1, Y_2, \dots, Y_n with $E[X_j^2] < \infty$ for all j and $E[Y_i^2] < \infty$ for all i , define $U_1 = \sum_{i=1}^n a_i Y_i$ and $U_2 = \sum_{j=1}^m b_j X_j$ for constants a_1, a_2, \dots, a_n and b_1, b_2, \dots, b_m . Then

$$1. E[U_1] = \sum_{i=1}^n a_i E[Y_i] = a_1 E[Y_1] + a_2 E[Y_2] + \dots + a_n E[Y_n]$$

$$2. \text{Var}(U_1) = \sum_{i=1}^n a_i^2 \text{Var}(Y_i) + 2 \sum \sum_{i < j} a_i a_j \text{Cov}(Y_i, Y_j)$$

$$3. \text{Cov}(U_1, U_2) = \sum_{i=1}^n \sum_{j=1}^m a_i b_j \text{Cov}(Y_i, X_j)$$

Some “special case” corollaries:

$$a_1 = 1 \quad a_2 = 1$$

$$i. \quad \underline{Var(Y_1 + Y_2)} = \underline{Var(Y_1)} + \underline{Var(Y_2)} + \underline{2Cov(Y_1, Y_2)}$$

$$ii. \quad \underline{Var(Y_1 - Y_2)} = \underline{Var(Y_1)} + \underline{Var(Y_2)} - \underline{2Cov(Y_1, Y_2)}$$

$$iii. \quad \underline{Var(aY_1 + bY_2)} = \underline{a^2Var(Y_1)} + \underline{b^2Var(Y_2)} + \underline{2abCov(Y_1, Y_2)}$$

$$iv. \quad \underline{Cov(aW + bX, cY + dZ)} = \underline{acCov(W, Y)} + \underline{adCov(W, Z)} + \underline{bcCov(X, Y)} + \underline{bdCov(X, Z)}$$

def. of \underline{Var}

Proof (i)

$$\begin{aligned} \underline{Var(Y_1 - Y_2)} &= E[(Y_1 - Y_2 - E[Y_1 - Y_2])^2] \\ &= E[(Y_1 - E[Y_1] - E[Y_2] + E[Y_2])^2] \end{aligned}$$

↑ ↑ ↑ ↗

$$\begin{aligned}
&= E \left[(Y_1 - E[Y_1]) - (Y_2 - E[Y_2]) \right]^2 \\
&= E \left[(Y_1 - E[Y_1])^2 + (Y_2 - E[Y_2])^2 \right. \\
&\quad \left. - 2(Y_1 - E[Y_1])(Y_2 - E[Y_2]) \right] \\
&= E[(Y_1 - E[Y_1])^2] + E[(Y_2 - E[Y_2])^2] \\
&\quad - 2E[(Y_1 - E[Y_1])(Y_2 - E[Y_2])] \\
&= \text{Var}(Y_1) + \text{Var}(Y_2) - 2\text{Cov}(Y_1, Y_2) \quad \square
\end{aligned}$$

Linear functions of ~~independent~~ random variables

$$\Leftrightarrow \text{Cov}(Y_1, Y_2) = 0$$

- Corollary: If Y_1 and Y_2 are independent random variables, then

$$1. \overbrace{\text{Var}(Y_1 + Y_2)} = \overbrace{\text{Var}(Y_1)} + \overbrace{\text{Var}(Y_2)}$$

$$2. \overbrace{\text{Var}(Y_1 - Y_2)} = \overbrace{\text{Var}(Y_1)} + \overbrace{\text{Var}(Y_2)}$$

$$3. \overbrace{\text{Var}(aY_1 + bY_2)} = \overbrace{a^2 \text{Var}(Y_1)} + \overbrace{b^2 \text{Var}(Y_2)}$$

Already done: $E[Y_1] = \frac{1}{2}$ $E[Y_2] = \frac{3}{4}$ $Cov(Y_1, Y_2) = \frac{1}{40}$

$$Var(Y_1) = E[Y_1^2] - \underbrace{(E[Y_1])^2}_{\dots} = \frac{1}{20}$$

Example 7 re-revisited again: Y_1 and Y_2 are both proportions and we know that $Y_1 < Y_2$. If their joint pdf is $f(y_1, y_2) = 6y_1$ for $0 < y_1 < y_2 < 1$ (and zero otherwise), Find $Var(Y_2 - Y_1)$, $Cov(Y_1, Y_2 - Y_1)$, and $Cov(Y_1 + Y_2, Y_2 - Y_1)$.

$$\textcircled{1} \quad Var(Y_2 - Y_1) = Var(Y_2) + Var(Y_1) - 2Cov(Y_1, Y_2) \quad Var(Y_1) = \dots = \frac{3}{80}$$

$$= \frac{3}{80} + \frac{1}{20} - 2 \frac{1}{40} =$$

$$\textcircled{2} \quad Cov(Y_1, Y_2 - Y_1) = Cov(Y_1, Y_2) - Cov(Y_1, Y_1) = \frac{1}{40} - \frac{1}{20} = \frac{1}{40}$$

$$\textcircled{3} \quad Cov(Y_1 + Y_2, Y_2 - Y_1) = \cancel{Cov(Y_1, Y_2)} - \cancel{Cov(Y_1, Y_1)} + Cov(Y_2, Y_2 - Y_1) - \cancel{Cov(Y_2, Y_1)}$$

$$= -\frac{1}{20} + \frac{3}{80} = \boxed{-\frac{1}{80}}$$

