

Multivariate distributions

Covariance

Definition **Covariance of X_i and X_j** is

$$\underline{\text{Cov}(X_i, X_j)} = \sigma_{X_i, X_j} = E\left[\underbrace{(X_i - EX_i)}_{\text{deviation from mean}} \underbrace{(X_j - EX_j)}_{\text{deviation from mean}}\right] = EX_i X_j - (EX_i)(EX_j)$$

Interpretation:

- ✓ • $\text{Cov}(X_i, X_j) > 0$ means that larger (or smaller) than average values of X_i tend to occur with larger (or smaller) than average values of X_j
- ✓ • $\text{Cov}(X_i, X_j) < 0$ means that larger (or smaller) than average values of X_i tend to occur with smaller (or larger) than average values of X_j

Relationships:

1. $\text{Cov}(X_i, X_i) = \text{Var}(X_i)$
2. $\text{Cov}(X_i, X_j) = \text{Cov}(X_j, X_i)$
3. $\text{Cov}(aX_i + c, bX_j + d) = ab\text{Cov}(X_i, X_j)$
4. $\underline{\text{Var}(aX_i + bX_j + c)} = a^2\text{Var}(X_i) + b^2\text{Var}(X_j) + 2ab\text{Cov}(X_i, X_j)$

Proof

$$\begin{aligned} & \text{Var}(aX_i + bX_j + c) \\ &= E\left(\left[aX_i + bX_j + c - E(aX_i + bX_j + c)\right]^2\right) \\ &= E\left(\left[aX_i + bX_j + c - aEX_i - bEX_j - c\right]^2\right) \\ &= E\left(\left[a(X_i - EX_i) + b(X_j - EX_j)\right]^2\right) \\ &= E\left(a^2(X_i - EX_i)^2 + b^2(X_j - EX_j)^2 + 2ab(X_i - EX_i)(X_j - EX_j)\right) \end{aligned}$$

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Covariance (cont'd)

5. more generally,

$$\text{Cov} \left(\underbrace{c + \sum_{i=1}^n a_i X_i}_V, \underbrace{d + \sum_{j=1}^n b_j X_j}_W \right) \stackrel{?}{=} \sum_{i=1}^n \sum_{j=1}^n a_i b_j \text{Cov}(X_i, X_j) \quad \textcircled{I}$$

$$\stackrel{?}{=} \sum_{i=1}^n a_i b_i \text{Var}(X_i) + 2 \sum_{1 \leq i < j \leq n} a_i b_j \text{Cov}(X_i, X_j) \quad \textcircled{II}$$

$$\begin{aligned} \text{Cov}(V, W) &\stackrel{\text{def}}{=} \mathbb{E} \left[\underbrace{(V - \mathbb{E}V)}_{(*)} \underbrace{(W - \mathbb{E}W)}_{(**)} \right] \\ &= \mathbb{E} \left[\underbrace{\sum_{i=1}^n a_i (X_i - \mathbb{E}X_i)}_{(*)} \underbrace{\sum_{j=1}^n b_j (X_j - \mathbb{E}X_j)}_{(**)} \right] \\ &= \mathbb{E} \left[\sum_{i=1}^n \sum_{j=1}^n a_i b_j (X_i - \mathbb{E}X_i)(X_j - \mathbb{E}X_j) \right] \\ &= \sum_{i=1}^n \sum_{j=1}^n a_i b_j \mathbb{E} \left[(X_i - \mathbb{E}X_i)(X_j - \mathbb{E}X_j) \right] \\ &= \sum_{i=1}^n \sum_{j=1}^n a_i b_j \text{Cov}(X_i, X_j) \end{aligned}$$

$$\begin{aligned} V &= c + \sum_{i=1}^n a_i X_i \\ \mathbb{E}(V) &= c + \sum_{i=1}^n a_i \mathbb{E}X_i \\ \mathbb{E}(W) &= d + \sum_{j=1}^n b_j \mathbb{E}X_j \\ W &= d + \sum_{j=1}^n b_j X_j \end{aligned}$$

6. also, (4. above is a special case of the following)

$$\text{Var} \left(c + \sum_{i=1}^n a_i X_i \right) = \sum_{i=1}^n \sum_{j=1}^n a_i a_j \text{Cov}(X_i, X_j) \quad \textcircled{I}$$

$$= \sum_{i=1}^n a_i^2 \text{Var}(X_i) + 2 \sum_{1 \leq i < j \leq n} a_i a_j \text{Cov}(X_i, X_j) \quad \textcircled{II}$$

$$\text{Var}(\star) = \text{Cov}(\star, \star)$$

$$\text{Var} \left(c + \sum_{i=1}^n a_i X_i \right) = \text{Cov} \left(c + \sum_{i=1}^n a_i X_i, c + \sum_{j=1}^n a_j X_j \right)$$

Multivariate distributions

Covariance: examples

Discrete example: $\mathbb{E}X = \mathbb{E}Y = 2, \mathbb{E}XY = 50/12$
 $\text{Cov}(X, Y) = \mathbb{E}XY - \mathbb{E}X \mathbb{E}Y = 50/12 - 4 = \left(\frac{1}{6}\right)$

Continuous example: $\otimes f(x, y) = \frac{1}{x}$ for $0 < y < x < 1$
 $\text{Cov}(X, Y) = \mathbb{E}XY - \mathbb{E}X \mathbb{E}Y = \frac{1}{6} - \frac{1}{2} \frac{1}{4} = \left(\frac{1}{24}\right)$

$\text{Cov}(2X - 8Y, 4X + 4Y + \cancel{7})$
 $= \text{Cov}(2X - 8Y, 4X + 4Y)$
 $= (2 \times 4) \underbrace{\text{Cov}(X, X)}_{1/2} + (2 \times 4) \underbrace{\text{Cov}(X, Y)}_{1/24} - (8 \times 4) \underbrace{\text{Cov}(Y, X)}_{1/24} - (8 \times 4) \underbrace{\text{Cov}(Y, Y)}_{7/44}$

$$\text{Cov}(X, X) = \text{Var}(X) = \mathbb{E}X^2 - (\mathbb{E}X)^2 = \frac{1}{3} - \left(\frac{1}{2}\right)^2 = \left(\frac{1}{12}\right)$$

$$\text{Cov}(Y, Y) = \text{Var}(Y) = \mathbb{E}Y^2 - (\mathbb{E}Y)^2 = \left(\frac{1}{9}\right) - \left(\frac{1}{4}\right)^2 = \left(\frac{7}{144}\right)$$

Note: $\mathbb{E}(X+Y) = \iint (x+y) f_{X,Y}(x,y) dx dy$
 $= \iint x f_{X,Y}(x,y) dx dy + \iint y f_{X,Y}(x,y) dx dy$
 $= \int x \left[\int f_{X,Y}(x,y) dy \right] dx + \int y \left[\int f_{X,Y}(x,y) dx \right] dy$
 $= \underbrace{\int x f_X(x) dx}_{\mathbb{E}X} + \underbrace{\int y f_Y(y) dy}_{\mathbb{E}Y}$
 $= \mathbb{E}X + \mathbb{E}Y$

Multivariate distributions

Correlation

- Covariance has no natural scale

$$\text{Cov}(X, Y) = 42.6$$

- Correlation of X_i and X_j is a standardized measure of association

$$\text{Corr}(X_i, X_j) = \rho_{X_i, X_j} = \frac{\text{Cov}(X_i, X_j)}{\sqrt{\text{Var}(X_i)} \sqrt{\text{Var}(X_j)}} = \frac{\text{Cov}(X_i, X_j)}{\sigma_{X_i} \sigma_{X_j}}$$

$\text{Var } X_i < \infty, \text{Var } X_j < \infty$

- Example

Continuous case: $f(x, y) = \frac{1}{x}$ for $0 < y < x < 1$

$$\text{Corr}(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)} \sqrt{\text{Var}(Y)}} = \frac{1/24}{\sqrt{1/12} \sqrt{7/44}} \approx 0.655$$

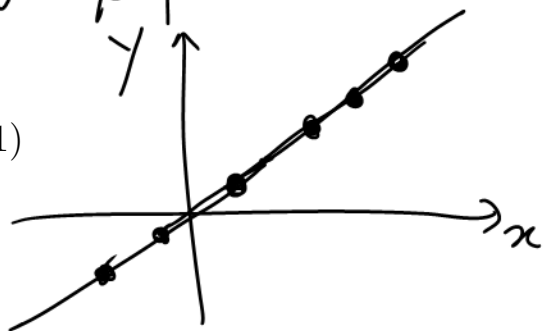
- Theorem:

$$1. -1 \leq \rho_{X, Y} \leq 1$$

$$2. \rho_{X, Y} = 1 \text{ if and only if } P(X = aY + b) = 1$$

(where $a > 0$ if $\rho_{X, Y} = +1$ and $a < 0$ if $\rho_{X, Y} = -1$)

$$\rho_{X, Y} = \left| \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)} \sqrt{\text{Var}(Y)}} \right| \leq 1$$



Multivariate distributions

Correlation (cont'd)

• Proof:

$$|\rho_{X,Y}| \leq 1$$

– Define a function

$$h(t) = E\left(\underbrace{(X - EX)t}_{a} + \underbrace{(Y - EY)}_b\right)^2 = \underbrace{\sigma_X^2 t^2}_{at^2 + bt + C} + 2Cov(X, Y)t + \underbrace{\sigma_Y^2}_{\Delta = b^2 - 4ac}$$

$h(t) \geq 0$ so either $h(\cdot)$ has one real root or two complex roots

roots of $h(t)$ are $\frac{-b \pm \sqrt{\Delta}}{2a}$.

$\begin{cases} a = \sigma_X^2 \\ b = 2 \text{Cov}(X, Y) \\ c = \sigma_Y^2 \end{cases}$

But $\Delta \leq 0 \Rightarrow b^2 - 4ac \leq 0$

$$\Rightarrow [2\text{Cov}(X, Y)]^2 - 4(\sigma_X^2)(\sigma_Y^2) \leq 0$$

$$\cancel{4} \text{Cov}(X, Y)^2 \leq \cancel{4} \sigma_X^2 \sigma_Y^2$$

$$\frac{(\text{Cov}(X, Y))^2}{\sigma_X^2 \sigma_Y^2} = |\rho(X, Y)|^2 \leq 1$$

$$\Leftrightarrow -1 \leq \rho(X, Y) \leq 1$$

$$|x|^2 \leq a^2 \Leftrightarrow -a \leq x \leq a$$

Multivariate distributions

Moment generating functions

Definition: The joint moment generating function of (X_1, \dots, X_n) is

$$\longrightarrow M_{X_1, \dots, X_n}(t_1, \dots, t_n) = \mathbb{E} e^{t_1 X_1 + \dots + t_n X_n}, \quad t_1, \dots, t_n \in \mathbb{R}$$

if the expectation exists for all $\underbrace{-h < t_1, \dots, t_n < h}$ for some $h > 0$

- Joint mgf can provide univariate mgfs

$$M_{X_i}(t_i) = M_{X_1, \dots, X_n}(t_1 = 0, \dots, t_{i-1} = 0, t_i, t_{i+1} = 0, \dots, t_n = 0)$$

$n=2 \quad X, Y$

$$M_{\begin{pmatrix} X \\ Y \end{pmatrix}}(0, t_2) = \mathbb{E} [e^{0 \cdot X + t_2 Y}] = \mathbb{E} [e^{t_2 Y}] = M_Y(t_2)$$

- Applications as before (more later):

- characterizes distributions

e.g., if (X_1, \dots, X_n) and (Y_1, \dots, Y_n) have the same mgfs, then these vectors have the same distribution

- transformations

e.g., mgf of $(a_1 X_1, \dots, a_n X_n)$ is $M_{X_1, \dots, X_n}(a_1 t_1, \dots, a_n t_n)$

- convergence (later)

- moments, e.g,

$$\mathbb{E}(X_i^q X_j^r X_k^s) = \frac{\partial^{q+r+s}}{\partial t_i^q \partial t_j^r \partial t_k^s} M_{X_1, \dots, X_n}(t_1, \dots, t_n) \Big|_{(t_1, \dots, t_n) = (0, \dots, 0)}$$

$$\mathbb{E} X^r = \frac{d^r}{dt^r} M_X(t) \Big|_{t=0}$$