

## Covariance

context: Two jointly distributed r.v.s  $X, Y$

$$\text{Cov}(X, Y) = E(XY) - E(X)E(Y).$$

From the proof of Theorem 2.6.8 (iii):

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

W/out independence, still have this

$$\boxed{\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X, Y)}$$

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

$$\boxed{\text{Var}(X-Y) = \text{Var}(X) + \text{Var}(Y) - 2\text{Cov}(X, Y)}$$

True generally

If, in addition,  $X, Y$  independent, get 0 Covariance so

$$\text{Var}(X-Y) = \text{Var}(X) + \text{Var}(Y).$$

$$\begin{aligned}\text{Thm.: } \text{Cov}(X, Y) &= E((X - \mu_X)(Y - \mu_Y)) \\ &= E((X - E(X))(Y - E(Y)))\end{aligned}$$

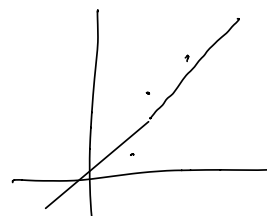
When is Covariance nearly 0?

large positive?

large negative?

Using Covariance, we can define a "normalized version": correlation

$$\rho = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X) \text{Var}(Y)}} = \frac{\sigma_{XY}}{\sigma_X \sigma_Y}$$



Facts about  $\rho$  (correlation between  $X$  and  $Y$ )

1)  $-1 \leq \rho \leq 1$

2) If  $\rho = -1$ , then  $P(Y = aX + b) = 1$   
for some choice of  $a < 0$  and  $b$ .

Some Covariance results

1.  $\text{Cov}(aX, bY) = ab \text{Cov}(X, Y)$

2.  $\text{Var}(X_1 + X_2 + \dots + X_n) = \sum_{j=1}^n \sum_{k=1}^n \text{Cov}(X_j, X_k)$

Useful

Covariance matrix

$$\begin{bmatrix} \text{Cov}(X_1, X_1) & \text{Cov}(X_1, X_2) & \dots & \text{Cov}(X_1, X_n) \\ \vdots & & & \\ \text{Cov}(X_n, X_1) & \dots & \text{Cov}(X_n, X_n) \end{bmatrix}$$

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