

Example

Ex. For some $\lambda > 0$, random variable X has the density function

$$f(x) = \lambda^2 x e^{-\lambda x}, \quad x > 0,$$

and given X , Y is a uniform random variable on the interval $[0, X]$.

1. What is the joint distribution of X and Y ?
2. What is the distribution of Y ?

Expectation of Functions

- Recall how we compute $E[h(X)]$. A similar result also holds for a function $h(X, Y)$ of two jointly distributed rv's.
- Let X and Y be jointly distributed rv's with pmf $p(x, y)$, if they are discrete; or pdf $f(x, y)$, if they are continuous. The expected value of a function $h(X, Y)$, denoted by $E[h(X, Y)]$ is given by

$$E[h(X, Y)] = \begin{cases} \sum_x \sum_y h(x, y) \cdot p(x, y) & \text{if } X \text{ and } Y \text{ are discrete} \\ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(x, y) \cdot f(x, y) dx dy & \text{if } X \text{ and } Y \text{ are continuous} \end{cases}$$

- This result can also be extended to multiple (>2) rv case.

Examples

Ex. (Important! **Linearity of expectations**) Show that for any two random variables X and Y , $E(X+Y) = E(X) + E(Y)$.

Example

Ex. If two random variables X and Y are independent, what is $E(XY)$? What about $E(g(X)h(Y))$?

Covariance

- When two random variables X and Y are not independent, it is often of interest to assess how strongly they are related to one another.
- A popular measurement to characterize the dependence of two rv's is called **correlation**. To calculate correlation of two rv's, we'll have calculate the **covariance** of the two rv's.
- The **covariance** between two rv's X and Y is

$$\begin{aligned}\text{Cov}(X, Y) &= E[(X - \mu_X)(Y - \mu_Y)] \\ &= \begin{cases} \sum_x \sum_y (x - \mu_X)(y - \mu_Y) \cdot p(x, y) & X, Y \text{ discrete} \\ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \mu_X)(y - \mu_Y) \cdot f(x, y) dx dy & X, Y \text{ continuous} \end{cases}\end{aligned}$$

Short cut

- Proposition:

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

- What happens if we set $Y=X$?

Example

Ex. Suppose the joint distribution of X and Y are

$$f(x, y) = \begin{cases} 24xy & 0 \leq x \leq 1, 0 \leq y \leq 1, x + y \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

What is the covariance of X and Y?

$$f_X(x) = \int_y f(x, y) dy = \int_0^{1-x} 24xy dy = 12x(1-x)^2$$

$$f_Y(y) = 12y(1-y)^2$$

$$E(X) = \int_0^1 x \cdot 12x(1-x)^2 dx = \frac{2}{5} = E(Y)$$

$$E(XY) = \int \int_{x,y} xy f(x, y) dx dy = \int_0^1 \int_0^{1-y} 24x^2 y^2 dx dy = \frac{2}{15}$$

$$\text{Cov}(X, Y) = E(XY) - E(X)E(Y) = \frac{2}{15} - \left(\frac{2}{5}\right)^2 = -\frac{2}{75}$$

Correlation

- The **correlation coefficient** of X and Y , denoted by $\text{Corr}(X, Y)$ or $\rho_{X,Y}$ is defined by

$$\rho_{X,Y} = \frac{\text{Cov}(X, Y)}{\sigma_X \cdot \sigma_Y}$$

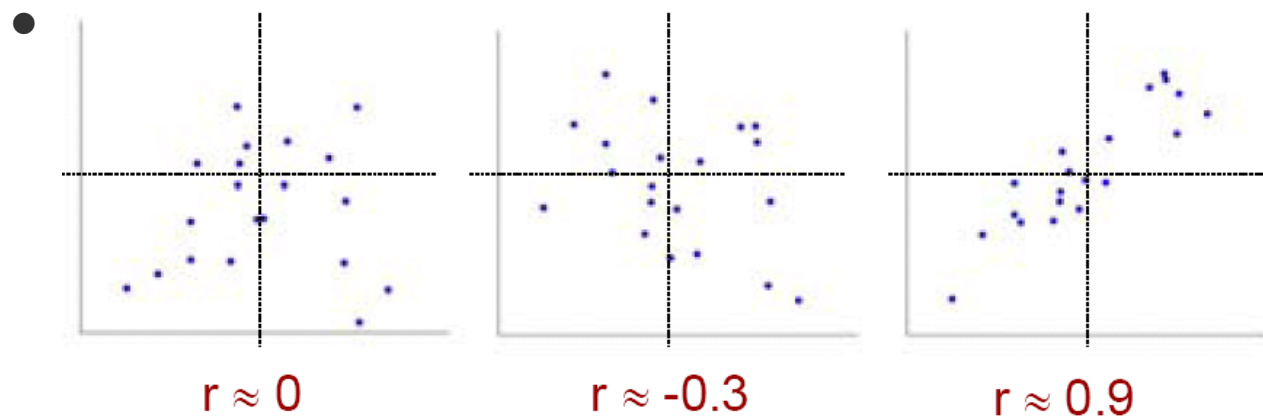
- Because of Cauchy-Schwarz inequality, we have

$$\text{Cov}^2(X, Y) \leq \text{Var}(X)\text{Var}(Y) \implies |\rho_{X,Y}| \leq 1$$

- The correlation coefficient $\rho_{X,Y}$ is **NOT** a completely general measure of the strength of a relationship. $\rho_{X,Y}$ is actually a measure of the degree of **linear** relationship between X and Y .

Remarks

- If X and Y are independent, then $\rho_{X,Y} = 0$ (why?). But $\rho_{X,Y} = 0$ does **NOT** imply independence.
- $\rho_{X,Y} = 1$ or -1 **iff** $Y = aX + b$ for some numbers a and b with $a \neq 0$.



Example

Ex. If X has a symmetric distribution centered at 0 with finite 3rd moment, $E(|X|^3) < \infty$, show that X^2 and X are uncorrelated.