

STAT 330: Lecture 7

2024 Spring

June 4, 2024

Last Lecture Independence

$$f(x,y) = f(x)f(y)$$

1. Definition: Connection with Independence of Events/Equivalence to the product of marginal pdf/pmf
2. Function of Independence Random Variables $X \perp Y \Rightarrow g(x) \perp h(y)$
3. Factorization Theorem $\begin{cases} f(x,y) = c g(x) h(y) \\ A = A_x \times A_y \end{cases} \Leftrightarrow X \perp Y$

This Lecture Joint Expectation, Variance, Covariance; Correlation Coefficient

Joint Expectation We extend the definition of expectation from univariate to bivariate (and multivariate) cases.

Defn: Suppose $h(x, y)$ is a real function. Then

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

if the expectation exists.

e.g. $E(XY) = \begin{cases} \sum_x \sum_y xy f(x, y) & \text{discrete} \\ \iint_{-\infty}^{\infty} xy f(x, y) dx dy & \text{continuous} \end{cases}$

$E(X) = \begin{cases} \sum_x \sum_y x f(x, y) & \text{discrete} \\ \iint_{-\infty}^{\infty} x f(x, y) dx dy & \text{continuous} \end{cases}$

OR.

$E(X) = \begin{cases} \sum_x x f(x) & \text{discrete} \\ \int_{-\infty}^{\infty} x f(x) dx & \text{continuous} \end{cases}$ First get $f(x)$ from $f(x, y)$

Properties:

1) Linearity: exchange the order of summation & expectation.

$$E[a g(X, Y) + b h(X, Y)] = a E[g(X, Y)] + b E[h(X, Y)]$$

$$E\left[\sum_{i=1}^n a_i X_i\right] = \sum_{i=1}^n a_i E(X_i)$$

2) $E(XY) \neq E(X)E(Y)$ in general.

But $E(XY) = E(X)E(Y)$ if $X \perp Y$

Proof.
$$\begin{aligned} E(XY) &= \iint xy f(x, y) dx dy \\ &= \iint xy f(x) f(y) dx dy \\ &= \left\{ \int x f(x) dx \right\} \left\{ \int y f(y) dy \right\} = E(X)E(Y) \end{aligned}$$

$$E\{g(X)h(Y)\} = E\{g(X)\} E\{h(Y)\} \text{ if } X \perp Y.$$

If $X_1 \dots X_n$ are independent.

$$E\left(\prod_{i=1}^n X_i\right) = \prod_{i=1}^n E(X_i)$$

Covariance: Covariance of $X \& Y$ is defined as

$$\begin{aligned}\text{Cov}(X, Y) &= E\{(X - E(X))(Y - E(Y))\} \\ &= E(XY) - E(X)E(Y)\end{aligned}$$

If $X \perp Y$, $E(XY) = E(X)E(Y) \Rightarrow \text{Cov}(X, Y) = 0$

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

Variance Formulas:

$$1) \text{Var}(aX + bY) = a^2 \text{Var}(X) + b^2 \text{Var}(Y) + 2ab \text{Cov}(X, Y)$$

$$2) \text{Var}\left(\sum_{i=1}^n a_i X_i\right) = \sum_{i=1}^n a_i^2 \text{Var}(X_i) + \sum_{i \neq j} a_i a_j \text{Cov}(X_i, X_j)$$

NOT a proof

$$\left\{ \begin{array}{l} (aX + bY)^2 = a^2 \underbrace{X^2}_{\text{Var}(X)} + b^2 \underbrace{Y^2}_{\text{Var}(Y)} + 2ab \underbrace{XY}_{\text{Cov}(X, Y)} \\ \left(\sum_{i=1}^n a_i X_i \right)^2 = \underbrace{a_1^2 X_1^2}_{\text{Var}(X_1)} + \underbrace{a_2^2 X_2^2}_{\text{Var}(X_2)} + \dots + \underbrace{a_n^2 X_n^2}_{\text{Var}(X_n)} + \sum_{i \neq j} a_i a_j \underbrace{X_i X_j}_{\text{Cov}(X_i, X_j)} \end{array} \right.$$

3). If $X_1 \dots X_n$ are independent.

$$\text{Var}\left(\sum_{i=1}^n a_i X_i\right) = \sum_{i=1}^n a_i^2 \text{Var}(X_i)$$

Examples: Suppose we have joint pmf. for (X, Y)

$$f(x,y) = \frac{\theta^{x+y} e^{-2\theta}}{x! y!}, \quad x, y \in \{0, 1, 2, \dots\}$$

Find $\text{Var}(2X+3Y)$

$$f(x,y) = e^{-2\theta} \cdot \frac{\theta^x}{x!} \cdot \frac{\theta^y}{y!} \Rightarrow X \perp Y \text{ by factorization theorem.}$$

$$\text{Var}(2X+3Y) = 4\text{Var}(X) + 9\text{Var}(Y)$$

$$X, Y \sim \text{Poi}(\theta), \quad \text{Var}(X) = \text{Var}(Y) = \theta$$

$$\Rightarrow \text{Var}(2X+3Y) = 13\theta.$$

$X \& Y$ joint pdf. $f(x,y) = \begin{cases} x+y & , 0 \leq x \leq 1, 0 \leq y \leq 1 \\ 0 & \text{otherwise.} \end{cases}$

Find out $\text{Var}(X+Y)$

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

$\text{Var}(X) = \text{Var}(Y)$ due to Symmetry.

$$\text{Var}(X) = E(X^2) - \{E(X)\}^2$$

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

We need. $E(X^2), E(X), E(XY).$

$$E(X) = E(Y) = \int_0^1 x f(x) dx = \int_0^1 x \cdot (x + \frac{1}{2}) dx = \frac{7}{12}$$

marginal of X

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

$$E(XY) = \int_0^1 \int_0^1 xy (x+y) dx dy = \int_0^1 (\frac{y}{3} + \frac{y^2}{2}) dy = \frac{1}{3}$$

$$\text{Cov}(X, Y) = E(XY) - E(X)E(Y) = \frac{1}{3} - (\frac{7}{12})^2 = -\frac{1}{144}$$

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

$$= \frac{11}{144} \cdot 2 - \frac{2}{144} = \frac{5}{36}.$$

Correlation Coefficient

Definition: The correlation coefficient of X and Y is defined as

$$\rho(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)} \sqrt{\text{Var}(Y)}} = \frac{\text{Cov}(X, Y)}{\text{sd}(X) \cdot \text{sd}(Y)}$$

if $X \perp Y$.
 $\rho(X, Y) = 0$

Properties: ① $-1 \leq \rho(X, Y) \leq 1$

Cauchy Schwarz Inequality: X, Y rvs
 $\{E(XY)\}^2 \leq E(X^2) E(Y^2)$

$$\begin{aligned} [E\{X - E(X)\}\{Y - E(Y)\}]^2 &\leq E\{(X - E(X))^2\} \cdot E\{(Y - E(Y))^2\} \\ \{\text{Cov}(X, Y)\}^2 &\leq \text{Var}(X) \cdot \text{Var}(Y) \\ -\sqrt{\text{Var}(X)} \sqrt{\text{Var}(Y)} &\leq \text{Cov}(X, Y) \leq \sqrt{\text{Var}(X)} \cdot \sqrt{\text{Var}(Y)} \\ \Leftrightarrow \rho(X, Y) &\in [-1, 1] \end{aligned}$$

② Let $Y = aX + b$

$$\text{Cov}(X, Y) = \text{Cov}(X, aX + b) = \text{Cov}(X, aX) = a \text{Cov}(X, X)$$

$$\text{Example: } \rho(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)} \cdot \sqrt{\text{Var}(Y)}} = \frac{a \text{Var}(X)}{\sqrt{\text{Var}(X)} \sqrt{a^2 \text{Var}(X)}} = \frac{a}{|a|} = \begin{cases} 1, & a > 0 \\ -1, & a < 0 \end{cases}$$

$$\text{Example: } f(x, y) = \begin{cases} x+y, & x \in [0, 1], y \in [0, 1] \\ 0, & \text{otherwise.} \end{cases}$$

Find out $\rho(X, Y)$

$$\rho(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)} \cdot \sqrt{\text{Var}(Y)}} = \frac{-Y_{144}}{\frac{11}{144}} = -\frac{1}{11}$$

Conditional Distribution*continuous/discrete.*

Definition: Suppose X and Y are joint discrete with joint pdf/pmf $f(x, y)$. Then the conditional pdf/pmf of X given $Y = y$ is

$$f(x|y) = \frac{f(x, y)}{f(y)}, \quad \begin{matrix} \text{random.} \\ \text{fix } Y=y \end{matrix} \quad \begin{matrix} \text{non-random} \\ \text{fix } Y=y \end{matrix}$$

given that $f(y) > 0$. The conditional pdf/pmf of Y given $X = x$ is

$$f(y|x) = \frac{f(x, y)}{f(x)}, \quad \text{fix } X=x$$

given that $f(x) > 0$.

Properties: ① Conditional pdf/pmf are still valid pdf/pmf.

$$\left\{ \begin{array}{l} f(x|y) \geq 0 \text{ & } \sum_x f(x|y) = 1 \end{array} \right. \quad \text{discrete}$$

$$\left\{ \begin{array}{l} f(y|x) \geq 0 \text{ & } \sum_y f(y|x) = 1 \end{array} \right.$$

$$\left\{ \begin{array}{l} f(x|y) \geq 0 \text{ & } \int_{-\infty}^{\infty} f(x|y) = 1 \\ f(y|x) \geq 0 \text{ & } \int_{-\infty}^{\infty} f(y|x) = 1 \end{array} \right. \quad \text{continuous}$$

Example:

Example. 1.

$$f(x, y) = \begin{cases} 8xy & , 0 < y < x < 1 \\ 0 & , \text{otherwise.} \end{cases}$$

Find out 1) $f(x|y)$ 2) $f(y|x)$

First step: $f(x) = 4x^3$, $0 < x < 1$

Find marginals $f(y) = 4y - 4y^3$, $0 < y < 1$.

$$f(x|y) = \frac{f(x,y)}{f(y)} = \frac{8xy}{4y - 4y^3} = \frac{2x}{1-y^2}, \quad x \in (y, 1)$$

$$f(y|x) = \frac{f(x,y)}{f(x)} = \frac{8xy}{4x^3} = \frac{2y}{x^2}, \quad y \in (0, x)$$

Example 2.

$$f(x,y) = \begin{cases} x+y & , x,y \in [0,1] \\ 0 & , \text{otherwise} \end{cases}$$

First, find out the marginals.

$$f(x) = x + \sum_{y=0}^1 y , x \in [0,1]$$

$$f(y) = y + \sum_{x=0}^1 x , y \in [0,1]$$

Second, take the ratio.

$$f(x|y) = \frac{f(x,y)}{f(y)} = \frac{x+y}{y+1} , x \in [0,1]$$

$$f(y|x) = \frac{f(x,y)}{f(x)} = \frac{x+y}{x+1} , y \in [0,1]$$

Example 3. X, Y rvs. joint discrete.

$$f(x,y) = q^2 \cdot p^{x+y} , q = \text{tp. } \underline{y \in \{0, 1, 2, \dots\}}$$

marginals. $f(x) = q^2 p^x$, $f(y) = q p^y$

$$f(x,y) = q^2 \cdot p^x \cdot p^y \Rightarrow X \perp Y \text{ by Factorization theorem.}$$

$$f(x|y) = \frac{f(x,y)}{f(y)} = \frac{q^2 \cdot p^{x+y}}{q p^y} = q \cdot p^x = f(x)$$

$$f(y|x) = \frac{f(x,y)}{f(x)} = q \cdot p^y = f(y)$$

marginal dist'n = conditional dist'n if $X \perp Y$