

## Question 5: Bivariate Normal Variables

### - Introduction

- Difference Between Multivariate & Bivariate - Bivariate  $\rightarrow n=2$

$$\text{- Joint PDF: } \frac{1}{(2\pi)^{n/2} \cdot |\mathbf{V}|^{1/2}} \exp\left(-\frac{1}{2} (\mathbf{x}-\mathbf{m})^\top \mathbf{V}^{-1} (\mathbf{x}-\mathbf{m})\right)$$

-  $\mathbf{X}$ : N-dimensional Random Vector, represents values of random variables

-  $\mathbf{m}$ : N-dimensional Vector of EV, represents EVs of each variable

-  $|\mathbf{V}|$ : Determinant of Covariance Matrix

-  $\mathbf{V}^{-1}$ : Inverse of Covariance Matrix

-  $(2\pi)^{n/2} \cdot |\mathbf{V}|^{1/2}$ : Normalization Constant

### - Question 5a

-  $\mathbf{X} = [x_1, x_2]^\top \rightarrow$  bivariate normal random vector  $\rightarrow$  Mean vector  $\begin{bmatrix} M_1 \\ M_2 \end{bmatrix}$

- Covariance Matrix:  $\mathbf{V} = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix} \quad |\mathbf{V}| = \sigma_1^2 \cdot \sigma_2^2 \cdot (1-\rho^2)$

$$- |\mathbf{V}|^{1/2} = \sigma_1\sigma_2\sqrt{1-\rho^2} \rightarrow \frac{1}{(2\pi)\cdot\sigma_1\sigma_2\sqrt{1-\rho^2}}$$

$$- \mathbf{V}^{-1} = \frac{1}{\sigma_1^2\sigma_2^2(1-\rho^2)} \begin{bmatrix} \sigma_2^2 & -\rho\sigma_1\sigma_2 \\ -\rho\sigma_1\sigma_2 & \sigma_1^2 \end{bmatrix}$$

$$- (\mathbf{x}-\mathbf{m})^\top = [x_1 - M_1, x_2 - M_2] \rightarrow (\mathbf{x}-\mathbf{m}) = \begin{bmatrix} x_1 - M_1 \\ x_2 - M_2 \end{bmatrix}$$

$$- \text{Exponent: } -\frac{1}{2} [x_1 - M_1, x_2 - M_2] \frac{1}{\sigma_1^2\sigma_2^2(1-\rho^2)} \begin{bmatrix} \sigma_2^2 & -\rho\sigma_1\sigma_2 \\ -\rho\sigma_1\sigma_2 & \sigma_1^2 \end{bmatrix} \cdot \begin{bmatrix} x_1 - M_1 \\ x_2 - M_2 \end{bmatrix}$$

$$- \text{Matrix Multiplication: } -\frac{1}{2} \cdot \frac{1}{1-\rho^2} \left[ \frac{(x_1 - M_1)^2}{\sigma_1^2} + \frac{(x_2 - M_2)^2}{\sigma_2^2} - \frac{2\rho(x_1 - M_1)(x_2 - M_2)}{\sigma_1\sigma_2} \right]$$

$$f(x_1, x_2) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \exp\left[-\frac{1}{2(1-\rho^2)} \left( \frac{(x_1 - M_1)^2}{\sigma_1^2} + \frac{(x_2 - M_2)^2}{\sigma_2^2} - \frac{2\rho(x_1 - M_1)(x_2 - M_2)}{\sigma_1\sigma_2} \right)\right]$$

Independence:  $f(x_1, x_2) = f(x_1) \cdot f(x_2)$

1. Show if  $\rho=0$ ,  $x_1$  and  $x_2$  are independent

- Substituting  $\rho=0 \rightarrow f(x_1, x_2) = \frac{1}{2\pi\sigma_1\sigma_2} \exp\left[-\frac{1}{2}\left(\frac{(x_1-\mu_1)^2}{\sigma_1^2} + \frac{(x_2-\mu_2)^2}{\sigma_2^2}\right)\right]$

$= \frac{1}{\sqrt{2\pi}\sigma_1} \exp\left[-\frac{1}{2}\left(\frac{(x_1-\mu_1)^2}{\sigma_1^2}\right)\right] \cdot \frac{1}{\sqrt{2\pi}\sigma_2} \exp\left[-\frac{1}{2}\left(\frac{(x_2-\mu_2)^2}{\sigma_2^2}\right)\right] = f(x_1) \cdot f(x_2) \quad \checkmark$

2. Show if  $x_1$  and  $x_2$  are independent,  $\rho$  must equal 0

- If  $x_1$  &  $x_2$  are independent,  $\frac{2\rho(x_1-\mu_1)(x_2-\mu_2)}{\sigma_1\sigma_2}$  must equal 0  $\rightarrow \rho=0 \quad \checkmark$

Question 5b.

-  $Z_1, Z_2 \sim N(0,1)$   $X = Z_1, Y = \rho Z_1 + \sqrt{1-\rho^2} Z_2$  for  $\rho \in (-1,1)$

$E[X] = E[Z_1] = 0 \quad E[Y] = E[\rho Z_1] + E[\sqrt{1-\rho^2} Z_2] = 0+0=0 \quad \begin{bmatrix} Z_1 \\ Z_2 \end{bmatrix}$  is

$\text{Var}(X) = \text{Var}(Z_1) = 1 \quad \text{Var}(Y) = \rho^2 \text{Var}(Z_1) + (1-\rho^2) \text{Var}(Z_2) = 1 \quad \text{multivariate normal}$

$\rightarrow X \sim N(0,1) \quad \rightarrow Y \sim N(0,1)$

$\begin{bmatrix} X \\ Y \end{bmatrix}$  = Linear Combination of Multivariate Normal Variables = Multivariate (Bivariate) Normal

-  $\text{Corr}(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X) \cdot \text{Var}(Y)}}$   $\text{Var}(X) = \text{Var}(Z_1) = 1 \quad \text{Var}(Y) = \text{Var}(\rho Z_1 + \sqrt{1-\rho^2} Z_2)$

$Z_1$  and  $Z_2$  are independent, so  $\text{Var}(\rho Z_1 + \sqrt{1-\rho^2} Z_2) = \text{Var}(\rho Z_1) + \text{Var}(\sqrt{1-\rho^2} Z_2)$

$\rightarrow \rho^2 \text{Var}(Z_1) + (1-\rho^2) \text{Var}(Z_2) \rightarrow \text{Var}(Z_1) = \text{Var}(Z_2) = 1 \rightarrow \text{Var}(Y) = \rho^2 + 1-\rho^2 = 1$

$\rightarrow \sqrt{\text{Var}(X) \cdot \text{Var}(Y)} = \sqrt{1 \cdot 1} = 1 \rightarrow \text{Corr}(X, Y) = \text{Cov}(X, Y)$

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

$E[X] = E[Z_1] = 0 \quad E[Y] = E[\rho Z_1 + \sqrt{1-\rho^2} Z_2] = \rho E[Z_1] + (1-\rho^2) E[Z_2] = 0+0=0$

$$E[XY] = E[Z_1(pZ_1 + \sqrt{1-p^2}Z_2)] = E[pZ_1^2 + \sqrt{1-p^2}Z_1Z_2] = pE[Z_1^2] + \sqrt{1-p^2}E[Z_1Z_2]$$

$$E[Z_1^2] = Var(Z_1) + E[Z_1]^2 = 1+0 = 1 \quad Z_1, Z_2 \text{ are independent}$$

$$E[Z_1Z_2] = Cov(Z_1, Z_2) + E[Z_1]E[Z_2] = 0+0=0$$

$$Cov(X, Y) = E[XY] = p(1) + \sqrt{1-p^2}(0) = p \quad \text{Thus, } \text{Corr}(X, Y) = \text{Cov}(X, Y)/\sigma_X\sigma_Y = p$$

Question 5c.  $X = Z_1$ ,  $Y = SZ$ ,  $Z \sim N(0, 1)$ , independent of  $S$

$S \pm 1$  simply changes the sign of  $Y$ .  $S$  &  $Z$  are independent, so  $Y \sim N(0, 1)$  as well

$$\text{Cov}(X, Y) = E[XY] - E[X] \cdot E[Y] \quad E[X] = E[Y] = 0 \Rightarrow = E[XY]$$

$$E[XY] = E[Z_1 \cdot SZ] \rightarrow S \& Z \text{ are independent, so } E[SZ^2] = E[S] \cdot E[Z^2]$$

$$E[S] = \frac{1}{2} \cdot -1 + \frac{1}{2} \cdot 1 = 0 \quad E[Z^2] = Var(Z) + (E[Z])^2 = 1+0=1$$

$$\text{Cov}(X, Y) = E[XY] = E[S] \cdot E[Z^2] = 0 \cdot 1 = 0 \rightarrow X \& Y \text{ are uncorrelated}$$

If  $\tilde{X}$  and  $\tilde{Y}$  are not independent,  $Y$  depends on  $X \rightarrow Y$  depends on  $Z$

$Y = SZ \Rightarrow$  depends on the value of  $Z$  ( $X = Z$ )  $\Rightarrow X$  and  $Y$  are not independent

By definition, a random vector  $\begin{pmatrix} X \\ Y \end{pmatrix}$  is bivariate normal if  $X$  and  $Y$  are linear transformations/combinations of iid normal variables

written in the form  $X = a_1 Z_1 + a_2 Z_2$ ,  $Y = b_1 Z_1 + b_2 Z_2$ ,  $a_1, a_2, b_1, b_2$  are constants

$X$  and  $Y$  are functions of a single variable ( $Z_1$ )

Non-Trivial LC:  $Z_1$  &  $Z_2$  both contribute nonzero weights for either  $X$  or  $Y$

If  $a_1 = b_1 = 0$  (as in question),  $X$  and  $Y$  are not independent

Question Sd.

Suppose  $E[X] = M_x$  and  $E[Y] = M_y$ , with SDs  $\sigma_x$  and  $\sigma_y$

Given  $X, Y$  are bivariate normal, they must be normally distributed

Since  $X \sim N(M_x, \sigma_x^2)$ ,  $Z_x = \frac{X - M_x}{\sigma_x}$ , so  $X = M_x + \sigma_x Z_x$

From part b., we know for any correlation value  $\rho$ , the vector  $(X, Y)$  is bivariate Normal

$$\rightarrow X = Z_x, Y = \rho Z_x + \sqrt{1-\rho^2} Z_y, \text{ where } Z_x, Z_y \stackrel{iid}{\sim} N(0, 1)$$

$$\rightarrow Y = M_y + \sigma_y Z_y \rightarrow Y = M_y + \sigma_y (\rho Z_x + \sqrt{1-\rho^2} Z_y)$$

$$\rightarrow Y = M_y + \sigma_y \left( \rho \frac{X - M_x}{\sigma_x} + \sqrt{1-\rho^2} Z_y \right) = M_y + \rho \frac{\sigma_y}{\sigma_x} (X - M_x) + \sigma_y \sqrt{1-\rho^2} Z_y$$

$$E[Y|X=x] + \text{Var}[Y|X=x]$$

$$\text{Since } \text{Var}[Y|X=x] = \text{Var}\left(\sigma_y \sqrt{1-\rho^2} Z_y\right) = \sigma_y^2 (1-\rho^2) \text{ Var}(Z_y) = \sigma_y^2 (1-\rho^2)$$

$$\rightarrow Y|X=x \sim N\left(M_y + \rho \frac{\sigma_y}{\sigma_x} (x - M_x), \sigma_y^2 (1-\rho^2)\right)$$

Linear Regression:  $E[Y|X] = M_y + \rho \frac{\sigma_y}{\sigma_x} (X - M_x) = M_y - \underbrace{\rho \frac{\sigma_y}{\sigma_x} M_x}_{\beta_0} + \underbrace{\rho \frac{\sigma_y}{\sigma_x} X}_{\beta_1}$

$$Y = \beta_0 + \beta_1 X + \varepsilon$$