

LECTURE 5

JOINT, MARGINAL, CONDITIONAL
DISTRIBUTION

MULTIVARIATE RANDOM VARIABLES

- In many applications there will be more than one random variable X_1, X_2, \dots, X_k
- Often used to study the relationship among characteristics and the prediction of one based on the other(s)
- Three types of distributions:
 - Joint: Distribution of outcomes across all combinations of variables levels
 - Marginal: Distribution of outcomes for a single variable
 - Conditional: Distribution of outcomes for a single variable, given the level(s) of the other variable(s)

JOINT DISCRETE DISTRIBUTION

Let X_1, X_2, \dots, X_k denote k discrete random variables, then

$$p(x_1, x_2, \dots, x_k)$$

is joint probability function of X_1, X_2, \dots, X_k if

1. $0 \leq p(x_1, \dots, x_n) \leq 1$
2. $\sum_{x_1} \dots \sum_{x_n} p(x_1, \dots, x_n) = 1$
3. $P[X_1, \dots, X_n \in A] = \sum_{x_1, \dots, x_n \in A} p(x_1, \dots, x_n)$

Example

- For e.g.: Tossing two fair dice \rightarrow 36 possible sample points
- Let X : sum of the two dice;
 Y : difference of the two dice
 - For $(3,3)$, $X=6$ and $Y=0$.
 - For both $(4,1)$ and $(1,4)$, $X=5$, $Y=3$.

- Joint pmf (pdf) of (x,y)

		x										
		2	3	4	5	6	7	8	9	10	11	12
y	0	1/36		1/36		1/36		1/36		1/36		1/36
	1		1/18		1/18		1/18		1/18		1/18	
	2			1/18		1/18		1/18		1/18		
	3				1/18		1/18		1/18			
	4					1/18		1/18				
	5						1/18					

Empty cells are equal to 0.

e.g. $P(X=7, Y \leq 4) = f(7,0) + f(7,1) + f(7,2) + f(7,3) + f(7,4) = 0 + 1/18 + 0 + 1/18 + 0 = 1/9$

Example

- A bridge hand (13 cards) is selected from a deck of 52 cards.
- X = the number of spades in the hand.
- Y = the number of hearts in the hand.
- In this example we will define:
- $p(x,y) = P[X = x, Y = y]$

(Extended Hypergeometric Distribution)

Note:

The possible values of X are $0, 1, 2, \dots, 13$

The possible values of Y are also $0, 1, 2, \dots, 13$
and $X + Y \leq 13$.

$$p_{x, y} = P_{X = x, Y = y}$$

The number of ways of choosing the x **spades** for the hand

The number of ways of choosing the y **hearts** for the hand

The number of ways of completing the hand

$$= \frac{\binom{13}{x} \binom{13}{y} \binom{26}{13-x-y}}{\binom{52}{13}}$$

The total number of ways of choosing the 13 cards for the hand

Example

Suppose that we observe an experiment that has k possible outcomes $\{O_1, O_2, \dots, O_k\}$ independently n times.

Let p_1, p_2, \dots, p_k denote probabilities of O_1, O_2, \dots, O_k respectively.

Let X_i denote the number of times that outcome O_i occurs in the n repetitions of the experiment.

Then the joint probability function of the random variables X_1, X_2, \dots, X_k is (The Multinomial distribution)

$$P_{x_1, \dots, x_n} = \frac{n!}{x_1! x_2! \dots x_k!} p_1^{x_1} p_2^{x_2} \dots p_k^{x_k}$$

Note:

$$p_1^{x_1} p_2^{x_2} \cdots p_k^{x_k}$$

is the probability of a sequence of length n containing

x_1 outcomes O_1

x_2 outcomes O_2

...

x_k outcomes O_k

$$\frac{n!}{x_1!x_2!\dots x_k!} = \binom{n}{x_1 \quad x_2 \quad \dots \quad x_k}$$

is the number of ways of choosing the positions for the x_1 outcomes O_1 , x_2 outcomes O_2 , ..., x_k outcomes O_k

$$\begin{aligned} & \binom{n}{x_1} \binom{n-x_1}{x_2} \binom{n-x_1-x_2}{x_3} \dots \binom{x_k}{x_k} \\ &= \left(\frac{n!}{x_1! (n-x_1)!} \right) \left(\frac{n-x_1!}{x_2! (n-x_1-x_2)!} \right) \left(\frac{n-x_1-x_2!}{x_3! (n-x_1-x_2-x_3)!} \right) \dots \\ &= \frac{n!}{x_1!x_2!\dots x_k!} \end{aligned}$$

$$P(x_1, \dots, x_n) = \frac{n!}{x_1! x_2! \dots x_k!} p_1^{x_1} p_2^{x_2} \dots p_k^{x_k}$$
$$= \binom{n}{x_1 \quad x_2 \quad \dots \quad x_k} p_1^{x_1} p_2^{x_2} \dots p_k^{x_k}$$

is called the **Multinomial** distribution

Suppose that a treatment for back pain has three possible outcomes:

O_1 - Complete cure (no pain) – (30% chance)

O_2 - Reduced pain – (50% chance)

O_3 - No change – (20% chance)

Hence $p_1 = 0.30$, $p_2 = 0.50$, $p_3 = 0.20$.

Suppose the treatment is applied to $n = 4$ patients suffering back pain and let X = the number that result in a complete cure, Y = the number that result in just reduced pain, and Z = the number that result in no change.

Find the distribution of X , Y and Z .

$$P_{x, y, z} = \frac{4!}{x!y!z!} 0.30^x 0.50^y 0.20^z \quad x + y + z = 4$$

Table: $p(x,y,z)$

x	y	z				
		0	1	2	3	4
0	0	0	0	0	0	0.0016
0	1	0	0	0	0.0160	0
0	2	0	0	0.0600	0	0
0	3	0	0.1000	0	0	0
0	4	0.0625	0	0	0	0
1	0	0	0	0	0.0096	0
1	1	0	0	0.0720	0	0
1	2	0	0.1800	0	0	0
1	3	0.1500	0	0	0	0
1	4	0	0	0	0	0
2	0	0	0	0.0216	0	0
2	1	0	0.1080	0	0	0
2	2	0.1350	0	0	0	0
2	3	0	0	0	0	0
2	4	0	0	0	0	0
3	0	0	0.0216	0	0	0
3	1	0.0540	0	0	0	0
3	2	0	0	0	0	0
3	3	0	0	0	0	0
3	4	0	0	0	0	0
4	0	0.0081	0	0	0	0
4	1	0	0	0	0	0
4	2	0	0	0	0	0
4	3	0	0	0	0	0
4	4	0	0	0	0	0

MARGINAL DISCRETE DISTRIBUTIONS

Let $X_1, X_2, \dots, X_q, X_{q+1}, \dots, X_k$ denote k discrete random variables with joint probability function

$$p(x_1, x_2, \dots, x_q, x_{q+1}, \dots, x_k)$$

then the marginal joint probability function of X_1, X_2, \dots, X_q is

$$p_{12\dots q}(x_1, \dots, x_q) = \sum_{x_{q+1}} \dots \sum_{x_n} p(x_1, \dots, x_n)$$

- If the pair (X_1, X_2) of discrete random variables has the joint pmf $p(x_1, x_2)$, then the marginal pmfs of X_1 and X_2 are

$$p_1(x_1) = \sum_{x_2} p(x_1, x_2) \quad \text{and} \quad p_2(x_2) = \sum_{x_1} p(x_1, x_2)$$

Example

A die is rolled $n = 5$ times

X = the number of times a “**six**” appears.

Y = the number of times a “**five**” appears.

	0	1	2	3	4	5	$p_X(x)$
0	0.1317	0.1646	0.0823	0.0206	0.0026	0.0001	0.4019
1	0.1646	0.1646	0.0617	0.0103	0.0006	0	0.4019
2	0.0823	0.0617	0.0154	0.0013	0	0	0.1608
3	0.0206	0.0103	0.0013	0	0	0	0.0322
4	0.0026	0.0006	0	0	0	0	0.0032
5	0.0001	0	0	0	0	0	0.0001
$p_Y(y)$	0.4019	0.4019	0.1608	0.0322	0.0032	0.0001	

Example

Assume that the random variables X and Y have the joint probability mass function given as

$$f(x, y) = \frac{\lambda^{x+y} e^{-2\lambda}}{x! y!} \quad \begin{array}{l} x = 0, 1, 2, \dots \\ y = 0, 1, 2, \dots \end{array}$$

Find the marginal distribution of X

$$f(x) = \sum \frac{\lambda^{x+y} e^{-2\lambda}}{x! y!} = \sum_{Y=0}^{\infty} \frac{\lambda^Y \lambda^x}{Y! X!} e^{-2\lambda}$$

$$= \frac{\lambda^x e^{-\lambda}}{x!}$$

$$[\text{Using } e^{\lambda} = \sum_{t=0}^{\infty} \frac{\lambda^t}{t!}]$$

Example

Let the joint distribution of X and Y be given as

$$f(x, y) = \frac{x + y}{30} \quad x = 0, 1, 2, 3 \quad y = 0, 1, 2,$$

Find the marginal distribution function of X and Y. Marginal of X

$$f(x) = \sum_{y=0}^2 f(x, y) = \sum_{y=0}^2 \frac{x + y}{30} = \frac{1}{30} [(x + 0) + (x + 1) + (x + 2)] = \frac{1}{30} [3x + 3] = \frac{x + 1}{10}$$

Similarly, $f(y) = (3 + 2x)/15$

Or , since the joint is

y \ x	0	1	2	3
0	0	1/30	1/15	1/10
1	1/30	1/15	1/10	2/15
2	1/15	1/10	2/15	1/6
	1/10	1/5	3/10	2/5

x	0	1	2	3
f(x)	1/10	1/5	3/10	2/5

Y	0	1	2
f(y)	1/5	1/3	7/15

JOINT DISCRETE CUMULATIVE DISTRIBUTION FUNCTION

$$F(x_1, x_2, \dots, x_k) = P(X_1 \leq x_1, \dots, X_k \leq x_k)$$

- $F(x_1, x_2)$ is a cdf iff

$$\lim_{x_1 \rightarrow -\infty} F(x_1, x_2) = F(-\infty, x_2) = 0, \forall x_2.$$

$$\lim_{x_2 \rightarrow -\infty} F(x_1, x_2) = F(x_1, -\infty) = 0, \forall x_1.$$

$$\lim_{\substack{x_1 \rightarrow \infty \\ x_2 \rightarrow \infty}} F(x_1, x_2) = F(\infty, \infty) = 1$$

$$P(a < X_1 \leq b, c < X_2 \leq d) = F(b, d) - F(b, c) - F(a, d) + F(a, c) \geq 0, \forall a < b \text{ and } c < d.$$

$$\lim_{h \rightarrow 0^+} F(x_1 + h, x_2) = \lim_{h \rightarrow 0^+} F(x_1, x_2 + h) = F(x_1, x_2), \forall x_1 \text{ and } x_2.$$

CONDITIONAL DISCRETE DISTRIBUTION

Let $X_1, X_2, \dots, X_q, X_{q+1}, \dots, X_k$ denote k discrete random variables with joint probability function

$$p(x_1, x_2, \dots, x_q, x_{q+1}, \dots, x_k)$$

then the **conditional** joint probability function of X_1, X_2, \dots, X_q given $X_{q+1} = x_{q+1}, \dots, X_k = x_k$ is

$$p_{1\dots q|q+1\dots k}(x_1, \dots, x_q | x_{q+1}, \dots, x_k) = \frac{p(x_1, \dots, x_k)}{p_{q+1\dots k}(x_{q+1}, \dots, x_k)}$$

Let X and Y denote two discrete random variables with joint probability function

$$p(x, y) = P[X = x, Y = y]$$

Then

$p_{X|Y}(x|y) = P[X = x|Y = y]$ is called the **conditional probability function** of X given $Y = y$

and

$p_{Y|X}(y|x) = P[Y = y|X = x]$ is called the **conditional probability function** of Y given $X = x$

Note

$$\begin{aligned}P_{X|Y} \quad x|y &= P[X = x|Y = y] \\ &= \frac{P[X = x, Y = y]}{P[Y = y]} = \frac{p_{x, y}}{p_Y \quad y}\end{aligned}$$

and

$$\begin{aligned}P_{Y|X} \quad y|x &= P[Y = y|X = x] \\ &= \frac{P[X = x, Y = y]}{P[X = x]} = \frac{p_{x, y}}{p_X \quad x}\end{aligned}$$

Example

A die is rolled $n = 5$ times

X = the number of times a “**six**” appears.

Y = the number of times a “**five**” appears.

		y						
		0	1	2	3	4	5	$p_X(x)$
x	0	0.1317	0.1646	0.0823	0.0206	0.0026	0.0001	0.4019
	1	0.1646	0.1646	0.0617	0.0103	0.0006	0	0.4019
	2	0.0823	0.0617	0.0154	0.0013	0	0	0.1608
	3	0.0206	0.0103	0.0013	0	0	0	0.0322
	4	0.0026	0.0006	0	0	0	0	0.0032
	5	0.0001	0	0	0	0	0	0.0001
$p_Y(y)$		0.4019	0.4019	0.1608	0.0322	0.0032	0.0001	

The conditional distribution of X given $Y = y$.

$$p_{X|Y}(x|y) = P[X = x | Y = y]$$

y

	0	1	2	3	4	5
0	0.3277	0.4096	0.5120	0.6400	0.8000	1.0000
1	0.4096	0.4096	0.3840	0.3200	0.2000	0.0000
2	0.2048	0.1536	0.0960	0.0400	0.0000	0.0000
3	0.0512	0.0256	0.0080	0.0000	0.0000	0.0000
4	0.0064	0.0016	0.0000	0.0000	0.0000	0.0000
5	0.0003	0.0000	0.0000	0.0000	0.0000	0.0000

The conditional distribution of Y given $X = x$.

$$p_{Y|X}(y|x) = P[Y = y|X = x]$$

	y					
	0	1	2	3	4	5
0	0.3277	0.4096	0.2048	0.0512	0.0064	0.0003
1	0.4096	0.4096	0.1536	0.0256	0.0016	0.0000
2	0.5120	0.3840	0.0960	0.0080	0.0000	0.0000
3	0.6400	0.3200	0.0400	0.0000	0.0000	0.0000
4	0.8000	0.2000	0.0000	0.0000	0.0000	0.0000
5	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Example

The joint probability mass function of X and Y is given by

$$f(1,1) = \frac{1}{8} \quad f(1,2) = \frac{1}{4} \quad f(2,1) = \frac{1}{8} \quad f(2,2) = \frac{1}{2}$$

1. Compute the conditional mass function of X given $Y = i, i = 1, 2$
2. Compute $P(XY \leq 3) = f(1, 1) + f(1, 2) + f(2, 1) = 1/2$
3. $P(X/Y > 1) = f(2, 1) = 1/8$

Y \ x	1	2	Sum
1	1/8	1/8	2/8
2	1/4	1/2	6/8
sum	3/8	5/8	1

Marginal of y

y	1	2
f(y)	2/8	6/8

The conditional mass f^n of $X/Y = 1$

x	1	2
f(x y=1)	1/2	1/2

The conditional of $X/Y = 2$

y	1	2	Sum
f(x y=2)	1/3	2/3	1

JOINT CONTINUOUS DISTRIBUTION

Let X_1, X_2, \dots, X_k denote k continuous random variables, then

$$f(x_1, x_2, \dots, x_k)$$

is joint density function of X_1, X_2, \dots, X_k if

1. $f(x_1, \dots, x_n) \geq 0$

2.
$$\int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} f(x_1, \dots, x_n) dx_1, \dots, dx_n = 1$$

3.
$$P[X_1, \dots, X_n \in A] = \int \dots \int_A f(x_1, \dots, x_n) dx_1, \dots, dx_n$$

Example

- Assume that joint pdf of random variable X and Y is $f(x, y) = 4xy$ $0 < x < 1$, $0 < y < 1$ the joint cdf is

$$F(x, y) = \int_0^x \int_0^y 4t_1 t_2 dt_1 dt_2 = x^2 y^2 \quad 0 < x < 1, \quad 0 < y < 1$$

MARGINAL CONTINUOUS DISTRIBUTION

Let $X_1, X_2, \dots, X_q, X_{q+1}, \dots, X_k$ denote k continuous random variables with joint probability density function

$$f(x_1, x_2, \dots, x_q, x_{q+1}, \dots, x_k)$$

then the marginal joint probability function of X_1, X_2, \dots, X_q is

$$f_{12\dots q}(x_1, \dots, x_q) = \int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} f(x_1, \dots, x_n) dx_{q+1} \dots dx_n$$

- If the pair (X_1, X_2) of discrete random variables has the joint pdf $f(x_1, x_2)$, then the marginal pdfs of X_1 and X_2 are

$$f_1(x_1) = \int_{-\infty}^{\infty} f(x_1, x_2) dx_2 \text{ and } f_2(x_2) = \int_{-\infty}^{\infty} f(x_1, x_2) dx_1.$$

Example

Joint density $f(x,y)$ for X and Y :

$$f(x,y) = \begin{cases} \frac{2}{5}(2x+3y) & 0 \leq x \leq 1, 0 \leq y \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Marginal density function for X :

$$\begin{aligned} g(x) &= \int_{-\infty}^{\infty} f(x,y) dy \\ &= \int_0^1 \frac{2}{5}(2x+3y) dy \\ &= \left[\frac{2}{5} 2xy + \frac{1}{5} 3y^2 \right]_0^1 = \frac{4}{5}x + \frac{3}{5} \end{aligned}$$

INDEPENDENCE OF RANDOM VARIABLES

- If X_1, X_2, \dots, X_k are independent from each other, then the joint pdf can be given as

$$f(x_1, x_2, \dots, x_k) = f(x_1) f(x_2) \dots f(x_k)$$

And the joint cdf can be written as

$$F(x_1, x_2, \dots, x_k) = F(x_1) F(x_2) \dots F(x_k)$$

CONTINUOUS CONDITIONAL DISTRIBUTIONS

Let $X_1, X_2, \dots, X_q, X_{q+1}, \dots, X_k$ denote k continuous random variables with joint probability density function

$$f(x_1, x_2, \dots, x_q, x_{q+1}, \dots, x_k)$$

then the **conditional** joint probability function of X_1, X_2, \dots, X_q given $X_{q+1} = x_{q+1}, \dots, X_k = x_k$ is

$$f_{1\dots q|q+1\dots k}(x_1, \dots, x_q | x_{q+1}, \dots, x_k) = \frac{f(x_1, \dots, x_k)}{f_{q+1\dots k}(x_{q+1}, \dots, x_k)}$$

- If X_1 and X_2 are continuous random variables with joint pdf $f(x_1, x_2)$, then the conditional pdf of X_2 given $X_1 = x_1$ is defined by

$$f(x_2|x_1) = \frac{f(x_1, x_2)}{f(x_1)}, \forall x_1 \text{ such that } f(x_1) > 0, 0 \text{ elsewhere.}$$

- For independent rvs,

$$f(x_2|x_1) = f(x_2)$$

$$f(x_1|x_2) = f(x_1)$$

- If X and Y are random variables with joint pdf $f(x, y)$ and marginal pdf's $f(x)$, $f(y)$

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

and if X and Y are independent then

$$f(x | y) = f(x)$$

$$f(y | x) = f(y)$$

Example

Suppose that a rectangle is constructed by first choosing its length, X and then choosing its width Y .

Its length X is selected from an exponential distribution with mean $\mu = 1/\lambda = 5$. Once the length has been chosen its width, Y , is selected from a uniform distribution from 0 to half its length.

Find the joint distribution function.

$$f_X(x) = \frac{1}{5} e^{-\frac{1}{5}x} \quad \text{for } x \geq 0$$

$$f_{Y|X}(y|x) = \frac{1}{x/2} \quad \text{if } 0 \leq y \leq x/2$$

$$\begin{aligned} f(x, y) &= f_X(x) f_{Y|X}(y|x) \\ &= \frac{1}{5} e^{-\frac{1}{5}x} \frac{1}{x/2} = \frac{2}{5x} e^{-\frac{1}{5}x} \quad \text{if } 0 \leq y \leq x/2, x \geq 0 \end{aligned}$$

Example

Let X, Y, Z denote 3 jointly distributed random variable with joint density function then

$$f(x, y, z) = \begin{cases} K(x^2 + yz) & 0 \leq x \leq 1, 0 \leq y \leq 1, 0 \leq z \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Find the value of K .

Determine the marginal distributions of X, Y and Z .

Determine the joint marginal distributions of

X, Y

X, Z

Y, Z

Determining the value of K .

$$1 = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y, z) \, dx dy dz = \int_0^1 \int_0^1 \int_0^1 K(x^2 + yz) \, dx dy dz$$

$$= K \int_0^1 \int_0^1 \left[\frac{x^3}{3} + xyz \right]_{x=0}^{x=1} dy dz = K \int_0^1 \int_0^1 \left(\frac{1}{3} + yz \right) dy dz$$

$$= K \int_0^1 \left[\frac{1}{3}y + z \frac{y^2}{2} \right]_{y=0}^{y=1} dz = K \int_0^1 \left(\frac{1}{3} + z \frac{1}{2} \right) dz$$

$$= K \left[\frac{z}{3} + \frac{z^2}{4} \right]_0^1 = K \left(\frac{1}{3} + \frac{1}{4} \right) = K \frac{7}{12} = 1 \quad \text{if } K = \frac{12}{7}$$

The marginal distribution of X .

$$\begin{aligned} f_1(x) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y, z) \, dy \, dz = \frac{12}{7} \int_0^1 \int_0^1 (x^2 + yz) \, dy \, dz \\ &= \frac{12}{7} \int_0^1 \left[x^2 y + \frac{y^2}{2} z \right]_{y=0}^{y=1} dz = \frac{12}{7} \int_0^1 \left(x^2 + \frac{1}{2} z \right) dz \\ &= \frac{12}{7} \left[x^2 z + \frac{z^2}{4} \right]_0^1 = \frac{12}{7} \left(x^2 + \frac{1}{4} \right) \quad \text{for } 0 \leq x \leq 1 \end{aligned}$$

The marginal distribution of X, Y .

$$\begin{aligned} f_{12}(x, y) &= \int_{-\infty}^{\infty} f(x, y, z) dz = \frac{12}{7} \int_0^1 (x^2 + yz) dz \\ &= \frac{12}{7} \left[x^2 z + y \frac{z^2}{2} \right]_{z=0}^{z=1} \\ &= \frac{12}{7} \left(x^2 + \frac{1}{2} y \right) \text{ for } 0 \leq x \leq 1, 0 \leq y \leq 1 \end{aligned}$$

The marginal distribution of X, Y .

$$f_{12}(x, y) = \frac{12}{7} \left(x^2 + \frac{1}{2}y \right) \text{ for } 0 \leq x \leq 1, 0 \leq y \leq 1$$

Thus the conditional distribution of Z given $X = x, Y = y$ is

$$\begin{aligned} \frac{f(x, y, z)}{f_{12}(x, y)} &= \frac{\frac{12}{7} (x^2 + yz)}{\frac{12}{7} \left(x^2 + \frac{1}{2}y \right)} \\ &= \frac{x^2 + yz}{x^2 + \frac{1}{2}y} \text{ for } 0 \leq z \leq 1 \end{aligned}$$

The marginal distribution of X .

$$f_1(x) = \frac{12}{7} \left(x^2 + \frac{1}{4} \right) \text{ for } 0 \leq x \leq 1$$

Thus the conditional distribution of Y, Z given $X = x$ is

$$\begin{aligned} \frac{f(x, y, z)}{f_1(x)} &= \frac{\frac{12}{7} (x^2 + yz)}{\frac{12}{7} \left(x^2 + \frac{1}{4} \right)} \\ &= \frac{x^2 + yz}{x^2 + \frac{1}{4}} \text{ for } 0 \leq y \leq 1, 0 \leq z \leq 1 \end{aligned}$$

Example (Bivariate Normal Distribution)

- A pair of continuous rvs X and Y is said to have a bivariate normal distribution if it has a joint pdf of the form

$$f(x, y) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \exp\left\{-\frac{1}{2(1-\rho^2)}\left[\left(\frac{x-\mu_x}{\sigma_1}\right)^2 - 2\rho\left(\frac{x-\mu_x}{\sigma_1}\right)\left(\frac{y-\mu_y}{\sigma_2}\right) + \left(\frac{y-\mu_y}{\sigma_2}\right)^2\right]\right\}$$

$$-\infty < x < \infty, -\infty < y < \infty, \sigma_1 > 0, \sigma_2 > 0, -1 < \rho < 1.$$

If $(X, Y) \sim BVN(\mu_x, \mu_y, \sigma_1^2, \sigma_2^2, \rho)$, then
 $X \sim N(\mu_x, \sigma_1^2)$ and $Y \sim N(\mu_y, \sigma_2^2)$

and ρ is the correlation coefficient btw X and Y .

1. Conditional on $X=x$,

$$Y|x \sim N\left(\mu_y + \rho \frac{\sigma_2}{\sigma_1} (x - \mu_X), \sigma_2^2 (1 - \rho^2)\right)$$

2. Conditional on $Y=y$,

$$X|y \sim N\left(\mu_x + \rho \frac{\sigma_1}{\sigma_2} (y - \mu_Y), \sigma_1^2 (1 - \rho^2)\right)$$

CONDITIONAL EXPECTATION

- For X, Y discrete random variables, the conditional expectation of Y given $X = x$ is

$$E(Y | X = x) = \sum_y y \cdot p_{Y|X}(y | x)$$

and the conditional variance of Y given $X = x$ is

$$\begin{aligned} V(Y | X = x) &= \sum_y (y - E(Y | X = x))^2 \cdot p_{Y|X}(y | x) \\ &= E(Y^2 | X = x) - (E(Y | X = x))^2 \end{aligned}$$

where these are defined only if the sums converges absolutely.

- In general, $E(h(Y) | X = x) = \sum_y h(y) \cdot p_{Y|X}(y | x)$

- For X, Y continuous random variables, the conditional expectation of Y given $X = x$ is

$$E(Y | X = x) = \int_{-\infty}^{\infty} y \cdot f_{Y|X}(y | x) dy$$

and the conditional variance of Y given $X = x$ is

$$\begin{aligned} V(Y | X = x) &= \int_{-\infty}^{\infty} [y - E(Y | X = x)]^2 \cdot f_{Y|X}(y | x) dy \\ &= E(Y^2 | X = x) - [E(Y | X = x)]^2 \end{aligned}$$

- In general, $E(h(Y) | X = x) = \int_y h(y) \cdot f_{Y|X}(y | x) dy$

- If X and Y are jointly distributed random variables then,

$$E[E(Y|X)] = E(Y)$$

- If X and Y are independent random variables then,

$$E(Y|X) = E(Y)$$

$$E(X|Y) = E(X)$$

- If X and Y are jointly distributed random variables then,

$$\text{Var}(Y) = E_X [\text{Var}(Y|X)] + \text{Var}_X [E(Y | X)]$$

MOMENT GENERATING FUNCTION OF A JOINT DISTRIBUTION

- The $E(e^{tX})$ and $M'(0)$ approaches both work

$$M_{X,Y}(t_1, t_2) = E[e^{t_1 X + t_2 Y}]$$

$$E[X^n Y^m] = \frac{d^{n+m}}{d^n t_1 d^m t_2} M_{X,Y}(t_1, t_2) \Big|_{t_1=t_2=0}$$

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