

Advanced Engineering Mathematics
Prof. P.N. Agrawal
Department of Mathematics
Indian Institute of Technology – Roorkee

Lecture – 54
Joint Probability Distribution - III

Hello friends welcome to my lecture on joint probability distribution, this is the third and final lecture on joint probability distribution. First we define function of random variable. Let x and y , xy be a random variable with probability function are density f_{xy} and the cumulative distribution function F_{xy} and let g_{xy} be any continuous function which is defined for all xy and is not a constant.

(Refer Slide Time: 00:50)

Functions of random variable

Let (X, Y) be a random variable with probability function or density $f(x, y)$ and distribution function $F(x, y)$, and let $g(x, y)$ be any continuous function which is defined for all (x, y) and is not constant. Then $Z = g(X, Y)$ is a random variable too. For example, if we roll two dice and X is the number that the first die turns up whereas Y is the number that the second die turns up, then $Z = X + Y$ is the sum of these two numbers.

Then $Z = g_{xy}$ is a random variable 2 okay. For example, if we roll 2 dice, if x is the number then the first dice turns up whereas y is the number that the second dice turns up then $Z = x + y$ is the sum of these 2 numbers.

(Refer Slide Time: 01:12)

Functions of random variable cont...

In the case of a discrete random variable (X, Y) we may obtain the probability function $f(z)$ of $Z = g(X, Y)$ by summing all $f(x, y)$ for which $g(x, y)$ equals the value of z considered, thus

$$f(z) = P(Z = z) = \sum_{g(x,y)=z} f(x, y).$$

The distribution function of Z is

$$F(z) = P(Z \leq z) = \sum_{g(x,y) \leq z} f(x, y),$$

where we sum all values of $f(x, y)$ for which $g(x, y) \leq z$.

In the case of a discrete random variable xy we may obtain the probability function f_z of $z = g_{xy}$ by summing all f_{xy} for which $g_{xy} =$ to the value of z considered okay, that is $f_z =$ probability that z takes the value z will be $=$ double sigma f_{xy} where $g_{xy} = z$, that is sum of the values of x and y becomes $= z$. We will take the sum over all those values of x and those values of y , where the sum of x and y values give you z okay.

The distribution function of z will be $f_z = p_z \leq z$ where we will sum over all those xy where the sum of the values of x and y are or where the g_{xy} , g_{xy} not necessarily the sum of x and y in the example we have taken g_{xy} as $x + y$ but it is arbitrary here. So g_{xy} must be $\leq z$. So in the case of the probability function f_z , we will take the sum over all those pairs of values of xy , such that $g_{xy} = z$ in the case of cumulative distribution function f_z , we shall take the sum over all those values of f_{xy} where the pair of values of xy satisfy $g_{xy} \leq z$.

Okay, so where we sum overall values of f_{xy} where g_{xy} is $\leq z$.

(Refer Slide Time: 02:49)

Functions of random variable cont...

In the case of a continuous random variable (X, Y) , we similarly have

$$F(z) = P(Z \leq z) = \iint_{g(x,y) \leq z} f(x,y) dx dy,$$

where for each z we integrate over the region $g(x, y) \leq z$ in the xy -plane.

0

Now functions of random variable, if you consider here continuous random variable xy okay we earlier discussed discrete case, now let us consider the case of continuous random variable xy . So we similarly have $fz =$ probability that z is $\leq z$, we integrate over all those values of xy which satisfy the inequality $gxy \leq z$ okay. So $fx y dx dy$. So where each z we integrate over the region $gxy \leq z$ in the xy plane okay.

And when you take the probability okay the probability here, then we will take a small fz , small fz will be we will integrate over all those xy for which $gxy = z$ okay.

(Refer Slide Time: 03:42)

Expectation of $g(X, Y)$. Addition of means and variances

The number

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

is called the mathematical expectation or briefly, the expectation of $g(X, Y)$. Here it is assumed that the double series converges absolutely and the integral of $|g(x, y)| f(x, y)$ over the xy -plane exists. It can be proved that

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

An important special case is $E(X + Y) = E(X) + E(Y)$.

So the number $Eg XY$ okay, we have defined, this is discrete case in the case of continuous random variable we have the distribution function fz , now we have to consider the expectation of gxy . The number expectation of $gxy = \sigma$ over x , σ over y , gxy , $fx y$

when xy is a discrete probability distribution and when g_{xy} is a continuous, joint continuous distribution, we have integral over $-\infty$ to ∞ , integral over $-\infty$ to ∞ $g_{xy} f_{xy} dx dy$.

This is called the mathematical expectation or expectation of g_{xy} . We assume here that the double series in the discrete case converges absolutely and the integrals here okay, over the xy plane okay, edges, integral of mod of $g_{xy} * f_{xy}$ over the xy plane edges okay. So it can be shown that expectation of $ag_{xy} + b h_{xy} = a$ times $Eg_{xy} + b h_{xy}$ okay. An important special case here you can take as expectation of ax .

You can take $1 b = 1$ and g_{xy} as x h_{xy} as y . So you can say expectation of $x + y =$ expectation of $x +$ expectation of y .

(Refer Slide Time: 05:11)

Conditional distribution



We know that the conditional probability of an event A given event B as

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \text{ if } P(B) \neq 0.$$

Suppose that A and B are the events $X = x$ and $Y = y$, where X and Y are discrete random variables having the joint probability mass function $f(x, y)$. Then we have

$$P(X = x|Y = y) = \frac{P(X = x, Y = y)}{P(Y = y)} = \frac{f(x, y)}{f_Y(y)}$$

provided that $f_Y(y) = P(Y = y) \neq 0$, where f_Y is the marginal distribution of Y . Let us denote the conditional probability by $f_{X|Y}(x|y)$ to indicate that x is a variable and y is fixed, we have the following definition.

IIT ROORKEE
 NPTEL ONLINE
 CERTIFICATION COURSE

6

Now we know that the conditional probability of an event A given event B is given by this formula okay. Probability that A given $B =$ probability of A intersection B /probability of B . So if PB is not $= 0$. Now suppose that A and B are the events $X = x$ and $Y = y$ where x and y are discrete random variables okay, having the joint probability mass function f_{xy} , then we have probability that x takes the value x , y takes the value $y =$ probability that x takes the value x , y takes the value y /probability of that y takes the value y .

And then now probability that x takes the value x , y takes the value y is f_{xy} and probability that y takes the value y is the marginal distribution function of y with respect to the joint distribution okay, provided that the marginal distribution function or marginal density of y

with respect to the joint distribution is not 0. So this is the marginal distribution of y. Now let us denote the conditional probability by $f_{X|Y}(x|y)$ given by x given by y okay.

So this can be denoted by $f_{X|Y}(x|y)$ given by x given by y to indicate that x is a variable and y is fixed okay.

(Refer Slide Time: 06:38)

Conditional distribution cont...

Definition
If (X, Y) is a two dimensional discrete random variable with joint probability mass function f and if f_X and f_Y are the marginal distributions of X and Y , respectively, then the conditional probability of X given $Y = y$ is denoted by $f_{X|Y}(x|y)$, and is defined as

$$f_{X|Y}(x|y) = \frac{f(x, y)}{f_Y(y)}, \text{ where } f_Y(y) \neq 0$$

for each x within the range of X . Similarly the conditional distribution of Y given $X = x$ is denoted by $f_{Y|X}(y|x)$, and is defined as

$$f_{Y|X}(y|x) = \frac{f(x, y)}{f_X(x)}, \text{ where } f_X(x) \neq 0$$

for each y within the range of Y .

IF ROORKEE NPTEL ONLINE CERTIFICATION COURSE 7

So we have the following definition. If xy is the 2 dimensional discrete random variable with joint probability mass function f and if f_X f_Y are the marginal distribution functions of x and y , then the conditional probability of x given $y = y$ is denoted by $f_{X|Y}(x|y)$ given by x given by y and is defined as $f_{X|Y}(x|y) = \frac{f_{XY}(x, y)}{f_Y(y)}$, f_Y is the marginal density of f , marginal density of y with respect to the joint distribution.

So for each x within the range of x . Similarly, conditional distribution of y given $x = x$ is denoted by $f_{Y|X}(y|x)$ given by y given by x and is defined as $f_{Y|X}(y|x) = \frac{f_{XY}(x, y)}{f_X(x)}$ over marginal distribution of x with respect to the joint distribution. For each y in the range of y okay. Here we assume that marginal densities f_{XX} and f_{YY} are not 0.

(Refer Slide Time: 07:41)

Conditional distribution cont...

Since

$$f_{X|Y}(x|y) = \frac{f(x,y)}{f_Y(y)} \geq 0$$

for all values of x and y within their range and

$$\sum_x f_{X|Y}(x|y) = \frac{\sum_x f(x,y)}{f_Y(y)} = \frac{f_Y(y)}{f_Y(y)} = 1 \quad \checkmark$$

from the definition of the marginal distribution $f_Y(y)$, it follows that $f_{X|Y}(x|y)$ is a probability function. Similarly we can show that $f_{Y|X}(y|x)$ is a probability function.

$$\begin{aligned} \sum_y f_{Y|X}(y|x) &= \sum_y \frac{f(x,y)}{f_X(x)} \\ &= \frac{\sum_y f(x,y)}{f_X(x)} \\ &= \frac{f_X(x)}{f_X(x)} \\ &= 1 \end{aligned}$$

Now since f_X given y , x given $y = f_{X|Y}(x|y)$ $f_{X|Y}$ is ≥ 0 f_Y is also ≥ 0 , this is density function, this is marginal density. So they are both nonnegative and therefore their quotient is nonnegative. This is valid for all xy in the range and $\sum_x f_X$ given by x given by $= \sum_x / x$ $f_{X|Y}$. When you keep y fixed and sum over, when you keep $y = y$, when you keep y fixed and sum over all the values of x okay.

Then you are getting f_Y okay, so $f_Y/f_Y = 1$ okay and that is this follows from the definition of marginal distribution and so what happens is that the conditional distribution okay, f_X given by x given by is a probability function. This is a probability function, similarly we can show that f_Y given x , y given x is also a probability function, there we will, if you want to show this then you sum over all y such that f_Y/x y/x $y/x = \sum_y / y$ $f_{Y|X}$ we will have okay.

Now here we are summing over all y , x is fixed so we get f_{XX}/f_{XX} which is $= 1$. So both the conditional distributions are probability functions okay. This is conditional probability function of x given $y = y$, this is conditional probability function of y given $x = x$.

(Refer Slide Time: 09:38)

Remark

If X and Y are independent discrete random variables, then we know that

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

for all values of x and y within their range hence

$$f_{X|Y}(x|y) = \frac{f(x, y)}{f_Y(y)} = \frac{f_X(x)f_Y(y)}{f_Y(y)} = f_X(x)$$

Similarly

$$f_{Y|X}(y|x) = \frac{f(x, y)}{f_X(x)} = \frac{f_X(x)f_Y(y)}{f_X(x)} = f_Y(y)$$

Now if x and y are independent and they are discrete random variables, independent discrete random variables then we know that $f_{xy} = f_{xx} * f_{yy}$ for all values of xy within their range okay. So now f_x given by x given by $= f_{xy}/f_{yy}$, y definition okay. This is by definition and if x and y are independent by definition, $f_{xy} = f_{xx} * f_{yy}$. So let us put it here what we get f_{xx} .

So if x and y are discrete random variables and they are independent okay, then the conditional distribution of x given $y = y$ = marginal distribution of x with respect to the joint distribution. Similarly, $f_{y/x} y/x = f_{x/y}/f_{xx} = f_{yy}$ okay. So if x and y are independent discrete random variables then the conditional distribution of x given then the condition distribution of x given $y = y$ = marginal distribution of x with respect to joint distribution and conditional distribution of y given $x = x$ is marginal distribution of y .

(Refer Slide Time: 10:58)

The converse is also true. If

$$f_{X|Y}(x|y) = f_X(x) \checkmark$$

for all values of x and y within their range, then

$$f(x, y) = f_{X|Y}(x|y)f_Y(y) = f_X(x)f_Y(y)$$

so that X and Y are independent random variables. Similarly, if

$$f_{Y|X}(y|x) = f_Y(y)$$

for all values of x and y within their range, then

$$f(x, y) = f_{Y|X}(y|x)f_X(x) = f_Y(y)f_X(x)$$

so that X and Y are independent random variables.

By def
 $f_{X|Y}(x|y) = \frac{f(x,y)}{f_Y(y)}$
or
 $f(x,y) = f_{X|Y}(x|y)f_Y(y)$
 $= f_X(x)f_Y(y)$

So the converse is also true, if $f_{x/y}$, x given $y = f_{xx}$ for all values of x and y within range then $f_{xy} = f_{xx} * f_{yy}$. How it will follow let us see, $f_{xy} =$ see by definition. By definition f_x given y x given $y = f_{xy}/f_{yy}$ okay, so we can say or $f_{xy} = f_x$ given y x given $y * f_{yy}$ okay. Now f_x given y x given $y = f_{xx}$ okay. So $f_{xx} = f_{xx} * f_{yy}$ and therefore x and y are independent random variables okay.

Similarly, if $f_{y/x}$ given $x = f_{yy}$ then $f_{xy} = f_y$ given x given x $f_{xx} = f_{yy} * f_{xx}$, so that x and y are independent random variables.

(Refer Slide Time: 12:17)

We can similarly define the conditional distribution for two dimensional continuous random variables by replacing probability distributions with probability density functions.

Definition

If (X, Y) is a two-dimensional continuous random variable with joint probability density function f and if f_X and f_Y are the marginal density function of X given $Y = y$ is denoted by $f_{X|Y}(x|y)$ and is defined as

$$f_{X|Y}(x|y) = \frac{f(x, y)}{f_Y(y)}, \text{ where } f_Y(y) \neq 0$$

for $-\infty < x < \infty$.

Now we can similarly define the conditional distribution for 2 dimensional continuous random variables by replacing probability distributions with probability density functions. So if xy is a 2 dimensional continuous random variable with joint probability density function f and if f_x and f_y are the marginal density function of x given $y = y$, then f_x given y x/y x given $y =$ is defined as f_x given y x given $y = f_{xy}/f_{yy}$ where f_y y is not $= 0$ and x grounds to the interval $-\infty$ to ∞ .

(Refer Slide Time: 12:55)

Definition cont...

Similarly the conditional density function of Y given $X = x$ is denoted by $f_{Y|X}(y|x)$, and is defined as

$$f_{Y|X}(y|x) = \frac{f(x, y)}{f_X(x)}, \text{ where } f_X(x) \neq 0$$

for $-\infty < y < \infty$. Again

$$f_{X|Y}(x|y) = \frac{f(x, y)}{f_Y(y)} \geq 0 \quad \forall (x, y) \in \mathbb{R}^2$$

and

$$\int_{x=-\infty}^{\infty} f_{X|Y}(x|y) dx = \frac{\int_{x=-\infty}^{\infty} f(x, y) dx}{f_Y(y)} = \frac{f_Y(y)}{f_Y(y)} = 1$$

from the definition of the marginal density function $f_Y(y)$, hence it follows that $f_{X|Y}(x|y)$ is a probability density function.

The conditional density function of y given $x = x$ similarly is defined as f_Y given x , y given $x = f_{X|Y}(y|x)$, where $f_{X|Y}$ is not $= 0$ and x belongs to the interval $-\infty$ to y belongs to the interval $-\infty$ to ∞ . Again f_X given by x given by $f_{X|Y}(x|y)$ is ≥ 0 for all x, y belonging to \mathbb{R}^2 and integral over $-\infty$ to ∞ f_X given by x given by $dx = \int_{x=-\infty}^{\infty} f_X(x|y) dx$ and this is independent of x so f_Y .

And we get this integral as f_Y , so $f_Y/f_Y = 1$, so from the definition of marginal density function we find that this value is $= 1$, so f_X given y x given y is a probability density function.

(Refer Slide Time: 13:52)

Definition cont...

Similarly we can show that $f_{Y|X}(y|x)$ is a probability density function.

Remark

If X and Y are independent continuous random variables, then we know that

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

for all value of $(x, y) \in \mathbb{R}^2$. Then

$$f_{X|Y}(x|y) = \frac{f(x, y)}{f_Y(y)} = \frac{f_X(x)f_Y(y)}{f_Y(y)} = f_X(x)$$

Similarly, we can show that f_Y given x , y given x is a probability density function. If x and y are independent continuous random variables, then we have $f_{X|Y}(x|y) = f_X$ given x $f_X * f_Y$ for all

value of x y belonging to \mathbb{R}^2 and then f_X given y x given y by definition is f_{XY}/f_Y but $f_{XY} = f_{XX} * f_{YY}$. So when you put it here you get f_X given y x given $y =$ marginal density function of x with respect to the joint distribution.

(Refer Slide Time: 14:27)

Remark cont...

Similarly, we have

$$f_{Y|X}(y|x) = \frac{f(x, y)}{f_X(x)} = \frac{f_X(x)f_Y(y)}{f_X(x)} = f_Y(y).$$

The converse is also true. If

$$f_{X|Y}(x|y) = f_X(x)$$

for all value of $(x, y) \in \mathbb{R}^2$, then

$$f(x, y) = f_{X|Y}(x|y)f_Y(y) = f_X(x)f_Y(y)$$

so that X and Y are independent random variables.

And f_Y given x y given $x = f_{XY}/f_X$ okay, which is $f_{XX} * f_{YY}/f_{XX}$, so this is f_{YY} okay. So we have the same result okay like in the discrete case, the converse is also true if f_X given y x given $y = f_{XX}$ for all values of xy belonging to \mathbb{R}^2 , then $f_{XY} = f_X$ of given y , x given $y = f_{YY}$, this will follow from the definition of conditional distribution and this is $= f_{XX}$, so we get $f_{XX} * f_{YY}$ and then x and y are independent random variables.

(Refer Slide Time: 15:05)

Remark cont...

Similarly, if

$$f_{Y|X}(y|x) = f_Y(y)$$

for all values of $(x, y) \in \mathbb{R}^2$, then

$$f(x, y) = f_{Y|X}(y|x)f_X(x) = f_Y(y)f_X(x)$$

so that X and Y are independent random variables.

And similarly we can see for f_Y given x , y given x , if it is $= f_{YY}$ then $f_{XY} = f_{YY} * f_{XX}$ and so x and y are independent random variables.

(Refer Slide Time: 15:20)

$f_{X|Y}(x|y) = \frac{k(2x+3y)}{f_Y(y)}$

Example 1

The joint probability mass function of (X, Y) is given by $f_{X|Y}(x|y=0) = \frac{k \cdot 2x}{\frac{6}{45}} = \frac{45}{6} \cdot k \cdot 2x = \frac{15}{2} \cdot k \cdot 2x = 15kx$

$p(x, y) = k(2x + 3y), x = 0, 1, 2; y = 0, 1, 2.$

Find all the marginal and conditional probability distributions.

	Y	0	1	2	$f_X(x)$
X	0	0	3k	6k	9k
	1	2k	5k	8k	15k
	2	4k	7k	10k	21k
	$f_Y(y)$	6k	15k	24k	45k

$\sum_{y=0}^2 f(x, y) = f_X(x)$
 $45k = 1$
 $k = \frac{1}{45}$

	Y	0	1	2
$f_X(x)$	9	15	21	45

$\sum_{x=0}^2 f(x, y) = f_Y(y)$
 $45k = 1$
 $k = \frac{1}{45}$

$f_{X|Y}(x|y) = \frac{f(x, y)}{f_Y(y)}$

16

Now let us consider a problem on marginal and conditional probability distributions. So the joint probability mass function f_{xy} is given by $p_{xy} = k$ times $2x + 3y$, $x = 0, 1, 2$, $y = 0, 1, 2$. Let us find first the joint probability distribution okay. So x varies from 0, 1, 2 and y varies from 0, 1, 2. So let us say here we have x , here we have y and x varies from 0 to 2, okay. So when x is 0, y is 0 okay, $p_{00} = 0$.

When x is 0, y is 1, okay we have $3k$, when x is 0 and $y = 2$ we have $6k$, when x is 1, y is 0 we have $2k$, when x is 1 okay, $y = 1$, so we get $3+2$ $5k$ okay, and when x is 1, y is 2, so $3+2$ are 6 , $6+2$, $8k$ and when x is 2 we have 4 here $y=0$ okay, so we have $4k$. When x is 2 we have 4 here, $y = 1$ so we have $7k$ and when x is 2 we have 4 here, $y = 2$, so we have 6 here, $6+4$, $10k$ okay.

So $6k + 3k$, $9k$ here we have $8+5$, 13 , $13+2$ $15k$ and we have $10+7$, 17 , $17+4$, $21k$. Let us check again, when x is 0, y is 0 we have $p_{xy} = 0$ when x is 0, okay $y = 1$, we have $3k$ when x is 0, $y = 2$ we have $6k$, when $x = 1$ we have here 2 okay, so y is 0, so we have $2k$, when x is 1, we have 2 here, here we have 1 , we have $3+2$, $5k$, when x is 1 y is 2 we have $3+2$ are $6+2$ so $8k$.

When $x = 2$ we have 4 here y is 0 so $4k$, when x is 2, y is 1 we have $7k$ when x is 2 y is 2 we have $3+2$ are $6+4$, $10k$ okay. So this is $15+9$, 24 , $24+21$, $45k$ okay, alright. Thus it is the sum of the columns, so here what is happening, we are getting f_{xx} because when you sum

along the row okay, you get the value of f_{xx} because you are summing f_{xy} $\sum f_{xy}$, you are summing along the row.

So y varies from 0 to 2 okay, so this gives you f_{xx} , okay, so now f_{yy} , so this is $6k$, this is $7 + 5$, $12 + 3$, $15k$ and this is $10 + 8$, $18 + 6$, $24k$. So $24 + 15$, $39 + 6$, $45k$. So $45k$ is the total okay. Now this is $45k$ okay. So $45k$ must be $= 1$ okay and this means that $k = 1/45$, $\sum f_{xx}$ okay, when x varies from 0 to 2 $= 1$ okay, so this implies $45k = 1$, so $k = 1/45$ okay. Now we find the marginal probability function.

Marginal distribution of x , so let us form the table of marginal distribution function of x . So f_{xx} . So x takes the value 0, 1, 2 okay. So when $x = 0$, we have $f_{xx} = 9k$ that is $9/45$ okay. When $x = 1$, we have $15k$, $15/45$ and when $x = 2$ we have $21k$, so $21/45$ okay, and we have similarly marginal density function of y . So 0, 1, 2, f_y . So when $y = 0$ okay, we have $6k$ okay, so $6/45$ okay.

When we have $y = 1$ it is $15/45$ and when $y = 2$ it is $24/45$ okay. So this is the marginal density function of y , this is marginal density function of x . Now let us find conditional probability distributions okay. So conditional probability distributions means we have to find f_x given y x given y okay this will be $= f_{xy}/f_y$ okay. So f_x given y x over y okay. So f_y , $f_{xy} = k$ times $2x + 3y$.

So we have f_x given y x given $y = k$ times $2x + 3y$, f_y okay, $f_y = 6/45$, $15/45$, $24/45$ okay. So we have to do it for $y = 1, 2, 3$ okay, $y = 0, 1, 2$, and so on. So f_x we have to first find f_x given y by x $y = 0$ okay. So $y = 0$ means we have k times $2x$ okay, $2x$ $y = 0$ means f_y is $6/45$ okay. So this is $= 45/6 * k * 2x$, okay. So $45/6 * k$ $45k = 1$, so we have $1/6 * 2x$ okay, $1/6 * 2x$ that is $x/3$ okay.

And similarly we have to do it for $y = 1, y = 2$ okay. So we have to do it for $y = 1, y = 2$.

(Refer Slide Time: 23:40)

$$\begin{aligned}
f_{x|y}(x|y) &= \frac{f(x,y)}{f_y(y)} \\
\text{for } y=1 & f_{x|y}(x|1) = \frac{f(x,1)}{f_y(1)} = \frac{k(2x+3)}{\frac{15}{45} \cdot 3} = \frac{3k(2x+3)}{\frac{15}{45}} = \frac{3k(2x+3)}{15} \\
&= \frac{1}{5}(2x+3) \\
\text{for } y=2 & f_{x|y}(x|2) = \frac{f(x,2)}{f_y(2)} = \frac{k(2x+6)}{\frac{24}{45}} = \frac{45k(2x+6)}{24} \\
&= \frac{2x+6}{24} = \frac{x+3}{8} \\
f_{x|y}(x|y) &= \frac{f(x,y)}{f_y(y)} \\
\begin{array}{ccc}
y=0 & y=1 & y=2 \\
\frac{x}{3} & \frac{2x+3}{15} & \frac{2x+3}{8} \\
x=0 & x=1 & x=2 \\
\frac{4}{3} & \frac{2+3y}{15} & \frac{4+3y}{24}
\end{array}
\end{aligned}$$

So f_x given by x/y , x given y , okay, we have to do it for this is f_{xy}/f_{yy} okay, let us take $y = 1$ now okay. So f_x given by x given y okay, we have to do it for, this is f_{xy}/f_{yy} okay, let us take $y = 1$ now okay. So f_x given by okay, we have found for $y = 0$, for $y = 1$ we have to find, so f_{x1} , f_{y1} , $f_{x1} = k$ times $2x + 3/15/45$ k times $2x + 3/15/45$ okay. So $15/45$ means $1/3$ okay, so $3k * 2x + 3$ okay.

So $3/45$, k is $1/45$, so $3/45 * 2x + 3$ okay, so we have $1/15$, $2x + 3$ okay and then f_x given by for $y = 2$ okay. So this if for $y = 1$, and we have earlier found for $y = 0$, for $y = 2$ okay. So f_{x2} , f_{y2} okay. This is $= k$ times $2x + 6/24/45$ okay. So this is $45k * 2x + 6/24$ okay, $45k = 1$ so we have $2x + 6/24$ okay, so we have $x + 3/8$ okay. So f_x given y , x given y okay. For $y = 0$ we found to be $x/3$ okay.

For $y = 1$ we found it to be $2x + 3/15$ and for $y = 2$ we found it to be $x + 3/8$ okay, similarly we can find f_y given x y given x okay. For $x = 0$, for $x = 1$, for $x = 2$ okay. Let us find f_y given x , y given x for $x = 0$. So we have f_{0y}/f_{x0} okay. So f_{0y} , f_{0y} will be = sorry p_{0y} you can say $p_{0y} = x_0$. So $3ky$ okay, $3ky/f_{x0} = 9/45$ okay. Now what this is $45/9 * 3ky$ okay, $45k = 1$, $3/9$ is $1/3$, so it is $y/3$ okay.

So $x = 0$ we have found okay, $x = 1$ if you want. So f_y given x y given x will be $= f$, instead of f actually we have taken p okay. So let us write p , so p_{1y}/f_{x1} . So how much p_{1y} will be, p_{1y} will be $= k$ times $2 + 3y/15/45$ okay. So this will be = you can say this will be $= 45k = 1$. So $2 + 3y/15$. So f_y given x y given $x = 2 + 3y/15$ when $y = 2$ okay, and f_y given x given x can similarly be found for $x = 2$ okay.

So $p_{Y|X}$, this is k times $2x + 3y$ we had, so $4 + 3y/24$ we found to be $= 24/45$ okay so this is $45k$ will be $= 1$. So $4 + 3y/24$ okay. So f_Y given x given x we find for $x = 0$ to be $y/3$, for $x = 1$ we found it to be $=$, for $x = 0$ it was $y/3$, for $x = 1$ it was so $2+3y/15$ okay and when I take $x = 2$ y , I wrote $y = 2$ there, okay this is for $x = 1$, for $x = 2$ we got to be $4+3y/24$ okay, so this is how we find the conditional distribution of x given y and y given x okay.

(Refer Slide Time: 30:38)

Example 2

Suppose the random variables X and Y have the joint probability density function

$$f(x, y) = xy e^{-\frac{1}{2}(x^2 + y^2)}, \quad x > 0, y > 0 \text{ and } 0 \text{ otherwise.}$$

Find (a) the marginal PDF of X .

(b) The marginal PDF of Y .

(c) The conditional PDF of X given $Y = y$.

(d) Whether X and Y are independent.

$$\begin{aligned} f_X(x) &= \int_{-\infty}^{\infty} f(x, y) dy \\ &= \int_0^{\infty} xy e^{-\frac{1}{2}(x^2 + y^2)} dy \\ &= x e^{-\frac{1}{2}x^2} \int_0^{\infty} y e^{-\frac{1}{2}y^2} dy \\ &= x e^{-\frac{1}{2}x^2} \int_0^{\infty} e^{-t} dt \quad \left(\frac{1}{2}y^2 = t, \quad y dy = dt \right) \\ &= x e^{-\frac{1}{2}x^2} \int_0^{\infty} e^{-t} dt \\ &= x e^{-\frac{1}{2}x^2} \cdot 1 \quad \left(\int_0^{\infty} e^{-t} dt = 1 \right) \\ &= x e^{-\frac{1}{2}x^2}, \quad x > 0 \\ &= 0, \text{ otherwise} \end{aligned}$$

Now suppose we have the random variables x and y , whose joint probability density function is $f_{xy} = x * y e$ to the power $-1/2$, x square $+ y$ square, $x > 0$, $y > 0$ and 0 otherwise okay, so when in the first quadrant f_{xy} is given by $xy * e$ to the power $-1/2$ x square $+ y$ square. So marginal density function of x let us find first okay. That is we want to find f_{xx} okay. So f_{xx} will be integral over $-\infty$ to ∞ $f_{xy} dy$ okay.

So we will have it over first quadrant only, okay, x is > 0 , y is > 0 , so we have to integrate over in that with respect to y okay. So integral over the first quadrant okay. So we are integrating, when we integrate we here keep x as fixed okay. Probability that $x = x$ we want, y varies okay. So we take a vertical strip. For the vertical strip in the region x is fixed okay, y varies from 0 to ∞ .

So 0 to ∞ $x * y e$ to the power $-1/2$, x square $+ y$ square dy , okay, so x times e to the power $-1/2$ x square we can write outside okay, x times e to the power $-1/2$ x square we can write outside, integral 0 to ∞ $y e$ to the power $-1/2$ y square we can integrate. Okay so let us make the substitution $1/2 y$ square $=$ let us say t then we get $y dy = dt$. So we get

here limits remain the same, we get $x e$ to the power $-1/2 x$ square e to the power $-tdt$, which comes out to be, this integral comes out to be 1 okay.

So we have $x e$ to the power $-1/2 x$ square, where x is > 0 okay and so $f_{xx} = x e$ to the power $-1/2 x$ square when x is > 0 and 0 otherwise okay. So $f_{xx} = x e$ to the power $-1/2 x$ square when x is > 0 and 0 otherwise okay, then marginal pdf of y , marginal pdf density function of y similarly we can find okay. So marginal density function of y we can find to be.


(Refer Slide Time: 33:37)

$$\begin{aligned}
 f_Y(y) &= \int_{-\infty}^{\infty} f(x,y) dx \\
 &= \int_0^{\infty} xy e^{-\frac{1}{2}(x^2+y^2)} dx \\
 &= y e^{-\frac{1}{2}y^2} \int_0^{\infty} x e^{-\frac{1}{2}x^2} dx \\
 &= y e^{-\frac{1}{2}y^2}, y > 0
 \end{aligned}$$

Thus, $f_Y(y) = \begin{cases} y e^{-\frac{1}{2}y^2}, y > 0 \\ 0, \text{ otherwise} \end{cases}$

Conditional PDF of X given $Y=y = \frac{f(x,y)}{f_Y(y)} = \frac{xy e^{-\frac{1}{2}(x^2+y^2)}}{y e^{-\frac{1}{2}y^2}} = x e^{-\frac{1}{2}x^2} = f_X(x)$

$f(x,y) = f_X(x)f_Y(y) \Rightarrow X$ and Y are independent



$f_Y(y) = \int_{-\infty}^{\infty} f_{xy}$, we are integrating in this first quadrant okay because there only f_{xy} is nonzero. So we are taking now y fixed okay, y fixed means we have to take a horizontal strip okay. So horizontal strip we have to take in the region like this. So we have to take okay, so this is for where y fixed okay. So this will be $= \int_0$ to infinity, $xy e$ to the power $-1/2 x$ square $+ y$ square dx okay.

So $y e$ to the power $-1/2 y$ square we shall write outside and integral 0 to infinity $x e$ to the power $-1/2 x$ square dx , this we have just now seen, this comes out to be 1, so this is $y * e$ to the power $-1/2 y$ square and this is valid when y is > 0 , this equal to $f_{yy} =$ this when y is > 0 , thus $f_{yy} = y e$ to the power $-1/2 y$ square when y is > 0 and 0 otherwise. Okay, now conditional PDF okay of x given $Y=y$.

So we have to find this okay. Conditional PDF given $Y = y$ okay, conditional PDF of x given $Y = y$, so this means that we want the let us go to the definition, conditional okay. So we define the conditional distribution of x given $Y = y$ okay. If xy is a 2 dimensional discrete

random variable, this is for the case where $f_{x/y}$ in the case of continuous we have $f_{x/y} = f_x \cdot f_y$ okay.

So we come to this one okay. So conditional probability of x given $Y = y$ is $f_{x/y}$ okay given $Y = y$, given $Y = y$ means f_y okay. So this will be $= \frac{f_{x/y}}{f_y}$ okay. So this will be $= \frac{f_{x/y}}{f_y} = \frac{f_x \cdot f_y}{f_y} = f_x$ okay. So this comes out to be f_x okay, f_x okay which is nothing but you can see this is $= f_x$ okay.

So we can see here that $f_{x/y} = f_x \cdot f_y$ okay and therefore x and y are independent random variable okay. So it answers this question also. We have found the conditional probability distribution of x , given $Y = y$ it came out to be f_x okay. So f_x so it turns out that $f_{x/y} = f_x \cdot f_y$ and therefore x and y are independent okay.

(Refer Slide Time: 37:30)

Theorem 1 (Addition of means)

The mean (expectation) of a sum of random variables equals the sum of the means, that is,

$$E(X_1 + X_2 + \dots + X_n) = E(X_1) + E(X_2) + \dots + E(X_n).$$

Theorem 2 (Multiplication of means)

The mean of the product of independent random variables equals the product of the means, that is,

$$E(X_1 X_2 \dots X_n) = E(X_1) E(X_2) \dots E(X_n).$$

Theorem 3 (Addition of variances)

The variance of the sum of independent random variables equals the sum of the variances of these variables.

So then we have these theorems which are important ones, the mean or expectation of a sum of random variables equals the sum of the means that is expected value of $X_1 + X_2$ and so on X_n is expected value of $X_1 +$ expected value of X_2 and so on expected value of X_n and then the mean or expectation of the product of independent random variable.

Suppose X_1, X_2, X_n are independent random variables then expectation of their product is product of their expectations and then variance of the sum of independent random variables equals the sum of the variances of those random variables. So that is all in this lecture. Thank you very much for your attention.