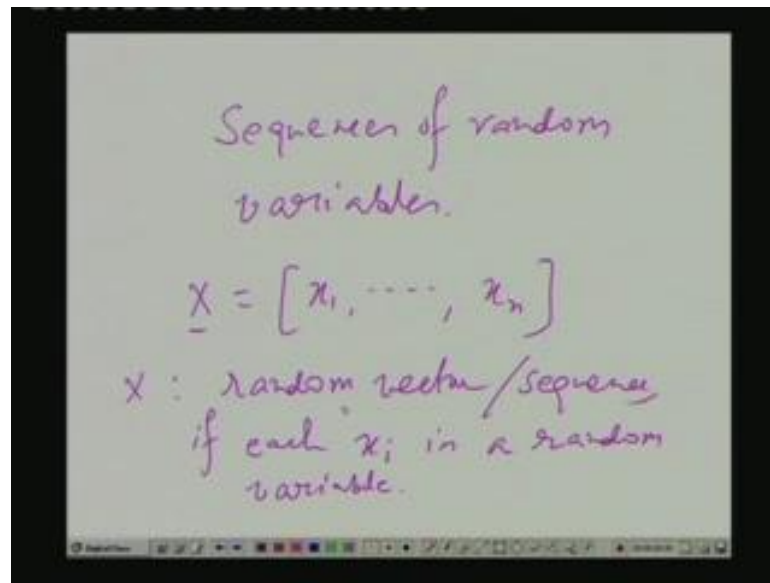


Probability and Random Variables
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Lecture - 21
Sequences of Random Variables

So, today we will discuss an important topic that is we start this topic sequence of random variables.

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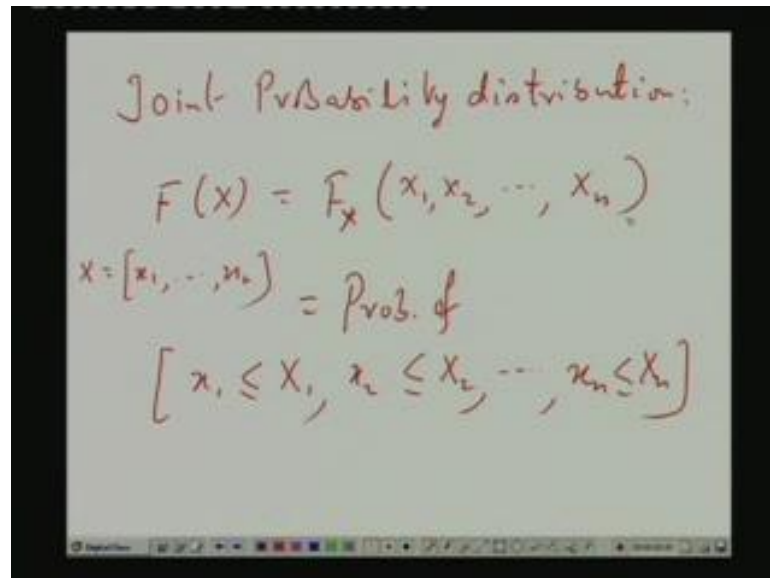


You see we started with first a single random variable, right and we considered a function of single random variable. Then, we generalized it to two. I mean two random variables. So, you know you can then say that it is a sequence just of two. I mean elements, two random variables, two elements sequence, and we consider function of two random variables and functions of two random variables and all that, right. The whole treatment will now be generalized where we will be considering a vector say $\underline{X}$ as x_1 dot dot dot dot x_n . This $\underline{X}$ will be called a random vector. If each element x_1 to x_n is a random variable that is $\underline{X}$ will be called a random vector, or say sequence if each x_i is a random variable.

So, there you see earlier we considered two random variables. So, we had a vector of two elements x_1 and x_2 . We call it $\underline{xy}$. This is a defined notation, but now it is more general in such random variables, right. So, for the hindsight, you can see that if you talk of the

joint density or joint probability distribution of x , it will be basically a function of n variables, right x_1 to x_n .

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Joint Probability distribution:

$$F(x) = F_x(x_1, x_2, \dots, x_n)$$

$$x = [x_1, \dots, x_n] = \text{Prob. of}$$

$$[x_1 \leq X_1, x_2 \leq X_2, \dots, x_n \leq X_n]$$

So, we can define joint probability distribution. Actually x would write like F_x for x say takes values x_1 , this specific value x_2 dot dot dot x_n , and this capital X , actually the vector consisting of the variables small x_1 dot dot dot small x_n . Here capital X_1 is a particular value for small x_1 . X_1 is variable. Capital X_2 is a particular value for the variables small x_2 and likewise. What does this mean? It means the probability of this event that x_1 is less than equal to capital X_1 , x_2 less than equal capital X_2 dot dot dot x_n less than equal capital X_n .

This would occur jointly. There are n joint events that is one is small x_1 less than equal capital X_1 . Another is small x_2 less than equal capital X_2 so on and so forth. This should occur jointly simultaneously. That is why it is called joint distribution, right and that is denoted by $F_x x_1$ up to x_n . Sometimes when I do not need, I may not I may skip the subscript x and I will put x_1 to x_n . I think you can really understand sometimes, but when there is confusion, when suppose I am dealing with more than two such distribution functions, then to differentiate between the functions, I will put the subscript. Now, for the joint probability distribution, but as a same token you can then define, and you can easily see that is now a function of n variables x_1 to x_n . By the same way, I can next define the joint probability density function.

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Joint Probability Density

$$p_x(x_1, \dots, x_n) = \frac{\partial^n F(x_1, \dots, x_n)}{\partial x_1 \partial x_2 \dots \partial x_n}$$

$x_1, \dots, x_n$ $dx_1, dx_2, \dots, dx_n$

$x_1: \quad x_1 \quad \text{---} \quad x_1 + dx_1$
 $x_2: \quad x_2 \quad \text{---} \quad x_2 + dx_2$
 $x_n: \quad x_n \quad \text{---} \quad x_n + dx_n$

Joint Probability Density-Recently you know that we have to differentiate. When you differentiate the joint probability distribution function, so you define like this $P_x X_1$ up to X_n is nothing but $\frac{\partial^n F(x_1, \dots, x_n)}{\partial x_1 \partial x_2 \dots \partial x_n}$, and such skipping the subscript here X_1 dot dot dot X_n with respect to $\frac{\partial}{\partial x_1} \frac{\partial}{\partial x_2} \dots \frac{\partial}{\partial x_n}$. This is the joint probability density. What does it mean actually? It means that if you now consider n dimensional space whose axis are x_1, x_2 up to x_n and there if you take an infinitesimally small volume i mean mass, in fact as far as region whose value is say dx_1, dx_2 up to dx_n , that is along x_1 axis. That is suppose in n dimensional space, you are located at a point up to x_n .

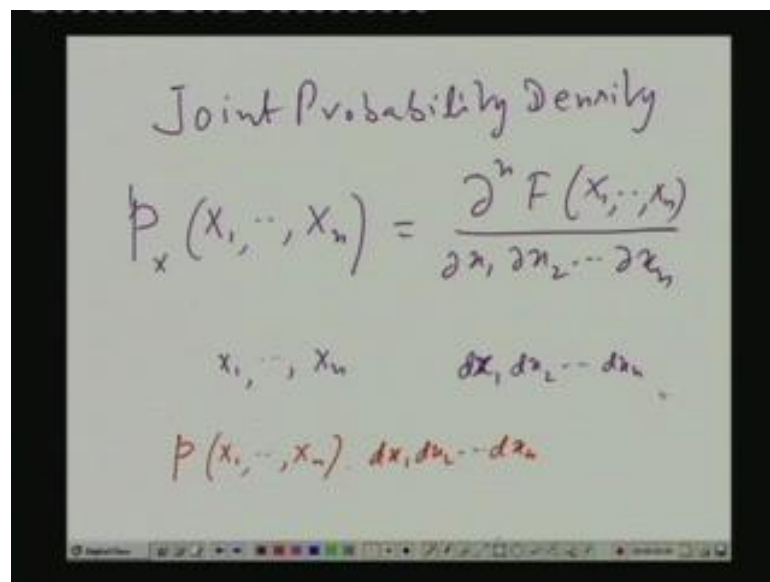
At this point you are considering an infinitesimally or infinitely small or infinitesimally small, I mean region or cell whose sides are we call it actually hyper cube, where actually real life cube means it has got only three sides, but in n dimensional space, I will call it n dimensional hyper cube whose sides are dx_1, dx_2 up to dx_n . So, volume is this. So, basically it defines an area where x goes x . The variable x_1 goes from capital X_1 to capital X_1 plus dx_1 , capital X_2 goes for that is this zone. This is for variable x_1 . Therefore, variable x_2 again this is the range dot dot dot. So, that means, at this point capital X_1 to capital X_n at that point, I am considering a small cell, a small region.

In fact, this hyper cube I would say whose sides are of length $dx_1, dx_2, \dots, dx_n$ along that $x_1, x_2, \dots, x_n$ axis. This variable small dx_1, dx_2 along the axis small x_1, x_2 and so and so forth. So, I basically cover a volume of value $dx_1, dx_2 \dots dx_n$, and then the probability that the random variable x_1, x_2 up to x_n , these variables lie within that hyper cube located at

this point capital X_1 up to capital X_n and of this volume, that is small x_1 lie within this range, small x_2 lie within this range, small x_n lie within this range simultaneously. I repeat again, this means that I am looking for probability of these elements X_1 to X_n lying within the small hyper cube located where at the point capital X_1 P_{x_n} .

In this manner, that is starts at X_1 along the smaller x_1 axis goes up to capital X_1 plus dx_1 to side. It covers the side of length dx_1 . Then, along the small x_2 axis, it starts at x_2 and goes up to x_2 plus dx_2 , so covers a side of distance dx_2 and likewise. So, at this point capital X_1 to capital X_n a small hyper cube is formed infinitely. Hyper cube is formed because volume is this $dx_1, dx_2 \dots dx_n$. The probability of this variables lying within that hyper cube together will be given by nothing but just minute. That will be given by I am dropping the subscript this times $dx_1, dx_2 \dots dx_n$.

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Joint Probability Density

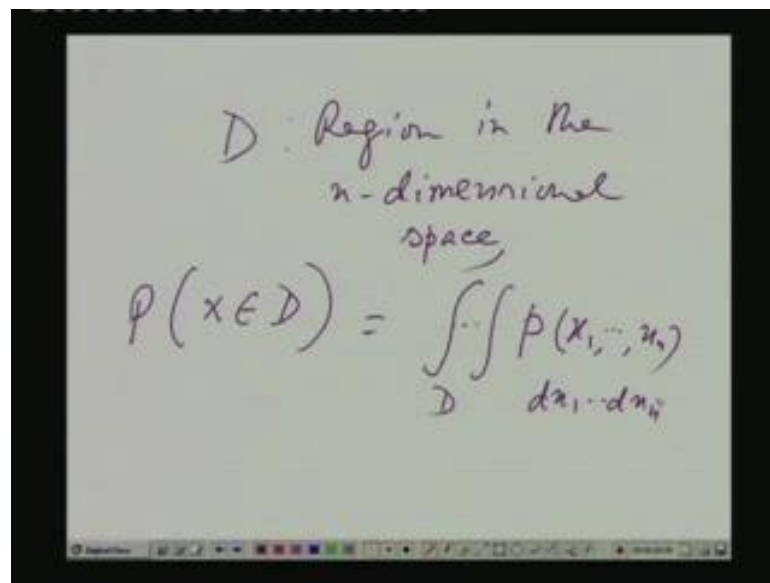
$$p_x(x_1, \dots, x_n) = \frac{\partial^n F(x_1, \dots, x_n)}{\partial x_1 \partial x_2 \dots \partial x_n}$$

$x_1, \dots, x_n$ $dx_1, dx_2, \dots, dx_n$

$$p(x_1, \dots, x_n) \cdot dx_1, dx_2, \dots, dx_n$$

This image actually follows from this formula that basically this is nothing but the derivative, partial derivative of distribution function. So, if you multiply this probability density with dx_1, dx_2 up to dx_n , then that means nothing but the probability of the variables X_1 to X_n lying within the hyper cube located at capital X_1 capital X_n of sides dx_1, dx_2 up to dx_n .

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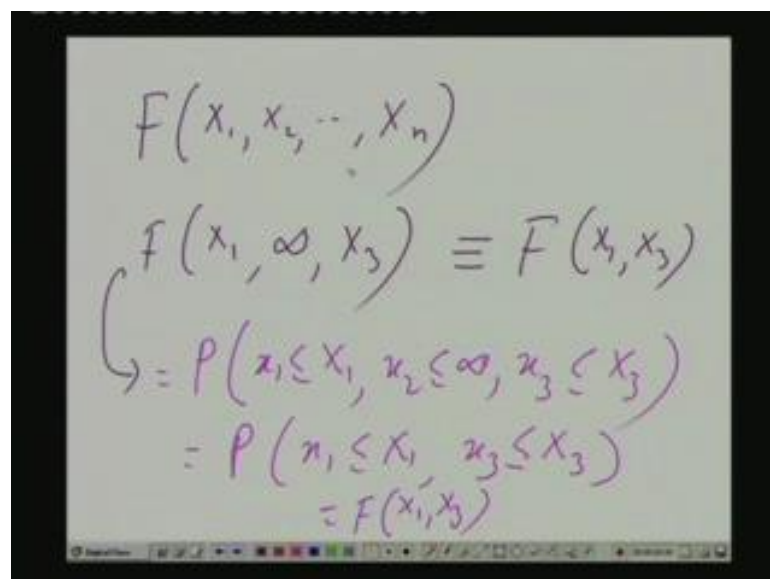


D : Region in the n -dimensional space,

$$P(X \in D) = \int \int_D p(x_1, \dots, x_n) dx_1 \dots dx_n$$

This means that if I consider a region D , the arbitrary region in the n dimensional space, then probability of this vector X falling within D , that region is nothing but integral. Actually it will be n -dimensional integral. I will call it what D p x dx x is a vector. You got to say x 1 up to if you even want you can write it like this. You can see that is nothing but just generalization of our previous concepts. It is generalization of our previous concepts from two variables, two in the general case of n variables. Certainly certain more things also you can see some other things.

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$F(x_1, x_2, \dots, x_n)$

$$F(x_1, \infty, x_3) \equiv F(x_1, x_3)$$
$$\rightarrow = P(x_1 \leq x_1, x_2 \leq \infty, x_3 \leq x_3)$$
$$= P(x_1 \leq x_1, x_3 \leq x_3)$$
$$= F(x_1, x_3)$$

For instance, if you consider the distribution function F . Suppose here some of the values I put as infinity for examples suppose I have got X_1 infinity X_3 , then my claim is this will be nothing but the joint distribution for just X_1, X_3 . Why? After all what is this? This is nothing but probability of x_1 less than this, x_2 less than equal to infinity, x_3 less than equal to x_3 . Now, x_2 less than equal to infinity means all possible values of x_2 are covered which effectively means that I am basically looking at the probability just of this event. I am not selecting a particular choice of x_2 because all possible x_2 's are covered. X_1 should be less than equal to capital X_2, X_1 , but all cases of x_1 will be considered for which x_2 can take value from minus infinity to infinity.

So, this is nothing but this F . I guess you understand this. I repeat again in case there is confusion. X_1 less than equal to capital X_2 , capital X_1, x_2 less than equal to infinity. I am considering the joint events at x still less than equal to capital X_3 . This is equivalent to this joint event x_1 less than equal to capital X_1 still less than equal to capital X_3 because this have to consider all possible cases for which x_2 can take some finite value, some other value sign another value up to infinity up to minus infinity. So, there the whole range of x_2 is absorbed in this joint event.

So, these two joint events are equivalent, but in this case I am getting the probability distribution for just x_2, x_1 to x_3 which means in general if this probability distribution functions of n random variables. If you put infinity for some, then what I get is nothing but the joint probability distribution of rest of the variables is most important, right, rest of the variables. Then, you define with respect to those variables, those remaining variables; you get the corresponding joint probability density, that is just by the normal definition.

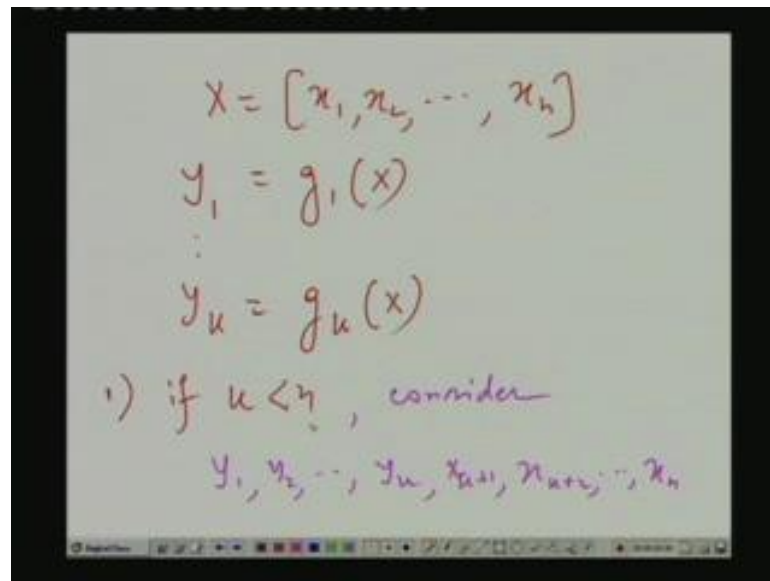
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$$\begin{aligned} & \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} p_x(x_1, x_2, x_3, x_4) dx_2 dx_4 \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} p_x(x_2, x_4 / x_1, x_3) \\ & \quad p(x_1, x_3) dx_2 dx_4 \\ &= p(x_1, x_3) \end{aligned}$$

Similarly, suppose this probability density function say an example, take any example say x_1, x_2, x_3, x_4 . Suppose I integrate it with respect to say one or two variables, not all of them because if I integrate with respect to all of them I get one of course, but total probability is 1, but suppose I integrate it with respect to say two variables, say $dx_2 dx_4$ minus infinity to infinity. This is my X vector for x vector is x_1, x_2 up to x_4 . I put a subscript here purposely. What does it mean? You can easily see you can write this as conditional probability of given some x_3, x_4 times $P_{x_3 x_4} dx_2 dx_4$. Sorry there will be some change here which is $x_1 x_3$.

Now, $P_{x_1 x_3}$ go outside. This integration is with respect to x_2 and x_4 , and if you integrate it, integrate the spot with respect to x_2 and x_4 , you have minus infinity to infinity. Obviously, that will be 1, because subject to this given condition, I mean sorry that $x_1 x_3$ are given. Probability of x_2 falling within minus infinity to infinity and x_4 falling within minus infinity to infinity, that has to be 1 because it covers all possible values. So, you get nothing but $P_{x_1 x_3}$. That means, if the probability density functions of all these random variables is integrated with respect to some of the random variables, then what we get is the joint probability density function for the rest of the variables. Then, you remember when you considered two random variables; there we moved to function of random variables. We considered two functions of two random variables, right.

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The image shows a whiteboard with handwritten mathematical expressions in red ink. The first line is $X = [x_1, x_2, \dots, x_n]$. The second line is $y_1 = g_1(x)$. The third line is $y_k = g_k(x)$. The fourth line is a note: "1) if $k < n$, consider". The fifth line is $y_1, y_2, \dots, y_k, x_{k+1}, x_{k+2}, \dots, x_n$.

Here what you are given is this X as we consider some functions y_1 to y_k . Our purpose will be to find out the joint statistics, that is the joint distribution or joint density. I would say I mean both are equivalent. You can obtain one from the other. Joint density say of this random variables y_1 to y_k given the joint density or distribution of the random variables x_1 to x_n . We have already tackled this problem when n was two, that is for the case of two random variables, we have already tackled this case. That time we took two functions g_1 and g_2 , but now it is general case we have k functions.

Obviously, there are three choices possible. k can be less than n , k can be equal to n and k can be greater than n , but we will finally consider only k equal to n case because the other two cases can be easily handled. If you know the result for k equal to n , let us first see how that is possible, and then we will come to k equal to n case and find out the expression for the joint density of the random variables y_1 to y_k . First if k is less than n , then we will consider y_1, y_2 up to y_k , and then to make the total number of such variables equal to n , I simply add $x_{k+1}, x_{k+2}, \dots, x_n$. That is from this random vector, I take out the last $n - k$ entries.

Now, y_1 is $g_1(x)$, y_2 is $g_2(x)$, y_k is $g_k(x)$ and x_{k+1} also, you can say it is a function of x where given x you only pick up one particular element that is x_{k+1} . x_{k+2} is also a function of x after all given the entire vector x , you just take out one particular element that is x_{k+2} and same for x_n . So, then the length becomes n . We already know joint density of x or this random variable vector x . Then, for this case, the length

becomes the length of this modified random vector if you call it k' k' is equal to n , and we have already told that for the case where the total number of random variables or total number of functions is same as the total number of random variables x , that is n , we will consider that case soon. That theory can be applied here.

What I mean is that we have already made this statement that we will state the result for the joint density of the random variables y_1 to y_k for the case, where k equal n . So, that result should be applicable to this modified random vector. So, when k is less than n , we simply can append some elements from the vector x to make it length n , and then apply the theory which we have to discuss soon to find the joint density of this entire stuff. That should not be difficult. If we look at that theory, we will come back to this later as an application of that theory when total number of random variable is same as total number of these functions g_1 to g_k , that is k is same as the total number of random variables x_1 to x_n that is n , but when k greater than n , then some problem comes.

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Handwritten notes on a whiteboard:

ii) $k > n$

$y_1, y_2, \dots, y_n$

$y_{n+1} = g_{n+1}(x)$

Vertical line:

$y_1 = g_1(x)$

$y_2 = g_2(x)$

$\vdots$

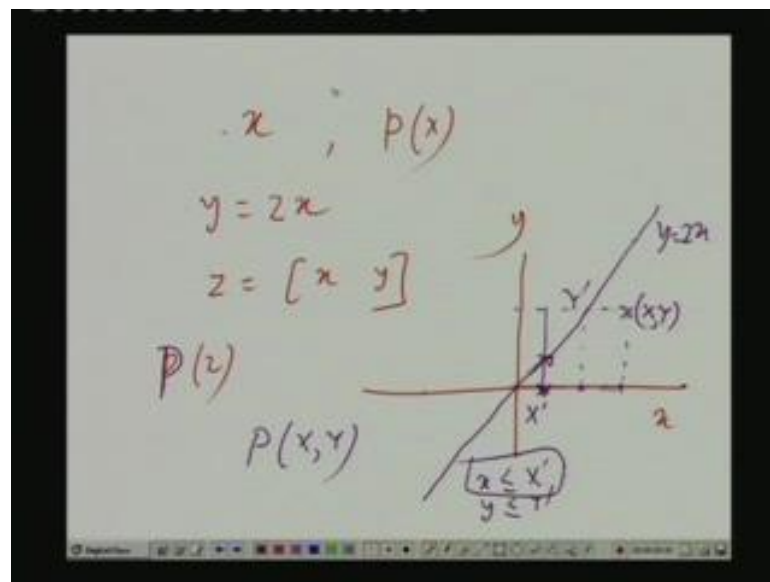
$y_n = g_n(x)$

Here, you can see one thing. We consider y_1, y_2 up to y_n . So, the length is up to this is same as the total number of random variables x , that is x_1 to x_n . So, that functions y_1 after all is function $g_1(x)$, y_2 is a function which is $g_2(x)$. So, the total number of functions up to this is same as the total number of random variables, it is n , k is greater than n . So, you have got k minus n extra functions. How about that because I have to actually find out the joint density of this k function y_1 to y_k , but I have only considered a part of it y_1 to y_n . How about the rest?

Now, if you consider for that matter y_{n+1} which is nothing but say $g_{n+1}(x)$. Now, my claim, my statement is that most of n , you can express this x in terms of that is the vector x . That is the elements of x , x_1 to x_n in terms of y_1 to y_n . How? That is we know that y_1 is $g_1(x)$, y_2 is $g_2(x)$. For example, suppose these are all linear functions, some linear combinations of the elements of x . Suppose y_1 is twice x_1 plus thrice x_2 plus dot dot dot plus say $v_{10} x_n$ similarly another. So, that means to linear equations. Similarly, suppose you get 1, the linear equations that another here. So, you can solve them and get a solution for y in terms of x .

In general case, you can get more than one solutions. That is fine, but what it means is this you can replace x by this y , either one possible y or several possible y 's. Given random variables x , x_1 to x_n , you can replace them by y_1 to y_n , right which means y_{n+1} , y_{n+2} up to y_k , this extra function, they can be expressed in terms of y_1 to y_n . Then, my claim is joint density of $y_1, y_2, \dots, y_k$ can be expressed just by the joint density of y_1 to y_n . If I find out the joint density of y_1 to y_n , then that is enough for me. With that I can find out the joint density of y_1 to y_k . Now, how to explain that I just considered the example? Forget all these for the time being.

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Suppose x is a random variable and you got this probability density functions say p_x , and you define another variable y as $2x$. Now, we have to find out and now you follow vector say z as xy . You have to find out P_z . My claim is since y is expressible in terms of x to find out the joint density of xy , this vector is enough. If you know the joint

probability density of x , P_z can be easily written in terms of that. This is not very difficult. What it means is this suppose x and y with a plane and this is the line y equal to $2x$.

We start with probability distribution for that matter because that is easier to explain and suppose you got say other any point here, some x as corresponding y . In this case, what is the probability? Suppose you call it capital X capital Y this point. So, where is a joint distribution P_{xy} ? That means, what is the probability that small x is less than equal to capital X and small y is less than equal capital Y . Remember that for any given x y lies precisely on this line and nowhere else.

So, if you got at this point now capital X , the probability that small y lies below this point is 0. If you go a little left, the probability that small y lies again below this height again 0 because if you are at this x corresponding y is here on this line. If you are at this x corresponding y is here, but if you are looking for small y taking value less than this height, so obviously this point is not on this line. So, probability is 0, but if you go up to here call it say x prime, then there is no problem. I mean x prime what to the left of it, there is no problem because there is a probability.

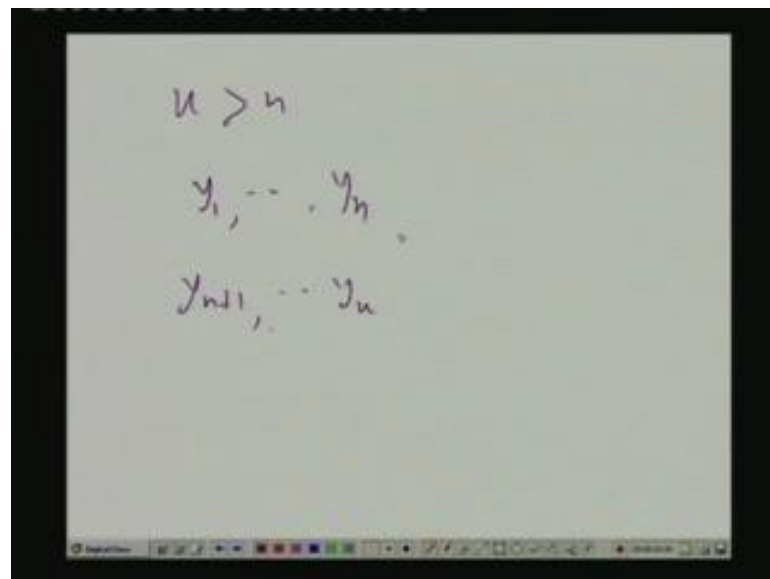
What is the probability of say x less than equal to x prime, y less than equal to y prime? What will that? For instance, suppose you are here. Probability that small x is less than equal this and small y is less than equal to this, what will that be. Obviously, that will not be 0 because if small x is here, y will be here. So, that is less than this, but then what is the probability. Then, simply the probability distribution of x is up to this point. This is because y is purely determined by x . If small x is up to this point, y has to be here, so that the joint density x will transfer to mean.

There is a probability, the joint distribution transfer to mean the simple probability distribution of x . I repeat again suppose you are now here x double prime. Probably you call this xy prime. Forget this. Call it y prime. Suppose x prime is here and this is y prime. So, now the probability of x taking values less than equal to x prime and y taking value less than equal to capital Y , see the probability of x here x taking value x prime and y less than equal to y prime, that is not 0. If you go backward, same thing occurs that is because for any choice of given x be it x prime, the corresponding y is here that is below this height.

So, probability is not 0, and then what is probability of then x lying I mean, what is the probability of x lying to the left of say x prime and y lying x less than equal to x prime and y less than equal to y prime, what is the probability? It is simply the probability of x less than equal to x prime. So, we see if that is satisfied, these are all satisfied because y is equal to $2x$. So, if small x is less than equal to x prime, y has to be less than equal capital Y prime because y will be on this line and that is below this height. That is automatically satisfied. So, this is enough to have only this. If this is satisfied, these are always satisfied. So, basically this is the event or distributions are same. I mean this is the event, right. This is not that these two events are same, but this is the event if it is satisfied, the other is automatically satisfied.

So, the joint probability is nothing but joint probability of these two events occurring together. Simply the probability of this event alone means for such cases, where one variable is expressible in terms of the other. The joint density of the vector is obtainable simply from the joint distribution of the original vector is obtainable simply from the original probability distribution, and then by the same logic, it apply I mean and by extension, the same logic applies to the probability density function also. So, this explains why.

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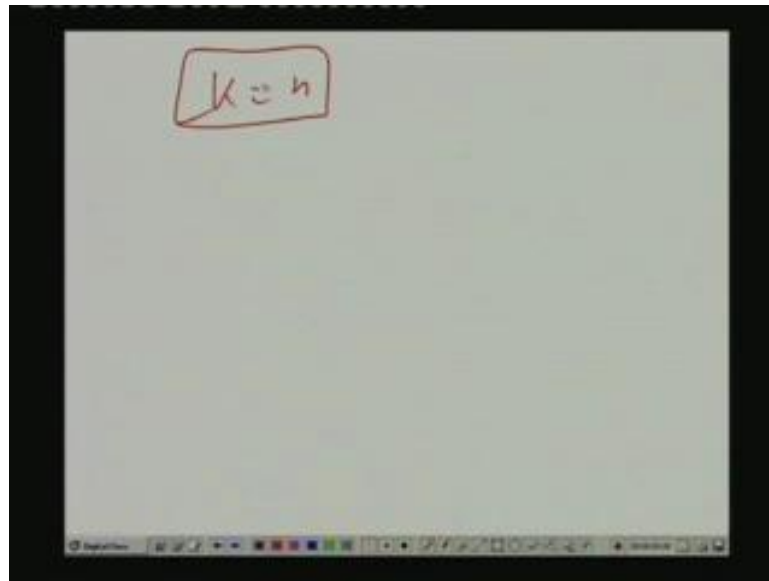


The image shows a whiteboard with handwritten mathematical expressions. The first line is $u > u$. The second line is $y_1, \dots, y_n$. The third line is $y_{n+1}, \dots, y_n$.

For the case k greater than n , we can just happily take up to y_1 to y_n and find out the probability density of this because I have told you y_{n+1} to y_k . Each of them can be expressed I mean in terms of this. How? Because each of them y_1 is g_1 , x y_2 is g_2 x ,

y_n is $g_n x$. If you solve them, then all the elements of the x vector x_1 to x_n , they can be expressed in terms of these variables, and by that process y_{n+1} can be written in terms of these variables, y_{n+2} also can be in terms of these variables y_1 to y_n like that. As I told you if y_{n+1} is expressible in terms of these variables or y here up to y_k , so y_k also is expressible in terms of these variables. The overall joint distribution can be written down just in terms of the joint distribution of y_1 up to y_n .

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So, this means we can simply take K equal n . So, if there are n random variables, we take n functions y_1 to y_n . I repeat x_1 to x_n , there are n random variables and we take these functions. I mean y_1 as $g_1 x$, y_2 as $g_2 x$ up to y_n as $g_n x$. In this case, what is the joint density of y_1 to y_n ?

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$$p_y(y_1, y_2, \dots, y_n)$$
$$\text{Solve } \begin{cases} y_1 = g_1(x) \\ \vdots \\ y_n = g_n(x) \end{cases}$$

i) No solution
 $\Rightarrow p_y(y_1, y_2, \dots, y_n) = 0$

That is what is you could now put a subscript say y . Some values are given the joint density at these values. Capital Y 1 for small y 1, capital Y 2 for small y 2. This is specific values and small y 1 is the variable, small y 2 is variable and like that. What is that you have to find out? For that first we solve these equations. First, this we solve by solving each component of the vector x , that is x 1 up to x n will be written in terms y 1 to y n . As I told before that now first possibility is no solution. Suppose no solution exists, then the theory says that this would be 0. It is 0.

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ii) Only one solution
 $x = [x_1, \dots, x_n]$

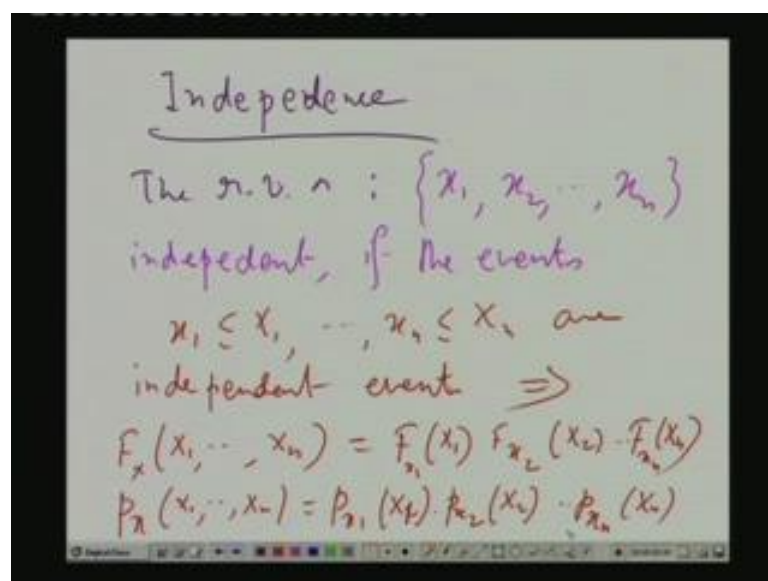
$$\Rightarrow p_y(y_1, y_2, \dots, y_n) = \frac{p_x(x_1, \dots, x_n)}{|J(x_1, \dots, x_n)|}$$
$$J(x_1, \dots, x_n) = \begin{bmatrix} \frac{\partial g_1}{\partial x_1} & \frac{\partial g_1}{\partial x_2} & \dots & \frac{\partial g_1}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial g_n}{\partial x_1} & \frac{\partial g_n}{\partial x_2} & \dots & \frac{\partial g_n}{\partial x_n} \end{bmatrix}$$

Then, suppose only one solution is in this case is by the theory you replace, put the solutions here. So, capital X_1 for small x_1 , capital X_2 for small x_2 up to capital X_n for small x_n . Remember each of the variables capital X , each of these elements capital X_1 to 2 Capital X_n . They are basically I mean expressed, they are basically obtained in terms of y_1 to y_n . So, this becomes actually a function of y_1 to y_n . This is divided by determinant of a matrix. The matrix is called Jacobian. Again it is evaluated at this.

What is Jacobian? This partial derivative, but that evaluated at this solution point. They are not general expressions $\frac{\partial x_1}{\partial g_2} \frac{\partial g_1}{\partial x_2} \dots \frac{\partial g_n}{\partial x_1}$ up to $\frac{\partial g_n}{\partial x_n}$. So, if these partial derivatives are evaluated at x_1 equal capital X_1 small x_2 equal to capital X_2 and dot dot dot small x_n equal to capital X_n , then this matrix you compute the determinant and ratio of this will be the probability density. As I told you each of this capital X_1 to capital X_n , they are actually functions of, they are already expressed by our solution in terms of y_1 to y_n .

So, right hand side actually becomes a function of y_1 to y_n and if you have more than one solution, then you will have such terms just added. Suppose there is one solution x_1 up to x_n , there is another solution x_1 prime up to x_n prime and call it capital X prime. In that case, a total probability density will be this plus again $P_{x_1 \text{ prime } \dots x_n \text{ prime}}$ divided by the Jacobian determinants of the Jacobian evaluated at x_1 prime to x_n prime and so and so forth, that is the theory.

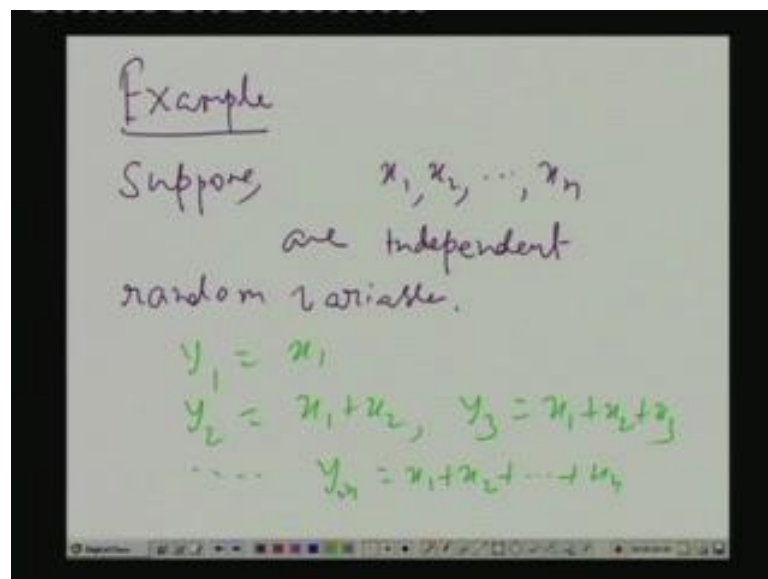
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The random variables, there is a random variable and they are called independent is just extension of the concept of statically independent. Earlier we have independents of two random variables, the case of n random variables nothing else. They are called statically independent. If you consider the joint event and if the events are independent events meaning the joint probability of these events together, basically the joint probability which is nothing but the distribution will be nothing but probability of x_1 less than equal to capital X_1 multiplied by probability of x_2 less than equal capital X_2 dot dot dot dot.

As a result if you want to find out the joint density, then as by your theory you have to define say this with respect to x_1 up to x_n , but if they are statically independent, the distribution is a product of the individual distributions. So, when you differentiate the right hand side with respect to x_1 , x_2 and x_n , then obviously the density becomes where you differentiate this with respect to x_1 , only this guy is a function of x_1 . So, this is it gets differentiated with respect to x_1 which gives rise to the probability density of x_1 . Similarly, it is probability density of x_2 so and so forth. So, it becomes sorry x_1 . Just consider an example as to how to apply the theory.

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Suppose x_1, x_2 dot dot dot x_n are independent and you form y_1 as x_1 , y_2 , x_1 plus x_2 , y_3 x_1 plus x_2 plus x_3 dot dot dot up to y_n up to x_n , so essentially we have got some linear functions here. y_1, y_2 up to y_n , there all functions of x_1 up to x_n , but they are some linear functions of this specific time. Now, we are given the fact that x_1 to x_n , they are independent and we know their joint density because we know the individual

densities. This is given. We have to find out the joint density of y_1 to y_n by the previous theory. So, first to do that we fix up, that is we have to find out.

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The image shows a whiteboard with handwritten mathematical derivations. On the left, the joint probability density function is given as $p_y(y_1, y_2, \dots, y_n)$. Below it, the Jacobian matrix J is defined as a lower triangular matrix of ones: $J = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & \dots & 0 \\ 1 & 1 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & 1 & \dots & 1 \end{bmatrix}$. On the right, the transformation equations are listed: $x_1 = y_1$, $x_2 = y_2 - y_1$, $x_3 = y_3 - y_2$, and $x_n = y_n - y_{n-1}$. At the bottom, the inverse transformations are shown: $y_1 = x_1$, $y_2 = x_1 + x_2$, $y_3 = x_1 + x_2 + x_3$, and $y_n = x_1 + x_2 + \dots + x_n$.

We have to find out P_y capital Y_1 . Some specific value capital Y_2 dot dot dot say Y_n , where you find out there is a way to find out the joint probability density of y at a specific value say capital Y_1 capital Y_n . This will be chosen arbitrarily. So, you will get the above all functions. So, as per our theory, we first solve for x_1 to x_n given this Y_1 to Y_n . So, you can easily see the solution that x_1 is nothing but from this first equation Y_1 itself X_2 is nothing but Y_2 minus x_1 and x_1 is Y_1 , so Y_2 minus Y_1 . X_3 is nothing but you can easily see Y_3 . If you put Y_3 here, what is x_3 ? It is y_3 minus x_1 minus x_2 which is y_3 minus Y_2 so on and so forth.

Actually in general, x_k is nothing but Y_k minus Y_{k-1} this way. So, the solution is unique. So, it is not the solution. Solution does exist, but only one solution. No other solution. It is probably a linear equation. This is number one and how about the Jacobian to form the Jacobian plus del Y_1 with respect to del x_1 . That is 1 because del x_1 with del x_1 that is 1 and del y_1 with respect to del y_2 del y_1 by del x_2 that is 0 because it is not present here. It is same for other entries. Then, del y_2 del x_1 that is one del y_2 del x_2 , again 1 and then 0, then 1, 1, 1, 0, 1, 1, 1, dot dot dot 1.

You can easily know, you can easily see determinant of this matrix is 1 because 1 times whatever be a square matrix, then 0 times raised they all go. Again apply the same thing

here. Finally, 1 into 1 into 1 into 1 into 1 is 1. So, Jacobian, all they are has determinant equal to 1. So, now, the theory is very simple.

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$$p_y(y_1, y_2, \dots, y_n)$$

$$J = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & \dots & 0 \\ 1 & 1 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & 1 & \dots & 1 \end{bmatrix}$$

$$\begin{cases} x_1 = y_1 \\ x_2 = y_2 - y_1 \\ x_3 = y_3 - y_2 \\ \vdots \\ x_n = y_n - y_{n-1} \end{cases}$$

$$p_y(y_1, y_2, \dots, y_n) = p_x(x_1, \dots, x_n)$$

$$= p_{x_1}(y_1) p_{x_2}(y_2 - y_1) \dots p_{x_n}(y_n - y_{n-1})$$

You can easily see it will be nothing but p_x at this choice x_1 up to x_n divided by the determinant that is 1, and we are given the fact that the random variables x_1 up to x_n , they are independent. So, this joint density is nothing but the product of the individual densities. So, p_{x_1} and capital x_1 is y_1 p_{x_2} which is y_2 minus y_1 dot dot dot p_{x_n} y_n minus y_{n-1} . So, you can easily see that the concepts involved here, they are nothing new. They are simple generalization of the concepts that our valid or those were introduced rather in the case of two random variables. That is why I am not giving you the proof and all that. You can argue about this on your own.

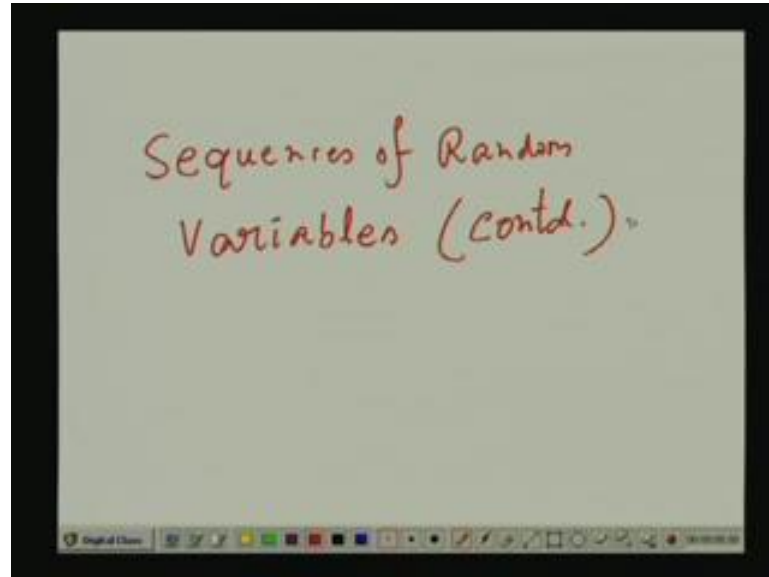
So, I stop here today. In the next class, I consider this issue further and going to things like you know mean, covariance, correlation. In fact, we will have a correlation matrix, now covariance matrix and things. Again the characteristic function issue as relevant here and that takes us to a very important theorem called central limit theorem. So, that is all for today. Thank you very much.

Preview of the next lecture.

Probability and Random Variables
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Lecture - 22
Sequences of Random Variable (contd.)

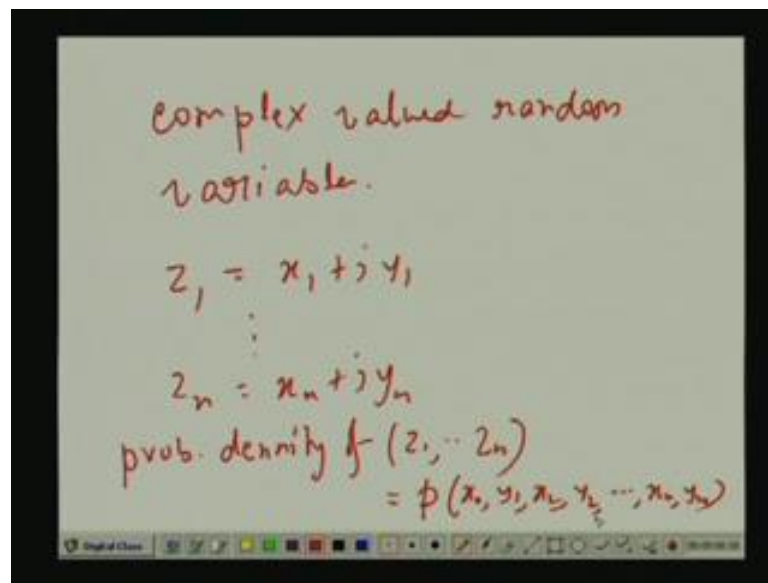
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So, you know we have been discussing this issue of random sequences. That is just for a recap. We initially started with just one random variable and function of one random variable, then two random variables, then one function involving two random variables and two functions involving two random variables. Here, we tried to generalize that to a set of n random variables which are ordered as sequences x_1, x_2 up to x_n , and we first considered one function of such n random variables, and then n functions of such n random variables, right.

So, there are several issues which we did not discuss last time. There are all you know just analogous to those issues which we considered in the case of two random variables. So, we will just continue from where we left last time, but just one remark. We have so long used real value random variables, but random variables could be complex value also. Now, suppose we have got this.

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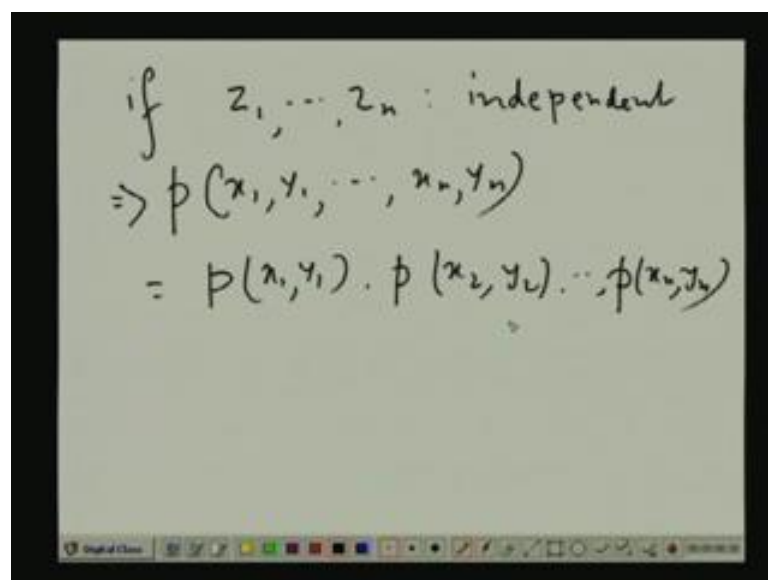
complex valued random
variable.

$$z_1 = x_1 + jy_1$$
$$\vdots$$
$$z_n = x_n + jy_n$$

prob. density $f(z_1, \dots, z_n)$
 $= p(x_1, y_1, x_2, y_2, \dots, x_n, y_n)$

Suppose z_1 is x_1 plus jy_1 dot dot dot up to say $z_n = x_n$ plus jy_n . So, z_1 to z_n , we have got set of n complex random variables, but remember each of these z_1 to z_n , they have got two components. One is the real component and another imaginary component x_1 y_1 , and now x_1 also is random variable, y_1 also is random variable. Similarly, x_2 is a random variable; y_2 is a random variable. So, a set of n complex random variable equivalent being is a set of twice n real value random variables which means probability density of z_n is same as actually probability function probability density function of two n variables x_1 y_1 x_2 y_2 dot dot dot x_n y_n .

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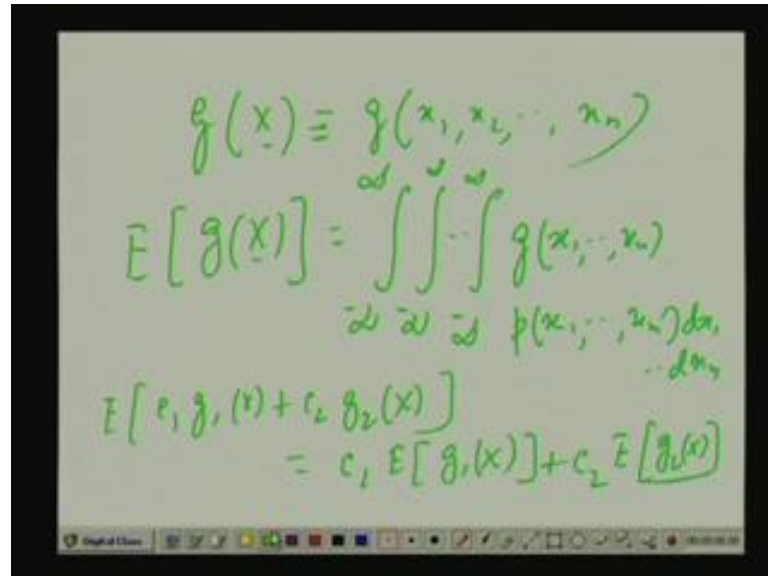


if $z_1, \dots, z_n$: independent

$$\Rightarrow p(x_1, y_1, \dots, x_n, y_n)$$
$$= p(x_1, y_1) \cdot p(x_2, y_2) \cdot \dots \cdot p(x_n, y_n)$$

Further if $z_1, \dots, z_n$, they are independent, then it means that $p(x_1, y_1, \dots, x_n, y_n)$, that will be like this which stands for the probability density for z_1 because z_1 has two random variables, real value random variables x_1, y_1 in it, and then $p(x_2, y_2, \dots, x_n, y_n)$.

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The image shows handwritten mathematical derivations on a green background. The first line defines a function $g(x) \equiv g(x_1, x_2, \dots, x_n)$. The second line shows the expectation $E[g(x)]$ as a multiple integral over the range of each variable, with the probability density function $p(x_1, \dots, x_n)$ as the integrand. The third line shows the linearity of expectation: $E[c_1 g_1(x) + c_2 g_2(x)] = c_1 E[g_1(x)] + c_2 E[g_2(x)]$.

$$g(x) \equiv g(x_1, x_2, \dots, x_n)$$

$$E[g(x)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} g(x_1, \dots, x_n) p(x_1, \dots, x_n) dx_1 \dots dx_n$$

$$E[c_1 g_1(x) + c_2 g_2(x)] = c_1 E[g_1(x)] + c_2 E[g_2(x)]$$

Then, again suppose we have got single function $g(x)$. X is vector. Basically x means actually is a function of n random variables $x_1, x_2, \dots, x_n$. Now, by extending our previous argument, we can then say that expected value of $g(x)$ is nothing but times the corresponding probability density function $dx_1, \dots, dx_n$. Obviously, if instead of these real variables $x_1, x_2, \dots, x_n$, we are a set of complex n number of complex valued random variables $z_1, z_2, \dots, z_n$, then instead of having n fold multiple integral, you would have had twice n fold multiple integral, and the probability density function would have been I mean this is $g(z_1, \dots, z_n)$ and probability density function as we proved have been $p(x_1, y_1, x_2, y_2, \dots, x_n, y_n)$.

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$$A = \begin{bmatrix} A_{11} & A_{12} & A_{13} \\ A_{21} & A_{22} & A_{23} \\ A_{31} & A_{32} & A_{33} \end{bmatrix}$$

$$A^H = \begin{bmatrix} A_{11}^* & A_{21}^* & A_{31}^* \\ A_{12}^* & A_{22}^* & A_{32}^* \\ A_{13}^* & A_{23}^* & A_{33}^* \end{bmatrix}$$

$A_{21} = A_{12}^*$
 $A_{31} = A_{13}^*$

$(2,1)$ of A^H : $(1,2)^*$ of A

Then, A will be called a Hermitian matrix. That means, firstly the diagonal elements A_{11} must be A_{11} star which means, it must be real valued element. So, the diagonal similarly for A_{22} , similarly for A_{33} . So, for a Hermitian matrix, diagonal entries are real. Other entries are conjugates symmetric of each other like 21th element of A^H , that is second row first column. This is nothing but 12th element of there is 218 of A^H is same as 12th star of A .

So, 21th element, it is this at 12th element of A is this. If you put a star here, you get back this element. That means, A^H this matrix it is i jth element is nothing but A matrix. It is j ith element star, this is Hermitian transposition. Now, if A , and A^H are same, that means, A_{21} and this that is we should have A_{21} is equal A_{21} should be just a conjugate of this A_{12} star. A_{31} should be A_{13} star because this and this are to be same likewise. So, the transposition, the Hermitian matrix i jth element means I think I will continue from here in the next class because some more properties are to be discussed because Hermitian matrices, they give rise to what is called correlation and covariance matrices. So, that is all for today. We continue for another because time is up.

Thank you very much.