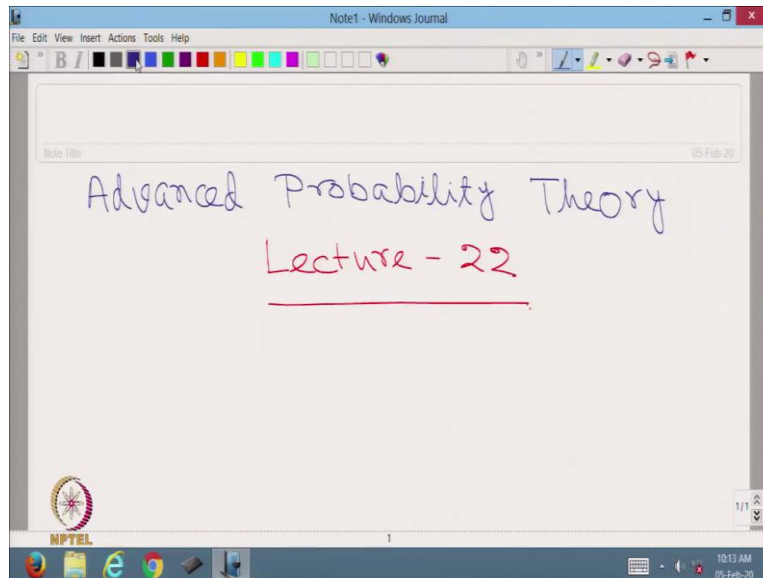


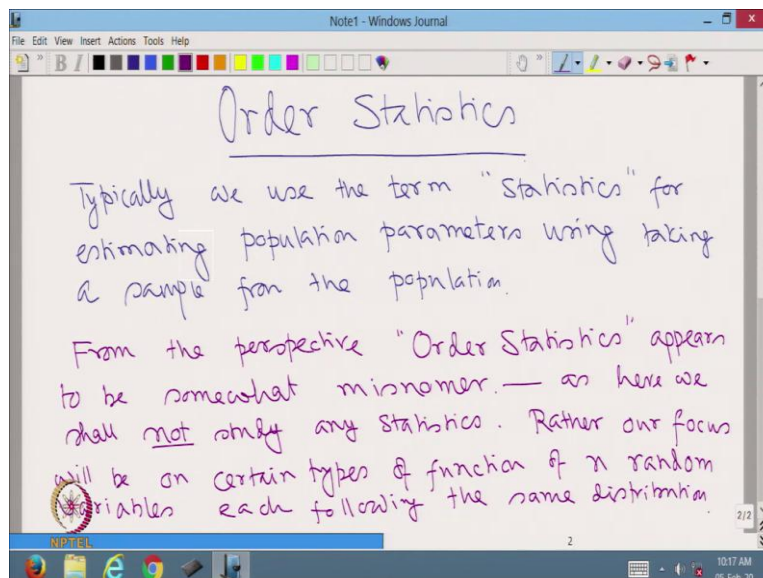
**Advanced Probability Theory**  
**Professor Niladri Chatterjee**  
**Department of Mathematics**  
**Indian Institute of Technology, Delhi**  
**Lecture 22**

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Welcome students to the MOOCS lecture series on Advanced Probability Theory. This is lecture number 22.

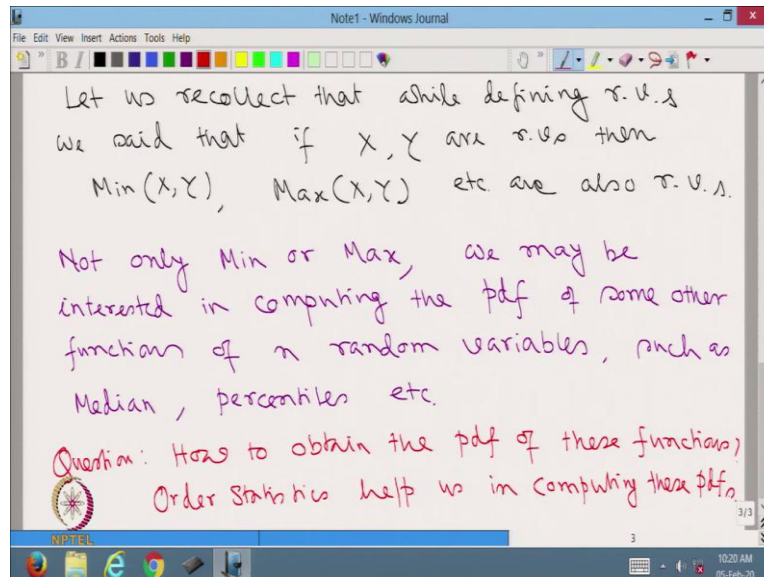
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As I said at the end of the last class, that today we shall start with Order Statistics. Typically, we use the term “statistics” for estimating population parameters using taking a sample from the population. From that perspective “Order Statistics” appears to be somewhat misnomer as here we shall not study any statistics. Rather, our focus will be on certain types of functions

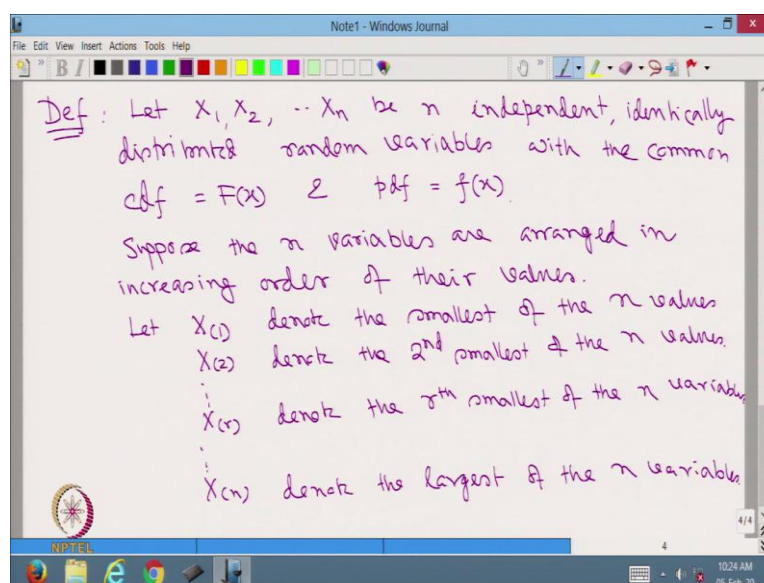
of  $n$  random variables, each following the same distribution. So, we are actually looking at probabilities of certain function of in random variables.

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Let us recollect that, while defining random variables, we said that, if  $X, Y$  are random variables then minimum over  $X, Y$ , maximum of  $X, Y$  etc are also random variables. Not only min or max, we may be interested in computing the pdf, Probability Density Function of some other functions of  $n$  random variables, such as say, median, percentiles, etc. Question is, how to obtain the pdf of these functions? Order Statistics help us in computing these pdf's. So, with that small introduction, let us define what is an order statistics.

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So, definition, let  $X_1, X_2, \dots, X_n$  be  $n$  independent and identically distributed random variables with the common cdf, the cumulative distribution function is equal to  $F(x)$  and pdf is equal to  $f(x)$ . Now, suppose, these  $n$  variables are arranged in increasing order of their values. Let  $X_{(1)}$  denote the smallest of the  $n$  values.  $X_{(2)}$  denote the second smallest of the  $n$  values.  $X_{(r)}$  denote the  $r$ 'th smallest of the  $n$  values or  $n$  variables and  $X_{(n)}$  denote the largest of the  $n$  variables.

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These  $X_{(1)}, X_{(2)} \dots X_{(n)}$  are called the Order Statistics of the  $n$  variables  $X_1, X_2 \dots X_n$ .  
 In particular,  $X_{(r)}$  is called the  $r$ th Order statistic.  
 Note that each  $X_{(i)}$   $i=1 \dots n$  is a random variable.

These  $X_1, X_2, \dots, X_n$  are called the order statistics of the  $n$  variables,  $X_1, X_2, \dots, X_n$ . In particular,  $X_{(r)}$  is called the  $r$ th order statistic. Note that each  $X_i$ ,  $i$  is equal to 1 to  $n$  is a random variable.

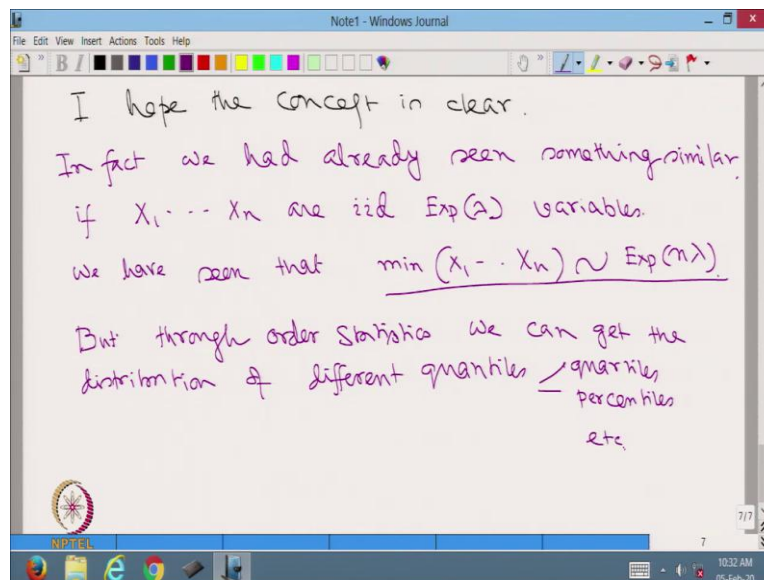
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For illustration let us consider three samples from  $U(0, 5)$ . Let  $X_1 = 4$   $X_2 = 1.5$   $X_3 = 2.75$   
 $\therefore$  When we write using Order Statistics, we have  $X_{(1)} = 1.5$   $X_{(2)} = 2.75$   $X_{(3)} = 4$ .  
 Note that there may be 6 possible ways of getting these three values 1.5, 2.75 & 4 from 3 random variables  $X_1, X_2$  &  $X_3$ :  
 $X_1 = 2.75$   $X_1 = 4$   $X_2 = 4$  or  $X_2 = 1.5$   $X_3 = 1.5$   $X_3 = 2.75$  All of them will have the same Order Statistics.

For illustration, let us consider 3 samples from uniform 0, 5. Let  $X_1$  is equal to 4,  $X_2$  is equal to 1.5 and  $X_3$  is equal to 2.75. Therefore, when we write using order statistics, we have  $X_1$  is equal to 1.5,  $X_2$  is equal to 2.75 and  $X_3$  is equal to 4. That is, the smallest of the 3 random variables is taking the value 1.5. The second smallest of the 3 variables is taking the value 2.75 and the largest of them is taking the value 4.

Note that there may be 6 possible ways of getting these 3 values 1.5, 2.75 and 4 from 3 random variables  $X_1$ ,  $X_2$  and  $X_3$ . Namely it can be  $X_1$  is equal to 2.75,  $X_2$  is equal to 4,  $X_3$  is equal to 1.5 or it can be  $X_1$  is equal to 4,  $X_2$  is equal to 1.5, and  $X_3$  is equal to 2.75, etc. we know that there can be 6 possible permutations. All of them will have the same order statistic namely this one.

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I hope that the concept is clear. In fact, we had already seen something similar if  $X_1, X_2, X_n$  are independent identically distributed exponential lambda variables. We have seen that minimum of  $X_1, X_2, X_n$  is distributed as exponential with  $n$  lambda. This we have already seen. But through order statistics, we can get the distribution of different quantiles. So, by quantile we mean it can be quantiles, percentiles, etc.

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Question is how to obtain their pdf's.

First let us consider  $X_{(n)}$  i.e. the  $n^{\text{th}}$  order statistic

Let its cdf be  $F_n$  & pdf be  $f_n$  i.e.  $\text{Max}(X_1, X_2, \dots, X_n)$

$$\begin{aligned} \therefore F_n(x) &= P(X_{(n)} \leq x) = P(\text{Max}(X_1, \dots, X_n) \leq x) \\ &= P(\text{all } X_1, \dots, X_n \leq x) \\ &= P(X_1 \leq x) P(X_2 \leq x) \dots P(X_n \leq x) \\ &= F(x) \times F(x) \times \dots \times F(x) \quad \leftarrow n \text{ times} \\ &= (F(x))^n \end{aligned}$$

Question is how to obtain their pdf's. So, first let us consider  $X_n$  that is the  $n$ th order statistic that is maximum of  $X_1, X_2, X_n$ . Let its cdf be  $F_n$  and pdf be small  $f_n$ . Therefore,  $F_n x$  is equal to probability  $X_n$  less than equal to  $x$  is equal to probability maximum of  $X_1, X_2, X_n$  less than equal to  $x$ . Is equal to probability all  $X_1, X_2, X_n$  less than equal to  $x$ . And since they are independent and identically distributed, this is is equal to probability  $X_1$  less than equal to  $x$  probability  $X_2$  less than equal to  $x$  and probability  $X_n$  less than equal to  $x$ . Is equal to  $F x$  into  $F x$  into  $F x$   $n$  times is equal to  $F x$  whole to the power  $n$ .

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$$\therefore F_n(x) = (F(x))^n \Rightarrow f_n(x) = \frac{d}{dx} F_n(x) = n(F(x))^{n-1} \cdot f(x)$$

Let us find  $F_1(x)$  &  $f_1(x)$  which are the cdf and pdf of the first ord statistic.

$$\begin{aligned} F_1(x) &= P(X_{(1)} \leq x) \\ &= P(\text{At least one of } X_1, \dots, X_n \leq x) \\ &= 1 - P(\text{All of } X_1, \dots, X_n > x) \\ &= 1 - (1 - F(x))^n \end{aligned}$$

Since  $P(X > x) = 1 - P(X \leq x) = 1 - F(x)$

Therefore,  $F_n x$  is equal to  $F x$  whole to the power  $n$  implies small  $f_n x$  which is equal to  $\frac{d}{dx}$  of  $F_n x$  is equal to  $n$  into  $F x$  to the power  $n$  minus 1 times  $f x$ . So, that is the pdf of  $n$ th



order statistic. Let us find  $F_1(x)$  and  $f_1(x)$  which are the cdf and pdf of the first order statistic. So,  $F_1(x)$  is equal to probability  $X_1$  less than equal to  $x$  is equal to probability at least one of  $X_1, X_2, X_n$  less than equal to  $x$ .

Is equal to 1 minus probability all of  $X_1, X_2, X_n$  is greater than  $x$  is equal to 1 minus 1 minus  $F(x)$  whole to the power  $n$ . Why? Since probability  $X$  greater than  $x$  is equal to 1 minus probability  $X$  less than equal to  $x$ . Is equal to 1 minus  $F(x)$ . Therefore, we get this term and now we have subtracted it from 1.

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The image shows a digital whiteboard with handwritten mathematical derivations. At the top, it states  $F_1(x) = 1 - (1 - F(x))^n$ . Below this, it shows the differentiation  $\frac{dF_1(x)}{dx} = f_1(x) = n(1 - F(x))^{n-1} \cdot f(x)$ . A note below the equation says "This is the pdf of first order statistic,  $X_1$ ". Further down, it says "Note that the pdf's of the Order Statistics involve both  $F(x)$  and  $f(x)$ ". Then, it says "Now for  $\text{Exp}(\lambda)$  and  $U(a, b)$  distributions we have closed form of  $F(x)$ , viz:". It then lists the cdf for  $\text{Exp}(\lambda)$  as  $1 - e^{-\lambda x}$  for  $0 \leq x < \infty$  and the cdf for  $U(a, b)$  as  $\frac{x-a}{b-a}$  for  $a \leq x \leq b$ . A side note in a bracket says "Since for these two variables we have closed form of  $F(x)$  we shall use them mostly in our examples".

Therefore,  $F_1(x)$  is equal to 1 minus 1 minus  $F(x)$  whole to the power  $n$ . Therefore,  $\frac{dF_1(x)}{dx}$  is equal to  $f_1(x)$  is equal to  $n$  into 1 minus  $F(x)$  whole to the power  $n$  minus 1 into small  $f(x)$ . After differentiating with respect to  $x$ . So, this is the pdf of first order statistic,  $X_1$ . Note that the pdf's of the order statistics involve both  $F(x)$  and small  $f(x)$ .

Now, for exponential  $\lambda$  and uniform  $a, b$  distributions we have closed form of  $F(x)$ , namely cdf of exponential  $\lambda$  is equal to 1 minus  $e$  to the power minus  $\lambda x$ ,  $0 \leq x < \infty$ . And cdf of uniform  $a, b$  is equal to  $x - a$  upon  $b - a$ , for  $a \leq x \leq b$ . Since, for these two variables we have closed form of  $F(x)$ . We shall use them mostly in our examples.

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Notation

$X_1, \dots, X_n$  are iid's  $\sim f(x)$

$X_{(1)}, \dots, X_{(n)}$  are the Order Statistics

The pdf of  $X_{(r)}$  should be  $f_{(r)}$ . But in literature you may find both  $f_r$  &  $f_{(r)}$

Similarly for cdf one can use  $F_r$  or  $F_{(r)}$

In this series of lectures I shall use both interchangeably.

So, let me give you little bit about notation. So,  $X_1, X_2, X_n$  are iid's following some  $f_x$ .  $X_1, X_2, X_n$  are the order statistics. The pdf of  $X_r$  should be  $f_r$  but in literature you may find both  $f_r$  and  $f_{(r)}$  with the parentheses. Similarly, for cdf, one can use  $F_r$  or  $F_{(r)}$  with the parentheses. In this series of lectures, I shall use both interchangeably. So, that you have to remember and there should not be any confusion.

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For illustration let us go back to  $\text{Exp}(\lambda)$ .

We know that  $\min(X_1, \dots, X_n) = \text{Exp}(n\lambda)$   
when each  $X_i \sim \text{Exp}(\lambda)$ .

Let us apply the formula for  $f_{(1)}(x)$ :

We have  $f_{(1)}(x) = n(1 - F(x))^{n-1} \cdot f(x)$

Here,  $f(x) = \lambda e^{-\lambda x}$   
 $F(x) = 1 - e^{-\lambda x}$

$\therefore$  Putting these values:  $f_{(1)}(x) = n(1 - (1 - e^{-\lambda x}))^{n-1} \lambda e^{-\lambda x}$

$= n(e^{-\lambda x})^{n-1} \lambda e^{-\lambda x}$

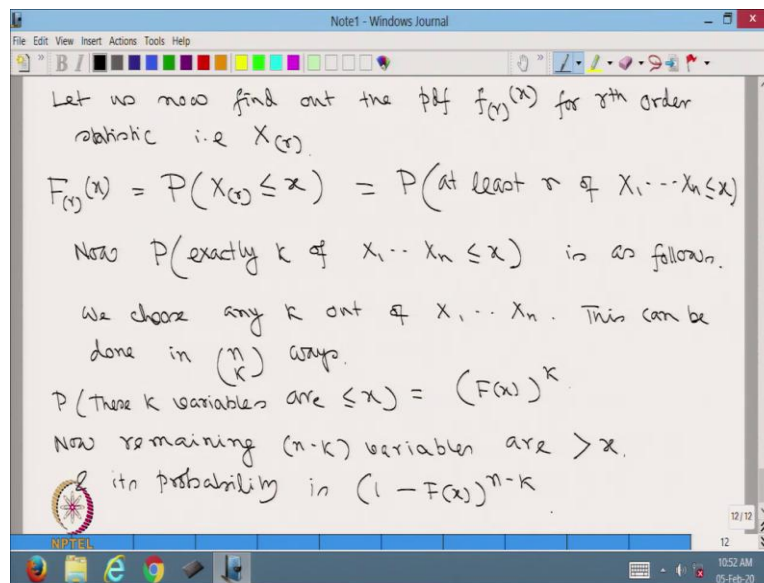
$= n\lambda (e^{-\lambda x})^{n-1+1} = n\lambda e^{-n\lambda x}$

$\therefore$  Verified for  $\text{Exp}(\lambda)$

So, for illustration, let us go back to exponential lambda. We know that minimum of  $X_1, X_2, X_n$  is distributed as exponential with  $n$  lambda when each  $X_i$  is an exponential lambda variable. Let us apply the formula for  $f_1 x$ , we have  $f_1 x$  is equal to  $n$  into  $1$  minus  $F x$  whole to the power  $n$  minus  $1$  into small  $f x$ .

Here,  $f(x)$  is equal to  $\lambda e^{-\lambda x}$ .  $F(x)$  is equal to  $1 - e^{-\lambda x}$ . Therefore, putting these values,  $f_{(r)}(x)$  is equal to  $n$  into  $1 - e^{-\lambda x}$  minus  $e^{-\lambda x}$  to the power  $n$  minus  $1$  into  $\lambda e^{-\lambda x}$ . Is equal to  $n$  into  $e^{-\lambda x}$  to the power  $n$  minus  $1$  into  $\lambda e^{-\lambda x}$ . Is equal to  $n \lambda e^{-\lambda x}$  to the power  $n$  minus  $1$  plus  $1$ . Is equal to  $n \lambda e^{-\lambda x}$  to the power  $n$  minus  $n \lambda x$ . Thus, verified for exponential lambda.

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Let us now find out the pdf  $f_r(x)$  for  $r$ th order statistic that is,  $X_r$ .  $F_r(x)$  is equal to probability  $X_r$  less than equal to  $x$  is equal to probability at least  $r$  of  $X_1, X_2, X_n$  less than equal to  $x$ . Now, probability exactly  $k$  of  $X_1, X_2, X_n$  less than equal to  $x$  is as follows. We choose any  $k$  out of  $X_1, X_2, X_n$ . This can be done in  $n k$  ways.

Probability these  $k$  variables are less than equal to  $x$  is equal to  $F(x)$  to the power  $k$ . Now, remaining  $n$  minus  $k$  variables are greater than  $x$  and its probability is  $1 - F(x)$  whole to the power  $n$  minus  $k$ .



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Therefore  $P(\text{exactly } k \text{ of } X_1, \dots, X_n \leq x)$   
 $= \binom{n}{k} (F(x))^k (1-F(x))^{n-k} \leftarrow \text{Binomial dist.}$

$\therefore P(X_{(r)} \leq x)$   
 $= P(\text{exactly } r \text{ of } X_1, \dots, X_n \leq x)$   
 $+ P(\text{exactly } r+1 \text{ of } X_1, \dots, X_n \leq x)$   
 $+ P(\text{exactly } r+2 \text{ of } X_1, \dots, X_n \leq x)$   
 $\vdots$   
 $+ P(\text{all of } X_1, \dots, X_n \leq x)$

Therefore, probability exactly k of  $X_1, X_2, X_n$  less than equal to x is equal to  $n C k F x$  to the power k 1 minus F x to the power n minus k. It is clear that this is a binomial distribution which is very clear if we call this to be as success, this to be a failure, we get the binomial distribution.

Therefore, the probability  $X_r$  less than equal to x is equal to union of the disjoint events. Probability exactly r of  $X_1, X_2, X_n$  less than equal to x plus probability exactly r plus 1 of  $X_1, X_2, X_n$  less than equal to x plus probability exactly r plus 2 of  $X_1, X_2, X_n$  less than equal to x. Like that we go up to probability all of  $X_1, X_2, X_n$  less than equal to x.

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$\therefore P(X_{(r)} \leq x) = \sum_{k=r}^n \binom{n}{k} (F(x))^k (1-F(x))^{n-k}$

$\therefore f_{(r)}(x) = \frac{d}{dx} F_{(r)}(x) = \frac{d}{dx} \left( \sum_{k=r}^n \binom{n}{k} F(x)^k (1-F(x))^{n-k} \right)$

$\uparrow$   
 pdf of  $X_{(r)}$

Since it is a summation we may differentiate term by term by varying k from r to n.

What is  $\frac{d}{dx} \left( \binom{n}{k} F(x)^k (1-F(x))^{n-k} \right)$ ?

Therefore, probability  $X_r$  less than equal to  $x$  is equal to  $\sum_{k=r}^n \binom{n}{k} F(x)^k (1-F(x))^{n-k}$ . Therefore,  $f_r(x)$  that is, pdf of  $X_r$  is equal to  $\frac{d}{dx}$  of  $F_r(x)$  is equal to  $\frac{d}{dx}$  of  $\sum_{k=r}^n \binom{n}{k} F(x)^k (1-F(x))^{n-k}$  whole to the power  $n$  minus  $k$ .

Since, it is a summation we may differentiate them term by term by varying  $k$  from  $r$  to  $n$ . So, what is  $\frac{d}{dx}$  of  $\binom{n}{k} F(x)^k (1-F(x))^{n-k}$ ? So, let us first compute this.

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The image shows a handwritten derivation in a Windows Journal window titled 'Note1 - Windows Journal'. The derivation is as follows:

$$\begin{aligned} \frac{d}{dx} \left( \binom{n}{k} F(x)^k (1-F(x))^{n-k} \right) &= \binom{n}{k} k F(x)^{k-1} \cdot f(x) \cdot (1-F(x))^{n-k} - \binom{n}{k} F(x)^k (n-k) (1-F(x))^{n-k-1} f(x) \\ &= \frac{n!}{k!(n-k)!} \cdot k F(x)^{k-1} (1-F(x))^{n-k} f(x) - \frac{n!}{k!(n-k)!} F(x)^k (n-k) (1-F(x))^{n-k-1} f(x) \\ &= \frac{n!}{(k-1)!(n-k)!} F(x)^{k-1} (1-F(x))^{n-k} f(x) - \frac{n!}{k!(n-k-1)!} F(x)^k (1-F(x))^{n-k-1} f(x) \end{aligned}$$

Below the equations, it says: 'This is for general k. We need to find  $f_k = 0, 1, \dots, n$ . 2' and 'add them' with a circular arrow icon.

$\frac{d}{dx}$  of  $\binom{n}{k} F(x)^k (1-F(x))^{n-k}$  is equal to  $\binom{n}{k} k F(x)^{k-1} (1-F(x))^{n-k} f(x) - \binom{n}{k} F(x)^k (n-k) (1-F(x))^{n-k-1} f(x)$ .

Since, here  $F(x)$  is with a minus term therefore, we get a negative sign there. This is for general  $k$ . Let us simplify it, is equal to  $\frac{n!}{(k-1)!(n-k)!} F(x)^{k-1} (1-F(x))^{n-k} f(x) - \frac{n!}{k!(n-k-1)!} F(x)^k (1-F(x))^{n-k-1} f(x)$ .

Is equal to after cancellation  $\frac{n!}{(k-1)!(n-k)!} F(x)^{k-1} (1-F(x))^{n-k} f(x) - \frac{n!}{k!(n-k-1)!} F(x)^k (1-F(x))^{n-k-1} f(x)$ .

minus  $k$  minus 1 into  $f(x)$ . This is for general  $k$ . We need to find for all  $k$  is equal to  $r$ ,  $r$  plus 1 up to  $n$  and add them.

(Refer Slide Time: 38:47)

Handwritten notes in a Windows Journal window showing the binomial expansion of  $f(x)$  for various values of  $k$ :

- $k=r$ :  $\frac{n!}{(r-1)!(n-r)!} F(x)^{r-1} (1-F(x))^{n-r} f(x) - \frac{n!}{r!(n-r-1)!} F(x)^r (1-F(x))^{n-r-1} f(x)$
- $k=r+1$ :  $\frac{n!}{r!(n-r-1)!} F(x)^r (1-F(x))^{n-r-1} f(x) - \frac{n!}{(r+1)!(n-r-2)!} F(x)^{r+1} (1-F(x))^{n-r-2} f(x)$
- $k=r+2$ :  $\frac{n!}{(r+1)!(n-r-2)!} F(x)^{r+1} (1-F(x))^{n-r-2} f(x) - \frac{n!}{(r+2)!(n-r-3)!} F(x)^{r+2} (1-F(x))^{n-r-3} f(x)$
- $k=n$ :  $\frac{n!}{(n-1)!(n-n)!} F(x)^{n-1} (1-F(x))^{n-n} f(x) - \frac{n!}{n!(-1)!} (F(x))^n (1-F(x))^{-1} f(x)$

↑ does not exist!  
∴ We can ignore this

So, let us start  $k$  is equal to  $r$ . Therefore, we have factorial  $n$  upon factorial  $r$  minus 1 into factorial  $n$  minus  $r$   $F(x)$  to the power  $r$  minus 1, 1 minus  $F(x)$  to the power  $n$  minus  $r$  into  $f(x)$  minus  $n$  factorial upon  $r$  factorial  $n$  minus  $r$  minus 1 factorial  $F(x)$  to the power  $r$  1 minus  $F(x)$  to the power  $n$  minus  $r$  minus 1 into  $f(x)$ .  $k$  is equal to  $r$  plus 1 that gives us.

Put  $k$  is equal to  $r$  plus 1, therefore we will get  $n$  factorial upon  $r$  factorial into  $n$  minus  $r$  minus 1 factorial. We are putting  $r$  plus 1 in place of  $r$ .  $F(x)$  to the power  $r$  1 minus  $F(x)$  to the power  $n$  minus  $r$  minus 1  $f(x)$  minus  $n$  factorial upon  $r$  plus 1 factorial  $n$  minus  $r$  minus 2 factorial  $F(x)$  to the power  $r$  plus 1, 1 minus  $F(x)$  to the power  $n$  minus  $r$  minus 2 into  $f(x)$ .

Now, let us put  $k$  is equal to  $r$  plus 2. This we will get by putting  $r$  is equal to  $r$  plus 2 in this expression therefore, this is going to be  $n$  factorial  $r$  plus 1 factorial  $n$  minus  $r$  minus 2 factorial  $F(x)$  to the power  $r$  plus 1, 1 minus  $F(x)$  whole to the power  $n$  minus  $r$  minus 2 minus  $n$  factorial  $r$  plus 2 factorial into  $n$  minus  $r$  minus 3 factorial to  $F(x)$  to the power  $r$  plus 2 into 1 minus  $F(x)$  whole to the power  $n$  minus  $r$  minus 3 into  $f(x)$ .

We will go like that but in the meantime, we noticed that, this term is same as this term so, they cancel each other. In a similar way, this cancels with this therefore, this is going to cancel with this therefore, at the end of the day what we will have so, let us calculate for  $k$  is equal to  $n$ , this is going to be  $n$  factorial  $n$  minus 1 factorial into  $n$  minus  $n$  factorial which is 0 factorial to  $F(x)$  to the power  $n$  minus 1, 1 minus  $F(x)$  whole to the power  $n$  minus  $n$  small  $f(x)$

minus  $n$  factorial upon  $n$  factorial minus 1 factorial  $F(x)$  to the power  $n-1$  minus  $F(x)$  to the power minus 1 into  $f(x)$ . Now, minus 1 factorial does not exist therefore, we can ignore this. Therefore, we are left with only 1 term that is this.

(Refer Slide Time: 44:12)

The image shows a handwritten derivation in a Windows Journal window. The derivation starts with the formula for the probability density function of the  $r$ -th order statistic,  $f_{(r)}(x)$ , and simplifies it to the beta distribution form. It then verifies the result for  $r=1$ , showing that it reduces to the probability density function of the first order statistic, which is the same as the original probability density function  $f(x)$ .

$$\begin{aligned} \therefore f_{(r)}(x) &= \frac{n!}{(r-1)!(n-r)!} F(x)^{r-1} (1-F(x))^{n-r} \cdot f(x) \\ &= \frac{\Gamma(n+1)}{\Gamma(r) \Gamma(n-r+1)} F(x)^{r-1} (1-F(x))^{n-r} \cdot f(x) \\ &= \frac{1}{B(r, n-r+1)} F(x)^{r-1} (1-F(x))^{n-r} \cdot f(x) \end{aligned}$$

pdf of  $X_{(r)}$ .

Verify:  $r=1$

$$\begin{aligned} &= \frac{1}{B(1, n)} F(x)^0 (1-F(x))^{n-1} f(x) \\ &= \frac{\Gamma(n+1)}{\Gamma(1) \Gamma(n)} (1-F(x))^{n-1} f(x) = \frac{n!}{n!} (1-F(x))^{n-1} f(x) = (1-F(x))^{n-1} f(x) \end{aligned}$$

$\therefore \Gamma(n+1) = n! \Gamma(n)$

Therefore,  $f_{(r)}$  of  $x$  is equal to factorial  $n$  upon factorial  $r$  minus 1 factorial  $n$  minus  $r$   $F(x)$  to the power  $r$  minus 1,  $1$  minus  $F(x)$  whole to the power  $n$  minus  $r$  into  $f(x)$  which is equal to gamma  $n$  plus 1. We know that gamma  $n$  plus 1 is equal to  $n$  factorial gamma  $r$  gamma  $n$  minus  $r$  plus 1  $F(x)$  to the power  $r$  minus 1,  $1$  minus  $F(x)$  to the power  $n$  minus  $r$  into  $f(x)$ . Is equal to 1 upon beta of  $r$ , comma  $n$  minus  $r$  plus 1 into  $F(x)$  to the power  $r$  minus 1,  $1$  minus  $F(x)$  to the power  $n$  minus  $r$  into small  $f(x)$ . So, this is the pdf of  $r$ th order statistic namely,  $X_r$ .

Verify  $r$  is equal to 1 therefore, we are getting 1 upon beta of 1, comma  $n$   $F(x)$  to the power 0  $1$  minus  $F(x)$  whole to the power  $n$  minus 1  $f(x)$ . Is equal to gamma  $n$  plus 1 upon gamma  $n$  gamma 1,  $1$  minus  $F(x)$  to the power  $n$  minus 1 into  $f(x)$ . Is equal to since, gamma  $n$  plus 1 is equal to  $n$  into gamma  $n$ . Therefore, this is equal to  $n$  into  $1$  minus  $F(x)$  whole to the power  $n$  minus 1 into  $f(x)$ . The same result that we got earlier.

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Handwritten derivation of the formula for  $f_r(x)$  in a Windows Journal window. The text reads: "Here is an alternative derivation of the formula for  $f_r(x)$ ." Below this, a diagram shows a horizontal line with a point  $x$  marked. To the left of  $x$ , there are  $r-1$  observations, represented by a bracket and the expression  $(F(x))^{r-1}$ . To the right of  $x$ , there are  $n-r$  observations, represented by a bracket and the expression  $(1-F(x))^{n-r}$ . The point  $x$  is labeled with  $f(x)$  above it. Below the diagram, the formula for  $f_r(x)$  is derived as follows:

$$f_r(x) = \frac{n!}{(r-1)!(n-r+1)!} \times \frac{(n-r+1)!}{1!(n-r)!} F(x)^{r-1} (1-F(x))^{n-r} f(x)$$

Now, some of you may find the formula to be complicated so, here is an alternative derivation of the formula for  $f_r(x)$ . So, we have the observations on the real line and suppose this is the point  $x$  and we are looking at  $f_r(x)$  so one observation will come at  $x$  that will have the pdf  $f(x)$ ,  $r$  minus 1 observations will be here and each of them are less than  $x$  therefore, that should give us  $F(x)$  to the power  $r$  minus 1 and remaining  $n$  minus  $r$  are in this region because they are greater than  $x$  so, that should give us  $1 - F(x)$  to the power  $n$  minus  $r$ .

Now, this  $r$  minus 1 can be chosen out of  $n$  in  $n C r$  minus 1 ways so, that is being multiplied by this probability. This one has to be chosen from the remaining  $n$  minus  $r$  plus 1 and that can be done in  $n$  minus  $r$  plus 1  $C 1$  ways that multiplied by  $f(x)$  and remaining all of them are going there. So, that will be  $1 - F(x)$  whole to the power  $n$  minus  $r$ .

Therefore, if  $f_r(x)$  is equal to factorial  $n$  upon factorial  $r$  minus 1 into factorial  $n$  minus  $r$  plus 1 into let me take out the constant  $n$  minus  $r$  plus 1 factorial upon 1 factorial into  $n$  minus  $r$  factorial multiplied by  $F(x)$  to the power  $r$  minus 1,  $1 - F(x)$  to the power  $n$  minus  $r$  multiplied by  $f(x)$ .



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Thus  $f_r(x) = \frac{n!}{(r-1)!(n-r)!} F(x)^{r-1} (1-F(x))^{n-r} \cdot f(x)$ .

So this is an easy way to remember the formula

Thus,  $f_r(x)$  is equal to factorial  $n$  upon factorial  $r$  minus 1 into  $n$  minus  $r$  factorial  $F(x)$  to the power  $r$  minus 1,  $1$  minus  $F(x)$  to the power  $n$  minus  $r$  into  $f(x)$ . So, this is an easy way to remember the formula.

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This alternative approach can be deduced mathematically

$$f_r(x) = \frac{d}{dx} F_r(x) = \lim_{\Delta x \rightarrow 0} \frac{F_r(x+\Delta x) - F_r(x)}{\Delta x}$$

Now  $F_r(x+\Delta x) - F_r(x) = P(X_r \text{ lies in the interval } (x, x+\Delta x))$

$$= {}^n C_{r-1} (F(x))^{r-1} {}^{n-r+1} C_1 (F(x+\Delta x) - F(x)) (1-F(x+\Delta x))^{n-r}$$

$\therefore$

Dividing by  $\Delta x$ , & taking  $\lim_{\Delta x \rightarrow 0}$  we have the following.

Now, this above trick can be deduced mathematically so, what is  $f_r(x)$ ? This is equal to  $\frac{d}{dx}$  of  $f_r(x)$  is equal to limit  $\Delta x$  going to infinity  $F_r(x + \Delta x) - F_r(x)$  upon  $\Delta x$ . Now,  $F_r(x + \Delta x) - F_r(x)$  is equal to probability  $X_r$  lies in the interval  $x$  to  $x + \Delta x$ . Is equal to  $n C_{r-1} F(x)^{r-1} (F(x+\Delta x) - F(x)) (1-F(x+\Delta x))^{n-r}$ .

So, out of  $n - r + 1$  are chosen, they are below  $x$ . Therefore,  $F(x)$  to the power  $r - 1$ . From the remaining  $n - r + 1$ , we choose 1 and that goes between  $x$  to  $x + \Delta x$ .

Therefore, we can write it as  $F(x + \Delta x) - F(x)$  multiplied by the remaining one so, that is  $(1 - F(x + \Delta x))^{n-r}$ . This is because suppose this is the real line.

This is  $x$ , this is  $x + \Delta x$ . one of them is going to be here,  $r - 1$  are going to be here and  $n - r$  are going to be above  $x + \Delta x$ . Therefore, dividing by  $\Delta x$  and taking limit  $\Delta x$  going to 0, we have the following.

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$$f_r(x) = \lim_{\Delta x \rightarrow 0} \binom{n}{r-1} F(x)^{r-1} (1-F(x+\Delta x))^{n-r} \frac{F(x+\Delta x) - F(x)}{\Delta x}$$

$$= \frac{n!}{(r-1)!(n-r)!} F(x)^{r-1} f(x) (1-F(x))^{n-r}$$

$$= \frac{n!}{(r-1)!(n-r)!} F(x)^{r-1} f(x) (1-F(x))^{n-r}$$

$f_r(x)$  is equal to limit  $\Delta x$  going to 0,  $\binom{n}{r-1} F(x)^{r-1} (1-F(x+\Delta x))^{n-r} \frac{F(x+\Delta x) - F(x)}{\Delta x}$  multiplied by  $(1-F(x+\Delta x))^{n-r}$ . Is equal to  $\frac{n!}{(r-1)!(n-r)!} F(x)^{r-1} f(x) (1-F(x))^{n-r}$ .

Now, this gives up  $F(x)$  to the power  $r - 1$ . This gives us  $f(x)$  and from here we get  $(1 - F(x))^{n-r}$ . Is equal to  $\frac{n!}{(r-1)!(n-r)!} F(x)^{r-1} f(x) (1-F(x))^{n-r}$ . So, this is a mathematically justified the way we have proved the, the way we have derived the formulae. Okay friends. I stop here today. In the next class, I shall start at this point and we will solve several problems of order statistics.

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Ex: Suppose 5 observations are taken from  $U(0,1)$ .  
 Let them be  $X_1, X_2, X_3, X_4, X_5$   
 what is the expectation of  $X_{(3)}$  — 3rd order statistic  
 which in this case is the Median.  
 Since the underlying dist<sup>n</sup> is  $U(0,1)$   
 $\therefore F(x) = x \quad 0 \leq x \leq 1$   
 $f(x) = 1 \quad 0 \leq x \leq 1$   
 $\therefore f_{(3)}(x) = \frac{1}{B(3, 5-3+1)} x^{3-1} (1-x)^{5-3} \cdot 1$   
 $= \frac{1}{B(3,3)} x^2 (1-x)^2 \quad 0 \leq x \leq 1$   
 Thus  $X_{(3)}$  has a  $\text{Beta}(3,3)$ .

Now, let me give you an example. Suppose, 5 observations are taken from uniform 0, 1. Let them be  $X_1, X_2, X_3, X_4$  and  $X_5$ . What is the expectation of  $X_3$  that is the third order statistic which in this case is the median. Answer. Since, the underlying distribution is uniform 0, 1 therefore  $F(x)$  is equal to  $x$  for  $0 \leq x \leq 1$  and  $f(x)$  is equal to 1 for  $0 \leq x \leq 1$ .

Therefore,  $f_{(3)}(x)$  is equal to  $\frac{1}{B(3, 5-3+1)} x^{3-1} (1-x)^{5-3} \cdot 1$ . Is equal to  $\frac{1}{B(3,3)} x^2 (1-x)^2$  for  $0 \leq x \leq 1$ . Thus,  $X_3$  has a beta distribution with parameter 3, comma 3.

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$\therefore E(X_{(3)}) = \frac{3}{3+3} = \frac{1}{2}$   
 And  $E(X_{(3)}^2) = \int_0^1 x^2 \frac{1}{B(3,3)} x^2 (1-x)^2 dx$   
 $= \frac{1}{B(3,3)} \int_0^1 x^{5-1} (1-x)^{3-1} dx$   
 $= \frac{1}{B(3,3)} B(5,3) = \frac{\Gamma(6)}{\Gamma(3)\Gamma(3)} \times \frac{\Gamma(5)\Gamma(3)}{\Gamma(8)} = \frac{16 \cdot 4 \cdot 3 \cdot 3}{13 \cdot 3 \cdot 7 \cdot 6 \cdot 16}$   
 $= \frac{12}{42} = \frac{2}{7}$   
 $\therefore V(X_{(3)}) = \frac{2}{7} - \left(\frac{1}{2}\right)^2 = \frac{1}{28}$   
 This is the Variance of the 3rd order statistic.

Is equal to  $\frac{6}{4} \times \frac{3}{3} \times \frac{3}{3} \times \frac{3}{7} \times \frac{3}{6} \times \frac{6}{6}$ . Is equal to  $\frac{12}{42}$  is equal to  $\frac{2}{7}$ . Therefore, variance of this is  $X_3^2$  square, variance of  $X_3$  is equal to  $\frac{2}{7}$  minus half square is equal to  $\frac{1}{28}$ . So, this is the variance of the third order statistic. Okay friends. I stop here today. In the next lecture we shall do joint distribution of  $r$ th and  $s$ th order statistic and also we shall solve a few problems on order statistic. Okay friends. Thank you so much.