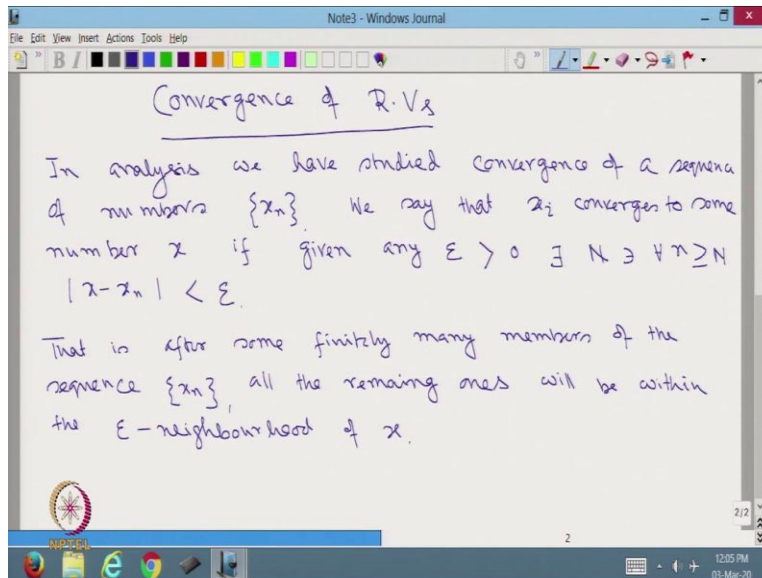


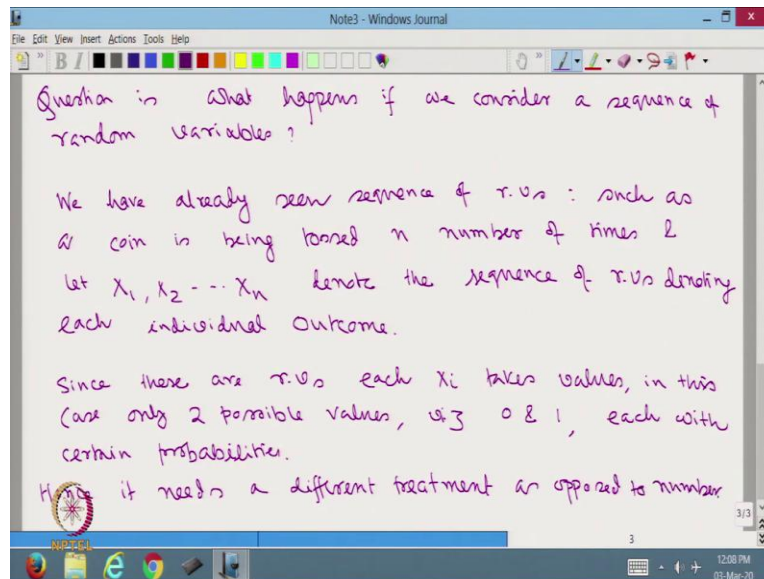
Advanced Probability Theory
Professor Niladri Chatterjee
Department of Mathematics
Indian Institute of Technology, Delhi
Lecture 24

(Refer Slide Time: 0:32)



Welcome students to MOOCs lecture series on Advanced Probability Theory. This is lecture number 24. As I said from this lecture, I shall start convergence of random variables. In analysis we have studied convergence of a sequence of numbers X_n . We say that X_i convergence to some number if given any epsilon greater than 0, there exists N such that for all n greater than or equal to N modulus of x minus X_n is less than epsilon. That is after some finitely many members of the sequence all the remaining ones will be within the epsilon neighborhood of x . This is what all of us know I assume.

(Refer Slide Time: 3:02)



The question is what happens if we consider a sequence of random variables? We have already seen sequence of random variables such as say a coin is being tossed n number of times and let X_1, X_2 upto X_n denote the sequence of random variables denoting each individual outcome. Since, these are random variables each X_i takes values, in this case only two possible values, namely 0 and 1, each with certain probabilities.

Hence, it needs a different treatment as opposed to numbers, I hope the concept is clear. So, we have X_1, X_2, \dots, X_n are sequence of random variables, each random variable can take a set of values depending upon its ω , each one with certain probability. Then how, what do you want to see is where the sequence of random variable actually converges to. So, let me give an example.

(Refer Slide Time: 6:39)

Ex Consider X_1, X_2, \dots, X_n such that each X_i takes two values as follows:

$$X_i: \begin{matrix} 0 & 1 \\ \frac{1}{2} - \frac{1}{i+1} & \frac{1}{2} + \frac{1}{i+1} \end{matrix}$$

Note: $X_1: \begin{matrix} 0 & 1 \\ 0 & 1 \end{matrix}$ i.e. it is a degenerate variable & not of any interest for the long run.

$X_2: \begin{matrix} 0 & \frac{1}{2} - \frac{1}{3} = \frac{1}{6} \\ 1 & \frac{1}{2} + \frac{1}{3} = \frac{5}{6} \end{matrix}$ Like that we can compute the pmf for each $X_i, i \geq 1$.

$X_3: \begin{matrix} 0 & \frac{1}{2} - \frac{1}{4} = \frac{1}{4} \\ 1 & \frac{1}{2} + \frac{1}{4} = \frac{3}{4} \end{matrix}$ Question is what happens if $n \rightarrow \infty$?

Consider X_1, X_2, X_n such that each X_i takes two values as follows X_i takes only 0 and 1 with probabilities half minus 1 upon i plus 1 and half plus 1 upon i plus 1. So, this is the probability mass function for X_i . Note, X_1 therefore test values 0 with probability 0 and 1 with probability 1 that is, it is a degenerate variable and not of any interest for the long run.

What about X_2 ? X_2 takes values 0 with half minus 1 by 3 and 1 with half plus 1 by 3. That is it is equal to 1 by 6. And this is is equal to 5 by 6. What about X_3 x takes 0 with half minus 1 by 4 is equal to 1 by 4, and 1 with probability half plus 1 by 4 is equal to 3 by 4. Like that we can compute the pmf for each X_i, i greater than equal to 1. Question is what happens if n goes to infinity?

(Refer Slide Time: 9:42)

Now pmf for X_n is $X_n: 0 \frac{1}{2} - \frac{1}{n+1}$
 $1 \frac{1}{2} + \frac{1}{n+1}$

\therefore As $n \rightarrow \infty$ $P(X_n=0) \rightarrow \lim_{n \rightarrow \infty} \left(\frac{1}{2} - \frac{1}{n+1} \right) = \frac{1}{2}$
 $\& P(X_n=1) \rightarrow \lim_{n \rightarrow \infty} \left(\frac{1}{2} + \frac{1}{n+1} \right) = \frac{1}{2}$

Thus $\lim_{n \rightarrow \infty} X_n$ is a Bernoulli r.v. with parameter $= \frac{1}{2}$.

Now, pmf for X_n is, it takes 0 with probability half minus 1 upon n plus 1 and 1 with probability half plus 1 upon n plus 1. Therefore, as n goes to infinity, probability X_n is equal to 0 that goes to limit n going to infinity half of half minus 1 upon n plus 1 is equal to half and probability X_n is equal to 1 that converges to limit n going to infinity half plus 1 upon n plus 1 is equal to half. Thus, limit n going to infinity of X_n is a Bernoulli random variable with parameter is equal to half. Let us consider another example.

(Refer Slide Time: 11:16)

EX: Suppose $X_1, X_2, \dots, X_n, \dots$ is a sequence of independent & identically distributed r.v. s.t. $X_i: 0 \rightarrow 1$ p.

Now let us consider a new sequence of r.v.s $\{S_n\}$ defined as follows:

$$S_n = \frac{X_1 + X_2 + \dots + X_n}{n}$$

i.e. $S_1 = X_1$
 $S_2 = \frac{X_1 + X_2}{2}$
 $S_3 = \frac{X_1 + X_2 + X_3}{3}$
 $S_k = \frac{X_1 + X_2 + \dots + X_k}{k}$

Question is: what happens as $n \rightarrow \infty$ i.e. what is long term behaviour of $S_n = \frac{X_1 + X_2 + \dots + X_n}{n}$.

Suppose X_1, X_2, X_n is a sequence of independent and identically distributed random variables such that each X_i takes two values 0 with probability $1 - p$ and 1 with probability p . Now, let us consider a new sequence of random variables S_n defined as follows. S_n is equal to X_1 plus X_2 plus X_n by n . That is, S_1 is equal to X_1 , S_2 is equal to X_1 plus X_2 plus 2, S_3 is equal to X_1 plus X_2 plus X_3 by 3, S_k is equal to X_1 plus X_2 plus X_k by k like that question is what happens as n goes to infinity, that is what is the long term behavior of S_n is equal to X_1 plus X_2 plus X_n upon n .

(Refer Slide Time: 14:00)

Handwritten text in a Windows Journal window:

We know that $X_1 + X_2 + \dots + X_n \sim \text{Bin}(n, p)$

$$\therefore E(S_n) = E\left(\frac{\sum_{i=1}^n X_i}{n}\right) = \frac{1}{n} E(\text{Bin}(n, p)) = \frac{np}{n} = p$$

Also note that $\text{Var}(S_n) = \frac{1}{n^2} \text{Var}\left(\sum_{i=1}^n X_i\right) = \frac{npq}{n^2} = \frac{pq}{n}$

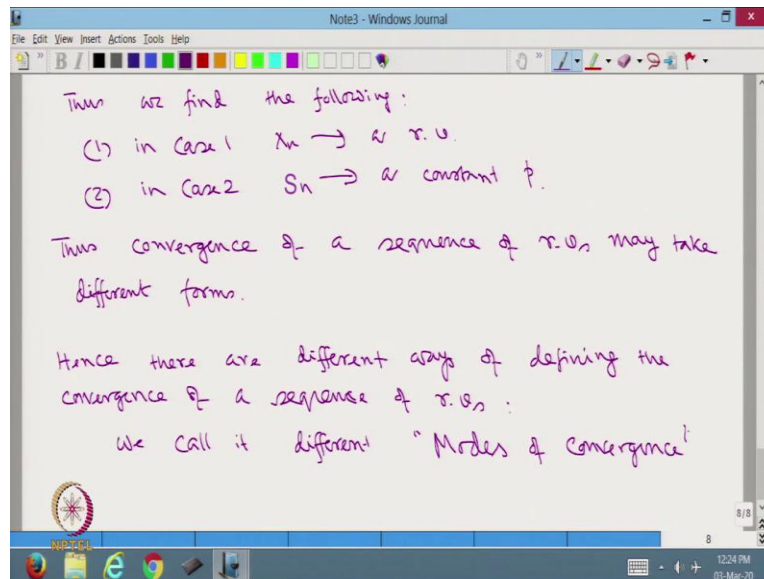
\therefore As $n \rightarrow \infty$ $\text{Var}(S_n) \rightarrow 0$

$\therefore S_n \rightarrow$ its expectation i.e. the sequence S_n converges to the constant 'p' which is the unknown probability of success of the parameter of the Bernoulli r.v.s X_i

We know that X_1 plus X_2 plus X_n is distributed as binomial with n, p . Therefore, the expected value of S_n is equal to expected value of $\sum_{i=1}^n X_i$, i equal to 1 to n divided by n is equal to 1 by n expected value of binomial n, p is equal to np upon n is equal to p . Also note that variance of S_n is equal to 1 by n square into variance of $\sum_{i=1}^n X_i$, i is equal to 1 to n is equal to n $p q$ upon n square is equal to $p q$ by n .

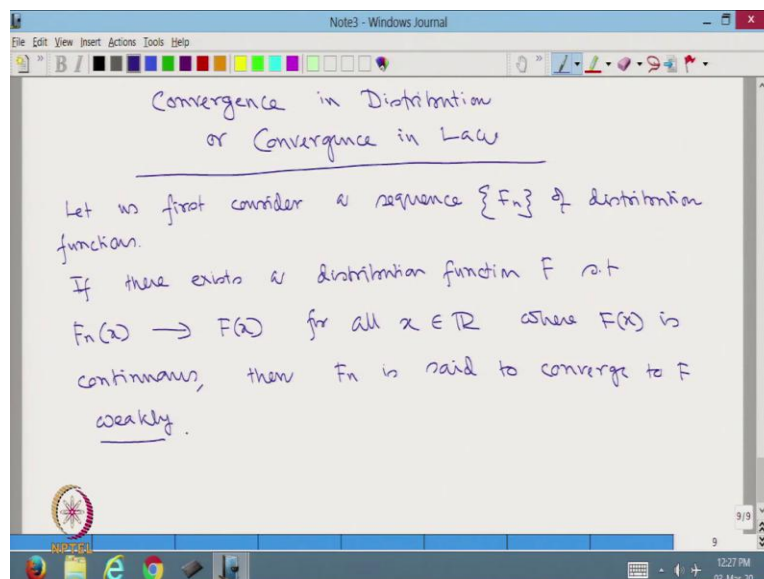
Therefore, as n goes to infinity, variance of the S_n converges to 0. Therefore, S_n converges to its expectation. That is, the sequence S_n converges to the constant 'p' which is the unknown probability of success of the parameter of the Bernoulli random variables X_i .

(Refer Slide Time: 16:47)



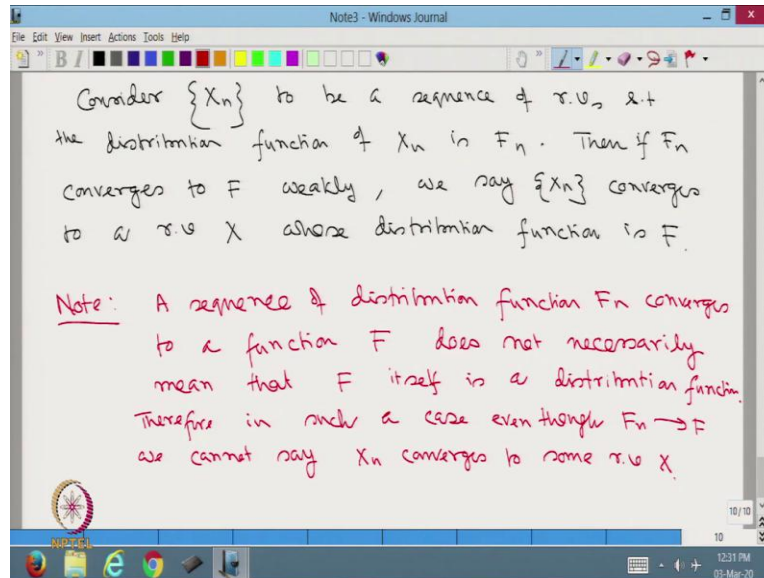
Thus we find the following in case 1, X_n converges to a random variable in case 2, X_n converges to a constant which is p. Thus, convergence of a sequence of random variables may take different forms. Hence, there are different ways of defining the convergence of a sequence of random variables or in other words, we call it different "modes of convergence". So, in this lectures, we shall study a few of the different modes of convergence for a sequence of random variables.

(Refer Slide Time: 19:07)



One of the weakest form of convergence is called convergence in distribution or convergence in law. To understand that let us first consider a sequence F_n of distribution functions. If there exists a distribution function F such that, $F_n(x)$ converges to $F(x)$ for all x belonging to \mathbb{R} where F is continuous, then F_n is said to converge to F weakly. That is it is a weak form of convergence of the distribution functions.

(Refer Slide Time: 21:17)



Now, consider X_n to be a sequence of random variables such that the distribution function of X_n is F_n . Then if F_n converges to F weakly, we say X_n converges to a random variable X , whose distribution function is F . Note, a sequence of distribution functions F_n converges to a function F does not necessarily mean that F itself is a distribution function. Therefore, in such a case even though F_n converges to F we cannot say X_n converges to some random variable X . So, this is one point that you have to understand. So, I shall give you examples so that this is going to be clear to you.

(Refer Slide Time: 24:22)

Ex 1 Let $X_1, X_2, \dots, X_n, \dots$ be a sequence of r.v.s with the following distribution:

$$X_n = \begin{cases} 0 & \text{with prob } 1 - \frac{1}{n} \\ n & \text{with prob } \frac{1}{n} \end{cases}$$

So how do they look like?

X_1 : 0 with prob = 0
1 with prob = 1

X_2 : 0 with prob = $\frac{1}{2}$
2 with prob = $\frac{1}{2}$

X_3 : 0 with prob $\frac{2}{3}$
1 with prob $\frac{1}{3}$

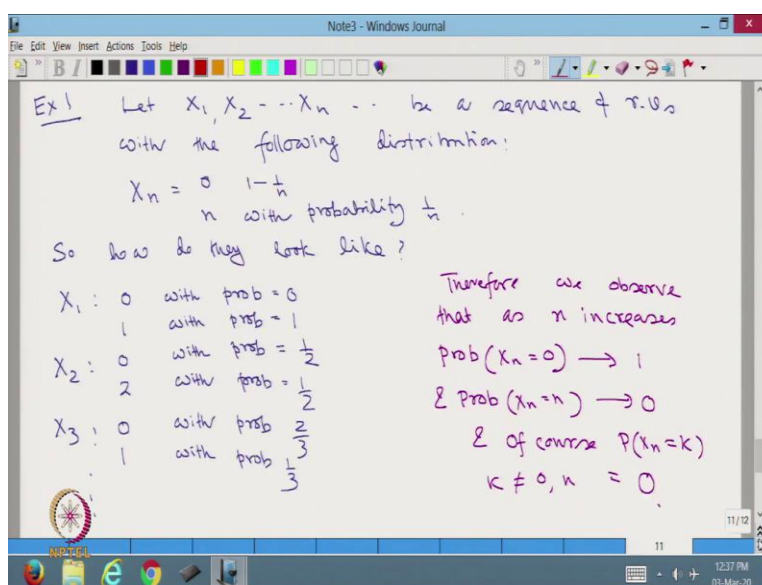
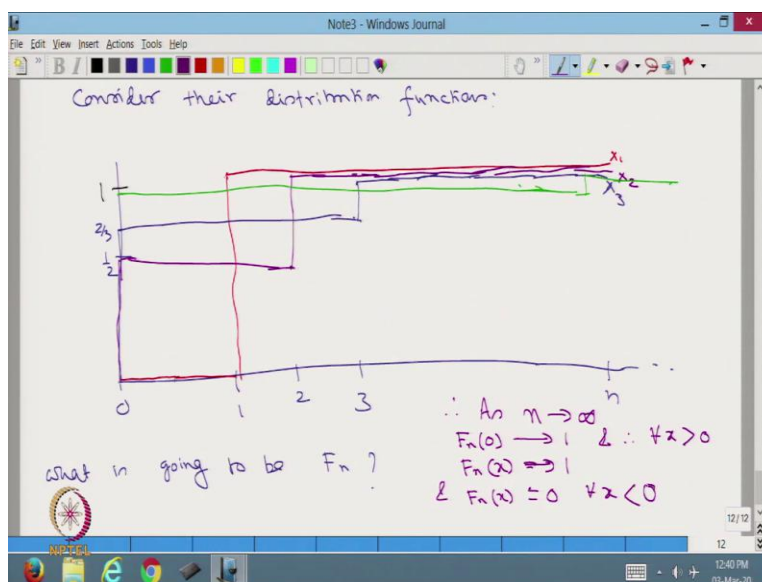
Therefore we observe that as n increases

$\text{Prob}(X_n=0) \rightarrow 1$
 $\& \text{Prob}(X_n=n) \rightarrow 0$
 $\& \text{of course } P(X_n=k)$
 $k \neq 0, n = 0$

Example 1, let X_1, X_2, X_n be a sequence of random variables with the following distribution X_n is equal to 0 with probability $1 - \frac{1}{n}$ and n with probability $\frac{1}{n}$. So, how do they look like? So, X_1 takes the values 0 with probability 0 and 1 with probability is equal to 1, X_2 takes 0 with probability is equal to half and it takes the value 2 with probability is equal to half. So, let us consider X_3 , which takes the value 0 with probability $\frac{2}{3}$ and it takes the value 1 with probability $\frac{1}{3}$.

Therefore, we observe that as n increases probability X_n is equal to 0 converges to 1 and probability X_n is equal to n converges to 0. And of course, probability X_n is equal to k , k not equal to 0 or n is equal to 0.

(Refer Slide Time: 27:50)



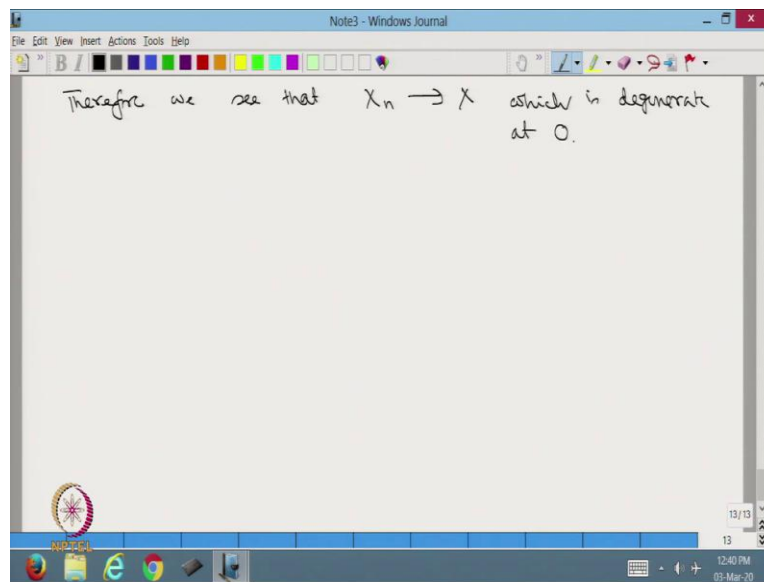
So, let us consider their distribution functions. So, let us assume 0, 1, 2, 3, n. So, what is the distribution function for X_1 ? It takes the value 0 with probability 0 and it takes the value 1 with probability 1. So, if this is the value 1, then the distribution function of X_1 is going to be something like this what about X_2 ? X_2 takes the value 0 and 2 with half and half.

So, if this is my half after 0 the cumulative distribution function goes to half and at 2 it goes to 1 and it remains 1 throughout. So, this is for X_2 . This is for X_1 . What about X_3 ? X_3 takes the

value 0 with probability $\frac{2}{3}$ and it takes the value 3 with $\frac{1}{3}$ therefore, each distribution function will be something like this.

Therefore, what is going to happen? If that is the question, we can understand that it will take the value $1 - \frac{1}{n}$ and go up to n and then at n it becomes 1. Therefore, as n goes to infinity if n at 0 is converging to 1 and therefore, for all x greater than 0, $F_n(x)$ is going to be converging to 1 and $F_n(x)$ is 0 for all x less than 0.

(Refer Slide Time: 31:40)



Therefore, we see that X_n converges to a variable X which is degenerate at 0.

(Refer Slide Time: 32:06)

Ex 2 Let X_1, X_2, \dots, X_n be iid r.v.s with $U(0, \theta)$.
 i.e. $f(x) = \begin{cases} 0 & \text{if } x < 0 \text{ or } x > \theta \\ \frac{1}{\theta} & \text{if } 0 \leq x \leq \theta \end{cases}$

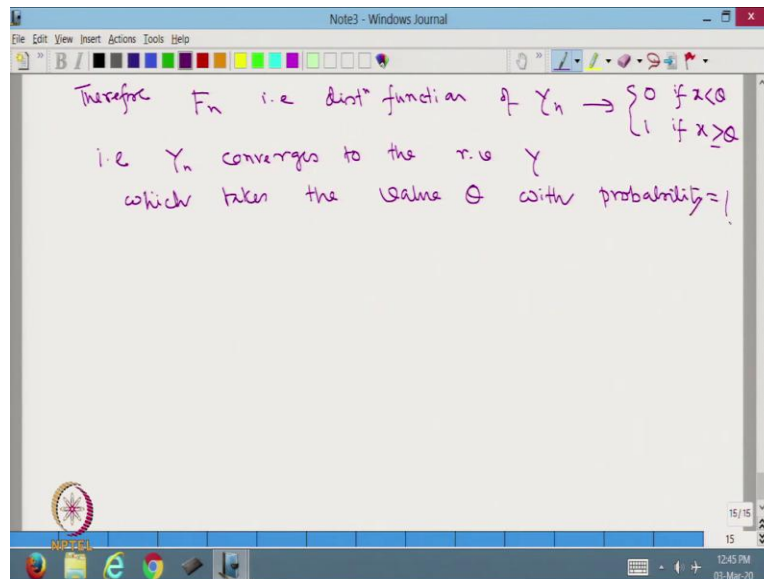
Let Y_n be defined as $Y_n = \max(X_1, \dots, X_n)$
 $\therefore Y_n$ has the following distⁿ function:

$$F_n = \begin{cases} 0 & \text{if } x < 0 \\ \left(\frac{x}{\theta}\right)^n & \text{if } 0 \leq x \leq \theta \\ 1 & \text{if } x > \theta \end{cases}$$

Now for all $x \ni 0 \leq x < \theta$
 Strictly less than $\frac{x}{\theta} < 1 \therefore \left(\frac{x}{\theta}\right)^n \rightarrow 0$ as $n \rightarrow \infty$

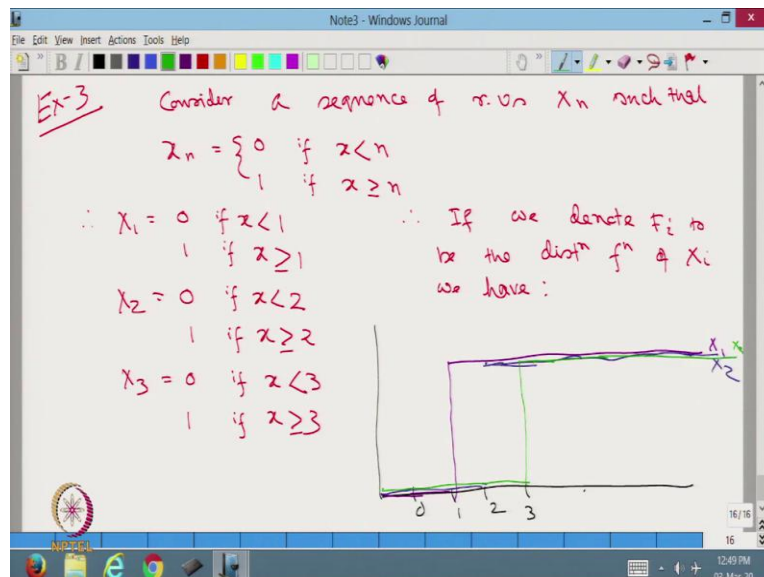
Example 2, let X_1, X_2, \dots, X_n be iid random variables with uniform $0, \theta$ that is F_n of x is equal to 0 if x less than 0, or x greater than θ and is equal to 1 by θ . If 0 less than equal to x less than or equal to θ . Let Y_n be defined as Y_n is equal to maximum of X_1, X_2, \dots, X_n . Therefore, Y_n has the following distribution function that is the F_n is equal to 0 if x less than 0, x by θ whole to the power n , if 0 less than equal to x less than equal to θ and 1 if x is greater than θ . Now, for all x , such that 0 less than equal to x less than θ , it is strictly less than x by θ is less than 1. Therefore, x by θ whole to the power n goes to 0 as n goes to infinity.

(Refer Slide Time: 34:42)



Therefore, F_n that is distribution function of cumulative distribution, cumulative distribution function you can say of Y_n converges to 0 if x is less than theta, and 1 if x is greater than equal to theta, that means Y_n converges to the random variable say Y , which takes the value theta with probability is equal to 1.

(Refer Slide Time: 35:46)

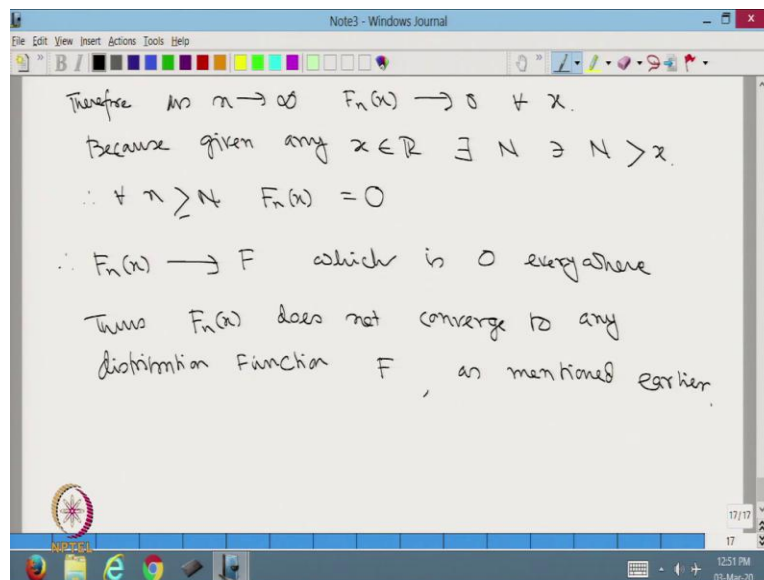


Example 3, consider, consider a sequence of random variables X_n such that X_n is equal to 0 if x is less than n and 1 if x is greater than equal to n . Therefore, X_1 is equal to 0 if x less than 1, and

is equal to 1, if x greater than equal to 1, therefore x^2 is equal to 0 if x less than 2 and 1 if x greater than equal to 2, X_3 is equal to 0 if x less than 3 and it is equal to 1 if x greater than or equal to 3.

Therefore, if we denote, F_i to be the distribution function of X_i , we have the pdf of, we have the distribution function of X_1 is equal to 0 if x is less than 1 and 1 if x is 1, for X_2 we have it is 0 till this point and at 2 it takes the value 1 and it remains there, after that the X_3 , X_3 will remain at 0 till 3 and that 3 it will take the value 1.

(Refer Slide Time: 38:29)



Therefore, as n goes to infinity F_n at x goes to 0 for all x , because given any x belonging to \mathbb{R} there exist N such that N is bigger than x . Therefore, for all n greater than equal to N , $F_n(x)$ is equal to 0. Therefore, $F_n(x)$ converges to a function F , which is 0 everywhere. Thus, $F_n(x)$ does not converge to any distribution function F as mentioned earlier.

(Refer Slide Time: 40:06)

Theorem: Let X_n be a sequence of integer valued r.v.s. s.t. $f_n(k) = P(X_n = k)$.
 $k = 0, 1, 2, \dots$

Suppose $f_n(x) \rightarrow f(x) \quad \forall x$
 $\Leftrightarrow X_n \xrightarrow{L} X$ which has the pmf $f(x)$.

PF: Let us first observe the following:
 X_i has the distribution

X_i	0	1	2	3	...	n	...
	$f_i(0)$	$f_i(1)$	$f_i(2)$	$f_i(3)$...	$f_i(n)$...

Similarly X :

X	0	1	2	3	...	n	...
	$f(0)$	$f(1)$	$f(2)$	$f(3)$...	$f(n)$...

Now, let me give you a theorem, let X_n be a sequence of integer valued random variables such that $F_n(k)$ is equal to probability X_n is equal to k , when k is equal to $0, 1, 2$ up to infinity. Suppose $F_n(x)$ converges to $F(x)$ for all x , this implies that X_n is converging by law to the random variable x , which has the pmf $F(x)$.

Proof, let us first observe the following, X_i has the distribution, X_i takes the value $0, 1, 2, 3, n$, etc with probabilities $f_{i0}, f_{i1}, f_{i2}, f_{i3}, f_{in}$ like that. Similarly, X takes the same values $0, 1, 2, 3, n$ with probabilities f_0, f_1, f_2, f_3, f_n like that.

(Refer Slide Time: 42:43)

∴ Distribution function for X is

$$F(x) = \begin{cases} 0 & \text{if } x < 0 \\ f(0) & \text{if } 0 \leq x < 1 \\ f(0) + f(1) & \text{if } 1 \leq x < 2 \\ \vdots \\ \sum_{i=0}^k f_i & \text{if } k \leq x < k+1 \end{cases}$$

Therefore it is step function

Therefore, distribution function for X is F_x is equal to 0 if x less than 0, it is F_0 if 0 less than equal to x less than equal to 1 less than 1, F_0 plus F_1 if 1 less than equal to x less than 2, σf_i , i is equal to 0 to k , if k less than equal to x less than k plus 1 like that. Therefore, it is a step function.

(Refer Slide Time: 43:55)

Now it is given that $f_n(k) \rightarrow f(k) \quad \forall k = 0, 1, 2, \dots$

∴ Consider $x < 0$ ∴ Trivially $F_n(x) = 0 \quad \forall x$
 $\therefore F_n(x) \rightarrow F(x)$

2) Consider $0 \leq x < 1$ ∴ $F_n(x) = f_n(0) \rightarrow f(0) \rightarrow F(0)$

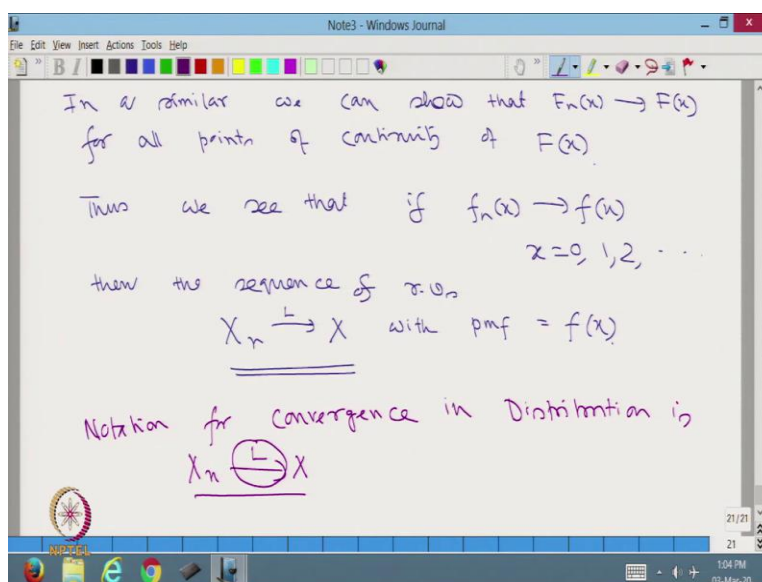
3) Consider $1 \leq x < 2$ ∴ $F_n(x) = f_n(0) + f_n(1)$
 We know that if $a_n \rightarrow a$
 $b_n \rightarrow b$
 Then $a_n + b_n \rightarrow a + b$
 $\therefore F_n(x) \rightarrow f(0) + f(1) = F(x) \quad 0 \leq x < 1$

Now, it is given that $F_n k$ converges to $F k$ for all k is equal to 0, 1, 2, etc. Therefore, consider x less than 0. Therefore, trivially if $F_n x$ is equal to 0 for all x , therefore, $F_n x$ converges to F_x to

consider $0 \leq x \leq 1$. Therefore, $F_n(x)$ is equal to F_0 which converges to F_0 , which is equal to F at 0.

Similarly, consider $1 \leq x \leq 2$. Therefore, $F_n(x)$ is equal to F_0 plus F_1 and we know that if a_n converges to a and b_n converges to b , then $a_n + b_n$ converges to $a + b$. So, this we know from our high school mathematics. Therefore, $F_n(x)$ converges to F_0 plus F_1 which is equal to F at x when $0 \leq x \leq 1$.

(Refer Slide Time: 46:27)



In a similar way we can show that $F_n(x)$ converges to $F(x)$ for all points of continuity of $F(x)$. Thus, we see that if $F_n(x)$ converges to $F(x)$, x is equal to 0, 1, 2 etc. Then the sequence of random variables X_n converges in law to the random variable X with pmf is equal to $F(x)$. So, I want you to remember this notation.

So, notation for convergence in distribution is X_n convergence in distribution in law or X_n that is we have, we are using the (sym), we are using the symbol L to denote that it is a convergence in distribution. Now, there is a converse part of it that is if X_n converges to X_n distribution then for all X , $F_n(x)$ converges to $F(x)$, this we shall prove in the next class. Okay friend, thank you so much. Thank you.