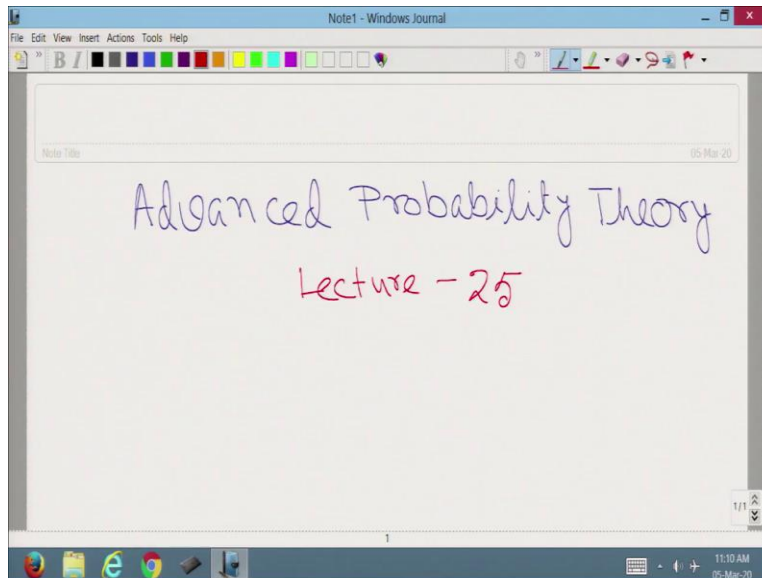


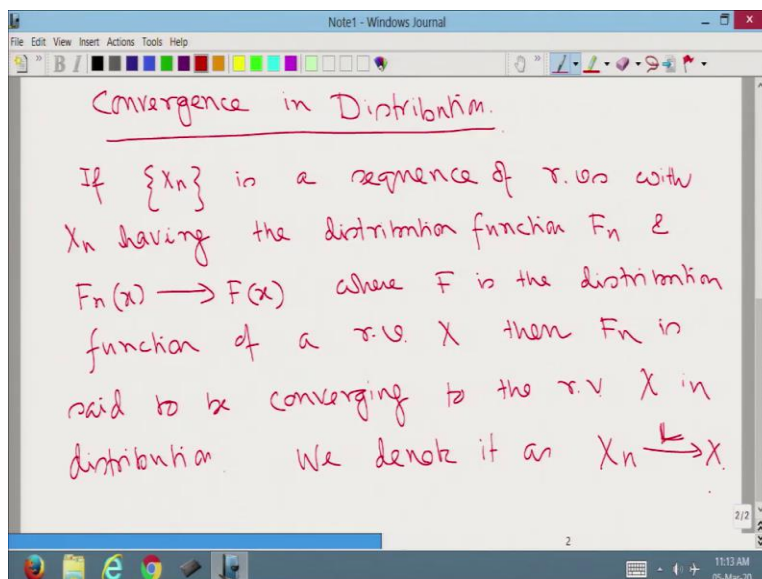
Advanced Probability Theory
Professor Niladri Chatterjee
Department of Mathematics
Indian Institute of Technology, Delhi
Lecture-25

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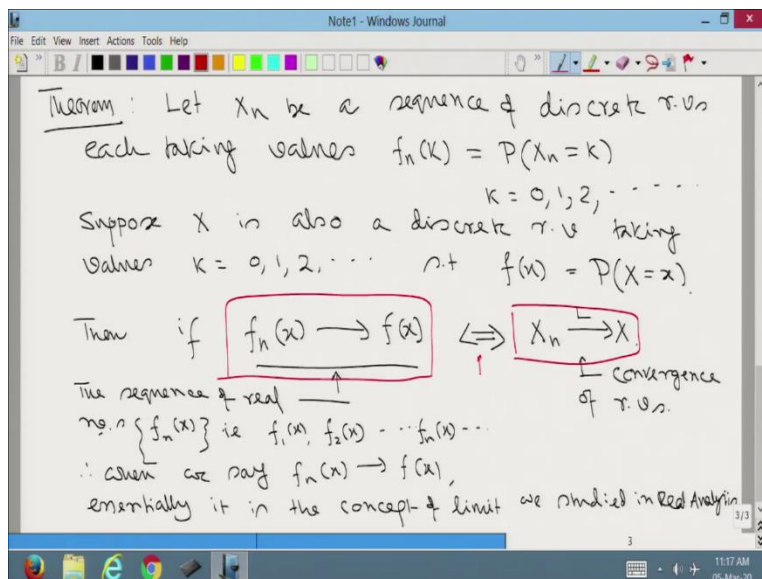
Welcome students to the MOOCs series of lectures on advanced probability theory. This is lecture number 25.

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If you remember, we were discussing convergence in distribution. That is if x_n is a sequence of random variables with x_n having the distribution function F_n and F_n converges to F_x , where F is the distribution function of a random variable x then F_n is said to be converging to the random variable x in distribution and we denote it as x_n converges to x with this script L , which means convergence in law and that is how we typically denote convergence distribution.

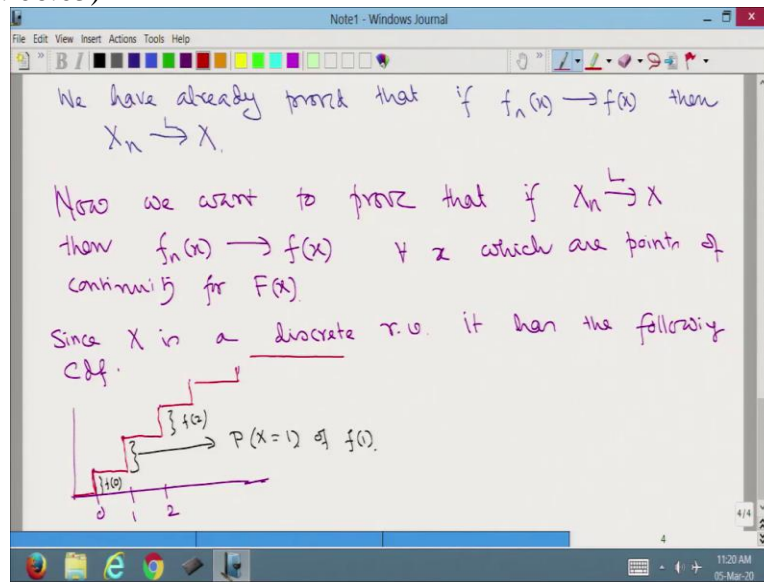
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We are working out on the following theorem. Let x_n be a sequence of discrete random variables each taking values $F_n k$ is equal to probability x_n is equal to k , when k is equal to $0, 1, 2$ up to infinity and suppose x is also a discrete random variable taking values, k is equal to $0, 1, 2$ etc, such that F at x is equal to probability x is equal to x , then if, $F_n x$ converges to F_x .

That implies and implied by x_n convergence converges in law to the random variable x . Note that this is convergence of distribution, convergence of random variables, whereas, this is the sequence of reals $F_n x$ that is $F_1 x, F_2 x, F_n x$ this sequence and when we are saying $F_n x$ converges to F_x . Essentially it is the concept of limit we studied in real analysis.

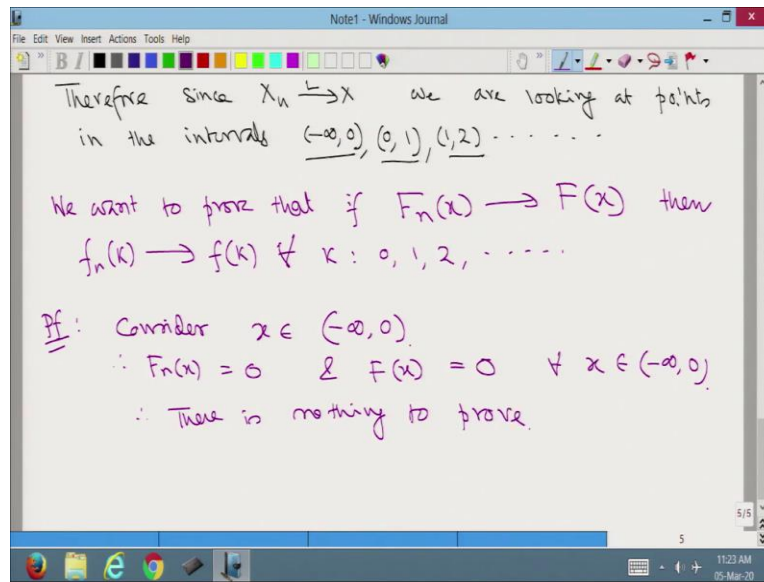
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So, the distinction between this and this should be clear and this means if and only if we have already proved that if F_n converges to F_x , then X_n converging in law or distribution to the random variable X . Now, we want to prove that if X_n converges to x in distribution then F_n converges to F_x for all x which are points of continuity for F_x .

Now, since x is a discrete random variable it has the following Cdf 0,1,2 etc so the distribution function is going to be a step function something like this below 0, it is 0 at 0 it goes to some height, what is going to be that height? I am telling you it is coming to 1 at 1, it is also having a jump thus we are getting a step function of this type where this jump is probability x is equal to 1 or F_1 . Similarly, this is F_2 this is F_0 and ultimately it will be 1 this must be clear to you.

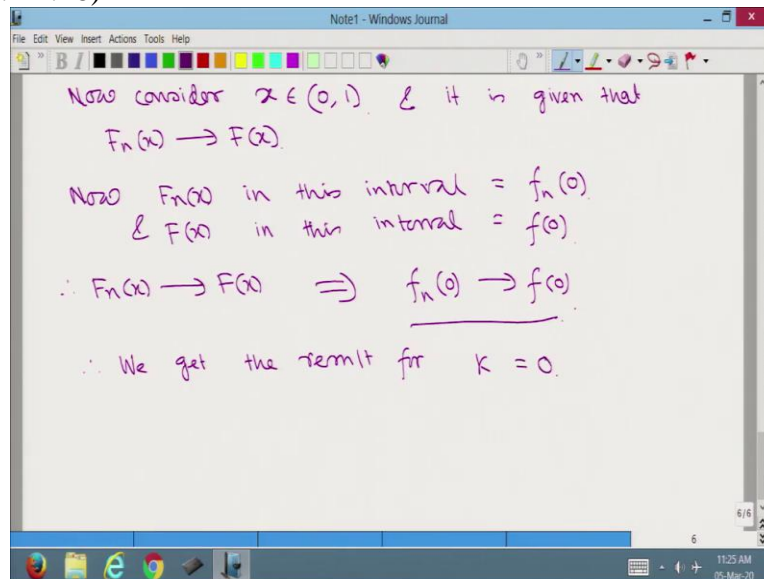
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Therefore, since x_n convergence, convergence in distribution to x , we are looking at points in the intervals minus infinity to 0 at 0 there is a jump, therefore, 0 to 1 open intervals at 1 there is a jump and therefore, we are looking at the this set of intervals or we are looking at points, which is in the union of these intervals.

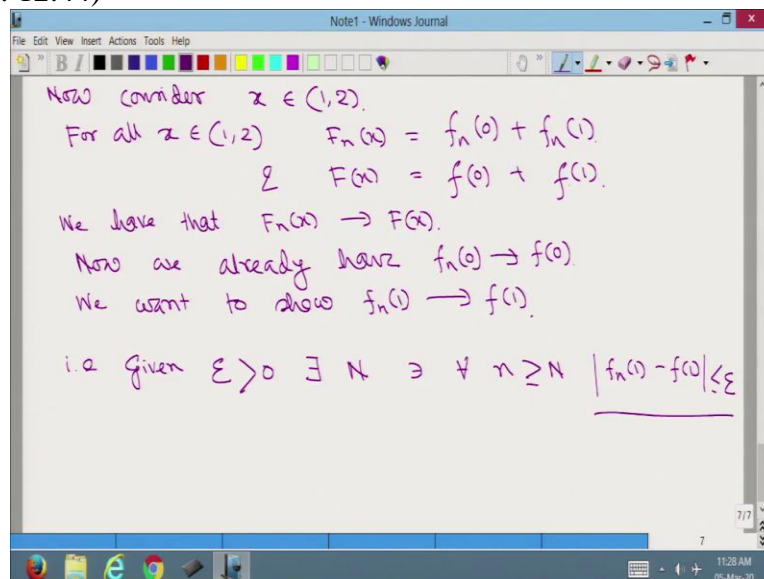
We want to prove that if $F_n x$ converges to $F x$, then $f_n k$ converges to $f k$ for all k in 0, 1, 2 etc proof. Consider x belonging to minus infinity to 0. Therefore, $F_n x$ is equal to 0 and $F x$ is equal to 0 for all x belonging to minus infinity to 0. Therefore, there is nothing to prove.

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Now, consider x belonging to 0 comma 1 . And it has given that $F_n x$ converges to a $F x$, now $F_n x$ in this interval is equal to $F_n 0$ and $F x$ in this interval is equal to $F 0$. Therefore, $F_n x$ converging to $F x$ implies $F_n 0$ converges to F at 0 . Therefore, we get the result for K is equal to 0 .

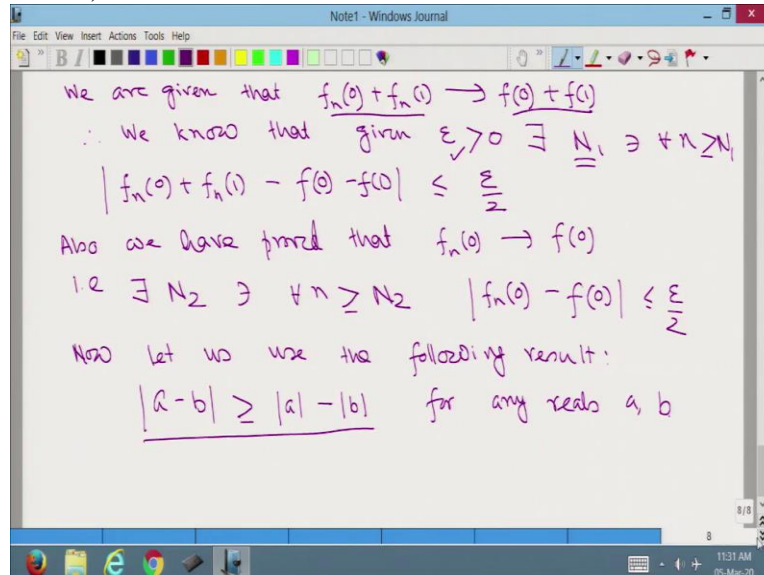
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Now, consider x belonging to 1 comma 2 for all x belonging to 1 comma 2 $F_n x$ is equal to $f_n 0$ plus $f_n 1$ and F of x is equal to small f_0 plus small f_1 , we have that $F_n x$ converges to $F x$. Now, we already have, $f_n 0$ converges to f_0 we want to show f_1 converges to f_1 that is given epsilon

greater than 0, there exists n such that for all n greater than equal to n modulus of f_n minus f is less than equal to epsilon. This is what we need to prove.

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We are given that f_n plus f_n converges to f_0 plus f_1 . Therefore, we know that given epsilon greater than 0, they are exist n_1 such that for all n greater than equal to n_1 modulus of F_n plus f_n minus f_0 minus f_1 is less than equal to epsilon by 2, because this is converging to this given any epsilon, we can find such an n_1 also we have proved that F_n converges to F_0 that is there exist n_2 for the same epsilon such that for all n greater than equal to n_2 modulus of f_n minus f_0 is less than equal to epsilon by 2.

Now, let us use the following result modulus of a minus b is greater than or equal to modulus of a minus modulus of b for any reals a comma b. This we know from our school level mathematics.

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The image shows a handwritten mathematical proof in a Windows Journal window. The text is as follows:

$$\begin{aligned} \text{We write } & |f_n(x) + f_n(y) - f(x) - f(y)| \\ &= \left| \frac{f_n(x) - f(x)}{a} - \frac{(f(x) - f_n(y))}{b} \right| \\ &\geq |f_n(x) - f(x)| - |f(x) - f_n(y)| \end{aligned}$$

∴ We can write $|f_n(x) - f(x)| \leq \frac{|f_n(x) + f_n(y) - f(x) - f(y)|}{1} + |f(x) - f_n(y)|$

Consider $N = \max(N_1, N_2)$

∴ $\forall n \geq N \quad |f_n(x) - f(x)| \leq \frac{\epsilon}{2} + \frac{\epsilon}{2} = \epsilon$

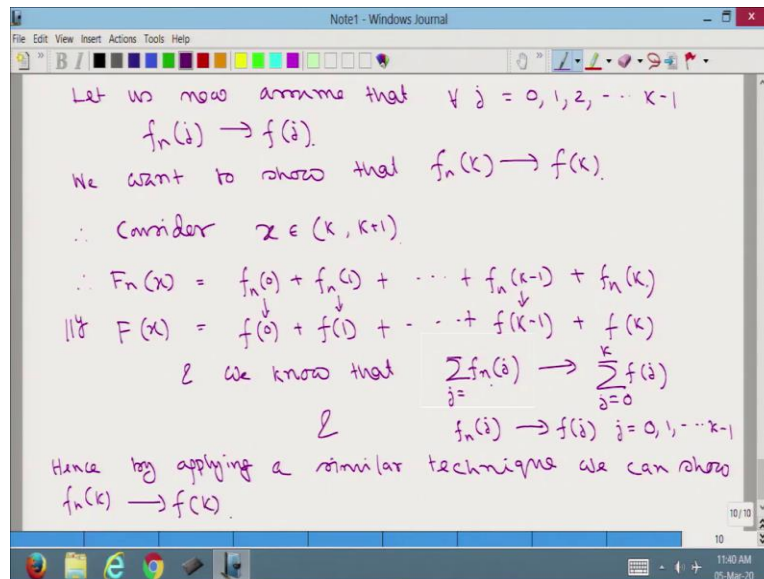
It implies that $f_n(x) \rightarrow f(x)$.

So, we write modulus of f_n1 plus f_n0 minus $f0$ minus $f1$ is equal to modulus of f_n1 minus $f1$ minus $f0$ minus f_n0 . So, this is let us call a and this let us call b . Therefore, this is greater than equal to modulus of f_n1 minus $f1$ minus modulus of $f0$ minus f_n0 therefore, we can write, modulus of f_n1 minus $f1$.

This quantity is less than or equal to, modulus of f_n1 plus f_n0 minus $f0$, minus $f1$ plus modulus of $f0$ minus f_n0 , considered n is equal to maximum of $n1$ comma $n2$, where $n1$ and $n2$ we have just defined. Therefore, for all n greater than equal to n modulus of F_n1 minus $F1$ is less than equal to ϵ by 2 plus ϵ by 2, which is equal to ϵ .

Because we have already shown that this will be less than ϵ by 2 and this is going to be less than ϵ by 2. Therefore, together their sum is ϵ . Therefore, for all n greater than equal to n modulus of F_n1 minus $F1$ is less than equal to ϵ , what does it mean? It implies that f_n1 converges to $f1$.

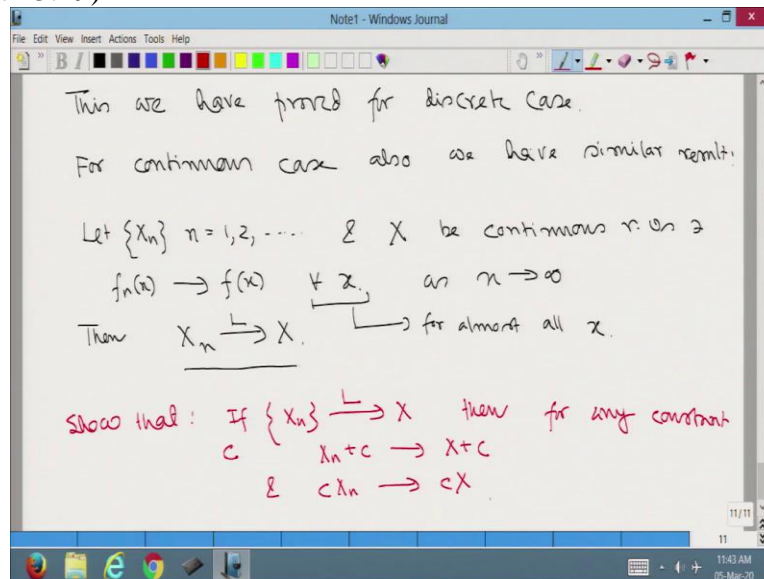
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Let us now assume that for all j is equal to 0, 1, 2 up to K minus 1, f_{nj} converges to f_j we want to show that f_{nk} converges to f_k . Therefore, consider x belonging to K to K plus 1. Therefore, $F_n x$ is equal to $f_n 0$ plus $f_n 1$ up to $f_n k$ minus 1 plus f and K . Similarly, $f x$ is equal to $f 0$ plus $f 1$ plus $f k$ minus 1 plus $f k$.

And we know that $f_n 0$ converges to $f 0$, $f_n 1$ converges to $f 1$, and $f_n k$ minus 1 converges to $f k$ minus 1 and we also know that $\sum_{j=0}^k f_{nj}$, j is equal 0 to k converges to $\sum_{j=0}^k f_j$ and f_{nj} converges to f_j for j is equal to 0, 1, 2 up to k minus 1 hence by applying a similar technique we can show f_{nk} converges to f_k . I leave this as an exercise, you just have to imitate what I did for 1 and in a similar way you can do it for k .

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So, this we have proved for discrete case, for continuous case also we have a similar result which says that let x_n n is equal to 1, 2, 3 etc and x be continuous random variables such that f_{x_n} converges to f_x for all x as n goes to infinity, then x_n converges in distribution to x . Actually, it is not for all x , it is actually for almost all x , but that concept still I have not given.

So, let us assume that this is true for all x . And in that case, we can show that the sequence x_n of random variables will be converging to the random variable x , I am not going to give the proof because that needs more mathematical treatment, but we can accept that result, show that if x_n is a sequence of random variables, which is converging in distribution to x then for any constant C , x_n plus c converges to x plus c and c times x_n converges to c times x . You can prove them very easily from the definition I leave that as exercise.

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Ex Let X_1, X_2, \dots be iid r.v.s each $X_i \sim \text{Beta}(1, \beta)$.
Let $X_{(n)}$ be $\max(X_1, X_2, \dots, X_n)$.
For $n=1, 2, 3, \dots$ we define a new r.v Y_n :
$$Y_n = n^\lambda (1 - X_{(n)})$$

For which value of λ the sequence Y_n converges to some distⁿ F. Identify the distⁿ.

So, let me give you an example very interesting example to understand the convergence in distribution. So, let x_1, x_2, x_n etc be iid random variables each x_i distributed as beta 1 distribution with parameter 1 comma say beta let x_n be maximum of x_1, x_2, x_n for all n equal to 1, 2, 3 etc.

We define a new random variable y_n as follows that y_n is equal to n to the power λ 1 minus x_n . Question is for which value of λ the sequence y_n converges to some distribution f and identify the distribution.

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Soln: Y_n converges to some r.v. Y in distribution if

$$\lim_{n \rightarrow \infty} F_n(y) = F_Y(y)$$

Now $F_n(y) = P(Y_n \leq y)$

$$= P(n^\lambda(1-X_n) \leq y)$$

$$= P(1-X_n \leq \frac{y}{n^\lambda})$$

$$= P(1 - \frac{y}{n^\lambda} \leq X_n)$$

$$= 1 - P(X_n < 1 - \frac{y}{n^\lambda})$$

$$= 1 - P(X_1 < 1 - \frac{y}{n^\lambda}, X_2 < 1 - \frac{y}{n^\lambda}, \dots, X_n < 1 - \frac{y}{n^\lambda})$$

Solution y_n converges to some random variable y in distribution if limit n going to infinity, f_{ny} is equal to f_y of y now, f_{ny} is equal to probability y_n less than equal to y is equal to probability n to the power λ $1 - x_n$ less than equal to y is equal to probability $1 - x_n$ less than equal to y upon n to the power λ which is is equal to probability $1 - y$ upon n to the power λ less than equal to x_n by transposing the variables is equal to $1 - \text{probability } x_n \text{ less than } 1 - y \text{ upon } n \text{ to the power } \lambda$ is equal to $1 - \text{probability } x_1 \text{ less than } 1 - y \text{ upon } n \text{ to the power } \lambda$ $x_2 \text{ less than } 1 - y \text{ upon } n \text{ to the power } \lambda$ etc up to $x_n \text{ less than } 1 - y \text{ upon } n \text{ to the power } \lambda$.

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The image shows a handwritten derivation on a digital whiteboard. The text is as follows:

$$= 1 - \left(P(X_1 < 1 - \frac{y}{n}) \right)^n \quad \because X_1, X_2, \dots, X_n \text{ are iid r.v.s.}$$

$$\therefore F_n(y) = P(Y_n \leq y)$$

$$= 1 - \left(\int_0^{1 - \frac{y}{n}} \beta (1-x)^{\beta-1} dx \right)^n$$

$$= 1 - \left(1 - \left(\frac{y}{n} \right)^\beta \right)^n$$

$$\therefore \text{If } \lambda = \frac{1}{\beta} \text{ then we have}$$

$$F_n(y) = 1 - \left(1 - \frac{y^\lambda}{n} \right)^n$$

$$\therefore \text{Taking limit } n \rightarrow \infty \quad F_n(y) = 1 - e^{-y^\lambda}$$

This is Weibull distⁿ.

Therefore, for $\lambda = \frac{1}{\beta}$ $Y_n \xrightarrow{d} Y \sim \text{Weibull dist}^1$

Now $X_1 \sim \text{Beta}(1, \beta)$

$$\therefore f_{X_1}(x) = \frac{1}{\text{Beta}(1, \beta)} x^{1-1} (1-x)^{\beta-1}$$

$$= \frac{\Gamma(\beta+1)}{\Gamma(1)\Gamma(\beta)} (1-x)^{\beta-1}$$

$$= \frac{\beta \Gamma(\beta)}{\Gamma(\beta)} (1-x)^{\beta-1}$$

$$= \beta (1-x)^{\beta-1}$$

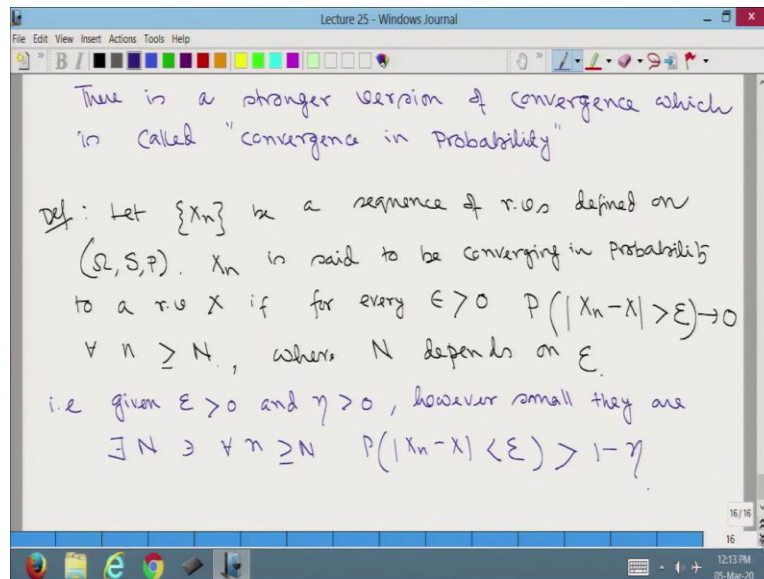
$0 < x < 1$
 $\beta > 0$

Which is equal to 1 minus probability x_1 less than 1 minus y upon n to the power λ whole to the power n since x_1, x_2 etc up to x_n are iid random variables. Now, x_1 is distributed as beta 1 with parameter 1 comma beta therefore f_{x_1} at a point x is equal to 1 upon beta 1 comma beta x to the power 1 minus 1, 1 minus x to the power beta minus 1 is equal to gamma beta plus 1 upon gamma beta gamma 1, 1 minus x to the power beta minus 1 is equal to beta gamma beta upon gamma beta 1 minus x to the power beta minus 1 is equal to beta 1 minus x beta minus 1 for 0 less than x less than 1 and beta greater than 0.

Therefore, $f_{n,y}$ is equal to probability y_n less than equal to y is equal to 1 minus integration of 0 to 1 minus y upon n to the power λ beta 1 minus x whole to the power beta minus 1, this whole power n is equal to, I would like you to work out on this to, to check that 1 minus 1 minus y upon n to the power λ whole to the power beta whole to the power n you please do the integration to come to this point.

Therefore, if λ is equal to 1 upon beta then we have $f_{n,y}$ is equal to 1 minus 1 minus y to the power beta upon n whole to the power n therefore, taking limit n going to infinity, we have $f_{n,y}$ is equal to 1 minus e to the power minus y to the power beta. Can you recognize this distribution we have already seen that this is weibull distribution. Therefore, for λ is equal to 1 upon beta y_n converges distribution to y which is weibull distribution. Okay friends, this is about convergence in distribution, this is not a very strong convergence.

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So, there is a stronger version of convergence which is called convergence in probability, let definition let X_n be a sequence of random variables defined on some probability space Ω, S and P . X_n is said to be converging in probability to a random variable X , if for every epsilon greater than 0 probability modulus of X_n minus X greater than epsilon converges to 0.

For all n , greater than equal to some n where n depends on epsilon or in other words given epsilon greater than 0 and γ greater than 0, however small they are, they are exist in such that for all n greater than equal to n probability modulus of x_n minus x less than epsilon is greater than $1 - \gamma$.

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Note that Convergence in Probability does not imply that
 $|X_n - X| < \epsilon \quad \forall n > N$. Rather it says that
the probability that $|X_n - X| > \epsilon$ can be made
arbitrarily small.

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

To show that the sequence of r.v.s converges to
in Probability to the constant 0.

Although 0 is a constant we may treat it
as a r.v. $X : 0$ with probability 1.

Note that convergence in probability does not imply that modulus of x_n minus x is less than epsilon for all n greater than capital N . So, that is not the implication. Rather it says that the probability that modulus of x_n minus x greater than epsilon can be made arbitrarily small. So, let me give you an example.

Let x_n is equal to, it takes two values 1 with probability $1/n$ and 0 with probability $1 - 1/n$ by n . To show that the sequence of random variables converges to in probability to the constant 0. So, all the 0 is a constant we may treat it as a random variable x , which takes values 0 with probability is equal to 1.

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We need to show that given any $\epsilon, \eta > 0$ we can find $N \ni \forall n \geq N \quad P(|X_n - 0| < \epsilon) > 1 - \eta$
ie $P(|X_n| < \epsilon) > 1 - \eta$

Consider $N \ni \forall n > N \quad \frac{1}{n} < \eta$
That is always possible as $\frac{1}{n} \rightarrow 0$

$\therefore \forall n > N \quad P(|X_n| > 0) \rightarrow 1 - \frac{1}{n} > 1 - \eta$

\therefore we can easily see that $P(X_n = 0) \rightarrow 1$
Hence $X_n \xrightarrow{P} 0$

So, we need to show that given any epsilon and eta greater than 0, we can find n such that for all n greater than equal to n probability modulus of x_n minus 0 less than epsilon is greater than 1 minus eta that is, probability modulus of x_n less than epsilon is greater than 1 minus eta. Consider, capital N such that for all n greater than N $1/n$ is less than eta, that is always possible as $1/n$ goes to 0.

Therefore, for all n greater than in probability modulus of x_n greater than 0 that probability goes to 1 minus $1/n$ which is greater than 1 minus eta. Therefore, we can easily see that probability x_n is equal to 0 converges to 1 hence x_n convergence in, convergence in probability to 0.

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The following results are true:

1) If $X_n \xrightarrow{P} X$ & $Y_n \xrightarrow{P} Y$

$$\Rightarrow \begin{aligned} X_n + Y_n &\xrightarrow{P} X + Y \\ X_n - Y_n &\xrightarrow{P} X - Y \\ X_n Y_n &\xrightarrow{P} XY \\ k \cdot X_n &\xrightarrow{P} kX \end{aligned}$$

2) $X_n \xrightarrow{P} X$ & g is any continuous function
then $g(X_n) \xrightarrow{P} g(X)$.

The following results are true if x_n convergence in probability to X and Y_n convergence in probability to y implies that X_n plus Y_n convergence in probability to X plus Y , X_n minus Y_n converges in probability to X minus Y , $X_n Y_n$ converges to XY in probability k times X_n converges to k times x in probability and also if x_n converges in probability to x and g is any continuous function then g of x_n converges in probability to g of x . This comes from the definition of continuity and I like you to prove this results as an exercise.

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A natural question is does convergence in Distribution \Rightarrow Convergence in Probability?

— NO.

We prove it by showing a counter example.

Consider a r.v X & a sequence of r.v.s $\{X_n\}$ jointly distributed as follows.

(X, X_n) takes the values $(0,0)$ $(0,1)$ $(1,0)$ & $(1,1)$

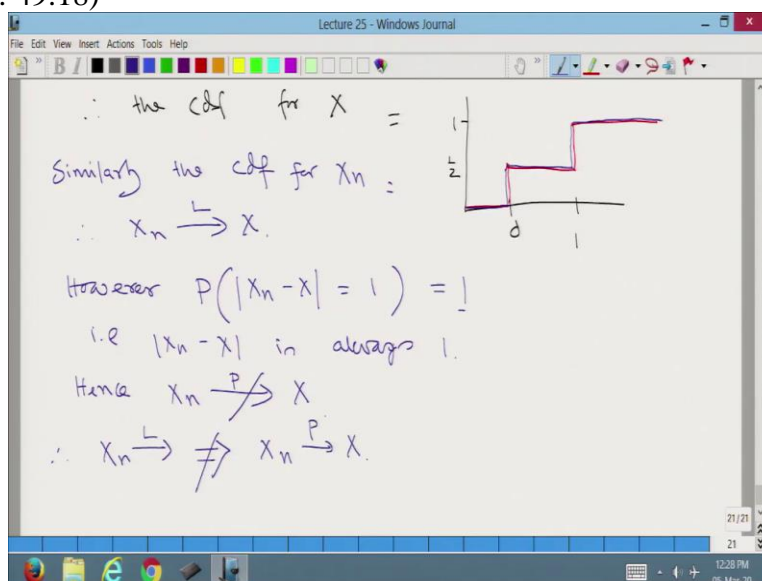
	X_n	0	1
X	0	0	$\frac{1}{2}$
	1	$\frac{1}{2}$	0

\therefore Marginal distrib of X
 $= X = \begin{cases} 0 & \frac{1}{2} \\ 1 & \frac{1}{2} \end{cases}$ & $X_n = \begin{cases} 0 & \frac{1}{2} \\ 1 & \frac{1}{2} \end{cases}$

A natural question is does convergence in distribution imply convergence in probability? The answer is no and we give you a counter example. Consider a random variable x and a sequence of random variables x_n jointly distributed as follows x comma x_n takes the values 00,01,10 and 11 with probabilities 0, half half and 0 say something like this, x_n takes the value, 0 and 1, and x takes the value 0 and 1.

So, that this has probability 0, this has probability half, this has probability half and this is 0. Therefore, marginal density of x is equal to 0 with probability half and 1 with probability half by adding these rows and for x_n also it is 0 with half and 1 with half.

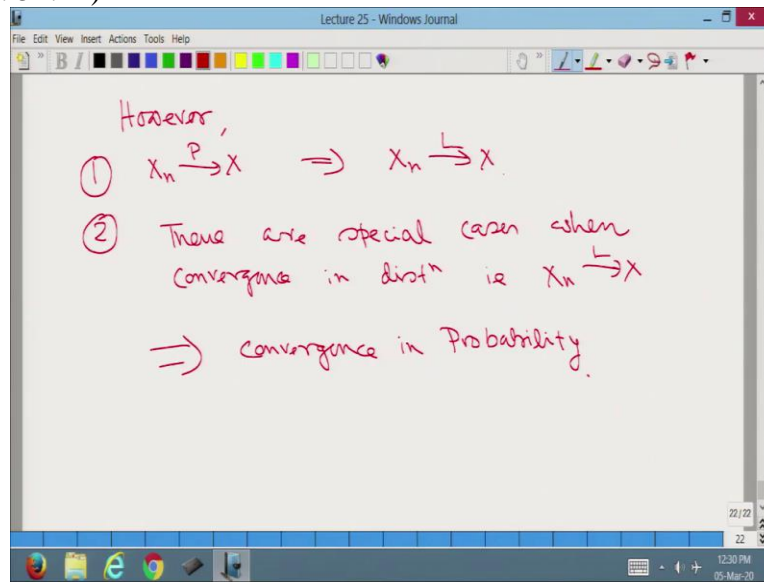
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Therefore, the cumulative distribution function for x is equal to, when this is the value 1 and this is the value half and similarly the cdf for x_n is also the same it takes that values 0 before 0 at 0 there is a jump at half then it continues like that till 1 then there is a jump and it continues with the value 1 till infinity.

Therefore, x_n converges in distribution to x . However probability modules of x_n minus x is equal to 1 is equal to 1 that is modules of x_n minus x is always 1 hence x_n does not converge in probability to x . Therefore, convergence in distribution does not imply convergence in probability.

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However, there are two things to know one is that convergence in probability implies convergence in distribution and two there are special cases when convergence in distribution that is x_n converging to x in distribution implies convergence in probability. Okay friends, I stop here today, in the next class I shall prove this result and all also, I shall introduce you to some stronger versions or stronger modes of convergence for random variables. Okay friends thank you so much.