

Next example. Let X_1, X_2 and so on be a sequence of random variables each having CDF, Cumulative Distribution Function, F suffix X_n of X from minus infinity to 0 and it takes a value $1 - (1 - \frac{x}{n})^n$, for X is lies between 0 to n . From n onwards till infinity the value is 1. So this is the cumulative distribution function for the random variables X_i 's. It's a function of n therefore I have made it F suffix X of X_n that means this is a CDF for the random variable n for every n you have this form.

As n tends to infinity we get F suffix X_n of X that becomes zero from minus infinity to zero and it takes a value $1 - e^{-x}$ from zero to infinity as n tends to infinity the CDF of the random variables X_n becomes 0 between the interval minus infinity to 0 and the value becomes $1 - e^{-x}$ where X is lies between 0 to infinity.

2) Let X_1, X_2, \dots be a sequence of r.v.s each having CDF

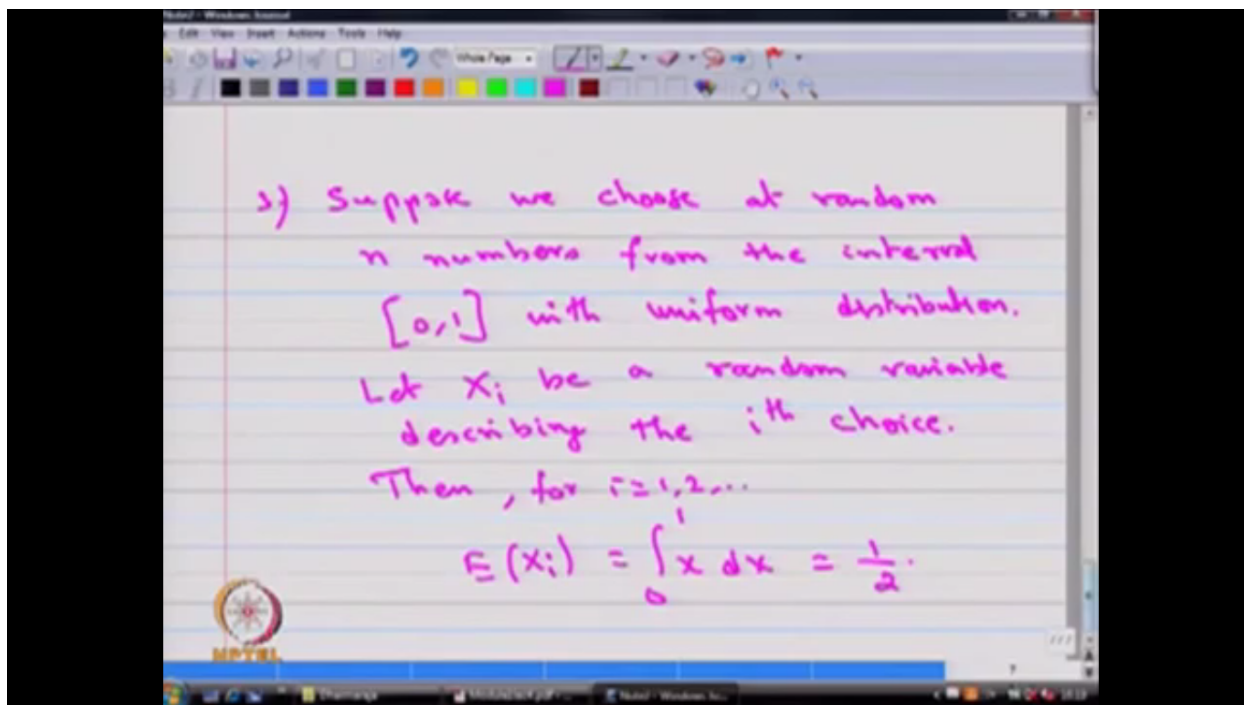
$$F_{X_n}(x) = \begin{cases} 0, & -\infty < x < 0 \\ 1 - \left(1 - \frac{x}{n}\right)^n, & 0 \leq x < n \\ 1, & n \leq x < \infty \end{cases}$$

As $n \rightarrow \infty$

$$F_{X_n}(x) = \begin{cases} 0, & -\infty < x < 0 \\ 1 - e^{-x}, & 0 \leq x < \infty \end{cases}$$

Suppose X is a random variable with the CDF that is F_X of X that is 0 between the interval minus infinity to 0 and $1 - e^{-x}$ where X is lies between 0 to infinity then one can conclude X_n converges to X in distribution since the sequence of F_X suffix n of X tends to F of X for X is greater or equal to 0 and the value is $1 - e^{-x}$. Hence one can conclude the sequence of random variable X_n converges to the random variable X in distribution. Here the X is an exponential distribution with the parameter 1. So this is one example of how the sequence of random variable converges to a random variable in distribution.

Next I will move into the third example. Suppose we choose at random n numbers from the interval 0 to 1 with uniform distribution. Let X_i be a random variable describing the i th choice. Then for i is equal to 1, 2 and so on you can find out what is the expectation of X_i 's that is nothing but the integration from 0 to 1 X times the probability density function for uniform distribution with the interval 0 to 1 that is 1. Therefore $\int_0^1 x \cdot 1 \, dx$ if you compute the expectation of X_i 's is going to be $\frac{1}{2}$.

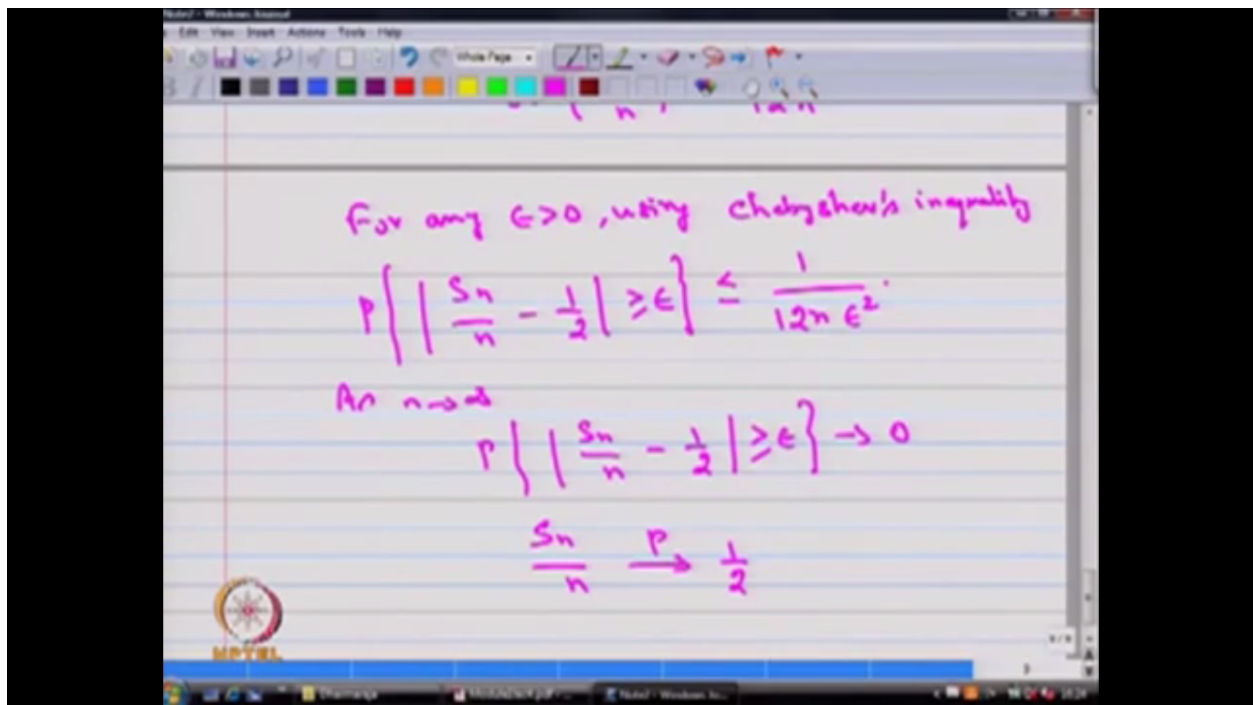


Similarly one can evaluate the variance of X_i 's that is nothing but $\int_0^1 x^2 dx$ minus the mean square expectation of X square minus expectation of X whole square so the expectation of X square is $\int_0^1 x^2 dx$. So if you evaluate this quantity that is $\frac{1}{3}$ minus $(\frac{1}{2})^2$. So if you simplify you will get $\frac{1}{12}$. If you remember the formula of variance of a uniformly distributed random variable between the interval A to B then the variance of X_i 's X is nothing but you can get it and by substituting the value of A is equal to 0 and B is equal to 1 you will get $\frac{1}{12}$.

Let S_n suffix n be X_1 plus X_2 and so on till X_n . One can find mean and variance of S because you know the mean and variance of X_i 's using that you can find out what is the mean of S_n but our interest is not finding the mean of S_n . Our interest is to find out the mean of S_n by n that is basically suppose X_i 's are the samples then S_n divided by n is nothing but the sample mean. So expectation of S_n divided by n that becomes $\frac{1}{2}$. Similarly if you calculate variance of S_n by n that becomes $\frac{1}{12}$ times n because the variance of X_i 's is $\frac{1}{12}$ so the variance of S_n is a summation of X_i 's from 1 to n therefore variance of S_n by n becomes $\frac{1}{12}$ times n .

For any ϵ greater than 0 using Chebyshev's inequality one can conclude the probability of absolute of S_n by n minus $\frac{1}{2}$ greater than or equal to ϵ that is less than or equal to $\frac{1}{12n\epsilon^2}$. I am using the Chebyshev's inequality by knowing mean of S_n by n is $\frac{1}{2}$ and variance of S_n by n is $\frac{1}{12}$ [Indiscernible] [00:09:03] I get this inequality. Now as n tends to infinity the probability of absolute of S_n by n minus $\frac{1}{2}$ which is greater than or equal to ϵ will tends to 0 because ϵ is in the denominator because n is the denominator as n tends to infinity this probability tends to 0 . That is nothing but S_n by n tends to the value $\frac{1}{2}$ and this convergence takes place in probability. The sequence of random variable S_n by n converges to $\frac{1}{2}$ in probability. Therefore, we say the sequence of random variable X_n for n is equal to $1, 2,$ and so on obeys the weak law of large numbers

because the S_n by n converges to $1/2$ in probability therefore we say the sequence of random variables say S_n obeys the weak law of large numbers.



So that is the intention of giving this example.