

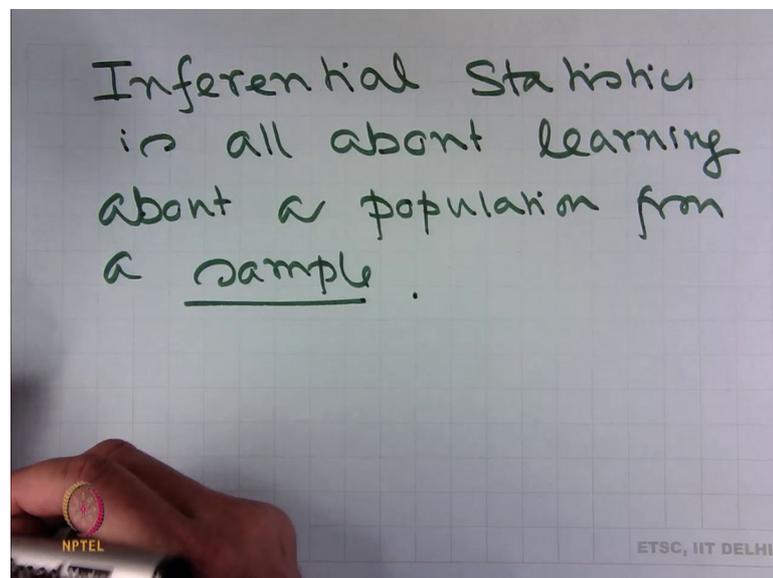
Statistical Inference
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Lecture – 02
Statistical Inference

Welcome students to the second lecture on the MOOC's series of lectures on Statistical Inference. In the first lecture, I have given a brief introduction to what statistics, or in particular statistical inference means to us, and also I have revised some very popular and commonly used probability distribution. Among them in discrete we had binomial for as so and geometric distribution, for continuous case we have used or we have learnt normal uniform exponential and gamma distribution.

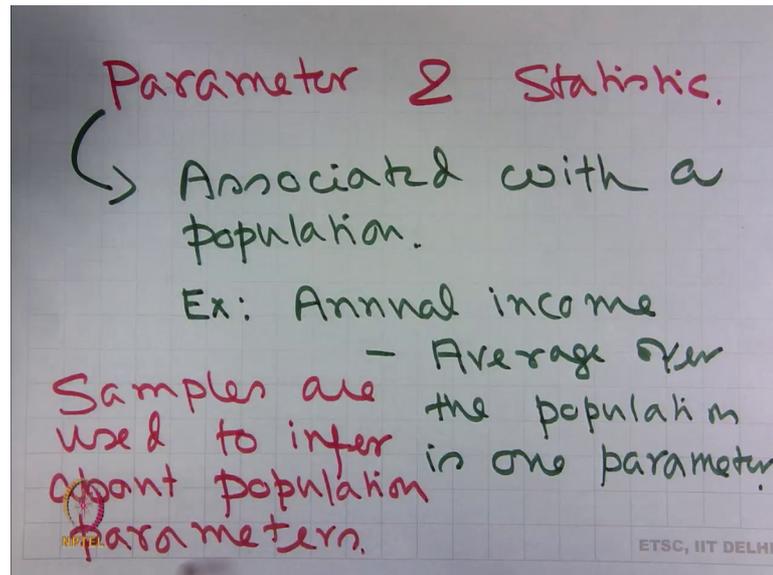
We will be using the main future. In today's term, I will give you some brief idea about sampling and sampling statistics.

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We know that the inferential statistics is all about learning about population from a sample. At this juncture I like to distinguish between 2 terms parameter and statistic; a parameter associated with a population.

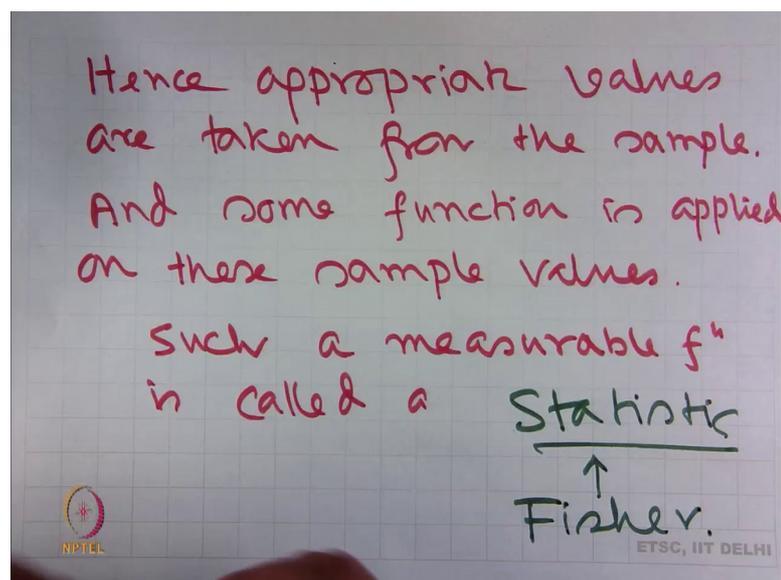
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So, this is property of the population we can say; for example, if you are considering the annual income, then it is average over the population is one parameter. That is population parameter that is fixed, but often this is unknown to us. And the whole purpose of inferential statistic is, to understand the population parameter on the basis of some sample.

So, samples are used to infer about population parameter.

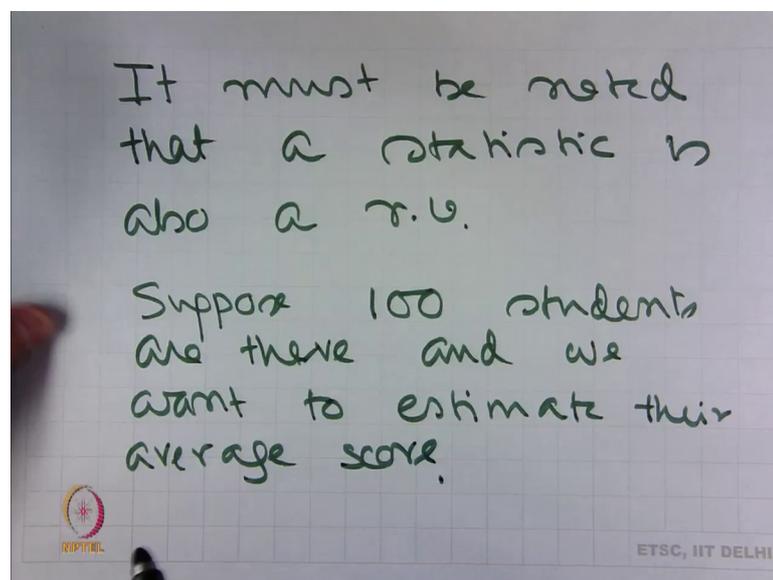
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You know that to do that appropriate values are taken from the sample and some function is applied on those sample values; such a measurable function is called a statistic. The name is given by Fisher. So, we have the population, we want to know about some of its parameters. We have taken sample from the population, we have measured certain values, and applied a function on that one in such a way that from that function value, we can get an idea about the population parameter.

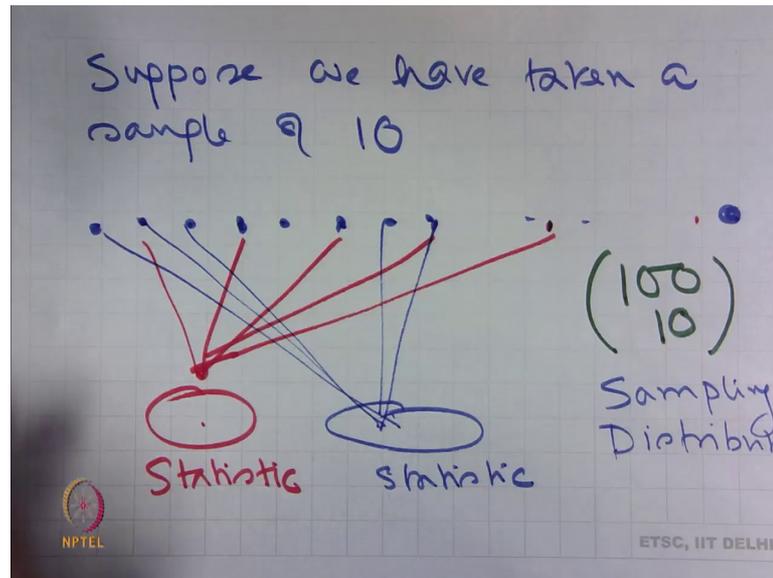
Such a function of the sample values is called a statistic, ok.

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It must be noted the statistic is also a random variable; for illustration suppose 100 students are there, and I want to know the average score of the students in statistics, o, what we do?

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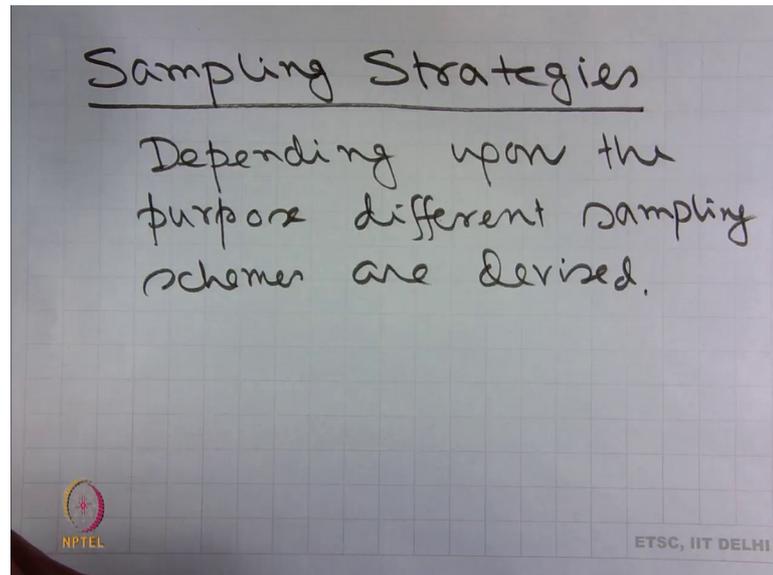


Suppose we have taken a sample of 10. So, suppose this is the entire population. And we have taken tens samples out of it, and suppose like that 10 samples are taken, and suppose I compute the statistic, why this is random variable because if I do the repeat the same experiment, it is not mandatory that I will be selecting the same state of samples.

Now, I will be selecting may be some different samples, and therefore, I compute it is corresponding statistic. It is clear that if there are 100 students, and I take 10 out of it, then I can get 100 see 10 so many difference sample. Each one of them we produce as statistics. This is the statistic that I am going to use to estimate the population parameter; however, these statistic is random as there can be as many as 100 see 10 so many different statistic. Therefore, it make sense to talk about the distribution of that statistic which is called sampling distribution.

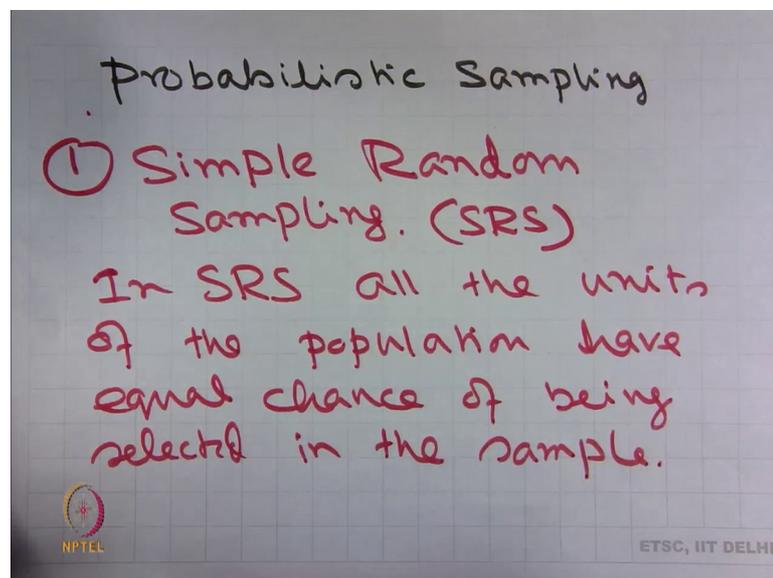
In today's lecture I will be talking about some sampling distributions which will be helpful in estimating population parameters.

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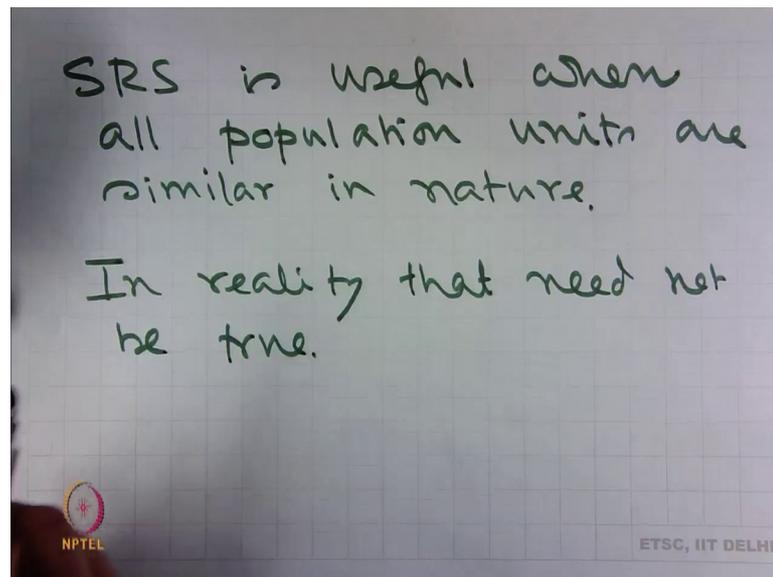
Before that sampling strategies depending upon the purpose different sampling schemes are devised. First of all, it can be probabilistic or non-probabilistic.

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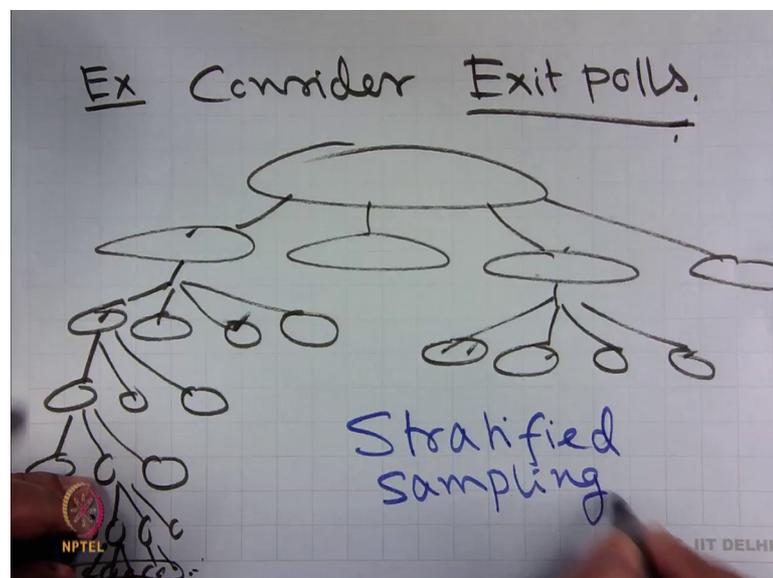
Let us focus on probabilistic sampling. The simplest form is simple random sampling. In simple random sampling, which we often write as SRS, all the units of the population have equal chance of being selected in the sample. It is sometimes difficult to design and time-consuming to execute, but it is very simple in understanding and it gives equal chance to all the members of the population.

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Simple random sampling is useful when all population members or all population units are similar in nature, but in reality that need not be true.

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For example, consider exit polls. There are so many voters in terms of millions of voters scattered all over the country in different states different district different blocks different polling booths. It is impossible to consider all of them with equal probability.

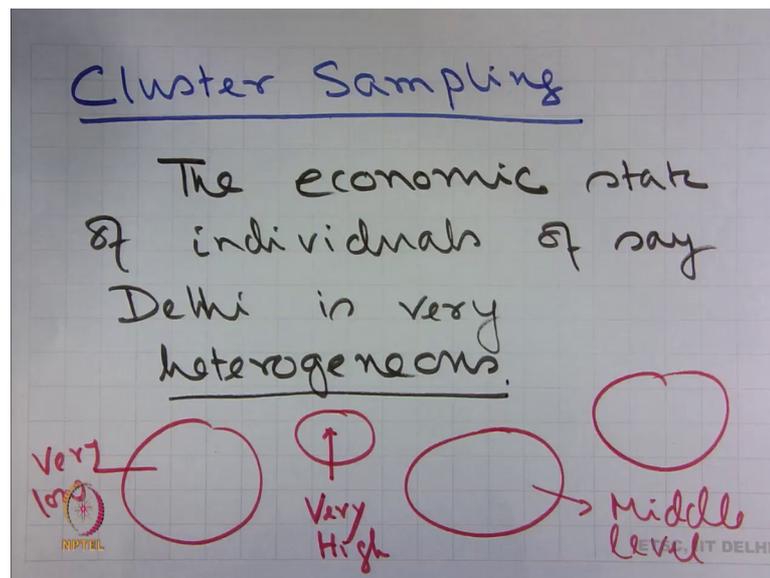
So, what can be done? If this is the country, we can break it into different states. You may choose some of the states randomly. Within those states they are may be many districts.

Again it is not possible to consider all the voters of one district. So, what is done suppose some of the district are chosen randomly. Then with in a district, there may be different sub division. Within the sub division there may be different blocks, within each block there may be several booths, within each booth there may be several voters.

We need to take the opinion of some of these voters to predict what is going to happen therefore, giving equal probability to all the members or to all the voting population of the countries impossible. So, what is done the population is divided into different stratum, right. At each level it is subdivided into lower order stratum like that until we reach to the very basic units, and from home the actual data has to be collected.

Such way of sampling is called stratified sampling.

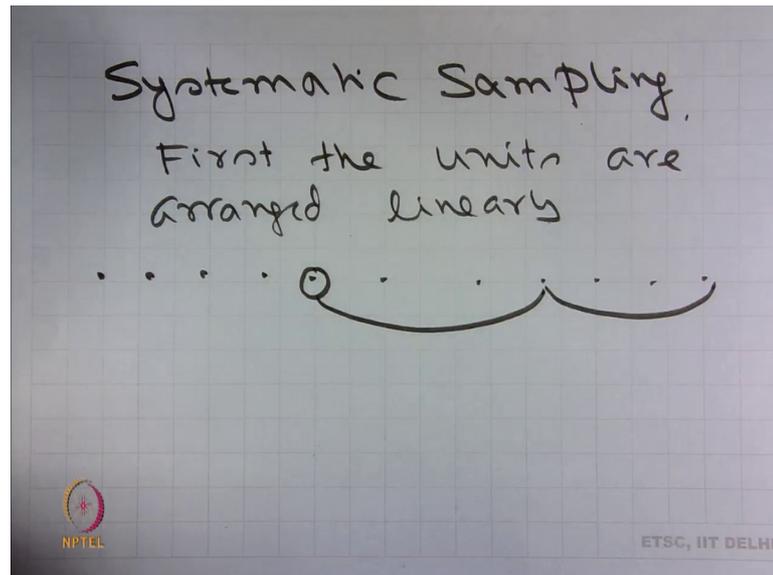
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Another way of sampling is called cluster sampling. For example, your making an economic survey on the population of Delhi. Delhi has huge population, but the problem here is all the elements of that population and not somewhat homogeneous in nature. In fact, they are highly heterogeneous, therefore, application of simple random sampling will lead to very erroneous result or a result with a huge variance because the outcome of the survey will be very different based upon the samples that you have chosen. Therefore, it is more meaningful to divide the entire population into different clusters such that the clusters are homogeneous in nature.

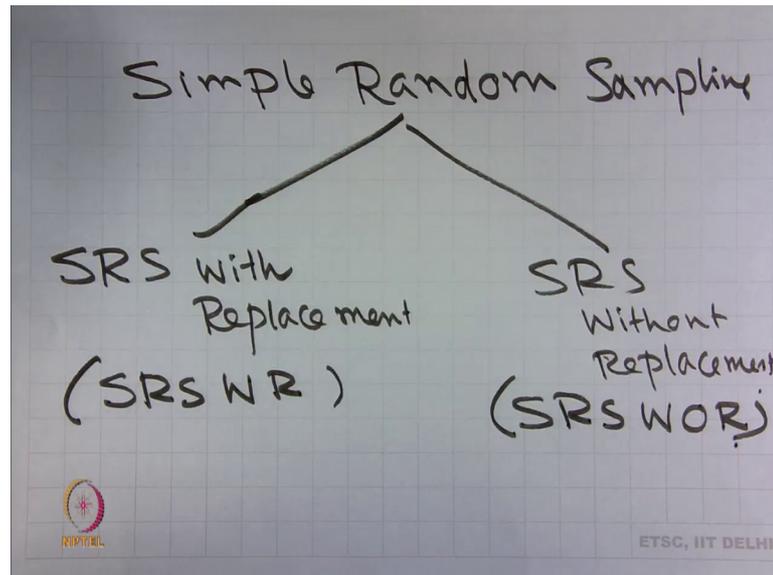
Say for example, this may be a cluster of people with very high income. This may be a cluster of very low income; this may be a cluster of say middle level income. Therefore, choosing the sample over the entire population randomly, first we divide it into some clusters which are more homogeneous. And then depending upon the size of cluster we can decide how many samples will be taken from each of the clusters.

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By sampling in such fashion is called cluster sampling similarly, there is something called systematic sampling; it is a mixture of strategies. So, first the units are arranged linearly say by sorting them according to their names. Then instead of applying simple random sampling over the entire population one of the, this starting point is randomly chosen over the entire population. After that the members are chosen according to some fixed interval. This is also very useful technique for sampling as it is much less time consuming and costly in comparison with a simple random sampling.

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So, in today's class we will be focusing on simple random sampling, which again can be subdivided into 2 ways simple random sampling, which replacement and simple random sampling without replacement. In short we call it SRSWR and this is called SRSW or what is the difference? The difference is as follows.

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$X_1 X_2 X_3 \dots X_N$
is the population.

we take a sample $x_1 \dots x_n$
 $n < N$

SRSWR: The sampled unit is put back into the population before taking the next sample.

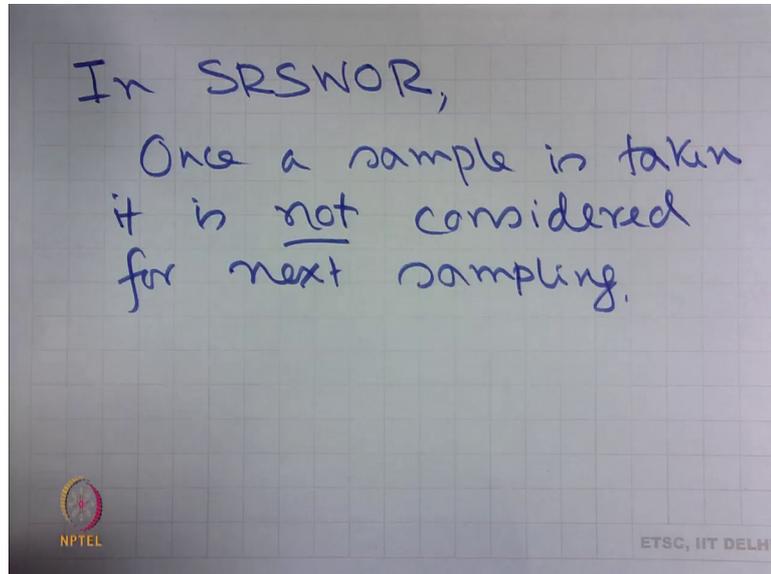
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Suppose, $X_1 X_2 X_3 \dots X_N$ is the population and we take a sample $X_1 X_2 \dots X_n$ where n is much less than N . If after taking one sample, we put it back again into the population,

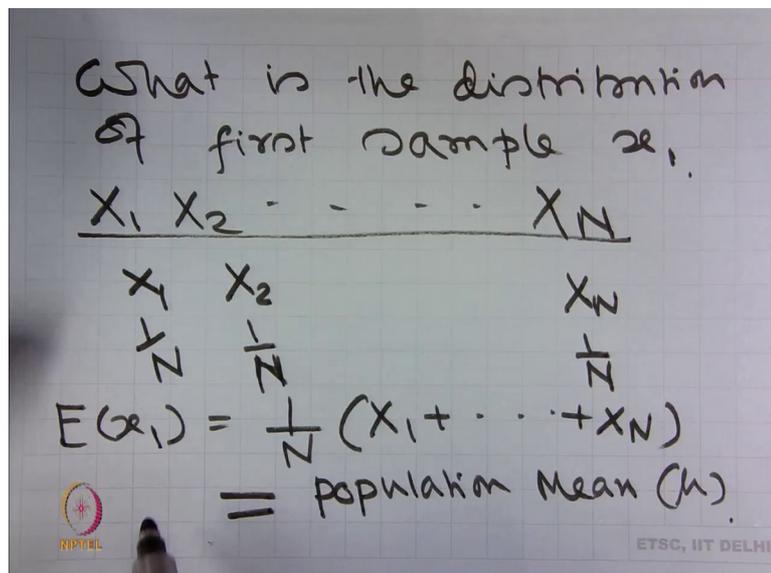
before choosing the next sample this is called simple random sampling with replacement, the sampled unit is put back into the population before taking the next sample.

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On the other hand,, in SRS WOR once sample is taken it is not considered for next sampling. Therefore, in SRSWOR one individual unit can be represented only once at the most in the sample. On the other hand, in SRSWR theoretically in all the N samples there is a possibility that you can choose only the same element small N number of times.

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Therefore, let us look at what is the distribution of the first sample. So, you have X_1, X_2, \dots, X_N as the population. X_1 is the very first sample taken out of it, and each one of them has equal probability. So, it can be X_1 with probability $1/N$. It can be X_2 with probability $1/N$ and it can be X_n with probability $1/N$. Therefore, what is the expected value of x_1 which is equal to the population mean; let us denote it by μ .

Therefore, the first sample has expected value equal to population mean. That is irrespective of whether it is with replacement or without replacement. Now let us look at X_2 under a SRSWR.

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Now let us look at x_2 .

SRSWR:

X_1	X_2	...	X_N
$\frac{1}{N}$	$\frac{1}{N}$...	$\frac{1}{N}$

$\therefore E(x_2) = \frac{1}{N} \sum_{i=1}^N x_i = \mu$.

So, if you are doing simple random sampling with replacement, then whichever element has been taken in the first sample or as the first unit of the sample, it is put back into the population again.

So, for SRSWR again I have all X_1, X_2, \dots, X_n , and they are all equally likely. So, all of them will have the same probability $1/N, 1/N, \dots, 1/N$. And therefore, expected value of X_2 is equal to again $1/N$ into $\sum_{i=1}^N x_i$ is equal to $1/N$ is equal to μ .

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SRSWOR
What is the probability
that $x_2 = X_k$ (fixed k)
 $P(x_2 = X_k)$
 $= \sum_{\substack{j=1 \\ j \neq k}}^N P(x_2 = X_k \mid x_1 = X_j) * (P(x_1 = X_j))$

But now things change with respect to SRSWOR. So, what will happen in this case? What is let us look at what is the probability that X_2 is equal to X_k fixed k , right. Say what is the probability that the second unit taken as a sample is actually the k th member of the population.

So, probability X_2 is equal to X_k is same as probability X_2 is equal to X_k given that the first sample is equal to X_j j not equal to k multiplied by probability X_1 is equal to X_j , right. And this we need to sum over, all j j is equal to 1 to N j not equal to k . Because it is without replacement, there for second sample can be X_k if the first sample is something different from X_k and given that that then the second sample is actually x_k and this has to be multiplied by what is the probability of first sample is X_j .

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For a particular j

$$P(x_2 = X_k \mid x_1 = X_j) = \frac{1}{N-1} \quad (\dots)$$

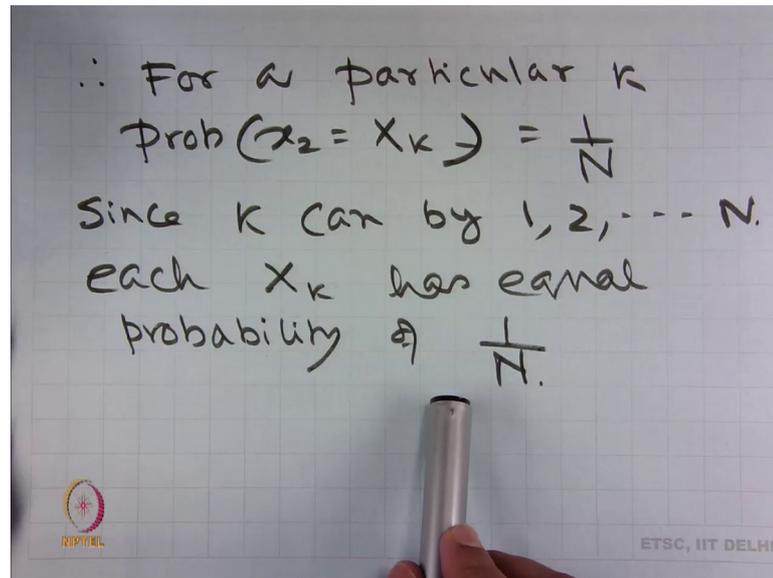
$$P(x_1 = X_j) = \frac{1}{N}$$

$$\therefore \sum_{\substack{j=1 \\ j \neq k}}^N \frac{1}{N-1} \times \frac{1}{N} = (N-1) \times \frac{1}{N(N-1)} = \frac{1}{N}$$

For a particular j probability X_2 is equal to X_k given X_1 is equal to X_j is equal to 1 upon N minus 1 because there are N many capital N many elements in the population. The j th one has been taken now there are N minus 1 element, out of this we are choosing one element with simple random sampling. And therefore, all the N minus 1 of them have the same probability therefore, it is 1 upon N minus 1 .

Now what is the probability x_1 is equal to X_j probability x_1 is equal to X_j is 1 upon N , right? Therefore, what we are getting 1 upon N minus 1 into 1 upon N , and this we are summing over j is equal to 1 to N j not equal to k . Therefore, actually we are summing it for N minus 1 times therefore, it is N minus 1 into 1 upon N into N minus one is equal to 1 upon N .

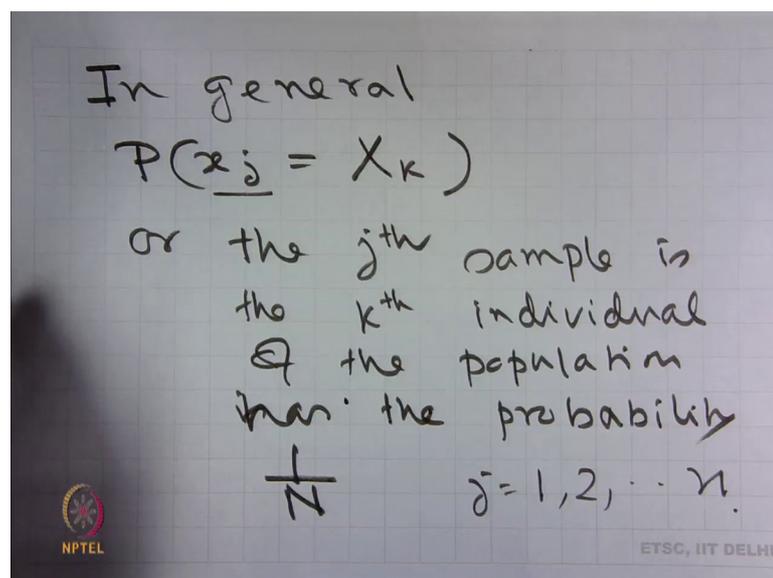
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If you remember we have selected a particular X_k , probability that X_2 is equal to X_k is equal to 1 upon N .

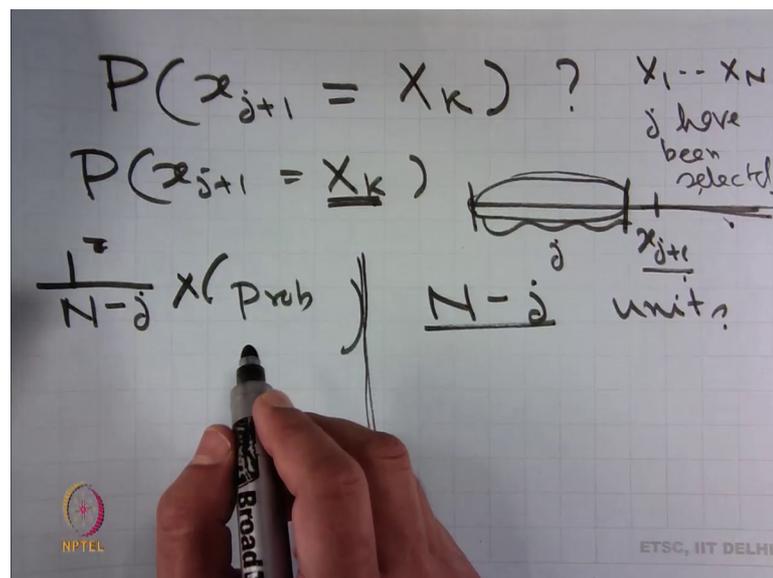
Since k can be anything between 1 to capital N , each X_k has equal probability of 1 upon N . Therefore, we see that whether we have chosen it with replacement or without replacement it does not matter, thus second unit that is being chosen also has equal probability of getting one of the capital N many units as the second selection.

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In general, probability X_j is equal to X_k or the j th sample is the k th individual of the population is has the probability 1 by N ; that is, each one of the original population members will have equal chance of getting selected in the sample at the j th instance for j is equal to 1 2 up to N . Because we are choosing N samples from the population. This can be shown in the following way, what is the probability that the j plus 1 it is selection is equal to the k th member of the population?

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So, this we can calculate in the following way probability x_{j+1} is equal to X_k is equal to; consider the following first j samples have been chosen, and I am looking at the j plus 1 at sample. In the first j samples out of $X_1 X_2 X_N$, j have been selected, since j of them have been selected, how many are left? You are left with N minus j units, right?

So, in the j plus 1 th instance, I am choosing a particular element x_k . First of all, X_k has to be here, it has not been chosen yet in the already selected j many samples. And now I am going to choose X_k as the j plus 1 th unit in the sample. So, that is of equal probability therefore, probability of selecting X_k as that one is 1 upon N minus j , multiplied by the probability that it has not been chosen at all right so, we do it in the following way.

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The image shows a handwritten derivation on a grid background. The equations are as follows:

$$x_1 = \frac{N-1}{N} \quad (x_1 \neq X_k)$$
$$x_2 = \frac{N-2}{N-1}$$
$$x_3 = \frac{N-3}{N-2}$$
$$\vdots$$
$$x_j = \frac{N-j}{N-j+1}$$

To the right of the last equation, there is a small correction: $\frac{N-j}{N-j+1}$ with a superscript $j-1$ above the numerator, indicating the correct probability for the j-th step.

Logos for RUPAAL and ETSC, IIT DELHI are visible at the bottom of the grid.

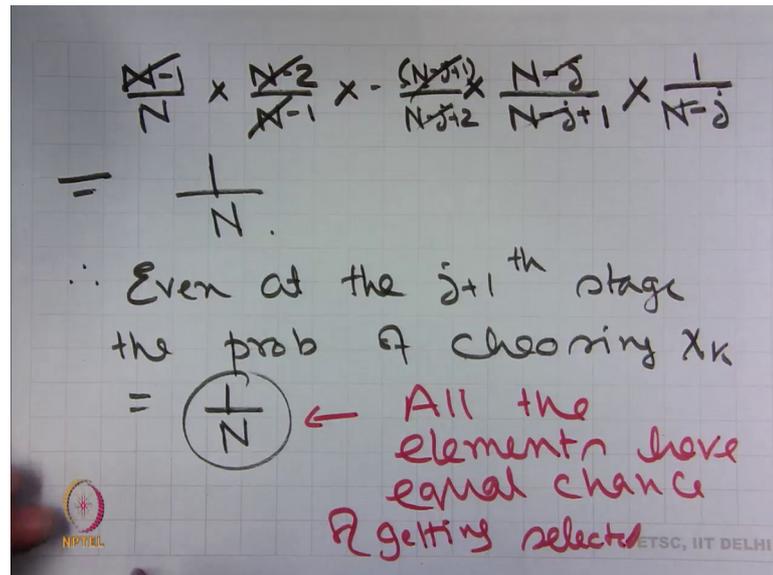
So, in the first instance, we can choose something other than the X_k that has the probability N minus 1 upon N . Because out of N one of them is X_k and so, that we cannot select at the first instance I can select any of the remaining N minus 1 of them. In the second instance therefore, what I will choose? I will choose one from among the remaining N minus 1, but not k and that probabilities N minus 2 upon N minus 1.

Similarly, x_3 will have the probability N minus 3 upon N minus 2. And when I am selecting the x_j I have already selected j minus 1. So, how many are left? The number of elements left is N minus j plus 1, out of that I will be choosing one of them except X_k . So, I have the selections possibility of N minus j of them out of N minus j plus 1. Therefore, what we are getting is that we have not chosen X_k till the j th sample that probability is N minus 1 upon N multiplied by N minus 2 upon N minus 1 multiplied by up to N minus j upon N minus j plus 1.

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$$\frac{N-1}{N} \times \frac{N-2}{N-1} \times \dots \times \frac{(N-j+1)}{N-j+2} \times \frac{N-j}{N-j+1} \times \frac{1}{N-j}$$
$$= \frac{1}{N}$$

\therefore Even at the $j+1^{\text{th}}$ stage
the prob of choosing x_k
 $= \frac{1}{N}$ ← All the elements have equal chance of getting selected



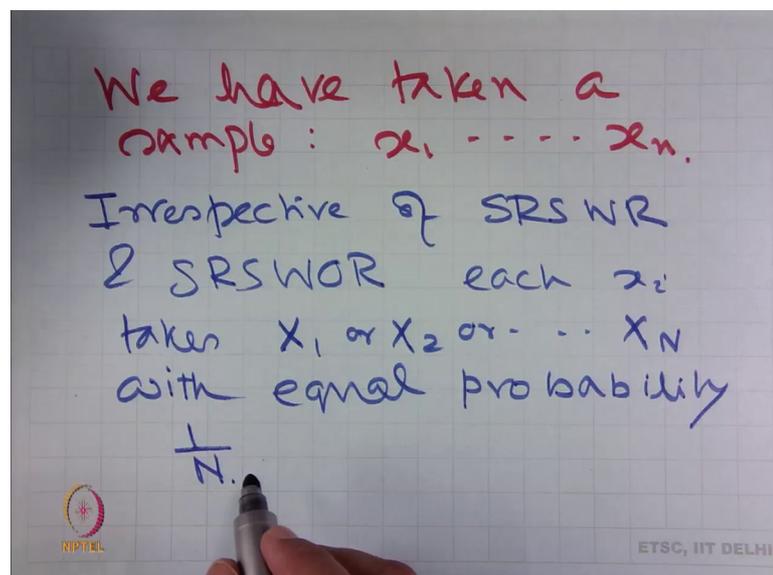
So, this one has to be N minus j plus 1 upon N minus j plus 2, multiplied by now that out of that N minus j element I am choosing x_k that probabilities 1 upon N minus j . So, what we are getting? These terms cancel each other, and what we are left with is 1 upon N . Therefore, even at the j plus 1 th stage, the probability of choosing x_k is equal to 1 upon N .

Therefore, it suggests that all the elements have equal chance of getting selected. In all the 1 2 3 or N th selection, what is the effect of it?

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We have taken a sample: x_1, \dots, x_n .

Irrespective of SRSWR & SRSWOR each x_i taken x_1 or x_2 or \dots or x_N with equal probability $\frac{1}{N}$.



The effect of is the following so, we have taken a sample irrespective of SRS or and SRSWOR, each x_i takes X_1 or X_2 or X_N with equal probability 1 upon N .

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$$\therefore E(x_i) = \frac{X_1 + X_2 + \dots + X_N}{N}$$

= population Mean
= μ

\therefore What is Expected value of Sample mean!

$$\frac{x_1 + x_2 + \dots + x_n}{n}$$

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Therefore, expected value of x_i is equal to X_1 plus X_2 plus X_N upon N ; is equal to population mean is equal to μ . And this is irrespective of SRSWR or SRSWOR.

Therefore, what is the expected value of sample mean; which is X_1 plus X_2 plus X_N upon N . We know that from the theory of expectation that expectation of sum is equal to sum of expectation.

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$$\therefore E(\bar{x}) = \frac{E(x_1) + E(x_2) + \dots + E(x_n)}{n}$$

Sample Mean

$$= \frac{\mu + \mu + \dots + \mu}{n}$$

$$= \mu$$

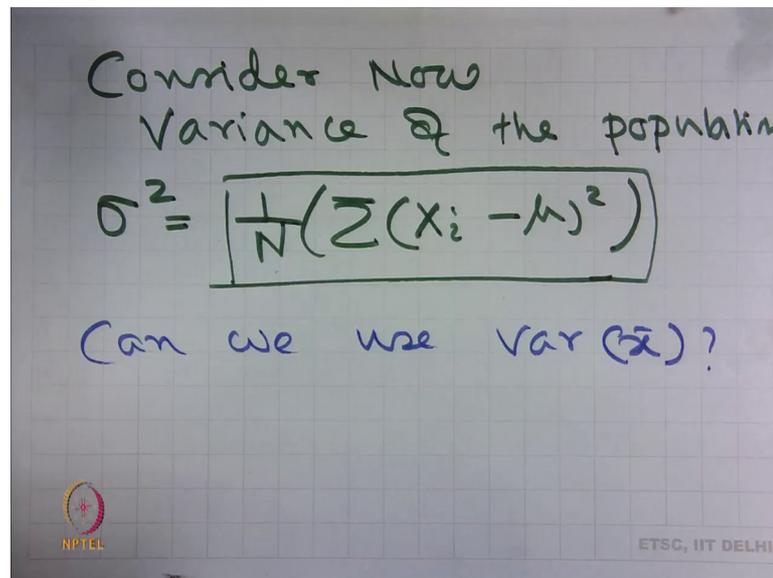
$\therefore E(\text{sample Mean}) = \text{population Mean.}$

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Therefore, expected value of \bar{x} which is the sample mean, as I already said that this is a random variable is equal to expected value of X_1 plus expected value of X_2 plus expected value of X_n divided by N is equal to μ plus μ plus μ .

Therefore, expected value of sample mean is equal to population mean. Thus we can see that sample mean can be used to estimate the population mean. Let us now consider variance of the population.

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The variance of the population is σ^2 is equal to $\frac{1}{N} \sum (X_i - \mu)^2$. Suppose you want to estimate the population variance; can we use variance of \bar{x} for that purpose? Let us see. So, question is what is the variance of \bar{x} , as \bar{x} is a random variable itself this makes sense.

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What is the variance of \bar{x} .

$$\begin{aligned} \text{Var}(\bar{x}) &= E(\bar{x} - E(\bar{x}))^2 \\ &= E\left(\frac{x_1 + x_2 + \dots + x_n}{n} - \frac{E(x_1) + E(x_2) + \dots + E(x_n)}{n}\right)^2 \\ &= \frac{1}{n^2} E\left(x_1 + x_2 + \dots + x_n - E(x_1) - E(x_2) - \dots - E(x_n)\right)^2 \end{aligned}$$

Now, variance of \bar{x} is equal to expected value of \bar{x} minus expected value of \bar{x} whole square is equal to expected value of x_1 plus x_2 plus x_n by n minus expected value of x_1 plus expected value of x_2 . Now 1 by n we can take out as common. So, it is 1 by n square into expected value of x_1 plus x_2 plus x_n minus expected value of x_1 minus expected value of x_2 minus expected value of x_n whole square.

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$$\begin{aligned} &= \frac{1}{n^2} E\left(\frac{(x_1 - E(x_1))}{n} + \frac{(x_2 - E(x_2))}{n} + \dots + \frac{(x_n - E(x_n))}{n}\right)^2 \\ &= \frac{1}{n^2} E\left(\sum_{i=1}^n (x_i - E(x_i))^2 + E\left(\sum_i \sum_{j \neq i} (x_i - E(x_i))(x_j - E(x_j))\right)\right) \end{aligned}$$

We rewrite it as expected value of x_1 minus expected e of x_1 , plus x_2 minus e of x_2 plus x_n minus e of x_n whole square. So, it is n terms and their square it is expectation.

This N terms square can be written as so, e square plus these square plus these square up to X_n minus $E(x_n)$ whole square. So, this we can write it as x_i minus expected value of x_i whole square i is equal to 1 to n . Plus, expected value of σ^2 over i σ^2 over j , j not equal to i x_i minus expected value of x_i multiplied by x_j minus expected value of x_j .

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$$\begin{aligned}
 & E(x_i - E(x_i))^2 \\
 &= E(x_i - \mu)^2 \\
 &= \frac{(x_1 - \mu)^2 + \dots + (x_N - \mu)^2}{N} \\
 &= \frac{\sum (x_i - \mu)^2}{N} \\
 &= \sigma^2
 \end{aligned}$$

The image shows a handwritten derivation on a grid background. It starts with $E(x_i - E(x_i))^2$, which is simplified to $E(x_i - \mu)^2$. This is then expanded as a sum of squares: $(x_1 - \mu)^2 + \dots + (x_N - \mu)^2$. This sum is divided by N to get $\frac{\sum (x_i - \mu)^2}{N}$, which is finally equated to σ^2 . In the bottom left corner, there is a logo for NPTEL, and in the bottom right corner, it says 'ETSC, IIT DELHI'.

Now, expected value of x_i minus expected value of x_i whole square is equal to expected value of x_i minus μ whole square; is equal to X_1 minus μ whole square plus X_n minus μ whole square divided by N , is equal to σ^2 . This is nothing but the population variance which is σ^2 .

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$$\begin{aligned} & \therefore \frac{1}{n^2} \sum_i E(x_i - E(x_i))^2 \\ &= \frac{\sum_i \sigma^2}{n^2} = \frac{n\sigma^2}{n^2} \\ &= \frac{\sigma^2}{n} \end{aligned}$$

Therefore $\frac{1}{N^2}$ into sigma over i expected value of x_i minus expected value of x_i whole square is equal to summation over i sigma square divided by n^2 ; is equal to n sigma square upon n^2 is equal to sigma square by n .

So, that is the first part of the expansion.

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$$\begin{aligned} & \frac{1}{n^2} E\left(\sum_i \sum_{j \neq i} (x_i - E(x_i))(x_j - E(x_j))\right) \\ &= \frac{1}{n^2} \sum_i \sum_{j \neq i} E((x_i - E(x_i))(x_j - E(x_j))) \\ &= \frac{1}{n^2} \left[\sum_i \sum_{j \neq i} \text{COV}(x_i, x_j) \right] \\ & \text{Var}(\bar{x}) = \frac{\sigma^2}{n} = 0 \text{ if SRS WR} \end{aligned}$$

The second part is $\frac{1}{n^2}$ into expectation of sigma over i sigma over j not equal to i x_i minus expected value of x_i into x_j minus expected value of x_j is equal to $\frac{1}{n^2}$ sigma over i sigma over j not equal to i , expected value of x_i minus expected

value of x_i is equal to $1/n$ upon $n^2 \sigma^2$. So, this is giving us $1/n^2$ into summation over $x_i x_j$, covariance of $x_i x_j$ for all possible pairs $i \neq j$.

Now, if it is a simple random sampling with replacement, then we can see that x_i and x_j they behave in the same way. In fact, they are independent of each other. Therefore, if we are considering simple random sampling with replacement, then each of the covariance term will become 0. Therefore, we are left with variance of \bar{x} is equal to σ^2/n if simple random sampling with replacement.

But when we are using simple random sampling without replacement, this covariance will not be 0. Because what is we are getting in the j th term will depend upon what will what we have got at the i th time. And therefore, this will have some contribution therefore, the variance of \bar{x} will not be σ^2/n rather it has to be adjusted by a quantity. In the next class I will start with this point and then I will go further with sampling distribution.

Thank you so much.