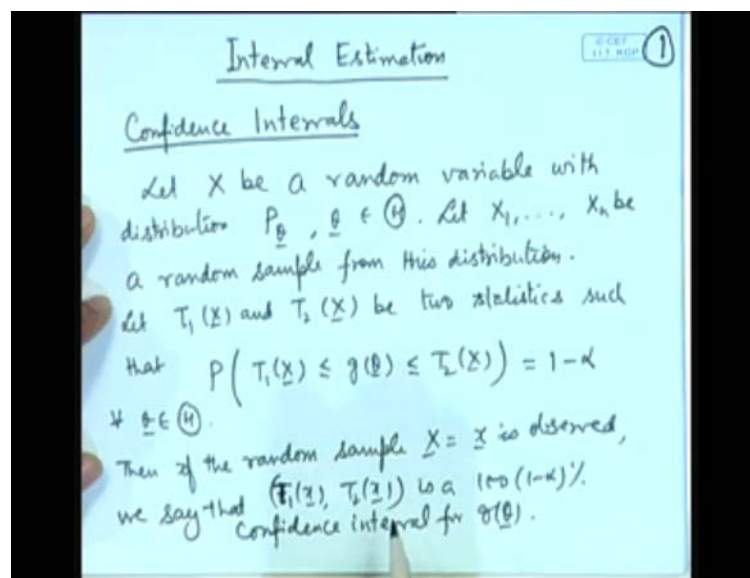


**Probability and Statistics**  
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**Module No. #01**  
**Lecture No. #31**  
**Estimation-V**

We will consider confidence interval estimation. Till now, we have concentrated on the point estimation of a given parameter. So, in the point estimation we propose one value for the parameter to be estimated. For example, if we are estimating say average income levels of persons of a particular state. So, we give a value say, we say the value is 2000 Rupees per month. So, we are assigning a single value, but the problem with the point estimation is that, that value is not necessarily the actual value because we do not know the true value. A more practical approach could be to give an interval of the values, rather than saying it is 2000 rupees per month, we may say the value is say 1900 rupees per month to 21 rupees, 2100 rupees per month. So now, since we are basing our decision on a random sample therefore, a certain probability is associated with this statement. This is known as confidence level. So, formally speaking, we define a confidence interval as follows.

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Interval Estimation

Confidence Intervals

Let  $X$  be a random variable with distribution  $P_{\theta}$ ,  $\theta \in \Theta$ . Let  $X_1, \dots, X_n$  be a random sample from this distribution.

Let  $T_1(X)$  and  $T_2(X)$  be two statistics such that  $P(T_1(X) \leq g(\theta) \leq T_2(X)) = 1 - \alpha$   $\forall \theta \in \Theta$ .

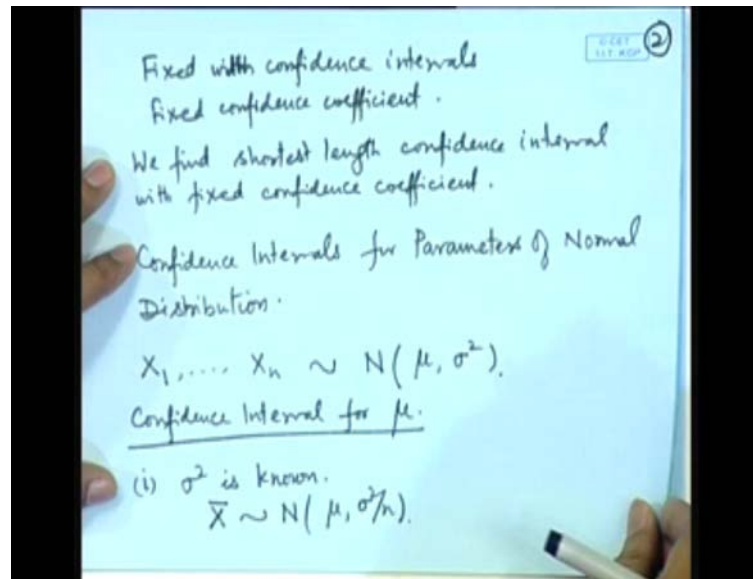
Then if the random sample  $X = x$  is observed, we say that  $(T_1(x), T_2(x))$  is a  $100(1-\alpha)\%$  confidence interval for  $g(\theta)$ .

So, we are discussing interval estimation and as I mentioned that, since a probability statement is associated with that, we consider confidence intervals. So, let  $X$  be a random variable with distribution, say  $P_\theta$ ,  $\theta$  belonging to  $\mathcal{T}$ . So, let  $X_1, X_2, \dots, X_n$  be a random sample from this distribution. So, let say  $T_1(X)$  and  $T_2(X)$  be two statistics, such that probability that  $T_1(X)$  is less than or equal to, say  $g_\theta$ , less than or equal to  $T_2(X)$  is equal to  $1 - \alpha$  for all  $\theta$ . Then, if the random sample  $X$  is equal to  $x$  is observed, we say that  $T_1(x)$  to  $T_2(x)$  is a  $100(1 - \alpha)$  percent confidence interval for  $g_\theta$ .

So, what is the interpretation of this, that if we take 100 samples and we calculate the value  $T_1(x)$  and  $T_2(x)$ , then this interval is likely to include the  $g_\theta$  value, 95 percent of the times. So, this is the meaning of the confidence interval because the probability of this statement that  $T_1(x) \leq g_\theta \leq T_2(x)$  is  $1 - \alpha$ . Therefore,  $100(1 - \alpha)$  percent of the times, the interval  $T_1(x)$  to  $T_2(x)$  will include the true parameter value  $g_\theta$ .

So, now from here we understand that, if I take  $\alpha$  to be a small value, say I take  $\alpha$  is equal to 0.1; that means,  $1 - \alpha$  is 0.99. So that means, we will have 99 percent confidence interval. So, the smaller  $\alpha$  value the larger is the confidence level. Now, how to find out the confidence intervals? What you will call to be a desirable confidence interval? Naturally, if we have higher confidence level then, it is good because we can say that, this is likely to include the true value. However, there is a certain contradiction here, because if we increase the probability, then naturally the size of the interval will also increase. So, there is a conflicting goal that either we increase the length of the interval, either we increase the length of the coefficient that is magnitude of a coefficient or we decrease the length of the interval.

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So, we have a theory of fixed width, fixed width confidence intervals or fixed confidence coefficient. That means, we find shortest length confidence interval with fixed confidence coefficient. This theory is closely related with the theory of finding out best tests of hypothesis. So, we will not get into that right now. So, what is required here is that by given parameter we should be able to find out two statistics such that, this probability is independent of the parameter, because this is fixed value  $1 - \alpha$ . It is nondependent upon  $\theta$ . That means, we should be able to consider certain quantity where  $\theta$  is involved and I am able to write down the distribution of that which is free from the parameters. So, a well known technique here is called the pivoting technique and we make use of the well known sampling distributions, that we have done. So, let us consider confidence intervals for parameters of normal distribution.

So, we have the following setup that I have a random sample  $X_1, X_2, \dots, X_n$  from a normal population with mean  $\mu$  and variance say  $\sigma^2$ . So, here the parameters are mean and variance and we are interested in the confidence intervals for mean and variance. So, let us consider say confidence interval for  $\mu$ , that is the mean. Now, there can be two cases. One case is that  $\sigma^2$  is known. Now, here we make use of the sampling distributions of  $\bar{X}$  and  $S^2$ . So, when we are considering  $\mu$ , let us consider  $\bar{X}$ . We know that the distribution of  $\bar{X}$  is normal with mean  $\mu$  and variance  $\sigma^2/n$ .

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$$Z = \frac{\sqrt{n}(\bar{X} - \mu)}{\sigma} \sim N(0, 1)$$

$$P(-z_{\alpha/2} \leq Z \leq z_{\alpha/2}) = 1 - \alpha$$

$$\Leftrightarrow P\left(-z_{\alpha/2} \leq \frac{\sqrt{n}(\bar{X} - \mu)}{\sigma} \leq z_{\alpha/2}\right) = 1 - \alpha$$

$$\Rightarrow P\left(-\frac{\sigma}{\sqrt{n}} z_{\alpha/2} \leq \bar{X} - \mu \leq \frac{\sigma}{\sqrt{n}} z_{\alpha/2}\right) = 1 - \alpha$$

$$\Leftrightarrow P\left(\bar{X} - \frac{\sigma}{\sqrt{n}} z_{\alpha/2} \leq \mu \leq \bar{X} + \frac{\sigma}{\sqrt{n}} z_{\alpha/2}\right) = 1 - \alpha$$
 So  $\left(\bar{X} - \frac{\sigma}{\sqrt{n}} z_{\alpha/2}, \bar{X} + \frac{\sigma}{\sqrt{n}} z_{\alpha/2}\right)$  is a  $100(1 - \alpha)\%$  confidence interval for  $\mu$ .

So, from here we can construct  $Z$  is equal to  $\bar{X}$  minus  $\mu$  divided by  $\sigma$  by root  $n$ . So, this will have normal  $0, 1$  distribution. Now, you see this is an important statement because here, I have been able to create a function of random variables and the parameter for which I need the confidence interval such that the distribution of this quantity is free from the parameters. So, now if we make use of the normal distribution's probability points. So, if this is the pdf of a standard normal distribution then, let us consider the point  $z_{\alpha/2}$  and  $-z_{\alpha/2}$ , that is, this probability is  $\alpha/2$ , this probability is  $\alpha/2$ . Then, I can write down the statement probability,  $-z_{\alpha/2} \leq Z \leq z_{\alpha/2}$  is equal to  $1 - \alpha$ , that is, the probability of this random variable lying between this range is  $1 - \alpha$ . We are showing  $\phi(z)$ , here this is  $z$ .

Let us write down this statement elaborately. So, this statement is equivalent to probability of  $-z_{\alpha/2} \leq \frac{\sqrt{n}(\bar{X} - \mu)}{\sigma} \leq z_{\alpha/2}$  is equal to  $1 - \alpha$ . We adjust this term, we multiply by  $\sigma$  by root  $n$  on both sides. So, we get  $-\sigma \sqrt{n} z_{\alpha/2} \leq \bar{X} - \mu \leq \sigma \sqrt{n} z_{\alpha/2}$  that is equal to  $1 - \alpha$ . Now, this is equivalent to, now, if you look at this one this is equivalent to that  $\mu$  is greater than or equal to  $\bar{X} - \sigma \sqrt{n} z_{\alpha/2}$  and if I take this side then, it is equivalent to  $\mu$  is less than or equal to  $\bar{X} + \sigma \sqrt{n} z_{\alpha/2}$ .



value and the length of the confidence interval will shrink. That means, accuracy will be more. For example, suppose here  $n$  is equal to say 25, then this value will become 2 plus minus 1 by 5 1.96. So, the value is actually 0.392. So, that is equal to 1.806 to 2.392. So, you can see that the interval is sharper and therefore, you have more confidence in a smaller interval rather than a large interval and this will give you more precise information.

You can see another thing, suppose I have alpha is equal to 0.1 or suppose I have alpha is equal to 0.01, then you can see that if I have alpha is equal to 0.1, that means, I need only 90 percent confidence here. That is 1 minus alpha will become 0.9. Naturally, the interval will become smaller, if I have alpha is equal to 0.01, that means, it is a 95 percent confidence interval. So, the interval length will become more. So, depending upon your compromise situation that, how much confidence you need for the parameter, you can appropriately adjust your interval.

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(ii)  $\sigma$  is unknown

$$S^2 = \frac{1}{n} \sum (X_i - \bar{X})^2$$

$$\bar{X} \sim N(\mu, \sigma^2/n) \Rightarrow \frac{\sqrt{n}(\bar{X} - \mu)}{\sigma} \sim N(0, 1)$$

$$\frac{(n-1)S^2}{\sigma^2} \sim \chi^2_{n-1}$$

$\bar{X}$  and  $S^2$  are independently distributed.

$$\frac{\frac{\sqrt{n}(\bar{X} - \mu)/\sigma}{\sqrt{(n-1)S^2/\sigma^2}}}{\sqrt{(n-1)S^2/\sigma^2}} \sim t_{n-1}$$

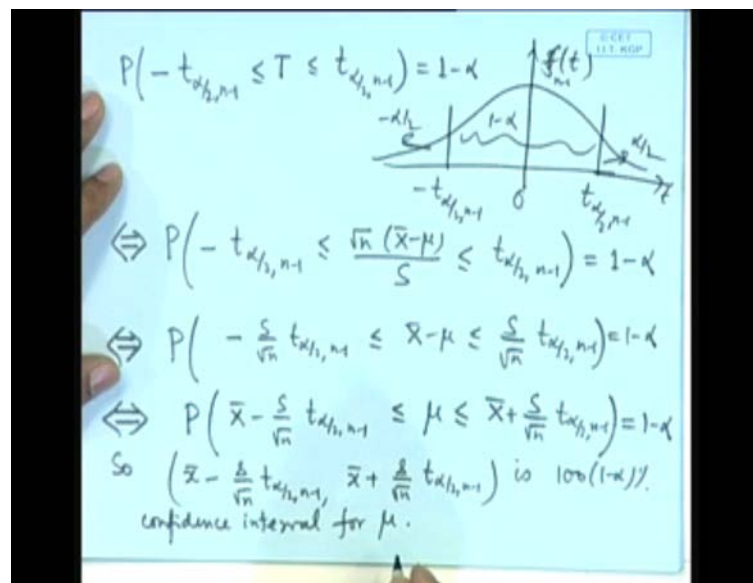
$$\Rightarrow \frac{\sqrt{n}(\bar{X} - \mu)}{S} \sim t_{n-1}$$

Now, let us take another case here. Because, in general sigma may be unknown. Then, naturally you can see here that this confidence interval cannot be utilized because this requires a knowledge of sigma. So, here we make use of the sampling distribution of  $S$  also. So, we have  $\bar{X}$  follows normal  $\mu$  sigma square by  $n$ . Then, if we consider  $n$  minus 1  $S$  square by sigma square where  $S$  square was defined as 1 by  $n$  minus 1 sigma  $X_i$  minus  $\bar{X}$  whole square, that is the sample variance. Then, this follows chi square distribution on  $n$  minus 1 degrees of freedom. We also know that,  $\bar{X}$  and  $S$  square are

independently distributed. This we had done in the theory of sampling distributions. So, if I have a normal variable, I can convert it to standard normal that is  $\sqrt{n}(\bar{X} - \mu) / \sigma$ . This follows normal 0 1. So,  $\sqrt{n}(\bar{X} - \mu) / \sigma$  divided by  $\sqrt{n-1} S$  follows t distribution on  $n-1$  degrees of freedom.

So, after adjustment of this coefficients, we can see that this is equivalent to  $\sqrt{n}(\bar{X} - \mu) / S$ . This follows t distribution on  $n-1$  degrees of freedom. Once again, you observe this statement. This involves the random observables, the parameter for which I need the confidence interval that is  $\mu$  and the distribution of this function of observation and the parameter is a distribution which is known. That means, it does not depend upon the unknown parameters  $\mu$  and  $\sigma^2$ . Therefore, once again we can make use of, let me call this quantity as  $T$ .

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Then, the distribution of  $T$ , as we know it is symmetric about the origin. So, if we have  $t_{\alpha/2, n-1}$  and  $-t_{\alpha/2, n-1}$ . This is the density of a  $t$  variable on  $n-1$  degrees of freedom. Then, this probability is  $\alpha/2$ , this probability is  $\alpha/2$ . So, this in term region probability is  $1 - \alpha$ . So, we can write down the statement probability  $-t_{\alpha/2, n-1} \leq T \leq t_{\alpha/2, n-1}$  is equal to  $1 - \alpha$ . So, from manipulating this statement, we will be able to derive the confidence intervals for  $\mu$ . So, let us see this. This is equivalent to probability of  $-t_{\alpha/2, n-1} \leq T \leq t_{\alpha/2, n-1}$  is equal to  $1 - \alpha$ .



root n  $\bar{X}$  minus  $\mu$  by  $S$  less than or equal to  $t_{\alpha/2, n-1}$ . So, this probability is equal to  $1 - \alpha$ .

So, once again if we multiply by  $S$  by root  $n$ , we get minus  $S$  by root  $n$   $t_{\alpha/2, n-1}$  less than or equal to  $\bar{X}$  minus  $\mu$  less than or equal to  $S$  by root  $n$   $t_{\alpha/2, n-1}$ , that is equal to  $1 - \alpha$ . So, once again after simplification, this condition is equivalent to  $\mu$  is greater than or equal to  $\bar{X}$  minus  $S$  by root  $n$   $t_{\alpha/2, n-1}$  and  $\mu$  is greater than or equal to  $\bar{X}$  plus  $S$  by root  $n$   $t_{\alpha/2, n-1}$ . So,  $\bar{X}$  minus  $S$  by root  $n$   $t_{\alpha/2, n-1}$  less than or equal to  $\mu$  less than or equal to  $\bar{X}$  plus  $S$  by root  $n$   $t_{\alpha/2, n-1}$ . So, this probability is equal to  $1 - \alpha$ . So,  $\bar{X}$  minus  $S$  by root  $n$   $t_{\alpha/2, n-1}$  to  $\bar{X}$  plus  $S$  by root  $n$   $t_{\alpha/2, n-1}$ . This is a  $100(1 - \alpha)$  percent confidence interval for  $\mu$ . So, how to obtain the confidence interval in a practical situation, we observe the sample, we calculate the mean and the sample variance and then, we look at the confidence level that we want. Suppose  $\alpha$  is equal to 0.1 then, we look at  $t$  at 0.05. Now, suppose there are 10 observations, then we look at  $t_{0.05, 9}$  from the tables of the  $t$  distribution and evaluate this value. So, that will be a 90 percent confidence interval for the parameter  $\mu$ . Let me give one example here.

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Example: 10 bearings made from a certain process have a mean diameter 0.0506 cm and a s.d. 0.004 cm. Assuming that the data may be looked upon as a random sample from a normal population, construct a 95% confidence interval for the actual average diameter of bearings made by this process.

$$X_1, \dots, X_{10} \sim N(\mu, \sigma^2)$$

$$t_{0.025, 9} = 2.262$$

$$\bar{x} \pm \frac{s}{\sqrt{n}} t_{0.025, 9} \equiv 0.0506 \pm \frac{0.004}{\sqrt{10}} \times 2.262$$

$$\equiv 0.0506 \pm 0.0028612$$

$$= (0.0477, 0.0535) \rightarrow 95\% \text{ confidence interval for } \mu.$$

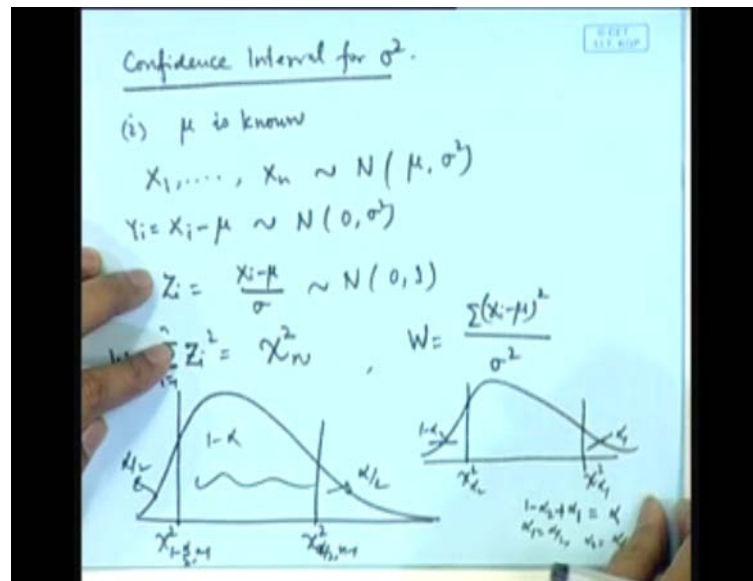
So, 10 bearings made from a certain process have a mean diameter 0.0506 centimeter and a standard deviation 0.004 centimeter. That means, a sample has been collected on 10 bearings and its mean that is  $\bar{X}$  has been calculated and the standard deviation, that



means, S has been calculated and n is 10 here. Assuming that the data may be looked upon as a random sample from a normal population, construct a 95 percent confidence interval for the actual average diameter of bearings made by this process. So, if we are considering  $X_1, X_2, \dots, X_{10}$  as the 10 observations on this bearings, so that means, these are denoting the diameters. Then, this is following normal  $\mu$  sigma square.

So, this actual average diameter is  $\mu$  here. Now, we do not know the values of  $\mu$  and sigma square. So, from the sample  $\bar{X}$  has been calculated and S has been calculated here, n is equal to 10 here. So, if we want a 95 percent confidence interval, that means, we need the value of  $t_{0.025, n-1}$ , that is 9. So, this value from the tables of t distribution can be found and that is 2.262. So, we calculate here  $\bar{X} \pm S$  by root n  $t_{0.025, 9}$ , that is this value is 0.0506 plus minus 0.004 divided by root 10 into 2.262, which is equivalent to 0.0506 plus minus 0.0028612. So, if we evaluate the lower and upper limits, it is 0.0477 and 0.0535. So, this is a 95 percent confidence interval for  $\mu$ .

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Now, let us look at confidence interval for sigma square. **Confidence interval for**, once again, we have two cases,  $\mu$  is known and  $\mu$  is unknown. So, if  $\mu$  is known, let us consider here. See we are given that  $X_1, X_2, \dots, X_n$  follow normal  $\mu$  sigma square. So, if we consider say  $Y_i$  is equal to  $X_i$  minus  $\mu$  then, that will follow normal 0 sigma square.

So, if we consider, say this thing divided by sigma, let us call it Zi that is Xi minus mu by sigma that follows normal 0 1. So, if we consider sigma Zi square, that will be, let us call it W. Then, that will follow a chi square distribution on n degrees of freedom.

We have seen that the sum of squares of n independent standard normal variables is a chi square distribution on n degrees of freedom. So, this since Xi's are independent, this Zi's are also independent and therefore, sum of squares will follow a chi square distribution on n degrees of freedom. Now, you look at this statistic W here. W is actually sigma Xi minus mu square divided by sigma square. Now, if mu is known then this numerator quantity is a quantity which is based on the observations only, because mu is known and the denominator is involving the parameter which is there. So, according to over principle of pivoting quantity, this quantity can be taken as a pivot quantity because the distribution of that is distribution which is free from parameters.

So, if we make use of the distribution of chi square, we consider say chi square alpha by 2 n minus 1 and chi square 1 minus alpha by 2 n minus 1. In general, in chi square distribution because, it is not a symmetric distribution. So, one may consider say chi square alpha 1, that means, this probability is alpha 1 and chi square say alpha 2, that means, this probability is 1 minus alpha 2 such that 1 minus alpha 2 plus alpha 1 is equal to alpha. But for convenience, because in that case we may have several different values. So, for convenience one takes actually, alpha 1 is equal to alpha by 2 and alpha 2 is equal to also alpha by 2, in that case this value becomes easy. So, this probability is 1 minus alpha, this probability is alpha by 2, this probability is again alpha by 2.

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Handwritten mathematical derivation on a whiteboard:

$$P\left(\chi_{1-\frac{\alpha}{2}, n-1}^2 \leq W \leq \chi_{\frac{\alpha}{2}, n-1}^2\right) = 1-\alpha$$

$$\Leftrightarrow P\left(\chi_{1-\frac{\alpha}{2}, n-1}^2 \leq \frac{\sum (X_i - \mu)^2}{\sigma^2} \leq \chi_{\frac{\alpha}{2}, n-1}^2\right) = 1-\alpha$$

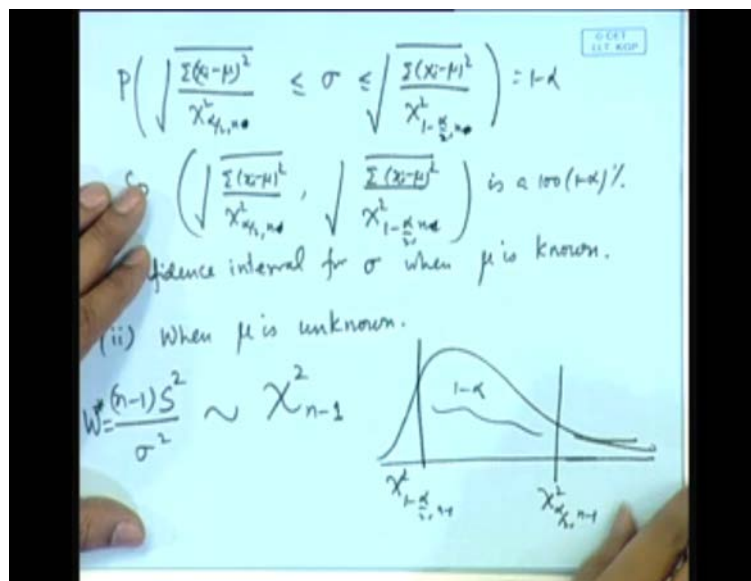
$$\Rightarrow P\left(\frac{\sum (X_i - \mu)^2}{\chi_{\frac{\alpha}{2}, n-1}^2} \leq \sigma^2 \leq \frac{\sum (X_i - \mu)^2}{\chi_{1-\frac{\alpha}{2}, n-1}^2}\right) = 1-\alpha$$

So  $\left(\frac{\sum (X_i - \mu)^2}{\chi_{\frac{\alpha}{2}, n-1}^2}, \frac{\sum (X_i - \mu)^2}{\chi_{1-\frac{\alpha}{2}, n-1}^2}\right)$  is  $100(1-\alpha)\%$  confidence interval for  $\sigma^2$ .

So, we can write down the statement probability that  $\chi^2_{1-\alpha, 2n-1} \leq W \leq \chi^2_{\alpha, 2n-1}$ . This probability is equal to  $1 - \alpha$ . So, by manipulating this statement, we can get a confidence interval for  $\sigma^2$  in the following way. This is  $\frac{\sum (X_i - \mu)^2}{\sigma^2} \leq \chi^2_{\alpha, 2n-1}$  that is equal to  $1 - \alpha$ . So, if we look at this statement, this is equivalent to  $\sigma^2 \geq \frac{\sum (X_i - \mu)^2}{\chi^2_{\alpha, 2n-1}}$ .

If I look at the left hand inequality then, this is equivalent to  $\frac{\sum (X_i - \mu)^2}{\sigma^2} \leq \chi^2_{1-\alpha, 2n-1}$ . So, this statement is equivalent to probability that  $\frac{\sum (X_i - \mu)^2}{\sigma^2} \leq \chi^2_{1-\alpha, 2n-1}$  less than or equal to  $\sigma^2 \leq \frac{\sum (X_i - \mu)^2}{\chi^2_{1-\alpha, 2n-1}}$ . So,  $\frac{\sum (X_i - \mu)^2}{\chi^2_{\alpha, 2n-1}} \leq \sigma^2 \leq \frac{\sum (X_i - \mu)^2}{\chi^2_{1-\alpha, 2n-1}}$ . This is a  $100(1 - \alpha)\%$  confidence interval for  $\sigma^2$ , this is when  $\mu$  is known. So, if the sample is observed, then we can evaluate  $\sum (X_i - \mu)^2$  and the  $\chi^2$  values can be seen from the tables of a  $\chi^2$  distribution and the values can be substituted here. Now, we observe here that this statement can also be written to create a confidence interval for  $\sigma$  also. That means, if we want a confidence interval for standard deviation.

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So, this statement can also be written as probability of square root of sigma Xi minus mu square divided by chi square alpha by 2 n minus 1 less than or equal to sigma less than or equal to sigma Xi minus mu square by chi square 1 minus alpha by 2 n minus 1. So, we get a confidence interval for sigma also that is sigma of Xi minus mu whole square by chi square alpha by 2 n minus 1 to square root sigma Xi minus mu square by chi square 1 minus alpha by 2 n minus 1. This is a 100 1 minus alpha percent confidence interval for sigma, when mu is known. Now; obviously, if mu is unknown then, this cannot be used because this quantity involves unknown value of mu. So, when mu is unknown then, we make use of S square. So, remember here that S square is defined as the sample variance, that is 1 by n minus 1 sigma of Xi minus X bar Whole Square. So, n minus 1 S square by sigma square follows chi square distribution on n minus 1 degrees of freedom. So, you can observe here that, this is a perfect quantity to be used as a pivot quantity. Let me call it W star n minus 1 S square by sigma square. So, here the numerator involves the observations and the denominator involves the parameter for which we want the confidence interval and the distribution of this quantity is free from the parameters. Therefore, this W star can be used as a pivot quantity.

So, once again if we make use of the distribution of chi square on n minus 1 degrees of freedom. So, this is chi square. So, I made a small error in the previous discussion, this one was chi square on n degrees of freedom. So, this is n everywhere not n minus 1. So, this point will be n. So, the 100 1 minus alpha percent confidence interval is sigma Xi

minus mu whole square by chi square alpha by 2n to sigma Xi minus mu whole square by chi square 1 minus alpha by 2n and likewise, when we consider for sigma then, it is square root of the upper and the lower limits here. Here, the degrees of freedom is n. Whereas, if I am considering mu to be unknown, then this is having a chi square distribution on n minus 1 degrees of freedom. So, we will consider the point chi square alpha by 2n minus 1 and chi square 1 minus alpha by 2n minus 1. So, this probability is 1 minus alpha.

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$$P\left(\chi^2_{1-\frac{\alpha}{2}, n-1} \leq W^* \leq \chi^2_{\frac{\alpha}{2}, n-1}\right) = 1-\alpha$$

$$\Leftrightarrow P\left(\chi^2_{1-\frac{\alpha}{2}, n-1} \leq \frac{(n-1)S^2}{\sigma^2} \leq \chi^2_{\frac{\alpha}{2}, n-1}\right) = 1-\alpha$$

$$\Leftrightarrow P\left(\frac{(n-1)S^2}{\chi^2_{\frac{\alpha}{2}, n-1}} \leq \sigma^2 \leq \frac{(n-1)S^2}{\chi^2_{1-\frac{\alpha}{2}, n-1}}\right) = 1-\alpha$$

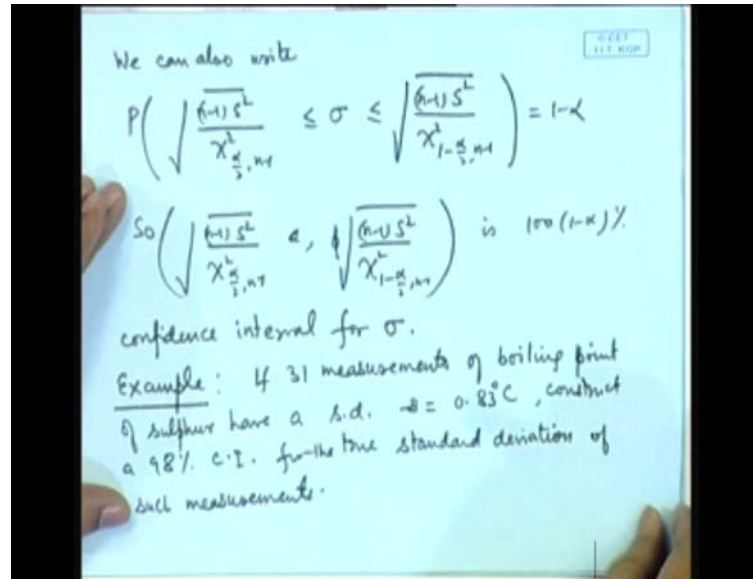
So  $\left(\frac{(n-1)S^2}{\chi^2_{\frac{\alpha}{2}, n-1}}, \frac{(n-1)S^2}{\chi^2_{1-\frac{\alpha}{2}, n-1}}\right)$  is a  $100(1-\alpha)\%$  confidence interval for  $\sigma^2$ .

And we will have the statement probability of n minus 1. So, we Firstly, write here chi square 1 minus alpha by 2n minus 1 less than or equal to W star less than or equal to chi square alpha by 2 n minus 1 is equal to 1 minus alpha. So, this statement is then equivalent to probability of chi square 1 minus alpha by 2 n minus 1 less than or equal to n minus 1 s square by sigma square less than or equal to chi square alpha by 2 n minus 1, that is equal to 1 minus alpha, that is equivalent to, now from here, if we look at the right handed equality, it is equivalent to sigma square greater than or equal to n minus 1 S square by chi square alpha by 2 n minus 1. If you look at the left handed equality that is equivalent to sigma square is less than or equal to n minus 1 S square by chi square 1 minus alpha by 2 n minus 1.

Therefore, this entire statement is equivalent to n minus 1 S square by chi square alpha by 2 n minus 1 less than or equal to sigma square less than or equal to n minus 1 S square by chi square 1 minus alpha by 2 n minus 1 that is equal to 1 minus alpha. So, n minus 1 S square by chi square alpha by 2 n minus 1 to n minus 1 S square by chi square 1 minus

alpha by 2 n minus 1. This is a 100 1 minus alpha percent confidence interval for sigma square. So, if a sample is observed, we evaluate the value sigma Xi minus X bar whole square and get the sample variance and the chi square values can be seen from the tables of the chi square distribution and confidence interval can be obtained. Once again you observe here, that we may take the square root of the statements here and then, we get a confidence interval for sigma also.

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So, we can also write probability of square root n minus 1 S square by chi square alpha by 2 n minus 1 less than or equal to sigma less than or equal to root n minus 1 S square by chi square 1 minus alpha by 2 n minus 1. So, this root n minus 1 s square by chi square alpha by 2 n minus 1 to root n minus 1 s square by chi square 1 minus alpha by 2 n minus 1. This is 100 1 minus alpha percent confidence interval for sigma.

Let me do one example here. If 31 measurements of boiling point of Sulphur have as.d., that is s equal to 0.83 Celsius, construct a 98 percent confidence interval for the true standard deviation of such measurements. So, here we need the chi square value on 0.01 n minus 1 is 30 here. So, chi square 0.99 30. So, these two values can be seen from the tables of the chi square distribution to be this value is 14.95 and this value is 50.89. So, we calculate root 30 s square divided by 50.89 and root 30 s square by 14.95 where s value is given by 0.83. So, if we substitute these values we get the interval to be 0.6373 to 1.1756. So, this is a 98 percent confidence interval for sigma.

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$\chi^2_{0.01, 30} = 50.99, \chi^2_{0.99, 30} = 14.95$   
 $\left( \sqrt{\frac{30s_1^2}{50.99}}, \sqrt{\frac{30s_1^2}{14.95}} \right) = (0.6373, 1.1758)$   
is 98% C.I. for  $\sigma$ .

Two Normal Populations

indep  $\left\{ \begin{array}{l} X_1, \dots, X_m \sim N(\mu_1, \sigma_1^2) \\ Y_1, \dots, Y_n \sim N(\mu_2, \sigma_2^2) \end{array} \right.$

Confidence Interval for  $\mu_1 - \mu_2$   
Case (i):  $\sigma_1^2$  and  $\sigma_2^2$  are known.

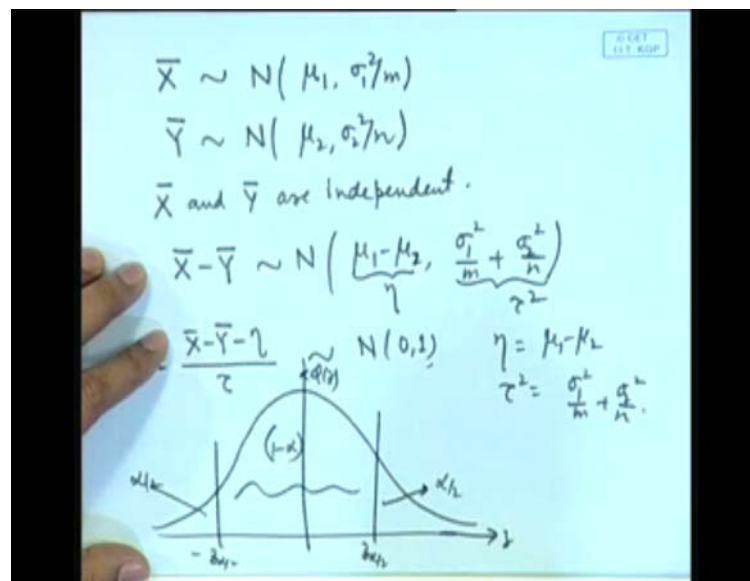
Now, many a times in place of one normal population, we may have two normal populations and in that case, we will require the confidence intervals, say for the difference of the means, we may require for the ratios of the variances, etcetera. We may also have populations, where the proportions are important. So, we may need a confidence interval for a binomial proportion, we may need a confidence interval for the difference of the proportions etcetera. So, let me consider in the first case the normal populations. So, we have two normal population problems. So, we may have a different type of models one could be that I have independent random samples say  $X_1, X_2, \dots, X_m$  following normal say  $\mu_1, \sigma_1^2$  and  $Y_1, Y_2, \dots, Y_n$  is another sample from normal  $\mu_2, \sigma_2^2$  and these two populations are such that the sampling is done independently. So, one problem could be to create confidence interval for say  $\mu_1 - \mu_2$ , because we may be interested in the comparative difference between the two means.

For example, it could be that the first set of observations is based on certain patients and we are looking at the average effectiveness of a certain drug. So, the average effectiveness is  $\mu_1$  and the variability is  $\sigma_1^2$  and suppose there is another drug and whose effectiveness is measured by  $Y_1, Y_2, \dots, Y_n$  and the average is  $\mu_2$  and the variability is  $\sigma_2^2$  the sampling is done independently. It means that the patients on which the drugs have been applied, they are different groups and then, differently we are interested to compare the effectiveness of the two that is, what is the difference between  $\mu_1$  and  $\mu_2$ . So, an important problem is to look at the confidence



interval for  $\mu_1 - \mu_2$ . So, let us look at this problem. There may be again different type of cases, it could be that  $\sigma_1^2$  and  $\sigma_2^2$  are known they are unknown, but equal they may be completely unknown or the sampling may be co related. So, we will consider all of these cases one by one. Let us take case, when  $\sigma_1^2$  and  $\sigma_2^2$  are known. So, in this case, we take help of the sampling distribution of  $\bar{X}$  and  $\bar{Y}$ .

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So,  $\bar{X}$  follows normal  $\mu_1$   $\sigma_1^2$  by  $m$ , if we consider  $\bar{Y}$ , then that will follow normal  $\mu_2$   $\sigma_2^2$  by  $n$ . Another thing is that, since sampling is independent  $\bar{X}$  and  $\bar{Y}$  are independent. So, we can consider  $\bar{X}$  minus  $\bar{Y}$ , that will have normal  $\mu_1 - \mu_2$  and the variance will be  $\sigma_1^2$  by  $m$  plus  $\sigma_2^2$  by  $n$ . Let us call, this quantity say  $\tau^2$ . So, we have  $\bar{X}$  minus  $\bar{Y}$  and this quantity we can call say  $\eta$ ,  $\eta$  divided by  $\tau$  that will follow normal 0 1 where,  $\eta$  is  $\mu_1 - \mu_2$  and say  $\tau^2$  is equal to  $\sigma_1^2$  by  $m$  plus  $\sigma_2^2$  by  $n$ .

Now, if we observe this random variable then, this is involving the observations and the parameter under discussion. That means, we wanted a confidence interval for the parameter  $\mu_1 - \mu_2$  and that is appearing here and the distribution of this quantity is free from the parameters therefore, this can be considered as a pivot quantity and as before, we can make use of the points of the standard normal distribution to write down a confidence interval. So, if this is the  $\phi(z)$  that is the density of the standard

normal distribution then  $z_{\alpha/2}$  is this point such that this probability is  $\alpha/2$ , then on this side you have minus  $z_{\alpha/2}$  that is, this probability is  $\alpha/2$ . So, intermediate probability is  $1 - \alpha$ .

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Handwritten mathematical derivation on a whiteboard:

$$P(-z_{\alpha/2} \leq Z \leq z_{\alpha/2}) = 1 - \alpha$$

$$\Leftrightarrow P\left(-z_{\alpha/2} \leq \frac{\bar{X} - \bar{Y} - \eta}{\tau} \leq z_{\alpha/2}\right) = 1 - \alpha$$

$$\Leftrightarrow P\left(\bar{X} - \bar{Y} - \tau z_{\alpha/2} \leq \eta \leq \bar{X} - \bar{Y} + \tau z_{\alpha/2}\right) = 1 - \alpha$$

So  $\left(\bar{X} - \bar{Y} - \sqrt{\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}} z_{\alpha/2}, \bar{X} - \bar{Y} + \sqrt{\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}} z_{\alpha/2}\right)$   
 is a  $100(1 - \alpha)\%$  confidence interval for  $\mu_1 - \mu_2$  when  $\sigma_1^2$  and  $\sigma_2^2$  are known.

So, we are able to write down the statement probability of minus  $z_{\alpha/2}$  less than or equal to  $Z$  less than or equal to  $z_{\alpha/2}$  is equal to  $1 - \alpha$ . So, this is equivalent to probability of minus  $z_{\alpha/2}$  less than or equal to  $\frac{\bar{X} - \bar{Y} - \eta}{\tau}$  less than or equal to  $z_{\alpha/2}$  is equal to  $1 - \alpha$ . So, if we multiply by  $\tau$  and then utilize this condition that  $\eta$  is greater than or equal to  $\bar{X} - \bar{Y} - \tau z_{\alpha/2}$  and  $\eta$  is also less than or equal to  $\bar{X} - \bar{Y} + \tau z_{\alpha/2}$ . So, the statement is equivalent to  $\bar{X} - \bar{Y} - \tau z_{\alpha/2} \leq \eta \leq \bar{X} - \bar{Y} + \tau z_{\alpha/2}$  that is equal to  $1 - \alpha$ . So, we get  $\bar{X} - \bar{Y} - \sqrt{\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}} z_{\alpha/2} \leq \eta \leq \bar{X} - \bar{Y} + \sqrt{\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}} z_{\alpha/2}$  as a  $100(1 - \alpha)\%$  confidence interval for  $\mu_1 - \mu_2$  when  $\sigma_1^2$  and  $\sigma_2^2$  are known.

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Example :  $m = 36, n = 64$   
 $\bar{x} = 10, \bar{y} = 8, \sigma_1^2 = 1, \sigma_2^2 = 1$   
 $\alpha = 0.05, z_{0.025} = 1.96.$   
 $(\bar{x} - \bar{y} \pm \sqrt{\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}} z_{\alpha/2})$   
 $\equiv 2 \pm \sqrt{\frac{1}{36} + \frac{1}{64}} \cdot (1.96)$   
 $\equiv 2 \pm \frac{5}{6 \times 8} \times 1.96 = 2 \pm \frac{5}{24} \times 1.96$   
 $\equiv (\dots, \dots)$   
 95% confidence interval for  $\mu_1 - \mu_2.$

Let us take one example here, suppose we have a sample of size say  $m$  is equal to 36  $n$  is equal to say 64  $\bar{X}$  value is say 10  $\bar{Y}$  is equal to say 8  $\sigma_1^2$  is equal to say 1  $\sigma_2^2$  is equal to say 1 for convenience and let me take, say  $\alpha$  is equal to 0.05, then  $z$  of 0.025 is equal to 1.96. So, the confidence interval will become  $\bar{X}$  minus  $\bar{Y}$  plus minus square root  $\sigma_1^2$  by  $m$  plus  $\sigma_2^2$  by  $n$   $z_{\alpha/2}$ . So, this confidence interval will be equal to 10 minus 8 is twice square root 1 by 36 plus 1 by 64  $1.96$ . So, this value can be evaluated 64 plus 36 is 100. So, 10 by 6 into 8 into 1.96 5 by 24 into 1.96. So, we get a 95 percent confidence interval for  $\mu_1$  minus  $\mu_2$ .

Now, this procedure specially for the normal distribution here, it suggests here, that in place of  $\mu_1$  minus  $\mu_2$ , suppose, we are interested in say  $\mu_1$  plus  $\mu_2$  then, the procedure will be similar because in place of minus, I may consider  $\bar{X}$  plus  $\bar{Y}$  I may also consider any linear parametric function of  $\mu_1$  and  $\mu_2$ . Suppose, I consider 2  $\mu_1$  plus 3  $\mu_2$  then I can consider here 2  $\bar{X}$  plus 3  $\bar{Y}$  and here the variance quantity will be appropriately changing. For example, this will become 4  $\sigma_1^2$  square by  $m$  plus 9  $\sigma_2^2$  square by  $n$ . It may happen that, we feel that the new procedure is say three times as much effective as the previous procedure. So, in that case you would like to check whether  $\mu_2$  is equal to 3  $\mu_1$ .

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$$\xi = 3\mu_1 - \mu_2$$
$$3\bar{X} - \bar{Y} \sim N\left(3\mu_1 - \mu_2, \underbrace{9\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}}_{\tau^*}\right)$$
$$\left(3\bar{X} - \bar{Y} - \tau^* \sqrt{9\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}}, 3\bar{X} - \bar{Y} + \tau^* \sqrt{9\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}}\right)$$

And therefore, you will like to find out the confidence interval for  $3\mu_1 - \mu_2$ , let me call it say  $\psi$ . So, now we will consider  $3\bar{X} - \bar{Y}$  then, that will have a normal distribution with mean  $3\mu_1 - \mu_2$  plus and variance will be  $9\sigma_1^2/m + \sigma_2^2/n$ . So, the confidence interval will be appropriately changing, if I call this quantity as say  $\tau^*$ , then the confidence interval will become  $3\bar{X} - \bar{Y} - \tau^* \sqrt{9\sigma_1^2/m + \sigma_2^2/n}$  to  $3\bar{X} - \bar{Y} + \tau^* \sqrt{9\sigma_1^2/m + \sigma_2^2/n}$ . That means, in this particular situation for any linear parametric function of  $\mu_1$  and  $\mu_2$ , I can calculate the confidence interval. In the forth coming lecture, I will be discussing the case when  $\sigma_1^2$  and  $\sigma_2^2$  are unknown and what type of problems that may lead to.