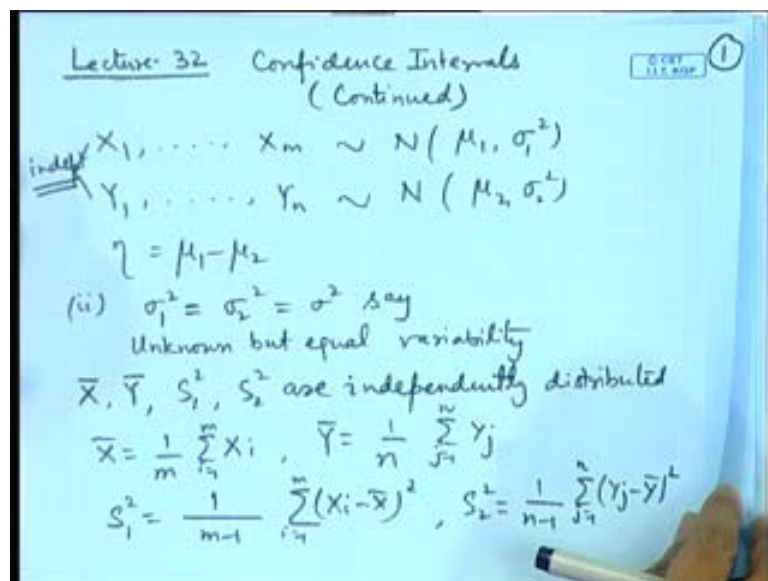


Probability and Statistics
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Module No. #01
Lecture No. #32
Estimation-VI

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So, we continue our discussion on the confidence interval estimation. Let me repeat the setup here, we are interested in the comparison of the means of two normal populations. So, we have a sample X_1, X_2, \dots, X_m from normal μ_1, σ_1^2 , Y_1, Y_2, \dots, Y_n is another independent random sample from normal μ_2, σ_2^2 population- these two samples are taken to be independent. So, we are interested in the confidence interval for $\mu_1 - \mu_2$, let us call it η . So, we have earlier found out the confidence interval for the situation when σ_1^2 and σ_2^2 are known, but in general, the σ_1^2 and σ_2^2 may be unknown and we may be required to find out the confidence interval.

So, we take the case two, that σ_1^2 and σ_2^2 are unknown, but are equal that is, unknown, but equal variability. Now, this type of situation may arise for example, you are looking at two brands of certain product. So, now the variability of the

say, average life for example, it may be same, but average lives themselves may be different, so in such cases this model is useful. Let us look at the analysis of this. So, as we have seen that the sampling distributions of \bar{X} , \bar{Y} , S_1^2 , S_2^2 will be of interest here. So, \bar{X} , \bar{Y} , S_1^2 and S_2^2 are independent- in the sampling from normal distribution we know this fact, independently distributed.

Here \bar{X} is $\frac{1}{m} \sum_{i=1}^m X_i$, i is equal to 1 to m ; \bar{Y} is the mean of the second sample that is, $\frac{1}{n} \sum_{j=1}^n Y_j$, j is equal to 1 to n . If we consider the sample variance of the first sample that is, $\frac{1}{m-1} \sum_{i=1}^m (X_i - \bar{X})^2$, i is equal to 1 to m and S_2^2 is equal to $\frac{1}{n-1} \sum_{j=1}^n (Y_j - \bar{Y})^2$, that is the sample variance of the second sample.

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The image shows handwritten mathematical derivations on a blue background. The equations are as follows:

$$\bar{X} \sim N(\mu_1, \sigma^2/m)$$

$$\bar{Y} \sim N(\mu_2, \sigma^2/n)$$

$$\bar{X} - \bar{Y} \sim N\left(\frac{\mu_1 - \mu_2}{1}, \sigma^2\left(\frac{1}{m} + \frac{1}{n}\right)\right)$$

$$\frac{\bar{X} - \bar{Y} - \eta}{\sigma \sqrt{\frac{1}{m} + \frac{1}{n}}} \sim N(0, 1)$$

$$\frac{(m-1)S_1^2}{\sigma^2} \sim \chi_{m-1}^2, \quad \frac{(n-1)S_2^2}{\sigma^2} \sim \chi_{n-1}^2$$

$$\frac{(m-1)S_1^2 + (n-1)S_2^2}{\sigma^2} \sim \chi_{m+n-2}^2$$

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If we consider these quantities, then we have the following observation: that is, \bar{X} follows normal distribution with mean μ_1 and variance σ^2/m , so, here S_1^2 and S_2^2 are same. Then, \bar{Y} follows normal μ_2 σ^2/n . So, if we consider here, $\bar{X} - \bar{Y}$, that will follow normal with mean $\mu_1 - \mu_2$ and variance will be $\sigma^2(1/m + 1/n)$.

So, if we want, so, this is the quantity η . So, we get $\bar{X} - \bar{Y} - \eta$ divided by σ and root of this that is, root of $\frac{1}{m} + \frac{1}{n}$, that will follow a standard normal distribution. However, this involves the unknown parameter σ also,

so we cannot straight away use it as a pivot quantity. So, we need an estimator for sigma also. So, we can get it here by considering m minus 1 S1 square by sigma square follows chi square on m minus 1 degrees of freedom, and n minus 1 S2 square by sigma square follows chi square on n minus 1 degrees of freedom. Once again, these two quantities are also independent, so I can add this and we get m minus 1 S1 square plus n minus 1 S2 square divided by sigma square, that follows chi square distribution on m plus n minus 2 degrees of freedom.

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$$S_p^2 = \frac{(m-1)S_1^2 + (n-1)S_2^2}{m+n-2} \rightarrow \text{Pooled Sample Variance}$$

$$W = (m+n-2) \frac{S_p^2}{\sigma^2} \sim \chi_{m+n-2}^2$$

and Z and W are independently distributed.

$$T = \frac{Z}{\sqrt{W/(m+n-2)}} \sim t_{m+n-2}$$

$$T = \sqrt{\frac{mn}{m+n}} \frac{(\bar{X} - \bar{Y} - \eta)}{S_p} \sim t_{m+n-2}$$

Let me define a quantity S_p square, that is equal to m minus 1 S1 square plus n minus 1 S2 square divided by m plus n minus 2- that is, pooled sample variance. If we used this pooled sample variance, then what we are having is m plus n minus 2 S_p square by sigma square is following chi square distribution on m plus n minus 2 degrees of freedom.

Now, we have the distribution of \bar{X} minus \bar{Y} minus η divided by sigma multiplied by a constant as a standard normal distribution and let me call this quantity as say, Z , and I have a quantity let us call it say, W , this is having a chi square distribution. Another thing we can notice here is that Z is involving only \bar{X} and \bar{Y} , and W is involving only S_1 square and S_2 square that is, S_p square. So, Z and W are independently distributed. So, if they are independently distributed, I can look at the

distribution of Z divided by W by m plus n minus 2 square root, that will have t distribution on m plus n minus 2 degrees of freedom. So, this quantity is equivalent to root mn by m plus n X bar minus Y bar minus eta divided by Sp, so, that follows t distribution on m plus n minus 2 degrees of freedom.

Now, let us observe, given the samples Xis and Yjs, we can evaluate X bar, Y bar and Sp, and this involves the parameter eta for which we need the confidence interval and the distribution of this quantity is free from the parameters of the distribution. Therefore, this value T can be considered as a pivot quantity and we can make use of this to construct a confidence interval for eta that is, mu1 minus mu2.

So, we look at the t distribution, it is symmetric about the axis, it is symmetric about zero and, so, this is fm plus n minus 2 t. So, we look at the point here, this point is t alpha by 2 m plus n minus 2 and we have on the left hand side the similar point, that is minus t alpha by 2 m plus n minus 2. So, this intermediate probability is 1 minus alpha.

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$$P(-t_{\frac{\alpha}{2}, m+n-2} \leq T \leq t_{\frac{\alpha}{2}, m+n-2}) = 1 - \alpha$$

$$\Leftrightarrow P\left(-t_{\frac{\alpha}{2}, m+n-2} \leq \sqrt{\frac{mn}{m+n}} \frac{(\bar{X} - \bar{Y} - \eta)}{S_p} \leq t_{\frac{\alpha}{2}, m+n-2}\right) = 1 - \alpha$$

$$P\left(-\sqrt{\frac{mn}{m+n}} S_p t_{\frac{\alpha}{2}, m+n-2} \leq \bar{X} - \bar{Y} - \eta \leq \sqrt{\frac{mn}{m+n}} S_p t_{\frac{\alpha}{2}, m+n-2}\right) = 1 - \alpha$$

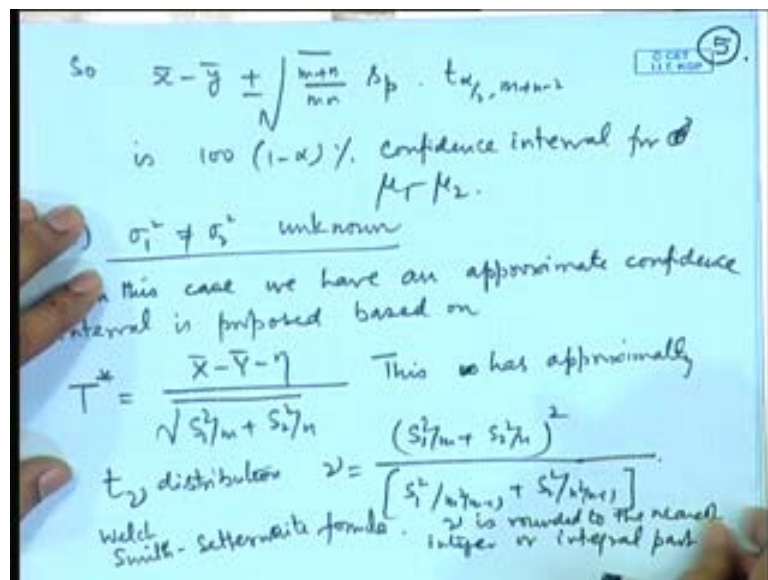
$$\Leftrightarrow P\left(\bar{X} - \bar{Y} - \sqrt{\frac{mn}{m+n}} S_p t_{\frac{\alpha}{2}, m+n-2} \leq \eta \leq \bar{X} - \bar{Y} + \sqrt{\frac{mn}{m+n}} S_p t_{\frac{\alpha}{2}, m+n-2}\right) = 1 - \alpha$$

And we are in a position to write the statement that probability of minus t alpha by 2 m plus n minus 2 less than or equal to T is less than or equal to t alpha by 2 m plus n minus 2, that is equal to 1 minus alpha. So, expanding this T and then adjusting the terms, we will be able to construct a confidence interval for mu1 minus mu2. So, T is here square

root of $m + n$ by $m + n$ $\bar{X} - \bar{Y} - \eta$ divided by S_p , that is less than or equal to $t_{\alpha/2, m+n-2}$, that is equal to $1 - \alpha$. So, this is equivalent to $\sqrt{m + n} / \sqrt{mn} S_p t_{\alpha/2, m+n-2} \leq \bar{X} - \bar{Y} - \eta \leq \sqrt{m + n} / \sqrt{mn} S_p t_{\alpha/2, m+n-2}$, that is equal to $1 - \alpha$.

So, this means that $\bar{X} - \bar{Y} - \sqrt{m + n} / \sqrt{mn} S_p t_{\alpha/2, m+n-2} \leq \bar{X} - \bar{Y} - \eta \leq \bar{X} - \bar{Y} + \sqrt{m + n} / \sqrt{mn} S_p t_{\alpha/2, m+n-2}$, that is equal to $1 - \alpha$.

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So, in the situation when the variances of the two populations are unknown, but equal, the confidence interval for $\mu_1 - \mu_2$ is obtained as $\bar{X} - \bar{Y} \pm \sqrt{m + n} / \sqrt{mn} S_p t_{\alpha/2, m+n-2}$, so, this is giving a $100(1 - \alpha)$ percent confidence intervals for $\mu_1 - \mu_2$.

Notice here is that since the variances were assumed to be equal, we are making use of a pooled sample variance. Now, one may ask a question that in place of this suppose we consider simply S_1^2 or S_2^2 only, because in that case also we are getting a variable which is free from the parameters, which is having a distribution free from the parameters, so, why not use only this, or only this? The question is that if we use only say, S_1^2 ,

then the degrees of freedom that we will get for the T variable will be $m - 1$, so, if we get only $m - 1$, then in that case, the interval will be having the width $\bar{X} - \bar{Y} \pm \sqrt{\frac{m+n}{mn}}$, now, this term will not come here, rather we will have S_1 only, this coefficient will not come here, here we will have only S_1 , and the degrees of freedom will be $m - 1$ naturally, the length of the interval will increase if we have less number of, less degrees of freedom. So, in order to get more accuracy, or you can say more precision, we need a smaller interval with the same confidence coefficient therefore, it is beneficial to use more information here.

Let us take the case when both μ_1 and μ_2 may be unknown. Then, let us look at the procedure here that has helped us to create this confidence interval. The procedure that we adopted was that the distribution of S_p^2 by σ^2 that is, chi square and the Z variable that we utilized, that also has a σ in the denominator, so, we were able to get rid of this. If the variances are not equal, then in the first place we will be getting σ_1^2 here and here we will get σ_2^2 square, so when we add the two terms in the denominators I will get S_1^2 square by σ_1^2 square and here S_2^2 square by σ_2^2 square, and the same thing will happen with the Z also, where we will get σ_1^2 square by m plus σ_2^2 squares by n . So, in no way by taking the ratios I can get rid of σ_1^2 square and σ_2^2 square actually, turns out that there is no exact confidence interval that means, the interval which is having the length a shortest length and as well as a fixed confidence coefficient that means, the distribution free term we are not getting.

In this case, this is known as a variance special situation. So, we will consider this case, σ_1^2 square is not equal to σ_2^2 squares and unknown, that means they are completely unknown. In this case a approximate, an approximate confidence interval is proposed based on, let us call it T^* , that is $\bar{X} - \bar{Y} \pm \eta$ divided by square root S_1^2 square by m plus S_2^2 square by n . So, how this has come? In the first case where σ_1^2 square by m plus σ_2^2 squares by n was there, we have simply replaced σ_1^2 square and σ_2^2 squares by their unbiased estimates. So, it was proved by Welch, etcetera, that this is having, has approximate, this has approximately t distribution on ν degrees of freedom, where ν is given by S_1^2 square by m plus S_2^2 square by n whole square divided by S_1^2 square by m square into $m - 1$ plus S_2^2 square by n square into $n - 1$ - it is by Welch and it is known as smith-satterthwaite formula.

So, now, this need not be an integer, so, nu is rounded off to the nearest integer, or integral part that means, suppose it is turning out to be 11.37 we take only 11.

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Using T^* we can construct a $100(1-\alpha)\%$ confidence interval for $\mu_1 - \mu_2$ as

$$\bar{X} - \bar{Y} \pm t_{\alpha/2, \nu} \sqrt{\frac{S_1^2}{m} + \frac{S_2^2}{n}}$$

Paired Observations

$$(X_1, \dots, X_n) \sim N(\mu_1, \sigma_1^2)$$

$$(Y_1, \dots, Y_n) \sim N(\mu_2, \sigma_2^2)$$

$$(X_1, Y_1), \dots, (X_n, Y_n) \sim \text{BVN}(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, \rho)$$

So, using this one can write a confidence interval. Using T star we can construct a 100 1 minus alpha percent confidence interval for mu1 minus mu2 as X bar minus Y bar plus minus t alpha by 2 nu square root of S1 square by m plus S2 square by n- this will be the confidence interval when there is no information about the equality of sigma1 square and sigma2 square.

Now, there is another situation which occurs quite frequently. For example, we are considering the comparison of the two training procedures. So, suppose there are two training procedures for certain learning. So, we select say, ten peoples and we give them instructions using one training procedure, a test is conducted to measure the outcome of that, now, for the same set of ten peoples another learning procedure is imparted for a fixed period of time and another test is conducted. Now, the scores are not independent because our subjects are not independent, same people, same set of people has been selected. For example, it could be some weight reduction procedure like, the fatty people are there and we are giving them certain weight reduction program, so, by taking certain procedure for one month, their weight is reducing by this much, now, for the same set of

people another procedure is adopted then how much weights have been reduced- so, we compare the same set of people with respect to their scores.

So, here this is related to paired observations, paired observations. So, here although you are saying X_1, X_2, \dots, X_n say, follow normal μ_1 σ_1^2 and Y_1, Y_2, \dots, Y_n , they follow normal μ_2 σ_2^2 squares, but actually the sample has not been selected in this way because these observations may be paired. So, basically, the model becomes that $X_1, Y_1, X_2, Y_2, \dots, X_n, Y_n$, this is having some sort of bivariate normal distribution with parameters $\mu_1, \mu_2, \sigma_1^2, \sigma_2^2$ and some correlation coefficient, ρ may be there.

Once again we are interested in the interval for $\mu_1 - \mu_2$ that is, we want to look at the difference in the average effectiveness, etcetera. A simple procedure for this is obtained by using the linearity property of bivariate normal distribution. Because we know that if the random variable X, Y is having a bivariate normal distribution, then any linear combination $aX + bY$ is again having a univariate normal distribution, so, here if I make use of say, observations, let me call it d_i , that is equal to $X_i - Y_i$, then that will follow normal distribution with mean $\mu_1 - \mu_2$ and some variance, let me call it σ_D^2 - actually it, will be $\sigma_1^2 + \sigma_2^2 - 2\rho\sigma_1\sigma_2$ - so, $\sigma_1^2 + \sigma_2^2 - 2\rho\sigma_1\sigma_2$, let me call it σ_D^2 , that is not important here because they are all unknown and we need only an estimate of this because we are interested here in the confidence interval about $\mu_1 - \mu_2$.

So, we can make use of, now, this looks like a problem of the confidence interval for a mean of a normal distribution, which we have done in the first place.

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$$\bar{d} = \frac{1}{n} \sum_{i=1}^n d_i, \quad S_d^2 = \frac{1}{n-1} \sum (d_i - \bar{d})^2$$

$$\bar{d} \sim N(\eta, \sigma_d^2/n), \quad \frac{\sqrt{n}(\bar{d} - \eta)}{\sigma_d} \sim N(0, 1)$$

$$\frac{(n-1)S_d^2}{\sigma_d^2} \sim \chi_{n-1}^2$$

$$\frac{\sqrt{n}(\bar{d} - \eta)}{S_d} \sim t_{n-1}$$

$$\left(\bar{d} - \frac{S_d}{\sqrt{n}} t_{\alpha/2, n-1}, \bar{d} + \frac{S_d}{\sqrt{n}} t_{\alpha/2, n-1} \right)$$
 is a $100(1-\alpha)\%$ confidence interval for $\eta = \mu_1 - \mu_2$.

So, we can consider say \bar{d} as $\frac{1}{n} \sum_{i=1}^n d_i$, i is equal to 1 to n , and we consider S_d square as $\frac{1}{n-1} \sum (d_i - \bar{d})^2$. So, if you look at this, then we can see that \bar{d} follows normal η σ_d^2/n , and, so, from here we can get $\bar{d} - \eta$ \sqrt{n} by σ_d follows normal 0, 1; also $(n-1) S_d^2$ by σ_d^2 will follow chi square distribution on $n-1$ degrees of freedom, and once again, these two variables will be statistically independent. So, using this we can write $\frac{\sqrt{n}(\bar{d} - \eta)}{S_d}$, that will be having a t distribution on $n-1$ degrees of freedom.

Now, observe this function here, it is involving the random variables, that is observations X_i and Y_i , \bar{d} is the mean calculated from the differences and S_d square is calculated as the variance of the difference observations, and here the parameter of interest η is appearing and σ_e^2 , etcetera, are absent here, so this can be used as a pivot quantity and we get a confidence interval by writing down from the distribution of the t on $n-1$ degrees of freedom. So, this probability is $1 - \alpha$ and we get $\bar{d} - \frac{S_d}{\sqrt{n}} t_{\alpha/2, n-1}$ to $\bar{d} + \frac{S_d}{\sqrt{n}} t_{\alpha/2, n-1}$, so this becomes $100(1-\alpha)\%$ confidence intervals for η , that is equal to $\mu_1 - \mu_2$.

So, we observe here that all these cases are differently handled that is, when we observe a sample, we have to look at carefully, so, if the variance is known to us, then we have some procedure, if the variances are unknown, but we suspect that the variances may be equal, then we have another procedure, if the variances are completely unknown, then we have another procedure, on the other hand, if the sampling is not done in the independent fashion that means, we have correlated observations, then we may arrange the data in a paired way and then we can apply a pairing formula. So, the confidence interval for the same parameter $\mu_1 - \mu_2$ when we are sampling from two normal populations, it is dependent upon the situation, we have to, a statistician has to carefully see that which type of method will be adopted here for finding out the confidence interval otherwise, he will be coming up with the faulty conclusions.

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Ex To compare the gripping strength of left hand and right hand of 10 left handed persons the measurements are made on 10 persons

Person	1	2	3	4	5	6	7	8	9	10
Left Hand	140	90	125	130	95	121	85	97	131	110
Right hand	138	87	110	132	96	120	86	90	129	109

Confidence interval for $\mu_1 - \mu_2$

d_i

	2	3	15	-2	-1	1	-1	7	2	10
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$$\bar{d} = 3.6, \quad S_d = \frac{1}{9} \sum d_i^2 - \bar{d}^2$$

$$t_{0.05, 9} = 1.833 = \frac{1}{9} (4+9+225+4+1+1+1+49+4+100) - (3.6)^2$$

$$(3.6 \pm \frac{S_d}{\sqrt{n}} \cdot 1.833) = \dots$$

Let me take up some examples here to illustrate the situations. So, to compare, to compare the strength, the gripping strengths of left hand and right hand of ten left handed, of left handed persons, the measurements are made on ten persons and the data is observed. So, left hand and right hand, and we have persons 1, 2, 3, 4, 5, 6, 7, 8 9 and 10; the gripping strengths are measured as 140, 90, 125, 130, 95, 121, 85, 97, 131, 110; for the right hand it is 138, 87, 110, 132, 96, 120, 86, 90, 129, 100.

So, we need the confidence interval for say μ_1 minus μ_2 . Now, observe here that this is the data related with the correlated observations, so, we will need here the means of, so, let me call this as the first set, so, this is X_i data this is Y_i data. So, we will look at dis, the differences here; so, the differences here is 2, 3, 15, minus 2, minus 1, 1, minus 1, 2, and 10. So, we look at the \bar{d} value here, which is the mean of this that is, 20... so, 17... 24... 26... 36... so, that is 3.6. Similarly, we calculate sd, that will be equal to 1 by 9 sigma di square minus \bar{d} square. So, once again, it can be easily evaluated it is 4 plus 9 plus 225 plus 4 plus 1 plus 1 plus 1 plus 49 plus 4 plus 100 minus 3.6 square- so, this value can be evaluated.

Now, we look at the value of t on, suppose we want a 90 percent confidence interval, so we need .059 that is equal to 1.83. So, we get the confidence interval as 3 .6 plus minus sd by root 10 into 1.833, that will be the confidence interval for the difference in the gripping strengths of left hand and the right hand of the left handed persons.

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Ex To compare age at marriage of women in two ethnic groups. a random sample of 100 women is taken from each group.

$\bar{x} = 18.5, \bar{y} = 20.7, s_1 = 5.8, s_2 = 6.3$

$$S_p^2 = \frac{(m-1)S_1^2 + (n-1)S_2^2}{m+n-2} = \frac{99S_1^2 + 99S_2^2}{198}$$

$$= \frac{(5.8)^2 + (6.3)^2}{2} = \dots$$

90%
 $t_{0.05, 198} = 1.645$
 $\frac{\sqrt{198}}{100}$

$$\bar{x} - \bar{y} \pm \sqrt{\frac{m+n}{mn}} S_p \cdot t_{0.05, 198}$$

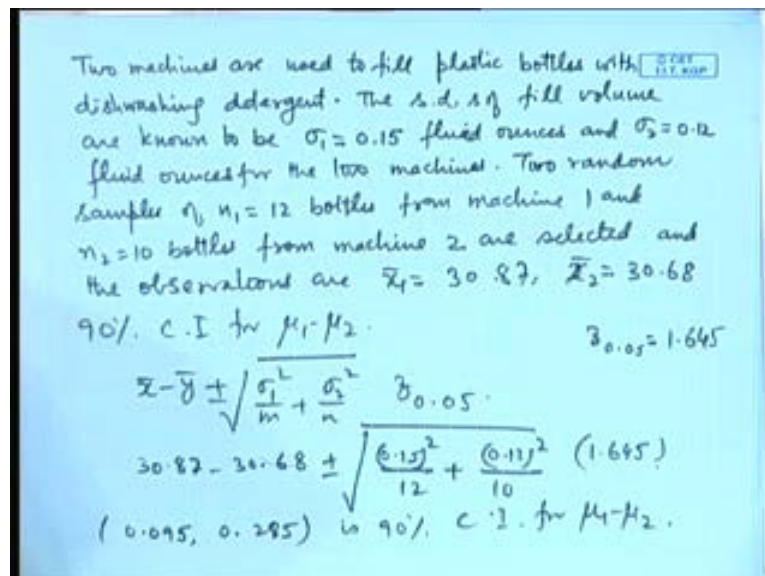
$$\left(18.5 - 20.7 \pm \frac{\sqrt{2}}{10} \cdot 1.645 \right)$$

Let me take another example here, to compare age at marriage of women in two ethnic groups a random sample of hundred women is taken, and we observe that \bar{X} is equal to 18.5 years, \bar{Y} is equal to 20.7 years and S_1 is equal to 5.8, S_2 is equal to 6.3 and we want say, a confidence interval for this. So, we calculate here that we may use the model for S_p square. So, S_p square is equal to m minus 1 S_1 square plus n minus 1 S_2

square divided by m plus n minus 2, that is equal to 99 S1 square plus 99 S2 square by 198, that is equal to 5.8 square plus 6.3 square by 2- so, this value can be evaluated.

In a similar way, so, we have the confidence interval as X bar minus Y bar minus root m plus n by mn that is, and then, Sp into t alpha by 2- suppose I want 90 percent confidence interval- so, 0.05 and the degrees of freedom will be m plus n minus 2; so, this value we can see t 0.05, 198 which is almost as a normal distribution 1.645. So, we substitute these values here, 18.5 minus 20.7 minus- this is 100 plus 100, that is 200 by 100- so, that is root 2 by 10 into 1.645, so, plus minus. That gives the confidence interval for the difference in the ages at marriage of women in two ethnic groups. So, here we have the pooled formula, we may actually do a testing of hypothesis for sigma1 square is equal to sigma2 square, and if sigma1 square is equal to sigma2 square is accepted, then we may go for this formula.

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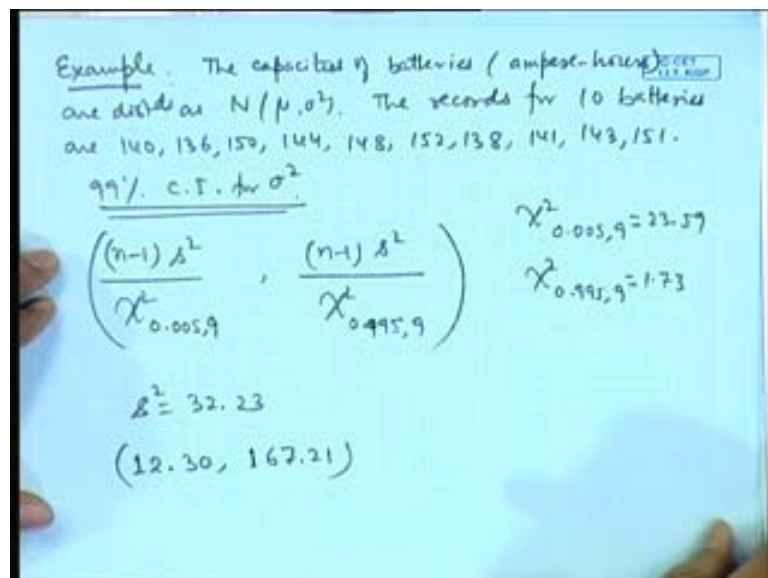


Let me take another example here. Two machines are used to fill plastic bottles with dishwashing detergent. The standard deviations of fill volume are known to be sigma1 is equal to 0.15 fluid ounces and sigma2 is equal to 0.12 fluid ounces for the two machines. Now, two random samples of n1 is equal to 12 bottles from machine one and n2 is equal to ten bottles from machine two are selected and the observations are X1 bar

is equal to 30.87, \bar{X}^2 is equal to 30.68. So, find 90 percent confidence interval for $\mu_1 - \mu_2$.

So, here we can see, we can look at the confidence interval as $\bar{X} \pm \sqrt{\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}}$. Now, $\alpha = 0.05$, we can see from the tables of normal distribution, it is 1.645. So, this interval becomes $30.87 \pm 1.645 \sqrt{\frac{0.15}{12} + \frac{0.12}{10}}$. So, after simplification, these values turn out to be 0.095 to 0.285, so, this is 90 percent confidence interval for the main difference that is $\mu_1 - \mu_2$. So, here the variances were known, σ_1^2 and σ_2^2 , so we have adopted a procedure where the formula for non variances is utilized here.

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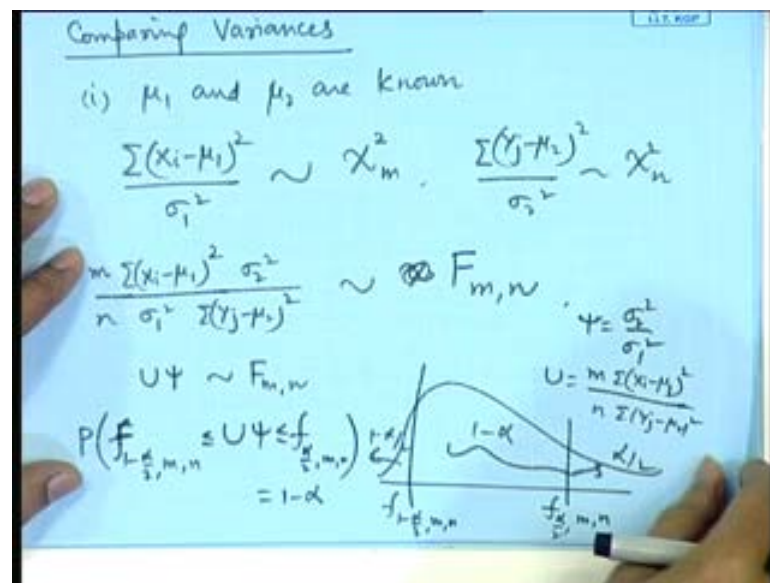


Let me take another example here. The capacities of batteries, so, these are measured in say ampere-hours; they are distributed as normal μ , σ^2 . The records for ten batteries are say 140, 136, 150, 144, 148, 152, 138, 141, 143, 151. We want 99 percent confidence interval for σ^2 .

So, now, here, we will make use of the fact that μ is unknown. So, if μ is unknown, then the formula for confidence interval for σ^2 is based on chi square on n

minus 1 degrees of freedom, the formula is $n - 1$ times s^2 by χ^2 . So, $0.005 n - 1$ is 9, so this is 9 to $n - 1$ times s^2 by χ^2 0.995 , so, 995 . So, these values we see from the tables of the chi square distribution that is, chi square 0.005 , it is 23.99 and chi square 0.995 on 9 degrees of freedom is 1.73 . So, s^2 we calculate here, it is turning out to be 32.23 . So, after substitution of these values, the confidence interval turns out to be 12.30 to 167.21 , which is pretty large confidence interval, but that will be there because we are considering for sigma square and the variability of the original sample itself is large, this is, s^2 is 32.23 here. If we reduce the confidence level, suppose we make it 90 percent, then this will be shrinking, since we have made a very high confidence level that is why the confidence interval is very large, which looks slightly impractical also.

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Next, we look at the confidence intervals for variances- so, comparing variances. Again, we have two cases, that is μ_1 and μ_2 are known; if μ_1 and μ_2 are known, then we make use of $\sum (x_i - \mu_1)^2$ by σ_1^2 following chi square distribution on m degrees of freedom, and $\sum (y_j - \mu_2)^2$ by σ_2^2 following chi square distribution on n degrees of freedom. So, if you take the ratios here, $\sum (x_i - \mu_1)^2$ by σ_1^2 m , so, that is m here, divided by $\sum (y_j - \mu_2)^2$ by σ_2^2 , so, that will come in the numerator, divided by n , that will have chi square, f distribution on m and n degrees of freedom.

So, if we look at this quantity, if μ_1 and μ_2 are known, then here the ratio σ_2^2 square by σ_1^2 square is coming, let us denote it by say, ψ that is σ_2^2 square by σ_1^2 square; so, we are having, and let me use the notation say, U as $m \sum (X_i - \mu_1)^2$ divided by $n \sum (Y_j - \mu_2)^2$. So, if you look at this one, then we are having $U \psi$ following F distribution on m, n degrees of freedom. So, if we make use of the tables of F distribution that is, F on m and n degrees of freedom here, and $F_{1-\alpha/2}$ on m, n degrees of freedom, this is $\alpha/2$ and this is $1 - \alpha/2$, so, this is $1 - \alpha$; so, probability of $F_{1-\alpha/2} < U \psi < F_{\alpha/2}$, that is equal to $1 - \alpha$.

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$$P\left(\frac{U}{F_{\alpha/2, m, n}} \leq \frac{\sigma_1^2}{\sigma_2^2} \leq \frac{U}{F_{1-\alpha/2, m, n}}\right) = 1 - \alpha$$

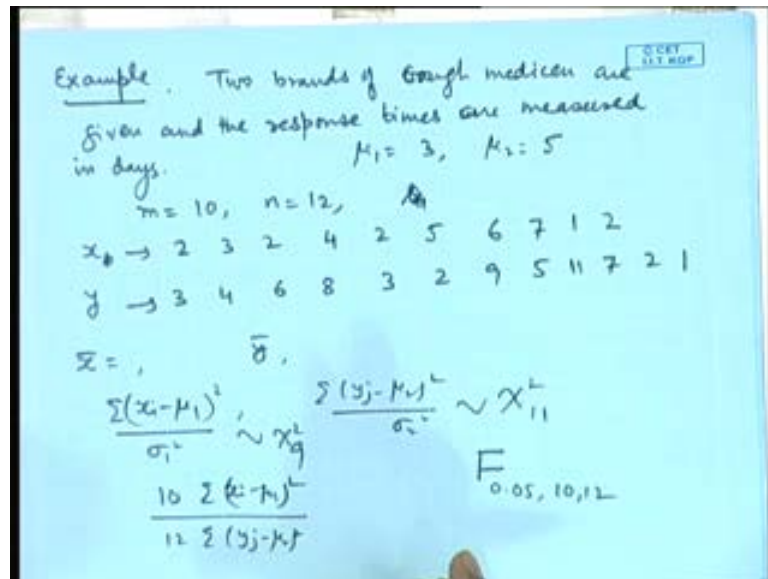
So a $(1-\alpha)$ C.I. for σ_1^2/σ_2^2

$$U F_{1-\alpha/2, m, n} < \frac{\sigma_1^2}{\sigma_2^2} < U F_{\alpha/2, m, n}$$

$\frac{1}{F_{\alpha/2}} = F_{1-\alpha/2}$

So, we can write probability of U , so, divided by F of $\alpha/2, m, n$ less than or equal to σ_1^2 square that is, 1 by ψ , it becomes σ_1^2 square by σ_2^2 square less than or equal to U divided by $F_{1-\alpha/2, m, n}$, that is equal to $1 - \alpha$. So, we have a $1 - \alpha$ confidence interval for σ_1^2 square by σ_2^2 square, this can also be written as $U F_{1-\alpha/2, m, n} < \sigma_1^2/\sigma_2^2 < U F_{\alpha/2, m, n}$, by using the ratio, or you can say reciprocal property of the F distribution, because we know that $1/F_{\alpha/2, m, n}$ is equal to $F_{1-\alpha/2, n, m}$, so, this property can be utilized here.

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Let me give one example here for confidence interval for the ratios. So, two brands of say, cough medicine are given and the response times are measured in days. So, here we are having the data, m is equal to say 10, n is equal to 12, S1 and, we are getting the observations as **x1** is equal to say, 2, 3, 2, 4, 2, 5, 6, so, 3, 7 and then, 1, 2, so, we have ten data here and for y we have the data say, 3, 4, 6, 8, 3, 2, 9, 5, 11, 7, 2, 1. Now, based on this we calculate \bar{x} and \bar{y} and we calculate $\sum (x_i - \mu_1)^2$. So, it is given that μ_1 is say, 3 and μ_2 is equal to 5. So, if we are looking at $\sum (x_i - \mu_1)^2$ and $\sum (y_j - \mu_2)^2$, then that will follow chi square on 9 and this divided by σ_1^2 will follow chi square on 11 degrees of freedom. So, we can construct $\frac{\sum (x_i - \mu_1)^2}{10 \sum (x_i - \bar{x})^2}$ and $\frac{\sum (y_j - \mu_2)^2}{12 \sum (y_j - \bar{y})^2}$, and then, we need to look at the tables of f on say 0.05, 10 and 12 degrees of freedom.

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(ii) μ_1 and μ_2 are unknown.

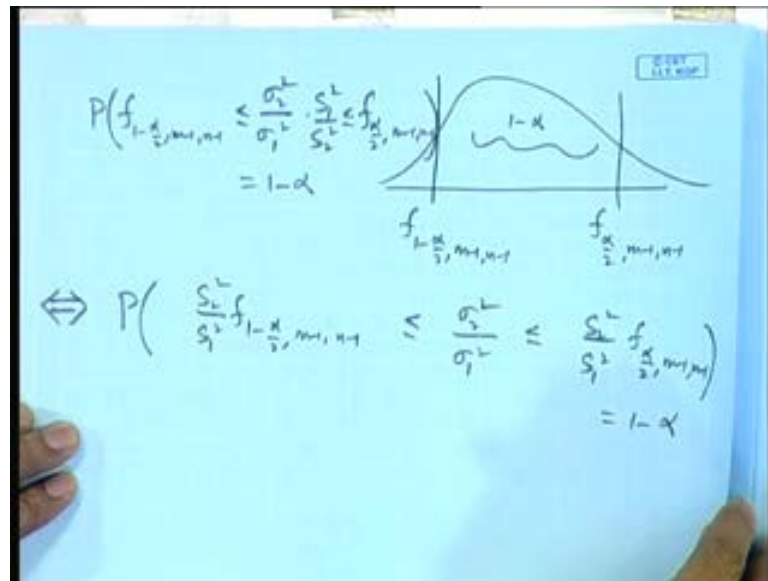
$$\frac{(m-1)S_1^2}{\sigma_1^2} \sim \chi_{m-1}^2, \quad \frac{(n-1)S_2^2}{\sigma_2^2} \sim \chi_{n-1}^2$$

indep't.

$$\frac{\frac{(m-1)S_1^2}{\sigma_1^2(m-1)}}{\frac{(n-1)S_2^2}{\sigma_2^2(n-1)}} \sim F_{m-1, n-1}$$
$$\Rightarrow \frac{\sigma_2^2}{\sigma_1^2} \frac{S_1^2}{S_2^2} \sim F_{m-1, n-1}$$

Now, another situation may occur when μ_1 and μ_2 are unknown. If μ_1 and μ_2 are unknown, then we will not be able to make use of the formula that we derived earlier because there in the confidence interval μ_1 and μ_2 are actually appearing, so what we do, we make use of S_1 square and S_2 square. So, we have m minus 1 S_1 square follows chi square distribution on m minus 1 degrees of freedom and n minus 1 S_2 square by σ_2^2 square follows chi square distribution on n minus 1 degrees of freedom. Furthermore, these two random variables are independent. So, we can make use of the ratios m minus 1 S_1 square by σ_1^2 square divided by m minus 1 divided by n minus 1 S_2 square by σ_2^2 square into n minus 1, that will follow f distribution on m minus 1, n minus 1 degrees of freedom, which is reducing to σ_2^2 square by σ_1^2 square S_1 square by S_2 square, this follows f distribution on m minus 1 n minus 1 degrees of freedom.

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So, making use of distribution of f that is, we have f_{α} by $2m - 1$, $n - 1$ and $f_{1-\alpha}$ by $2m - 1$, $n - 1$, intermediate probability is $1 - \alpha$; so, probability that $f_{1-\alpha}$ by $2m - 1$, $n - 1$ is less than or equal to $\frac{\sigma_2^2}{\sigma_1^2} \frac{S_1^2}{S_2^2}$ is less than or equal to f_{α} by $2m - 1$, $n - 1$, that is equal to $1 - \alpha$. So, we make use of this and adjust the coefficients as probability that $\frac{S_2^2}{S_1^2} f_{1-\alpha}$ by $2m - 1$, $n - 1$ less than or equal to $\frac{\sigma_2^2}{\sigma_1^2}$ less than or equal to $\frac{S_2^2}{S_1^2} f_{\alpha}$ by $2m - 1$, $n - 1$, that is equal to $1 - \alpha$. So, we are getting $100(1 - \alpha)$ percent confidence intervals for $\frac{\sigma_2^2}{\sigma_1^2}$. We can reverse it, if we want for $\frac{\sigma_1^2}{\sigma_2^2}$, then we interchange the roles here, we put $\frac{S_1^2}{S_2^2}$ and the degrees of freedom will get reverse, it will become $n - 1$, $m - 1$.

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Handwritten mathematical derivation on a blue background:

$$\Leftrightarrow P\left(\frac{\sum_{i=1}^m f_{1-\frac{\alpha}{2}, m, n-1}}{S_1^2} \leq \frac{\sigma_2^2}{\sigma_1^2} \leq \frac{\sum_{i=1}^m f_{\frac{\alpha}{2}, m, n-1}}{S_2^2}\right) = 1 - \alpha$$

So $\left(\frac{S_2^2}{S_1^2} f_{1-\frac{\alpha}{2}, m, n-1}, \frac{S_2^2}{S_1^2} f_{\frac{\alpha}{2}, m, n-1}\right)$ is $100(1-\alpha)\%$ C.I. for σ_2^2/σ_1^2 .

So, we give one example here. So, S_2 square by S_1 square $f_{1-\alpha/2}$ by $2m-1$ to S_2 square by S_1 square $f_{\alpha/2}$ by $2m-1$ is $100(1-\alpha)$ percent confidence interval for σ_2^2/σ_1^2 .

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Handwritten example problem on a blue background:

Viscosity of two brands of oil used in cars is measured and the following data is recorded:

Brand 1: 10.62 10.58 10.33 10.72 10.44

Brand 2: 10.50 10.52 10.62 10.53

$S_1^2 = 0.02362$ $\frac{S_1^2}{S_2^2} = 8.36$

$S_2^2 = 0.002825$

$f_{0.05, 4, 3} = 9.1122$

$f_{0.95, 4, 3} = 0.1517$

90% C.I. for $\sigma_1^2/\sigma_2^2 = (8.36 \times 0.1517, 0.3649 \cdot 1172)$

So, say viscosity of two brands of oil used in cars is measured and the following data is recorded. So, from brand one you have 10.62, 10.58, 10.33, 10.72, 10.44. For brand two

it is 10.50, 10.52, 10.62, 10.53. Suppose we want a confidence interval for σ_1^2 squares by σ_2^2 square. So, we will calculate the values here, s_1^2 square s_2^2 square; so, s_1^2 square turns out to be 0.02362, s_2^2 square is equal to 0.002825, you can see here there is a 10 times difference here. So, the f values that s_1^2 square by s_2^2 square will be equal to 8.36. So, if you look at the f value on 0.5 say, 1, 2, 3, 4, 5, so, 4, 3 degrees of freedom, that is equal to 9.1172, and f value 0.9543, that is equal to 0.1517.

So, a 90 percent confidence interval for σ_1^2 square by σ_2^2 square, that will be equal to 8.36 into 0.1517 to 8.36 into 9.1172. So, this is the confidence interval for the ratio of the variances here.

So, in a given practical situation we need to analyze that what is the model that will be applicable and accordingly we make use of the formulae. So, for example, when we are looking at the confidence intervals for $\mu_1 - \mu_2$, then we worry about that what is the status of the variances, if the variances are known, then we have some formula, if the, that is, based on the Z that is, normal distribution, if we have variances unknown, but equal, then we have a formula which is based on T distribution, based on the pooling of the concept, pooling of the variances, and if we have variances to be completely unknown, then in that case we have another approximate T distribution formula and we make use of that.

On the other hand, if the data is correlated, then we make use of pairing and a paired T formula is used. Similarly, when we are worried about the confidence interval for the σ_1^2 square and σ_2^2 square, then we look at the knowledge about the means, if the means are known, then we have a formula based on f distribution on the total degrees of freedom m and n, if the means are unknown, then we have another formula which is based on S_1^2 square S_2^2 square and the degrees of freedom are slightly reduced to m minus 1, n minus 1.

Now, these formulae are quite standard because they are making use of the sampling distribution from the normal populations. When we do not have normal populations then in that case, we may have to look for appropriate sampling distribution, for example, if we are dealing with uniform distribution, if we are dealing with from the exponential

populations, then we look at from the description that what is the sufficient statistics, from there we find out the pivoting quantity if we are able to derive the sampling distribution of that. So, the techniques for that and also for the proportions are available and one can work out various formulae for confidence interval from other populations as well. So, that is part of another course, that is statistical inference that, we will be doing later on.