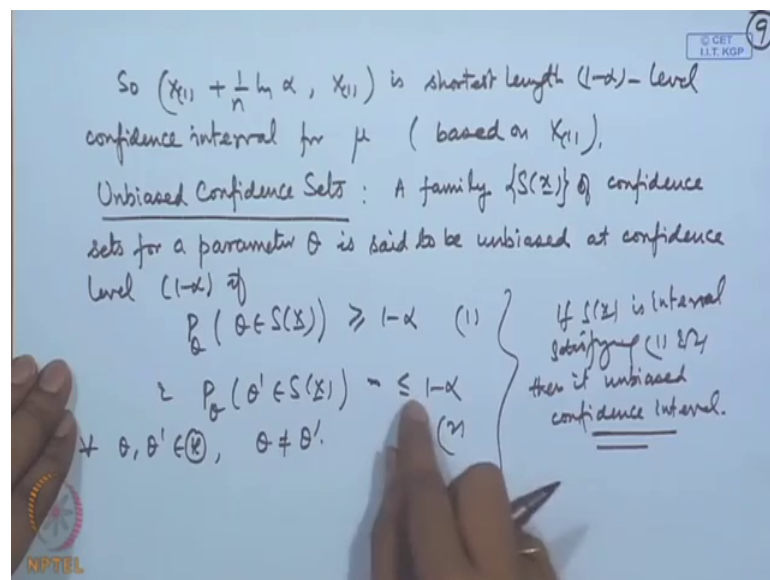


Statistical Inference
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Lecture – 64
Interval Estimation – IV

Now I will also consider the situations where in the testing problem we had considered where UMP test does not exist therefore, we were trying to find out UMP unbiased tester also. Now corresponding to that, here we have UMA unbiased confidence intervals. So, what is an unbiased confidence interval let me define that.

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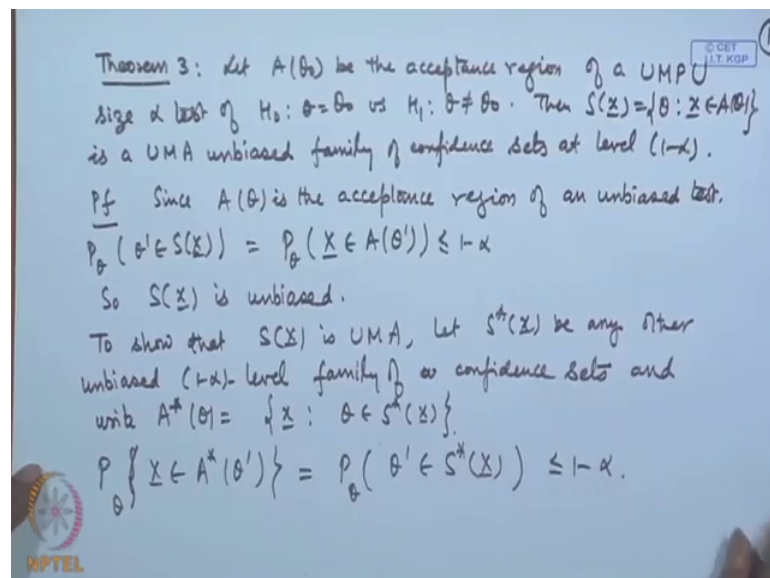
A family $S(x)$ of confidence sets for a parameter θ is said to be unbiased at confidence level $1 - \alpha$ if probability of θ belonging to $S(x)$ is greater than or equal to $1 - \alpha$ and $P_{\theta'}(\theta' \in S(x)) \leq 1 - \alpha$ for all θ and θ' where of course, $\theta \neq \theta'$.

So, so this is a $1 - \alpha$ level confidence set and in case $S(x)$ is an interval, then this will be called if $S(x)$ is interval satisfying this conditions 1 and 2, then it is unbiased confidence interval. So, what is the actually interpretation of this? What we are saying here is that the if the true value is θ then the true value is included in the confidence set with probability at least $1 - \alpha$ and if θ' is the true value then θ' is a false value then that value is included with probability less than or equal to $1 - \alpha$.

alpha; that means, this confidence interval will actually cover the true parameter value with a higher probability than a false parameter value; that means, the value which is true should have a higher chance of getting included in the interval rather than the and the false value that is the wrong value should have less chance of getting included.

So, this is an actual condition of unbiasedness as in the testing problem you remember unbiased test was that $\beta(\theta) \leq \alpha$ for θ belonging to null parameter space and for alternative, it was greater than or equal to α . So, similarly here it is based on $1 - \alpha$. Now there is a direct relation with the UMPU test that is the Uniformly Most Powerful Unbiased test with UMAU that is Uniformly Most Accurate Unbiased test I will state this result here.

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So, these results etcetera they are from Rohatgi and Salehs book they statements of the theorems and also the discussion and proofs of those theorems. Let $A(\theta)$ be the acceptance region of a UMPU size α test of $H_0: \theta = \theta_0$ against $H_1: \theta \neq \theta_0$ then $S(x) = \{\theta: x \in A(\theta)\}$ is a UMA unbiased family of confidence sets at level $1 - \alpha$.

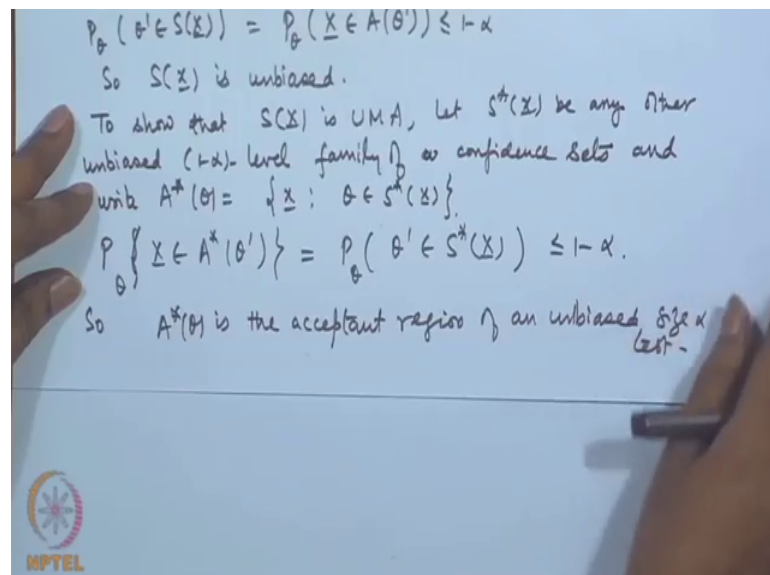
Let us look at the proof of this. Since $A(\theta)$ is the acceptance region of an unbiased test $P(\theta', \theta) \leq \alpha$ for $\theta \in \Theta_0$ and $P(\theta', \theta) \geq 1 - \alpha$ for $\theta \in \Theta_1$. $P(\theta', \theta) = P(x \in A(\theta))$. So $P(\theta', \theta) \leq \alpha$ for $\theta \in \Theta_0$ is equivalent to $P(x \in A(\theta)) \leq \alpha$ for $\theta \in \Theta_0$. Similarly $P(\theta', \theta) \geq 1 - \alpha$ for $\theta \in \Theta_1$ is equivalent to $P(x \in A(\theta)) \geq 1 - \alpha$ for $\theta \in \Theta_1$. So $A(\theta)$ is the acceptance region of an unbiased test if and only if $P(x \in A(\theta)) \leq \alpha$ for $\theta \in \Theta_0$ and $P(x \in A(\theta)) \geq 1 - \alpha$ for $\theta \in \Theta_1$. Now let $S(x) = \{\theta: x \in A(\theta)\}$ be the family of confidence sets corresponding to $A(\theta)$. Then $P(\theta', \theta) = P(x \in A(\theta)) = P(\theta \in S(x))$. So $P(\theta', \theta) \leq \alpha$ for $\theta \in \Theta_0$ is equivalent to $P(\theta \in S(x)) \leq \alpha$ for $\theta \in \Theta_0$. Similarly $P(\theta', \theta) \geq 1 - \alpha$ for $\theta \in \Theta_1$ is equivalent to $P(\theta \in S(x)) \geq 1 - \alpha$ for $\theta \in \Theta_1$. So $S(x)$ is a UMA unbiased family of confidence sets at level $1 - \alpha$ if and only if $P(\theta \in S(x)) \leq \alpha$ for $\theta \in \Theta_0$ and $P(\theta \in S(x)) \geq 1 - \alpha$ for $\theta \in \Theta_1$. Now let $S^*(x)$ be any other unbiased $(1 - \alpha)$ -level family of confidence sets. Then $P(\theta', \theta) = P(\theta \in S^*(x)) \leq \alpha$ for $\theta \in \Theta_0$ and $P(\theta', \theta) = P(\theta \in S^*(x)) \geq 1 - \alpha$ for $\theta \in \Theta_1$. So $P(\theta \in S(x)) \leq \alpha$ for $\theta \in \Theta_0$ and $P(\theta \in S(x)) \geq 1 - \alpha$ for $\theta \in \Theta_1$ implies $P(\theta \in S(x)) \leq P(\theta \in S^*(x)) \leq \alpha$ for $\theta \in \Theta_0$ and $P(\theta \in S(x)) \geq 1 - \alpha \geq P(\theta \in S^*(x)) \geq 1 - \alpha$ for $\theta \in \Theta_1$. So $S(x)$ is more accurate than $S^*(x)$. Since $S^*(x)$ is arbitrary, $S(x)$ is UMA.

true is the same as this that is equal to less than or equal to 1 minus alpha. So, $S(x)$ is unbiased.

To show that it is UMA, let us consider $S^*(x)$ be any other unbiased 1 minus alpha level family of confidence sets and we write here $A^*(\theta)$ is equal to x such that θ belonging to $S^*(x)$; that means, the corresponding acceptance regions are denoted by $A^*(\theta)$.

So, probability of x belonging to $A^*(\theta)$ that will be probability of θ prime belonging to $S^*(x)$ that is less than or equal to 1 minus alpha.

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So, we can say that, $A^*(\theta)$ is the acceptance region of an unbiased size alpha test.

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The image shows a whiteboard with handwritten mathematical expressions. At the top, it states $P_{\theta}(\theta' \in S^*(x)) = P_{\theta}(x \in A^*(\theta'))$. Below this, a circled greater-than-or-equal-to symbol (\geq) is written, with an arrow pointing to the word "UMP" which is underlined twice. To the right of the symbol, the expression $P_{\theta}(x \in A(\theta')) = P_{\theta}(\theta' \in S(x))$ is written. In the top right corner of the whiteboard, there is a small logo for "CET I.I.T. KGP" and a circled number "11".

Therefore we can write the statement that probability of theta prime belonging to S star x is equal to x belonging to A star theta prime that is greater than or equal to P theta x belonging to A theta prime that is equal to P theta, theta prime belonging to S x.

So, this inequality is there because of UMPU test. So, this proves that this is the uniformly most accurate region here. Now I will consider certain confidence intervals for parameters of normal populations. I have already given the confidence intervals for the mean of a normal population both when the variance is known or unknown and also for sigma S square when the mean may be known or unknown.

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Confidence Intervals for Parameters of Two Normal Populations

Let X_1, \dots, X_m be a r.s from $N(\mu_1, \sigma_1^2)$ popⁿ
Let Y_1, \dots, Y_n be a r.s from $N(\mu_2, \sigma_2^2)$ popⁿ
Let X & Y be indep^t

We want confidence interval for $\mu_1 - \mu_2$.

Case I : σ_1^2 & σ_2^2 are known.

$\bar{X} \sim N(\mu_1, \sigma_1^2/m)$, $\bar{Y} \sim N(\mu_2, \sigma_2^2/n)$
 $\bar{X} - \bar{Y} \sim N(\mu_1 - \mu_2, \sigma_1^2/m + \sigma_2^2/n)$

Now let us consider two sample problems confidence intervals for parameters of two normal populations. Let us consider say X_1, X_2, \dots, X_m be a random sample from say a normal μ_1 σ_1^2 population and Y_1, Y_2, \dots, Y_n be a random sample from say normal μ_2 σ_2^2 population and assume that these two samples are independent let me call it X sample and this is Y sample. Let X and Y be independent.

We are interested in finding out confidence interval for say $\mu_1 - \mu_2$. Let us take the first case when σ_1^2 and σ_2^2 are known. If they are known we can formulate nicely the pivot quantity, the distribution of \bar{X} is normal μ_1 σ_1^2/m , the distribution of \bar{Y} is normal μ_2 σ_2^2/n .

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$$W = \frac{\bar{X} - \bar{Y} - (\mu_1 - \mu_2)}{\sqrt{\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}}} \sim N(0,1)$$
 So W can be taken pivot

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

$$\Leftrightarrow P\left(\bar{X} - \bar{Y} - \sqrt{\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}} z_{\alpha/2} \leq \mu_1 - \mu_2 \leq \bar{X} - \bar{Y} + \sqrt{\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}} z_{\alpha/2}\right) = 1 - \alpha$$

So $\left(\bar{X} - \bar{Y} \pm \sqrt{\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}} z_{\alpha/2}\right)$ is $(1 - \alpha)$ -level conf. interval for $(\mu_1 - \mu_2)$.

So, the distribution of $\bar{X} - \bar{Y}$ is normal $\mu_1 - \mu_2$ with variance $\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}$ and therefore, $\frac{\bar{X} - \bar{Y} - (\mu_1 - \mu_2)}{\sqrt{\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}}}$ has a distribution free from the parameters. So, this can be considered as the pivot quantity. So, W can be taken as pivot because this involves $\mu_1 - \mu_2$ and random variables and the distribution is free from the parameters. So, if I consider the shortest length confidence interval based on this, then I should consider $z_{\alpha/2}$ and $-z_{\alpha/2}$ points.

So, probability of $-z_{\alpha/2} \leq W \leq z_{\alpha/2}$ that is equal to $1 - \alpha$ this is equivalent to the statement $\bar{X} - \bar{Y} - \sqrt{\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}} z_{\alpha/2} \leq \mu_1 - \mu_2 \leq \bar{X} - \bar{Y} + \sqrt{\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}} z_{\alpha/2}$ that is equal to $1 - \alpha$ here.

So, $\bar{X} - \bar{Y} \pm \sqrt{\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}} z_{\alpha/2}$ this is $1 - \alpha$ level confidence interval for $\mu_1 - \mu_2$, but if σ_1^2 and σ_2^2 are unknown we cannot use this. In that case we consider another pivot quantity $\frac{s_1^2 + s_2^2}{m + n}$ is equal to σ^2 , but unknown.

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Case II: $\sigma_1^2 = \sigma_2^2 = \sigma^2$ (unknown)

$\bar{X} \sim N(\mu_1, \sigma^2/m)$, $\bar{Y} \sim N(\mu_2, \sigma^2/n)$

$\frac{(m-1)S_1^2}{\sigma^2} \sim \chi_{m-1}^2$, $\frac{(n-1)S_2^2}{\sigma^2} \sim \chi_{n-1}^2$ } all variables are indep

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

$\frac{\bar{X} - \bar{Y} - (\mu_1 - \mu_2)}{\sigma \sqrt{\frac{1}{m} + \frac{1}{n}}} \sim N(0,1)$

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

$W = \frac{\sqrt{mn}}{m+n} \frac{(\bar{X} - \bar{Y} - (\mu_1 - \mu_2))}{S_p} \sim t_{m+n-2}$

Now these statements are true, that \bar{X} follows normal μ_1 sigma square by m and \bar{Y} follows normal μ_2 sigma square by n , but at the same time let us also consider say $m-1$ S_1^2 or S_1^2 square by sigma square that follows chi square distribution on $m-1$ degrees of freedom and $n-1$ S_2^2 square by sigma square this follows chi square distribution on $n-1$ degrees of freedom where S_1^2 denotes $\frac{1}{m-1} \sum (x_i - \bar{x})^2$ and S_2^2 denotes $\frac{1}{n-1} \sum (y_j - \bar{y})^2$ that is the two sample variances and these are all independent random variables all these variables are independently distributed.

If they are independently distributed, I can consider say $m-1$ S_1^2 plus $n-1$ S_2^2 by sigma square that follows chi square distribution on $m+n-2$ degrees of freedom and therefore, I can write down $\bar{X} - \bar{Y} - \mu_1 + \mu_2$ divided by $\sigma \sqrt{\frac{1}{m} + \frac{1}{n}}$ this follows normal $0,1$ and these two are also independent and let me define S_p^2 as $\frac{m-1}{m+n-2} S_1^2 + \frac{n-1}{m+n-2} S_2^2$, then $\bar{X} - \bar{Y} - \mu_1 + \mu_2$ divided by $S_p \sqrt{\frac{mn}{m+n}}$ this will follow t distribution on $m+n-2$ degrees of freedom.

So, this can be used as a pivot W because this involves certain random variable which is of interest to us because we wanted the confidence interval $\mu_1 - \mu_2$ random variable is involved here and the distribution is free from the parameters here.

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Handwritten mathematical derivation on a whiteboard:

$$P\left(-t_{m+n-2, \frac{\alpha}{2}} < W < t_{m+n-2, \frac{\alpha}{2}}\right) = 1 - \alpha$$

$$P\left(-t_{m+n-2, \frac{\alpha}{2}} < \sqrt{\frac{mn}{m+n}} \frac{\bar{X} - \bar{Y} - (\mu_1 - \mu_2)}{S_p} < t_{m+n-2, \frac{\alpha}{2}}\right) = 1 - \alpha$$

$$\Leftrightarrow P\left(\bar{X} - \bar{Y} - \sqrt{\frac{m+n}{mn}} S_p \cdot t_{m+n-2, \frac{\alpha}{2}} \leq \mu_1 - \mu_2 \leq \bar{X} - \bar{Y} + \sqrt{\frac{m+n}{mn}} S_p \cdot t_{m+n-2, \frac{\alpha}{2}}\right) = 1 - \alpha$$

The whiteboard also features a normal distribution curve with a central peak and two vertical lines marking the confidence interval boundaries. The area under the curve between these lines is labeled as $1 - \alpha$. The MPTEL logo is visible in the bottom left corner.

So, this can be used as a pivot quantity based on this I can write down the confidence interval. Probability of minus $t_{m+n-2, \frac{\alpha}{2}}$ less than W less than $t_{m+n-2, \frac{\alpha}{2}}$ that is equal to $1 - \alpha$. Once again I have chosen symmetric because the t distribution is symmetric. So, shortest length interval will be the one which will be symmetric around the origin here. So, this probability is $1 - \alpha$.

So, we can simplify this statement here, probability of minus $t_{m+n-2, \frac{\alpha}{2}}$ less than W so W is $\sqrt{\frac{mn}{m+n}} \frac{\bar{X} - \bar{Y} - (\mu_1 - \mu_2)}{S_p}$ less than $t_{m+n-2, \frac{\alpha}{2}}$ that is equal to $1 - \alpha$. So, after certain manipulation, I consider multiplication by S_p and divide by this term then I adjust $\bar{X} - \bar{Y}$ on both the sides that is statement will be then equal to $\bar{X} - \bar{Y} - \sqrt{\frac{m+n}{mn}} S_p \cdot t_{m+n-2, \frac{\alpha}{2}} \leq \mu_1 - \mu_2 \leq \bar{X} - \bar{Y} + \sqrt{\frac{m+n}{mn}} S_p \cdot t_{m+n-2, \frac{\alpha}{2}}$, this is equal to $1 - \alpha$.

So, we get $100(1 - \alpha)\%$ confidence interval as $\bar{X} - \bar{Y} \pm \sqrt{\frac{m+n}{mn}} S_p \cdot t_{m+n-2, \frac{\alpha}{2}}$. Now remember here, we have taken $\sigma_1^2 = \sigma_2^2$ assumption here which could have been done by making a test of hypothesis first that is we test whether $\sigma_1^2 = \sigma_2^2$, if it is accepted then we apply this method, but suppose it is not

accepted that sigma 1 square by sigma 2 square, the hypothesis sigma 1 square is equal to sigma 2 square is rejected if it is rejected then this test procedure will not be useful.

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Case III: $\sigma_1^2 \neq \sigma_2^2$ (unknown) Behrens-Fisher

$$W^* = \frac{\bar{X} - \bar{Y} - (\mu_1 - \mu_2)}{\sqrt{S_1^2/m + S_2^2/n}}$$

has approximate t distⁿ on k dof.

where $k = \frac{(S_1^2/m + S_2^2/n)^2}{[S_1^4/(m^2(m-1)) + S_2^4/(n^2(n-1))]}$
we take k to be integral part.

So based on W^* an approximate $(1-\alpha)$ -level confidence interval for $\mu_1 - \mu_2$ is

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

In this case an approximate procedure has been proposed by Welch in nineteen. So, that is let me say case 3, sigma 1 square not equal to sigma 2 square and they are unknown. So, this is known as famous Behrens Fisher situation, even in the testing problem we have not considered this because in this case theory of Neyman Pearsons test fails we cannot find out UMPN bias test in the situation. We can also not derive a likely would ratio test in that situation it does not give a region there.

So, approximate this is famous Behrens Fisher situation and in approximate procedures were proposed and one procedure which is based on let me call it W star that is X bar minus Y bar minus mu 1 minus mu 2 divided by square root of S 1 square by m plus S 2 square by n. So, basically this statistic if you see why it has been considered you considered the case of known sigma 1 square sigma 2 square. In the known sigma 1 square sigma 2 square case this was the statistic that we considered as the pivot quantity.

So, in place of sigma 1 square and sigma 2 square you are placed by S 1 square and S 2 square. So, this has approximate t distribution on say k degrees of freedom where k is actually random quantity. It is a S 1 square by m plus S 2 square by n whole square divided by S 1 to the power 4 divided by m square into m minus 1 plus S 2 to the power 4 divided by n square into n minus 1 and again problem is that this not be an integer. So,

we consider we usually take k to be integral part of this. So, based on W star an approximate $1 - \alpha$ level confidence interval for $\mu_1 - \mu_2$ that will be $\bar{X} - \bar{Y} \pm t_{\alpha/2, k} \sqrt{S_1^2/m + S_2^2/n}$.

Now another interesting case is that, when the number of observations is a same and there is some sort of pairing if there is a pairing here then like in the paired test paired considered the quantity $\bar{X} - \bar{Y}$ divided by based on the standard the variance of the differences.

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Case IV : Paired Observations
 $(X_i, Y_i) \sim \text{BVN}$
 $D_i = X_i - Y_i \sim N(\mu_1 - \mu_2, \sigma_D^2)$
 $\bar{D}, S_D^2 = \frac{1}{n-1} \sum (D_i - \bar{D})^2$
 $W_1 = \frac{\sqrt{n}(\bar{D} - (\mu_1 - \mu_2))}{S_D} \sim t_{n-1}$
 (1- α)-level confidence interval for $\mu_1 - \mu_2$ is then
 $\bar{D} \pm \frac{S_D}{\sqrt{n}} t_{n-1, \alpha/2}$

So, let me consider that situation also, case 4 that is paired observations. So, as before, we are considering X_i, Y_i this is following bivariate normal. So, in that case, if I am considering D_i as equal to $X_i - Y_i$, that follows normal $\mu_1 - \mu_2$ and some variance σ_D^2 . So, we considered \bar{D} and S_D^2 that is $\frac{1}{n-1} \sum (D_i - \bar{D})^2$. So, $\sqrt{n}(\bar{D} - (\mu_1 - \mu_2)) / S_D$ this will have t distribution on $n - 1$ degrees of freedom. So, this can be considered as a pivot. So, if we use this as a pivot, then the confidence interval $1 - \alpha$ level confidence interval for $\mu_1 - \mu_2$ is then $\bar{D} \pm \frac{S_D}{\sqrt{n}} t_{n-1, \alpha/2}$.

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Confidence Interval for $\frac{\sigma_1^2}{\sigma_2^2}$

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

$$W = \frac{\sigma_1^2}{\sigma_2^2} \frac{S_1^2}{S_2^2} \sim F_{m-1, n-1}$$

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

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

I will end up this lecture by confidence interval for variance ratios if I have variance ratio I can consider confidence interval for say sigma 2 square by sigma 1 square, then I can consider this quantity see S 1 square m minus 1 S 1 square by sigma 1 square follows chi square distribution on m minus 1 degrees of freedom n minus 1 S 2 square by sigma 2 square follows chi square n minus 1 degrees of freedom and they are independent. So, if I frame the ratio S 1 is square by a S 2 square sigma 2 square by sigma 1 square let me call it by W this will followed F distribution on m minus 1 n minus 1 degrees of freedom.

So, probability of course, F is a skew distribution, but for convenience we may still consider $f_{1-\frac{\alpha}{2}, m-1, n-1}$ and $f_{\frac{\alpha}{2}, m-1, n-1}$ points $f_{\frac{\alpha}{2}, m-1, n-1}$ and $1-\frac{\alpha}{2}$ $m-1$ $n-1$ less than or equal to this W less than or equal to $f_{\frac{\alpha}{2}, m-1, n-1}$ that is equal to $1-\alpha$.

So, this is equivalent to saying that probability of sigma 2 square by sigma 1 square in the interval $f_{1-\frac{\alpha}{2}, m-1, n-1} S_2^2$ by S_1^2 to $f_{\frac{\alpha}{2}, m-1, n-1} S_2^2$ by S_1^2 that is equal to $1-\alpha$. So, we get $1-\alpha$ level confidence interval as left and limit as $f_{1-\frac{\alpha}{2}, m-1, n-1}$ on $m-1$ $n-1$ degrees of freedom S_2^2 by S_1^2 and the right hand limit as $f_{\frac{\alpha}{2}, m-1, n-1} S_2^2$ by S_1^2 .

I have discussed the general methods of finding out the confidence interval using the pivot method. I have also discussed the a special confidence interval for the parameters of normal distributions, exponential distributions etcetera.

Now in this let me have a summary of this course. We have considered major methods of statistical inference as developed in the classical statistics. The originators of most of this concepts were primarily RA Fisher and who in 1920's and 30's laid the foundations of theoretically statistics and Neyman and Pearson who were credited with the theory of testing of hypothesis, which I have covered in a major way in this particular course and also the theory of confidence intervals was developed by Neman.

I have in this particular course derived the methods; that means, what method should be used using what philosophy that we have done now given a practical problem you will have a data for example, you may have a data. So, you say may treat it as a data from a normal distribution say normal distribution with parameters μ and σ^2 . Now you may like to find out a point estimator of μ and σ^2 .

So, you may calculate MLEs you may calculate base or minimize estimators you may also consider testing problem so you may use one of the methods, you may also like to consider confidence intervals for the parameters, you may also have say two populations you may have samples from that. So, in this particular course we have derived all the methodologies which one can use as a statistician. I will be putting up certain assignment sheets, that is a problem sets and some of their hints and solutions for those sets which will have actually the practical data sets there. So, from the data sets you actually solve the problem and see which method will be used. So, that will be quite useful.

We have come to the end of this course. So, the topic of inferences actually very very wide I have covered only what is known as classical inference or you can say classical statistics there are many many modern methods which are being used, but I have not been able to cover in this particular course, but these courses will these things will be useful for most of the practical problems that people face. So, with this end we come to an end. I advise all the readers to solve the problem sets that I will be putting.