

Statistical Inference
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Lecture - 62
Interval Estimation – II

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Expected length of confidence interval

$$E(S) = \frac{2}{\sqrt{n}} t_{n-1, \alpha/2} k_n \sigma$$

One sided interval

$$k_n = \sqrt{\frac{2}{n-1}} \cdot \frac{\Gamma(n/2)}{\Gamma(n/2)}$$

$$P(\mu < \bar{X} - c) = 1 - \alpha$$

$$P(\bar{X} - \mu > c) = 1 - \alpha$$

$$\Leftrightarrow P\left(\frac{\sqrt{n}(\bar{X} - \mu)}{S} > \frac{\sqrt{n}c}{S}\right) = 1 - \alpha$$

$$t_{n-1, \alpha} \quad \frac{\sqrt{n}c}{S} = -t_{n-1, \alpha}$$

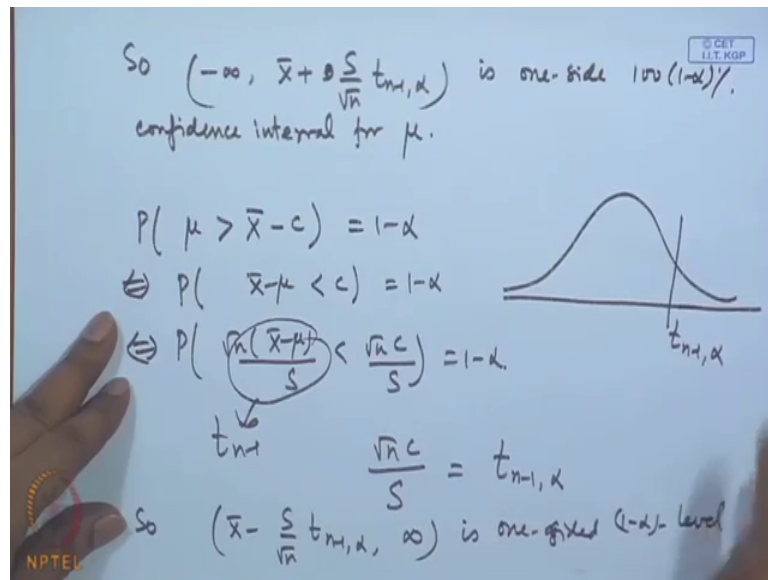
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I may also look at expected length. Expected length of confidence interval. That is equal to $2 \text{ by root } n \text{ } t_{n-1, \alpha/2} \text{ expectation of } S$. If you remember our lecture on the point estimation when we are considering the minimum variance and bias estimation of sigma and normal distribution then expectation of S was some coefficient times sigma. So, $2 \text{ by root } n \text{ } t_{n-1, \alpha/2}$. Some coefficient I will call it k_n times sigma where of course, k_n was given by $\sqrt{2 \text{ by } n-1} \cdot \frac{\Gamma(n/2)}{\Gamma(n/2)}$.

So, this coefficient of course, you can see again it will go to 0 as n tends infinity. So, that is satisfied here. Let me consider here one sided interval also. Because in both the cases I have given 2 sided, but we may sometimes require one sided interval. If we want one sided so, for example, you may say $\bar{X} - c$ that is equal to $1 - \alpha$ for one sided interval; that means, what we are saying probability of $\bar{X} - \mu > c$ is equal to $1 - \alpha$. Or probability of $\frac{\sqrt{n}(\bar{X} - \mu)}{S} > \frac{\sqrt{n}c}{S}$ is equal to $1 - \alpha$.

Now, this is having t distribution on n minus 1 degrees of freedom. So, what we are looking at is the point on the t distribution curve beyond which the probabilities 1 minus alpha. So, we may choose root n c by S is equal to minus t n minus 1 basically this is alpha this is minus t n minus 1 alpha beyond which this probability is 1 minus alpha.

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So, the interval is minus infinity to X bar plus S by root n t n minus 1 alpha. This is one sided 100 1 minus alpha percent confidence interval.

Here we have given an upper bound here. We may also take a lower bound. You may say what is the probability of mu greater than say X bar minus C equal to 1 minus alpha. If we see from this point of you then it will become probability of X bar minus mu less than C that is equal to 1 minus alpha are probability of root n X bar minus mu by S less than root n c by S that is equal to 1 minus alpha.

So, this is nothing but a t distribution on n minus 1 degrees of freedom. So, what we are saying is a probability below a certain point is 1 minus alpha. So, this value can be chosen to be t root n C by S can be chosen to be t n minus 1 alpha. So, we are getting X bar minus S by root in t n minus 1 alpha to infinity. This is one sided 1 minus alpha level confidence interval.

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confidence interval for μ . is one-side $100(1-\alpha)\%$.

$$P(\mu > \bar{X} - c) = 1 - \alpha$$

$$\Leftrightarrow P(\bar{X} - \mu < c) = 1 - \alpha$$

$$\Leftrightarrow P\left(\frac{\sqrt{n}(\bar{X} - \mu)}{S} < \frac{\sqrt{n}c}{S}\right) = 1 - \alpha$$

So $\frac{\sqrt{n}c}{S} = t_{n-1, \alpha}$

is one-sided $(1-\alpha)$ -level confidence interval for μ .

So, here we have given a lower bound. In this one we are having an upper bound here.

So, this only goes on to show that what we are doing here is that we are considering a quantity based on which it is easy to derive a confidence interval, but that brings us to a question that how to choose this quantity. Like in the case of normal distribution we have chosen \bar{X} , but in other distributions what we will do. So, that is an important concept it is called the method of pivoting.

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Pivoting Method for Deriving Confidence Intervals

Let $X = (X_1, \dots, X_n)$ be a random sample from a population with distⁿ P_{θ} , $\theta \in \Theta$. A function $W(X, \theta)$ is said to be pivot if its distⁿ does not depend on θ .

Examples 1. Let X_1, \dots, X_n a r.s. from $U(0, \theta), \theta > 0$.

$Y = X_{(n)}$ $f_Y(y) = \begin{cases} \frac{ny^{n-1}}{\theta^n}, & 0 < y < \theta \\ 0, & \text{ew.} \end{cases}$

$W = \frac{Y}{\theta}$, $\text{dist}^n W = f_W(w) = \begin{cases} nw^{n-1}, & 0 < w < 1 \\ 0, & \text{ew} \end{cases}$

So W is pivot.

So, let me discuss that now pivoting method for deriving confidence intervals. So, as before we are having X is equal to X_1, X_2, \dots, X_n .

This is a random sample from a population with distribution say $P(\theta)$ in general we may have vector of parameters. Then a function say W of $X(\theta)$ this is said to be pivot if its distribution does not depend on θ . So, in the previous problem let us consider $\sqrt{n}(\bar{X} - \mu) / S$ this is having a distribution which is not dependent on μ or σ^2 . So, this is a pivot. In this exercise $\sqrt{n}(\bar{X} - \mu)$ has a distribution which is independent of μ . So, this is a pivot.

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examples. 1. Let $X_1, \dots, X_n \sim N(\mu, \sigma^2)$.
 We want confidence interval for μ .
 \bar{X} is minimal sufficient statistic.
 We consider confidence interval of the type
 $(\bar{X} - c_1, \bar{X} + c_2)$ so that
 $P(\bar{X} - c_1 < \mu < \bar{X} + c_2) \geq 1 - \alpha$
 $\Leftrightarrow P(-c_2 < \bar{X} - \mu < c_1) \geq 1 - \alpha$
 $\Leftrightarrow P(-\sqrt{n}c_2 < \sqrt{n}(\bar{X} - \mu) < \sqrt{n}c_1) \geq 1 - \alpha$
 $P\left(\frac{-\sqrt{n}c_2}{\sigma} < Z < \frac{\sqrt{n}c_1}{\sigma}\right) \geq 1 - \alpha$
 may take equality at $(1 - \alpha)$ as
 are considering continuous dist.

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

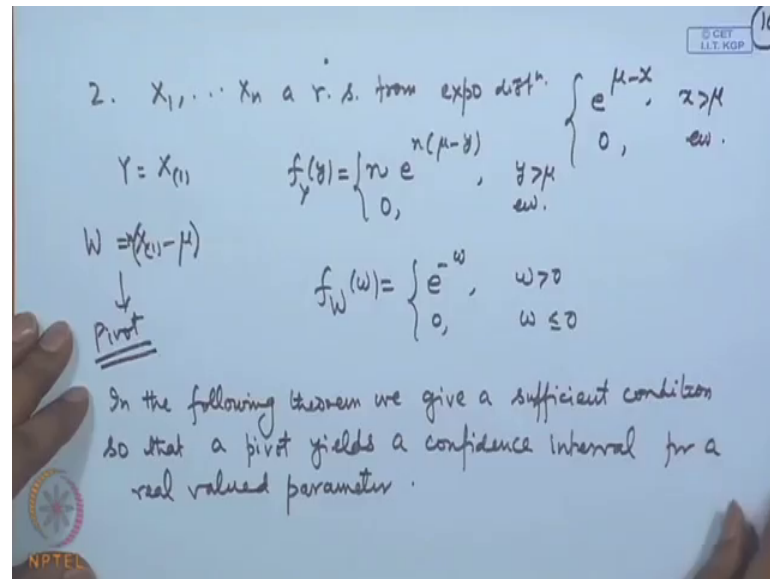
So, in the pivot method we consider a quantity which is having a distribution independent of the parameter. At the same time the pivot must include the random variables as well as the parameter. In such a way that by resolving the interval or you can say by resolving the inequalities we are able to get an interval, which is free from; that means, in between we get the parameter or one side we get the parameter and on the other side we get the quantity which is dependent upon the variable.

So, let me just one or two more examples of the pivot quantity. Let us consider say X_1, X_2, \dots, X_n a random sample from uniform $0, \theta$ distribution. Now consider say X_n let me call Y you know the distribution of y that is $n y$ to the power $n - 1$ by θ to the power n , it is 0 elsewhere. In this if I define say W is equal to Y divided by θ . Then what is the distribution of W ? Distribution of W and this is equal to $n W$ to the power n

minus 1 for 0 less than W less than one and it is 0 elsewhere. So, this distribution is free from the parameters. And this W involves the random variable X_n as well as the parameter which is coming here.

So, this is. So, W is pivot in this problem. Let me just give one more example here.

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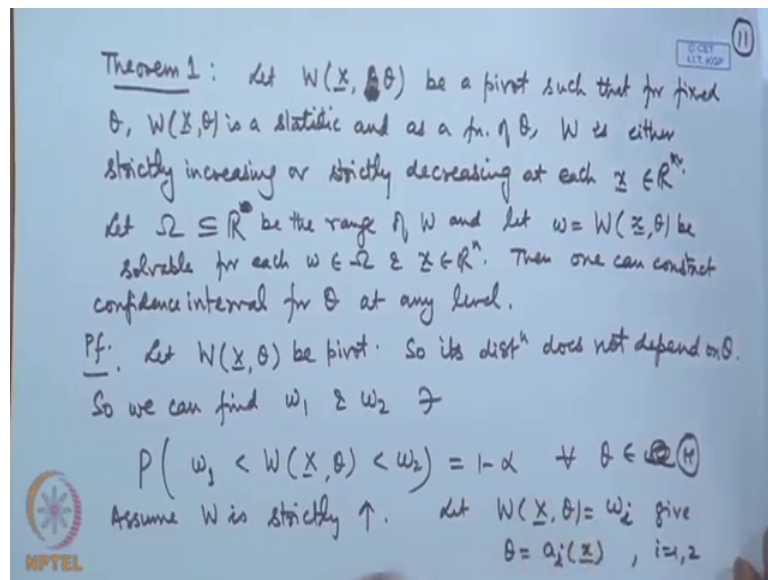
Let us consider say X_1, X_2, \dots, X_n a random sample from exponential distribution with density function of the form say $e^{-\mu x}$ let us consider say X_1 what is the distribution of X_1 let me call it Y then the distribution of Y that can be calculated to be $n e^{-ny}$.

So, in that case if I consider $X_1 - \mu$ then what is the distribution of W or I can consider n times that then what is the distribution of W ? That is equal to e^{-w} . That is simply the exponential distribution.

So, this W is a pivot and again the interesting point is that.

This involves a random variable and the parameter which is unknown parameter of the distribution. Now in the following theorem, we give a sufficient condition. So, that a pivot yields a confidence interval for a real valued parameter.

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The theorem is as follows. Let me call theorem 1. Let $W(X, \theta)$ so, I am taking one dimensional case for parameters while right just θ here, be a pivot such that for fixed θ $W(X, \theta)$ is a statistic. And as a function of θ W is either a strictly increasing or a strictly decreasing at each x . Let Ω that is a subset of \mathbb{R}^n be the range of now I am assuming this to be real. So, let this be the range of W and let the equation say small w is equal to capital W of X, θ be solvable for each Ω and each x then one can construct the confidence interval for θ at any level. Let t W of X, θ be pivot. And so, it is distribution does not depend on θ .

If it does not depend upon θ . So, we can find say ω_1 and ω_2 such that probability of $\omega_1 < W(X, \theta) < \omega_2$ that is equal to $1 - \alpha$. And this statement now will be true for all θ because the parameter does not depend upon the distribution of W does not depend upon the parameter. See this is I think script θ here the range of the parameter here. Now assume that W is a strictly increasing and let $W(X, \theta) = \omega_i$ give $\theta = a_i(x)$, $i=1, 2$.

Because we are assuming that this can be solved. If it can be solved then this condition say one then this condition 1.

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Then condition (1) is equivalent to

$$P(a_1(X) < \theta < a_2(X)) = 1 - \alpha \quad \forall \theta \in \Theta$$

So $(a_1(X), a_2(X))$ is $(1 - \alpha)$ -level confidence interval for θ .

In case W was strictly ↓

Then (1) will be equivalent to

$$P(a_2(X) < \theta < a_1(X)) = 1 - \alpha \quad \forall \theta \in \Theta$$

So that $(1 - \alpha)$ -level conf interval for θ is now $(a_2(X), a_1(X))$.

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This is equivalent to probability of a 1 X less than theta less than a 2 X is equal to 1 minus alpha. So, a 1 X to a 2 X is 1 minus alpha level confidence; confidence interval for theta. In case W was decreasing suppose it is strictly decreasing then this will change. Then one will be equivalent to probability of a 2 X less than theta less than a 1 X equal to 1 minus alpha.

So, that 1 minus alpha level confidence interval for theta is now a 2 X 2 a 1 X. Now I have considered the simplistic situation where I have put here equality as 1 minus alpha; however, it may happen that the distribution of W is a discrete distribution. In that case we may not be able to achieve 1 minus alpha. We may say it is greater than or equal to 1 minus alpha. So, a value which is slightly higher than 1 minus alpha maybe at achieve, but in that case we will have that as the confidence level. In the case of continuous W any level can be achieved here. Another point when I mentioned this result here, I am considering the solvability and I am considering theta as a scalar.

Suppose theta as a vector. Even in that case it may be possible to write down a statistic which involves the parameter which is free from the which as a distribution free from the parameters. However, in that case if the parameter theta is not a scalar, in that case we do not say confidence interval rather we say a confidence band or a confidence set in general that we are talking about. I will just consider one case when we may deal with multi parameter situations.

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The above theorem may be extended to case where θ may be vector.

$$X_1, \dots, X_n \sim N_p(\mu, I) \text{ (Multivariate Normal)}$$

$$\bar{X} - \mu \sim N_p(0, I)$$

$$W = (\bar{X} - \mu)' (\bar{X} - \mu) \sim \chi^2_p.$$

$$P(\chi^2_{p+2} \leq W \leq \chi^2_{p, \alpha/2}) = 1 - \alpha$$

↓
($\bar{X} - \mu$)' ($\bar{X} - \mu$)

The above theorem may be extended to case where theta maybe vector.

For example, I say X_1, X_2, \dots, X_n this follows a multivariate normal with mean vector μ and variance covariance matrix and this is p dimensional. So, this is multivariate normal; however, even this case we may consider thing like $x_i - \mu$. Or we may considered $\bar{X} - \mu$. That will follow normal 0 in p and if I consider say $(\bar{X} - \mu)'$ into $(\bar{X} - \mu)$. That will follow chi square distribution on p degree of freedom this may be treated as W . And in that case what we can write here is W this is chi square.

So, we may write say $\chi^2_{p+2} \leq W \leq \chi^2_{p, \alpha/2}$ probability of this is equal to $1 - \alpha$. And then now this W is nothing but $(\bar{X} - \mu)' (\bar{X} - \mu)$. So, we get a confidence band here. Rather than because if we write down this thing as an equation in μ this is denoting an ellipsoid. So, actually it is concentration ellipsoid that we will be getting here. I will complete this part by giving confidence interval for the variance in a normal distribution by using this method of pivoting.

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Example: $X_1, \dots, X_n \sim N(\mu, \sigma^2)$

⊙ We want confidence interval for σ^2 .

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

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

We can choose

$$P(\chi^2_{1-\alpha_1, n-1} < W < \chi^2_{\alpha_2, n-1}) = 1-\alpha$$

$$P(\chi^2_{1-\alpha_1, n-1} < \frac{(n-1)S^2}{\sigma^2} < \chi^2_{\alpha_2, n-1}) = 1-\alpha$$

$$\Leftrightarrow P\left(\frac{(n-1)S^2}{\chi^2_{\alpha_2, n-1}} < \sigma^2 < \frac{(n-1)S^2}{\chi^2_{1-\alpha_1, n-1}}\right) = 1-\alpha$$

$\alpha_1 + \alpha_2 = \alpha$

Let us consider say X_1, X_2, \dots, X_n following normal μ, σ^2 . And we want the confidence interval for say σ^2 . If I consider this S^2 as $\frac{1}{n-1} \sum (X_i - \bar{X})^2$, then we may take $\frac{(n-1)S^2}{\sigma^2}$ as the pivot quantity. This is simply chi square distribution on $n-1$ degrees of freedom.

So, this is of course, a skewed distribution. Now we may choose in general 2 points here say $\chi^2_{1-\alpha_1, n-1}$ and $\chi^2_{\alpha_2, n-1}$ on $n-1$ degrees of freedom. So this probability is α_2 , this probability is $1-\alpha_1$, say in between probability is actually so, we may put $1-\alpha$ on say here. So, this probability is α_1 . So, this middle probabilities actually $1-\alpha_1-\alpha_2$. So, we can choose probability of $\chi^2_{1-\alpha_1, n-1} < W < \chi^2_{\alpha_2, n-1}$ is equal to $1-\alpha$; that means, what we are saying $\alpha_1 + \alpha_2 = \alpha$ here.

This will give me $\chi^2_{1-\alpha_1, n-1} < \frac{(n-1)S^2}{\sigma^2} < \chi^2_{\alpha_2, n-1}$ it is equal to $1-\alpha$; which is statement we can write as $\frac{(n-1)S^2}{\chi^2_{\alpha_2, n-1}} < \sigma^2 < \frac{(n-1)S^2}{\chi^2_{1-\alpha_1, n-1}}$. And greater than $\sigma^2 > \frac{(n-1)S^2}{\chi^2_{1-\alpha_1, n-1}}$ that is equal to $1-\alpha$.

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$W = \frac{(n-1)S^2}{\sigma^2} \sim \chi^2_{n-1}$
 We can choose
 $P(\chi^2_{1-\alpha_1, n-1} < W < \chi^2_{\alpha_2, n-1}) = 1-\alpha$
 $P(\chi^2_{1-\alpha_1, n-1} < \frac{(n-1)S^2}{\sigma^2} < \chi^2_{\alpha_2, n-1}) = 1-\alpha$
 $\Leftrightarrow P\left(\frac{(n-1)S^2}{\chi^2_{\alpha_2, n-1}} < \sigma^2 < \frac{(n-1)S^2}{\chi^2_{1-\alpha_1, n-1}}\right) = 1-\alpha$
 We choose $\alpha_1 = \alpha_2 = \frac{\alpha}{2}$ for convenience

For convenience we may choose say alpha 1 is equal to alpha 2 is equal to alpha i 2 for convenience. What I am saying here is that we may get actually several intervals which will have the same confidence level 1 minus alpha, but for practical purpose one may fix up so, that we can come to a unique solution.

So, we can choose alpha 1 alpha 2 is equal to alpha by 2.

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Then $\left(\frac{(n-1)S^2}{\chi^2_{1-\frac{\alpha}{2}, n}}, \frac{(n-1)S^2}{\chi^2_{\frac{\alpha}{2}, n}}\right)$ is $(1-\alpha)$ -level confidence interval for σ^2 .
 Remark: If μ is known, say $\mu = \mu_0$, then we can choose pivot as $W^* = \frac{\sum (X_i - \mu_0)^2}{\sigma^2} \sim \chi^2_n$
 $P(\chi^2_{1-\frac{\alpha}{2}, n} < W^* < \chi^2_{\frac{\alpha}{2}, n}) = 1-\alpha$
 $\Leftrightarrow P\left(\frac{\sum (X_i - \mu_0)^2}{\chi^2_{\frac{\alpha}{2}, n}} < \sigma^2 < \frac{\sum (X_i - \mu_0)^2}{\chi^2_{1-\frac{\alpha}{2}, n}}\right) = 1-\alpha$

In that case then what we are saying is n minus 1 S square by chi square alpha by 2 n minus to n minus 1 S square by chi square 1 minus alpha by 2 n minus 1. This is 1 minus

alpha level confidence interval for sigma square. Now see we have considered this pivot quantity when mu is unknown here.

But if mu is known, if mu is known in this problem, say mu is equal to mu naught in that case we can choose pivot as let me call it W star. $\sum (X_i - \mu_0)^2 / \sigma^2$. Now this is as a chi square distribution on n degrees of freedom. Now if we give the same argument by writing down chi square say $1 - \alpha$ by $2n$ less than W star less than chi square α by $2n$ that is equal to $1 - \alpha$. Then this is equivalent to saying probability of $\sum (X_i - \mu_0)^2 / \sigma^2$ to $\chi^2_{1-\alpha, 2n}$ that will be equal to $1 - \alpha$.

So, $\sum (X_i - \mu_0)^2 / \sigma^2$ to $\chi^2_{1-\alpha, 2n}$ to $\sum (X_i - \mu_0)^2 / \sigma^2$ to $\chi^2_{\alpha, 2n}$ to $\sum (X_i - \mu_0)^2 / \sigma^2$ to $\chi^2_{1-\alpha, 2n}$ this will be the $1 - \alpha$ level confidence interval for sigma square. So, when mu is known we may use this, but when mu is unknown then suddenly we cannot use this and we make use of this as an interval.

Now, when I was driving this I considered the level of in a confidence level. So, there is a connection between the level of significance in testing problem to the confidence level in a confidence interval. So, I will state a result about this in the next class. We establish a connection between these and derive confidence intervals for various problems. For example, parameters of a normal distribution, parameters of 2 normal distributions binomial proportions etcetera so, that I will be covering in the next lecture.