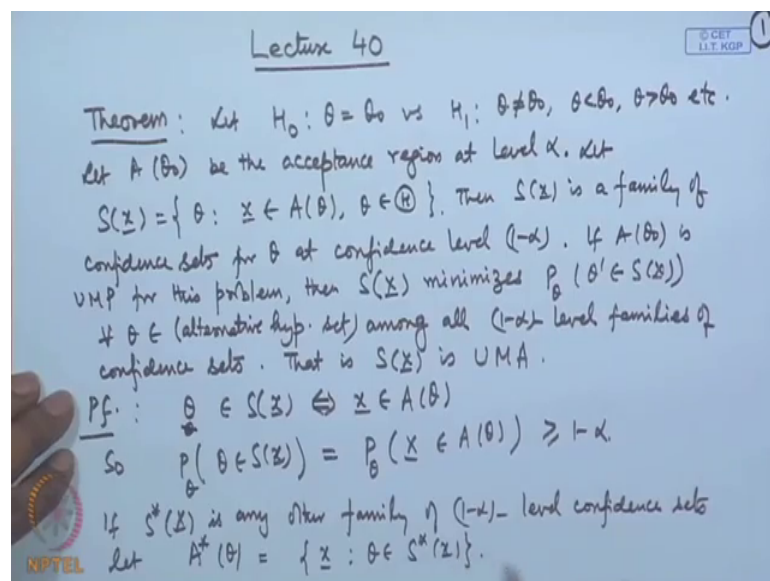


Statistical Inference
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Lecture - 63
Interval Estimation – III

In the previous lecture, I have introduced the concept of Interval Estimation confidence intervals with a certain confidence level. We also discussed a method that is the method of pivoting for obtaining confidence intervals for particular confidence levels. Now what I want to mention is that the theory of uniformly most powerful test or the uniformly most powerful unbiased test is intimately related with the theory of uniformly most accurate confidence intervals or uniformly most accurate unbiased intervals.

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So, we restrict attention to the non ms tests and then we have the following result. So, let us consider say hypothesis testing problem say theta is equal to theta naught against some alterative actually that alternative I am not writing it specifically it could be say theta naught is equal to theta naught theta less than theta naught or theta greater than theta naught etcetera and any of the alternatives can be there ok; that means, based on any of the alternatives are rejection region or you can say the alternative hypothesis set will be.

For example, here in the acceptance region you have θ naught in the rejection region you may have all the points except θ naught or you may have all the points below θ naught or you may have all the points above θ naught. Let us consider say A_{θ} as the acceptance region; acceptance region at level α and let us consider say S_x to be the set of parameters θ such that x belongs to A_{θ} .

Then S_x is a family of confidence sets for θ at confidence level $1 - \alpha$; that means, if I am having critical region or you can say a level α test and if I consider the acceptance region for that, then from there I can derive $1 - \alpha$ level confidence set ok. Now moreover, if A_{θ} is uniformly most powerful for this problem then S_x minimizes $P_{\theta'}(S_x)$ for all θ belonging to alternative hypothesis set. As I mentioned here it could be all the θ s other than θ naught it could be θ s less than θ naught or could be θ greater than θ naught etcetera, among all $1 - \alpha$ level. That is S_x is uniformly most accurate confidence region.

Let me look at the proof of this of course, it is very simple because we are just following the definition see if I say θ belongs to S_x then this is equivalent to saying that x belongs to A_{θ} . So, the probability of θ belonging to S_x that is S_x including θ is same as probability of x belonging to A_{θ} greater than or equal to $1 - \alpha$.

So, what does it mean? It means that if A_{θ} is acceptance region of a α level test then S_x will be a family of confidence sets of $1 - \alpha$ level that is one thing. Now next let us to prove that uniformly most accurate. So, if S^*_x is any other family of $1 - \alpha$ level confidence sets, let us define say A^*_{θ} that is equal to x such that θ belongs to S^*_x .

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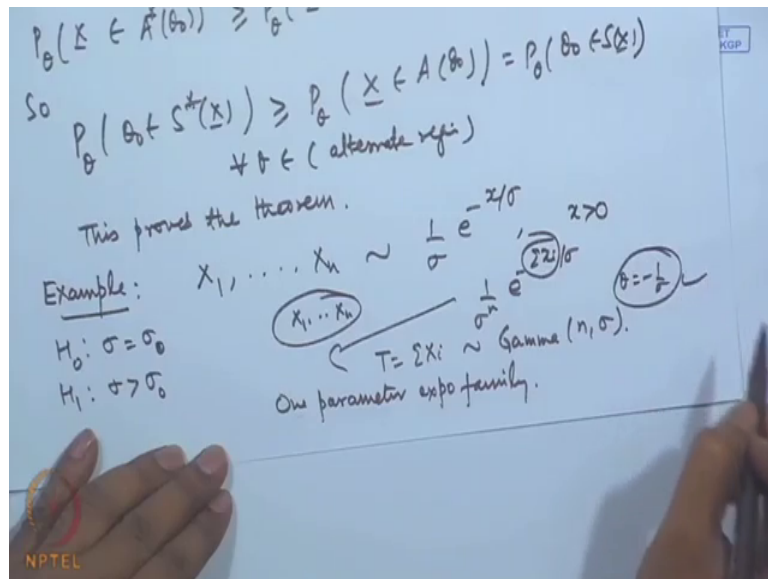
Then $P_{\theta}(X \in A^*(\theta)) = P_{\theta}(\theta \in S^*(X)) \geq 1 - \alpha$
 and also since $A(\theta_0)$ is UMP, we have
 $P_{\theta}(X \in A^*(\theta_0)) \geq P_{\theta}(X \in A(\theta_0))$ for any $\theta \in (\text{alternative region})$
 So $P_{\theta}(\theta_0 \in S^*(X)) \geq P_{\theta}(X \in A(\theta_0)) = P_{\theta}(\theta_0 \in S(\theta_0))$
 $\forall \theta \in (\text{alternative region})$
 This proved the theorem.
 Example: $X_1, \dots, X_n \sim \frac{1}{\sigma} e^{-x/\sigma}, x > 0$
 $H_0: \sigma = \sigma_0$
 $H_1: \sigma > \sigma_0$
 $T = \sum X_i \sim \text{Gamma}(n, \sigma)$

Then $P_{\theta}(X \in A^*(\theta)) = P_{\theta}(\theta \in S^*(X)) \geq 1 - \alpha$ and also since $A(\theta_0)$ is UMP, we have that $P_{\theta}(X \in A^*(\theta_0)) \geq P_{\theta}(X \in A(\theta_0))$, for any θ in the alternative region; region of the alternative hypothesis.

So, probability of θ_0 belonging to $S^*(X)$ is greater than or equal to probability of X belonging to $A(\theta_0)$ that is $P_{\theta}(\theta_0 \in S^*(X)) \geq P_{\theta}(X \in A(\theta_0))$, for all θ belonging to alternate region. So, this proves that the $S^*(X)$ family is the family of uniformly most accurate confidence regions or confidence sets.

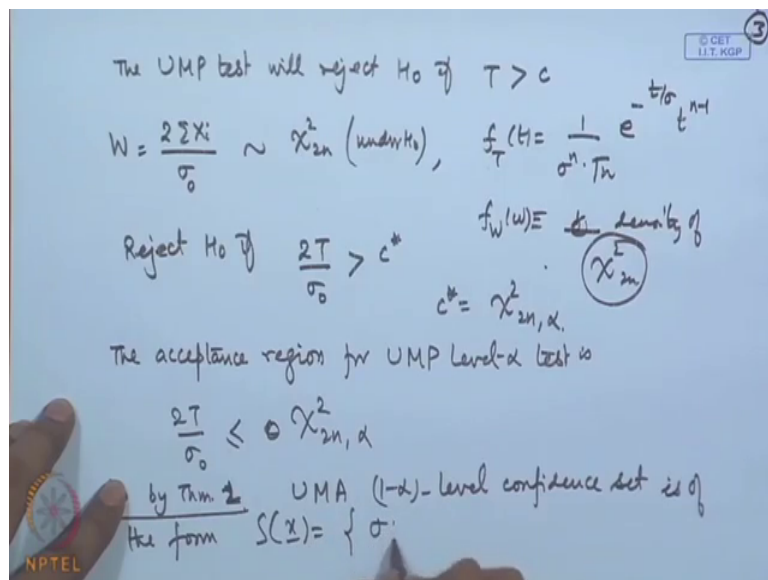
Let me consider one example here say X_1, X_2, \dots, X_n this follows $1/\sigma e^{-x/\sigma}$ to the power minus x by σ and let us consider the testing problem σ is equal to σ_0 against σ is greater than σ_0 . Now, in this problem we have derived see this is 1 parameter exponential family, if I consider the joint distribution of X_1, X_2, \dots, X_n , the joint distribution that is $1/\sigma^n e^{-\sum x_i/\sigma}$ to the power minus $\sum x_i$ by σ . So, this is the one parameter exponential family $T = \sum X_i$ let us call it $T = \sum X_i$ and that follows gamma distribution with parameters n and σ ok.

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This is one parameter exponential family therefore and also you are having minus 1 by sigma which is it is quickly increasing in sigma. So, theta is equal to minus 1 by sigma therefore, the test will exist, the test will be actually rejecting in favor of the larger value of T.

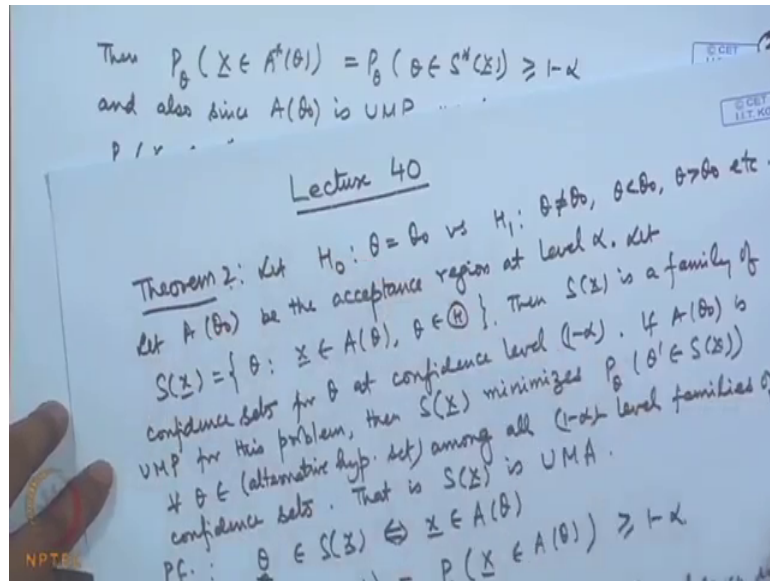
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So, the uniformly most powerful test will reject H_0 if T is greater than some c and then we determine this thing actually you look at the distribution of twice sigma X_i by sigma naught, let me call it W. So, that will follow a chi square distribution on 2 n degrees of freedom because what is the distribution of T? The distribution of T is 1 by sigma to the power n gamma n e to the power minus t by sigma t to the power n minus 1.

So, if I consider this is under H_0 naught, say if I consider $2T$ by σ naught then the distribution of f_w that will come equal to 1 by gamma same thing. So, that will be the density of chi square distribution on $2n$ degree of freedom. So, we can write rejection reject H_0 naught if $2T$ by σ naught is greater than say c^* where c^* is nothing, but chi square $2n$ alpha ok. So, the acceptance region for UMP level alpha test is $2T$ by σ naught less than or equal to chi square $2n$ alpha.

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So, by the previous theorem which we call theorem 2 say, we can call this as theorem 2, uniformly more accurate $1 - \alpha$ level confidence set is of the form σ such that, twice σ X by σ is less than or equal to chi square $2n$ alpha.

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The UMP test will reject H_0 if $T > c$

$W = \frac{2 \sum X_i}{\sigma_0} \sim \chi^2_{2n}$ (under H_0), $f_T(t) = \frac{1}{\sigma_0^n \Gamma_n} e^{-t/\sigma_0} t^{n-1}$

Reject H_0 if $\frac{2T}{\sigma_0} > c^*$ $f_W(w) = \frac{1}{\Gamma_n} e^{-w} w^{n-1}$ (density of χ^2_{2n})

$c^* = \chi^2_{2n, \alpha}$

The acceptance region for UMP level- α test is

$\frac{2T}{\sigma_0} \leq \chi^2_{2n, \alpha}$

UMA $(1-\alpha)$ -level confidence set is of

$S(X) = \left\{ \sigma : \frac{2 \sum X_i}{\sigma} \leq \chi^2_{2n, \alpha} \right\}$

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or $\frac{2 \sum X_i}{\chi^2_{2n, \alpha}} \leq \sigma$

$\left(\frac{2T}{\chi^2_{2n, \alpha}}, \infty \right)$ is $(1-\alpha)$ -level one-sided confidence (region) interval for σ .

Shortest Length Confidence Intervals :

Let $W(X, \theta)$ be pivot. We choose w_1, w_2 s.t.

$P(w_1 < W < w_2) = 1-\alpha \Leftrightarrow P(a(X) < \theta < b(X)) = 1-\alpha$

So that $b(X) - a(X)$ is minimum

Then $(a(X), b(X))$ is called shortest length confidence interval for θ with level $(1-\alpha)$.

So, you can simplify this condition here twice sigma X i by chi square 2 n alpha less than or equal to sigma. That is we are saying twice T by chi square 2 n alpha to infinity, this is 1 minus alpha level one sided confidence interval actually for sigma. So, the theorem the theory of UMP test is intimately connected with the theory of finding out uniformly most accurate test. So, particularly when we are dealing with the one parameter exponential family etcetera, then straight forwardly we can translate the acceptance region into a confidence interval by replacing that parameter theta naught or theta whatever we are saying by a general parameter theory.

Now, also I talk about the shortest length confidence intervals. So, let W and X be pivot and we are choosing say w_1 and w_2 , such that this is equivalent to some interval. So, that the length of the interval $b - a$ is minimum, so this is our interest. For a fixed confidence level we would like to have the shortest length, as I mentioned if I am giving a 2 statements.

For example, I am looking at the rate of the cure by a certain medicine. So, we say we are 95 percent sure or we can say we are 90 percent confident that the rate of cure by this medicine is at least 75 percent and second statement is we are 95 percent confident that the rate of cure is more than 80 percent. Then which statement will be better? Obviously, the second statement is better because it is giving a shorter interval.

So, the problem of determining shortest length intervals is of interest. So, we say this is the, then a to b this is called shortest length confidence interval for confidence interval with level $1 - \alpha$ of course, it is based on there is W , if we change the W we may get another interval here.

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Examples. 1. $X_1, \dots, X_n \sim N(\mu, \sigma^2)$, σ^2 known

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

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

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

So $\left(\bar{X} - \frac{\sigma}{\sqrt{n}} z_{\alpha/2}, \bar{X} + \frac{\sigma}{\sqrt{n}} z_{\alpha/2}\right)$ is $(1 - \alpha)$ level confidence interval for μ .

Similarly when σ^2 is unknown, based on $\frac{\sqrt{n}(\bar{X} - \mu)}{S}$ the shortest length $(1 - \alpha)$ -level conf. int for μ is $\left(\bar{X} \pm \frac{S}{\sqrt{n}} t_{\alpha/2, n-1}\right)$

So, let us look at the examples here. So, if we are considering X_1, X_2, \dots, X_n following normal μ, σ^2 is known; σ^2 is known. Then based on $\bar{X} - \mu$ root n by σ this follows normal $0, 1$, since the normal distribution is symmetric if I consider is symmetric interval around 0 this will have the highest probability.

If I consider a non symmetric interval, then the length will increase therefore, the shortest interval will be a symmetric interval about this. So, that if you use this logic then we will get minus $z_{\alpha/2}$ less than $\sqrt{n} \bar{X}$ minus μ by σ less than $z_{\alpha/2}$ that is equal to $1 - \alpha$ which gives the interval $\bar{X} - \sigma$ by $\sqrt{n} z_{\alpha/2}$ to $\bar{X} + \sigma$ by $\sqrt{n} z_{\alpha/2}$, that is $\bar{X} - \sigma$ by $\sqrt{n} z_{\alpha/2}$ to $\bar{X} + \sigma$ by $\sqrt{n} z_{\alpha/2}$ as $1 - \alpha$ level confidence interval for μ .

Similarly when we are considering sigma square is unknown in that case based on square root $\sqrt{n} \bar{X} - \mu$ by S , the shortest length $1 - \alpha$ level confidence interval for μ is $\bar{X} \pm s$ by $\sqrt{n} t_{\alpha/2, n-1}$.

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2. Let X_1, \dots, X_n be a random sample from $U(0, \theta)$.

$T = X_{(n)}, W = \frac{X_{(n)}}{\theta}$, $f_W(w) = \begin{cases} n w^{n-1}, & 0 < w < 1 \\ 0, & \text{else} \end{cases}$

$P\left(w_1 < \frac{X_{(n)}}{\theta} < w_2\right) = 1 - \alpha \rightarrow \boxed{w_2^n - w_1^n = 1 - \alpha}$

$\Rightarrow P\left(\frac{X_{(n)}}{w_2} < \theta < \frac{X_{(n)}}{w_1}\right) = 1 - \alpha$

length of the interval is $X_{(n)} \left(\frac{1}{w_1} - \frac{1}{w_2}\right) = L$

We want to minimize $L \rightarrow (1)$ is true.

$\frac{dL}{dw_2} = X_{(n)} \left(\frac{1}{w_2^2} - \frac{1}{w_1^2} \cdot \frac{dw_1}{dw_2}\right) = X_{(n)} \left(\frac{1}{w_2^2} - \frac{1}{w_1^2} \cdot \left(\frac{w_2}{w_1}\right)^{n-1}\right)$

$= X_{(n)} \left(\frac{w_1^n - w_2^n}{w_1^{n+1} \cdot w_2^2}\right) = X_{(n)} \left(\frac{w_1(w_2^n - (1-\alpha)) - w_2^{n+1}}{w_1^{n+1} \cdot w_2^2}\right)$

And let me solve it as an optimization problem also I will explain this through one example, where let X_1, X_2, \dots, X_n be a random sample from uniform 0 to θ interval. So, we consider say T is equal to X_n and here we can use the pivot quantity as X_n by θ , we have actually seen the distribution of this is $n w$ to the power $n - 1$. So, we may consider an interval of the nature say w_1 less than X_n by θ less than w_2 is equal to $1 - \alpha$. So, this implies probability of this is equal to $1 - \alpha$.

So, what is the length of the interval? Length of the interval is X_n into 1 by w_1 minus 1 by w_2 , let me write it as equal to say L and at the same time this condition

will imply that w_2 to the power n minus w_1 to the power n is equal to $1 - \alpha$, let me call this condition as (1). So, we want to minimize L subject to the condition (1) ok.

Now let us consider differentiation of this with respect to say ω_2 , then that will give me X_{n+1} by ω_2 square minus 1 by ω_1 square $d\omega_1$ by $d\omega_2$, but what is $d\omega_1$ by $d\omega_2$? Let us consider also differentiation of this condition. If I differentiate this I get $n\omega_2^{n-1}$ to the power n minus 1 minus $n\omega_1$ to the power n minus 1 $d\omega_1$ by $d\omega_2$ is equal to 0 .

But this condition will give me $d\omega_1$ by $d\omega_2$ is equal to ω_2 by ω_1 to the power n minus 1 if I substitute it here I get this as equal to X_{n+1} by ω_2 square minus 1 by ω_1 square ω_2 by ω_1 to the power n minus 1 . So, I can simplify this and I can write it as X_n into well ω_1 to the power n plus 1 minus ω_2 to the power n plus 1 divided by ω_1 to the power n plus 1 ω_2 square.

Now, also if we see from this condition I can consider it as X_n and of course, this denominator term will come here the numerator term I can substitute here see from here the value of ω_1 to the power n I can put it in terms of ω_2 . So, this becomes ω_2 to the power n minus 1 minus α minus ω_2 to the power n plus 1 .

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$$= X_{(n)} \frac{w_2^n (w_1 - w_2) - w_1 (1 - w_2)}{(\quad)} < 0$$

So L is decreasing in w_2 so minimum will occur at max value of w_2 i.e. $w_2 = 1$.

Then from (1), we get $1 - w_1^n = 1 - \alpha$
 $\Rightarrow w_1 = \alpha^{1/n}$.

So $(X_{(n)}, X_{(n)} \cdot \alpha^{-1/n})$ is shortest length C.I. with conf. level $(1 - \alpha)$ (based on $X_{(n)}$).

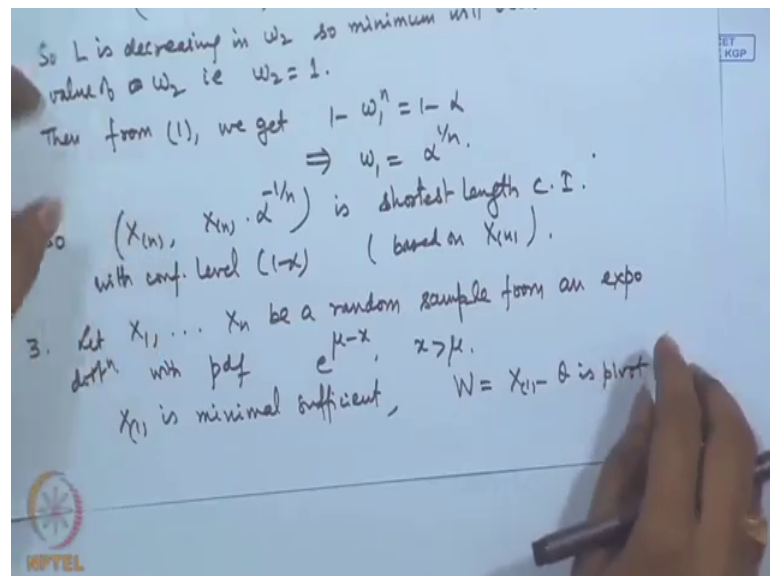
This I can write it as X_n and then w ω_2 to the power n ω_1 minus ω_2 minus ω_1 into $1 - \alpha$ divided by some term this is clearly negative because

omega 1 is less than omega 2. So, what it means, so L is actually decreasing in omega 2, so minimum will occur at maximum value of omega 2. Now what are the ranges of omega 1, omega 2? Because here I have taken this and the range of this distribution is 0 to 1. So, the maximum value of omega 2 can be equal to 1 only, so that is omega 2 is equal to 1.

If I have omega 2 is equal to 1, then this will give me from 1 we get 1 minus omega 1 to the power n is equal to 1 minus alpha which gives me omega 1 is equal to alpha to the power 1 by n. So, X_n to X_n divided by are be multiplied by alpha to the power minus 1 by n, this is shortest length confidence interval with confidence level 1 minus alpha this is based on X_n . So, here I have shown through direct optimization that this is the shortest length interval here I have actually minimize the length of the interval here.

Let me give one more example here of an exponential distribution. Let X_1, X_2, X_n be a random sample from an exponential distribution with pdf $e^{-\mu x}$ say $\mu > 0$. Now, this example we have considered here if I consider X_1 this is minimal sufficient here and we can consider the pivot quantity W is equal to $X_1 - \theta$, this can be taken as pivot.

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The pdf of W is

$$f_W(w) = \begin{cases} n e^{-nw}, & w > 0 \\ 0, & w \leq 0 \end{cases}$$

$$P(a < W < b) = 1 - \alpha \Leftrightarrow e^{-na} - e^{-nb} = 1 - \alpha \quad \dots (1)$$

$$\Leftrightarrow P(a < X_{(1)} - \theta < b) = 1 - \alpha$$

$$\Leftrightarrow P(X_{(1)} - b < \theta < X_{(1)} - a) = 1 - \alpha$$

Length of the interval $L = b - a$.

$$\frac{\partial L}{\partial a} = \frac{\partial b}{\partial a} - 1 = e^{n(b-a)} - 1 > 0$$

So L will be minimized for min value of a i.e. $a = 0$

The distribution of w will be the distribution of W is f W is equal to n e to the power minus n W where W is positive it is 0. So, we take probability of say to points a less than W to less than b it is equal to 1 minus alpha. Now in this distribution if I integrate out this condition is equal lent to same e to the power minus n a minus e to the power minus n b is equal to 1 minus alpha this is condition 1.

Now based on this when we are considering, the confidence interval this is becoming X 1 minus theta less than b is equal to 1 minus alpha which is equivalent to probability of theta less than X 1 minus a and it is greater than X 1 minus b that is equal to 1 minus alpha. So, here length of the interval b minus a and we want to minimize this, suppose I want to minimize is respect to a here, then I will get d b minus del a minus 1.

Now if I differentiate this relation I will get minus n times e to the power minus n a plus n times e to the power minus nb del b minus del a equal to 0. Now from here del b by del a that will turn out to be e to the power n times b minus a. So, this will be equal to e to the power n b minus a minus 1; obviously, since b is greater than a this is positive, so this is greater than 1; that means, this is greater than 0. So, L will be minimized for minimum value of a, that is a is equal to 0 because I am considering interval from a to b for W and the range of the W is greater than 0. So, the minimum value of a that can be simply 0 itself.

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$$P(a < W < b) = 1 - \alpha \Leftrightarrow e^{-na} - e^{-nb} = 1 - \alpha \quad \dots (1)$$

$$\Leftrightarrow P(a < X_{(1)} - \theta < b) = 1 - \alpha$$

$$\Leftrightarrow P(X_{(1)} - b < \theta < X_{(1)} - a) = 1 - \alpha.$$

Length of the interval $L = b - a.$

$$\frac{\partial L}{\partial a} = \frac{\partial b}{\partial a} - 1 = e^{n(b-a)} - 1 > 0$$

So L will be minimized for min value of a i.e. $a = 0$

From (1), $1 - e^{-nb} = 1 - \alpha \Rightarrow b = -\frac{1}{n} \ln \alpha \quad (> 0)$

If I put a equal to 0 in this one, this will give me $1 - e^{-nb}$ is equal to $1 - \alpha$; that means, b is equal to $-\frac{1}{n} \ln \alpha$ of course, this is positive because α is a number between 0 to 1, so this is positive.

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So $(X_{(1)} + \frac{1}{n} \ln \alpha, X_{(1)})$ is shortest length $(1 - \alpha)$ -level confidence interval for μ (based on $X_{(1)}$).

So, the interval that we will get here $X_1 + \frac{1}{n} \ln \alpha$ to X_1 , this is shortest length $1 - \alpha$ level confidence interval for μ this is based on X_1 .

So, here I have shown that directly by considering the minimization of the length of the interval subject to the condition that we are achieving a certain confidence level it is possible to derive the shortest length confidence interval.