

Statistical Methods for Scientists and Engineers
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Lecture - 40
Nonparametric Methods - XIII

As I mentioned that, in place of considering location alternative or the scale alternative, one may consider general alternative that means we simply say that the 2 distributions are not the same. So now an analogous situation you can think of in the case of parametric or nonparametric situation is that we may think of not specifying the distribution and then talking about the location parameter or the scale parameter rather we considered simply the specification of the distribution itself.

Now in the one sample problem one solution was given by the Chi-square test for goodness of fit, and another solution is given by the Kolmogorov-Smirnov test statistics. Now let us define the general 2 sample problems and discuss the analogous test here.

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Lecture 40

General Two Sample Problem

Let X_1, \dots, X_m be a random sample from a continuous distⁿ $F_X(x)$

$\&$ Y_1, \dots, Y_n be another independent random sample from a continuous distⁿ $G_Y(x)$.

$H_0: G_Y(x) = F_X(x) \forall x.$

$\vee H_1: G_Y(x) \neq F_X(x) \text{ for some } x.$

Kolmogorov-Smirnov Two Sample Test Statistic

Let $F_n(x)$ & $G_n(x)$ be empirical distⁿ. frs based on X-sample & Y-sample respectively

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So the general two sample problems, so let X_1, X_2, \dots, X_m be a random sample from a continuous distribution F_X , and say Y_1, Y_2, \dots, Y_n be another independent random sample from a continuous distribution G_Y okay. So we want to test the hypothesis whether $G_Y(x) = F_X(x)$ for all x against the

alternative $G_Y(x) \neq F_X(x)$ for some x , for this problem one of the you can say most possible solutions is the Kolmogorov-Smirnov two sample test statistic..

So let us define firstly the empirical distribution functions based on X_1, X_2, \dots, X_m and Y_1, Y_2, \dots, Y_n , so let $F_m(x)$ and $G_n(x)$ be empirical distribution functions based on X sample and Y sample respectively.

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Handwritten mathematical definitions for empirical distribution functions $F_m(x)$ and $G_n(x)$, and the definition of the Kolmogorov-Smirnov two sample test statistic $D_{m,n}$.

$$F_m(x) = \begin{cases} 0 & \text{if } x < X_{(1)} \\ i/m, & X_{(i)} \leq x < X_{(i+1)}, \quad i=1, 2, \dots, m-1 \\ 1, & x \geq X_{(m)} \end{cases}$$

$$G_n(x) = \begin{cases} 0 & \text{if } x < Y_{(1)} \\ i/n, & \text{if } Y_{(i)} \leq x < Y_{(i+1)} \\ 1 & , x \geq Y_{(n)}. \end{cases}$$

Then $D_{m,n} = \max_x |F_m(x) - G_n(x)|$ is Kolmogorov-Smirnov two sample test statistic for testing H_0 .

So we are defining like $F_m(x)=0$ if $x < X_1$, it is $=i/m$ if $X_i \leq x < X_{i+1}$ for $i=1, 2, \dots, m-1$, it is $=1$ if $x \geq X_m$. Similarly, $G_n(x)=0$ if $x < Y_1$, it is $=i/n$ if $Y_i \leq x < Y_{i+1}$ and it is $=1$ if $x \geq Y_n$. Then $D_{m,n}$ that is $=$ maximum of $F_m(x) - G_n(x)$, if you remember in the case of one sample problem it was defined as $F_m(x) - F(x)$, here now I am considering the difference between the distribution, the 2 distributions basically, so this is actually the Kolmogorov-Smirnov two sample test statistic for testing H_0 .

Now naturally if the 2 distributions are close, then naturally their sample values will be closer to each other and therefore, there will be region where F_m and G_n will be similar. So therefore, the differences will be smaller otherwise the difference will be large, so we can simply say that large values of $D_{m,n}$ indicate that H_0 is false, so $D_{m,n}$ is actually distribution free. We will actually discuss the method how to determine the probability, the probability of type 1 error, type 2 error based on this thing.

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Hodges' method for determining $P(D_{m,n} \geq d | H_0)$

Consider the combined sample of X & Y values and then arrange it in increasing order of magnitude.

Depict on a Cartesian system of co-ordinates by a path which starts at the origin and moves one step right for an x and one step up for a y ending in (m,n)

Observed values of $m F_m(x)$ & $n G_n(x)$ are respectively the coordinates of all points (u,v) on the path, (u,v) are integers.

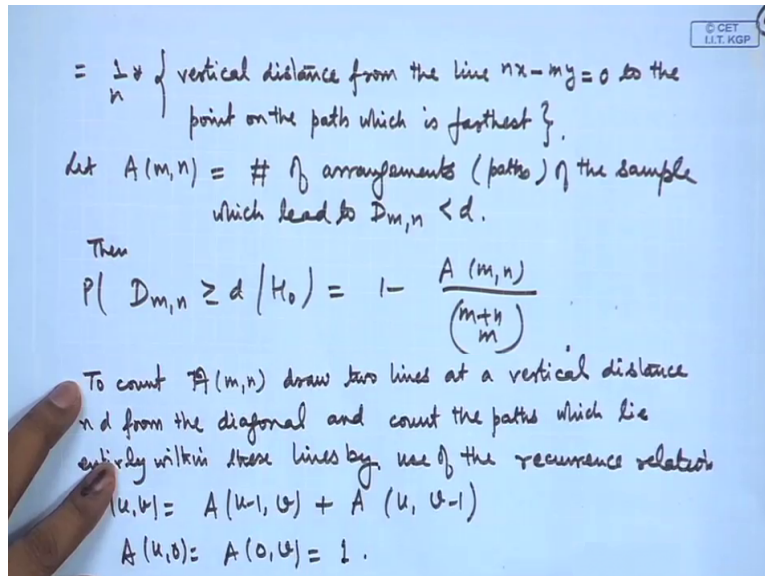
$$d = \max \left| \frac{u}{m} - \frac{v}{n} \right| = \frac{1}{n} \left| v - \frac{n}{m} u \right|$$

So this is distribution free let us discuss these methods now, so one method that has discussed it is actually by Hodges' method, Hodges' method for determining probability of $D_{m,n} \geq d$ under H_0 , so first thing is that we consider the combined sample of X and Y values, and then arrange it in increasing order that means we rank them of magnitude. So we consider a Cartesian system in the following fashion.

Depict on a Cartesian system of coordinates by a path which starts at the origin, and moves one step right for an x , and one step up for a y , ending in m, n , so it is like this if x is next then we come like this otherwise it go like this so it could be like this and so on. So observed values of $m F_m(x)$ and $n G_n(x)$ they are actually the all the coordinates of the points of u, v on this path, where u and v are integers.

Observed values of $m F_m(x)$ and $n G_n(x)$ they are respectively the coordinates of all points u, v on the path, where u and v are integers, so $d =$ maximum of basically $u/m - v/n$ which we can write as $1/n (v - n/m u)$.

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We can express it as $1/n$ * the vertical distance from the line $nx - my = 0$ to the point on the path which is farthest, so m, n is a number of arrangements that is paths of the sample which lead to $D_{m, n} < d$. Then you will have probability of $D_{m, n} \geq d$ under H_0 that is $1 - A(m, n) / \binom{m+n}{m}$ because $\binom{m+n}{m}$ will be all the paths. We can have the extreme cases when all the X_i 's are below all the Y_j 's are one could be in which the all of them are like $1 \ X_1 \ Y$ like that all, it could be like that also.

So $A(m, n)$ is the arrangements of the paths of the sample which leads to $D_{m, n} < d$, then it is probability that $D_{m, n} \geq d = 1 - A(m, n) / \binom{m+n}{m}$, so to count $A(m, n)$ we have to draw 2 lines at a vertical distance $n d$ from the diagonal, and count the paths which lie entirely within these lines by use of the recurrence relation that is $A(u, v)$ is actually $= A(u-1, v) + A(u, v-1)$, and of course $A(u, 0)$ that will be $= A(0, v)$ that is $= 1$.

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If $m, n \rightarrow \infty$, $\rightarrow \frac{m}{n} \rightarrow \text{constant}$

$P\left(D_{m,n} \sqrt{\frac{mn}{m+n}} \leq z\right) \rightarrow 1 - 2 \sum_{i=1}^{\infty} (-1)^{i-1} e^{-2i^2 z^2}$


For testing H_0 vs $H_1: G_Y(x) \leq F_X(x) \forall x \text{ vs } G_Y(x) < F_X(x)$
 for some x , one uses

$D_{m,n}^+ = \max_x \{F_m(x) - G_n(x)\}$

Hodges method can be used to find

$P_{H_0}(D_{m,n}^+ \geq d)$

for small values of m, n with obvious modifications.



Let us also consider this, if m, n tend to infinity such that m/n goes to a constant, then probability that $D_{m,n} \sqrt{\frac{mn}{m+n}} \leq z$ converges to $1 - 2 \sum_{i=1}^{\infty} (-1)^{i-1} e^{-2i^2 z^2}$. So asymptotic distribution is obtained here for testing H_0 versus H_1 , where H_1 could be like stochastic ordering that is say $G_Y(x) \leq F_X(x)$ basically it means $Y \leq X$ with probability $X \leq x$.

That means basically what we are saying is that X is stochastically smaller than the Y is stochastically smaller than Y , and for all x $G_Y(x) \leq F_X(x)$ for some x , so one uses a version of this let us call it $D_{m,n}^+$ that is maximum of that means we consider only one sided maximum of $F_m(x) - G_n(x)$. Hodges Method can be used to find probability of $D_{m,n}^+ \geq d$ under H_0 for small values of m, n with obvious modifications

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Let $m, n \rightarrow \infty$
 $m/n = \text{const}$

$$P\left(\sqrt{\frac{mn}{m+n}} D_{m,n}^+ \leq z \mid H_0\right) = 1 - e^{-z^2}$$

We reject H_0 if $D_{m,n}^+ \geq C_\alpha$ where C_α is determined by

$$P(D_{m,n}^+ \geq C_\alpha \mid H_0) = \alpha.$$

To test H_0 against $H_1: G_Y(x) \geq F_X(x) \neq x$
 $\exists G_Y(x) > F_X(x)$ for some x ,

we interchange the role of X 's & Y 's in the above.

One can talk about the full-fledged asymptotic distributions of $D_{m,n}$ also, let me give that here, limit of m, n tending to infinity such that m/n is a constant of the probability root $mn/(m+n)$ $D_{m,n} \leq z$ under H_0 that is $1 - e^{-z^2}$. We reject if $D_{m,n} \geq C_\alpha$, where C_α is determined by probability of $D_{m,n} \geq C_\alpha$ under $H_0 = \alpha$. To test H_0 against $H_1: G_Y(x) \geq F_X(x) \neq x$, we interchange the role of X 's and Y 's in the above. So basically you can consider here $G_n(x) - F_m(x)$, and then the similar things will be holding here.

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Efficiency of Tests:

Power Efficiency: $\Omega \rightarrow$ parameter space
 $\omega \subseteq \Omega$. $H_0: \theta \in \omega$
 $H_1: \theta \in \Omega - \omega$.

Let $\{T_n\}$ & $\{S_{n^*}\}$ be two sequences of test statistics for testing H_0 against H_1 (where n & n^* are respective sample sizes). $\theta^* \in \Omega - \omega$

$C_n \rightarrow$ size α critical region for test $\{T_n\}$
 $D_{n^*} \rightarrow$ size α critical region for test $\{S_{n^*}\}$.

$P(T_n \in C_n) \leq \alpha \quad \forall \theta \in \omega$
 $P(S_{n^*} \in D_{n^*}) \leq \alpha \quad \forall \theta \in \omega$

Another concept is that of efficiency of the tests here, like the consistency of the test, like consistency of estimators we have an analog of the efficiency of the test. So first is the power efficiency, let us consider that power efficiency. This concept, I am introducing because in the

usual classical theory of testing of hypothesis in the parametric situations, we have the concepts of the most powerful test, uniformly most powerful test, unbiasedness and other things.

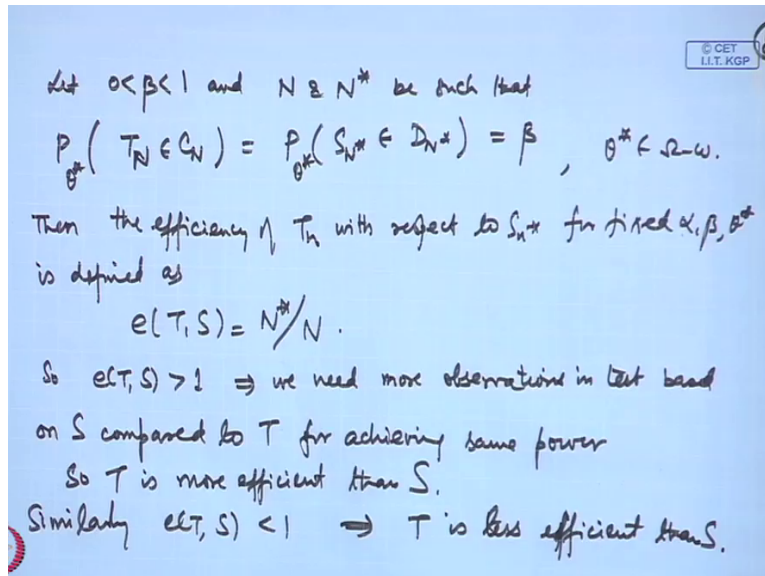
Now when we are dealing with the distribution free situations or the non-parametric situations, then certainly those type of most powerful and other concepts are not valid, and therefore, we need to look at the asymptotic properties, so that is why consistency and now we are talking about efficiency, so first thing is that about the power efficiency. So let us consider say ω is the parameter space here.

So suppose I have a point a subset of ω , so we are considering the hypothesis testing problem H_0 θ belonging to small ω against H_1 θ belonging to capital ω -small ω . So let us consider say T_n and S_n so let me put a S_n^* here be 2 sequences of test statistics, we considered sequence because they are based on a sample size, and so sample size may vary, so that is why we are calling it for testing H_0 against H_1 .

So here n and n^* are the respective sizes, so let us take n arbitrary point θ^* belonging to alternative hypothesis that, so let us consider C_n is the size α critical region for test T_n and let us call say D_n^* is the size α critical region for test S_n^* . So now let us consider probability of T_n belonging to C_n , then this will be certainly $\leq \alpha$ for all θ belonging to ω .

And probability of S_n^* belonging to D_n^* that will be $\leq \alpha$ for all θ belonging to ω . So these are 2 size α test and critical regions are identified by C_n and D_n^* respectively based on T_n and S_n^* , let us consider now the power here.

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Let us fix powers say beta and suppose we require N and N* as the sample sizes that probability of TN belonging to CN* that is= beta under some value say theta*, then and here this theta* belongs to actually omega-omega. So then the efficiency of Tn with respect to Sn* this is for fixed alpha, beta and theta*, this is defined as e T, S=N*/N, so naturally you can have the interpretation here.

So for example if e T, S >1, if it is >1 that means for achieving the same level of power I need more observations in as compared to T that means T is more efficient than S, if this is <1 e T, S <1 then it will mean that I need more observations in T compared to S for achieving the same level, so T is less efficient than P. So we can write that, so e T, S >1 implies that we need more observations in test based on S compared to T for achieving same power, so T is more efficient than S.

Similarly, e T, S <1 implies T is less efficient than S, so for this efficiency we have some sort of interpretation here, but of course this definition is having unlimited usage here because we have fixed here alpha, beta and theta*, if we change the theta* and the underline distribution changes here, then I mean for different underline distributions it may quite complicated to adopt here, but anyway this is the definition let me consider some example here.

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Example : $X_1, \dots, X_n \sim N(\theta, 1)$
 $H_0: \theta = 0$
 $H_1: \theta > 0$, $\theta^* = 1$,

T: Usual normal test : Reject H_0 if $\sqrt{n}\bar{X} > a_n$
 $\alpha = 0.05$, $a_n = z_{0.05} = 1.64$, $\beta = 0.9$
 $P_{\theta^*=1}(\sqrt{n}\bar{X} > 1.64) = 0.9$
 $\Rightarrow P(\sqrt{n}(\bar{X} - 1) > 1.64 - \sqrt{n}) = 0.9$
 $\Rightarrow \cancel{0.9} \quad 1.64 - \sqrt{n} = -1.28$
 $\Rightarrow n \approx 9$.

Let us consider the usual problem based on say normal distribution say normal theta 1, and I consider H_0 theta=0, H_1 theta !=0 or say theta >0 for example let us take, so let me take theta* in the alternative hypothesis set as 1. So the usual normal test is okay, the usual normal test that is reject H_0 if root n X bar > a n basically that is say alpha, so if I am taking say alpha=0.05 then a n=z0.05 that is= 1.64.

So if I considered say probability theta*=1 root n X bar>1.64=say 0.9, so I am taking say beta= 0.9 say for example, so this will mean probability root n X bar-1> so this will become 1.64-root n=0.9, so that means 0.9= sorry 1.64-root n=-1.28, so this you can simplify so this is n is approximately 9 okay.

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S → Usual sign test:

Reject H_0 if $K_n^* > d_n^*$

$\alpha = 0.05$

$$F_x(0) = P(X > 0) = \begin{cases} \frac{1}{2} & \text{if } \theta = 0 \\ 1 - \frac{\Phi(-1)}{0.85} & \text{if } \theta = 1 \end{cases}$$

$$\sum_{i=k+1}^N \binom{N}{i} \left(\frac{1}{2}\right)^N = 0.05 \quad \dots (1)$$

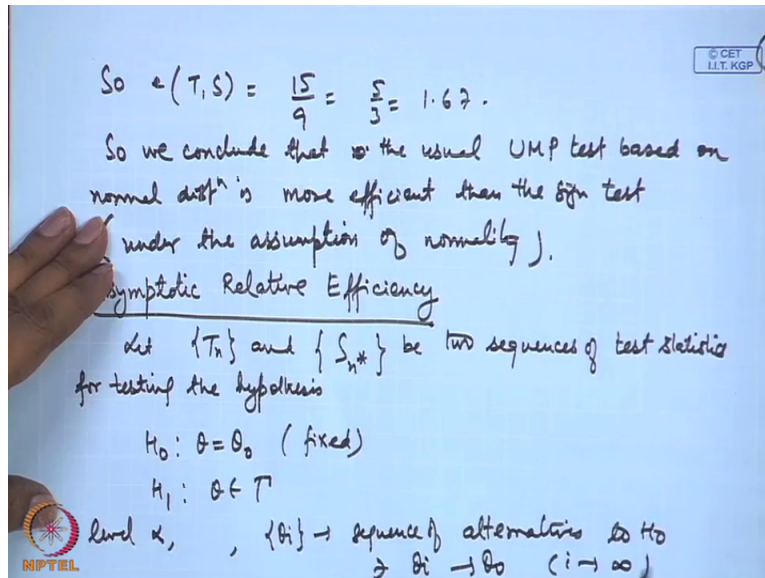
$$\sum_{i=k+1}^N \binom{N}{i} (0.85)^i (0.15)^{N-i} = 0.9 \quad \dots (2)$$

Solving (1) & (2), we get $N=15, k=12$.

Let us take second test say based on the sign test function here S say usual sign test, for usual sign test you are saying reject H_0 if $K_n > d_n$ so let me put here *, so if I am taking $\alpha=0.05$ and so okay, let us see $F_x(0)$ that is = probability $X > 0$ that is $1/2$ if $\theta=0$ it is $1 - \Phi(-1)$ that is approximately 0.85 if $\theta=1$ for example okay. So now we are having 2 equations $\sum_{i=k+1}^N \binom{N}{i} (1/2)^N = 0.05$, this is for $i=k+1$ to N , this is one equation.

And the second equation is $\sum_{i=k+1}^N \binom{N}{i} (0.85)^i (0.15)^{N-i} = 0.9$ for $i=k+1$ to N that should be $=0.9$, so you need actually to solve these 2 equations to get the value of N , and actually K is also required here because at which point that cutoff will come. So solving 1 and 2 we get $N=15$ and $K=12$.

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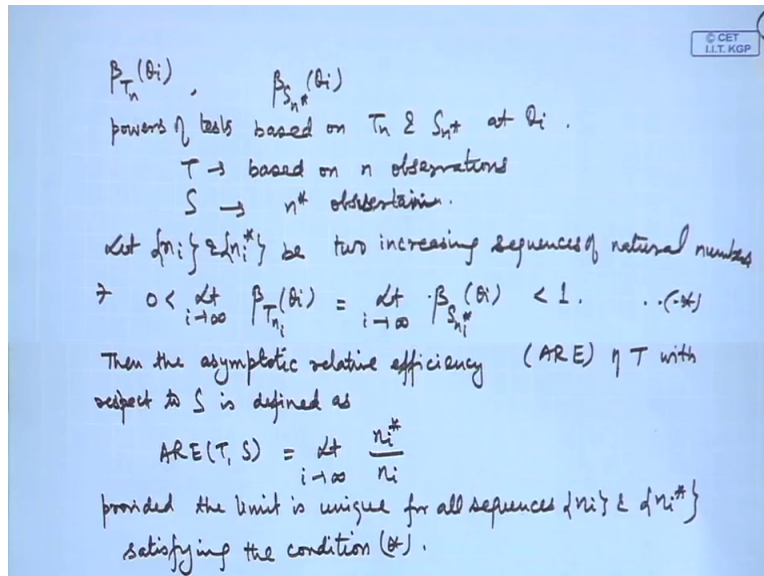


so what we conclude then, so efficiency of normal test corresponding to this one will become=15/9 that is=5/3 that is=1.67 etc. so basically we conclude that the usual UMP test based on normal distribution is more efficient than the sign test, now this is under the information that the under the assumption of the distribution, if the normal distribution is not then certainly you cannot use this, under the assumption of normality.

So if the distribution is known certainly we will use that information, now this is for the power 0.9, if we use some other power say 0.95 or 0.92 then certainly this efficiency level will change, but certainly it means that the test based on the normal test is certainly more efficient than the sign test here. Since this is completely dependent upon the values of alpha, beta and the point that we have chosen, there is another concept that is called the asymptotic relative efficiency of the test, let us consider this concept now.

Asymptotic Relative Efficiency, let T_n and S_n^* be 2 sequences of test statistics for testing the hypothesis H_0 $\theta = \theta_0$ this is fixed against the alternative θ belonging to some γ , and we are considering level α and θ_i 's this is a sequence of alternatives to H_0 such that θ_i converges to θ_0 as i tend to infinity, so we are considering alternatives but they approach the null hypothesis value.

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So let us now consider say $\beta_{T_n}(\theta_i)$, and $\beta_{S_{n^*}}(\theta_i)$, so these are the power of tests based on T_n and S_{n^*} at θ_i , so T is based on n observations, and S is based on n^* observations, so we consider this n_i and n_i^* sequences and I consider the conditions such that n_i and n_i^* increasing sequences of natural numbers such that $0 < \lim_{i \rightarrow \infty} \beta_{T_{n_i}}(\theta_i) = \lim_{i \rightarrow \infty} \beta_{S_{n_i^*}}(\theta_i) < 1$.

Then the asymptotic relative efficiency that is ARE of T with respect to S is defined as $ARE(T, S) = \lim_{i \rightarrow \infty} \frac{n_i^*}{n_i}$ provided the limit is unique for all sequences n_i and n_i^* which satisfying the condition* okay. So what does it roughly mean? It roughly mean that suppose I say this values= say 1.2, then it would mean that in test based on S I need on the average 120 observations if there are 100 observations needed by the test based on T to achieve the same level of power.

So now since this definition is a limiting definition, this is you can say better definition than the definition of efficiency which I gave just before this, because that was a fixed sample size definition here, and here it is an asymptotic kind of definition.

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Methods for Estimating ARE

$H_0: \theta = \theta_0$ vs $H_1: \theta \in T$ $\{T_n\}, \{S_n^*\}$.

We assume that both are level α consistent tests and large values are significant (right handed sided critical regions).

$$E_{\theta}(T_n) = \mu_{T_n}(\theta) \quad E_{\theta}(S_n^*) = \mu_{S_n^*}(\theta)$$

$$V_{\theta}(T_n) = \sigma_{T_n}^2(\theta) \quad V_{\theta}(S_n^*) = \sigma_{S_n^*}^2(\theta)$$

Let T be a r.v. with absolutely continuous d.f. $H(x) \forall \theta \in T$
& assume that

Now there are several ways of calculating the asymptotic relative efficiency, let me briefly mention about that. Methods for estimating the asymptotic relative efficiency, so we are having 2 test sequences, so we have the hypothesis testing problem $\theta = \theta_0$ against H_1 belongs θ to some γ , and we have T_n as a test sequence and S_n^* is having another test sequence. And we assume that both are level α consistent tests.

That means they are one sided let me say and large values are significant, basically it means that we are having right handed critical regions, right sided or right handed critical regions this is as for convenience otherwise to compare 2 test it will become quite complicated. So let us consider that say the expectation of T_n is say $\mu_{T_n}(\theta)$, expectation of say S_n^* that is $\mu_{S_n^*}(\theta)$, variance of T_n say that is $\sigma_{T_n}^2(\theta)$, and variance of S_n^* say = $\sigma_{S_n^*}^2(\theta)$.

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$$\frac{T_n - \mu_{T_n}(\theta)}{\sigma_{T_n}(\theta)} \xrightarrow{d} T \quad \text{as } n \rightarrow \infty$$

$$\frac{S_{n^*} - \mu_{S_{n^*}}(\theta)}{\sigma_{S_{n^*}}(\theta)} \xrightarrow{d} T \quad \text{as } n^* \rightarrow \infty.$$

Let $\{\theta_i : \theta_i \in \Gamma\}$ be a sequence such that $\theta_i \rightarrow \theta_0 (i \rightarrow \infty)$
 and let $\{n_i\}, \{n_i^*\}$ be two sequences of sample sizes such
 that $0 < \lim_{i \rightarrow \infty} \beta_{T_{n_i}}(\theta_i) = \lim_{i \rightarrow \infty} \beta_{S_{n_i^*}}(\theta_i) < 1$ (*)
 Let $0 < \alpha < 1$, let $C_{n_i} \in \mathcal{D}_{n_i}$ be \rightarrow

So let us assume that let T be a random variable with absolutely continuous distribution function $H(x)$ for all θ belonging to Γ , and we assume that the asymptotic distributions of standardized variables of T_n and S_n they are based on the T , they are basically T we are saying that they converge to distribution T as n tends to infinity, we also assume that $S_{n^*} - \mu_{S_{n^*}}(\theta) / \sigma_{S_{n^*}}(\theta)$ converges in T .

Let θ_i, θ_i belonging to Γ be a sequence such that θ_i goes to θ_0 as i tends to infinity, and let n_i, n_i^* be 2 sequences of sample sizes such that $0 < \lim_{i \rightarrow \infty} \beta_{T_{n_i}}(\theta_i) = \lim_{i \rightarrow \infty} \beta_{S_{n_i^*}}(\theta_i) < 1$. So let us take say α between to be 0 and 1, and let the critical region points be such that.

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$$P_{\theta_0}(T_{n_i} \geq C_{n_i}) = P_{\theta_0}(S_{n_i}^* \geq D_{n_i}^*) = \alpha.$$

Then $0 < \lim_{i \rightarrow \infty} \beta_{T_{n_i}}(\theta_i) = \lim_{i \rightarrow \infty} P_{\theta_i}(T_{n_i} \geq C_{n_i})$

$$= \lim_{i \rightarrow \infty} P_{\theta_i} \left(\frac{T_{n_i} - \mu_{T_{n_i}}(\theta_i)}{\sigma_{T_{n_i}}(\theta_i)} \geq \frac{C_{n_i} - \mu_{T_{n_i}}(\theta_i)}{\sigma_{T_{n_i}}(\theta_i)} \right)$$

$$= \lim_{i \rightarrow \infty} \beta_{S_{n_i}^*}(\theta_i) = \lim_{i \rightarrow \infty} P_{\theta_i} \left(\frac{S_{n_i}^* - \mu_{S_{n_i}^*}(\theta_i)}{\sigma_{S_{n_i}^*}(\theta_i)} \geq \frac{D_{n_i}^* - \mu_{S_{n_i}^*}(\theta_i)}{\sigma_{S_{n_i}^*}(\theta_i)} \right)$$

$$< 1.$$

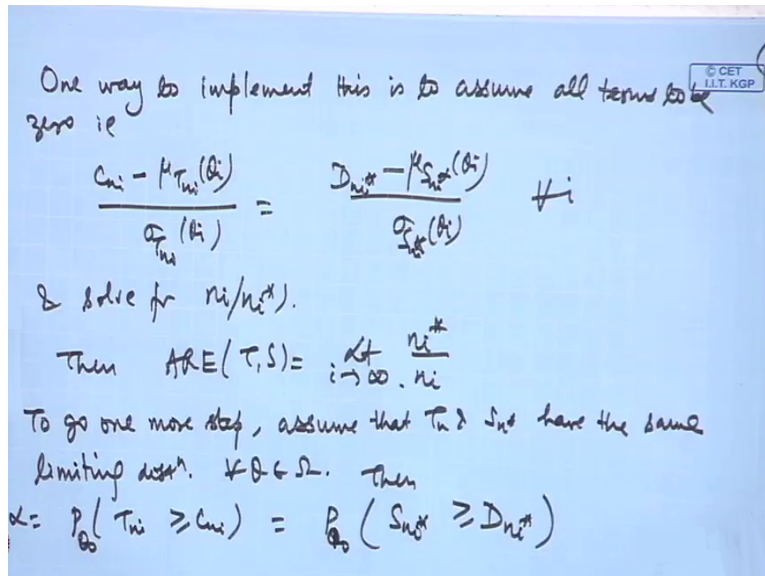
(*) & (**) imply that

$$\lim_{i \rightarrow \infty} \left[\frac{C_{n_i} - \mu_{T_{n_i}}(\theta_i)}{\sigma_{T_{n_i}}(\theta_i)} - \frac{D_{n_i}^* - \mu_{S_{n_i}^*}(\theta_i)}{\sigma_{S_{n_i}^*}(\theta_i)} \right] = 0$$

Probability of $T_{n_i} \geq C_{n_i}$ that $= S_{n_i}^* \geq D_{n_i}^* = \alpha$, so then you can consider here $0 < \lim_{i \rightarrow \infty} \beta_{T_{n_i}}(\theta_i)$, as i tends to infinity that is $= \lim_{i \rightarrow \infty} P_{\theta_i}(T_{n_i} \geq C_{n_i})$ as i tends to infinity. Now based on the asymptotic distribution of T_{n_i} , we can express it as limit as i tends to infinity probability of $\theta_i T_{n_i} - \mu_{T_{n_i}}(\theta_i) / \sigma_{T_{n_i}}(\theta_i) \geq C_{n_i} - \mu_{T_{n_i}}(\theta_i) / \sigma_{T_{n_i}}(\theta_i)$,

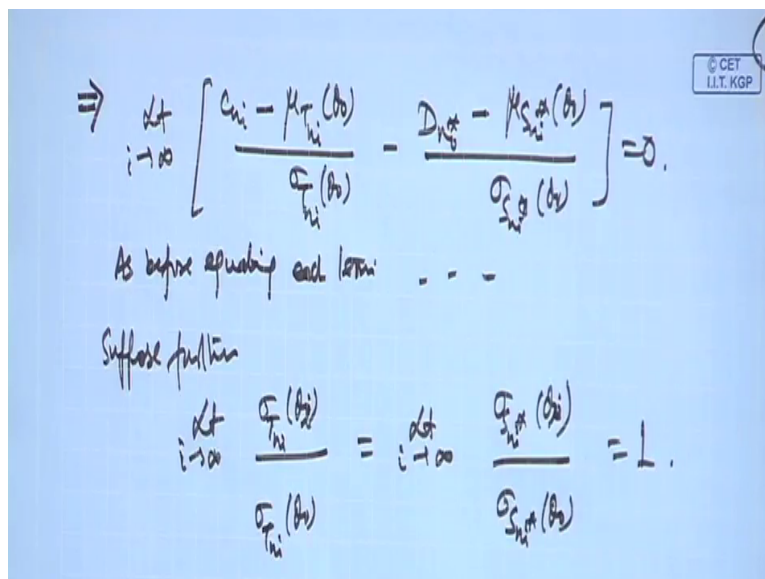
That is $= \lim_{i \rightarrow \infty} \beta_{S_{n_i}^*}(\theta_i)$ that is $= \lim_{i \rightarrow \infty} P_{\theta_i}(S_{n_i}^* \geq D_{n_i}^*)$ that is $= \lim_{i \rightarrow \infty} P_{\theta_i} \left(\frac{S_{n_i}^* - \mu_{S_{n_i}^*}(\theta_i)}{\sigma_{S_{n_i}^*}(\theta_i)} \geq \frac{D_{n_i}^* - \mu_{S_{n_i}^*}(\theta_i)}{\sigma_{S_{n_i}^*}(\theta_i)} \right)$ that is < 1 . So if we compare the let me call this as $*$, so from these 2 relations we get this imply that limit as i tends to infinity of $C_{n_i} - \mu_{T_{n_i}}(\theta_i) / \sigma_{T_{n_i}}(\theta_i) - D_{n_i}^* - \mu_{S_{n_i}^*}(\theta_i) / \sigma_{S_{n_i}^*}(\theta_i) = 0$ okay.

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So, one way to implement this is to assume all terms to be 0 that is $C_{ni} - \mu_{T_{ni}}(\theta_i) / \sigma_{T_{ni}}(\theta_i) = D_{ni}^* - \mu_{S_{ni}^*}(\theta_i) / \sigma_{S_{ni}^*}(\theta_i)$ for all i , and solve for n_i/n_i^* . Then ARE of T, S= limit as n_i^*/n_i for I tending to infinity that is one way. Now to go one step further, you can assume that T_n and S_n^* have the same limiting distribution for all θ , if that is so then you will have $\alpha = P_{\theta_0}(T_{ni} \geq C_{ni}) = P_{\theta_0}(S_{ni}^* \geq D_{ni}^*)$.

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So this will imply that limit as i tending to infinity $C_{ni} - \mu_{T_{ni}}(\theta_0) / \sigma_{T_{ni}}(\theta_0) - D_{ni}^* - \mu_{S_{ni}^*}(\theta_0) / \sigma_{S_{ni}^*}(\theta_0) = 0$, so if we can equate each term then again we can define, equating each term we can get the ARE. We can also assume, so let me just briefly mention this

thing because all of them are leading to an additional condition here, we can also assume the standard deviation that is this one that is=1, then again we can get the condition here.

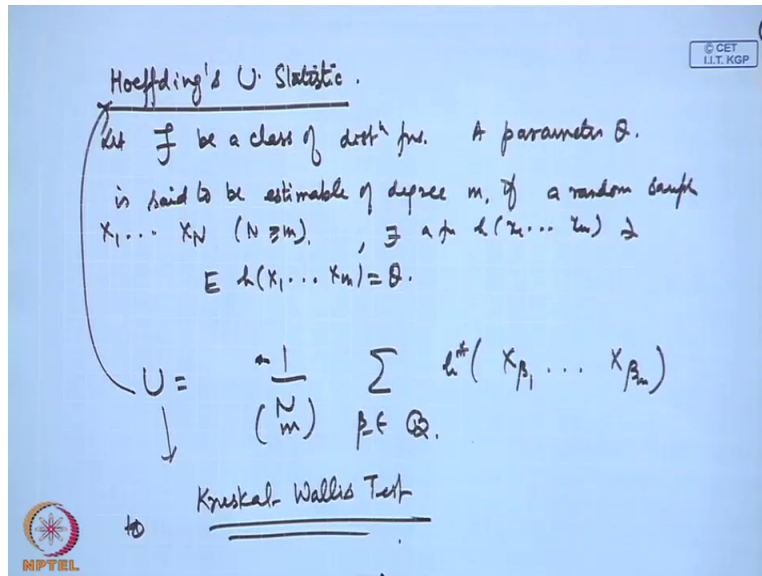
So these are the methods for estimating the asymptotic relative efficiency, there are certain results regarding this, but I am not getting into this thing. In nonparametric statistics I have discussed main methodologies that is based on the, firstly we discussed in detail the role of the order statistics, asymptotic distributions of the order statistics under various conditions. We also discuss the estimation of the distribution function based on the empirical distribution function.

We considered the ranks, the distribution of the ranks based on the ranks we considered several 1 sample and 2 sample testing problems basically based on the location and scale, we gave certain test. Towards the end I have introduced the concept of asymptotic relative efficiency, the concept of the efficiency of the test. The subject of a non-parametric test or you can say the distribution free procedures is quite vast, it has developed a lot in past 50 years.

And there are various other aspects of it, for example there is a huge class of problem which is known as the Hoeffding's U statistics, let me briefly mention about this one, we will very briefly talked about the Kruskal-Wallis and also the say Kendall's Tau and Spearman's thing, in the remaining 5 minutes or so or 10 minutes or so, let me just briefly mention about these topics. There are other things like density estimation based on the Kernel method.

And there are so many other topics that have developed over the past few years in the field of nonparametric, but in this particular course we can cover only this much, maybe in another course we will discuss in detail about those procedures also.

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So let me talk now about the Hoeffding's U statistic, so what is a Hoeffding's U statistic? Hoeffding's U statistic is defined as that let F be a class of distribution functions, a parameter θ is said to be estimable of degree m , if a random sample X_1, X_2, \dots, X_N ($N \geq m$), there exist a function h of x_1, x_2, \dots, x_m such that expectation of h of $X_1, X_2, \dots, X_m = \theta$, so this is based on this we define a Kernel, so h of X_1, X_2, \dots, X_m is called a Kernel.

Now based on this we can define a Hoeffding's U statistic as $\frac{1}{\binom{N}{m}} \sum_{\beta \in Q} h^*(X_{\beta_1}, \dots, X_{\beta_m})$ up to X_{β_m} by taking all the permutations of that means by taking all m permutations from N here that means it based on that, this is called Hoeffding's U statistic, so this is actually the name of this. So basically this is a symmetric function and its arguments, and you can actually see that most of the standard estimates in the parametric situations.

And also in the nonparametric situation like Sign test, Wilcoxon signed-rank test, Mann Whitney test statistic they will be actually based on the Hoeffding's test. The good thing about the Hoeffding's U test statistic is that the asymptotic theory is established that means the asymptotic normality is there. And therefore, various procedures for this can be established for this one. As I mentioned in nonparametric methods are also applicable, when the normality assumption is not satisfied, there also situation like when we have large scale data.

So when we were unable to fit a distribution or it is impossible to say that which distribution will be applicable, because there may be too much variations when you are doing the fitting of the distributions, then certainly nonparametric distributions non-parametric methodologies are used. One of the important methodologies for example you can think of is the analysis of variance, in analysis of variance we assume that the errors are normally distributed.

But if the normal errors are not normally distributed, then we go for a distribution free procedure that is called Kruskal-Wallis test, so Kruskal-Wallis test procedure is based on the again ranks here actually, so if the ranks are here we are considering let me just very very briefly mention about this one.

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K samples n_1, \dots, n_k
 $N = \sum n_i$
 $R_i \rightarrow$ actual sum of ranks based on X_{i1}, \dots, X_{in}

$$S = \sum_{i=1}^k \left(R_i - \frac{n_i(N+1)}{2} \right)^2$$

$$H = \frac{12}{N(N+1)} \sum_{i=1}^k \frac{1}{n_i} \left(R_i - \frac{n_i(N+1)}{2} \right)^2$$
 Kendall's Tau Coefficient / Spearman's Rank Correlation.

So we have K samples and the sample sizes are n_1, n_2, n_k and $n = \sum n_i$, we consider all the observations mixed up, and we consider that R_i is the actual sum of ranks based on $X_{i1}, X_{i2}, \dots, X_{in}$ in the combined sample, then you define the statistic $R_i - n_i * N + 1/2$ whole square $i = 1$ to k , so this is actually for the Kruskal-Wallis, and then we define $H = 12/n * N + 1 / n_i R_i - n_i * N + 1/2$ whole square $i = 1$ to k . So based on this the testing procedure has been developed, so this is called the Kruskal-Wallis formula.

The general linear rank statistics for a sample problems have been also define and then again versions of like Wonderwaden statistics theory, test statistics etc. are also defined. Another thing

is regarding the coefficient of correlation or the coefficient of association etc. so we have the usual Karl Pearson coefficient and the distribution for theory for that has been developed which I mentioned we have discussing the multivariate statistics.

But again that is based on the normality assumption, if the normality assumption is not there then we define measure of association and also a correlation coefficient, which is based on the ranks. So we have the 2 following things, one is called Kendall's Tau Coefficient, and another one is called Spearman's Rank Correlation, so I mentioned about this thing how they are used for example when we are discussing the same side concordance or discordance then Kendall's Tau Coefficient is used.

For example we have seen which side the values are like $X_i < X_j$ then Y_i 's also $< Y_j$, $X_i > X_j$ then $Y_i > Y_j$, in such cases the Kendall's Tau Coefficient is used here. And there are other situations like we are considering the coefficient of correlation then it is based on the observed values X_i, Y_i that is $X_1 X_2, X_1 Y_1, X_2 Y_2, X_n Y_n$ are taken and we based on this we define the coefficient, but here the actual observations are used.

That means for example we may considering weights, we may considering heights and so on for 2 sets of this one. But suppose we are not interested in the actual values, rather we are interested in the ranks, because it could be a measurements maybe related to something which may not give actual picture for example if you consider the how much agreement is there between the ranks given by 2 judges for ranking certain athlete.

So for examples some gymnastic competition is there, and then there are several competitors and there are 3 judges or 2 judges are there, so those 2 judges will give ranks on the basis of each performance, now then whether there is an agreement that means whether they are on the same side that means the good performer is appreciated similarly, by the 2 judges or they are biased that means whether 1 judge judges one candidate as better compared to the other one, in such cases we use Spearman rank correlation coefficient and it is much more useful.

We end this course at this note, as I mentioned that there are so many other things in the statistical methods for scientists and engineers, there are so many new methodologies have been developed for example large literature is available in the regression methodologies, time series and other thing. But of course then certain other course will be available for that. There is a vast area of Bayesian methodologies and frequent test decision theory, so one may look at those topics for applications. I will end this course at this particular note.