

Statistical Methods for Scientists and Engineers
Prof. Somesh Kumar
Department of Mathematics
Indian Institute of Technology - Kharagpur

Lecture - 33
Nonparametric Methods - VI

In the previous lecture, I had defined 2 types of a Statistics let me recall those things.

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In fact $F_m(x) \xrightarrow{a.s.} F(x)$

Glivenko-Cantelli Lemma

$$\lim_{m \rightarrow \infty} P \left(\sup_{x \in \mathbb{R}} |F_m(x) - F(x)| > \epsilon \right) = 0$$

Let us now consider a random sample X_1, \dots, X_m from cdf $F(x)$
 $\& Y_1, \dots, Y_n$ a random sample from $G(y)$. Also the two samples
are taken independently.

Define $U_i = F_m(Y_i), i=1, \dots, n$

\swarrow Empirical distⁿ fn (EDF)
base X_1, \dots, X_m

$$= \frac{1}{m} (\text{no. of } X_j\text{'s} \leq Y_i)$$

So we are considering that random sample X_1, X_2, X_n is taken from cdf F x and Y_1, Y_2, Y_n is a random sample from cdf G y, and we also assumed that the 2 samples are taken independently, then based on the empirical distribution function of first sample we defined $U_i = F_m$ of Y_i .

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$$U_{(i)} = \frac{1}{m} F_m(Y_{(i)}) = \frac{1}{m} (\text{no. of } X_j \text{'s } \leq Y_{(i)})$$

$$U_i \rightarrow 0, \frac{1}{m}, \frac{2}{m}, \dots, \frac{m-1}{m}, 1$$

$$U_{(i)} \rightarrow 0, \frac{1}{m}, \frac{2}{m}, \dots, \frac{m-1}{m}, 1$$


Distⁿ of U_i :

$$P\left(U_i = \frac{j}{m}\right) = P(m U_i = j) = P(j \text{ of } X_1, \dots, X_m \leq Y_i, (m-j) \text{ of } X_1, \dots, X_m > Y_i)$$

$$= \int_{-\infty}^{\infty} P(j \text{ of } X_1, \dots, X_m \leq y, (m-j) \text{ of } X_1, \dots, X_m > y \mid Y_i = y) dG(y)$$

$$= \int_{-\infty}^{\infty} \binom{m}{j} [F(y)]^j [1-F(y)]^{m-j} dG(y), \quad j=0, 1, \dots, m.$$

Take particular case $F=G$



And similarly, we defined U bracket $i=F_m$ of Y of bracketed I , here again F_m is the empirical distribution function of the first sample. So this is the number of X_j is $\leq Y_i$ and of course divided by m , and here it is the number of X_j 's $\leq Y_i/m$, and both U_i and U bracket i they take values $0, 1/m, 2/m, \dots$ up to $m-1/m, 1$. And we consider the forms of the distribution of U_i , and the distribution of U bracketed i . We also considered the special case when $F=G$.

Now let us, and we also consider the joint distributions of U_i, U_j, U bracket i, U_j , we also looked at the moment structure of these quantities, let me now proceed from here.

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We will now show that $U_{(q)} - U_{(p)} \stackrel{d}{=} U_{(q-p)}$

Consider $P(U_{(q)} - U_{(p)} = \frac{k}{m}) = \sum_{i=0}^{m-k} P(U_{(p)} = \frac{i}{m}, U_{(q)} = \frac{i+k}{m})$

$$= \sum_{i=0}^{m-k} \frac{\binom{q+k-p-1}{i} \binom{m+n-i-k-q}{m-i-k} \binom{i+k-i+q-p-1}{i+k-i}}{\binom{m+n}{m}}$$

$$= \frac{\binom{q+k-p-1}{k}}{\binom{m+n}{m}} \sum_{i=0}^{m-k} \binom{q+k-p-1}{i} \binom{m+n-i-k-q}{m-i-k} \left| \sum_{j=0}^k \binom{q+k-j-1}{kj} \binom{q+j-1}{j} \right|$$

$$= \frac{\binom{q+k-p-1}{k} \binom{m+n-k-q+p}{m-k}}{\binom{m+n}{m}} = P(U_{(q-p)} = k)$$

So first thing is that we consider the joint distribution of U_p and U_q , now I look at the distribution of the difference so we have the following result. We will now show that the distribution of $U_q - U_p$ is the same as the distribution of U_{q-p} , so for that let us consider the distribution of $U_q - U_p =$ say something like k/m since the values taken by these are of the form p/m .

So we can consider like this the difference is that k/m type only that means one of them is i/m and other one is of the form $i+k/m$ where i is varying from 0 to $m-k$ that is= now here I write down the joint distribution of this which we derived in the previous lecture let me recollect that thing. The joint distribution of U_p and U_q , so the values taken are j/m and l/m , then it is given by this expression $j^{p-1} \binom{m-j}{j}$ and all these things.

So here for j I will substitute i , and for l I will substitute $i+k$, so when we do that we will get the expression as $i^{p-1} \binom{m+n-i-k-q}{i} \binom{m-i-k}{i+k-i+q-p-1} \binom{m-i-k}{i+k-i}$, $i=0$ to $m-k/m+n \binom{m}{m}$, so this term you can see becomes free from i so we can take it out, so that is become $a^{q+k-p-1} \binom{m}{k/m+n} \binom{m}{m}$, so the second one this is $i^{p-1} \binom{m+n-i-k-q}{i}$ then this is $m+n-i-k-q \binom{m-i-k}{m-i-k}$ on this we apply this formula. Let me write that formula here we have $a^{k-j-1} \binom{m-k-j}{k-j}$, $j=0$ to k that is= $a^{a+b+k-1} \binom{m}{k}$.

So this becomes simply= then $a^{q+k-p-1} \binom{m+n-k-q+p}{k} \binom{m-k}{m+n} \binom{m}{m}$, but if you see this is also the probability of $U_{q-p}=k$.

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$$\begin{aligned}
 P(U_{(i)} = \frac{j}{m}) &= \int_{-\infty}^{\infty} \binom{m}{j} [F(y)]^j [1-F(y)]^{m-j} \frac{n! [F(y)]^{i-1} [1-F(y)]^{n-i}}{(i-1)!(n-i)!} dF(y) \\
 &= \int_0^1 \binom{m}{j} \frac{n!}{(i-1)!(n-i)!} u^{i+j-1} (1-u)^{m+n-i-j} du \quad F(y) = u \\
 &= \frac{m! n! (i+j)! (m+n-i-j)!}{j! (m-j)! (i-1)! (n-i)! (m+n)!} = \frac{\binom{m+n-i-j}{m-j} \binom{i+j-1}{j}}{\binom{m+n}{m}}
 \end{aligned}$$

which is hypergeometric distⁿ.

We can look at the distribution that I derived for U_i here that is $i=j/m=m+n-i-j$ c $m-j$ $i+j-1$ c j , so here if I put $i=q-p$ and $j=k$ then I get exactly this quantity, so this proves that the distributions of U_q-U_p and U_q-p is same that means it is dependent upon the difference.

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Next we derive the moments of U_i & U_j , when $F \equiv G$

$$\begin{aligned}
 E(U_{(i)}) &= E F_m(Y_{(i)}) = E E\{F_m(Y_{(i)}) | Y_{(i)}\} = E F(Y_{(i)}) \\
 &= E U_{(i)}^* \rightarrow \text{ith o.s. from } U[0,1] \\
 &= \frac{i}{n+1} \\
 \text{Var}(U_{(i)}) &= \text{Var}\{E\{F_m(Y_{(i)}) | Y_{(i)}\}\} + E[\text{Var}\{F_m(Y_{(i)}) | Y_{(i)}\}] \\
 &= \text{Var}(F(Y_{(i)})) + E \frac{F(Y_{(i)})(1-F(Y_{(i)}))}{m} \\
 &= \frac{i(n-i+1)}{(n+1)^2(n+2)} + \frac{1}{m} \left(\frac{i}{n+1} - \frac{i(i+1)}{(n+1)(n+2)} \right) \\
 &= \frac{i(n-i+1)}{(n+1)^2(n+2)} \frac{(m+n+1)}{m} \\
 \text{Cov}(U_{(i)}, U_{(j)}) &= \text{Cov}(F_m(Y_{(i)}), F_m(Y_{(j)})) \\
 &= \text{Cov}(E(F_m(Y_{(i)}) | Y_{(i)}), E(F_m(Y_{(j)}) | Y_{(j)})) \\
 &\quad + E(\text{Cov}(F_m(Y_{(i)}), F_m(Y_{(j)})) | Y_{(i)}, Y_{(j)})
 \end{aligned}$$

Now let us consider the moments of the U_i , U_j , we derive the moments of U_i and U_j of course we consider the case when $F=G$, when $F \neq G$ then only expressions can be written but here we can derive the exact values. So expectation of U_i that is expectation F_m of Y_i , we can consider it as expectation of expectation F_m Y_i given Y_i okay. So what we are doing here that here the sample, the first sample and the second sample both are involved here.

So expectation means expectation with respect to both the distributions of F and G , so we do it iteratively firstly condition on Y_i , so when we condition on Y_i then it will become the expectation with respect to the X sample and after that we will do the second one. Now if Y_i is fixed then this is the empirical distribution function and that we know it unbiased for the population cdf.

Now this quantity is nothing but expectation of U_i that is the U_i of the not this U_i , this U_i is actually the one which we derived as the i th order statistics from a uniform distribution, so this quantity okay let me call it U_i^* that is the i th order statistics from the uniform $0,1$. This we have already seen is $i/n+1$, because for the order statistics from the uniform distribution we have seen that the it is a beta distribution with parameters $i-1$ with parameters i and $n-i+1$.

So the mean will become $i/i+n-i+1$ that is $n+1$, so it is $= i/n+1$. Similarly, if I consider variance of U_i we can consider it as a variance of expectation of $F_m Y_i$ given Y_i + expectation of variance $F_m Y_i$ given Y_i . Once again this inner term will become F of Y_i , and this term as we can see the distribution of $F_m x$ that we have seen it is binomial distribution, we have derived it in the previous class.

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$$\binom{m}{j} p^j (1-p)^{m-j}, \quad j=0,1,\dots,m$$
 where $p = F(x)$.
 ie $m F_m(x) \sim \text{Bin}(m, F(x))$

$$E(m F_m(x)) = m F(x)$$

$$\Rightarrow F_m(x) \text{ is unbiased for } F(x)$$

 ie Sample distⁿ fn. is an unbiased estimator of the cdf.

$$V(m F_m(x)) = m \cdot F(x) (1-F(x))$$

$$\Rightarrow V(F_m(x)) = \frac{F(x) (1-F(x))}{m} \rightarrow 0 \text{ as } m \rightarrow \infty.$$

$$F_m(x) \rightarrow F(x) \text{ in square } m.$$

Let me just show the result once again that we had obtained the distribution of $m F_m x$ is a binomial distribution, and from here the variance of $F_m x$ was $F x * 1 - F x / m$, so if you use this

then this will become $=F$ of $Y_i * 1 - F$ of Y_i/m , now this term is turning out to be the variance of the i th order statistics from the uniform distribution, now variance in beta distribution the formula is known, so it is becoming $i * n - i + 1 / n + 1$ square $* n + 2$.

In the second case, so $1/m$ we can keep outside, and this is becoming expectation of F of Y_i that is $i/n + 1$ and this will become the second moment that is $i * i + 1 / n + 1 * n + 2$, so anyway this terms can be simplified and we get it as $= i * n - i + 1 / n + 1$ square $* n + 2$ $m + n + 1 / m$, so we are able to derive the mean and the variance of U_i , of course under the conditions when the 2 populations are the same. In a similar way we can try for the covariance term also.

Let us look at covariance between U_i and U_j , of course here I am taking $i > j$ so without loss of generality let us take say $i < j$, so that is covariance of F_m of Y_i , F_m of Y_j , so that is $=$ once again we can write it as covariance of expectation + expectation of covariance, so this one will become given Y_i and this one will become expectation of F_m of Y_j given Y_j + expectation of covariance between $F_m Y_i$, $F_m Y_j$ this is given Y_i , Y_j .

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$$\begin{aligned}
 &= \text{Cov} (F(Y_i), F(Y_j)) + E \frac{F(Y_i) (1 - F(Y_j))}{m} \\
 &= \frac{i(n-j+1)}{(n+1)^2(n+2)} + \frac{1}{m} \left[\frac{i}{n+1} - \frac{i(j+1)}{(n+1)(n+2)} \right] \\
 &= \frac{i(n-j+1)}{(n+1)^2(n+2)} \cdot \left(\frac{m+n+1}{m} \right) \\
 \text{Then } \text{Corr} (U_i, U_j) &= \frac{\frac{i(n-j+1)}{(n+1)^2(n+2)} \cdot \frac{m+n+1}{m}}{\sqrt{\frac{i(n-i+1)}{(n+1)^2(n+2)} \cdot \frac{m+n+1}{m} \cdot \frac{j(n-j+1)}{(n+1)^2(n+2)} \cdot \frac{m+n+1}{m}}} \\
 &= \sqrt{\frac{i(n-j+1)}{j(n-i+1)}}
 \end{aligned}$$

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So this is $=$ covariance between so you look at the first term here expectation of $F_m Y_i$ given Y_i then this will become F of Y_i , second term will become F of Y_j , and the next one is the now this type of term also we have seen because if I look at 2 of them then this will become a F of $Y_i * 1 - F$

of Y_j , so it will become expectation of this/m okay. So now these are the order statistics i th and j th from the uniform distribution.

So the formula for the formula for the covariance we have derived earlier $i^*n-j+1/n+1$ square $*n+2+ 1/m i/n+1-i*j+1/n+1*n+2$, so after simplification this turns out to be $i^*n-j+1/n+1$ square $*n+2 m+n+1/m$. Then let us also look at the coefficient of correlation between U_i and U_j and that is=covariance divided by the square root of the variances, so it is becoming $i^*n-j+1/n+1$ square $*n+2 m+n+1/m/$.

So you can easily see that these terms will get cancelled out, and we left with here simply root of $i^*n-j+1/j* n-i+1$, se we are able to completely determine the moment structure of the distributions of U_i and also joint distributions of U_i, U_j , and we have seen without the bracket and with the bracket also. Now we will see the applications of the certain 2 sample testing problems.

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Some Applications of $U_i, U_{(i)}$

Consider independent random samples X_1, \dots, X_m from $F(x)$
 & Y_1, \dots, Y_n from $G(y)$ respectively. Let ψ denote the median
 of F and η denote the median of G .
 We test the hypothesis $H_0: \psi = \eta$ ($H_1: \psi > \eta, H_2: \psi < \eta$)
 $H_1: \psi < \eta$

Mann-Whitney - Median Test

Let $T_1 =$ no. of X 's \leq median of Y 's
 $= \begin{cases} m U_{(\frac{n+1}{2})} & \text{if } n \text{ is odd} \\ m F_m \left(\frac{Y_{(\frac{n}{2})} + Y_{(\frac{n}{2}+1)} \right) & \text{if } n \text{ is even} \end{cases}$

Some applications of these terms, so let us go to our original assumption that we are having independent random samples X_1, X_2, X_m say from $F(x)$, and Y_1, Y_2, Y_n from say $G(y)$ respectively. Let us assume that, let ψ denote the median of F and say η denote the median of G . So for the 2 distributions I am considering the medians, like in the classical parametric

inference problems we assume the means to be μ_1, μ_2 and variance is to be σ_1^2, σ_2^2 .

Then our problem of interest is to test whether $\mu_1 = \mu_2$ or $\sigma_1^2 = \sigma_2^2$ etc. So similarly, when we are considering the nonparametric situation we would be interested in testing whether $\psi = \eta$ or $\psi < \eta$ or $\psi > \eta$ etc. so we can consider this hypothesis problem, $\psi = \eta$ against say $\psi < \eta$, so it could be also $\psi > \eta$, $\psi \neq \eta$ all these type of testing problems can be considered, let me call it H_2 and this as H_3 .

One of the first test is actually called Mathisan-Median test, in this test what we do? We define T_1 to be the number of X 's \leq median of Y 's, so actually depending upon what is the number of observations in Y second sample, so n could be odd, n could be even, so n is odd then you will have a unique median, so how many x 's are \leq that, that is exactly given by this U_i term, so we can consider it as m times that is $U_{n+1/2}$ that is same as $F_m(Y_{n+1/2})$ if n is odd.

And it is $Y_{n/2} + Y_{n/2+1/2}$, if n is even, now in the case of odd actually the distribution of this has already been worked out, we already know its mean and variance under the null distribution let me write that here.

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When n is odd, let us find the null mean and variance of T_1

$$E_0(T_1) = E(T_1 \text{ when } H_0 \text{ is true}) = m E\left(U_{\frac{n+1}{2}} \mid H_0\right)$$

$$= \frac{m \cdot \frac{n+1}{2}}{n+1} = \frac{m}{2}$$

$$V_0(T_1) = \frac{m^2 \left(\frac{n+1}{2}\right) \left(n - \frac{n+1}{2} + 1\right)}{(n+1)^2 n+2} \cdot \frac{m+n+1}{m} = \frac{m(m+n+1)}{4(n+2)}$$

We reject H_0 in favour of H_1 if T_1 is too large.
 H_2 if T_1 is too small
 H_3 if T_1 is either too large or too small.

Legend:
 $\text{No. of } X\text{'s} > Y_{(n)}$
 $= m - \text{No. of } X\text{'s} \leq Y_{(n)} = m - m F_m(Y_{(n)}) = m(1 - U_{(n)})$

When n is odd let us find the null mean and variance of T_1 , so we consider expectations of T_1 under H_0 that is expectations of T_1 when H_0 is true that means when $F=G$, when $F=G$ that means we can consider this = given H_0 that = m times $n+1/2/n+1$ that = $m/2$, and variance of T_1 of course it is m square $n+1/2$ $n-n+1/2+1/n+1$ square $n+2$ $m+n+1/m$ so that = $m^2 * m+n+1/4 * n+2$, so this is the mean and this is the variance under the null hypothesis certainly we can consider the normalization actually.

And of course I know the distribution of T_1 also here, so we can actually check whether it is too large or too small, we can also apply this Neyman-Pearson type thing that means we can consider the probability of type 1 error = α , and then we find the value of the critical point. So we can consider say, we reject H_0 in favor of H_1 if T_1 is too large, and we can also define reverse of this that is in favor of H_2 if T_1 is too small, and in favor of H_3 if T_1 is either too large or too small.

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Handwritten mathematical derivations on a blue background:

- $$E_0(T_2) = m \left(1 - \frac{n}{n+1} \right) = \frac{m}{n+1}$$
- $$V_0(T_2) = m^2 \cdot n \cdot \frac{(n-n+1)}{(n+1)^2 n+1} \cdot \frac{m+n+1}{m} = \frac{mn(m+n+1)}{(n+1)^2 n+1}$$
- $T_2 \rightarrow$ Rosenbaum Statistic I
 - If T_2 is small, we reject H_0 in favour of H_1
 - $H_0 \Rightarrow T_2$ is large
 - $H_2 \Rightarrow T_2$ is too large or too small.
- $$U = \sum_{j=1}^n (\text{no. of } X\text{'s} \leq Y_j) = m \sum_{j=1}^n F_m(Y_j) = m \sum_{j=1}^n U_j$$
- $$= \sum_{j=1}^n (\text{no. of } X\text{'s} \leq Y_j) = m \sum_{j=1}^n F_m(Y_j) = m \sum_{j=1}^n U_j$$
- $$E(U) = m \cdot \sum_{j=1}^n E_0(U_j) = \frac{m \cdot n}{2}$$

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See we can actually consider T_2 as the number of X 's $\leq Y_n$ that is m -number of X 's which are $\leq Y_n$ that = $m \cdot F_m$ of Y_n that = m times $1 - U_n$ that = $m/n+1$, variance of T_2 = m square $n-n+1/n+1$ square $n+2$ $m+n+1/m$ that = $mn^2 * m+n+1/n+1$ square $n+2$, so one can use this also, this T_2 is called Rosen Baum statistic 1. So we can actually do the testing based on this also, for example here it is greater, so if it is in the reverse way, we can consider that.

If T_2 is small, then we reject H_0 in favor of H_1 , so you can see it is the reverse of this, T_1 is too large and here it is T_2 is a small and reverse will happen against H_2 if T_2 is large, and in favor of H_3 if T_2 is too large or too small. The drawback with this 2 statistic that I defined that is Mathisan-median test is that this is based on median only, and in the Rosen Baum this is based on only the largest one.

Now one can think of using all of them, then that is called Mann-Whitney U statistic that is based on the summation of all such terms that is number of $X's \leq Y_j$ and you sum from $j=1$ to n that that= summation $j=1$ to n , actually here if I put this or if I put this they are same, number of $X's \leq Y_j$, because when I am summing over all j 's so when whether it is ordered or unordered both are same, so both of them I write like this.

Now the advantage of this term is that it is simply F times sigma U_j , and if I consider this form that is m times sigma F_m of Y_j that= m times sigma of U_j , so this is known as the Mann Whitney U statistic we can consider the mean and variance under the null hypothesis, then it is simply= m times $j=1$ to n , we know that this was= $1/2$ so it is $m n/2$.

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The image shows handwritten mathematical derivations on a blue background. At the top right, there is a small logo for '© CET I.I.T. KGP'. The main derivation starts with the variance of the U statistic:

$$\text{Var}_0(U) = m^2 \left\{ \sum_{j=1}^n \text{Var}_0(U_j) + \sum_{j \neq k} \text{Cov}(U_j, U_k) \right\}$$

$$= m^2 \left\{ n \cdot \left(\frac{m+1}{12m} \right) + n(n-1) \cdot \frac{1}{12m} \right\}$$

$$= \frac{mn(m+n+1)}{12}$$

Below this, the Rosenbaum Statistic-II is defined as:

$$T_3 \rightarrow \text{Rosenbaum Statistic-II}$$

$$= [\text{no. of } X's \leq Y_{(1)}] + [\text{no. of } X's > Y_{(n)}]$$

$$= m U_{(1)} + m(1 - U_{(n)}) = m(1 + U_{(1)} - U_{(n)})$$

The expected value of T_3 is then calculated as:

$$E_0(T_3) = m \left(1 + \frac{1}{n+1} - \frac{n}{n+1} \right) = \frac{2m}{n+1}$$

Finally, the variance of T_3 is given by:

$$\text{Var}_0(T_3) = m^2 \left(\text{Var}_0(U_{(1)}) + \text{Var}_0(U_{(n)}) - 2 \text{Cov}(U_{(1)}, U_{(n)}) \right)$$

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And if you look at the variance term, variance under the null hypothesis then it= m square summation variance of U_j + double summation covariance of U_j, U_k $j \neq k$, so that= m square and this is n and we actually derived this expressions in the previous lecture, let me just recall those

expressions here. So you can see here expression for this was $1/2$ and the expectations of this was derived, variance was derived as $2/m$ that is $m+2/12m$, so these expressions were derived.

And also the covariance term was derived here, the covariance terms of this was $1/12m$, so we substitute all these terms here $m+2/12m+n*n-1/12$, so we can simplify this easily this $=mn+m+n+1/12$. Once again if there are more number of X's which are $\leq Y_j$'s then the median of X's will be $>$ the median of Y's, so for large value of U will be rejecting H_0 in favor of H_1 , and similarly for the other hypothesis.

So in a similar way we have another one which is called again Rosen Baum statistic 2, I had defined 1 that was T_2 here, now I am defining T_3 this I am defining as the number of X's $\leq Y_1 +$ the number of X's $> Y_n$, this one you can see it is more useful for the range that means if we are checking the variability of the scale parameter, then this will be more useful for example there are more X's which are outside of Y_1 and Y_n then certainly it means that the variability of X will be more than the variability of Y's okay.

So this can be written as m times $U_1 + m$ times $1 - U_n = m*U_1 + U_1 - U_n$, of course under this $=m$ $1 + 1/n + 1 - n/n + 1$ that $=2m/n + 1$, the variability of this can be calculated that will become m square * variance of this + variance of this and covariance term here. So this is becoming m square variance of $U_1 +$ variance of $U_n -$ twice covariance of U_1, U_n .

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$$= m^2 \left[\frac{1(n-1)}{(n+1)^2 n+2} \cdot \left(\frac{m+n+1}{m}\right) + \frac{n(n-1)}{(n+1)^2 n+2} \cdot \left(\frac{m+n+1}{m}\right) - \frac{2 \cdot 1 \cdot (n-1)}{(n+1)^2 n+2} \cdot \left(\frac{m+n+1}{m}\right) \right]$$

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

Linear Rank Statistics : $N = m+n$
 Let $H_N(x) \rightarrow$ Sample d.f (Empirical dist'n) based on the combined sample of X's & Y's.

$N H_N(Y_{(j)}) = \text{no. of } X\text{'s \& } Y\text{'s} \leq Y_{(j)}$
 $H_N(Y_{(j)}) - j = \# \text{ of } X\text{'s} \leq Y_{(j)} = m U_{(j)} = m F_m(Y_{(j)})$
 linear rank statistics is a fn. of $H_N(x)$

So we can substitute the expressions for this here and we will get $m^2 \frac{(n-1)}{(n+1)^2 n+2} \cdot \left(\frac{m+n+1}{m}\right) + \frac{n(n-1)}{(n+1)^2 n+2} \cdot \left(\frac{m+n+1}{m}\right) - \frac{2 \cdot 1 \cdot (n-1)}{(n+1)^2 n+2} \cdot \left(\frac{m+n+1}{m}\right)$ since it is a first one, so $1 \cdot \frac{n-1}{(n+1)^2 n+2} \cdot \left(\frac{m+n+1}{m}\right) + \frac{n(n-1)}{(n+1)^2 n+2} \cdot \left(\frac{m+n+1}{m}\right) - 2 \cdot \frac{1 \cdot (n-1)}{(n+1)^2 n+2} \cdot \left(\frac{m+n+1}{m}\right)$ so this term is common and then you have $\frac{n-1}{(n+1)^2 n+2} \cdot \left(\frac{m+n+1}{m}\right)$ is also common, so you get $m^2 \cdot \frac{n-1}{(n+1)^2 n+2}$ and after simplification this term becomes $2m-2$, so 2 times $\frac{n-1}{(n+1)^2 n+2}$, so once again we are able to obtain the null mean and variance of this thing.

And for testing purpose this is more as I mentioned it is more useful for the scale, so if we get a large value of T_3 it means that the range of first sample is more than the range of the second sample, if T_3 is too small then it means that the range of the second distribution is more than the range of the first distribution, so this can also be used for the testing for the range. In general, we can define Linear Rank statistics, 2 samples of sizes m and n are there let us consider the composite samples sizes= N .

And let us define $H_N(x)$ is the sample distribution function or empirical distribution function based on the combined sample of X 's and Y 's that means I consider all the observations together and then I looked at the order statistics of them not separately, it is not that I write X_1, X_2, X_m first and then Y_1, Y_2, Y_n , I merge the 2 and then I considered the full ordering, and from that I define the empirical distribution that means if I consider N times H_N of Y_j then it is the number of X 's and Y 's which are \leq say Y .

So if I consider N times HN of Y_j then it = number of X 's $\leq Y_j$ that = m times U_j which is the one I defined earlier, that was m times F_m of Y_j , so I establish a relationship between the empirical distribution of the first sample with the empirical distribution function of the combined sample in terms of the value of Y_j . So in general we say that any linear rank statistics is a function of HN x . In other words, it is also a function of $F_m Y_j$.

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Prediction Intervals

X_1, \dots, X_m random sample from $F(x)$ $\left. \begin{array}{l} \\ \\ \end{array} \right\}$ independent.
 Y_1, \dots, Y_n random sample from $G(y)$

Let g be a function of Y_1, \dots, Y_n .
 L & U be functions of X_1, \dots, X_m .

Then if $P(L(X) \leq g(Y) \leq U(X)) = 1 - \gamma$
then we say that $[L, U]$ is $100(1 - \gamma)\%$ prediction interval for g .

Let $F \equiv G$ $L = X_{(r_1)}$, $U = X_{(r_2)}$

Prediction interval for at least k of Y_1, \dots, Y_n is to find r_1 & r_2
 $P(\text{at least } k \text{ of } Y_1, \dots, Y_n \text{ are between } X_{(r_1)} \text{ \& } X_{(r_2)}) = 1 - \gamma$

Next, we define Prediction Intervals, as before we have the 2 samples that is X_1, X_2, X_m is a random sample from $F x$, Y_1, Y_2, Y_n is a random sample from $G y$ and we assume that these are independently taken. Let us consider say g be a function of Y_1, Y_2, Y_n , and L and U be functions of X_1, X_2, X_m . Then if we have the statement like that means probability of $g y$ lying between 2 functions of X , if this = $1 - \gamma$.

Then we say that L, U is $100 1 - \gamma\%$ prediction interval for g , now let us consider the interpretation of this. See, we already seen the confidence intervals, in the confidence intervals the parametric term is to be fixed, so we find out the probability of 2 statistics including that parametric value = $1 - \alpha$, so that is called the $100 1 - \alpha\%$ confidence interval. Now this there is a difference in the terminology.

So in general it could be that we may be using see there may be some relationship between the 2 distributions, so we may be using the relationship to predict the value of a function of second sample based on the values of the first sample, so this is basically based on the relationship that is available between the 2. Let us take the special case, let $F = G$ then how do we look at it? So let us consider say L to be the r_1 th order statistics and U to be say r_2 th order statistics.

So we consider say prediction interval for at least k of Y_1, Y_2, \dots, Y_n that is to find r_1 and r_2 such that probability of at least k of Y_1, Y_2, \dots, Y_n are between $X_{(r_1)}$ and $X_{(r_2)}$ that $= 1 - \gamma$, at least k of Y_1, Y_2, \dots, Y_n are between $X_{(r_1)}$ and $X_{(r_2)}$, and I want this probability to be $1 - \gamma$, so we want prediction interval for this. So this is something like a location problem, but this is more general kind of location problem.

See if we consider parametric inference then we consider say if I am having 2 samples then we can consider $\theta_1 - \theta_2$, so a confidence interval for that, we can consider confidence interval for linear combination of θ_1 and θ_2 , we can also consider linear like σ_1 / σ_2 some sort of parametric function, when we are not having that then we are considering order statistics here, and on the basis of that we are talking about some sort of location problem.

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Handwritten mathematical derivation on a blue background:

$$n F_n(x) = \text{no. of } Y's \leq x$$

$$n F_n(X_{(r_1)}) = \text{no. of } Y's \leq X_{(r_1)}$$

$$n F_n(X_{(r_2)}) = \text{no. of } Y's \leq X_{(r_2)}$$

$$n F_n(X_{(r_2)}) - n F_n(X_{(r_1)}) = \text{no. of } Y's \text{ between } X_{(r_1)} \text{ and } X_{(r_2)}$$

We want to find r_1 and $r_2 \rightarrow$

$$P(n F_n(X_{(r_2)}) - n F_n(X_{(r_1)}) \geq k) = 1 - \gamma$$

$$\Rightarrow P(U_{(r_2)} - U_{(r_1)} \geq \frac{k}{n}) = 1 - \gamma$$

$$\Rightarrow P(U_{(r_2 - r_1)} \geq \frac{k}{n}) = 1 - \gamma$$

$$\sum_{i=k}^n P(U_{(r_2 - r_1)} = \frac{i}{n}) = 1 - \gamma$$

So let us consider then n times $F_n(x)$ that $=$ number of Y 's $\leq x$, then we can consider n times F_n of $X_{(r_1)}$ and that $=$ number of Y 's $\leq X_{(r_1)}$, then we can also consider n times F_n of $X_{(r_2)}$ that $=$ number

of Y 's $\leq X_{r_2}$, so here F_n denoting the empirical distribution function based on the second sample rather than the first sample. So n times $F_n(X_{r_2}) - n$ times $F_n(X_{r_1})$ that is the number of Y 's between X_{r_1} and X_{r_2} .

So we want to find r_1 and r_2 such that probability of n times $F_n(X_{r_2}) - n$ times $F_n(X_{r_1})$ that is $\geq k$ that $= 1 - \gamma$. Now the expressions for this is it is simply $U_{r_2} - U_{r_1} \geq k/n$ so I can divide here by n that $= 1 - \gamma$, we have seen that the distribution of the difference is same as the U of $U_q - U_p$ as same distribution as U_{q-p} so that $= 1 - \gamma$ here, so this is nothing but sigma probability of $U_{r_2 - r_1} = \text{some } i/n$, where $i = k$ to n that $= 1 - \gamma$.

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or
$$\sum_{i=k}^n \frac{\binom{m+n-r_2+r_1-i}{n-i} \binom{r_2-r_1+i-1}{i}}{\binom{m+n}{m} \binom{m+n}{n}} = 1 - \gamma$$

Prediction interval for $Y_{(i)}$
 We want r_1 & $r_2 \Rightarrow$

$$P(X_{(r_1)} \leq Y_{(i)} \leq X_{(r_2)}) = 1 - \gamma$$

$$\Rightarrow P(F_m(X_{(r_1)}) \leq F_m(Y_{(i)}) \leq F_m(X_{(r_2)})) = 1 - \gamma$$

$$\Rightarrow P\left(\frac{r_1}{m} \leq U_{(i)} \leq \frac{r_2}{m}\right) = 1 - \gamma$$

$$\sum_{j=r_1}^{r_2} \frac{\binom{m+n-i-j}{m-j} \binom{i+j-1}{j}}{\binom{m+n}{m}} = 1 - \gamma$$

The distribution of this is known to us so we substitute this value it is turning out to be simply $i = k$ to n $\binom{m+n-r_2+r_1-i}{n-i} \binom{r_2-r_1+i-1}{i} / \binom{m+n}{m} \binom{m+n}{n}$ that $= 1 - \gamma$, so from the tables of the factorials of hypergeometric distribution, then this can be calculated here, so basically this is hypergeometric here, this is $\binom{m+n}{m}$ that is also same as $\binom{m+n}{n}$ so both are same therefore, this is the proper hypergeometric term here.

In a similar way I can consider prediction interval i th order statistics from the second sample say that means we want now r_1 and r_2 such that probability of $X_{r_1} \leq Y_i \leq X_{r_2} = 1 - \gamma$, let us take here empirical distribution function, then this is nothing but $r_1/m \leq U_i \leq r_2/m$ that $= 1 - \gamma$.

gamma, the distribution of this is known so it is simply reducing to simply $m=n-i-j$ $m-j$ $i+j-1$ c $j/m+n$ c m from r_1 to r_2 .

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Prediction interval for at least $(j-i+1)$ of Y 's.
 We want r_1 & r_2 such that
 $P([X(r_1), X(r_2)] \text{ contains at least } j-i+1 \text{ of } Y\text{'s}) = 1-\gamma$
 or $P(X(r_1) \leq Y_{(i)} \leq Y_{(j)} \leq X(r_2)) = 1-\gamma$
 or $P(F_m(X(r_1)) \leq f_m(Y_{(i)}) \leq f_m(Y_{(j)}) \leq F_m(X(r_2))) = 1-\gamma$
 or $P(\frac{Y_1}{m} \leq U_{(i)} \leq U_{(j)} \leq \frac{r_2}{m}) = 1-\gamma$
 $\Rightarrow \sum_{t=r_1}^{r_2} \sum_{k=r_1}^t P(U_{(i)} = \frac{k}{m}, U_{(j)} = \frac{t}{m}) = 1-\gamma$
 $\Rightarrow \sum_{t=r_1}^{r_2} \sum_{k=r_1}^t \frac{\binom{k+i-1}{k} \binom{m+n-i-j}{m-t} \binom{t-k+j-i-1}{t-k}}{\binom{m+n}{m}} = 1-\gamma.$

Similarly, we can consider prediction interval for at least $j-i+1$ of Y 's, so we want r_1 and r_2 such that probability of the interval X_{r_1} to X_{r_2} contains at least $j-i+1$ of Y 's that $=1-\gamma$ that is probability that $X_{r_1} \leq Y_i \leq Y_j \leq X_{r_2}$ it $=1-\gamma$, so F_m of $X_{r_1} \leq F_m$ of $Y_i \leq F_m$ of $Y_j \leq F_m$ of X_{r_2} , where F_m is denoting the empirical distribution function of X sample, so this is nothing but $r_1/m \leq U_i \leq U_j \leq r_2/m$ that $=1-\gamma$.

So we can consider it as a double summation probability of $U_i = \text{some } k/m$, $U_j = \text{some } t/m$, where $t = \text{say } r_1 \text{ to } r_2$ and $k = r_1 \text{ to } t$ that $=1-\gamma$, the joint distribution of U_i and U_j has been obtained, so this is nothing $k+i-1$ c k $m+n-t-j$ c $m-t$ $t-k+j-1-1$ c $t-k/m+n$ c m $t = \text{say } r_1 \text{ to } r_2$ and $k = r_1 \text{ to } t$ that $=1-\gamma$. So this is the bivariate hypergeometric type of term here, and once again from the tables of factorials or the tables of bivariate hypergeometric this can be evaluated.

I have given here some elementary applications of this statistics which are based on the empirical distribution function. So we have the, let me summarize I have given here several applications here, one is to find out the test for the comparison of the medians, I also mentioned that one of them can be used for the scales also that means for the range. We have also defined what is known as the prediction interval.

So when we have the 2 samples, then what is the use of prediction interval? That means based on 2 values of the first sample or order statistics from the first sample, I can predict something about the value of the random variable, so basically we are talking about the probability that this much probability we can say that its value will lie in this interval. So in this one I discussed several of them, for example what is the prediction interval for Y_i 's, what is the prediction interval for at least $j-i+1$ of Y 's, what is the prediction interval for at least k of Y_1, Y_2, Y_n etc.

So these different type of formulae, they are useful for various type of nonparametric location or scalar matrix problems. We will talk more about this in the next lecture. Now there is another problem that is very commonly used by all the people working in different areas of Science and Engineering, that is given the data how to decide that which particular distributional model will be useful. One of the most popular applications or test for this is known as the Chi square test goodness of fit, which is originally given by Karl Pearson, so I will talk about that.

Later on another powerful test was given by Kolmogorov and Smirnov, so in the next lecture I will be discussing both these tests for fitting of a distribution, so they are called goodness of fit test, and as you can see that the structure of these test is extremely simple, they are not dependent upon what is the original distributional model only what assumption we are making it is dependent upon that. So in the next lecture will be discussing these.