

Applied Multivariate Analysis

Prof. Amit Mitra

Prof. Sharmishtha Mitra

Department of Mathematics and Statistics

Indian Institute of Technology, Kanpur

Lecture No. #14

Hotelling's T² Distribution and Various Confidence Intervals and Regions

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Relationship bet T^2 and likelihood ratio

X_1, \dots, X_n r.s. from $N_m(\underline{\mu}, \Sigma), \Sigma > 0$

$H_0: \underline{\mu} = \underline{0}$ ag $H_A: \underline{\mu} \neq \underline{0}$.

Likelihood fⁿ

$$L(\underline{\mu}, \Sigma | X) = (2\pi)^{-mn/2} |\Sigma|^{-n/2} \exp\left(-\frac{1}{2} \sum_{j=1}^n (\underline{x}_j - \underline{\mu})' \Sigma^{-1} (\underline{x}_j - \underline{\mu})\right)$$

In the last lecture, we were establishing the relationship between hotelling's T square statistic, and the likelihood ratio statistic, and we had considered the that X_1, X_2, \dots, X_n is a random sample from a multivariate normal distribution with mean vector as $\underline{\mu}$, and a covariance matrix positive definite Σ , and we were looking at this null hypothesis to be tested that $\underline{\mu}$ equal to a null vector, against an alternate hypothesis that $\underline{\mu}$ is not equal to a null vector.

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$$\Lambda = \frac{\sup_{\Theta_0} L(\underline{\mu}, \Sigma)}{\sup_{\Theta} L(\underline{\mu}, \Sigma)}$$

using (x^1) & (x^2) , we get

$$\Lambda = \frac{(2\pi)^{-m/2} n^{m/2} |A + n \bar{x} \bar{x}'|^{-1/2} \exp\left(-\frac{mn}{2}\right)}{(2\pi)^{-m/2} n^{m/2} |A|^{-1/2} \exp\left(-\frac{mn}{2}\right)}$$

$$\Rightarrow \left(\Lambda^{2/n} = \frac{|A|}{|A + n \bar{x} \bar{x}'|}\right) \checkmark$$

And we had derived the likelihood ratio statistic lambda which is given by supremum under script theta naught, where script theta naught was the parameter space under the null hypothesis of the likelihood function L mu sigma; that divided by the supremum of the likelihood function under script theta, where script theta is the unrestricted parameter space not restricting oneself to the null hypothesis space. And then, we had come up to the point that we had shown that this lambda to the 2 by n is equal to determinant of A divided by determinant of A plus n times x bar, x bar transpose.

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$$\Lambda^{2/n} = \frac{|A|}{|A + n \bar{x} \bar{x}'|}$$

$$= \frac{|A|}{|A| |I_m + n A^{-1} \bar{x} \bar{x}'|}$$

$$= \frac{1}{|I_m + \frac{n A^{-1} \bar{x} \bar{x}'}{P} \frac{Q}{Q}|} \checkmark$$

Note that $\begin{vmatrix} I_p & P \\ -Q & I_q \end{vmatrix} = |I_p + PQ| = |I_q + QP|$

$$\Rightarrow \Lambda^{2/n} = \frac{1}{|I_1 + n \bar{x}' A^{-1} \bar{x}|} = \left(1 + n \bar{x}' A^{-1} \bar{x}\right)^{-1}$$

So, we continue from this particular point; we have this lambda to the power 2 by n. That is given by determinant of A, that divided by determinant of A plus n times x bar x bar transpose this is determinant. Now, what we can do here is that we can take determinant

of A outside from this denominator to get to the form that this is determinant of A. So, if we take A outside here, what will be having here is I m; that is the dimension there, this plus n times A inverse and x bar x bar transpose it is determinant. So, that this term is just equal to one upon determinant of I m plus n times A inverse x bar x bar transpose.

Now, we note that we have a following result that, if we are looking at determinant of I say of P dimension I q minus Q A matrix and A matrix P here. Now, the dimension of this P is P by Q, and the dimension here is Q rows, and P columns. So, this determinant can be written as I p this plus P times Q that using the result of this partition the matrixes determinant; this is also I q plus Q times P. Now, in this expression here, if we take, if we use this same result; here, we will take this term as say P matrix; this actually is a vector, this is an m by 1 vector, and this is a Q, which also is a vector.

So, we will be able to write using this result here, this lambda to the power 2 by n that is equal to 1 divided by determinant of I 1. So, it is basically a scalar quantity, it is just equal to 1 that plus Q times P. So, we can interchange this, and we can write this as now, this note that this n is a scalar quantity. So, what will be having here is x bar n times x bar transpose A inverse and x bar determinant of that now, this is a scalar quantity **this also is a scalar quantity**. So, this is nothing, but 1 plus n x bar transpose A inverse x bar to the power minus 1.

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Handwritten mathematical derivation on a whiteboard:

$$H_0: \mu = 0 \text{ ag } H_A: \mu \neq 0$$

$$\bar{X} \sim N_m(0, \Sigma/n) \text{ under } H_0$$

$$(n-1)S = A \sim W_m(n-1, \Sigma)$$

T^2 statistic is given by

$$T^2 = n(n-1) \bar{X}' A^{-1} \bar{X}$$

$$\Rightarrow \frac{T^2}{n-1} = n \bar{X}' A^{-1} \bar{X}$$

$$\Rightarrow \Lambda^{2/n} = \left(1 + \frac{T^2}{n-1}\right)^{-1} \Rightarrow \Lambda = \left(1 + \frac{T^2}{n-1}\right)^{-n/2}$$

Now, we will see what is the relationship of this with a T square statistic? Now, the corresponding T square statistic, if we have H naught, mu equal to a null vector; this is to be tested against our alternate hypothesis that this mu is not equal to a null vector. We

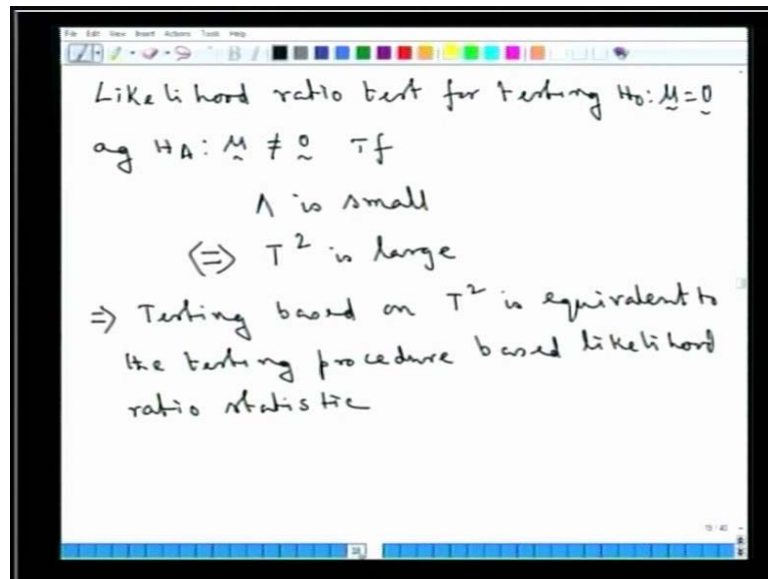
will have the distribution of \bar{x} to be a multivariate normal with a mean vector as a null vector, and a covariance matrix as Σ by n this under H_0 , and what more is $n - 1$ times S with a divisor $n - 1$. Let us, write that to be equal to A , which is actually equal to A , this would follow a wishart distribution on m dimension with degrees of freedom as $n - 1$, and an associated variance, covariance matrix as Σ .

So, what would be the T square statistic from here so, if we have this setup; then the T square statistic is given by T^2 ; which is, if we recall the result that T^2 square, how T^2 square is formed from a wishart distribution, and a multivariate normal distribution; this would be given by n times n ; n is the degrees of freedom of the associated wishart which is $n - 1$ times this \bar{x} transpose and then this wishart matrices inverse \bar{x} . So, this statistic is going to be given by this, and hence, this would imply that this T^2 square by $n - 1$ this is equal to n times \bar{x} transpose A^{-1} \bar{x} .

So, T^2 square by $n - 1$ in case of testing from a multivariate normal distribution with mean vector equal to a null vector is going to be given by this, and thus, if we have this λ to the power 2 by n to be given by this actually as, we can see is same as, what we have obtained out here; so, this would imply that this λ . Let me, take that 2 by n to the other side; and let me, first keep it in the form, that it was this would be given by $1 + T^2$ square the observed value in case of small \bar{x} , and the associated A matrix. So, this is T^2 square by $n - 1$ whole to the power minus 1 .

This would further imply that the likelihood ratio statistic is going to be given by $1 + T^2$ square by $n - 1$ whole raise to the power minus n by 2 . So, if this is the relationship between the likelihood ratio statistic, and the hotelling's T^2 square statistic. We can say the following, that the likelihood ratio test would reject the null hypothesis likelihood ratio test for testing this H_0 may be equal to a null vector against the alternate hypothesis H_A , that μ is not equal to the null vector. If λ is small, that is, how a likelihood ratio test goes along, because it is looking at the ratio of the two supremums: one in the denominator is supremum over the null space, and the one in the denominator is a supremum over the entire parameter; space not restricting oneself to the null space.

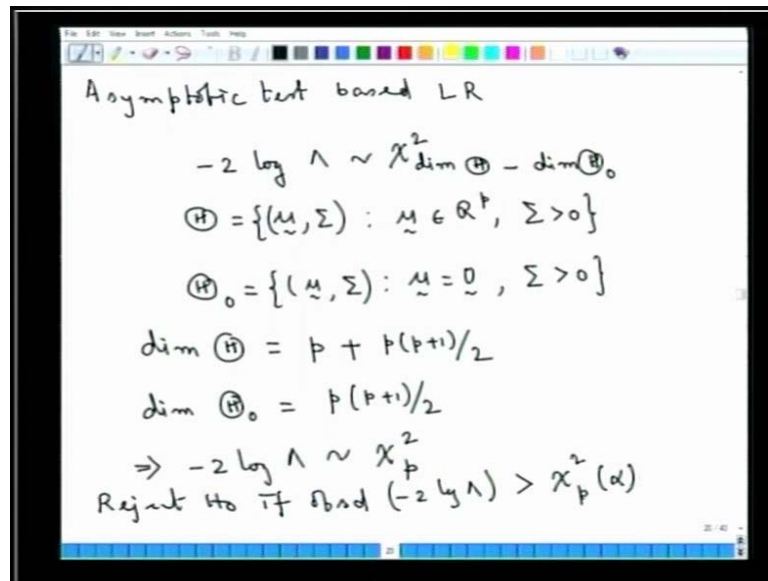
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So, the likelihood ratio test would reject if lambda is small; this is equivalent, because we have this relationship; that this lambda is $1 / (1 + T^2)^{n/2}$, and hence lambda being small is equivalent to saying that; T square is large, and that is, what is the desired thing. So, this is equivalent to saying that, if T square is large. So, this would imply that the testing based on T square is equivalent to the testing procedure based on the likelihood ratio, likelihood ratio statistic.

So, the two actually are equivalent this gives us another justification actually of the T square, a Hotelling's T square statistic; that, if we are looking at using the Hotelling's T square statistic for testing such null hypothesis as, what is framed that testing procedure is equivalent to a likelihood ratio test principle. Now if this lambda, what we have derived is this particular quantity? We can derive the distribution of this lambda or we can use an asymptotic distribution; another distribution of lambda is going to be based on the distribution of T square **T square** remember another null hypothesis has got a F distribution on $m n - m + 1$ degrees of freedom, and hence the distribution of this lambda can theoretically be derived, when we have the relationship between this lambda, and T square.

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Asymptotic test based LR

$$-2 \log \Lambda \sim \chi^2_{\dim(\Theta) - \dim(\Theta_0)}$$

$$\Theta = \{(\underline{\mu}, \Sigma) : \underline{\mu} \in \mathbb{R}^p, \Sigma > 0\}$$

$$\Theta_0 = \{(\underline{\mu}, \Sigma) : \underline{\mu} = \underline{0}, \Sigma > 0\}$$

$$\dim(\Theta) = p + p(p+1)/2$$

$$\dim(\Theta_0) = p(p+1)/2$$

$$\Rightarrow -2 \log \Lambda \sim \chi^2_p$$

Reject H_0 if observed $(-2 \log \Lambda) > \chi^2_p(\alpha)$

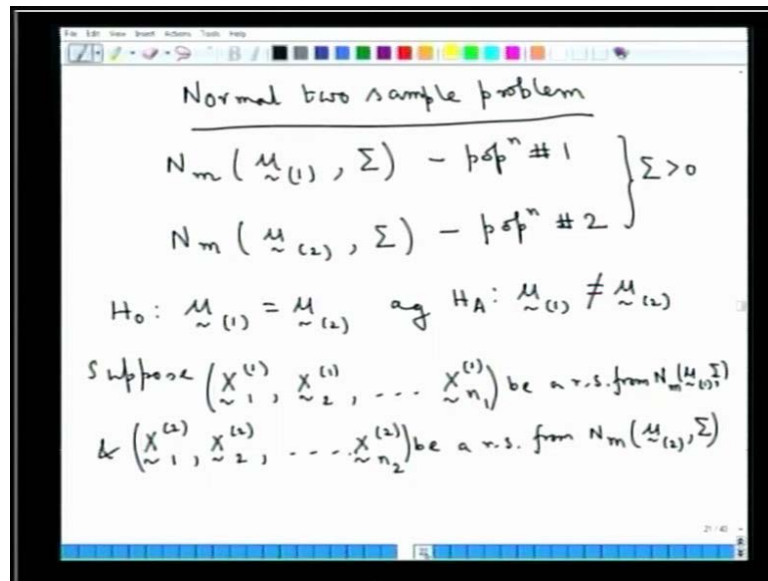
For large sample asymptotic test based on this likelihood principle can be obtained an asymptotic test based on L R, likelihood ratio is going to be given or rather would be based on the following fact, that this minus 2 log lambda, this would follow a central chi square on the degrees of freedom, which is the difference of the dimension of script theta, and the dimension of script theta naught. So, this minus 2 log lambda, while lambda is given by this likelihood ratio, which is this particular quantity; one can look at what is this degrees of freedom; now, what is the dimension of script theta, and dimension of script theta naught. Let me, write the two spaces that it would be easy to see, what is the dimension of the two spaces.

So, this is mu sigma space, where this mu belongs to R to the power P, and this sigma is positive definite; it is a symmetric matrix with P into p plus 1 by 2 distinct elements, and script theta naught is the null space, which is the set of all mu sigmas; such that, mu under the restriction of the null spaces, the null vector, and this sigma is still positive definite. So, the dimension of script theta would be the P dimensions; that are present in mu, this plus the number of free parameters in sigma, which is p into p plus 1 by 2, and the dimension of script theta naught, this is equal to p into p plus 1 by 2. The distinct element corresponding to the sigma matrix and mu is specified and nothing comes actually from there. So, this would imply that minus 2 log lambda would follow asymptotically a chi square random variate on just P degrees of freedom. Now reject, we will reject the null hypothesis, reject H naught, if observed value of this test statistic that is minus 2 log lambda. The observed value of that is greater than chi square P alpha,

when this is the upper alpha percent cut off point of a central chi square P degrees of freedom.

So, this is the asymptotic test, that is based on the likelihood ratio principle, which of course we have shown, that it is equivalent to the Hotelling's test that is going to be based on the Hotelling's T square statistic.

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Now, let us look at this a normal two sample problem, and how to use the Hotelling's T square statistic in order to perform testing. In this situation, normal two sample problem: what is the problem here? We have two multivariate normal populations, say N p 1 will be using N m. So, let me stick to that particular notation that, multivariate normal with a mean vector as mu 1, and a covariance matrix as sigma.

So, this is population number 1, **this is population number one** and the second population is multivariate normal m with a different mean vector, and the same covariance matrix sigma. So, this is what is characterizing the second population, and sigma of course is positive definite, we have this common assumption that sigma is positive definite for the two populations. So, we have two multivariate normal populations different in the mean vector and the covariance matrix are same. Now, in this particular situation the point of interest is to test the following null hypothesis, that this mu 1 vector is equal to mu 2 vector; this is to be tested against the alternate hypothesis that this mu 1 vector is not equal to this mu 2 vector.

It is a standard testing procedure, if we look at the corresponding univariate counter part then the clearly the univariate counter part also, we have done the testing of course in univariate counter part, when we have two univariate normal populations with same variance, and different mean component; then the testing of that of course is obtained using the T statistic the students T statistic, and this we are going to show that, the testing of this particular problem in the multivariate to sample to multivariate normal population can also be obtained using a hotelling's T square statistic.

Now, suppose we have two sets of random samples; now suppose $X^{(1)}_1, X^{(1)}_2, \dots, X^{(1)}_{n_1}$, be a random sample from the first population; which is $N_m(\mu_1, \Sigma/n_1)$, and we have a second set of sample from the second population $X^{(2)}_1, X^{(2)}_2, \dots, X^{(2)}_{n_2}$, be a random sample from the second multivariate normal population. That is, it is a random sample from $N_m(\mu_2, \Sigma/n_2)$. So, we will be using this two sets of random samples; this is the set of random samples n_1 size from the first population; this is the set of random sample from the second population of size n_2 .

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The image shows a whiteboard with handwritten mathematical derivations. The equations are as follows:

$$\bar{X}^{(1)} = \frac{1}{n_1} \sum_{i=1}^{n_1} X^{(1)}_i \sim N_m(\mu_1, \Sigma/n_1)$$

$$\text{Sly } \bar{X}^{(2)} = \frac{1}{n_2} \sum_{i=1}^{n_2} X^{(2)}_i \sim N_m(\mu_2, \Sigma/n_2)$$

$$(n_1-1) S_1 \sim W_m(n_1-1, \Sigma)$$

$$\& (n_2-1) S_2 \sim W_m(n_2-1, \Sigma)$$

$$\bar{X}^{(1)} - \bar{X}^{(2)} \sim N_m(\mu_1 - \mu_2, \Sigma(\frac{1}{n_1} + \frac{1}{n_2}))$$

$$\sim N_m(0, \frac{n_1+n_2}{n_1 n_2} \Sigma)$$

Under H_0 .

Now, if we have this particular setup then the following can be easily said that, suppose $\bar{X}^{(1)}$ is one upon n_1 summation i equal to 1 to n_1 of $X^{(1)}_i$. So, I am looking at the first population, i equal to 1 to up to n_1 of this $X^{(1)}_i$. So, this is the sample mean random vector from the first population; this has got a distribution multivariate normal m with a mean vector as μ_1 and a covariance matrix as Σ/n_1 .

Now, similarly we have the second population giving us, this mean vector, sample mean vector based on the n_2 random samples from the second population; this is $\frac{1}{n_2} \sum_{i=1}^{n_2} X_i$ random samples from the second population. So, these follow a multivariate normal similarly, with a mean vector as μ_2 , and a covariance matrix as Σ_2 . Now, these two are going to be independent, why because this \bar{X}_1 is based on X_{i1} terms n_1 of them, and this is going to be based on the other set of random samples from the second population.

Now, these being set of random samples this, and this. So, this set of random sample is independent of this set of random samples, and within the random samples sets actually this X_{11} would be independent with each of them. So, this set is also, set of independent random vectors, and this set also is independent random vectors, and the two are mutually independent, because they are random samples from two different multivariate normal populations. So, we have first of all this particular result. Now, corresponding to the sample variance, covariance matrix; what we can say is that $n_1 - 1$ times S_1 , where S_1 is a sample variance, covariance matrix based on the set of n_1 random samples from the first population. This would follow a wishart distribution on degrees of freedom as $n_1 - 1$, and a covariance matrix as Σ_1 , and similarly based on the second set of random samples $n_2 - 1$ times S_2 ; this would also follow, a wishart distribution wishart $m, n_2 - 1$, and Σ_2 .

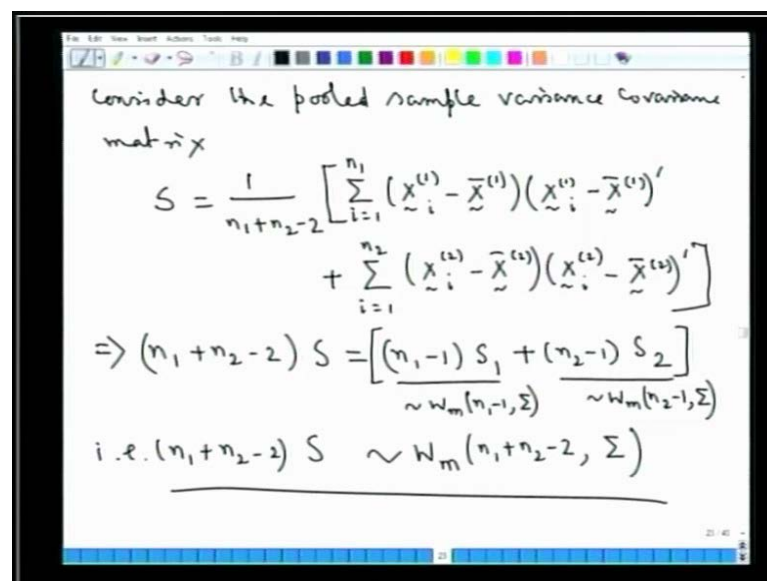
Now, once again these two are independent, and what is more important is to realize that this \bar{X}_1 is independent of S_1 ; that is the result that, we have proved for multivariate normal distribution \bar{X}_2 is independent of this S_2 quantity. So, that what we can further say that all these four statistic. They are mutually independent, first of all from the set of random samples of size n_1 ; this \bar{X}_1 and S_1 are independent from the set of random samples of size n_2 from the second population. These \bar{X}_2 , and S_2 are independent, and they are mutually independent, because they are random samples from two different multivariate normal populations.

So, this is what we are? These are the building blocks for getting into the [Hotelling's] T^2 square statistic for this particular setup. Now let us, look at the distribution of this $\bar{X}_1 - \bar{X}_2$, what is going to be the distribution of this; we have \bar{X}_1 to be this multivariate normal \bar{X}_2 to be this multivariate normal distribution these two are independent. So, one can very easily show that, this also is following a multivariate normal distribution m dimensional with $\mu_1 - \mu_2$; as it

is mean vector, and the covariance matrix would just be the sum of the two covariance matrices, because \bar{X}_1 and \bar{X}_2 are independent.

So, what is it that is equal to σ^2 times 1 upon n_1 plus 1 upon n_2 . So, this is 1 upon n_1 plus 1 upon n_2 . Now, this would follow under the null hypothesis that μ_1 is equal to μ_2 . This would follow a multivariate normal with a mean vector as null vector, and a covariance matrix, as n_1 plus n_2 by n_1 n_2 times σ^2 . This is the distribution under the null hypothesis H_0 being true. So, this as far as combining the two mean sample mean vectors.

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Consider the pooled sample variance covariance matrix

$$S = \frac{1}{n_1+n_2-2} \left[\sum_{i=1}^{n_1} (\tilde{x}_i^{(1)} - \bar{\tilde{x}}^{(1)}) (\tilde{x}_i^{(1)} - \bar{\tilde{x}}^{(1)})' + \sum_{i=1}^{n_2} (\tilde{x}_i^{(2)} - \bar{\tilde{x}}^{(2)}) (\tilde{x}_i^{(2)} - \bar{\tilde{x}}^{(2)})' \right]$$

$$\Rightarrow (n_1+n_2-2) S = \left[\underbrace{(n_1-1) S_1}_{\sim W_m(n_1-1, \Sigma)} + \underbrace{(n_2-1) S_2}_{\sim W_m(n_2-1, \Sigma)} \right]$$

i.e. $(n_1+n_2-2) S \sim W_m(n_1+n_2-2, \Sigma)$

Now, what we can say further is that consider the pooled sample variance, covariance matrix, **consider the pooled sample variance covariance matrix** that would be given by S , which is 1 upon n_1 plus n_2 minus 2 . This is actually same as that type; what we usually do with univariate theory also. So, that would be the pooling here 1 upon n_1 $X_i^{(1)}$ minus \bar{X}_1 . So, this is for the part that is coming from the first set of random samples. So, it is $X_i^{(1)}$ minus the mean coming from all these $X_i^{(1)}$ quantities that multiplied by $X_i^{(1)}$ vectors, minus \bar{X}_1 vector transpose, this plus the second set of random samples i equal to 1 to up to n_2 $X_i^{(2)}$. So, these are based on the second set of random samples deviation taken from the second the random mean vector. The sample mean vector is based on the second set of random samples; this is $X_1^{(2)} X_i^{(2)}$ minus \bar{X}_2 ; it is transpose.

So, this is the pooled sample variance, covariance matrix, and what is this term equal to this term is nothing, but $n_1 - 1 S_1$. So, that we can say that this is $n_1 + n_2 - 2$ times S , this is equal to the first term; which is $n_1 - 1$ times S_1 plus $n_2 - 1$ times S_2 . So, we have these two the sum of these two giving us $n_1 + n_2 - 2$ times the pooled sample variance, covariance matrix. Now, what can we say about the distribution of this note that this quantity here follows, a wishart distribution wishart $m, n_1 - 1$ degrees of freedom, and an associated variance, covariance matrix as σ .

And Similarly, the second part here; this follows, a wishart distribution with the same dimensionality as the degrees of freedom changes; it is $n_2 - 1$, and the same variance, covariance matrix as σ . Now these two are independent; that is what we had said in the previous slide here, that this these two statistic, they are going to be independent, because they are based on two different random samples, and hence this is just the sum of two independent wishart distributions; now by the additive property of the wishart distribution keeping the dimensionality, and the associated σ the associated variance, covariance matrix to be same.

We will have this particular sum of two independent wishart distributions with the same dimension, and same σ , this will have a wishart distribution m , and the degrees of freedom pooling up. So, its $n_1 + n_2 - 2$ degrees of freedom, and the same variance, covariance matrix as σ ; that is, what we now have is $n_1 + n_2 - 2$ times this pooled sample variance, covariance matrix to have this particular distribution.

Now, we **we now** have the building blocks for getting into the [hotelling's] T square statistic; one building block is here, and the second building block is basically here, **right** because we have one part here a multivariate normal distribution, and we have another wishart distribution. Now critically, this multivariate normal distribution, and **this this multivariate normal distribution** and this wishart distribution, they are going to be independent.

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$$\begin{pmatrix} \bar{X}^{(1)} \\ \bar{X}^{(2)} \end{pmatrix} - \bar{X}^{(2)} \sim N_m \left(0, \frac{n_1 + n_2}{n_1 n_2} \Sigma \right) \text{ under } H_0$$

$$\& (n_1 + n_2 - 2) S \sim W_m (n_1 + n_2 - 2, \Sigma) \quad \left. \begin{array}{l} \\ \end{array} \right\} \text{indep}$$

Recall, $S \sim W_m(n, \Sigma)$ & $d \sim N_m(\delta, c^{-1}\Sigma)$ are indep.

$$T^2 = c n d' S^{-1} d \quad \text{Hotelling's } T^2 \text{ on } n \text{ d.f.}$$

$$\frac{T^2}{n} \cdot \frac{n-m+1}{m} \sim F_{m, n-m+1}(\gamma^2)$$

$$\Rightarrow T^2 = \left(\frac{n_1 n_2}{n_1 + n_2} \right) \cdot (n_1 + n_2 - 2) \cdot \begin{pmatrix} \bar{X}^{(1)} - \bar{X}^{(2)} \end{pmatrix}' \cdot \begin{pmatrix} n_1 + n_2 - 2 \end{pmatrix} S^{-1} \cdot \begin{pmatrix} \bar{X}^{(1)} - \bar{X}^{(2)} \end{pmatrix}$$

Hotelling's T^2 on $(n_1 + n_2 - 2)$ d.f.

Let me, write it in a compact form here, that this $\bar{X}^{(1)} - \bar{X}^{(2)}$ this is a random vector. This follows a multivariate normal distribution m with a null vector, as it is mean vector under the null hypothesis, and this $n_1 + n_2$ divided by $n_1 n_2$ times sigma under H_0 . We are looking at it under H_0 , because any way we will have to look at the distribution of the test statistic which is going to be Hotelling's T^2 under the null hypothesis; otherwise, this remains $\mu_1 - \mu_2$; this, and we also have $n_1 + n_2 - 2$ times S ; this to follow a Wishart distribution, Wishart m the use of freedom as $n_1 + n_2 - 2$, and an associated variance, covariance matrix as sigma, and the two are independent.

So, we can use; let me, write once again what **we are now going to** recall we are going to recall, that if S has a Wishart m n sigma, and d ; a random vector this is; how we had defined a Hotelling's T^2 statistic? We have d ; a random vector, which is having a multivariate normal with a mean vector as delta, and the covariance matrix as c inverse sigma, where c is a scalar quantity? If we have these two random vector, and random matrix are independent. Then this T^2 statistic was given by c times $d' S^{-1} d$. This is, how we had defined Hotelling's T^2 . So, this is Hotelling's T^2 on n degrees of freedom; the degrees of freedom is associated with this n ; here, which is the degrees of freedom of the associated Wishart distribution. So, if we have that further more what we will be having is T^2 by n in to $n - m + 1$; that divided by m , this to follow a non-central F distribution on m $n - m + 1$ degrees of

freedom, and a non-centrality parameter equal to tau square; which is going to be given by c times delta prime sigma inverse delta.

So, this is what is the definition, and the distribution of a hotelling's T square, which can be framed from a wishart distribution, and a multivariate normal distribution that being independent. So, we are going to use this definition, and the distribution of the hotelling's T square statistic, in order to frame the hotelling's T square statistic out of this particular problem. So, this would imply that the T square for the given problem would be given by what is c here; c is the inverse of this particular quantity. So, that is $\frac{1}{n_1 + n_2}$ this divided by $n_1 + n_2$. So, that is how a c term, and then what is n in our problem; n is the degrees of freedom associated with the wishart distribution, which is in our case $n_1 + n_2 - 2$.

So, we have taken care of these two terms; what is d prime? The d prime is the prime of this particular term here, because that is the multivariate normal distribution out there. So, we will have this $\bar{X}_1 - \bar{X}_2$ transpose, and then we have S^{-1} **S inverse S** is, what S is the associated wishart distribution. So, we will have that as $n_1 + n_2 - 2$ this multiplied by this S ; the pooled sample variance, covariance matrix inverse of that, and that multiplied by this d . So, this d is once again this $\bar{X}_1 - \bar{X}_2$.

So, this is now our hotelling's T square; this is the hotelling's T square for the given problem, for the given two sample normal problem hotelling's T square on how many degrees of freedom? The degrees of freedom would be associated with the degrees of freedom of the underline wishart distribution. So, this is a hotelling's T square on $n_1 + n_2 - 2$ degrees of freedom. So, what happens here? This term cancels out with this term, and whatever remains is the hotelling's T square statistic.

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i.e. $T^2 = \frac{n_1 n_2}{n_1 + n_2} (\bar{X}^{(1)} - \bar{X}^{(2)})' S^{-1} (\bar{X}^{(1)} - \bar{X}^{(2)})$.

Furthermore,

$$\left(\frac{T^2}{n_1 + n_2 - 2} \cdot \frac{(n_1 + n_2 - 2) - m + 1}{m} \right) \sim F_{m, n_1 + n_2 - m - 1}$$

under H_0

Reject $H_0: \mu^{(1)} = \mu^{(2)}$ in favour of $H_A: \mu^{(1)} \neq \mu^{(2)}$

if $\text{obsd.} \left(\frac{T^2}{n_1 + n_2 - 2} \cdot \frac{n_1 + n_2 - m - 1}{m} \right) > F_{m, n_1 + n_2 - m - 1}(\alpha)$

and accept H_0 otherwise.

That is, this T square is nothing, but this $n_1 n_2$, this divided by $n_1 + n_2$, this times $\bar{X}_1 - \bar{X}_2$; it is transpose S inverse, where S is the pooled sample variance, covariance matrix $\bar{X}_1 - \bar{X}_2$. Now, further more we will have to find the distribution of this T square or some constant times; this T square function in order to find the distribution of that, what we are going to use is this result for the general hotelling's T square distribution. So, that we will have this T square; now T square divided by what here divided by n ? What is n ; n is the degrees of freedom associated with the wishart distribution.

So, we have $n_1 + n_2 - 2$, which is now playing the role of n ; then we have the constant here which was $n - m + 1$. So, that this is now our $n - m$; m is the dimension. So, m remains as, it is this plus 1 this divided by m . So, this is equal to this will, this is going to follow a F distribution on what degrees of freedom; degrees of freedom is first is m , and the second is this is $n_1 + n_2 - 2 - m + 1$. So, this is equal to $n_1 + n_2 - m - 1$.

And what is the non-centrality parameter? The non-centrality parameter of this F distribution if μ all that would be given from this particular mean vector here μ . So, that is going to be this null vector prime, the inverse of this into the null vector which is equal to 0. So, this is a central F distribution on these degrees of freedom. So, if we have the hotelling's T square, which is from the two sample normal problem to have this particular distribution; we will reject the null hypothesis, we know it is distribution. This is under the null hypothesis **this is under the null hypothesis**.

So, if it is not under the null hypothesis, then what we will be having is this to be a non central F distribution, and the non-centrality parameter in such a situation would be given by $\mu_1 - \mu_2$, and then inverse of this particular quantity, that is $\frac{1}{n_1 + n_2} \frac{1}{\sigma^2}$, that multiplied by $\mu_1 - \mu_2$ that would be the distribution or rather that would be the non-centrality parameter of the F distribution; if this is not considered under the null hypothesis. Now, using this, what we can do is to look at the rejection regions. So, reject H_0 , which is $\mu_1 = \mu_2$ against the alternate hypothesis H_A , which is $\mu_1 \neq \mu_2$, if observed value of this T square divided by $n_1 + n_2 - 2$ this multiplied by $n_1 + n_2 - m - 1$ this divided by m is greater than the upper alpha percent tabulated value of the central F distribution on $n_1 + n_2 - m - 1$ degrees of freedom.

So, this is the upper alpha percent cut off point of a central F distribution on $n_1 + n_2 - m - 1$ degrees of freedom, and thus this testing of this problem of testing, this null hypothesis against this alternate hypothesis; here, would be achieved, and we will reject the null hypothesis, if the observed value of this quantity the test statistic exceeds, the tabulated value, and we accept H_0 ; otherwise so, that completes the proof actually or rather the derivation of the test statistic, and formulation of this particular testing problem. In case of two sample multivariate normal population, we have seen how this testing problem can actually be framed, and testing can be carried out for one sample multivariate or rather one population multivariate normal problem, and two population multivariate normal problems.

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Applications of Hotelling's T^2

Example 1: Patients of diabetes are given a certain drug and the changes in blood sugar level (x_1), systolic (x_2) and diastolic (x_3) pressures are recorded.

Data:

	Subjects			
	1	2	...	n
variables	x_{11}	x_{12}	...	x_{1n}
	x_2	-	-	-
	x_3	-	-	-

3xn

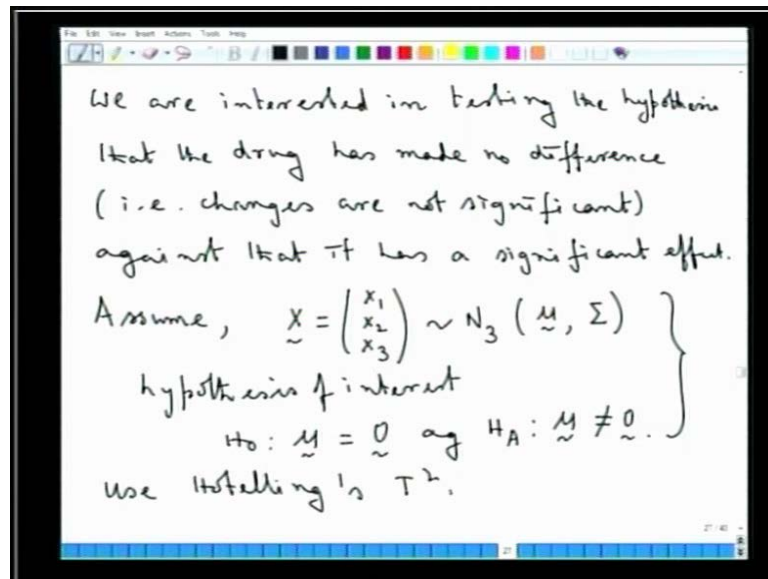
Let us, now look at some practical data in order to see, how this particular concept of Hotelling's T square can be applied for real life data. So, applications of Hotelling's T square is, what we are now going to see from somewhere life data examples; these are standard examples, Hotelling's T square; we will look at two examples as, I said that these are standard examples; now, the problem is the following we have patients of diabetes are given a certain drug, **certain drug** and the changes in blood sugar level. Let, that be denoted by variable X_1 systolic. Let us, denote that by X_2 variable, and diastolic **diastolic** say X_3 variable pressures are recorded.

So, the problem is the following; it is a practical data example; that there are patients say n of them having diabetes are given a particular drug, and then in order to check whether the drug is effective the following three variables are recorded; the recording on the three variables are taken the three variables are blood sugar level changes; changes in the blood sugar level changes in the systolic pressure, and the changes in the diastolic pressures are recorded. Now, what is the structure of the data the data looks like the following; suppose, I have got these as subjects, that is patients, we have n such patients. So, these are n patients; the data are recorded for these n patients; **all the three variables** there are three variables X_1 , X_2 , and X_3 .

So, corresponding to these three variables corresponding to the subject; one we record that patients change in the blood sugar level, and record it out here, that patients change in the systolic pressure here, and the change in the diastolic pressure here. So, we will be able to complete this particular data completely. So, this now is a three by n data matrix which holds all the recording for the n patients on these three variables of interest.

Now, the problem is framed or rather the question; that is **posed is** whether the drug which was administered on these n patients looks as, if it is an effective drug or not.

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So, the question in hand is to answer is the following: we are interested in testing the hypothesis that the drug which is administered; which is under study has made no difference **no difference** with respect to the three variables; that is the changes are not **significant that is the changes are not significant** significantly different from 0 or not significant. This is to be tested against that it has made a change or it has **it has** a significant effect **it has a significant effect**.

So, this basically is a **problem**; practical problem; now, in order to test this particular or rather carry forward this particular problem, and then use this particular data in order to answer the question of interest that, whether the drug at all is effective or not that is going to be tested on the based **based** on **on** the basis of the three variables; that we have taken recordings on we assume the following: we assume that this X 3 random vector which is comprising of this X 1 variable, X 2 variable, and this X 3 variable. This follows a three dimensional normal distribution with a mean vector as μ , and a covariance matrix as σ .

So, this is the mean vector corresponding to this random vector out here. So, the first component would not correspond to the expected change in X 1 variable in that multivariate normal population. Now, in terms of this assumption that we are made on this random vector, if we are interested in testing the hypothesis; that the drug had made no difference, that is the changes are not significant. These are the variables denoting the changes in the respective variables. So, the hypothesis of interest **hypothesis of interest** is

thus the testing of H_0 what is that it is testing for this change vector in the population V is a null vector.

This is to be tested against the alternate hypothesis, that this μ vector is not equal to a null vector. Now the problem looks intractable form now. So, if we have made this particular assumption, and translated this particular hypothesis in terms of the mean vector of this multivariate normal population we can use a hotelling's T square statistic in order to test this practical problem use hotelling's T square.

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The image shows a whiteboard with handwritten mathematical derivations. At the top, it states $\bar{x} \sim N_3(0, \Sigma/n)$ under H_0 . Below this, it states $(n-1)S \sim W_3(n-1, \Sigma)$. A bracket groups these two statements with the word "indep". The next line shows the formula for $T^2 = n \cdot (n/1) \bar{x}' ((n/1)S)^{-1} \bar{x}$, which simplifies to $= n \bar{x}' S^{-1} \bar{x}$. The following line shows $k \frac{T^2}{n-1} \cdot \frac{(n-1)-3+1}{3} \sim F_{3, n-3}$ under H_0 . The final line shows $i.e. \frac{T^2}{n-1} \cdot \frac{n-3}{3} \sim F_{3, n-3}$ under H_0 .

In what way what are the things that we will be requiring we will be requiring as the constituent elements as this \bar{x} to have a three dimensional normal distribution with a mean vector as null vector under the null hypothesis and Σ/n to be it is covariance matrix. So, this is under the null hypothesis; that the μ vector, the mean vector μ is equal to a null vector; otherwise, this would be just a general μ vector, and what more we have a random sample of size n . So, we will have n minus 1 times S ; S is the sample variance covariance matrix with a divisor n minus 1. So, this will have a wishart distribution; now, three dimension with a degrees of freedom as the number of samples that has been taken n minus 1, and the covariance matrix as Σ , which is of course, unknown the two are going to be independent from the multivariate normal sampling distribution theory.

So, this is what we have already so, using these two we can frame a hotelling's T square statistic, which is going to be given by n times degrees of freedom into this \bar{x}

transpose; the mean vector is a null vector, and this is an n minus 1 times S whole inverse of that that multiplied by this \bar{X} vector. So, what we have we have these two cancelling out, and this is our good old Hotelling's T square statistic; that is n times \bar{X} S inverse \bar{X} .

Now, further more we will have this T square; this T square divided by it is degrees of freedom; degrees of freedom is n minus 1, then this is n minus n ; n here is 3 this plus 1 that divided by 3. This would follow a central F distribution under H_0 1 degrees of freedom as 3, and what is this equal to this is n minus 1 degrees of freedom minus m , that is 3 plus 1. So, this one cancels out plus 1, and minus 1. So, we will have this as n minus 3 this under H_0 .

So, we have the null distribution of T square this divided by n minus 1 into this n minus 3 by 3; this follows central f distribution 3 n minus 3 under our H_0 . So, if we have this particular term here from the data **the data** is this. So, we will have the data as this say X_1 , X_2 , X_3 , say X the way that we write it **it** is no unique way of representing this indexes. So, these are basically the small x is **are** the data that we have in our hand.

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Given $(\underset{\sim}{x}_1, \underset{\sim}{x}_2, \dots, \underset{\sim}{x}_n)$,
 \uparrow record for patient #1 \uparrow record for patient #n.

Compute $\bar{\underset{\sim}{x}} = \frac{1}{n} \sum_{i=1}^n \underset{\sim}{x}_i$ ✓
 and $S = \frac{1}{n-1} \sum_{i=1}^n (\underset{\sim}{x}_i - \bar{\underset{\sim}{x}})(\underset{\sim}{x}_i - \bar{\underset{\sim}{x}})'$ ✓

Compute $T_{\text{obs}}^2 = n \bar{\underset{\sim}{x}}' S^{-1} \bar{\underset{\sim}{x}}$. ✓

Reject $H_0: \underset{\sim}{\mu} = \underset{\sim}{0}$ in favor of $H_1: \underset{\sim}{\mu} \neq \underset{\sim}{0}$ at level α
 if $S_{\text{obs}}^{-1} \cdot \left(\frac{T_{\text{obs}}^2}{n-1} \cdot \frac{n-3}{3} \right) > F_{3, n-3}(\alpha)$

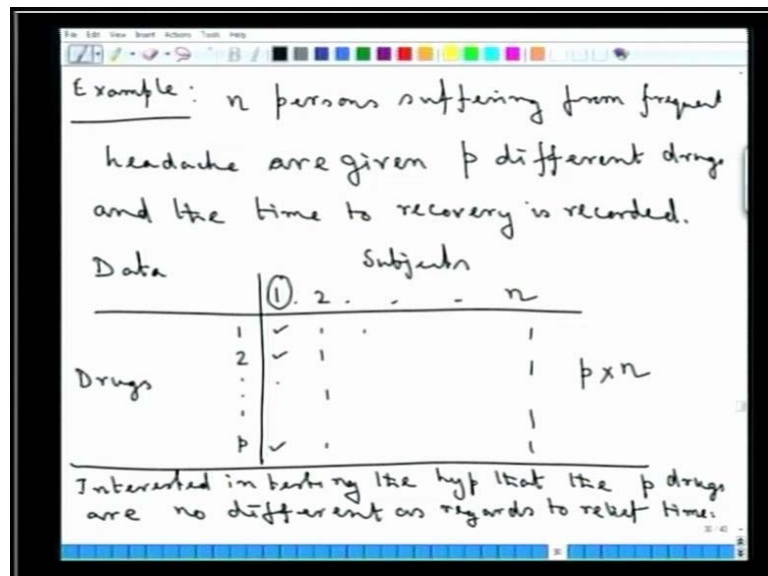
So, given the data **given the data** which is X_1 ? This is three dimensional vector. So, this is the recordings or the record for patient one; then we have this X_2 vector these are the actual recordings. So, this is X_n this is the three dimensional record for patient number n . So, these are the data. So, given this particular set of information; we compute \bar{X} ; the sample mean, and well this is going to be given by 1 upon n summation i

equal to 1 to n of these X_i vectors, and the S matrix with a divisor n minus 1. So, that that is given by $\frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})(X_i - \bar{X})^T$; it is transpose the random matrix, and this is actually the observed sample variance, covariance matrix.

So, given these two one can easily compute this T square observed **T square observed** would be $n \bar{X}^T S^{-1} \bar{X}$, and we will reject once this is computed we have the testing reject H_0 ; that is **that** our new vector is a null vector reject H_0 equal to a null vector against the alternate hypothesis H_A ; that this mean vector is not equal to a null vector at level alpha say, if we have observed value of this T square divided by what was it? It was T square by n minus 1 n minus 3 by 3.

Now, once we have computed this is T square observed. So, if this quantity; now, we will reject the null hypothesis if of course, T square is large, because that is what is going to give us the more deviation from the null hypothesis point, and hence we will reject the null hypothesis; if this observed value of this quantity here exceeds the tabulated value of this F distribution on three n minus 3 degrees of freedom at alpha point. So, this is the upper alpha percent cut off point of a central F distribution on three n minus three degrees of freedom. So, that is how we obtain from the given data this testing problem.

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Now, let us look at example number two: this also is a standard type of example that one comes across in real life examples. So, that this is this problem that n persons suffering from frequent headaches; headaches are given p different drugs; this setup is a **bit**

different p different drugs; and the time to recovery; recovery is recorded. So, the problem is the following: that, we have n persons suffering from headache for the given problem, it may be for some other disease also; the same approach can be applied there given p different drugs, and then the time to recovery corresponding to each of these persons for each of these p drugs are now recorded.

Now, the data structure is of the following form in this problem. So, these are what we have as the subjects, which are these patients 1 2 up to n , and then what we have here is the drugs. So, we have p drugs being administered. So, we have all these p drugs on this side. Now, corresponding to this person number 1; we will administer all these p drugs to the same person, and then the time to recovery from a particular headache by administering drug number 1 is put here, the time to recovery of the same patient; when drug two is administered at some other point of time is recorded, and like this, we have all the recordings taken for the first patient, and likewise for the second patient, and the third, and all the patients are recorded.

So, we have this data in the form of a p by n matrix; now what can be the point of interest in such a problem, the point of interest in such a problem for any practical purposes would be to know whether these p drugs that, when actually administered or rather p drugs under consideration whether they are same with respect to time to recovery or not. So, we would be interested in the following problem let me write it. So, we may be interested in testing the hypothesis that the p different drugs the p different drugs are no different as regards to relief time. So, that is the setup of the problem we have p drugs, and we are trying to see whether the drugs differ among themselves or there is no significant difference at all between the p drugs that were administered for this particular illness,

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$$A \text{ assume } X = \begin{pmatrix} X_1 \\ \vdots \\ X_p \end{pmatrix} \sim N_p(\mu, \Sigma)$$

$$H_0: \mu_1 = \mu_2 = \dots = \mu_p \text{ ag } H_A: \text{they are not equal}$$

$$\Leftrightarrow \left(H_0: A \mu = 0 \text{ ag } H_A: A \mu \neq 0 \right)$$

$$A = \begin{bmatrix} 1 & 0 & 0 & \dots & -1 \\ 0 & 1 & 0 & \dots & -1 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & 1 & -1 \end{bmatrix}$$

Now, how to frame this particular problem? We would require some assumptions in order to test this particular problem; we will assume that this X , which is the time to recovery for the p different drugs these are p random variables here. So, X_1 is the random variable which denotes the time to recovery for drug number one x_2 denotes the random variable; denoting the time to recovery for the second drug and so on, X_p denotes the time to recovery for the p th drug.

So, we will assume that this p dimensional random vector this has got a multivariate normal distribution $N_p(\mu, \Sigma)$, where each of these elements here μ_1, μ_2, μ_p ; they are the mean time to recovery for the p drugs. Now, what is the null hypothesis in terms of this multivariate normal distribution assumption the null hypothesis would be $\mu_1 = \mu_2 = \dots = \mu_p$; this is to be tested against the alternate hypothesis H_A , that they are not equal that is the alternate hypothesis is not H_0 .

Now, in terms of what we have framed here, I will be able to write this in terms of an alternate hypothesis that, I will say for the moment, it is $\mu = 0$ against the alternate hypothesis. Let me, write first as H_0' , and H_A' against the alternate hypothesis that $A\mu \neq 0$; what is A a $(p-1) \times p$ matrix of constants; which is going to be given by the following: that the first entry here is 1, 0; here minus 1 here. So, that when I multiply this A by μ ? What we will be at the first element is $\mu_1 - \mu_p$; that is equal to 0. So, that we will be able to say from this first line that $\mu_1 = \mu_p$, the second would be $\mu_2 = \mu_p$, and likewise $\mu_1 = \mu_2, \mu_1 = \mu_p, \mu_2 = \mu_p$

and so on. The last, that is p minus 1th row of this matrix of constant this will be minus 1, and the previous element would be 1.

So, this will lead us to, if we look at, what is a μ equal to null? This would give us μ_1 equal to μ_p , μ_2 equal to μ_p , μ_{p-1} equal to μ_p . So, all of them basically are equal. So, μ_1 equal to μ_2 equal to μ_p ; this hypothesis is translated in terms of this hypothesis. So, with this as, we will have this particular problem being carried forward by defining a new set of random variables; a random vector Y is defined as A times X ; now this is our $p-1$ by p matrix of constant, and hence this Y vector is, now A $p-1$ dimensional random vector.

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Define $Y = AX$ where A is $(p-1) \times p$ and X is $p \times 1$. $Y \sim N_{p-1}(A\mu, A\Sigma A')$

$H_0: A\mu = 0$ vs $H_A: A\mu \neq 0$

$\Leftrightarrow H_0: \underline{Y} = \underline{0}$ vs $H_A: \underline{Y} \neq \underline{0}$

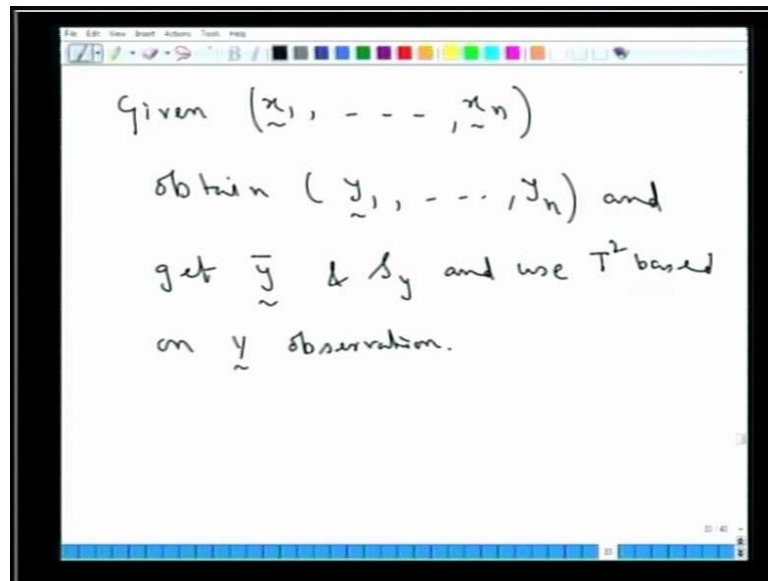
Use word Hotelling T^2 statistic for testing

Now, this is going to have a multivariate normal distribution n p minus 1, and with the mean as $A\mu$, and a covariance matrix, as $S\sigma A$ prime. Now, if that is there let us, denote this by equal to a vector γ ; now this H naught that $A\mu$ equal to null vector to be tested against the alternate hypothesis H_A ; that $A\mu$ is not equal to a null vector is thus equivalent to this hypothesis. In terms of the y random variables, Y random vector, this γ is equal to a null vector against the alternate hypothesis; that γ is not equal to a null vector.

So, we have cleverly translated the given problem in terms of this random p minus one dimensional random vector Y , which is now having this as it is multivariate normal distribution, and we are going to test that the mean of that particular multivariate normal distribution is a null vector, against this particular null that γ is not equal to a null

vector, and the testing for that would be carried forward using exactly the previous approach, which we had in the previous setup, that X follows a multivariate normal with a mean vector μ , and some variance, covariance matrix. **We** If we are interested in testing, the mean vector to be a null vector against that it is not then use we can use the usual Hotelling's T square statistic for testing.

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So, from the given problem what we had **was** this in terms of x , we will translate this particular problem in terms of y that is possible, because given this set x_1, x_2, x_n , **given this x_1, x_2, x_n** , that is what was the original random sample obtained this y_1, y_2, y_n , which is going to have a dimensionless; now y_1, y_2, y_n , and based on this y_1, y_2, y_n ; we can get this \bar{y} vector, and this S_Y matrix. The sample variance, covariance matrix that is based on y_1, y_2, y_n , and use T square based on y observations, and that completes the testing for this particular problem; in the next lecture, what we are going to see is to look at some important properties of Hotelling's T square statistic. Thank you.