

Applied Multivariate Analysis

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Lecture No. # 41

Canonical Correlation Analysis

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$$U_1 = e_1' \Sigma_{11}^{-1/2} X$$
$$V_1 = f_1' \Sigma_{22}^{-1/2} Y$$
$$\begin{matrix} X \\ Y \end{matrix} \Rightarrow \text{Cov} \begin{pmatrix} X \\ Y \end{pmatrix} = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix}$$
$$\left(\begin{matrix} \Sigma_{11}^{-1/2} & \Sigma_{12}^{-1} \Sigma_{22}^{-1/2} \\ \Sigma_{21}^{-1/2} & \Sigma_{22}^{-1/2} \end{matrix} \right) \rightarrow (\lambda_i, e_i)$$

$i = 1, \dots, p$
 $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_p$

Derivation of 2nd Canonical variables.

U_1 and any arbitrary linear combination $a_2' X = c_2' \Sigma_{11}^{-1/2} X$
where $\Sigma_{11}^{-1/2} a_2 = c_2$
are uncorrelated if

$$\text{Cov}(U_1, c_2' \Sigma_{11}^{-1/2} X) = \text{Cov}(e_1' \Sigma_{11}^{-1/2} X, c_2' \Sigma_{11}^{-1/2} X) = 0$$

i.e. $e_1' \Sigma_{11}^{-1/2} \Sigma_{11}^{-1/2} c_2 = 0$
i.e. $e_1' c_2 = 0$, i.e. $c_2 \perp e_1$.

In the last lecture, we had started our discussion on canonical correlation variables. We had given the basic definition, and also had looked at how to derive first pair of canonical variables. As we had seen that the first pair of canonical variables are given by the following, that this is given by U_1 equal to e_1' prime Σ_{11} to the power minus half times X . So, X is the original setup random variables, X vector is p dimensional, and the second component of the first canonical variable was given by f_1' prime Σ_{22} to the power minus half times this Y vector

Now, where in we had of course, define that X is that p by 1 random vector, and Y is the q by 1 random vector, this such that we will have the covariance matrix of X and Y augmented, that was given by Σ_{11} , Σ_{12} , Σ_{21} and Σ_{22} . So, this was the **covariance** covariance structure of this X, Y random vector. And starting from this, we were trying to derive the first pair canonical variables, which we had denoted by

U_1 and V_1 ; we had derived that of this particular form, wherein of course we have that we consider this matrix, which was Σ_{11} to the power minus half $\Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21} \Sigma_{11}$ to the power minus half.

So, considering this matrix, which is p by p matrix, and then its Eigen value, Eigen vector pairs were denoted as $\lambda_i e_i$, i equal to 1 to up to p . So, these e_i of course, are orthonormalized Eigen vectors, corresponding to the Eigen values, which are λ_i . And we use those orthonormalized Eigen values, Eigen vectors e_i , in framing the first canonical variable U_1 , which is U_1' . So, e_1 is the Eigen orthonormalized Eigen vector of this matrix, corresponding to the largest Eigen value; which was λ_1 . So, we had this particular setup; that λ_1 is greater than or equal to λ_2 is greater than or equal to λ_p .

We also saw that this f_1' or rather f_1 is the Eigen vector, corresponding to the largest Eigen value of the matrix which was Σ_{22} to the power minus half $\Sigma_{21} \Sigma_{11}^{-1} \Sigma_{12} \Sigma_{22}$ to the power minus half. So, and the Eigen values of both these matrix a transpose and a transpose a of course, are same the non-zero Eigen values are same. Only Eigen values with 0 multiplicities actually can differ, the multiplicity of 0 Eigen values in the 2 matrices can only differ. So, what we first going to take up today, is how we can derive the second third and in general k th canonical variable.

So, let us first look at that. So, we are trying to look at the derivation of second canonical variables. Now, in the definition of canonical variables 1 we recall that; we had said that, when we are moving on from the first do the second and in general to the k th cannot pair of canonical variables. The second pair of canonical variables will be such that, the U_2 which will be the first component of the second pair, that will be uncorrelated with the **first** corresponding first component of the first pair of canonical variables.

The second component of the second pair is V_2 , if we have denoted by V_2 . So, that V_2 is going to be uncorrelated with second component of the first pair; that is V_1 . So, we would require these two follow, actually that the third pair **will have** will be uncorrelated with previous 2 pairs; that is the first in the second pair. And in general for the k th pair, we will have the components in the k th pair to be uncorrelated with the previous k minus 1, principal the canonical variables.

So, we will require that, and we will see that U_1 , and any arbitrary linear combination of X is say given by $a_2' X$. Now you may recall that while deriving the first pair of canonical variables. What we had done was to replace this a_2 vector, by something which was a c vector. So, in terms of that c vector, we can write this as a c_2 $\Sigma^{-1/2}$ the power minus half times this X . Where, we had $\Sigma^{-1/2}$ to the power plus half times a_2 that is equal to c_2 . So, the c_2 vector was newly defining vector, similar to the c_1 vector; which we have defined, while deriving the first pair of canonical variables, in order to make the denominator to be equal to $c_1' c_1$ or $d_1' d_1$ as we will see.

So, with this definition, this arbitrary linear combination $a_2' X$, which is $c_2' \Sigma^{-1/2} X$ are uncorrelated or going to be uncorrelated. If the covariance between U_1 , and this $c_2' \Sigma^{-1/2} X$; which of courses, is equal to the covariance between now, U_1 is given by e_1' . So, this is **this** $e_1' \Sigma^{-1/2} X$ that, and c_2' **this is c_2'** $\Sigma^{-1/2} X$ is equal to 0.

So, if we have the covariance between U_1 , and this arbitrary linear combination to be equal to 0. We would require the covariance between these 2 terms to be equal to 0. That is; if we look at, what is the covariance between this random variable, and this random variable. It is going to be $e_1' \Sigma^{-1/2}$ times the covariance matrix of X which is $\Sigma^{-1/2}$ into $\Sigma^{-1/2}$ times this c_2 equal to 0. That is these terms here, $\Sigma^{-1/2} \Sigma^{-1/2}$ will make this as an identity matrix. So, we would require this $e_1' c_2$ this to be equal to 0; or in other words, we would require this c_2 to be an orthogonal vector, orthogonal to the e_1 vector which is the ortho normalized Eigen vector, corresponding to the largest Eigen value, λ_1 of this $\Sigma^{-1/2}$ the power minus half this matrix.

So, while deriving the second canonical variable, we have to make this c_2 . We have to choose this c_2 vectors, in such a way that this c_2 needs to be orthogonal to e_1 . The first ortho normalized Eigen vector corresponding to the largest Eigen value

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The image shows a handwritten derivation of the correlation coefficient between two linear combinations of variables, $a_2'x$ and $b_2'y$. The derivation is as follows:

$$\text{Correl}^n (a_2'x, b_2'y) = \frac{\text{Cov}(a_2'x, b_2'y)}{(\text{V}(a_2'x) \cdot \text{V}(b_2'y))^{1/2}}$$

$$= \frac{a_2' \Sigma_{12} b_2}{((a_2' \Sigma_{11} a_2) \cdot (b_2' \Sigma_{22} b_2))^{1/2}}$$

$$= \frac{(c_2' \Sigma_{11}^{-1/2} \Sigma_{12} \Sigma_{22}^{-1/2} d_2)}{(c_2' c_2 \cdot d_2' d_2)^{1/2}}$$

$$\underbrace{(c_2' \Sigma_{11}^{-1/2} \Sigma_{12} \Sigma_{22}^{-1/2} d_2)}_{\leftarrow} \leq \underbrace{(c_2' \Sigma_{11}^{-1/2} \Sigma_{12} \Sigma_{22}^{-1/2} \Sigma_{21} \Sigma_{11}^{-1/2} c_2)}_{\leftarrow} \cdot \underbrace{(d_2' d_2)^{1/2}}$$

On the left side of the slide, there are handwritten notes defining the vectors c_2 and d_2 :

$$\begin{cases} \frac{1}{\sqrt{2}} a_2 = c_2 \\ \Sigma_{11}^{-1/2} a_2 = d_2 \\ \frac{1}{\sqrt{2}} b_2 = d_2 \\ \Sigma_{22}^{-1/2} b_2 = d_2 \end{cases}$$

Now, let us look at what is the correlation coefficient between this. Let me take this as first to start with a 2 prime X that is the original linear combination forms that, and b 2 prime Y. So, we are trying to look at, what is that a 2 and b 2? Such that, we will have this correlation to be maximized subject of course to the condition, that these a 2 and b 2 should be such that this a 2 prime X will be uncorrelated with U 1, and b 2 prime y will be uncorrelated with V 1.

So, this correlation is nothing, but the covariance between a 2 prime X, and b 2 prime Y this divided by under root of variance of a 2 prime X, and variance of b 2 prime Y. So, this expression, we can write as simply a 2 prime sigma 1 2 times this b 2 prime, this divided by a 2 prime sigma 1 1 a 2. This is the first term, and this second term is similar to the first term, b 2 prime sigma 2 2 times and b 2 and whole raise to the power half.

So, similar to the derivation of the first pair of canonical variables, what we are going to do is redefined. So, we will take this sigma 1 1 to the power half a 2 vector, we will define that as a new vector c 2 as we have seen in here, this is the transformation. So, under this transformation and also with sigma 2 2 to the power half times b 2 that 2 be equal to say it b 2 vector. What we will be having in the denominator, is that this e 2 prime sigma 1 1 e 2 is just equal to c 2 prime c 2, that multiplied by this d 2 prime d 2 whole raise to the power half. And here, if we have this particular definition this would further imply that; our a 2 vector is equal to sigma 1 1 to the power minus half times c 2,

and this b_2 vector is equal to Σ_{22} to the power minus half of the redefined vector; which is d_2 . So, we give a we can unplug in this values here in the numerator of this expression, which will read us to this c_2 prime Σ_{11} to the power minus half that times $\Sigma_{12} V_2$ prime. I am sorry, this is going to be just b_2 , this is not b_2 prime; this is e_2 prime $\Sigma_{12} b_2$

So, this b_2 is going to be given by this Σ_{22} to the power minus half times this d_2 vector. So, the correlation between these two components is given by this, now similar to once again the derivation of the first pair of canonical variables, what we can do is to apply the Cauchy Schwarz inequality on the numerator of this expression.

And we can say that this c_2 prime Σ_{11} to the power minus half $\Sigma_{12} \Sigma_{22}$ to the power minus half times this d_2 vector, that is less than or equal to we will take this as 1 vector, say U prime as this vector, and V as this vector. So, it will be prime U_2 the power half. So, that this is going to be $c_1 c_2$ prime Σ_{11} to the power minus half $\Sigma_{12} \Sigma_{22}$ to the power minus half, and that also augmented with Σ_{22} to the power minus half, will give us Σ_{22} to the power minus 1, and the transpose of Σ_{12} which is Σ_{21} . Σ_{11} to the power minus half times c_2 this raise to the power half, and that multiplied by this d_2 prime d_2 , that also raise to the power half. Now, we will concentrate on this particular expression here, and try to see what can be given as an upper bound of this particular expression.

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Recall that for real sym $B_{n \times n}$ with eigenvalue-eigenvalue (λ_i, e_i) $i = 1, \dots, n$ ($\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n$)

Max $\frac{x' B x}{x' x} = \lambda_2$ with equality at $x = e_2$.

Max $\left(\frac{x' B x}{x' x} \right) = \lambda_{k+1}$ with equality at $x = e_{k+1}$

$\Rightarrow (c_2' \Sigma_{11}^{-1/2} \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21} \Sigma_{11}^{-1/2} c_2) \leq \lambda_2 (c_2' c_2)$

$\Rightarrow \text{Corr}^2 \left(a_2' x, b_2' y \right) \leq \frac{\lambda_2^{1/2} (c_2' c_2)^{1/2} (d_2' d_2)^{1/2}}{(c_2' e_2)^{1/2} (d_2' d_2)^{1/2}}$

So, in order to get that, we will recall once again result from matrix theory, recall that for real symmetric matrix b say p by p with Eigen value, Eigen vectors pairs **with Eigen value Eigen vector pairs** as $\lambda_i e_i$, for i equal to 1 to up to p this is. Such that, of course, λ_1 is the largest Eigen value, λ_1 is greater than or equal to λ_2 is greater than or equal to λ_p with such a structure, if we try to look at what is the maximum over x of the expression $x^T b x$ this divided by $X^T X$. Now this X here, if we try to look at all x , such that x is orthogonal to e_1 .

The first ortho normalized Eigen vector corresponding to the largest Eigen value, which is λ_1 ; then this maximum **maximum** over all x . Such that, they are all orthogonal to this e_1 is going to be achieved at the second largest Eigen value, which is λ_2 with equality at X equal to c_2 .

Now, we cannot use the first version of this particular result, while deriving the first pair of canonical variables. Recall that, if we do not have this particular condition that we are looking at all x , such that, it is orthogonal to e_1 . If we just look at maximum of this $x^T V x$ by $x^T x$ for all x , then this is going to be achieved at the largest Eigen value; which is λ_1 .

And the equality would be attained at x equal to e_1 . Now, if we restrict the set of other region of x do the situation that all x , which are orthogonal to e_1 , then what we are going to get is, this Maximum is going to be attained at the second largest Eigen values. Now in general, what also one can say is that maximum x , such that x is orthogonal to e_1, e_2 and e_k . So, e_1, e_2, e_k are the k ortho normalized Eigen vectors, corresponding to the k largest Eigen values of this b matrix. If we now look at all x such that they are orthogonal to the first k Eigen vectors of the quantity. Which is same as the previous quantity $x^T a x$ divided by $x^T x$.

Now, this Maximum under this condition is going to be attained at the point, which is λ_{k+1} . So, it is nice result with equality here, with x equal to e_{k+1} . So, this is the standard result any way in matrix series. So, we will use this particular result, in order to derive the second, third and forth, and in general k th pair of canonical variables. Now at what point we are going to use this particular result of Eigen values, we are going to use that result in this particular expression.

Now, let us write this expression. So, this will imply that over c^2 prime σ_{11} to the power minus half $\sigma_{12} \sigma_{22}^{-1} \sigma_{21}$ σ_{11} to the power minus half this c^2 , this quantity here will be less than or equal to what if we are looking at c^2 , we are looking at all c is such that, that is orthogonal to the first. **That is** it is a uncorrelated with the first canonical variable U_1 .

And we had seen in here, in the first discussion that in order to have this c^2 ; c^2 should be such that, it should be uncorrelated with U_1 . And the condition is that, we have to look at all such c^2 s which are orthogonal to e_1 . So, **we will** we can apply this particular result here, because we are looking at all c^2 s, such that c^2 is orthogonal to e_1 ; e_1 is the eigen vector corresponding to the matrix defined earlier. So, this is going to be less than or equal to this λ_2 times c^2 prime, **c^2 right**

In here, the equality will be attained, if we take c^2 to be equal to e_2 ; With equality here, with equality at c^2 equal to the e_2 vector which is the second, **a** which is ortho normalized eigen vector corresponding to the second largest Eigen value. Now, if we have this particular expression, then we can go back to this expression out here. And say that, this is going to be less than or equal to that particular term. So, this would imply, we can actually come to this particular point here. And say, what is the upper bound of this expression is straight away; this would imply that, the correlation coefficient between e_2 prime x and b_2 prime y . This is going to be less than or equal to λ_2 to the power half c^2 prime c^2 ; this to the power half d^2 prime d^2 to the power half; this half coming from the Cauchy Schwarz inequality of the numerator and in the denominator, we **as such** have this as c^2 prime c^2 to the power half and d^2 prime d^2 ; this to the power half.

So, as we see that the λ_2 terms cancel out, and we see that the correlation coefficient between this is bounded by this λ_2 to the power half.

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$\Rightarrow \text{Corr}^n(\underline{a}_2' \underline{X}, \underline{b}_2' \underline{Y}) \leq \rho_2^*$
 with equality at $\underline{c}_2 = \underline{e}_2$, $\underline{a}_2 = \Sigma_{11}^{-1/2} \underline{e}_2$.
 and $\underline{b}_2 = \Sigma_{22}^{-1/2} \underline{f}_2$.
 \Rightarrow 2nd canonical variables
 $U_2 = \underline{e}_2' \Sigma_{11}^{-1/2} \underline{X}$
 $\& V_2 = \underline{f}_2' \Sigma_{22}^{-1/2} \underline{Y}$.
 $\&$ The 2nd canonical corrⁿ coeff ρ_2^*
 i.e. $\text{Max Corr}^n(\underline{a}_2' \underline{X}, \underline{b}_2' \underline{Y}) = \rho_2^*$
 (\exists uncorrel) $= \text{Corr}^n(U_2, V_2)$.

Now, we had denoted this lambda i as rho i star square. So, we will have the correlation; the Maximum correlation between this a 2 prime X and b 2 prime Y, such that the uncorrelated with the first canonical variable wholes. This is going to be less than or equal to this lambda 2 star, where lambda 2 star square is the Eigen value of that a; a transpose matrix.

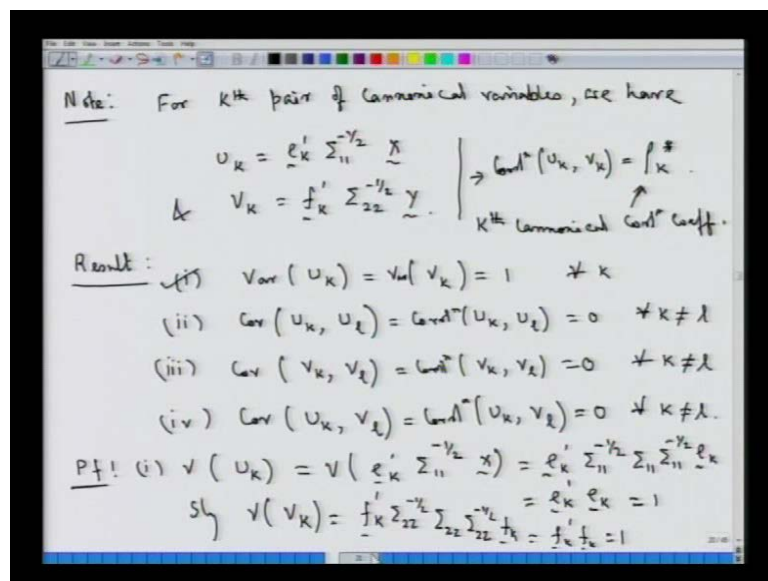
And, with equality at what points a what are the points, where in we have applied inequality? So, we in order to have this equality to whole, we would require this c 2 to be equal to e 2. And in the previous expression, wherein we have got this as the inequality, we would require this d 2 vector to be proportional to sigma 2 to the power minus half sigma 2 1; sigma 1 1 to the power minus half times c 2. So, in the all the previous steps with equality at c 2 vector to be equal to e 2 vector

Now, c 2 vector is in terms of the a 2 vector a; the relationship between c 2 and a 2 is this. Thus we would require this a 2 to be sigma 1 1 to the power minus half times e 2; that is we would require this a 2 to be sigma 1 1 to the power minus of half times e 2. So, this is as for as the choice of e 2 is concerned, and we would also required the choice of b 2. Because, that is going to a play a role in this Cauchy Schwarz inequality; here the equality is going to whole if we have as a said d 2 proportional to this particular vector which would lead us to the following. That this b 2 vector, would just be equal to sigma 2 to the power minus half times f 2 vector. So, this will imply the second canonical

variable pairs are going to be given by this e_2 , which is going to be equal to e_2 prime σ_{11} to the power minus half times X vector, and V 2 vector is going to be equal to f_2 prime σ_{22} to the power minus half times this Y vector. If we chose e_1 U 1 and U 2 to be of this particular form then not only will this U 1 U 2 and V 2, will be uncorrelated with U corresponding U 1 and V 1, We will have the maximum correlation of course, being attained

And the second canonical correlation coefficient **second canonical correlation coefficient** is going to be given by ρ_2^* , that is the maximum correlation between this e_2 prime X, and b_2 prime Y this maximum of courses. Such that, this **uncorrelatedness holds** uncorrelatedness holds this is going to be attained at this ρ_2^* . One can actually find out, what is a correlation between these 2 variables; this is going to be just the correlation coefficient between the e_2 and V 2; that we have derived.

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So, we are been able to thus derive the second pair of canonical variables, we will a thus generalized this approach for k^{th} pair of canonical variables **K th pair of canonical variables**, we have this U k to be given by e_k prime σ_{11} to the power minus half times X, and our w_k is going to be 1; that is going to be based on a f_k prime σ_{22} to the power minus half times this vector y, with **the correlation** the k^{th} canonical correlation will be the correlation between U k and V k. This is going to be equal to ρ_k^* .

So, this is what is the canonical k th canonical correlation co-efficiency; this will be the k th canonical correlation coefficient, and the construction will be similar to the construction of the second pair of canonical variables; that is this U_k will be uncorrelated with U_1, U_2, \dots, U_{k-1} , and this V_k is going to be uncorrelated with V_1, V_2, \dots, V_{k-1} .

So, entire that uncorrelated a structure will still hold, and while deriving this k th pair of canonical variables, we will precisely be using this particular result. That we would at the case k th stage would require the c_k vector; similar to the a_2 vector. Here you would require thus c_k vector corresponding to the k th canonical variable pair to be orthogonal to e_1, e_2, \dots, e_k . Because we would require that a particularly combination are the k th canonical variable to be uncorrelated with all the previous canonical variables. And hence that particular type of orthogonal structure would be required while deriving the k th pair of canonical variables.

So, this is what concludes actually the derivation of all the canonical variable pairs. Now, how many such canonical variables are there? If we look at U_1, U_2, \dots, U_k , that particular series of canonical variables, then we are going to have p of them. And if we look at this $V_k, V_1, V_2, \dots, V_k$, so that is going to go up to V_q , because we have $f(q)$ of the Eigen vectors present in that $A^T A$ matrix which is σ_1^2 to the power minus half σ_1^2 σ_1^2 to the power minus 1; σ_1^2 to the power minus 1; σ_1^2 σ_2^2 to the power minus half. So, these f_1, f_2, \dots, f_k are associated Eigen Ortho normalized, Eigen vectors of that matrix; whereas, as these e_i are the ortho normalized Eigen vectors of the other matrix, which is p by p . And f_k s are the once which is corresponding to the q by q , Eigen q by q matrix, right.

Now, let us look at the following result which is going to summarize the variance, covariance structure among these canonical variables. The results are I will just list four of those results which are enough actually to capture the entire structure of the variance covariance fracture of this canonical variables. So, we will have as we had seen, it is prevail actually; that variance of U_k is equal to variance of V_k . I will just drop this may be, this right variance of k equal to variance of any other V_k ; this is going to be equal to 1; this they are 1 will have the covariance between U_k and U_l . This since we have this is to for all k since we have variances to be 1, the covariance between U_k and U_l is also equal to the correlation between U_k and U_l .

And they are equal to 0 for every k which is going to be not equal to 1 number 3 is that the covariance between U_k and v_l , that is equal to the correlation coefficient between V_k and V_l ; that also be into be equal to 0 for every k which is not equal to l, and also the 4th one which is covariance between U_k and v_l ; that is going to be equal to the correlation coefficient between U_k and v_l . This is also equal to 0 for every k which is not equal to l, **right**.

So, if we are to prove this results, these are simple element re Results actually. Now, in order to prove that the first term that variance of U_k , now U_k , as we have derive it is given by variance of this e_k prime sigma 1 1 to the power minus half times x. So, that is going to be equal to e_k prime sigma 1 1 to the power minus half covariance matrix of X which is sigma 1 1 times; thus this sigma 1 1 to the power minus half times e_k . So, this will give us an identity matrix. So, this is e_k prime, e_k which is equal to 1. Similarly, exactly in the same way, we can prove that variance of this V_k for every k; that is also going to be given by... Now, what is going to happen? When we are looking at variance of V_k , it is going to variance of this particular term; we will have this as f; we are going to have this as f_k prime sigma 2 to the power of minus half times the covariance matrix of y which is sigma 2 to times sigma 2 2 to the power minus half times f_k . And that is once again equal to f_k prime time's f_k that is equal to 1. So we will have variance of U_k and V_k for every k to be equal to 1.

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(ii)
$$\text{Cov}(U_k, U_l) = \text{Cov}\left(\underline{e}_k' \Sigma_{11}^{-1/2} \underline{x}, \underline{e}_l' \Sigma_{11}^{-1/2} \underline{x}\right)$$

$$= \underline{e}_k' \Sigma_{11}^{-1/2} \Sigma_{11} \Sigma_{11}^{-1/2} \underline{e}_l$$

$$= \underline{e}_k' \underline{e}_l = 0 \quad \forall k \neq l.$$

(iii) Similarly
$$\text{Cov}(V_k, V_l) = \underline{f}_k' \underline{f}_l = 0 \quad \forall k \neq l.$$

(iv)
$$\text{Cov}(U_k, V_l) = \text{Cov}\left(\underline{e}_k' \Sigma_{11}^{-1/2} \underline{x}, \underline{f}_l' \Sigma_{22}^{-1/2} \underline{y}\right)$$

$$= \underline{e}_k' \Sigma_{11}^{-1/2} \Sigma_{12} \Sigma_{22}^{-1/2} \underline{f}_l \quad (*)$$

Recall that \underline{f}_k is prop to $\Sigma_{22}^{-1/2} \Sigma_{21} \Sigma_{11}^{-1/2} \underline{e}_k$.

$$\Rightarrow (*) = c \underline{f}_k' \underline{f}_l = 0 \quad \forall k \neq l. \because \underline{f}_k \perp \underline{f}_l.$$

Let us look at the covariance between U_k and V_k , well in the way that we have constructed it, they are having the correlation equal to correlation or the covariance is to be 0.

Now, we can specifically see how that term is equal to 0. This is covariance between e_k prime $\Sigma^{-1/2}$ to the power minus half times X . And this U_l is e_l prime $\Sigma^{-1/2}$ to the power minus half times X . So, that this term is equal to e_k prime, and once again this same matrix is going to come here which is going to lead us to an identity matrix. So, this is $\Sigma^{-1/2}$; this term here which is multiplied by this e_l vector. So, this will be an identity matrix, and what we are left with is simply e_k prime e_l . Now, since we have e_k orthogonal to e_l will have this to be equal to 0 for every k , which is not equal to l ; thus the covariance between U_k and V_l will be equal to 0.

Similarly, the covariance which is equal to the correlation also; this is going to be given by f_k prime f_l . And that by orthogonality half f_k and f_l will be equal to 0 for every k not equal to l . So, we had proved the second part, the first part and the third part. In the fourth part, **what we are** this is the third part; in the fourth part, what we are trying to show is that covariance between U_k and v_l . **What is this equal to** this is equal to covariance between e_k prime $\Sigma^{-1/2}$ to the power minus half times; this X and V_l is going to be given by f_l transpose $\Sigma^{-1/2}$ to the power minus half times Y . So, the covariance between these 2 would be given by this p_k prime $\Sigma^{-1/2}$ to the power minus half time's covariance matrix of between X and Y

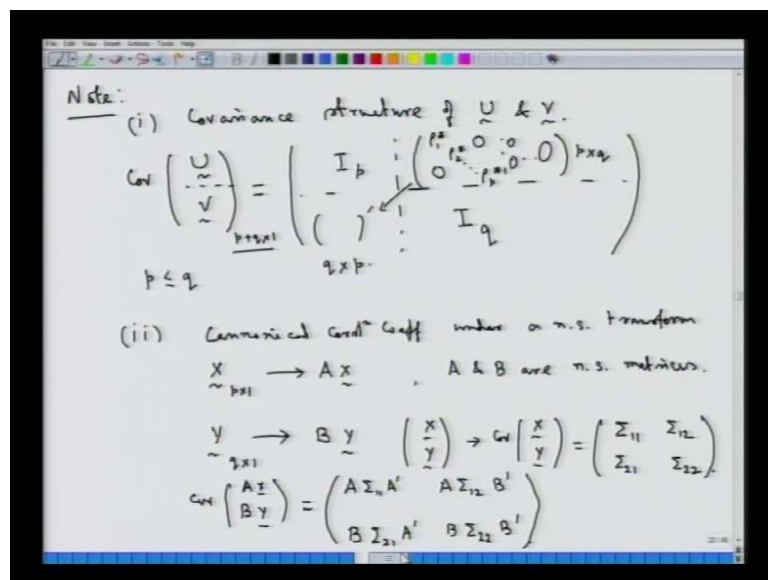
So, that is going to be equal to $\Sigma^{-1/2}$, and this is followed by the transpose of the coefficient vector. So, that is $\Sigma^{-1/2}$ to the power of minus half times f_l , **right**. Now, we had a result which are stated that, f_l is proportional to **...** Recall let me put this equation as s^* ; recall that f_k or f in general f_l ; so, this f_k is proportional to this $\Sigma^{-1/2}$ to the power minus half $\Sigma^{-1/2}$ times $\Sigma^{-1/2}$ to the power minus half times e_k . **right** This as what we had seen; while deriving the first a pair of canonical variable. So, this f_k is proportional to this term.

So, what we are going to have this 1 ; this basically is going to be a constant times f_k vector, because if f_k is proportional to $\Sigma^{-1/2}$ to minus of $\Sigma^{-1/2}$ to the power minus half times e_k , we will have the transpose of this to be equal to c times f_k prime. So, this will imply that this star expression is going to be equal to a constant C times f_k

prime f_1 . Now, this will imply that this product is equal to 0 for every k which is not equal to 1 **this is**. So, because this is once again, this f_k is orthogonal to f_1 .

Now, since we have this, we will have the covariance between U_k and V_1 which is also equal to the correlation between U_k and v_1 , because these are unit variances U_k and v_1 . And thus, we will have this covariance going to be equal to 0 for every k which is not equal to 1. For k equal to 1, what is going to happen is that this will be equal to 1. And then this will be equal to the constant of proportionality which links this f_k and e_k .

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So, we have proved this result also. So, to conclude we will look at this structure here the first noticed that we will look at the covariance structure covariance structure of U and g vector. So, we will first look at this covariance between this v vector, and the v vector. So, this is going to be given by the blocks which I write in here. So, the first block here is the covariance matrix of U vector what is that by the previous Result? This is just an I_p matrix now the covariance matrix of v vector is nothing, but this is an I_q matrix here and the half diagonal block here. This is what? This is the covariance between U and v right the covariance between U and v .

So, covariance between U_1 and V_1 . What is that? That is the correlation between U_1 and V_1 . What is that in terms of first canonical correlation. So, that is ρ_{11} , ρ_{22} , and this is ρ_{p+1} after the point where we can remember what we had taken was p less than or equal to q where p is the order of X or the order of U naturally and q is the order of Y .

which corresponds to the order also of this v . So, we will have this p of them which are the p canonical correlation co-efficiency. And what about the half diagonal entries these are all 0 (s), and there are of course, more 0 here after this p by p block here, because we can have the correlation between U_1 and v_{p+1} up to U_1 and v_q .

So, we will have all this to be equal to 0 augmented, and here we will just the transpose of this particular matrix. So, this is actually this is going to be the p by q matrix here this is going to be the q by p matrix here and this vector is p by q dimensional random vector. So, its covariance matrix variance covariance matrix structure is going to be given by this p plus q by p plus q dimensional matrix as in here or in the second node. What we are going to see is that, this is canonical correlation coefficients canonical correlation coefficients under a nonsingular transformation.

So, what we are trying convey is the following that we have X as the original setup of p dimensional random vector. And y which is q dimensional random vector v make a transformation from X to Ax and from y to By wherein v are talking about a and b are non-singular matrices now the point of interest Note is to look at what is the change in the canonical correlation coefficient, if any in the transformed setup random vectors. So, instead of considering X and y as original setup random variable vectors, if we look at Ax and By , then what is going to be the corresponding change, if any in the canonical correlation coefficient. So, these are the 2 not singular matrices

Now, if we have this X y , then this has got the covariance structure X . And y as we had define earlier this is σ_{11} , σ_{12} , σ_{21} and σ_{22} . Now, let us see what is the covariance structure of this; Ax and By it is easy to see that the covariance structure is going to be $A \sigma_{11} A^T$; this is $B \sigma_{22} B^T$ and this is $A \sigma_{12} B^T$. And this is going to be just the transpose of this of this is $B \sigma_{21} A^T$. So, this variance covariance matrix which the this original variance covariance matrix between X and y , and this is the covariance matrix on the changed random variables

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$\rho_1^*, \rho_2^*, \dots, \rho_p^*$ - Canonical Correlation Coeff for $\begin{pmatrix} X \\ Y \end{pmatrix}$.
 $\rho_1^{*2}, \rho_2^{*2}, \dots, \rho_p^{*2}$ are the eigen values of
 $\Sigma_{11}^{-1/2} \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21} \Sigma_{11}^{-1/2}$.
 i.e. $\rho_1^{*2}, \dots, \rho_p^{*2}$ are the roots of
 $\left| \Sigma_{11}^{-1/2} \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21} \Sigma_{11}^{-1/2} - \lambda I \right| = 0$
 i.e. $\left| \Sigma_{11}^{1/2} \Sigma_{11}^{-1/2} \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21} \Sigma_{11}^{-1/2} \Sigma_{11}^{1/2} - \lambda I \right| = 0$
 i.e. $\left| \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21} \Sigma_{11}^{-1} - \lambda I \right| = 0$

Now, we have this rho 1 star rho 2 star rho p star these are the canonical correlation coefficients canonical correlation coefficients for this X y setup; **right** That is what we have Derived. Now, we are going to see, what are the canonical correlation coefficients? If we are going to look at A x here and B y now this rho 1 star square rho 2 star square rho p star square are the Eigen values of the matrix that we had defined earlier which was sigma 1 1 to the power minus half sigma 1 2 sigma 2 2 the power minus half sigma 2 1 sigma 1 1 to the power minus half that is this rho star square rho 2 star square rho p this rho p star square rho p star square are the roots of this equation which is sigma 1 1 determinant of sigma 1 1 to the power minus half sigma 1 2 sigma 2 2 inverse sigma 2 1 sigma 1 1 to the power minus half minus lambda i this determinant of this matrix to be equal to 0 just the Eigen value equation

Now, here what we will do is to pre and post multiply with suitable matrices, such that let me right those matrices. This is sigma 1 1 to the power half; say here, pre multiplication sigma 1 1 to the power minus half sigma 1 2 sigma 2 2 inverse sigma 2 1 sigma 1 1 to the power minus half, and this gets post multiplied with sigma 1 1 to the power minus half

So, if we do that, we are pre multiplied by determinant of sigma 1 1 to the power half and post multiplying; this equation with sigma 1 1 determinant of sigma 1 1 to the power minus half. And hence, there is no change in this term here; this still is lambda i, because

the multiplication here is Σ_{11}^{-1} to the power half into Σ_{11} to the power minus half which is an identity matrix now if we have done that then this ρ_1 star squawroot to ρ_1 star square other roots also of the following equation which is this is an identity matrix $\Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21}$ and this is Σ_{11}^{-1} to the power minus 1 minus λ_i equal to 0 this equation **right**.

Now, what we will do is that we will look at this particular matrix here and see under the nonsingular transformation with A and V nonsingular matrices what is happening to this particular matrix.

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The image shows a whiteboard with handwritten mathematical derivations. The top part shows the transformation of a block matrix $\begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}$ under a nonsingular transformation A, B . The result is $(A \Sigma_{12} B') (B \Sigma_{22} B')^{-1} (B \Sigma_{21} A')$, which simplifies to $(A \Sigma_{11} A')^{-1} = A \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21} \Sigma_{11}^{-1} A^{-1}$. Below this, it states that the non-zero eigenvalues of $A \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21} \Sigma_{11}^{-1} A^{-1}$ are the same as the non-zero eigenvalues of $\Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21} \Sigma_{11}^{-1}$. The final conclusion is that the canonical coefficients under the n.s. transformation are unchanged.

So, let us write this matrix here this is $\Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21}$ times Σ_{11}^{-1} now this under the nonsingular transformation set A and B where is this getting transformed to now Σ_{12} if we look at this variance covariance structure this is the variance covariance matrix structure

So, what we can say is that Σ_{11} is transformed to this Σ_{11} is getting to a Σ_{11} to be prime and so on. So, what we can right in place of Σ_{12} is that under A, B transformation this is going to $A \Sigma_{12} B'$ transpose. So, this is corresponding to Σ_{12} corresponding to Σ_{22} what we have is $B \Sigma_{22} B'$ times B transpose whole inverse then Σ_{21} is getting transformed to the transpose of this which is $B \Sigma_{21} A'$ times A transpose and Σ_{11} in verse is what we have as a Σ_{11} a transpose times whole inverse we can look at this inverses because all the matrices this B

$\Sigma^{-1} B^T A \Sigma^{-1}$ all of them are nonsingular matrices. So, we can open up to see that this is just equal to $A \Sigma^{-1} \Sigma^{-1} \Sigma^{-1}$ times Σ^{-1} times Σ^{-1} to the power minus 1 times A^T , right.

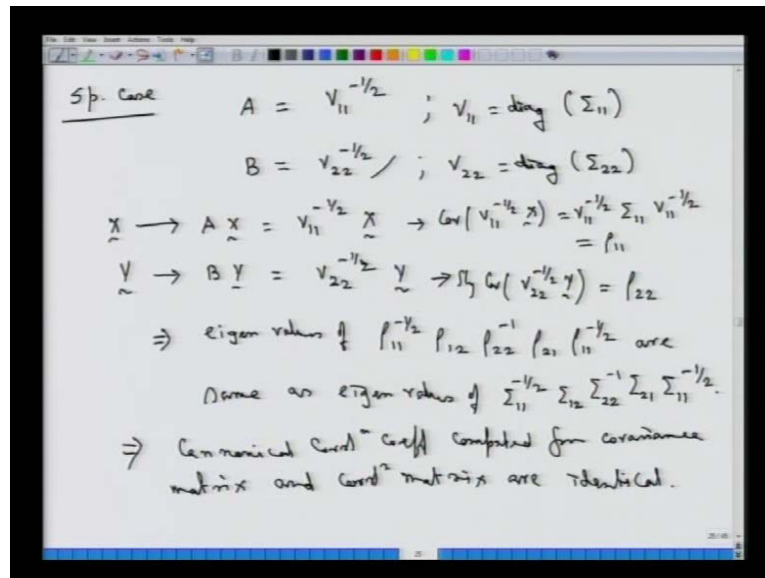
So, this matrix here which plays a crucial role in determining what are the canonical correlation coefficients because this matrix is involved in solving this equation here, and the roots are the canonical correlation coefficients what we are going to have is that matrix being transformed this matrix is being transformed here to this matrix.

Now, if we look at the roots of this particular matrix we can also say that further roots of $A \Sigma^{-1} \Sigma^{-1} \Sigma^{-1} \Sigma^{-1} A^T$ the I will should write the Non-zero Eigen values of further the non-zero Eigen values of this are same as the Non-zero as the Non-zero Eigen values of... If we consider this to be C matrix then what we are going to have is that I am sorry, this is going to be a inverse here, because we are looking at the last term which is a $\Sigma^{-1} A^T$ whole inverse is A^T here. So, this matrix is the transpose matrix here.

So, the non-zero Eigen values of this matrix times this matrix is going to be same as the Non-zero Eigen values of this matrix multiplied by this matrix. So, Non-zero Eigen values of this are going to be same as the Non-zero Eigen values of $\Sigma^{-1} \Sigma^{-1} \Sigma^{-1} \Sigma^{-1}$ inverse $\Sigma^{-1} \Sigma^{-1}$ inverse now what is this is just equal to $\Sigma^{-1} \Sigma^{-1}$ inverse Σ^{-1} this now if we look at the previous line here these are the Eigen values are $\rho_1^2 \rho_2^2 \dots \rho_p^2$ and hence if the Non-zero Eigen values in the transformed situation are same as that of this particular matrix what does that imply this implies that the canonical correlation coefficients are unchanged under this non-zero singular transformation this implies that the canonical correlation coefficients under the nonsingular transformation under the nonsingular transformation transformation $A B$ we are unchanged

So, whether we look at the canonical correlation coefficients from the original setup variables X and y or we look at in the transform setup with $A x$ and $B y$ the canonical correlation coefficients in the 2 steps are going to be precisely the same right.

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Now, as a special case of this result we will take A and B to be the following, if we consider a as the following matrix which is $v_{11}^{-1/2}$ wherein v_{11} is equal to the diagonal matrix of Σ_{11} , and if we chose this v matrix as $v_{22}^{-1/2}$ to be equal to the diagonal matrix corresponding to Σ_{22} . Then if we look at this the note is the covariance matrix of this Ax matrix this is A as vector other $v_{11}^{-1/2}$ times X , similarly this is X is getting transformed to this Ax and y is getting transformed to By which is equal to $v_{22}^{-1/2}$ times y now what is the covariance matrix of this it would be $B \rho_{11} B^{-1} \rho_{12} \rho_{22}^{-1} \rho_{21} \rho_{11}^{-1/2}$ what will that ρ that will we just the correlation matrix

So, this is the covariance matrix of $v_{11}^{-1/2} X$ this is going to be $v_{11}^{-1/2} \rho_{11} v_{11}^{-1/2}$ which is nothing, but the correlation matrix if we look at the X original X vector that is a correlation matrix. And similarly the covariance matrix between a covariance matrix of $v_{22}^{-1/2} y$ is going to be equal to $v_{22}^{-1/2} \rho_{22} v_{22}^{-1/2}$. So, and we will have that as ρ_{22} matrix which Σ_{22} the correlation matrix of the y .

So, this will imply that the canonical correlation coefficients let me also write the $\rho_{11}^{-1/2} \rho_{12} \rho_{22}^{-1} \rho_{21} \rho_{11}^{-1/2}$ most n Eigen values of $\rho_{11}^{-1/2} \rho_{12} \rho_{22}^{-1} \rho_{21} \rho_{11}^{-1/2}$ the power

minus half rho 2 1 times rho 1 1 to the power minus half are same as Eigen values of this sigma 1 1 to the power minus half, because this is what is that A x matrix and B y matrixes Eigen values and this is sigma 1 1 to the power minus half sigma 1 2 sigma 2 2 to the power minus 1 sigma 2 2 1 sigma 1 1 to the power minus half.

So, this will imply that the canonical correlation coefficients canonical correlation coefficients computed from covariance matrix and correlation matrix are identical, because under the nonsingular transformation there is no change as such in the canonical correlation coefficients. If we take this particular nonsingular transformation as v 1 1 to the power minus half as a and v 2 2 to the power minus half as B, then the canonical correlation coefficients are also not going to change. And hence whether we look at this sigma matrix, and compute the canonical correlation coefficients form the sigma matrix or will look at the rho matrix is a correlation matrix of X and y the canonical correlation coefficients are going to be the same, **right**.

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Correl. coeffs bet. Canonical variable & the original var

$$U_k = e_k' \Sigma_{11}^{-1/2} X \quad ; \quad V_k = f_k' \Sigma_{22}^{-1/2} Y$$

$$k = 1 \dots p \quad \quad \quad k = 1 \dots q$$

$$U_{p \times 1} = \begin{pmatrix} U_1 \\ U_2 \\ \vdots \\ U_p \end{pmatrix} = \begin{pmatrix} e_1' \\ e_2' \\ \vdots \\ e_p' \end{pmatrix} \Sigma_{11}^{-1/2} X = A X$$

$$A = \begin{pmatrix} e_1' \\ \vdots \\ e_p' \end{pmatrix} \Sigma_{11}^{-1/2}$$

$$\text{Similarly } V_{q \times 1} = \begin{pmatrix} V_1 \\ \vdots \\ V_q \end{pmatrix} = \begin{pmatrix} f_1' \\ \vdots \\ f_q' \end{pmatrix} \Sigma_{22}^{-1/2} Y = B Y$$

$$B = \begin{pmatrix} f_1' \\ \vdots \\ f_q' \end{pmatrix} \Sigma_{22}^{-1/2}$$

Now, we look at the next important result which is going to look at the following thing that what is a correlation between the canonical variables and the original setup variables. So, we on now looking at the correlation a coefficient between correlation coefficient between canonical variables and the original variables original variables. So, what we are looking at this these are the canonical variables that we have Derived these are e k prime sigma 1 1 to the power minus half times X we have k equal to 1 to up to p

we still work with that particular order and we have V_k this is given by $V_k = \frac{1}{\sigma_k} \sum_{i=1}^p U_i X_i$, and this k is from 1 to q . So, if we look at the U vector the vector containing all the first components of the canonical variable pairs.

So, this is U_1, U_2, \dots, U_p . So, this is going to be given by this simple matrix which is e_1, e_2, \dots, e_p and this is e_p that times σ_1 to the power minus half times X , right.

So, if we have this B just write that as a matrix this a matrix is different from the previous a matrix of course, well right this as $A X$ where this A is equal to this matrix of Eigen vectors A_1, A_2, \dots, A_p that multiplied by σ_1 to the power minus half. So, if we now one to look at now this is as for as U is concerned similarly we can write this v vector this is p by 1 vector this is going to be q by 1 vector this is v_1, v_2, \dots, v_q , and this will be given by f_1, f_2, \dots, f_q that times σ_2 to the power minus half times this y vector let us denote that by a matrix B times this y vector wherein B similar to this A is given by f_1, f_2, \dots, f_q times σ_2 to the power minus half.

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The image shows a whiteboard with handwritten mathematical derivations. The first derivation shows the covariance of the U vector and the X vector. It starts with $\Rightarrow \text{Cov}(U, X) = \text{Cov}(A X, X) = A \Sigma_{11}$. Then it shows $= \begin{pmatrix} e_1' \\ \vdots \\ e_p' \end{pmatrix} \Sigma_{11}^{1/2}$. The second derivation shows the covariance of the V vector and the Y vector. It starts with $\text{Cov}(V, Y) = \text{Cov}(B Y, Y) = B \Sigma_{22}$. Then it shows $= \begin{pmatrix} f_1' \\ \vdots \\ f_q' \end{pmatrix} \Sigma_{22}^{1/2}$.

So, if we have U vector equal to this $A X$ and V equal to $B Y$ it is very simple actually to see that how we are going to have compute this covariance between this U vector and the X vector now U vector in terms of the X vector is equal to $A X$ times this X vector. So,

this is simply a times the covariance matrix of X which is σ_{11} and what was a equal to a was equal to our this $e_1^T e_2^T \dots e_p^T$ that times σ_{11} to the power minus half. So, that combine with this gives us σ_{11} to the power half. So, this just is the correlation covariance matrix between U and x

Now, we can use similarly the covariance matrix of v vector and the y vector what is that going to turn out that is going to be given by covariance between $B y$ vector and the y vector which is going to be given by b times σ_{22} vector. and that is going to be given by $f_1^T f_2^T \dots f_q^T$ times σ_{22} to the power half. So, we will stop this Lecture at this particular point then continue from here.