

Elementary Numerical Analysis
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Lecture No. # 19
Cholesky Decomposition

We are considering solution of linear system of equation. So, we have got n equations in n unknowns. We describe the method, which is known as gauss elimination method. So, the system of linear equation, we write as $Ax = b$ and then using elementary row transformations, we reduce the system $Ax = b$ to an upper triangular system $Ux = y$. So, the coefficient matrix U is upper triangular it will mean that the last equation has got only one unknown x_n last but **what but** one equation has got only two unknowns x_{n-1} and x_n and So, on.

So, the solution of upper triangular system can be obtained by back substitution. The gauss elimination method which we described, we needed an additional assumption to the assumption that A is invertible; that look at the matrix A it is n by n matrix. Consider, sub matrix formed by first k rows and first k columns of matrix A , we denote that matrix by A_k it is k by k matrix, it is known as principle leading sub matrix. And then, we assume that determinant of A_k is not equal to 0 for k is equal to 1 to up to n . Under this assumption, we showed that gauss elimination method is equivalent to writing coefficient matrix A as product of two matrices L and U , L is unit lower triangular matrix; that means, on the diagonal you have got the entries to be equal to 1 and it is a lower triangular matrix.

U is upper triangular matrix, such decomposition we proved that it is unique. And then the system $Ax = b$ it is decomposed into two systems. So, you have got $Ax = b$ then that is equal to $L^{-1}Ux = b$. So, we look at $Ux = y$ and $L^{-1}y = b$. So, the system $L^{-1}y = b$ b is given to us. So, we calculate y by forward substitution. Now, y which we have obtain that becomes A right hand side and then we have got $Ux = y$. So, you apply back substitution. So, thus $Ax = b$

to b can be obtained as solution of two systems, one lower triangular another upper triangular.

Next, yesterday, from the L U D composition we deduced, what is known as L D V decomposition? In the L U D composition L was unit lower triangular and u was upper triangular. So, the upper triangular the diagonal entries of U need not be equal to 1. Now, this U we decompose or we write U is equal to D into V ; where D is going to be a diagonal matrix and V is going to be unit upper triangular.

Then, using the uniqueness of L U D composition, one can show that - this L D V decomposition is also unique. And now, today, we are going to look at the case, when A is positive definite and for the positive definite matrix, we are going to prove Cholesky decomposition; where we are writing A as g into g transpose, where g is a lower triangular matrix. So, our starting point is going to be L D V decomposition, which is available for matrices satisfying the condition that determinant of A_k is not equal to 0, for k is equal to 1 to up to n , the notation is A is equal to $L U$ by n matrix. Assumption, determinant A_k not equal to 0, for k is equal to 1 to up to n , A is equal to $L U$ L unit lower triangular u upper triangular.

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LDV decomposition

$A = [a_{ij}]_n: n \times n$ matrix, $\det(A_k) \neq 0, k = 1, \dots, n$

$A = LU$, L : unit lower triangular,
 U : upper triangular

$\det(A) = \det(L) \det(U) = u_{11} u_{22} \dots u_{nn} \neq 0,$
 $u_{ii} \neq 0, i = 1, \dots, n$

$D = \text{diag}(u_{11}, u_{22}, \dots, u_{nn}), V = D^{-1}U$
 V : unit upper triangular

Now, determinant of A is determinant of L into determinant of U , determinant of L is equal to 1, determinant of U is product of the diagonal entries. So, you have got $u_{11} u_{22} \dots u_{nn}$ not equal to 0. That will imply that u_{ii} not equal to 0 for i is equal to 1 to up to

n. Now, write d as diagonal $u_{11} \ u_{22} \ \dots \ u_{nn}$ and define v is equal to $d^{-1}u$, then this v becomes unit upper triangular and when you substitute in $l u$, then you are going to get A is equal to $l d v$. Now, this decomposition is unique l unit lower triangular d diagonal and u unit upper triangular. So, now, let us look at the case, when A is symmetric matrix.

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$A = L D V$
 $A^T = V^T D^T L^T$
 $= V^T D L^T$

A : symmetric
 $A^T = V^T D L^T$
 $A = L D V$
 $L = V^T$
 $A = L D L^T$

L : unit lower tri.
 V : unit upper tri.
 D : diagonal.
 V^T : unit lower tri.
 L^T : unit upper tri.

So, we have got A is equal to $L D V$ that will give us A transpose to be equal to V transpose, D transpose, L transpose. Our L is unit lower triangular, V is unit upper triangular. And D is diagonal, since D is diagonal it becomes V transpose D and then L transpose, if A is a symmetric matrix, then we have got A transpose is equal to A , A transpose is V transpose, $D L$ transpose, A is $L D V$. Now, V transpose is going to be unit lower triangular L transpose is going to be unit upper triangular.

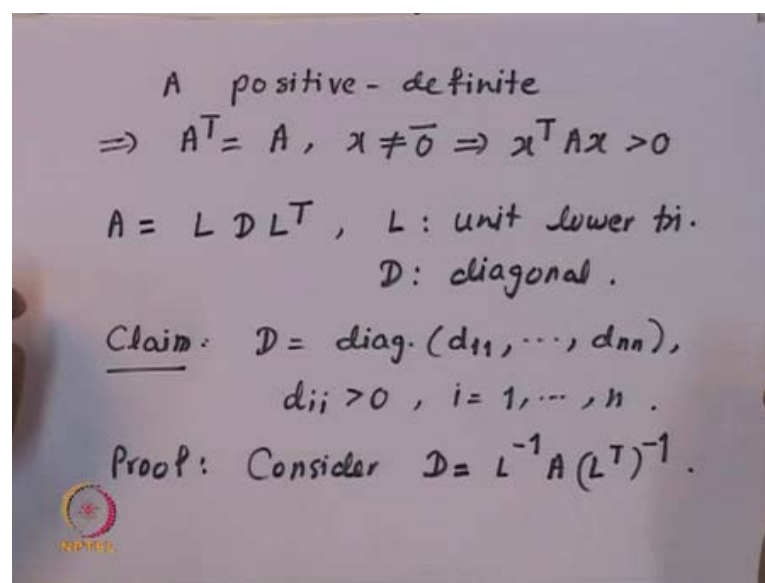
These two are equal. So, by uniqueness of the $L D V$ decomposition, what we get is L has to be equal to V transpose and does for A symmetric matrix, A is going to be equal to $L D L$ transpose. So, we have this, provided A is symmetric. So, now, this is for symmetric matrix. Now, we will consider A positive definite matrix, A positive definite matrix has got 2 properties it is A symmetric matrix and if you look at A non-zero vector x .

Then x transpose $A x$ is going to be bigger than 0. So, now, for A positive definite matrix, we are going to have A is equal to $L D L$ transpose, where L is a unit lower

triangular matrix. For positive definite matrix, we will show that the diagonal entries of D , they are going to be all strictly bigger than 0. Once we prove that we define a new diagonal matrix, which we denote by D raised to half consisting of diagonal entries as square root of D_{11} , square root of D_{22} square root of D_{nn} .

So, we have got A is equal to $L D L^T$, this D we write as D raised to half into D raised to half and then associate L with L and another d raised to half with v and that will give us Cholesky decomposition G, G^T . So, let us do that.

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We have a positive definite; that means, A transpose is equal to A and x not equal to 0 vector, implies $x^T A x$ is going to be bigger than 0. This is definition of positive definite matrix. Now, A is written as $L D L^T$, where L is unit lower triangular and D is diagonal. So, our claim is that if I write D as diagonal d_{11} up to d_{nn} , then each d_{ii} is greater than 0. This is our claim; so, in order to prove the claim. So, proof: you consider, matrix D to be equal to $L^{-1} A (L^T)^{-1}$. L is a unit lower triangular matrix. So, that means, determinant of L is going to be equal to 1 and hence it will be invertible.

And if L is invertible, L^T is also invertible. In fact, for an invertible matrix A transpose inverse is nothing but A^{-1} transpose. So, we have written D as $L^{-1} A (L^T)^{-1}$. We will show that the D is positive definite or in fact, that we do

not need to show that D to be positive definite what we want is d_{ii} , they should be bigger than 0.

So, these entries d_{ii} , they are going to be given by $e_i^T D e_i$, where e_i is our canonical vector and using positive definiteness of our matrix A , we will show that all these entries they are bigger than 0.

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Handwritten derivation on a whiteboard:

$$D = L^{-1} A (L^T)^{-1}$$

$$d_{ii} = e_i^T D e_i \quad e_i = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \rightarrow \text{ith place.}$$

$$= e_i^T L^{-1} A (L^T)^{-1} e_i$$

Let $y = (L^T)^{-1} e_i$ i : fixed.

$$y^T = e_i^T [(L^T)^{-1}]^T = e_i^T L^{-1}$$

$$d_{ii} = y^T A y \cdot y \neq \bar{0} \quad e_i \neq \bar{0}$$

$$> 0 \quad (L^T)^{-1} e_i \neq \bar{0}$$

" y

So, now, D is L inverse A L transpose inverse. d_{ii} is going to be $e_i^T D e_i$, where e_i is canonical vector with 1 at i th place and 0 else where, you can verify that d_{ii} is going to be $e_i^T D e_i$, that is going to be $e_i^T L^{-1} A (L^T)^{-1} e_i$, i is fixed in that case y^T is going to be $e_i^T L^{-1}$ and then transpose of whole thing. Now, the transpose and inverse they compute L transpose inverse will be L inverse transpose and transpose of transpose gives us original matrix. So, this is nothing but $e_i^T L^{-1}$.

And hence, d_{ii} will be $y^T A y$. Our vector e_i is not a 0 vector, because you have got one entry which is equal to 1, when you consider L transpose inverse e_i , this is also not equal to 0, because if y is equal to 0, then i can multiply throughout by L transpose and then i will get e_i , which is equal to L transpose y it is equal to 0. So, this y is a non-zero vector. And now recall the definition of positive definite matrix that for positive definite matrix whenever vector x is not equal to 0 $x^T A x$ is greater

than 0. And hence, y is not equal to 0 vector and you will get $y^T A y$ is bigger than 0.

So, let us recapitulate what we have done, we are assuming our matrix A to be positive definite; using symmetry we know that A can be written as $L D L^T$, where L is a unit lower triangular matrix and D is a diagonal matrix and then using the other property of positive definiteness of matrix A we proved the diagonal entries they are going to be all bigger than 0. So, now, we are ready for proving the Cholesky decomposition.

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$$A = L D L^T \quad D = \text{diag.}(d_{11}, \dots, d_{nn})$$

$$d_{ij} > 0$$
 Define $D^{1/2} = \text{diag.}(\sqrt{d_{11}}, \dots, \sqrt{d_{nn}})$

$$(D^{1/2})^2 = D$$

$$A = L D^{1/2} D^{1/2} L^T \quad G = L D^{1/2}$$

$$= G G^T \quad G^T = (D^{1/2})^T L^T = D^{1/2} L^T$$

$$A \text{ positive definite}$$

$$G: \text{lower tri. matrix.}$$

So, we have A is equal to $L D L^T$ D being a diagonal matrix and d_i they are bigger than 0, you define D raise to half its a notation to be a diagonal matrix with diagonal entries as square root of d_{11} square root of d_{nn} . This matrix will have property that D raise to half its square is going to be your matrix D .

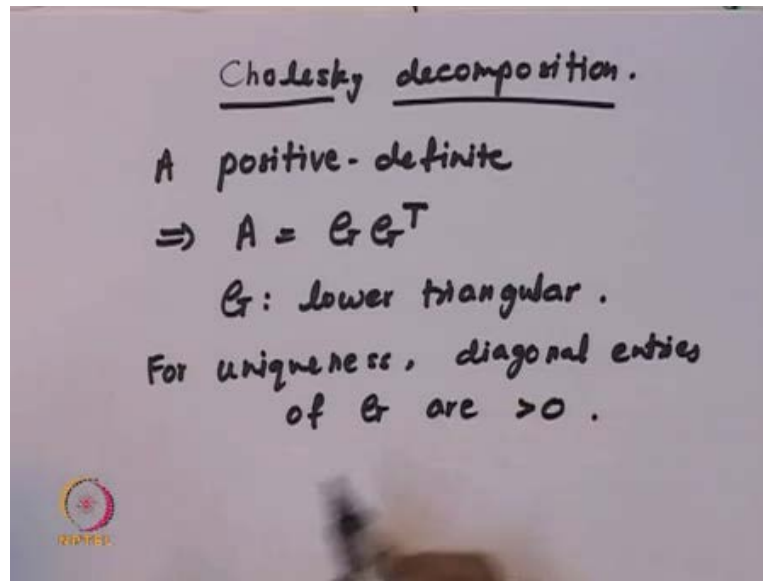
And hence, A is going to be equal to $L D^{1/2} D^{1/2} L^T$. Now, let me call this matrix to be G . So, if G is equal to $L D^{1/2}$, G^T will be $D^{1/2} L^T$, but D is a diagonal matrix. So, it is $D^{1/2} L^T$. So, that means, A is equal to $G G^T$. So, A positive definite will imply that A can be written as a $G G^T$. And G is going to be a lower triangular matrix. Now, the diagonal entries of G need not be equal to 1. So, compare with $L U D$ composition. In case of $L U D$ composition, you had A is equal to $L U L^T$ unit lower

triangular U upper triangular, if the matrix is positive definite A is equal to $G G^T$ where G is a lower triangular matrix and then G^T lower triangular it will mean that G^T is upper triangular.

So, what have we achieved, when we want to determine L U D composition of our matrix A, we need to determine L and we need to determine U. Now, we have got A is equal to $G G^T$. So, one's I determine G, then G^T is determine.

So, that means, our work is going to get reduced by half. Now, what about uniqueness like you have A is equal to $G G^T$, whether such a decomposition will be unique. If you do not impose any condition, if you just say that G should be a lower triangular matrix, then such a decomposition will not be unique, because remember how we have done this $G G^T$, it was we had our diagonal matrix D. We proved that diagonal matrix the entries are bigger than 0 and then we looked at positive square root now for a each of the entry, if I take negative square root, then also my D raise to half will have property that D raise to half square is equal to D. So, if you want uniqueness, then you have to put some extra condition for example, you can say that G should be a lower triangular matrix with diagonal entries to be bigger than 0. The normalization could be that it should be said that the diagonal entries are less than 0 or some other, but then for the sake of the definiteness, we will consider the matrix G to be such that it is lower triangular and its diagonal entries they are all bigger than 0. So, this is Cholesky decomposition.

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So, we have A positive definite implies A can be written as $G G^T$, where G is lower triangular matrix and for uniqueness impose the condition that diagonal entries of G are strictly bigger than 0.

Now, this it has a converse, if you are given that A is equal to say, $M M^T$; where M is invertible matrix, then A is going to be positive definite. So, this part we will prove but before that let us look at how to determine G and G^T like we have done in case of L U D composition. One way of finding L U D composition is reduce the coefficient matrix A to an upper triangular form using gauss elimination method. The final form which you get upper triangular form that is our u and when you do gauss elimination method you have got those multipliers.

Using those multipliers, you construct your lower triangular matrix, other way is start with A is equal to L into U. So, entries of L and entries of U they are determined by taking matrix multiplication of L into U and equating to the corresponding element of A.

So, now in order to find the Cholesky decomposition that is what we are going to do, we will not go through like start with - gauss elimination method that get L U D composition then get L D V decomposition and then write D raise to half. So, instead of that we will just start with a is equal to $G G^T$ the entries of G are unknown and they will be obtained by taking the matrix multiplication of G and G^T and equating with the corresponding entry of your matrix A.

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$$A : n \times n \text{ positive-definite matrix} : A = G G^T$$
$$\begin{bmatrix} g_{11} & & & & 0 \\ g_{21} & g_{22} & & & \\ g_{31} & g_{32} & g_{33} & & \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ g_{n1} & g_{n2} & g_{n3} & \dots & g_{nn} \end{bmatrix} \begin{bmatrix} g_{11} & g_{21} & g_{31} & \dots & g_{n1} \\ 0 & g_{22} & g_{32} & \dots & g_{n2} \\ 0 & 0 & g_{33} & \dots & g_{n3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & g_{nn} \end{bmatrix} = A$$

As in LU decomposition,

1st step : determine 1st row of G^T (= 1st column of G).

2nd step : determine 2nd row of G^T (= 2nd column of G)

So, here is n by n positive matrix given. Now, you want to write it as $G G^T$, where G is a lower triangular matrix. So, all the entries here they are 0, when you look at its G^T all the entries below diagonal they will be 0. So, as in case of LU decomposition our first step is going to be determine the first row of G^T and that will also be in first column of G .

So, consider the first row here and multiplied by first column. So, that will give us the entry a_{11} , then first row into second column, first row into third column and first row into n th column, exactly same as we have done in case of LU decomposition with a difference that in LU decomposition; you determine the first row of U and you need to determine then first column of L . Now, here once you determine, this row this column will be automatically determine. So, that is what makes our work to be reduced by half.

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1st row of G x j th Column of G^T

$$A = G G^T : a_{1j} = \sum_{k=1}^n G_{(1,k)} G^T(k,j) = g_{11} g_{j1}, \quad j=1, \dots, n$$

$$g_{11}^2 = a_{11}, \quad a_{j1} = a_{1j} = g_{11} g_{j1}, \quad j=2, \dots, n$$

$$g_{11} = \sqrt{a_{11}}, \quad g_{j1} = \frac{a_{j1}}{g_{11}}, \quad j=2, \dots, n$$

2nd row of G x j th column of $G^T : j=2, \dots, n$

$$g_{21}^2 + g_{22}^2 = a_{22}, \quad g_{21} g_{j1} + g_{22} g_{j2} = a_{j2}, \quad j=3, \dots, n$$

$$g_{21} = \sqrt{a_{22} - g_{22}^2}, \quad g_{j2} = \frac{a_{j2} - g_{21} g_{j1}}{g_{22}}, \quad j=3, \dots, n$$

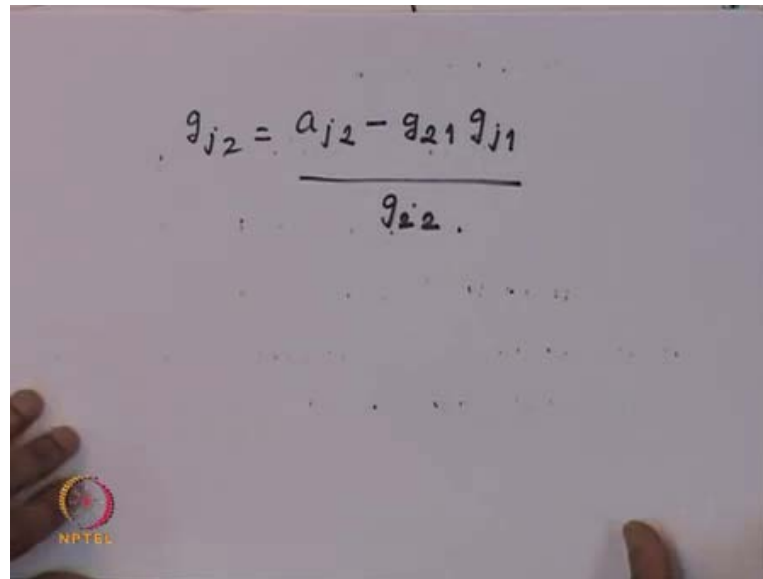
So, now let us look at first row into various columns of G transpose. So, first row of G into j th column of G transpose, when you do that you are going to get the entry a_{1j} is equal to summation k goes from 1 to n . First row of G the entries will be g_{1k} then G transpose the entries of j th column. So, they will be G transpose k_j , the notation is slightly different. So, here 1 denotes the row index and k denotes the column index. So, first row that is y this one is fixed with j th row. So, that is why this j is fixed

Now, remember that our G is a lower triangular matrix. So, in the first row only one entry is non-zero and that is g_{11} . So, the summation will get reduce to g_{11} and then G transpose $1,j$. So, that is going to be g_{j1} going from 1 to up to 1. So, put j is equal to 1 that will give you g_{11}^2 to be equal to a_{11} and; that means, g_{11} , we take positive square root. So, you have got root of a_{11} then for the other values a_{j1} is same as a_{1j} because our matrix is symmetric. And then you have got $g_{11} g_{j1}$ for j is equal to 2 up to n g_{11} is determined. So, g_{j1} will be a_{j1} divided by g_{11} j is equal to 2 up to 1.

So, we have determined the first row of G transpose, which is same as first column of G . Now, second row of G into j th column of G transpose. So, in the second row of G , you have got only two entries in the first row there was only one non-zero entry. Now, there are possibly two non-zero entries. So, the summation will be g_{21}^2 plus g_{22}^2 is equal to a_{22} and then you will have $g_{21} g_{j1}$ plus $g_{22} g_{j2}$ a_{j2} for j is

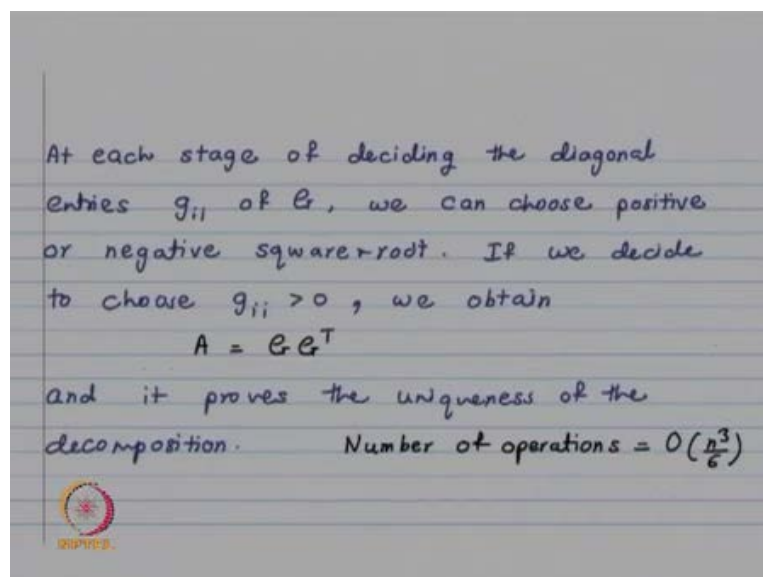
equal to 3 up to n. So, you determine g_{22} by square root of a_{22} minus g_{21} square and g_{j2} will be equal to a_{j2} minus $g_{22} g_{j2}$ divided by g_{22} , you are considering. So, $g_{j2} g_{21} g_{j1} g_{22} g_{j2}$ that is correct and g_{j2} . So, it will be a_{j2} minus actually this term should be $g_{21} g_{j1}$, this should be different it should be our g_{j2} is going to be equal to a_{j2} minus $g_{21} g_{j1}$ divided by g_{22} .

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$$g_{j2} = \frac{a_{j2} - g_{21} g_{j1}}{g_{22}}$$

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At each stage of deciding the diagonal entries g_{ii} of G , we can choose positive or negative square root. If we decide to choose $g_{ii} > 0$, we obtain

$$A = GG^T$$

and it proves the uniqueness of the decomposition. Number of operations = $O\left(\frac{n^3}{6}\right)$

So, we continue like this and then we determine GG^T , we have calculated GG^T transpose. And this will be the number of operations; they are going to be of the order of

n cube by 6. In case of L U D composition, they were of the order of the n cube b 3. And now, because of the symmetry you have got A is equal to G G transpose it is going to be of the order of the n cube by six half the number. So, now, more than this reducing the number of operations by half that is an important factor, but this decomposition is a stable way. So, now, what to stability means we are going to discuss it later on. So, if matrix A given to be a positive definite then you can write this G G transpose.

Now, let us prove converse that if i have got matrix A to be equal to M M transpose M need not be even lower triangular, if M is a invertible matrix then A is equal to M M transpose is going to be positive definite.

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Consider $A = M M^T$, M invertible.

$$A^T = (M M^T)^T = (M^T)^T M^T = M M^T = A$$

A : symmetric.

Let $x \neq \bar{0}$, $M^T x = y \neq \bar{0}$

Were $M^T x = \bar{0} \Rightarrow (M^T)^{-1} M^T x = (M^T)^{-1} \bar{0}$

$$x^T A x = x^T M M^T x \Rightarrow x = \bar{0}$$

contradiction.

So, consider A is equal to M M transpose, where M is invertible; look at A transpose. A transpose will be M M transpose transpose of that then when you take the A B transpose that is B transpose A transpose. So, you get M transpose transpose into M transpose, but the M transpose transpose gives us M and then M transpose which is equal to A.

So, A is symmetric. Now, let x be not equal to 0 vector, m invertible means M transpose also is invertible. So, you consider, M transpose x. This will be let me call it y, this is not a 0 vector, because where M transpose x equal to 0 vector; this will imply that M transpose inverse M transpose x will be equal to M transpose inverse into 0 vector. This will imply that x to be equal to 0 vectors. So, that will be contradiction, because you are

starting with x is equal to 0 vectors. So, now, $M^T x$ is equal to y which is not a 0 vector.

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$$\begin{aligned}
 x^T A x &= x^T M \underbrace{M^T x}_y \\
 &= y^T y = y_1^2 + \dots + y_n^2 > 0
 \end{aligned}$$

$$y = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \quad y^T = [y_1 \dots y_n]$$

$$y \neq \bar{0} \Rightarrow y_i \neq 0 \text{ for some } i$$

So, look at $x^T A x$. I am starting with x to be a non-zero vector and I am looking at $x^T A x$. This will be $x^T M M^T x$ substituting for A then we have $M^T x$ is equal to y . So, $x^T A x$ will be equal to $x^T M M^T x$, this is y . So, this will become $y^T y$. If y is our vector y_1, y_2, y_n . Then y^T is row vector y_1, y_2, y_n . So, $y^T y$ becomes you consider this y is this and you have got $y^T y$, you have to consider y^T into y . So, that will give you $y_1^2 + y_n^2$. Now, $y \neq \bar{0}$ implies $y_i \neq 0$ for some i , at least 1 y_i has to be non-zero. Now, $y_1^2 + y_2^2 + y_n^2$, this will be strictly bigger than 0, because each entry is bigger than or equal to 0 and 1 entry is strictly bigger than 0. So, we have proved that if A is equal to $M M^T$ with M to be an invertible matrix, then it is a symmetric matrix and $x^T A x$ is bigger than 0. So, it is a positive definite matrix. So, now, we have got, if A is a positive definite matrix then you can write A as $G G^T$, conversely if A can be written as $G G^T$ with G to be invertible then A is going to be positive definite. So, this gives us a practical way to determine whether your A is going to be positive definite or not.

Look at the definition of positive definiteness, we say that it should be symmetric, fine I can verify that it is a symmetric. The other part is for every non-zero vector x , we want $x^T A x$ is bigger than zero. So, now, how am I going to verify this, we have got infinitely many vectors. So, for all non-zero vectors we want $x^T A x$ to be bigger than 0. So, now, we have got, if and only if condition, A is positive definite if and only if A can be written as $G G^T$ with G to be an invertible matrix in the Cholesky decomposition for the normalization we had said that all the diagonal entries they should be bigger than 0. So, G being a lower triangular matrix its determinant will be product of the diagonal entries and it will be bigger than 0's it will be invertible.

So, given a matrix A , you first verify whether a transpose is equal to A , you write a computer program for that next you try to write a $G G^T$. So, look at a matrix A is given to you try to do like this. So, in the first stage you are trying to determine the first row, if a_{11} your taking positive square root, if this number is less than 0, then your matrix is not positive definite, if this number is equal to 0, you are dividing. So, then your matrix is not positive definite. So, at any stage when matrix A is given to you, you have verified that it is a symmetric matrix, now you try to write A as $G G^T$ for this also you can write a program, if at any stage your algorithm breaks down, now how can the algorithm break down? you are taking square roots. So, if at any stage the number of which you need to take the square root, if it turns out to be less than 0 your matrix is not positive definite; if your diagonal entry becomes 0 then again your procedure is going to break down. And then your matrix is not positive definite. So, here is a practical test for determining whether a matrix A is positive definite or not and such cases they are prayer. So, it is one of the occasions where practically you can determine whether matrix A is positive definite or not.


So, now, So, far we had considered system, where the coefficient matrix A was invertible and in addition determinant of a k is not equal to 0 for k is equal to 1 to up to n where k is the principle leading sub matrix. And we have a class of matrices which is the positive definite matrices where this is applicable, but then if you have given only that A is an invertible matrix you are going to come across the systems that $A x = y$ A is invertible matrix. So, I know that $A x = y$ is going to have a unique solution.

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Gauss elimination with partial pivoting

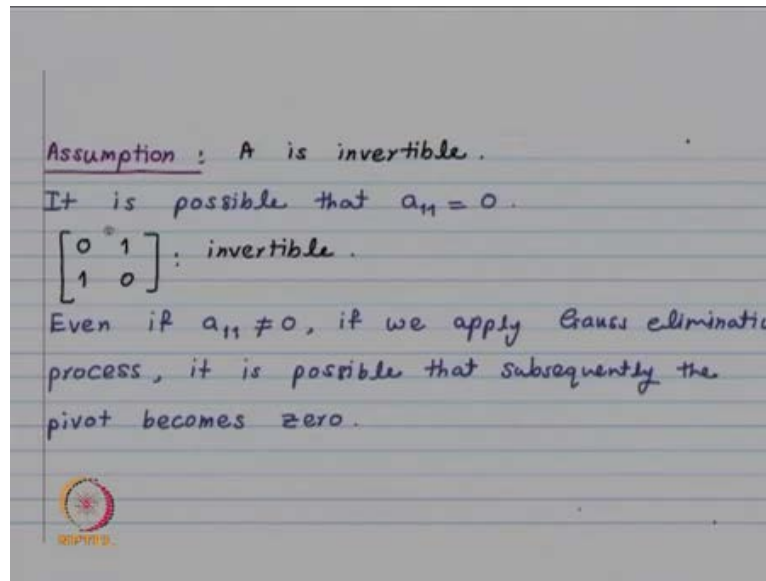
$$Ax = b$$

Assumption: A is invertible, $\det(A) \neq 0$

$$\begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}$$


Now, how to find that solution that is where the modification of gauss elimination comes into picture and that is known as gauss elimination with partial pivoting. So, now let us discuss that gauss elimination with partial pivoting. So, now, our assumption is A is invertible; that means, determinant of A is not equal to 0, this is only given to us and we look at the system in the gauss elimination what we were doing where we were introducing 0's in the first column below the diagonal. So, a 1 1 was our pivot and we looked at multiplier when we want to introduce 0 here, we multiplied the first row by a 2 1 by a 1 1 and subtracted from the second row. And So, on now if A is invertible it can very well happen that this a 1 1 is equal to 0.

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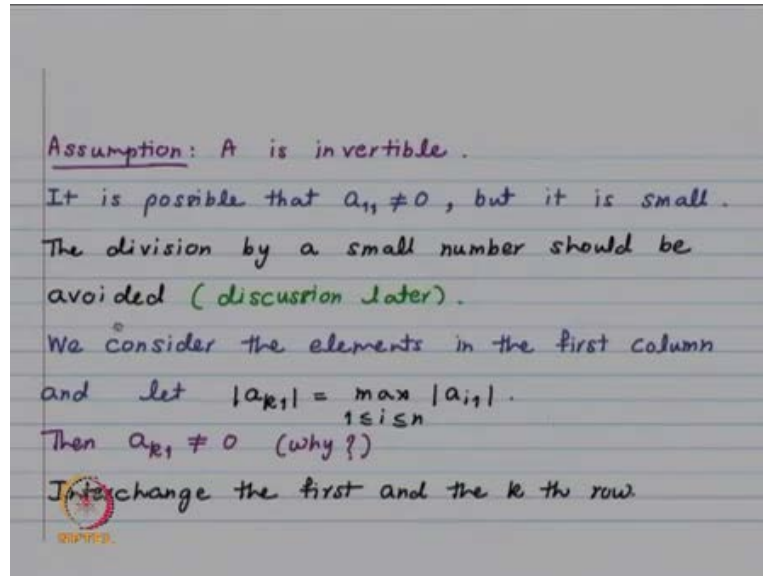
we had already considered this example a 2 by 2 matrix it is a invertible matrix because determinant is equal to minus one and the pivot or the first entry a_{11} is equal to 0 now even if a_{11} is not equal to 0. You should avoid to divide by a small number, when you are doing exact computations are or when we do is a mathematics we say that you cannot divide by 0.

When your computations are going to be with the help of a computer you should not divide by a small number, now what happens when you divide by a small number that discussion we will do later on. So, now what I can do is I have been given that matrix A is invertible e, I look at the first column it can very well happen that the first entry a_{11} is equal to 0, but at least 1 of the entry in the first column it has to be non-zero because if all entries are equal to 0 I have go to zero column; that means, determinant of A is 0. So, A will not be invertible.

So, I will look at the entries in the first column and look the entry, which has got maximum modulus. So, suppose that is in the k th row. So, I will interchange k th row and the first row. So, by this interchange I have done my best I am going to divide by the entry which is going to occupy the position a_{11} in the matrix. So, in the first column among the entries I take the entry with the maximum modulus.

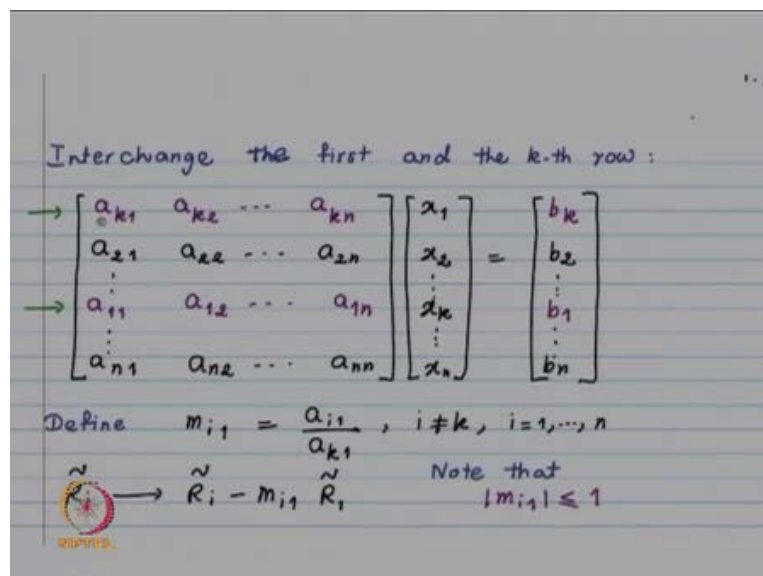
After interchanging these two rows I proceed as before and then this will take care of first column, then one do similar thing for the second column. So, on and this is known as gauss elimination with partial pivoting.

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So, here suppose modulus of a k one is maximum of modulus of a i 1 less than or equal to i less than or equal to n . So I am considering the entries in the first column and looking at the entry which has got maximum modulus and then interchange the first and the k th row.

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So, what was k th row before that has become the first row, what was first row that has become the k th row. Now, notice that by interchanging the 2 rows; that means, I am interchanging the order of my system of equations, I do not change the system because we want to find solution of $Ax = b$. So, whatever changes we make it should give us an equivalent system.

Now, n questions are given to you **you** are just changing the order of the equation. So, you do not change the system. So, we have interchange and now our multipliers are going to be m_{i1} is equal to a_{i1} by a_{k1} the modified entry and **and** then R_i tilde are my new roots. So, this is my r_2 tilde r_3 tilde r_n tilde. So, all the rows are going to be same as before except for one row and then I introduce 0 here. So, as I said is going to be exactly same as gauss elimination method, which we had discussed earlier. Now, I will like to you to notice one thing that if do this modulus of m_{i1} is going to be less than or equal to 1. So, this factor becomes important, when we are going to discuss the stability. So, when I do this my matrix will get modified to this matrix.

So, because we are interchanging rows, the new entries I am denoting by a_{11} tilde a_{21} tilde a_{n1} tilde i have introduced all 0 here and then this is the modified matrix, sub matrix and this now I want to do similar thing for the second column. So, in the second column look at the entries diagonal onwards and look at the maximum entry, this maximum entry again should not be 0, because what will happen is if all the entries here they are 0 then, what our matrix looks like a_{11} tilde 0 0 0 a_{21} tilde 0 0 0. So, you have got two columns which are linearly dependent or what I can do is multiple or a subtract a multiple of the first column from the 2 column and then get a 0 column.

So, think about it. So, all these entries among these entries at least one has to be not equal to zero. So, we will interchange second and k th equation and continue as before.

So, the difference between gauss elimination, which we discuss before and gauss elimination with partial pivoting is at each stage we are interchanging roots. So, that is the gauss elimination with partial pivoting and tomorrow we will show that the gauss elimination was equivalent to writing $A = LU$. So, this gauss elimination with partial pivoting is equivalent to writing $pA = LU$, where p is a permutation matrix; that means, it is obtained from the identity matrix by interchange

of roots, this again will be useful when we want to consider the backward error analysis.
So, we will continue tomorrow, thank you.

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