


Numerical Methods in Civil Engineering
Prof. Arghya Deb
Department of Civil Engineering
Indian Institute of Technology, Kharagpur

Lecture - 5
Linear Systems-III

(Refer Slide Time: 00:25)

Matrices which do not need pivoting

- There are two types of special matrices which do not require any pivoting i.e. they can be reduced to triangular form without any row or column interchanges.
- A diagonally dominant matrix i.e. a matrix with components such that $a_{ii} \geq \sum_{j=1, j \neq i}^n |a_{ij}|$, $i = 1 \dots n$ always has the largest elements on its diagonal, thus no row or column interchanges can improve the natural pivot i.e. the diagonal element.
- A symmetric and positive definite matrix A, i.e. A such that $A^T = A$ and $x^T A x > 0$ for all x not equal to zero



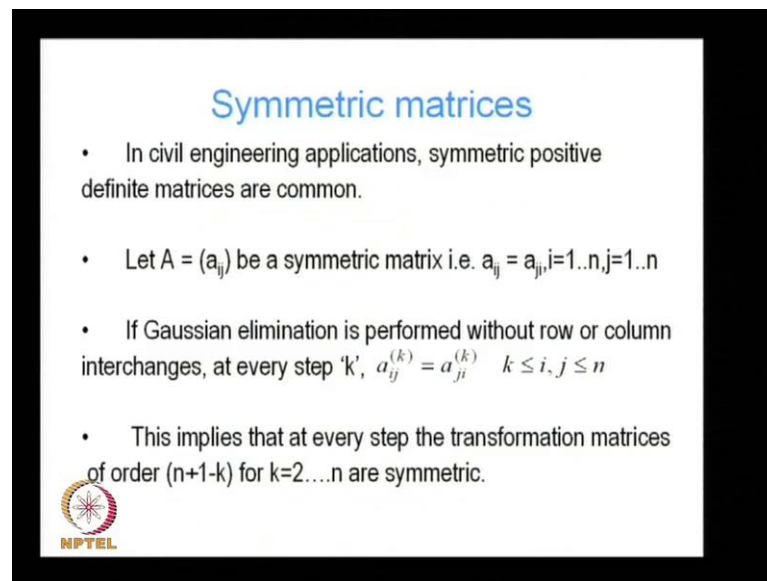
Methods in civil engineering we will continue our discussion on linear systems, which we talked about last times. Last time we ended our lecture talking about the need pivoting. We found that most matrices, if we have to perform Gaussian elimination on those matrices to solve the linear systems successfully they require pivoting. However, today we will concentrate on types of matrices, which do not need pivoting. There are two types of special matrices, which do not require any pivoting that is they can be reduced to triangular form without any row or column interchanges.

A diagonally dominant matrix that is a matrix with components a_{ij} diagonal elements a_{ii} such that each diagonal element is greater than the sum of the absolute magnitudes of the off diagonal elements is known as a diagonally dominant matrix. It always has the largest elements on its diagonal thus no row or column interchanges can improve the natural pivot that is the diagonal element. Since the diagonal element is the largest

element in the row, it always is assured to be nonzero.


Another type of matrix, which does not need any pivoting is a symmetric positive definite matrix. A positive definite matrix is defined such that it is symmetric first of all a symmetric positive definite matrix by definition is symmetric, which means that a transpose is equal to A, and in addition $x^T A x$ is greater than zero for all x not equal to zero given any arbitrary vector x and given that that vector is not identically equal to zero. We can be assured that if it if we perform the operation $x^T A x$. We are going to get a positive number for a positive definite matrix. So, for these two types of matrices we do not need any pivoting by performing Gaussian elimination.

(Refer Slide Time: 02:42)



Symmetric matrices

- In civil engineering applications, symmetric positive definite matrices are common.
- Let $A = (a_{ij})$ be a symmetric matrix i.e. $a_{ij} = a_{ji}, i=1..n, j=1..n$
- If Gaussian elimination is performed without row or column interchanges, at every step 'k', $a_{ij}^{(k)} = a_{ji}^{(k)} \quad k \leq i, j \leq n$
- This implies that at every step the transformation matrices of order $(n+1-k)$ for $k=2, \dots, n$ are symmetric.


NPTEL

We will talk about positive definite matrices in lot of detail, because in many civil engineering applications we encounter positive definite symmetric, positive definite matrices. First let us talk in more detail about symmetric matrices we will come back to talk about positive definite matrices further on in the lecture. Let A is equal to a_{ij} with components a_{ij} be a symmetric matrix which; obviously, means that a_{ij} is equal to a_{ji} that is elements on either side of the principal diagonals are mirror images of each other that is, if we change the row and column we are going to get if we transpose the row and column we are going to get identical elements of the matrix. So, a_{ij} is equal to a_{ji} for

all i equal to 1 to n , j equal to 1 to n .

If Gaussian elimination is performed without row or column interchanges at every step k we can be assured that the matrix is going to remain symmetric that is a_{ij} after the k th step is going to be equal to a_{ji} after the k th step. So, for a symmetric matrix, if we performed Gaussian elimination that is if we are able to perform Gaussian elimination without any row or column interchanges we can be assured that at every step the matrix is going to be symmetric. So, at every step the matrices of order n plus one minus k for k equal to two through n are going to be symmetric.


(Refer Slide Time: 04:35)

Symmetric matrices

- According to the elimination algorithm:

$$a_{ij}^{(k+1)} = a_{ij}^{(k)} - \frac{a_{ik}^{(k)} a_{kj}^{(k)}}{a_{kk}^{(k)}}$$
- From the symmetry of the transformed matrix at step 'k':

$$a_{ij}^{(k+1)} = a_{ji}^{(k)} - \frac{a_{jk}^{(k)} a_{ki}^{(k)}}{a_{kk}^{(k)}} = a_{ji}^{(k+1)}$$
- Thus if the transformed matrix at step 'k' is symmetric, the transformed matrix at step 'k+1' is bound to be symmetric.
- Since at $k=1$, the starting matrix is by definition symmetric, the transformed matrix must be symmetric for all $k=1,2,\dots,n$

 NPTEL

According to the elimination algorithm lets go back to the elimination algorithm, which we derived last time for Gaussian matrices for Gaussian elimination according to that elimination algorithm at any step k plus 1 the transformed element a_{ij} at k plus 1 is given in terms of the elements at step k according to the following relationship a_{ij} at k plus 1 is equal to a_{ij} at k minus a_{ik} at k times a_{kj} at k divided by a_{kk} of k , we uncounted this equation this transformation relation in our last lecture.

From the symmetry of the transformed matrix at step k , we can write a_{ij} at step k plus 1 is equal to a_{ji} at step k . Please note the difference between these two equations in the

first equation we had a a_{jk} at the right on the right hand side, second equation in the we use symmetry to write a a_{ij} in terms of a a_{ji} . So, we replace a a_{jk} by a a_{ji} . Similarly, we replace a a_{kk} by a a_{kk} and a a_{kj} by a a_{jk} .

So, these two expressions are identical for symmetric matrices. So, this tells us that if the transformed matrix at step k is symmetric, the transformed matrix at step $k + 1$ is also bound to be symmetric, because this is this expression is identically equal to a a_{ji} $k + 1$ since a a_{ji} $k + 1$ is equal to a a_{ij} $k + 1$; that means, at step $k + 1$ also the transformation matrix is symmetric. This is a a_{ji} $k + 1$ by definition by definition at.


Since at k equal to 1 the starting matrix is by definition symmetric that is, because are initial matrix was symmetric. So, i starting matrix is by definition symmetric, the transformed matrix must be symmetric for all k equal to 1, 2 through n why is that, because i starting matrix is symmetric and we have assure that, if the if at step k my transformation is matrix is symmetric at step $k + 1$, it is bound to be symmetric. So, at k equal to 1, if it is starts with symmetric matrix that is at k equal to 1, it is symmetric then it is obvious that at k equal 2, it is going to be symmetric at k equal to 3. It is going to be symmetric and it is going to be symmetric through all the steps of the Gaussian elimination.

(Refer Slide Time: 07:47)

Symmetric matrices

- Because of the symmetry of the transformed matrix at every step 'k' we only have to compute and store terms in $A^{(k)}$ on or above the main diagonal
- Thus for symmetric Gaussian elimination the transformation rule becomes:

$$a_{ij}^{(k+1)} = a_{ij}^{(k)} - \frac{a_{ki}^{(k)}}{a_{kk}^{(k)}} a_{kj}^{(k)} \quad i = k + 1, \dots, n, j = i, i + 1, \dots, n$$
- This means the number of operations is approximately halved from $\frac{n^3}{3}$ to $\frac{n^3}{6}$. In addition nearly half the memory is




Because of the symmetry of the transformed matrix at every step k we only have to compute and store terms in a k on or above the main diagonal. The advantage of symmetry is this it reduces drastically the storage required. So, since the matrix is symmetric since at each stage the transformation matrix is symmetric, we will take advantage of symmetric and store only the terms above the main diagonal we will no longer the stored the whole matrix. So, this automatically reduces the storage requirement by 2.

Thus the symmetric Gaussian elimination the transformation rule becomes $a_{ij} - \frac{a_{ik}a_{kj}}{a_{kk}}$ for $i, j > k$ is equal to $a_{ij} - \frac{a_{ki}a_{kj}}{a_{kk}}$ as you can see from the previous slide this is basically identical to what we obtain in the previous slide. Except, you note that we are now taking i is equal to $k + 1$ through n , and j is equal to i through n , which is basically we are doing the computations only for the one half of the matrix right. We have reduced to the number of operations. The number of operations is approximately half from n^3 by 3 to n^3 by 6 in addition nearly half the memory is save. So, we are performing the operations only on the elements, which are above the main diagonal and we have also storing only half the previous the storage is also half the previous storage.

(Refer Slide Time: 09:43)

Symmetric matrices

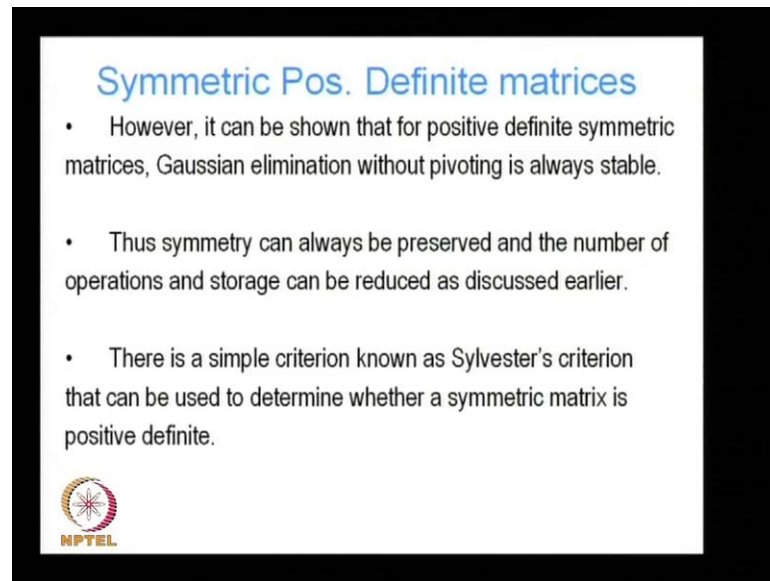
- It is not always possible to perform Gaussian elimination on symmetric matrices without pivoting.
- Symmetry is preserved if a diagonal element is chosen as the pivot and complete pivoting is done
- Partial pivoting, involving just a row interchange, will however destroy the symmetry.
- Thus symmetric Gaussian elimination cannot be used on all symmetric matrices.



However, we should enter a void of caution here, it is not always possible to perform Gaussian elimination on symmetric matrices without pivoting, symmetry is preserved we note that symmetry is preserved if only if we perform the Gaussian elimination on a symmetric matrix without performing any row or column interchanges right. So, this is only possible, if we do pivoting on a diagonal element either this is possible only in 2 situations either we perform Gaussian elimination without performing any row or column interchanges or we took do pivoting on a diagonal element, and when we do pivoting on a diagonal element we do complete pivoting that is we interchange both the rows and the columns to preserve the symmetry of the matrix. So, either we do not do any pivoting at all or we do complete pivoting on the diagonal elements, if we do partial pivoting we just involves the row interchange we will destroy the symmetry of the matrix.


Thus symmetric Gaussian elimination cannot be used on all symmetric matrices, it is important to note that symmetric Gaussian elimination cannot be used on all symmetric matrices particularly when we encounter elements on the pivot, which are either zero or too small we have to go for pivoting, and in that case if we do partial pivoting we are going to destroy the symmetric only vocation when we can preserve the symmetry is if we do pivoting on a diagonal element, and then we do total pivoting that is we interchange the rows as well as the columns.

(Refer Slide Time: 11:36)



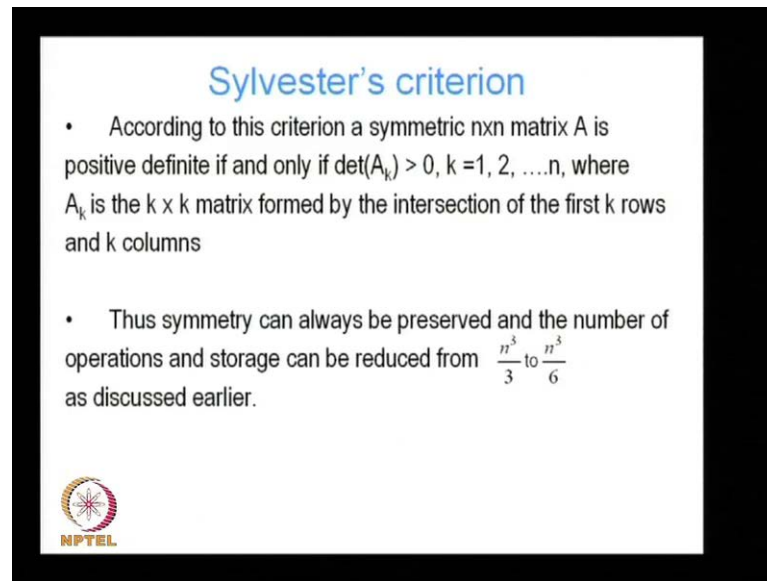
Symmetric Pos. Definite matrices

- However, it can be shown that for positive definite symmetric matrices, Gaussian elimination without pivoting is always stable.
- Thus symmetry can always be preserved and the number of operations and storage can be reduced as discussed earlier.
- There is a simple criterion known as Sylvester's criterion that can be used to determine whether a symmetric matrix is positive definite.




However, this is where the advantage of positive definite matrices come in, because it can be shown that for positive definite matrices Gaussian elimination without pivoting is always stable that is no need to do any pivoting for positive definite symmetric matrices, in that case symmetry can always be preserved and the number of operations, and storage can be halved as discussed earlier. There is a simple criterion known as Sylvester's criterion, which enables us to determine whether a matrix is positive to whether a symmetric matrix is positive definite or not.

(Refer Slide Time: 12:22)



Sylvester's criterion

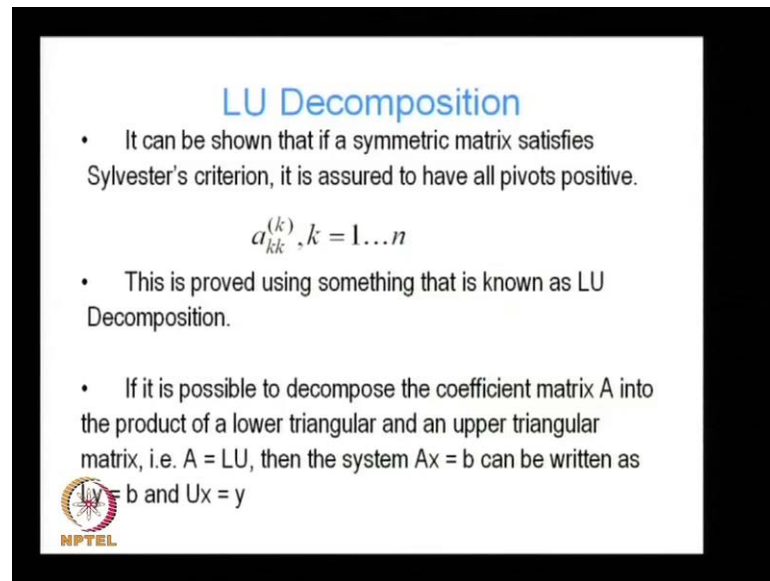
- According to this criterion a symmetric $n \times n$ matrix A is positive definite if and only if $\det(A_k) > 0$, $k = 1, 2, \dots, n$, where A_k is the $k \times k$ matrix formed by the intersection of the first k rows and k columns
- Thus symmetry can always be preserved and the number of operations and storage can be reduced from $\frac{n^3}{3}$ to $\frac{n^3}{6}$ as discussed earlier.



According to this criterion a symmetric n by n matrix, a symmetric matrix A with n rows and n columns is positive definite if and only if that is, it is necessary and sufficient condition that the determinant of a k must be greater than 0 for all k equal to 1 to n , where A_k is the k by k matrix formed by the intersection of the first k rows and k columns. So, we basically look at series of sub matrices starting with k equal to 1, which is basically just the element a_{11} then with A_k equal to 2 we are basically looking at the elements of the first row and the first column the square matrix formed by the L intersection of the first row and the first column, which is going to be a 2 by 2 matrix with elements a_{11} a_{12} a_{21} a_{22} .

Similarly, for k equal to 3 we look at the square matrix formed by the intersection of the first 3 rows and 3 columns with elements a_{11} a_{12} a_{13} a_{21} a_{22} a_{23} a_{31} a_{32} a_{33} if all these sub matrices turn out to have positive determinants, if all those determinants are positive then the symmetric matrix is going to be positive definite, in that case symmetry will always be preserved by Gaussian elimination and the number of operations can be reduced from n cube by 3 to n cube by 6 as discussed as we discussed earlier. Similarly, the storage two can be halved.

(Refer Slide Time: 14:18)




LU Decomposition

- It can be shown that if a symmetric matrix satisfies Sylvester's criterion, it is assured to have all pivots positive.

$$a_{kk}^{(k)}, k = 1 \dots n$$

- This is proved using something that is known as LU Decomposition.
- If it is possible to decompose the coefficient matrix A into the product of a lower triangular and an upper triangular matrix, i.e. $A = LU$, then the system $Ax = b$ can be written as $Ly = b$ and $Ux = y$

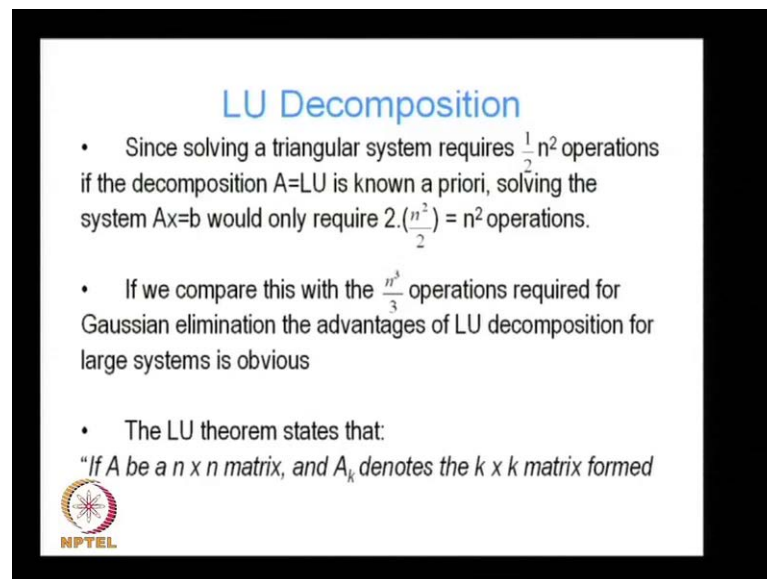
 NPTEL

It can be shown that if a symmetric matrix satisfies Sylvester's criterion that is, it is positive definite it is assured to have all its pivots positive that is a $k \times k$, k is equal to 1 through n is always going to be greater than 0 that is all these pivots $a_{kk}^{(k)}$ with superscripts k equal to 1 through n are going to be greater than 0. This can be shown by something known as L U decomposition, if it is possible to decompose the coefficient matrix A into the product of a lower triangular and an upper triangular matrix that is A is equal to LU recall, what is a lower triangular matrix? A lower triangular matrix has got elements, which are above the principal diagonal zero, it is got elements non zero elements only below or at the principal diagonal, where an upper triangular matrix is A matrix, which is got elements above the at or above the principal diagonal greater than 0 well all elements below the principal diagonal are zero.

So, if it is possible to decompose the coefficient matrix A into the product of a lower triangular and upper triangular matrix that is A is equal to LU then the system $Ax = b$ can be written as $Ly = b$, where y is an intermediate variable, $Ly = b$ and $Ux = y$. So, basically $Ax = b$ is basically $LUx = b$ we denote $Ux = y$ and we solve the system $Ly = b$ to determine y , and then we solve we again solve the system $Ux = y$ to determine x .


So, instead of solving $Ax = b$ at one go we are solving two triangular systems. First we are solving the system $Ly = b$ to determine y , and then we are solving the system $Ux = y$ to determine x , but each of these solutions of these triangular systems as we have seen earlier is very simple, it just involves back or forward substitution.

(Refer Slide Time: 16:56)



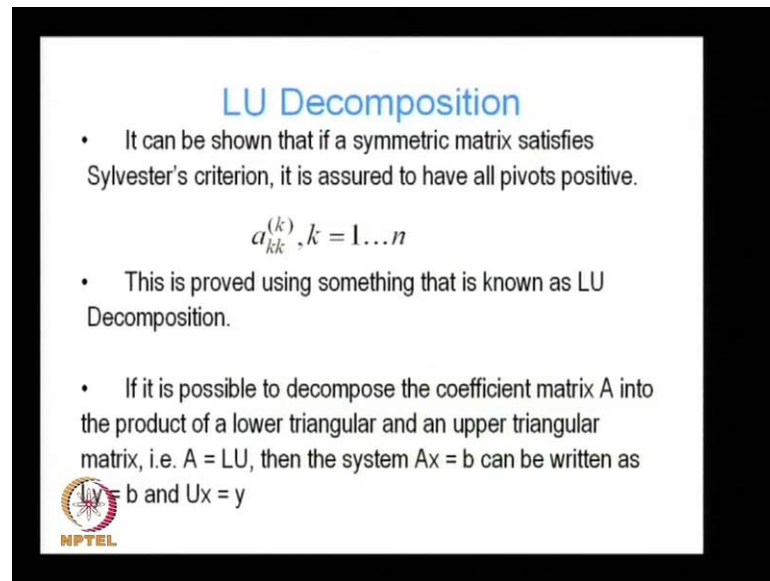
LU Decomposition

- Since solving a triangular system requires $\frac{1}{2}n^2$ operations if the decomposition $A=LU$ is known a priori, solving the system $Ax=b$ would only require $2 \cdot \left(\frac{n^2}{2}\right) = n^2$ operations.
- If we compare this with the $\frac{n^3}{3}$ operations required for Gaussian elimination the advantages of LU decomposition for large systems is obvious
- The LU theorem states that:
"If A be a $n \times n$ matrix, and A_k denotes the $k \times k$ matrix formed



Since solving a triangular system requires half n square operations basically the number of operations in a typical back substitution operation, if the decomposition A is equal to L U is known a priori solving the system $Ax = b$ would only require two times n square by 2 is equal to n square operations.

(Refer Slide Time: 17:25)




LU Decomposition

- It can be shown that if a symmetric matrix satisfies Sylvester's criterion, it is assured to have all pivots positive.

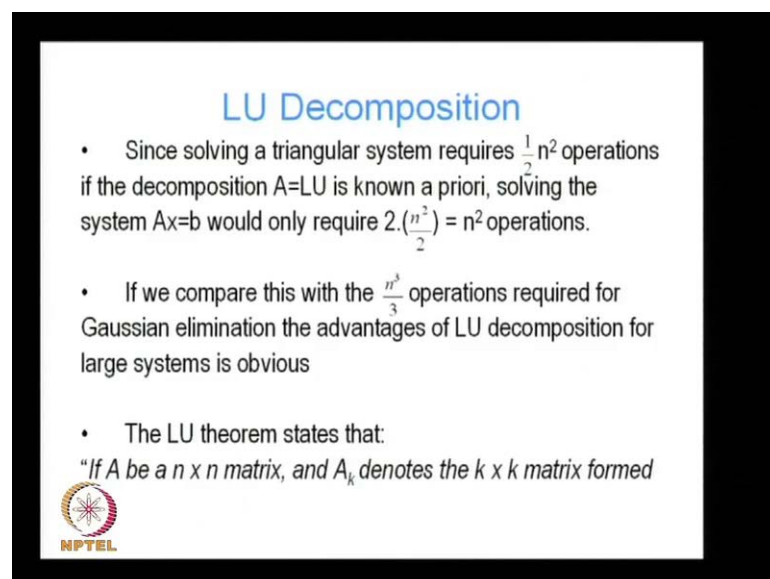
$$a_{kk}^{(k)}, k = 1 \dots n$$

- This is proved using something that is known as LU Decomposition.
- If it is possible to decompose the coefficient matrix A into the product of a lower triangular and an upper triangular matrix, i.e. $A = LU$, then the system $Ax = b$ can be written as $Ly = b$ and $Ux = y$




Basically we will solve the system $Ax = b$ by solving the system $Ly = b$, which is a triangular system which would require n^2 operations similarly solving the system $Ux = y$ is again going to require another n^2 operations.

(Refer Slide Time: 17:45)



LU Decomposition

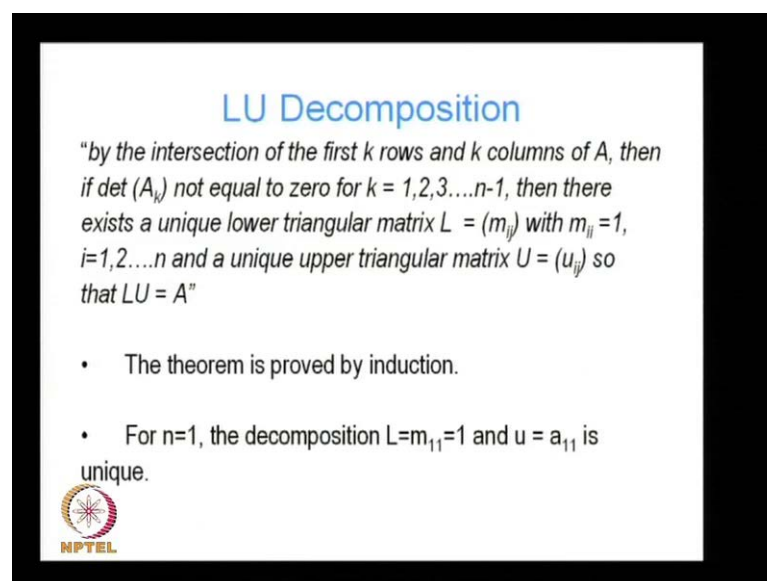
- Since solving a triangular system requires $\frac{1}{2}n^2$ operations if the decomposition $A=LU$ is known a priori, solving the system $Ax=b$ would only require $2 \cdot \left(\frac{n^2}{2}\right) = n^2$ operations.
- If we compare this with the $\frac{n^3}{3}$ operations required for Gaussian elimination the advantages of LU decomposition for large systems is obvious
- The LU theorem states that:
"If A be a $n \times n$ matrix, and A_k denotes the $k \times k$ matrix formed



So, the total number of operations is equal to two times n^2 by 2 is equal to n^2 this of course, assumes that we know the decomposition the decomposition of A into $L U$ is known a priori is known before hand.

If we compare the number of operations n^2 to the number of operations required for Gaussian elimination, which is n^3 , the advantages of $L U$ decomposition for large systems is obvious. So, if we can perform the $L U$ decomposition then we can solve the equation just by we can solve repeated systems $A x$ of the type $A x = b$ by just performing n^2 operations. The $L U$ theorems states that, if A is an n by n matrix and A_k denotes the k by k matrix formed by the intersection of the first k rows and k columns of A .


(Refer Slide Time: 18:50)



LU Decomposition

"by the intersection of the first k rows and k columns of A , then if $\det(A_k)$ not equal to zero for $k = 1, 2, 3, \dots, n-1$, then there exists a unique lower triangular matrix $L = (m_{ij})$ with $m_{ii} = 1$, $i = 1, 2, \dots, n$ and a unique upper triangular matrix $U = (u_{ij})$ so that $LU = A$ "

- The theorem is proved by induction.
- For $n=1$, the decomposition $L=m_{11}=1$ and $u = a_{11}$ is unique.




Then, if determinant of A_k is not equal to 0 for k equal to 1 through n minus 1 then there exists a unique lower triangular matrix L with components denoted by m_{ij} and the diagonal components $m_{ii} = 1$ and unique upper triangular matrix U that components u_{ij} . So, that LU is equal to A .

(Refer Slide Time: 19:26)

LU Decomposition

- Since solving a triangular system requires $\frac{1}{2}n^2$ operations if the decomposition $A=LU$ is known a priori, solving the system $Ax=b$ would only require $2 \cdot (\frac{n^2}{2}) = n^2$ operations.
- If we compare this with the $\frac{n^3}{3}$ operations required for Gaussian elimination the advantages of LU decomposition for large systems is obvious
- The LU theorem states that:
"If A be a $n \times n$ matrix, and A_k denotes the $k \times k$ matrix formed




So, let us take a look at it again says, that if A is an n by n matrix and A_k is the k by k sub matrix.

(Refer Slide Time: 19:36)

LU Decomposition

"by the intersection of the first k rows and k columns of A , then if $\det(A_k) \neq 0$ for $k = 1, 2, 3, \dots, n-1$, then there exists a unique lower triangular matrix $L = (m_{ij})$ with $m_{ii} = 1$, $i = 1, 2, \dots, n$ and a unique upper triangular matrix $U = (u_{ij})$ so that $LU = A$ "

- The theorem is proved by induction.
- For $n=1$, the decomposition $L=m_{11}=1$ and $u = a_{11}$ is unique.



Formed by the intersection of the first k rows and k columns of A and if the determinant $\det(A_k) \neq 0$ for k equal to 1 through n minus 1 then there exists a unique lower

triangular matrix L with components m_{ij} , m and with diagonal components m_{ii} equal to 1 and a unique upper triangular matrix U with components u_{ij} . So, that LU is equal to A . So, what this tells may is that if these conditions are satisfied that is, if all the A_k is have positive determinant then there are unique matrices upper triangular and lower triangular matrices LU and L such that A can be written as LU equal to A .

How can we show this well this can be shown quite easily by induction suppose the matrix is our size one, which is basically it is a scalar in that case the decomposition is obvious, because we have assume that the diagonal elements of the lower triangular matrix L or 1 right. So, it is obvious that the upper triangular matrix is now just a 11 an; obviously, these decomposition is unique.


(Refer Slide Time: 20:58)

LU Decomposition

- Suppose the theorem is true for $n = k-1$. For $n = k$, we partition A_k as:

$$A_k = \begin{pmatrix} A_{k-1} & \mathbf{b} \\ \mathbf{c}^T & a_{kk} \end{pmatrix} \quad \text{where } \mathbf{b} \text{ and } \mathbf{c} \text{ are column vectors with } k-1 \text{ components}$$

- Since A_{k-1} satisfies the LU theorem we can write, $A_{k-1} = L_{k-1}U_{k-1}$ where L_{k-1} and U_{k-1} are the unique lower and upper triangular matrices corresponding to the LU decomposition of A_{k-1} .



Now, suppose the theorem is true for n equal to K minus one for any k right. So, it is suppose that it is true for K minus one then for K for n equal to K we can partition A_k into the following A_k can be written as A_{k-1} , which is the A_{k-1} denoting the part, which is formed by the intersection of the first $k-1$ rows and $k-1$ columns of my original matrix and the remaining part which is \mathbf{b} to \mathbf{b} is a \mathbf{b} and \mathbf{c} comprising column vectors with $k-1$ components. So, \mathbf{b} is a column vector with a minus 1 components, \mathbf{c}^T is a column vector \mathbf{c}^T is actually a row vector

with $k-1$ components, and then the diagonal term a_{kk} .

Now, we know that since A_{k-1} satisfies the LU theorem we can write A_{k-1} is equal to L_{k-1} times product with U_{k-1} , where L_{k-1} and U_{k-1} are the unique lower and upper triangular matrices corresponding to the LU decomposition of A_{k-1} . Since A_{k-1} satisfies the LU theorem, we know basically that there is a unique L_{k-1} and unique U_{k-1} such that A_{k-1} is equal to L_{k-1} product U_{k-1} .


(Refer Slide Time: 22:42)

LU Decomposition

- Since $\det(L_{k-1}) \cdot \det(U_{k-1}) = \det(A_{k-1})$ is not equal to zero they are non-singular.
- Then A can be written as:

$$\begin{bmatrix} A_{k-1} & \mathbf{b} \\ \mathbf{c}^T & a_{kk} \end{bmatrix} = \begin{bmatrix} L_{k-1} & \mathbf{0} \\ \mathbf{m}^T & 1 \end{bmatrix} \begin{bmatrix} U_{k-1} & \mathbf{u} \\ \mathbf{0} & u_{kk} \end{bmatrix}$$

provided $L_{k-1}\mathbf{u} = \mathbf{b}$, $\mathbf{m}^T U_{k-1} = \mathbf{c}^T$ and $\mathbf{m}^T \mathbf{u} + u_{kk} = a_{kk}$, \mathbf{m} and \mathbf{u} being column vectors with $k-1$ components.



Since determinant of L_{k-1} times determinant of U_{k-1} is equal to determinant of A_{k-1} , because the product of two matrices is equal to the product of the determinants and since we know the determinant of A_{k-1} is not equal to 0 it; obviously, means that both U_{k-1} and L_{k-1} have non zero determinants since the product of two of these two numbers determinant of L_{k-1} and determinant of U_{k-1} is greater than 0, it is obvious that none of this individual numbers can be 0. So, each of these matrices L_{k-1} and U_{k-1} have positive determinant, which means they are non singular and they can be inverted.

Thus, then we can then if we can write $A_{k-1} \mathbf{b} \mathbf{c}^T a_{kk}$ has L_{k-1}

zero m transpose one times $U_{k-1} u_0 u_k k$ note the form of these matrices on the right hand side. The first matrix is of the form of a lower triangular matrix, because all the elements above the principal diagonal as 0 while the second element on the right hand side is in as an upper triangular matrix, because all the elements below the principal diagonal as 0.

So, we are saying that if A_{k-1} has an LU decomposition then we can write A_k in terms of the product of these two matrices provided that $L_{k-1} u$ is equal to b basically L_{k-1} operating on this row, $L_{k-1} u$ operating on this row $u u k$. So, basically $L_{k-1} u$ is equal to b , m transpose U_{k-1} equal to c transpose. So, basically it is this row operating on this column gives me c transpose, and m transpose u plus $u k k$ is equal to $a k k$. So, if these conditions are satisfied then we can write this matrix $a k a k$ in terms of two a lower in terms of a lower triangular and a upper triangular matrix, but


(Refer Slide Time: 25:24)

LU Decomposition

- Since L_{k-1} and U_{k-1} are non-singular u and m are uniquely determined by the triangular systems:

$$L_{k-1}u = b; \quad U_{k-1}m = c$$

- Once u and m have been uniquely determined, u_{kk} can be determined uniquely from $a_{kk} - m^T u$
- Then if the decomposition $A_{k-1} = L_{k-1}U_{k-1}$ exists then the decomposition $A_k = L_k U_k$ also exists and is unique.



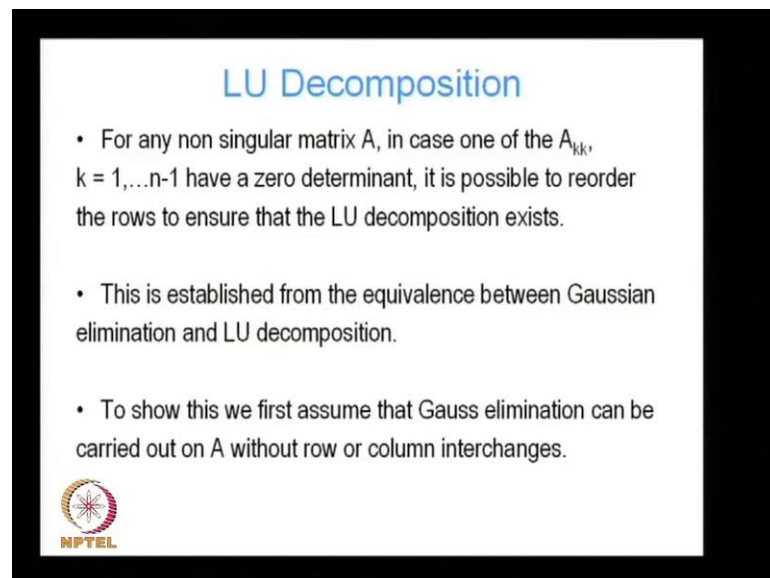
Since we now that L_{k-1} and U_{k-1} are non-singular; that means, that if we try to solve this equation $L_{k-1} u$ equal to b or for that matrix this equation m transpose U_{k-1} equal to c transpose, since L_{k-1} is non singular, U_{k-1} is non singular; that means, that we can always solve this system and get the

appropriate values for m and u .

So, once we have determined u and m uniquely, u_k can be uniquely determined from $a_{k, k-m} - u_k$. Thus, if the decomposition A_{k-1} is equal to $L_{k-1} U_{k-1}$ exists then the decomposition A_k is equal to $L_k U_k$ also exists and is unique. So, what is the meaning of this? We have seen that for $k=1$ it is just scalar right and that the submatrix formed by the intersection of the first row and the first column and for that submatrix we have shown that an LU decomposition trivially exists with the L component equal to 1 and the U component just equal to A_{11} itself.


So, since the LU decomposition exists for $k=1$ and we have shown that if the LU decomposition exists for $k-1$ it also exists for k . So, if it exists for $k=1$, it exists for $k=2$ since it exists for $k=2$, it also exists for $k=3$ and so on so forth. So, if the condition the determinant A_k is greater than 0 is satisfied then the LU decomposition exists for any matrix A of size n by n .

(Refer Slide Time: 27:37)



LU Decomposition

- For any non-singular matrix A , in case one of the A_{kk} , $k = 1, \dots, n-1$ have a zero determinant, it is possible to reorder the rows to ensure that the LU decomposition exists.
- This is established from the equivalence between Gaussian elimination and LU decomposition.
- To show this we first assume that Gauss elimination can be carried out on A without row or column interchanges.


NPTEL

For any non-singular matrix A in case one of the A_{kk} , k equal to 1 through $n-1$, L U have a zero determinant, it is possible to reorder the rows to ensure that the LU decomposition exists right? Why? Because what we saying is that the LU decomposition is

going to exist is each of those sub matrices A_k have a positive determinant now if it. So, happen that it 11 matrix A which is non singular, the non singular matrix A one of the k by k sub matrices suppose of some order have a zero determinant then it is possible to reorder the matrix to reorder the rows to ensure that k by k sub matrix no longer has a zero determinant that is it has a positive determinant. So, if they can basically by interchanging the rows we can ensure that for any non-singular matrix, all the sub matrices $A_{k \times k}$ equal to 1 through n minus 1 have a non zero determinant, which means that the $L U$ decomposition is going to exist for that matrix and each of these L and U matrices are going to be unique.

How can we show this well this can be shown from the equivalence we can show that there is an equivalence between Gaussian elimination and $L U$ decomposition that is, if we perform Gaussian elimination on a matrix without any row or column interchanges we can we are going to get very close to the $L U$ decomposition bearing a minor modification. So, basically what we are saying is that if we take a matrix n by n and suppose we can perform Gaussian elimination on that matrix without performing any row or column interchanges in that case it is possible to recover the $L U$ decomposition of A with just a minor modification.


(Refer Slide Time: 29:54)

Equivalence with LU

- Next we consider the evolution of a certain element a_{ij} during the elimination.
- If a_{ij} is on or above the principal diagonal i.e. i is less than or equal to j , then a_{ij} stops evolving, i.e. gets frozen at its value after the i^{th} step of the elimination:

$$a_{ij}^{(i)} = a_{ij}^{(i+1)} \dots a_{ij}^{(n)}$$
- If a_{ij} is below the principal diagonal i.e. $i > j$ then a_{ij} becomes zero after the j^{th} step of the elimination:

$$a_{ij}^{(j+1)} = a_{ij}^{(j+2)} \dots a_{ij}^{(n)} = 0$$




we want to show the equivalence of LU decomposition with Gaussian elimination in order to do this we consider the evolution of a certain element a_{ij} in my original matrix during Gaussian elimination. if a_{ij} is on or above the principal diagonal that is i is less than or equal to j that is the column index is always higher than the row index in that case a_{ij} stops evolving that is it gets frozen at its value after the i th step of the elimination, because after the i th step that element is it has reached its final value, it does not change any further.

So, $a_{ij}^{(i)}$ is equal to $a_{ij}^{(i-1)}$ plus 1 through $a_{ij}^{(n)}$, where the superscript now denotes the various steps in the Gaussian elimination. Similarly, if a_{ij} is below the principal diagonal that is if i is greater than j that is its row index is greater than the value of the column index then a_{ij} become 0 after the j th step of the elimination, because recall at the end of the Gaussian elimination what are we going to get an upper triangular matrix, which means that the elements below the principal diagonal are all going to be 0 and any a_{ij} reaches its final value 0 value after the j th step of the elimination. So, $a_{ij}^{(j+1)}$ is equal to 0 and it is going to remain 0 for the $j+2$ through $j+3$ through n th step.

(Refer Slide Time: 31:52)

Equivalence with LU

- This means that any a_{ij} is only transformed for the first r steps in the elimination where $r = \min(i-1, j)$ following which its value is frozen.
- The transformation rule for Gaussian elimination, we recall is: $a_{ij}^{(k+1)} = a_{ij}^{(k)} - m_{ik}a_{kj}^{(k)}$
- Summing the values of a_{ij} over $k=1,2,\dots,r$, we get:

$$\sum_{k=1}^r a_{ij}^{(k+1)} - \sum_{k=1}^r a_{ij}^{(k)} = -\sum_{k=1}^r m_{ik}a_{kj}^{(k)}$$


This means that any a_{ij} is only transformed for the first r steps in the elimination, where

r is the smaller of $i - 1$ and $j - i$ being the row index, and $j - i$ being the column index following, which its value is frozen. So, basically we are combining these two statements that if a_{ij} is on or above the principal diagonal, it stops evolving after the i th step of the elimination, and if a_{ij} is below the principal diagonal it stops evolving after the j th step of the elimination and noting that i is the row index and j is the column index we are combining these two statements together and making this additional this new statement that a_{ij} only changes for the first r steps in the elimination, where r is the smaller of $i - 1$ and $j - i$ following, which its value is frozen.


(Refer Slide Time: 32:18)

Equivalence with LU

- Next we consider the evolution of a certain element a_{ij} during the elimination.
- If a_{ij} is on or above the principal diagonal i.e. $i \leq j$, then a_{ij} stops evolving, i.e. gets frozen at its value after the i th step of the elimination:

$$a_{ij}^{(i)} = a_{ij}^{(i+1)} \dots a_{ij}^{(n)}$$
- If a_{ij} is below the principal diagonal i.e. $i > j$ then a_{ij} becomes zero after the j th step of the elimination:

$$a_{ij}^{(j+1)} = a_{ij}^{(j+2)} \dots a_{ij}^{(n)} = 0$$




Let us go back to the transformation rule for Gaussian elimination, which is let us recall $a_{ik} + 1$ is equal to a_{ik} minus the multiplied m_{ik} times a_{kj} with a multiplied m_{ik} if we recall is nothing, but a_{ki} divided by a_{kk} .

(Refer Slide Time: 33:35)

Equivalence with LU

- This means that any a_{ij} is only transformed for the first r steps in the elimination where $r = \min(i-1, j)$ following which its value is frozen.
- The transformation rule for Gaussian elimination, we recall is:
$$a_{ij}^{(k+1)} = a_{ij}^{(k)} - m_{ik} a_{kj}^{(k)}$$
- Summing the values of a_{ij} over $k=1,2,\dots,r$, we get:

$$\sum_{k=1}^r a_{ij}^{(k+1)} - \sum_{k=1}^r a_{ij}^{(k)} = - \sum_{k=1}^r m_{ik} a_{kj}^{(k)}$$


So, let us look at this equation and we sum the values over k equal to 1 through r . So, apply a summation on both sides for k equal to 1 through r , and then we. So, basically we are just taking this equation and summing it for k equal to 1 to r to get this expression nothing changes we have just added a summation sign in front and we have performing the summation for k equal to 1 to r why are we performing summations for up to r only, because we know that after r when k reaches, when k goes beyond r the elements do not change at all. So, we are performing the summation for the first r steps of the Gaussian elimination.

(Refer Slide Time: 34:20)

Equivalence with LU


- Cancellation of terms on the left hand side results in:

$$a_{ij}^{(r+1)} - a_{ij} = - \sum_{k=1}^r m_{ik} a_{kj}^{(k)}$$
- Since $a_{ij}^{(r+1)} = 0$ for $i > j$,

$$a_{ij} = \sum_{k=1}^j m_{ik} a_{kj}^{(k)}, \text{ for } i > j$$
- And since for $i \leq j$, $a_{ij}^{(r+1)} = a_{ij}^{(i)}$ then

$$a_{ij} = a_{ij}^{(i)} + \sum_{k=1}^{i-1} m_{ik} a_{kj}^{(k)}$$

$$= \sum_{k=1}^j m_{ik} a_{kj}^{(k)} \quad [\text{if } m_{ii} = 1 \forall i = 1, 2, \dots, n]$$



If we cancel the terms on the left hand side how can we cancel the terms, if we look at the left hand side you can see that this minus this right. So, all the terms will cancel out except the r contribution from this term $a_{ij}^{(r+1)}$ and the k equal to 1 contribution for this term, which is going to be $a_{ij}^{(1)}$ otherwise for instance for k equal to 1 here we are going to get $a_{ij}^{(2)}$ and this is going to cancel out from the $a_{ij}^{(2)}$ contribution from the second term. So, only terms which are going to survive are going to be $a_{ij}^{(r+1)}$ and $a_{ij}^{(1)}$. So, that gives me my left hand side the right hand side remains identical, which is equal to minus k equal to minus summation k equal to 1 through r $m_{ik} a_{kj}$.

Since $a_{ij}^{(r+1)}$ is equal to 0 for i greater than j recall that all the terms, which are below the principal diagonal are going to become zero at the end of Gaussian elimination. So, when r is when for $r+1$ $a_{ij}^{(r+1)}$ is going to be 0 for i greater than j . So, we can write we can get rid of the $a_{ij}^{(r+1)}$ on the left hand side in the first equation, and we can write this equation as a_{ij} is equal to summation of over k equal to 1 to j of $m_{ik} a_{kj}^{(k)}$ for i greater than j again let us recall that for i lesser than or equal to j that is for elements above the principal diagonal $a_{ij}^{(r+1)}$ is equal to $a_{ij}^{(i)}$ that is it gets frozen at its value at $a_{ij}^{(i)}$ right.


(Refer Slide Time: 37:14)

Equivalence with LU

- The two expressions can be combined to give:

$$a_{ij} = \sum_{k=1}^p m_{ik} a_{kj}^{(k)}, \quad p = \min(i, j) \quad (*)$$

- Suppose we define a matrix L with components m_{ik} . It is clear that m_{ik} only defines the components of L at or below the principal diagonal.
- If we define the elements of L above the principal diagonal to be zero, then L becomes a lower triangular matrix.



Then we can write a_{ij} is equal to a_{ij} plus $\sum_{k=1}^{i-1} m_{ik} a_{kj}^{(k)}$, which we can combine these two terms together and write it as $\sum_{k=1}^i m_{ik} a_{kj}^{(k)}$, if we assume that for $a_{ii} = 1$. So, we are putting these two terms together and writing it within the summation, and extending the summation index from $i-1$ to i . So, we can combine these two expressions we can combine this expression and that expression right we can combine this expression, and that expression to get this expression a_{ij} is equal to $\sum_{k=1}^p m_{ik} a_{kj}^{(k)}$, where p is the smaller of i and j . So, p is equal to j in this case right and p is equal to i in this case. So, we add we are combining these two expressions together to get this expression.

From this expression, if we look at the contributions of m_{ik} it is clear that m_{ik} is we are only using the values of m_{ik} that are, if we consider m_{ik} to be representing a matrix m , m_{ik} being the components of a matrix n , it is clear from this expression that we are using only the components of m , which are at or below the principal diagonal why because m_{ik} , k is summed from k goes from one to p and p is again the minimum of i and j . So, j cannot exceed i right. So, it is p is equal to minimum of i and j . So, that


the second index here k , which is denoting the column index cannot be more than the row index so; that means, that since the column index cannot be more than the row index; that means, we are only considering the elements of m_{ik} , which are at or below the principal diagonal. So, if we take these elements m_{ik} and then on that elements above the principal diagonal we make those elements zero then this matrix m becomes a lower triangular matrix and we can denote it as L , which is the notation for a lower triangular matrix.

Similarly, it is clear that a_{kj} define the elements at and above the principal diagonal. Let us consider the term a_{kj} and it is clear that k cannot be greater than j as k is being summed from one to p and k cannot be greater than p cannot be greater than j right. So, basically the first index the row index cannot be greater than the column index; that means, that we are only concerned with that a_{kj} , which are at or above the principal diagonal. So, again if we assume that the elements of a_{kj} below the principal diagonal are 0 in that case we can write a_{kj} as an upper triangular matrix.

(Refer Slide Time: 40:38)

Equivalence with LU

- Similarly it is clear that $a_{kj}^{(k)}$ define the elements at and above the principal diagonal of a matrix, say U
- Defining the elements below the principal diagonal of this matrix to be zero (since they are undefined), it is clear that U is an upper triangular matrix.
- Hence, we can rewrite (*) as $A = LU$ where the elements of L are the multipliers and U is the final triangular matrix obtained after Gaussian elimination.



Similarly, it is clear that a_{kj} define the elements at and above the principal diagonals of a matrix, and if we defined the elements below the principal diagonal of this matrix to be zero, it is clear that that U , which we have used to denote the matrix


comprising the components a_{kj} is an upper triangular matrix hence we can rewrite our previous equation a_{ij} equal to summation k equal to one to p $m_{ik} a_{kj}$ as the product of a lower triangular and an upper triangular matrix, and since recall the this expression that we have obtained from usual from Gaussian elimination we did not do anything special to get here right. So, this is what we get after gaussian elimination and we can see that is can be written as in terms of the product of an upper triangular, and lower triangular matrix provided that in the Gaussian elimination in the normal Gaussian elimination we just to out the upper triangular part, but now in the lower part below the principal diagonal, which individual Gaussian elimination is zero.

(Refer Slide Time: 42:10)

Equivalence with LU

- The two expressions can be combined to give:

$$a_{ij} = \sum_{k=1}^p m_{ik} a_{kj}^{(k)}, \quad p = \min(i, j) \quad (*)$$
- Suppose we define a matrix L with components m_{ik} . It is clear that m_{ik} only defines the components of L at or below the principal diagonal.
- If we define the elements of L above the principal diagonal to be zero, then L becomes a lower triangular matrix.



If we instead of making a_{ij} zero we store these multipliers m_{ik} then Gaussian elimination we are going to recover our LU decomposition bearing the trivial diagonal elements of L, which are always equal to 1.


(Refer Slide Time: 42:33)

Equivalence with LU

- Thus if we perform Gaussian elimination on a matrix A , we automatically get its LU decomposition also.

- Typically, the elements below the principal diagonal of A are used to store the multipliers (other than the trivial diagonal elements of L) while the elements on or above the principal diagonal are used to store the upper triangular matrix.

- Thus no additional storage is required.




NPTEL

Thus, if we perform Gaussian elimination on a matrix A , we automatically get its LU decomposition also typically the elements below the principal diagonal of A are used to store the multipliers other than the trivial diagonal elements of L while the elements on or above the principal diagonal are used to store the usual upper triangular matrix of Gaussian obtain that the end of Gaussian elimination thus LU decomposition does not required any additional storage. So, basically if you over write are original matrix after storing the upper triangular elements above or below the above the principal at above the principal diagonal and used the elements below the principal diagonal to store the multipliers.

(Refer Slide Time: 43:35)

Equivalence with LU

- Recall that if the $k \times k$ matrix formed by the first k rows and k columns of A , A_k , has a positive definite determinant, then we can write $A_k = L_k U_k$ where L_k and U_k are lower and upper triangular matrices.
- Also $\det(A_k) = \det(L_k) \det(U_k)$.
- But $\det(L_k) = 1$ and $\det(U_k) = a_{11}^{(k)} a_{22}^{(k)} a_{33}^{(k)} \dots a_{kk}^{(k)}$ which is the product of the first k pivots.



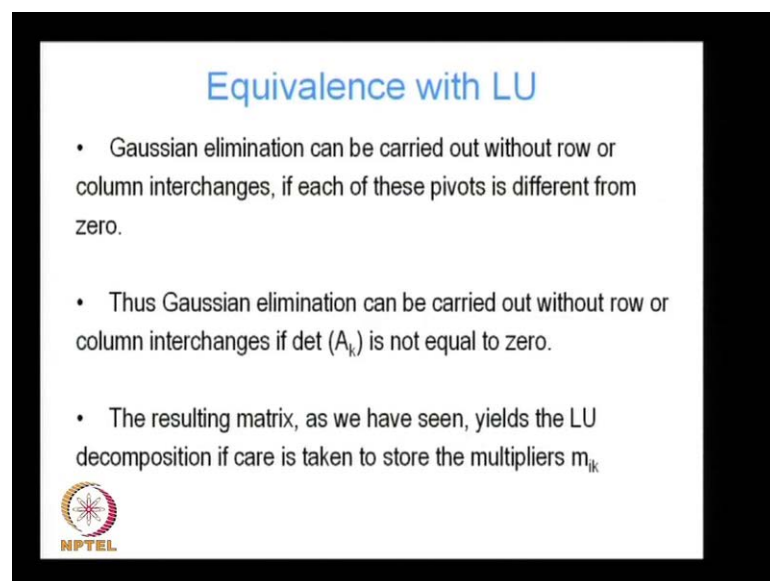
We are automatically going to get our LU decomposition recall that if the k by k matrix formed by the first k rows and k columns of A , A_k has a positive determinant then we can write A_k is equal to $L_k U_k$, where L_k and U_k are lower and upper triangular matrix also let us remember the determinant of A_k is equal to determinant of L_k times, determinant of U_k the product of the determinants is equal to the determinant of the products.

But we have seen that the determinant of the L_k is equal to 1 why is that, because all the diagonal elements of L are identically equal to 1 we have seen in a previous lecture that the determinant of a triangular matrix is nothing, but the product of its diagonal elements. Since all the diagonal elements are one determinant of L_k is equal to 1 and determinant of U_k is again the product of its diagonal elements and its diagonal elements a_{11} a_{22} a_{33} etcetera are nothing, but the pivots in the Gaussian elimination. So, the determinant of U_k is nothing that the, but the product of the first k pivots.

.So, Gaussian elimination can be carried out without row or column interchanges, if each of those pivots is different from zero. So, basically each of these pivots is different from zero then determinant of U_k is going to be non zero always determinant of A_k is refer


for is also going to be always non zero, because determinant of L_k is always going to be 1 and determinant of U_k is always going to be positive. Since determinant of A_k is always going to be positive what does that mean; that means, this matrix is going to be positive definite, and since it is positive definite it is for all if this determinant is not greater than 0 for all case in that matrix is positive definite, and in that case we can perform Gaussian elimination without the need to perform any pivoting.

(Refer Slide Time: 45:51)



Equivalence with LU

- Gaussian elimination can be carried out without row or column interchanges, if each of these pivots is different from zero.
- Thus Gaussian elimination can be carried out without row or column interchanges if $\det(A_k)$ is not equal to zero.
- The resulting matrix, as we have seen, yields the LU decomposition if care is taken to store the multipliers m_{ik}


NPTEL

So, Gaussian elimination can be carried on carried out without row or column interchanges, if each of these pivot elements is different from zero each of these pivot elements different from zero means U_k as positive determinant, L_k by definition has positive determinant, the A_k always has positive determinant thus Gaussian elimination can be carried out without row or column interchanges, if determinant of A_k is not equal to 0 resultant matrix as we have seen yields the L U decomposition, if care is taken to store the multipliers m_{ik} below the principal diagonal.

(Refer Slide Time: 46:42)

Positive Definite matrices

- If one or more of the pivots become very small or are equal to zero, partial pivoting becomes necessary for stability.
- Then at the end of Gaussian elimination we get $LU=A^*$ where A^* is the matrix which results if the row interchanges are performed in the order on matrix A .
- For a positive definite matrix, by definition, each of the $k \times k$ matrices, $k = 1 \dots n$ are assured to have $\det(A_k) > 0$

Hence the pivots $a_{11}^{(1)}, a_{22}^{(2)}, a_{33}^{(3)}, \dots, a_{nn}^{(n)}$ are each non-zero:
Gaussian elimination can be carried out with no interchanges

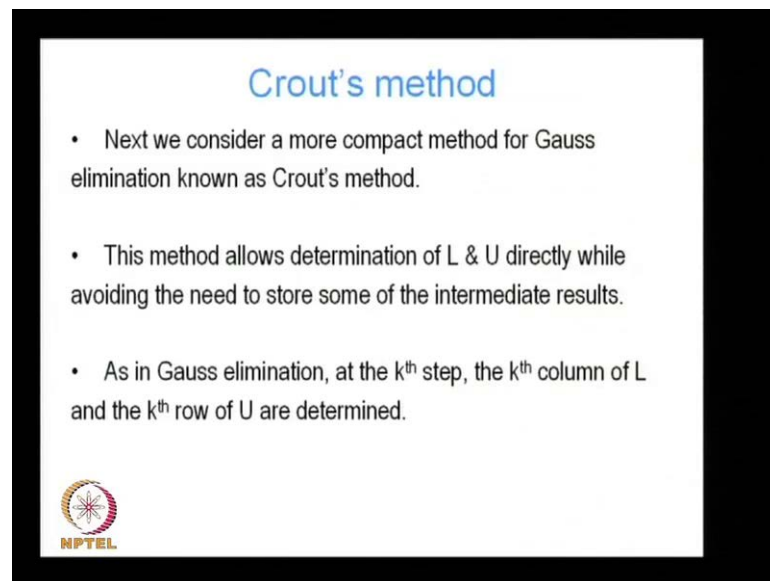
If one or more of the pivots become very small or are equal to 0 partial pivoting becomes necessary for stability we have seen that right, if any of the pivots is not required only of each of the these pivots is greater than 0; however, if one of the pivots becomes very small or actually becomes 0 then we have to do pivoting right. It also means that the matrix is no longer positive definite right, then at the end of if we if it. So, happens that the matrix is not positive definite. And we have to perform pivoting then at the end of Gaussian elimination, if we take care to store the multipliers below the principal diagonal we are still going to get an L U decomposition, but that L U decomposition that we are going to get is not going to be the L U decomposition of the original matrix A . It is going to be the L U decomposition of another matrix A^* , where A^* has been obtained by performing the same row interchanges performed on A .

So, let me repeat. So, in while we performing Gaussian elimination on A . We found that in order to do in order to make maintain this stability of this solution we have to do sum pivoting. So, we entertain certain rows of A right, and then at the end of Gaussian elimination we to care to store the multiplies below the principal diagonals. So, we got a L U decomposition, but the L U decomposition we got is not the L U decomposition of my original matrix A . It is the L U decomposition of another matrix A^* , which is not which we which can be obtained by performing the same row interchanges, which we

performed in the course of Gaussian elimination on my original matrix A .


However, for a positive definite matrix by definition each of my k by k sub matrices k through n are assured to have positive determinant therefore, the pivots a_{11} a_{22} a_{33} a_{nn} are each non-zero and therefore, Gaussian elimination can be performed with no interchanges what does it mean; that means, that if we if while performing Gaussian elimination, we take care to store the multipliers at locations below the principal diagonal then at the end of Gaussian elimination are going to get an $L U$ decomposition, and that $L U$ decomposition is going to be the $L U$ decomposition of my original matrix A .

(Refer Slide Time: 49:32)



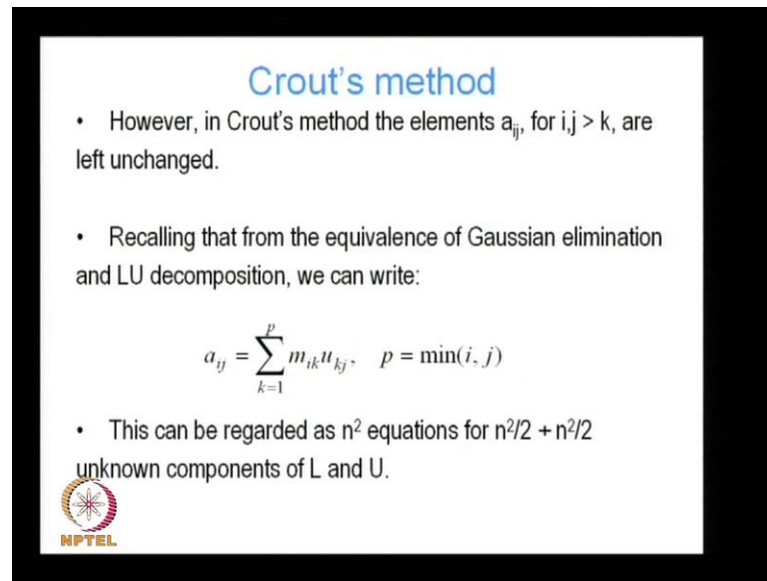
Crout's method

- Next we consider a more compact method for Gauss elimination known as Crout's method.
- This method allows determination of L & U directly while avoiding the need to store some of the intermediate results.
- As in Gauss elimination, at the k^{th} step, the k^{th} column of L and the k^{th} row of U are determined.

 NPTEL

So, next we compare we consider a more compact method for Gaussian elimination this is known as crout's method. This method allows determination of L and U directly while avoiding the need to store some of the intermediate results as in the gauss elimination at the k^{th} step. We compute the k^{th} column of L and the k^{th} row of U .

(Refer Slide Time: 50:04)




Crout's method

- However, in Crout's method the elements a_{ij} , for $i, j > k$, are left unchanged.
- Recalling that from the equivalence of Gaussian elimination and LU decomposition, we can write:

$$a_{ij} = \sum_{k=1}^p m_{ik}u_{kj}, \quad p = \min(i, j)$$

- This can be regarded as n^2 equations for $n^2/2 + n^2/2$ unknown components of L and U.



However, in crout's method the elements a_{ij} for i, j greater than k are left unchanged how would does that happen while to see how that happens let us recall our equation for Gaussian elimination in terms of L U components, which we have obtain just little while earlier right, and which gave as basically the equivalence between Gaussian elimination and L U decomposition that is recalled that equation which says a_{ij} is equal to product of $m_{ik}u_{kj}$ summed over k is equal to 1 to p , where p is the smaller of i and j . So, it is smaller of the column, if the row and the column index of a_{ij} .

We can think of this equation as n square equations, because i is going to vary from 1 to n , j is going to vary from 1 to n . So, they are going to be n square terms rights. So, this is basically we can think of this as n square equations for the unknowns m and u and we remember that m and u are the non zero components of lower and upper triangular matrices. So, m and u have each n square by 2 terms. So, m has n square by 2 terms, u has n square by 2 terms. So, the total number of unknown is n square by 2 plus n square by 2. So, we can think of this as n square equations for n square unknowns, where by unknowns are m and u , which are the components of the lower and upper triangular matrix. So, we can think of this equation as except of n square equations for determining the unknown coefficient unknown components of my lower and upper triangular matrix.

(Refer Slide Time: 52:11)


Crout's method

- For the k^{th} step, the following equations can then be used to determine the k^{th} row of U and the k^{th} column of L:

$$a_{kj} = \sum_{p=1}^k m_{kp} u_{pj}, \quad j \geq k \qquad a_{ik} = \sum_{p=1}^k m_{ip} u_{pk}, \quad i > k$$

- Putting $u_{kk} = 1, k = 1, \dots, n$, in the above equations, we can write:

$$u_{kj} = \frac{a_{kj} - \sum_{p=1}^{k-1} m_{kp} u_{pj}}{m_{kk}}, \quad j = k, k+1, \dots, n$$

$$m_{ik} = a_{ik} - \sum_{p=1}^{k-1} m_{ip} u_{pk}, \quad i = k+1, k+2, \dots, n$$


For the k^{th} step the following equations can then be used to determine the k^{th} row of U and the k^{th} column of L. So, basically I am rewriting those same equations, but once I am assuming that j is greater than or equal to k that is I am trying to find a k, j such that j is greater than or equal to k . So, basically I am finding the components, which are above the principal diagonal right. Since j is greater than k the column index is more than the row index. So, I am looking at terms above the principal diagonal and that I can find by using my this equation, but now the summation has changed in the limit of the summation has changed from p to k why is that, because of this condition the j must be greater than or equal to k , and this condition that p is the minimum of i and j .

Similarly, a_{ik} , I can obtain from the same from the previous equation, but now I am considering only the I am trying to find the k^{th} columns of L hence because of that i is greater than k i is greater than k . So, I am using the same equation as before except that the limit of this sum is now k right, the limit of the sum is now k simply, because i is greater than k and let us recall from our previous equation p is the smaller of i and j and p is the minimum of i and j , and since i is greater than k , p is equal to k right.

So, we can use we can. So, now, splitting the previous equation into two parts and we will continue next time with this discussion and show that how it is using this equations.

It is possible to write u_{k+1} and m_{k+1} in terms of the previous. So, we can these equations have this from the crout's method is useful, because you can see these u_{k+1} and m_{k+1} . It compute u_{k+1} and m_{k+1} , and only taking summing terms up to k minus 1 right. So, I am only using up known term that is terms, which are known up to the k minus 1 th step we will continue our discussion with crout's of crout's method in our next lecture.

Thank you very much.