

**Elementary Numerical Analysis**  
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**Lecture No. # 17**  
**Gauss Elimination**

Last time we have seen that, when we consider numerical differentiation, so when we try to approximate  $f'(a)$  by derivative of an interpolating polynomial, then there is some problem which we face. So, when we go on reducing value of  $h$ , then there comes a stage when instead of the error being decreasing, it starts increasing and this phenomena is because the computations which we do these are done in finite precision. So, a number is represented on a computer and there is some round off error. Now, this problem does not come into picture when we consider numerical integration. So, I want to quickly explain the difference between numerical differentiation and numerical integration using a composite rule.

I am going to explain it for the **derivative** first derivative  $f'(a)$  and let us look at central difference formula, that means,  $f'(a)$  we are going to approximate it by  $\frac{f(a+h) - f(a-h)}{2h}$ .

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Numerical Differentiation

$$f'(a) = \frac{f(a+h) - f(a-h)}{2h} - \frac{h^2}{6} f'''(\xi)$$

$$f'_{\text{comp}} = \frac{f(a+h) + E_1 - \{f(a-h) + E_2\}}{2h} \quad E_1, E_2: \text{round-off errors}$$

$$f'(a) = f'_{\text{comp}} + \frac{E_2 - E_1}{2h} - \frac{h^2}{6} f'''(\xi)$$

↓  
does not decrease

So, we have  $f'(a)$  to be equal to  $\frac{f(a+h) - f(a-h)}{2h} - \frac{h^2}{6} f'''(\xi)$ . So, this formula tells us that, if you do exact computations, then as  $h$  tends to 0, the error will tend to 0 and the quotient  $\frac{f(a+h) - f(a-h)}{2h}$  will tend to  $f'(a)$ .

In practice, what happens is  $f(a+h)$  is not represented exactly. So, instead of that, we have  $f(a+h) + E_1$  minus  $\{f(a-h) + E_2\}$  by  $2h$ . So, if I substitute for  $\frac{f(a+h) - f(a-h)}{2h}$  to be equal to  $f'_{\text{comp}} + \frac{E_2 - E_1}{2h} - \frac{h^2}{6} f'''(\xi)$  in this formula, what we get is  $f'(a)$ , this is our  $f'_{\text{comp}}$  plus term  $\frac{E_2 - E_1}{2h} - \frac{h^2}{6} f'''(\xi)$ .

So, thus our error consists of two parts: one part is the discretization error, which is  $-\frac{h^2}{6} f'''(\xi)$  and other error is  $\frac{E_2 - E_1}{2h}$ , which is because of the round off error. Now, there is no reason to expect that, the round off error  $E_1$  and  $E_2$ , they will cancel. So,  $E_2 - E_1$  this need not be equal to 0.

Then  $\frac{E_2 - E_1}{2h}$ , when you increase  $h$  or whether we are actually letting  $h$  to tend to 0. So, when you decrease  $h$ , there will come a stage when this factor  $\frac{E_2 - E_1}{2h}$ , this will start dominating the other factor, which is  $-\frac{h^2}{6} f'''(\xi)$ .

by 6 f triple dash of psi and that is why when you are doing numerical differentiation, there is going to be a limit to the accuracy which we attend.

Theoretically yes, as  $h$  tends to 0, error should tend to 0, but in practice it does not happen. After a certain stage when you go on reducing value of  $h$ , after a certain stage the round off errors they start dominating the total error and they go on increasing, because you are diving by a small number. Now, in case of numerical integration, there are also we are letting  $h$  to tend to 0, because there  $h$  was length of our subinterval. When you look at a composite numerical quadrature rule, we have our interval  $A b$ , we sub divide it into smaller intervals and on each subinterval, we apply some basic rule. So, this is how we construct, the composite rules and then as the number of subintervals increase,  $n$  tends to infinity or equivalently when the length of the subinterval  $h$ , which is  $b$  minus  $a$  by  $n$  that tends to 0, our numerical quadrature formula is going to give us better and better approximation of integral  $a$  to  $b$   $f(x) dx$ .

So, look at composite trapezoidal rule. So, you have integral  $a$  to  $b$   $f(x) dx$  is approximately equal to  $h$  by 2  $f(a) + f(b) + h$  times summation  $f(t_i)$ ;  $i$  goes from 1 to  $n$  minus 1 interior partition points. Now, each of the value  $f(t_i)$  and  $f(a)$  and  $f(b)$ , there is going to be some round off error, but here you are multiplying by  $h$ ; you are not diving by  $h$ .

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Numerical Integration

$$\int_a^b f(x) dx \approx \frac{h}{2}(f(a) + f(b)) + h \sum_{i=1}^{n-1} f(t_i) = T_n$$

$$T_n^{\text{comp.}} = T_n + \frac{h}{2}(E_0 + E_n) + h \sum_{i=1}^{n-1} E_i$$

Round-off error

So,  $T_n$  computed is going to be  $T_n$  the trapezoidal rule plus this round off error. So,  $E_0$  plus  $E_n$  and then you have got  $E_i$  and you are multiplying by a number  $h$ . So, this

makes a difference and you are going to get an approximate value of integral  $\int_a^b f(x) dx$  which is acceptable; there will be some part because of the round off errors, but that will not dominate the total error. So, we started with interpolating polynomials, we wrote down the divided difference form that allowed us to get an error formula and we integrated interpolating polynomial in order to get numerical quadrature rules. Differentiating this polynomial gives us a way to calculate approximate value of derivatives.

Now, we are going to start a new topic and that topic is solution of system of linear equations. So, we will have  $n$  equations in  $n$  unknowns; we are going to consider a square system. So,  $n$  equations in  $n$  unknowns, we will assume that the coefficient matrix is invertible, that means, our system is going to have a unique solution. So, that is our starting point.

Now, we want to solve this system; we are going to consider real numbers. So, all the quantities involved, they are all going to be real number. There is a classical way of finding a solution; so that is known as Cramer's rule. So, Cramer's rule is theoretically important; it is an elegant formula for calculating the solution, but it is going to be very expensive. So, in practice, one does not use Cramer's rule for finding solution of system of linear equations. Our starting point is going to be gauss elimination method, a simple method to describe.

So, this gauss elimination method, we will first describe, then we will show equivalence of gauss elimination method with LU decomposition of matrix  $A$ . What we will be interested in is the number of computations needed. So, we will calculate the numbers of operations needed in the gauss elimination method for solving system of linear equation. From LU decomposition for positive definite systems, we will show what is known as Cholesky decomposition, then we are also going to consider the conditioning of the matrix. So, for that we need to define what a norm of a matrix is and so on.

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System of linear equations

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

$Ax = b$ ,  $A = [a_{ij}]$  : coefficient matrix  
 $b = [b_1 \ b_2 \ \dots \ b_n]^T$  : Right Hand Side  
 $x = [x_1 \ x_2 \ \dots \ x_n]^T$  : unknown vector  
 $[A \ b]$  :  $n \times (n+1)$  : augmented matrix.

So, let us start with description of Gauss elimination method; so we have our system. So, the system is a  $1 \times 1$  plus a  $2 \times 2$  plus a  $1 \times n$  is equal to  $b_1$ , then the second equation is a  $2 \times 1$  plus a  $2 \times 2$  plus  $a_{2n}$  is equal to  $b_2$  and a  $n \times 1$  plus a  $n \times 2$  plus a  $n \times n$  is equal to  $b_n$ . The right side  $b_1 \ b_2 \ b_n$  that is given to us;  $a_{ij}$ 's they are also given. So, what is unknown is vector  $x$ . So,  $x_1, x_2, x_n$ , we want to find  $x_1, x_2, x_n$  which satisfy this system.

If you look at the powers of  $x$ 's, they are all equal to 1 and that is why it is known as a linear equation. This system in a compact form we write as  $Ax = b$ , where  $A$  is coefficient matrix  $a_{ij}$ ;  $i$  denotes the row index;  $j$  denotes the column index. So,  $A$  is going to be  $n$  by  $n$  coefficient matrix; our vector we denote by as column vectors. So, that is why  $b$  is equal to  $b_1 \ b_2 \ b_n^T$ , that means, transpose. So, this is a row vector and its transpose that is the right hand side;  $x$  is equal to  $x_1 \ x_2 \ x_n^T$  that is the unknown vector. So, this system is written as  $Ax = b$   $A$  is the coefficient matrix and if to the matrix  $A$ , we Add one more column which consists of  $b_1 \ b_2 \ b_n$ , then you get a matrix of size  $n$  rows and  $n + 1$  columns. So, that is known as the augmented matrix.

Now, we will assume that  $A$  is invertible matrix; if  $A$  is invertible,  $Ax = b$  whatever is the right hand side it is going to have unique solution; that unique solution will be given by  $x = A^{-1}b$ . Now, let me first describe Cramer's rule. So,

in Cramer's rule, we are assuming that A is invertible matrix that means determinant of A is not equal to 0.

If you want to calculate  $x_j$ , then what you have to do is, **look at the determine** look at the matrix A; in that matrix A, replace the  $j$ th column. So, the  $j$ th column of the matrix will be given by  $a_{1j}$ ,  $a_{2j}$ ,  $a_{nj}$ . So, replace this by right hand side  $b_1$ ,  $b_2$ ,  $b_n$  take the quotient that is going to be equal to  $x_j$ . So, it is a very nice formula for calculating the unknown vector  $x_1$ ,  $x_2$  up to  $x_n$ . So,  $x_j$  is determinant of this matrix with  $j$ th column replaced by  $b_1$ ,  $b_2$ ,  $b_n$  divided by determinant  $a$ ;  $j$  is equal to 1 to up to  $n$ .

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$Ax = b$ . If A is invertible, then the system has a unique solution:  $x = A^{-1}b$ .

Cramer's Rule

$$x_j = \frac{\begin{vmatrix} a_{11} & \dots & b_1 & \dots & a_{1n} \\ a_{21} & & b_2 & & a_{2n} \\ \vdots & & \vdots & & \vdots \\ a_{n1} & & b_n & & a_{nn} \end{vmatrix}}{\det A}, \quad j = 1, \dots, n.$$

= too expensive.

The problem with this formula is, it is too expensive. If you want to calculate determinant of A, where A is  $n$  by  $n$  matrix; you will need at least  $n$  factorial multiplications or plus  $n$  factorial additions slash subtraction and  $n$  factorial grows very fast with  $n$ . So, no matter how big your computer is, if you try to calculate determinant of A by traditional way, soon your computer memory will not be enough. So, this Cramer's rule is going to be too expensive to use in practice.

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Upper triangular system.

$$u_{11}x_1 + u_{12}x_2 + \dots + u_{1n}x_n = y_1$$

$$u_{22}x_2 + \dots + u_{2n}x_n = y_2$$

$$\dots$$

$$u_{n-1,n-1}x_{n-1} + u_{n-1,n}x_n = y_{n-1}$$

$$u_{nn}x_n = y_n$$

$\det(U) = u_{11}u_{22}\dots u_{nn} \neq 0 \Rightarrow u_{ii} \neq 0$

$$x_n = \frac{y_n}{u_{nn}}, \quad x_{n-1} = \frac{y_{n-1} - u_{n-1,n}x_n}{u_{n-1,n-1}}, \dots$$

So, now, suppose your system is upper triangular, that means, in the first equation all unknowns appear  $x_1 \times x_2 \times \dots \times x_n$ ; in the second equation, there is no  $x_1$ ; in  $n$  minus first equation what is coming into picture is only  $x_{n-1}$  and  $x_n$  and in the last equation you have got only  $x_n$ . The coefficient matrix invertible will mean determinant of  $U$  which is product of diagonal entries  $u_{11} u_{22} \dots u_{nn}$  this is not equal to 0. So, all  $u_{ii}$ 's they are not equal to 0, what I can do is start with  $x_n$ ;  $x_n$  is going to be equal to  $y_n$  upon  $u_{nn}$ , then having determined  $x_n$ , go to this equation; now  $x_n$  is known. So, take it on the other side and calculate  $x_{n-1}$  as  $y_{n-1} - u_{n-1,n}x_n$  divided by  $u_{n-1,n-1}$  and so on.

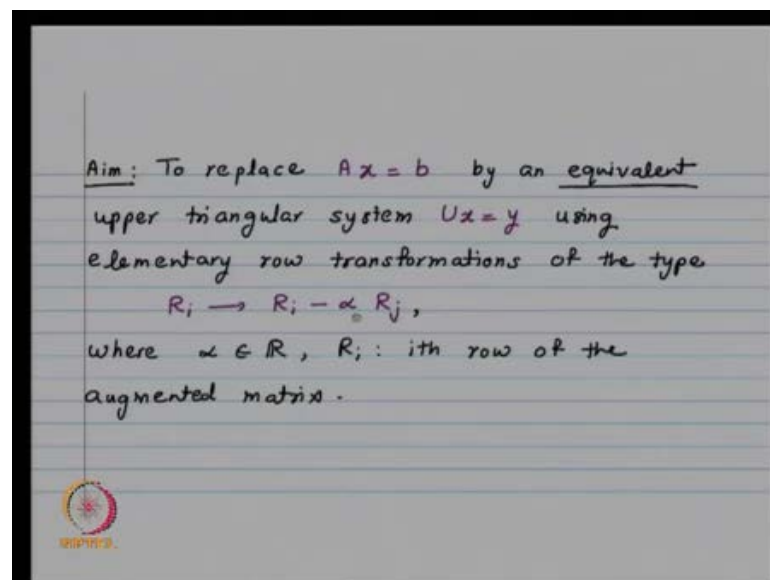
So, this is known as back substitution. So, if your coefficient matrix is upper triangular, then you can determine vector  $x$  in the order  $x_n, x_{n-1}, x_{n-2}$  and so on. So, our aim will be to replace our system  $Ax = b$  by an equivalent system  $Ux = y$  what I mean by equivalent is both the systems they should have the same solution. We are interested in solution of  $Ax = b$ . So, if you replace by another system, then the new system should have the same solution.

Because we are interested **in the system of original we are interested** in the solution of the original system not some other system. So, coefficient matrix  $A$ , we want to reduce it to upper triangular form. Now, whatever you will do for  $A$ , you will have to do on the right hand side, because we do not want to change our system. So, we are going to use

elementary row transformation, that means, what we can do is multiply a equation by a number alpha non zero number and subtract it from other equation; if you do this, you are going to get a system which is equivalent. Now, this equivalence we will show later on.

So, first we are going to describe the gauss elimination method, calculate the number of operations in it and then we will come back to equivalence. So, aim is to replace  $Ax = b$  by an equivalent upper triangular system  $Ux = y$ .

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Using elementary row transformations of the type  $R_i$  becomes  $R_i - \alpha R_j$ , that means, you are multiplying  $j$ th through by a constant alpha and subtracting it from  $R_i$ . So, this was our original one original  $i$ th equation and this is the new equation.



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Additional Assumption

$$\begin{bmatrix} a_{11} & a_{12} & \dots & a_{1k} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2k} & \dots & a_{2n} \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ a_{k1} & a_{k2} & \dots & a_{kk} & \dots & a_{kn} \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nk} & \dots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_k \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_k \\ \vdots \\ b_n \end{bmatrix}$$

$A_k$ : principal leading submatrix.  
Assumption:  $\det(A_k) \neq 0, k = 1, 2, \dots, n$

Now, we are going to make an additional assumption A is invertible, but we will look at principle leading sub matrix. So, that is formed by first k rows and first k columns. Our assumption is determinant  $A_k \neq 0$  for  $k = 1$  to up to  $n$ . When  $k$  is equal to  $n$ , that is determinant of  $A \neq 0$  that we have already assumed. Now, we are saying something more, what should happen is  $a_{11}$  should not be 0; determinant of  $a_{11}$   $a_{12}$   $a_{21}$   $a_{22}$  should not be 0 and then. So, on this is additional assumption.

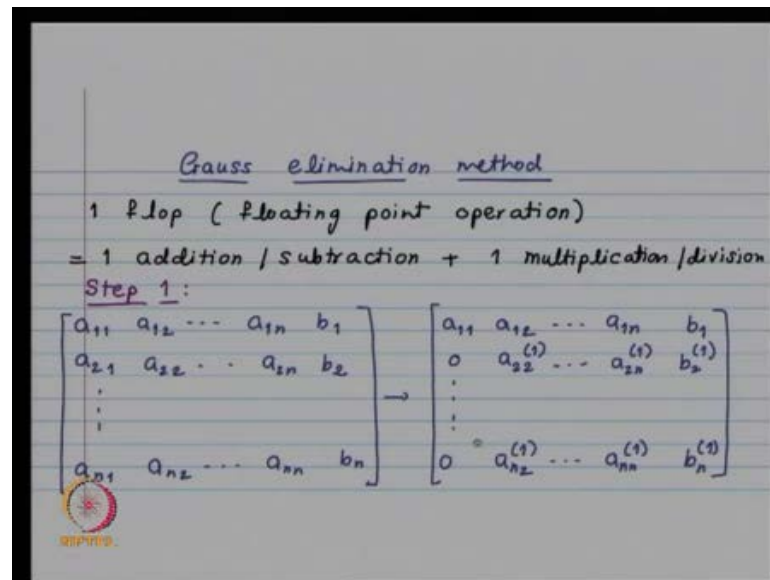
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$$A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \quad \det(A) = -1 \neq 0.$$
$$\det(A_1) = 0$$
$$\det(A_k) \neq 0, k = 1, \dots, n:$$

additional assumption.

Like let me look at example, say 2 by 2 matrix  $\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$  this matrix is such that determinant of A is equal to minus 1 which is not equal 0, but when I look at determinant of A 1 then that is equal to 0. So, this assumption that determinant of a k not equal to 0 for k is equal to 1 to up to n this is additional.

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Now, we are going to show that there is a class of matrices for which **the** this condition is satisfied and those are known as positive definite matrices. By one flop, because as I said we are going to calculate the number of computations, so 1 flop, where flops stands for floating point operation, it consists of 1 addition or subtraction plus 1 multiplication slash division; addition and subtraction, they are considered on par and multiplication slash division they are also considered on par.

Generally, total number of multiplications slash divisions is same as total number of additions slashes subtractions. So, 1 flop is going to consists of this 1 addition slash subtraction plus 1 multiplication slash division. In the first type of gauss elimination method what we want to do is, we want to look at the entries in the first column below the diagonal entry and we want to make all of them 0; this entry a to 1 can be made 0 by multiplying the first equation by a 2 1 by a 1 1 and then subtract it and then so on.

So, when you do that, the first row will remain as it is; all these entries they will become 0 and the entries in this sub matrix, they are all going to get modified. So, that is going to

be the first step; in the second step, we will work with this sub matrix; we will not touch the first row or the first column.

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$$\begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} & b_1 \\ a_{21} & a_{22} & \dots & a_{2n} & b_2 \\ \vdots & \vdots & & \vdots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} & b_n \end{bmatrix} \rightarrow \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} & b_1 \\ 0 & a_{22}^{(1)} & \dots & a_{2n}^{(1)} & b_2^{(1)} \\ \vdots & \vdots & & \vdots & \vdots \\ 0 & a_{n2}^{(1)} & \dots & a_{nn}^{(1)} & b_n^{(1)} \end{bmatrix}$$

$a_{11} \neq 0$  (why?), Define  $m_{i1} = \frac{a_{i1}}{a_{11}}, i = 2, \dots, n$   
 $R_i \rightarrow R_i - m_{i1} R_1, i = 2, \dots, n$   
 $a_{ij}^{(1)} = a_{ij} - m_{i1} a_{1j}, b_i^{(1)} = b_i - m_{i1} b_1, i = 2, \dots, n$   
 $j = 2, \dots, n$   
 $(n-1)n$  mult. +  $(n-1)n$  subtractions +  $n-1$  divisions

So, first we have to notice that  $a_{11}$  is not equal to 0 that is because we are assuming that determinant  $a$  is going to be not 0, next we define multipliers  $m_{i1}$  to be  $a_{i1}$  divided by  $a_{11}$   $i$  goes from 2 up to  $n$ .  $a_{11}$  is not equal to 0. So,  $m_{i1}$ 's they are well defined and  $i$ th row, from the  $i$ th row we will subtract first row multiplied by  $m_{i1}$  for  $i$  is equal to 2 up to  $n$ . We want to economize the computations. So, these 0's we will write down directly; we would not make the subtraction, because we have chosen the multipliers in such a manner that this operation will produce 0's in the first column below diagonal  $a_{ij}$  1, these will be given by  $a_{ij}$  original entry minus  $m_{i1}$  times the corresponding entry in the first column; the first suffix denotes the row. So, that is why you have got a and then,  $j$ . So,  $i$ th entry minus  $m_{i1}$  times corresponding entry in the first row.

You have to do it for the last column also. So, it is  $b_i$  is equal to  $b_i$  minus  $m_{i1} b_1$ ;  $i$  going from 1 to  $n$ ;  $j$  going from 2 to  $n$ . So, let us now calculate the number of operations. You are going to have two multiplications here and then one subtraction here; this you are going to do it for this whole square. So, that is going to be  $n$  minus 1 square, but you are also doing it here. So, it becomes  $n$  minus 1 into  $n$  multiplications plus those many subtractions. So,  $n$  minus 1 into  $n$  subtractions plus in order to calculate  $m_{i1}$ , you need to do this division. So, there are  $n$  minus 1 division.

So, these many computations are needed for the first step. In the second step, we are going to work with a matrix which has got  $n$  minus 1 rows and  $n$  columns and exactly the same computations. So, now, the number of operations will be obtained by replacing in this relation  $n$  by  $n$  minus 1.

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The slide contains the following handwritten text:

$$A_2 = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \rightarrow \begin{bmatrix} a_{11} & a_{12} \\ 0 & a_{22}^{(1)} \end{bmatrix}$$

$\det(A_2) = a_{11} a_{22}^{(1)} \Rightarrow a_{22}^{(1)} \neq 0$   
 $\neq 0$  by assumption

Perform similar operations on  $(n-1) \times n$  matrix.

$$[A : b] \rightarrow [A^{(1)} : b^{(1)}] \rightarrow [A^{(2)} : b^{(2)}]$$

Now, we have to confirm that our procedure is going to work for the sub matrix also; to start with our matrix, in our matrix  $A$ ,  $a_{11}$  is not 0, because you are assuming determinant of  $A_k$  not equal to 0 for  $k$  is equal to 1 to up to  $n$ . You do some operations, you get a new matrix; in the new matrix which consists of second, third up to  $n$ th row and second, third up to  $n$  plus first column, now the entry which we are going to divide by that is going to be  $a_{22}$  the modified entry. So, we have to make sure that  $a_{22}$  is not equal to 0. What we have done is, we have used elementary row transformation that means, we have multiplied a row by a fix real number and subtracted from other row. Now, this operation does not change the determinant of the matrix; the determinant of the matrix remains invariant. So, look at the 2 by 2 matrix which is formed by first 2 rows and first 2 columns. So, that is our capital  $A_2$ .

By assumption determinant  $A_2$  is not equal to 0 and this 2 by 2 matrix after the first stage of our gauss elimination method, it is transformed to the first row as it is,  $a_{11}$   $a_{12}$ ; second row 0; below the diagonal in the first column we have got 0 and then  $a_{22}$ . So,

determinant  $A_2$  will be  $a_{11}$  times  $a_{22}^{(1)}$ ;  $a_{11}$  is not 0;  $a_{22}^{(1)}$  also should not be 0, because determinant  $A_2$  is not equal to 0.

So that means our second step of gauss elimination method we can perform and then one uses the same argument that, you can do this process till your coefficient matrix  $A$  is reduced to an upper triangular form.

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The image shows a handwritten derivation on a slide. It starts with the matrix  $A_2 = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$  which is transformed into  $\begin{bmatrix} a_{11} & a_{12} \\ 0 & a_{22}^{(1)} \end{bmatrix}$ . Below this, it states  $\det(A_2) = a_{11} a_{22}^{(1)} \Rightarrow a_{22}^{(1)} \neq 0$ , with a note that  $a_{22}^{(1)}$  is not 0 by assumption. The next line says "Perform similar operations on  $(n-1) \times n$  matrix." and shows the transformation of an augmented matrix:  $[A : b] \rightarrow [A^{(1)} : b^{(1)}] \rightarrow [A^{(2)} : b^{(2)}]$ . There is a small logo in the bottom left corner of the slide.

So, our starting matrix was  $A$  augmented matrix; we transformed it to  $A_1 b_1$ , then using similar operations we have transformed it to  $A_2 b_2$  and so on. In order to do **do** this **this** transformation, we need the fact that  $a_{22}^{(1)}$  is not equal to 0.

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$$\begin{aligned}
 & [A : b] \rightarrow [A^{(1)} : b^{(1)}] \\
 & (n-1)n \text{ multi.} + (n-1)n \text{ subtractions} + n-1 \text{ divisions} \\
 & [A^{(1)} : b^{(1)}] \rightarrow [A^{(2)} : b^{(2)}] \\
 & (n-2)(n-1) \text{ multi.} + (n-2)(n-1) \text{ sub.} + n-2 \text{ divisions} \\
 & \text{Total number of operations : } [A : b] \rightarrow [U : y] \\
 & [(n-1)^2 + (n-2)^2 + \dots + 1] + [(n-1) + (n-2) + \dots + 1] \text{ flops} \\
 & + [(n-1) + (n-2) + \dots + 1] \text{ divisions} \\
 & = \frac{(n-1)n(2n-1)}{6} + \frac{(n-1)n}{2} \text{ flops} + \frac{(n-1)n}{2} \text{ divisions} \\
 & \qquad \qquad \qquad O\left(\frac{n^3}{3}\right)
 \end{aligned}$$

So, now, the number of computations, we have seen that for the first step of gauss elimination method, we had  $n$  minus 1 into  $n$  multiplications plus  $n$  minus 1 into  $n$  subtractions plus  $n$  minus 1 divisions. In the second step, you are performing a similar operation on a sub matrix with  $n$  minus 1 rows and  $n$  columns.

So, everywhere you have to replace by  $n$  by  $n$  minus 1. So, it will be  $n$  minus 2 into  $n$  minus 1 multiplications plus  $n$  minus 2 into  $n$  minus 1 subtractions plus  $n$  minus 1 division. So, when you consider total number of operations which are needed to reduce the system  $A b$  to a system  $U y$ , where  $U$  is upper triangular matrix, **it will be given by.** So, here write this  $n$  as  $n$  minus 1 plus 1. So, you will have  $n$  minus 1 square. So, you will have  $n$  minus square plus  $n$  minus 2 square plus 1 plus this  $n$  we are writing as  $n$  minus 1 plus 1. So, that is why you will have plus  $n$  minus 1 from here, then  $n$  minus 2 plus 1 and now I am writing as flops number of multiplications and subtractions, they are the same and 1 multiplication plus 1 subtraction is 1 flop.

So, that takes care of this and what is remaining is divisions. So, you have  $n$  minus 1 plus  $n$  minus 2 plus 1 division. Now, this is square of natural numbers; so we have got a formula. So, it is  $n$  minus 1 into  $n$  minus 1 by 6 plus sum of these will be given by  $n$  minus 1 into  $n$  by 2; so, these many flops plus  $n$  minus 1 into  $n$  by 2 divisions. Now, this gauss elimination method which I have described it is for solving big system of linear equations using computer. If you are trying to solve a 3 by 3 system by hand, it will not

matter which method you use, you can use Cramer's rule, but in practice one comes across big systems of equation; so then one has to worry about the number of operations. Now, we have calculated the number of operations; these number of operations, they are some constant times  $n^3$  plus another constant times  $n^2$  plus constant times  $n$  plus constant.

Now, when  $n$  is big what matters is, what will be coefficient of  $n^3$  like between  $n^3$  and  $n^2$ . For  $n$  begin off you can ignore what is  $n^2$  like, if your  $n$  is 10000, then  $n^3$  is going to be much bigger than  $n^2$ . So, the dominating factor becomes  $n^3$ , but you should retain the coefficient of  $n^3$ , because there is a difference between  $n^3$  and  $2n^3$  the  $2n^3$  is double the number of operations. So, in this gauss elimination method coefficient of  $n^3$  is 1 by 3. So, 1 says that you can reduce your system to a upper triangular system by doing the number of operations of order  $n^3$  by 3.

So, now, we have reduced our system to upper triangular system, but still it remains to find a solution we do this, because we want to solve  $Ax = b$ . So, now, let us calculate the number of operations in the back substitution.  $Ax = b$  is our original system; this we have reduced it to upper triangular system  $Ux = y$  by performing number of operations of the order in cube by 3 and now let us see what effort is needed for getting vector  $x_1 \times 2 \times n$  from  $Ux = y$ . So, that we are going to do it by back substitution.

$Ax = b$   $A$  is invertible matrix. So, determinant of  $A$  is not equal to 0. All the operations which we have used, those are elementary row operation  $R_i - \alpha R_j$ . So, this leaves the determinant invariant. So, determinant of  $U$  will be same as determinant of  $A$   $U$  is a upper triangular matrix; for an upper triangular matrix, determinant is product of the diagonal entries. So, you are going to have  $u_{11} u_{22} \dots u_{nn}$  as determinant of  $U$ ; determinant of  $U$  not equal to 0 will mean that all the diagonal entries  $u_{ii}$ , they are not equal to 0.

And we have already talked about the back substitution start with the last equation determine  $x_n$ , then go to  $n-1$  first equation determine  $x_{n-1}$  and so on.

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Back Substitution

$$Ax = b \rightarrow Ux = y, \quad U = [u_{ij}]$$

$$u_{ij} \neq 0, \quad i = 1, \dots, n, \quad u_{ij} = 0 \text{ if } i > j.$$

$$u_{ii} x_i + u_{i,i+1} x_{i+1} + \dots + u_{in} x_n = y_i \quad : \text{ith eq.}^n$$

$$x_i = \frac{y_i - \sum_{j=i+1}^n u_{ij} x_j}{u_{ii}}, \quad i = n, n-1, \dots, 1.$$

$$\text{Number of operations} = \sum_{i=1}^{n-1} (n-i) \text{ flops} + n \text{ divisions}$$

$$= \frac{(n-1)n}{2} \text{ flops} + n \text{ divisions} \quad O\left(\frac{n^2}{2}\right)$$

So, here  $U$  being an upper triangular matrix  $u_{ij}$  will be 0 if  $i$  bigger than  $j$  and hence  $i$ th equation is going to be of the form  $u_{ii} x_i + u_{i,i+1} x_{i+1} + \dots + u_{in} x_n = y_i$ . So, now,  $x_i$  will be equal to  $y_i$  minus summation  $j$  is equal to  $i+1$  to  $n$   $u_{ij} x_j$  divided by  $u_{ii}$  is equal to  $n$  minus  $1$  up to  $1$ . With the convention that if  $i$  is equal to  $n$ , then this summation is absent. Now, how many numbers of operations? So, here you have got  $j$  is equal to  $i+1$  to  $n$ . So, you are doing  $n-i$  multiplications  $u_{ij} x_j$  you have got  $n-i$  terms when you add them up, you will need  $n-i-1$  additions, because when you want to add two numbers you do one addition, but then there is one subtraction here. So, that means, in order to calculate the numerator, you will need  $n-i$  flops and there is going to be one division; this you will be doing it for  $i$  is equal to  $n$  minus  $1$  up to  $1$ .

So, the total number of operations they will be given by summation  $i$  goes from  $1$  to  $n-1$   $(n-i)$  flops plus  $n$  divisions and this summation is nothing, but  $n-1$  into  $n$  by  $2$  flops plus  $n$  division. So, that means, it is going to be of the order of  $n^2$  by  $2$ . So, thus the major chunk of our computations they are needed to replace our matrix  $A$  by an upper triangular matrix; **the** once you have done that, back substitution is of the order of  $n^2$  or  $n^2$  by  $2$ , if we want to be really precise. So, suppose sometimes one wants to solve the same system of equations for different right hand side, so in that case what you should do is you should retain your say number of operation or whatever you are doing. Because see what you have now is  $Ax = b$ . So, the

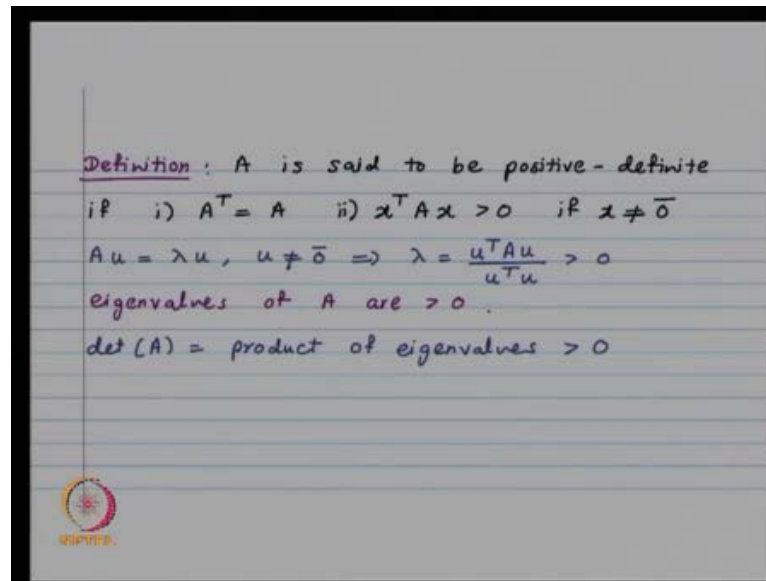


coefficient matrix  $A$  is the same, but on the right hand side you have got  $b_1, b_2, \dots, b_n$  those will be different. So, you should keep the track of the operations reduce  $A$  to upper triangular for once for all, whatever are those operations you have to perform them on the right hand side also and then, solve system of linear equations. So, this is gauss elimination method; it is also known as gauss elimination method without partial pivoting.

We will see what pivoting means, but at present this is the simplest method. This method is applicable provided determinant  $A_k$  is not equal to 0 for  $k$  is equal to 1, 2 up to  $n$ . Because if at any stage, the number by which we are dividing in our multipliers we need to divide by certain number. So, if this becomes 0, then our system or our method will be it will fail then we cannot proceed. So, there is a big class of matrices for which this condition determinant  $A_k$  not equal to 0 for  $k$  is equal to 1, 2 up to  $n$  is satisfied and that class of matrices that is known as class of positive definite matrices.

So, our definition of positive definite matrix is going to be matrix is a real matrix; it should be a symmetric matrix  $A^T$  is equal to  $A$  and in addition, if you look at a nonzero vector  $x$ , then  $x^T A x$  should be bigger than 0;  $A$  is  $n$  by  $n$  matrix  $x$  is  $n$  by 1 vector. So,  $A x$  is going to be a  $n$  by 1 vector; our  $x^T$  will be 1 by  $n$  row vector. So, when you consider  $x^T A x$ , what you get is a 1 by 1 matrix or a real number; if that number is bigger than 0, for all nonzero vectors, then our matrix is going to be positive definite.

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Now, for the positive definite matrix when we look at its Eigen values, so we are going to look at the Eigen values of matrix little later, but at present lambda is an Eigen value of a provided, there exist a nonzero vector such that  $A u$  is equal to  $\lambda u$  that is definition of Eigen value. Lambda is going to be equal to  $u^T A u$  divided by  $u^T u$ . Now, when  $A$  is positive definite,  $u^T A u$  will be bigger than 0;  $u^T u$  anyway it is going to be bigger than 0 and hence, the Eigen values of  $A$ , they are going to be strictly bigger than 0.

So, for positive definite matrices, Eigen values of  $A$ , they are bigger than 0 and determinant of  $A$  is product of Eigen values. So, determinant of  $A$  is bigger than 0. So, that means, for a positive definite matrix, determinant of  $A$  is going to be not only equal to 0, it will not be equal to 0, but it will be strictly bigger than 0. Now, what we want is additional condition; we want determinant  $A_k$  should not be equal to 0. In order to show that positive definite matrices satisfy this property, what we are going to show is that  $A_k$  which is a sub matrix formed by first  $k$  rows and first  $k$  columns of the matrix, they are also going to be positive definite. In order to show this we will have to go by definition.

So, for positive definite first it should be symmetric. So, checking symmetry of  $A_k$  is no problem, but showing that  $y^T A_k y$  is bigger than 0 for  $y$  not equal to 0 that will need some proof. So, we will show next time that if  $A$  is positive definite, then all its principal sub matrices, they are also going to be positive definite, which will mean that

determinant of  $A$  bigger than 0 for  $k$  is equal to 0 to up to  $n$  which means  $(( ))$  method which we described just now we can apply it to this class of matrices and then, we will also see some decomposition of positive definite matrix which is known as the colicky decomposition. So, we will continue next time.

Thank you.