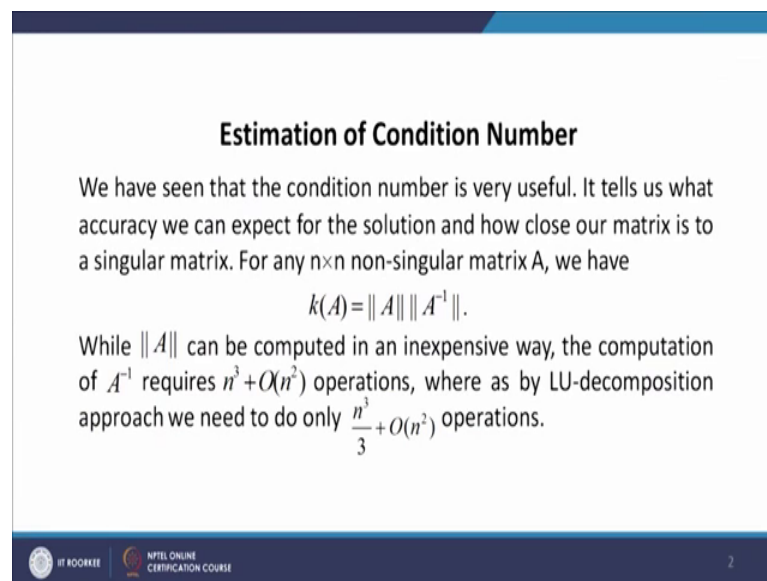


Numerical Linear Algebra
Dr. P. N. Agrawal
Department of Mathematics
Indian Institute of Technology, Roorkee

Lecture - 41
Estimation of Condition Number

Hello friends. Welcome to my lecture on estimation of condition number. We know that the condition number is very useful.

(Refer Slide Time: 00:32)



Estimation of Condition Number

We have seen that the condition number is very useful. It tells us what accuracy we can expect for the solution and how close our matrix is to a singular matrix. For any $n \times n$ non-singular matrix A , we have

$$k(A) = \|A\| \|A^{-1}\|.$$

While $\|A\|$ can be computed in an inexpensive way, the computation of A^{-1} requires $n^3 + O(n^2)$ operations, whereas by LU-decomposition approach we need to do only $\frac{n^3}{3} + O(n^2)$ operations.

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It tells us the accuracy which we can expect for the solution, and how close our matrix is to a singular matrix. And we also know that for $n \times n$ non-singular matrix A , the condition number is given by norm of A into norm of A inverse. Now while norm of A can be computed in an expensive way, the computation of A inverse requires n^3 plus capital order n square operations. If you apply LU-decomposition approach, it will need only $\frac{n^3}{3}$ plus capital order n square operations.

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Therefore the computation of condition number would make the solution of a linear system 3 times as expensive. For large problems, this is too expensive a way to compute the $k(A)$.

For all practical purposes, we do not need to compute the condition number with full machine accuracy, we need only a good estimate of $k(A)$. So there is no need to calculate A^{-1} explicitly.

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So, the computation of condition number would make the solution of a linear system 3 times as expensive. For large problems this is too expensive a way to compute the condition number. Now for all practical purposes, we do not need to compute the condition number with full machine accuracy. We only need a good estimate of the condition number. So, there is no need to determine the inverse of the matrix A explicitly. What we are going to do is, we are going to discuss a method of the estimation of norm of A inverse.

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We shall discuss the method of estimation of $\|A^{-1}\|$ by **Hager's method**.

Since $\|A\|$ can be calculated explicitly, we can find an estimate of the condition number $k_1(A) = \|A\|_1 \|A^{-1}\|_1$.

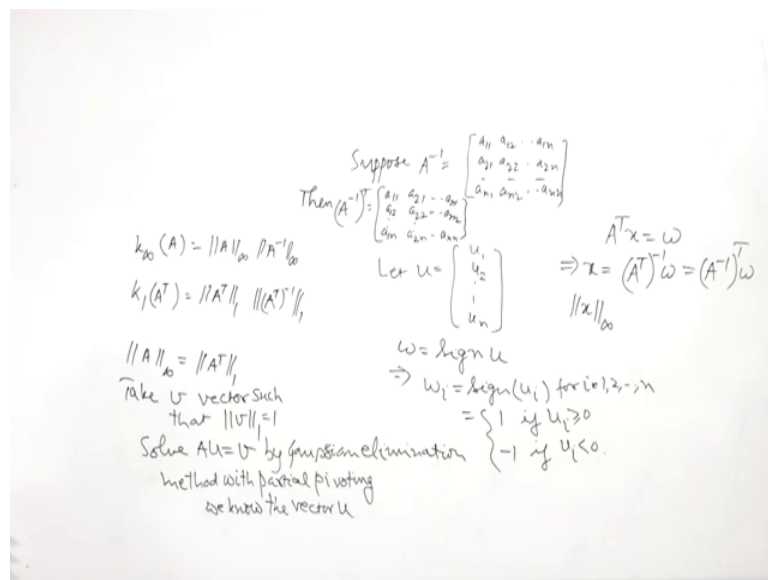
Note that $k_\infty(A) = k_1(A^T)$, we can also get an estimate for $k_\infty(A)$ by applying **Hager's algorithm** to estimate $k_1(A^T)$.

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And the method which we will use is the method given by Hager's. So, Hager's method we are going to discuss. since norm of A can be calculated explicitly, once we have an estimate of norm of A inverse by Hager's method, we shall be able to estimate the condition number k_A .

Now, here we shall be using the norm 1 norm. So, norm of it is condition number with one norm is equal to norm of A 1 into norm of A inverse 1. And you we know that $k_{\infty} A$ is equal to $k_1 A^T$.

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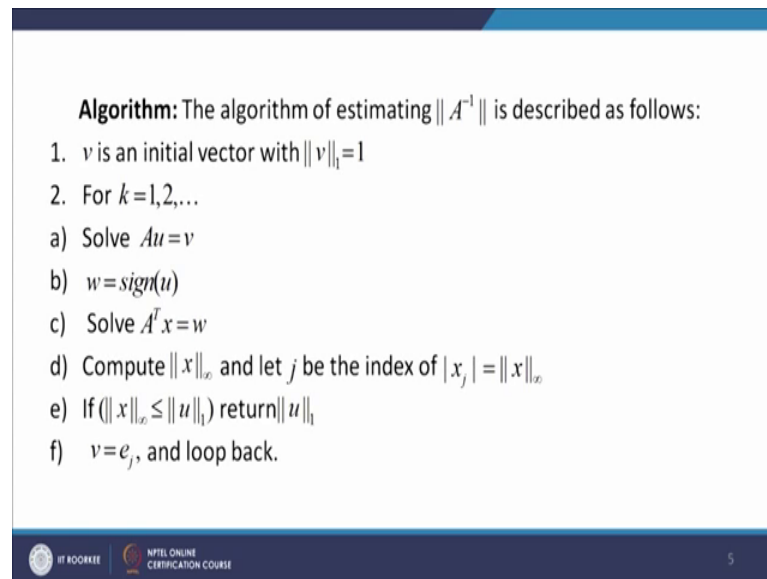


$k_{\infty} A$ is equal to norm of A infinity into norm of A inverse infinity, and $k_1 A^T$ will be equal to norm of A transpose, one norm of A inverse A transpose inverse 1 ok. And norm of it is norm of A infinity is equal to norm of A transpose 1. Because norm of A transpose one is the absolute column maximum absolute column sum, and this is maximum absolute row sum.

So, here norm of A infinity is the maximum absolute row sum while when you take the transpose of the matrix A ok, the rows becomes columns. So, norm of A transpose one is the maximum absolute column sum. So, sum so, they are both equal. So, once we have the once we know the norm of A inverse 1 ok, and norm of A 1 we can determine $k_1 A$. Hence once we have the estimate of $k_1 A$, we can similarly get the estimate of $k_{\infty} A$, by finding the condition number of A 1 transpose in the one norm.

So, k infinity a can also be estimated by this Hager's algorithm.

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Algorithm: The algorithm of estimating $\|A^{-1}\|$ is described as follows:

1. v is an initial vector with $\|v\|_1 = 1$
2. For $k=1, 2, \dots$
 - a) Solve $Au = v$
 - b) $w = \text{sign}(u)$
 - c) Solve $A^T x = w$
 - d) Compute $\|x\|_\infty$ and let j be the index of $|x_j| = \|x\|_\infty$
 - e) If $(\|x\|_\infty \leq \|u\|_1)$ return $\|u\|_1$
 - f) $v = e_j$, and loop back.

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Now the algorithm goes like this, to estimate norm of A inverse, we begin with an initial vector, say v with norm of v in one norm equal to 1. So, let us take an initial vector v with norm 1 in the one norm. And then let us take k equal to 1. So, we are doing first iteration. So, k equal to 1, then solve Au equal to v . So, we what we do? We take v vector such that norm of v 1 equal to 1. And then solve the equation Au equal to v .

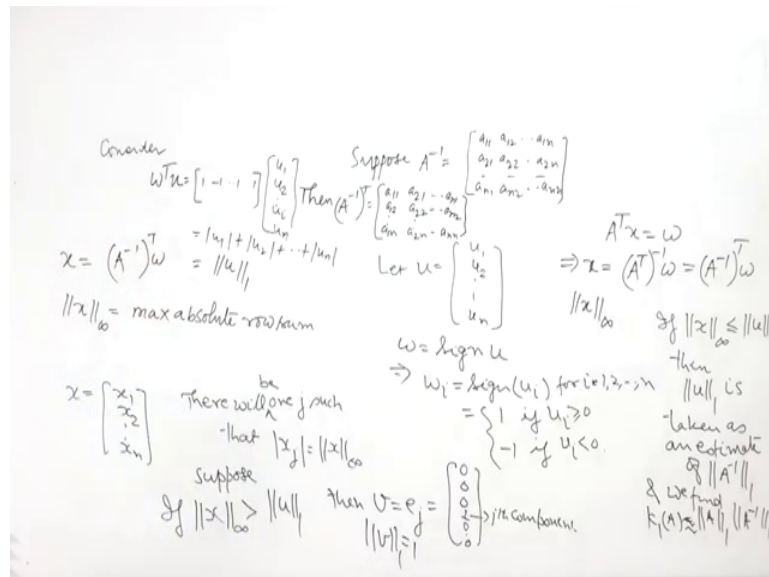
We can solve this equation by Gaussian elimination method with partial pivoting. So, when you solve Au equal to v , by the Gaussian elimination method with partial pivoting. We know the vector u ; let us say u equal to $u_1 u_2$ and so on; U_n , then we define w equal to sign of u , w equal to sign of u . So, this sign of u means, the r that is to say we get w_i equal to sign of u_i for i equal to 1 to n . So, on up to n sign of u_i is equal to 1, if u_i is greater than or equal to 0. And minus 1, this is defined as one if u_i is greater than or equal to 0, and minus 1 if u_i is strictly less than 0.

So, we get w_i the value of w_i corresponding to the component u_i of u . So, this w_i will be having values plus minus 1. Now what we do is we solve A transpose x equals to w equation. A transpose x equals to w gives what? We have w vector with u w is plus minus; where w is the vector signed of u , where components of w are plus minus plus 1 minus 1 like that. So, A transpose x we solve this equation, again by Gaussian elimination method with partial pivoting. So, this gives you x equal to A transpose

inverse w ok. We can solve this equation, $A^T A^{-1} w$. Now what we do let us find the norm of x infinity norm of x infinity gives what? this is $A^T A^{-1}$ inverse let us say, I can also write this as $A^{-1} A^T w$; now suppose A^{-1} inverse matrix is like this.

Say $A_{11}, A_{12}, \dots, A_{1n}; A_{21}, A_{22}, \dots, A_{2n}$ and so on. $A_{n1}, A_{n2}, \dots, A_{nn}$ ok. Suppose A^{-1} inverse matrix is this; then $A^{-1} A^T$ will be $A_{11}, A_{12}, \dots, A_{1n}; A_{21}, A_{22}, \dots, A_{2n}$ and so on. $A_{n1}, A_{n2}, \dots, A_{nn}$ ok. When $A^{-1} A^T$ is multiplied by w ok, when $A^{-1} A^T$ is multiplied by w , the components the w s are plus 1 or minus 1 like that ok. So, norm of x infinity will be equal to norm of w infinity we are multiplying $A^{-1} A^T$ by w .

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w means one or minus 1 like that. So, w is equal to x ok, this x equal to $A^{-1} A^T$ transpose the x norm of x infinity will be equal to maximum absolute maximum absolute row sum ok. This maximum absolute row sum of $A^{-1} A^T$ into w .

Now, let us say since it is maximum absolute row sum, there will be one a for which suppose norm of x ah, suppose x is $x_1 \times x_2 \times \dots \times x_n$ suppose x is $x_1 \times x_2 \times \dots \times x_n$. Then norm of x infinity will be equal to maximum absolute row sum. So, there will be one a such that norm such that norm of x infinity will be equal to mod of x_j . So, there will be one a such that mod of x_j equal to norm of x infinity.

Now, if norm of x infinity is less than or equal to norm of u^{-1} ok. Suppose, and what is norm of u^{-1} let us see. $W^T u$ ok, $w^T u$ will be ok, now here we will have corresponding to $A u = i$ which is positive we will have $w = i$ and if u_i is negative we will have minus 1 ok.

So, $w^T u$ will give you suppose this is $u_1 u_2 \dots u_n$. If u_1 is positive I shall write one here, if u_2 is negative I shall write minus 1 here, and so on if u_i is say positive value I will write one here if u_1 is positive I will write one here. So, when you multiply them ok, this row vector with this column vector, what you will get you will get u_1 plus. So, mod of u_1 , plus mod of u_2 and so on mod of u_n that is what is. So, if $u = u_1 u_2 \dots u_n$, you get the norm of u^{-1} ok. So, $w^T u$ is norm of u^{-1} . So, what happens be compare norm of x infinity with norm of u^{-1} ok. Now if norm of x infinity is less than or equal to norm of u^{-1} ok.

Then norm of u^{-1} will be an estimate of the condition number. We written norm of u^{-1} as the value of the condition number, if norm of x infinity is strictly greater than, it is greater than norm of u^{-1} ok, norm of x infinity is greater than is strictly greater than norm of u^{-1} , then we will take v equal to e_j , e_j is the vector belonging to r to the power n whose j th component is one other component are 0. So, this is equal to $0, 0, 0$ and so on $1, 0, 0, 0$. And this is the j th component. And this j is the same value for which mod of x_j becomes norm of x infinity ok. The component of x such that, mod of x_j becomes equal to norm of x infinity.

So, we will take with we we equal to e_j , when you take v equal to e_j norm of v becomes norm of v^{-1} becomes 1, and we again go back, and start the process with k equal to 2. The first time it is k equal to 1, when we go back k will be 2. Again, we will find Au equal to v with this vector v ok. We will find u , and then we will find w equal to sign u , we will solve the equation $A^T x = w$, again compute norm of x infinity, and find the value of j such that mod of x_j equal to norm of x infinity if norm of x infinity is less than or equal to norm of u^{-1} . Then norm of u^{-1} will be the condition number estimate of the estimate of norm of A^{-1} .

So, if norm of x infinity less than or equal to norm of u^{-1} ok. Then norm of u^{-1} is taken as an estimate of norm of A^{-1} ok. And we find $k = 1/A$ equal to norm of A^{-1} into norm of A^{-1} , an approximate value of the condition number. So, as so, long as

norm of x infinity is greater than norm of u 1, we we look back ok. Now let us see let us explain this algorithm further. So, in the Hager's algorithm what we are doing we are initially picking an arbitrary vector with norm $\|v\|_1$ equal to 1.

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Hager's Algorithm

Initially, we pick an arbitrary vector v with $\|v\|_1=1$ because by the definition of matrix norm we have,

$$\|A^{-1}\|_1 = \max_{\|x\|_1=1} \|A^{-1}x\|_1. \quad \dots(1)$$

In step 2(b), the algorithm defines an auxiliary vector $w = \text{sign}(u)$ ($w_i = \text{sign}(u_i)$, $i=1,2,\dots,n$). By using that, $\|u\|_1$ can be expressed as $w^T u$ since elements in w are ± 1 because $w = \text{sign}(u)$

$$\Rightarrow w_i = \begin{cases} 1 & \text{if } u_i \geq 0 \\ -1 & \text{if } u_i < 0 \end{cases}, i=1,2,\dots,n.$$

Why we are doing this? Because norm of A inverse 1 is equal to maximum of norm of A inverse x 1 with norm of x 1 equal to 1. So, see we this is the definition of matrix norm by definition of matrix norm A inverse 1 is equal to maximum of norm of A inverse x 1 over all vectors x , such that norm of x 1 equal to 1.

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The handwritten notes on the whiteboard show the following derivations:

- $\|A^{-1}\|_1 = \max_{\|x\|_1=1} \|A^{-1}x\|_1$
- $\|A^{-1}e_j\|_1 \geq |w^T A^{-1}e_j|$ for any j
- $A^{-1}e_j = \begin{bmatrix} e_{j1} \\ e_{j2} \\ \vdots \\ e_{jn} \end{bmatrix}$
- $\|A^{-1}e_j\|_1 = |e_{j1}| + |e_{j2}| + \dots + |e_{jn}|$
- but $w^T A^{-1}e_j = \begin{bmatrix} 1 & -1 & \dots & 1 \end{bmatrix} \begin{bmatrix} e_{j1} \\ e_{j2} \\ \vdots \\ e_{jn} \end{bmatrix} \leq |e_{j1}| + |e_{j2}| + \dots + |e_{jn}|$
- $\exists j \|x\|_\infty > \|u\|_1$
- $U = e_j$
- $U = \begin{bmatrix} 1/4 \\ 1/4 \\ 1/4 \\ 1/4 \end{bmatrix}$
- $\|U\|_1 = 1$
- $x = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$
- $\|x\|_\infty = 1$
- then $j=k$ is such that $x_j = |x_j| = \|x\|_\infty$

So, we begin with a vector $v \in \mathbb{R}^n$, such that $\|v\|_1 = 1$. And then we shall try to find the maximum of $\|A^{-1}v\|_1$. So, that we get an estimate of $\|A^{-1}\|_1$. Now in this step 2 b. So, let us take k equal to 1. Then in the step b in the in the step 2 a b solve the equation $Au = v$ for the value of u . In the step 2 b what we do? In the step 2 b we define an auxiliary vector w equal to $\text{sign } u$. So, that $w_i = \text{sign } u_i$ if $u_i \neq 0$ and $w_i = 1$ or -1 if $u_i = 0$ and so on up to n , by using that as I had told you $\|u\|_1 = w^T u$.

Because the w elements in w are plus minus 1, because w equal to $\text{sign } u$ means $w_i = 1$ if u_i is greater than or equal to 0 minus 1, if u_i is less than 0 for $i = 1, 2, 3$ and so on up to n . So, $w^T u$ is nothing but $\|u\|_1$.

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Now $\|A^{-1}e_j\|_1 \geq |w^T A^{-1}e_j|$, for any j .
Hence, the problem can be simplified as : find a j such that
 $|w^T A^{-1}e_j| > \|u\|_1 \quad \dots(2)$
Thus, we need to search a vector $w^T A$. Step 2(c) defines
 $x = (A^T)^{-1} w = (A^{-1})^T w$
and hence $x^T = w^T A^{-1} \Rightarrow x^T e_j = w^T A^{-1} e_j$.
Thus, equation (2) is equivalent to find an element x_j in x such that
 $|x_j| > \|u\|_1$.

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Now, $\|A^{-1}e_j\|_1$ is strictly greater than or equal to $\|A^{-1}e_j\|_1$ is greater than or equal to $w^T A^{-1}e_j$ for any j . Why because w transpose the components of w transpose are 1 minus 1 plus minus 1, and you are multiplying that by $A^{-1}e_j$ ok.

So, what you are doing actually you are you are $A^{-1}e_j$ is a column vector ok. When you multiply $A^{-1}e_j$ by a multiply to this row vector, then what you get is you get some value with that value will always be less than or equal to this ok. Because here you are multiplying say, say suppose $A^{-1}e_j$ is this. Say I write e_{j1}, e_{j2} and so on, e_{jn} ok. As such norm of if you calculate $\|A^{-1}e_j\|_1$ is this equal to

modulus of e_{j1} plus modulus of e_{j2} and so on modulus of e_{jn} ok. It will be like this. But if you multiply $w^T A^{-1} e_j$ ok. This will be here you will have $1 - 1 - 1$ like this ok. Or even you will have so, components are $1 - 1$ like that, you are multiplying them by $e_{1j} e_{2j} \dots e_{nj}$.

If these components are the same sign as the sign of suppose, you take $e_j^T I$ here, $e_j^T I$ has the same sign as the sign of I th component here. Then only you will get mod of e_{j1} mod of e_{j2} mod of e_{jn} . Otherwise the value when you multiply this row vector by this column vector will always be less than or equal to this ok. So, this is always less than or equal to norm of modulus of $e_{1j} e_{j1}$ plus mod of e_{j2} and so on mod of e_{jn} is always than this. So, that is why we write norm of $A^{-1} e_j$ is always greater than or equal to modulus of $w^T A^{-1} e_j$ for n a hence, the problem can be simplified as, we have to find a j such that mod of $w^T A^{-1} e_j$ is strictly greater than norm of u_1 .

And so, we need to search a vector $w^T A^{-1} c$ defines c , step 2 c defines $A^T x = w$ ok. And what it does? So, $x = A^{-T} w$, or it is equal to $A^{-1} w^T$, and hence $x^T = w^T A^{-1}$ ok. And $x^T e_j = w^T A^{-1} e_j$. Thus, equation 2 is equivalent to find an element x_j in x see equation 2 this equation.

This equation 2, mod of $w^T A^{-1} e_j$ greater than greater than norm of greater than norm of u_1 is equivalent to finding an element x_j in x such that mod of x_j is greater than norm of u_1 ok. Because you can see x^T is equal to $w^T A^{-1} e_j$ vector ok.

So, we this is equivalent to finding an element x_j in x such that modulus of x_j is greater than norm of u_1 .

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In step 2(c), we compare $\|x\|_\infty$ and $\|u\|_1$. If $\|x\|_\infty$ is larger then one finds j , since

$$\|A^{-1}e_j\|_1 \geq |w^T A^{-1}e_j| = \|x\|_\infty > \|u\|_1$$

otherwise, the program returns $\|u\|_1$ as the estimation.

4

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Now, in step 2 c we compare norm of x infinity, and norm of u 1, if norm of x infinity is larger than larger, then one finds j ah, such that mod of x j is equal to norm of x infinity. And since norm of A inverse e_j 1 is greater than or equal to modulus of f w transpose A inverse e_j , which is equal to norm of x infinity. We have just now seen see norm of x infinity is equal to this one, norm of x infinity equal to modulus of x w transpose A inverse e_j for every j .

So, norm of A inverse e_j 1 is greater than or equal to this ok. And this is equal to norm of x infinity and norm of x infinity is greater than norm of u 1. Now if norm of x t infinity is greater than norm of u 1 ok, then we will take v v equal to; as I said v equal to e_j . If norm of x infinity is greater than norm of u 1, we take v equal to e_j where j th component is one other components are 0. And then norm of v will be equal to 1 and v , again look back if norm of x infinity is less than or equal to norm of u 1, then norm of u 1 is written as the estimate of norm of A inverse 1. And we find the approximate value and approximate value of the condition number.

So, this is algorithm.

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Example: Consider

$$A = \begin{bmatrix} 1 & -10 & 0 & 0 \\ 0 & 1 & -10 & 0 \\ 0 & 0 & 1 & -10 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

then it is easy to see that

$$A^{-1} = \begin{bmatrix} 1 & 10 & 10^2 & 10^3 \\ 0 & 1 & 10 & 10^2 \\ 0 & 0 & 1 & 10 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

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Let us see how we apply this algorithm to solve problems, suppose we take this matrix A equal to a is 1 minus 10, 0, 0, 0, 1 minus 10, 0, 0, 0 and then 0 0 1 minus 10, 0, 0, 0, 1. So, this is 4 by 4 matrix, now for this matrix it is not difficult you can easily find A inverse. And A inverse is 1 10 10 square 10 cube 0, 1, 10, 10 square 0, 0, 1, 10. And 0 0 0 1.

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and hence

$$\|A\|_1 = 11, \|A^{-1}\|_1 = 1111$$
$$\Rightarrow k_1(A) = \|A\|_1 \|A^{-1}\|_1 = 12221$$

$\Rightarrow A$ is an ill-conditioned matrix.

Now, we apply the Hager's algorithm to find an estimate of $k_1(A)$.

Iteration 1:

Set $v = \begin{bmatrix} \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \end{bmatrix}^T$

Solving $Au = v$, we obtain $u = \begin{bmatrix} 277.75 & 27.75 & 2.75 & 0.25 \end{bmatrix}^T$

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Now so, we can easily see that, norm of A 1 norm of A 1 is 11 norm of A 1 means maximum absolute column sum. So, maximum absolute column sum you can see in the matrix A first column has sum 1, and the second column has absolute sum 1 11 third

column has absolute sum 11. 4th column has absolute sum 11. So, maximum absolute column sum is equal to 11. And therefore, norm of A is equal to 11. While in the case of A inverse matrix. If we find norm of A inverse, then what do we notice here you can see the absolute column sum. Maximum absolute column sum will come from the last column ok. So, 10 cube is 1000; 1000 plus 100, that is 1100 then 110 then 1. So, 1111. So, we have 1111. So, that is norm of A inverse. And so, condition number of A is equal to norm of A into norm of A inverse; which is one double 221 ok, which is quite high.



So, we can say that a is an ill conditioned matrix. Now let us apply the Hager's algorithm to find an estimate of the condition number of A in 1 norm ok. So, as we said in the algorithm, we start with a vector ah, say v whose norm is equal to 1. So, let us take the vector v to be 1 by 4 1 by 4 1 by 4 1 by 4, because we are start we have taken the 4 by 4 matrix ok. So, if it if we take a to be n by n matrix, we will take v equal to 1 by n 1 by n 1 by n like that. Since we are taking 4 by 4 matrix we take the vector v to be 1 by 4, 1 by 4, 1 by 4, 1 by 4 transpose of that. So, we get a column vector. And the column sum then is 1 by 4 plus 1 by 4 plus 1 by 4 plus 1 by 4 equal to 1. So, norm of v is equal to 1.

So, norm of v is equal to 1. Now we solve the equation Au equal to v. And it turns out that u comes out to be 277.75, 27.75, 2.75, 0.25. Then you can see, in the in the vector u all the components are positive ok, positive real numbers.

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$$w = \text{sign}(u) = [1 \ 1 \ 1 \ 1]^T$$
 Solving $A^T x = w$, we get $x = [1 \ 11 \ 111 \ 1111]^T$.
 Hence $\|x\|_\infty = 1111$. Clearly $j=4$ is such that $|x_j| = \|x\|_\infty = 1111$.
 Since $\|x\|_\infty > \|u\|_1 = 308.5$ we update v by setting $v = [0 \ 0 \ 0 \ 1]^T$.
Iteration 2:
 We have $\|u\|_1 = 308.5$ and $v = [0 \ 0 \ 0 \ 1]^T$.
 Solving $Au = v$, we obtain $u = [1000 \ 100 \ 10 \ 1]^T$.

$$w = \text{sign}(u) = [1 \ 1 \ 1 \ 1]^T$$
 Solving $A^T x = w$, we get $x = [1 \ 11 \ 111 \ 1111]^T$.



11

So, when we find w equal to $\text{sign } u$, we have said that $\text{sign } u_i$ is equal to one if u_i is greater than or equal to 0, and minus 1 if u_i is less than 0. So, still here u is all positive. So, w equal to $\text{sign } u$ will be $1, 1, 1, 1$ and we are taking transpose. Now let us solve the equation $A^T x = w$.

When we solve this equation $A^T x = w$, it turns out that x is equal to $1, 11, 100, 11$ and then $1, 1, 1, 1$ transpose ok. So, here we can see. Norm of x infinity norm of x infinity is the maximum absolute row sum ok. So, first row is of the vector x first row is one second row is 11 third row is 100 and 4th row is 11. So, norm of x infinity is 100 . And further more we have to find the value of j such that $\text{mod of } x_j$ is equal to norm of x infinity.

So, since norm so, x is equal to $1, 11, 100, 11$ ok. So, norm of x infinity is equal to 100 and this j equal to 3 ok. J is equal to 3 is the component of x , x such that $\text{mod of } x_j$ equal to. So, here j is equal to 3 is such that $\text{mod of } x_j$ ok. This x_1, x_2, x_3, x_4 ok. So, $\text{mod of } x_j$ is equal to norm of x infinity. Here all the components are positive. So, I can write x_j . So, $x_3 = 100$ is norm of x infinity ok. Now what we have? What we notice that norm of x infinity is 100 . While norm of u , norm of u is how much? If you find norm of u , u is this vector $277.75, 27.75, 2.75, 0.25$. If you add all of them norm of u means maximum absolute column sum.

So, you add all of them. What we get is 308.5 . So, norm of x infinity is strictly greater than 308.5 . And therefore, we update v by taking v equal to e_j vector. e_j means e_4 vector. e_4 is equal to $0, 0, 0, 1$ ok. 4th component will be one other component will be 0. So, v is now new vector $0, 0, 0, 1$ and we do the iteration 2 ok, k equal to 2.

So now we start with this vector v ok, for this vector v ok. We solve again. And this time we have norm of u equal to 308.5 . We have with us solving $Au = v$ now what we do ok. We solve the equation $Au = v$ do not confuse this $Au = v$ with the u we have earlier ok. So, this is new new u vector ok.

So, solve $Au = v$; v is $0, 0, 0, 1$ column vector. And we get u equal to $1, 10, 10, 1$ that is 10 and one column vector and again all the components of u are positive. So, we will get w equal to $1, 1, 1, 1$ transpose. Now we solve then the equation $A^T x = w$, x comes out to be the column vector $1, 11, 100, 11$ and then $1, 1, 1, 1$ transpose ok.

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Hence $\|x\|_\infty = 1111$.
Again, it is clear that $j=4$ is such that $|x_j| = \|x\|_\infty = 1111 = \|u\|_1$.
Hence $\|A^{-1}\|_1 = \|u\|_1 = 1111$
and thus $k_1(A) = \|A\|_1 \|A^{-1}\|_1 \approx 11 \times 1111 = 12221$.
We observe that Hager's algorithm converges in two iterations.
In this example Hager's estimate for $k_1(A)$ coincides with the exact value of $k_1(A)$.

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So, now we can again find the norm x infinity. Norm of x infinity is 1 1 1 1, and v is again see that for j equal to 4, mod of x_j is equal to norm of x infinity. And norm of x infinity is 1 1 1 1. And norm of u 1, let us see norm of u 1 this time. So, this is our new u , this our new u 1 thousand 100 10 1. And you can add all of them, you get 1 1 1 1. So, norm of new u new vector u has norm 11, 11.

So, norm of x infinity is equal to norm of u 1. And therefore, norm of u 1 is written as an estimate of norm of A inverse 1 ok. So, norm of A inverse 1 is equal to norm of u 1 is equal to 1 1 1 1. And thus an estimate of $k_1 A$ is equal to 11, 11 is norm of A 1 into norm of A inverse 1, that is 1 1 1 1.

So, one double 2 2 1. So, here when we apply the Hager's algorithm, we find that the Hager's algorithm converges in just 2 iterations. And it is value the estimate that we get of the condition number coincides with the exact value of the condition number in one norm in just 2 iterations ok.

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Example: Let us consider

$$A = \begin{bmatrix} 19 & 2 & 8 & -1 \\ 2 & 21 & 10 & -3 \\ 8 & 10 & 20 & 14 \\ 1 & -3 & 14 & 19 \end{bmatrix}$$

Let us set $v = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 4 & 4 & 4 & 4 \end{bmatrix}^T$

then solving $Au = v$, we get

$$u = [-33.8125 \quad -46.0938 \quad 83.4844 \quad -67.0000]^T.$$

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Let us take one more example. So, let us take this time again 4 by 4 matrix A with the entries 19 2 8 minus 1 21 10 minus 3 8 10 20 14 1 minus 3 14 19. Again, we take v to be a vector with norm 1. So, since we are having 4 by 4 matrix, we take the vector v to be 1 by 4, 1 by 4, 1 by 4, 1 by 4. Then we solve the matrix equation Au equal to v. We get u equal to minus 33.8125 minus 46.0938 83.4844 minus 67.0000.

(Refer Slide Time: 32:50)

Hence $w = \text{sign}(u) = [-1 \quad -1 \quad 1 \quad -1]^T$.

Now, solving $A^T x = w$, we find $x = 10^3 \times [0.4023 \quad 0.7186 \quad -1.2688 \quad 1.0695]^T$.

Hence $\|x\|_\infty = 1.2688 \times 10^3$. Further, $j = 3$ is such that

$$|x_j| = \|x\|_\infty = 1.2688 \times 10^3.$$

Since $\|x\|_\infty > \|u\|_1 = 230.3906$, we update v by setting $v = [0 \quad 0 \quad 1 \quad 0]^T$.

Solving $Au = v$, we get $u = [186.2500 \quad 253.8750 \quad -459.6875 \quad 369.0000]^T$.

Hence $w = \text{sign}(u) = [1 \quad 1 \quad -1 \quad 1]^T$.

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And here we can see some components are positive some components are negative. So, first component is negative in u, and therefore, when you write w equal to sign u ok.

Since u_1 is negative the component of w . That is w_1 will be minus 1 corresponding to the second component u_2 which is negative the component w_2 will be minus 1. This is positive. So, w_3 will be plus 1, and this is negative. So, w_4 will be minus 1. So, you can see w equal to sign u is minus 1 minus 1 1 and minus 1. Now we solve the equation $A^T x = w$. And we find x equal to 10^3 into $0.4023 \ 0.7186 \ -1.2688 \ 1.0695$ transpose.

And so, we can see norm of x infinity, norm of x infinity is again the maximum absolute row sum. So, when you multiply 10^3 here. And the maximum absolute value is 1.2688 into 10^3 . So, we get 1.2688 into 10^3 . Again, we can see that the third component ok. The third component is such that, its absolute value equals norm of x infinity ok.

So, modulus of x_j is equal to norm of x infinity which is equal to 1.2688 into 10^3 . Now norm of x infinity here is 1.2688 into 10^3 , while norm of u_1 we can find. So, we can take the absolute sum of all these values ok. because norm of u_1 is absolute column sum absolute. So, so, we can take the absolute values of all these numbers and take their sum. And it turns out to be 230.3906 .

Now, you can see that 1.2688 into 10^3 is much greater than 230.3906 . So, we update v by setting v equal to e_j . e_j means e_3 because j was equal to 3 when mod of x_j became equal to norm of x infinity.

So, v is equal to $0, 0, 1, 0$. We solve $Au = v$, and you get u equal to $183.2500 \ 253.8750 \ -459.86875, \ 369.0000$ transpose ok. Now first component here is positive. So, w equal to sign u is equal to 1 . First component is one second component is 1 . Because this is positive, third component is minus 1 here. Because this is negative. And 4th component is one because this is positive 369.0000 .

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Solving $A^T x = w$, we get $x = 10^3 \times [-0.4023 \quad -0.7186 \quad 1.2688 \quad -1.0695]^T$.
 Clearly $j = 3$ is such that $|x_j| = \|x\|_\infty = 1.2688 \times 10^3$.
 Also, $\|x\|_\infty = \|u\|_1 = 1.2688 \times 10^3$.
 Thus, Hager's algorithm converges in two iterations and
 $\|A^{-1}\|_1 \approx 1.2688 \times 10^3$.
 Thus, $k_1(A) = \|A\|_1 \|A^{-1}\|_1 \approx 52 \times (1.2688 \times 10^3)$
 $= 65.9776 \times 10^3 = 6.5978 \times 10^4$.

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So, we get the vector w like this. And then we solve the equation, A transpose x equal to w ok. We shall get x equal to 10 to the power 3 into minus 0.4023 minus 0.7186 1.2688 minus 1.0695 . Now let us see which value here. The absolute value is is is the greatest. So, you can see here 1.2688 ok, 1.2688 is the greatest value multiplied by 10 to the power 3 . So, clearly a equal to 3 such that $\text{mod of } x_j$ is equal to $\text{norm of } x$ infinity is equal to 1.2688 into 10 to the power 3 . Now $\text{norm of } u_1$, let us find $\text{norm of } u_1$. Here you can consider the absolute values of all these 4 components of u , and add them.

What we get is 1.2688 into 10 to the power 3 . So, $\text{norm of } x$ infinity equals $\text{norm of } u_1$. So, $\text{norm of } u_1$ is written as the as an estimate of $\text{norm of } A$ inverse 1 ok. So, $\text{norm of } A$ inverse 1 is approximately taken as 1.2688 into 10 to the power 3 . So, an estimate of the condition number $k_1(A)$ is $\text{norm of } A_1 \text{ norm of } A^{-1}_1$ you can see you can look at the matrix A $\text{norm of } A_1$ here. The first column has sum 19 plus 221 plus 829 plus 130 . So, first column has sum 30 absolute sum of absolute values in the first column in the second column 2 plus 21 20 23 then ten. So, 30 3 plus 3 absolute value of minus 3 is 3 . So, we get 36 ok.

And here 8 plus 10 18 18 plus 20 38 38 plus 14 is 52 ok. So, and here what we get? 1 plus 3 4 4 plus 14 18 plus 19 37 . So, 52 is the maximum maximum absolute column sum. So, $\text{norm of } A_1$ is equal to 52 . And we multiply it by an estimate of the $\text{norm of } A$ inverse 1 . So, 1.2688 into 10 to the power 3 . And this is equal to 35.9776 into 10 to the

power 3; which is 6.5978 into 10 to the power 4; which is quite high number ok. Now so, we can say, that this matrix is also an ill conditioned matrix. With that I would like to conclude my lecture.

Thank you very much for your attention.