

## Direct method

### Remarks:

- ▶ Zeros may be created in the diagonal position.
- ▶ Rearrange the system to have the largest coefficient in the diagonal position.
- ▶ Where there are many equations, the round-off error may cause large effect.
- ▶ If the matrix is **ill-conditioned**, results are particularly sensitive to round-off error.

## Direct method

### LU decomposition method:

Any square matrix  $A$  can be expressed as

$$A = LU,$$

where  $L$  is the lower triangular matrix:

$$L = \begin{bmatrix} l_{11} & 0 & 0 & \cdot & \cdot & 0 \\ l_{21} & l_{22} & 0 & \cdot & \cdot & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ l_{n1} & l_{n2} & 0 & \cdot & \cdot & l_{nn} \end{bmatrix}$$

## Direct method

and  $U$  is the upper triangular matrix:

$$U = \begin{bmatrix} u_{11} & u_{12} & u_{13} & \cdot & \cdot & u_{1n} \\ 0 & u_{22} & u_{23} & \cdot & \cdot & u_{2n} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & 0 & \cdot & \cdot & u_{nn} \end{bmatrix}$$

## Direct method

### LU decomposition method:

A given linear system takes the following form using  $LU$  decomposition:

$$A\mathbf{x} = LU\mathbf{x} = \mathbf{b}.$$

Define the vector  $\mathbf{z} = U\mathbf{x}$ .

The system takes the form:

$$L\mathbf{z} = \mathbf{b}.$$

## Direct method

LU decomposition method:

First, solve

$$Lz = \mathbf{b}$$

for  $\mathbf{z}$ .

Secondly, set

$$U\mathbf{x} = \mathbf{z}$$

and solve for  $\mathbf{x}$ .

## Direct method

### Example:

Develop an algorithm for LU factorization.

### Solution

There are three algorithms available.

1. Doolittle's factorization.

$$l_{ij} = 1 \text{ for } 1 \leq i \leq n.$$

2. Crout's factorization.

$$u_{ij} = 1 \text{ for } 1 \leq i \leq n.$$

3. Cholesky's factorization.

$$U = L^T \text{ so that } l_{ij} = u_{ij} \text{ for } 1 \leq i \leq n.$$

## Direct method

Crout's factorization.

The elements of  $L$  and  $U$  are determined by

$$u_{ii} = 1; i = 1, 2, \dots, n.$$

$$l_{ij} = \left\{ a_{ij} - \sum_{k=1}^{j-1} l_{ik} u_{kj} \right\}; i \geq j; i = 1, 2, \dots, n$$

$$u_{ij} = \left\{ \frac{a_{ij} - \sum_{k=1}^{i-1} l_{ik} u_{kj}}{l_{ii}} \right\}; i < j; j = 2, 3, \dots, n.$$

## Eigenvalues and eigenvectors

If  $A$  is a square matrix, then the roots  $\lambda$ 's of  $\det(A - \lambda I) = 0$  are eigenvalues of  $A$ . Further, if  $x = [x_1, x_2, \dots, x_n]^T \neq 0$  satisfies  $(A - \lambda I)x = 0$ , then  $x$  is an eigenvector.



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With matlab

`[V,D]=eig(A)` produces a diagonal matrix  $D$  of eigenvalues and full matrix  $V$  whose columns are the corresponding eigenvectors so that  $A*V=V*D$ .

## Eigenvalues and eigenvectors

The **spectral radius** of a matrix  $A$  is defined as

$$\rho(A) = \max |\lambda|,$$

where  $\lambda$  is an eigenvalue of  $A$ .

# Norms

Vector norm:

$l_p$  norm of the vector  $x = [x_1, x_2, \dots, x_n]^T$  is

$$\|x\|_p = \left\{ \sum_{i=1}^n x_i^2 \right\}^{1/p},$$

where  $0 < p < \infty$ , and the  $l_\infty$  norm is

$$\|x\|_\infty = \max_{1 \leq i \leq n} |x_i|$$

# Norms

## Exercise

For each  $x \in \mathbb{R}^n$ , show that  $\|x\|_\infty \leq \|x\|_2 \leq \sqrt{n}\|x\|_\infty$

## Matrix norm:

The norm of the matrix is a measure of the magnitude of the matrix, and is denoted by  $\|A\|$ .

# Norms

Matrix norm:

$$\|A\|_1 = \max_{1 \leq j \leq n} \sum_{i=1}^n |a_{ij}| = \text{maximum column sum}$$

$$\|A\|_\infty = \max_{1 \leq i \leq n} \sum_{j=1}^n |a_{ij}| = \text{maximum row sum}$$

$$\|A\|_f = \left( \sum_{i=1}^m \sum_{j=1}^n a_{ij}^2 \right)^{1/2} \quad (\text{Frobenius norm})$$

# Norms

$L_2$  norm of a matrix:

The **spectral radius** of a matrix  $A$  is defined as

$$\rho(A) = \max_{1 \leq i \leq n} |\lambda_i|,$$

where  $\lambda_i$ 's are eigenvalues of  $A$ . This is also known as the  $L_2$  norm of a matrix.

# Norms

Properties of matrix norm:

1.  $\|A\| \geq 0$  and  $\|A\| = 0$  if and only if  $A = 0$ .
2.  $\|kA\| = |k|\|A\|$ .
3.  $\|A + B\| \leq \|A\| + \|B\|$ .
4.  $\|AB\| \leq \|A\|\|B\|$ .

## Sensitivity of linear system

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For an ill-conditioned system, the matrix  $A$  is nearly singular.

The degree of ill-conditioning of a matrix is measured by its condition number.

## Sensitivity of linear system

**Problem:** Express upper and lower bounds for relative error using the condition number of the coefficient matrix.

**Solution:**

Define the error  $e = \mathbf{x} - \tilde{\mathbf{x}}$ .

## Sensitivity of linear system

Hence,  $\mathbf{e} = A^{-1}\mathbf{r}$ .

Taking norms:  $\|\mathbf{e}\| \leq \|A^{-1}\|\|\mathbf{r}\|$ .

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Taking norms:  $\|\mathbf{e}\| \leq \|A^{-1}\| \|\mathbf{r}\|$ .

Taking the norm of  $\mathbf{r} = A\mathbf{e}$ , we get  $\|\mathbf{r}\| \leq \|A\| \|\mathbf{e}\|$ .

Therefore,

$$\frac{\|\mathbf{r}\|}{\|A\|} \leq \|\mathbf{e}\| \leq \|A^{-1}\| \|\mathbf{r}\|.$$

## Sensitivity of linear system

Taking norm of  $A\mathbf{x} = \mathbf{b}$  and  $\mathbf{x} = A^{-1}\mathbf{b}$ , we get

$$\frac{\|\mathbf{b}\|}{\|A\|} \leq \|\mathbf{x}\| \leq \|A^{-1}\| \|\mathbf{b}\|.$$

## Sensitivity of linear system

Taking norm of  $A\mathbf{x} = \mathbf{b}$  and  $\mathbf{x} = A^{-1}\mathbf{b}$ , we get

$$\frac{\|\mathbf{b}\|}{\|A\|} \leq \|\mathbf{x}\| \leq \|A^{-1}\| \|\mathbf{b}\|.$$

Hence,

$$\frac{1}{\text{cond}(A)} \frac{\|\mathbf{r}\|}{\|\mathbf{b}\|} \leq \frac{\|\mathbf{e}\|}{\|\mathbf{x}\|} \leq \text{cond}(A) \frac{\|\mathbf{r}\|}{\|\mathbf{b}\|}.$$

**This is the desired relationship.** (Here,  $\text{cond}(A) = \|A\| \cdot \|A^{-1}\|$  or  $C(A) = \|A\| \cdot \|A^{-1}\|$ .)



## Sensitivity of linear system

Relative error can be as large as the relative residual multiplied by the condition number.

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If condition number is large, relative residual gives little information about the accuracy.

If the condition number is near unity, the relative residual is a good measure of the relative error.

## Sensitivity of linear system

**Problem:**

**Show** that the error of the solution relative to the norm of the computed solution can be as large as the relative error in the coefficients of  $A$  multiplied by the condition number of  $A$ .

**Proof:**

Want to show that

$$\frac{\|\mathbf{x} - \tilde{\mathbf{x}}\|}{\|\tilde{\mathbf{x}}\|} \leq C(A) \frac{\|E\|}{\|A\|}.$$

## Sensitivity of linear system

Let  $\tilde{A} = A + E$  be the perturbed coefficient matrix. We desire to know how large is  $\mathbf{x} - \tilde{\mathbf{x}}$ , where  $\mathbf{x}$  is the solution of  $A\mathbf{x} = \mathbf{b}$  and  $\tilde{\mathbf{x}}$  is the solution of  $\tilde{A}\tilde{\mathbf{x}} = \mathbf{b}$ .

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Since  $A\mathbf{x} = \mathbf{b}$  and  $\tilde{A}\tilde{\mathbf{x}} = \mathbf{b}$ , we get

$$\mathbf{x} = A^{-1}(\tilde{A}\tilde{\mathbf{x}}) = \tilde{\mathbf{x}} + A^{-1}E\tilde{\mathbf{x}}.$$

Taking norm of  $\mathbf{x} - \tilde{\mathbf{x}}$  we conclude the proof.

## Sensitivity of linear system

### Exercise

Suppose that  $\tilde{x}$  is an approximation to the solution of  $Ax = b$ ,  $A$  is a non-singular matrix, and  $r$  is the residual vector for  $\tilde{x}$ . Then, show that

$$(i) \|x - \tilde{x}\| \leq \|r\| \cdot \|A^{-1}\|$$

$$(ii) \frac{\|x - \tilde{x}\|}{\|x\|} \leq \|A\| \cdot \|A^{-1}\| \frac{\|r\|}{\|b\|}.$$



## Iterative method

Can we think for an alternate method for solving  $Ax = b$ ?

The solution requires the inversion of the coefficient matrix:

$$x = A^{-1}b.$$

In Matlab, we use

$$x = A \setminus b$$

## Iterative method

Let us consider the system:

$$\begin{aligned}6x - 2y + z &= 11 \\ -2x + 7y + 2z &= 5 \\ x + 2y - 5z &= -1\end{aligned}$$

We have a  $3 \times 3$  matrix

$$A = \begin{bmatrix} 6 & -2 & 1 \\ -2 & 7 & 2 \\ 1 & 2 & -5 \end{bmatrix}$$

## Iterative method

How about any of the following matrices:

$$L = \begin{bmatrix} 0 & 0 & 0 \\ -2 & 0 & 0 \\ 1 & 2 & 0 \end{bmatrix}, \quad D = \begin{bmatrix} 6 & 0 & 0 \\ 0 & 7 & 0 \\ 0 & 0 & -5 \end{bmatrix}, \quad U = \begin{bmatrix} 0 & -2 & 1 \\ 0 & 0 & 2 \\ 0 & 0 & 0 \end{bmatrix}$$

Each of these matrices are easy to invert.

None of these matrices are obtained by an appropriate elimination process.

$Dx = b$  is easier to solve than  $Ax = b$ .

## Iterative method

Let us go back to the example and solve each equation for one variable.

$$\begin{aligned}6x - 2y + z &= 11 \\ -2x + 7y + 2z &= 5 \\ x + 2y - 5z &= -1\end{aligned}$$

## Iterative method

Let us go back to the example and solve each equation for one variable.

$$x = \frac{1}{6}(11 + 2y - z)$$

$$y = \frac{1}{7}(5 + 2x - 2z)$$

$$z = \frac{1}{-5}(-1 - x - 2y)$$

## Iterative method

If we assume

$$x = 0, y = 0, z = 0$$

an approximate solution, then we get

$$x = 11/6, y = 5/7, z = 1/5.$$

We can switch between **assumed** solution and **obtained** solution to end up with an approximate solution iteratively.

## Iterative method

### Jacobi iteration

Let us consider the decomposition

$$A = L + D + U,$$

where

$D$  is the diagonal elements of  $A$ ,

$L$  is the strictly lower triangular elements of  $A$ , and

$U$  is the strictly upper triangular elements of  $A$ .

## Iterative method

### Jacobi iteration

We can re-write the system  $Ax = b$  as

$$Dx = b - (L + U)x.$$

Since  $D$  is a diagonal matrix and it is easy to find  $D^{-1}$ , we construct the Jacobi method:

$$x^{k+1} = D^{-1}[b - (L + U)x^k].$$



## Iterative method

Let  $A = M + B$ . A linear system  $Ax = b$  can be written as

$$Mx = b - Bx,$$

where  $M$  is a non-singular matrix that is easy to invert.

Therefore, one writes

$$x = M^{-1}(b - Bx).$$