

# Announcements

- Next week: midterm exam
  - starts at 14:20
  - about 80-90 minutes
  - [Optional] bring a A4 cheat sheet (one side only)

# Solving linear systems III

Mei-Chen Yeh

# Review

- ***Direct*** methods for solving linear systems
  - Gaussian elimination with *partial pivoting*
  - The  $PA = LU$  factorization

# Today

- ***Iterative*** methods for solving linear systems
  - Jacobi method
  - Gauss-Seidel method
  - Successive over-relaxation (SOR)

# Solving $\underline{Ax} = \underline{b}$

- $A$  is given, real,  $n \times n$ , and  $\underline{b}$  is given, real vector.
- Two types of approaches
  - Direct methods: yield exact solution in absence of roundoff error  
Example: Gaussian elimination and its variants
  - **Iterative** methods: iterate in a similar fashion to what we do for solving nonlinear equations

# Iterative methods for solving $\underline{Ax} = \underline{b}$

- Starting from initial guess  $\underline{x}_0$ , generate iterates  $\underline{x}_1$ ,  $\underline{x}_2$ , ...,  $\underline{x}_k$ , hopefully converging to solution  $\underline{x}$ .
- But why not simply using a direct method (e.g., LU decomposition)?



# Why using iterative methods?

- Can be faster if the input matrix is large
  - One step of an iterative method requires only a fraction of the floating operations of a full LU factorization.
- A good approximation to the solution is already known.
- The input matrix is *sparse*.

# Direct vs. iterative linear solvers

- Direct solvers
  - Computation is numerically stable in many relevant cases. 😊
  - Can solve economically for several right-hand sides. 😊
  - But: fill-in limits usefulness (memory). ☹️
- Iterative solvers
  - Only a rough approximation to  $\underline{x}$  is required. 😊
  - A good  $\underline{x}_0$  approximating  $\underline{x}$  is generally known (warm start). 😊
  - Quality often depends on “right” choice of parameters. ☹️



# Typical scenarios

- **Direct** solvers
  - Many linear systems with the same matrix  $A$
  - Applications that require very accurate solutions
- **Iterative** solvers
  - Many linear systems with “slightly changing” matrices
  - Matrix-free applications
  - Very large problems

# Iterative methods

- Jacobi method
- Gauss-Seidel method
- Successive over-relaxation (SOR)

# Jacobi method

- A form of fixed-point iteration
- Example: Solve the linear system
 
$$\begin{aligned} 3u + v &= 5 \\ u + 2v &= 5 \end{aligned}$$
- The answer is  $u = 1, v = 2$ .
- First, we have

$$u = \frac{5 - v}{3}$$

$$v = \frac{5 - u}{2}$$

$$\begin{bmatrix} u_1 \\ v_1 \end{bmatrix} = \begin{bmatrix} \frac{5-v_0}{3} \\ \frac{5-u_0}{2} \end{bmatrix} = \begin{bmatrix} \frac{5-0}{3} \\ \frac{5-0}{2} \end{bmatrix} = \begin{bmatrix} \frac{5}{3} \\ \frac{5}{2} \end{bmatrix}$$

$$\begin{bmatrix} u_2 \\ v_2 \end{bmatrix} = \begin{bmatrix} \frac{5-v_1}{3} \\ \frac{5-u_1}{2} \end{bmatrix} = \begin{bmatrix} \frac{5-5/2}{3} \\ \frac{5-5/3}{2} \end{bmatrix} = \begin{bmatrix} \frac{5}{6} \\ \frac{5}{3} \end{bmatrix}$$

$$\begin{bmatrix} u_3 \\ v_3 \end{bmatrix} = \begin{bmatrix} \frac{5-5/3}{3} \\ \frac{5-5/6}{2} \end{bmatrix} = \begin{bmatrix} \frac{10}{9} \\ \frac{25}{12} \end{bmatrix}$$

⋮

- Start from an initial guess  $(0, 0)$

[continue](#)

# Jacobi method

- Use the example again, but now the equations are given in the *reverse* order.

$$u + 2v = 5 \quad \begin{bmatrix} u_0 \\ v_0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$3u + v = 5$$

- The answer is  $u = 1, v =$   $\begin{bmatrix} u_1 \\ v_1 \end{bmatrix} = \begin{bmatrix} 5 - 2v_0 \\ 5 - 3u_0 \end{bmatrix} = \begin{bmatrix} 5 \\ 5 \end{bmatrix}$

- We have

$$\begin{bmatrix} u_2 \\ v_2 \end{bmatrix} = \begin{bmatrix} 5 - 2v_1 \\ 5 - 3u_1 \end{bmatrix} = \begin{bmatrix} -5 \\ -10 \end{bmatrix}$$

$$u = 5 - 2v$$

$$v = 5 - 3u$$

$$\begin{bmatrix} u_3 \\ v_3 \end{bmatrix} = \begin{bmatrix} 5 - 2(-10) \\ 5 - 3(-5) \end{bmatrix} = \begin{bmatrix} 25 \\ 20 \end{bmatrix}$$

- Start from an initial guess (0, 0)

⋮

# The difference?

- $3u + v = 5$
- $u + 2v = 5$

**VS.**

- $u + 2v = 5$
- $3u + v = 5$

$$A = \begin{bmatrix} 3 & 1 \\ 1 & 2 \end{bmatrix}$$

$$A = \begin{bmatrix} 1 & 2 \\ 3 & 1 \end{bmatrix}$$

The Jacobi method converges. 😊

The Jacobi method diverges. ☹️

# Strictly diagonally dominant

- **Definition.** The  $n \times n$  matrix  $A = (a_{ij})$  is **strictly diagonally dominant** if, for each  $1 \leq i \leq n$ ,  
 $|a_{ii}| > \sum_{j \neq i} |a_{ij}|$ .
- Which matrix is strictly diagonally dominant?

$$A = \begin{bmatrix} 3 & 1 & -1 \\ 2 & -5 & 2 \\ 1 & 6 & 8 \end{bmatrix}$$

$$B = \begin{bmatrix} 3 & 2 & 6 \\ 1 & 8 & 1 \\ 9 & 2 & -2 \end{bmatrix}$$



**Theorem.** If the  $n \times n$  matrix  $A$  is strictly diagonally dominant, then

1.  $A$  is a nonsingular matrix, and
2. for every vector  $\underline{b}$  and every starting guess, the Jacobi method applied to  $A\underline{x} = \underline{b}$  converges to the solution.

# The previous example

- $3u + v = 5$
- $u + 2v = 5$

VS.

- $u + 2v = 5$
- $3u + v = 5$

$$A = \begin{bmatrix} 3 & 1 \\ 1 & 2 \end{bmatrix}$$

$$A = \begin{bmatrix} 1 & 2 \\ 3 & 1 \end{bmatrix}$$

**strictly diagonally dominant**

The Jacobi method converges. 😊

**NOT strictly diagonally dominant**

The Jacobi method diverges. ☹️



# A form of fixed-point iteration $\underline{x} = g(\underline{x})$

- Start with  $A\underline{x} = \underline{b}$

$$(D + L + U)\underline{x} = \underline{b}$$

$$D\underline{x} = \underline{b} - (L + U)\underline{x}$$

$$\underline{x} = D^{-1}(\underline{b} - (L + U)\underline{x})$$

$$\underbrace{\quad}_{g(\underline{x})}$$

$$A = \begin{bmatrix} 3 & 1 & -1 \\ 2 & -5 & 2 \\ 1 & 6 & 8 \end{bmatrix}$$

L
D
U

$$D = \begin{bmatrix} 3 & 0 & 0 \\ 0 & -5 & 0 \\ 0 & 0 & 8 \end{bmatrix} \quad L = \begin{bmatrix} 0 & 0 & 0 \\ 2 & 0 & 0 \\ 1 & 6 & 0 \end{bmatrix} \quad U = \begin{bmatrix} 0 & 1 & -1 \\ 0 & 0 & 2 \\ 0 & 0 & 0 \end{bmatrix}$$

- Jacobi Method

$x_0$  = initial vector

$$x_{k+1} = D^{-1}(b - (L + U)x_k) \text{ for } k = 0, 1, 2, \dots$$

# Example: Jacobi method

- Jacobi method

$x_0$  = initial vector

$$x_{k+1} = D^{-1}(b - (L + U)x_k) \text{ for } k = 0, 1, 2, \dots$$

- The previous example

$$-3u + v = 5$$

$$-u + 2v = 5$$

$$D = \begin{bmatrix} 3 & 0 \\ 0 & 2 \end{bmatrix}, L = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, U = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, b = \begin{bmatrix} 5 \\ 5 \end{bmatrix}$$

$$\begin{bmatrix} u_{k+1} \\ v_{k+1} \end{bmatrix} = \begin{bmatrix} 1/3 & 0 \\ 0 & 1/2 \end{bmatrix} \left( \begin{bmatrix} 5 \\ 5 \end{bmatrix} - \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} u_k \\ v_k \end{bmatrix} \right) = \begin{bmatrix} (5 - v_k)/3 \\ (5 - u_k)/2 \end{bmatrix}$$

$$\mathbf{D}^{-1} \quad \underline{\mathbf{b}} \quad \mathbf{L+U} \quad \underline{\mathbf{x}}_k$$

check

# Iterative methods

- Jacobi method
- Gauss-Seidel method
- Successive over-relaxation (SOR)

# Gauss-Seidel method

- Uses **the most recently updated** values of the knowns, even if the updating occurs in the current step!

• The previous example

$$\begin{aligned} 3u + v &= 5 \\ u + 2v &= 5 \end{aligned}$$

$$u = \frac{5 - v}{3}$$

$$v = \frac{5 - u}{2}$$

$$\begin{aligned} \begin{bmatrix} u_0 \\ v_0 \end{bmatrix} &= \begin{bmatrix} 0 \\ 0 \end{bmatrix} \\ \begin{bmatrix} u_1 \\ v_1 \end{bmatrix} &= \begin{bmatrix} \frac{5-v_0}{3} \\ \frac{5-u_1}{2} \end{bmatrix} = \begin{bmatrix} \frac{5-0}{3} \\ \frac{5-5/3}{2} \end{bmatrix} = \begin{bmatrix} \frac{5}{3} \\ \frac{5}{3} \end{bmatrix} \\ \begin{bmatrix} u_2 \\ v_2 \end{bmatrix} &= \begin{bmatrix} \frac{5-v_1}{3} \\ \frac{5-u_2}{2} \end{bmatrix} = \begin{bmatrix} \frac{5-5/3}{3} \\ \frac{5-10/9}{2} \end{bmatrix} = \begin{bmatrix} \frac{10}{9} \\ \frac{35}{18} \end{bmatrix} \\ \begin{bmatrix} u_3 \\ v_3 \end{bmatrix} &= \begin{bmatrix} \frac{5-v_2}{3} \\ \frac{5-u_3}{2} \end{bmatrix} = \begin{bmatrix} \frac{5-35/18}{3} \\ \frac{5-55/54}{2} \end{bmatrix} = \begin{bmatrix} \frac{55}{54} \\ \frac{215}{108} \end{bmatrix} \\ &\vdots \end{aligned}$$

# A form of fixed-point iteration $\underline{x} = g(\underline{x})$

- Start with  $A\underline{x} = \underline{b}$

$$(L+D+U)\underline{x} = \underline{b}$$

$$(L+D)\underline{x}_{k+1} = \underline{b} - U\underline{x}_k$$

$$D\underline{x}_{k+1} = \underline{b} - U\underline{x}_k - L\underline{x}_{k+1}$$

$$\underline{x}_{k+1} = \underbrace{D^{-1}(\underline{b} - U\underline{x}_k - L\underline{x}_{k+1})}_{g(\underline{x})}$$

$$A = \begin{bmatrix} 3 & 1 & -1 \\ 2 & -5 & 2 \\ 1 & 6 & 8 \end{bmatrix}$$

L
D
U

$$D = \begin{bmatrix} 3 & 0 & 0 \\ 0 & -5 & 0 \\ 0 & 0 & 8 \end{bmatrix} \quad L = \begin{bmatrix} 0 & 0 & 0 \\ 2 & 0 & 0 \\ 1 & 6 & 0 \end{bmatrix}$$

$$U = \begin{bmatrix} 0 & 1 & -1 \\ 0 & 0 & 2 \\ 0 & 0 & 0 \end{bmatrix}$$

- Gauss-Seidel Method

$x_0$  = initial vector

$$x_{k+1} = D^{-1}(b - Ux_k - Lx_{k+1}) \text{ for } k = 0, 1, 2, \dots$$

- Gauss-Seidel Method

$x_0$  = initial vector

$$x_{k+1} = D^{-1}(b - Ux_k - Lx_{k+1}) \text{ for } k = 0, 1, 2, \dots$$

- Example

$$\begin{bmatrix} 3 & 1 & -1 \\ 2 & 4 & 1 \\ -1 & 2 & 5 \end{bmatrix} \begin{bmatrix} u \\ v \\ w \end{bmatrix} = \begin{bmatrix} 4 \\ 1 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} u_{k+1} \\ v_{k+1} \\ w_{k+1} \end{bmatrix} = \begin{bmatrix} 1/3 & 0 & 0 \\ 0 & 1/4 & 0 \\ 0 & 0 & 1/5 \end{bmatrix} \left( \begin{bmatrix} 4 \\ 1 \\ 1 \end{bmatrix} - \begin{bmatrix} 0 & 1 & -1 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} u_k \\ v_k \\ w_k \end{bmatrix} - \begin{bmatrix} 0 & 0 & 0 \\ 2 & 0 & 0 \\ -1 & 2 & 0 \end{bmatrix} \begin{bmatrix} u_{k+1} \\ v_{k+1} \\ w_{k+1} \end{bmatrix} \right)$$

$$= \begin{bmatrix} 1/3 & 0 & 0 \\ 0 & 1/4 & 0 \\ 0 & 0 & 1/5 \end{bmatrix} \left( \begin{bmatrix} 4 - v_k + w_k \\ 1 - w_k - 2u_{k+1} \\ 1 + u_{k+1} - 2v_{k+1} \end{bmatrix} \right)$$

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$$3u + v - w = 4 \Rightarrow u = \frac{1}{3}(4 - v + w) \quad -u + 2v + 5w = 1 \Rightarrow w = \frac{1}{5}(1 + u - 2v)$$

$$2u + 4v + w = 1 \Rightarrow v = \frac{1}{4}(1 - w - 2u)$$

# Jacobi vs. Gauss-Seidel

$$\begin{bmatrix} u_0 \\ v_0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} u_1 \\ v_1 \end{bmatrix} = \begin{bmatrix} \frac{5-v_0}{3} \\ \frac{5-u_0}{2} \end{bmatrix} = \begin{bmatrix} \frac{5-0}{3} \\ \frac{5-0}{2} \end{bmatrix} = \begin{bmatrix} \frac{5}{3} \\ \frac{5}{2} \end{bmatrix}$$

$$\begin{bmatrix} u_2 \\ v_2 \end{bmatrix} = \begin{bmatrix} \frac{5-v_1}{3} \\ \frac{5-u_1}{2} \end{bmatrix} = \begin{bmatrix} \frac{5-5/2}{3} \\ \frac{5-5/3}{2} \end{bmatrix} = \begin{bmatrix} \frac{5}{6} \\ \frac{5}{3} \end{bmatrix}$$

$$\begin{bmatrix} u_3 \\ v_3 \end{bmatrix} = \begin{bmatrix} \frac{5-5/3}{3} \\ \frac{5-5/6}{2} \end{bmatrix} = \begin{bmatrix} \frac{10}{9} \\ \frac{25}{12} \end{bmatrix}$$

$$\underline{x}_{k+1} = D^{-1}(\underline{b} - (L+U)\underline{x}_k)$$

$$\begin{bmatrix} u_0 \\ v_0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} u_1 \\ v_1 \end{bmatrix} = \begin{bmatrix} \frac{5-v_0}{3} \\ \frac{5-u_1}{2} \end{bmatrix} = \begin{bmatrix} \frac{5-0}{3} \\ \frac{5-5/3}{2} \end{bmatrix} = \begin{bmatrix} \frac{5}{3} \\ \frac{5}{3} \end{bmatrix}$$

$$\begin{bmatrix} u_2 \\ v_2 \end{bmatrix} = \begin{bmatrix} \frac{5-v_1}{3} \\ \frac{5-u_2}{2} \end{bmatrix} = \begin{bmatrix} \frac{5-5/3}{3} \\ \frac{5-10/9}{2} \end{bmatrix} = \begin{bmatrix} \frac{10}{9} \\ \frac{35}{18} \end{bmatrix}$$

$$\begin{bmatrix} u_3 \\ v_3 \end{bmatrix} = \begin{bmatrix} \frac{5-v_2}{3} \\ \frac{5-u_3}{2} \end{bmatrix} = \begin{bmatrix} \frac{5-35/18}{3} \\ \frac{5-55/54}{2} \end{bmatrix} = \begin{bmatrix} \frac{55}{54} \\ \frac{215}{108} \end{bmatrix}$$

$$\underline{x}_{k+1} = D^{-1}(\underline{b} - U\underline{x}_k - L\underline{x}_{k+1})$$

# Iterative methods

- Jacobi method
- Gauss-Seidel method
- Successive over-relaxation (SOR)



# Successive Over-Relaxation (SOR)

- Uses a weighted average of the Gauss-Seidel and the current guess

$$\mathbf{x}_{k+1} \leftarrow \omega \mathbf{x}_{k+1} + (1 - \omega) \mathbf{x}_k$$

- The relaxation parameter:  $\omega$ 
  - $\omega \cdot$  Gauss-Seidel
  - $(1 - \omega) \cdot$  current guess
- **Over-relaxation:  $\omega > 1$**
- Also can be written as a form of fixed-point iteration

# Gauss-Seidel vs. SOR

$$\begin{bmatrix} 3 & 1 & -1 \\ 2 & 4 & 1 \\ -1 & 2 & 5 \end{bmatrix} \begin{bmatrix} u \\ v \\ w \end{bmatrix} = \begin{bmatrix} 4 \\ 1 \\ 1 \end{bmatrix}$$

## Gauss-Seidel

$$u_{k+1} = \frac{4 - v_k + w_k}{3}$$

$$v_{k+1} = \frac{1 - 2u_{k+1} - w_k}{4}$$

$$w_{k+1} = \frac{1 + u_{k+1} - 2v_{k+1}}{5}$$

## SOR

$$u_{k+1} = (1 - \omega)u_k + \omega \frac{4 - v_k + w_k}{3}$$

$$v_{k+1} = (1 - \omega)v_k + \omega \frac{1 - 2u_{k+1} - w_k}{4}$$

$$w_{k+1} = (1 - \omega)w_k + \omega \frac{1 + u_{k+1} - 2v_{k+1}}{5}$$

# Successive Over-Relaxation (SOR)

- Also can be written as a form of fixed-point iteration

$x_0$  = initial vector

$$x_{k+1} = (\omega L + D)^{-1}[(1 - \omega)Dx_k - \omega Ux_k] + \omega(D + \omega L)^{-1}b \text{ for } k = 0, 1, 2, \dots$$

# 程式練習

And, please upload your program on moodle2.

- Please use Jacobi, Gauss-Seidel or SOR to solve the system of 10 equations in 10 unknowns:

$$\begin{pmatrix} 3 & -1 & & & & \\ -1 & 3 & -1 & & & \\ & \ddots & \ddots & \ddots & & \\ & & & -1 & 3 & -1 \\ & & & & -1 & 3 \end{pmatrix} \begin{pmatrix} x_1 \\ \vdots \\ x_{10} \end{pmatrix} = \begin{pmatrix} 2 \\ 1 \\ \vdots \\ 1 \\ 2 \end{pmatrix}$$