

## 7.3 The Jacobi and Gauss-Seidel Iterative Methods

### The Jacobi Method

*Two assumptions made on Jacobi Method:*

1. The system given by

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

Has a unique solution.

2. The coefficient matrix  $A$  has no zeros on its main diagonal, namely,  $a_{11}, a_{22}, \dots, a_{nn}$  are nonzeros.

#### Main idea of Jacobi

To begin, solve the 1<sup>st</sup> equation for  $x_1$ , the 2<sup>nd</sup> equation for  $x_2$  and so on to obtain the rewritten equations:

$$\begin{aligned}x_1 &= \frac{1}{a_{11}}(b_1 - a_{12}x_2 - a_{13}x_3 - \cdots a_{1n}x_n) \\x_2 &= \frac{1}{a_{22}}(b_2 - a_{21}x_1 - a_{23}x_3 - \cdots a_{2n}x_n) \\&\vdots \\x_n &= \frac{1}{a_{nn}}(b_n - a_{n1}x_1 - a_{n2}x_2 - \cdots a_{n,n-1}x_{n-1})\end{aligned}$$

Then make an initial guess of the solution  $\mathbf{x}^{(0)} = (x_1^{(0)}, x_2^{(0)}, x_3^{(0)}, \dots, x_n^{(0)})$ . Substitute these values into the right hand side the of the rewritten equations to obtain the *first approximation*,  $(x_1^{(1)}, x_2^{(1)}, x_3^{(1)}, \dots, x_n^{(1)})$ .

This accomplishes one **iteration**.

In the same way, the *second approximation*  $(x_1^{(2)}, x_2^{(2)}, x_3^{(2)}, \dots, x_n^{(2)})$  is computed by substituting the first approximation's  $x$ -vales into the right hand side of the rewritten equations.

By repeated iterations, we form a sequence of approximations  $\mathbf{x}^{(k)} = (x_1^{(k)}, x_2^{(k)}, x_3^{(k)}, \dots, x_n^{(k)})^t$ ,  $k = 1, 2, 3, \dots$

**The Jacobi Method.** For each  $k \geq 1$ , generate the components  $x_i^{(k)}$  of  $\mathbf{x}^{(k)}$  from  $\mathbf{x}^{(k-1)}$  by

$$x_i^{(k)} = \frac{1}{a_{ii}} \left[ \sum_{\substack{j=1, \\ j \neq i}}^n (-a_{ij}x_j^{(k-1)}) + b_i \right], \quad \text{for } i = 1, 2, \dots, n$$

**Example.** Apply the Jacobi method to solve

$$\begin{aligned} 5x_1 - 2x_2 + 3x_3 &= -1 \\ -3x_1 + 9x_2 + x_3 &= 2 \\ 2x_1 - x_2 - 7x_3 &= 3 \end{aligned}$$

Continue iterations until two successive approximations are identical when rounded to three significant digits.

**Solution** To begin, rewrite the system

$$\begin{aligned} x_1 &= \frac{-1}{5} + \frac{2}{5}x_2 - \frac{3}{5}x_3 \\ x_2 &= \frac{2}{9} + \frac{3}{9}x_1 - \frac{1}{9}x_3 \\ x_3 &= -\frac{3}{7} + \frac{2}{7}x_1 - \frac{1}{7}x_2 \end{aligned}$$

Choose the initial guess  $x_1 = 0, x_2 = 0, x_3 = 0$

The first approximation is

$$\begin{aligned} x_1^{(1)} &= \frac{-1}{5} + \frac{2}{5}(0) - \frac{3}{5}(0) = -0.200 \\ x_2^{(1)} &= \frac{2}{9} + \frac{3}{9}(0) - \frac{1}{9}(0) = 0.222 \\ x_3^{(1)} &= -\frac{3}{7} + \frac{2}{7}(0) - \frac{1}{7}(0) = -0.429 \end{aligned}$$

Continue iteration, we obtain

$n$	$k = 0$	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 6$
$x_1^{(k)}$	0.000	-0.200	0.146	0.192			
$x_2^{(k)}$	0.000	0.222	0.203	0.328			
$x_2^{(k)}$	0.000	-0.429	-0.517	-0.416			

**When to stop:** 1.  $\frac{\|\mathbf{x}^{(k)} - \mathbf{x}^{(k-1)}\|}{\|\mathbf{x}^{(k)}\|} < \varepsilon$ ; or 2.  $\|\mathbf{x}^{(k)} - \mathbf{x}^{(k-1)}\| < \varepsilon$ . Here  $\varepsilon$  is a given small number.

### The Jacobi Method in Matrix Form

Consider to solve an  $n \times n$  size system of linear equations  $A\mathbf{x} = \mathbf{b}$  with  $A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix}$  and  $\mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}$  for  $\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$ .

We split  $A$  into

$$A = \begin{bmatrix} a_{11} & 0 & \dots & 0 \\ 0 & a_{22} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & a_{nn} \end{bmatrix} - \begin{bmatrix} 0 & \dots & 0 & 0 \\ -a_{21} & \dots & 0 & 0 \\ \vdots & & \ddots & \vdots \\ -a_{n1} & \dots & -a_{n,n-1} & 0 \end{bmatrix} - \begin{bmatrix} 0 & -a_{12} & \dots & -a_{1n} \\ 0 & 0 & & \vdots \\ \vdots & \vdots & \ddots & -a_{n-1,n} \\ 0 & 0 & \dots & 0 \end{bmatrix} = D - L - U$$

$A\mathbf{x} = \mathbf{b}$  is transformed into  $(D - L - U)\mathbf{x} = \mathbf{b}$

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

Assume  $D^{-1}$  exists and  $D^{-1} = \begin{bmatrix} \frac{1}{a_{11}} & 0 & \dots & 0 \\ 0 & \frac{1}{a_{22}} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \frac{1}{a_{nn}} \end{bmatrix}$

Then

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

The matrix form of Jacobi iterative method is

$$\mathbf{x}^{(k)} = D^{-1}(L + U)\mathbf{x}^{(k-1)} + D^{-1}\mathbf{b} \quad k = 1, 2, 3, \dots$$

Define  $T_j = D^{-1}(L + U)$  and  $\mathbf{c} = D^{-1}\mathbf{b}$ , Jacobi iteration method can also be written as

$$\mathbf{x}^{(k)} = T_j\mathbf{x}^{(k-1)} + \mathbf{c} \quad k = 1, 2, 3, \dots$$

### Numerical Algorithm of Jacobi Method

Input:  $A = [a_{ij}]$ ,  $\mathbf{b}$ ,  $\mathbf{XO} = \mathbf{x}^{(0)}$ , tolerance  $TOL$ , maximum number of iterations  $N$ .

Step 1 Set  $k = 1$

Step 2 while ( $k \leq N$ ) do Steps 3-6

Step 3 For for  $i = 1, 2, \dots, n$

$$x_i = \frac{1}{a_{ii}} \left[ \sum_{\substack{j=1, \\ j \neq i}}^n (-a_{ij}\mathbf{XO}_j) + b_i \right],$$

Step 4 If  $\|\mathbf{x} - \mathbf{XO}\| < TOL$ , then OUTPUT ( $x_1, x_2, x_3, \dots, x_n$ );  
STOP.

Step 5 Set  $k = k + 1$ .

Step 6 For for  $i = 1, 2, \dots, n$

Set  $\mathbf{XO}_i = x_i$ .

Step 7 OUTPUT ( $x_1, x_2, x_3, \dots, x_n$ );  
STOP.

Another stopping criterion in Step 4:  $\frac{\|\mathbf{x}^{(k)} - \mathbf{x}^{(k-1)}\|}{\|\mathbf{x}^{(k)}\|}$

## The Gauss-Seidel Method

### Main idea of Gauss-Seidel

With the Jacobi method, only the values of  $x_i^{(k)}$  obtained in the  $k$ th iteration are used to compute  $x_i^{(k+1)}$ . With the Gauss-Seidel method, we use the new values  $x_i^{(k+1)}$  as soon as they are known. For example, once we have computed  $x_1^{(k+1)}$  from the first equation, its value is then used in the second equation to obtain the new  $x_2^{(k+1)}$ , and so on.

**Example.** Derive iteration equations for the Jacobi method and Gauss-Seidel method to solve

$$\begin{aligned} 5x_1 - 2x_2 + 3x_3 &= -1 \\ -3x_1 + 9x_2 + x_3 &= 2 \\ 2x_1 - x_2 - 7x_3 &= 3 \end{aligned}$$

Choose the initial guess  $x_1 = 0, x_2 = 0, x_3 = 0$

$n$	$k = 0$	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 6$
$x_1^{(k)}$	0.000	-0.200	0.167				
$x_2^{(k)}$	0.000	0.156	0.334				
$x_3^{(k)}$	0.000	-0.508	-0.429				

**The Gauss-Seidel Method.** For each  $k \geq 1$ , generate the components  $x_i^{(k)}$  of  $\mathbf{x}^{(k)}$  from  $\mathbf{x}^{(k-1)}$  by

$$x_i^{(k)} = \frac{1}{a_{ii}} \left[ - \sum_{j=1}^{i-1} (a_{ij}x_j^{(k)}) - \sum_{j=i+1}^n (a_{ij}x_j^{(k-1)}) + b_i \right], \quad \text{for } i = 1, 2, \dots, n$$

Namely,

$$\begin{aligned} a_{11}x_1^{(k)} &= -a_{12}x_2^{(k-1)} - \dots - a_{1n}x_n^{(k-1)} + b_1 \\ a_{22}x_2^{(k)} &= -a_{21}x_1^{(k)} - a_{23}x_3^{(k-1)} - \dots - a_{2n}x_n^{(k-1)} + b_2 \\ &\vdots \\ a_{nn}x_n^{(k)} &= -a_{n1}x_1^{(k)} - a_{n2}x_2^{(k)} - \dots + b_n \end{aligned}$$

Matrix form of Gauss-Seidel method.

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

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

Define  $T_g = (D - L)^{-1}U$  and  $\mathbf{c}_g = (D - L)^{-1}\mathbf{b}$ , Gauss-Seidel method can be written as

$$\mathbf{x}^{(k)} = T_g\mathbf{x}^{(k-1)} + \mathbf{c}_g \quad k = 1, 2, 3, \dots$$

### Numerical Algorithm of Gauss-Seidel Method

Input:  $A = [a_{ij}]$ ,  $\mathbf{b}$ ,  $\mathbf{XO} = \mathbf{x}^{(0)}$ , tolerance  $TOL$ , maximum number of iterations  $N$ .

Step 1 Set  $k = 1$

Step 2 while ( $k \leq N$ ) do Steps 3-6

Step 3 For for  $i = 1, 2, \dots, n$

$$x_i = \frac{1}{a_{ii}} \left[ -\sum_{j=1}^{i-1} (a_{ij}x_j) - \sum_{j=i+1}^n (a_{ij}\mathbf{XO}_j) + b_i \right],$$

Step 4 If  $\|\mathbf{x} - \mathbf{XO}\| < TOL$ , then OUTPUT ( $x_1, x_2, x_3, \dots, x_n$ );  
STOP.

Step 5 Set  $k = k + 1$ .

Step 6 For for  $i = 1, 2, \dots, n$

Set  $\mathbf{XO}_i = x_i$ .

Step 7 OUTPUT ( $x_1, x_2, x_3, \dots, x_n$ );  
STOP.

## Convergence theorems of the iteration methods

Let the iteration method be written as  
 $\mathbf{x}^{(k)} = T\mathbf{x}^{(k-1)} + \mathbf{c}$  for each  $k = 1, 2, 3, \dots$

**Lemma 7.18** If the spectral radius satisfies  $\rho(T) < 1$ , then  $(I - T)^{-1}$  exists, and

$$(I - T)^{-1} = I + T + T^2 + \dots = \sum_{j=0}^{\infty} T^j$$

**Theorem 7.19** For any  $\mathbf{x}^{(0)} \in R^n$ , the sequence  $\{\mathbf{x}^{(k)}\}_{k=0}^{\infty}$  defined by

$$\mathbf{x}^{(k)} = T\mathbf{x}^{(k-1)} + \mathbf{c} \quad \text{for each } k \geq 1$$

converges to the unique solution of  $\mathbf{x} = T\mathbf{x} + \mathbf{c}$  if and only if  $\rho(T) < 1$ .

**Proof** (only show  $\rho(T) < 1$  is sufficient condition)

$$\mathbf{x}^{(k)} = T\mathbf{x}^{(k-1)} + \mathbf{c} = T(T\mathbf{x}^{(k-2)} + \mathbf{c}) + \mathbf{c} = \dots = T^k\mathbf{x}^{(0)} + (T^{k-1} + \dots + T + I)\mathbf{c}$$

Since  $\rho(T) < 1$ ,  $\lim_{k \rightarrow \infty} T^k\mathbf{x}^{(0)} = \mathbf{0}$

$$\lim_{k \rightarrow \infty} \mathbf{x}^{(k)} = \mathbf{0} + \lim_{k \rightarrow \infty} \left( \sum_{j=0}^{k-1} T^j \right) \mathbf{c} = (I - T)^{-1} \mathbf{c}$$

**Corollary 7.20** If  $\|T\| < 1$  for any natural matrix norm and  $\mathbf{c}$  is a given vector, then the sequence  $\{\mathbf{x}^{(k)}\}_{k=0}^{\infty}$  defined by  $\mathbf{x}^{(k)} = T\mathbf{x}^{(k-1)} + \mathbf{c}$  converges, for any  $\mathbf{x}^{(0)} \in R^n$ , to a vector  $\mathbf{x} \in R^n$ , with  $\mathbf{x} = T\mathbf{x} + \mathbf{c}$ , and the following error bound hold:

- (i)  $\|\mathbf{x} - \mathbf{x}^{(k)}\| \leq \|T\|^k \|\mathbf{x}^{(0)} - \mathbf{x}\|$
- (ii)  $\|\mathbf{x} - \mathbf{x}^{(k)}\| \leq \frac{\|T\|^k}{1 - \|T\|} \|\mathbf{x}^{(1)} - \mathbf{x}^{(0)}\|$

**Theorem 7.21** If  $A$  is strictly diagonally dominant, then for any choice of  $\mathbf{x}^{(0)}$ , both the Jacobi and Gauss-Seidel methods give sequences  $\{\mathbf{x}^{(k)}\}_{k=0}^{\infty}$  that converges to the unique solution of  $A\mathbf{x} = \mathbf{b}$ .

### Rate of Convergence

**Corollary 7.20** (i) implies  $\|\mathbf{x} - \mathbf{x}^{(k)}\| \approx \rho(T)^k \|\mathbf{x}^{(0)} - \mathbf{x}\|$

**Theorem 7.22 (Stein-Rosenberg)** If  $a_{ij} \leq 0$ , for each  $i \neq j$  and  $a_{ii} \geq 0$ , for each  $i = 1, 2, \dots, n$ , then one and only one of following statements holds:

- (i)  $0 \leq \rho(T_g) < \rho(T_j) < 1$ ;
- (ii)  $1 < \rho(T_j) < \rho(T_g)$ ;
- (iii)  $\rho(T_j) = \rho(T_g) = 0$ ;
- (iv)  $\rho(T_j) = \rho(T_g) = 1$ .



## Simple iteration

Assume there is an initial guess  $\mathbf{x}^{(0)}$  for the solution to  $A\mathbf{x} = \mathbf{b}$ . If one could compute the *error*  $\mathbf{e}^{(0)} = A^{-1}\mathbf{b} - \mathbf{x}^{(0)}$ , then one could find the solution  $\mathbf{x} = \mathbf{x}^{(0)} + \mathbf{e}^{(0)}$ . However,  $A^{-1}\mathbf{b}$  is expensive to compute.

Instead, let's compute the *residual*  $\mathbf{r}^{(0)} = \mathbf{b} - A\mathbf{x}^{(0)}$ . Note that  $\mathbf{r}^{(0)} = A\mathbf{e}^{(0)}$ .

If  $M$  is a matrix with the property that  $M^{-1}A$  approximates the identity, yet  $\mathbf{r}^{(0)} = M\mathbf{z}^{(0)}$  is easy to solve for  $\mathbf{z}^{(0)}$ , one could approximate the *error* by  $M^{-1}\mathbf{r}^{(0)}$ .

Thus, one solve  $M\mathbf{z}^{(0)} = \mathbf{r}^{(0)}$  for  $\mathbf{z}^{(0)}$ , which approximates  $\mathbf{e}^{(0)}$ , and then replace  $\mathbf{x}^{(0)}$  by  $\mathbf{x}^{(1)} \equiv \mathbf{x}^{(0)} + \mathbf{z}^{(0)}$ . Repeat this process with  $\mathbf{x}^{(1)}$ .

## Simple iteration algorithm

Given an initial guess  $\mathbf{x}^{(0)}$ , compute  $\mathbf{r}^{(0)} = \mathbf{b} - A\mathbf{x}^{(0)}$ , and solve  $\mathbf{r}^{(0)} = M\mathbf{z}^{(0)}$  for  $\mathbf{z}^{(0)}$ .

for  $k = 1, 2, \dots$

Set  $\mathbf{x}^{(k)} \equiv \mathbf{x}^{(k-1)} + \mathbf{z}^{(k-1)}$ .

Compute  $\mathbf{r}^{(k)} = \mathbf{b} - A\mathbf{x}^{(k)}$ .

Solve  $M\mathbf{z}^{(k)} = \mathbf{r}^{(k)}$  for  $\mathbf{z}^{(k)}$ .

## Remark:

1. For  $M \equiv D$ , the method is Jacobi iteration

$$\begin{aligned}\mathbf{x}^{(k)} &= D^{-1}(L + U)\mathbf{x}^{(k-1)} + D^{-1}\mathbf{b} = D^{-1}(D - D + L + U)\mathbf{x}^{(k-1)} + D^{-1}\mathbf{b} = D^{-1}(D - A)\mathbf{x}^{(k-1)} + D^{-1}\mathbf{b} = \mathbf{x}^{(k-1)} + \\ &D^{-1}(\mathbf{b} - A\mathbf{x}^{(k-1)}) \equiv \mathbf{x}^{(k-1)} + \mathbf{z}^{(k-1)},\end{aligned}$$

2. For  $M \equiv D - L$ , the method is GS.

$$\begin{aligned}\mathbf{x}^{(k)} &= (D - L)^{-1}U\mathbf{x}^{(k-1)} + (D - L)^{-1}\mathbf{b} = (D - L)^{-1}(U - D + L + D - L)\mathbf{x}^{(k-1)} + (D - L)^{-1}\mathbf{b} \\ &= (D - L)^{-1}(D - L - A)\mathbf{x}^{(k-1)} + (D - L)^{-1}\mathbf{b} = \mathbf{x}^{(k-1)} - (D - L)^{-1}(\mathbf{b} - A\mathbf{x}^{(k-1)}) \equiv \mathbf{x}^{(k-1)} + \mathbf{z}^{(k-1)}\end{aligned}$$