

Is this Jacobi or Gauss-Seidel iteration? Why

$\vec{x}^{(k+1)} = \vec{x}^{(k)}$ ($x_2 = x_1$)

for $i=1:n$

$$x_i^{(k+1)} = \left(b_i - \sum_{j=1, j \neq i}^n a_{ij} x_j^{(k+1)} \right) / a_{ii}$$

end

How many $\vec{x}^{(k)}$ do we need to store?

for J, G-S. 2. for stopping criteria.

$\vec{x}^{(k)} = \vec{x}^{(k+1)}$

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Ex: ODE BVP $\begin{cases} u''(x) = f(x), 0 < x < 1 \\ u(0) = 0, u(1) = 0 \end{cases}$

$u_i = u(x_i)$

Given an n , $h = \frac{1}{n}$

$x_i = ih, i=0, 1, \dots, n, x_0=0, x_n=1$

$$\frac{u_{i-1} - 2u_i + u_{i+1}}{h^2} = f(x_i), i=1, 2, \dots, n-1$$

$u_0=0, u_n=0$

$AU = F, A = \frac{1}{h^2} \begin{bmatrix} -2 & 1 & & 0 \\ & 1 & -2 & 1 \\ & & \ddots & \ddots \\ 0 & & & 1 & -2 \\ & & & & & 1 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_{n-1} \end{bmatrix} = \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_{n-1} \end{bmatrix}$

Ordering: Index of unknown and equation. Using the same ordering.

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The coefficients in front of diagonals are $-\frac{2}{h^2}$. Solve for the diagonal

$$u_i = \frac{u_{i-1} + u_{i+1}}{2} + \frac{h^2}{2} f(x_i)$$

Form an iteration

$$u_i^{(k+1)} = \frac{u_{i-1}^{(k)} + u_{i+1}^{(k)}}{2} - \frac{h^2}{2} f(x_i), i=1, 2, \dots, n-1$$

Jacobi iteration.

$$\vec{u}^{(k+1)} = \vec{u}^{(k)}$$

G-S.

$$u_i^{(k+1)} = \frac{u_{i-1}^{(k+1)} + u_{i+1}^{(k+1)}}{2} - \frac{h^2}{2} f(x_i)$$

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SOR(ω): Successive over-relaxation

$0 < \omega < 1$

$\vec{x}^{(k+1)}_{SOR} = (1-\omega)\vec{x}^{(k)} + \omega\vec{x}^{(k+1)}_{GS}$

$\omega = 0, \vec{x}^{(k)}$ $\omega = 1, \vec{x}^{(k+1)}_{GS}$

$0 < \omega < 1$, interpolation

$1 < \omega < 2$, extrapolation \rightarrow over-relaxation

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Component form. Matrix-vector convergence analysis

Implementation.

$$x_i^{(k+1)} = (1-\omega)x_i^{(k)} + \omega \left(b_i - \sum_{j=1}^{i-1} a_{ij} x_j^{(k+1)} - \sum_{j=i+1}^n a_{ij} x_j^{(k)} \right) / a_{ii}$$

$i=1, 2, \dots, n$

Pseudo-code

$$\vec{x}^{(k+1)} = \vec{x}^{(k)}$$

$$x_i^{(k+1)} = (1-\omega)x_i^{(k)} + \omega \left(b_i - \sum_{j=1}^{i-1} a_{ij} x_j^{(k+1)} - \sum_{j=i+1}^n a_{ij} x_j^{(k)} \right) / a_{ii}$$

$i=1, 2, \dots, n$. ω is a given parameter.

How do we choose ω , $\omega \sim 2$.

Oct 15-10:02 AM

Matrix-vector form of SOR(ω)

$$\begin{pmatrix} \dots \end{pmatrix} \vec{x}^{(k+1)} = \begin{pmatrix} \dots \end{pmatrix} \vec{x}^{(k)} + \vec{c}$$

$$\vec{x}^{(k+1)} = \begin{pmatrix} \dots \end{pmatrix} \vec{x}^{(k)} + \begin{pmatrix} \dots \end{pmatrix} \vec{c}$$

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

$$A = D - L - U$$

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

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

$$= R\vec{x}^{(k)} + \vec{c}$$

$R = (D - \omega L)^{-1} ((1-\omega)D + \omega U)$, $\vec{c} = \omega (D - \omega L)^{-1} \vec{b}$

If $\omega = 1$, $R_{SOR(1)} = R_{GS} = (D - L)^{-1} U$, $\vec{c} = (D - L)^{-1} \vec{b}$

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Is this the SOR iteration?

$$\checkmark \quad \vec{x}_{GS}^{(k+1)} = \left(b_i - \sum_{j=1}^{i-1} a_{ij} x_j^{(k+1)} - \sum_{j=i+1}^n a_{ij} x_j^{(k)} \right) / a_{ii}$$

$$\vec{x}_{SOR(\omega)} = (1-\omega) \vec{x}^{(k)} + \omega \vec{x}_{GS}^{(k+1)}$$

Does not use the most updated info.

Oct 15-10:17 AM

Convergence. Fix-point iteration.

$$\vec{x}^{(k+1)} = G(\vec{x}^{(k)}), \quad \|G'\| < 1$$

$$\vec{x}^{(k+1)} = R \vec{x}^{(k)} + c$$

$$\frac{DG(R \vec{x}^{(k)} + c)}{d\vec{x}} = R \quad \|R\| < 1$$

A sufficient condition

Thus, If there is a matrix norm such that $\|R\| < 1$ then the iterative method will converge.

$$\|\vec{x}^* - \vec{x}^{(k)}\| \leq \frac{\|R\|^k}{1 - \|R\|} \|\vec{x}^{(1)} - \vec{x}^*\|$$

$$\vec{x}^* = R \vec{x}^* + c$$

$$\|R\|^k \rightarrow 0$$

Oct 15-10:21 AM

Convergence of basic iterative methods.
 $x^{k+1} = R x^k + c$
 Consistent condition $x^* = R x^* + c$ is solvable
 $\lim_{k \rightarrow \infty} x^k = x^*$ for any x^0 , initial
Thm If there is a matrix norm such that $\|R\| < 1$, then the iterative method always converges.

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Proof. $x^* = R x^* + c$
 $x^{k+1} = R x^k + c$
 $x^{k+1} - x^* = R(x^k - x^*)$
 $= R R(x^{k-1} - x^*)$
 $= \dots = R^{k+1}(x^0 - x^*) \checkmark$
 $\|x^{k+1} - x^*\| \leq \|R^{k+1}\| \|x^0 - x^*\|$
 $\|R\|^k \quad \|R\| < 1$
 $\|R^k = R^{k-1} \cdot R\| \leq \|R^{k-1}\| \|R\|$
 $\leq \|R^{k-2}\| \|R\| \|R\| \leq \|R\|^k$
 $\lim_{k \rightarrow \infty} \|x^{k+1} - x^*\| = 0$ since $\|R\| < 1 \checkmark$

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Convergence speed. If we know $\|R\| < 1$, then how many iterations do we need such that $\|e^k\| \leq 10^{-8}$?
 $x^{k+1} = R x^k + c$
 $x^k = R x^{k-1} + c$
 $x^{k+1} - x^k = R(x^k - x^{k-1}) = R R(x^{k-1} - x^{k-2})$
 $x^k - x^* = R(x^{k-1} - x^*) = R^k(x^0 - x^*)$
 $R(x^k - x^*) - (x^k - x^*) = R^k(x^0 - x^*) - (x^k - x^*)$
 $(R - I)(x^k - x^*) = R^k(x^0 - x^*) - (x^k - x^*)$
 $-(x^k - x^*) = (I - R)R^k(x^0 - x^*)$
 $\|x^k - x^*\| \leq \|(I - R)^{-1}\| \|R\|^k \|x^0 - x^*\|$
 convergence speed $\leq \frac{\|R\|^k}{1 - \|R\|} \|x^0 - x^*\|$
 $\|R\|^k \leq 10^{-8}$
 $k \log_{10} \|R\| \leq -8$
 $k \geq \frac{-8}{\log_{10} \|R\|}$

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Ex: $R = \begin{bmatrix} 0.9 & 0.05 \\ 0.8 & 0.1 \end{bmatrix}$ $x^{k+1} = R x^k + c$
 Converges or not? $\|R\|_{\infty} = \max\{1.9, 0.9\} = 1.9 > 1$
 $\|R\|_1 = 1.7 < 1$
 Ex: $R = \begin{bmatrix} 0.2 & 0.81 \\ 0.81 & 0 \end{bmatrix}$ $\|R\|_1 = \|R\|_{\infty} = 1.61 < 1$
 No conclusion.

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If and only if condition, is $\rho(R) < 1$.
 The spectral radius is defined by $\rho(R) = \max_{|\lambda| \in \sigma(R)} |\lambda|$
 Sketch of the proof. $\rho(R) < 1 \rightarrow \|R\| < 1$
 From linear algebra, there is a matrix S such that
 $S^{-1} R S = J = \begin{bmatrix} J_1 & & 0 \\ & \ddots & \\ 0 & & J_p \end{bmatrix}$, $J_k = \begin{bmatrix} \lambda_k & & 0 \\ & \lambda_k & \\ & & \ddots \\ 0 & & & \lambda_k \end{bmatrix}$
 One block $\|J\|_{\infty} = \rho(R)$, $\|J\|_{\infty} = \rho(R) + 1$ otherwise $\leq \rho(R) + 1$

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$D(\epsilon) S^{-1} R S D = \begin{bmatrix} J_1(\epsilon) & & 0 \\ & \ddots & \\ 0 & & J_p(\epsilon) \end{bmatrix}$
 $J_k(\epsilon) = \begin{bmatrix} \lambda_k + \epsilon & & 0 \\ & \lambda_k + \epsilon & \\ & & \ddots \\ 0 & & & \lambda_k + \epsilon \end{bmatrix}$ $\rho(R) + \epsilon < 1$
 $\epsilon = \frac{1 - \rho(R)}{2}$
 $D = \begin{bmatrix} D_1(\epsilon) & & 0 \\ & \ddots & \\ 0 & & D_p(\epsilon) \end{bmatrix}$ $D_k(\epsilon) = \begin{bmatrix} \epsilon & & 0 \\ & \epsilon & \\ & & \ddots \\ 0 & & & \epsilon \end{bmatrix}$
 $T^{-1} R T = \begin{bmatrix} J_1(\epsilon) & & 0 \\ & \ddots & \\ 0 & & J_p(\epsilon) \end{bmatrix} = J(\epsilon)$
 $\|T^{-1} R T\|_{\infty} \leq \rho(R) + \epsilon < 1$ $T = S D$
 Define a new matrix norm, $T^{-1} = D^{-1} S^{-1}$
 $\|B\| = \|T^{-1} B T\|_{\infty}$, can you prove it is a matrix norm.

Oct 17-10:19 AM

Convergence of $x^{k+1} = R x^k + c$

If and only if condition $\rho(R) < 1$,

Sufficient: If $\rho(R) < 1$, \rightarrow convergence

A. New matrix norm

$$B. \quad \|R\|_{\text{new}} = \| \underbrace{D^{-1} S^{-1} A S D}_{\text{Jordan blocks}} \|_{\infty}$$

In the Jordan blocks, we can use any non-zero number.

necessary condition: If it converges,
then $\rho(R) < 1$. Counter proof

If not true, $\rho(R) \stackrel{=1}{> 1}$. There is an
eigen-pair (λ^*, x^*) such that

$$R x^* = \lambda^* x^* \quad |\lambda^*| = \rho(R) > 1$$

$$x^0 = x^*, \quad x^1 = R x^0 = \lambda^* x^0 \quad x^* = \vec{0}.$$

$$x^2 = R x^1 = \lambda^* R x^0 = (\lambda^*)^2 x^0$$

$$x^{k+1} = (\lambda^*)^{k+1} x^0 \rightarrow \infty$$

$$x^{k+1} = (-1)^k x^k$$

$h=1$
no limit.

Special matrices.

Type A: Strict row diagonally dominant

$$|a_{ii}| > \sum_{\substack{j=1 \\ j \neq i}}^n |a_{ij}| \quad \text{SRDD.} \quad i=1, 2, \dots, n$$

Thm. If A is SRDD, $Ax=b$
 then both Jacobi, G-S iterative methods converge.
 $x^{k+1} = Rx^k + c$

$$\rho(R_{G-S}) \leq \rho(R_J) < 1. \quad A = D - L - U$$

$$R_J = D^{-1}(L+U) = \begin{bmatrix} 0 & -\frac{a_{12}}{a_{11}} & \dots & -\frac{a_{1n}}{a_{11}} \\ \frac{a_{21}}{a_{22}} & 0 & \dots & \dots \\ \dots & \dots & \ddots & \dots \\ \dots & \dots & \dots & 0 \end{bmatrix}$$

$$\|R_J\| = \max_i \sum_{\substack{j=1 \\ j \neq i}}^n \frac{|a_{ij}|}{|a_{ii}|} < 1 = \max_i \frac{\sum_{j \neq i} |a_{ij}|}{|a_{ii}|}$$

Type B. S.P.D. symmetric positive definite.

Thm. If A is an S.P.D., then
Gauss-Seidel and SOR(ω), $0 < \omega < 2$
converge (as well as Jacobi).

The proof is not easy.

Ex: $A = \frac{1}{h^2} \begin{bmatrix} 2 & -1 & & 0 \\ -1 & 2 & \dots & \\ & \dots & \dots & -1 \\ 0 & \dots & -1 & 2 \end{bmatrix}$ $\begin{cases} -u'' = f, a < x < b \\ u(a) = \alpha, u(b) = \beta \end{cases}$

Is A SRDD?

i $|+2| \geq |-1| + |-1|$ $|2| > |-1|$

Weakly row diagonally dominant. $|2| > |-1|$

If A is "irreducible" and weakly row diagonally dominant, then Jacobi,

G-S, SOR(ω), $a < \omega < 2$. converge \geq

Weakly diagonally dominant

$|a_{ii}| \geq \sum_{\substack{j=1 \\ j \neq i}}^n |a_{ij}|$ and at least

one of them satisfies $|a_{ii}| > \sum_{\substack{j=1 \\ j \neq i}}^n |a_{ij}|$

A is irreducible, means there is no

permutation matrix $P = P_{12} P_{23} \dots P_{ij}$

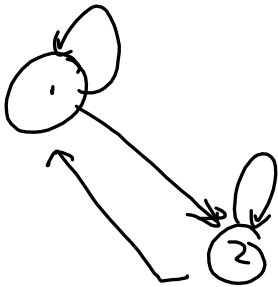
such that

$$P^T A P = \begin{bmatrix} A_{11} & A_{12} \\ 0 & A_{22} \end{bmatrix} \quad P_{ij}^{-1} = P_{ij}^T$$

$$P^{-1} \quad Ax = b$$

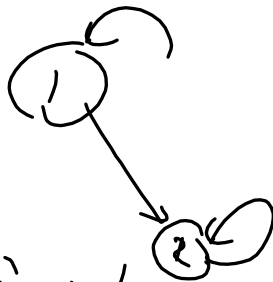
$$P^T A P P^T x = P^T b = \begin{bmatrix} A_{11} & A_{12} \\ 0 & A_{22} \end{bmatrix} P^T x = P^T b$$

Graph theory.



$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}, \text{ probability matrix.}$$

$$\begin{bmatrix} a_{11} & a_{12} \\ 0 & a_{22} \end{bmatrix}$$



maximum principle

→ elliptic
parabolic

not with wave eqn,

A is reducible.

For Poisson Equ. convergence speed best ω . $P(R)$

1D. $A = \frac{1}{h^2} \begin{bmatrix} 2 & -1 & & & 0 \\ -1 & 2 & & & \\ & & \ddots & & \\ 0 & & & -1 & 2 \\ & & & & & -1 & 2 \end{bmatrix}$ $\frac{u_{i-1} - 2u_i + u_{i+1}}{h^2} = f(x_i)$

SOR(ω) $u_i^{k+1} = \frac{u_{i-1}^k + u_{i+1}^k}{2} + \frac{h^2 f(x_i)}{2}, \quad i=1, 2, \dots, n-1.$

$R_J = D^{-1}(L+U)$

$\det(\lambda I - D^{-1}(L+U)) = 0$

$\lambda_i(R), \frac{\lambda_i(A)}{\text{known}}$

$\det(D^{-1}(\lambda D - (L+U))) = 0$

$A = D - L - U$

$\det(D^{-1}) \det(\lambda D - (L+U)) = 0$

$\det(AB) = \det(A)\det(B)$

$\det((\lambda-1)D + D - (L+U)) = 0$

$\det((\lambda-1)D + A) = 0$

$\det(\lambda I - A)$

$\det(+2(\lambda-1)I + A) = 0$

\uparrow
 $-2(1-\lambda)I - A$

$\lambda_J = \frac{-\lambda_i(A)}{2} + 1 \quad P(R_J)$