

Today's Agenda

- Iterative methods for solving linear systems
 - (Gauss) Jacobi (GJ)
 - Gauss Seidel (GS)
 - Successive Over-Relaxation (SOR)
- Case study: Solving PDE

Golub and Van Loan, *Matrix Computations 4th edition*, Johns Hopkins Press



GJ v.s. GS

• GJ: $x^{(k)} = D^{-1}b - D^{-1}(L+U) x^{(k-1)}$

for
$$i=1:n$$

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

• GS: $x^{(k)} = (L+D)^{-1}b - (L+D)^{-1}Ux^{(k-1)}$

for
$$i=1:n$$

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



Splitting and convergence

• A splitting A = M - N is proposed when Mz = d is "easy" to solve.

- For GJ and GS, diagonal elements of A should be nonzero; otherwise not invertible.
- Spectral radius of the matrix $M^{-1}N$ must be bounded above 1 for convergence: $\rho(M^{-1}N) < 1$ and the smaller the better.



GJ vs GS

Consider four systems, with matrix A_i given below. Consider their iteration matrices G_i and G_s .

$$A_1 = \begin{bmatrix} 3 & 0 & 4 \\ 7 & 4 & 2 \\ -1 & 1 & 2 \end{bmatrix}, \qquad A_2 = \begin{bmatrix} -3 & 3 & -6 \\ -4 & 7 & -8 \\ 5 & 7 & -9 \end{bmatrix},$$

$$A_3 = \begin{bmatrix} 4 & 1 & 1 \\ 2 & -9 & 0 \\ 0 & -8 & -6 \end{bmatrix}, \qquad A_4 = \begin{bmatrix} 7 & 6 & 9 \\ 4 & 5 & -4 \\ -7 & -3 & 8 \end{bmatrix}.$$

```
Matlab:

D = diag(diag(A));

L = tril(A,-1);

U = triu(A,1);

GJ = -inv(D)*(L+U);

GS = -inv(L+D)*U;

max(abs(eig(GJ)))

max(abs(eig(GS)))
```



GJ vs GS

- For the system given by A₁, ρ(G_J)>1 but ρ(G_S)<1 → GJ diverges but GS converges
- For the system given by A₂, $\rho(G_J)<1$ but $\rho(G_S)>1$ \rightarrow GJ converges but GS diverges
- For the system given by A₃, $\rho(G_J)$ =0.44 and $\rho(G_S)$ =0.018 \rightarrow both converge but GJ typically converges slower than GS
- For the system given by A_4 , $\rho(G_J)=0.64$ and $\rho(G_S)=0.77 \rightarrow$ both converge but GJ typically converges faster than GS
- → Take-away: there isn't a "one size fits all" answer for algorithm selection.

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Motivation of a new scheme

An example

```
N = 11; A = toeplitz([2 -1 zeros(1,N-3)])

D=diag(diag(A)); U=triu(A,1); L=tril(A,-1);

max(abs(eig(-inv(D+L) *U)))
```

• Observe, $A = M - N = (L + D) - (-U) = (L + \frac{1}{w}D)$

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-((\frac{1}{w}-1)D-U) for any w...
```

• In fact G = @(w) (D/w+L)\((1./w-1).*D-U); SR = @(w) max(abs(eig(G(w))));

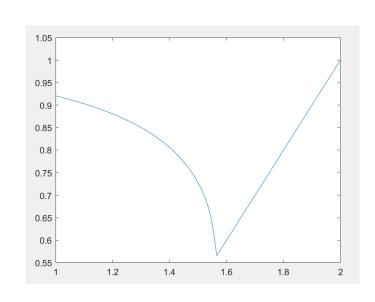
w = linspace(1,2);

for j=1:length(w)

f(j) = SR(w(j));

end

plot(w,f)





SOR

Successive over relaxation (SOR)

• Write A = L + D + U +
$$\frac{1}{w}$$
D - $\frac{1}{w}$ D

• Ax = b
$$\rightarrow$$
 (L + D + U + $\frac{1}{w}$ D - $\frac{1}{w}$ D)x = b \rightarrow

$$(L+\frac{1}{w}D)x = b - (D-\frac{1}{w}D+U)x \rightarrow$$

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



SOR (cont'd)

Recall

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

• Written iteratively, we get...

for
$$i = 1:n$$

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

Relaxation term

Momentum term

GS-update



SOR convergence

• SOR reduces to GS when w=1.

 A necessary condition for SOR to converge is 0<w<2.

 When the matrix A is SPD, then the condition becomes sufficient!



A case study

Solving the Poisson equation



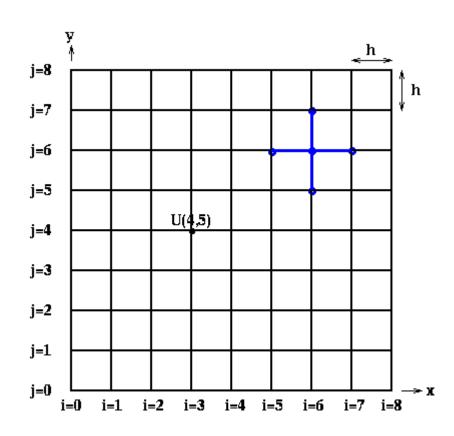
Problem setup

Poisson equation

u(x,y) = 0 if (x,y) is on the boundary of Omega

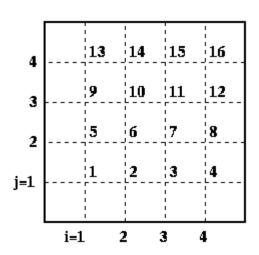
Discretization

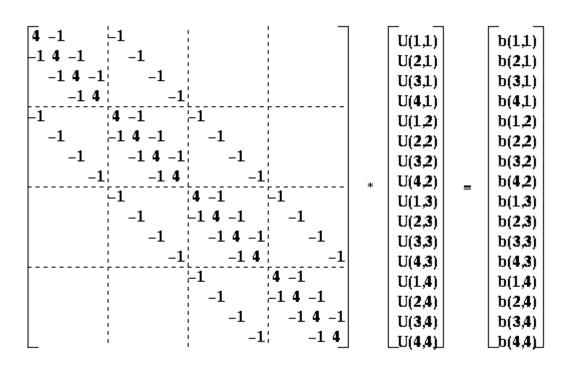
$$4*U(ij) - U(i-1j) - U(i+1j) - U(ij-1) - U(ij+1) = b(ij)$$





Small-scale example







Solving the Poisson equation

Recall

$$4*U(i,j) - U(i-1,j) - U(i+1,j) - U(i,j-1) - U(i,j+1) = b(i,j)$$

• GS:
$$U(i,j) = [U(i-1,j)+U(i+1,j)+U(i,j+1)+U(i,j-1)+b(i,j)]/4$$

• SOR: V(i,j) = [U(i-1,j)+U(i+1,j)+U(i,j+1)+U(i,j-1)+b(i,j)]/4U(i,j) = U(i,j)+w(V(i,j)-U(i,j))