

## Today:

- Gauss-Seidel and SOR iterative methods
- Totalview debugging

## Next:

- GPUs, Python

**Read:** Class notes and references

# Jacobi iteration

$$(U_{i-1} - 2U_i + U_{i+1}) = -\Delta x^2 f(x_i)$$

Solve for  $U_i$ :

$$U_i = \frac{1}{2} (U_{i-1} + U_{i+1} + \Delta x^2 f(x_i)) .$$

**Note:** With no heat source,  $f(x) = 0$ ,  
the temperature at each point is average of neighbors.

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the temperature at each point is average of neighbors.

Suppose  $U^{[k]}$  is a approximation to solution. Set

$$U_i^{[k+1]} = \frac{1}{2} \left( U_{i-1}^{[k]} + U_{i+1}^{[k]} + \Delta x^2 f(x_i) \right) \quad \text{for } i = 1, 2, \dots, n.$$

**Repeat** for  $k = 0, 1, 2, \dots$  until convergence.

Can be shown to converge (eventually... **very slow!**)

# Jacobi iteration in Fortran

```
uold = u  ! starting values before updating
do iter=1,maxiter
  dumax = 0.d0
  do i=1,n
    u(i) = 0.5d0*(uold(i-1) + uold(i+1) + dx**2*f(i))
    dumax = max(dumax, abs(u(i)-uold(i)))
  enddo

  ! check for convergence:
  if (dumax .lt. tol) exit

  uold = u  ! for next iteration
enddo
```

**Note:** we must use old value at  $i - 1$  for Jacobi.

Otherwise we get the **Gauss-Seidel** method.

# Gauss-Seidel iteration in Fortran

```
do iter=1,maxiter
  dumax = 0.d0
  do i=1,n
    uold = u(i)
    u(i) = 0.5d0*(u(i-1) + u(i+1) + dx**2*f(i))
    dumax = max(dumax, abs(u(i)-uold))
  enddo

  ! check for convergence:
  if (dumax .lt. tol) exit

enddo
```

**Note:** Now  $u(i)$  depends on value of  $u(i-1)$  that has already been updated for previous  $i$ .

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**Good news:** This converges about twice as fast as Jacobi!

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**But... loop carried dependence!** Cannot parallelize so easily.

# Red-black ordering

We are free to write equations of linear system in any order...  
reordering rows of coefficient matrix, right hand side.

Can also number unknowns of linear system in any order...  
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**Red-black ordering:** Iterate through points with odd index first ( $i = 1, 3, 5, \dots$ ) and then even index points ( $i = 2, 4, 6, \dots$ ).

Then all black points can be updated in any order,  
all red points can then be updated in any order.

Same asymptotic convergence rate as natural ordering.



# Red-Black Gauss-Seidel

```
do iter=1,maxiter
  dumax = 0.d0

  ! UPDATE ODD INDEX POINTS:
  !$omp parallel do reduction(max : dumax) &
  !$omp private(uold)
  do i=1,n,2
    uold = u(i)
    u(i) = 0.5d0*(u(i-1) + u(i+1) + dx**2*f(i))
    dumax = max(dumax, abs(u(i)-uold))
  enddo

  ! UPDATE EVEN INDEX POINTS:
  !$omp parallel do reduction(max : dumax) &
  !$omp private(uold)
  do i=2,n,2
    uold = u(i)
    u(i) = 0.5d0*(u(i-1) + u(i+1) + dx**2*f(i))
    dumax = max(dumax, abs(u(i)-uold))
  enddo

  ! check for convergence:
  if (dumax .lt. tol) exit
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```

# Gauss-Seidel method in 2D

If  $\Delta x = \Delta y = h$ :

$$\frac{1}{h^2} (U_{i-1,j} + U_{i+1,j} + U_{i,j-1} + U_{i,j+1} - 4U_{i,j}) = -f(x_i, y_j).$$

Solve for  $U_{i,j}$  and iterate:

$$u_{i,j}^{[k+1]} = \frac{1}{4} (u_{i-1,j}^{[k+1]} + u_{i+1,j}^{[k]} + u_{i,j-1}^{[k+1]} + u_{i,j+1}^{[k]} - h^2 f_{i,j})$$

Again no need for matrix  $A$ .

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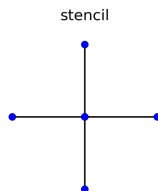
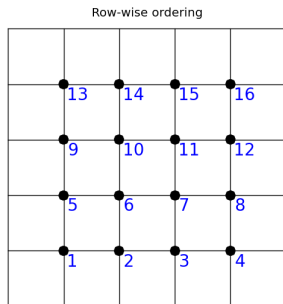
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**Note:** Above indices for old and new values assumes we iterate in the **natural row-wise order**.

# Gauss-Seidel in 2D

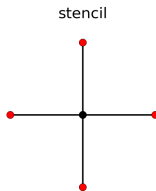
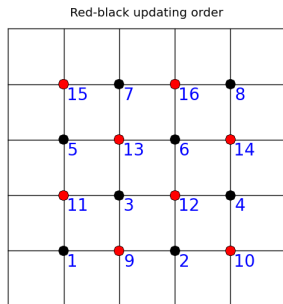


Updating point 7 for example ( $u_{32}$ ):

Depends on **new values** at points 6 and 3, **old** values at points 7 and 10.

$$U_{32}^{[k+1]} = \frac{1}{4}(U_{22}^{[k+1]} + U_{42}^{[k]} + U_{21}^{[k+1]} + U_{41}^{[k]} + h^2 f_{32})$$

# Red-black ordering in 2D



Again all black points can be updated in any order:

New value depends only on red neighbors.

Then all red points can be updated in any order:

New value depends only on black neighbors.

# SOR method

Gauss-Seidel move solution in right direction but not far enough in general.

Iterates “relax” towards solution.

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Successive Over-Relaxation (SOR):

Compute Gauss-Seidel approximation and then go further:

$$U_i^{GS} = \frac{1}{2}(U_{i-1}^{[k+1]} + U_{i+1}^{[k]} + \Delta x^2 f(x_i))$$
$$U_i^{[k+1]} = U_i^{[k]} + \omega(U_i^{GS} - U_i^{[k]})$$

where  $1 < \omega < 2$ .



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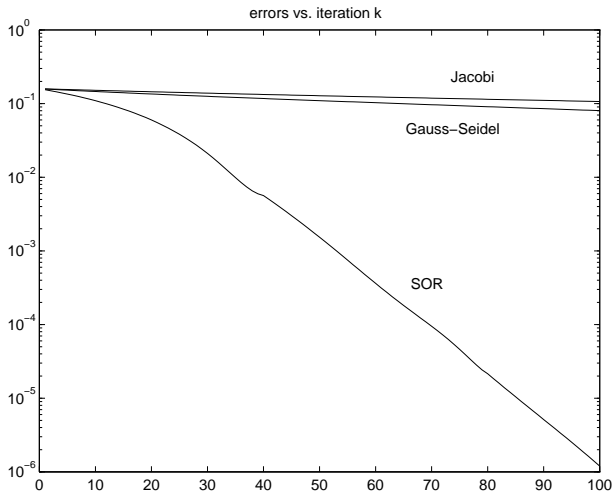
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$$U_i^{[k+1]} = U_i^{[k]} + \omega(U_i^{GS} - U_i^{[k]})$$

where  $1 < \omega < 2$ .

Optimal omega (For this problem):  $\omega = 2 - 2\pi\Delta x$ .

# Convergence rates



# Red-Black SOR in 1D

```
do iter=1,maxiter
  dumax = 0.d0

  ! UPDATE ODD INDEX POINTS:
  !$omp parallel do reduction(max : dumax) &
  !$omp private(uold, ugs)
  do i=1,n,2
    uold = u(i)
    ugs = 0.5d0*(u(i-1) + u(i+1) + dx**2*f(i))
    u(i) = uold + omega*(ugs-uold)
    dumax = max(dumax, abs(u(i)-uold))
  enddo

  ! UPDATE EVEN INDEX POINTS:
  !$omp parallel do reduction(max : dumax) &
  !$omp private(uold, ugs)
  do i=2,n,2
    uold = u(i)
    ugs = 0.5d0*(u(i-1) + u(i+1) + dx**2*f(i))
    u(i) = uold + omega*(ugs-uold)
    dumax = max(dumax, abs(u(i)-uold))
  enddo

  ! check for convergence...
```

Note that `uold`, `ugs` must be private!

# Totalview debugger

<http://www.roguewave.com/products/totalview-family>

Student versions available — see email to class.