



Parallel Iterative Matrix Algorithms

CS121 Parallel Computing
Fall 2023



Iterative matrix algorithms

- To solve a dense system of linear equations $Ax = b$, we saw direct methods such as Gaussian Elimination.
- When the A is very large (millions of variables), GE is too slow.
- For structured matrices, e.g. banded matrices, special solution methods can be developed.
- For general sparse matrices, we use iterative algorithms that compute approximate solutions which eventually converge to the true solution.



Iterative matrix algorithms

- Given $A \in \mathbb{R}^{n \times n}$, write $A = M - N$, where M and N are matrices such that M^{-1} is easy to compute (e.g. a diagonal matrix).
 - Let x^* be the solution to $Ax = b$. Then $Mx^* = Nx^* + b$.
- Let $C = M^{-1}N$, $d = M^{-1}b$.
 - So $x^* = Cx^* + d$.
- Starting from an initial x , repeatedly compute $Cx + d$.
 - Denote k 'th iterate of x as $x^{(k)}$.
 - Then $x^{(k+1)} = Cx^{(k)} + d$.

Convergence criteria

- We want the iterations to converge, starting from any initial vector $x^{(0)} \in \mathbb{R}^n$.
 - I.e. we want $\lim_{k \rightarrow \infty} x^{(k)} = x^*$, so that $x^* = Cx^* + d$.
- Since $x^{(k+1)} = Cx^{(k)} + d$, then subtracting, we get $x^{(k+1)} - x^* = C(x^{(k)} - x^*)$.
 - Also, $x^{(k)} - x^* = C(x^{(k-1)} - x^*)$, etc.
 - So in general $x^{(k)} - x^* = C^k(x^{(0)} - x^*)$.
- Let $\rho(C)$ be the magnitude of the largest eigenvalue of C .
- **Thm** The following are equivalent
 - The iterative algorithm converges for any initial $x^{(0)}$.
 - $\lim_{k \rightarrow \infty} C^k = 0$.
 - $\rho(C) < 1$.

Jacobi method

- Write $A = D - L - R$, where D is the diagonal elements of A , $-L$ is the lower triangular part of A without D , and $-R$ is the upper triangular part without D .
- Let $M = D, N = L + R$. Note that M is easy to invert.
- Then $C = D^{-1}(L + R)$, and $d = D^{-1}b$.
 - So $c_{ij} = -a_{ij}/a_{ii}$ if $j \neq i$, and $c_{ii} = 0$ for all i .
 - Also, $d_i = b_i/a_{ii}$ for all i .
- Convergence is guaranteed if the matrix is diagonally dominant, i.e. $|a_{ii}| > \sum_{j=1, j \neq i}^n |a_{ij}|$ for all i .
- Recall $x^{(k+1)} = Cx^{(k)} + d$. So the i 'th component of $x^{(k+1)}$ is
$$x_i^{(k+1)} = \frac{1}{a_{ii}} \left(b_i - \sum_{j=1, j \neq i}^n a_{ij} x_j^{(k)} \right).$$
- $x^{(k+1)}$ depends only on $x^{(k)}$, and different components of $x^{(k+1)}$ do not have any dependencies.
 - Thus, all components of $x^{(k+1)}$ can be computed in parallel.

Jacobi method example

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

Jacobi Method

Consider 4x4 case

$$\begin{bmatrix} 10 & -1 & 2 & 0 \\ -1 & 11 & -1 & 3 \\ 2 & -1 & 10 & -1 \\ 0 & 3 & -1 & 8 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 6 \\ 25 \\ -11 \\ 15 \end{bmatrix}$$

Example

$$\begin{aligned} 10x_1 - x_2 + 2x_3 &= 6 \\ -x_1 + 11x_2 - x_3 + 3x_4 &= 25 \\ 2x_1 - x_2 + 10x_3 - x_4 &= -11 \\ 3x_2 - x_3 - 8x_4 &= 15 \end{aligned}$$

$$\begin{aligned} x_1 &= (x_2 - 2x_3 + 6) / 10 \\ x_2 &= (x_1 + x_3 - 3x_4 + 25) / 11 \\ x_3 &= (-2x_1 + x_2 + x_4 - 11) / 10 \\ x_4 &= (-3x_2 + x_3 + 15) / (-8) \end{aligned}$$

$$\text{given } x^{(0)} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \Rightarrow \begin{aligned} x_1^{(1)} &= (x_2^{(0)} - 2x_3^{(0)} + 6) / 10 \\ x_2^{(1)} &= (x_1^{(0)} + x_3^{(0)} - 3x_4^{(0)} + 25) / 11 \\ x_3^{(1)} &= (-2x_1^{(0)} + x_2^{(0)} + x_4^{(0)} - 11) / 10 \\ x_4^{(1)} &= (-3x_2^{(0)} + x_3^{(0)} + 15) / (-8) \end{aligned} \Rightarrow x^{(1)} = \begin{bmatrix} 0.6000 \\ 2.2727 \\ -1.1000 \\ 1.8750 \end{bmatrix}$$

Parallel Jacobi method

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

- Since all components of $x^{(k+1)}$ are independent, we can use up to n processors.
- In distributed memory, matrix A and vector b are stored in row-wise block format across the processors.
- $x^{(k+1)}$ and $x^{(k)}$ are computed in x_new and x_old , resp.
- Each processor needs all the values of x .
- After all processors compute their part of x_new , the whole vector is distributed to all processors using `MPI_Allgather`.

Source: Parallel Programming for Multicore and Cluster Systems, Rauber and Runger

```
int Parallel_jacobi(int n, int p, int max_it, float tol)
{
    int i_local, i_global, j, i;
    int n_local, it_num;
    float x_temp1[GLOB_MAX], x_temp2[GLOB_MAX], local_x[GLOB_MAX];
    float *x_old, *x_new, *temp;

    n_local = n/p; /* local blocksize */
    MPI_Allgather(local_b, n_local, MPI_FLOAT, x_temp1, n_local,
                  MPI_FLOAT, MPI_COMM_WORLD);

    x_new = x_temp1;
    x_old = x_temp2;
    it_num = 0;
    do {
        it_num++;
        temp = x_new; x_new = x_old; x_old = temp;
        for (i_local = 0; i_local < n_local; i_local++) {
            i_global = i_local + me * n_local;
            local_x[i_local] = local_b[i_local];
            for (j = 0; j < i_global; j++)
                local_x[i_local] = local_x[i_local] -
                                    local_A[i_local][j] * x_old[j];
            for (j = i_global+1; j < n; j++)
                local_x[i_local] = local_x[i_local] -
                                    local_A[i_local][j] * x_old[j];
            local_x[i_local] = local_x[i_local] / local_A[i_local][i_global];
        }
        MPI_Allgather(local_x, n_local, MPI_FLOAT, x_new, n_local,
                      MPI_FLOAT, MPI_COMM_WORLD);
    } while ((it_num < max_it) && (distance(x_old, x_new, n) >= tol));
    output(x_new, global_x);
    if (distance(x_old, x_new, n) < tol) return 1;
    else return 0;
}
```

Gauss-Seidel method

- The Gauss-Seidel method usually converges faster than the Jacobi method.
- Again write $A = D - L - R$, but set $M = D - L$ and $N = R$.
 - Thus, we have $C = (D - L)^{-1}R$.
 - Since $D - L$ is lower triangular, it can be inverted by forward substitution.
- Convergence is again guaranteed if the matrix is diagonally dominant, i.e. $|a_{ii}| > \sum_{j=1, j \neq i}^n |a_{ij}|$ for all i .
- As before, $x^{(k+1)} = Cx^{(k)} + d$. So in components form we have
$$x_i^{(k+1)} = \frac{1}{a_{ii}} \left(b_i - \sum_{j=1}^{i-1} a_{ij} x_j^{(k+1)} - \sum_{j=i+1}^n a_{ij} x_j^{(k)} \right).$$
- Unlike Jacobi method, $x_i^{(k+1)}$ depends on all $x_j^{(k+1)}$ for $j < i$ and $a_{ij} \neq 0$.
 - Thus, unless many values of $a_{ij} = 0$, different $x_i^{(k+1)}$ cannot be computed in parallel.
- While Gauss-Seidel converges faster than Jacobi, it has less parallelism, and may not run faster.



SOR method

- Successive over-relaxation modifies the Gauss-Seidel method to obtain faster convergence.
- x is updated as a linear combination of Gauss-Seidel update and its previous value.

- In components form,

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

- Convergence depends on properties of A and ω .
E.g. if A is symmetric and positive definite and $\omega \in (0,2)$ then SOR converges.

Parallel Gauss-Seidel method

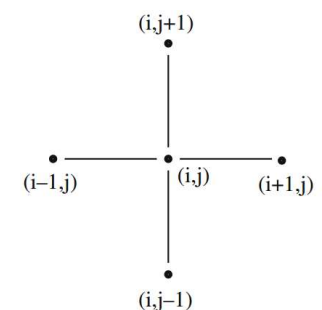
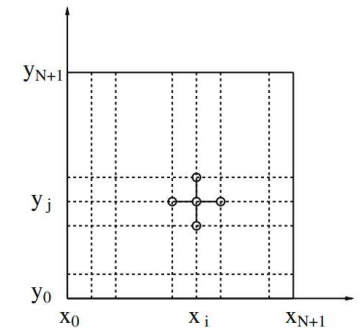
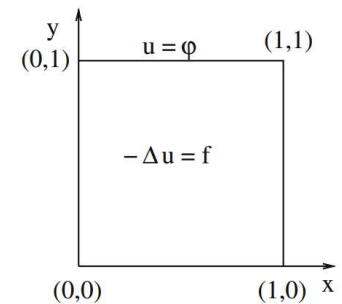
- Since in general $x_i^{(k+1)}$ depends on $x_j^{(k+1)}$ for all $j < i$, we compute the $x_i^{(k+1)}$ sequentially, for $i=0,1,2,\dots$
- Each $x_i^{(k+1)}$ is a dot product of $(x_1^{(k+1)}, \dots, x_{i-1}^{(k+1)}, 0, x_{i+1}^{(k)}, x_n^{(k)})$ with the i 'th row of A .
 - This dot product can be split into multiple parts and computed in parallel.
- Use block column-wise decomposition of A and x across the processors.
- Each processor computes part of $x_i^{(k+1)}$.
 - The parts are then summed and distributed to all the processors using `MPI_Allreduce`.
- Repeat the do loop until x converges.
- Each processor only does n/p computations for each reduce communication step, so speedup is limited unless $n \gg p$.

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

```
n_local = n/p;
do {
    delta_x = 0.0;
    for (i = 0; i < n; i++) {
        s_k = 0.0;
        for (j = 0; j < n_local; j++)
            if (j + me * n_local != i)
                s_k = s_k + local_A[i][j] * x[j];
        root = i/n_local;
        i_local = i % n_local;
        MPI_Reduce(&s_k, &x[i_local], 1, MPI_FLOAT, MPI_SUM, root,
                  MPI_COMM_WORLD);
        if (me == root) {
            x_new = (b[i_local] - x[i_local]) / local_A[i][i_local];
            delta_x = max(delta_x, abs(x[i_local] - x_new));
            x[i_local] = x_new;
        }
    }
    MPI_Allreduce(&delta_x, &global_delta, 1, MPI_FLOAT,
                  MPI_MAX, MPI_COMM_WORLD);
} while(global_delta > tol);
```

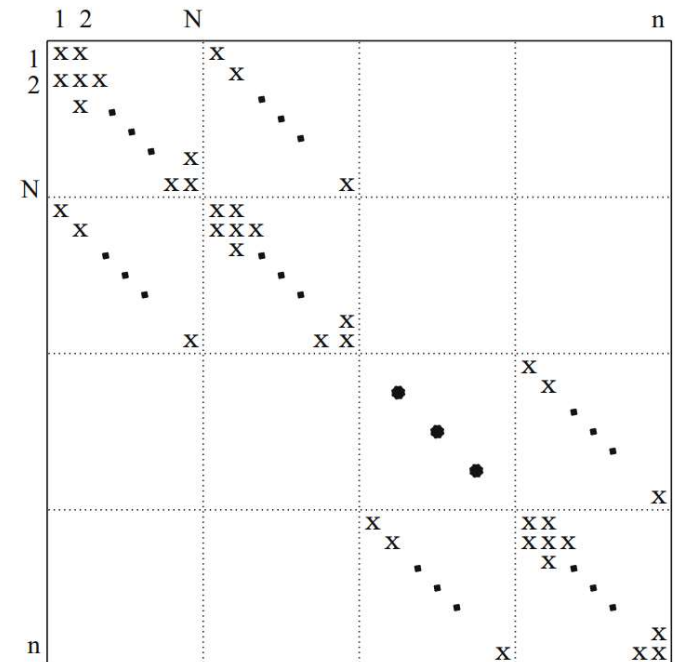
Poisson's equation

- Poisson's equation is a partial differential equation (PDE) to describe the potential field caused by a mass or electrostatic density distribution.
 - We'll look at Poisson's equation in 2D space.
- Given a function $f(x, y)$, we want to find a function $\phi(x, y)$ with $-\Delta\phi = f$.
 - Here $\Delta\phi = \nabla^2\phi = \frac{\partial^2\phi}{\partial x^2} + \frac{\partial^2\phi}{\partial y^2}$.
- Poisson's equation can be solved numerically by discretizing 2D space.
 - For simplicity, we divide $[0,1] \times [0,1]$ evenly into $N+1$ points along each axis.
 - Let $h = 1/(N + 1)$, and let $u_{ij} = \phi(x_i, y_j)$, and $f_{ij} = f(x_i, y_j)$.
- Then $\frac{1}{h^2} (4u_{ij} - u_{i+1,j} - u_{i-1,j} - u_{i,j+1} - u_{i,j-1}) = f_{ij}$, for $0 \leq i, j \leq N + 1$.
- For simplicity, fix the value of ϕ on the boundary of the square, and divide out both sides by $1/h^2$.
- Look for the value of ϕ in the square's interior.
 - This leads to a set of N^2 linear equations, one for each $1 \leq i, j \leq N$.



Matrix form of Poisson's equation

- Let $x_k = u_{ij}$ for $k = i + (j - 1)N$, $1 \leq i, j \leq N$.
- Each equation from the discretization has the form $4x_k - x_{k+1} - x_{k-1} - x_{k+N} - x_{k-N} = b_k$, for some $1 \leq k \leq N^2$ and b_k .
- Let $n = N^2$, and create an $n \times n$ matrix A for the nonzero coefficients of all the equations.
- A has the following nonzero structure.
 - There are three bands of nonzeros, on the diagonal, and above and below the diagonal.
 - There are two additional bands of nonzeros distance $N = \sqrt{n}$ above and below the diagonal.



Gauss-Seidel for Poisson's equation

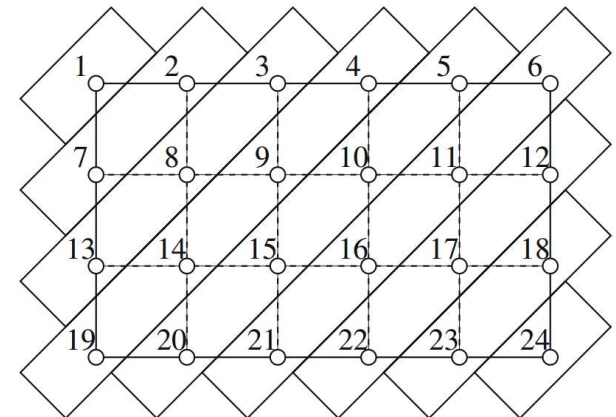
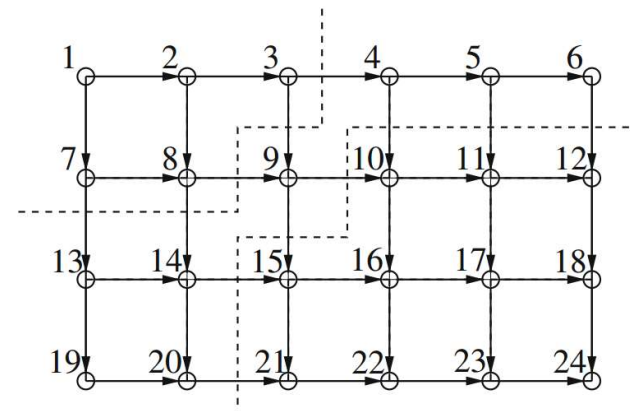
- Recall the Gauss-Seidel iteration is

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

- Applied to Poisson's equation, we have

$$x_i^{(k+1)} = \frac{1}{a_{ii}} \left(b_i - a_{i,i-\sqrt{n}} \cdot x_{i-\sqrt{n}}^{(k+1)} - a_{i,i-1} \cdot x_{i-1}^{(k+1)} - a_{i,i+1} \cdot x_{i+1}^{(k)} - a_{i,i+\sqrt{n}} \cdot x_{i+\sqrt{n}}^{(k)} \right), \text{ for } i = 1, \dots, n.$$

- The values $x_{i-\sqrt{n}}^{(k+1)}$ and $x_{i-1}^{(k+1)}$ need to be computed before $x_i^{(k+1)}$.
- Place the x values on the grid in row major order.
- Each x value depends on value directly above and to its left.
 - Ex Point 9 depends on 3 and 8.
- Notice the x values along each diagonal are all independent.
- There are $2\sqrt{n} - 1$ diagonals.
 - Each diagonal has $O(\sqrt{n})$ points, giving a large amount of parallelism.
- The first \sqrt{n} diagonals $l = 1, \dots, \sqrt{n}$ each contain l points, with indices $i = l + j(\sqrt{n} - 1)$, for $0 \leq j \leq l$.
- The last $\sqrt{n} - 1$ diagonals $l = 2, \dots, \sqrt{n}$ contain $\sqrt{n} - l + 1$ points, with indices $i = l\sqrt{n} + j(\sqrt{n} - 1)$, for $0 \leq j \leq \sqrt{n} - l$.



Gauss-Seidel for Poisson's equation

- We parallelize Gauss-Seidel for Poisson's equation by iterating through the diagonals sequentially, and computing all the values in each diagonal in parallel.
- Given p processors, each processor computes every p 'th value $x[i]$ on the l 'th diagonal.
- Notice the sizes of the diagonals first increases, then decreases.
 - The two for loops compute x during the increasing and decreasing phase, resp.
- The function `collect_elements` sends the x values from the l 'th diagonal to neighboring processors to compute the $l+1$ 'st diagonal.
- Repeat the `do` loop until x converges.

$$x_i^{(k+1)} = \frac{1}{a_{ii}} (b_i - a_{i,i-\sqrt{n}} \cdot x_{i-\sqrt{n}}^{(k+1)} - a_{i,i-1} \cdot x_{i-1}^{(k+1)} - a_{i,i+1} \cdot x_{i+1}^{(k)} - a_{i,i+\sqrt{n}} \cdot x_{i+\sqrt{n}}^{(k)})$$

```
sqn = sqrt(n);
do {
    for (l = 1; l <= sqn; l++) {
        for (j = me; j < l; j+=p) {
            i = l + j * (sqn-1) - 1; /* start numbering with 0 */
            x[i] = 0;
            if (i-sqn >= 0) x[i] = x[i] - a[i][i-sqn] * x[i-sqn];
            if (i > 0) x[i] = x[i] - a[i][i-1] * x[i-1];
            if (i+1 < n) x[i] = x[i] - a[i][i+1] * x[i+1];
            if (i+sqn < n) x[i] = x[i] - a[i][i+sqn] * x[i+sqn];
            x[i] = (x[i] + b[i]) / a[i][i];
        }
        collect_elements(x,l);
    }
    for (l = 2; l <= sqn; l++) {
        for (j = me - l + 1; j <= sqn - l; j+=p) {
            if (j >= 0) {
                i = l * sqn + j * (sqn-1) - 1;
                x[i] = 0;
                if (i-sqn >= 0) x[i] = x[i] - a[i][i-sqn] * x[i-sqn];
                if (i > 0) x[i] = x[i] - a[i][i-1] * x[i-1];
                if (i+1 < n) x[i] = x[i] - a[i][i+1] * x[i+1];
                if (i+sqn < n) x[i] = x[i] - a[i][i+sqn] * x[i+sqn];
                x[i] = (x[i] + b[i]) / a[i][i];
            }
        }
        collect_elements(x,l);
    }
} while(convergence_test() < tol);
```

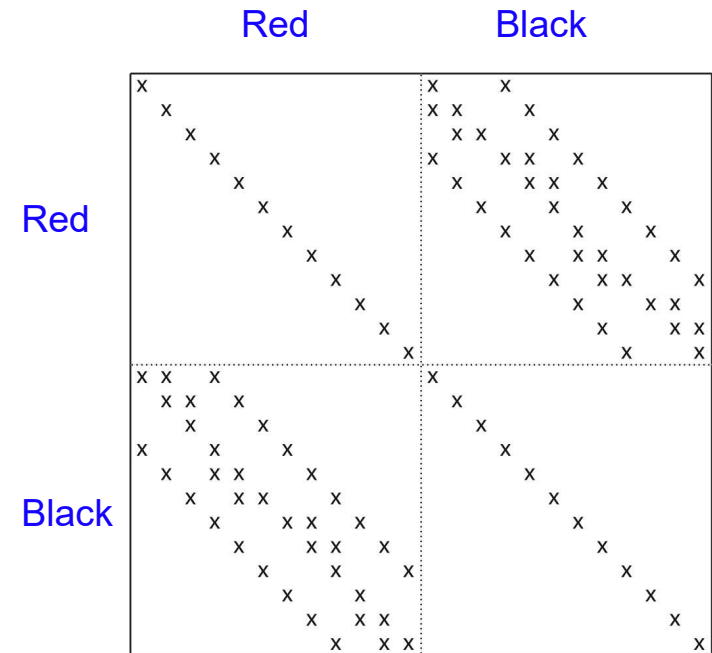
Government	Percentage
Current government	~80%
Previous government	~20%

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1	2	3	4	5	6
7	8	9	10	11	12
13	14	15	16	17	18
19	20	21	22	23	24

Red-black ordering

- Matrix A has a different structure after reordering.
- The red points for $x^{(k+1)}$ only depend on the black points for $x^{(k)}$, and the black points for $x^{(k+1)}$ only depend on the red points for $x^{(k+1)}$.
 - Thus, we can compute all $n/2$ red points in $x^{(k+1)}$ in parallel, then compute all the $n/2$ black points in $x^{(k+1)}$ in parallel.
- Write matrix $A = \begin{pmatrix} D_R & F \\ E & D_B \end{pmatrix}$, where D_R and D_B are diagonal matrices corresponding to the red and black points resp, and E and F are banded matrices.
- Also write $x = (x_R \ x_B)$, where x_R, x_B are the set of red and black x values, resp.



Red-black ordering

- Let $D = \begin{pmatrix} D_R & 0 \\ 0 & D_B \end{pmatrix}$, $L = \begin{pmatrix} 0 & 0 \\ -E & 0 \end{pmatrix}$ and $U = \begin{pmatrix} 0 & -F \\ 0 & 0 \end{pmatrix}$.
- Write the Gauss-Seidel iteration as $\begin{pmatrix} D_R & 0 \\ E & D_B \end{pmatrix} \begin{pmatrix} x_R^{(k+1)} \\ x_B^{(k+1)} \end{pmatrix} = \begin{pmatrix} b_1 \\ b_2 \end{pmatrix} - \begin{pmatrix} 0 & F \\ 0 & 0 \end{pmatrix} \begin{pmatrix} x_R^{(k)} \\ x_B^{(k)} \end{pmatrix}$.
- So $D_R \cdot x_R^{(k+1)} = b_1 - F \cdot x_B^{(k)}$ for $k = 1, 2, \dots$, and $D_B \cdot x_B^{(k+1)} = b_2 - E \cdot x_R^{(k+1)}$, for $k = 1, 2, \dots$
- Let n_R and n_B be the number of red and black points, resp.
- For each point i , let $N(i)$ be its neighbors in the grid.
- In component form, we have

$$\left(x_R^{(k+1)}\right)_i = \frac{1}{a_{ii}} \left(b_i - \sum_{j \in N(i)} a_{ij} \cdot \left(x_B^{(k)}\right)_j \right) \text{ for } i = 1, \dots, n_R$$

$$\left(x_B^{(k+1)}\right)_i = \frac{1}{a_{i+n_R, i+n_R}} \left(b_{i+n_R} - \sum_{j \in N(i)} a_{i+n_R, j} \cdot \left(x_R^{(k+1)}\right)_j \right) \text{ for } i = 1, \dots, n_B$$

- Thus, we first compute $x^{(k+1)}$ for all the red points, then $x^{(k+1)}$ for all the black points.

Parallel red-black algorithm

- Use a block row-wise decomposition of A and x across the processors.
- Use barrier synchronization between the two loops to compute black values after red ones.
- `collect_elements` sends newly computed values of x that lie on the boundary between two processors to the other processor.

```
local_nr = nr/p; local_nb = nb/p;
do {
    mestartr = me * local_nr;
    for (i= mestartr; i < mestartr + local_nr; i++) {
        xr[i] = 0;
        for (j ∈ N(i))
            xr[i] = xr[i] - a[i][j] * xb[j];
        xr[i] = (xr[i]+b[i]) / a[i][i] ;
    }
    collect_elements(xr);
    mestartb = me * local_nb + nr;
    for (i= mestartb; i < mestartb + local_nb; i++) {
        xb[i] = 0;
        for (j ∈ N(i))
            xb[i] = xb[i] - a[i+nr][j] * xr[j];
        xb[i]= (xb[i] + b[i+nr]) / a[i+nr][i+nr];
    }
    collect_elements(xb);
} while (convergence_test());
```