

## Jacobi algorithm

In numerical linear algebra, the Jacobi method is an iterative algorithm for determining the solutions of a strictly diagonally dominant system of linear equations. Let  $Ax=B$ , be a square system of  $n$  linear equations, where:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix} \quad \text{Then}$$

$A$  can be decomposed into a diagonal component  $D$ , a lower triangular part  $L$  and an upper triangular part  $U$ :

$$A = D + L + U$$

$$\text{Where } D = \begin{bmatrix} a_{11} & 0 & \cdots & 0 \\ 0 & a_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & a_{nn} \end{bmatrix}$$

$$\text{And } L + U = \begin{bmatrix} 0 & a_{12} & \cdots & a_{1n} \\ a_{21} & 0 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 0 \end{bmatrix}$$

The solution is then obtained iteratively via

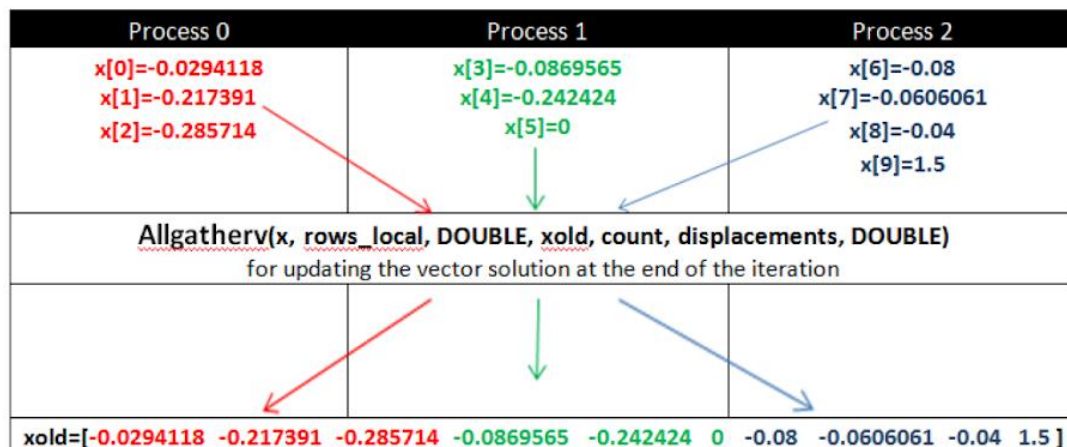
$$x^{(k+1)} = D^{-1}(b - (L + U)x^k)$$

where  $x^k$  is the  $k^{\text{th}}$  approximation of  $x$ .

Hence the formula in terms of its elements can be given as:

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

*The parallel algorithm for Jacobi*



This method assumes

we have all the input values of  $x$  in the previous iteration ( $k$ ). But, usually all the  $x$  values are not given. Make an initial preprocessing for  $x$  and to generate another group of solutions for  $x$  from the equation (1), which in fact will represent the input values for the next iteration ( $k+1$ ). After we have found the group of  $x$  values for the previous iteration we continue generating new groups again and again until we arrive at an acceptable solution. Jacobi puts borders between iterations; values of the vector-solution  $x$  are calculated only from the vector-solution of the previous iteration.

Based on Eq (1), we partition the problem as

$$D_1: \text{sum}_1 = 0$$

$$D_2: \text{sum}_2 = \sum_{j=2}^n a_{1j} x_j$$

$$D_3: x_1 = (-\text{sum}_1 - \text{sum}_2 + b_1) / A_{11}$$

$$D_4: \text{sum}_1 = a_{11} x_1$$

$$D_5: \text{sum}_3 = \sum_{j=3}^n a_{1j} x_j$$

$$D_6: x_1 = (-\text{sum}_1 - \text{sum}_2 + b_2) / A_{22}$$

$$D_7: \text{sum}_1 = a_{11} x_1 + a_{12} x_2$$

Likewise, we can decompose. On observation you will find that there are independent sub problems like 1, 2, 4, 5, 7, 8, etc. and dependent like 3 depends on 1 and 2, 6 depends on 4 and 5, and so on. A dependency graph can be constructed and strategy for parallelism can be made.

Process 0: sends the first three components of the vector solution  $x(0,1,2)$

Process 1: sends the next coming three components of the vector solution  $x(3,4,5)$

Repeat for k=0 to maxit

Initialize error\_sum\_local,sum1,sum2  $\leftarrow$  0.0

Repeat for j=0 to i\_global

sum1 = sum1 + A[i][j]\*xold[j]

Repeat for j=i\_global+1 to N

sum2 = sum2 + A[i][j]\*xold[j]

x[i] = (-sum1 - sum2 + b[i])/A[i][i\_global]

error\_sum\_local += (x[i]-xold[i\_global])\*(x[i]-xold[i\_global])

Computing  $x^{(k+1)} := x^{(k)} + D^{-1} (b - Ax^{(k)})$  with p processors costs:

$$t_{comp} = \frac{n(2n+3)}{p}$$

The communication cost is:

$$t_{comm} = p \left( t_{startup} + \frac{n}{p} t_{data} \right)$$