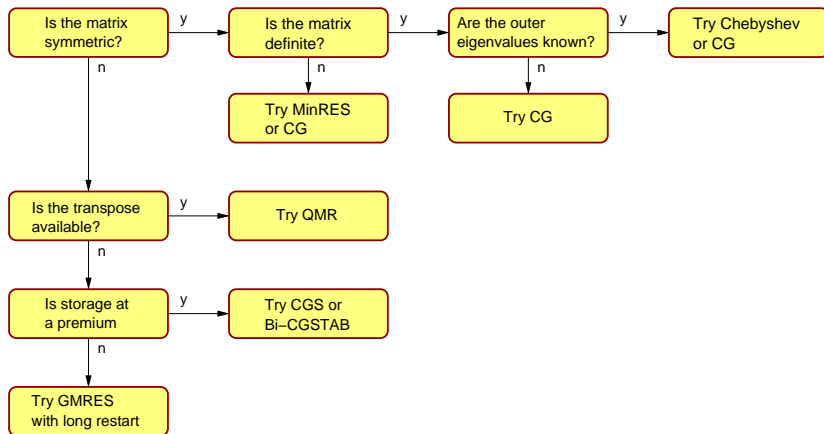


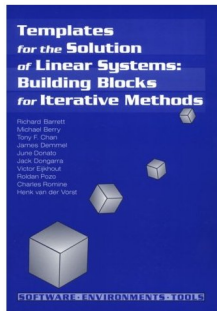


## Iterative Methods

Flowchart with suggestions for the selection of iterative methods.

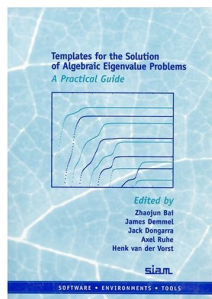


## Iterative Methods



This book is also available in Postscript from  
**<ftp.netlib.org/templates/templates.ps>**.

# Iterative Methods for Algebraic Eigenvalue Problems



There exists also a similar book for algebraic eigenvalue problems.

This is also available as online document at

[www.cs.utk.edu/~dongarra/etemplates/book.html](http://www.cs.utk.edu/~dongarra/etemplates/book.html).

## Preconditioner

Convergence rate of iterative methods depends on spectral properties of the coefficient matrix.

**Example:** CG-method

$$\|x - x^{(k)}\|_A \leq 2\rho^k \|x - x^{(k)}\|_A \quad \text{with } \rho^2 := \frac{\kappa_2(A) - 1}{\kappa_2(A) + 1}$$

and  $\|x - x^{(k)}\|_A^2 := \langle x - x^{(k)}, A(x - x^{(k)}) \rangle$ .

**Note:** The number of iterations to reach a relative reduction of  $\epsilon$  in the error is proportional to  $\sqrt{\kappa_2}$ .

## Preconditioner

Convergence rate of iterative methods depends on spectral properties of the coefficient matrix.

Hence, one may attempt to **transform the linear system** into one that is equivalent in the sense that it has the **same solution**, but that has more **favorable spectral properties**.

A preconditioner is a matrix that effects such a transformation.

For instance, if a matrix  $W$  approximates the coefficient matrix  $A$  in some way, the transformed system

$$W^{-1}Ax = W^{-1}b$$

has the same solution as the original system  $Ax = b$ , but the spectral properties of its coefficient matrix  $W^{-1}A$  may be more favorable.

## Preconditioner

In devising a preconditioner, we are faced with a choice between

finding a matrix  $W$  that approximates  $A$ ,

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On parallel machines there is a further trade-off between the efficacy of a preconditioner in the classical sense, and its parallel efficiency.

Many of the traditional preconditioners have a large sequential component.

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and the parallelization of the **Gauß-Seidel** and **SOR** method with

- ▶ **wavefront numbering**,

## Preconditioner

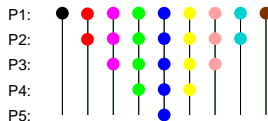
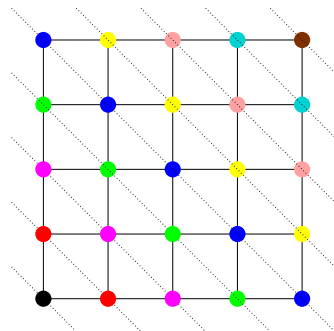
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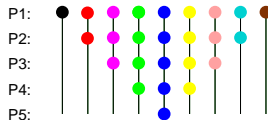
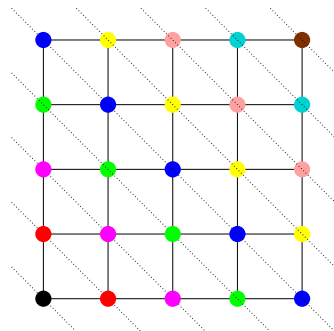
# Wavefront Numbering



## Algorithm

1. on each diagonale, each component can be computed separately

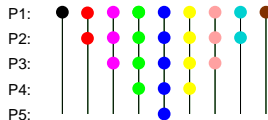
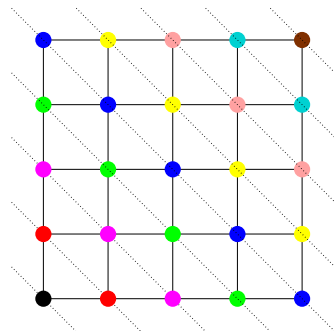
# Wavefront Numbering



## Algorithm

1. on each diagonale, each component can be computed seperatly
2. work load unbalanced

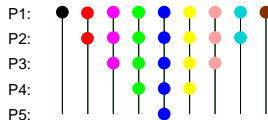
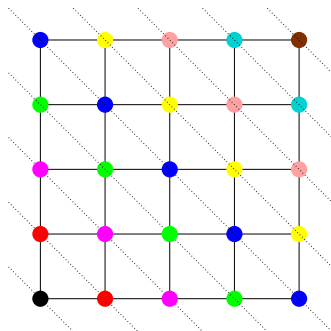
# Wavefront Numbering



## Algorithm

1. on each diagonale, each component can be computed seperatly
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3. maximal possible speed-up in a  $P \times P$ -mesh is  $\approx P/2$

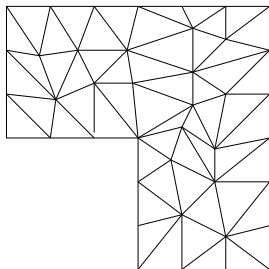
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## Algorithm

1. on each diagonale, each component can be computed seperatly
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3. maximal possible speed-up in a  $P \times P$ -mesh is  $\approx P/2$
4. what about more general meshes (no 'quadratic' mesh)?

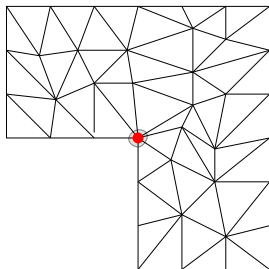
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## Algorithm

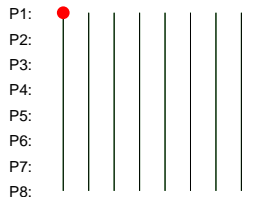
P1: | | | | | | | | | |  
P2: | | | | | | | | | |  
P3: | | | | | | | | | |  
P4: | | | | | | | | | |  
P5: | | | | | | | | | |  
P6: | | | | | | | | | |  
P7: | | | | | | | | | |  
P8: | | | | | | | | | |

# Wavefront Numbering



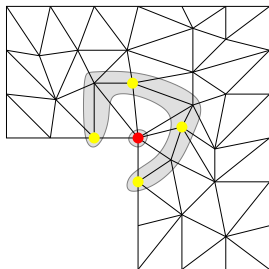
## Algorithm

1. start at a node s.t. number of layers is 'minimal'



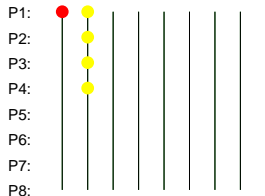


# Wavefront Numbering

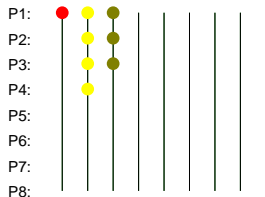
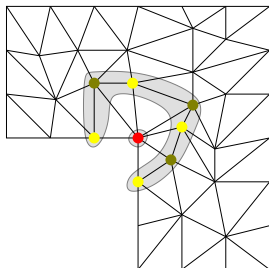


## Algorithm

1. start at a node s.t. number of layers is 'minimal'
2. mark next layer and update as much nodes as possible



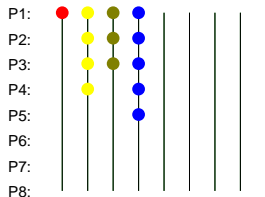
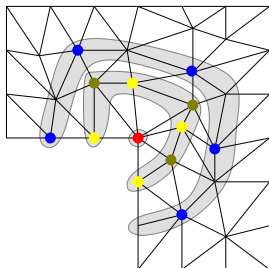
# Wavefront Numbering



## Algorithm

1. start at a node s.t. number of layers is 'minimal'
2. mark next layer and update as much nodes as possible
3. update remaining nodes before marking next layer

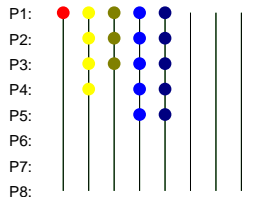
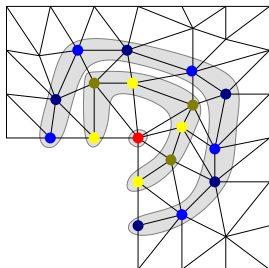
# Wavefront Numbering



## Algorithm

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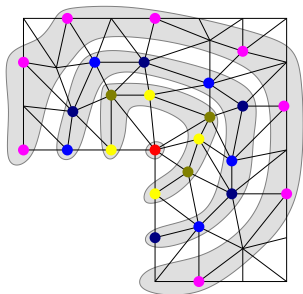
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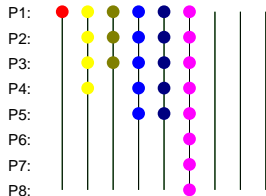
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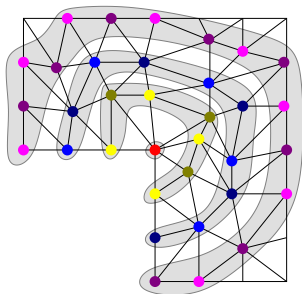


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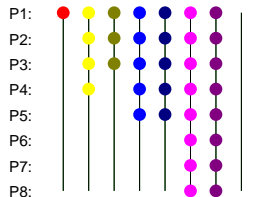


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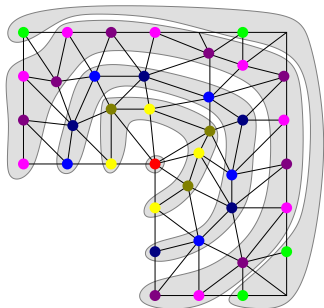


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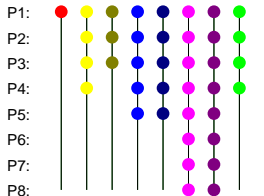


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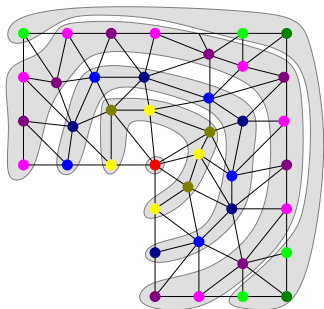


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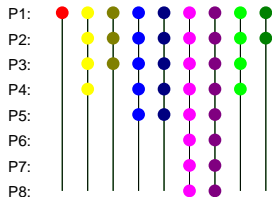


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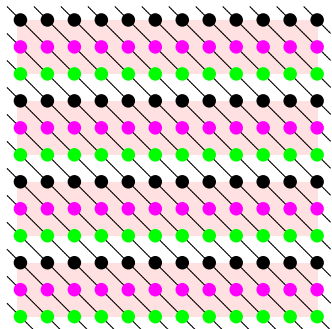
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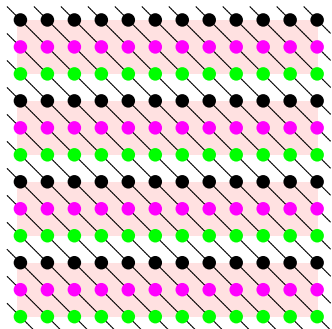
# Block-Strips



## Algorithm

1. each block strip will be computed one after another

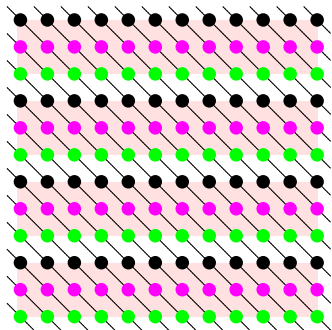
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1. each block strip will be computed one after another
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(optimal for  $kP \times kP$ -meshes)

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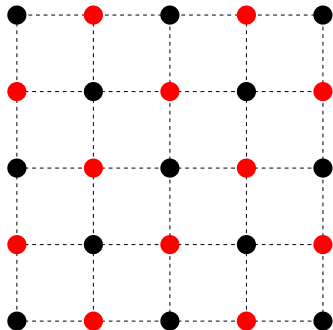


### Algorithm

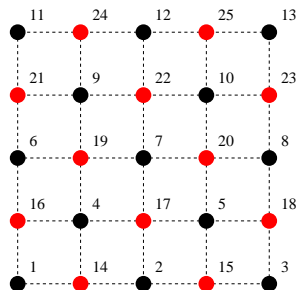
1. each block strip will be computed one after another
2. work load balanced  
(optimal for  $kP \times kP$ -meshes)
3. maximal possible speed-up is  $kP/(k + 1)$

## Red-Black Numbering

What happens, if we number all red nodes first?



# Red-Black Numbering



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\* \* \* \* \*

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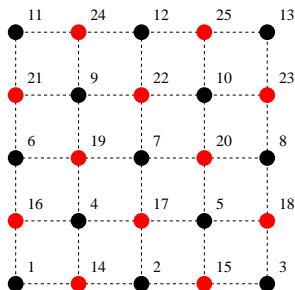
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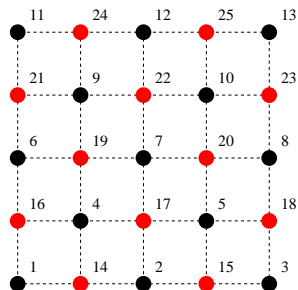


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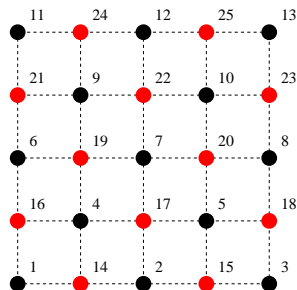
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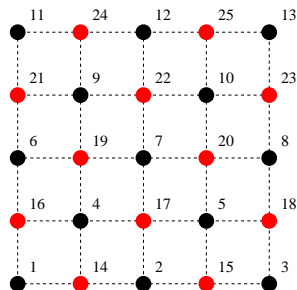
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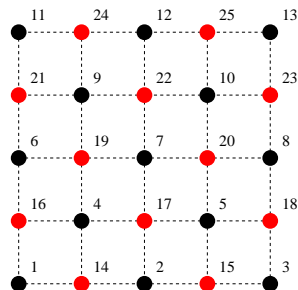
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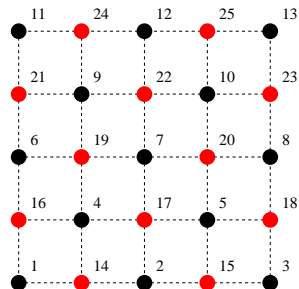
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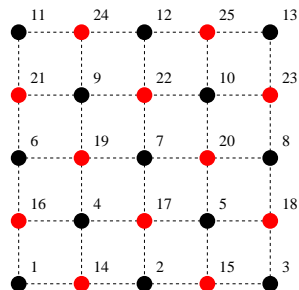
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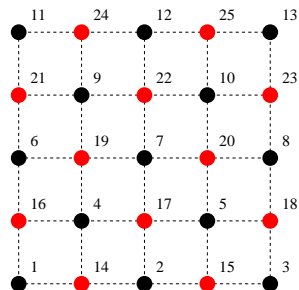
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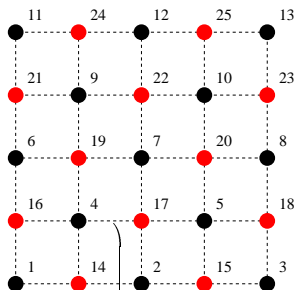
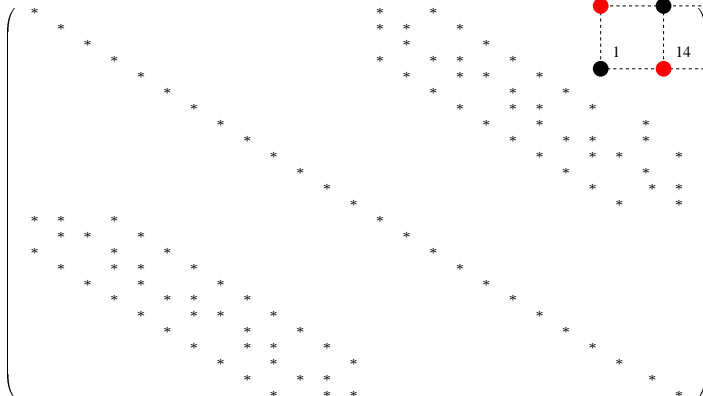
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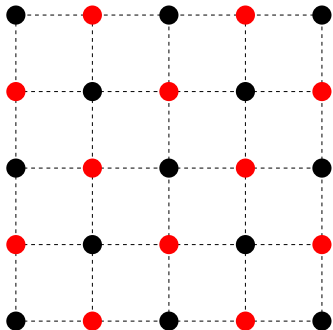


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## Red-Black Numbering

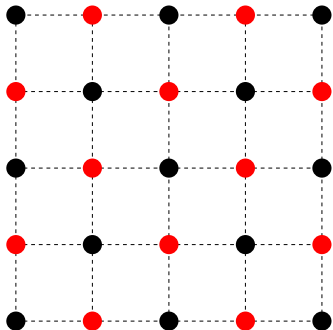


What happens, if we number all red nodes first?

### Properties

1. FEM-matrix with swapped rows and columns

## Red-Black Numbering



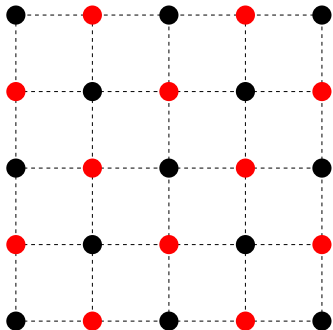
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### Properties

1. FEM-matrix with swapped rows and columns
2.  $2 \times 2$  block matrix



## Red-Black Numbering



What happens, if we number all red nodes first?

### Properties

1. FEM-matrix with swapped rows and columns
2.  $2 \times 2$  block matrix
3. diagonal blocks are diagonal matrices

## Jacobi / Gauß-Seidel Iteration

Consider the system  $Ax = b$  and the decomposition  $A = L + D + U$ .

Sequential version of **Jacobi** iteration.

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

If  $D^{-1}$  is available on each processor, only communication is necessary to exchange parts of  $x^{(k+1)}$  after updating.

Sequential version of **Gauß-Seidel** iteration.

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

or

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

## Parallel Gauß-Seidel Iteration (Red-Black-Numbering)

Let  $A = (a_{ij}) \in \mathbb{R}^{n \times n}$ .

Assume, we have at least two disjoint index sets  $I_{red}$  and  $I_{black}$ ,  
s.t.  $a_{ij} \equiv 0$  for all  $i \neq j \in I_{red}$  resp.  $I_{black}$ .

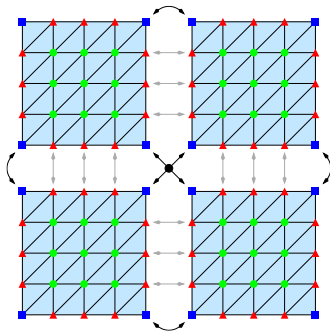
Parallel version of **Gauß-Seidel** iteration.

$$x_{red}^{(k+1)} := D_{red}^{-1}(b_{red} - (L_{rb} + U_{rb})x_{black}^{(k)})$$

$$x_{black}^{(k+1)} := D_{black}^{-1}(b_{black} - (L_{br} + U_{br})x_{red}^{(k)})$$

If  $P \geq 2$  it is recommended to use a block version,  
s.t. blocks of the same color need no communication.

## Non-overlapping Subdomains



### Different Indices

1. **I** nodes in interior of subdomains  
 $[N_I = \sum_{j=1}^p N_{I,j}]$ .
2. **E** nodes in interior of subdomains-edges  
 $[N_E = \sum_{j=1}^{n_e} N_{E,j}]$ .  
 ( $n_e$  number of subdomain-edges)
3. **V** crosspoints, i.e. endpoints of subdomain-edges  
 $[N_V]$

## Types of Vectors

Two types of vectors, depending on the storage type:

**type I:**  $\bar{u}$  is stored on  $P_k$  as restriction  $\bar{u}_k = C_k \bar{u}$ .  
'Complete' value accessible on  $P_k$ .

**type II:**  $\underline{r}$  is stored on  $P_k$  as  $\underline{r}_k$ , s.t.  
 $\underline{r} = \sum_{k=1}^p C_k^T \underline{r}_k$ .  
Nodes on the interface have only a part of the full value.

How should we parallelize the Gauß-Seidel iteration if we have non-overlapping subdomains?

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

resp.

$$\underline{x}_i^{(k+1)} := \left( C_i \sum_{k=1}^p C_k^T \text{diag}(D) \right)^{-1} \sum_{\ell=1}^p C_\ell^T (\underline{b} - L\bar{\underline{x}}^{(k+1)} - U\bar{\underline{x}}^{(k)})$$

## Parallel Gauß-Seidel (Non-Overlapping Domains)

Consider the following ordering of global index set:  $(V, E, I)$

$$\begin{pmatrix} A_{VV} & A_{VE} & A_{VI} \\ A_{EV} & A_{EE} & A_{EI} \\ A_{IV} & A_{IE} & A_{II} \end{pmatrix} \begin{pmatrix} x_V \\ x_E \\ x_I \end{pmatrix} = \begin{pmatrix} b_V \\ b_E \\ b_I \end{pmatrix}$$

## Parallel Gauß-Seidel (Non-Overlapping Domains, Draft)

Let  $\bar{d} := \{1/d_{ii}\}_{i=1,\dots,n}$ ,  $\otimes$  componentwise multiplication.

$$\underline{r}_V := \underline{b}_V - A_{VV}\bar{x}_V^k - A_{VE}\bar{x}_E^k - A_{VI}\bar{x}_I^k$$

$$\bar{w}_V := \sum_{\ell=1}^p C_{V,\ell}^T \underline{r}_{V,\ell} \quad \text{communication}$$

$$\bar{x}_V^{k+1} := \bar{x}_V^k + \bar{d}_V \otimes \bar{w}_V$$

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$$\bar{w}_I := \sum_{\ell=1}^p C_{I,\ell}^T \underline{r}_{I,\ell} \quad \text{no communication!!!}$$

$$\bar{x}_I^{k+1} := \bar{x}_I^k + \bar{d}_I \otimes \bar{w}_I$$

## Parallel Gauß-Seidel (Non-Overlapping Domains, **modified**)

Assume at least one node on each coupling edge and no connection between different edges.

$$\underline{r}_V := \underline{b}_V - A_{VV}\bar{x}_V^k - A_{VE}\bar{x}_E^k - A_{VI}\bar{x}_I^k$$

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$$\bar{w}_I := \sum_{\ell=1}^P C_{I,\ell}^T \underline{r}_{I,\ell} \quad \text{no communication!!!}$$

$$\bar{x}_I^{k+1} := \bar{x}_I^k + A_{II}^{-1} \bar{w}_I$$

## Gauß-Seidel via Jacobi

**Definition:** A Matrix  $A \in \mathbb{R}^{m \times n}$  is called non-negativ, if all coefficients  $a_{ij}$  of  $A$  are non-negativ.

**Satz: [Stein and Rosenberg]** Let the iteration matrix  $C_J \in \mathbb{R}^{n \times n}$  of the Jacobi-iteration be non-negativ. Then there hold the following properties

- i)  $\varrho(C_J) = \varrho(C_G) = 0$
- ii)  $\varrho(C_J) = \varrho(C_G) = 1$
- iii)  $0 < \varrho(C_G) < \varrho(C_J) < 1$
- iv)  $1 < \varrho(C_J) < \varrho(C_G)$

**Example:**

$$A = \begin{pmatrix} 2 & -1 & 0 & 0 \\ -1 & 2 & -1 & 0 \\ 0 & -1 & 2 & -1 \\ 0 & 0 & -1 & 2 \end{pmatrix}, C_J = \begin{pmatrix} 0 & \frac{1}{2} & 0 & 0 \\ \frac{1}{2} & 0 & \frac{1}{2} & 0 \\ 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 0 & \frac{1}{2} & 0 \end{pmatrix}$$

⇒ Gauß-Seidel is faster than Jacobi (for FEM matrices, also in 2D/3D)!