

Equation Formulation KCL, KVL, BCR  
NA, MNA, STA

$$Ax = b$$

Solve this system of equations to obtain  $x$  for a given  $b$

Gaussian elimination (GE)

Triangularization  $\rightarrow$

$$\begin{bmatrix} \cdot & \cdot & \cdot & \cdot & \cdot \\ & \cdot & \cdot & \cdot & \cdot \\ & & \cdot & \cdot & \cdot \\ & & & \cdot & \cdot \\ & & & & \cdot \end{bmatrix} U \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix} \sim \frac{n^3}{3}$$

Solution is obtained by backward substitution  $\sim \frac{n^2}{2}$ .

What do we do with multiple 'b' vectors

LU decomposition  $\sim \frac{n^3}{3}$

Forward/Back Substitutions  $\sim \frac{n^2}{2}$

$$Ax = b \rightarrow L \underbrace{Ux}_y = b$$

$Ly = b$  where  $L$  is lower triangular  
 $y$  obtained by forward substitution

$Ux = y \rightarrow x$  by back subst.

Pivoting of the matrix elements

## Partial Pivoting for Small Pivots

swap

$$\begin{bmatrix} 1.25 \cdot 10^{-4} & 1.25 \\ 12.5 & 12.5 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 6.25 \\ 75 \end{bmatrix}$$

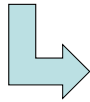
$$\begin{bmatrix} 12.5 & 12.5 \\ 1.25 \cdot 10^{-4} & 1.25 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 75 \\ 6.25 \end{bmatrix}$$

GE

$$\begin{bmatrix} 12.5 & 12.5 \\ 0 & 1.25 - 12.5 \cdot 10^{-5} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 75 \\ 6.25 - 75 \cdot 10^{-5} \end{bmatrix}$$

Rounded to 3 digits

$$\begin{bmatrix} 12.5 & 12.5 \\ 0 & 1.25 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 75 \\ 6.25 \end{bmatrix}$$



$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{3 \text{ digits}} = \begin{bmatrix} 1 \\ 5 \end{bmatrix}$$

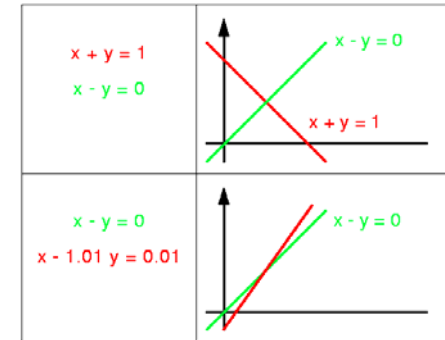
$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{5 \text{ digits}} = \begin{bmatrix} 1.0001 \\ 4.9999 \end{bmatrix}$$

From: A. Nardi

## Error Mechanism

- ILL Conditioning (almost singular)  
Bad Luck
- Numerical Stability of Method

## ILL Conditioning



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From: A. Sangiovanni-Vincentelli

## Error Mechanisms

- **Round-off error**
  - Pivoting helps
- **Ill conditioning (almost singular)**
  - Bad luck: property of the matrix
  - Pivoting does not help
- **Numerical Stability of Method**

From: A. Nardi

## Ill-Conditioning : Norms

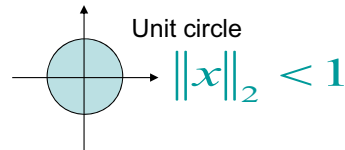
- **Norms useful to discuss error in numerical problems**
- **Norm**  $\|\cdot\| : V \rightarrow \mathbb{R}^+$ 
  - (1)  $\|x\| > 0$  if  $x \neq 0, x \in V$
  - (2)  $\|\alpha x\| = |\alpha| \|x\|$  if  $\alpha \in \mathbb{R}, x \in V$
  - (3)  $\|x + y\| \leq \|x\| + \|y\|$  if  $x, y \in V$

From: A. Nardi

## III-Conditioning : Vector Norms

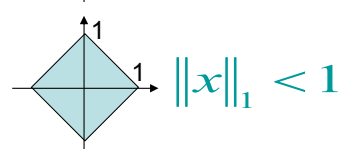
$L_2$  (Euclidean) norm :

$$\|x\|_2 = \sqrt{\sum_{i=1}^n |x_i|^2}$$



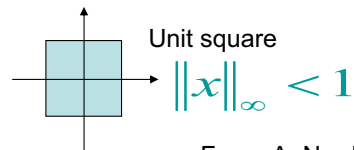
$L_1$  norm :

$$\|x\|_1 = \sum_{i=1}^n |x_i|$$



$L_\infty$  norm :

$$\|x\|_\infty = \max_i |x_i|$$



From: A. Nardi

## III-Conditioning : Matrix Norms

Vector induced norm : 
$$\|A\| = \max_{x \neq 0} \frac{\|Ax\|}{\|x\|} = \max_{\|x\|=1} \|Ax\|$$

$$\|A\|_1 = \max_{1 \leq j \leq n} \sum_{i=1}^n |a_{ij}| = \text{max abs column sum}$$

$$\|A\|_\infty = \max_{1 \leq i \leq n} \sum_{j=1}^n |a_{ij}| = \text{max abs row sum}$$

$$\|A\|_2 = (\text{largest eigenvalue of } A^T A)^{1/2}$$

From: A. Nardi

## III-Conditioning : Matrix Norms

- **More properties on the matrix norm:**

$$\|I\| = 1$$

$$\|AB\| \leq \|A\| \|B\|$$

- **Condition Number:**

$$\kappa(A) = \|A^{-1}\| \|A\|$$

-It can be shown that:  $\kappa(A) \geq 1$

-Large  $\kappa(A)$  means matrix is almost singular (ill-conditioned)

From: A. Nardi

## Perturbation of A due to round off in GE when solving $Ax=b$

$$A \rightarrow A + \delta A \Rightarrow x \rightarrow x + \delta x$$

$$(A + \delta A)(x + \delta x) = b$$

~~$$Ax + A\delta x + \delta Ax + \delta A\delta x = b$$~~

$$A\delta x + \delta A(x + \delta x) = 0$$

$$\delta x = -A^{-1} \delta A(x + \delta x)$$

$$\|\delta x\| \leq \|A^{-1}\| \|\delta A\| \|x + \delta x\|$$

$$\frac{\|\delta x\|}{\|x + \delta x\|} \leq \|A^{-1}\| \|A\| \frac{\|\delta A\|}{\|A\|} \Rightarrow \frac{\|\delta x\|}{\|x + \delta x\|} \leq \kappa(A) \frac{\|\delta A\|}{\|A\|}$$

$\Rightarrow \kappa(A)$  large is bad

**If matrix is ill-conditioned, then round-off causes problems**

## Perturbation in b

$$b \rightarrow b + \delta b \Rightarrow x \rightarrow x + \delta x$$

$$A(x + \delta x) = b + \delta b$$

~~$$Ax + A\delta x = b + \delta b$$~~

$$A\delta x = \delta b$$

$$\delta x = A^{-1}\delta b$$

$$\|\delta x\| \leq \|A^{-1}\| \|\delta b\|$$

$$\|\delta x\| \leq \|A^{-1}\| \|\delta b\| \frac{\|b\|}{\|b\|} \leq \|A^{-1}\| \frac{\|\delta b\|}{\|b\|} \|A\| \|x\|$$

$$\frac{\|\delta x\|}{\|x\|} \leq \|A^{-1}\| \|A\| \frac{\|\delta b\|}{\|b\|} \Rightarrow \frac{\|\delta x\|}{\|x\|} \leq \kappa(A) \frac{\|\delta b\|}{\|b\|}$$

$\Rightarrow \kappa(A)$  large is bad

From: A. Nardi

## Perturbations in both A and b

$$A \rightarrow A + \delta A \text{ and } b \rightarrow b + \delta b \Rightarrow x \rightarrow x + \delta x$$

Let  $\varepsilon$  be the machine precision or resolution

Single precision:  $\varepsilon \cong 10^{-8}$

Double precision:  $\varepsilon \cong 10^{-16}$

For any floating point number a,  $\bar{a}$  is its machine representation and  $|a - \bar{a}| \leq \varepsilon |a|$

$$\|\delta A\| = \|A - \bar{A}\| \leq \varepsilon \|A\|$$

$$\|\delta b\| = \|b - \bar{b}\| \leq \varepsilon \|b\|$$

$$\|\delta x\| = \|\delta x\|_A + \|\delta x\|_b \leq 2\varepsilon \kappa(A) \|x\|$$

## Numerical Stability

- Even if the algorithm is perfect we still have an error in the solution on a computer
- Rounding errors may accumulate and propagate in a bad algorithm
- For Gaussian elimination the accumulated error is bounded

## Growth During Solution

$$\begin{array}{ccc}
 \begin{bmatrix} 0.1 & & & 1 \\ 1 & 0.1 & & 1 \\ & 1 & 0.1 & 1 \\ & & 1 & 0.1 \end{bmatrix} & \xrightarrow{\text{GE Step 1}} & \begin{bmatrix} 0.1 & & & 1 \\ 0 & 0.1 & & -9 \\ & 1 & 0.1 & 1 \\ & & 1 & 0.1 \end{bmatrix} \\
 \begin{bmatrix} 0.1 & & & 1 \\ 0 & 0.1 & & -9 \\ & 0 & 0.1 & 91 \\ & & 1 & 0.1 \end{bmatrix} & \xrightarrow{\text{GE Step 3}} & \begin{bmatrix} 0.1 & & & 1 \\ 0 & 0.1 & & -9 \\ & 0 & 0.1 & 91 \\ & & 0 & 0.1 \end{bmatrix}
 \end{array}$$

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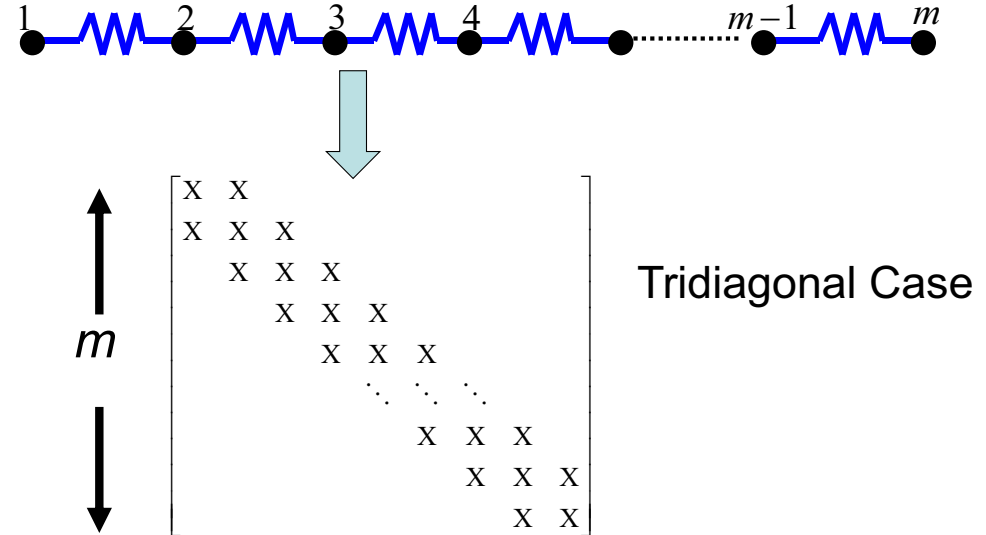
## With Partial Pivoting

$$\begin{bmatrix} 0.1 & & & & 1 \\ 1 & 0.1 & & & 1 \\ & 1 & 0.1 & & 1 \\ & & 1 & 0.1 & 1 \\ & & & 1 & 0.1 \end{bmatrix} \xrightarrow{\text{Reorder}} \begin{bmatrix} 1 & 0.1 & & & 1 \\ 0.1 & 0 & & & 1 \\ & 1 & 0.1 & & 1 \\ & & 1 & 0.1 & 1 \\ & & & 1 & 0.1 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 0.1 & & & 1 \\ 0 & -0.01 & & & 0.9 \\ & 1 & 0.1 & & 1 \\ & & 1 & 0.1 & 1 \\ & & & 1 & 0.1 \end{bmatrix} \xrightarrow{\text{Reorder}} \begin{bmatrix} 0.1 & & & & 1 \\ 0 & 1 & 0.1 & & 1 \\ & -0.01 & 0 & & 0.9 \\ & & 1 & 0.1 & 1 \\ & & & 1 & 0.1 \end{bmatrix}$$

## Circuit Matrices are Sparse

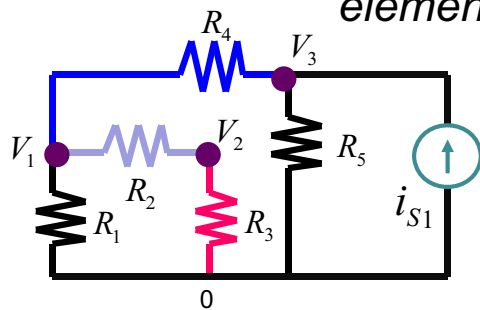
Example: Line of  $M$  Resistors



From: A. Nardi

## Sparse Matrices – Structural zero

Matrix element that is zero regardless of element values



Nodal Matrix

$$\begin{bmatrix} \frac{1}{R_1} + \frac{1}{R_2} + \frac{1}{R_4} & -\frac{1}{R_2} & -\frac{1}{R_4} \\ -\frac{1}{R_2} & \frac{1}{R_2} + \frac{1}{R_3} & 0 \\ -\frac{1}{R_4} & 0 & \frac{1}{R_4} + \frac{1}{R_5} \end{bmatrix} \begin{bmatrix} V_1 \\ V_2 \\ V_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ i_{s1} \end{bmatrix}$$

Symmetric  
Diagonally Dominant

Structural zeros: No connection between nodes 2 and 3

From: A. Nardi

## Sparse Matrices – Fill-in

Structural zero that becomes nonzero during factorization

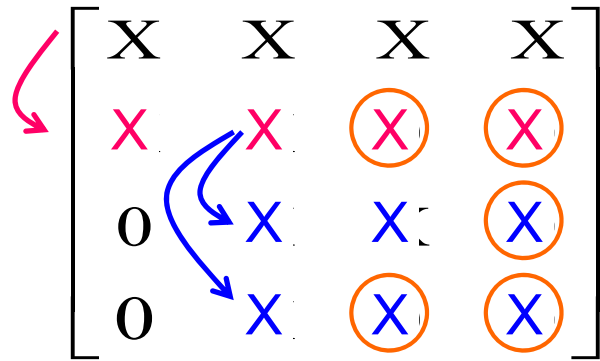
Matrix Non zero structure      Matrix after one LU step

$$\begin{bmatrix} X & X & X \\ X & X & 0 \\ X & 0 & X \end{bmatrix} \rightarrow \begin{bmatrix} X & X & X \\ X & X & X \\ X & X & X \end{bmatrix}$$

Fill-in

From: A. Nardi

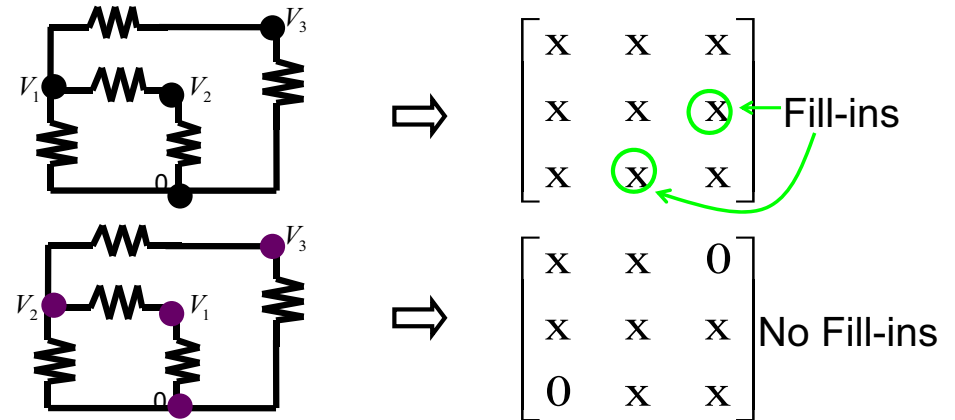
## Fill-ins Propagate



Fill-ins from Step 1 result in Fill-ins in step 2

From: A. Nardi

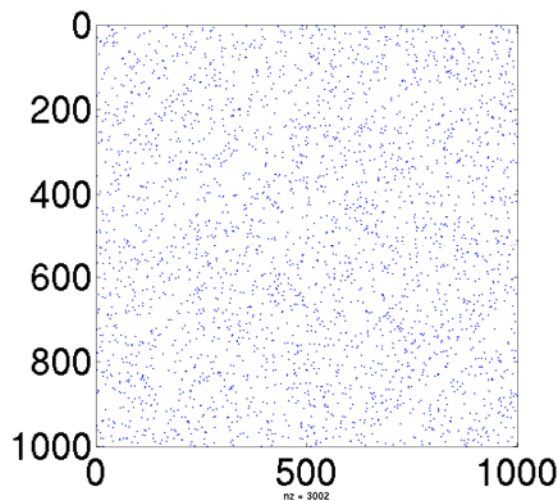
## Fill-in and Reordering



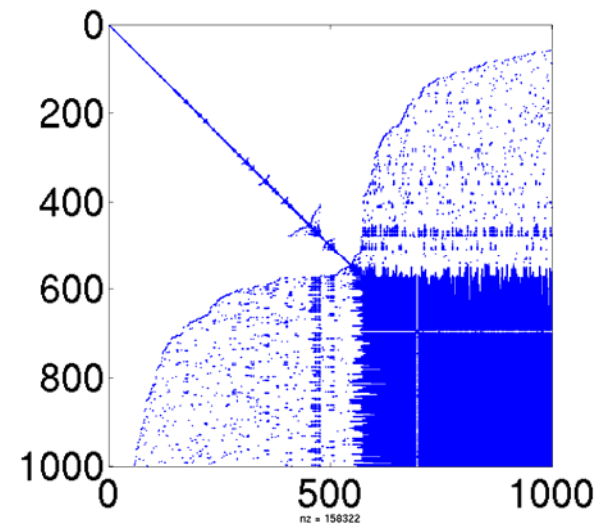
Reordering can reduce fill-in

From: A. Nardi

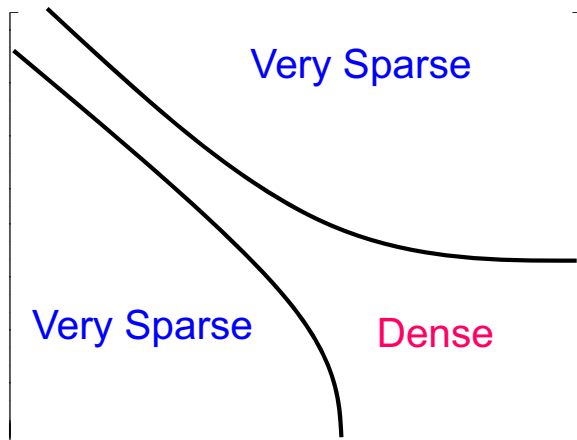
## Unfactored Random Matrix



## Factored Random Matrix



# Pattern of a Filled-in Matrix



From: A. Nardi

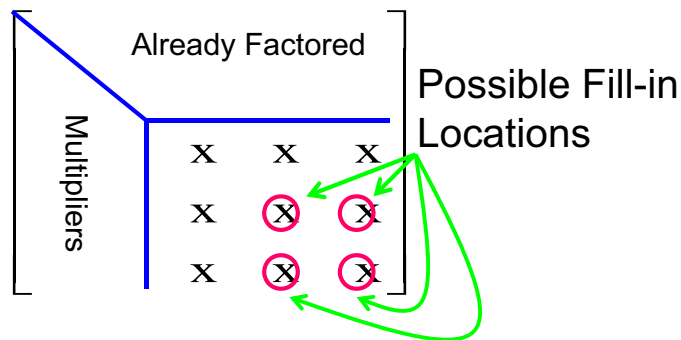
# Exploiting and Maintaining Sparsity

- **Criteria for exploiting sparsity:**
  - Minimum number of ops
  - Minimum number of fill-ins
- **Pivoting to maintain sparsity: NP-complete problem → heuristics are used**
  - Markowitz, Berry, Hsieh and Ghausi, Nakhla and Singhal and Vlach
  - Choice: Markowitz
    - **Faster**
- **Pivoting for accuracy may conflict with pivoting for sparsity**

From: A. Nardi

# Fill-in and Reordering

**Where can fill-in occur ?**



Fill-in Estimate = (# NZ in Row -1) (# NZ in Col -1)  
**Markowitz product**

From: A. Nardi

# Example of Fill-ins/Markowitz Reordering

1	1	1	1	4	3	9	6	3
1	1	0	0	2	1	3	–	–
0	1	1	0	2	–	3	2	–
0	1	1	1	3	–	6	4	2
2	4	3	2					

**Markowitz products**

**Choose  $a_{21}$  as the pivot**

## Tie breaking criterion

NZUR = # of non zeros in an upper triangular row including the diagonal

NZLC = # of non zeros in a lower triangular column including the diagonal

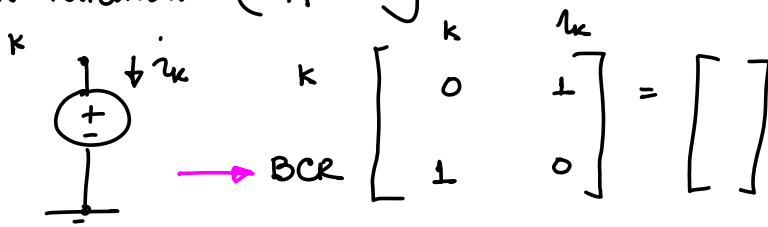
Markowitz: 1)  $\min (NZUR - 1) (NZLC - 1)$   
 $\sim 1950$  2)  $\min NZLC$  avoid divisions for multipliers

Berry: 1)  $\min$  fill-in ← actual fill in calculation  
 2)  $\max NZUR$   
 3)  $\max NZLC$

Hsieh: 1) Row singleton ( $NZUR = 1$ )  
 2) Column " ( $NZLC = 1$ )  
 3)  $(NZUR, NZLC) = (2, 2), (2, 3), (2, 4), (4, 2), (3, 3)$   
 4)  $\min (NZUR - 1) (NZLC - 1)$   
 5)  $\max NZLC$

Nakhla: 1)  $\min$  fill-in  
 2)  $\min NZUR$   
 3)  $\min NZLC$

MNA formulation (exploiting the matrix structure)



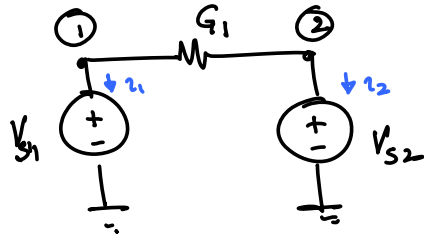
Have a singleton in a row



⇒ excellent choice for a Markowitz pivot  
(Markowitz count = 0)

However, this singleton doesn't exist on a diagonal

⇒ preorder for MNA matrices



$$\begin{bmatrix} v_1 & v_2 & i & i_2 \\ G_1 & -G_1 & 1 & 0 \\ -G_1 & G_1 & 0 & 1 \\ \perp & 0 & 0 & 0 \\ 0 & \perp & 0 & 0 \end{bmatrix}$$

row singletons

Swap rows 1 & 3, 2 & 4

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ G_1 & -G_1 & 1 & 0 \\ -G_1 & G_1 & 0 & 1 \end{bmatrix}$$

## SPICE Pivoting Strategy

- 1) Choose "Markowitz element" on main diagonal  $a_m$
- 2) Check with the largest element in column  $|a_{max}|$

if  $|a_m| < \epsilon_a + \epsilon_r |a_{max}|$  reject pivot and go back to step 1

$\uparrow$  PIVTOL  $\uparrow$  PIVREL  
 $10^{-13}$   $10^{-3}$

If all elements on diagonal fail test, select pivot outside diagonal

$$G_{MIN} = 10^{-12}$$

If  $G_{MIN}$  is reduced the PIVTOL should also be reduced

# Working with sparse matrices

$$n = 1000$$

dense matrix  $1000 \times 1000$   $10^6$  numbers  
 $\rightarrow$  8 MB of storage

Gaussian elimination  $\sim n^3$  operations  
 $10^9$  flops

If we exploit sparsity:

Store only the nonzero terms of the matrix  
MNA matrices  $\sim 3$  nonzeros/row  
 $\sim 3000$  nonzeros

GE  $\sim n^{1.1} - n^{1.5}$  or 2k-32k flops

Need to work with sparse matrix techniques

- do not <sup>store</sup> zeros (use special data structure)
- Avoid trivial operations  $0x=0$ ,  $1x=x$   
 $0+x=x$ , . . .

• avoid losing sparsity

Example

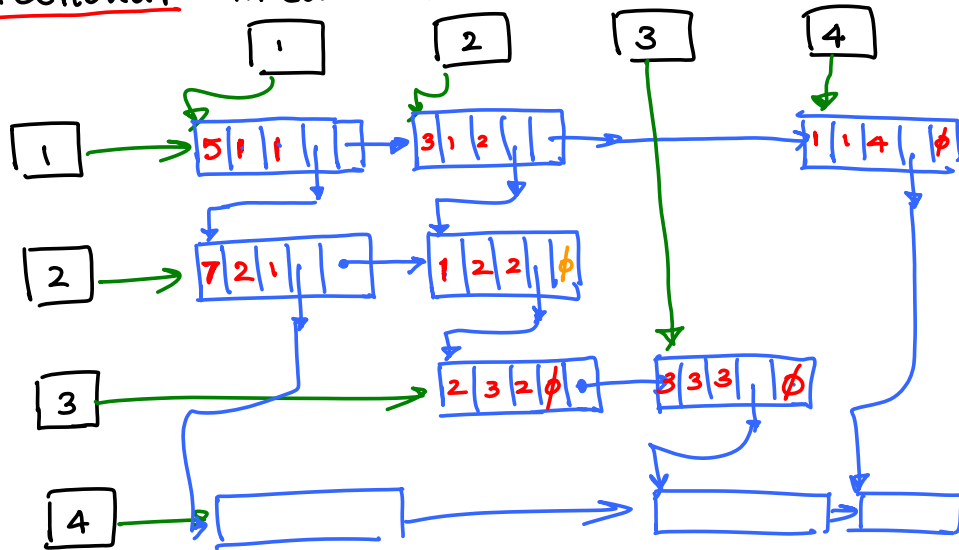
$$A = \begin{bmatrix} 5 & 3 & 0 & 1 \\ 7 & 1 & 0 & 0 \\ 0 & 2 & 3 & 0 \\ -1 & 0 & 5 & 2 \end{bmatrix}$$

$$A_{ij} = \begin{bmatrix} 5 \\ 3 \\ 1 \\ 7 \\ 1 \\ 2 \\ 3 \\ 3 \\ -1 \\ 5 \\ 2 \end{bmatrix}$$

$$I = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 2 \\ 2 \\ 3 \\ 3 \\ 4 \\ 4 \\ 4 \end{bmatrix}$$

$$J = \begin{bmatrix} 1 \\ 2 \\ 4 \\ 1 \\ 2 \\ 2 \\ 3 \\ 1 \\ 3 \\ 4 \end{bmatrix}$$

## Bidirectional Threaded List



In C language

```
Element = struct {
    double value
    int row
    int col
    ptr (Element) * next In Col
    ptr (Element) * next In Row
}
```

## Functions:

createElement (Matrix, Row, Col)

- creates and splices a new element in Matrix

getElement (Matrix, Row, Col)

- return element if it exists  
otherwise calls create element

createFillin (Matrix, Row, Col)

- creates a fill-in

ExchangeRowAndCol (Matrix, Row1, Row2,  
Col1, Col2)