



# GMRES preconditioned by a perturbed $LDL^T$ decomposition with static pivoting

M. Arioli, I. S. Duff, S. Gratton, and S. Pralet

<http://www.numerical.rl.ac.uk/people/marioli/marioli.html>



# Outline

- Multifrontal
- Static pivoting
- GMRES and Flexible GMRES
- Flexible GMRES: a roundoff error analysis
- GMRES right preconditioned: a roundoff error analysis
- Test problems
- Numerical experiments



# Linear system

We wish to solve large sparse systems

$$Ax = b$$

where  $A \in \mathbf{R}^{N \times N}$  is symmetric indefinite



## Linear system

A particular and important case arises in saddle-point problems where the coefficient matrix is of the form

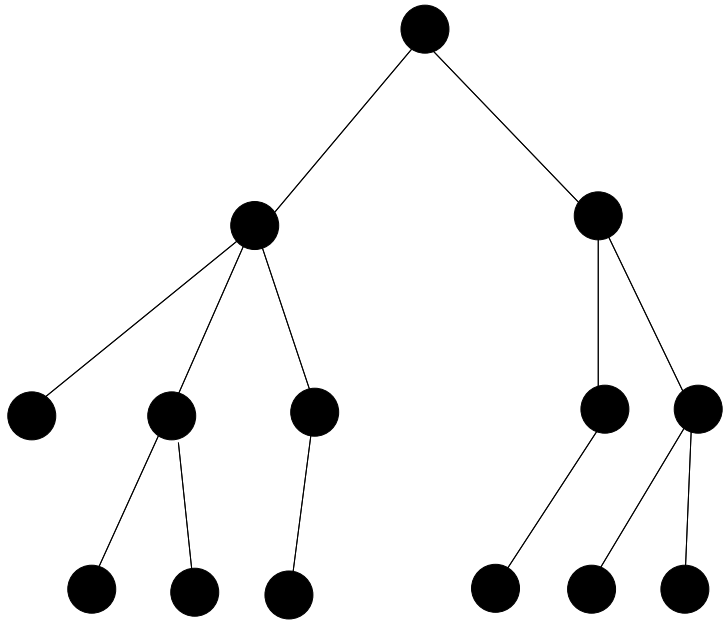
$$\begin{bmatrix} H & A \\ A^T & 0 \end{bmatrix}$$

Since we want accurate solutions, we would prefer to use a direct method of solution and our method of choice uses a multifrontal approach.



# Multifrontal method

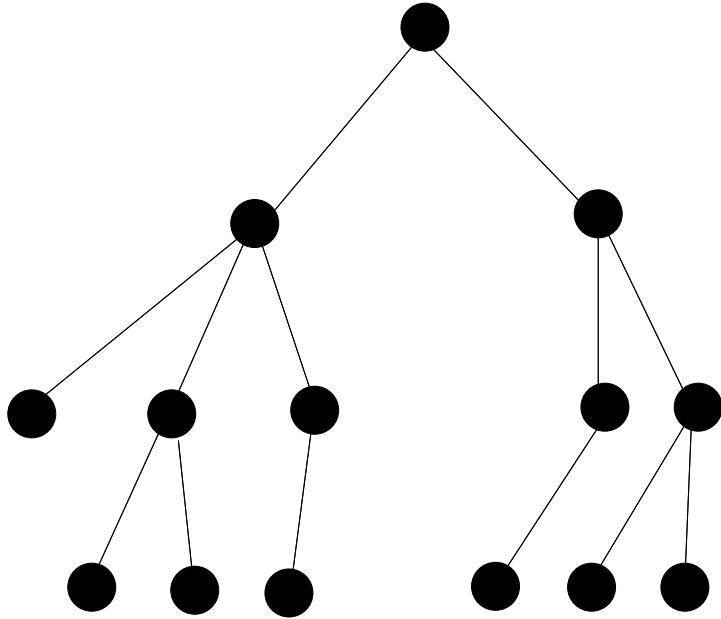
## ASSEMBLY TREE





# Multifrontal method

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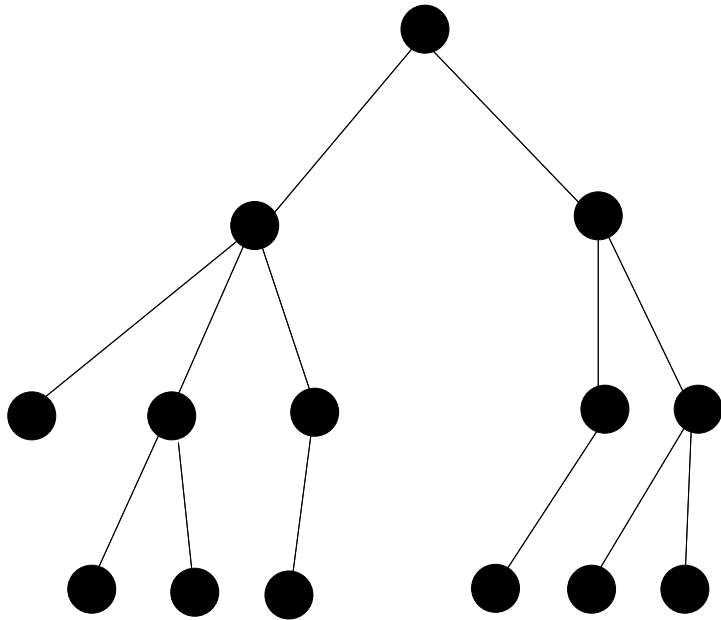
## AT EACH NODE

$F_{11}$	$F_{12}$
$F_{12}^T$	$F_{22}$

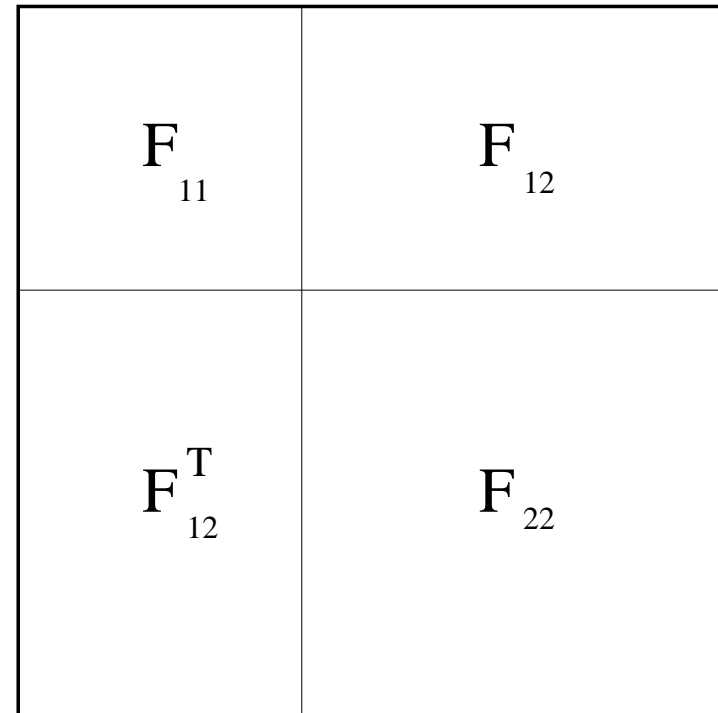


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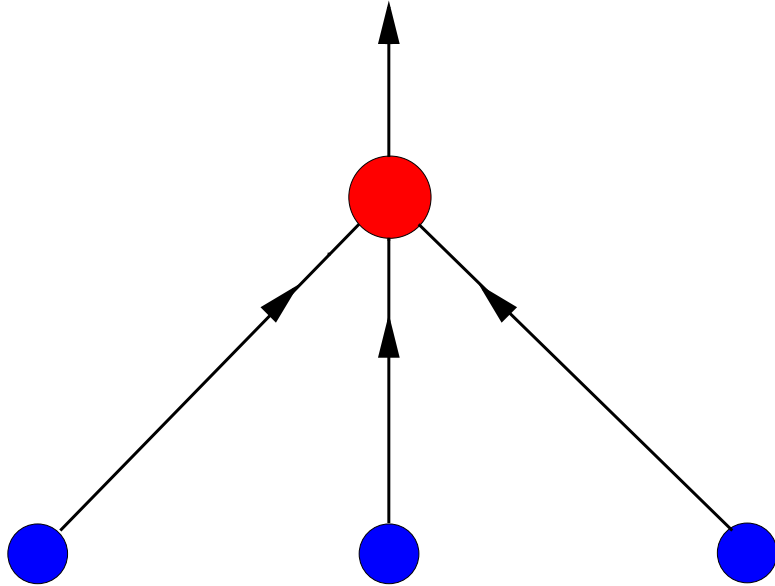
## AT EACH NODE



$$F_{22} \leftarrow F_{22} - F_{12}^T F_{11}^{-1} F_{12}$$



# Multifrontal method

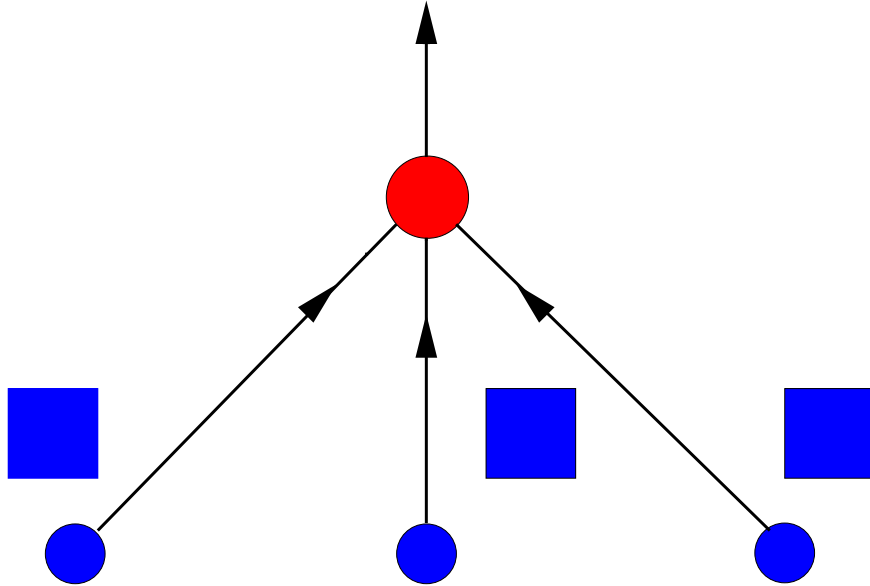


■ From children to parent





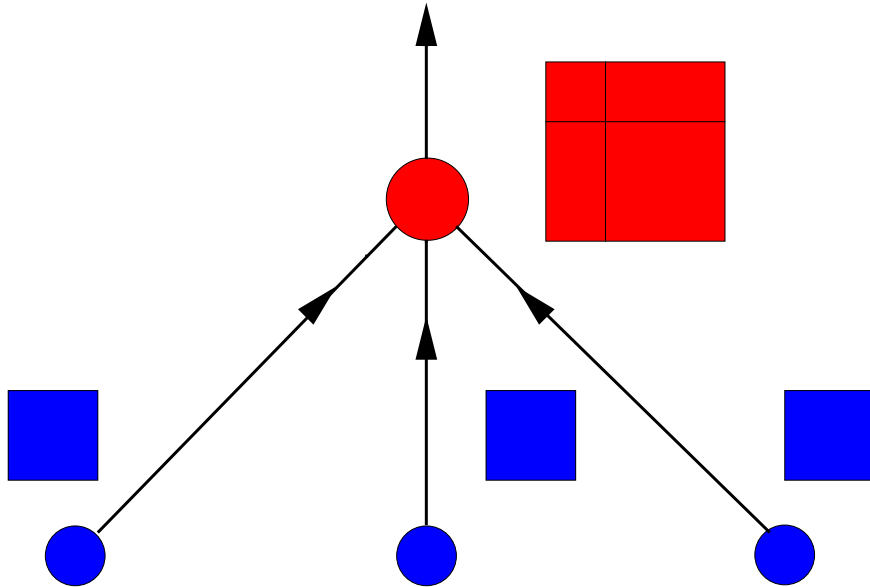
# Multifrontal method



- From children to parent
- **ASSEMBLY** Gather/Scatter operations (indirect addressing)



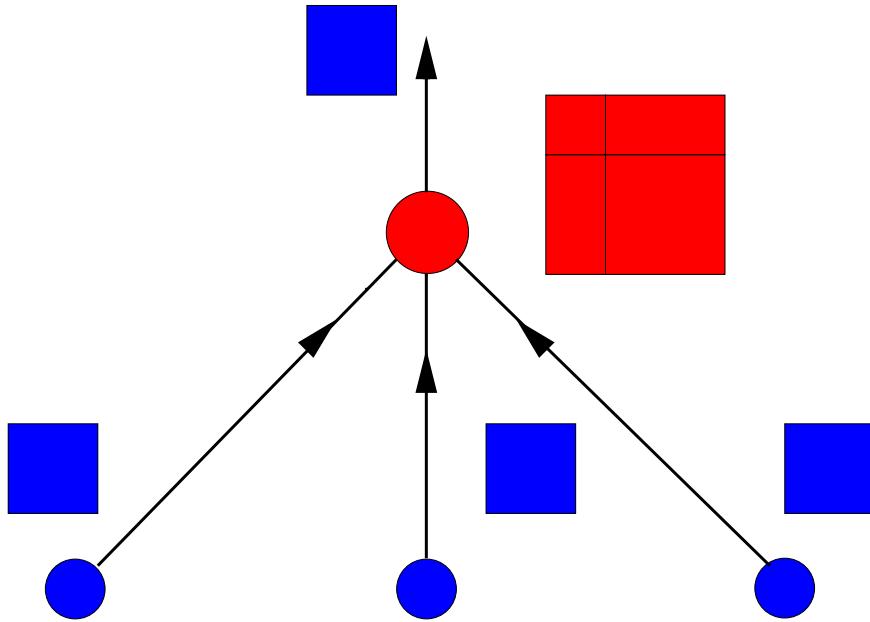
# Multifrontal method



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- **ASSEMBLY** Gather/Scatter operations (indirect addressing)
- **ELIMINATION** Full Gaussian elimination, Level 3 BLAS (TRSM, GEMM)



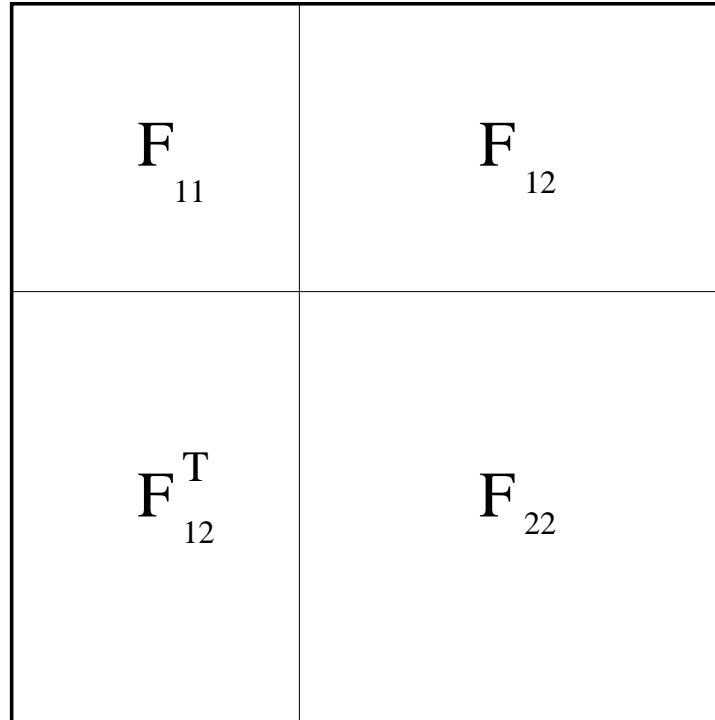
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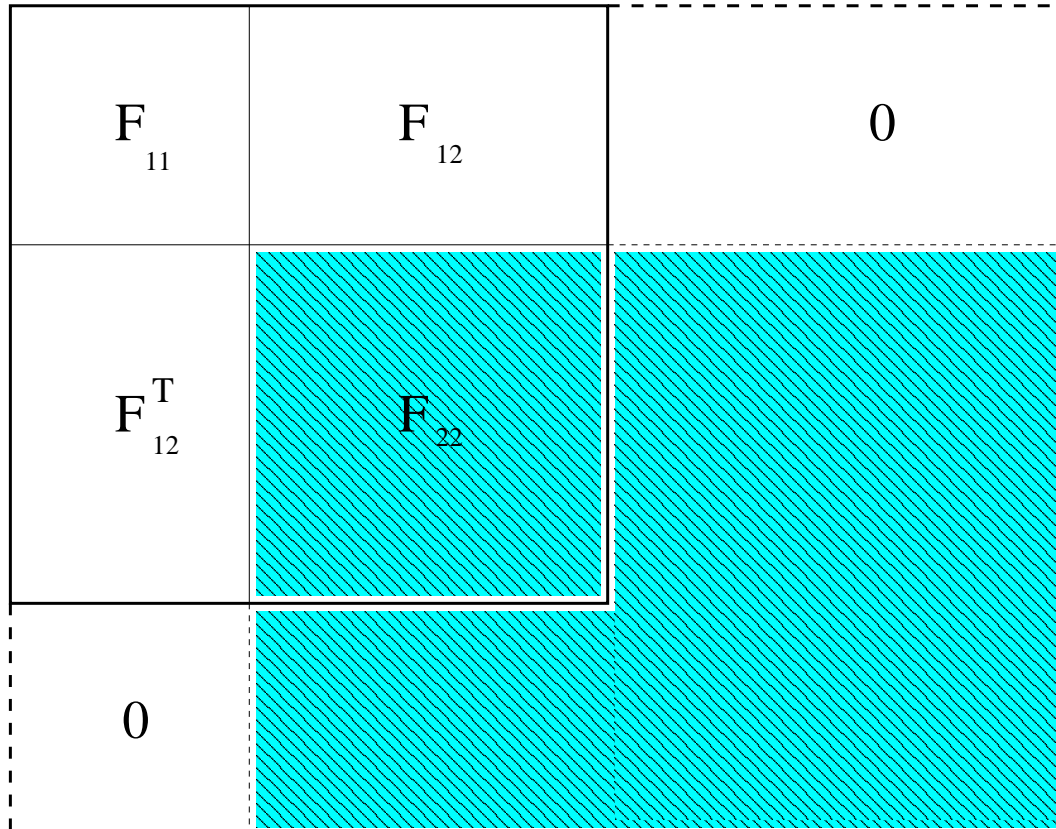
# Multifrontal method



Pivot can only be chosen from  $F_{11}$  block since  $F_{22}$  is **NOT** fully summed.



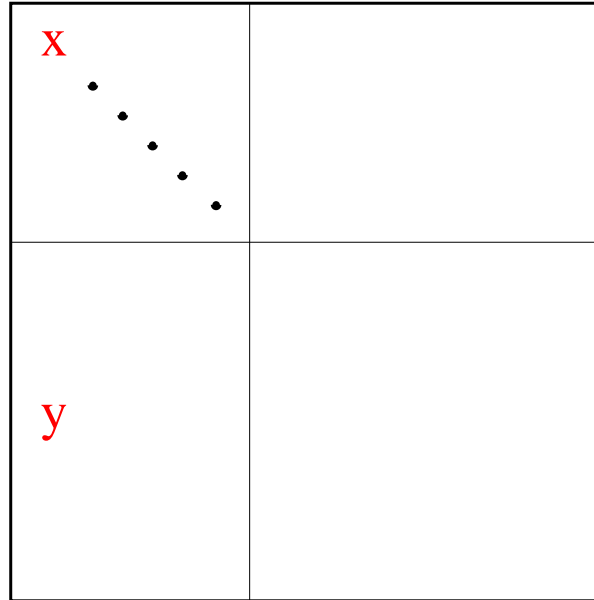
# Multifrontal method



Situation wrt rest of matrix



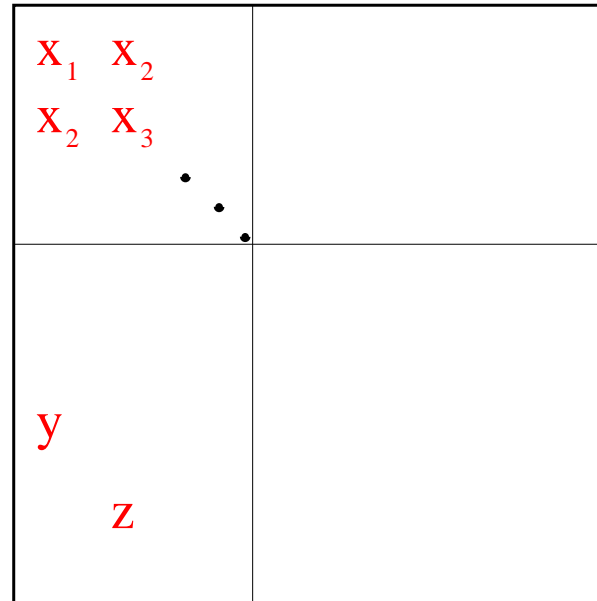
# Pivoting ( $1 \times 1$ )



Choose  $x$  as  $1 \times 1$  **pivot** if  $|x| > u|y|$   
where  $|y|$  is the largest in column.



# Pivoting ( $2 \times 2$ )



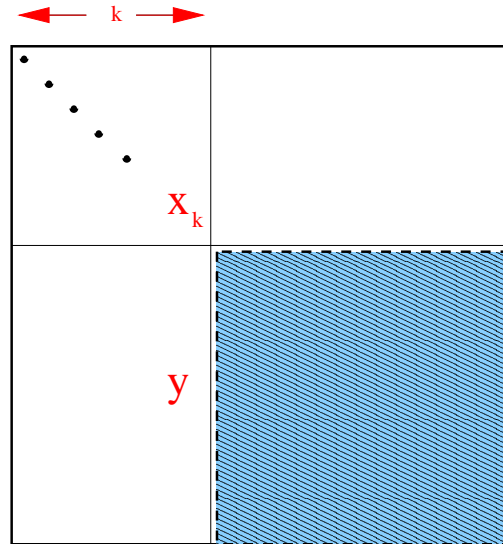
For the indefinite case, we can choose  $2 \times 2$  **pivot** where we require

$$\left| \begin{bmatrix} x_1 & x_2 \\ x_2 & x_3 \end{bmatrix}^{-1} \right| \begin{bmatrix} |y| \\ |z| \end{bmatrix} \leq \begin{bmatrix} \frac{1}{u} \\ \frac{1}{u} \end{bmatrix}$$

where again  $|y|$  and  $|z|$  are the largest in their columns.



# Pivoting

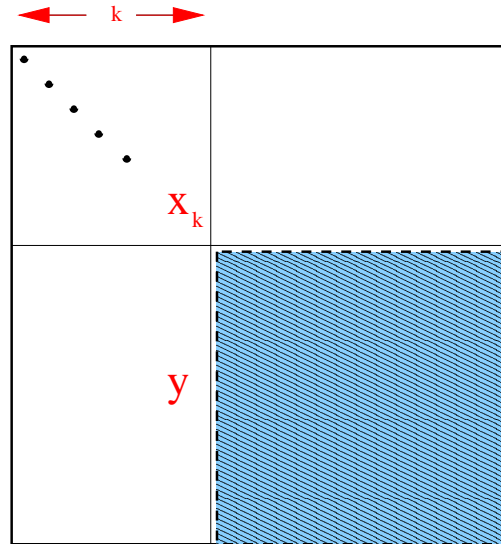


If we assume that  $k - 1$  pivots are chosen but  $|x_k| < u|y|$  :





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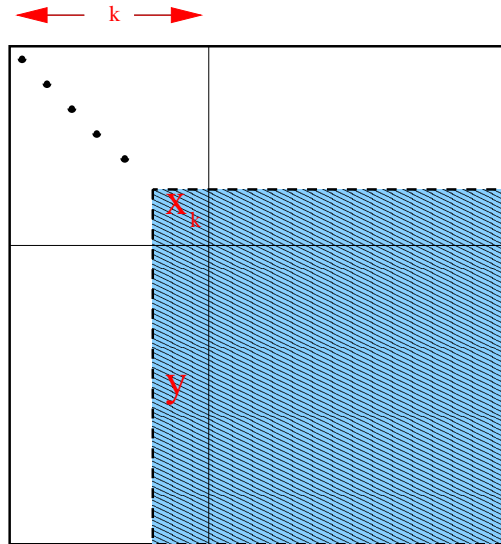


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- we can either take the **RISK** and use it or



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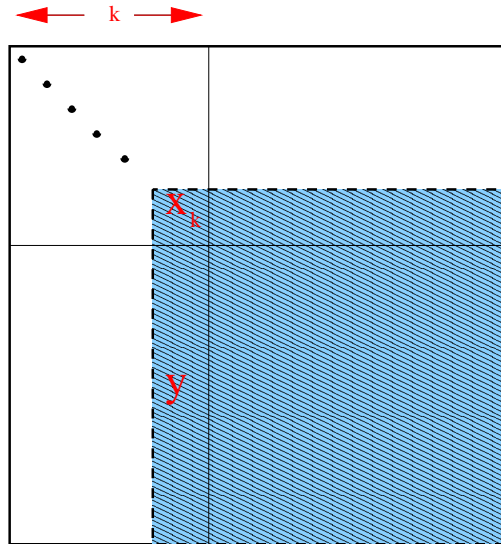


If we assume that  $k - 1$  pivots are chosen but  $|x_k| < u|y|$  :

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This can cause more work and storage



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An **ALTERNATIVE** is to use **Static Pivoting**, by replacing  $x_k$  by

$$x_k + \tau$$

and **CONTINUE**.



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and **CONTINUE**.

This is even more important in the case of parallel implementation where static data structures are often preferred



# Static Pivoting

Several codes use (or have an option for) this device:

- SuperLU (Demmel and Li)
- PARDISO (Gärtner and Schenk)
- MA57 (Duff and Pralet)



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We thus have factorized

$$A + E = LDL^T = M$$

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We thus have factorized

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The three codes then have an **Iterative Refinement** option.  
IR will converge if  $\rho(M^{-1}E) < 1$





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- $\approx \varepsilon \implies$  big growth in preconditioning matrix  $M$
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In real life  $\rho(M^{-1}E) > 1$



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If  $\rho(M^{-1}E) > 1$  then

**PLAN A** (Iterative Refinement Algorithm) fails!!!



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**GMRES and Flexible GMRES**



# Right preconditioned GMRES and Flexible GMRES

```

procedure [x] = right_Prec_GMRES(A,M,b)
   $x_0 = M^{-1}b$ ,  $r_0 = b - Ax_0$  and  $\beta = \|r_0\|$ 
   $v_1 = r_0/\beta$ ;  $k=0$ ;
  while  $\|r_k\| > \mu(\|b\| + \|A\| \|x_k\|)$ 
     $k = k + 1$ ;
     $z_k = M^{-1}v_k$ ;  $w = Az_k$ ;
    for  $i = 1, \dots, k$  do
       $h_{i,k} = v_i^T w$ ;
       $w = w - h_{i,k}v_i$ ;
    end for;
     $h_{k+1,k} = \|w\|$ ;
     $v_{k+1} = w/h_{k+1,k}$ ;
     $V_k = [v_1, \dots, v_k]$ ;
     $H_k = \{h_{i,j}\}_{1 \leq i \leq j+1; 1 \leq j \leq k}$ ;
     $y_k = \arg \min_y \|\beta e_1 - H_k y\|$ ;
     $x_k = x_0 + M^{-1}V_k y_k$  and  $r_k = b - Ax_k$ ;
  end while ;
end procedure.

```

```

procedure [x] =FGMRES(A,M_i,b)
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```



# Roundoff error 1

The computed  $\hat{L}$  and  $\hat{D}$  in floating-point arithmetic satisfy

$$\left\{ \begin{array}{l} A + \delta A + \tau E = M \\ \|\delta A\| \leq c(n)\varepsilon \|\hat{L}\|\hat{D}\|\hat{L}^T\| \\ \|E\| \leq 1. \end{array} \right.$$

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Moreover, we assume that

$$\max\{\|M^{-1}\|, \|\bar{Z}_k\|\} \leq \frac{\tilde{c}}{\tau}.$$



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MGS applied to

$$C = (z_1, Az_1, Az_2, \dots)$$



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4. Use of the static pivoting properties and of  $A + E = LDL^T$  in order to have the final expressions.



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The first two stages of the roundoff error analysis are the same for both FGMRES and GMRES. the last two stages are specific to each one of the two algorithms.



# Roundoff error FGMRES

*Theorem 1.*

$$\sigma_{\min}(\bar{H}_k) > c_7(k, 1)\varepsilon\|\bar{H}_k\| + \mathcal{O}(\varepsilon^2) \quad \forall k,$$

$$|\bar{s}_k| < 1 - \varepsilon, \quad \forall k,$$

(where  $\bar{s}_k$  are the sines computed during the Givens algorithm)

and

$$2.12(n + 1)\varepsilon < 0.01 \text{ and } 18.53\varepsilon n^{\frac{3}{2}} \kappa(C^{(k)}) < 0.1 \quad \forall k$$

$$\exists \hat{k}, \quad \hat{k} \leq n$$

such that,  $\forall k \geq \hat{k}$ , we have

$$\|b - A\bar{x}_k\| \leq c_1(n, k)\varepsilon \left( \|b\| + \|A\| \|\bar{x}_0\| + \|A\| \|\bar{Z}_k\| \|\bar{y}_k\| \right) + \mathcal{O}(\varepsilon^2).$$



# Roundoff error FGMRES

Moreover, if  $M_i = M, \forall i$ ,

$$\rho = 1.3 \|\hat{W}_k\| + c_2(k, 1)\varepsilon \|M\| \|\bar{Z}_k\| < 1 \quad \forall k < \hat{k},$$

where

$$\hat{W}_k = [M\bar{z}_1 - \bar{v}_1, \dots, M\bar{z}_k - \bar{v}_k],$$

we have:

$$\|b - A\bar{x}_k\| \leq c(n, k)\gamma\varepsilon(\|b\| + \|A\|\|\bar{x}_0\| + \|A\|\|\bar{Z}_k\|\|M(\bar{x}_k - \bar{x}_0)\|) + \mathcal{O}(\varepsilon^2)$$

$$\gamma = \frac{1.3}{1 - \rho}.$$



# Roundoff error FGMRES

## Theorem 2

Under the Hypotheses of Theorem 1, and

$$\mathbf{c}(n)\varepsilon\|\hat{L}\|\hat{D}\|\hat{L}^T\| < \tau$$

$$c(n, k)\gamma\varepsilon\|A\|\|\bar{Z}_k\| < 1 \quad \forall k < \hat{k}$$

$$\max\{\|M^{-1}\|, \|\bar{Z}_k\|\} \leq \frac{\tilde{c}}{\tau}$$

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# Roundoff error FGMRES

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we have

$$\|b - A\bar{x}_k\| \leq 2\mu\varepsilon (\|b\| + \|A\| (\|\bar{x}_0\| + \|\bar{x}_k\|)) + \mathcal{O}(\varepsilon^2).$$

$$\mu = \frac{c(n, k)}{1 - c(n, k)\varepsilon \|A\| \|\bar{Z}_k\|}$$



# Roundoff error right preconditioned GMRES

## Theorem 3

We assume of applying Iterative Refinement for solving  $M(\bar{x}_k - \bar{x}_0) = \bar{V}_k \bar{y}_k$  at last step.

Under the Hypotheses of Theorem 1 and  $c(n)\varepsilon \kappa(M) < 1$

$$\exists \hat{k}, \quad \hat{k} \leq n$$

such that,  $\forall k \geq \hat{k}$ , we have

$$\begin{aligned} \|b - A\bar{x}_k\| \leq & c_1(n, k)\varepsilon \left\{ \|b\| + \|A\| \|\bar{x}_0\| + \|A\| \|\bar{Z}_k\| \|M(\bar{x}_k - \bar{x}_0)\| + \right. \\ & \|AM^{-1}\| \|M\| \|\bar{x}_k - \bar{x}_0\| + \\ & \left. \|AM^{-1}\| \|\hat{L}\| \|\hat{D}\| \|\hat{L}^T\| \|M(\bar{x}_k - \bar{x}_0)\| \right\} + \mathcal{O}(\varepsilon^2). \end{aligned}$$



# Roundoff error right preconditioned GMRES

As we did for FGMRES, if

$$\mathbf{c}(n)\varepsilon |||\hat{L}|\hat{D}|\hat{L}^T||| < \tau$$



# Roundoff error right preconditioned GMRES

As we did for FGMRES, if

$$\mathbf{c}(n)\varepsilon \|\hat{L}\| \|\hat{D}\| \|\hat{L}^T\| < \tau$$

we can prove that  $\exists k^*$  s.t.  $\forall k \geq k^*$  the right preconditioned GMRES computes a  $\bar{x}_k$  s.t.

$$\|b - A\bar{x}_k\| \leq c(n, k) \varepsilon \left[ \|b\| + \|A\| \|\bar{x}_0\| + \|A\| \|\bar{Z}_k\| \|M(\bar{x}_k - \bar{x}_0)\| + \|\hat{L}\| \|\hat{D}\| \|\hat{L}^T\| \|M(\bar{x}_k - \bar{x}_0)\| \right] + \mathcal{O}(\varepsilon^2).$$



# Test Problems

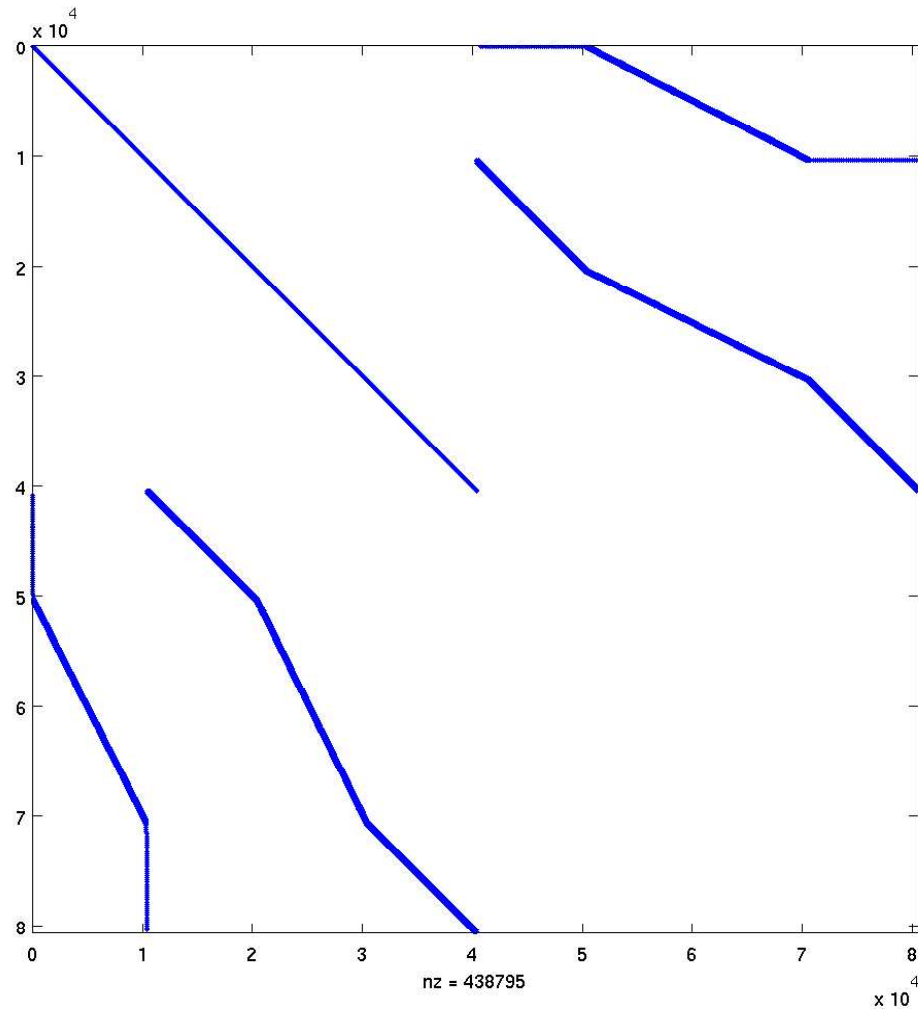
	n	nnz	Description
CONT_201	80595	239596	KKT matrix Convex QP (M2)
CONT_300	180895	562496	KKT matrix Convex QP (M2)
TUMA_1	22967	76199	Mixed-Hybrid finite-element

Test problems





# Test Problems: CONT-201





## MA57 tests

	n	nnz(L)+nnz(D)	Factorization time
CONT_201	80595	9106766	9.0 sec
CONT_300	180895	22535492	28.8 sec

MA57 without static pivot





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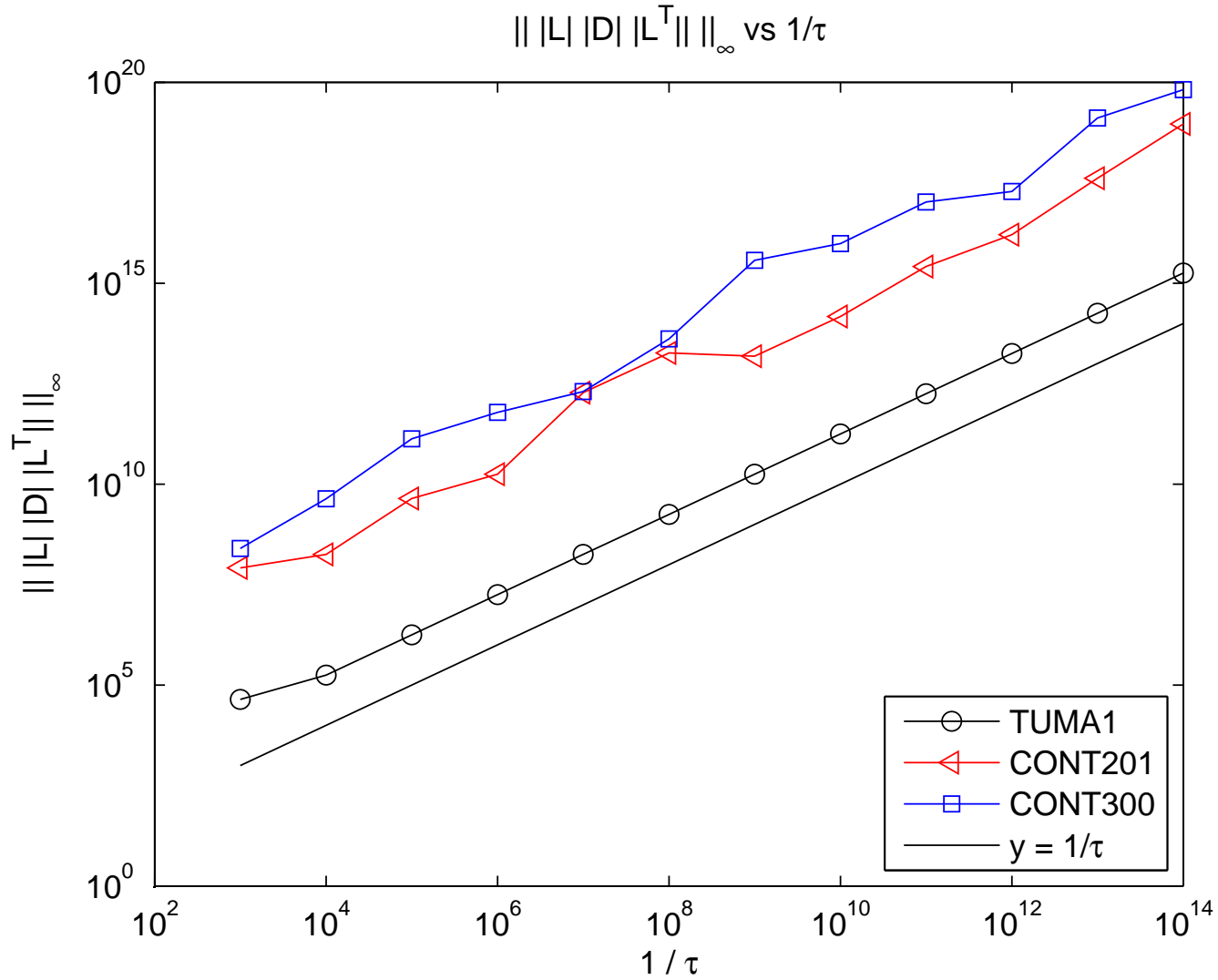
### MA57 without static pivot

	nnz(L)+nnz(D)+ FGMRES (#it)	Factorization time	# static pivots
CONT_201	5563735 (6)	3.1 sec	27867
CONT_300	12752337 (8)	8.9 sec	60585

MA57 with static pivot  $\tau = 10^{-8}$

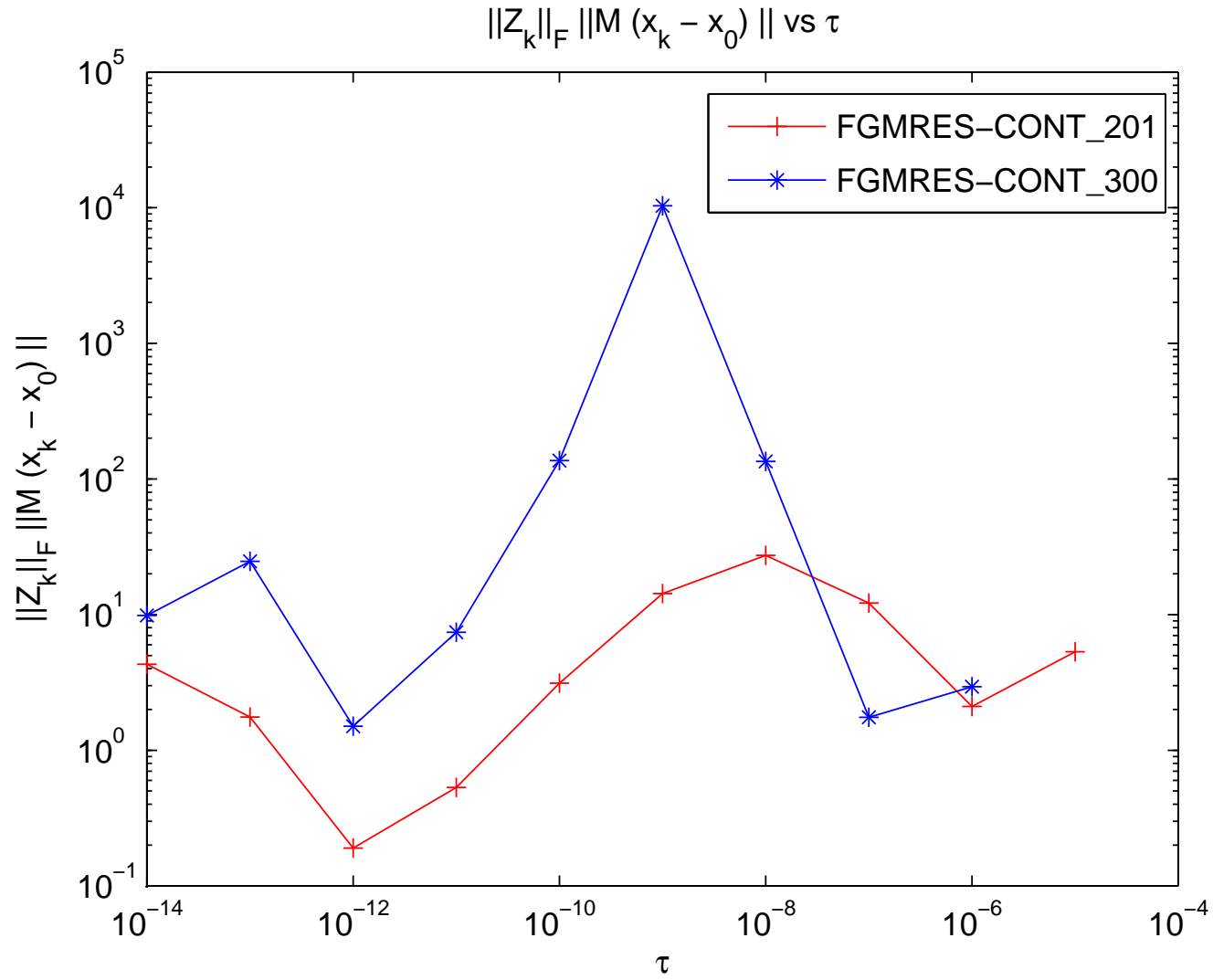


# $|| |\hat{L}| |\hat{D}| |\hat{L}^T| ||$ vs $1/\tau$





# $\|\bar{Z}_k\|_F \|M(x_k - x_0)\|$ vs $\tau$





# Numerical experiments: TUMA 1

$\tau$	$\frac{\ b - A\bar{x}_k\ }{\ b\  + \ A\ \ \bar{x}_k\ }$			$\ Z_k\ $	$\ M(\bar{x}_k - \bar{x}_0)\ $		$\ L\  \ D\  \ L^T\ $
	IR	GMRES	FGMRES		GMRES	FGMRES	
1.0e-03	3.0e-03	1.0e-14	7.2e-17	1.2e+02	3.5e-03	3.5e-03	4.4e+04
1.0e-04	5.3e-17	1.8e-16	3.1e-17	4.7e+01	4.4e-04	4.4e-04	1.8e+05
1.0e-05	5.1e-17	1.3e-16	1.9e-17	4.4e+01	4.5e-05	4.5e-05	1.8e+06
1.0e-06	1.5e-16	1.3e-16	1.9e-17	4.4e+01	4.5e-06	4.5e-06	1.8e+07
1.0e-07	1.8e-17	1.2e-16	2.0e-17	4.3e+01	4.5e-07	4.5e-07	1.8e+08
1.0e-08	1.7e-17	1.3e-16	1.8e-17	4.3e+01	4.5e-08	4.5e-08	1.8e+09
1.0e-09	1.8e-17	2.8e-15	1.8e-17	2.6e+01	4.0e-08	4.0e-08	1.8e+10
1.0e-10	1.7e-17	4.2e-13	1.8e-17	8.8e+00	4.0e-07	4.0e-07	1.8e+11
1.0e-11	6.7e-17	1.0e-10	6.2e-17	6.8e+00	4.0e-06	4.0e-06	1.8e+12
1.0e-12	2.1e-17	1.0e-08	2.2e-17	3.2e+01	4.3e-05	4.3e-05	1.8e+13
1.0e-13	2.0e-17	2.4e-07	1.9e-17	1.3e+02	3.9e-04	3.9e-04	1.8e+14
1.0e-14	8.6e-17	8.6e-06	2.1e-17	1.8e+02	4.3e-03	4.3e-03	1.8e+15

TUMA 1 results



# Numerical experiments: CONT\_201

$\tau$	$\frac{\ b - A\bar{x}_k\ }{\ b\  + \ A\ \ \bar{x}_k\ }$			$\ Z_k\ $	$\ M(\bar{x}_k - \bar{x}_0)\ $		$\ L\  \ D\  \ L^T\ $
	IR	GMRES	FGMRES		GMRES	FGMRES	
1.0e-03	4.0e-04	1.8e-05	9.8e-06	*	7.1e-04	1.5e-04	8.3e+07
1.0e-04	4.0e-05	2.0e-07	2.0e-07	*	1.5e-05	1.9e-05	1.8e+08
1.0e-05	3.5e-06	1.8e-12	1.1e-16	4.1e+05	5.9e-06	1.3e-05	4.4e+09
1.0e-06	3.5e-07	1.1e-11	2.1e-16	2.7e+06	7.8e-07	7.8e-07	1.8e+10
1.0e-07	4.0e-08	4.8e-11	1.8e-16	1.4e+08	8.7e-08	8.7e-08	1.9e+12
1.0e-08	3.8e-13	2.7e-10	5.8e-17	2.1e+07	1.3e-06	1.3e-06	1.8e+13
1.0e-09	5.5e-17	1.8e-09	4.5e-17	1.1e+07	1.3e-06	1.3e-06	1.5e+13
1.0e-10	7.7e-17	3.2e-09	7.2e-17	3.4e+05	9.2e-06	9.2e-06	1.5e+14
1.0e-11	4.6e-17	2.1e-09	4.5e-17	1.9e+03	2.8e-04	2.8e-04	2.6e+15
1.0e-12	5.2e-17	4.5e-07	3.8e-17	2.0e+02	9.5e-04	9.5e-04	1.6e+16
1.0e-13	1.3e-16	1.3e-04	2.6e-16	1.6e+02	1.1e-02	1.1e-02	4.1e+17
1.0e-14	1.2e-03	2.3e-01	2.5e-14	4.3e+02	1.9e-02	1.0e-02	9.2e+18

CONT\_201 results



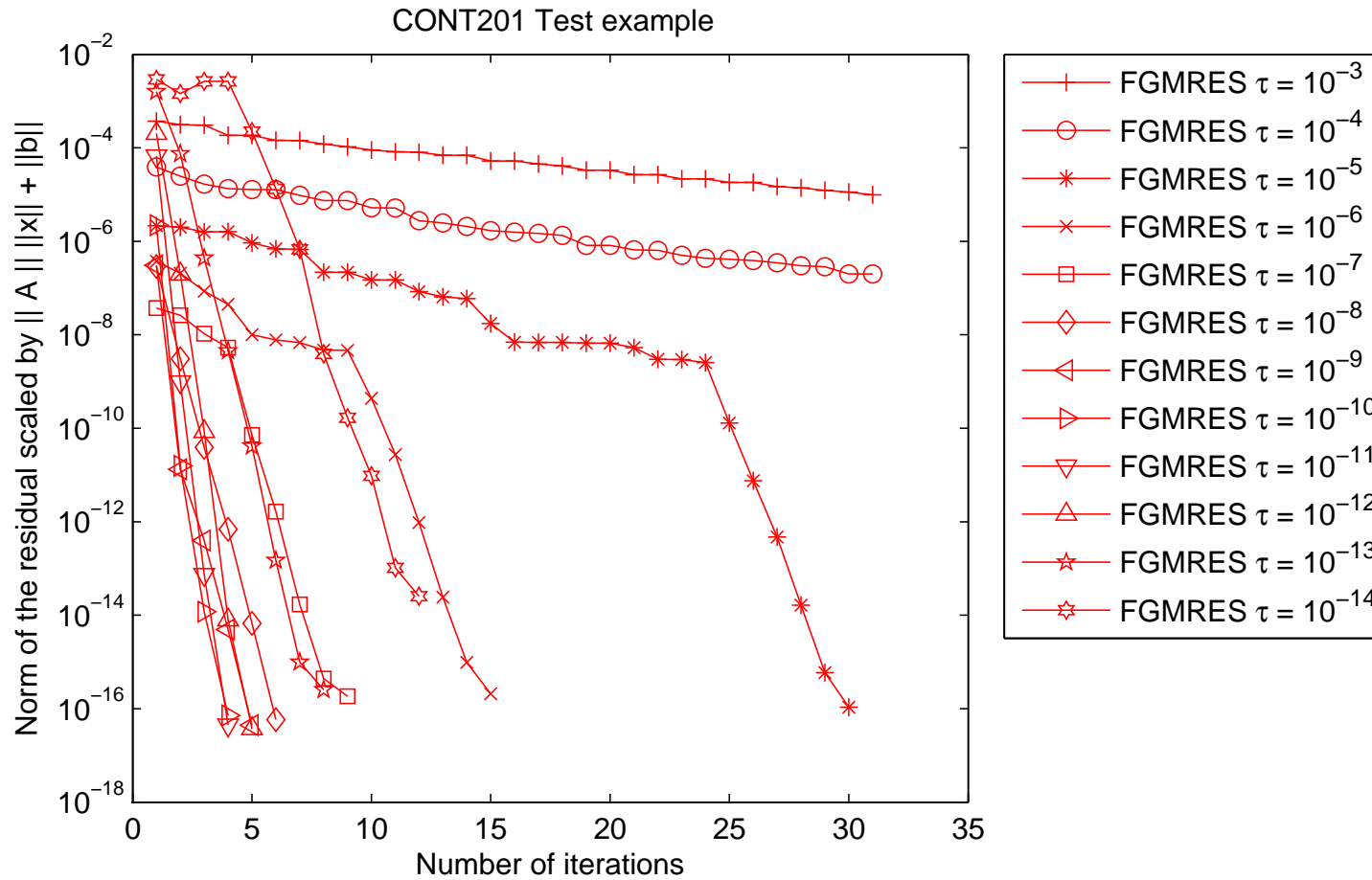
# Numerical experiments: CONT\_300

$\tau$	$\frac{\ b - A\bar{x}_k\ }{\ b\  + \ A\ \ \bar{x}_k\ }$			$\ Z_k\ $	$\ M(\bar{x}_k - \bar{x}_0)\ $		$\ L\  \ D\  \ L^T\ $
	IR	GMRES	FGMRES		GMRES	FGMRES	
1.0e-03	3.8e-04	3.6e-05	2.5e-05	*	8.7e-04	1.3e-04	2.5e+08
1.0e-04	3.6e-05	5.5e-07	5.5e-07	*	6.5e-05	2.8e-05	4.3e+09
1.0e-05	4.3e-06	8.7e-09	8.7e-09	*	3.7e-06	6.1e-06	1.4e+11
1.0e-06	3.7e-07	6.9e-11	1.4e-16	3.0e+06	5.7e-07	9.8e-07	6.2e+11
1.0e-07	6.8e-08	2.1e-10	8.2e-17	7.6e+06	2.3e-07	2.3e-07	2.0e+12
1.0e-08	2.1e-09	1.4e-08	1.2e-16	7.5e+07	1.8e-06	1.8e-06	4.1e+13
1.0e-09	1.1e-16	1.6e-05	8.8e-17	3.7e+07	2.8e-04	2.8e-04	3.7e+15
1.0e-10	3.9e-17	6.8e-07	4.1e-17	3.8e+05	3.6e-04	3.6e-04	9.6e+15
1.0e-11	4.0e-17	1.6e-06	8.7e-17	1.4e+03	5.3e-03	5.3e-03	1.0e+17
1.0e-12	7.3e-17	1.1e-06	2.7e-16	1.5e+02	1.0e-02	1.0e-02	1.9e+17
1.0e-13	1.8e-16	3.4e-03	9.2e-16	1.3e+02	1.9e-01	1.9e-01	1.3e+19
1.0e-14	1.1e-15	1.4e-01	1.8e-14	2.1e+02	4.7e-02	4.7e-02	6.6e+19

CONT\_300 results



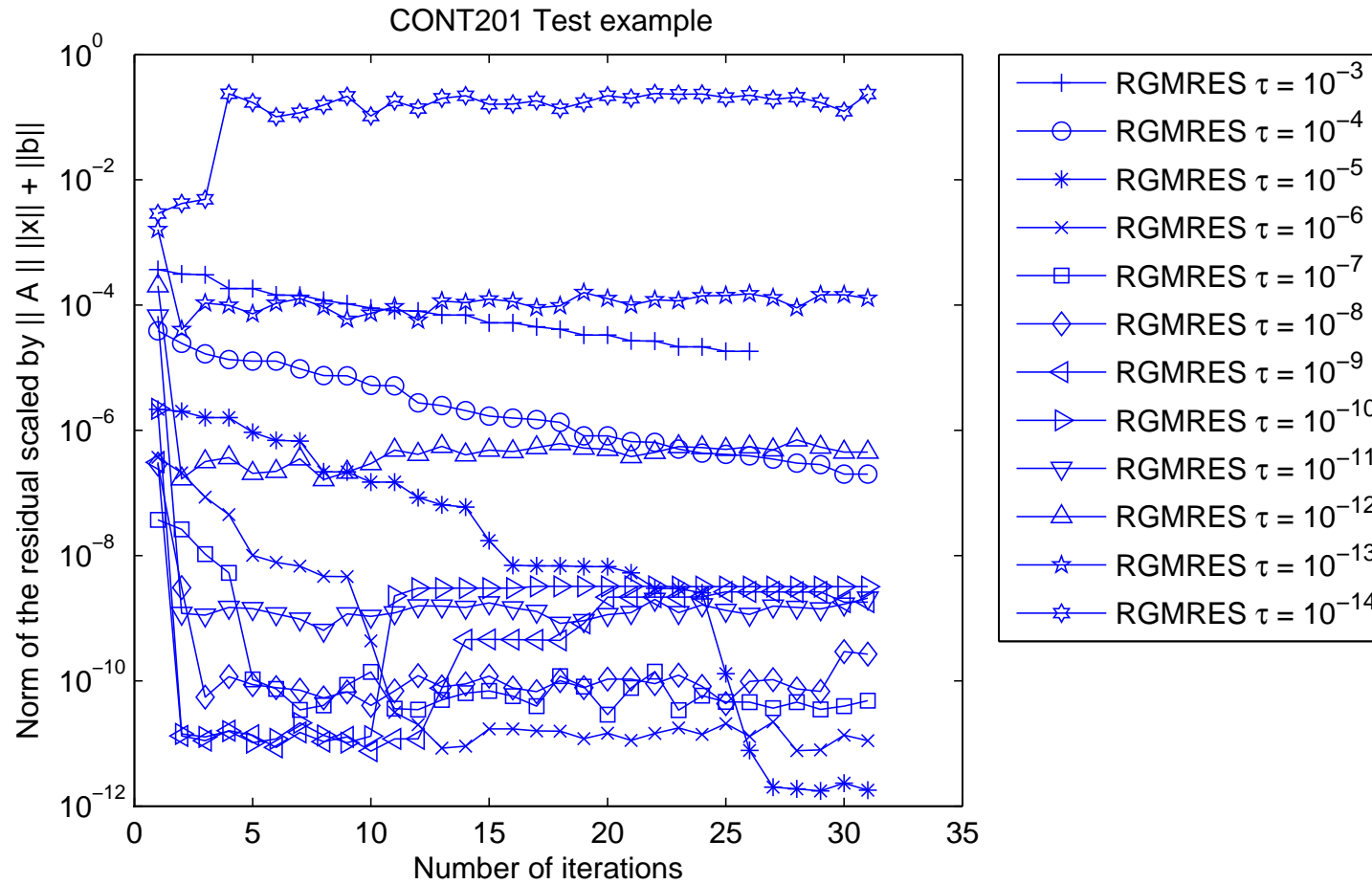
# Numerical experiments



FGMRES on CONT-201 test example



# Numerical experiments

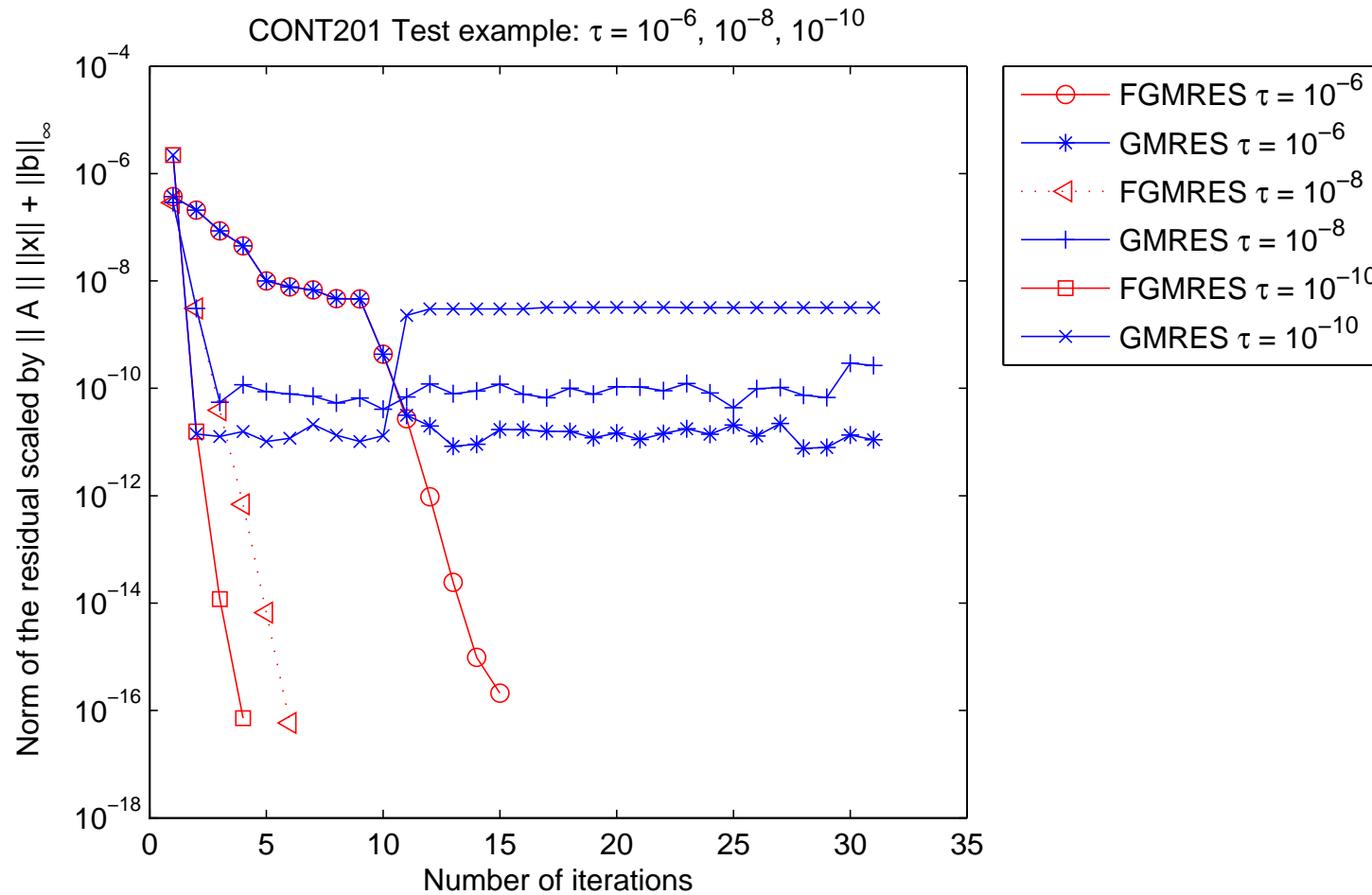


GMRES on CONT-201 test example





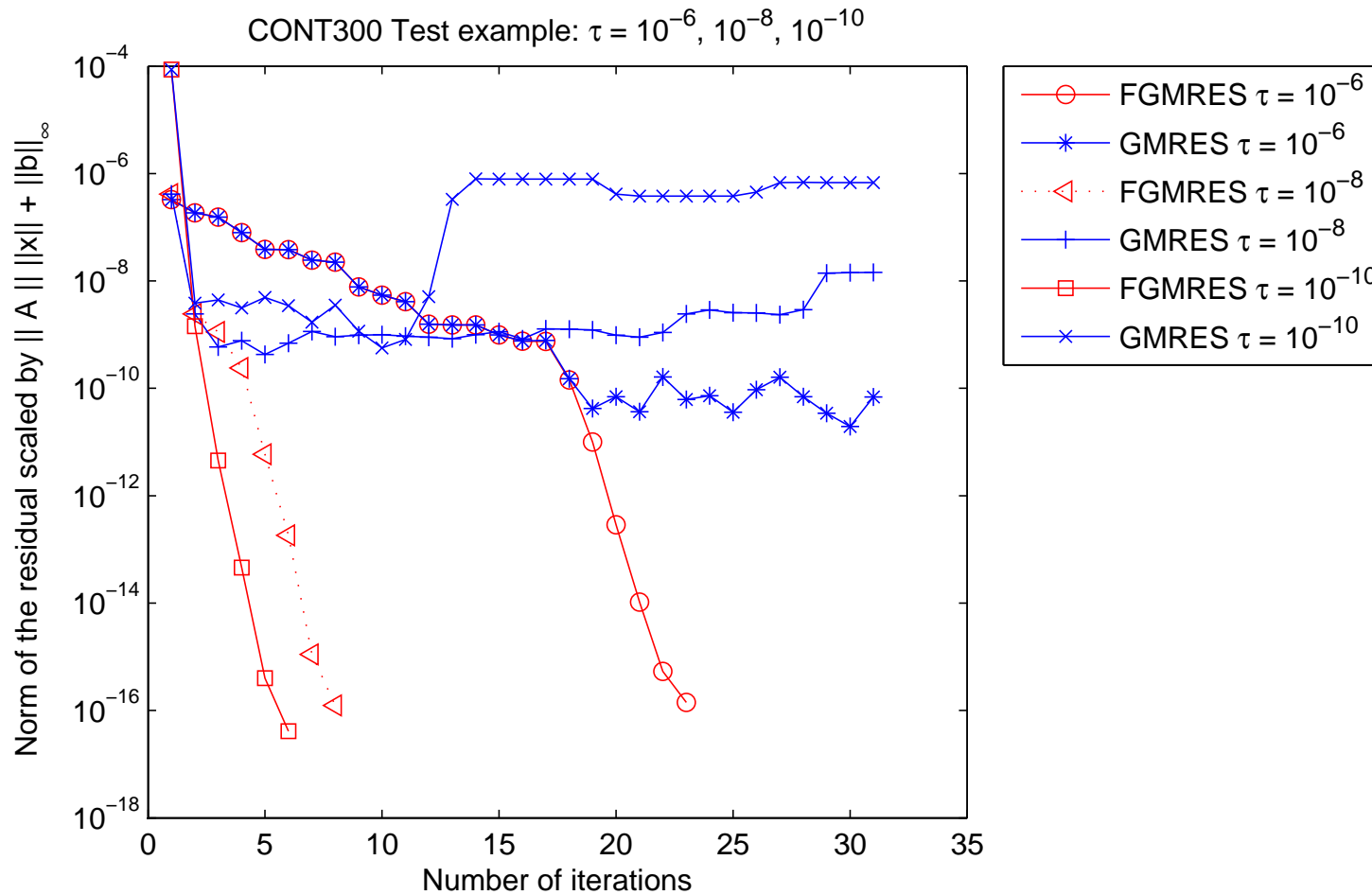
# Numerical experiments



GMRES vs. FGMRES on CONT-201 test example:  
 $\tau = 10^{-6}, 10^{-8}, 10^{-10}$



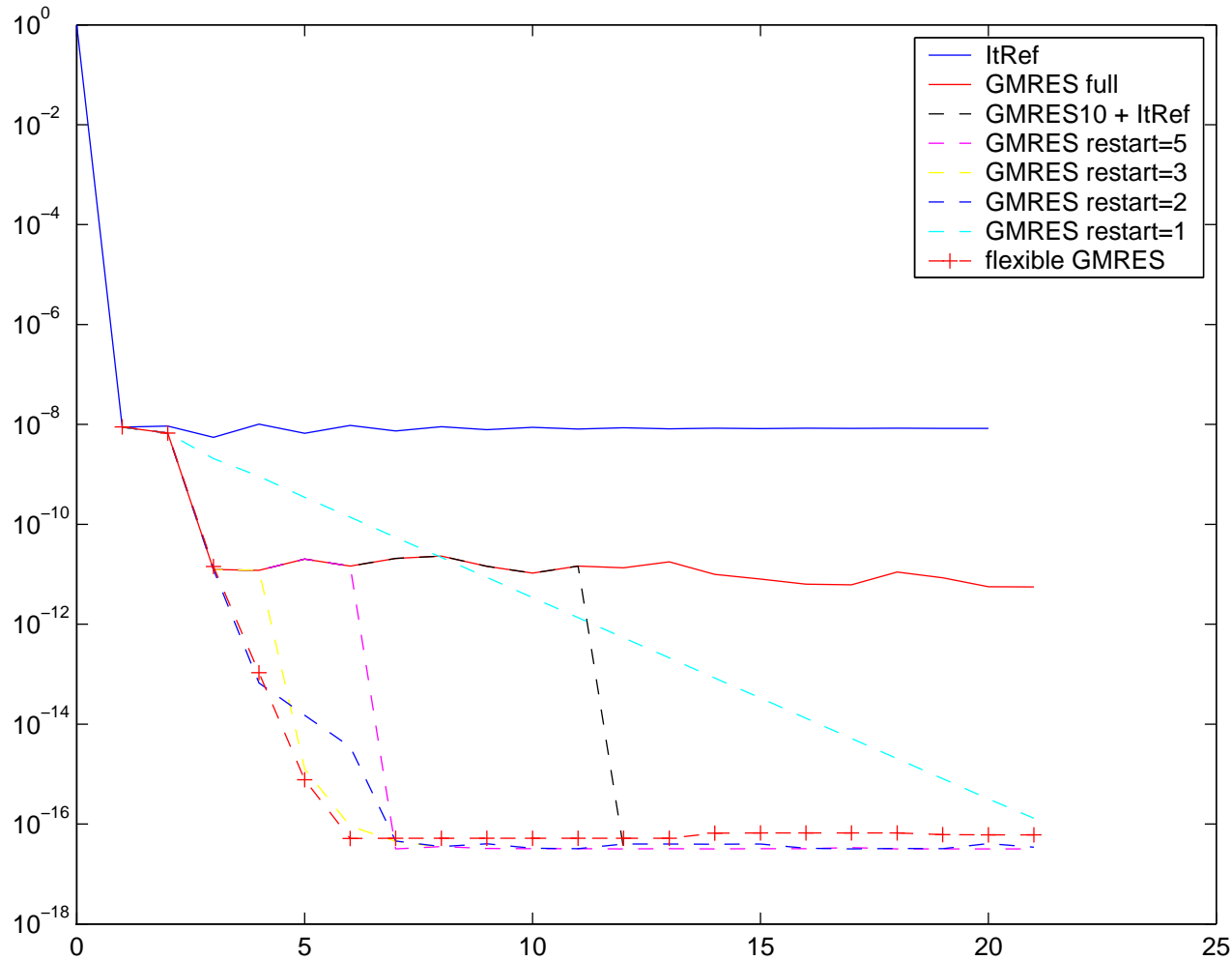
# Numerical experiments



GMRES vs. FGMRES on CONT-300 test example:  
 $\tau = 10^{-6}, 10^{-8}, 10^{-10}$



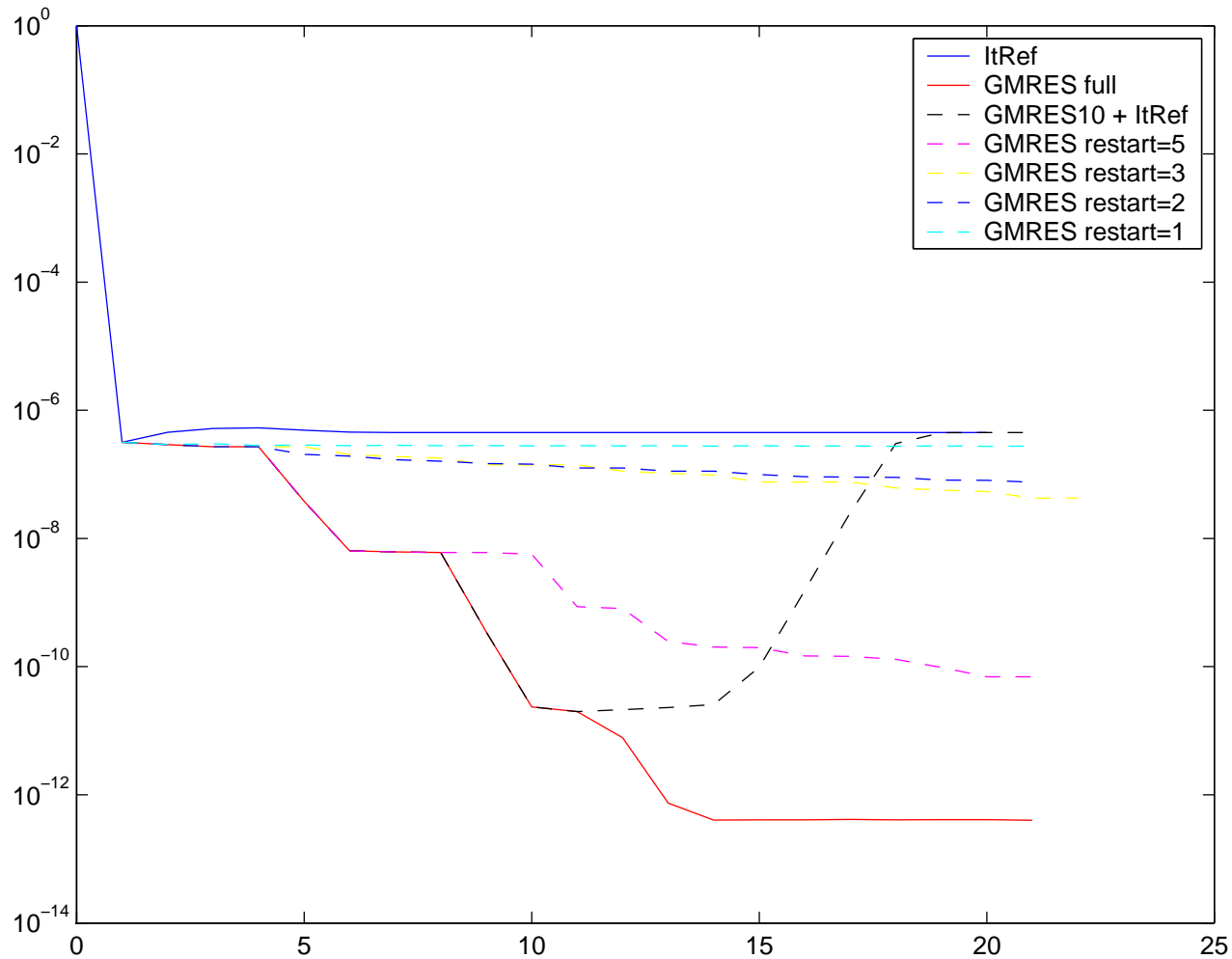
# Numerical experiments



Restarted GMRES vs. FGMRES on CONT-201 test example:  $\tau = 10^{-8}$



# Numerical experiments



Restarted GMRES on CONT-201 test example:  $\tau = 10^{-6}$



# Summary

- IR with static pivoting is very sensitive to  $\tau$  and not robust



# Summary

- IR with static pivoting is very sensitive to  $\tau$  and not robust
- GMRES is also sensitive and not robust



# Summary

- IR with static pivoting is very sensitive to  $\tau$  and not robust
- GMRES is also sensitive and not robust
- **FGMRES is robust and less sensitive (see roundoff analysis)**



# Summary

- IR with static pivoting is very sensitive to  $\tau$  and not robust
- GMRES is also sensitive and not robust
- FGMRES is robust and less sensitive (see roundoff analysis)
- Gains from restarting. Makes GMRES more robust, saves storage in FGMRES ( but not really needed)





# Summary

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- GMRES is also sensitive and not robust
- FGMRES is robust and less sensitive (see roundoff analysis)
- Gains from restarting. Makes GMRES more robust, saves storage in FGMRES ( but not really needed)
- Understanding of why  $\tau \approx \sqrt{\epsilon}$  is best.



# Summary

- IR with static pivoting is very sensitive to  $\tau$  and not robust
- GMRES is also sensitive and not robust
- FGMRES is robust and less sensitive (see roundoff analysis)
- Gains from restarting. Makes GMRES more robust, saves storage in FGMRES ( but not really needed)
- Understanding of why  $\tau \approx \sqrt{\epsilon}$  is best.
- PLAN B is working