

Worksheet #3

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Course: *PUF - High Performance Computing*

Due date: *December 01th, 2022*

Let A be the

- a) matrix defined in worksheet 1
- b) The 1D Finite Difference Matrix for the Laplace operator
- c) The 2D Finite Difference Matrix for the Laplace operator
- d) Matrices defined in Matrix Market.

1. Exercise 1

With the codes that Prof. Halpern sent you, compare the incomplete Cholewski with an **ILU(0)** decomposition of the lap2D matrix. Let A be a small size sparse symmetric matrix ($n = 10$) . Comment the incomplete Cholewski and **ILU(0)**, **ILU(1)**

Conjugate gradient with preconditioner

```
1 function [x,res,iter]=CGprecd(C,A,b,x0,tol,maxiter)
2
3 %
4 % Gradient conjugue preconditionne:
5 % [x,e]=CGprecd(A,b,x0,tol,maxiter) resout Ax=b en
6 % utilisant l'algorithme du gradient conjugue
7 % preconditionne ar une matrice C^{-1}.
8 % tol est la tolerance, x0 le vecteur initial,
9 % maxiter le
10 % nombre d'iteratios maximal, et e contient l'erreur
11 % relative a chaque iteration.
12 % la matrice A doit etre symetrique definie positive.
13
14
15 r=b-A*x0;
16 res(1)=norm(r);
17 z=C\r;
18 p=z;
19 k=1;
20
21 while res(k)>tol && k<maxiter
22
23     Ap=A*p; % pour avoir seulement un produit
```

```

24  pAp=p'*Ap; % matrice vecteur par iteration
25  num=z'*r;
26  alpha=num/pAp;
27
28  x=x0+alpha*p;
29  x0=x;
30
31  r=r-alpha*Ap;
32  z=C\r;
33  beta=z'*r/num;
34  p=z+beta*p;
35  res(k+1)= norm(r);
36  k=k+1;
37
38 end
39
40 iter = k;

```

Main input:

```

1 n = 10; N = n*n;
2 A = lap2d(n,n);
3 xex = rand(N,1);
4 b = A*xex;
5 x0 = zeros(N,1);
6 tol = 10^(-12);
7 maxiter = N;

```

Compare number of iteration and error of difference method:

Method	Number of iterations	Error
Conjugate Gradient	45	2.7898e-15
CG preconditioning with Gauss Seidel	37	2.6953e-15
CG preconditioning with SSOR	36	1.7973e-15
CG preconditioning with Incomplete Cholewski	23	3.106e-15
CG preconditioning with L+U-speye(size(A))	24	2.476e-15
CG preconditioning with LU(0) decomposition	23	1.7581e-15
CG preconditioning with LU(1) decomposition	57	2.7105e-15

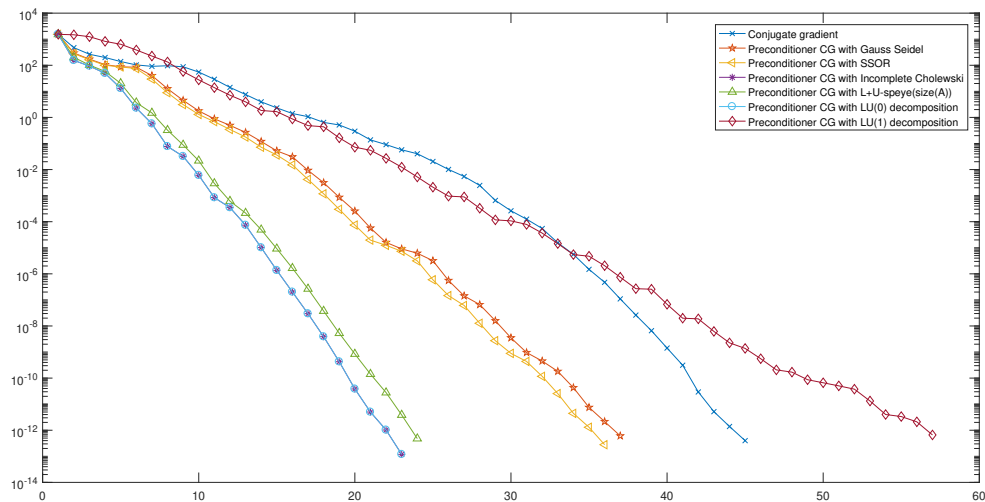


Figure 1: Comparison of value of residual of different method with *semilogy*

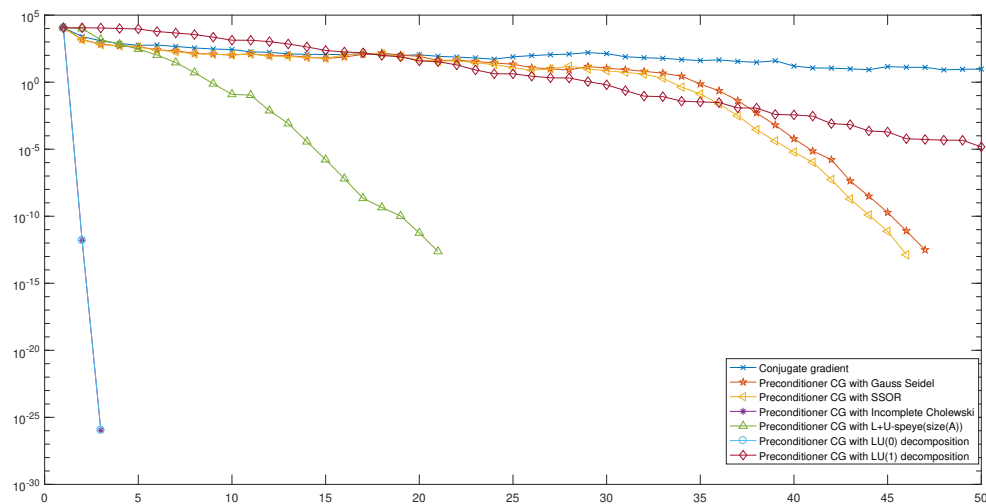
Using matrix of 1D Finite Difference Matrix for the Laplace operator

Main input:

```
1 n = 50;
2 A = lap1d(n);
```

Compare number of iteration and error of difference method:

Method	Number of iterations	Error
Conjugate Gradient	50	0.017617
CG preconditioning with Gauss Seidel	47	5.3029e-15
CG preconditioning with SSOR	46	6.6699e-15
CG preconditioning with Incomplete Cholewski	3	4.4365e-15
CG preconditioning with L+U-speye(size(A))	21	2.847e-14
CG preconditioning with LU(0) decomposition	3	4.4365e-15
CG preconditioning with LU(1) decomposition	50	3.3842e-09

Figure 2: Comparison of value of residual of different method with *semilog*

Using matrix defined in worksheet 1

Main input:

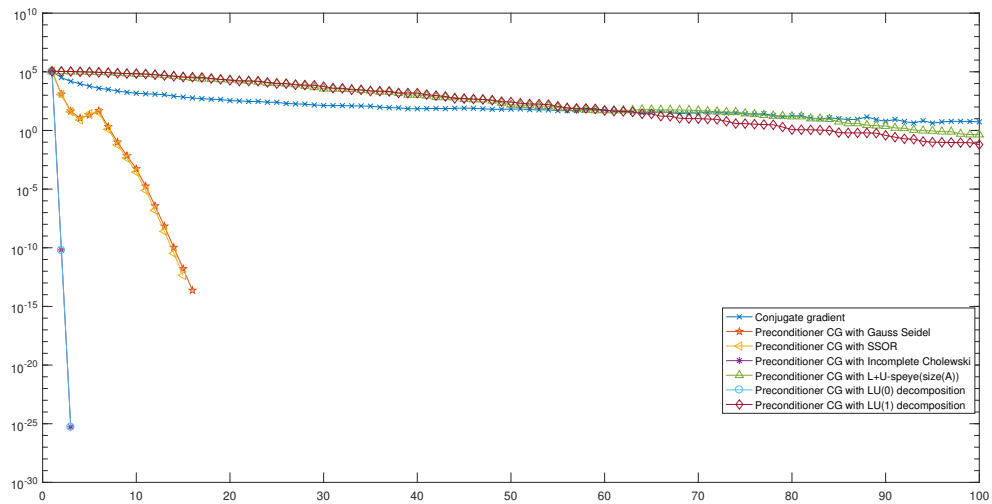
```

1 N = 100;
2 beta = 0.9;
3 alp = 2;
4 A = createMatrix(N, beta, alp);
5 A = A*A';

```

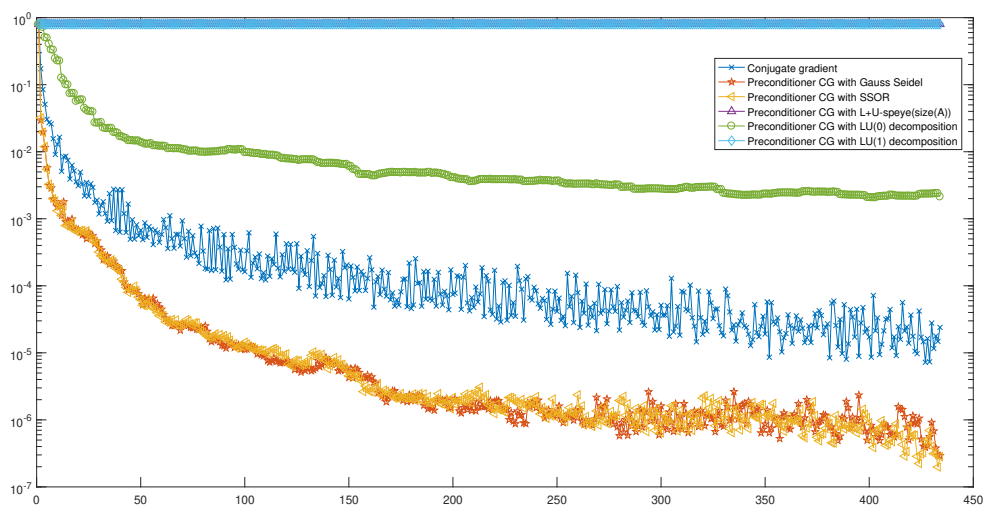
Compare number of iteration and error of difference method:

Method	Number of iterations	Error
Conjugate Gradient	100	0.25986
CG preconditioning with Gauss Seidel	16	1.4056e-13
CG preconditioning with SSOR	15	6.9301e-14
CG preconditioning with Incomplete Cholewski	3	3.2393e-14
CG preconditioning with L+U-speye(size(A))	100	4.9069e-05
CG preconditioning with LU(0) decomposition	3	1.9305e-14
CG preconditioning with LU(1) decomposition	100	1.6991e-05

Figure 3: Comparison of value of residual of different method with *semilogy*

Using matrix from Matrix Market

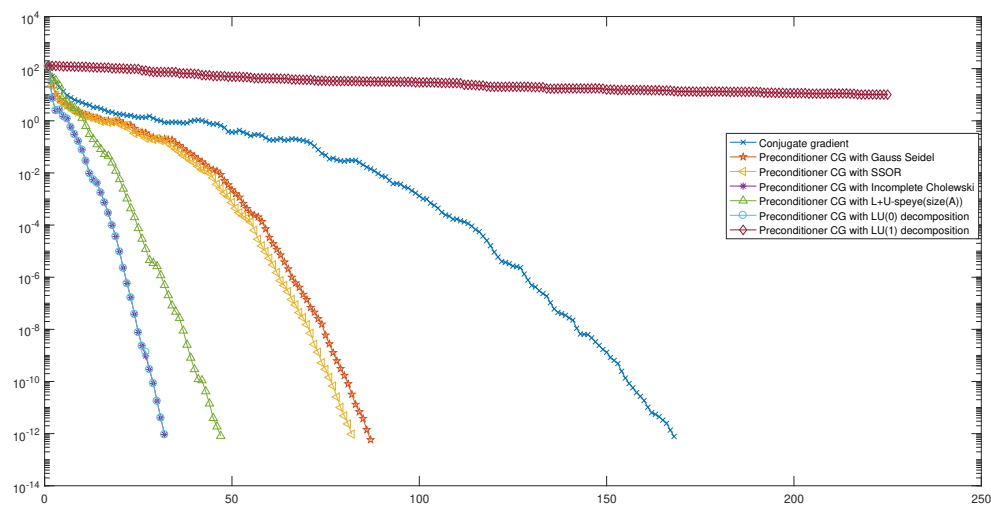
1 FILE : 'hor131.mtx'

Figure 4: Comparison of value of residual of different method with *semilogy*

2 FILE : 'pde225.mtx'

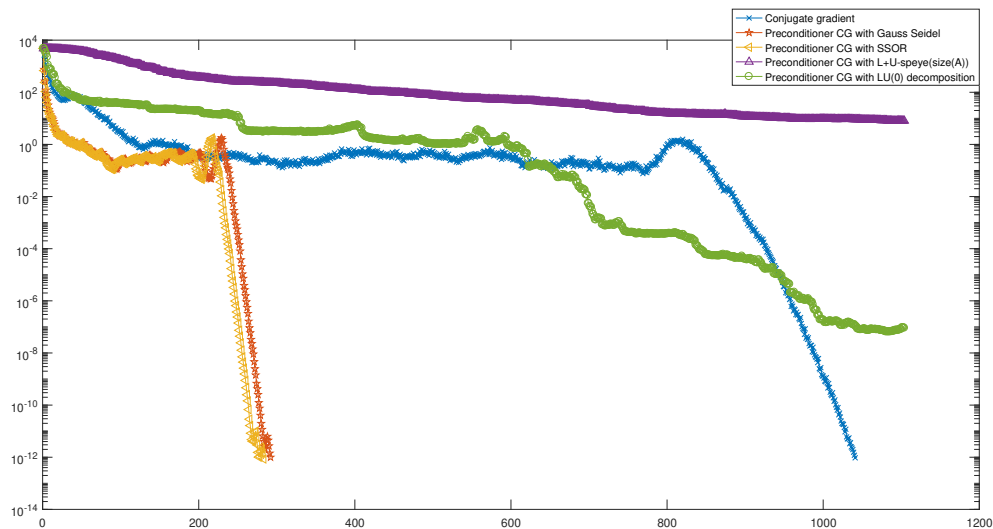
Compare number of iteration and error of difference method:

Method	Number of iterations	Error
Conjugate Gradient	168	9.6661e-14
CG preconditioning with Gauss Seidel	87	7.0933e-14
CG preconditioning with SSOR	82	9.8406e-14
CG preconditioning with Incomplete Cholewski	32	2.1736e-13
CG preconditioning with L+U-speye(size(A))	47	9.8092e-14
CG preconditioning with LU(0) decomposition	32	2.0082e-13
CG preconditioning with LU(1) decomposition	225	4.6775

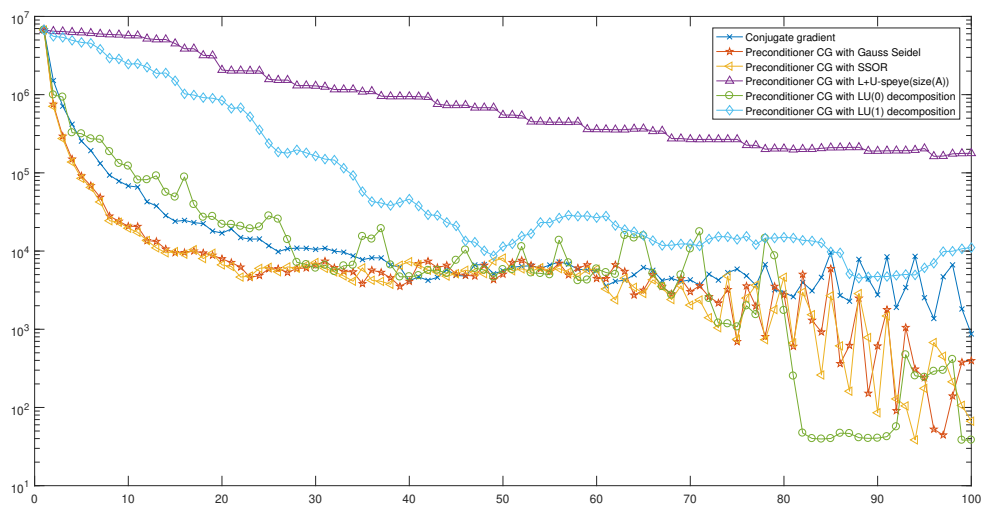
Figure 5: Comparison of value of residual of different method with *semilog*

3 FILE : 'sherman4.mtx'

Method	Number of iterations	Error
Conjugate Gradient	1041	1.3094e-12
CG preconditioning with Gauss Seidel	292	5.677e-11
CG preconditioning with SSOR	283	4.667e-11
CG preconditioning with L+U-speye(size(A))	1104	16.3103
CG preconditioning with LU(0) decomposition	1104	2.9827e-07

Figure 6: Comparison of value of residual of different method with *semilog*

4 FILE : 'tub1000.mtx'

Figure 7: Comparison of value of residual of different method with *semilog*

Exercise 2 and Exercise 3 already done in ws2.

2. Exercise 4

Look into the matlab function `schur` that performs a Schur decomposition of a matrix.
(help `schur`)

Schur decomposition:

$[U, T] = \text{schur}(X)$ produces a *quasitriangular* **Schur** matrix T and a *unitary* matrix U so that $X = U^* T U$ and $U^* U = \text{EYE}(\text{SIZE}(U))$. X must be square.

$T = \text{schur}(X)$ returns just the Schur matrix T .

If X is real, two different decompositions are available. $\text{schur}(X, \text{'real'})$ has the real eigenvalues on the diagonal and the complex eigenvalues in 2-by-2 blocks on the diagonal. $\text{schur}(X, \text{'complex'})$ is triangular and is complex if X has complex eigenvalues. $\text{schur}(X, \text{'real'})$ is the default.

If X is complex, the complex Schur form is returned in matrix T . The complex Schur form is upper triangular with the eigenvalues of X on the diagonal. The second input is ignored in this case.

3. Exercise 5

Following the algorithm below, modify `pregmres.m` to obtain a function that performs a Deflation Preconditioned Gmres

Algorithm : DEFLGMRES

Require: Choose x_0 , $M = I_n$

1: $r_0 = b - Ax$, $\beta = \|r_0\|$, $v_1 := r_0/\beta$

2: Generate the Arnoldi basis applied to AM^{-1}

and the associated Hessenberg matrix \tilde{H}_m starting with v_1

3: Compute y_m which minimises $\|\beta e_1 - \tilde{H}_m y\|$ and $x_m = x_0 + M^{-1}V_m y_m$

4: If convergence Stop, else set ;

$x_0 = x_m$

Compute 1 Schur vectors of H_m noted S_l ;

Compute the approximation of $|\lambda_n|$;

Orthogonalize $V_m S_l$ against U ;

Increase U with $V_m S_l$;

$T = U^T A U$;

$M^{-1} = I_n + U \left(|\lambda_n| T^{-1} - I_r \right) U^T$;

Go To 1 ;

```

1 %*****
2 function [x,error,iter, itv] = DEFLGMRESR(A,b,x,M,m,l,itmax,epsi)
3 %*****
4 % DEFLGMRESR.m solves the linear system Ax=b
5 % using the Generalized Minimal residual ( GMRESm ) method with restarts
6 %
7 % With Right preconditioning and Schur decomposition
8 %
9 % input      A          REAL nonsymmetric positive definite matrix
10 %           x          REAL initial guess vector
11 %           bb         REAL right hand side vector
12 %           m          INTEGER number of iterations between restarts
13 %           l          INTEGER maximum number of iterations
14 %           epsi       REAL error tolerance
15 %           M          Right Preconditioner

```



```

16 %
17 % output  x      REAL solution vector
18 %         error   REAL error norm
19 %         iter    INTEGER number of iterations performed
20 %         itv     Total number of iterations
21
22
23 % initialization
24 normb = norm( b );
25 if ( normb == 0.0 ),
26     normb = 1.0;
27 end
28 % invM = inv(M);
29 % residual
30 r = b - A*(M\x);
31 error(1) = norm( r )/normb;
32
33 if ( error(1) < epsi )
34     return;
35 end
36
37 n = size(A,1);
38 V(1:n,1:m+1) = zeros(n,m+1);
39 H(1:m+1,1:m) = zeros(m+1,m); % Hessenberg matrix
40 U = [];
41 cs(1:m) = zeros(m,1);
42 sn(1:m) = zeros(m,1);
43 e1 = zeros(n,1); % basic vector
44 e1(1) = 1.0;
45 iter=1; % step of iterator
46 itv= 0 ; % Total iterations
47 while iter <= itmax % begin iteration
48     r = b - A*(M\x);
49     V(:,1)=r/norm(r);
50     s = norm(r)*e1;
51     for j = 1:m % construct orthonormal
52         itv = itv + 1 ; % basis using Gram-
53         Schmidt
54         w = A*(M\V(:,j));
55         for i = 1:j
56             H(i,j)= w'*V(:,i);
57             w = w - H(i,j)*V(:,i);
58         end
59         H(j+1,j) = norm(w);
60         V(:,j+1) = w/H(j+1,j);
61         % We transform the Hessenberg matrix H into a triangular matrix by
62         % applying Givens rotation
63         for i = 1:j-1
64             temp = cs(i)*H(i,j) + sn(i)*H(i+1,j);
65             H(i+1,j) = -sn(i)*H(i,j) + cs(i)*H(i+1,j);
66             H(i,j) = temp;
67         end
68         [cs(j),sn(j)] = rotmat( H(j,j), H(j+1,j) ); % form i-th rotation
69         matrix
70         temp = cs(j)*s(j);
71         s(j+1) = -sn(j)*s(j);
72         s(j) = temp;
73         H(j,j) = cs(j)*H(j,j) + sn(j)*H(j+1,j);

```

```

71     H(j+1,j) = 0.0; %eliminate H(j+1,j)
72     error(j+1) = abs(s(j+1)) / normb;
73     if ( error(j+1) <= epsi ) % update approximation
74         y = H(1:j,1:j) \ s(1:j); % and exit
75         x = x + V(:,1:j)*y;
76         % error(i+1) = abs(s(i+1)) / bnorm2;
77         break;
78     end
79 end
80
81 if ( error(j+1) <= epsi ), break, end
82 y = H(1:m,1:m)\s(1:m);
83 % x = x + V*y; % update
84 % approximation
85 x = x + V(:,1:j)*y; % update
86 % approximation
87
88 % Compute Shur vectors of H noted S1, l = 2
89 [eigvals] = eig(H(1:m,1:m));
90 eigval_new = [];
91 for i = 1:length(eigvals)
92     if (eigvals(i) ~= min(eigvals))
93         eigval_new = [eigval_new; eigvals(i)];
94     end
95 end
96 min_eigval = [min(eigvals); min(eigval_new)];
97 [U_Hess,T] = schur(H(1:m,1:m));
98 S1 = zeros(m,1);
99 for i = 1:l
100     for jj = 1:size(T,2)
101         if T(jj,jj) == min_eigval(i)
102             S1(:,i) = T(:,jj);
103         end
104     end
105 end
106 k = size(U,2);
107 W = V(:,1:m)*S1;
108 U = [U W];
109 % Orthogonalize VmS1 against U
110 U(:,1) = U(:,1) / sqrt(U(:,1)'*U(:,1));
111 for i = 2:k
112     for ii = 1:k-1
113         U(:,i) = U(:,i) - ( U(:,ii)'*U(:,i) ) / ( U(:,ii)'*U(:,ii) ) * U(:,ii);
114     end
115     U(:,i) = U(:,i) / sqrt(U(:,i)'*U(:,i));
116 end
117 T = U'*A*U;
118 invM = eye(n,n) + U*(abs(max(eig(full(A))))*inv(T) - eye(size(T,1)))*U';
119
120 % compute residual
121 r = b - A*(M\x);
122 s(j+1) = norm(r);
123 error(j+1) = s(j+1) / normb; % check
124 convergence
125 if ( error(j+1) <= epsi )
126     break;

```

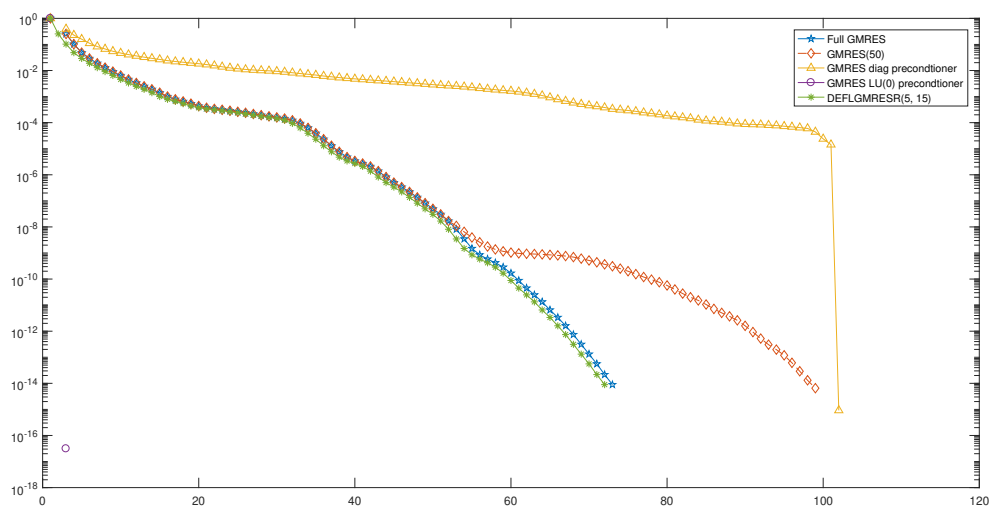
```

124     end
125     iter=iter+1;
126 end
127 x = M\x;      % true solution after preconditioning

```

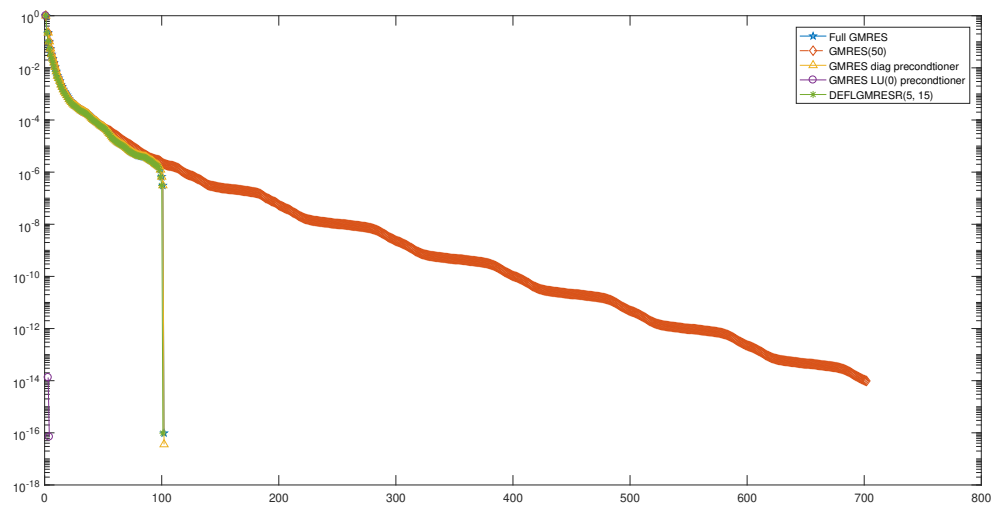
Matrix in worksheet 1:

Method	error	iter	Time (seconds)
Full GMRES	74	6.925e-12	0.044242
GMRES(50)	101	1.6963e-11	0.029979
GMRES diag precondtioner	101	2.6924e-12	0.044937
GMRES LU(0) precondtioner	2	2.8741e-13	0.0097826
DEFLGMRESR(5, 15)	72	6.925e-12	0.048682



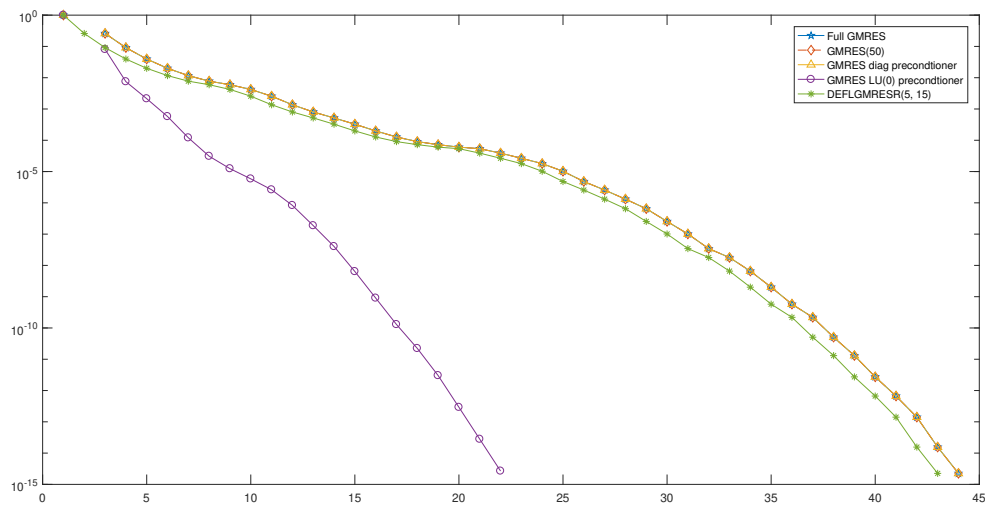
Matrix Laplace 1d:

Method	error	iter	Time (seconds)
Full GMRES	102	2.7435e-11	0.053413
GMRES(50)	702	2.3873e-09	0.090297
GMRES diag precondtioner	101	2.6785e-11	0.041346
GMRES LU(0) precondtioner	3	2.325e-10	0.0087148
DEFLGMRESR(5, 15)	100	2.7435e-11	0.065002



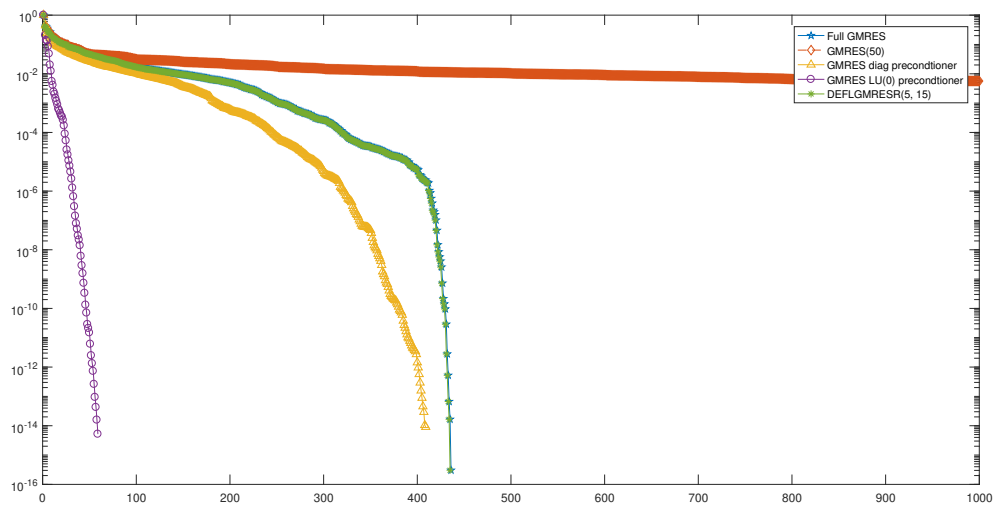
Matrix Laplace 2d:

Method	error	iter	Time (seconds)
Full GMRES	44	1.0666e-12	0.034555
GMRES(50)	44	1.0666e-12	0.010509
GMRES diag precondtioner	43	1.1324e-12	0.034507
GMRES LU(0) precondtioner	21	2.161e-12	0.019295
DEFLGMRESR(5, 15)	42	1.0666e-12	0.041744



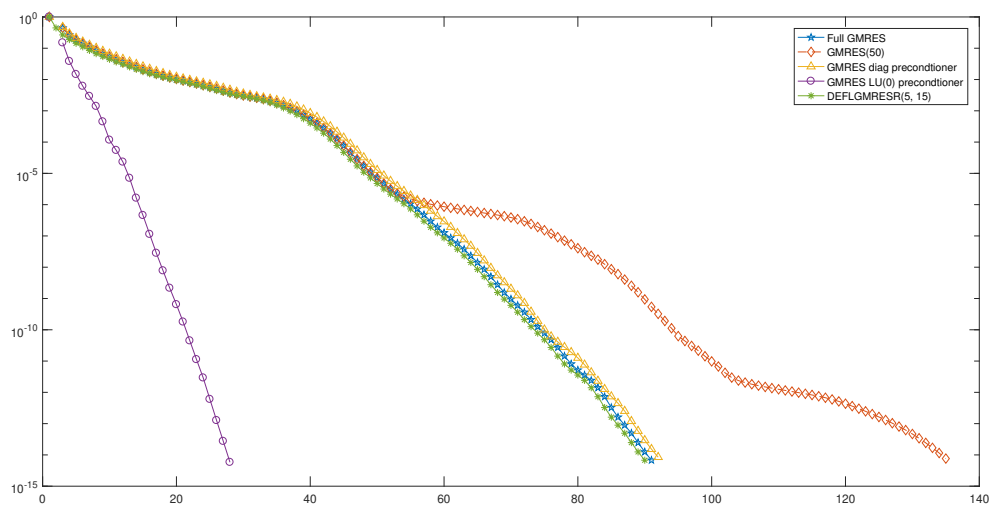
Matrix Market
File 'hor131.mtx'

Method	error	iter	Time (seconds)
Full GMRES	436	2.0039e-11	0.44593
GMRES(50)	5002	187.66	0.59435
GMRES diag precondtioner	408	6.2006e-09	0.39461
GMRES LU(0) precondtioner	58	7.7192e-10	0.97
DEFLGMRESR(5, 15)	434	2.0039e-11	0.48991



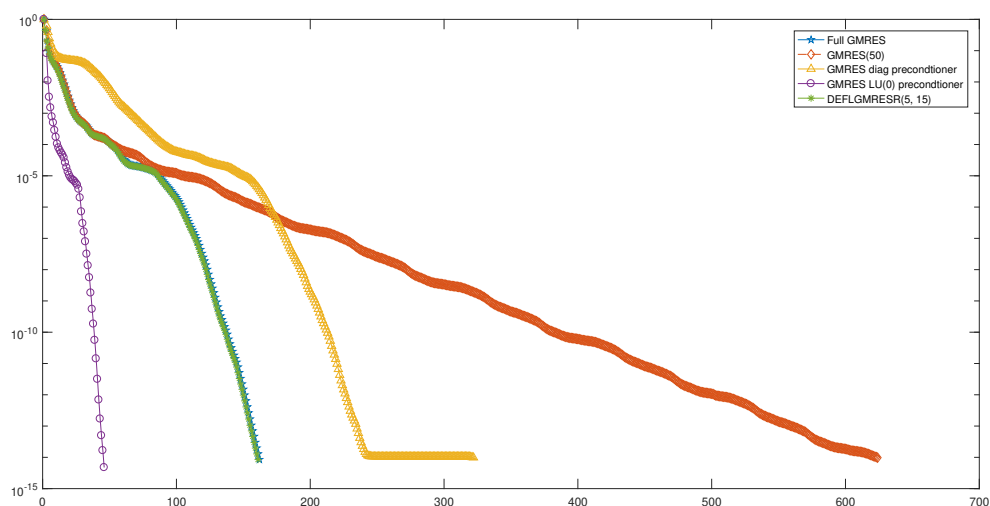
File 'pde225.mtx'

Method	error	iter	Time (seconds)
Full GMRES	91	4.9422e-12	0.063074
GMRES(50)	135	1.0202e-11	0.038621
GMRES diag precondtioner	91	1.0492e-11	0.048552
GMRES LU(0) precondtioner	27	8.1211e-12	0.060863
DEFLGMRESR(5, 15)	89	4.9422e-12	0.081825

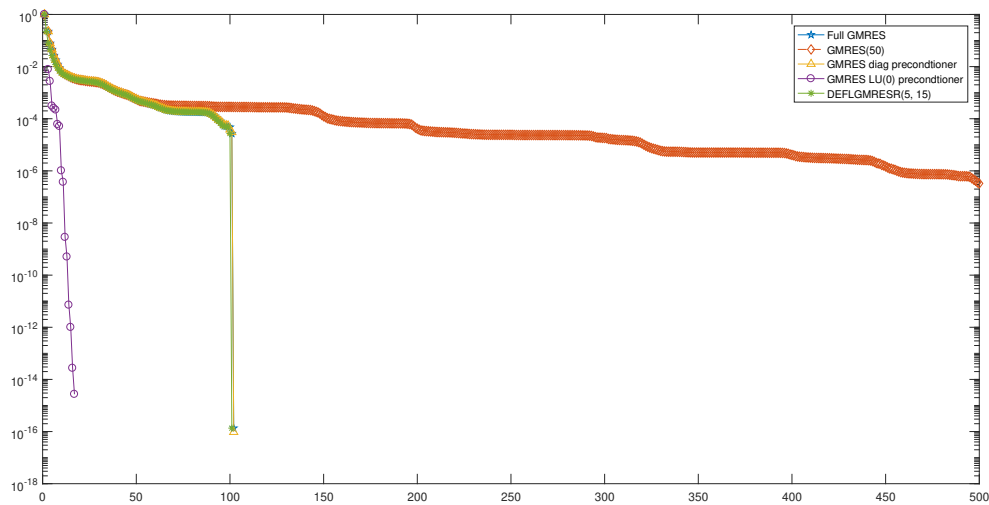


File 'sherman4.mtx'

Method	error	iter	Time (seconds)
Full GMRES	162	5.7276e-11	0.15503
GMRES(50)	624	3.3599e-09	0.10939
GMRES diag precondtioner	321	1.1896e-10	0.35844
GMRES LU(0) precondtioner	45	5.8692e-11	0.70376
DEFLGMRESR(5, 15)	160	5.7276e-11	0.14505

**File 'tub100.mtx'**

Method	error	iter	Time (seconds)
Full GMRES	102	1.9944e-11	0.041509
GMRES(50)	5002	2.4806e-07	0.46914
GMRES diag precondtioner	101	1.2226e-10	0.048416
GMRES LU(0) precondtioner	16	4.3016e-10	0.015504
DEFLGMRESR(5, 15)	100	1.9944e-11	0.070726



Commend: Those method give us solution to solve $Ax = b$, where A is not necessary symmetric. Among all, GMRES method using LU(0) as preconditioner give the best behaviour.