

[Q1] (10 pts) (a) For a generic Krylov subspace method that takes the initial approximation x_0 , gets the initial residual $r_0 = b - Ax_0$, develops the sequence of Krylov subspaces $\mathcal{K}_k(A, r_0)$ and constructs the approximate solution $x_k = x_0 + z_k$ where $z_k \in \mathcal{K}_k(A, r_0)$, the residual $r_k = b - Ax_k$ can be written as $r_k = p_k(A)r_0$, where p_k is a polynomial of degree no greater than k with $p_k(0) = 1$.

Consider $r_k = r_0 - AV_k y_k$
 Since $\text{col}(V_k) = \mathcal{K}_k(A, r_0)$, we can write $V_k y_k$ as
 $q_{k-1}(A)r_0$

Thus, $r_k = (I - Aq_{k-1}(A))r_0$

Note $p_k(0) = 1$ since $I \rightarrow I$ \square

(b) Let A be SPD, and x_0 and $r_0 = b - Ax_0$ be the initial approximation and residual, respectively. Consider the Lanczos relation $AU_k = U_k T_k + \beta_k u_{k+1} e_k^T$ (Arnoldi's method applied to a symmetric A), where $u_1 = \frac{r_0}{\|r_0\|_2}$. Show that the k -th iterate of CG can be written as $x_k = x_0 + U_k y_k$, where y_k satisfies $T_k y_k = \|r_0\|_2 e_1$.
 (Hint: use the fact that $r_k = b - Ax_k = r_0 - AU_k y_k \perp \mathcal{K}_k(A, r_0) = \text{col}(U_k)$)

$$r_k = b - Ax_k = r_0 - AU_k y_k$$

$$r_k \perp \mathcal{K}_k(A, r_0) = \text{col}(U_k)$$

$$r_0 = b - Ax_0$$

$$x_k = x_0 + U_k y_k$$

$$r_k = b - Ax_k$$

$$= b - A(x_0 + U_k y_k)$$

$$= b - Ax_0 - AU_k y_k$$

$$= r_0 - AU_k y_k$$

$$r_k = r_0 - (U_k T_k + \beta_k u_{k+1} e_k^T) y_k$$

$$U_k^T r_k = U_k^T r_0 - T_k y_k$$

$$U_k^T(b - Ax_k) = U_k^T(b - Ax_0) - T_k y_k$$

$$U_k^T A X_0 = U_k^T A X_k - T_k y_k$$

$$U_k^T A X_0 + T_k y_k = U_k^T A X_k$$

$$\cancel{U_k^T A}(X_0 + U_k y_k) = \cancel{U_k^T A} X_k$$

$$U_k^T A U_k = T_k$$

$$X_k = X_0 + U_k y_k$$

(c) Show that the k -th residual of GMRES $r_k = b - Ax_k$ satisfies $r_k \in \mathcal{K}_{k+1}(A, r_0)$, $r_k \perp A\mathcal{K}_k(A, r_0)$, $(r_k, r_k) = (r_j, r_k)$ for all $0 \leq j \leq k-1$, and therefore $\|r_k\|_2 \leq \|r_j\|_2$.

$$\text{Span}\{A^n r_0\}_{n=1}^k \quad r_0 = b - Ax_0$$

$$r_k = b - A Q_k y \quad r_k \in \mathcal{K}_k(A, r_0)$$

Assume

$$r_k \in \mathcal{K}_k(A, r_0) \quad r_k = b - Ax_k \in \text{Span}\{A^n r_0\}_{n=0}^{k-1}$$

$$r_{k+1} = b - Ax_{k+1} \quad x_{k+1} = Q_k y$$

$$x_{k+1} \in \text{Col}(Q_k) \quad = \mathcal{K}_k(A, r_0)$$

$$\Rightarrow b - Ax_{k+1} \in \mathcal{K}_{k+1}(A, r_0)$$

$$\therefore r_{k+1} \in \mathcal{K}_{k+1}(A, r_0)$$

$$\langle r_k, v \rangle = \langle r_0 - Ax_k, v \rangle \quad \text{Let } v \in A\mathcal{K}_k(A, r_0)$$

$$\begin{aligned} &= v^T r_0 - v^T A x_k \\ &= 0 + 0 \end{aligned}$$

$$\therefore \|r_k\| \leq \|r_j\| \quad \forall \quad k \geq j$$

Since by Arnoldi process
they are orthogonal

35.2. (a) Let $S \subseteq \mathbb{C}$ be a set whose convex hull contains 0 in its interior. That is, S is contained in no half-plane disjoint from the origin. Show that there is no $p \in P_1$ (i.e., no polynomial p of degree 1 with $p(0) = 1$) such that $\|p\|_S < 1$.

(b) Let A be a matrix, not necessarily normal, whose spectrum $\Lambda(A)$ has the property (a). Show that there is no $p \in P_1$ such that $\|p(A)\| < 1$.

(c) Though the convergence in Figure 35.5 is slow, it is clear that $\|r_1\| < \|r_0\|$. Explain why this does not contradict the result of (b). Describe what kind of polynomial $p_1 \in P_1$ GMRES has probably found to achieve $\|r_1\| < \|r_0\|$.

$$a) \|p\|_S = \sup_{z \in S} |p(z)|$$

Assume $\exists p \in P_1 \ni$

$$\begin{aligned} p(0) &= 1 \\ p(z) &= a + bz \\ p(0) &= a = 1 \\ \Rightarrow p(z) &= 1 + bz \end{aligned}$$

WLOG assume S is a circle if not take $S' \subseteq S$ that is a circle and what is shown for S' will hold for S

$$\text{Let } S = B(0, r) \text{ so } \|p\|_S = \sup_{z \in S} |1 + bz| = 1 + br > 1$$

(b) Let A be a matrix, not necessarily normal, whose spectrum $\Lambda(A)$ has the property (a). Show that there is no $p \in P_1$ such that $\|p(A)\| < 1$.

$$b) \|p(0)\| = 1 \Rightarrow p(A) = I + \beta A$$

Consider an eigenpair (λ, v) of A .

Let v be normalized. Choose direction of $v \ni \beta \lambda \geq 0$

$$\begin{aligned} \|I + \beta A\| &= \sup_{\|x\|=1} \|(I + \beta A)x\| \\ &\geq \|v + \beta Av\| \\ &= \|v + \beta \lambda v\| \\ &= \|(1 + \beta \lambda)v\| \\ &= |1 + \beta \lambda| \\ &> 1 \end{aligned}$$

(c) Though the convergence in Figure 35.5 is slow, it is clear that $\|r_1\| < \|r_0\|$. Explain why this does not contradict the result of (b). Describe what kind of polynomial $p_1 \in P_1$ GMRES has probably found to achieve $\|r_1\| < \|r_0\|$.

$$r_0 = b \quad r_1 = b - Ax_0$$

It does not contradict since the residual decreases by looking at the minimized residual. So $\|r_{n+1}\| \leq \|r_n\| \ \forall n$ (problem 1)

$$p(A) = I + bA$$

$$r_1 = p(A)r_0$$

$$\|r_1\| = \|p(A)r_0\| \leq \|p(A)\| \|r_0\|$$

If $\|p(A)\| = 1$ then $\|r_1\| \leq \|r_0\|$

(b) Let $A \in \mathbb{R}^{n \times n}$ be nonsymmetric and diagonalizable. Assume that all eigenvalues of A lie in the disk centered at $c \in \mathbb{C} \setminus \{0\}$ with radius $r < |c|$. Consider using GMRES to solve the linear system $Ax = b$ iteratively. Show that the k -th relative residual satisfies $\frac{\|r_k\|_2}{\|r_0\|_2} \leq C \left(\frac{r}{|c|} \right)^k$ for some constant C independent of k . What if A has a small number, say, $m \ll n$ eigenvalues outside such a disk?

$$\|r_k\| = \min_p \|p_k(A)r_0\|$$

$$\frac{\|r_k\|}{\|r_0\|} \leq \min_p \|p_k(A)\|$$

$$A = V D V^{-1}$$

$$\frac{\|r_k\|}{\|r_0\|} \leq \min_p \chi(V) \|p_k(A)\|$$

$$= \max_K |\chi_k - \lambda_i| \quad \text{from class min}$$

$$= \chi(V) \lambda_i^k \quad \text{is characteristic polynomial}$$

$$\leq \chi(V) \left(\frac{r}{|c|} \right)^k \quad \text{max of H}$$

Since $\Lambda(A) \subseteq B(c, r)$

I^+ would depend on the magnitude of the eigenvalues outside of the disk.

c) If A is an SPD matrix with the smallest eigenvalue λ_1 and the largest eigenvalue λ_n , what is the convergence factor obtained in part (b)? Compare this factor with that of CG we learned in class. Which one is better?

$$\frac{\lambda_1}{\lambda_n}$$

which would be larger

$\frac{1}{\lambda_n}$ which would be larger
than CG's $\sqrt{\frac{\lambda_1}{\lambda_n}}$ rate

Note $\Lambda(A) = \mathcal{B}(1c, \lambda_n) \setminus \mathcal{B}(1c, \lambda_1)$ in this case

3. [Q3] (10 pts) Let x^* be the true solution of $Ax = b$ with SPD A , x_k be the k -th iterate of CG, and $\varphi(x) = \frac{1}{2}x^T Ax - b^T x$ for CG minimization.

(a) Note that $r_k \perp r_j$ for $0 \leq j \leq k-1$, and hence $r_k \perp U_k = \text{span}\{p_0, p_1, \dots, p_{k-1}\}$. Also note that $r_k = -\nabla \varphi(x_k)$, and any vector $x \in W_k = x_0 + U_k$. Explain from the optimization point of view, why $x_k = \operatorname{argmin}_{x \in W_k} \varphi(x)$.

Hint: one possible (and easier) solution is to show that W_k is a convex set, and $\varphi(x)$ is a convex function defined on W_k ; then local minimizer of $\varphi(x)$ is necessarily a global minimizer. Please do a little search on convex set/functions yourselves. The condition $r_k \perp U_k$ is crucial to show the optimality here.

(b) Show directly that $x_k = \operatorname{argmin}_{x \in W_k} \|x - x^*\|_A$, without referring to the connection between $\varphi(x)$ and $\|e_k\|_A$. (Hint: consider a different $\tilde{x}_k \in W_k$, with $d_k = \tilde{x}_k - x_k \neq 0$. Show that $\|\tilde{x}_k - x^*\|_A = \|d_k + x_k - x^*\|_A \geq \|x_k - x^*\|_A$)

a) Since $W_k = x_0 + U_k$ where U_k is a vector space,
it follows U_k is convex $\Rightarrow W_k$ is convex.

$$\text{Let } x_1 = \sum_{l=1}^n \alpha_l p_l \quad x_2 = \sum_{l=1}^k \beta_l p_l$$

$$\begin{aligned} \text{WTS } & \Psi(\lambda x_1 + (1-\lambda)x_2) \leq \lambda \Psi(x_1) + (1-\lambda) \Psi(x_2) \\ & \frac{1}{2}(\lambda x_1 + (1-\lambda)x_2)^T A (\lambda x_1 + (1-\lambda)x_2) - b^T (\lambda x_1 + (1-\lambda)x_2) \\ & = \frac{1}{2} \lambda^2 x_1^T A x_1 + \frac{1}{2} (1-\lambda)^2 x_2^T A x_2 + \lambda(1-\lambda) x_1^T A x_2 - \lambda b^T x_1 + (1-\lambda) b^T x_2 \\ & = \lambda^2 \Psi(x_1) + (1-\lambda)^2 \Psi(x_2) + \lambda(1-\lambda) x_1^T A x_2 \\ & \leq \lambda \Psi(x_1) + (1-\lambda) \Psi(x_2) + \lambda(1-\lambda) x_1^T A x_2 \end{aligned}$$

Bc A is spd $\lambda(1-\lambda) x_1^T A x_2$ is convex

Thus by the sum of two convex functions being convex, we see $\Psi(x)$ is convex

Therefore the local minimizer $x_k \in W_k$ for $\Psi(x)$ is the global minimizer.

- (b) Show directly that $x_k = \operatorname{argmin}_{x \in W_k} \|x - x^*\|_A$, without referring to the connection

(b) Show directly that $x_k = \operatorname{argmin}_{x \in W_k} \|x - x^*\|_A$, without referring to the connection between $\varphi(x)$ and $\|e_k\|_A$. (Hint: consider a different $\tilde{x}_k \in W_k$, with $d_k = \tilde{x}_k - x_k \neq 0$. Show that $\|\tilde{x}_k - x^*\|_A = \|d_k + x_k - x^*\|_A \geq \|x_k - x^*\|_A$)

$$d_k = \tilde{x}_k - x_k \neq 0 \Rightarrow \tilde{x}_k = d_k + x_k$$

$$\|\tilde{x}_k - x^*\|_A = \|d_k + x_k - x^*\|_A \geq \|x_k - x^*\|_A - \|d_k\|_A \geq \|x_k - x^*\|_A$$

Since $\|d_k\|_A \geq 0$

4a) B has pos & neg eig vals ✓
 \hat{B} has pos eig vals ✓
 Both symmetric

A & \hat{A} are not symmetric

The eigvals are close to the origin

There does not seem to be
 an obvious correlation to condition number
 as \hat{B} was largest

```
>> HW9_linsolvecomp
Loading problem data completed.
SPD matrix A: preconditioner setup time 4.762 secs.
P-CG converges in 70 iters (12.203 secs) to relative tol 1.000e-08.
MATLAB's sparse Cholesky direct solver takes 369.842 secs.
nnz of A, incomplete and complete Cholesky factors: 6141493 27725520
1140363654.
```

```
Symmetric indefinite C: indefinite preconditioner constructed already.
P-SQMR converges in 67 iters (2.059 secs) to relative tol 1.000e-08.
```

```
Transforming the indefinite preconditioner to an SPD preconditioner.
Transformation to SPD preconditioner takes 0.186 secs.
P-MINRES converges in 210 iters (2.701 secs) to relative tol 1.000e-08.
MATLAB's sparse LDL direct solver takes 156.538 secs.
nnz of C, incomplete and complete LDL factors: 738598 617410 82593444.
```

```
Unsymmetric matrix A: preconditioner setup time 2.858 secs.
P-BICGSTAB(2) solve: 93 mvps (10.342 secs) to tolerance 1.000e-08.
P-IDR(4) solve: 86 mvps (10.190 secs) to tolerance 1.000e-08.
P-GMRES(60) solve: 90 mvps (24.967 secs) to tolerance 1.000e-08.
MATLAB's sparse LU direct solution takes 1129.186 secs.
nnz of B, incomplete and complete LU factors: 3604989 5659826 856629224.
```

It was more manageable and faster

```

rng('default'); n = 1024; A = randn(n,n); [A,R] = qr(A);
Ahat = A+1.2*eye(n); E = randn(n,n); E = E+E';
B = (A+A')/2; B = B+1e-4*E; Bhat = B+1.01*eye(n);

D=eig(B);
D=sort(D);

F=eig(Bhat);
F=sort(F);

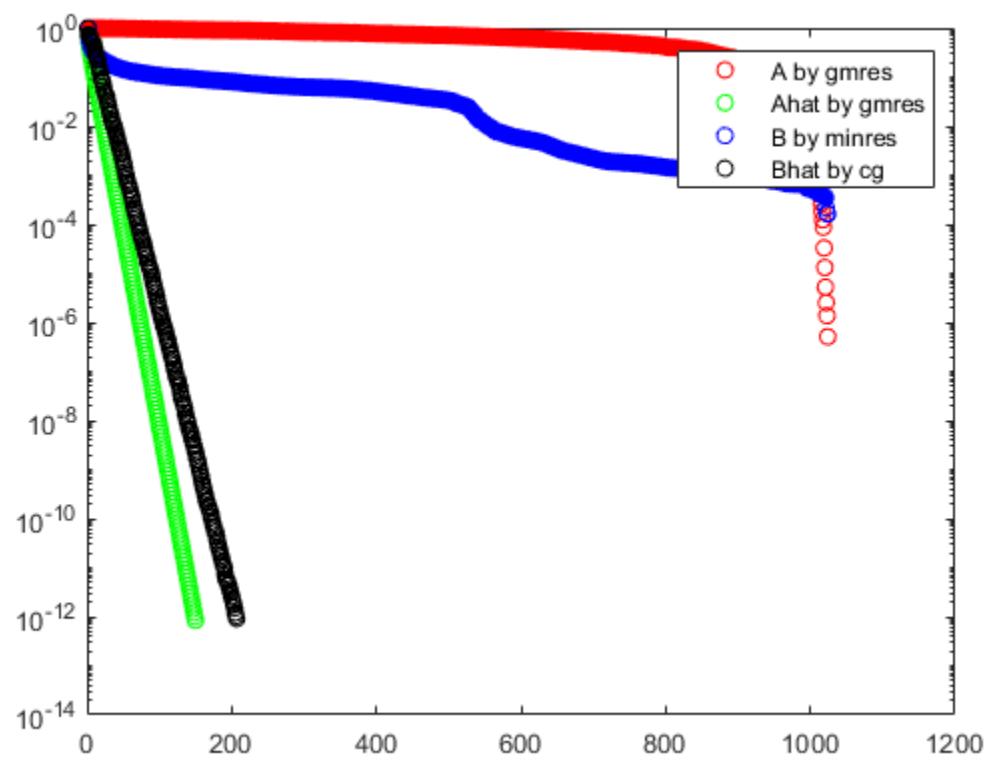
ca=cond(A);
cahat=cond(Ahat);
cb=cond(B);
cbhat=cond(Bhat);

L=eig(A);
M=eig(Ahat);

hold on
plot(real(M),imag(M),'o')
plot(real(L),imag(L),'o')
plot(real(D),imag(D),'o')
plot(real(F),imag(F),'o')
hold off

f = ones(n,1); m = n-1; restart = 1; tol = 1e-12;
[x1,flag1,relres1,iter1,resvec1] = gmres(A,f,m,tol,1);
semilogy(resvec1/norm(f),'ro'); hold on;
[x2,flag2,relres2,iter2,resvec2] = gmres(Ahat,f,m,tol,1);
semilogy(resvec2/norm(f),'go'); hold on;
[x3,flag3,relres3,iter3,resvec3] = minres(B,f,tol,m);
semilogy(resvec3/norm(f),'bo'); hold on;
[x4,flag4,relres4,iter4,resvec4] = pcg(Bhat,f,tol,m);
semilogy(resvec4/norm(f),'ko'); hold on;
legend('A by gmres','Ahat by gmres','B by minres','Bhat by cg');

```



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