18.335 Midterm, Fall 2011

Problem 1: (10+15 points)

Suppose A is a diagonalizable matrix with eigenvectors $\mathbf{v}_k$ and eigenvalues λ_k, in decreasing order $|\lambda_1| \geq |\lambda_2| \geq \cdots$. Recall that the power method starts with a random $\mathbf{x}$ and repeatedly computes $\mathbf{x} \leftarrow A\mathbf{x}/\|A\mathbf{x}\|_2$.

(a) Suppose $|\lambda_1| = |\lambda_2| > |\lambda_3|$, but $\lambda_1 \neq \lambda_2$. Explain why the power method will not in general converge.

(b) Give a *simple* fix to obtain λ_1 and λ_2 and $\mathbf{v}_1$ and $\mathbf{v}_2$ from the power method or some small modification thereof. (No fair going to some much more complicated/expensive algorithm like inverse iteration, Arnoldi, QR, or simultaneous iteration!)

Problem 2: (25 points)

Review: We described GMRES as minimizing the norm $\|\mathbf{r}\|_2$ of the residual $\mathbf{r} = \mathbf{b} - A\mathbf{x}$ over all $\mathbf{x} \in \mathscr{K}_n$ where $\mathscr{K}_n = \text{span}\langle \mathbf{b}, A\mathbf{b}, \ldots, A^{n-1}\mathbf{b} \rangle$. This was done using Arnoldi (starting with $\mathbf{q}_1 = \mathbf{b}/\|\mathbf{b}\|_2$) to build up an orthonormal basis Q_n of A, where $AQ_n = Q_{n+1}\tilde{H}_n$ ($\tilde{H}_n$ being an $(n+1) \times n$ upper-Hessenberg matrix), in terms of which we wrote $\mathbf{x} = Q_n\mathbf{y}$ and solved the least-square problem $\min_{\mathbf{y}} \|\tilde{H}_n\mathbf{y} - b\mathbf{e}_1\|_2$ where $b = \|b\|_2$ and $\mathbf{e}_1 = (1,0,0,\ldots)^T$ (since $\mathbf{b} = Q_{n+1}b\mathbf{e}_1$).

- Suppose, after n steps, we want to *restart* GMRES. That is, we want to restart our Arnoldi process with *one* vector $\tilde{\mathbf{q}}_1$ based (somehow) on the solution $\mathbf{x}_0 = Q_n\mathbf{y}$ from the n-th step, and build up a *new* Krylov space. What should $\tilde{\mathbf{q}}_1$ be, and what minimal-residual problem should we solve on each step of the new GMRES iterations, to obtain *improved* solutions $\mathbf{x}$ in *some* Krylov space?

(*Note:* if you're remembering implicitly restarted Lanczos now and panicking, *relax*: all the complexity there was to restart with a subspace of dimension > 1, which doesn't apply when we are restarting with only one vector. Think simpler.)

(*Note:* be sure to obtain a *small* least-squared problem on each step. No $m \times n$ problems! This may screw up the first thing you try. Hint: think about residuals.)

Problem 3: (15+10 points)

(a) The following two sub-parts can be solved independently (you can answer the second part even if you fail to prove the first part):

(i) Suppose A is an $m \times n$ matrix with rank n (i.e., independent columns). Let $B = A_{:,1:p}$ be the first p ($1 \leq p \leq n$) columns of A. Show that $\kappa(A) \geq \kappa(B)$. (Hint: recall that our first way of defining $\kappa(A)$ was by $\kappa(A) = \left[\max_{\mathbf{x}\neq 0} \frac{\|A\mathbf{x}\|}{\|\mathbf{x}\|}\right] \cdot \left[\max_{\mathbf{x}\neq 0} \frac{\|\mathbf{x}\|}{\|A\mathbf{x}\|}\right]$.)

(ii) Suppose that we are doing least-square fitting of a bunch of data points (containing some experimental errors) to a polynomial. Does the $\kappa(A) \geq \kappa(B)$ result from the previous part tell you about what happens about the sensitivity to errors as you increase the number of data points *or* as you increase the degree of the polynomial, and what does it tell you?

(b) Prove that if $\kappa(A) = 1$ then $A = cQ$ where $Q^*Q = I$ and c is some scalar. (The SVD definition of κ might be easiest here: $\kappa(A) = \frac{\sigma_{\max}}{\sigma_{\min}}$ when A has full column rank.)

Problem 4: (8+8+9 points)

Recall that an IEEE double-precision binary floating-point number is of the form $\pm s \cdot 2^e$ where the significand $s = 1.xxxx\ldots$ has 53 binary digits (about 16 decimal digits, $\varepsilon_{\text{machine}} \approx 10^{-16}$) and the exponent e has 11 binary digits ($e \in [-1022, 1023] \implies 10^{-308} \lesssim 2^e \lesssim 10^{308}$).

(a) Computing $\sqrt{x^2+y^2}$ by the obvious method, $\sqrt{(x \otimes x) \oplus (y \otimes y)}$ sometimes yields "∞" (Inf) even when x and y are well within the representable range. Propose a solution.

(b) Explain why solving $x^2 + 2bx + 1 = 0$ for x by the usual quadratic formula $x = -b \pm \sqrt{b^2 - 1}$ might be very inaccurate for some b, and propose a solution.

(c) How might you compute $1 - \cos x$ accurately for small $|x|$? Assume you have floating-point $\widetilde{\sin}$ and $\widetilde{\cos}$ functions that compute exactly rounded results, i.e. $\widetilde{\sin} x = \text{fl}(\sin x)$ and $\widetilde{\cos} x = \text{fl}(\cos x)$.