18.335 Midterm, Spring 2015

Problem 1: (10+(10+10) points)

(a) Suppose you have a forwards-stable algorithm $\tilde{f}$ to compute $f(x) \in \mathbb{R}$ for $x \in \mathbb{R}$, i.e. $\|\tilde{f}(x) - f(x)\| = \|f\| O(\varepsilon_{\text{mach}})$. Suppose f is bounded below and analytic (has a convergent Taylor series) everywhere; suppose it has some global minimum $f_{\min} > 0$ at $x_{\min}$. Suppose that we compute $x_{\min}$ in floating-point arithmetic by exhaustive search: we just evaluate $\tilde{f}$ for all $x \in \mathbb{F}$ and return the x where $\tilde{f}$ is smallest. Is this procedure stable or unstable? Why? (Hint: look at a Taylor series of f.)

(b) Consider the function $f(x) = Ax$ where $A \in \mathbb{C}^{m \times n}$ is an $m \times n$ matrix.

  (i) In class, we proved that naive summation (by the obvious in-order loop) is stable, and in the book it was similarly proved that the function $g(x) = b^T x$ (dot products of x with $\bar{b}$) is backwards stable for $x \in \mathbb{C}^n$ when computed in the obvious loop $\tilde{g}$ [that is: for each x there exists an $\tilde{x}$ such that $\tilde{g}(x) = g(\tilde{x})$ and $\|\tilde{x} - x\| = \|x\| O(\varepsilon_{\text{mach}})$]. Your friend Simplicio points out that each component f_i of $f(x)$ is simply a dot product $f_i(x) = a_i^T x$ (where a_i^T is the i-th row of A)—so, he argues, since each component of f is backwards stable, $f(x)$ must be backwards stable (when computed by the same obvious dot-product loop for each component). What is wrong with this argument (assuming $m > 1$)?

  (ii) Give an example A for which $f(x)$ is definitely *not* backwards stable for the obvious $\tilde{f}$ algorithm.

Problem 2: (10+10+10 points)

In figure 1 are shown, from class, the classical/modified Gram–Schmidt (CGS/MGS) and Householder algorithms to compute the QR factorization $A = \hat{Q}\hat{R}$ (reduced: $\hat{Q}$ is $m \times n$) or $A = QR$ (Q is $m \times m$) respectively of an $m \times n$ matrix A. Recall that, using the QR factorization, we can solve the least-squares problem $\min \|Ax - b\|_2$ by $\hat{R}\hat{x} = \hat{Q}^* b$. Recall that we can compute the right-hand side $\hat{Q}^* b$ by forming an augmented $m \times (n+1)$ matrix $\breve{A} = (A, b)$, finding its QR factorization $\breve{A} = \breve{Q}\breve{R}$ and obtaining $\hat{Q}^* b$ from the last column of $\breve{R} = \breve{Q}^* \breve{A}$.

Classical/Modified Gram-Schmidt

for $j = 1$ **to** n
  $v_j = a_j$
  for $i = 1$ **to** $j - 1$
    $r_{ij} = q_i^* a_j$ (CGS)
    $r_{ij} = q_i^* v_j$ (MGS)
    $v_j = v_j - r_{ij} q_i$
  $r_{jj} = \|v_j\|_2$
  $q_j = v_j / r_{jj}$

Algorithm: Householder QR Factorization

for $k = 1$ **to** n
  $x = A_{k:m,k}$
  $v_k = \text{sign}(x_1)\|x\|_2 e_1 + x$
  $v_k = v_k / \|v_k\|_2$
  $A_{k:m,k:n} = A_{k:m,k:n} - 2v_k(v_k^* A_{k:m,k:n})$

Figure 1: Left: Classical/Modified Gram-Schmidt algorithm. Right: Householder QR algorithm. (Figures borrowed from Per Persson's 18.335 slides.)

Explain whether this procedure is better than computing $\hat{Q}^* b$ directly for:

(a) Classical Gram–Schmidt.

(b) Modified Gram–Schmidt.

(c) Householder QR. (Recall that, for Householder QR, we don't actually compute Q explicitly, but instead store the reflectors v_k and re-use them as needed to multiply by Q or Q^*.)

That is, each of the above three algorithms computes the QR factorization of A—for *each* of the three algorithms is it an improvement to compute $\hat{Q}^* b$ via *that* algorithm on $\breve{A}$ compared with computing $\hat{Q}$ (or its equivalent) by *that* algorithm and *then* performing the $\hat{Q}^* b$ multiplication?

Problem 3: (10+20+10 points)

Suppose A and B are $m \times m$ matrices, $A = A^*$, $B = B^*$, and B is positive-definite. Consider the "generalized" eigenproblem of finding solutions $x \neq 0$ and λ to $Ax = \lambda Bx$, or equivalently solve the ordinary eigenproblem $B^{-1}Ax = \lambda x$. (In general, $B^{-1}A$ is *not*

Hermitian.) Suppose that there are m distinct eigenvalues $|\lambda_1| > |\lambda_2| > \cdots > |\lambda_m|$ and corresponding eigenvectors $x_1, \ldots, x_m$.

(a) Show that the λ_k are real and that $x_i^* B x_j = 0$ for $i \neq j$. (Hint: multiply both sides of $Ax = \lambda Bx$ by x^*, similar to the derivation for Hermitian problems in class.)

(b) Explain how to generalize the modified Gram–Schmidt algorithm (figure 1) to compute an "SR" factorization $B^{-1}A = SR$ where $S^* B S = I$. (That is, the columns s_k of S form a basis for the columns of $B^{-1}A$ as in QR, but orthogonalized so that $s_i^* B s_j = 0$ for $i \neq j$ and $= 1$ for $i = j$.) Make sure your algorithm still requires $\Theta(m^3)$ operations!

(c) In *exact arithmetic*, what would S in the SR factorization of $(B^{-1}A)^k$ converge to as $k \to \infty$, and why? (Assume the "generic" case where none of the eigenvectors happen to be orthogonal to the columns of B.)