

MS/PhD QUALIFYING EXAMINATION

Numerical Analysis, Fall 2007

1. Let $A \in \mathfrak{R}^{n \times n}$ be an invertible, symmetric positive definite matrix, $\mathbf{b} \in \mathfrak{R}^n$. This problem regards the method of steepest descent to find the solution \mathbf{x}^* of $A\mathbf{x} = \mathbf{b}$. Steepest descent is an iterative method that defines a sequence \mathbf{x}_n which converges to the minimizer of the function

$$\phi(x) = \frac{1}{2} \mathbf{x}^T A \mathbf{x} - \mathbf{x}^T \mathbf{b} .$$

- (a) Let $e(\mathbf{x}) = \mathbf{x} - \mathbf{x}^*$ and $\|x\|_A = \sqrt{x^T A x}$, where $\mathbf{x}^* = A^{-1} \mathbf{b}$ solves $A\mathbf{x} = \mathbf{b}$. Prove that \mathbf{x} minimizes $\phi(\mathbf{x})$ if and only if \mathbf{x} minimizes $\|e(\mathbf{x})\|_A$, and thus $\mathbf{x} = \mathbf{x}^*$, unique.
- (b) Derive a formula for $-\nabla\phi$.
- (c) The vector $-\nabla\phi(\mathbf{x})$ points in the direction of steepest descent of ϕ at \mathbf{x} . The method of steepest descent consists of iterating

$$x_{n+1} = x_n - \alpha_n \nabla\phi(x_n)$$

starting from an initial guess \mathbf{x}_0 . That is, one steps from x_n to x_{n+1} by moving along the direction of steepest descent. Determine the optimal step length α_n that minimizes $\phi(\mathbf{x}_{n+1})$. Explain why the method always converges to the minimizer \mathbf{x}^* of ϕ .

- (d) Write down an algorithm for the full steepest descent iteration. There are three operations inside the main loop.
2. Consider a matrix $A \in \mathbf{C}^{n \times n}$, vector $\mathbf{x} \in \mathbf{C}^n$ with $\mathbf{x} \neq 0$. The Rayleigh Quotient of A , $\mathcal{R}_A(\mathbf{x})$, is defined as the quantity

$$\mathcal{R}_A(\mathbf{x}) = \frac{x^* A x}{x^* x} .$$

- (a) State the definition of a **Hermitian** matrix and characterize its spectrum, eigenvectors and diagonalizability.
- (b) Prove that if A is Hermitian then $\mathcal{R}_A(\mathbf{x})$ is real and

$$\lambda_1 \leq \mathcal{R}_A(\mathbf{x}) \leq \lambda_n ,$$

where λ_1 (resp. λ_n) is the least (resp. greatest) eigenvalue of A .

- (c) Determine the maximum and minimum values of the ratio

$$R(\mathbf{x}) = \frac{x_1^2 - 2x_1x_2 + 2x_2^2 + x_3^2}{x_1^2 + x_2^2 + 4x_3^2}$$

by identifying with the Rayleigh quotient of an appropriate Hermitian matrix.

3. (Proof and application of Gershgorin's theorem.) Let $A \in \mathfrak{R}^{n \times n}$.

- (a) Prove: Every eigenvalue of A lies in at least one of the n circular disks in the complex plane with centers a_{ii} and radii $\sum_{\substack{j=1 \\ j \neq i}}^n |a_{ij}|$,

$$|\lambda - a_{ii}| \leq \sum_{\substack{j=1 \\ j \neq i}}^n |a_{ij}|$$

(Hint: let λ be an eigenvalue of A , and \mathbf{x} be a corresponding eigenvector with largest entry 1.)

- (b) Prove: Moreover, if m of these disks form a connected domain that is disjoint from the other $n - m$ disks, then there are precisely m eigenvalues of A within this domain. (Hint: Consider the continuous deformation $C(t) = D + tB$ of A , where $D = \text{diag}(a_{11}, a_{22}, \dots, a_{nn})$ and $B = A - D$, and use the fact that the eigenvalues of a matrix are continuous functions of its entries.)
- (c) Explain why in (a) the deleted absolute row sums can be replaced by the deleted absolute column sums

$$|\lambda - a_{ii}| \leq \sum_{\substack{j=1 \\ j \neq i}}^n |a_{ji}|$$

- (d) Give estimates based on Gershgorin's theorem ((a,b) above) for the eigenvalues of

$$A = \begin{pmatrix} 8 & 1 & 0 \\ 1 & 4 & \epsilon \\ 0 & \epsilon & 1 \end{pmatrix}, \quad |\epsilon| < 1$$

- (e) Find a way to establish the tighter bound $|\lambda_3 - 1| \leq \epsilon^2$ on the smallest eigenvalue of A . (Hint: consider a diagonal similarity transformation)
- (f) Explain why Gershgorin's theorem implies that $A = \begin{pmatrix} 1 & 0 & -2 & 0 \\ 0 & 12 & 0 & -4 \\ 1 & 0 & -1 & 0 \\ 0 & 5 & 0 & 0 \end{pmatrix}$ has at least 2 real roots.

4. Consider a matrix $A \in \mathbf{C}^{n \times n}$.

- (a) Define the spectral radius, $\rho(A)$ and the matrix norms $\|A\|_k$, $k = 1, 2, \infty$.
- (b) Show that $\rho(A) \leq \|A\|$ where $\|\dots\|$ is any matrix norm induced by a vector norm.
- (c) Show that

$$\|A\|_2^2 = \rho(A^*A) = \sigma_1^2$$

where σ_1 is the largest singular value of A .

- (d) Show that

$$\|A\|_2^2 \leq \|A\|_1 \|A\|_\infty.$$