# MATH 231 : Numerical ODEs Random Examples

Pratham Lalwani

March 12, 2025

### Question 1: Eigenvalues of special tridiagonal matrices

This question is about finding eigenvalues of tridiagonal linear systems arising from applications, specifically finding the eigenvalues of an  $n \times n$  matrix of the form,

$$A = \left(\begin{array}{cccc} a & b & & \\ c & a & b & & \\ & \ddots & \ddots & \ddots & \\ & & c & a & b \\ & & c & a \end{array}\right)$$

where a, b, c are real numbers with bc > 0 (i.e. b and c have the same signs).

(a) Show that the eigenvalue problem of A is equivalent to the equations

$$cv_{j-1} + (a - \lambda)v_j + bv_{j+1} = 0, \quad j = 1, \dots, n$$
  
 $v_0 = 0 = v_{n+1}$ 

where  $\mathbf{v} = (v_1, \dots, v_n)^T$  is an eigenvector of A associated with the eigenvalue  $\lambda$ .

(b) The recurrence relation (1) is a second order linear difference equation and can be solved similar to second order linear differential equations. By guessing  $v_j = r^j$  for some constant r, show that r satisfies

$$r_{\pm} = \frac{\lambda - a \pm \sqrt{(\lambda - a)^2 - 4bc}}{2b}$$
, with  $r_{+}r_{-} = \frac{c}{b}$ 

(c) Show by contradiction that  $r_{+}$  must be distinct.

Hint: if  $r_{\pm} = r$  are repeated, then  $v_j = Ar^j + Bjr^j$  for some constants A, B.

(d) Since  $r_{\pm}$  are distinct, the general solution for (1) is  $v_j = Ar_+^j + Br_-^j$  for constants A, B. Use this to conclude from (2) and (3) that,

$$\left(\frac{br_+^2}{c}\right)^{n+1} = 1$$

(e) From part (c), (3) and (4), show that  $r_{\pm}$  must be complex valued and conclude that (4) has the solutions for k = 1, ..., n,

$$r_{\pm,k} = \sqrt{\frac{c}{b}} \exp\left(\frac{\pm ik\pi}{n+1}\right), \quad \text{where } i = \sqrt{-1}$$

(f) Using part (e), conclude that the eigenvalues of A is given by

$$\lambda_k = a + 2 \operatorname{sgn} \sqrt{bc} \cos \left( \frac{\pi k}{n+1} \right), \quad k = 1, \dots, n$$

(g) (g) Find the eigenvalues of the  $n \times n$  finite difference matrix  $A_h = \frac{1}{h^2} \begin{pmatrix} -1 & 2 & \ddots & \\ & \ddots & \ddots & \\ & & -1 & 2 & -1 \\ & & & -1 & 2 \end{pmatrix}$ ,

where  $h = \frac{1}{n+1}$ .

Conclude that  $A_h$  is symmetric positive definite and find its condition number  $\kappa(A_h)$  with respect to  $\|\cdot\|_2$ . Show that  $\kappa(A_h) = O(h^{-2})$  as number of grid points n increases. What does this mean for solving  $A_h \mathbf{x} = \mathbf{b}$  when n is large?

1

#### Solution

(a) Let  $(\lambda, \vec{v})$  be an eigenpair of A

### Question 2: Classical iterative methods for strictly diagonally dominant matrices

- (a) Show that the diagonal part of any strictly diagonally dominant (S.D.D.) matrix is invertible.
- (b) Recall the Gershgorin's theorem below, which can give useful information about the eigenvalues of a matrix. The eigenvalues of a complex valued matrix A lies in the union of n discs  $\bigcup_{i=1}^{n} D_i$  on the complex plane, where

$$D_i = \left\{ z \in \mathbb{C} : |z - a_{ii}| \le \sum_{j \ne i} |a_{ij}| \right\}$$

Using Gershgorin's theorem, conclude S.D.D. matrices are invertible. Hint: Show that  $0 \notin D_i$  for all i = 1, ..., n. The next two parts are about showing convergence of Jacobi and Gauss-Seidel iterations for S.D.D. matrices.

- (c) Recall the matrix  $-M^{-1}N$  associated with the Jacobi iteration takes the form  $-D^{-1}(L+U)$ , where A=L+D+U.
- (d) Let A be S.D.D. and  $\lambda$  be any eigenvalue of  $-D^{-1}(L+U)$ . Show that  $\det(L+U+\lambda D)=0$  using part (a). (ii) Now suppose  $|\lambda| \ge 1$ . Deduce from A being S.D.D. that  $L+U+\lambda D$  must also be S.D.D. (iii) Deduce a contradiction by applying the result from part (b) to  $L+U+\lambda D$ , and conclude that  $|\lambda| < 1$ . (iv) Combine parts (i)-(iii) to conclude that Jacobi iteration converges for S.D.D. matrices.
- (e) Follow a similar argument as part (c) to show that Gauss-Seidel iterations converges for S.D.D. matrices.

## Question 3: Classical iterative methods for symmetric positive definite matrices

This question is about coding and comparing classical iterative methods for the S.P.D. matrix  $A_h$  from Q1(g).

- (a) Write a pseudocode for the classical iterative methods: Richardson, optimal Richardson, Jacobi, Gauss-Seidel, S.O.R., and optimal S.O.R.
- (b) Implement a program to solve  $A_h \mathbf{x} = \mathbf{b}$  with  $\mathbf{b} = (1, \dots, 1)^T \in \mathbb{R}^{20}$  and  $\mathbf{x}_0 = (1, 0, \dots, 0)^T \in \mathbb{R}^{20}$  using Richardson (with  $\omega = \lambda_{\text{max}}^{-1}$ ), optimal Richardson, Jacobi, Gauss-Seidel, S.O.R. (with  $\theta = 1.2$ ) and optimal S.O.R. Generate a plot comparing the log of their residual in  $\ell_2$  norm versus iterations up to 5000. Rank the performance of each method by comparing the iterations needed to reach the residual tolerance of  $10^{-14}$ . Use sparse representation when appropriate. Hint: Use Q1(g) to find parameters for Richardson and vary  $\theta$  to find an approximate optimal parameter for S.O.R. (c) Comment on the decreases in performance when n = 1000. Explain briefly how this relates to  $\kappa (A_h) = O(h^{-2})$ .

#### Question 4: Steepest Descent and Conjugate Gradient

- (a) Let A be a S.P.D. matrix. Show that  $(x,y)_A := x^T A y$  for  $x,y \in \mathbb{R}^n$  forms an inner product on  $\mathbb{R}^n$ .
- (b) Using part (a), conclude that  $\|x\| = (x, x)_A^{1/2}$  for  $x \in \mathbb{R}^n$  is a norm on  $\mathbb{R}^n$ . Hint: You can assume the Cauchy-Schwarz inequality  $|(x, y)_A| \leq \|x\|_A \|y\|_A$  holds.
- (c) For the method of Steepest Descent, show that  $\nabla f(\mathbf{x}_k)$  and  $\nabla f(\mathbf{x}_{k+1})$  are orthogonal (i.e. zig-zaging behavior), where  $f(\mathbf{y}) = \frac{1}{2}\mathbf{y}^T A \mathbf{y} \mathbf{y}^T \mathbf{b}$ . Hint: Recall how the step size for Steepest Descent is determined.
- (d) Repeat the experiment from  $\mathbf{Q3}(\mathbf{b})$  with  $\boldsymbol{b}=(1,\ldots,1)^T\in\mathbb{R}^{1000}$  and  $\boldsymbol{x}_0=(1,0,\ldots,0)^T\in\mathbb{R}^{1000}$  using the method of Steepest Descent and Conjugate Gradient. Generate a plot comparing the log of their residual in  $\ell_2$  norm versus iterations up to 5000. Rank their performance by comparing the iterations needed to reach the residual tolerance of  $10^{-14}$ , as well as versus the classical iterative methods. Verify your CG method terminates after the desired number of iterations. Use sparse representation when appropriate.