Jacobs University Spring Semester 2022

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CA-MATH-804: Numerical Analysis

Exam & Solutions

All trigonometric values are in radians.

Question 1 [20 Points]: On the scaled unit square $\Omega = h[0,1]^2$, $h \in (0,1)$, consider the partial differential equation

$$-(\partial_{xx}u(x,y) + 2\partial_{yy}u(x,y)) = f(x,y)$$
 in Ω ,

$$u(x,y) = 0$$
 on $\partial \Omega$.

Show that the weak form takes the form a(u, v) = (f, v), where

$$a(u,v) = \int_{\Omega} \frac{\partial u}{\partial x} \frac{\partial v}{\partial x} + 2 \frac{\partial u}{\partial y} \frac{\partial v}{\partial y} d\Omega$$

and

$$(f,v) = \int_{\Omega} fv \,\mathrm{d}\Omega$$

What conditions are imposed on the test function v(x,y)?

Let $\Omega = h[0,1]^2 \subset \mathbb{R}^2$ and consider

$$-(u_{xx}(x,y) + 2u_{yy}(x,y)) = f(x,y)$$
 in Ω , with $u = 0$ on $\partial\Omega$.

Multiply by a test function v and integrate over Ω :

$$\int_{\Omega} \left(-u_{xx} - 2 u_{yy} \right) v \, d\Omega = \int_{\Omega} f \, v \, d\Omega.$$

Integrate by parts and use v = 0 on $\partial \Omega$ to kill the boundary terms:

$$\int_{\Omega} u_{xx} \, v \, \mathrm{d}\Omega = -\int_{\Omega} u_x \, v_x \, \mathrm{d}\Omega, \quad \int_{\Omega} u_{yy} \, v \, \mathrm{d}\Omega = -\int_{\Omega} u_y \, v_y \, \mathrm{d}\Omega.$$

Hence the weak form is

$$a(u,v) = (f,v), \text{ where } a(u,v) = \int_{\Omega} (u_x v_x + 2 u_y v_y) d\Omega, \quad (f,v) = \int_{\Omega} f v d\Omega.$$

The test functions v are taken from

$$H_0^1(\Omega) = \{ v \in H^1(\Omega) : v = 0 \text{ on } \partial \Omega \}.$$

Question 2 [20 Points]: For given $v, w \in \mathbb{R}^n$ and $A \in \mathbb{R}^{n \times n}$ symmetric positive definite consider the function $\varphi : \mathbb{R} \to \mathbb{R}$ where $\varphi(\alpha) = \|v + \alpha w\|_A^2$ and $\|\cdot\|_A$ is the energy norm given by $\|x\|_A = \sqrt{x \cdot Ax}$. Find α such that φ becomes minimal.

If A is a diagonal matrix D, show that $||x||_{D^2}^2 = ||Dx||_2^2$.

The energy-norm expands as

$$\phi(\alpha) = \|v + \alpha w\|_A^2$$
$$= (v + \alpha w)^T A (v + \alpha w)$$
$$= v^T A v + 2\alpha v^T A w + \alpha^2 w^T A w.$$

Differentiating w.r.t. α and setting to zero gives

$$\phi'(\alpha) = 2v^T A w + 2\alpha w^T A w \implies \alpha = -\frac{v^T A w}{w^T A w}$$

Hence the minimizer is

$$\alpha^* = -\frac{v^T A w}{w^T A w}.$$

If A is a diagonal matrix D,

$$||x||_{D^{2}}^{2} = x^{T} D^{2} x$$

$$= x^{T} D^{T} D x$$

$$= (D x)^{T} (D x)$$

$$= ||D x||_{2}^{2}.$$

Using the half-angle identity

$$1 + \cos\theta = 2\cos^2\frac{\theta}{2}$$

then

$$\lambda_j = \frac{2}{h^2} \Big(1 + \cos \frac{\pi j}{n+1} \Big) = \frac{4}{h^2} \cos^2 \left(\frac{\pi j}{2(n+1)} \right).$$

Thus

$$\lambda_{\max} = \lambda_1 = \frac{4}{h^2} \cos^2 \left(\frac{\pi}{2(n+1)} \right), \qquad \lambda_{\min} = \lambda_n = \frac{4}{h^2} \cos^2 \left(\frac{n\pi}{2(n+1)} \right) = \frac{4}{h^2} \sin^2 \left(\frac{\pi}{2(n+1)} \right).$$

Hence the spectral ratio is

$$\frac{\lambda_{\max}}{\lambda_{\min}} = \frac{\cos^2\left(\frac{\pi}{2(n+1)}\right)}{\sin^2\left(\frac{\pi}{2(n+1)}\right)} = \cot^2\left(\frac{\pi}{2(n+1)}\right).$$

Question 3 [20 Points]: Using

$$D^+f = \frac{f(x+h) - f(x)}{h},$$

and

$$D^{-}f = \frac{f(x) - f(x - h)}{h}$$

derive the discrete approximation to the second-order derivative as a matrix $A \in \mathbb{R}^{n \times n}$, when $u_0 = 0$ and $u_{n+1} = 0$.

The matrix has eigenvalues

$$\lambda_j = \frac{2}{h^2} \left(1 + \cos\left(\frac{\pi j}{n+1}\right) \right)$$
 for $j = 1, \dots, n$.

Using the half-angle formula

$$\cos^2\frac{\theta}{2} = \frac{1+\cos\theta}{2},$$

find the ratio of the maximum and minimum eigenvalues.

Let $h = \frac{1}{n+1}$, and $x_i = ih$, i = 0, 1, ..., n+1, with $u_0 = u_{n+1} = 0$.

$$D_+u_i = \frac{u_{i+1} - u_i}{h}, \quad D_-u_i = \frac{u_i - u_{i-1}}{h},$$

So that Discrete second derivative by backward of forwards (or vice versa):

$$D_-D_+u_i = \frac{1}{h}\Big(D_+u_i - D_+u_{i-1}\Big) = \frac{u_{i-1} - 2u_i + u_{i+1}}{h^2}.$$

Hence the discrete approximation to u'' = f leads to

$$\frac{u_{i-1} - 2u_i + u_{i+1}}{h^2} = f_i, \quad i = 1, \dots, n$$

In matrix form Au = f, where

$$A = \frac{1}{h^2} \begin{pmatrix} -2 & 1 & & & 0\\ 1 & -2 & 1 & & \\ & \ddots & \ddots & \ddots & \\ & & 1 & -2 & 1\\ 0 & & & 1 & -2 \end{pmatrix} \in \mathbb{R}^{n \times n}.$$

With this A and the Dirichlet boundary conditions $u_0 = u_{n+1} = 0$, the finite-difference approximation to u = f is simply Au = f.

Question 4 [20 Points]: Show that a solution which minimizes

$$\Phi(y) = \frac{1}{2}y \cdot Ay - y \cdot b$$

also solves the linear system Ax = b. Define the residue $r^{(k)}$ for an iterative scheme which solves the linear system. Show that $\nabla \Phi(x^{(k)}) = -r^{(k)}$. Consider the iterative scheme

$$x^{(k+1)} = x^{(k)} + \alpha^{(k)}d^{(k)}$$

and set $d^{(k)} = r^{(k)}$. By considering the minimum of $\Phi(x^{(k+1)})$, i.e. $\Phi(x^{(k)} + \alpha^{(k)}d^{(k)})$, with respect to α , show that

$$\alpha^{(k)} = \frac{r^{(k)} \cdot r^{(k)}}{r^{(k)} \cdot Ar^{(k)}}.$$

Note assume A is symmetric (so that $\nabla(\frac{1}{2}y^TAy) = Ay$). Then, to show that minimiser of

$$\Phi(y) = \frac{1}{2} y^T A y - y^T b$$

satisfies Ay = b. first compute the gradient $\nabla \Phi(y) = Ay - b$. and show that stationarity $\nabla \Phi(y) = 0$ gives Ay = b. Define the residual at step k by

$$r^{(k)} = b - A x^{(k)}.$$

Then

$$\nabla \Phi(x^{(k)}) = A x^{(k)} - b = -r^{(k)}.$$

For the scheme

$$x^{(k+1)} = x^{(k)} + \alpha^{(k)} d^{(k)}, \quad d^{(k)} = r^{(k)},$$

$$\varphi(\alpha) = \Phi(x^{(k)} + \alpha r^{(k)}).$$

consider the one-variable function

$$\varphi(\alpha) = \Phi(x^{(k)} + \alpha r^{(k)})$$

Expand and differentiate:

$$\varphi(\alpha) = \frac{1}{2} (x^{(k)} + \alpha r^{(k)})^T A (x^{(k)} + \alpha r^{(k)}) - (x^{(k)} + \alpha r^{(k)})^T b,$$

and

$$\varphi(\alpha) = \frac{1}{2} (x^{(k)} + \alpha r^{(k)})^T A (x^{(k)} + \alpha r^{(k)}) - (x^{(k)} + \alpha r^{(k)})^T b,$$

$$\varphi'(\alpha) = (x^{(k)})^T A r^{(k)} + \alpha (r^{(k)})^T A r^{(k)} - (r^{(k)})^T b$$

$$= -(r^{(k)})^T r^{(k)} + \alpha (r^{(k)})^T A r^{(k)}.$$

Setting $\varphi'(\alpha) = 0$ yields

$$\alpha^{(k)} = \frac{\left(r^{(k)}\right)^T r^{(k)}}{\left(r^{(k)}\right)^T A r^{(k)}}$$

Hence the optimal step-size is

$$\alpha^{(k)} = \frac{r^{(k)} \cdot r^{(k)}}{r^{(k)} \cdot A r^{(k)}}.$$

Question 5 [20 Points]: Show, by deriving the weights of the quadrature scheme using the Lagrange interpolating polynomials defined via

$$l_i(x) = \prod_{\substack{j=1,\\j\neq i}}^n \frac{x - x_j}{x_i - x_j}$$

that the scheme

$$I(f) = \sum_{i=1}^{3} \alpha_i f(x_i) = \frac{2}{3} \left[2f\left(-\frac{1}{2}\right) - f(0) + 2f\left(\frac{1}{2}\right) \right]$$

where $\alpha_i = \int_{-1}^1 l_i(x) dx$, is a Lagrange quadrature formula for 3 nodes $x_1 = -\frac{1}{2}$, $x_2 = 0$ and $x_3 = \frac{1}{2}$ on the interval [-1,1].

Determine the quadrature error of I(f).

To approximate

$$I(f) = \int_{-1}^{1} f(x) \, \mathrm{d}x$$

by a three-point Lagrange-quadrature formula with nodes

$$x_1 = -\frac{1}{2}, \quad x_2 = 0, \quad x_3 = +\frac{1}{2},$$

let

$$\ell_i(x) = \prod_{\substack{j=1\\j\neq i}}^3 \frac{x-x_j}{x_i-x_j}, \qquad i=1,2,3,$$

be the Lagrange basis polynomials. Then the weights are

$$\alpha_i = \int_{-1}^1 \ell_i(x) \, \mathrm{d}x, \qquad i = 1, 2, 3,$$

and the quadrature reads

$$I(f) \approx \sum_{i=1}^{3} \alpha_i f(x_i).$$

For the computation of the weights,

$$\ell_1(x) = \frac{(x-0)(x-\frac{1}{2})}{(-\frac{1}{2}-0)(-\frac{1}{2}-\frac{1}{2})}$$

$$= \frac{(x)(x-\frac{1}{2})}{\frac{1}{4}}$$

$$= 4x(x-\frac{1}{2}),$$

$$\ell_2(x) = \frac{(x+\frac{1}{2})(x-\frac{1}{2})}{(0+\frac{1}{2})(0-\frac{1}{2})}$$

$$= -4(x^2-\frac{1}{4}),$$

$$\ell_3(x) = \frac{(x+\frac{1}{2})(x-0)}{(\frac{1}{2}+\frac{1}{2})(\frac{1}{2}-0)}$$

$$= \frac{(x+\frac{1}{2})x}{\frac{1}{4}}$$

$$= 4x(x+\frac{1}{2}).$$

Hence

$$\alpha_1 = \int_{-1}^{1} 4x \left(x - \frac{1}{2}\right) dx = \frac{4}{3}, \quad \alpha_2 = \int_{-1}^{1} -4\left(x^2 - \frac{1}{4}\right) dx = -\frac{2}{3}, \quad \alpha_3 = \int_{-1}^{1} 4x \left(x + \frac{1}{2}\right) dx = \frac{4}{3}.$$

One then checks easily that

$$\sum_{i=1}^{3} \alpha_i = 2, \quad \sum_{i=1}^{3} \alpha_i \, x_i = 0, \quad \sum_{i=1}^{3} \alpha_i \, x_i^2 = \frac{2}{3}, \quad \sum_{i=1}^{3} \alpha_i \, x_i^3 = 0,$$

so the rule is exact for all polynomials of degree up to 3. In the compact form

$$I(f) \approx \frac{2}{3} \Big[2f(-\frac{1}{2}) - f(0) + 2f(\frac{1}{2}) \Big].$$

To compute the error term, note that since the rule integrates exactly all polynomials of degree ≤ 3 , the first non-zero error appears at degree 4. A standard remainder-of-Lagrange-interpolation argument gives: for some $\xi \in (-1,1)$,

$$E(f) = \int_{-1}^{1} f(x) dx - \sum_{i=1}^{3} \alpha_{i} f(x_{i}) = \frac{f^{(4)}(\xi)}{4!}$$
$$\int_{-1}^{1} (x - x_{1})(x - x_{2})(x - x_{3}) dx.$$

A direct evaluation of the integral shows

$$\int_{-1}^{1} (x + \frac{1}{2}) x (x - \frac{1}{2}) dx = \frac{7}{30},$$

and hence

$$E(f) = \frac{f^{(4)}(\xi)}{24} \frac{7}{30} = \frac{7}{720} f^{(4)}(\xi).$$

Thus the three-point Lagrange quadrature on [-1,1] with nodes $\{-\frac{1}{2},0,\frac{1}{2}\}$ has error

$$\int_{-1}^{1} f(x) dx - \frac{2}{3} \left[2f(-\frac{1}{2}) - f(0) + 2f(\frac{1}{2}) \right] = \frac{7}{720} f^{(4)}(\xi).$$

Question 6 [20 Points]: Consider the function $H: \mathbb{R} \to \mathbb{R}$ with

$$H(x) = \begin{cases} 0 & \text{for } x \le 0, \\ 1 & \text{else.} \end{cases}$$

Show that this function has a distributional derivative.

Define the Heaviside function $H: \mathbb{R} \mapsto \{0,1\}$ by

$$H(x) = \begin{cases} 0, & x < 0, \\ 1, & x \ge 0. \end{cases}$$

As a distribution, for any test function $\varphi(x) \in C_c^{\infty}(\mathbb{R})$,

$$\langle H, \varphi \rangle = \int_{\mathbb{R}} H(x) \varphi(x) dx$$

= $\int_{0}^{\infty} \varphi(x) dx$.

The distributional derivative H'(x) is defined by

$$\langle H', \psi \rangle = -\langle H, \psi' \rangle$$

$$= -\int_0^\infty \psi'(x) dx$$

$$= -[\psi(x)]_0^\infty$$

$$= -(0 - \psi(0))$$

$$= \psi(0).$$

Since $\langle \delta, \psi \rangle = \psi(0)$, it follows that

$$H'(x) = \delta(x)$$

in the sense of distributions.