Final Review Problems

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These sample review problems do not necessarily represent the content, length, or depth of the material you will be tested on.

Among other things, it is also a good idea to go over the homework sets.

1 Fourier Series

Problem: Find the general continuous least squares trigonometric polynomial $S_n(x)$ for

$$f(x) = \begin{cases} 0, & \text{if } -\pi < x \le 0, \\ 1, & \text{if } 0 < x < \pi. \end{cases}$$

Solution: The continuous least squares approximation $S_n(x)$ is in the form

$$S_n(x) = \frac{a_0}{2} + \sum_{k=1}^n (a_k \cos kx + b_k \sin kx),$$

where, for k = 1, 2, ...,

$$a_{0} = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) dx,$$

$$= \frac{1}{\pi} \int_{-\pi}^{0} 0 dx + \frac{1}{\pi} \int_{0}^{\pi} 1 dx = 1, \quad \checkmark$$

$$a_{k} = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \cos kx dx,$$

$$= \frac{1}{\pi} \int_{-\pi}^{0} 0 \cdot \cos kx dx + \frac{1}{\pi} \int_{0}^{\pi} 1 \cdot \cos kx dx,$$

$$= \frac{1}{\pi} \frac{\sin kx}{k} \Big|_{x=0}^{x=\pi} = 0, \quad \checkmark$$

$$b_{k} = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \sin kx dx$$

$$= \frac{1}{\pi} \int_{-\pi}^{0} 0 \cdot \sin kx dx + \frac{1}{\pi} \int_{0}^{\pi} 1 \cdot \sin kx dx,$$

$$= -\frac{1}{\pi} \frac{\cos kx}{k} \Big|_{x=0}^{x=\pi} = -\frac{1}{\pi} \left(\frac{(-1)^{k} - 1}{k} \right) = \frac{1}{\pi} \left(\frac{1 - (-1)^{k}}{k} \right). \quad \checkmark$$

Thus,

$$S_n(x) = \frac{1}{2} + \frac{1}{\pi} \sum_{k=1}^n \left(\frac{1 - (-1)^k}{k}\right) \sin kx. \quad \checkmark$$

2 QR decomposition and Least Squares

The QR decomposition (also called the QR factorization) of a matrix is a decomposition of the matrix into an orthogonal matrix and a triangular matrix. A QR decomposition of a real square matrix A is a decomposition of A as

$$A = QR,$$

where Q is an orthogonal matrix (i.e. $Q^T Q = I$) and R is an upper triangular matrix. If A is nonsingular, then this factorization is unique.

There are several methods for actually computing the QR decomposition. One of such method is the Gram-Schmidt process.

2.1 Gram-Schmidt process

Consider the GramSchmidt procedure, with the vectors to be considered in the process as columns of the 3x3 matrix A. That is,

$$A = \left[\mathbf{a}_1 \mid \mathbf{a}_2 \mid \cdots \mid \mathbf{a}_n \right].$$

Then,

$$egin{array}{rcl} ilde{\mathbf{q}}_1 &=& \mathbf{a}_1, \qquad \mathbf{q}_1 = rac{ ilde{\mathbf{q}}_1}{|| ilde{\mathbf{q}}_1||_2}, \ ilde{\mathbf{q}}_2 &=& \mathbf{a}_2 - (\mathbf{q}_1^T \mathbf{a}_2) \mathbf{q}_1, \qquad \mathbf{q}_2 = rac{ ilde{\mathbf{q}}_2}{|| ilde{\mathbf{q}}_2||_2}, \ ilde{\mathbf{q}}_3 &=& \mathbf{a}_3 - (\mathbf{q}_1^T \mathbf{a}_3) \mathbf{q}_1 - (\mathbf{q}_2^T \mathbf{a}_3) \mathbf{q}_2, \qquad \mathbf{q}_3 = rac{ ilde{\mathbf{q}}_3}{|| ilde{\mathbf{q}}_3||_2}. \end{array}$$

2.2 QR Factorization

The resulting QR factorization is

$$A = \begin{bmatrix} \mathbf{a}_1 \mid \mathbf{a}_2 \mid \mathbf{a}_3 \end{bmatrix} = \begin{bmatrix} \mathbf{q}_1 \mid \mathbf{q}_2 \mid \mathbf{q}_3 \end{bmatrix} \begin{bmatrix} ||\mathbf{\tilde{q}}_1||_2 & \mathbf{q}_1^T \mathbf{a}_2 & \mathbf{q}_1^T \mathbf{a}_3 \\ 0 & ||\mathbf{\tilde{q}}_2||_2 & \mathbf{q}_2^T \mathbf{a}_3 \\ 0 & 0 & ||\mathbf{\tilde{q}}_3||_2 \end{bmatrix} = QR.$$

2.3 Example

Consider the matrix

$$A = \left[\begin{array}{rrrr} 1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 1 \end{array} \right],$$

with the vectors $\mathbf{a}_1 = (1, 1, 0)^T$, $\mathbf{a}_2 = (1, 0, 1)^T$, $\mathbf{a}_3 = (0, 1, 1)^T$.

Note that all the vectors considered above and below are column vectors. From now on, I will drop T notation for simplicity, but we have to remember that all the vectors are column vectors.

Performing the Gram-Schmidt procedure, we obtain:

$$\begin{split} \tilde{\mathbf{q}}_{1} &= \mathbf{a}_{1} = (1, 1, 0), \\ \mathbf{q}_{1} &= \frac{\tilde{\mathbf{q}}_{1}}{||\tilde{\mathbf{q}}_{1}||_{2}} = \frac{1}{\sqrt{2}}(1, 1, 0) = \left(\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}, 0\right), \\ \tilde{\mathbf{q}}_{2} &= \mathbf{a}_{2} - (\mathbf{q}_{1}^{T}\mathbf{a}_{2})\mathbf{q}_{1} = (1, 0, 1) - \frac{1}{\sqrt{2}}\left(\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}, 0\right) = \left(\frac{1}{2}, -\frac{1}{2}, 1\right), \\ \mathbf{q}_{2} &= \frac{\tilde{\mathbf{q}}_{2}}{||\tilde{\mathbf{q}}_{2}||_{2}} = \frac{1}{\sqrt{3/2}}\left(\frac{1}{2}, -\frac{1}{2}, 1\right) = \left(\frac{1}{\sqrt{6}}, -\frac{1}{\sqrt{6}}, \frac{2}{\sqrt{6}}\right), \\ \tilde{\mathbf{q}}_{3} &= \mathbf{a}_{3} - (\mathbf{q}_{1}^{T}\mathbf{a}_{3})\mathbf{q}_{1} - (\mathbf{q}_{2}^{T}\mathbf{a}_{3})\mathbf{q}_{2} \\ &= (0, 1, 1) - \frac{1}{\sqrt{2}}\left(\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}, 0\right) - \frac{1}{\sqrt{6}}\left(\frac{1}{\sqrt{6}}, -\frac{1}{\sqrt{6}}, \frac{2}{\sqrt{6}}\right) = \left(-\frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}}\right), \\ \mathbf{q}_{3} &= \frac{\tilde{\mathbf{q}}_{3}}{||\tilde{\mathbf{q}}_{3}||_{2}} = \left(-\frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}}\right). \end{split}$$

Thus,

$$Q = \begin{bmatrix} \mathbf{q}_1 & | \mathbf{q}_2 & | \mathbf{q}_3 \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{6}} & -\frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{6}} & \frac{1}{\sqrt{3}} \\ 0 & \frac{2}{\sqrt{6}} & \frac{1}{\sqrt{3}} \end{bmatrix},$$

$$R = \begin{bmatrix} ||\mathbf{\tilde{q}}_1||_2 & \mathbf{q}_1^T a_2 & \mathbf{q}_1^T \mathbf{a}_3 \\ 0 & ||\mathbf{\tilde{q}}_2||_2 & \mathbf{q}_2^T \mathbf{a}_3 \\ 0 & 0 & ||\mathbf{\tilde{q}}_3||_2 \end{bmatrix} = \begin{bmatrix} \frac{2}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ 0 & \frac{3}{\sqrt{6}} & \frac{1}{\sqrt{6}} \\ 0 & 0 & \frac{2}{\sqrt{3}} \end{bmatrix}.$$

Also, review homework problems on solving linear least squares problem with QR decomposition.

3 Vector and Matrix Norms

The L_{∞} and L_2 norms for the vector $\mathbf{x} = (x_1, x_2, \dots, x_n)^T$ are defined by

$$||\mathbf{x}||_{\infty} = \max_{1 \le i \le n} |x_i|,$$

$$||\mathbf{x}||_2 = \left\{ \sum_{i=1}^n x_i^2 \right\}^{\frac{1}{2}}.$$

For matrices, the definitions of $|| \cdot ||_{\infty}$, $|| \cdot ||_{F}$, and $|| \cdot ||_{2}$ norms are:

$$||A||_{\infty} = \max_{1 \le i \le n} \sum_{j=1}^{n} |a_{ij}|,$$

$$||A||_{F} = \left(\sum_{i=1}^{n} \sum_{j=1}^{n} |a_{ij}|^{2}\right)^{\frac{1}{2}},$$

$$||A||_{2} = \max_{||\mathbf{x}||_{2}=1} ||A\mathbf{x}||_{2}.$$

Note, that $A\mathbf{x}$ is a vector:

$$A\mathbf{x} = \begin{bmatrix} \sum_{j=1}^{n} a_{1j} x_j \\ \sum_{j=1}^{n} a_{2j} x_j \\ \vdots \\ \sum_{j=1}^{n} a_{nj} x_j \end{bmatrix}.$$

Thus, we have

$$||A\mathbf{x}||_2 = \left(\sum_{i=1}^n \left(\sum_{j=1}^n a_{ij}x_j\right)^2\right)^{\frac{1}{2}}.$$

4 Iterative methods for the solution of linear systems of equations.

4.1 Jacobi Method

A general $n \times n$ linear system can be written as $A\mathbf{x} = \mathbf{b}$, where

 $A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}.$

Jacobi method is written in the form $\mathbf{x}^{(\mathbf{k})} = T\mathbf{x}^{(\mathbf{k}-1)} + \mathbf{c}$ by splitting A. Let D be the diagonal matrix whose diagonal entries are those of A, -L be the strictly lower-triangular part of A, and -U be the strictly upper-triangular part of A. Hence,

$$A = \begin{bmatrix} a_{11} & 0 & \cdots & 0 \\ 0 & a_{22} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & a_{nn} \end{bmatrix} - \begin{bmatrix} 0 & \cdots & \cdots & 0 \\ -a_{21} & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ -a_{n1} & \cdots & -a_{n,n-1} & 0 \end{bmatrix} - \begin{bmatrix} 0 & -a_{12} & \cdots & -a_{1n} \\ \vdots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & 0 \end{bmatrix}$$
$$= D - L - U.$$

The equation $A\mathbf{x} = \mathbf{b}$, or

$$(D - L - U)\mathbf{x} = \mathbf{b},\tag{1}$$

is then transformed into

$$D\mathbf{x} = (L+U)\mathbf{x} + \mathbf{b},$$

and, if D^{-1} exists,

$$\mathbf{x} = D^{-1}(L+U)\mathbf{x} + D^{-1}\mathbf{b}.$$

This results in the matrix form of the Jacobi iterative technique:

$$\mathbf{x}^{(k)} = D^{-1}(L+U)\mathbf{x}^{(k-1)} + D^{-1}\mathbf{b}.$$

Introducing $T_j = D^{-1}(L+U)$ and $c_j = D^{-1}\mathbf{b}$ (here, "j" stands for "Jacobi"), the Jacobi method has the form

$$\mathbf{x}^{(k)} = T_j \mathbf{x}^{(k-1)} + \mathbf{c}_j.$$

4.2 Gauss-Seidel Method

Equation (1) can be written as

$$(D-L)\mathbf{x} = U\mathbf{x} + \mathbf{b},$$

which gives the Gauss-Seidel method:

$$(D-L)\mathbf{x}^{(k)} = U\mathbf{x}^{(k-1)} + \mathbf{b}$$

or

$$\mathbf{x}^{(k)} = (D - L)^{-1} U \mathbf{x}^{(k-1)} + (D - L)^{-1} \mathbf{b}.$$

Introducing $T_g = (D-L)^{-1}U$ and $c_g = (D-L)^{-1}\mathbf{b}$ (here, "g" stands for "Gauss-Seidel"), the Gauss-Seidel method has the form

$$\mathbf{x}^{(k)} = T_g \mathbf{x}^{(k-1)} + \mathbf{c}_g.$$

Please see relevant homework problems for examples.

4.3 Spectral Radius

The **spectral radius** $\rho(A)$ of matrix A is defined by

 $\rho(A) = \max |\lambda|, \text{ where } \lambda \text{ is an eigenvalue of } A.$

4.4 Diagonal Dominance

The $n \times n$ matrix A is said to be strictly diagonally dominant when

$$|a_{ii}| > \sum_{j=1, \, j \neq i} |a_{ij}|,$$
(2)

holds for each $i = 1, 2, \ldots, n$.

4.5 Condition Number

The condition number of the nonsingular matrix A relative to a norm $|| \cdot ||$ is

 $K(A) = ||A|| \cdot ||A^{-1}||.$

In particular, the condition number of A relative to $||\cdot||_\infty$ is

$$K(A) = ||A||_{\infty} \cdot ||A^{-1}||_{\infty},$$

where

$$||A||_{\infty} = \max_{1 \le i \le n} \sum_{j=1}^{n} |a_{ij}|.$$

5 Consistency, Stability and Convergence of Numerical Methods

A one-step difference equation method with local truncation error $\tau_i(h)$ at the *i*th step is said to be **consistent** if

$$\lim_{h \to 0} \max_{1 \le i \le N} |\tau_i(h)| = 0.$$
(3)

A one-step difference equation method is said to be **convergent** if

$$\lim_{h \to 0} \max_{1 \le i \le N} |w_i - y(t_i)| = 0, \tag{4}$$

where y_i is the exact solution and w_i is the approximation obtained from the difference method. Recall that for Euler's method, we have

$$\max_{1 \le i \le N} |w_i - y(t_i)| \le \frac{Mh}{2L} |e^{L(b-a)} - 1|,$$
(5)

and, therefore, Euler's method is convergent with the linear (first order) rate of convergence of O(h).

A method is **stable** if its results depend continuously on the initial data.

5.1 Stability of Multistep Methods

Problem: To approximate the initial value problem

$$y' = f(t, y) \tag{6}$$

for t > 0, consider a multistep method

$$w_{i+1} = 2w_{i-1} - w_i + h \Big[\frac{5}{2} f(t_i, w_i) + \frac{1}{2} f(t_{i-1}, w_{i-1}) \Big].$$

Is this method stable?

Solution: For a multistep method to be stable, it has to satisfy the root condition. A multistep method is said to satisfy the root condition if all roots λ_i of the characteristic polynomial $P(\lambda)$ (for a general form of $P(\lambda)$ see equation (5.57) in the book) are such that $|\lambda_i| \leq 1$, and if $|\lambda_i| = 1$, then λ_i is simple.

The characteristic polynomial of the following multistep method

$$w_{i+1} + w_i - 2w_{i-1} = h \Big[\frac{5}{2} f(t_i, w_i) + \frac{1}{2} f(t_{i-1}, w_{i-1}) \Big].$$

is

$$P(\lambda) = -2 + \lambda + \lambda^2,$$

which has roots

 $\lambda_1 = 1, \ \lambda_2 = -2.$

Thus this multistep method does not satisfy the root condition, and therefore is unstable. \checkmark

Note that a quick way of writing a characteristic polynomial is to associate the coefficient a_0 to the leftmost grid point in the method's stencil. In the example above, the leftmost grid point has an index i - 1, and therefore, $a_0 = -2$, $a_1 = 1$, $a_2 = 1$.

5.2 Local Truncation Errors and Consistency

Problem: To approximate the initial value problem

$$y' = f(t, y) \tag{7}$$

for t > 0, consider a multistep method

$$w_{i+1} = 2w_{i-1} - w_i + h \Big[\frac{5}{2} f(t_i, w_i) + \frac{1}{2} f(t_{i-1}, w_{i-1}) \Big].$$

Find the local truncation error.

Solution: Expanding terms in Taylor's series around t_i , we obtain the following local truncation error $\tau(h)$:

$$\begin{split} \tau_{i+1}(h) &= \frac{1}{h} \bigg(y(t_{i+1}) + y(t_i) - 2y(t_{i-1}) - h \bigg[\frac{5}{2} f(t_i, y(t_i)) + \frac{1}{2} f(t_{i-1}, y(t_{i-1})) \bigg] \bigg) = \\ &= \frac{1}{h} \bigg[y(t_{i+1}) + y(t_i) - 2y(t_{i-1}) \bigg] - \frac{5}{2} y'(t_i) - \frac{1}{2} y'(t_{i-1}) \\ &= \frac{1}{h} \bigg[y(t_i) + h y'(t_i) + \frac{h^2}{2} y''(t_i) + \frac{h^3}{6} y'''(\xi_{i1}) \\ &\quad + y(t_i) \\ - 2 \big(y(t_i) - h y'(t_i) + \frac{h^2}{2} y''(t_i) - \frac{h^3}{6} y'''(\xi_{i2}) \big) \bigg] \\ &\quad - \frac{5}{2} y'(t_i) \\ &\quad - \frac{1}{2} \bigg[y'(t_i) - h y''(t_i) + \frac{h^2}{2} y'''(\xi_{i3}) \bigg] \\ &= \frac{1}{4} h^2 y'''(\xi_i), \end{split}$$

where $t_{i-1} < \xi_i < t_{i+1}$.

5.3 Regions of Absolute Stability

Problem: Show that the Backward Euler (or Implicit Euler) method

$$w_{i+1} = w_i + hf(t_{i+1}, w_{i+1})$$

is A-stable.

Solution: The region R of absolute stability is $R = \{h\lambda \in \mathbb{C} \mid |Q(h\lambda)| < 1\}$, where $w_{i+1} = Q(h\lambda)w_i$. A numerical method is said to be A-stable if its region of stability R contains the entire left half-plane.

In other words, in order to show that the method is A-stable, we need to show that when it is applied to the scalar test equation $y' = \lambda y = f$, whose solutions tend to zero for $\lambda < 0$, all the solutions of the method also tend to zero for a fixed h > 0 as $i \to \infty$.

For the Backward Euler method, we have

$$w_{i+1} = w_i + h\lambda w_{i+1}, w_{i+1} - h\lambda w_{i+1} = w_i, w_{i+1}(1 - h\lambda) = w_i, w_{i+1} = \frac{1}{1 - h\lambda} w_i, w_{i+1} = \left(\frac{1}{1 - h\lambda}\right)^{n+1} w_0$$

Thus,

$$Q(h\lambda) = \frac{1}{1 - h\lambda}.$$

Note that for $Re(h\lambda) < 0$, $|Q(h\lambda)| < 1$. Therefore, the region of absolute stability R for the Backward Euler method contains the entire left half-plane, and hence, the method is A-stable.

Note that the region of absolute stability contains the interval $(2, +\infty)$.

6 Boundary Value Problems

Given the second-order boundary-value problem

$$\begin{split} y''(x) &= p(x)y'(x) + q(x)y(x) + r(x),\\ a &\leq x \leq b,\\ y(a) &= \alpha, \quad y(b) = \beta, \end{split}$$

the differential equation to be approximated at the interior points x_i is

$$y''(x_i) = p(x_i)y'(x_i) + q(x_i)y(x_i) + r(x_i).$$
(8)

It might be helpful to know how to derive the following approximations to the first and second derivatives of $y(x_i)$ (pages 656-657 in the book). Expanding $y(x_{i+1})$ and $y(x_{i-1})$ in Taylor polynomials about x_i , and doing some arithmetic manipulations (as in the book), we obtain the following formulas:

$$y''(x_i) = \frac{1}{h^2} [y(x_{i+1}) - 2y(x_i) + y(x_{i-1})] - \frac{h^2}{12} y''''(\xi_i),$$

$$y'(x_i) = \frac{1}{2h} [y(x_{i+1}) - y(x_{i-1})] - \frac{h^2}{6} y'''(\eta_i).$$

The approximation to (8) is therefore:

$$\left(\frac{-w_{i+1}+2w_i-w_{i-1}}{h^2}\right) + p(x_i)\left(\frac{w_{i+1}-w_{i-1}}{2h}\right) + q(x_i)w_i = -r(x_i).$$
(9)

Problem: Write the discretization of the following boundary value problem

$$y'' = -\frac{4}{x}y' + \frac{2}{x^2}y - \frac{2}{x^2}\log x,$$

$$1 \le x \le 2,$$

$$y(1) = -\frac{1}{2}, \quad y(2) = \log 2,$$

in matrix-vector notation $A\mathbf{w} = \mathbf{b}$.

Solution: At the interior points x_i , for i = 1, 2, ..., N, the differential equation to be approximated is

$$y''(x_i) = -\frac{4}{x_i}y'(x_i) + \frac{2}{x_i^2}y(x_i) - \frac{2}{x_i^2}\log x_i.$$
(10)

Since

$$y''(x_i) = \frac{y(x_{i+1}) - 2y(x_i) + y(x_{i-1})}{h^2} - \frac{h^2}{12}y^{(4)}(\xi_i),$$

$$y'(x_i) = \frac{y(x_{i+1}) - y(x_{i-1})}{2h} - \frac{h^2}{6}y'''(\eta_i),$$

we can write the numerical approximation to (10) as

$$\frac{w_{i+1} - 2w_i + w_{i-1}}{h^2} + \frac{4}{x_i} \left(\frac{w_{i+1} - w_{i-1}}{2h}\right) - \frac{2}{x_i^2} w_i = -\frac{2}{x_i^2} \log x_i.$$
(11)

Multiplying both sides of (11) by $-h^2$ gives

$$-(w_{i+1} - 2w_i + w_{i-1}) - \frac{2h}{x_i}(w_{i+1} - w_{i-1}) + \frac{2h^2}{x_i^2}w_i = \frac{2h^2}{x_i^2}\log x_i.$$

Collecting w_{i-1} , w_i , and w_{i+1} terms, we obtain

where

 $A\mathbf{w} = \mathbf{b},$

$$-\left(1-\frac{2h}{x_i}\right)w_{i-1} + \left(2+\frac{2h^2}{x_i^2}\right)w_i - \left(1+\frac{2h}{x_i}\right)w_{i+1} = \frac{2h^2}{x_i^2}\log x_i.$$
(12)

The resulting system of equations can be expressed in the tridiagonal $N \times N$ matrix form

$$A = \begin{bmatrix} 2 + \frac{2h^2}{x_1^2} & -1 - \frac{2h}{x_1} & 0 & \cdots & 0\\ -1 + \frac{2h}{x_2} & 2 + \frac{2h^2}{x_2^2} & -1 - \frac{2h}{x_2} & \ddots & \vdots\\ 0 & \ddots & \ddots & \ddots & 0\\ \vdots & \ddots & \ddots & \ddots & -1 - \frac{2h}{x_{N-1}}\\ 0 & \cdots & 0 & -1 + \frac{2h}{x_N} & 2 + \frac{2h^2}{x_N^2} \end{bmatrix},$$

$$\mathbf{w} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_{N-1} \\ w_N \end{bmatrix}, \text{ and } \mathbf{b} = \begin{bmatrix} \frac{2h^2}{x_1^2}\log x_1 + \left(1 - \frac{2h}{x_1}\right)w_0 \\ \frac{2h^2}{x_2^2}\log x_2 \\ \vdots \\ \frac{2h^2}{x_{N-1}^2}\log x_{N-1} \\ \frac{2h^2}{x_N^2}\log x_N + \left(1 + \frac{2h}{x_N}\right)w_{N+1} \end{bmatrix}.$$

In order to see that this system satisfies (12), look at a couple of rows of matrix A, for example, the second row:

$$-\left(1-\frac{2h}{x_2}\right)w_1+\left(2+\frac{2h^2}{x_2^2}\right)w_2-\left(1+\frac{2h}{x_2}\right)w_3=\frac{2h^2}{x_2^2}\log x_2.$$

Also, first and last elements of \mathbf{b} might be a little daunting. However, if we look at the first row (for example), we see that

$$\left(2 + \frac{2h^2}{x_1^2}\right)w_1 - \left(1 + \frac{2h}{x_1}\right)w_2 = \frac{2h^2}{x_1^2}\log x_1 + \left(1 - \frac{2h}{x_1}\right)w_0$$

or

$$-\left(1-\frac{2h}{x_1}\right)w_0+\left(2+\frac{2h^2}{x_1^2}\right)w_1-\left(1+\frac{2h}{x_1}\right)w_2=\frac{2h^2}{x_1^2}\log x_1,$$

which satisfies equation (12).

Also, note that the book considers the general second-order boundary value problem:

$$y''(x) = p(x)y'(x) + q(x)y(x) + r(x).$$

For our problem, $p(x) = -\frac{4}{x}$, $q(x) = \frac{2}{x^2}$, and $r(x) = -\frac{2}{x^2} \log x$. Plugging these values into the formulas in the book, we can verify whether our calculations are correct.