Numerical Analysis Assignment 1

Name: Nate Stemen (20906566)

Due: Fri, Sep 25, 2020 5:00 PM

Email: nate.stemen@uwaterloo.ca

Course: AMATH 740

Problem 1. Eigenvalues and eigenvectors of the 1D Laplacian.

(a) Show that the n eigenvectors are given by the vectors $\mathbf{x}^{(p)}$ with components

$$x_i^{(p)} = \sin(jp\pi h)$$

and with eigenvalues

$$\lambda_p = \frac{2}{h^2}(\cos(p\pi h) - 1).$$

- (b) Verify the functions $u^{(p)}(x) = \sin(p\pi x)$ with $p \in \mathbb{N}$ are eigenfunctions of the continuous differential operator d^2/dx^2 on domain [0,1] with boundary conditions u(0) = 0 = u(1).
- (c) Compare the eigenvectors and the eigenvalues for the discrete and continuous operators and comment. Are the discrete and continuous eigenvalues similar for small values of $h \cdot p$?

Solution. (a) We start by verifying the the eigenvectors and eigenvalues given are correct.

$$A\mathbf{x}^{(p)} = \frac{1}{h^2} \begin{bmatrix} -2 & 1 & & & \\ 1 & -2 & 1 & & & \\ & \ddots & \ddots & \ddots & \\ & & 1 & -2 & 1 \\ & & & 1 & -2 \end{bmatrix} \begin{bmatrix} \sin(p\pi h) & \\ \sin(2p\pi h) & \\ \vdots & \\ \sin((n-1)p\pi h) & \vdots \\ \sin((n-1)p\pi h) & \\ \sin(p\pi h) - 2\sin(2p\pi h) + \sin(3p\pi h) \\ \vdots & \\ \sin((n-1)p\pi h) - 2\sin(np\pi h) \end{bmatrix}$$

We can compute a an elemente $(A\mathbf{x}^{(p)})_j$ as follows. We use $\varphi = p\pi h$ to make the

trig identity easier to see.

$$(A\mathbf{x}^{(p)})_{j} = \frac{1}{h^{2}}(\sin((j-1)\varphi) - 2\sin(j\varphi) + \sin((j+1)\varphi))$$

$$= \frac{1}{h^{2}}(-2\sin(j\varphi) + \sin(j\varphi + \varphi) + \sin(j\varphi - \varphi))$$

$$= \frac{1}{h^{2}}(-2\sin(j\varphi) + 2\sin(j\varphi)\cos(\varphi))$$

$$= \frac{2}{h^{2}}(\cos(p\pi h) - 1)\sin(jp\pi h)$$

$$= \lambda_{p}\sin(jp\pi h) = \lambda_{p}(\mathbf{x}^{(p)})_{j}$$

By product to sum identity

It's worth noting that the first and last elements of $\mathbf{x}^{(p)}$ are slightly different because they don't get 3 terms, but the above calculation still works. For the first element $(A\mathbf{x}^{(p)})_1$ the first sin term disappears because $\sin 0 = 0$, and for $(A\mathbf{x}^{(p)})_n$ the last sin term vanishes because (n+1)h = 1 and $\sin(n\pi) = 0$.

(b) First it's simple to verify the boundary conditions because $\sin 0 = 0$ and $\sin(p\pi) = 0$ for $p \in \mathbb{N}$. Now to show it's an eigenvector of the second derivative operator.

$$\frac{\mathrm{d}^2}{\mathrm{d}x^2}u^{(p)}(x) = p\pi \frac{\mathrm{d}}{\mathrm{d}x}\cos(p\pi x) = \underbrace{-p^2\pi^2}_{\lambda_p}\sin(p\pi x) = \lambda_p u^{(p)}(x)$$

So the eigenvalues here are $\lambda_p = -p^2\pi^2$.

(c) At first glance the eigenvectors look very similar for these two problems, but the eigenvalues look quite different. However if we make *n* very large (make the numerical grid much finer) then we can use the Taylor series for cos get get the follow approximation.

$$\frac{2}{h^2}(\cos(p\pi h) - 1) \approx \frac{2}{h^2} \left(1 - \frac{p^2 \pi^2 h^2}{2} + \mathcal{O}(h^4) - 1 \right)$$
$$= -p^2 \pi^2 + \mathcal{O}(h^2)$$

So in the limit $n \to \infty$ we do recover the continuous eigenvalues which is a sign we are doing something right.

Problem 2. Find the *LU* decomposition of

$$A = \begin{bmatrix} 1 & 4 & 7 \\ 2 & 5 & 8 \\ 3 & 6 & 10 \end{bmatrix}$$

and briefly explain the steps.

Solution.

$$\begin{bmatrix} 1 & 4 & 7 \\ 2 & 5 & 8 \\ 3 & 6 & 10 \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ l_{21} & 1 & 0 \\ l_{31} & l_{32} & 1 \end{bmatrix}}_{L} \underbrace{\begin{bmatrix} u_{11} & u_{12} & u_{13} \\ 0 & u_{22} & u_{23} \\ 0 & 0 & u_{33} \end{bmatrix}}_{U13}$$
$$= \underbrace{\begin{bmatrix} u_{11} & u_{12} & u_{13} \\ l_{21}u_{11} & l_{21}u_{12} + u_{22} & l_{21}u_{13} + u_{23} \\ l_{31}u_{11} & l_{31}u_{12} + l_{23}u_{22} & l_{31}u_{13} + l_{32}u_{23} + u_{33} \end{bmatrix}}_{L}$$

With this we can immediately see $u_{11} = 1$, $u_{12} = 4$, $u_{13} = 7$, $l_{21} = 2$ and $l_{31} = 3$. We can then plug these numbers into the other 4 equations to work out the rest of the components. With that we obtain the following lower and upper matrices.

$$L = \begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 3 & 6 & 1 \end{bmatrix} \qquad \qquad U = \begin{bmatrix} 1 & 4 & 7 \\ 0 & -1 & -6 \\ 0 & 0 & 25 \end{bmatrix}$$

Problem 3. Computational work for recursive determinant computation.

Solution. Using the following recursive definition of the determinant

$$\det A = \sum_{i=1}^{n} (-1)^{i+j} a_{ij} \det(A_{ij})$$

we can calculate the work needed to compute the determinant of an $n \times n$ matrix as W_n .

$$W_n = \sum_{i=1}^{n} (1M + W_{n-1}) = n(1 + W_{n-1})$$

In order to solve this recursive recurrence relation it is helpful to expand it out a few times.

$$W_{n} = n(1 + W_{n-1})$$

$$= n(1 + (n-1)(1 + (n-2)(1 + W_{n-3})))$$

$$= n + n(n-1) + n(n-1)(n-2) + n(n-1)(n-2)W_{n-3}$$

$$= \frac{n!}{(n-1)!} + \frac{n!}{(n-2)!} + \frac{n!}{(n-3)!}W_{n-3}$$

Writing the expression in the last form allows us to more easily see a pattern arising. We are summing progressively less "cut off" forms of the factorial which can be expressed as follows.

$$W_n = n! \sum_{k=1}^{n-1} \frac{1}{k!}$$

In the limit of large n this approaches $W_n = en!$. Nice.

Problem 4. Vector norm inequalities.

Show that $\|\mathbf{x}\|_{\infty} \leq \|\mathbf{x}\|_{1} \leq n\|\mathbf{x}\|_{\infty}$ for $\mathbf{x} \in \mathbb{R}^{n}$.

Solution. First, let $|x_j| := \max_i |x_i| = ||\mathbf{x}||_{\infty}$.

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

$$\leq |x_{j}| + \sum_{\substack{i=1 \ i \ne j}}^{n} |x_{i}| \qquad \text{(bc second term is positive)}$$

$$= \sum_{i=1}^{n} |x_{i}| = \|\mathbf{x}\|_{1}$$

$$\leq \sum_{i=1}^{n} n|x_{j}| \qquad \text{(bc } |x_{j}| \ge |x_{i}| \text{ for all } i\text{)}$$

$$= n \sum_{i=1}^{n} |x_{j}| = n \|\mathbf{x}\|_{\infty}$$

Problem 5. Matrix norm formula.

Let $A \in \mathbb{R}^{n \times n}$. Show that

$$||A||_1 = \max_{1 \le j \le n} \sum_{i=1}^n |a_{ij}|.$$

Solution. We begin by showing the 1-norm of a matrix must be less or equal to the maximum absolute column sum. Once that is established we will find a vector that brings the matrix norm up to that bound, which shows the maximum can be attained and hence the equality true.

$$||A\mathbf{x}||_{1} = \sum_{i=1}^{n} \left| \sum_{j=1}^{n} a_{ij} x_{j} \right|$$

$$\leq \sum_{i} \sum_{j} |a_{ij} x_{j}|$$

$$\leq \sum_{i} |x_{j}| \sum_{i} |a_{ij}|$$

$$\leq \left[\max_{k} \sum_{i} |a_{ik}| \right] \underbrace{\sum_{j} |x_{j}|}_{\|\mathbf{x}\|_{1}}$$

If we use the following definition of the matrix norm $||A||_1 = \max_{|\mathbf{x}_1||=1} ||A\mathbf{x}||_1$, then the last term in the above inequality vanishes (goes to 1) and hence we have established the 1-norm of this matrix is always less than or equal to the maximum absolute column sum.

Now let ν be the index where the maximum absolute column sum lives $(\max_j \sum_i |a_{ij}| = \sum_i |a_{i\nu}|)$. Choose $\mathbf{x} = \mathbf{e}_{\nu}$ where \mathbf{e}_{ν} is the unit normal vector with 1 in the ν th position, and 0 everywhere else. Now we can evaluate the norm of A times this vector.

$$||A\mathbf{x}||_1 = ||A\mathbf{e}_{\nu}||_1 = \sum_{i} \left| \sum_{j} a_{ij} e_j \right|$$
$$= \sum_{i} |a_{i\nu}|$$
$$= \max_{1 \le j \le n} \sum_{i=1}^{n} |a_{ij}|$$

Clearly $\|\mathbf{e}_{\nu}\|_1 = 1$, so we've found a vector on the unit sphere that attains the maximum which shows the equality of the given statement.

Problem 6. Inverse update formula.

Let $A \in \mathbb{R}^{n \times n}$ be a nonsingular matrix, and $\mathbf{u}, \mathbf{v} \in \mathbb{R}^n$. Show that if $A + \mathbf{u}\mathbf{v}^{\mathsf{T}}$ is nonsingular, then it's inverse can be expressed by the formula

$$(A + \mathbf{u}\mathbf{v}^{\mathsf{T}})^{-1} = A^{-1} - \frac{1}{1 + \mathbf{v}^{\mathsf{T}}A^{-1}\mathbf{u}}A^{-1}\mathbf{u}\mathbf{v}^{\mathsf{T}}A^{-1}$$

Solution. We start by showing $1 + \mathbf{v}^{\mathsf{T}} A^{-1} \mathbf{u} \neq 0$ by contradiction. So assume $1 + \mathbf{v}^{\mathsf{T}} A^{-1} \mathbf{u} = 0$.

$$1 + \mathbf{v}^{\mathsf{T}} A^{-1} \mathbf{u} = 0$$
$$\mathbf{u} + \mathbf{u} \mathbf{v}^{\mathsf{T}} A^{-1} \mathbf{u} = \mathbf{0}$$
$$(\mathbb{1} + \mathbf{u} \mathbf{v}^{\mathsf{T}} A^{-1}) \mathbf{u} = \mathbf{0}$$
$$\mathbb{1} + \mathbf{u} \mathbf{v}^{\mathsf{T}} A^{-1} = 0^{n \times n}$$
$$A + \mathbf{u} \mathbf{v}^{\mathsf{T}} = 0^{n \times n}$$

Where we've arrived at a contradiction on the last equation, because we took $A + \mathbf{u}\mathbf{v}^{\mathsf{T}}$ to be nonsingular (and hence not be the 0 matrix).

With this proved we can now show the formula is indeed an inverse. For notational convenience we use $\alpha = \frac{1}{1+\mathbf{v}\mathsf{T}A^{-1}\mathbf{u}}$.

$$(A + \mathbf{u}\mathbf{v}^{\mathsf{T}}) \left(A^{-1} - \frac{1}{1 + \mathbf{v}^{\mathsf{T}}A^{-1}\mathbf{u}} A^{-1}\mathbf{u}\mathbf{v}^{\mathsf{T}}A^{-1} \right)$$

$$= \mathbb{1} - \alpha \mathbf{u}\mathbf{v}^{\mathsf{T}}A^{-1} + \mathbf{u}\mathbf{v}^{\mathsf{T}}A^{-1} - \alpha \mathbf{u}\mathbf{v}^{\mathsf{T}}A^{-1}\mathbf{u}\mathbf{v}^{\mathsf{T}}A^{-1}$$

$$= \mathbb{1} + \mathbf{u} \left(-\alpha + 1 - \alpha \mathbf{v}^{\mathsf{T}}A^{-1}\mathbf{u} \right) \mathbf{v}^{\mathsf{T}}A^{-1}$$

$$= \mathbb{1} + \mathbf{u} \left(1 + -\alpha \left[1 + \mathbf{v}^{\mathsf{T}}A^{-1}\mathbf{u} \right] \right) \mathbf{v}^{\mathsf{T}}A^{-1}$$

$$= \mathbb{1} + \mathbf{u}(1 - 1)\mathbf{v}^{\mathsf{T}}A^{-1} = \mathbb{1}$$

If a square matrix has a left (or right) inverse, then it also has a right (left) inverse and they are equal. We can now conclude that the formula given is indeed an inverse for $A + \mathbf{u}\mathbf{v}^{\mathsf{T}}$.

¹If $AB = \mathbb{1}$, then $1 = \det AB = \det A \det B$ so we know B is nonsingular. $BAB = B \implies (BA - \mathbb{1})B = 0 \implies BA = \mathbb{1}$