
MATHEMATICS 714 HOMEWORK 2

A PREPRINT

Haley Colgate

November 1, 2020

A

- (a) If we have $v \in \text{span}\{w_1, w_2, \dots, w_n\}$ then $v = a_1 w_1 + a_2 w_2 + \dots + a_n w_n$ for some set of scalars a_i . We can then take the inner product of both sides with w_k for $k = 1, 2, \dots, n$ to find

$$\begin{aligned}\langle v, w_k \rangle &= \langle a_1 w_1 + a_2 w_2 + \dots + a_n w_n, w_k \rangle \\ &= \sum_{i=1}^n a_i \langle w_i, w_k \rangle \\ &= a_k \|w_k\|^2.\end{aligned}$$

Therefore $a_k = \frac{\langle v, w_k \rangle}{\|w_k\|^2}$ so

$$v = \sum_{j=1}^n \frac{\langle v, w_j \rangle}{\|w_j\|^2} w_j.$$

- (b) (i) The number of iterations to convergence may be strictly smaller than N because if we have an initial guess such that the solution lies in a Krylov subspace we can converge sooner than N iterations.
- (ii) Our base case is $n = 1$ so the only allowable j value is $j = 0$. We have $p_0 = r_0$ and $r_0 = f - Ax_0$. We also have $p_1 = r_1 - \frac{\langle r_1, p_0 \rangle_A}{\|p_0\|_A^2} p_0 = r_1 - \frac{\langle r_1, r_0 \rangle_A}{\|r_0\|_A^2} r_0$. The algorithm gives $w_0 = Ar_0$ and $\alpha_0 = \frac{\|r_0\|^2}{p_0^T w_0} = \frac{\|r_0\|_A^2}{\|r_0\|_A^2}$. Therefore $r_1 = r_0 - \alpha_0 w_0 = r_0 - \frac{\|r_0\|_A^2}{\|r_0\|_A^2} Ar_0$. Now we show

$$\begin{aligned}\langle p_1, p_0 \rangle_A &= \langle p_1, r_0 \rangle_A \\ &= r_1^T Ar_0 - \frac{\langle r_1, r_0 \rangle_A}{\|r_0\|_A^2} \langle r_0, r_0 \rangle_A \\ &= \langle r_1, r_0 \rangle_A - \frac{\|r_0\|_A^2}{\|r_0\|_A^2} \langle r_1, r_0 \rangle_A \\ &= 0.\end{aligned}$$

Now for the induction step assume that for $k < n$, with $0 \leq l < k < n \leq n^* - 1$ we have $\langle p_k, p_j \rangle_A = 0$. We want to show that for $0 \leq l < n \leq n^* - 1$ we still have $\langle p_n, p_l \rangle_A = 0$. Note that by our induction hypothesis, $\langle p_j, p_l \rangle = 0$ when $j \neq l$ and $\max l, j < n$. By our formula for p_n , we get

$$\begin{aligned}\langle p_n, p_l \rangle_A &= \langle r_n, p_l \rangle_A - \sum_{j=0}^{n-1} \frac{\langle r_n, p_j \rangle_A}{\|p_j\|_A^2} \langle p_j, p_l \rangle_A \\ &= \langle r_n, p_l \rangle_A - \frac{\langle p_l, p_l \rangle_A}{\|p_l\|_A^2} \langle r_n, p_l \rangle_A \\ &= \langle r_n, p_l \rangle_A - \frac{\|p_l\|_A^2}{\|p_l\|_A^2} \langle r_n, p_l \rangle_A \\ &= 0.\end{aligned}$$

- (c) (i) Since $\{\phi_n\}$ form an orthonormal basis for \mathbb{R}^N , we have $v, w \in \text{span}\{\phi_1, \dots, \phi_N\}$ and $\|\phi_n\| = 1$. Thus by part (a), we can write $v = \sum_{n=1}^N \langle v, \phi_n \rangle \phi_n$. Therefore

$$\langle Av, w \rangle = \sum_{n=1}^N \langle v, \phi_n \rangle \langle A\phi_n, w \rangle = \sum_{n=1}^N \langle v, \phi_n \rangle \langle \lambda_n \phi_n, w \rangle = \sum_{n=1}^N \lambda_n \langle v, \phi_n \rangle \langle \phi_n, w \rangle.$$

- (ii) For $1 \leq n \leq N$, since A is positive definite we have $\phi_n^T A \phi_n > 0$, but $A\phi_n = \lambda_n \phi_n$ so $\phi_n^T A \phi_n = \lambda_n \|\phi_n\|^2 > 0$ which implies $\lambda_n > 0$.
 (iii) Note that $\|v\|^2 = \sum_{n=1}^N \langle v, \phi_n \rangle^2$ and $Av = \sum_{n=1}^N \langle v, \phi_n \rangle A\phi_n = \sum_{n=1}^N \langle v, \phi_n \rangle \lambda_n \phi_n$. Then since $\langle \phi_n, \phi_m \rangle = \delta_{n,m}$,

$$\langle Av, v \rangle = \sum_{j=1}^N \sum_{n=1}^N \langle v, \phi_n \rangle \langle v, \phi_j \rangle \lambda_n \langle \phi_n, \phi_j \rangle = \sum_{n=1}^N \langle v, \phi_n \rangle^2 \|\phi_n\|^2 \lambda_n.$$

Therefore $\lambda_1 \|v\|^2 \leq \langle Av, v \rangle \leq \lambda_N \|v\|^2$.

- (iv) We can write $\|v\|^2 = \sum_{j=1}^N \langle v, \phi_j \rangle^2$. Note that $Av = \sum_{j=1}^N \langle v, \phi_j \rangle A\phi_j = \sum_{j=1}^N \langle v, \phi_j \rangle \lambda_j \phi_j$, and $A^T = A$ since A is symmetric. Then

$$\begin{aligned} \|Av\|^2 &= \langle Av, Av \rangle \\ &= v^T A \sum_{j=1}^N \langle v, \phi_j \rangle \lambda_j \phi_j \\ &= v^T \sum_{j=1}^N \langle v, \phi_j \rangle \lambda_j^2 \phi_j \\ &= \sum_{j=1}^N \sum_{k=1}^N \langle v, \phi_j \rangle \langle v, \phi_k \rangle \lambda_j^2 \langle \phi_j, \phi_k \rangle \\ &= \sum_{j=1}^N \langle v, \phi_j \rangle^2 \lambda_j^2 \\ &\leq \lambda_N^2 \sum_{j=1}^N \langle v, \phi_j \rangle^2. \end{aligned}$$

Therefore $\|Av\| \leq \lambda_N \|v\|$.

- (d) By definition, $p_{n+1} = r_{n+1} + \beta_n p_n$. From the algorithm, $w_n = Ap_n$ so $r_{n+1} = r_n - \alpha_n w_n = r_n - \alpha_n Ap_n$. From the formula for p we find $p_n = r_n + \beta_{n-1} p_{n-1}$ so we can write $r_n = p_n - \beta_{n-1} p_{n-1}$. Therefore our equation for r_{n+1} becomes $r_{n+1} = p_n - \beta_{n-1} p_{n-1} - \alpha_n Ap_n$. Substituting this in to our equation for p_{n+1} gives

$$p_{n+1} = p_n - \beta_{n-1} p_{n-1} - \alpha_n Ap_n + \beta_n p_n = (1 + \beta_n) p_n - \alpha_n p_n - \beta_{n-1} p_{n-1}$$

- (e) By the Cayley-Hamilton theorem, since A is nonsingular, we have

$$A^n + c_{N-1} A^{N-1} + \dots + c_1 A + (-1)^N \det(A) I = 0$$

for constants c_n, \dots, c_1 based on the eigenvalues of A . We can then write

$$A^N = -c_{N-1} A^{N-1} - \dots - c_1 A + (-1)^{N-1} \det(A) I$$

and since $\det A \neq 0$ we have at least one nonzero coefficient, and $A^N \neq 0$, so A^N is a linear combination of $I, A, A^2, \dots, A^{N-1}$.

- (f) (i) By definition,

$$\begin{aligned} e_{n+1} &= u_{n+1} - u \\ &= u_n + \alpha f - \alpha A u_n - u - \alpha f + \alpha A u \\ &= (u_n - u) - \alpha A (u_n - u) \\ &= (I - \alpha A) e_n. \end{aligned}$$

- (ii) Since $\|I - \alpha A\| \leq \rho$, and by (i) we have $e_{n+1} = (I - \alpha A)e_n$, $\|e_{n+1}\| \leq \|I - \alpha A\| \|e_n\| \leq \rho \|e_n\|$.
 (iii) Since λ_1 and λ_N are the largest and smallest eigenvalues,

$$\rho = \max_{1 \leq j \leq N} |1 - \alpha \lambda_j| = \max\{|1 - \alpha \lambda_1|, |1 - \alpha \lambda_N|\}.$$

As we make one of those terms smaller we make the other bigger, so the optimal α makes the two equal. This happens when α is the reciprocal of the average, so $\alpha = \frac{2}{\lambda_1 + \lambda_N}$.

- (iv) Since ρ is determined by λ_1 and λ_N , we first consider

$$\begin{aligned} |1 - \alpha \lambda_1| &= \left| 1 - \frac{2\lambda_1}{c + C} \right| \\ &= \left| \frac{c + C - 2\lambda_1}{c + C} \right| \\ &\leq \left| \frac{c + C - 2c}{c + C} \right| \\ &= \left| \frac{C - c}{C + c} \right|. \end{aligned}$$

Next we consider

$$\begin{aligned} |1 - \alpha \lambda_N| &= \left| 1 - \frac{2\lambda_N}{c + C} \right| \\ &= \left| \frac{c + C - 2\lambda_N}{c + C} \right| \\ &\leq \left| \frac{C - c}{c + C} \right|. \end{aligned}$$

Therefore $\rho \leq |C - c|/|C + c|$.

- (g) (i) From the algorithm $p_0 = r_0$ so $w_0 = Ap_0 = Ar_0$. Therefore $r_1 = \alpha_0 w_0 = r_0 - \alpha_0 Ar_0$.
 (ii) We begin with the formula for r_n , substituting $w_{n-1} = Ap_{n-1}$, to find $r_n = r_{n-1} - \alpha_{n-1} Ap_{n-1}$ which gives $Ap_{n-1} = \frac{1}{\alpha_{n-1}}(r_{n-1} - r_n)$. Then, from the update formula for p_n , using the identity we just found for Ap_{n-1} , we find

$$w_n = Ap_n = Ar_n + \beta_{n-1} Ap_{n-1} = Ar_n - \frac{\beta_{n-1}}{\alpha_{n-1}}(r_n - r_{n-1}).$$

We then return to the formula for r_{n+1} to find

$$\begin{aligned} r_{n+1} &= r_n - \alpha_n w_n \\ &= r_n - \alpha_n Ar_n + \frac{\alpha_n \beta_{n-1}}{\alpha_{n-1}}(r_n - r_{n-1}). \end{aligned}$$

- (iii) From the update formula for β_0 , we have $\sqrt{\beta_0} = \frac{\|r_1\|}{\|r_0\|}$. Therefore $\delta + 0 = \frac{\sqrt{\beta_0}}{\alpha_0} = \frac{\|r_1\|}{\alpha_0 \|r_0\|}$. By part (i) $r_1 = r_0 - \alpha_0 Ar_0$. If we divide through by $\|r_1\|$ and multiply through by δ_0 we find

$$\begin{aligned} r_1 &= r_0 - \alpha_0 Ar_0 \\ q_1 &= \frac{r_0}{\|r_1\|} Ar_0 \\ \delta_0 q_1 &= \frac{r_0}{\alpha_0 \|r_0\|} - \frac{1}{\|r_0\|} Ar_0 \\ &= \gamma_0 q_0 - Aq_0. \end{aligned}$$

Rearranging gives $Aq_0 = \gamma_0 q_0 - \delta_0 q_1$.

Note that from the algorithm, $\beta_{n-1} = \frac{\|r_n\|^2}{\|r_{n-1}\|^2}$ so $-\delta_{n-1} = -\frac{1}{\alpha_{n-1}} \frac{\|r_n\|}{\|r_{n-1}\|}$, $-\delta_n = -\frac{1}{\alpha_n} \frac{\|r_{n+1}\|}{\|r_n\|}$, and $\gamma_n = \frac{1}{\alpha_n} + \frac{\|r_n\|^2}{\alpha_{n-1}\|r_{n-1}\|^2}$. Using the identity in part (ii), we have

$$\begin{aligned} r_{n+1} &= r_n - \alpha_n A r_n + \frac{\alpha_n \beta_{n-1}}{\alpha_{n-1}} r_n - \frac{\alpha_n \beta_{n-1}}{\alpha_{n-1}} r_{n-1} \\ &= r_n - \alpha_n A r_n + \frac{\alpha_n \|r_n\|^2}{\alpha_{n-1} \|r_{n-1}\|^2} r_n - \frac{\alpha_n \|r_n\|^2}{\alpha_{n-1} \|r_{n-1}\|^2} r_{n-1} \\ &= r_n - \alpha_n A r_n + \frac{\alpha_n \|r_n\|^2}{\alpha_{n-1} \|r_{n-1}\|^2} r_n + \alpha_n \|r_n\| (-\delta_{n-1} q_{n-1}). \end{aligned}$$

Dividing through by $\alpha_n \|r_n\|$ gives

$$\begin{aligned} \frac{r_{n+1}}{\alpha_n \|r_n\|} &= \left(\frac{1}{\alpha_n} + \frac{\|r_n\|^2}{\alpha_{n-1} \|r_{n-1}\|^2} \right) q_n - A q_n - \delta_{n-1} q_{n-1} \\ \frac{\|r_{n+1}\|}{\|r_{n+1}\|} \frac{r_{n+1}}{\alpha_n \|r_n\|} &= \gamma_n q_n - A q_n - \delta_{n-1} q_{n-1} \\ \delta_n q_{n+1} &= \gamma_n q_n - A q_n - \delta_{n-1} q_{n-1}. \end{aligned}$$

Rearranging gives $A q_n = -\delta_{n-1} q_{n-1} + \gamma_n q_n - \delta_n q_{n+1}$ as desired.

(iv) By part (iii),

$$\begin{aligned} A Q_n &= [A q_0 \quad A q_1 \quad \cdots \quad A q_{n-1}] \\ &= [\gamma_0 q_0 - \delta_0 q_1 \quad -\delta_0 q_0 + \gamma_1 q_1 - \delta_1 q_2 \quad \cdots \quad -\delta_{n-2} q_{n-2} + \gamma_{n-1} q_{n-1} - \delta_{n-1} q_n]. \end{aligned}$$

We see that this is exactly $Q_n T_n$ except in the last column, where we're missing a term of $-\delta_{n-1} q_n e_n^T$ since Q_n only goes up to q_{n-1} . Thus $A Q_n = Q_n T_n - \delta_{n-1} q_n e_n^T$.

(v) Applying Q_n^T on the left to both sides of part (iv) gives us

$$Q_n^T A Q_n = Q_n^T Q_n T_n - \delta_{n-1} Q_n q_n e_n^T = T_n$$

since the q_n are orthonormal.

B

Odd N values consistently perform worse than even values because odd values have an interval that straddles 0.5, so checking odd values of N ensures that even values will also meet the tolerance. With that, the lowest value of N that meets the required tolerance is $N = 100$.

The Matlab code is on my github, file HW2b: <https://github.com/HaleyColgate/Math714>

C

(a) We initialize the scheme with the first time step, $t = 0$, as all zeros which the edges continue on with for the Dirichlet conditions. The next time step uses an approximation of the first derivative $U_t(x_i, y_j) \approx \frac{1}{\delta t} (U_{ij}^1 - U_{ij}^0)$ so $U_{ij} = \delta t f(x_i) f(y_j)$ to account for the initial condition of $u_t = f(x) f(y)$. Following that, we have the 3-point second derivative formula and the 5-point Laplacian which gives

$$\frac{U_{ij}^{n+1} - 2U_{ij}^n + U_{ij}^{n-1}}{\delta t^2} = \frac{U_{i+1j}^n + U_{i-1j}^n + U_{ij+1}^n + U_{ij-1}^n - 4U_{ij}^n}{\delta x^2}.$$

Therefore our update rule is

$$U_{ij}^{n+1} = 2U_{ij}^n - U_{ij}^{n-1} + \frac{\delta t^2}{\delta x^2} (U_{i+1j}^n + U_{i-1j}^n + U_{ij+1}^n + U_{ij-1}^n - 4U_{ij}^n).$$

See Figure 1 and note the slope of 2. This method is second order. Error should be worst at the largest time value. The Matlab code is on my github, file HW2C: <https://github.com/HaleyColgate/Math714>

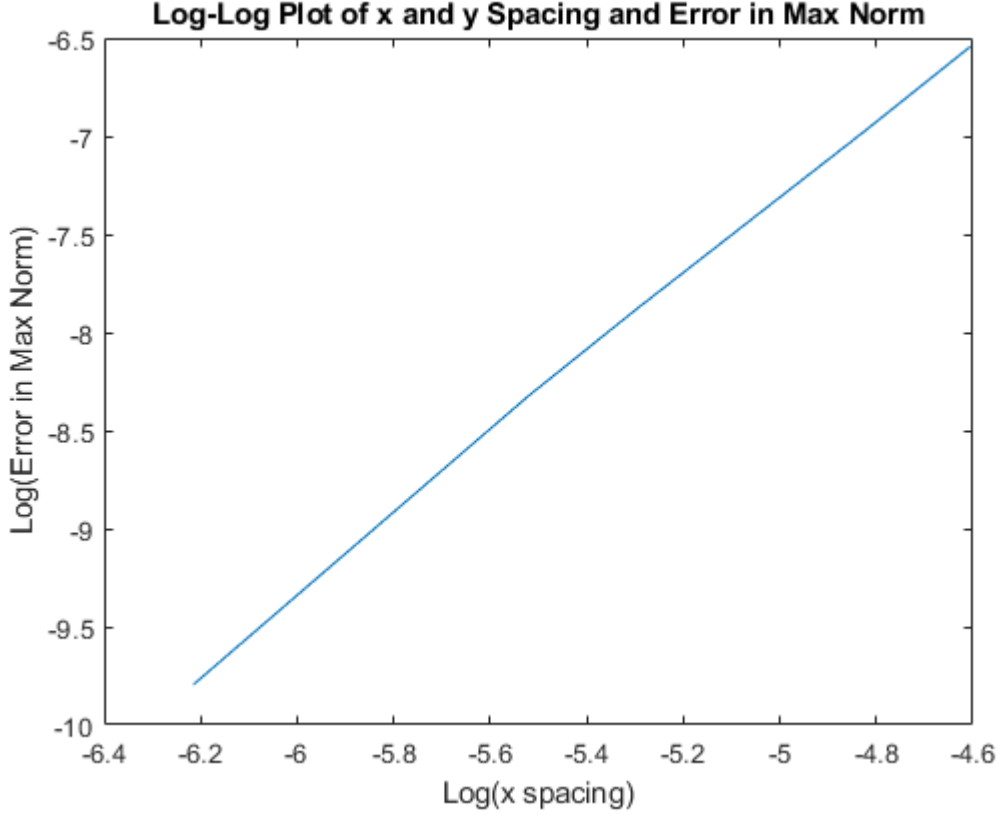


Figure 1: Log-Log Error Plot

- (b) With the 3-point rule for y'' as a two step explicit time integrator we get the equation

$$\frac{y_{n+1} - 2y_n + y_{n-1}}{\Delta t^2} = \lambda y_n$$

which simplifies to

$$0 = y_{n+1} - (\lambda \Delta t^2 + 2)y_n + y_{n-1}.$$

Our characteristic polynomial is then $\rho^2 - (\lambda \Delta t^2 + 2)\rho + 1$. We define $\alpha = \lambda \Delta t^2$ so $\rho = 1 + \frac{1}{2}\alpha \pm \sqrt{\frac{\alpha^2}{4} - 1}$. We need the magnitude of both values of ρ to be less than or equal to one, but as one gets smaller the other grows larger, so this happens only when they both have a magnitude of 1, for $-4 < \alpha < 0$.

- (c) Our semi-discrete scheme is $y'' = \Delta_h y$ where $\Delta_h = I \otimes A + A \otimes I$ with

$$A = \frac{1}{h^2} \begin{bmatrix} -2 & 1 & & 0 \\ 1 & \ddots & \ddots & \\ & \ddots & \ddots & \ddots \\ 0 & & \ddots & \ddots & 1 & -2 \end{bmatrix}.$$

We know the k th eigenvalue of A is given by $\lambda_k(A) = -\frac{4}{h^2} \sin^2\left(\frac{k\pi h}{2}\right)$ for $k = 1, \dots, N+1$ so as we've shown in the last homework

$$\lambda_{ij}(\Delta_h) = -\frac{4}{h^2} \sin^2\left(\frac{i\pi h}{2}\right) - \frac{4}{h^2} \sin^2\left(\frac{j\pi h}{2}\right).$$

We need $\lambda(\Delta_h)\delta t^2$ to be between -4 and 0 based on what we found in part (b). Conveniently, $\sin^2(i\pi h/2) + \sin^2(j\pi h/2)$ is bounded below by 0 and above by 2 . We have

$$-4 < -\frac{4\Delta t^2}{h^2} \left(\sin^2\left(\frac{i\pi h}{2}\right) + \sin^2\left(\frac{j\pi h}{2}\right) \right) < 0$$

which simplifies to

$$0 < \frac{\Delta t^2}{h^2} \left(\sin^2 \left(\frac{i\pi h}{2} \right) = \sin^2 \left(\frac{j\pi h}{2} \right) \right) < 1.$$

With the bound on the sines this gives us $2 \frac{\Delta t^2}{h^2} < 1$ or $\frac{\Delta t^2}{h^2} < \frac{1}{2}$.

- (d) We suppose $U_{mj}^n = g(k_1, k_2) e^{ik_x m h} e^{ik_y j h}$ so $U^n = g(k_x, k_y) U^{n-1}$ so $U^{n+1} = g(k_x, k_y)^2 U^{n-1}$. For ease of notation from here forward $g = g(k_x, k_y)$. With our update rule this gives

$$\begin{aligned} e^{ik_x m h} e^{ik_y j h} g^2 &= g \frac{\Delta t^2}{h^2} (e^{ik_x (m+1) h} e^{ik_y j h} + e^{ik_x (m-1) h} e^{ik_y j h} + e^{ik_x m h} e^{ik_y (j-1) h} + e^{ik_x m h} e^{ik_y (j+1) h} \\ &\quad + \left(2 \frac{h^2}{\Delta t^2} - 4 \right) e^{ik_x m h} e^{ik_y j h}) - e^{ik_x m h} e^{ik_y j h}. \end{aligned}$$

This simplifies to

$$g^2 = g \frac{\delta t^2}{h^2} \left(e^{ik_x h} + e^{-ik_x h} + e^{ik_y h} + e^{-ik_y h} + \left(2 \frac{h^2}{\Delta t^2} - 4 \right) \right) - 1$$

or

$$0 = g^2 - 2g \frac{\Delta t^2}{h^2} \left(\cos(k_x h) + \cos(k_y h) + \left(\frac{h^2}{\Delta t^2} - 2 \right) \right) + 1.$$

Using the half angle formula $\cos(x) = 1 - 2 \sin^2(x/2)$ and simplifying we get

$$\begin{aligned} 0 &= g^2 - 2g \frac{\Delta t^2}{h^2} (1 - 2 \sin^2(k_x h/2) + 1 - 2 \sin^2(k_y h/2) + (h^2/\Delta t^2 - 2)) + 1 \\ &= g^2 - 2g \frac{\Delta t^2}{h^2} (-2 \sin^2(k_x h/2) - 2 \sin^2(k_y h/2) + h^2/\Delta t^2) + 1 \\ &= g^2 + g \left(4 \frac{\Delta t^2}{h^2} \sin^2 \left(\frac{k_x h}{2} \right) + 4 \frac{\Delta t^2}{h^2} \sin^2 \left(\frac{k_y h}{2} \right) - 2 \right) - 2. \end{aligned}$$

If we define

$$-\alpha = 4 \frac{\Delta t^2}{h^2} \sin^2 \left(\frac{k_x h}{2} \right) + 4 \frac{\Delta t^2}{h^2} \sin^2 \left(\frac{k_y h}{2} \right)$$

we find $0 = g^2 - (\alpha + 2)g - 2$ so $g = 1 + \frac{\alpha}{2} \pm \sqrt{\frac{\alpha^2}{4} - 1}$ and from part (a) we know $|g| \leq 1$ when $-4 < \alpha < 0$ and by part (c) this happens when $\frac{\Delta t^2}{h^2} < \frac{1}{2}$.