David Zikel, Nov. 1, 2020

GitHub: https://github.com/dzikel/dzikel-714

- (Aa) Suppose that v is in the span of  $w_1, w_2, \dots, w_n$  i.e., that  $v = c_1w_1 + c_2w_2 + \dots + c_nw_n$  for  $c_1, c_2, \dots, c_n \in \mathbf{R}$ . Then, for any  $w_i, w_i \cdot v = c_1(w_i \cdot w_1) + \dots + c_i(w_i \cdot w_i) + \dots + c_n(w_i \cdot w_n) = 0 + \dots + c_i|w_i|^2 + \dots + 0 = c_i|w_i|^2$ . Dividing by  $|w_i|^2$  yields simply  $c_i$ , so the  $w_i$  component of v is simply  $\frac{w_i \cdot v}{|w_i|^2}w_i$ . Summing for  $i = 1 \cdots n$  gives the formula shown for v.
- (Ab) i. If, for example, the solution lies directly on the 1st, 2nd, etc. gradient line, then the algorithm will converge early. In general, if step  $n^*-1$  does not change the estimate, then the algorithm will converge with less than N iterations. ii. Note that, if n=1 (so j=0),  $\langle p_n, p_j \rangle_A = \langle p_0, r_1 \rangle_A \frac{\langle p_0, p_0 \rangle_A}{\langle p_0, p_0 \rangle_A} \langle p_0, r_1 \rangle_A = 0$ . Suppose that, for  $n=1, \cdots, k$  we have that  $\langle p_n, p_j \rangle_A = 0$  for j < n. Then, for j < n+1,  $\langle p_{n+1}, p_j \rangle_A = \langle p_j, r_{n+1} \rangle_A 0 0 \cdots \frac{\langle p_j, p_j \rangle_A}{\langle p_j, p_j \rangle_A} \langle p_j, r_{n+1} \rangle_A \cdots 0 = 0$ . As such,  $\langle p_j p_n \rangle_A = 0$  for all  $0 \le j < n \le n^* 1$ .
- (Ac) i. We see from the proof of (Aa) that the component of v in the direction of  $\phi_n$  is  $x_n = \frac{v \cdot \phi_n}{1} \phi_n = (v \cdot \phi_n) \phi_n$ , and  $Ax_n \cdot w = \lambda_n (v \cdot \phi_n) (\phi_n \cdot w)$ . Since both multiplication by A and the dot product are linear, we can find  $Av \cdot w$  by summing  $Ax_n \cdot w$  for n from 1 to N, which is the formula shown. ii. Suppose that one of the eigenvalues  $\lambda_n \leq 0$ . Then this eigenvalue must be associated with a nonzero eigenvector  $\phi_n$ , such that  $\langle \phi_n, \phi_n \rangle_A = \phi_n \cdot \lambda \phi_n < 0$ — but, as A is positive definite, this is a contradiction. iii. Decomposing v as  $c_1\phi_1 + \cdots + c_N\phi_N$ , we see that  $\lambda_1|v|^2 = \lambda_1c_1^2 + \cdots + \lambda_1c_N^2$ ,  $\lambda_N|v|^2 = \lambda_1c_1^2 + \cdots + \lambda_1c_N^2$  $\lambda_N c_1^2 + \dots + \lambda_N c_N^2$ , and, by (Aci),  $Av \cdot v = \lambda_1 c_1^2 + \lambda_2 c_2^2 + \dots + \lambda_N c_N^2$ . Since each  $c_n^2$  is nonnegative and the  $\lambda_n$  are nondecreasing, we have that  $\lambda_1|v|^2$  is a lower bound and  $\lambda_N |v|^2$  is an upper bound for  $Av \cdot v$ . iv. Since both sides are nonnegative (the right side by (Acii)), the equation remains unchanged when both sides are squared:  $|Av|^2 \leq \lambda_N^2 |v|^2$ . Again decomposing v as  $c_1\phi_1 + \cdots + c_N\phi_N$ , we see that  $Av = \lambda_1c_1\phi_1 + \cdots + \lambda_Nc_N\phi_N$ , so  $|Av|^2 =$  $\lambda_1^2 c_1^2 + \cdots + \lambda_N^2 c_N^2$ . Since the  $\lambda_n$  are nondecreasing, this is bounded from above by  $\lambda_N^2 c_1^2 + \dots + \lambda_N^2 c_N^2 = \lambda_N^2 |v|^2$ .
- (Ad)  $p_{n+1} = r_{n+1} + \beta_n p_n = r_n \alpha_n w_n + \beta_n p_n = r_n \alpha_n A p_n + \beta_n p_n = p_n \beta_{n-1} p_{n-1} \alpha_n A p_n + \beta_n p_n = (1 + \beta_n) p_n \alpha_n A p_n \beta_{n-1} p_{n-1}.$
- (Ae) If A has characteristic equation  $\lambda^N + c_{N-1}\lambda^{N-1} + \cdots + c_0$ , then, by the Cayley-Hamilton theorem,  $A^N + c_{N-1}A^{N-1} + \cdots + c_0I = 0$ , so subtracting all of the left side but the  $A^N$  term from both sides shows that  $A^N = -c_{N-1}A^{N-1} \cdots c_0I$ , a linear combination of the desired form.

(Af) i. If  $u_n = u + e_n$ , then  $u_{n+1} = u_n + \alpha(f - Au_n) = u + e_n + \alpha(f - Au - Ae_n) = u + (I - \alpha A)e_n$ . ii. Note that the eigenvalues of  $I - \alpha A$ ) are  $1 - \lambda_1, \dots, 1 - \lambda_N$ . By a proof similar to that for (Aciv), but using the magnitudes of the new eigenvalues as they are no longer guaranteed to be positive, we see that  $|e_{n+1}| \leq |1 - \alpha \lambda_j| |e_n|$  for j making these bounds least strict. iii. The smallest  $\rho$  is found when  $1 - \alpha \lambda_1 = -1 + \alpha \lambda_N$  — for  $\alpha$  higher,  $|1 - \alpha \lambda_N|$  will be larger, and for  $\alpha$  lower  $|1 - \alpha \lambda_1|$  will be larger. As such, we set  $2 - \alpha(\lambda_1 + \lambda_N) = 0$ , so  $\alpha = \frac{2}{\lambda_1 + \lambda_N}$ , and  $\rho = \frac{\lambda_N - \lambda_1}{\lambda_N + \lambda_1} < 1$ . iv. Since c and c bound the c is less than or equal to c is less than or equal to c is less than or equal to c is holds for all c is it must hold for the value of c maximizing the bounds.

(Ag) i.  $r_1=r_0-\alpha_0w_0$ ,  $w_0$  is defined as  $Ap_0$ , and  $r_0=p_0$ , so  $r_1=r_0-\alpha_0Ar_0$ . ii.  $r_{n+1}=r_n-\alpha_nw_n=r_n-\alpha_nAp_n=r_n-\alpha_nA(r_n+\beta_{n-1}p_{n-1})=r_n-\alpha_nAr_n+\alpha_n\beta_{n-1}(-w_{n-1})=r_n-\alpha_nAr_n+\frac{\alpha_n\beta_{n-1}}{\alpha_{n-1}}(r_n-r_{n-1})$ . iii.  $q_1=\frac{r_1}{|r_1|}=\frac{r_1/|r_0|}{|r_1|/|r_0|}=\frac{r_1/|r_0|}{\sqrt{\beta_0}}$ , so  $Aq_0=\frac{Ar_0}{|r_0|}=\frac{r_0-r_1}{\alpha_0|r_0|}=\gamma_0q_0-\delta_0q_1$ . For  $n\geq 1$ ,  $q_{n+1}=\frac{r_{n+1}/|r_n|}{\sqrt{\beta_n}}$  and  $q_{n-1}=\sqrt{\beta_{n-1}}r_{n-1}/|r_n|$ , so  $Aq_n=\frac{Ar_n}{|r_n|}=\frac{1}{\alpha_n|r_n|}(r_n-r_{n-1})=\frac{1}{\alpha_n|r_n|}((1+\frac{\alpha_n\beta_{n-1}}{\alpha_{n-1}})r_n-r_{n+1}-\frac{\alpha_n\beta_{n-1}}{\alpha_{n-1}}r_{n-1})=\gamma_nq_n-\delta_nq_{n+1}-\delta_{n-1}q_{n-1}$ . iv. Converting the equations from (Agiii) into matrix form (provided the matrix will be on the right) yields the coefficients of  $T_n$ , with the notable exception of the  $-\delta_{n-1}q_n$  term from the equation for  $Aq_{n-1}$ . Manually subtracting this term yields the formula  $AQ_n=Q_nT_n-\delta_{n-1}q_ne_n^T$ , as printed. v.  $Q_n^TAQ_n=Q_n^TQ_nT_n-Q_n^t\delta_{n-1}q_ne_n^T$ , which, as the  $q_j$  are orthonormal, is  $T_n-0\delta_{n-1}e_n^T=T_n$ .

- (B) Dividing [0, 1] into N subintervals i.e., taking N+1 samples and performing brute-force calculations on a very fine grid (1000000 times finer than the value of N tested) shows that the uniform error appears to shrink to less than 0.01 at N=1716.
- (Ca) Estimating the function's second derivatives using the standard 3-and 5-point stencils and treating its value as 0 outside of the boundaries, in addition to initializing the function to 0 at time 0 and to  $f(x)f(y)\Delta t$  after the first step, results in a solver found on GitHub (Python 3). Unfortunately, due to the large quantity of variables considered, I ran out of memory before being able to compute many high-quality numerical solutions. A log-log plot is found in the GitHub repository, with the admittedly low  $\Delta t$  of 0.05, showing a slope of roughly 4 quadratic in the total number of grid points, and even more efficient in terms of the grid spacing.

- (Cb) We see that  $\frac{1}{\Delta t^2}(y_{i+1}-2y_i+y_{i-1})=\lambda y_i$ , so  $y_{i+1}=(2+\lambda\Delta t^2)y_i-y_{i-1}$ . Setting  $z=\lambda\Delta t^2$ , we see that the two generating solutions to this equation are consecutive powers of  $\frac{1}{2}(2+z+\sqrt{4z+z^2})$  and its reciprocal. The system is stable, then, when the absolute value of this root is 1 that is, when  $z \in (-4,0)$ . A graph of this (simple) region is in the GitHub.
- (Cc) The one-dimensional Laplacian with grid spacing  $\Delta x$  has eigenvalues ranging from 0 to  $\frac{-4}{\Delta x^2}$  and the two-dimensional case has double this range (by HW1's (Cd)), so our criterion for stability is  $\frac{-8\Delta t^2}{\Delta x^2} \in (0,4)$  (i.e.  $\frac{\Delta t^2}{\Delta x^2} \in (0,0.5)$ ).
- (Cd) Performing the discrete Laplacian on a plane wave  $e^{i\Delta x(xj+yk)}$  for j,k wave parameters results in  $\nabla^2 y = \frac{2}{\Delta x^2}(\cos j\Delta x + \cos k\Delta x 2)y$ , which lies between 0 and  $\frac{-8y}{\Delta x^2}$ . The resulting quadratic equation for the scaling factor in time is  $g^2 (2 \frac{8\Delta t^2}{\Delta x^2})g + 1 = 0$ , which results in the same range  $\frac{\Delta t^2}{\Delta x^2} \in (0, 0.5)$  found in (Cc).
- (Ce) A simple analysis of the component second-derivative formulas for this method yields the modified equation  $v_{xx} + v_{yy} + \frac{\Delta x^2}{12}(v_{xxxx} + v_{yyyy}) = v_{tt} + \frac{\Delta t^2}{12}v_{tttt}$ . For comparison, the normal heat equation implies the PDE  $v_{xx} + v_{yy} + \frac{\Delta t^2}{12}(v_{xxxx} + v_{yyyy} + 2v_{xxyy}) = v_{tt} + \frac{\Delta t^2}{12}v_{tttt}$ , so we see that if  $\Delta x = \Delta t$  then v only solves the heat equation when  $v_{xxyy} = 0$ . Looking at the behavior of plane waves  $v(x, y, t) = e^{i(a_x x + a_y y + a_t t)}$  gives us the criterion that  $\frac{\Delta x^2}{12}(a_x^4 + a_y^4) a_x^2 a_y^2 = \frac{\Delta t^2}{12}a_t^4 a_t^2$ , resulting in different solution waves from the normal heat equation  $(a_x^2 + a_y^2 = a_t^2)$ . The extra terms are fourth-order and therefore dissipative.
- (D) I have not completed this problem, but I would imagine an approach could be taken which considers roots of polynomials akin to the roots required to be  $\leq 1$  for the stability of second-order equations. This notion of stability likely applies to second-order equations much like Lax-Richtmyer stability does for first-order ones, similarly to how eigenvalues for new equations created by the method of lines can be checked for in preexisting stability regions.