

- plan
- finish functional analysis review
 - stability analysis of $D_t^+ u = D_x^+ D_x^- u$ in the 1-norm, 2-norm
 - amplification factor (how it is used. Theory next time)
-

Linear operators

$$A: X \rightarrow Y$$

↑ ↑
Banach spaces

$$A(x+y) = Ax + Ay$$

$$A(\alpha x) = \alpha Ax$$

Linear functionals

$$\rho: X \rightarrow \mathbb{C}$$

(or \mathbb{R} if X is real) ↗

$$\rho(f+g) = \rho(f) + \rho(g)$$

$$\rho(\alpha f) = \alpha \rho(f)$$

An operator is bounded if there is a constant C s.t.

$$\|Ax\| \leq C\|x\| \quad \forall x \in X \quad \textcircled{+}$$

The smallest constant C that works is the norm of the operator

$$\|A\| = \sup_{x \neq 0} \frac{\|Ax\|}{\|x\|} = \sup_{\|x\|=1} \|Ax\|$$

sup means supremum, or least upper bound

note $\|A\| \geq \frac{\|Ax_0\|}{\|x_0\|}$ for any particular x_0

(it's the maximum value attained or approached, which is equivalent to being the smallest among all upper bounds)

if $\|Ax\| \leq C\|x\|$ for all x , then $\|A\| \leq C$ $\left(\begin{array}{l} C \text{ is an upper} \\ \text{bound on} \\ \left\{ \frac{\|Ax\|}{\|x\|} : x \neq 0 \right\} \end{array} \right)$

To prove that $\|A\| = C$

① show $\|Ax\| \leq C\|x\| \quad \forall x \in X$ (so $\|A\| \leq C$ and $C \geq 0$)

and $\left\{ \begin{array}{l} \text{or} \\ \text{(2a)} \end{array} \right. \begin{array}{l} \exists x_0 \neq 0 \text{ s.t. } \|Ax_0\| \geq C\|x_0\| \\ \text{(this covers the case of } C=0 \text{)} \end{array} \left(\text{so } \|A\| \geq \frac{\|Ax_0\|}{\|x_0\|} \geq C \right)$

$\left(\text{2b} \right)$ if $0 < K < C$ then $\exists x_0$ s.t. $\|Ax_0\| > K\|x_0\|$
(so $\|A\| \geq \frac{\|Ax_0\|}{\|x_0\|} > K$ for all $K < C$, which implies $\|A\| \geq C$)
(note that $\|Ax_0\| > K\|x_0\| \geq 0 \Rightarrow x_0 \neq 0$)

$\left(\text{2a} \right)$ is usually easier to prove if such an x_0 exists,
but in ∞ -dimensions, there may not be a maximizer of $\|Ax\|$
over $\|x\|=1$ (that's why we write sup instead of max)

The norm notation is used because the

space of bounded operators $A: X \rightarrow Y$ is a Banach space

with this norm $\left(\begin{array}{l} A+B \text{ is the operator } (A+B)x = Ax + Bx \\ \alpha A \text{ " " " } (\alpha A)x = \alpha(Ax) \end{array} \right)$

exercise: show that ① $\|A+B\| \leq \|A\| + \|B\|$ ($A, B: X \rightarrow Y$)

② $\|BA\| \leq \|B\| \cdot \|A\|$ ($B: Y \rightarrow Z$)

③ $\|A^n\| \leq \|A\|^n$ ($Y = X$)

An $m \times n$ matrix is an operator from $\mathbb{R}^n \rightarrow \mathbb{R}^m$ (or $\mathbb{C}^n \rightarrow \mathbb{C}^m$)

$$1\text{-norm: } \|A\|_1 = \max_j \sum_i |a_{ij}| \quad \left\{ \begin{array}{l} \text{maximum absolute} \\ \text{column sum} \\ \text{(sum over the} \\ \text{entries of each column)} \end{array} \right.$$

$$\infty\text{-norm: } \|A\|_\infty = \max_i \sum_j |a_{ij}| \quad \left\{ \begin{array}{l} \text{max absolute} \\ \text{row sum} \end{array} \right.$$

$$2\text{-norm: } \|A\|_2 = \sigma_1 \quad \left\{ \begin{array}{l} \text{largest singular value} \\ A = U S V^H, \quad \leftarrow \text{Hermitian transpose} \\ S = (\sigma_1 \dots \sigma_n) \\ \sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n \geq 0 \\ U \text{ } m \times n, V \text{ } n \times n \\ U, V \text{ isometries } (U^H U = I) \end{array} \right. \quad \left. \begin{array}{l} m \geq n \\ \text{case} \end{array} \right\} \quad \begin{array}{l} v^H = \overline{v^T} \\ \text{A.K.A. conjugate transpose} \end{array}$$

Proof for the ∞ -norm case.

Let i_0 be the row maximizing the absolute row sum

$$\text{and let } C = \sum_j |a_{i_0 j}|$$

$$\text{step 1. for any } x \in \mathbb{R}^n, |(Ax)_{i_0}| = |a_{i_0 1} x_1 + \dots + a_{i_0 n} x_n|$$

$$\leq \sum_j |a_{i_0 j}| |x_j|$$

$$\leq \left(\sum_j |a_{i_0 j}| \right) \max_k |x_k| \leq C \|x\|_\infty$$

$$\text{So } \|Ax\| = \max_i |(Ax)_i| \leq C \|x\|_\infty$$

step 2. let $y_j = \text{sgn}(a_{i_0 j}) = \begin{cases} 1 & a_{i_0 j} > 0 \\ 0 & " = 0 \\ -1 & " < 0 \end{cases}$ (writing y instead of x_0)

Then $\|y\|_\infty = 1$ and $(Ay)_{i_0} = \sum_j a_{i_0 j} \text{sgn}(a_{i_0 j}) = C$

so $\|Ay\|_\infty \geq C \|y\|_\infty$. $\therefore \|A\| = C$.

Recall that we can think of our discrete evolution operator B ($u^{n+1} = B u^n$) as an infinite tridiagonal

Toeplitz matrix:

$$B = \begin{pmatrix} & & & \\ & \text{diag} & & \\ & \nu & 1-2\nu & \nu \\ & & & \end{pmatrix} \leftarrow \text{row zero}$$

The max norm (operator norm of B acting on ℓ^∞) is the maximum absolute row sum

$$\|B\|_\infty = |\nu| + |1-2\nu| + |\nu| = \begin{cases} 1 & 0 \leq \nu \leq \frac{1}{2} \\ 4\nu-1 & \nu > \frac{1}{2} \\ 1-4\nu & \nu < 0 \end{cases}$$

(all row sums are the same)

\nearrow less important since $\nu = \frac{k}{h^2} > 0$

similarly, $\|B\|_1 = \text{max absolute column sum}$

which has the same numerical value as $\|B\|_\infty$

$$|\nu| + |1-2\nu| + |\nu|$$



$$\begin{pmatrix} & & & \\ & \text{diag} & & \\ & \nu & 1-2\nu & \nu \\ & & & \end{pmatrix}$$

One can repeat the Lax-Richtmyer analysis in the 1-norm.

First, this is reasonable as the heat equation does not lead to growth in the 1-norm

$$\begin{aligned} u_t &= u_{xx} \\ u(x,0) &= g(x) \end{aligned} \quad \rightarrow \quad u(x,t) = \frac{1}{\sqrt{4\pi t}} \int_{-\infty}^{\infty} e^{-\frac{(x-\xi)^2}{4t}} g(\xi) d\xi$$

$$\text{so } |u(x,t)| \leq \frac{1}{\sqrt{4\pi t}} \int_{-\infty}^{\infty} e^{-\frac{(x-\xi)^2}{4t}} |g(\xi)| d\xi$$

↑
equality if $g(x) \geq 0$

$$\begin{aligned} \therefore \int_{-\infty}^{\infty} |u(x,t)| dx &\leq \int_{-\infty}^{\infty} \frac{1}{\sqrt{4\pi t}} \int_{-\infty}^{\infty} e^{-\frac{(x-\xi)^2}{4t}} |g(\xi)| d\xi dx \\ &= \int_{-\infty}^{\infty} \left(\int_{-\infty}^{\infty} \frac{1}{\sqrt{4\pi t}} e^{-\frac{(x-\xi)^2}{4t}} dx \right) |g(\xi)| d\xi \end{aligned}$$

↑
legal to change order of integration when the integrand is positive.

result: for all positive times,

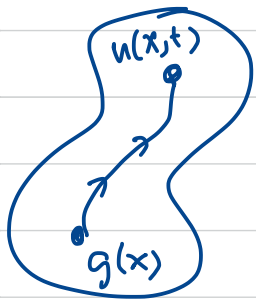
$$\int_{-\infty}^{\infty} |u(x,t)| dx \leq \int_{-\infty}^{\infty} |g(x)| dx$$

↑

and if $g(x) \geq 0$ this inequality is an equality.

(it becomes an inequality again on a finite interval with Dirichlet b.c.'s)

In our "evolution on a Banach space" framework,



$B = C^1(\mathbb{R}) =$ "integrable functions on \mathbb{R} "

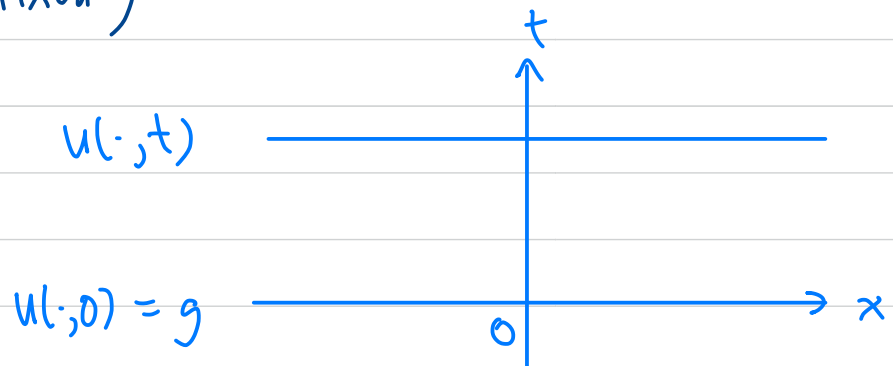
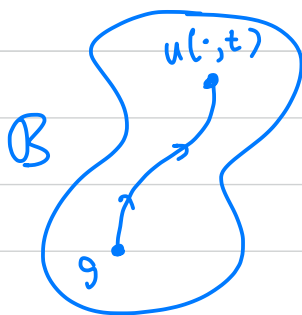
$$\|g\| = \int_{-\infty}^{\infty} |g(x)| dx \quad \leftarrow \text{norm in } B$$

B

the solution $u(x,t)$ of $\begin{cases} u_t = u_{xx} \\ u(x,0) = g(x) \end{cases}$ satisfies

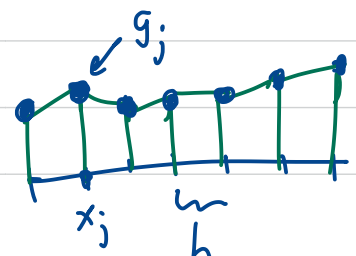
$$\|u(\cdot, t)\| \leq \|g\| \quad (t \geq 0)$$

The dot indicates that we're thinking of u as a function of its first argument only (with the parameter t fixed)



$B_h = \ell_h^1 =$ "summable sequences"

$$\|g\|_{1,h} = h \sum_{j=-\infty}^{\infty} |g_j|$$

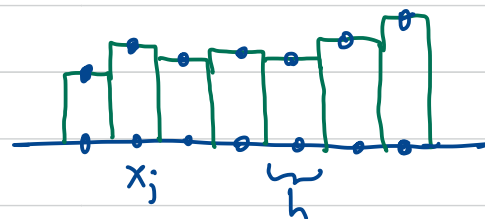


This is the trapezoidal rule approximation

if you sample $g_j = g(x_j)$, $x_j = jh$

Same result but different picture:

(midpoint rule)
same quadrature rule



The h in the norm definition doesn't affect the "max absolute column sum" formula $\|B\|_1 = |v| + |1-2v| + |v|$

Since
$$\|B\|_{1,h} \sup_{u \neq 0} \frac{\|Bu\|_{1,h}}{\|u\|_{1,h}} = \sup \frac{h \|Bu\|_1}{h \|u\|_1} = \|B\|_1$$

One can still prove that
$$\|T^n\|_{1,h} \leq \begin{cases} (\frac{h}{2} + \frac{h^2}{12})M & v \neq \frac{1}{6} \\ (\frac{h^2}{6} + \frac{h^4}{360})M & v = \frac{1}{6} \end{cases} \quad (*)$$

but now (in a 1-norm analysis)

$$M = \max_{\substack{0 \leq h \leq 1 \\ 0 \leq x \leq h}} h \sum_j |g^{(\mu)}(x+jh)|$$

arbitrary upper bound on h

$$\mu = \begin{cases} 4 & v \neq 1/6 \\ 6 & v = 1/6 \end{cases}$$

worst (largest) discrete integral of $|g_{xxxxx}(x)|$ or $|x^6 g(x)|$

(see pages 38-40 of my 2007 notes for full details
 ↳ posted on my Berkeley webpage
 I use the Cauchy form of Taylor's theorem with remainder)

Lax-Richtmyer analysis

The error $e_j^n = u_j^n - u(jh, nk)$ satisfies $e^{n+1} = B e^n - k \tau^n$

$$k \leq \varepsilon = \nu \quad \Rightarrow \quad \|e^n\| \leq K k n \max_{0 \leq l \leq n-1} \|\tau^l\|, \quad (nk \leq T)$$

need $\nu \leq \frac{1}{2}$ so $\|B^n\|_1 \leq K = 1$ and $h \leq 1$ to use \oplus here

result: if $\nu \leq \frac{1}{2}$ and $0 < k \leq \varepsilon = \nu$ then $(h = \sqrt{k/\nu} \leq 1 \Leftrightarrow k \leq \nu)$ 10
 $\varepsilon = \nu$

$$\max_{0 \leq nk \leq T} h \sum_{j=-\infty}^{\infty} |e_j^n| \leq \begin{cases} \left(\frac{k}{2} + \frac{h^2}{12}\right) TM & \nu \neq \frac{1}{6}, \nu \leq \frac{1}{2} \\ \left(\frac{k^2}{6} + \frac{h^4}{360}\right) TM & \nu = \frac{1}{6} \end{cases}$$

In the max norm analysis this

was $\max_j |e_j^n|$ and M was $\max_x |g^{(\mu)}(x)|$
 $(\mu = 4 \text{ if } \nu \neq \frac{1}{6}, \mu = 6 \text{ if } \nu = \frac{1}{6})$

Final variant: 2-norm

$$B = L^2(\mathbb{R}), \quad \|g\| = \sqrt{\int_{-\infty}^{\infty} |g(x)|^2 dx}$$

$$B_h = \ell_h^2, \quad \|g\|_{2,h} = \sqrt{h \sum_j |g_j|^2}$$

To determine the stability of B acting on ℓ_h^2 , one computes the amplification factor of the scheme

finite difference
operator

$$B u_j = \nu u_{j+1} + (1-2\nu)u_j + \nu u_{j-1}$$

amplification
factor

$$\begin{aligned} G(\xi) &= \nu e^{i\xi} + (1-2\nu)e^0 + \nu e^{-i\xi} \\ &= 1 + \nu(e^{i\xi/2} - e^{-i\xi/2})^2 \\ &= 1 - 4\nu \sin^2 \frac{\xi}{2} \end{aligned}$$

$$\sin x = \frac{e^{ix} - e^{-ix}}{2i}$$

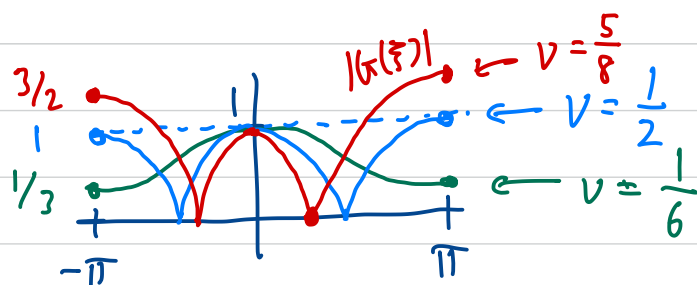
$$\sin^2 x = \left(\frac{\quad}{-4} \right)^2$$

We will see that $\|B\|_{\ell_h^2} = \|G\|_{\infty}$



max norm on $[-\pi, \pi]$

$$|G(\xi)| = \left| 1 - 4\nu \sin^2 \frac{\xi}{2} \right|$$



if $\nu > \frac{1}{2}$ then

$$-4\nu \sin^2 \frac{\pi}{2} < -2$$

$$\text{so } 1 - 4\nu \sin^2 \frac{\pi}{2} < -1$$

$$|1 - 4\nu \dots| > 1$$

As expected, the transition from $\|B\| \leq 1$ to $\|B\| > 1$

occurs at $\nu = \frac{1}{2}$

The rest of the Lax-Richtmyer convergence proof in the 2-norm is very similar to the 1-norm analysis.

first show that $\|T^n\|_{2,h} \leq \begin{cases} M \sqrt{\frac{2}{3}k^2 + \frac{1}{63}h^4} & v \neq \frac{1}{6} \\ M \sqrt{\frac{k^4}{10} + \frac{h^8}{39600}} & v = \frac{1}{6} \end{cases}$

(see scratch work below)

where $M = \max_{\substack{0 \leq h \leq 1 \\ 0 \leq x \leq h}} \sqrt{h \sum_j |g^{(\mu)}(x+jh)|^2}$

$\mu = 4$ if $v \neq \frac{1}{6}$
 $= 6$ if $v = \frac{1}{6}$

Conclusion from Lax-Richtmyer:

if $v \leq \frac{1}{2}$ and $0 < h \leq v$ then $\|B(k)^n\| \leq 1$ and

$$\max_{0 \leq nk \leq T} \sqrt{h \sum_j |e_j^n|^2} \leq \begin{cases} MT \sqrt{\frac{2}{3}k^2 + \frac{1}{63}h^4} & v \neq \frac{1}{6}, v \leq \frac{1}{2} \\ MT \sqrt{\frac{k^4}{10} + \frac{h^8}{39600}} & v = \frac{1}{6} \end{cases}$$

The 2-norm analysis (von-Neumann stability analysis) is the version that generalizes most easily to implicit methods. This is the topic of the next lecture.

scratch work for $v \neq \frac{1}{6}$ case of L_h^2 truncation error analysis

$$|\tau_j^n| \leq \begin{cases} k \int_0^1 |u_{xxxx}(x_j, t_n + \theta k)| (1-\theta) d\theta \\ + \frac{h^2}{6} \int_0^1 |u_{xxxx}(x_j + \theta h, t_n)| (1-\theta)^3 d\theta \\ + \frac{h^2}{6} \int_0^1 |u_{xxxx}(x_j - \theta h, t_n)| (1-\theta)^3 d\theta \end{cases}$$

$\tau = a + b + c$, each positive

$$\tau^2 \leq a^2 + b^2 + c^2 + 2ab + 2ac + 2bc$$

$$\leq 2(a^2 + b^2 + c^2)$$

$$\begin{aligned} a^2 &= k^2 \left(\int_0^1 |\tilde{u}(\theta)| (1-\theta) d\theta \right)^2 \leq k^2 \int_0^1 |\tilde{u}(\theta)|^2 d\theta \int_0^1 (1-\theta)^2 d\theta \\ &= \frac{k^2}{3} \int_0^1 |\tilde{u}(\theta)|^2 d\theta \end{aligned}$$

$$b^2 = \frac{h^4}{36} \left(\int_0^1 |\tilde{u}(\theta)| (1-\theta)^3 d\theta \right)^2 \leq \frac{h^4}{36} \int_0^1 |\tilde{u}(\theta)|^2 d\theta \int_0^1 (1-\theta)^6 d\theta$$

$$c^2 = \frac{h^4}{36 \cdot 7} \int_0^1 |\tilde{u}(\theta)|^2 d\theta$$

$$h \sum_j 2(a^2 + b^2 + c^2) \leq \left(\frac{2}{3} k^2 + \frac{h^4}{63} \right) \max_x h \sum_j |\tilde{u}_j(\theta)|^2$$

$$|u(x)|^2 \leq \left(\frac{1}{\sqrt{4\pi t}} \int e^{-\frac{(x-\xi)^2}{4t}} |g(\xi)| d\xi \right)^2 \leq \frac{1}{\sqrt{4\pi t}} \int e^{-\dots} |g(\xi)|^2 d\xi$$

$$\begin{aligned} h \sum_j |u(x+jh)|^2 &\leq \frac{1}{\sqrt{4\pi t}} \int e^{-\dots} h \sum_j |g(\xi+jh)|^2 d\xi \\ &\leq \max_x h \sum_j |\tilde{g}(\xi+jh)|^2 \end{aligned}$$

$$\sqrt{h \sum_j |\tau_j^n|^2} \leq \sqrt{\left(\frac{2}{3} k^2 + \frac{1}{63} h^4 \right)} \sqrt{\max_{\substack{0 \leq h \leq 1 \\ 0 \leq x \leq h}} h \sum_j |g_{xxxx}(x+jh)|^2}$$

$$\left(\sqrt{\frac{2}{3}} k + \sqrt{\frac{1}{63}} h^2 \right)$$

scratch work for $\nu = \frac{1}{6}$ in L_h^2 analysis

$$\nu = \frac{1}{6} \quad \underbrace{\frac{k^2}{2} \int_0^1 |\tilde{u}| (1-\theta)^2 d\theta}_{a} + \underbrace{\frac{h^4}{5!} \int_0^1 |\tilde{u}| (1-\theta)^5 d\theta}_{L, c}$$

u_{ttt} u_{xxxxxx}

$$\tau = a + L + c$$

$$\tau^2 \leq 2(a^2 + L^2 + c^2)$$

$$a^2 \leq \frac{k^4}{4} \int_0^1 |\tilde{u}|^2 d\theta \int_0^1 (1-\theta)^4 d\theta = \frac{k^4}{20} \int_0^1 |\tilde{u}|^2 d\theta$$

$$L^2, c^2 \leq \frac{h^8}{(5!)^2} \int_0^1 |\tilde{u}|^2 d\theta \int_0^1 (1-\theta)^{10} d\theta = \frac{h^8}{(5!)^2 \cdot 11} \int_0^1 |\tilde{u}|^2 d\theta$$

$$h \sum_j |\tau_j^n|^2 \leq \sum_j 2(a^2 + L^2 + c^2) \leq \left(\frac{k^4}{10} + \frac{4h^8}{(5!)^2 \cdot 11} \right) \int_0^1 h \sum_j |\tilde{u}_j|^2 d\theta$$

$$\sqrt{h \sum_j |\tau_j^n|^2} \leq \sqrt{\frac{k^4}{10} + \frac{h^8}{39600}} M$$

← max
(get rid of integral)

$$M = \max_{\substack{0 \leq h \leq 1 \\ 0 \leq x \leq h}} \sqrt{h \sum_j |g^{(k)}(x+jh)|^2}$$

$$\nu = \frac{k}{h^2} = \frac{1}{6} \quad h = \frac{1}{6} k^2$$

$$\sqrt{a^2 + L^2} \leq 19.44 \quad \left\| \begin{pmatrix} a \\ 0 \end{pmatrix} + \begin{pmatrix} 0 \\ L \end{pmatrix} \right\| \quad \frac{k^2}{\sqrt{10}} + \frac{h^4}{60\sqrt{11}}$$