

## Convergence

$$\|L^h E^h\|_p \leq \|L^h\|_p \|E^h\|_p$$

[consistency + stability  $\Rightarrow$  convergence]

Consistency:  $\tau = O(h^2) \checkmark$        $L^h E^h = \tau$

Stability?

$$L^h U^h = f^h$$

$$L^h u^h = f^h + \tau$$

$$L^h (u^h - U^h) = \tau$$

# Stability

$$E^h = (L^h)^{-1} \varepsilon$$

$$\|E^h\|_p \leq \|(L^h)^{-1}\|_p \|\varepsilon\|_p$$

$$L^h E^h = \varepsilon$$

- Every: does  $(L^h)^{-1}$  scale up the small errors  $\varepsilon$ ?

$$\|(L^h)^{-1}\|_p \leq C$$

as  $h \rightarrow 0$

$$\frac{1}{h^2} \begin{bmatrix} a \\ b \end{bmatrix} \leftarrow$$

Stability

$$E^h = (L^h)^{-1} \tau \quad u_{xx} = f$$

$$\|E^h\|_p \leq \|(L^h)^{-1}\|_p \|\tau\|_p$$

$$L^h E^h = \tau$$

- Every: does  $(L^h)^{-1}$  scale up the small errors  $\tau$ ?

$$e'' = \tau \quad e = 0 \text{ at } 0, l.$$

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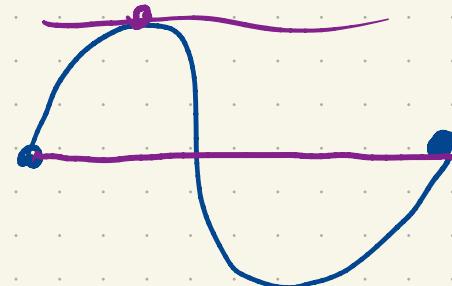
$$L^h E^h = \varepsilon$$

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$$e'' = \varepsilon \quad e=0 \text{ at } 0, l.$$

$$e' = \int_0^x \varepsilon ds$$

$$e'(a) = 0$$



Stability

$$E^h = (L^h)^{-1} \tau$$

$$\|E^h\|_p \leq \|(L^h)^{-1}\|_p \|\tau\|_p$$

$$L^h E^h = \tau$$

- Every: does  $(L^h)^{-1}$  scale up the small errors  $\tau$ ?

$$e'' = \tau \quad e=0 \text{ at } 0, l.$$

$$e' = \int_0^x \tau ds \quad (e'(a)=0)$$

$$e = \int_a^x \int_0^a \tau ds da \quad |e| \leq L^2 \max |\tau|$$

Stability:

$$\| (L^h)^{-1} \|_2 \leq c h^2 \quad \text{as } h \rightarrow 0$$

If  $\| (L^h)^{-1} \|_p \leq C$  as  $h \rightarrow 0$ ,

stability in  $p$ -norm.

$$\| E^h \|_\infty \leq C_\infty \| z \|_\infty = O(h^2)$$

Stability:

If  $\|(\mathcal{L}^h)^{-1}\|_p \leq C$  as  $h \rightarrow 0$ ,

stability in  $p$ -norm.

$$\left[ \sum_{k=1}^N (\varepsilon_k)^2 \right]^{1/2}$$

$$\|\mathcal{E}^h\|_2 \leq C_2 \|\varepsilon\|_2 \leq C_2 \sqrt{N} \|\varepsilon\|_\infty$$

Stability:

If  $\|(\mathcal{L}^h)^{-1}\|_p \leq C$  as  $h \rightarrow 0$ ,

stability in  $p$ -norm.

$$\|E^h\|_2 \leq C_2 \|\boldsymbol{\zeta}\|_2 \leq C_2 \sqrt{N} \|\boldsymbol{\zeta}\|_\infty$$

$$\left[ \int e^z \right]^{l_2} \frac{1}{\sqrt{N}} \|E_2^h\|_2 \leq C_2 \|\boldsymbol{\zeta}\|_\infty = O(h^2)$$

Stability in 2-norm (special case)

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

$$a_{kx} = f$$

$$L^h = L \text{ is symmetric} \Rightarrow L^{-1} \text{ is symmetric}$$

Stability in 2-norm (special case)

$$\frac{1}{\sqrt{100}}$$

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

$$L = \begin{bmatrix} -10 & 0 \\ 0 & 0.01 \end{bmatrix} \quad \|L\| \approx$$

$$L^{-1} = \begin{bmatrix} -1/10 & 0 \\ 0 & 100 \end{bmatrix}$$

$$L^h = L \text{ is symmetric} \Rightarrow L^{-1} \text{ is symmetric}$$

$$\|L^{-1}\| = 100$$

For a symmetric matrix,  $\|B\|_2$  is  $|\lambda|$

↳ largest eigenvalue

$$\|L^{-1}\|_2 = \frac{1}{|\lambda|} \leftarrow \begin{array}{l} \text{smallest} \\ \text{eigenvalue} \end{array}$$

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

Eigenvectors:  $w_i = \sin(r_k x_i)$   $r_k = \frac{\pi}{l} k$   $1 \leq k \leq N$

$$\sin(x) \approx x$$

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

Eigenvectors:  $w_i = \sin(r_k x_i)$        $r_k = \frac{\pi}{l} k \quad 1 \leq k \leq N$

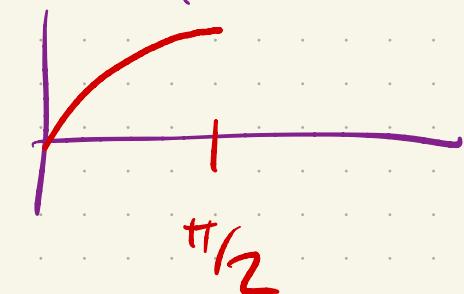
$$\lambda_k = \frac{1}{h^2} \left[ -2 + 2 \cos(r_k h) \right] \quad -1 + \cos(\theta)$$

$$= -\frac{4}{h^2} \sin^2\left(\frac{r_k h}{2}\right)$$

$$h = \frac{l}{N+1}$$

$$r_1 = \frac{\pi}{N+1}$$

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



Eigenvectors:  $w_i = \sin(r_k x_i)$        $r_k = \frac{\pi}{l} k \quad 1 \leq k \leq N$

$$\begin{aligned} \lambda_k &= \frac{1}{h^2} \left[ -2 + 2 \cos\left(\frac{r_k h}{2}\right) \right] \\ &= -\frac{4}{h^2} \sin^2\left(\frac{\frac{r_k h}{2}}{2}\right) \end{aligned}$$

$0 < \frac{r_k h}{2} < \frac{\pi}{2}$

$\frac{1}{2} \frac{\pi}{l} \frac{k}{N+1} l$   
 $\frac{k}{N+1} \frac{\pi}{2}$

$$\lambda_k = -\frac{4}{h^2} \sin^2\left(\frac{r_k h}{2}\right) \quad 1 \leq k \leq N$$
$$r_k = \frac{\pi}{L} k$$

Eigenvalues of  $(L^h)^{-1}$  are  $\frac{1}{\lambda_k}$ ,  $\lambda$  an eigenvalue  
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of  $L$

Smallest eigenvalue,  $h$  small

$$\lambda_1 \approx -\frac{4}{h^2} \left( \frac{r_1^2 h^2}{4} \right) = -r_1^2 = -\frac{\pi^2}{\ell^2}$$

$$\frac{1}{|\lambda|} \approx \frac{l^2}{\pi^2}$$

$$e'' = \tau$$

$$\|(L^h)^{-1}\|_2 \rightarrow \frac{l^2}{\pi^2} \quad \text{as } h \rightarrow 0$$

Stability in 2-norm!

$$\|(\mathbf{h})^{-1}\|_2 \approx \frac{l^2}{\pi^2} \leftarrow \text{as predicted.}$$

$$\partial_x^2 \sin(k\pi x) \quad [0, l]$$

$$-(k\pi)^2 \sin(k\pi x)$$

$$\|(\mathbf{L}^h)^{-1}\|_2 \approx \frac{l^2}{\pi^2} \quad \leftarrow \text{as predicted.}$$

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Biggest eigenvalues of  $(\mathbf{L}^h)$ ?  $\frac{\pi}{2} \frac{N}{N+1}$

$$-\frac{4}{h^2} \sin^2\left(\frac{nh}{2}\right) \quad \text{controlled by } \frac{1}{h^2} = O(N^2)$$

$$\sin''(kx) = -k^2 \sin(kx)$$

## Direct Proof of $L^\infty$ Convergence

$$a_k E_k = -b_k E_{k-1} - c_k E_{k+1} + \gamma_k h^2$$

$$b_k = 1 - \frac{p_k h}{2}, \quad c_k = 1 + \frac{p_k h}{2}, \quad a_k = -2 - q_k h^2$$

$$\frac{1}{h^2} \begin{bmatrix} b & c \\ 0 & b & c \\ 0 & 0 & b & c \end{bmatrix}$$

## Direct Proof of $L^\infty$ Convergence

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$$\text{Assuming } q_* \leq \gamma < 0, \quad \left| \frac{p_k h}{2} \right| \leq \frac{1}{2}$$

# Direct Proof of $L^\infty$ Convergence

$$a_k E_k = -b_k E_{k-1} - c_k E_{k+1} + \gamma_k h^2$$

$$b_k = 1 - \frac{p_k h}{2}, \quad c_k = 1 + \frac{p_k h}{2}, \quad a_k = -2 + q_k h^2$$

Assuming  $q_k \leq \gamma < 0$ ,  $\left| \frac{p_k h}{2} \right| < 1$

$$(2 - \gamma h^2) |E_k|$$

$$\leq 2 \left[ \left( \frac{1}{2} - \frac{p_k h}{4} \right) |E_{k-1}| + \left( \frac{1}{2} + \frac{p_k h}{4} \right) |E_{k+1}| \right] + h^2 |\gamma_k|$$

$$2|E_k| \leq \left(1 - \frac{p_k h}{2}\right)|E_{k-1}| + \left(1 + \frac{p_k h}{2}\right)|E_{k+1}| + h|\tilde{\epsilon}_k|$$

$$\hat{E} = \max_{1 \leq k \leq N} |E_k|, \quad \hat{\epsilon} = \max_{1 \leq k \leq N} |\tilde{\epsilon}_k|$$

$$(2 + \gamma h^2) \hat{E} \leq 2 \max(\hat{E}, |E_0|, |E_{N+1}|) + h |\hat{\epsilon}|$$

$$\leq 2 \hat{E} + 2 \max(|E_0|, |E_{N+1}|) + h^2 |\hat{\epsilon}|$$

$$\gamma h^2 \hat{E} \leq 2 \max(|E_0|, |E_{N+1}|) + h^2 |\hat{\epsilon}|$$

$$(2 + \gamma h^2) |E_k|$$

$$E_0, E_{N+1} = 0$$

$$\leq 2 \left[ \left( \frac{1}{2} - \frac{p_k h}{4} \right) |E_{k-1}| + \left( \frac{1}{2} + \frac{p_k h}{4} \right) |E_{k+1}| \right] + h^2 |\tilde{\tau}_k|$$

$$\hat{E} = \max_{1 \leq k \leq N} |E_k| ; \quad \hat{\tau} = \max | \tilde{\tau}_k |$$

$$(2 + \gamma h^2) |E_k| \leq 2 \hat{E} + h^2 \hat{\tau}$$

$$(2 \leq k \leq N-1)$$

almost:  $\hat{E} \leq \gamma^{-1} \hat{\tau}$

$$\max_k |E_k|$$

$$(2 - \gamma h^2) |E_k| \leq 2 \hat{E} + h^2 \hat{\sigma}$$

$$2 |E_k| - \gamma h^2 |E_k| \leq 2 \hat{E} + h^2 \hat{\sigma}$$

$$2 \hat{E} - \gamma h^2 \hat{E} \leq 2 \hat{E} + h^2 \hat{\sigma}$$

$$-\gamma h^2 \hat{E} \leq h^2 \hat{\sigma} \Rightarrow -\gamma \hat{E} \leq \hat{\sigma}$$

$$(2 + \gamma h^2) |E_k|$$

$$\leq 2 \left[ \left( \frac{1}{2} - \frac{p_k h}{4} \right) |E_{k-1}| + \left( \frac{1}{2} + \frac{p_k h}{4} \right) |E_{k+1}| \right] + h^2 |\tau_k|$$

$$(2 + \gamma h^2) |E_1| \leq 2 \left[ \frac{3}{4} |E_2| + \frac{3}{4} |E_0| \right] + h^2 |\tau_k|$$

$$(2 + \gamma h^2) |E_1| \leq \frac{3}{2} \hat{E} + \frac{3}{2} |E_0| + h^2 |\tau_k|$$

$$|E_1| \leq \frac{3}{4} \hat{E} + \frac{3}{4} |E_0| + |\tau_k| \quad (h \leq 1)$$

Upshot

$$\hat{E} \leq C \left[ \max(|E_0|, |E_{NH}|) + \hat{\tau} \right]$$

## Related Issue: Condition Number.

We want to solve  $Ax = b$  but  $b$  isn't exact.

We solve  $\hat{A}\hat{x} = \hat{b}$  instead.

What's the relative error in  $x$ ?

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$$Ax = b \quad x = A^{-1}b$$
$$A\hat{x} = \hat{b} \quad \hat{x} = A^{-1}\hat{b}$$

$$\frac{\|\hat{x} - x\|}{\|x\|} = \frac{\|A^{-1}(\hat{b} - b)\|}{\|x\|^2}$$

What's the relative error in  $\hat{x}$ ?

$$\frac{\|\hat{x} - x\|}{\|x\|^2} = \frac{\|A^{-1}(\hat{b} - b)\|}{\|x\|} \leq \frac{\|A^{-1}\| \| \hat{b} - b \|}{\|x\|}$$

$$Ax = b$$

What's the relative error in  $x$ ?

$$\begin{aligned}\frac{\|\hat{x} - x\|}{\|x\|} &= \frac{\|A^{-1}(\hat{b} - b)\|}{\|x\|^2} \leq \frac{\|A^{-1}\| \| \hat{b} - b \|}{\|x\|} \\ &= \frac{\|A^{-1}\| \|b\|}{\|x\|} \frac{\|\hat{b} - b\|}{\|b\|}\end{aligned}$$

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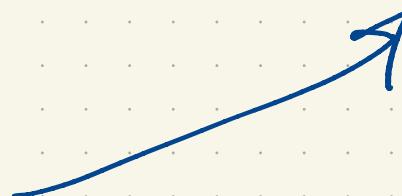
$$\begin{aligned}\frac{\|\hat{x} - x\|}{\|x\|} &= \frac{\|A^{-1}(\hat{b} - b)\|}{\|x\|^2} \leq \frac{\|A^{-1}\| \| \hat{b} - b \|}{\|x\|} \\ &= \frac{\|A^{-1}\| \|b\|}{\|x\|} \frac{\|\hat{b} - b\|}{\|b\|} \\ &\leq \|A^{-1}\| \frac{\|A\|}{\|x\|} \frac{\|\hat{b} - b\|}{\|b\|} \\ &\leq \|A^{-1}\| \|A\| \frac{\|\hat{b} - b\|}{\|b\|}\end{aligned}$$

$\rightarrow K \rightarrow$  condition number

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relative  
error  
in  $b$



# Condition Number

$$\frac{\|\hat{x} - x\|}{\|x\|^2} \leq \|A^{-1}\| \|A\| \frac{\|\hat{b} - b\|}{\|b\|}$$

relative  
error in  
r.h.s  
( double  
precision:  
 $10^{-15}$ )

you can't, in general,  
beat this

$$K(A) = \|A\| \|A^{-1}\| \quad \text{in some norm}$$

Condition Number of  $L^h$

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

$$\|(L^h)^{-1}\|_2 \approx 1 \quad K \approx 1 \cdot N^2$$

$$\|L^h\|_2 = O(N^2)$$

$\hookrightarrow |\lambda| \leftarrow$  biggest eigenvalue

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$\|A\|_2 = \max(|\lambda|)$  &  $A$  is symmetric.

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$$\|A^{-1}\|_2 = \max(|\lambda|^{-1}) = [\min(|\lambda|)]^2$$

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$$h = \frac{\lambda}{N}$$

$\|A\|_2 = \max(|\lambda|)$  &  $A$  is symmetric.

$$\|A^{-1}\|_2 = \max(|\lambda|^{-1}) = [\min(|\lambda|)]^2$$

$$\min(|\lambda|) \rightarrow \frac{\pi^2}{L^2}, \quad \max(|\lambda|) = \sim \frac{1}{h^2} \sim \frac{N^3}{L^2}$$

$$K \sim \frac{1}{\pi^2} N^2$$

$$N=1000 \Rightarrow K \sim 10^6$$

$\Rightarrow$  if r.h.s. has a relative error  $10^{-15}$

solution has a relative error  $10^{-9}$

$$10^6 \cdot 10^{-15} = 10^{-9}$$