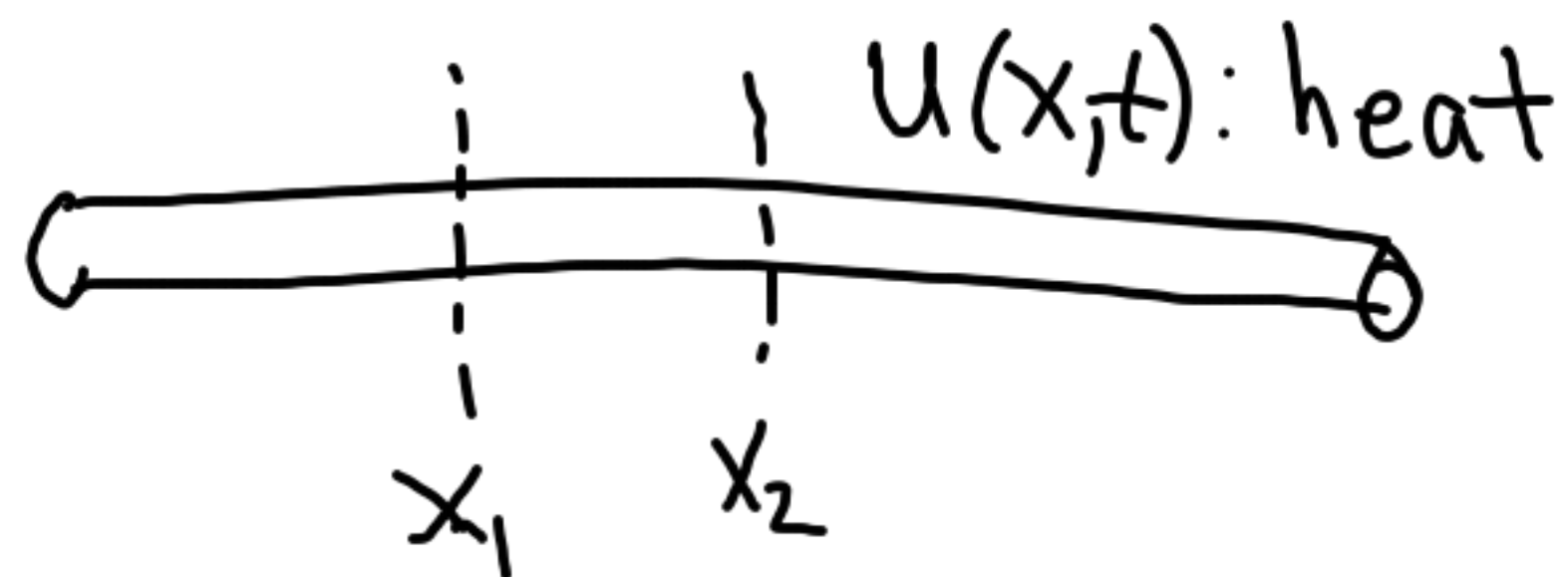


Distribution of heat in a rod



Total heat in (x_1, x_2) : $\int_{x_1}^{x_2} u(x,t) dx$

This changes only due to flux through the endpoints x_1, x_2

$$\frac{d}{dt} \int_{x_1}^{x_2} u(x,t) dx = f(u(x_1,t)) - f(u(x_2,t))$$

$$\int_{x_1}^{x_2} \frac{\partial}{\partial t} u(x,t) dx = - \int_{x_1}^{x_2} \frac{\partial}{\partial x} f(u(x,t)) dx$$

$$\int_{x_1}^{x_2} \left(\frac{\partial}{\partial t} u(x,t) + \frac{\partial}{\partial x} f(u(x,t)) \right) dx = 0$$

This integrand must vanish everywhere:

$$u_t + f(u)_x = 0 \quad (1)$$

This is the general form of a conservation law.

Fick's law of diffusion:

$$f(u) = -Ku_x$$

Substitute into (1):

$$u_t = Ku_{xx}$$

Heat
Equation

Let's include a heat source/sink
along the length of the rod:

$$u_t = Ku_{xx} + \psi(x) \quad \begin{matrix} 0 < x < 1 \\ t > 0 \end{matrix}$$

Fix the temperature at each end:

$$u(0, t) = \alpha \quad u(1, t) = \beta$$

Dirichlet
Boundary
Conditions

As $t \rightarrow \infty$, $u(x, t)$ will tend to
a steady state.

$$Ku_{xx} + \psi(x) = 0$$

$$u_{xx} = -\frac{\psi(x)}{K} = f(x) \leftarrow \text{(not the flux)}$$

$$u''(x) = f(x)$$

$$u(0) = \alpha \quad u(1) = \beta$$

Discretize:

$$0 = x_0 \quad x_1 \quad x_2 \quad x_3 \quad \dots \quad x_{m+1} = 1$$

$$U = \begin{bmatrix} U_0 \\ U_1 \\ \vdots \\ U_{m+1} \end{bmatrix}$$

$$U_j \approx u(x_j) \quad h = \frac{1}{m+1}$$

$$U_0 = \alpha \quad U_{m+1} = \beta$$

of unknowns = m

$$u''(x_j) = \frac{U_{j+1} - 2U_j + U_{j-1}}{h^2}$$

So we have:

for $j=1, \dots, m$

$$\frac{U_{j+1} - 2U_j + U_{j-1}}{h^2} = f(x_j)$$

$$\frac{1}{h^2} \begin{bmatrix} -2 & 1 & & & \\ 1 & -2 & 1 & & \\ & \ddots & \ddots & \ddots & \\ & & 1 & -2 & 1 \\ & & & 1 & -2 \end{bmatrix} \begin{bmatrix} U_1 \\ U_2 \\ \vdots \\ U_m \end{bmatrix} = \begin{bmatrix} f(x_1) - \frac{\alpha}{h^2} \\ f(x_2) \\ \vdots \\ f(x_m) - \frac{\beta}{h^2} \end{bmatrix}$$

$j=1: \frac{U_2 - 2U_1 + \cancel{U_0}}{h^2} = f(x_1)$

$AU = F$

$$\frac{U_2 - 2U_1}{h^2} = f(x_1) - \frac{\alpha}{h^2}$$

$$\hat{U} = \begin{bmatrix} U(x_1) \\ U(x_2) \\ \vdots \\ U(x_m) \end{bmatrix}$$

Global error:

$$E = U - \hat{U}$$

Definition

Let U^h denote the numerical solution obtained with mesh width h , and let \hat{U}^h denote the exact solution restricted to the same mesh. We say the solution is convergent if

$$\lim_{h \rightarrow 0} \|U^h - \hat{U}^h\| = 0$$

To prove convergence, we need 2 things:

- ① Consistency
- ② Stability

Consistency

The exact solution does not satisfy the numerical scheme:

$$\underbrace{\frac{U(x_{j+1}) - 2U(x_j) + U(x_{j-1}))}{h^2}}_{\text{Local Truncation Error}} = f(x_j) + \tau_j$$

$$\cancel{U''(x_j)} + \frac{1}{12} h^2 U^{(4)}(x_j) + O(h^4) = \cancel{f(x_j)} + \tau_j$$

$$\tau_j = \frac{1}{12} h^2 U^{(4)}(x_j) + O(h^4)$$

We say a discretization is consistent if $\lim_{h \rightarrow 0} \tau_j = 0$.

We have $AU = F$
 $A\hat{U} = F + \tau$

$$\Rightarrow A(U - \hat{U}) = -\tau$$

$$AE = -\tau$$

For discretizations of linear differential equations, the error satisfies the same equation as the numerical solution, but with the LTE as RHS.

✓ $\|AE\| = \|\tau\|$
 $\|AE\| \leq \|A\| \cdot \|E\|$ (submultiplicativity)

Here $\|A\|$ is the induced matrix norm:

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

$$E = -A^{-1}\tau$$

$$\|E\| = \|A^{-1}\tau\| \leq \|A^{-1}\| \cdot \|\tau\|$$

We just need to show that

$$\|A^{-1}\| < C \text{ for small enough } h$$

C is independent of h .

Stability

So we have

$$\|E\| \leq C \underbrace{\|\tau\|}_{\text{here we should use a grid norm (see text appendix)}} = C O(h^2) \Rightarrow \text{convergence}$$

here we should use
a grid norm (see text appendix)

Consider $\|A^{-1}\|_2$:

Since A is symmetric (normal),

$$\|A\|_2 = \max_{\lambda_p \in \sigma(A)} |\lambda_p| = \rho(A) \quad \text{spectral radius}$$

Let $\lambda_p, p=1, 2, \dots, m$ denote eigenvalues of A .

What are the eigenvalues of A^{-1} ?

$$\frac{1}{\lambda_p} \Rightarrow \|A^{-1}\|_2 = \frac{1}{\min |\lambda_p|}$$

$$h^2 A = \begin{bmatrix} -2 & 1 & & \\ 1 & \ddots & \ddots & \\ & \ddots & \ddots & 1 \\ & & 1 & -2 \end{bmatrix} = \hat{A}^{m \times m}$$

$$\hat{A}v = \lambda v$$

$$v_{j-1} - 2v_j + v_{j+1} = \lambda v_j, \quad j=1, \dots, m$$

$$v_0 = 0 \quad v_{m+1} = 0$$

Linear difference equations

$$\text{Ansatz: } v_j = \sum$$

$$y^{j-1} - 2y^j + y^{j+1} = \lambda y^j$$

$$y^2 - (2+\lambda)y + 1 = 0$$

$$y_{\pm} = \frac{2+\lambda}{2} \pm \frac{\sqrt{(2+\lambda)^2 - 4}}{2}$$

$$y_{\pm} = 1 + \frac{\lambda}{2} \pm \frac{\sqrt{\lambda^2 + 4\lambda}}{2} \quad \left. \vphantom{y_{\pm}} \right\} \text{Fundamental Solutions}$$

$$V_j = a y_+^j + b y_-^j$$

$$V_0 = a + b = 0$$

$$b = -a$$

$$\text{so } V_j = a(y_+^j - y_-^j)$$

$$V_{m+1} = a(y_+^{m+1} - y_-^{m+1}) = 0$$

$$y_+^{m+1} = y_-^{m+1}$$

$$y_+ y_- = 1$$

$$y_+^{m+1} y_+^{m+1} = (y_+ y_-)^{m+1} = 1$$

$$y_+^{2m+2} = 1 \Rightarrow y_+ = e^{i\pi \left(\frac{p}{m+1}\right)}$$

$$y_- = \frac{1}{y_+} = e^{-i\pi \left(\frac{p}{m+1}\right)}$$

$$p = 1, 2, \dots, m$$

$$J_+ + J_- = 2 + \lambda$$

$$e^{i \frac{p\pi}{m+1}} + e^{-i \frac{p\pi}{m+1}} = 2 + \lambda$$

$$2 \cos\left(\frac{p\pi}{m+1}\right) = 2 + \lambda$$

$$\lambda_p = 2 \left(\cos\left(\frac{p\pi}{m+1}\right) - 1 \right) \quad p = 1, \dots, m$$

Eigenvalues of A :

$$\frac{2}{h^2} \left(\cos\left(\frac{p\pi}{m+1}\right) - 1 \right) < 0$$

The smallest one is $\approx -\pi^2 + O(h^2)$

$$\|A^{-1}\| = \frac{1}{\pi^2} + O(h^2) \Rightarrow \|A^{-1}\| < C$$