

Diffusion Equation

Method of Lines (MOL)

- Brande refers to this as Semi-discretization.

- Basic Idea

$$\begin{aligned}
 u_t &= \alpha^2 u_{xx} & t \geq 0 & \quad 0 \leq x \leq 1 \\
 u(0, t) &= \varphi_0(t) & & \quad u(x, 0) = g(x) \\
 u(1, t) &= \varphi_1(t) & &
 \end{aligned}$$

Discretize in space only.

$$\Rightarrow \frac{\partial}{\partial t} u(x_n, t) = \alpha^2 \frac{u(x_{n-1}, t) - 2u(x_n, t) + u(x_{n+1}, t))}{h^2} + \mathcal{O}(h^2)$$

In vector form

$$\frac{\partial}{\partial t} \begin{bmatrix} u_1(t) \\ u_2(t) \\ \vdots \\ u_n(t) \end{bmatrix} \equiv \frac{\alpha^2}{h^2} \begin{bmatrix} -2 & 1 & & \\ & 1 & -2 & 1 \\ & & \ddots & \ddots \\ & & & 1 & -2 \end{bmatrix} \begin{bmatrix} u_1(t) \\ u_2(t) \\ \vdots \\ u_n(t) \end{bmatrix} + \frac{\alpha^2}{h^2} \begin{bmatrix} \varphi_0(t) \\ 0 \\ \vdots \\ \varphi_1(t) \end{bmatrix} + \mathcal{O}(h^2)$$

$\underline{u}(t)$

$$\Rightarrow \frac{\partial}{\partial t} u(x, t) \approx \frac{d}{dt} \underline{u}(t) = \alpha^2 D_{2,x} \underline{u}(t) + \frac{\alpha^2}{h^2} \varphi_0(t) e_1 + \frac{\alpha^2}{h^2} \varphi_1(t) e_n$$

⇒ we have semi-discretized the PDE so that it is now a coupled linear system of ODEs.

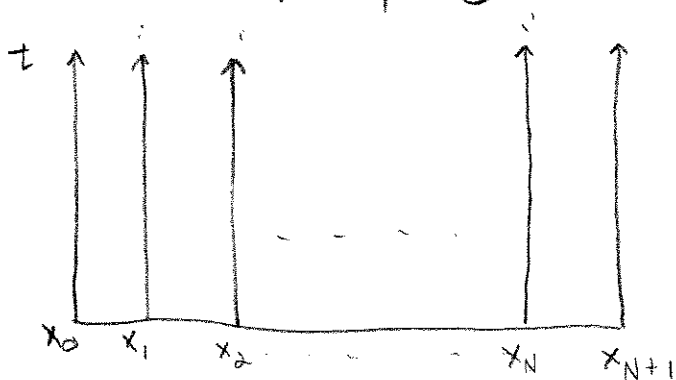
Diffusion Equation.

- origin of MOL

- Together with the initial conditions

$$u_1(0) = g(x_1), \quad u_2(0) = g(x_2), \quad \dots, \quad u_N(0) = g(x_N),$$

the approximate solution of the PDE is given by the solution of the system of ODEs on lines in the (x,t) plane



- Coupling the semi-discretization with ODE solver

- Now that we have reduced the problem to a linear system of ODEs, we can ^{try to} apply any of the ODE methods we learned to advance the system forward in time.

General ODE method: Problem

$$u'(t) = f(t, u) \quad t \geq 0 \quad u(0) = \underline{g}$$

our problem is with

$$f(t, u) = D_{\frac{\partial^2}{\partial x^2}} u(t) + \frac{\alpha^2}{h^2} \varphi_0(t) e_1 + \frac{\alpha^2}{h^2} \varphi_1(t) e_N$$

- We can now apply our knowledge for ODE methods (eg. stability, adaptivity, error control) to PDE methods

Diffusion Equation:

Forward Euler:



$$\underline{u}^{j+1} = \underline{u}^j + k \underline{F}^j$$

$$\Rightarrow \underline{u}^{j+1} = \underline{u}^j + 2k D_{xx} \underline{u}^j + \frac{\alpha^2}{h^2} \varphi_0(t_j) e_1 + \frac{\alpha^2}{h^2} \varphi_N(t_j) e_N$$

Same as Full discretization scheme

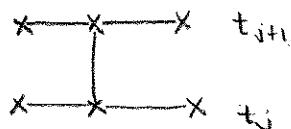
- Similar for backward Euler.

- Trapezoidal Rule (AM2)

$$\underline{u}^{j+1} = \underline{u}^j + \frac{\alpha k}{2} [D_{xx} \underline{u}^{j+1} + D_{xx} \underline{u}^j] + \frac{\alpha^2}{2h^2} [(\varphi_0(t_{j+1}) + \varphi_0(t_j)) e_1 + (\varphi_N(t_{j+1}) + \varphi_N(t_j)) e_N]$$

$$\Rightarrow \left(I - \frac{\alpha k}{2} D_{xx} \right) \underline{u}^{j+1} = \left(I + \frac{\alpha k}{2} D_{xx} \right) \underline{u}^j + (\text{Boundary Data})$$

Stencil:



- called Crank-Nicholson when applied to PDEs.

- one of the most popular methods for solving the diffusion equation.

- Second order accurate in space and time and unconditionally stable.

Diffusion Equation

Example: $u_t = u_{xx}$ ($\alpha=1$) $0 \leq x \leq 1$ $t \geq 0$
 $g(x) = \sin(\frac{\pi}{8}x) + \frac{1}{2}\sin(2\pi x)$
 $\phi_0(t) \equiv 0$, $\phi_1(t) = e^{-\pi^2 t/4}$

Max Error: $u(1/2, t)$

	$1/128$	$1/256$	$1/512$
$1/8$	7.53×10^{-5}	7.59×10^{-5}	7.60×10^{-5}
$1/16$	1.84×10^{-5}	1.89×10^{-5}	1.91×10^{-5}
$1/32$	4.04×10^{-6}	4.59×10^{-6}	4.73×10^{-6}

Reduced by a factor of 4

Convergence

- Recall that a numerical method is useless unless it converges to the true solution.
- Like the Dahlquist equivalence theorem, the following theorem gives us an algebraic set of conditions to determine convergence
- The theorem works for ^{general} linear evolutionary PDEs

$$\frac{\partial}{\partial t} u(x,t) = \mathcal{L}u(x,t) + f$$

$$t \geq 0$$

\mathcal{L} is some linear differential operator
 i.e. $\mathcal{L} = \nabla^2, \frac{\partial^2}{\partial x^2}, \frac{\partial}{\partial x}, \nabla,$
 etc.
- We will apply it to $u_t = \alpha^2 u_{xx}$ & $u_t + cu_x = 0$