

CG, CR, MR, GMRES, BiCG, BICG stab, BiCG stab2

Preconditioning

This approach is very robust, reliable but may not very efficient and Labor.

(B) change the scheme Approximate Factorization.

This approach is very efficient, if works

find something between implicit and explicit.

3月1日

§3.2 + §3.3

ADI

AF: approximate factorization

$$\begin{cases} u_t = \Delta u & \text{in } \Omega = (0,1) \times (0,1) \\ u = 0 & \text{on } \partial\Omega \end{cases}$$

work for regular domains

and rectangular meshes

very restrictive!!

$$u_t = \frac{\partial u}{\partial x^2} + \frac{\partial u}{\partial y^2}$$

$$\frac{u^{n+1} - u^n}{\Delta t} = \frac{1}{\Delta x^2} \delta_x^2 u^{n+1}_{j,k} + \frac{1}{\Delta y^2} \delta_y^2 u^{n+1}_{j,k}$$

Define: increment variable

$$\Delta u_{j,k}^n := u_{j,k}^{n+1} - u_{j,k}^n = 0(\Delta t)$$

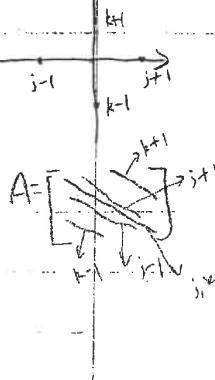
$$\frac{\Delta u_{j,k}^n}{\Delta t} = \frac{1}{\Delta x^2} \delta_x^2 \Delta u_{j,k}^n + \frac{1}{\Delta y^2} \delta_y^2 \Delta u_{j,k}^n + \frac{1}{\Delta x^2} \delta_x^2 u_{j,k}^n + \frac{1}{\Delta y^2} \delta_y^2 u_{j,k}^n$$

I means $I u_{j,k} = u_{j,k}$
可設 $\Delta u_{j,k} = 0$

$$\left[I - \frac{\Delta t}{\Delta x^2} \delta_x^2 - \frac{\Delta t}{\Delta y^2} \delta_y^2 \right] \Delta u_{j,k}^n = \Delta t \left[\frac{1}{\Delta x^2} \delta_x^2 + \frac{1}{\Delta y^2} \delta_y^2 \right] u_{j,k}^n$$

$$1 - a - b = (1-a)(1-b) - ab$$

$\approx (1-a)(1-b)$
if small, drop



$$I - \frac{\Delta t}{\Delta x^2} \delta_x^2 - \frac{\Delta t}{\Delta y^2} \delta_y^2 = (I - \frac{\Delta t}{\Delta x^2} \delta_x^2)(I - \frac{\Delta t}{\Delta y^2} \delta_y^2) - \frac{\Delta t^2}{\Delta x^2 \Delta y^2} \delta_x^2 \delta_y^2$$

$$\approx (I - \frac{\Delta t}{\Delta x^2} \delta_x^2)(I - \frac{\Delta t}{\Delta y^2} \delta_y^2)$$

(24)

$$\frac{\Delta t^2}{\Delta x^2 \Delta y^2} \partial_x^2 \partial_y^2 \Delta U_{j,k}^n = \frac{\Delta t^2}{\Delta x^2 \Delta y^2} \partial_x^2 \partial_y^2 (U_{j,k}^{n+1} - U_{j,k}^n)$$

$$\approx \frac{\Delta t^2}{\Delta x^2 \Delta y^2} \partial_x^2 \partial_y^2 (\Delta t \frac{\partial u}{\partial t})_{j,k}$$

$$\approx \frac{\Delta t^3}{\Delta x^2} \partial_x^2 \frac{\partial u}{\partial y^2} (\Delta t \frac{\partial u}{\partial t})_{j,k}$$

$$\therefore \frac{\partial u}{\partial y^2} \approx \frac{\partial^2 u}{\partial y^2} \quad \approx \frac{\Delta t^3}{\Delta x^2} \partial_x^2 ((\frac{\partial u}{\partial t})_{yy} + O(\Delta y^2))$$

$$\therefore \frac{\partial^2}{\partial x^2} \approx \frac{\partial^2}{\partial t^2} \quad \approx \Delta t^3 \frac{\partial^5 u}{\partial t \partial x^2 \partial y^2}$$

$$\therefore \frac{\Delta t^2}{\Delta x^2 \Delta y^2} \partial_x^2 \partial_y^2 \Delta U_{j,k}^n = O(\Delta t^3)$$

$$I \Delta U_{j,k}^n = O(\Delta t)$$

implicit Euler:

The truncation error is $O(\Delta t) + O(\Delta x^2) + O(\Delta y^2)$

$$(I - \frac{\Delta t}{\Delta x^2} \partial_x^2 - \frac{\Delta t}{\Delta y^2} \partial_y^2) \Delta U_{j,k}^n = \Delta t (\frac{1}{\Delta x^2} \partial_x^2 + \frac{1}{\Delta y^2} \partial_y^2) U_{j,k}^n$$

||

$$(I - \frac{\Delta t}{\Delta x^2} \partial_x^2) (I - \frac{\Delta t}{\Delta y^2} \partial_y^2) \Delta U_{j,k}^n = \Delta t (\frac{1}{\Delta x^2} \partial_x^2 + \frac{1}{\Delta y^2} \partial_y^2) U_{j,k}^n + \underbrace{\frac{\Delta t^2}{\Delta x^2 \Delta y^2} \partial_x \partial_y^2 \Delta U_{j,k}^n}_{O(\Delta t^4)} \quad \text{drop it}$$

drop it

drop it
truncation error is
still same as before. \therefore drop it

approximate implicit Euler

$$(I - \frac{\theta \Delta t}{\Delta x^2} \partial_x^2) (I - \frac{(1-\theta) \Delta t}{\Delta y^2} \partial_y^2) \Delta U_{j,k}^n = \Delta t (\frac{1}{\Delta x^2} \partial_x^2 + \frac{1}{\Delta y^2} \partial_y^2) U_{j,k}^n$$

For theta method

$$(I - \frac{\theta \Delta t}{\Delta x^2} \partial_x^2) (I - \frac{(1-\theta) \Delta t}{\Delta y^2} \partial_y^2) \Delta U_{j,k}^n = \Delta t (\frac{1}{\Delta x^2} \partial_x^2 + \frac{1}{\Delta y^2} \partial_y^2) U_{j,k}^n$$

How to solve the equation

$$\text{let } V_{j,k} = (I - \frac{\theta \Delta t}{\Delta y^2} \partial_y^2) \Delta U_{j,k}^n$$

$$[I - \frac{(1-\theta) \Delta t}{\Delta x^2} \partial_x^2] V_{j,k} = \Delta t (\frac{1}{\Delta x^2} \partial_x^2 + \frac{1}{\Delta y^2} \partial_y^2) U_{j,k}^n$$

(\therefore solve $V_{j,k}$, then solve $\Delta U_{j,k}^n$ i.e. $U_{j,k}^{n+1}$)

ADI ①

Implementation of ADI:

$$\left\{ \begin{array}{l} U_t = \Delta U + f(x, y, t) \text{ in } \Omega \\ U|_{\partial\Omega} = g(x, y, t), (x, y) \text{ on } \partial\Omega \end{array} \right.$$

$$U|_{\partial\Omega} = g(x, y, t), (x, y) \text{ on } \partial\Omega$$

The Crank-Nicolson scheme.

Time symmetric ADI (AF) method

$$(I - \frac{V_x}{2} \Delta x^2) (I - \frac{V_y}{2} \Delta y^2) U_{j,k}^{n+1} = (I + \frac{V_x}{2} \Delta x^2) (I + \frac{V_y}{2} \Delta y^2) U_{j,k}^n + \Delta t f(x_j, y_k, t_n + \frac{1}{2} \Delta t)$$

$$V_x = \frac{\partial f}{\partial x}$$

$$V_y = \frac{\partial f}{\partial y}$$

$$\text{Define: } V_{j,k} = (I - \frac{V_y}{2} \Delta y^2) U_{j,k}^{n+1}$$

$$\left\{ \begin{array}{l} (I - \frac{V_x}{2} \Delta x^2) V_{j,k} = (I + \frac{V_x}{2} \Delta x^2) (I + \frac{V_y}{2} \Delta y^2) U_{j,k}^n \\ \quad + \Delta t f(x_j, y_k, t_n + \frac{1}{2} \Delta t) \\ V_{0,k} = (I - \frac{V_y}{2} \Delta y^2) U_{0,k}^{n+1} \\ V_{J,k} = (I - \frac{V_y}{2} \Delta y^2) U_{J,k}^{n+1} \end{array} \right\} \text{boundary condition}$$

Given J and k and N (how many time steps), T, $u^0(x_j, y_k)$

Initial calculation: $\Delta x, \Delta y, \Delta t, V_x, V_y, t=0$

and make mesh (x_j, y_k) .

$$x_0, j=0 \dots J$$

$$y_{k=0} \dots k$$

$$U_{j,k} = u^0(x_j, y_k), j=0, 1, \dots, J$$

$$k=0, 1, \dots, K$$

Define work arrays: $ax[0:J], bx, cx, dx$

$$ay[0:k], by, cy, dy$$

For $n=0 \dots N-1$: (time loop, usually called time integration)

↑ calculate BCS for U^{n+1}

$$W_{j,k} = g(x_j, y_k, t_n + \Delta t) \quad \text{for } j=0 \text{ or } j=J \\ \text{or } k=0 \text{ or } k=K$$

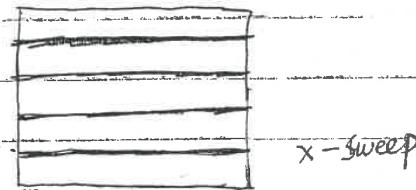
$$\text{Laplace} \quad -\frac{\partial \sigma}{\partial x} U_{j+1,k} + (1 + \frac{\partial \sigma}{\partial x}) U_{j,k} - \frac{\partial \sigma}{\partial x} U_{j-1,k} = d_{j,k}$$

For $k=1, 2, \dots, k-1$

$$\left\{ \begin{array}{l} -\frac{\partial \sigma}{\partial x} U_{j+1,k} + (1 + \frac{\partial \sigma}{\partial x}) U_{j,k} - \frac{\partial \sigma}{\partial x} U_{j-1,k} = d_{j,k} \quad j=1 \dots J-1 \\ U_{0,k} = (I - \frac{\partial \sigma}{\partial y} \Delta y^2) \Delta u_{0,k} = -\frac{\partial \sigma}{\partial y} \Delta u_{0,k-1} + (1 + \frac{\partial \sigma}{\partial y}) \Delta u_{0,k} - \frac{\partial \sigma}{\partial y} \Delta u_{0,k+1} \\ U_{J,k} = (I - \frac{\partial \sigma}{\partial y} \Delta y^2) \Delta u_{J,k} = \end{array} \right.$$

the matrix looks like this:

$$\left[\begin{array}{cccc} & & & \\ & & & \\ & & & \\ & & & \\ & & & \end{array} \right] (J+1) \times (J+1) \quad \left[\begin{array}{c} U_{0,k} \\ \vdots \\ U_{J,k} \end{array} \right] = \left[\begin{array}{c} 0 \\ d_{1,k} \\ \vdots \\ d_{J,k} \\ 0 \end{array} \right]$$



for $\Delta u_{j,k}^n$

For $j=1 \dots J-1$

$$\left\{ \begin{array}{l} -\frac{\partial \sigma}{\partial y} \Delta u_{j+1,k-1}^n + (1 + \frac{2\partial \sigma}{\partial y}) \Delta u_{j,k}^n - \frac{\partial \sigma}{\partial y} \Delta u_{j-1,k+1}^n = U_{j,k} \quad k=1 \dots k-1 \\ \Delta u_{j,0}^n = ? \\ \Delta u_{j,k}^n = ? \end{array} \right\} \text{given boundary condition} \quad \text{just need inside}$$



To show the stability for the new scheme. (*)

something like Θ -method

lecture 15

(25)

3月3日

$$Au = b$$



result from the discretization of a PDE

$$A \approx (I - \frac{\theta \Delta t}{\Delta x^2} \Delta x^2) (I - \frac{\theta \Delta t}{\Delta y^2} \Delta y^2)$$

P

$$A - P = O(\Delta t^2)$$

$(P^T A)U = P^T b$ easy to solve using iterative methods.

$$\text{speed: } \propto k(A) = \|A\| \cdot \|A^{-1}\|$$

$$k(A) = O(\frac{1}{h^2})$$

$$\frac{\|v^{(i+1)} - v^*\|}{\|v^{(i)} - v^*\|} = \frac{\sqrt{k(A)} - 1}{\sqrt{k(A)} + 1} \xrightarrow{\text{asym 稳定} \rightarrow 0}$$

$$\sim 1 - O(h).$$

但 P 很难解 ∴ 需用特殊的方法来解。

Apply the O-method and operator splitting to

$$u_t = u_{xx} + u_{yy}$$

$$\Rightarrow (I - \frac{\Delta t}{\Delta x^2} \Delta x^2) (I - \frac{\Delta t}{\Delta y^2} \Delta y^2) u_{j,k}^{n+1} = \Delta t [\frac{1}{\Delta x^2} \Delta x^2 + \frac{1}{\Delta y^2} \Delta y^2] u_{j,k}^n$$

For purpose of stability analysis,

$$\Delta u_{j,k}^n = u_{j,k}^{n+1} - u_{j,k}^n \quad \text{then get the system like this.}$$

$$(I - \frac{\Delta t}{\Delta x^2} \Delta x^2) (I - \frac{\Delta t}{\Delta y^2} \Delta y^2) u_{j,k}^{n+1} = \Delta t (\frac{1}{\Delta x^2} \Delta x^2 + \frac{1}{\Delta y^2} \Delta y^2) u_{j,k}^n + (I - \frac{\Delta t}{\Delta x^2} \Delta x^2) (I - \frac{\Delta t}{\Delta y^2} \Delta y^2)$$

$$= [I + \frac{(1-\theta)\Delta t}{\Delta x^2} \Delta x^2 + \frac{(1-\theta)\Delta t}{\Delta y^2} \Delta y^2 + \frac{\theta^2 \Delta t^2}{\Delta x^2 \Delta y^2} \Delta x^2 \Delta y^2] u_{j,k}^n \quad \rightarrow \text{由上步得}$$

$$= (I + \frac{(1-\theta)\Delta t}{\Delta x^2} \Delta x^2) (I + \frac{(1-\theta)\Delta t}{\Delta y^2} \Delta y^2) u_{j,k}^n$$

$$+ [-\frac{(1-\theta)^2 \Delta t^2}{\Delta x^2 \Delta y^2} \Delta x^2 \Delta y^2 + \frac{\theta^2 \Delta t^2}{\Delta x^2 \Delta y^2} \Delta x^2 \Delta y^2] u_{j,k}^n$$

$$(A^2 - (1-\theta)^2) \Delta t^2 / \Delta x^2 \Delta y^2 \cdot \Delta x^2 \Delta y^2$$

(*)

For the stability analysis:

$$U_{j,k}^n = \lambda^n e^{im\pi x_j + iey_0 y_k} \quad (m, e)$$

$$\delta_x^2 U_{j,k}^n = -4 \sin^2 \frac{m\pi x}{2} U_{j,k}^n$$

$$\delta_y^2 U_{j,k}^n = -4 \sin^2 \frac{e\pi y}{2} U_{j,k}^n$$

$$\text{so the L.H.S. of (2)} = (1 + \frac{\partial t}{\partial x} 4 \sin^2 \frac{m\pi x}{2}) (1 + \frac{\partial t}{\partial y} 4 \sin^2 \frac{e\pi y}{2}) U_{j,k}^{n+1}$$

$$= (1 - \frac{(1-\theta)\Delta t}{\Delta x^2} 4 \sin^2 \frac{m\pi x}{2}) (1 - \frac{(1-\theta)\Delta t}{\Delta y^2} 4 \sin^2 \frac{e\pi y}{2}) U_{j,k}^n$$

$$+ (\theta^2 - (1-\theta)^2) \frac{\Delta t^2}{\Delta x^2 \Delta y^2} 16 \sin^2 \frac{m\pi x}{2} \sin^2 \frac{e\pi y}{2} U_{j,k}^n$$

$$\text{let } \xi = \sin^2 \left(\frac{m\pi x}{2} \right) \quad \eta = \sin^2 \left(\frac{e\pi y}{2} \right) \quad 0 \leq \xi, \eta \leq 1$$

$$(1 + \frac{4\Delta t}{\Delta x} \xi) (1 + \frac{4\Delta t}{\Delta y} \eta) \lambda = (1 - \frac{4(1-\theta)\Delta t}{\Delta x^2} \xi) (1 - \frac{4(1-\theta)\Delta t}{\Delta y^2} \eta)$$

$$+ [\theta^2 - (1-\theta)^2] 16 \frac{\Delta t^2 \xi \eta}{\Delta x^2 \Delta y^2}$$

$|\lambda| \leq 1$ then stable

$$\theta = \frac{1}{2}: \quad \lambda = \frac{(1 - \frac{2\Delta t}{\Delta x^2} \xi)(1 - \frac{2\Delta t}{\Delta y^2} \eta)}{(1 + \frac{2\Delta t}{\Delta x^2} \xi)(1 + \frac{2\Delta t}{\Delta y^2} \eta)}$$

$$|\lambda| \leq 1 \quad (\text{to } \frac{2\Delta t}{\Delta x^2} \xi \geq 1 \text{ 则 } \lambda \leq (\frac{2\Delta t}{\Delta y^2} \eta - 1)(\frac{2\Delta t}{\Delta x^2} \xi - 1) \text{ 這樣 easy to see?})$$

$$\theta = 0$$

time symmetry: → indicate how fast the (m, e) mode is damped.

$$U_t = U_{xx} + U_{yy} \quad \rightarrow \text{damping factor}$$

$$U(x, y, z) = \sum_{m, e} U_{m, e} e^{-[(m^2 + e^2)\pi^2]^{\frac{1}{2}} t}$$

$$e^{imx + ieiy}$$

(m, e) fourier mode

proper damping factor,

numerical diffusion

similar to transformation: $t \rightarrow -t$