

Numerical Methods for PDEs

Alternating direction implicit (ADI) schemes

(Lecture 11, Week 4)

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1 The ADI method

A more practical 2D scheme: The ADI method

For u smooth enough, the Taylor expansion of $u(x_j + h_x, y_l, t_n)$ admits an **Exponential operator notation**

$$\begin{aligned}u(x_j + h_x, y_l, t_n) &= \left[u + h_x \frac{\partial u}{\partial x} + \frac{h_x^2}{2!} \frac{\partial^2 u}{\partial x^2} + \frac{h_x^3}{3!} \frac{\partial^3 u}{\partial x^3} + \dots \right]_{(x_j, y_l, t_n)} \\&= \left[1 + h_x \frac{\partial}{\partial x} + \frac{h_x^2}{2!} \frac{\partial^2}{\partial x^2} + \frac{h_x^3}{3!} \frac{\partial^3}{\partial x^3} + \dots \right] u \Big|_{(x_j, y_l, t_n)} \\&= \exp \left(h_x \frac{\partial}{\partial x} \right) u \Big|_{(x_j, y_l, t_n)}.\end{aligned}$$

Similarly (missing out the steps in between) we can write

$$u(x_j, y_l + h_y, t_n) = \exp \left(h_y \frac{\partial}{\partial y} \right) u \Big|_{(x_j, y_l, t_n)}$$

and

$$u(x_j, y_l, t_n + k) = \exp \left(k \frac{\partial}{\partial t} \right) u \Big|_{(x_j, y_l, t_n)}$$

With the help of this notation, we derive a different implicit scheme for

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

Suppose that $u(x, y, t)$ is a smooth solution of the PDE. Taylor expanding $u(x, y, t_n + k)$ about (x, y, t_n) gives

$$u(x, y, t_n + k) = \exp\left(k \frac{\partial}{\partial t}\right) u|_{(x, y, t_n)}.$$

Use $e^a = e^{a/2} \cdot e^{a/2}$ to rewrite this as

$$u|_{t=t_n+k} = \exp\left(\frac{k}{2} \frac{\partial}{\partial t}\right) \exp\left(\frac{k}{2} \frac{\partial}{\partial t}\right) u|_{t=t_n}$$

and hence

$$\underbrace{\exp\left(-\frac{k}{2} \frac{\partial}{\partial t}\right) u|_{t=t_n+k}}_{\text{new time-level}} = \underbrace{\exp\left(\frac{k}{2} \frac{\partial}{\partial t}\right) u|_{t=t_n}}_{\text{old time-level}}. \quad [*]$$

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We now use the fact that u solves the PDE to write

$$\begin{aligned}\exp\left(\pm\frac{k}{2}\frac{\partial}{\partial t}\right)u &= \exp\left(\pm\frac{k}{2}\left[\frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2}\right]\right)u \\ &= \exp\left(\pm\frac{k}{2}\frac{\partial^2}{\partial x^2}\right)\exp\left(\pm\frac{k}{2}\frac{\partial^2}{\partial y^2}\right)u\end{aligned}$$

(using $e^{a+b} = e^a \cdot e^b$). Plugging this into [*] gives

$$\begin{aligned}\exp\left(-\frac{k}{2}\frac{\partial^2}{\partial x^2}\right)\exp\left(-\frac{k}{2}\frac{\partial^2}{\partial y^2}\right)u|_{t=t_n+k} \\ = \exp\left(\frac{k}{2}\frac{\partial^2}{\partial x^2}\right)\exp\left(\frac{k}{2}\frac{\partial^2}{\partial y^2}\right)u|_{t=t_n}.\end{aligned}$$

We now chop the exponentials at first order ($e^{\pm q} \approx 1 \pm q$) to get

$$\left(1 - \frac{k}{2}\frac{\partial^2}{\partial x^2}\right)\left(1 - \frac{k}{2}\frac{\partial^2}{\partial y^2}\right)u|_{t=t_n+k} \approx \left(1 + \frac{k}{2}\frac{\partial^2}{\partial x^2}\right)\left(1 + \frac{k}{2}\frac{\partial^2}{\partial y^2}\right)u|_{t=t_n},$$

and with second central differences in space leads to

$$\left(1 - \frac{r_x}{2}\delta_x^2\right)\left(1 - \frac{r_y}{2}\delta_y^2\right)w_{j,l}^{n+1} = \left(1 + \frac{r_x}{2}\delta_x^2\right)\left(1 + \frac{r_y}{2}\delta_y^2\right)w_{j,l}^n,$$

where r_x, r_y defined as before.

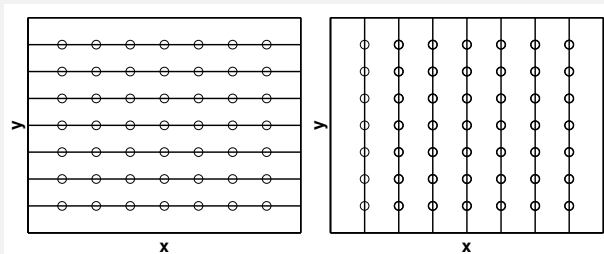
The scheme

$$\left(1 - \frac{r_x}{2} \delta_x^2\right) \left(1 - \frac{r_y}{2} \delta_y^2\right) w_{j,l}^{n+1} = \left(1 + \frac{r_x}{2} \delta_x^2\right) \left(1 + \frac{r_y}{2} \delta_y^2\right) w_{j,l}^n,$$

it is **much easier and quicker to use than it looks** as it splits into two stages with an intermediate quantity $v_{j,l} := \left(1 - \frac{r_y}{2} \delta_y^2\right) w_{j,l}^{n+1}$:

$$\left. \begin{array}{l} \text{Stage 1: } \left(1 - \frac{r_x}{2} \delta_x^2\right) v_{j,l} = \left(1 + \frac{r_y}{2} \delta_y^2\right) w_{j,l}^n \\ \text{Stage 2: } \left(1 - \frac{r_y}{2} \delta_y^2\right) w_{j,l}^{n+1} = \left(1 + \frac{r_x}{2} \delta_x^2\right) v_{j,l} \end{array} \right\} \text{ADI scheme}$$

The name **ADI** comes from this idea of alternately solving along the x -direction and y -direction.



The two step splitting solves the full scheme: Applying $(1 - \frac{r_x}{2} \delta_x^2)$ to Stage 2 gives

$$\begin{aligned} & \left(1 - \frac{r_x}{2} \delta_x^2\right) \left(1 - \frac{r_y}{2} \delta_y^2\right) w_{j,l}^{n+1} = \left(1 - \frac{r_x}{2} \delta_x^2\right) \left(1 + \frac{r_x}{2} \delta_x^2\right) v_{j,l} \\ & = \left(1 + \frac{r_x}{2} \delta_x^2\right) \left(1 - \frac{r_x}{2} \delta_x^2\right) v_{j,l} \quad (\text{difference operators commute (Why?)}) \\ & = \left(1 + \frac{r_x}{2} \delta_x^2\right) \left(1 + \frac{r_y}{2} \delta_y^2\right) w_{j,l}^n \quad \text{by Stage 1.} \end{aligned}$$

Advantages:

Faster than 2D θ -method: Matrices are tridiagonal and involve only J or L unknowns with operations of $O(JL)$ compared to $O(J^3 L^3)$ (for the θ -scheme).

Exercise for the remaining part of today's lecture:

Show that the 2D ADI scheme is *unconditionally stable*.

The **generalisation to 3D** (with 2 intermediate variables) of the 2D ADI is **not unconditionally stable!**

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