

Numerical Methods for PDEs

The θ -method

(Lecture 6, Week 2)

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- 1 The BTCS scheme
- 2 Generalisation of the FTCS and BTCS schemes: The θ -method
- 3 LTE analysis of the θ -method

The BTCS scheme

Goal: Schemes with better stability properties (so-called θ -schemes)

Idea: Study **BTCS schemes**, i.e., work at the **forward point** (x_j, t_{n+1}) and **use Backward Difference Approximation in time** (B_t/k) and again **Central Difference Approximation in space** (δ_x^2/h^2),

$$\frac{w_j^{n+1} - w_j^n}{k} =: \frac{B_t}{k} w_j^{n+1} = \frac{\delta_x^2}{h^2} w_j^{n+1} := \frac{w_{j-1}^{n+1} - 2w_j^{n+1} + w_{j+1}^{n+1}}{h^2},$$

which reads for $r := k/h^2$ as the following *implicit scheme*

$$-rw_{j-1}^{n+1} + (1 + 2r)w_j^{n+1} - rw_{j+1}^{n+1} = w_j^n \quad \text{for } j = 1, 2, \dots, J-1.$$

(Implicit means: Solve a set of simultaneous equations for each time level.)

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Matrix form of the BTCS scheme

$$S\mathbf{w}^{n+1} = \mathbf{w}^n + \mathbf{b}^{n+1}$$

where

$$S = \begin{pmatrix} 1+2r & -r & 0 & \dots & & \\ -r & 1+2r & -r & 0 & \dots & \\ 0 & -r & 1+2r & -r & 0 & \\ \ddots & \ddots & \ddots & \ddots & \ddots & \\ & \ddots & 0 & -r & 1+2r & \end{pmatrix}, \quad \mathbf{w}^n = \begin{pmatrix} w_1^n \\ w_2^n \\ \vdots \\ \vdots \\ w_{J-1}^n \end{pmatrix},$$

$$\mathbf{b}^{n+1} = \begin{pmatrix} r\alpha(t_{n+1}) \\ 0 \\ \vdots \\ 0 \\ r\beta(t_{n+1}) \end{pmatrix}.$$

Example

Problem: For $r = 0.4$ and $J = 4$ solve

$$\begin{cases} u_t = u_{xx}, \\ u(0, t) = u(1, t) = 0, & t > 0 \quad (\text{BC}) \\ u(x, 0) = \sin(x\pi), & (\text{IC}). \end{cases}$$

Solution: The I.C.s tell us that

$$w^0 = [0, 1/\sqrt{2}, 1, 1/\sqrt{2}, 0].$$

At $n = 1$ the BCs tell us that $w_0^1 = w_4^1 = 0$. Setting $n = 0$ in the BTCS scheme gives ($j = 1, 2, 3$)

$$\begin{aligned} (1 + 0.8)w_1^1 - 0.4w_2^1 &= w_1^0 + 0.4w_0^1 \\ -0.4w_1^1 + (1 + 0.8)w_2^1 - 0.4w_3^1 &= w_2^0 \\ -0.4w_2^1 + (1 + 0.8)w_3^1 &= w_3^0 + 0.4w_4^1 \end{aligned}$$

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or

$$\begin{aligned}1.8w_1^1 - 0.4w_2^1 &= \frac{1}{\sqrt{2}} + 0.4 \times 0 \\-0.4w_1^1 + 1.8w_2^1 - 0.4w_3^1 &= 1 \\-0.4w_2^1 + 1.8w_3^1 &= \frac{1}{\sqrt{2}} + 0.4 \times 0\end{aligned}$$

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Solving this by Gauss elimination gives

$$\mathbf{w}^1 = [0, 0.5729, 0.8102, 0.5729, 0].$$

We now repeat this process to get $\mathbf{w}^2, \mathbf{w}^3$, etc. The exact result is

$$\mathbf{u}^1 = \exp(-\pi^2 k) \sin(\pi x_j) = [0, 0.5525, 0.7813, 0.5525, 0].$$

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Natural generalisation: The θ -method

Take a weighted average of the FTCS and BTCS scheme

$$\frac{F_t}{k} w_j^n = (1 - \theta) \frac{\delta_x^2}{h^2} w_j^n + \theta \frac{\delta_x^2}{h^2} w_j^{n+1}, \quad \text{with } \theta \in (0, 1),$$

is called the θ -method for $u_t = u_{xx}$.

Remark. The θ -scheme is

1. the FTCS scheme for $\theta = 0$,
2. the BTCS scheme for $\theta = 1$,
3. implicit for any $\theta > 0$.

For $\theta \in (0, 1)$ the computational molecule looks as follows

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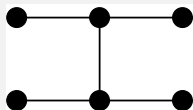
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The Crank-Nicolson method: $\theta = 1/2$

For $\theta = 0.5$ we get the so-called *Crank-Nicolson* scheme

$$\frac{F_t}{k} w_j^n = \frac{1}{2} \frac{\delta_x^2}{h^2} w_j^n + \frac{1}{2} \frac{\delta_x^2}{h^2} w_j^{n+1}.$$

Setting again $r := k/h^2$ and re-arranging terms leads to

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LTE analysis of the θ -method

The θ -scheme can be written as

$$L_{\Delta} w_j^n := \frac{F_t}{k} w_j^n - (1 - \theta) \frac{\delta_x^2}{h^2} w_j^n - \theta \frac{\delta_x^2}{h^2} w_j^{n+1} = 0.$$

LTE-procedure:

1. Plug in the exact solution $u(x_j, t_n)$ instead of w_j^n (for all j, n) into $L_{\Delta} w_j^n$,
2. Taylor expand about $(x, t) = (x_j, t_n)$,
3. Eliminate terms using the PDE.

Remember, do not multiply or divide $L_{\Delta} w_j^n$ by k or h when working out the LTE.

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We make Taylor series of smooth enough functions $u(x, t)$, i.e.,

$$\begin{aligned}F_t u(x_j, t_n) &= u(x_j, t_n+k) - u(x_j, t_n) \\&= \left[k \frac{\partial}{\partial t} + \frac{k^2}{2!} \frac{\partial^2}{\partial t^2} + \frac{k^3}{3!} \frac{\partial^3}{\partial t^3} + O(k^4) \right] u(x_j, t_n) \\&= \left[k u_t + \frac{k^2}{2!} u_{tt} + \frac{k^3}{3!} u_{ttt} \right]_{(x_j, t_n)} + O(k^4).\end{aligned}$$

Expanding the 2nd central space difference term $\delta_x^2 u(x_j, t_n)$ gives

$$\begin{aligned}\delta_x^2 u(x_j, t_n) &= u(x_j+h, t_n) - 2u(x_j, t_n) + u(x_j-h, t_n) \\&= \left[h^2 \frac{\partial^2}{\partial x^2} + \frac{2h^4}{4!} \frac{\partial^4}{\partial x^4} + O(h^6) \right] u(x_j, t_n) \\&= \left[h^2 u_{xx} + \frac{h^4}{12} u_{xxxx} \right]_{(x_j, t_n)} + O(h^6).\end{aligned}$$

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The similar term $\delta_x^2 u(x_j, t_{n+1})$ (time level $n + 1$) becomes

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Note that this term is evaluated at time $t = t_n + k$ and so it must also be expanded in k . That is

$$\begin{aligned}\delta_x^2 u(x_j, t_n+k) &= \left[h^2 u_{xx} + \frac{h^4}{12} u_{xxxx} + O(h^6) \right]_{(x_j, t_n+k)} \\ &= \left[1 + k \frac{\partial}{\partial t} + \frac{k^2}{2!} \frac{\partial^2}{\partial t^2} + \dots \right] \left[h^2 u_{xx} + \frac{h^4}{12} u_{xxxx} + O(h^6) \right]_{(x_j, t_n)} \\ &= \left[h^2 u_{xx} + kh^2 u_{xxt} + \frac{h^4}{12} u_{xxxx} \right]_{(x_j, t_n)} + O(kh^4, k^2h^2, h^6).\end{aligned}$$

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$$\begin{aligned}\delta_x^2 u(x_j, t_n+k) &= u(x_j+h, t_n+k) - 2u(x_j, t_n+k) + u(x_j-h, t_n+k) \\ &= \left[h^2 u_{xx} + \frac{h^4}{12} u_{xxxx} + O(h^6) \right]_{(x_j, t_n+k)}.\end{aligned}$$

Note that this term is evaluated at time $t = t_n + k$ and so it must also be expanded in k . That is

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We now substitute each of the three terms into $L_{\Delta} w_j^n$ and collect terms of the same order to get

$$\text{LTE} = (u_t - u_{xx}) + k \left(\frac{1}{2} u_{tt} - \theta u_{txx} \right) - \frac{h^2}{12} u_{xxxx} + O(k^2, kh^2, h^4).$$

Since u is a solution of the PDE, this eliminates $u_t - u_{xx}$. Also, differentiating the PDE once with respect to t gives

$$u_{tt} = u_{txx} = u_{xxxx}$$

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Therefore,

$$\text{LTE} = \begin{cases} \mathcal{O}(k, h^2) & \text{for } \theta, k, h \text{ arbitrary,} \\ \mathcal{O}(h^2) & \text{for } k = \mathcal{O}(h^2), \\ \mathcal{O}(k^2, h^2) & \text{for } \theta = 1/2, \\ \mathcal{O}(h^4) & \text{for } \theta = \frac{1}{2} - \frac{1}{12r}, r = k/h^2, k = \mathcal{O}(h^2), \end{cases}$$

where the last property (4th order accurate) is a result of setting

$$k \left(\frac{1}{2} - \theta \right) - \frac{h^2}{12} = 0,$$

which can be achieved by the FTCS scheme for $\theta = 0$, i.e., $r = 1/6$.

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