

Comparison of different methods applied to the heat equation

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October 2018

1 Problem

We consider the heat equation



Evolutionary Model Problem 1D: Heat Equation

Find $u : [0, T] \times [0, 1] \rightarrow \mathbb{R}$ solution of

$$\frac{\partial u(t, x)}{\partial t} + \frac{\partial^2 u(t, x)}{\partial x^2} = 0, \quad (t, x) \in [0, T] \times [0, 1] \quad (1)$$

$$u(t, 0) = u(t, 1) = 0, \quad \forall t > 0 \quad (2)$$

$$u(0, x) = u_0(x), \quad \forall 0 \leq x \leq 1 \quad (3)$$

with initial condition

$$u_0(x) = x(1 - x) \quad (4)$$

We want to get numerical approximations to the solution applying the θ method with $\theta = 0$ (explicit method), $\theta = 1/2$ (Crank-Nicolson method) and $\theta = 1$ (implicit method). We choose as final time $T = 0.6$ and we consider a uniform mesh in the spatial variable x with mesh size Δx and in the temporal variable t with mesh size Δt .

Let us denote by N_x the number of nodes in x variable and by N_t the number of nodes in the t variable.

Let $(x_i)_0^{N_x}$ the regular discretization of the interval $[0, 1]$ in N_x+1 points :

$$x_i = i \cdot \Delta x, \quad \forall i \in \llbracket 0, N_x \rrbracket, \quad \text{with} \quad \Delta x = \frac{1}{N_x}$$

and $(t_n)_0^{N_t}$ the regular discretization of the interval $[0, T]$ in N_t+1 points :

$$t_n = n \cdot \Delta t, \quad \forall n \in \llbracket 0, N_t \rrbracket, \quad \text{with} \quad \Delta t = \frac{T}{N_t}$$



Evolutionary Model Problem 1D: Heat Equation, formulation at the points of discretization

Find $u(t_n, x_i) \in \mathbb{R}, \forall n \in \llbracket 0, N_t \rrbracket, \forall i \in \llbracket 0, N_x \rrbracket$ such as


$$\frac{\partial u(t_n, x_i)}{\partial t} + \frac{\partial^2 u(t_n, x_i)}{\partial x^2} = 0, \quad \forall n \in \llbracket 0, N_t \rrbracket, \quad \forall i \in \llbracket 0, N_x \rrbracket \quad (5)$$

$$u(t_n, 0) = u(t_n, 1) = 0, \quad \forall n \in \llbracket 0, N_t \rrbracket \quad (6)$$

$$u(0, x_i) = u_0(x_i), \quad \forall i \in \llbracket 0, N_x \rrbracket \quad (7)$$

We now have to approach the partial derivative operators. For it we can use a scheme called θ -scheme.

2 The θ -scheme

 **Evolutionary Model Problem 1D: Heat Equation, θ -scheme**

Find $u(t_n, x_i) \in \mathbb{R}, \forall n \in \llbracket 0, Nt \rrbracket, \forall i \in \llbracket 0, Nx \rrbracket$ such as

$$\frac{u_i^{n+1} - u_i^n}{\Delta t} - \left[\theta \frac{u_{i+1}^{n+1} - 2u_i^{n+1} + u_{i-1}^{n+1}}{(\Delta x)^2} + (1-\theta) \frac{u_{i+1}^n - 2u_i^n + u_{i-1}^n}{(\Delta x)^2} \right] = 0, \quad \forall n \in \llbracket 0, Nt \rrbracket, \quad \forall i \in \llbracket 0, Nx \rrbracket$$

$$u_0^n = u_{Nx}^n = 0, \quad \forall n \in \llbracket 0, Nt \rrbracket$$

$$u_i^0 = x_i(1 - x_i), \quad \forall i \in \llbracket 0, Nx \rrbracket$$

Remark :

The θ -schema is implicit for $\theta \neq 0$ and explicit for $\theta = 0$.

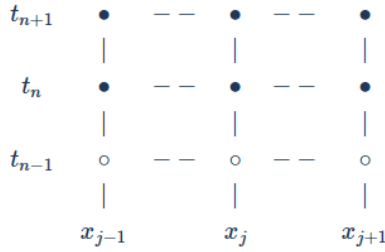


Figure 1: Stencil of the θ method

Now we have $\forall n \in \llbracket 0, Nt \rrbracket$ and $\forall i \in \llbracket 0, Nx \rrbracket$: $\frac{u_i^{n+1} - u_i^n}{\Delta t} - \left[\theta \frac{u_{i+1}^{n+1} - 2u_i^{n+1} + u_{i-1}^{n+1}}{(\Delta x)^2} + (1-\theta) \frac{u_{i+1}^n - 2u_i^n + u_{i-1}^n}{(\Delta x)^2} \right] = 0$
So,

$$-\nu\theta u_{i+1}^{n+1} + (1 + 2\nu\theta)u_i^{n+1} - \nu\theta u_{i-1}^{n+1} = \nu(1-\theta)u_{i+1}^n + (1 - 2\nu(1-\theta))u_i^n + \nu(1-\theta)u_{i-1}^n, \quad \text{with } \nu = \frac{\Delta t}{(\Delta x)^2}$$

and so the linear system is written :

$$AU_{n+1} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ -\nu\theta & 1 + 2\nu\theta & -\nu\theta & 0 & 0 \\ 0 & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & 0 & -\nu\theta & 1 + 2\nu\theta & -\nu\theta \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} u_0^{n+1} \\ u_1^{n+1} \\ \vdots \\ \vdots \\ u_{Nx-1}^{n+1} \\ u_{Nx}^{n+1} \end{pmatrix} =$$

$$\begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ \nu(1-\theta) & 1 - 2\nu(1-\theta) & \nu(1-\theta) & 0 & 0 \\ 0 & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & 0 & \nu(1-\theta) & 1 - 2\nu(1-\theta) & \nu(1-\theta) \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} u_0^n \\ u_1^n \\ \vdots \\ \vdots \\ u_{Nx-1}^n \\ u_{Nx}^n \end{pmatrix} = BU_n$$

2.1 Consistency and order of the θ -scheme

To evaluate the order of the method we study the local truncation error of the schema defined by :

$$\epsilon_i^n = \frac{u(x_i, t_{n+1}) - u(x_i, t_n)}{\Delta t} - \left[\theta \frac{u(x_{i+1}, t_{n+1}) - 2u(x_i, t_{n+1}) + u(x_{i-1}, t_{n+1})}{(\Delta x)^2} + (1-\theta) \frac{u(x_{i+1}, t_n) - 2u(x_i, t_n) + u(x_{i-1}, t_n)}{(\Delta x)^2} \right]$$

According to the Taylor-Young formula, we have:

$$u(x_i, t_{n+1}) = u(x_i, t_n) + \Delta t \frac{\partial u}{\partial t}(x_i, t_n) + \frac{\Delta t^2}{2} \frac{\partial^2 u}{\partial t^2}(x_i, t_n) + O(\Delta t^3)$$

So,

$$\frac{u(x_i, t_{n+1}) - u(x_i, t_n)}{\Delta t} = \frac{\partial u}{\partial t}(x_i, t_n) + \frac{\Delta t}{2} \frac{\partial^2 u}{\partial t^2}(x_i, t_n) + O(\Delta t^2)$$

And,

$$u(x_{i+1}, t_n) = u(x_i, t_n) + \Delta x \frac{\partial u}{\partial x}(x_i, t_n) + \frac{\Delta x^2}{2} \frac{\partial^2 u}{\partial x^2}(x_i, t_n) + \frac{\Delta x^3}{6} \frac{\partial^3 u}{\partial x^3}(x_i, t_n) + O(\Delta x^4)$$

$$u(x_{i-1}, t_n) = u(x_i, t_n) - \Delta x \frac{\partial u}{\partial x}(x_i, t_n) + \frac{\Delta x^2}{2} \frac{\partial^2 u}{\partial x^2}(x_i, t_n) - \frac{\Delta x^3}{6} \frac{\partial^3 u}{\partial x^3}(x_i, t_n) + O(\Delta x^4)$$

Therefore,

$$\theta \left(\frac{u(x_{i+1}, t_n) - 2u(x_i, t_n) + u(x_{i-1}, t_n)}{(\Delta x)^2} \right) = \theta \frac{\partial^2 u}{\partial x^2}(x_i, t_n) + O(\Delta x^2).$$

Then,

$$\begin{aligned} u(x_{i+1}, t_{n+1}) &= u(x_i, t_n) + \Delta x \frac{\partial u}{\partial x}(x_i, t_n) + \frac{\Delta x^2}{2} \frac{\partial^2 u}{\partial x^2}(x_i, t_n) + \frac{\Delta x^3}{6} \frac{\partial^3 u}{\partial x^3}(x_i, t_n) + O(\Delta x^4) \\ &\quad + \Delta t \frac{\partial u}{\partial t}(x_i, t_n) + \Delta x \Delta t \frac{\partial^2 u}{\partial x \partial t}(x_i, t_n) + \frac{\Delta x^2 \Delta t}{2} \frac{\partial^3 u}{\partial x^2 \partial t}(x_i, t_n) + \frac{\Delta x^3 \Delta t}{6} \frac{\partial^4 u}{\partial x^3 \partial t}(x_i, t_n) + O(\Delta t \Delta x^4) \\ &\quad + \frac{\Delta t^2}{2} \frac{\partial^2 u}{\partial t^2}(x_i, t_n) + \frac{\Delta t^2 \Delta x}{2} \frac{\partial^3 u}{\partial t^2 \partial x}(x_i, t_n) + \frac{\Delta t^2 \Delta x^2}{2} \frac{\partial^4 u}{\partial t^2 \partial x^2}(x_i, t_n) + \frac{\Delta t^2 \Delta x^3}{6} \frac{\partial^5 u}{\partial t^2 \partial x^3}(x_i, t_n) + O(\Delta t^2 \Delta x^4) \\ &\quad + \frac{\Delta t^3}{6} \frac{\partial^3 u}{\partial t^3}(x_i, t_n) + \frac{\Delta t^3 \Delta x}{6} \frac{\partial^4 u}{\partial t^3 \partial x}(x_i, t_n) + \frac{\Delta t^3 \Delta x^2}{12} \frac{\partial^5 u}{\partial t^3 \partial x^2}(x_i, t_n) + \frac{\Delta t^3 \Delta x^3}{36} \frac{\partial^6 u}{\partial t^3 \partial x^3}(x_i, t_n) + O(\Delta t^3 \Delta x^4) \end{aligned}$$

And,

$$\begin{aligned} u(x_{i-1}, t_{n+1}) &= u(x_i, t_n) - \Delta x \frac{\partial u}{\partial x}(x_i, t_n) + \frac{\Delta x^2}{2} \frac{\partial^2 u}{\partial x^2}(x_i, t_n) - \frac{\Delta x^3}{6} \frac{\partial^3 u}{\partial x^3}(x_i, t_n) + O(\Delta x^4) \\ &\quad + \Delta t \frac{\partial u}{\partial t}(x_i, t_n) - \Delta x \Delta t \frac{\partial^2 u}{\partial x \partial t}(x_i, t_n) + \frac{\Delta x^2 \Delta t}{2} \frac{\partial^3 u}{\partial x^2 \partial t}(x_i, t_n) - \frac{\Delta x^3 \Delta t}{6} \frac{\partial^4 u}{\partial x^3 \partial t}(x_i, t_n) + O(\Delta t \Delta x^4) \\ &\quad + \frac{\Delta t^2}{2} \frac{\partial^2 u}{\partial t^2}(x_i, t_n) - \frac{\Delta t^2 \Delta x}{2} \frac{\partial^3 u}{\partial t^2 \partial x}(x_i, t_n) + \frac{\Delta t^2 \Delta x^2}{2} \frac{\partial^4 u}{\partial t^2 \partial x^2}(x_i, t_n) - \frac{\Delta t^2 \Delta x^3}{6} \frac{\partial^5 u}{\partial t^2 \partial x^3}(x_i, t_n) + O(\Delta t^2 \Delta x^4) \\ &\quad + \frac{\Delta t^3}{6} \frac{\partial^3 u}{\partial t^3}(x_i, t_n) - \frac{\Delta t^3 \Delta x}{6} \frac{\partial^4 u}{\partial t^3 \partial x}(x_i, t_n) + \frac{\Delta t^3 \Delta x^2}{12} \frac{\partial^5 u}{\partial t^3 \partial x^2}(x_i, t_n) - \frac{\Delta t^3 \Delta x^3}{36} \frac{\partial^6 u}{\partial t^3 \partial x^3}(x_i, t_n) + O(\Delta t^3 \Delta x^4) \end{aligned}$$

And,

$$u(x_i, t_{n+1}) = u(x_i, t_n) + \Delta t \frac{\partial u}{\partial t}(x_i, t_n) + \frac{\Delta t^2}{2} \frac{\partial^2 u}{\partial t^2}(x_i, t_n) + \frac{\Delta t^3}{6} \frac{\partial^3 u}{\partial t^3}(x_i, t_n) + O(\Delta t^4)$$

Thus,

$$\begin{aligned} \frac{u(x_{i+1}, t_{n+1}) - 2u(x_i, t_{n+1}) + u(x_{i-1}, t_{n+1})}{(\Delta x)^2} &= \frac{\partial^2 u}{\partial x^2}(x_i, t_n) + \Delta t \frac{\partial^3 u}{\partial x^2 \partial t}(x_i, t_n) \\ &\quad + \Delta t^2 \frac{\partial^4 u}{\partial x^2 \partial t^2}(x_i, t_n) + \frac{\Delta t^3}{6} \frac{\partial^5 u}{\partial x^2 \partial t^3}(x_i, t_n) + O(\Delta x^2) + O(\Delta t \Delta x^2) + O\left(\frac{\Delta t^4}{\Delta x^2}\right) + O(\Delta t^2 \Delta x^2) + O(\Delta t^3 \Delta x^2) \\ &= \frac{\partial^2 u}{\partial x^2}(x_i, t_n) + \Delta t \frac{\partial^3 u}{\partial x^2 \partial t}(x_i, t_n) + O(\Delta t^2) + O(\Delta x^2) \end{aligned}$$

Therefore,

$$\epsilon_i^n = \frac{\partial u}{\partial t}(x_i, t_n) + \frac{\Delta t}{2} \frac{\partial^2 u}{\partial t^2}(x_i, t_n) - \theta \frac{\partial^2 u}{\partial x^2}(x_i, t_n) - (1-\theta) \left(\frac{\partial^2 u}{\partial x^2}(x_i, t_n) + \Delta t \frac{\partial^3 u}{\partial x^2 \partial t}(x_i, t_n) \right) + O(\Delta t^2) + O(\Delta x^2)$$

So,

$$\epsilon_i^n = \Delta t \left[\frac{1}{2} \frac{\partial^2 u}{\partial t^2}(x_i, t_n) - (1 - \theta) \frac{\partial^3 u}{\partial x^2 \partial t}(x_i, t_n) \right] + O(\Delta t^2) + O(\Delta x^2)$$

Or,

$$\frac{\partial u}{\partial t} = \frac{\partial^2 u}{\partial x^2} \Rightarrow \frac{\partial^2 u}{\partial t^2} = \frac{\partial^3 u}{\partial x^2 \partial t}$$

Thus,

$$\epsilon_i^n = \Delta t \left(\theta - \frac{1}{2} \right) \frac{\partial^3 u}{\partial x^2 \partial t}(x_i, t_n) + O(\Delta t^2) + O(\Delta x^2) \quad (8)$$

From where,

$$\begin{cases} \epsilon_i^n = O(\Delta t^2) + O(\Delta x^2), & \text{pour } \theta = \frac{1}{2} \\ \epsilon_i^n = O(\Delta t) + O(\Delta x^2), & \text{pour } \theta \neq \frac{1}{2} \end{cases}$$

Conclusion : The scheme is therefore consistent and of order 2 in time and space for $\theta = \frac{1}{2}$ and order 1 in time and 2 in space for $\theta \neq 0$.

2.2 Stability L^2 of the θ -scheme

Method of Von Neumann

- We consider a particular discrete solution in the form $u_i^n = A_n e^{ikx_i}$
- By injecting this solution into the scheme we find a formula for the amplification coefficient A.

Condition of stability of *Von Neumann* : the scheme is stable only if the amplification coefficient checks $|A| \leq 1$.

We have,

$$(1 + 2\nu\theta)u_i^{n+1} - \nu\theta(u_{i+1}^{n+1} + u_{i-1}^{n+1}) = (1 - 2\nu(1 - \theta))u_i^n + \nu(1 - \theta)(u_{i+1}^n + u_{i-1}^n)$$

We inject $u_i^n = A_n e^{ikx_i}$ in the scheme,

$$A_{n+1} e^{ikx_i} (1 + 2\nu\theta - 2\nu\theta \cos(k\Delta x)) = A_n e^{ikx_i} (1 - 2\nu(1 - \theta) + 2\nu(1 - \theta) \cos(k\Delta x))$$

So,

$$A_{n+1} (1 + 2\nu\theta(1 - \cos(k\Delta x))) = A_n (1 - 2\nu(1 - \theta)(1 - \cos(k\Delta x)))$$

$$\text{Or, } \sin^2(x) = \frac{1 - \cos(2x)}{2}$$

$$\frac{A_{n+1}}{A_n} = \frac{1 - 4\nu(1 - \theta) \sin^2(\frac{k\Delta x}{2})}{1 + 4\nu\theta \sin^2(\frac{k\Delta x}{2})}$$

For the scheme to be L^2 -stable, the amplification factor $|\frac{A_{n+1}}{A_n}|$ must be less than 1 :

$$4\nu(1 - \theta) \sin^2(\frac{k\Delta x}{2}) - 1 \leq 1 + 4\nu\theta \sin^2(\frac{k\Delta x}{2})$$

$$1 + 2\nu(2\theta - 1) \geq 0$$

If $\frac{1}{2} \leq \theta \leq 1$ we always have $1 + 2\nu(2\theta - 1) \geq 0$

If $0 \leq \theta < \frac{1}{2}$, it is necessary that

$$\nu \leq \frac{1}{2 - 4\theta}$$

2.3 Stability L^∞ of the θ -scheme

The scheme is L^∞ -stable if :

$$\frac{\Delta t}{(\Delta x)^2} \leq \frac{1}{2(1 - \theta)}$$

2.4 Convergence

The scheme is consistent and stable under certain conditions on θ and ν . According to Lax-Richtmyer's theorem, the scheme is convergent.

3 Separation of variables

We look for solutions of the form

$$u(t, x) = X(x).T(t)$$

where X and T are function which have to be determined. Substituting $u(t, x) = X(x).T(t)$ into the equation, we obtain :

$$X(x).T'(t) = X''(x).T(t)$$

from which, after dividing by $X(x).T(t)$, we get

$$\frac{T'(t)}{T(t)} = \frac{X''(x)}{X(x)}$$

The left side depends only on t whereas the right hand side depends only on x. Since they are equal, they must be equal to some constant $-\lambda$. Thus

$$T' + \lambda T = 0 \quad (9)$$

and

$$X'' + \lambda X = 0 \quad (10)$$

The general solution of the first equation is given

$$T(t) = Ae^{-\lambda t} \text{ for an arbitrary constant } A$$

The general solutions of the second equation are as follows.

1. $\lambda < 0$. Let $\lambda = -k^2 < 0$. Then the solution to (10) is

$$X(x) = C_1 e^{kx} + C_2 e^{-kx}$$

for integration constants C_1 and C_2 found from imposing BC's,

$$X(0) = C_1 + C_2 = 0, \quad X(1) = C_1 e^k + C_2 e^{-k} = 0$$

The first gives $C_1 = -C_2$, the second then gives $C_1(e^{2k} - 1) = 0$ and since $|k| > 0$ we have $A = B = u = 0$, which is the trivial solution. Thus we discard the case $\lambda < 0$.

2. $\lambda = 0$. Then $X(x) = C_1 x + C_2$ and the BCs imply $X(0) = C_2 = 0, X(1) = C_1 = 0$, so that $C_1 = C_2 = u = 0$. We discard this case also.
3. $\lambda > 0$. In this case, (2) is the simple harmonic equation whose solution is

$$X(x) = C_1 \cos(\sqrt{\lambda}x) + C_2 \sin(\sqrt{\lambda}x)$$

The BCs imply $X(0) = C_1 = 0$ and $C_2 \sin(\sqrt{\lambda}) = 0$. We don't want $C_2 = 0$, since that would give the trivial solution $u = 0$, so we must have

$$\sin(\sqrt{\lambda}) = 0$$

Thus,

$$\sqrt{\lambda} = n\pi$$

Consequently,

$$\lambda_n = n^2 \pi^2 \text{ for } n = 1, 2, 3, \dots$$

The problem (10) is called the eigenvalue problem, a nontrivial solution is called an eigenfunction associated with the eigenvalue λ . And the corresponding eigenfunction is given by

$$X_n(x) = \sin(n\pi x)$$

After substituting $\lambda_n = n^2 \pi^2$ to (9), we get the family of solutions

$$T_n(t) = A_n e^{-n^2 \pi^2 t}$$

Thus we have obtained the following sequence of solutions

$$u_n(t, x) = T_n(t)X_n(x) = A_n e^{-n^2 \pi^2 t} \sin(n\pi x)$$

We obtain more solutions by taking linear combinations of the u_n (recall the superposition principle)

$$u(t, x) = \sum_{i=1}^N u_n(t, x) = \sum_{i=1}^N A_n e^{-n^2 \pi^2 t} \sin(n\pi x)$$

and then by passing to the limit $N \rightarrow +\infty$

$$u(t, x) = \sum_{i=1}^{+\infty} A_n e^{-n^2 \pi^2 t} \sin(n\pi x)$$

Finally, we consider the initial condition. At $t = 0$, we must have

$$u(0, x) = \sum_{i=1}^{+\infty} A_n \sin(n\pi x) = u_0(x) = f(x)$$

The coefficients, B_n can be computed as follows. Fix $m \in \mathbf{N}$. Multiplying the above equality by $\sin(m\pi x)$ and then integrating over $[0, 1]$, we get

$$\int_0^1 f(x) \sin(m\pi x) dx = \int_0^1 \sum_{i=1}^{+\infty} A_n \sin(n\pi x) \sin(m\pi x) dx = \sum_{i=1}^{+\infty} \int_0^1 A_n \sin(n\pi x) \sin(m\pi x) dx$$

Since

$$\int_0^1 A_n \sin(n\pi x) \sin(m\pi x) dx = \begin{cases} 0 & \text{if } n \neq m \\ \frac{1}{2} & \text{if } n = m \end{cases}$$

We find that

$$A_n = 2 \int_0^1 f(x) \sin(n\pi x) dx$$

So,

$$A_n = 2 \int_0^1 x(1-x) \sin(n\pi x) dx = 2 \left[\frac{1-2x}{n^2 \pi^2} \cos(n\pi x) + \left(\frac{x^2-x}{n\pi} - \frac{2}{n^3 \pi^3} \right) \cos(n\pi x) \right]_0^1$$

Thus,

$$A_n = \frac{4}{n^3 \pi^3} (1 - (-1)^n)$$

Thus, the solution of the PDE as,

$$u(t, x) = \frac{4}{\pi^3} \sum_{i=1}^{+\infty} \frac{(1 - (-1)^n)}{n^3} e^{-n^2 \pi^2 t} \sin(n\pi x) \quad (11)$$

4 Numerical solutions

4.1 Case where $\theta = 0$

For $\theta = 0$,

- The scheme is consistent and of order 1 in time and 2 in space.
- L^2 -stable, if $\frac{\Delta t}{(\Delta x)^2} = \nu \leq \frac{1}{2}$
- L^∞ -stable, if $\frac{\Delta t}{(\Delta x)^2} = \nu \leq \frac{1}{2}$

We represent the orders of the scheme : order 2 in space if $\nu = \frac{1}{2}$ and order 4 in space if $\nu = \frac{1}{6}$ (left) and CPU time required to compute the error (right).

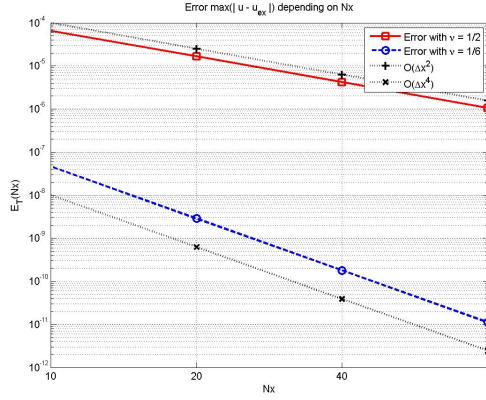


Figure 2: Orders for the explicit scheme, with $\nu = \frac{1}{2}$ and $\nu = \frac{1}{6}$

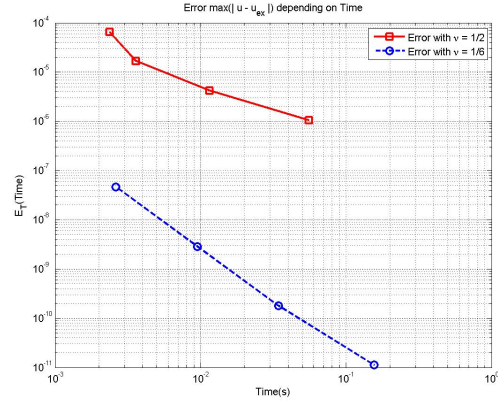


Figure 3: CPU time required to compute the error, with $\nu = \frac{1}{2}$ and $\nu = \frac{1}{6}$

Analysis of numerical results

- The scheme with $\nu = \frac{1}{2}$ is order 2 in space.
- The scheme is more accurate with $\nu = \frac{1}{6}$ than with $\nu = \frac{1}{2}$.
- The more we increase in precision, the more we increase the calculation time.
- The scheme with $\nu = \frac{1}{6}$ is order 4 in space (why?).

As can be seen in Figure 2 the scheme is order 4 in space with $\nu = \frac{1}{6}$, because the blue dotted ($O(\Delta x^4)$) curve and the orange curve have the same slope. Why ? ...

Let $\nu = \frac{1}{6}$ and $\theta = 0$, so

$$u_i^{n+1} = \frac{2}{3}u_i^n + \frac{1}{6}(u_{i+1}^n + u_{i-1}^n)$$

To evaluate the order of the method we study the local truncation error of the schema defined by :

$$\epsilon_i^n = u(x_i, t_{n+1}) - \frac{2}{3}u(x_i, t_n) - \frac{1}{6}(u(x_{i+1}, t_n) + u(x_{i-1}, t_n))$$

According to the Taylor-Young formula, we have:

$$u(x_i, t_{n+1}) = u(x_i, t_n) + \Delta t \frac{\partial u}{\partial t}(x_i, t_n) + \frac{\Delta t^2}{2} \frac{\partial^2 u}{\partial t^2}(x_i, t_n) + O(\Delta t^3)$$

And,

$$\begin{aligned} u(x_{i+1}, t_n) &= u(x_i, t_n) + \Delta x \frac{\partial u}{\partial x}(x_i, t_n) + \frac{\Delta x^2}{2!} \frac{\partial^2 u}{\partial x^2}(x_i, t_n) + \frac{\Delta x^3}{3!} \frac{\partial^3 u}{\partial x^3}(x_i, t_n) + O(\Delta x^4) \\ u(x_{i-1}, t_n) &= u(x_i, t_n) - \Delta x \frac{\partial u}{\partial x}(x_i, t_n) + \frac{\Delta x^2}{2!} \frac{\partial^2 u}{\partial x^2}(x_i, t_n) - \frac{\Delta x^3}{3!} \frac{\partial^3 u}{\partial x^3}(x_i, t_n) + O(\Delta x^4) \end{aligned}$$

Therefore,

$$\epsilon_i^n = \frac{1}{3}u(x_i, t_n) + \Delta t \frac{\partial u}{\partial t}(x_i, t_n) + O(\Delta t^2) - \frac{1}{6}(2u(x_i, t_n) + \Delta x^2 \frac{\partial^2 u}{\partial x^2}(x_i, t_n)) + O(\Delta x^4)$$

Thus,

$$\epsilon_i^n = \Delta t \frac{\partial u}{\partial t}(x_i, t_n) - \frac{1}{6}\Delta x^2 \frac{\partial^2 u}{\partial x^2}(x_i, t_n) + O(\Delta x^4) + O(\Delta t^2)$$

Or we know that,

$$\frac{\partial u}{\partial t}(x_i, t_n) = \frac{\partial^2 u}{\partial x^2}(x_i, t_n)$$

Hence,

$$\epsilon_i^n = \frac{\partial^2 u}{\partial x^2}(x_i, t_n)(\Delta t - \frac{1}{6}\Delta x^2) + O(\Delta x^4) + O(\Delta t^2)$$

Or, $\nu = \frac{1}{6} \Rightarrow \Delta t = \frac{1}{6}\Delta x^2$ So,

$$\epsilon_i^n = O(\Delta x^4) + O(\Delta t^2)$$

So the scheme is of order 4 in space and 2 in time, if $\nu = \frac{1}{6}$.

Instability, for $\theta = 0$ and $\nu = 0.535 > \frac{1}{2}$,

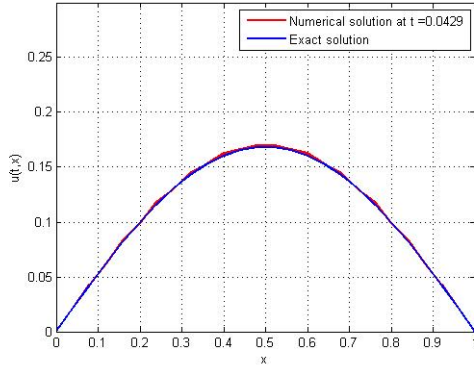


Figure 4: 1D heat equation with exact solution (in blue) at $t = 0.043$. Beginning of the phenomenon of instability

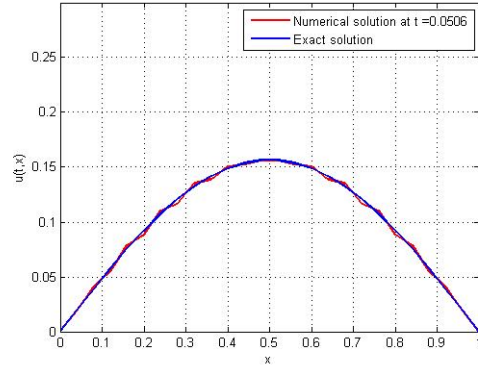


Figure 5: 1D heat equation with exact solution (in blue) at $t = 0.051$. Beginning of the phenomenon of instability

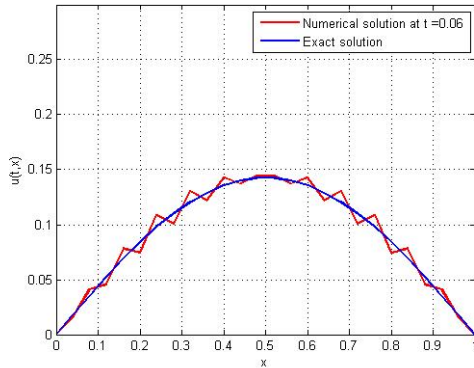


Figure 6: 1D heat equation with exact solution (in blue) at $t = 0.060$. Beginning of the phenomenon of instability

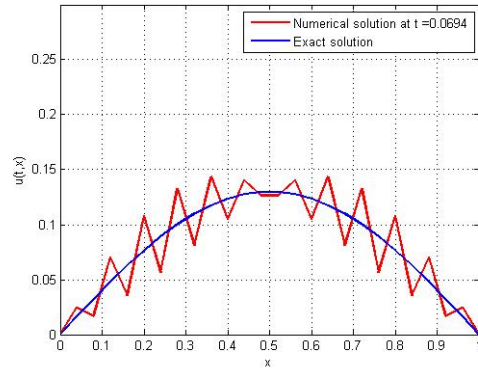


Figure 7: 1D heat equation with exact solution (in blue) at $t = 0.069$. Beginning of the phenomenon of instability

4.2 Case where $\theta = \frac{1}{2}$

For $\theta = \frac{1}{2}$,

- The scheme is consistent and of order 2 in space and 2 in time.
- L^2 -stable
- L^∞ -stable, if $\frac{\Delta t}{(\Delta x)^2} = \nu \leq 1$

We represent the orders of the scheme : order 2 in space (left) and CPU time required to compute the error (right).

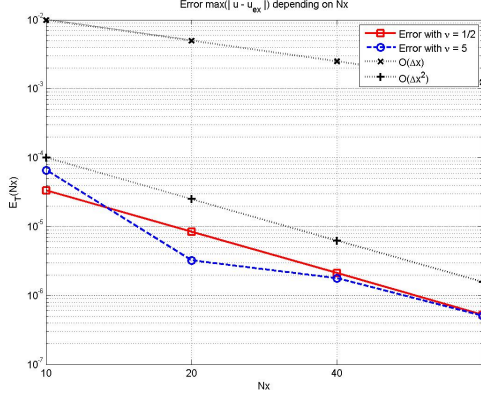


Figure 8: Orders for the Crank-Nicolson scheme in space, with $\nu = \frac{1}{2}$ and $\nu = 5$

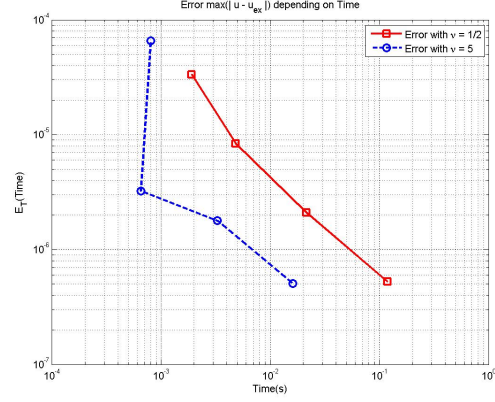


Figure 9: CPU time required to compute the error, with $\nu = \frac{1}{2}$ and $\nu = 5$

Nx	Nt	Crank-Nicolson, $\nu = \frac{1}{2}$	CPU	Nt	Crank-Nicolson, $\nu = 5$	CPU
10	120	3.35207766e-05	0.0015	12	6.59457365e-05	0.0011
20	480	8.41138182e-06	0.0051	48	3.24557177e-06	0.0009
40	1920	2.10464911e-06	0.0234	192	1.78278864e-06	0.0021
80	7680	5.26272705e-07	0.1128	768	5.06177310e-07	0.0114

Analysis of numerical results

- The figure 8 shows the Crank-Nicolson scheme, but here $\nu = 5$ is much larger. The numerical solution has oscillatory behaviour for small t .
- For Nx larger than this the two graphs with $\nu = \frac{1}{2}$ and $\nu = 5$ are close together, illustrating the fact that the leading term in the truncation error in (8) is independent of ν .

4.3 Case where $\theta = 1$

For $\theta = 1$,

- The scheme is consistent and of order 2 in space and 1 in time.
- L^2 -stable
- L^∞ -stable, if $\frac{\Delta t}{(\Delta x)^2} = \nu \leq 1$

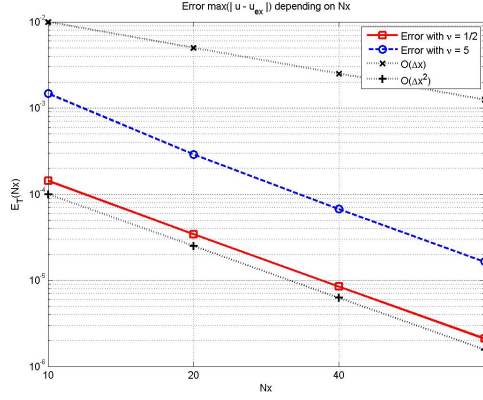


Figure 10: Orders for the implicit scheme, with $\nu = 5$ and $\nu = \frac{1}{2}$

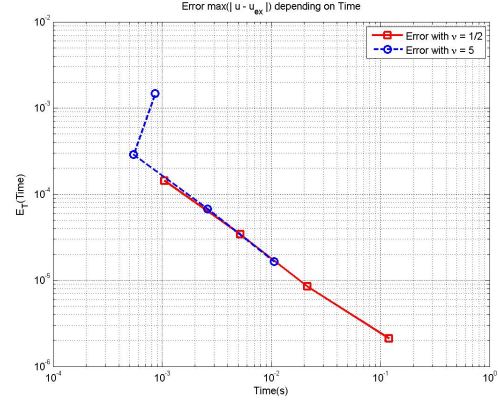


Figure 11: CPU time required to compute the error, with $\nu = \frac{1}{2}$ and $\nu = 5$

Nx	Nt	implicit scheme, $\nu = \frac{1}{2}$	CPU	Nt	implicit scheme, $\nu = 5$	CPU
10	120	1.42800859e-04	0.0011	12	1.47293997e-03	0.0012
20	480	3.41848185e-05	0.0044	48	2.88452161e-04	0.0006
40	1920	8.45221179e-06	0.0217	192	6.69774977e-05	0.0023
80	7680	2.10719036e-06	0.1232	768	1.64227881e-05	0.0119

Analysis of numerical results

- As we can see on both curves the scheme is order 2 in space for $\nu = \frac{1}{2}$ and $\nu = 5$.
- The scheme is more accurate with $\nu = \frac{1}{6}$ than with $\nu = 5$.

4.4 Comparison between the 3 cases

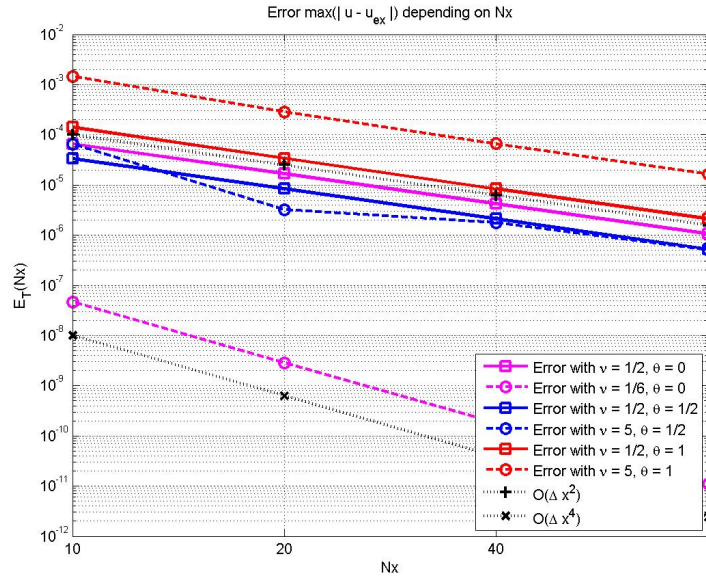


Figure 12: Orders for different scheme

These graphs do not give a true picture of the relative effectiveness of the various θ – *methods* because they do not take account of the work involved in each calculation. So in the graphs in Fig. 13 the same results are plotted against a measure of the computational effort involved in each calculation.

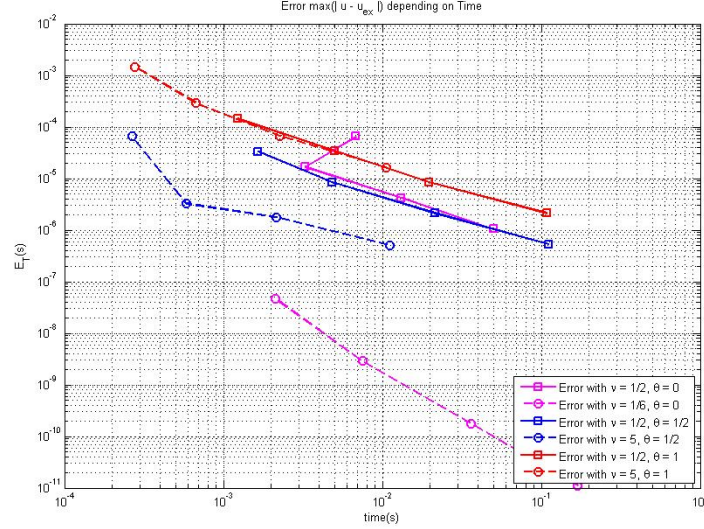


Figure 13: CPU time required to compute the error

5 Conclusion

- The explicit method require less effort than the implicit methods.
- These graphs show that, for this problem, the Crank–Nicolson method with $\nu = \frac{1}{2}$ is the most efficient of those tested.
- In the case $\theta = \frac{1}{2}$ and $\nu = 5 > 1$ the maximum principle does not hold, and we see that at the first time level the numerical solution becomes negative. This would normally be regarded as unacceptable.
- The exact solution of the problem will have only a single maximum for all t .
- These results correspond to a rather extreme case, and the unacceptable behaviour only persists for a few time steps, thereafter the solution becomes very smooth in each case.

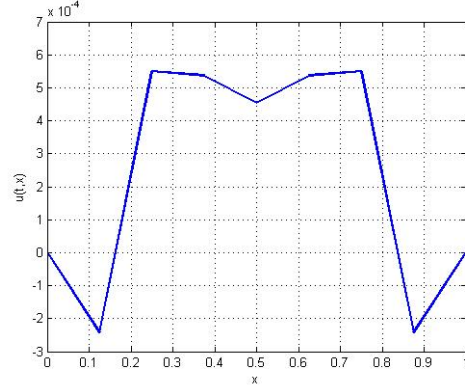


Figure 14: A maximum principle and convergence $\nu = 5 > 1$