# Crank-Nicholson Method

15 PDEs

## Diffusion equation: stability

$$\frac{\partial u}{\partial t} = D\nabla^2 u(x, t)$$

$$\frac{\partial T}{\partial t} = \frac{K}{C\rho} \nabla^2 T(x, t)$$

 leap frog (forward) difference): only stable  $\eta = \frac{D\Delta t}{\Delta x^2} < \frac{1}{2}$ for

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$$\eta = \frac{K\Delta t}{C\rho\Delta x^2} < \frac{1}{2}$$

## Diffusion interpretation of the forward difference stability criterion

- random walk in 1D
- compare to stability condition:
  - grid spacing > than diffusion distance (squared) over one integration step
  - max. allowed dt = diffusion time across one grid cell

$$2D\Delta t = \Delta x^2$$

$$\eta = \frac{D\Delta t}{\Delta x^2} < \frac{1}{2}$$

$$\Delta x^2 > 2D\Delta t$$

$$\Delta t < \frac{\Delta x^2}{2D}$$

## Computational cost

- features of interest
  - length scale
  - time scale

$$\lambda \gg \Delta x$$

$$au pprox rac{\lambda^2}{D}$$

number of steps needed:

$$\frac{\tau}{\Delta t} \approx \frac{\lambda^2}{D} \frac{2D}{\Delta x^2} \approx \frac{\lambda^2}{\Delta x^2}$$

## Crank-Nicholson algorithm

- Goals:
  - better stability (larger time steps)
  - higher accuracy (than forward difference 1st order)
- Key ideas:
  - use "split time steps" as intermediate
  - implicit scheme (coupled equation, matrix problem)

$$\frac{\partial T}{\partial t} = D \frac{\partial^2 T(x,t)}{\partial x^2}$$

$$\frac{\partial T(x, t + \frac{\Delta t}{2})}{\partial t} = \dots$$

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$$\frac{\partial T}{\partial t} = D \frac{\partial^2 T(x,t)}{\partial x^2} \qquad \frac{\partial T(x,t+\frac{\Delta t}{2})}{\partial t} = .$$

#### Taylor expansion around split time step

(1) 
$$T(x,t) = T(x,t+\frac{dt}{2}) - \frac{dt}{2} \frac{\partial T(x,t+\frac{dt}{2})}{\partial t} + o(at^2)$$
  
(2)  $T(x,t+at) = T(x,t+\frac{dt}{2}) + \frac{dt}{2} \frac{\partial T(x,t+\frac{dt}{2})}{\partial t} + o(at^2)$ 

Eq 2 - Eq 1
$$\Delta t \frac{\Im T(\kappa_1 t + \frac{at}{2})}{\partial t} = T(\kappa_1 t + at) - T(\kappa_1 t) + O(at^3)$$

$$\frac{\partial T}{\partial t} = D \frac{\partial^2 T(x,t)}{\partial x^2}$$

$$\frac{\partial T(x, t + \frac{\Delta t}{2})}{\partial t} = \dots$$

Previously:

$$\frac{\partial T(x,t)}{\partial t} = \frac{T(x,t+\Delta t) - T(x,t)}{\Delta t} + \mathcal{O}(\Delta t)$$

$$\frac{\partial T}{\partial t} = D \frac{\partial^2 T(x,t)}{\partial x^2} \qquad \frac{\partial^2 T(x,t)}{\partial x^2} = \dots$$

Finite difference derivative for split time step

(3) 
$$\frac{\partial^{2}T(x, t+\frac{4b}{2})}{\partial x^{2}} = \frac{1}{\Delta x^{2}} \left[ T(x+\Delta x, t+\frac{4b}{2}) + T(x-\Delta x, t+\frac{4b}{2}) - 2T(x, t+\frac{4b}{2}) + o(\Delta x^{2}) \right]$$

From the first order derivatives: Eq 1 + Eq 2

2 
$$T(x,t+\frac{\Delta t}{2}) = T(x,t) + T(x,t+\Delta t) + \sigma(\Delta t^2)$$
(4)
$$T(x,t+\frac{\Delta t}{2}) = \frac{1}{2}(T(x,t) + T(x,t+\Delta t)) + \sigma(\Delta t^2)$$

$$\frac{\partial T}{\partial t} = D \frac{\partial^2 T(x,t)}{\partial x^2} \qquad \frac{\partial^2 T(x,t)}{\partial x^2} = \frac{\partial^2 T(x,t)}{\partial x^2} = \frac{\partial^2 T(x,t)}{\partial x^2}$$

#### Insert (4) into (3)

$$\Delta x^{2} \frac{\partial^{2} T(x_{1}(+a\frac{d}{2}))}{\partial x^{2}} = \frac{1}{2} \left[ T(x_{1}+ax_{1}) + T(x_{1}+ax_{1}) + T(x_{2}+ax_{1}) + T(x_{3}+ax_{1}) + T(x_{4}-ax_{1}) + T(x_{4}-ax_{1}) + T(x_{4}-ax_{1}) + T(x_{5}+ab) \right]$$

$$- 2(T(x_{1}+a) + T(x_{5}+ab)$$

$$\frac{\partial T}{\partial t} = D \frac{\partial^2 T(x,t)}{\partial x^2}$$

$$t = j\Delta t$$
$$x = i\Delta x$$

$$T(x, t) \equiv T_{ij}$$
$$T(x + \Delta x, t + \Delta t) \equiv T_{i+1, j+1}$$

$$\frac{1}{\Delta t} \left( T_{i,j+1} - T_{i,j} \right) = \frac{D}{2\Delta x^2} \left[ T_{i+1,j} + T_{i+1,j+1} + T_{i+1,j+1} + T_{i-1,j+1} - 2 \left( T_{i,j} + T_{i,j+1} \right) \right]$$

discretized diffusion equation (split time step)

$$\mathcal{O}(\Delta t^2)$$

$$\frac{1}{\Delta t} \left( T_{i,j+1} - T_{i,j} \right) = \frac{D}{2\Delta x^2} \left[ T_{i+1,j} + T_{i+1,j+1} + T_{i+1,j+1} + T_{i+1,j+1} - 2 \left( T_{i,j} + T_{i,j+1} \right) \right]$$

$$\eta := \frac{D\Delta t}{\Delta x^2}$$

#### **Collect future terms on LHS**

$$-T_{i-1,j+1} + \left(\frac{2}{n} + 2\right)T_{i,j+1} - T_{i+1,j+1} = T_{i-1,j} + \left(\frac{2}{n} - 2\right)T_{i} + T_{i-1,j}$$

#### implicit scheme

LHS = future 
$$j+1$$

RHS = present 
$$j$$

$$-T_{i-l,j+l} + \left(\frac{2}{\eta} + 2\right)T_{i,j+l} - T_{i+l,j+l} = T_{i-l,j} + \left(\frac{2}{\eta} - 2\right)T_{i,j} + T_{i-l,j}$$

$$-T_{i-l,j+1} + \alpha T_{i,j+1} - T_{i+1,j+1} = T_{i-1,j} + \beta T_{i,j} + T_{i-1,j}$$

$$\alpha := \frac{2}{\eta} + 2$$
Rewrite as matrix equation 
$$A\mathbf{x} = \mathbf{b}$$

$$\beta := \frac{2}{\eta} - 2$$

*N*-2 unknowns

#### **Boundaries?**

$$T_{0,j} = \mathbf{const}$$
 
$$T_{N-1,j} = \mathbf{const} \equiv T_{-1,j}$$

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#### Special equations for

$$T_{1,j+1}$$

$$T_{-2,j+1}$$

$$-T_{-3,j+1} + \alpha T_{2,j+1} - T_{-1,j+1} = T_{-3,j} + \beta T_{-2,j} + T_{-1,j} + T_{-1,j+1}$$

$$-T_{-3,j+1} + \alpha T_{-2,j+1} = T_{-3,j} + \beta T_{-2,j} + T_{-1,j} + T_{-1,j+1}$$

$$= T_{-3,j} + \beta T_{-2,j} + T_{-1,j} + T_{-1,j+1}$$

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### Crank-Nicholson

- 1. Set-up matrix A (N-2,N-2)
- $A = M(\eta) = \begin{pmatrix} \alpha & -1 \\ -1 & \alpha & -1 \\ & -1 & \alpha & -1 \\ & \ddots & \ddots & \ddots \\ & & -1 & \alpha \end{pmatrix}$

- 2. For each time step
  - 1. Set-up RHS vector
  - 2. solve matrix equation

$$\mathbf{x} = \begin{pmatrix} T_{1} \\ \vdots \\ T_{i} \\ \vdots \\ T_{-2} \end{pmatrix} \qquad \mathbf{b} = \begin{pmatrix} T_{0,j+1} + T_{0,j} + \beta T_{1,j} + T_{2,j} \\ \vdots \\ T_{i-1,j} + \beta T_{i,j} + T_{i+1,j} \\ \vdots \\ T_{i-1,j} + \beta T_{i-1,j} + T_{i+1,j} \end{pmatrix}$$

Ax = b

# Crank-Nicholson: Performance Improvements

- pre-compute inverse of **constant** matrix  $\mathbf{A} = \mathbf{M}(\eta)$  and solve matrix problem as  $\mathbf{x} = \mathbf{A}^{-1}\mathbf{b}$
- take advantage of the tridiagonal structure
  - Thomas algorithm
  - routines for banded matrices (scipy.linalg.solve\_banded())

## Crank-Nicholson: Stability

von Neumann stability analysis yields

$$|\xi(k)| = \frac{1 - 2\eta \sin^2 \frac{k\Delta x}{2}}{1 + 2\eta \sin^2 \frac{k\Delta x}{2}}$$

- because  $\sin^2 \alpha \le 1$ , we always have  $|\xi(k)| \le 1$
- always stable (any combination of  $\Delta x$  and  $\Delta t$ )