Partial differential equations

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Numerical Methods (6E5X0), 2023-2024

Today's outline

- Introduction
- Instationary diffusion equation
 - Discretization
 - Solving the diffusion equation
 - Non-linear source terms
- Convection
 - Discretization
 - Central difference scheme
 - Upwind scheme
- Conclusions
 - Other methods
 - Summary



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Overview

Main question

How to solve parabolic PDEs like:

$$\frac{\partial c}{\partial t} = \mathcal{D}\frac{\partial^2 c}{\partial x^2} - u\frac{\partial c}{\partial x} + R$$

$$t = 0; 0 \le x \le \ell \implies c = c_0$$

with

$$t > 0; x = 0$$
 $\Rightarrow -\mathcal{D}\frac{\partial c}{\partial x} + uc = u_{\text{in}}c_{\text{in}}$

$$t > 0; x = \ell$$
 $\Rightarrow \frac{\partial c}{\partial x} = 0$

accurately and efficiently?



What is a PDE?

Partial differential equation

An equation containing a function and their derivatives to multiple independent variables.

Order of PDE

The highest derivative appearing in the PDE



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General second order PDE:

$$A\frac{\partial^2 f}{\partial x^2} + B\frac{\partial^2 f}{\partial x \partial y} + C\frac{\partial^2 f}{\partial y^2} + D\frac{\partial f}{\partial x} + E\frac{\partial f}{\partial y} + Ff = G$$

- Linear equation: Coefficients A, B, ..., G do not depend on x and y.
- Non-linear equation: Coefficients A, B, ..., G are a function of x and y.



Classification of PDE's

$$A\frac{\partial^2 f}{\partial x^2} + B\frac{\partial^2 f}{\partial x \partial y} + C\frac{\partial^2 f}{\partial y^2} + D\frac{\partial f}{\partial x} + E\frac{\partial f}{\partial y} + Ff = G$$

The discriminant Δ of a quadratic polynomial is computed as (note: only the higher order coefficients are important):

$$\Delta = B^2 - 4AC$$

Introduction



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The discriminant Δ of a quadratic polynomial is computed as (note: only the higher order coefficients are important): $\Delta = B^2 - 4AC$

- Δ < 0 ⇒ Elliptic equation (e.g. Laplace equation for stationary diffusion in 2D)
- Δ = 0 ⇒ Parabolic equation (e.g. instationary heat penetration in 1D)
- ∆ > 0 ⇒ Hyperbolic equation (e.g. wave equation)



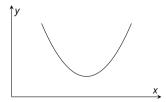
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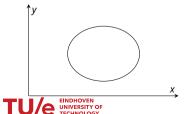
Introduction

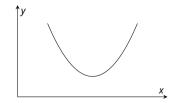
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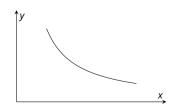
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Different PDE types require different solution techniques because of the difference in range of influence:

- Characteristics
- Domain of dependence of point P points in xv-domain which influence the value of f in point P
- Range of influence of point P points in xy-domain which are influenced by the value of f in point P



Introduction 000000000

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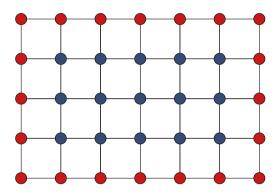
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Example elliptic PDE (boundary value problems: BVP)



Grid point at which dependent variable has to be computed Grid point at which boundary condition is specified

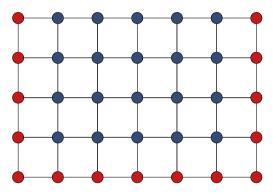
Typical example: Poisson equation

$$\frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} = f(x, y)$$

Introduction 000000000

Efficiency (memory requirements, CPU time) of the numerical method is of crucial importance.

Example parabolic PDE (initial value problem: IVP)



Grid point at which dependent variable has to be computed Grid point at which boundary condition is specified

Typical example: Poisson equation

$$\frac{\partial c}{\partial t} + u \frac{\partial c}{\partial x} = \mathcal{D} \frac{\partial^2 c}{\partial x^2} + R$$

Introduction 000000000

Stability (in numerical sense) of the numerical method is of crucial importance.

Boundary conditions

• Dirichlet or fixed condition: prescribed value of *f* at boundary

$$f = f_0$$
 f_0 is a known function

ullet Neumann condition: prescribed value of derivative of f at boundary

$$\frac{\partial f}{\partial n} = q$$
 q is a known function

• Mixed or Robin condition: relation between f and $\frac{\partial f}{\partial n}$ at boundary

$$a\frac{\partial f}{\partial n} + bf = c$$
 a, b and c are known functions



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Numerical solution method

Finite differences (method of lines, MOL):

- 1 Discretize spatial domain in discrete grid points
- Find suitable approximation for the spatial derivatives
- Substitute approximations in PDE, which gives a system of ODE's, one for every grid points
- Advance in time with a suitable ODE solver

Alternative methods: collocation, Galerkin or Finite Element methods



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$$\frac{\partial c}{\partial t} = \mathcal{D} \frac{\partial^2 c}{\partial x^2}, \quad \text{with} \quad \begin{array}{l} t = 0; 0 \leq x \leq \ell \Rightarrow c = c_0 \\ t > 0; x = 0 \Rightarrow c = c_L \\ t > 0; x = \ell \Rightarrow c = c_R \end{array}$$

Second derivative
$$\frac{\partial^2 c}{\partial x^2}$$
 $\stackrel{c_{i-1}}{\bullet}$ $\stackrel{c_{i}}{\bullet}$ $\stackrel{c_{i+1}}{\bullet}$



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$$c_{i+1} = c_i + \frac{\partial c}{\partial x}\Big|_i \Delta x + \frac{1}{2} \frac{\partial^2 c}{\partial x^2}\Big|_i \Delta x^2 + \frac{1}{6} \frac{\partial^3 c}{\partial x^3}\Big|_i \Delta x^3 + \dots$$

$$c_{i-1} = c_i - \frac{\partial c}{\partial x}\Big|_i \Delta x + \frac{1}{2} \frac{\partial^2 c}{\partial x^2}\Big|_i \Delta x^2 - \frac{1}{6} \frac{\partial^3 c}{\partial x^3}\Big|_i \Delta x^3 + \dots$$



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Second derivative $\frac{\partial^2 c}{\partial x^2}$ c_{i-1}

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$$c_{i+1} + c_{i-1} = 2c_i + \frac{\partial^2 c}{\partial x^2} \bigg|_i \Delta x^2 + \mathcal{O}(\Delta x^4)$$

$$\Rightarrow \frac{\partial^2 c}{\partial x^2}\bigg|_i = \frac{c_{i+1} - 2c_i + c_{i-1}}{\Delta x^2} + \mathcal{O}(\Delta x^2)$$



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Second derivative
$$\frac{\partial^2 c}{\partial v^2}$$
 c_{i-1}

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$$\Rightarrow \frac{\partial^2 c}{\partial x^2}\bigg|_i = \frac{c_{i+1} - 2c_i + c_{i-1}}{\Delta x^2} + \mathcal{O}(\Delta x^2)$$



Due to symmetric discretization: second order (central discretization).

An alternative discretization:

$$\left. \frac{\partial^2 c}{\partial x^2} \right|_i = \frac{\left. \frac{\partial c}{\partial x} \right|_{i+\frac{1}{2}} - \left. \frac{\partial c}{\partial x} \right|_{i-\frac{1}{2}}}{\Delta x} + \mathcal{O}(\Delta x^2)$$

$$c_{i-1} \xrightarrow{\frac{\partial c}{\partial x}\Big|_{i-\frac{1}{2}}} c_{i} \xrightarrow{\frac{\partial c}{\partial x}\Big|_{i+\frac{1}{2}}} c_{i+1}$$



An alternative discretization:

$$\frac{\partial^{2} c}{\partial x^{2}}\Big|_{i} = \frac{\frac{\partial c}{\partial x}\Big|_{i+\frac{1}{2}} - \frac{\partial c}{\partial x}\Big|_{i-\frac{1}{2}}}{\Delta x} + \mathcal{O}(\Delta x^{2}) \xrightarrow{c_{i-1}} \frac{\frac{\partial c}{\partial x}\Big|_{i-\frac{1}{2}}}{X} \xrightarrow{c_{i}} \frac{\frac{\partial c}{\partial x}\Big|_{i+\frac{1}{2}}}{X} \xrightarrow{c_{i+\frac{1}{2}}} \frac{c_{i+\frac{1}{2}}}{X}$$

$$= \frac{c_{i+1} - c_{i}}{\Delta x} - \frac{c_{i} - c_{i-1}}{\Delta x}}{\Delta x} = \frac{c_{i+1} - 2c_{i} + c_{i-1}}{\Delta x^{2}}$$



An alternative discretization:

$$\frac{\partial^{2} c}{\partial x^{2}}\Big|_{i} = \frac{\frac{\partial c}{\partial x}\Big|_{i+\frac{1}{2}} - \frac{\partial c}{\partial x}\Big|_{i-\frac{1}{2}}}{\Delta x} + \mathcal{O}(\Delta x^{2}) \qquad \bullet \qquad \bullet \qquad \bullet \qquad \bullet \qquad \bullet$$

$$= \frac{c_{i+1} - c_{i}}{\Delta x} - \frac{c_{i} - c_{i-1}}{\Delta x} = \frac{c_{i+1} - 2c_{i} + c_{i-1}}{\Delta x^{2}}$$

This is convenient for the derivation of $\frac{\partial}{\partial x} \left(\mathcal{D} \frac{\partial c}{\partial x} \right)$:

$$\frac{\partial}{\partial x} \left(\mathcal{D} \frac{\partial c}{\partial x} \right) = \frac{\mathcal{D}_{i+\frac{1}{2}} \frac{\partial c}{\partial x} \Big|_{i+\frac{1}{2}} - \mathcal{D}_{i-\frac{1}{2}} \frac{\partial c}{\partial x} \Big|_{i-\frac{1}{2}}}{\Delta x} = \frac{\mathcal{D}_{i+\frac{1}{2}} \frac{c_{i+1} - c_i}{\Delta x} - \mathcal{D}_{i-\frac{1}{2}} \frac{c_i - c_{i-1}}{\Delta x}}{\Delta x}$$

$$= \frac{\mathcal{D}_{i+\frac{1}{2}} c_{i+1} - \left(\mathcal{D}_{i+\frac{1}{2}} + \mathcal{D}_{i-\frac{1}{2}} \right) c_i + \mathcal{D}_{i-\frac{1}{2}} c_{i-1}}{(\Delta x)^2}$$



$$\frac{\partial^2 f}{\partial x^2}$$

$$i-1$$
 $i-\frac{1}{2}$ i $i+\frac{1}{2}$ $i+1$



$$\frac{\partial^2 f}{\partial x^2}$$
 $i - 1$ $\frac{i - \frac{1}{2}}{\sqrt{2}}$ i $i + \frac{1}{2}$ $i + 1$

$$f_{i+\frac{1}{2}} = f_i + \frac{1}{2}\Delta x \frac{\partial f}{\partial x} \Big|_i \Delta x + \frac{1}{2} \left(\frac{1}{2}\Delta x \right)^2 \frac{\partial^2 f}{\partial x^2} \Big|_i + \mathcal{O}(\Delta x^3)$$

$$f_{i-\frac{1}{2}} = f_i - \frac{1}{2}\Delta x \frac{\partial f}{\partial x} \Big|_i \Delta x + \frac{1}{2} \left(\frac{1}{2}\Delta x \right)^2 \frac{\partial^2 f}{\partial x^2} \Big|_i + \mathcal{O}(\Delta x^3)$$

$$f_{i+\frac{1}{2}} - f_{i-\frac{1}{2}} = \Delta x \frac{\partial f}{\partial x} + \mathcal{O}(\Delta x^3)$$



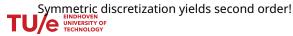
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$$f_{i+\frac{1}{2}} - f_{i-\frac{1}{2}} = \Delta x \frac{\partial f}{\partial x} + \mathcal{O}(\Delta x^3)$$

$$\Rightarrow \frac{\partial f}{\partial x}\bigg|_{i} = \frac{f_{i+\frac{1}{2}} - f_{i-\frac{1}{2}}}{\Delta x} + \mathcal{O}(\Delta x^{2})$$



Instationary diffusion equation: spatial discretization

Substitution of spatial derivatives yields:

$$\frac{dc_i}{dt} = \mathcal{D}\frac{c_{i-1} - 2c_i + c_{i+1}}{\Delta x^2} \quad \text{for } i = 0, \dots, N$$



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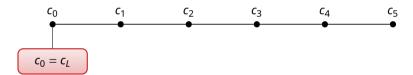
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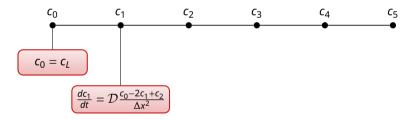




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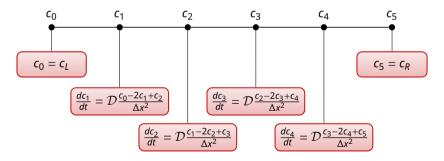




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Instationary diffusion equation: boundary conditions

Two options:

1 Keep boundary conditions as additional equations:

$$c_{0} = c_{L}, \frac{dc_{1}}{dt} = \mathcal{D}\frac{c_{0} - 2c_{1} + c_{2}}{\Delta x^{2}}, \frac{dc_{2}}{dt} = \mathcal{D}\frac{c_{1} - 2c_{2} + c_{3}}{\Delta x^{2}},$$

$$\frac{dc_{3}}{dt} = \mathcal{D}\frac{c_{2} - 2c_{3} + c_{4}}{\Delta x^{2}}, \frac{dc_{4}}{dt} = \mathcal{D}\frac{c_{3} - 2c_{4} + c_{5}}{\Delta x^{2}}, c_{5} = c_{R}$$

Substitute boundary conditions to reduce number of equations:

$$\begin{split} \frac{dc_{1}}{dt} &= \mathcal{D} \frac{c_{L} - 2c_{1} + c_{2}}{\Delta x^{2}}, \frac{dc_{2}}{dt} = \mathcal{D} \frac{c_{1} - 2c_{2} + c_{3}}{\Delta x^{2}}, \\ \frac{dc_{3}}{dt} &= \mathcal{D} \frac{c_{2} - 2c_{3} + c_{4}}{\Delta x^{2}}, \frac{dc_{4}}{dt} = \mathcal{D} \frac{c_{3} - 2c_{4} + c_{R}}{\Delta x^{2}} \end{split}$$



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Substitute boundary conditions to reduce number of equations:

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Instationary diffusion equation: temporal discretization

$$\frac{dc_i}{dt} = \mathcal{D}\frac{c_{i-1} - 2c_i + c_{i+1}}{\Delta x^2}$$

Time discretization: forward Euler (explicit)

$$\frac{c_{i}^{n+1} - c_{i}^{n}}{\Delta t} = \mathcal{D}\frac{c_{i-1}^{n} - 2c_{i}^{n} + c_{i+1}^{n}}{\Delta x^{2}}$$

$$\Rightarrow c_i^{n+1} = \operatorname{Foc}_{i-1}^n + (1 - 2\operatorname{Fo})c_i^n + \operatorname{Foc}_{i+1}^n \quad \text{with Fo} = \frac{\mathcal{D}\Delta t}{\Delta x^2}$$

Straightforward updating (explicit equation), simple to implement in a program but stability constraint Fo = $\frac{D\Delta t}{\Delta v^2} < \frac{1}{2}!$

Small $\Delta x \Rightarrow$ small $\Delta t \Rightarrow$ patience required \odot



Instationary diffusion equation: temporal discretization

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Time discretization: backward Euler (implicit)

$$\frac{c_{i}^{n+1} - c_{i}^{n}}{\Delta t} = \mathcal{D} \frac{c_{i-1}^{n+1} - 2c_{i}^{n+1} + c_{i+1}^{n+1}}{\Delta x^{2}}$$

$$\Rightarrow -\text{Foc}_{i-1}^{n+1} + (1 + 2\text{Fo})c_{i}^{n+1} - \text{Foc}_{i+1}^{n+1} = c_{i}^{n} \quad \text{with Fo} = \frac{\mathcal{D}\Delta t}{\Delta x^{2}}$$

Requires the solution of a system of linear equations, but no stability constraints!

Note: extension to higher order schemes (with time step adaptation) straightforward. Often second or third order optimal, because for each Euler-like step in the additional order an often large system needs to be solved (not treated in this course).



Solve the diffusion problem using explicit discretization:

$$\frac{\partial c_i}{\partial t} = \mathcal{D} \frac{\partial^2 c}{\partial x^2} \quad \text{with} \quad \begin{aligned} 0 &\leq x \leq \delta, \ \delta = 5 \cdot 10^{-3} \text{ m} \\ \delta/\Delta x &= 100 \text{ grid cells} \\ \mathcal{D} &= 1 \cdot 10^{-8} \text{ m}^2 \text{ s}^{-1} \\ t_{\text{end}} &= 5000 \text{ s} \\ c_{\text{L}} &= 1 \text{ mol m}^{-3} \ c_{\text{R}} = 0 \text{ mol m}^{-3} \end{aligned}$$



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$$c_i^{n+1} = \operatorname{Foc}_{i-1}^n + (1 - 2\operatorname{Fo})c_i^n + \operatorname{Foc}_{i+1}^n$$
 with $\operatorname{Fo} = \frac{D\Delta t}{\Delta x^2}$



Solve the diffusion problem using explicit discretization:

$$\frac{\partial c_i}{\partial t} = \mathcal{D} \frac{\partial^2 c}{\partial x^2} \quad \text{with} \quad \begin{aligned} 0 &\leq x \leq \delta, \ \delta = 5 \cdot 10^{-3} \text{ m} \\ \delta/\Delta x &= 100 \text{ grid cells} \\ \mathcal{D} &= 1 \cdot 10^{-8} \text{ m}^2 \text{ s}^{-1} \\ t_{\text{end}} &= 5000 \text{ s} \\ c_{\text{L}} &= 1 \text{ mol m}^{-3} \ c_{\text{R}} = 0 \text{ mol m}^{-3} \end{aligned}$$

$$c_i^{n+1} = \text{Fo}c_{i-1}^n + (1-2\text{Fo})c_i^n + \text{Fo}c_{i+1}^n$$
 with $\text{Fo} = \frac{\mathcal{D}\Delta t}{\Delta x^2}$

- Initialise variables
- 2 Compute time step so that Fo $\leq \frac{1}{2} \Rightarrow \Delta t = 0.125$ s!
- Compute 40000 time steps times 100 grid nodes!
- Store solution



Initialise the variables and matrices:

```
import numpy as np
  Nx = 100 \# Nx \text{ grid points}
  Nt = 40000 \# Nt time steps
  D = 1e-8 \# m/s
  c L = 1.0: c R = 0 \# mol/m3
  t end = 5000.0 # s
  x end = 5e-3 # m
10 # Time step and grid size
  dt = t end / Nt
  dx = x \text{ end } / Nx
14 # Fourier number
15 Fo = D * dt / dx / dx
# Initial matrices for solutions (Nx times Nt)
18 c = np.zeros((Nt + 1, Nx + 1)) # All concentrations are zero
19 c[:, 0] = c_L # Concentration at the left side
  c[:. Nx] = c R # Concentration at the right side
# Grid node and time step positions
  x = np.linspace(0, x_end, Nx + 1)
```

Compute the solution (nested time-and-grid loop):

```
for n in range(Nt): # time loop
    for i in range(1, Nx): # Nested loop for grid nodes
        c[n+1, i] = Fo*c[n, i-1] + (1-2*Fo)*c[n, i] + Fo*c[n, i+1];
```



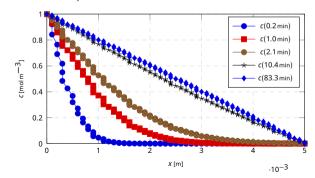
Compute the solution (nested time-and-grid loop):

Plotting the solution at $t = \{12.5, 62.5, 125, 625, 5000\}$ s:

```
# Output times
outt = [12.5, 62.5, 125, 625, 5000]

# Convert+round to time steps
outt_dt = [int(t // dt) for t in outt]

# Plot all time steps at once
import matplotlib.pyplot as plt
plt.plot(x, c[outt_dt, :].T)
plt.show()
```





A double-loop can impose serious computation times if the number of grid points increases:

```
for n in range(Nt - 1): # time loop
    for i in range(1, Nx): # Nested loop for grid nodes
        c[n+1, i] = Fo * c[n, i-1] + (1 - 2*Fo) * c[n, i] + Fo * c[n, i+1]
```

Remedy: vectorization. Construct a 3-point stencil Laplacian matrix first, then use the matrix product to evolve the simulation:

```
from scipy.sparse import diags

# Construct sparse matrix
e = np.ones(Nx-1)
md = np.concatenate(([1], (1 - 2 * Fo) * e, [1]))
ld = np.concatenate((Fo * e, [0]))
ud = np.concatenate(([0], Fo * e))
A = diags([ld, md, ud], offsets=[-1, 0, 1])

# Time evolution
for n in range(Nt - 1): # time loop
    c[n+1, :] = A.dot(c[n,:])
```



Linear system
$$A\mathbf{x} = \mathbf{b}$$
 from $-\text{Foc}_{i-1}^{n+1} + (1 + 2\text{Fo})c_i^{n+1} - \text{Foc}_{i+1}^{n+1} = c_i^n$

$$\begin{pmatrix} 1 & 0 & 0 & 0 & \cdots & 0 \\ -Fo & (1+2Fo) & -Fo & 0 & \cdots & 0 \\ 0 & -Fo & (1+2Fo) & -Fo & \cdots & 0 \\ 0 & 0 & -Fo & (1+2Fo) & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 1 \end{pmatrix} \cdot \begin{pmatrix} c_0^{n+1} \\ c_1^{n+1} \\ c_2^{n+1} \\ \vdots \\ c_m^{n+1} \\ c_m^n \end{pmatrix} = \begin{pmatrix} c_0^{n+1} \\ c_1^{n+1} \\ c_2^{n} \\ \vdots \\ c_m^{n} \end{pmatrix}$$



Linear system
$$A\mathbf{x} = \mathbf{b}$$
 from $-\text{Foc}_{i-1}^{n+1} + (1 + 2\text{Fo})c_i^{n+1} - \text{Foc}_{i+1}^{n+1} = c_i^n$

$$\begin{pmatrix} 1 & 0 & 0 & 0 & \cdots & 0 \\ -Fo & (1+2Fo) & -Fo & 0 & \cdots & 0 \\ 0 & -Fo & (1+2Fo) & -Fo & \cdots & 0 \\ 0 & 0 & -Fo & (1+2Fo) & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 1 \end{pmatrix} \cdot \begin{pmatrix} c_0^{n+1} \\ c_0^{n+1} \\ c_1^{n+1} \\ c_2^{n+1} \\ \vdots \\ c_m^{n+1} \end{pmatrix} = \begin{pmatrix} c_0^n \\ c_1^n \\ c_1^n \\ c_2^n \\ c_3^n \\ \vdots \\ c_m^{n+1} \end{pmatrix}$$

$$1 \times c_0^{n+1} = c_0^n$$
 (boundary condition)



Linear system
$$A\mathbf{x} = \mathbf{b}$$
 from $-\text{Foc}_{i-1}^{n+1} + (1 + 2\text{Fo})c_i^{n+1} - \text{Foc}_{i+1}^{n+1} = c_i^n$

$$\begin{pmatrix} 1 & 0 & 0 & 0 & \cdots & 0 \\ -Fo & (1+2Fo) & -Fo & 0 & \cdots & 0 \\ 0 & -Fo & (1+2Fo) & -Fo & \cdots & 0 \\ 0 & 0 & -Fo & (1+2Fo) & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 1 \end{pmatrix} \cdot \begin{pmatrix} c_0^{n+1} \\ c_0^{n+1} \\ c_1^{n+1} \\ c_2^{n+1} \\ \vdots \\ c_m^{n+1} \end{pmatrix} = \begin{pmatrix} c_0^n \\ c_0^n \\ c_1^n \\ c_2^n \\ \vdots \\ c_m^{n+1} \\ c_m^n \end{pmatrix}$$

$$1 \times c_0^{n+1} = c_0^n$$
 (boundary condition)

$$-\mathsf{Foc}_0^{n+1} + (1+2\mathsf{Fo})c_1^{n+1} - \mathsf{Foc}_2^{n+1} = c_1^n$$



Linear system
$$A\mathbf{x} = \mathbf{b}$$
 from $-\text{Foc}_{i-1}^{n+1} + (1 + 2\text{Fo})c_i^{n+1} - \text{Foc}_{i+1}^{n+1} = c_i^n$

$$\begin{pmatrix} 1 & 0 & 0 & 0 & \cdots & 0 \\ -Fo & (1+2Fo) & -Fo & 0 & \cdots & 0 \\ 0 & -Fo & (1+2Fo) & -Fo & \cdots & 0 \\ 0 & 0 & -Fo & (1+2Fo) & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 1 \end{pmatrix} \cdot \begin{pmatrix} c_0^{n+1} \\ c_0^{n+1} \\ c_1^{n+1} \\ c_2^{n+1} \\ \vdots \\ c_m^{n+1} \end{pmatrix} = \begin{pmatrix} c_0^n \\ c_1^n \\ c_2^n \\ \vdots \\ c_m^{n+1} \\ c_m^n \end{pmatrix}$$

 $1 \times c_0^{n+1} = c_0^n$ (boundary condition)

$$-\mathsf{Foc}_0^{n+1} + (1+2\mathsf{Fo})c_1^{n+1} - \mathsf{Foc}_2^{n+1} = c_1^n$$

$$-\operatorname{Foc}_1^{n+1} + (1+2\operatorname{Fo})c_2^{n+1} - \operatorname{Foc}_3^{n+1} = c_2^n$$



Linear system
$$A\mathbf{x} = \mathbf{b}$$
 from $-\text{Foc}_{i-1}^{n+1} + (1 + 2\text{Fo})c_i^{n+1} - \text{Foc}_{i+1}^{n+1} = c_i^n$

$$\begin{pmatrix} 1 & 0 & 0 & 0 & \cdots & 0 \\ -Fo & (1+2Fo) & -Fo & 0 & \cdots & 0 \\ 0 & -Fo & (1+2Fo) & -Fo & \cdots & 0 \\ 0 & 0 & -Fo & (1+2Fo) & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 1 \end{pmatrix} \cdot \begin{pmatrix} c_0^{n+1} \\ c_0^{n+1} \\ c_1^{n+1} \\ c_2^{n+1} \\ \vdots \\ c_m^{n+1} \end{pmatrix} = \begin{pmatrix} c_0^n \\ c_1^n \\ c_2^n \\ \vdots \\ c_m^{n+1} \\ c_m^n \end{pmatrix}$$

$$1 \times c_0^{n+1} = c_0^n$$
 (boundary condition)

$$-\mathsf{Foc}_0^{n+1} + (1+2\mathsf{Fo})c_1^{n+1} - \mathsf{Foc}_2^{n+1} = c_1^n$$

$$-\operatorname{Foc}_1^{n+1} + (1+2\operatorname{Fo})c_2^{n+1} - \operatorname{Foc}_3^{n+1} = c_2^n$$

$$-\operatorname{Foc}_{2}^{n+1} + (1+2\operatorname{Fo})c_{3}^{n+1} - \operatorname{Foc}_{4}^{n+1} = c_{3}^{n}$$



Linear system
$$A\mathbf{x} = \mathbf{b}$$
 from $-\text{Foc}_{i-1}^{n+1} + (1 + 2\text{Fo})c_i^{n+1} - \text{Foc}_{i+1}^{n+1} = c_i^n$

$$\begin{pmatrix} 1 & 0 & 0 & 0 & \cdots & 0 \\ -Fo & (1+2Fo) & -Fo & 0 & \cdots & 0 \\ 0 & -Fo & (1+2Fo) & -Fo & \cdots & 0 \\ 0 & 0 & -Fo & (1+2Fo) & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 1 \end{pmatrix} \cdot \begin{pmatrix} c_0^{n+1} \\ c_0^{n+1} \\ c_2^{n+1} \\ c_3^{n+1} \\ \vdots \\ c_m^{n+1} \end{pmatrix} = \begin{pmatrix} c_0^n \\ c_1^n \\ c_2^n \\ \vdots \\ c_m^{n+1} \\ c_m^n \end{pmatrix}$$

 $1 \times c_0^{n+1} = c_0^n$ (boundary condition)

$$-\mathsf{Foc}_0^{n+1} + (1+2\mathsf{Fo})c_1^{n+1} - \mathsf{Foc}_2^{n+1} = c_1^n$$

$$-\operatorname{Foc}_1^{n+1} + (1+2\operatorname{Fo})c_2^{n+1} - \operatorname{Foc}_3^{n+1} = c_2^n$$

$$-\operatorname{Foc}_{2}^{n+1} + (1+2\operatorname{Fo})c_{3}^{n+1} - \operatorname{Foc}_{4}^{n+1} = c_{3}^{n}$$

 $1 \times c_m^{n+1} = c_m^n$ (boundary condition)



Solving the diffusion equation implicitly in Python

To solve the linear system, we need to define matrix *A*. It is clear that storing many zeros is not efficient in terms of memory. We use a *sparse matrix* format. Two alternative ways to set up the matrix:

Set individual elements of the matrix:

```
from scipy.sparse import lil_matrix

# Bands in matrix (internal cells)
A = lil_matrix((Nx+1, Nx+1))
for i in range(1, Nx):
    A[i, i-1] = -Fo

A[i, i] = 1 + 2*Fo
    A[i, i+1] = -Fo

**Set boundary cells, only main diag:
A[0, 0] = 1 # Left
A[Nx, Nx] = 1 # Right
```

Set matrix using bands:

```
from scipy.sparse import diags

# Bands in matrix (internal cells)

e = np.ones(Nx-1) # Ones for internal cells

md = np.concatenate(([1], e * (1 + 2*Fo), [1])) #

Main diagonal

ld = np.concatenate((-e * Fo, [0])) # Lower diagonal

ud = np.concatenate(([0], -e * Fo)) # Upper diagonal

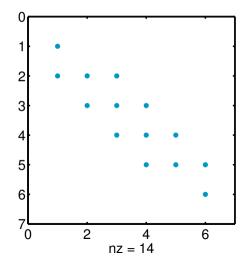
A = diags([ld, md, ud], offsets=[-1, 0, 1])
```

Note: The first argument of diags defines each column as a diagonal, starting at row 0 (for lower-diagonal) or column 0 (for upper-diagonal).



Solving the diffusion equation implicitly in Python

The command plt.spy(A) shows a figure with the non-zero positions.





The concentration matrix is initialised and the boundary conditions are set as follows:

```
# Initial matrices for solutions (Nx times Nt)
c = np.zeros((Nt+1, Nx+1)) # All concentrations are zero
c[:, 0] = c_L # Concentration at left side
c[:, Nx] = c_R # Concentration at right side
```

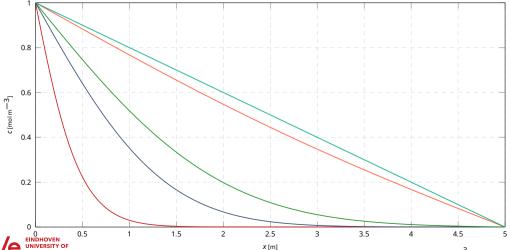
The right hand side vector (**b**) can now be set during the time-loop:

```
from scipv.sparse.linalg import spsolve
for n in range(Nt-1): # time loop
   b = c[n, :] # Set right hand side
   solX = spsolve(A, b) # Solve linear system
   c[n+1, :] = solX # Store solution each time step
```



Solving the diffusion equation implicitly in Matlab

Plotting the solution at $t = \{12.5, 62.5, 125, 625, 5000\}$ s.





About explicit vs. implicit solutions

- Explicit solution:
 - Easy to implement
 - Very small time steps required.
 - This problem took about 0.5 s.
- Implicit solution:
 - Harder to implement, needs sparse matrix solver
 - No stability constraint
 - This problem took about 0.05 s
- The difference will become much larger for systems with e.g. more grid nodes!



Extension with non-linear source terms

$$\begin{array}{c} t = 0; 0 \leq x \leq \ell \Rightarrow c = c_0 \\ \frac{\partial c}{\partial t} = \mathcal{D} \frac{\partial^2 c}{\partial x^2} + R(c) \quad \text{with} \quad \begin{array}{c} t = 0; 0 \leq x \leq \ell \Rightarrow c = c_0 \\ t > 0; x = 0 \Rightarrow c = c_L \\ t > 0; x = \ell \Rightarrow c = c_R \end{array}$$

Extension with non-linear source terms

$$\frac{\partial c}{\partial t} = \mathcal{D}\frac{\partial^{2} c}{\partial x^{2}} + R(c) \quad \text{with} \quad \begin{aligned} t &= 0; 0 \leq x \leq \ell \Rightarrow c = c_{0} \\ t &> 0; x = 0 \Rightarrow c = c_{L} \\ t &> 0; x = \ell \Rightarrow c = c_{R} \end{aligned}$$

• Forward Euler (explicit): simply add to right-hand side

$$\frac{c_i^{n+1} - c_i^n}{\Delta t} = \mathcal{D}\frac{c_{i-1}^n - 2c_i^n + c_{i+1}^n}{\Delta x^2} + R(c_i^n)$$

$$\Rightarrow c_i^{n+1} = \operatorname{Foc}_{i-1}^n + (1 - 2\operatorname{Fo})c_i^n + \operatorname{Foc}_{i+1}^n + R_i^n \Delta t$$

Extension with non-linear source terms

$$\frac{\partial c}{\partial t} = \mathcal{D}\frac{\partial^{2} c}{\partial x^{2}} + R(c) \quad \text{with} \quad \begin{aligned} t &= 0; 0 \le x \le \ell \Rightarrow c = c_{0} \\ t &> 0; x = 0 \Rightarrow c = c_{L} \\ t &> 0; x = \ell \Rightarrow c = c_{P} \end{aligned}$$

Forward Euler (explicit): simply add to right-hand side

$$\frac{c_{i}^{n+1} - c_{i}^{n}}{\Delta t} = \mathcal{D}\frac{c_{i-1}^{n} - 2c_{i}^{n} + c_{i+1}^{n}}{\Delta x^{2}} + R(c_{i}^{n})$$

$$\Rightarrow c_{i}^{n+1} = \text{Foc}_{i-1}^{n} + (1 - 2\text{Fo})c_{i}^{n} + \text{Foc}_{i+1}^{n} + R_{i}^{n}\Delta t$$

Backward Euler (implicit): linearization required

$$R(c_{i}^{n+1}) = R(c_{i}^{n}) + \frac{dR}{dc} \Big|_{i}^{n} (c_{i}^{n+1} - c_{i}^{n})$$

$$\frac{c_{i}^{n+1} - c_{i}^{n}}{\Delta t} = \mathcal{D} \frac{c_{i-1}^{n+1} - 2c_{i}^{n+1} + c_{i+1}^{n+1}}{\Delta x^{2}} + R(c_{i}^{n+1})$$

$$\Rightarrow -\text{Foc}_{i-1}^{n+1} + (1 + 2\text{Fo} - \frac{dR}{dc} \Big|_{i}^{n} \Delta t) c_{i}^{n+1} - \text{Foc}_{i+1}^{n+1} = c_{i}^{n} + \left(R_{i}^{n} - \frac{dR}{dc} \Big|_{i}^{n} c_{i}^{n} \right) \Delta t$$

Today's outline

- Introduction
- Instationary diffusion equation
- Convection
 - Discretization
 - Central difference scheme
 - Upwind scheme
- Conclusions



Extension with convection terms

$$\frac{\partial c}{\partial t} = \mathcal{D}\frac{\partial^2 c}{\partial x^2} - u\frac{\partial c}{\partial x} + R$$

Discretization of first derivative $\frac{dc}{dx}$, looks simple but is numerical headache!

Central discretization:

$$\frac{dc}{dx} = \frac{c_{i+1} - c_{i-1}}{2\Delta x}$$

 \Rightarrow simple and easy, too bad it doesn't work: yields unstable solutions if convection dominated.





Unsteady convection:

$$\frac{\partial c}{\partial t} = -u \frac{\partial c}{\partial x}$$

Central difference for first derivative:

$$\frac{dc}{dx} = \frac{c_{i+1} - c_{i-1}}{2\Delta x}$$





Unsteady convection:

$$\frac{\partial c}{\partial t} = -u \frac{\partial c}{\partial x}$$

Central difference for first derivative:

$$\frac{dc}{dx} = \frac{c_{i+1} - c_{i-1}}{2\Delta x}$$

$$\frac{c_i^{n+1}-c_i^n}{\Delta t}=-u\frac{c_{i+1}-c_{i-1}}{2\Delta x}\Rightarrow c_i^{n+1}=c_i^n-u\frac{c_{i+1}^n-c_{i-1}^n}{2\Delta x}\Delta t$$





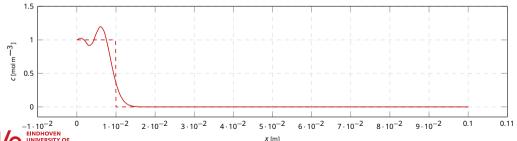
Unsteady convection:

$$\frac{\partial c}{\partial t} = -u \frac{\partial c}{\partial x}$$

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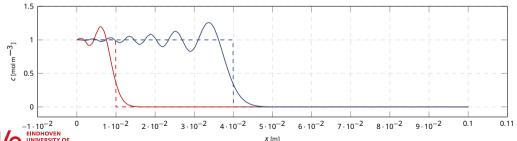
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$$\frac{\partial c}{\partial t} = -u \frac{\partial c}{\partial x}$$

Central difference for first derivative:

$$\frac{dc}{dx} = \frac{c_{i+1} - c_{i-1}}{2\Delta x}$$

$$\frac{c_i^{n+1}-c_i^n}{\Delta t}=-u\frac{c_{i+1}-c_{i-1}}{2\Delta x}\Rightarrow c_i^{n+1}=c_i^n-u\frac{c_{i+1}^n-c_{i-1}^n}{2\Delta x}\Delta t$$





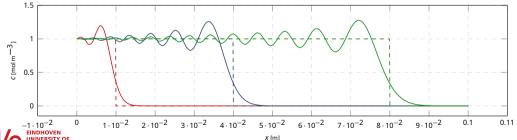
Unsteady convection:

$$\frac{\partial c}{\partial t} = -u \frac{\partial c}{\partial x}$$

Central difference for first derivative:

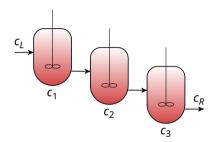
$$\frac{dc}{dx} = \frac{c_{i+1} - c_{i-1}}{2\Delta x}$$

$$\frac{c_i^{n+1}-c_i^n}{\Delta t}=-u\frac{c_{i+1}-c_{i-1}}{2\Delta x}\Rightarrow c_i^{n+1}=c_i^n-u\frac{c_{i+1}^n-c_{i-1}^n}{2\Delta x}\Delta t$$



Extension with convection terms

Solution: upwind discretization, like CSTR's in series:

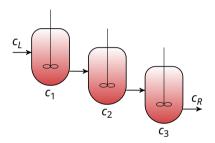


First order upwind:
$$-u \frac{dc}{dx}\Big|_{i} = \begin{cases} -u \frac{c_{i} - c_{i-1}}{\Delta x} & \text{if } u \ge 0 \\ -u \frac{c_{i+1} - c_{i}}{\Delta x} & \text{if } u < 0 \end{cases}$$

Convection

Extension with convection terms

Solution: upwind discretization, like CSTR's in series:



First order upwind:
$$-u\frac{dc}{dx}\Big|_i = \begin{cases} -u\frac{c_i - c_{i-1}}{\Delta x} & \text{if } u \ge 0 \\ & \text{Stable if Co} = \frac{u\Delta t}{\Delta x} < 1 \text{ (with Co the } -u\frac{c_{i+1} - c_i}{\Delta x} & \text{if } u < 0 \end{cases}$$

Courant number). However, only 1st order accurate (large smearing of concentration fronts). Higher order upwind requires TVD schemes (trick of the trade)...

First order upwind scheme of 1st derivative

Unsteady convection:

$$\frac{\partial c}{\partial t} = -u \frac{\partial c}{\partial x}$$

Upwind scheme for first derivative:

$$-u\frac{dc}{dx}\Big|_{i} = \begin{cases} -u\frac{c_{i} - c_{i-1}}{\Delta x} & \text{if } u \ge 0 \\ -u\frac{c_{i+1} - c_{i}}{\Delta x} & \text{if } u < 0 \end{cases}$$

First order upwind scheme of 1st derivative

Unsteady convection:

$$\frac{\partial c}{\partial t} = -u \frac{\partial c}{\partial x}$$

Upwind scheme for first derivative:

$$-u\frac{dc}{dx}\Big|_{i} = \begin{cases} -u\frac{c_{i}-c_{i-1}}{\Delta x} & \text{if } u \ge 0\\ -u\frac{c_{i+1}-c_{i}}{\Delta x} & \text{if } u < 0 \end{cases}$$

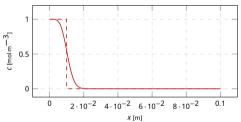
$$\frac{c_i^{n+1} - c_i^n}{\Delta t} = -u \frac{c_{i+1} - c_{i-1}}{2\Delta x}$$

$$\Rightarrow c_i^{n+1} = \begin{cases} c_i^n - u\Delta t \frac{c_i - c_{i-1}}{\Delta x} & \text{if } u \ge 0 \\ c_i^n - u\Delta t \frac{c_{i+1} - c_i}{\Delta x} & \text{if } u < 0 \end{cases}$$

$$\frac{\partial c}{\partial t} = -u \frac{\partial c}{\partial x} \quad \text{with} \quad u = 0.1 \text{ms}^{-1} \Rightarrow c_i^{n+1} = c_i^n - u \frac{c_i - c_{i-1}}{\Delta x} \Delta t$$

$$\frac{\partial c}{\partial t} = -u \frac{\partial c}{\partial x}$$
 with $u = 0.1 \text{ms}^{-1} \Rightarrow c_i^{n+1} = c_i^n - u \frac{c_i - c_{i-1}}{\Delta x} \Delta t$

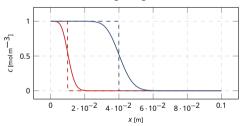






$$\frac{\partial c}{\partial t} = -u \frac{\partial c}{\partial x} \quad \text{with} \quad u = 0.1 \text{ms}^{-1} \Rightarrow c_i^{n+1} = c_i^n - u \frac{c_i - c_{i-1}}{\Delta x} \Delta t$$





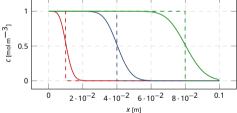


Unsteady convection through a pipe:

$$\frac{\partial c}{\partial t} = -u \frac{\partial c}{\partial x}$$
 with $u = 0.1 \text{ms}^{-1} \Rightarrow c_i^{n+1} = c_i^n - u \frac{c_i - c_{i-1}}{\Delta x} \Delta t$



Using 100 grid cells





0

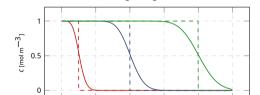


Upwind scheme: example

Unsteady convection through a pipe:

$$\frac{\partial c}{\partial t} = -u \frac{\partial c}{\partial x} \quad \text{with} \quad u = 0.1 \,\text{ms}^{-1} \Rightarrow c_i^{n+1} = c_i^n - u \frac{c_i - c_{i-1}}{\Delta x} \Delta t$$

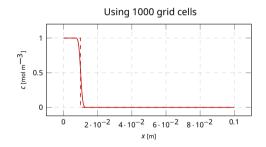
Using 100 grid cells





 $2 \cdot 10^{-2}$ $4 \cdot 10^{-2}$ $6 \cdot 10^{-2}$ $8 \cdot 10^{-2}$

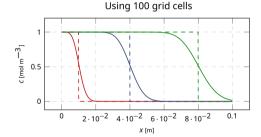
X [m]



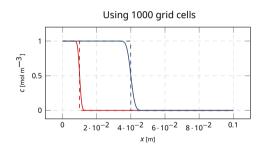




$$\frac{\partial c}{\partial t} = -u \frac{\partial c}{\partial x} \quad \text{with} \quad u = 0.1 \text{ms}^{-1} \Rightarrow c_i^{n+1} = c_i^n - u \frac{c_i - c_{i-1}}{\Delta x} \Delta t$$

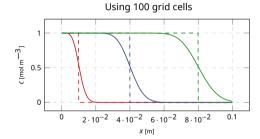




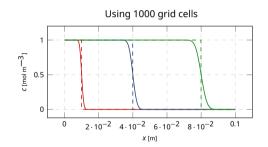




$$\frac{\partial c}{\partial t} = -u \frac{\partial c}{\partial x} \quad \text{with} \quad u = 0.1 \text{ms}^{-1} \Rightarrow c_i^{n+1} = c_i^n - u \frac{c_i - c_{i-1}}{\Delta x} \Delta t$$









TECHNOLOGY

Central difference and upwind in Python

The results from the previous slides were computed using this script:

```
import numpy as np
  Nx, Nt = 1000, 10000 # Nc grid points Nt time steps
  u = 0.001 \# m/s
  c in = 1.0 \# mol/m3
  t end = 100.0 # s
  x end = 0.1 # m
9 # Time step and grid size
  dt, dx = t_end/Nt, x_end/Nx
  # Courant number
  Co = u*dt/dx
14
# Initial matrices for solutions (Nx times Nt)
16 c1 = np.zeros((Nt+1, Nx+1)) # All concentrations are zero
  c1[:. 0] = c_in # Concentration at inlet (all time steps)
an = np.copy(c1)
  c2 = np.copy(c1) # Analytical and upwind solution
20
# Grid node and time step positions
x = \text{np.linspace}(0, x_{end}, Nx+1)
  t = np.linspace(0, t_end, Nt+1)
```

Central difference and upwind in Python

(continued)

```
for n in range(Nt): # time loop
    for i in range(1, Nx): # Nested loop for grid nodes
    # Central difference
    c1[n+1, i] = c1[n, i] - u*((c1[n, i+1] - c1[n, i-1])/(2*dx))*dt
    # Upwind
    c2[n+1, i] = c2[n, i] - u*((c2[n, i] - c2[n, i-1])/dx)*dt
    # Analytical
    an[n+1, i] = (x[i] < u*t[n+1])*c_in</pre>
```



Today's outline

- Introduction
- Instationary diffusion equation
- Convection
- Conclusions
 - Other methods
 - Summary



Extension to systems of PDE's

- Explicit methods: straightforward extension
- Implicit methods: yields block-tridiagonal matrix (note ordering of equations: all variables per grid cell)



Extension to 2D or 3D systems

Spatial discretization in 2 directions — different methods available:

- Explicit
- Fully implicit
 - 1D gives tri-diagonal matrix
 - 2D gives penta-diagonal matrix
 - 3D gives hepta-diagonal matrix

Use of dedicated matrix solvers (e.g. ICCG, multigrid, ...)

- Alternating direction implicit (ADI)
 - Per direction implicit, but still overall unconditionally stable



Further extensions for parabolic PDEs

- Higher order temporal discretization (multi-step) with time step adaptation
- Non-uniform grids with automatic grid adaptation
- Higher-order discretization methods, especially higher order TVD (flux delimited) schemes for convective fluxes (e.g. WENO schemes)
- Higher-order finite volume schemes (Riemann solvers)



Summary

- Several classes of PDEs were introduced.
 - Elliptic, Parabolic, Hyperbolic PDEs
- Diffusion equation: discretization of temporal and spatial domain was discussed
 - Solutions of the diffusion equation using explicit and implicit methods
 - How to add non-linear source terms
- Convection: upwind vs. central difference schemes

