

Lecture 1:

A first numerical example:

Radioactive decays

Learning outcomes of course

- ▶ Scientific computing for complex (=realistic) problems
- ▶ Basic numerical methods and their implementation
 - ▶ solving differential equations
 - ▶ root finding: solutions for $f(x) = 0$
 - ▶ numerical integration
 - ▶ Monte Carlo methods & simulation
- ▶ Assignments in Python notebooks

<https://dmaitre.phyip3.dur.ac.uk/notebooks/nm/>

Material

- ▶ The course is entirely based on
Giordano & Nakanishi: “Computational physics”
- ▶ Course homepage at

<https://www.ippp.dur.ac.uk/~krauss/Lectures/NumericalMethods/index.html>

Scientific computing:

- ▶ Start with a physical system/phenomenon, typically isolated, self-contained \implies **idealised**
- ▶ Formulate a mathematical model, for example pendulum:

$$\frac{d^2\theta}{dt^2} = \ddot{\theta} = -\frac{g}{l} \sin \theta .$$

- ▶ Sometimes must simplify further for analytical result (here: small angle approximation, i.e. $\sin \theta \rightarrow \theta$)
- ▶ Computer enters to go beyond highly idealised cases: **no analytical solution \rightarrow approximate numerically!**
- ▶ Implement/code numerical solution, but then the real work only begins:
 - ▶ **code verification** (aka “debugging”)
 - ▶ **model validation/refinement** (against “reality”)

Some vocabulary

- ▶ Solutions of mathematical models: typically **functions** like, e.g., $\theta(t)$ for pendulum or similar.
- ▶ Functions are **maps**:
set of input points \longrightarrow set of output points
domain \longrightarrow **range**.
- ▶ **Computations** evaluate functions.
- ▶ An **algorithm** is a recipe to transform inputs to outputs.
- ▶ In the digital world (computers),
the domain and range are discrete, and
the algorithm terminates after a finite number of steps

Types of errors

- ▶ **Truncation errors:**

Many functions given as series

like, e.g., $\sin x = x - \frac{x^3}{3!} + \dots$ or similar.

In their evaluation, computer must stop at some point.

- ▶ **Accuracy errors:**

Computer uses finite number of bits for representing a number, therefore finite precision only. This leads to round-off errors.

Example: $10^{30} + 1 - 10^{30} = 0$.

- ▶ **Discretisation errors:**

Representing smooth functions with discrete steps.

Should decrease with step-size.

These types of error can accumulate!

⇒ **Can lead to instabilities!**

(Correct algorithm produces wrong solution - no issue here)

Starting with physics: Radioactive decays

- ▶ Simple differential equation (1st order):

$$\frac{dN}{dt} = -\frac{N}{\tau} \stackrel{!}{=} f(N),$$

where $N(t)$ is the number of atoms in the material at any given time t , and τ is the time-constant of the decay. It is linked to the half-life $T_{1/2}$ like

$$T_{1/2} = \tau \cdot \ln 2.$$

- ▶ Analytical solution is equally straightforward:

$$N(t) = N(0) \exp\left(-\frac{t}{\tau}\right).$$

Numerical solution: discretisation

- ▶ Basic idea: continuous time $t \leftrightarrow$ discrete times t_i $i \in N$.
- ▶ How does this work out?
 - ▶ Remember definition of derivative:

$$\frac{dN}{dt} = \lim_{\Delta t \rightarrow 0} \frac{N(t + \Delta t) - N(t)}{\Delta t}$$

- ▶ Approximate $\Delta t \rightarrow 0$ with Δt “small enough”:

$$\frac{dN}{dt} \approx \frac{N(t + \Delta t) - f(t)}{\Delta t}$$

- ▶ Therefore rewrite differential eqn as difference eqn:

$$\frac{dN}{dt} = -\frac{N}{\tau} \iff N(t + \Delta t) - N(t) = -\frac{N(t)\Delta t}{\tau}.$$

Numerical solution: discretisation (cont'd)

- ▶ With discrete times:

$$\begin{aligned}N_{i+1} = N(t_{i+1}) &= N(t_i) - N(t_i) \frac{\Delta t}{\tau} \\t_{i+1} &= t_i + \Delta t\end{aligned}$$

- ▶ Simple general solution for first order differential eqn's:
Euler method

The first order differential equation $\frac{dx}{dt} = f(x, t)$ can be solved numerically (vector form) by

$$\begin{aligned}\underline{x}_{i+1} &= \underline{x}_i + f(\underline{x}_i, t) \Delta t \\t_{i+1} &= t_i + \Delta t.\end{aligned}$$

Error estimate (for discretisation error)

- ▶ To estimate error inherent in Euler method, start with Taylor expansion of

$$x(t + \Delta t) = x(t) + \frac{dx(t)}{dt} \Delta t + \frac{d^2x(t)}{dt^2} \frac{(\Delta t)^2}{2!} + \dots$$

- ▶ Algorithm uses first two terms, but ignores all others starting at the third one.

$$\implies \text{Error per step: } \mathcal{O}[(\Delta t)^2]$$

- ▶ But number of steps from t_0 to $t_{\text{end}} \sim 1/\Delta t!$

$$\implies \text{Overall error: } \mathcal{O}[(\Delta t)]$$

Pseudo-code for solution

Main program

- ▶ Input of initial conditions
- ▶ Initialise **classes** “Radioactive” and “DEq_Solver”
- ▶ Calculate the trajectory.
- ▶ Print/plot the result.

Initialisation of physics problem (in “Radioactive”)

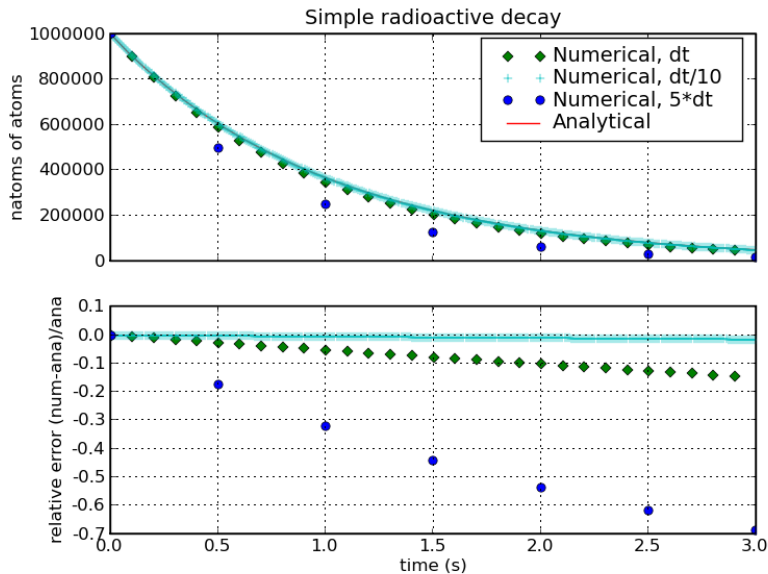
- ▶ Fix $t_0 = 0$, t_{end} , N_0 , τ
- ▶ δt part of the calculation, not the physics

Calculation (in “DEq_Solver”)

- ▶ Iterate time steps until $t_i \geq t_{\text{end}}$ is reached:

$$\begin{aligned} t_{i+1} &= t_i + \Delta t \\ \underline{x}(t_{i+1}) &= \underline{x}_{i+1} = \underline{x}_i + \underline{f}(\underline{x}_i, t_i) \Delta t. \end{aligned}$$

Results



Summary

- ▶ Computer methods paramount when realistic physical situations/phenomena to be described quantitatively. There, typically, analytical solutions are not available, enforcing the use of numerical approaches.
- ▶ Various types of error intrinsic to using computers: truncation, accuracy, discretisation.
- ▶ A classical problem in physics: solving differential eqn's. Strategy (like nearly always): discretisation and rewriting differential eqn's as difference eqn's.
First method: Euler method - accurate to first order.