Computational Physics Lecture 11 – Evaluating Finite Difference Methods

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Slides available from https://bb.imperial.ac.uk/



Outline

- Consistency
- 2 Accuracy
- 3 Stability & Convergence

Goals

By the end of this lecture, you should be able to

- Determine if a given finite difference equation is actually a consistent representation of the DE you want to solve
- Determine the expected numerical accuracy of a given finite difference method
- Evaluate the stability properties of a finite differencing scheme

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Given a finite difference expression, you can work out what DE it actually exactly corresponds to.

 \rightarrow always a good consistency check to do before you run off writing and optimising code!

Start with your finite difference expression – e.g. for the Euler Method:

$$y(x_n+h)\approx y(x_n)+h\,f(x_n,y_n) \tag{1}$$

Taylor expand the lefthand side around $x = x_n$:

$$y(x_n)+y'(x_n)h+\frac{y''(x_n)}{2}h^2+\frac{y'''(x_n)}{3!}h^3+\ldots \approx y(x_n)+hf(x_n,y_n)$$
(2)

$$y(x_n) + y'(x_n)h + \frac{y''(x_n)}{2}h^2 + \frac{y'''(x_n)}{3!}h^3 + \ldots \approx y(x_n) + hf(x_n, y_n)$$

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$$y(x_n) + y'(x_n)h + \frac{y''(x_n)}{2}h^2 + \frac{y'''(x_n)}{3!}h^{3/2} + \ldots \approx y(x_n) + hf(x_n, y_n)$$

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$$y(x_n) + y'(x_n)h + \frac{y''(x_n)}{2}h^2 + \frac{y'''(x_n)}{3!}h^{32} + \dots \approx y(x_n) + hf(x_n, y_n)$$

$$y'(x_n) = f(x_n, y_n) - \frac{y''(x_n)}{2}h - \frac{y'''(x_n)}{3!}h^2 - \dots$$

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$$y'(x_n) = f(x_n, y_n) - \frac{y''(x_n)}{2}h - \frac{y'''(x_n)}{3!}h^2 - \dots$$

 \implies same as the desired DE y'(x) = f(x, y) to order $\mathcal{O}(h)$.

This **modified differential equation** is the one that the finite difference scheme is actually solving.



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Question: So how are these equivalent?

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Question: So how are these equivalent?

Answer: global (total) error is the sum of error in each step:

global error \approx local error \times number of steps

Assuming we have properly normalised variables so that *x* varies over the unit interval or thereabouts, these terms are of order

$$\mathcal{O}(\text{local error}) \times \mathcal{O}(\text{number of steps}) = \mathcal{O}(h^2) \times \mathcal{O}(1/h) = \mathcal{O}(h)$$



 \rightarrow A method is "*n*th-order" if it has local error $\mathcal{O}(h^{n+1})$ and global error $\mathcal{O}(h^n)$.

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Also remember that floating-point roundoff error accumulates as you keep taking each step:

- \rightarrow with roundoff error μ at each step, actual error at each step is $\mathcal{O}(\mu + h^2)$
- \rightarrow global error is then actually $\mathcal{O}(\frac{\mu}{h} + h)$
- \implies there is no gain in taking h arbitrarily small actually there is a 'sweet spot' when $h \sim \sqrt{\mu}$



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Take error at step *n* to be ϵ_n :

$$\tilde{y}_n = y_n + \epsilon_n,$$
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Stability requires that the error from each step decreases or stays steady from step to step:

$$\left|\frac{\epsilon_{n+1}}{\epsilon_n}\right| \le 1\tag{4}$$

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Only stable methods converge — unstable ones diverge as you take more steps.

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You can work this out by substituting the finite difference rule into the expression for the n + 1th value

$$\tilde{\mathbf{y}}_{n+1} = \mathbf{y}_{n+1} + \epsilon_{n+1},\tag{5}$$

and linearising the resulting expression about $y = y_n$, then rearranging to get an expression for $\epsilon_{n+1}/\epsilon_n$.

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$$\tilde{y}(x_n + h) = \tilde{y}(x_n) + h f(x_n, \tilde{y}_n)$$
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This gives

$$y(x_n + h) + \epsilon_{n+1} = y(x_n) + \epsilon_n + h f(x_n, y_n + \epsilon_n)$$
 (9)



2 Now linearise this expression

$$y(x_n + h) + \epsilon_{n+1} = y(x_n) + \epsilon_n + h f(x_n, y_n + \epsilon_n)$$
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around $y = y_n$. To first order in ϵ_n , we have

$$f(x_n, y_n + \epsilon_n) = f(x_n, y_n) + \epsilon_n \frac{\partial f}{\partial y}(x_n) + \mathcal{O}(\epsilon_n^2).$$
 (11)

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Therefore, the linearised version is

$$y(x_n + h) + \epsilon_{n+1} = y(x_n) + \epsilon_n + h \left[f(x_n, y_n) + \epsilon_n \frac{\partial f}{\partial y}(x_n) + \mathcal{O}(\epsilon_n^2) \right]$$
(12)

Now linearise this expression

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Therefore, the linearised version is

$$y(x_{n} + h) + \epsilon_{n+1} = y(x_{n}) + \epsilon_{n} + h \left[f(x_{n}, y_{n}) + \epsilon_{n} \frac{\partial f}{\partial y}(x_{n}) + \mathcal{O}(\epsilon_{n}^{2}) \right]$$

$$= y(x_{n}) + h f(x_{n}, y_{n}) + \epsilon_{n} \left[1 + h \frac{\partial f}{\partial y}(x_{n}) \right]$$

$$+ \mathcal{O}(\epsilon_{n}^{2})$$

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$$(13)$$

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So, we can rewrite the linearised expression as just

$$\epsilon_{n+1} + \mathcal{O}(h^2) = \epsilon_n \left[1 + h \frac{\partial f}{\partial y}(x_n) \right] + \mathcal{O}(\epsilon_n^2)$$
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 (15)

Dropping the higher-order terms, this is

$$\frac{\epsilon_{n+1}}{\epsilon_n} \approx 1 + h \frac{\partial f}{\partial v}(x_n). \tag{16}$$



$$\left|\frac{\epsilon_{n+1}}{\epsilon_n}\right| \approx \left|1 + h\frac{\partial f}{\partial y}(x_n)\right| \le 1. \tag{17}$$

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$$\Longrightarrow \qquad \qquad \frac{\partial f}{\partial y}(x_n) \leq 0 \qquad (18)$$

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Let's explore the stability of the Euler method in a real example – Jupyter notebook

Note that none of the topics covered today says anything about *efficiency*.

That is where more advanced methods come in – which is what the next 3 lectures are about.

Housekeeping

- Assignment ongoing tomorrow's lab the last chance to ask extended questions
- Friday: Solving ODE Initial Value Problems