

Lecture 11: rounding errors + solving IVPs with FDs

- Computers can only store numbers within a limited precision. Therefore, for most real numbers such as $1/3$, π and $\sqrt{2}$, there will always be a round-off error (the difference between the actual value and the computer representation).

Example: Euler's number (e)

$$e = \lim_{x \rightarrow 0} (1+x)^{1/x}$$

- To compute e very accurately, we can take x very small. However, if x gets close to the so-called machine accuracy, we will lose precision: the computer will round $1+x$ to 1.

• Rounding errors in numerical differentiation

- Let's say we want to use, e.g., a forward FD to approximate some $y'(t)$:

$$y'(t) \approx \frac{\Delta y}{\Delta t} = \frac{y(t+h) - y(t)}{h}$$

- In practice, however, we can only compute Δy up to machine accuracy $\epsilon_m \approx 10^{-16}$. Therefore, what we actually get is

$$\underbrace{\frac{\Delta y}{h}}_{\text{ideal}} \rightarrow \underbrace{\frac{\tilde{\Delta y}}{h}}_{\text{real}} = \frac{\underbrace{\Delta y}_{\text{exact difference}} \pm \underbrace{\Theta(\epsilon_m)}_{\text{round-off}}}{h} = \frac{\Delta y}{h} \pm \Theta\left(\frac{\epsilon_m}{h}\right)$$

→ Remember: for the forward FD, we have $y'(t) - \frac{\Delta y}{h} = \mathcal{O}(h)$ (1st-order convergence)

$$\text{Hence: } \frac{\tilde{\Delta y}}{h} = \underbrace{y'}_{\Delta y/h} - \underbrace{\Theta(h)}_{\text{actual error}} \pm \underbrace{\Theta\left(\frac{\epsilon_m}{h}\right)}_{\text{rounding error}} \Rightarrow \underbrace{y' - \frac{\tilde{\Delta y}}{h}}_{\text{actual error}} = \underbrace{\Theta(h)}_{\text{truncation error}} \pm \underbrace{\Theta\left(\frac{\epsilon_m}{h}\right)}_{\text{rounding error}}$$

— We see that the total error is composed of a truncation error (numerical) and a rounding error. As $h \rightarrow 0$, the former decreases, while the latter increases. As long as h is large enough, the rounding error $\Theta(\epsilon_m/h)$ will be negligible. As we reduce h , however, the two errors will at some point become of comparable magnitude! This will happen when

$$\underbrace{\Theta(h)}_{\text{truncation}} = \underbrace{\Theta\left(\frac{\epsilon_m}{h}\right)}_{\text{rounding}}, \text{ that is, when } \Theta(h^2) = \Theta(\epsilon_m), \text{ or } \boxed{h = \Theta(\sqrt{\epsilon_m})}$$

For the standard $\epsilon_m = 10^{-16}$, we could then expect the convergence to break down when $h = \Theta(\sqrt{10^{-16}}) = \Theta(10^{-8})$. Mind that this result is specific to the forward/backward formulas. What if we use the central formula?

- In that case, we have second-order (theoretical) convergence, as seen previously. Thus, we have a truncation error of $\Theta(h^2)$, and a rounding error of $\Theta(\epsilon_m/h)$. Those will become comparable when

$$\Theta(h^2) = \Theta(\epsilon_m/h), \text{ that is, } \Theta(h^3) = \Theta(\epsilon_m), \text{ or } h = \Theta(\sqrt[3]{\epsilon_m})$$

→ For $\epsilon_m = 10^{-16}$, the convergence should break down when $h = \Theta(10^{-5.33})$

► General case

- In general, an FD formula to approximate the n -th derivative can be written as

$$y^{(n)}(t) = \frac{\sum_{i=0}^N \alpha_i y_i}{h^n} + \Theta(h^p)$$

- Since round-off happens in the numerator, we will have

$$y^{(n)} = \frac{\sum_{i=0}^N \alpha_i y_i + \Theta(\epsilon_m)}{h^n} + \Theta(h^p)$$

hⁿ *rounding error*

Therefore, the convergence should break down when

$$\Theta\left(\frac{\epsilon_m}{h^n}\right) = \Theta(h^p), \text{ that is, when } h = \Theta\left(\epsilon_m^{\frac{1}{n+p}}\right)$$

Example: $y''(t) = \frac{y(t+h) - 2y(t) + y(t-h)}{h^2} + \Theta(h^2)^p$

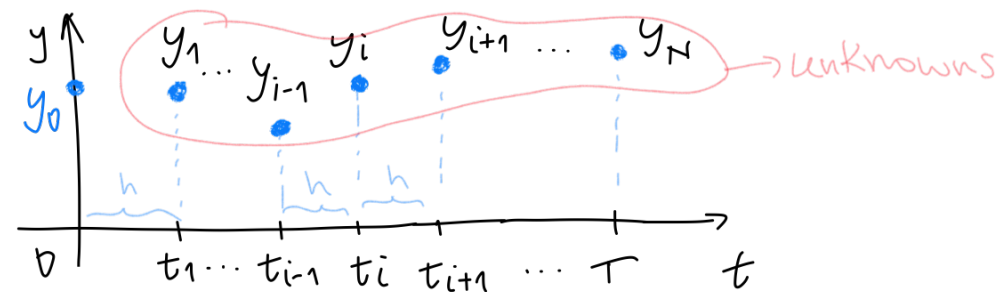
$$\Rightarrow h_{\text{break down}} = \Theta\left(\epsilon_m^{\frac{1}{2+2}}\right) = \Theta\left(\sqrt[4]{10^{-16}}\right) = \Theta(10^{-4})$$

• Using finite differences to solve IVPs

- As an example, let's finally consider the pendulum problem:

$$y'' + a \sin y = 0, \quad a = g/L, \quad y(0) = y_0, \quad y'(0) = v_0$$

- To use FDs, we will consider time steps:



- We know $y(0) = y_0$, and we want to compute (approximate) y_1, y_2, \dots, y_N .

Remember that $y'(t_i) \approx \frac{y_{i+1} - y_i}{h}$. Therefore:

$y'(0) \approx \frac{y_1 - y_0}{h}$, but $y'(0) = \sqrt{0}$. Hence: $y_1 \approx y_0 + h\sqrt{0}$

Annotations: $\sqrt{0}$ is underlined. Arrows point from "given" to y_1 , y_0 , and $\sqrt{0}$.

- How do we now compute y_2, y_3, \dots ?

→ Remember that $y''(t_i) \approx \frac{y_{i+1} - 2y_i + y_{i-1}}{h^2}$. Insert this into the ODE at t_i :

$$\frac{y_{i+1} - 2y_i + y_{i-1}}{h^2} + a \sin y_i \approx 0 \Rightarrow y_{i+1} \approx 2y_i - y_{i-1} - h^2 a \sin y_i$$

Annotation: The boxed equation is labeled "general formula (algorithm)".

This gives us a formula to compute the next value y_{i+1} in terms of past values y_i, y_{i-1} :

- * $i=1$: $y_2 \approx 2y_1 - y_0 - h^2 a \sin y_1 = \text{known}$ (because y_0 and y_1 are known at this point)
 - * $i=2$: $y_3 \approx 2y_2 - y_1 - h^2 a \sin y_2 = \text{known}$ (y_2 and y_1 are now both known)
 - ⋮
- Annotations: Arrows point from "known" to y_0 and y_1 in the first equation, and to y_2 and y_1 in the second equation.*