

## Systems of 1<sup>st</sup>-order ODEs

$$\dot{\underline{u}} = \underline{A}\underline{u} + \underline{f}(t) \rightarrow \underline{u}(t) = \underline{u}_h(t) + \underline{u}_p(t)$$

$$(1) \underline{u}_h(t) = \underline{x} e^{\lambda t} \rightarrow \dot{\underline{u}}_h = \underline{A}\underline{u}_h$$

$$\lambda \underline{x} e^{\lambda t} = \underline{A}\underline{x} e^{\lambda t} \Rightarrow \underline{A}\underline{x} = \lambda \underline{x}$$

Cases for  $\lambda$ :

a.) Real & distinct,  $\underline{u}_h = \underline{x} e^{\lambda t}$

b.) Real & repeated

independent

If  $\lambda$  is complete (# of <sup>independent</sup> eigenvectors = # of repeated values of  $\lambda$ ), then

$$\underline{u}_h(t) = C_1 \underline{x}_1 e^{\lambda t} + C_2 \underline{x}_2 e^{\lambda t} + C_3 \underline{x}_3 e^{\lambda t} + \dots$$

If defective eigenvalue, w/  
deficiency  $d$  (multiplicity of  $\lambda$  minus  
# of independent eigenvectors)

Need to do generalized eigen problem.

Let  $\underline{x}_1$  be the solution to

$$(\underline{A} - \lambda \underline{I})^{d+1} \underline{x}_1 = \underline{0}$$

Then define the sequence

$$(A - \lambda I) \underline{x}_1 = \underline{x}_2$$

$$(A - \lambda I) \underline{x}_2 = \underline{x}_3$$

$$\vdots$$

$$(A - \lambda I) \underline{x}_{d-1} = \underline{x}_d$$

Then  $\underline{u}_{n_1}(t) = \underline{x}_1 e^{\lambda t}$

$$\underline{u}_{n_2}(t) = (\underline{x}_1 t + \underline{x}_2) e^{\lambda t}$$

$$\vdots$$

$$\underline{u}_{n_d}(t) = \left( \frac{\underline{x}_1 t^{d-1}}{(d-1)!} + \dots + \underline{x}_{d-1} t + \underline{x}_d \right) e^{\lambda t}$$

② Complex roots: If  $A$  is real, then if  $\lambda + i\mu$  is an eigen value, then so is  $\lambda - i\mu$ .

Eigenvectors:  $\underline{a} + i\underline{b}$  &  $\underline{a} - i\underline{b}$

$$(\underline{a} + i\underline{b}) e^{(\lambda + i\mu)t} = (\underline{a} + i\underline{b}) e^{\lambda t} [\cos(\mu t) + i \sin(\mu t)]$$

$$= e^{\lambda t} \underbrace{[\underline{a} \cos(\mu t) - \underline{b} \sin(\mu t)]}_{\underline{y}(t)} + i e^{\lambda t} \underbrace{[\underline{a} \sin(\mu t) + \underline{b} \cos(\mu t)]}_{\underline{z}(t)}$$

$$= \underline{y}(t) + i \underline{z}(t)$$

It turns out both  $\underline{y}(t)$  &  $\underline{z}(t)$  solve  $\dot{\underline{u}}_h = A \underline{u}_h$

$$\Rightarrow \underline{u}_h(t) = c_1 \underline{y}(t) + c_2 \underline{z}(t)$$


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ex1) Solve  $\begin{bmatrix} \dot{x} \\ \dot{v} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -4 & 0 \end{bmatrix} \begin{bmatrix} x \\ v \end{bmatrix} + \begin{bmatrix} 2e^{-2t} \\ 3t \end{bmatrix}$

$$\dot{\underline{u}} = \underline{A} \underline{u} + \underline{f}(t)$$

(1)  $\underline{u}_h(t) : \dot{\underline{u}}_h = \underline{A} \underline{u}_h$

Eigenpairs of  $\underline{A} \Rightarrow 2i, \begin{bmatrix} -1/2 \\ 1 \end{bmatrix} \in$   
 $-2i, \begin{bmatrix} 1/2 \\ 1 \end{bmatrix}$

$$\Rightarrow \lambda = 0, \mu = 2, \underline{a} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \underline{b} = \begin{bmatrix} -1/2 \\ 0 \end{bmatrix}$$

From prior work

$$\underline{y}(t) = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \cos(2t) - \begin{bmatrix} -1/2 \\ 0 \end{bmatrix} \sin(2t)$$

$$\underline{z}(t) = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \sin(2t) + \begin{bmatrix} -1/2 \\ 0 \end{bmatrix} \cos(2t)$$

$$\Rightarrow \underline{u}_h(t) = c_1 \underline{y}(t) + c_2 \underline{z}(t)$$

$$(2) \quad \underline{u}_p(t), \quad \underline{f}(t) = \begin{bmatrix} 2e^{-2t} \\ 3t \end{bmatrix}$$

$$\text{Try } \underline{u}_p(t) = \underline{a}t + \underline{b} + \underline{c}e^{-2t}$$

$$\dot{\underline{u}}_p = \underline{a} - 2\underline{c}e^{-2t}$$

$$\ddot{\underline{u}}_p = \underline{A}\underline{u}_p + \underline{f}$$

$$\underline{a} - 2\underline{c}e^{-2t} = \underline{A}\underline{a}t + \underline{A}\underline{b} + \underline{A}\underline{c}e^{-2t} + \begin{bmatrix} 2 \\ 0 \end{bmatrix}e^{-2t} + \begin{bmatrix} 0 \\ 3 \end{bmatrix}t$$

$$\Rightarrow \underline{a} = \underline{A}\underline{b}$$

$$\Rightarrow \underline{A}\underline{b} = \underline{a}$$

$$-2\underline{c} = \underline{A}\underline{c} + \begin{bmatrix} 2 \\ 0 \end{bmatrix} \Rightarrow (\underline{A} - 2\underline{I})\underline{c} = \begin{bmatrix} 0 \\ -3 \end{bmatrix}$$

$$\underline{0} = \underline{A}\underline{a} + \begin{bmatrix} 0 \\ 3 \end{bmatrix} \Rightarrow \underline{A}\underline{a} = \begin{bmatrix} 0 \\ -3 \end{bmatrix}$$

$$\underline{a} = \begin{bmatrix} 3/4 \\ 0 \end{bmatrix} \quad \underline{b} = \begin{bmatrix} 0 \\ 3/4 \end{bmatrix} \quad \underline{c} = \begin{bmatrix} -1/2 \\ 1 \end{bmatrix}$$

$$\Rightarrow \underline{u}_p(t) = \begin{bmatrix} 3/4 \\ 0 \end{bmatrix}t + \begin{bmatrix} 0 \\ 3/4 \end{bmatrix} + \begin{bmatrix} -1/2 \\ 1 \end{bmatrix}e^{-2t}$$

w/  $\underline{u} = \underline{u}_h(t) + \underline{u}_p(t)$  + 2 boundary conditions

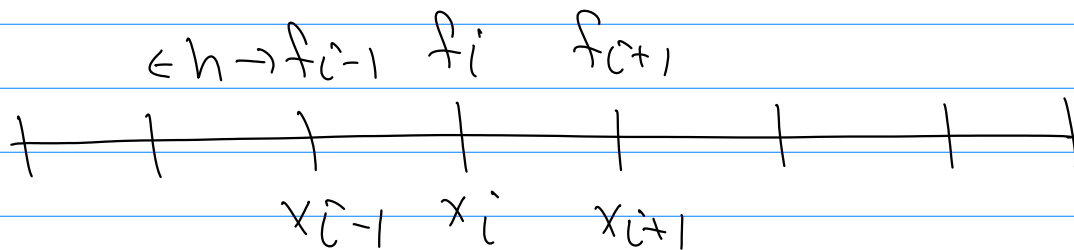
# Numeric Differentiation - Finite Difference.

Consider the definition of the derivative:

$$\frac{df}{dx} = \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h}$$

If you evaluate  $\frac{f(x+h) - f(x)}{h}$  at finite  $h$  ( $h > 0$ ), then this is an approximate derivative.

Consider a 1D Grid:



Try to approximate  $\frac{df}{dx}$  at  $x_i$

$$\frac{df}{dx} = a f_i + b f_{i+1} \quad \text{for some constants } a \text{ and } b$$

Write the Taylor Series of  $f_i$  about  $x_i$

$$f_i = f_i$$

$$f_{i+1} = f_i + f'_i h + \frac{1}{2} f''_i h^2 + O(h^3)$$

then

$$\begin{aligned} a f_i + b f_{i+1} &= a f_i + b f_i + b f'_i h + \frac{1}{2} b f''_i h^2 + O(h^3) \\ &= f'_i = \frac{df}{dx} \end{aligned}$$

$$\Rightarrow \left. \begin{array}{ll} a+b=0 & (\text{so coefficient of } f_i = 0) \\ bh=1 & (\text{so } f'_i = 1) \end{array} \right\}$$

$$\Rightarrow b = 1/h, \quad a = -1/h$$

$\Rightarrow$  Our approximation is then

$$\begin{aligned} \frac{df}{dx} &\approx -\frac{1}{h} f_i + \frac{1}{h} f_{i+1} + \frac{1}{h} O(h^2) \\ &= \frac{f_{i+1} - f_i}{h} + O(h) \end{aligned}$$

What about using  $f_{i-1}$ ,  $f_i$  &  $f_{i+1}$ ?

$$f_{i-1} = f_i - h f'_i + \frac{1}{2} h^2 f''_i$$

$$f_i = f_i$$

$$f_{i+1} = f_i + h f'_i + \frac{1}{2} h^2 f''_i$$

$$\begin{aligned} & \text{Use } a f_{i-1} + b f_i + c f_{i+1} \\ \Rightarrow & (a+b+c) f_i + (-ah+ch) f_i' \\ & + \left( \frac{1}{2} ah^2 + \frac{1}{2} ch^2 \right) f_i'' + (a+c) O(h^3) \end{aligned}$$

$$\begin{aligned} \Rightarrow & \begin{aligned} a+b+c &= 0 & a &= -1/2h \\ -ah+ch &= 1 & \Rightarrow & b=0 \\ 1/2 ah^2 + 1/2 ch^2 &= 0 & c &= +1/2h \end{aligned} \end{aligned}$$

$$\Rightarrow \frac{\partial f_i}{\partial x} = \frac{f_{i+1} - f_{i-1}}{2h} + O(h^2)$$

Alternative method: fit a polynomial,

ex.) fit a line through  $(x_i, f_i)$  &  $(x_{i+1}, f_{i+1})$

$$f(x) = f_i + \frac{(f_{i+1} - f_i)(x - x_i)}{(x_{i+1} - x_i)}$$

$$f'(x) = \frac{f_{i+1} - f_i}{x_{i+1} - x_i} = \frac{f_{i+1} - f_i}{h}$$

## Higher-Order Derivatives.

Fit a cubic polynomial through

$$(x_{i-1}, f_{i-1}), (x_i, f_i), (x_{i+1}, f_{i+1})$$

Take 2<sup>nd</sup> derivative at  $x_i$ , you get

$$\frac{\partial^2 f}{\partial x^2} \approx \frac{f_{i+1} - 2f_i + f_{i-1}}{h^2}$$

Plus in Taylor series for  $f_{i+1}$ ,  $f_i$  &  $f_{i-1}$ ,

$$\frac{f_{i+1} - 2f_i + f_{i-1}}{h^2} = \frac{\partial^2 f}{\partial x_i^2} + \frac{h^2}{12} \frac{\partial^4 f}{\partial x_i^4} = \frac{\partial^2 f}{\partial x^2} + O(h^2)$$

Finite Differences are classified via their direction!

Let the set of points used in a finite difference stencil be  $f_{i+k}$ ,

(1)  $k \leq 0$  : Backward finite difference

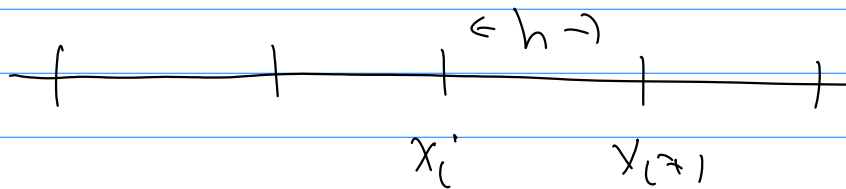
(2)  $k \geq 0$  : Forward " "

(3)  $-d \leq k \leq d$  : Center " "

Coefficients in textbooks & online,



ex<sub>1</sub>) let  $f(x) = \sin(x)$  w/  $x_i = \frac{\pi}{2}$ ,  $h = 0.05$



$$f_i = \sin(x_i) = 1$$

$$f_{i+1} = \sin(x_{i+1}) = \sin(x_i + h) = 0.99875, \dots$$

$$f_{i+2} = \sin(x_{i+2}) = \sin(x_i + 2h) = 0.995, \dots$$

$$f'(x_i) = 0$$

$$O(h): f'_i \approx \frac{f_{i+1} - f_i}{h} = \frac{0.99875 - 1}{0.05} = -0.025$$

Close to  $h$ !

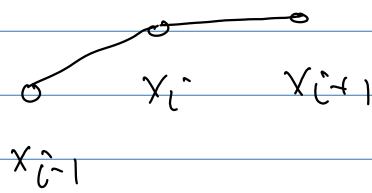
$$O(h^2): f'_i \approx \frac{-f_{i+2} + 4f_{i+1} - 3f_i}{2h} = -3.124 \times 10^{-5} \ll h^2$$

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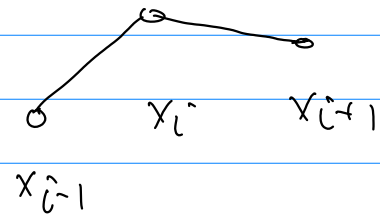
Issue: Noisy Data

Using finite differences magnifies data errors.

$f_i$   
↑



Red  
error



To formally show this, replace

$f_i$  by  $f_i + \epsilon$ ,  $\epsilon = \text{small error in function value,}$

$$\begin{aligned} \frac{\partial^2 f}{\partial x^2} &= \frac{f_{i+1} - 2(f_i + \epsilon) + f_{i-1} + O(h^2)}{h^2} \\ &= \frac{f_{i+1} - 2f_i + f_{i-1}}{h^2} - \frac{2\epsilon}{h^2} + O(h^2) \end{aligned}$$

(let  $\epsilon = O(h^2)$  (still small!))

$$\Rightarrow \frac{\partial^2 f}{\partial x^2} = \frac{2 O(h^2)}{h^2} + O(h^2)$$

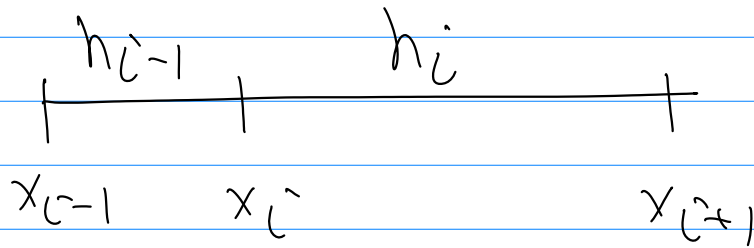
$$\frac{\partial^2 f}{\partial x^2} = 2 O(1) + O(h^2)$$



An order-1 error,

Need higher order to get valid results,

## Non-uniform Grids



$$f'(x_i) = a f_{i-1} + b f_i + c f_{i+1} \leftarrow \text{Stencil}$$

$$f_{i-1} = f_i - h_{i-1} f'_i + \frac{1}{2} h_{i-1}^2 f''_i + O(h^3)$$

$$f_{i+1} = f_i + h_i f'_i + \frac{1}{2} h_i^2 f''_i + O(h^3)$$

Plus into stencil & make coefficients  
of  $f_i$  &  $f''_i$  zero, coefficient  
of  $f'_i$  be one,

$$\Rightarrow a = \frac{-h_i}{h_{i-1}(h_{i-1} + h_i)} \quad b = \frac{h_i - h_{i-1}}{h_i h_{i-1}} \quad c = \frac{h_{i-1}}{h_i(h_{i-1} - h_i)}$$

$$\text{error: } \frac{h_i h_{i-1}}{6} \frac{\partial^2 f}{\partial x^2} + O(h^3)$$

$$\text{If } h_i = h_{i-1} = h, \quad a = \frac{-1}{2h}, \quad b = 0, \quad c = \frac{1}{2h}$$

# Partial Derivatives

One method: Multi-Dimensional Taylor Series,

Alternative: Stencil Composition

$$\text{ex1) } \frac{\partial^2 f}{\partial x \partial y} = \frac{\partial}{\partial y} \left( \frac{\partial f}{\partial x} \right)$$

$$\frac{\partial g}{\partial y} = \frac{g(i, j+1) - g(i, j-1)}{2 h_y} \quad \text{w/} \quad g(i, j) = \frac{\partial f}{\partial x} = \frac{f(i+1, j) - f(i-1, j)}{2 h_x}$$

$$\Rightarrow \frac{\partial^2 f}{\partial x \partial y} = \frac{\frac{f(i+1, j+1) - f(i-1, j+1)}{2 h_x} - \frac{f(i+1, j-1) - f(i-1, j-1)}{2 h_x}}{2 h_y}$$

$$= \frac{f(i+1, j+1) + f(i-1, j-1) - f(i+1, j-1) - f(i-1, j+1)}{4 h_x h_y}$$

Plus in Taylor series to see this is

$O(h_x h_y)$  accurate.

Note: The diff command in Matlab is useful:

Let  $f$  be an array

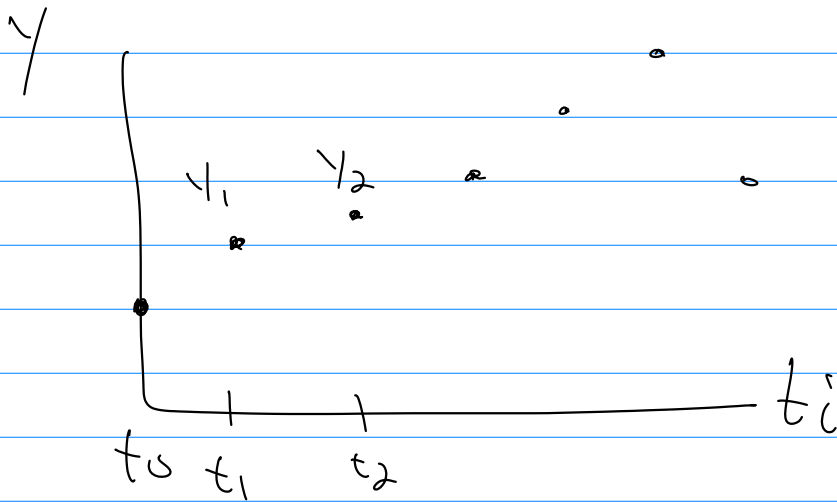
$\text{diff}(f)$  returns: for  $i = 1 : \text{length}(f) - 1$   
 $\text{df}(i) = f(i+1) - f(i)$

# Numerical Solution to IVP

Let's apply these ideas to ODE IVP,

Consider  $\frac{dy}{dt} - g(y) = f(t)$  w/  $y(0) = y_0$

Discretize in time & find solution at finite times,



(Given  $y_i$  &  $\Delta t$ , find  $y_{i+1}$ )

Look at  $O(\Delta t)$  schemes for now,

- Forward/Explicit Euler

$$\frac{y_{i+1} - y_i}{\Delta t} - g(y_i) = f(t_i) \quad \begin{array}{l} y_i \text{ is known} \\ y_{i+1} \text{ is not} \end{array}$$

$$\Rightarrow y_{i+1} = y_i + \Delta t g(y_i) + \Delta t f(t_i) \quad \leftarrow \text{fully explicit}$$

- Backward / Implicit Euler

$$\frac{y_{i+1} - y_i}{\Delta t} - g(y_{i+1}) = f(t_{i+1})$$

$\Rightarrow$  Need to solve

$$\underbrace{y_{i+1} - \Delta t g(y_{i+1})}_{\text{Implicit}} = y_i + \Delta t f(t_i)$$

Both are  $O(\Delta t)$   $\rightarrow$  errors will be about the same.

So why do the harder (implicit) one?

Stability  $\rightarrow$  Larger  $\Delta t$ .