

# *Advanced Computational Methods in Condensed Matter Physics*

## Lecture 4

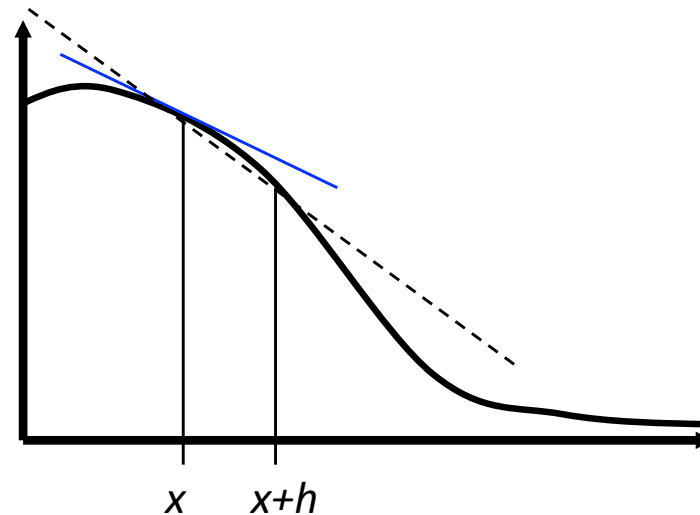
Explicit and implicit PDE  
discretization

# Numerical Differentiation

- The mathematical definition:

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

- Graphically, as the tangential line:



- Numerically, we can not calculate the limit as  $h$  goes to zero, so we need to approximate it.
- Apply directly for a non-zero  $h$  leads to the slope of the secant curve.

...

- This is called **Forward Differences** and can be derived using Taylor's Series:

$$\begin{aligned} f(x+h) &= f(x) + f'(x)h + f''(\xi)\frac{h^2}{2!} \\ \therefore f(x+h) - f(x) &= f'(x)h + f''(\xi)\frac{h^2}{2!} \\ \therefore f'(x) &= \frac{f(x+h) - f(x)}{h} - f''(\xi)\frac{h}{2!} \\ \therefore \frac{f(x+h) - f(x)}{h} &\rightarrow f'(x) \text{ as } h \rightarrow 0 \end{aligned}$$

# Reminder: errors

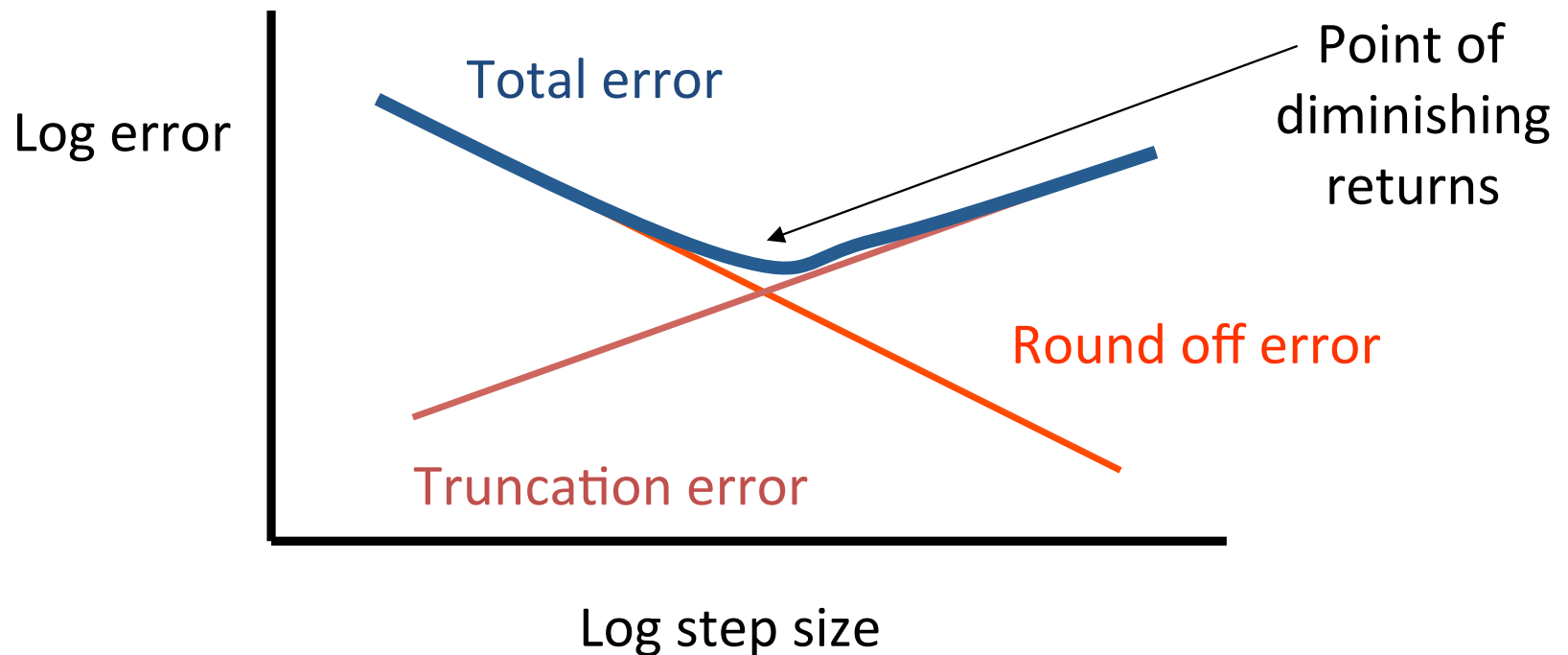
- ***Truncation Error:*** introduced in the solution by the approximation of the derivative
- ***Round-off Error:*** introduced in the computation by the finite number of digits used by the computer
- Solving differential equations is done in multiple steps. Therefore we also have:
  - ***Local Error:*** from each term of the equation
  - ***Global Error:*** from the accumulation of local error

# Truncation errors

- Let  $f(x) = a+e$ , and  $f(x+h) = a+f$ .
- Then, as  $h$  approaches zero,  $e \ll a$  and  $f \ll a$ .
- With limited precision on our computer, our representation of  $f(x) \approx a \approx f(x+h)$ .
- We can easily get a random round-off bit as the most significant digit in the subtraction.
- Dividing by  $h$ , leads to a very wrong answer for  $f'(x)$ .

# Error trade-off

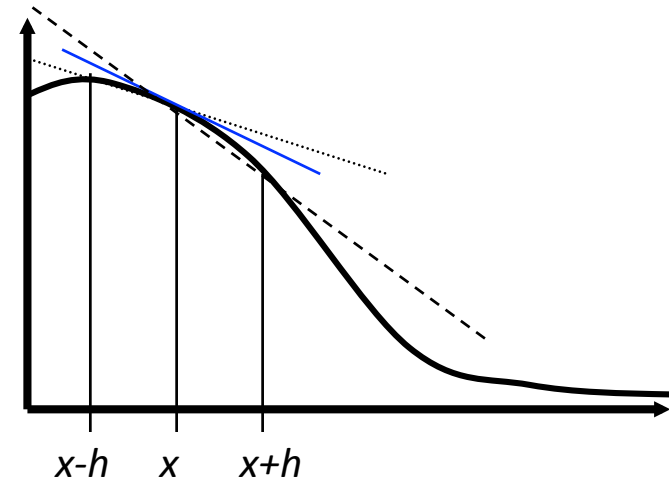
- Using a smaller step size reduces truncation error.
- However, it increases the round-off error.
- Trade off/diminishing returns occurs: Always think and test!



# “Backward” Differentiation

- This forward differentiation formula favors (or biases towards) the right-hand side of the curve.
- Why not use the left?
- This leads to the **Backward Differences** formula:

$$\begin{aligned} f(x-h) &= f(x) - f'(x)h + f''(\xi)\frac{h^2}{2!} \\ \therefore f'(x) &= \frac{f(x) - f(x-h)}{h} + f''(\xi)\frac{h}{2!} \\ \therefore \frac{f(x) - f(x-h)}{h} &\rightarrow f'(x) \text{ as } h \rightarrow 0 \end{aligned}$$



# Central difference

- Can we do better?
- Let's average the two:

$$f'(x) \approx \frac{1}{2} \left( \underbrace{\frac{f(x+h) - f(x)}{h}}_{\text{Forward difference}} + \underbrace{\frac{f(x) - f(x-h)}{h}}_{\text{Backward difference}} \right) = \frac{f(x+h) - f(x-h)}{2h}$$

*Forward difference*      *Backward difference*

- This is called the **Central Difference** formula.
- This formula does not *seem* very good.
  - It does not follow the calculus formula.
  - It takes the slope of the secant with width  $2h$ .
  - The actual point we are interested in is not even evaluated.



...

- But, is this any better?
- Use the Taylor series to examine the error:

$$f(x+h) = f(x) + f'(x)h + f''(x)\frac{h^2}{2} + f'''(\xi)\frac{h^3}{3!}$$

$$f(x-h) = f(x) - f'(x)h + f''(x)\frac{h^2}{2} - f'''(\varsigma)\frac{h^3}{3!}$$

*subtracting*

$$f(x+h) - f(x-h) = 2f'(x)h + \left( f'''(\xi)\frac{h^3}{3!} + f'''(\varsigma)\frac{h^3}{3!} \right)$$

- The central differences formula has much better convergence.

$$f'(x) = \frac{f(x+h) - f(x-h)}{2h} - \frac{1}{6}f'''(\xi)h^2, \xi \in [x-h, x+h]$$

- Approaches the derivative as  $h^2$  goes to zero!!

$$f'(x) = \frac{f(x+h) - f(x-h)}{2h} + O(h^2)$$

# But:

- **Still have truncation error problem.**

- Consider the case of:

$$f(x) = \frac{x}{100}$$

- Build a table with smaller values of  $h$ .

$$f'(x) \approx \frac{\left\lfloor \frac{x+h}{100} \right\rfloor - \left\lfloor \frac{x-h}{100} \right\rfloor}{2h}$$

at  $x = 1, h = 0.000333$ , with 6 significant digits

$$f'(x) \approx \frac{0.0100033 - 0.0099966}{0.000666666} = 0.010050$$

Relative error:

$$\frac{|0.01 - 0.010050|}{0.01} = 0.5\%$$

- What about large values of  $h$  for this function?

# Richardson Extrapolation

- Can one do better?
- Is my choice of  $h$  a good one?
- Let's start with the Taylor series of the difference:

$$f(x+h) - f(x-h) = 2f'(x)h + 2\frac{f'''(x)}{3!}h^3 + 2\frac{f^{(5)}(x)}{5!}h^5 + \dots$$

- Assuming the higher derivatives exist:

$$f'(x) = \varphi(h) + a_2h^2 + a_4h^4 + a_6h^6 + \dots$$

with  $\varphi(h) = \frac{1}{2h} [f(x+h) - f(x-h)]$

- Richardson Extrapolation examines the operator  $\varphi(h)$  as a function of  $h$ , which approximates  $f'(x)$  to  $O(h^2)$ .
- For  $h \rightarrow 0$ :

$$\varphi(h) = f'(x) - a_2h^2 - a_4h^4 - a_6h^6 - L$$

$$\varphi\left(\frac{h}{2}\right) = f'(x) - a_2\left(\frac{h}{2}\right)^2 - a_4\left(\frac{h}{2}\right)^4 - a_6\left(\frac{h}{2}\right)^6 - L$$

...

- Using these two formula's, we can come up with another estimate for the derivative that cancels out the  $h^2$  terms.

$$\varphi(h) - 4\varphi\left(\frac{h}{2}\right) = -3f'(x) - \frac{3}{4}a_4h^4 - \frac{15}{16}a_6h^6 - \dots$$

$$\text{or } f'(x) = \varphi\left(\frac{h}{2}\right) + \frac{1}{3}\left[\varphi\left(\frac{h}{2}\right) - \varphi(h)\right] + O(h^4)$$

*new estimate*

*difference between old  
and new estimates*

- If  $h$  is small ( $h \ll 1$ ), then  $h^4$  goes to zero much faster than  $h^2$ .
- Can we cancel out the  $h^6$  term?
  - Yes, by using  $h/4$  to estimate the derivative.

# Generalization

- Let us define the central differences operator for different values of  $h$ :

$$D(n,0) \equiv \varphi\left(\frac{h}{2^n}\right) = L + \sum_{k=1}^{\infty} A(k,0) \left(\frac{h}{2^n}\right)^{2k}$$

$$L = \lim_{h \rightarrow 0} \varphi(h) = f'(x)$$

- i.e.

$$\begin{aligned} f'(x) &= \varphi\left(\frac{h}{2}\right) + \frac{1}{3} \left[ \varphi\left(\frac{h}{2}\right) - \varphi(h) \right] + O(h^4) \\ &= D(1,0) + \frac{1}{4-1} [D(1,0) - D(0,0)] + O(h^4) \end{aligned}$$

- Or for  $h \rightarrow h/2$ :

$$f'(x) = D(n,0) + \frac{1}{4-1} [D(n,0) - D(n-1,0)] + O\left(\left(\frac{h}{2^n}\right)^4\right)$$

- Define Richardson's extrapolation operator:

$$D(n,m) = D(n,m-1) + \frac{1}{4^m - 1} [D(n,m-1) - D(n-1,m-1)], \quad (1 \leq m \leq n)$$

Giving:  $f'(x) = D(n,1) + O\left(\left(\frac{h}{2^n}\right)^4\right)$

# Richardson Extrapolation Theorem

- These terms approach  $f'(x)$  very quickly.

$$D(n, m) = L + \sum_{k=m+1}^{\infty} A(k, m) \left( \frac{h}{2^n} \right)^{2k}$$

*Order starts much higher!!!!*

- Since  $m \leq n$ , this leads to a two-dimensional triangular array of values as follows:

$$\begin{array}{ccccccc} D(0,0) & & & & & & \\ D(1,0) & D(1,1) & & & & & \\ D(2,0) & D(2,1) & D(2,2) & & & & \\ \vdots & \vdots & \vdots & \ddots & & & \\ D(N,0) & D(N,1) & D(N,2) & \cdots & D(N,N) & & \end{array}$$

- We must pick an initial value of  $h$  and a max iteration value  $N$ .

# Example

$$f(x) = \frac{(\cos(100x^2))^5}{x^3}$$

$$x = 1.3, h = \frac{1}{128}, N = 5$$

16.696386					
40.583393	48.583393				
109.322528	132.235574	137.814897			
135.031747	143.601487	144.359214	144.463092		
142.068615	144.414238	144.468421	144.470154	144.470182	
143.866937	144.466377	144.469853	144.469876	144.469875	$D(5,5) = 144.469875$

Which converges up to eight decimal places, exact result:

$$f'(13/10) = -((30000 \cos^5(169))/28561) - 100000/169 \cos^4(169) \sin(169)$$

$$\approx 144.46987425310895128951775669783203991279122284388...$$

# Second Derivative

- For the second derivative we can start with

$$f(x+h) = f(x) + f'(x)h + f''(x)\frac{h^2}{2} + f'''(x)\frac{h^3}{3!} + f^{(4)}(x)\frac{h^4}{4!} + f^{(5)}(x)\frac{h^5}{5!} + \dots$$

$$f(x-h) = f(x) - f'(x)h + f''(x)\frac{h^2}{2} - f'''(\xi)\frac{h^3}{3!} + f^{(4)}(x)\frac{h^4}{4!} - f^{(5)}(x)\frac{h^5}{5!} + \dots$$

- And add them (cancelling odd derivatives):

$$f(x+h) + f(x-h) = 2f(x) + 2f''(x)\frac{h^2}{2} + 2f^{(4)}(x)\frac{h^4}{4!} + \dots$$

- And therefore:

$$f''(x) \approx \frac{f(x+h) - 2f(x) + f(x-h)}{h^2}$$

- With error term:  $-\frac{1}{12}h^2 f^{(4)}(\xi)$



# Partial derivatives

- Nothing special about them:

$$\frac{\partial f}{\partial x}(x, y) \approx \frac{f(x+h, y) - f(x-h, y)}{2h}$$
$$\frac{\partial f}{\partial y}(x, y) \approx \frac{f(x, y+h) - f(x, y-h)}{2h}$$

# differential equations

## Ordinary differential equations (ODE)

- Define:

$$x^{(k)}(t) = \frac{d^k x}{dt^k}, \quad k = 1, 2, \dots, n$$

- the ODE is an equation involving  $t$  and  $x^{(k)}(t)$ :  
 $F(t, x, x', x'', \dots, x^{(n)}) = 0$ .
- A restricted family of ODEs can be written as  
 $x^{(n)}(t) = F(t, x, x', x'', \dots, x^{(n-1)})$ ,
- and can be reduced to a system of the first order ODEs

$$\frac{dy_i}{dt} = f_i(t, y_1, y_2, \dots, y_n), \quad y_k := \frac{d^{k-1} x}{dt^{k-1}}.$$

- Therefore, we consider ODEs with one variable, since most of results for this single ODE can be applicable for the above  $n$ -coupled ODEs.

$$\frac{dy}{dt} = f(t, y)$$

# Existence, uniqueness, and stability of solution for ODEs

$$\begin{aligned}\frac{dy}{dt} &= f(t, y) \\ y(a) &= \alpha.\end{aligned}$$

**Definition:**(Lipschits condition)

$D \subset \mathbb{R}^2$ ,  $f : D \rightarrow \mathbb{R}$ : a function,  $f : (t, y) \mapsto \mathbb{R}$

A function  $f(t, y)$  satisfies a Lipschits condition, if

$\exists L > 0$ : a constant such that,  $|f(t, y_1) - f(t, y_2)| < L|y_1 - y_2|$  for  $\forall (t, y_1), (t, y_2) \in D$ .  $L$ : Lipschitz constant for  $f$

**Theorem:**(Existence and uniqueness)

$D := \{(t, y) \mid a \leq t \leq T, |y - \alpha| \leq \beta\}$  for some  $\beta > 0$ .

If  $f(t, y)$  is continuous on  $D$  (or  $\exists M > |f(t, y)|$ ),

and  $f(t, y)$  satisfies Lipschitz condition in  $y$  on  $D$ ,

then  $\exists [a, b] \subset [a, T]$  on which a unique solution to the ODE  $y = \phi(t)$  exists with an initial value  $\phi(a) = \alpha$ .

**Definition:**(Stability)

Consider a *perturbed* equation  $\frac{dz}{dt} = f(t, z) + \delta(t)$ .

The initial value problem is called stable, if  $\exists \epsilon > 0$ , and  $K > 0$ , such that, whenever  $|\epsilon_0| < \epsilon$  and  $|\delta(t)| < \epsilon$  for  $\forall t \in [a, b]$ , the perturbed equation has a unique solution that satisfies  $|z(t) - y(t)| < K\epsilon$  for  $\forall t \in [a, b]$ .

# Euler's method

Consider the initial value problem

$$\frac{dy}{dt} = f(t, y) \quad y(a) = \alpha, \quad t \in [a, b]$$

- Let  $w_i$  be the numerical approximation to the exact value  $y_i := y(t_i)$ ,
- It is determined at the set of discrete points,  $a = t_0 < t_1 < \dots < t_n = b$
- We choose equally spaced points  $t_i := a + ih$ , with  $h := (b-a)/N$ ,  $i = 0, \dots, N$ .

From Taylor expansion of  $y(t)$  in  $t \in [t_i, t_{i+1}]$ ,  $\exists \xi \in [t_i, t_{i+1}]$

$$y(t) = y_i + y'_i(t - t_i) + \frac{1}{2!}y''(\xi)(t - t_i)^2,$$

we have at  $t = t_{i+1}$ ,

$$y'_i = \frac{y_{i+1} - y_i}{h} - \frac{1}{2!}y''(\xi)h = f(t_i, y_i).$$

Euler's method approximate this equation by

$$w_0 = \alpha,$$

$$\frac{w_{i+1} - w_i}{h} = f(t_i, w_i), \quad \text{where } i = 0, \dots, N-1$$

• • •

Error of the Euler method:

- Assuming  $f$  is twice differentiable on  $[a, b]$ , the error at time step  $i$  is given by

$$\tau_i = \frac{y_{i+1} - y_i}{h} - f(t_i, y_i) = \frac{h}{2!} y''(\xi_i),$$

- And

$$|\tau_i| = \frac{h}{2!} \max_{t \in [a, b]} |y''|, \quad (\text{local error}).$$

Note that  $|y_i - w_i| = O(h)$ , and, clearly,  $|y_i - w_i| \rightarrow 0$  as  $h \rightarrow 0$

**Theorem:** (Global error for Euler's method)

Let  $y(t)$  be the unique solution to  $\frac{dy}{dt} = f(t, y)$ ,  $y(a) = \alpha$ ,  $t \in [a, b]$ .

Let  $w_0, w_1, \dots, w_N$  be generated by Euler's method.

If  $f$  satisfies Lipschitz condition in  $y$  on  $D = \{(t, y) \mid t \in [a, b], y \in \mathbb{R}\}$  with Lipschitz constant  $L$ , and  $\exists M$  a constant such that

$$\max_{t \in [a, b]} |y''(t)| \leq M$$

then

$$|y_i - w_i| \leq \frac{hM}{2L} \left[ e^{L(t_i - a)} - 1 \right].$$

If  $\frac{\partial f}{\partial y}$  and  $\frac{\partial f}{\partial y}$  exists,  $y'' = \frac{\partial f}{\partial t} + \frac{\partial f}{\partial y} y' = \frac{\partial f}{\partial t} + \frac{\partial f}{\partial y} f$  may be used to estimate the bound  $M$

# Stability of Euler's method

Theorem:

$y(t)$ : the unique solution to  $\frac{dy}{dt} = f(t, y)$ ,  $y(a) = \alpha$ ,  $t \in [a, b]$ .

$u_i$ : generated by Euler's method **with finite precision arithmetic**,

$$u_0 = \alpha + \delta_0, \quad (1)$$

$$u_{i+1} = u_i + hf(t_i, u_i) + \delta_i,$$

$$\text{where } |\delta_i| < \delta \text{ for } i = 0, \dots, N.$$

If  $f$  satisfies Lipschitz condition in  $y$  on  $D = \{(t, y) \mid t \in [a, b], y \in \mathbb{R}\}$  with Lipschitz constant  $L$ , and  $\exists M$  a constant such that

$$\max_{t \in [a, b]} |y''(t)| \leq M$$

then

$$|y_i - u_i| \leq \left( \frac{hM}{2L} + \frac{\delta}{hL} \right) [e^{L(t_i-a)} - 1] + \delta e^{L(t_i-a)}.$$

**Remarks:**  $\frac{hM}{2} \gg \frac{\delta}{h}$ , we will observe  $O(h)$  convergence, while global error would grow for sufficiently small  $h$ .

Difference in the initial data  $\alpha$  results in  $|\tilde{w}_i - w_i| \leq e^{L(t_i-a)} |\tilde{\alpha} - \alpha|$ .

Therefore the Euler's method is stable.

# Taylor's method

If the higher order continuous derivatives of  $y(t)$ , and those for  $f(t, y)$  exist, Taylor expansion of  $y(t)$ ,  $t \in [t_i, t_{i+1}]$ , is written; namely,  $\exists \xi \in [t_i, t_{i+1}]$ ,

$$y(t) = y_i + y'_i(t - t_i) + \frac{1}{2!}y''_i(t - t_i)^2 + \dots + \frac{1}{n!}y_i^{(n)}(t - t_i)^n + \frac{1}{(n+1)!}y^{(n+1)}(\xi)(t - t_i)^{(n+1)}.$$

We may substitute the followings to the higher derivatives terms

$$y''_i = \frac{d}{dt}f(t, y)|_{t=t_i} = \left( \frac{\partial f}{\partial t} + \frac{\partial f}{\partial y}f \right)_{t=t_i},$$

$$y'''_i = \frac{d^2}{dt^2}f(t, y)|_{t=t_i} = \left( \frac{\partial^2 f}{\partial t^2} + 2f \frac{\partial^2 f}{\partial t \partial y} + \frac{\partial^2 f}{\partial y^2}f^2 + \frac{\partial f}{\partial y} \frac{\partial f}{\partial t} + \left( \frac{\partial f}{\partial y} \right)^2 f \right)_{t=t_i},$$

and so on.

The **second order** Taylor method:  $w_{i+1} = w_i + hf(t_i, w_i) + \frac{h^2}{2} \frac{df}{dt}(t_i, w_i)$ .

The **fourth order** Taylor method:

$$w_{i+1} = w_i + hf(t_i, w_i) + \frac{h^2}{2} \frac{df}{dt}(t_i, w_i) + \frac{h^3}{3!} \frac{d^2 f}{dt^2}(t_i, w_i) + \frac{h^4}{4!} \frac{d^3 f}{dt^3}(t_i, w_i).$$

# Definitions

(Consistency, Convergence and Stability)

If  $\tau_i \rightarrow 0$  as  $h \rightarrow 0$ , the method is called **consistent**.

If  $\tau_i = O(h^p)$ , the method is of order  $p$ .

If  $\lim_{h \rightarrow 0} \max_{1 \leq i \leq N} |y_i - w_i| = 0$ , the method is called **convergent**.

If  $\exists k(t)$  s.t.  $|\tilde{w}_i - w_i| \leq k(t_i)|\tilde{\alpha} - \alpha|$  for  $\forall i$ , the method is called **stable**.



# One-step methods

$$\frac{w_{i+1} - w_i}{h} = \phi(f, t_i, w_i, h)$$

$$\lim_{h \rightarrow 0} \tau_i = \frac{dy}{dt}(t_i) - \phi(f, t_i, y_i, 0) = f(t_i, y_i) - \phi(f, t_i, y_i, 0)$$

One-step method is consistent if  $f(t_i, y_i) = \phi(f, t_i, y_i, 0)$ .

**Remark:** If the one-step method is consistent  $\Rightarrow$  convergent.  
It can be shown that under certain conditions: one-step method is  
convergent  $\Leftrightarrow$  consistent.

## 2<sup>nd</sup> order Runge-Kutta method.

$$\frac{w_{i+1} - w_i}{h} = \phi(f, t_i, w_i, h)$$

$$\phi(f, t, y, h) = a_1 f(t, y) + a_2 f(t + \delta_2, y + \Delta_2 f(t, y))$$

Determine constants  $a_1$ ,  $a_2$ ,  $\delta_2$ ,  $\Delta_2$ , so that  $\phi$  becomes  $O(h^2)$  approximation of the  $O(h^2)$  Taylor method.

$$a_1 + a_2 = 1, \quad \text{and} \quad \delta_2 = \Delta_2 = \frac{h}{2a_2}.$$

- **Modified Euler method.** (Half step Euler + Midpoint integration.)

$$\begin{aligned} \tilde{w} &= w_i + \frac{h}{2} f(t_i, w_i), & \implies & k_1 = f(t_i, w_i), \\ w_{i+1} &= w_i + h f\left(t_i + \frac{h}{2}, \tilde{w}\right). & & k_2 = f\left(t_i + \frac{h}{2}, w_i + \frac{h}{2} k_1\right), \\ & & & w_{i+1} = w_i + h k_2. \end{aligned}$$

- **Heun method.** (One step Euler + Trapezoidal integration.)

$$\begin{aligned} \tilde{w} &= w_i + h f(t_i, w_i), & \implies & k_1 = f(t_i, w_i), \\ w_{i+1} &= w_i + \frac{h}{2} [f(t_i, w_i) + f(t_i + h, \tilde{w})] & & k_2 = f(t_i + h, w_i + h k_1), \\ & & & w_{i+1} = w_i + \frac{h}{2} (k_1 + k_2). \end{aligned}$$

- Optimal RK2 method.

$$\begin{aligned}
 \tilde{w} &= w_i + \frac{2h}{3} f(t_i, w_i), \\
 w_{i+1} &= w_i + \frac{h}{4} f(t_i, w_i) + \frac{3h}{4} f\left(t_i + \frac{2h}{3}, \tilde{w}\right)
 \end{aligned}
 \Longrightarrow
 \begin{aligned}
 k_1 &= f(t_i, w_i), \\
 k_2 &= f\left(t_i + \frac{2h}{3}, w_i + \frac{2h}{3}k_1\right), \\
 w_{i+1} &= w_i + \frac{h}{4}(k_1 + 3k_2).
 \end{aligned}$$

- Classical 4<sup>th</sup> order Runge-Kutta method.

$$\begin{aligned}
 k_1 &= f(t_i, w_i), \\
 k_2 &= f\left(t_i + \frac{h}{2}, w_i + \frac{h}{2}k_1\right), \\
 k_3 &= f\left(t_i + \frac{h}{2}, w_i + \frac{h}{2}k_2\right), \\
 k_4 &= f(t_i + h, w_i + hk_3), \\
 w_{i+1} &= w_i + \frac{h}{6}(k_1 + 2k_2 + 2k_3 + k_4).
 \end{aligned}$$

The local truncation error of the classical 4<sup>th</sup>-order Runge-Kutta method is  $O(h^4)$ .

# Linear (m-step) Multistep method

$$\frac{w_{i+1} - \sum_{j=1}^m a_j w_{i+1-j}}{h_i} = \sum_{j=0}^m b_j f(t_{i+1-j}, w_{i+1-j}) \quad \begin{array}{ll} b_0 = 0 & : \text{Explicit} \\ b_0 \neq 0 & : \text{Implicit} \end{array}$$

**Adams method:**  $a_j = 0$ , for  $j = 2, \dots, m$

**Derivation:** Integrating the both side of the ODE,

$$y(t_{i+1}) = y(t_i) + \int_{t_i}^{t_{i+1}} f(t, y(t)) dt. \Leftrightarrow \frac{dy}{dt} = f(t, y)$$

- **The Implicit** linear multistep method is derived from interpolating  $f(t, y(t))$  to polynomial of order  $m$ .
- **The Explicit** linear multistep method from interpolating polynomial of order  $m-1$

Substitute the form  $f(t, y(t)) = \mathbf{p(t)} + \mathbf{R(t)}$  in the integral form of ODE, and integrate it to calculate  $b_j$ .

# Remarks

- The explicit scheme is also called Adams-Bashforth, implicit Adams-Moulton.
- Explicit scheme may be efficient since the  $f(t_i, w_i)$  of earlier steps are used.
- The starting values for  $w_0$  (initial value),  $w_1, \dots, w_{m-1}$  are required for the  $m$ -step method.
- These are calculated from one-step method of the same order.
- For the **implicit** method, value at  $t_{i+1}, w_{i+1}$ , is calculated from an algebraic equation. It is iteratively solved using  $w_{i+1}$  of an **explicit** multistep method of the same order as an initial guess.
- Usually this iteration is done by direct substitution, and only one or two iterations are made. This procedure is called **predictor – corrector schemes**.
- For this scheme, the 4<sup>th</sup>-order formula is the most popular.

Predictor step (explicit formula)

$$\frac{\tilde{w}_{i+1} - w_i}{h} = \sum_{j=1}^4 b_j f(t_{i+1-j}, w_{i+1-j})$$

Corrector step (implicit formula)

$$\frac{w_{i+1} - w_i}{h} = b_0 f(t_{i+1}, \tilde{w}_{i+1}) + \sum_{j=1}^3 b_j f(t_{i+1-j}, w_{i+1-j})$$

# PDEs

- In contrast to ODEs, PDEs are differential equation that contains unknown *multivariable* (ODE: single variable) functions and their partial derivatives:

$$F\left(x_1, \dots, x_n, u, \frac{\partial u}{\partial x_1}, \dots, \frac{\partial u}{\partial x_n}, \frac{\partial^2 u}{\partial x_1 \partial x_1}, \dots, \frac{\partial^2 u}{\partial x_1 \partial x_n}, \dots\right) = 0.$$

- They describe a wide variety of phenomena such as: sound, heat, electrostatics, electrodynamics, fluid flow, elasticity, or quantum mechanics.
- If  $F$  is a linear function of  $u$  and its derivatives, then the PDE is called linear. Common examples of linear PDEs include the heat equation, the wave equation, Laplace's equation, Helmholtz equation, Klein–Gordon equation, and Poisson's equation.
- ODEs often model one-dimensional dynamical systems, PDEs often model multidimensional systems. [for the ODEs before:  $n=1$ ,  $u=y$ ,  $x_1=t$ ]

...

- Common notation:

$$u_x = \frac{\partial u}{\partial x}$$

$$u_{xy} = \frac{\partial^2 u}{\partial y \partial x} = \frac{\partial}{\partial y} \left( \frac{\partial u}{\partial x} \right)$$

$$\ddot{u} = c^2 \nabla^2 u$$

$$\ddot{u} = c^2 \Delta u$$

- subscripts for spatial derivatives
- dots for time derivatives
- $\nabla$  for gradients
- And  $\Delta$  for the Laplacian

- Many methods for ODEs are simply adapted to PDEs

# Example: 1D heat equation

- Consider  $u_t = u_{xx}$  and initial condition  $u(x,0) = g(x)$
- We will use the finite difference method to approximate the solution
- Forward difference for  $u_t$
- Centered difference for  $u_{xx}$  (we discretize function  $u$  with respect to  $x$  with grid size  $h_x$  and denote the value at  $x=jh_x$  as  $u_j$ )
- Re-write equation in terms of the finite difference approximations:

$$(u_j^{n+1} - u_j^n)/h_t = (u_{j+1}^n - 2u_j^n + u_{j-1}^n)/h_x^2$$

- **Error:** The local truncation error is  $O(h_t)$  from the left hand side and is  $O(h_x^2)$  from the right hand side. The parameter  $s=h_t/h_x^2$  determines the stability
- **Remarks:** Now all function values  $u_j$  need to be stored and calculated separately. All initial value of  $u_j$  at  $t=0$  need to be given by  $g_j$ . The finite difference method above is explicit.



# Boundary condition types

- The normal derivative of the problem is given: **Neumann boundary condition**.

*For example, if there is a heater at one end of an iron rod, then energy would be added at a constant rate but the actual temperature would not be known.*

For an ODE on an interval  $[a,b]$ :  $y'(a) = \alpha$  and  $y'(b) = \beta$

For a PDE 
$$\frac{\partial y}{\partial \mathbf{n}}(\mathbf{x}) = \nabla y(\mathbf{x}) \cdot \mathbf{n}(\mathbf{x}) = f(\mathbf{x}) \quad \forall \mathbf{x} \in \partial\Omega.$$

- The boundary values to the problem are given: **Dirichlet boundary condition**.

*For example, if one end of an iron rod is held at absolute zero, then the value of the problem would be known at that point in space.*

$$y(x) = f(x) \quad \forall x \in \partial\Omega$$

- Boundary has the form of a curve or surface that gives a value to the normal derivative and the variable: **Cauchy boundary condition**.  
*These are natural for, e.g., second order ODE, where  $y(a)$  and  $y'(a)$  are given*

# Crank-Nicolson scheme

- Let us consider again the heat equation and define

$$(\delta u^2)_j^n = (u_{j+1}^n - 2u_j^n + u_{j-1}^n)/h_x^2$$

- Define the  $\theta$ -scheme for  $0 < \theta < 1$ :

$$\frac{u_j^{n+1} - u_j^n}{\Delta t} = (1 - \theta)(\delta u^2)_j^n + \theta(\delta u^2)_j^{n+1}$$

- For  $\theta = 1/2$ : Crank-Nicolson
- Can avoid any restrictions on stability conditions
- Unconditionally stable no matter what the value of  $s$  is if  $\frac{1}{2} \leq \theta \leq 1$ .
- Is implicit: to get the "next" value of  $u$  in time and that a system of algebraic equations must be solved. In many problems, especially linear diffusion, the algebraic problem is tridiagonal and may be efficiently solved with the tridiagonal matrix algorithm
- For  $\theta < 1/2$  we need the condition  $s < 1/(2 - 4\theta)$  for stability

# Summary

- Forward Euler method (explicit):

$$\frac{u_i^{n+1} - u_i^n}{\Delta t} = F_i^n \left( u, x, t, \frac{\partial u}{\partial x}, \frac{\partial^2 u}{\partial x^2} \right)$$

- Backward Euler method (implicit):

$$\frac{u_i^{n+1} - u_i^n}{\Delta t} = F_i^{n+1} \left( u, x, t, \frac{\partial u}{\partial x}, \frac{\partial^2 u}{\partial x^2} \right)$$

- Crank-Nicolson (implicit):

$$\frac{u_i^{n+1} - u_i^n}{\Delta t} = \frac{1}{2} \left[ F_i^{n+1} \left( u, x, t, \frac{\partial u}{\partial x}, \frac{\partial^2 u}{\partial x^2} \right) + F_i^n \left( u, x, t, \frac{\partial u}{\partial x}, \frac{\partial^2 u}{\partial x^2} \right) \right]$$

# Iterative Solvers for PDE's

Many PDE's can be rewritten as linear equation systems after discretization (in particular for implicit schemes). For the following equation:

$$F(x_1, \dots, x_n, u, \frac{\partial u}{\partial x_1}, \dots, \frac{\partial u}{\partial x_n}, \frac{\partial^2 u}{\partial x_1 \partial x_1}, \dots, \frac{\partial^2 u}{\partial x_1 \partial x_n}, \dots) = \frac{\partial u}{\partial t},$$

where  $x_i$  are spatial coordinates and  $t$  time

- If  $F$  is linear in  $u$  this is clear: spatial derivative discretizations lead to off-diagonal elements in the matrix for the linear equation
- In the presence of non-linear terms in  $u$ , those can be approximated by, e.g., explicit solvers and then used as constants for the iterative scheme
- Then iterative solver for the linear(ized) equation system can be used
- If the time discretization is sufficiently small, changes in  $u$  are typically small and the convergence of the iterative solvers can be fast

# Spectral methods

- **Finite difference method** – approximate a function **locally** using lower order interpolating polynomials.
- **Spectral method** – approximate a function using global higher order interpolating polynomials.
- Using spectral method, a higher order approximation can be made with moderate computational resources.

# Next lecture:

- (Pseudo) random number generators
- Data analysis