

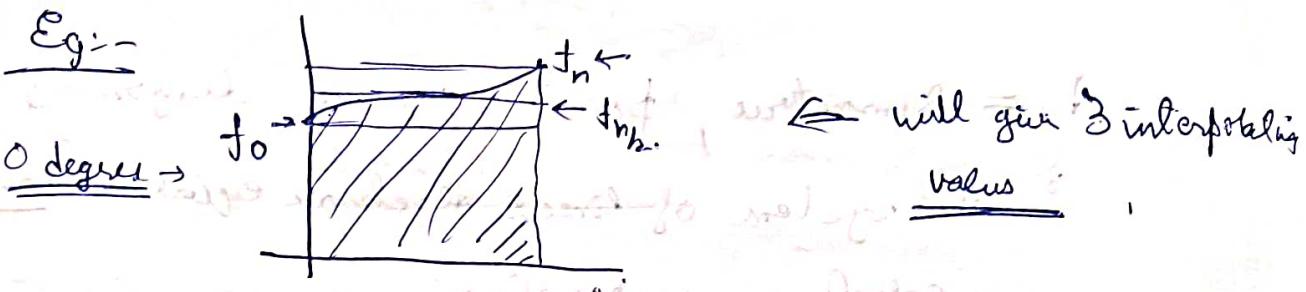
Numerical Integration (Quadrature).

Suppose you want to evaluate

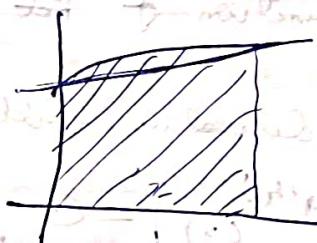
$$\int_a^b f(x) dx = \sum_{i=0}^{n-1} w_i f_i$$

Idea:- Replace $f(x)$ by polynomial interpolation

Eg:-



1 degree →



Numerical quadrature Suppose you want to approximate

the integral $\int_a^b f(x) dx$.

(x^* - m^*) with $\int_a^b f(x) dx \approx \int_a^b f(x) dx$.
[finite interval (a, b)].

Most of such integrals cannot be evaluated explicitly.

One has to seek some numerical approximation which is faster to evaluate rather than calculating the exact integral.

When we have tabulated values, i.e. (x_i, y_i) , then we have to use the numerical quadrature to approximate the integral.

We can approximate as

$$\int_a^b f(x) dx = \sum_{i=0}^n w_i f_i, \text{ where } w_i = \text{weights}$$

In other words, we replace the integrand $f(x)$ by the appropriate interpolating polynomial.

20/2/24 Suppose $f(n)$ is sufficiently smooth on interval $[a, b]$,

which contains $[a, b]$, target: $\int_a^b f(x) dx$

then we can express $f(x) = p_k(x) + f[x_0, x_1, \dots, x_k, x] \psi_k(x)$

Then, the $\psi_k(x) = \prod_{j=0}^k (x - x_j)$

Error. $E(f) = \int_a^b f[x_0, x_1, \dots, x_k, x] \psi_k(x) dx.$

$I(f) = \int_a^b p_k(n) dx$

In some particular cases, the error can be simplified

if $\psi_k(x)$ is entirely of one sign on $[a, b]$,

then using MVT on the interval, you can express

$$E(f) = f[x_0, x_1, \dots, x_k, \xi] \int_a^b \psi_k(u) du.$$

$\xi \in (a, b)$

Suppose ~~f is $(k+1)$ -times differentiable on $[a, b]$~~ $f \in \mathcal{C}^{k+1}[a, b]$.

$$E(f) = \frac{f(n)}{(k+1)!} \int_a^b \Psi_k(x) dx.$$

$n \in (c, d)$

same sign

Even if $\Psi_k(n)$ may not be ~~everywhere~~ everywhere, then also,

We can do some simplifications.

A particular case of this kind occurs when the integral

$$\text{of } \int_a^b \Psi_k(x) dx = 0. \text{ In such a case, we can use}$$

the following identity:-

$$f[x_0, \dots, x_k, x] = f[x_0, x, \dots, x_{k+1}]$$

$$+ f[x_0, (x), x_{k+1}, x](x - x_{k+1}).$$

Where x_{k+1} is an arbitrarily chosen point.

$$E(f) = \int_a^b f[x_0, \dots, x_k, x_{k+1}] \Psi_k(x) dx.$$

$$+ \int_a^b f[x_0, x, \dots, x_{k+1}, x](x - x_{k+1}) \Psi_k(x) dx$$

$$\Psi_{k+1}(x).$$

Suppose x_{k+1} is chosen such that $\Psi_{k+1}(x) = (x - x_{k+1}) \Psi_k(x)$.

Ψ_{k+1} is of one sign on $[a, b]$.

Suppose $f \in \mathcal{C}^{K+2}[a, b]$, then the error is given by

$$E(f) = \frac{f^{(K+2)}(n)}{(K+2)!} \int_a^b \varphi_{K+1}(x) dx. \quad \text{where } \underline{\varphi_{K+1}(a, b)}.$$

Case 1 In case ~~$\varphi_{K+1}(a, b) > 0$~~ $\Rightarrow E(f) = 0$
missed \Rightarrow This rule is exact upto $(K+1)$ degree polynomial

$$S(x-a) = f(a) + f'(a)(x-a) + \dots + f^{(K+1)}(a) \frac{(x-a)^{K+1}}{(K+1)!}$$

Case 1 :- $K=0$. $\Rightarrow f(x) = f(x_0) + f[x_0, x](x-x_0)$.

$$I(f) = I(f_0)$$

$$= \int_a^b f(x_0) dx = f(x_0) [b-a].$$

Say $x_0 = a \Rightarrow I(f) = f(a)[b-a] \leftarrow \boxed{\text{Rectangle formula}}$

\Rightarrow Then we have obtained the so called Rectangle rule, where we have taken $f_0 = \text{left boundary}$.

$$\boxed{\varphi_0(x) = x - x_0 = x - a}.$$

$$\Rightarrow E(f) = E^R = f'(\eta) \int_a^b (x-a) dx$$

$$\Rightarrow \boxed{E^R = f'(\eta) \frac{(b-a)^2}{2}} \text{ with } \underline{\eta \in [a, b]},$$

\Rightarrow Rectangle rule: exact upto 0 degree (constant) poly.

Taking $x_0 = b$: Some (very similar thing).

Suppose we take $x_0 = \frac{a+b}{2}$.

$\Rightarrow \Psi_0(x) = (x - x_0)$ fails to be of one sign on $[a, b]$

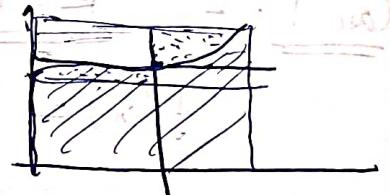
$$\int_a^b (x - x_0) dx = 0.$$

$$\Psi_{k+1}(x) = \Psi_1(x) = (x - x_0)(x - x_1) = (x - x_0)^2$$

mid point

(taking $x_1 = x_0$)

$$E^M = \frac{f''(x)(b-a)^3}{24}$$



$$I(f) = f\left(\frac{a+b}{2}\right) \cdot (b-a) := M.$$

Mid point rule

for other points

approx. better about Bernstein and not f \Leftarrow
and $f(x) = f$ and not x and f

$$f(x) = x - x_0 + o(x)$$

$$ab(x-x_0) + o(x) = \mathcal{E} = (f) \mathcal{E} \Leftarrow$$

$$\left[f(x-x_0) \cdot (b-a) = \mathcal{E} \right] \Leftarrow$$

$(d, d) = f$

$k=1$

$$f(x) = f(a) + f(b) \quad \text{Interval} = [a, b]$$

$$f(x) = P_1(x) = f(x_0) + f[x_0, x](x - x_0) + f[x_0, x_1, x] \\ + E(f).$$

$$\Psi_1(x) = (x - x_0)(x - x_1)$$

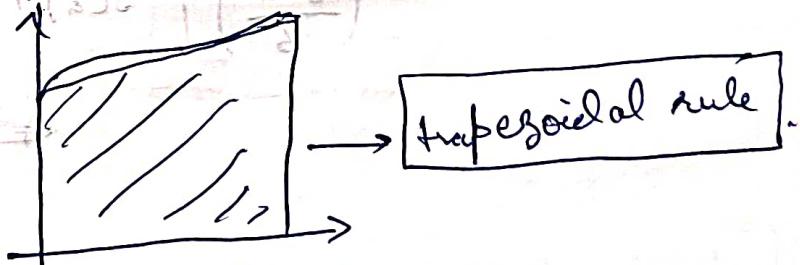
If we choose $x_0 = a$, $x_1 = b$. $\Rightarrow \Psi_1 = \underline{\text{one sign}}$ on $[a, b]$.

$$\therefore E(f) = \frac{f''(n)}{2!} \int_a^b (x-a)(x-b) dx \\ = -\frac{f''(n)}{12} (b-a)^3$$

$$T = I(f) = \int_a^b f(a) + f[a, b] (x-a) dx \\ = \frac{1}{2} (f(a) + f(b))(b-a)$$

$$T = \frac{1}{2} (f(a) + f(b))(b-a).$$

$$E^T(f) = -\frac{f''(n)}{12} (b-a)^3.$$



Q8 [If we approximate $f\left(\frac{a+b}{2}\right) \approx \frac{f(a) + f(b)}{2}$, we get the same formula].

$$K=2$$

$$f(x) = \phi_2(x) + f[x_0, x_1, x_2, x] \Psi_2(x).$$

$$[\text{where } \Psi_2(x) = (x-x_0)(x-x_1)(x-x_2)]$$

$$\text{Choose } x_0 = a, x_2 = b, \text{ & } x_1 = \frac{a+b}{2}.$$

$$\Rightarrow \int_a^b \Psi_2(x) dx = 0.$$

$$\Rightarrow E^{(k=2)}(f) = \frac{f^{(4)}(n)}{4!} \int_a^b \Psi_3(x) dx = \frac{(f^{(4)}(n))}{4!}$$

$$[\text{by taking } x_3 = x_1 = \frac{a+b}{2}],$$

Simpson's quadrature

$$\begin{aligned} I(f) &= I(\phi_2) = \int_a^b \phi_2(x) dx \\ &= \left(\frac{b-a}{6}\right) \left[f(a) + 4f\left(\frac{a+b}{2}\right) + f(b) \right] \end{aligned}$$



Ques. $\frac{(b-a)}{6} [f(a) + 4f\left(\frac{a+b}{2}\right) + f(b)]$ denotes $\frac{1}{3}$ of the area under the curve $y=f(x)$ between $x=a$ and $x=b$.

Consider $k=3$ (cubic polynomial).

$$f(x) = P_3(x) + f[x_0, x_1, x_2, x_3, x] \Psi_3(x)$$

Take $x_0, x_1 = a, x_2 = x_3 = b$.

$$\Rightarrow \Psi_3(x) = (x-a)^2 \cdot (x-b)^2.$$

$$E(f) = \frac{1}{4!} f^{(4)}(n) \int_a^b (x-a)^2 (x-b)^2 dx.$$

$$= \frac{f^{(4)}(n)}{720} (b-a)^5.$$

and $I(f) = \int_a^b P_3(x) dx$.

$$P_3(x) = f(a) + f[a, a](x-a) + f[a, a, b](x-a)^2 + f[a, a, b, b](x-a)^3$$

$$\Rightarrow I(f) = f(a) + f[a, a] \frac{(b-a)}{2} + f[a, a, b] \frac{(b-a)^3}{3}$$

$$+ f[a, a, b, b] \cdot \int_a^b (x-a)^2 (x-b) dx.$$

↓ Simplifying

$$I(f) = \left(\frac{b-a}{2} \right) [f[a] + f(b)] + \frac{(b-a)^2}{12} [f'(a) - f'(b)].$$

$$\approx \boxed{\text{corrected trapezoidal}} \quad (\text{CT}).$$

In the end we are basically getting:-

$$\int_a^b f(x) dx \approx \sum_{i=0}^n w_i f(x_i). \quad \text{where } w_i = \frac{h}{n!}.$$

Now, we consider the Lagrange Interpolating polynomial

$$P_n(x), \quad n \geq 1, \quad P_n = \left(\frac{b-a}{h} \right) \cdot \dots \cdot \left(\frac{x-x_0}{x_1-x_0} \right) \left(\frac{x-x_1}{x_2-x_1} \right) \dots \left(\frac{x-x_{n-1}}{x_n-x_{n-1}} \right).$$

at points: $x_j = a + j h \quad j = 0, 1, \dots, n$.

$$I(t) = I_n(t) = \int_a^b P_n(x) dx$$

$$= \int_a^b \sum_{j=0}^n l_{j,n}(x) f(x_j) dx$$

$$= \sum_{j=0}^n w_{j,n} f(x_j).$$

$$w_{j,n} = \int_a^b l_{j,n}(x) dx.$$

$$\boxed{n=1: \quad w_{0,1} = w_{1,0,1} = \left(\frac{b-a}{2} \right)}.$$

$$\boxed{n=3: \quad w_0 = \int_a^b l_0(x) dx.}$$

$$= \int_a^b \frac{(x-x_1)(x-x_2)(x-x_3)}{(x_0-x_1)(x_1-x_2)(x_2-x_3)} dx.$$

$$= \int_0^h \frac{(m-1)(m-2)(m-3)}{-6h^3} h^4 dx. = \frac{3h}{8}.$$

$$w_1 = \int_a^b l_1(x) dx.$$

$$= \int_a^b \frac{(x-x_0)(x-x_1)(x-x_2)}{(x_1-x_0)(x_2-x_1)(x_3-x_2)} dx.$$

$$= \frac{3}{2} \int_0^h \frac{(u)(u-z)(u-3)}{z h^3} dz = u$$

danpas berekendens in combinatie met stappen breed

$$= \frac{q^* h}{8} \left[f(x_0) + 3f(x_1) + 3f(x_2) + f(x_3) \right] = (t) I$$

$$\Rightarrow I_n(f) = \frac{3h}{8} \left[f(x_0) + 3f(x_1) + 3f(x_2) + f(x_3) \right].$$

Error

(i) for even n : $f(x) \in C^{(n+2)}([a, b]) \Rightarrow f \in \mathcal{G}^{(n+2)}([a, b])$.

$$E(f) = I(f) - I_n(f) = c_n h^{n+3} f^{(n+2)}(r).$$

$$\text{where } c_n = \frac{1}{(n+2)!} \int_0^n u^2(u-1)\cdots(u-n) du.$$

(ii) for odd n : $f \in \mathcal{G}^{(n+1)}([a, b])$.

$$E_n(f) = c_n \cdot h^{n+2} f^{(n+1)}(r)$$

$$c_n = \frac{1}{(n+1)!} \int_0^n u(u-1)(u-2)\cdots(u-n) du.$$

Deze formule is Newton-Cotes formula.

Σ (cont.)

Newton-Cotes formula

Composite Quadrature

Always, it is achievable to divide the interval $[a, b]$ into n intervals of equal size.

$$a = x_0 < x_1 < \dots < x_{n-1} < x_n = b.$$

and apply the quadrature formulas in each interval separately.

$$I(f) = \int_a^b f(x) dx = \sum_{i=1}^n \int_{x_{i-1}}^{x_i} f(x) dx.$$

\rightarrow the idea is that the error will be less than that with the same method on the entire interval.

where $\int f(x) dx$ is approximated as $\int P_{i,*}(x) dx$.

$$(+) + (-) = (+) - (+) = 0$$

If we take rectangle rule:

$$h = \frac{b-a}{N}, \quad I(f) \approx \left(\frac{b-a}{N}\right) \sum_{i=0}^{N-1} f(x_i).$$

$$E(R) = \sum_{i=0}^{N-1} \frac{|f''(m_i)| h^2}{2!} = O(h^2)$$

then, error = less than the original quadrature?

If you use ' k ' grid points in each Interval, exact upto $k+1$ degree (check)?

Using Hermite interpolation, using 'k' grid points, exact upto

$2k+1$ degree \leftarrow Gaussian Quadrature.

Consider numerical quadrature of $\int_a^b f(x) dx = \int_a^b w(x) g(x) dx$.

$$I(g) \approx A_0 g(x_0) + A_1 g(x_1) + \dots + A_k g(x_k)$$

$\underbrace{\quad\quad\quad}_{\downarrow}$

Note:- A_i are independent of function

So far, we have taken $x_0, x_1, x_2, \dots, x_k$ are equally spaced.

Sulcosp

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$$(i) \text{ Error} = g^{(K+1)}(n).$$

~~exact upto~~ exact upto any polynomial of deg $\leq K$.

$$E(g) = I(g) - I(p_K).$$

$$= \int_a^b g[x_0, x_1, \dots, x_{K+1}, x] \underbrace{\varphi_{K+1}(x) w(x)}_{\text{integral} = 0} dx.$$

$$\text{suppose} \Rightarrow \text{i.e. } \int_a^b \varphi_{K+1}(x) w(x) dx = 0$$

\Rightarrow we know that

$$E(g) = \int_a^b g(x_0, x_1, \dots, x_{K+1}, x) \varphi_{K+1}(x) w(x) dx$$

now suppose $\int_a^b \varphi_{K+1}(x) w(x) dx \neq 0$, then take another point x_{K+2} , then x_{K+3}, \dots

$$E(g) = \int_a^b g(x_0, x_1, \dots, x_{K+2}, x) \varphi_{K+2}(x) w(x) dx$$

$x_k, x_{k+1}, \dots, \underline{x_{K+1}}$

↓

$$E(g) = I(g) - I(p_K)$$

$$= \int_a^b g[x_0, x_1, \dots, x_{K+1}, x] \varphi_{K+1}(x) w(x) dx.$$

for several choices of $w(x)$, we can find $p_{K+1}(x)$ at.

$$\int_a^b p_{K+1}(x) q(x) w(x) dx = 0 \text{ where } \deg(q(x)) \leq K,$$

which tells that the polynomials are orthogonal wrt the weight $w(n)$.

We can express, the polynomial (orthogonal polynomial) $f_{k+r}(x)$ as

$$\phi_{k+1}(x) = \alpha_{k+1} (x - \xi_0) \dots (x - \xi_k).$$

where ξ_i 's are $k+1$ distinct

points in the interval $[a_1, b]$ where $f_{k_1}(x)$ vanishes.

Hence, if we set $x_j = \xi_j$ for $j=0$ to K and let x_{K+j} be arbitrary points in the interval $[a, b]$, where $j=1$ to $k+1$

$$\frac{1}{k} \quad n = k.$$

$$\Rightarrow g(x) = (x - x_{k+1}) \cancel{(x - x_{k+2})} \dots (x - x_{k+i})$$

α in km^{-1} $\text{deg} \text{ s}^{-1}$

The error $E_g = g[x_0, x_1, \dots, x_{k+m+1}, x] \Psi_{2k+1}(x) w(x) dx$

In order to obtain the desired error, we can choose

$$x_{k+j} = \xi_{j-1}, \quad j=1, 2, \dots, k+1$$

$$\Psi_{2k+1}(x) = (x - x_0)(x - x_1) \dots (x - x_{2k+1})$$

$$= (x - \xi_0)(x - \xi_1) \dots (x - \xi_k)$$

$$\left(\frac{P_{k+1}(x)}{\alpha_{k+1}} \right)^2$$

∴ By applying the MVT,

$$E(g) = g[x_0, x_1, \dots, x_{2k+1}] \left(\frac{P_{k+1}(x)}{\alpha_{k+1}} \right)^2 w(x) dx$$

$$\frac{d^{2k+2}g}{dx^{2k+2}}(n) = \frac{(2k+2)!}{(2k+1)!} S_{k+1} \quad ; \quad S_{k+1} = \int_a^b P_{k+1}^2(x) w(x) dx$$

To summarise the gaussian quadrature, we have to choose the nodal points as zeroes of the polynomial $P_{k+1}(x)$, which is orthogonal with the weight function $w(x)$ on $I = [a, b]$, which tells a gaussian quadrature is exact upto $(2k+1)$.

Assume this polynomial P_{k+1} or Legendre's polynomial

$$P_1(x) = x, \quad \xi_0 = 0$$

$$P_2(x) = \frac{3}{2} \left(x^2 - \frac{1}{3} \right), \quad \xi_0, \xi_1 = \pm \frac{1}{\sqrt{3}}$$

~~$$P_3(x) = \frac{5}{2} \left(x^3 - \frac{3}{5}x \right), \quad \xi_0 =$$~~

~~$$P_3(x) = \frac{5}{2} \left(x^3 - \frac{3}{5}x \right).$$~~

~~$$\xi_0 = -\sqrt{\frac{3}{5}}, \quad \xi_1 = 0, \quad \xi_2 = \sqrt{\frac{3}{5}}.$$~~

~~Product rule~~

$$P_{n+1}(x) = x P_n(x) - \frac{n^2}{4n^2-1} P_{n-1}(x).$$

$$\text{take } \int_a^b f(x) dx = \int_{-1}^1 f(x(t)) x'(t) dt.$$

$$\text{take } x(t) = \left(\frac{b-a}{2} \right) t + \frac{a+b}{2}.$$

Take $k=1$, then quadrature is exact

and now we can do the same for $k=2$.
In short, (5) is exact for degree 1 and not for 2.

Under $\int_a^b f(x) dx = \int_{-1}^1 f(x(t)) x'(t) dt$ we have $x'(t) = \frac{b-a}{2}$.

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$$\underline{k=1}$$

$$x_0 = \underline{\Sigma}_0 = -\sqrt{3}, x_1 = \underline{\Sigma}_1 = \sqrt{3}.$$

$$\int_{-1}^1 g(x) dx = A_0 g\left(\frac{-1}{\sqrt{3}}\right) + A_1 g\left(\frac{1}{\sqrt{3}}\right).$$

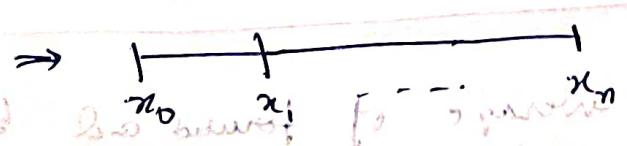
$$E = \langle g^{(4)}(\eta) \rangle.$$

$$A_1 = \int_{-1}^1 \frac{x - (-\frac{1}{\sqrt{3}})}{dx} dx = 1 = A_0$$

$$\int_{-1}^1 g(x) dx = g\left(\frac{1}{\sqrt{3}}\right) + g\left(-\frac{1}{\sqrt{3}}\right)$$

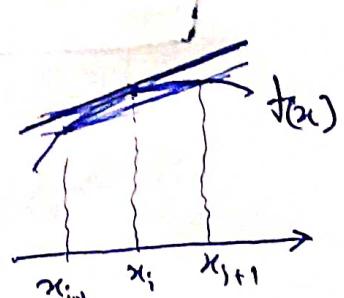
$$E = \frac{1}{135} g^{(iv)}(\eta).$$

$$\underline{k=n}$$



forward diff

$$f'(x_i) = \frac{f_{i+1} - f_i}{h} \xrightarrow{\text{toward diff.}} O(h).$$



backward diff $\leftarrow = \frac{f_i - f_{i-1}}{h} \Rightarrow O(h)$

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

$$f_{i+1} = f(x_{i+1}) = f(x_i) + h f'(x_i) + \frac{h^2}{2!} f''(\xi_i),$$

$$\frac{f(x_{i+1}) - f(x_i)}{h} - f'(x_i) = \frac{h}{2!} f''(\xi_i).$$

$$f_{i+1} = f(x_i) + h f'(x_i) + \frac{h^2}{2!} f''(x_i) - \frac{h^3}{3!} f'''(\xi_i) + \frac{h^4}{4!} f^{(4)}(\xi_{n_i}).$$

$$f_{i+1} = f(x_i) + h f'(x_i) + \frac{h^2}{2!} f''(x_i) + \frac{h^3}{3!} f'''(x_i) + \frac{h^4}{4!} f^{(4)}(\xi_i).$$

~~limit~~

$$\frac{f_{i+1} - f_{i-1}}{2h} - f'(x_i) \Rightarrow \frac{h^2}{2!} f'''(x_i) \leftarrow O(h^2)$$

$\frac{f_{i+1} - f_{i-1}}{2h}$ = average of forward and backward difference.

Cent

$$(A) \Delta \leftarrow \frac{f_{i+1} - f_{i-1}}{2h} = (i)^{\text{th}}$$

forward diff

$$(B) \Delta \leftarrow \frac{f_{i+1} - f_i}{h} = (i)^{\text{th}}$$

$$(C) \Delta \leftarrow \frac{f_i - f_{i-1}}{h} =$$

Numerical differentiation

Suppose we are given the tabulated values, we want to determine the derivative of the data.

Eg:- Velocity from displacement,

or acceleration = 2nd derivative of displacement.

~~Let $f(x) \in C^2$~~

Let $f(x)$ be continuously differentiable function on interval $[c, d]$ that contains interval $[a, b]$.

divide $[c, d]$ into equally distributed k nodal points $x_0, x_1, x_2, \dots, x_k$.

\Rightarrow we can approximate $f(x)$ by a polynomial of degree k .

$$\textcircled{1} - f(x) = p_k(x) + f[x_0, x_1, \dots, x_k, x] \Psi_k(x).$$

furthermore, $\frac{d}{dx} f[x_0, x_1, \dots, x_k, x]$

$$= f[x_0, x_1, \dots, x_k, x, x].$$

$$\Rightarrow \text{differentiate } \textcircled{1}: f'(x) = p'_k(x) + [f[x_0, x_1, \dots, x_k, x, x] \Psi'_k(x)].$$

$$\text{Hence } f'(x) = p'_k(x) + f[x_0, x_1, \dots, x_k, x] \Psi'_k(x).$$

Let D denote the derivative of f at the point a [differentiation operator].

where $a \in [c, d]$ is some point.

$$D(f) = p'_k(a), E(f) = D(f) - D(p_k) =$$

$$f[x_0, x_1, \dots, x_k, a] \Psi_k(a) + f[x_0, x_1, \dots, x_k, a] \Psi'_k(a).$$

at x_0 , we have $\Psi_k(a)$ will vanish as $a = x_0$.

Since, the error is contained in two terms, by choosing $a = x_i$;

$$\Rightarrow \Psi_k(a) = 0. \Rightarrow \text{first term will be dropped out.}$$

Similarly for $x_{k-1} = a$ we have $\Psi'_k(a) = 0$.

Whereas, if you choose a such that $\Psi'_k(a) = 0$, \Rightarrow 2nd term will be dropped.

Case 1: $\Psi_k(a) = 0 \Rightarrow a = x_i$

Suppose $\Psi'_k(a) = q(a)$, where $q(x) = \frac{\Psi_k(x)}{(x-x_0)(x-x_1)\dots(x-x_{i-1})}$.
 \Rightarrow $\Psi'_k(x) = q(x) \prod_{j=0}^{i-1} (x-x_j)$.
 \Rightarrow $\Psi'_k(x)$ is a polynomial of degree $i-1$ in x .

assume $a = x_i$; so $\Psi'_k(a) = 0$ if $f \in \mathcal{P}^{(K+1)}([c, d])$.

$$(i) \Rightarrow E(f) = \frac{1}{(K+1)!} f^{(K+1)}(x) \prod_{j=0}^K (x-x_j). \quad (1)$$

$[x_0, x_1, \dots, x_{i-1}, x_i, x_{i+1}, \dots, x_K]$ symmetric.

Case 2. Suppose $\Psi'_k(a) = q(a) \neq 0$.

\Rightarrow E 2nd will vanish.

\Rightarrow E will be $\frac{1}{(K+1)!} + \dots + \frac{1}{(n+1)!}$. \Rightarrow then we can achieve this.

Say $K = \text{odd number} \Rightarrow$ by placing x_j 's symmetric about the point a .

so $x_{K-j} - a = a - x_j$, $j = 0, 1, 2, \dots, \frac{K-1}{2}$. Now

$$x_{K-j} - a = a - x_j \Rightarrow j = 0, 1, 2, \dots, \frac{K-1}{2}. \text{ Now}$$

$$= (x_0)C_0 + (x_1)C_1 + \dots + (x_{\frac{K-1}{2}})C_{\frac{K-1}{2}} = (E)C$$

Now,

$$(x - x_j)(x - x_{k-j}) = (x - a + a - x_j)(x - a + a - x_{k-j}) \\ = (x - a)^2 - (a - x_j)^2.$$

From this, $\Psi_k(x) = \prod_{j=0}^k (x - x_j) = \prod_{j=0}^k [(x - a)^2 - (a - x_j)^2]$.

derivative of $\Psi_k(x) = \cancel{\psi'(x)} \psi'(a)$

at a

$$\text{Ansatz: } f''(a) + \cancel{\frac{f'''(a)}{2!}} = (a)^{k+1}$$

$$\therefore \text{Error: } E(f) = \frac{(a-a)^{k+1}}{(k+2)!} f^{(k+2)}(a) \prod_{j=0}^{(k-1)/2} [-(a-x_j)^2].$$

If $k=0$, then, this is, constant interpolant $\Rightarrow D(p_k) = 0$.

$$\text{If } k=1, p_k(x) = \frac{f_1 - f_0}{x_1 - x_0} (x - x_0) + f_0.$$

$$= f[x_0, x_1] \Psi_1(x) + f_0, \quad \text{Ansatz}$$

$$D(f) = D(p_k) = 0 + f[x_0, x_1].$$

$$\text{Since } k=\text{odd} \Rightarrow \text{Ansatz: } \frac{x_0+x_1}{2}$$

cheaper answer \rightarrow

Ansatz: (d, a) is the midpoint \Rightarrow

$$(d, \Psi_1(a)) \text{ and } (d, 0) \text{ since } \Psi_1(0) = 0$$

$$a = \frac{x_0 + x_1}{2}$$

$$(x_0 - a + h)(x_1 - a + h) / (h^2) \quad (h = (x_1 - x_0)/2)$$

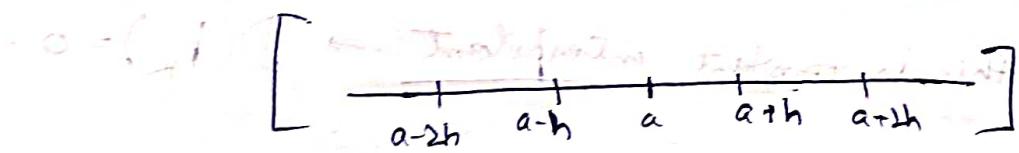
$$\Rightarrow f'(a) \approx \frac{f(a+h) - f(a-h)}{2h}$$

$$E(h) = \frac{h^2}{6} f'''(n) = \Theta(h^2)$$

Assumption: $f \in C^3(I)$

$$f''(a) = \alpha f(a+h) + \beta f(a-h) + \gamma f(a).$$

$$\begin{aligned} f'''(a) &= \alpha(f(a) + \beta f(a+h) + \gamma f(a+2h)) \\ &= \alpha f(a-2h) + \beta f(a-h) + \gamma f(a). \end{aligned}$$



Solving diff. eqns.: (try by)

$$y'' + 2y' + 5y = 0 \quad (\rightarrow \text{constant coefficients})$$

$$- 2y'' - (x+1)y' - 5x^2y = 0$$

\hookrightarrow variable coefficients

\Rightarrow always feasible $x \in (a, b)$.

and limits: $y(a), y'(a) / y(a), y'(b) / y'(a), y'(b)$.

General eqn: $P(x)y'' + Q(x)y' + R(x)y = f(x)$

General PDE: $P(x)y'' + Q(x)y' + R(x)y = 0$ is linear.

why linear: $L[y] = P(x)y'' + Q(x)y' + R(x)y = 0$

Op erator $L = \frac{P(x)d^2}{dx^2} + \frac{Q(x)}{dx} + R(x) I$

another case: $u(x,t)$: $u_t + a u_x = 0$

another: $P_t + Q_x = R$ $\Rightarrow \frac{\partial u}{\partial t} = \frac{\partial u}{\partial x} = \frac{R}{P}$

order 1

order 2

$u_t = u_{xx}, (x,t) \in (0,1) \times (0,T)$.

$$\Rightarrow u(x,t) = X(x)T(t)$$

similarly

$$u_{tt} = C^2 u_{xx} \leftarrow \text{unsteady.}$$

$$u_{tt} + C^2 u_{xx} = 0 \leftarrow \text{steady.}$$

Air flow is an example of place where this is useful.

Eg:- Concorde was stopped because of 1 accident, because nose-shape.

\Rightarrow here, idea is to find solutions when exact analytic solution are provably impossible to find.

$$B = \int_0^t \left((1 + \frac{1}{2}C^2 s^2)^{-1} \right) ds = (0)t - \left(\frac{1}{2}C^2 \right) \frac{1}{1 + \frac{1}{2}C^2 t^2}$$

$$\boxed{\text{IVP}} \quad \left\{ \begin{array}{l} y'(t) = f(t, y), \quad t \in [a, b], \\ y(a) = \alpha. \end{array} \right.$$

domain of definition

$t \rightarrow$ independent variable
 $y \rightarrow$ dependent variable
initial value.

\Rightarrow Knowing when this problem will have a solution.

\Rightarrow called well-posedness:

A problem is well-posed if

it admits solution st:

- (1) Existence
- (2) Uniqueness
- (3) Stability / Continuous dependence

Condition for uniqueness:

Strong condition: f cont., f' cont.

Weak condition: $|f(x_1) - f(x_2)| \leq L|x_1 - x_2|$.

(better because less constrained).

Lipschitz condition.

$$\text{Eg: } y' = t + y, \quad t \in (0, 1).$$

$$y(0) = \frac{1}{2}.$$

definition of Lipschitz condition for uniqueness of IVPs

$$\text{function is Lipschitz if } |f(x_1) - f(x_2)| \leq L|x_1 - x_2|$$

continuous function

$$y' - e^{-t}y = e^{-t}$$

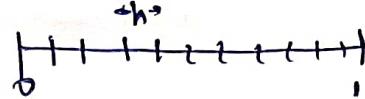
$$\Rightarrow (e^{-t}y)' = e^{-t} \Rightarrow (e^{-t}y)|_0^t = e^{-t}(t+1)$$

$$\Rightarrow e^{-t} y - \frac{1}{2} = 1 - e^{-t}(Ct + 1)$$

$$\Rightarrow y(t) = \frac{3}{2} e^t - (t + 1).$$

Step 1: Discretize

Euler's Method



Say problem: $\begin{cases} y'(t) = f(t, y) \\ y(a) = \alpha \end{cases} \quad t \in [a, b].$

$\Rightarrow 'N'$ points $\Rightarrow h = \frac{(b-a)}{N}$.

$t_0 = a, t_1 = a+h, t_2 = a+2h, \dots, t_n = a+nh.$

Step 2: Replacing derivative by finite difference.

$$(1) y' = \frac{y_{n+1} - y_n}{h} \rightarrow O(h)$$

$$y' = \frac{y_n - y_{n-1}}{h} \rightarrow O(h) \quad \leftarrow \text{any one can be taken}$$

$$y' = \frac{y_{n+1} - y_{n-1}}{2h} \rightarrow O(h^2)$$

Say we take forward difference, $\frac{y_{n+1} - y_n}{h} = f(t_n, y_n).$

Difference Equation

$$\Rightarrow y_{n+1} = t_n + h f(t_n, y_n), \quad n = 0, 1, \dots, N-1.$$

$$y_0 = \alpha$$

\Rightarrow this is a recurrence relation

Euler's Method Code:

Input: (a, b, N, α) , $f(t, y) = t^2 + y^2$

$$h = (b - a)/N.$$

~~$t = a : h : b;$~~

$y(1) = \alpha;$

for $i = 1:N$

$$\underline{y(i+1) = y(i) + h \cdot f(t(i), y(i))},$$

$$\underline{\text{exact}(i) = y_exact(t, y);}$$

end.

$$\Rightarrow \underline{\text{Error}(i) = abs(y(i) - y_exact(i));}$$

\Rightarrow for each N , we will have table

t_i	Approx	Exact	Error
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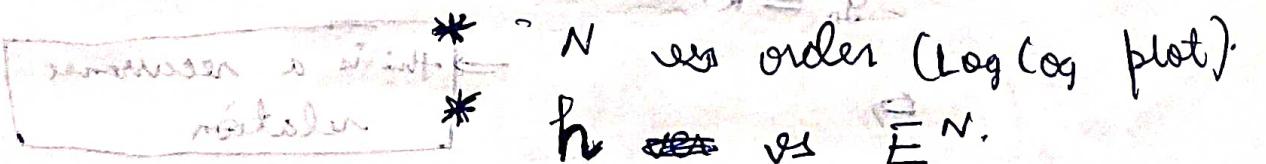
$$\text{order} = \log_2 \left(\frac{E^N}{E^{2N}} \right) \quad E^N = \text{error.} = \frac{\text{max error with } N}{N}$$

N	E^N	order
20		
40		
80		

~~Graph~~ \rightarrow ~~Graph~~ \rightarrow ~~Graph~~
~~Graph~~ \rightarrow ~~Graph~~ \rightarrow ~~Graph~~
~~Graph~~ \rightarrow ~~Graph~~ \rightarrow ~~Graph~~

3 plots: * t vs y & y_exact (2 in 1).

(Or 4, if you want) * t vs error.



$$\text{Backward: } \frac{y_n - y_{n-1}}{h} = f(t_n, y_n). \quad \boxed{\begin{array}{l} \text{Implicit Euler} \\ \text{(or Backward Euler)} \end{array}}$$

$$y_n = y_{n-1} + h \cdot f(t_n, y_n) + (\Delta t) \beta =$$

$$y_{n+1} = y_n + h \cdot f(t_{n+1}, y_{n+1}) + (\Delta t) \beta.$$

$$\text{Max Iter} = 10^4, \delta = 10^{-8}.$$

$$\int \cdot (x, \dot{x}) dx + g(x) = \text{rhs}$$

$$(x_0) = \frac{(3T - 2H)^\top}{\alpha} = \text{initial value}$$

$$(x_0) \text{ iteration } \textcircled{1}$$

$$\text{iteration} \leftarrow 0 \leftarrow 0 \leftarrow 3T, \text{rhs}$$

$$(x_0) \text{ iteration } \textcircled{2}$$

$$\text{Iteration} = \text{new } x \text{ if } \text{diff} < \epsilon$$

$$\text{diff} \leftarrow$$

$$\text{diff} = \|x - x_{\text{old}}\| = \epsilon$$

$$\text{Iteration} = \left\{ \begin{array}{l} x - (\Delta t) f \\ \text{if } \text{diff} < \epsilon \end{array} \right\} = \text{new } x$$

$$\text{and so } 0 \leftarrow \text{first diff}$$

18/3/24

$$y(t_{i+1}) = y(t_i + h)$$

$$= y(t_i) + h y'(t_i) + \frac{h^2}{2!} y''(\xi_i)$$

$$= y(t_i) + h f(t_i, y(t_i)) + \frac{h^2}{2!} y''(\xi_i),$$

$\xi_i \in [t_i, t_{i+1}]$.

$$y_{i+1} = y_i + h f(t_i, y_i).$$

$$\text{Truncation Error} = \frac{(LHS - RHS)}{h} = O(h).$$

① Consistency (TE)

If $TE \rightarrow 0$ as $h \rightarrow 0 \Rightarrow$ Consistent.

② Stability (Round-off).

If Round off error = bouned
 \Rightarrow Stable.

③ Convergence

$$\text{Error} = |y(t_i) - y_i| \leq C h^{p \rightarrow \text{order}}.$$

\downarrow
exact
approx
soln.

If error $\rightarrow 0$ as $h \rightarrow 0$

Explicit Euler, we want Consistency & Stability \Rightarrow Convergence
and 2 values help (& integrated)

$$w_{i+1} = w_i + h f(t_i, w_i)$$

$t_i \in [t_0, t_1], t_1 - t_0$

consistency is, suppose
 $w_0 = \alpha$.

I stated the values obtained with different book
Lemma 1: $\forall x \geq -1, m > 0$, we have

$$0 \leq (1+x)^m \leq e^{mx}$$

$\because x \geq -1$, the Taylor's expansion of $\exp(x)$ will be

$$e^x = 1 + x + \frac{x^2}{2!} + \sum_{n=3}^{\infty} \frac{(x^n)}{n!}$$

$x \in (0, \infty)$

$$(1+x)^m = e^{mx} \Rightarrow (1+x)^m \leq e^{mx}$$

Lemma 2: Let s, t be two positive real numbers

and $\{a_i\}$ be a sequence satisfying, $a_0 \geq -t/s$.

& $(i+1)$ th entry $a_{i+1} \leq (1+s)a_i + t, i = 0, \dots, k$.

$$a_{i+1} \leq \exp((i+1)s) \left[a_0 + \frac{t}{s} \right] - \frac{t}{s}$$

$$\left[a_{i+1} \leq (1+s)^{i+1} (a_0 + \frac{t}{s}) \right] - \frac{t}{s}, i = 0, 1, \dots, k.$$

$$a_{i+1} \leq (1+s)^{i+1} a_0 + t, i = 0, 1, \dots, k$$

$$\begin{aligned} a_{i+1} &\leq (1+s)^{i+1} a_0 + \left[(1+s)^{i+1} + \dots + (1+s)^0 \right] t \\ &\leq (1+s)^{i+1} a_0 + t [(1+s)^{i+1} - 1] \end{aligned}$$

$$\text{Then } t - (1+s)^{i+1} t \leq e^{s(i+1)} \left[a_0 + \frac{t}{s} \right] - \frac{t}{s}$$

[Replacing $(1+s)^{i+1}$ with $e^{s(i+1)}$ because $a_0 + \frac{t}{s} \geq 0$]

Theorem: Convergence \Rightarrow explicit Euler scheme.

Suppose f is continuous. $[y' = f(t, y)]$.

and satisfies the Lipschitz condition with constant L .

on the domain $\mathcal{D} = \{(t, y) : a \leq t \leq b, -\infty < y < \infty\}$.

and $\exists M > 0$ s.t. $|y''(at)| \leq M$ for all $t \in [a, b]$.

$$|y''(at)| \leq M \quad a, t \in [a, b].$$

Proof:-

Let $y(t)$ be the unique soln of IVP $\begin{cases} y'(t) = f(t, y) \\ y(a) = \alpha \end{cases}$

$$\boxed{y(t) = \alpha + \int_a^t f(s, y(s)) ds}.$$

$$w_0, w_1, \dots, w_N$$

satisfy s.t. $w_i = y(t_i)$ for $i = 0, 1, \dots, N$.

$$w_{i+1} = w_i + h f(t_i, w_i).$$

$$\text{Error} = |y(t_i) - w_i| \leq \frac{h}{2L} \exp(L(t_i - a)) \leq \frac{h}{2L} \exp(L(b - a)).$$

$$\leq Ch \exp(L(t_i - a)) \leq Ch.$$

$$y(t_{i+1}) = y(t_i) + h y'(t_i) + \frac{h^2}{2!} y''(\xi_i).$$

$$w_{i+1} = w_i + h f(t_i, w_i).$$

$$y(t_{i+1}) - w_{i+1} = (y(t_i) - w_i) + h [f(t_i, y_i) - f(t_i, w_i)].$$

$$\leq Ch \exp(L(t_i - a)) + \frac{h^2}{2!} y''(\xi_i).$$

$$\Rightarrow |y(t_{i+1}) - w_{i+1}| \leq |y(t_i) - w_i| + h |f(t_i, y_i) - f(t_i, w_i)| + \frac{h^2}{2!} \|y''(\xi_i)\|.$$

$$|y(t_{i+1}) - w_{i+1}| \leq (|y(t_i) - w_i| [1 + hL] + \frac{h^2}{2} M).$$

$$\text{Error} \leq \boxed{\exp((i+1)hL)} \left[\frac{hM}{2L} \right].$$

$$\rightarrow \boxed{\text{Error} \leq \frac{h^n}{2L} [\exp(L(t_i - a)) - 1]}.$$

In the previous theorem, we assumed all the calculations are free from round off errors. However, it is not true in practice.

If we consider the round off error, then the scheme becomes

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

Proof:-

Assume $|\delta_i| < \delta_0$ (unit round off).

$$|y(t_i) - w_i| \leq \frac{1}{L} \left(\frac{hM}{2} + \frac{\delta}{h} \right) [\exp(L(t_i - a)) - 1].$$

$$+ |\delta_0| \exp(L(t_i - a)) \quad \forall i = 0, 1, \dots, N.$$

Proof (Haw),

$$= \frac{1}{2} \left(\omega_1^2 + \omega_2^2 \right) t^2 + \frac{1}{2} \left(\omega_1^2 - \omega_2^2 \right) t^2 \cos(\omega_1 t) +$$

$$\text{Ansatz: } \frac{d\theta}{dt} = \frac{\omega_1^2 + \omega_2^2}{2} t^2 + \frac{\omega_1^2 - \omega_2^2}{2} t^2 \cos(\omega_1 t)$$

$$G(t) = \left[\omega_1^2 t^2 + \omega_2^2 t^2 \right] + \left[\frac{\omega_1^2 - \omega_2^2}{2} t^2 \cos(\omega_1 t) \right]$$

$$= \omega_1^2 t^2 + \omega_2^2 t^2 + \frac{\omega_1^2 - \omega_2^2}{2} t^2 \cos(\omega_1 t)$$

$$\left[\frac{\omega_1^2 - \omega_2^2}{2} t^2 \cos(\omega_1 t) \right] = \text{const}$$

$$\left[1 - (\omega_1^2 - \omega_2^2) \frac{t^2}{2} \right] \frac{d\theta}{dt} = \text{const}$$

$\lim_{h \rightarrow 0} \left(\frac{h M}{2} + \frac{J}{h} \right)$ mit $M > 0$, mit $J < 0$ ist ∞ .
mit $h \rightarrow 0$, $J \rightarrow 0$, respektiv $M \rightarrow 0$ ∞ .

$$E(h) = \frac{h M}{2} + \frac{J}{h} \text{ folgt mit rechnen in f.}$$

$$\text{aus } \left(\omega_1^2 + \omega_2^2 + \left(\omega_1^2 - \omega_2^2 \right) \frac{t^2}{2} + J_0 \omega \right) \frac{d\theta}{dt} = \omega_1 \omega \text{ folgt}$$

$$\frac{M}{2} - \frac{J}{h^2} = 0 \Rightarrow h = \sqrt{\frac{2J}{M}}$$

$$\textcircled{1} \quad \text{If } h < -\sqrt{\frac{2J}{M}} \Rightarrow E^I = -\text{ve.}$$

$$\text{aus } \left(\omega_1^2 + \omega_2^2 + \left(\omega_1^2 - \omega_2^2 \right) \frac{t^2}{2} + J_0 \omega \right) \frac{d\theta}{dt} = \left(\omega_1 \omega - J_0 \omega \right) \frac{d\theta}{dt}$$

$$\textcircled{2} \quad \text{If } h > \sqrt{\frac{2J}{M}} \Rightarrow E^I = +\text{ve.}$$

$$\omega_1 \omega_2 = \pm \sqrt{\frac{2J}{M}}$$

$$\text{aus } \left(\omega_1^2 + \omega_2^2 + \left(\omega_1^2 - \omega_2^2 \right) \frac{t^2}{2} + J_0 \omega \right) \frac{d\theta}{dt} = \left(\omega_1 \omega - J_0 \omega \right) \frac{d\theta}{dt}$$

19/3/24 (3-1) & (3-2) \Rightarrow $\alpha = \beta = \gamma$

$$(1) \left\{ \begin{array}{l} \text{order 3 for part } \alpha = \beta = \gamma \\ \text{order 2 for part } \alpha = \beta = \gamma \end{array} \right.$$

$\Leftarrow \frac{1}{2} \cdot 6$

$$\text{Therefore } 6 = (2 \cdot 2 + 2 \cdot 1) \cdot 2 = 12$$

Bottom pole weight

Bottom pole weight

Bottom pole is bent at 45° for system -

and has length a and is bent to 45° to receive
a force of F at its midpoint from a horizontal

$$(d(\alpha \beta \gamma)) D d(\alpha \beta) Y = (1 + \delta) \cdot 5 \quad \left(\begin{array}{l} \text{bottom} \\ \text{pole} \end{array} \right)$$

Bottom pole weight

(loads) bottom bending

Bottom pole weight

below as well as first part, first part to

bottom bending

Bottom pole weight bottom bending

$$y_{n+1} = y_n + \theta h [\theta f(t_n, y_n) + (1-\theta) f(t_{n+1}, y_{n+1})]$$

$\theta = 0 \Rightarrow$ Implicit Euler }
 $\theta = 1 \Rightarrow$ Explicit Euler } $O(h)$

$\theta = \frac{1}{2} \Rightarrow \overbrace{\rightarrow O(h^2)}^{TE}$.

$$TE = \frac{1}{n} (LHS - RHS).$$

Runge-Kutta Method.

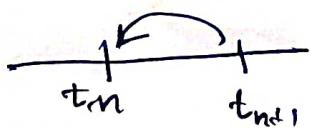
- underlying idea of R-K method is to take weighted average of slope of tangent in order to increase/enhance the order of truncation error.

$$\left\{ \begin{array}{l} y(t_{n+1}) = Y(t_n) + h \Phi(t_n, y(t_n), h) \\ y_1 = a \end{array} \right.$$

incorrigent function: (check)

Defn: Single-Step method.

at time t_{n+1} , only time t_n values are needed.



Using Central difference \rightarrow 2-Step / Multi-Step.

$$\text{R-stage} \quad \text{R-K} \quad y_{n+1} = y_n + \Phi(t_n, y_n, h)$$

$$y_{n+1} = y_n + \Phi(t_n, y_n, h) \\ = y_n + h f(t_n, y_n) + \frac{h^2}{2} f'_t(t_n, y_n) + \frac{h^3}{3!} f''_t(t_n, y_n) + \dots$$

$$\Phi(t, y, h) = \sum_{r=1}^R w_r k_r.$$

$$k_1 = h f(t_n, y_n)$$

$$k_R = h f(t_n + h c_R, y_n + \sum_{s=1}^{R-1} a_{rs} k_s).$$

$$c_r = \sum_{s=1}^{R-1} a_{rs}, \quad r = 2, \dots, R$$

Take R=2:

$$y_{n+1} = y_n + w_1 k_1 + w_2 k_2. \quad \textcircled{D}$$

$$\textcircled{2} \quad \begin{cases} k_1 = h f(t_n, y_n) \\ k_2 = h f(t_n + c_2 h, y_n + a_{21} k_1) \end{cases}$$

We have 4 unknowns $\rightarrow w_1, w_2, c_2, a_{21}$

In order to determine the values for the parameters, we use the Taylor series expansion around t_n

$$y(t_{n+1}) = y(t_n + h) = y(t_n) + h y'(t_n)$$

Starts and we go up to $\frac{h^2}{2} y''(t_n) + \dots$.
Finalized

$$y'(t_n) = f(t_n, y_n), \quad \text{and } w_1, w_2$$

$$y'' = f_t + f_y y' = f_t + f_y f.$$

$$y''' = f_{ttt} + f_{tyy} + (f_y)^2 + f_{yy} + \dots$$

$$y''' = f_{ttt} + f_{yy} + (f_y)^2 + f_{yy} + \dots$$

$$\therefore y''' = (f_{ttt} + f_{yy}) + (f_y)^2$$

$$y(t_{n+1}) = y(t_{n+h}) =$$

$$(f_{ttt} + f_{yy}) = \dots$$

$$\therefore k_2 = h f(t_n + C_2 h, y_n + a_2, k_1) \cdot$$

$$= h f(t_n, y_n) + C_2 h f_t(t_n, y_n)$$

$$+ a_{21} k_1 + a_{21} k_1 f_y(t_n, y_n)$$

$$+ \frac{(C_2 h)^2}{2} f_{tt}(t_n, y_n)$$

$$+ (C_2 h)(a_{21} k_1) + f_y(t_n, y_n)$$

$$+ \frac{(a_{21} k_1)^2}{2} = f_{yy}(t_n, y_n)$$

\Rightarrow

$$w_1 + w_2 = 1 \quad \text{and} \quad \left. \begin{array}{l} \\ \end{array} \right\} \text{we have 4 unknowns}$$

$$\text{and} \quad C_2 w_2 = \frac{1}{2} \quad \text{we have 3 equations for 4 unknowns}$$

$$\therefore a_{21} w_2 = \frac{1}{2} - \frac{1}{2} w_2 \quad \text{we have 3 equations for 4 unknowns}$$

$$(a_{21} + b_1) w_2 + (d + b_2) w_1 = (c_1 + b_3) w_1$$

\therefore we have only 3 eqns \Rightarrow we can choose C_2 arbitrarily.

$$w_1 + w_2 = 1 \Rightarrow w_1 = 1 - w_2 = 1 - \frac{1}{2} \frac{1}{2} = \frac{1}{2}$$

$$\therefore \text{for different values of } C_2, \text{ we get different families of soln}$$

$$q_{21} = C_2$$

$$\omega_2 = \frac{1}{2C_2}$$

$$\omega_1 = 1 - \frac{1}{2C_2}$$

$$y_{n+1} = y_n + h f_n + \frac{h^2}{2} (J_T + J_n J_B)$$

$$+ C_2 h^3 (f_{t+h} + 2f_n f_{t+h} + f_n^2 + g_y)$$

John Butcher's Table

$$C_2 | q_{21}$$

$$\omega_1 \quad \omega_2$$

$$\rightarrow \begin{array}{c|cc} & 1/2 \\ \hline & 0 & 1 \end{array}$$

$$\begin{array}{c|ccc} & 2/3 & 2/3 & 3/4 \\ \hline & y_3 & y_4 & 3/4 \end{array}$$

Optimal method.

Improved Tangent

$$\begin{array}{c|cc} & 1/2 & 1/2 \\ \hline & 1 & 1 \end{array}$$

Euler-Cauchy.

Backward Euler

Backward Euler

3-Stage R-K

$$\begin{array}{c|cc} C_2 & a_{21} \\ \hline C_3 & a_{31} & a_{32} \\ \hline & \omega_1 & \omega_2 & \omega_3 \end{array}$$

Nyström method.

$$\begin{array}{c|cc} 2/3 & 2/3 \\ \hline 2/3 & 0 & 2/3 \\ \hline & 2/8 & 3/8 & 3/8 \end{array}$$

Classical Method

$$\begin{array}{c|cc} Y_2 & Y_2 \\ \hline 1 & -1 & 2 \\ \hline Y_6 & 4/6 & 1/6 \end{array}$$

Nearly Optimal.

$$\begin{array}{c|cc} 1/2 & Y_2 \\ \hline 3/4 & 0 & 3/4 \\ \hline 2/9 & 3/9 & 4/9 \end{array}$$

4-Stage R-K

Runge

$$\begin{array}{c|ccc} Y_1 & Y_2 & & \\ \hline Y_2 & 0 & Y_2 & \\ \hline 1 & 0 & 0 & 1 \\ \hline Y_6 & 2/6 & 2/6 & 1/6 \end{array}$$

Kutta Method.

$$\begin{array}{c|ccc} Y_3 & Y_3 & & \\ \hline 2/3 & -1/2 & 1 & \\ \hline 1 & 1 & -1 & 1 \\ \hline Y_8 & 3/8 & 3/8 & 1/8 \end{array}$$

Classical Method.

$$TE = \frac{1}{h} (LHS - RHS)$$

(Stability of numerical method)

Stability

$$\left\{ \begin{array}{l} y' = \lambda y, \text{ and } 0 \in \text{R} \\ y(0) = y_0 \end{array} \right.$$

(ODE) for stability (check at infinity)

exact: $y(t) = y_0 e^{\lambda t}$

soln:

\Rightarrow now plot $y \leftarrow y_0 e^{\lambda t}$ this condition should hold for all of the R-K methods.

$$y_{n+1} = y_n + h f(t_n, y_n).$$

$$= y_n + h f(y_n) t_n + nh = 1 + nh$$

$$\rightarrow y_{n+1} = (1 + \lambda h)^{n+1} y_0.$$

$$\boxed{y_n = (1 + \lambda h)^n y_0.}$$

Say interval $[0, 1]$. $= nh$

y_n converges if $(1 + \lambda h)$ is st $0 < \alpha < 1 < d \beta$. $|1 + \lambda h| < 1$

$$\Rightarrow -1 < 1 + \lambda h < 1$$

for stability $\Rightarrow h \in \left(0, \frac{-2}{\lambda}\right)$.

or $h \in (0, \min(\alpha, \frac{2}{|\lambda|}))$

$$h \in \left[0, \frac{2}{|\lambda|}\right].$$

$\Rightarrow h$ must be reduced as n increases.

CONDITION for Stability:

\Rightarrow the converge of any soln will happen

only when $|1+dh| < 1$ or $h \in \left(0, \frac{2}{|f'_b|}\right)$.

(this can be checked, NEEDS TO BE CHECKED
IN NEXT LAB)

Check
in Lab
That

I.e. as $n \rightarrow \infty, y_n \rightarrow 0$ only when $h \in \left(0, \frac{2}{|f'_b|}\right)$.

Case 2:

$$y_{n+1} = y_n + n f(t_{n+1}, y_{n+1}).$$

$$= y_n + \lambda h y_{n+1}$$

$$\Rightarrow (1-\lambda h) y_{n+1} = y_n$$

$$\Rightarrow y_n = \frac{1}{(1-\lambda h)^n} y_0$$

$$1 - \lambda h > 1 \Rightarrow \lambda h < 0$$

$$\Rightarrow y_n \rightarrow 0 \text{ as } n \rightarrow \infty.$$

\therefore This method is unconditionally stable,
(no condition on n).

$$\left[\frac{\partial}{\partial t}, \varphi \right] = d$$

Case 3:

$$y_{n+1} = y_n + \omega_1 k_1 + \omega_2 k_2$$

$$y_{n+1} = \left(1 + \lambda h + \frac{(\lambda h)^2}{2}\right) y_n$$

$$\Rightarrow y_n = \left(1 + \lambda h + \frac{(\lambda h)^2}{2}\right)^n y_0$$

Condition for Stability: If $y_n \rightarrow 0$ as $n \rightarrow \infty$

$$\left|1 + \lambda h + \frac{(\lambda h)^2}{2}\right| < 1$$

$$\Rightarrow -2 < \lambda h + \frac{(\lambda h)^2}{2} < 0$$

(if λh is not wrong sign is stable)

$$-2 < \lambda h < 0$$

λh , it says about stability $\Rightarrow h \in (0, \frac{2}{|\lambda|})$ same condition as in explicit

This interval is called region of absolute stability.

$$\text{Order 3: } \left(0, \frac{2.51}{|\lambda|}\right)$$

region of absolute stability.

$$\text{Order 4: } \left(0, \frac{2.78}{|\lambda|}\right)$$

Order 5: $\left(0, \frac{3.05}{|\lambda|}\right)$

Original problem

$$y'(t) = f(t, y)$$

$$\Rightarrow \int_{t_n}^{t_{n+1}} y'(t) dt = \int_{t_n}^{t_{n+1}} f(t, y) dt$$

$$y_{n+1} - y_n = \leftarrow \text{use only } t_n \text{ to ansll.}$$

Multi-step
Scheme

why not use



to interpolate a polynomial for $f(t, y)$.

Using $t_n, t_{n-1}, \dots, t_{n-m}$

Multi Step Scheme / Method

In the R-K Method, we had to evaluate the slopes k_1, k_2, k_3 , which are computationally expensive in order to overcome the computational cost.

In order to overcome the computational cost, one can use the multistep method, which make use of interpolating integrant at more than one previous points

$$\int_{t_n}^{t_{n+1}} y'(s) ds = \int_{t_n}^{t_{n+1}} f(s, y(s)) ds$$

$$\Rightarrow y_{n+1} - y_n = - \int_{t_n}^{t_{n+1}} f(s, y(s)) ds. \quad \textcircled{1}$$

In order to evaluate the integral, we evaluate a polynomial which interpolates $f(t, y)$ at $t_n, t_{n-1}, \dots, t_{n-m}$ ($m+1$ nodal points), by using Newton's backward difference formula (to make a polynomial of degree m)

$$\phi_m(t) = \sum_{k=0}^m \frac{(-\gamma+k)}{k} \Delta^k f[x_n, x_{n-1}, \dots, x_{n-k}]$$

$$\gamma = x_n - x$$

(~~FOR FDP - WE USE FORWARD DIFFERENCE~~ we will use forward difference notation for backward difference,

$$\phi_m(t) = \sum_{k=0}^m (-1)^k \binom{-\alpha}{k} \Delta^k f_{n-k}. \quad (2)$$

$\alpha = (t - t_n)/h$ where $\alpha = (t - t_n)/h$

$$y_{n+1} = y_n + h \sum_{k=0}^m (-1)^k \binom{-\alpha}{k} \Delta^k f_{n-k} \Delta \alpha.$$

$$= (y_n + h \sum_{k=0}^m (-1)^k \binom{-\alpha}{k} \Delta^k f_{n-k}) \Delta \alpha.$$

Now we, $y_{n+1} = y_n + h [v_0 f_n + v_1 \Delta f_{n-1} + \dots + v_m \Delta f_{n-m}]$ $\leftrightarrow (3)$

$$v_{k+1} = (-1)^k \int_0^{\alpha} \binom{-\alpha}{k} dz$$

$$v_0 = 1, v_1 = \frac{1}{2}, v_2 = \frac{5}{12}, v_3 = \frac{3}{8}, v_4 = \frac{251}{720}.$$

(2) is known as Adams - Bashforth formula.

n=3			
<u>Forward difference</u>	y_{n-3}	f_{n-3}	Δf_{n-3}
<u>Calculated by</u>	t_{n-2}	y_{n-2}	Δf_{n-2}
<u>Calculated by</u>	t_{n-1}	y_{n-1}	$\Delta^2 f_{n-2}$
<u>Calculated by</u>	t_n	y_n	$\Delta^3 f_{n-3}$

Scheme:

$$\frac{y_n - y_{n-3}}{h} = f_i$$

$$y_{n+1} = y_n + \frac{h}{24} (55f_n - 59f_{n-1} + 37f_{n-2} - 9f_{n-3})$$

$$\text{Error in Newton's BD} = \frac{h^4}{4!} f^{(4)}(n) \binom{-3}{4}$$

~~E_{AB}~~ $E_{AB} = \frac{h^4}{4!} f^{(4)}(n) \binom{-3}{4} d =$

$$\text{Error in } \Delta \binom{-3}{4} = \frac{720}{720} h \sum y^{(3)}(\xi)$$

$$\Rightarrow TE = O(h^4) \quad (\text{Error} = E_{AB})$$

Problem here - It is not self-starting (because, we will

first need 3 points).

$$\frac{dy}{dx} = u, \frac{d^2y}{dx^2} = v, \frac{d^3y}{dx^3} = w, \frac{d^4y}{dx^4} = x$$

1/4/24

$$y_n = C_1 \beta_1^n + C_2 \beta_2^n + \dots + C_k \beta_k^n \quad \begin{matrix} \beta_1, \beta_2, \dots, \beta_k \\ \text{roots of characteristic equation} \end{matrix}$$

$$y_{n+1} = y_n - \frac{\lambda h}{24} [55y_n - 59y_{n-1} + 37y_{n-2} - 9y_{n-3}]$$

⇒ Characteristic equation:

$$\beta^4 - \beta^3 - \frac{\lambda h}{24} [55\beta^3 - 59\beta^2 + 37\beta - 9] = 0$$

$$\Rightarrow f(\beta) + \lambda h \sigma(\beta) = 0$$

where $f(\beta) = \beta^4 - \beta^3 = \beta^3(\beta^4 - 1)$.

$$\sigma(\beta) = \dots$$

→ This gives (IDK why) strongly stable.

(multiple types of stability).

$$\text{Q: } y_{n+1} = y_{n-1} + \frac{h}{3} (f_{n+1} + 4f_n + f_{n-1}).$$

$$y' = \lambda y. \quad \underline{\text{stability?}}$$

Ans:-

Conditionally stable, depends on the value of λ .

Round off error

$$\begin{aligned} & \text{Let } (x^*, y^*) \text{ be the solution.} \\ & \text{Then } (x^*, y^*) \text{ satisfies all the equations.} \\ & \text{So, } (x^*, y^*) \text{ satisfies the system of linear equations.} \\ & \text{Therefore, } (x^*, y^*) \text{ is the unique solution.} \end{aligned}$$

$$y_{n+1} = y_n + h f(t_n, y_n)$$

$$\tilde{g}_{n+1} = \tilde{g}_n + h f(t_n, \tilde{g}_n).$$

$$\left(y_n - \tilde{y}_n \right), y_0 = \alpha \pm \varepsilon.$$

$$\text{Error} = \left| y(t_n) - y_n \right| = \left| y(t_n) - y_n + \tilde{y}_n - \tilde{y}_n \right|.$$

$$\leq \left| y(t_n) - y_n \right| + \left| t_n - y_n \right|.$$

~~Let b be a number and m its truncation error.~~

$$\leq C h^{\frac{1}{p}}, \quad p > 0.$$

(consistency constant) (Taylor expansion → first non-zero term).

26 $\otimes \otimes^o(-r)$.

System of first order ODEs

$$y'_1 = f_1(t, y_1, y_2),$$

$$y'_2 = f_2(t, y_1, y_2).$$

$$y_1(0) = \alpha, \quad y_2(0) = \beta.$$

$$\vec{y}' = \vec{f}(t, \vec{y}).$$

2nd order → can always be converted system of equations

$$y''(t) + p(t)y'(t) + q(t)y(t) = 0, \quad t \in (0, 1).$$

$$y(0) = \alpha$$

$$y'(0) = \beta.$$

~~the equation be converted to~~

$$y' - v = 0,$$

$$v' + p(t)v + q(t)y = 0.$$

(most of the time)

$$(v(t))' = -p(t)v(t) - q(t)y(t)$$

or

$$v(t) = e^{-\int p(t) dt} \left(C - \int q(t) e^{\int p(t) dt} dt \right)$$

or

BVP

$$u''(x) + f(x) u'(x) + g(x) u(x) = h(x) \quad (x \in (0,1)).$$

$$u(0) = \alpha, u(1) = \beta$$

Here:- Shooting technique

- Converting the BVP into suitable IVP with some initial condition $u'(0)$:

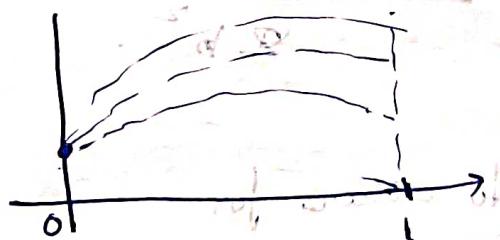
(if we have $u'(0)$, already have $u(0)$) \Rightarrow we can solve as if it is an IVP.

\Rightarrow start with $u'(0) = \varepsilon \pm \delta$.

\Rightarrow change $u'(0)$ till the

$$\text{difference } |u_n - u(1)| < \text{Tolerance}$$

\Rightarrow choosing $u'(0)$ we are shooting.



Pros:- ① Solve non-linear P.E. : all the methods studied for IVPs can be dealt with.

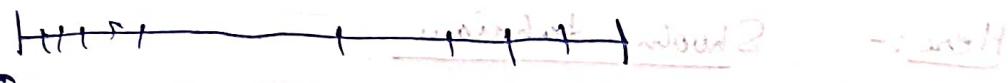


Cons:- ① Solve IVP for several values of δ .

Finite difference schemes

Step 1 :- Discretize the domain

$$0 = x_0 < x_1 < \dots < x_{n-1} < x_n < x_{n+1} (= 1) . u$$



Also PDE is discretized to FVE $\frac{d}{dx} f(x) \approx \frac{x_{n+1} - x_n}{h}$

Step 2 :- Replace the derivatives by finite difference equation
 and use (1), (2) and (3) to get an ODE

$$u'(x_i) = \frac{u_{i+1} - u_i}{h} \quad (\text{at } x_i)$$

$$\frac{u_i - u_{i-1}}{h} \quad \text{using } h = 1/n \quad O(h)$$

$$u''(x_i) = \frac{u_{i+1} - 2u_i + u_{i-1}}{h^2} \quad O(h^2)$$

$$u''(x_i) = \frac{u_{i+1} - 2u_i + u_{i-1}}{h^2}$$

\Rightarrow 3 schemes to solve for

$$\frac{u_{i+1} - 2u_i + u_{i-1}}{h^2} + f(x_i) = \frac{u_{i+1} - u_i}{h} + g_i \quad i = 1, 2, \dots, n$$

$$u_0 = \alpha, u_{n+1} = \beta$$

$$\left(\frac{1}{h^2} + \frac{p_i}{2h} \right) u_{i+1} - \left(\frac{2}{h^2} - q_i \right) u_i + \left(\frac{1}{h^2} - \frac{p_i}{2h} \right) u_{i-1} = r_i$$

$$i=1 \Rightarrow \left(\frac{1}{h^2} + \frac{p_1}{2h} \right) u_2 - \left(\frac{2}{h^2} - q_1 \right) u_1 = r_1 - \left(\frac{1-p_1}{h^2} \right) u_{-1}$$

$i=2 \text{ to } N-1$

$$\Rightarrow \left(\frac{1}{h^2} + \frac{p_i}{2h} \right) u_{i+1} - \left(\frac{2}{h^2} - q_i \right) u_i + \left(\frac{1}{h^2} - \frac{p_i}{2h} \right) u_{i-1} = r_i$$

$i=N$

$$\Rightarrow \left(\frac{1}{h^2} - \frac{p_N}{2h} \right) u_{N-1} - \left(\frac{2}{h^2} - q_N \right) u_N = r_N - \left(\frac{1-p_N}{h^2} \right) u_{N+1}$$

\rightarrow N equations, N variables.
(u_1 to u_N)

Here, if we ~~deal~~ write the system of equations as

$$A u = r$$

Sparse matrix.

$$\text{because } A \rightarrow \begin{pmatrix} 1 & p_1 & & & \\ 0 & 1 & -q_1 & & \\ & & 1 & p_2 & \\ & & & 1 & -q_2 \\ & & & & \ddots \end{pmatrix}$$

If A is invertible then, there is a unique solution.

2/5/24

~~the details~~:

$$u''(x) + p(x) \cdot u' + q(x) \cdot u = r(x), \quad (0,1).$$

Dirichlet Boundary Condition



$$\Rightarrow u(0) = \alpha, \quad u(1) = \beta. \quad TE = LHS - RHS \rightarrow O(h^2)$$

$$Au = b \quad u_{n+1} = \beta. \quad \Rightarrow TE = -\frac{h^2}{24} (u^{(4)}(\xi_1) - 2p_i u^{(3)}(\gamma_i))$$

Neumann Boundary Condition

$$\Rightarrow -u'(0) = \alpha, \quad u'(1) = \beta.$$

$$\left(\frac{1}{h}\right) u_0 - \left(\frac{1}{h}\right) u_1 \leftarrow \frac{u_1 - u_0}{h} = \alpha \Rightarrow \\ = \alpha$$

$$\frac{u_{N+1} - u_N}{h} = \beta \quad \alpha(h) \rightarrow \boxed{\alpha(h)}$$

$$-\left(\frac{1}{h}\right) u_N + \left(\frac{1}{h}\right) u_{N+1} = \beta \quad \text{also } \alpha(h) \rightarrow \boxed{\alpha(h)}$$

Robin-type Mixed BCs

$$u(0) - u'(0) = \alpha.$$

$$u(1) + u'(1) = \beta$$

$$u_0 - \frac{u_1 - u_0}{h} = \alpha, \quad u_{N+1} - \frac{u_{N+1} - u_N}{h} = \beta.$$

$$\left(1 + \frac{1}{h}\right) u_0 - \left(\frac{1}{h}\right) u_1 = \alpha$$

$$\frac{1}{h} u_N + \left(1 - \frac{1}{h}\right) u_{N+1} = \beta$$

Inputs : a, b, N, α, β , α, β, γ .

$$A(1,1) =$$

$$A(1,2) =$$

$$b(1) =$$

for $i=2:N-1$

$$\underline{A(i,i) = A(i,i-1) + A(i,i+1)} \Rightarrow b(i) =$$

$$A(i,i) =$$

$$A(i,i-1) =$$

$$A(i,i+1) =$$

$$A(N+1,N) =$$

$$A(N+1,N+1) =$$

$$b(N+1) =$$

$$\boxed{A U B \quad A U \vec{v} = \vec{b}.}$$

Solve using:

① Gaussian.

② Jacobi.

③ Gauss Seidel.

④ SOR.

only one computation
unlike shooting tech.

$$-u''(x) + f(x, u) = 0, \text{ in } (0, 1),$$

$$u(0) = \alpha, u(1) = \beta.$$

$$Lu = u''(x) + p(x)u'(x) + q(x)u = g(x). \quad \hookrightarrow \text{force.}$$

If not
linear

Fully
nonlinear

Auxiliary

Semilinear

$$f(x) = 0,$$

$$Lu \equiv u'' + q(x)u = r(x).$$

$$= (1, 1) A$$

$$= (-1, 1) A$$

$$A u = b \Rightarrow \text{quadratic form}$$

$$G = x^T A x - x^T b.$$

$$\nabla G = 0 \text{ gives } Ax = b.$$

If A is positive definite

\Rightarrow ~~$x^T A x$~~ is convex??

$\Rightarrow \nabla G = 0$ can be found easily using methods like ~~gradient descent~~, Steepest descent

Jacobi, Gauss-Cayley

Static: Jacobi, Gauss-Cayley, SOR

(check)

Dynamic: Steepest descent, gradient descent etc.

$$(1, 1) \times \infty$$

$$x^{(k+1)} = x^{(k)} - \alpha^{(k)} \nabla f(x^{(k)})$$

$$\alpha^{(k)} = \frac{-\nabla f(x^{(k)})^T \nabla f(x^{(k)})}{\nabla f(x^{(k)})^T \nabla f(x^{(k)})}$$

inspired

$(x, u^{(m)})$.

$$f(x, u) = f(x, u^{(m)}) + (u - u^{(m)}) f_u(x, u^{(m)}) + \text{higher order terms. (non linear).}$$

(terms dropped)

$u^{(0)}$ - initial approximation.

$$-u_{xx} + [f(x, u^{(m)}) + (u - u^{(m)}) f_u(x, u^{(m)})] = 0.$$

System of linear equations \Rightarrow solve using $Au = b$.

$$\Rightarrow -u_{xx}^{(m+1)} - f_u(x, u^{(m)}) u^{(m+1)} = -f(x, u^{(m)})$$

$$u^{(0)} = \left(\frac{\partial}{\partial x}\right)^2 u^{(m)} + f_u(x, u^{(m)}) u^{(m)}$$

$$u(0) = \alpha, u(1) = \beta.$$

(Here, you are iterating multiple times because of truncation).

\Rightarrow You can solve when $f(x, u)$ is non linear.

using either the shooting technique,

or by truncating Taylor series and making linear (linearizing semi linear).

$$y'' + \phi(x, u, u') = 0.$$

\rightarrow Solve this by linearizing the quasi lin

Stability analysis

$$u''(x) + \kappa u'(x) = 0 \quad (\omega - \alpha) + (\beta\omega, \alpha)t = (\alpha, \beta)$$

$|K| > 1$
 (and ω is positive)
 (but not zero)

$$u''(x) \rightarrow D^+ D^- \quad (\text{single scheme}).$$

$$u'(x) \rightarrow D^+ \downarrow \text{forward} \quad D^- \downarrow \text{backward} \quad D^0 \rightarrow$$

$$(i) \frac{U_{i+1} - 2U_i + U_{i-1}}{h^2} + \kappa \frac{U_{i+1} - U_{i-1}}{2h} = 0.$$

$$(ii) \frac{U_{i+1} - 2U_i + U_{i-1}}{h^2} + \kappa \left(\frac{U_{i+1} - U_i}{h} \right) = 0.$$

$$(iii) \frac{U_{i+1} - 2U_i + U_{i-1}}{h^2} + \kappa \left(\frac{U_i - U_{i-1}}{h} \right) = 0.$$

$$(i) \rightarrow \left(\frac{1}{h^2} + \frac{\kappa}{2h} \right) U_{i+1} - \frac{2}{h^2} U_i + \left(\frac{1}{h^2} - \frac{\kappa}{2h} \right) U_{i-1} = 0.$$

$$\Rightarrow \left(\frac{1}{h^2} + \frac{\kappa}{2h} \right) \beta^2 - \frac{2}{h^2} \beta + \left(\frac{1}{h^2} - \frac{\kappa}{2h} \right) = 0.$$

$$(2\alpha + \kappa h)\beta^2 - 4\beta + (2 - \kappa h) = 0.$$

$$\Rightarrow \frac{4 \pm \cancel{4\kappa h}}{2(2 + \kappa h)} = 1, \frac{2 - \kappa h}{2 + \kappa h}$$

$$\Rightarrow u_n = C_1 \beta_1^n + C_2 \beta_2^n$$

$$= C_1 + C_2 \left(\frac{2-kh}{2+kh} \right)^n$$

exact solution $\Rightarrow u(x) = A + Be^{-kx}$

Case (i) $K \rightarrow +\infty$ $\Rightarrow e^{kx} \rightarrow 0$ as $x \rightarrow \infty$.

$$2-kh > 0 \Rightarrow h < \frac{2}{K}$$

\rightarrow if K is large, and $h \geq \frac{2}{K}$,

Ansatz \rightarrow $\left(\frac{-1}{1} \right) \Rightarrow \frac{2-kh}{2+kh} (1), -1 \Rightarrow C_1 + C_2 (-1)^n$.
Ansatz \rightarrow oscillation.

Ansatz \Rightarrow for large K , h has to be very small in value.

Case (ii) $K \rightarrow -\infty$ $\Rightarrow e^{-kx} \rightarrow 0$ as $x \rightarrow \infty$.

$$2+kh > 0, \quad h < \frac{2}{|K|}.$$

$y \neq h > \frac{2}{|K|} \Rightarrow$ denominator negative.

$$\Rightarrow \frac{2-kh}{2+kh} < -1 \Rightarrow C_1 + C_2 (-1)^n$$

$(d_2 - 1) > + (i_2, j_2) =$ spurious oscillation
that diverges.

initiates at $\leftarrow o \geq k, j_2$

$$\frac{1}{2} \geq n \Leftrightarrow 0 \leq n \leq 1 \Leftrightarrow 0 \leq n \leq 1$$

3/4/24

$$u'' + \kappa u = 0$$

Central diff \rightarrow Stability condition is $\beta < \frac{2}{|\kappa|}$

Forward diff: - D^+

$$\beta = 1, \quad p = 0 - \kappa h - s$$

$$1 + \kappa h.$$

$$(1 + \kappa h)^n U_n = C_1 (1)^n + C_2 \left(\frac{1}{1 + \kappa h} \right)^n.$$

These approximations are called Pade' approx.

$$\text{No restriction} \leftarrow \kappa > 0, h > 0$$

$$\text{If } \kappa < 0, h > 0 \quad 1 + \kappa h > 0 \Rightarrow h < \frac{1}{|\kappa|}$$

backward diff: - D^-

$$(1 - \kappa h)^n + \beta = 1 - \kappa h.$$

$$U_n = C_1 (1)^n + C_2 (1 - \kappa h)^n.$$

$$\text{If } \kappa < 0 \Rightarrow \text{No restriction.}$$

$$\kappa > 0 \Rightarrow 1 - \kappa h > 0 \Rightarrow h < \frac{1}{\kappa}.$$

more, why is D_+ restricted in both because
average of D_+, D_-

This flow equation, there is some concept of against or along flow here.

When going along flow, resistance $\rightarrow 0$.

against flow, resistance $\neq 0$.

$$(D_{\text{eff}})^{\pm} = (\pm, 1) D_{\pm} + (\pm, 0) \rightarrow \text{follows}$$

One has to be careful when approximating the convective term.

It depends on connecting coefficient

$$u_i = \begin{cases} D^+ u_i = \frac{u_{i+1} - u_i}{h} : k > 0 \\ D^- u_i = \frac{u_i - u_{i-1}}{h}, \quad k < 0 \end{cases}$$

$$u_i = \frac{u_{i+1} - u_{i-1}}{2h}, \quad k = 0$$

unsteady $P_p + Q_f = R$.

time dependent $u_t + a u_x = 0 \leftarrow \text{hyperbolic}$.

$$u_t - u_{xx} = 0 \leftarrow \text{parabolic}$$

$$u_{tt} = c^2 u_{xx} \leftarrow \text{hyperbolic}$$

Steady State $\Delta u = u_{xx} + u_{yy} = 0 \leftarrow \text{elliptic}$

time independent.

$$u_t - (u_{xx} + u_{yy}) = 0 \rightarrow \text{time dependent.}$$

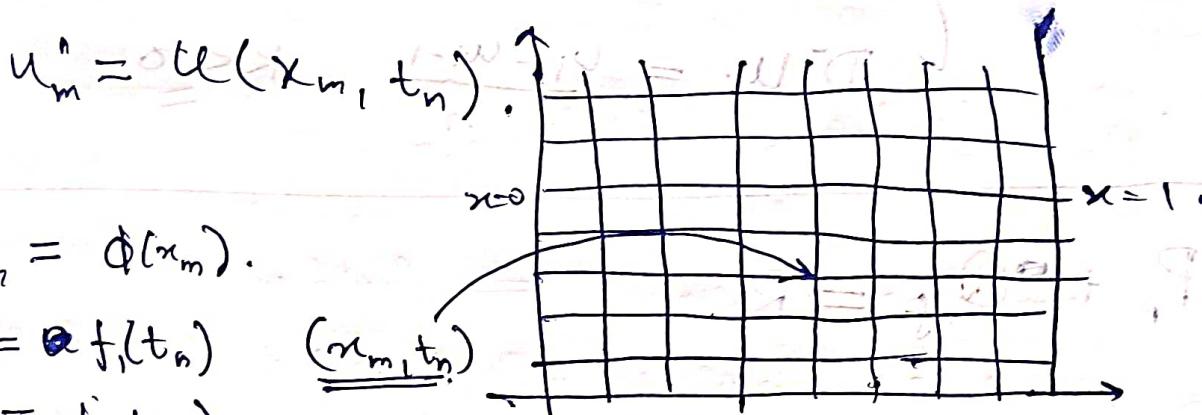
Parabolic PDEs

Initial value problem (I.V.P) $\frac{\partial u}{\partial t} - \frac{\partial^2 u}{\partial x^2} = 0$, $(x, t) \in (0, 1) \times (0, T)$

$t=0 \leftarrow u(x, 0) = \phi(x)$ initial condition $\{$
 $x=0 \leftarrow u(0, t) = f_1(t)$ boundary condition $\{$
 $x=1 \leftarrow u(1, t) = f_2(t)$ boundary condition $\}$ I.B.V.P.

(check) If homogeneous boundary conditions \Rightarrow Separable

$$u(x, t) = X(x)T(t).$$



I.C: $u_m^0 = \phi(x_m)$.

B.C: $u_0^n = f_1(t_n)$ $\quad (x_0, t_n)$

$v_M^n = f_2(t_n)$, $\rightarrow q = 0$

Step 1: Discretization of the domain.

$$\Delta t = k = \gamma_N.$$

$$\Delta x = h = \gamma_M.$$

Step 2: Derivatives using finite diff.

$$\text{Discretized } \frac{\partial u}{\partial t}(x_m, t_n) = \begin{cases} \frac{u_m^{n+1} - u_m^n}{k} & \rightarrow D^+ \\ \frac{u_m^n - u_m^{n-1}}{k} & \rightarrow D^- \\ \frac{u_m^{n+1} - u_m^{n-1}}{2k} & \rightarrow D^0 \end{cases}$$

$$U_{xx} \mid_{(x_m, t_n)} = \frac{U_{m+1}^n - 2U_m^n + U_{m-1}^n}{h^2}$$

(Forward Difference in Space)

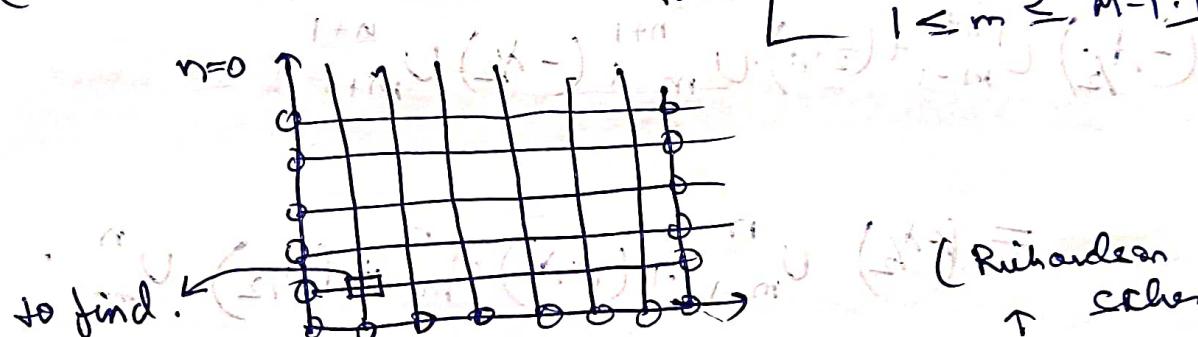
$$\frac{U_m^{n+1} - U_m^n}{K} = \frac{U_{m+1}^n - 2U_m^n + U_{m-1}^n}{h^2} = 0$$

(Backward Difference in Time)

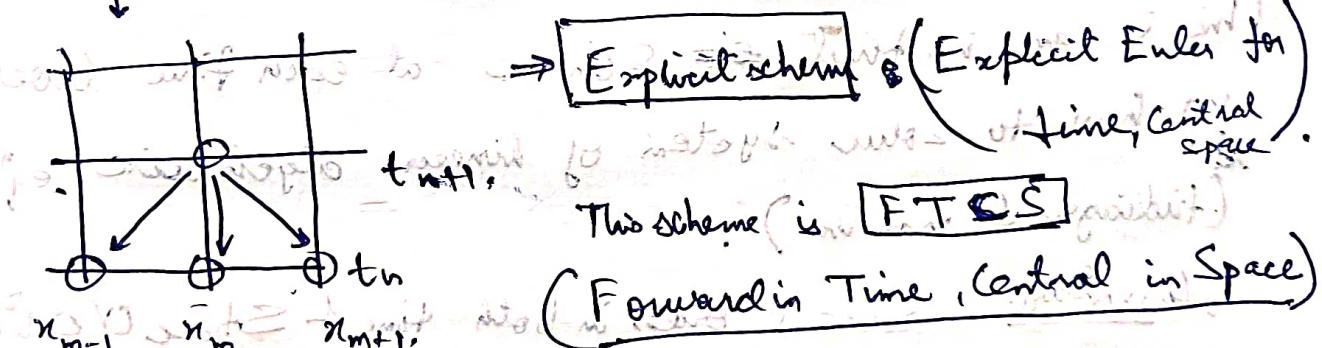
$$\text{D}^+ : U_m^{n+1} = \lambda U_{m-1}^n + (1-2\lambda) U_m^n + \lambda U_{m+1}^n$$

$$(\lambda = K/h^2).$$

Here $0 \leq n \leq N-1$
 $1 \leq m \leq M-1$.



to find. (Richardson scheme).



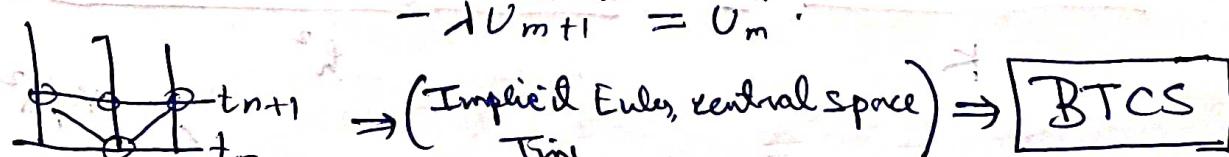
$$\text{D}^- : \frac{U_m^{n+1} - U_m^n}{K} = - \frac{U_{m+1}^{n+1} - 2U_m^{n+1} + U_{m-1}^{n+1}}{h^2} = 0,$$

$$-\lambda U_{m-1}^{n+1} + (1+2\lambda) U_m^{n+1}$$

$$-\lambda U_{m+1}^{n+1} = U_m^n.$$

$$0 \leq n \leq N-1$$

$$1 \leq m \leq M-1$$



Because of its implicit nature, one has to solve system of linear algebraic equations at each time level. This is computationally expensive.

Compound to FTCS.

Hint: Calculate the truncation error of FTCS & BTCS.

$$\hookrightarrow (\Delta t + \Delta x^2)$$

New scheme: $\frac{1}{2} (\text{FTCS} + \text{BTCS}) \rightarrow \text{Crank-Nicolson scheme}$

$$\left(-\frac{1}{2} \right) U_{m-1}^{n+1} + (0) U_m^{n+1} +$$

$$(-\lambda_1) U_{m-1}^{n+1} + \left(\frac{1}{2} + \lambda \right) U_m^{n+1} + (-\lambda_2) U_{m+1}^{n+1}$$

$$= \left(\frac{\lambda}{2} \right) U_{m-1}^n + (1 + \lambda) U_m^n + \left(\frac{\lambda}{2} \right) U_{m+1}^n$$

This is an implicit scheme at each fine level, we have to solve system of linear algebraic eqns (tridiagonal matrix).

Advantages: Second order in both time & Space ($\Delta t^2 + \Delta x^2$)

Note:- These are all 1/2-level schemes.

W.L. central diff.

$$\frac{U_m^{n+1} - U_m^n}{\Delta t}$$

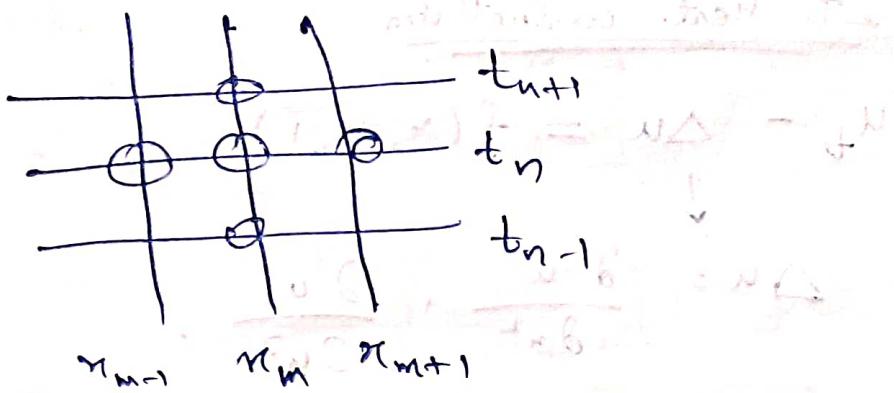
$$\frac{U_{m+1}^{n+1} - 2U_m^n + U_{m-1}^n}{\Delta t^2} = 0.$$

ODE: $\frac{dU}{dt} + (1 + \lambda) U = 0 \Rightarrow \lambda = K/h^2$.

$$U_m^{n+1} = U_m^n + \lambda U_{m-1}^n - 2\lambda U_m^n + \lambda U_{m+1}^n$$

leads to matrix which is not diagonally dominant so we have to use iterative methods to solve it.

\hookrightarrow Three level Scheme.



new points =

2nd & 3rd order

middle points without gaps

\rightarrow intervals \rightarrow (possibly) \rightarrow \dots

(second) $\cdot T = 26$ no. $(g(x)) \in (5, \infty)$

1st

middle points

$w = (g(x))$ also changed w/ (0)

$w(x_2) = 1$

$w(x_2) = 1$

so this is subdivided w/ mixed off - 1st

therefore

width of bins = 1.162

first bin

middle point of first bin

middle point of first bin

$g(1.162) + 0.162 + 1.162 + 1.162 = 6.161$

3/4/24. 2D Heat conduction

$$u_t - \Delta u = f(x, y, t)$$

$$\begin{aligned}\Delta u &= \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}, \\ &= u_{xx} + u_{yy}.\end{aligned}$$

Poisson Eqn in 2D

Elliptic boundary value problems

$$\Delta u = f(x, y) \quad \leftarrow \Omega = \text{domain.}$$

$$u(x, y) = g(x, y) \text{ on } \partial\Omega = \Gamma. \text{ (boundary).}$$

Step 1:

Discretization

of the domain.

call $u(x_i, y_j) = u_{ij}$.

$$h = (b-a)/N$$

$$k = (d-c)/M$$

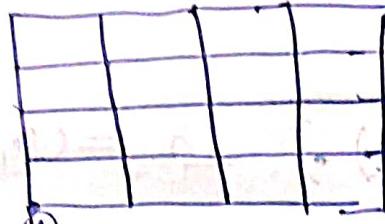
Step 2: - Replacing the derivatives by difference quotient.

$$\frac{u_{i+1,j} - 2u_{ij} + u_{i-1,j}}{h^2} + \frac{u_{i,j+1} - 2u_{ij} + u_{i,j-1}}{h^2} = f_{ij} \quad 1 \leq i, j \leq M.$$

$$u_{i+1,j} - 4u_{ij} + u_{i-1,j} + u_{i,j+1} + u_{i,j-1} = h^2 f_{ij}$$

Say unit square:

$$N=4.$$



25 variables.

represent u_{ij} as U_p where $p = (j-1)(N+1) + i$
for $i, j = 1 \dots 5$.

make a matrix to solve ESL of U_p .

$\Rightarrow 25 \times 25 \Rightarrow (5 \times 5)$.



Only non-negative will be

$$A(p, p), A(p, p-1), A(p, p+1),$$

$$A(p, p-N), A(p, p+N).$$

The matrix A is diagonally dominant, irreducible.

$$(means |a_{ii}| \geq \sum |a_{ij}|).$$

[IS it
tri-diagonal
definite?]

if $9 \times 9 \rightarrow$ not taking known quantities

if $25 \times 25 \rightarrow$ taking known quantities, adding
to the row if known.

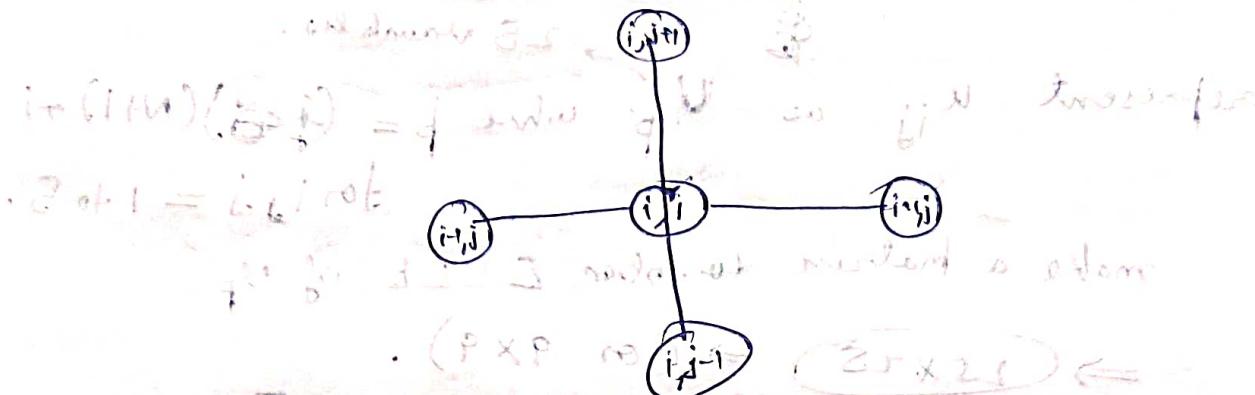
Mixed boundary conditions may be given.

$$\text{like } u(x, y) = g(x, y) \text{ on } \Gamma_1$$

$$\begin{cases} u_{xx}(x, y) = g_1(x, y) & \text{on } \Gamma_2 \\ u_{yy}(x, y) = g_2(x, y) & \text{on } \Gamma_3 \end{cases}$$

9/4/24

$$\Delta u = f(x, y), \quad \Omega = (0, 1)^2, \quad TE = O(h^2).$$



$$LHS - RHS = TE.$$

$$u'' = f \rightarrow O(h^2).$$

$$u_{ij\pm} = u_{ij} \pm h \frac{\partial u}{\partial y} + \frac{h^2}{2!} \frac{\partial^2 u}{\partial y^2} \pm \frac{h^3}{3!} \frac{\partial^3 u}{\partial y^3} + \frac{h^4}{4!} \frac{\partial^4 u}{\partial y^4} + \dots$$

$$\Rightarrow \text{taking } u \in C^4(\Omega) \Rightarrow 3^{rd} \text{ order cancel}$$

$$\Rightarrow \boxed{\text{Error} = O(h^2)}.$$

$$\text{Using } AU = F, \quad u_{ij} = \frac{1}{4}(u_{ij+1} + u_{ij-1} + u_{i+1,j} + u_{i-1,j}) - \frac{h^2}{4} f_{ij},$$

Poisson solvers

$$u_{ij}^{(n+1)} = \frac{1}{4} \left(u_{ij+1}^{(n)} + u_{ij-1}^{(n)} + u_{i+1,j}^{(n)} + u_{i-1,j}^{(n)} \right) - \frac{h^2}{4} f_{ij}.$$

Jacobi iteration.

(gauß cycl.).

$$u_{ij}^{(n+1)} = \frac{1}{4} \left(u_{ij+1}^{(n+1)} + u_{ij-1}^{(n+1)} + u_{i+1,j}^{(n+1)} + u_{i-1,j}^{(n+1)} \right) - \frac{h^2}{4} f_{ij}.$$

Stopping criterion

$$|f_{\text{new}} - f_{\text{old}}| = |u_{ij}^{(k+1)} - u_{ij}^{(k)}| < \text{TOL} = 10^{-8}$$

Maximum principle: If $f \geq 0 \Rightarrow$ maximum is attained at boundary.

~~Red Black ordering (for parallel computing)~~

If I colour the nodes red/black such that black only rely only on red, red only on black.

\Rightarrow Chess board.

Eg:-

4	0	9	5
		3	8
7	6	2	
1	8	2	

(domain Ω discretized by b)

Maximum Principle

$$\nabla^2 u_{ij} = \frac{(u_{i+1,j} + u_{i-1,j} + u_{i,j+1} + u_{i,j-1}) - 4u_{ij}}{h^2} = f_{ij}$$

$$\text{if } (\nabla^2 v_{ij}) \geq 0 \text{ at } ij$$

$$\max_{\Gamma_h} v_{ij} \geq \max_{\Gamma_h} u_{ij}$$

$P=0$

for proof.

$$\nabla^2 v_{ij} = f_{ij} \rightarrow v_{ij} = v_{i,j} + iV_{,j} + jV_{,i} = V_{,ij}$$

Proof:- assume contrary.

Max at interior (i_0, j_0) . $\max_{ij} v_{i_0, j_0} = \max_{ij} v_{ij}$

$v_{i_0, j_0} > \max_{ij} v_{ij}$ \Rightarrow Redundant maximum

Given $L^h v_{ij} \geq 0 \forall i, j$.

(as if not then it gives contradiction)

$$v_{i_0, j_0} \leq \frac{1}{4}(v_{(i_0+1), j_0} + v_{i_0-1, j_0} + v_{i_0, j_0+1} + v_{i_0, j_0-1}).$$

check all points, but no other point has

$$v_{i_0, j_0} \geq \max \{ v_{i_0+1, j_0}, v_{i_0-1, j_0}, v_{i_0, j_0+1}, v_{i_0, j_0-1} \}.$$

Equality

\Rightarrow All values are same.

If any of the 4 neighbouring points on boundary.

otherwise, repeat until we have a boundary point.

Thm. If max or minimum exists on interior \Rightarrow function remain constant. \Rightarrow Ily, we can show minimum principle. $(L^h v_{ij} \leq 0)$.

Corollary:- Let ~~be two~~ u_{ij}, v_{ij} be two solutions of $L^h u_{ij} = f_{ij}$ (Uniqueness)

then $u_{ij} = v_{ij}$. [Problem $\begin{cases} Lu = f \\ u = g \end{cases} : \Omega$]

Proof:- $w_{ij} = u_{ij} - v_{ij}$.

$$L^n w_{ij} = L^n u_{ij} - L^n v_{ij} = f_{ij} - f_{ij} = 0 : \Omega$$

Ily. $w_{ij} = 0 : \Omega$.

$$\max_{\mathbb{R}^h} w_{ij} \geq \max_{\mathbb{R}^h} w_{ij} \geq \min_{\mathbb{R}^h} w_{ij} \geq \min_{\mathbb{R}^h} w_{ij}.$$

$$\therefore w_{ij} = 0 \forall i, j.$$

\square here is a discrete operator.

(in terms of lin. alg., it is a matrix).

The discrete soln v_{ij} satisfies the following bound:

$$\max_{\mathbb{R}^h} |v_{ij}| \leq \max_{\mathbb{R}^h} |v_{ij}| + \frac{1}{2} \max_{\mathbb{R}^h} |L^h v_{ij}|$$

$$\text{Take: } \Phi_{ij} = (i/h)^2 / 2. \quad \max_{\mathbb{R}^h} |\Phi_{ij}| = \frac{1}{2}.$$

$$L^h \Phi_{ij} = 1$$

$$M = \max_{\mathbb{R}^h} |L^h v_{ij}|.$$

$$w_{ij}^+, w_{ij}^- \quad \therefore w_{ij}^\pm = \pm v_{ij} + M Q_{ij}.$$

$$\Rightarrow L^h w_{ij}^\pm \geq 0. \Rightarrow \max_{\mathbb{R}^h} w_{ij}^\pm \leq \max_{\mathbb{R}^h} w_{ij}^\pm$$

** Missed 1 lecture **

$$(A - \lambda I) = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix} - \lambda \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

16/4/24

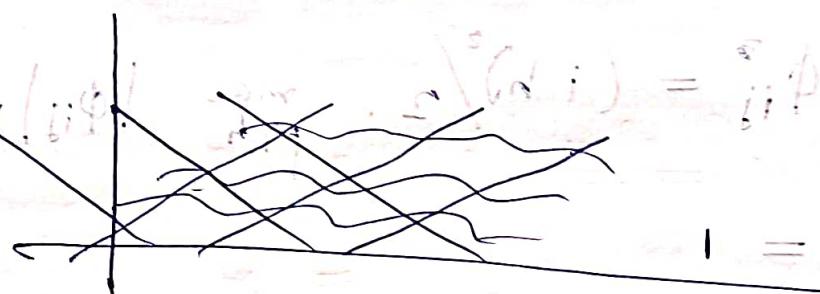
$$\frac{U_m^{n+1} - U_m^n}{R} + \alpha \frac{U_{m+1}^n - U_{m-1}^n}{h} = 0.$$

(x terms cancel, left and right vanish)

Dif. eqn: $u_t + \alpha u_x = g(x, t) \quad x \in \mathbb{R}$.

$$u(x, 0) = f(x).$$

$$u(x, t) = f(x - at) \rightarrow \text{wave equation:}$$



FTFS

$$\frac{U_m^{n+1} - U_m^n}{R} + \alpha \frac{U_{m+1}^n - U_{m-1}^n}{h} = g(x_m, t_n).$$

FTCS \Rightarrow $\frac{\partial u}{\partial t} \approx \frac{u - u}{\Delta t} = \frac{u - u}{\Delta t}$

B TFS, B TBS, B TCS

CTFS, CT BS, CTCS

$$TE = \frac{1}{K} (LHS - RHS).$$

Stability (FFT, DFT)

We know that Fourier transform of \mathbb{R} valued function

$u(x)$ is given by

$$\hat{U}(\omega) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{i\omega x} u(x) dx. \quad \text{--- (1) (continuous)}$$

$$u(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-i\omega x} \hat{U}(\omega) d\omega. \quad \text{--- (2) (inverse).}$$

The Fourier transform inversion formula expresses that $u(x)$ function as a superposition of the waves given by the exponential ~~exp~~ with different amplitude \hat{U} .

In a similar way, we can define the Fourier transform for any mesh function/grid function.

$$h\mathbb{Z} = \{h_m : m \in \mathbb{Z}\}.$$

Suppose v is a grid function defined on integers m

$$\hat{v}(\xi) = \frac{1}{\sqrt{2\pi}} \sum_{m=-\infty}^{\infty} e^{-im\xi} v_m \quad \text{--- (3)}$$

$$\hat{v}(-\xi) = \hat{v}(\xi) \quad \rightarrow \xi = [-\pi, \pi].$$

$$v_m = \frac{1}{\sqrt{2\pi}} \int_{-\pi}^{\pi} e^{im\xi} \hat{v}(\xi) d\xi$$

In finite difference, it is natural to start with some grid function

$$(4) \quad v_m = \frac{1}{\sqrt{2\pi}} \int_{-\pi}^{\pi} e^{im\xi} \hat{v}(\xi) d\xi.$$

Let $h = \frac{\pi}{N}$ uniform step size (equally spaced grid is not necessary).
and $\theta = \frac{2\pi}{N}$ uniform mesh & first column.

$$(S) - \hat{v}(\xi) = \frac{1}{\sqrt{2\pi}} \sum_{m=0}^{m=0} e^{im\xi h} v_n h.$$

General Discrete (FD) $\frac{1}{h} \frac{d}{dx} v_n h = \frac{1}{h} \hat{v}(\xi) h$, $\xi \in [-\pi/h, \pi/h]$.

$$(D) - v_m = \frac{1}{\sqrt{2\pi}} \int_{-\pi/h}^{\pi/h} e^{im\xi h} \hat{v}(\xi) d\xi.$$

discrete Fourier transform is called $\hat{v}(\xi)$ and it is not

If we differentiate our inversion formula (D),

$$\frac{\partial u(x)}{\partial x} = \frac{1}{\sqrt{2\pi}} \int_{-\pi/h}^{\pi/h} i w e^{iwx} \hat{v}(w) dw.$$

\Rightarrow Fourier transform of $\frac{\partial u(x)}{\partial x}$ is given by

$$\left(\frac{\partial u(x)}{\partial x} \right) = i w \hat{v}(w).$$

$$(B) - \frac{1}{h} \frac{d}{dx} v_n h = \sum_{m=0}^{m=0} \hat{v}(\xi) h = \hat{v}(\xi).$$

This relation shows that under the Fourier transform, the operation of differentiation is turned into the operation of multiplication.

Below, we will state some properties of Fourier transform.

Consider the first order hyperbolic PDE.

$$u_t + a u_x = 0 \quad \text{with } a \neq 0$$

Here, we apply the transform only to the spatial variable x , then we obtain $\hat{u}(t, \omega) + (a\omega - i) = (\hat{z})^n v$

$$\textcircled{7} - \hat{u}_t = -i a \omega \hat{u} \quad \xrightarrow{\text{ODE in time}} \hat{u}(t, \omega)$$

\Rightarrow Solution is $\hat{u}(t, \omega) = e^{-i a \omega t} \hat{v}_0(\omega)$.

Consider the following recurrence scheme (finite difference scheme).

$$\frac{u_m^{n+1} - u_m^n}{h} + a \frac{u_m^n - u_{m-1}^n}{h} = 0.$$

$$u_m^{n+1} = (1-a)u_m^n + a u_{m-1}^n, \quad \lambda = kh. \quad \text{--- (9)}$$

We need to initialize u_0 and u_1 to start the iteration.

Using the discrete Fourier transform (in (6)), we get

$$U_m^n = \frac{1}{\sqrt{2\pi}} \int_{-\pi/h}^{\pi/h} e^{imh\xi} \hat{u}(\xi) d\xi. \quad \text{--- (10)}$$

For all the terms in equation (9), you get $\frac{U_m^{n+1}}{h}$

$$\frac{1}{\sqrt{2\pi}} \int_{-\pi/h}^{\pi/h} e^{imh\xi} \hat{u}^{n+1}(\xi) d\xi = U_m^{n+1} = \frac{1}{\sqrt{2\pi}} \int_{-\pi/h}^{\pi/h} e^{imh\xi} \left[(1-a) + a e^{-ih\xi} \right] \hat{u}^n(\xi) d\xi.$$

~~Since, Fourier transform is unique,~~ we deduce that the integrant

of LHS is same as RHS.

∴ observe basis of the transformation with $\hat{v}^{n+1}(\xi)$, we get

$$\hat{v}^{n+1}(\xi) = [(1 - \alpha\lambda) + \alpha\lambda e^{-ih\xi}] \hat{u}^n(\xi),$$

but $\hat{u}^n = g(h\xi) \hat{u}^n(\xi)$. — (1)

The discrete fourier transform helps in converting the two different indices in the difference equation, into one index.

This formula shows that advancing the solution of the difference scheme by 1 step is equivalent to multiplying the fourier transform of the solution by the amplification factor.

This is called amplification factor because its amplitude is the amount by which the amplitude of each solution is given the

$$e.g., (\text{as of work done}) \hat{v}_n(\xi)$$

From this recurrence relation, we can obtain:

$$\hat{u}^n(\xi) = (g(h\xi))^n \hat{u}^0(\xi).$$

$$\Rightarrow g(\theta) = (1 - \alpha\lambda)^n + \alpha\lambda e^{i\theta}.$$

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$|g(\alpha)| < 1$: one-step $\Rightarrow \exists k, \theta, K, h$

$$|g(\theta, K, h)| \leq 1 + kh + \dots \quad K, h \in \mathbb{R}^+$$

g_θ is independent of $K, h \Rightarrow |g(\theta)| \leq 1$.



$$\left[0, \frac{1}{\alpha}\right] : |g(\alpha)| = 1.$$

(α is the stability condition for FTCS)

$$u_t = u_{xx}$$

FTCS: (conditionally stable).

$$\frac{u_m^{n+1} - u_m^n}{k} = \frac{u_m^n - 2u_m^n + u_{m-1}^n}{h^2}$$

$$\text{stability condition} \Rightarrow u_m^{n+1} = \lambda u_{m+1}^n + (1-2\lambda)u_m^n + \lambda u_{m-1}^n.$$

$$\lambda = \frac{k}{h^2}$$

$$\lambda = \frac{k}{h^2}$$

~~if $2\lambda T > \pi$ then unstable at steady state~~

$$u_m^n = g^n e^{im\theta}.$$

$$g^{n+1} e^{im\theta} = \lambda g^n e^{i(m+1)\theta} + (1-2\lambda)g^n e^{im\theta} + \lambda g^n e^{i(m-1)\theta}$$

$$\Rightarrow g(\theta) = \lambda e^{i\theta} + (1-2\lambda) + \lambda e^{-i\theta} = 1 - 4\lambda \sin^2 \theta / 2.$$

then if $\theta = \pi$

$$\Rightarrow |g(\theta)| \leq 1 \Rightarrow \lambda \in (0, \frac{1}{2}).$$

$$\Rightarrow \begin{cases} \frac{k}{h^2} \leq \frac{1}{2} & \text{for stability} \\ k < h & \text{so that } 0 < \lambda < \frac{1}{2} \end{cases}$$

conditionally (because implicit).

BTCS: (should be stable). $\frac{u^{n+1} - u^n}{k} = \frac{u_{m+1}^{n+1} - 2u_m^{n+1} + u_{m-1}^{n+1}}{h^2}$

$$\text{stability of BTCS} \Leftrightarrow 1 - 4\lambda \sin^2 \theta / 2 \geq 1 \Rightarrow 1 - 4\lambda \sin^2 \theta / 2 \geq 1$$

$$(1 - 4\lambda \sin^2 \theta / 2) + (1 - 4\lambda \sin^2 \theta / 2 + 1) = 3(1 - \lambda \sin^2 \theta / 2)$$

classmate
Date _____
Page _____

$\Delta t, \Delta x, \Delta z \in \mathbb{R}$ s.t. $1 = (\Delta t)(\Delta x)$

$U^{n+1} \geq U^n \geq (k, x, z)B$

Willing to adapt to boundary.

GTCG

Grant nicholson: Unconditionally stable (implied).

Average of these two equations:

$$\frac{U_m^{n+1} - U_m^n}{K \Delta t + \Delta x^2} = \frac{1}{2} \left(\frac{U_{m+1}^{n+1} - 2U_m^{n+1} + U_{m-1}^{n+1}}{h^2} + \frac{U_{m+1}^n + 2U_m^n + U_{m-1}^n}{h^2} \right)$$

$$\Rightarrow R + g(\theta) = (-1) \frac{1 - 2 \lambda \sin^2 \theta / 2}{1 + 2 \lambda \sin^2 \theta / 2} \Leftrightarrow \text{unconditionally stable.}$$

$$\lambda = h$$

$$R = \alpha k$$

HW: Study the stability of ~~FTCS~~ FTCS, BICS for 2D parabolic schemes.

$$\text{FTFS: } U_t + a U_x = 0 \quad \Rightarrow \quad \frac{\partial U}{\partial t} + a \frac{\partial U}{\partial x} = 0$$

$$\frac{U_m^{n+1} - U_m^n}{\Delta t} + a \frac{U_{m+1}^n - U_m^n}{\Delta x} = 0$$

$$R = a k \Leftrightarrow \Delta t$$

$$(1, 0) \rightarrow R = 1 \geq |(\cos \theta)| \quad h \leftarrow \Delta x$$

$$g(\theta) = (1 + R) - R e^{i\theta}$$

Case 1: $a > 0$

Always unstable

Case 2: $a < 0$

Unstable

$|R| \leq 1 \Rightarrow$ difference scheme is stable.

$$|g(\theta)| = \sqrt{(1 + 2R \sin^2 \theta / 2)^2 + (R \sin \theta)^2}$$

Here, you have to use an alternate way to study the stability, for that determine the max & min of $|g^2(\theta)|$, for $\theta \in [-\pi, \pi]$.

$$|g(\theta)| = 1, |g(\pm\pi)| = |R^2 - R|.$$

$$\Rightarrow -1 \leq R \leq 0.$$

\therefore

Case 1: if $a < 0 \Rightarrow R < 0$,
 \Rightarrow scheme is conditionally stable.

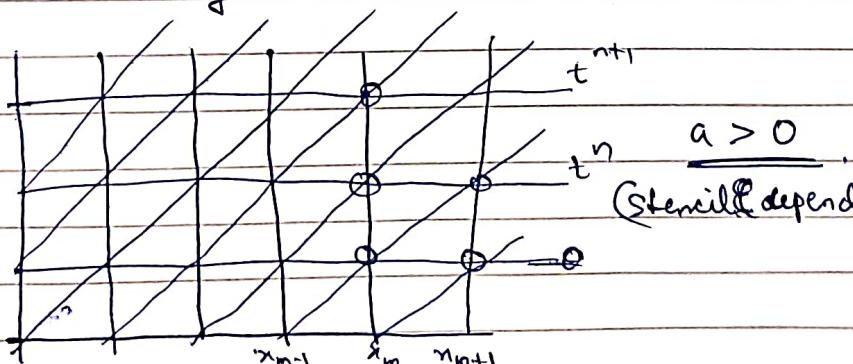
$$R \geq -1$$

Case 2: if $a > 0 \Rightarrow R > 0$,

\Rightarrow Scheme is unconditionally unstable.

if $a = 0 \Rightarrow$ Just an ODE.

Characteristic:



Characteristic:

