

Error Analysis

What we have is ODE  $\frac{dy}{dx} = f(x, y)$

and IC  $y(x_0) = y_0$

Computing the error will suggest, how stable the method is?

In computation, two types of errors

→ Round off error

$$y_{\text{machine}} + R = y_{\text{true representation}}$$

$$R = y_{\text{true}} - y_{\text{machine}}$$

→ Truncation error

$$y_{\text{true-representation}} + T = y_{\text{exact}}$$

This depends on the order of the method

$$\Rightarrow y_{n+1} = y(x_{n+1}) + O(h^{p+1}).$$

In truncation error

→ Local truncation error

→ Total error

a) Local truncation error:- is the error one gets at the each time step or the iteration.

~~$$e_k = \frac{y_k - y_{k+1}}{h}$$~~

$$e_k = |y_{k+1} - \hat{y}(x_{k+1})|$$

✓  $\rightarrow$  exact solution  
approximated by some method

let say one uses Taylor series

$$y(x, h) = y_1 + h y_1' + \frac{h^2}{2!} y_1'' + \frac{h^3}{3!} y_1''' + \dots + \frac{h^m}{m!} y_1^{(m)} + O(h^{m+1})$$

if one uses  $m$ -order then

$$e_k = |y_{k+1} - y(x_{k+1})| = \frac{h^{m+1}}{(m+1)!} \left| y^{(m+1)}(x_k, x_{k+1}) \right|$$

$$= \frac{h^{m+1}}{(m+1)!} \left| \frac{d^{m+1} f(x, y(x))}{dx^{m+1}} \right|$$

Assume  $\frac{d^{m+1} f}{dx^{m+1}}$  is bounded such that  $\left| \frac{d^{m+1} f}{dx^{m+1}} \right| \leq M$

Then one gets

$$e_k \leq \frac{M}{(m+1)!} h^{m+1} = O(h^{m+1})$$

One gets  $\mu$  local error to be of order  $(m+1)$   $O(h^{m+1})$

Now, Total error

Final computing time

$x = 0$  to  $x_{k+1}$

let say  $T$ ; one we have chosen the  
step to be of  $h$  (grid size)

N - total no. of steps one has to perform

$$\text{Here } N = \frac{T}{h}$$

$$\boxed{N \cdot h = T}$$

②

Small  $h$ ; more steps one has to perform

$$\text{Total error is } E = |y(T) - y_N|$$

Let assume that  $\frac{dy}{dx} = f(y, x)$ ;  $I \subset y(x_0) = y_0$  is

well-posed [i.e. the solution is stable w.r.t. any perturbation on the initial condition] If one has 2 initial data (not far away) from each other then the soln. (for both) should not be very far away.

Let  ~~$y_0, \bar{y}_0$~~   $y_0, \bar{y}_0$  be two initial conditions

$y(x), \bar{y}(x)$  be the two solutions, respectively,

$$\text{Then } |y(x) - \bar{y}(x)| \leq C |y_0 - \bar{y}_0|$$

↳ initial error

$$0 \leq x \leq \infty$$

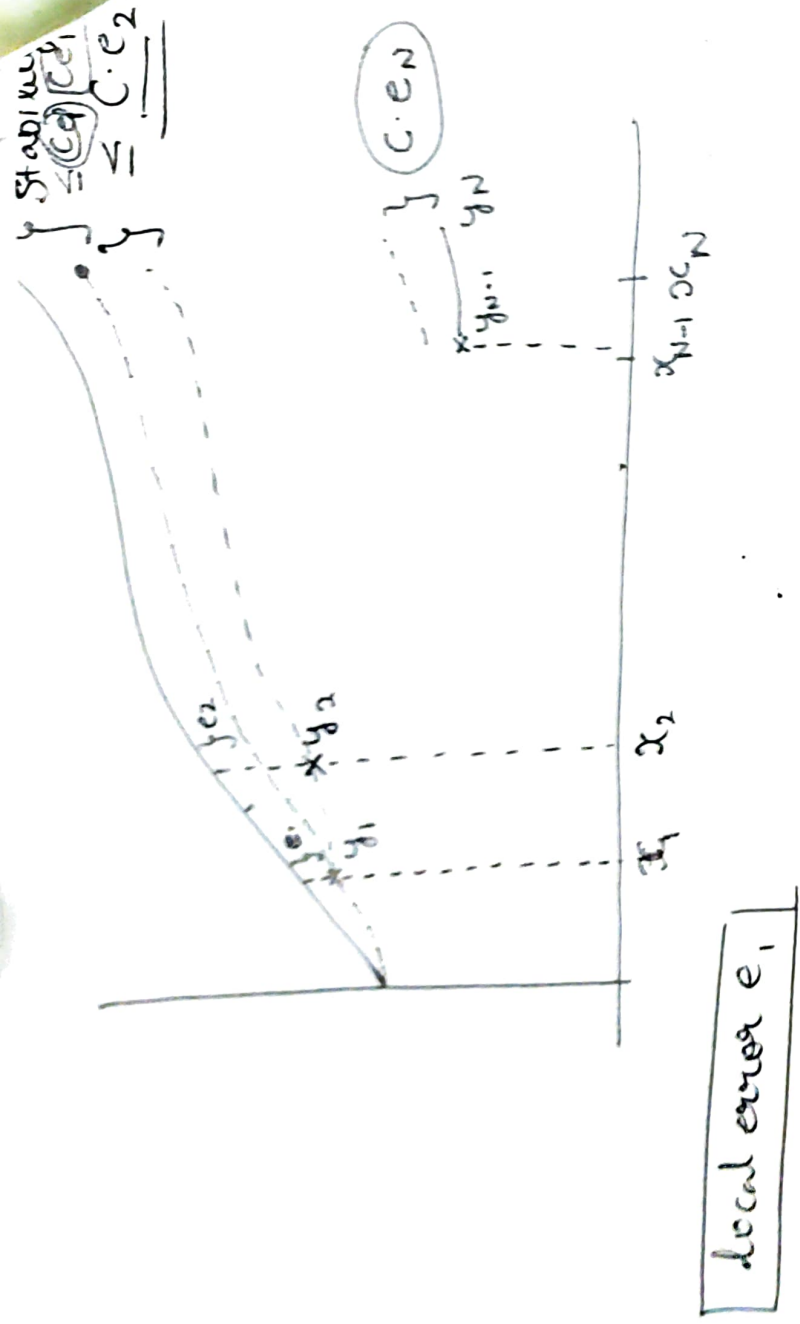
$C$  - const. (independent on  $x$ )

Discrete error

Error at each step

Then keep accumulating.

Let look at the fig.



Add up the total error in order to get the accumulate behaviour

$$E = C \sum_{k=1}^N |e_k|$$

As we saw,  $e_k \sim O(h^{m+1}) \leq \frac{M}{(m+1)!} h^{m+1}$

$$E \leq C \sum_{k=1}^N \frac{M}{(m+1)!} h^{m+1}$$

$$N C M \frac{h^{m+1}}{(m+1)!} \Rightarrow \underbrace{N \cdot h}_{\text{this is constant}} \underbrace{\frac{C M}{(m+1)!}}_{\text{constant}} h^m$$

$$|E| \leq C' \cdot h^m \sim O(h^m)$$

Taylor series is  $m^{\text{th}}$  order  
 local truncation error is order  $O(h^{m+1})$   
 Then total error is  $O(h^m)$

Total error is one order less than local error

Let's check some method

Most simplest will be to do

Heun's Method is 2<sup>nd</sup> order RK method

$$y_{i+1} = y_i + \left(\frac{1}{2} k_1 + \frac{1}{2} k_2\right) h$$

$$k_1 = f(x_i, y_i)$$

$$k_2 = f(x_i + h, y_i + k_1 h)$$

Taylor series for two variable fn

$$f(x+h, y+k) = f(x, y) + h \frac{\partial f}{\partial x} + k \frac{\partial f}{\partial y} + \dots$$

$$f(x_i + h, y_i + k_1 h) =$$

$$f(x_i, y_i) + h \frac{\partial f}{\partial x}(x_i, y_i) + k_1 h \frac{\partial f}{\partial y}(x_i, y_i) + O(h^2, k_1^2)$$

$\downarrow$   
 $k_1 = f$

$$k_2 = f(x_i, y_i) + h \frac{\partial f}{\partial x} + k_1 h \frac{\partial f}{\partial y} + O(h^2)$$

$\rightarrow k_1 = f$

$$y_{i+1} = y_i + \frac{1}{2} \left[ h f + h f + h^2 \frac{\partial f}{\partial x} + h^2 f \frac{\partial f}{\partial y} + O(h^3) \right]$$

$$= y_i + h f + \frac{1}{2} h^2 \left( \frac{\partial f}{\partial x} + f \frac{\partial f}{\partial y} \right) + O(h^3) \quad \text{--- (A)}$$

Compare with Taylor expansion for  $y(x_{i+1}) = y(x_i + h)$

$$y(x_i + h) = y(x_i) + h y'(x_i) + \frac{1}{2} h^2 y''(x_i) + O(h^3)$$

$$= y(x_i) + h f(x_i, y_i) + \frac{1}{2} h^2 \left[ \frac{\partial f}{\partial x} + f \frac{\partial f}{\partial y} \right] + O(h^3)$$

$$= y_i + h f + \frac{1}{2} h^2 \left[ \frac{\partial f}{\partial x} + f \frac{\partial f}{\partial y} \right] + O(h^3) \quad \text{--- (B)}$$



Compare (A) & (B)

first three terms cancel

One is left with  $O(h^3)$

Which give local truncation error

$$e_L = O(h^3)$$

Hence 2nd order method has local truncation error of  $O(h^3)$

In general, R-K method of order  $m$  takes the form

$$y_{i+1} = y_i + \phi(x_i, y_i, h)$$

$$\phi(x_i, y_i, h) = a_1 k_1 + a_2 k_2 + \dots + a_n k_n$$

$$k_1 = f(x_i, y_i)$$

$$k_2 = f(x_i + p_1 h, y_i + p q_{11} k_1 h)$$

$$k_3 = f(x_i + p_2 h, y_i + q_{21} k_1 h + q_{22} k_2 h)$$

.

$$k_n = f(x_i + p_{n-1} h; y_i + q_{n-1,1} k_1 h + q_{n-1,2} k_2 h + \dots + q_{n-1,(n-1)} k_{n-1} h)$$

Local truncation error is  $O(h^{m+1})$

while total error is  $O(h^m)$ .

what we can say or have observed

- ① small value of  $h$  leads to smaller error.
- ② Higher the order used for approximation provides better smaller error.
- ③ Uniform grid  $\rightarrow$  local error different at ~~varying~~ every step [not same error].

Adaptive methods where we change the  $h$  size, helps in setting  $h$  such that one get uniform error at each step.

### Stability of a method

A method is said to be stable if the effect of any single fixed round off error is not really growing and is independent of the no. of the mesh points

Let take  $y' = 2y$  as reference equation

but why

~~Consider~~  $y' = f(x, y); y(x_0) = y_0$

is the IVP.

$$y' = f(x, y); y(x_0) = y_0$$

Let predict the behavior of the IVP in the neighbourhood of a point  $(\bar{x}, \bar{y})$

One can linearize  $[y' = f(x, y); y(x_0) = y_0]$

$$f(x, y) = f(\bar{x}, \bar{y}) + \frac{\partial f}{\partial x} (x - \bar{x}) + \frac{\partial f}{\partial y} (y - \bar{y}) + 2^{\text{nd}} \text{ order} + \dots$$

$$= y \frac{\partial f}{\partial y} (\bar{x}, \bar{y}) + f(\bar{x}, \bar{y}) - \bar{y} \frac{\partial f}{\partial y} (\bar{x}, \bar{y}) + (x - \bar{x}) \frac{\partial f}{\partial x} (\bar{x}, \bar{y})$$

One can write it as

$$f'' \quad x \in [x_0, b]$$

$$f(x, y) = \lambda y + C$$

$$\text{where } \lambda = \frac{\partial f}{\partial y} (\bar{x}, \bar{y})$$

$$\text{and } C = f(\bar{x}, \bar{y}) - \bar{y} \frac{\partial f}{\partial y} (\bar{x}, \bar{y}) + (x - \bar{x}) \frac{\partial f}{\partial x} (\bar{x}, \bar{y})$$

$$\text{One get } y' = \lambda y + C$$

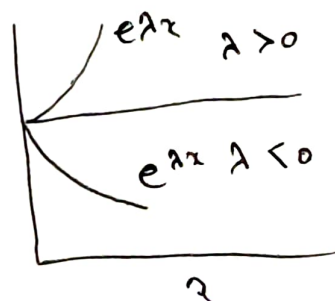
$$\text{lets transform } y \text{ as } \lambda w = \lambda y + C$$

$$\Rightarrow w' = y'$$

$$\text{So, } w' = \lambda w$$

$$\text{whose soln is } w(x) = e^{\lambda x}$$

One can linearize  $f(x, y)$  and estimate the behavior solution behavior





$$y' = \lambda y \quad y(x_0) = y_0$$

$$x \in [x_0, b]$$

— . —

One get exact soln at that point

$$y(x) = C e^{\lambda x}$$

$$y(x) = y_0 e^{\lambda(x-x_0)}$$

In order to compute  $y(x)$  at  $x = x_0 + kh$

$$k = 1, 2, \dots, N$$

$$y(x_1) = y_0 e^{\lambda h}$$

$$y(x_2) = y(x_1) e^{\lambda h}$$

$$y(x_{n+1}) = y_0(x_n) e^{\lambda h} \quad n = 0, 1, 2, \dots$$

$e^{\lambda h}$  is difficult to compute

One can approximate  $e^{\lambda h}$  suitably

$$y_{n+1} = y_n + h f(x_n, y_n) \quad [\text{Euler}]$$

$$y' = \lambda y = f(x, y)$$

$$\text{So } y_{n+1} \approx y_n + \lambda h y_n$$

$$= (1 + \lambda h) y_n$$

$$y(x_{n+1}) = y(x_n) e^{\lambda h} \Rightarrow$$

$$\boxed{e^{\lambda h} = 1 + \lambda h}$$

$$\text{For Euler } e^{\lambda h} = 1 + \lambda h + O(|\lambda h|^2)$$

Take Taylor Series

$$y_{n+1} = y_n + h f(x_n, y_n) + \frac{h^2}{2!} \left( \frac{\partial f}{\partial x} + f \frac{\partial f}{\partial y} \right)$$

$$y' = \lambda y$$

$$\Rightarrow y_n + h \lambda y_n + \frac{h^2}{2!} \left( \underline{\quad} + \lambda^2 y_n \right) + O(\lambda^3 h^3)$$

$$\approx (1 + \lambda h + \frac{\lambda^2 h^2}{2}) + O(\lambda^3 h^3)$$

$$e^{\lambda h} \approx \left(1 + \lambda h + \frac{\lambda^2 h^2}{2}\right) + O(|\lambda h|^3)$$

$$\approx E(\lambda h)$$

$$y_{n+1} \approx y_n E(\lambda h), n = 0, 1, 2, \dots$$

$$y(x_{n+1}) + E_{n+1} = E(\lambda h) [y(x_n) + E_n]$$

$$E_{n+1} = E(\lambda h) y(x_n) + E(\lambda h) E_n - y(x_{n+1})$$

$$E y(x_{n+1}) = e^{\lambda h} y(x_n)$$

$$= (E(\lambda h) - e^{\lambda h}) y(x_n) + E(\lambda h) E_n$$

Absolute stable

$$E_{n+1} = \underbrace{(E(\lambda h) - e^{\lambda h}) y(x_n)}_{\substack{\text{approx exact} \\ \downarrow \\ \text{local truncation error}}} + \underbrace{E(\lambda h) E_n}_{\substack{\text{error at } N \text{ stage} \\ \text{propagation error}}}$$

relative

Minimizing by  $E(\lambda h)$  more closer to  $e^{\lambda h}$ .

Propagation error  $E(\lambda h) \rightarrow$  not magnifying

$E(\lambda h)$  is stability factor

$$|E(\lambda h)| \leq 1$$

$E(\lambda h)$  should not grow faster than  $e^{\lambda h}$

Euler's method

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

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

$$\therefore E(\lambda h) = (1 + \lambda h)$$

$$|E(\lambda h)| \leq 1 \Rightarrow -2 < \lambda h < 0$$

region of stability

In Taylor's method

2<sup>nd</sup> order

L4 - (6)

$$\left| 1 + \lambda h + \frac{\lambda^2 h^2}{2} \right| \leq 1 \quad -2 \leq \lambda h < 0$$

3<sup>rd</sup> order.

$$-2.5 < \lambda h < 0 \quad (3^{\text{rd}} \text{ order})$$

$$\left| 1 + \lambda h + \frac{\lambda^2 h^2}{2} + \frac{\lambda^3 h^3}{6} \right| \leq 1$$

Example  $y' = x^2 - y^2 \quad y(0) = 1$

Analyze behavior of soln around  $(-1, 1)$  and  $(0, 2)$

$$f(x, y) = x^2 - y^2 \quad \frac{\partial f}{\partial y} = -2y$$

$$\lambda = \frac{\partial f}{\partial y}(\bar{x}, \bar{y})$$

$$\lambda(1, -1) = 2 \quad \lambda > 0$$

$$\lambda(0, 2) = -4 = \lambda < 0$$

Stability of Runge Method

$$y_{i+1} = y_i + \left( \frac{1}{2} k_1 + \frac{1}{2} k_2 \right) h$$

$$k_1 = f(x_i, y_i)$$

$$k_2 = f(x_i + h, y_i + k_1 h)$$

$$y_{i+1} = y_i + \left( \frac{1}{2} k_1 + \frac{1}{2} k_2 \right) h$$

$$y_{i+1} = y_i + \frac{h}{2} f(x_i, y_i) + \frac{1}{2} f(x_i + h, y_i + f(x_i, y_i) h) h$$

$$y_i' = \lambda y_i \quad f_i = \lambda y_i$$

$$f(x_i+h, y_i+h\lambda y_i) = \lambda(y_i + h\lambda y_i)$$

~~y\_i~~

$$y_{i+1} = y_i + \frac{h\lambda y_i}{2} + \frac{h}{2}(\lambda(y_i + h\lambda y_i))h$$

$$= y_i + \frac{h\lambda y_i}{2} + \frac{h\lambda y_i}{2} + \frac{h^2\lambda y_i}{2}$$

$$= y_i + h\lambda + \frac{h^2\lambda y_i}{2}$$

$$y_{i+1} = \underbrace{\left( y_i + h\lambda + \frac{h^2\lambda}{2} \right)}_{E(\lambda h)} y_i$$

Absolute stability  $|E(\lambda h)| \leq 1$

$$\boxed{a' \leq \lambda h \leq b'} \quad \text{interval of}$$

absolute stability

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# Multi step method

Two explicit  
Implicit

One can write

$$y_{n+1} = a_1 y_n + a_2 y_{n-1} + \dots + a_k y_{n-k+1} + h(b_0 y'_{n+1} + b_1 y'_n + \dots + b_k y'_{n-k+1})$$

$b_0 \neq 0$  : Implicit

$b_0 = 0$  : Explicit

## Multistep method

Uses past values of  $y(x)$  and/or  $y'(x)$  to create a polynomial which can approximate the derivative and extrapolates into the next interval

General method of writing  $y_{n+1}$

$$y_{n+1} = a_1 y_n + a_2 y_{n-1} + \dots + a_k y_{n-k+1} + h \phi(x_{n+1}, x_n, \dots, x_{n-k+1}, y'_{n+1}, y'_n, \dots, y'_{n-k+1})$$

If one want to estimate the value of  $y$  at  $(x_{n+1})$  then it demands values  $y(x_n), y(x_{n-1})$  till  $y(x_{n-k+1})$  and also derivatives values

One can write

$$y_{n+1} = \sum_{i=1}^k a_i y_{n-i+1} + h \sum_{i=0}^k b_i y'_{n-i+1}$$

(a) If  $b_0 = 0$  then the method is known as explicit

One only knows the past values.

(b) If  $b_0 \neq 0$ , then the method is known as implicit

One also needs the current value of  $(n+1)$

### Explicit Method

$$y' = f(x, y) ; y(x_0) = y_0$$

$$y(x_{n+1}) = y(x_n) + \int_{x_n}^{x_{n+1}} f(x, y) dx$$

→ how to approximate

As we did in previous lecture

Newton's backward difference formula of degree  $(k-1)$   
[if the points are  $k$ ]

$$P_{k-1}(x) = f_n + \frac{(x-x_n)}{h} \nabla f_n + \frac{(x-x_n)(x-x_{n-1})}{2! h^2} \nabla^2 f_n + \dots$$
$$+ \frac{(x-x_n)(x-x_{n-1}) \dots (x-x_{n-k+2})}{(k-1)! h^{k-1}} \nabla^{k-1} f_n$$
$$+ \frac{(x-x_n)(x-x_{n-1}) \dots (x-x_{n-k+1})}{k!} f^{(k)}(\xi)$$

one gets

$$(\xi \in [x_{n-k+1}, x_n])$$

$$u = \frac{x - x_n}{h} ; u+1 = \frac{x - x_{n-1}}{h}$$

$$P_{k-1}(x) = f_n + u \nabla f_n + \frac{u(u+1)}{2!} \nabla^2 f_n + \dots$$
$$+ \frac{u(u+1)(u+2) \dots (u+k-2)}{(k-1)!} \nabla^{k-1} f_n$$
$$+ \frac{u(u+1) \dots (u+k-1)}{k!} f^{(k)}(\xi)$$



$$y_k = y_{k-1} + h \left( P_{k-1}(x) \right)$$

Due to which

$h^{k+1}$

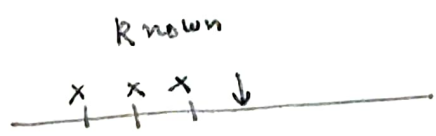
3<sup>rd</sup> order Adams - Bashforth method

$$y_{n+1} \approx y_n + \frac{h}{12} [23f_n - 16f_{n-1} + 5f_{n-2}] + \underbrace{O(h^4)}_{\text{error}}$$

ex) 

$(x_n, y_n)$   
 $(x_{n-1}, y_{n-1})$   
 $(x_{n-2}, y_{n-2})$

3 previous No.



4<sup>th</sup> order Adams - Bashforth method

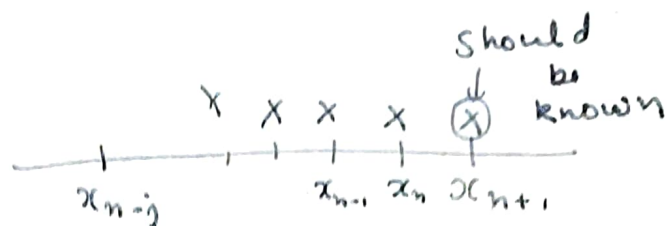
$$y_{n+1} \approx y_n + \frac{h}{24} [55f_n - 59f_{n-1} + 37f_{n-2} - 9f_{n-3}] + \underbrace{O(h^5)}_{\text{error}}$$

error

One can see that the error depends upon the <sup>m</sup> order method. Local error is  $O(h^{m+1})$

## Implicit Method

To compute value at  $n+1$ ; one need to have value at  $(n+1)$  itself



$$y(x_{n+1}) = y(x_{n-j}) + \int_{x_{n-j}}^{x_{n+1}} f(x, y) dx$$

approximate  $f(x, y)$  by a polynomial that interpolates at  $(k+1)$  points  $x_{n+1}, x_n, \dots, x_{n-k+1}$ ,  $k > 0$

Here  $(x_{n+1})$  is included

$$P_k(x) = f_{n+1} + (u-1) \nabla f_{n+1} + \frac{(u-1)u}{2!} \nabla^2 f_{n+1} + \dots$$

$$+ \frac{(u-1)u(u+1)\dots(u-k-2)}{k!} \nabla^k f_{n+1}$$

$$+ \frac{(u-1)u(u+1)\dots(u+k-1)}{(k+1)!} \nabla^{k+1} f_{n+1} + \dots$$

$$y_{n+1} = y_n + h P_k(x)$$

$$y_n + \dots + O(h^{k+2})$$

Here the error is  $O(h^{k+2})$

$$k=3 \quad (x_{n+1}, y_{n+1}), (x_n, y_n), (x_{n-1}, y_{n-1}), (x_{n-2}, y_{n-2})$$

$$y_{n+1} \approx y_n + \frac{h}{24} [9f_{n+1} + 19f_n - 5f_{n-1} + f_{n-2}]$$

$$+ O(h^5) \quad \text{Adams-Moulton Method}$$

One need  $f_{n+1} \approx f(x_{n+1}, y_{n+1})$  That's why Implicit

local truncation errors

L4-9

$$T_{n+1} \approx y(x_{n+1}) - \sum_{i=1}^h a_i y(x_{n-i+1}) - h \sum_{i=0}^k b_i y'(x_{n-i+1})$$

$O(h^{n+1}) \rightarrow$  Adams-Bashforth Method

$O(h^{n+2}) \rightarrow$  Adams-Moulton Method

Predictor - Corrector

Adams-Bashforth is used as predictor (P)

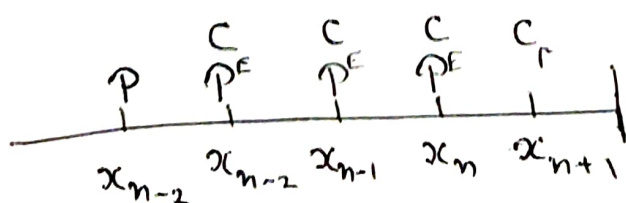
while Adams-Moulton is used as corrector (C)

One can keep doing the method as Estimator (E)

$$P(E) \rightarrow P(E C)^N$$

N times till the precision of the interest is achieved

In order to get the initial point one use Runge-Kutta 4 method for best precision



L-7-4

Adams Bashforth 5<sup>th</sup> order

$$y_{n+1} = y_n + \frac{h}{720} [1901y'_n - 2774y'_{n-1} + 2616y'_{n-2} - 1274y'_{n-3} + 251y'_{n-4}]$$

truncation error  $\propto O(h^6)$

Adams Moulton 5<sup>th</sup> order.

$$y_{n+1} = y_n + \frac{h}{251} [251y'_{n+1} + 646y'_n - 264y'_{n-1} + 106y'_{n-2} - 19y'_{n-3}]$$

truncation  $O(h^6)$

Method	global error
Euler's	$O(h)$
Heun's	$O(h^2)$
Midpoint	$O(h^2)$
Second RK	$O(h^2)$
4 <sup>th</sup> order RK	$O(h^4)$
RK-45	$O(h^5)$