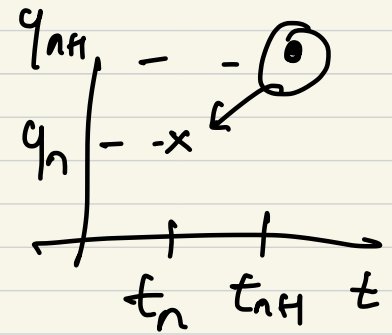


# 4.4 Implicit Euler or backward Euler method

$$y' = f(y, t) \xrightarrow{IE}$$

$$\frac{y_{n+1} - y_n}{h} = f(y_{n+1}, t_{n+1})$$

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



cost/timestep is higher than explicit Euler

model prob.  $y' = \lambda y$

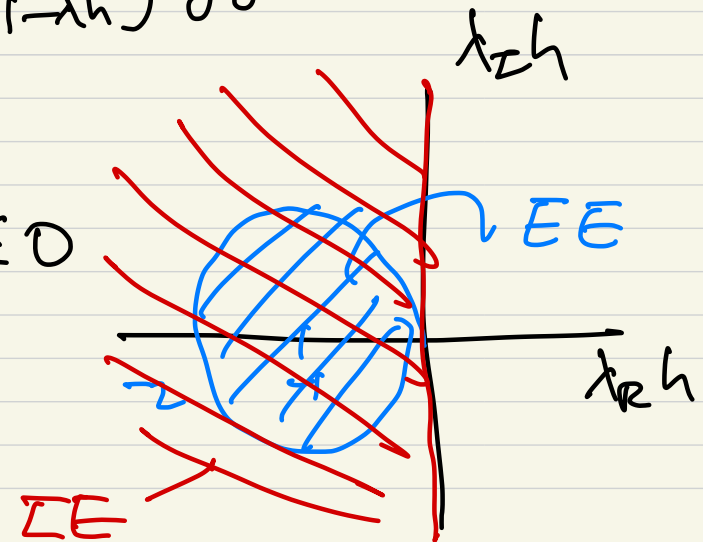
$$IE: y_{n+1} = y_n + h\lambda y_{n+1} \rightarrow y_{n+1} = \frac{1}{1 - \lambda h} y_n$$

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

$$\sigma = \frac{1}{1 - \lambda h} = \frac{1}{1 - \lambda_r h - i\lambda_i h}$$

$$|\sigma|^2 = \frac{1}{(1 - \lambda_r h)^2 + (\lambda_i h)^2} \leq 1 \quad \text{for } \lambda_r \leq 0$$

$\therefore$  IE is unconditionally stable.  
A-stable



## 4.5 Numerical accuracy

$$\text{IE: } \sigma = \frac{1}{1-\lambda h} = 1 + \lambda h + (\lambda h)^2 + (\lambda h)^3 + \dots$$

$$\text{Exact sol.: } e^{\lambda h} = 1 + \lambda h + \frac{1}{2}(\lambda h)^2 + \frac{1}{6}(\lambda h)^3 + \dots$$

$$\text{IE: } y_n = \sigma^n y_0 = (1 + \lambda h + (\lambda h)^2 + (\lambda h)^3 + \dots)^n y_0$$

$$\lambda^2 h^2 \cdot n = \lambda^2 h^2 \cdot \frac{t}{h} \\ = \mathcal{O}(h)$$

$\therefore$  IE is 2nd-order accurate for one timestep.

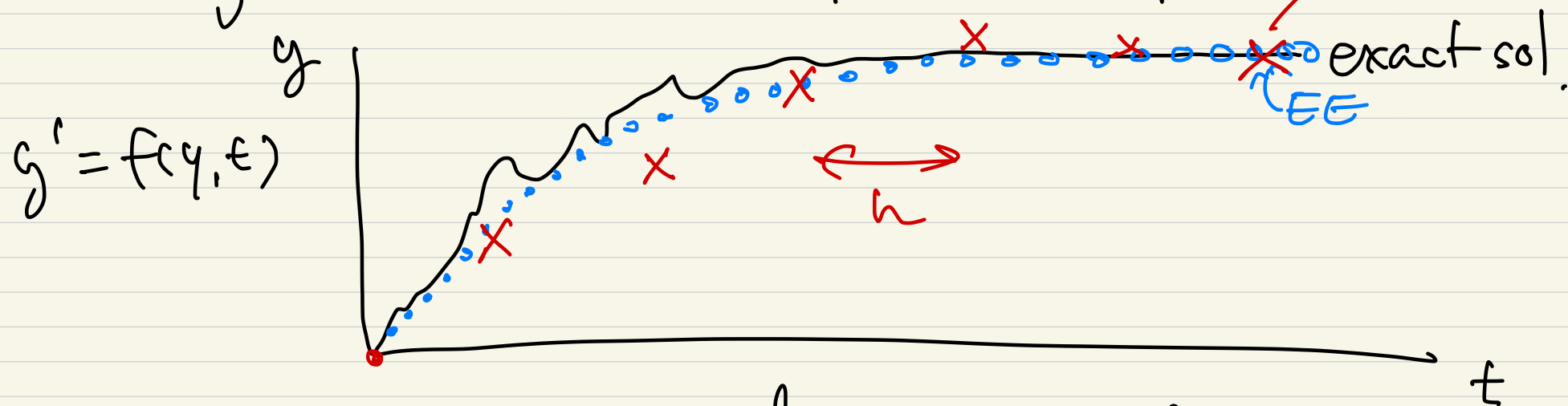
$\therefore$  IE is 1st-order accurate

$$\text{IE: } e^{\lambda h} - \sigma = e^{\lambda h} - \frac{1}{1-\lambda h} = -\frac{1}{2}\lambda^2 h^2 + \dots$$

$$\text{EE: } e^{\lambda h} - \sigma = e^{\lambda h} - (1 + \lambda h) = \frac{1}{2}\lambda^2 h^2 + \dots$$

$\Rightarrow$  stability is nothing to do with accuracy.

From stability point of view,  
our objective is to take largest time step  $h$ .



- Accuracy for  $\lambda = i\omega$  (purely imaginary)

$$y' = \lambda y = i\omega y$$

$$\text{exact sol. } y = y_0 e^{i\omega t} = y_0 (\cos \omega t + i \sin \omega t)$$

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

$$\rightarrow y_n = (1 + i\omega h)^n y_0 = \sigma^n y_0, \quad \sigma = 1 + i\omega h$$

$$\text{exact sol. : amplitude } |e^{i\omega t}| = 1$$

EE : amplitude  $|\sigma| = \sqrt{1 + \omega^2 h^2} > 1$  unstable!

$$\sigma = |\sigma| e^{i\theta}$$

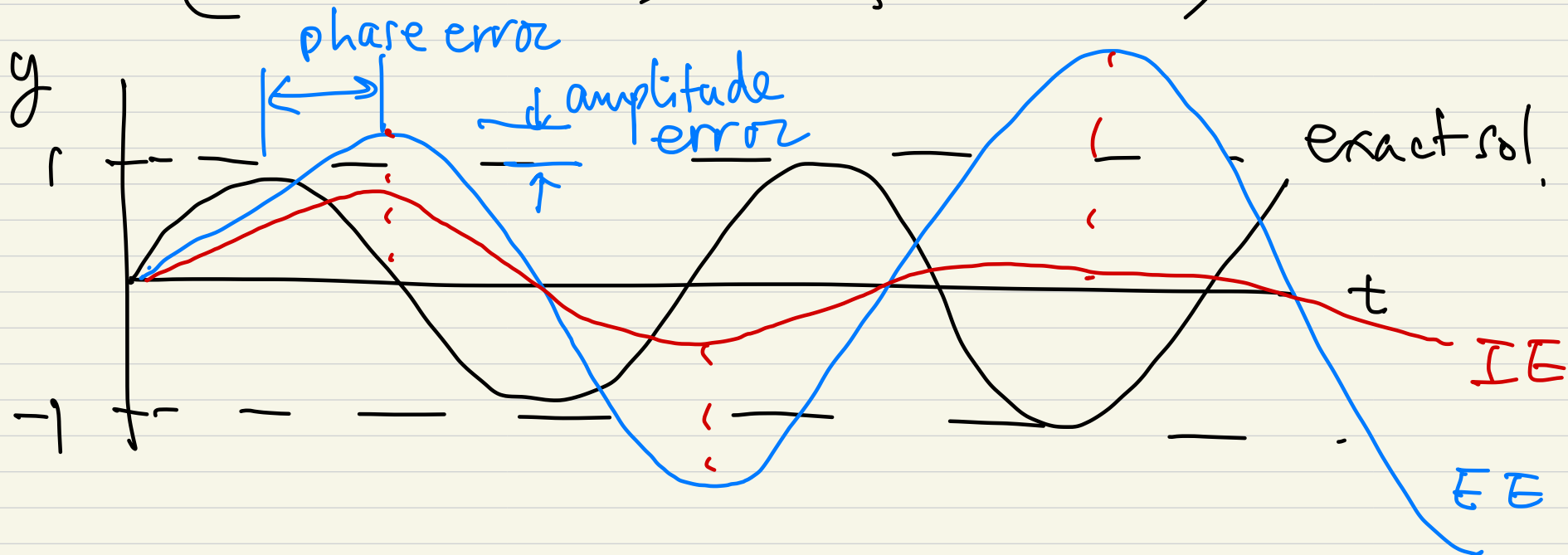
$$\text{phase } \theta = \tan^{-1} \frac{\text{Im}(\sigma)}{\text{Re}(\sigma)} = \tan^{-1} \frac{\omega h}{1} = \tan^{-1} \omega h$$

$$\text{exact sol. : } y = y_0 e^{i\omega t} = y_0 e^{i\omega h n} = y_0 \cdot 1 \cdot e^{i\omega h n}$$

$$\text{EE : } y_n = \sigma^n y_0 = y_0 |\sigma|^n e^{i\theta n}$$

$$\text{phase error} = \omega h - \theta = \omega h - \tan^{-1} \omega h = \frac{1}{3} (\omega h)^3 + \dots$$

$$\left( \tan^{-1} \omega h = \omega h - \frac{1}{3} (\omega h)^3 + \frac{1}{5} (\omega h)^5 + \dots \right)$$



$$IE: y_{n+1} = \frac{1}{1 - i\omega h} y_n = \frac{1}{1 - i\omega h} y_n \rightarrow y_n = \left( \frac{1}{1 - i\omega h} \right)^n y_0$$

$$\frac{1 + i\omega h}{1 + \omega^2 h^2}$$

$$\sigma = \frac{1}{1 - i\omega h} = |\sigma| e^{i\theta}$$

$$|\sigma|^2 = \frac{1}{1 + \omega^2 h^2} < 1 \quad \text{stable} \rightarrow \text{decaying sol.} \quad \text{but}$$

$$\theta = \tan^{-1} \frac{\omega h}{1} = \tan^{-1} \omega h; \text{ same as that of EE.}$$

$$\text{phase error} = \omega h - \theta = \frac{1}{3} (\omega h)^3 + \dots$$

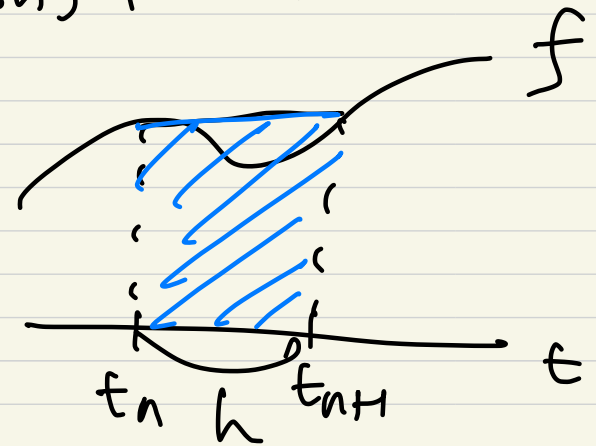
## 4.6 Trapezoidal method (TR)

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

$$\rightarrow y_{n+1} = y_n + \int_{t_n}^{t_{n+1}} f(y, t) dt$$

$$\rightarrow y_{n+1} = y_n + \frac{h}{2} [f(y_{n+1}, t_{n+1}) + f(y_n, t_n)]$$

TR  
implicit  
method



$$y' = f \Rightarrow \frac{y_{n+1} - y_n}{h} = \frac{1}{2}(f_{n+1} + f_n) : \text{TR implicit}$$

$$= f_n : \text{EE explicit}$$

$$= f_{n+1} : \text{IE implicit}$$

When TR is applied to PDE, it is called  
'Crank-Nicolson' method.

Model prob.  $y' = \lambda y$

TR:  $y_{n+1} = y_n + \frac{h}{2}(\lambda y_{n+1} + \lambda y_n)$

$$\rightarrow y_{n+1} = \frac{1 + \lambda h/2}{1 - \lambda h/2} y_n = \sigma y_n$$

$$\sigma = \frac{1 + \lambda h/2}{1 - \lambda h/2} = 1 + \lambda h + \frac{1}{2} \lambda^2 h^2 + \frac{1}{6} \lambda^3 h^3 + \dots$$

←  $\left(\frac{1}{1-\epsilon} = 1 + \epsilon + \epsilon^2 + \dots\right)$   
error

exact sol.  $e^{\lambda h} = 1 + \lambda h + \frac{1}{2} \lambda^2 h^2 + \frac{1}{6} \lambda^3 h^3 + \dots$

$\therefore$  TR is 3rd-order accurate for one timestep  
globally 2nd-order accurate.

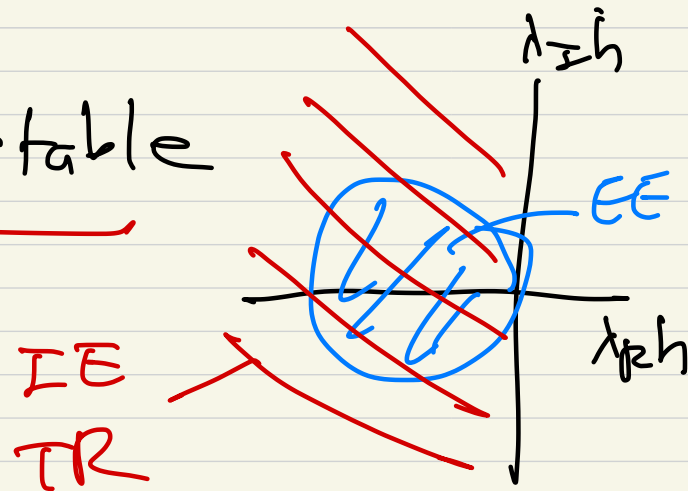
stability:  $\lambda = \lambda_R + i\lambda_I$

$$\sigma = \frac{1 + \lambda h/2}{1 - \lambda h/2} = \frac{1 + \lambda_R h/2 + i\lambda_I h/2}{1 - \lambda_R h/2 - i\lambda_I h/2} = \frac{A e^{i\theta}}{B e^{i\alpha}} = \frac{A}{B} e^{i(\theta - \alpha)}$$

$$\theta = \tan^{-1} \frac{\frac{1}{2}\lambda_I h}{1 + \frac{1}{2}\lambda_R h}, \quad \alpha = \tan^{-1} \frac{-\frac{1}{2}\lambda_I h}{1 - \frac{1}{2}\lambda_R h}$$

$$|\sigma| = \frac{A}{B} = \frac{\sqrt{(1 + \frac{1}{2}\lambda_R h)^2 + (\frac{1}{2}\lambda_I h)^2}}{\sqrt{(1 - \frac{1}{2}\lambda_R h)^2 + (\frac{1}{2}\lambda_I h)^2}} \leq 1 \text{ for } \lambda_R \leq 0$$

$\therefore$  TR is unconditionally stable



For  $\lambda_R = 0$ ,  $y' = i\omega y$  ( $\lambda = i\omega$ )

TR:  $|G| = 1 \quad \therefore$  no amplitude error

phase:  $G = \frac{1 + i\frac{1}{2}\omega h}{1 - i\frac{1}{2}\omega h} = e^{i \cdot 2\theta} \quad \theta = \tan^{-1} \frac{\omega h}{2}$

phase error =  $\omega h - 2 \tan^{-1} \frac{\omega h}{2}$

$$= \omega h - 2 \left[ \frac{\omega h}{2} - \frac{1}{24} (\omega h)^3 + \dots \right] = \frac{1}{12} (\omega h)^3 + \dots$$

four times better than that of EE & IE.





For  $\lambda_I = 0$ ,  $\lambda$  is real & negative ( $\lambda_R \leq 0$ )

$$\text{TR: } \sigma = \frac{1 + \frac{1}{2}\lambda_R h}{1 - \frac{1}{2}\lambda_R h} \rightarrow y_n = \sigma^n y_0$$

for large  $h$ ,  $\sigma \rightarrow -1$

$\sigma^n$  oscillates between  $-1$  and  $1$ , but never blows up.



try different numerical method.

$$* \quad y'' + \omega^2 y = 0 \quad y(0) = y_0, \quad y'(0) = 0$$

$$y_1 = y$$

$$y_2 = y_1' \rightarrow y_2' = y_1'' = -\omega^2 y_1$$

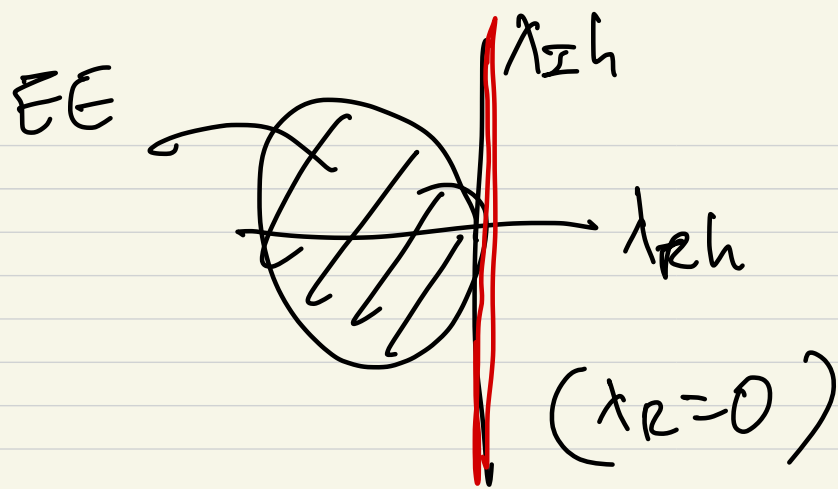
$$\Rightarrow \begin{pmatrix} y_1' \\ y_2' \end{pmatrix} = \underbrace{\begin{pmatrix} 0 & 1 \\ -\omega^2 & 0 \end{pmatrix}}_A \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = S^T \Lambda S \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}$$

$$\det(A - \lambda I) = \begin{vmatrix} -\lambda & 1 \\ -\omega^2 & -\lambda \end{vmatrix} = 0 \rightarrow \lambda^2 = -\omega^2$$

$\lambda = \pm i\omega$   
purely imaginary  
eigenvalues

$$\underbrace{S \begin{pmatrix} y_1' \\ y_2' \end{pmatrix}} = \Lambda \underbrace{S \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}} \Rightarrow \begin{pmatrix} z_1' \\ z_2' \end{pmatrix} = \Lambda \begin{pmatrix} z_1 \\ z_2 \end{pmatrix} \rightarrow \begin{matrix} z_1' = \lambda_1 z_1 \\ z_2' = \lambda_2 z_2 \end{matrix}$$

model prob.



$EE$  is unstable



$\Sigma E$  &  $TR$  are stable

# 4.7 Linearization for implicit methods

TR:  $y' = f(y, t) \rightarrow y_{n+1} = y_n + \frac{h}{2} \left[ f(y_{n+1}, t_{n+1}) + f(y_n, t_n) \right] + O(h^3)$

⇒ solve nonlinear algebraic eq.

→ require iterative solution procedure

⇒ can be avoided by linearization technique.

$$f(y_{n+1}, t_{n+1}) = f(y_n, t_{n+1}) + (y_{n+1} - y_n) \frac{\partial f}{\partial y} \Big|_{y_n, t_{n+1}} + \frac{1}{2} (y_{n+1} - y_n)^2 \frac{\partial^2 f}{\partial y^2} \Big|_{y_n, t_{n+1}} + \dots$$

*(Annotations: The first term is circled in red. The second term is underlined in blue. The third term is circled in red and has a red arrow pointing to the text "neglect this term w/o losing any accuracy".)*

neglect this term w/o losing any accuracy

⇒  $y_{n+1} = y_n + \frac{h}{2} \left( f(y_n, t_{n+1}) + (y_{n+1} - y_n) \frac{\partial f}{\partial y} \Big|_{y_n, t_{n+1}} + f(y_n, t_n) \right) + O(h^3)$

$$\rightarrow y_{n+1} = y_n + \frac{h}{2} \frac{f(y_n, t_{n+1}) + f(y_n, t_n)}{1 - \frac{h}{2} \frac{\partial f}{\partial y} \Big|_{y_n, t_{n+1}}} + O(h^3)$$

linearized TR  
(LTR)

this formula does not require iteration,  
while retaining global second-order accuracy.

Linear stability analysis

$$(y' = \lambda y)$$

$$y_{n+1} = y_n + \frac{h}{2} \cdot \frac{\lambda y_n + \lambda y_n}{1 - \frac{h}{2} \lambda}$$

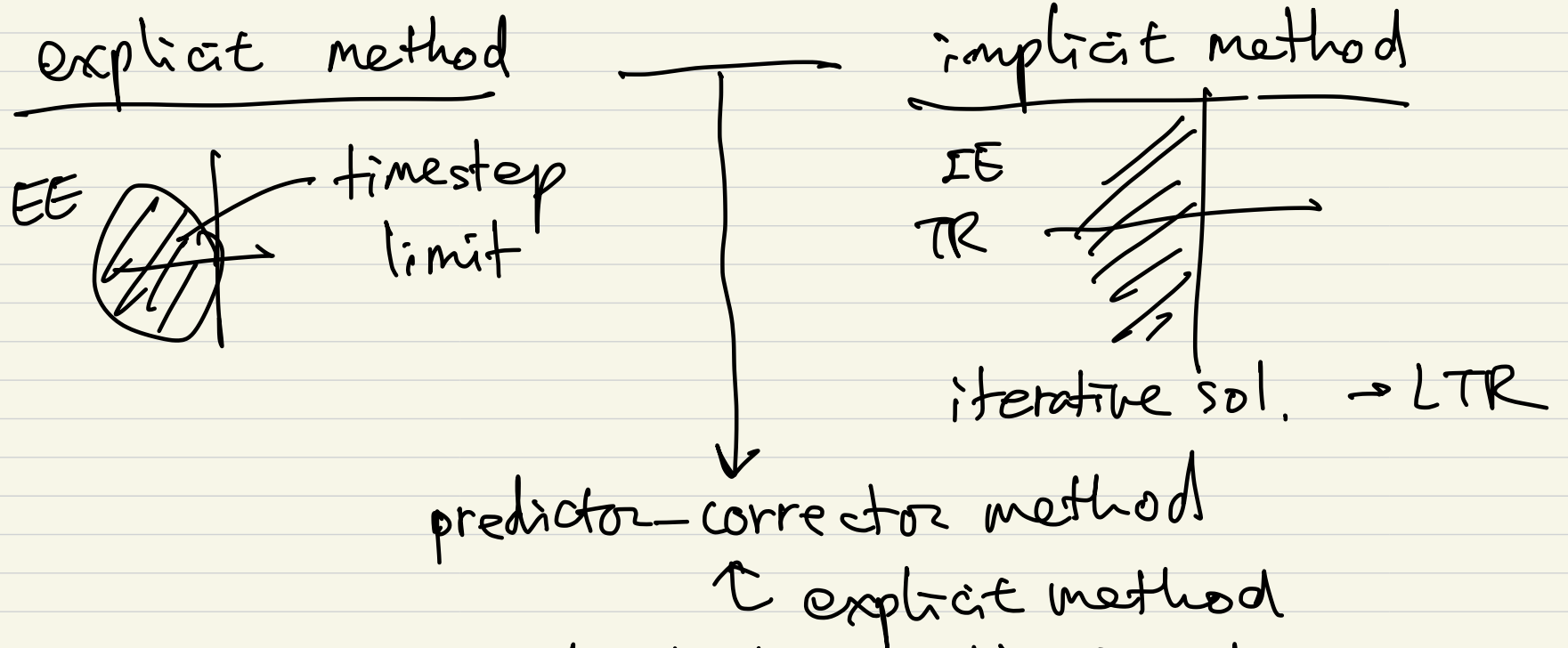
$$= \frac{1 + \frac{1}{2} \lambda h}{1 - \frac{1}{2} \lambda h} y_n = \sigma y_n$$

unconditionally stable

Linearization may lead to some loss of total stability  
for nonlinear  $f$ .

# 4.8 Runge-Kutta methods (RK)

## ① Predictor-corrector method (PC)



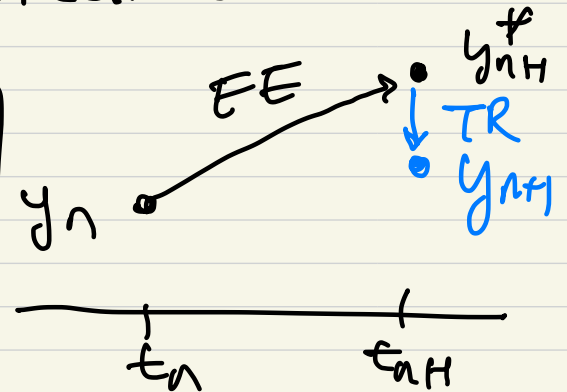
PC & RK methods provide better stability than explicit method like EE but less work/timestep than implicit method.

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

$$\textcircled{1} y_{n+1}^* = y_n + h f(y_n, t_n) : EE \text{ as predictor}$$

$$\textcircled{2} y_{n+1} = y_n + \frac{h}{2} [f(y_{n+1}^*, t_{n+1}) + f(y_n, t_n)]$$

TR as corrector



$$\text{model prob.: } y' = \lambda y$$

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

$$\textcircled{2} y_{n+1} = y_n + \frac{h}{2} [\lambda (1 + \lambda h) y_n + \lambda y_n]$$

$$= y_n \left( 1 + \lambda h + \frac{1}{2} \lambda^2 h^2 \right) = \sigma y_n \quad O(h^3)$$

$$\text{exact sol. } e^{\lambda h} = \underline{1 + \lambda h + \frac{1}{2} \lambda^2 h^2} + \frac{1}{6} \lambda^3 h^3 + \dots$$

$\therefore$  PC is 2nd-order accurate.

$$\text{stability: } y_n = \sigma^n y_0, \quad \sigma = 1 + \lambda h + \frac{1}{2} \lambda^2 h^2$$

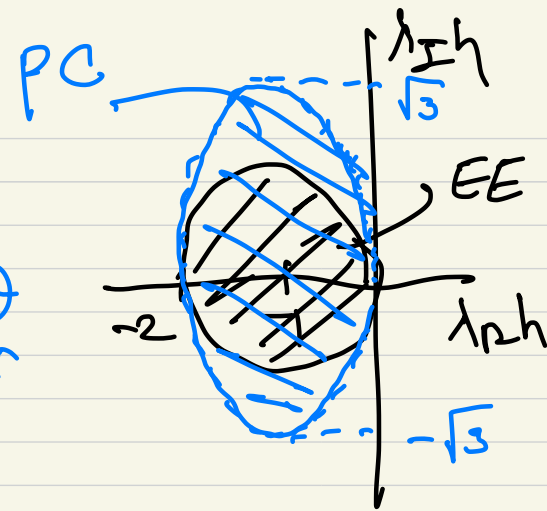
$$\Rightarrow |\sigma| \leq 1 \text{ to be stable}$$

$$|1 + \lambda h + \frac{1}{2} \lambda^2 h^2| \leq 1$$

$$1 + \lambda h + \frac{1}{2} \lambda^2 h^2 = e^{i\theta}$$

find  $\lambda h$  for different trials for  $\theta$

$\therefore$  PC is conditionally stable



For  $\lambda = i\omega$ ,  $\sigma = 1 + \lambda h + \frac{1}{2} \lambda^2 h^2 = 1 + i\omega h - \frac{1}{2} \omega^2 h^2$

$$|\sigma|^2 = (1 - \frac{1}{2} \omega^2 h^2)^2 + (\omega h)^2 = 1 + \frac{1}{4} \omega^4 h^4 > 1$$

unstable for purely imaginary  $\lambda$ .

① Runge-Kutta methods - explicit methods

advantages: ① good stability properties

② timestep size can be changed during computation.

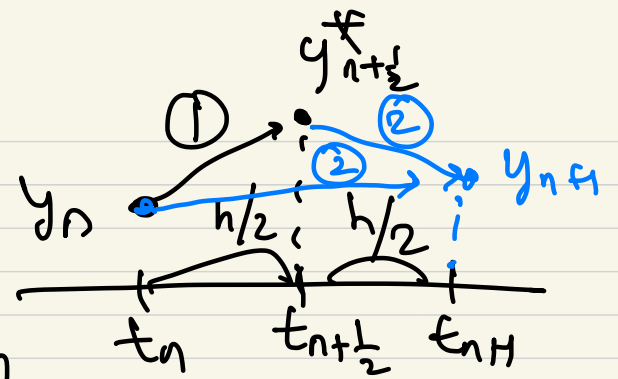
③ self starting



# 2nd-order Runge-Kutta method (RK2)

①  $y_{n+\frac{1}{2}}^* = y_n + \frac{h}{2} f(y_n, t_n) : EE$

②  $y_{n+1} = y_n + hf(y_{n+\frac{1}{2}}^*, t_{n+\frac{1}{2}}) : \text{Midpoint rule}$



model prob.  $y' = \lambda y$

①②  $y_{n+1} = y_n (1 + \lambda h + \frac{1}{2} \lambda^2 h^2)$   
2nd-order accurate

For  $\lambda = i\omega$ , unstable

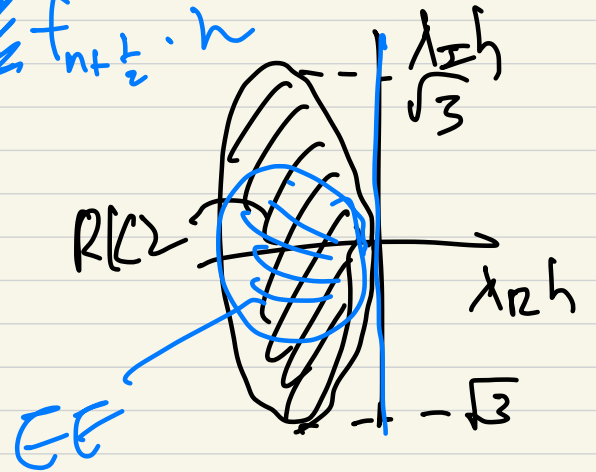
$$\delta = 1 + i\omega h - \frac{1}{2} \omega^2 h^2$$

$$= |\delta| e^{i\theta}, \quad \theta = \tan^{-1} \frac{\omega h}{1 - \frac{1}{2} \omega^2 h^2}$$

$$|\delta| > 1$$

phase error:  $\omega h - \theta = -\frac{1}{6} \omega^3 h^3 + \dots$

$$\int_{t_n}^{t_{n+1}} f dt = f_{n+\frac{1}{2}} \cdot h$$



- RK4 (most popular scheme) - explicit

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

$$\textcircled{1} \quad y_{n+\frac{1}{2}}^* = y_n + \frac{h}{2} \underline{f(y_n, t_n)}$$

requires

$$\textcircled{2} \quad y_{n+\frac{1}{2}}^{**} = y_n + \frac{h}{2} \underline{f(y_{n+\frac{1}{2}}^*, t_{n+\frac{1}{2}})} \Rightarrow$$

4 function evaluations / time step

$$\textcircled{3} \quad y_{n+1}^{***} = y_n + h \underline{f(y_{n+\frac{1}{2}}^{**}, t_{n+\frac{1}{2}})}$$

→ expensive

$$\textcircled{4} \quad y_{n+1} = y_n + h \left[ \frac{1}{6} f(y_n, t_n) + \frac{1}{3} f(y_{n+\frac{1}{2}}^*, t_{n+\frac{1}{2}}) + \frac{1}{3} f(y_{n+\frac{1}{2}}^{**}, t_{n+\frac{1}{2}}) + \frac{1}{6} f(y_{n+1}^{***}, t_{n+1}) \right]$$

$$y' = \lambda y : y_{n+1} = G y_n$$

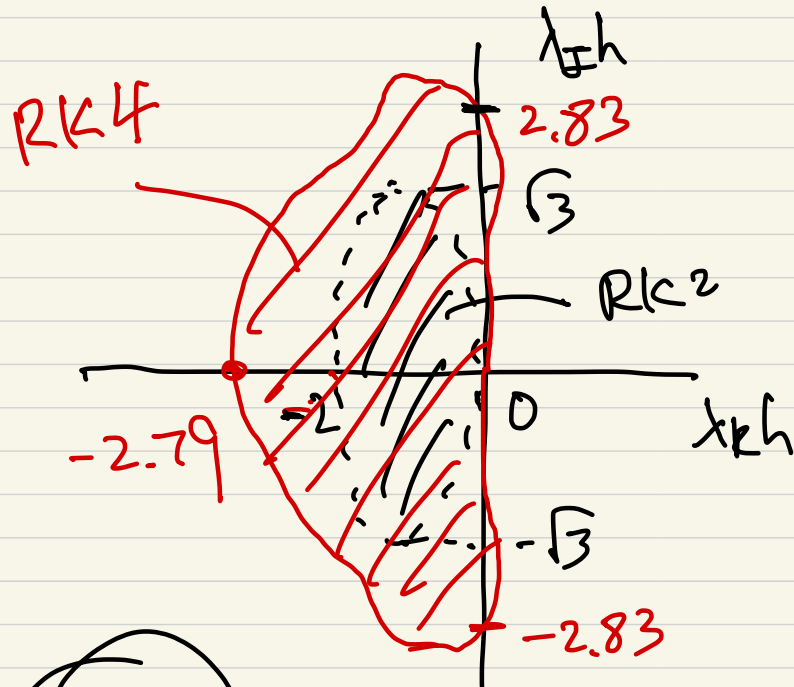
$$\rightarrow G = \underline{1 + \lambda h + \frac{1}{2} \lambda^2 h^2 + \frac{1}{6} \lambda^3 h^3 + \frac{1}{24} \lambda^4 h^4}$$

$$\text{exact sol. : } e^{\lambda h} = \underline{1 + \lambda h + \frac{1}{2} \lambda^2 h^2 + \frac{1}{6} \lambda^3 h^3 + \frac{1}{24} \lambda^4 h^4 + \dots}$$

∴ RK4 is fourth-order accurate.

stability  $|G| \leq 1$  to be stable

$$1 + \lambda h + \frac{1}{2} \lambda^2 h^2 + \frac{1}{6} \lambda^3 h^3 + \frac{1}{24} \lambda^4 h^4 = e^{\lambda t}$$



conditionally stable

for  $\lambda = i\omega$ ,  $|\lambda_{\pm} h| \leq 2.83$

conditionally stable

for  $\lambda_{\pm} = 0$ ,  $|\lambda_{\pm} h| \leq 2.79$

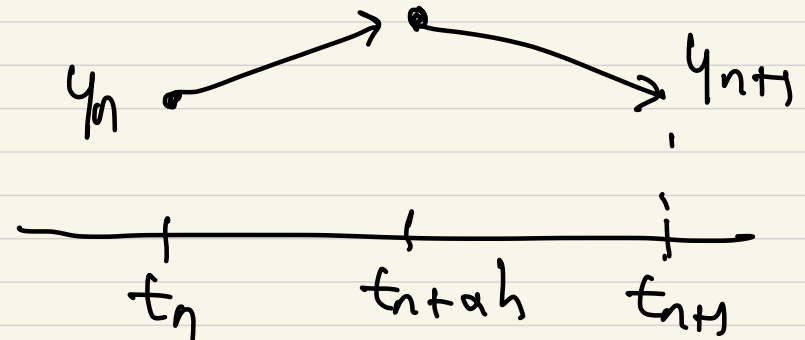
**RK3**

• How to construct RK2?

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

$$y_n + \beta k_1$$

$$\begin{cases} k_1 = h f(y_n, t_n) \\ k_2 = h f(y_n + \beta k_1, t_n + \alpha h) \\ y_{n+1} = y_n + \gamma_1 k_1 + \gamma_2 k_2 \end{cases}$$



Find  $\alpha, \beta, \gamma_1, \gamma_2$  to ensure the highest order of accuracy for the method.

Taylor series for  $k_2$

$$k_2 = h \left[ f(y_n, t_n) + \beta h \frac{\partial f}{\partial y} \Big|_n + \alpha h \frac{\partial f}{\partial t} \Big|_n + \dots \right]$$

$$\begin{aligned} \rightarrow y_{n+1} &= y_n + \gamma_1 h f_n + \gamma_2 h \left( f_n + \beta h f_n f_{y_n} + \alpha h f_{t_n} + \dots \right) \\ &= y_n + \underbrace{(\gamma_1 + \gamma_2) h f_n}_{\text{blue underline}} + \underbrace{\gamma_2 \beta h^2 f_n f_{y_n}}_{\text{blue wavy}} + \underbrace{\gamma_2 \alpha h^2 f_{t_n}}_{\text{blue wavy}} + \dots \end{aligned}$$

$$\left( \begin{aligned} y(t_{n+1}) &= y(t_n) + h y'(t_n) + \frac{1}{2} h^2 y''(t_n) + \dots \\ &= y_n + \underbrace{h f_n}_{\text{blue underline}} + \underbrace{\frac{1}{2} h^2 (f_{t_n} + f_{y_n} f_n)}_{\text{blue wavy}} + \dots \end{aligned} \right)$$

match the coeffs.

$$\left\{ \begin{aligned} \gamma_1 + \gamma_2 &= 1 \\ \gamma_2 \beta &= \frac{1}{2} \\ \gamma_2 \alpha &= \frac{1}{2} \end{aligned} \right.$$

4 unknowns and 3 eqs.

↓

$\alpha$  as a free parameter

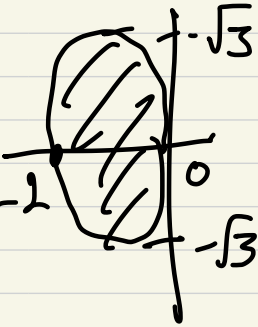
$$\Rightarrow \gamma_2 = \frac{1}{2\alpha}, \quad \beta = \alpha, \quad \gamma_1 = 1 - \frac{1}{2\alpha}$$

$$\text{RK2: } \begin{cases} k_1 = hf(y_n, t_n) \\ k_2 = hf(y_n + \alpha k_1, t_n + \alpha h) \\ y_{n+1} = y_n + (1 - \frac{1}{2\alpha}) k_1 + \frac{1}{2\alpha} k_2 \end{cases}$$

$$0 < \alpha < 1$$

model prob.  $y' = \lambda y \rightarrow y_{n+1} = y_n (1 + \lambda h + \frac{1}{2} \lambda^2 h^2)^{-1}$

2nd-order accurate,



$$y' = f(y, t) : \text{ EE, IE, TR, LTR, FC, RK2, RK4}$$