

Reduction to first order system

Given an n -th order ODE

$$y^{(n)}(t) = F(t, y(t), \dot{y}(t), \ddot{y}(t), \dots, y^{(n-1)}(t))$$

We define

$$\begin{aligned} z_0(t) &= y(t) \\ z_1(t) &= \dot{y}(t) = \dot{z}_0(t) \\ z_2(t) &= \ddot{y}(t) = \dot{z}_1(t) \\ &\vdots \\ z_{n-1}(t) &= y^{(n-1)}(t) = \dot{z}_{n-2}(t) \end{aligned} \quad \left. \vphantom{\begin{aligned} z_0(t) &= y(t) \\ z_1(t) &= \dot{y}(t) = \dot{z}_0(t) \\ z_2(t) &= \ddot{y}(t) = \dot{z}_1(t) \\ &\vdots \\ z_{n-1}(t) &= y^{(n-1)}(t) = \dot{z}_{n-2}(t) \end{aligned}} \right\} \begin{array}{l} n-1 \text{ first} \\ \text{order ODEs} \end{array}$$

Now

$$\begin{aligned} z_n(t) &= y^{(n)}(t) = \underline{\dot{z}_{n-1}(t)} \\ &= F(t, y(t), \dot{y}(t), \ddot{y}(t), \dots, y^{(n-1)}(t)) \\ &= \underline{F(t, z_0(t), z_1(t), z_2(t), \dots, z_{n-1}(t))} \end{aligned}$$

\leadsto n first order ODEs!

By defining

$$\vec{z}(t) = \begin{pmatrix} z_0(t) \\ z_1(t) \\ \vdots \\ z_{n-2}(t) \\ z_{n-1}(t) \end{pmatrix} \quad \text{and} \quad \vec{g}(t, \vec{z}) = \begin{pmatrix} z_1(t) \\ z_2(t) \\ \vdots \\ z_{n-1}(t) \\ f(t, z_0(t), \dots, z_{n-1}(t)) \end{pmatrix}$$

we get a first order system of ODEs

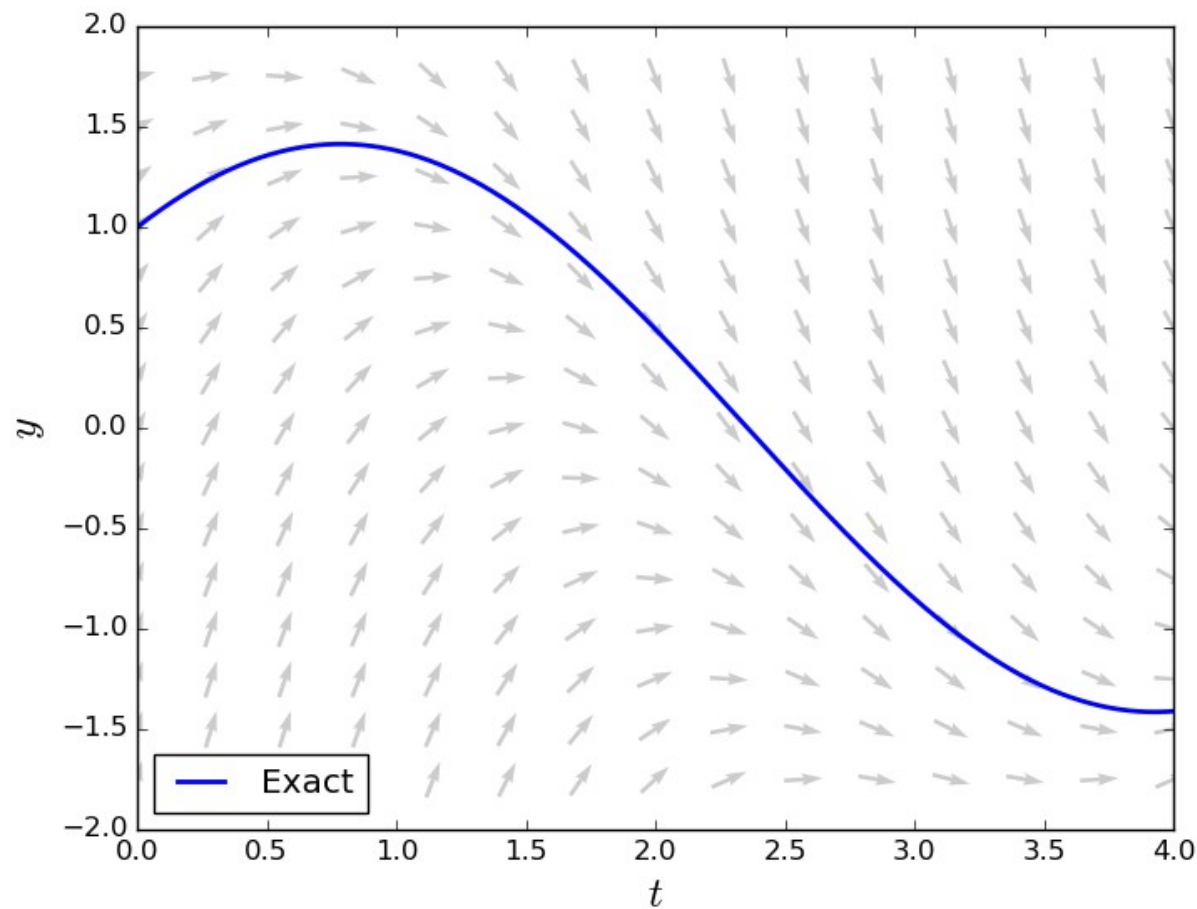
$$\dot{\vec{z}}(t) = \vec{g}(t, \vec{z}(t))$$

Together with the IVs we get a first order IPV.

Ex. (6)

The Euler Methods

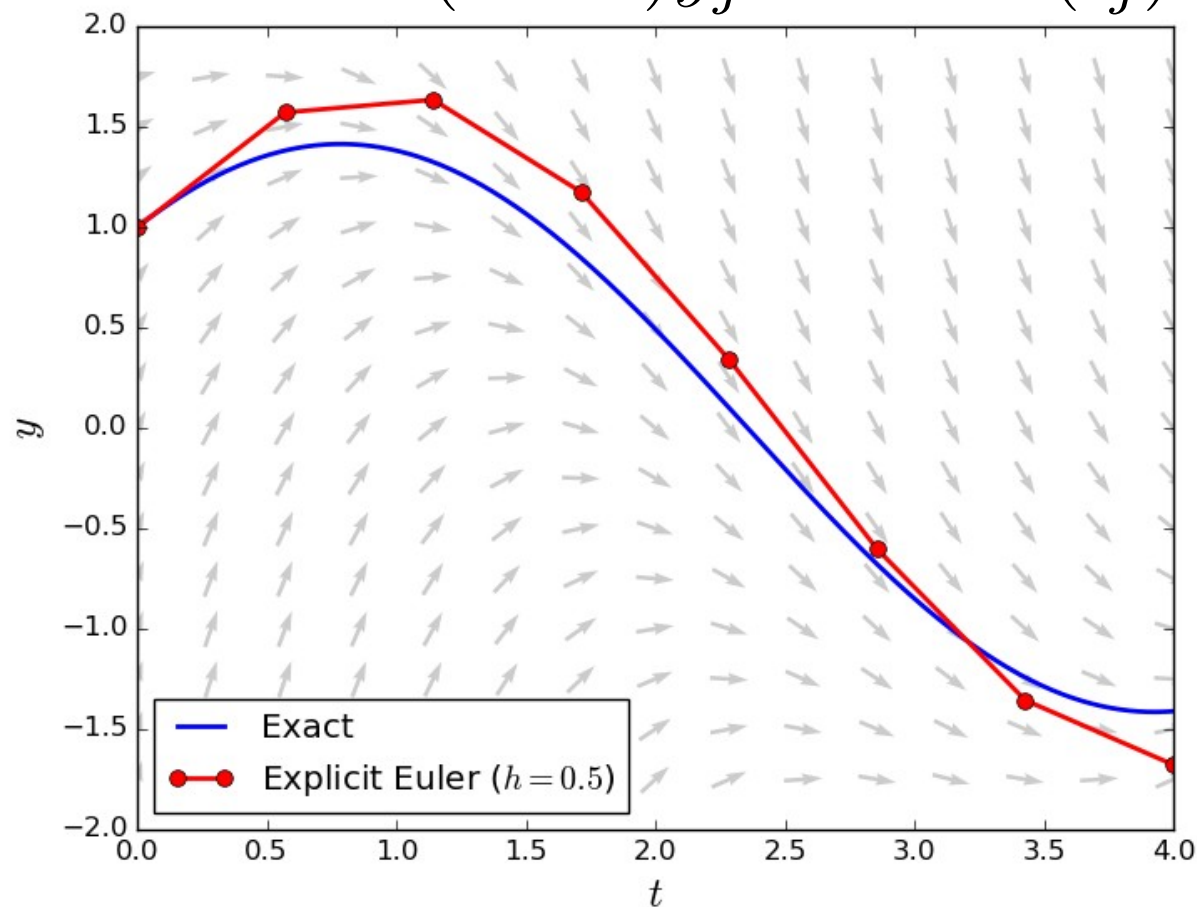
IVP
$$\begin{cases} \dot{y}(t) = -y(t) + 2 \cos(t) \\ y(0) = 1 \end{cases} \quad y(t) = \sin(t) + \cos(t)$$



The Euler Methods

Explicit

$$\begin{aligned}y_{j+1} &= y_j + hf(t_j, y_j) \\ &= y_j + h(-y_j + 2\cos(t_j)) \\ &= (1-h)y_j + 2h\cos(t_j)\end{aligned}$$



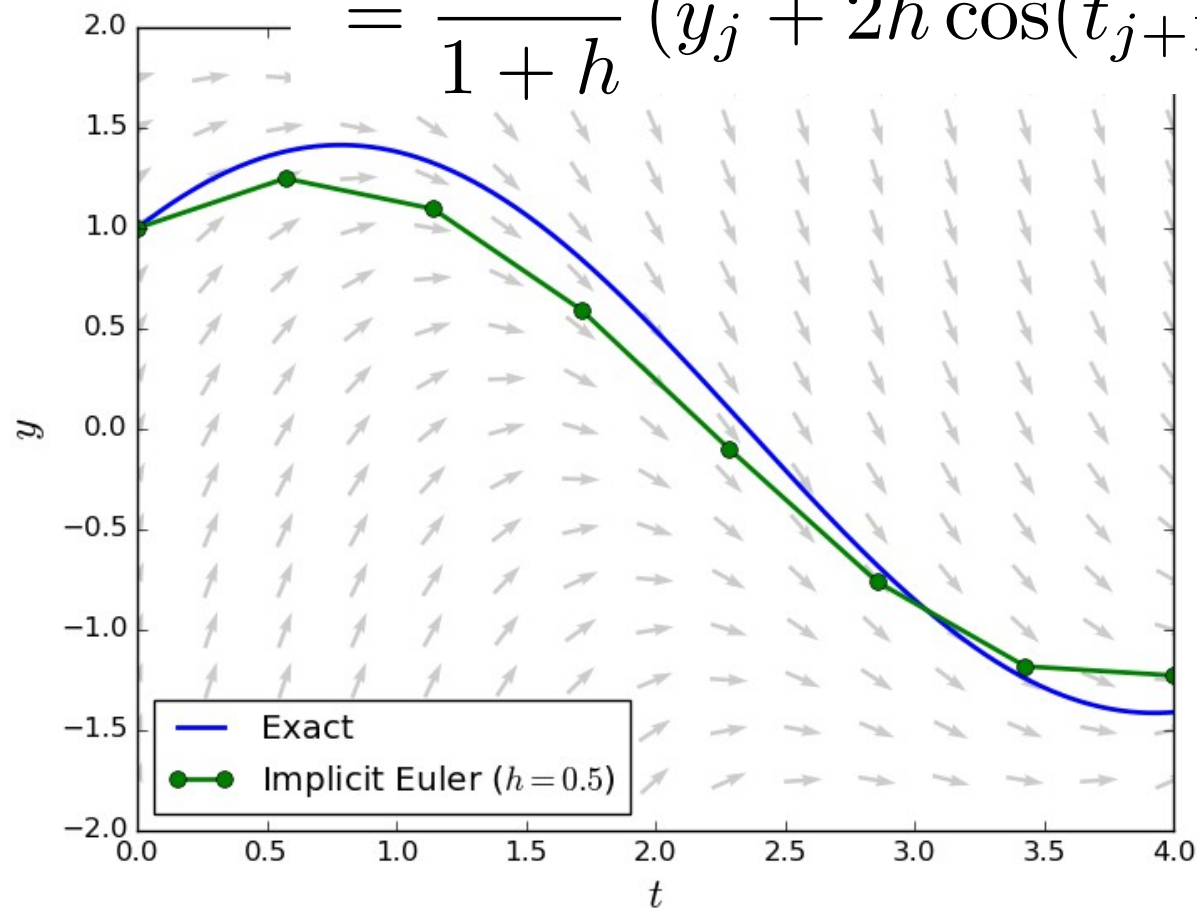
The Euler Methods

Implicit

$$y_{j+1} = y_j + hf(t_{j+1}, y_{j+1})$$

$$= y_j + h(-y_{j+1} + 2\cos(t_{j+1}))$$

$$= \frac{1}{1+h} (y_j + 2h\cos(t_{j+1}))$$

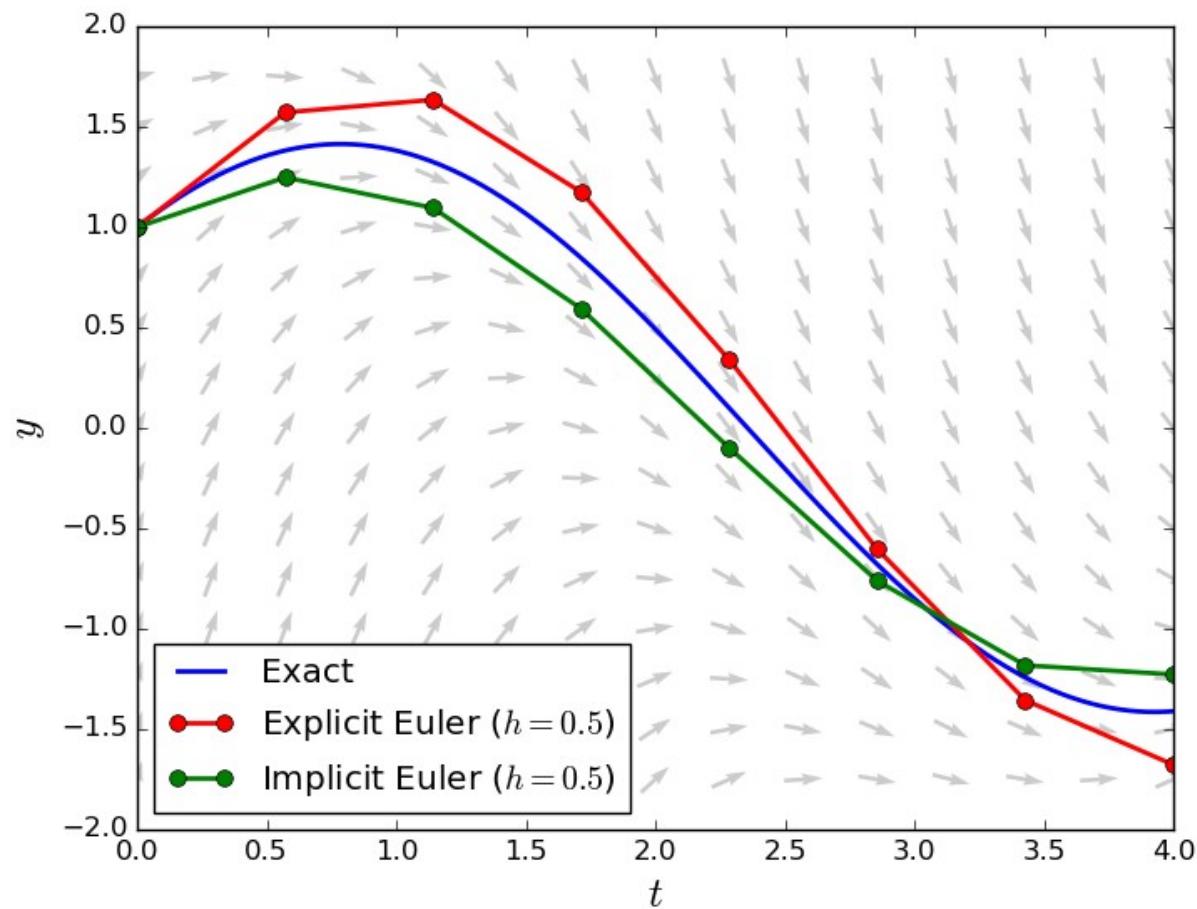


Ex. (6)

The Euler Methods

$$E_N = |y(\bar{T}) - y_N|$$

Error



The Euler Methods

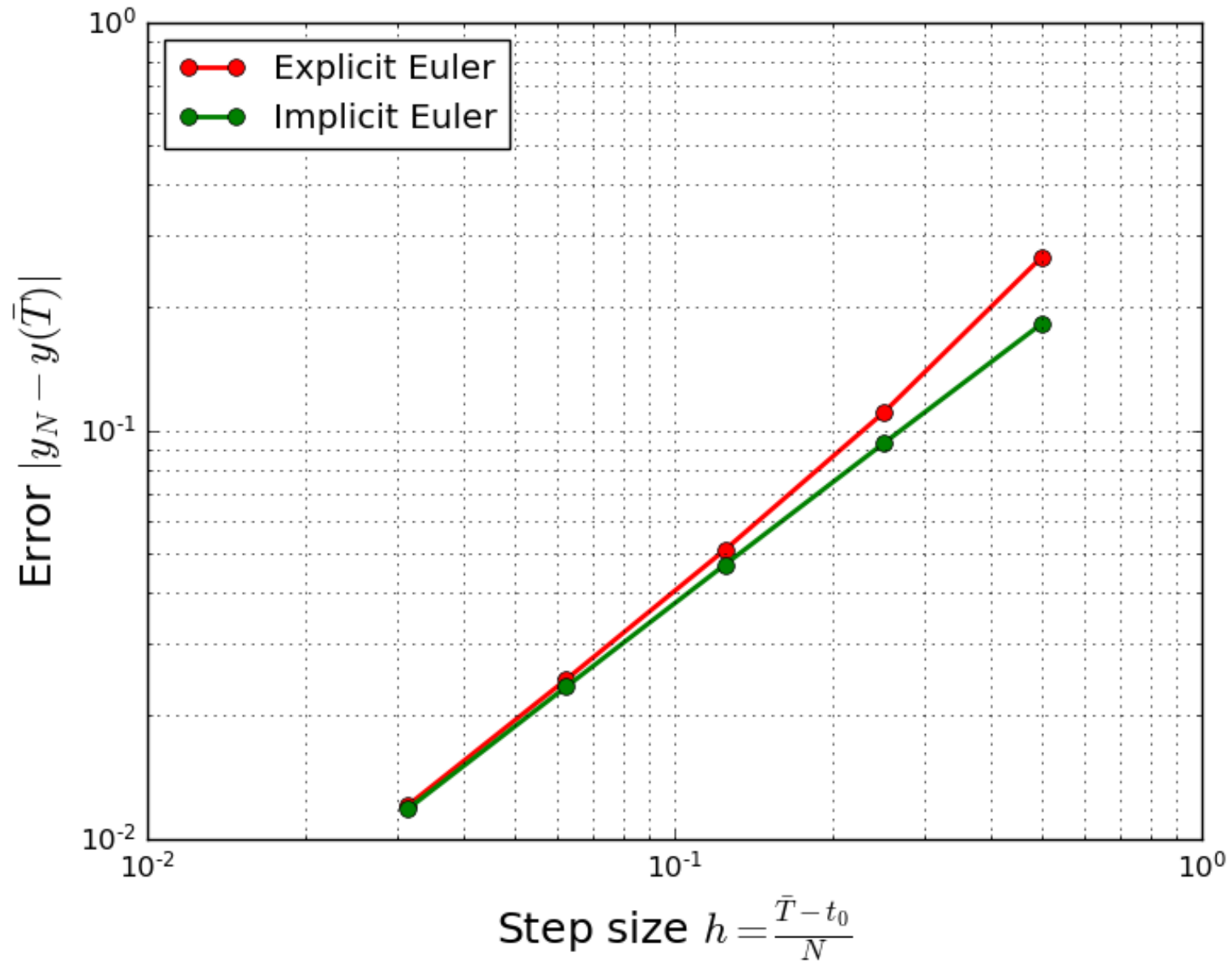
N	h	EE $ y_N - y(\bar{T}) $	IE $ y_N - y(\bar{T}) $
8	2^{-1}	2.666E-01	1.830E-01
16	2^{-2}	1.105E-01	9.295E-02
32	2^{-3}	5.097E-02	4.688E-02
64	2^{-4}	2.453E-02	2.354E-02
128	2^{-5}	1.204E-02	1.180E-02

$O(h)$

We observe that the GTE is directly proportional to the stepsize h , although the LTE is proportional to its square....

$O(h^2)$

The Euler Methods



LTE, GTE and order of accuracy

Actually, one can show (under requirements that are anyway necessary for the existence and uniqueness of solutions to an IVP) that the LTEs accumulate in each step:

$$|E_N| \leq N \cdot \max_{1 \leq j \leq N} |e_j| = \mathcal{O}(h)$$

\uparrow $\sim \frac{1}{h}$ \uparrow $\mathcal{O}(h^2)$

And we have convergence: $y_N \xrightarrow{h \rightarrow 0} y(T)$

This motivates the following definition

Def.: We say that a method has order of accuracy p if the LTE is

$$|e_j| = \mathcal{O}(h^{p+1})$$

or equivalently

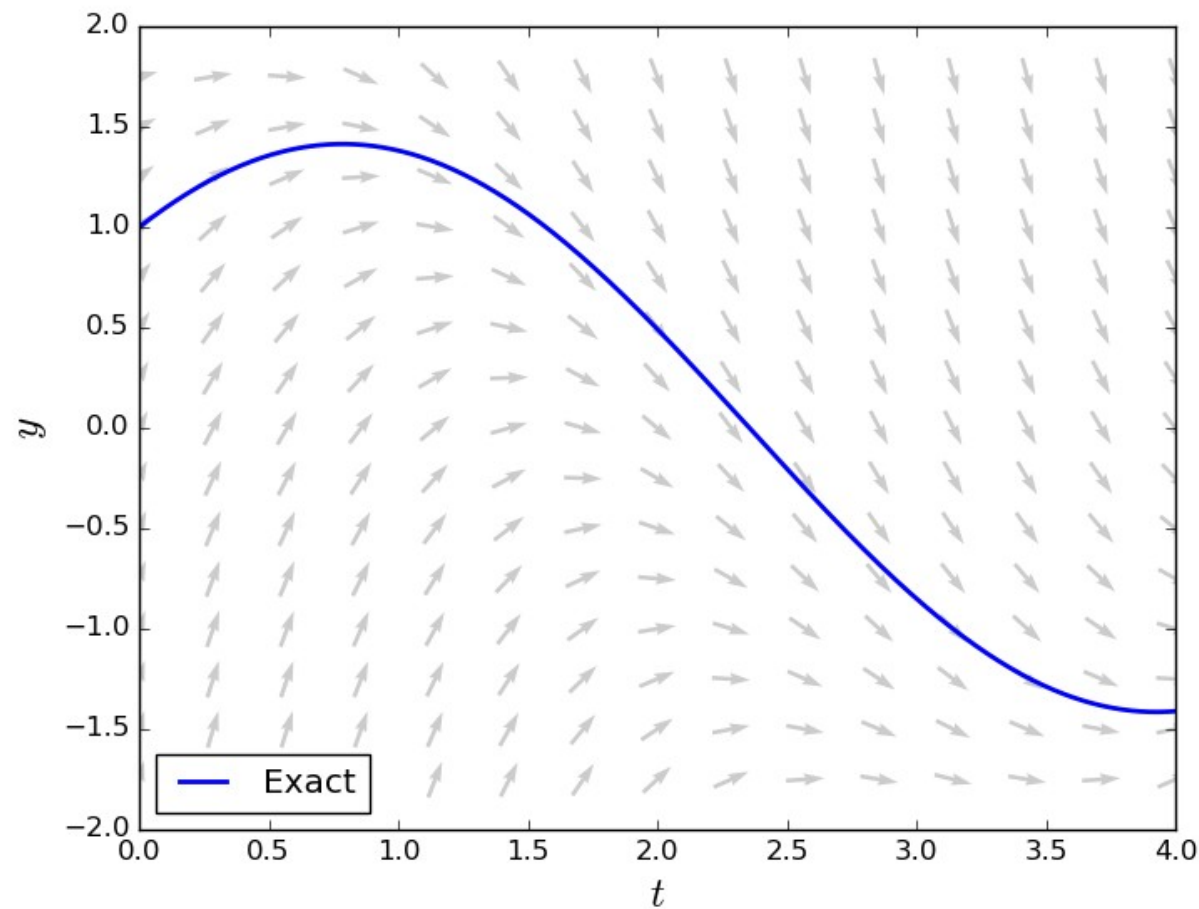
$$|E_j| = \mathcal{O}(h^p)$$

Rem.: EE and IE have order of accuracy $p=1$.

Ex. (10)

Runge's Method

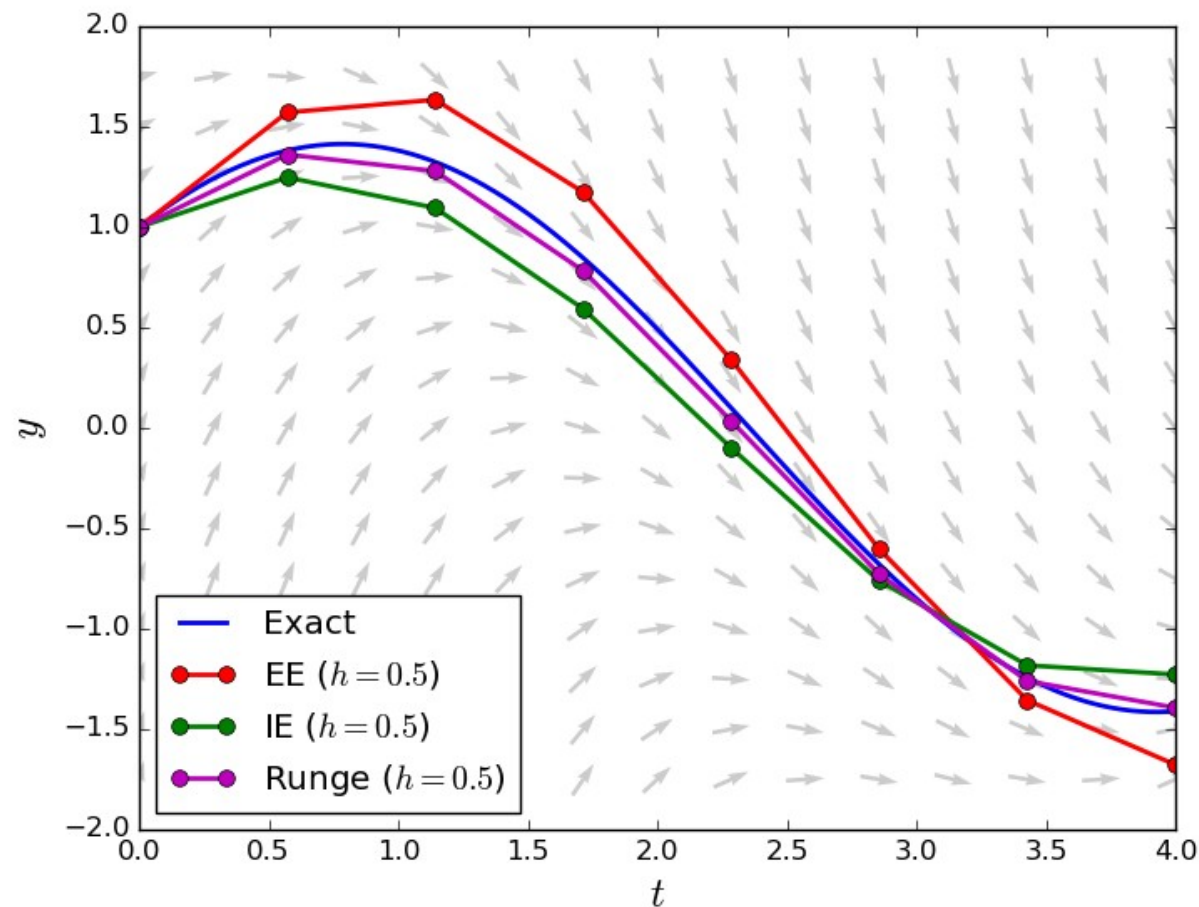
IVP
$$\begin{cases} \dot{y}(t) = -y(t) + 2 \cos(t) \\ y(0) = 1 \end{cases} \quad y(t) = \sin(t) + \cos(t)$$



Ex. (10)

Runge's Method

IVP
$$\begin{cases} \dot{y}(t) = -y(t) + 2 \cos(t) \\ y(0) = 1 \end{cases} \quad y(t) = \sin(t) + \cos(t)$$



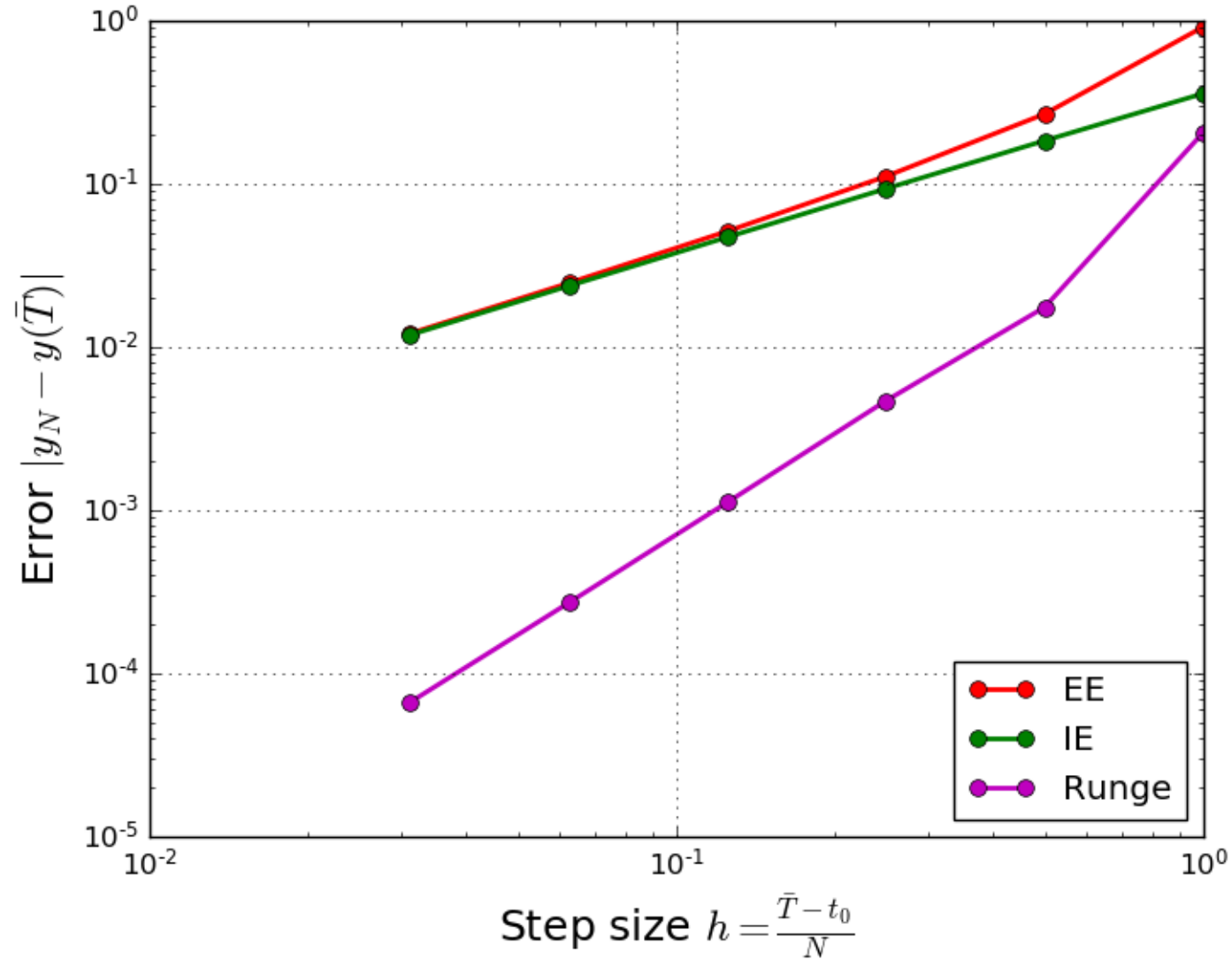
Ex. (10)

Runge's Methods

N	h	EE $ y_N - y(\bar{T}) $	IE $ y_N - y(\bar{T}) $	EM $ y_N - y(\bar{T}) $
4	2^{-0}	9.109E-01	3.559E-01	2.056E-01
8	2^{-1}	2.666E-01	1.830E-01	1.745E-02
16	2^{-2}	1.105E-01	9.295E-02	4.662E-03
32	2^{-3}	5.097E-02	4.688E-02	1.112E-03
64	2^{-4}	2.453E-02	2.354E-02	2.694E-04
128	2^{-5}	1.204E-02	1.180E-02	6.621E-05

Ex. (10)

Runge's Methods



Runge-Kutta Methods

Number of stages

s

$$y_{j+1} = y_j + h \sum_{i=1}^s b_i k_i$$

Stages

$$k_i = f \left(t_j + c_i h, y_j + h \sum_{l=1}^s a_{il} k_l \right)$$

Nodes

Runge-Kutta matrix

c_1	a_{11}	a_{12}	\cdots	a_{1s}	$= \frac{\mathbf{c} \mid A}{\mid \mathbf{b}^T}$
c_2	a_{21}	a_{22}	\cdots	a_{2s}	
\vdots	\vdots	\vdots	\ddots	\vdots	
c_s	a_{s1}	a_{s2}	\cdots	a_{ss}	
	b_1	b_2	\cdots	b_s	

Weights

Runge-Kutta Methods

- Explicit Euler

$$\begin{array}{c|c} 0 & 0 \\ \hline & 1 \end{array}$$

- Implicit Euler

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

- Runge's

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

Zeros usually not written!



- Heun's

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

Runge-Kutta Methods

- Implicit Midpoint

$\frac{1}{2}$	$\frac{1}{2}$
	1

- Implicit Trapezoidal

0	0	0
1	$\frac{1}{2}$	$\frac{1}{2}$
	$\frac{1}{2}$	$\frac{1}{2}$

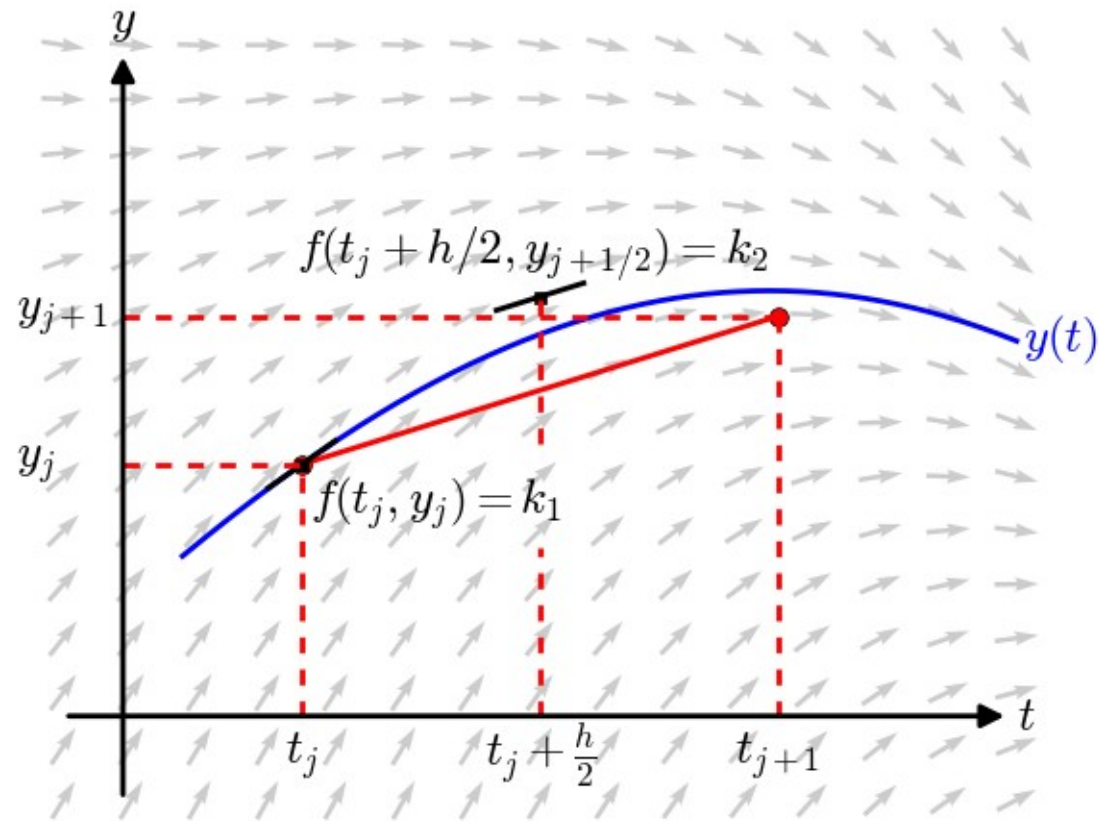
Zeros usually not written!

- Classic Runge-Kutta

0	0	0	0	0
$\frac{1}{2}$	$\frac{1}{2}$	0	0	0
$\frac{1}{2}$	0	$\frac{1}{2}$	0	0
1	0	0	1	0
	$\frac{1}{6}$	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{6}$

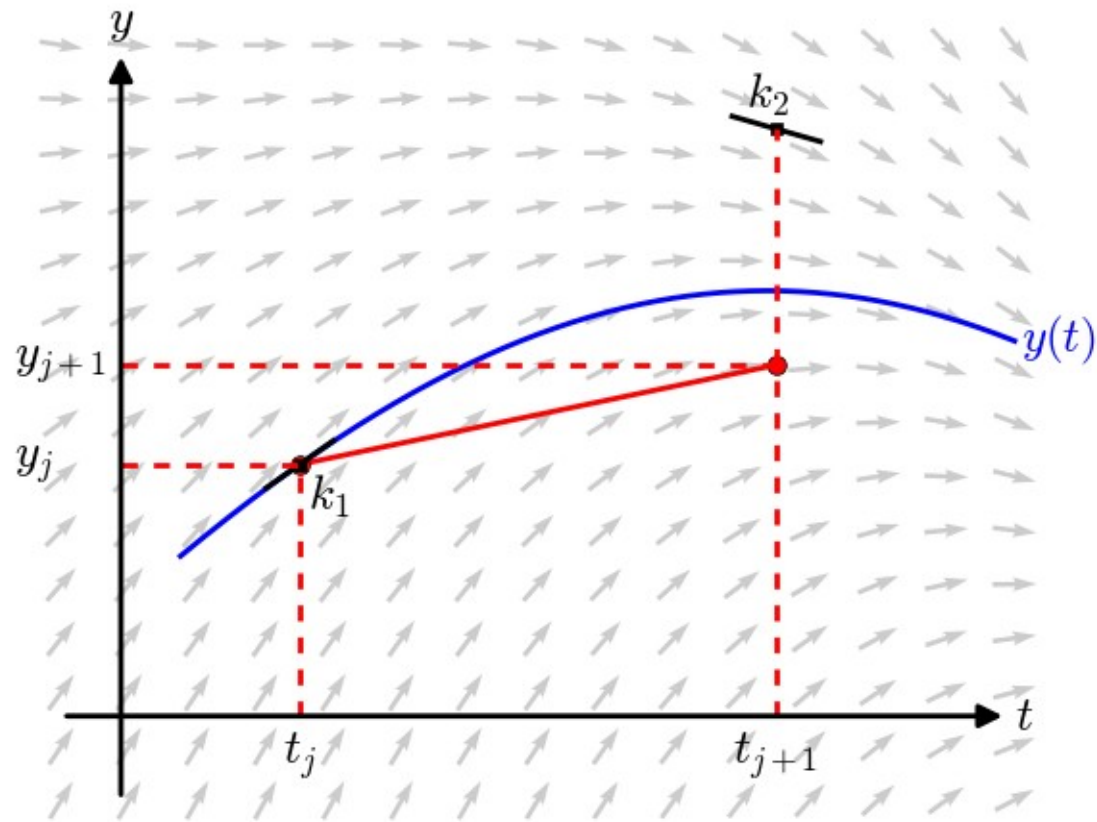
Ex. (11)

Runge's method



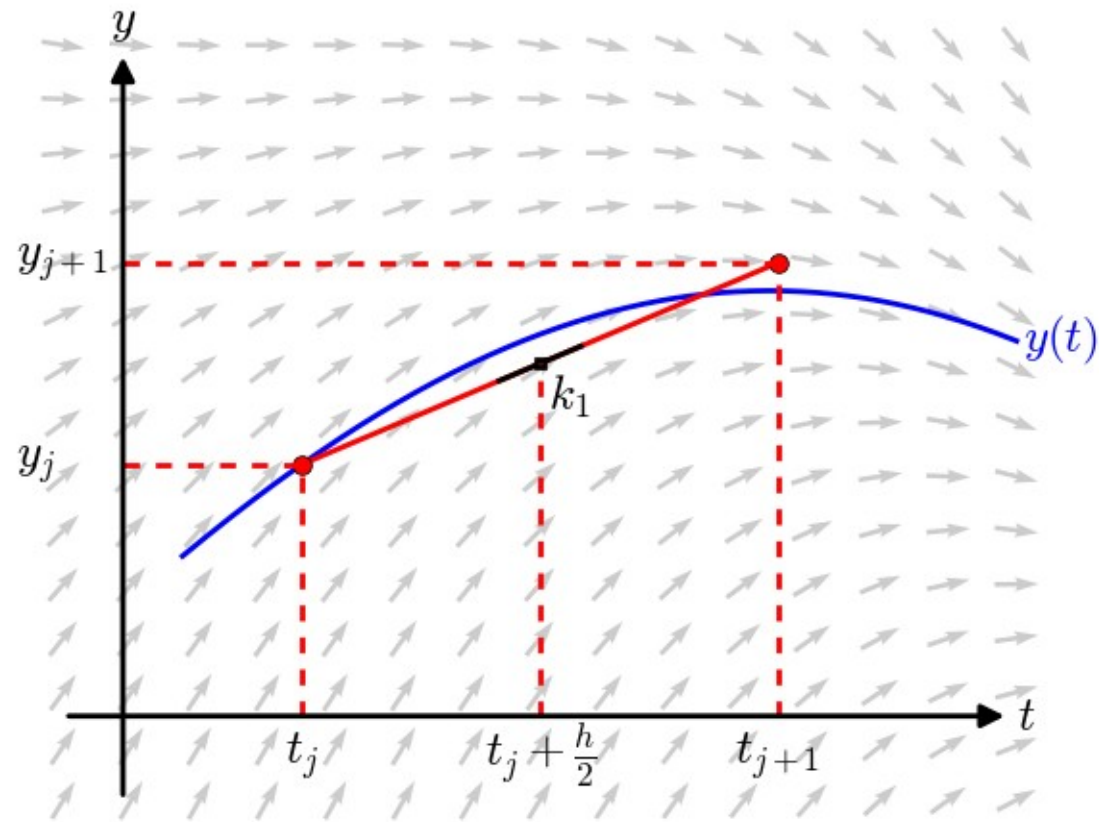
Ex. (11)

Heun's method



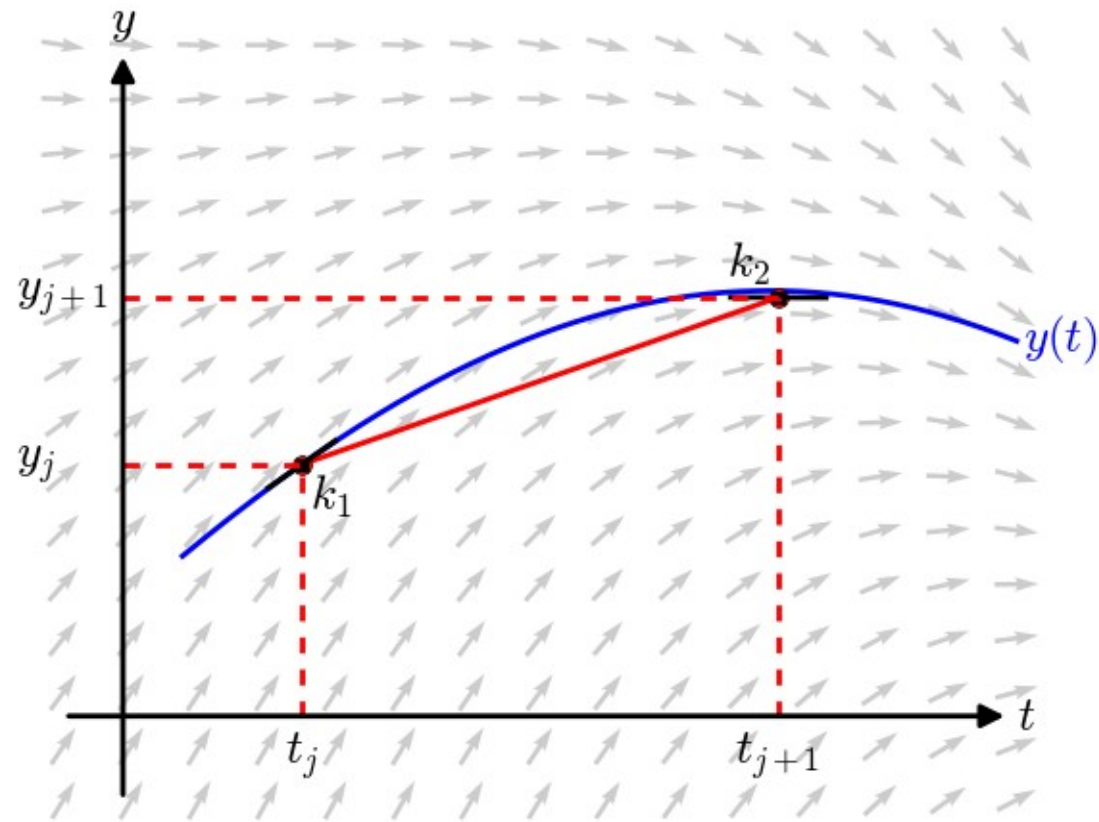
Ex. (11)

Implicit midpoint method



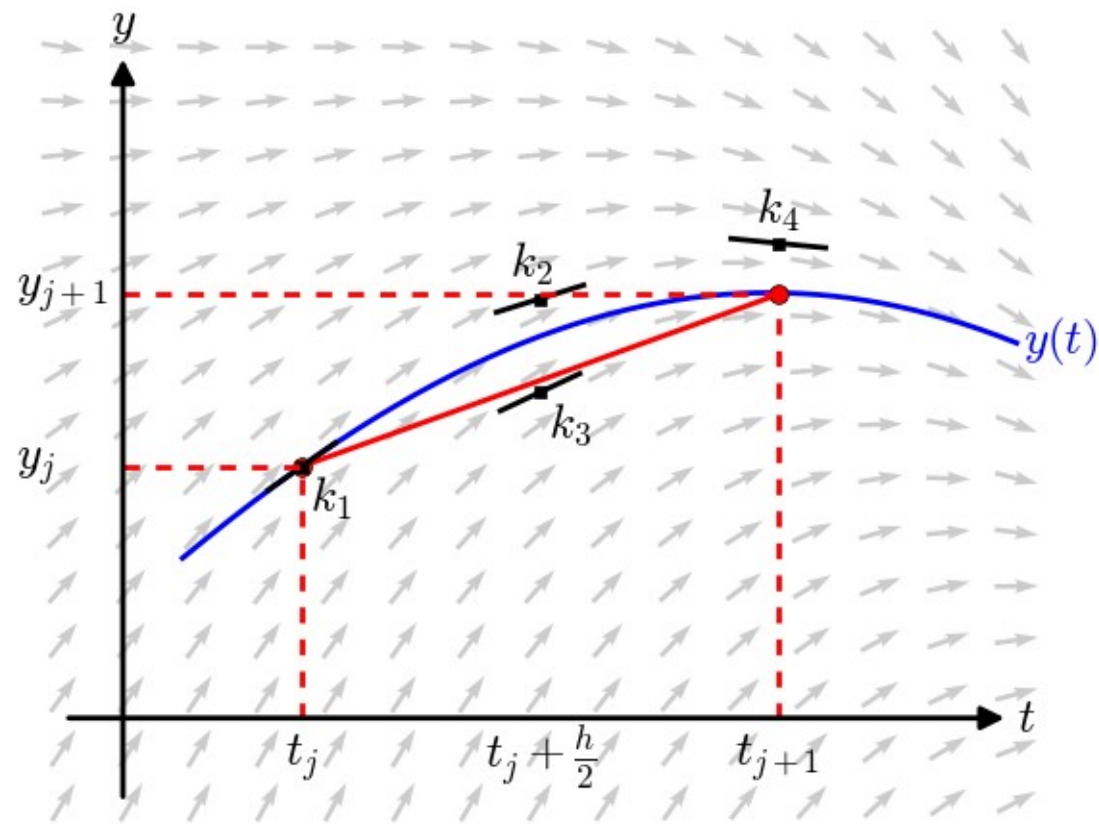
Ex. (11)

Implicit trapezoidal method



Ex. (11)

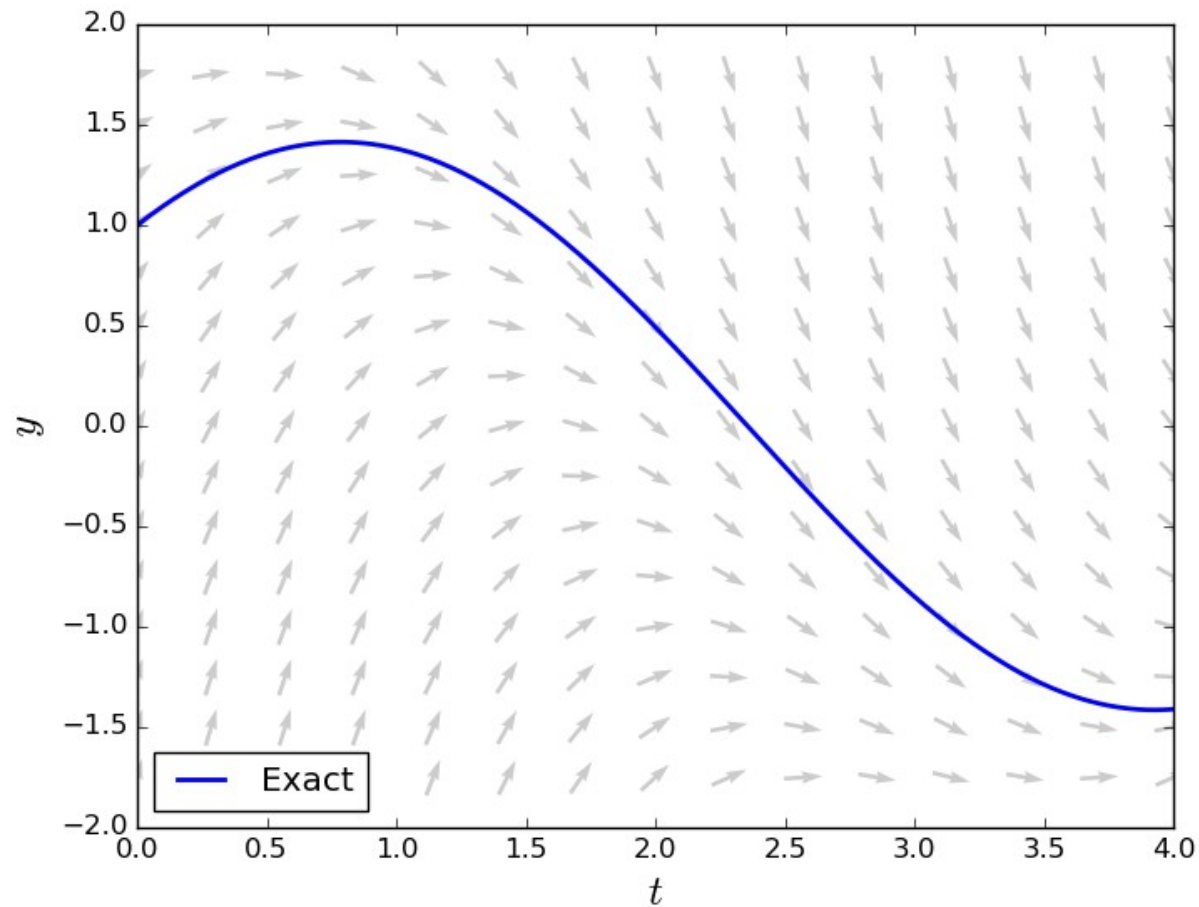
Classical Runge-Kutta (RK4)



Ex. (12)

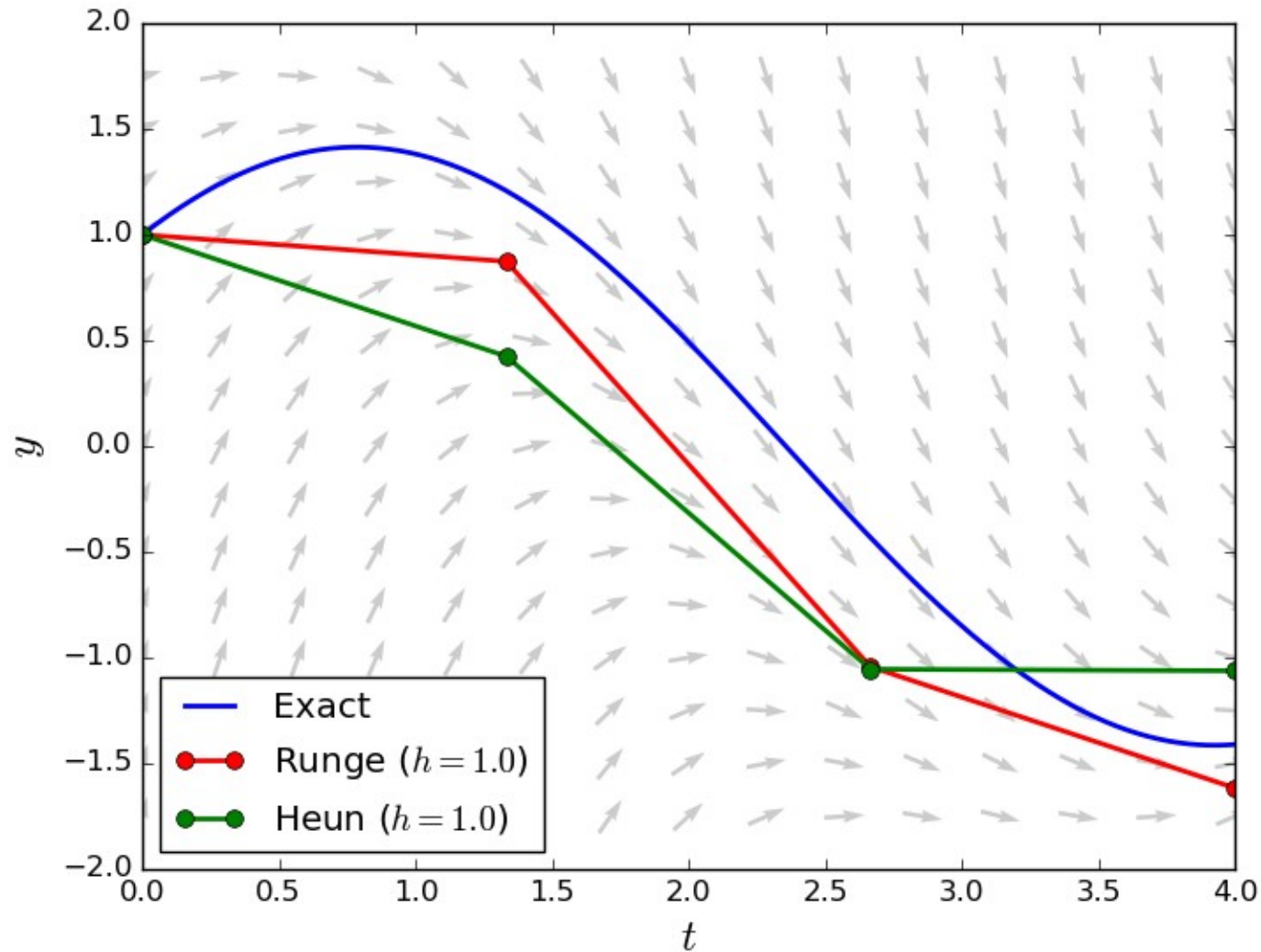
Example

IVP
$$\begin{cases} \dot{y}(t) = -y(t) + 2 \cos(t) \\ y(0) = 1 \end{cases} \quad y(t) = \sin(t) + \cos(t)$$



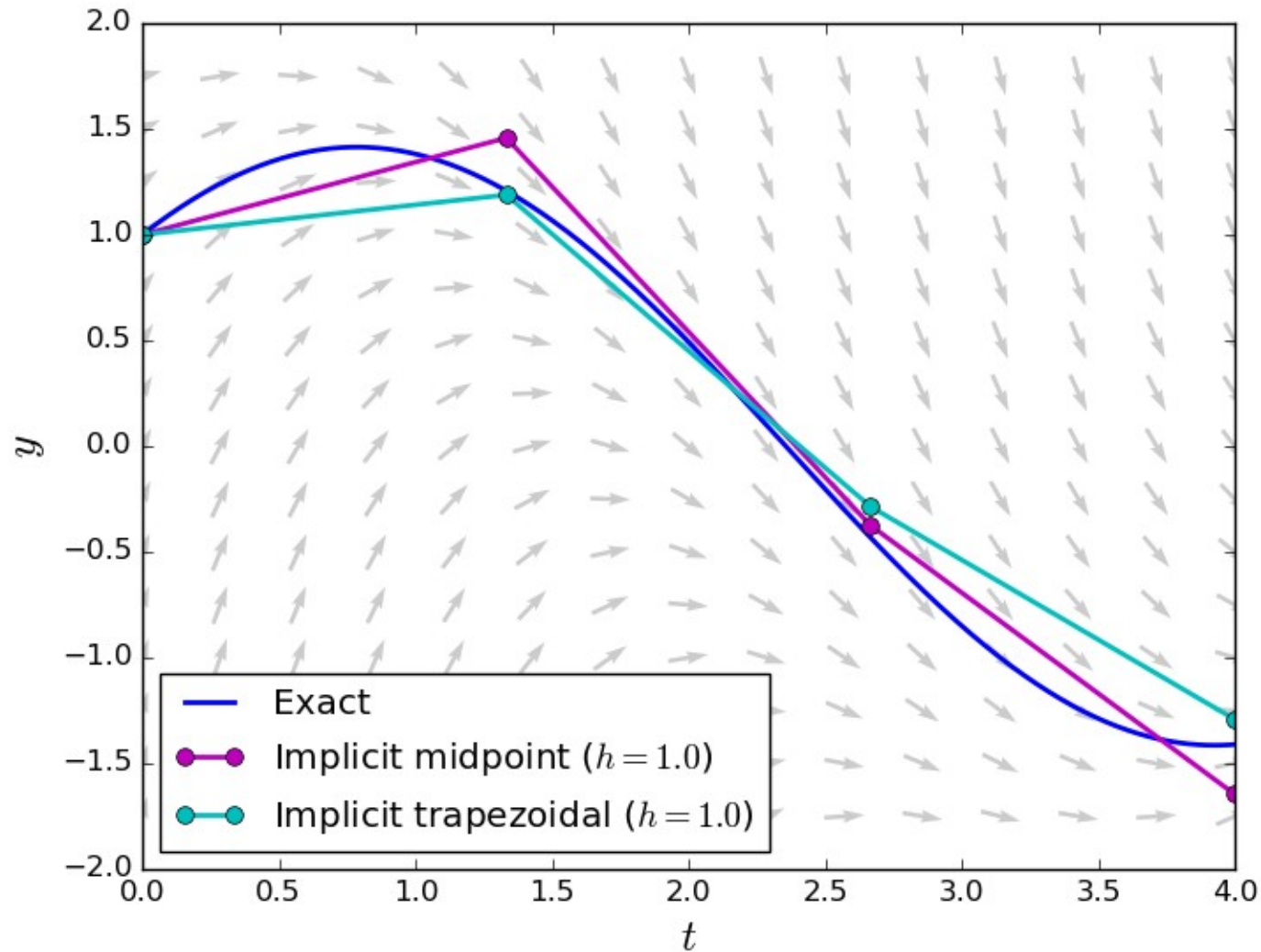
Ex. (12)

Runge's & Heun's method



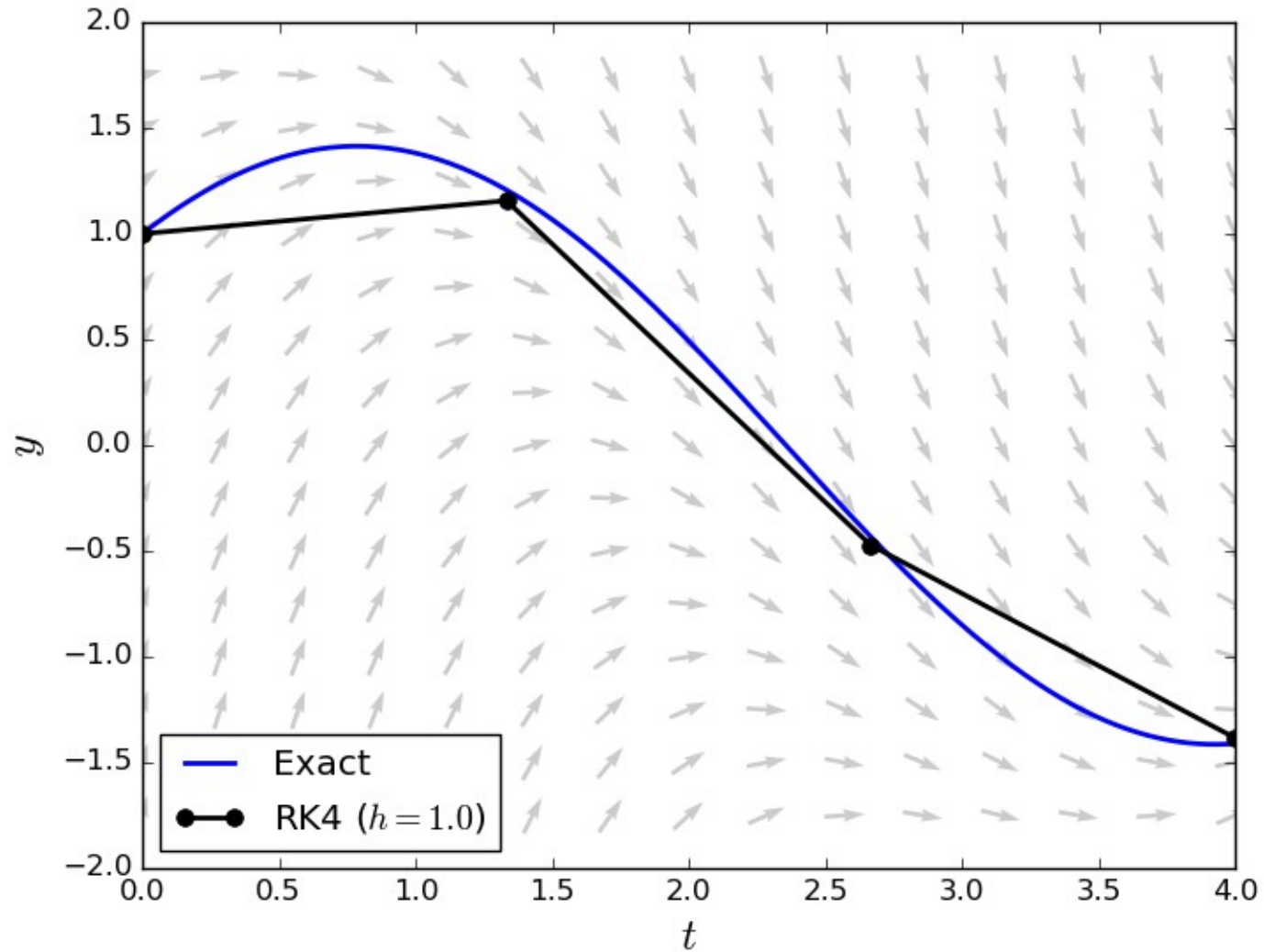
Ex. (12)

Implicit midpoint & trapezoidal



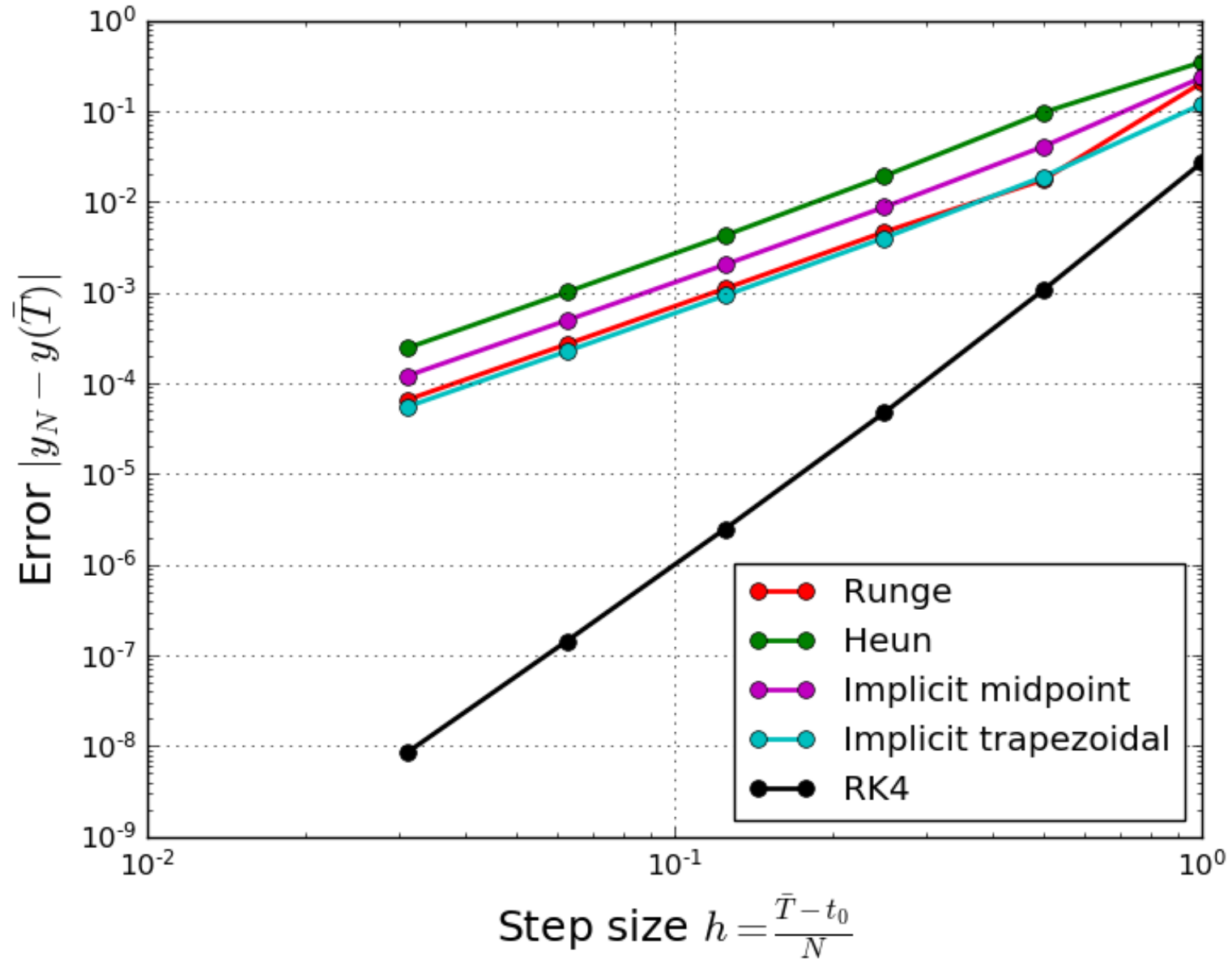
Ex. (12)

Runge-Kutta 4



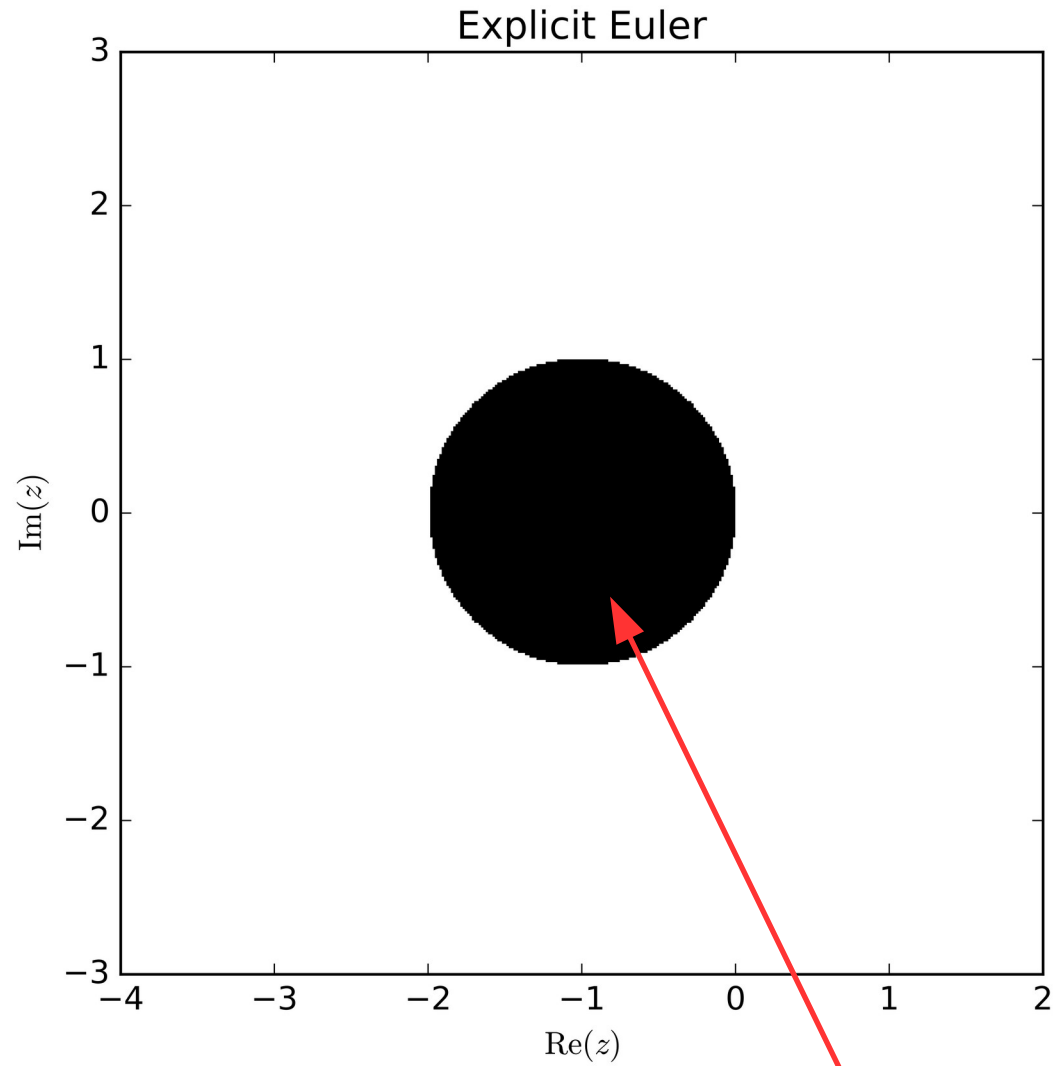
Ex. (12)

Errors



Ex. (15)

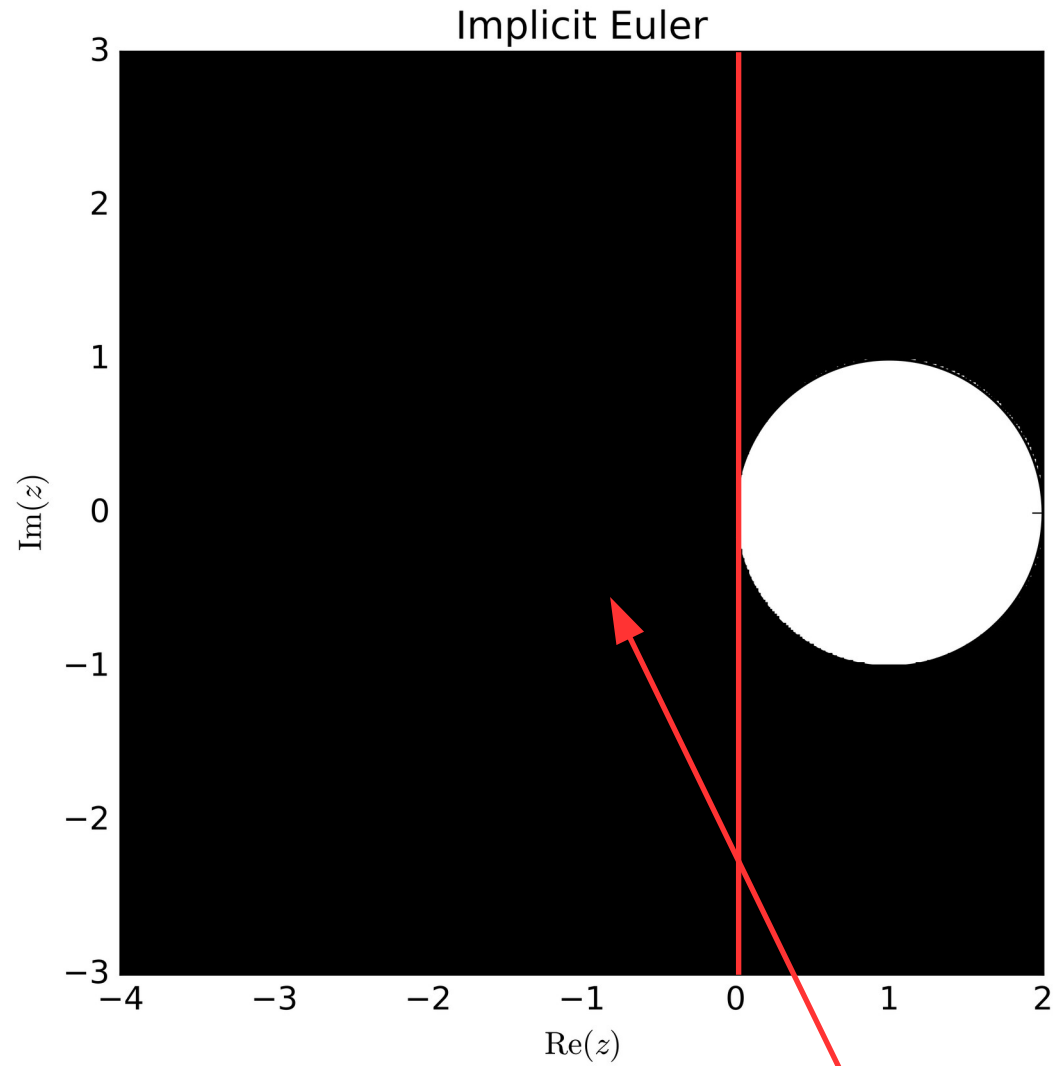
Stability Regions



Stability Region

Ex. (15)

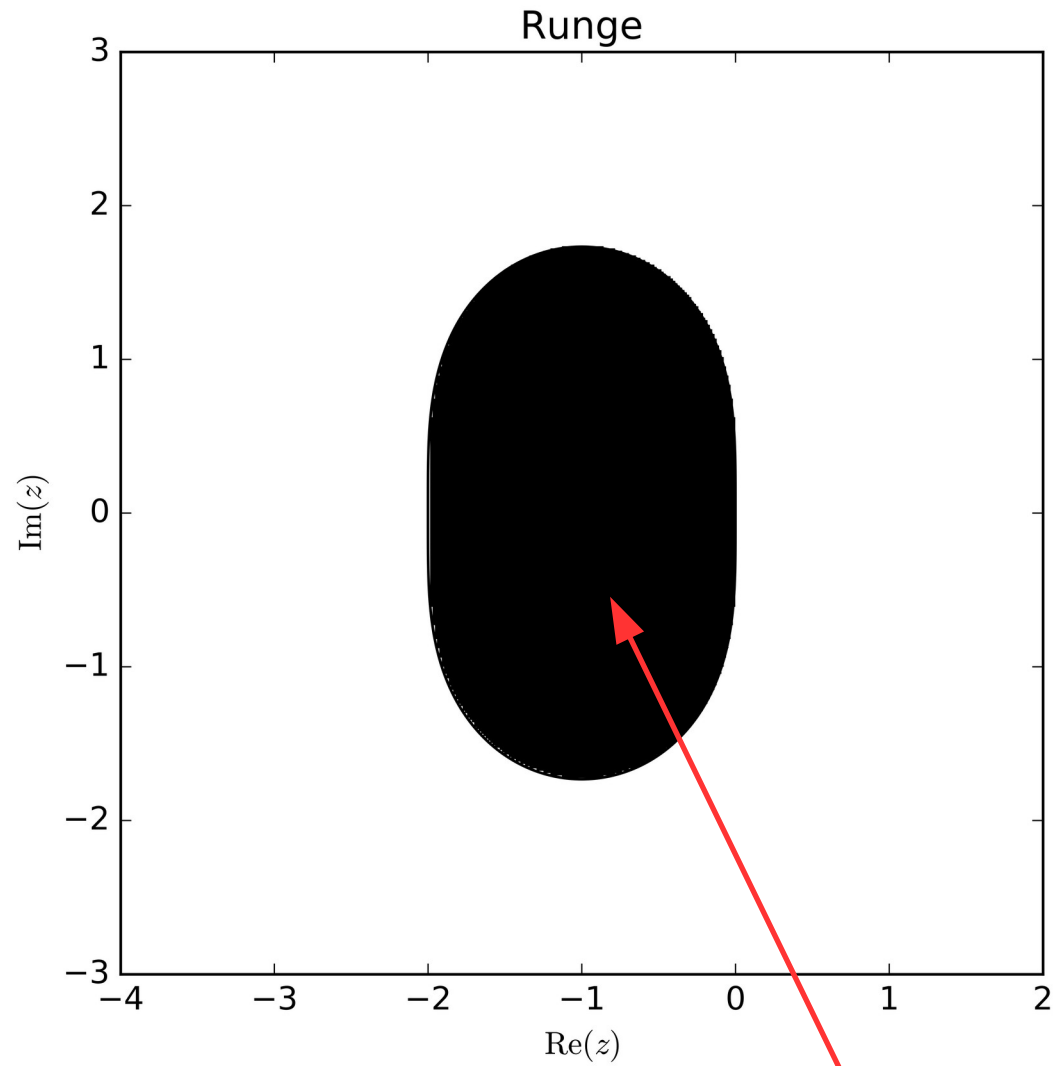
Stability Regions



Stability region

Ex. (15)

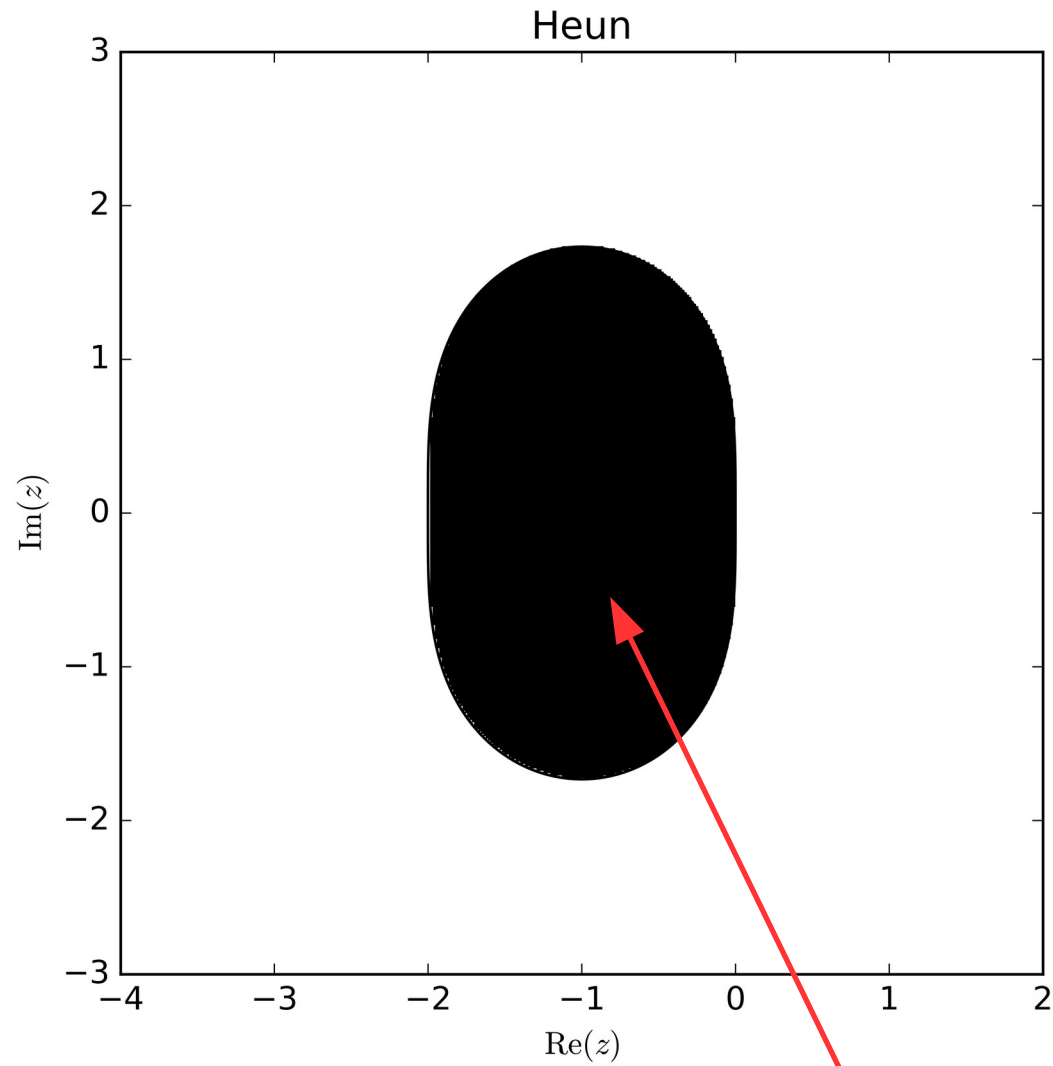
Stability Regions



Stability region

Ex. (15)

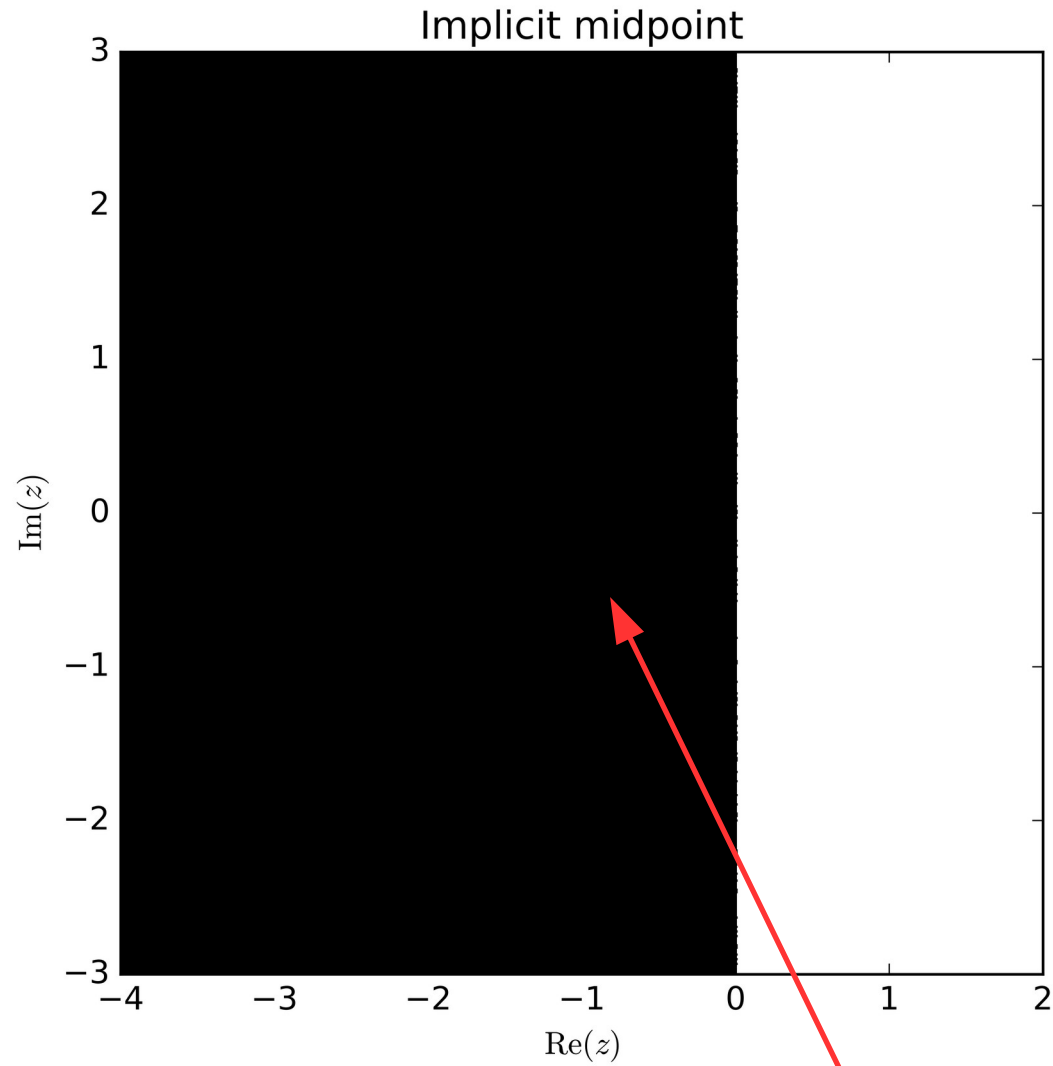
Stability Regions



Stability region

Ex. (15)

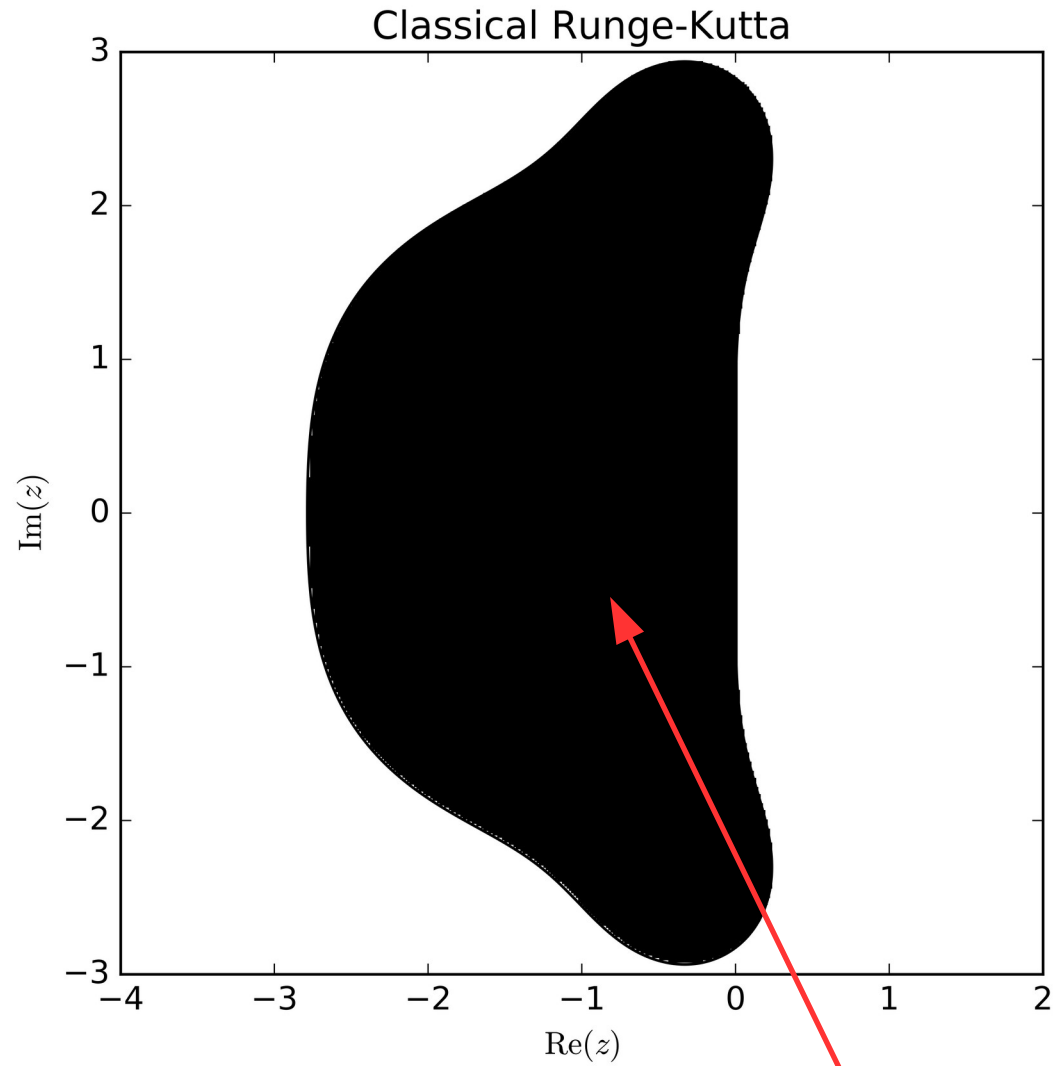
Stability Regions



Stability region

Ex. (15)

Stability Regions



Stability region

Ex. (16)

Stiff linear IVP


$$\dot{\mathbf{y}}(t) = A\mathbf{y}(t)$$

$$\mathbf{y} = \begin{pmatrix} y_1(t) \\ y_2(t) \\ y_3(t) \end{pmatrix} \quad A = \begin{pmatrix} -\frac{1}{2} & -\frac{869}{10} & \frac{1521}{5} \\ 0 & -\frac{227}{2} & \frac{591}{2} \\ 0 & \frac{591}{2} & -\frac{1803}{2} \end{pmatrix}$$

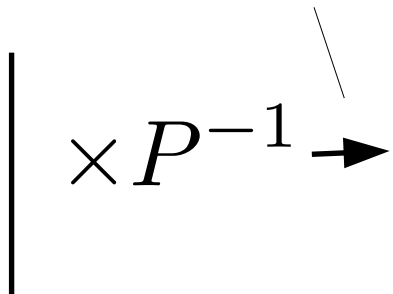
$$\mathbf{y}_0 = \begin{pmatrix} 1 \\ 6 \\ 2 \end{pmatrix} \quad 0 \leq t \leq 2$$

Stiff linear IVP

$$\begin{aligned}\dot{\mathbf{y}}(t) &= A\mathbf{y}(t) \\ &= PDP^{-1}\mathbf{y}(t)\end{aligned}$$


 Diagonal!

I.e. „from the left“


 $\times P^{-1} \rightarrow$

$$P^{-1}\dot{\mathbf{y}}(t) = D \underbrace{P^{-1}\mathbf{y}(t)}_{\mathbf{z}(t)}$$

$$\dot{\mathbf{z}}(t) = D\mathbf{z}(t)$$

Ex. (16)

Stiff linear IVP

Simple computations (e.g. with CAS!):

$$D = \begin{pmatrix} -\frac{1}{2} & 0 & 0 \\ 0 & -15 & 0 \\ 0 & 0 & -1000 \end{pmatrix}$$

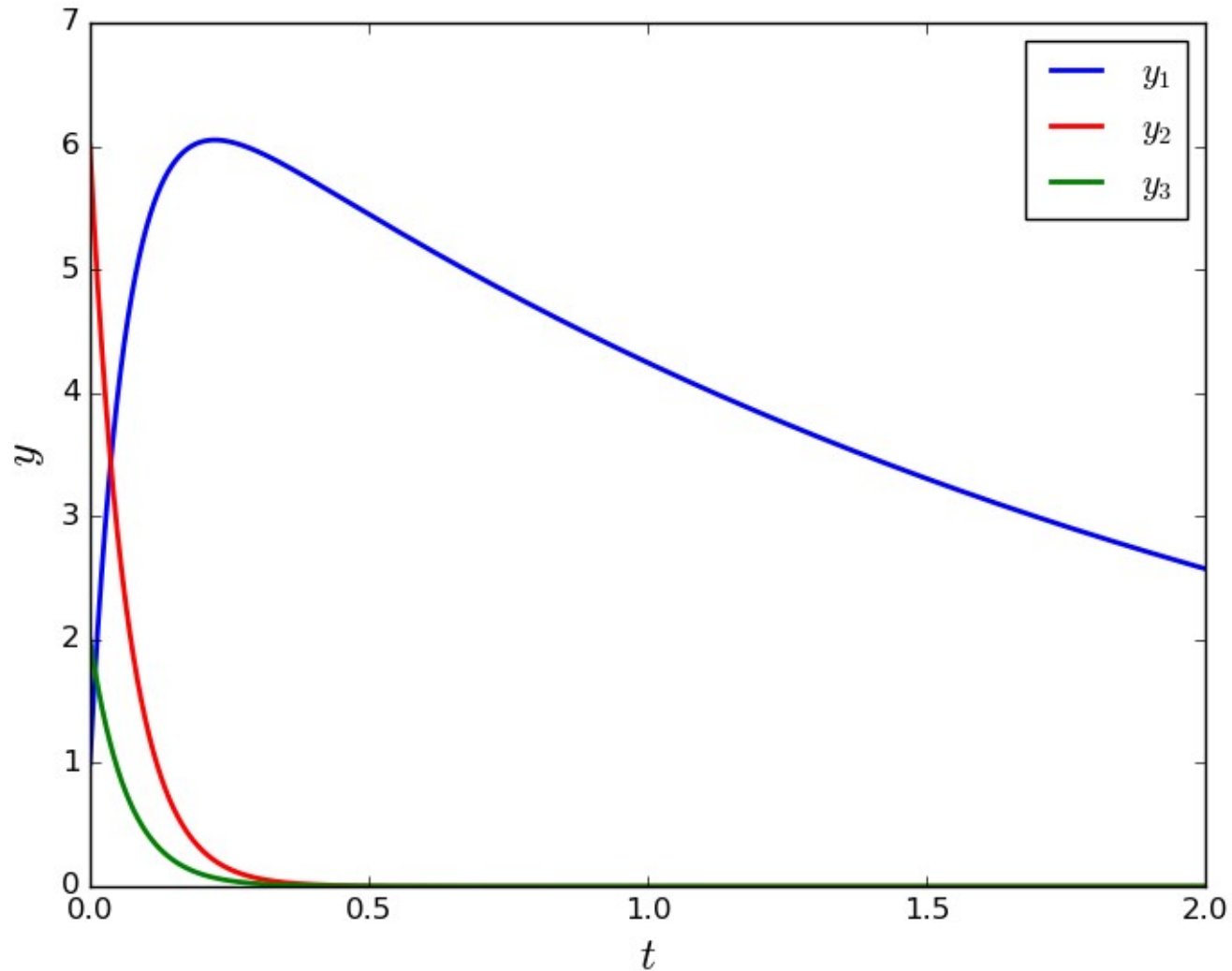
$$P = \begin{pmatrix} 15 & -12 & 1 \\ 0 & 12 & 1 \\ 0 & 4 & -3 \end{pmatrix} \quad P^{-1} = \begin{pmatrix} \frac{1}{15} & \frac{4}{75} & \frac{1}{25} \\ 0 & \frac{3}{40} & \frac{1}{40} \\ 0 & \frac{1}{10} & -\frac{3}{10} \end{pmatrix}$$

Plugging in the IV gives:

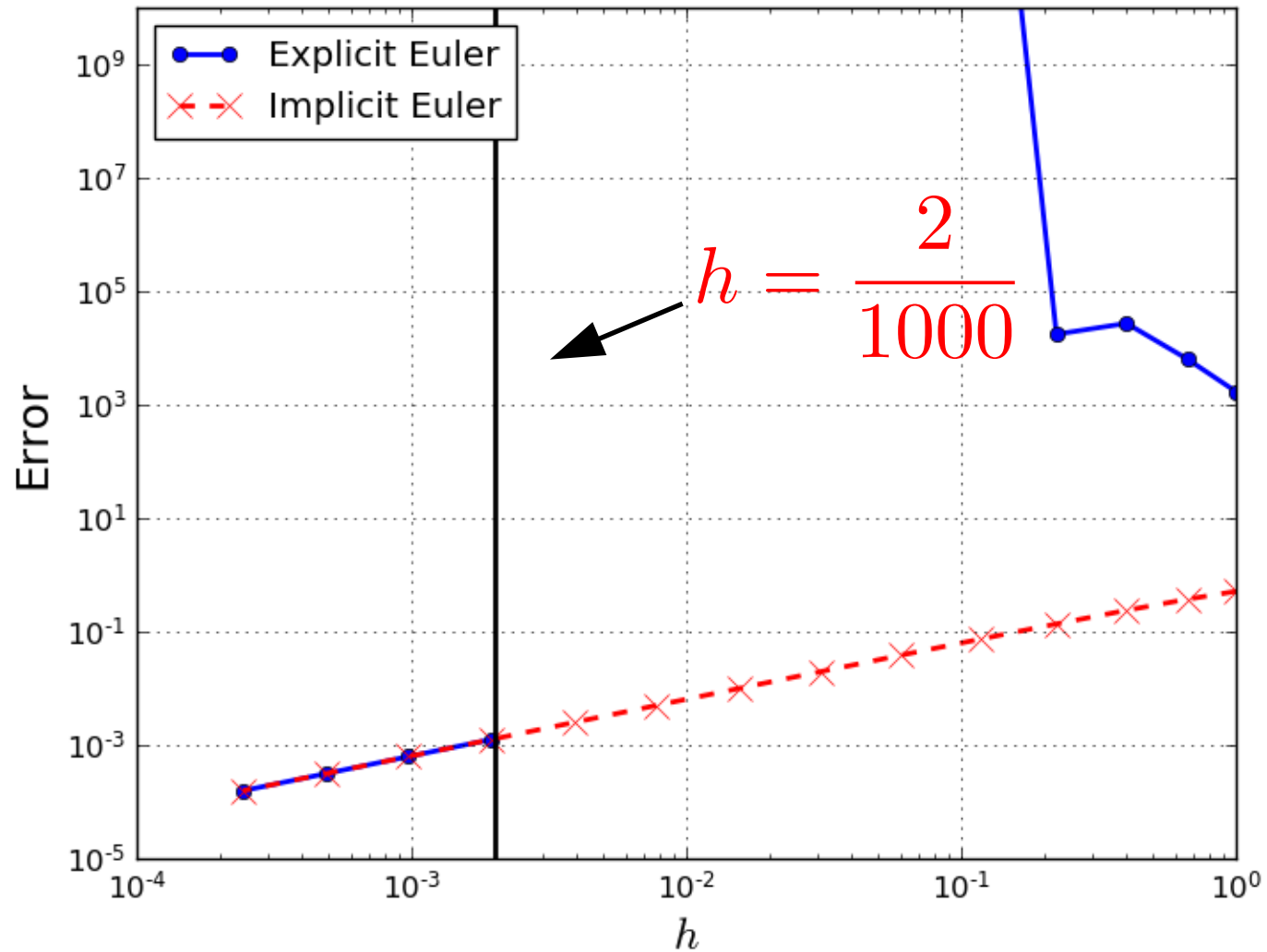
$$\mathbf{y}(t) = \begin{pmatrix} 7 \\ 0 \\ 0 \end{pmatrix} e^{-\frac{1}{2}t} + \begin{pmatrix} -6 \\ 6 \\ 2 \end{pmatrix} e^{-15t} + \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} e^{-1000t}$$

Ex. (16)

Stiff linear IVP



Stiff linear IVP



Stiff equations

A linear inhomogeneous system of ODEs

$$\dot{\vec{y}}(t) = A\vec{y}(t) + \vec{b}(t)$$

↙
n×n Matrix

is called stiff if the eigenvalues of

A , λ_i ($i=1,2,\dots,n$), have very different negative real parts:

$$S = \frac{\max_j |\operatorname{Re}(\lambda_j)|}{\min_j |\operatorname{Re}(\lambda_j)|}, \quad \operatorname{Re}(\lambda_j) < 0$$

That is: the stiffness ratio S is "large".

Ex. (17)

Stiff Nonlinear IVP

$$\begin{aligned}\dot{y}_A &= -0.1y_A + 100y_B y_C \\ \dot{y}_B &= +0.1y_A - 100y_B y_C - 500y_B^2 \\ \dot{y}_C &= +500y_B^2 - 0.5y_C\end{aligned}$$

$$y_A(0) = 0.5 \quad y_B(0) = 0.5 \quad y_C(0) = 0.5$$

$$0 \leq t \leq 1$$

Ex. (17)

Stiff Nonlinear IVP

$$\begin{aligned}\dot{y}_A &= -0.1y_A + 100y_B y_C \\ \dot{y}_B &= +0.1y_A - 100y_B y_C - 500y_B^2 \\ \dot{y}_C &= +500y_B^2 - 0.5y_C\end{aligned}$$

NON-LINEAR!!!

$$\mathbf{y} = \begin{pmatrix} y_A \\ y_B \\ y_C \end{pmatrix} \quad \mathbf{f}(t, \mathbf{y}) = \begin{pmatrix} -0.1y_A + 100y_B y_C \\ +0.1y_A - 100y_B y_C - 500y_B^2 \\ +500y_B^2 - 0.5y_C \end{pmatrix}$$

$$y_A(0) = 0.5 \quad y_B(0) = 0.5 \quad y_C(0) = 0.5 \quad \mathbf{y}_0 = \begin{pmatrix} 0.5 \\ 0.5 \\ 0.5 \end{pmatrix}$$

Local measure of stiffness

A local measure of stiffness is obtained by linearizing the system of ODEs at some point (of interest!) t_n, \vec{y}_n :

$$\begin{aligned} \vec{f}(t, \vec{y}) \approx & \vec{f}(t_n, \vec{y}_n) + \frac{\partial \vec{f}}{\partial t}(t_n, \vec{y}_n) \cdot (t - t_n) \\ & + \underbrace{\frac{\partial \vec{f}}{\partial \vec{y}}(t_n, \vec{y}_n)}_{\text{Jacobian matrix } \mathcal{J} = \frac{\partial \vec{f}}{\partial \vec{y}}} \cdot (\vec{y} - \vec{y}_n) \end{aligned}$$

So one obtains the following inhomogeneous linear system of ODEs

$$\dot{\vec{y}}(t) = \underbrace{\mathcal{J}(t_n, \vec{y}_n)}_A \vec{y}(t) + \underbrace{\left(\vec{f}(t_n, \vec{y}_n) + \frac{\partial \vec{f}}{\partial t}(t_n, \vec{y}_n) \cdot (t - t_n) - \mathcal{J}(t_n, \vec{y}_n) \vec{y}_n \right)}_{\vec{b}(t)}$$

Local measure of stiffness

$$\dot{\mathbf{y}}(t) = \overbrace{A(t_1, \mathbf{y}_1)}^{\text{Constant Matrix}} \mathbf{y}(t) + \overbrace{\mathbf{b}(t_1, \mathbf{y}_1)}^{\text{Constant Vector}}$$

If this is stiff, then one says that the nonlinear system of ODEs is locally stiff around (t_1, \vec{y}_1) .

Stiff Stiff Nonlinear IVP

Stiff?

Let's linearize the RHS:

$$\mathbf{f}(t, \mathbf{y}) = \begin{pmatrix} -0.1y_A + 100y_B y_C \\ +0.1y_A - 100y_B y_C - 500y_B^2 \\ +500y_B^2 - 0.5y_C \end{pmatrix}$$

$$\mathbf{f}(t, \mathbf{y}) \approx \mathbf{f}(t_1, \mathbf{y}_1) + \underbrace{\frac{\partial \mathbf{f}}{\partial t}(t_1, \mathbf{y}_1)}_0 + \underbrace{\frac{\partial \mathbf{f}}{\partial \mathbf{y}}(t_1, \mathbf{y}_1)}_{/}$$

$$J(t, \mathbf{y}) = \frac{\partial \mathbf{f}}{\partial \mathbf{y}}(t, \mathbf{y}) = \begin{pmatrix} -0.1 & 100y_C & 100y_B \\ +0.1 & -1000y_B - 100y_C & -100y_B \\ 0 & 1000y_B & -0.5 \end{pmatrix}$$

Stiff Nonlinear IVP

Locally Stiff?

Let's linearize the RHS at the initial value: $\mathbf{y}_0 = \begin{pmatrix} 0.5 \\ 0.5 \\ 0.5 \end{pmatrix}$

$$J(t_0, \mathbf{y}_0) = \frac{\partial \mathbf{f}}{\partial \mathbf{y}}(t_0, \mathbf{y}_0) = \begin{pmatrix} -0.1 & 50 & 50 \\ +0.1 & -550 & -50 \\ 0 & 500 & -0.5 \end{pmatrix}$$

MATLAB: eig \longrightarrow

$$\lambda_1 \approx -5.00 \times 10^2$$

$$\lambda_2 \approx -9.87 \times 10^{-4}$$

$$\lambda_3 \approx -5.07 \times 10^1$$

$$S = \frac{\max_j |\operatorname{Re}(\lambda_j)|}{\min_j |\operatorname{Re}(\lambda_j)|} \approx 5.06 \times 10^5$$

Yes!!!

Error control and adaptive step size

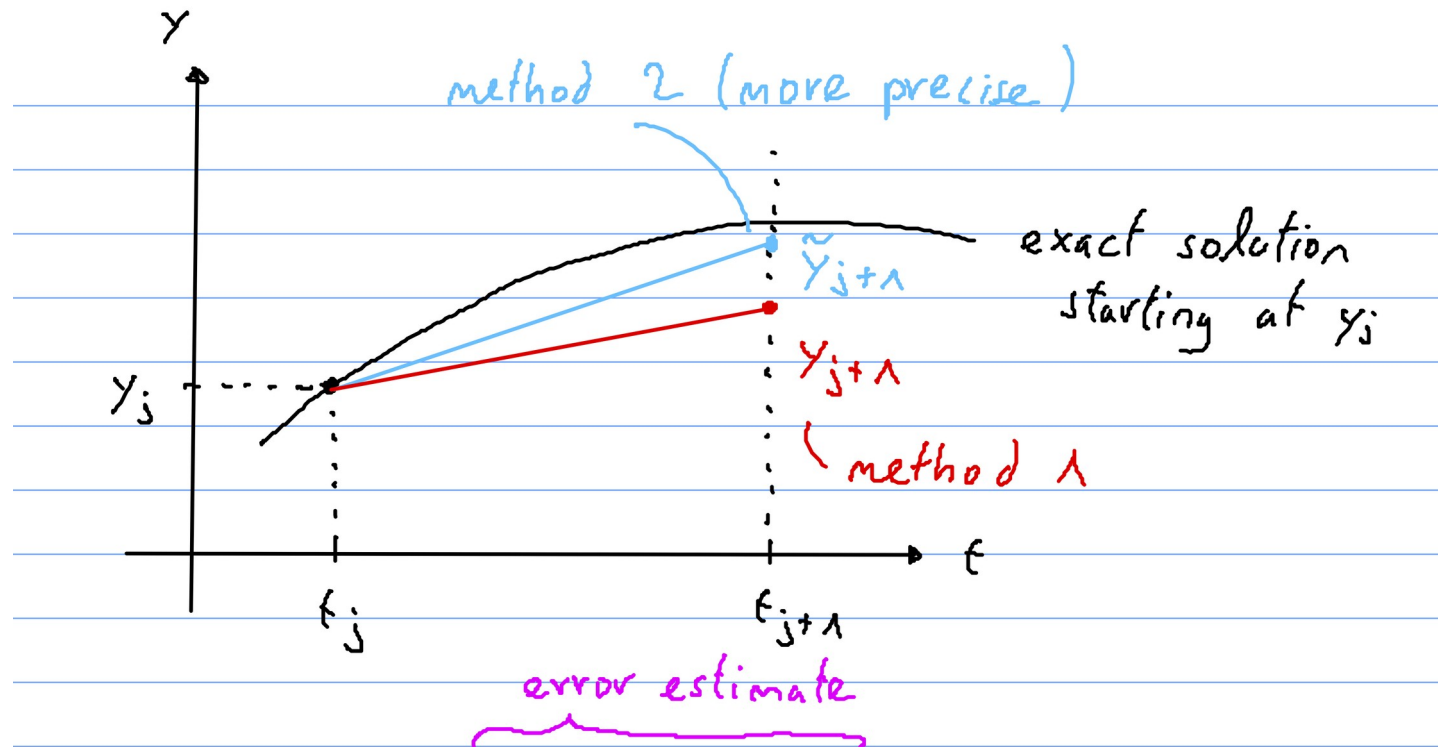
In practice, one wants to choose the step size (the h !) sufficiently small to ensure some required precision and sufficiently large to avoid unnecessary computational work.

To achieve this, we need some local error estimate to indicate if the step size should be "small" or "large".

Idea: perform a step with two methods, where a first method is compared to the result of a second, more precise, method

↳ the digits that match are assumed to be correct !

Error control and adaptive step size



Now: IF: $|y_{j+1} - \tilde{y}_{j+1}| \leq \text{tolerance}$

accept step

AbsTol or
RelTol in
MATLAB

Else:

repeat step with smaller step size
and check again

Error control and adaptive step size

Rem.: (i) the more precise method (method 2) could be of higher order than method 1

or method 2 could be the same as method 1 but with a smaller step size h (substeps!)

(ii) the above pseudo-code is far from complete as one also wishes to increase the step size if possible

(iii) no guarantee that the error estimate reflects the true error.

However, often works well in practice.

Ex. (18)

Error control and adaptive step size

Ex.: (18) Adaptive step size method (MATLAB ode45)
for the van der Pol ODE:

$$\dot{y}_1 = y_2$$

$$\dot{y}_2 = \mu(1 - y_1^2)y_2 - y_1$$

with $\mu = 1$ and $\vec{y} = \begin{pmatrix} 2 \\ 0 \end{pmatrix}$, $t \in [0, 20]$

no slides

(locally)
makes the problem stiff!

(19) ^h with $\mu = 1000$ and $t \in [0, 3000]$

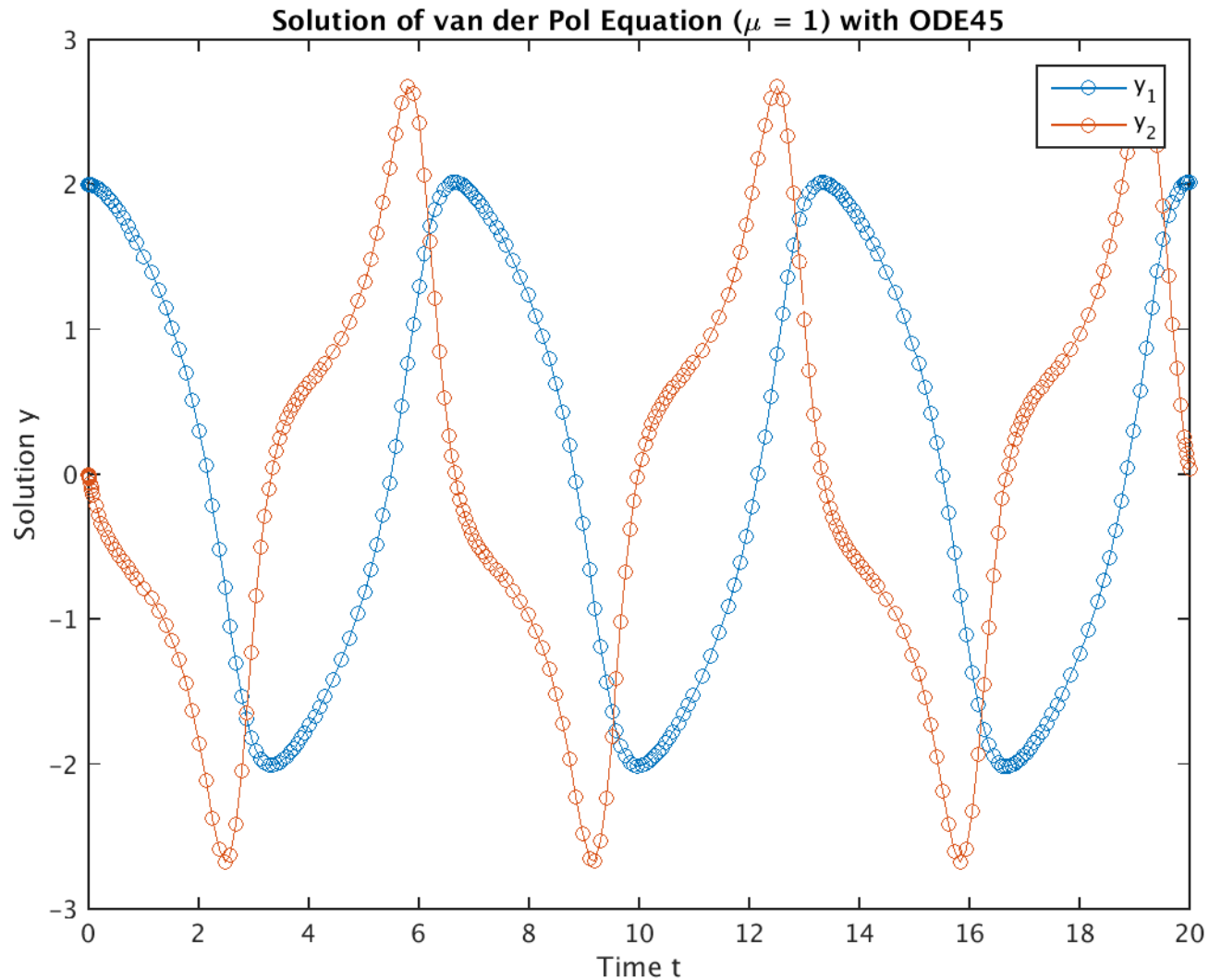
no slides & exercises

Ex. (18)

Adaptive step size

$$\dot{y}_1 = y_2$$

$$\dot{y}_2 = \mu(1 - y_1^2)y_2 - y_1 \quad \mu = 1 \quad \mathbf{y}_0 = \begin{pmatrix} 0 \\ 2 \end{pmatrix} \quad t \in [0, 20]$$

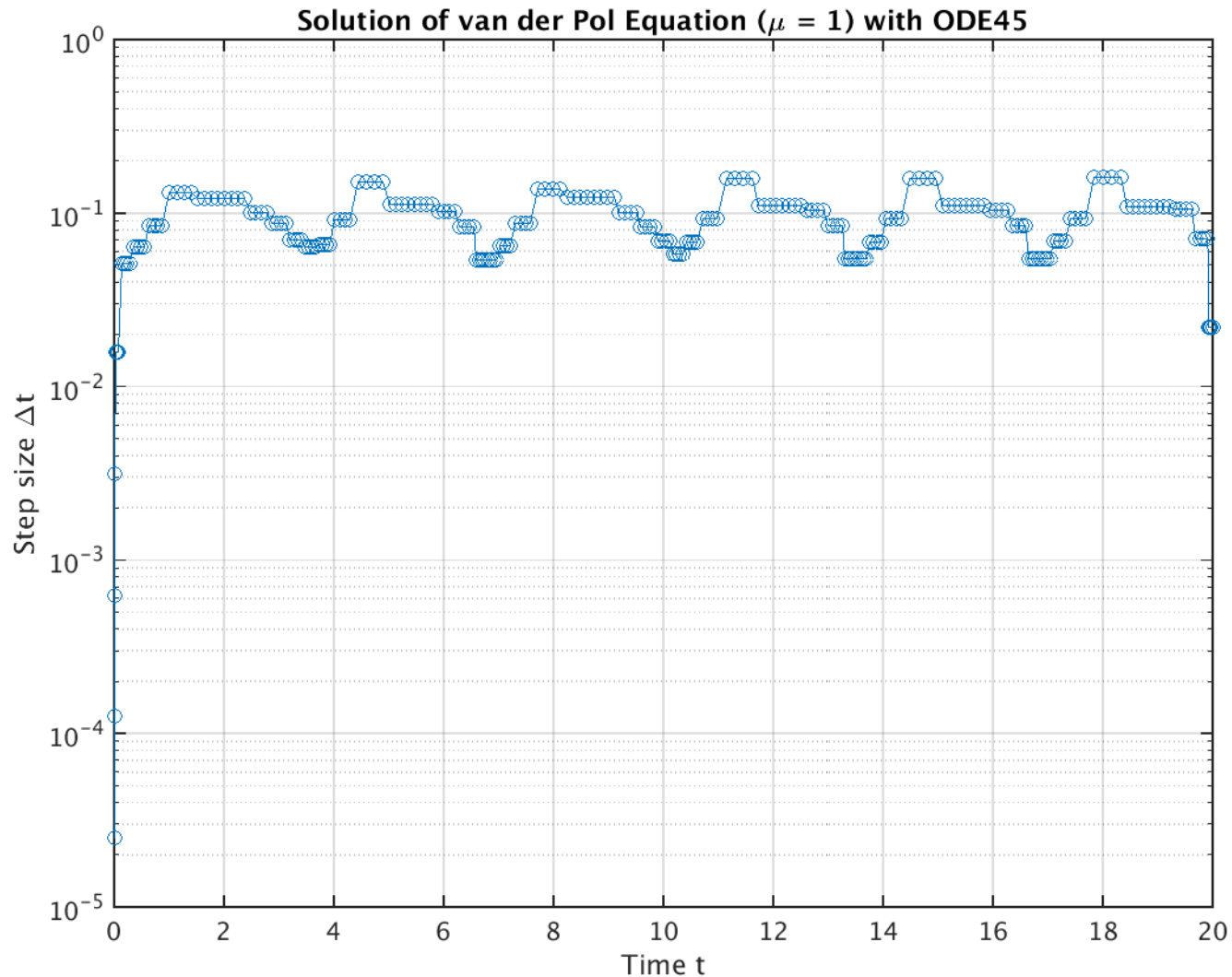


Ex. (18)

Adaptive step size

$$\dot{y}_1 = y_2$$

$$\dot{y}_2 = \mu(1 - y_1^2)y_2 - y_1 \quad \mu = 1 \quad y_0 = \begin{pmatrix} 0 \\ 2 \end{pmatrix} \quad t \in [0, 20]$$

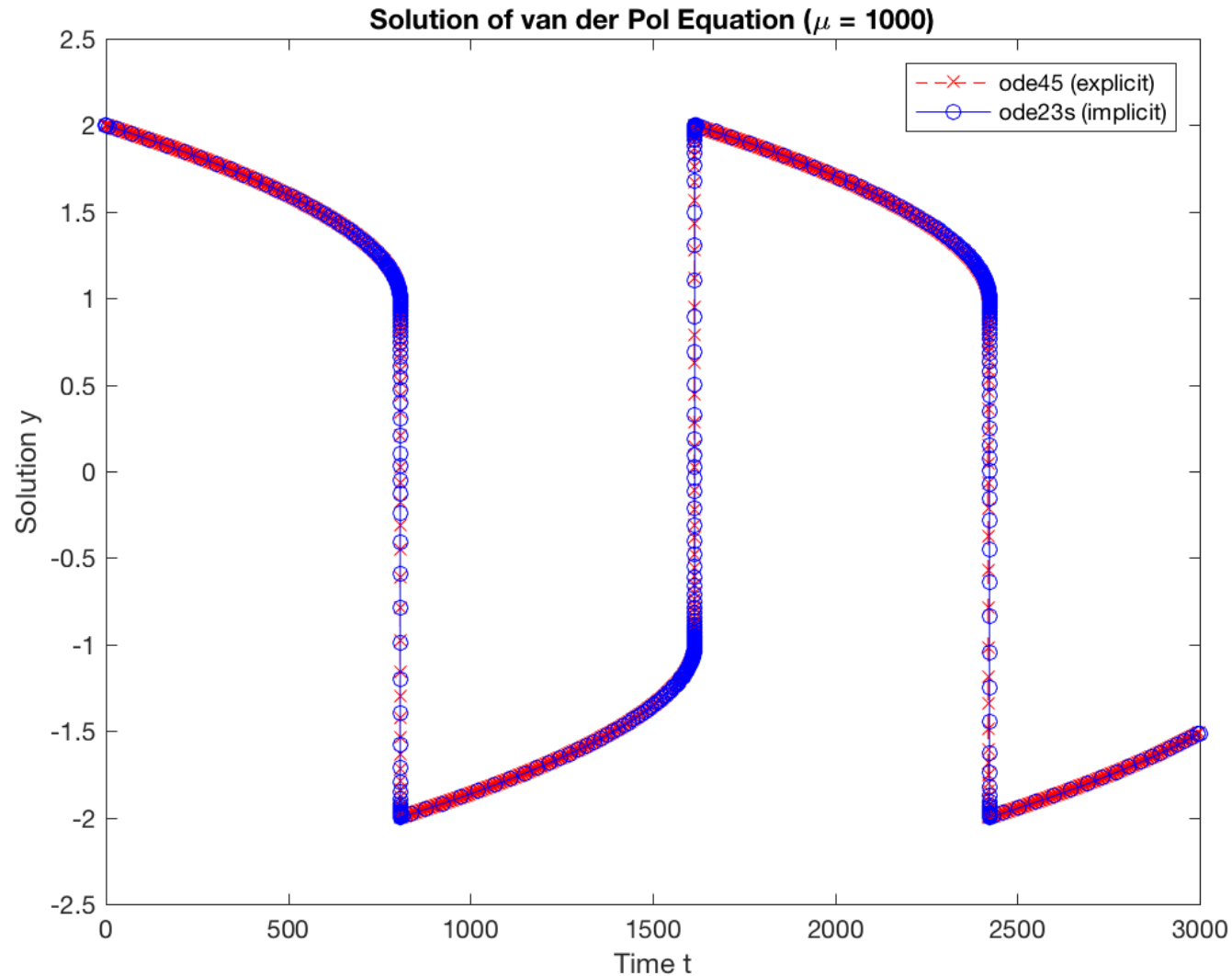


Ex. (19)

Adaptive step size

$$\dot{y}_1 = y_2$$

$$\dot{y}_2 = \mu(1 - y_1^2)y_2 - y_1 \quad \mu = 1000 \quad y_0 = \begin{pmatrix} 0 \\ 2 \end{pmatrix} \quad t \in [0, 3000]$$

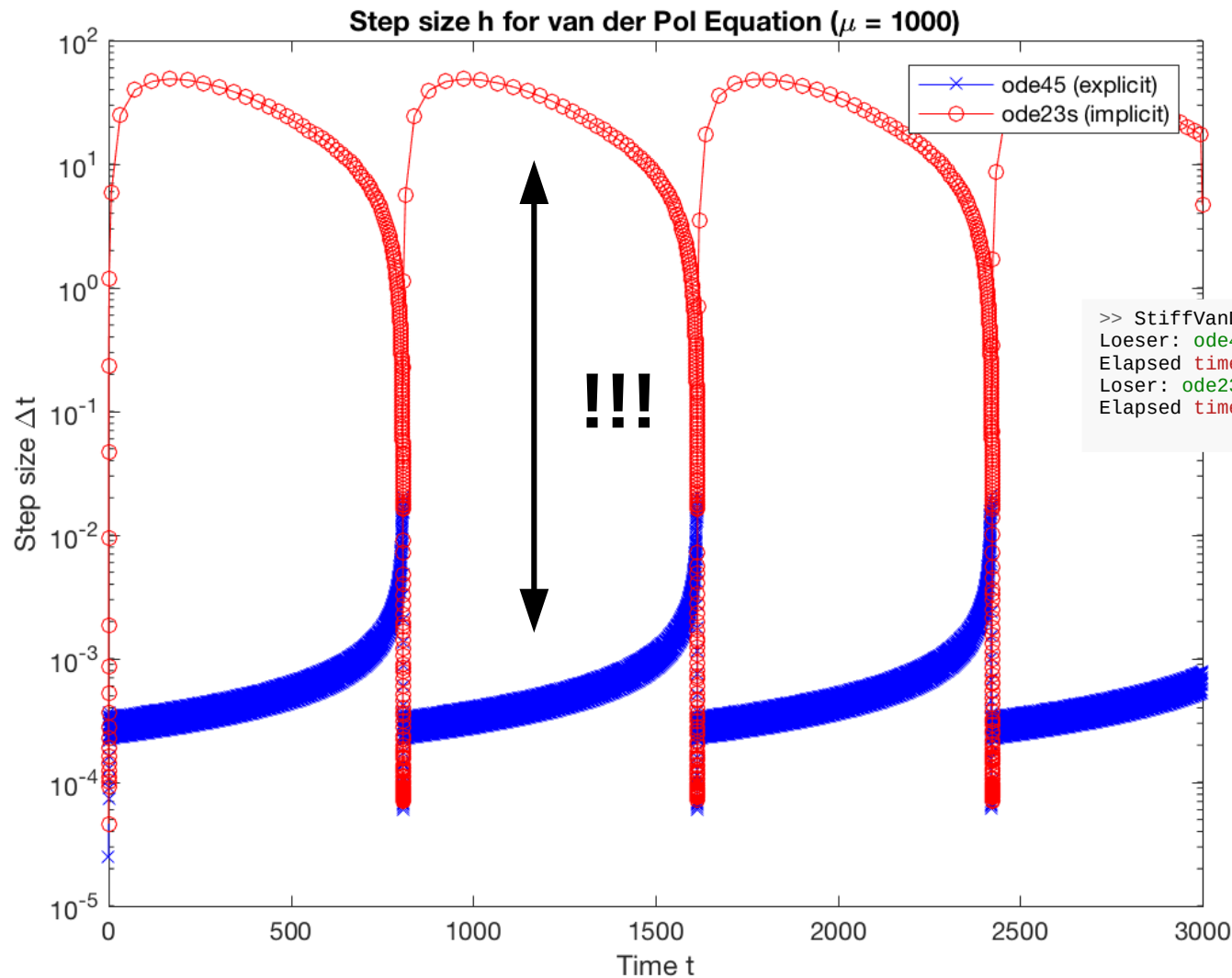


Ex. (19)

Adaptive step size

$$\dot{y}_1 = y_2$$

$$\dot{y}_2 = \mu(1 - y_1^2)y_2 - y_1 \quad \mu = 1000 \quad y_0 = \begin{pmatrix} 0 \\ 2 \end{pmatrix} \quad t \in [0, 3000]$$



```
>> StiffVanDerPol  
Loeser: ode45  
Elapsed time is 73.490408 seconds.  
Loser: ode23s  
Elapsed time is 0.167961 seconds.
```

Ex. (19)

Adaptive step size

$$\dot{y}_1 = y_2$$

$$\dot{y}_2 = \mu(1 - y_1^2)y_2 - y_1 \quad \mu = 1000 \quad y_0 = \begin{pmatrix} 0 \\ 2 \end{pmatrix} \quad t \in [0, 3000]$$

