Scientific Computation and Differential Equations

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Within Scientific Computation, the approximate solution of differential equations has always been an area of special challenge.

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- We will then look at some particular questions concerning the theory of general linear methods.

We will also look at some aspects of their practical implementation.

A short history of numerical differential equations

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A short history of numerical ODEs

We will make use of three standard types of initial value problems

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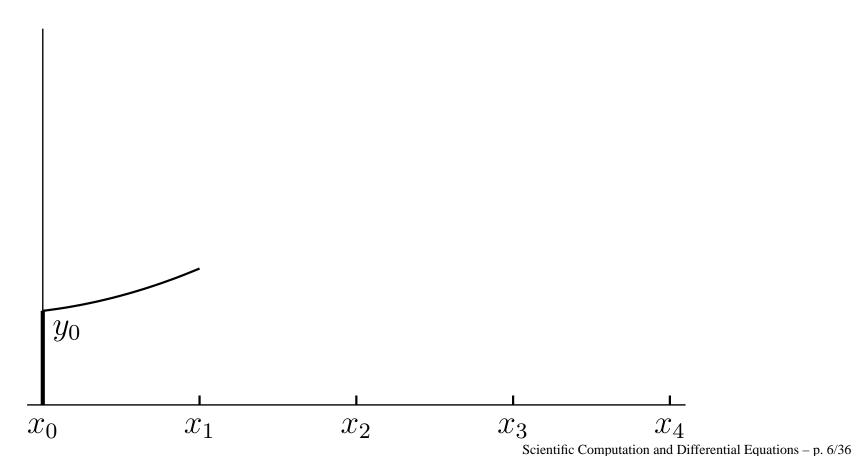
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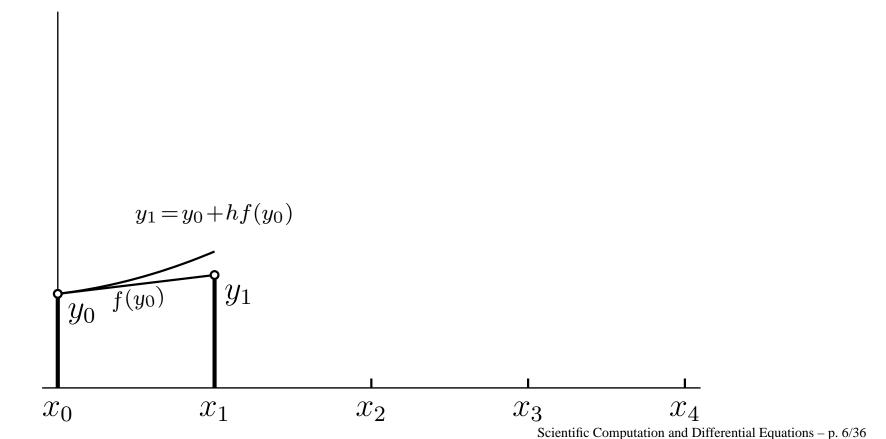
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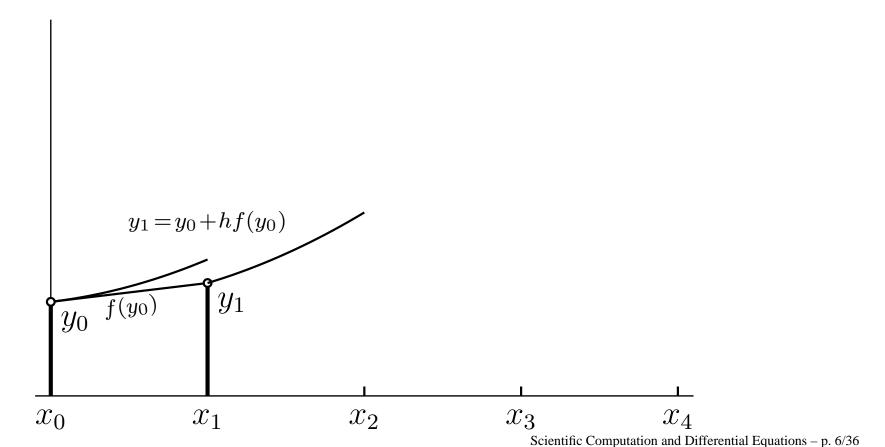
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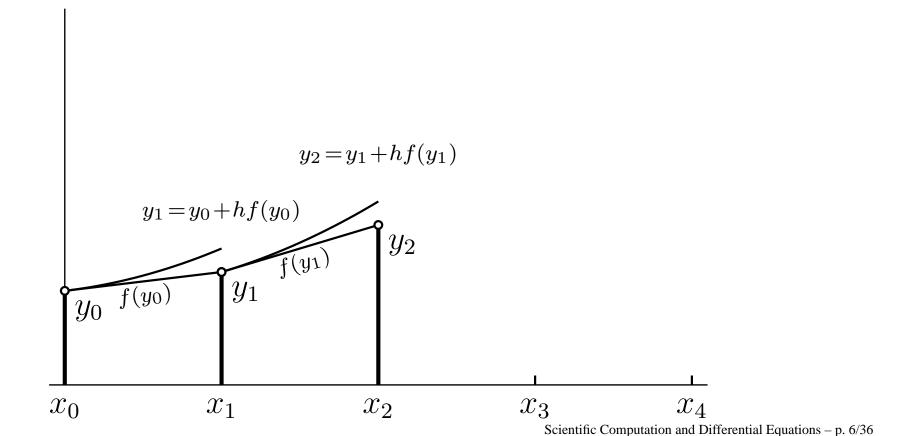
These are actually equivalent and we will often use (3) instead of (2) because of its simplicity.

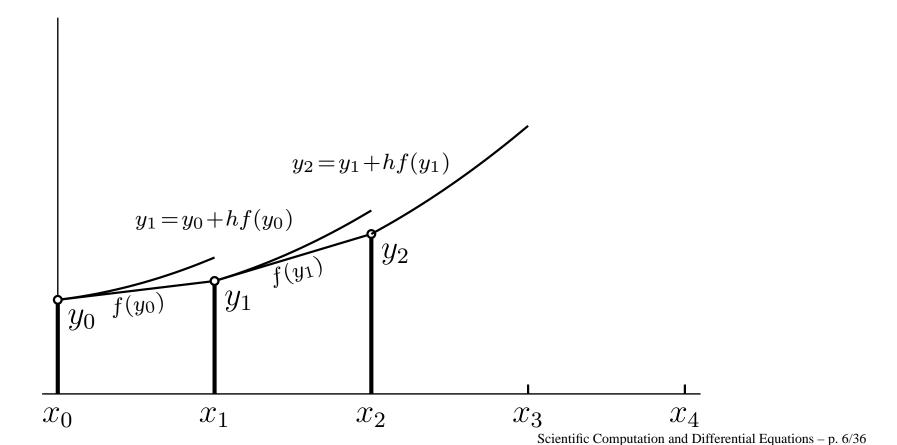
Euler proposed a simple numerical scheme in approximately 1770; this can be used for a system of first order equations.

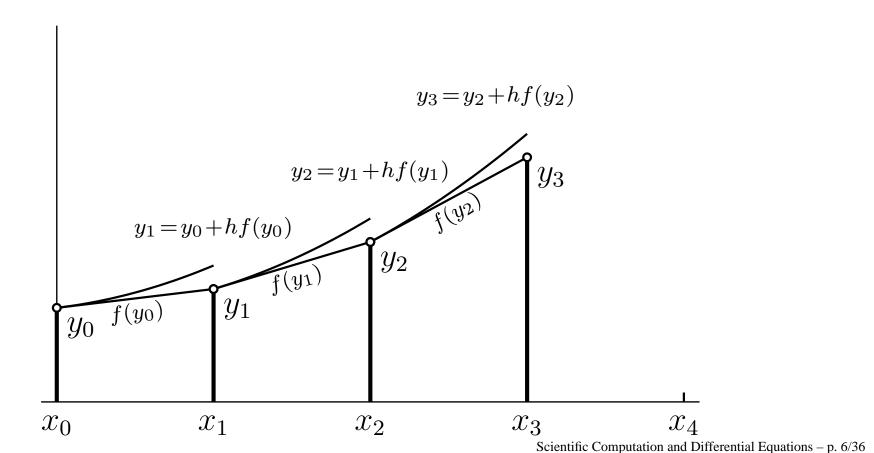


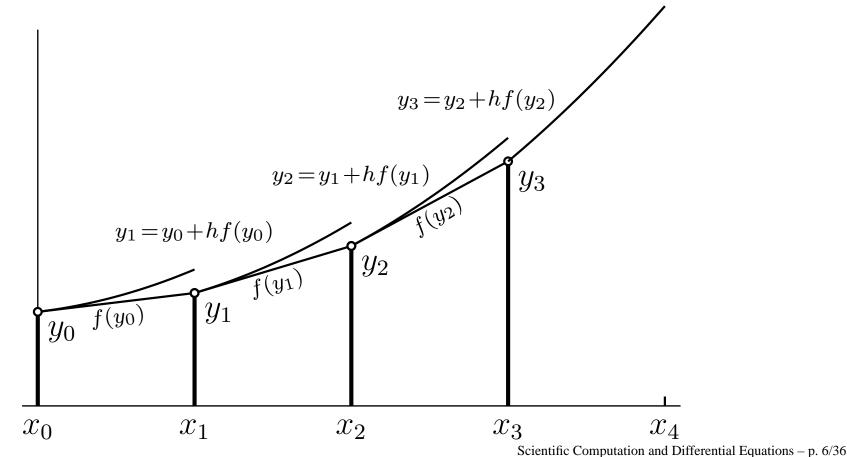


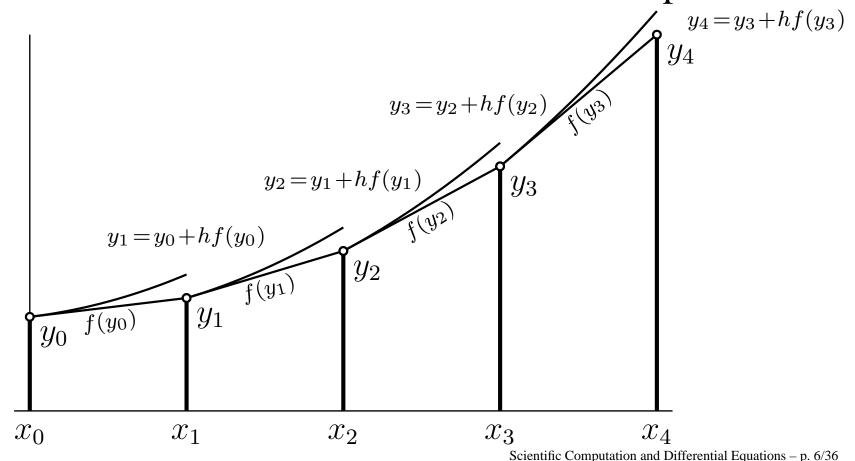












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1. Using more past history

- Linear multistep methods

2. Doing more complicated calculations in each step

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3. Doing both of these

- General linear methods

Some important dates

- 1883 Adams & Bashforth
- 1895 Runge
- 1901 Kutta
- 1925 Nyström
- 1926 Moulton

Linear multistep methods

Runge-Kutta method

Special methods for second order Adams-Moulton method

1952 Curtiss & Hirschfelder Stiff problems

Linear multistep methods

We will write the differential equation in autonomous form

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Linear multistep methods base the approximation to $y(x_n)$ on a linear combination of approximations to $y(x_{n-i})$ and approximations to $y'(x_{n-i})$, i = 1, 2, ..., k.

A linear multistep method can be written as

$$y_{n} = \sum_{i=1}^{k} \alpha_{i} y_{n-i} + h \sum_{i=0}^{k} \beta_{i} f_{n-i}$$

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$$Y_i = y_{n-1} + h \sum_{j=1}^s a_{ij} f(Y_j), \quad i = 1, 2, \dots, s,$$

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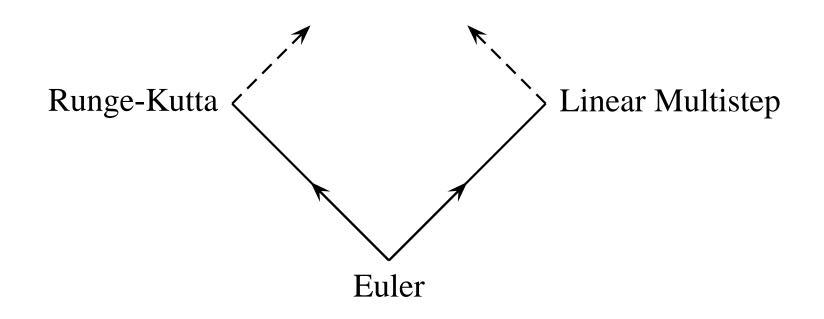
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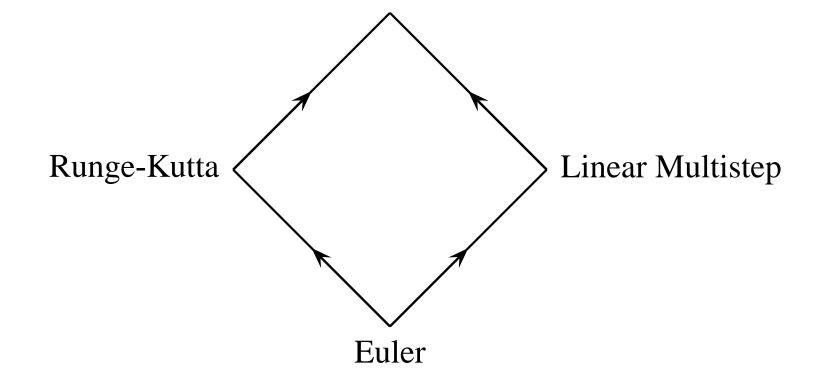
This is an *s*-stage 1-value method.

It is natural to ask if there are useful methods which are multistage (as for Runge–Kutta methods) and multivalue (as for linear multistep methods).

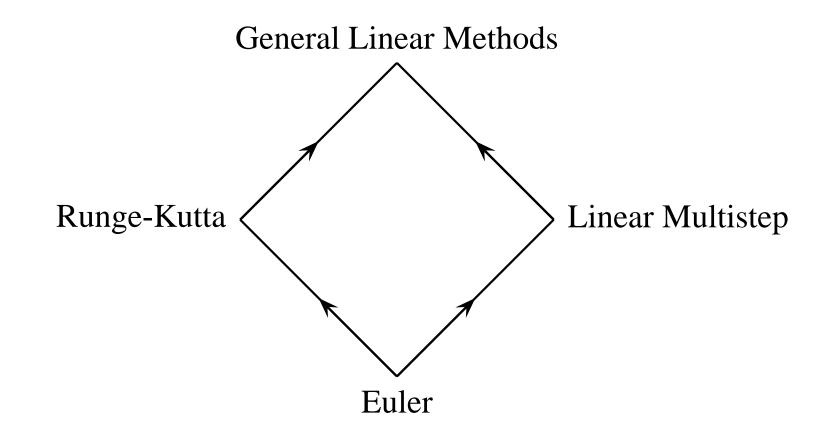
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General linear methods

We will consider methods characterised by an $(s+r) \times (s+r)$ partitioned matrix of the form $s \neq \left[\overbrace{A \mid U}_{--- \downarrow ---}^{s} R \mid V\right].$

The *r* values input to step n - 1 will be denoted by $y_i^{[n-1]}$, i = 1, 2, ..., r with corresponding output values $y_i^{[n]}$ and the stage values by Y_i , i = 1, 2, ..., s.

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The stage derivatives will be denoted by $F_i = f(Y_i)$.

The formula for computing the stages (and simultaneously the stage derivatives) are:

$$Y_{i} = h \sum_{j=1}^{s} a_{ij} F_{j} + \sum_{j=1}^{r} u_{ij} y_{j}^{[n-1]}, \quad F_{i} = f(Y_{i}),$$

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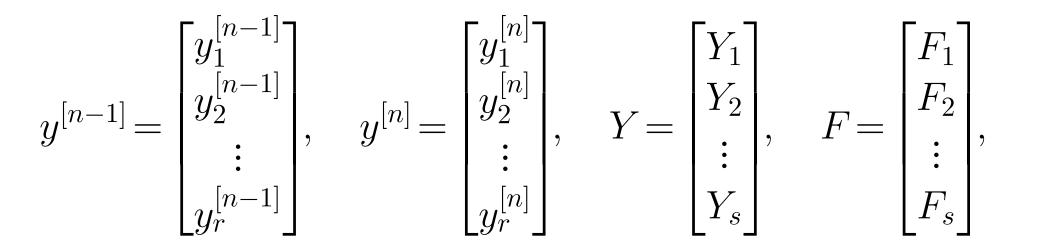
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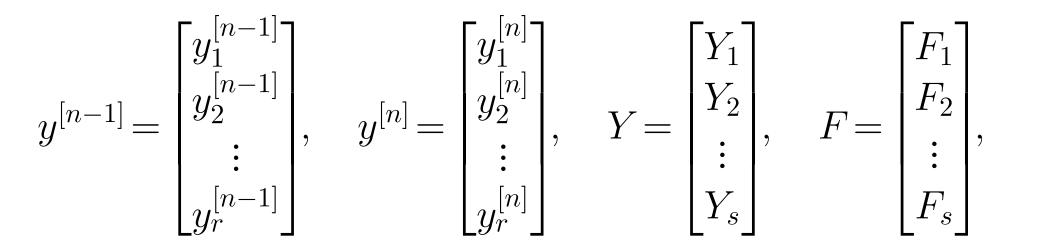
To compute the output values, use the formula

$$y_i^{[n]} = h \sum_{j=1}^s b_{ij} F_j + \sum_{j=1}^r v_{ij} y_j^{[n-1]}, \quad i = 1, 2, \dots, r.$$

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so that we can write the calculations in a step more simply as

$$\begin{bmatrix} Y\\ y^{[n]} \end{bmatrix} = \begin{bmatrix} A & U\\ B & V \end{bmatrix} \begin{bmatrix} hF\\ y^{[n-1]} \end{bmatrix}$$

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A Runge–Kutta method

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- A modified linear multistep method

One of the famous families of fourth order methods of Kutta, written as a general linear method, is

$$\begin{bmatrix} A & U \\ B & V \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ \theta & 0 & 0 & 0 & 1 \\ \frac{1}{2} - \frac{1}{8\theta} & \frac{1}{8\theta} & 0 & 0 & 1 \\ \frac{1}{2\theta} - 1 & -\frac{1}{2\theta} & 2 & 0 & 1 \\ \frac{1}{6} & 0 & \frac{2}{3} & \frac{1}{6} & 1 \end{bmatrix}$$

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In a step from x_{n-1} to $x_n = x_{n-1} + h$, the stages give approximations at

 x_{n-1} , $x_{n-1} + \theta h$, $x_{n-1} + \frac{1}{2}h$ and $x_{n-1} + h$.

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 and $x_{n-1} + h.$

We will look at the special case $\theta = -\frac{1}{2}$.

In the special $\theta = -\frac{1}{2}$ case $\begin{bmatrix} A & U \\ B & V \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ -\frac{1}{2} & 0 & 0 & 0 & 1 \\ -\frac{1}{2} & 0 & 0 & 0 & 1 \\ \frac{3}{4} & -\frac{1}{4} & 0 & 0 & 1 \\ -2 & 1 & 2 & 0 & 1 \\ \hline -\frac{1}{6} & 0 & \frac{2}{3} & \frac{1}{6} & 1 \end{bmatrix}$ In the special $\theta = -\frac{1}{2}$ case

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Because the derivative at

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This will save one function evaluation.

A 're-use' method

This gives the re-use method

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- Stepsize change is complicated and difficult
- The stability region is smaller

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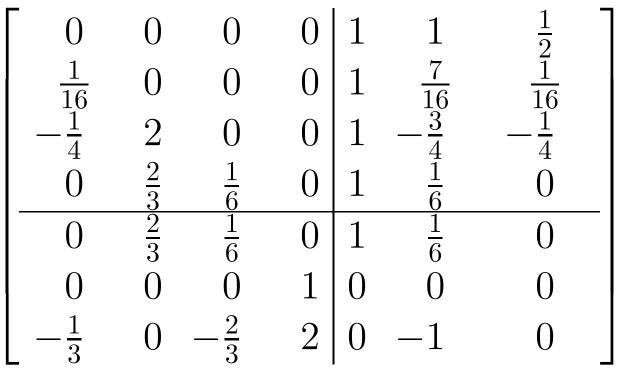
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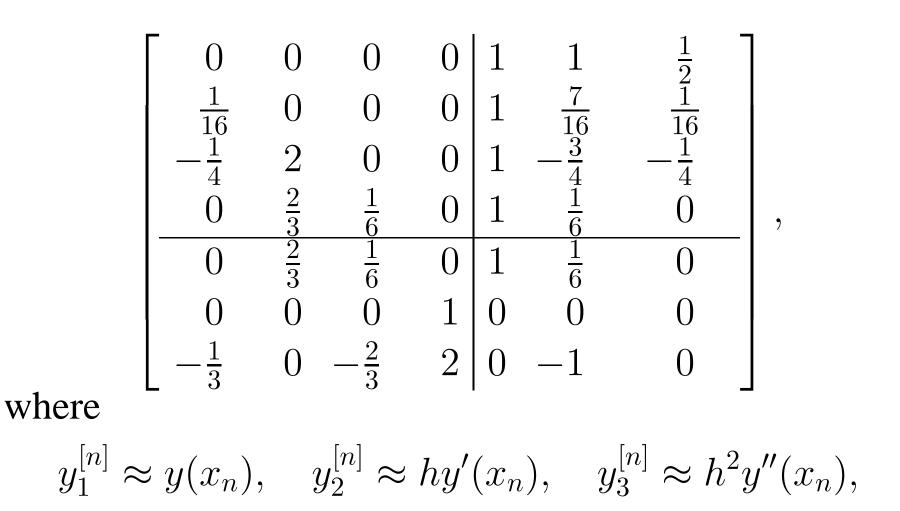
We then get methods like the following:

An ARK method



,

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An ARK method

$$\begin{split} & \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 1 & \frac{1}{2} \\ \frac{1}{16} & 0 & 0 & 0 & 1 & \frac{7}{16} & \frac{1}{16} \\ -\frac{1}{4} & 2 & 0 & 0 & 1 & -\frac{3}{4} & -\frac{1}{4} \\ 0 & \frac{2}{3} & \frac{1}{6} & 0 & 1 & \frac{1}{6} & 0 \\ \hline 0 & \frac{2}{3} & \frac{1}{6} & 0 & 1 & \frac{1}{6} & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ -\frac{1}{3} & 0 & -\frac{2}{3} & 2 & 0 & -1 & 0 \end{bmatrix} , \\ \end{split}$$
 where
$$\begin{split} & y_1^{[n]} \approx y(x_n), \quad y_2^{[n]} \approx hy'(x_n), \quad y_3^{[n]} \approx h^2 y''(x_n), \\ & \text{with} \end{split}$$

$$Y_1 \approx Y_3 \approx Y_4 \approx y(x_n),$$

$$Y_2 \approx y(x_{n-1} + \frac{1}{2}h).$$

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 This means that the stage values are computed to the same accuracy as an order 2 Runge-Kutta method.
- Although it is a multi-value method, both starting the method and changing stepsize are essentially cost-free operations.

An Adams-Bashforth/Adams-Moulton method

It is usual practice to combine Adams–Bashforth and Adams–Moulton methods as a predictor corrector pair.

For example, the 'PECE' method of order 3 computes a predictor y_n^* and a corrector y_n by the formulae

$$y_n^* = y_{n-1} + h\left(\frac{23}{12}f(y_{n-1}) - \frac{4}{3}f(y_{n-2}) + \frac{5}{12}f(y_{n-3})\right),$$

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$$y_n = y_{n-1} + h\left(\frac{5}{12}f(y_n^*) + \frac{2}{3}f(y_{n-1}) - \frac{1}{12}f(y_{n-2})\right).$$

It might be asked: Is it possible to obtain improved order by using values of y_{n-2} , y_{n-3} in the formulae?

For example, the 'PECE' method of order 3 computes a predictor y_n^* and a corrector y_n by the formulae

$$y_n^* = y_{n-1} + h\left(\frac{23}{12}f(y_{n-1}) - \frac{4}{3}f(y_{n-2}) + \frac{5}{12}f(y_{n-3})\right),$$

$$y_n = y_{n-1} + h\left(\frac{5}{12}f(y_n^*) + \frac{2}{3}f(y_{n-1}) - \frac{1}{12}f(y_{n-2})\right).$$

It might be asked: Is it possible to obtain improved order by using values of y_{n-2} , y_{n-3} in the formulae?

The answer is that not much can be gained because we are limited by the famous 'Dahlquist barrier'.

A modified linear multistep method

But what if we allow off-step points?

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This new method, with predictors at the off-step point and also at the end of the step, is

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$$y_{n} = \frac{32}{31}y_{n-1} - \frac{1}{31}y_{n-2}$$

$$+ h\left(\frac{64}{93}f(y_{n-\frac{1}{2}}^{*}) + \frac{5}{31}f(y_{n}^{*}) + \frac{4}{31}f(y_{n-1}) - \frac{1}{93}f(y_{n-2})\right)$$

Order of general linear methods

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We want to understand order in a similar general way.

The key ideas are

- Use a general starting method to represent the input to a step.
- Require the output to be similarly related to the starting method applied one time-step later.

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We will refer to the calculation which produces $y^{[n-1]}$ from $y(x_{n-1})$ as a "starting method".

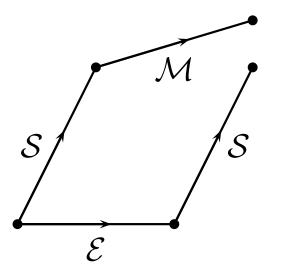
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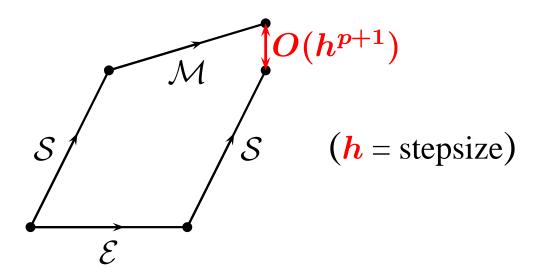
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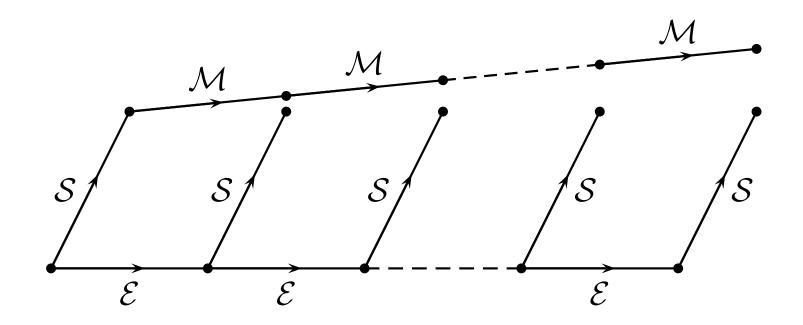
The order of accuracy of a multivalue method is defined in terms of the diagram

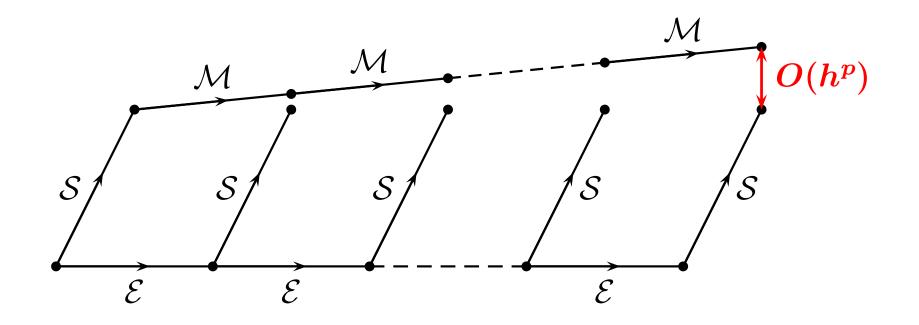


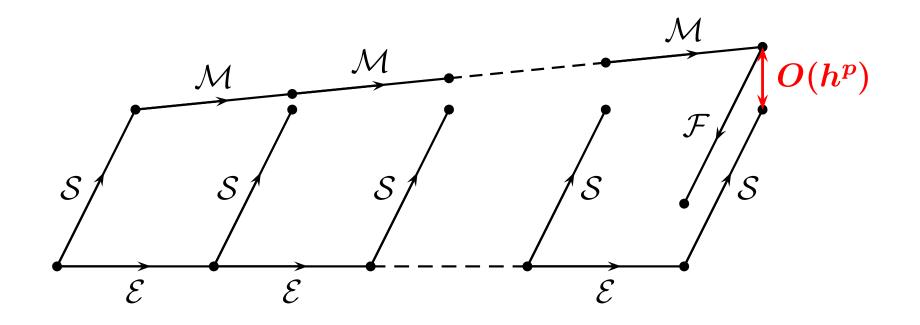
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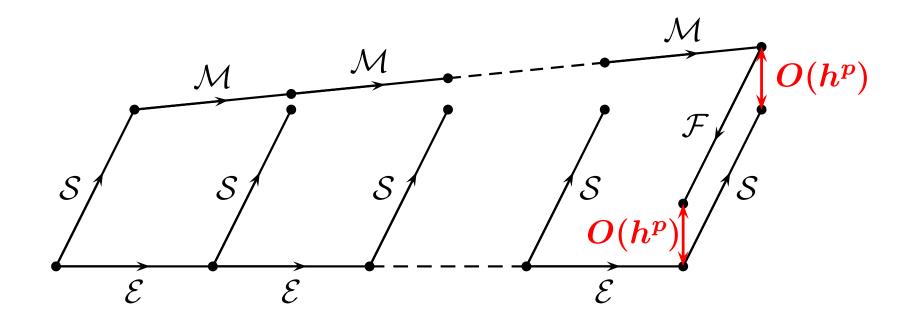
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Methods with the IRK Stability property

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$$M(z) = V + zB(I - zA)^{-1}U.$$

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In the special case of a Runge–Kutta method, M(z) is a scalar R(z).

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An L-stable method is A-stable and, in addition,

$$R(\infty) = 0.$$

A general linear method is said to have "Runge–Kutta stability"

if the stability matrix for the method M(z) has characteristic polynomial of the form

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This means that the method has exactly the same stability region as a Runge–Kutta method whose stability function is R(z).

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We will give just two examples.

The following third order method is explicit and suitable for the solution of non-stiff problems

	0	0	0	0	1	$\frac{1}{4}$	$\frac{1}{32}$	$\frac{1}{384}$
	$-\frac{176}{1885}$	0	0	0	1	$\frac{2237}{3770}$	$\frac{2237}{15080}$	$\frac{2149}{90480}$
	$-rac{335624}{311025}$	$\frac{29}{55}$	0	0	1	$\frac{1619591}{1244100}$	$\frac{260027}{904800}$	$\frac{1517801}{39811200}$
AU	$-rac{67843}{6435}$	$\frac{395}{33}$	-5	0	1	$\frac{29428}{6435}$	$\frac{527}{585}$	$\frac{41819}{102960}$
$BV \end{bmatrix}^{-}$	$-\frac{67843}{6435}$	$\frac{395}{33}$	-5	0	1	$\frac{29428}{6435}$	$\frac{527}{585}$	$\frac{41819}{102960}$
	0	0	0	1	0	0	0	0
	$\frac{82}{33}$	$-\frac{274}{11}$	$\frac{170}{9}$	$-\frac{4}{3}$	0	$\frac{482}{99}$	0	$-\frac{161}{264}$
	-8	-12	$\frac{40}{3}$	-2	0	$\frac{26}{3}$	0	0

The following fourth order method is implicit, L-stable, and suitable for the solution of stiff problems

$\begin{bmatrix} \frac{1}{4} \end{bmatrix}$	0	0	0	0	$1 \frac{3}{4}$		$\frac{1}{2}$	$\frac{1}{4}$	0]
$ \frac{513}{54272} \\ 3706119 $	$\frac{1}{4}$ 488	0	0	0	1	$\frac{27649}{54272}\\15366379$	$rac{5601}{27136}$ 756057	$\frac{1539}{54272}\\1620299$	$\frac{459}{6784}$ 4854
69088256 32161061	3819 <u>111814</u> 222050	$\frac{4}{134}$	$\frac{1}{4}$	0	1 1-	$207264768 \\ 32609017 \\ 107540222$	34544128 929753	69088256 4008881 22024872	454528 <u>174981</u> 2465776
$ \begin{array}{r} 197549232 \\ \underline{135425} \\ \underline{2948496} \\ \end{array} $		$ 183 \\ \overline{73} \\ \overline{183} $	$\frac{4}{1}$	$\frac{1}{4}$	1	$ \begin{array}{r} 197549232 \\ \underline{367313} \\ \underline{8845488} \\ \end{array} $	$32924872 \\ - 22727 \\ - 1474248 \\ 22727 \\ 2727 \\ 2727 \\ 2727 \\ 2727 \\ 2727 \\ 2727 \\ -$	$32924872 \\ 40979 \\ 982832 \\ \hline$	3465776 <u>323</u> <u>25864</u>
$ \begin{array}{c} \underline{135425} \\ \underline{2948496} \\ \end{array} $	$-\frac{641}{10431}$	$\frac{73}{183}$	$\frac{1}{2}$	<u>1</u> 4 1	1	$\frac{367313}{8845488}$	$\frac{22727}{1474248}$	$\frac{40979}{982832}$	$\frac{323}{25864}$
$ \begin{array}{r} \frac{2255}{2318} \\ \frac{12620}{10431} \\ \frac{414}{1159} \end{array} $	$ \begin{array}{r} $	$ \frac{447}{122} \\ \frac{3364}{549} \\ \frac{130}{61} $	$-\frac{11}{4}$ $-\frac{10}{3}$ -1	$\frac{4}{3}$ $\frac{4}{3}$ $\frac{1}{3}$	0 0 0 0	$ \begin{array}{r} 28745 \\ 20862 \\ 70634 \\ 31293 \\ 27052 \\ 31293 \\ \end{array} $	$ \begin{array}{r} $	$ \begin{array}{r} 351 \\ 18544 \\ \underline{187} \\ 2318 \\ \underline{491} \\ 4636 \end{array} $	$ \begin{array}{r} \underline{65} \\ 976 \\ \underline{113} \\ 366 \\ \underline{161} \\ 732 \end{bmatrix} $

Implementation questions for IRKS methods

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- Estimate the local truncation error of the current step
- Estimate the local truncation error of an alternative method of higher order
- Change the stepsize with little cost and with little impact on stability

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I also express my thanks to other colleagues who are closely associated with this project, especially:

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