Lecture Notes on Numerical Differential Equations: IVP

Professor Biswa Nath Datta

Department of Mathematical Sciences Northern Illinois University DeKalb, IL. 60115 USA

E-mail: dattab@math.niu.edu

URL: www.math.niu.edu/~dattab

File faclib/dattab/LECTURE-NOTES/diff-equation-S06.tex, 5/1/2008 at 13:17, version 7

1 Initial Value Problem for Ordinary Differential Equations

We consider the problem of numerically solving a system of differential equations of the form

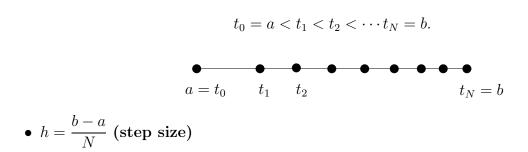
$$\frac{dy}{dt} = f(t, y), \ a \le t \le b, \ y(a) = \alpha$$
(given).

Such a problem is called the **Initial Value Problem** or in short **IVP**, because the initial value of the solution $y(a) = \alpha$ is given.

Since there are infinitely many values between a and b, we will only be concerned here to find approximations of the solution y(t) at several specified values of t in [a, b], rather than finding y(t) at every value between a and b.

Denote

- $y_i = (\text{an approximate value of } y(at) \text{ at } t = t_i.)$
- Divide [a, b] into N equal subintervals of length h:



The Initial Value Problem Given (1) $y' = f(y,t), a \le t \le b$ (2) The initial value $y(t_0) = y(a) = \alpha$ (3) The step-size h. Find y_i (an approximation of $y(t_i)$), $i = 1, \dots, N$, where $N = \frac{b-a}{h}$.

We will briefly describe here the well-known numerical methods for solving the IVP, such as the

- The Euler Method
- The Taylor Method of higher order
- The Runge-Kutta Method
- The Adams-Moulton Method
- The Milne Method

etc.

We will also discuss the error behavior and convergence of these methods.

However, before doing so, we state a result **without proof**, in the following section on the **existence** and **uniqueness** of the solution for the IVP. The proof can be found in most books on ordinary differential equations.

Existence and Uniqueness of the Solution for the IVP

Theorem: (Existence and Uniqueness Theorem for the IVP).

The initial value problem:

$$\begin{cases} y' = f(t, y) \\ y(a) = \alpha \end{cases}$$

has a unique solution y(t) for $a \le t \le b$, if f(t, y) is continuous on the domain, given by $R = \{a \le t \le b, \infty < y < \infty\}$ and satisfies the following inequality:

$$|f(t,y) - f(t,y^*)| \le L|y - y^*|,$$

Whenever (t, y) and $(t, y^*) \in R$.

Definition. The condition $|f(t, y) - f(t, y^*)| \le L|y - y^*|$ is called the **Lipschitz Condi**tion. The number L is called a **Lipschitz Constant**.

Definition.

A set S is said to be convex if whenever (t_1, y_1) and (t_2, y_2) belong to S, the point $((1 - \lambda)t_1 + 2t_2, (1 - \lambda)y_1 + \lambda y_2)$ also belongs to S for each λ when $0 \le \lambda \le 1$.

Simplification of the Lipschitz Condition for the Convex Domain

If the domain happens to be a **convex set**, then the condition of the above Theorem reduces to

$$\left| \frac{\partial f}{\partial y}(t,y) \right| \le L \text{ for all } (t,y) \in R$$

Liptischitz Condition and Well-Posednes

Definition.

An IVP is said to be **well-posed** if a small perhubation in the data of the problem leads to only a small change in the solution.

Since numerical computation may very well introduce some perhubations to the problem, it is important that the problem that is to be solved is well-posed.

Fortunately, the Lipschitz condition is a sufficient condition for the IVP problem to be wellposed.

> **Theorem (Well-Posedness of the IVP problem)**. If f(t, y) Satisfies the Lipschitz Condition, then the IVP is well-posed.

2 The Euler Method

One of the simplest methods for solving the IVP is the classical Euler method.

The method is derived from the Taylor Series expansion of the function y(t).

The function y(t) has the following Taylor series expansion of order n at $t = t_{i+1}$:

$$y(t_{i+1}) = y(t_i) + (t_{i+1} - t_i)y'(t_i) + \frac{(t_{i+1} - t_i)^2}{2!}y''(t_i) + \dots + \frac{(t_{i+1} - t_i)^n}{n!}y^{(n)}(t_i) + \frac{(t_{i+1} - t_i)^{n+1}}{(n+1)!}y^{n+1}(\xi_i), \text{ where } \xi_i \text{ is in } (t_i, t_{i+1}).$$

Substitute $h = t_{i+1} - t_i$. Then

Taylor Series Expansion under
$$n$$
 of $y(t)$
$$y(t_{i+1}) = y(t_i) + hy'(t_i) + \frac{h^2}{2!}y''(t_i) + \dots + \frac{h^n}{n!}y^{(n)}(t_i) + \frac{h^{n+1}}{(n+1)!}y^{(n+1)}(\xi_i).$$

For n = 1, this formula reduces to

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

The term $= \frac{h^2}{2!} y^{(2)}(\xi_i)$ is call the **remainder term**.

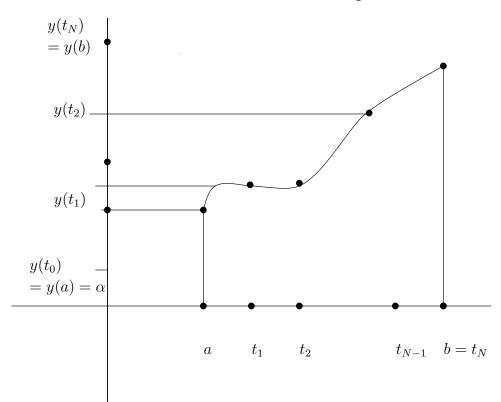
Neglecting the remainder term, we have

Euler's Method

$$y_{i+1} = y_i + hy'(t_i)$$

$$= y_i + hf(t_i, y_i), \quad i = 0, 1, 2, \cdots, N-1$$

This formula is known as the **Euler method** and now can be used to approximate $y(t_{i+1})$.



Geometrical Interpretation

| Algorithm: | Euler's Method for IVP |
|------------|------------------------------------------------------------------------------------------------------------------------------------------------|
| Input: | (i). The function $f(t, y)$ (ii). The end points of the interval $[a, b] : a$ and b (iii). The initial value: $\alpha = y(t_0) = y(a)$ |
| Output: | Approximations y_{i+1} of $y(t_i+1)$, $i = 0, 1, \cdots, N-1$. |
| Step 1. | Initialization: Set $t_0 = a, y_0 = y(t_0) = y(a) = \alpha$. |
| | and $N = \frac{b-a}{h}$. |
| Step 2. | For $i = 0, 1, \dots, N - 1$ do |
| | Compute $y_{i+1} = y_i + hf(t_i, y_i)$ |
| | End |
| - | and $N = \frac{b-a}{h}$. For $i = 0, 1, \dots, N-1$ do Compute $y_{i+1} = y_i + hf(t_i, y_i)$ |

Example: $y' = t^2 + 5,$

$$y(0) = 0, h = 0.25$$

The points of subdivisions are: $t_0 = 0, t_1 = 0.25, t_2 = 0.50, t_3 = 0.75$ and $t_4 = 1$.

e initial value: $\alpha = y(t_0) = y(a)$ mations y_{i+1} of $y(t_i + 1)$, $i = 0, 1, \dots, N - 1$. **pation:** Set $t_0 = a, y_0 = y(t_0) = y(a) = \alpha$. $= \frac{b-a}{h}$. $0, 1, \dots, N - 1$ do $e y_{i+1} = y_i + hf(t_i, y_i)$ $0 \le t \le 1$. 0) = 0, h = 0.25as are: $t_0 = 0, t_1 = 0.25, t_2 = 0.50, t_3 = 0.75$ and $t_4 = 1$. 0.25 $y_1 = y_0 + hf(t_0, y_0) = 0 + .25(5) = 1.25$ (exact value of y(1): 1.2552 $y_1 = y_0 + hf(t_1, y_1)$ $= 1.25 + 0.25(t_1^2 + 5) = 1.25 + 0.25((0.25)^2 + 5)$ = 2.5156 (exact value of y(2): 2.5417) 0.75 $y_3 = y_2 + hf(t_2, y_2)$ $= 2.5156 + .25((.5)^2 + 5) = 3.8281$ (exact value of y(3): 3.8906) above are correct up to 4 decimal digits. $0 \le t \le 2$, i = 0: $t_1 = t_0 + h = 0.25$ i = 1: $t_2 = t_1 + h = 0.50$ i = 2: $t_3 = t_2 + h = 0.75$

Note: The exact values above are correct up to 4 decimal digits.

 $y' = t^2 + 5, \ 0 \le t \le 2,$ Example:

$$y(0) = 0, h = 0.5$$

So, the points of subdivisions are: $t_0 = 0$, $t_1 = 0.5$, $t_2 = 1$, $t_3 = 1.5$, $t_4 = 2$.

We compute y_1, y_2, y_3 , and y_4 , which are, respectively, approximations to y(0.5), y(1), y(1.5), and y(2).

$$i = 0: \qquad y_1 = y_0 + hf(t_0, y_0) = y(0) + hf(0, 0) = 0 + 0.5 \times 5 = 2.5$$
(exact Value = 2.5417).

$$i = 1: \qquad y_2 = y_1 + hf(t_1, y_1) = 2.5 + 0.5((0.5)^2 + 5) = 5.1250$$
(exact Value = 5.3333).

$$i = 2: \quad y_3 = y_2 + hf(t_2, y_2) = 5.1250 + 0.5(t_2^2 + 5) = 5.1250 + 0.5(1.5) = 8.1250$$
(exact Value = 8.6250)

The Errors in Euler's Method

The approximations obtained by a numerical method to solve the IVP are usually subjected to three types of errors:

- Local Truncation Error
- Global Truncation Error
- Round-off Error

Definition. The **local truncation error** is the error made at a **single step** due to the truncation of the series used to solve the problem.

Definition. The global truncation error is the truncation error at any step, that is, the total of the accumulative single-step truncation errors at previous steps.

Recall that the Euler Method was obtained by truncating the Taylor series

$$y(t_{i+1}) = y(t_i) + hy'(t_i) + \frac{h^2}{2}y''(t_i) + \cdots$$

after two terms. Thus, in obtaining Euler's method, the first term neglected was $\frac{h^2}{2}y''(t)$.

So the local error in Euler's method is: $E_L = \frac{h^2}{2}y''(\xi_i)$, where ξ_i lies between t_i and t_{i+1} . In this case, we say that the local error is of order h^2 , written as $O(h^2)$.

On the other hand, the global truncation error is of order h : O(h), as can be seen from the following theorem.

Denote the global error at Step i by E_i , that is, $E_i = y(t_i) - y_i$.

Below we give a bound for this error assuming that certain properties of the derivatives of the solution are known. The proof of the result can be found in the book by Gear [Numerical Initial Value Problems in Ordinary Differential Equations, Prentice Hall, Inc., (1971)]

Theorem: (Global Error Bound for the Euler Method)

Let y(t) be the unique solution of the IVP: $y' = f(t, y); y(a) = \alpha$.

 $a \le t \le b, -\infty < y < \infty,$

Let L and M be two numbers such that

$$\left|\frac{\partial f(t,y)}{\partial y}\right| \le L$$
, and $||y''(t)|| \le M$ in $[a,b]$.

Then the global error E_i at $t = t_i$ satisfies

$$|E_i| = |y(t_i) - y_i| \le \frac{hM}{2L}(e^{L(t_i - a)} - 1).$$

Thus, The global error bound for Euler's method depends upon h, whereas the local error depends upon h^2 .

Remark. Since the exact solution y(t) of the IVP is not known, the above bound may not be of practical importance as far as knowing how large the error can be a priori. However, from this error bound, we can say that the *Euler method can be made to converge faster by decreasing the step-size.* Furthermore, if the equalities, L and M of the above theorem can be found, then we can determine what step-size will be needed to achieve a certain accuracy, as the following example shows.

Example:
$$\frac{dy}{dt} = \frac{t^2 + y^2}{2}, y(0) = 0$$

 $0 \le t \le 1, \ -1 \le y(t) \le 1$

Determine how small the step-size should be so that the error

does not exceed $\epsilon = 10^{-4}$.

Since
$$f(t, y) = \frac{t^2 + y^2}{2}$$
, we have
 $\frac{\partial f}{\partial y} = y$
Thus, $\left| \frac{\partial f}{\partial y} \right| \le 1$ for all y , giving $L = 1$.

To find M, we compute the second-derivative of y(t) as follows:

$$y' = \frac{dy}{dt} = f(t, y)(\text{Given})$$

By implicit differentiation, $y'' = \frac{\partial f}{\partial t} + f \frac{\partial f}{\partial y}$
$$= t + \left(\frac{t^2 + y^2}{2}\right) y = t + \frac{y}{2}(t^2 + y^2)$$
So, $|y''(t)| = |t + \frac{y}{2}(t^2 + y^2)| \le 2$, for $1 \le y \le 1$.
Thus, $M = 2$,
and $|E| = |y(t)| = y| \le \frac{2h}{2}(e^{(t)} - 1) = h(e^{(t)} - 1) = h(t - 1)$

and
$$|E_i| = |y(t_i) - y_i| \le \frac{2h}{2L}(e^{(t_i)} - 1) = h(e^{(t_i)} - 1) = h(e - 1).$$

Now, for the error not to exceed 10^{-4} , we must have: $h(e-1) < 10^{-4}$ or $h < \frac{10^{-4}}{e-1} \approx 5.8198 \times 10^{-5}$.

3 High-order Taylor Methods

Recall that the Taylor's series expansion of y(t) of degree n is given by

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

Now,

(i)
$$y'(t) = f(t, y(t))$$
 (given).
(ii) $y''(t) = f'(t, y(t))$.
(iii) $y^{(i)}(t) = f^{(i-1)}(t, y(t)), i = 1, 2, ..., n$

Thus,

$$y(t_{i+1}) = y(t_i) + hf(t_i, y(t_i)) + \frac{h^2}{2} f'(t_i, y(t_i)) + \dots + \frac{h^{n-1}}{(n-1)!} f^{(n-1)}(t_i, y_i) + \frac{h^n}{n!} f^{(n-1)}(t_i, y(t_i)) + \frac{h^{n+1}}{(n+1)!} f^{(n-1)}(\xi_i, y(\xi_i))$$

$$= y(t_i) + h \left[f(t_i, y(t_i)) + \frac{h}{2} f'(t_i, y(t_i)) + \dots + \frac{h^{n-1}}{n!} f^{n-1}(t_i, y(t_i)) \right] + \text{Remainder Term}$$
Neglecting the remainder term the above formula can be written in compact form as follows:

$$y_{i+1} = y_i + hT_k(t_i, y_i), \ i = 0, 1, \dots, N-1, \text{ where } T_k(t_i.y_i) \text{ is defined by:}$$

$$T_k(t_i, y_1) = f(t_i, y_i) + \frac{h}{2}f'(t_i, y_i) + \dots + \frac{h^{k-1}}{k!}f^{(k-1)}(t_i, y_i)$$

So, if we truncate the Taylor Series after (k+1) terms and use the truncated series to obtain the approximating of y_{1+1} of $y(t_{i+1})$, we have the following of k-th order Taylor's algorithm for the IVP. Taylor's Algorithm of order k for IVPInput:(i) The function f(t, y)(ii) The end points: a and b(iii) The initial value: $\alpha = y(t_o) = y(a)$ (iv) The order of the algorithm: k(v) The step size: hStep 1Initialization: $t_0 = a, y_0 = \alpha, N = \frac{b-a}{h}$ Step 2.For $i = \dots, N-1$ do2.1 Compute $T_k(t_i, y_i) = f(t_i, y_i) + \frac{h}{2}f'(t_i, y_i) + \dots + \frac{h^{k-1}}{k!}f^{(k-1)}(t_i, y_i)$ 2.2 Compute $y_{i+1} = y_i + hT_k(t_i, y_i)$ End

Example:

$$y' = y - t^{2} + 1, \quad 0 \le t \le 2, \ y(0) = 0.5, h = 0 \cdot 2.$$

$$f(t, y(t)) = y - t^{2} + 1 \text{ (Given)}.$$

$$f'(t, y(t)) = \frac{d}{dt}(y - t^{2} + 1) = y' - 2t$$

$$= y - t^{2} + 1 - 2t$$

$$f''(t, y(t)) = \frac{d}{dt}(y - t^{2} + 1 - 2t) = y - t^{2} + 1 - 2t - 2 \qquad = y - t^{2} - 2t - 1$$
so,
$$y(0.2) \simeq y_{1} = y_{0} + hf(t_{0}, y(t_{0})) + \frac{h^{2}}{2}f'(t_{0}, y(t_{0}))$$

$$= 0.5 + 0.2 \times 1.5 + \frac{(0.2)^{2}}{2}(0.5 + 1) = 2.2300 \text{check}.$$

$$y(0.4) \simeq y_{2} = 1.215800$$

4 Runge-Kutta Methods

- The Euler's method is the simplest to implement; however, even for a reasonable accuracy the step-size h needs to be very small.
- The difficulties with higher order Taylor's series methods are that the derivatives of higher orders of f(t, y) need to be computed, which are very often difficult to compute/ needles to say that if f(t, y) is not explicitly known in many areas.

The Runge-Kutta methods aim at achieving the accuracy of higher order Taylor series methods without computing the higher order derivatives.

We first develop the simplest one: The Runge-Kutta Methods of order 2.

The Runge-Kutta Methods of order 2

Suppose that we want an expression of the approximation y_{i+1} in the form:

$$y_{i+1} = y_i + \alpha_1 k_1 + \alpha_2 k_2, \tag{4.1}$$

where
$$k_1 = hf(t_i, y_i),$$
 (4.2)

and

$$k_2 = h f(t_i + \alpha h, \ y_i + \beta k_1).$$
(4.3)

The constants α_1 and α_2 and α and β are to be chosen so that the formula is as accurate as the Taylor's Series Method with n = 1.

To develop the method we need an important result from Calculus: **Taylor's series for function to two variables.**

Taylor's Theorem for Function of Two Variables

Let f(t, y) and its partial derivatives of orders up to (n + 1) are continuous in the domain $D = \{(t, y) | a \le t \le b, c \le y \le d\}.$

Then

$$\begin{aligned} f(t,y) &= f(t_0,y_0) + \left[(t-t_0) \frac{\partial f}{\partial t}(t_0,y_0) + (y-y_0) \frac{\partial f}{\partial y}(t_0,y_0) \right] + \cdots \\ &+ \left[\frac{1}{n!} \sum_{h=0}^n \binom{n}{i} (t-t_0)^{h-i} (y-y_0)^i \frac{\partial^n f}{\partial t^{n-1} \partial y^i}(t_0,y_0) \right] + R_n(t,y), \\ \text{where } R_n(t,y) \text{ is the remainder after } n \text{ terms and involves the partial derivative of order} \\ n+1. \end{aligned}$$

Using the above theorem with n = 1, we have

$$f(t_i + \alpha h, y_i + \beta k_1) = f(t_i, y_i) + \alpha h \frac{\partial f}{\partial t}(t_i, y_i) + \beta k_1 \frac{\partial f}{\partial y}(t_i, y_i)$$
(4.4)

From (4.4) and (4.3), we obtain

$$\frac{k_2}{h} = f(t_i, y_i) + \alpha h \frac{\partial f}{\partial t}(t_i. y_i) + \beta k_1 \frac{\partial f}{\partial y}(t_i, y_i).$$
(4.5)

Again, substituting the value of k_1 from (4.2) and k_2 from (4.3) in (4.1) we get (after some rearrangement):

$$y_{i+1} = y_i + \alpha_1 h f(t_i, y_i) + \alpha_1 h \left[f(t_i, y_i) + \alpha h \frac{\partial f}{\partial t}(t_i, y_i) + \beta h f(t_i, y_i) \frac{\partial f}{\partial y}(t_i, y_i) \right]$$

$$= y_i + (\alpha_1 + \alpha_2) h f(t_i, y_i) + \alpha_2 h^2 \left[\alpha \frac{\partial f}{\partial t}(t_i, y_i) + \beta f(t_i, y_i) \frac{\partial f}{\partial y}(t_i, y_i) \right]$$

(4.6)

Also, note that $y(t_{i+1}) = y(t_i) + hf(t_i, y_i) + \frac{h^2}{2} \left(\frac{\partial f}{\partial t}(t_i, y_i) + f(t_i, y_i) \frac{\partial f}{\partial y}(t_i, y_i) \right) + \text{ higher order terms.}$

So, neglecting the higher order terms, we can write

$$y_{i+1} = y_i + hf(t_i, y_i) + \frac{h^2}{2} \left(\frac{\partial f}{\partial t}(t_i, y_i) + f \frac{\partial f}{\partial y}(t_i, y_i) \right).$$

$$(4.7)$$

If we want (4.6) and (4.7) to agree for numerical approximations, then we must have

- $\alpha_1 + \alpha_2 = 1$ (comparing the coefficients of $hf(t_i, y_i)$).
- $\alpha_2 \alpha = \frac{1}{2}$ (comparing the coefficients of $h^2 \frac{\partial f}{\partial t}(t_i, y_i)$.
- $\alpha_2\beta = \frac{1}{2}$ (comparing the coefficients of $h^2 f(t_i, y_i) \frac{\partial f}{\partial y}(t_i y_i)$.

Since the number of unknowns here exceeds the number of equations, there are infinitely many possible solutions. The simplest solution is:

$$\alpha_1 = \alpha_2 = \frac{1}{2}, \ \alpha = \beta = 1$$

With these choices we can generate y_{i+1} from y_i as follows. The process is known as the **Modified Euler's Method**.

Generating y_{i+1} from y_i in Modified Euler's Method

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

where $k_1 = hf(t_i, y_i)$
 $k_2 = hf(t_i + h, y_i + k_1).$
or
 $y_{i+1} = y_i + \frac{h}{2} \Big[f(t_i, y_i) + f(t_i + h, y_i + hf(t_i, y_i)) \Big]$

Algorithm: The Modified Euler Method

| Inputs: | The given function: $f(t, y)$ The end points of the interval: a and b The step-size: h The initial value $y(t_0) = y(a) = \alpha$ |
|----------|------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Outputs: | Approximations y_{i+1} of $y(t_{i+1}) = y(t_0 + ih)$, $i = 0, 1, 2, \cdots, N - 1$ |
| Step 1 | (Initialization) Set $t_0 = a$, $y_0 = y(t_0) = y(a) = \alpha$ $N = \frac{b-a}{h}$ |
| Step 2 | For $i = 0, 1, 2, \dots, N-1$ do Compute $k_1 = hf(t_i, y_i)$ Compute $k_2 = hf(t_i + h, y_i + k_1)$ Compute $y_{i+1} = y_i + \frac{1}{2}(k_1 + k_2)$. |
| End | 2 |

Local Error in the Modified Euler Method

Since in deriving the modified Euler method, we neglected the terms involving h^3 and higher powers of h, the local error for this method is $O(h^3)$. Thus with the Modified Euler method, we will be able to use larger step-size h than the Euler Method to obtain the same accuracy.

Example:
$$y' = t + y$$
, $y(0) = 1$
 $h = 0.01, y_0 = y(0) = 1$.
 $i = 0$: $y_1 = y_0 + \frac{1}{2}(k_1 + k_2)$
 $k_1 = hf(t_0, y_0) = 0.01(0 + 1) = 0.01$
 $k_2 = hf(t_0 + h, y_0 + k_1) = 0.01 \times f(0.01, 1 + 0.01)$
 $= 0.01 \times (0.01 + 1.01) = 0.01 \times 1.02 = 0.0102$
 $y(0.01) \approx y_1 = 1 + \frac{1}{2}(0.01 + 0.0102) = 1.0101$

1

$$i = 1: \quad y_2 = y_1 + \frac{1}{2}(k_1 + k_2)$$

$$k_1 = hf(t_1, y_1)$$

$$= 0.01 \times f(0.01, 1.0101) = 0.01 \times (0.01 + 1.0101)$$

$$= 0.0102$$

$$k_2 = hf(t_1 + h, y_1 + k_1)$$

= 0.01 × f(0.02, 1.0101 + 0.0102) = 0.01 × (0.02 + 1.0203)
= -0.0104

 $y(0.02) \approx y_2 = 1.0101 + \frac{1}{2}(0.0102 + 0.0104) = 1.0204$

The Midpoint and Heun's Methods

In deriving the modified Euler's Method, we have considered only one set of possible values of $\alpha_1, \alpha_2, \alpha_1$ and β . We will now consider two more sets of values.

•
$$\alpha = 0, \ \alpha_2 = 1, \ \alpha = \beta = \frac{1}{2}.$$

This gives us the **Midpoint Method**.

The Midpoint Method

$$y_{i+1} = y_i + k_2$$
where $k_1 = hf(t_i, y_i)$

$$k_2 = hf\left(t_i + \frac{h}{2}, y_i + \frac{k_1}{2}\right)$$
or
$$y_{i+1} = y_i + hf\left(t_i + \frac{h}{2}, y_i + \frac{h}{2}f(t_i, y_i)\right), i = 0, 1, \dots, N-1.$$

•
$$\alpha_1 = \frac{1}{4}, \ \beta_1 = \frac{3}{4}, \ \alpha = \beta = \frac{2}{3}$$

Then we have **Heun's Method**.

Heun's Method

$$y_{i+1} = y_i + \frac{1}{4}k_1 + \frac{3}{4}k_2$$
where $k_1 = hf(t_i, y_i)$

$$k_2 = hf\left(t_i + \frac{2}{3}h, y_i + \frac{2}{3}k_1\right)$$
or
$$y_{i+1} = y_i + \frac{h}{4}f(t_i, y_i) + \frac{3h}{4}f\left(t_i + \frac{2}{3}h, y_i + \frac{2h}{3}f(t_i, y_i)\right), i = 0, 1, \dots, N-1$$

Heun's Method and the Modified Euler's Method are classified as the Runge-Kutta methods of order 2.

The Runge-Kutta Method of order 4.

A method very widely used in practice is the Runge-Kutta method of order 4. It's derivation is complicated. We will just state the method, without proof.

| Algorithm: The Runge-Kutta Method of Order 4 | |
|----------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------|
| Inputs: | f(t, y) - the given function a, b - the end points of the interval α - the initial value $y(t_0)$ h - the step size |
| Outputs: | The approximations y_{i+1} of $y(t_{i+1})$, $i = 0, 1, \dots, N-1$ |
| Step 1: | (Initialization) Set $t_0 = a$, $y_0 = y(t_0) = y(a) = \alpha$ $N = \frac{b-a}{h}$. |
| Step 2: | (Computations of the Runge-Kutta Coefficients) For $i = 0, 1, 2, \dots, n$ do $k_1 = hf(t_i, y_i)$ |
| | $k_2 = hf(t_i + \frac{h}{2}, y_i + \frac{1}{2}k_1)$ |
| | $k_3 = hf(t_i + \frac{h}{2}, y_i + \frac{1}{2}k_2)$ |
| | $k_4 = hf(t_i + h, y_i + k_3)$ |
| Step 3: | (Computation of the Approximate Solution) |
| Compute: | $y_{i+1} = y_i + \frac{1}{6}(k_1 + 2k_2 + 2k_3 + k_4)$ |

The Local Truncation Error: The local truncation error of the Runge-Kutta Method of order 4 is $O(h^5)$.

Example:

$$y' = t + y, y(0) = 1$$

 $h = 0.01$

Let's complete y(0.01) using the Runge-Kutta Method of order 4.

i = 0

$$y(0.01) \approx y_1 = y_0 + \frac{1}{6}(k_1 + 2k_2 + 2k_3 + k_4)$$

where $k_1 = hf(t_0, y_0) = 0.01f(0, 1) = 0.01 \times 1 = 0.01.$

$$k_{2} = hf(t_{0} + \frac{h}{2}, y_{0} + \frac{k_{1}}{2}) = 0.01f\left(\frac{0.01}{2}, 1 + \frac{0.01}{2}\right) = 0.01\left[\frac{0.01}{2} + \frac{1+0.01}{2}\right] = 0.0101.$$

$$k_{3} = hf\left(t_{0} + \frac{h}{2}, y_{0} + \frac{k_{2}}{2}\right) = h\left(t_{0} + \frac{h}{2} + y_{0} + \frac{k_{2}}{2}\right) = 0.0101005.$$

$$k_{4} = hf(t_{0} + h, y_{0} + k_{3}) = h(t_{0} + h + y_{0} + k_{3}) = 0.01020100$$

$$y_{1} = y_{0} + \frac{1}{6}(k_{1} + 2k_{2} + 2k_{3} + k_{4}) = 1.010100334$$
and so on.