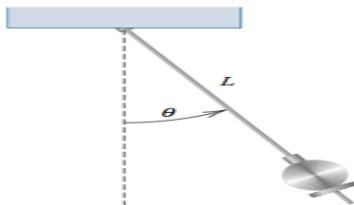


Initial Value ODE

- ▶ The motion of a swinging pendulum

$$\frac{d^2\theta}{dt^2} + \frac{g}{L} \sin \theta = 0,$$



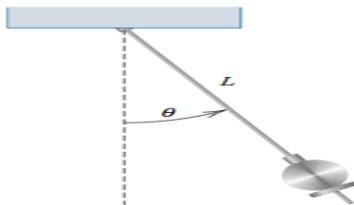
- ▶ Initial Value conditions

$$\theta(t_0) = \theta_0, \quad \text{and} \quad \theta'(t_0) = \theta'_0.$$

Initial Value ODE

- ▶ The motion of a swinging pendulum

$$\frac{d^2\theta}{dt^2} + \frac{g}{L} \sin \theta = 0,$$



- ▶ Initial Value conditions

$$\theta(t_0) = \theta_0, \quad \text{and} \quad \theta'(t_0) = \theta'_0.$$

When does ODE have a solution? How to compute it?

Lipschitz condition

Definition: function $f(t, y)$ satisfies a **Lipschitz condition** in the variable y on a set $D \subset \mathbf{R}^2$ if a constant $L > 0$ exists with

$$|f(t, y_1) - f(t, y_2)| \leq L |y_1 - y_2|,$$

whenever $(t, y_1), (t, y_2)$ are in D . L is Lipschitz constant.

- ▶ **Example 1:** Show that $f(t, y) = t|y|$ satisfies a Lipschitz condition on the region

$$D = \{(t, y) \mid 0 \leq t \leq T\}.$$

Solution: For any $(t, y_1), (t, y_2)$ in D ,

$$|f(t, y_1) - f(t, y_2)| = |t|y_1| - t|y_2|| \leq t |y_1 - y_2| \leq L |y_1 - y_2|,$$

for $L = T$.

Lipschitz condition

Definition: function $f(t, y)$ satisfies a **Lipschitz condition** in the variable y on a set $D \subset \mathbf{R}^2$ if a constant $L > 0$ exists with

$$|f(t, y_1) - f(t, y_2)| \leq L |y_1 - y_2|,$$

whenever $(t, y_1), (t, y_2)$ are in D . L is Lipschitz constant.

- ▶ **Example 2:** Show that $f(t, y) = t y^2$ does not satisfy any Lipschitz condition on the region

$$D = \{(t, y) \mid 0 \leq t \leq T\}.$$

Solution: Choose $(T, y_1), (T, y_2)$ in D with $y_1 = 0, y_2 > 0$,

$$\frac{|f(T, y_1) - f(T, y_2)|}{|y_1 - y_2|} = T y_2,$$

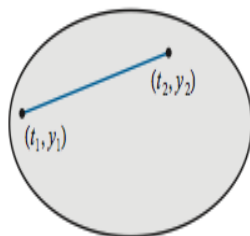
which can be larger than L for any fixed $L > 0$.

Convex Set

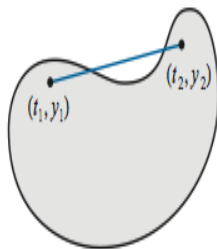
Definition: A set $D \subset \mathbf{R}^2$ is convex if

whenever (t_1, y_1) and $(t_2, y_2) \in D$

→ line segment $(1 - \lambda)(t_1, y_1) + \lambda(t_2, y_2) \in D$ for all $\lambda \in [0, 1]$.



Convex



Not convex

Theorem: Suppose $f(t, y)$ is defined on a convex set $D \subset \mathbf{R}^2$. If a constant $L > 0$ exists with

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

then f satisfies a Lipschitz condition with Lipschitz constant L .

Theorem: Suppose $f(t, y)$ is defined on a convex set $D \subset \mathbf{R}^2$. If a constant $L > 0$ exists with

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

then f satisfies a Lipschitz condition with Lipschitz constant L .

- ▶ **Example 1:** Show that $f(t, y) = t y^2$ satisfies Lipschitz condition on the region

$$D = \{(t, y) \mid 0 \leq t \leq T, \quad -Y \leq y \leq Y\}.$$

Solution:

$$\frac{\partial f}{\partial y}(t, y) = 2ty, \quad \left| \frac{\partial f}{\partial y}(t, y) \right| \leq 2TY \quad \text{for all } (t, y) \in D.$$

so $f(t, y) = t y^2$ satisfies Lipschitz condition with $L = 2TY$.

What is going on with $f(t, y) = t y^2$?

- ▶ $f(t, y) = t y^2$ satisfies Lipschitz condition on the region

$$D = \{(t, y) \mid 0 \leq t \leq T, \quad -Y \leq y \leq Y\}.$$

- ▶ $f(t, y) = t y^2$ doesn't satisfy Lipschitz condition on region

$$D = \{(t, y) \mid 0 \leq t \leq T\}.$$

Initial value problem

$$y'(t) = t y^2(t), \quad y(t_0) = \alpha > 0$$

has unique, but unbounded solution

$$y(t) = \frac{2\alpha}{2 + \alpha(t_0^2 - t^2)},$$

the denominator of which vanishes at

$$t = \sqrt{\frac{2}{\alpha} + t_0^2}.$$

What is going on with $f(t, y) = t y^2$?

Initial value problem

$$y'(t) = t y^2(t), \quad y(t_0) = \alpha > 0$$

has unique, but unbounded solution

$$y(t) = \frac{2\alpha}{2 + \alpha(t_0^2 - t^2)},$$

the denominator of which vanishes at

$$t = \sqrt{\frac{2}{\alpha} + t_0^2}.$$

- ▶ for $|t_0| < T$, ODE has unique solution on

$$D = \{(t, y) \mid 0 \leq t \leq T, \quad -Y \leq y \leq Y\}.$$

- ▶ for $\sqrt{\frac{2}{\alpha} + t_0^2} < T$ ODE solution breaks down at $t = \sqrt{\frac{2}{\alpha} + t_0^2}$
on

$$D = \{(t, y) \mid 0 \leq t \leq T\}.$$

Well-posed problem

Definition in English: ODE is well-posed if

- ▶ A unique ODE solution exists, and
- ▶ Small changes (perturbation) to ODE imply small changes to solution.

Well-posed problem

The initial-value problem

$$\frac{dy}{dt} = f(t, y), \quad a \leq t \leq b, \quad y(a) = \alpha, \quad (5.2)$$

is said to be a **well-posed problem** if:

- A unique solution, $y(t)$, to the problem exists, and
- There exist constants $\varepsilon_0 > 0$ and $k > 0$ such that for any ε , with $\varepsilon_0 > \varepsilon > 0$, whenever $\delta(t)$ is continuous with $|\delta(t)| < \varepsilon$ for all t in $[a, b]$, and when $|\delta_0| < \varepsilon$, the initial-value problem

$$\frac{dz}{dt} = f(t, z) + \delta(t), \quad a \leq t \leq b, \quad z(a) = \alpha + \delta_0, \quad (5.3)$$

has a unique solution $z(t)$ that satisfies

$$|z(t) - y(t)| < k\varepsilon \quad \text{for all } t \text{ in } [a, b]. \quad \blacksquare$$

Well-posed problem

Definition in English: ODE is well-posed if

- ▶ A unique ODE solution exists, and
- ▶ Small changes (perturbation) to ODE imply small changes to solution.

Theorem

Suppose $D = \{(t, y) \mid a \leq t \leq b \text{ and } -\infty < y < \infty\}$. If f is continuous and satisfies a Lipschitz condition in the variable y on the set D , then the initial-value problem

$$\frac{dy}{dt} = f(t, y), \quad a \leq t \leq b, \quad y(a) = \alpha$$

is well-posed. ■

Well-posed problem, example

Show that the initial-value problem

$$\frac{dy}{dt} = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5. \quad (5.4)$$

is well posed on $D = \{(t, y) \mid 0 \leq t \leq 2 \text{ and } -\infty < y < \infty\}$.

Solution: Because

$$\frac{\partial f}{\partial y}(t, y) = 1, \quad \left| \frac{\partial f}{\partial y}(t, y) \right| = 1.$$

$f(t, y) = y - t^2 + 1$ satisfies a Lipschitz condition in y on D with Lipschitz constant 1. Therefore this ODE is well-posed. In fact,

$$y(t) = 1 + t^2 + 2t - \frac{1}{2}e^t.$$

Euler's Method: Initial value ODE to solve

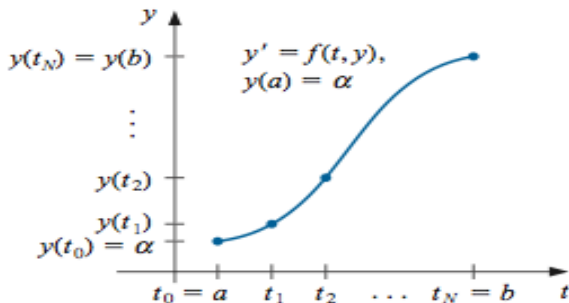
$$\frac{dy}{dt} = f(t, y), \quad a \leq t \leq b, \quad y(a) = \alpha.$$

Euler's Method: Initial value ODE to solve

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

- ▶ Choose positive integer N , and select mesh points

$$t_j = a + j h, \quad \text{for } j = 0, 1, 2, \dots, N, \quad \text{where } h = (b - a)/N.$$



Euler's Method: Initial value ODE to solve

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

Euler's Method: Initial value ODE to solve

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

- ▶ Choose positive integer N , and select mesh points

$$t_j = a + j h, \quad \text{for } j = 0, 1, 2, \dots, N, \quad \text{where } h = (b - a)/N.$$

Euler's Method: Initial value ODE to solve

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

- ▶ Choose positive integer N , and select mesh points

$$t_j = a + j h, \quad \text{for } j = 0, 1, 2, \dots, N, \quad \text{where } h = (b - a)/N.$$

- ▶ For each j , do 2-term Taylor expansion

$$y(t_{j+1}) = y(t_j) + h y'(t_j) + \frac{h^2}{2} y''(\xi_j), \quad j = 0, 1, \dots, N - 1.$$

Euler's Method: Initial value ODE to solve

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

- ▶ Choose positive integer N , and select mesh points

$$t_j = a + jh, \quad \text{for } j = 0, 1, 2, \dots, N, \quad \text{where } h = (b - a)/N.$$

- ▶ For each j , do 2-term Taylor expansion

$$y(t_{j+1}) = y(t_j) + h y'(t_j) + \frac{h^2}{2} y''(\xi_j), \quad j = 0, 1, \dots, N - 1.$$

- ▶ Because $y(t)$ satisfies ODE,

$$y(t_{j+1}) = y(t_j) + h f(t_j, y(t_j)) + \frac{h^2}{2} y''(\xi_j), \quad j = 0, 1, \dots, N - 1.$$

Euler's Method: Initial value ODE to solve

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

- ▶ Choose positive integer N , and select mesh points

$$t_j = a + jh, \quad \text{for } j = 0, 1, 2, \dots, N, \quad \text{where } h = (b - a)/N.$$

- ▶ For each j , do 2-term Taylor expansion

$$y(t_{j+1}) = y(t_j) + h y'(t_j) + \frac{h^2}{2} y''(\xi_j), \quad j = 0, 1, \dots, N - 1.$$

- ▶ Because $y(t)$ satisfies ODE,

$$y(t_{j+1}) = y(t_j) + h f(t_j, y(t_j)) + \frac{h^2}{2} y''(\xi_j), \quad j = 0, 1, \dots, N - 1.$$

- ▶ Ignore error term, set $w_0 = \alpha$,

$$w_{j+1} = w_j + h f(t_j, w_j), \quad j = 0, 1, \dots, N - 1.$$

Euler's Method: Initial value ODE to solve

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

Euler's Method: Initial value ODE to solve

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

- ▶ Choose positive integer N , and select mesh points

$$t_j = a + j h, \quad \text{for } j = 0, 1, 2, \dots, N, \quad \text{where } h = (b - a)/N.$$

Euler's Method: Initial value ODE to solve

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

- ▶ Choose positive integer N , and select mesh points
 $t_j = a + jh$, for $j = 0, 1, 2, \dots, N$, where $h = (b - a)/N$.

- ▶ Set $w_0 = \alpha$,

$$w_{j+1} = w_j + hf(t_j, w_j), \quad j = 0, 1, \dots, N - 1.$$

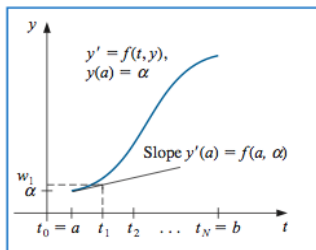
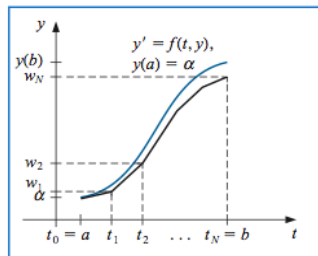


Figure 5.4



Euler's Method: example

Initial Value ODE $\frac{dy}{dt} = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5,$
exact solution $y(t) = (1 + t)^2 - 0.5 e^t.$

- ▶ Choose positive integer $N = 10$, so

$$h = 0.2, \quad t_j = 0.2j, \quad \text{for } j = 0, 1, 2, \dots, 10.$$

Euler's Method: example

Initial Value ODE $\frac{dy}{dt} = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5,$
exact solution $y(t) = (1 + t)^2 - 0.5 e^t.$

- ▶ Choose positive integer $N = 10$, so

$$h = 0.2, \quad t_j = 0.2j, \quad \text{for } j = 0, 1, 2, \dots, 10.$$

- ▶ Set $w_0 = 0.5$. For $j = 0, 1, \dots, 9$,

$$\begin{aligned} w_{j+1} &= w_j + h(w_j - t_j^2 + 1) = w_j + 0.2(w_j - 0.04j^2 + 1) \\ &= 1.2w_j - 0.008j^2 + 0.2. \end{aligned}$$

Euler's Method: example

Initial Value ODE $\frac{dy}{dt} = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5,$

exact solution $y(t) = (1 + t)^2 - 0.5 e^t.$

- ▶ Set $w_0 = 0.5$. For $j = 0, 1, \dots, 9,$

$$w_{j+1} = 1.2w_j - 0.008j^2 + 0.2.$$

Euler's Method: example

Initial Value ODE $\frac{dy}{dt} = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5,$

exact solution $y(t) = (1 + t)^2 - 0.5 e^t.$

- ▶ Set $w_0 = 0.5$. For $j = 0, 1, \dots, 9,$

$$w_{j+1} = 1.2w_j - 0.008j^2 + 0.2.$$

t_i	w_i	$y_i = y(t_i)$	$ y_i - w_i $
0.0	0.5000000	0.5000000	0.0000000
0.2	0.8000000	0.8292986	0.0292986
0.4	1.1520000	1.2140877	0.0620877
0.6	1.5504000	1.6489406	0.0985406
0.8	1.9884800	2.1272295	0.1387495
1.0	2.4581760	2.6408591	0.1826831
1.2	2.9498112	3.1799415	0.2301303
1.4	3.4517734	3.7324000	0.2806266
1.6	3.9501281	4.2834838	0.3333557
1.8	4.4281538	4.8151763	0.3870225
2.0	4.8657845	5.3054720	0.4396874

Error Bounds for Euler's Method

$$D = \{(t, y) \mid 0 \leq t \leq T, \quad -Y \leq y \leq Y\}.$$

- ▶ Set $w_0 = 0.5$. For $j = 0, 1, \dots, 9$,

$$w_{j+1} = 1.2w_j - 0.008j^2 + 0.2.$$

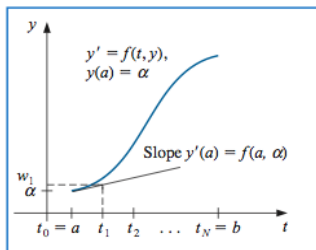
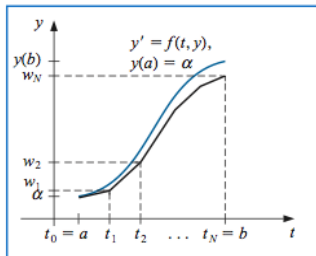


Figure 5.4



Theorem: Suppose that in the initial value ODE,

$$\frac{dy}{dt} = f(t, y), \quad a \leq t \leq b, \quad y(a) = \alpha,$$

- ▶ $f(t, y)$ is continuous,
- ▶ $f(t, y)$ satisfies Lipschitz condition

$$\begin{aligned} |f(t, y_1) - f(t, y_2)| &\leq L |y_1 - y_2| \quad \text{on domain} \\ D &= \{(t, y) \mid a \leq t \leq b, \quad -\infty < y < \infty\}. \end{aligned}$$

Let w_0, w_1, \dots, w_N be the approximations generated by Euler's method for some positive integer N . Then for each $j = 0, 1, \dots, N$,

$$|y(t_j) - w_j| \leq \frac{hM}{2L} \left(e^{L(t_j-a)} - 1 \right),$$

where $h = (b - a)/N$, $t_j = a + j h$, $M = \mathbf{max}_{t \in [a, b]} |y''(t)|$.

Theorem is a mixed bag

Theorem:

$$|y(t_j) - w_j| \leq \frac{hM}{2L} \left(e^{L(t_j-a)} - 1 \right), \quad (1)$$

where $h = (b - a)/N$, $t_j = a + j h$, $M = \mathbf{max}_{t \in [a,b]} |y''(t)|$.

Theorem is a mixed bag

Theorem:

$$|y(t_j) - w_j| \leq \frac{hM}{2L} \left(e^{L(t_j-a)} - 1 \right), \quad (1)$$

where $h = (b - a)/N$, $t_j = a + j h$, $M = \mathbf{max}_{t \in [a,b]} |y''(t)|$.

How good is Theorem?

Theorem is a mixed bag

Theorem:

$$|y(t_j) - w_j| \leq \frac{hM}{2L} \left(e^{L(t_j-a)} - 1 \right), \quad (1)$$

where $h = (b - a)/N$, $t_j = a + j h$, $M = \max_{t \in [a, b]} |y''(t)|$.

How good is Theorem?

► **Good News:** Euler's method converges:

$$\lim_{N \rightarrow \infty} \frac{hM}{2L} \left(e^{L(t_j-a)} - 1 \right) = 0.$$

Theorem is a mixed bag

Theorem:

$$|y(t_j) - w_j| \leq \frac{hM}{2L} \left(e^{L(t_j-a)} - 1 \right), \quad (1)$$

where $h = (b - a)/N$, $t_j = a + j h$, $M = \mathbf{max}_{t \in [a, b]} |y''(t)|$.

How good is Theorem?

- ▶ **Good News:** Euler's method converges:

$$\lim_{N \rightarrow \infty} \frac{hM}{2L} \left(e^{L(t_j-a)} - 1 \right) = 0.$$

- ▶ **Bad News:** N may have to be impossibly large:

$$e^{L(t_N-a)} = e^{L(b-a)} > 10^{43} \quad \text{if} \quad L > 10 \quad \text{and} \quad b - a > 10.$$

Theorem: Suppose that in the initial value ODE,

$$\frac{dy}{dt} = f(t, y), \quad a \leq t \leq b, \quad y(a) = \alpha,$$

- ▶ $f(t, y)$ is continuous,
- ▶ $f(t, y)$ satisfies Lipschitz condition

$$\begin{aligned} |f(t, y_1) - f(t, y_2)| &\leq L |y_1 - y_2| \quad \text{on domain} \\ D &= \{(t, y) \mid a \leq t \leq b, \quad -\infty < y < \infty\}. \end{aligned}$$

Let w_0, w_1, \dots, w_N be the approximations generated by Euler's method for some positive integer N . Then for each $j = 0, 1, \dots, N$,

$$|y(t_j) - w_j| \leq \frac{hM}{2L} \left(e^{L(t_j-a)} - 1 \right),$$

where $h = (b - a)/N$, $t_j = a + j h$, $M = \mathbf{max}_{t \in [a, b]} |y''(t)|$.

Proof of **Theorem 1**

- ▶ Mesh points

$$t_j = a + j h, \quad \text{for } j = 0, 1, 2, \dots, N, \quad \text{where } h = (b - a)/N.$$

Proof of Theorem 1

- ▶ Mesh points

$$t_j = a + j h, \quad \text{for } j = 0, 1, 2, \dots, N, \quad \text{where } h = (b - a)/N.$$

- ▶ For each j , we have 2-term Taylor expansion

$$\begin{aligned} y(t_{j+1}) &= y(t_j) + h y'(t_j) + \frac{h^2}{2} y''(\xi_j) \\ &= y(t_j) + h f(t_j, y(t_j)) + \frac{h^2}{2} y''(\xi_j), \quad j = 0, 1, \dots, N - 1. \end{aligned}$$

Proof of Theorem 1

- ▶ Mesh points

$$t_j = a + j h, \quad \text{for } j = 0, 1, 2, \dots, N, \quad \text{where } h = (b - a)/N.$$

- ▶ For each j , we have 2-term Taylor expansion

$$\begin{aligned} y(t_{j+1}) &= y(t_j) + h y'(t_j) + \frac{h^2}{2} y''(\xi_j) \\ &= y(t_j) + h f(t_j, y(t_j)) + \frac{h^2}{2} y''(\xi_j), \quad j = 0, 1, \dots, N - 1. \end{aligned}$$

- ▶ Euler's method for each j

$$w_{j+1} = w_j + h f(t_j, w_j).$$

Proof of Theorem 1

- ▶ Mesh points

$$t_j = a + j h, \quad \text{for } j = 0, 1, 2, \dots, N, \quad \text{where } h = (b - a)/N.$$

- ▶ For each j , we have 2-term Taylor expansion

$$\begin{aligned} y(t_{j+1}) &= y(t_j) + h y'(t_j) + \frac{h^2}{2} y''(\xi_j) \\ &= y(t_j) + h f(t_j, y(t_j)) + \frac{h^2}{2} y''(\xi_j), \quad j = 0, 1, \dots, N - 1. \end{aligned}$$

- ▶ Euler's method for each j

$$w_{j+1} = w_j + h f(t_j, w_j).$$

- ▶ Subtraction of two equations:

$$y(t_{j+1}) - w_{j+1} = y(t_j) - w_j + h (f(t_j, y(t_j)) - f(t_j, w_j)) + \frac{h^2}{2} y''(\xi_j).$$

Proof of **Theorem II**

- ▶ Difference of two equations:

$$y(t_{j+1}) - w_{j+1} = y(t_j) - w_j + h(f(t_j, y(t_j)) - f(t_j, w_j)) + \frac{h^2}{2} y''(\xi_j).$$

Proof of Theorem II

- ▶ Difference of two equations:

$$y(t_{j+1}) - w_{j+1} = y(t_j) - w_j + h(f(t_j, y(t_j)) - f(t_j, w_j)) + \frac{h^2}{2} y''(\xi_j).$$

- ▶ This implies a linear recursion:

$$\begin{aligned} |y(t_{j+1}) - w_{j+1}| &\leq |y(t_j) - w_j| + h |f(t_j, y(t_j)) - f(t_j, w_j)| + \frac{h^2}{2} |y''(\xi_j)| \\ &\leq |y(t_j) - w_j| + hL |y(t_j) - w_j| + \frac{h^2}{2} M \\ &= (1 + hL) |y(t_j) - w_j| + \frac{h^2}{2} M. \end{aligned}$$

Proof of Theorem II

- ▶ Difference of two equations:

$$y(t_{j+1}) - w_{j+1} = y(t_j) - w_j + h(f(t_j, y(t_j)) - f(t_j, w_j)) + \frac{h^2}{2} y''(\xi_j).$$

- ▶ This implies a linear recursion:

$$\begin{aligned} |y(t_{j+1}) - w_{j+1}| &\leq |y(t_j) - w_j| + h |f(t_j, y(t_j)) - f(t_j, w_j)| + \frac{h^2}{2} |y''(\xi_j)| \\ &\leq |y(t_j) - w_j| + hL |y(t_j) - w_j| + \frac{h^2}{2} M \\ &= (1 + hL) |y(t_j) - w_j| + \frac{h^2}{2} M. \end{aligned}$$

- ▶ Further simplification for $j = 0, \dots, N - 1$,

$$\begin{aligned} |y(t_{j+1}) - w_{j+1}| + \frac{hM}{2L} &\leq (1 + hL) |y(t_j) - w_j| + \frac{h^2}{2} M + \frac{hM}{2L} \\ &= (1 + hL) \left(|y(t_j) - w_j| + \frac{hM}{2L} \right). \end{aligned}$$

Proof of Theorem III

- ▶ Solving linear recursion:

$$\begin{aligned} |y(t_{j+1}) - w_{j+1}| + \frac{hM}{2L} &\leq (1 + hL) \left(|y(t_j) - w_j| + \frac{hM}{2L} \right) \\ &\leq (1 + hL)^2 \left(|y(t_{j-1}) - w_{j-1}| + \frac{hM}{2L} \right) \\ &\vdots \\ &\leq (1 + hL)^{j+1} \left(|y(t_0) - w_0| + \frac{hM}{2L} \right). \end{aligned}$$

- ▶ Since $y(t_0) = w_0 = \alpha$,

$$|y(t_{j+1}) - w_{j+1}| + \frac{hM}{2L} \leq (1 + hL)^{j+1} \frac{hM}{2L},$$

it follows that

$$\begin{aligned} |y(t_{j+1}) - w_{j+1}| &\leq \frac{hM}{2L} \left((1 + hL)^{j+1} - 1 \right) \\ &\leq \frac{hM}{2L} \left(e^{L(t_{j+1}-a)} - 1 \right). \end{aligned}$$

Theorem: Suppose that in the initial value ODE,

$$\frac{dy}{dt} = f(t, y), \quad a \leq t \leq b, \quad y(a) = \alpha,$$

- ▶ $f(t, y)$ is continuous,
- ▶ $f(t, y)$ satisfies Lipschitz condition

$$\begin{aligned} |f(t, y_1) - f(t, y_2)| &\leq L |y_1 - y_2| \quad \text{on domain} \\ D &= \{(t, y) \mid a \leq t \leq b, \quad -\infty < y < \infty\}. \end{aligned}$$

Let w_0, w_1, \dots, w_N be the approximations generated by Euler's method for some positive integer N . Then for each $j = 0, 1, \dots, N$,

$$|y(t_j) - w_j| \leq \frac{hM}{2L} \left(e^{L(t_j-a)} - 1 \right),$$

where $h = (b - a)/N$, $t_j = a + j h$, $M = \mathbf{max}_{t \in [a, b]} |y''(t)|$.

Euler's Method: example (I)

Initial Value ODE $\frac{dy}{dt} = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5,$

exact solution $y(t) = (1 + t)^2 - 0.5 e^t.$

- ▶ Choose positive integer $N = 10$, so

$$h = 0.2, \quad t_j = 0.2j, \quad \text{for } j = 0, 1, 2, \dots, 10.$$

Euler's Method: example (I)

Initial Value ODE $\frac{dy}{dt} = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5,$

exact solution $y(t) = (1 + t)^2 - 0.5 e^t.$

- ▶ Choose positive integer $N = 10$, so

$$h = 0.2, \quad t_j = 0.2j, \quad \text{for } j = 0, 1, 2, \dots, 10.$$

- ▶ Set $w_0 = 0.5$. For $j = 0, 1, \dots, 9$,

$$\begin{aligned} w_{j+1} &= w_j + h(w_j - t_j^2 + 1) = w_j + 0.2(w_j - 0.04j^2 + 1) \\ &= 1.2w_j - 0.008j^2 + 0.2. \end{aligned}$$

Euler's Method: example (I)

Initial Value ODE $\frac{dy}{dt} = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5,$

exact solution $y(t) = (1 + t)^2 - 0.5 e^t.$

- ▶ Choose positive integer $N = 10$, so

$$h = 0.2, \quad t_j = 0.2j, \quad \text{for } j = 0, 1, 2, \dots, 10.$$

- ▶ Set $w_0 = 0.5$. For $j = 0, 1, \dots, 9$,

$$\begin{aligned} w_{j+1} &= w_j + h(w_j - t_j^2 + 1) = w_j + 0.2(w_j - 0.04j^2 + 1) \\ &= 1.2w_j - 0.008j^2 + 0.2. \end{aligned}$$

Since $y''(t) = 2 - 0.5 e^t, \quad \frac{\partial f}{\partial y}(t, y) = 1,$

it follows that $|y''(t)| \leq 0.5 e^2 - 2 \stackrel{\text{def}}{=} M, \quad L = 1.$

Euler's Method: example (II)

Initial Value ODE $\frac{dy}{dt} = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5,$
exact solution $y(t) = (1 + t)^2 - 0.5 e^t.$

- ▶ Therefore $M = 0.5 e^2 - 2, L = 1,$

$$|y(t_i) - w_i| \leq \frac{hM}{2L} \left(e^{L(t_i-a)} - 1 \right) = 0.1 (0.5 e^2 - 2) (e^{t_i} - 1).$$

Euler's Method: example (II)

Initial Value ODE $\frac{dy}{dt} = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5,$

exact solution $y(t) = (1 + t)^2 - 0.5 e^t.$

- ▶ Therefore $M = 0.5 e^2 - 2, L = 1,$

$$|y(t_i) - w_i| \leq \frac{hM}{2L} \left(e^{L(t_i-a)} - 1 \right) = 0.1 (0.5 e^2 - 2) (e^{t_i} - 1).$$

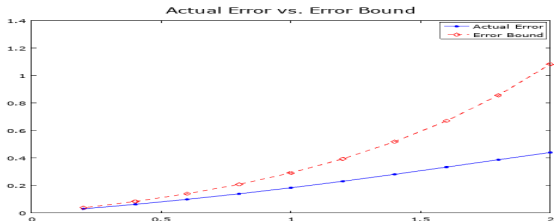
t_i	w_i	$y_i = y(t_i)$	$ y_i - w_i $
0.0	0.5000000	0.5000000	0.0000000
0.2	0.8000000	0.8292986	0.0292986
0.4	1.1520000	1.2140877	0.0620877
0.6	1.5504000	1.6489406	0.0985406
0.8	1.9884800	2.1272295	0.1387495
1.0	2.4581760	2.6408591	0.1826831
1.2	2.9498112	3.1799415	0.2301303
1.4	3.4517734	3.7324000	0.2806266
1.6	3.9501281	4.2834838	0.3333557
1.8	4.4281538	4.8151763	0.3870225
2.0	4.8657845	5.3054720	0.4396874

$$|y(t_i) - w_i| \leq 0.1 (0.5 e^2 - 2) (e^{t_i} - 1)$$

t_i	Actual Error	Error Bound
0.200000	0.029300	0.037520
0.400000	0.062090	0.083340
0.600000	0.098540	0.139310
0.800000	0.138750	0.207670
1.000000	0.182680	0.291170
1.200000	0.230130	0.393150
1.400000	0.280630	0.517710
1.600000	0.333360	0.669850
1.800000	0.387020	0.855680
2.000000	0.439690	1.082640

$$|y(t_i) - w_i| \leq 0.1 (0.5 e^2 - 2) (e^{t_i} - 1)$$

t_i	Actual Error	Error Bound
0.200000	0.029300	0.037520
0.400000	0.062090	0.083340
0.600000	0.098540	0.139310
0.800000	0.138750	0.207670
1.000000	0.182680	0.291170
1.200000	0.230130	0.393150
1.400000	0.280630	0.517710
1.600000	0.333360	0.669850
1.800000	0.387020	0.855680
2.000000	0.439690	1.082640



Euler's Method in Finite Precision, I

- ▶ Mesh points

$$t_j = a + j h, \quad \text{for } j = 0, 1, 2, \dots, N, \quad \text{where } h = (b - a)/N.$$

Euler's Method in Finite Precision, I

- ▶ Mesh points

$$t_j = a + j h, \quad \text{for } j = 0, 1, 2, \dots, N, \quad \text{where } h = (b - a)/N.$$

- ▶ For each j , we have 2-term Taylor expansion

$$\begin{aligned} y(t_{j+1}) &= y(t_j) + h y'(t_j) + \frac{h^2}{2} y''(\xi_j) \\ &= y(t_j) + h f(t_j, y(t_j)) + \frac{h^2}{2} y''(\xi_j), \quad j = 0, 1, \dots, N - 1. \end{aligned}$$

Euler's Method in Finite Precision, I

- ▶ Mesh points

$$t_j = a + j h, \quad \text{for } j = 0, 1, 2, \dots, N, \quad \text{where } h = (b - a)/N.$$

- ▶ For each j , we have 2-term Taylor expansion

$$\begin{aligned} y(t_{j+1}) &= y(t_j) + h y'(t_j) + \frac{h^2}{2} y''(\xi_j) \\ &= y(t_j) + h f(t_j, y(t_j)) + \frac{h^2}{2} y''(\xi_j), \quad j = 0, 1, \dots, N - 1. \end{aligned}$$

- ▶ Euler's method for each j , in finite precision

$$u_{j+1} = u_j + h f(t_j, u_j) + \delta_{j+1},$$

where $|\delta_{j+1}| \leq \delta$.

Euler's Method in Finite Precision, I

- ▶ Mesh points

$$t_j = a + j h, \quad \text{for } j = 0, 1, 2, \dots, N, \quad \text{where } h = (b - a)/N.$$

- ▶ For each j , we have 2-term Taylor expansion

$$\begin{aligned} y(t_{j+1}) &= y(t_j) + h y'(t_j) + \frac{h^2}{2} y''(\xi_j) \\ &= y(t_j) + h f(t_j, y(t_j)) + \frac{h^2}{2} y''(\xi_j), \quad j = 0, 1, \dots, N - 1. \end{aligned}$$

- ▶ Euler's method for each j , in finite precision

$$u_{j+1} = u_j + h f(t_j, u_j) + \delta_{j+1},$$

where $|\delta_{j+1}| \leq \delta$.

- ▶ Subtraction of two equations:

$$y(t_{j+1}) - u_{j+1} = y(t_j) - u_j + h (f(t_j, y(t_j)) - f(t_j, u_j)) + \frac{h^2}{2} y''(\xi_j) - \delta_{j+1}.$$

Euler's Method in Finite Precision, II

- ▶ Difference of two equations:

$$y(t_{j+1}) - u_{j+1} = y(t_j) - u_j + h(f(t_j, y(t_j)) - f(t_j, u_j)) + \frac{h^2}{2} y''(\xi_j) - \delta_{j+1}.$$

Euler's Method in Finite Precision, II

- ▶ Difference of two equations:

$$y(t_{j+1}) - u_{j+1} = y(t_j) - u_j + h(f(t_j, y(t_j)) - f(t_j, u_j)) + \frac{h^2}{2} y''(\xi_j) - \delta_{j+1}.$$

- ▶ This implies a linear recursion:

$$\begin{aligned} |y(t_{j+1}) - u_{j+1}| &\leq |y(t_j) - u_j| + h |f(t_j, y(t_j)) - f(t_j, u_j)| + \frac{h^2}{2} |y''(\xi_j)| + |\delta_{j+1}| \\ &\leq |y(t_j) - u_j| + hL |y(t_j) - u_j| + \frac{h^2}{2} M + \delta \\ &= (1 + hL) |y(t_j) - u_j| + \frac{h^2}{2} M + \delta. \end{aligned}$$

Euler's Method in Finite Precision, II

- ▶ Difference of two equations:

$$y(t_{j+1}) - u_{j+1} = y(t_j) - u_j + h(f(t_j, y(t_j)) - f(t_j, u_j)) + \frac{h^2}{2} y''(\xi_j) - \delta_{j+1}.$$

- ▶ This implies a linear recursion:

$$\begin{aligned} |y(t_{j+1}) - u_{j+1}| &\leq |y(t_j) - u_j| + h |f(t_j, y(t_j)) - f(t_j, u_j)| + \frac{h^2}{2} |y''(\xi_j)| + |\delta_{j+1}| \\ &\leq |y(t_j) - u_j| + hL |y(t_j) - u_j| + \frac{h^2}{2} M + \delta \\ &= (1 + hL) |y(t_j) - u_j| + \frac{h^2}{2} M + \delta. \end{aligned}$$

- ▶ Further simplification for $j = 0, \dots, N-1$,

$$\begin{aligned} |y(t_{j+1}) - u_{j+1}| + \frac{hM}{2L} + \frac{\delta}{hL} &\leq (1 + hL) |y(t_j) - u_j| + \frac{h^2}{2} M + \frac{hM}{2L} + \delta + \frac{\delta}{hL} \\ &= (1 + hL) \left(|y(t_j) - u_j| + \frac{hM}{2L} + \frac{\delta}{hL} \right). \end{aligned}$$

Euler's Method in Finite Precision, III

- ▶ Solving linear recursion:

$$\begin{aligned} |y(t_{j+1}) - u_{j+1}| + \frac{hM}{2L} + \frac{\delta}{hL} &\leq (1 + hL) \left(|y(t_j) - u_j| + \frac{hM}{2L} + \frac{\delta}{hL} \right) \\ &\vdots \\ &\leq (1 + hL)^{j+1} \left(|y(t_0) - u_0| + \frac{hM}{2L} + \frac{\delta}{hL} \right). \end{aligned}$$

- ▶ Assume $|y(t_0) - u_0| = |\alpha - u_0| \leq \delta$,

$$|y(t_{j+1}) - u_{j+1}| + \frac{hM}{2L} + \frac{\delta}{hL} \leq (1 + hL)^{j+1} \left(\delta + \frac{hM}{2L} + \frac{\delta}{hL} \right),$$

it follows that

$$\begin{aligned} |y(t_{j+1}) - u_{j+1}| &\leq \frac{1}{L} \left(\frac{hM}{2} + \frac{\delta}{h} \right) \left((1 + hL)^{j+1} - 1 \right) + \delta (1 + hL)^{j+1} \\ &\leq \frac{1}{L} \left(\frac{hM}{2} + \frac{\delta}{h} \right) \left(e^{L(t_{j+1}-a)} - 1 \right) + \delta e^{L(t_{j+1}-a)}. \end{aligned}$$

Euler's Method in Finite Precision, IV

- ▶ Error bound in finite precision

$$|y(t_{j+1}) - u_{j+1}| \leq \frac{1}{L} \left(\frac{hM}{2} + \frac{\delta}{h} \right) \left(e^{L(t_{j+1}-a)} - 1 \right) + \delta e^{L(t_{j+1}-a)}.$$

Euler's Method in Finite Precision, IV

- ▶ Error bound in finite precision

$$|y(t_{j+1}) - u_{j+1}| \leq \frac{1}{L} \left(\frac{hM}{2} + \frac{\delta}{h} \right) \left(e^{L(t_{j+1}-a)} - 1 \right) + \delta e^{L(t_{j+1}-a)}.$$

- ▶ Value of h can't be too small:

$$\lim_{h \rightarrow 0} \left(\frac{hM}{2} + \frac{\delta}{h} \right) = \infty.$$

Euler's Method in Finite Precision, IV

- ▶ Error bound in finite precision

$$|y(t_{j+1}) - u_{j+1}| \leq \frac{1}{L} \left(\frac{hM}{2} + \frac{\delta}{h} \right) \left(e^{L(t_{j+1}-a)} - 1 \right) + \delta e^{L(t_{j+1}-a)}.$$

- ▶ Value of h can't be too small:

$$\lim_{h \rightarrow 0} \left(\frac{hM}{2} + \frac{\delta}{h} \right) = \infty.$$

- ▶ "Optimal" value of h

$$h_{\mathbf{opt}} = \sqrt{\frac{2\delta}{M}}, \quad \text{and} \quad \left(\frac{h_{\mathbf{opt}}M}{2} + \frac{\delta}{h_{\mathbf{opt}}} \right) = \sqrt{2\delta M}.$$

Euler's Method in Finite Precision, IV

- ▶ Error bound in finite precision

$$|y(t_{j+1}) - u_{j+1}| \leq \frac{1}{L} \left(\frac{hM}{2} + \frac{\delta}{h} \right) \left(e^{L(t_{j+1}-a)} - 1 \right) + \delta e^{L(t_{j+1}-a)}.$$

- ▶ Value of h can't be too small:

$$\lim_{h \rightarrow 0} \left(\frac{hM}{2} + \frac{\delta}{h} \right) = \infty.$$

- ▶ "Optimal" value of h

$$h_{\mathbf{opt}} = \sqrt{\frac{2\delta}{M}}, \quad \text{and} \quad \left(\frac{h_{\mathbf{opt}}M}{2} + \frac{\delta}{h_{\mathbf{opt}}} \right) = \sqrt{2\delta M}.$$

- ▶ "Practical" value of $h \gg h_{\mathbf{opt}}$.

Local Truncation Error for a general difference method

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

Definition: The difference method

$$\begin{aligned} w_0 &= \alpha, \\ w_{j+1} &= w_j + h\phi(t_j, w_j), \quad \text{for } j = 0, 1, \dots, N-1 \end{aligned}$$

has **local truncation error**

$$\begin{aligned} \tau_{j+1}(h) &\stackrel{\text{def}}{=} \frac{y(t_{j+1}) - (y(t_j) + h\phi(t_j, y(t_j)))}{h} \\ &= \frac{y(t_{j+1}) - y(t_j)}{h} - \phi(t_j, y(t_j)). \end{aligned}$$

Local Truncation Error for Euler's method

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

Euler's method

$$\begin{aligned} w_0 &= \alpha, \\ w_{j+1} &= w_j + hf(t_j, w_j), \quad \text{for } j = 0, 1, \dots, N-1 \end{aligned}$$

has **local truncation error**

$$\begin{aligned} \tau_{j+1}(h) &= \frac{y(t_{j+1}) - y(t_j)}{h} - f(t_j, y(t_j)) \\ &= \frac{y(t_{j+1}) - y(t_j)}{h} - y'(t_j) = \frac{h}{2} y''(\xi_j), \quad \xi_j \in (t_j, t_{j+1}). \end{aligned}$$

This implies

$$|\tau_{j+1}(h)| \leq \frac{h}{2} \max_{t \in [a, b]} |y''(t)| \stackrel{\text{def}}{=} \frac{hM}{2}, \quad \text{a first order method.}$$

n -th Order Taylor Methods:

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

n -th Order Taylor Methods:

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

- ▶ $(n + 1)$ -term Taylor expansion

$$\begin{aligned} y(t_{j+1}) = & y(t_j) + hy'(t_j) + \frac{h^2}{2}y''(t_j) + \cdots + \frac{h^n}{n!}y^{(n)}(t_j) \\ & + \frac{h^{n+1}}{(n+1)!}y^{(n+1)}(\xi_j). \end{aligned}$$

n -th Order Taylor Methods:

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

- ▶ $(n + 1)$ -term Taylor expansion

$$\begin{aligned} y(t_{j+1}) &= y(t_j) + hy'(t_j) + \frac{h^2}{2}y''(t_j) + \cdots + \frac{h^n}{n!}y^{(n)}(t_j) \\ &\quad + \frac{h^{n+1}}{(n+1)!}y^{(n+1)}(\xi_j). \end{aligned}$$

- ▶ On the other hand,

$$\begin{aligned} y'(t_j) &= f(t_j, y(t_j)), \quad y''(t_j) = f'(t_j, y(t_j)), \cdots \\ y^{(n)}(t_j) &= f^{(n-1)}(t_j, y(t_j)). \end{aligned}$$

n -th Order Taylor Method:

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

n -th Order Taylor Method:

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

► $(n + 1)$ -term Taylor expansion

$$y(t_{j+1}) = y(t_j) + hf(t_j, y(t_j)) + \frac{h^2}{2}f'(t_j, y(t_j)) + \cdots + \frac{h^n}{n!}f^{(n-1)}(t_j, y(t_j)) \\ + \frac{h^{n+1}}{(n+1)!}f^{(n)}(\xi_j, y(\xi_j)).$$

n -th Order Taylor Method:

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

- ▶ $(n + 1)$ -term Taylor expansion

$$y(t_{j+1}) = y(t_j) + hf(t_j, y(t_j)) + \frac{h^2}{2}f'(t_j, y(t_j)) + \cdots + \frac{h^n}{n!}f^{(n-1)}(t_j, y(t_j)) \\ + \frac{h^{n+1}}{(n+1)!}f^{(n)}(\xi_j, y(\xi_j)).$$

- ▶ n -th order Taylor method

$$w_0 = \alpha,$$

$$w_{j+1} = w_j + h\mathbf{T}^{(n)}(t_j, w_j), \quad j = 0, 1, \dots, N-1,$$

where $\mathbf{T}^{(n)}(t_j, w_j) = f(t_j, w_j) + \frac{h}{2}f'(t_j, w_j) + \cdots + \frac{h^{n-1}}{n!}f^{(n-1)}(t_j, w_j).$

Example: Second Order Taylor Method:

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

Example: Second Order Taylor Method:

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

- ▶ Second order Taylor method

$$w_0 = \alpha,$$

$$w_{j+1} = w_j + h\mathbf{T}^{(2)}(t_j, w_j), \quad j = 0, 1, \dots, N-1,$$

$$\text{where } \mathbf{T}^{(2)}(t_j, w_j) = f(t_j, w_j) + \frac{h}{2}f'(t_j, w_j) \quad \text{with}$$

Example: Second Order Taylor Method:

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

- ▶ Second order Taylor method

$$w_0 = \alpha,$$

$$w_{j+1} = w_j + h\mathbf{T}^{(2)}(t_j, w_j), \quad j = 0, 1, \dots, N-1,$$

$$\text{where } \mathbf{T}^{(2)}(t_j, w_j) = f(t_j, w_j) + \frac{h}{2}f'(t_j, w_j) \quad \text{with}$$

$$\begin{aligned} f'(t, y(t)) &= \frac{d}{dt}f(t, y(t)) = \frac{\partial f}{\partial t}(t, y(t)) + \frac{\partial f}{\partial y}(t, y(t))y'(t) \\ &= \frac{\partial f}{\partial t}(t, y(t)) + \frac{\partial f}{\partial y}(t, y(t))f(t, y(t)). \end{aligned}$$

Example: Second Order Taylor Method:

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

- ▶ Second order Taylor method

$$w_0 = \alpha,$$

$$w_{j+1} = w_j + h\mathbf{T}^{(2)}(t_j, w_j), \quad j = 0, 1, \dots, N-1,$$

$$\text{where } \mathbf{T}^{(2)}(t_j, w_j) = f(t_j, w_j) + \frac{h}{2}f'(t_j, w_j) \quad \text{with}$$

$$\begin{aligned} f'(t, y(t)) &= \frac{d}{dt}f(t, y(t)) = \frac{\partial f}{\partial t}(t, y(t)) + \frac{\partial f}{\partial y}(t, y(t))y'(t) \\ &= \frac{\partial f}{\partial t}(t, y(t)) + \frac{\partial f}{\partial y}(t, y(t))f(t, y(t)). \end{aligned}$$

- ▶ Second order Taylor method in explicit form

$$w_{j+1} = w_j + h \left(f(t_j, w_j) + \frac{h}{2} \left(\frac{\partial f}{\partial t}(t_j, w_j) + \frac{\partial f}{\partial y}(t_j, w_j) f(t_j, w_j) \right) \right).$$

Example: Second Order Taylor Method:

$$\frac{dy}{dt} = f(t, y), \quad f(t, y) = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5.$$

Example: Second Order Taylor Method:

$$\frac{dy}{dt} = f(t, y), \quad f(t, y) = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5.$$

► Second order Taylor method

$$w_{j+1} = w_j + h \left(f(t_j, w_j) + \frac{h}{2} \left(\frac{\partial f}{\partial t}(t_j, w_j) + \frac{\partial f}{\partial y}(t_j, w_j) f(t_j, w_j) \right) \right).$$

$$\frac{\partial f}{\partial t}(t, y(t)) = -2t, \quad \frac{\partial f}{\partial y}(t, y(t)) = 1.$$

Thus,

$$\begin{aligned} w_{j+1} &= w_j + h \left(w_j - t_j^2 + 1 + \frac{h}{2} (-2t_j + w_j - t_j^2 + 1) \right) \\ &= \left(1 + h + \frac{h^2}{2} \right) w_j + \left(h + \frac{h^2}{2} \right) (1 - t_j^2) - h^2 t_j. \end{aligned}$$

Euler's Method vs. Second Order Taylor Method: $N = 10$

$$\frac{dy}{dt} = f(t, y), \quad f(t, y) = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5.$$

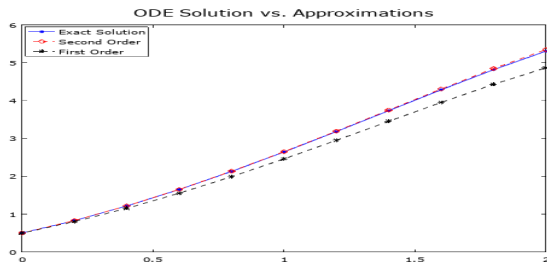
Euler's Method vs. Second Order Taylor Method: $N = 10$

$$\frac{dy}{dt} = f(t, y), \quad f(t, y) = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5.$$

t_i	Euler's Method	Taylor Method	Exact Solution
0.00000	0.50000	0.50000	0.50000
0.20000	0.80000	0.83000	0.82930
0.40000	1.15200	1.21580	1.21409
0.60000	1.55040	1.65208	1.64894
0.80000	1.98848	2.13233	2.12723
1.00000	2.45818	2.64865	2.64086
1.20000	2.94981	3.19135	3.17994
1.40000	3.45177	3.74864	3.73240
1.60000	3.95013	4.30615	4.28348
1.80000	4.42815	4.84630	4.81518
2.00000	4.86578	5.34768	5.30547

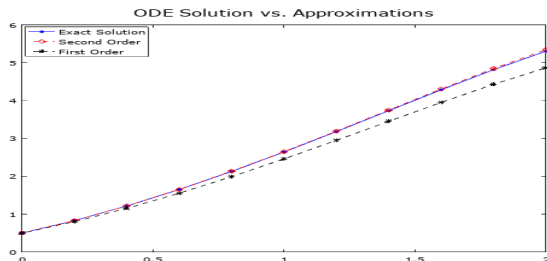
Euler's Method vs. Second Order Taylor Method: $N = 10$

- ▶ Second order method looks more accurate.

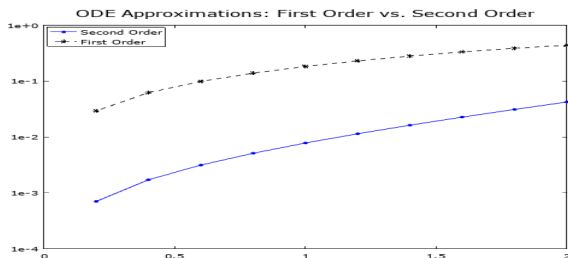


Euler's Method vs. Second Order Taylor Method: $N = 10$

- ▶ Second order method looks more accurate.



- ▶ Second order method has much smaller errors.



Runge-Kutta methods

With orders of Taylor methods yet without derivatives of $f(t, y(t))$

First order Taylor expansion in two variables

Theorem: Suppose that $f(t, y)$ and all its partial derivatives are

continuous on $D \stackrel{\text{def}}{=} \{(t, y) \mid a \leq t \leq b, \quad c \leq y \leq d.\}$

Let $(t_0, y_0), (t, y) \in D, \Delta_t = t - t_0, \Delta_y = y - y_0$. **Then**

$$f(t, y) = P_1(t, y) + R_1(t, y), \quad \text{where}$$

First order Taylor expansion in two variables

Theorem: Suppose that $f(t, y)$ and all its partial derivatives are

continuous on $D \stackrel{\text{def}}{=} \{(t, y) \mid a \leq t \leq b, \quad c \leq y \leq d.\}$

Let $(t_0, y_0), (t, y) \in D, \Delta_t = t - t_0, \Delta_y = y - y_0$. **Then**

$$f(t, y) = P_1(t, y) + R_1(t, y), \quad \text{where}$$

$$P_1(t, y) = f(t_0, y_0) + \Delta_t \frac{\partial f}{\partial t}(t_0, y_0) + \Delta_y \frac{\partial f}{\partial y}(t_0, y_0),$$

$$R_1(t, y) = \frac{\Delta_t^2}{2} \frac{\partial^2 f}{\partial t^2}(\xi, \mu) + \Delta_t \Delta_y \frac{\partial^2 f}{\partial t \partial y}(\xi, \mu) + \frac{\Delta_y^2}{2} \frac{\partial^2 f}{\partial y^2}(\xi, \mu),$$

for some point $(\xi, \mu) \in D$.

Second order Taylor expansion in two variables

Theorem: Suppose that $f(t, y)$ and all its partial derivatives are

continuous on $D \stackrel{\text{def}}{=} \{(t, y) \mid a \leq t \leq b, \quad c \leq y \leq d.\}$

Let $(t_0, y_0), (t, y) \in D, \Delta_t = t - t_0, \Delta_y = y - y_0$. **Then**

$$f(t, y) = P_2(t, y) + R_2(t, y), \quad \text{where}$$

Second order Taylor expansion in two variables

Theorem: Suppose that $f(t, y)$ and all its partial derivatives are

continuous on $D \stackrel{\text{def}}{=} \{(t, y) \mid a \leq t \leq b, c \leq y \leq d.\}$

Let $(t_0, y_0), (t, y) \in D, \Delta_t = t - t_0, \Delta_y = y - y_0$. **Then**

$f(t, y) = P_2(t, y) + R_2(t, y)$, where

$$\begin{aligned} P_2(t, y) = & f(t_0, y_0) + \left(\Delta_t \frac{\partial f}{\partial t}(t_0, y_0) + \Delta_y \frac{\partial f}{\partial y}(t_0, y_0) \right) \\ & + \left(\frac{\Delta_t^2}{2} \frac{\partial^2 f}{\partial t^2}(t_0, y_0) + \Delta_t \Delta_y \frac{\partial^2 f}{\partial t \partial y}(t_0, y_0) + \frac{\Delta_y^2}{2} \frac{\partial^2 f}{\partial y^2}(t_0, y_0) \right), \end{aligned}$$

Second order Taylor expansion in two variables

Theorem: Suppose that $f(t, y)$ and all its partial derivatives are

continuous on $D \stackrel{\text{def}}{=} \{(t, y) \mid a \leq t \leq b, c \leq y \leq d.\}$

Let $(t_0, y_0), (t, y) \in D, \Delta_t = t - t_0, \Delta_y = y - y_0$. **Then**

$f(t, y) = P_2(t, y) + R_2(t, y)$, where

$$P_2(t, y) = f(t_0, y_0) + \left(\Delta_t \frac{\partial f}{\partial t}(t_0, y_0) + \Delta_y \frac{\partial f}{\partial y}(t_0, y_0) \right) + \left(\frac{\Delta_t^2}{2} \frac{\partial^2 f}{\partial t^2}(t_0, y_0) + \Delta_t \Delta_y \frac{\partial^2 f}{\partial t \partial y}(t_0, y_0) + \frac{\Delta_y^2}{2} \frac{\partial^2 f}{\partial y^2}(t_0, y_0) \right),$$

$$R_2(t, y) = \frac{1}{3!} \left(\sum_{j=0}^3 \binom{3}{j} \Delta_t^{3-j} \Delta_y^j \frac{\partial^3 f}{\partial t^{3-j} \partial y^j}(\xi, \mu) \right)$$

Example: Second order Taylor expansion in two variables

$$\begin{aligned} f(t, y) &= \mathbf{exp} \left(-\frac{(t-2)^2}{4} - \frac{(y-3)^2}{4} \right) \mathbf{cos}(2t + y - 7) \\ &= P_2(t, y) + R_2(t, y), \quad \text{with } (t_0, y_0) = (2, 3). \end{aligned}$$

Example: Second order Taylor expansion in two variables

$$\begin{aligned} f(t, y) &= \exp\left(-\frac{(t-2)^2}{4} - \frac{(y-3)^2}{4}\right) \cos(2t + y - 7) \\ &= P_2(t, y) + R_2(t, y), \quad \text{with } (t_0, y_0) = (2, 3). \end{aligned}$$

Let $\Delta_t = t - 2$, $\Delta_y = y - 3$,

$$\begin{aligned} P_2(t, y) &= f(t_0, y_0) + \left(\Delta_t \frac{\partial f}{\partial t}(t_0, y_0) + \Delta_y \frac{\partial f}{\partial y}(t_0, y_0) \right) \\ &\quad + \left(\frac{\Delta_t^2}{2} \frac{\partial^2 f}{\partial t^2}(t_0, y_0) + \Delta_t \Delta_y \frac{\partial^2 f}{\partial t \partial y}(t_0, y_0) + \frac{\Delta_y^2}{2} \frac{\partial^2 f}{\partial y^2}(t_0, y_0) \right) \end{aligned}$$

Example: Second order Taylor expansion in two variables

$$\begin{aligned} f(t, y) &= \exp\left(-\frac{(t-2)^2}{4} - \frac{(y-3)^2}{4}\right) \cos(2t + y - 7) \\ &= P_2(t, y) + R_2(t, y), \quad \text{with } (t_0, y_0) = (2, 3). \end{aligned}$$

$$\text{Let } \Delta_t = t - 2, \Delta_y = y - 3,$$

$$\begin{aligned} P_2(t, y) &= f(t_0, y_0) + \left(\Delta_t \frac{\partial f}{\partial t}(t_0, y_0) + \Delta_y \frac{\partial f}{\partial y}(t_0, y_0) \right) \\ &\quad + \left(\frac{\Delta_t^2}{2} \frac{\partial^2 f}{\partial t^2}(t_0, y_0) + \Delta_t \Delta_y \frac{\partial^2 f}{\partial t \partial y}(t_0, y_0) + \frac{\Delta_y^2}{2} \frac{\partial^2 f}{\partial y^2}(t_0, y_0) \right) \\ &= 1 - \frac{9}{4} \Delta_t^2 - 2 \Delta_t \Delta_y - \frac{3}{4} \Delta_y^2. \end{aligned}$$

Example: Second order Taylor expansion in two variables

$$\begin{aligned}f(t, y) &= \exp\left(-\frac{(t-2)^2}{4} - \frac{(y-3)^2}{4}\right) \cos(2t + y - 7) \\ &= P_2(t, y) + R_2(t, y), \quad \text{with } (t_0, y_0) = (2, 3).\end{aligned}$$

$$\text{Let } \Delta_t = t - 2, \Delta_y = y - 3,$$

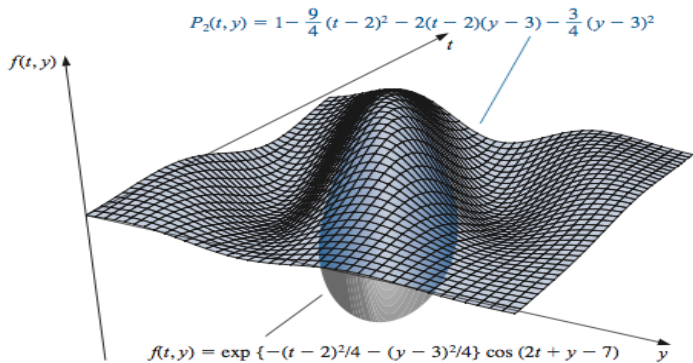
$$\begin{aligned}P_2(t, y) &= f(t_0, y_0) + \left(\Delta_t \frac{\partial f}{\partial t}(t_0, y_0) + \Delta_y \frac{\partial f}{\partial y}(t_0, y_0)\right) \\ &\quad + \left(\frac{\Delta_t^2}{2} \frac{\partial^2 f}{\partial t^2}(t_0, y_0) + \Delta_t \Delta_y \frac{\partial^2 f}{\partial t \partial y}(t_0, y_0) + \frac{\Delta_y^2}{2} \frac{\partial^2 f}{\partial y^2}(t_0, y_0)\right) \\ &= 1 - \frac{9}{4} \Delta_t^2 - 2 \Delta_t \Delta_y - \frac{3}{4} \Delta_y^2.\end{aligned}$$

$$\text{so } f(t, y) \approx P_2(t, y) = 1 - \frac{9}{4}(t-2)^2 - 2(t-2)(y-3) - \frac{3}{4}(y-3)^2.$$

$$\begin{aligned} f(t, y) &= \mathbf{exp} \left(-\frac{(t-2)^2}{4} - \frac{(y-3)^2}{4} \right) \mathbf{cos}(2t + y - 7) \\ &\approx 1 - \frac{9}{4}(t-2)^2 - 2(t-1)(y-3) - \frac{3}{4}(y-3)^2. \end{aligned}$$

$$f(t, y) = \exp\left(-\frac{(t-2)^2}{4} - \frac{(y-3)^2}{4}\right) \cos(2t + y - 7)$$

$$\approx 1 - \frac{9}{4}(t-2)^2 - 2(t-1)(y-3) - \frac{3}{4}(y-3)^2.$$



Approximation good near (2, 3), bad elsewhere

Taylor's Theorem in two variables

Theorem: Suppose that $f(t, y)$ and all its partial derivatives are continuous on $D \stackrel{\text{def}}{=} \{(t, y) \mid a \leq t \leq b, c \leq y \leq d.\}$

Let $(t_0, y_0), (t, y) \in D, \Delta_t = t - t_0, \Delta_y = y - y_0$. **Then** for $n \geq 1$,

$$f(t, y) = P_n(t, y) + R_n(t, y), \quad \text{where}$$

Taylor's Theorem in two variables

Theorem: Suppose that $f(t, y)$ and all its partial derivatives are continuous on $D \stackrel{\text{def}}{=} \{(t, y) \mid a \leq t \leq b, c \leq y \leq d.\}$

Let $(t_0, y_0), (t, y) \in D, \Delta_t = t - t_0, \Delta_y = y - y_0$. **Then** for $n \geq 1$,

$$f(t, y) = P_n(t, y) + R_n(t, y), \quad \text{where}$$

$$\begin{aligned} P_n(t, y) = & f(t_0, y_0) + \left(\Delta_t \frac{\partial f}{\partial t}(t_0, y_0) + \Delta_y \frac{\partial f}{\partial y}(t_0, y_0) \right) \\ & + \left(\frac{\Delta_t^2}{2} \frac{\partial^2 f}{\partial t^2}(t_0, y_0) + \Delta_t \Delta_y \frac{\partial^2 f}{\partial t \partial y}(t_0, y_0) + \frac{\Delta_y^2}{2} \frac{\partial^2 f}{\partial y^2}(t_0, y_0) \right) \\ & + \cdots + \frac{1}{n!} \left(\sum_{j=0}^n \binom{n}{j} \Delta_t^{n-j} \Delta_y^j \frac{\partial^n f}{\partial t^{n-j} \partial y^j}(t_0, y_0) \right), \end{aligned}$$

Taylor's Theorem in two variables

Theorem: Suppose that $f(t, y)$ and all its partial derivatives are continuous on $D \stackrel{\text{def}}{=} \{(t, y) \mid a \leq t \leq b, c \leq y \leq d.\}$

Let $(t_0, y_0), (t, y) \in D, \Delta_t = t - t_0, \Delta_y = y - y_0$. **Then** for $n \geq 1$,

$$f(t, y) = P_n(t, y) + R_n(t, y), \quad \text{where}$$

$$\begin{aligned} P_n(t, y) &= f(t_0, y_0) + \left(\Delta_t \frac{\partial f}{\partial t}(t_0, y_0) + \Delta_y \frac{\partial f}{\partial y}(t_0, y_0) \right) \\ &+ \left(\frac{\Delta_t^2}{2} \frac{\partial^2 f}{\partial t^2}(t_0, y_0) + \Delta_t \Delta_y \frac{\partial^2 f}{\partial t \partial y}(t_0, y_0) + \frac{\Delta_y^2}{2} \frac{\partial^2 f}{\partial y^2}(t_0, y_0) \right) \\ &+ \cdots + \frac{1}{n!} \left(\sum_{j=0}^n \binom{n}{j} \Delta_t^{n-j} \Delta_y^j \frac{\partial^n f}{\partial t^{n-j} \partial y^j}(t_0, y_0) \right), \\ R_n(t, y) &= \frac{1}{(n+1)!} \left(\sum_{j=0}^{n+1} \binom{n+1}{j} \Delta_t^{n+1-j} \Delta_y^j \frac{\partial^{n+1} f}{\partial t^{n+1-j} \partial y^j}(\xi, \mu) \right) \end{aligned}$$

Runge-Kutta Method of Order Two (I)

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

Runge-Kutta Method of Order Two (I)

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

- ▶ Second order Taylor method

$$w_0 = \alpha,$$

$$w_{j+1} = w_j + h\mathbf{T}^{(2)}(t_j, w_j), \quad j = 0, 1, \dots, N-1, \quad \text{where}$$

$$\begin{aligned}\mathbf{T}^{(2)}(t, y) &= f(t, y) + \frac{h}{2}f'(t, y) \\ &= f(t, y) + \frac{h}{2} \left(\frac{\partial f}{\partial t}(t, y) + \frac{\partial f}{\partial y}(t, y) \frac{dy}{dt} \right) \\ &= f(t, y) + \frac{h}{2} \left(\frac{\partial f}{\partial t}(t, y) + \frac{\partial f}{\partial y}(t, y) f(t, y) \right) \\ &= f \left(t + \frac{h}{2}, y + \frac{h}{2}f(t, y) \right) - R_1 \left(t + \frac{h}{2}, y + \frac{h}{2}f(t, y) \right)\end{aligned}$$

Runge-Kutta Method of Order Two (II)

- ▶ Second order Taylor method

$$w_0 = \alpha,$$

$$w_{j+1} = w_j + h\mathbf{T}^{(2)}(t_j, w_j), \quad j = 0, 1, \dots, N-1, \quad \text{where}$$

$$\mathbf{T}^{(2)}(t, y) = f\left(t + \frac{h}{2}, y + \frac{h}{2}f(t, y)\right) - R_1\left(t + \frac{h}{2}, y + \frac{h}{2}f(t, y)\right),$$

- ▶ From first order Taylor expansion,

$$\begin{aligned} R_1\left(t + \frac{h}{2}, y + \frac{h}{2}f(t, y)\right) &= \frac{h^2}{8} \frac{\partial^2 f}{\partial t^2}(\xi, \mu) + \frac{h^2 f(t, y)}{4} \Delta_t \Delta_y \frac{\partial^2 f}{\partial t \partial y}(\xi, \mu) \\ &+ \frac{h^2 f^2(t, y)}{8} \frac{\partial^2 f}{\partial y^2}(\xi, \mu) = O(h^2). \end{aligned}$$

Method remains second order after dropping $R_1\left(t + \frac{h}{2}, y + \frac{h}{2}f(t, y)\right)$

Runge-Kutta Method of Order Two (III)

► Midpoint Method

$$w_0 = \alpha,$$

$$w_{j+1} = w_j + h f \left(t_j + \frac{h}{2}, w_j + \frac{h}{2} f(t_j, w_j) \right), \quad j = 0, 1, \dots, N-1.$$

- Two function evaluations for each j ,
- Second order accuracy.

No need for derivative calculations

General 2nd order Runge-Kutta Methods

► $w_0 = \alpha$; for $j = 0, 1, \dots, N - 1$,

$$w_{j+1} = w_j + h (a_1 f(t_j, w_j) + a_2 f(t_j + \alpha_2, w_j + \delta_2 f(t_j, w_j))).$$

General 2nd order Runge-Kutta Methods

- ▶ $w_0 = \alpha$; for $j = 0, 1, \dots, N - 1$,

$$w_{j+1} = w_j + h (a_1 f(t_j, w_j) + a_2 f(t_j + \alpha_2, w_j + \delta_2 f(t_j, w_j))).$$

- ▶ Two function evaluations for each j ,
- ▶ Want to choose $a_1, a_2, \alpha_2, \delta_2$ for highest possible order of accuracy.

General 2nd order Runge-Kutta Methods

▶ $w_0 = \alpha$; for $j = 0, 1, \dots, N - 1$,

$$w_{j+1} = w_j + h (a_1 f(t_j, w_j) + a_2 f(t_j + \alpha_2, w_j + \delta_2 f(t_j, w_j))).$$

- ▶ Two function evaluations for each j ,
- ▶ Want to choose $a_1, a_2, \alpha_2, \delta_2$ for highest possible order of accuracy.

local truncation error

$$\begin{aligned} \tau_{j+1}(h) &= \frac{y(t_{j+1}) - y(t_j)}{h} - (a_1 f(t_j, y(t_j)) + a_2 f(t_j + \alpha_2, y(t_j) + \delta_2 f(t_j, y(t_j)))) \\ &= y'(t_j) + \frac{h}{2} y''(t_j) + O(h^2) \\ &\quad - \left((a_1 + a_2) f(t_j, y(t_j)) + a_2 \alpha_2 \frac{\partial f}{\partial t}(t_j, y(t_j)) \right. \\ &\quad \left. + a_2 \delta_2 f(t_j, y(t_j)) \frac{\partial f}{\partial y}(t_j, y(t_j)) + O(h^2) \right). \end{aligned}$$

local truncation error

$$\begin{aligned}\tau_{j+1}(h) = & y'(t_j) + \frac{h}{2}y''(t_j) + O(h^2) \\ & - \left((a_1 + a_2) f(t_j, y(t_j)) + a_2 \alpha_2 \frac{\partial f}{\partial t}(t_j, y(t_j)) \right. \\ & \left. + a_2 \delta_2 f(t_j, y(t_j)) \frac{\partial f}{\partial y}(t_j, y(t_j)) + O(h^2) \right).\end{aligned}$$

where $y'(t_j) = f(t_j, y(t_j))$,

local truncation error

$$\begin{aligned}\tau_{j+1}(h) = & y'(t_j) + \frac{h}{2}y''(t_j) + O(h^2) \\ & - \left((a_1 + a_2) f(t_j, y(t_j)) + a_2 \alpha_2 \frac{\partial f}{\partial t}(t_j, y(t_j)) \right. \\ & \left. + a_2 \delta_2 f(t_j, y(t_j)) \frac{\partial f}{\partial y}(t_j, y(t_j)) + O(h^2) \right).\end{aligned}$$

where $y'(t_j) = f(t_j, y(t_j))$,

$$y''(t_j) = \frac{d f}{d t}(t_j, y(t_j)) = \frac{\partial f}{\partial t}(t_j, y(t_j)) + f(t_j, y(t_j)) \frac{\partial f}{\partial y}(t_j, y(t_j)).$$

For any choice with

$$a_1 + a_2 = 1, \quad a_2 \alpha_2 = a_2 \delta_2 = \frac{h}{2},$$

we have a second order method

$$\tau_{j+1}(h) = O(h^2).$$

local truncation error

$$\begin{aligned}\tau_{j+1}(h) = & y'(t_j) + \frac{h}{2}y''(t_j) + O(h^2) \\ & - \left((a_1 + a_2) f(t_j, y(t_j)) + a_2 \alpha_2 \frac{\partial f}{\partial t}(t_j, y(t_j)) \right. \\ & \left. + a_2 \delta_2 f(t_j, y(t_j)) \frac{\partial f}{\partial y}(t_j, y(t_j)) + O(h^2) \right).\end{aligned}$$

where $y'(t_j) = f(t_j, y(t_j))$,

$$y''(t_j) = \frac{d f}{d t}(t_j, y(t_j)) = \frac{\partial f}{\partial t}(t_j, y(t_j)) + f(t_j, y(t_j)) \frac{\partial f}{\partial y}(t_j, y(t_j)).$$

For any choice with

$$a_1 + a_2 = 1, \quad a_2 \alpha_2 = a_2 \delta_2 = \frac{h}{2},$$

we have a second order method

$$\tau_{j+1}(h) = O(h^2).$$

Four parameters, three equations

General 2nd order Runge-Kutta Methods

$$w_0 = \alpha; \text{ for } j = 0, 1, \dots, N - 1,$$

$$w_{j+1} = w_j + h (a_1 f(t_j, w_j) + a_2 f(t_j + \alpha_2, w_j + \delta_2 f(t_j, w_j))).$$

$$a_1 + a_2 = 1, \quad a_2 \alpha_2 = a_2 \delta_2 = \frac{h}{2},$$

- ▶ **Midpoint method:** $a_1 = 0, a_2 = 1, \alpha_2 = \delta_2 = \frac{h}{2},$

$$w_{j+1} = w_j + h f \left(t_j + \frac{h}{2}, w_j + \frac{h}{2} f(t_j, w_j) \right).$$

- ▶ **Modified Euler method:** $a_1 = a_2 = \frac{1}{2}, \alpha_2 = \delta_2 = h,$

$$w_{j+1} = w_j + \frac{h}{2} (f(t_j, w_j) + f(t_{j+1}, w_j + h f(t_j, w_j))).$$

3rd order Runge-Kutta Method (rarely used in practice)

$$w_0 = \alpha;$$

for $j = 0, 1, \dots, N - 1,$

$$w_{j+1} = w_j + \frac{h}{4} \left(f(t_j, w_j) + 3f \left(t_j + \frac{2h}{3}, w_j + \frac{2h}{3} f \left(t_j + \frac{h}{3}, w_j + \frac{h}{3} f(t_j, w_j) \right) \right) \right)$$

$$\stackrel{\text{def}}{=} w_j + h \phi(t_j, w_j).$$

3rd order Runge-Kutta Method (rarely used in practice)

$$w_0 = \alpha;$$

for $j = 0, 1, \dots, N - 1,$

$$w_{j+1} = w_j + \frac{h}{4} \left(f(t_j, w_j) + 3f \left(t_j + \frac{2h}{3}, w_j + \frac{2h}{3} f \left(t_j + \frac{h}{3}, w_j + \frac{h}{3} f(t_j, w_j) \right) \right) \right) \\ \stackrel{\text{def}}{=} w_j + h \phi(t_j, w_j).$$

local truncation error

$$\tau_{j+1}(h) = \frac{y(t_{j+1})y(t_j)}{h} - \phi(t_j, y(t_j)) = O(h^3).$$

4th order Runge-Kutta Method

$$w_0 = \alpha;$$

for $j = 0, 1, \dots, N - 1,$

$$k_1 = hf(t_j, w_j),$$

$$k_2 = hf\left(t_j + \frac{h}{2}, w_j + \frac{1}{2}k_1\right),$$

$$k_3 = hf\left(t_j + \frac{h}{2}, w_j + \frac{1}{2}k_2\right),$$

$$k_4 = hf(t_{j+1}, w_j + k_3),$$

$$w_{j+1} = w_j + \frac{1}{6}(k_1 + 2k_2 + 2k_3 + k_4).$$

4 function evaluations per step

Example

Initial Value ODE $\frac{dy}{dt} = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5,$
exact solution $y(t) = (1 + t)^2 - 0.5 e^t.$

Example

Initial Value ODE $\frac{dy}{dt} = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5,$
exact solution $y(t) = (1 + t)^2 - 0.5 e^t.$

t_i	Exact	Euler $h = 0.025$	Modified Euler $h = 0.05$	Runge-Kutta Order Four $h = 0.1$
0.0	0.5000000	0.5000000	0.5000000	0.5000000
0.1	0.6574145	0.6554982	0.6573085	0.6574144
0.2	0.8292986	0.8253385	0.8290778	0.8292983
0.3	1.0150706	1.0089334	1.0147254	1.0150701
0.4	1.2140877	1.2056345	1.2136079	1.2140869
0.5	1.4256394	1.4147264	1.4250141	1.4256384

Example

Initial Value ODE $\frac{dy}{dt} = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5,$
exact solution $y(t) = (1 + t)^2 - 0.5 e^t.$

Example

Initial Value ODE $\frac{dy}{dt} = y - t^2 + 1, \quad 0 \leq t \leq 2, \quad y(0) = 0.5,$

exact solution $y(t) = (1 + t)^2 - 0.5 e^t.$

Approximation Errors: First Order, Second Order, 4th Order

