

Some remarks on the Taylor Series Method:  $\begin{cases} x' = f(t, x) \\ x(t_0) = x_0 \end{cases}$

- We need to compute several derivatives (possibly by hand) first.
- The function  $f(t, x)$  may not have derivatives near  $(t_0, x_0)$
- If it is easy to compute several derivatives of  $f$  (e.g.  $f$  is polynomial of  $t$  and  $x$ ), then many terms may be used and high precision can be achieved even with a large value of  $h$ .
- The Taylor-series method of order  $n=1$  is called Euler's method.

$$\underline{x(t+h) = x(t) + h x'(t) = x(t) + h f(t, x)} \quad \text{Error } \mathcal{O}(h)$$

### 8.3 Runge-Kutta Methods

Notation:

Say  $f = f(x, y)$ . Then  $f_x = \frac{\partial f}{\partial x}$   $f_y = \frac{\partial f}{\partial y}$

Recall: (Chain Rule in several variables)

Suppose further that  $x = x(u)$  and  $y = y(u)$ . Then

$$f' = \frac{df}{du} = \frac{\partial f}{\partial x} \frac{dx}{du} + \frac{\partial f}{\partial y} \frac{dy}{du} = f_x x' + f_y y'$$

Thus, if  $f = f(t, x)$ , then

$$\frac{df}{dt} = \frac{\partial f}{\partial t} \frac{dt}{dt} + \frac{\partial f}{\partial x} \frac{dx}{dt} = f_t + f_x x'$$

Recall: (Taylor series in two variables)

For  $f = f(x, y)$ ,

$$f(x+h, y+k) = \underbrace{f + h f_x + k f_y + \text{higher order terms}}_{\text{evaluated at } (x, y)}$$

e.g. If  $f = f(t, x)$ ,

$$f(t+\alpha h, x+\beta h f) = \underbrace{f + \alpha h f_t + \beta h f f_x + \text{higher order terms}}_{\text{evaluated at } (t, x)}$$

Example (Second Order)

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

$$x(t_0) = x_0$$

$$\underline{x(t+h) = x(t) + h x'(t) + \frac{h^2}{2!} x''(t) + \frac{h^3}{3!} x'''(t) + \dots}$$

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

$$x'' = f_t + f_x x'$$

$$= f_t + f_x f$$

$$x''' = \underline{f_{tt} + f_{tx} x'} + \underline{(f_{xt} + f_{xx} x')} f + \underline{f_x (f_t + f_x x')}$$

$$= f_{tt} + f_{tx} f + (f_{xt} + f_{xx} f) f + f_x (f_t + f_x f)$$

Thus,

$$\underline{x(t+h) = x + h f + \frac{1}{2} h^2 (f_t + f_x f) + \mathcal{O}(h^3)}$$

$$= x + \frac{1}{2} h f + \frac{1}{2} h f + \frac{1}{2} h^2 f_t + \frac{1}{2} h^2 f_x f + \mathcal{O}(h^3)$$

$$(*) = x + \frac{1}{2} h f + \frac{1}{2} h (f + h f_t + h f f_x) + \mathcal{O}(h^3)$$

Taylor series in 2 variables:

$$f(t+h, x+h f) = f + h f_t + h f f_x + \mathcal{O}(h^2)$$

Thus

$$x(t+h) = x + \frac{1}{2} h f + \frac{1}{2} h f(t+h, x+h f) + \mathcal{O}(h^3)$$

Thus we can use

$$(**) x(t+h) = x(t) + \frac{1}{2} h f(t, x) + \frac{1}{2} h f(t+h, x+h f(t, x))$$

for an iteration. More compactly,

$$x(t+h) = x(t) + \frac{1}{2} (F_1 + F_2)$$

$$\text{where } F_1 = h f(t, x)$$

$$F_2 = h f(t+h, x+F_1)$$

More generally a second-order Runge-Kutta formula is of the form

$$x(t+h) = x + w_1 h f + w_2 h f(t+\alpha h, x+\beta h f) + \mathcal{O}(h^3)$$

where  $w_1, w_2, \alpha, \beta$  are some constant satisfying a system of equation.

Using Taylor series in two variables again we see that

$$x(t+h) = x + \underline{w_1 h f} + \underline{w_2 h (f + \alpha h f_t + \beta h f f_x)} + \mathcal{O}(h^3)$$

Recall (\*):

$$x(t+h) = x + \frac{1}{2} h f + \frac{1}{2} h (f + h f_t + h f f_x) + \mathcal{O}(h^3)$$

⇒ we must have

$$w_1 + w_2 = 1 \quad \alpha w_2 = \frac{1}{2} \quad \beta w_2 = \frac{1}{2}$$

If we choose  $w_1 = w_2 = \frac{1}{2}$   $\alpha = \beta = 1$ ,

we obtain the formula  $\times \times$

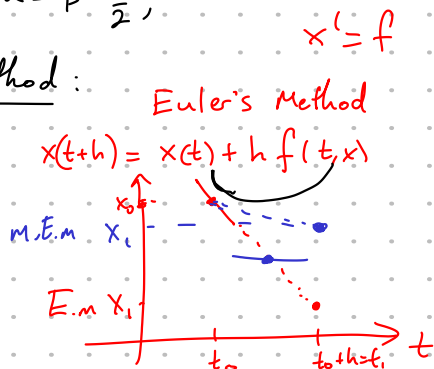
If we choose  $w_1 = 0$   $w_2 = 1$   $\alpha = \beta = \frac{1}{2}$ ,

we obtain the modified Euler method:

$$x(t+h) = x(t) + F_2$$

where  $F_1 = hf(t, x)$

$$F_2 = hf\left(t + \frac{1}{2}h, x + \frac{1}{2}F_1\right)$$



Example (Fourth-Order Runge-Kutta Method)

$$x(t+h) = x(t) + \frac{1}{6}(F_1 + 2F_2 + 2F_3 + F_4)$$

where  $F_1 = hf(t, x)$

$$F_2 = hf\left(t + \frac{1}{2}h, x + \frac{1}{2}F_1\right)$$

$$F_3 = hf\left(t + \frac{1}{2}h, x + \frac{1}{2}F_2\right)$$

$$F_4 = hf(t+h, x+F_3)$$

Example Apply the 4<sup>th</sup> order RK method to  $x' = \lambda x$ .

Note that  $f(t, x) = \lambda x$  so

$$F_1 = hf(t, x) = h\lambda x$$

$$F_2 = hf\left(t + \frac{1}{2}h, x + \frac{1}{2}F_1\right) = h\lambda\left(x + \frac{1}{2}h\lambda x\right) = \left(h\lambda + \frac{1}{2}h^2\lambda^2\right)x$$

$$F_3 = h\lambda\left(x + \frac{1}{2}F_2\right) = h\lambda x + \frac{1}{2}h\lambda\left(h\lambda + \frac{1}{2}h^2\lambda^2\right)x = \left(h\lambda + \frac{1}{2}h^2\lambda^2 + \frac{1}{4}h^3\lambda^3\right)x$$

$$F_4 = h\lambda\left(x + F_3\right) = h\lambda x + h\lambda\left(h\lambda + \frac{1}{2}h^2\lambda^2 + \frac{1}{4}h^3\lambda^3\right)x = \left(h\lambda + h^2\lambda^2 + \frac{1}{2}h^3\lambda^3 + \frac{1}{4}h^4\lambda^4\right)x$$

Thus,

$$F_1 + 2F_2 + 2F_3 + F_4$$

$$= \underline{h\lambda}x + 2\left(\underline{h\lambda} + \frac{1}{2}\underline{h^2\lambda^2}\right)x + 2\left(\underline{h\lambda} + \frac{1}{2}\underline{h^2\lambda^2} + \frac{1}{4}\underline{h^3\lambda^3}\right)x + \left(\underline{h\lambda} + \underline{h^2\lambda^2} + \frac{1}{2}\underline{h^3\lambda^3} + \frac{1}{4}\underline{h^4\lambda^4}\right)x$$

$$= \left[ \underline{6h\lambda} + \underline{3h^2\lambda^2} + \underline{h^3\lambda^3} + \frac{1}{4}\underline{h^4\lambda^4} \right] x$$

Thus,  $x(t+h) = x + \frac{1}{6}(F_1 + 2F_2 + 2F_3 + F_4)$

$$x(t+h) = \left[ 1 + h\lambda + \frac{1}{2}h^2\lambda^2 + \frac{1}{6}h^3\lambda^3 + \frac{1}{24}h^4\lambda^4 \right] x(t)$$

Note that analytic solutions of  $x' = \lambda x$  are given by

$$x(t) = C e^{\lambda t}. \text{ Thus,}$$

$$x(t+h) = C e^{\lambda(t+h)} = C e^{\lambda t} \cdot e^{\lambda h} = x(t) e^{\lambda h} = \left(1 + \lambda h + \frac{1}{2}\lambda^2 h^2 + \frac{1}{3!}\lambda^3 h^3 + \frac{1}{4!}\lambda^4 h^4 + \dots\right) x(t)$$

Common Mistakes from HW4 and HW5

1)  $A, B$   $n \times n$  matrices.

$$\|A\| \|B\| \neq \|AB\|$$

$\|AB\| \leq \|A\| \|B\|$  is typically not an equality!

2)  $\|I - A\| < 1 \Rightarrow A$  is invertible.

However, the converse is not true:

$$A \text{ is invertible } \not\Rightarrow \|I - A\| < 1$$

e.g.  $A = 101I$  then  $A$  is invertible ( $A^{-1} = \frac{1}{101}I$ )

but  $\|I - A\| = \|-100I\| = 100\|I\| = 100 > 1$ .

3) When we want to find a SVD for a matrix  $A_{m \times n}$

$$(A = P D Q) \quad A_{m \times n} = P_{m \times m} D_{n \times n} Q_{n \times n} \quad \text{P and Q are square}$$

First, we find  $n$ -eigenvectors of  $(A^*A)_{n \times n}$  that are orthonormal

In particular, we choose all of them as unit vectors. Call

them  $u_1, u_2, \dots, u_n$ . (They completely define  $Q$ .)

Then we set  $v_i = \sigma_i^{-1} A u_i \in \mathbb{C}^m$  for  $i \leq r$

( $\sigma_i \neq 0$  and  $\sigma_i = 0$  for  $i > r$ ).  $r = \text{rank}(A) \leq \min(m, n)$

$P$  needs to be an  $m \times m$  matrix so  $v_1, v_2, \dots, v_r$  is not enough to completely determine  $P$  if  $r < m$ .

In that case, we have to extend  $v_1, v_2, \dots, v_r$  to an orthonormal basis for  $\mathbb{C}^m$ . (Find  $(m-r)$  new unit vectors and every pair of vectors  $v_1, \dots, v_r, \dots, v_m$  is orthogonal.)