NODEA Note

1 Basic Knowledge

Def of ODE & ODEs: (1st order) ODE: $\frac{dy}{dt} = f(t,y)$ & ODEs: $\frac{dy}{dt} = \mathbf{f}(t,\mathbf{y})$, $\mathbf{y} = (y_1,...,y_d)^T$, $\mathbf{f}(t,\mathbf{y}) = (f_1(t,\mathbf{y}),...,f_d(t,\mathbf{y}))^T$ **Autonomous**: $\frac{dy}{dt} = \mathbf{f}(\mathbf{y}) \Rightarrow \text{ autonomous ODE}(\mathbf{s})$. $|| \Downarrow \text{ New Autonomous ODEs}: \frac{dy}{ds} = \mathbf{f}(y_{d+1},\mathbf{y}) \text{ and } \frac{dy_{d+1}}{ds} = 1$ • **Change to Autonomous**: For $\frac{dy}{dt} = \mathbf{f}(t,\mathbf{y})$. Let $y_{d+1} = t$ and *new* independent variable s s.t. $\frac{dt}{ds} = 1$

Linearity: ODE: $\frac{dy}{dt} = f(t, y)$ is linearity if f(t, y) = a(t)y + b(t) || ODEs: If each ODE is linear, then the ODEs are linear.

Picard's Theorem: If f(t,y) is continuous in $D := \{(t,y) : t_0 \le t \le T, |y-y_0| < K\}$ and $\exists L > 0$ (Lipschitz constant) s.t.

 $\forall (t,u), (t,v) \in D \quad |f(t,u)-f(t,v)| \leq L|u-v| \text{ (ps:Can use MVT)}. \text{ And Assume that } M_f(T-t_0) \leq K, M_f := \max\{|f(t,u)|: (t,u) \in D\}$

 \Rightarrow **Then**, \exists a unique continuously differentiable solution y(t) to the IVP $\frac{dy}{dt} = f(t,y), y(t_0) = y_0$ on $t \in [t_0,T]$.

Existence & Uniqueness Theorem: IVP $\frac{d\mathbf{y}}{dt} = \mathbf{f}(t, \mathbf{y}), \mathbf{y}(t_0) = \mathbf{y}_0$. If f(t, y) and $\frac{\partial f}{\partial y_i}$ are continuous in a neighborhood of (t_0, \mathbf{y}_0) . ⇒ **Then**, $\exists I := (t_0 - \delta, t_0 + \delta)$ s.t. \exists a unique continuously differentiable solution $\mathbf{y}(t)$ to the IVP on $t \in I$.

Acknowledge

Notation	Meaning	Notation	Meaning
[<i>a</i> , <i>b</i>]	Approximate function for $t \in [a, b]$	$t_0 = a \mid t_N = b$	Assume that $t_0 = a$, $t_N = b$
N	number of timesteps (i.e. Break up interval [a, b] into N equal-length sub-intervals)	h	stepsize $(h = \frac{b-a}{N})$
t_i	Define $N+1$ points: $t_0, t_1,, t_N$	t_m	$t_m = a + h \cdot m = t_0 + h \cdot m$
y_i	Approximation of y at point $t = t_i$ (Except y_0)	$y(t_i)$	Exact value of y at point $t = t_i$

Euler's Method and Taylor Series Method

Euler's Method Algorithm: Approx $\frac{dy}{dt} = f(t, y), y(t_0) = y_0$ Euler Method: $y_{n+1} = y_n + hf(t_0 + nh, y_n) = y_n + hf(t_n, y_n)$

Lemma: If $v_{n+1} \leq Av_n + B \implies \text{Then } v_n \leq A^nv_0 + \frac{A^{n-1}}{A-1}B \qquad \text{If } |y''| < M \text{ and } v_n = e_n := y_n - y(t_n), \text{ then } A = 1 + hL, B = h^2M/2$

Boundedness Theorem|**Euler Method**: For $\frac{dy}{dt} = f(t, y), y(a) = y_0$:

 \exists 1 unique, 2 twice differentiable, solution y(t) on [a,b], 3y is continuous and 4 $|\frac{\partial f}{\partial y}| \le L$.

 \Rightarrow the solution y_n given by Euler's method satisfies: $e_n = |y_n - y(t_n)| \le Dh$, $D = e^{(b-a)L} \frac{M}{2L}$

Order Notation (\mathcal{O} **)**: we write $z(h) = \mathcal{O}(h^p)$ if $\exists \mathcal{C}, h_0 > 0$ s.t. $|z| \le Ch^p, 0 < h < h_0$

Flow Map (Φ , Ψ **)**: Consider $\frac{dy}{dt} = f(t, y)$.

1. **Exact Flow Map** (Φ): $\Phi_{t_n,h}(y_n) = y(t_n+h)$ 代表假设 $y(t_n) = y_n$ 的情况下,输入 y_n 在 t_n+h 时刻的精确值; 当不写 t_n 角标时,默认要算的前一个时间点已知/精确

2. Numerical Flow Map (Ψ): $\Psi_{t_n,h}(y_n) = y_{n+1}$ 代表假设 $y(t_n) = y_n$ 的情况下,输入 y_n 在 $t_n + h$ 时刻的数值解; 当不写 t_n 角标时,默认要算的前一个时间点已知/精确 **Remark**: $\Phi_h(y(t_n)) = y(t_n + h)$ $\Psi_h(y(t_n)) = y_{n+1}$

Find: Generally, use $\Phi_{t_0,h}(y_0) = y(t_0 + h)$ to find $y(t_0 + h)$; and $\Psi(y)$: Numerical method for ODE.

Find Numerical Method| **Taylor Series Method**: Approx $\frac{dy}{dt} = f(t, y), y(t_0) = y_0$ with *n-order Methods*

1. **Method**: 通过泰勒展开精确解, 取前 n 项作为近似解, 从而得到数值解.

2. **Taylor Series for** Φ : $\Phi_{t,h}(y) = y + hf(t,y) + \frac{1}{2}h^2[f_t(t,y) + f_y(t,y)f(t,y)] + \frac{1}{6}y'''(t,y)h^3 + \cdots$ (For one variable y) ps: $y' = f_t y'' = f_t + f_y f_t$

3. **Taylor Series**: $y(t_0 + h) = y(t_0) + hy'(t_0) + \frac{h^2}{2}y''(t_0) + \dots + \frac{h^{n-1}}{(n-1)!}y^{(n-1)}(t_0) + \frac{h^n}{n!}y^{(n)}(t^*), t^* \in [t, t+h]$

Convergence of One-Step Methods consider for autonomous y' = f(y)

4.1 Convergence | Consistent | Stable

Global Error: global error after n steps: $e_n := y_n - y(t_n)$ **Local Error**: For *one-step* method is: $le(y,h) = \Psi_h(y) - \Phi_h(y)$

Consistent: If $||le(y,h)|| \le Ch^{p+1} (\le \mathcal{O}(h^{p+1}))$, C > 0. \Rightarrow Consistent at order p. **Stable**: If $||\Psi_h(u) - \Psi_h(v)|| \le (1 + h\hat{L})||u - v||$

Convergent: A method is convergent if: $\forall T$, $\lim_{h \to 0, h = T/N} \max_{n = 0, 1, \dots, N} ||e_n|| = 0$ \Downarrow Then the global error satisfies: $\max_{n = 0, 1, \dots, N} ||e_n|| = \mathcal{O}(h^p)$ p-th order

Convergence of One-Step Method: For y' = f(y), and a one-step method $\Psi_h(y)$ is ¹ consistent at order p and ² stable with \hat{L} $\hat{\Gamma}$. (ps: $C = \frac{C}{\hat{T}}(e^{T\hat{L}} - 1)$)

More One-Step Methods | Runge-Kutta Methods | Collocation

Construction of More General one-step Method: For y' = f(y), $y(t_0) = y_0 \Rightarrow y(t+h) - y(t) = \int_t^{t+h} f(y(\tau)) d\tau$ **Lagrange Interpolating Polynomials**: For function p(x). Consider points: $(c_1, g_1), ..., (c_s, g_s)$. where $p(c_i) = g_i$.

1. Lagrange Interpolating Polynomials: Let $\ell_i(x) = \prod_{j=1, j \neq i}^s \frac{x - c_j}{c_i - c_i} \in \mathbb{P}_{s-1}$

2. **Polynomial Interpolation**: $\exists ! \ p(x) = \sum_{i=1}^{s} g_i \ell_i(x)$ (Can be proved by Honour Algebra)

Interpolatory Quadrature: 对于函数 $g(t) \in \mathbb{P}_{p-1}$, 我可以通过插值求积的方法来近似求解积分;以下展示 [a,b] 上的插值求积。

1. Choose c_i points in [a, b]: $c_1, ..., c_s$. Let $g_i = g(c_i)$. By using c_i, g_i , we can get $\ell_i(x)$.

2. Define weights: $b_i := \int_a^b \ell_i(x) \, dx$. Then $\int_a^b g(t) \, dt \; \approx \; \sum_{i=1}^s b_i \, g(c_i)$.

One-Step Collocation Methods: 对于 y' = f(y), $y_{n+1} = y_n + \int_{t_n}^{t_{n+1}} f(y(t)) dt$, 通过 Interpolatory Quadrature 来近似求解积分. 为了简化, 考虑 autonomous 的情况

1. Choose $c_1, ..., c_s$ in [0, 1], consider $t_i = t_n + c_i h$, then $t_i \in [t_n, t_{n+1}]$.

- 2. Let $F_i = f(y(t_i))$, then we can get $\ell_i(x)$ which pass through (c_i, F_i) .
- 3. Let weights: $b_i = \int_0^1 \ell_i(x) dx$, and $a_{ij} = \int_0^{c_i} \ell_j(x) dx$. Then $\star y_{n+1} = y_n + h \sum_{i=1}^s b_i F_i$.
- 4. Moreover, we can get: $F_i = f(Y_i)$, where $Y_i = y_n + h \sum_{i=1}^{s} a_{ij} F_i$.

Remark: For choice of c_i : The optimal choice is attained by *Gauss-Legendre collocation methods*.

e.g.
$$s = 1$$
: $c_1 = \frac{1}{2}$; $s = 2$: $c_1 = \frac{1}{2} - \frac{\sqrt{3}}{6}$, $c_2 = \frac{1}{2} + \frac{\sqrt{3}}{6}$; $s = 3$: $c_1 = \frac{1}{2} - \frac{\sqrt{15}}{10}$, $c_2 = \frac{1}{2}$, $c_3 = \frac{1}{2} + \frac{\sqrt{15}}{10}$

e.g. s = 1: $c_1 = \frac{1}{2}$; s = 2: $c_1 = \frac{1}{2} - \frac{\sqrt{3}}{6}$, $c_2 = \frac{1}{2} + \frac{\sqrt{3}}{6}$; s = 3: $c_1 = \frac{1}{2} - \frac{\sqrt{15}}{10}$, $c_2 = \frac{1}{2}$, $c_3 = \frac{1}{2} + \frac{\sqrt{15}}{10}$ **Runge-Kutta Methods**: Let y' = f(y) here we consider the autonomous case. The RK method has following form:

- 1. Stage Values: $Y_i = y_n + h \sum_{j=1}^{s} a_{ij} f(Y_j)$ $i \in \{1, ..., s\}$ $F_i = f(Y_i)$ 2. Update: $y_{n+1} = y_n + h \sum_{i=1}^{s} b_i F_i = y_n + h \sum_{i=1}^{s} b_i f(Y_i)$ For Autonomous: $c_i = \sum_{j=1}^{s} a_{ij}$

Remark: Flow-map: $\Psi_h(y) = y + h \sum_{i=1}^{s} b_i f(Y_i(y))$ ps:weights: b_i ; internal coefficients: $a_{i,j}$

ps: We can using Butcher Table to represent the RK method (Appendix)

Explicit: $a_{ij} = 0$ for $j \ge i$ (严格下三角行) **Implicit**: $\exists a_{ij} \ne 0$ for $j \ge i$ (Not Explicit)

Accuracy of RK Method | Order Condition

Some Notations: If
$$\mathbf{y} = f'(\mathbf{y})$$
 where $f(\mathbf{y}) : \mathbb{R}^d \to \mathbb{R}^d$. Def $f' = (\frac{\partial f_i}{\partial y_j}), 1 \le i \le d, 1 \le j \le d$ (fright) $f'' = (\frac{\partial^2 f_i}{\partial y_j \partial y_k}), 1 \le i \le d, 1 \le j, k \le d$. Def: $f''(\mathbf{a}, \mathbf{b}) = \sum_{j=1}^d \sum_{k=1}^d \frac{\partial^2 f_i}{\partial y_j \partial y_k} a_j b_k$ $|y'| = f$ $y''' = \sum_{j=1}^d \frac{\partial f_i}{\partial y_j} f_j = f'f$ $y'''' = \sum_{j=1}^d \sum_{k=1}^d \frac{\partial^2 f_i}{\partial y_j \partial y_k} y_j'(t) y_k'(t) + \sum_{j=1}^d \frac{\partial f_i}{\partial y_j} y_j''(t) + f'f'f'$

$$\cdot \text{ Def: } f''(\mathbf{a}, \mathbf{b}) = \sum_{j=1}^{d} \sum_{k=1}^{d} \frac{\partial^{2} f_{i}}{\partial y_{j} \partial y_{k}} a_{j} b_{k} \quad | \ y' = f \quad y''' = \sum_{j=1}^{d} \frac{\partial f_{i}}{\partial y_{j}} f_{j} = f'f \quad y'''' = \sum_{j=1}^{d} \sum_{k=1}^{d} \frac{\partial^{2} f_{i}}{\partial y_{j} \partial y_{k}} y_{j}'(t) y_{k}'(t) + \sum_{j=1}^{d} \frac{\partial f_{i}}{\partial y_{j}} y_{j}''(t) = f''(f, f) + f'f'f' f'(f, f) + f'f'f'(f, f) + f'f'f'(f, f) + f'f'f'(f, f) + f'f'(f, f) + f'f'(f,$$

$$\Phi_h(y) = y + hf + \frac{h^2}{2}f'f + \frac{h^3}{6}[f''(f,f) + f'f'f] + \mathcal{O}(h^4)$$

$$\Rightarrow$$
 If $z'(0) = y', z''(0) = y'', ..., z^{(n)} = y^{(n)} \Rightarrow$ Convergent at order n

$$\begin{array}{l} \cdot \Phi_h(y) = y + hf + \frac{h^2}{2} f'f + \frac{h^3}{6} [f''(f,f) + f'f'f] + \mathcal{O}(h^4) \\ \textbf{Order Condition} \colon \mathsf{RK} \ \mathsf{method} \colon y_{n+1} = y_n + h \sum_{i=1}^s b_i f(Y_i), \ \mathsf{Let} \ z(h) = \Phi_h(y) \\ \qquad \qquad \Rightarrow \mathsf{If} \ z'(0) = y', z''(0) = y'', ..., z^{(n)} = y^{(n)} \Rightarrow \textbf{Convergent at order } n \\ \cdot \ \mathsf{Order} \ 1 \colon \sum_{i=1}^s b_i = 1 \qquad \mathsf{Order} \ 2 \colon \ (\mathsf{add}) \sum_{i=1}^s b_i c_i = \frac{1}{2} \qquad \mathsf{Order} \ 3 \colon \ (\mathsf{add}) \sum_{i=1}^s b_i c_i^2 = \frac{1}{3} \ \mathsf{and} \ \sum_{i=1}^s \sum_{j=1}^s b_i a_{ij} c_j = \frac{1}{6} \end{array}$$

Stability of Runge-Kutta Methods consider for autonomous y' = f(y)

Basic Definition for Stability

Fixed Point-Exact: For ODEs $\frac{dy}{dt} = f(y)$, point y^* is fixed point if $f(y^*) = 0 \Leftrightarrow \Phi_t(y^*) = y^*$ Set of Fixed Points: $\mathcal{F} = \{y^* \in \mathbb{R}^d : f(y^*) = 0\}$

Fixed Point-Numerical: *One-step* method $\Psi_h(y)$, point y^* is fixed point if $y^* = \Psi_h(y^*)$ **Set of Fixed Points**: $\mathcal{F}_h = \{y^* \in \mathbb{R}^d : y^* = \Psi_h(y^*)\}$

Theorem: For Runge-Kutta method, $\mathcal{F} \subseteq \mathcal{F}_h$ **Remark**: $\mathcal{F}_h \subseteq \mathcal{F}$ is NOT always true. If $\mathcal{F}_h = \mathcal{F}$, then the method is **regular**. · the point in $\mathcal{F}_h \setminus \mathcal{F}$ is called **spurious fixed point**. As $h \to \infty$, the *spurious* fixed points will tends to infinity.

Stability of Fixed Points: Fixed point y^* , the ODEs $\frac{dy}{dt} = f(y)$ with $y(0) = y_0$.

1. **Stable in the sense of Lyapunov**: Fixed point y^* is stable if $\forall \varepsilon > 0$, $\exists \delta > 0$ s.t. $||y_0 - y^*|| < \delta \Rightarrow ||y(t; y_0) - y^*|| < \varepsilon \ \forall t > 0$

- 2. **Asymptotically Stable**: Fixed point y^* is asymptotically stable if $\exists \delta > 0$ s.t. $||y_0 y^*|| < \delta \Rightarrow \lim_{t \to \infty} ||y(t; y_0) y^*|| = 0$
- 3. **Unstable**: Fixed point y^* is unstable if it's not stable. i.e. $\exists \epsilon > 0, \forall \delta > 0$ s.t. $||y_0 y^*|| < \delta \Rightarrow ||y(t) y^*|| \ge \varepsilon$ for some t.

5.2 **Classification of Fixed Points**

Linearization Theorem: Suppose $\frac{dy}{dt} = f(y)$, y^* is a fixed point. Let $J = f'(y^*)$ be the Jacobian matrix of f at y^* . 1. If \forall eigenvalues of J in left complex half plane, then y^* is **asymptotically stable**.

- 2. If \exists eigenvalues of I in right complex half plane, then y^* is **unstable**.

(Following is a special cases from HDE)

Generalized Eigenvectors: If λ is an repeated eigenvalue with eigenvalue ξ then:

Generalized Eigenvectors: η s.t. $(A - \lambda I)\eta = \xi$ More generally: $(A - \lambda I)\eta_n = \eta_{n-1}$

Classification of Critical Points at y^* (Linear): r_1, r_2 be sol of $det(J - \lambda I) = 0$. $|| \mathbb{C} : r = \lambda \pm i\mu(\mu > 0)$

If J constant, write sol: $\mathbf{x} = c_1 e^{r_1 t} \xi_1 + c_2 e^{r_2 t} \xi_2$ || GM = 1: $\mathbf{x} = c_1 e^{r t} \xi + c_2 e^{r t} (t \xi + \eta)$ || $\int_{J} = \begin{pmatrix} \partial_x F(\mathbf{x}_0) & \partial_y F(\mathbf{x}_0) \\ \partial_x G(\mathbf{x}_0) & \partial_y G(\mathbf{x}_0) \end{pmatrix} \text{If } f(\mathbf{x}, \mathbf{y}) = \begin{pmatrix} F(\mathbf{x}, \mathbf{y}) \\ G(\mathbf{x}, \mathbf{y}) \end{pmatrix}$

R/C	Condition Stability	Type Name	Phase Plane Description	Other	
	$r_1 < r_2 < 0 \mid\mid$ asy.stab	N NSk	向原点, ξ_2 直线, ξ_1 曲线,and ξ_1 周围 $y = \pm x^3$	$c_2 \neq 0, t \rightarrow \infty$: ξ_2 主导方向; $c_2 = 0, t \rightarrow \infty$: ξ_1 主导方向	PS:
	$r_1 > r_2 > 0$ unstable	N NSo	原点向外, ξ_2 直线, ξ_1 曲线,and ξ_1 周围 $y = \pm x^3$	$c_1 \neq 0, t \rightarrow \infty$: ξ_1 主导方向; $c_1 = 0, t \rightarrow \infty$: ξ_2 主导方向	N = Node
	$r_1 > 0 > r_2$ unstable	SP SP	t → ∞, ξ_1 从原点向外, ξ_2 从外向原点	$t \to \pm \infty : \mathbf{x} \to \infty; t \to \infty : c_1, c_2 \neq 0, \mathbf{x} \to \infty, \xi_1 \pm \theta;$	PN = Proper Node
R	71 > 0 > 72 unstable		and: 像 $y = \pm \frac{1}{x}$, 同进同出	$t\rightarrow\infty:c_2=0, \mathbf{x} \rightarrow\infty, \xi_1\pm \mathbb{R}; t\rightarrow\infty:c_1=0, \mathbf{x} \rightarrow0, \xi_2\pm \mathbb{R}$	IN = Improper
	$r_1 = r_2 < 0$, GM=2 asy.stab	PN PN or Stable Star	直线 向原点	直线, u_1/u_2 is t independent	or: Degenerate Node
	$r_1 = r_2 > 0$, GM=2 unstable	PN PN or Unstable Star	直线 从原点向外	直线, u_1/u_2 is t independent	SP = Saddle Point
	$r_1 = r_2 < 0$, GM=1 asy.stab	IN (AL:Type: SpP) IN (Stable)	S 曲线, 向原点	$t \to \infty$, $ \mathbf{x} \to 0$, ξ 主导 ps: 旋转方向大体和 $\eta + c_2 \xi$ 方向相同	SpP = spiral point
	$r_1=r_2>0$, GM=1 unstable	IN (AL:Type: SpP) IN (Unstable)	S 曲线, 从原点向外	$t \to \infty$, $ \mathbf{x} \to \infty$, ξ 主导 ps: 旋转方向大体和 $\eta + c_2 \xi$ 方向相同	or: Focus Point
	$\lambda \neq 0, \lambda > 0 \mid\mid unstable$	SpP Unstable Focus	向外椭圆 (elliptical) 螺旋	$t \to \infty$, $ \mathbf{x} \to \infty$ ps: 考虑 $J = (a, b; c, d)$, 如果 bc>0, 顺时针, 如果 bc<0, 逆时针	C = Center
C	$\lambda \neq 0, \lambda < 0 \mid \mid asy.stab$	SpP Stable Focus	向内椭圆 (elliptical) 螺旋	t → ∞, $ \mathbf{x} $ → 0 ps: 考虑 $J = (a, b; c, d)$, 如果 bc>0, 顺时针, 如果 bc<0, 逆时针	NSk = Nodal Sink
	$\lambda = 0 \mid\mid \text{stable (AL:Indeterminate)}$	C (AL:C or SpP) C	椭圆 (elliptical) and 半长轴 ξ 实部方向	Bounded trajectory or ∃ Periodic Trajectories	NSo = Nodal Source

Stability of Fixed Points of Maps (Numerical)

Definition: For flow map Ψ from $\mathbb{R}^d \to \mathbb{R}^d$. Def $y^n(y_0) :=$ the n-th iterate of y_0 under Ψ . i.e. $y^n = y_n$; $y_n = \Psi(y_{n-1})$ **Stability of Fixed Points of Maps**: Fixed point y^* , the map Ψ with $y^* = \Psi(y^*)$.

- 1. **Stable in the sense of Lyapunov**: y^* is stable if $\forall \varepsilon > 0$, $\exists \delta > 0$ s.t. $||y_0 y^*|| < \delta \Rightarrow ||y^n(y_0) y^*|| < \varepsilon \ \forall n \ge 0$
- 2. **Asymptotically Stable**: y^* is asymptotically stable if $\exists \delta > 0$ s.t. $||y_0 y^*|| < \delta \Rightarrow \lim_{n \to \infty} ||y^n(y_0) y^*|| = 0$
- 3. **Unstable**: y^* is unstable if it's not stable. i.e. $\exists \epsilon > 0, \forall \delta > 0$ s.t. $||y_0 y^*|| < \delta \Rightarrow ||y^n(y_0) y^*|| \ge \varepsilon$ for some n.

Spectral Radius: For matrix K, $\rho(K) = \max\{|\lambda| : \lambda \text{ is eigenvalue of } K\}$

Theorem|Spectral Radius: Let $z_n = ||K^n y_0||$, where $K \in \mathbb{R}^{d \times d}$ is the matrix. Then:

- 1. $\rho(K) < 1 \Leftrightarrow \lim_{n \to \infty} z_n = 0$
- 2. $\rho(K) > 1 \Leftrightarrow \lim_{n \to \infty} z_n = \infty$
- 3. If $\rho(K)=1$ and eigenvalues of K are semisimple (i.e. No generalized eigenvector), then $\{z_n\}$ is bounded.

Theorem|Connect to Stability: For smooth (C^2) map Ψ , $y^* = \Psi(y^*)$. Let $K = \Psi'(y^*)$, for iteration $y_{n+1} = \Psi(y_n)$, we have:

- 1. $\rho(K) < 1 \Rightarrow y^*$ is asymptotically stable
- 2. $\rho(K) > 1 \Rightarrow y^*$ is unstable

5.4 Linear Stability of Numerical Methods

Special Case|Euler Method: For $\frac{dy}{dt} = By$, Using Euler method: $y_{n+1} = (I + hB)y_n$. where λ_i is eigenvalues of B. Assume $f(y) = \lambda y$

- 1. The origin is *stable* if $||I + h\lambda_i|| \le 1 \ \forall i$
- 2. The origin is asymptotically stable if $|I + h\lambda_i| < 1 \forall i$
- 3. The origin is *unstable* if |I + hB|| > 1ps: 即 $h\lambda_i$ 在复平面上以 z = -1 为圆心, 半径为 1 的圆内 ← 称为 Region of absolute stability

Stability function *R*, *P*: Let *P* be polynomial function and *R* be rational function.

If RK is *explicit*, then $y_{n+1} = P(\mu)y_n$; If RK is *implicit*, then $y_{n+1} = R(\mu)y_n$

Stability function $R(\mu)$ | **Special Case**: For $\frac{dy}{dt} = \lambda y$ All RK methods can be written as: where: b^T , A are from $Butcher\ Table$. $\mathbf{1} = [1, ..., 1]^T$

I.
$$Y_i = y_n + \mu \sum_{j=1}^{s} a_{ij} Y_j$$
 $(Y = y_n \mathbf{1} + \mu A Y)$ $y_{n+1} = y_n + \mu \sum_{b=1}^{s} b_i Y_j = y_n + \mu b^T Y$
II. $P_i(\mu) = 1 + \mu b^T (I - \mu A)^{-1} \mathbf{1}$ III. $y_{n+1} = P_i(\mu) y_n$ where $\mu = h$

II. $R(\mu) = 1 + \mu b^T (I - \mu A)^{-1}$ III. $y_{n+1} = R(\mu)y_n$ where $\mu = h\lambda$ Stability function $R(\mu)$ |General: For $\frac{dy}{dt} = By$ where: b^T , A are from Butcher Table. Λ , $U \neq B$ 的特征值分解 $U^{-1}BU = \Lambda$ 此时 z_n, y_n 是向量

I. Let $y_n = Uz_n$ and $Y_i = UZ_i$:

Then
$$Z_i = z_n + h \sum_{j=1}^s a_{ij} \Lambda Z_j$$
 $(Z_j^{(i)} = z_n^{(i)} \mathbf{1} + \mu A Z_j^{(i)} \ \forall i)$ $z_{n+1} = z_n + h \sum_{i=1}^s b_i \Lambda Z_i$ $(z_{n+1}^{(i)} = z_n^{(i)} + \mu \sum_{j=1}^s b_j Z_j^{(i)})$

II. $\frac{dz}{dt} = \Lambda z$ $\Rightarrow \frac{dz^{(i)}}{dt} = \lambda_i z^{(i)}$ $\Rightarrow z_{n+1}^{(i)} = R(\mu) z_n^{(i)}$ where $\mu = h \lambda_i$ (回到前一个)

Theorem: For $\frac{dy}{dt} = By$ with $\lambda_1, ..., \lambda_d$ be eigenvalues of B . The RK method is $stable | asy.stab$ at $origin$ iff:

The Same method also *stable*| *asy.stab* at *origin* for $\frac{dz}{dt} = \lambda_i z \ \forall i$

Corollary: For $\frac{dy}{dt} = By$ with B diagonalizable. An RK Method with stability function $R(\mu)$ is stable as $R(\mu)$ is stable at origin iff: Assume $R(\mu) = \lambda_i y$

 $|R(\mu)| \leq 1$ or $|R(\mu)| < 1$ or $|R(\mu)| > 1$ $\forall \mu = h\lambda_i \ \forall i$ we can write $\sigma(B) = \{\lambda_1, ..., \lambda_d\}$ the set of eigenvalues of B

Remark: 这里的 $R(\mu)$ 是指 B 分解后的每一个特征值 λ_i 的 $R(\mu)$, 而不是 B 的 $R(\mu)$

5.5 Stability Region and A-stability

- 2. Trapezoidal Rule: $\widehat{R}(\mu) = \left| \frac{1+\mu/2}{1-\mu/2} \right| \Rightarrow \mu \in \{z \in \mathbb{C} : |1+z/2| < |1-z/2| \}$ (left complex half-plane, A-stable)
- 3. Implicit Euler: $\widehat{R}(\mu) = |1 \mu|^{-1}$ \Rightarrow $\mu \in \{z \in \mathbb{C} : |1 z| > 1\}$ (-1 处半径为 1 的圆外侧)
- 4. RK4: $\widehat{R}(\mu) = \left|1 + \mu + \frac{\mu^2}{2} + \frac{\mu^3}{6} + \frac{\mu^4}{24}\right| \Rightarrow \text{Using } R(\mu) = e^{i\theta} \text{ to find the region.}$ **A-Stable**: An RK method is *A-stable* if its *stability region* contains the entire *left complex half-plane*. (i.e. $\Re(z) < 0$)

Linear Multistep Methods consider for autonomous y' = f(y)

Assume $\frac{dy}{dt} = f(y)$ with $y(t_0) = y_0$. Let y'_n denote $f(y_n)$.

Derivation of LMM | Algebra Operators

Linear Multistep Methods (LMM): For k-step LMM: $\alpha_k y_{n+k} + \sum_{j=0}^{k-1} \alpha_j y_{n+j} = h \sum_{j=0}^k \beta_j f(y_{n+j})$ where ${}^1\alpha_k \neq 0$, ${}^2\alpha_0 \neq 0$ or $\beta_0 \neq 0$ \cdot ps: Usually, coefficients are *normalized* to have $\alpha_k = 1$ or $\sum_{j=0}^k \beta_j = 1$. **Implicit**: If $\beta_k \neq 0$ **Explicit**: If $\beta_k = 0$

AB Schemes Construction | **Using Interpolation**: Adams-Bashforth schemes can be constructed by: Consider k points (t_{n+j}, y'_{n+j}) for j = 0, ..., k-1.

- 1. Let $\prod_{k}^{f}(t)$ be the *Lagrange polynomial* which passes through (t_{n+j}, y'_{n+j}) .
- 2. The AB scheme is: $y_{n+k}=y_{n+k-1}+\int_{t_{n+k-1}}^{t_{n+k}}\prod_k^f(t)dt$ Remark: Adams-Moulton schemes 同理: 考虑 k+1 points (t_{n+j},y'_{n+j}) for j=0,...,k.

Then, we can found $\widehat{\prod}_k^f(t)$, and $y_{n+k} = y_{n+k-1} + \int_{t_{n+k-1}}^{t_{n+k}} \widehat{\prod}_k^f(t) dt$

Algebra Operators: Algebra Operators is a function which maps a function to another function.

- 1. **shift operator**: $E_h g(t) = g(t+h)$ forward difference operator: $\Delta_h g(t) = g(t+h) - g(t)$
- **Differentiation operator**: Dg(t) = g'(t)2. **Identity Operator**: 1g(t) = g(t)
- 3. backward difference operator: $\nabla_h g(t) = g(t) g(t-h)$

Properties of Algebra Operators:

$\Delta_h =$	$E_{h} - 1$	$E_h = e^{hD}$	$e^{hD} =$	$1 + \Delta_h$	$D = \frac{1}{h} \ln[1 + \Delta_h]$	$g(t) = e^{(t-t_n)D}g(t_n)$	$g(t_{n+1}) = e^{hD}g(t_n)$
E_h^{-1}	$=e^{-hD}$	$D = -\frac{1}{h} \ln \frac{1}{h}$	$\mathbf{n}[E_h^{-1}] = -\frac{1}{h}$	$\ln[1-\nabla_h]$	$1 - E_h^{-1} = \nabla_h$	$D = \frac{1}{h} [\nabla_h + 1]$	$\frac{1}{2}\nabla_{h}^{2} + \frac{1}{3}\nabla_{h}^{3} + \cdots$
$e^{hD}g($	g(t) = g(t)	+h)=g(t)-	$+hDg(t)+\frac{h^2}{2}$	$D^2g(t) + \cdots$	$g(t) = \left[1 + \frac{t - t_n}{1 \cdot h} \Delta_h\right]$	$+\frac{(t-t_n)(t-t_n-h)}{2!\cdot h^2}\Delta_h^2+\frac{(t-t_n)(t-t_n-h)}{2!\cdot h^2}$	$\frac{-t_n-h)(t-t_n-2h)}{3!\cdot h^3}\Delta_h^3+\cdots g(t_n)$

BDF Method: For y'=f(t,y(t)). Since Dy(t)=y'(t) and $D=\frac{1}{h}[\nabla_h+\frac{1}{2}\nabla_h^2+\frac{1}{3}\nabla_h^3+\cdots]$. we can get the BDF method by $\frac{1}{h}[\nabla_h+\frac{1}{2}\nabla_h^2+\frac{1}{3}\nabla_h^3+\cdots]y(t)=f(t,y(t))$. 选择 D 的前几项作为估计.

6.2 Order of Accuracy

Appendix

7.1 Common Numerical Method | Order Condition

One-step Methods:

Method	Formula	Order	Stability
Euler's Method	$y_{n+1} = y_n + h f(t_n, y_n)$	1	$ 1+h\lambda <1$
Backward Euler	$y_{n+1} = y_n + h f(t_{n+1}, y_{n+1})$	1	$\left \frac{1}{1-h\lambda} \right < 1 \text{ (A-stable)}$
Trapezoidal Rule	$y_{n+1} = y_n + \frac{h}{2} [f(t_n, y_n) + f(t_{n+1}, y_{n+1})]$	2	A-stable; $R(z) = \frac{1+z/2}{1-z/2}$
Midpoint Method	$y_{n+1} = y_n + h f\left(t_n + \frac{h}{2}, y_n + \frac{h}{2}f(t_n, y_n)\right)$	2	$\left 1+h\lambda+\frac{(h\lambda)^2}{2}\right <1$
Heun's Method	$y_{n+1} = y_n + \frac{h}{2} [f(t_n, y_n) + f(t_{n+1}, y_n + h f(t_n, y_n))]$	2	$\left 1 + h\lambda + \frac{(h\lambda)^2}{2}\right < 1$
Theta Method	$y_{n+1} = y_n + h \Big[(1 - \theta) f(t_n, y_n) + \theta f(t_{n+1}, y_{n+1}) \Big]$	1 (or 2 if $\theta = \frac{1}{2}$)	$R(z) = \frac{1 + (1 - \theta)z}{1 - \theta z}$
RK4 Method	见 Butcher Table	4	$R(z) = 1 + z + \frac{z^2}{2} + \frac{z^3}{6} + \frac{z^4}{24}$
2-Stage Gauss-Legendre	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	4	A-stable

Multi-step Methods:

Name	Formula	Step	Accuracy	
Leapfrog Method	$y_{n+2} = y_n + 2h f(t_{n+1}, y_{n+1})$	2		
Adams-Bashforth Method 1	$y_{n+1} = y_n + h f(t_n, y_n)$	1		
Adams-Bashforth Method 2	$y_{n+2} = y_{n+1} + \frac{h}{2} \left[3f(t_{n+1}, y_{n+1}) - f(t_n, y_n) \right]$	2		
Adams-Bashforth Method 3	$y_{n+3} = y_{n+2} + \frac{h}{12} \left[23f(t_{n+2}, y_{n+2}) - 16f(t_{n+1}, y_{n+1}) + 5f(t_n, y_n) \right]$ $y_{n+2} = \frac{4}{3}y_{n+1} - \frac{1}{3}y_n + \frac{2h}{3}f(t_{n+2}, y_{n+2})$	3		
Backward Differentiation Formula 2	2			
Backward Differentiation Formula 3	entiation Formula 3 $y_{n+3} = \frac{18}{11}y_{n+2} - \frac{9}{11}y_{n+1} + \frac{2}{11}y_n + \frac{6h}{11}f(t_{n+3}, y_{n+3})$			
Class of Adams-Moulton Methods: $\alpha_k = 1, \alpha_{k-1} = -1, \alpha_j = 0, \forall j < k-1$ Class of Backward Differentiation Formula (BDF): $\beta_j = 0, \forall j < k-1$				

RK Order Condition

1. **order 1**: $\sum_{i=1}^{s} b_i = 1$

2. **order 2**: $\sum_{i=1}^{s} b_i c_i = \frac{1}{2}$

3. **order 3**: $\sum_{i=1}^{s} b_i c_i^2 = \frac{1}{3}$ and $\sum_{i=1}^{s} \sum_{j=1}^{s} b_i a_{ij} c_j = \frac{1}{6}$

4. **order 4**: $\sum_{i=1}^{s} b_i c_i^3 = \frac{1}{4}$, $\sum_{i=1}^{s} \sum_{j=1}^{s} b_i a_{ij} c_j^2 = \frac{1}{8}$, $\sum_{i=1}^{s} \sum_{j=1}^{s} b_i a_{ij} c_j^2 = \frac{1}{12}$, $\sum_{i=1}^{s} \sum_{j=1}^{s} \sum_{k=1}^{s} b_i a_{ij} a_{jk} c_k = \frac{1}{24}$

7.2 Useful Series | Common RK Methods

Common Runge-Kutta Methods (Butcher Table):

Useful Series:

Oseiui sei i	CS.						
f(x)	Taylor	Series	R	f(x)	Taylor	Series	R
$\frac{1}{1-x}$	$\sum_{n=0}^{\infty} x^n$	$1 + x + x^2 + x^3 + \dots$	1	$\frac{1}{(1-x)^2}$	$\sum_{n=1}^{\infty} n x^{n-1}$	$1 + 2x + 3x^2 + 4x^3 + \dots$	1
$\frac{2}{(1-x)^3}$	$\sum_{n=2}^{\infty} n(n-1)x^{n-2}$	$2 + 6x + 12x^2 + 20x^3 + \dots$	1	e^x	$\sum_{n=0}^{\infty} \frac{x^n}{n!}$	$1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \dots$	∞
ln(1+x)	$\sum_{n=1}^{\infty} (-1)^{n+1} \frac{x^n}{n}$	$x-\frac{x^2}{2}+\frac{x^3}{3}-\dots$	1	$-\ln(1-x)$	$\sum_{n=1}^{\infty} \frac{x^n}{n}$	$x + \frac{x^2}{2} + \frac{x^3}{3} + \dots$	1
sin x	$\sum_{n=0}^{\infty} (-1)^n \frac{x^{2n+1}}{(2n+1)!}$	$x - \frac{x^3}{3!} + \frac{x^5}{5!} - \dots$	∞	cos x	$\sum_{n=0}^{\infty} (-1)^n \frac{x^{2n}}{(2n)!}$	$1 - \frac{x^2}{2!} + \frac{x^4}{4!} - \dots$	∞
arctan x	$\sum_{n=0}^{\infty} (-1)^n \frac{x^{2n+1}}{2n+1}$	$x-\frac{x^3}{3}+\frac{x^5}{5}-\dots$	1	sinh x	$\sum_{n=0}^{\infty} \frac{x^{2n+1}}{(2n+1)!}$	$x + \frac{x^3}{3!} + \frac{x^5}{5!} + \dots$	∞
$\cosh x$	$\sum_{n=0}^{\infty} \frac{x^{2n}}{(2n)!}$	$1 + \frac{x^2}{2!} + \frac{x^4}{4!} + \dots$	∞	$(1+x)^k$	$\sum_{n=0}^{\infty} \binom{k}{n} x^n$	$1 + kx + \frac{k(k-1)x^2}{2!} + \dots$	1
$\ln x$	$\sum_{n=1}^{\infty} (-1)^{n+1} \frac{(x-1)^n}{n}$	$(x-1) - \frac{(x-1)^2}{2} + \frac{(x-1)^3}{3} - \dots$	1, 0 < x < 2	$\frac{1}{1+x}$	$\sum_{n=0}^{\infty} (-1)^n x^n$	$1 - x + x^2 - x^3 + \dots$	1