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1 Euler's Method and Beyond

1.1 Ordinary differential equations and Lipschitz condition

1. (Goal) Approximate solution to

$$y' = f(t, y)$$
 with initial condition $y(t_0) = y_0$

where $t > t_0$ and $f: [t_0, \infty) \times \mathbb{R}^d \to \mathbb{R}^d$ is a sufficiently well behaved function

2. (Lipschitz condition) Given f and norm $\|\cdot\|$, the Lipschitz condition is defined by

$$\|\boldsymbol{f}(t,\boldsymbol{x}) - \boldsymbol{f}(t,\boldsymbol{y})\| \le \lambda \|\boldsymbol{x} - \boldsymbol{y}\|$$
 for all $\boldsymbol{x}, \boldsymbol{y} \in \mathbb{R}^d$, $t > t_0$

where $\lambda \in \mathbb{R}$ is called Lipschitz constant.

3. (Picard Lindelof theorem) Consider initial value problem

$$y'(t) = f(t, y(t))$$
 $y(t_0) = y_0$

If f is uniformly Lipschitz continous in y and continous in t, then for some $\epsilon > 0$, there exists unique solution y(t) to the initial value problem on the interval $[t_0 - \epsilon, t_0 + \epsilon]$

- 4. (Analytic function) A function f is an analytic function if it is a function that is locally given by a convergent power series, i.e. an infinitely differentiable function such that at any point $(t, \mathbf{y}_0) \in [0, \infty) \times \mathbb{R}^d$ in its domain, the Taylor series converges to $f(\mathbf{x})$ for \mathbf{x} in a neighborhood of (t, \mathbf{y}_0) .
 - (a) (example) polynomial, exponential, trigonometric, logarithm, power function
 - (b) (note) if f is analytic, solution y to the initial value problem is also analytic
- 5. (Taylor Expansion) Given $f \in C^{\infty}(\mathbb{R})$, the Taylor expansion of f at a is given by

$$T(a) = \sum_{n=0}^{\infty} \frac{f^{(n)}(a)}{n!} (x-a)^n$$
$$= f(a) + \frac{f'(a)}{1!} (x-a) + \frac{f''(a)}{2!} (x-a)^2 + \cdots$$

6. (Taylor's Theorem) Let $k \geq 1$ and function $f : \mathbb{R} \to \mathbb{R}$ be k times differentiable at a point $a \in \mathbb{R}$, then exists $h_k : \mathbb{R} \to \mathbb{R}$ such that

$$f(x) = \sum_{n=0}^{k} \frac{f^{(n)}(a)}{n!} (x-a)^n + h_k(x)(x-a)^k$$

and $\lim_{x\to a} h_k(x) = 0$, i.e. the reminder term $R_k(x) = f(x) - P_k(x)$ is asymptotically trivial. If f is k+1 times differentiable on the open interval and f^k continous on the closed interval [a,x], then the Lagrange remind is given by

$$R_k(x) = \frac{f^{k+1}(\zeta)}{(k+1)!}(x-a)^{k+1}$$

for soem $\zeta \in [a, x]$ by the mean value theorem

- 7. (O notation) f(x) = O(g(x)) describes asymptotic behavior of function f
 - (a) (as $x \to \infty$) if there exists $M \ge 0$ and $x_0 \in \mathbb{R}$ such that $|f(x)| \le Mg(x)$ for all $x > x_0$.
 - (b) (as $x \to a$) if there exists $M \ge 0$ and $\delta \in \mathbb{R}$ such that $|f(x)| \le Mg(x)$ when $0 < |x a| < \delta$. Alternatively we can say

$$\lim_{x \to a} \sup \left| \frac{f(x)}{g(x)} \right| < \infty$$

1.2 Euler's method

Definition. (Euler's Method) Given initial value problem $\mathbf{y}' = \mathbf{f}(t, \mathbf{y})$ for $t \geq t_0$ and initial value $\mathbf{y}(t_0) = \mathbf{y}_0$. If we assume $\mathbf{y}'(t) = \mathbf{f}(t, \mathbf{y}(t)) \approx \mathbf{f}(t_0, \mathbf{y}(t_0))$ for $t \in [t_0, t_0 + h)$ (i.e. derivative in $[t_n, t_{n+1}]$ is approximated by value of derivative at t_n) for some sufficiently small time step h > 0, we can approximate the value of $\mathbf{y}(t)$ by

$$y(\mathbf{t}) = y(t_0) + \int_{t_0}^{t} f(\tau, y(\tau)) d\tau$$
$$\approx y_0 + (t - t_0) f(t_0, y_0)$$

Given a sequence of times $(t_n)_{n\in\mathbb{N}}=(t_0,t_0+h,\cdots)$ we have numerical approximation $(\boldsymbol{y}_n)_{n\in\mathbb{N}}$ by

$$\mathbf{y}_{n+1} = \mathbf{y}_n + h\mathbf{f}(t_n, \mathbf{y}_n)$$

(intuition) euler's method is a time-stepping numerical method that covers interval by an equidistant grid and produe numerical solution at the grid points. we can show that euler's method is convergent, i.e. as h → 0, grid is refined, the numerical solution tends to exact solution

Definition. (convergent method) Given a time-stepping numerical method on a compact inteval $[t_0, t_0 + t^*]$, we can compute numerical solutions dependent upon h

$$y_n = y_{n,h}$$
 for $n = 0, 1, \dots, |t * /h|$

A method is said to be convergent if for every ODE with Lipschitz function f, the numerical solution tends to the true solution as the grid becomes increasingly fine. More rigorously, if every ODE with Lipschitz function y and for every $t^* > 0$, then following holds

$$\lim_{h \to 0^+} \max_{n=0,1,\dots,|t*/h|} \| \boldsymbol{y}_{n,h} - \boldsymbol{y}(t_n) \| = 0$$

Theorem. (Euler's method is convergent)

Proof. Assume f and therefore also y is analytic, i.e. convergent Taylor expansion. Let $e_{n,h} = y_{n,h} - y(t_n)$ be the numerical error. Show $\lim_{h\to 0^+} \max_n \|e_{n,h}\| = 0$. By Taylor's theorem

$$y(t_{n+1}) = y(t_n) + hy'(t_n) + O(h^2) = y(t_n) + hf(t_n, y(t_n)) + O(h^2)$$

given y continuously differentiable, $\mathcal{O}(h^2)$ can be bounded uniformly for all h > 0 by a term ch^2 for some c > 0. Subtract previous from iterative formula of euler's method

$$e_{n+1,h} = e_{n,h} + h \left(f(t_n, y(t_n) + e_{n,h}) - f(t_m, y(t_n)) \right) + \mathcal{O}(h^2)$$

By triangle inequality and Lipschitz condition

$$\|e_{n+1,h}\| \le \|e_{n,h}\| + h \|f(t_n, y(t_n) + e_{n,h}) - f(t_n, y(t_n))\| + ch^2$$

 $\le (1 + h\lambda) \|e_{n,h}\| + ch^2$

for $n = 0, 1, \dots, \lfloor t^*/h \rfloor - 1$. By induction on n, we can show $\|e_{n,h}\| \leq \frac{c}{\lambda} h \left((1 + h\lambda)^n - 1\right)$. Since $1 + h\lambda < e^{h\lambda}$ we have $(1 + h\lambda)^n < e^{nh\lambda} < e^{\lfloor t*/h \rfloor h\lambda} \leq e^{t^*\lambda}$. Therefore

$$\|\boldsymbol{e}_{n,h}\| \le \frac{c}{\lambda} (e^{t^*\lambda} - 1)h$$

for $n = 0, 1, \dots, \lfloor t * /h \rfloor$. This is an upper bound on the error that is independent of h, hence $\lim_{h\to 0} \|e_{n,h}\| = 0$. from which we can infer that error decays globally as $\mathcal{O}(h)$

Definition. (order p method) Given arbitrary time-stepping method

$$y_{n+1} = y_n(f, h, y_0, y_1, \dots, y_n)$$
 $n = 0, 1, \dots$

for initial value problem, it is of order p if

$$\mathbf{y}(t_{n+1}) - \mathbf{\mathcal{Y}}_n(\mathbf{f}, h, \mathbf{y}(t_0), \mathbf{y}(t_1), \cdots, \mathbf{y}(t_n)) = \mathcal{O}(h^{p+1})$$

for every analytic \mathbf{f} and $n=0,1,\cdots$. Intuitively, a method is of order p if it recovers exactly every polynomial oslution of degrees p or less.

- 1. (intuition) order of a method gives information about local behavior, i.e. advancing from t_n to t_{n+1} where h > 0 is sufficiently small, we are incurring an error of $\mathcal{O}(h^{p+1})$. Generally want the the global (convergence) behavior of the method instead.
- 2. (fact) euler's method is order 1

Proof. Euler's method can be written as $\mathbf{y}_{n+1} - (\mathbf{y}_n + h\mathbf{f}(t_n, \mathbf{y}_n)) = 0$. Replace \mathbf{y}_k by $\mathbf{y}(t_k)$ and expand terms of Taylor series about t_n we have

$$y(t_{n+1}) - (y(t_n) + hf(t_n, y(t_n))) = (y(t_n) + hy'(t_n) + \mathcal{O}(h^2)) - (y(t_n) + hy'(t_n)) = \mathcal{O}(h^2)$$

1.3 The trapezoidal rule

Definition. (Trapezoidal Rule) Instead of approximating derivative by a constant in $[t_n, t_{n+1}]$, namely by its value at t_n , the trapezoidal rule approximates the value of the derivate by average of values at the endpoints. We can approximate solution y(t) by

$$y(t) = y(t_n) + \int_{t_n}^{t} f(\tau, f(\tau)) d\tau$$

$$\approx y(t_n) + \frac{1}{2} (t - t_n) \left(f(t_n, y(t_n)) + f(t, y(t)) \right)$$

Given a sequence of times $(t_n)_{n\in\mathbb{N}}=(t_0,t_0+h,\cdots)$ we have numerical approximation $(\boldsymbol{y}_n)_{n\in\mathbb{N}}$ by

$$\mathbf{y}_{n+1} = \mathbf{y}_n + \frac{1}{2}h\left(\mathbf{f}(t_n, \mathbf{y}_n) + \mathbf{f}(t_{n+1}, \mathbf{y}_{n+1})\right)$$

1. (theorem) order of trapezoidal rule is 2

Proof. Compute by performing Taylor expansion on $y(t_{n+1})$ and $y'(t_{n+1})$ about t_n

$$y(t_{n+1}) - \left\{ y(t_n) + \frac{1}{2}h\left\{ f(t_n, y(t_n)) + f(t_{n+1}, y(t_{n+1})) \right\} \right\} = \mathcal{O}(h^3)$$

2. (theorem) trapezoidal rule is convergent

Proof. Detail of proof here. We can show error is bounded by

$$\|e_{n,h}\| \le \frac{ch^2}{\lambda} exp\left(\frac{t^*\lambda}{1-\frac{1}{2}h\lambda}\right)$$

from which we can infer that error decays globally as $\mathcal{O}(h^2)$

3. (note) euler's method is explicit, since we can compute \mathbf{y}_{n+1} with a few arithmetic operations by computing \mathbf{f} , a function of a known \mathbf{y}_n . Trapezoidal rule is implicit, i.e. finding \mathbf{y}_{n+1} is not trivial and \mathbf{f} is a function of both \mathbf{y}_n and \mathbf{y}_{n+1} . We might need to solve a nonlinear equation of \mathbf{y}_{n+1}

$$y_{n+1} - \frac{1}{2}hf(t_{n+1}, y_{n+1}) = v$$

where $\mathbf{v} = \mathbf{y}_n + \frac{1}{2}h\mathbf{f}(t_n, \mathbf{y}_n)$ can be evaluated easily from assumptions.

1.4 The theta method

Definition. (theta method) is a generalization of Euler's method ($\theta = 1$) and the trapezoidal rule ($\theta = 1/2$), whereby the derivates are assumed to be piecewise constant and provided by a linear combination of derivatives at the endpoints of each interval. The numerical approximates are,

$$y_{n+1} = y_n + h(\theta f(t_n, y_n) + (1 - \theta) f(t_{n+1}, y_{n+1}))$$
 $n = 0, 1, \cdots$

for some fixed $\theta \in [0,1]$

- 1. (fact) theta method is explicit for $\theta = 1$ and implicit otherwise
- 2. (theorem) theta method is of order 2 for $\theta = 1/2$ and order 1 otherwise.
- 3. (theorem) theta method is convergent for every $\theta \in [0,1]$

2 Multistep Method

3 8 Finite Differences Schemes

3.1 8.1 Finite differences

Definition. (finite difference operators) Given real sequences $z = \{z_k\}_{k \in \mathbb{Z}}$, finite difference operators map the space $\mathbb{R}^{\mathbb{Z}}$ of all such sequences to itself.

- 1. (shift) $(\mathcal{E}z)_k = z_{k+1}$
- 2. (forward difference) $(\triangle_+ z)_k = z_{k+1} z_k$
- 3. (backward difference) $(\triangle_{-}z)_k = z_k z_{k-1}$
- 4. (central difference) $(\triangle_0 z)_k = z_{k+\frac{1}{2}} z_{k-\frac{1}{2}}$
- 5. (averaging) $(\Gamma_0 z)_k = \frac{1}{2}(z_{k-\frac{1}{2}} + z_{k+\frac{1}{2}})$
- 1. (note) central difference and averaging operator are not maps of z onto itself.