

Contents

1	Euler’s Method and Beyond	2
1.1	Ordinary differential equations and Lipschitz condition	2
1.2	Euler’s method	3
1.3	The trapezoidal rule	4
1.4	The theta method	5
2	Multistep Method	5
3	8 Finite Differences Schemes	5
3.1	8.1 Finite differences	5

1. **(Taylor Expansion)** Given $f \in C^\infty(\mathbb{R})$, the Taylor expansion of f at a is given by

$$\begin{aligned} T(a) &= \sum_{n=0}^{\infty} \frac{f^{(n)}(a)}{n!} (x-a)^n \\ &= f(a) + \frac{f'(a)}{1!} (x-a) + \frac{f''(a)}{2!} (x-a)^2 + \dots \end{aligned}$$

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

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

and $\lim_{x \rightarrow a} h_k(x) = 0$, 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 $f^{(k)}$ continuous 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

3. **(\mathcal{O} notation)** $f(x) = \mathcal{O}(g(x))$ describes asymptotic behavior of function f

- (a) (as $x \rightarrow \infty$) if there exists $M \geq 0$ and $x_0 \in \mathbb{R}$ such that $|f(x)| \leq Mg(x)$ for all $x > x_0$.
 (b) (as $x \rightarrow a$) if there exists $M \geq 0$ and $\delta \in \mathbb{R}$ such that $|f(x)| \leq Mg(x)$ when $0 < |x-a| < \delta$.
 Alternatively we can say

$$\limsup_{x \rightarrow a} \left| \frac{f(x)}{g(x)} \right| < \infty$$

4. **(power series expansions)**

$$\begin{aligned} \frac{1}{1-x} &= \sum_{n=0}^{\infty} x^n = 1 + x + x^2 + x^3 + \dots \\ e^x &= \sum_{n=0}^{\infty} \frac{x^n}{n!} = 1 + x + \frac{x^2}{2} + \frac{x^3}{3!} + \dots \\ (1+x)^\alpha &= \sum_{k=0}^{\infty} \binom{\alpha}{k} x^k \\ \ln(1+x) &= \sum_{n=1}^{\infty} (-1)^{n+1} \frac{x^n}{n} = x - \frac{x^2}{2} + \frac{x^3}{3} && \text{(convergent if } |x| < 1) \\ \ln(1+x) &= - \sum_{n=1}^{\infty} \frac{x^n}{n} = -x - \frac{x^2}{2} - \frac{x^3}{3} && \text{(convergent if } |x| < 1) \end{aligned}$$

1 Euler's Method and Beyond

1.1 Ordinary differential equations and Lipschitz condition

1. **(Goal)** Approximate solution to

$$\mathbf{y}' = \mathbf{f}(t, \mathbf{y}) \quad \text{with initial condition} \quad \mathbf{y}(t_0) = \mathbf{y}_0$$

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

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

$$\|\mathbf{f}(t, \mathbf{x}) - \mathbf{f}(t, \mathbf{y})\| \leq \lambda \|\mathbf{x} - \mathbf{y}\| \quad \text{for all } \mathbf{x}, \mathbf{y} \in \mathbb{R}^d, t > t_0$$

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

3. (**Picard Lindelof theorem**) Consider initial value problem

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

If f is uniformly Lipschitz continuous in y and continuous 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 \mathbf{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 $\mathbf{f}(\mathbf{x})$ for \mathbf{x} in a neighborhood of (t, \mathbf{y}_0) .

(a) (example) polynomial, exponential, trigonometric, logarithm, power function

(b) (note) if \mathbf{f} is analytic, solution \mathbf{y} to the initial value problem is also analytic

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

$$\begin{aligned} \mathbf{y}(t) &= \mathbf{y}(t_0) + \int_{t_0}^t \mathbf{f}(\tau, \mathbf{y}(\tau)) d\tau \\ &\approx \mathbf{y}_0 + (t - t_0) \mathbf{f}(t_0, \mathbf{y}_0) \end{aligned}$$

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

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

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

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

$$\mathbf{y}_n = \mathbf{y}_{n,h} \quad \text{for } n = 0, 1, \dots, \lfloor t^*/h \rfloor$$

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

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

Theorem. (Euler's method is convergent)

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

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

given \mathbf{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

$$\mathbf{e}_{n+1,h} = \mathbf{e}_{n,h} + h(\mathbf{f}(t_n, \mathbf{y}(t_n) + \mathbf{e}_{n,h}) - \mathbf{f}(t_n, \mathbf{y}(t_n))) + \mathcal{O}(h^2)$$

By triangle inequality and Lipschitz condition

$$\begin{aligned} \|\mathbf{e}_{n+1,h}\| &\leq \|\mathbf{e}_{n,h}\| + h \|\mathbf{f}(t_n, \mathbf{y}(t_n) + \mathbf{e}_{n,h}) - \mathbf{f}(t_n, \mathbf{y}(t_n))\| + ch^2 \\ &\leq (1 + h\lambda) \|\mathbf{e}_{n,h}\| + ch^2 \end{aligned}$$

for $n = 0, 1, \dots, \lfloor t^*/h \rfloor - 1$. By induction on n , we can show $\|\mathbf{e}_{n,h}\| \leq \frac{c}{\lambda} h ((1 + h\lambda)^n - 1)$. 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

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

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

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

$$\mathbf{y}_{n+1} = \mathcal{Y}_n(\mathbf{f}, h, \mathbf{y}_0, \mathbf{y}_1, \dots, \mathbf{y}_n) \quad n = 0, 1, \dots$$

for initial value problem, it is of order p if

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

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

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

\square

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 derivative by average of values at the endpoints. We can approximate solution $\mathbf{y}(t)$ by

$$\begin{aligned} \mathbf{y}(t) &= \mathbf{y}(t_n) + \int_{t_n}^t \mathbf{f}(\tau, \mathbf{y}(\tau)) d\tau \\ &\approx \mathbf{y}(t_n) + \frac{1}{2}(t - t_n) (\mathbf{f}(t_n, \mathbf{y}(t_n)) + \mathbf{f}(t, \mathbf{y}(t))) \end{aligned}$$

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

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

1. (theorem) order of trapezoidal rule is 2

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

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

□

2. (*theorem*) trapezoidal rule is convergent

Proof. Detail of proof [here](#) . We can show error is bounded by

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

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}

$$\mathbf{y}_{n+1} - \frac{1}{2}h\mathbf{f}(t_{n+1}, \mathbf{y}_{n+1}) = \mathbf{v}$$

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 derivatives are assumed to be piecewise constant and provided by a linear combination of derivatives at the endpoints of each interval. The numerical approximates are,

$$\mathbf{y}_{n+1} = \mathbf{y}_n + h(\theta\mathbf{f}(t_n, \mathbf{y}_n) + (1 - \theta)\mathbf{f}(t_{n+1}, \mathbf{y}_{n+1})) \quad n = 0, 1, \dots$$

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

1. (**Finite difference operators**) Given real sequences $\mathbf{z} = \{z_k\}_{k \in \mathbb{Z}} = z(kh)$ for $k \in \mathbb{Z}$ as discrete sampling of a function z for some $h > 0$. Let $x_k = kh$. We can define finite difference operators mapping the space $\mathbb{R}^{\mathbb{Z}}$ of all such sequences to itself.

$$\begin{aligned} (\mathcal{E}\mathbf{z})_k &= z_{k+1} && \text{(shift)} \\ (\Delta_+\mathbf{z})_k &= z_{k+1} - z_k && \text{(forward difference)} \\ (\Delta_-\mathbf{z})_k &= z_k - z_{k-1} && \text{(backward difference)} \\ (\Delta_0\mathbf{z})_k &= z_{k+\frac{1}{2}} - z_{k-\frac{1}{2}} && \text{(central difference)} \\ (\Upsilon_0\mathbf{z})_k &= \frac{1}{2}(z_{k-\frac{1}{2}} + z_{k+\frac{1}{2}}) && \text{(averaging)} \end{aligned}$$

Finite difference operators are composed under function composition.

(a) **(fact)** $\mathcal{T} \in \{\mathcal{E}, \Delta_+, \Delta_-, \Delta_0, \Upsilon_0, \mathcal{D}\}$ are linear operators

$$\mathcal{T}(a\mathbf{w} + b\mathbf{z}) = a\mathcal{T}\mathbf{w} + b\mathcal{T}\mathbf{z} \quad \text{for} \quad \mathbf{w}, \mathbf{z} \in \mathbb{R}^{\mathbb{Z}}, \quad a, b \in \mathbb{R}$$

(b) **(convention)** $\mathcal{T}z_k$ stands for $(\mathcal{T}\mathbf{z})_k$

2. **(Differential operator)** The goal is to approximate derivatives \mathcal{D} by expressing it with a linear combination of values along the grid.

$$(\mathcal{D}\mathbf{z})_k = z'(kh) \quad (\text{differential})$$

3. **(Functions of operators)** Finite difference operators are functions of h . Given an analytic function as Taylor series, $g(x) = \sum_{j=0}^{\infty} a_j x^j$, we can expand g about $\{\mathcal{E} - \mathcal{I}, \Upsilon_0 - \mathcal{I}, \Delta_+, \Delta_-, \Delta_0, h\mathcal{D}\}$,

$$g(\Delta_+)\mathbf{z} = \left(\sum_{j=0}^{\infty} a_j \Delta_+^j \right) \mathbf{z} = \sum_{j=0}^{\infty} a_j (\Delta_+^j \mathbf{z})$$

4. **(Asymptotics of operators)**

$$\{\mathcal{E} - \mathcal{I}, \Upsilon_0 - \mathcal{I}, \Delta_+, \Delta_-, \Delta_0, h\mathcal{D}\} \xrightarrow{h \rightarrow 0^+} O$$

(a) **(example)**

$$\Delta_+ z_k = z_{k+1} - z_k = z(x_k + h) - z(x_k) = h z'(\eta_k) = \mathcal{O}(h)$$

by some $\eta_k \in [x_k, x_{k+1}]$ by mean value theorem

5. **(Operator $\mathcal{E}^{1/2}$)**

$$(\mathcal{E}^{1/2} \mathbf{z})_k = z((k + \frac{1}{2})h)$$

by defining it with a power series expansion of $g(x) = \sqrt{1+x}$

$$\mathcal{E}^{1/2} = (\mathcal{I} + (\mathcal{E} - \mathcal{I}))^{1/2} = \mathcal{I} + \sum_{j=0}^{\infty} \frac{(-1)^{j-1}}{2^{2j-1}} \frac{(2j-2)!}{(j-1)!j!} (\mathcal{E} - \mathcal{I})^j$$

6. **(Operator ommutativity)** Idea is all operator can be expressed w.r.t. \mathcal{E} .

$$\Delta_+ = \mathcal{E} - \mathcal{I}$$

$$\Delta_- = \mathcal{I} - \mathcal{E}^{-1}$$

$$\Delta_0 = \mathcal{E}^{1/2} - \mathcal{E}^{-1/2}$$

$$\Upsilon_0 = \frac{1}{2}(\mathcal{E}^{1/2} + \mathcal{E}^{-1/2})$$

$$\mathcal{I} = \mathcal{E}^0$$