

CS 450: Numerical Analysis¹

Initial Value Problems for Ordinary Differential Equations

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¹*These slides have been drafted by Edgar Solomonik as lecture templates and supplementary material for the book “Scientific Computing: An Introductory Survey” by Michael T. Heath ([slides](#)).*

Ordinary Differential Equations

- ▶ An *ordinary differential equation (ODE)* usually describes time-varying system by a function $\mathbf{y}(t)$ that satisfies a set of equations in its derivatives
The general *implicit* form is

$$g(t, \mathbf{y}, \mathbf{y}', \mathbf{y}'', \dots, \mathbf{y}^{(k)}) = \mathbf{0},$$

but we restrict focus on the *explicit form*, $\mathbf{y}^{(k)} = \mathbf{f}(t, \mathbf{y}, \mathbf{y}', \mathbf{y}'', \dots, \mathbf{y}^{(k-1)})$.

- ▶ An ODE of any *order* k can be transformed into a first-order ODE,

$$\mathbf{u}' = \begin{bmatrix} \mathbf{u}'_1 \\ \vdots \\ \mathbf{u}'_{k-1} \\ \mathbf{u}'_k \end{bmatrix} = \begin{bmatrix} \mathbf{u}_2 \\ \vdots \\ \mathbf{u}_k \\ \mathbf{f}(t, \mathbf{u}_1, \dots, \mathbf{u}_k) \end{bmatrix} = \text{where } \mathbf{u}_i(t) = \mathbf{y}^{(i-1)}(t).$$

Consequently we restrict our focus to systems of first-order ODEs. Of particular importance are *linear ODEs*, which have the form $\mathbf{y}' = \mathbf{A}(t)\mathbf{y}$, whose *coefficients* are said to be *constant* if $\mathbf{A}(t) = \mathbf{A}$ for all t .

Example: Newton's Second Law

- ▶ $F = ma$ corresponds to a second order ODE

$$F(t, y(t), y'(t)) = my''(t)$$

$$y''(t) = f(t, y, y') = F(t, y(t), y'(t))/m$$

- ▶ We can transform it into a first order ODE in two variables

$$\mathbf{u} = \begin{bmatrix} y(t) \\ y'(t) \end{bmatrix}$$

$$\begin{bmatrix} u_1' \\ u_2' \end{bmatrix} = \mathbf{u}' = \mathbf{f}(t, \mathbf{u}) = \begin{bmatrix} u_2 \\ F(t, \mathbf{u})/m \end{bmatrix}$$

Initial Value Problems

- ▶ Generally, a first order ODE specifies only the derivative, so the solutions are non-unique, an *initial condition* addresses this:

$$\mathbf{y}(t_0) = \mathbf{y}_0$$

*This condition yields an initial value problem (IVP), which is the simplest example of a *boundary condition*.*

- ▶ Given an initial condition, an ODE must satisfy an integral equation for any given point t :

$$\mathbf{y}(t) = \mathbf{y}_0 + \int_{t_0}^t \mathbf{f}(s, \mathbf{y}(s)) ds$$

In the special case that $\mathbf{y}' = \mathbf{f}(t)$, the integral can be computed directly by numerical quadrature to solve the ODE.

Existence and Uniqueness of Solutions

- ▶ For an ODE to have a unique solution, it must be defined on a closed domain D and be *Lipschitz continuous*:

$$\forall \mathbf{y}, \hat{\mathbf{y}} \in D, \quad \|\mathbf{f}(t, \hat{\mathbf{y}}) - \mathbf{f}(t, \mathbf{y})\| \leq L\|\hat{\mathbf{y}} - \mathbf{y}\|,$$

i.e. the rate of change of the ODE should itself change continuously. Any differentiable function \mathbf{f} is Lipschitz continuous with

$$L = \max_{(t, \mathbf{y}) \in D} \|\mathbf{J}_{\mathbf{f}}(t, \mathbf{y})\|.$$

- ▶ The solutions of an ODE can be stable, unstable, or asymptotically stable: *Perturbation to the input causes a perturbation to the solution that has bounded growth for a stable ODE, unbounded for an unstable ODE, and shrinks for an asymptotically stable ODE.*

Stability of 1D ODEs

- ▶ The solution to the scalar ODE $y' = \lambda y$ is $y(t) = y_0 e^{\lambda t}$, with stability dependent on λ :

$$\lim_{t \rightarrow \infty} y(t) = \begin{cases} \infty & : \lambda > 0 \text{ (unstable)} \\ y_0 & : \lambda = 0 \text{ (stable)} \\ 0 & : \lambda < 0 \text{ (asymptotically stable)} \end{cases}$$

- ▶ A linear ODE generally has the form $\mathbf{y}' = \mathbf{A}\mathbf{y}$, with stability dependent on the spectral radius (largest eigenvalue) of \mathbf{A} :

For general ODEs, stability can be ascertained locally by considering a linear approximation $\mathbf{f}(t, \mathbf{y}) \approx \mathbf{y} + \mathbf{J}_f(t)^{-1}\mathbf{y}$ and measuring the spectral radius of $\mathbf{J}_f(t)^{-1}$.

Numerical Solutions to ODEs

- ▶ Methods for numerical ODEs seek to approximate $\mathbf{y}(t)$ at $\{t_k\}_{k=1}^m$.
Compute $\hat{\mathbf{y}}_k$ for $k \in \{1, \dots, m\}$ so as to approximate $\mathbf{y}(t_k) \approx \hat{\mathbf{y}}_k$. For an IVP, typically form $\hat{\mathbf{y}}_{k+1}$ using $\hat{\mathbf{y}}_k$ or additionally (for multistep methods) $\hat{\mathbf{y}}_{k-1}, \dots$

- ▶ Euler's method provides the simplest method (attempt) for obtaining a numerical solution:

Approximation solution to ODE at $t_k + h$ by linear segment from (t_k, \mathbf{y}_k) with slope $\mathbf{f}(t_k, \mathbf{y}_k)$,

$$\mathbf{y}_{k+1} = \mathbf{y}_k + h_k \mathbf{f}(t_k, \mathbf{y}_k).$$

Its instructive to observe that this approximation arises as the first order form of various models (Taylor series, finite differences, interpolation, quadrature, undetermined coefficients).

Error in Numerical Methods for ODEs

- ▶ Truncation error is typically the main quantity of interest, which can be defined *globally* or *locally*
Global error is measured at all points

$$e_k = \hat{\mathbf{y}}_k - \mathbf{y}(t_k),$$

which local error measures the deviation from the exact solution $\mathbf{u}_{k-1}(t)$ passing through the previous point $(t_{k-1}, \hat{\mathbf{y}}_{k-1})$,

$$\mathbf{l}_k = \hat{\mathbf{y}}_k - \mathbf{u}_{k-1}(t_k).$$

- ▶ The *order of accuracy* of Euler's method is one less than than the order of the leading order term in \mathbf{l}_k
Accuracy is of order p if $\mathbf{l}_k = O(h_k^{p+1})$. Euler's method is first order accurate by Taylor expansion analysis.

Stability of Numerical Methods for ODEs

- ▶ Stability can be defined for numerical methods similarly to ODEs themselves. *A method for an ODE with stable solutions can be unstable. Usually, we will seek to establish a **stability region** for a method, which describes the step-size conditions necessary for stability in terms of the step size h and (the largest) eigenvalue λ , usually as a function of $h\lambda$.*
- ▶ Basic stability properties follow from analysis of linear scalar ODE, which serves as a local approximation to more complex ODEs.

Consider forward Euler for the ODE $y' = \lambda y$, where

$$y_{k+1} = y_k + h\lambda y_k = (1 + h\lambda)y_k.$$

Euler's method requires $|1 + h\lambda| \leq 1$ to be stable, which implies $-2 \leq h\lambda \leq 0$ for real λ . For a general ODE, the eigenvalues of J_f must lie within a circle on the complex plane centered at -1 with radius 1.

Implicit Methods

- ▶ Implicit methods for ODEs form a sequence of solutions that satisfy conditions on a local approximation to the solution:

*The most basic implicit method is the **backward Euler** method*

$$\mathbf{y}_{k+1} = \mathbf{y}_k + h_k \mathbf{f}(t_{k+1}, \mathbf{y}_{k+1}),$$

which solves for \mathbf{y}_{k+1} so that a linear approximation of the solution at t_{k+1} passed through the point (t_k, \mathbf{y}_k) . Just like forward Euler, first-order accuracy is achieved by the linear approximation.

- ▶ The backward Euler method for a simple linear scalar ODE stability region is the left half of the complex plane:

*Such a method is called **unconditionally stable**. Note that the growth factor can be derived via*

$$y_{k+1} = y_k + h\lambda y_{k+1} = \frac{1}{1 - h\lambda} y_k,$$

and satisfies $|1/(1 - h\lambda)| \leq 1$ so long as $h\lambda \leq 0$.

Initial Value Problems for ODEs

- ▶ We restrict attention to first-order systems of ODEs and pay special attention to linear and constant-coefficient systems:

An IVP for an ODE usually has the form $\mathbf{y}' = \mathbf{f}(t, \mathbf{y})$ with initial value $(t_0, \mathbf{y}(t_0))$. A linear ODE \mathbf{f} has the form $\mathbf{f}(t, \mathbf{y}) = \mathbf{A}(t)\mathbf{y}(t)$, and is said to have constant coefficients if $\mathbf{A}(t)$ does not vary with t .

- ▶ Existence and uniqueness of a solution to an IVP is guaranteed over any domain D on which \mathbf{f} is Lipschitz continuous:

$$\exists L \in \mathbb{R}, \|\mathbf{f}(t, \mathbf{y}) - \mathbf{f}(t, \hat{\mathbf{y}})\| \leq L\|\mathbf{y} - \hat{\mathbf{y}}\|, \forall \mathbf{y}, \hat{\mathbf{y}} \in D$$

which is stronger than continuity of \mathbf{f} (differentiability of \mathbf{y}), but weaker than differentiability of \mathbf{f} , i.e. \mathbf{f} can suddenly begin to change at a different rate. The constant L bounds the rate at which similar solutions \mathbf{y} and $\hat{\mathbf{y}}$ can diverge or converge.

Convergence and Stability

- ▶ Generally, we seek to approximate $\mathbf{y}(t_k)$ for a set of points $t_k = t_0 + kh$ by $\hat{\mathbf{y}}_k$:
Would like to converge with decreasing step-size, i.e. $\lim_{h \rightarrow 0} \hat{\mathbf{y}}_k = \mathbf{y}(t_k)$. Can measure global error (deviation from true solution) or local error (deviation of $\hat{\mathbf{y}}_k$ from $\mathbf{u}_{k-1}(t_k)$ where $\mathbf{u}_{k-1}(t_{k-1}) = \hat{\mathbf{y}}_{k-1}$ and $\mathbf{u}'_{k-1} = \mathbf{y}'$).
- ▶ Stability ascertains behavior as $t \rightarrow \infty$ either of the ODE itself or of a numerical method:
 - ▶ *For an ODE, stability identifies convergence/divergence of perturbed solutions.*
 - ▶ *For a numerical method, it identifies step-size bounds necessary to ensure the method converges along with the ODE.*
 - ▶ *If a method is stable, the local error provides a trustworthy metric of global error.*
 - ▶ *A **stiff** ODE is a convergent ODE with rapidly varying small components, which poses a challenge for stability of methods.*

Accuracy and Taylor Series Methods

- ▶ By taking a degree- r Taylor expansion of the ODE in t , at each consecutive $(t_k, \hat{\mathbf{y}}_k)$, we achieve k th order accuracy.

We can bound the local approximation error as the error the Taylor expansion,

$$\mathbf{y}(t_k + h) = \mathbf{y}(t_k) + \mathbf{y}'(t_k)h + \dots + \mathbf{y}^{(r)}(t_k)h^{r-1}/r!$$

which is $O(h^{r+1})$, which leads to $O(h^r)$ accuracy in the approximation to $f(t, \mathbf{y})$. Euler's method is a first-order Taylor series method.

- ▶ Taylor series methods require high-order derivatives at each step:
Analytic differentiation is expensive, so seek to approximate. Can perform a finite-differencing approximation by evaluating at points near $(t_k, \hat{\mathbf{y}}_k)$ (multi-stage methods) or simply using previous points, e.g. $(t_{k-1}, \hat{\mathbf{y}}_{k-1})$ (multi-step methods).

Multi-Stage Methods

- ▶ Multi-stage methods construct $\hat{\mathbf{y}}_{k+1}$ by approximating \mathbf{y} between t_k and t_{k+1} :
Runge-Kutta methods are the most well-known family of these, simple example is Heun's method,

$$\hat{\mathbf{y}}_{k+1} = \hat{\mathbf{y}}_k + h \left[\underbrace{\mathbf{f}(t_k, \mathbf{y}_k)}_{\mathbf{v}_1} / 2 + \mathbf{f} \left(t_k + h, \mathbf{y}_k + h \underbrace{\mathbf{f}(t_k, \mathbf{y}_k)}_{\mathbf{v}_1} \right) / 2 \right].$$

We can think of the above method as employing the trapezoid quadrature rule. The difference between Heun's method and the (implicit) trapezoid method is that we evaluate at $\mathbf{f}(t_k + h, \mathbf{y}_k + h\mathbf{v}_1)$ rather than working with the implicit value of $\mathbf{f}(t_k + h, \mathbf{y}_{k+1})$.

- ▶ The 4th order Runge-Kutta scheme is particularly popular:
This scheme uses Simpson's rule

$$\hat{\mathbf{y}}_{k+1} = \hat{\mathbf{y}}_k + (h/6)(\mathbf{v}_1 + 2\mathbf{v}_2 + 2\mathbf{v}_3 + \mathbf{v}_4)$$

$$\mathbf{v}_1 = \mathbf{f}(t_k, \mathbf{y}_k),$$

$$\mathbf{v}_2 = \mathbf{f}(t_k + h/2, \mathbf{y}_k + (h/2)\mathbf{v}_1),$$

$$\mathbf{v}_3 = \mathbf{f}(t_k + h/2, \mathbf{y}_k + (h/2)\mathbf{v}_2),$$

$$\mathbf{v}_4 = \mathbf{f}(t_k + h, \mathbf{y}_k + h\mathbf{v}_3)$$

Runge-Kutta Methods

- ▶ Runge-Kutta methods evaluate f at $t_k + c_i h$ for $c_0, \dots, c_r \in [0, 1]$,
A Runge-Kutta method can be derived as a quadrature rule

$$\mathbf{u}_k(t_{k+1}) = \hat{\mathbf{y}}_k + \int_{t_k}^{t_k+h} \mathbf{f}(s, \mathbf{y}(s)) ds \approx \hat{\mathbf{y}}_k + h \sum_{i=0}^{r-1} w_i \mathbf{f}(t_k + c_i h, \hat{\mathbf{y}}_{ki}),$$

where $\{(c_i, w_i)\}_{i=0}^r$ are quadrature node, weight pairs, but we still have flexibility in choosing $\hat{\mathbf{y}}_{ki}$. One good choice is to successively construct

$$\hat{\mathbf{y}}_{ki} = \hat{\mathbf{y}}_k + h \sum_j a_{ij} \mathbf{f}(t_k + c_j h, \hat{\mathbf{y}}_{kj}) = \hat{\mathbf{y}}_k + h c_i \mathbf{f}(t_k + c_i h, \hat{\mathbf{y}}_{k,i-1}).$$

More general choices for a_{ij} are often represented by a Butcher tableau,

$$\begin{array}{c|c} \mathbf{c} & \mathbf{A} \\ \hline & \mathbf{w}^T \end{array} \quad \text{e.g. for RK4,} \quad \begin{array}{c|cccc} 0 & & & & \\ 1/2 & 1/2 & & & \\ 1/2 & 0 & 1/2 & & \\ 1 & 0 & 0 & 1 & \\ \hline & 1/6 & 1/3 & 1/3 & 1/6 \end{array}$$

If $a_{ij} = 0$ for $j \geq i$, the scheme is explicit, if for $j > i$ then diagonally implicit, and otherwise implicit.

Properties of Runge-Kutta and Extrapolation Methods

- ▶ Runge-Kutta methods are self-starting, but are harder to use to obtain error estimates.

Self-starting means that we only need \hat{y}_k to form \hat{y}_{k+1} . Embedded Runge-Kutta schemes provides 4th + 5th order results, yielding an error estimate.

- ▶ Extrapolation methods achieve high accuracy by successively reducing step-size.

Use single-step method with step sizes $h, h/2, h/4, \dots$ to approximate solution at $t_k + h$.

Multistep Methods

- ▶ Multistep methods employ $\{\hat{\mathbf{y}}_k\}_{i=0}^k$ to compute $\hat{\mathbf{y}}_{k+1}$:

Linear multistep methods have the form,

$$\hat{\mathbf{y}}_{k+1} = \sum_{i=1}^m \alpha_i \hat{\mathbf{y}}_{k+1-i} + h \sum_{i=0}^m \beta_i \mathbf{f}(t_{k+1-i}, \mathbf{y}_{k+1-i}).$$

Interpolation is used to determine each α_i and β_i , method is explicit if $\beta_0 = 0$.

- ▶ Multistep methods are not self-starting

However, they require few function evaluations. Multistep methods generalize multistep methods to non-uniformly-spaced points.