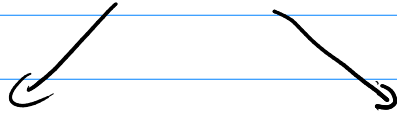


- ✓ linear systems
- ✓ non linear systems
- ✗ systems w/ derivatives



ODEs (d. in one direction)

PDEs (d. in multiple dir.) ⑪

IVP ⑨

BVP ⑩

Applications:

ODE/IVP

- population dynamics

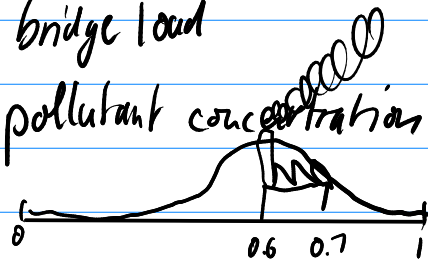
$$y_1 = -\alpha y_2 \leftarrow \text{prey}$$

$$y_2 = \beta y_1 \leftarrow \text{predator}$$

- chemical reactions
- equations of motion

BVP:

- bridge load
- pollutant concentration



- temperature



⑨ Initial Value Problems

$y: [0, T] \rightarrow \mathbb{R}^n$ desired solution

$$\left. \begin{aligned} f(t, y, y', y'', \dots, y^{(k)}) &= 0 \\ y^{(k)}(x) &= f(t, y, y', \dots, y^{(k-1)}) \end{aligned} \right\} \begin{array}{l} \text{(implicit)} \\ \text{(kth-order) ODE} \\ \text{(explicit)} \end{array}$$

↑ solvable as is?
○ consider simple example: $y' = \alpha y$
→ need initial values. how many?

$$\begin{aligned} y(0) &= g_0 \\ y'(0) &= g_1 \\ &\vdots \\ y^{(k-1)} &= g_{k-1} \end{aligned}$$

○ could swap some derivatives for conditions at other end:
 $y(T) = \tilde{g}_0$ } → BVP
...

ODE + initial values = IVP

Can always reduce to first order:

$$y''(t) = f(y) \rightarrow \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}'(t) = \begin{pmatrix} y_2(t) \\ f(y_1(t)) \end{pmatrix}$$

$$\rightarrow y_1''(t) = (y_1'(t))' = y_2'(t) = f(y_1(t))$$

Properties

autonomous : f does not depend on t

○ [can always make autonomous
using extra variable: $y_0'(t) = 1$ $y_0(0) = 0$
→ will omit explicit t dependency

linear : $f(x) = A(t)x + b$

lin + homogeneous : $f(x) = A(t)x$

constant - coefficient : $A(t) = A$

9.1 Existence, Uniqueness, Conditioning

Consider:

$$\otimes \begin{cases} y'(t) = f(y) \\ y(t_0) = y_0 \end{cases} \quad \hat{y}(t) = f(\hat{y}) \\ \hat{y}(t_0) = \hat{y}_0$$

Assume: f Lipschitz continuous ("bounded slope")

$$\|f(y) - f(\hat{y})\| \leq L \|y - \hat{y}\|$$

↑
Lipschitz constant

If so: ("Picard-Lindelöf theorem")

- there exists a solution of \otimes in a neighborhood of t_0
- $\|\hat{y}(t) - y(t)\| \leq e^{L(t-t_0)} \|\hat{y}_0 - y_0\|$

○ [What does this mean for uniqueness?]

Conditioning: (in ODE-speak: "stability")

↑ for us: "...of a method"
for them: used for both ODEs
and methods] 0

ODE stable iff solution continuously dependent on
on initial condition

in ϵ - δ speak:

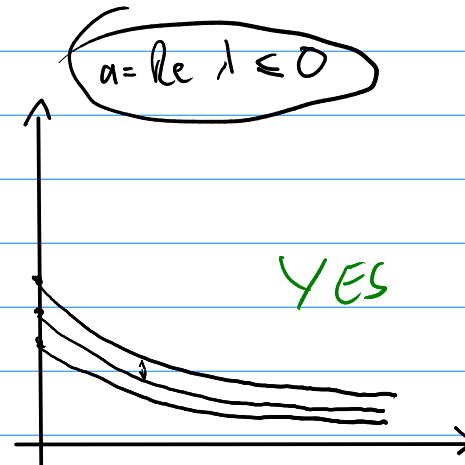
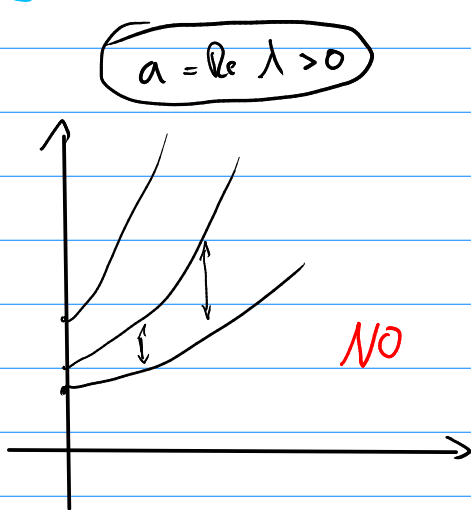
[For all $\epsilon > 0$ there exists a $\delta > 0$ such that
 $\|\hat{y}_0 - y_0\| \leq \delta \Rightarrow \|\hat{y}(t) - y(t)\| \leq \epsilon$ for all $t \geq t_0$.

ODE asymptotically stable iff $\|\hat{y}(t) - y(t)\| \rightarrow 0$ ($t \rightarrow \infty$)

Example I $y'(t) = \lambda y$ $\lambda = a + ib$
 $y(0) = y_0$

Solution: $y(t) = y_0 e^{\lambda t} = y_0 e^{at} e^{ib}$ $\rightarrow |y(t)| = |y_0 e^{at}|$

o [Stable?



Example II $\vec{y}'(t) = A \vec{y}(t)$
 $\vec{y}(0) = \vec{y}_0$

Assume A is diagonalizable $V^{-1}AV = \underbrace{\begin{pmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{pmatrix}}_D$

$\vec{w} = V^{-1} \vec{y}$

new IVP $\left\{ \begin{array}{l} \vec{w}'(t) = V^{-1} \vec{y}'(t) = V^{-1} A \vec{y}(t) = V^{-1} A V \vec{w}(t) \\ \quad = D \vec{w}(t) \\ \vec{w}_0 = V^{-1} \vec{y}_0 \end{array} \right.$

$\rightarrow \vec{y}(t) = V \vec{w}(t)$

o [Stable when?

WS 29 p 1

<lec32>

- exam on wed.
- finish WS29

9.2 Numerical Methods (pt. I)

Discrete times: t_1, t_2, \dots $t_{i+1} = t_i + h$ (for now)

Discrete function values: $y_k \approx y(t_k)$

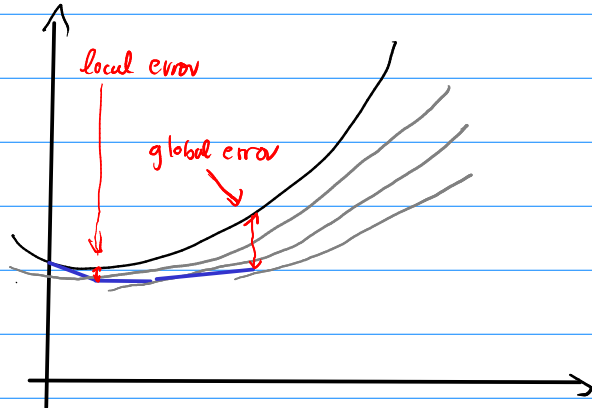
<u>IVP:</u> $y'(t) = f(y(t))$ $y(t_0) = y_0$	\leftrightarrow	<u>Integral equation:</u> $\otimes \quad y(t) = y_0 + \int_{t_0}^t f(y(\tau)) d\tau$
--	-------------------	---

Idea: Throw quadrature rule at \otimes . \circ [Which? (for solvability)]

$$y_{k+1} = y_k + h f(t_k, y_k) \quad (\text{Euler's method})$$

Demo

9.3 Accuracy and Stability



local error: $l_k = y_k - u_{k+1}(t_k)$ (where u_k solves the ODE with IV $u(t_0) = y_0$)

global error: $y(t_k) - y_k$

- o [Is global error = Σ (local errors)?
- o [Interest analogy.
- o [Local error much easier to estimate!

Time integrator of order $p \Rightarrow l_k = O(h^{p+1})$

↑
one higher than one might expect

Local error per length-1 step: $\frac{1}{h} \cdot O(h^{p+1})$

↑
 $O(h^p)$

(assuming limited "accumulation" of propagated error)

Stability of a method

Instability can be caused:

- by ODE
- by the method

○ [Will not really distinguish the two.]

in forward Euler, for $y'(t) = \lambda y(t)$:

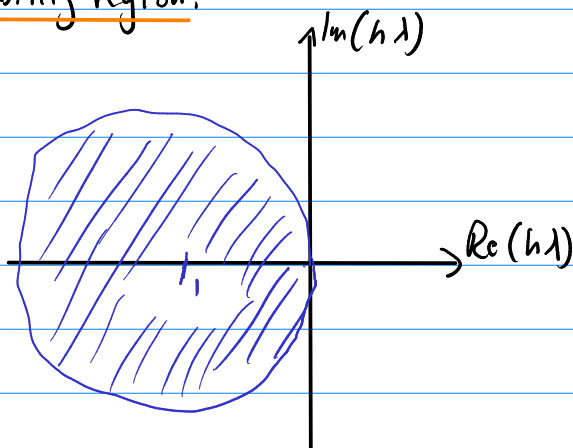
$$y_k = y_{k-1} + h \lambda y_{k-1} \\ = (1 + h\lambda) y_{k-1}$$

↑ growth factor

stable $\Leftrightarrow |1 + h\lambda| < 1$

$$y_k = (1 + h\lambda)^k y_0$$

"Stability region":



Stability in the nonlinear case

FW Euler: (A) $y_{k+1} = y_k + h f(y_k)$

Taylor: (B) $y(t_{k+1}) = y(t_k) + h f(y(t_k)) + O(h^2)$

$$(A) - (B) = e_{k+1} = \underbrace{(y_k - y(t_k))}_{e_k} + h \underbrace{(f(y_k) - f(y(t_k)))}_{l_k} + O(h^2)$$

↑ propagated error
 ↑ local error

$$\bar{J}_f := \int_0^1 J_f(\alpha y_k + (1-\alpha)y(t_k)) d\alpha$$

$$e_{k+1} = e_k (I + h \bar{J}_f) + l_k$$

Errors do not grow if $\rho(I + h \bar{J}_f) \leq 1$.

○ Difference from linear, scalar result?

Need intermediate result: a (not "the") mean value theorem

LEFT
OUT

Assume f differentiable:

$$\int_0^1 J_f(\alpha y + (1-\alpha)x) d\alpha (y-x)$$

$$= \int_0^1 \frac{\partial}{\partial x} (f(\odot)) d\alpha$$

$$= [f(\odot)]_0^1 = f(y) - f(x)$$

"Original" MVT:

$$\exists c: f(c) = \frac{f(b)-f(a)}{b-a}$$

(A Bug in book)

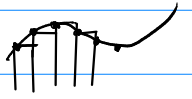
Then: $f(y_k) - f(y(t_k)) = \int_0^1 J_f(\alpha y_k + (1-\alpha)y(t_k)) d\alpha \cdot \underbrace{(y_k - y(t_k))}_{e_k}$

9.4 Numerical Methods (pt. II)

o [Obtained Euler method by throwing left rectangle rule of:

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

$$y_{k+1} = y_k + h f(y_k)$$



o [What if we had used right rectangle rule?

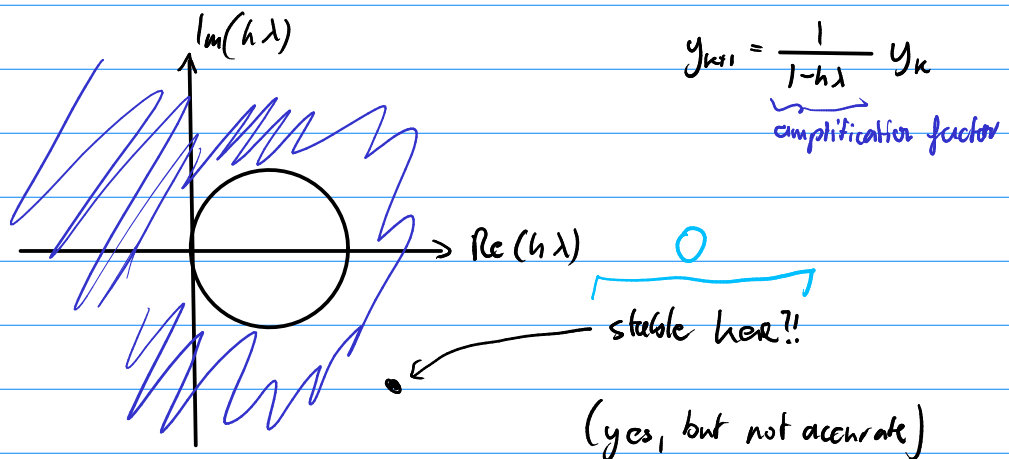
$$y_{k+1} = y_k + h f(y_{k+1})$$

Backward Euler method (earlier Euler method: Forward Euler by contrast)

→ need to solve equation → "implicit method"
(not implicit: "explicit method")

Example: $y'(t) = \lambda y(t)$

$$y_{k+1} = y_k + h \lambda y_{k+1} \quad \leadsto \quad (1 - h \lambda) y_{k+1} = y_k$$



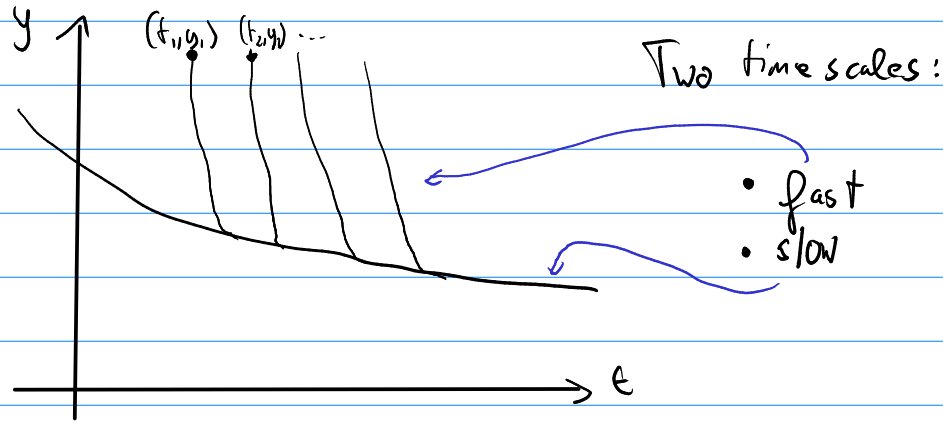
Generically (not just for implicit):

Two restrictions on time step:

- accuracy
- stability

9.5 Stiffness

Demo



$y'(t) = f(y(t))$ stiff if J_f has eigenvalues of very different magnitude

- [Why not just "small" or "large"?
- [What's the problem with applying explicit methods to stiff problems?
- [Express this \uparrow as conflict between stability and accuracy
- [Can an implicit method take arbitrarily large time steps?
Example: acoustic vs. flow

WS 30p1

9.6 Numerical Methods (pt. II)

Predictor-corrector methods

Idea: Obtain intermediate result, improve it (with same or different method). E.g.:

• predict with fw Euler $\tilde{y}_{n+1} = y_n + hf(y_n)$

• correct with trapezoidal $y_{n+1} = y_n + \frac{h}{2}(f(y_n) + f(\tilde{y}_{n+1}))$

↑ Heun's method (2nd order accurate)

More general than P-C: Methods that evaluate f multiple times per step:

- single-step
 - multi-stage
 - Runge-Kutta
- } methods

○ [Wikipedia Runge-Kutta :

- point out RK4
- equivalence to Simpson's rule (if no y dependency)

○ [point out "stages"

○ [implicit variants also exist

< 4/24 >

Systematic view of Runge-Kutta methods:

Butcher tableau

$$\begin{array}{l}
 \textcircled{1} \left\{ \begin{array}{l}
 r_1 = f(t_k + c_1 h, y_k + a_{11} \cdot r_1 + \dots + a_{1s} \cdot r_s) \\
 \vdots \\
 r_s = f(t_k + c_s h, y_k + a_{s1} \cdot r_1 + \dots + a_{ss} \cdot r_s)
 \end{array} \right.
 \end{array}
 \quad
 \begin{array}{c|ccc}
 c_1 & a_{11} & \dots & a_{1s} \\
 \vdots & \vdots & & \vdots \\
 c_s & a_{s1} & \dots & a_{ss} \\
 \hline
 & b_1 & \dots & b_s
 \end{array}$$

$\textcircled{2} \quad y_{k+1} = y_k + b_1 \cdot r_1 + \dots + b_s \cdot r_s$
(s = number of "stages")

o [When is this explicit? implicit? "diagonally implicit?"]

Embedded Runge-Kutta method

$$\begin{array}{c}
 y_{k+1} = \dots \\
 \tilde{y}_{k+1} = \dots
 \end{array}
 \quad
 \begin{array}{c|ccc}
 c_{\dots} & \dots & a_{\dots} & \dots \\
 \hline
 & b_1 & \dots & b_s \\
 & \bar{b}_1 & \dots & \bar{b}_s
 \end{array}$$

estimates of different order, to be used for error estimation/adaptation of h

Recap: Heun's method

Rk scheme:

$$\tilde{y}_{k+1} = y_k + h f(y_k)$$

$$r_1 = f(t_k, y_k)$$

$$r_2 = f(t_k + h, y_k + h r_1)$$

$$y_{k+1} = y_k + \frac{h}{2} (f(y_k) + f(\tilde{y}_{k+1}))$$

$$\begin{array}{c|cc}
 0 & & \\
 \hline
 1 & 1 & \\
 \hline
 & \frac{1}{2} & \frac{1}{2}
 \end{array}$$

o [Wikipedia]

Another Idea: Instead of computing stage values, use history

$$y_{k+1} = \sum_{i=1}^M \alpha_i y_{k+1-i} + h \sum_{i=1}^N \beta_i f(y_{k+1-i})$$

Known as:

- single-stage
 - multi-step
 - Adams-Bashforth (if $M=1$)
 - Backward Differencing Formulas (BDF) (if $N=1$)
-
- also exist in implicit variants
 - What if there is no history?

Demo: Stability regions

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