

Day 20 Numerical Analysis,

Last time: Started talking about ODEs. and Numerical Solns.

$$\text{given } \begin{aligned} y' &= f(x, y) \\ y(x_0) &= y_0 \end{aligned}$$

EULERS METHOD

$$y(x_0) = y_0$$

$$y(x_{n+1}) = y(x_n) + hf(x_n, y_n)$$

FROM THE HW $\longrightarrow$ what happened when you solved

$$\begin{aligned} y' &= \lambda y + (1-\lambda)\cos(x) - (1+\lambda)\sin(x) \\ y(0) &= 1 \end{aligned}$$

$\lambda = -1$ It worked $\lambda = 1$ Ill conditioned

$\lambda = -5$ It worked
but not for $h = .5$

$\lambda = 5$ Ill conditioned.

There are lots of cases where Euler is not stable.

Even when well conditioned,

CONVERGENCE vs. STABILITY.

$\downarrow$
as $h \rightarrow 0$ the
solns $y_n \rightarrow y(x)$

$\downarrow$
a small change
in $y_0 \rightarrow y_0 + \epsilon$
gives small change in final soln.

Often we can show convergence using our numerical code.

A numerical method with truncation error of order two or higher is convergent if and only if it is stable.

* Comes from LAX EQUIVALENCE THEOREM.

To illustrate this

Let's consider two Model Problems:

1.
$$\begin{aligned} y' &= \lambda y + g(x) \\ y(0) &= y_0 \end{aligned}$$

2.
$$\begin{aligned} y'_\epsilon &= \lambda y_\epsilon + g(x) \\ y_\epsilon(0) &= y_0 + \epsilon \end{aligned}$$

perturb the initial condition

Define
$$z_\epsilon(x) \equiv y_\epsilon(x) - y(x)$$

change in soln due to ϵ .

To get an ode for z_ϵ we subtract $y'_\epsilon - y'_0$:

$$\left. \begin{array}{l} z'_\epsilon = \lambda z_\epsilon \\ z_\epsilon(0) = \epsilon \end{array} \right\} \text{Solving This} \longrightarrow z_\epsilon = \epsilon e^{\lambda x}$$

Use this idea $\nearrow$

Typically for real world problems $\lambda < 0$ or $\text{Re}\{\lambda\} < 0$

$\lambda < 0$ means that the small change ϵ does not effect our soln. our method would be stable.

THE TEST

1. Solve the model problem $y' = \lambda y$ using the numerical method by hand.
 $y(0) = 1$
2. See what solns do and require that $y_h(x_n) \rightarrow 0$ as $x_n \rightarrow \infty$
3. This should give a set of values $h\lambda$ for which the method converges and is stable.

If $y_h(x_n) \rightarrow 0$ as $x_n \rightarrow \infty$ for any choice of h then we have ABSOLUTE STABILITY.

EX. Eulers Method

1 For The Model Problem:

$$y(n+1) = y_n + h\lambda y_n = (1+h\lambda)y_n$$

$$\text{so } y(0) = 1$$

$$y(1) = (1+h\lambda)1 = (1+h\lambda)$$

$$y(2) = (1+h\lambda)(1+h\lambda) = (1+h\lambda)^2$$

$\vdots$

$$y(n) = (1+h\lambda)^n$$

2. Require $y_h(n) \rightarrow 0$ as $n \rightarrow \infty$: $|1+h\lambda| < 1$

and for λ real and negative: $1 > 1+h\lambda > -1$

or

$$0 > h\lambda > -2$$

$$0 < h < \frac{-2}{\lambda}$$

If λ is large then h must be small !!

From the homework: $y' = \lambda y + (1-\lambda)\cos(x) - (1+\lambda)\sin(x)$
 $y(0) = 1$

when $\lambda = -5$ we need $0 < h < \frac{-2}{-5} = .4$

so $h = .5$ should not work!

Euler Method — simple and easy to program BUT
 we have strict restrictions on our step
 size to be sure that well conditioned
 problems converge.

Let's Talk about some improvements to This...

BACKWARD EULER METHOD:

$y' = f(x, y)$ $\longrightarrow$ Replace y' with a
 $y(x_0) = y_0$ backward derivative.
 Assume solns exist & are unique
 and problem is well conditioned.

$$y' \approx \frac{y(x) - y(x-h)}{h}$$

$$\frac{y(x) - y(x-h)}{h} = f(x, y) \quad \text{or} \quad \frac{y(x_n) - y(x_{n-1})}{h} = f(x_n, y_n)$$

so we could solve for $y(x_{n-1})$ and literally
 march backward in time... but usually we
 move time forward so

$$y(x_n) = y(x_{n-1}) + hf(x_n, y_n) \quad \text{OR...}$$

Given some starting value $y(x_0) = y_0$

$$\boxed{y(x_{n+1}) = y(x_n) + hf(x_{n+1}, y_{n+1})}$$

Use the model
problem to check
convergence

$$y' = \lambda y$$

$$y(0) = 1$$

$$y_{n+1} = y_n + h\lambda y_{n+1}$$

$$\text{solve for } y_{n+1} \dots y_{n+1} = (1 - h\lambda)^{-1} y_n$$

$$\text{then } y_1 = (1 - h\lambda)^{-1} y_0 = (1 - h\lambda)^{-1}$$

$$y_2 = (1 - h\lambda)^{-1} (1 - h\lambda)^{-1} = (1 - h\lambda)^{-2}$$

$$\vdots$$

$$y_n = (1 - h\lambda)^{-n}$$

when $\lambda < 0$, as $n \rightarrow \infty$ $y_n \rightarrow 0$ regardless of our choice of h
well conditioned

ABSOLUTELY STABLE

for any choice of h !

Why did we ever bother with EULER?

How would a computer solve $y' = \lambda y$
 $y(0) = 1$?

$h = .1$ we can pick this
as big or small as we want.
small $\rightarrow$ smooth soln curve.

$$y(1) = 1$$

then loop

$$y(2) = y(1) + .1 \lambda y(2); \text{ what is the problem?}$$

$\uparrow$
error we need to know
our soln at $y(2)$ to
get our soln at $y(2)$!!

IMPLICIT METHOD

Finding y_{n+1} is a
root finding problem.

At every x_n value... A few ways to
deal with this!

A. For simple enough ODE's we can solve by hand:

Ex $y' = \lambda y + (1-\lambda)\cos(x) - (1+\lambda)\sin(x)$

Backward Euler:

$$y_{n+1} = y_n + h[\lambda y_{n+1} + (1-\lambda)\cos(x_{n+1}) - (1+\lambda)\sin(x_{n+1})]$$

solve for $y_{n+1} \dots$

$$(1-h\lambda)y_{n+1} = y_n + h[(1-\lambda)\cos(x_{n+1}) - (1+\lambda)\sin(x_{n+1})]$$

$$\text{and } y_{n+1} = \frac{y_n + h[(1-\lambda)\cos(x_{n+1}) - (1+\lambda)\sin(x_{n+1})]}{(1-h\lambda)}$$

★ use this in your homework!

B. Use a Rootfinding method at every step

BRUTE
FORCE

for $i=1:N$

err = 1

while err > errtol

solve $y_{n+1} = y_n + hf(x_n, y_n)$

BISECTION

NEWTONS

end

end

Time Consuming.

Problem... if $N=100$ then
we are doing 100 rootfinding
problems!

C. USUALLY - take one step with forward euler
then use backward euler to iterate

for $i=1:N$

err = 1

$y_{old} = y(i) + hf(x_i, y(i))$ Euler

while err > errtol

$y_{new} = y(i) + hf(x_{i+1}, y_{old})$ Backward Euler

err = abs($y_{new} - y_{old}$)

$y_{old} = y_{new}$

end

$y(i+1) = y_{old}$

end.

Problem... now our method is no longer absolutely stable because of that first euler step.

consider the method: $y_{n+1} = y_n + h f(x_{n+1}, y_{n+1})$

vs.

the iteration: $y_{n+1}^{J+1} = y_n + h f(x_n, y_n^J)$

then error = $y_{n+1} - y_{n+1}^{J+1} = (y_n - y_n) + h [f(x_{n+1}, y_{n+1}) - f(x_n, y_n^J)]$

from iterating rather than using method
At $J+1^{\text{th}}$ iteration

$$= h [f(x_{n+1}, y_{n+1}) - f(x_n, y_n^J)]$$

$$= h \frac{\partial f}{\partial y}(\xi, \xi) [y_{n+1} - y_n^J] \approx h \frac{\partial f}{\partial y} \Big|_{x_{n+1}, y_{n+1}} [y_{n+1} - y_n^J]$$

Mean Value Thm $\uparrow$

$$x_n < \xi < x_{n+1} \quad y_n < \xi < y_{n+1}$$

For error in successive terms to decrease.

In our iteration.

$$\left| h \frac{\partial f}{\partial y} \Big|_{x_{n+1}, y_{n+1}} \right| < 1$$

as long as h is small enough our iterations will converge.

* still restricted somewhat by h !!