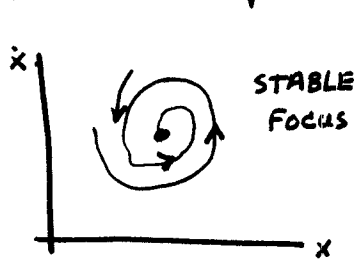


Review of ODE behavior in State Space.

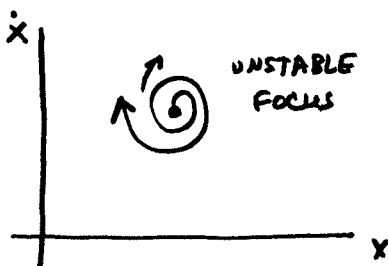
Sources

[Dic 91]
[EK88]

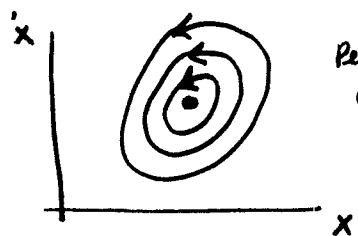
(2-d examples)



STABLE FOCUS



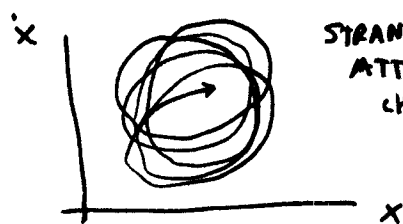
UNSTABLE FOCUS



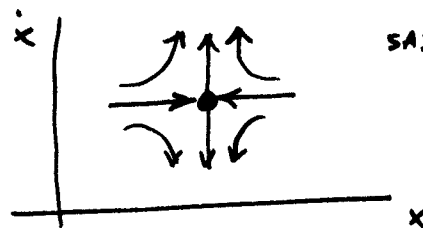
PERIODIC ORBITS, NEUTRAL CENTER



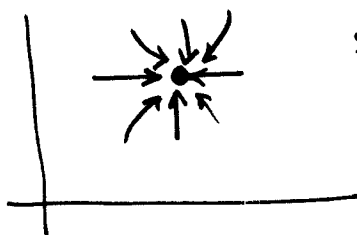
LIMIT CYCLE



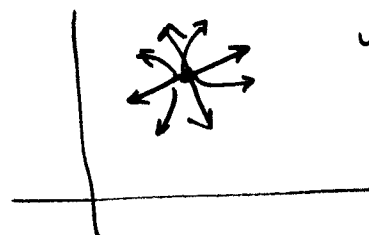
STRANGE ATTRACTOR, CHAOS



SADDLE POINT

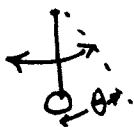


STABLE NODE

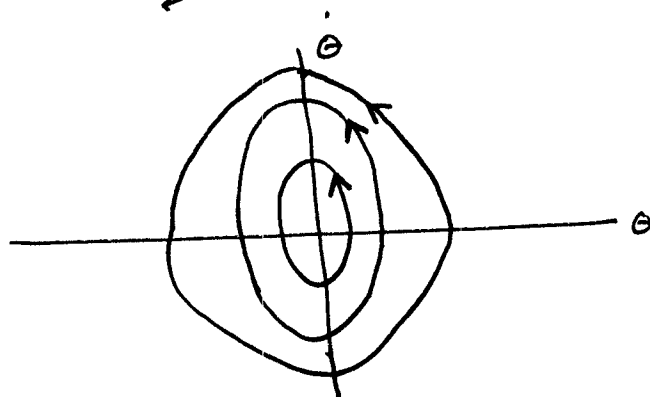


UNSTABLE NODE

PENDULUM:



$$\frac{d^2\theta}{dt^2} + g \sin \theta = 0$$



and then...?

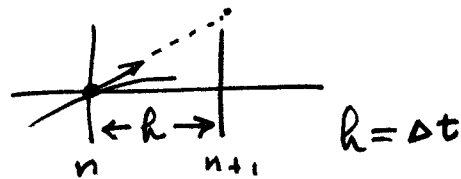
Why is Runge-Kutta better?

Let's analyze Euler & 2nd Order R-K.

Euler $\dot{x} = f(x)$ (x is in general a vector)

$$\hat{x}_{n+1} = x_n + h \dot{x}_n \leftarrow f(x_n)$$

true $x_{n+1} = x_n + h \dot{x}_n + O(h^2)$



Taylor's series

Local truncation Error

$$= x_{n+1} - \hat{x}_{n+1} = O(h^2)$$

2nd-Order R-K

$$\hat{x}_{n+1} = x_n + h \cdot f(\hat{x}_{n+1/2})$$

$$= x_n + h \cdot \left[f(x_{n+1/2}) + O(h^2) \right]$$

$$= x_n + h \cdot \left[f(x_n) + \frac{h}{2} \dot{f}(x_n) + O(h^2) \right] \quad \text{Taylor's series}$$

$$= x_n + h f(x_n) + \frac{h^2}{2} \dot{f}(x_n) + O(h^3)$$

true $x_{n+1} = x_n + h f(x_n) + \frac{h^2}{2} \dot{f}(x_n) + O(h^3)$ Taylor's series

$$x_{n+1} - \hat{x}_{n+1} = O(h^3)$$

Local truncation Error

(4th-order R-K is $O(h^5)$)

This is the local truncation error —
at one step. Error accumulates from step
to step.

In general, if equation is "well behaved"
(smooth derivatives, etc.), then

$$\begin{aligned} \text{total error} &\sim \# \text{ steps} \cdot (\text{local error}) \\ &\sim \frac{1}{h} \cdot (\text{local error}) \end{aligned}$$

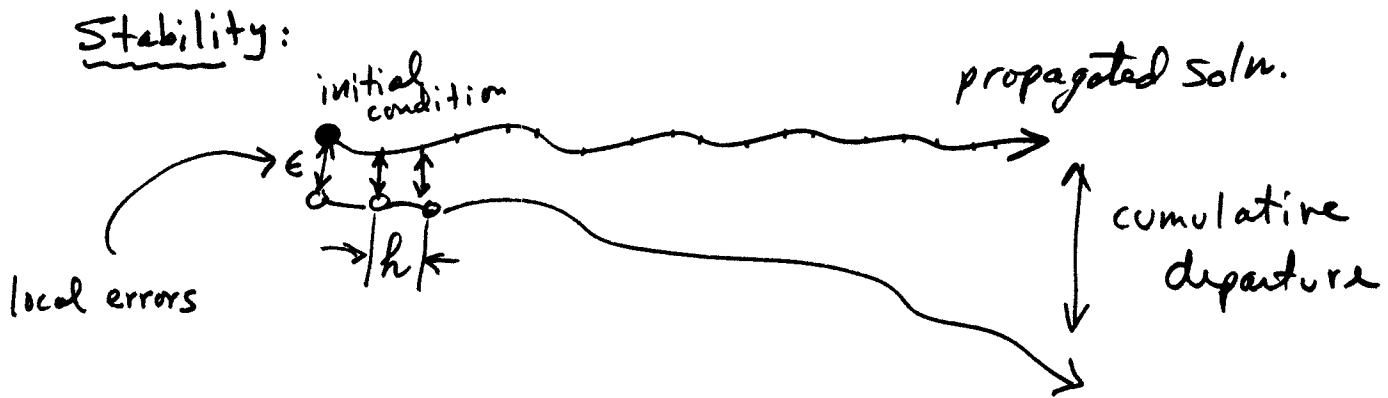
$$\therefore \frac{\text{total error}}{\text{for Euler's method}} \sim O(h)$$

$$\frac{\text{total error}}{\text{for } 4^{\text{th}} \text{ order}} \sim O(h^4)$$

$R-k$

See [Atk 93, p. 331]

Stability and Convergence



Said to be pointwise stable if cumulative departure

$\rightarrow 0$ as $|\epsilon's| \rightarrow 0$

& increases no faster than $O(1/h^k)$ as $h \rightarrow 0$
(not exponential)

Convergence: If soln. of discrete problem
 \rightarrow soln. of continuous problem
 as $h \rightarrow 0$ (no errors)

For ODE's, in general, Stability \Leftrightarrow Convergence

Not always so for PDE's.

We require an additional condition -

"Consistency"

Consistent if

4.1.5

Local truncation error $\rightarrow 0$ as grid size $(h) \rightarrow 0$

[not always true for PDE's!]

LAX'S EQUIVALENCE THEOREM

Given an initial boundary value problem &
a finite-difference approximation that
is consistent, then

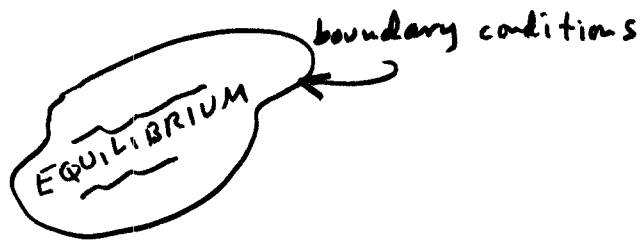
Stability \Leftrightarrow convergence

[AMES 92]
[SMITH 85]

Partial Differential Equations

Fall into three "physical" classes

Elliptic



STEADY-STATE TEMPERATURE
ELECTROSTATIC POTENTIAL
GRAVITATIONAL POTENTIAL

EXAMPLES

LAPLACE'S EQUATION

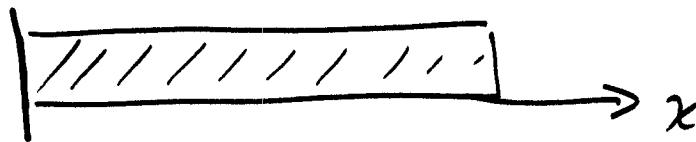
$$\frac{\partial^2 \phi}{\partial x^2} + \frac{\partial^2 \phi}{\partial y^2} = 0 \quad (\nabla^2 \phi = 0)$$

POISSON'S EQUATION

$$\frac{\partial^2 \phi}{\partial x^2} + \frac{\partial^2 \phi}{\partial y^2} + g = 0 \quad (\nabla^2 \phi = -g)$$

PARABOLIC (t is one of the independent variables)

Simplest example: heat conduction along bar



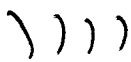
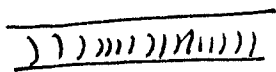
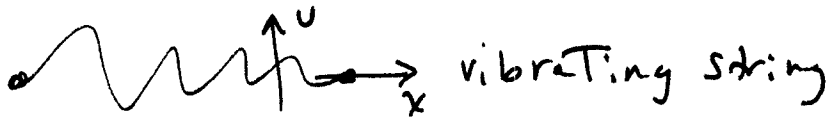
Given initial Temperature distribution, find temperature at later times.

$$\frac{\partial u}{\partial t} = k \frac{\partial^2 u}{\partial x^2}$$

Hyperbolic Equations (also involve time) 4.1.7

typically, vibration, propagation of shockwaves

simplest is $\boxed{\frac{\partial^2 u}{\partial t^2} = c^2 \frac{\partial^2 u}{\partial x^2}}$ wave eqn.



vibrating string

vibrating air in pipe

electromagnetic waves

Classification really a physical classification based on "characteristics" (see [Ames 93], eq.)

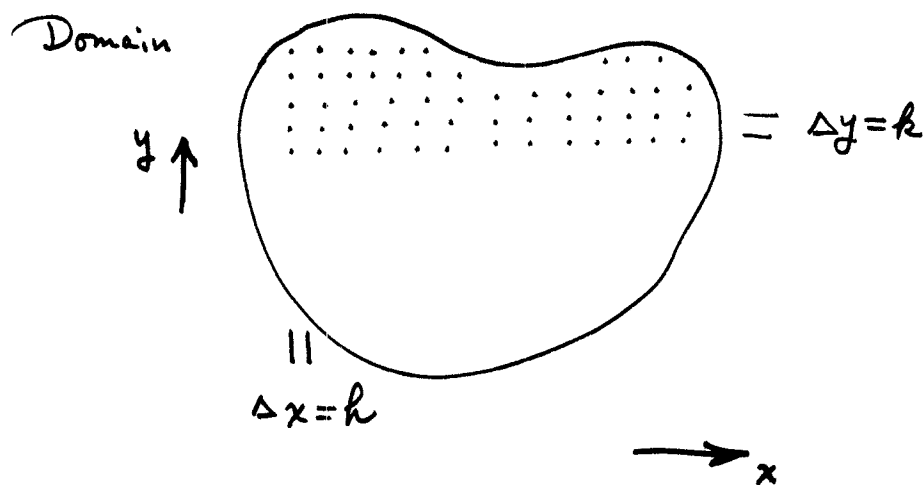
for 2nd Order Equations:

$$a \frac{\partial^2 \phi}{\partial x^2} + b \frac{\partial^2 \phi}{\partial x \partial y} + c \frac{\partial^2 \phi}{\partial y^2} + d \frac{\partial \phi}{\partial x} + e \frac{\partial \phi}{\partial y} + f \phi + g = 0$$

$$b^2 - 4ac < 0 \Rightarrow \text{Elliptic}$$

$$b^2 - 4ac = 0 \Rightarrow \text{parabolic}$$

$$b^2 - 4ac > 0 \Rightarrow \text{hyperbolic}$$



Notation Solution $u(x, y)$ (continuous)

$u_{ij} = u(ih, jk)$ (discrete approximation)

As always, start with Taylor Series (here in x)

$$u(x+\Delta x, y) = u(x, y) + \Delta x \frac{\partial u(x, y)}{\partial x} + \frac{(\Delta x)^2}{2!} \frac{\partial^2 u(x, y)}{\partial x^2} + \frac{(\Delta x)^3}{3!} \frac{\partial^3 u(x, y)}{\partial x^3} + O[(\Delta x)^4]$$

Divide by Δx

$$\frac{\partial u(x, y)}{\partial x} = \frac{u(x+\Delta x, y) - u(x, y)}{\Delta x} + O(\Delta x)$$

OR

$$\frac{\partial u}{\partial x} \Big|_{ij} = \frac{u_{i+1, j} - u_{i, j}}{h} + O(h)$$

forward
difference

Taylor Series for $x - \Delta x$:

$$u(x - \Delta x, y) = u(x, y) - \frac{\partial u}{\partial x} \Delta x + \frac{1}{2!} \frac{\partial^2 u}{\partial x^2} (\Delta x)^2 - \frac{1}{3!} \frac{\partial^3 u}{\partial x^3} (\Delta x)^3 + O[(\Delta x)^4]$$

Divide by Δx as before

$$\boxed{\frac{\partial u}{\partial x} \Big|_{i,j} = \frac{u_{i,j} - u_{i-1,j}}{h} + O(h)}$$

backward difference

Or, subtract the two Taylor Series above:

$$u(x + \Delta x, y) - u(x - \Delta x, y) = 2\Delta x \frac{\partial u}{\partial x} + 2 \frac{(\Delta x)^3}{3!} \frac{\partial^3 u}{\partial x^3} + O[(\Delta x)^5]$$

even powers cancel

Divide by $(2\Delta x)$

$$\boxed{\frac{\partial u}{\partial x} \Big|_{i,j} = \frac{u_{i+1,j} - u_{i-1,j}}{2h} + O(h^2)}$$

Second-order approximation to $\partial u / \partial x$

or, add the two Taylor Series:

$$\boxed{\frac{\partial^2 u}{\partial x^2} \Big|_{i,j} = \frac{u_{i+1,j} - 2u_{i,j} + u_{i-1,j}}{h^2} + O(h^2)}$$

approximation to $\partial^2 u / \partial x^2$

Etc.

"Molecules"

4.1.10

$$\frac{\partial u}{\partial x} \Big|_{i,j} = \frac{1}{h} \left\{ \begin{array}{c} (-1) \text{---} (1) \\ i-1,j \quad i,j \end{array} \right\} + O(h) \quad \text{backward diff.}$$

$$= \frac{1}{h} \left\{ \begin{array}{c} (-1) \text{---} (1) \\ i,j \quad i+1,j \end{array} \right\} + O(h) \quad \text{forward diff.}$$

$$= \frac{1}{2h} \left\{ \begin{array}{c} (-1) \text{---} (0) \text{---} (1) \\ i-1,j \quad i,j \quad i+1,j \end{array} \right\} + O(h^2)$$

$$\frac{\partial u}{\partial y} \Big|_{i,j} = \frac{1}{2k} \left\{ \begin{array}{c} (1) \text{---} (0) \text{---} (-1) \\ i,j+1 \\ i,j \\ i,j-1 \end{array} \right\} + O(k^2)$$

$$\frac{\partial^2 u}{\partial x^2} \Big|_{i,j} = \frac{1}{h^2} \left\{ \begin{array}{c} (1) \text{---} (-2) \text{---} (1) \\ i-1,j \quad i,j \quad i+1,j \end{array} \right\} + O(h^2)$$

$$\frac{\partial^2 u}{\partial x \partial y} \Big|_{i,j} = \frac{1}{4h^2} \left\{ \begin{array}{ccc} (-1) & (0) & (1) \\ (0) & (0) & (0) \\ (1) & (0) & (-1) \end{array} \right\} + O(h^2) \quad (h=k)$$

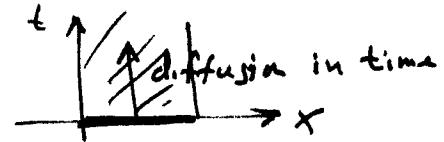
$$\nabla^2 u = \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} = \frac{1}{h^2} \left\{ \begin{array}{c} (1) \\ (1) \text{---} (-4) \text{---} (1) \\ (1) \end{array} \right\} + O(h^2)$$

these can be used to generate algorithms for obtaining approximate solutions, in analogy with Euler's Method or Runge-Kutta for ODE'S.

EXAMPLE: diffusion equation

forward difference $\frac{\partial u}{\partial t} = \frac{\partial^2 u}{\partial x^2}$

(normalized so const. = 1)



$$\frac{1}{k} [u_{i,j+1} - u_{i,j}] + O(k) = \frac{1}{h^2} [u_{i-1,j} - 2u_{i,j} + u_{i+1,j}] + O(h^2)$$

multiply by k & rearrange

$$u_{i,j+1} = r u_{i-1,j} + (1-2r) u_{i,j} + r u_{i+1,j} + O(k^2 + kh^2)$$

where $r = \frac{k}{h^2}$

this is an explicit marching algorithm

