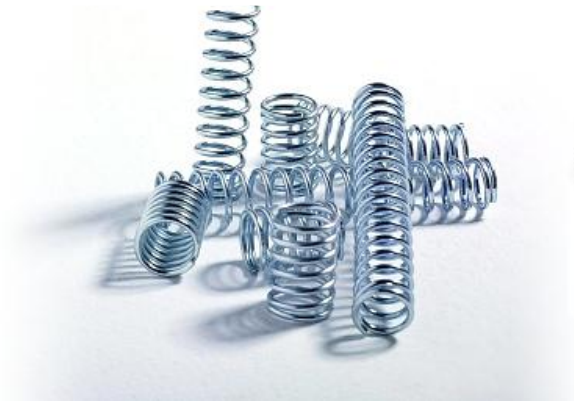


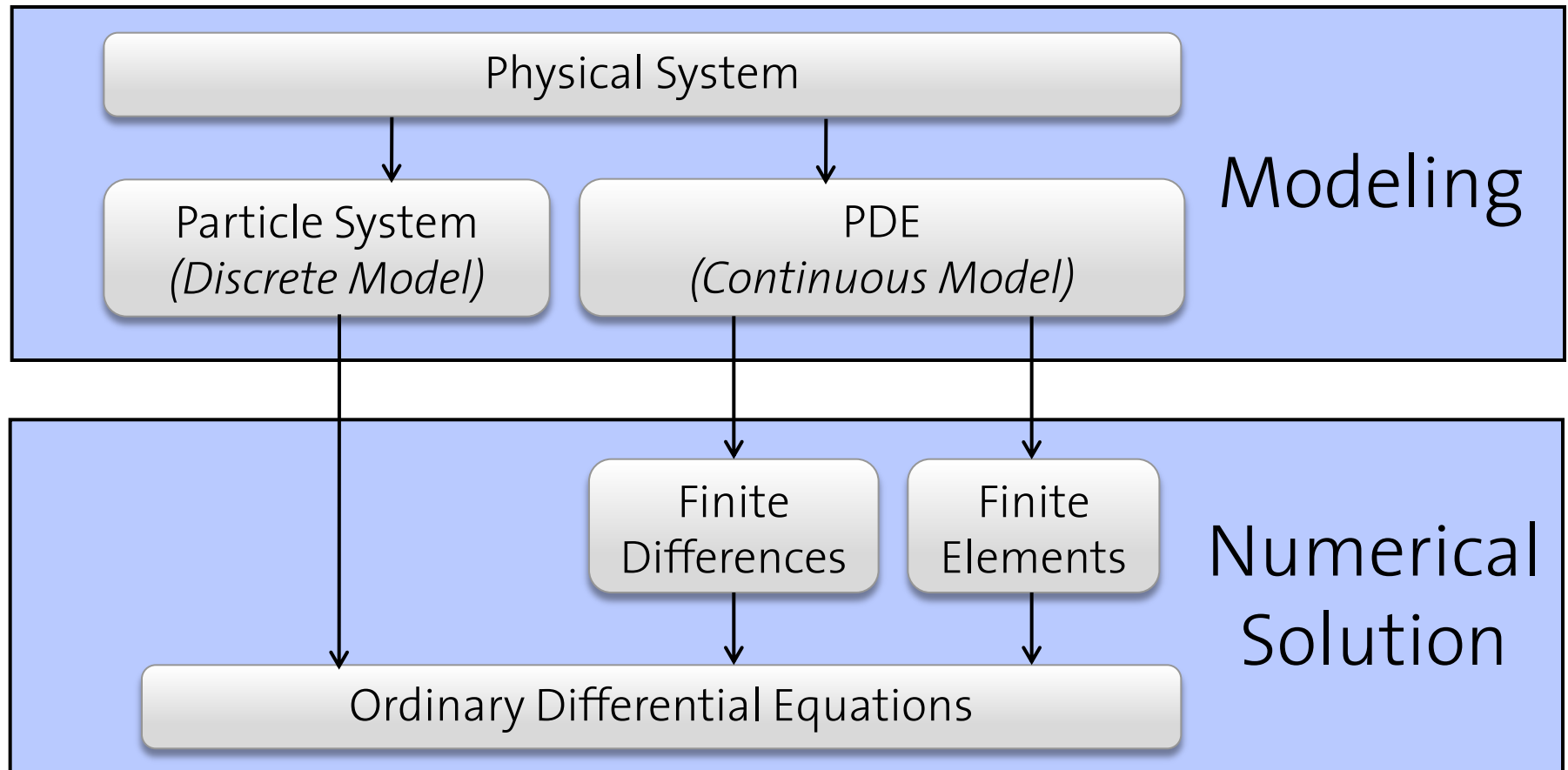
Mass-Spring Systems

A Basic Tool for Modeling
Deformable Objects

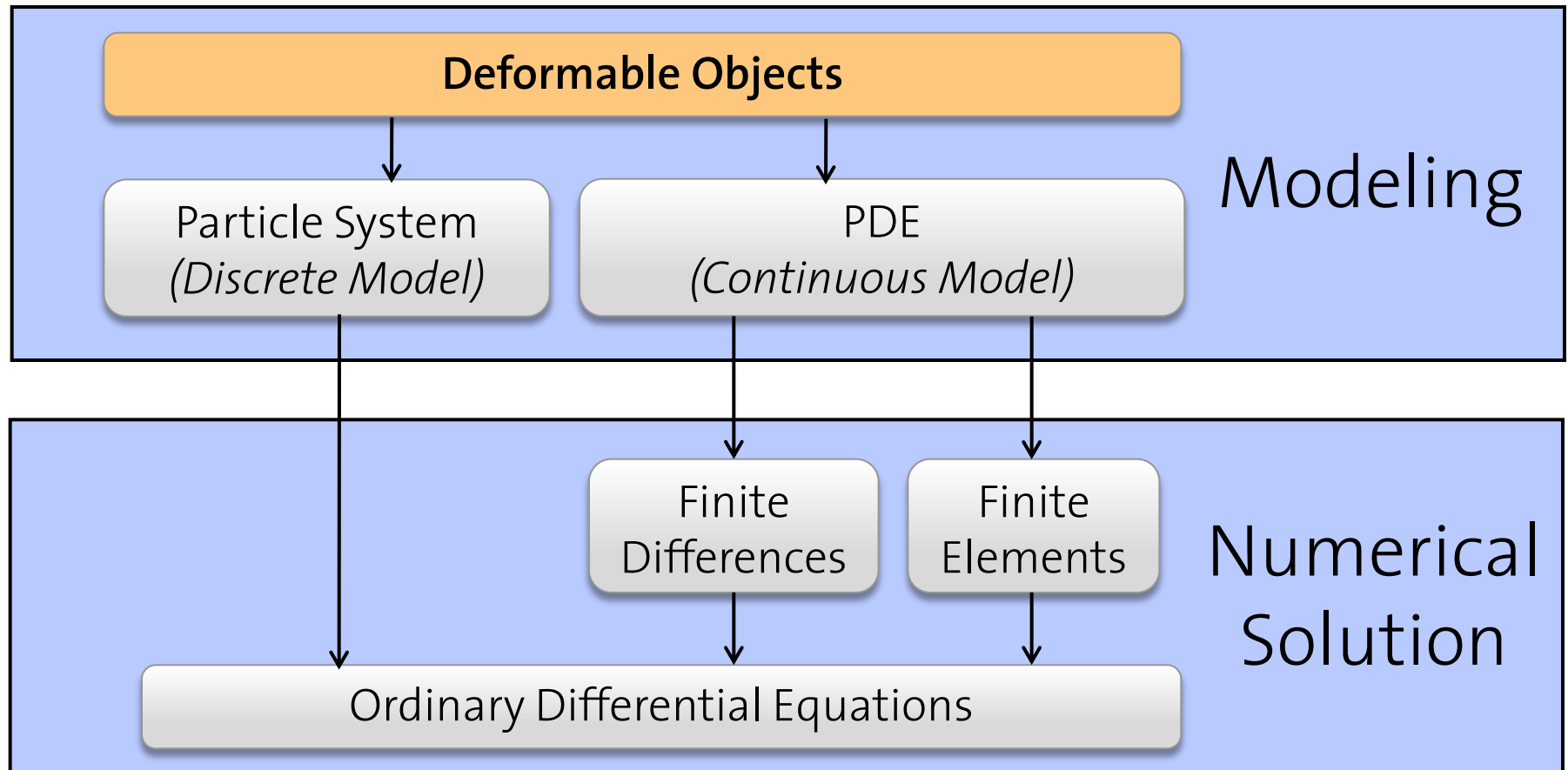
Part 1



Physical Simulation: How to... ?

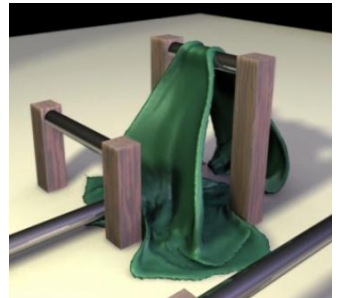
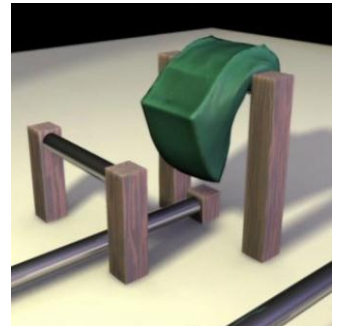
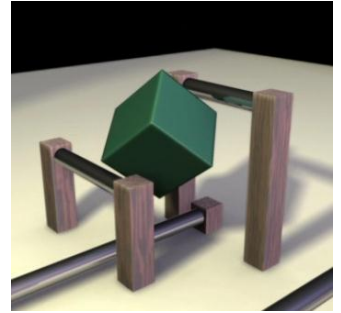


Physical Simulation: How to... ?

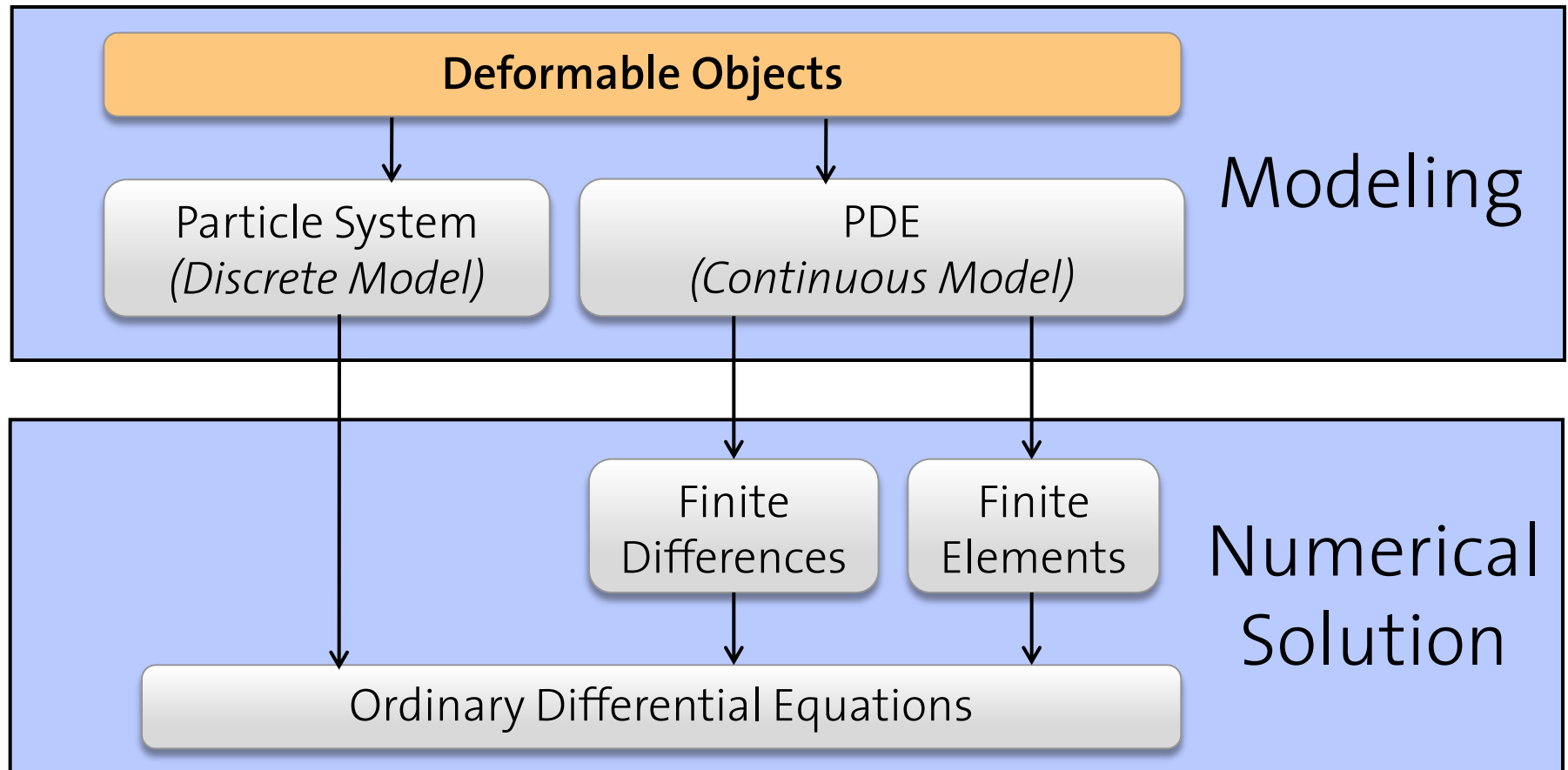


Deformable Objects

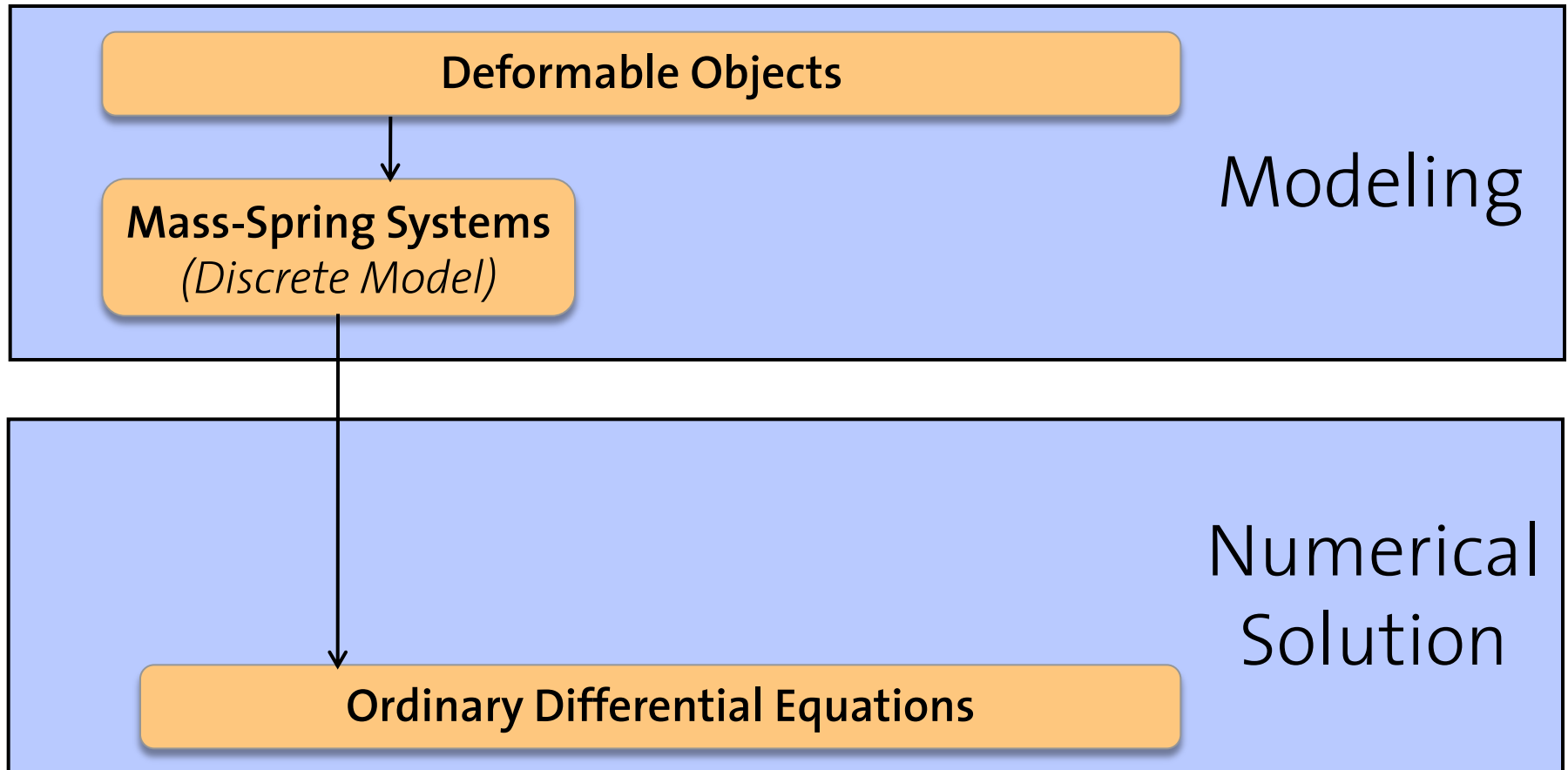
- Deformable objects
 - deformed under applied forces
 - resist deformation
- Common material properties
 - **Elastic:** deformations are reversible
 - **Viscous:** amplitude of oscillations is reduced
 - **Plastic:** irreversible deformations
 - Any combination thereof



Physical Simulation: How to... ?

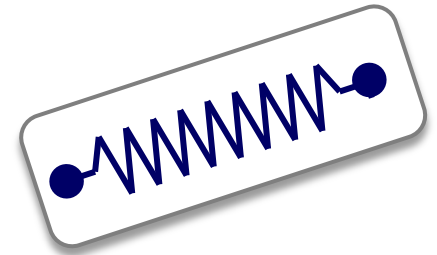


Physical Simulation: How to... ?



Outline

Mass-Spring Systems

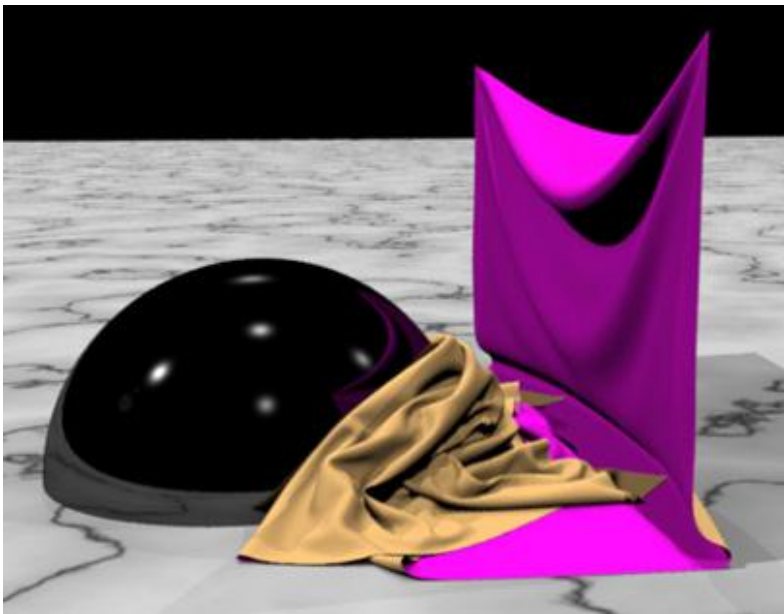


Steps towards simulation

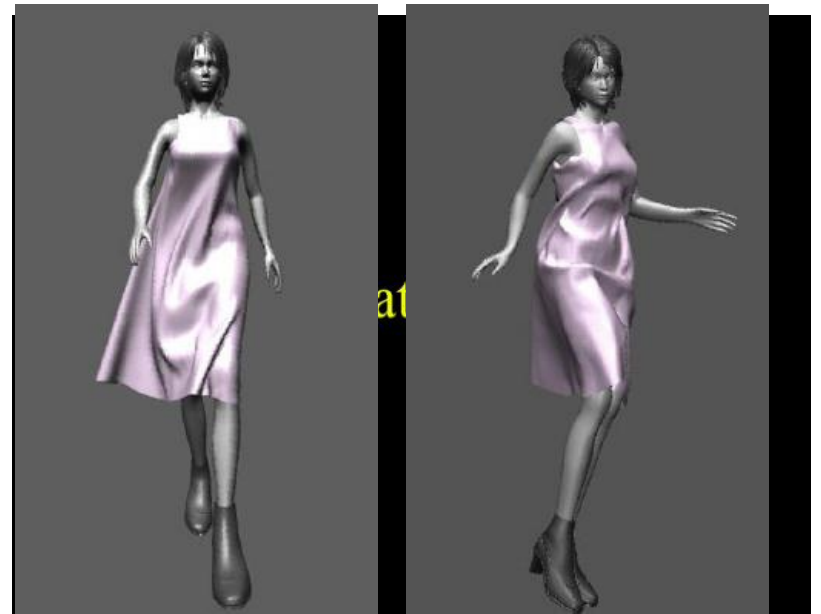
1. **Spatial discretization:** sample object with mass points
2. **Forces:** define internal (*springs!*) and external forces
3. **Dynamics:** set up equations of motion
4. **Temporal discretization:** solve equations of motion

Applications

Cloth Simulation



Bridson et al., 2002



Choi & Ko, 2002

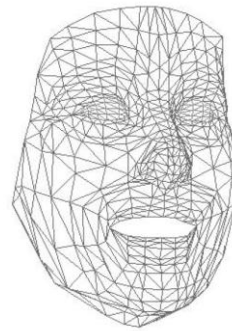
Applications

Hair animation



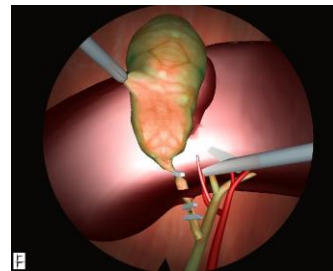
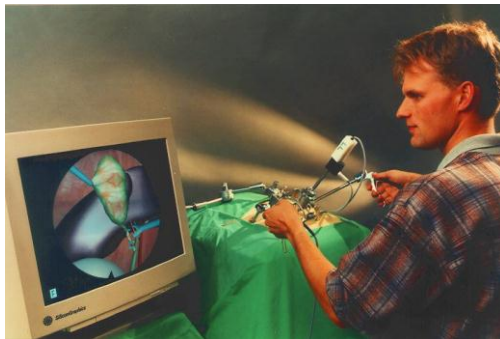
Selle et al., 2008

Facial animation



Lee et al., 1995

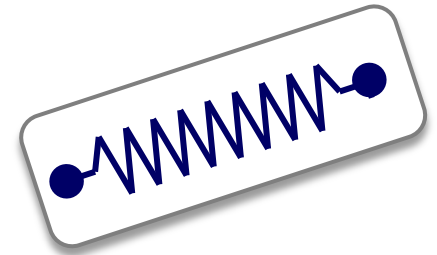
Medical simulation



Kuehnepfel et al., 1993

Outline

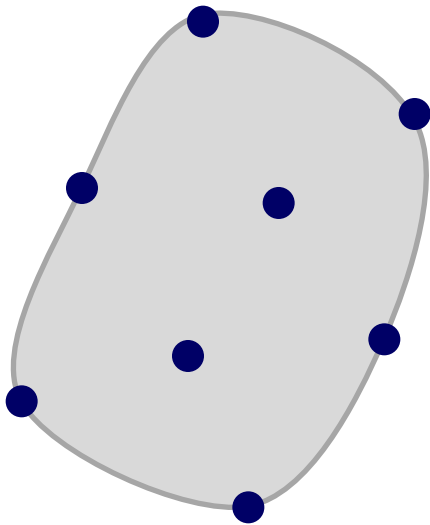
Mass-Spring Systems



Steps towards simulation

1. **Spatial discretization:** sample object with mass points
2. **Forces:** define internal (*springs!*) and external forces
3. **Dynamics:** set up equations of motion
4. **Temporal discretization:** solve equations of motion

Spatial Discretization



Sample object with mass points

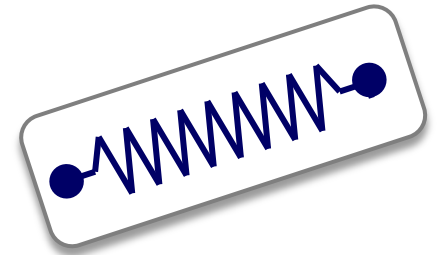
- Total mass of object: M
- Number of mass points: n
- Mass of each point: $m = M/n$
(*uniform distribution*)

Each point holds properties

- Mass m_i
- Position $\mathbf{x}_i(t)$
- Velocity $\mathbf{v}_i(t)$

Outline

Mass-Spring Systems

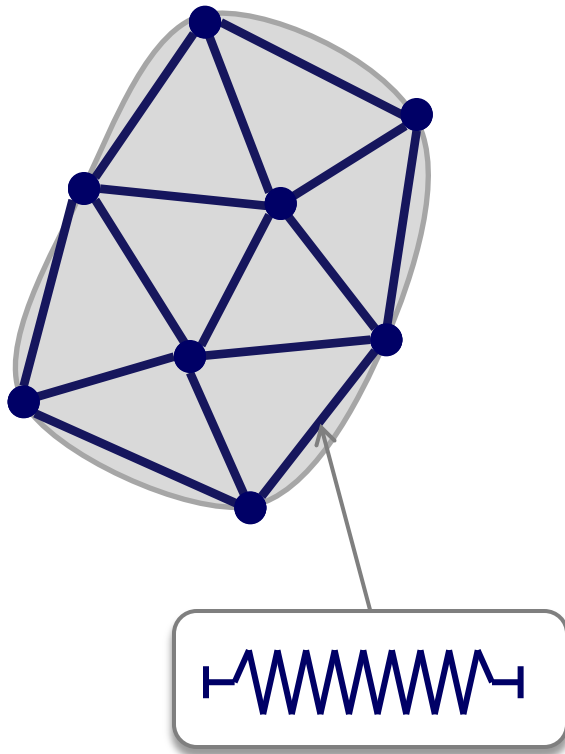


Steps towards simulation

1. **Spatial discretization:** sample object with mass points
2. **Forces:** define internal (*springs!*) and external forces
3. **Dynamics:** set up equations of motion
4. **Temporal discretization:** solve equations of motion

Forces

What are the forces that act on particle i ?



External forces

- Gravity $\mathbf{F}_i^g = m_i \begin{pmatrix} 0 \\ 0 \\ 9.81 \end{pmatrix} \frac{m}{s^2}$

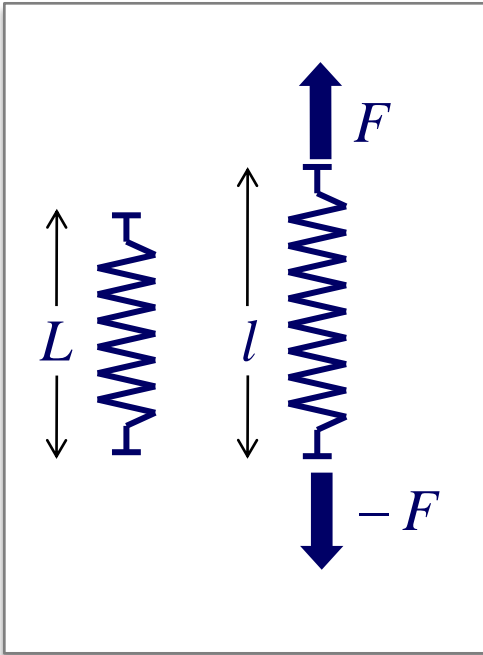
Internal forces

- Elastic spring forces
- Viscous damping forces

Total force $\mathbf{F}_i = \mathbf{F}_i^{\text{int}} + \mathbf{F}_i^{\text{ext}}$

Note: forces are 3D, $\mathbf{F}_i \in \mathbf{R}^3$

Internal Forces: Elastic Springs



Initial spring length L
Current spring length l
Spring stiffness k

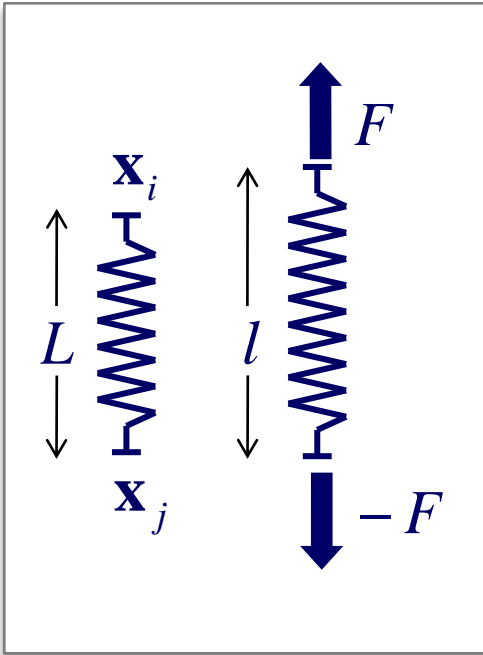
Elasticity: *Ability of a spring to return to its initial length when the deforming force is removed.*

Spring Force:

- *Ceiiinossttuv.* (Hooke, 1676)
- *Ut tensio, sic vis.* (Hooke, 1678)
→ *Force is linear w.r.t. extension!*

$$F = -k(l - L) \quad \text{Hooke's Law}$$

Internal Forces: Elastic Springs



Force in 1D

$$F = -k(l - L)$$

Force in 3D

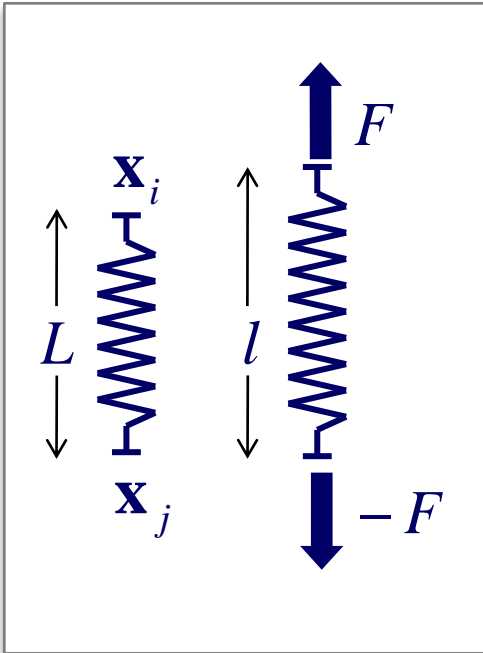
$$\mathbf{F}_i = -k\left(\|\mathbf{x}_i - \mathbf{x}_j\| - L\right) \frac{\mathbf{x}_i - \mathbf{x}_j}{\|\mathbf{x}_i - \mathbf{x}_j\|}$$

Initial spring length L

Current spring length l

Spring stiffness k

Elastic Energy



For purely elastic springs (*materials*)

- Force depends only on position
- No energy lost during deformation

Work done by forces

$$W = \int_L^l k(x - L) dx$$

Elastic spring energy

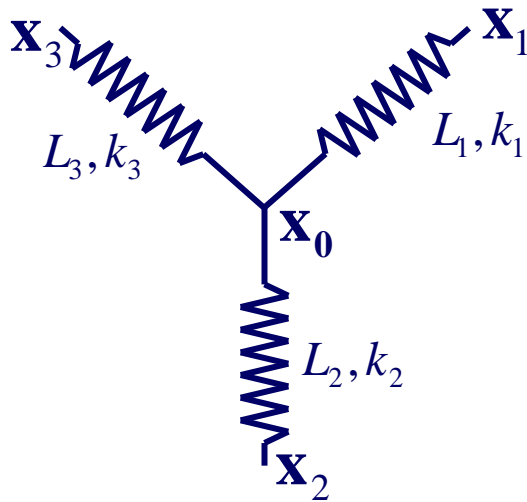
$$E = W = \frac{1}{2} k(l - L)^2$$

Force = - gradient of
energy

$$\mathbf{F}_i = - \frac{\partial E}{\partial \mathbf{x}_i}$$

Forces at Mass Point

Internal forces \mathbf{F}^{int}



External forces \mathbf{F}^{ext}

- Gravity
- Contact forces
- All forces that are not caused by springs

Total spring force

$$\mathbf{F}_0^{\text{int}} = - \sum_{i \in \{1,2,3\}} k_i (l_i - L_i) \frac{\mathbf{x}_i - \mathbf{x}_0}{l_i}$$

Resulting force at point i

$$\mathbf{F}_i = \mathbf{F}_i^{\text{int}} + \mathbf{F}_i^{\text{ext}}$$

Dissipative Forces

- Real-world mechanical systems dissipate energy over time
Internal friction → Thermal energy (irreversible process)
- Controllable dissipation useful for physics simulations
Do we want things to move indefinitely?
- Dissipation for mass-spring systems

Point damping

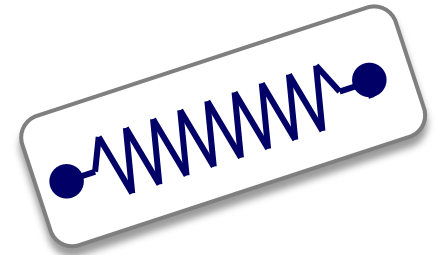
$$\mathbf{F}^{pd}(t) = -\gamma \cdot \mathbf{v}(t)$$

γ is damping coefficient

- + Simple and efficient
- Damps *all* motion (translations and rotations)

Outline

Mass-Spring Systems



Steps towards simulation

1. **Spatial discretization:** sample object with mass points
2. **Forces:** define internal (*springs!*) and external forces
3. **Dynamics:** set up equations of motion
4. **Temporal discretization:** solve equations of motion

Dynamics

Force is known for every particle.
How do we determine motion $\mathbf{x}_i(t)$?

- Kinematic relations

Velocity

$$\mathbf{v}_i(t) = \frac{d\mathbf{x}_i(t)}{dt}$$

Acceleration

$$\mathbf{a}_i(t) = \frac{d\mathbf{v}_i(t)}{dt} = \frac{d^2\mathbf{x}_i(t)}{dt^2}$$

- Motion follows from

Newton's 2nd Law

$$\mathbf{F}_i = m_i \mathbf{a}_i$$

Equations of Motion

Newton's 2nd Law

$$\mathbf{F}_i = m_i \mathbf{a}_i$$

Acceleration

$$\mathbf{a}_i(t) = \frac{d^2 \mathbf{x}_i(t)}{dt^2}$$

Equations of motion
for one mass point
(3 equations)

$$m_i \frac{d^2 \mathbf{x}_i(t)}{dt^2} = \mathbf{F}_i^{\text{int}}(t) + \mathbf{F}_i^{\text{ext}}(t)$$

Equations of motion
for system of mass points
(3n equations)

$$\mathbf{M} \frac{d^2 \mathbf{x}(t)}{dt^2} = \mathbf{F}^{\text{int}}(t) + \mathbf{F}^{\text{ext}}(t)$$

$\mathbf{M} \in \mathbf{R}^{3n \times 3n}$ is a diagonal matrix

Equations of Motion

Special case:
point damping

$$\mathbf{F}^{pd}(t) = -\gamma \cdot \mathbf{v}(t)$$

Equations of motion
($3n$ equations)

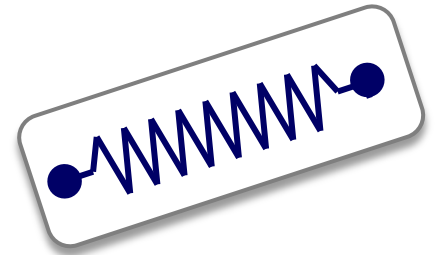
$$\mathbf{M} \frac{d^2 \mathbf{x}(t)}{dt^2} + \mathbf{D} \frac{d\mathbf{x}(t)}{dt} = \mathbf{F}^{\text{int}}(t) + \mathbf{F}^{\text{ext}}(t)$$

$\mathbf{D} \in \mathbf{R}^{3n \times 3n}$ is diagonal with entries γ

Motion is determined by a system of $3n$
 2^{nd} order Ordinary Differential Equations

Outline

Mass-Spring Systems



Steps towards simulation

1. **Spatial discretization:** sample object with mass points
2. **Forces:** define internal (*springs!*) and external forces
3. **Dynamics:** set up equations of motion
4. **Temporal discretization:** solve equations of motion

Differential Equations

- A **differential equation** describes an unknown function through its derivatives
- An ordinary differential equation (ODE) contains only derivatives with respect to a single variable

Example

$$\mathbf{x}''(t) = \frac{\mathbf{F}(t) - \gamma \mathbf{x}'(t)}{m_i}$$



Abstract form

$$y''(t) = f(t, y, y')$$

- Expressed as function of highest derivative

$$y^{(n)} = f(x, y, y', y'', \dots, y^{(n-1)})$$

n is the order of the ODE

Initial Value Problems

- Solving an ODE: given f , determine y

Example

$$y'(t) = f(t, y) = y(t)$$



Solution

$$y(t) = Ce^t$$

- Integration constant C is unknown, determined by

$$\text{Initial value } y(0) = 2 \quad \Rightarrow \quad C = 2$$

- ODE + initial value = *initial value problem* (IVP)

Picard–Lindelöf theorem:

IVP has unique solution if f is Lipschitz continuous!

Mass-Spring Systems

Applied to mass-spring systems?

We have:

- Initial position $\mathbf{x}_i(t_0)$
- Initial velocity $\mathbf{v}_i(t_0)$
- Governing ODE
(2nd order)

$$\frac{d^2 \mathbf{x}_i(t)}{dt^2} = \frac{\mathbf{F}_i(t) - \gamma \mathbf{v}_i(t)}{m_i}$$

We want:

- position $\mathbf{x}_i(t)$ over time

Rewriting the Problem

- *Easier* to deal with first order ODE
- Reduce 2nd order ODE to two coupled 1st order ODEs

$$m_i \frac{d^2 \mathbf{x}_i(t)}{dt^2} + \gamma \frac{d\mathbf{x}_i(t)}{dt} = \mathbf{F}_i(t)$$

velocity

$$\frac{d\mathbf{x}_i(t)}{dt} = \mathbf{v}_i(t)$$

acceleration

$$\frac{d\mathbf{v}_i(t)}{dt} = \frac{\mathbf{F}_i(t) - \gamma \mathbf{v}_i(t)}{m_i}$$

Rewriting the Problem

- Two coupled 1st order ODEs (2 times 3 equations)

$$\frac{d\mathbf{x}_i(t)}{dt} = \mathbf{v}_i(t) \qquad \frac{d\mathbf{v}_i(t)}{dt} = \frac{\mathbf{F}_i(t) - \gamma \mathbf{v}_i(t)}{m_i}$$

- Write as one system of 1st order ODEs

$$\mathbf{y}_i(t) = \begin{pmatrix} \mathbf{x}_i(t) \\ \mathbf{v}_i(t) \end{pmatrix} \qquad \mathbf{y}_i'(t) = \begin{pmatrix} \mathbf{v}_i(t) \\ \frac{\mathbf{F}_i(t) - \gamma \mathbf{v}_i(t)}{m_i} \end{pmatrix}$$

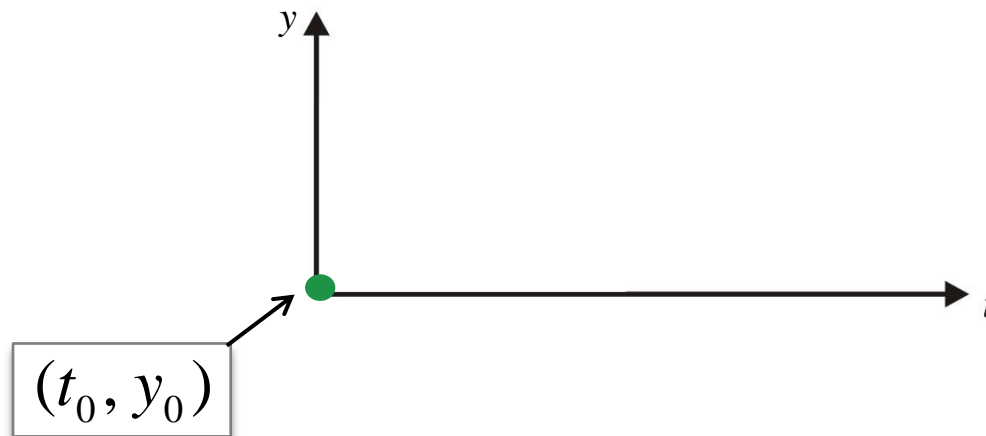
Solution

*Given first order ODE with initial conditions,
how can we solve for $y(t)$?*

$$\begin{aligned}y'(t) &= f(t, y) \\ y(t_0) &= y_0\end{aligned}$$

Analytical solution

- Provides exact solution $y(t)$ at any time value t
- In general not available (impractical for complex systems)



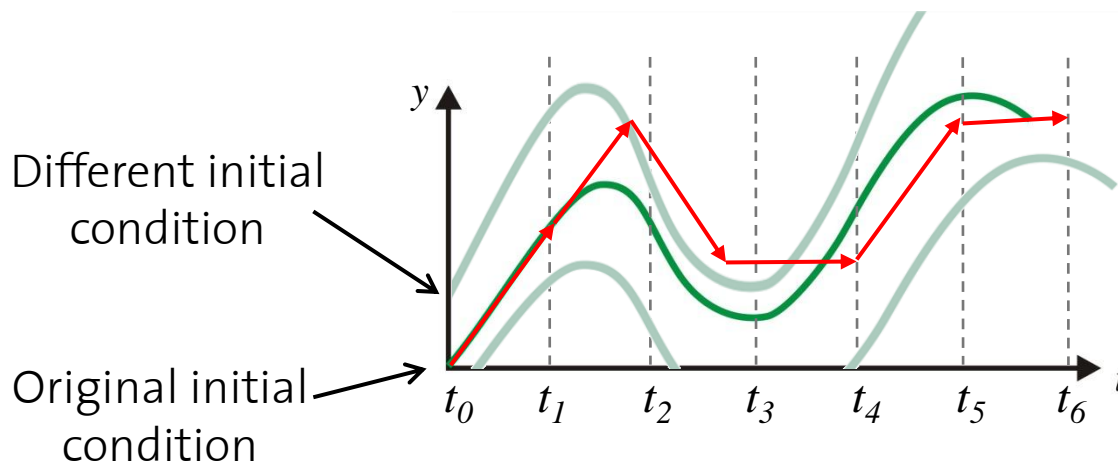
Solution

*Given first order ODE with initial conditions,
how can we solve for $y(t)$?*

$$\begin{aligned} y'(t) &= f(t, y) \\ y(t_0) &= y_0 \end{aligned}$$

Numerical solution

- Compute approximations y_i to true solution for **discrete** time instants t_i
- Compute solution at t_{i+1} based on previous solutions at t_{i-p}, t_{i-2}, \dots



$$y_n \rightarrow y_{n+1}$$

Numerical Integration

- Solve ODEs numerically \Rightarrow *Numerical Integration*
- Why called like that? $y(t+h) = y(t) + \int_t^{t+h} y'(t) dt$
- Integration schemes

Explicit Methods

Explicit Euler
Heun, Midpoint
Runge-Kutta methods

Implicit Methods

Backward Euler
Implicit Midpoint
BDF methods

Methods for higher order ODEs

Verlet
Leapfrog
Newmark methods

Computing Approximations

- Notation: $y(t)$ true solution
 y_i approximate solutions at $t_i = t_0 + i \cdot h$
 h time step (*fix*)
- Problem definition: given y_n , compute y_{n+1}
- How do we get from $y(t)$ to $y(t+h)$?

Taylor expansion

$$y(t+h) = y(t) + \frac{y'(t)}{1!}h + \frac{y''(t)}{2!}h^2 + \dots$$

- Compute first order approximation

$$y(t+h) \approx y(t) + h \cdot y'(t) \longrightarrow y_{n+1} = y_n + h \cdot f(t_n, y_n)$$

Euler's Method

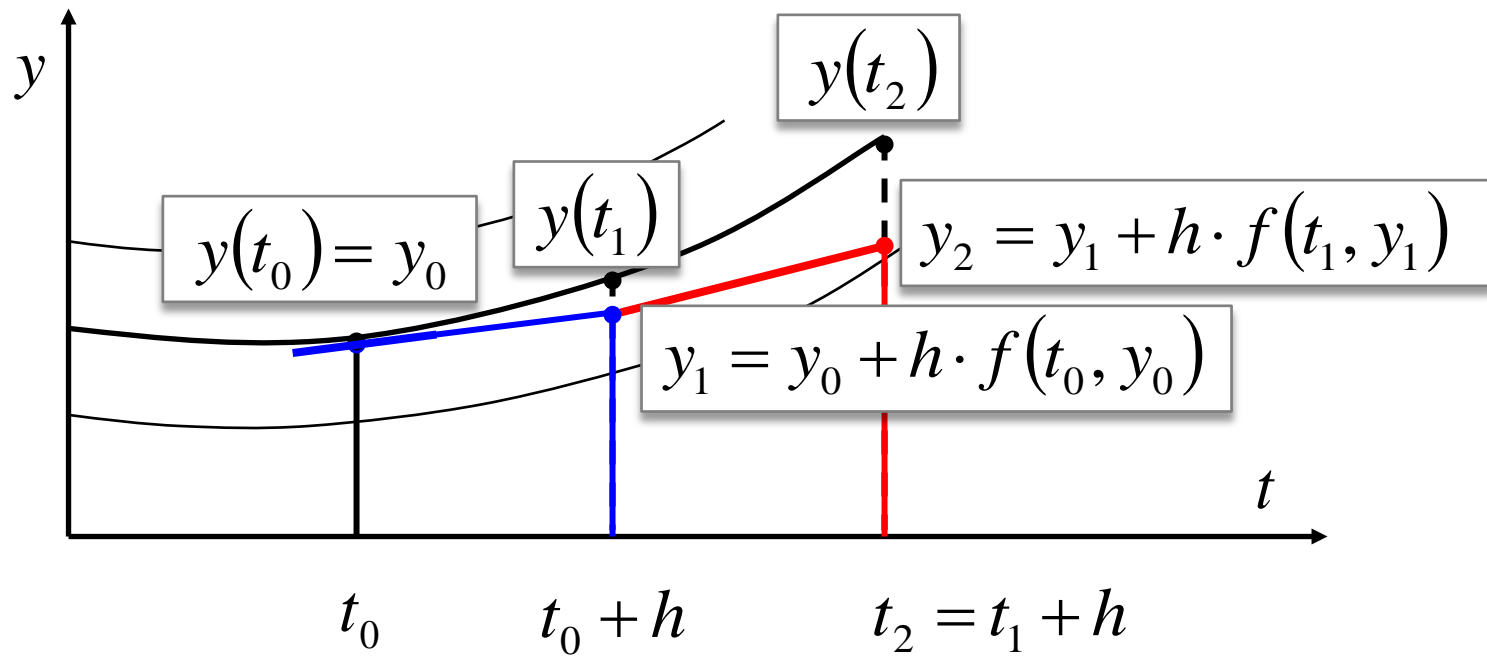
Euler Step (1768)

$$y_{n+1} = y_n + h \cdot f(t_n, y_n)$$

- Idea: start at initial condition and take a step into the direction of the tangent.
- Iteration scheme: $y_n \rightarrow f(t_n, y_n) \rightarrow y_{n+1} \rightarrow f(t_{n+1}, y_{n+1}) \rightarrow \dots$
- Bear in mind: *computations are approximate!*

$$\begin{array}{ll} y_1 = y_0 + h \cdot f(t_0, y_0) & \text{but} \quad y_2 = y_1 + h \cdot f(t_1, y_1) \\ f(t_0, y_0) = f(t_0, y(t_0)) & f(t_1, y_1) \neq f(t_1, y(t_1)) \end{array}$$

Euler's Method Graphically



Euler's Method

For 2nd order ODE

$$\mathbf{x}'(t) = \mathbf{v}(t) \quad \mathbf{v}'(t) = \frac{\mathbf{F}(t) - \gamma \mathbf{v}(t)}{m}$$

Compute

$$\mathbf{x}(t_0 + h) = \mathbf{x}(t_0) + h\mathbf{x}'(t_0) = \mathbf{x}(t_0) + h\mathbf{v}(t_0)$$

Compute

$$\mathbf{v}(t_0 + h) = \mathbf{v}(t_0) + h\mathbf{v}'(t_0) = \mathbf{v}(t_0) + h \frac{\mathbf{F}(t_0) - \gamma \mathbf{v}(t_0)}{m}$$

$\mathbf{F}(t)$ is computed from $\mathbf{x}(t)$ and external forces!

Analysis

How to evaluate an integration scheme?

Criteria

- **Convergence:** do approximations converge to true solution, i.e. $h \rightarrow 0 \Rightarrow y_i \rightarrow y(t_i)$?
- **Accuracy:** how fast does the error decrease as $h \rightarrow 0$?
- **Stability:** is the solution always bounded, i.e. $|y_n| < \infty$?
- **Efficiency:** is a given method a *good choice* for a given problem?

Accuracy

- Numerical solution exhibits error

$$\left| \left[y_n + \int_{t_n}^{t_{n+1}} y'(t) dt \right] - y_{n+1} \right|$$

Local error (*single step*)

$$| y_i - y(t_i) |$$

Global error (*accumulated*)

- Accuracy of integration schemes:

Local error is $O(h^{p+1}) \rightarrow$ method is accurate of order p !

- Error depends on the step size:

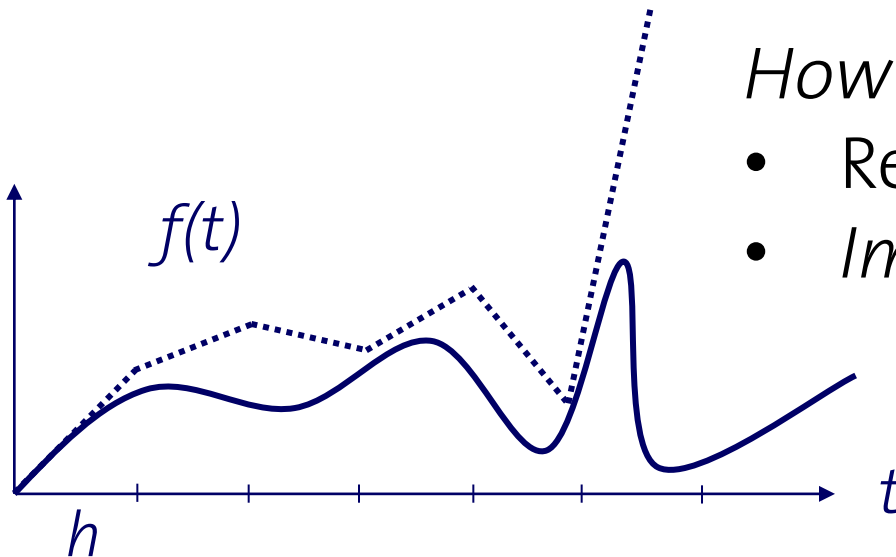
Explicit Euler is order 1 $\rightarrow O(h^2)$ error per step!

Problems

- Numerical integration is inaccurate
- Error accumulates
- can cause instability

$$f(t+h) = f(t) + f'(t)h + \underbrace{O(h^2)}_{\text{Error}}$$

$$\text{Error } 0 \leq e < \frac{h^2}{2} \cdot f''(t_e), \quad t_e \in [t, t+h]$$



How can we reduce the error?

- Reduce step size
- *Improve accuracy*

Higher Accuracy

Taylor expansion

$$y(t+h) = y(t) + \frac{y'(t)}{1!}h + \frac{y''(t)}{2!}h^2 + \dots$$

- Idea: use second order approximation (i.e. $O(h^3)$)

$$y(t+h) \approx y(t) + h \cdot y'(t) + \frac{h^2}{2} y''(t) \quad (1)$$

- $y''(t)$ unknown \rightarrow use difference approximation

$$y''(t) = \frac{y'(t+h) - y'(t)}{h} + O(h) \quad (2)$$

- Use (2) in (1): $y(t+h) \approx y(t) + \frac{h}{2}[y'(t) + y'(t+h)] \quad (3)$

- Eq. (3) is $O(h^3)$ as long as Eq. (2) is $O(h)$

Higher Accuracy

$$y(t+h) \approx y(t) + \frac{h}{2}[y'(t) + y'(t+h)] \quad (3)$$

- $y'(t+h)$ unknown \rightarrow use Euler step

- Step $\tilde{y}_{n+1} = y_n + h \cdot f(t_n, y_n)$

- Evaluate $y'_{n+1} = f(t_{n+1}, \tilde{y}_{n+1})$ (4)

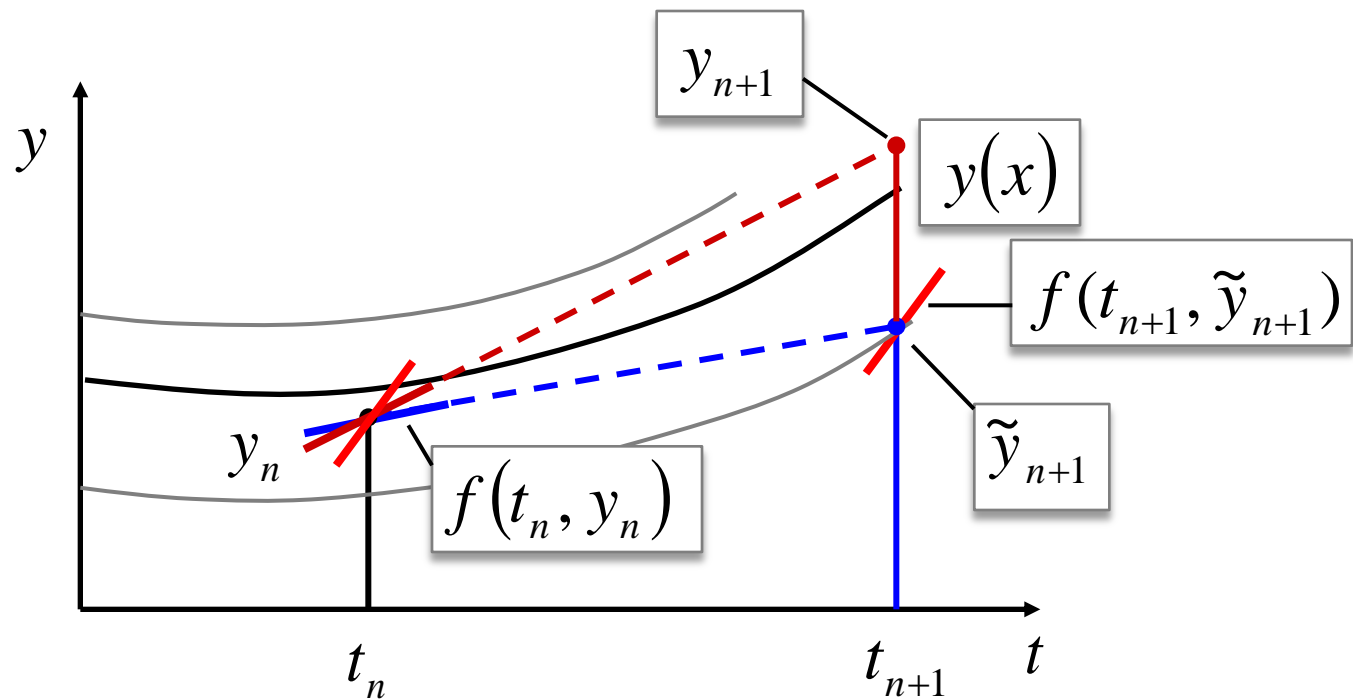
- Putting it together: **Heun's method**

$$\tilde{y}_{n+1} = y_n + h \cdot f(t_n, y_n)$$

$$y_{n+1} = y_n + \frac{h}{2}[f(t_n, y_n) + f(t_{n+1}, \tilde{y}_{n+1})]$$

*2nd order
accurate!*

Heun's Method Graphically



Heun's Method

For 2nd order ODE

$$\mathbf{x}'(t) = \mathbf{v}(t) \qquad \mathbf{v}'(t) = \mathbf{a}(\mathbf{x}(t), \mathbf{v}(t)) = \frac{\mathbf{F}(t) - \gamma \mathbf{v}(t)}{m}$$

Compute \mathbf{v} at t

Compute \mathbf{a} at t

Compute \mathbf{v} at $t+h$

Compute \mathbf{a} at $t+h$ with \mathbf{x} and \mathbf{v} at $t+h$

Compute \mathbf{x} at $t+h$ with its velocity at t and $t+h$

Compute \mathbf{v} at $t+h$ with the acceleration at $t, t+h$

$$\mathbf{k}_1 = \mathbf{v}(t)$$

$$\mathbf{l}_1 = \mathbf{a}(\mathbf{x}(t), \mathbf{v}(t))$$

$$\mathbf{k}_2 = \mathbf{v}(t) + \mathbf{l}_1 h$$

$$\mathbf{l}_2 = \mathbf{a}(\mathbf{x}(t) + \mathbf{k}_1 h, \mathbf{k}_2)$$

$$\mathbf{x}(t+h) = \mathbf{x}(t) + h \frac{\mathbf{k}_1 + \mathbf{k}_2}{2}$$

$$\mathbf{v}(t+h) = \mathbf{v}(t) + h \frac{\mathbf{l}_1 + \mathbf{l}_2}{2}$$

Explicit Midpoint Method

- Heun's method uses $f(t)$ and $f(t+h)$ to achieve 2nd order accuracy
- Alternative: use $f(t+h/2)$ → **Midpoint method**

$$y'(t + \frac{h}{2}) = \frac{y(t+h) - y(t)}{h} + O(h^2) \rightarrow 2^{\text{nd}} \text{ order accuracy!}$$

$$\tilde{y}_{n+1/2} = y_n + \frac{h}{2} \cdot f(t_n, y_n)$$

$$y_{n+1} = y_n + h \cdot f(t_{n+1/2}, \tilde{y}_{n+1/2})$$

- Note: both Heun and Midpoint achieve 2nd order via two evaluations of f

4th-Order Runge-Kutta Method

- RK4 is one of the most widely used integrators
- Four slope evaluations \rightarrow 4th-order accuracy:

$$k_1 = f(t_n, y_n)$$

slope at beginning of interval

$$k_2 = f(t_n + \frac{1}{2}h, y_n + \frac{1}{2}k_1)$$

slope at mid-interval

$$k_3 = f(t_n + \frac{1}{2}h, y_n + \frac{1}{2}k_2)$$

corrected slope at mid-interval

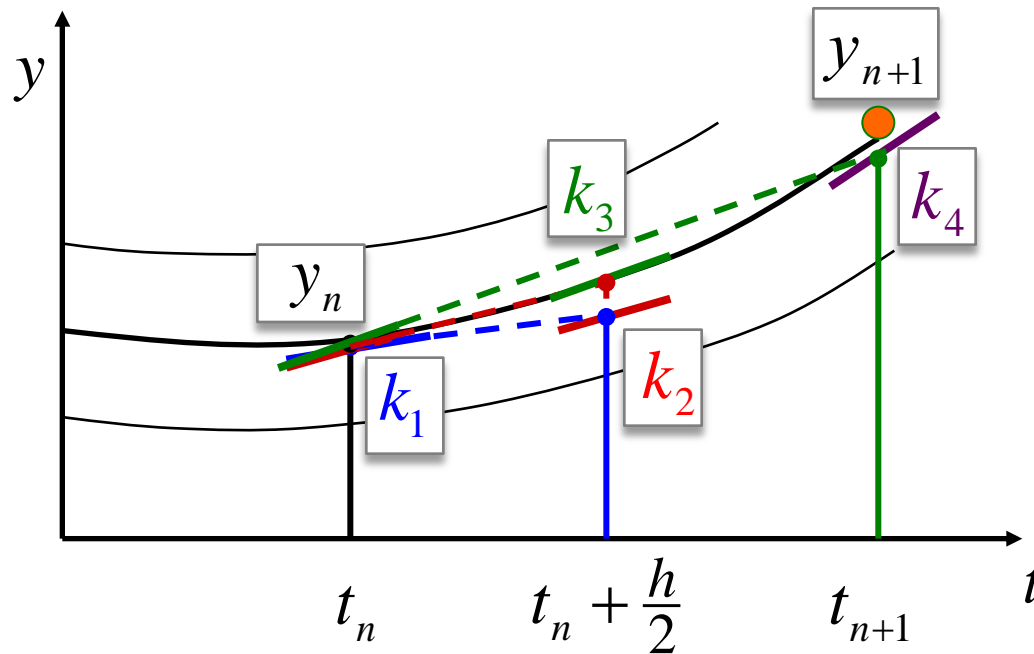
$$k_4 = f(t_n + h, y_n + hk_3)$$

slope at end of interval

- Use weighted average slope

$$y_{n+1} = y_n + \frac{1}{6}h(k_1 + 2k_2 + 2k_3 + k_4)$$

RK4 Graphically



$$y_{n+1} = y_n + \frac{1}{6}h(k_1 + 2k_2 + 2k_3 + k_4)$$

4th-Order Runge-Kutta

For 2nd order ODE

$$\mathbf{k}_1 = \mathbf{v}(t)$$

$$\mathbf{l}_1 = \mathbf{a}(\mathbf{x}(t), \mathbf{v}(t))$$

$$\mathbf{k}_2 = \mathbf{v}(t) + \mathbf{l}_1 \frac{h}{2}$$

$$\mathbf{l}_2 = \mathbf{a}\left(\mathbf{x}(t) + \mathbf{k}_1 \frac{h}{2}, \mathbf{k}_2\right)$$

$$\mathbf{k}_3 = \mathbf{v}(t) + \mathbf{l}_2 \frac{h}{2}$$

$$\mathbf{l}_3 = \mathbf{a}\left(\mathbf{x}(t) + \mathbf{k}_2 \frac{h}{2}, \mathbf{k}_3\right)$$

$$\mathbf{k}_4 = \mathbf{v}(t) + \mathbf{l}_3 h$$

$$\mathbf{l}_4 = \mathbf{a}(\mathbf{x}(t) + \mathbf{k}_3 h, \mathbf{k}_4)$$

$$\mathbf{x}(t+h) = \mathbf{x}(t) + \frac{h}{6}(\mathbf{k}_1 + 2\mathbf{k}_2 + 2\mathbf{k}_3 + \mathbf{k}_4)$$

$$\mathbf{v}(t+h) = \mathbf{v}(t) + \frac{h}{6}(\mathbf{l}_1 + 2\mathbf{l}_2 + 2\mathbf{l}_3 + \mathbf{l}_4)$$

Comparison

Which method is the best?

Comparing integration schemes is difficult

- Different costs per step
- Depends strongly on problem
- Not a single *best* method

Tools from numerical mathematics

- Evaluate on (standard) model problems
- Use work-precision diagrams

Test Equation

Dahlquist's Equation

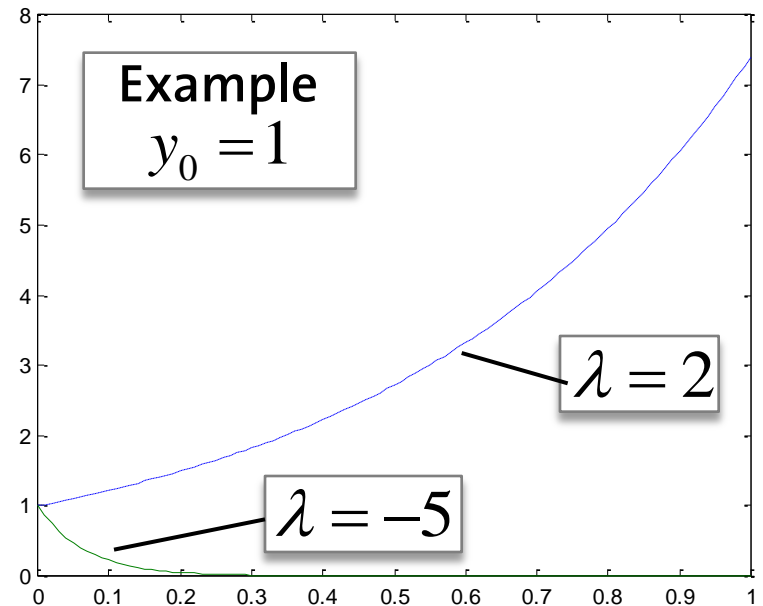
$$y'(t) = \lambda y(t)$$

For $\lambda \in \mathbb{R}$

- $\lambda > 0$ exponential growth
- $\lambda < 0$ exponential decay

Analytical Solution

$$y(t) = e^{\lambda t} y_0$$



Test Equation

Dahlquist's Equation

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

Analytical Solution

$$y(t) = e^{\lambda t} y_0$$

For $\lambda \in \mathbb{C}$: $\lambda = a + ib \Rightarrow y(t) = y_0 \cdot e^{at} \cdot e^{ibt}$

- $a < 0$ damped oscillator
- $a = 0$ undamped oscillator
- $a > 0$ unstable

damping

oscillation

*Prototype of
mass-spring systems*

Euler's Formula

$$e^{ibt} = \cos(bt) + i \sin(bt)$$

Numerical Example

Undamped Harmonic Oscillator

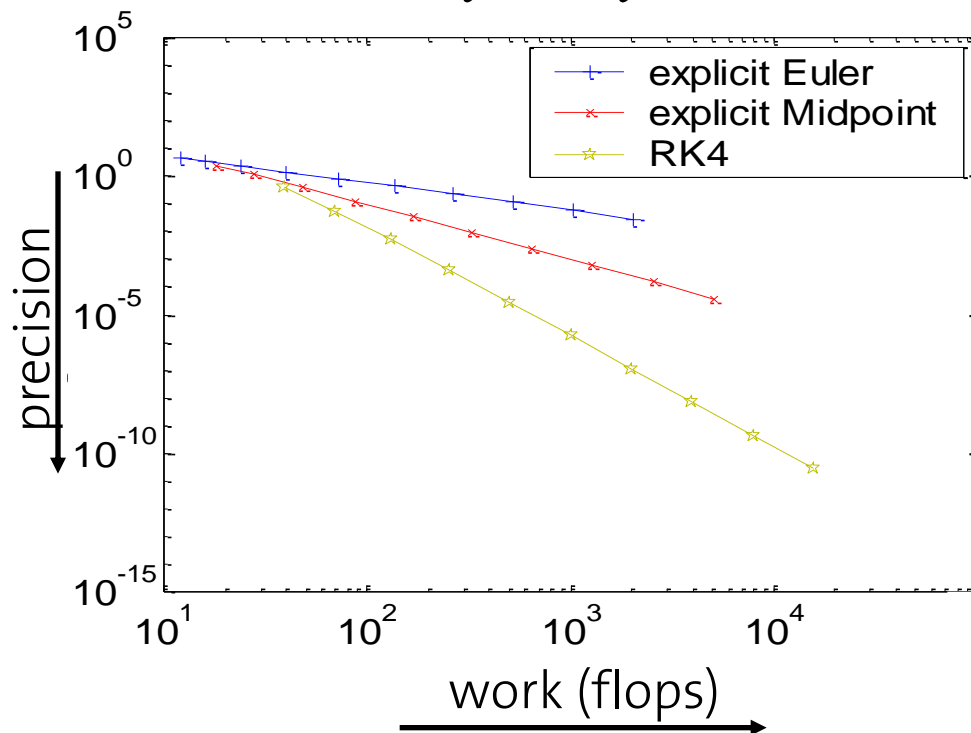


Maple 16 is available (for free) at ides.ethz.ch

Explicit Methods

Test equation $y' = \lambda y$ ($\lambda \in \mathbb{R}$)

$$y' = 2y$$



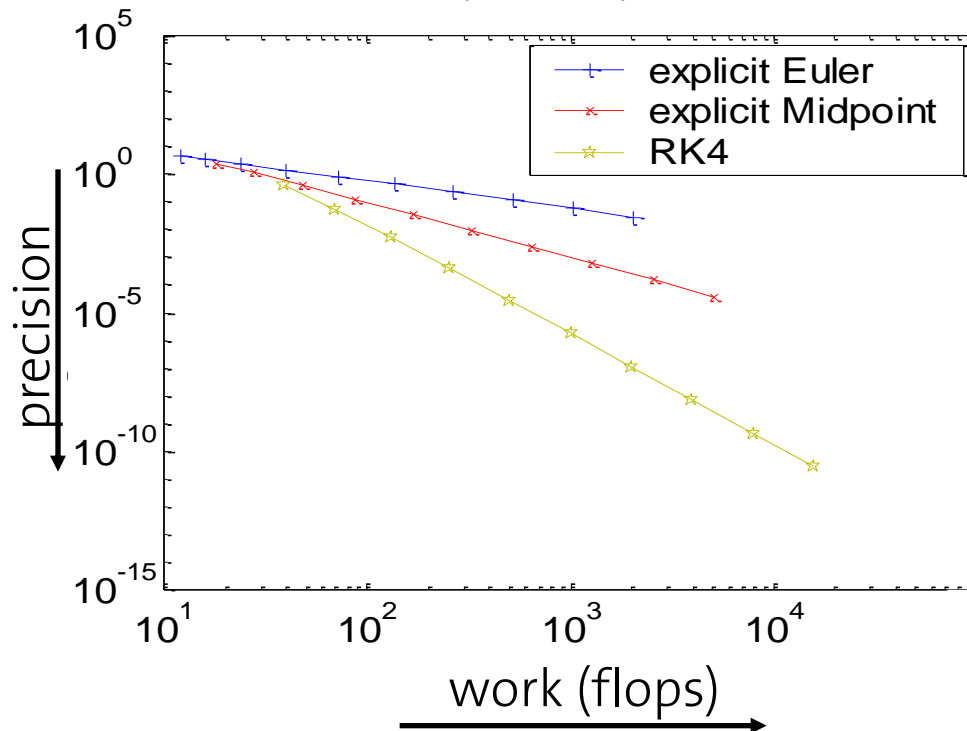
Work precision diagram

- precision = $|y_{end} - y(t_{end})|$
- work = flops
- *log-log plot*: functions x^b are lines with slope b
- slope \rightarrow order of method

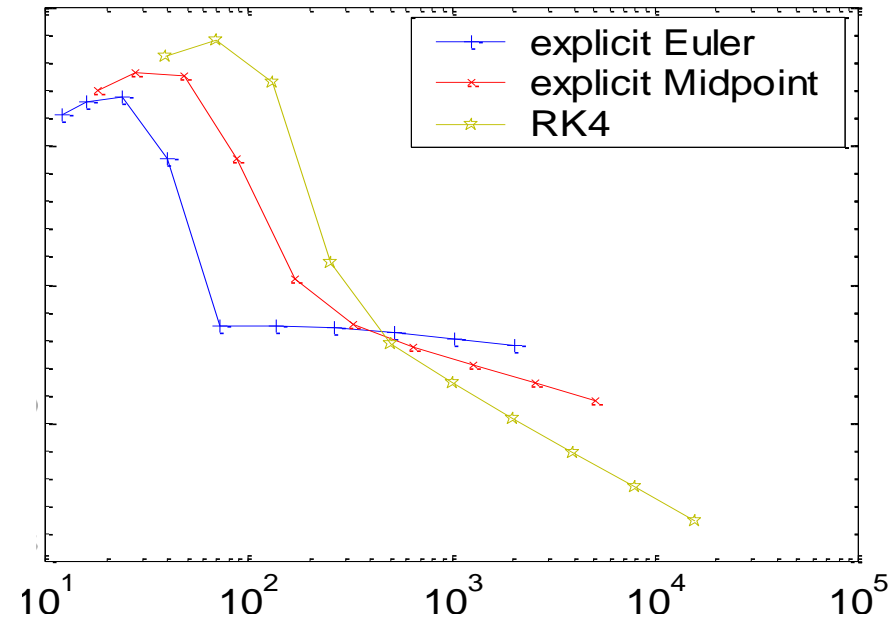
Explicit Methods

Test equation $y' = \lambda y$ ($\lambda \in \mathbb{R}$)

$$y' = 2y$$



$$y' = -5y \text{ ?}$$



Numerical Example

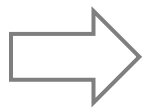
Damped Harmonic Oscillator



Stability Problem

What went wrong?

- Analyze
 - Test equation $y' = \lambda y, \lambda < 0$
 - Explicit Euler $y_{n+1} = y_n + h\lambda y_n = (1 + h\lambda)y_n$
- Solve recursion $y_{n+1} = (1 + h\lambda)^{n+1} y_0$



Step size restriction (*explicit Euler*)

$$y_{n+1} < \infty \iff |1 + h\lambda| < 1$$

Stiff Problems

Observations from test equation: explicit methods

- require very small time steps for stable integration
- are inefficient since step size is determined by stability, not accuracy requirements

Problems with this characteristic are termed *stiff*

Don't use explicit methods for stiff problems,
use *implicit* methods.