

PHY407: Computational Physics

Fall, 2016

Instructor: Paul Kushner

TAs: Miriam Diamond and Heather Fong

Marker: Chad Gu

Lecture 7: Ordinary differential equations, Part 2

Summary & Status

- Weeks 1-3: Programming basics, numerical errors, numerical integration and differentiation.
- Weeks 4-5: Solving linear & nonlinear systems and Fourier transforms.
- Week 6: ODEs Part 1: RK4, Leapfrog, Verlet, adaptive time stepping; customizing python output
- Week 7: ODEs Part 2: Bulirsch-Stoer, Boundary Value Problems/shooting
- Weeks 8-9: PDEs Parts 1 & 2
- Weeks 10-11: Random numbers & Monte Carlo methods

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Lecture 7: Ordinary differential equations, Part 2

- Burlisch-Stoer – fast leaps to a conservative solution
- Boundary value problems using shooting
- Brief look at stability of numerical methods

Solving ODEs

- Last week we introduced new methods for solving systems of ODEs

One dimension: $\frac{dx}{dt} = f(x, t)$, given $x(t = 0) = x_0$

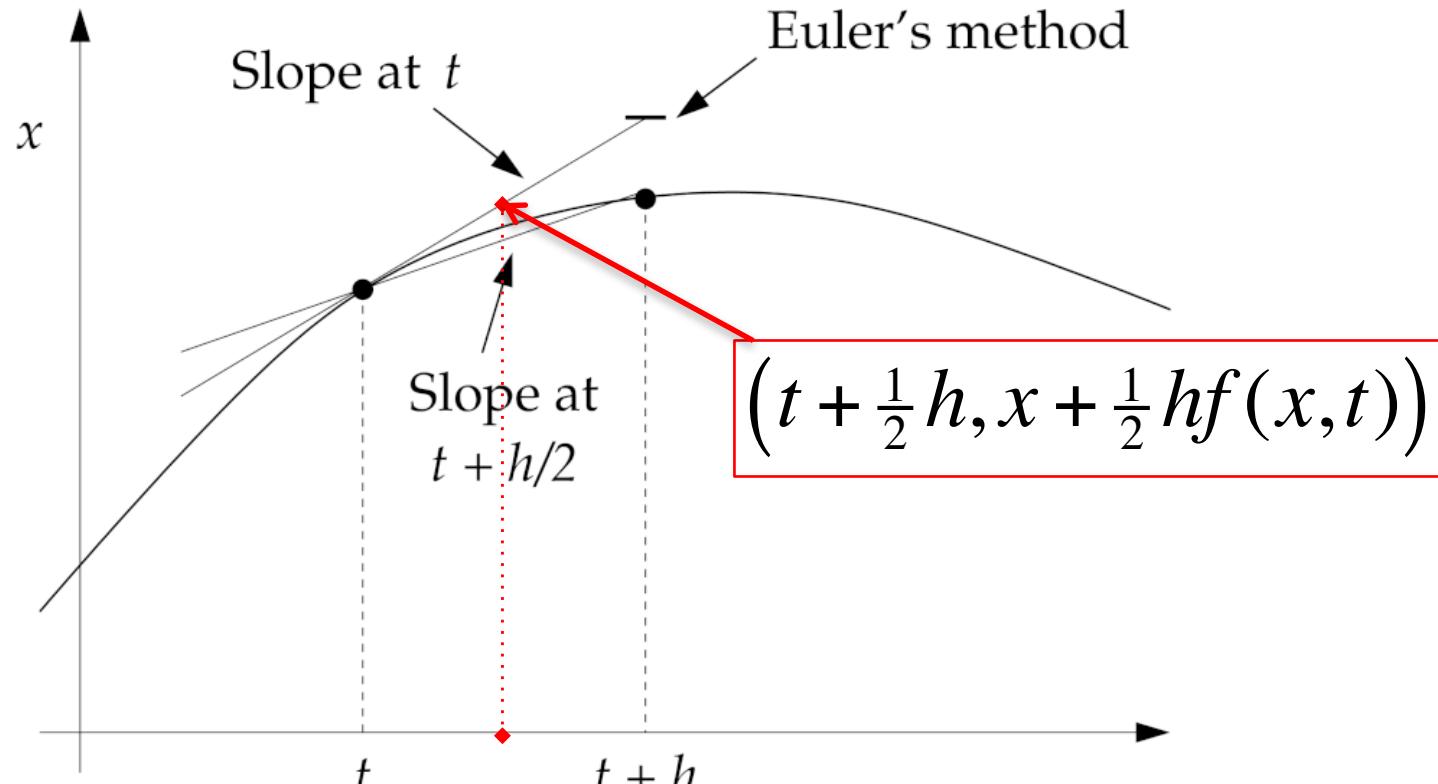
Multiple dimensions: $\frac{dx_i}{dt} = f_i(x_1, \dots, x_n, t)$, $x_i(t = 0) = x_{io}$, $i = 1, \dots, n$

$$\frac{dx}{dt} = v$$

Higher order: e.g. $\frac{d^3x}{dt^3} = g(x, t) \rightarrow \frac{dv}{dt} = a$

$$\frac{da}{dt} = g$$

Runge-Kutta Methods



E.g. second order Runge-Kutta:

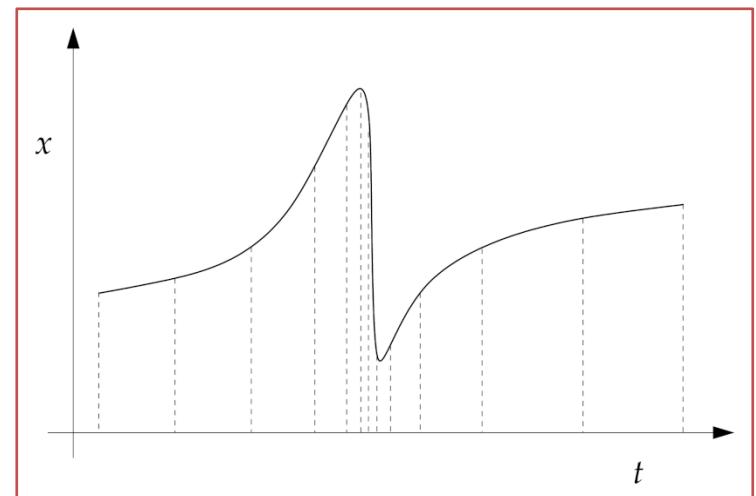
$$x(t+h) = x(t) + hf\left(x + \frac{1}{2}hf(x, t), t + \frac{1}{2}h\right)$$

Adaptive RK4

- It's worth investing computer time in error estimation as in

$$\rho = \frac{h\delta}{\varepsilon} = \frac{30h\delta}{|x_1 - x_2|} > 1,$$

- Then you can adjust h up or down as required.



Leapfrog and Verlet: Time Reversible

$$x(t+h) = x(t) + hf\left(x\left(t + \frac{1}{2}h\right), t + \frac{1}{2}h\right)$$

$$x\left(t + \frac{3}{2}h\right) = x\left(t + \frac{1}{2}h\right) + hf\left(x(t+h), t+h\right)$$

$$x\left(t + \frac{1}{2}h\right) = x\left(t + \frac{3}{2}h\right) - hf\left(x(t+h), t+h\right)$$

$$x(t) = x(t+h) - hf\left(x\left(t + \frac{1}{2}h\right), t + \frac{1}{2}h\right)$$

- Leapfrog gives same answer going forward or backward: reversible and energy conserving.
- Verlet Method: special case of leapfrog for Newton's second law, also reversible.

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- Leapfrog gives same answer going forward or backward: reversible and energy conserving.
- Verlet Method: special case of leapfrog for Newton's second law, also reversible.
- New point: Because leapfrog is time reversal symmetric, ε is an odd power of h :

$$\varepsilon(-h) = -\varepsilon(h)$$

- Cumulative error over integration interval is *even* in h .
- Put another way: this means that we can potentially get two orders of accuracy in h for each improvement.

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$$y_1 = x_0 + \frac{1}{2}hf(x_0, t)$$

$$x_1 = x_0 + hf(y_1, t + \frac{1}{2}h)$$

$$y_2 = y_1 + hf(x_1, t + h)$$

...

$$y_{m+1} = y_m + hf(x_m, t + mh)$$

$$x_{m+1} = x_m + hf(y_{m+1}, t + (m + \frac{1}{2})h)$$

...

$$y_n = y_{n-1} + hf(x_{n-1}, t + H - h)$$

$$x_n = x_{n-1} + hf(y_n, t + H - \frac{1}{2}h) \approx x(t + H)$$

This is new notation for leapfrog over the interval from t to $t+H$

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$$x(t + H)_{\text{final}} = \frac{1}{2}[x_n + x_n']$$

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... This *modified midpoint* method restores the accuracy (Gragg).

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This is what a single MMP step of length H looks like.

$$x_0 = x(t)$$

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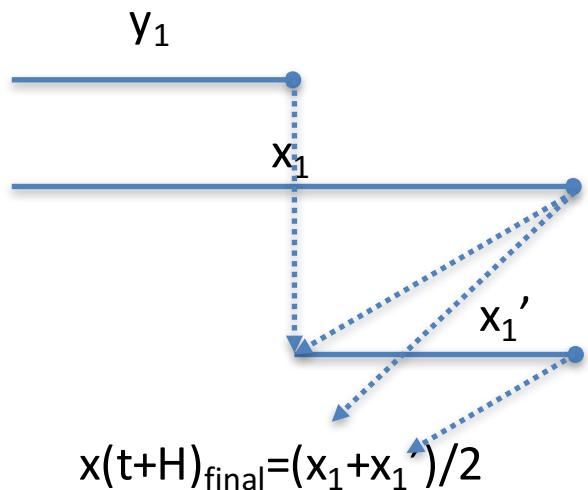
$$x(t + H)_{\text{final}} = \frac{1}{2} [x_1 + x_1'] = R_{1,1}$$

$$x(t + H) = R_{1,1} + c_1 H^2 + O(H^4)$$

$$= R_{2,1} + c_1 (H/2)^2 + O((H/2)^4)$$

$$\text{So } x(t + H) = R_{2,1} + \frac{1}{3} (R_{2,1} - R_{1,1}) + O((H/2)^4)$$

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Now combine the two to improve the estimate to be fourth order in $H/2$, instead of second order in H !

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$$R_{3,2} = R_{3,1} + \frac{4}{5} (R_{3,1} - R_{2,1})$$

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This procedure can be continued to another MMP with $H/3$, etc.

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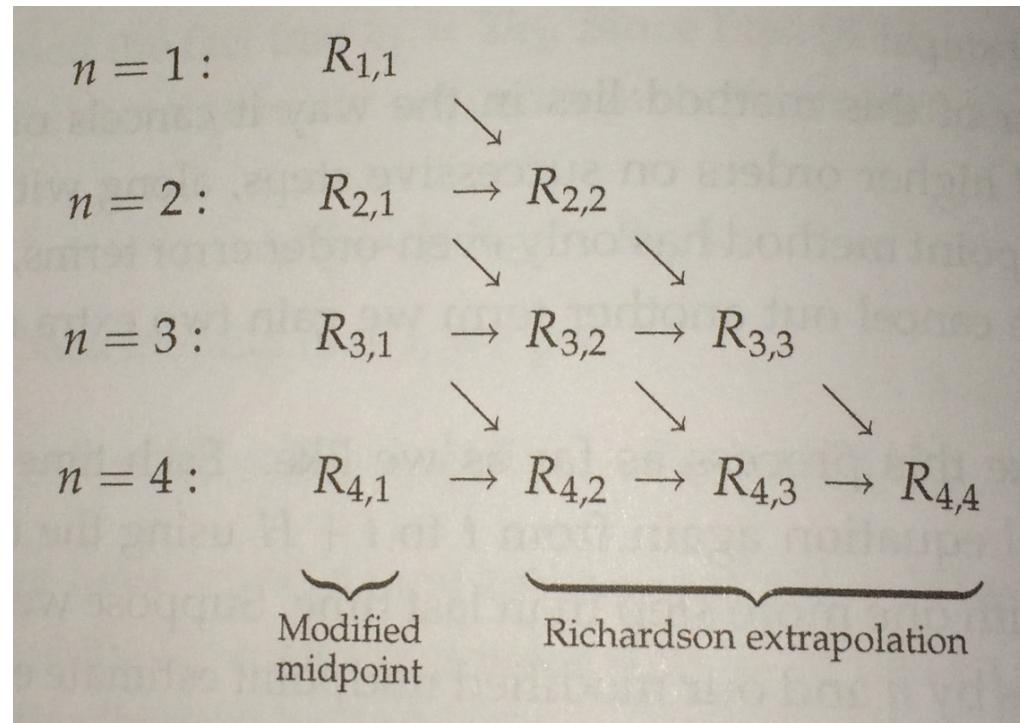
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$$x(t + H) = R_{3,3} + O((H/3)^6)$$

...

$$x(t + H) = R_{n,m+1} + O((H/n)^{2m+2})$$

Bulirsch-Stoer



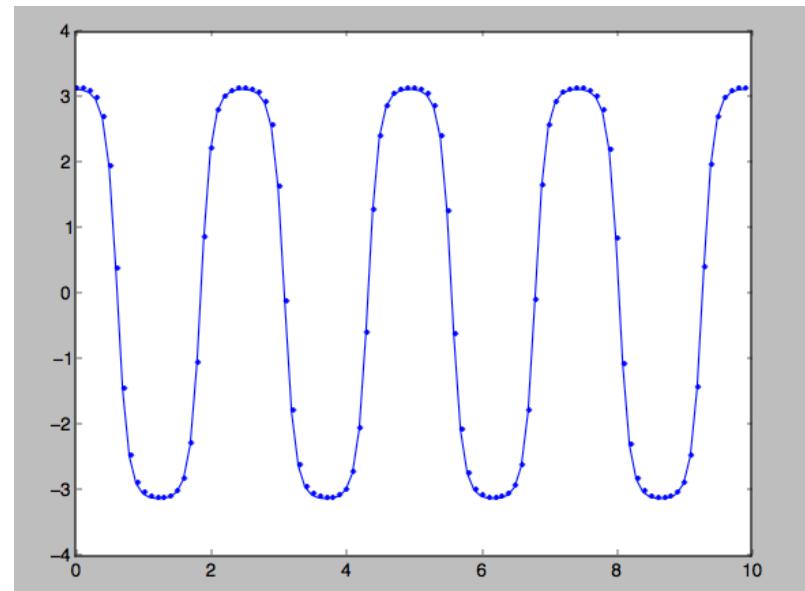
- Iterate over finer intervals to solve over a large “hop” in a conservative and efficient way.
- Your ODES need to be relatively well behaved for this to work well.

Hint for Lab

- To get the provided script `bulirsch.py` to work you need to stick in a line:

```
from __future__ import division
```

- Let's look at this script.
- Its output is at right.



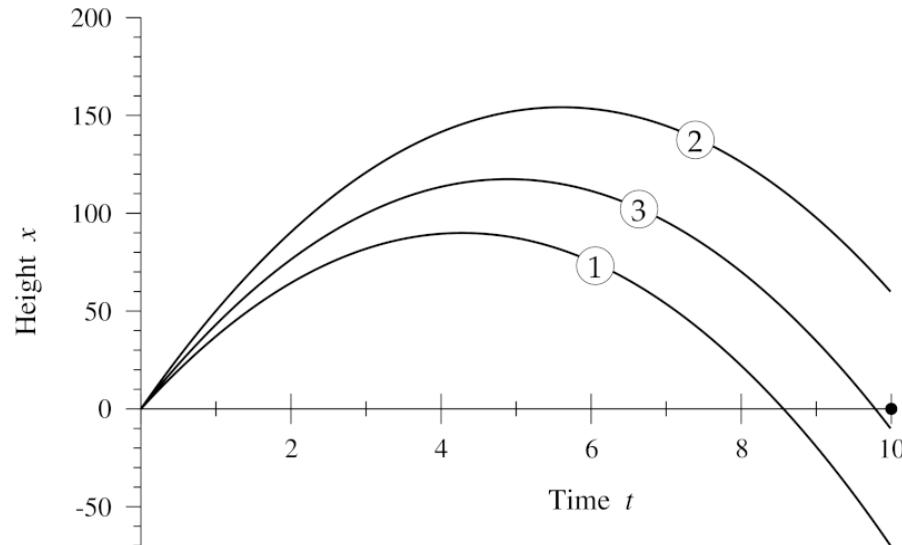
Choosing the Bulirsch-Stoer Timestep

- B-S works well if the number of modified midpoint steps is reasonable (8-10).
- Adaptive time stepping helps ensure this, for a given desired accuracy. Here's the approach:
 - Choose an N . For each subinterval of size $h=(b-a)/N$
 - Calculate error up to 8 or so steps (Lab07Q3).
 - If we haven't met our accuracy goal, subdivide this interval to $(b-a)/(2N)$ and try again on each subinterval.



- Although there are apparently wasted calculations, this focuses accuracy where it is necessary.

Shooting Method for Solving BVPs

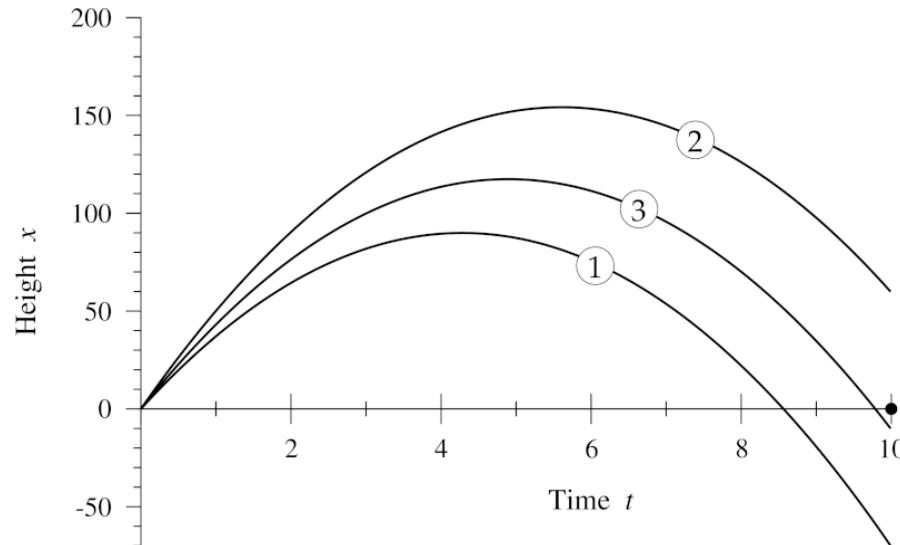


$$\frac{d^2x}{dt^2} = -g,$$

$$x(t = 0) = 0, v(t = 0) = v_0$$

- Suppose we wanted to choose an initial velocity for a projectile so it could land on the ground after $t=10s$.

Shooting Method for Solving BVPs

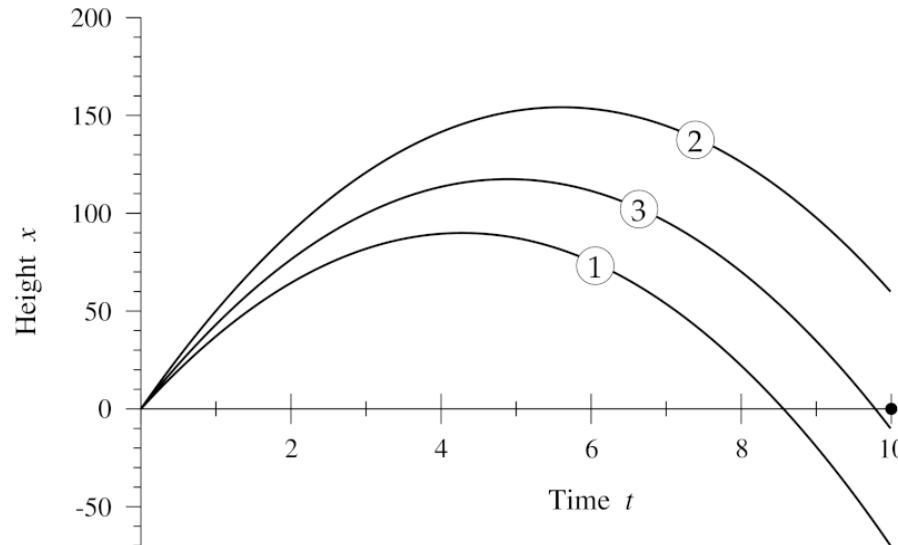


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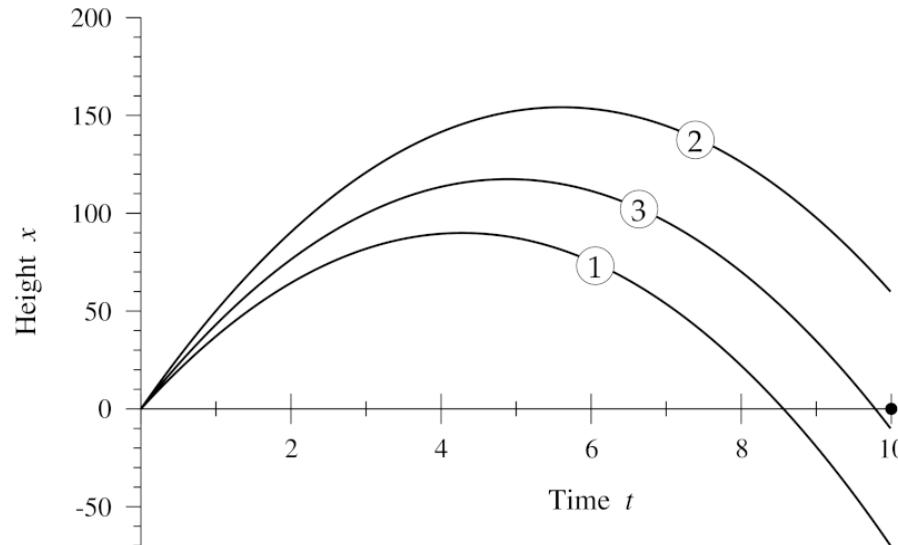


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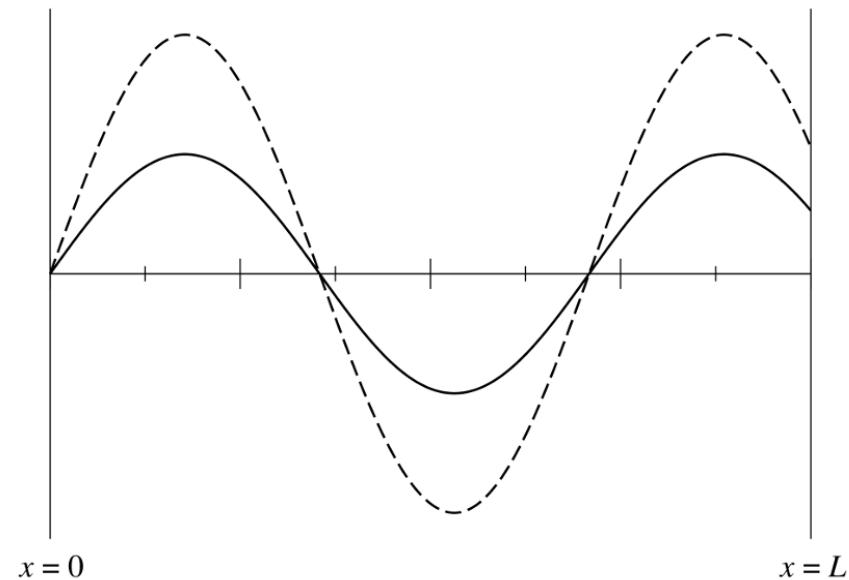
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Let's look at `throw.py`

- Suppose we wanted to choose an initial velocity for a projectile so it could land on the ground after $t=10s$.
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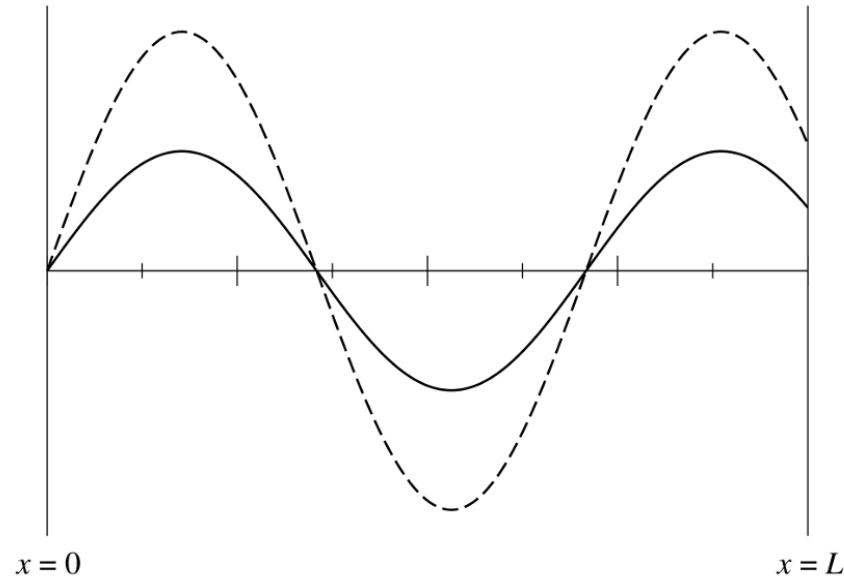
Shooting Method for Solving BVPs

$$-\frac{\hbar^2}{2m} \frac{d^2\psi}{dx^2} + V(x)\psi = E\psi,$$
$$\psi(x=0) = \psi(x=L) = 0$$



Shooting Method for Solving BVPs

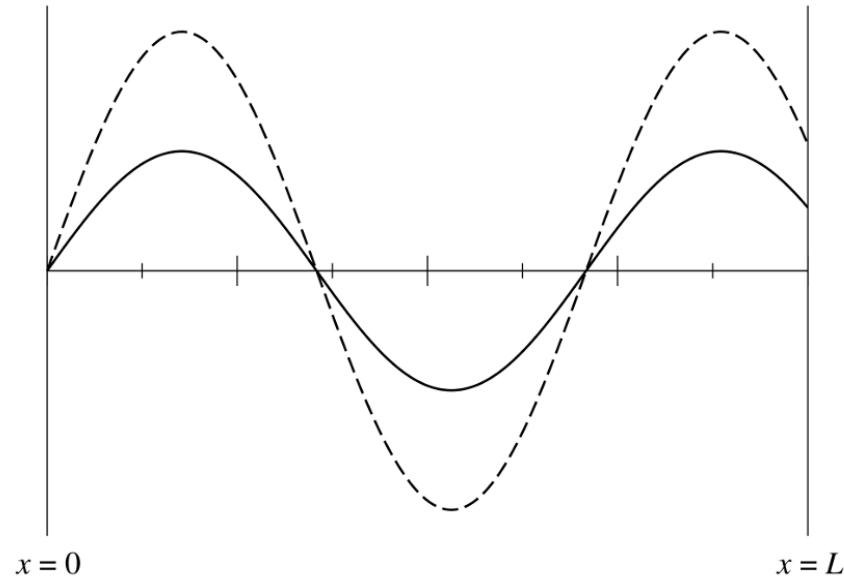
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- But this approach does not work for finding wavefunctions that satisfy two boundary conditions, as in QM square well, except for valid eigenvalues E.

Shooting Method for Solving BVPs

$$-\frac{\hbar^2}{2m} \frac{d^2\psi}{dx^2} + V(x)\psi = E\psi,$$
$$\psi(x=0) = \psi(x=L) = 0$$



- But this approach does not work for finding wavefunctions that satisfy two boundary conditions, as in QM square well, except for valid eigenvalues E.
- So for these problems, E is the parameter that must be varied instead of the leftmost slope of wavefunction.

Functional and Numerical Stability

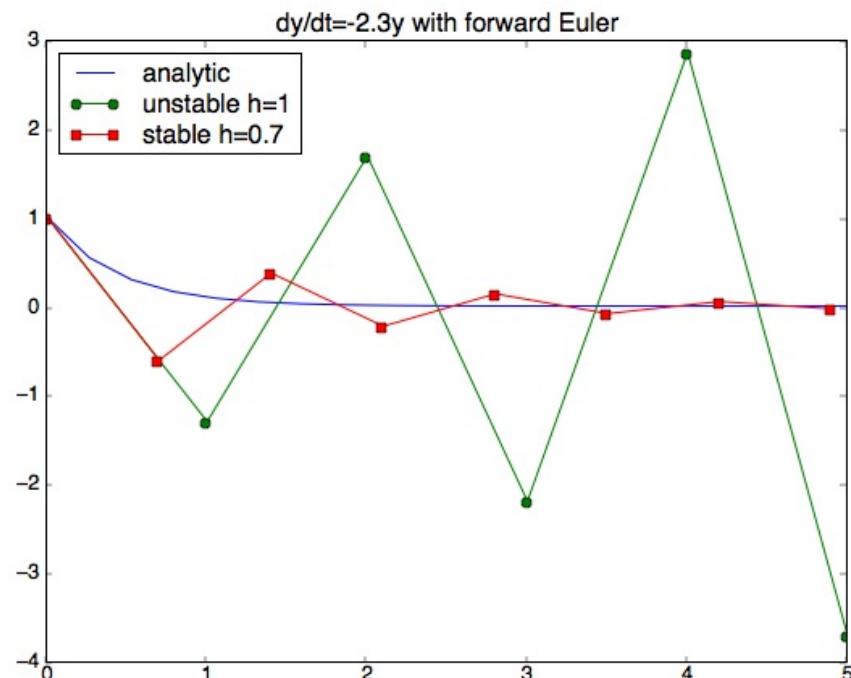
- We have focused on accuracy and speed in investigating our solutions to ODEs.
- But **stability** is also important. The stability of solutions tells us how fast initially close solutions diverge from each other.
- Some systems are inherently unstable and so will always be challenging to simulate.
- We will investigate this in some exercises in the coming labs.

Method Stability

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-
- Example: $dy/dt = -2.3y$ is a stable system.
 - Forward Euler unstable with $h = 1$ but stable with $h=0.7$
 - Need to determine stability of METHODS. Typically this depends on the ODE and the step size



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This is consistent with numerically determined results.

PHY407: Computational Physics

Fall, 2015

Lecture 7: Ordinary differential equations, Part 2

- Burlisch-Stoer – fast leaps to a conservative solution
- Boundary value problems using shooting
- Brief look at stability of numerical methods