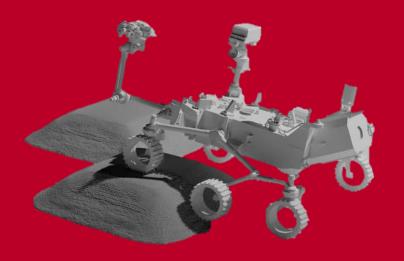
Carnegie Mellon University



Introductory Numerical Methods for Simulating Dynamic Systems

Dr. Joshua Pulsipher



Learning Outcomes

1. The relative advantages/disadvantages of using explicit and implicit Euler methods

2. How to implement explicit/implicit Euler to **simulate ODEs** using common computation environments (e.g., Julia)

3. How to simulate **reaction networks** using numerical methods

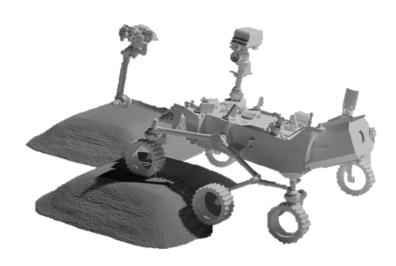
4. A familiarity of other **numerical methods/tools** for simulating ODEs



- Motivation
- Explicit Euler
- Implicit Euler
- Reaction Networks
- Other Methods



- Motivation
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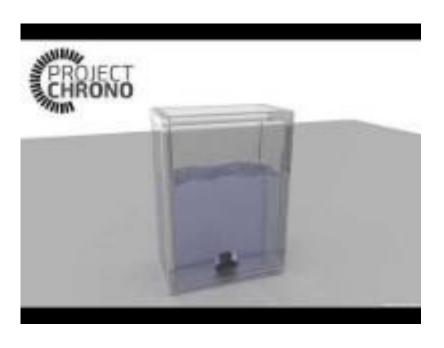




Simulating Dynamic Systems

Simulating dynamic systems is vital for enabling engineering applications





- Simulate using numerical methods to approximate dynamics (e.g., differential equations)
- Enables us to computationally experiment and implement automation



Differential Equations

Types

- Ordinary differential equations (ODEs)
 - Today's focus

$$\frac{dy(t)}{dt} = f(y(t), t)$$
$$y(0) = y_0$$

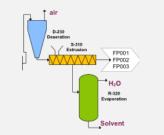
Partial differential equations (PDEs)

$$\frac{\partial y_c(t,x)}{\partial t} = \xi(x) \left(\frac{\partial^2 y_c(t,x)}{\partial x_1^2} + \frac{\partial^2 y_c(t,x)}{\partial x_2^2} \right) + y_g(t,x)$$
$$y_c(0,x), y_c(t, \text{boundary}) = 0$$

Applications

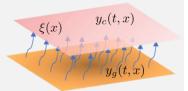
Transient flow balance

$$\frac{df(t)}{dt} = f_{in}(t) - f_{out}(t) + f_{gen}(t)$$



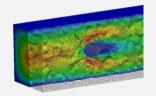
Heat/mass transfer

$$\frac{\partial T(t)}{\partial t} - \alpha \frac{\partial^2 T(t)}{\partial x^2} = 0$$



Fluid flow

$$\rho \frac{DV(t,x)}{Dt} = -\nabla p + \rho g(x) + \mu \nabla^2 V(t,x)$$



Kinetics

$$\frac{dc(t)}{dt} = kc(t)^{\alpha}$$





Analytical vs. Numerical Methods

Analytical Methods

Separate and integrate

$$g(y)\frac{dy}{dx} = h(x)$$
 \longrightarrow $\int g(y)dy = \int h(x)dx + C$

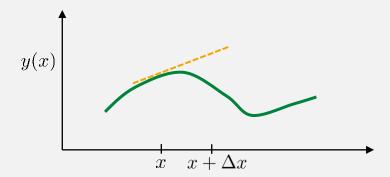
ODEs of special forms

$$\frac{dy}{dx} = \frac{x+y}{x-y} \longrightarrow \frac{1}{2}\log\left(\frac{y^2}{x^2} + 1\right) - \tan^{-1}\left(\frac{y}{x}\right) = C - \log(x)$$

Solving general ODEs is often difficult or not possible

Numerical Methods

- Seek to numerically approximate the solution
- Finite difference methods are common



- More advanced methods are available
 - Not the focus of today



My Teaching Philosophy

Idea: Promote a tutorial-like format that encourages active engagement.

Active Learning

- Mastery comes through deliberate practice
- Magnify class time to gain guided hands-on experiences



In-Class Exercises

- We will be using Jupyter notebooks with a Julia and/or a Python kernel today
- No downloads/installation are/is needed
- https://pulsipher.info/teaching/courses.html

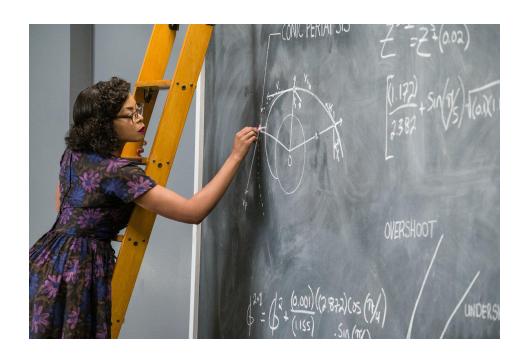








- Motivation
- Explicit Euler
- Implicit Euler
- Reaction Networks
- Other Methods





The Basics

Methodology

Consider a 1st order ODE

$$\frac{dy(t)}{dt} = f(y(t), t)$$
$$y(0) = y_0$$

• Define time steps Δt

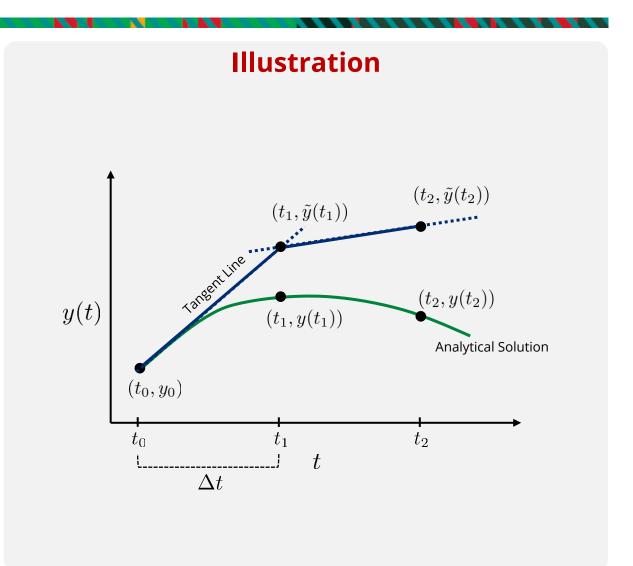
$$t \in [t_0, t_f] \qquad t_k = t_0 + k\Delta t$$

Approximate derivative as finite difference

$$\left. \frac{dy(t)}{dt} \right|_{t_k} \approx \frac{\tilde{y}(t_{k+1}) - \tilde{y}(t_k)}{\Delta t}$$

Define update rule

$$\tilde{y}(t_{k+1}) = \tilde{y}(t_k) + f(y(t_k), t_k) \Delta t$$





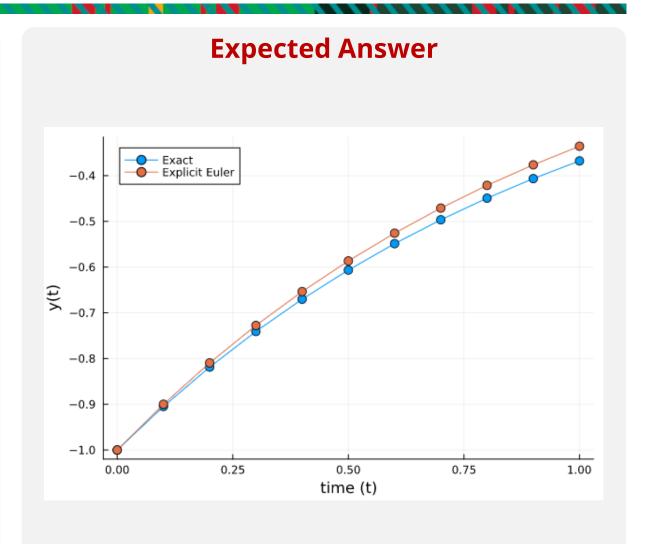
Exercise 1

Problem Setup

Solve the ODE

$$\frac{dy(t)}{dt} = e^{-t}$$
$$y(0) = -1$$

- Specifications
 - $t \in [0, 1]$
 - $\Delta t = 0.1$
- Plot the result against the analytical answer
- **Bonus:** Experiment with varied Δt





Simulating a System of ODEs

System of 1st order ODEs

General representation

$$\frac{dy_1(t)}{dt} = f_1(y_1, y_2, \dots, y_n)$$

$$\frac{dy_2(t)}{dt} = f_2(y_1, y_2, \dots, y_n)$$

$$\vdots$$

$$\frac{dy_n(t)}{dt} = f_n(y_1, y_2, \dots, y_n)$$

$$y_1(0) = y_{1,0}, y_2(0) = y_{2,0}, \dots, y_n(0) = y_{n,0}$$

Vectorize

$$\frac{d\mathbf{y}(t)}{dt} = \mathbf{f}(\mathbf{y}(t), t)$$
$$\mathbf{y}(0) = \mathbf{y_0}$$

We can represent a higher order ODE as a 1st order system

Vectorized Explicit Euler

Update rule uses vectorized representation

$$\tilde{\mathbf{y}}(t_{k+1}) = \tilde{\mathbf{y}}(t_k) + \mathbf{f}(\mathbf{y}(t_k), t_k) \Delta t$$

• Exercise 2: Simulate coupled ODEs w/ $\Delta t = 0.01$ and $t \in [0, 1]$

$$\frac{dx(t)}{dt} = -5x(t) + 5y(t)$$
$$\frac{dy(t)}{dt} = 14x(t) - 2y(t)$$
$$x(0) = y(0) = 1$$

Properties: Error

Local Truncation Error (LTE)

Recall update rule

$$\tilde{y}(t_{k+1}) = \tilde{y}(t_k) + f(y(t_k), t_k) \Delta t$$

Taylor series expansion of analytic solution

$$y(t_k + \Delta t) = y(t_k) + \Delta t \frac{dy(t)}{dt} \Big|_{t_k} + O(\Delta t^2)$$

Difference w/ explicit Euler

$$y(t_k + \Delta t) - \tilde{y}(t_{k+1}) = O(\Delta t^2)$$

Hence, the error incurred after one step is

$$O(\Delta t^2)$$

Global Truncation Error (GTE)

The number of steps

$$\frac{t - t_0}{\Delta t} \propto \frac{1}{\Delta t}$$

Multiplying this with the LTE, we get GTE that is

$$O(\Delta t)$$

Hence, explicit Euler is a first order method

Higher order methods are available



Properties: Stability

Exercise 3

• Simulate ODE w/ $\Delta t = 0.1$ in $t \in [0, 1]$

$$\frac{dy(t)}{dt} = -20y(t)$$
$$y(0) = 1$$

Compare w/ analytic answer

Linear Stability

Consider the linear ODE

$$\frac{dy(t)}{dt} = \lambda y(t)$$

For a stable solution we must have

$$|1 + \lambda \Delta t| < 1$$

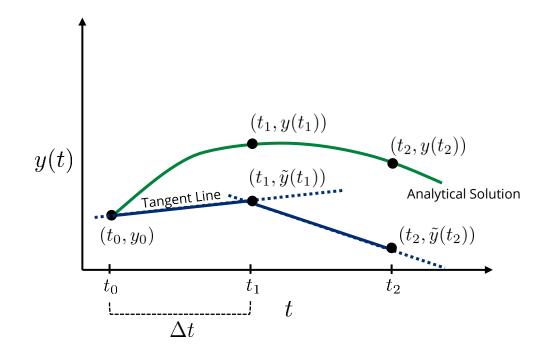
Stiff ODEs

- Systems that exhibit numerical instability
- Precise mathematical definition is nontrivial
- Common with reaction systems
 - Coexistence of small and large rate constants
- So, what can we do?



Outline

- Motivation
- Explicit Euler
- Implicit Euler
- Reaction Networks
- Other Methods





The Basics

Methodology

Consider a 1st order ODE

$$\frac{dy(t)}{dt} = f(y(t), t), \quad y(0) = y_0$$

• Define time steps Δt

$$t \in [t_0, t_f] \qquad t_k = t_0 + k\Delta t$$

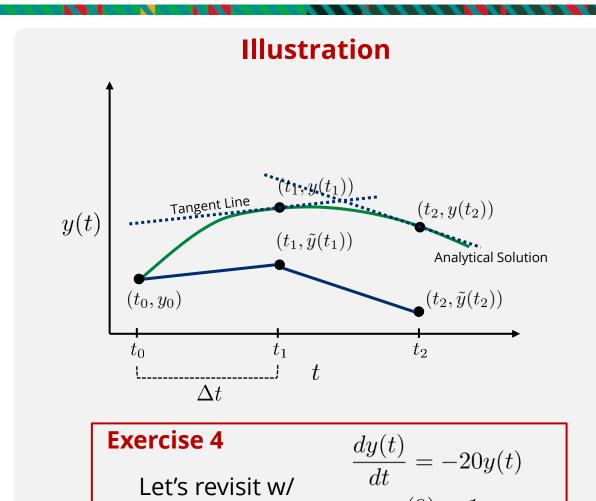
Approximate derivative as finite difference

$$\left. \frac{dy(t)}{dt} \right|_{t_{k+1}} \approx \frac{\tilde{y}(t_{k+1}) - \tilde{y}(t_k)}{\Delta t}$$

Define the update rule

$$\tilde{y}(t_{k+1}) = \tilde{y}(t_k) + \frac{f(y(t_{k+1}), t_{k+1})}{\Delta t}$$

• Implicit equation \rightarrow need to solve nonlinear eq.



 $\Delta t = 0.1 \text{ in } t \in [0, 1]$



System of ODEs

Generalize Methodology

Generalize implicit Euler for a system of ODEs

$$\frac{dy_1(t)}{dt} = f_1(y_1, y_2, \dots, y_n)$$

$$\frac{dy_2(t)}{dt} = f_2(y_1, y_2, \dots, y_n)$$

$$\vdots$$

$$\frac{dy_n(t)}{dt} = f_n(y_1, y_2, \dots, y_n)$$

$$y_1(0) = y_{1,0}, y_2(0) = y_{2,0}, \dots, y_n(0) = y_{n,0}$$

We vectorize

$$\tilde{\mathbf{y}}(t_{k+1}) = \tilde{\mathbf{y}}(t_k) + \mathbf{f}(\mathbf{y}(t_{k+1}), t_{k+1}) \Delta t$$

Now we must solve a system of nonlinear equations

Exercise 5

• Simulate coupled ODEs w/ $\Delta t = 0.01$ and $t \in [0, 1]$

$$\frac{dx(t)}{dt} = -5x(t) + 5y(t)$$
$$\frac{dy(t)}{dt} = 14x(t) - 2y(t)$$
$$x(0) = y(0) = 1$$



Properties

Error

- Local truncation error
 - Taylor series expansion

$$y(t_{k+1} - \Delta t) = y(t_{k+1}) - \Delta t \frac{dy(t)}{dt} \Big|_{t_{k+1}} + O(\Delta t^2)$$

Difference with rule gives

$$y(t_{k+1}) - \tilde{y}(t_{k+1}) = -O(\Delta t^2)$$

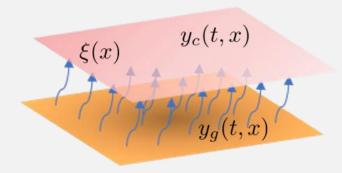
- Global truncation error
 - Multiply LTE with $\frac{1}{\Delta t} \rightarrow O(\Delta t)$
 - This is a 1st order method

Stability

Linear stability

$$\frac{dy(t)}{dt} = \lambda y(t) \qquad \frac{1}{1 - \lambda \Delta t} < 1$$

- Typically, stable for stiff systems
- Some exceptions (usually in certain PDEs)
 - e.g., diffusion with nonlinear diffusivity



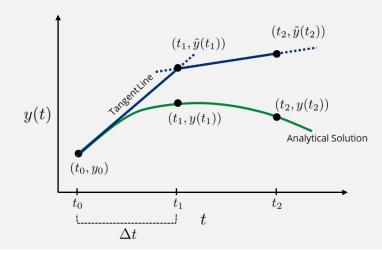


Explicit vs. Implicit Euler

Explicit Euler

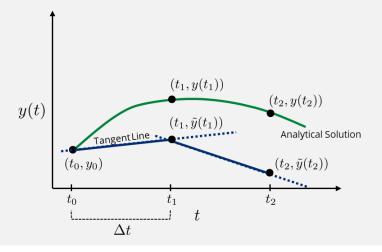
Simple and low computational cost

- Often unstable for stiff systems
- 1st order numerical method



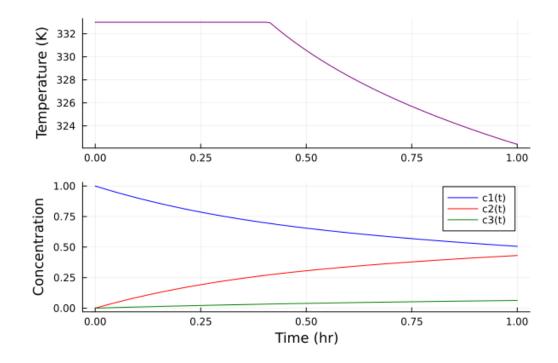
Implicit Euler

- Increased computational cost due to solving nonlinear equation at each step
- Stable for stiff systems
- 1st order numerical method





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Reaction Network Modeling

Simple ODE Model

Arrhenius equation for species i and reaction j

$$k_{ij}(t) = A_{ij} \exp\left(\frac{-E_{a,ij}}{RT(t)}\right)$$

Reaction rates

$$r_j(\mathbf{c},t) = \sum_{i \in I} k_{ij}(t) c_i^{\beta_{ij}}(t)$$

Species balances

$$\frac{dc_i(t)}{dt} = \sum_{j \in J} \gamma_{ij} r_j(\mathbf{c}, t), \quad i \in I$$

$$c_i(0) = c_{i,0}, i \in I$$

Example

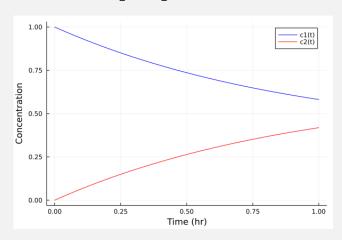
A ↔ B

$$\frac{dc_1(t)}{dt} = c_2(t)k_2(t) - c_1(t)k_1(t)$$

$$\frac{dc_2(t)}{dt} = c_1(t)k_1(t) - c_2(t)k_2(t)$$

$$c_1(0) = 1, \ c_2(0) = 0$$

Simulate with $t \in [0, 1]$ at T = 325





Exercise: Batch Reactor

Exercise 6

• Simulate the following reaction system using explicit Euler for $t \in [0, 1]$

$$A \rightleftharpoons B$$
$$A \rightleftharpoons C$$

• Experiment with different choices of Δt

Problem Information

$$R = 1.987$$

$$A = \begin{bmatrix} 3.6362e6 & 190.6879 \\ -2.5212e16 & 0 \\ 0 & -8.7409e24 \end{bmatrix}$$

$$E_a = \begin{bmatrix} 10000 & 5000 \\ 25000 & 0 \\ 0 & 40000 \end{bmatrix} \qquad \beta = 1 \qquad \gamma = \begin{bmatrix} -1 & -1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$T(t) = \begin{cases} 333, & t < 0.5 \\ 325, & t \ge 0.5 \end{cases} \qquad \mathbf{c}_0 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$



Optimizing Reaction Networks

- We can optimize certain outcomes using numerical approximations of ODEs and optimization software
- For instance, let's maximize the final concentration of B by controlling T(t)

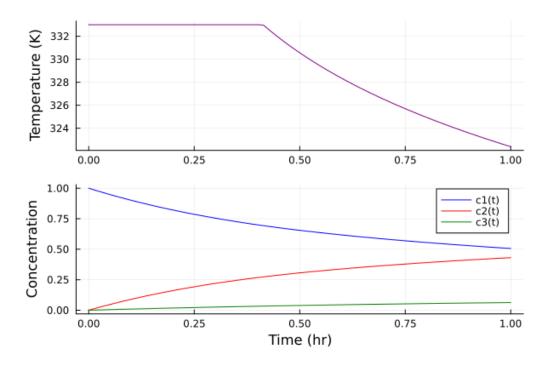
$$\max \quad c_2(t_f)$$
s.t.
$$\frac{dc_i(t)}{dt} = \sum_{j \in J} \gamma_{ij} r_j(\mathbf{c}, t), \quad t \in [0, 1]$$

$$0 \le \mathbf{c}(t) \le 1, \qquad t \in [0, 1]$$

$$\underline{T} \le T(t) \le \overline{T}, \qquad t \in [0, 1]$$

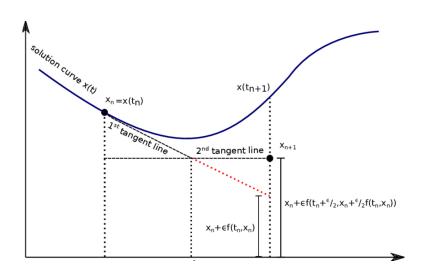
$$\mathbf{c}(0) = \mathbf{c}_0$$







- Motivation
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- Other Methods

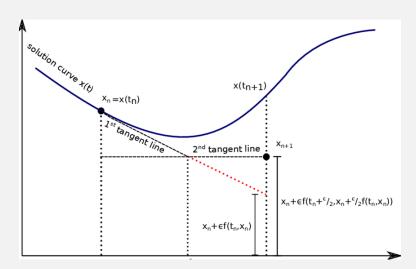




More Advanced Methods

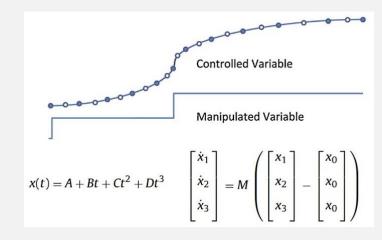
Runge-Kutta

- Family of explicit and implicit iterative methods
- Various orders based on GTE $O(h^p)$
 - 1st order methods are the Euler methods
 - 4th order methods are popular



Orthogonal Collocation over Finite Elements

- The discretization uses finite elements
- We approximate the solution in each element as a polynomial function
- End up solving a system of linear equations





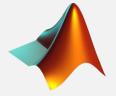
Common Simulation Tools

ODE Integrators

- Common in scripting languages
- Provide numerical solutions to ODE systems









Symbolic Solvers

- Can provide analytic solutions when possible
- Typically, not used for large problems





Optimization Tools

 Can incorporate differential equations when solving optimization problems







Problem Specific

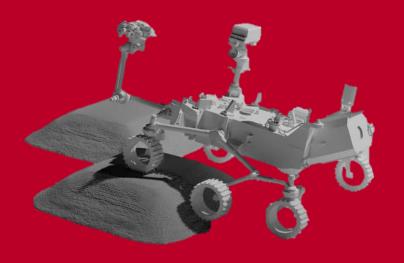
Simulate dynamics for particular systems







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