### **Neuromechanics of Human Motion**

Dynamical Systems and ODEs - A Primer

Joshua Cashaback, Ph.D.



### Recap

- 1. download and run Python (or another language)
- 2. https://www.anaconda.com/distribution/
- 3. plot functions
- 4. Any questions about the course?



### **Lecture Objectives**

- 1. Learn about dynamical systems
- 2. Understand and carry out numerical integration (Euler, RK4)
- 3. Program numerical integrators
- 4. convert nth order ODEs to n 1st order ODEs



## Why do we need to know ODEs?

A lot of nature can be better understood using differential equations

Some models in this course using ODEs:

- 1. Nerve Models (Hodgkin-Huxley model)
- 2. Muscle Models (e.g., crossbridge & Hill-type)
- 3. Limb Dynamics
- 4. Control Models (LQG)
- 5. Adaptation Models (Multiple time-scales)



# Behaviour of a Static System

### Static System

- a. An output that only depends on an input
- b. e.g., massless spring (theoretical construct)
- c. Hooke's Law (F = -kx)



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- d. change force???



# Behaviour of a Static System

### Static System

- a. An output that only depends on an input
- b. e.g., massless spring (theoretical construct)
- c. Hooke's Law (F = -kx)
- d. change force = instantaneous length change



### **Dynamical System**

A particle or ensemble of particles whose state varies over time and thus obeys differential equations involving time derivatives



### **Dynamical System**

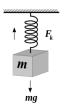
A particle or ensemble of particles whose state varies over time and thus obeys differential equations involving time derivatives

Spring length & mass position (depends on...)

→ acceleration of mass→ sum of forces

 $\rightarrow$  input F, mg,  $F_k*$ 

 $\rightarrow$  spring length



Acceleration of the mass *depends* on its position making this a dynamical system

### **Dynamical System**

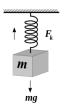
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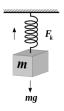
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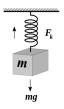
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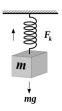
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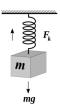
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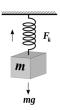
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#### State Variables

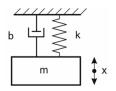
State Variables (initial conditions): the smallest possible subset of system variables that can represent the entire state of the system at any given time

#### **State Derivatives**

the derivatives of the state variables

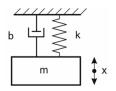
Dynamical Systems are characterized by differential equations that relate the state derivatives to state variables





$$m\ddot{x} = -kx - b\dot{x} + mg$$

what are the state derivatives and state variables?
what are the state derivatives (acceleration and velocity) and state
variables (velocity and position)?

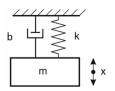


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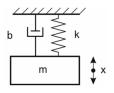
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# **System Order**

The system order is defined as the highest derivative that appears in the differential equation.

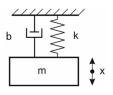


$$m\ddot{x} = -b\dot{x} - kx + mg$$

what is the system order(second order system)'

# **System Order**

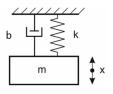
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 $m\ddot{x}=-b\dot{x}-kx+mg$  what is the system order second order

# **System Order**

The system order is defined as the highest derivative that appears in the differential equation.



$$m\ddot{x} = -b\dot{x} - kx + mg$$
 what is the system order(second order system)?

### **Coupled Differential Equations**

- 1. Knowledge from one equation is required to solve another equation (and also sometimes vice-versa)
- 2. Take for example the following the Lotka-Volterra equations (predator-prey model):

$$\dot{x} = x(\alpha - \beta y) \quad (1)$$

$$\dot{y} = -y(\gamma - \delta x) \quad (2)$$

- a. state variables (x = prey population, y = predator population)
- b. state derivatives ( $\dot{x}=$  prey reproduction rate,  $\dot{y}=$  predator reproduction rate



### **Integration Schemes**

### Common Integration Schemes:

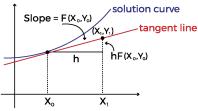
- 1. Euler
- 2. Runge-Kutta (RK4)



### Integration Schemes — Euler

$$dy/dt = f(t,y); y(t_0) = y_0$$
  $y_{n+1} = y_n + h * f(t_n, y_n)$   $t_{n+1} = t_n + h$   $newvalue = oldvalue + stepsize \cdot slope$ 

### NOTE FOR GRAPH: replace t with X!





## **Euler** — **Simple Example**

$$dy/dt = y' = 2t$$

$$s.t., h = 0.5; IC: t_0 = 0, y_0 = 0; solve until t = 0.5s (1 steps)$$



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white-board

### **Euler** — **Simple Example**

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#### white-board

n	t <sub>n</sub>	Уn	$f_n = f(t_n, y_n)$	$h \cdot f_n$	$y_n + h \cdot f_n$
0	0.0	0.0	0	0	0
1	0.5	0.0	1	0.5	0.5
2	1.0	0.5	2	1.0	1.5
3	1.5	1.5	3	1.5	3

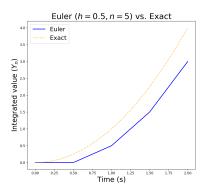


## **Euler** — Sample Python Code

```
#Euler's Method
import numpy, math, matplotlib
from pylab import *
t0, y0, h, n = 0.0, 0, 0.5, 5 \#initial conditions(<math>t0, y0), step size, number of steps
\#step, time, current integrated value (y_{n})
N, T, YN, = np.zeros(n), np.zeros(n), np.zeros(n)
# function (derivative), function * stepsize, n+1 integrated value (y_{-}\{n+1\})
F. FH. YN1 = np. zeros(n), np. zeros(n), np. zeros(n)
for i in range(n):
    v1 = v0 + h*(2*t0)
    t1 = t0 + h
    N[i], T[i], YN[i], F[i], FH[i], YN1[i] = i, to, yo, 2*to, h*(2*to), y1
    v0.t0 = v1.t1
plot(T, YN, linestyle = '-', linewidth = 2.0, color = 'blue')
show()
```

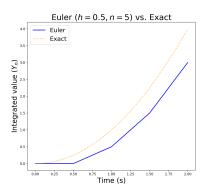
Write code to solve ODE, plot the exact value, change the steps (2001) and step size (0.001)—what do you notice?

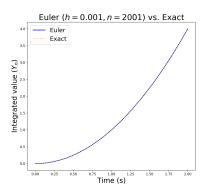
# **Euler** — Comparing step size





# **Euler** — Comparing step size



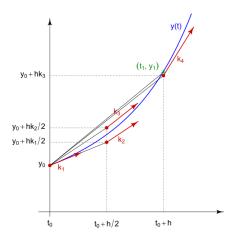




## **Euler Integration**

- 1. intuitive
- 2. computationally fast
- 3. can produce compounding errors (solutions = use small step sizes or RK4)
- 4. error calculations outside the scope of this course







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

$$t_{n+1} = t_n + h$$

$$k_1 = h \cdot f(t_n, y_n),$$

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

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

$$k_4 = h \cdot f(t_n + h, y_n + k_3).$$

$$dy/dt = y' = 2t$$

$$s.t., h = 0.5; IC : t_0 = 0, y_0 = 0; solve until t = 0.5s (1 step)$$

$$k1t = t_0$$

$$k1y = y_0$$

$$k1 = h(2 \cdot k1t)$$

$$k2t = t_0 + \frac{h}{2}$$

$$k2y = y_0 + \frac{k1}{2}$$

$$k2 = h(2 \cdot k2t)$$

$$k3t = t_0 + \frac{h}{2}$$

$$k3y = y_0 + \frac{k2}{2}$$

$$k3 = h(2 \cdot k3t)$$

$$k4t = t_0 + h$$

$$k4y = y_0 + k3$$

$$k4 = h(2 \cdot k4t)$$

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

### **Solution** — Runge-Kutta

$$dy/dt = y' = 2t$$

$$s.t., h = 0.5; IC : t_0 = 0, y_0 = 0; solve until t = 0.5s (1 step)$$

$$k1t = t_0; \quad [0 = 0]$$

$$k1y = y_0; \quad [0 = 0]$$

$$k1 = h(2 \cdot k1t); \quad [0 = 0.5(2 \cdot 0)]$$

$$k2t = t_0 + \frac{h}{2}; \quad \left[0.25 = 0 + \frac{0.5}{2}\right]$$

$$k2y = y_0 + \frac{k1}{2}; \quad \left[0 = 0 + \frac{0}{2}\right]$$

$$k2 = h(2 \cdot k2t); \quad \left[0.25 = 0.5(2 \cdot 0.25)\right]$$

### Solution — Runge-Kutta

$$k3t = t_0 + \frac{h}{2}; \quad \left[ 0.25 = 0 + \frac{0.5}{2} \right]$$

$$k3y = y_0 + \frac{k2}{2}; \quad \left[ 0.125 = 0 + \frac{0.25}{2} \right]$$

$$k3 = h(2 \cdot k3t); \quad \left[ 0.25 = 0.5(2 \cdot 0.25) \right]$$

$$k4t = t_0 + h; \quad \left[ 0.5 = 0 + 0.5 \right]$$

$$k4y = y_0 + k3; \quad \left[ 0.25 = 0 + 0.25 \right]$$

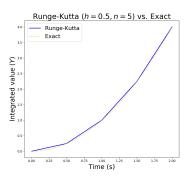
$$k4 = h(2 \cdot k4t); \quad \left[ 0.5 = 0.5(2 \cdot 0.5) \right]$$

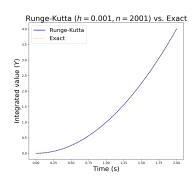
$$y_{n+1} = y_n + \frac{1}{6}(k_1 + 2k_2 + 2k_3 + k_4); \quad \left[ 0.25 = 0 + \frac{1}{6}(0 + 0.5 + 0.5 + 0.5) \right]$$

### **RK4** — Sample Python Code

```
#4th order Runge Kutta
#Equation: dy/dt = 2t; initial conditions: y(0) = 0, t(0) = 0, h = 0.5
\#exact solution y = t^2
import numpy, math, matplotlib
from pylab import *
\#t0, y0, h, n = 0, 0, 0.5, 5 \#initial conditions, step size, number of steps
T, YN = np.zeros(n), np.zeros(n) #place y0 in array
for i in range(n):
    k1t, k1y = t0, y0
    k1 = (2 * k1t) * h
    k2t, k2y = t0 + h/2.0, y0 + k1/2.0
    k2 = (2 * k2t) * h
    k3t. k3v = t0 + h/2.0. v0 + k2/2.0
    k3 = (2*k3t) * h
    k4t. k4v = t0 + h. v0 + k3
    k4 = (2*k4t) * h
    v1 = v0 + (1/6.0)*(k1 + 2*k2 + 2*k3 + k4)
    t1 = t0 + h
    T[i], YN[i] = t0, y0
    y0, t0 = y1, t1
plot(T, YN, linestyle = '-', linewidth = 2.0, color = 'blue')
show()
```

### RK4 vs. Exact



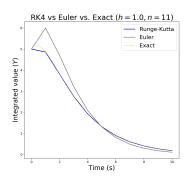


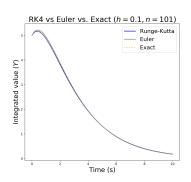


### RK4 — Sample Python Code II

```
#RK4
\#Equation: dy/dt = 3*exp(-t) - 0.4y; initial conditions: t(0) = 0, y(0) = 5, h = 1.5
#exact solution y = 10*exp(-0.4t) - 5*exp(-t)
#Runge-Kutta
t0, y0, h, n=0, 0, 1.0, 11 #initial conditions, step size, number of steps
\#t0, y0, h, n=0, 5, 0.1, 101 \#initial conditions, step size, number of steps
T, YN = np.zeros(n), np.zeros(n) #place y0 in array
for i in range(n):
    k1t, k1y = t0, y0
    k1 = (3*exp(-k1t) - 0.4*k1v) * h
    k2t, k2y = t0 + h/2.0, y0 + k1/2.0
    k2 = (3*exp(-k2t) - 0.4*k2v) * h
    k3t. k3v = t0 + h/2.0. v0 + k2/2.0
    k3 = (3*exp(-k3t) - 0.4*k3y) * h
    k4t. k4v = t0 + h. v0 + k3
    k4 = (3*exp(-k4t) - 0.4*k4v) * h
    v1 = v0 + (1/6.0)*(k1 + 2*k2 + 2*k3 + k4)
    t1 = t0 + h
    T[i], YN[i] = t0, y0
    y0, t0 = y1, t1
plot(T, YN, linestyle = '-', linewidth = 2.0, color = 'blue')
show()
                                                                           INIVERSITYO
                                                 26 / 43
```

### RK4 vs. Euler vs. Exact







### **Runge-Kutta Integration**

- 1. less intuitive
- 2. computationally intense
- 3. better approximation / smaller errors



### **ODE** to Joy

- 1. Python (and other languages) have numerical integrators to make your life easier!
- 2. odeint
- 3. RK4 with adaptive step sizes.

Lorenz Attractor (coupled ODE):

$$\frac{dx}{dt} = \sigma(y - x)$$

$$\frac{dy}{dt} = (\rho - z)x - y$$

$$\frac{dz}{dt} = xy - \beta z$$



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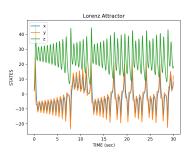


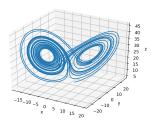
### **Lorenz Attractor** — Sample Python Code

```
# Attractive Lorenz
\#dx/dt = sigma(y-x)
\#dv/dt = x(rho - z) - v
\#dz/dt = x*v-beta*z
# inputs: state variables (x, y, z), time vector (t)
# outputs: state derivatives (xd, yd, zd)
from scipy integrate import odeint
import numpy as np
from pylab import *
# function defining differential equation
def Lorenz(state . t):
    x, y, z = \text{state}[0], \text{state}[1], \text{state}[2] \# \text{unpack the state vector}
    sigma, rho, beta = 10.0, 28.0, 8/3. # constants
    xd, yd, zd = sigma * (y - x), (rho-z) * x - y, x * y - beta * z # state derivatives
    return [xd, yd, zd]
# initial conditions (x, y, z)
state0 = np. array([2.0. 3.0. 4.0])
# time vector
tstart, tend, timestep = 0.0, 30.0, 0.01
t = arange(tstart, tend, timestep)
state = odeint(Lorenz, state0, t)
```

#### **Lorenz Attractor**

#### States vs Time & Phase Space





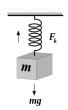


## **Converting Systems to 1st-Order ODEs**

- 1. Reducing nth-order ODEs to 1st-order ODEs
- 2. Partial Differential Equations to ODEs (outside the scope of this course)



# Convert higher order systems to 1st order ODEs



$$m\ddot{x} = -kx + mg$$
$$\ddot{x} = -\frac{k}{m}x + g$$

Here we want to convert this *2nd* order system into *two* ODEs White board example



# Solution — Convert higher order systems to 1st order ODEs

$$\ddot{x} = -\frac{k}{m}x + g \quad (1)$$

We can convert an nth order differential equation into n 1st order ODEs by using a change of variable. Lets define two new functions.

$$x_1 = x$$
 (2)

$$x_2 = \dot{x}$$
 (3)

Now, take the derivative of eq. (2) and (3):

$$\dot{x_1} = \dot{x}$$
 (4)



# Solution — Convert higher order systems to 1st order ODEs

Equations (4) and (5) will become our 2 first-order ODEs with the appropriate substitutions.

Sub (3) into (4)

$$\dot{x_1} = x_2$$
 (6)

Sub (1) into (5)

$$\dot{x_2} = -\frac{k}{m}x + g \quad (7)$$

Sub (2) into (7)

$$\dot{x_2} = -\frac{k}{m}x_1 + g$$
 (8)



# Solution — Convert higher order systems to 1st order ODEs

We now have our two 1st order ODEs (Eq. 6 and 8)!

$$\dot{x_1} = x_2$$

$$\dot{x_2} = -\frac{k}{m}x_1 + g$$

Which we can express in matrix form as:

$$\begin{bmatrix} \dot{x_1} \\ \dot{x_2} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\frac{k}{m} & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ g \end{bmatrix}$$

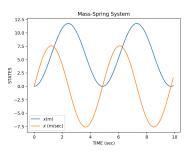
### Mass-Spring — Sample Python Code

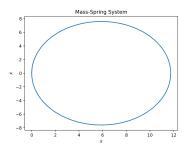
```
from scipy, integrate import odeint
import numpy as np
from pylab import *
# function defining differential equation
def MassSpring(state, t):
    x. xd = state # unpack the state vector
    k, m, g = 2.5, 1.5, 9.8 \# constants
    xdd = ((-k*x)/m) + g \# compute acceleration xdd
    # return the two state derivatives
    return [xd. xdd]
# initial conditions
state0 = np. array([0.0.0.0])
# time vector
tstart, tend, timestep = 0.0, 10.0, 0.1
t = arange(tstart, tend, timestep)
state = odeint(MassSpring, state0, t)
```



## **Spring Mass System**

#### States vs Time & Phase Space







#### **Take Homes**

- 1. Understand what is a dynamical system
- 2. Perform numerical integration by hand (Euler, RK4)
- 3. Program numerical integrators (Euler, RK4, odeint)
- 4. Convert nth order ODEs to n 1st order ODEs



# **QUESTIONS???**



### **Next Week**

- 1. Sensory Organs
- 2. Action Potentials
- 3. Nerve Models (Hodgkin-Huxley model)



### **Assignment**

see handout Office Hours



### **Acknowledgements**

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