

SECTION 9: ENGINEERING APPLICATIONS

ENGR 112 – Introduction to Engineering Computing

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Systems of Equations

Systems of Equations

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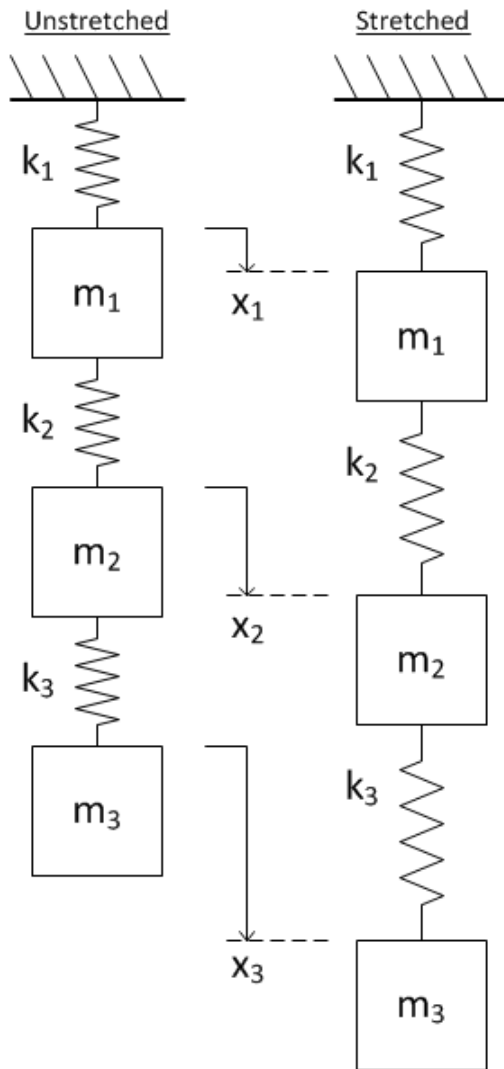
- Systems of equations common in all engineering disciplines
- For N unknown variables, we need a system of N equations
 - ▣ Can represent in matrix form:

$$\mathbf{Ax} = \mathbf{b}$$

- A : $N \times N$ matrix of known, constant coefficients
 - x : $N \times 1$ vector of unknowns
 - b : $N \times 1$ vector of known constants
- Many tools exist for solving:
 - ▣ By hand – substitution, Gaussian elimination, etc.
 - ▣ Scientific calculators
 - ▣ Here, we will look at the tools available within MATLAB

A System of Equations – Example

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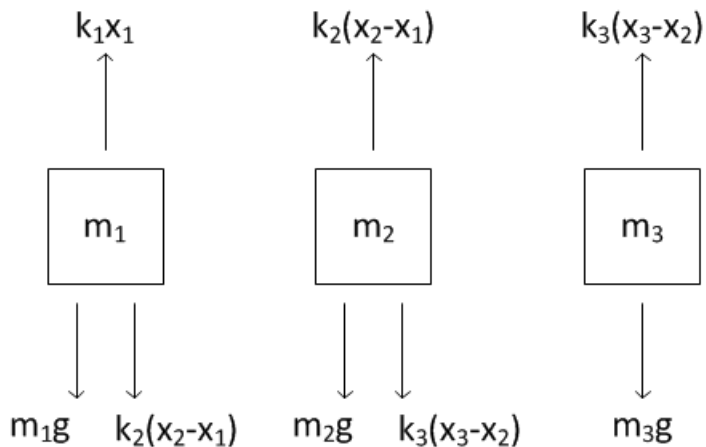


- Consider the following scenario
- Three masses
 - ▣ m_1 , m_2 , and m_3
- Three springs
 - ▣ k_1 , k_2 , k_3
- Connected in series and suspended
- Determine the displacement of each mass from its unstretched position

A System of Equations – Example

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- Three unknown displacements: x_1, x_2, x_3
 - ▣ Need three equations to find displacements
- Apply Newton's second law to each mass



- Three equations result:

$$m_1\ddot{x}_1 = m_1g + k_2(x_2 - x_1) - k_1x_1$$

$$m_2\ddot{x}_2 = m_2g + k_3(x_3 - x_2) - k_2(x_2 - x_1)$$

$$m_3\ddot{x}_3 = m_3g - k_3(x_3 - x_2)$$

A System of Equations – Example

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- Steady-state, so no acceleration: $\ddot{x}_i = 0, \forall i$

$$m_1 g + k_2(x_2 - x_1) - k_1 x_1 = 0$$

$$m_2 g + k_3(x_3 - x_2) - k_2(x_2 - x_1) = 0$$

$$m_3 g - k_3(x_3 - x_2) = 0$$

- Rearranging

$$(k_1 + k_2)x_1 - k_2x_2 + 0x_3 = m_1g$$

$$-k_2x_1 + (k_2 + k_3)x_2 - k_3x_3 = m_2g$$

$$0x_1 - k_3x_2 + k_3x_3 = m_3g$$

A System of Equations – Example

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- Our system of three equations

$$(k_1 + k_2)x_1 - k_2x_2 + 0x_3 = m_1g$$

$$-k_2x_1 + (k_2 + k_3)x_2 - k_3x_3 = m_2g$$

$$0x_1 - k_3x_2 + k_3x_3 = m_3g$$

can be put into matrix form

$$\begin{bmatrix} (k_1 + k_2) & -k_2 & 0 \\ -k_2 & (k_2 + k_3) & -k_3 \\ 0 & -k_3 & k_3 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} m_1g \\ m_2g \\ m_3g \end{bmatrix}$$

A System of Equations – Example

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$$\begin{bmatrix} (k_1 + k_2) & -k_2 & 0 \\ -k_2 & (k_2 + k_3) & -k_3 \\ 0 & -k_3 & k_3 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} m_1 g \\ m_2 g \\ m_3 g \end{bmatrix}$$

- We can rewrite this matrix equation as

$$\mathbf{Ax} = \mathbf{b}$$

- Can apply tools of linear algebra to determine the vector of unknown displacements

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

Solution Using Matrix Inverse

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- We have a system of equations:

$$\mathbf{Ax} = \mathbf{b}$$

- If a solution exists, then the coefficient matrix, \mathbf{A} , is invertible

- ▣ Not always the case

- Left-multiply by \mathbf{A}^{-1} to solve for the vector of unknowns, x

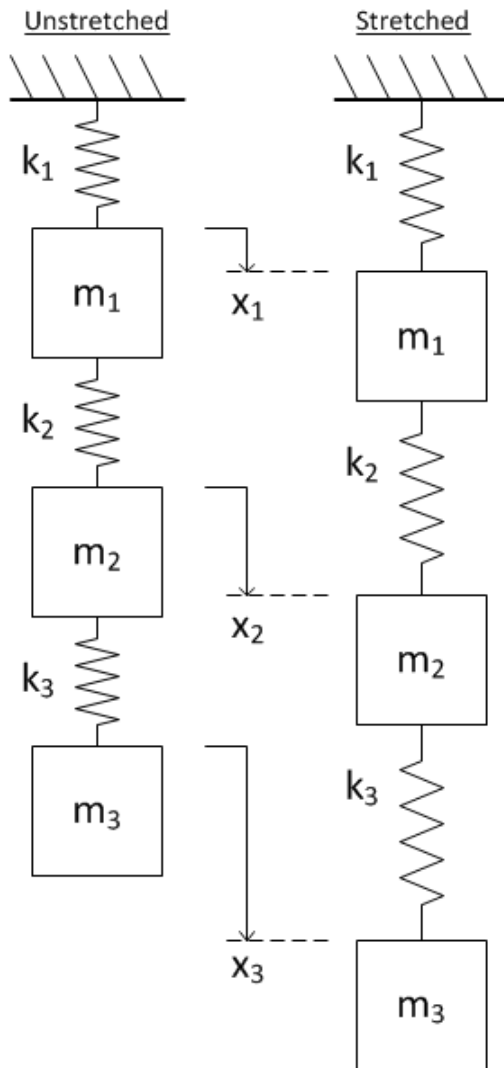
$$\mathbf{A}^{-1}\mathbf{Ax} = \mathbf{A}^{-1}\mathbf{b}$$

$$\mathbf{Ix} = \mathbf{A}^{-1}\mathbf{b}$$

$$\mathbf{x} = \mathbf{A}^{-1}\mathbf{b}$$

Solution Using Matrix Inverse

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- Our linear system is described by the matrix equation

$$\begin{bmatrix} (k_1 + k_2) & -k_2 & 0 \\ -k_2 & (k_2 + k_3) & -k_3 \\ 0 & -k_3 & k_3 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} m_1 g \\ m_2 g \\ m_3 g \end{bmatrix}$$

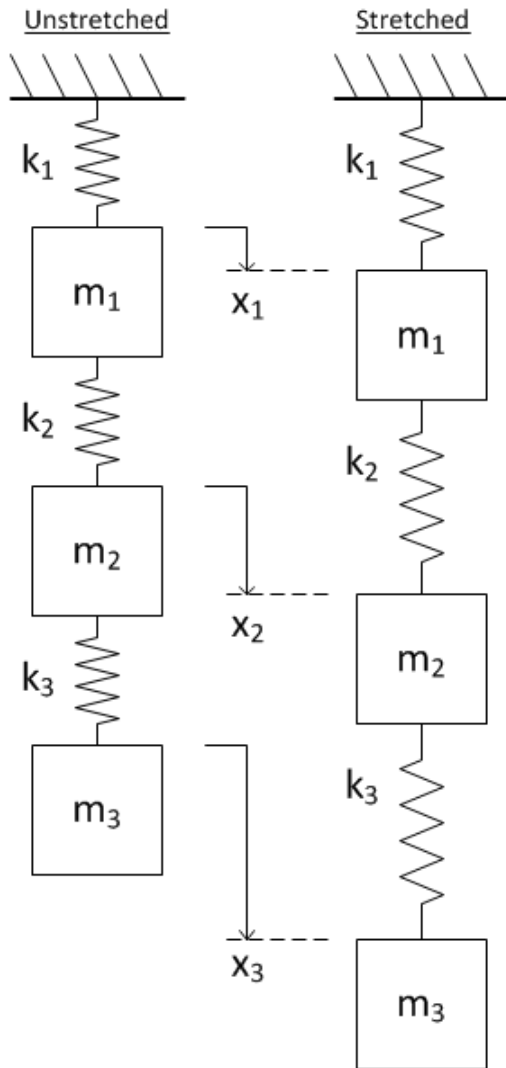
$$\mathbf{Ax} = \mathbf{b}$$

- Find the displacements, \mathbf{x} , for the following system parameters

- ▣ $k_1 = 500 \frac{N}{m}$, $k_2 = 800 \frac{N}{m}$, $k_3 = 400 \frac{N}{m}$
- ▣ $m_1 = 3kg$, $m_2 = 1kg$, $m_3 = 7kg$

Solution Using Matrix Inverse

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```
Editor - C:\Users\webbky\Box\KWebb\Classes\ENGR112\Notes\MATLAB...  
1   % linSysEx.m  
2  
3   clear all; clc  
4  
5   % spring constants [N/m]  
6   k1 = 500;  
7   k2 = 800;  
8   k3 = 400;  
9  
10  % masses [kg]  
11  m1 = 3;  
12  m2 = 1;  
13  m3 = 7;  
14  
15  % grav. accel. [m/s^2]  
16  g = 9.81;  
17  
18  A = [k1+k2,   -k2,   0;...  
19        -k2, k2+k3, -k3;...  
20         0,   -k3,  k3];  
21  
22  b = [m1*g; m2*g; m3*g];  
23  
24  x = inv(A) * b  
25
```

```
Command Window  
  
x =  
  
    0.2158  
    0.3139  
    0.4856  
  
fx >> |
```

$$x_1 = 21.6\text{cm}, \quad x_2 = 31.4\text{cm}, \quad x_3 = 48.6\text{cm}$$

Solution Using `mldivide.m`, `\`

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- MATLAB has a second division function
 - ▣ **Matrix left division:** `mldivide.m`, `\`

- Use `mldivide` to solve

$$\mathbf{Ax} = \mathbf{b}$$

- If \mathbf{A}^{-1} exists, then

$$\mathbf{x} = \mathbf{A} \backslash \mathbf{b};$$

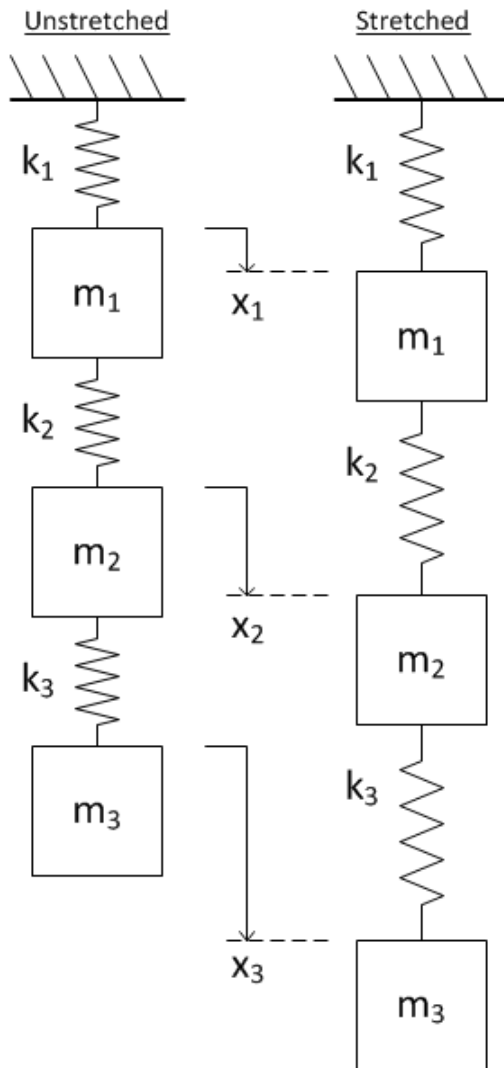
is equivalent to

$$\mathbf{x} = \text{inv}(\mathbf{A}) * \mathbf{b};$$

- But, does not calculate \mathbf{A}^{-1}
 - ▣ Faster and more numerically robust

Solution Using `mldivide.m`, \

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```
Editor - C:\Users\webbk\Box\KWebb\Classes\ENGR112\Notes\MATLAB\...  
1  % linSysEx.m  
2  
3  clear all; clc  
4  
5  % spring constants [N/m]  
6  k1 = 500;  
7  k2 = 800;  
8  k3 = 400;  
9  
10 % masses [kg]  
11 m1 = 3;  
12 m2 = 1;  
13 m3 = 7;  
14  
15 % grav. accel. [m/s^2]  
16 g = 9.81;  
17  
18 A = [k1+k2, -k2, 0;...  
19      -k2, k2+k3, -k3;...  
20      0, -k3, k3];  
21  
22 b = [m1*g; m2*g; m3*g];  
23  
24 x = inv(A)*b  
25  
26 x = A\b  
27
```

```
Command Window  
  
x =  
  
    0.2158  
    0.3139  
    0.4856  
  
x =  
  
    0.2158  
    0.3139  
    0.4856  
  
fx >> |
```

$$x_1 = 21.6\text{cm}, \quad x_2 = 31.4\text{cm}, \quad x_3 = 48.6\text{cm}$$

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Numerical Differentiation

Differentiation

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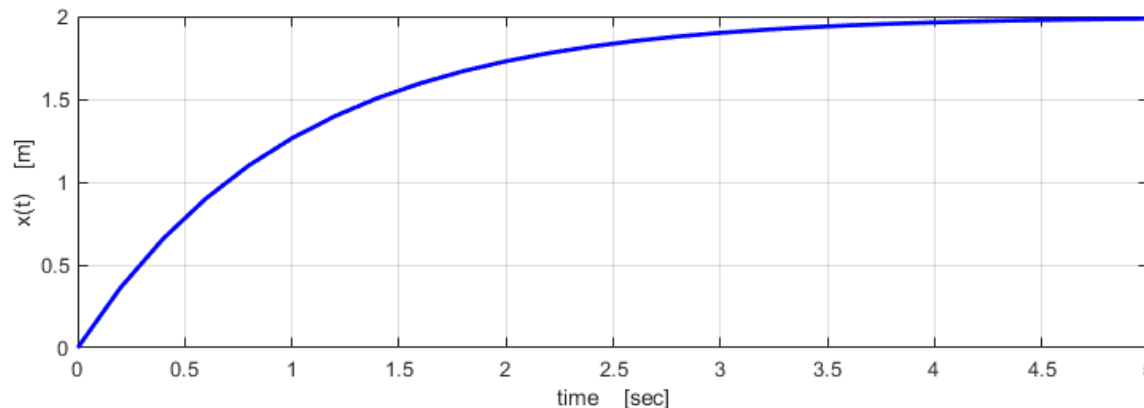
- As engineers, we often deal with ***rates***
 - ▣ ***Changes in on quantity with respect to another***
- Often these are rates with respect to time, e.g.:
 - ▣ ***Velocity***: change in position w.r.t. time
 - ▣ ***Acceleration***: change in velocity w.r.t. time
 - ▣ ***Power***: time rate of energy transfer
 - ▣ Changes in ***voltage*** or ***current*** w.r.t. time
 - ▣ Etc.
- Mathematically, these rates are described by ***derivatives***
- Calculation of a derivative is ***differentiation***

Derivatives

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- For example, consider an object whose ***position as a function of time*** is

$$x(t) = 2 \text{ m} \cdot (1 - e^{-t})$$



- At any point in time, t , the object's velocity, $v(t)$, is given by the time rate of change of position
 - ▣ That is, the ***derivative w.r.t. time*** of position

$$v(t) = \frac{dx}{dt} = \dot{x}(t) = x'(t)$$

Derivatives

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- Velocity is the **rate of change** of position w.r.t. time

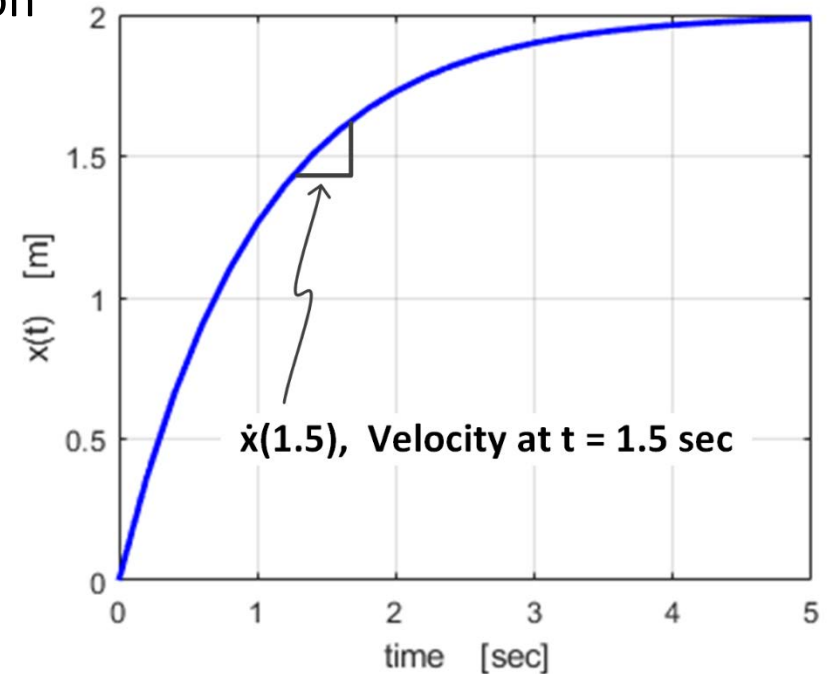
- **Slope** of the position graph
- The **derivative** of position

$$v(t) = \frac{dx}{dt} = \dot{x}(t)$$

- You know/will learn to differentiate mathematical expressions, e.g.

$$x(t) = 2 \text{ m} \cdot (1 - e^{-t})$$

$$\dot{x}(t) = v(t) = 2 \frac{\text{m}}{\text{s}} \cdot e^{-t}$$

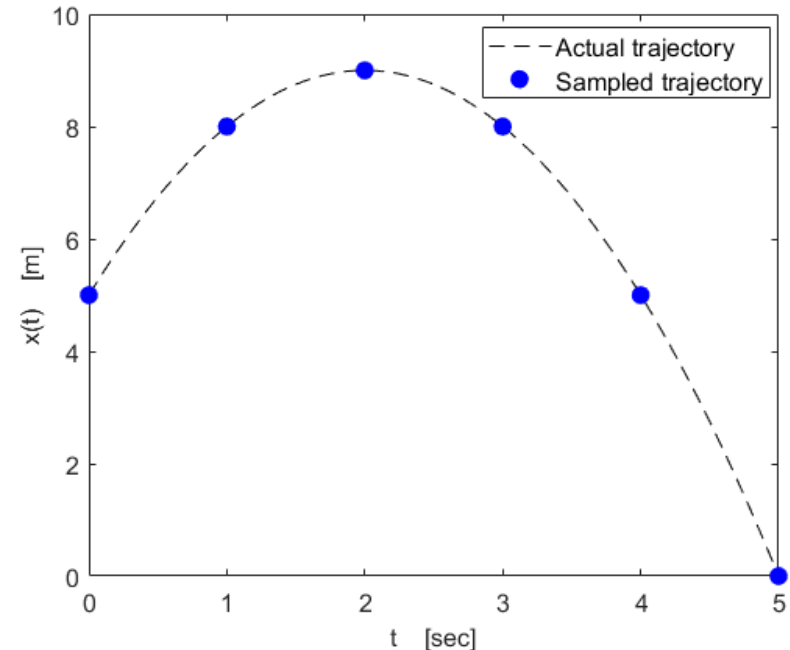


- Often, we would like to calculate a derivative, but we do not have a mathematical expression, e.g.
 - Measurement data
 - Simulation data, etc.
- Then, we can **approximate** the derivative **numerically**

Numerical Differentiation

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- Data we want to differentiate are **discrete**
 - ▣ **Sampled** – not continuous
 - ▣ Data only exist at **discrete** points in time
 - ▣ Result of simulation or measurement, etc.
- **Numerical differentiation**
 - ▣ Approximation of the slope at each discrete data point
- Several methods exist for numerical differentiation
 - ▣ Varying complexity and accuracy
- Here, we'll focus on the **forward difference method**



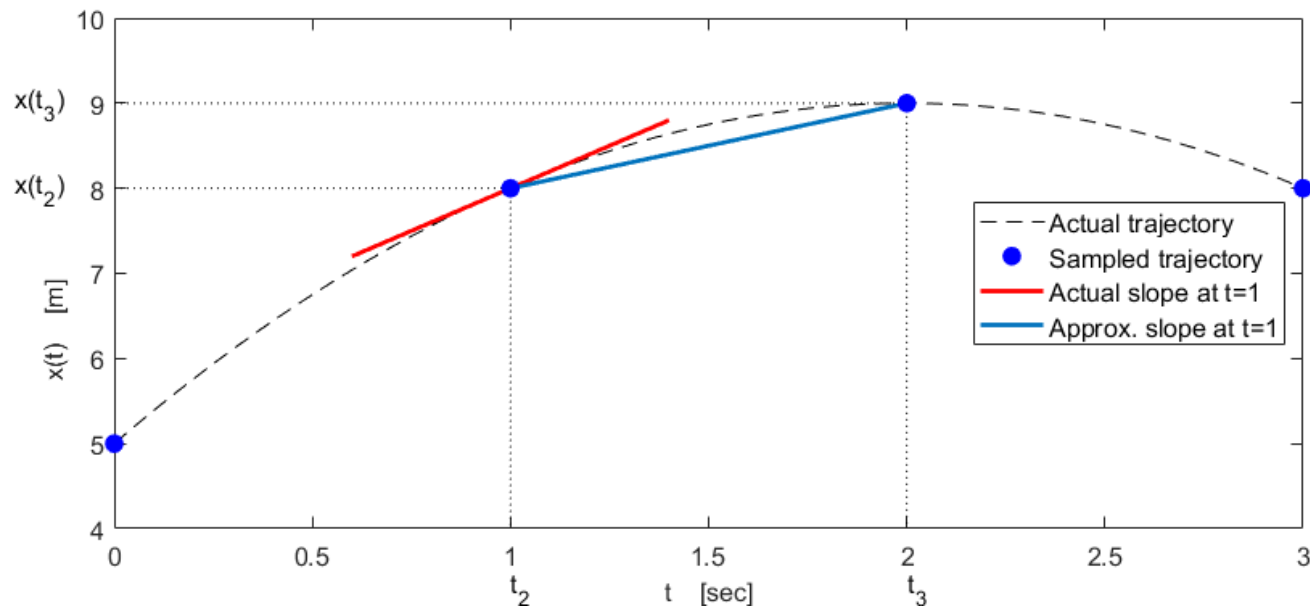
Forward Difference Method

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□ **Forward difference method**

- Approximate $\dot{x}(t_i)$ using $x(t_i)$ and $x(t_{i+1})$
 - Data at the current time point and one time step **forward**

$$\dot{x}(t_i) \approx \frac{x(t_{i+1}) - x(t_i)}{t_{i+1} - t_i} = \frac{\Delta x}{\Delta t}$$



Forward Difference in MATLAB

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- Numerical differentiation in MATLAB

$$\dot{x}(t_i) \approx \frac{x(t_{i+1}) - x(t_i)}{t_{i+1} - t_i} = \frac{\Delta x}{\Delta t}$$

- We would have:
 - ▣ Time vector, t
 - Possibly, but not necessarily evenly spaced
 - ▣ Data vector, $x(t)$
 - Function to be differentiated
- Use `diff .m` to calculate Δx and Δt vectors
- Use array division, `./`, to calculate $\Delta x/\Delta t$ at each time point
 - ▣ No $\Delta x/\Delta t$ value at the last time point

Numerical Differentiation – Example

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- Consider again an object whose position is given by:

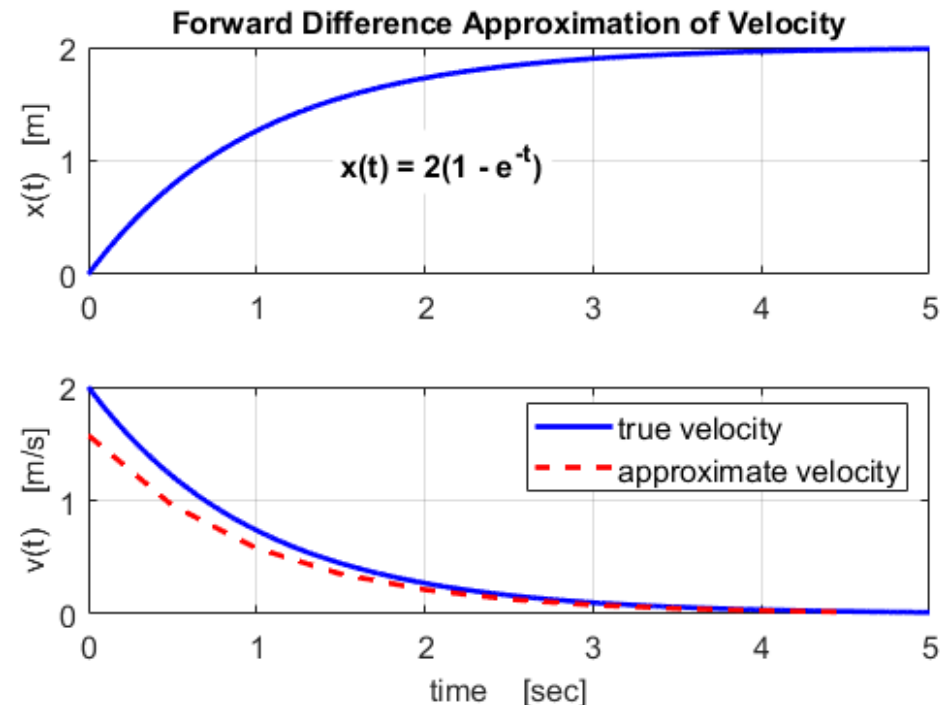
$$x(t) = 2 \text{ m} \cdot (1 - e^{-t})$$

- Use forward difference to approximate velocity

- ▣ Assume a 200 msec sample period

- Error would improve with smaller time steps

```
9      % sampled function
10     ts = 0:500e-3:5;
11     xs = 2*(1-exp(-ts));
12
13     dt = diff(ts);           % time differences
14     dx = diff(xs);          % position differences
15
16     dxdt = dx./dt;          % approximate derivative
17
```



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Numerical Integration

Integration

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$$\int_a^b f(t) dt$$

- **Integration** is a mathematical operation involving the calculation of a **continuous sum** over some interval
 - ▣ The inverse of differentiation – the antiderivative

$$\int f'(t) dt = f(t)$$

- We have seen that the derivative represents the rate of change of a function w.r.t. its independent variable
 - ▣ For example, consider the position of an object, $x(t)$
 - ▣ Velocity of the object is the derivative of position

$$v(t) = \frac{dx}{dt} = x'(t)$$

- ▣ The rate of change of position w.r.t. time

Integration

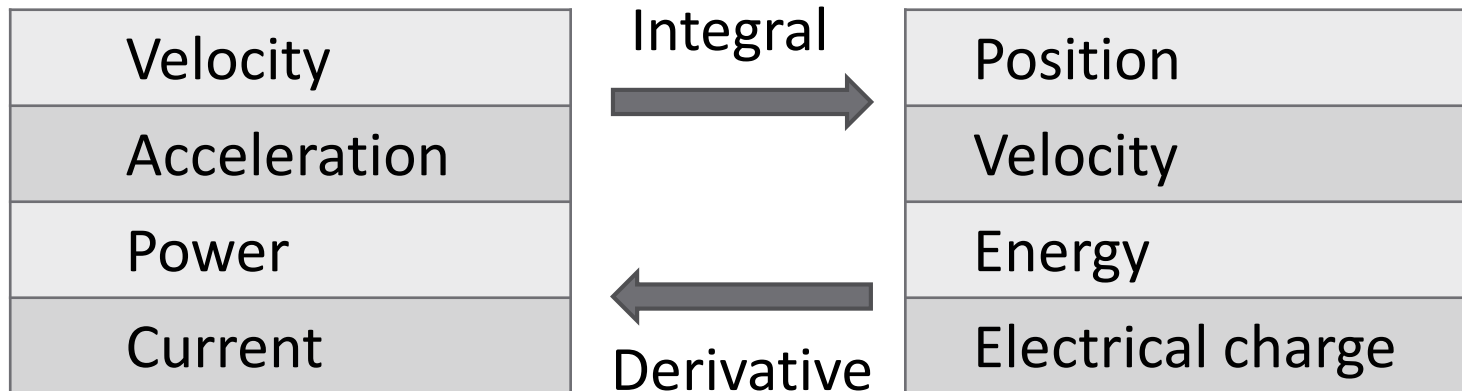
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□ ***Integration is the inverse of differentiation***

- Mathematical transform between a rate of a quantity (e.g., $v(t) = x'(t)$) and that quantity (e.g., $x(t)$)

$$x(t) = \int v(t) dt = \int x'(t) dt$$

□ Examples of integral/derivative relationships:



Integration

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- In your calculus class you learned/will learn to calculate the integral of functions, e.g.,

$$\begin{aligned}\int_0^1 e^{-\frac{t}{2}} dt &= -2 \cdot e^{-\frac{t}{2}} \Big|_0^1 \\ &= -2(0.6065 - 1)\end{aligned}$$

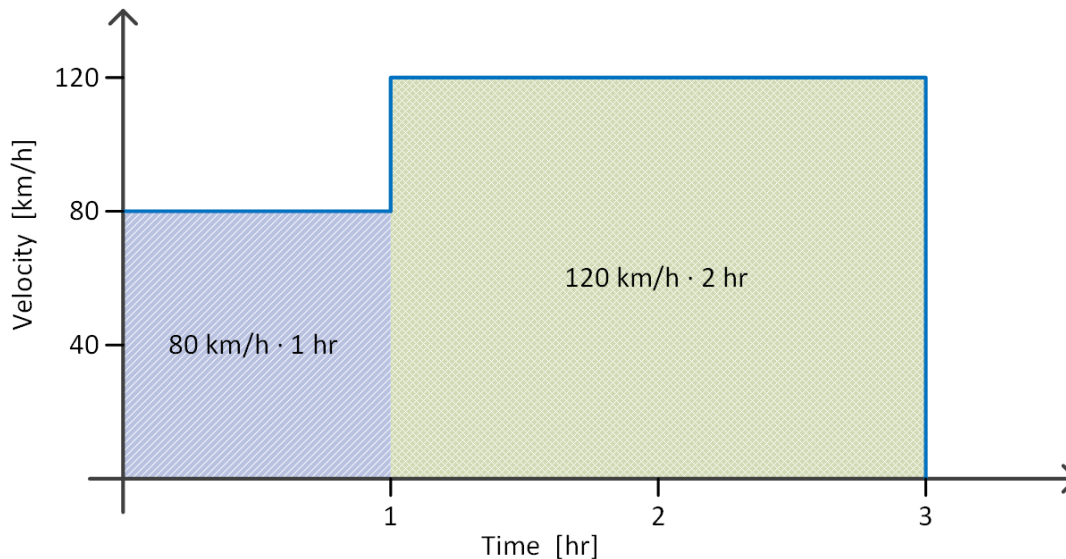
$$\int_0^1 e^{-\frac{t}{2}} dt = 0.787$$

- As was the case for differentiation, we often do not have a mathematical expression for the data we want to integrate
 - ▣ E.g., measurement data or simulation data
 - ▣ Only have discrete data points
 - ▣ Integrate ***numerically***

Numerical Integration

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- The ***derivative*** of a function is the ***slope of its graph***
- The ***integral*** of a function is the ***area under its graph***
- For example, distance traveled is the integral of velocity
 - Consider a car that travels at a speed of 80 km/h for 1 hour and 120 km/h for 2 hours
 - How far has the car traveled after three hours?



Numerical Integration

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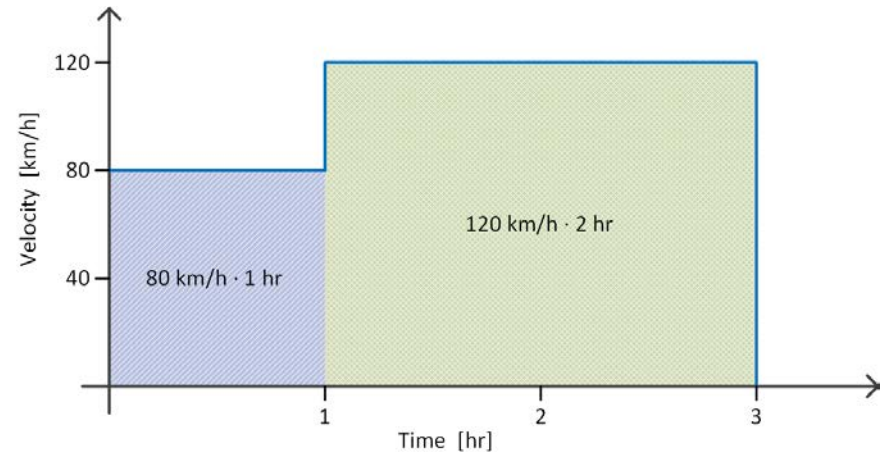
- Distance at $t = 3 \text{ hr}$:

$$x(3) = \int_0^3 v(t) dt$$

$$x(3) = \int_0^1 v(t) dt + \int_1^3 v(t) dt$$

$$x(3) = 80 \frac{\text{km}}{\text{h}} \cdot 1 \text{ hr} + 120 \frac{\text{km}}{\text{h}} \cdot 2 \text{ hr}$$

$$x(3) = 320 \text{ km}$$



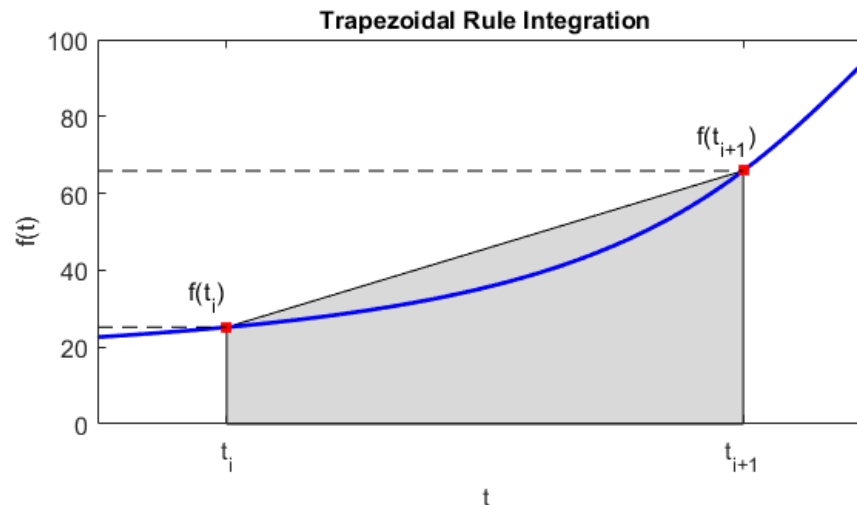
- **Numerical integration**

- Numerical approximation of area under a curve defined by a function or a discrete data set
- We will focus on one simple method: the **trapezoidal rule**

Trapezoidal Rule Integration

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- Approximate the integral between adjacent time point:
 - ▣ Approximate area under the curve between those time points
 - Area of a trapezoid



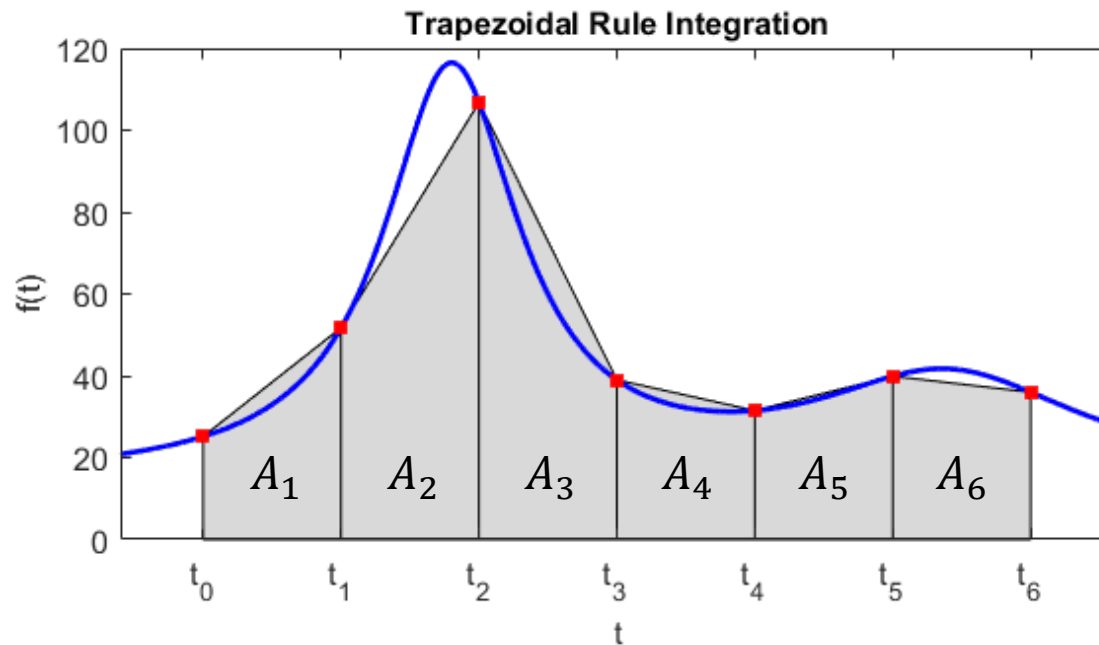
$$Area \approx \frac{f(t_i) + f(t_{i+1})}{2} \cdot (t_{i+1} - t_i)$$

$$Area \approx (Avg. height) \cdot (width)$$

Trapezoidal Rule Integration

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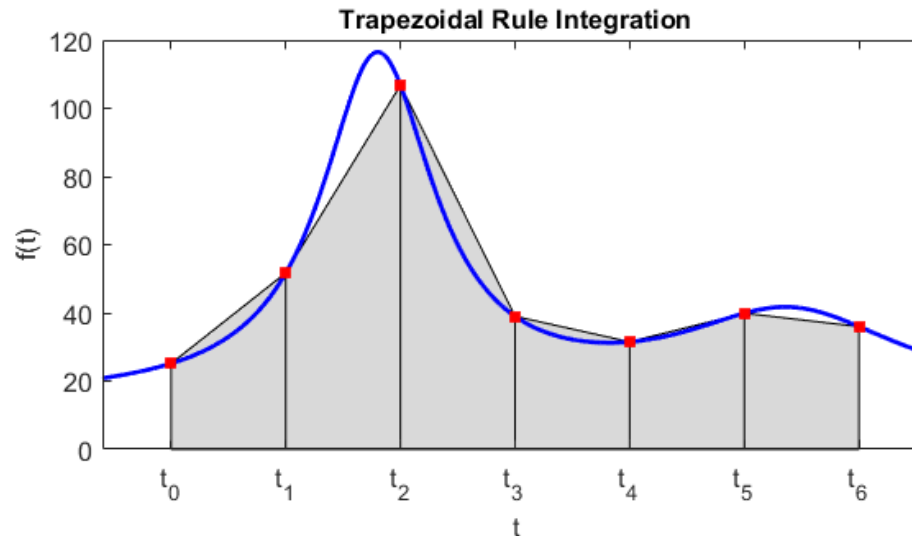
- Overall integral approximated by the approximate total area
 - ▣ Sum of all individual trapezoidal segment areas



$$\int_{t_0}^{t_6} f(t) dt \approx \sum_{i=1}^6 A_i = A_1 + A_2 + A_3 + A_4 + A_5 + A_6$$

Trapezoidal Rule Integration

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$$\int_{t_0}^{t_6} f(t) dt \approx \sum_{i=0}^5 \frac{f(t_i) + f(t_{i+1})}{2} \cdot (t_{i+1} - t_i)$$

$$\int_{t_0}^{t_6} f(t) dt \approx \left[\frac{f(t_0) + f(t_1)}{2} \cdot (t_1 - t_0) \right] + \left[\frac{f(t_1) + f(t_2)}{2} \cdot (t_2 - t_1) \right] + \dots$$
$$\dots + \left[\frac{f(t_5) + f(t_6)}{2} \cdot (t_6 - t_5) \right]$$

Trapezoidal Rule in MATLAB – `trapz.m`

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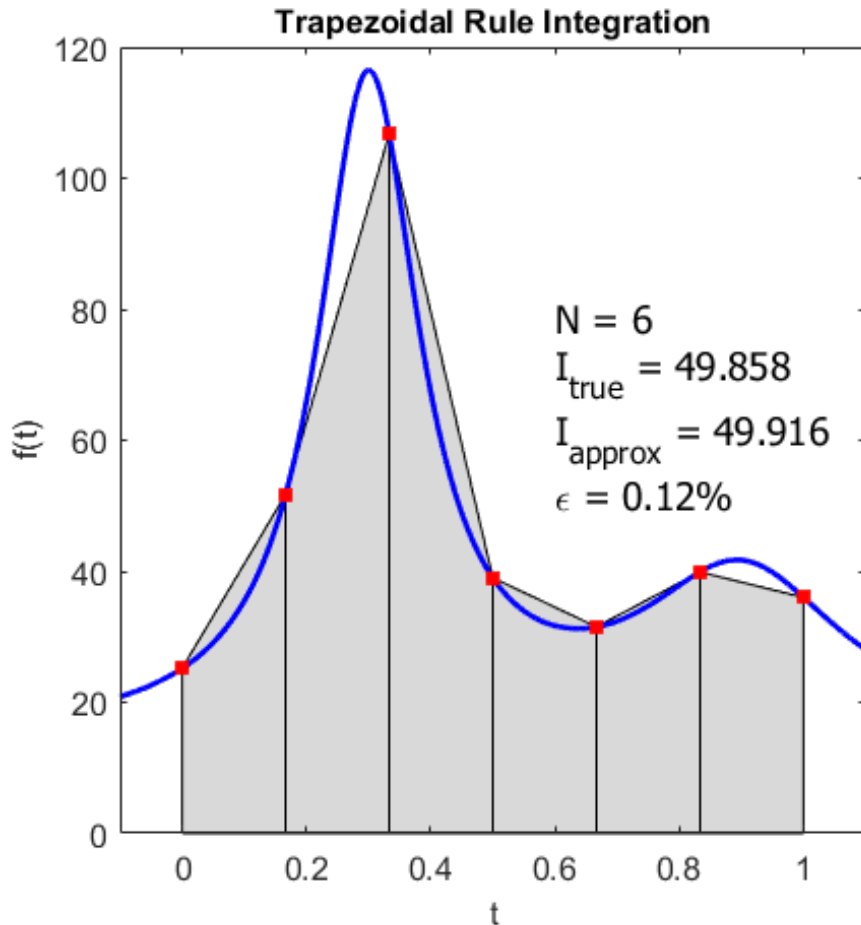
$$I = \text{trapz}(x, y)$$

- x : vector of independent variable data
- y : vector of dependent variable data
- I : trapezoidal rule approximation to the integral of y with respect to x (a scalar)

- Data need not be equally-spaced
 - Segment widths calculated from x values

Trapezoidal Rule – Example

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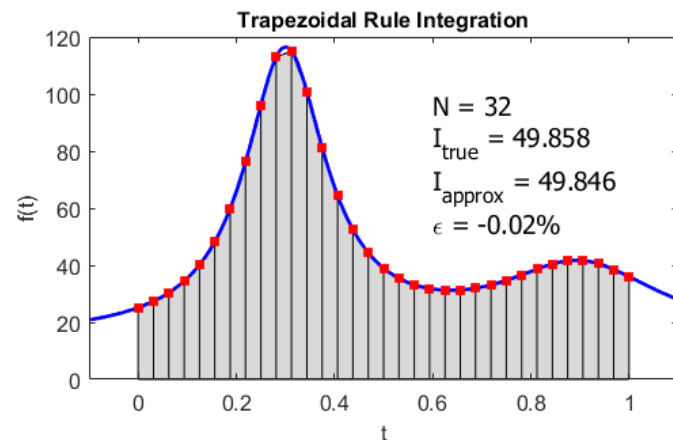
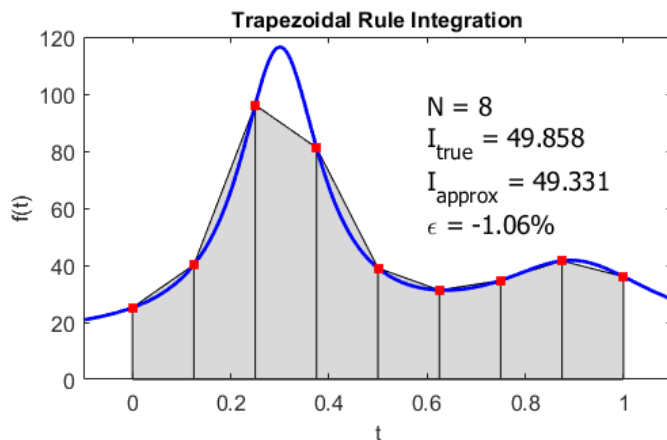
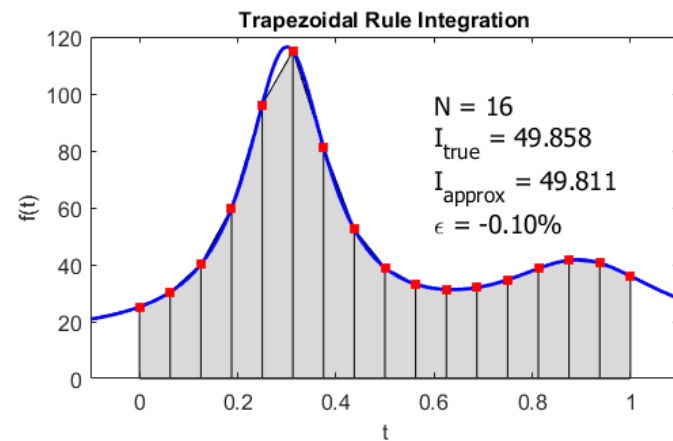
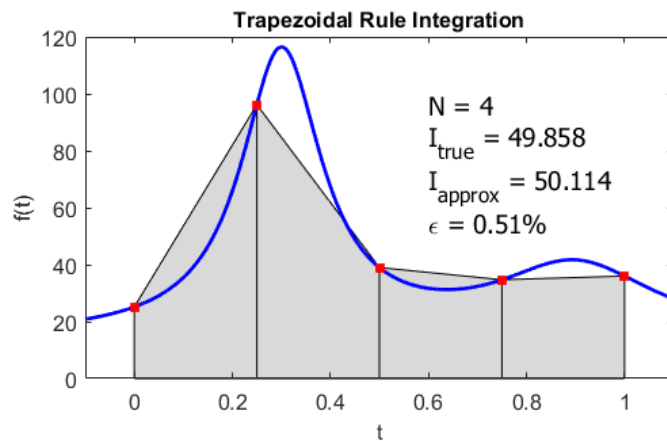


```
4
5 % the function to be integrated (MATLAB's humps.m + 20)
6 % in practice, we would generally not have this
7 f = @(t) 1./((t-.3).^2 + .01) + 1./((t-.9).^2 + .04) + 14;
8
9 % expression of true integral
10 % in practice, we would generally not have this either
11 intf = @(t) 14*t + 10*atan(10*t - 3) + 5*atan(5*t - 9/2);
12
13 % evaluate f(t) over [a,b] with N segments, N+1 samples
14 a = 0;
15 b = 1;
16 N = 6;
17 t = linspace(a,b,N+1);
18
19 y = f(t); % data to be integrated
20
21 % approx. the integral over [a,b] using trapz.m
22 Ihat = trapz(t,y);
23
24 % the value of the true integral over [a,b]
25 I = intf(b) - intf(a);
26
27 % percent error of the numerical approximation
28 err = (Ihat - I)/I * 100;
29
```


Trapezoidal Rule – Example

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- Error decreases as
 - Number of segments (sampling frequency) increases
 - Segment size (sampling period) decreases



Indefinite Integrals

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- Sometimes, we want to know the result of an integral from a to b
 - ▣ A ***definite integral***
 - ▣ A number
 - ▣ E.g., given velocity $v(t)$, find the total distance traveled

$$\Delta x = x(b) - x(a) = \int_a^b v(t) dt$$

- Other times, we would like the result of an integral as a function of time
 - ▣ An ***indefinite integral*** or a ***cumulative integral***
 - ▣ E.g., given $v(t)$, find the distance traveled as a function of time

$$x(t) = \int_0^t v(\tau) d\tau$$

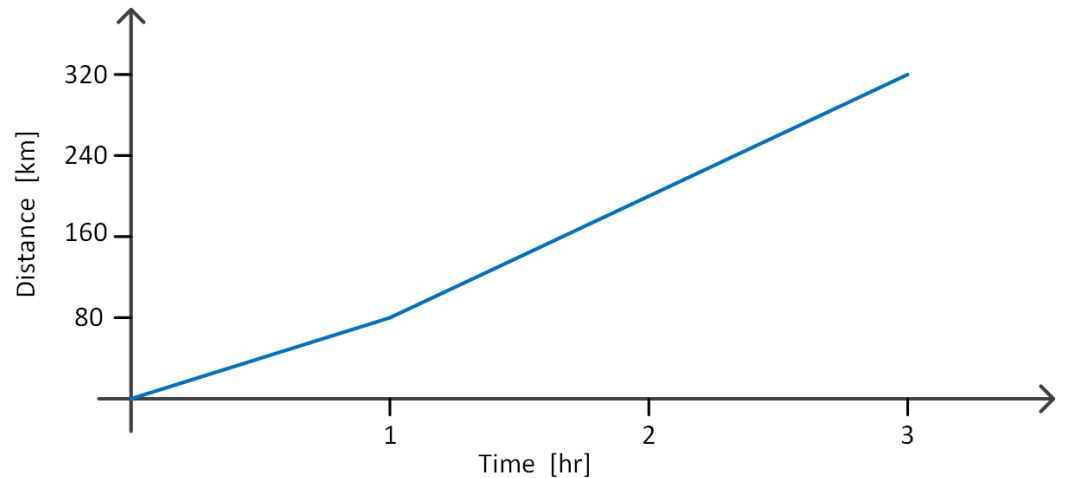
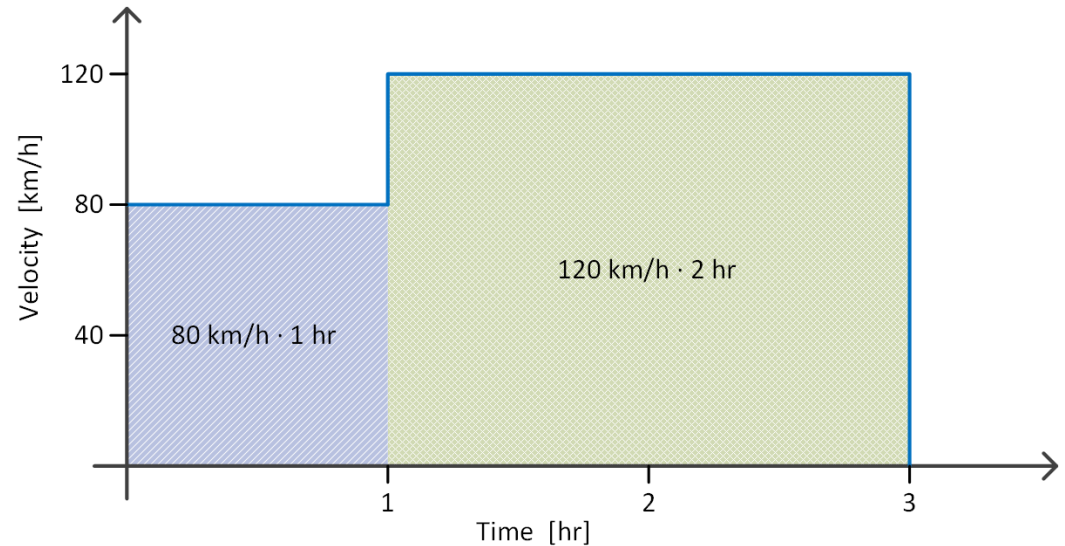
Indefinite Integrals

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□ Velocity, $v(t)$:

□ Integrate velocity to get distance as a function of time:

$$x(t) = \int v(t) dt$$



Trapezoidal Rule in MATLAB – `cumtrapz.m`

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$$I = \text{cumtrapz}(x, y)$$

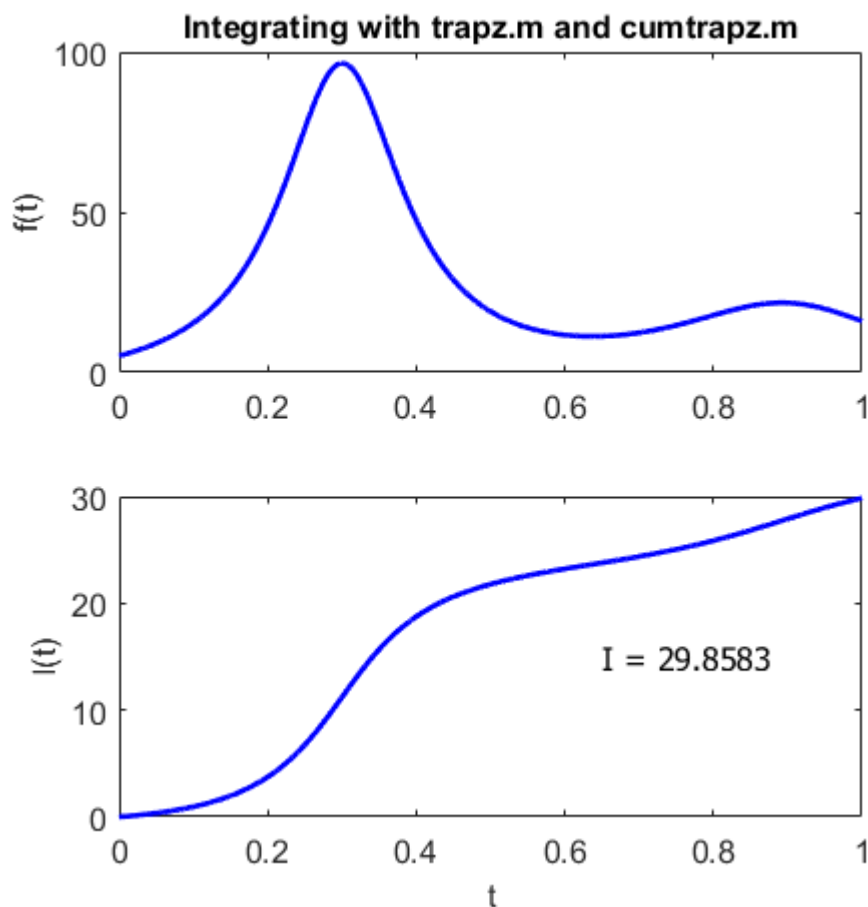
- ▣ x : n-vector of independent variable data
 - ▣ y : n-vector of dependent variable data
 - ▣ I : trapezoidal rule approximation to the ***cumulative integral*** of y with respect to x (an n-vector)
- ▣ Result is a vector – equivalent to:

$$I(x) = \int_{x_1}^x y(\tilde{x}) d\tilde{x}$$

- ▣ Data need not be equally-spaced

trapz.m and cumtrapz.m

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```
1 % trapz_test.m
2
3 clear all; clc
4
5 % create the data to be integrated
6 x = linspace(0,1,2000);
7 y = humps(x);
8
9 % definite integral
10 I = trapz(x,y);
11
12 % cumulative or indefinite integral
13 Ic = cumtrapz(x,y);
14
15 figure(1); clf
16 subplot(211)
17 plot(x,y,'-b','LineWidth',2);
18 ylabel('f(x)')
19 title('Integrating with trapz.m and cumtrapz.m',...
20       'FontWeight','Bold')
21
22 subplot(212)
23 plot(x,Ic,'-b','LineWidth',2);
24 xlabel('x'); ylabel('I(x)')
25 text(0.65,15,['I = ',num2str(I,'%1.4f')],...
26       'FontSize',12,'FontName','Tahoma')
27
28
```

Integrating Functions – `integral.m`

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- If we do have an expression for the function to be integrated, we can use MATLAB's `integral.m` function:

$$I = \text{integral}(f, a, b)$$

- `f`: handle to the function to be integrated
 - `a`: lower integration limit
 - `b`: upper integration limit
 - `I`: numerical approximation of the integral
- Calculates $I = \int_a^b f(x)dx$

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Curve Fitting

Curve Fitting

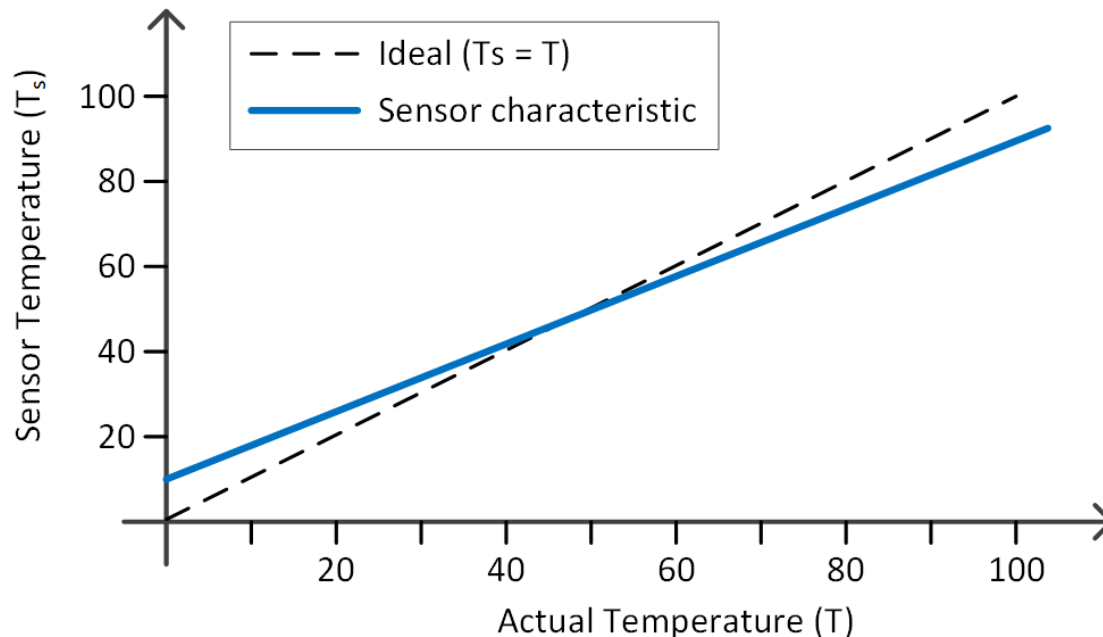
40

- Engineers often deal with discrete data sets, e.g.
 - E.g., measurement or simulation data
- Typically, that data is noisy
 - Measurement noise
 - Random variations, external disturbances, etc.
- Typically don't have a mathematical expression for the data
 - But, we may want one
 - Sometimes, we may know the data should follow a certain type of function
 - E.g., linear, quadratic, exponential, etc.
- We can ***fit a curve to the data***
 - Determine function parameters that best fit the data
 - E.g., slope and intercept values for a linear relationship
 - Or, determine what type of function provides the best fit
 - E.g., linear, quadratic, exponential, etc.

Curve Fitting

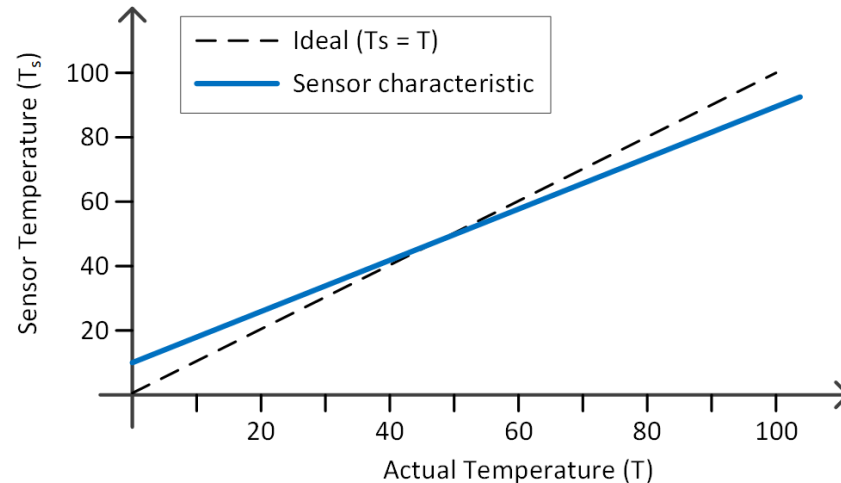
41

- Consider the following engineering example:
- An inexpensive temperature sensor is to be used to measure ambient temperature
 - ▣ Temperature measured and recorded by a micro-controller
 - ▣ Low accuracy (inexpensive)
- Sensor output compared to actual temperature may look like:



Curve Fitting

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- Ideally, the sensor temperature, T_S , would equal the true temperature, T :

$$T_S = T$$

- But, due to inaccuracy:

$$T_S = a_1 \cdot T + a_0$$

- ▣ a_1 : proportional error
- ▣ a_0 : offset error

Curve Fitting

43

- To achieve accurate measurements, we could **calibrate** the sensor
 - ▣ Measure a range of temperatures with the inexpensive sensor and an accurate sensor
 - ▣ Obtain a dataset representing sensor temperature, T_s , as a function of true temperature, T
 - ▣ That is, determine a_1 and a_0 such that

$$T_s = f(T) = a_1 T + a_0$$

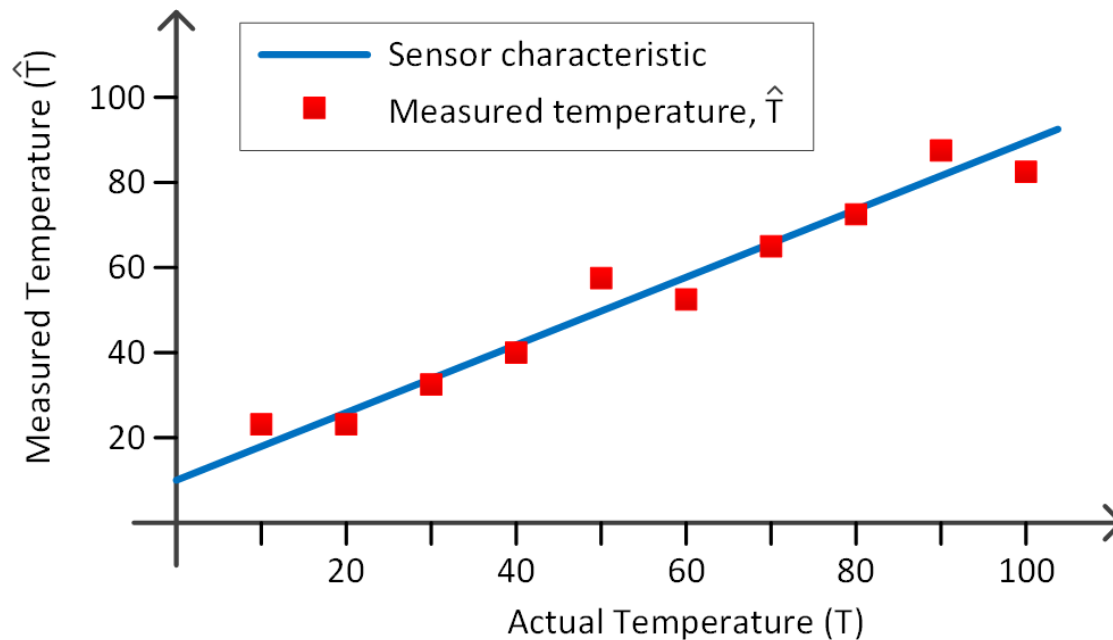
- Then, we can map sensor temperature to true temperature

$$T = \frac{T_s}{a_1} - \frac{a_0}{a_1}$$

Curve Fitting

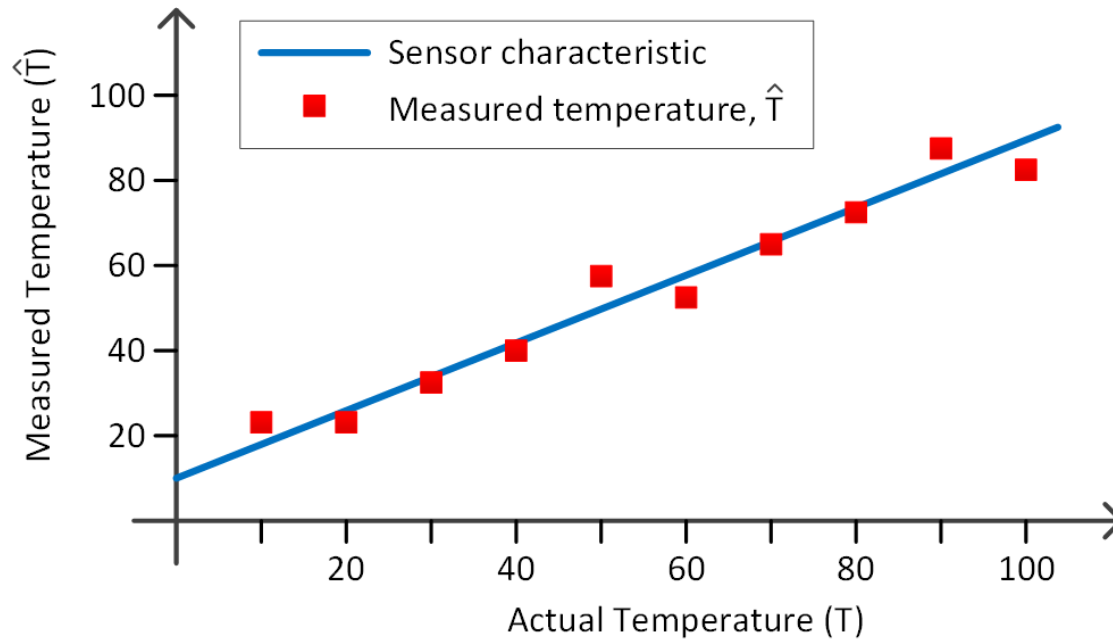
44

- In practice, there would be two sources of error between actual and measured temperatures
 - ▣ Inherent sensor inaccuracy
 - ▣ **Measurement noise**
- Actual **measured** data, \hat{T} , may look like:



Curve Fitting

45



- Determine the blue line (a_1 and a_0) that provides the **best fit** to the measured data (red squares)
- How do we define “**best fit**”?

Least-Squares Fit

46

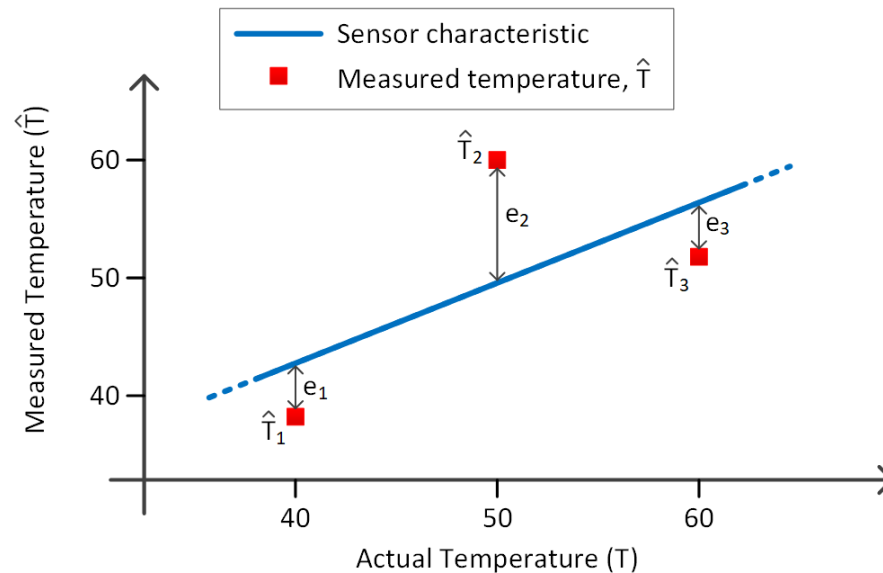
- What constitutes the **best fit**?
- Want to determine inherent sensor behavior,

$$T_s = a_1 \cdot T + a_0$$

given noisy measurement data,

$$\hat{T} = T_s + e$$

where e represents measurement error

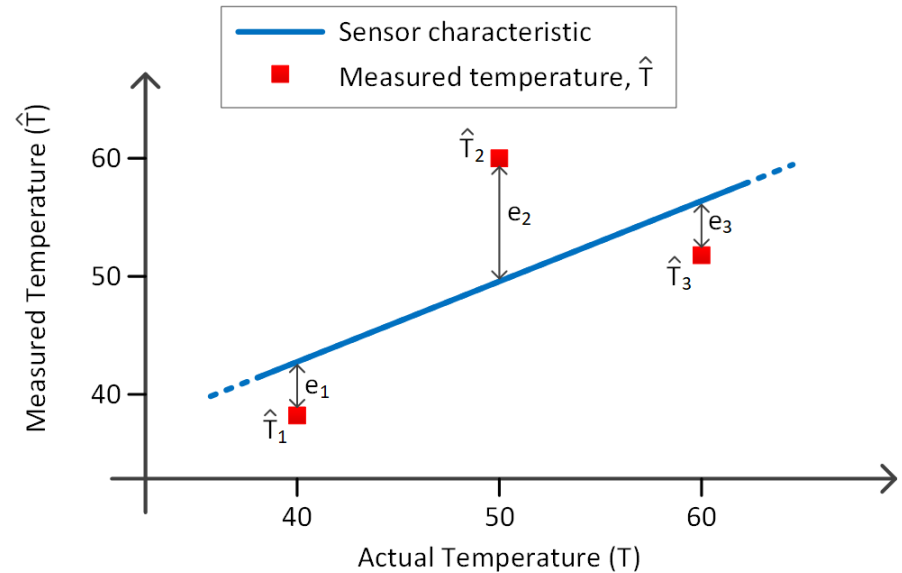


Least-Squares Fit

47

- Errors between data points and the line fit to the data are called ***residuals***
- Best fit criterion:
 - ▣ Minimize the ***sum of the squares of the residuals***
 - ▣ ***A least-squares fit***
- Minimize:

$$S_r = \sum_i e_i^2 = \sum_i [\hat{T}_i - (a_1 T_i + a_0)]^2$$



Goodness of Fit

48

- How well does a function fit the data?
 - Is a linear fit best? A quadratic, higher-order polynomial, or other non-linear function?
 - Want a way to be able to quantify **goodness of fit**
-
- Quantify **spread of data about the mean** prior to regression:

$$S_t = \sum (\hat{y}_i - \bar{y})^2$$

- Following regression, quantify **spread of data about the regression line** (or curve):

$$S_r = \sum (\hat{y}_i - a_0 - a_1 x_i)^2$$

Goodness of Fit

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- S_t quantifies the spread of the data about the mean
- S_r quantifies spread about the best-fit line (curve)
 - The spread that remains after the trend is explained
 - The ***unexplained sum of the squares***
- $S_t - S_r$ represents the reduction in data spread after regression explains the underlying trend
- Normalize to S_t - the ***coefficient of determination***

$$r^2 = \frac{S_t - S_r}{S_t}$$

Coefficient of Determination

50

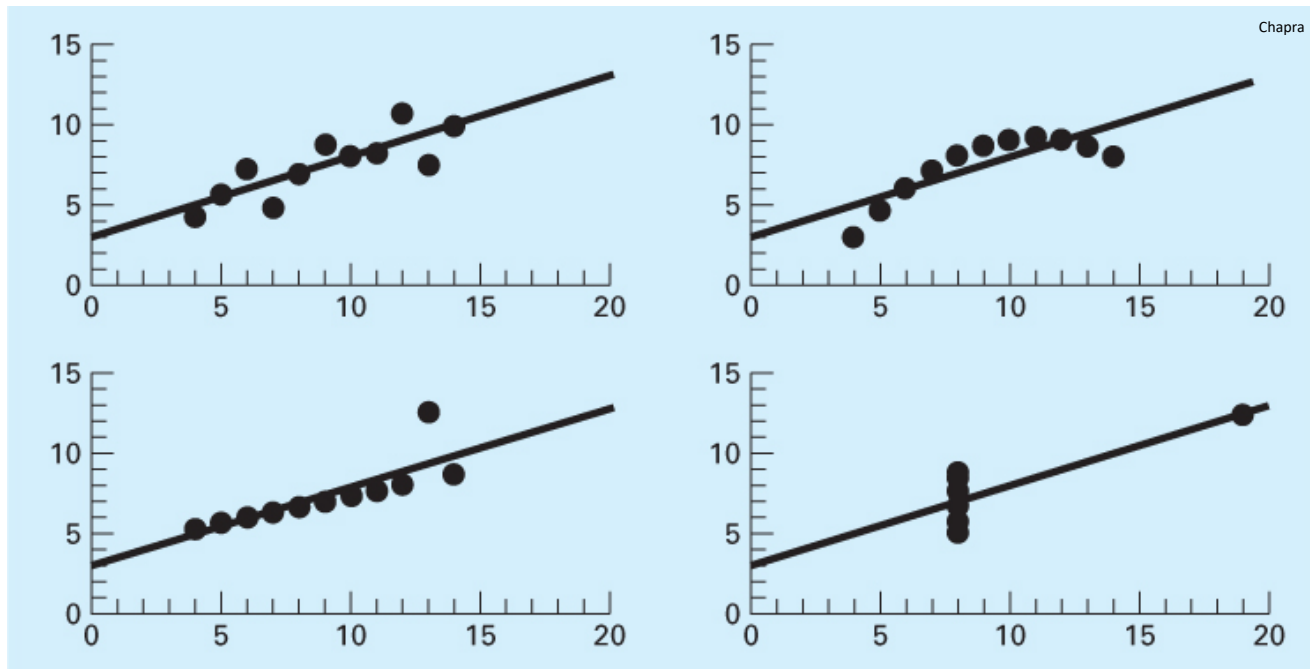
$$r^2 = \frac{S_t - S_r}{S_t}$$

- For a perfect fit:
 - ▣ No variation in data about the regression line
 - ▣ $S_r = 0 \rightarrow r^2 = 1$
- If the fit provides no improvement over simply characterizing data by its mean value:
 - ▣ $S_r = S_t \rightarrow r^2 = 0$
- If the fit is worse at explaining the data than their mean value:
 - ▣ $S_r > S_t \rightarrow r^2 < 0$

Coefficient of Determination

51

- Don't rely too heavily on the value of r^2
- Anscombe's famous data sets:



- Same line fit to all four data sets
- $r^2 = 0.67$ in each case

Curve Fitting in MATLAB

52

- So far we have considered fitting a line to data
 - ▣ A linear least-squares line fit
- Can also fit other functions to data, e.g.,
 - ▣ Higher-order polynomials – quadratic, cubic, etc.
 - ▣ Exponentials
 - ▣ Sinusoids
 - ▣ Power equation, etc.
- MATLAB has built-in functions to perform curve fitting
 - ▣ `polyfit.m` – for fitting polynomials
 - ▣ `fit.m` – for fitting any other user-specified curves

Polynomial Regression – `polyfit.m`

53

$$p = \text{polyfit}(x, y, m)$$

- ▣ x : n -vector of independent variable data values
 - ▣ y : n -vector of dependent variable data values
 - ▣ m : order of the polynomial to be fit to the data ($m < n$)
 - ▣ p : $(m + 1)$ -vector of best-fit polynomial coefficients
- ▣ Polynomial coefficients in MATLAB
- ▣ Consider a polynomial created by `polyfit.m`

$$y = a_2x^2 + a_1x + a_0$$

- ▣ MATLAB would return

$$p = [a_2, a_1, a_0]$$

Polynomial Evaluation – polyval.m

54

- n^{th} -order polynomial represented as $(n + 1)$ -vector
- For example, the cubic polynomial

$$y = 2x^3 - 8x^2 + 3x - 4$$

would be represented as

$$p = [2 , -8 , 3 , -4]$$

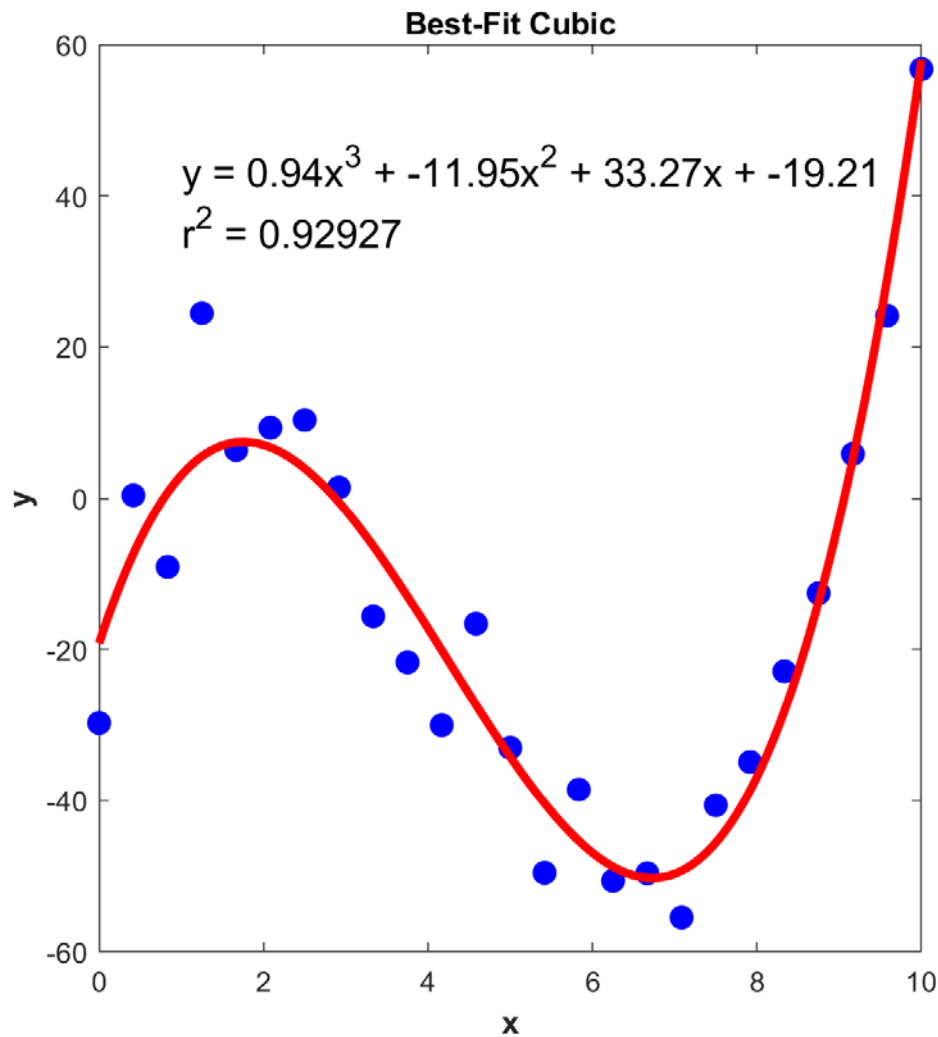
- Use polyval.m to evaluate that polynomial over a vector of independent variable values

$$y = \text{polyval}(p, x)$$

- ▣ p : $(n + 1)$ -vector of n^{th} -order polynomial coefficients
- ▣ x : vector of independent variable data values
- ▣ y : vector result of evaluating the polynomial at all values in x

Polynomial Fit – Example

55



```
8 %% create dataset
9 % noiseless data
10 % polynomial with roots at 1, 3, and 9
11 % y = x^3 - 13x^2 + 39x - 27
12 p = poly([1,3,9]);
13 x = linspace(0,10,25);
14 y = polyval(p,x);
15
16 %% add noise to y data
17 sig = 0*8;
18 v = sig*randn(size(y));
19 yn = y + v;
20
21
22 %% use polyfit.m to perform the fit
23
24 pfit = polyfit(x,yn,3);
25
26
27 %% evaluate the best-fit cubic
28
29 xfit = linspace(min(x),max(x),200);
30 y3 = polyval(pfit,xfit);
31 y3r2 = polyval(pfit,x);
32
33
34 %% coefficient of determination
35
36 ybar = mean(yn);
37 St = sum((yn - ybar).^2);
38 Sr = sum((yn - y3r2).^2);
39 r2 = (St - Sr)/St
```

Fitting User-Specified Curves – `fit.m`

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- To fit a curve other than a polynomial, use `fit.m`

```
fitobject = fit(x,y,fittype)
```

- `x`: **column** vector of independent variable data values
- `y`: **column** vector of dependent variable data values
- `fittype`: model type to fit – specified as a library model or created with the `fittype.m` function
- `fitobject`: `cfi` object containing fit parameters

Specifying the Model – `fittype.m`

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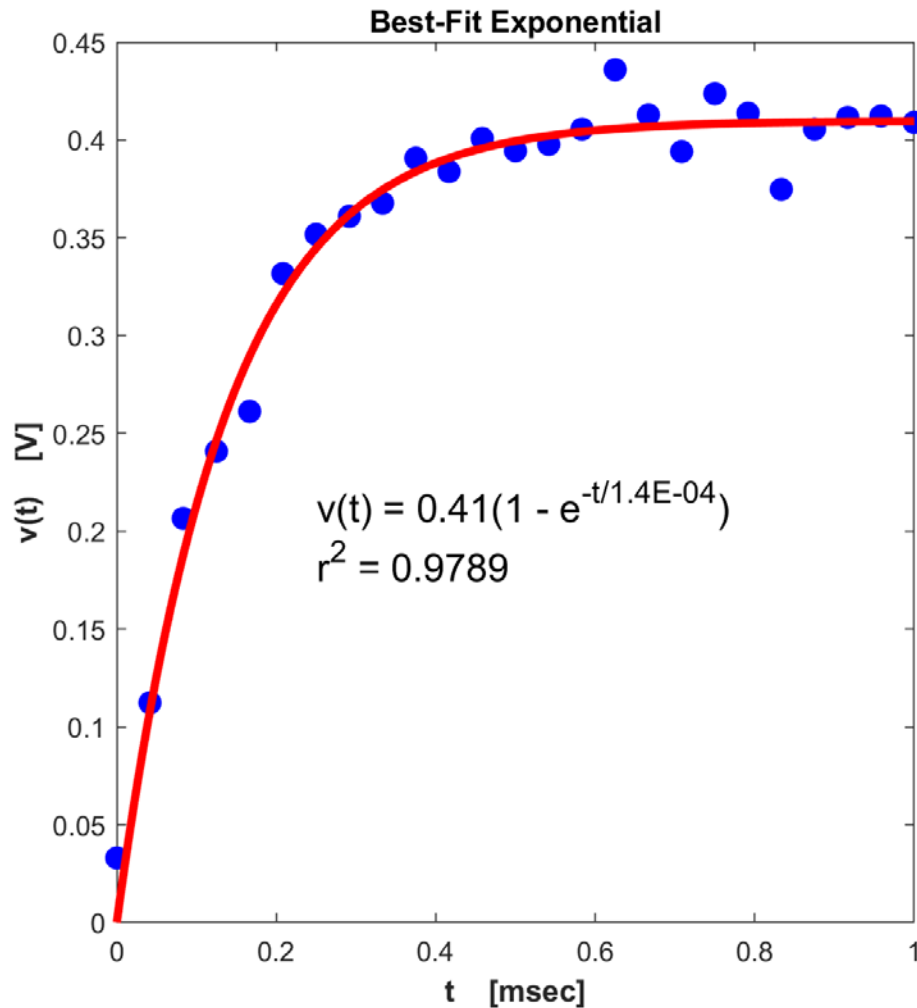
- Define the model to be used by `fit.m`

```
fitmod = fittype(expression, name, value, ...)
```

- `expression`: mathematical function to be fit to data
– user-specified or a standard library model (see help)
- `name`: property name to specify (see help)
- `value`: value assigned to `name` – can specify multiple property name/value pairs
- `fitmod`: `fittype` object to be passed to `fit.m`

Exponential Fit - Example

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```
8 %% create dataset
9 % noiseless data
10 t = linspace(0,1e-3,25)';
11 tau = 120e-6; % time constant
12 v = 400e-3*(1 - exp(-t/tau));
13
14 % add noise to y data
15 sig = 15e-3;
16 n = sig*randn(size(v));
17 vn = v + n;
18
19 %% fit an exponential to the data
20 expFit = fittype('Vf*(1 - exp(-t/tau))',...
21 'independent','t');
22
23 expFitObj = fit(t,vn,expFit);
24
25 %% extract fit parameters from cfit object
26 Vf_fit = expFitObj.Vf;
27 tau_fit = expFitObj.tau;
28
29 %% evaluate the fit
30 tfit = linspace(0,t(end),2000);
31 vfit = Vf_fit*(1 - exp(-tfit/tau_fit));
32 vfitr2 = Vf_fit*(1 - exp(-t/tau_fit));
33
34 %% coefficient of determination
35 vbar = mean(vn);
36 St = sum((vn - vbar).^2);
37 Sr = sum((vn - vfitr2).^2);
38 r2 = (St - Sr)/St
39
```