

# **ENGG 407**

# **Numerical Methods in Engineering**

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**Lecture #01**

**Dr. Sameh Nassar**

**L02**

**W12**

# Practical Information

## L02 Instructor:

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- **B.Sc.** (1995), Civil Engineering.
- **M.Sc.** (1999), Civil/Geomatics Engineering.
- **Ph.D.** (2004), Geomatics Engineering (U of C).

# Practical Information

## Office Hours:

- Open door policy  
(a request should be made in advance by email)
- Email questions are preferred  
(answer will be given within 48 hours)

# Practical Information

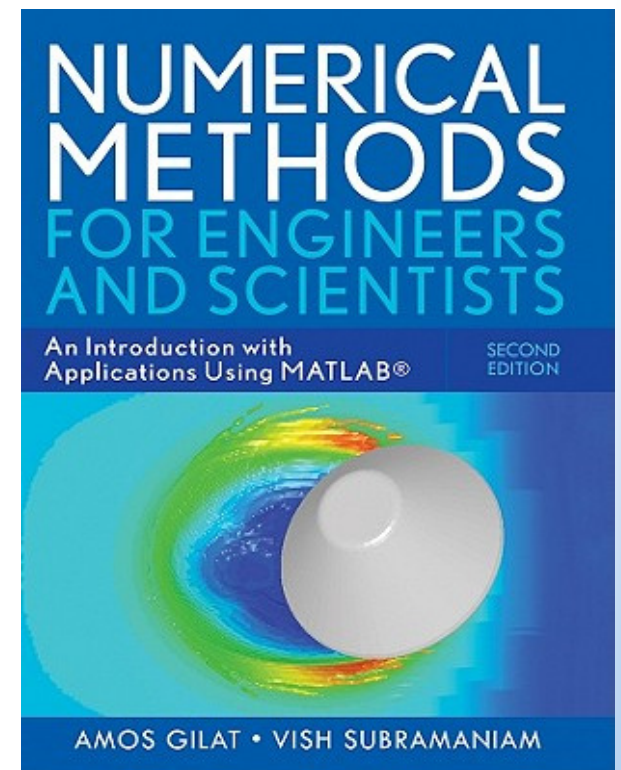
## Required Textbook:

### “Numerical Methods for Engineers and Scientists”

*2<sup>nd</sup> Edition, 2011*

*Amos Gilat & Vish Subramaniam*

John Wiley & Sons, Inc.



# Practical Information

## Course Grading:

**Assignments (*5 or 6*):** 30%

**Quiz #1 (*Feb 15*):** 15%

**Quiz #2 (*Mar 15*):** 15%

**Final Exam:** 40%

# Practical Information

## Teaching Assistants:

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# Introduction to Numerical Methods

## Remember from Previous Physics, Mechanics or Math Courses:

- In practice, a **mathematical problem** is derived from a **physical phenomenon** with making some **simplifying assumptions** to allow mathematical representation.
- However, the **mathematical problem** does not solve the **physical problem** exactly!

# Numerical Methods: Definitions

- “**Numerical Methods** are techniques by which mathematical problems are formulated so that they can be solved with arithmetic operations”.
- “**Numerical Methods** are techniques for approximating, in an efficient manner, the solutions to mathematically expressed problems, where the efficiency of the method depends on the accuracy required & the ease of implementation”.
- “**Numerical Methods** use *numbers* to simulate mathematical processes, which in turn usually simulate real-world situations”.

# Numerical Methods: Strategy

- In general, the **mathematical problem** does not solve the **physical problem** exactly. Thus, it is more appropriate to find an **approximation solution** to a more complicated mathematical model.
- To obtain such an approximation, a **method** “or an **algorithm**” is developed.
- The **algorithm** consists of a sequence of algebraic and logical operations that produces the **approximation** to the mathematical problem (with a hope to the physical problem too!) within a **prescribed accuracy**.

# Numerical Methods

In general, most real problems are difficult to solve, nonlinear, complex physics, complex geometry, not stationary..

Modeling, assumptions,

Methods of Solution

Experimental

Analytical

Computational

Numerical



# Numerical Methods & Engineers

- **Civil Engineering**
  - ◆ Structure health monitoring.....
- **Electrical Engineering**
  - ◆ Design of electric circuits.....
- **Biomedical & Biomechanical Engineering**
  - ◆ Modeling of motion of joints.....
- **Mechanical Engineering**
  - ◆ Vibration analysis.....
- **Chemical Engineering**
  - ◆ Gas Laws, Reactors.....
- **Geomatics Engineering**
  - ◆ Satellite tracking, Position determination.....

# ENGG 407 Topics

1. Introduction and Mathematical Background (*Ch. #1, #2*)
2. "*Roots of*" Nonlinear Equations (*Ch. #3*)
3. Linear Equations and Systems (*Ch. #4*)
4. Interpolation, Least-squares Estimation and Curve Fitting (*Ch. #5*)
5. Numerical Differentiation (*Ch. #6*)
6. Numerical Integration (*Ch. #7*)
7. Ordinary Differential Equations: Initial Value Problems (*Ch. #8*)
8. Ordinary Differential Equations: Boundary Value Problems (*Ch. #9*)
9. Optimization (*Tentative*).

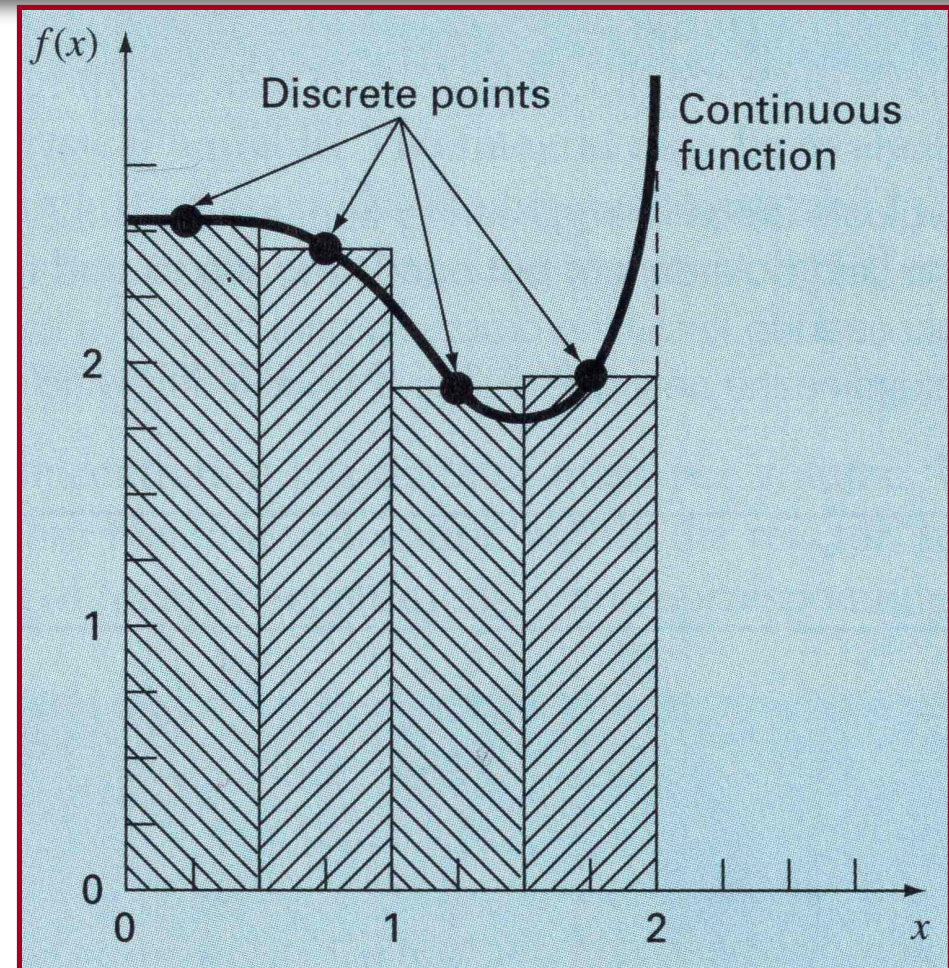
# Why Numerical Methods? "Case #1"

Complicated  
continuous function

$$\int_0^2 \frac{2 + \cos(1 + x^{3/2})}{\sqrt{1 + 0.5 \sin x}} e^{0.5x} dx$$

$x$	$f(x)$
0.25	2.599
0.75	2.414
1.25	1.945
1.75	1.993

Tabulated function



Numerical integration

# Why Numerical Methods? "*Case #1*"

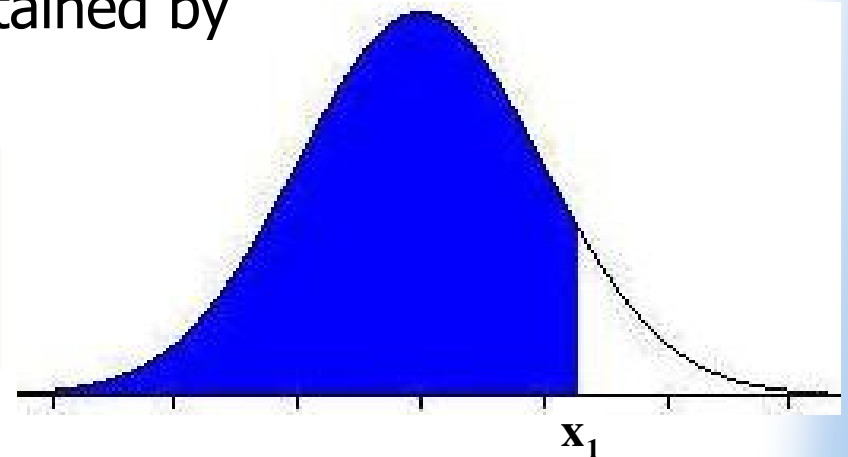
## Recall from ENGG 319 (Probability & Statistics for Engineers):

- The density of the normal random variable  $X$ , with mean  $\mu$  and variance  $\sigma^2$ , is:

$$n(x; \mu, \sigma) = f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\left(\frac{1}{2\sigma^2}\right)(x-\mu)^2}$$

- The probability for a specific value  $x_1$  (area under the curve from  $-\infty$  to  $x_1$ ) is obtained by integrating the above equation. i.e.:

$$P(x < x_1) = \int_{-\infty}^{x_1} \frac{1}{\sqrt{2\pi}\sigma} e^{-\left(\frac{1}{2\sigma^2}\right)(x-\mu)^2} dx$$



# Why Numerical Methods? "*Case #1*"

- Unfortunately, the integral in the previous slide cannot be evaluated in a closed form (i.e. analytically), and hence, **numerical** integration methods (i.e. here in ***ENGG 407***) are used instead.
- In such techniques, **tabulated values** of the integrals are obtained and recorded.
- So, you can remember the **z**, **t**,  $\chi^2$ , and **f** tables (distributions) you used in ***ENGG 319***.

# Why Numerical Methods? "*Case #II*"

## Something You Know:

$$f(x) = ax^2 + bx + c = 0$$



$$x = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

Analytic  
Solution

Roots (zeros) of  $f(x)$

## But if you have (for example):

$$f(x) = e^{-x} - x = 0$$



Cannot be solved  
analytically



Approximate sol.  
technique is the  
only alternative!

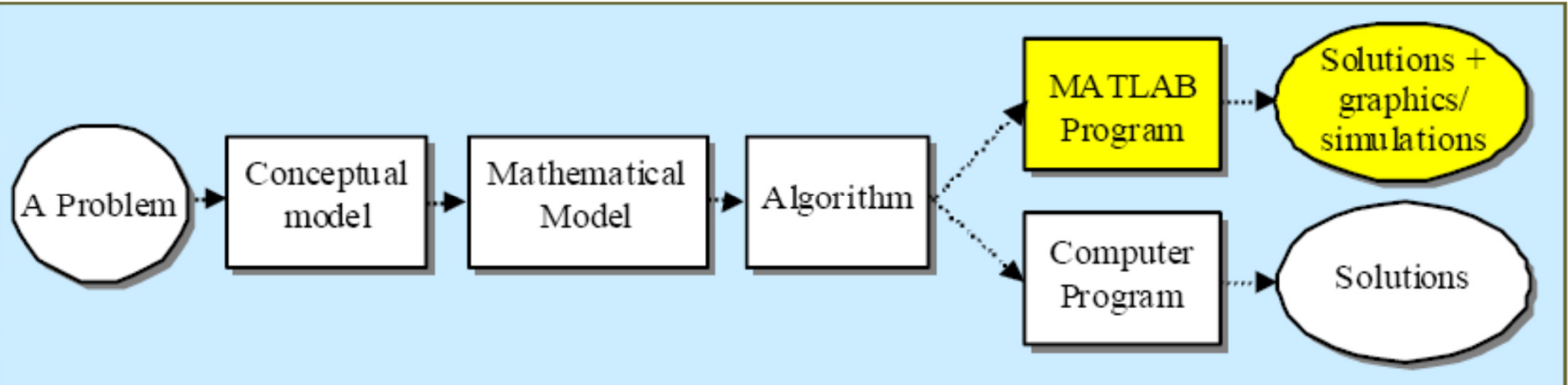
# Numerical Methods: Programming

- Although numerical methods are **approximate**, they employ "**systematic**" strategies to estimate the solution.
- In this case, the **convergence** "*quickness*" and the **accuracy** "*correctness*" of the approximate solution depends on the increment value, the used interval and the initial value (*Does this remind you with **ENGG 233?***).

# Numerical Methods: Programming

- So, in our case you need to implement an *algorithm* (methodology/steps of performing the numerical method) and a *code* (list of computer commands to execute the algorithm).
- Error analysis is necessary to evaluate the quality of the obtained approximate solution.
- Thus, what are the major differences between numerical and analytic Methods?

# Numerical Methods for Solving Engineering Problems



Yingxu Wang (ENGG 407 2011 notes)

# Numerical Methods: Errors

- Since **Numerical methods** involve an **approximate** solution of the problem, there will be always a discrepancy “an **error**” between the exact “**analytical**” solution and the numerical solution.
- In most situations, we don't know the exact solution, and hence, all we can do is to have an “**estimate**” or an “**approximation**” of the error.

# Representation of Numbers

- Numbers can be represented in various forms (number systems).
- A number can be written by a sequence of digits that correspond to multiple powers of a certain **base**.
- Any integer digit greater than "1" can be used as the **base** for a number system, e.g. 2, 8 (*octal*), 10, 16 (*hexadecimal*).
- If the **base** is larger than 10, the letters *A, B, C, D,...* are usually used to represent *10, 11, 12, 13,....*
- The familiar **decimal system** uses **base 10**.
- However, computers use the **binary system** (**base 2**) due to its easy implementation in computer operations.

# Representation of Numbers

## Decimal Representation (*Base 10*):

- The decimal system uses ten “*decimal*” digits: 0, 1, 2, ..., 9.
- A number is written by a sequence of digits that correspond to multiples of powers of 10.

$$\begin{array}{cccccccccc}
 10^4 & 10^3 & 10^2 & 10^1 & 10^0 & 10^{-1} & 10^{-2} & 10^{-3} & 10^{-4} \\
 \downarrow & \downarrow & \downarrow & \downarrow & \downarrow & \downarrow & \downarrow & \downarrow & \downarrow \\
 6 & 0 & 7 & 2 & 4 & . & 3 & 1 & 2 & 5
 \end{array}$$

$$6 \times 10^4 + 0 \times 10^3 + 7 \times 10^2 + 2 \times 10^1 + 4 \times 10^0 + 3 \times 10^{-1} + 1 \times 10^{-2} + 2 \times 10^{-3} + 5 \times 10^{-4} = 60,724.3125$$

# Representation of Numbers on Computers

## Binary Representation (*Base 2*):

- The binary system uses two "*binary*" digits: **0** and **1**.
- A number is written by a sequence of **zeros** and **ones** that correspond to multiples of powers of 2.

$2^{15}$   $2^{14}$   $2^{13}$   $2^{12}$   $2^{11}$   $2^{10}$   $2^9$   $2^8$   $2^7$   $2^6$   $2^5$   $2^4$   $2^3$   $2^2$   $2^1$   $2^0$   $2^{-1}$   $2^{-2}$   $2^{-3}$   $2^{-4}$

↓ ↓ ↓ ↓ ↓ ↓ ↓ ↓ ↓ ↓ ↓ ↓ ↓ ↓ ↓ ↓ ↓ ↓ ↓ ↓

1 1 1 0 1 1 0 1 0 0 1 1 0 1 0 0 . 0 1 0 1

$$1 \times 2^{15} + 1 \times 2^{14} + 1 \times 2^{13} + 0 \times 2^{12} + 1 \times 2^{11} + 1 \times 2^{10} + 0 \times 2^9 + 1 \times 2^8 + 0 \times 2^7 + 0 \times 2^6 + 1 \times 2^5$$

$$+ 1 \times 2^4 + 0 \times 2^3 + 1 \times 2^2 + 0 \times 2^1 + 0 \times 2^0 + 0 \times 2^{-1} + 1 \times 2^{-2} + 0 \times 2^{-3} + 1 \times 2^{-4} = 60,724.3125$$

# Representation of Numbers on Computers

Base 10	Base 2			
	$2^3$	$2^2$	$2^1$	$2^0$
1	0	0	0	1
2	0	0	1	0
3	0	0	1	1
4	0	1	0	0
5	0	1	0	1
6	0	1	1	0
7	0	1	1	1

$$\begin{aligned}
 & 0 \cdot 2^3 + 1 \cdot 2^2 + 1 \cdot 2^1 + 1 \cdot 2^0 \\
 &= 0 + 4 + 2 + 1 \\
 &= \mathbf{6}
 \end{aligned}$$

- Binary arithmetic is used by computers since transistors can be used as extremely fast switches where "**1**" and "**0**" refer to switch being "**on**" and "**off**", respectively.

# Representation of Numbers on Computers

- For binary arithmetic in computers, each binary digit (i.e. **1** or **0**) is called a **bit**.
- Sometimes, numbers having a finite representation in one system (with a specific **base**) may have infinite (or not exact) representation in another system with a different base. For Ex:  
 $0.1 \text{ (decimal)} = 0.0001100110011\dots \text{(binary)}$ .
- In these cases, round-off and truncation errors (to be discussed later) will occur.
- To accommodate for large and small numbers, real numbers are represented using the **floating point representation**.

# Floating Point Representation

## Decimal Floating Point Representation (*Scientific Notation*):

- It has the form:  $d_0.d_1d_2\dots d_n \times 10^p$ . (d's are decimal digits)
- The number  $0.d_1d_2\dots d_n$  is called the *mantissa*.
- The integer "p" (i.e. the power of 10) is called the *exponent*.
- "p" represents the number's order of magnitude (provided the preceding number is smaller than 5), otherwise the number is said to be of the order of  $p+1$ .

- For example:

$2.9543 \times 10^{-7}$  is of the order of  $10^{-7}$  "written as  $O(10^{-7})$ "

$7.954326 \times 10^3$  is of the order of  $10^4$  "written as  $O(10^4)$ "

# Floating Point Representation

## Decimal Floating Point Representation (*Scientific Notation*):

- For this form:  $d_0.d_1d_2\dots d_n \times 10^p$ , the number of significant digits is **n+1**.

<i>standard notat.</i>	<i>scientific notat.</i>	<i>order of magn.</i>	<i># of sign. digits</i>
4519.23	$4.51923 \times 10^3$	$O(10^3)$	6
732.5051	$7.325051 \times 10^2$	$O(10^3)$	7
-0.00012	$-1.2 \times 10^{-4}$	$O(10^{-4})$	2
-0.005612	$-5.612 \times 10^{-3}$	$O(10^{-2})$	4

# Floating Point Representation

## Binary Floating Point Representation:

- It has the form:  $1.b_1b_2\dots b_n \times 2^{B_1B_2\dots B_m}$ . (*b's and B's are binary digits*)
- The binary digits  $.b_1b_2\dots b_n$  is the ***mantissa***.
- The binary digits " $B_1B_2\dots B_m$ " (i.e. the power of 2) is the ***exponent***.
- A decimal number is converted to binary floating point representation using a ***two-step approach***:
  - (a) Normalize the decimal number with respect to the largest power of **2** that is smaller than the decimal number itself. Note that the new (*normalized*) decimal number will have the following form:  
 $1.d_1d_2\dots d_j \times 2^{D_1D_2\dots D_k}$  (*where the d's and D's are decimal digits*)
  - (b) Then, convert the mantissa and the power of 2 of the *normalized decimal number* from decimal to binary.

# Floating Point Representation

## Binary Floating Point Representation:

### Textbook Examples:

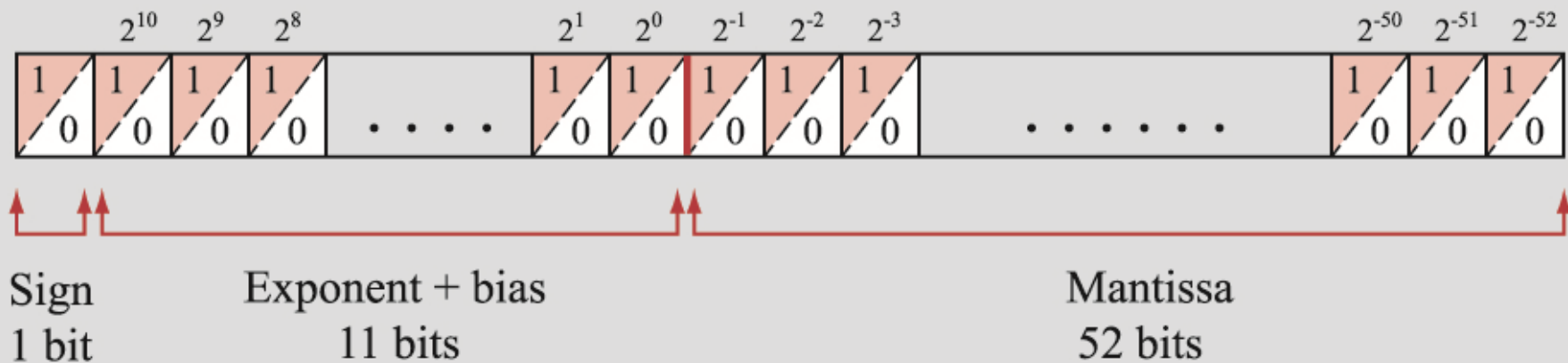
Decimal Number	Normalized Decimal Number	Binary Floating Point Rep.
50	$50/2^5 \times 2^5 = 1.5625 \times 2^5$ ( $50/32 \times 2^5$ )	$1.1001 \times 2^{101}$
0.3125	$0.3125/2^{-2} \times 2^{-2} = 1.25 \times 2^{-2}$ ( $0.3125/0.25 \times 2^{-2}$ )	$1.01 \times 2^{-10}$
1344	$1344/2^{10} \times 2^{10} = 1.3125 \times 2^{10}$ ( $1344/1024 \times 2^{10}$ )	$1.0101 \times 2^{1010}$

# Storing Numbers in Computer Memory

- Once in binary floating point representation, numbers are stored in the computer.
- Computers store the values of the exponent and the mantissa separately, while the leading "1" in front of the decimal point (i.e. that leads the mantissa is not stored).
- The memory in the computer is organized in bytes (each byte is 8 bits).
- Computers store numbers and perform calculations in either ***single precision*** (using a string of 32 bits, i.e. 4 bytes) or ***double precision*** (using a string of 64 bits, i.e. 8 bytes).
- This is according to the IEEE (Institute of Electrical and Electronics Engineers) IEEE-754 standard.

# Storing Numbers in Computer Memory

- In both cases (single & double precisions), the first bit stores the sign of the number (**0** for **+** and **1** for **-**).
- The following 8 bits in single precision (11 bits in double precision) are used to store the exponent.
- Then, the next 23 bits in single precision (52 bits in double precision) are used to store the mantissa.

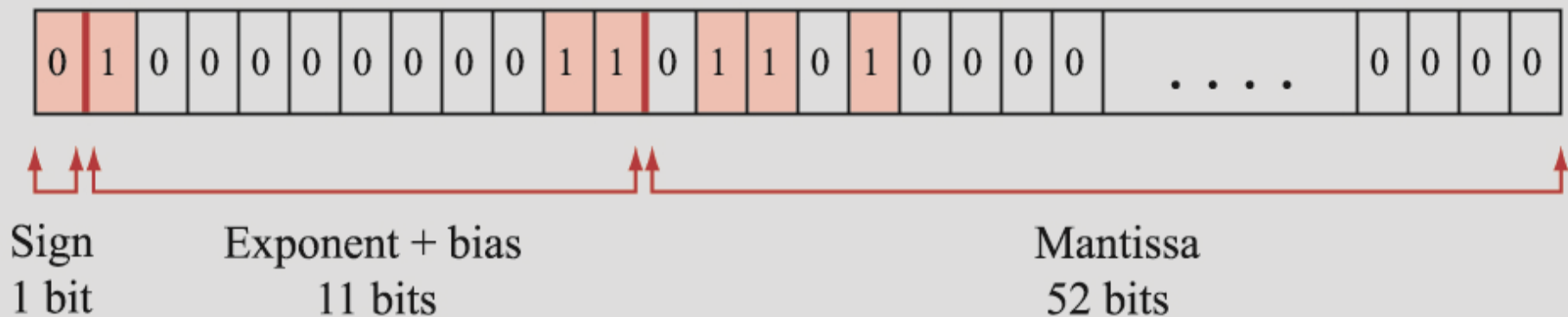


# Storing Numbers in Computer Memory

- As can be seen from the previous slide, the exponent is stored with adding a bias (a constant which is positive in this case) to avoid using one of the bits for the sign of the exponent.
- In double precision, the used bias is 1023.
- Thus, the largest (i.e. positive) *actual* exponent that can be stored is 1024 (stored as 2047), **why?**.
- Also, the smallest (i.e. negative) *actual* exponent that can be stored is -1023 (stored as 0).

# Storing Numbers in Computer Memory

- Here is how the decimal number 22.5 is stored (as a floating point representation) using double precision.
- Normalization:  $22.5/2^4 \times 2^4 = 22.5/16 \times 2^4 = 1.40625 \times 2^4$
- Exponent with bias (11 bits):  $4 + 1023 = 1027 \Rightarrow 1000000011$  (in binary).
- Mantissa (52 bits):  $.011010000\dots0000$  (in binary).
- Sign (1 bit): 0 (positive).



# Storing Numbers in Computer Memory

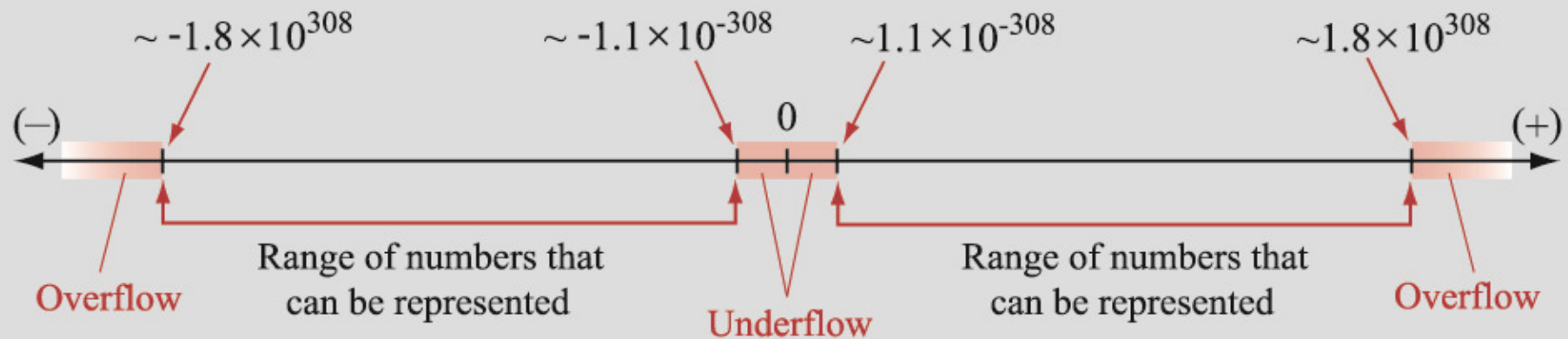
- Since a finite number of bits is used (either in single or double precision), not every number can be accurately represented in binary.

## In double precision:

- The smallest positive number that can be expressed is  $2^{-1023}$  (binary)  $\approx 1.1 \times 10^{-308}$  (decimal), i.e. not zero!.
- The corresponding largest negative number is  $-1.1 \times 10^{-308}$  (decimal).
- The largest positive number that can be expressed is  $2^{1024}$  (binary)  $\approx 1.8 \times 10^{308}$  (decimal), i.e. not  $\infty$ !.
- The corresponding smallest negative number is  $-1.8 \times 10^{308}$  (decimal).

# Storing Numbers in Computer Memory

- Numbers outside the ranges given in the previous slide will cause either **overflow errors** or **underflow errors** (depending on the case, see figure below).



- In addition to **underflow** and **overflow** errors, other errors will occur in case of infinite (or not exact) binary representation of some decimal numbers (*Recall the **0.1** example discussed earlier*).

# Required Mathematical Refreshments

- Limit of a function.
- Continuity of a function.
- Intermediate value theorem.
- **Derivative of a function.**
- Chain rule for ordinary differentiation.
- **Mean value theorem for derivatives.**
- Integral of a function.
- Fundamental theorem of calculus.
- Mean value theorem for integrals.
- Derivatives of functions of two independent variables (Partial derivatives & Chain rule).



# Errors Definition (1/4)

- **Truncation Errors:** Result when approximations are used to represent exact mathematical procedures. (*will be explained in Taylor Series discussion*)
- **Round-Off Errors:** Results when numbers having limited significant figures are used to represent exact numbers (This includes computers that can represent only quantities with a finite number of digits).

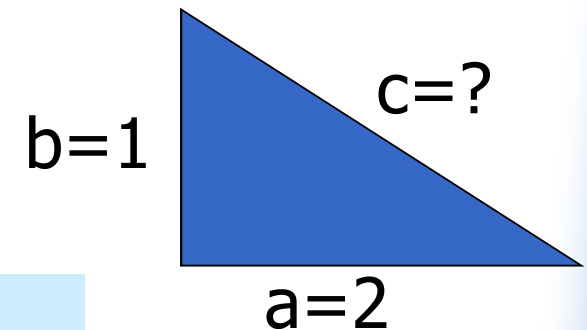
**Ex:**

$$c = \sqrt{a^2 + b^2} = \sqrt{2^2 + 1^2} = \sqrt{5}$$

$$c_1=2.2, \quad c_2= 2.24, \quad c_3=2.236, \quad c_4=2.2361, \quad \dots$$

$$c_{14} = 2.23606797749979$$

$$(c_3)^2 = (2.236)^2 = 4.9997 \sim 5 \quad (\text{but not exactly } 5)$$



# Errors Definition (2/4)

**Total Error = Truncation Errors + Round-Off Errors**

- **True Error ( $E_t$ ):**

$$E_t = \text{True Value} - \text{Approximation}$$

- **True Relative Error ( $e_t$ ):**

$$e_t = \frac{\text{True Error}}{\text{True Value}} = \frac{E_t}{\text{True Value}}$$

- **True Percent Relative Error ( $\varepsilon_t$ ):**

$$\varepsilon_t = \frac{\text{True Error}}{\text{True Value}} 100\% = \frac{E_t}{\text{True Value}} 100\%$$

# Errors Definition (3/4)

**Total Error = Truncation Errors + Round-Off Errors**

- **Approximate Error ( $E_a$ ):**

$$E_a = \text{Current Approximation} - \text{Previous Approximation}$$

- **Approximate Relative Error ( $e_a$ ):**

$$e_a = \frac{\text{Approximate Error}}{\text{Approximation}} = \frac{E_a}{\text{Approximation}}$$

- **Approximate Percent Relative Error ( $\varepsilon_a$ ):**

$$\varepsilon_a = \frac{\text{Approximate Error}}{\text{Approximation}} 100\% = \frac{E_a}{\text{Approximation}} 100\%$$

# Errors Definition (4/4)

When we should stop our “approximation”? i.e. what will be our latest computed  $\epsilon_a$ ?

This is obtained by using a prespecified percent tolerance (acceptable relative error)  $\epsilon_s$ , such that:

$$|\epsilon_a|_{last} < \epsilon_s$$



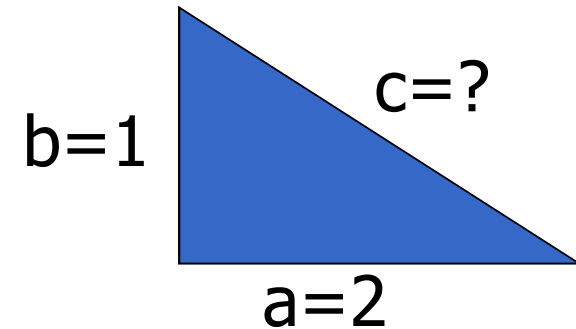
**We usually use  $|\epsilon_a|$**

# Example #1

Compute the value of  $c$  with approximating your answer to:

- (a) three decimals.
- (b) four decimals.

Then, obtain the following:



- (1) the true percent relative error for (a) and (b)
- (2) the approximate percent relative error using (a) and (b)

Assume the true value of  $c$  is the one with 14 decimals.

# Example #1 (Sol.)

$$c = \sqrt{a^2 + b^2} = \sqrt{2^2 + 1^2} = \sqrt{5}$$

$$c_{14} = 2.23606797749979 \quad (\text{assumed true value})$$

$$(a) c_3 = 2.236$$

$$(b) c_4 = 2.2361$$

$$(1) |\varepsilon_{t_3}| = \left| \frac{2.236 - 2.23606797749979}{2.23606797749979} \right| 100\% = 0.003\%$$

$$(1) |\varepsilon_{t_4}| = \left| \frac{2.2361 - 2.23606797749979}{2.23606797749979} \right| 100\% = 0.001\%$$

$$(2) |\varepsilon_{a_{4,3}}| = \left| \frac{2.2361 - 2.236}{2.2361} \right| 100\% = 0.005\%$$



**Comment!**

## Example #2

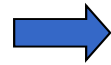
In **Example #1**, use an acceptable tolerance of 0.002% to “terminate” computing the value of  $c$  (start from one decimal).

$$c_1=2.2, c_2=2.24$$



$$|\varepsilon_{a_{2,1}}| = \left| \frac{2.24 - 2.2}{2.24} \right| 100\% = 1.667\%$$

$$c_2=2.24, c_3=2.236$$



$$|\varepsilon_{a_{3,2}}| = \left| \frac{2.236 - 2.24}{2.236} \right| 100\% = 0.179\%$$

$$c_3=2.236, c_4=2.2361$$



$$|\varepsilon_{a_{4,3}}| = \left| \frac{2.2361 - 2.236}{2.2361} \right| 100\% = 0.005\%$$

$$c_4=2.2361, c_5=2.23607$$



$$|\varepsilon_{a_{5,4}}| = \left| \frac{2.23607 - 2.2361}{2.23607} \right| 100\% = 0.001\%$$

# Rules for Significant Figures

- Engineers usually work with numbers that obtain several digits and hence should determine how many of them are significant.
- A ***significant digit*** in a number is the least *significant figure* that is considered reliable in the number as a result of measurements or calculations.
- The number of *significant figures* in a result indicates the number of digits that can be used with confidence.
- A common mistake is to show too many figures in the answer, which gives the impression that the answer is more accurate than it really is.

# Rules for Significant Figures

## Rule #1:

- Same significant digit must be used in a coherent set of engineering operations and data processing.
- When different significant digits are involved in an operation, a truncation and rounding operation must be carried out in processing the result.

## Rule #2:

- The rule of rounding in significant digits processing is to truncate 4 and round up 5. *For Example:*

6.2548  $\longrightarrow$  6.3 (for 1 significant decimal digit)

6.2548  $\longrightarrow$  6.25 (for 2 significant decimal digits)

6.2548  $\longrightarrow$  6.255 (for 3 significant decimal digits)

# Rules for Significant Figures

## Rule #3:

- The result of *addition* and *subtraction* should show significant digits only as far to the right as is seen in the least precise number in the calculation.
- The insignificant digits following the least significant figure should be rounded to the least significant figure.

## Examples:

$$1725.463 - 189.2 = 1536.263 \quad \longrightarrow \quad 1536.3$$

$$23578.3 + 0.1892 = 23578.4892 \quad \longrightarrow \quad 23578.5$$

$$3.510 + 2.246 + 0.0192 = 5.7752 \quad \longrightarrow \quad 5.775$$

# Rules for Significant Figures

## Rule #4:

- The result of *multiplication or division* should show significant digits only as far to the right as that are contained in the number with the fewest significant digits.
- The insignificant digits following the least significant figure should be rounded to the least significant figure.

## Examples:

$$2.43 \times 17.675 = 42.950250 \rightarrow 42.95$$

$$75.22 \div 25.1 = 2.9968127 \rightarrow 3.0$$

$$75.220 \div 25.100 = 2.9968127 \rightarrow 2.997$$

# Taylor Series

- “is a mathematical formulation that is used widely in numerical methods to express functions in an **approximate** fashion”.
- “provides a means to **predict** a function value at one point in terms of the function value and its derivatives at another point”.

# Taylor Series

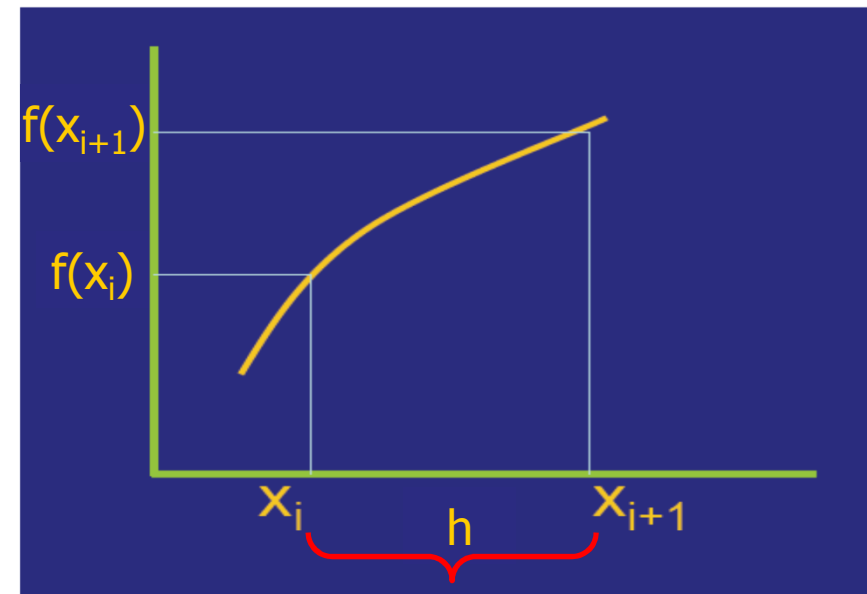
- For a function  $f(x)$  that depends on only one independent variable  $x$ , the value at point  $x_{i+1}$  can be **approximated** by the following Taylor Series:

$$f(x_{i+1}) = f(x_i) + f'(x_i)(x_{i+1} - x_i) + \frac{1}{2!}f''(x_i)(x_{i+1} - x_i)^2 + \dots + \frac{1}{n!}f^{(n)}(x_i)(x_{i+1} - x_i)^n + R^n$$

The term  $R^n$  is called the  
**“Remainder”**

$$R^n = \frac{1}{(n+1)!}f^{(n+1)}(\xi)(x_{i+1} - x_i)^{n+1}$$

where  $\xi$  is a value of  $x$  that lies between  $x_i$  and  $x_{i+1}$



# Taylor Series

$$f(x_{i+1}) = f(x_i) + f'(x_i)h + \frac{f''(x_i)}{2!}h^2 + \dots + \frac{f^{(n)}(x_i)}{n!}h^n + R^n$$

$$f(x_{i+1}) = \sum_{k=0}^{\infty} \frac{f^{(k)}(x_i)}{k!}h^k$$

$$f(x_{i+1}) \cong f(x_i)$$

zero order approximation

$$f(x_{i+1}) \cong f(x_i) + f'(x_i)h$$

1<sup>st</sup> order approximation

$$f(x_{i+1}) \cong f(x_i) + f'(x_i)h + \frac{f''(x_i)}{2!}h^2$$

2<sup>nd</sup> order approximation

⋮

$$f(x_{i+1}) \cong f(x_i) + f'(x_i)h + \frac{f''(x_i)}{2!}h^2 + \dots + \frac{f^{(n)}(x_i)}{n!}h^n$$

n<sup>th</sup> order approx.

## Example #3

Use Taylor series to expand the function:

$f(x) = \sin(x)$  with an expansion point of  $x=0.2$  to evaluate  $f(x)$  at  $x=0.8$

In your expansion, use zero order, 1<sup>st</sup> order, 2<sup>nd</sup> order, 3<sup>rd</sup> order, and 4<sup>th</sup> order approximations.

Then, estimate the true relative error for each case.

Hint: all  $x$  values are in radians

## Example #3 (Sol."1/5")

$$x_i = 0.2, \quad x_{i+1} = 0.8 \quad \longrightarrow \quad h = x_{i+1} - x_i = 0.6$$

$$\sin(0.8) = 0.717356090899523 \quad (\text{assumed true value})$$

$$f(x) = \sin(x), \quad f'(x) = \cos(x), \quad f''(x) = -\sin(x), \quad f^{(3)}(x) = -\cos(x), \quad f^{(4)}(x) = \sin(x)$$

$$f(x_{i+1}) \cong f(x_i) + f'(x_i)h + \frac{f''(x_i)}{2!}h^2 + \frac{f^{(3)}(x_i)}{3!}h^3 + \frac{f^{(4)}(x_i)}{4!}h^4$$

zero order approx.

1<sup>st</sup> order approx.

2<sup>nd</sup> order approx.

3<sup>rd</sup> order approx.

4<sup>th</sup> order approx.

## Example #3 (Sol."2/5")

$$\sin(0.8) \cong \sin(0.2) + \cos(0.2) * 0.6 - \frac{\sin(0.2)}{2!} * 0.6^2 - \frac{\cos(0.2)}{3!} * 0.6^3 + \frac{\sin(0.2)}{4!} * 0.6^4$$

### Zero order approx.

$$\sin(0.8) \cong \sin(0.2) = 0.198669330795061$$

$$|\varepsilon_{t_0}| = \left| \frac{0.717356090899523 - 0.198669330795061}{0.717356090899523} \right| 100\% = 72.3\%$$

### 1<sup>st</sup> order approx.

$$\sin(0.8) \cong \sin(0.2) + \cos(0.2) * 0.6 = 0.786709277499806$$

$$|\varepsilon_{t_1}| = \left| \frac{0.717356090899523 - 0.786709277499806}{0.717356090899523} \right| 100\% = 9.7\%$$

## Example #3 (Sol."3/5")

### 2<sup>nd</sup> order approx.

$$\sin(0.8) \cong \sin(0.2) + \cos(0.2) * 0.6 - \frac{\sin(0.2)}{2!} * 0.6^2 = 0.750948797956695$$

$$|\varepsilon_{t_2}| = \left| \frac{0.717356090899523 - 0.750948797956695}{0.717356090899523} \right| 100\% = 4.7\%$$

### 3<sup>rd</sup> order approx.

$$\begin{aligned} \sin(0.8) &\cong \sin(0.2) + \cos(0.2) * 0.6 - \frac{\sin(0.2)}{2!} * 0.6^2 - \frac{\cos(0.2)}{3!} * 0.6^3 \\ &= 0.71566640115441 \end{aligned}$$

$$|\varepsilon_{t_3}| = \left| \frac{0.717356090899523 - 0.71566640115441}{0.717356090899523} \right| 100\% = 0.24\%$$

## Example #3 (Sol."4/5")

4<sup>th</sup> order approx.

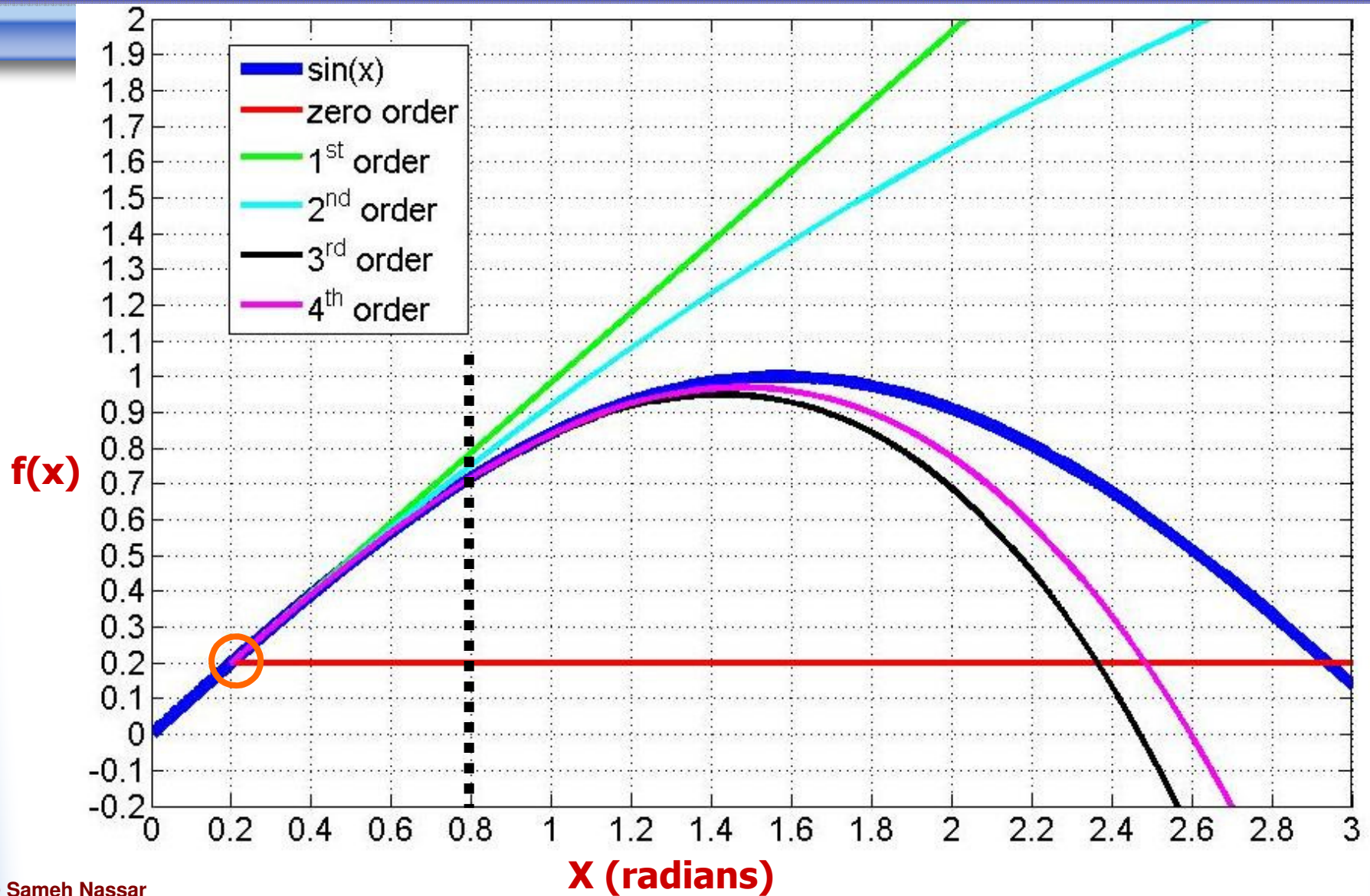
$$\begin{aligned}\sin(0.8) &\cong \sin(0.2) + \cos(0.2) * 0.6 + \frac{\sin(0.2)}{2!} * 0.6^2 - \frac{\cos(0.2)}{3!} * 0.6^3 - \frac{\sin(0.2)}{4!} * 0.6^4 \\ &= 0.716739215540704\end{aligned}$$

$$|\varepsilon_{t_4}| = \left| \frac{0.717356090899523 - 0.716739215540704}{0.717356090899523} \right| 100\% = 0.086\%$$



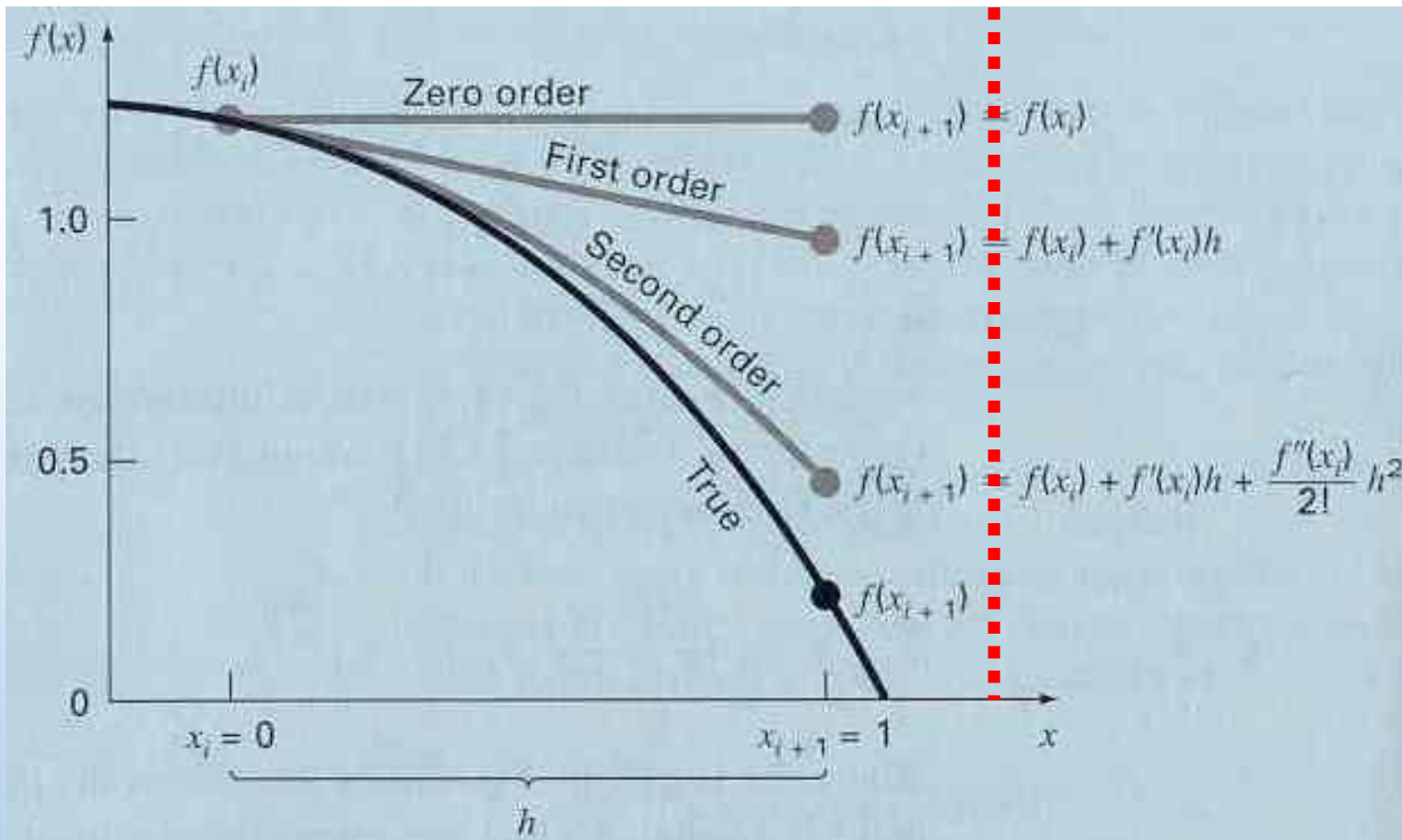
**Comment!**

# Example #3 (Sol."5/5")

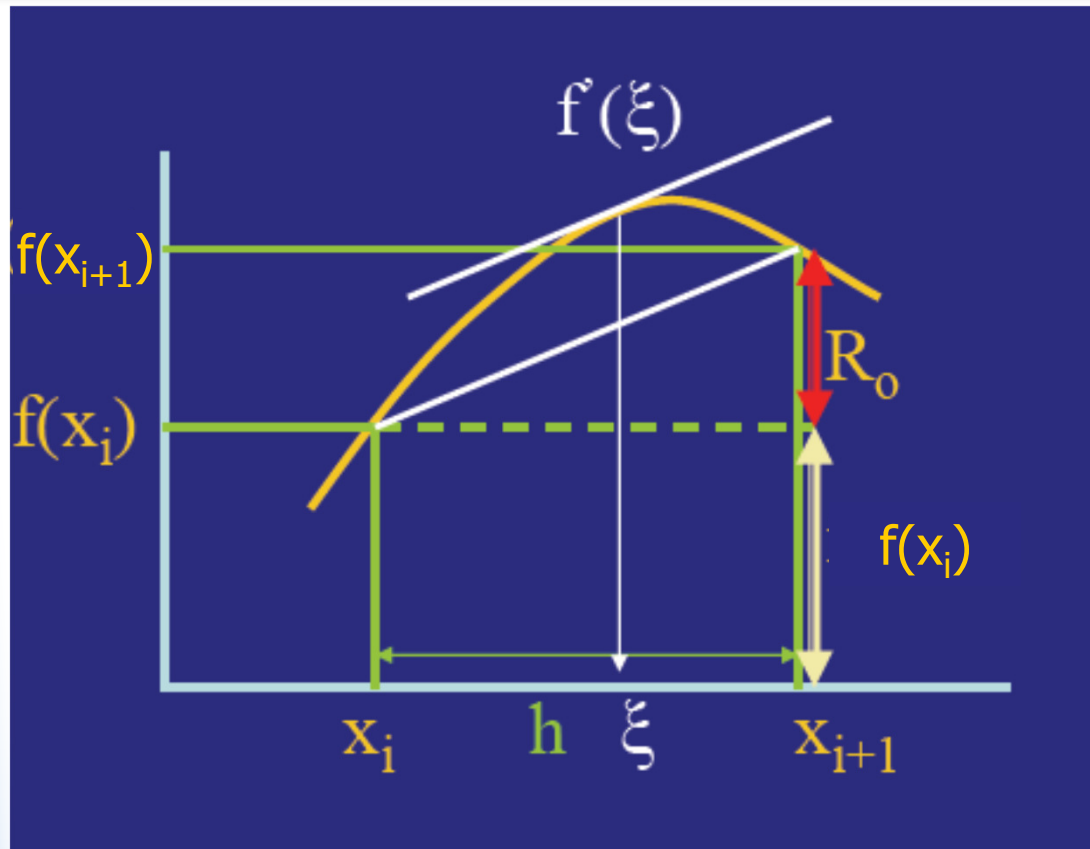


# Finite Number of Derivatives

$$f(x) = -0.1x^4 - 0.15x^3 - 0.5x^2 - 0.25x + 1.2$$



# Truncation Error (1/2)



$$\frac{R_0}{h} = f'(\xi)$$

$$R_0 = f'(\xi)h = O(h)$$

**Similarly:**

$$R_1 = \frac{f''(\xi)}{2!} h^2 = O(h^2)$$



$$R_n = O(h^{n+1})$$

**Truncation Error**

# Truncation Error (2/2)

- **In general, we can usually assume that the truncation error is decreased by:**
  - (1) adding more terms to the Taylor series
  - (2) Reducing the step size  $h$
- The Taylor series becomes more accurate when the approximated function behaves as a “straight-line” over the interval of interest (which is usually not the case!).
- To overcome this problem, we should perform (1) and (2) above.

# Why Taylor Series?

**Suppose that you have to deal with:**

$$f(x) = \ln \left[ x^4 + \cos(x) + \dots - \sum_{k=0}^{\infty} \frac{5}{x^k} \sin(x) + 2x \right]$$

- Difficult to manipulate for further processing
- Difficult to visualize (without plotting) in terms of slope and curvature for example.

## **Remember:**

In Taylor series expansion, we evaluate the  $f(x)$  value within a specific interval (not for the whole range of  $x$  values)

# Taylor Series: Remarks

- Sometimes, Taylor Series expansion can be written using the following format:

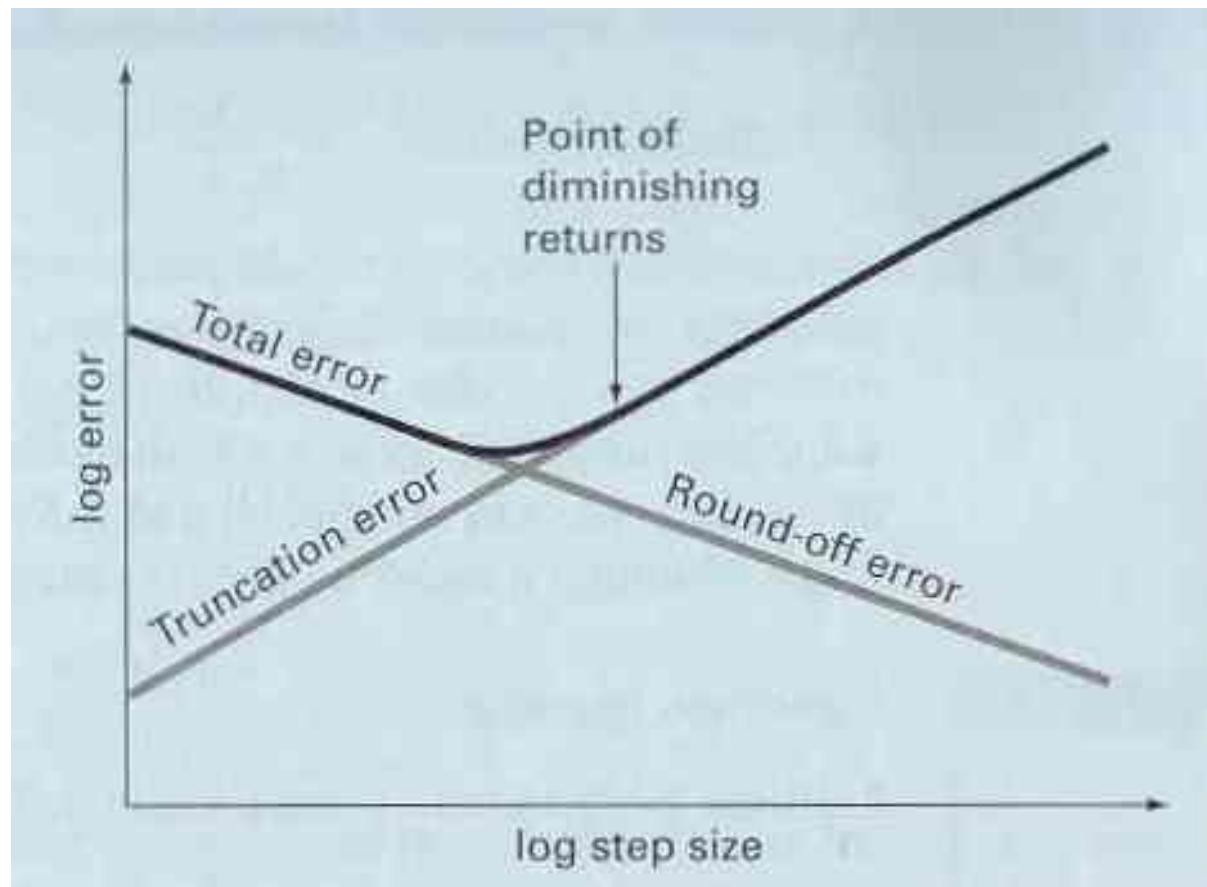
$$f(x) = f(a) + f'(a)(x-a) + \frac{f''(a)}{2!}(x-a)^2 + \dots + \frac{f^{(n)}(a)}{(n)!}(x-a)^n + R_n$$

i.e. replacing the symbols  $x_{i+1}$  by  $x$  and  $x_i$  (point of expansion) by  $a$ .

- For a function that is a function of two or more (independent) variables, Taylor Series can be applied in the same manner as for one variable, however, the differentiation will involve partial derivatives.

# Total Numerical Error

**Total Numerical Error =  
*Sum* (Truncation Errors + Round-Off Errors)**



# Textbook Readings

- **Sections Covered:**

1.1, 1.2, 1.3, 1.4, 2.1, 2.2, 2.7

- **Required Background Sections:**

2.4.1, 2.4.3, 2.4.4, 2.4.5, 2.6