

Introduction of Computer-Aided Nano Engineering

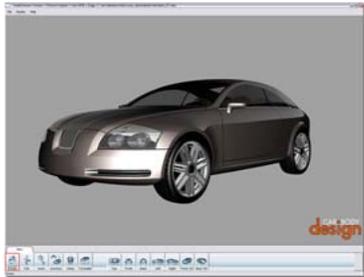
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Topics

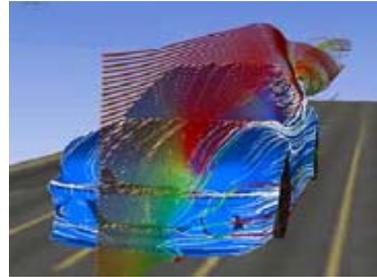
- ❑ Computational Nano Engineering
- ❑ Modeling & Simulation (M&S)
- ❑ Approximations in M&S

Computational Nano-Engineering

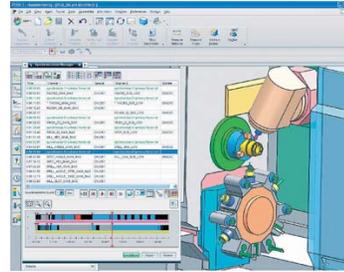
- ❑ Extensive applications of CAD/CAM/CAE software tools in traditional manufacturing lead to
 - Scalable processes
 - Cost effective and high-quality products with short time-to-market



(a) CAD



(b) CAE



(c) CAPP/CAM



(d) CAM

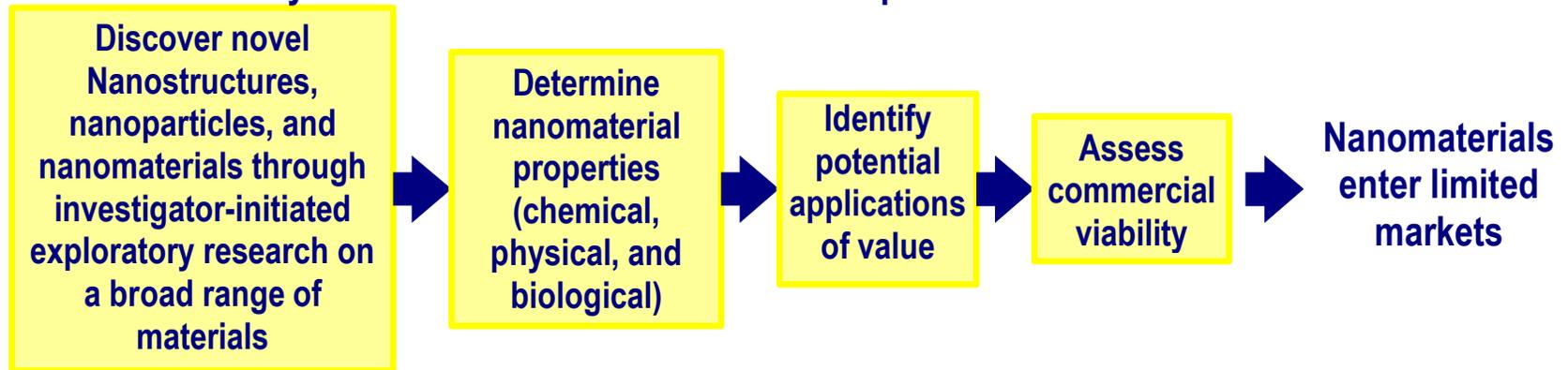
❑ *Virtual Prototyping* at nanoscales

- Computer-Aided Nano-Design (CAND)
- Computer-Aided Nano-Manufacturing (CANM)
- Computer-Aided Nano-Engineering (CANE)

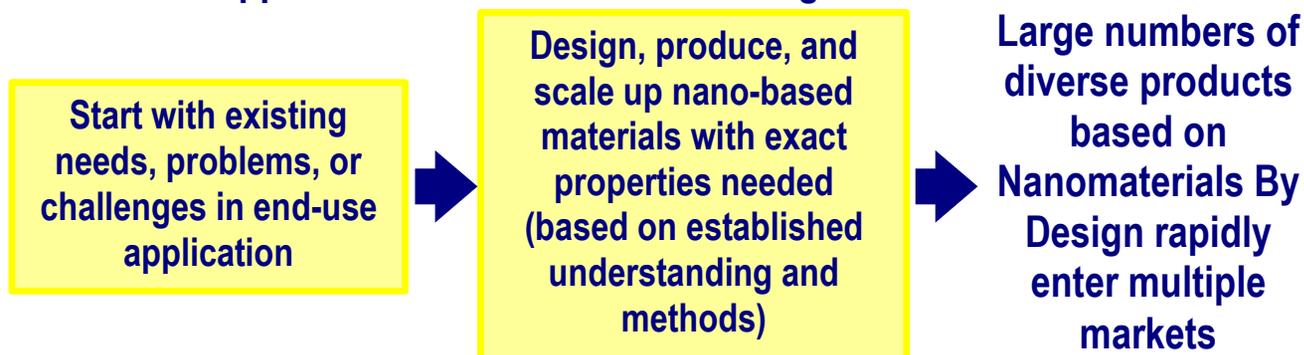
Computational Nano-Engineering

- Use Modeling & Simulation tools to systematically resolve the issue of “lack of design” at nano scales.

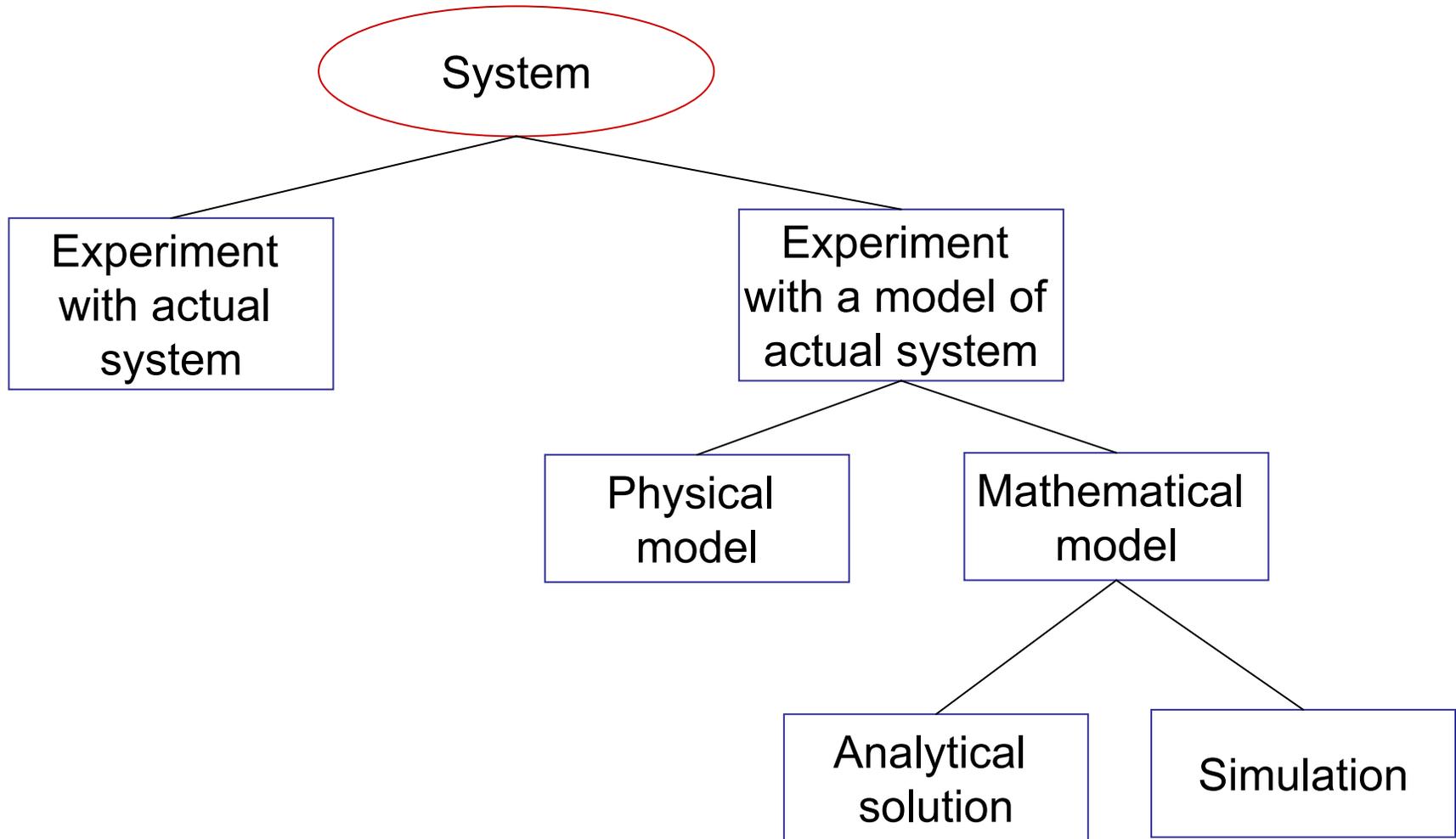
PAST: Discovery-Based Science and Product Development



FUTURE: Application-Based Problem Solving



How to study a system



What is Modeling?

Why mathematical modeling?

- Advantages

- Disadvantages

An example of modeling

□ Free fall model



Mathematical model

□ *Dependent variable = f (Independent variable)*

$$y = f(x)$$

□ High dimensional

$$y = f(x_1, x_2, \dots)$$

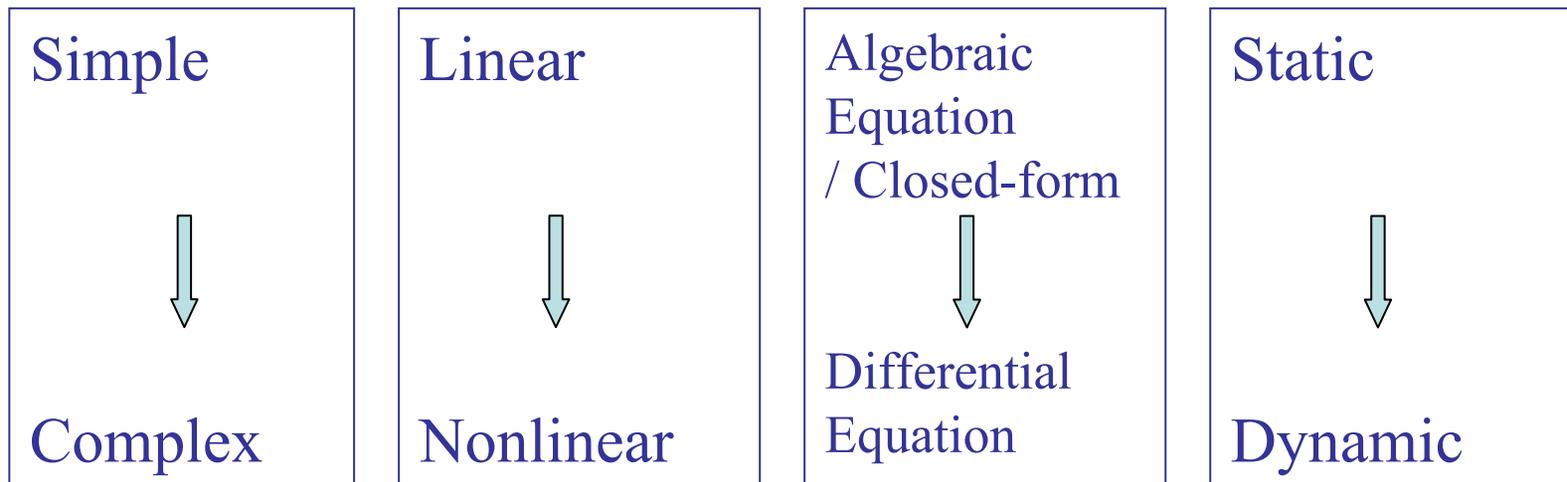
□ Parametric systems

$$y = f(x_1(u), x_2(u), \dots, x_n(u), u)$$

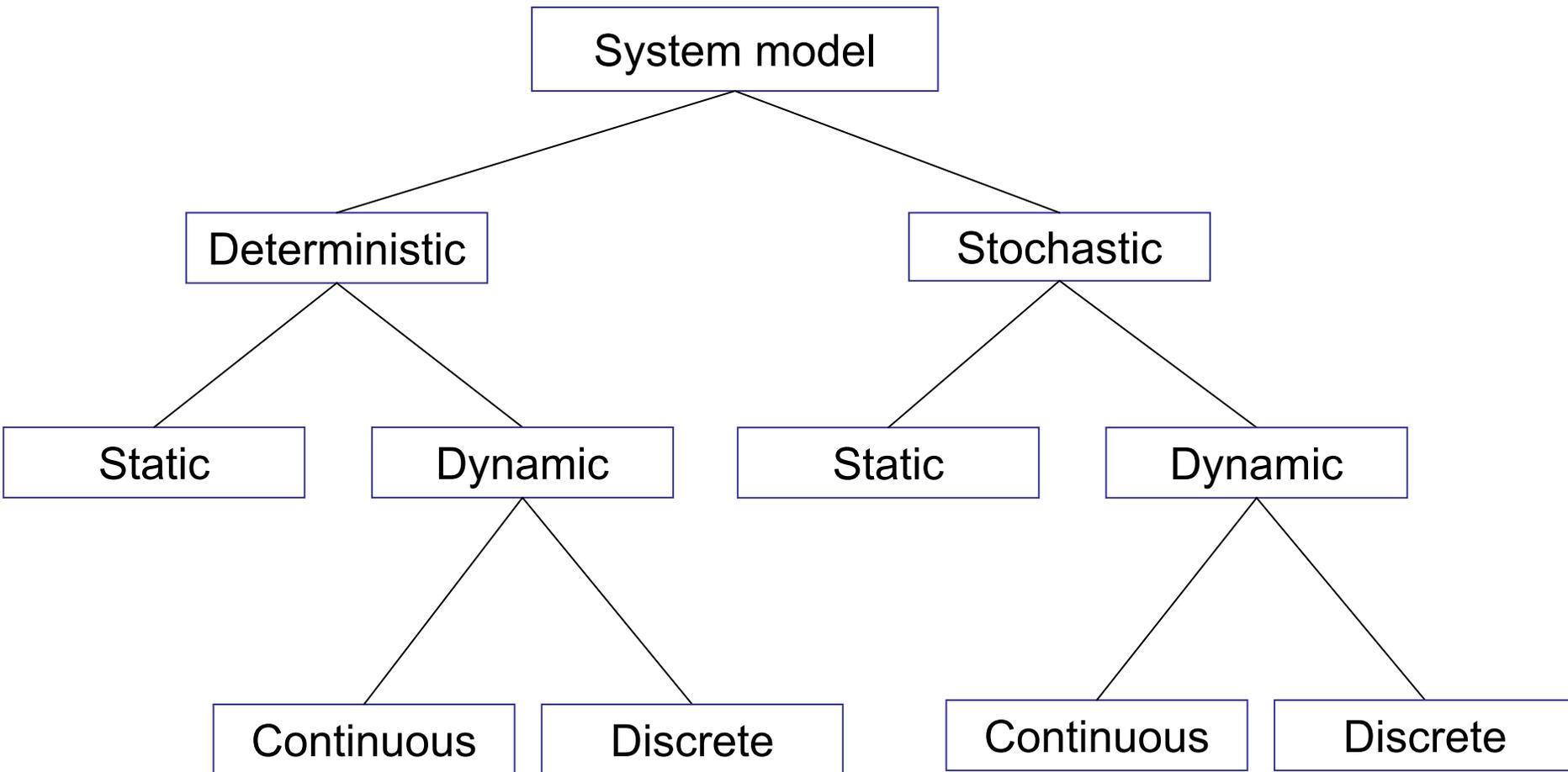
□ “Noisy” systems

$$y = f(x, \gamma)$$

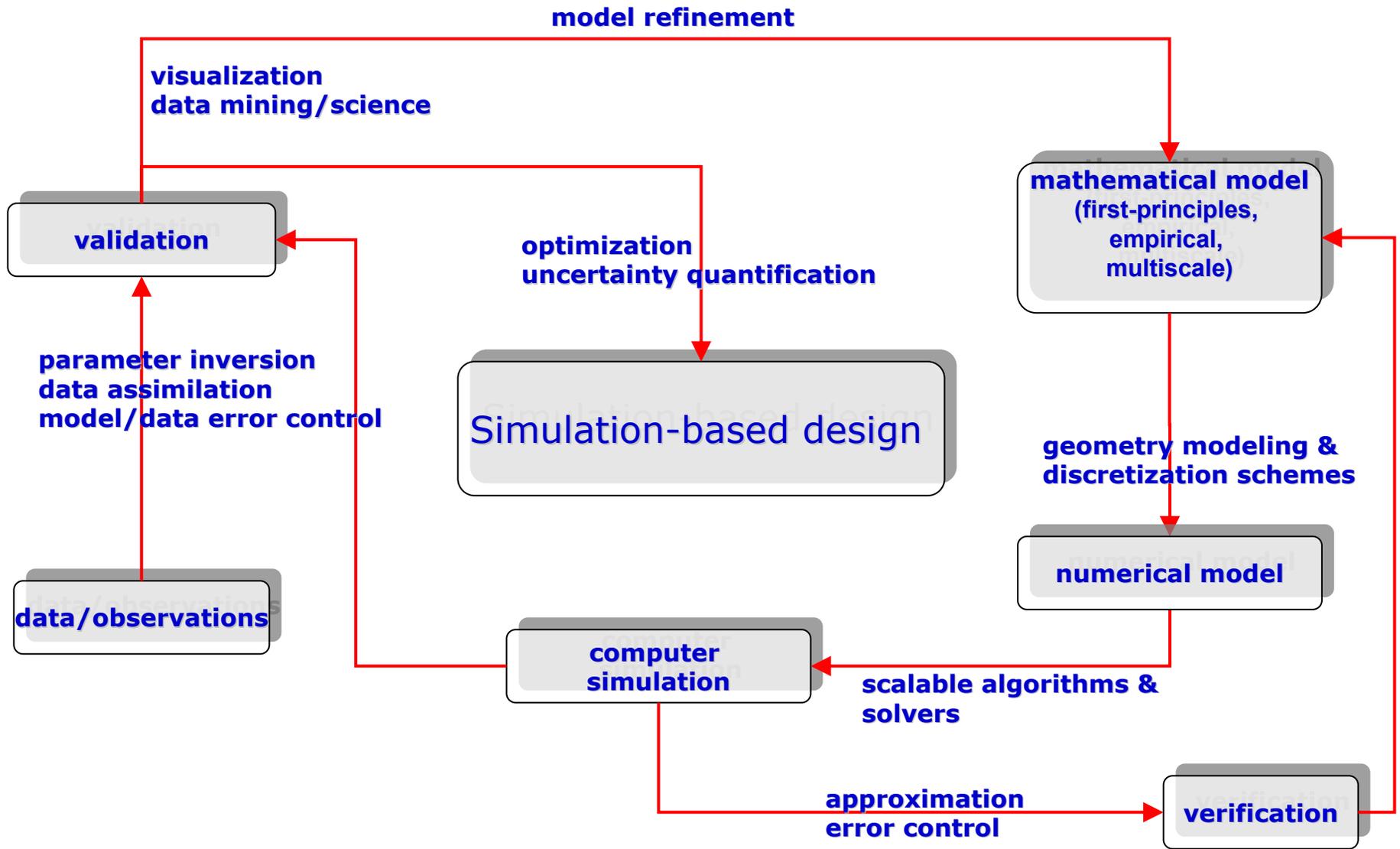
Complexity of Mathematical Models



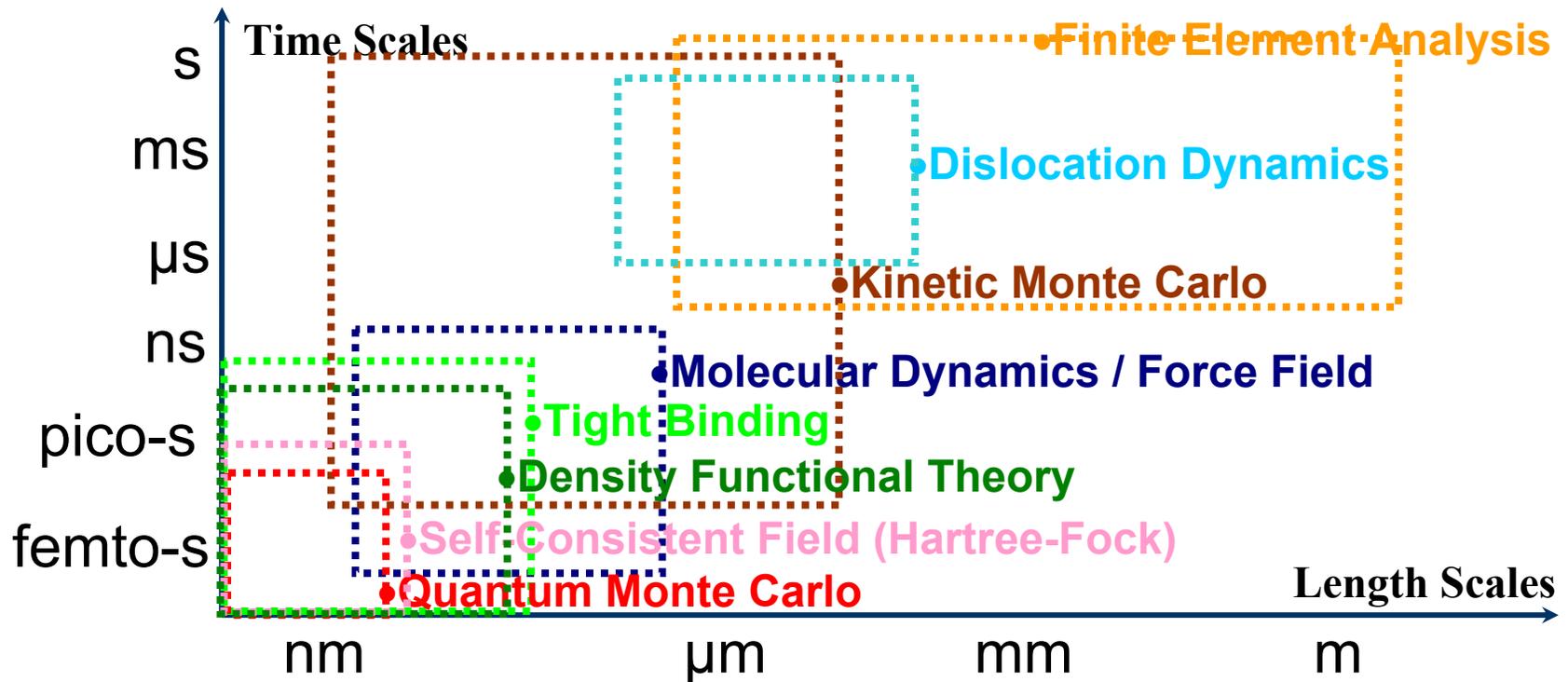
Model Taxonomy



Simulation-based Design



Modeling & Simulation at Multiple Scales



Various methods used to simulate at different length and time scales

Approximations in simulation

□ mathematical models → numerical models

- Taylor series
- Functional analysis

□ numerical models → computer codes

- Discretization (differentiation, integration)
- Searching algorithms (solving equations, optimization)
- Floating-point representation

Mathematical models \rightarrow Numerical models

Approximation in Taylor Series

□ Truncation

Mathematical models → Numerical models

Functional Analysis

- Convert complex functions into simple and computable ones by transformation in vector spaces
 - Fourier analysis
 - Wavelet transform
 - Polynomial chaos expansion
 - Spectral methods
 - Mesh-free methods
 - ...

Mathematical models \rightarrow Numerical models

Functional Analysis

- Approximate the original $f(x)$ by linear combinations of basis functions $\psi_i(x)$'s as

$$f(x) \approx \sum_{i=0}^N c_i \psi_i(x)$$

- In a vector space (e.g. Hilbert space) with an infinite number of dimensions

$$f(x) = \sum_{i=0}^{\infty} c_i \psi_i(x)$$

Mathematical models → Numerical models

Functional Analysis

- An *inner product* $\langle f, g \rangle$ is defined as a “projection” in the vector space, such as

$$\langle f, g \rangle := \int_{-\infty}^{\infty} f(x)g(x)W(x)dx$$

- Typically we choose orthogonal basis functions $\psi_i(x)$'s such that

$$\langle \psi_i, \psi_j \rangle = \int_{-\infty}^{\infty} \psi_i(x)\psi_j(x)W(x)dx = \begin{cases} \text{Constant} & (\forall i, j, i = j) \\ 0 & (i \neq j) \end{cases}$$

for orthonormal basis functions

$$\langle \psi_i, \psi_j \rangle = \int_{-\infty}^{\infty} \psi_i(x)\psi_j(x)W(x)dx = \begin{cases} 1 & (i = j) \\ 0 & (i \neq j) \end{cases}$$

Mathematical models \rightarrow Numerical models

Functional Analysis

- The coefficients c_i 's are computed by

$$c_i = \frac{\langle f, \psi_i \rangle}{\langle \psi_i, \psi_i \rangle}$$

- The computable function is

$$f(x) \approx \sum_{i=0}^N c_i \psi_i(x)$$

with ***truncation!***

Functional Analysis

– Fourier Series Approximations

$$\begin{aligned} f(t) &= a_0 + a_1 \cos(\omega_0 t) + b_1 \sin(\omega_0 t) + a_2 \cos(2\omega_0 t) + b_2 \sin(2\omega_0 t) + \dots \\ &= a_0 + \sum_{k=1}^{\infty} [a_k \cos(k\omega_0 t) + b_k \sin(k\omega_0 t)] \end{aligned}$$

where $\omega_0 = \frac{2\pi}{T}$ is called the *fundamental frequency*.

- All *periodic functions* can be approximated by Fourier Series well!
- Is used in *plane-wave density functional theory* simulations
- Because of efficient Fast Fourier Transform (FFT)!

Functional Analysis

– Fourier Series Approximations

Inner products

$$a_0 = \frac{1}{T} \int_0^T f(t) dt$$

$$a_k = \frac{2}{T} \int_0^T \cos(k\omega_0 t) f(t) dt \quad (k = 1, 2, \dots)$$

$$b_k = \frac{2}{T} \int_0^T \sin(k\omega_0 t) f(t) dt$$

<i>Fourier Series</i>	<i>Fourier Transform</i>	<i>Discrete Fourier Transform</i>
$\tilde{c}_k = \frac{1}{T} \int_0^T f(t) e^{-ik\omega_0 t} dt$	$\tilde{F}(i\omega_0) = \int_{-\infty}^{\infty} f(t) e^{-i\omega_0 t} dt$	$\tilde{F}_k = \sum_{n=0}^{N-1} f_n e^{-ik\omega_0 n} \quad (k = 0, \dots, N-1)$
$f(t) = \sum_{k=-\infty}^{\infty} \tilde{c}_k e^{ik\omega_0 t}$	$f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \tilde{F}(i\omega_0) e^{i\omega_0 t} d\omega_0$	$f_n = \frac{1}{N} \sum_{k=0}^{N-1} \tilde{F}_k e^{ik\omega_0 n} \quad (n = 0, \dots, N-1)$

- Computational complexity: $O(N^2)$
- FFT Complexity: $O(N \log_2 N)$

Functional Analysis

– Wavelet Transform

□ *Wavelet basis functions*

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}} \psi\left(\frac{x-b}{a}\right)$$

where $\psi(x)$ is a continuous function in *both* the real and reciprocal spaces called *mother wavelet*, a is the scale factor, and b is the translation factor.

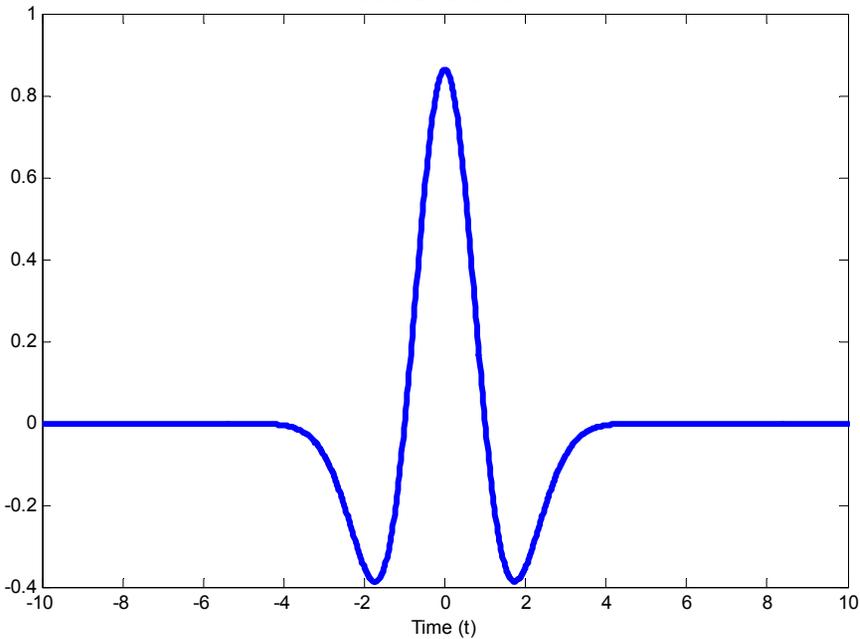
- $\psi(x)$ satisfies
 - Admissibility
 - Regularity condition

Example Continuous Wavelet Functions

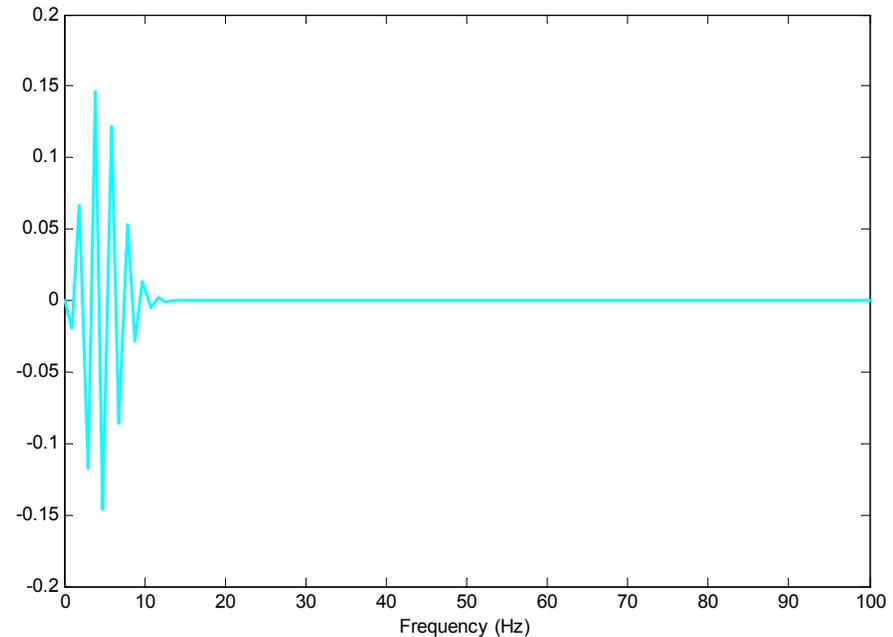
- Mexican hat

$$\psi(x) = \frac{2}{\sqrt{3}} \pi^{-1/4} (1 - x^2) e^{-x^2/2}$$

Mexican hat wavelet

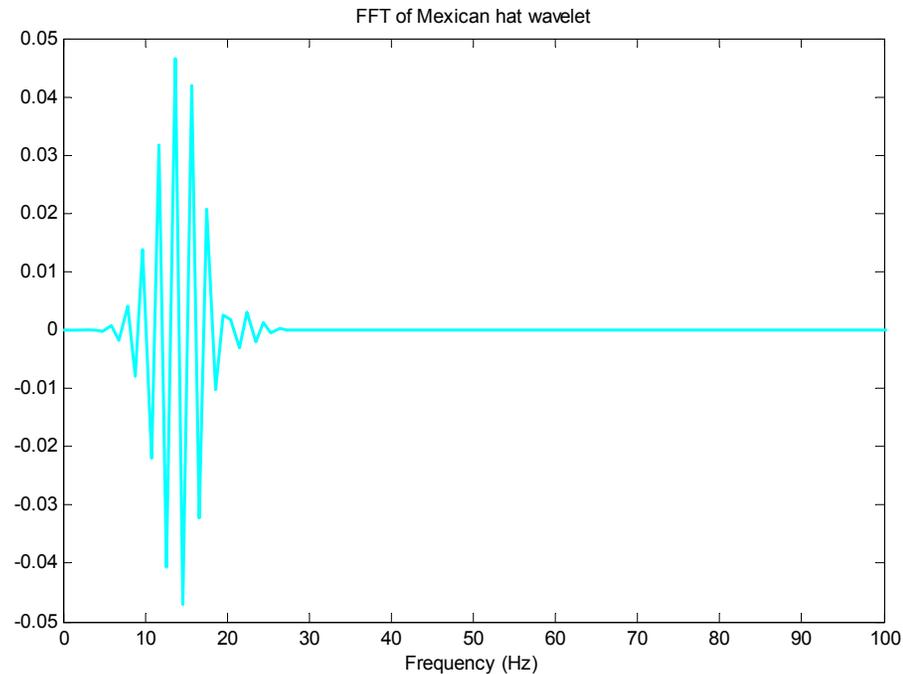
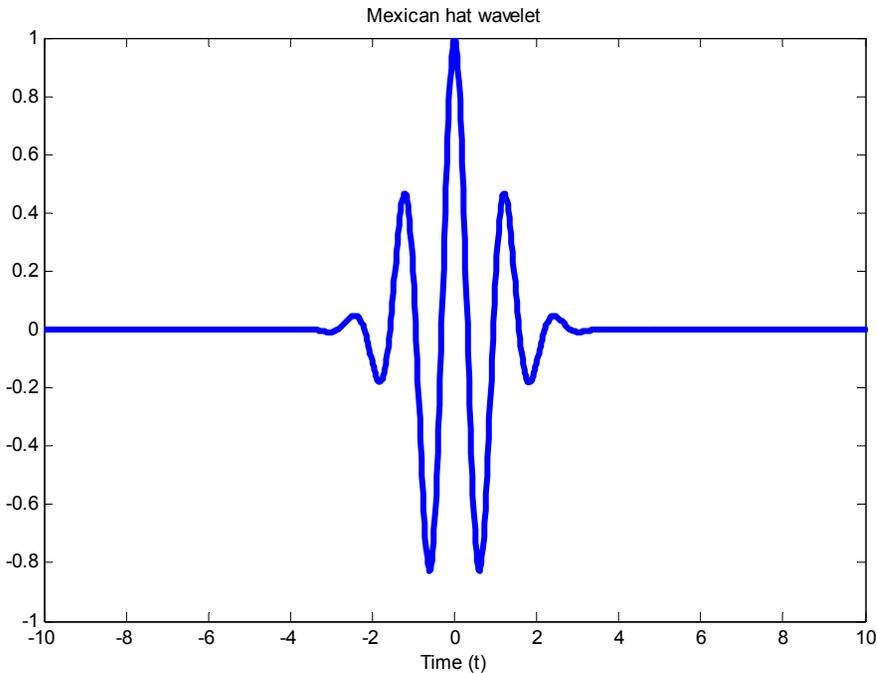


FFT of Mexican hat wavelet



Example Continuous Wavelet Functions - Morlet

$$\psi(x) = e^{-x^2/2} \cos(5x)$$



Functional Analysis

– Wavelet Transform

□ Continuous Transform

$$\tilde{f}(a, b) = \int_{-\infty}^{+\infty} f(x) \psi_{a,b}^*(x) dx$$

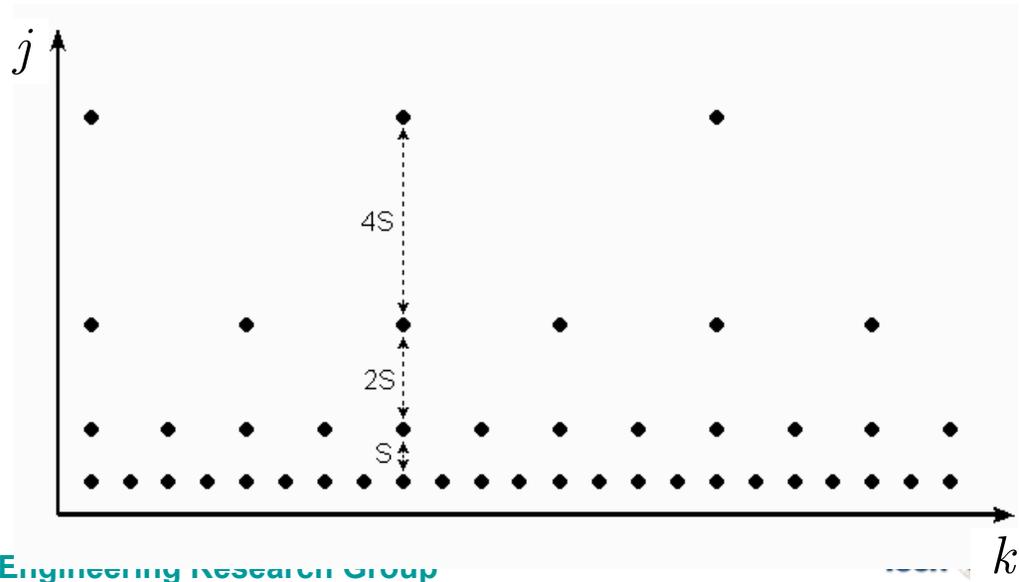
where $\psi_{a,b}^*(x)$ is the complex conjugate of $\psi_{a,b}(x)$.

□ Inverse Transform

$$f(x) = \frac{1}{c_\psi} \int_{-\infty}^{+\infty} \int_0^{+\infty} \tilde{f}(a, b) \psi_{a,b}(x) \frac{da}{a^2} db$$

□ Discrete Transform

$$\psi_{2^j, k}(x) = \frac{1}{\sqrt{2^j}} \psi\left(\frac{x - k}{2^j}\right)$$



Functional Analysis

– Wavelet Transform

□ Admissibility

$$\int_0^{+\infty} \frac{|\hat{\psi}(\omega)|^2}{|\omega|} d\omega < \infty$$

where $\hat{\psi}(\omega) = \int_{-\infty}^{\infty} \psi(x) e^{-i\omega x} dx$ is the Fourier transform of $\psi(x)$.

□ This implies $|\hat{\psi}(\omega = 0)|^2 = 0$ or equivalently $\int_{-\infty}^{\infty} \psi(x) dx = 0$
“No information loss in reconstruction”

□ “must be a wave with zero mean” -- **wave-**

Functional Analysis

– Wavelet Transform

□ Regularity condition

$$\begin{aligned}\tilde{f}(a, b=0) &\approx \frac{1}{\sqrt{a}} \left[\sum_{k=0}^N \frac{1}{k!} f^{(k)}(0) \int x^k \psi\left(\frac{x-0}{a}\right) dx + O(a^{k+1}) \right] \\ &= \frac{1}{\sqrt{a}} \left[\sum_{k=0}^N \frac{1}{k!} f^{(k)}(0) M_k a^{k+1} + O(a^{k+2}) \right] \\ &= \frac{1}{\sqrt{a}} \left[\frac{1}{0!} f(0) M_0 a + \frac{1}{1!} f^{(1)}(0) M_1 a^2 + \dots + \frac{1}{N!} f^{(N)}(0) M_N a^{N+1} + O(a^{k+2}) \right]\end{aligned}$$

□ wavelet functions should have some smoothness and concentration in both time and frequency domains

□ vanishing moments M_1, \dots, M_N as the scale factor a increases (admissibility: $M_0=0$)

□ “Fast Decay” -- **-let**

Approximations in M&S

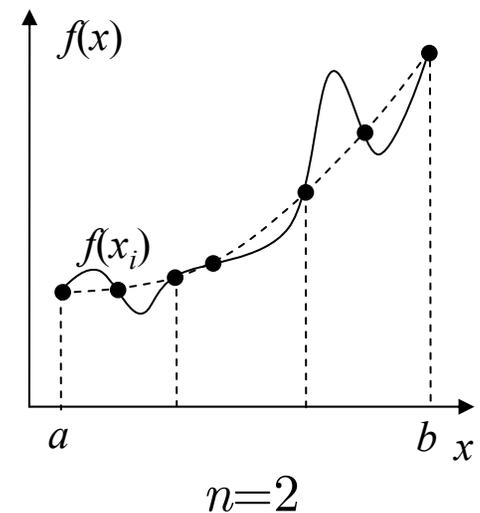
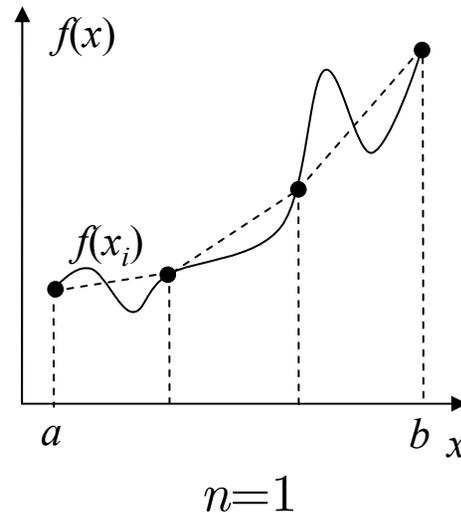
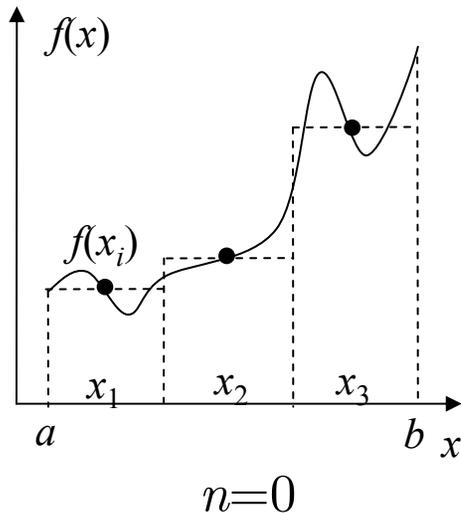
- mathematical models → numerical models
 - Taylor series
 - Functional analysis
- **numerical models → computer codes**
 - **Discretization (differentiation, integration)**
 - **Searching algorithms (solving equations, optimization)**
 - **Floating-point representation**

Numerical Model \rightarrow Computer Code

Compute integrals

□ Quadrature

- Approximate the integrand function by a polynomial of certain degree

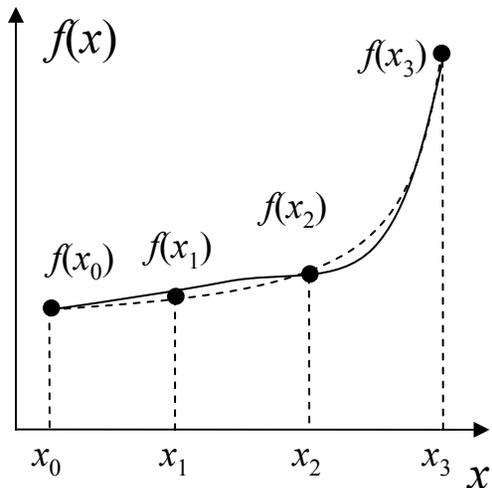


Numerical Model \rightarrow Computer Code

Compute integrals

□ Quadrature

- Approximate the integral by the weighted sum of regularly sampled functional values
 - e.g. Simpson's 3/8 rule



$$I \approx \int_{x_0}^{x_3} f^{(3)}(x) dx = \frac{3h}{8} [f(x_0) + 3f(x_1) + 3f(x_2) + f(x_3)]$$

Numerical Model \rightarrow Computer Code

Compute integrals

□ Monte Carlo simulation

- Let $p(u)$ denote uniform density function over $[a, b]$
- Let U_i denote i^{th} uniform random variable generated by Monte Carlo according to the density $p(u)$
- Then, for “large” N

$$\int_a^b f(x)dx \approx \frac{b-a}{N} \sum_{i=1}^N f(U_i)$$

- Variance reduction (importance sampling) to improve efficiency

Numerical Model → Computer Code

Compute derivatives

□ Finite-divided-difference methods

- Approximated derivatives come from Taylor series
 - e.g. forward-finite-difference

$$f(x_{i+1}) = f(x_i) + f'(x_i)(x_{i+1} - x_i) + O(h^2) = f(x_i) + f'(x_i)h + O(h^2)$$

$$f'(x_i) = \frac{f(x_{i+1}) - f(x_i)}{h} + O(h)$$

Floating-Point Representation

- How does computer represent numbers?



Perfect world



Imperfect world

Ariane 5

- Exploded 37 seconds after liftoff
- Cargo worth \$500 million
- Why
 - Computed horizontal velocity as floating point number
 - Converted to 16-bit integer
 - Worked OK for Ariane 4
 - Overflowed for Ariane 5
 - Used same software



Do you trust your computer?

Rump's function:

$$f(x, y) = 333.75y^6 + x^2(11x^2y^2 - y^6 - 121y^4 - 2) + 5.5y^8 + \frac{x}{2y}$$

$$f(x = 77617, y = 33096) = ?$$

- ❑ Single precision: $f = 1.172603\dots$
- ❑ Double precision: $f = 1.1726039400531\dots$
- ❑ Extended precision: $f = 1.172603940053178\dots$
- ❑ Correct one is: $f = -0.8273960599468213$



Bug?

Defect?



Another Story



- ❑ On February 25, 1991
- ❑ A Patriot missile battery assigned to protect a military installation at Dhahran, Saudi Arabia
- ❑ But ... failed to intercept a Scud missile
- ❑ 28 soldiers died
- ❑ ... an error in computer arithmetic

$$0.1 \times 10 \neq 1$$

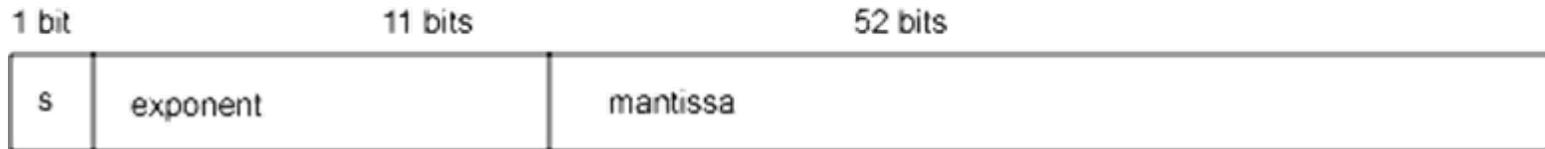


IEEE 754 Standard

IEEE Floating Point Representation



IEEE Double Precision Floating Point Representation

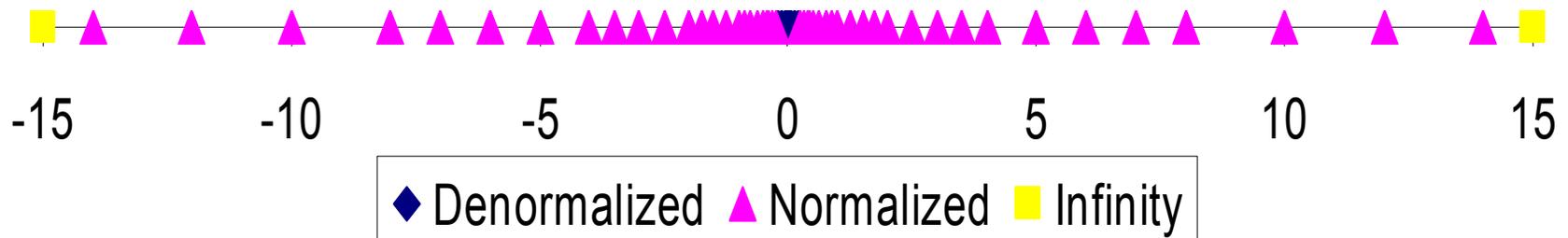


- If $E = 2^w - 1$ and $T \neq 0$, then v is **NaN** regardless of S .
 - If $E = 2^w - 1$ and $T = 0$, then $v = (-1)^S \times \infty$.
 - If $1 \leq E \leq 2^w - 2$, then $v = (-1)^S \times 2^{E - bias} \times (1 + 2^{1-p} \times T)$;
normalized numbers have an implicit leading significand bit of 1.
 - If $E = 0$ and $T \neq 0$, $v = (-1)^S \times 2^{emin} \times (0 + 2^{1-p} \times T)$;
denormalized numbers have an implicit leading significand bit of 0.
 - If $E = 0$ and $T = 0$, then $v = (-1)^S \times 0$ (signed zero)
- where $bias = 2^{w-1} - 1$ and $emin = 2 - 2^{w-1} = 1 - bias$

Distribution of Values

□ 6-bit IEEE-like format

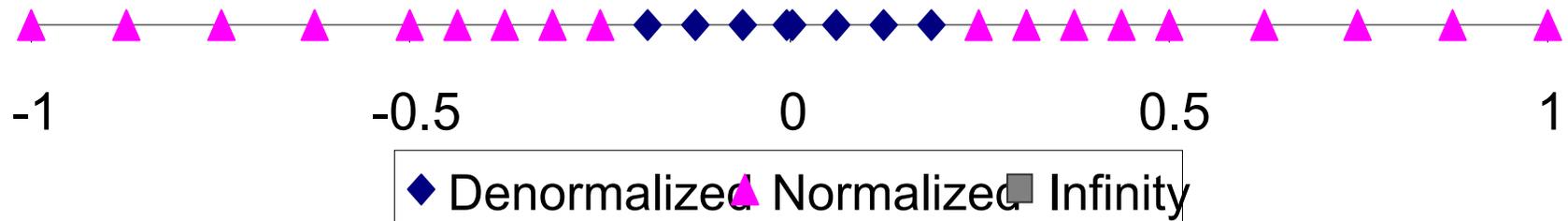
- $w = 3$ exponent bits
- $t = 2$ fraction/mantissa bits
- bias = 3



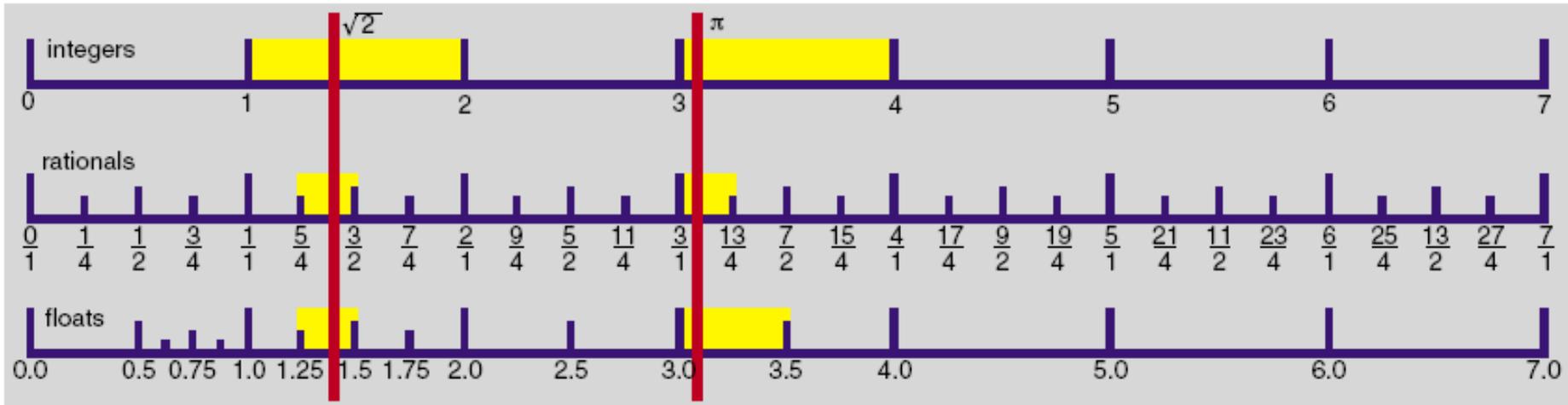
Distribution of Values (zoom-in view)

□ 6-bit IEEE-like format

- $w = 3$ exponent bits
- $t = 2$ fraction/mantissa bits
- bias = 3



Round-Off Errors



- ❑ Overflow error – “not large enough”
- ❑ Underflow error – “not small enough”
- ❑ Rounding error – “chopping”

❑ <http://www.cs.utah.edu/~zachary/isp/applets/FP/FP.html>

Special Numbers

Expression	Result
$0.0 / 0.0$	NaN
$1.0 / 0.0$	Infinity
$-1.0 / 0.0$	-Infinity
$\text{NaN} + 1.0$	NaN
$\text{Infinity} + 1.0$	Infinity
$\text{Infinity} + \text{Infinity}$	Infinity
$\text{NaN} > 1.0$	false
$\text{NaN} == 1.0$	false
$\text{NaN} < 1.0$	false
$\text{NaN} == \text{NaN}$	false
$0.0 == -0.0$	true

- standard range of values permitted by the encoding (from $1.4\text{e-}45$ to $3.4028235\text{e+}38$ for float)

Floating point Hazards

This expression	does NOT equal to this expression	when
$0.0 - f$	$-f$	f is 0
$f < g$	$!(f \geq g)$	f or g is NaN
$f == f$	true	f is NaN
$f + g - g$	f	g is infinity or NaN

```
double s=0;
for (int i=0; i<26; i++) s += 0.1;
System.out.println(s);
```

```
double d = 29.0 * 0.01;
System.out.println(d);
System.out.println((int) (d * 100));
```

❑ The result is
2.6000000000000001

❑ The result is
0.29
28

Comparing Floating Point Numbers

- ❑ Try to avoid floating point comparison directly
- ❑ Testing if a floating number is greater than or less than zero is even risky.
- ❑ *Instead*, you should compare the absolute value of the difference of two floating numbers with some pre-chosen epsilon value, and test if they are "close enough"
- ❑ If the scale of the underlying measurements is unknown, the test " $\text{abs}(a/b - 1) < \text{epsilon}$ " is more robust.
- ❑ Don't use floating point numbers for exact values

Uncertainties in M&S

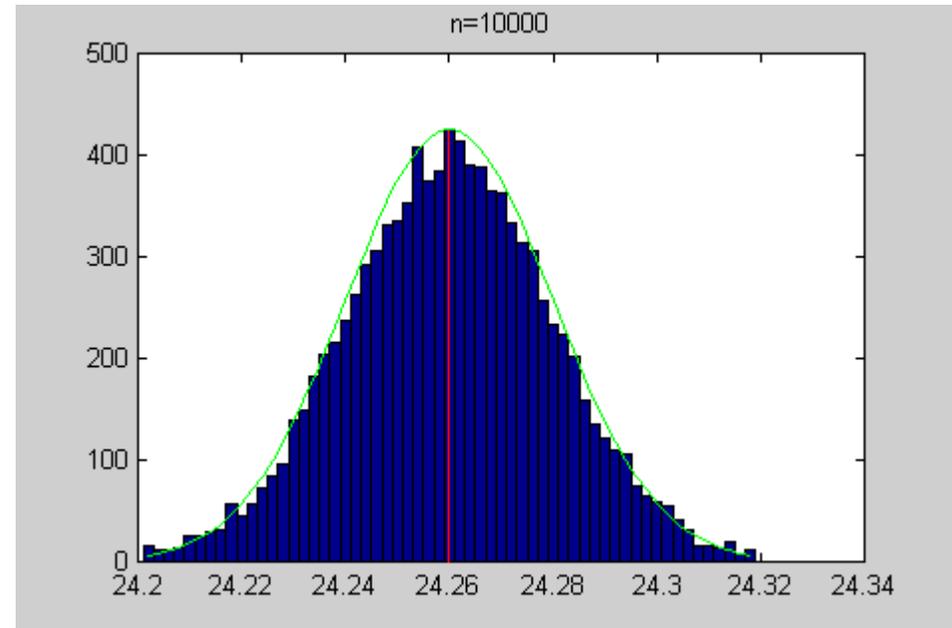
- ❑ Model errors due to approximations in truncation or sampling
 - Taylor approximation
 - Functional analysis
- ❑ Numerical errors due to floating-point representation
 - Round-off errors

Two types of “uncertainties”

- Aleatory uncertainty (variability, irreducible uncertainty, random error)
 - inherently associated with the randomness/fluctuation (e.g. environmental stochasticity, inhomogeneity of materials, fluctuation of measuring instruments)
 - can only be reduced by taking average of multiple measurements.
- Epistemic uncertainty (incertitude, reducible uncertainty, systematic error)
 - imprecision comes from scientific ignorance, inobservability, lack of knowledge, etc.
 - can be reduced by additional empirical effort (such as calibration).

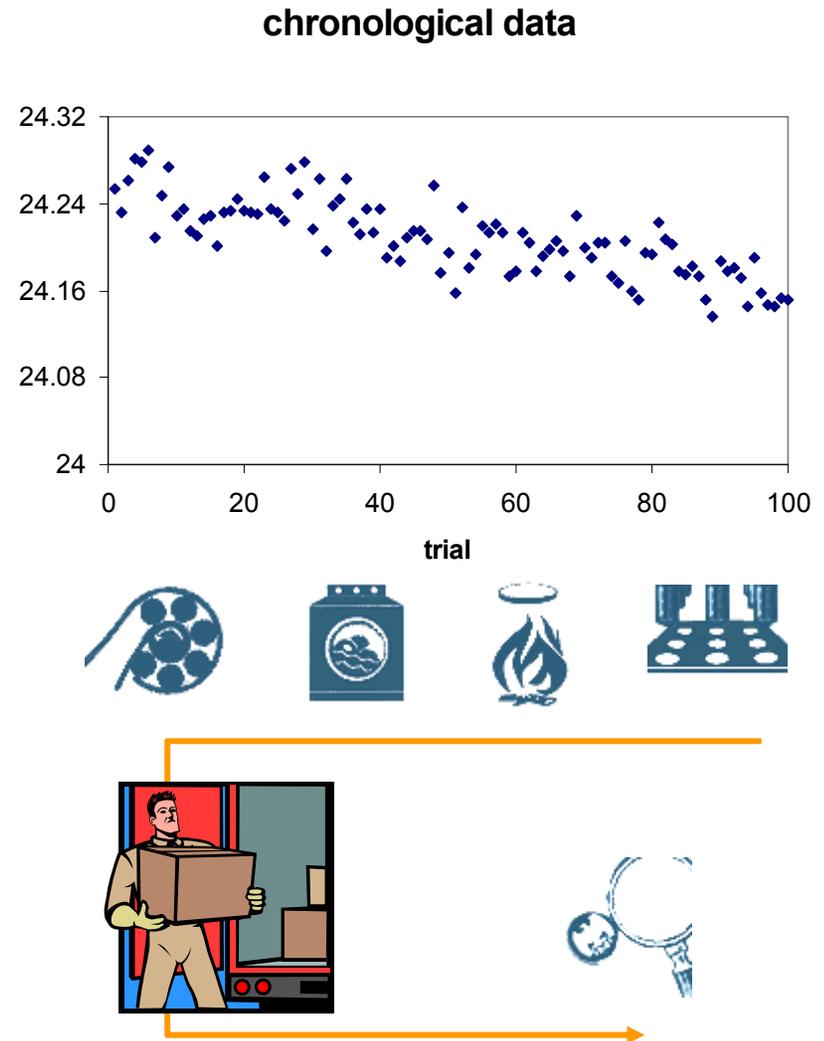
Random Error

- ❑ Determines the *precision* of any measurement
- ❑ *Always* present in every physical measurement
 - Better apparatus
 - Better procedure
 - Repeat
- ❑ Estimate



Systematic Error

- ❑ Determines the *accuracy* of any measurement
- ❑ *May* be present in every physical measurement
 - calibration
 - uniform or controlled conditions (e.g., avoid systematic changes in temperature, light intensity, air currents, etc.)
- ❑ Identify & eliminate or reduce



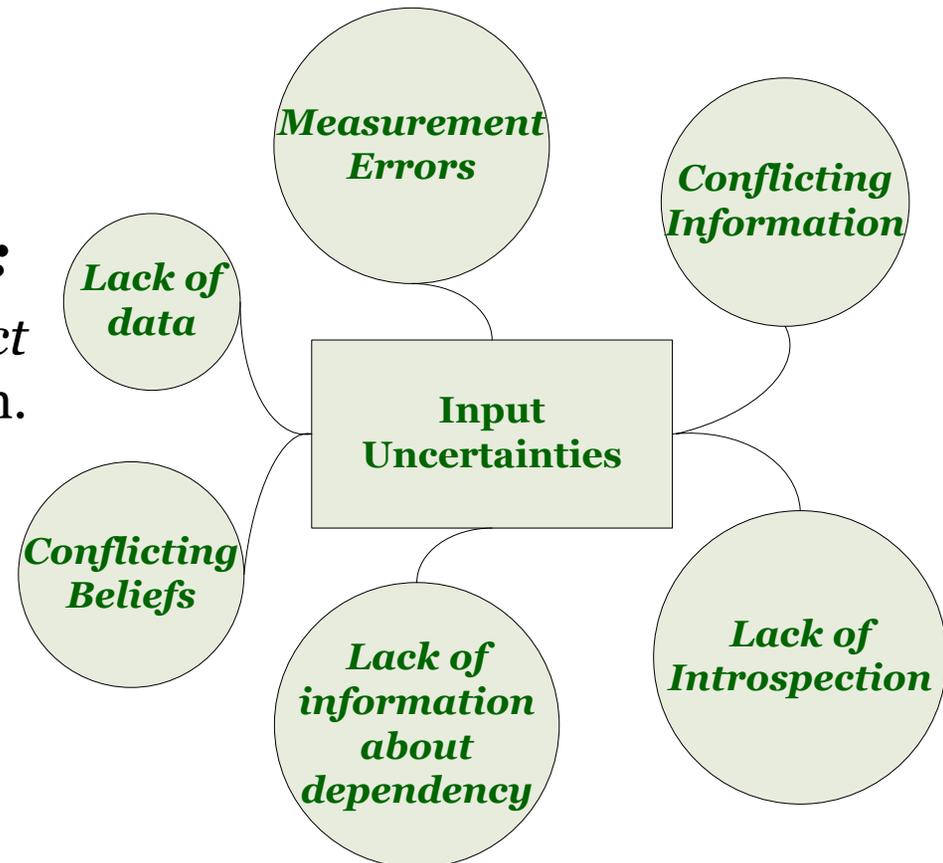
Uncertainties in Modeling & Simulation

□ ***Aleatory Uncertainty:***

- *inherent randomness* in the system. Also known as:
 - stochastic uncertainty
 - variability
 - irreducible uncertainty

□ ***Epistemic Uncertainty:***

- due to *lack of perfect knowledge* about the system. Also known as:
 - Incertitude
 - system error
 - reducible uncertainty



Summary

- ❑ Modeling is *abstraction*
- ❑ M&S ***always*** has *approximations* involved, which are important sources of epistemic uncertainty.
- ❑ Computer tricks us

Abstraction
Approximation
Round-off

Further Readings

- ❑ Goldberg, D. (1991) “What every computer scientist should know about floating-point arithmetic,” *ACM Computing Surveys*, **23**(1), 5-48