

# COS 323: Computing for the Physical and Social Sciences

---

Szymon Rusinkiewicz

# COS 323

---

- Course webpage

<http://www.cs.princeton.edu/~cos323/>

- Instructor:

Szymon Rusinkiewicz (smr@cs)

- TAs:

Connelly Barnes (csbarnes@cs), Cynthia Lu (jingwanl@cs), Dmitry Drutskoy (drutskoy@cs)

# What's This Course About?

---

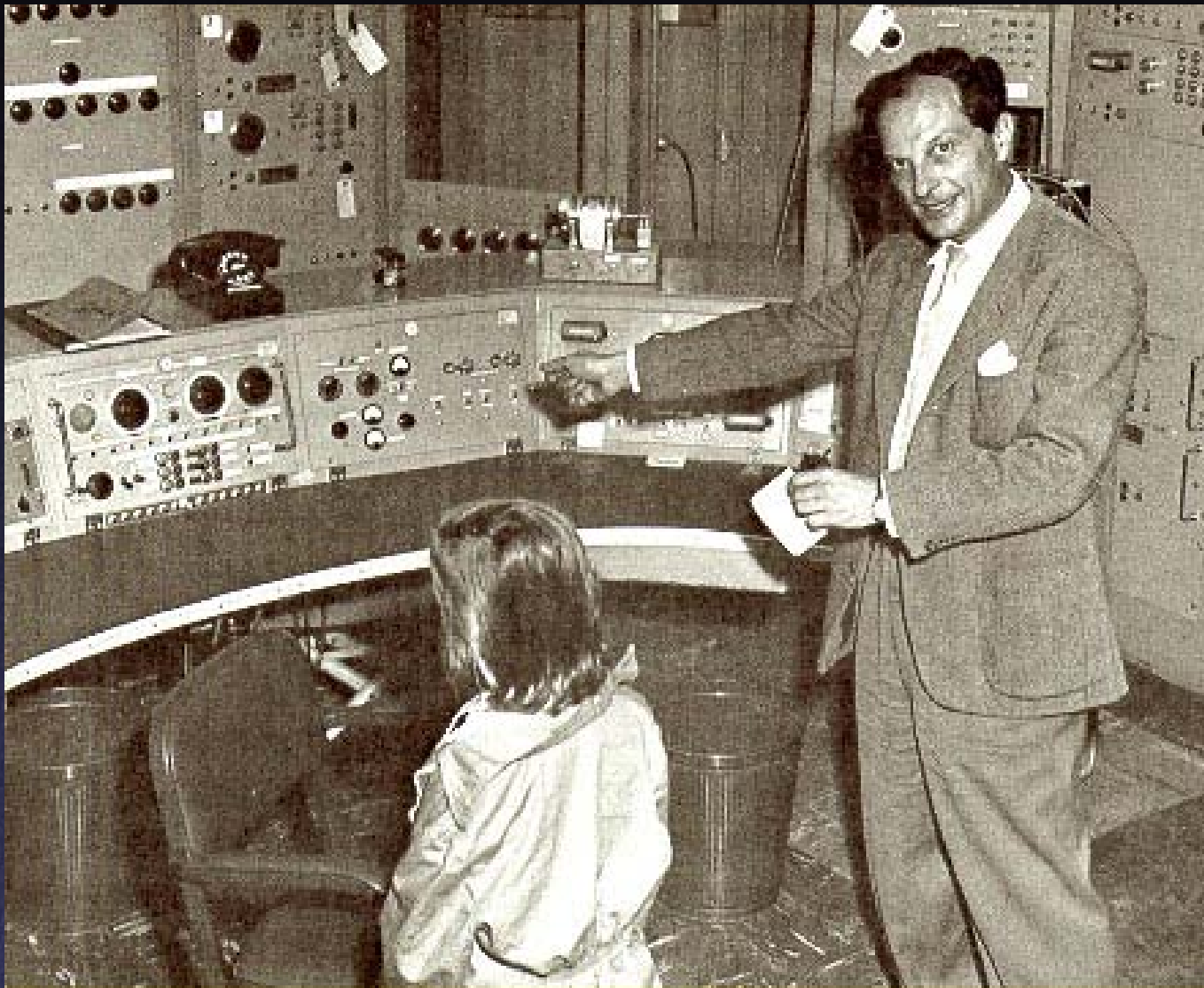
- Numerical Algorithms
- Analysis of Data
- Simulation
  - Learn through applications

# Scientific Computing

---

Computers through the 70s/80s were used mostly to solve problems

- Before “personal” computers (!)
- Users were scientists: producers of numerical “codes” rather than consumers of “applications”



Ojciec demonstruje córce komputer MANIAC,  
Los Alamos Scientific Laboratory, 1955

Stanisław Ulam with MANIAC I --- about  $10^4$  ops/sec



# Numerical Analysis

---

- Algorithms for solving numerical problems
  - Calculus, algebra, data analysis, etc.
  - Applications in all scientific and engineering fields
- Analyze/design algorithms based on:
  - Running time, memory usage  
(both asymptotic and constant factors)
  - Applicability, stability, and accuracy  
for different classes of problems

# Why Is This Hard/Interesting?

---

- “Numbers” in computers  $\neq$  numbers in math
  - Limited precision and range
- Algorithms sometimes don’t give right answer
  - Iterative, randomized, approximate
  - Unstable
- Running time / accuracy / stability tradeoffs



# Numbers in Computers

---

- “Integers”
  - Implemented in hardware: fast
  - Mostly sane, except for limited range
- Floating point
  - Implemented in most hardware
  - Much larger range  
(e.g.  $-2^{31}.. 2^{31}$  for integers, vs.  $-2^{127}.. 2^{127}$  for FP)
  - Lower precision (e.g. 7 digits vs. 9)
  - “Relative” precision: actual accuracy depends on size

# Floating Point Numbers

---

- Like scientific notation: e.g.,  $c$  is  
 $2.99792458 \times 10^8$  m/s

- This has the form  
 $(\text{multiplier}) \times (\text{base})^{(\text{power})}$

- In the computer,
  - **Multiplier** is called mantissa
  - **Base** is almost always 2
  - **Power** is called exponent

# Modern Floating Point Formats

---

- Almost all computers use IEEE 754 standard
- “Single precision”:
  - 24-bit mantissa, base = 2, 8-bit exponent, 1 bit sign
  - All fits into 32 bits (!)
- “Double precision”:
  - 53-bit mantissa, base = 2, 11-bit exponent, 1 bit sign
  - All fits into 64 bits
- Sometimes also have “extended formats”

# Other Number Representations

---

- Fixed point
  - *Absolute* accuracy doesn't vary with magnitude
  - Represent fractions to a fixed precision
  - Not supported directly in hardware, but can hack it
- “Infinite precision”
  - Integers or rationals allocated dynamically
  - Can grow up to available memory
  - No direct support in hardware, but libraries available

# Consequences of Floating Point

---

- “Machine epsilon”: smallest positive number you can add to 1.0 and get something other than 1.0
- For single precision:  $\varepsilon \approx 10^{-7}$ 
  - No such number as 1.0000000001
  - Rule of thumb: “almost 7 digits of precision”
- For double:  $\varepsilon \approx 2 \times 10^{-16}$ 
  - Rule of thumb: “not quite 16 digits of precision”
- These are all *relative* numbers

# So What?

---

- Simple example: add  $1/10$  to itself 10 times

# Yikes!

---

- Result:  $1/10 + 1/10 + \dots \neq 1$
- Reason: 0.1 can't be represented exactly in binary floating point
  - Like  $1/3$  in decimal
- **Rule of thumb:** comparing floating point numbers for equality is always wrong

# More Subtle Problem

---

- Using quadratic formula

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

to solve  $x^2 - 9999x + 1 = 0$

- Only 4 digits: single precision should be OK, right?
- Correct answers: 0.0001... and 9998.999...
- Actual answers in single precision: 0 and 9999
  - First answer is 100% off!
  - Total cancellation in numerator because  $b^2 \gg 4ac$

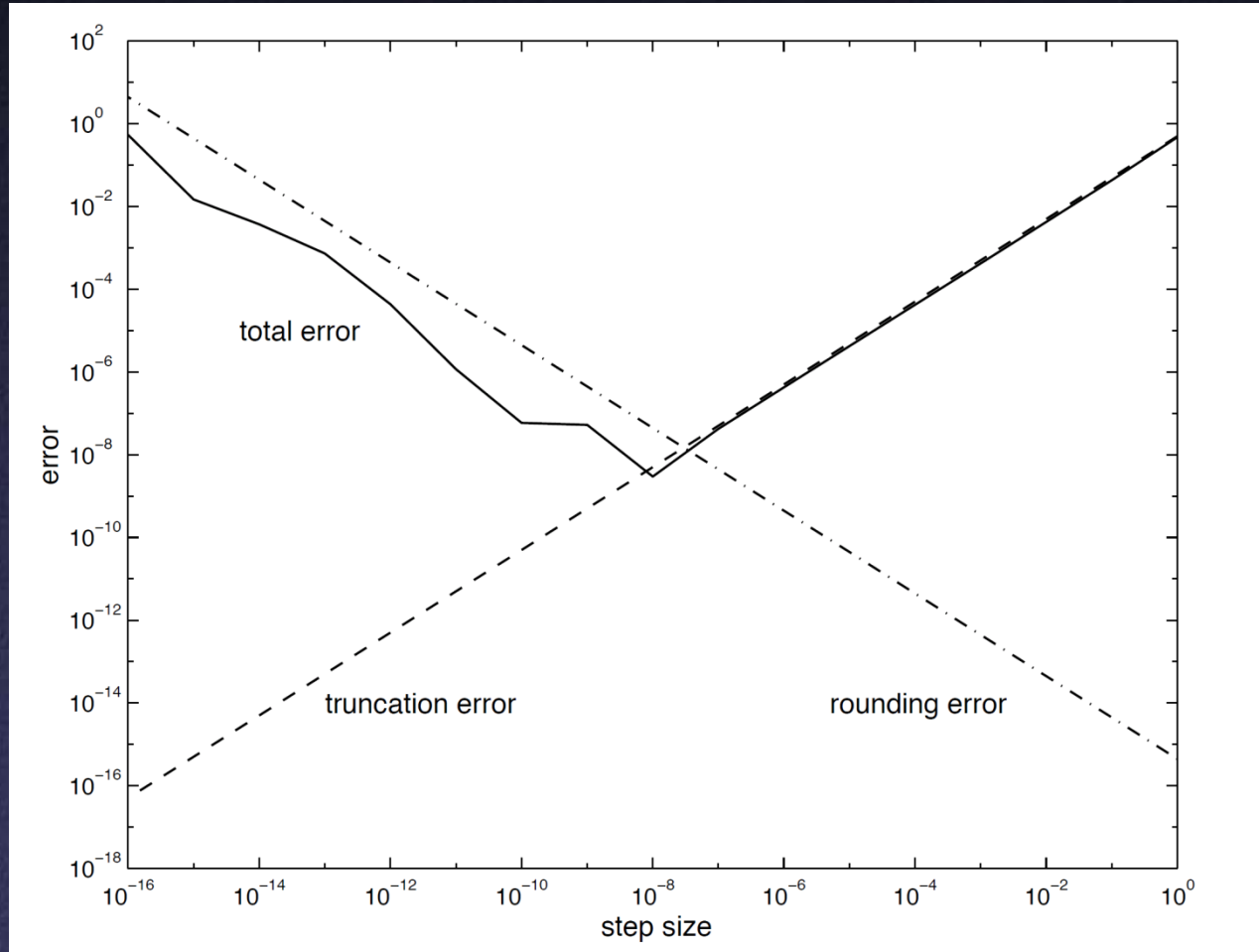


# Catalog of Errors

---

- **Roundoff error** – caused by limitations of floating-point “numbers”
- **Truncation error** – caused by stopping an approximate technique early
  - e.g., too few terms of Taylor series for  $\sin(\theta)$
- **Inherent error** – limitation on data available
  - GIGO
- **Statistical error** – too few random samples

# Error Tradeoff



# Well-Posedness and Sensitivity

---

- Problem is **well-posed** if solution
  - exists
  - is unique
  - depends continuously on problem data

Otherwise, problem is **ill-posed**

- Solution may still be sensitive to input data
  - **Ill-conditioned**: relative change in solution much larger than that in input data

# Running Time

---

- Depending on algorithm, we'll look at:
  - **Asymptotic analysis** for noniterative algorithms (e.g., inverting an  $n \times n$  matrix requires time proportional to  $n^3$ )
  - **Convergence order** for iterative approximate algorithms (e.g., an answer to precision  $\delta$  might require iterations proportional to  $1/\delta$  or  $1/\delta^2$ )

# Simulation and Modeling

---

- Purposes: quantitative or qualitative prediction, development of intuition, theory testing
- Often requires changing the problem (modeling)
  - Continuous  $\rightarrow$  discrete
  - Infinite  $\rightarrow$  finite
  - Omitting effects, variables, dimensions
  - **Q**: how accurate is the resulting approximation?

# Example Applications

---

- Population genetics
- Digital signal processing (including images/audio)
- Simulation of markets
- Classical mechanics
- Weather prediction

# This Course

---

- **Basic techniques:** root finding, optimization, linear systems
- **Data analysis and modeling:** least squares, dimensionality reduction, visualization, statistics
- **Signal processing:** sampling, filtering
- **Integration and differential equations**
- **Data analysis, fitting, and modeling**
- **Simulation**

# Mechanics

---

- Programming assignments
  - Typically more thought than coding
  - Some in MATLAB, some in Java
  - Analysis, writeup counts a lot!
- Final project