

# Fundamental Concepts in Computational and Applied Mathematics

Juan Meza <sup>1</sup>

Math 298 Fall 2014

# Course Goals

- Introduce fundamental concepts in computational and applied mathematics.
- Highlight some of the classic NA papers and algorithms.
- Demonstrate use of these concepts in real world applications.

## Disclaimer

Please note that we will not be able to go into any one subject in much depth. This course is a whirlwind tour of the fundamentals.

# Learning Outcomes

- Be familiar with key mathematical concepts and computational frameworks used in developing numerical algorithms.
- Understand some of the basic skills and resources necessary to start research in computational and applied mathematics.
- Be aware of basic communications skills needed to present mathematics clearly to a broad audience in writing and in speech.

# Ground Rules/Grading

- 50% Class participation – critical to getting the most out of this course
- 25% Some assigned reading and writing assignments
- 25% Presentations at the end of the semester

# Theory vs. Practice

- In theory there is no difference between theory and practice.
- In practice there is.

# Nick Trefethen's 13 Classic Numerical Analysis Papers.

- Cover some of the most important NA papers in the last 60 years
- Cover most of the areas mentioned in the next 3 slides
- It is your responsibility to be familiar with all of the papers
- Note: Copies of all of these have been uploaded into CROPS

# Phil Colella's 7 Dwarfs

- ① Dense linear algebra
- ② Sparse line algebra
- ③ Spectral methods (Fast Fourier transform)
- ④ N-body (particle) methods
- ⑤ Structured grids
- ⑥ Unstructured grids
- ⑦ Monte Carlo

**Defining Software Requirements for Scientific Computing**, P. Colella,  
DARPA presentation, 2004.

# 13 Motifs – Patterson et al.

- ① First 6 Dwarfs (Dense linear algebra, Sparse line algebra, Spectral methods, N-body methods, Structured grids, Unstructured grids) +
- ② MapReduce
- ③ Combinational Logic
- ④ Graph Traversal
- ⑤ Dynamic Programming
- ⑥ Backtrack and Branch-and-Bound
- ⑦ Graphical Models
- ⑧ Finite State Machines

The Landscape of Parallel Computing View from Berkeley



# Top 10 Algorithms of the Century

- 1946 Monte Carlo
- 1947 Simplex method for LP
- 1950 Conjugate gradient (Krylov subspace iteration methods)
- 1951 Decompositional approach to matrix computations
- 1957 Fortran compiler
- 1959 QR for computing eigenvalues
- 1962 Quicksort
- 1965 Fast Fourier transform
- 1977 PSLQ (integer relation detection algorithm)
- 1987 Fast Multipole

**Computing in Science and Engineering**, January/February 2000, Vol. 2, No. 1

# Finite Precision

- Difference between infinite precision and computer arithmetic
- You will almost always make an error when approximating a mathematical object on a computer
- One of the major types of errors is discretization(truncation), which is the difference between the solution of the discrete problem and the exact solution (representation) of the mathematical object

# Finite Precision

## Example

Suppose you have a function defined by an infinite series and you “truncate” it at some point, e.g.

$$\begin{aligned}\exp(x) &= 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \dots \\ &\approx 1 + x\end{aligned}$$

## Discussion:

How many terms in the series should we use? Are all values of  $x$  the same?

# Finite Precision

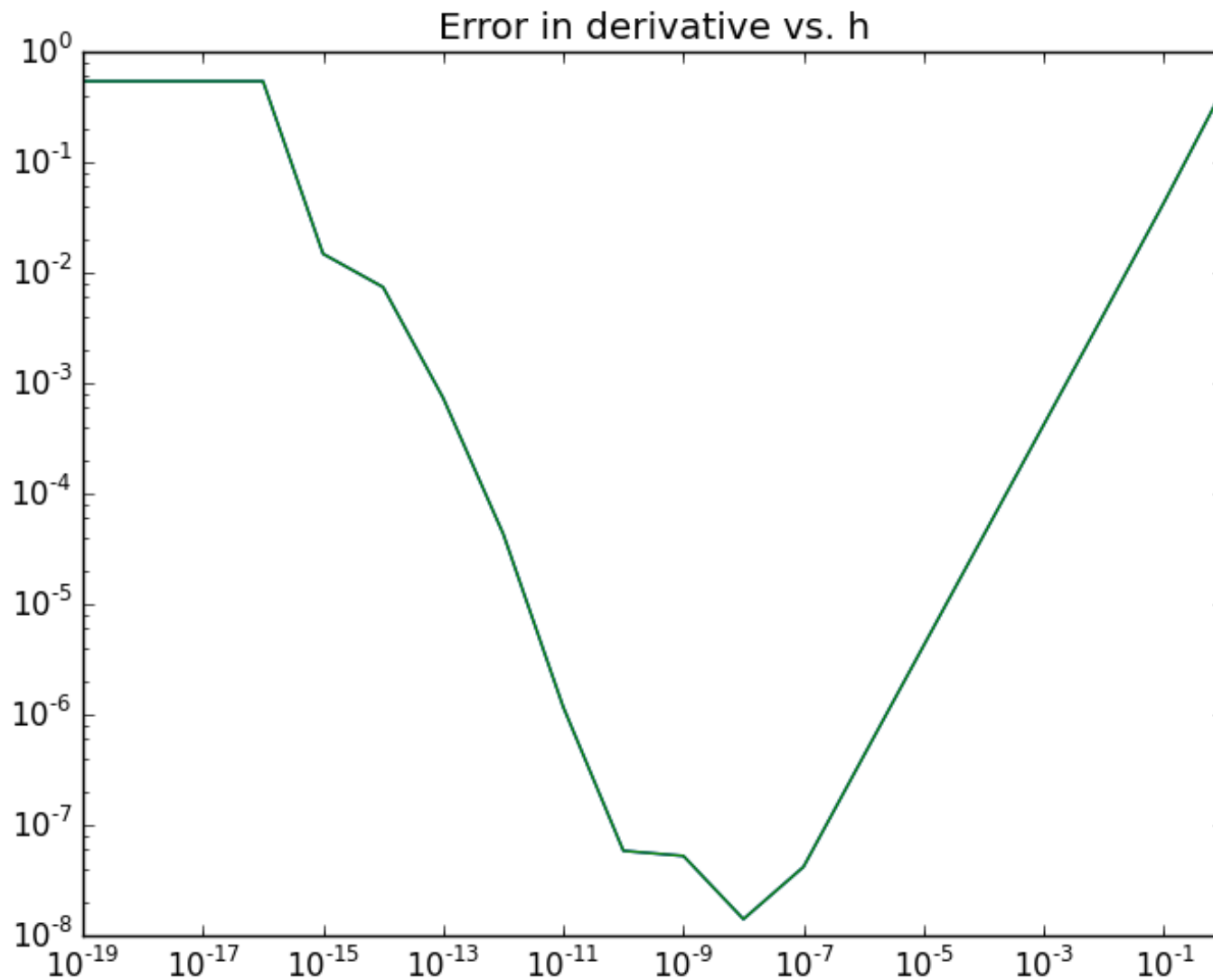
## Example

$$f'(x) = \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h}$$

## Discussion:

How do we pick  $h$  to get the best approximation? What value of  $h$  should we choose?

# Finite Precision Example: $f(x) = \sin(x)$ , $x = 1.0$



# Python Code

```
import numpy as np
from numpy import *
import matplotlib.pyplot as plt

n = 20
x = np.ones(n) # create an array of ones

h0 = 0.1*np.ones(n)
h = h0**np.arange(n) # create an array of increasingly
                      # smaller h values
yhat = (sin(x+h) - sin(x))/h # compute finite difference
err = abs(yhat - cos(x)) # error in numerical approx.

plt.loglog(h,err) # Plot the results
plt.title('Error in derivative vs. h')
plt.show
```

# Finite Precision

Important Lesson:

Don't solve an approximate problem too exactly!

## Rule of Thumb

To approximate

$$f'(x) = \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h}$$

choose  $h$  to perturb about half of the digits in  $x$ .

# Finite Precision Real World Examples

Applications requiring extra precision

- Climate Modeling
- Supernova Simulations
- Coulomb N-Body Atomic System Simulations
- Computational Geometry and Grid Generation
- Many, many more, ...

Reference: **High-Precision Floating-Point Arithmetic in Scientific Computation**, David H. Bailey, Computing in Science & Engineering, IEEE, May/June 2005.



# Conditioning

- Suppose we would like to know how perturbing  $x$  will affect the value of  $y = f(x)$

## Definition (Condition Number)

$$\kappa_f(x) = \frac{|x| \cdot |f'(x)|}{|f(x)|}$$

- Then

$$\frac{|\hat{y} - y|}{|y|} \approx \kappa_f(x) \cdot \frac{|\hat{x} - x|}{|x|}$$

- Fact: # decimal digits to which two numbers agree  
 $\approx -\log_{10}(\text{relative error})$

## Rule of Thumb

You will lose approximately  $\log_{10}(\kappa_f(x))$  decimal digits when computing anything

# Stability

- Informal definition of stability. An algorithm for computing  $\hat{y} = f(x)$  is **stable** if it returns a  $\hat{y}$  that satisfies:

$$\frac{|\hat{y} - y|}{|y|} \approx \kappa_f(x) \cdot \frac{|\hat{x} - x|}{|x|}.$$

## Discussion:


What do you think of the following algorithm for computing  $\exp(x)$ ?


$$\exp(x) = 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \dots$$

# Summary

- Beware catastrophic cancellation - know limits of precision
- Learn about the conditioning of a problem
- Choose stable algorithms so as to not introduce any more loss of precision than is necessary
- Always remember
  - **Conditioning** is fundamentally a characteristic of the problem while
  - **Stability** is related to algorithms

# Further Reading I

 M.L. Overton.  
*Numerical Computing with IEEE Floating Point Arithmetic.*  
SIAM, 2001.

 D. Goldberg.  
What Every Computer Scientist Should Know About Floating Point  
Arithmetic  
Computing Surveys, ACM, Vol. 23, No. 1, pp. 5–48, 1991.

 D.H. Bailey.  
High-Precision Floating-Point Arithmetic in Scientific Computation  
Computing in Science & Engineering, IEEE, May/June 2005.