

# Numerical analysis (1/7): Errors in numerical analysis

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# Outline

1. Introduction: types of errors
2. Computer representation of real numbers
3. Floating-point arithmetic
4. Conditioning and stability
5. Summary

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# Types of errors

What type of errors do we find in numerical analysis ?

1. Errors in the problem to be solved
  - errors in the mathematical model
  - errors in the input data: noise, measurement
2. **Round-off errors** (today's topic, computer floating-point representation)
3. Approximation errors
  - Discretization/truncation errors: going from the continuous to the discrete level
  - Convergence errors: iterative methods

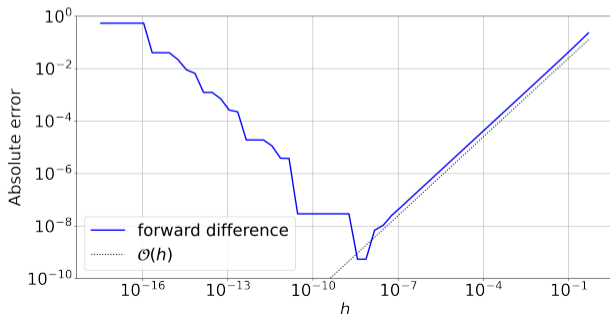
# Round-off vs discretization error: example

Derivative approximation (see exercise)

$$f'(x_0) = \frac{f(x_0 + h) - f(x_0)}{h} + \mathcal{O}(h)$$

The **discretization error** is linear with  $h$

But when  $h$  is too small, we have **round-off errors**



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# Floating-point representation

A computer has a finite capacity and cannot store all real numbers ( $\pi \approx 3.14159\dots$ )

Any number is approximated by a rational number, and has a finite number of digits  $d_i$

Floating point representation of  $x \in \mathbb{R}$

$$\text{fl}(x) = \pm m \times b^e, \quad m = \left( \frac{d_0}{b^0} + \frac{d_1}{b^1} + \dots + \frac{d_{p-1}}{b^{p-1}} \right)$$

$m$ : mantissa or significand,  $e$ : exponent,  $b$ : radix or basis,  $p$ : precision

Normalized (unique) representation:  $1 \leq m < b$ ,  $d_0 \neq 0$

## Examples

Let us choose  $\text{fl}(x) = +152853.50$ ,  $b = 10$ ,  $p = 8$ ,  $e = 5$

$$152853.50 = 1.5285350 \times 10^5 = \frac{15285350}{10^7} \times 10^5 = (1 \times 10^0 + 5 \times 10^{-1} + \dots + 0 \times 10^{-7}) \times 10^5$$

# Floating-point representation

## Examples

Approximate  $\pi$  in base 2,  $p = 24$ :  $\pi \approx 11001001\ 00001111\ 11011011$

Approximate 0.1 in base 2,  $p = 16$ :  $0.1 \approx 11001100\ 11001101$

$\text{fl}(\pi) = (1 + 1 \times 2^{-1} + \dots + 1 \times 2^{-23}) \times 2^1 = 3.1415927$ , 7 digits precision (why ?)

## Floating point system

A floating point system is characterized by 4 values:  $(b, p, U, L)$

base, precision, exponent upper and lower bound such as  $L \leq e \leq U$

## Double precision format (64 bit storage)

$b = 2, p = 52, L = -1022, U = 1023$

11 bit exponent, 52+1 bits for the significand (1 is implicit for the sign)

Let us look what Python uses...



# Floating-point representation

## Example

Single precision:  $p = 23$  bits significand, 8 bit exponent,  $U = 127$

The sequence of digits

1 0111 1110 100 0000 0000 0000 0000

considered as simple precision can be interpreted as follows:

- the first digit is 1, so the sign is negative
- the next 8 digits form the exponent:  
 $(01111110)_2 = 0 \times 2^7 + 2^6 + 2^5 + 2^4 + 2^3 + 2^2 + 2^1 + 0 \times 2^0 = 126$
- the next 23 digits form the significand, where the first bit is 1 by convention

The number in decimal is:

$$-2^{(126-U)} \times (1 + 1 \times 2^{-1} + 0 \times 2^{-2} + \dots + 0 \times 2^{-23}) = -0.5 \times 1.5 = -0.75$$

# Machine precision

When rounding, two adjacent numbers are spaced by  $\eta = b^{-p}/2$ , it defines the *machine precision*.

## Round-off error

Absolute *round-off* error:  $|\text{fl}(x) - x| \leq \eta b^e$

Relative *round-off* error:  $\left| \frac{\text{fl}(x) - x}{x} \right| \leq \eta$

The spacing of a floating point system is constant in the **relative sense**

## Overflow-underflow

If the exponent  $e$  is such as  $e > U$ , we have overflow, and if  $e < L$  we have underflow

Question: what are the minimum and maximum representable numbers in double precision ?

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# Operations in floating point arithmetic

The usual calculus rules are altered with the floating point representation

## Floating operation

$$x \bullet y = (x \bullet y)(1 + \varepsilon), \quad \bullet = (+, -, \times, \div), \quad |\varepsilon| \leq \eta$$

Addition is not associative in this context !  $(a + b) + c \neq a + (b + c)$

The relative errors are  $\frac{a+b}{a+b+c}\varepsilon_1(1 + \varepsilon_2) + \varepsilon_2$  and  $\frac{b+c}{a+b+c}\varepsilon_3(1 + \varepsilon_4) + \varepsilon_4$

## Examples

Derive the relative errors of the above additions

For  $p = 8$  try  $a = 2.3371258 \times 10^{-5}$ ,  $b = 3.3678429 \times 10^1$ ,  $c = -3.3677811 \times 10^1$

## Examples

Compute  $Q = \frac{\pi - 3.1415}{10^4(\pi - 3.1515) - 0.927}$  by truncating  $\pi$  with  $p$  significant digits

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Stability is an important concept in numerical analysis, and is found in different contexts:

- stability of numerical schemes (e.g. ODEs, finite differences),
- stability of numerical algorithms (e.g. linear systems),
- stability has also meanings at the continuous level (PDE, dynamical systems),

It is linked to the **propagation of errors during the computation**.

# Stability

## Forward and backward errors

- The forward error measures the difference between the computed and exact value  $|\hat{y} - y|$
- The backward error is the error on the input:  $|\hat{x} - x|$ , for a perturbed output  $\hat{y} = f(\hat{x})$

If the backward error is “small”, we say the algorithm to be backward-stable

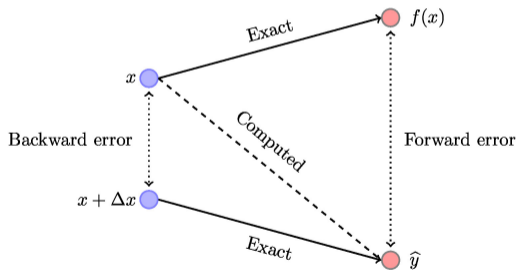


Figure: Illustration from Nicholas J. Higham blog

# Conditioning

The condition number is the ratio of a relative change in the output to a relative change in the input

Condition number  $\kappa$

$$\kappa = \frac{|(f(\hat{x}) - f(x))/f(x)|}{|(\hat{x} - x)/x|} = \frac{|(\hat{y} - y)/y|}{|(\hat{x} - x)/x|} = \frac{|\Delta y/y|}{|\Delta x/x|}$$

We have the relation

$$|\text{relative forward error}| = \text{Condition number} \times |\text{relative backward error}|$$

It represents the sensitivity related to the input data.

**Conditioning depends on the problem, stability depends on the algorithm**

Condition number of a  $C^1$  function  $f$

$$\text{when } \hat{x} \approx x, \text{ we have } \kappa_f \approx \left| \frac{xf'(x)}{f(x)} \right|$$



# Conditioning and stability - examples

## Examples

Find the conditioning of the functions  $\sqrt{x}$ ,  $a - x$ ,  $\tan(x)$

## Examples

Evaluate the stability of  $f(x) = \sqrt{x+1} - \sqrt{x}$  by computing  $f(12345)$  with  $p = 6$  significant digits

Try again using the formula  $f(x) = \frac{1}{\sqrt{x+1} + \sqrt{x}}$

Compare the stability properties of the two formulas

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# Summary

- All machines use a floating-point representation,
- We must be very careful during computations to avoid round-off errors,
- Conditioning and stability analysis are useful theoretical tools,
- Designing numerically stable algorithms is in general not trivial