

Computers use a finite number of bits (0's and 1's) to represent numbers.

For instance, an 8-bit unsigned integer (a.k.a a "char") is stored:

2^{7}	2^{6}	2^{5}	2^{4}	2^{3}	2^{2}	2^{1}	2^{0}
0	1	0	0	1	1	0	1

Here, $2^6 + 2^3 + 2^2 + 2^0 = 64 + 8 + 4 + 1 = 77$, which represents the upper-case character "M" (US-ASCII).

The Binary Floating Point Arithmetic Standard 754-1985

(IEEE — The Institute for Electrical and Electronics Engineers) standard specified the following layout for a 64-bit real number:

$s\,c_{10}\,c_9\,\ldots\,c_1\,c_0\,m_{51}\,m_{50}\,\ldots\,m_1\,m_0$

where

Symbol	Bits	Description
8	1	The sign bit -0 =positive, 1=negative
c	11	The characteristic (exponent)
m	52	The mantissa

$$r = (-1)^{s} 2^{c-1023} (1+m), \quad c = \sum_{k=0}^{10} c_k 2^k, \quad m = \sum_{k=0}^{51} \frac{m_k}{2^{52-k}}$$

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Binary Representation Something Missing ... Gaps

Examples: Finite Precision

$$r = (-1)^{s} 2^{c-1023} (1+f), \quad c = \sum_{k=0}^{10} c_k 2^k, \quad m = \sum_{k=0}^{51} \frac{m_k}{2^{52-k}}$$

Example 1: The number **3.0**

$$r_1 = (-1)^0 \cdot 2^{2^{10} - 1023} \cdot \left(1 + \frac{1}{2}\right) = 1 \cdot 2^1 \cdot \frac{3}{2} = 3.0$$

Example 2: The Smallest Positive Real Number

$$r_2 = (-1)^0 \cdot 2^{0-1023} \cdot (1+2^{-52}) = (1+2^{-52}) \cdot 2^{-1023} \cdot 1 \approx 10^{-308}$$

Examples: Finite Precision

Finite Precision

Numerical Errors

Algorithms and Convergence

$$r = (-1)^{s} 2^{c-1023} (1+f), \quad c = \sum_{k=0}^{10} c_k 2^k, \quad m = \sum_{k=0}^{51} \frac{m_k}{2^{52-k}}$$

Binary Representation

Something Missing ... Gaps

Example 3: The Largest Positive Real Number

$$r_{3} = (-1)^{0} \cdot 2^{1023} \cdot \left(1 + \frac{1}{2} + \frac{1}{2^{2}} + \dots + \frac{1}{2^{51}} + \frac{1}{2^{52}}\right)$$
$$= 2^{1024} \cdot \left(2 - \frac{1}{2^{52}}\right) \approx 10^{308}$$

Joseph M. Mahaffy, (jmahaffy@mail.sdsu.edu) -(5/33)Joseph M. Mahaffy, (jmahaffy@mail.sdsu.edu) -(6/33)**Finite Precision Finite Precision Binary Representation** Numerical Errors Numerical Errors Something Missing ... Gaps Something Missing ... Gaps Algorithms and Convergence Algorithms and Convergence **Special Numbers** Something is Missing — Gaps in the Representation 1 of 3

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Note that the IEEE standard does NOT allow **zero!**

- There are some special signals in IEEE-754-1985:
- All zeros for c and m produce **zero**
- c having 11 bits all 1 gives either NaN (Not a Number) or $\pm\infty$
- Further reference at http://www.freesoft.org/CIE/RFC/1832/32.htm

There are gaps in the floating-point representation!

Given the representation

for the value
$$\frac{2^{-1023}}{252}$$
.

The next larger floating-point value is

i.e. the value $\frac{2^{-1023}}{251}$.

The difference between these two values is $\frac{2^{-1023}}{2^{52}} = 2^{-1075}$, so any number in the interval $\left(\frac{2^{-1023}}{2^{52}}, \frac{2^{-1023}}{2^{51}}\right)$ is not representable!

A gap of 2^{-1075} doesn't seem too bad...

However, the size of the gap depends on the value itself...

Consider r = 3.0

and the next value

The difference is $\frac{2}{2^{52}} \approx 4.4 \cdot 10^{-16}$

At the other extreme, the difference between

and the previous value

is
$$\frac{2^{1023}}{2^{52}} = 2^{971} \approx 1.99 \cdot 10^{292}$$
.

That's a "fairly significant" gap!!!

The number of atoms in the observable universe can be estimated to be no more than $\sim 10^{80}$.



It makes more sense to factor the exponent out of the discussion and talk about the relative gap:

Exponent	Gap	Relative Gap (Gap/Exponent)
2^{-1023}	2^{-1075}	2^{-52}
2^{1}	2^{-51}	2^{-52}
2^{1023}	2^{971}	2^{-52}

Any difference between numbers smaller than the local gap is not representable, e.g. any number in the interval

$$\left[3.0, \, 3.0 + \frac{1}{2^{51}}\right)$$

is represented by the value 3.0.

The MatLab command eps (for epsilon tolerance) gives *double* **precision**, which is

$$2^{-52} \approx 2.2204 \times 10^{-16}$$

5757

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Floating point "numbers" represent intervals!

Since (most) humans find it hard to think in binary representation, from now on we will for simplicity and without loss of generality assume that floating point numbers are represented in the normalized floating point form as...

k-digit decimal machine numbers

$$\pm 0.d_1d_2\cdots d_{k-1}d_k\cdot 10^n$$

where

$$1 \le d_1 \le 9, \quad 0 \le d_i \le 9, \ i \ge 2, \quad n \in \mathbb{Z}$$

k-Digit Decimal Machine Numbers

Any real number can be written in the form

$$r = \pm 0.d_1 d_2 \cdots d_\infty \cdot 10^n$$

given infinite patience and storage space.

We can obtain the floating-point representation fl(r) in two ways:

- Truncating (chopping) just keep the first k digits (In MatLab use floor(r))
- 2 Rounding if $d_{k+1} \ge 5$ then add 1 to d_k . Truncate. (Standard for most languages)

Examples

$$fl_{t,5}(\pi) = 0.31415 \cdot 10^1, \quad fl_{r,5}(\pi) = 0.31416 \cdot 10^1$$

In both cases, the error introduced is called the **roundoff error**.

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Finite Precision Numerical Errors Algorithms and Convergence

Sources of Numerical Error

Some Sources of Numerical Error

- Representation Roundoff
- **2** Cancellation

Consider:

this value has (at most) 1 significant digit!!!

If you assume a "cancelled value" has more significant bits (the computer will happily give you some numbers) — Any use of these random digits is **GARBAGE**!!!

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Important!!!

$$|p-p^*|$$

Definition (The Relative Error) $\frac{|p - p^*|}{|p|}, \quad p \neq 0$

Definition (Significant Digits)

The number of **significant digits** is the largest value of t for which

$$\frac{|p - p^*|}{|p|} < 5 \cdot 10^{-t}$$

)50

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Numerical Errors Algorithms and Convergence

Finite Precision

Examples: 5-digit Arithmetic k-Digit Decimal Machine Numbers Rounding 5-digit arithmetic $(0.96384 \cdot 10^5 + 0.26678 \cdot 10^2) - 0.96410 \cdot 10^5 =$

Sources of Numerical Error

 $(0.96384 \cdot 10^5 + 0.00027 \cdot 10^5) - 0.96410 \cdot 10^5 =$ $0.96411 \cdot 10^5 - 0.96410 \cdot 10^5 = 0.10000 \cdot 10^1$

Truncating 5-digit arithmetic

 $\begin{array}{l} (0.96384 \cdot 10^5 + 0.26678 \cdot 10^2) - 0.96410 \cdot 10^5 = \\ (0.96384 \cdot 10^5 + 0.00026 \cdot 10^5) - 0.96410 \cdot 10^5 = \\ 0.96410 \cdot 10^5 - 0.96410 \cdot 10^5 = 0.0000 \cdot 10^0 \end{array}$

Rearrangement changes the result:

 $\begin{array}{l} (0.96384 \cdot 10^5 - 0.96410 \cdot 10^5) + 0.26678 \cdot 10^2 = \\ -0.26000 \cdot 10^2 + 0.26678 \cdot 10^2 = 0.67800 \cdot 10^0 \end{array}$

Numerically, order of computation matters! (This is a HARD problem)

This sequence can be shown to converge to $\mathbf{0}$

Subtractive cancellation produces an error, which is approximately equal to the machine precision times n!.

Consider the recursive relation

Sources of Numerical Error Subtractive Cancellation

Example: Loss of Significant Digits due to Subtractive Cancellation

 $x_{n+1} = 1 - (n+1)x_n$ with $x_0 = 1 - \frac{1}{e}$.

Sources of Numerical Error Subtractive Cancellation

 $n \to \infty$.

Example: Proof of Convergence to 0

The *recursive relation* is

$$x_{n+1} = 1 - (n+1)x_n$$

 $x_0 = 1 - \frac{1}{e} = 1 - \frac{1}{2!} + \frac{1}{3!} - \frac{1}{4!} + \dots$

From the recursive relation

$$\begin{aligned} x_1 &= 1 - x_0 = \frac{1}{2!} - \frac{1}{3!} + \frac{1}{4!} - \dots \\ x_2 &= 1 - 2x_1 = \frac{1}{3} - \frac{2}{4!} + \frac{2}{5!} - \dots \\ x_3 &= 1 - 3x_2 = \frac{3!}{4!} - \frac{3!}{5!} + \frac{3!}{6!} - \dots \\ &\vdots \\ x_n &= 1 - nx_{n-1} = \frac{n!}{(n+1)!} - \frac{n!}{(n+2)!} + \frac{n!}{(n+3)!} - \dots \end{aligned}$$

This shows that

$$x_n = \frac{1}{n+1} - \frac{1}{(n+1)(n+2)} + \dots \to 0$$
 as

Joseph M. Mahaffy, (jmahaffy@mail.sdsu.edu) -(17/33)Joseph M. Mahaffy, (jmahaffy@mail.sdsu.edu) -(18/33)Finite Precision **Finite Precision** Sources of Numerical Error Sources of Numerical Error Numerical Errors Algorithms and Convergence Numerical Errors Algorithms and Convergence Subtractive Cancellation Subtractive Cancellation Subtraction Error Subtractive Cancellation Example: Output

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The *recursive relation* $x_{n+1} = 1 - (n+1)x_n$ with $x_0 = 1 - \frac{1}{e}$

n	x_n	n!	n	x_n	n!
0	0.63212056	1	11	0.07735223	3.99e + 007
1	0.36787944	1	12	0.07177325	4.79e + 008
2	0.26424112	2	13	0.06694778	6.23e + 009
3	0.20727665	6	14	0.06273108	8.72e + 010
4	0.17089341	24	15	0.05903379	1.31e+012
5	0.14553294	120	16	0.05545930	2.09e+013
6	0.12680236	720	17	0.05719187	3.56e + 014
7	0.11238350	5.04e + 003	18	-0.02945367	6.4e + 015
8	0.10093197	4.03e + 004	19	1.55961974	1.22e + 017
9	0.09161229	3.63e + 005	20	-30.19239489	2.43e + 018
10	0.08387707	3.63e + 006			

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Sources of Numerical Error Subtractive Cancellation

Subtraction Error

Consider the **MatLab** computation near x = 1 of

$$y = x^{7} - 7x^{6} + 21x^{5} - 35x^{4} + 35x^{3} - 21x^{2} + 7x - 1$$

compared to $y = (x - 1)^{7}$



Finite Precision Numerical Errors Algorithms and Convergence

Sources of Numerical Error Subtractive Cancellation

Subtraction Error

The program graphs $x \in [0.988, 1.012]$ with the two forms of function:



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Algorithms

Definition (Algorithm)

An algorithm is a procedure that describes, in an *unambiguous manner*, a finite sequence of steps to be performed in a specific order.

In this class, the objective of an algorithm is to implement a procedure to solve a problem or approximate a solution to a problem.

There are many collection of algorithms "out there" called *Numerical Recipes*

Definition (Stability)

An algorithm is said to be stable if small changes in the input, generates small changes in the output.

Finite Precision

Key Concepts for Numerical Algorithms

Numerical Errors Algorithms and Convergence

- At some point we need to quantify what "small" means!
- If an algorithm is stable for a certain *range* of initial data, then is it said to be *conditionally stable*.
- Stability issues are discussed in great detail in *Math* 543 and our **Dynamical Systems** classes.

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Stability

Suppose $E_0 > 0$ denotes the initial error, and E_n represents the error after n operations.

- If $E_n \approx CE_0 \cdot n$ (for a constant C, which is independent of n), then the growth is *linear*.
- If $E_n \approx C^n E_0$, C > 1, then the growth is *exponential* in this case the error will dominate very fast(undesirable scenario).
- Linear error growth is usually unavoidable, and in the case where \mathcal{C} and E_0 are small the results are generally acceptable. — Stable algorithm.
- Exponential error growth is unacceptable. Regardless of the size of E_0 the error grows rapidly. — Unstable algorithm.
- One property of **chaos** in a dynamical system is the *exponential growth* of any error in initial conditions – leading to unpredictable behavior

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2 of 2

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Error Growth

Example

The *recursive equation*

$$p_n = \frac{10}{3}p_{n-1} - p_{n-2}, \quad n = 2, 3, \dots, \infty$$

has the exact solution

$$p_n = c_1 \left(\frac{1}{3}\right)^n + c_2 3^n$$

for any constants c_1 and c_2 . (Determined by starting values.)

In particular, if $p_0 = 1$ and $p_1 = \frac{1}{3}$, we get $c_1 = 1$ and $c_2 = 0$, so $p_n = \left(\frac{1}{3}\right)^n$ for all n.

What happens with some rounding error, as we don't know $\frac{1}{3}$ exactly?

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1 of 2

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Numerical Errors Algorithms and Convergence

Example

Consider what happens in **5-digit rounding arithmetic**, where the initial starting conditions are rounded.

$$p_0^* = 1.0000, \quad p_1^* = 0.33333$$

which modifies the constants (by solving the general solution for c_1 and c_2 with the p_0^* and p_1^*)

$$c_1^* = 1.0000, \quad c_2^* = -0.12500 \cdot 10^{-5}$$

The generated sequence is

$$p_n^* = 1.0000 (0.33333)^n - \underbrace{0.12500 \cdot 10^{-5} (3.0000)^n}_{\textbf{Exponential Growth}}$$

 p_n^* quickly becomes a very poor approximation to p_n due to the *exponential growth* of the initial roundoff error.

- The effects of roundoff error can be reduced by using higher-order-digit arithmetic such as the **double** or multiple-precision arithmetic available on most computers.
- Disadvantages in using double precision arithmetic are that it takes more computation time, and *the growth of* the roundoff error is not eliminated but only postponed.
- Sometimes, but not always, it is possible to reduce the growth of the roundoff error by restructuring the calculations.

Numerical Errors Algorithms and Convergence

Reducing the Effects of Roundoff Error

Key Concepts

Rate of Convergence

Definition (Rate of Convergence)

Suppose the sequence $\underline{\beta} = {\{\beta_n\}}_{n=1}^{\infty}$ converges to zero, and $\underline{\alpha} = {\{\alpha_n\}}_{n=1}^{\infty}$ converges to a number α .

If there exists K > 0: $|\alpha_n - \alpha| < K\beta_n$, for *n* large enough, then we say that $\{\alpha_n\}_{n=1}^{\infty}$ converges to α with a **Rate of Convergence** $\mathcal{O}(\beta_n)$ ("Big Oh of β_n ").

We write

 $\alpha_n = \alpha + \mathcal{O}(\beta_n)$

Note: The sequence $\beta = \{\beta_n\}_{n=1}^{\infty}$ is usually chosen to be

$$\beta_n = \frac{1}{n^p}$$

for some positive value of p.

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Finite Precision Numerical Errors Algorithms and Convergence

Examples: Rate of Convergence

Example 2: Consider the sequence (as $n \to \infty$)

$$\alpha_n = \sin\left(\frac{1}{n}\right) - \frac{1}{n}$$

The **Maclaurin series** expansion for sin(x) is:

 $\sin\left(\frac{1}{n}\right) \sim \frac{1}{n} - \frac{1}{6n^3} + \mathcal{O}\left(\frac{1}{n^5}\right)$

Hence

$$|\alpha_n| = \left|\frac{1}{6n^3} + \mathcal{O}\left(\frac{1}{n^5}\right)\right|$$

It follows that

 $\alpha_n = \mathbf{0} + \mathcal{O}\left(\frac{1}{n^3}\right)$

Note:

$$\mathcal{O}\left(\frac{1}{n^3}\right) + \mathcal{O}\left(\frac{1}{n^5}\right) = \mathcal{O}\left(\frac{1}{n^3}\right), \quad \text{since} \quad \frac{1}{n^5} \ll \frac{1}{n^3}, \quad \text{as} \quad n \to \infty \text{ source}$$
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Rate of Convergence

Examples: Rate of Convergence

If

$$\alpha_n = \alpha + \frac{1}{\sqrt{n}}$$

then for any $\varepsilon > 0$

$$|\alpha_n - \alpha| = \frac{1}{\sqrt{n}} \le \underbrace{(1+\varepsilon)}_{K} \underbrace{\frac{1}{\sqrt{n}}}_{\beta_n}$$

Hence,

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$$\alpha_n = \alpha + \mathcal{O}\left(\frac{1}{\sqrt{n}}\right)$$

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Rate of Convergence

Generalizing to Continuous Limits

Definition (Rate of Convergence)

Suppose

$$\lim_{h \to 0} G(h) = 0, \quad \text{and} \quad \lim_{h \to 0} F(h) = L$$

If there exists K > 0:

$$|F(h) - L| \le K |G(h)|$$

for all h < H (for some H > 0), then

$$F(h) = L + \mathcal{O}(G(h))$$

we say that F(h) converges to L with a **Rate of Convergence** $\mathcal{O}(G(h))$.

Usually $G(h) = h^p$, p > 0.

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Examples: Rate of Convergence

Example 2-b: Consider the function $\alpha(h)$ (as $h \to 0$)

$$\alpha(h) = \sin\left(h\right) - h$$

The **Maclaurin series** expansion for sin(x) is:

 $\sin\left(h\right) \sim h - \frac{h^3}{6} + \mathcal{O}\left(h^5\right)$

Hence

$$\left|\alpha(h)\right| = \left|\frac{h^3}{6} + \mathcal{O}\left(h^5\right)\right|$$

It follows that

$$\lim_{h \to 0} \alpha(h) = \mathbf{0} + \mathcal{O}\left(h^3\right)$$

Note:

$$\mathcal{O}(h^3) + \mathcal{O}(h^5) = \mathcal{O}(h^3)$$
, since $h^5 \ll h^3$, as $h \to 0$

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