

Numerical Analysis

NTNU

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- r is called the mantissa and n is the exponent.
- The leading digit in the fraction is not zero.
- For example,

$$\begin{aligned} 42.965 &= 0.42965 \times 10^2, \\ -0.00234 &= -0.234 \times 10^{-2}. \end{aligned}$$

- Scientific notation for the binary number system of x :

$$x = \pm q \times 2^m$$

with

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and some integer m .

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$$\begin{aligned}(1001.1101)_2 &= 1 \times 2^3 + 1 \times 2^0 + 1 \times 2^{-1} + 1 \times 2^{-2} + 1 \times 2^{-4} \\ &= 0.10011101 \times 2^4 \\ &= (9.8125)_{10}\end{aligned}$$

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Repeating the previous step, we arrive at

$$\frac{2}{3} = (0.101010\dots)_2.$$



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- This subset, which are called the *floating-point numbers*, contains only rational numbers, both positive and negative.
- When a number can not be represented exactly with the fixed finite number of digits in a computer, a near-by floating-point number is chosen for approximate representation.

- For any real number x , let

$$x = \pm 0.a_1a_2 \cdots a_t a_{t+1} a_{t+2} \cdots \times 2^m, \quad a_1 \neq 0,$$

denote the normalized scientific binary representation of x .

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 1. **chopping**: simply discard the excess bits a_{t+1}, a_{t+2}, \dots to obtain

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2. **rounding up**: add $2^{-(t+1)} \times 2^m$ to x and then chop the excess bits to obtain a number of the form

$$fl(x) = \pm 0.\delta_1 \delta_2 \cdots \delta_t \times 2^m.$$

In this method, if $a_{t+1} = 1$, we add 1 to a_t to obtain $fl(x)$, and if $a_{t+1} = 0$, we merely chop off all but the first t digits.

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Remark 1.1 *As a measure of accuracy, the absolute error may be misleading and the relative error more meaningful.*

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$$\begin{aligned}\frac{|x - fl(x)|}{|x|} &= \frac{|0.00 \cdots 0a_{t+1}a_{t+2} \cdots \times 2^m|}{|0.a_1a_2 \cdots a_t a_{t+1}a_{t+2} \cdots \times 2^m|} \\ &= \frac{|0.a_{t+1}a_{t+2} \cdots|}{|0.a_1a_2 \cdots a_t a_{t+1}a_{t+2} \cdots|} \times 2^{-t}.\end{aligned}$$

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Since $a_1 \neq 0$, the minimal value of the denominator is $\frac{1}{2}$. The numerator is bounded above by 1. As a consequence

$$\left| \frac{x - fl(x)}{x} \right| \leq 2^{-t+1}.$$

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– $a_{t+1} = 1$, then $fl(x) = \pm(0.a_1a_2 \cdots a_t + 2^{-t}) \times 2^m$. The upper bound for relative error becomes

$$\frac{|x - fl(x)|}{|x|} = \frac{|1 - 0.a_{t+1}a_{t+2} \cdots|}{|0.a_1a_2 \cdots a_t a_{t+1}a_{t+2} \cdots|} \times 2^{-t} \leq 2^{-t},$$

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- If t -digit rounding arithmetic is used and

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Therefore the relative error for rounding arithmetic is

$$\left| \frac{x - fl(x)}{x} \right| \leq 2^{-t} = \frac{1}{2} \times 2^{-t+1}.$$

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- In 1985, the IEEE (Institute for Electrical and Electronic Engineers) published a report called *Binary Floating Point Arithmetic Standard 754-1985*. In this report, formats were specified for single, double, and extended precisions, and these standards are generally followed by microcomputer manufactures using floating-point hardware.

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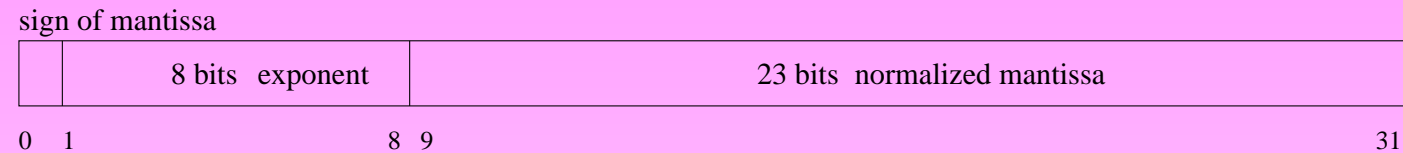


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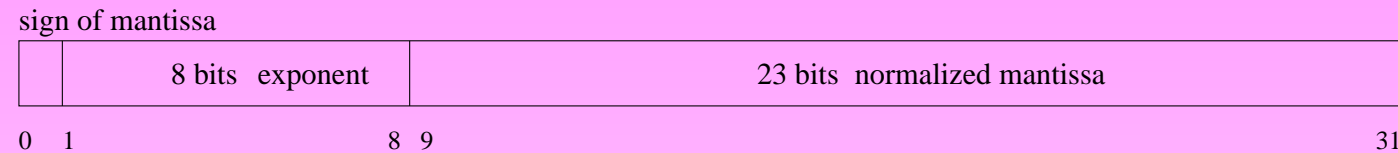


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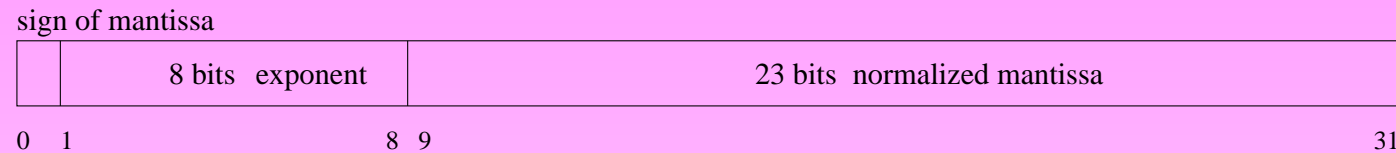


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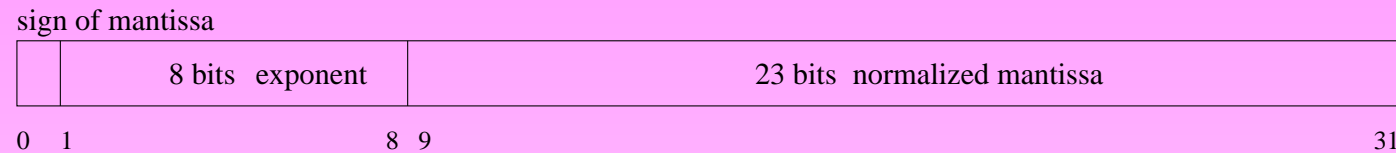


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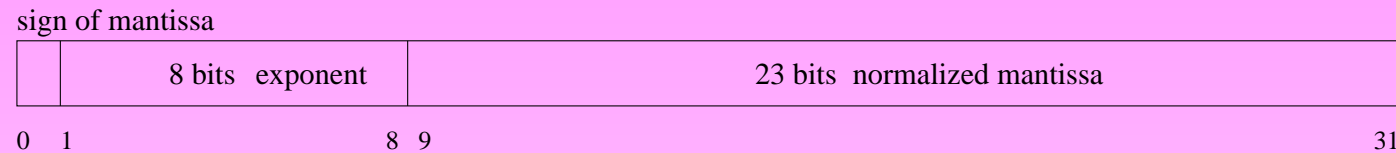


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- The actual exponent of the number is restricted by the inequality $-126 \leq c - 127 \leq 128$.
- A normalization is imposed that requires that the leading digit in fraction be 1, and this digit is not stored as part of the 23-bit mantissa.

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- The largest number that can be represented by the single precision format is approximately $2^{128} \approx 3.403 \times 10^{38}$, and the smallest positive number is $2^{-126} \approx 1.175 \times 10^{-38}$.

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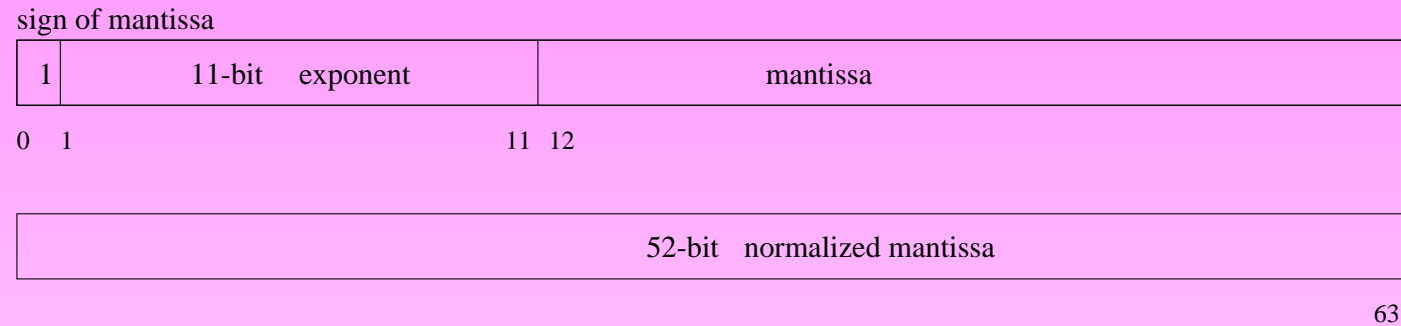


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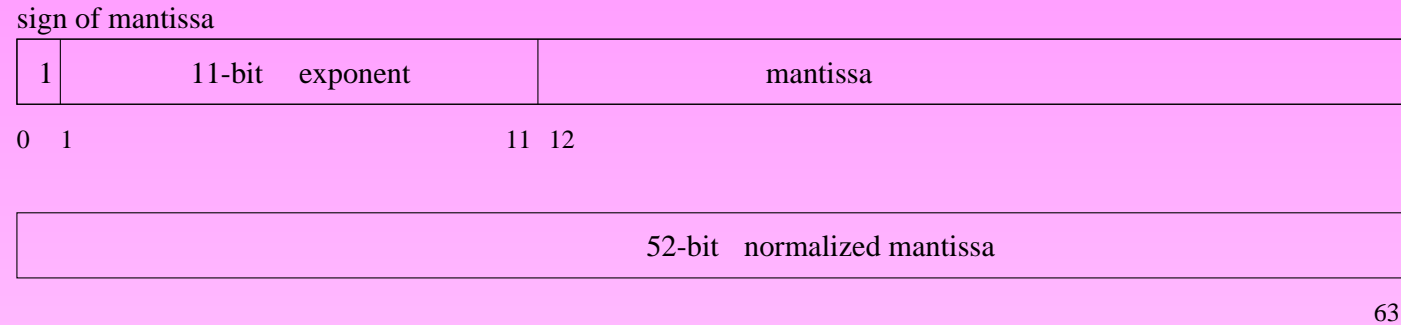


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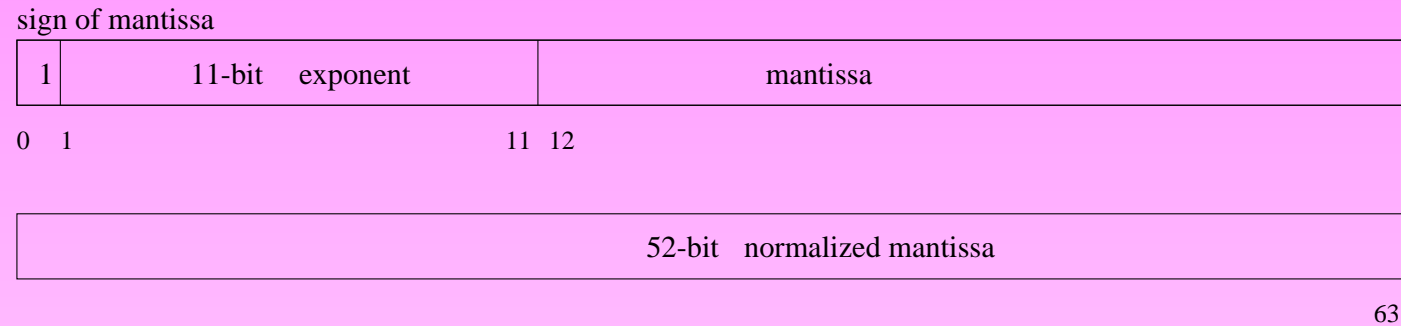


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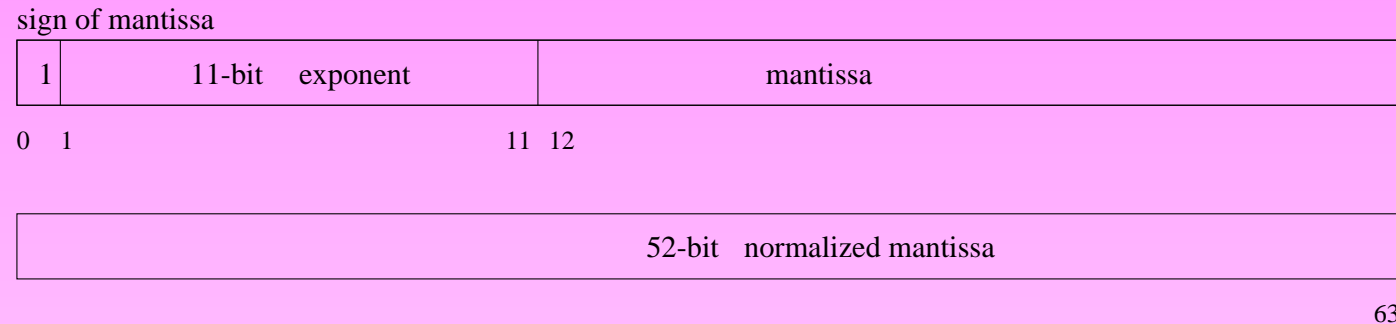


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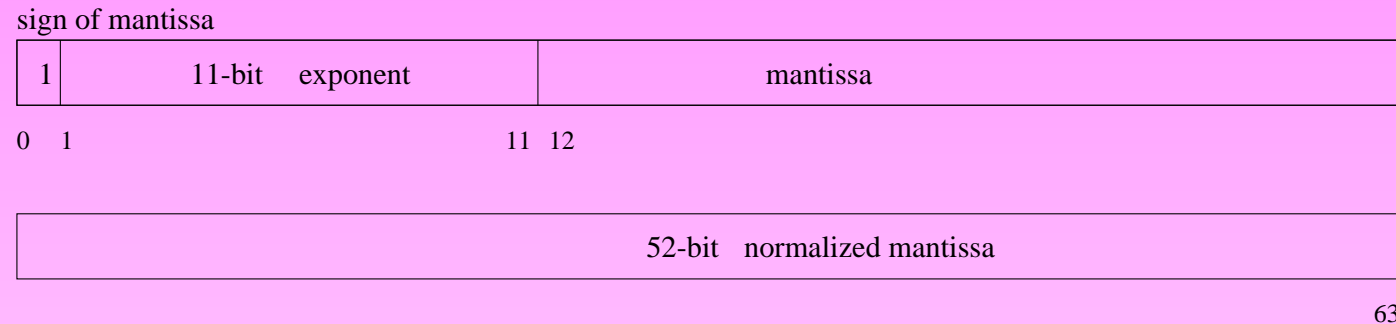


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- Range of approximately $2^{-1022} \approx 2.225 \times 10^{-308}$ to $2^{1024} \approx 1.798 \times 10^{308}$.

- Table 1 summarizes some characteristics of IEEE standard floating-point representations.

	single precision	double precision
ε_M	$2^{-23} \approx 1.192 \times 10^{-7}$	$2^{-52} \approx 2.220 \times 10^{-16}$
smallest positive number	$2^{-126} \approx 1.175 \times 10^{-38}$	$2^{-1022} \approx 2.225 \times 10^{-308}$
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- If a number $x = \pm q \times 2^m$ with m outside the computer's possible range (too large or too small), then we say that an *overflow* or an *underflow* has occurred.

- $+\text{Inf}$ and $-\text{Inf}$ correspond to two quite different numbers, $+\infty$ and $-\infty$. A **NaN** stands for **Not a Number** and is an error pattern rather than a number. Table 2 lists the IEEE exception handling standard.

big*big	$\pm \text{Inf}$	overflow
number/0.0	$\pm \text{Inf}$	division
0.0/0.0	NaN	invalid
small/big	subnormal number	underflow
2.0/3.0	rounded	

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- Under (1), the relative error of $fl(x \odot y)$ satisfies

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- But if x, y are not machine numbers, then they must first be rounded to floating-point format before the arithmetic operation and the resulting relative error becomes

$$fl(fl(x) \odot fl(y)) = (x(1 + \delta_1) \odot y(1 + \delta_2))(1 + \delta_3),$$

where $\delta_i \leq \varepsilon_M, i = 1, 2, 3$.

- The analysis (3) can be extended to arithmetic operations on three floating-point numbers.

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$$\begin{aligned} fl(x(y + z)) &= (x \cdot fl(y + z))(1 + \delta_1) \\ &= (x(y + z)(1 + \delta_2))(1 + \delta_1) \\ &= x(y + z)(1 + \delta_1 + \delta_2 + \delta_1\delta_2) \\ &\approx x(y + z)(1 + \delta_1 + \delta_2) \\ &= x(y + z)(1 + \delta_3) \end{aligned}$$

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3 Loss of Significance

- ➡ One of the most common error-producing calculations involves the cancellation of significant digits due to the subtraction of nearly equal numbers (or the addition of one very large number and one very small number).

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Then the floating-point form of $x - y$ is

$$fl(fl(x) - fl(y)) = 0.\sigma_{p+1}\sigma_{p+2} \cdots \sigma_t \times 10^n,$$

where

$$0.\sigma_{p+1}\sigma_{p+2} \cdots \sigma_t = 0.\alpha_{p+1}\alpha_{p+2} \cdots \alpha_t - 0.\beta_{p+1}\beta_{p+2} \cdots \beta_t.$$

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- The floating-point number used to represent $x - y$ has at most $t - p$ digits of significance. However, in most computers, $x - y$ will be assigned t digits, with the last p digits being either zero or randomly assigned.

Example 3.1 *If $x = 0.3721478693$ and $y = 0.3720230572$, what is the relative error in the computation of $x - y$ using five decimal digits of accuracy?*

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Therefore the relative error is

$$\frac{(x - y) - (fl(x) - fl(y))}{x - y} \approx 0.04 = 4\%.$$



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Theorem 3.1 *If $x \geq 0$ and $y \geq 0$ are normalized floating-point binary numbers such that $x > y$ and*

$$2^{-q} \leq 1 - \frac{y}{x} \leq 2^{-p},$$

then at most q and at least p significant binary digits are lost in the subtraction $x - y$.

Proof: Write

$$x = r \times 2^n, \quad \frac{1}{2} \leq r < 1 \quad \text{and} \quad y = s \times 2^m, \quad \frac{1}{2} \leq s < 1.$$

Since $x > y$, we must shift the decimal digits of y to the right

$$y = (s \times 2^{m-n}) \times 2^n.$$

Then

$$x - y = (r - s \times 2^{m-n}) \times 2^n = r \left(1 - \frac{s \times 2^m}{r \times 2^n} \right) \times 2^n = r \left(1 - \frac{y}{x} \right) \times 2^n.$$

By assumption $2^{-q} \leq 1 - \frac{y}{x} \leq 2^{-p}$, hence

$$r \left(1 - \frac{y}{x} \right) < 1 \cdot 2^{-p} = 2^{-p}.$$

This means that to normalize the result $x - y$, a shift of at least p bits to the left is required.

Similarly,

$$r \left(1 - \frac{y}{x} \right) \geq \frac{1}{2} \cdot 2^{-q} = 2^{-(q+1)},$$

and a shift of at most q bits to the right is required. ■

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Example 3.2 Consider the two equivalent functions

$$f(x) = x(\sqrt{x+1} - \sqrt{x}) \quad \text{and} \quad g(x) = \frac{x}{\sqrt{x+1} + \sqrt{x}}.$$

Compare the function evaluation of $f(500)$ and $g(500)$ using 6 digits and rounding.

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Compare the function evaluation of $f(500)$ and $g(500)$ using 6 digits and rounding.

Solution:

$$\begin{aligned} f(500) &= 0.500000 \times 10^3 \times (\sqrt{501} - \sqrt{500}) \\ &= 0.500000 \times 10^3 \times (0.223830 \times 10^2 - 0.223607 \times 10^2) \\ &= 0.500000 \times 10^3 \times 0.223000 \\ &= 0.111500 \times 10^3 \end{aligned}$$

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$$\begin{aligned}g(500) &= \frac{500}{\sqrt{501} + \sqrt{500}} \\ &= \frac{0.500000 \times 10^3}{0.223830 \times 10^2 + 0.223607 \times 10^2} \\ &= \frac{0.500000 \times 10^3}{0.447437 \times 10^2} \\ &= 0.111748 \times 10^2\end{aligned}$$

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If more digits are used, we can calculate

$$\begin{aligned}f(500) &= 500 \times (\sqrt{501} - \sqrt{500}) \\ &= 500 \times (22.38302929 - 22.36067977) \\ &= 500 \times 0.022349516 \\ &= 11.1747553\end{aligned}$$

Hence it can be argued that the formulation $g(x)$ is better. ■

Example 3.3 *The quadratic formulas for computing the roots of $ax^2 + bx + c = 0$, when $a \neq 0$, are*

$$x_1 = \frac{-b + \sqrt{b^2 - 4ac}}{2a} \quad \text{and} \quad x_2 = \frac{-b - \sqrt{b^2 - 4ac}}{2a}.$$

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$$\sqrt{b^2 - 4ac} = \sqrt{62.10^2 - 4.000} = \sqrt{3856 - 4.000} = \sqrt{3852} = 62.06,$$

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$$fl(x_1) = \frac{-62.10 + 62.06}{2.000} = \frac{-0.04000}{2.000} = -0.02000.$$

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The relative error in computing x_1 is

$$\frac{|fl(x_1) - x_1|}{|x_1|} = \frac{|-0.02000 + 0.01610723|}{|-0.01610723|} = \frac{0.00389277}{0.01610723} \approx 0.2417.$$

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To obtain a more accurate 4-digit rounding approximation for x_1 , we change the formulation by rationalizing the numerator, that is,

$$x_1 = \frac{-2c}{b + \sqrt{b^2 - 4ac}}.$$

Then

$$fl(x_1) = \frac{-2.000}{62.10 + 62.06} = \frac{-2.000}{124.2} = -0.01610.$$

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Example 3.4 *Let*

$$p(x) = ((x^3 - 3x^2) + 3x) - 1,$$

$$q(x) = ((x - 3)x + 3)x - 1.$$

Compare the function values at $x = 2.19$.

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Solution: Use 3-digit and rounding for $p(2.19)$ and $q(2.19)$.

$$\begin{aligned}\hat{p}(2.19) &= ((2.19^3 - 3 \times 2.19^2) + 3 \times 2.19) - 1 \\ &= ((10.5 - 14.4) + 3 \times 2.19) - 1 \\ &= (-3.9 + 6.57) - 1 \\ &= 2.67 - 1 \\ &= 1.67\end{aligned}$$

$$\begin{aligned}\hat{q}(2.19) &= ((2.19 - 3) \times 2.19 + 3) \times 2.19 - 1 \\ &= (-0.81 \times 2.19 + 3) \times 2.19 - 1 \\ &= (-1.77 + 3) \times 2.19 - 1 \\ &= 1.23 \times 2.19 - 1 \\ &= 2.69 - 1 \\ &= 1.69\end{aligned}$$

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Hence the absolute errors are

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respectively. One can observe that the evaluation formula $q(x)$ is better than $p(x)$. ■

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Alternatively, use Taylor series for $\sin x$ so that

$$\begin{aligned} y &= x - \left(x - \frac{x^3}{3!} + \frac{x^5}{5!} - \frac{x^7}{7!} + \frac{x^9}{9!} - \dots \right) \\ &= \frac{x^3}{3!} - \frac{x^5}{5!} + \frac{x^7}{7!} - \frac{x^9}{9!} + \dots \\ &= \frac{x^3}{6} - \frac{x^5}{6 \times 20} + \frac{x^7}{6 \times 20 \times 42} - \frac{x^9}{6 \times 20 \times 42 \times 72} \dots \\ &= \frac{x^3}{6} \left(1 - \frac{x^2}{20} \left(1 - \frac{x^2}{42} \left(1 - \frac{x^2}{72} (\dots) \right) \right) \right) \end{aligned}$$



4 Stability and Conditioning

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Example 4.1 Consider the following recurrence algorithm

$$\begin{cases} x_0 = 1, & x_1 = \frac{1}{3} \\ x_{n+1} = \frac{13}{3}x_n - \frac{4}{3}x_{n-1} \end{cases}$$

for computing the sequence of $\{x_n = (\frac{1}{3})^n\}$. This algorithm is unstable.

Solution: A computer implementation of the recurrence algorithm gives the following result.

n	x_n	n	x_n	n	x_n	n	x_n
0	1.0000000	4	0.0123466	8	0.0003757	12	0.0571502
1	0.3333333	5	0.0041187	9	0.0009437	13	0.2285939
2	0.1111112	6	0.0013857	10	0.0035887	14	0.9143735
3	0.0370373	7	0.0005153	11	0.0142927	15	3.6574934

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- ➡ For a general rectangular matrix, the singular values are used to characterize the condition number

$$\kappa(A) = \frac{\sigma_{max}}{\sigma_{min}},$$

where σ_{max} is the **largest singular value** of A and σ_{min} the **smallest singular value**.

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- ➡ In general, ill-conditioning is not easy to detect.
- ➡ In solving a system of linear equations $Ax = b$ in which A is ill-conditioned, small perturbation in b will cause large perturbation in x .