Computer Arithmetic

Victor Eijkhout

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Justification

This short session will explain the basics of floating point arithmetic, mostly focusing on round-off and its influence on computations. There is a surprising application to parallelism.

Numbers in scientific computing

- Integers: $\ldots, -2, -1, 0, 1, 2, \ldots$
- Rational numbers: $1/3, 22/7$: not often encountered
- Real numbers $0, 1, -1.5, 2/3, \sqrt{2}, \log 10, \ldots$
- Complex numbers $1 + 2i, \sqrt{3} - \sqrt{5}i, \ldots$

Computers use a finite number of bits to represent numbers,
so only a finite number of numbers can be represented, and no irrational numbers (even some rational numbers).

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Integers

Scientific computation mostly uses real numbers. Integers are mostly used for array indexing.

16/32/64 bit: `short`,`int`,`long`,`long long` in C, size not standardized, use `sizeof(long)` et cetera. (Also `unsigned int` et cetera)

`INTEGER*2/4/8` Fortran

Negative integers

Use of sign bit: typically first bit

s	$i_1 \ldots i_n$

Simplest solution: $n > 0$, $\mathrm{fl}(n) = +1, i_1, \ldots i_{31}$, then $\mathrm{fl}(-n) = -1, i_1, \ldots i_{31}$

Problem: $+0$ and -0; also impractical in other ways.

Sign bit

bitstring	$00\cdots0$	$\ldots$	$01\cdots1$	$10\cdots0$	$\ldots$	$11\cdots1$
as unsigned int	0	$\ldots$	$2^{31}-1$	2^{31}	$\ldots$	$2^{32}-1$
as naive signed	0	$\ldots$	$2^{31}-1$	-0	$\ldots$	$-2^{31}+1$

Shifting

Interpret unsigned number n as $n - B$

bitstring	$00\cdots0$	$\ldots$	$01\cdots1$	$10\cdots0$	$\ldots$	$11\cdots1$
as unsigned int	0	$\ldots$	$2^{31}-1$	2^{31}	$\ldots$	$2^{32}-1$
as shifted int	-2^{31}	$\ldots$	-1	0	$\ldots$	$2^{31}-1$

2's complement

Better solution: if $0 \leq n \leq 2^{31} - 1$, then $\mathrm{fl}(n) = 0, i_1, \ldots, i_{31}$;
$1 \leq n \leq 2^{31}$ then $\mathrm{fl}(-n) = \mathrm{fl}(2^{32} - n)$.

bitstring	$00\cdots0$	$\ldots$	$01\cdots1$	$10\cdots0$	$\ldots$	$11\cdots1$
as unsigned int	0	$\ldots$	$2^{31}-1$	2^{31}	$\ldots$	$2^{32}-1$
as 2's comp. integer	0	$\cdots$	$2^{31}-1$	-2^{31}	$\cdots$	-1

Subtraction in 2's complement

Subtraction $m-n$ is easy.

- Case: $m<n$. Observe that $-n$ has the bit pattern of $2^{32}-n$. Also, $m+(2^{32}-n)=2^{32}-(n-m)$ where $0<n-m<2^{31}-1$, so $2^{32}-(n-m)$ is the 2's complement bit pattern of $m-n$.
- Case: $m>n$. The bit pattern for $-n$ is $2^{32}-n$, so $m+(-n)$ as unsigned is $m+2^{32}-n=2^{32}+(m-n)$. Here $m-n>0$. The 2^{32} is an overflow bit; ignore.

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Floating point numbers

Analogous to scientific notation $x = 6.022 \cdot 10^{23}$:

$$x = \pm \Sigma_{i=0}^{t-1} d_i \beta^{-i} \beta^e$$

- sign bit
- β is the base of the number system
- $0 \leq d_i \leq \beta - 1$ the digits of the *mantissa*: with the *radix point* mantissa $< \beta$
- $e \in [L, U]$ exponent, stored with bias: unsigned int where $\mathrm{fl}(L) = 0$

Examples of floating point systems

	β	t	L	U
IEEE single (32 bit)	2	24	-126	127
IEEE double (64 bit)	2	53	-1022	1023
Old Cray 64bit	2	48	-16383	16384
IBM mainframe 32 bit	16	6	-64	63
packed decimal	10	50	-999	999

BCD is tricky: 3 decimal digits in 10 bits

(we will often use $\beta = 10$ in the examples, because it's easier to read for humans, but all practical computers use $\beta = 2$)

Internal processing in 80 bit

Limitations

Overflow: more than $\beta(1-\beta^{-t+1})\beta^U$ or less than $\beta(1-\beta^{-t+1})\beta^L$

Underflow: numbers less than $\beta^{-t+1}\cdot\beta^L$

Normalized numbers

Require first digit in the mantissa to be nonzero.
Equivalent: mantissa part $1 \leq x_m < \beta$

Unique representation for each number,
(do you see a problem?)
also: in binary this makes the first digit 1, so we don't need to store that.

With normalized numbers, underflow threshold is $1 \cdot \beta^L$;
'gradual underflow' possible, but usually not efficient.

IEEE 754

sign	exponent	mantissa
s	$e_1 \cdots e_8$	$s_1 \ldots s_{23}$
31	$30 \cdots 23$	$22 \cdots 0$

$(e_1 \cdots e_8)$	numerical value
$(0 \cdots 0) = 0$	$\pm 0.s_1 \cdots s_{23} \times 2^{-126}$
$(0 \cdots 01) = 1$	$\pm 1.s_1 \cdots s_{23} \times 2^{-126}$
$(0 \cdots 010) = 2$	$\pm 1.s_1 \cdots s_{23} \times 2^{-125}$
$\cdots$	
$(01111111) = 127$	$\pm 1.s_1 \cdots s_{23} \times 2^{0}$
$(10000000) = 128$	$\pm 1.s_1 \cdots s_{23} \times 2^{1}$
$\cdots$	
$(11111110) = 254$	$\pm 1.s_1 \cdots s_{23} \times 2^{127}$
$(11111111) = 255$	$\pm\infty$ if $s_1 \cdots s_{23} = 0$, otherwise `NaN`

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Representation error

Error between number x and representation $\tilde{x}$:
absolute $x - \tilde{x}$ or $|x - \tilde{x}|$
relative $\frac{x-\tilde{x}}{x}$ or $\left|\frac{x-\tilde{x}}{x}\right|$

Equivalent: $\tilde{x} = x \pm \varepsilon \Leftrightarrow |x - \tilde{x}| \leq \varepsilon \Leftrightarrow \tilde{x} \in [x - \varepsilon, x + \varepsilon]$.

Also: $\tilde{x} = x(1 + \varepsilon)$ often shorthand for $\left|\frac{\tilde{x}-x}{x}\right| \leq \varepsilon$

Example

Decimal, $t = 3$ digit mantissa: let $x = 1.256$, $\tilde{x}_{\mathrm{round}} = 1.26$, $\tilde{x}_{\mathrm{truncate}} = 1.25$

Error in the 4th digit: $|\varepsilon| < \beta^{t-1}$ (this example had no exponent, how about if it does?)

Machine precision

Any real number can be represented to a certain precision: $\tilde{x} = x(1+\varepsilon)$ where
truncation: $\varepsilon = \beta^{-t+1}$
rounding: $\varepsilon = \frac{1}{2}\beta^{-t+1}$

This is called *machine precision*: maximum relative error.

32-bit single precision: $mp \approx 10^{-7}$
64-bit double precision: $mp \approx 10^{-16}$

Maximum attainable accuracy.

Another definition of machine precision: smallest number ε such that $1+\varepsilon > 1$.

Addition

1. align exponents
2. add mantissas
3. adjust exponent to normalize

Example: $1.00 + 2.00 \times 10^{-2} = 1.00 + .02 = 1.02$. This is exact, but what happens with $1.00 + 2.55 \times 10^{-2}$?

Example: $5.00 \times 10^{1} + 5.04 = (5.00 + 0.504) \times 10^{1} \rightarrow 5.50 \times 10^{1}$

Any error comes from truncating the mantissa: if x is the true sum and $\tilde{x}$ the computed sum, then $\tilde{x} = x(1+\varepsilon)$ with $|\varepsilon| < 10^{-2}$

The 'correctly rounded arithmetic' model

Assumption (enforced by IEEE 754):

> *The numerical result of an operation is the rounding of the exactly computed result.*

$$\mathrm{fl}(x_1 \odot x_2) = (x_1 \odot x_2)(1+\varepsilon)$$

where $\odot = +, -, *, /$

Note: this holds only for a single operation!

Guard digits

Correctly rounding is not trivial, especially for subtraction.

Example: $t = 2, \beta = 10$: $1.0 - 9.5 \times 10^{-1}$, exact result $0.05 = 5.0 \times 10^{-2}$.

- Simple approach: $1.0 - 9.5 \times 10^{-1} = 1.0 - 0.9 = 0.1 = 1.0 \times 10^{-1}$
- Using 'guard digit': $1.0 - 9.5 \times 10^{-1} = 1.0 - 0.95 = 0.05 = 5.0 \times 10^{-2}$, exact.

In general 3 extra bits needed.

Error propagation under addition

Let $s = x_1 + x_2$, and $x = \tilde{s} = \tilde{x}_1 + \tilde{x}_2$ with $\tilde{x}_i = x_i(1+\varepsilon_i)$

$$\begin{aligned}
\tilde{x} &= \tilde{s}(1+\varepsilon_3) \\
&= x_1(1+\varepsilon_1)(1+\varepsilon_3) + x_2(1+\varepsilon_2)(1+\varepsilon_3) \\
&= x_1 + x_2 + x_1(\varepsilon_1+\varepsilon_3) + x_2(\varepsilon_2+\varepsilon_3) \\
\Rightarrow \tilde{x} &= s(1+2\varepsilon)
\end{aligned}$$

$\Rightarrow$ errors are added

Assumptions: all ε_i approximately equal size and small;
$x_i > 0$

Multiplication

1. add exponents
2. multiply mantissas
3. adjust exponent

Example: $.123 \times .567 \times 10^1 = .069741 \times 10^1 \rightarrow .69741 \times 10^0 \rightarrow .697 \times 10^0$.

What happens with relative errors?

Associativity

- A single operation is covered by 'exact rounding'; two operations is no longer exact.
- Associativity starts to play a role:

$$(a+b)+c \neq a+(b+c)$$

- Example: $4+6+7$, one significant digit, one guard digit.
- C language has left-to-right evaluation; Fortran has no rule: compiler limited in what it is allowed to optimize.

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Subtraction

Correct rounding only applies to a single operation.

Example: $1.24 - 1.23 = .001 \to 1. \times 10^{-2}$:
result is exact, but only one significant digit.

What if $1.24 = \mathrm{fl}(1.244)$ and $1.23 = \mathrm{fl}(1.225)$? Correct result 1.9×10^{-2}; almost 100% error.

- *Cancellation* leads to loss of precision
- subsequent operations with this result are inaccurate
- this can not be fixed with guard digits and such
- $\Rightarrow$ avoid subtracting numbers that are likely close.

ABC-formula

Example: $ax^2 + bx + c = 0 \rightarrow x = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$
suppose $b > 0$ and $b^2 \gg 4ac$ then the '$+$' solution will be inaccurate
Better: compute $x_- = \frac{-b - \sqrt{b^2 - 4ac}}{2a}$ and use $x_+ \cdot x_- = -c/a$.

Serious example

Evaluate $\Sigma_{n=1}^{10000} \frac{1}{n^2} = 1.644834$
in 6 digits: machine precision is 10^{-6} in single precision

First term is 1, so partial sums are ≥ 1, so $1/n^2 < 10^{-6}$ gets ignored, $\Rightarrow$ last 7000 terms (or more) are ignored, $\Rightarrow$ sum is 1.644725: 4 correct digits

Solution: sum in reverse order; exact result in single precision
Why? Consider ratio of two terms:

$$\frac{n^2}{(n-1)^2} = \frac{n^2}{n^2-2n+1} = \frac{1}{1-2/n+1/n^2} \approx 1 + \frac{2}{n}$$

with aligned exponents:

$$\begin{array}{rl|l} n-1: & .00\cdots0 & 10\cdots00 \\ n: & .00\cdots0 & 10\cdots01 \quad 0\cdots0 \\ & & k = \log(n/2) \text{ positions} \end{array}$$

The last digit in the smaller number is not lost if $n < 2/\varepsilon$

Another serious example

Previous example was due to finite representation; this example is more due to algorithm itself.

Consider $y_n = \int_0^1 \frac{x^n}{x-5} dx = \frac{1}{n} - 5y_{n-1}$ (monotonically decreasing)
$y_0 = \ln 6 - \ln 5$.

In 3 decimal digits:

computation		correct result
$y_0 = \ln 6 - \ln 5 = .182 \vert 322 \times 10^1 \ldots$		1.82
$y_1 = .900 \times 10^{-1}$		.884
$y_2 = .500 \times 10^{-1}$		.0580
$y_3 = .830 \times 10^{-1}$	going up?	.0431
$y_4 = -.165$	negative?	.0343

Reason? Define error as $\tilde{y}_n = y_n + \varepsilon_n$, then

$$\tilde{y}_n = 1/n - 5\tilde{y}_{n-1} = 1/n + 5n_{n-1} + 5\varepsilon_{n-1} = y_n + 5\varepsilon_{n-1}$$

so $\varepsilon_n \geq 5\varepsilon_{n-1}$: exponential growth.

Stability of linear system solving

Problem: solve $Ax = b$, where b inexact.

$$A(x+\Delta x) = b+\Delta b.$$

Since $Ax = b$, we get $A\Delta x = \Delta b$. From this,

$$\left\{ \begin{array}{ll} Ax & = b \\ \Delta x & = A^{-1}\Delta b \end{array} \right\} \Rightarrow \left\{ \begin{array}{rl} \|A\|\|x\| & \geq \|b\| \\ \|\Delta x\| & \leq \|A^{-1}\|\|\Delta b\| \end{array} \right.$$

$$\Rightarrow \frac{\|\Delta x\|}{\|x\|} \leq \|A\|\|A^{-1}\|\frac{\|\Delta b\|}{\|b\|}$$

'Condition number'. Attainable accuracy depends on matrix properties

Consequences for parallel computation

Multiplication and addition are not associative:
problems for parallel computations.

Sequential results are not reproducible.
Note: parallel results need not be worse!

Wild idea: do reductions in fixed-point arithmetic
(requires about 4000 bits for a floating point number)

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Complex numbers

Two real numbers: real and imaginary part.

Storage:

- Store real/imaginary adjacent: easy to pass address of one number
- Store array of real, then array of imaginary. Better for stride 1 access if only real parts are needed. Other considerations.

Other arithmetic systems

Some compilers support higher precisions.

Arbitrary precision: GMPlib

Interval arithmetic