

Computational Physics

Lecture 2 – Introduction to Numerical Calculations

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Slides available from <https://bb.imperial.ac.uk/>

Outline

- 1 Variables, errors and arithmetic
- 2 Dealing with units
- 3 Solving equations

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● **logicals/booleans**

- Single bit
- 0/1 = true/false

● **integers**

- multiple logicals, each corresponding to a power of 2
- i.e. just natural numbers base 2
- unsigned or signed (+1 *sign bit*)

$$\begin{array}{cccccccc} 0 & 0 & 1 & 1 & 0 & 1 & 0 & 0 \\ + & 0 & 32 & 16 & 0 & 4 & 0 & 0 & = 52 \end{array}$$

- ‘fixed’ point
- short (15+1-bit binary strings) or long (31+1)

- **strings/characters**

- 'cat', 'dog', 'Physics', etc.
- each character is encoded by some set number of bits
- In standard ASCII, there are 7 bits encoding $2^7 = 128$ characters (not all printable)
- 'a' = 97 (decimal) = 61 (Hexadecimal) = 0110 0001 (binary)

- **pointers**

- Integer memory addresses saved as variables
- used to refer to other variables, functions, subroutines, pointers, objects, etc

- **references (mostly relevant to C++)**

- Like pointers, but more of an alias than a variable

- **arrays, structures, classes, objects, etc**

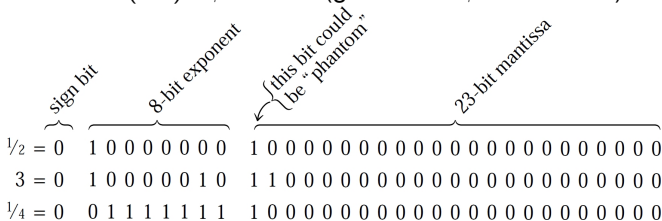
Just bundles of other variables, often with additional operations defined on them

● 'floating' point

- inexact representation of \mathbb{R}
- **sign bit** s , **exponent** E and **mantissa/significand** M
- number = $(-1)^s \cdot \beta^{E-e} \cdot M$ (given base β and bias e)

For *this* example
 $\beta = 2, e = 129$

IEEE754-1985
has $e = 127$



- single (1 + 23 + 8 = 32-bit), double (1 + 52 + 11 = 64-bit), extended/quadruple (1 + 112 + 15 = 128-bit)

● complex

- composite of two floating-point numbers
- plus some 'interaction terms'

The bible: What Every Computer Scientist Should Know About Floating-Point Arithmetic – Goldberg (1991) ([available on Blackboard](#))

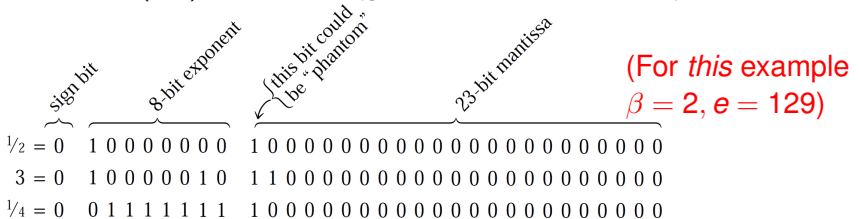
How would you represent -2.5 ?

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2 minutes to think about this for yourselves (don't talk to others).

2 minutes to discuss with your neighbour.

$$\text{number} = (-1)^s \cdot \beta^{E-e} \cdot M \text{ (given base } \beta \text{ and bias } e)$$

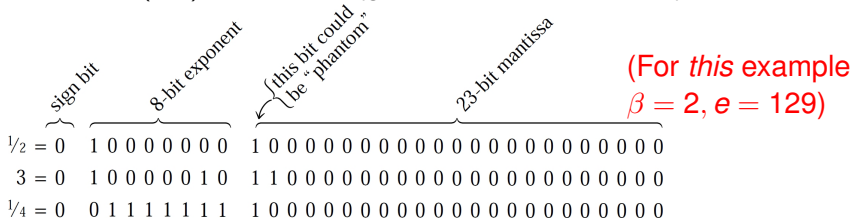


How would you represent 3.25?

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2 minutes to think and discuss with your neighbour.

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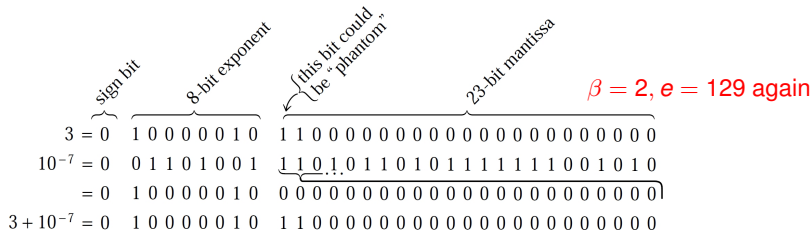
Floating-point Addition and Subtraction

$A + B$ (when $A > B$)

- 1 shift B to the same exponent as A
- 2 integer add/subtract the mantissae

Floating-point Addition and Subtraction

What about when the two numbers are very different?



Two numbers are very different in size \implies the smaller is ignored

- There exists a smallest number that can be added/subtracted meaningfully from 1.0 – machine accuracy

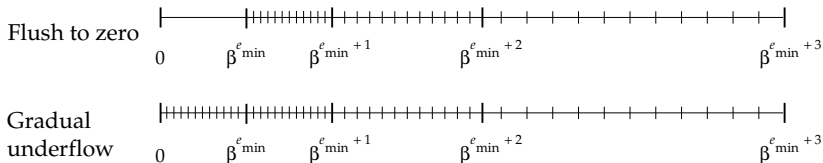
Two numbers very similar size \implies subtraction causes cancellation errors

- Significant digits are lost, only those affected by round-off remain

Floating-point Multiplication & Division

$A \times B$

- 1 XOR (multiply) the sign bit
- 2 integer add/subtract the exponents
- 3 integer multiply/divide the mantissae



Going $<$ smallest *normalisable* number in the rep. causes headaches

- subnormal/denormalised numbers are inaccurate and slow

Rounding/representation error

- multiplies as floats are operated on
- always a problem, but magnified with denormalised numbers

Other limitations

Overflows

- Above the representable range for `|number|`
- Integers tend to wrap around (or throw errors)
- Floats go to $\pm\text{Inf}$

Underflows

- Only an issue for floats
- `number` $\rightarrow \pm 0$

NaNs

- Not a Number
- Only really exists in floating-point specification
- Most often results from
 - 1 a divide by 0
 - 2 operations on $\pm\text{Inf}$
 - 3 imaginary results for real functions

Operations on integers

- Integer operations and arithmetic are *fast* and exact
- Well, except for division
 - in this case the remainder is truncated
 - there are other tricks to get quick rounded results
- Standard logical operations can be performed bitwise on whole integers at once

This is good for:

- quick multiplication or division by 2
- extracting/setting combinations of flags (booleans)

Comparison using floating-point variables

- Never, ever write

```
if (myVar == 0.) Or if (myVar1 == myVar2)
```

- Floating point numbers cannot be trusted to be exactly equal to **anything!!!**

- Much safer to write

```
if (abs(myVar) < absprec)
```

or

```
if (abs(myVar1/myVar2 - 1.0) < relprec)
```

where $\text{absprec} = A\epsilon$ and $\text{relprec} = B\epsilon$

- Floating point comparisons only OK to within some suitable multiple $A, B \gg 1$ of ϵ !!!
- In practice A and B are set per-algorithm (according to round-off error, speed, truncation error, etc)

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Renormalisation of variables ('natural units')

- Avoid working with very big floats
 - **Speed** - most CPUs are quicker doing double prec than extended prec
 - **Space** - doubles take less space than extendeds (does matter sometimes)
 - **Accuracy** - it is easy to go beyond the max/min representable number
- Also avoid working with very small floats
 - **Speed** - denormalised arithmetic is sloooooow
 - **Space** - as with big floats: prefer lower precision
 - **Accuracy** - denormalised arithmetic is inaccurate
- Instead, choose a scale and renormalise

$$A \rightarrow B \equiv A/A_{\max}$$

- Easier + faster to multiply by a scalefactor afterwards, even if that requires type conversion

Renormalisation of variables ('natural units')

- Consider working in log space
 - if your data span a huge range of scales, and you care about the small ones
 - e.g. a range of 2–70 is way easier to work with than $100\text{--}10^{70}$
 - often a lot faster and more accurate; no huge or tiny floats
- Easier + faster to exponentiate afterwards, even if that requires type conversion

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Solving equations

Everybody needs to solve an equation numerically eventually...

$$f(x) + a = g(x) + b$$

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$$f(x) + a = g(x) + b$$

$$f(x) - g(x) + a - b = 0 \quad (1)$$

$$\text{i.e. } h(x) = 0 \quad (2)$$

Recast it as homogeneous and you have

The classic root-finding problem

For what x does $h(x) = 0$?

First...

Guess!

First. . .

Guess!

Then guess again!

First. . .

Guess!

Then guess again!

If your guesses have the same sign for $h(x)$, keep guessing. . .

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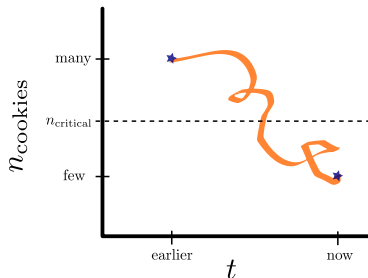
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Intermediate value theorem

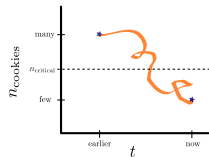
\implies there must be some root between the guesses



Bracketing

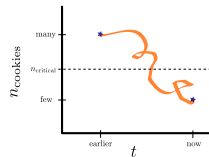
Intermediate value theorem \implies there must be some root between the guesses

- The point of root-finding is to refine these ‘brackets’ as quickly as possible.
- Bracketing is essential.



Bracketing

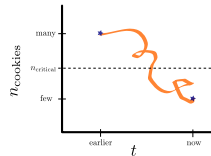
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Bracketing

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- Bracketing is essential.
- If *all* your guesses have the same sign for $h(x)$, you’re a bit screwed – find something better than guessing. Actually, work out how to guess smarter.
- **Always** eyeball your function before trying to find its roots, unless you know it **very** well.

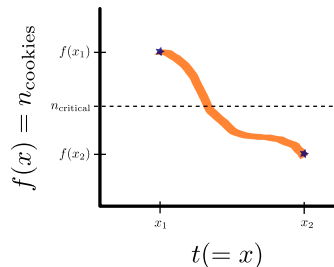
Bisection

Divide and conquer:

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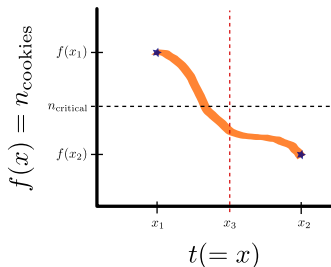
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Bisection

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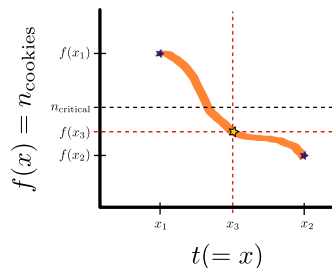
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Bisection

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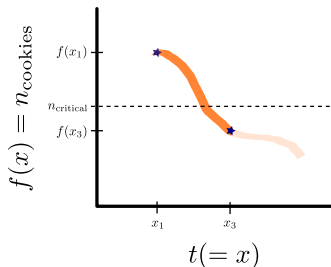
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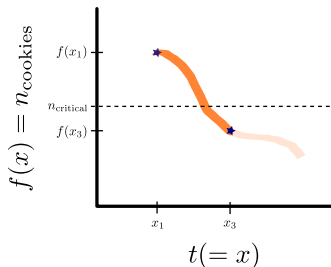
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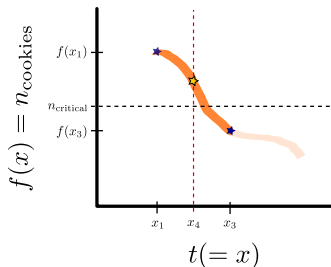
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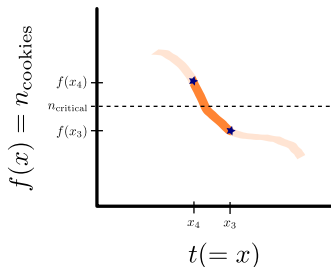
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Improving on bisection

General idea for improving is to use some (convergent) approximation / guess function

- Linear interpolation = secant, false position method
- Exponential functions = Ridder's method
- Quadratic interpolation (+bisection) = Müller's method
- Inverse quadratic interpol (+bisection) = Brent's method
- Tangent extrapolation = Newton-Raphson

More info available in the lecture notes.

- Problem Sheet for this lecture is available on Blackboard
 - Floating point issues
 - Variable rescaling / natural units
- Next lecture:
 - 11am Tuesday
 - Matrix Methods

Bonus content: a horror story about default variable widths

- Most new systems are 64-bit
- Most scientific code was written on 32-bit machines
- Variable widths can differ!

Classic nasty bug: passing pointers between C and Fortran

- C pointer has same width as long int (32 bits) on 32-bit, but twice the width on 64-bit
- Fortran has no separate pointer type (attribute only)
- compilers don't care/know → linked C-F90 code compiles fine on both machines
- Crashes with seg fault on 64-bit machine, runs OK on 32-bit
- ⇒ not enough space reserved for 64-bit pointer in C-F90 interface