## \# 3

Errors in computation; where do they come from?

## L. Olson

September 1, 2015
Department of Computer Science
University of Illinois at Urbana-Champaign

- look at floating point representation in its basic form
- expose errors of a different form: rounding error
- highlight IEEE-754 standard
- Errors come in two forms: truncation error and rounding error
- we always have them ...
- case study: Intel
- our jobs as developers: reduce impact
example: calculating $x=x+0.1$


## next: floating point numbers

- We're familiar with base 10 representation of numbers:

$$
1234=4 \times 10^{0}+3 \times 10^{1}+2 \times 10^{2}+1 \times 10^{3}
$$

and

$$
.1234=1 \times 10^{-1}+2 \times 10^{-2}+3 \times 10^{-3}+4 \times 10^{-4}
$$

- we write 1234.1234 as an integer part and a fractional part:

$$
a_{3} a_{2} a_{1} a_{0} \cdot b_{1} b_{2} b_{3} b_{4}
$$

- For some (even simple) numbers, there may be an infinite number of digits to the right:

$$
\begin{aligned}
\pi & =3.14159 \ldots \\
1 / 9 & =0.11111 \ldots \\
\sqrt{2} & =1.41421 \ldots
\end{aligned}
$$

## other bases

- So far, we have just base 10 . What about base $\beta$ ?
- binary $(\beta=2)$, octal $(\beta=8)$, hexadecimal $(\beta=16)$, etc
- In the $\beta$-system we have

$$
\left(a_{n} \ldots a_{2} a_{1} a_{0} \cdot b_{1} b_{2} b_{3} b_{4} \ldots\right)_{\beta}=\sum_{k=0}^{n} a_{k} \beta^{k}+\sum_{k=0}^{\infty} b_{k} \beta^{-k}
$$

## integer conversion

An algorithm to compute the base 2 representation of a base 10 integer

$$
\begin{aligned}
(N)_{10} & =\left(a_{j} a_{j-1} \cdots a_{2} a_{0}\right)_{2} \\
& =a_{j} \cdot 2^{j}+\cdots+a_{1} \cdot 2^{1}+a_{0} \cdot 2^{0}
\end{aligned}
$$

Compute $(N)_{10} / 2=Q+R / 2$ :

$$
\frac{N}{2}=\underbrace{a_{j} \cdot 2^{j-1}+\cdots+a_{1} \cdot 2^{0}}_{=Q}+\underbrace{\frac{a_{0}}{2}}_{=R / 2}
$$

## Example

Example: compute (11) $)_{10}$ base 2

$$
\begin{array}{rll}
11 / 2=5 R 1 & \Rightarrow & a_{0}=1 \\
5 / 2=2 R 1 & \Rightarrow & a_{1}=1 \\
2 / 2=1 R 0 & \Rightarrow & a_{2}=0 \\
1 / 2=0 R 1 & \Rightarrow & a_{3}=1
\end{array}
$$

So $(11)_{10}=(1011)_{2}$

Convert a base-2 number to base-10:
$(11000101)_{2}$
$=1 \times 2^{7}+1 \times 2^{6}+0 \times 2^{5}+0 \times 2^{4}+0 \times 2^{3}+1 \times 2^{2}+0 \times 2^{1}+1 \times 2^{0}$
$=1+2(0+2(1+2(0+2(0+2(0+2(1+2(1)))))))$
$=197$

## converting fractions

- straight forward way is not easy
- goal: for $x \in[0,1]$ write

$$
x=0 . b_{1} b_{2} b_{3} b_{4} \cdots=\sum_{k=1}^{\infty} c_{k} \beta^{-k}=\left(0 . c_{1} c_{2} c_{3} \ldots\right)_{\beta}
$$

- $\beta(x)=\left(c_{1} \cdot c_{2} c_{3} c_{4} \ldots\right)_{\beta}$
- multiplication by $\beta$ in base- $\beta$ only shifts the radix


## fraction algorithm

An algorithm to compute the binary representation of a fraction $x$ :

$$
\begin{aligned}
x & =0 . b_{1} b_{2} b_{3} b_{4} \ldots \\
& =b_{1} \cdot 2^{-1}+\ldots
\end{aligned}
$$

Multiply $x$ by 2 . The integer part of $2 x$ is $b_{1}$

$$
2 x=b_{1} \cdot 2^{0}+b_{2} \cdot 2^{-1}+b_{3} \cdot 2^{-2}+\ldots
$$

## Example

Example:Compute the binary representation of 0.625

$$
\begin{array}{rll}
2 \cdot 0.625=1.25 & \Rightarrow & b_{-1}=1 \\
2 \cdot 0.25=0.5 & \Rightarrow & b_{-2}=0 \\
2 \cdot 0.5=1.0 & \Rightarrow & b_{-3}=1
\end{array}
$$

So $(0.625)_{10}=(0.101)_{2}$

## a problem with precision

$$
\begin{aligned}
& 1 \\
& r_{0}=x \\
& 2 \\
& \text { for } k=1,2, \ldots, m \\
& 3 \\
& \text { if } r_{k-1} \geq 2^{-k} \\
& 4
\end{aligned} \quad b_{k}=1 .
$$

| $k$ | $2^{-k}$ | $b_{k}$ | $r_{k}=r_{k-1}-b_{k} 2^{-k}$ |
| :--- | :--- | :--- | :--- |
| 0 |  |  | 0.8125 |
| 1 | 0.5 | 1 | 0.3125 |
| 2 | 0.25 | 1 | 0.0625 |
| 3 | 0.125 | 0 | 0.0625 |
| 4 | 0.0625 | 1 | 0.0000 |

binary fraction example

For other numbers, such as $\frac{1}{5}=0.2$, an infinite length is needed.
$0.2 \rightarrow .001100110011 \ldots$

So 0.2 is stored just fine in base-10, but needs infinite number of digits in base-2
!!!
This is roundoff error in its basic form...

## intel

## Business Day

## Che New Hork Times

## Digest

| Dow | $\begin{gathered} \text { DOLLAR } \\ \text { vs. Jopanese } \\ \text { ven } \\ \text { 90. } 47 \text { Yen } \\ +0.24 \text { Yen } \end{gathered}$ | OLL | $\frac{\text { BoNDS }}{\text { 30-Year }}$ |
| :---: | :---: | :---: | :---: |
| 30, |  | met |  |
| $\begin{gathered} 3.674 .63 \\ -3.36 \\ \hline \end{gathered}$ |  | $\begin{aligned} & \$ 18.15 \\ & +\$ 0.39 \end{aligned}$ | $\begin{aligned} & 7.99 \% \\ & -0.08 \end{aligned}$ |

## Companies

A haw he the Pentiom, the top chip mode by Intat, can cause

 milition or about 30 parcent of the 520.7 mation thit 2,











## Markets



 Seoek markets fell nharply yerous Europe no inventars took thes

Flaw Undermines Accuracy of Pentium Chips


## Four Sharp Corrections in the Dow





Intel's centemions that the error mistide unly sectur in exaremsty rare cauk some wasiormat, Ns.id They are bumed an anaritionk nbeuk



 Tuapmod for mour the had been Continued on Pape DS

## Gibson Suit On Trades Is Settled

Bankers Trust Gets 30\% of Debt Claimed By michazl quint
Gabaon Grewtinum Inc. and the


Under the nut of-ceurl sothomend:
 While neliter side beamed of vic-


Flaw Undermines Accuracy of Pentium Chips
By JOHN MARKOFFSpecial to The New York Times
New York Times (1857-Current file); Nov 24, 1994; ProQuest Historical Newspapers The New York Times (1851-2002) pg. D1

## Flaw Undermines Accuracy of Pentium Chips

## By JOHN MARKOFF

SAN FRANCISCO, Nov. 23 -An elusive circuitry error is causing a chip used in millions of computers to tain rare cases, heightening anxiety among many scientists and englneers who rely on their machines for precise calculations.
The flaw, an error in division, has rent top microprocessor of the curCorporation, the world's largest chip maker. The chip, in several different
configurations, is used in many com-
puters soid for home and business use, including those made by I.B.M. ers.
The flaw appears in all Pentium hips now on the market, in certain ypes of division problems involving more than five significant digits, a numbers before and after a decimal point.
Intel declined to say how many Pentlum chips it made or sold, but Dataquest, a market research comthat in 1994 Intel would sell 5.5 mil on to 6 million Pentiums, roughly 10 percent of the number of personal
computers sold worldwide.
Intel said yesterday that it did not belleve the chip needed to be re user would have but one chance in more than nine billion of encounter ing an inaccurate result as a consequence of the error, and thus ther was no noticeable consequence of business or home comput ers. Indeed, the company said it was continuing to send computer maker Pentium chips built before the prob em was detected.
of the University of California at Berkeley, one of the matics, expressed skepticism about
intel's contentions that the error would only occur in extremely rare nstances.
avse some kinds of statistics have to "They are based on assertions abou the probability of events whose prob bility we don't know."
At the Jet Propulsion Laboratory in Pasadena, Calif., one satellite communications researcher who learned of the error this week, said six Pentium machines were used in his group and their use had been uspended for now

The Pentium appeared as a cost
Continued on Page DS

## tium Chips

## In some complex division problems, annoying errors.

## corrected.

Some computer users said they believed that Intel had not acted quickly enough after discovering the error.
"Intel has known about this since the summer; why didn't they tell anyone?" said Andrew Schulman, the author of a series of technical books on PC's. "It's a hot issue, and I don't think they've handled this well.

The company said that after it discovered the problem this summer, it ran months of simulations of different applications, with the help of outside experts, to determine whether the problem was serious.

The Pentium error occurs in a portion of the chip known as the floating point unit, which is used for extremely precise computations. In rare cases, the error shows up in the result of a division operation.

Intel said the error occurred because of an omission in the translation of a formila info comnitor

## Close, buit Not Close Enough

The owners of computers thet use intel's pentlum microprocessors fíve found that the chips sometlmes do not perform division. calculations accurately enough.
The problems arise when the chip tias to round a number in a preliminary calculation to get the tinal result, a task that all processors normally periom. In these ceses? however, the Pontlum's figures are exact to onlys digits, not 16 ae are trose of other computer processors. The Pentlim's error, while smail. on ba 10 billon times as large as those of most chips.
Here is an example of the way the mpreclse rounding Changes the resulte of a calculation and the way the daviation rom the expected result ls calcuilated:

## PROBLEM

$$
4,195,835-\lfloor(4,195,835+3,145,727) \times 3,145,727]
$$

CORRECT CALCULATION


## intel timeline

June 1994 Intel engineers discover the division error. Managers decide the error will not impact many people. Keep the issue internal.

June 1994 Dr Nicely at Lynchburg College notices computation problems
Oct 19, 1994 After months of testing, Nicely confirms that other errors are not the cause. The problem is in the Intel Processor.

Oct 24, 1994 Nicely contacts Intel. Intel duplicates error.
Oct 30, 1994 After no action from Intel, Nicely sends an email

## intel timeline

```
FROM: Dr. Thomas R. Nicely
Professor of Mathematics
Lynchburg College
1501 Lakeside Drive
Lynchburg, Virginia 24501-3199
    Phone: 804-522-8374
    Fax: 804-522-8499
    Internet: nicely@acavax.lynchburg.edu
T0: Whom it may concern
RE: Bug in the Pentium FPU
DATE: 30 October 1994
```

It appears that there is a bug in the floating point unit (numeric coprocessor) of many, and perhaps all, Pentium processors.

In short, the Pentium FPU is returning erroneous values for certain division operations. For example, 0001/824633702441.0
is calculated incorrectly (all digits beyond the eighth
significant digit are in error). This can be verified in compiled code, an ordinary spreadsheet such as Quattro Pro or Excel, or even the Windows calculator (use the
scientific mode), by computing $00(824633702441.0) *(1 / 824633702441.0)$,
which should equal 1 exactly (within some extremely small rounding error; in general, coprocessor results should contain 19 significant decimal digits). However, the Pentiums tested return
0000.999999996274709702

## intel timeline

Nov 1, 1994 Software company Phar Lap Software receives Nicely's email. Sends to colleagues at Microsoft, Borland, Watcom, etc. decide the error will not impact many people. Keep the issue internal.
Nov 2, 1994 Email with description goes global.
Nov 15, 1994 USC reverse-engineers the chip to expose the problem. Intel still denies a problem. Stock falls.
Nov 22, 1994 CNN Moneyline interviews Intel. Says the problem is minor.
Nov 23, 1994 The MathWorks develops a fix.
Nov 24, 1994 New York Times story. Intel still sending out flawed chips.
Will replace chips only if it caused a problem in an important application.
Dec 12, 1994 IBM halts shipment of Pentium based PCs
Dec 16, 1994 Intel stock falls again.
Dec 19, 1994 More reports in the NYT: lawsuits, etc.
Dec 20, 1994 Intel admits. Sets aside $\$ 420$ million to fix.

## numerical "bugs"

## Obvious

Software has bugs

## Not-SO-Obvious

Numerical software has two unique bugs:

1. roundoff error
2. truncation error

## numerical errors

## Roundoff

Roundoff occurs when digits in a decimal point (0.3333...) are lost (0.3333) due to a limit on the memory available for storing one numerical value.

## Truncation

Truncation error occurs when discrete values are used to approximate a mathematical expression.

## uncertainty: well- or ill-conditioned?

Errors in input data can cause uncertain results

- input data can be experimental or rounded. leads to a certain variation in the results
- well-conditioned: numerical results are insensitive to small variations in the input
- ill-conditioned: small variations lead to drastically different numerical calculations (a.k.a. poorly conditioned)


## our job

As numerical analysts, we need to

1. solve a problem so that the calculation is not susceptible to large roundoff error
2. solve a problem so that the approximation has a tolerable truncation error

How?

- incorporate roundoff-truncation knowledge into
- the mathematical model
- the method
- the algorithm
- the software design
- awareness $\rightarrow$ correct interpretation of results


## floating points

Normalized Floating-Point Representation Real numbers are stored as

$$
x= \pm\left(0 . d_{1} d_{2} d_{3} \ldots d_{m}\right)_{\beta} \times \beta^{e}
$$

- $d_{1} d_{2} d_{3} \ldots d_{m}$ is the mantissa, $e$ is the exponent
- $e$ is negative, positive or zero
- the general normalized form requires $d_{1} \neq 0$


## floating point

## Example

In base 10

- 1000.12345 can be written as

$$
(0.100012345)_{10} \times 10^{4}
$$

- 0.000812345 can be written as

$$
(0.812345)_{10} \times 10^{-3}
$$

## floating point

Suppose we have only 3 bits for a mantissa and a 1 bit exponent stored like

| .$d_{1}$ | $d_{2}$ | $d_{3}$ | $e_{1}$ |
| :--- | :--- | :--- | :--- |

All possible combinations give:

$$
\begin{aligned}
000_{2} & =0 \\
\ldots & \\
111_{2} & =7
\end{aligned}
$$

So we get $0, \frac{1}{16}, \frac{2}{16}, \ldots, \frac{7}{16}, 0, \frac{1}{4}, \frac{2}{4}, \ldots, \frac{7}{4}$, and $0, \frac{1}{8}, \frac{2}{8}, \ldots, \frac{7}{8}$. On the real line:


## overflow, underflow



- computations too close to zero may result in underflow
- computations too large may result in overflow
- overflow error is considered more severe
- underflow can just fall back to 0


## normalizing

If we use the normalized form in our 4-bit case, we lose $0.001_{2} \times 2^{-1,0,1}$ along with other. So we cannot represent $\frac{1}{16}, \frac{1}{8}$, and $\frac{3}{16}$.


## ieee-754 why this is important:

- IEEE-754 is a widely used standard accepted by hardware/software makers
- defines the floating point distribution for our computation
- offer several rounding modes which effect accuracy
- Floating point arithmetic emerges in nearly every piece of code
- even modest mathematical operation yield loss of significant bits
- several pitfalls in common mathematical expressions


## ieee floating point (v. 754)

- How much storage do we actually use in practice?
- 32-bit word lengths are typical
- IEEE Single-precision floating-point numbers use 32 bits
- IEEE Double-precision floating-point numbers use 64 bits
- Goal: use the 32-bits to best represent the normalized floating point number



## ieee single precision (marc-32)

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



Notes:

- 1-bit sign
- 8-bit exponent $|m|$
- 23-bit mantissa $q$
- The leading one in the mantissa $q$ does not need to be represented:
$b_{1}=1$ is hidden bit
- IEEE 754: put $x$ in 1.f normalized form
- $0<m+127=c<255$
- Largest exponent $=127$, Smallest exponent $=-126$
- Special cases: $c=0,255$


## ieee single precision

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

Process for $x=-52.125$ :

1. Convert both integer and fractional to binary: $x=-(110100.00100000000)_{2}$
2. Convert to 1.f form: $x=\underbrace{-}_{1}(1 . \underbrace{101000010000 \ldots 0}_{23})_{2} \times 2^{5}$
3. Convert exponent $5=c-127 \Rightarrow c=132 \Rightarrow c=(\underbrace{10000100}_{8})_{2}$


## ieee single precision

Special Cases:

- denormalized/subnormal numbers: use 1 extra bit in the significant: exponent is now -126 (less precision, more range), indicated by $00000000_{2}$ in the exponent field
- two zeros: +0 and -0 ( 0 mantissa, 0 exponent)
- two $\infty$ 's: $+\infty$ and $-\infty$
- $\infty$ (0 mantissa, $11111111_{2}$ exponenet)
- NaN (any mantissa, $11111111_{2}$ exponent)
- see appendix C. 1 in NMC 6th ed.


## ieee double precision



- 1-bit sign
- 11-bit exponent
- 52-bit mantissa
- single-precision: about 6 decimal digits of precision
- double-precision: about 15 decimal digits of precision
- $m=c-1023$


## precision vs. range

| type | range | approx range |
| :--- | :---: | :---: |
| single | $-3.40 \times 10^{38} \leq x \leq-1.18 \times 10^{-38}$ |  |
|  | $1.18 \times 10^{-38} \leq x \leq 3.40 \times 10^{38}$ | $2^{-126} \rightarrow 2^{128}$ |
|  | $-1.80 \times 10^{318} \leq x \leq-2.23 \times 10^{-308}$ |  |
| double | 0 | $2^{-1022} \rightarrow 2^{1024}$ |
|  | $2.23 \times 10^{-308} \leq x \leq 1.80 \times 10^{308}$ |  |

small numbers example
plus one example

Take $x=1.0$ and add $1 / 2,1 / 4, \ldots, 2^{-i}$ :
Hidden bit

| $\leftarrow$ |  |  |  | 52 bits |  |  |  | $\rightarrow$ |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | e | e |
| 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | e | e |
| 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | e | e |


| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | e | e |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | e | e |

- Ooops!
- use $f(x)$ to represent the floating point machine number for the real number $x$
- $f\left(1+2^{-52}\right) \neq 1$, but $f\left(1+2^{-53}\right)=1$


## $\epsilon_{m}:$ machine epsilon

Machine epsilon $\epsilon_{m}$ is the smallest number such that

$$
f \prime\left(1+\epsilon_{m}\right) \neq 1
$$

- The double precision machine epsilon is about $2^{-52}$.
- The single precision machine epsilon is about $2^{-23}$.


## Floating Point Number Line



## floating point errors

- Not all reals can be exactly represented as a machine floating point number. Then what?
- Round-off error
- IEEE options:
- Round to next nearest FP (preferred), Round to 0, Round up, and Round down

Let $x_{+}$and $x_{-}$be the two floating point machine numbers closest to $x$

- round to nearest: $\operatorname{round}(x)=x_{-}$or $x_{+}$, whichever is closest
- round toward 0 : $\operatorname{round}(x)=x_{-}$or $x_{+}$, whichever is between 0 and $x$
- round toward $-\infty$ (down): round $(x)=x_{-}$
- round toward $+\infty$ (up): round $(x)=x_{+}$


## floating point errors

How big is this error? Suppose ( $x$ is closer to $x_{-}$)

$$
\begin{aligned}
x & =\left(0.1 b_{2} b_{3} \ldots b_{24} b_{25} b_{26}\right)_{2} \times 2^{m} \\
x_{-} & =\left(0.1 b_{2} b_{3} \ldots b_{24}\right)_{2} \times 2^{m} \\
x_{+} & =\left(\left(0.1 b_{2} b_{3} \ldots b_{24}\right)_{2}+2^{-24}\right) \times 2^{m} \\
\left|x-x_{-}\right| & \leq \frac{\left|x_{+}-x_{-}\right|}{2}=2^{m-25} \\
\left|\frac{x-x_{-}}{x}\right| & \leq \frac{2^{m-25}}{1 / 2 \times 2^{m}} \leq 2^{-24}=\epsilon_{m} / 2
\end{aligned}
$$

## floating point arithmetic

- Problem: The set of representable machine numbers is FINITE.
- So not all math operations are well defined!
- Basic algebra breaks down in floating point arithmetic


## Example

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



## floating point arithmetic

Rule 1.

$$
f l(x)=x(1+\epsilon), \quad \text { where } \quad|\epsilon| \leq \epsilon_{m}
$$

Rule 2.
For all operations $\odot($ one of $+,-, *, /)$

$$
f \prime(x \odot y)=(x \odot y)\left(1+\epsilon_{\odot}\right), \quad \text { where } \quad\left|\epsilon_{\odot}\right| \leq \epsilon_{m}
$$

Rule 3.
For + ,* operations

$$
f \prime(a \odot b)=f \prime(b \odot a)
$$

There were many discussions on what conditions/rules should be satisfied by floating point arithmetic. The IEEE standard is a set of standards adopted by many CPU manufacturers.

## floating point arithmetic

Consider the sum of 3 numbers: $y=a+b+c$.

Done as $f l(f l(a+b)+c)$

$$
\begin{aligned}
\eta & =f \prime(a+b)=(a+b)\left(1+\epsilon_{1}\right) \\
y_{1} & =f \prime(\eta+c)=(\eta+c)\left(1+\epsilon_{2}\right) \\
& =\left[(a+b)\left(1+\epsilon_{1}\right)+c\right]\left(1+\epsilon_{2}\right) \\
& \left.=\left[(a+b+c)+(a+b) \epsilon_{1}\right)\right]\left(1+\epsilon_{2}\right) \\
& =(a+b+c)\left[1+\frac{a+b}{a+b+c} \epsilon_{1}\left(1+\epsilon_{2}\right)+\epsilon_{2}\right]
\end{aligned}
$$

So disregarding the high order term $\epsilon_{1} \epsilon_{2}$

$$
f I(f I(a+b)+c)=(a+b+c)\left(1+\epsilon_{3}\right) \quad \text { with } \quad \epsilon_{3} \approx \frac{a+b}{a+b+c} \epsilon_{1}+\epsilon_{2}
$$

## floating point arithmetic

If we redid the computation as $y_{2}=f /(a+f l(b+c))$ we would find

$$
f \prime(a+f \prime(b+c))=(a+b+c)\left(1+\epsilon_{4}\right) \quad \text { with } \quad \epsilon_{4} \approx \frac{b+c}{a+b+c} \epsilon_{1}+\epsilon_{2}
$$

Main conclusion:

The first error is amplified by the factor $(a+b) / y$ in the first case and $(b+c) / y$ in the second case.

In order to sum $n$ numbers more accurately, it is better to start with the small numbers first. [However, sorting before adding is usually not worth the cost!]

## floating point arithmetic

One of the most serious problems in floating point arithmetic is that of cancellation. If two large and close-by numbers are subtracted the result (a small number) carries very few accurate digits (why?). This is fine if the result is not reused. If the result is part of another calculation, then there may be a serious problem

## Example

Roots of the equation

$$
x^{2}+2 p x-q=0
$$

Assume we want the root with smallest absolute value:

$$
y=-p+\sqrt{p^{2}+q}=\frac{q}{p+\sqrt{p^{2}+q}}
$$

## catastrophic cancellation

Adding $c=a+b$ will result in a large error if

- $a \gg b$
- $a \ll b$

Let

$$
\begin{aligned}
& a=x \cdot x x x \cdots \times 10^{0} \\
& b=y \cdot y y y \cdots \times 10^{-8}
\end{aligned}
$$



## catastrophic cancellation

Subtracting $c=a-b$ will result in large error if $a \approx b$. For example

$$
\begin{aligned}
& a=x \cdot x x x x x x x x x x x \times 1 \overbrace{\text { ssss } \ldots}^{\text {lost }} \\
& b=x \cdot x x x x \times x x x \times x \times 00 \overbrace{t t t t \ldots}^{\text {lost }}
\end{aligned}
$$



## summary

- addition: $c=a+b$ if $a \gg b$ or $a \ll b$
- subtraction: $c=a-b$ if $a \approx b$
- catastrophic: caused by a single operation, not by an accumulation of errors
- can often be fixed by mathematical rearrangement


## loss of significance

## Example

$x=0.3721448693$ and $y=0.3720214371$. What is the relative error in $x-y$ in a computer with 5 decimal digits of accuracy?

$$
\begin{aligned}
\frac{|x-y-(\bar{x}-\bar{y})|}{|x-y|} & =\frac{|0.3721448693-0.3720214371-0.37214+0.37202|}{|0.3721448693-0.3720214371|} \\
& \approx 3 \times 10^{-2}
\end{aligned}
$$

## loss of significance

## Loss of Precision Theorem

Let $x$ and $y$ be (normalized) floating point machine numbers with $x>$ $y>0$.

If $2^{-p} \leq 1-\frac{y}{x} \leq 2^{-q}$ for positive integers $p$ and $q$, the significant binary digits lost in calculating $x-y$ is between $q$ and $p$.

## loss of significance

## Example

Consider $x=37.593621$ and $y=37.584216$.

$$
2^{-11}<1-\frac{y}{x}=0.0002501754<2^{-12}
$$

So we lose 11 or 12 bits in the computation of $x-y$. yikes!

## Example

Back to the other example ( 5 digits): $x=0.37214$ and $y=0.37202$.

$$
10^{-4}<1-\frac{y}{x}=0.00032<10^{-5}
$$

So we lose 4 or 5 bits in the computation of $x-y$. Here, $x-y=0.00012$
which has only 1 significant digit that we can be sure about

## loss of significance

So what to do? Mainly rearrangement.

$$
f(x)=\sqrt{x^{2}+1}-1
$$

## loss of significance

So what to do? Mainly rearrangement.

$$
f(x)=\sqrt{x^{2}+1}-1
$$

Problem at $x \approx 0$.

## loss of significance

So what to do? Mainly rearrangement.

$$
f(x)=\sqrt{x^{2}+1}-1
$$

Problem at $x \approx 0$.
One type of fix:

$$
\begin{aligned}
f(x) & =\left(\sqrt{x^{2}+1}-1\right)\left(\frac{\sqrt{x^{2}+1}+1}{\sqrt{x^{2}+1}+1}\right) \\
& =\frac{x^{2}}{\sqrt{x^{2}+1}+1}
\end{aligned}
$$

no subtraction!

