## Floating Point Numbers

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## Fractional binary numbers

What is $1011.101_{2}$ ?

- we use the same idea that we use when interpreting the decimal numbers, except here we multiply by powers of 2 , not 10
- the above number is
$1^{*} 2^{3}+0 * 2^{2}+1^{*} 2^{1}+1^{*} 2^{0}+1^{*} 2^{-1}+0 * 2^{-2}+1^{*} 2^{-3}$
$=8+2+1+1 / 2+1 / 8=11.625$
Simple enough?

DNHI: Try to convert the following numbers to their binary representation $5 \frac{1}{16}, 27 / 8$, $153 / 4$. Now, try $\frac{1}{10}$ and and see how that goes.
Convert the following binary numbers to their decimal representations: 0.1101 101.010, 10.101

Fractions in Binary

## Not good enough

That way of representing floating point numbers is simple, but has many imitations.

- Only numbers that can be written as the sum of powers of 2 can be represented exactly, other numbers have repeating bit representation (this is the same problem as trying to represent $1 / 3$ in decimal as $0.3333333 \ldots$...).
- $1 / 3$ is 0.010101010101
- $1 / 8$ is 0.01100110011
$1 / 10$ is 0.001100110011
- Just one possible location for the binary point. This limits how many bits can be used for the fractional part and the whole number part. We can either represent very large numbers well or very small numbers well, but not both.

Up until 1985 floating point numbers were computer scientist nightmare because everybody was using different standards that dealt with the above problems

But do not forget that notation just yet - we will use it as part of the better notation.

## IEEE Floating Point

- Established 1985
- Provides uniform standard for floating point arithmetic used by most (if not all) of current CPUs
- Standards for rounding, overflow, underflow
- Concerns for numerical accuracy were more important than fast hardware implementation $\Rightarrow$ not very good hardware performance


## Floating Point Representation

- Numerical Form:

$$
(-1)^{\mathrm{s}} \mathrm{M} * 2^{\mathrm{E}}
$$

- Sign bit $\mathbf{s}$ determines whether number is negative or positive
- Significand M (mantissa) normally a fractional value in range $[1.0,2.0$ ).
- Exponent $\mathbf{E}$ weighs value by powers of two
- Encoding
- the most significant bit $\mathbf{s}$ is the sign bit $\mathbf{s}$
- $\quad \exp$ field encodes $E$ (but is not equal to $E$ )
- frac field encodes $\mathbf{M}$ (but is not equal to $M$



## Using Different Number of Bytes

Single precision: 32 bits


Double precision: 64 bits

| s | $\exp$ | frac |  |
| :--- | :--- | :--- | :--- |
| 1 | 11 -bits | 52 -bits |  |

Extended precision: 80 bits (Intel only)


## Interpreting Values of IEEE 754

## Normalized Values

- Condition: $\exp \neq 000 \ldots 0$ and $\exp \neq 111 \ldots 1$
- Exponent is: $\mathbf{E}=\exp -\overbrace{\left(2^{\mathbf{k}-1}-1\right)}, \mathrm{k}$ is the $\#$ of exponent bit Single precision: $2^{k-1}-1=127, \exp =1 \ldots 254 \Rightarrow E=-126 \ldots 127$
Double precision: $2^{k-1}-1=1023$, exp $=1 \ldots 2046 \Rightarrow E=-1022 \ldots 1023$
(once we know the number of bits in exp, we can figure out the bias)
- Significand has implied leading 1: $M=1 . x x x \ldots x_{2}$
- xxx...x - bits of frac
- Smallest value when all bits are zero: $000 \ldots 0, \mathrm{M}=1.0$
- Largest value when all bits are one: $111 \ldots 1, M=2.0-\varepsilon$
- By assuming the leading bit is 1 , we get "an extra bit for free"

$$
\begin{aligned}
& \text { value }=(-1)^{S} M * 2^{E} \\
& E=\exp -\left(2^{k-1}-1\right)
\end{aligned}
$$

Normalized Values - Example

- Value: floating point number $F=15213.0$ represented using single precision
$152131.0=11101101101101.0$
$=1.1101101101101_{2}{ }^{*} 2^{13}$ (same binary sequence)
Significand
$\mathrm{M}=1.1101101101101_{2}$
$\Rightarrow$ frac $=11011011011010000000000$
- Exponent

```
Bias = 127 (for single precision)
Exp}=14010=10001100 2
```

Result:
1000110011011011011010000000000 s exp frac

## Why is this encoding better?

- For single precision
- The value of exp is in the range $0<=\exp <=255$
$\circ \Rightarrow$ the value of E is in the range $-127<=\mathrm{E}<=128$
$\circ \quad \Rightarrow$ we can represent fairly large numbers when using $2^{128}$ and some fairly small numbers when using $2^{-127}$
- For double precision
- well, you get the point

But we always have the leading one in the value of significand/mantissa, so we cannot represent numbers that are reeeeeaaaaly small

- We need to talk about what happens when exp is all zeroes or all ones.


## Special Values Encoding

- Condition: $\exp =111$... 1

There are only two (well three cases here):

- Case 1, 2: exp $=111 \ldots 1$, frac $=000 \ldots 0$
- Represents value $\infty$ (infinity)
- Operations that overflow
- Both positive and negative
- Eg: 1.0/0.0 $=-1.0 /-0.0=+\infty,-1.0 / 0.0=1.0 /-0.0=-\infty$
- Case 3: $\exp =111 \ldots 1$, frac $\neq 000 \ldots 0$
- Not-a-Number (NaN)
- Represents case when no numeric value can be determined
- Eg: sqrt(-1), $\infty-\infty, \infty * 0$


## Denormalized Encoding

- Condition: $\exp =000 \ldots 0$ (all zeroes)
- Exponent value: $\mathbf{E = 1}$ - bias (instead of 0 - bias)
- Significand has implied leading 0 (not 1 ): $\mathbf{M}=\mathbf{0} . \mathbf{x x x} \ldots .$. x2 - xxx...x - bits of frac

Cases:

- $\exp =000 \ldots 0$, frac $=000 \ldots 0$ represents zero value Note that we have two distinct values for zero: +0 and -0 (Why?)
- $\exp =000 \ldots 0$, frac $\neq 000 \ldots 0$ represent numbers very close to zero (all denormalized encodings represent reeeeeaaaaly small numbers)


## Number Line (not to scale)




## 6-bit IEEE-like encoding

| $s$ | $\exp$ | frac |
| :---: | :---: | :---: |
| 1 | 3-bits | 2-bits |

- most significant bit is the sign bit
- 3-bit encoding for exp
- 2-bit encoding for frac 011100, 011101,
- denormalized values: $000000,000001,000010$,
smallest ne 100001, 100010, 10001
smallest negative: 100011
$M=0.11, E=1-$ bias $=-2$, val $=-0.11 * 2^{-2}=-0.1875$,
$\mathrm{M}=0.01, \mathrm{E}=1-$ bias $=-2$, val $=0.01 * 2^{-2}=0.0625$
- normalized values: all others
$\begin{aligned} & \text { Smallest positive: } 0 \text { oias }=-2, ~ v a l ~ \\ & M=1.00, ~ \\ & =1.0\end{aligned} 2^{-2}=0.25_{10}$
$M=1.00, E=1-$ bias $=-2$, val $=1.0 * 2^{-2}=0.25_{10}$
largest positive: 011011
$M=1.11, E=6-$ bias $=3$, val $=1.11 * 2^{3}=14.00_{10}$


 $\Delta \Delta \Delta t \Delta \Delta \Delta \Delta+\cdots \ldots \cdot \Delta \Delta \Delta \Delta A \Rightarrow \Delta \Delta \Delta$ | $-0.5 \quad 0$ |
| :--- |
| $\oplus$ Denormaized $\Delta$ Normalized $■$ Infinity |

All possible 6-bit sequences:

| 000000 | 010000 | 100000 | 110000 |
| :---: | :---: | :---: | :---: |
| 000001 | 010001 | 100001 | 110001 |
| 000010 | 010010 | 100010 | 110010 |
| 000011 | 010011 | 100011 | 110011 |
| 000100 | 010100 | 100100 | 110100 |
| 000101 | 010101 | 100101 | 110101 |
| 000110 | 010110 | 100110 | 110110 |
| 000111 | 010111 | 100111 | 110111 |
| 001000 | 011000 | 101000 | 111000 |
| 001001 | 011001 | 101001 | 111001 |
| 001010 | 011010 | 101010 | 111010 |
| 001011 | 011011 | 101011 | 111011 |
| 001100 | 011100 | 101100 | 111100 |
| 001101 | 011101 | 101101 | 111101 |
| 001110 | 011110 | 101110 | 111110 |
| 001111 | 011111 | 101111 | 111111 |

DNHI: Pick 10 different sequences from the table above and figure out freir values in decimal.

## Special properties of IEEE encoding

- FP Zero Same as Integer Zero: all bits $=0$
- Can (Almost) Use Unsigned Integer Comparison
- Must first compare sign bits
- Must consider $-0=0$
- NaNs problematic
- will be greater than any other values
- what should comparison yield?
- Otherwise proper ordering
- denorm vs. normalized
- normalized vs. infinity


## Arithmetic Operations with Rounding

- $x_{f} y=\operatorname{Round}(x+y)$
- $x^{*} y=\operatorname{Round}\left(x^{*} y\right)$
- Basic idea
- Compute exact result
- Make it fit into desired precision
- Possibly overflow if exponent too large
- Possibly round to fit into frac


## Different Rounding Modes

Rounding Modes (illustrate with \$ rounding)


## Rounding Binary Numbers

- Binary Fractional Numbers
- "Even" when least significant bit is 0
- "Half way" when bits to right of rounding position $=100 \ldots_{2}$
- All others are statistically biased
- Sum of a set of positive numbers will consistently be over- or under- estimated
- Applying to Other Decimal Places
- When exactly halfway between two possible values
- Round so that least significant digit is even
- E.g., round to nearest hundredth
- 7.89499997 .89 (Less than halfway - round down)
- 7.89500017 .90 (Greater than halfway - round up)
- 7.89500007 .90 (Halfway - round up)
- 7.8850000 7.88 (Half way - round down)


## Multiplication

- $(-1)^{\mathrm{s} 1} \mathrm{M} 1 \quad 2^{\mathrm{E} 1} \quad$ * $(-1)^{\mathrm{s} 2} \mathrm{M} 2 \quad 2^{\mathrm{E} 2}$
- Exact Result: $(-1)^{\mathrm{s}} \mathrm{M} \quad 2^{\mathrm{E}}$
- Sign s: s1 ^ s2 (this is xor, not exponentiation)
- Significand M: M1 * M2
- Exponent E: E1 + E2
- Fixing
- If $M \geq 2$, shift $M$ right, increment $E$
- If E out of range, overflow
- Round M to fit frac precision
- Implementation

Most expensive is multiplication of significands (but that is done just like for integers)

## Properties of Floating Point Addition

- Closed under addition?
- But may generate infinity or NaN
- Commutative? YES
- Associative? NO
- Overflow and inexactness of rounding:
$\left(3.14+1 e^{10}\right)-1 e^{10}=0, \quad 3.14+\left(1 e^{10}-1 e^{10}\right)=3.14$
- 0 is additive identity? YES
- Every element has additive inverse? ALMOST
- Yes, except for infinities \& NaNs
- Monotonicity

ALMOST

- $a \geq b \Rightarrow a+c \geq b+c$ ?
- Except for infinities \& NaNs


## Addition

- $(-1)^{\mathrm{s} 1} \mathrm{M} 12^{\mathrm{E} 1}+(-1)^{\mathrm{s} 2} \mathrm{M} 2 \quad 2^{\mathrm{E} 2}$
assume E1 > E2
- Exact Result: $(-1)^{\mathrm{S}}$ M $2^{\mathrm{E}}$
- Sign s , significand m :
- result of signed align \& add
- Exponent E: E1

- Fixing

If $M \geq 2$, shift $M$ right, increment $E$

- if $M<1$, shift $M$ left $k$ positions, decrement $E$ by k
- Overflow if E out of range
- Round M to fit frac precision


## Properties of Floating Point Multiplication

- Closed under multiplication?

YES

- But may generate infinity or NaN
- Multiplication Commutative?YES
- Multiplication is Associative? NO
- Possibility of overflow, inexactness of rounding Ex: $\left(1 \mathrm{e}^{20 *} 1 \mathrm{e}^{20}\right) * 1 \mathrm{e}^{-20}=\inf , 1 \mathrm{e}^{20 *}\left(1 \mathrm{e}^{20 *} 1 \mathrm{e}^{-20}\right)=1 \mathrm{e}^{20}$
- 1 is multiplicative identity?
- Multiplication distributes over addition?
- Possibility of overflow, inexactness of rounding $1 \mathrm{e}^{20 *}\left(1 \mathrm{e}^{20}-1 \mathrm{e}^{20}\right)=0.0,1 \mathrm{e}^{20 *} 1 \mathrm{e}^{20}-1 \mathrm{e}^{20 *} 1 \mathrm{e}^{20}=\mathrm{NaN}$
- Monotonicity
- $a \geq b \& c \geq 0 \Rightarrow a * c \geq b * c$ ?
- Except for infinities \& NaNs

Floating Point in C

## C Language

- C Guarantees Two Levels
- float single precision
- double double precision
- Conversions/Casting
- casting between int, float, and double changes bit representation double/float $\rightarrow$ int
- Truncates fractional part
- Like rounding toward zero
- Not defined when out of range or NaN: Generally sets to TMin
nt $\rightarrow$ double
- Exact conversion, as long as int has $\leq 53$ bit word size
int $\rightarrow$ float
- Will round according to rounding mode


## Puzzles (DNHI)

For each of the following $C$ expressions, either:

- Argue that it is true for all possible argument values
- Explain why if not true
- $x==$ (int) (float) $x$

Assume:

- $x==$ (int) (double) $x$
- int $x=$...; $\quad f==$ (float) (double) $f$ float $f=$...; $d==$ (double) (float) $d$ double $\mathbf{d}=$...
- $\mathrm{f}==-(-\mathrm{f})$;
- neither $d$ nor $f$ is NaN
- $2 / 3==2 / 3.0$
- $\mathrm{d}<0.0 \quad \Rightarrow \quad((d \star 2)<0.0)$
- $d>f \quad \Rightarrow \quad-f>-d$
- d * d >= 0.0
- $(d+f)-d==f$

