## CMSC216: Binary Floating Point Numbers

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## Logistics

### Reading Bryant/O'Hallaron

- ▶ Ch 2.1-3: Integers
- ▶ Ch 2.4-5: Floats (Optional)
- ▶ 2021 Quick Guide to GDB

#### Goals

- ▶ Finish Ints / Bitwise Ops
- ▶ Briefily: Floating Point layout
- ▶ Thu: Assembly

#### Assignments

- ▶ Lab05: Bits and GDB
- ▶ HW05: Assembly Intro
- ▶ Project 2: Bitwise Ops, GDB, C Application
- P2 will go up within the next day

Grading on Exam 1 / Project 1 ongoing, release grades towards end of week

### Announcements

### Midterm Feedback Survey

- ▶ Available on Canvas; Anonymous Feedback
- ▶ Worth 1 Full Engagement Point (like labs)
- ▶ Due 11:59pm Wed 02-Oct

#### Exam 1 Makeup

- ▶ Prof K has emailed all students with permission to make up exam 1 about scheduling
- ▶ If you expected to take the makeup exam and have not heard from Prof K **email him ASAP**

## Don't Give Up, Stay Determined!



- $\blacktriangleright$  If Project 1 / Exam 1 went awesome, count yourself lucky
- ▶ If things did not go well, Don't Give Up
- $\triangleright$  Spend some time contemplating why things didn't go well, talk to course staff about it, learn from any mistakes
- ▶ There is a LOT of semester left and plenty of time to recover from a bad start

## Note on Float Coverage

- $\blacktriangleright$  Floating point layout is complex and interesting but...
- ▶ It's not a core topic that will appear on any exams, only tangentially on assignments
- $\triangleright$  Our coverage will be brief, examine slides / textbook if you want more depth
- ▶ GOAL: Demonstrate that (1) Real numbers can be approximated and (2) doing so uses bits in a very different way than integer representations

## Parts of a Fractional Number

The meaning of the "decimal point" is as follows:

$$
123.406_{10} = 1 \times 10^{2} + 2 \times 10^{1} + 3 \times 10^{0} + 123 = 100 + 20 + 3
$$
  

$$
4 \times 10^{-1} + 0 \times 10^{-2} + 6 \times 10^{-3} \quad 0.406 = \frac{4}{10} + \frac{6}{1000}
$$
  
= 123.406<sub>10</sub>

Changing to base 2 induces a "binary point" with similar meaning:

$$
110.1012 = 1 \times 22 + 1 \times 21 + 0 \times 20 + 6 = 4 + 2
$$
  

$$
1 \times 2-1 + 0 \times 2-2 + 1 \times 2-3 0.625 = \frac{1}{2} + \frac{1}{8}
$$
  
= 6.625<sub>10</sub>

One could represent fractional numbers with a **fixed point** e.g.

- $\triangleright$  32 bit fractional number with
- ▶ 10 bits left of Binary Point (integer part)
- ▶ 22 bits right of Binary Point (fractional part)

**BUT** most applications require a more flexible scheme

## Scientific Notation for Numbers

"Scientific" or "Engineering" notation for numbers with a fractional part is



- ▶ **Always** includes one **non-zero** digit left of decimal place
- ▶ Has some **significant** digits after the decimal place
- ▶ Multiplies by a **power of 10** to get actual number

Binary Floating Point Layout Uses Scientific Convention

- $\triangleright$  Some bits for integer/fractional part
- ▶ Some bits for exponent part
- $\blacktriangleright$  All in base 2: 1's and 0's, powers of 2

## Conversion Example

Below steps convert a decimal number to a fractional binary number equivalent then adjusts to scientific representation. float  $f1 = -248.75$ :

 $7 \quad 6 \quad 5 \quad 4 \quad 3 \quad 2 \quad 1 \quad 0 \quad -1 \quad -2$  $-248.75 = -(128+64+32+16+8+0+0+0)$ .  $(1/2+1/4)$  $= -11111000.11 *2^0$ 76543210 12  $= -1111100.011 *2^1$ 6543210 123  $= -111110.0011 *2^2$ 543210 1234 ... MANTISSA EXPONENT  $= -1.111100011 * 2^2$ 0 123456789 Mantissa *≡* Significand *≡* Fractional Part

## Principle and Practice of Binary Floating Point Numbers

- ▶ In early computing, computer manufacturers used similar principles for floating point numbers but varied specifics
- ▶ Example of Early float data/hardware
	- $\blacktriangleright$  Univac: 36 bits, 1-bit sign, 8-bit exponent, 27-bit significand<sup>1</sup>
	- $\blacktriangleright$  IBM: 32 bits, 1-bit sign, 7-bit exponent, 24-bit significand<sup>2</sup>
- ▶ Manufacturers implemented circuits with different rounding behavior, with/without infinity, and other inconsistencies
- ▶ Troublesome for reliability: code produced different results on different machines
- ▶ This was resolved with the adoption of the IEEE 754 Floating Point Standard which specifies
	- ▶ Bit layout of 32-bit float and 64-bit double
	- $\blacktriangleright$  Rounding behavior, special values like Infinity
- ▶ Turing Award to William Kahan for his work on the standard

 $\alpha$ 

## IEEE 754 Format: The Standard for Floating Point



- ▶ Most commonly implemented format for floating point numbers in hardware to do arithmetic: processor has physical circuits to add/mult/etc. for this bit layout of floats
- ▶ Numbers/Bit Patterns divided into three categories



## Example float Layout of -248.75: float\_examples.c



not in binary layout

## Normalized Floating Point: General Case

- ▶ A "normalized" floating point number is in the standard range for float/double, bit layout follows previous slide
- Example:  $-248.75 = -1.111100011 * 2^77$

### Exponent is in **Bias Form** (not Two's Complement)

- ▶ Unsigned positive integer minus constant **bias number**
- ▶ **Consequence**: exponent of 0 is not bitstring of 0's
- ▶ **Consequence**: tiny exponents like -125 close to bitstring of 0's; this makes resulting number close to 0
- $\triangleright$  8-bit exponent 1000 0110 = 128+4+2 = 134 so exponent value is  $134 - 127 = 7$

#### Integer and Mantissa Parts

- ▶ The leading 1 before the binary point is **implied** so does not show up in the bit string
- $\blacktriangleright$  Remaining fractional/mantissa portion shows up in the low-order bits 12

## Fixed Bit Standards for Floating Point

### IEEE Standard Layouts



Standard allows hardware to be created that is as efficient as possible to do calculation on these numbers

### Consequences of Fixed Bits

- ▶ Since a fixed # of bit is used, **some numbers cannot be exactly represented**, happens in any numbering system:
- $\blacktriangleright$  Base 10 and Base 2 cannot represent  $\frac{1}{3}$  in finite digits

► Base 2 cannot represent 
$$
\frac{1}{10}
$$
 in finite digits  
float f = 0.1;  
printf("0.1 = %.20e\n", f);  
0.1 = 1.00000001490116119385e-01  
Try show float.c to see this in action

## Exercise: Quick Checks

- 1. What distinct parts are represented by bits in a floating point number (according to IEEE)
- 2. What is the "bias" of the exponent for 32-bit floats
- 3. Represent 7.125 in binary using "binary point" notation
- 4. Lay out 7.125 in IEEE-754 format
- 5. What does the number 1.0 look like as a float?



Source: IEEE-754 Tutorial, www.puntoflotante.net

The diagram above may help in recalling IEEE 754 layout

## Special Cases: See float examples.c

### Special Values

- ▶ Infinity: exponent bits all 1, fraction all 0, sign bit indicates +*∞* or *−∞*
- $\blacktriangleright$  Infinity results from overflow/underflow or certain ops like float  $x = 1.0 / 0.0$ ;
- ▶ #include <math.h> gets macro INFINITY and -INFINITY
- ▶ **NaN**: not a number, exponent bits all 1, fraction has some 1s
- ▶ Errors in floating point like 0.0 / 0.0

### Denormalized values: Exponent bits all 0

- $\triangleright$  Fractional/Mantissa portion evaluates without implied leading one, still an unsigned integer though
- **Exponent is**  $Bias + 1$ :  $2^{-126}$  for float
- ▶ Result: very small numbers close to zero, smaller than any other representation, degrade uniformly to 0
- $\triangleright$  Zero: bit string of all 0s, optional leading 1 (*negative zero*);

### Other Float Notes







#### Approximations and Roundings

- ▶ Approximate  $\frac{2}{3}$  with 4 digits, usually 0.6667 with standard rounding in base 10
- ▶ Similarly, some numbers cannot be exactly represented with fixed number of bits:  $\frac{1}{10}$  approximated
- $\blacktriangleright$  IEEE 754 specifies various rounding modes to approximate numbers

#### Clever Engineering

- ▶ IEEE 754 allows floating point numbers to sort using signed integer sorting routines
- ▶ Bit patterns for float follows are ordered nearly the same as bit patterns for signed int
- ▶ Integer comparisons are usually fewer clock cycles than floating comparisons

## Sidebar: The Weird and Wonderful Union

- ▶ Bitwise operations like & are not valid for float/double
- ▶ Can use pointers/casting to get around this OR. . .
- ▶ Use a **union**: somewhat unique construct to C
- ▶ Defined like a struct with several fields
- ▶ BUT fields occupy the same memory location (!?!)
- ▶ Allows one to treat a byte position as multiple different types, ex: int / float / char[]
- $\blacktriangleright$  Memory size of the union is the **max** of its fields

```
// union.c
typedef union { // shared memory
  float fl; // float 4 bytes
  int in; // int 4 bytes
char ch[4]; \frac{1}{4} array 4 bytes<br>} flint t; \frac{1}{4} bytes total
                \frac{1}{4} bytes total (?!)// all fields are in the same memory
// so max of (4,4,4) rather than sum
int main(){
  flint t flint:
  flint.in = 0xC378C000:
  printf("%.4f\n", flint.fl);
  printf("%08x %d\n",flint.in,flint.in);
  for(int i=0; i<4; i++){
    unsigned char c = flint.ch[i];
    printf("%d: %02x '%c'\n",i,c,c);
  }
}
 Symbol | Mem | Val
|-------------------+-------+------|
 | flint.ch[3] | #1027 | 0xC3 |
 | flint.ch[2] | #1026 | 0x78 |
 | flint.ch[1] | #1025 | 0xC0 |
 | flint.in/fl/ch[0] | #1024 | 0x00 |
 \frac{1}{1} \frac{1}{1020} \frac{1}{2}
```
## Floating Point Operation Efficiencies

- ▶ Floating Point Operations per Second, **FLOPS** is a major measure for numerical code/hardware efficiency
- ▶ Often used to benchmark and evaluate scientific computer resources, (e.g. top super computers in the world)
- ▶ Tricky to evaluate because of
	- ▶ A single FLOP (add/sub/mul/div) may take 3 clock cycles to finish: **latency 3**
	- ▶ Another FLOP **can start** before the first one finishes: **pipelined**
	- ▶ Enough FLOPs lined up can get **average 1 FLOP per cycle**
	- ▶ FP Instructions may automatically operate on multiple FPs stored in memory to feed pipeline: **vectorized ops**
	- ▶ Generally referred to as **superscalar**
	- ▶ Processors schedule things **out of order** too
- ▶ All of this makes micro-evaluation error-prone and pointless
- ▶ Run a real application like an N-body simulation and compute

 $FLOPS = \frac{number of floating ops done}{m}$ 

time taken in seconds



https://www.top500.org/lists/top500/2022/06/

\*: An average US Home uses 909 kWh of power per month



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