

# Lecture 04

# Floating Point

CS213 – Intro to Computer Systems  
Branden Ghen a – Winter 2022


Slides adapted from:

St-Amour, Hardavellas, Bustamente (Northwestern), Bryant, O'Hallaron (CMU), Garcia, Weaver (UC Berkeley)

# Regarding in-person classes returning

- As currently scheduled, we'll be back in person on Tuesday
  - Tech, Ryan Auditorium
- Rationale from the University is that classrooms are safe due to:
  - Vaccination mandate
  - Mask mandate
  - Testing strategy
- CS213 is going to roll with whatever we've got to do
  - We'll do our best to make sure you have an environment for learning
  - Definitely need buy-in from you all too
    - Wear masks, Don't come in when you're sick, Support your classmates

# Administrivia

- Homework 1 due today! (11:59 pm Central)
  - Submit on Gradescope
  - About half of the class has submitted so far 
- Data Lab due next week Thursday
- Homework 2 and Bomb Lab next week Thursday

# Today's Goals

- Explore representing real (decimal) numbers with binary
- Understand IEEE754 encoding
- Discuss encoding impacts on floating-point arithmetic

# Outline

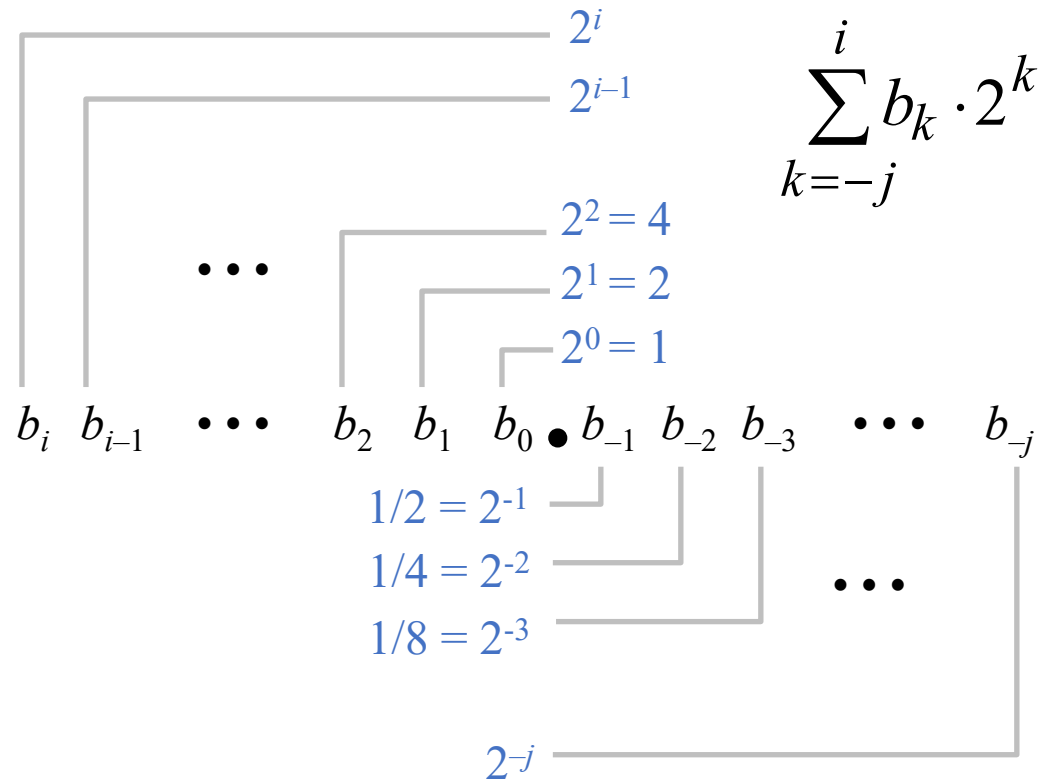
- **Fractional Binary Numbers**
- Representing Floating Point
- Smaller Floating Point
- Floating Point Arithmetic

# Floating point numbers

- In decimal:
  - $123450_{10}$
  - $123.450_{10}$
  - $1.23450_{10}$
- We can use this same system in binary as well:
  - $1010110_2$  ( $86_{10}$ )
  - $1010.110_2$  ( $10.75_{10} = \frac{86}{2^3}$ )
  - $1.010110_2$  ( $1.34375_{10} = \frac{86}{2^6}$ )

# Fractional Binary Numbers

- Representation
  - Bits to right of "binary point" represent fractional powers of 2
  - Represents rational number:



# Fractional Binary Number Examples

- $5 + 3/4 = 0b101.\boxed{11}$  Note:  
This is the number 3!
- $2 + 7/8 = 0b10.\boxed{111}$  This is the number 7!
- $63/64 = 0b0.\boxed{1111111}$  This is the number 63!



# Real numbers are possible in binary

- Some problems remain:

1. Computers are finite, but real numbers are not

- Need to choose how many bits to use
- Many decimal numbers would take infinite binary bits to represent perfectly
  - $3.14_{10} = 11.0010001111010111_2$  (we could keep going)

2. We also need to represent where the “binary point” is located

- We'll use some of our bits to do so

3. Should do signed numbers while we're at it

# Outline

- Fractional Binary Numbers
- **Representing Floating Point**
- Smaller Floating Point
- Floating Point Arithmetic

# IEEE Floating Point

- Floating point representations
  - Encodes rational numbers of the form  $V = m \times 2^e$
  - Base 2 scientific notation!
- IEEE Standard 754 (IEEE floating point)
  - Established in 1985 as uniform standard for floating point arithmetic
    - Before that, many idiosyncratic formats
  - Headed by William Kahan, CS prof. at UC Berkeley (later won Turing Award)
  - Supported by all major CPUs
- Driven by numerical concerns and numerical analysts
  - Nice standards for rounding, overflow, underflow
  - Had to be implementable in fast hardware as well and support many languages

# Floating Point Representation

- Numerical form

- $V = (-1)^S * M * 2^E$ 
    - Sign bit  $S$
    - Significand (Mantissa)  $M$
    - Exponent  $E$

- Sign bit **S** determines whether number is negative or positive
  - Significand **M** normally a fractional value in range [1.0,2.0) or [0.0,1.0)
    - Called ***mantissa*** or ***significand***
  - Exponent **E** weights value by power of two

- Encoding

- MSb is sign bit (can still look at most-significant bit alone to determine sign!)
  - **exp** field encodes  $E$ ,  $k$ -bits (note: "encodes  $E$ "  $\neq$  "is  $E$ ")
  - **frac** field encodes  $M$ ,  $n$ -bits



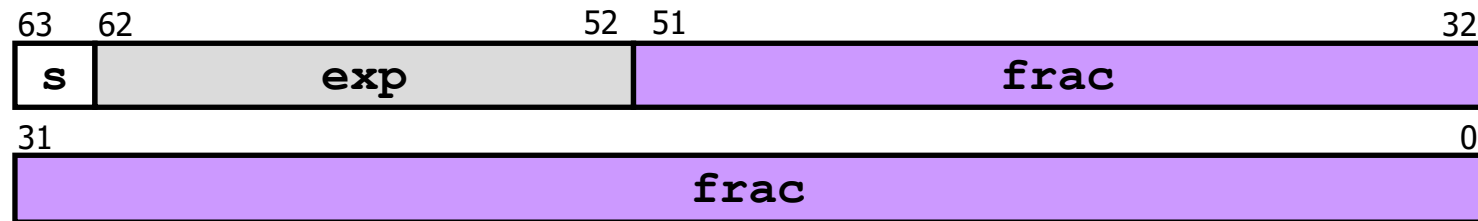
# Floating Point Precision

- Sizes

- Single precision:  $k = 8$  exp bits,  $n = 23$  frac bits (32b total). `float` in C



- Double precision:  $k = 11$  exp bits,  $n = 52$  frac bits (64b total). `double` in C



# Categories for Encoded Values

- Value encoded – three cases, depending on value of **exp**
  1. Normalized, the most common



2. Denormalized (very small values)



3. Special values – infinity and NaN



# Categories for Encoded Values

- Value encoded – three cases, depending on value of **exp**

## 1. Normalized, the most common



## 2. Denormalized



## 3. Special values – infinity and NaN



# Normalized Numeric Values

$$V = (-1)^s * M * 2^E$$

- Condition: not a special exponent (all zeros or ones)
- Significand coded with implied leading 1
  - $M = 1.xxx...x_2$  ( $1+f$  where  $f = 0.xxx_2$ )
    - $xxx...x$ : bits of **frac**
- Exponent coded as biased value
  - $E = \text{Exp} - \text{Bias}$ 
    - **Exp** : unsigned value denoted by **exp**
    - **Bias** : Bias value =  $2^{k-1} - 1$ ,  $k$  is number of exponent bits
      - Single precision (8-bit exp): 127 (Exp: 1...254, E: -126...127)
      - Double precision (11-bit exp): 1023 (Exp: 1...2046, E: -1022...1023)





# Decoding example for normalized floating point (32-bit)

- $0x41900000 = 0b01000001100100000000000000000000$ 
  - Group bits **s**: 0 **exp**: 10000011 **frac**: 001000000000000000000000
  - **exp** is not all zeros or all ones => not a special case
- $M = 1.001000000000000000000000 = 1.001$
- $E = \mathbf{exp} - \mathbf{bias} = 131 - 127 = 4$ 
  - $\mathbf{bias} = 2^{k-1} - 1, k=8 \rightarrow 2^7 - 1 = 127$
- $\mathbf{Result} = (-1)^0 * 1.001_2 * 2^4 = 10.01_2 * 2^3 = 10010.2 = 18$

$V = (-1)^s * M * 2^E$	<b>s</b>	<b>exp</b>	<b>frac</b>
------------------------	----------	------------	-------------

# Normalized Encoding Example

- **Value**

- `float F = 15213.0; // single precision: 8 exp bits, 23 frac bits`
- $15213_{10} = 11101101101101_2 = 1.1101101101101_2 \times 2^{13}$

- **Significand**

- $M = 1.\underline{1101101101101}_2$
- $\text{frac} = \underline{1101101101101}0000000000$  pad with 0s *on the right*. (example: 1.5 = 1.500)

- **Exponent**

- $E = 13$
- Bias = 127
- $\text{exp} = E + \text{Bias} = 140 = 10001100_2$

More examples in the  
bonus slides after the end

Floating Point Representation:

Hex:	4	6	6	D	B	4	0	0
Binary:	0100	0110	0110	1101	1011	0100	0000	0000
exp:	100	0110	0					
frac:				110	1101	1011	0100	0000 0000

# Normalized Numbers: Why These Choices?

- Significand coded with **implied leading 1**
  - Any non-zero integer will start with a 1 bit somewhere
  - Leading 1 carries no information, so don't need to store it!
  - Can express mantissas between:
    - 1.0 when frac is all 0s
    - 2.0 (nearly) when frac is all 1s
      - Want smaller? Use a smaller exponent!
- Exponent coded as biased value
  - $E = Exp - Bias$
  - Alternative to using two's complement to represent signed integers
  - Reasons are a bit tricky
    - Floating point binary values increase in the same order as unsigned = share comparisons!
    - Bias provides a more useful range (when considering denormalized)

# Question + Break

- $0x3f800000 = 0b00111111100000000000000000000000$ 
  - Group bits **s**: 0 **exp**: 01111111 **frac**: 0000000000000000000000000000
  - **exp** is not 0...0 or 1...1 => not a special case
- $M =$
- $E = \mathbf{exp} - \mathbf{bias} =$ 
  - $\mathbf{bias} = 2^{k-1} - 1, k=8 \rightarrow 2^7 - 1 = 127$



# Question + Break

- $0x3f800000 = 0b00111111100000000000000000000000$ 
  - Group bits **s**: 0 **exp**: 01111111 **frac**: 0000000000000000000000000000
  - **exp** is not 0...0 or 1...1 => not a special case
- $M = 1.0000000000000000000000000000 = 1.0$
- $E = \mathbf{exp} - \mathbf{bias} = 127 - 127 = 0$ 
  - $\mathbf{bias} = 2^{k-1} - 1, k=8 \rightarrow 2^7 - 1 = 127$
- $\mathbf{Result} = (-1)^0 * 1.0_2 * 2^0 = 1$



# Live Practice

- $0xF2190000 = 0b1\ 11100100\ 001100100000000000000000$ 
  - $S = 1$  (negative number)
  - $M = \mathbf{1}.001100100000000000000000 = 1.0011001$
  - $\text{Exp} = 11100100 = 128+64+32+4 = 228$ 
    - $\text{Bias} = 2^{k-1}-1 = 128-1 = 127$
    - $E = \text{Exp} - \text{Bias} = 228 - 127 = 101$
- $\text{Value} = (-1)^1 * 1.0011001_2 * 2^{101} = -(1 + 1/8 + 1/16 + 1/128) * 2^{101}$

$$V = (-1)^S * M * 2^E$$

# Categories for Encoded Values

- Value encoded – three cases, depending on value of **exp**
  1. Normalized, the most common



## 2. Denormalized

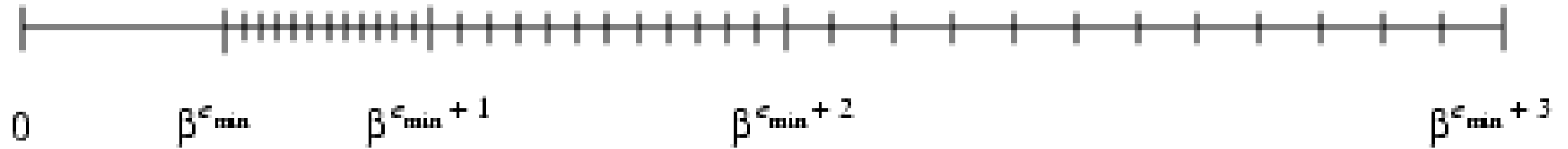


## 3. Special values – infinity and NaN

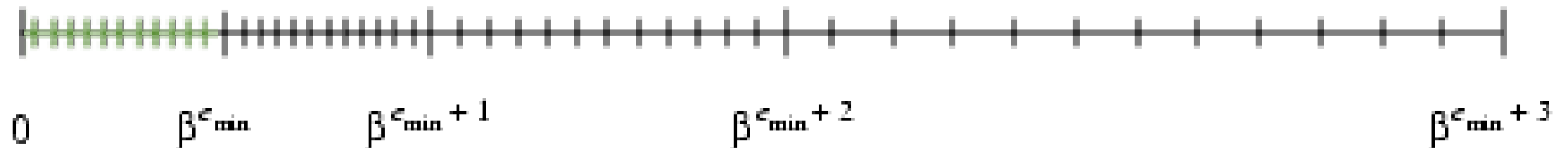


# Normalized floating point leaves a gap around zero

- Gap is the size of  $1.0000 * 2^{\text{Min Exponent}}$  (due to leading 1 bit)



- Solution: fill in numbers between 0 and  $1 * 2^{\text{Min Exponent}}$ 
  - Using same spacing as the previous range, in the form **0**.XXXXX



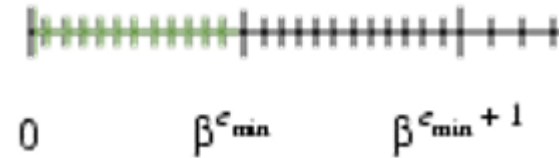


# Denormalized Values

$$V = (-1)^s * M * 2^E$$

- Purpose: gracefully represent numbers approaching  $\pm 0$

- Condition:  $\text{exp} = 000\dots 0_2$



- Value

- Exponent value  $E = \mathbf{1 - Bias}$

- Note: not simply  $E = 0 - \text{Bias}$  as it would be if we followed the previous rules
- This means we're re-using the spacing from smallest normalized numbers

- Significand value  $M = \mathbf{0.xxx\dots x}_2$  ( $0.f$ )

- xxx...x: bits of frac. Leading 0 instead of leading 1

- Cases

- $\text{exp} = 000\dots 0$ ,  $\text{frac} = 000\dots 0 \Rightarrow$  Represents value 0

- Note that we have distinct values +0 and -0

- $\text{exp} = 000\dots 0$ ,  $\text{frac} \neq 000\dots 0 \Rightarrow$  Numbers very close to 0.0

# Categories for Encoded Values

- Value encoded – three cases, depending on value of **exp**
  1. Normalized, the most common



2. Denormalized



## 3. Special values – infinity and NaN



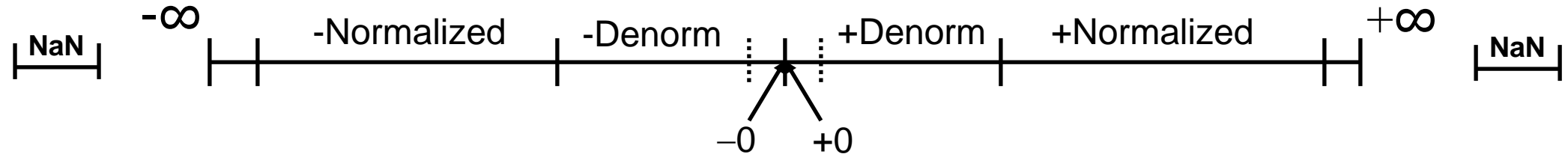
# Special Values

- Purpose: represent quantities that  $(-1)^s * M * 2^E$  cannot
- Condition:  $\text{exp} = 111\dots 1_2$
- Cases
  - $\text{exp} = 111\dots 1_2, \text{frac} = 000\dots 0_2$ 
    - Represents value  $\infty$  (infinity)
    - Both positive and negative infinity (sign bit to tell apart)
    - Operation that overflows: nicer mathematical behavior than modulo!
    - E.g.,  $1.0/0.0 = -1.0/-0.0 = +\infty, -1.0/0.0 = -\infty$
  - $\text{exp} = 111\dots 1_2, \text{frac} \neq 000\dots 0_2$ 
    - Not-a-Number (NaN)
    - Represents case when no numeric value can be determined
      - Fraction could be used to distinguish sources (rarely used in practice)
    - E.g.,  $\sqrt{-1}, \infty - \infty, \infty * 0$

# Floating Point in C

- C guarantees two levels
  - `float` single precision
  - `double` double precision
- Conversions
  - `int` → `float`
    - maybe rounded
    - less bits for actual value (32 → 23)
  - `int` or `float` → `double`
    - exact value preserved
    - double has greater range and higher precision (52 bits for `frac`)
  - `double` → `float`
    - may overflow, underflow (too small to represent), or be rounded (IEEE 754)
    - C99 standard says **undefined** if value out of range
  - `double` or `float` → `int`
    - rounded toward zero (-1.999 → -1)
    - C99 standard says **undefined** if value out of range

# Break + Summary of FP Real Number Encodings



$$V = (-1)^s * M * 2^E$$

	Normalized	Denormalized
s	0/1 means +/-	0/1 means +/-
exp	exp $\neq$ 000...0 <sub>2</sub> and exp $\neq$ 111...1 <sub>2</sub>	exp = 000...0 <sub>2</sub>
frac	x <sub>1</sub> x <sub>2</sub> x <sub>3</sub> ...x <sub>j</sub>	x <sub>1</sub> x <sub>2</sub> x <sub>3</sub> ...x <sub>j</sub>
Bias=	2 <sup>(k-1)</sup> - 1, for k exponent bits	2 <sup>(k-1)</sup> - 1, for k exponent bits
E=	exp - Bias	1 - Bias
M=	1. x <sub>1</sub> x <sub>2</sub> x <sub>3</sub> ...x <sub>j</sub> a.k.a. 1.frac	0. x <sub>1</sub> x <sub>2</sub> x <sub>3</sub> ...x <sub>j</sub> a.k.a. 0.frac
V=	(-1) <sup>s</sup> × (1.frac) × 2 <sup>(exp - Bias)</sup>	(-1) <sup>s</sup> × (0.frac) × 2 <sup>(1 - Bias)</sup>

# Outline

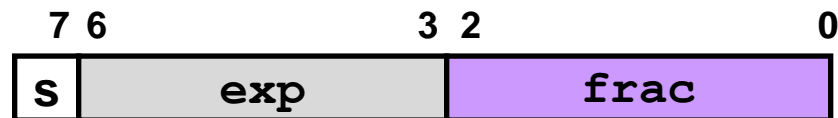
- Fractional Binary Numbers
- Representing Floating Point
- **Smaller Floating Point**
- Floating Point Arithmetic

# Floating point examples

- We'll often do floating point in custom bit widths
  - Rather than 32-bit (float) or 64-bit (double)
- Reasons
  1. They are just too many bits to write out and think about
  2. Make sure you understand the concepts of floating point
    - Smaller versions still demonstrate concepts! (e.g., 8-bit)

# Example: Tiny Floating Point

- 8-bit Floating Point Representation
  - Sign bit is in the most significant bit.
  - Next four (k) bits are exp, with a bias of 7 ( $2^{k-1}-1$ )
  - Last three (n) bits are frac
- Same general form as IEEE 754 format
  - normalized, denormalized numbers
  - representation of 0, NaN, infinity



Sidebar: increasingly useful for Machine Learning use!

- Models often don't need 32-bits of precision



# Exponents for 8-bit tiny floats

$$\text{Bias} = 2^{4-1} - 1 = 7$$

(4-bit exp)

	exp	exp	E	$2^E$	
Denormalized $E = 1 - \text{Bias}$	0	0000	-6	1/64	(denorms)
	1	0001	-6	1/64	
	2	0010	-5	1/32	
	3	0011	-4	1/16	
	4	0100	-3	1/8	
	5	0101	-2	1/4	
	6	0110	-1	1/2	
Normalized $E = \text{exp} - \text{Bias}$	7	0111	0	1	
	8	1000	+1	2	
	9	1001	+2	4	
	10	1010	+3	8	
	11	1011	+4	16	
	12	1100	+5	32	
	13	1101	+6	64	
	14	1110	+7	128	
Special	15	1111	n/a		(inf, NaN)

# Dynamic Range of 8-bit tiny float

```
0 0000 000
0 0000 001
0 0000 010
...
0 0000 110
0 0000 111
0 0001 000
0 0001 001
...
0 0110 110
0 0110 111
0 0111 000
0 0111 001
0 0111 010
...
0 1110 110
0 1110 111
0 1111 000
0 1111 001
...
0 1111 111
```

# Dynamic Range of 8-bit tiny float

<b>s</b>	<b>exp</b>	<b>frac</b>
0	0000	000
0	0000	001
0	0000	010
...		
0	0000	110
0	0000	111
0	0001	000
0	0001	001
...		
0	0110	110
0	0110	111
0	0111	000
0	0111	001
0	0111	010
...		
0	1110	110
0	1110	111
0	1111	000
0	1111	001
...		
0	1111	111

# Dynamic Range of 8-bit tiny float

Bias = 7

	<b>s</b>	<b>exp</b>	<b>frac</b>
$V = (-1)^s$	0	0000	000
$\times (0.\text{frac})$	0	0000	001
$\times 2^{(1 - \text{Bias})}$	0	0000	010
<b>Denormalized numbers</b>	...	0 0000	110
		0 0000	111
.....			
<b>Normalized numbers</b>	0	0001	000
	0	0001	001
	...	0 0110	110
$V = (-1)^s$	0	0110	111
$\times (1.\text{frac})$	0	0111	000
$\times 2^{(\text{exp} - \text{Bias})}$	0	0111	001
	0	0111	010
	...	0 1110	110
	0	1110	111
.....			
<b>Special values</b>	0	1111	000
	0	1111	001
	...	0 1111	111

# Dynamic Range of 8-bit tiny float

Bias = 7

$$V = (-1)^s$$

$$\times (0.\text{frac})$$

$$\times 2^{(1 - \text{Bias})}$$

**Denormalized numbers**

**Normalized numbers**

$$V = (-1)^s$$

$$\times (1.\text{frac})$$

$$\times 2^{(\text{exp} - \text{Bias})}$$

**Special values**

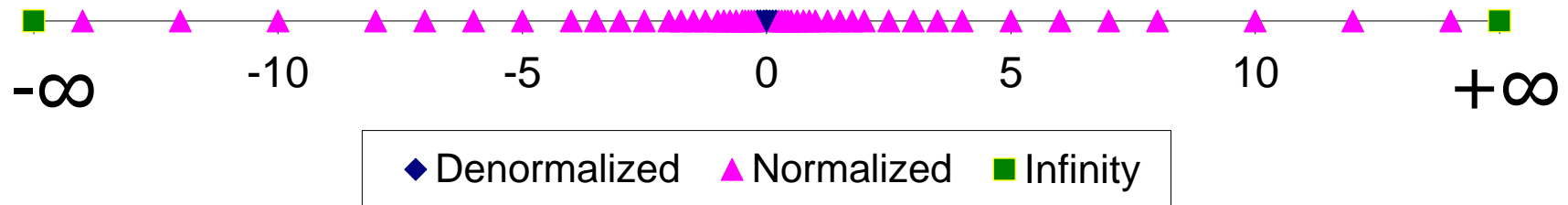
	s	exp	frac	E	Value
	0	0000	000	-6	0
	0	0000	001	-6	$1/8 * 1/64 (2^{-6}) = 1/512$
	0	0000	010	-6	$2/8 * 1/64 = 2/512$
	...				
	0	0000	110	-6	$6/8 * 1/64 = 6/512$
	0	0000	111	-6	$7/8 * 1/64 = 7/512$
<hr/>					
	0	0001	000	-6	$8/8 * 1/64 = 8/512$
	0	0001	001	-6	$9/8 * 1/64 = 9/512$
	...				
	0	0110	110	-1	$14/8 * 1/2 = 14/16$
	0	0110	111	-1	$15/8 * 1/2 = 15/16$
	0	0111	000	0	$8/8 * 1 = 1$
	0	0111	001	0	$9/8 * 1 = 9/8$
	0	0111	010	0	$10/8 * 1 = 10/8$
	...				
	0	1110	110	7	$14/8 * 128 = 224$
	0	1110	111	7	$15/8 * 128 = 240$
<hr/>					
	0	1111	000	n/a	inf
	0	1111	001	n/a	NaN
	...				
	0	1111	111	n/a	NaN

# Dynamic Range of 8-bit tiny float

Bias = 7	s	exp	frac	E	Value	Notes of Interest
$V = (-1)^s$	0	0000	000	-6	0	
$\times (0.\text{frac})$	0	0000	001	-6	$1/8 * 1/64 (2^{-6}) = 1/512$	closest to zero
$\times 2^{(1 - \text{Bias})}$	0	0000	010	-6	$2/8 * 1/64 = 2/512$	
<b>Denormalized numbers</b>	...					
	0	0000	110	-6	$6/8 * 1/64 = 6/512$	
	0	0000	111	-6	$7/8 * 1/64 = 7/512$	largest denorm
	0	0001	000	-6	$8/8 * 1/64 = 8/512$	smallest norm > 0
<b>Normalized numbers</b>	...					
	0	0110	110	-1	$14/8 * 1/2 = 14/16$	
$V = (-1)^s$	0	0110	111	-1	$15/8 * 1/2 = 15/16$	closest to 1 below
$\times (1.\text{frac})$	0	0111	000	0	$8/8 * 1 = 1$	
$\times 2^{(\text{exp} - \text{Bias})}$	0	0111	001	0	$9/8 * 1 = 9/8$	closest to 1 above
	0	0111	010	0	$10/8 * 1 = 10/8$	
	...					
	0	1110	110	7	$14/8 * 128 = 224$	
	0	1110	111	7	$15/8 * 128 = 240$	largest norm
<b>Special values</b>	0	1111	000	n/a	inf	
	0	1111	001	n/a	NaN	
	...					
	0	1111	111	n/a	NaN	

# Distribution of Values

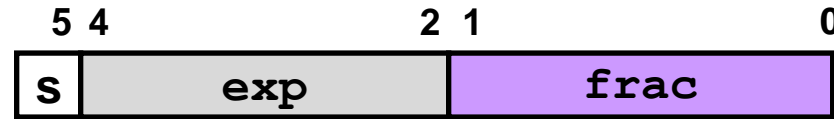
- 6-bit IEEE-like format
  - exp = 3 exponent bits
  - frac = 2 fraction bits
  - Bias is 3 ( $2^{3-1}-1$ )
- Notice how the distribution gets denser toward zero.



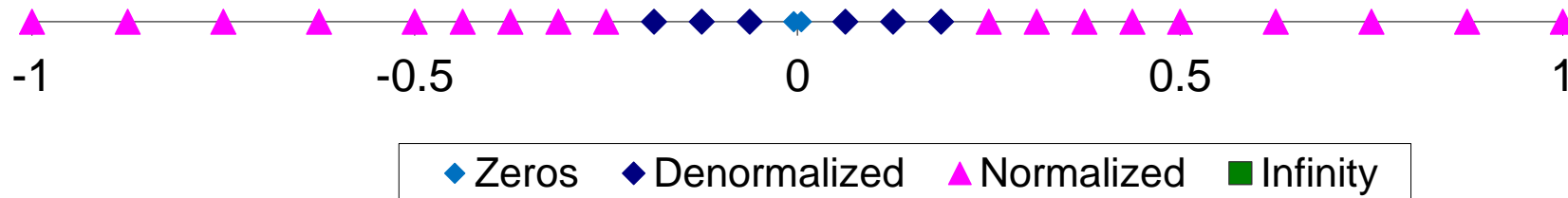
# Distribution of Values (Close-up View)

- 6-bit IEEE-like format

- exp = 3 exponent bits
- frac = 2 fraction bits
- Bias is 3 ( $2^{3-1}-1$ )



- Smooth transition between normalized and de-normalized numbers due to definition  $E = 1 - \text{Bias}$  for denormalized values
  - Zeros are denormalized numbers too! (+0 and -0)





# Outline

- Fractional Binary Numbers
- Representing Floating Point
- Smaller Floating Point
- **Floating Point Arithmetic**

# Floating Point Operations

- Conceptual view

- $x +_{\text{float}} y = \text{Fit}(x +_{\text{math}} y)$
  - $x *_{\text{float}} y = \text{Fit}(x *_{\text{math}} y)$

- First compute exact, mathematical result

- Compute the numerical value of the operands
  - Do the operation as in grade school arithmetic

- Then make it fit into desired precision

- **Step 1:** Determine frac, exp
    - Frac must be of the form 1.xxxx (0.xxx if denormalized)
    - Change exp if needed to get frac to that form (e.g., result is 101.xxx)
  - **Step 2:** Possibly overflow if exponent too is large
    - Unlike integer overflow, result is mathematically reasonable: infinity
  - **Step 3:** Possibly round to fit into frac if we have too many mantissa bits

# Rounding

- Default rounding mode for IEEE floating point is Round-to-even
  - Other methods are statistically biased (round up, round down, round-to-zero)
    - Sum of set of positive numbers will consistently be over- or under- estimated
  - Round to nearest number
    - If exactly in between, round to nearest even number
- Round-to-even example
  - Illustrated with rounding of money (round to whole number)

	\$1.40	\$1.60
Rounded	\$1	\$2

# Rounding

- Default rounding mode for IEEE floating point is Round-to-even
  - Other methods are statistically biased (round up, round down, round-to-zero)
    - Sum of set of positive numbers will consistently be over- or under- estimated
  - Round to nearest number
    - If exactly in between, round to nearest even number
- Round-to-even example
  - Illustrated with rounding of money

	\$1.40	\$1.60	\$1.50	\$2.50	-\$1.50
Rounded	\$1	\$2			

# Rounding

- Default rounding mode for IEEE floating point is Round-to-even
  - Other methods are statistically biased (round up, round down, round-to-zero)
    - Sum of set of positive numbers will consistently be over- or under- estimated
  - Round to nearest number
    - If exactly in between, round to nearest even number
- Round-to-even example
  - Illustrated with rounding of money

	\$1.40	\$1.60	\$1.50	\$2.50	-\$1.50
Rounded	\$1	\$2	\$2	\$2	-\$2

# Closer Look at Round-to-even

- Rounding to other decimal places than the decimal point
  - When exactly halfway between two possible values
    - Round so that least significant digit is even
- E.g., round to nearest hundredth (i.e., 2 decimal digits in fractional part)
  - $1.23\textbf{49999}$   $\Rightarrow$  1.23 (Less than half way)
  - $1.23\textbf{50001}$   $\Rightarrow$  1.24 (Greater than half way)
  - $1.23\textbf{50000}$   $\Rightarrow$  1.24 (Half way—round to even)
  - $1.24\textbf{50000}$   $\Rightarrow$  1.24 (Half way—round to even)

# Rounding Binary Numbers

- Binary fractional numbers

- Are "even" when least significant bit is 0
- Are half-way when bits to right of rounding position =  $100...0_2$   
 General form  $XX...X.YY...Y100...0_2$   
 last  $Y$  is the position to which we want to round

- Examples

- Round to nearest  $1/4$  (2 bits right of binary point)

Value	Binary	Rounded	Action	Rounded Value
$2+3/32$	$10.00\underline{011}_2$	$10.00_2$	( $<1/2$ —down)	2
$2+3/16$	$10.00\underline{110}_2$	$10.01_2$	( $>1/2$ —up)	$2+1/4$
$2+3/8$	$10.01\underline{100}_2$	$10.10_2$	( $1/2$ —up to even)	$2+1/2$
$2+5/8$	$10.10\underline{100}_2$	$10.10_2$	( $1/2$ —down to even)	$2+1/2$
$2+7/8$	$10.11\underline{100}_2$	$11.00_2$	( $1/2$ —up to even)	3

# Mathematical Properties of FP Arithmetic

- Mathematical properties of FP Addition
  - Addition is Associative? **NO**
    - $(x + y) + z = x + (y + z)$
    - Possibility of overflow and inexactness of rounding
      - $(3.14 + 1e10) - 1e10 = 0$  (rounding)
      - $3.14 + (1e10 - 1e10) = 3.14$
- Mathematical properties of FP Multiplication
  - Multiplication is Associative? **NO**
    - $(x \times y) \times z = x \times (y \times z)$
    - Possibility of overflow, inexactness of rounding
  - Multiplication distributes over addition? **NO**
    - $x \times (y + z) = (x \times y) + (x \times z)$
    - Possibility of overflow, inexactness of rounding
- More in bonus slides



# Floating Point Summary

- IEEE Floating point (IEEE 754) has clear mathematical properties
  - But not always the ones you may expect!
- Represents numbers of form  $(-1)^S \times M \times 2^E$
- One can reason about operations independent of implementation
  - As if computed with perfect precision and then rounded
- Not the same as arithmetic on real numbers
  - Violates associativity/distributivity
  - Makes life difficult for compilers & serious numerical applications programmers

# Outline

- Fractional Binary Numbers
- Representing Floating Point
- Smaller Floating Point
- Floating Point Arithmetic

# Outline

- Bonus slides
  - Use these for additional practice
  - And if you're interested in additional topics

# Interesting Numbers for `float/double`

<b>Description</b>	<b>exp</b>	<b>frac</b>	<b>Numeric Value</b> <sup>{single prec., double prec.}</sup>
Zero	00...00	00...00	0.0
Smallest Pos. Denorm. <ul style="list-style-type: none"> <li>• Single <math>\sim 1.4 \times 10^{-45}</math></li> <li>• Double <math>\sim 4.9 \times 10^{-324}</math></li> </ul>	00...00	00...01	$2^{-\{23,52\}} \times 2^{-\{126,1022\}}$
Largest Denormalized <ul style="list-style-type: none"> <li>• Single <math>\sim 1.18 \times 10^{-38}</math></li> <li>• Double <math>\sim 2.2 \times 10^{-308}</math></li> </ul>	00...00	11...11	$(1.0 - \epsilon) \times 2^{-\{126,1022\}}$
Smallest Pos. Normalized <ul style="list-style-type: none"> <li>• Just slightly larger than largest denormalized</li> </ul>	00...01	00...00	$1.0 \times 2^{-\{126,1022\}}$
One	01...11	00...00	1.0
Largest Normalized <ul style="list-style-type: none"> <li>• Single <math>\sim 3.4 \times 10^{38}</math></li> <li>• Double <math>\sim 1.8 \times 10^{308}</math></li> </ul>	11...10	11...11	$(2.0 - \epsilon) \times 2^{\{127,1023\}}$

# Normalized Encoding Example

- Value

- `float F = 12345.0; // single precision: k=8, n=23`

- $12345_{10} = 11000000111001_2 = 1.1000000111001_2 \times 2^{13}$

- Significand

- $M = 1.1000000111001_2$

- $\text{frac} = 1000000111001$  **0000000000**

(drop leading 1, add 10 zeros)

- Exponent

- $E = 13$

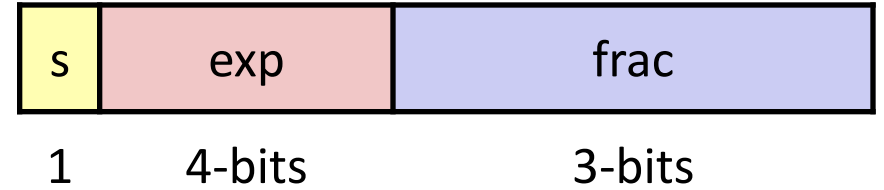
- Bias = 127

- $E = \text{exp} - \text{Bias} \rightarrow \text{exp} = E + \text{Bias} = 140 = 10001100_2$

**Floating Point Representation:**

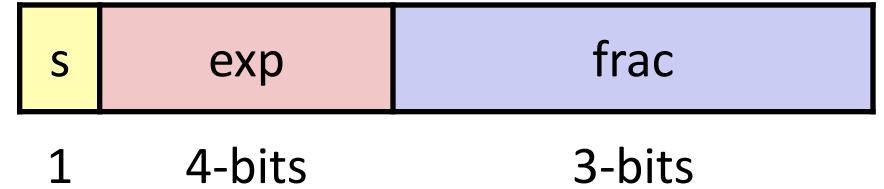
<b>Hex:</b>	4	6	4	0	E	4	0	0
<b>Binary:</b>	0100	0110	0100	0000	1110	0100	0000	0000

# Creating a Floating Point Number



- Steps
  - Is the number within the range  $(-2^{1-\text{Bias}}, +2^{1-\text{Bias}})$ ?
    - If yes, “denormalize” to have a leading 0
    - otherwise, normalize to have leading 1
  - Round to fit within fraction
  - Postnormalize to deal with effects of rounding
- QUIZ in next three slides
  - Convert 8-bit unsigned numbers to tiny floating point format

# Step 1: Normalize

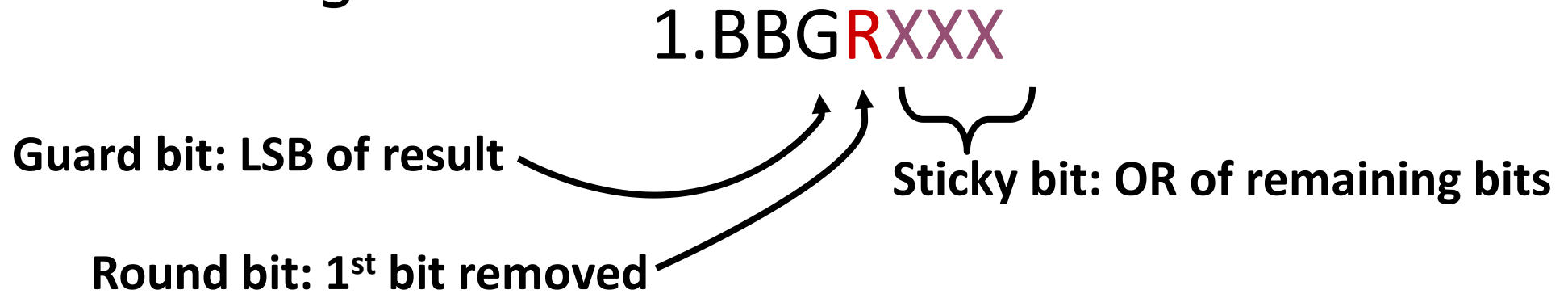


- Requirement

- Set binary point so that numbers of form 1.xxxxx
- Adjust all to have leading one
  - Decrement exponent as shift left

<i>Value</i>	<i>Binary</i>	<i>Fraction</i>	<i>Exponent</i>
128	10000000	1.0000000	7
13	00001101	1.1010000	3
17	00010001	1.0001000	4
19	00010011	1.0011000	4
138	10001010	1.0001010	7
63	00111111	1.1111100	5

# Step 2: Rounding



- Round up conditions

- round up if  $\langle \text{Guard, Round, Sticky} \rangle = \langle x11 \rangle$  because  $>0.5$
- round up if  $\langle \text{Guard, Round, Sticky} \rangle = \langle 110 \rangle$  as per round to even rules

<i>Value</i>	<i>Fraction</i>	<i>GRS</i>	<i>Incr?</i>	<i>Rounded</i>
128	1.000 <b>0</b> 000	000	N	1.000
13	1.101 <b>0</b> 000	100	N	1.101
17	1.000 <b>1</b> 000	010	N	1.000
19	1.001 <b>1</b> 000	110	Y	1.010
138	1.000 <b>1</b> 010	011	Y	1.001
63	1.111 <b>1</b> 100	111	Y	10.000



# Step 3: Postnormalize

- Issue

- Rounding may have caused overflow
- Handle by shifting right once & incrementing exponent

<i>Value</i>	<i>Rounded</i>	<i>Exp</i>	<i>Adjusted</i>	<i>Result</i>
128	1.000	7		128
13	1.101	3		13
17	1.000	4		16
19	1.010	4		20
138	1.001	7		144
63	10.000	5	M=1.000 exp=6	64

# Floating Point Puzzles

- For each of the following C expressions, either:
  - Argue that it is true for all argument values
  - Explain why not true

```
int x = ...;  
float f = ...;  
double d = ...;
```

**Assume neither  
d nor f is NaN**

```
x == (int) (double) x
```

```
x == (int) (float) x
```

```
d == (double) (float) d
```

```
f == (float) (double) f
```

```
f == -(-f);
```

```
1.0/2 == 1/2.0
```

```
d*d >= 0.0
```

```
(f+d) - f == d
```

# Floating Point Puzzles

- For each of the following C expressions, either:
  - Argue that it is true for all argument values
  - Explain why not true

```
int x = ...;  
float f = ...;  
double d = ...;
```

Assume neither  
d nor f is NaN

<code>x == (int) (double) x</code>	<i>Yes</i>
<code>x == (int) (float) x</code>	<i>No (x = TMax)</i>
<code>d == (double) (float) d</code>	<i>No (d = 1e40)</i>
<code>f == (float) (double) f</code>	<i>Yes</i>
<code>f == -(-f);</code>	<i>Yes</i>
<code>1.0/2 == 1/2.0</code>	<i>Yes</i>
<code>d*d &gt;= 0.0</code>	<i>Yes</i>
<code>(f+d) - f == d</code>	<i>No (f = 1.0e20, d = 1.0; f+d rounded to 1.0e20)</i>

# Floating-Point Multiplication, Directly

- For cases where you can't work with exact results
  - E.g., when doing it in hardware

- Operands

- $(-1)^{s1} M1 2^{E1} * (-1)^{s2} M2 2^{E2}$

- Exact result

- $(-1)^s M 2^E$
  - Sign s:  $s1 \wedge s2$
  - 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

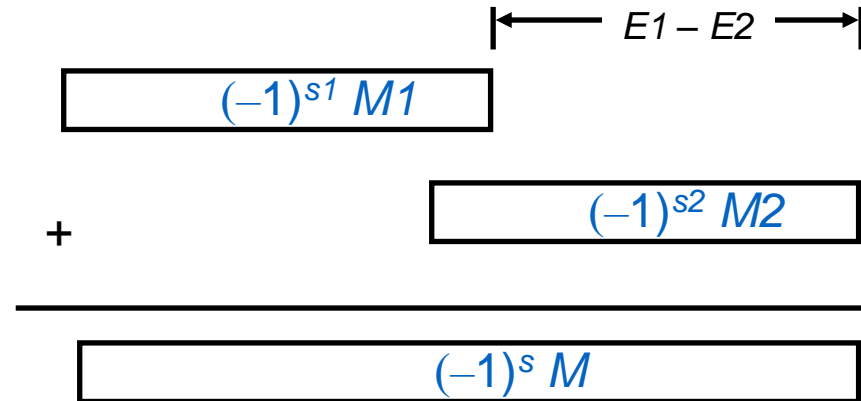
- Biggest chore is multiplying significands

E1=3	M1=1.11010010
E2=5	M2=1.11001110
-----	
E=8	M=11.01001000111111
E=8+1	M=1.101001000111111
E=9	M=1.1010010010

# Floating-Point Addition, Directly

- Operands

- $(-1)^{s1} M1 2^{E1}$
- $(-1)^{s2} M2 2^{E2}$
- Assume  $E^1 > E^2$



- Exact Result

- $(-1)^s M 2^E$
- Sign  $s$ , significand  $M$ : Result of signed align & add
- Exponent  $E$ :  $E^1$

- Fixing

- If  $M \geq 2$ , shift  $M$  right, increment  $E$
- if  $M < 1$ , shift  $M$  left  $k$  places, decrement  $E$  by  $k$
- Overflow if  $E$  out of range
- Round  $M$  to fit frac precision

```

E1=5 M1=1.11010010
E2=2 M2=1.11001110
E2=2 M2=0001.11001110
-----
E1=5 M1=1.11010010
E2=5 M2=0.00111001110
-----
E =5  M =10.00001011110
E =6  M =1.000001011110
    
```

# Mathematical Properties of FP Add

- Compare to those of Abelian Group
  - Closed under addition? YES
    - But may generate infinity or NaN
  - Commutative? YES
  - **Associative? NO**
    - Overflow and inexactness of rounding
      - $(3.14+1e10)-1e10=0$  (rounding)
      - $3.14+(1e10-1e10)=3.14$
  - 0 is additive identity? YES
  - Every element has additive inverse? ALMOST
    - Except for infinities & NaNs
- Monotonicity
  - $a \geq b \Rightarrow a+c \geq b+c$ ? ALMOST
    - Except for NaNs

# Mathematical Properties of FP Multiplication

- Compare to commutative ring
  - Closed under multiplication? YES
    - But may generate infinity or NaN
  - Multiplication Commutative? YES
  - Multiplication is Associative? NO
    - Possibility of overflow, inexactness of rounding
  - 1 is multiplicative identity? YES
  - Multiplication distributes over addition? NO
    - Possibility of overflow, inexactness of rounding
- Monotonicity
  - $a \geq b \ \& \ c \geq 0 \Rightarrow a * c \geq b * c$ ? ALMOST
    - Except for NaNs