# **Floating Point Numbers**

Prof. Usagi



# Floating point numbers



# Let's revisit the 4-bit binary adding



 If you add the largest integer with 1, the result will become the smallest integer.



# "Floating" v.s. "Fixed" point

- We want to express both a relational number's "integer" and "fraction" parts
- Fixed point
  - One bit is used for representing positive or negative
  - Fixed number of bits is used for the integer part
  - Fixed number of bits is used for the fraction part
  - Therefore, the decimal point is fixed
- Floating point
  - One bit is used for representing positive or negative
  - A fixed number of bits is used for exponent
  - A fixed number of bits is used for fraction
  - Therefore, the decimal point is floating depending on the value of exponent

Integer

+/-

+/-



## Fraction is always here

### Can be anywhere in the fraction

**Exponent** 

Fraction

## **IEEE 754 format**

### **32-bit float**

+/- Exponent (8-bit)

Fraction (23-bit)

- Realign the number into 1.**F** \* 2<sup>e</sup>
- Exponent stores **e** + 127
- Fraction only stores F



# **Floating point adder**



# **Demo** — what's in c?

```
#include <stdio.h>
int main(int argc, char **argv)
{
```

}

```
float a, b, c;
a = 1280.245;
b = 0.0004;
c = a + b;
printf("1280.245 + 0.0004 = \%f(n'',c);
return 0;
```



# **Other floating point formats**

<b>16-bit half</b>	+/-	Exp (5-bit) Fracti	on (10-bit) added
32-bit float	+/-	Exponent (8-bit)	Fraction (23
64-bit double	+/-	Exponent (11-bit)	Fract

- Not all applications require "high precision"
- Deep neural networks are surprisingly error tolerable



## in 2008

## -bit)

## ion (52-bit)

## **Can you tell the difference?**

### **Higher resolution**



But we all can tell they are our mascots!





## How about this?



# **Other floating point formats**

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## in 2008

### -bit)

### ion (52-bit)

## **Mixed-precision**

### **Double Precision Results**

GPU	Tesla T4	Tesla V100	Tesla P100
Max Flops (GFLOPS)	253.38	7072.86	4736.76
Fast Fourier Transform (GFLOPS)	132.60	1148.75	756.29
Matrix Multiplication (GFLOPS)	249.57	5920.01	4256.08
Molecular Dynamics (GFLOPS)	105.26	908.62	402.96
S3D (GFLOPS)	59.97	227.85	161.54
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Single Precision Pesults			
Single Precision Results			
Single Precision Results	Tesla T4	Tesla V100	Tesla P100
Single Precision Results GPU Max Flops (GFLOPS)	<b>Tesla T4</b> 8073.26	<b>Tesla V100</b> 14016.50	<b>Tesla P100</b> 9322.46
Single Precision Results GPU Max Flops (GFLOPS) Fast Fourier Transform (GFLOPS)	<b>Tesla T4</b> 8073.26 660.05	<b>Tesla V100</b> 14016.50 2301.32	<b>Tesla P100</b> 9322.46 1510.49
Single Precision Results GPU Max Flops (GFLOPS) Fast Fourier Transform (GFLOPS) Matrix Multiplication (GFLOPS)	<b>Tesla T4</b> 8073.26 660.05 3290.94	<b>Tesla V100</b> 14016.50 2301.32 13480.40	<b>Tesla P100</b> 9322.46 1510.49 8793.33
Single Precision Results GPU Max Flops (GFLOPS) Fast Fourier Transform (GFLOPS) Matrix Multiplication (GFLOPS) Molecular Dynamics (GFLOPS)	Tesla T4       8073.26       660.05       3290.94       572.91	Tesla V100         14016.50         2301.32         13480.40         997.61	Tesla P100       P322.46         1510.49       8793.33         480.02       1480.02
Single Precision Results GPU Max Flops (GFLOPS) Fast Fourier Transform (GFLOPS) Matrix Multiplication (GFLOPS) Molecular Dynamics (GFLOPS) S3D (GFLOPS)	Tesla T4       8073.26         660.05       3290.94         572.91       99.42	Tesla V100         14016.50         2301.32         13480.40         997.61         434.78	Tesla P100       P322.46         1510.49       8793.33         480.02       295.20



GPU Architecture	NVIDIA Turing	
NVIDIA Turing Tensor Cores	320	
NVIDIA CUDA® Cores	2,560	
Single-Precision	8.1 TFLOPS	
Mixed-Precision (FP16/FP32)	65 TFLOPS	
INT8	130 TOPS	
INT4	260 TOPS	
GPU Memory	16 GB GDDR6 300 GB/sec	
ECC	Yes	
Interconnect Bandwidth	32 GB/sec	
System Interface	x16 PCle Gen3	
Form Factor	Low-Profile PCI	e
Thermal Solution	Passive	
Compute APIs	CUDA, NVIDIA TO ONNX	ensorRT <sup>™</sup> ,

ECC	
Intercon	ır

### SPECIFICATIONS

# **Google's Tensor Processing Units**



TPU v2 - 4 chips, 2 cores per chip



TPU v3 - 4 chips, 2 cores per chip

Each TPU core has scalar, vector, and matrix units (MXU). The MXU provides the bulk of the compute power in a TPU chip. Each MXU is capable of performing 16K multiply-accumulate operations in each cycle. While the MXU inputs and outputs are 32-bit floating point values, the MXU performs multiplies at reduced bfloat16 precision. Bfloat16 is a 16-bit floating point representation that provides better training and model accuracy than the IEEE half-precision representation.



https://cloud.google.com/tpu/docs/system-architecture

# EdgeTPU



Figure 1. The basic workflow to create a model for the Edge TPU

### Frozen graph

.pb file



# Announcement

- Reading quiz 5 due 4/28 **BEFORE** the lecture
  - Under iLearn > reading guizzes
- Lab 3 due 4/30
  - Watch the video and read the instruction BEFORE your session
  - There are links on both course webpage and iLearn lab section
  - Submit through iLearn > Labs
- Midterm on 5/7 during the lecture time, access through iLearn — no late submission is allowed — make sure you will be able to take that at the time
- Check your grades in iLearn

# Electrical Computer Science Engineering





