UC San Diego

DSC 102
Systems for Scalable Analytics

Rod Albuyeh

Topic 1: Basics of Machine Resources
Part 1: Computer Organization

Ch. 1, 2.1-2.3, 2.12, 4.1, and 5.1-5.5 of CompOrg Book

DSC 102
Systems for Scalable Analytics

Logistics:

- PA0 update
- PA group sign ups
- “Look under the hood” videos

Survey Says...

- What do you want to learn from this course?

AWS, Spark, job applicable skills, ambivalent...

- Experience with cluster + cloud computing?

Mostly none.

- Linux + Shell scripting?

Mostly none.

- Anything else you'd like us to know?

Excitement, intimidation, first 8am class

Outline

- Basics of Computer Organization
  - Digital Representation of Data
  - Processors and Memory Hierarchy
- Basics of Operating Systems
  - Process Management: Virtualization; Concurrency
  - Filesystem and Data Files
  - Main Memory Management
- Persistent Data Storage

(REVIEW) Digital Representation of Data

- The *size* and *interpretation* of a data type depends on PL
- A **Byte** (B; 8 bits) is typically the basic unit of data types
- **Boolean**:
  - Examples in data sci.: Y/N or T/F responses
  - Just 1 bit needed but actual size is almost always 1B, i.e., 7 bits are wasted!
- **Integer**:
  - Examples in data science: # of friends, age, # oflikes
  - Typically 4 bytes; many variants (short, unsigned, etc.)
  - Java *int* can represent -2^{31} to $(2^{31} - 1)$;
  - C *unsigned int* can represent 0 to $(2^{32} - 1)$;
  - Python3 *int* is effectively unlimited length (PL magic!)

(REVIEW) Digital Representation of Data

Q: *How many unique data items can be represented by 3 bytes?*

- Given k bits, we can represent 2^k unique data items
- 3 bytes = 24 bits => 2^{24} items, i.e., 16,777,216 items
- Common approximation: 2^{10} (i.e., 1024) ~ 10^3 (i.e., 1000); kibibyte (KiB) = 1024 bytes, vs kilobyte (KB) = 1000 bytes

Q: *How many bits are needed to distinguish 97 unique items?*

- For k unique items, invert the exponent to get $\log_2(k)$
- But #bits is an integer! So, we only need $\lceil \log_2(k) \rceil$
- So, we only need the next higher power of 2
- So... 7 bits

(REVIEW) Digital Representation of Data

1. Given decimal n
   if n is power of 2 (say, 2^k), put 1 at bit position k; if k=0, stop; else pad with trailing 0s till position 0
   if n is not power of 2, identify the power of 2 just below n (say, 2^k); #bits is then k; put 1 at position k
2. Reset n as n - 2^k; return to Steps 1-2
3. Fill remaining positions in between with 0s

	7	6	5	4	3	2	1	0	Position/Exponent of 2
Decimal	128	64	32	16	8	4	2	1	Power of 2
5_{10}						1	0	1	
47_{10}			1	0	1	1	1	1	
163_{10}	1	0	1	0	0	0	1	1	
16_{10}				1	0	0	0	0	

Digital Representation of Data

- *Hexadecimal* representation is a common stand-in for binary representation; more succinct and readable
  - Base 16 instead of base 2 cuts display length by ~4x
  - Digits are 0, 1, ... 9, A (10_{10}), B, … F (15_{10})
  - Each hexadecimal digit represents 4 bits.

Decimal	Binary	Hexadecimal
5_{10}	101_2	5_{16}
47_{10}	$10\ 1111_2$	$2F_{16}$
163_{10}	$1010\ 0011_2$	$A3_{16}$
16_{10}	$1\ 0000_2$	$1\ 0_{16}$

Alternative notations

0xA3 or $A3_H$

Digital Representation of Data

Let's unpack:

Base 10...

0 1 2 3 4 5 6 7 8 9

Base 2...

0 1

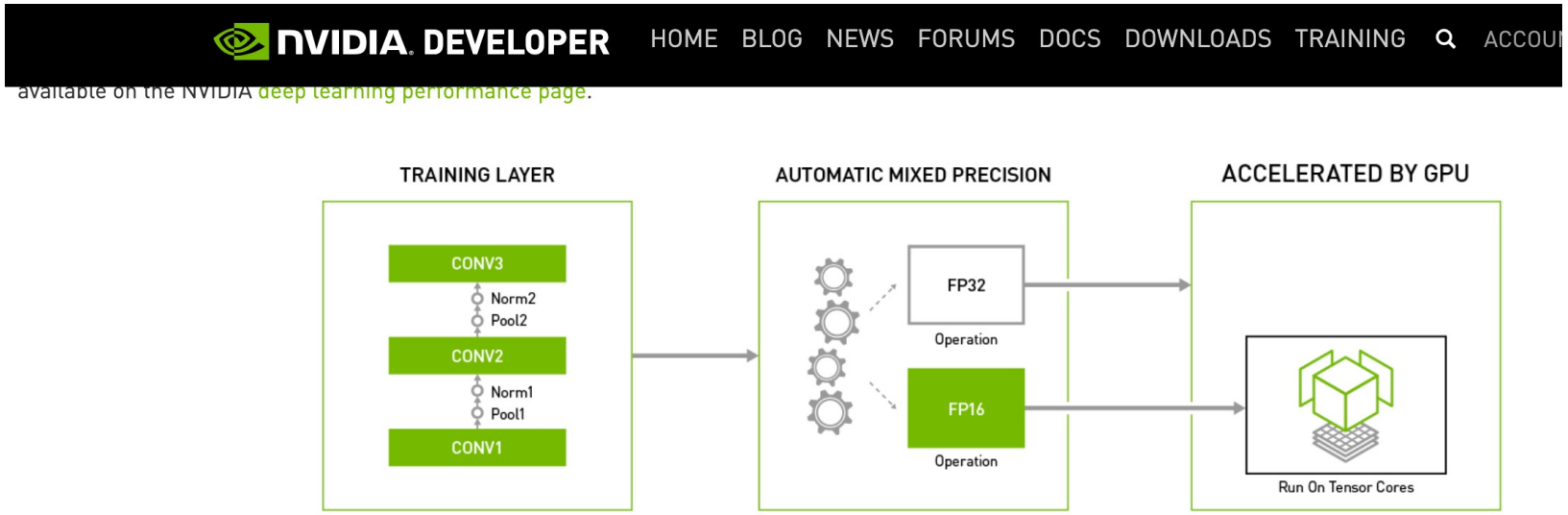
Base-16 Hexadecimal...

0 1 2 3 4 5 6 7 8 9 A B C D E F

10 11 12 13 14 15

Digital Representation of Data

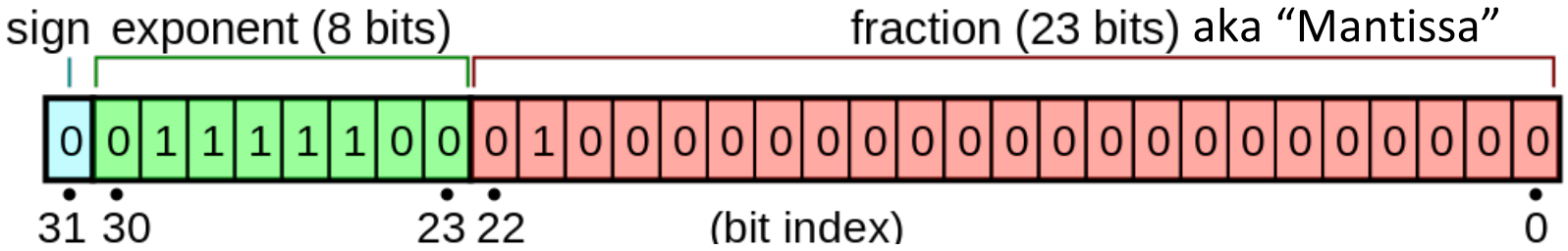
- **Float**:
  - Examples in data sci.: salary, scores, model weights
  - IEEE-754 single-precision format is 4B long; double-precision format is 8B long. Single precision is ~ 8 decimal digits. Double precision is ~ 16 decimal digits.
  - Java and C *float* is single; Python *float* is double!



Using Automatic Mixed Precision for Major Deep Learning Frameworks

Digital Representation of Data

- **Float**:
  - Standard IEEE format for single (aka binary32):



$$(-1)^{sign} \times 2^{exponent-127} \times (1 + \sum_{i=1}^{23} b_{23-i} 2^{-i})$$

$$(-1)^0 \times 2^{124-127} \times (1 + 1 \cdot 2^{-2}) = (1/8) \times (1 + (1/4)) = 0.15625$$

(**Note:** Converting decimal reals/fractions to float is NOT on exams)

Digital Representation of Data

- Due to representation imprecision issues, floating point arithmetic (addition and multiplication) is not associative!

```
(base) rodalbuyeh@Rods-MacBook-Pro ~ % python
Python 3.9.12 (main, Apr  5 2022, 01:53:17)
[Clang 12.0.0 ] :: Anaconda, Inc. on darwin
Type "help", "copyright", "credits" or "license" for more information.
>>> 0.1 + 0.2
0.30000000000000004
>>> (0.1 + 0.2) + 0.7
1.0
>>> 0.1 + (0.2 + 0.7)
0.9999999999999999
```

- In binary32, special encodings recognized:
  - Exponent 0xFF and fraction 0 is +/- “Infinity”
  - Exponent 0xFF and fraction <> 0 is “NaN”

Digital Representation of Data

- More float standards: double-precision (float64; 8B) and half-precision (float16; 2B); different #bits for exponent, fraction
- Float16 is now common for *deep learning* parameters:
  - Native support in PyTorch, TensorFlow, etc.; APIs also exist for weight quantization/rounding post training
  - NVIDIA Deep Learning SDK support mixed-precision training; 2-3x speedup with similar accuracy!
- New processor hardware (FPGAs, ASICs, etc.) enable arbitrary precision, even 1-bit (!), but accuracy is lower

https://docs.nvidia.com/deeplearning/sdk/mixed-precision-training/index.html

Digital Representation of Data

- Representing **Character (char)** and **String**:
  - Represents letters, numerals, punctuations, etc.
  - A string is typically just a variable-sized array of char
  - C *char* is 1 byte; Java char is 2 bytes; Python does not have a char type (use *str* or *bytes*)
  - American Standard Code for Information Interchange (*ASCII*) for encoding characters; initially 7-bit; later extended to 8-bit (1 byte)
    - Examples: 'A' is 65 (dec), 'a' is 97 (dec), '@' is 64 (dec), etc.
  - *Unicode UTF-8* is now most common; subsumes ASCII; 4 bytes for ~1.1 million "code points" incl. many other language scripts, math symbols ∜, emojis 👻, etc.

Digital Representation of Data

- All digital objects are *collections* of basic data types (bytes, integers, floats, and characters)
  - SQL dates/timestamp: string (w/ known format)
  - ML feature vector: *array* of floats (w/ known length)
  - Neural network weights: *set* of multi-dimensional *arrays* (matrices or tensors) of floats (w/ known dimensions)
  - Graph: an *abstract data type* (ADT) with *set* of vertices (say, integers) and *set* of edges (*pair* of integers)
  - Program in PL, SQL query: string (w/ grammar)
  - DRAM addresses: *array* of bytes (w/ known length)
  - Instruction in machine code: *array* of bytes (w/ ISA)
  - Other data structures or digital objects?

Digital Representation of Data

- **Serialization** and **Deserialization:**
  - A data structure often needs to be persisted (stored in a file) or transmitted over a network
  - Serialization is the process of converting a data structure (or program objects in general) into a neat sequence of bytes that can be exactly recovered; deserialization is the reverse, i.e., bytes to data structure
  - Serializing bytes and characters/strings is trivial
  - 2 alternatives for serializing integers/floats:
    - As *byte stream* (aka “binary type” in SQL)
    - As *string*, e.g., 4B integer *5* -> 2B string as *“5”*
    - String ser. common in data science (CSV, TSV, etc.)

Serialization and Deserialization in ML

- We often convert a trained model into a format that can be stored or transmitted. This involves transforming it into a sequence of bytes that can be written to disk or sent over network (i.e. we have to serialize it).
- Deserialization is the process of converting a serialized model back to its original data structure so that it can be used for inference. We load it back into memory for inference or evaluation purposes.
- Can be implemented in various formats, such as JSON, protocol buffers, or Apache Avro.
- We can serialize any other ML related artifacts like transformers, data, metadata, etc.

A Common Serialization Scenario...

```python
import pandas as pd
from sklearn.linear_model import LogisticRegression
import pickle

# Load the Iris dataset
iris_df = pd.read_csv('iris.data', header=None)
X = iris_df.iloc[:, :-1]
y = iris_df.iloc[:, -1]

# Initialize a logistic regression model
clf = LogisticRegression(random_state=0, max_iter=1000)

# Fit the model on the data
clf.fit(X, y)

# Serialize the model to disk
filename = 'logistic_regression_model.pkl'
with open(filename, 'wb') as file:
    pickle.dump(clf, file)

print(f'Saved the model to {filename}')
```

Review Questions

- What is the difference between data and code?
- What kind of software is TensorFlow? Linux?
- Why do computers use binary numbers?
- What is a byte?
- How many integers can you represent with 5 bits?
- How many bits do you need to represent 5 integers?
- What is the hexadecimal representation of 20_{10}?
- Why is a floating point standard needed?
- Why should a data scientist know about float formats?
- What does “lower precision” mean for a float weight in DL?
- Why is serialization needed on a computer?
- Is code a string? Is a string code?
- Is reality a computer simulation? :)

Outline

- Basics of Computer Organization
  - Digital Representation of Data
  - Processors and Memory Hierarchy
- Basics of Operating Systems
  - Process Management: Virtualization; Concurrency
  - Filesystem and Data Files
  - Main Memory Management
- Persistent Data Storage

In class activity

What is 64 in base 2 notation? If you think you might need partial credit, show your work.

( ) 110001
( ) 111111
( ) 1010000
( ) 1000000
( ) 1001000

Which of the following is NOT a potential disadvantage of serializing a machine learning model? If you think you might need partial credit, explain your justification.

( ) Increase in the model's size due to the inclusion of architecture and state information.
( ) Reduced compatibility with different programming languages and versions.
( ) Loss of interpretability and ability to modify the model's internal workings.
( ) Risk of privacy breaches due to unauthorized access to the model's data or parameters.
( ) Increased computational overheads during model inference due to serialization and deserialization processes.