UC San Diego

DSC 102
Systems for Scalable Analytics

Fall 2023

Haojian Jin

Now for the course logistics …

Prerequisites

- **DSC 100** (or equivalent) is necessary
- Transitively **DSC 80**; a mainstream ML algorithmics course is necessary
- Proficiency in Python programming
- For all other cases, email me with proper justification; a waiver can be considered

https://haojian.github.io/DSC102FA23/

Components and Grading

- **3 Programming Assignments: 40%** (8% + 16% + 16%)
  - No late days! Plan your work well ahead.
  - **Plan your credit as well!**
- **Midterm Exam: 15%**
  - **TBD**; in-class only (50min)
- **Cumulative Final Exam: 35%**
  - Dec**. 15**; Canvas Quiz only (3hrs long but 4hrs limit)
- **10 (of 12) Peer Instruction Activities: 10%**
- **Extra Credit Peer Evaluation Activities: 4%** (likely)
- LMK ahead of time if you need makeup exam slot

https://haojian.github.io/DSC102FA23/

Grading Scheme

Hybrid of relative and absolute; grade is <u>better</u> of the two

Grade	Relative Bin (Use strictest)	Absolute Cutoff (>=)
A+	Highest 5%	95
A	Next 10% (5-15)	90
A-	Next 15% (15-30)	85
B+	Next 15% (30-45)	80
B	Next 15% (45-60)	75
B-	Next 15% (60-75)	70
C+	Next 5% (75-80)	65
C	Next 5% (80-85)	60
C-	Next 5% (85-90)	55
D	Next 5% (90-95)	50

Example: Score 82 but 33%le; Rel.: B-; Abs.: B+; so, B+

Programming Assignments

- **PA0: Setting up AWS and Dask**
  - Oct 6 to Oct 22
- **PA1: Data Exploration with Dask**
  - Oct 23 to Nov 12
- **PA2: Feature Eng. and Model Selection with Spark**
  - Nov 13 to Dec 04
- **Expectations on the PAs:**
  - Teams of 2 or 1 (individual); see webpage on academic integrity
  - I will cover the concepts and tools' tradeoffs in the lectures
  - TAs will explain and demo the tools; handle all Q&A
  - You are expected to put in the effort to learn the details of the tools' APIs using their documentation on your own!

https://haojian.github.io/DSC102FA23/

Course Administrivia

- **Lectures**: **MWF 3pm-3:50pm PT** at **CENTR 214**
  - Attendance optional but encouraged; podcast available
  - No need for clickers.
- **Discussions: Friday 9-9:50am PT on Zoom**
  - Only for talks on PAs by TAs, for pre-exam review by me
- **Instructor**: Haojian Jin; haojian@ucsd.edu
  - OHs: **Wednesday 4-5 pm PT** at **341 HDSI**
- **Slack** for all communications
- **Canvas** for PA submission, Peer Evaluation Activities, Final Exam

https://haojian.github.io/DSC102FA23/

Office hours

- Rohit Ramaprasad’s OHs: Tuesday 1:00 PM - 2:00 PM
- Sai Sree Harsha’s OHs: Thursday 1:00 PM - 2:00 PM
- Golokesh Patra’s OHs: Monday 11:00 AM - 12:00 PM
- Post questions to the ta-public channel.
- Avoid asking repetitive questions.

General Dos and Do NOTs

Do:

- Follow all announcements on Piazza
- Try to join the lectures/discussions live
- Raise your hand before speaking
- View/review podcast videos asynchronously by yourself
- To contact me/TAs, use private Slack; if you really need to email, use “DSC 102:” as subject prefix

Do NOT:

- Harass, intimidate, or intentionally talk over others
- Violate academic integrity on the PAs, exams, or other components; I am *very strict* on this matter!

Reasonable person.

(1) Everyone will be reasonable.
(2) Everyone expects everyone else to be reasonable.
(3) No one is special.
(4) Do not be offended if someone suggests you are not being reasonable.

Now for the course structure …

DSC 102 will get you thinking about the <u>fundamentals of systems for scalable analytics</u>

1. "**Systems**": What resources does a computer have? How to store and efficiently compute over large data? What is cloud?
2. "**Scalability**": How to scale and parallelize data-intensive computations?
3. **For "Analytics"**:
    1. **Source**: Data acquisition & preparation for ML
    2. **Build**: Model selection & deep learning systems
    3. **Deploying** ML models
4. Hands-on experience with scalable analytics tools

Data Systems Concerns in ML

Q: How do “ML Systems” relate to ML?

ML Systems : ML :: Computer Systems : TCS

Key concerns in ML:

Accuracy

Runtime efficiency (sometimes)

Additional key *practical* concerns in ML Systems:

Scalability (and efficiency at scale)

Usability

Manageability

Developability

*Long-standing concerns in the **DB systems** world!*

Q: [illegible]?

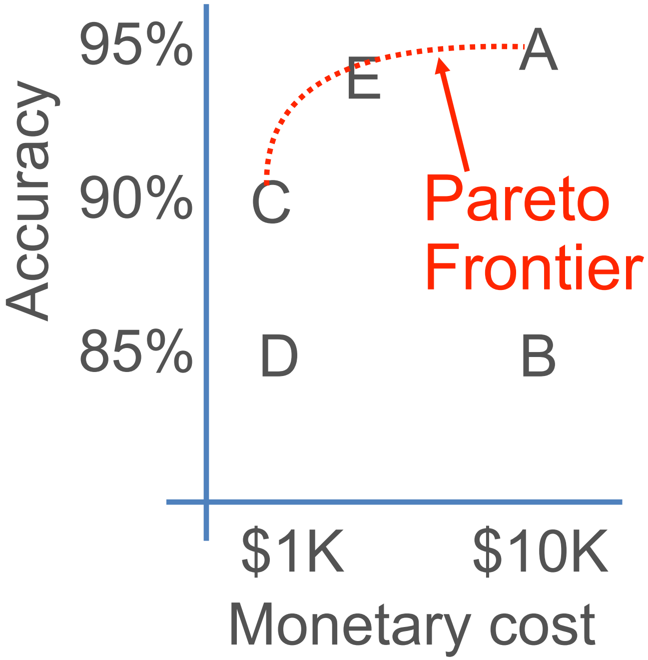
Conceptual System Stack Analogy

	Relational DB Systems	ML Systems
Theory	First-Order Logic Complexity Theory	Learning Theory Optimization Theory
Program Formalism	Relational Algebra	Tensor Algebra Gradient Descent
Program Specification	SQL	TensorFlow? Scikit-learn?
Program Modification	Query Optimization	???
Execution Primitives	Parallel Relational Operator Dataflows	Depends on ML Algorithm
Hardware	CPU, GPU, FPGA, NVM, RDMA, etc.	

Real-World ML: Pareto Surfaces

Q: *Suppose you are given ad click-through prediction models A, B, C, and D with accuracies of 95%, 85%, 90%, and 85%, respectively. Which one will you pick?*

Q: *What about now?*



- Real-world ML users must grapple with multi-dimensional *Pareto surfaces*: accuracy, monetary cost, training time, scalability, inference latency, tool availability, interpretability, fairness, etc.
- *Multi-objective optimization* criteria set by application needs / business policies.

Learning Outcomes of this course

- **Explain** the basic principles of the memory hierarchy, parallelism paradigms, scalable data systems, and cloud computing.
- **Identify** the abstract data access patterns of, and opportunities for parallelism and efficiency gains in, data processing and ML algorithms at scale.
- **Outline** how to use cluster and cloud services, dataflow (“Big Data”) programming with MapReduce and Spark, and ML tools at scale.
- **Apply** the above programming skills to create end-to-end pipelines for data preparation, feature engineering, and model selection on large-scale datasets.
- **Reason** critically about practical tradeoffs between accuracy, runtimes, scalability, usability, and total cost.

What this course is NOT about

- NOT a course on databases, relational model, or SQL
  - Take DSC 100 instead (pre-requisite)
- NOT a course on internal details of RDBMSs
  - Take CSE 132C instead
- NOT a training module for how to use Spark
- NOT a course on ML or data mining *algorithmics*; instead, we focus on ML *systems*

Tentative Course Schedule

Week	Topic
	Basics of Machine Resources: Computer Organization
	Basics of Machine Resources: Operating Systems
4	Basics of Cloud Computing
4-5	Parallel and Scalable Data Processing: Parallelism Basics
	Midterm Exam on TBD
6-7	Parallel and Scalable Data Processing: Scalable Data Access
7-8	Parallel and Scalable Data Processing: Data Parallelism
9	Dataflow Systems
10	ML Model Building Systems
11	**Final Exam on Dec 15**

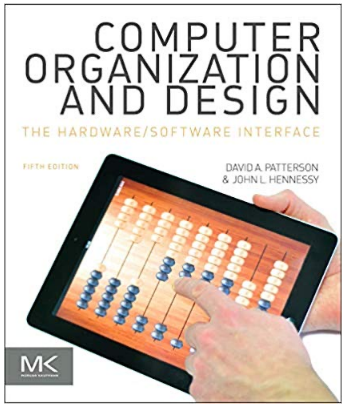
Systems Principles

Scalability Principles

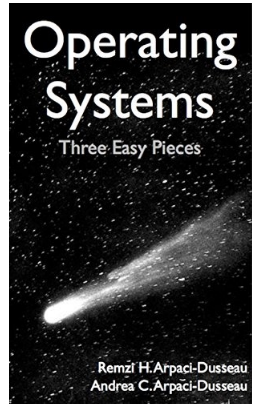
Scalable Analytics Systems

There will be 2 industry guest lectures (maybe 3)

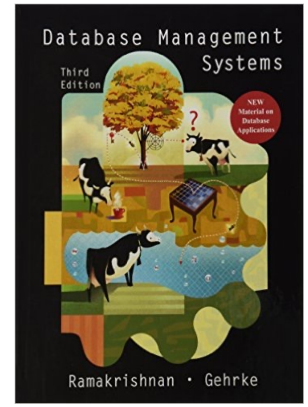
Suggested Textbooks



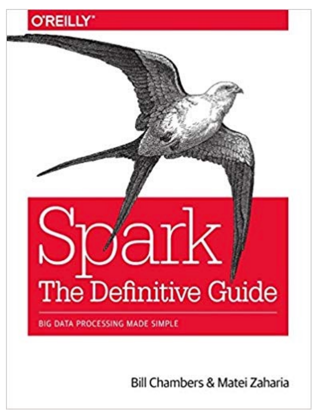
Aka “CompOrg Book”



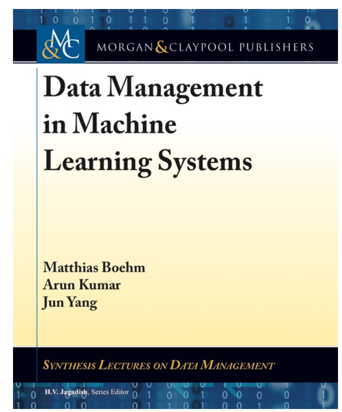
Aka “Comet Book”



Aka “Cow Book”



Aka “Spark Book”

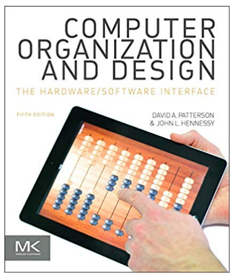


Aka “MLSys Book”

(Free PDFs available online; also check out our library)

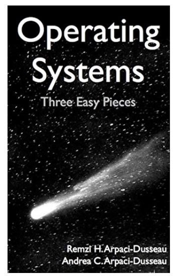
Why so many textbooks?!

1. Computer systems are about carefully layering *levels of abstraction*.

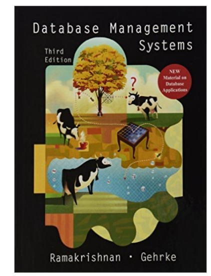


Hardware

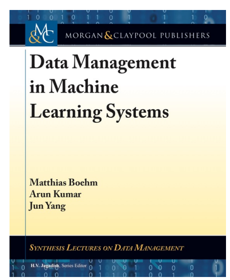
Low-level systems software

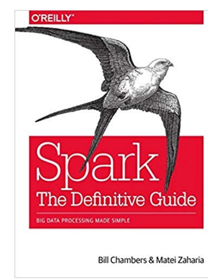


Higher-level relational dataflows



ML-oriented dataflows & lifecycle





More general scalable dataflows

2. Analytics/ML Systems is a recent/emerging area of research.
3. Also, DSC 102 is the first UG course of its kind in the world!

Tentative Course Schedule

Systems Principles

Week	Topic
1-2	Basics of Machine Resources: Computer Organization
	Basics of Machine Resources: Operating Systems
	Basics of Cloud Computing
4-5	Parallel and Scalable Data Processing: Parallelism Basics
6	**Midterm Exam on TBD**
6-7	Parallel and Scalable Data Processing: Scalable Data Access
7-8	Parallel and Scalable Data Processing: Data Parallelism
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DSC 102
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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

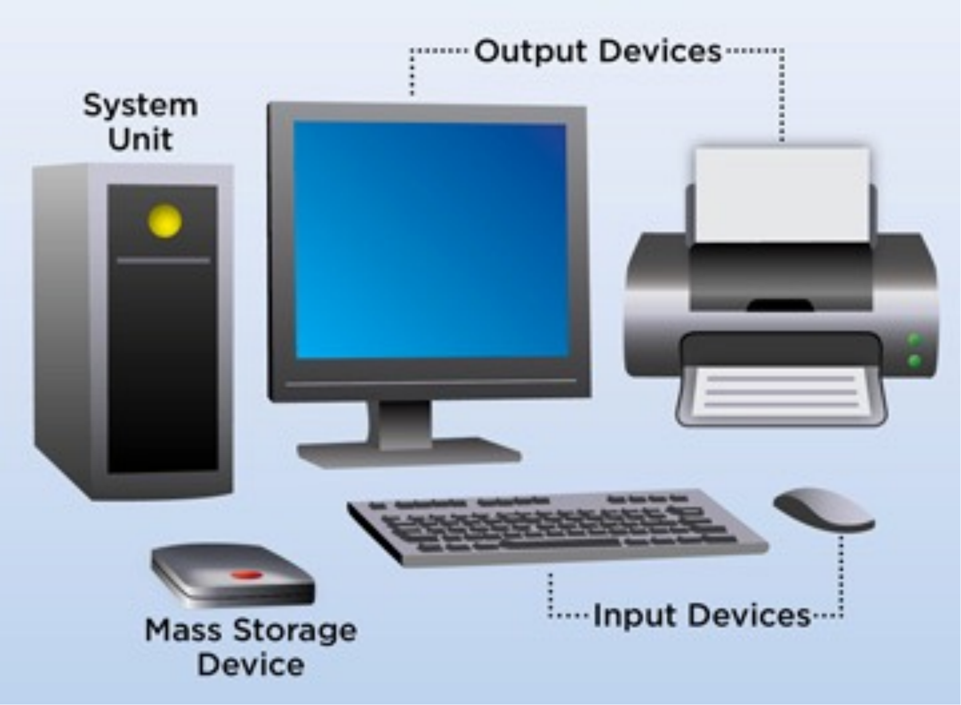
Q: *What is a computer?*

A programmable electronic device that can store, retrieve, and process digital data.

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

Parts of a Computer



Hardware:
The electronic machinery (wires, circuits, transistors, capacitors, devices, etc.)

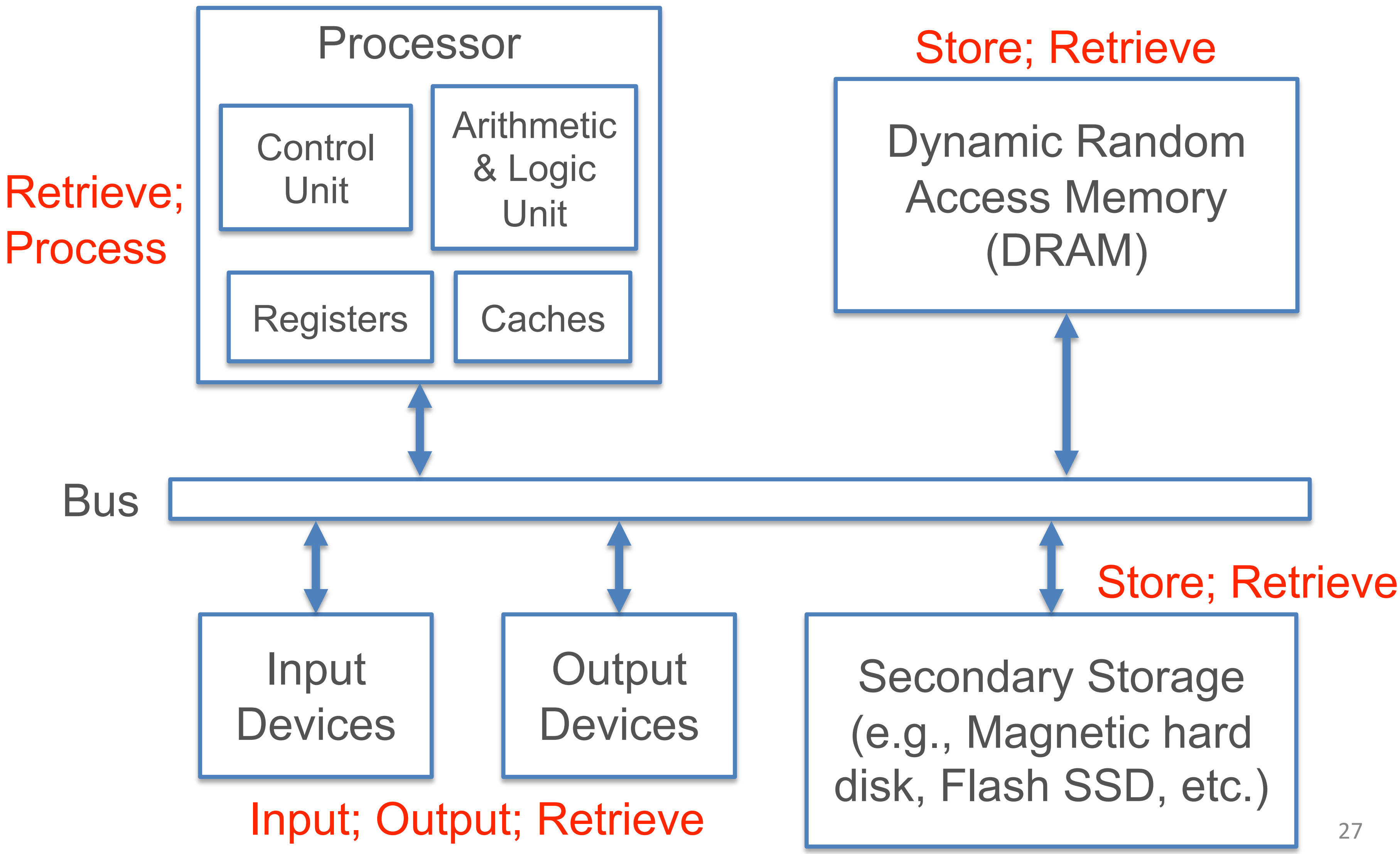
Software:
Programs (instructions) and data

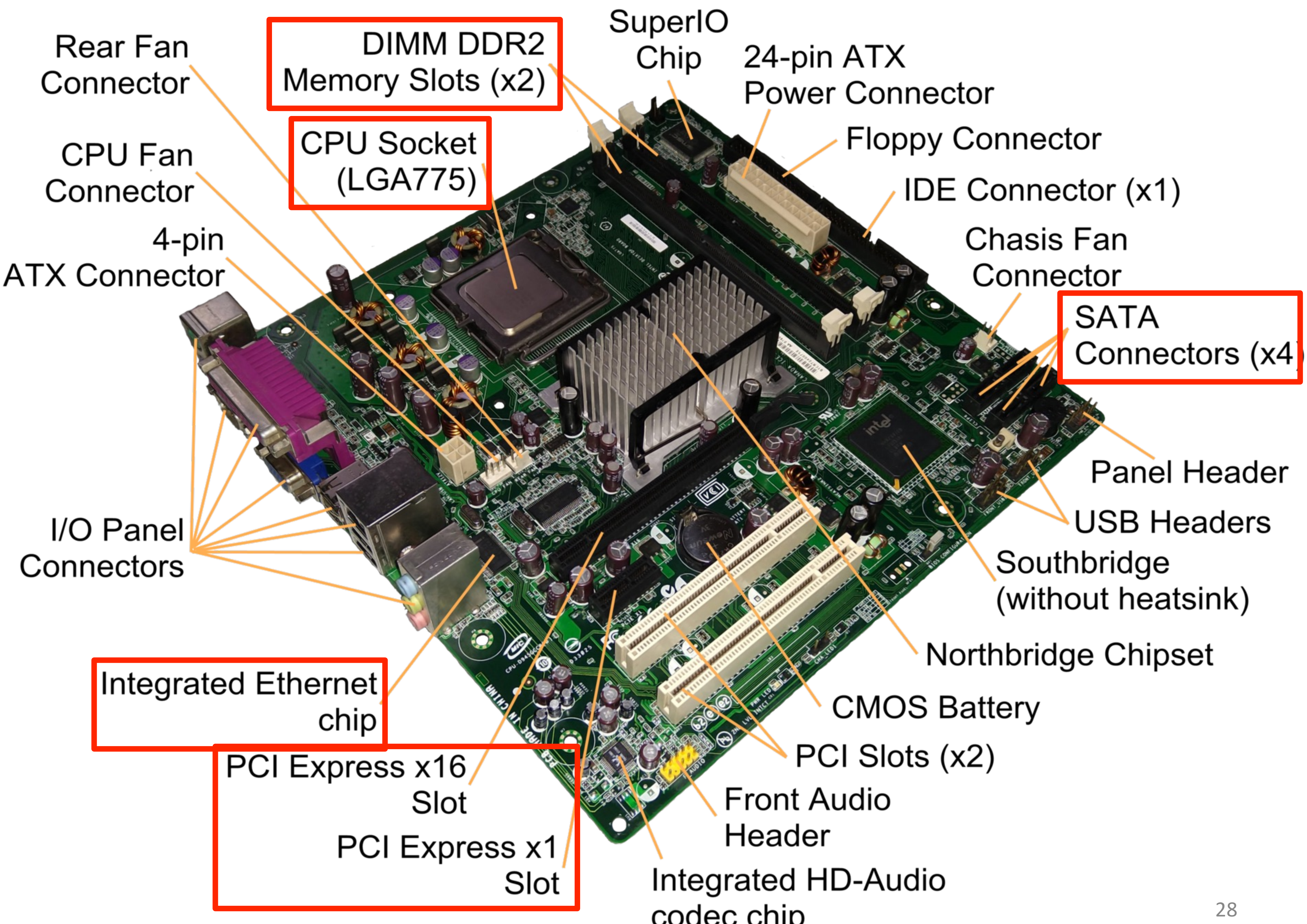
https://www.webopedia.com/TERM/C/computer.html

Key Parts of Computer Hardware

- **Processor** (CPU, GPU, etc.)
  - Hardware to orchestrate and execute *instructions* to manipulate *data* as specified by a *program*
- **Main Memory** (aka Dynamic Random Access Memory)
  - Hardware to store *data* and *programs* that allows very fast location/retrieval; byte-level *addressing* scheme
- **Disk** (aka secondary/persistent storage)
  - Similar to memory but *persistent*, *slower*, and higher capacity / cost ratio; various addressing schemes
- **Network** interface controller (NIC)
  - Hardware to send data to / retrieve data over network of interconnected computers/devices

Abstract Computer Parts and Data




Rear Fan Connector
DIMM DDR2 Memory Slots (x2)
SuperIO Chip
24-pin ATX Power Connector
CPU Socket (LGA775)
Floppy Connector
CPU Fan Connector
IDE Connector (x1)
4-pin ATX Connector
Chasis Fan Connector
SATA Connectors (x4)
Panel Header
USB Headers
I/O Panel Connectors
Southbridge (without heatsink)
Northbridge Chipset
Integrated Ethernet chip
CMOS Battery
PCI Express x16 Slot
PCI Slots (x2)
PCI Express x1 Slot
Front Audio Header
Integrated HD-Audio codec chip

Key Aspects of Software

- **Instruction**
  - A command understood by hardware; finite vocabulary for a processor: Instruction Set Architecture (ISA); bridge between hardware and software
- **Program** (aka code)
  - A collection of instructions for hardware to execute
- **Programming Language (PL)**
  - A human-readable *formal* language to write programs; at a much higher level of *abstraction* than ISA
- **Application Programming Interface (API)**
  - A set of functions (“interface”) exposed by a program/set of programs for use by humans/other programs
- **Data**
  - Digital representation of *information* that is stored, processed, displayed, retrieved, or sent by a program

Main Kinds of Software

- **Firmware**
  - Read-only programs “baked into” a device to offer basic hardware control functionalities
- **Operating System (OS)**
  - Collection of interrelated programs that work as an intermediary platform/service to enable application software to use hardware more effectively/easily
  - Examples: Linux, Windows, MacOS, etc.
- **Application Software**
  - A program or a collection of interrelated programs to manipulate data, typically designed for human use
  - Examples: Excel, Chrome, PostgreSQL, etc.

Outline

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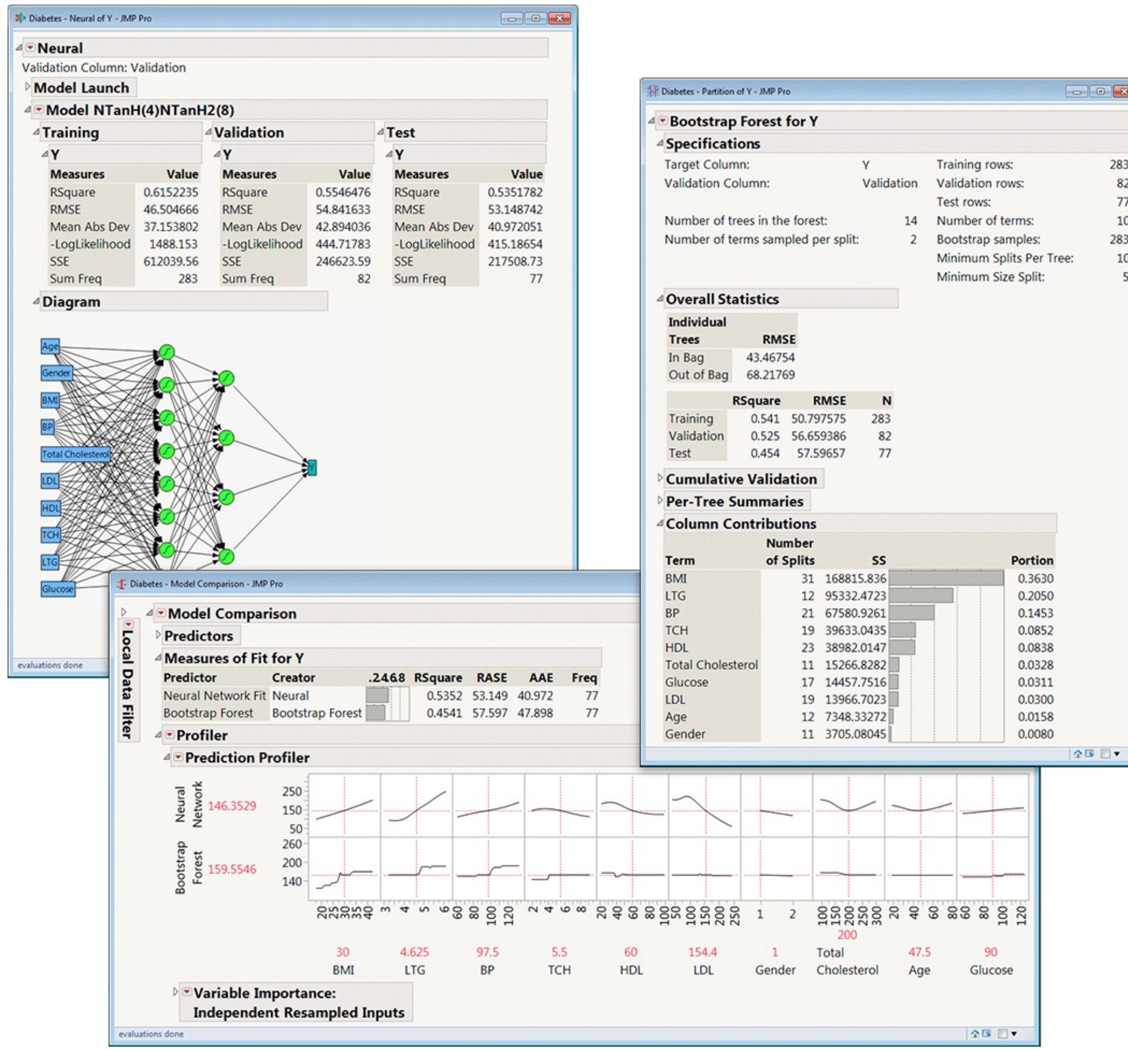
Q: *But why bother learning such low-level computer sciencey stuff in Data Science?*

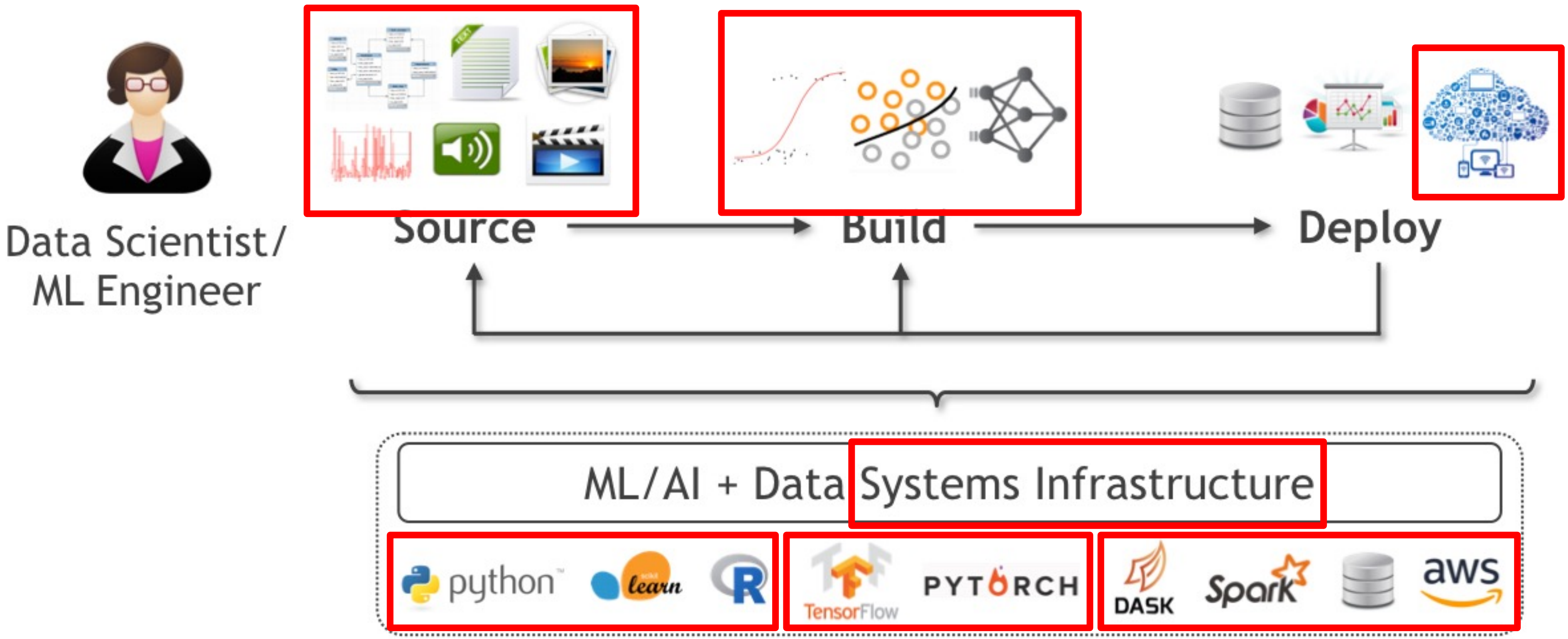
Luxury of “Statisticians”/“Analysts” of Yore

- **Methods:** Sufficed to learn just math/stats, maybe some SQL
- **Types:** Mostly tabular (relational), maybe some time series
- **Scale:** Mostly small (KBs to few GBs)
- **Tools:** Simple GUIs for both analysis and deployment; maybe an R-like console



https://www.jmp.com/en_au/offers/jmp-pro-for-academic-research.html
https://www.technologymagazine.com/data-and-data-analytics/sas-tops-worldwide-advanced-and-predictive-analytics-market-share

Reality of Today's "Data Scientists"



Data acquisition
Data preparation

Feature Engineering
Training & Inference
Model Selection

Serving
Monitoring

Why bother with these in Data Science?

- Basics of Computer Organization
  - Digital Representation of Data
  - Processors and Memory Hierarchy
- Basics of Operating Systems
  - Process Management: Virtualization; Concurrency
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You will face myriad and new data types

Compute hardware is evolving fast

You will need to use new methods on evolving data file formats on clusters / cloud

Storage hardware is evolving fast

glassdoor

statistician | Location

Statistician Salaries

United States

Overview | **Salaries** | Interviews | Insights | Career Path

How much does a Statistician make?

Updated Jan 4, 2022

Industry: All industries

Employer Size: All company sizes

Experience: All years of Experience

Very High Confidence

$88,989 /yr

Average Base Pay

2,398 salaries

glassdoor

data scientist | Location

Data Scientist Salaries
United States

Overview | **Salaries** | Interviews | Insights | Career Path

How much does a Data Scientist make?

Updated Jan 4, 2022

Industry: All industries
Employer Size: All company sizes
Experience: All years of Experience

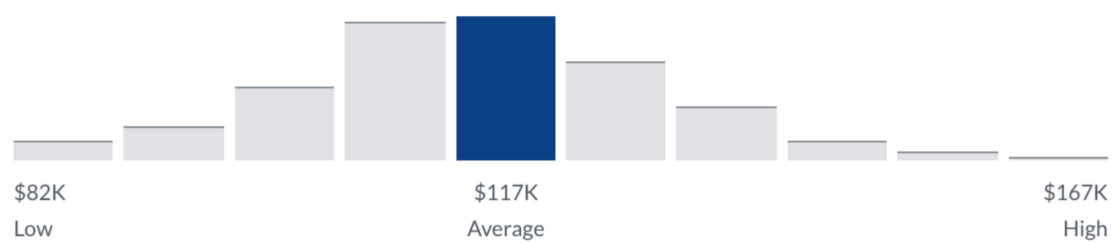
To filter salaries for Data Scientist, **Sign In** or **Register**.

Very High Confidence

$117,212 /yr

Average Base Pay

18,354 salaries



— 88,989

= 28,223!

Outline

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

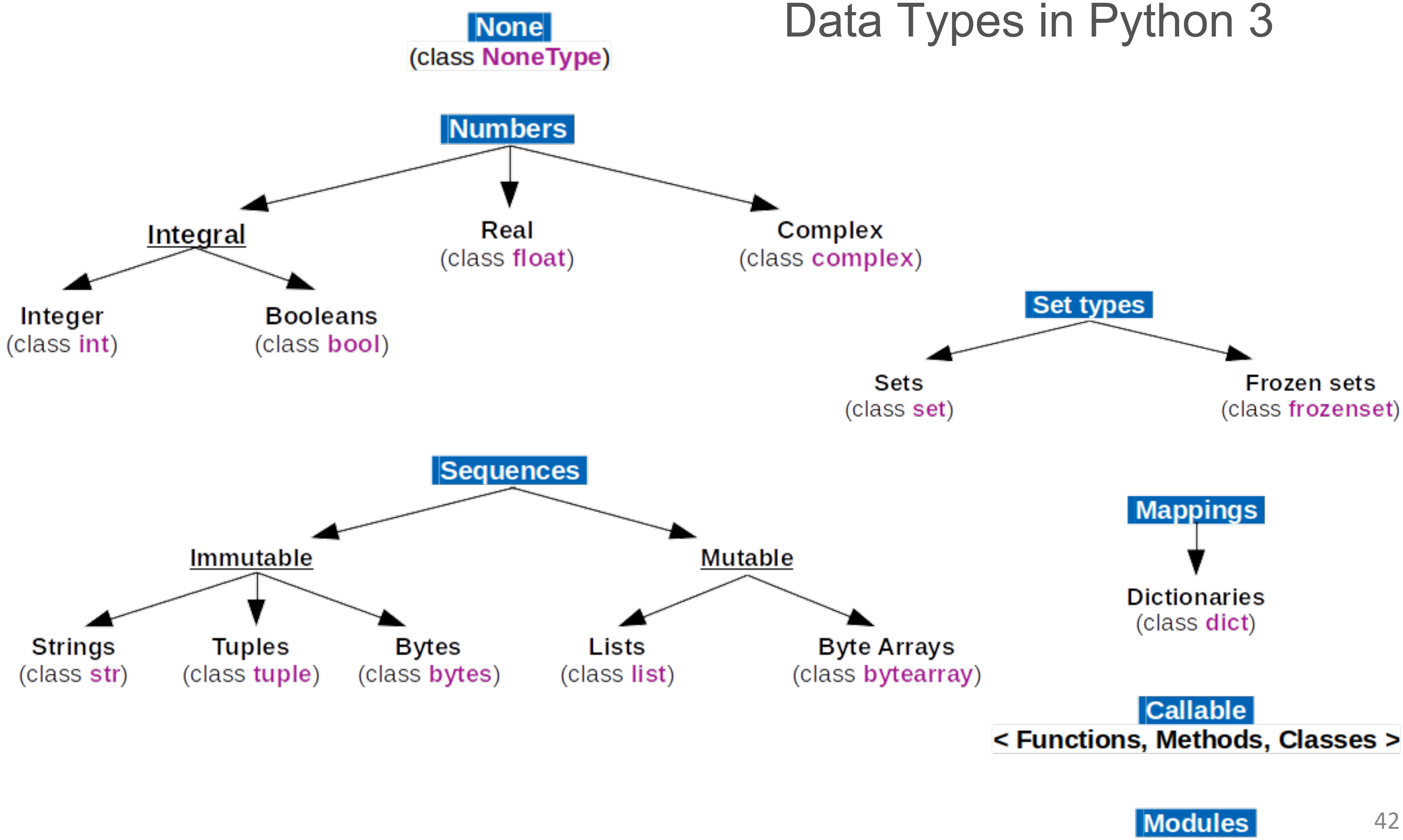
Q: *What is data?*

Digital Representation of Data

- **Bits:** All digital data are sequences of 0 & 1 (binary digits)
  - Amenable to high-low/off-on electromagnetism
  - Layers of *abstraction* to interpret bit sequences
- **Data type:** First layer of abstraction to interpret a bit sequence with a human-understandable category of information; interpretation fixed by the PL
  - Example common datatypes: Boolean, Byte, Integer, "floating point" number (Float), Character, and String
- **Data structure:** A second layer of abstraction to *organize* multiple instances of same or varied data types as a more complex object with specified properties
  - Examples: Array, Linked list, Tuple, Graph, etc.

Digital Representation of Data

Data Types in Python 3



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! (***Q:*** *Why?*)
- **Integer**:
  - Examples in data science: #friends, age, #likes
  - 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!)

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); recall kibibyte (KiB) vs kilobyte (KB) and so on

***Q:** How many bits are needed to distinguish 97 data 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
- 97 ->128 = 2^7; so, 7 bits

Digital Representation of Data

Q: *How to convert from decimal to binary representation?*

1. Given decimal n, if power of 2 (say, 2^k), put 1 at bit position k; if k=0, stop; else pad with trailing 0s till position 0
2. 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
3. Reset n as n - 2^k; return to Steps 1-2
4. 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	

Q: *Binary to decimal?*

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})
  - From binary: combine 4 bits at a time from lowest

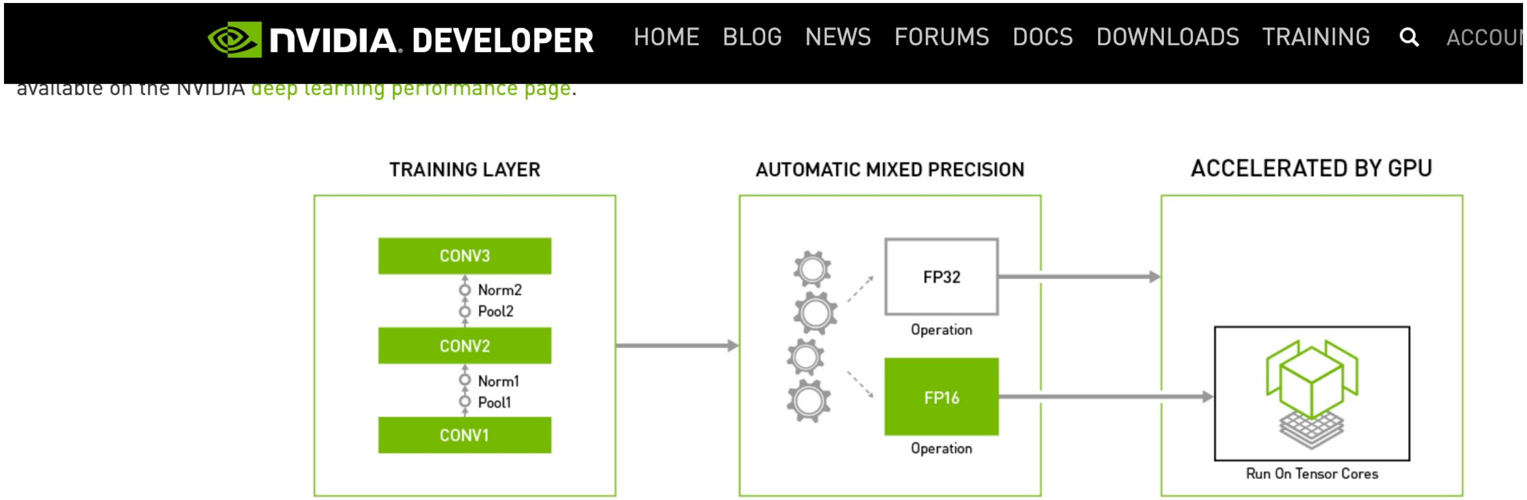
Decimal	Binary	Hexadecimal
5_{10}	101_2	5_{16}
47_{10}	$10\ 1111_2$	$2\,F_{16}$
163_{10}	$1010\ 0011_2$	$A\,3_{16}$
16_{10}	$1\ 0000_2$	$1\,0_{16}$

Alternative notations

0xA3 or $A3_H$

Digital Representation of Data

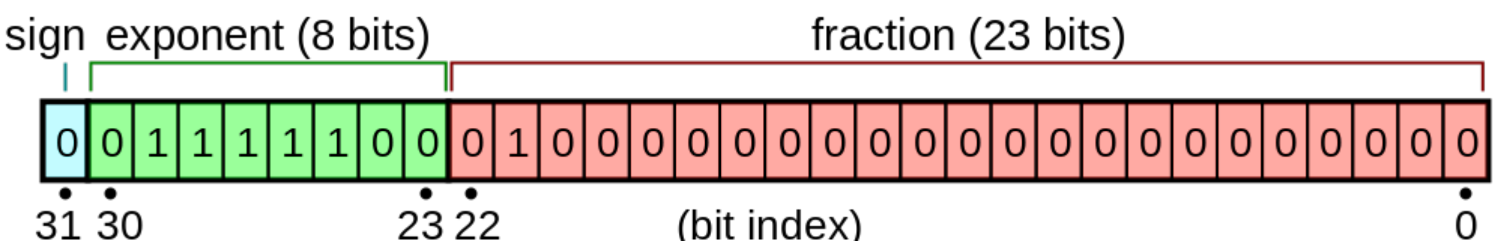
- **Float**:
  - Examples in data sci.: salary, scores, model weights
  - IEEE-754 single-precision format is 4B long; double-precision format is 8B long
  - Java and C *float* is single; Python *float* is double!



Using Automatic Mixed Precision for Major Deep Learning Frameworks

Digital Representation of Data

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



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

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

(**NB:** Converting decimal reals/fractions to float is NOT in syllabus!)

Digital Representation of Data

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

```
(base) arun@Aruns-MacBook-Pro:~$ python
Python 3.7.1 (default, Dec 14 2018, 13:28:58)
[Clang 4.0.1 (tags/RELEASE_401/final)] :: 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”
  - Max is ~ 3.4×10^{38}; min +ve is ~ 1.4×10^{-45}

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