Big Data Computing

Master's Degree in Computer Science

2021-2022

SAPIENZA
UNIVERSITÀ DI ROMA

Gabriele Tolomei

Department of Computer Science

Sapienza Università di Roma

tolomei@di.uniroma1.it

Who Am I?

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UniPI
(1999-2005)

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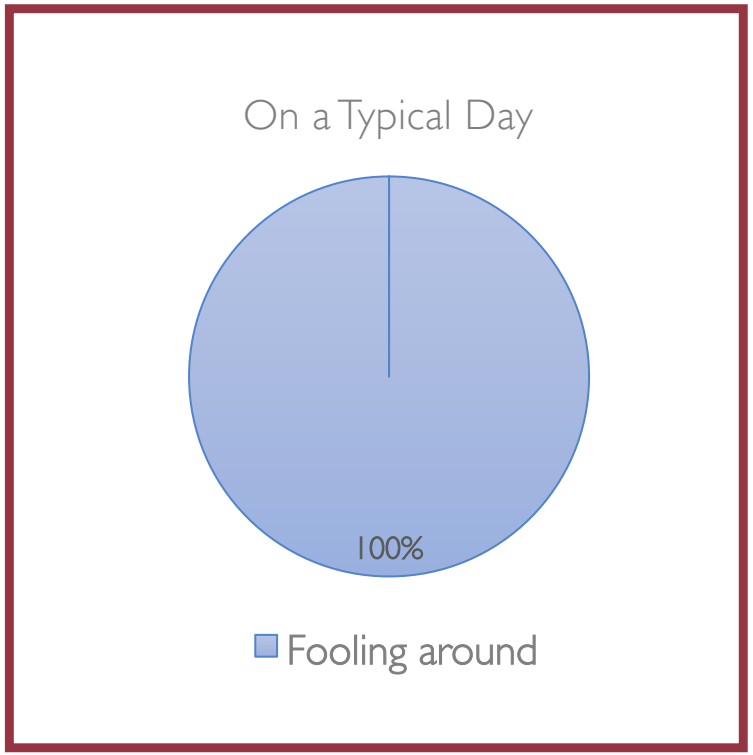

Expectation

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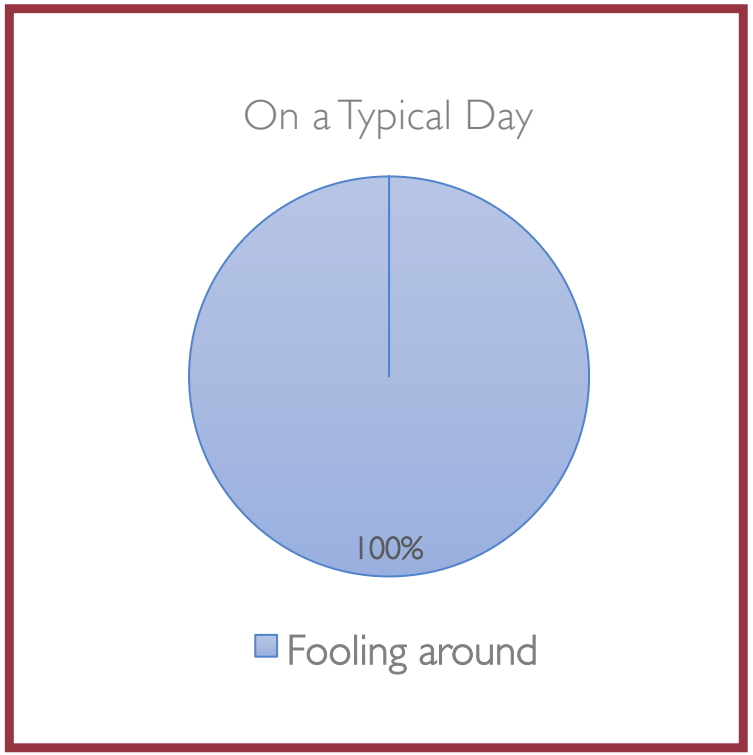

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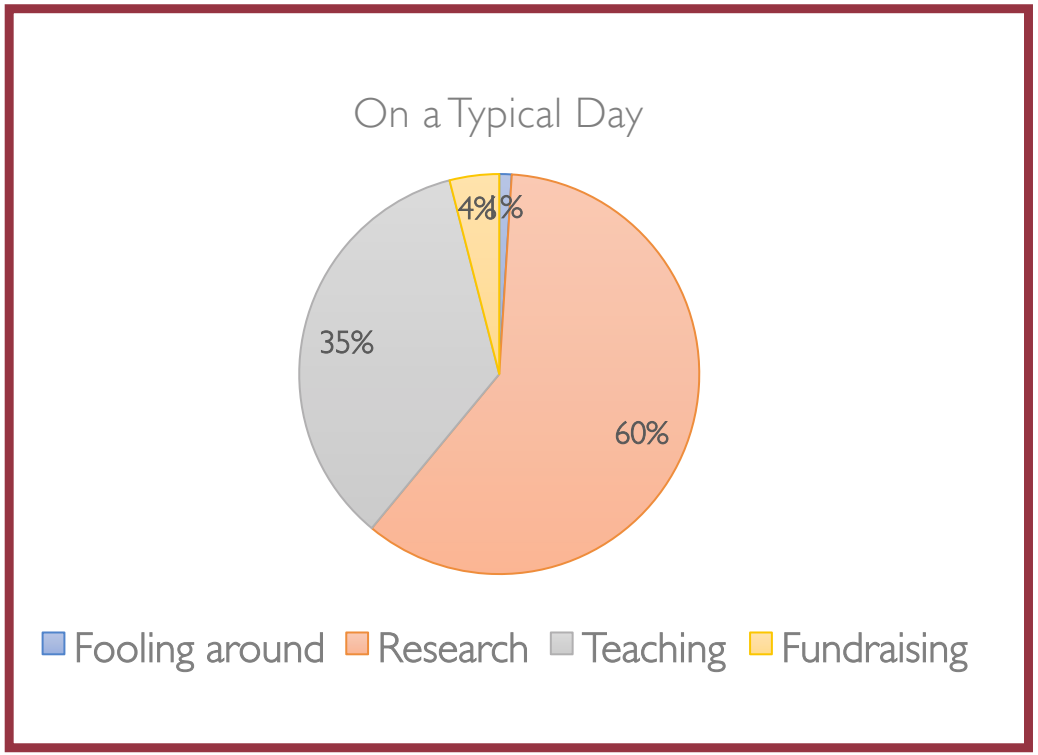
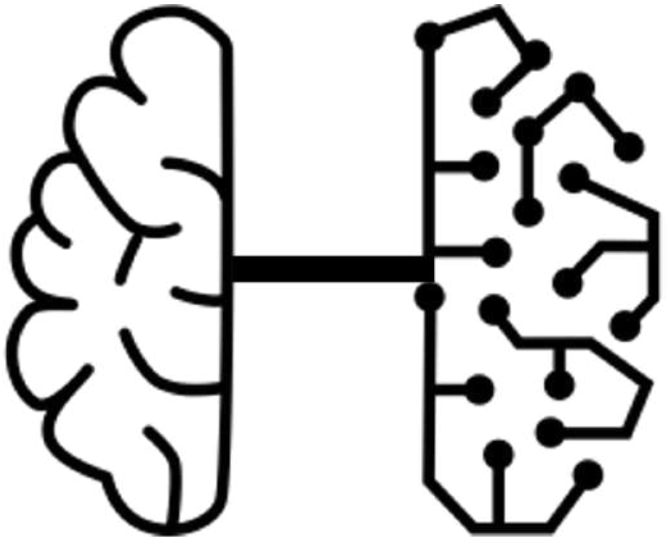
vs.



Reality

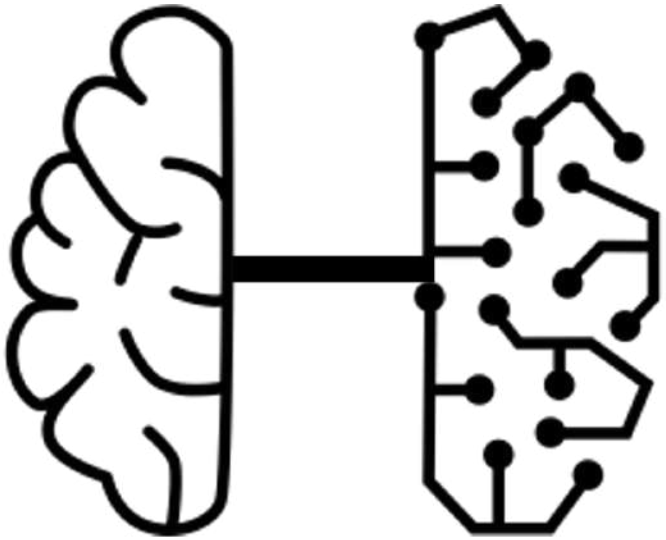
Research On What?



HERCOLE Lab

Research On What?

Human-Explainable



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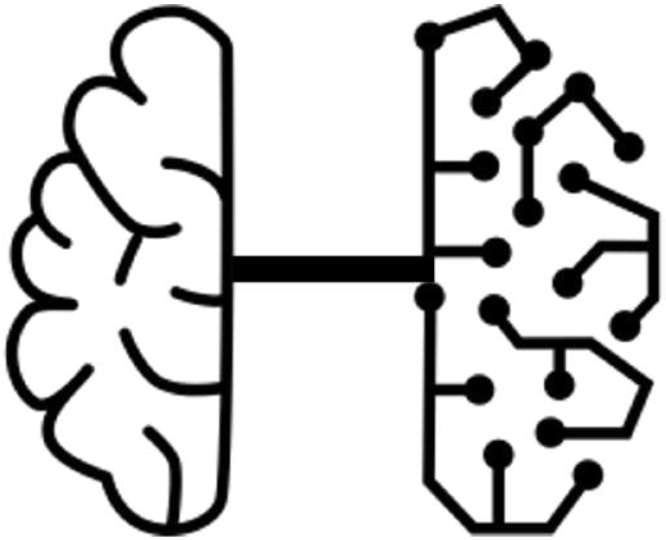

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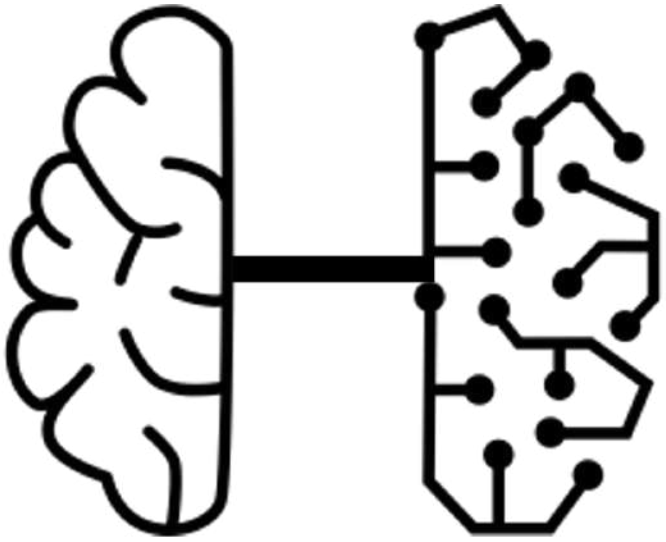

COllaborative

HERCOLE Lab

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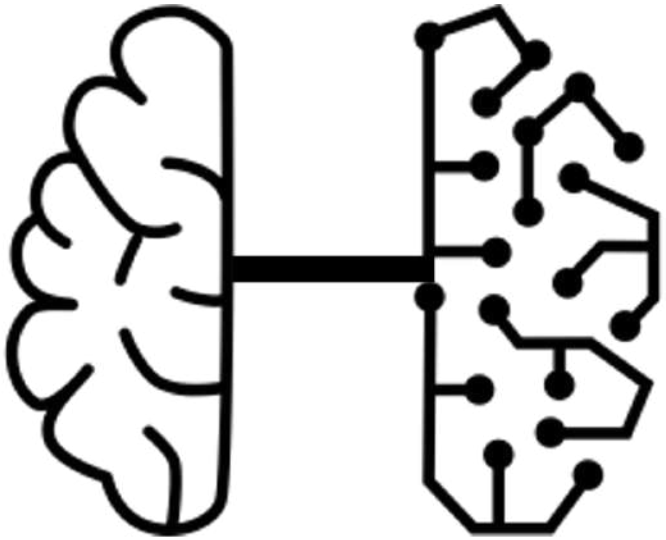

COllaborative

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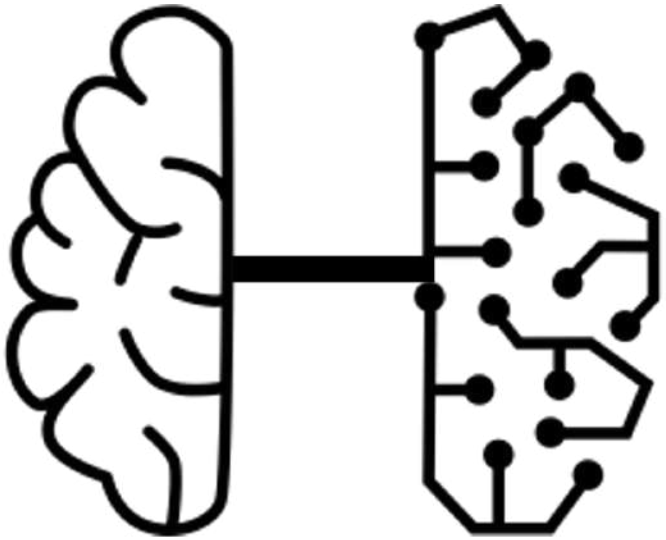
LEarning

Research On What?

Sounds cool?



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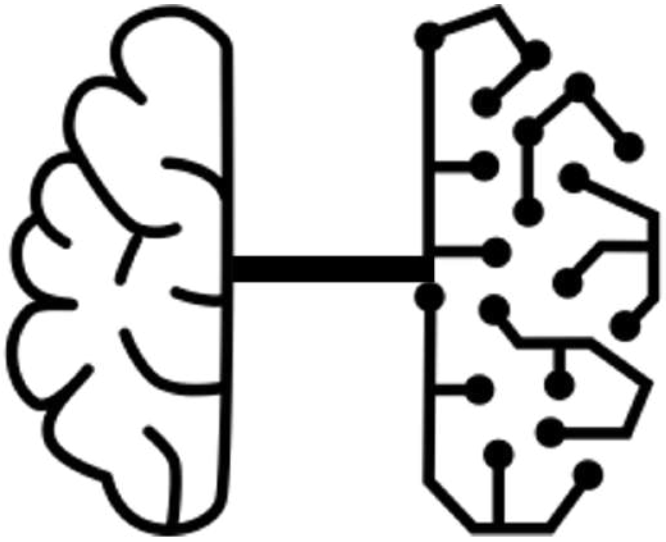

HERCOLE Lab

Check out the lab's

[home page]

(still under construction, sic!)

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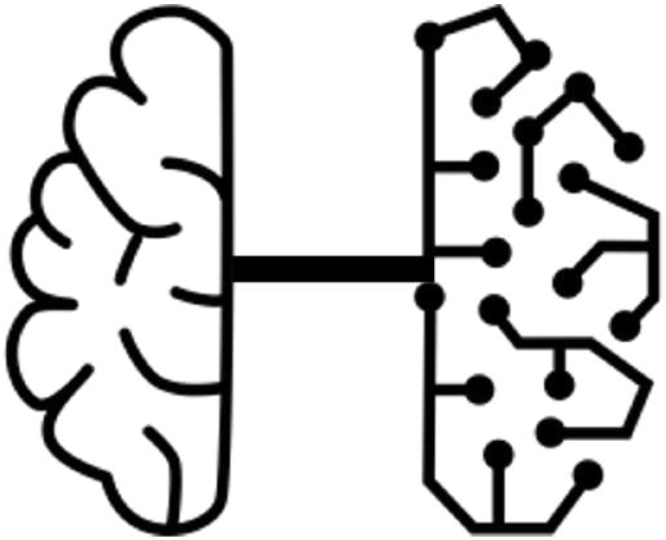

HERCOLE Lab

Meanwhile you can follow us on Twitter @HercoleLab

Administrivia

- Class schedule:
  - Tuesday from 5:00 p.m. to 7:00 p.m.
  - Wednesday from 8:00 a.m. to 11:00 a.m.

Room 1L @ Via del Castro Laurenziano, 7a

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- Office hours:
  - Drop me a message to ask for a meeting online (Google Meet or Zoom) or in-person at my office (Room 106 @ Viale Regina Elena, 295 – 1st Floor, Building E)

Administrivia

- Contacts:
  - Personal homepage: https://www.di.uniroma1.it/~tolomei
  - Email: tolomei@di.uniroma1.it

Administrivia

- Resources:
  - Course's website: https://github.com/gtolomei/big-data-computing
  - Moodle's web page: https://elearning.uniroma1.it/course/view.php?id=14454

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- Moodle will be used to send out communications via the built-in "News" forum

Please, remember to enroll using the Moodle link above!

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  - Familiarity with basics of Data Science and Machine Learning
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No worries!
Many subjects will be anyway revisited during class lectures

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  - Other questions on all the topics covered in classes may be asked

Questions?

Outline of the Course

Big Data Phenomenon

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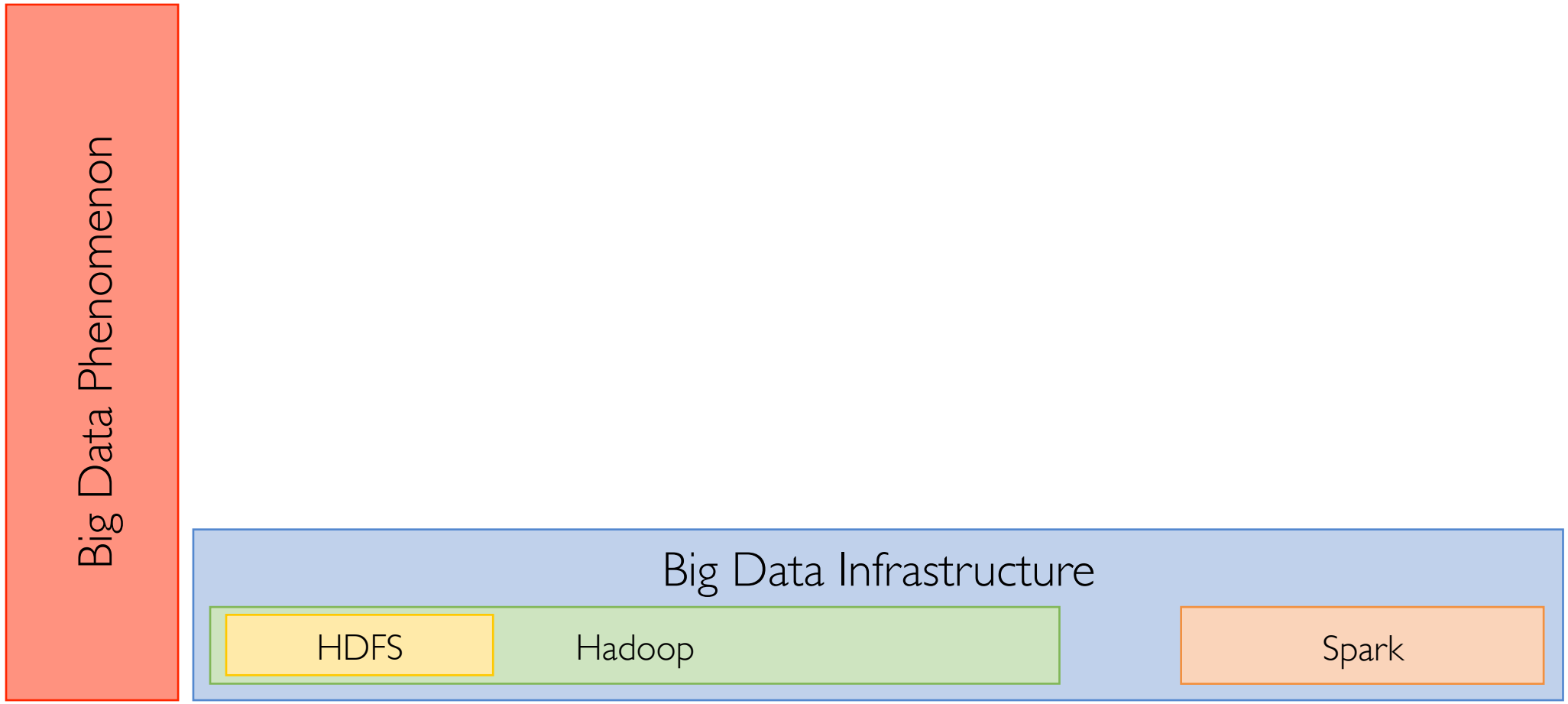

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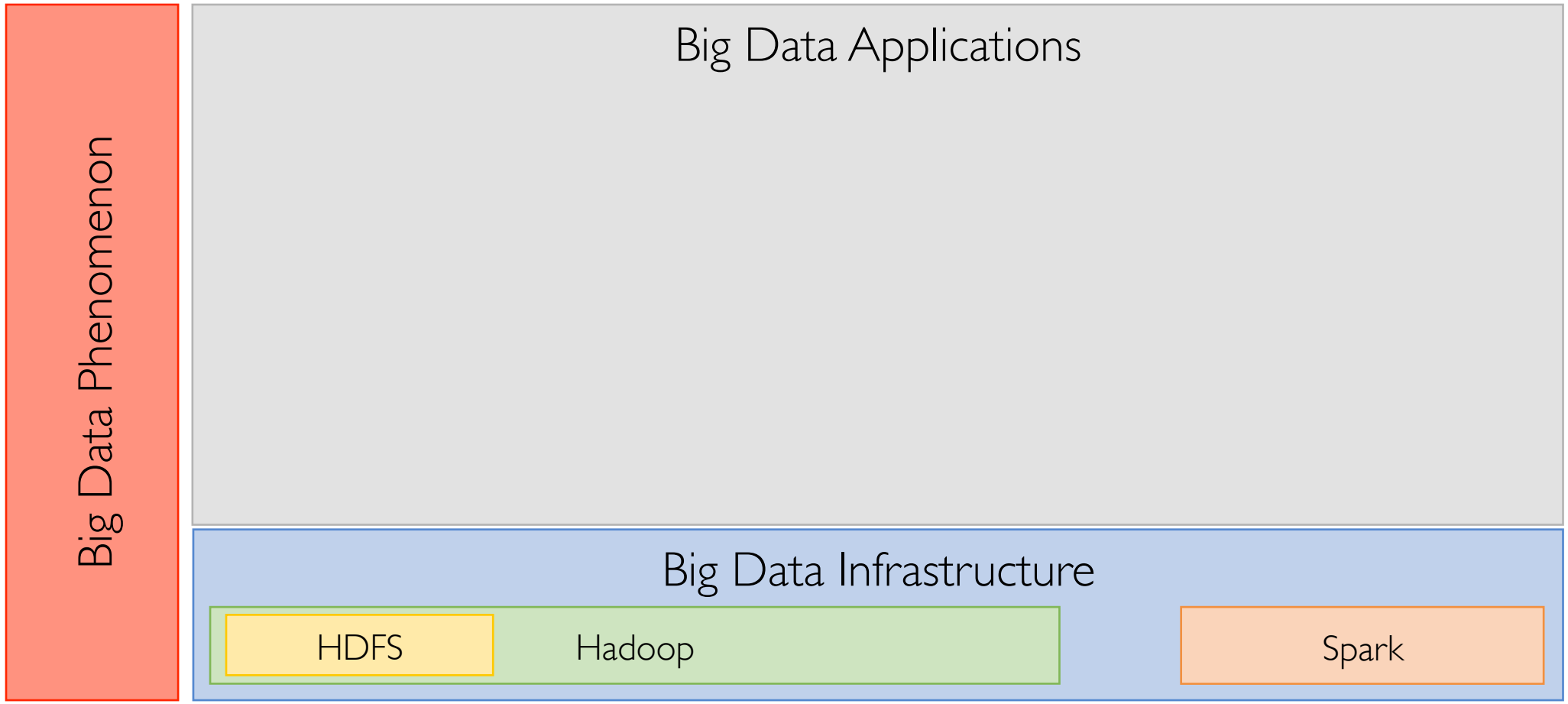

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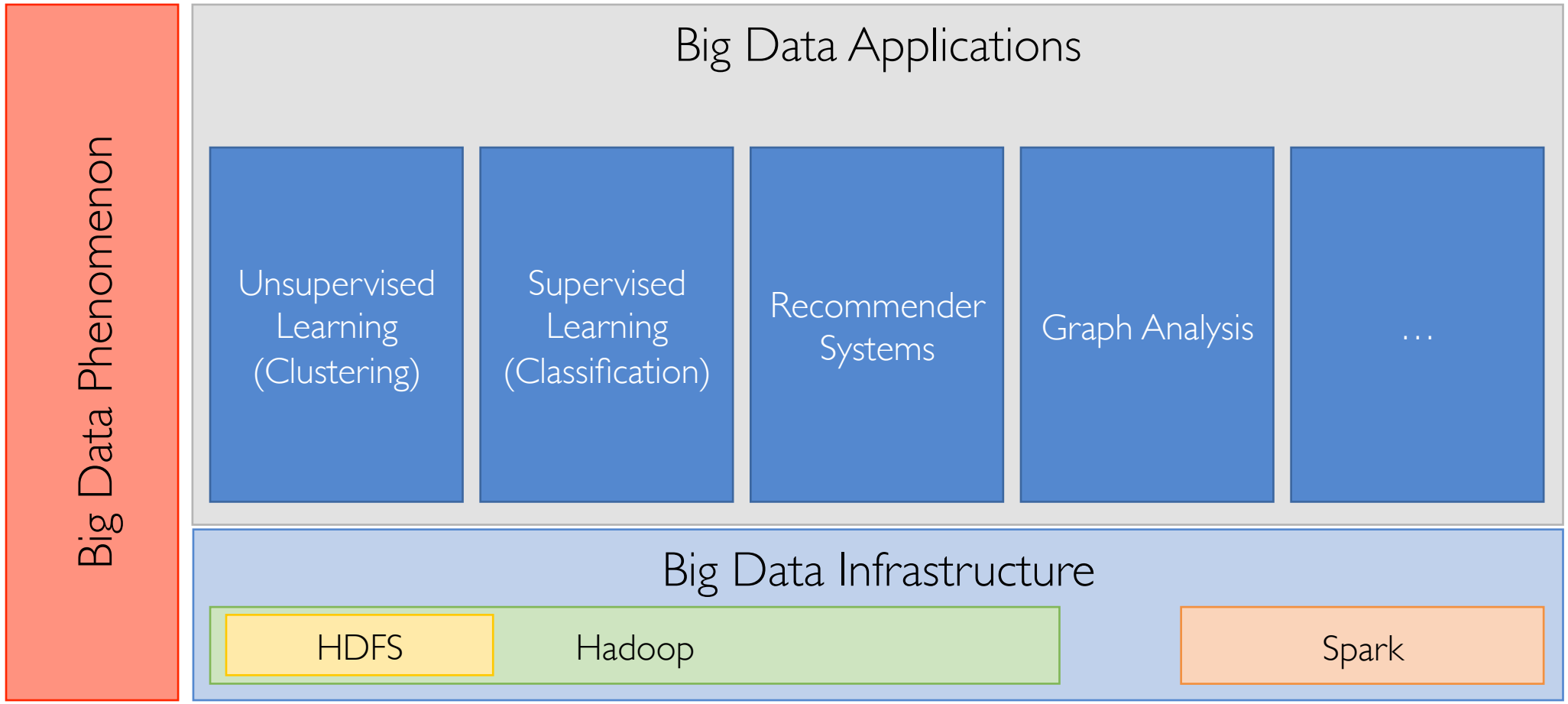

Let's Get Started!

What the He…ck is That?

source: Wikipedia

The Apollo Guidance Computer (AGC)

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A few numbers:

- ~2 MHz CPU clock frequency
- 16-bit architecture
- 3,840 bytes of main memory (RAM)
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All the running software was written in AGC assembly language, now also available on GitHub

More than 50 Years Have Passed…

… And The World Has Changed

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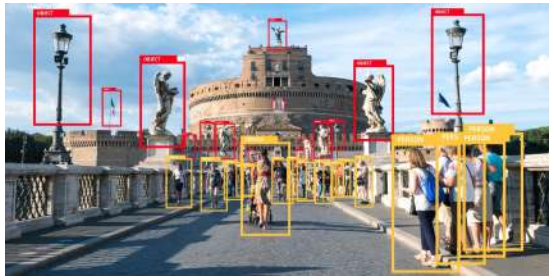

AGC vs. Our Smartphone

- Most recent smartphones have
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~3 orders of magnitude faster (~1,000x)

~6÷7 orders of magnitude larger RAM and internal storage (up to 10,000,000x)

A Side Note on Units

Prefixes for multiples of bits (bit) or bytes (B)

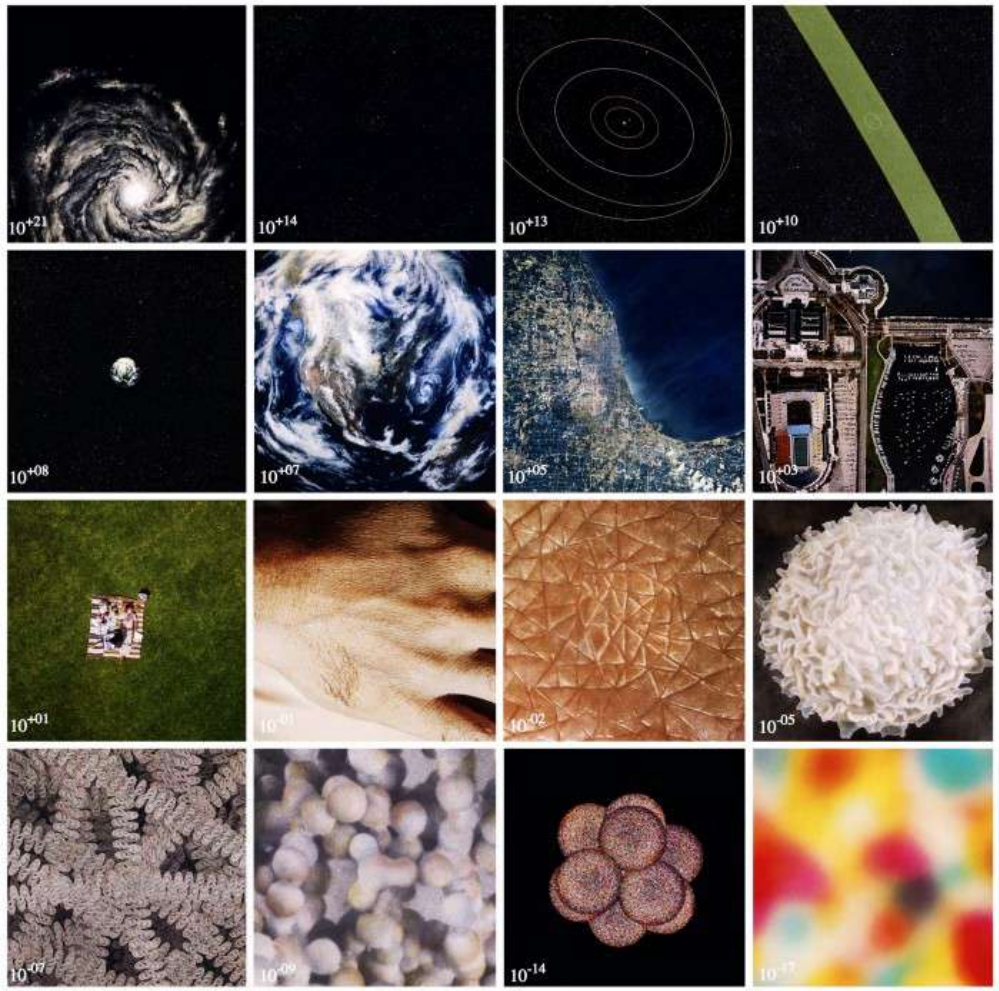
Decimal				Binary				
Value		SI		Value		IEC		JEDEC
1000	10^3	k	kilo	1024	2^{10}	Ki	kibi	K kilo
1000^2	10^6	M	mega	1024^2	2^{20}	Mi	mebi	M mega
1000^3	10^9	G	giga	1024^3	2^{30}	Gi	gibi	G giga
1000^4	10^{12}	T	tera	1024^4	2^{40}	Ti	tebi	–
1000^5	10^{15}	P	peta	1024^5	2^{50}	Pi	pebi	–
1000^6	10^{18}	E	exa	1024^6	2^{60}	Ei	exbi	–
1000^7	10^{21}	Z	zetta	1024^7	2^{70}	Zi	zebi	–
1000^8	10^{24}	Y	yotta	1024^8	2^{80}	Yi	yobi	–

Orders of Magnitude

source: https://www.youtube.com/watch?v=Ww4gYNrOkkg

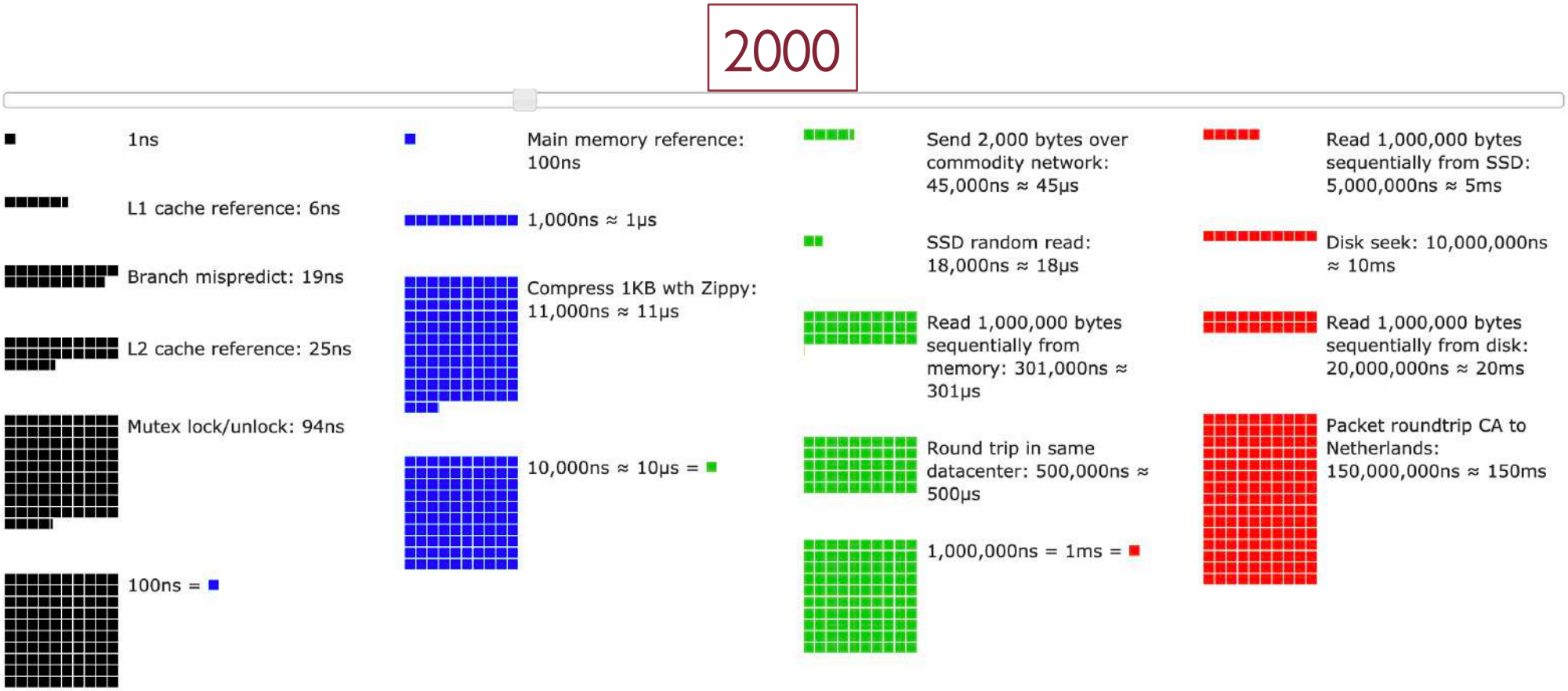
$10^0 = 1$

Orders of Magnitude



Numbers Every Computer Scientist Should Know

Colin Scott's updated and interactive version of Jeff Dean's previous one



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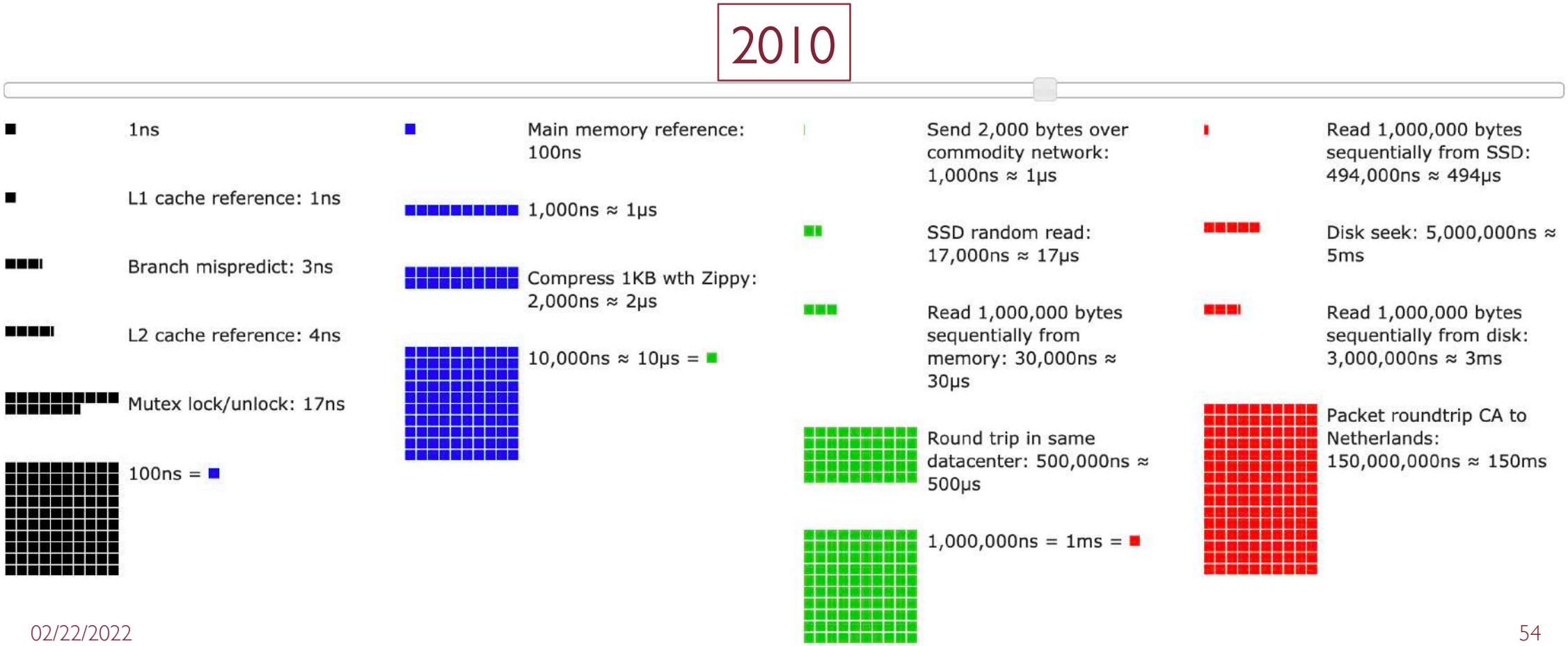

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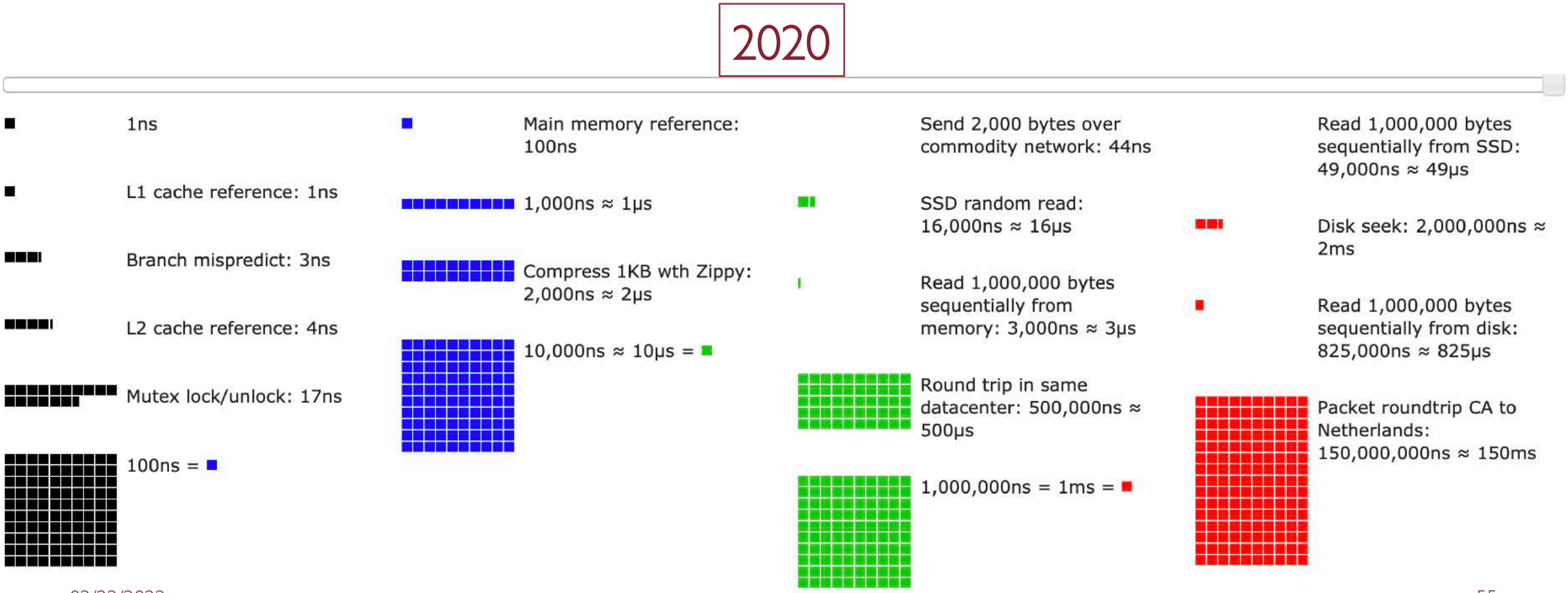

The Information Technology (IT) Revolution

- Started almost 60 years ago and still rocketing
- Driven by:
  - Science/Engineering
  - Business
  - Society

What Happens on the Internet in 1 Minute?

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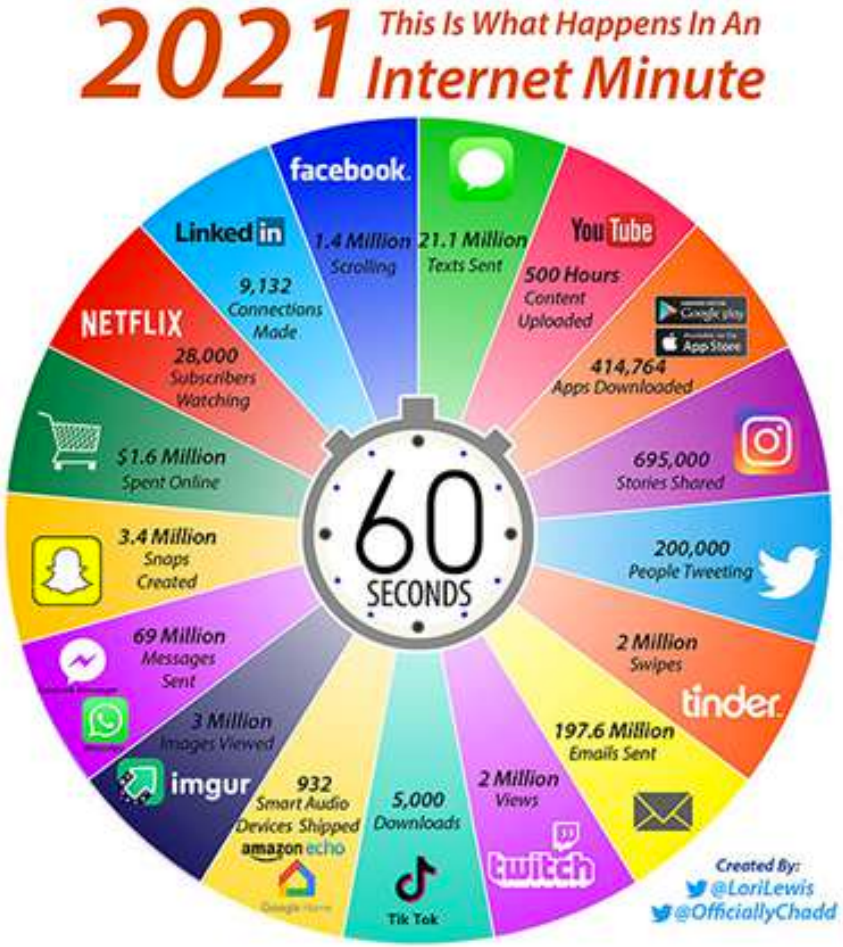
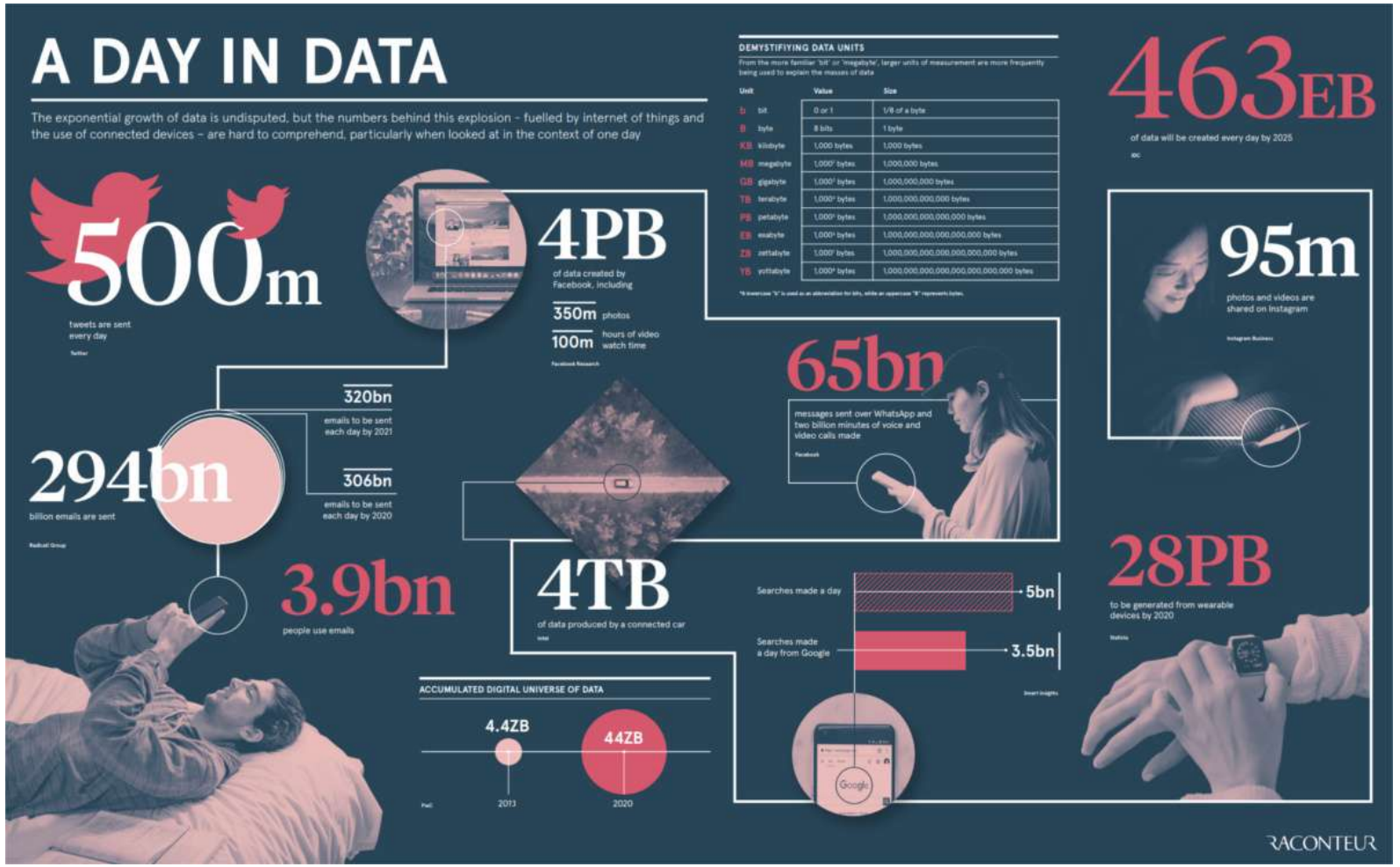


How Much Data is Generated Each Day?



https://www.visualcapitalist.com/how-much-data-is-generated-each-day/

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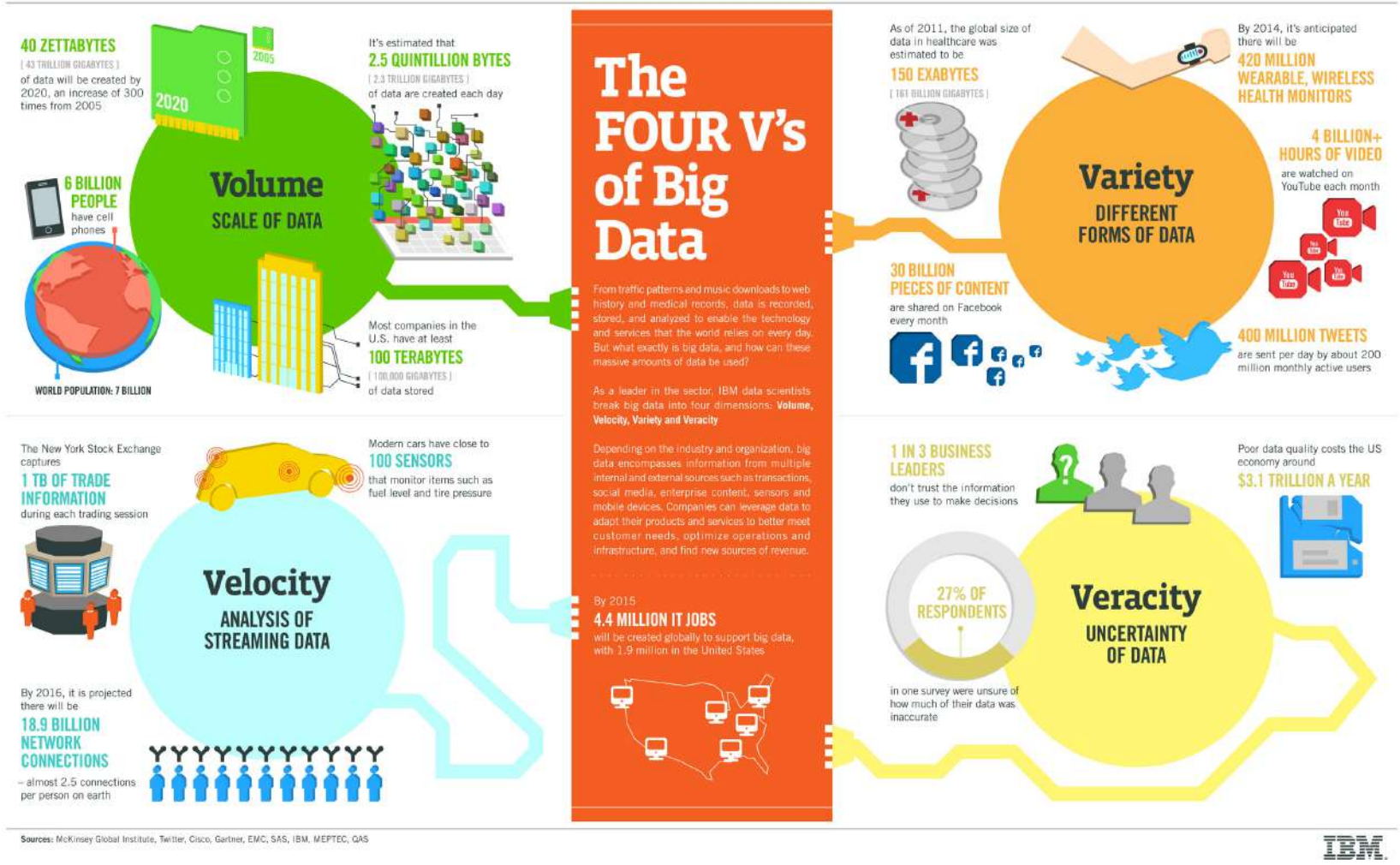
  - Veracity → reliability of the data used to drive decision processes

The 4 V's of Big Data



https://www.ibmbigdatahub.com/infographic/four-vs-big-data

The Value of Big Data

- Extracting knowledge from data is incredibly valuable
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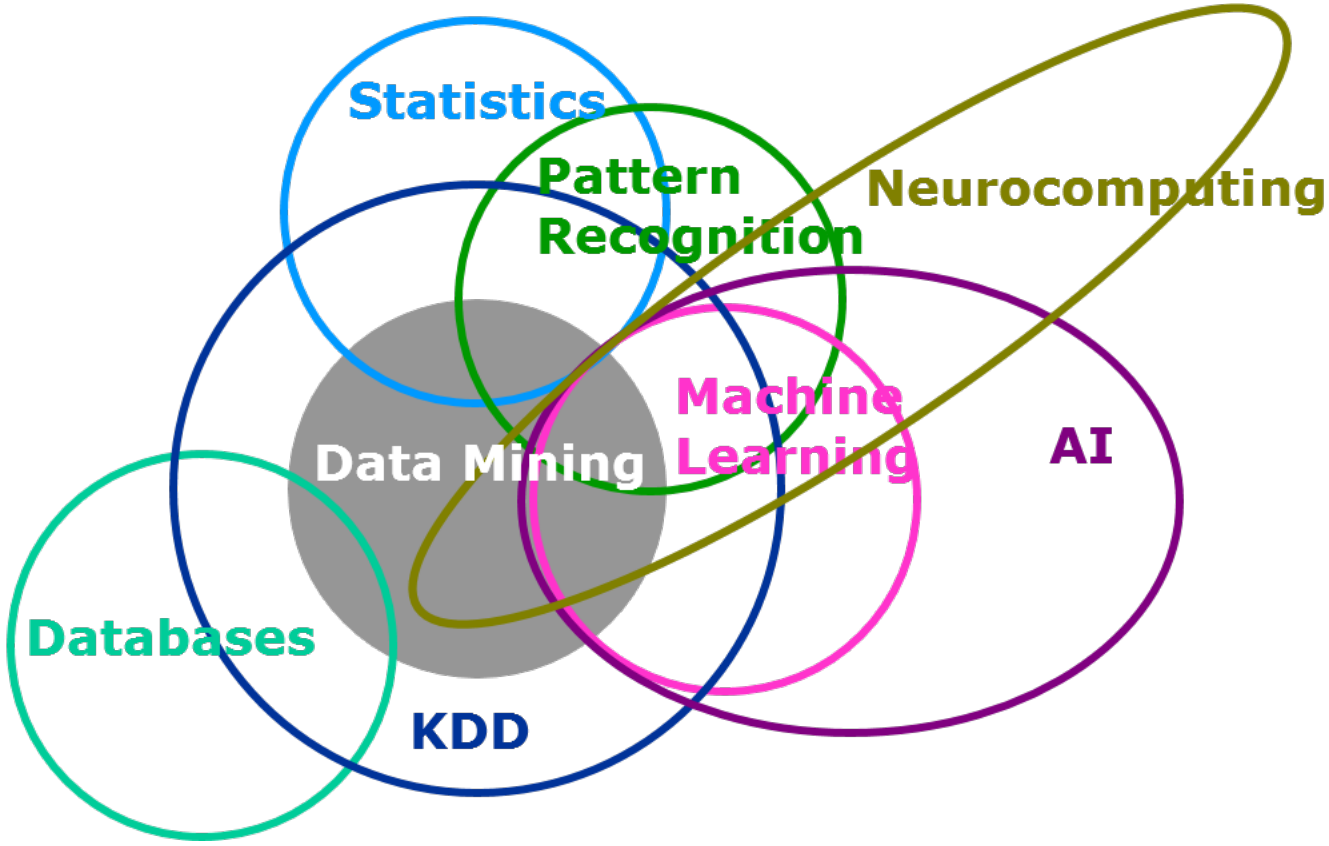
  - 5 out of 6 of the biggest companies in the world are "data companies"
- To get the most value out of it, data has to be:
  - Stored
  - Managed
  - Analyzed

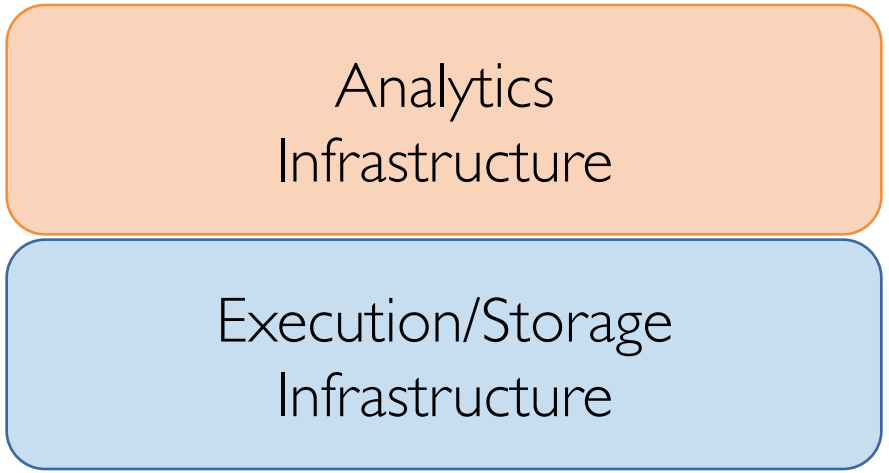
Big Data Analysis: Landscape



Big Data Analysis Stack

Execution/Storage
Infrastructure

Big Data Analysis Stack



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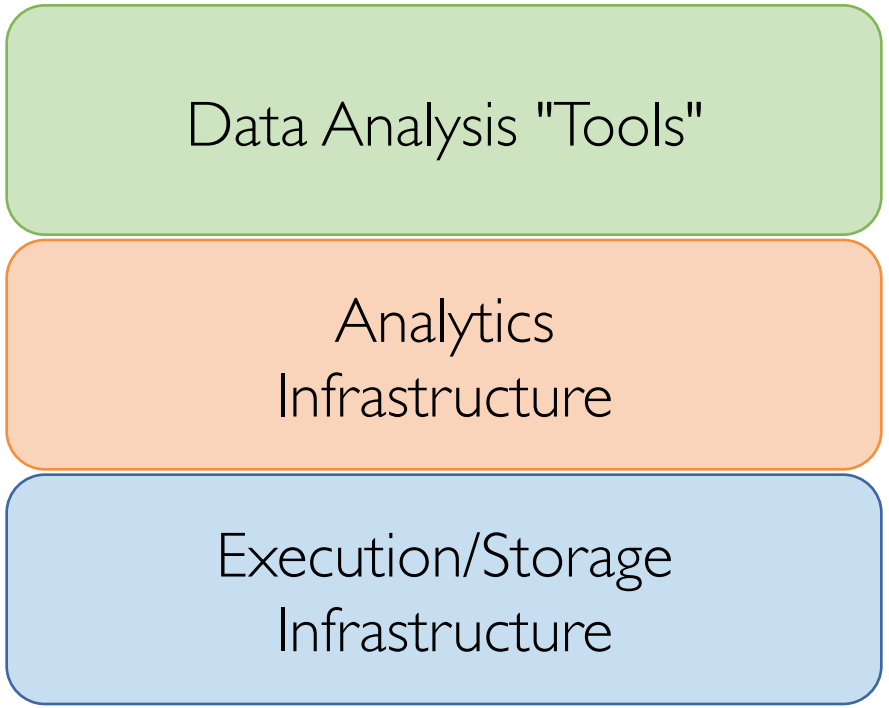

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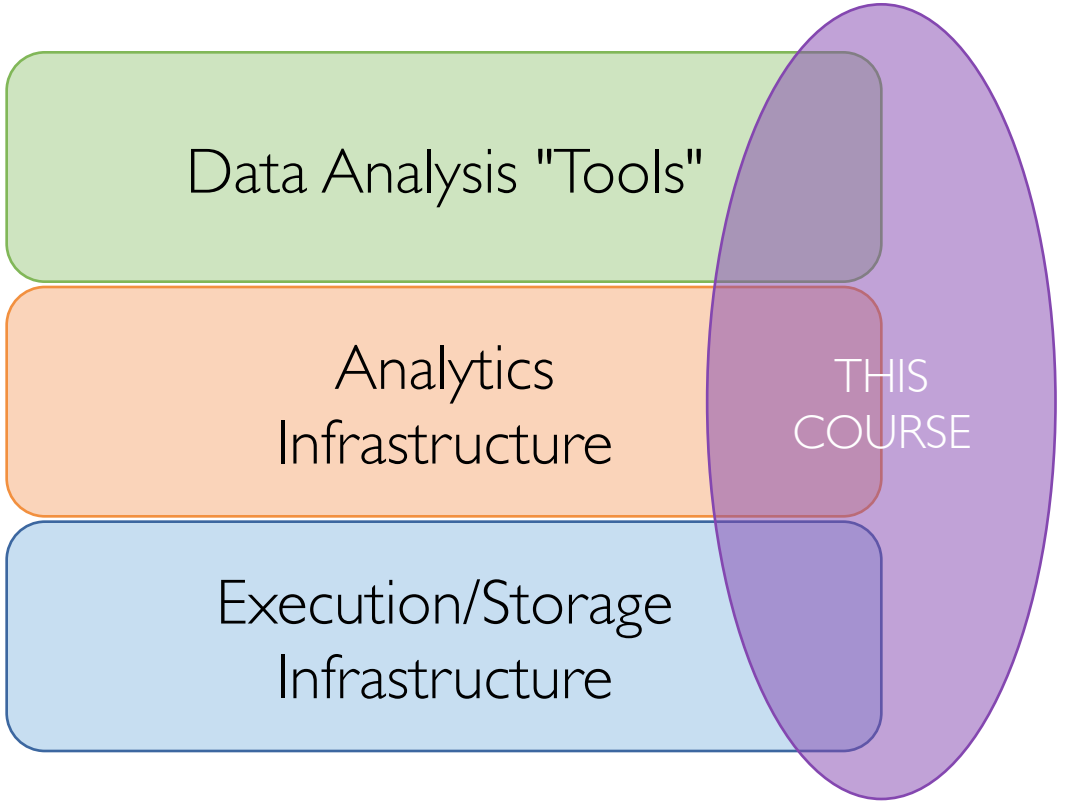


What Will We Learn?

- To extract knowledge from different types of data
  - High-dimensional
  - Unlabeled/Labeled
  - Graph-based
  - Infinite/never-ending streams

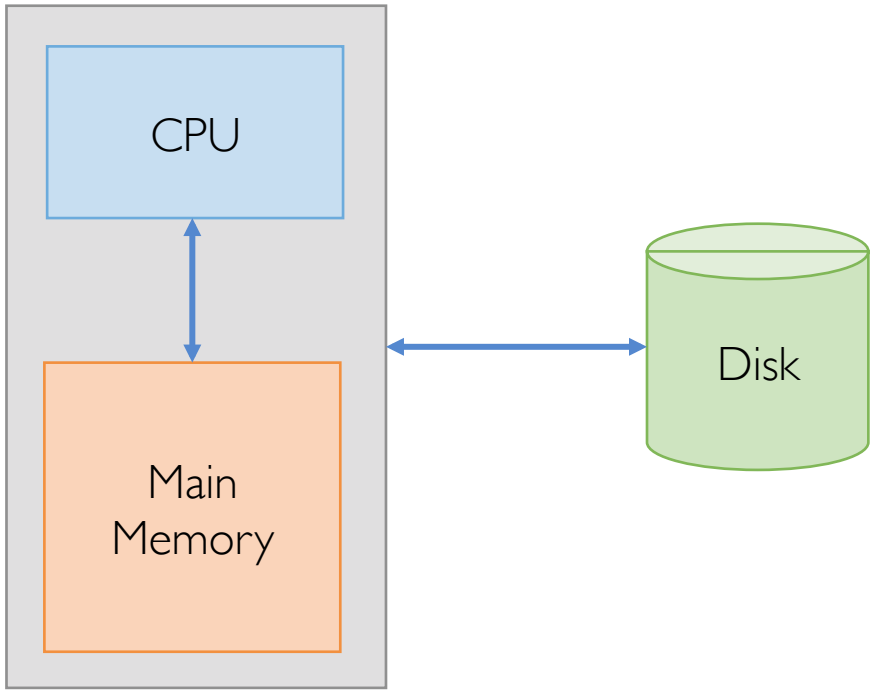
What Will We Learn?

- To use different models of computation
  - MapReduce
  - Streams and online algorithms
  - Single machine in-memory

What Will We Learn?

- To apply big data analysis to actually solve real-world problems
  - Clustering
  - Predictive Analysis
  - Recommender Systems
  - Graph Analysis
  - Stream Processing
  - …

The Single-Node Architecture



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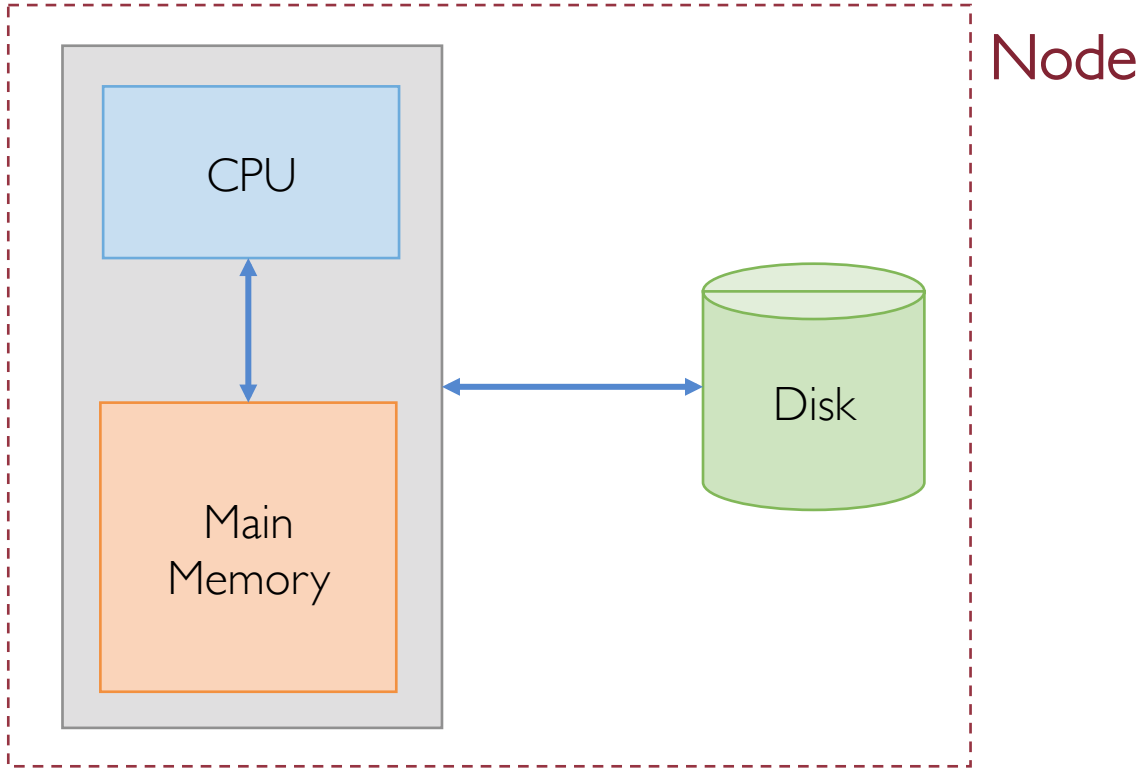
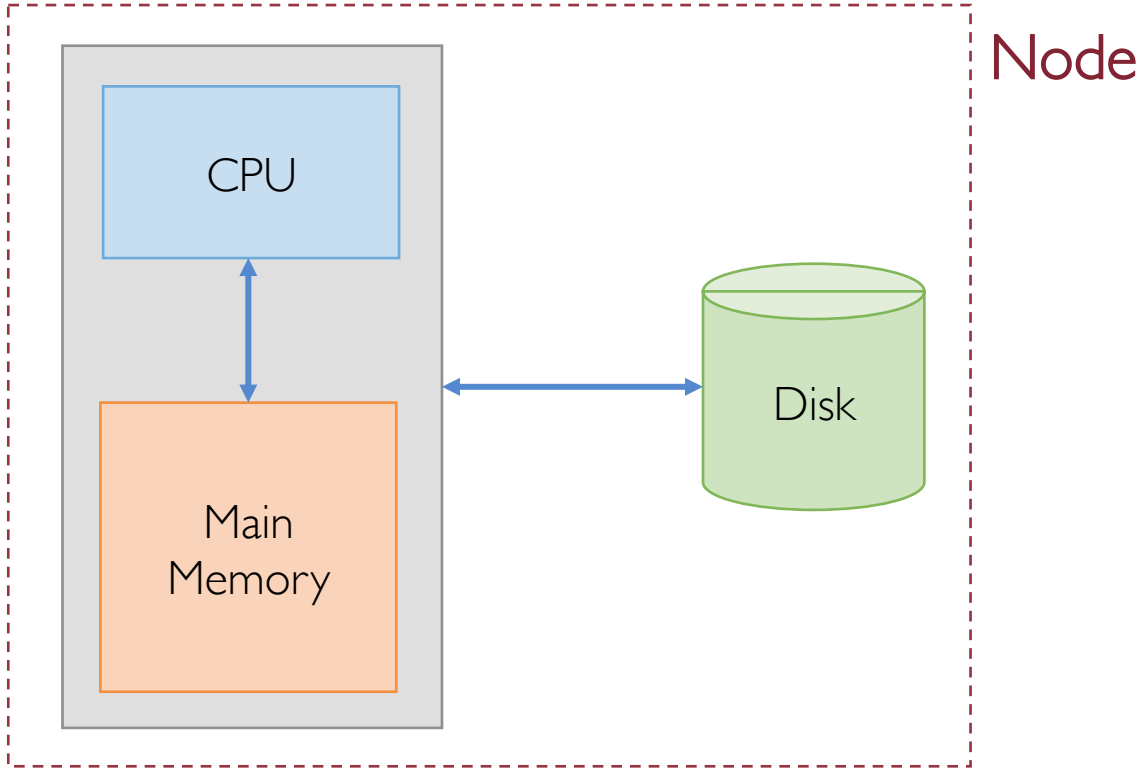


The Single-Node Architecture

Everything is ok as long as data fits entirely into main memory
(few accesses to the disk are still tolerated)



Example: Google (Toy) Index

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Main Memory

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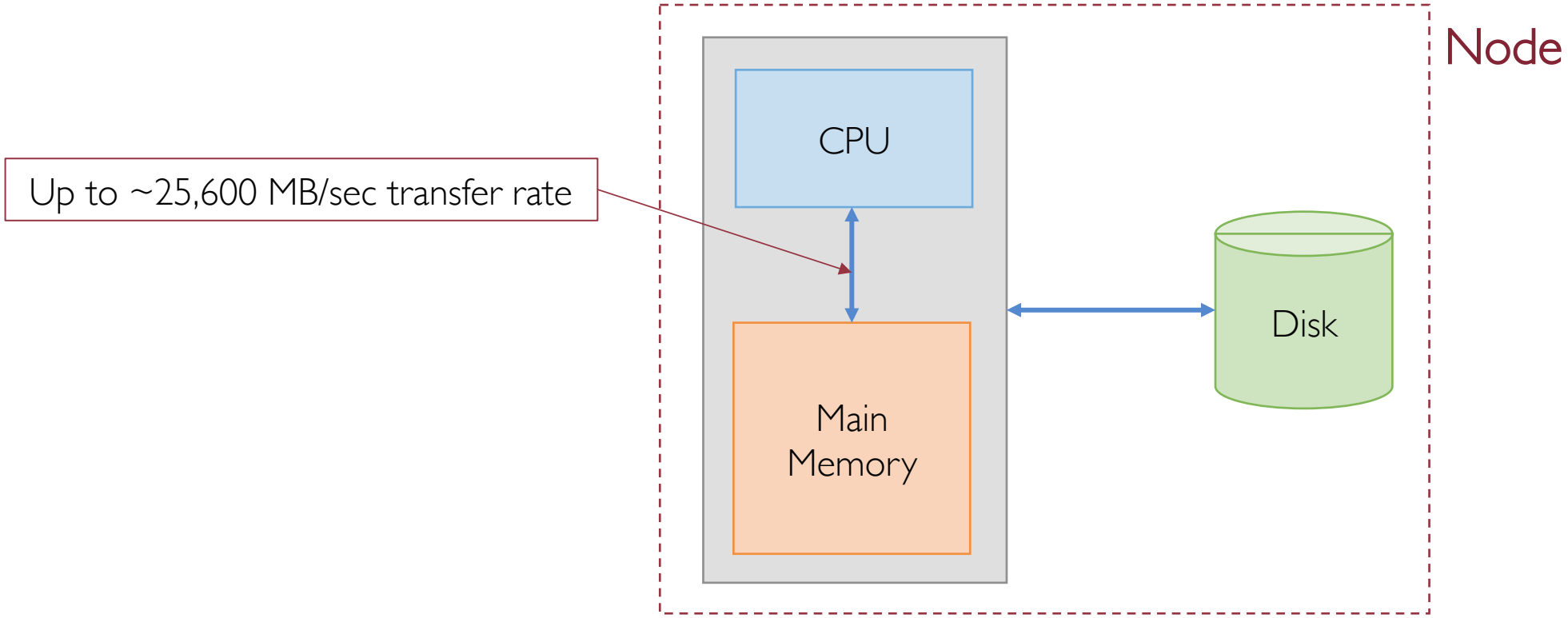

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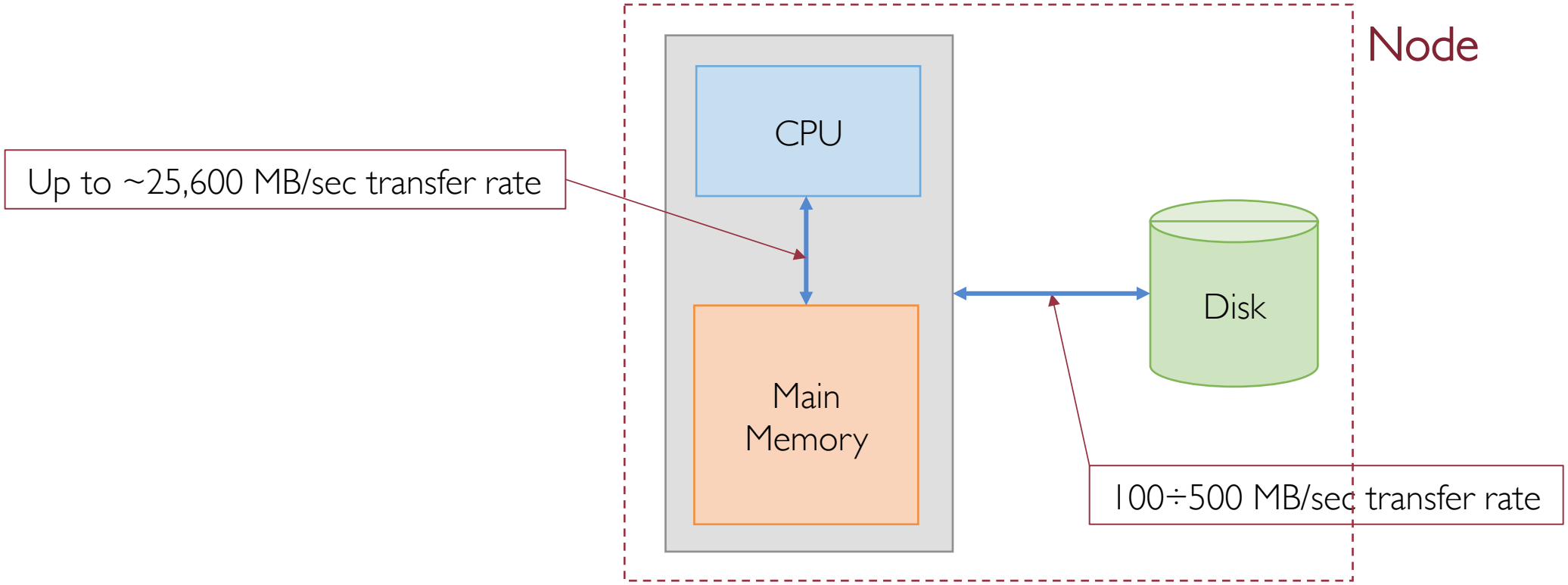

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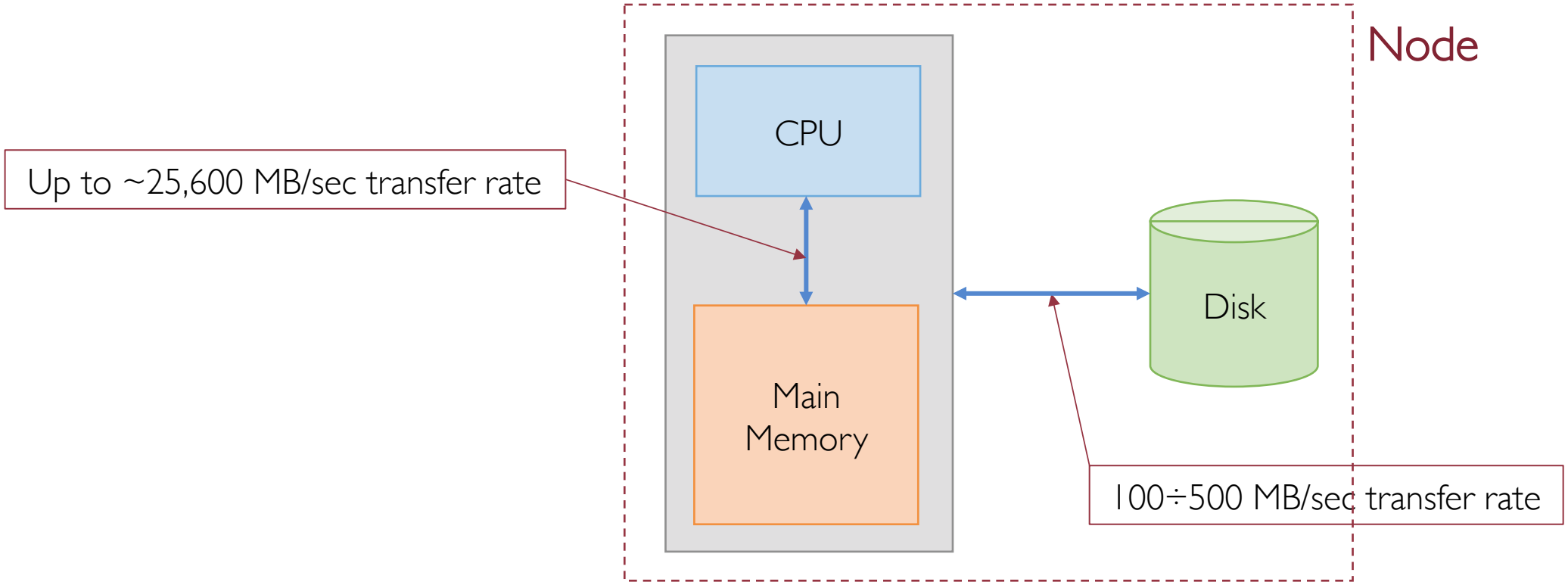

2 orders of magnitude difference between data transfer rate

Example: Google (Toy) Index

- Assuming the disk transfer rate is 100 MB/sec the total time to read the entire index will be:

5×10^{12} bytes/10^{8} bytes/sec = 5×10^{4} seconds ~14 hours

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- Single-node architecture is clearly not enough here
  - Scaling Up vs. Scaling Out

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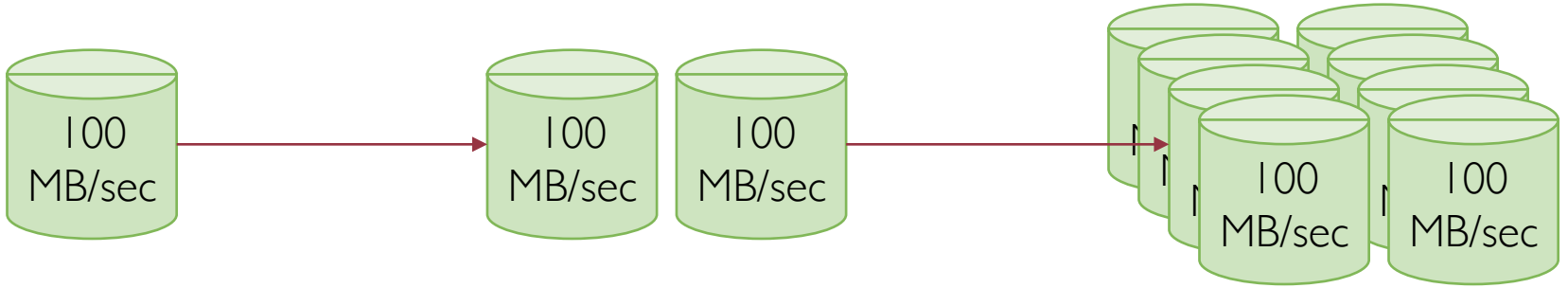

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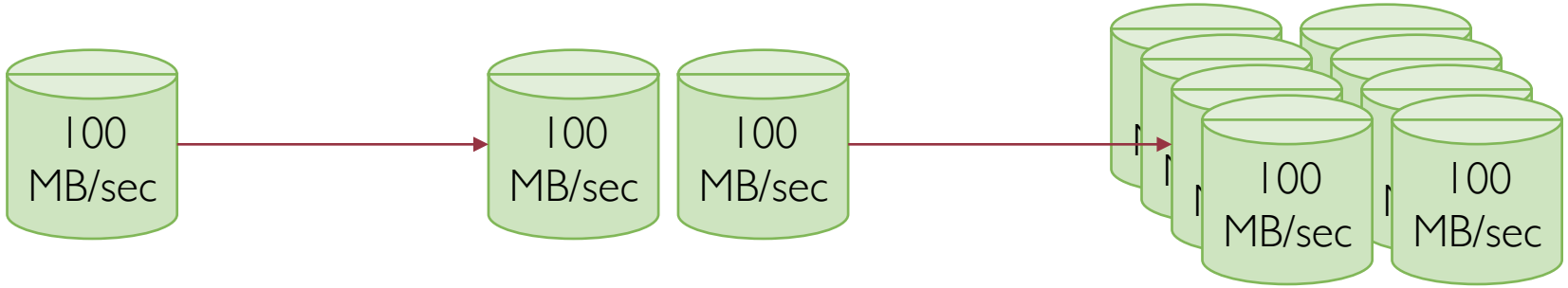

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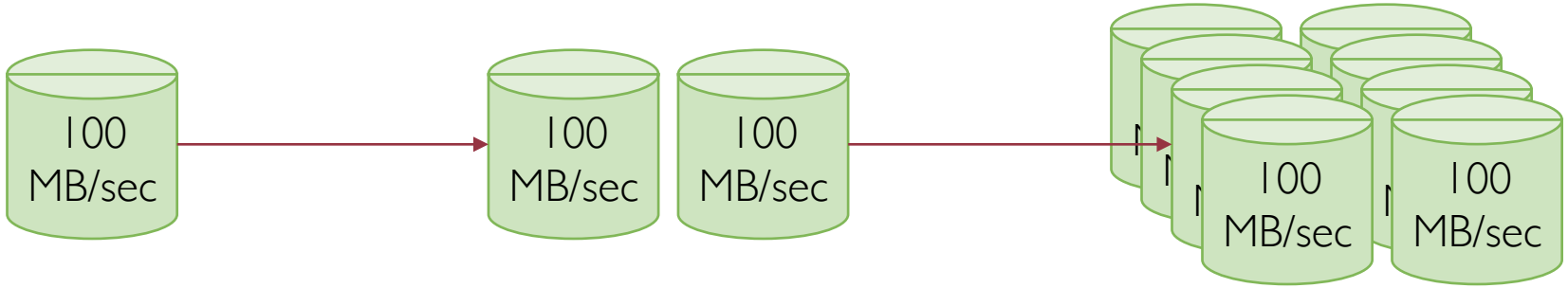

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- A cluster is made of multiple racks
- Network switches enabling node communication
  - 1 Gbps (inter-rack)
  - 2÷10 Gbps (intra-rack)

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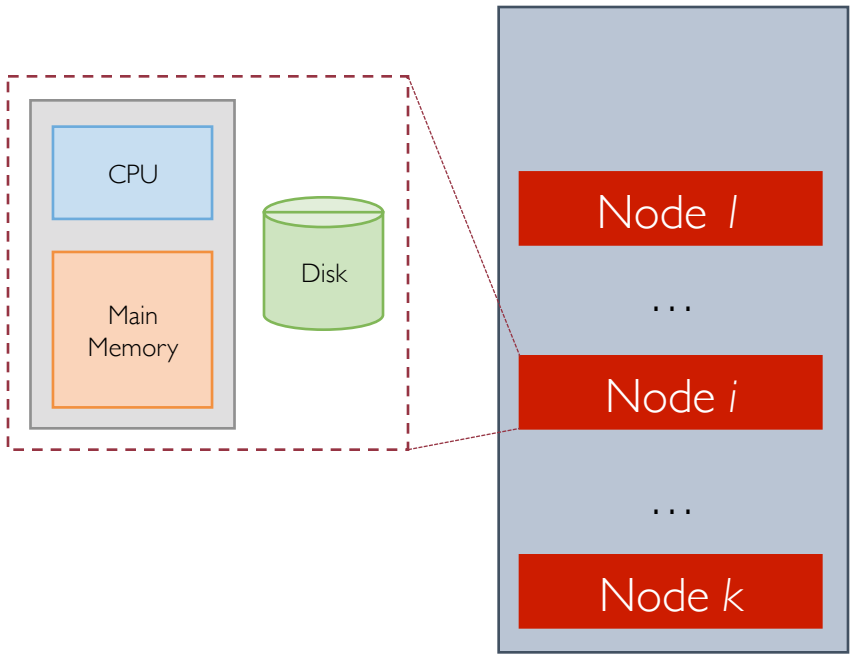

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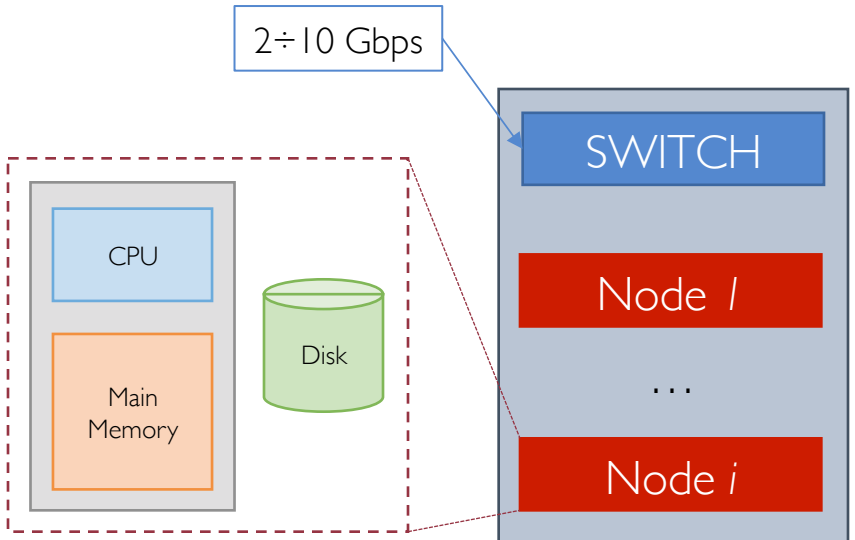
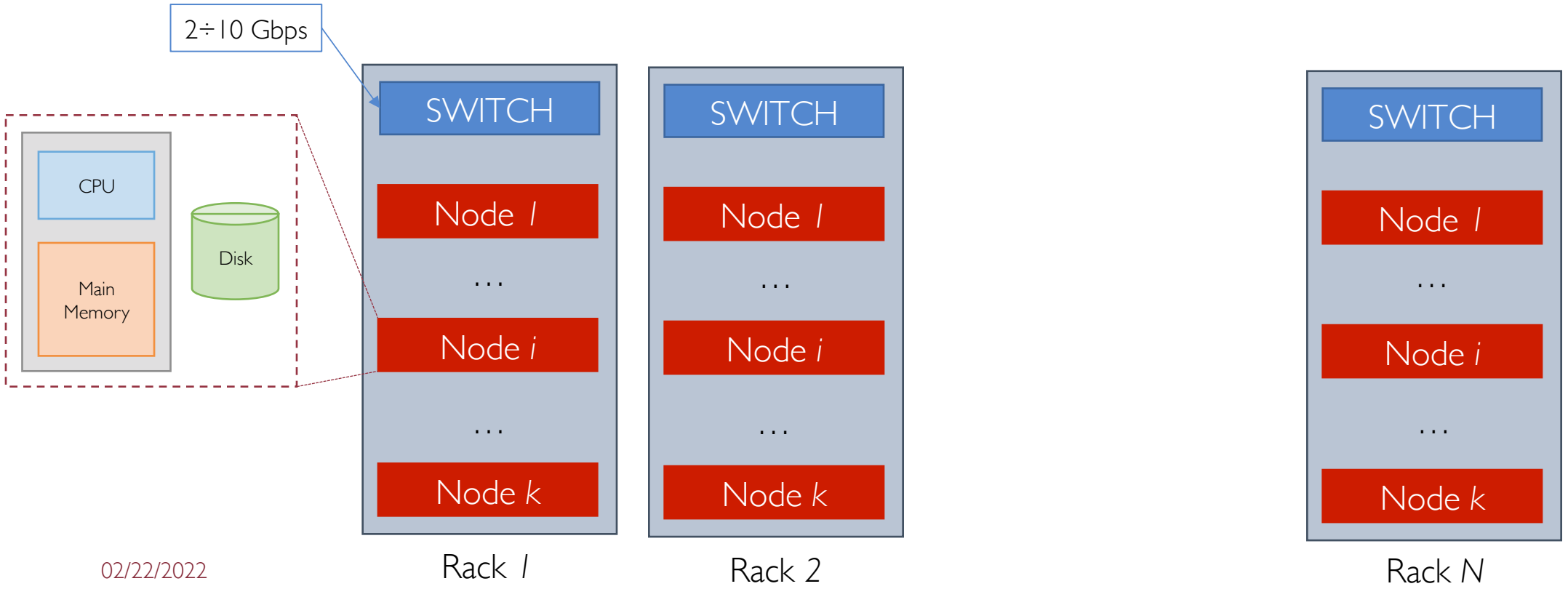


Rack 1

Cluster Architecture



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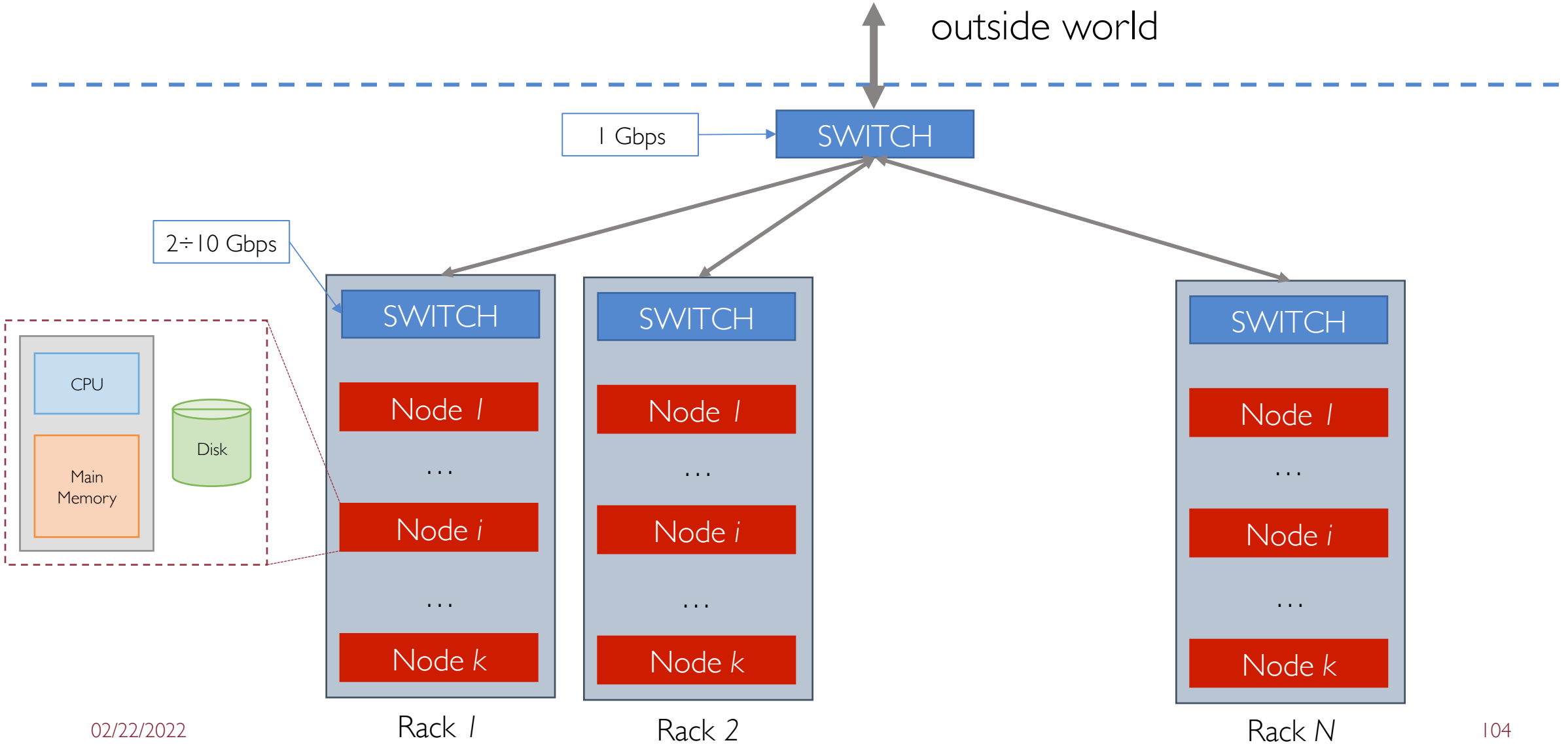

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Q1: How to make data and computation resilient to node failures?

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Q2: How to minimize data tranfers so as to reduce network communications?

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Q3: How to implement algorithms which take advantage of the distributed infrastructure without worrying about its complexities?

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- There is the need for new "tools" which allow storing, managing, and analyzing big data painlessly