

Big Data Computing

Master's Degree in Computer Science

2020-2021

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SAPIENZA
UNIVERSITÀ DI ROMA

Administrivia

- Class schedule:
 - Tuesday from 5:00PM to 7:00PM
 - Wednesday from 4:00PM to 7:00PM

Room G50 @ Viale Regina Elena, 295
Building G

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- Office hours:

- Drop me a message to ask for a meeting **online** (Google Meet or Zoom)

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=12771>

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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!

Administrivia

- Prerequisites:
 - Familiarity with basics of Data Science and Machine Learning
 - Solid knowledge of Calculus, Linear Algebra, and Probability&Statistics
 - Programming skills (preferably in Python)

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No worries!

Many subjects will be anyway revisited during class lectures

Administrivia

- Exam:
 - Development of a software project on a typical Big Data task
 - The subject of the project must be agreed in advance with the professor
 - Available sources exist like Kaggle (<https://www.kaggle.com/>)
 - Can be done either **individually** or in team of **at most 2 students**
 - A brief presentation (in english) describing the project is **mandatory**
 - Other questions on all the topics covered in classes may be asked

Questions?

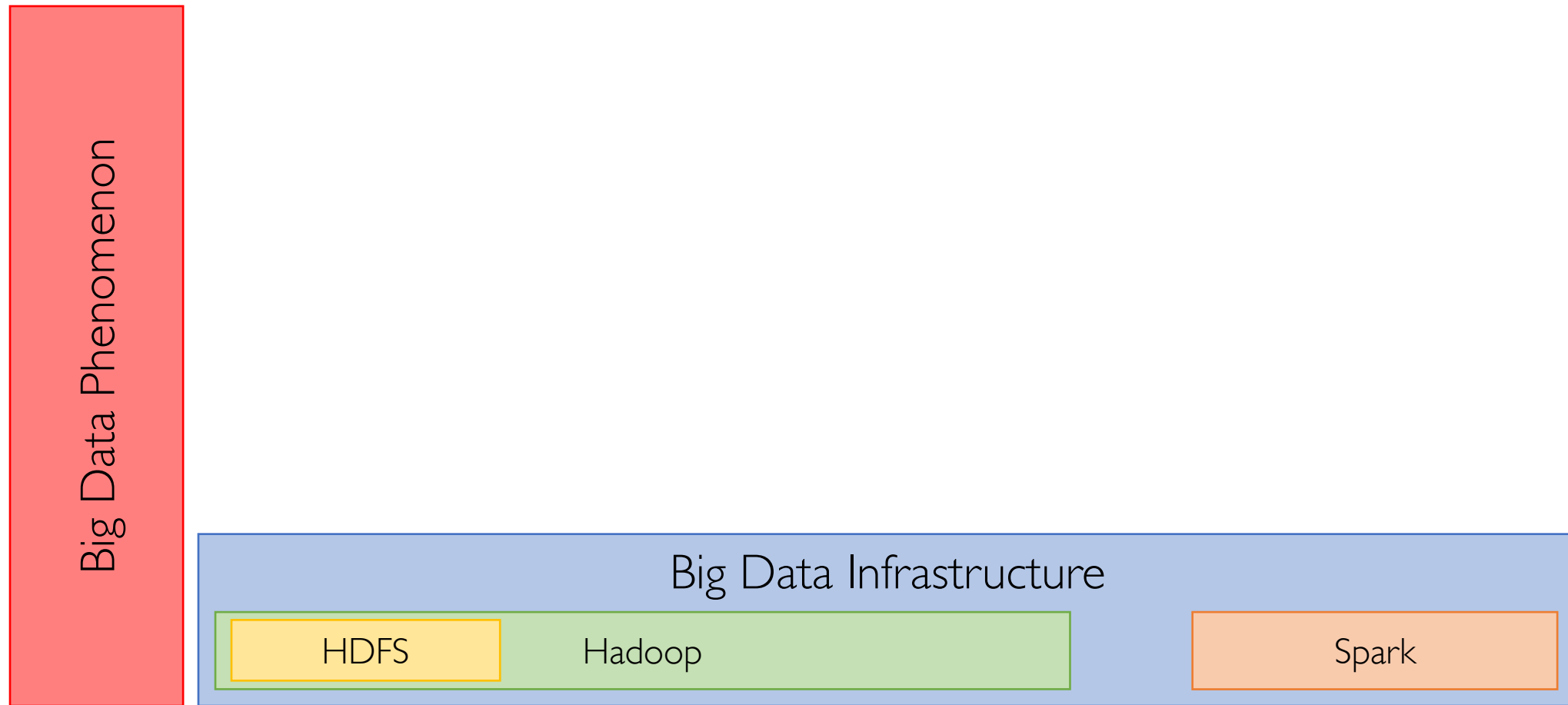
Outline of the Course

Big Data Phenomenon

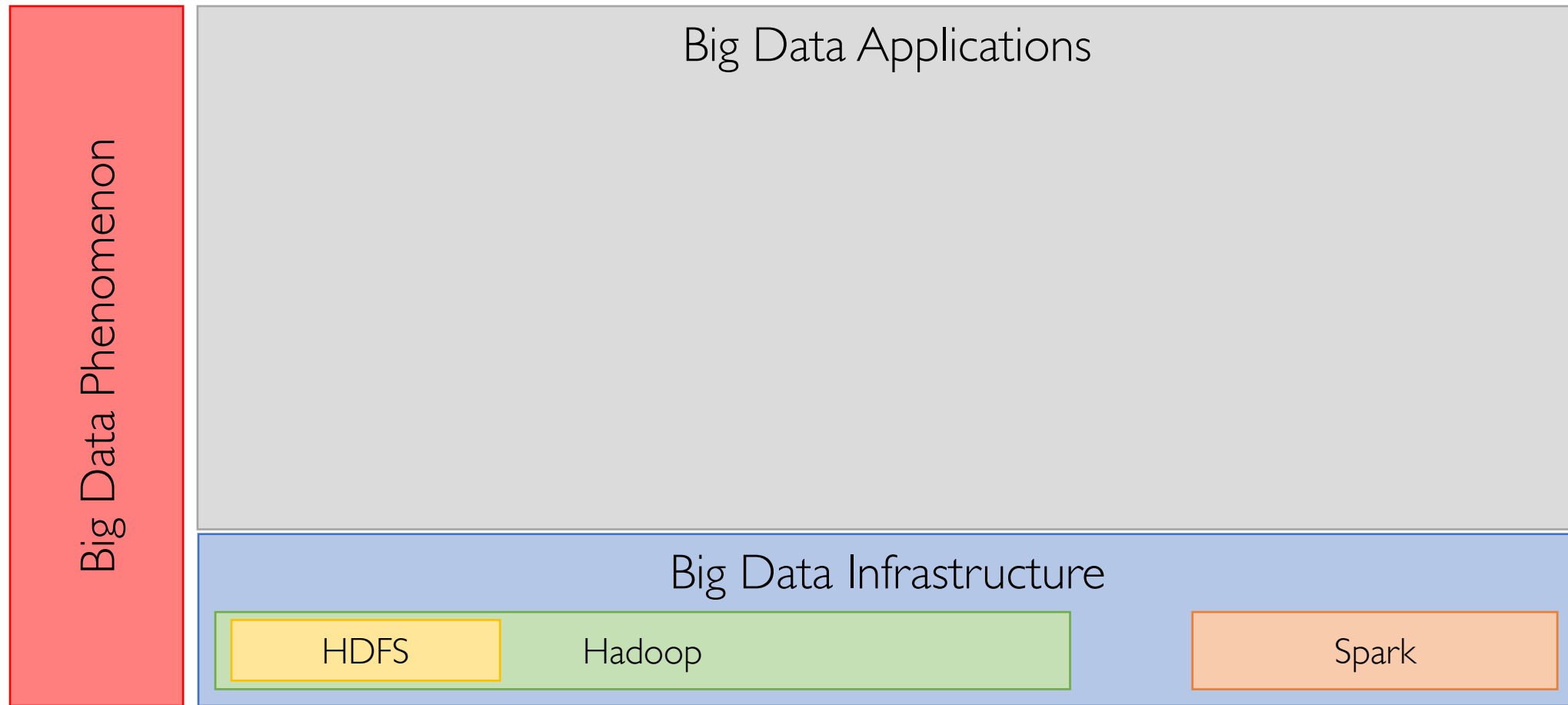
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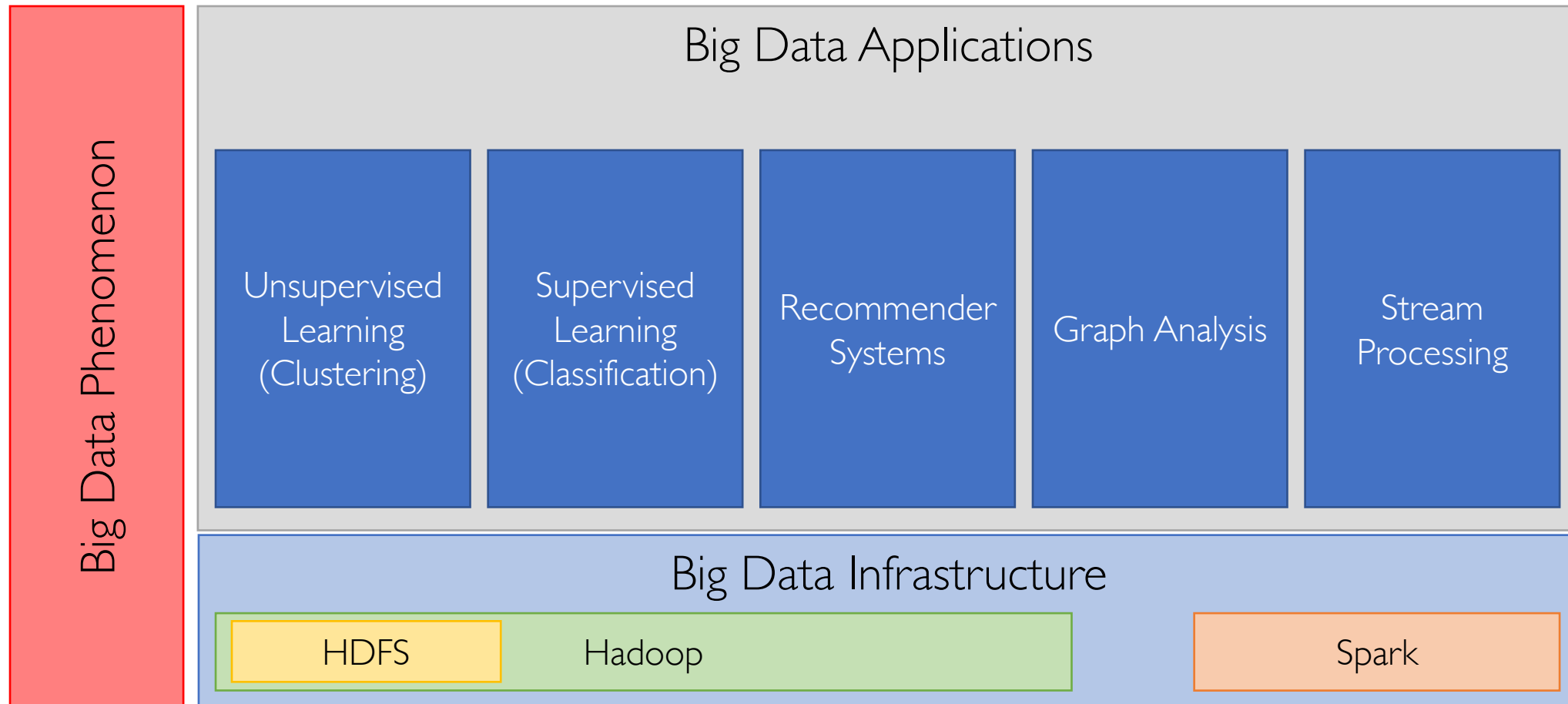
Outline of the Course



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Let's Get Started!

What the He...ck is That?



source: [Wikipedia](https://en.wikipedia.org/wiki/Heck)

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The computer installed on each command and lunar module of all the Apollo program's missions



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A few numbers:

- ~2 MHz CPU clock frequency
- 16 bit architecture
- 3,840 bytes of main memory (RAM)
- 69,120 bytes of non-volatile read-only memory (ROM)



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The computer installed on each command and lunar module of all the Apollo program's missions

A few numbers:

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All the running software was written in AGC assembly language, now also available on [GitHub](#)



50 Years Have Passed...

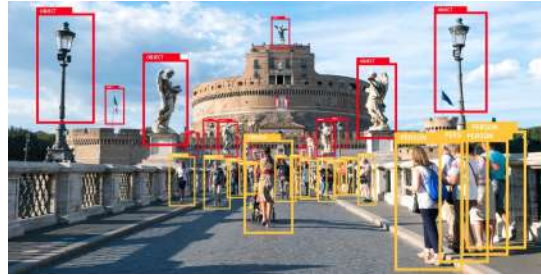
... And The World Has Changed



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... And The World Has Changed



AGC vs. Our Smartphone

- Most recent smartphones have
 - ~2.4 GHz CPU clock frequency
 - 4÷12 GB of RAM
 - 64÷256 GB of internal storage (**don't** call it ROM!)



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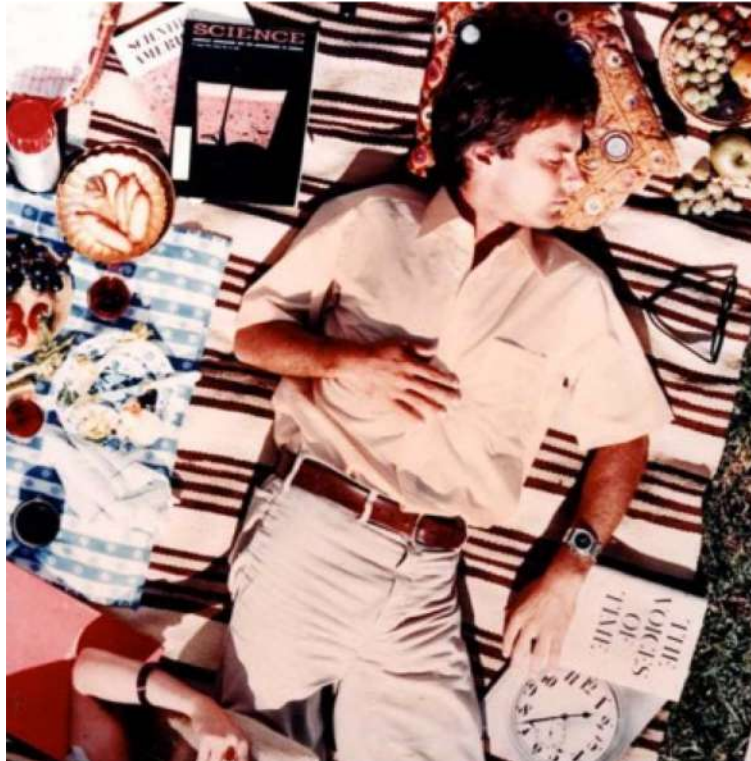
~ 3 orders of magnitude faster ($\sim 1,000\times$)

$\sim 6 \div 7$ orders of magnitude larger RAM and internal storage (up to $10,000,000\times$)

A Side Note on Units

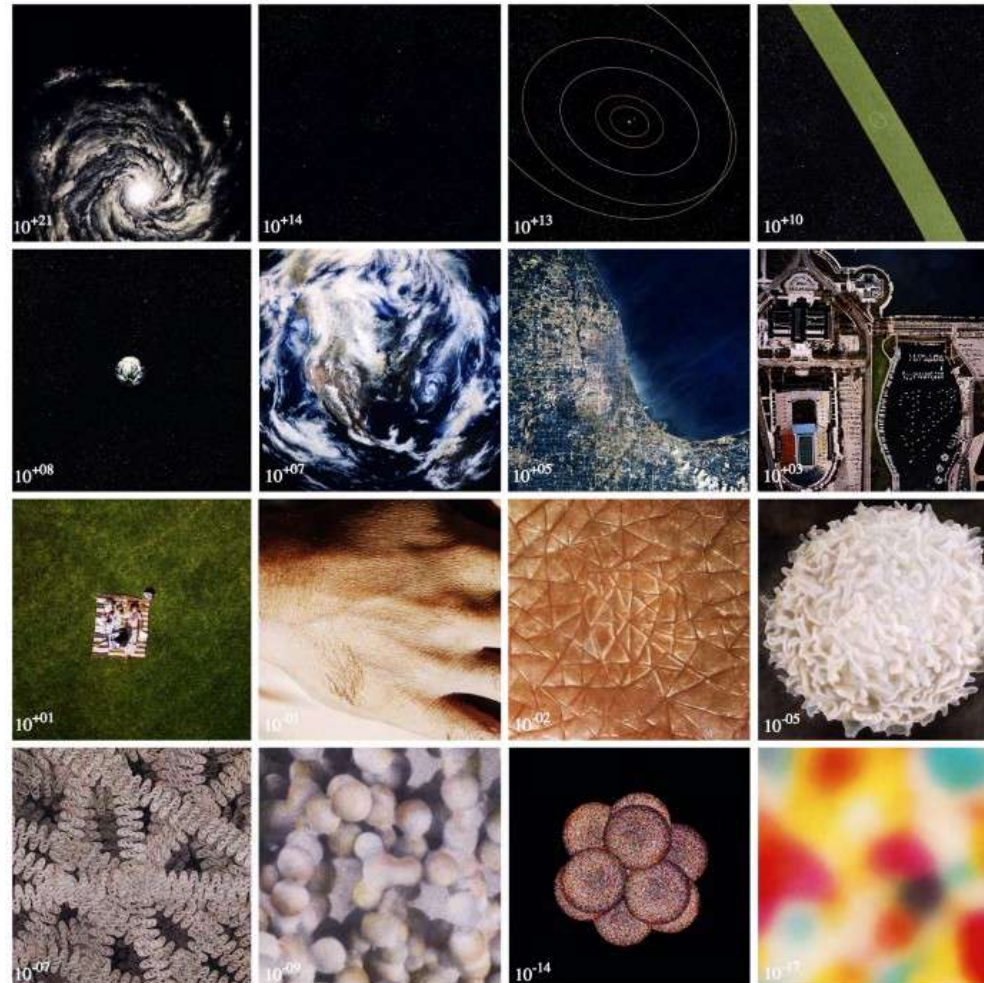
Prefixes for multiples of bits (bit) or bytes (B)						
Decimal				Binary		
Value		SI		Value	IEC	JEDEC
1000	10^3	k	kilo	1024	2^{10}	Ki kibi K kilo
1000 ²	10^6	M	mega	1024 ²	2^{20}	Mi mebi M mega
1000 ³	10^9	G	giga	1024 ³	2^{30}	Gi gibi G giga
1000 ⁴	10^{12}	T	tera	1024 ⁴	2^{40}	Ti tebi –
1000 ⁵	10^{15}	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



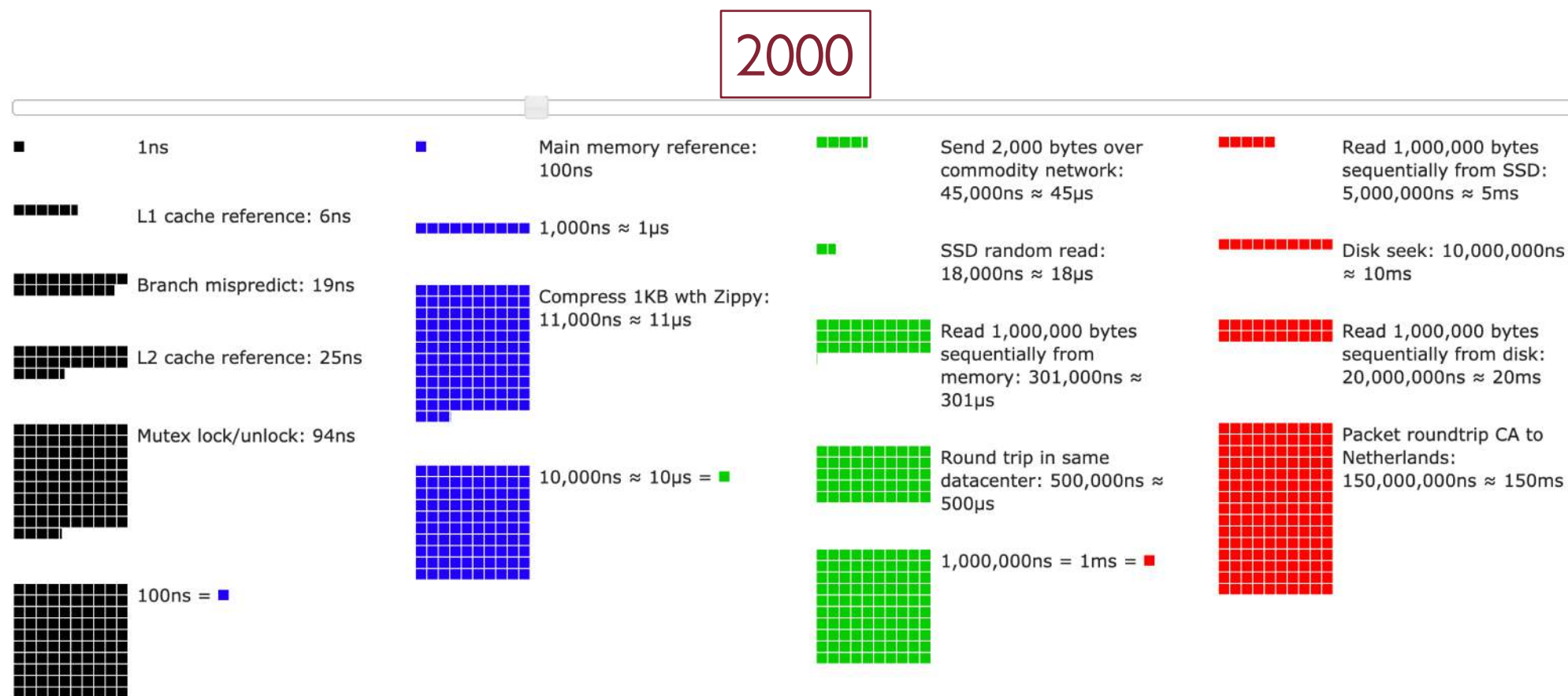
$$10^0 = 1$$

Orders of Magnitude



Numbers Every Computer Scientist Should Know

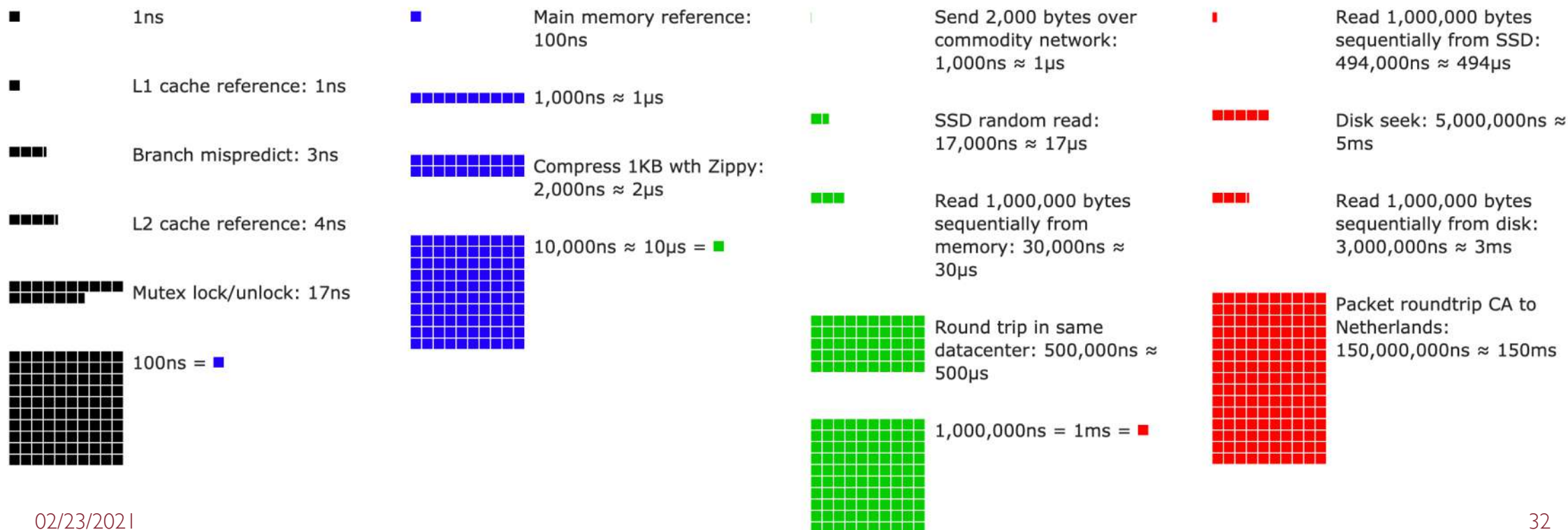
[Colin Scott](#)'s updated and interactive version of [Jeff Dean](#)'s previous one



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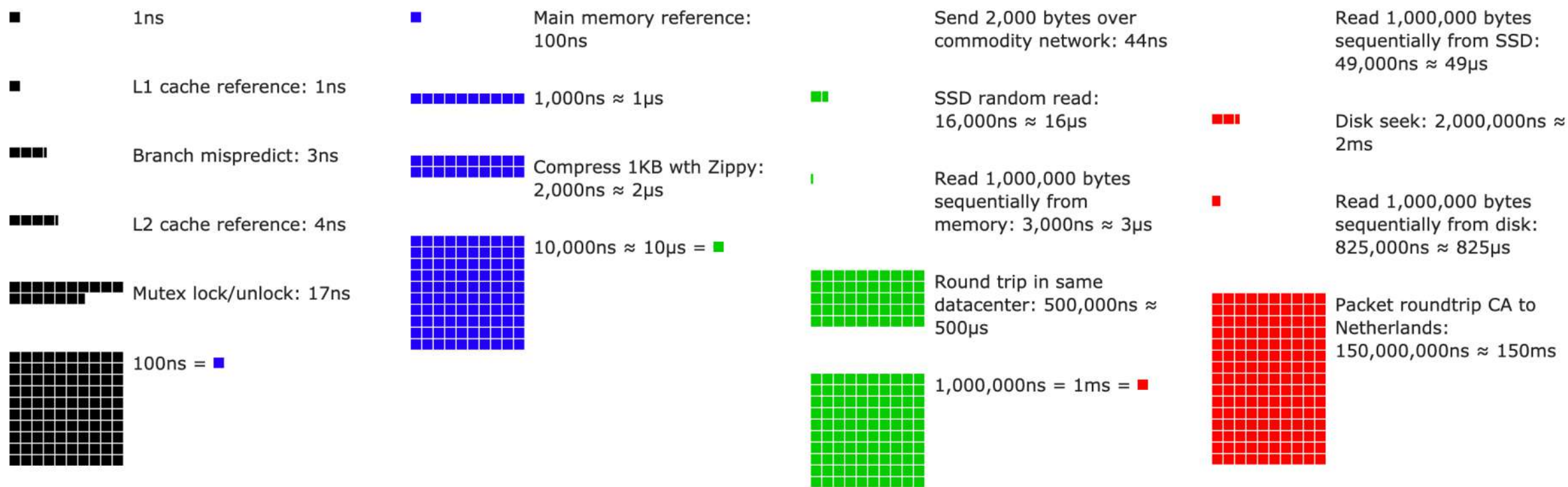
2010



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2020

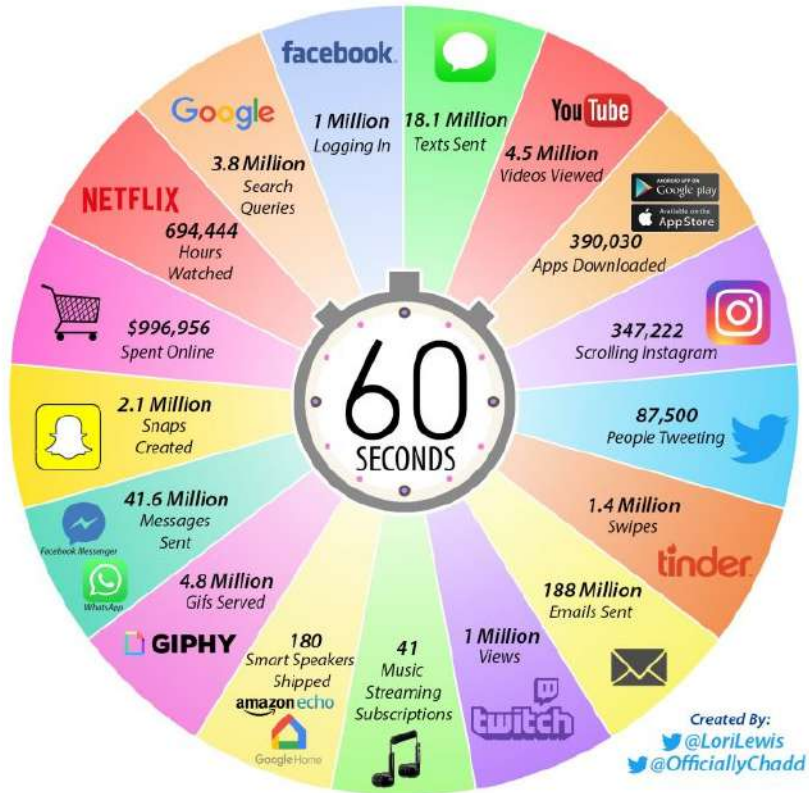


The Information Technology (IT) Revolution

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

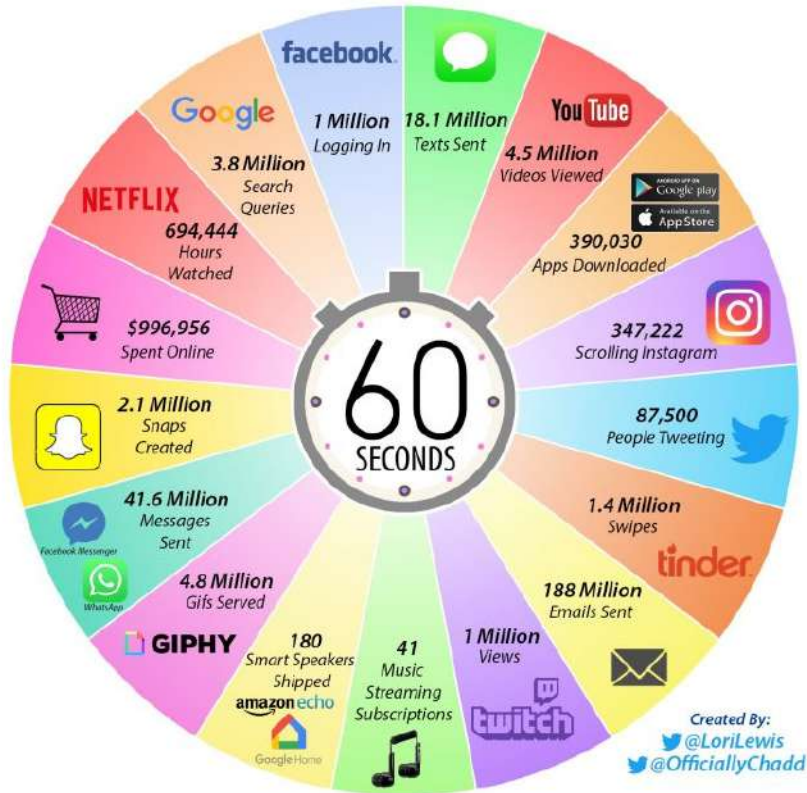
What Happens on the Internet in 1 Minute?

2019 *This Is What Happens In An Internet Minute*



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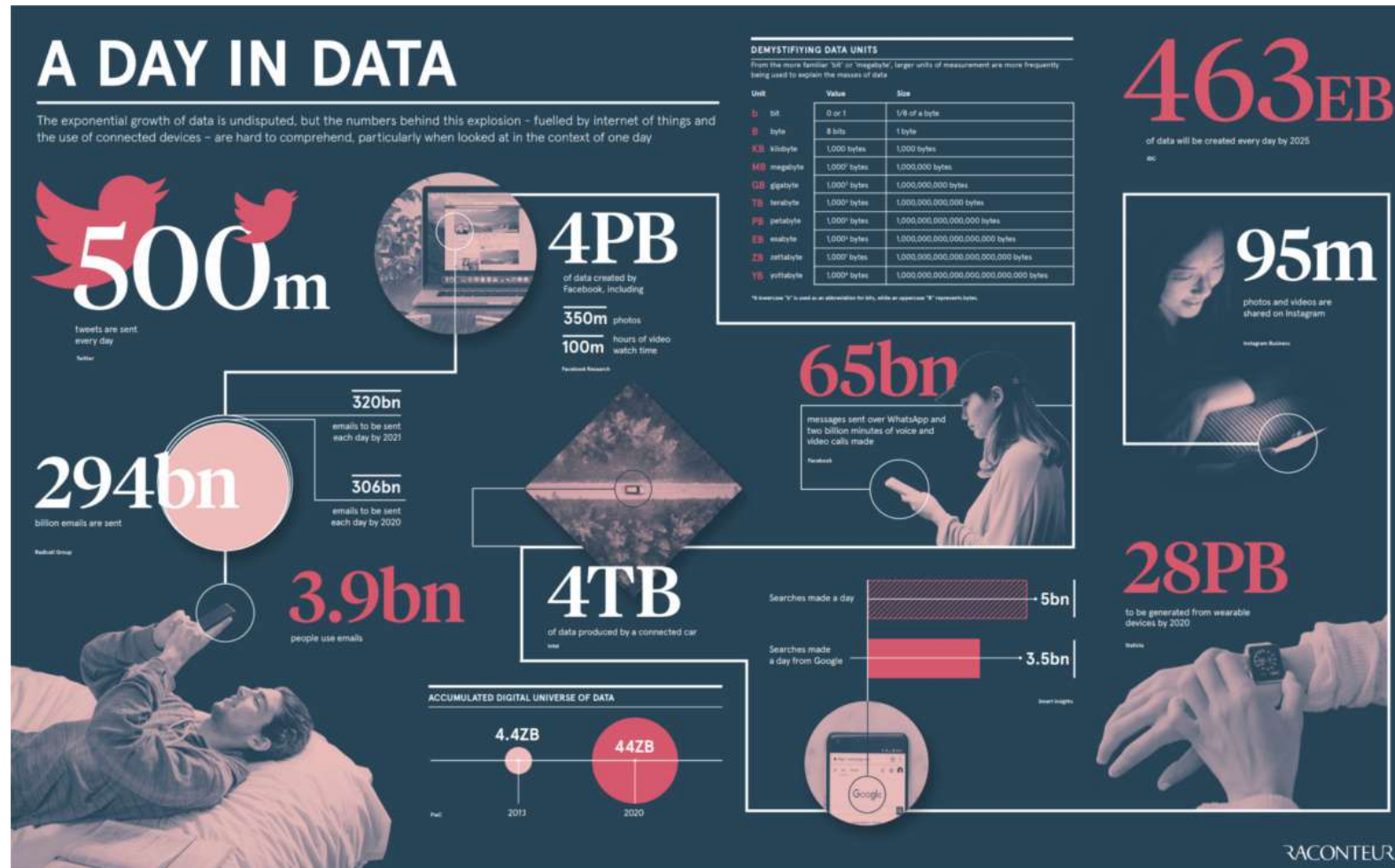
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How Much Data is Generated Each Day?



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- Sometimes a buzzword yet describing an actual phenomenon

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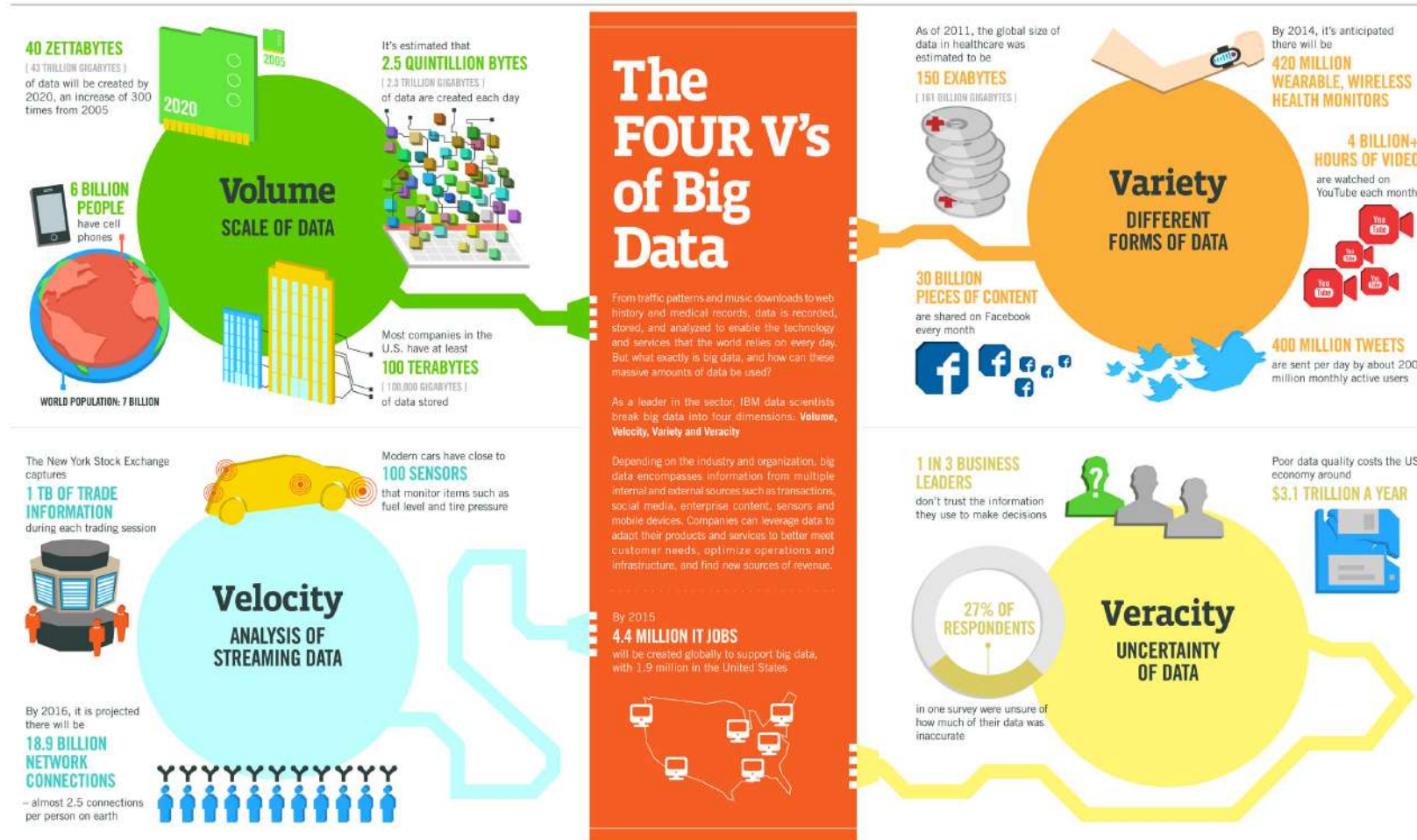
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 - **Velocity** → insane speed at which data is generated (e.g., Twitter stream)
 - **Veracity** → reliability of the data used to drive decision processes

The 4 V's of Big Data



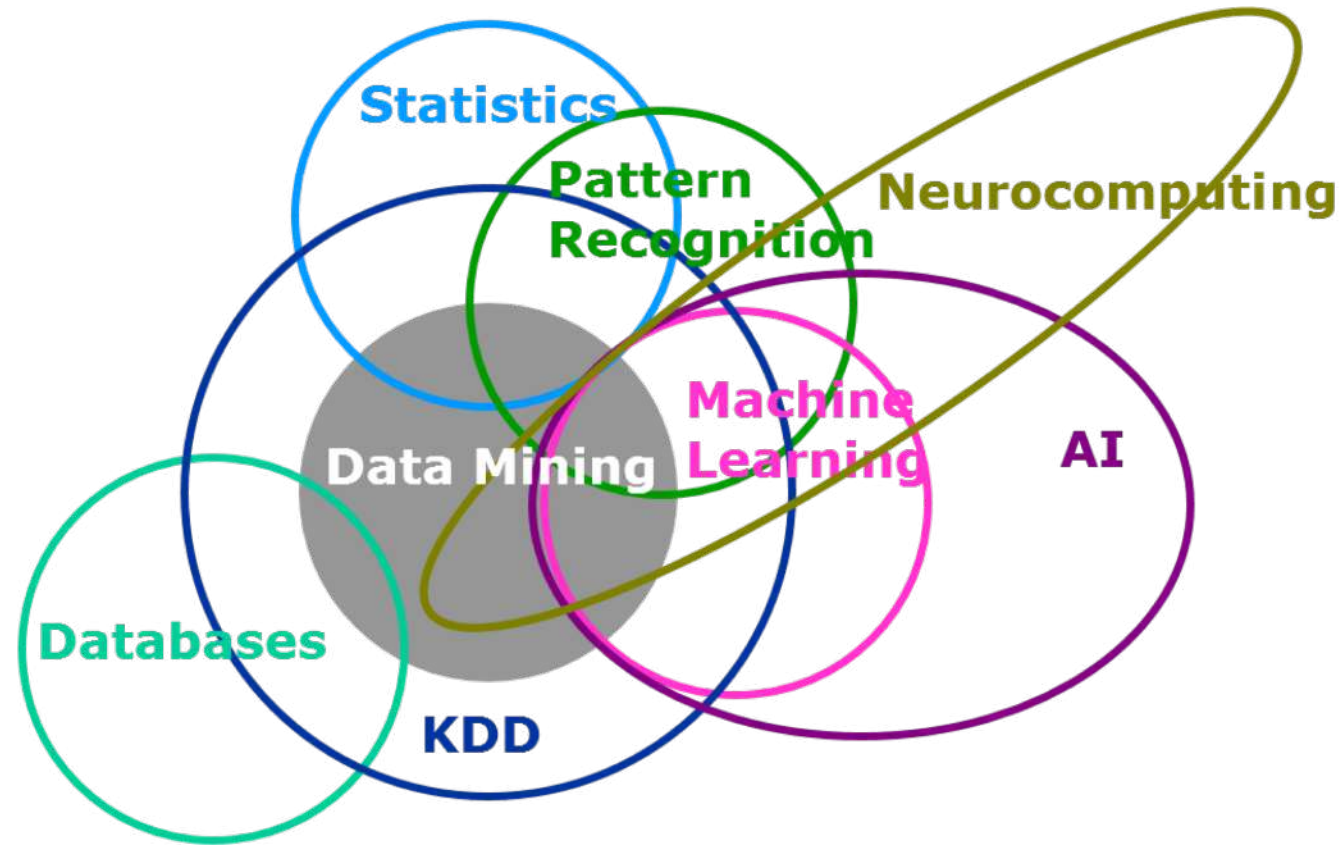
The Value of Big Data

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- Extracting knowledge from data is incredibly valuable
 - [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

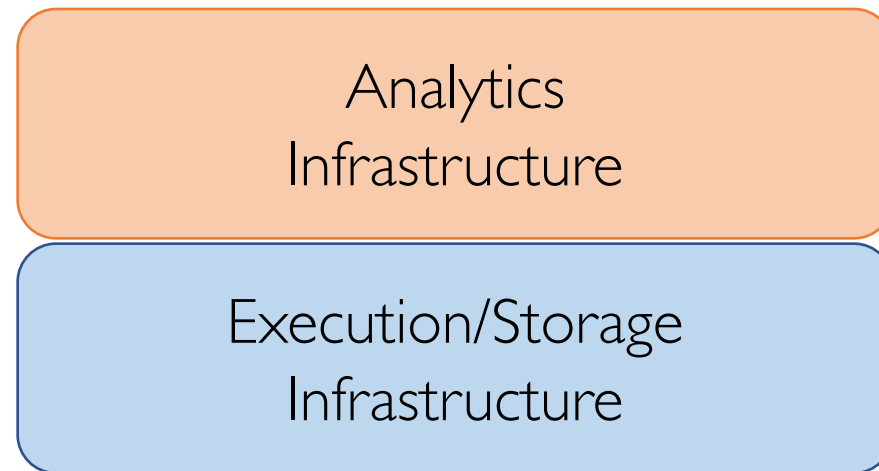


Big Data Analysis Stack

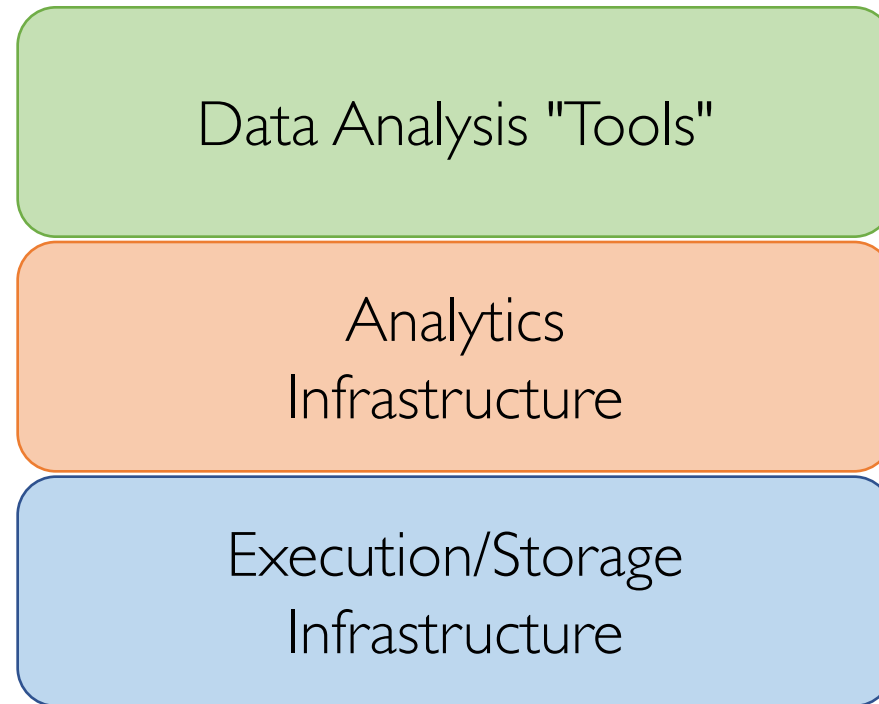


Execution/Storage
Infrastructure

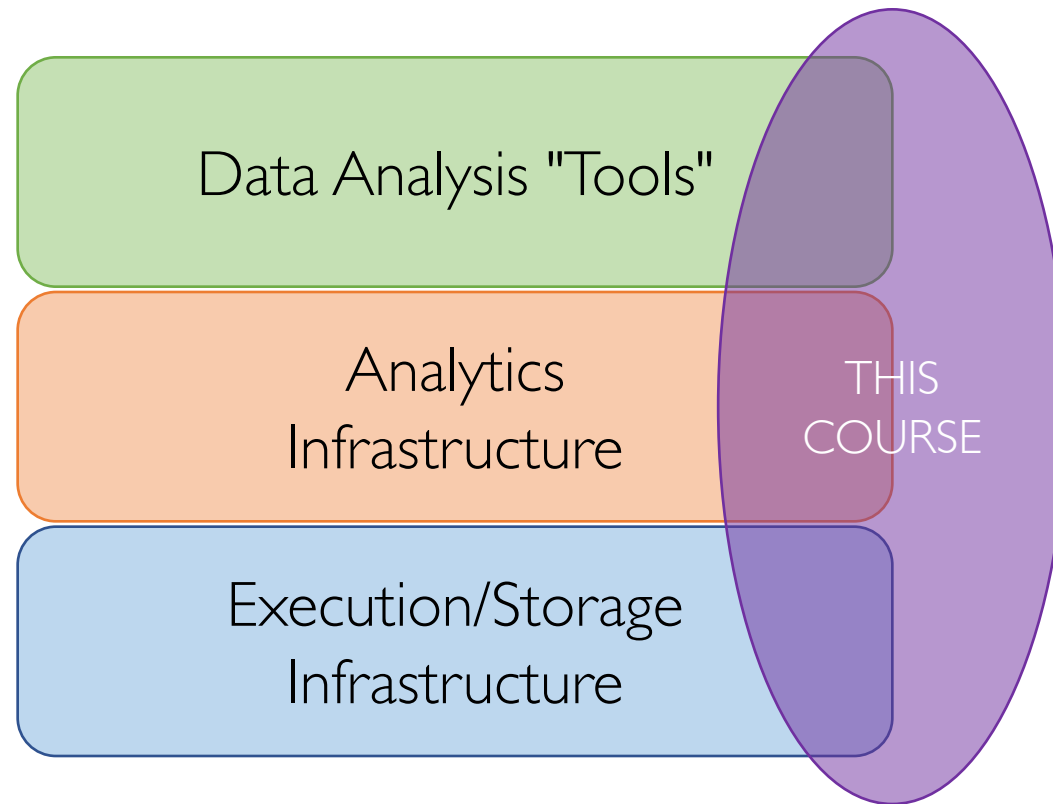
Big Data Analysis Stack



Big Data Analysis Stack



Big Data Analysis Stack



What Will We Learn?

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

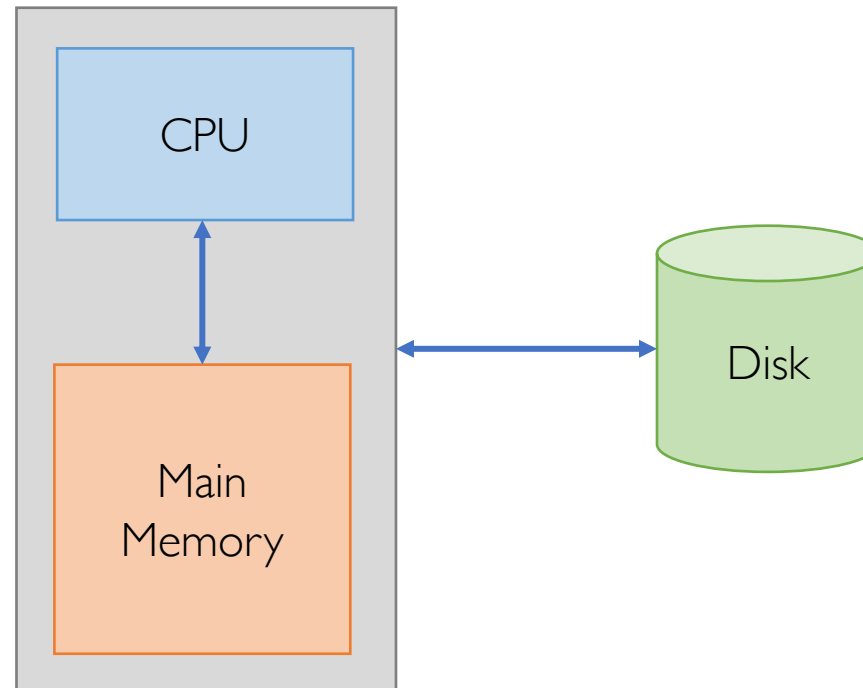
What Will We Learn?

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

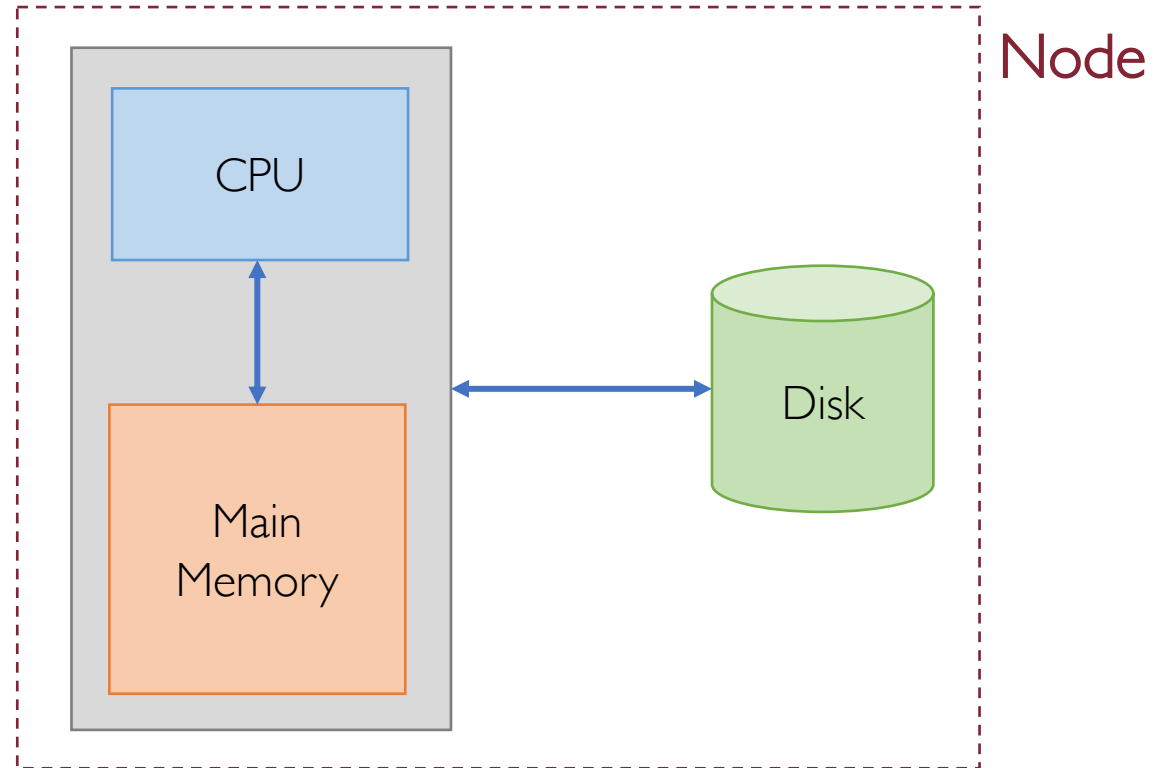
What Will We Learn?

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

The Single-Node Architecture

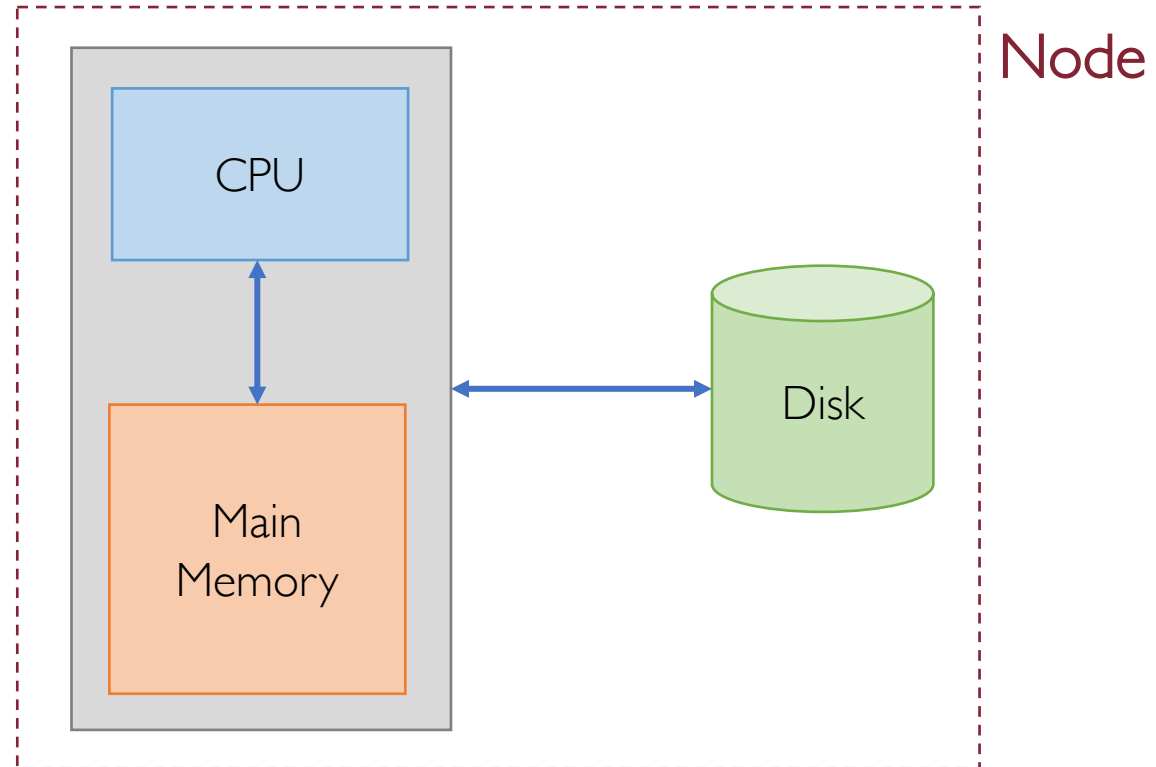


The Single-Node Architecture



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

- Google has crawled 50 million web pages (a tiny fraction of the Web!)
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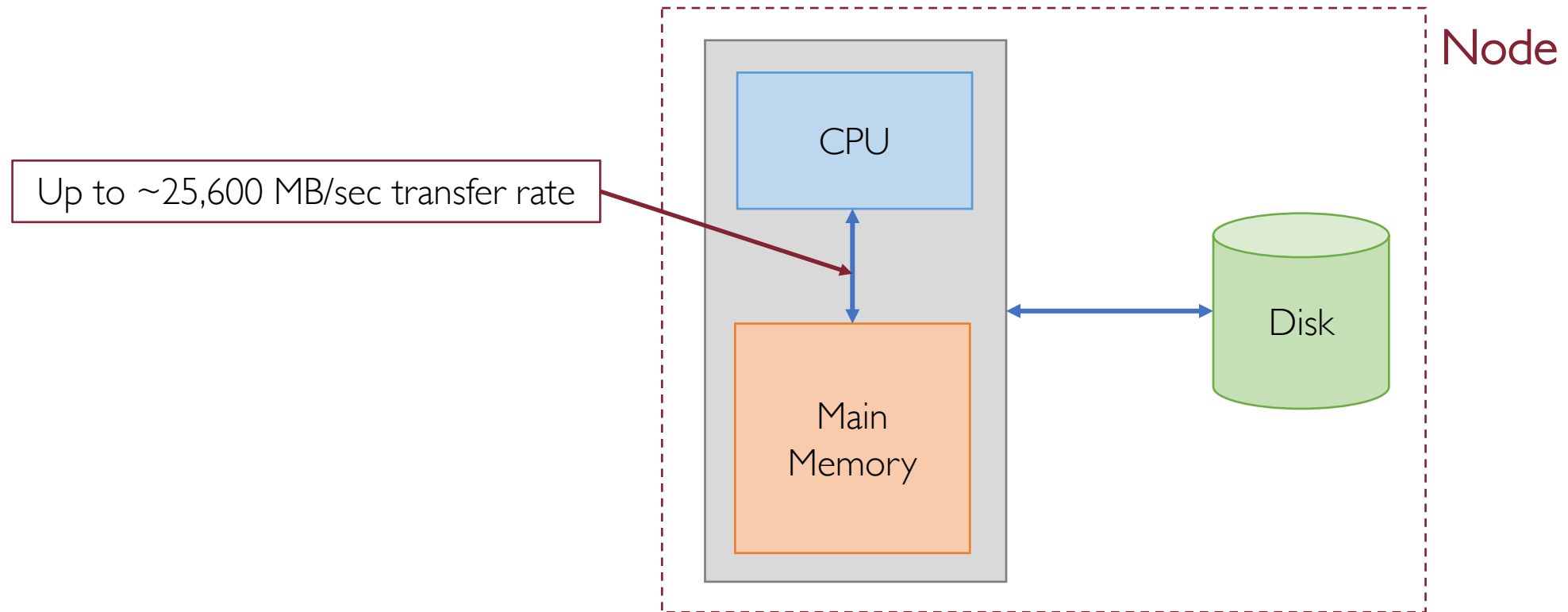
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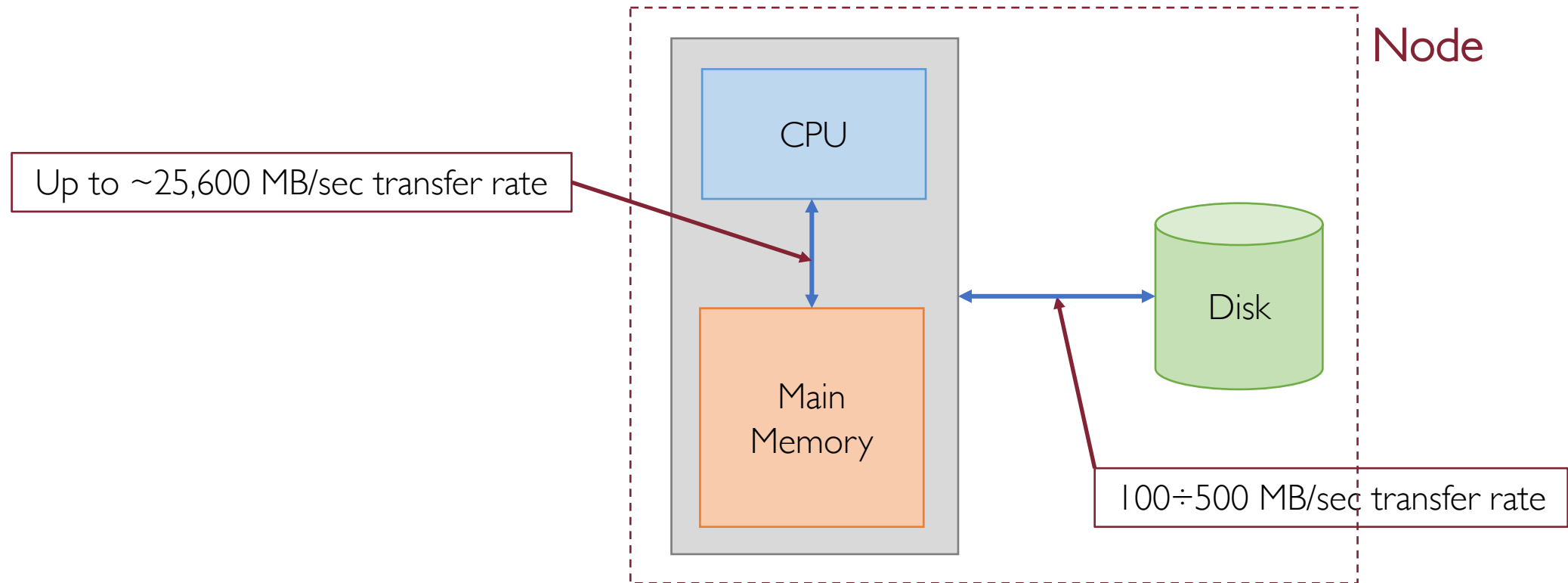
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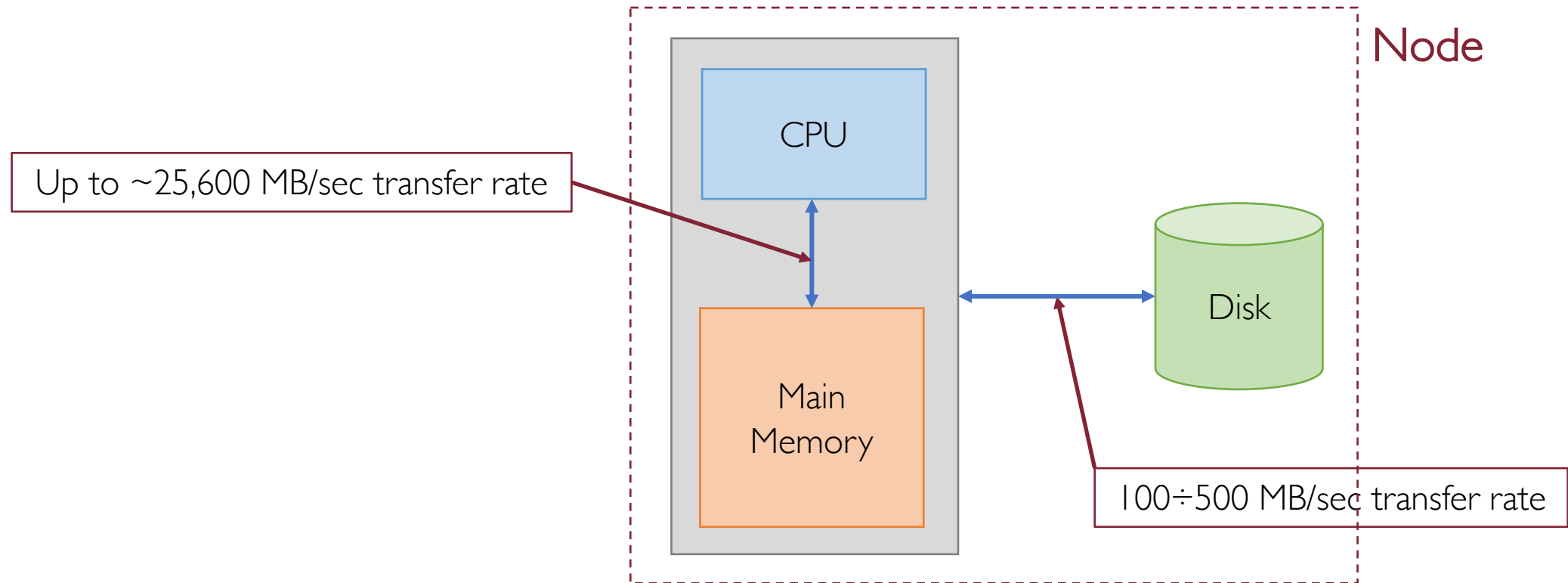
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2 orders of magnitude difference between data transfer rate

Example: Google (Toy) Index

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

$$5 \times 10^{12} \text{ bytes} / 10^8 \text{ bytes/sec} = 5 \times 10^4 \text{ seconds} \sim 14 \text{ hours}$$

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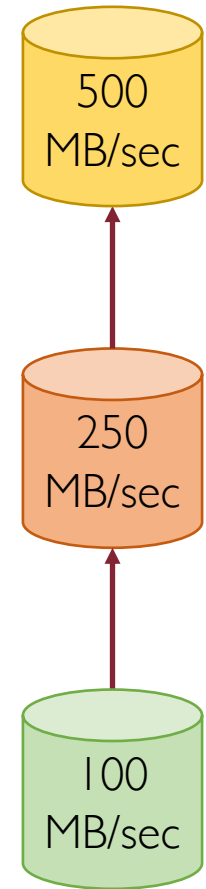
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- Single-node architecture is clearly not enough here
 - Scaling Up vs. Scaling Out

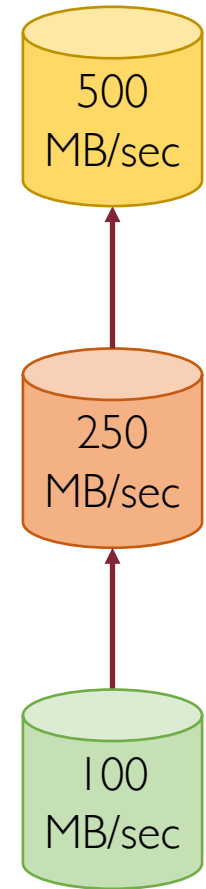
Scaling Up/Vertical Scaling

- Buy a more performing disk (e.g., 250 or 500 MB/sec transfer rate)



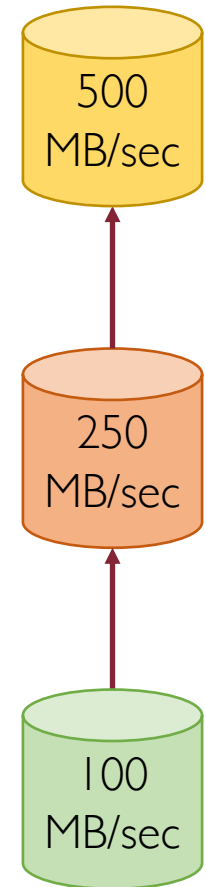
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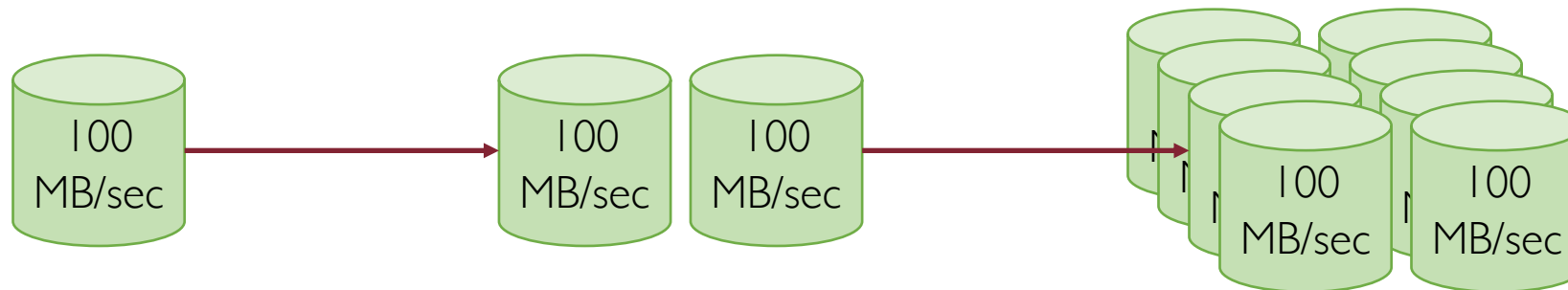
Scaling Up/Vertical Scaling

- Buy a more performing disk (e.g., 250 or 500 MB/sec transfer rate)
- **PRO**
 - Easiest solution
- **CON**
 - Improvement is physically-limited (e.g., 2.5x or 5x)
 - Expensive



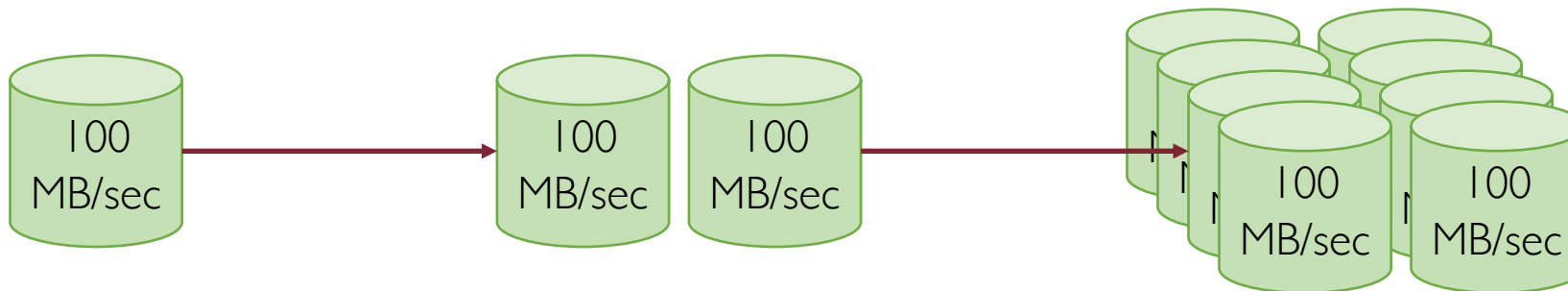
Scaling Out/Horizontal Scaling

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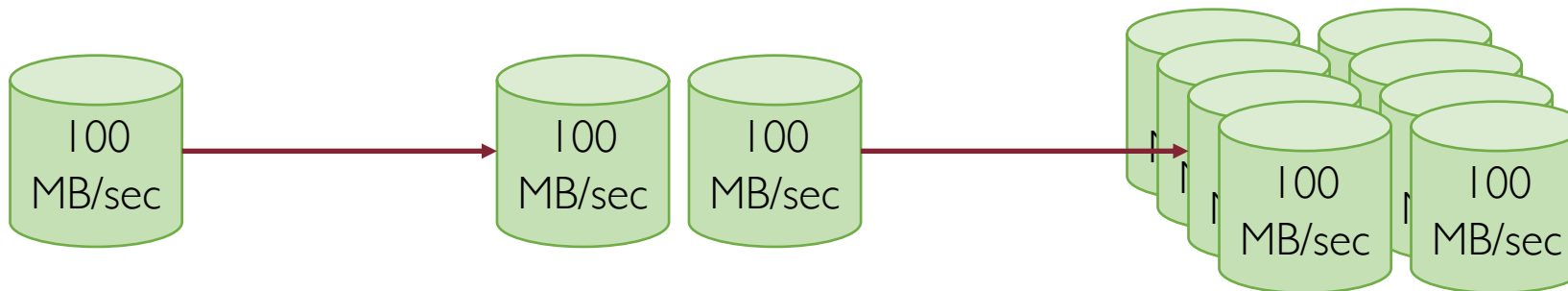
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 - Flexibility (improvement is not bound apriori, just add new disks as needed)
- CON
 - Extra overhead required to manage parallel work



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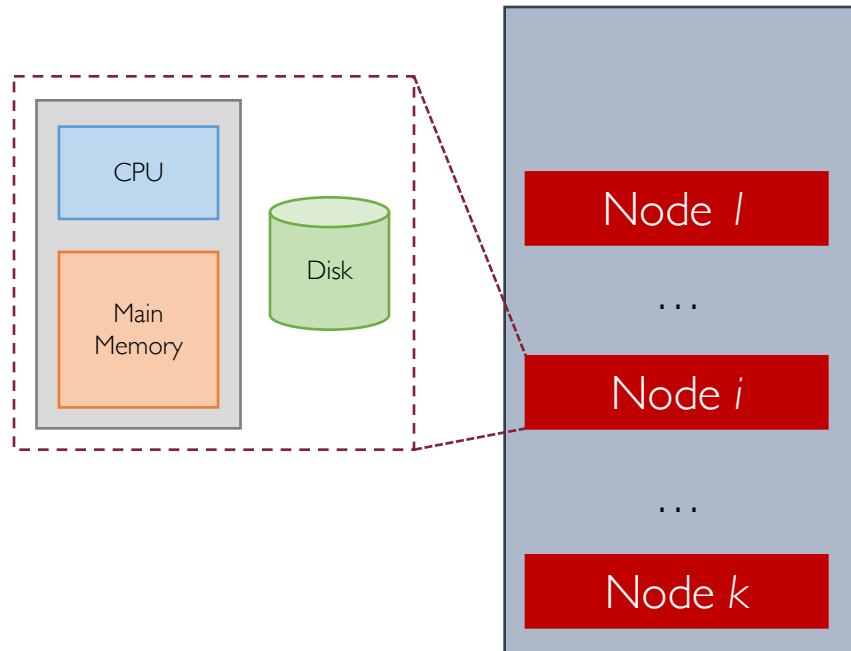
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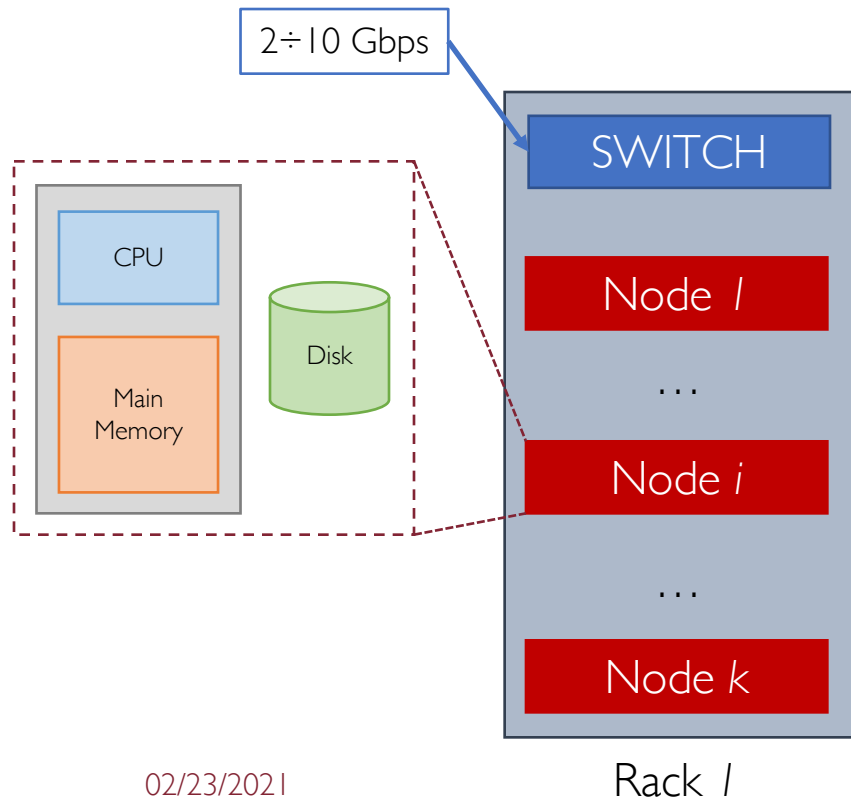
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- Network **switches** enabling node communication
 - 1 Gbps (inter-rack)
 - 2÷10 Gbps (intra-rack)

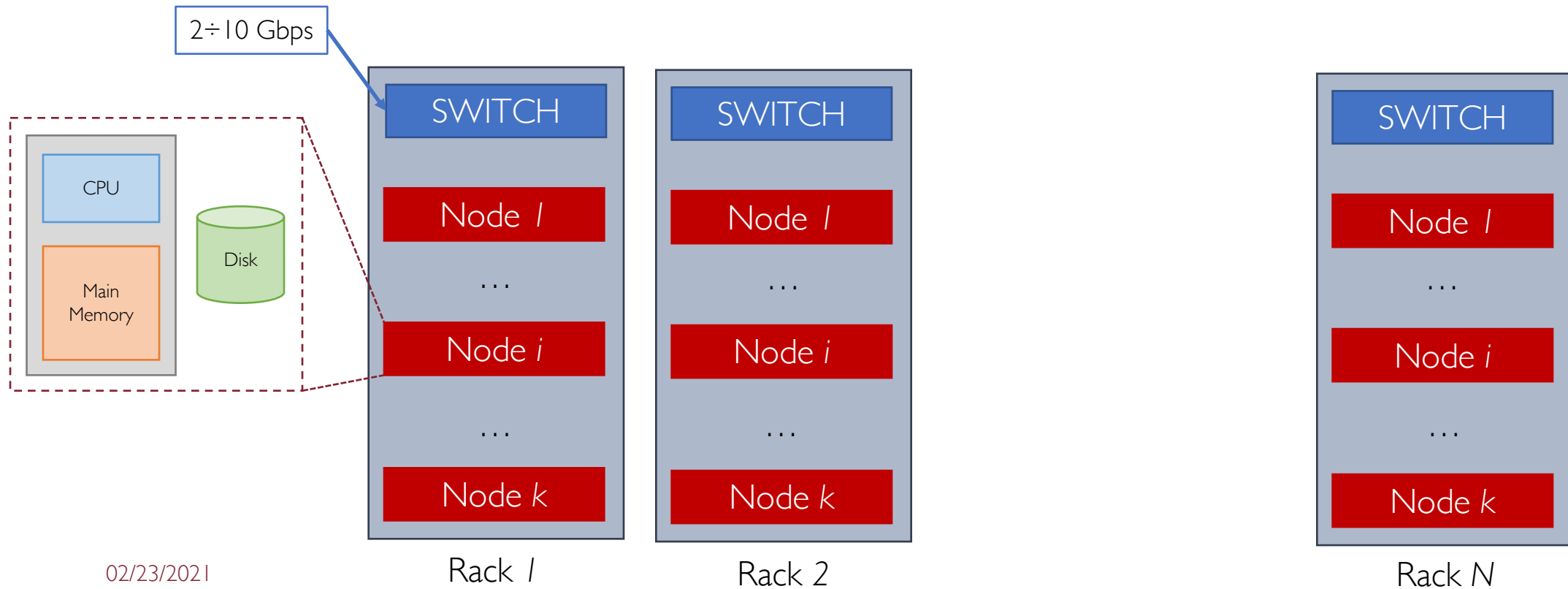
Cluster Architecture



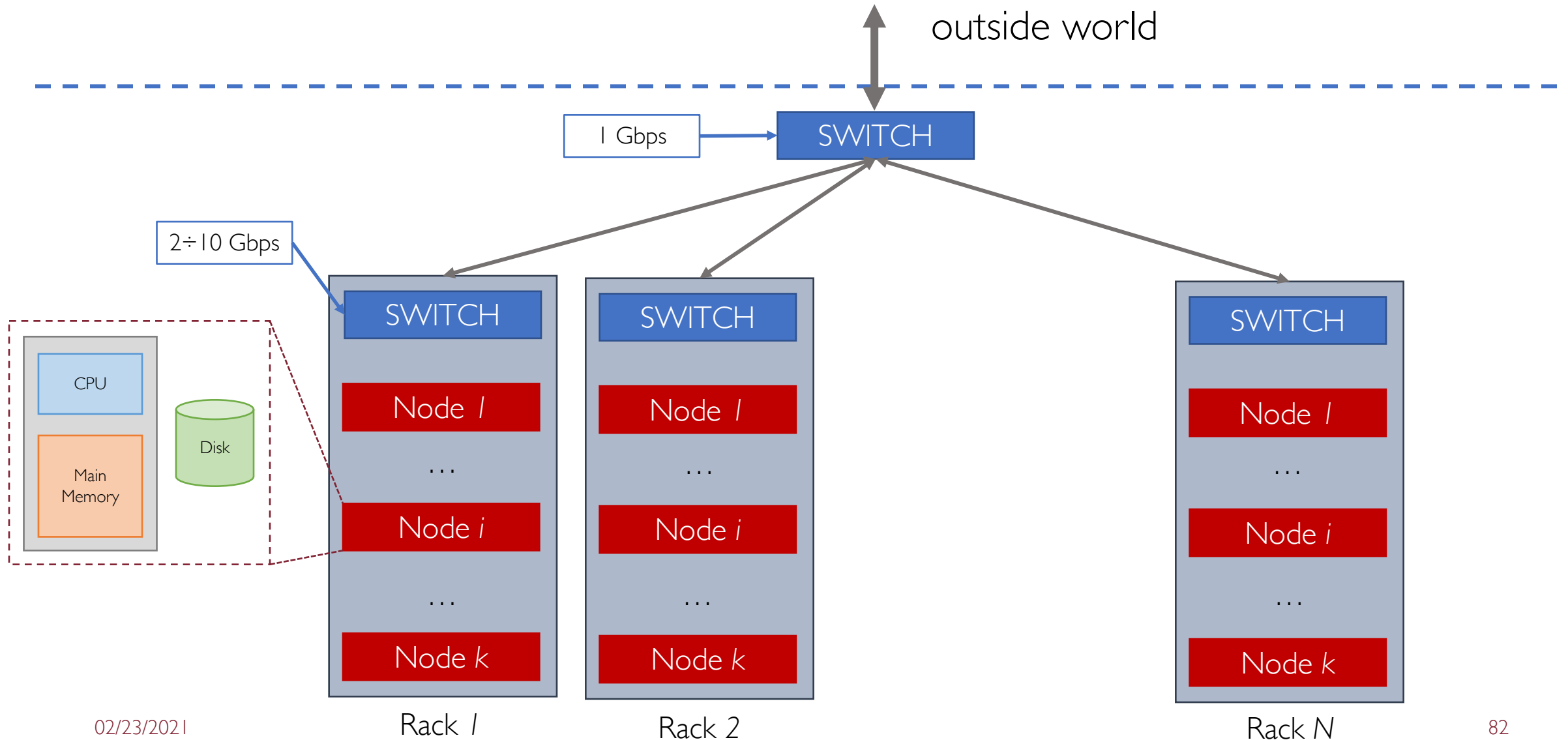
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Cluster Architecture: Challenges

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 - Ensure reliability upon node failure
 - Minimize network communication bottleneck
 - Ease distributed programming model

Challenge: Node Failure

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$$p = P(\text{node}_i \text{ fails}) = 1/1,000 = 0.001$$

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- Associate with each node a random variable $X_{i,t}$
 - $X_{i,t} \sim \text{Bernoulli}(p)$ outputs 1 (failure) with probability $p = 0.001$ and 0 (working) with probability $(1-p) = 0.999$
 - Assume for simplicity p is the same for all nodes and independent from each other

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$$E[T] = Np$$

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

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Q2: How to minimize data transfers 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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- Data is generated at an unprecedented rate → Big Data
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- Traditional algorithms/techniques often don't scale very well
- There is the need for new "tools" which allow storing, managing, and analyzing big data painlessly