Big Data Computing

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- 16-bit architecture
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All the running software was written in AGC assembly language, now also available on <u>GitHub</u>



Almost 55 Years Have Passed...

... And The World Has Changed



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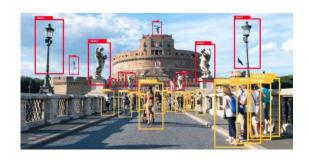






... And The World Has Changed



















AGC vs. Our Smartphone

- Most recent smartphones have
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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							
Val	ue	SI					
1000	10 ³	k	kilo				
1000 ²	10 ⁶	M	mega				
1000 ³	10 ⁹	G	giga				
1000 ⁴	10 ¹²	T	tera				
1000 ⁵	10 ¹⁵	Р	peta				
1000 ⁶	10 ¹⁸	Ε	exa				
1000 ⁷	10 ²¹	Z	zetta				
1000 ⁸	10 ²⁴	Υ	yotta				

and Garage							
Binary							
Valu	e	IEC		JEDEC			
1024	2 ¹⁰	Ki	kibi	K	kilo		
1024 ²	2 ²⁰	Mi	mebi	M	mega		
1024 ³	2 ³⁰	Gi	gibi	G	giga		
1024 ⁴	2 ⁴⁰	Ti	tebi	-			
1024 ⁵	2 ⁵⁰	Pi	pebi	_			
1024 ⁶	2 ⁶⁰	Ei	exbi	_			
1024 ⁷	2 ⁷⁰	Zi	zebi	_			
1024 ⁸	2 ⁸⁰	Yi	yobi	_			

Orders of Magnitude



100 = 1

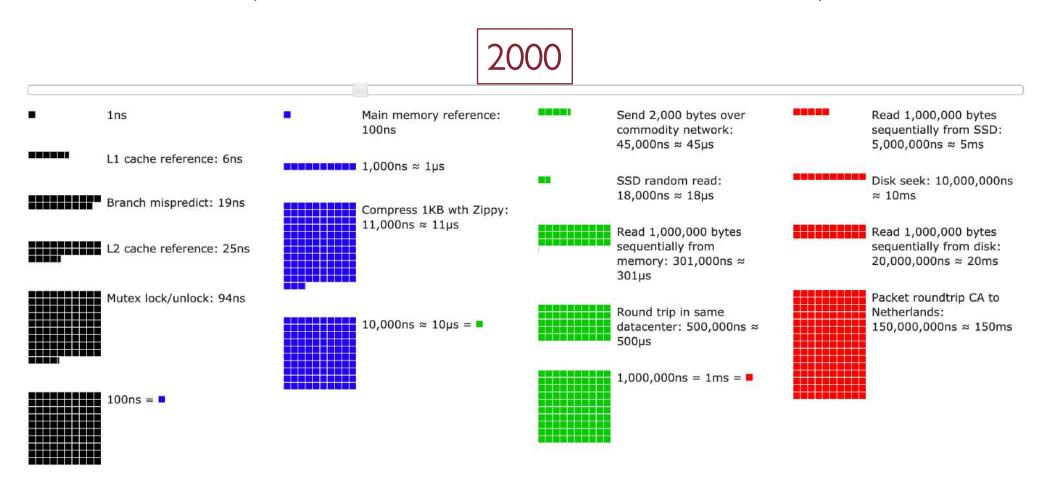
source: https://www.youtube.com/watch?v=Ww4gYNrOkkg

Orders of Magnitude



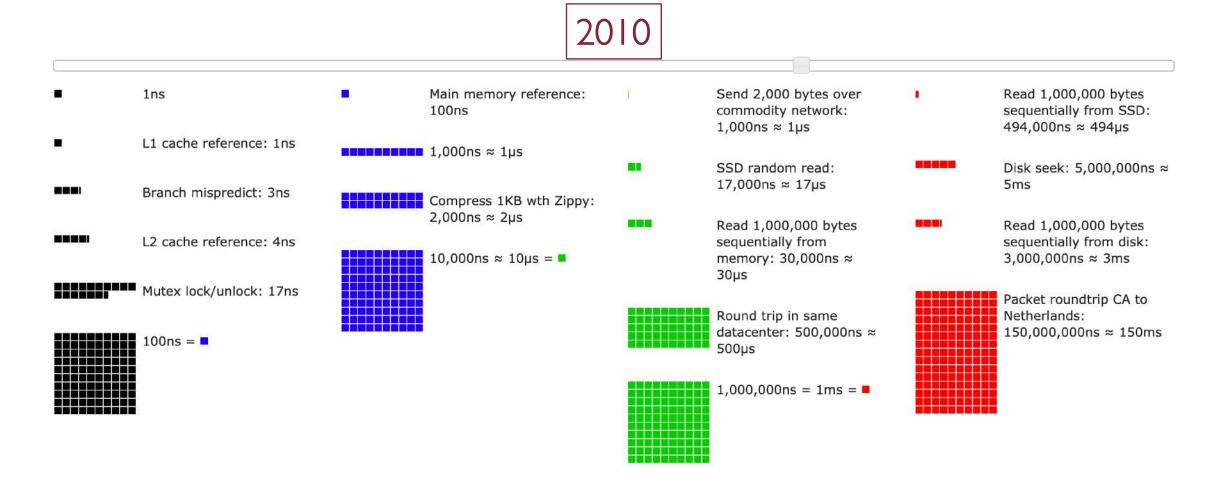
Numbers Every Computer Scientist Should Know

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



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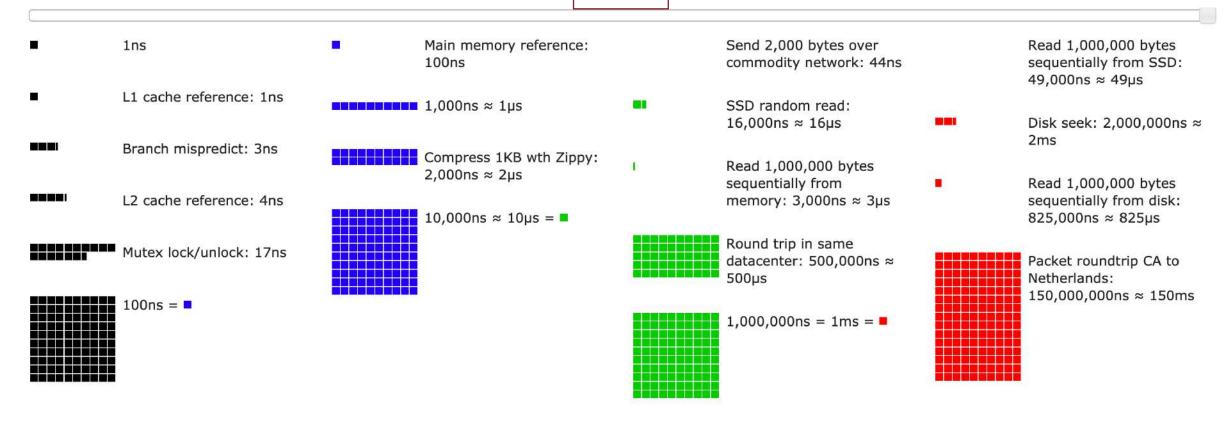
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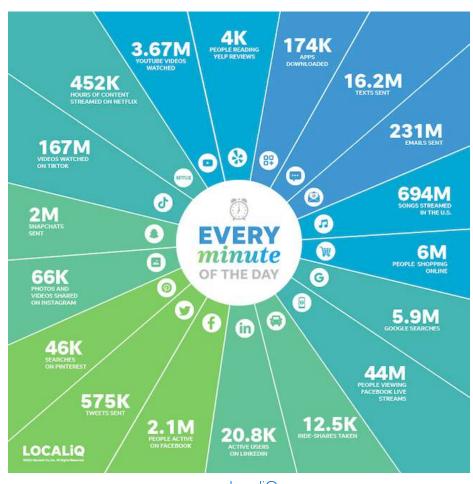
2020



The Information Technology (IT) Revolution

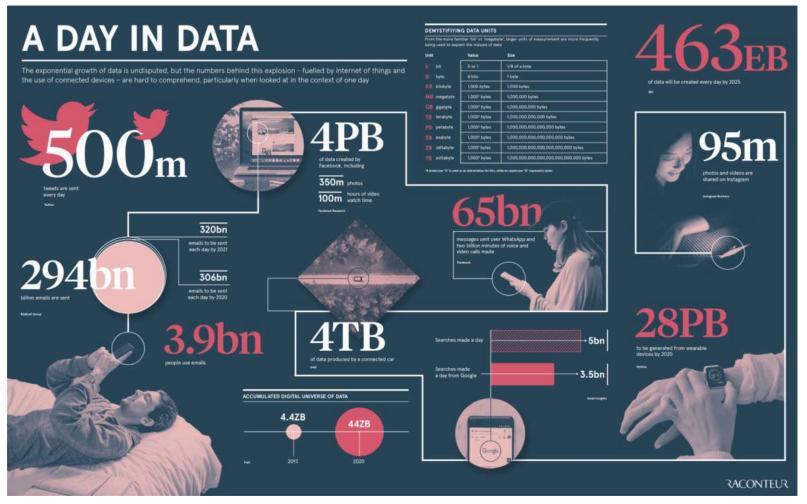
- Started almost 60 years ago and still rocketing
- Driven by:
 - Science/Engineering
 - Business
 - Society

What Happens on the Internet in 1 Minute?



source: LocaliQ

How Much Data is Generated Each Day?



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- 4V's (sometimes, 5, 6 or even 7!)

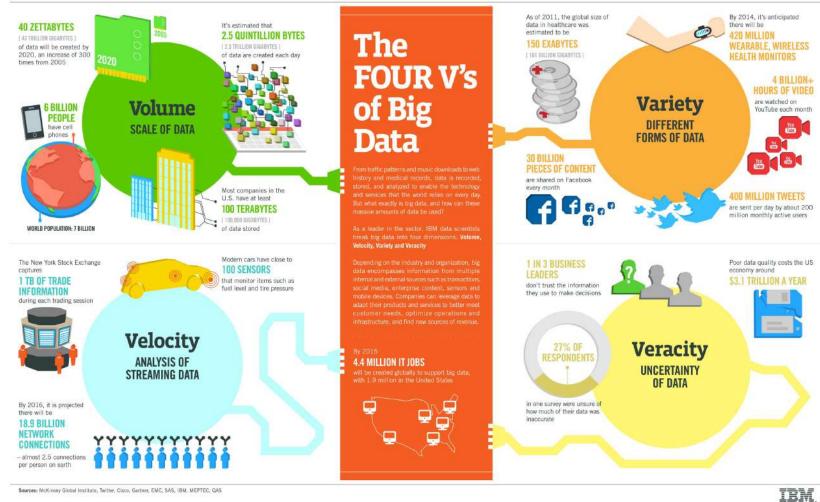
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 - Veracity -> reliability of the data used to drive decision processes

The 4 V's of Big Data



source: IBM

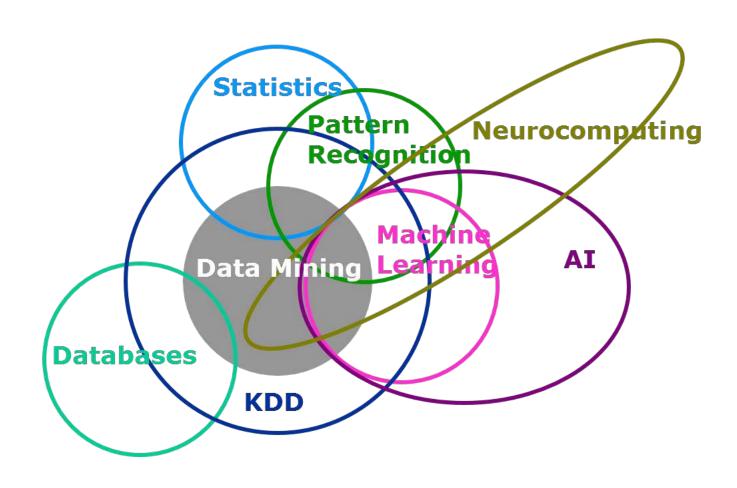
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- To get the most value out of it, data has to be:
 - Stored
 - Managed
 - Analyzed

Big Data Analysis: Landscape



Execution/Storage Infrastructure

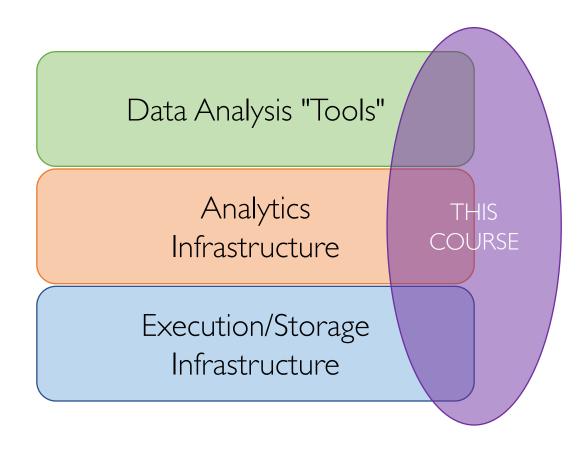
Analytics Infrastructure

Execution/Storage Infrastructure

Data Analysis "Tools"

Analytics Infrastructure

Execution/Storage Infrastructure



What Will We Learn?

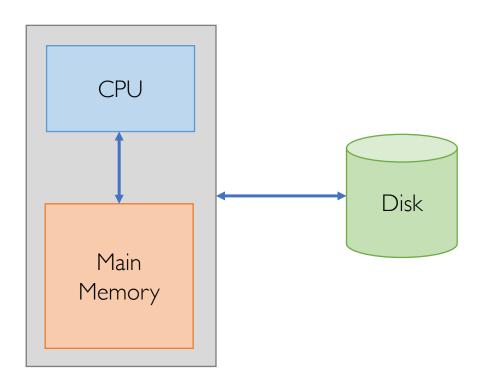
- To extract knowledge from different types of data
 - High-dimensional
 - Unlabeled/Labeled
 - Graph-based
 - Infinite/never-ending streams

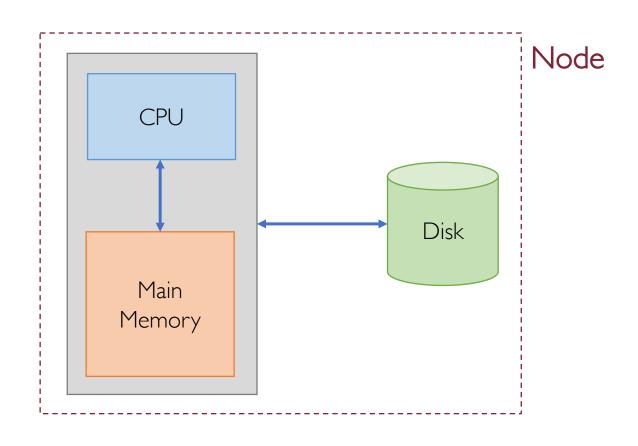
What Will We Learn?

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

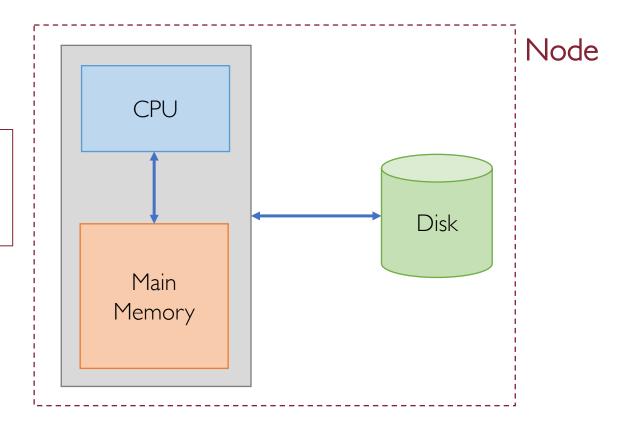
What Will We Learn?

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





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



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- The average size of each web page (HTML only) is ~100 KB
- The total size of the index will be

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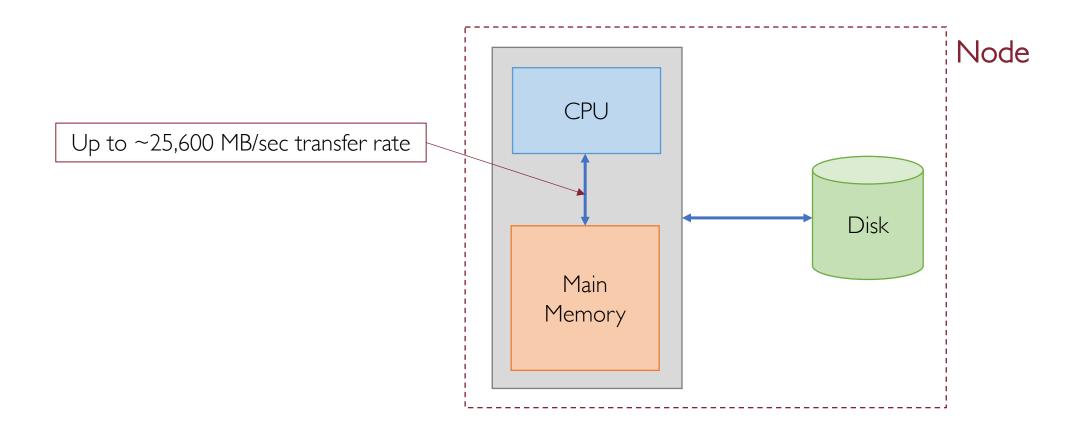
Main Memory

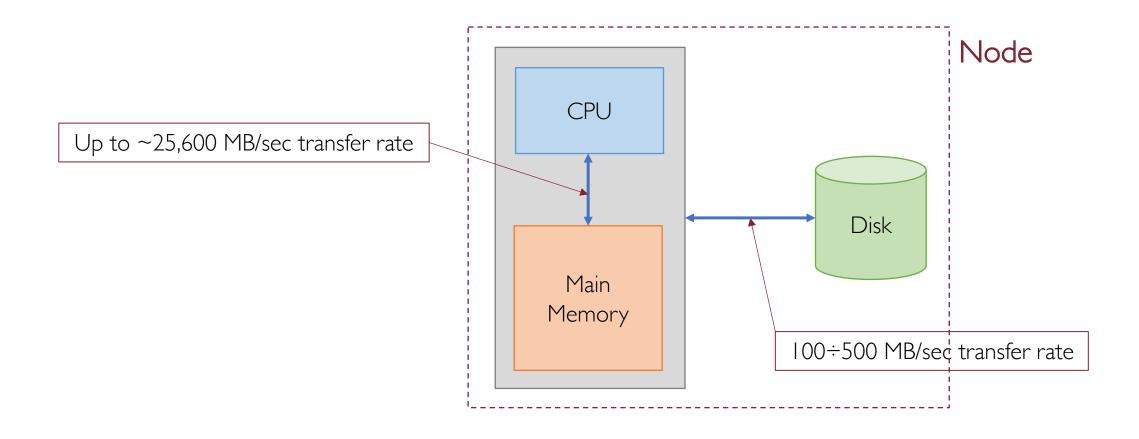
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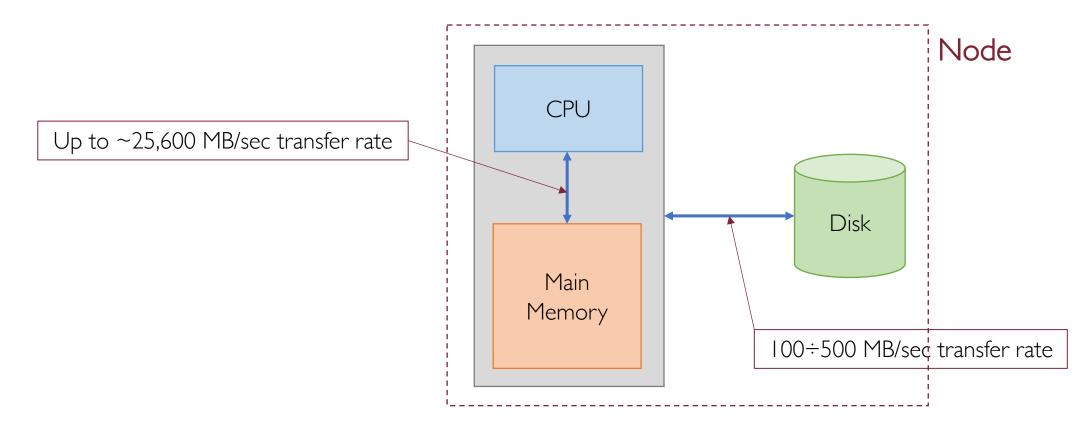
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2 orders of magnitude difference between data transfer rate

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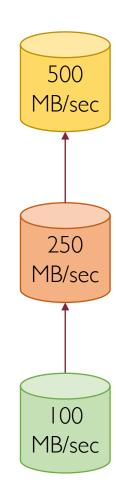
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- Single-node architecture is clearly not enough here
 - Scaling Up vs. Scaling Out

Scaling Up/Vertical Scaling

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

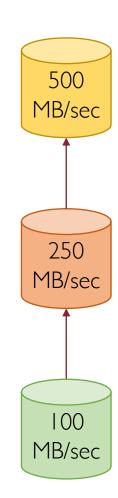


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• PRO

• Easiest solution



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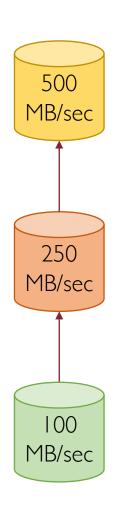
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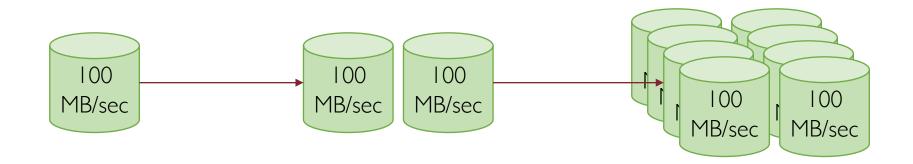
CON

- Improvement is physically-limited (e.g., 2.5x or 5x)
- Expensive



Scaling Out/Horizontal Scaling

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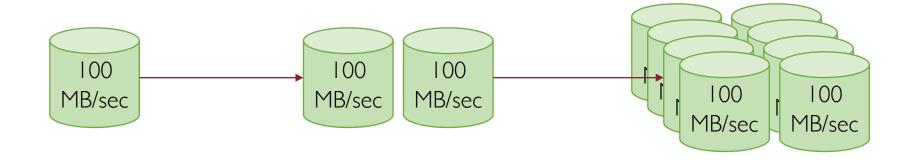


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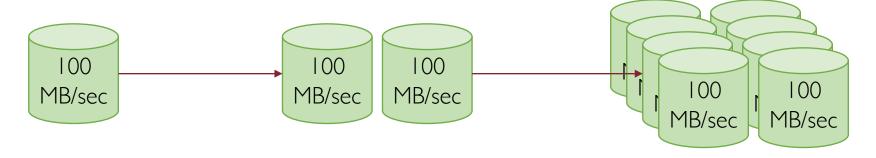
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• Extra overhead required to manage parallel work



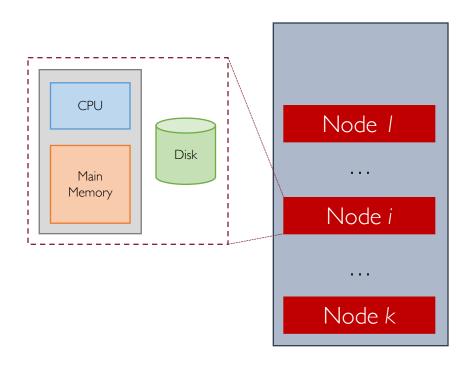
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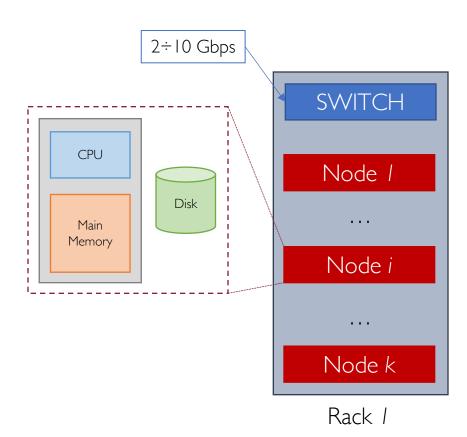
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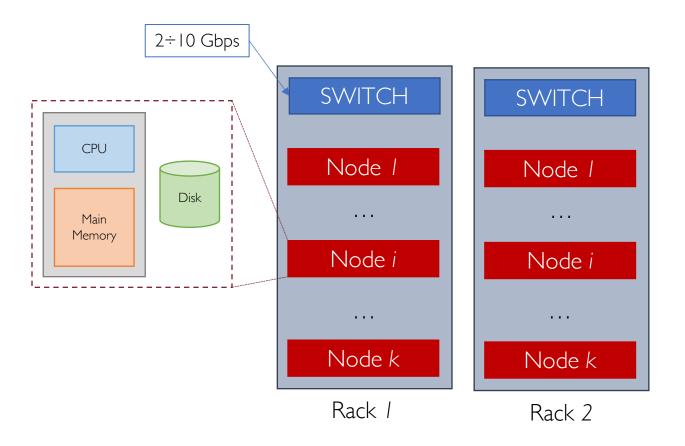
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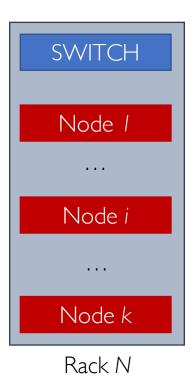
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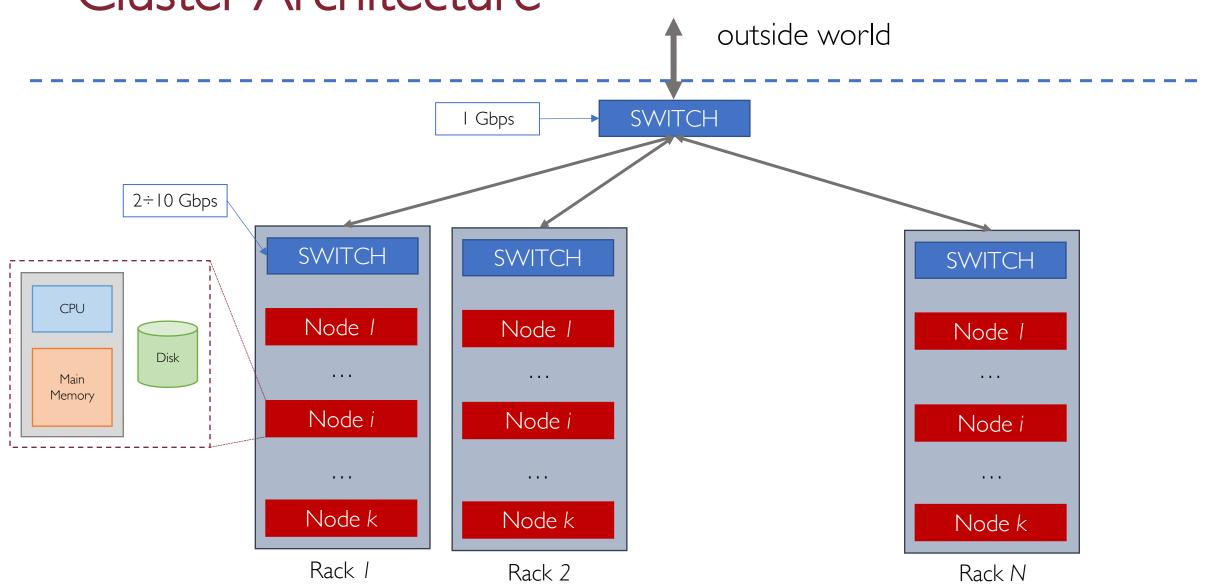
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- Network switches enabling node communication
 - I Gbps (inter-rack)
 - 2÷10 Gbps (intra-rack)











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 - Ease distributed programming model

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 - Assume for semplicity p is the same for all nodes and independent from each other

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$$E[T] = Np$$

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

Challenge: Network Bottleneck

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- For example, if we have to transfer IOTB of data at I Gbps

 8×10^{13} bits / 1×10^9 bit/sec = 8×10^4 secs ~ 1 day

Challenge: Network Bottleneck

- Moving data across nodes both intra- and inter racks may be costly
- For example, if we have to transfer 10TB of data at 1 Gbps

 8×10^{13} bits / 1×10^9 bit/sec = 8×10^4 secs ~ 1 day

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

Challenge: Distributed Programming

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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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- Extracting knowledge from such big data is incredibly valuable
- 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