UNIVERSITY OF WATERLOO

Data-Intensive Distributed Computing

CS 431/631 451/651 (Winter 2019)

Part 1: MapReduce Algorithm Design (3/4)

January 15, 2019

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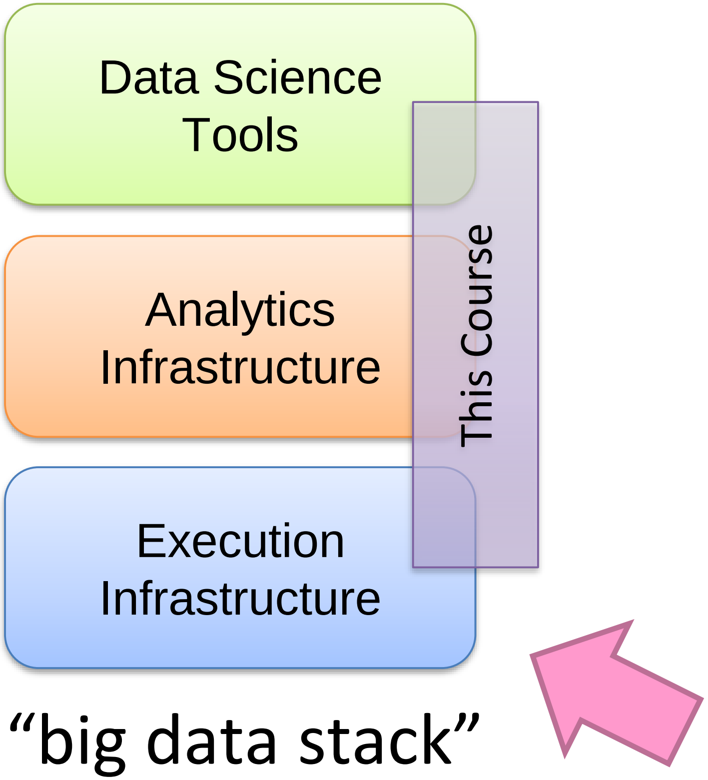
Kira Systems

These slides are available at http://lintool.github.io/bigdata-2018f/

Agenda for Today

Cloud computing
Datacenter architectures
Hadoop cluster architecture
MapReduce physical execution

Today



“big data stack”

Aside: Cloud Computing

Source: Wikipedia (Clouds)

The best thing since sliced bread?

Before clouds…

Grids

Connection machine

Vector supercomputers

…

Cloud computing means many different things:

Big data

Rebranding of web 2.0

Utility computing

Everything as a service

Rebranding of web 2.0

Rich, interactive web applications

Clouds refer to the servers that run them

Javascript! (ugh)

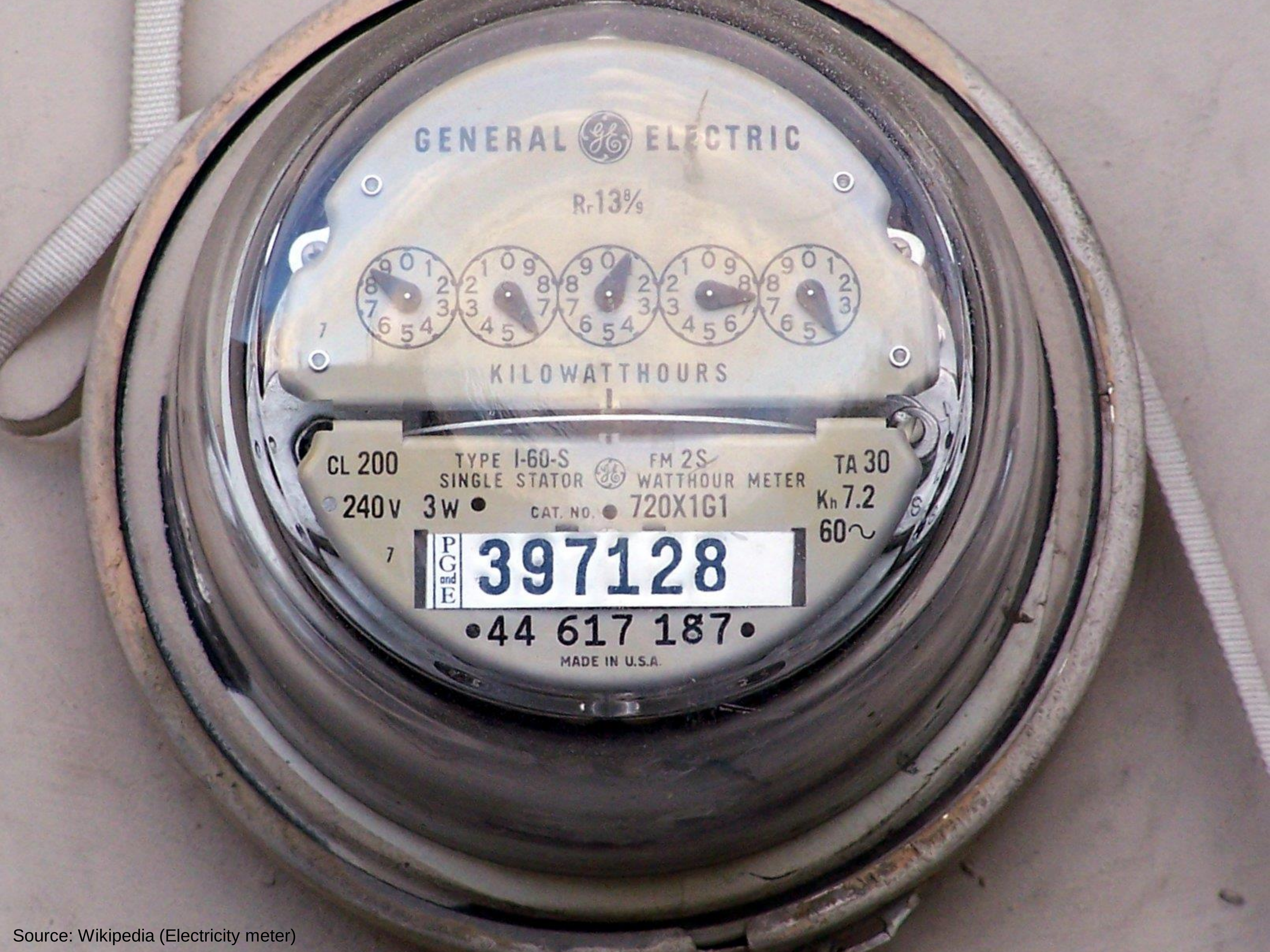
Examples: Facebook, YouTube, Gmail, …

“The network is the computer”: take two

User data is stored “in the clouds”

Rise of the tablets, smartphones, etc. (“thin clients”)

Browser is the OS



Source: Wikipedia (Electricity meter)

Utility Computing

What?

Computing resources as a metered service ("pay as you go")

Why?

Cost: capital vs. operating expenses

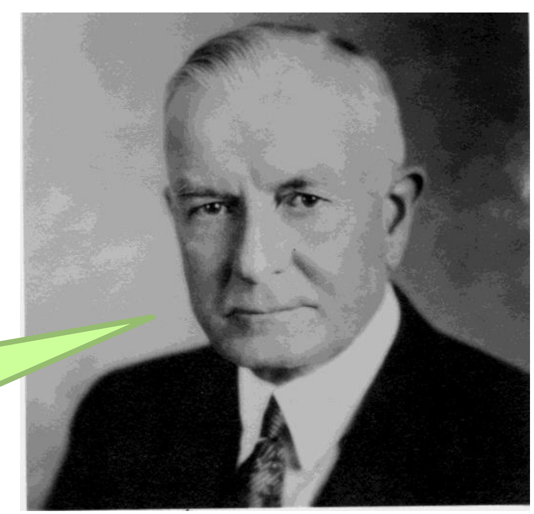
Scalability: "infinite" capacity

Elasticity: scale up or down on demand

Does it make sense?

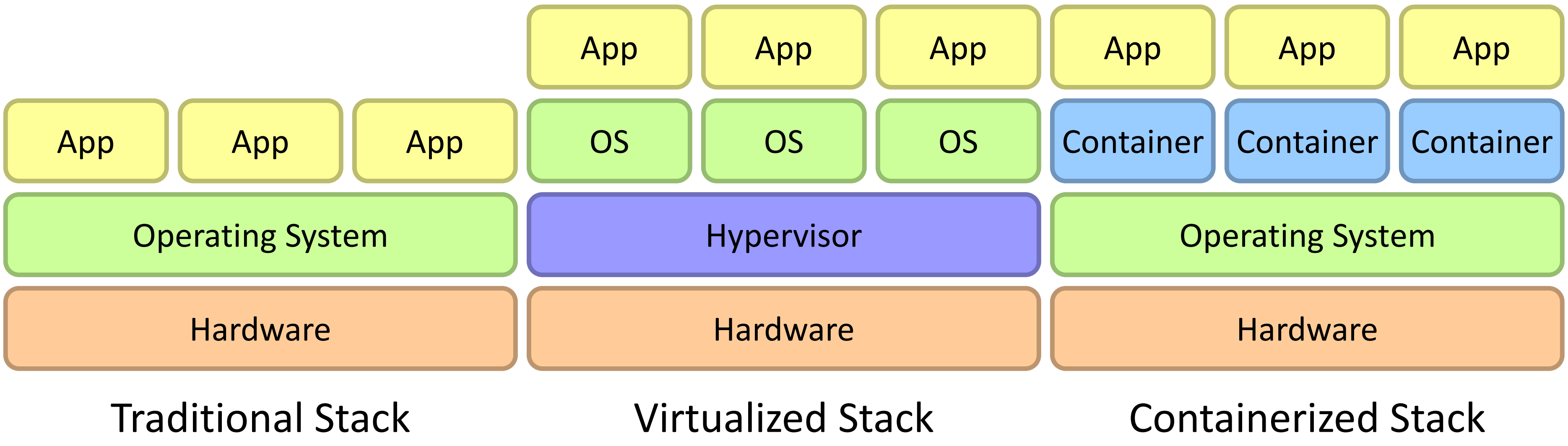
Benefits to cloud users

Business case for cloud providers



I think there is a world market for about five computers.

Evolution of the Stack



Everything as a Service

Infrastructure as a Service (IaaS)

Why buy machines when you can rent them instead?

Examples: Amazon EC2, Microsoft Azure, Google Compute

Platform as a Service (PaaS)

Give me a nice platform and take care of maintenance, upgrades, …

Example: Google App Engine

Software as a Service (SaaS)

Just run the application for me!

Example: Gmail, Salesforce

Everything as a Service

Database as a Service

Run a database for me

Examples: Amazon RDS, Microsoft Azure SQL, Google Cloud BigTable

Search as a Service

Run a search engine for me

Example: Amazon Elasticsearch Service

Function as a Service

Run this function for me

Example: Amazon Lambda, Google Cloud Functions

Who cares?

A source of problems…

Cloud-based services generate big data

Clouds make it easier to start companies that generate big data

As well as a solution…

Ability to provision clusters on-demand in the cloud

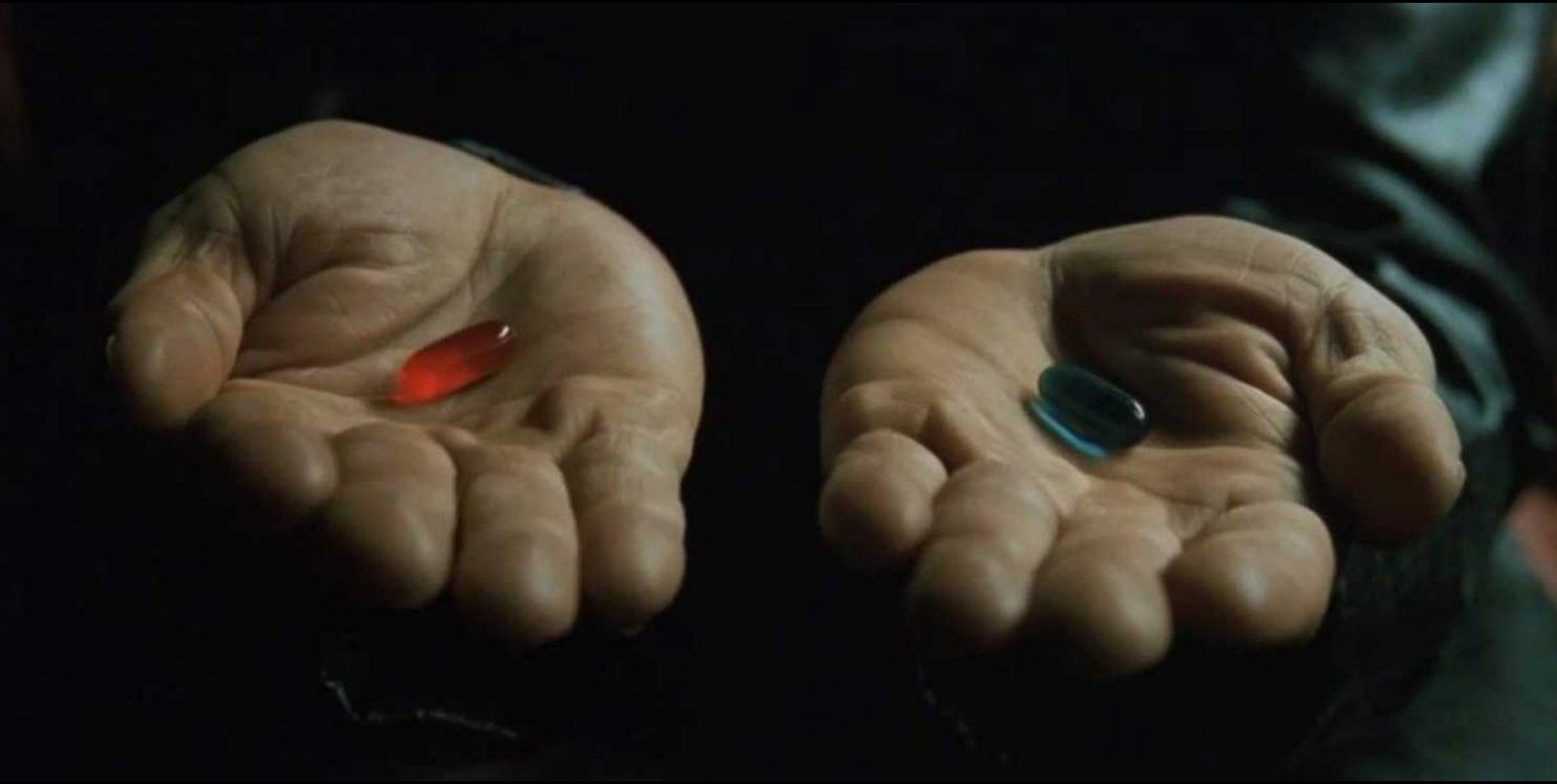
Commoditization and democratization of big data capabilities

So, what *is* the cloud?

Source: Wikipedia (Clouds)

What *is* the Matrix?

Source: The Matrix - PPC Wiki - Wikia



Source: The Matrix

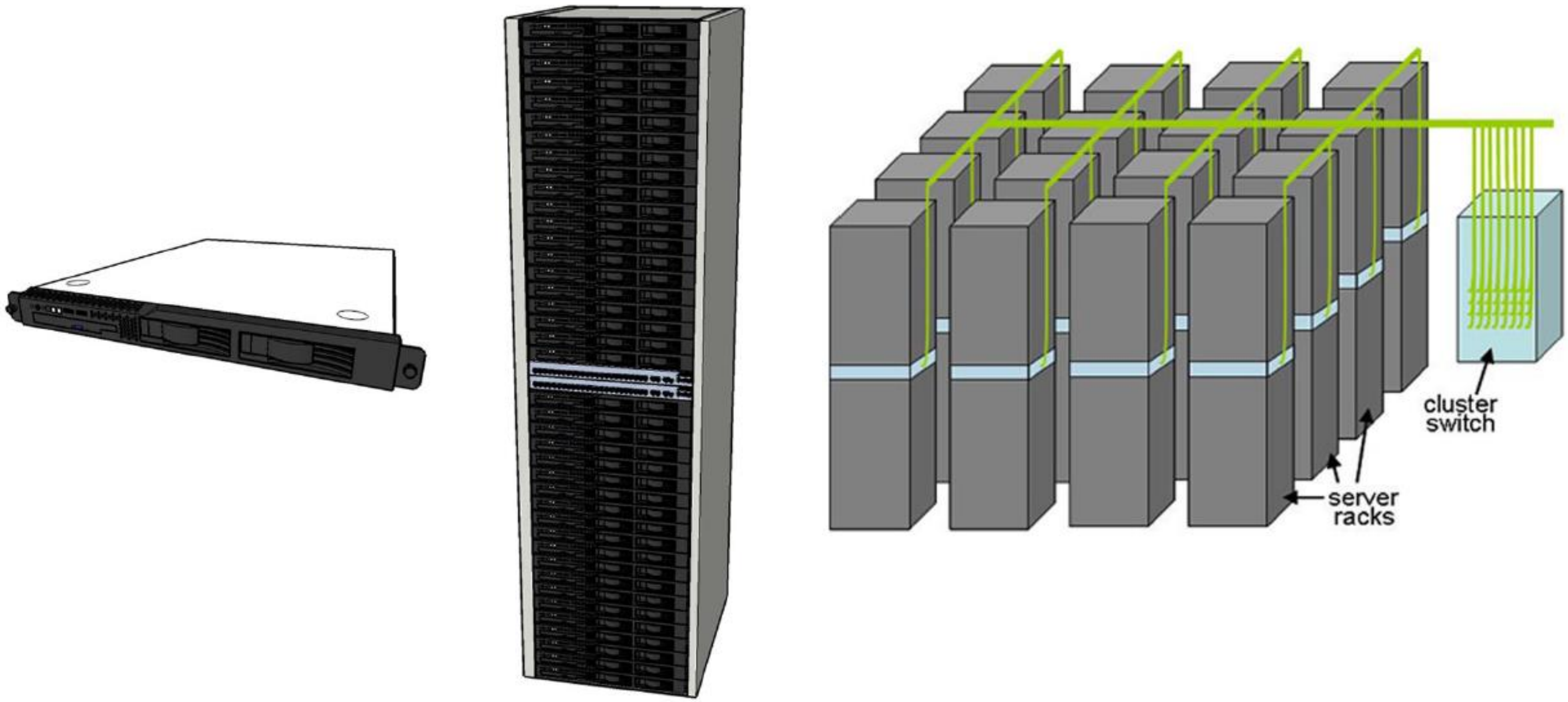
Source: Wikipedia (The Dalles, Oregon)

Source: Bonneville Power Administration

Source: Google

Source: Google

Building Blocks



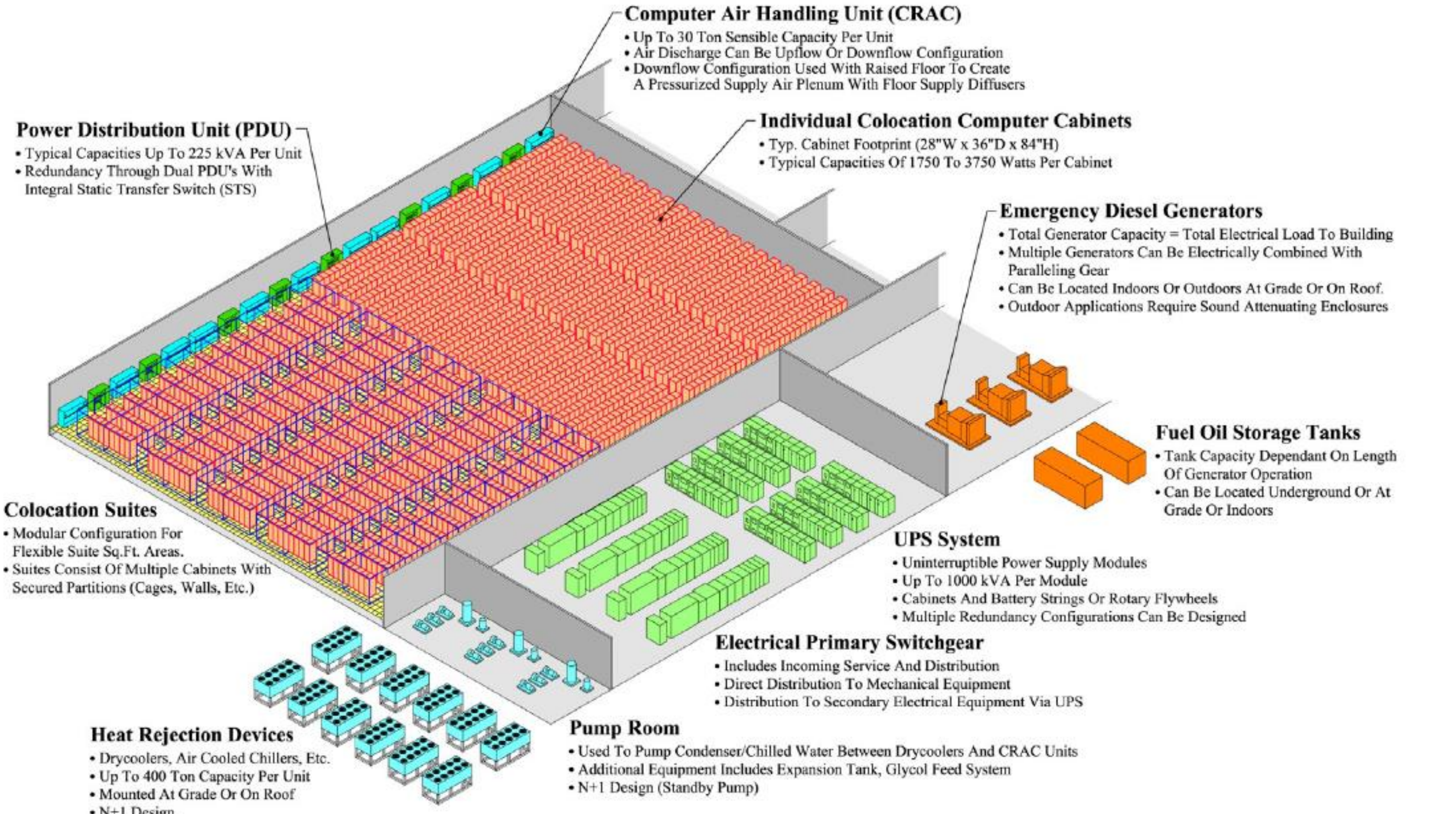
Source: Barroso and Urs Hölzle (2009)


Source: Google

Source: Google

Source: Facebook

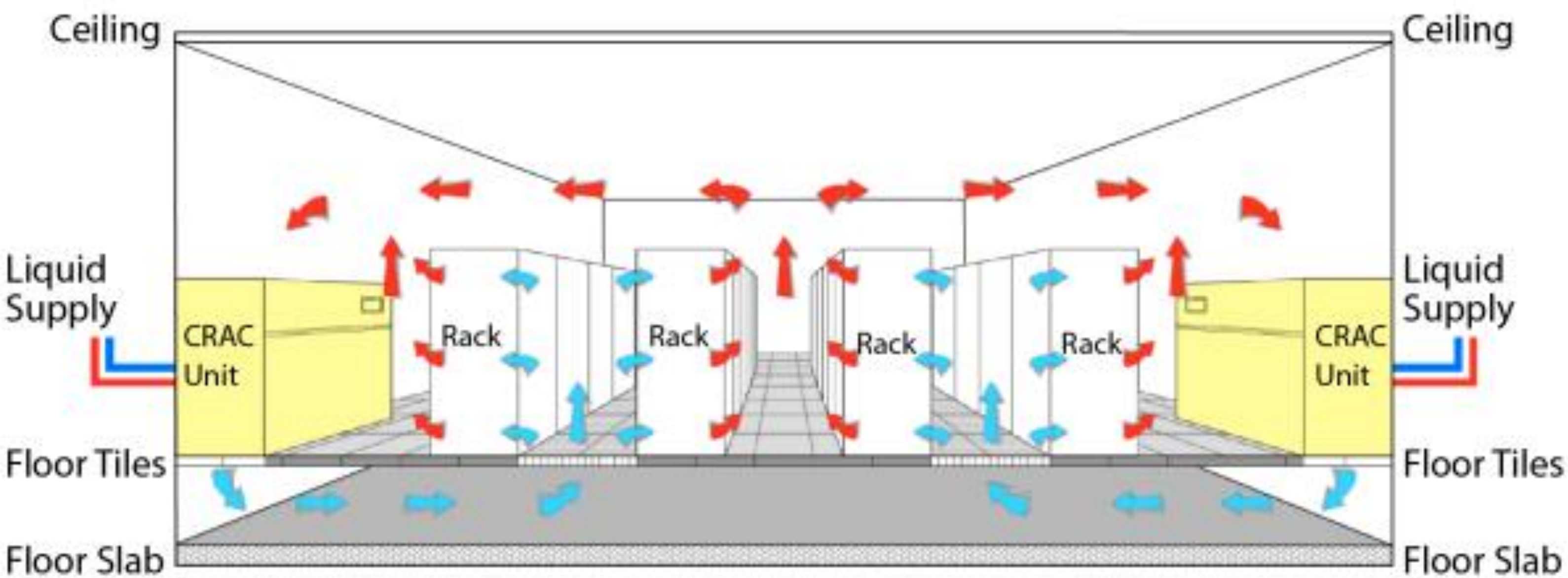
Anatomy of a Datacenter



Source: Barroso and Urs Hölzle (2013)

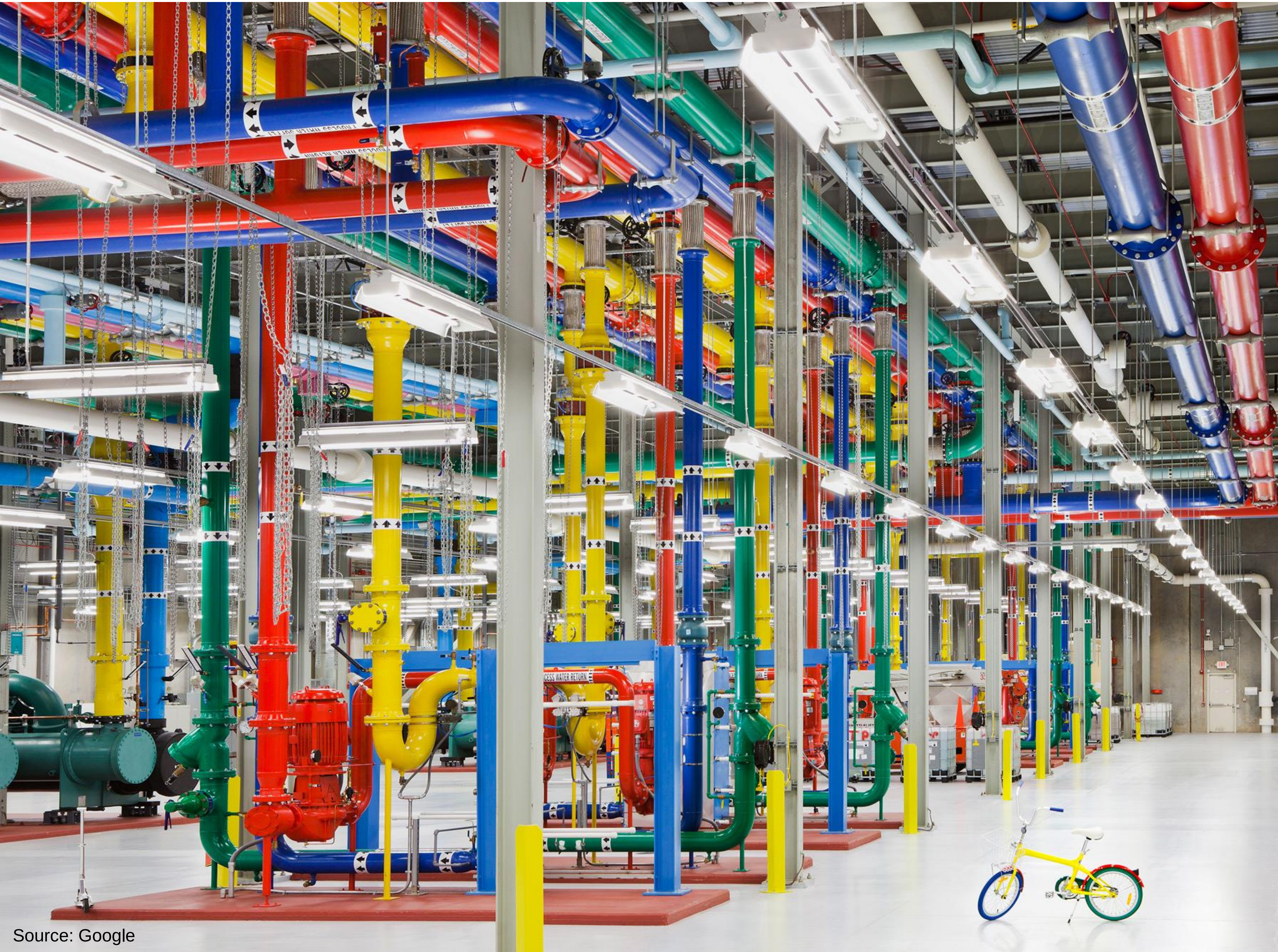
Datacenter cooling

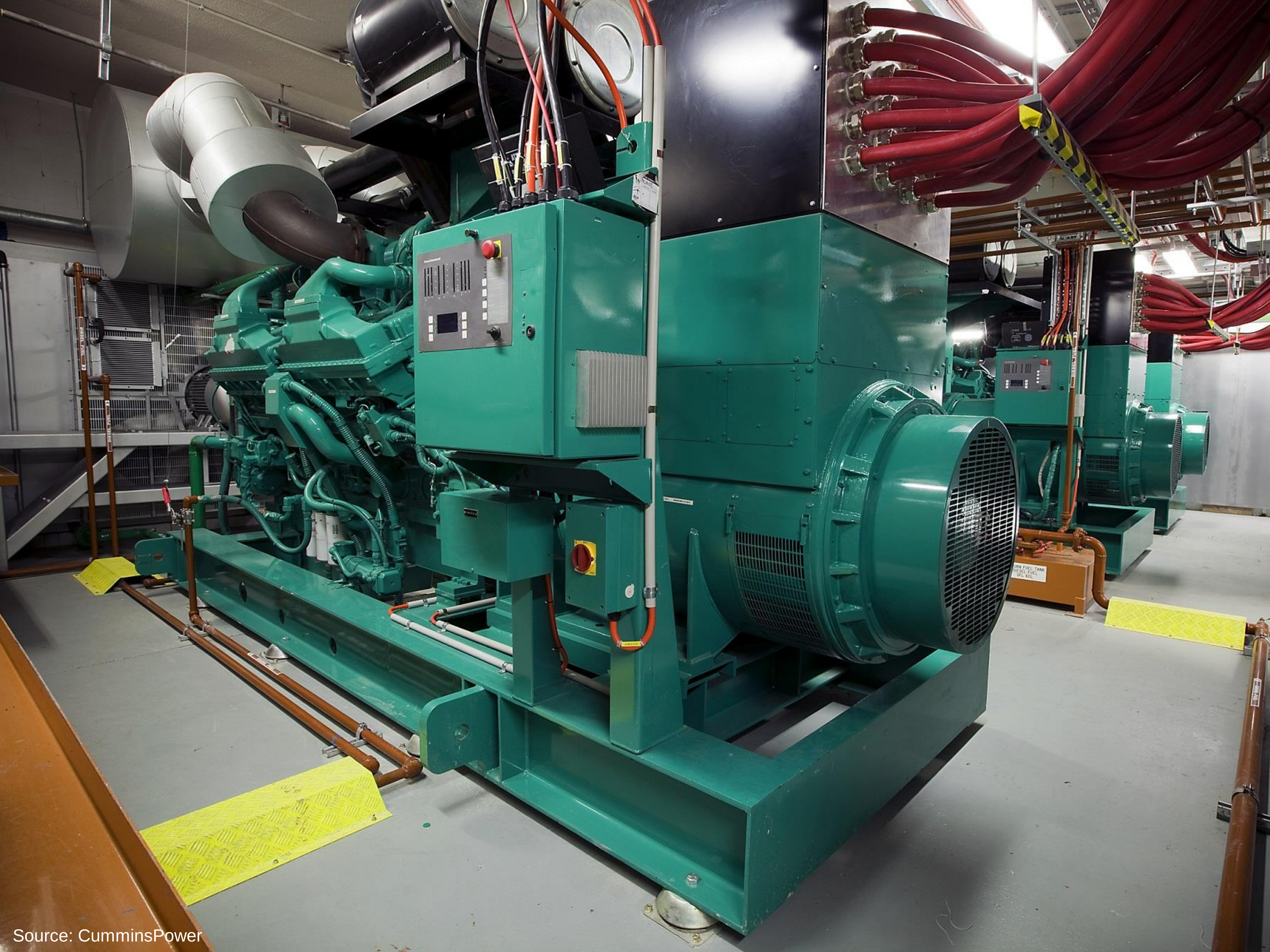
What's a computer?



Source: Barroso and Urs Hölzle (2013)

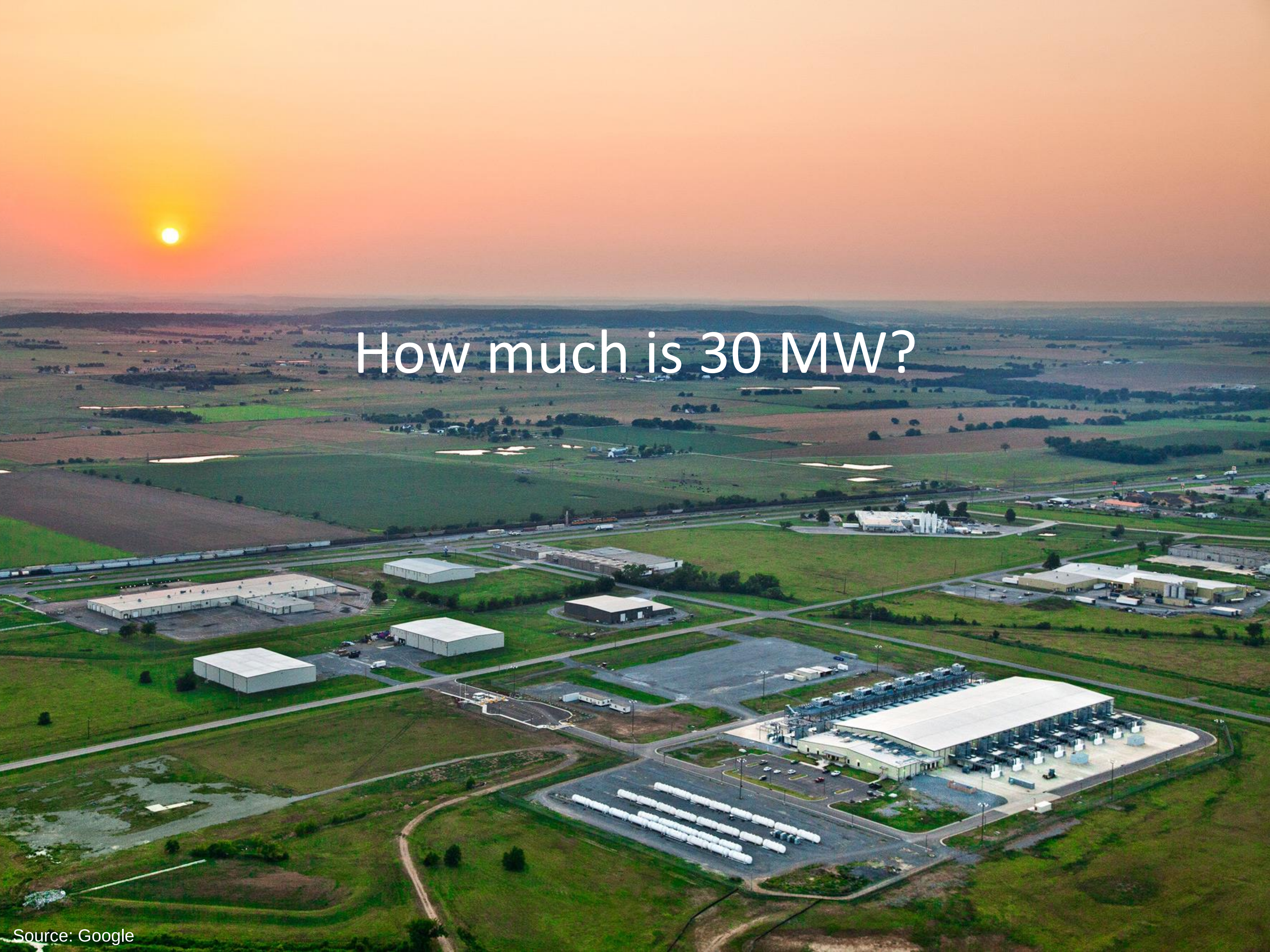
Source: Google


Source: Google

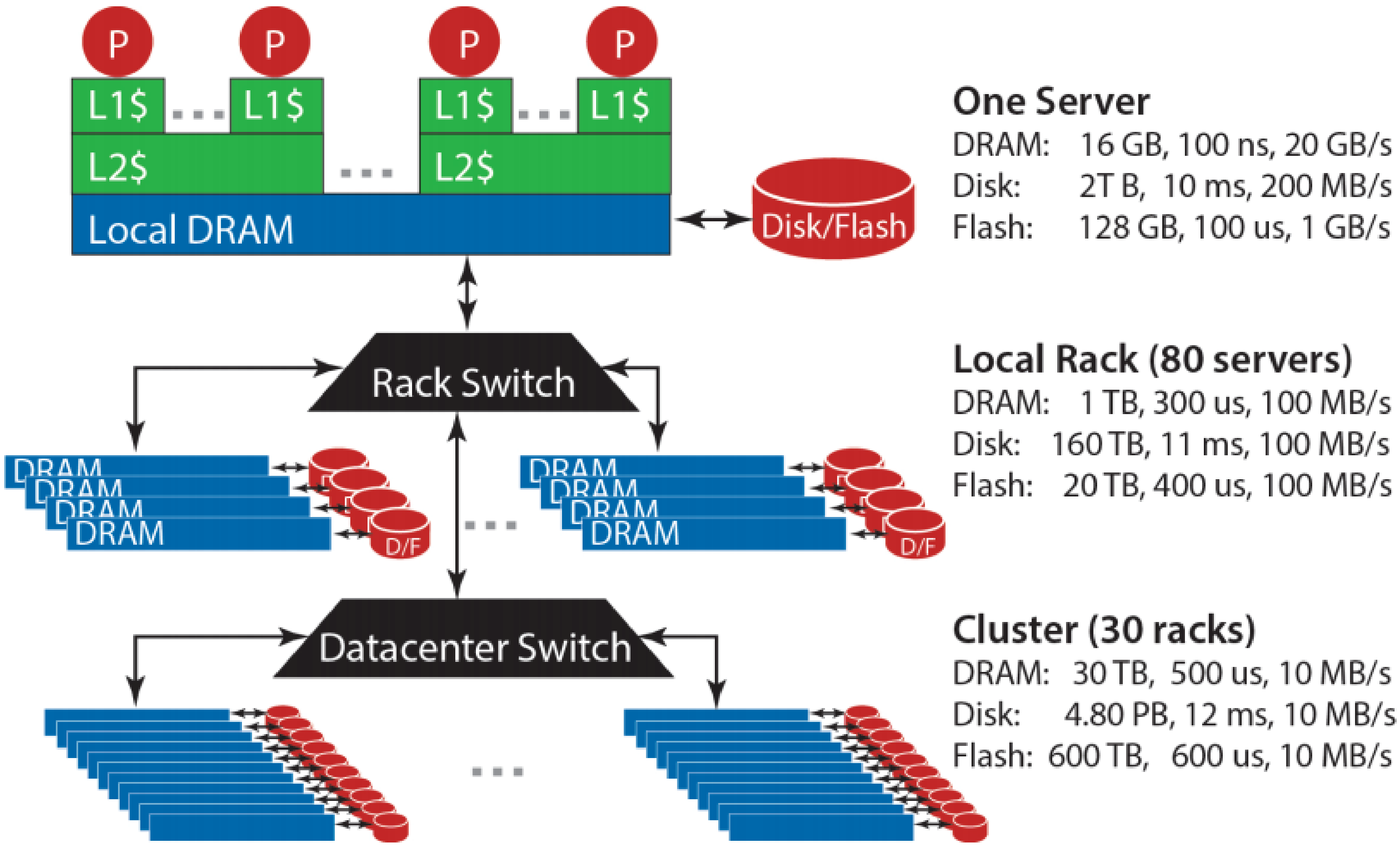


Source: CumminsPower

Source: Google


How much is 30 MW?
Source: Google

Datacenter Organization



Source: Barroso and Urs Hölzle (2013)

The datacenter *is* the computer!

It's all about the right level of abstraction

Moving beyond the von Neumann architecture

What's the "instruction set" of the datacenter computer?

Hide system-level details from the developers

No more race conditions, lock contention, etc.

No need to explicitly worry about reliability, fault tolerance, etc.

Separating the *what* from the *how*

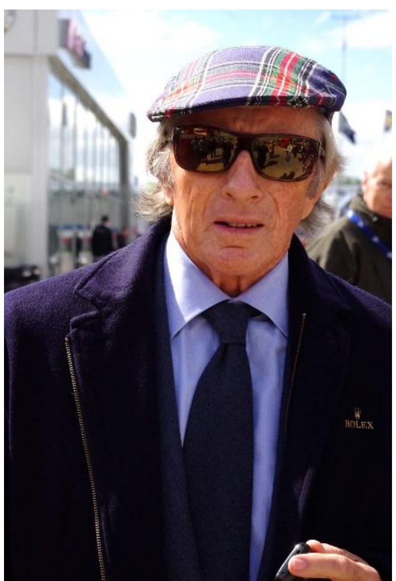
Developer specifies the computation that needs to be performed

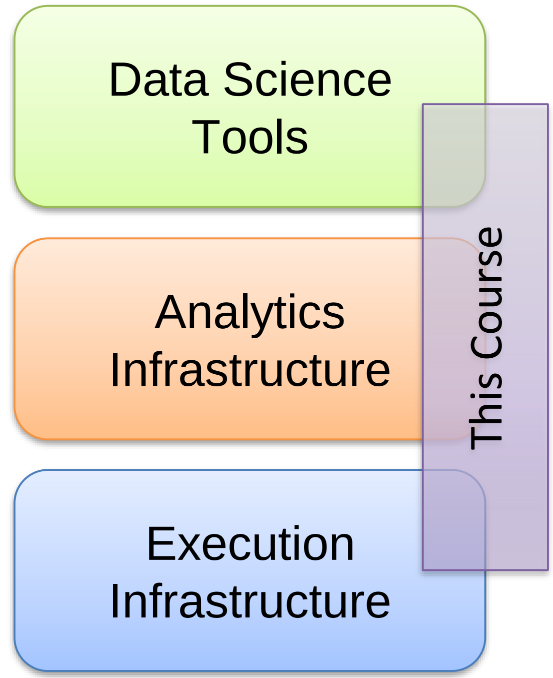
Execution framework ("runtime") handles actual execution

Wait, why do we care?

Mechanical Sympathy

"You don't have to be an engineer to be be a racing driver, but you do have to have mechanical sympathy"
– Formula One driver Jackie Stewart





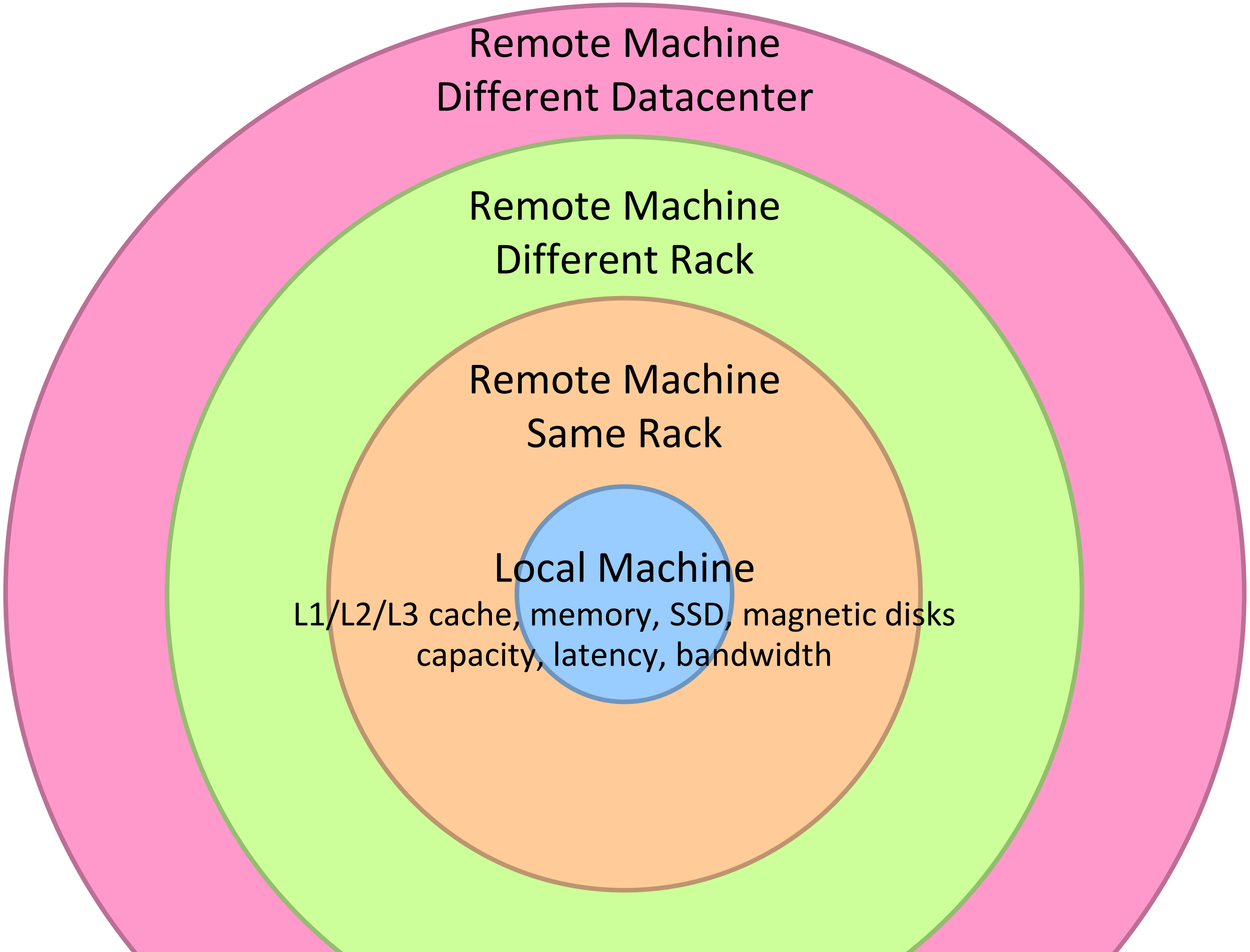
"big data stack"

Intuitions of time and space

How long does it take to read 100 TBs from 100 hard drives?
Now, what about SSDs?

How long will it take to exchange 1b key-value pairs:
Between machines on the same rack?
Between datacenters across the Atlantic?

Storage Hierarchy



Numbers Everyone Should Know

According to Jeff Dean

L1 cache reference	0.5 ns
Branch mispredict	5 ns
L2 cache reference	7 ns
Mutex lock/unlock	100 ns
Main memory reference	100 ns
Compress 1K bytes with Zippy	10,000 ns
Send 2K bytes over 1 Gbps network	20,000 ns
Read 1 MB sequentially from memory	250,000 ns
Round trip within same datacenter	500,000 ns
Disk seek	10,000,000 ns
Read 1 MB sequentially from network	10,000,000 ns
Read 1 MB sequentially from disk	30,000,000 ns
Send packet CA->Netherlands->CA	150,000,000 ns

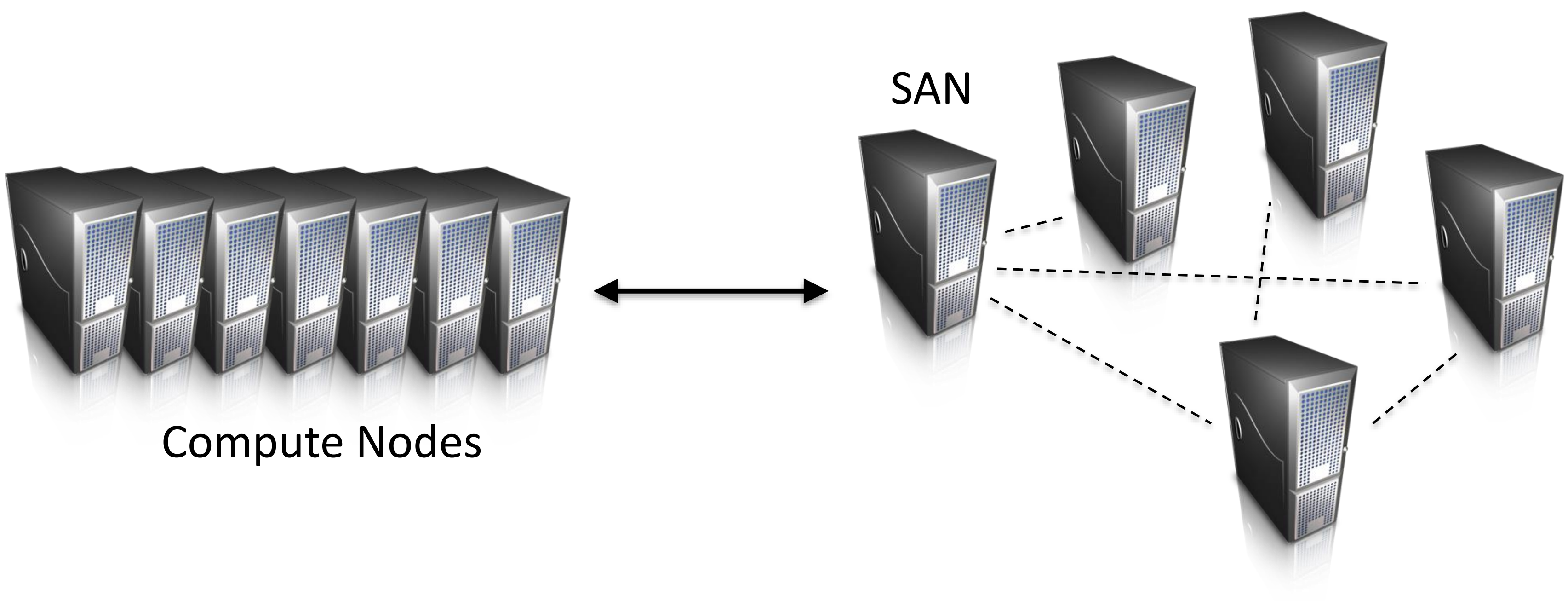
Google™

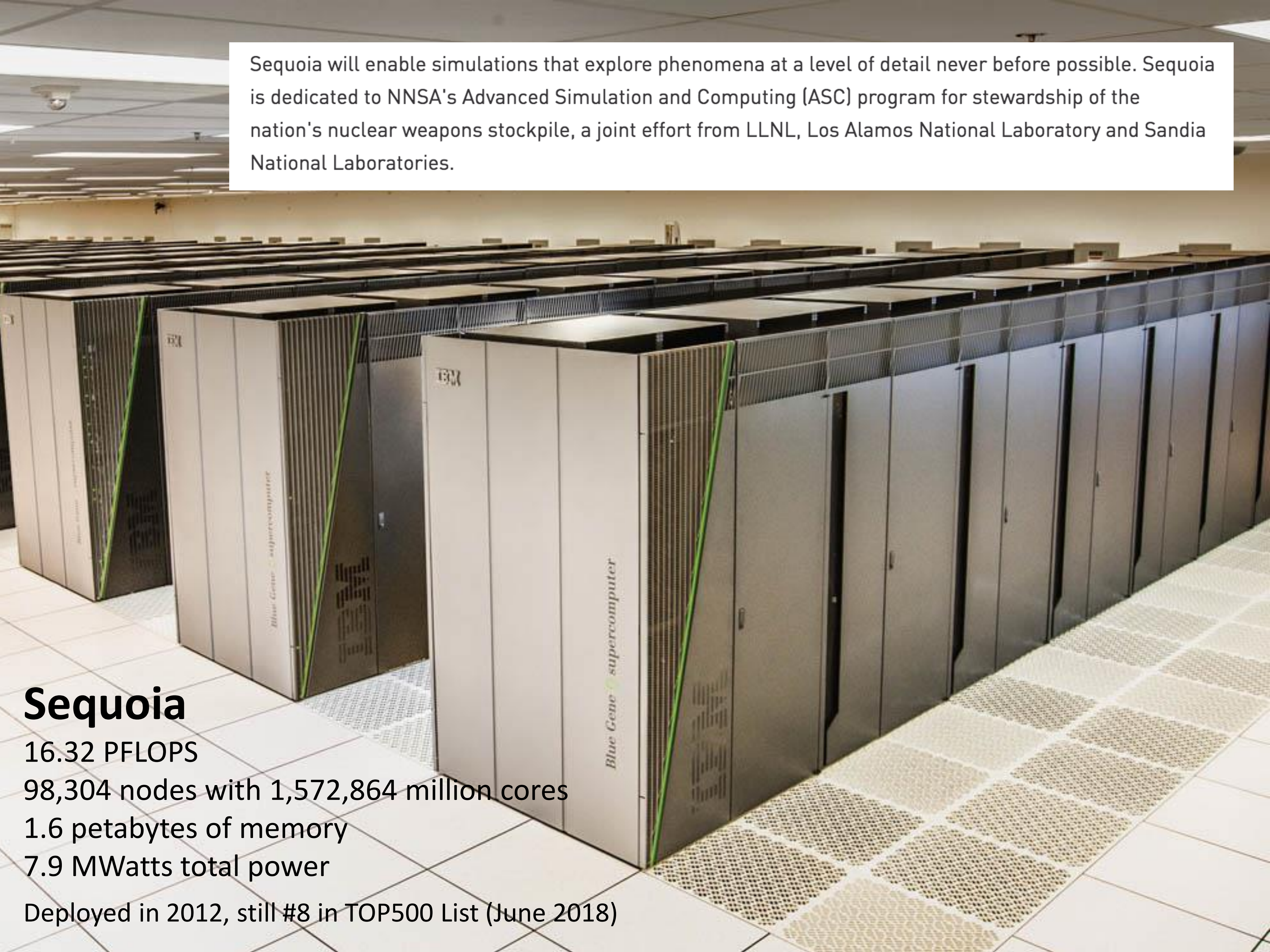
Hadoop Cluster Architecture

Source: Google

How do we get data to the workers?

Let's consider a typical supercomputer…





Sequoia will enable simulations that explore phenomena at a level of detail never before possible. Sequoia is dedicated to NNSA's Advanced Simulation and Computing (ASC) program for stewardship of the nation's nuclear weapons stockpile, a joint effort from LLNL, Los Alamos National Laboratory and Sandia National Laboratories.

Sequoia

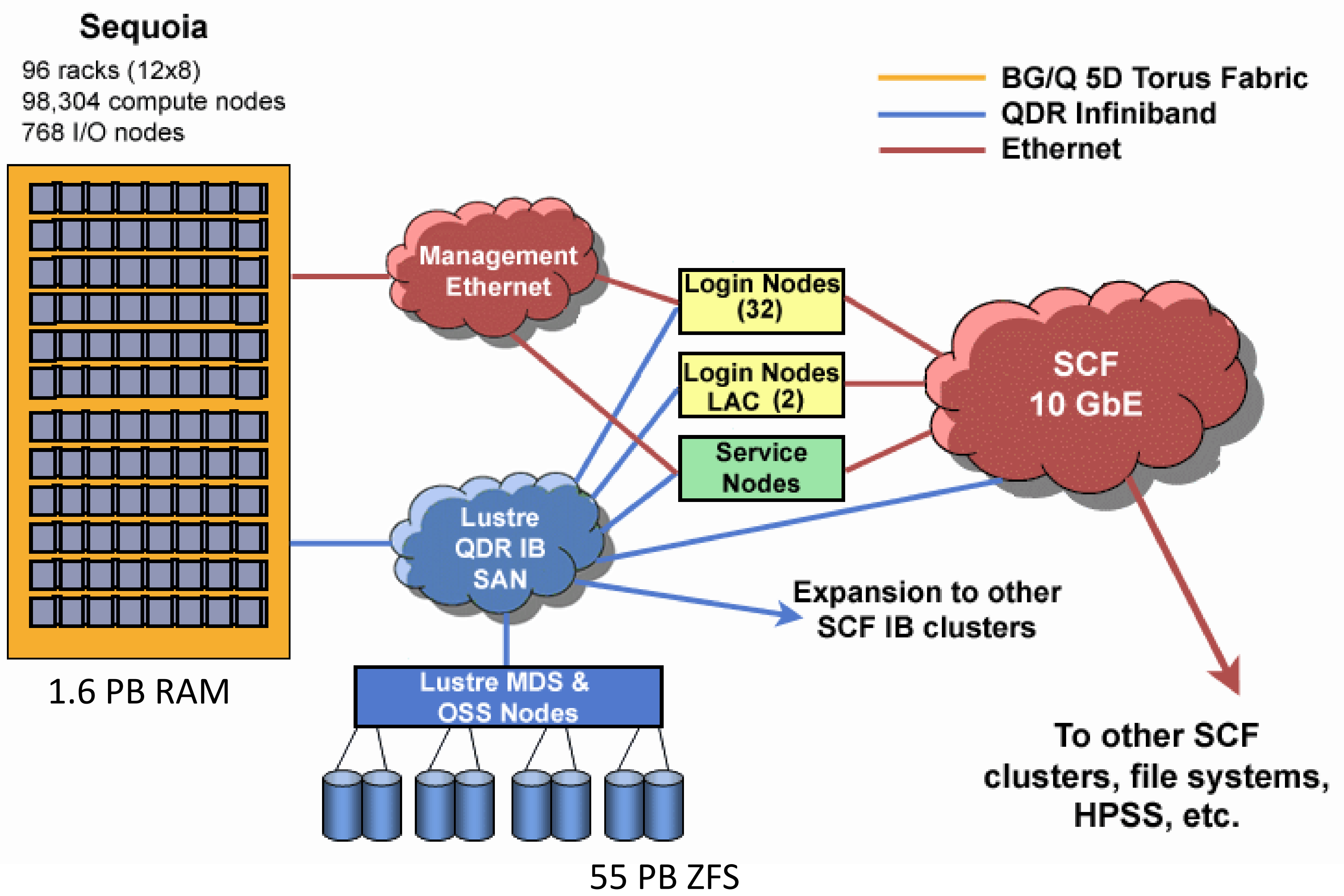
16.32 PFLOPS

98,304 nodes with 1,572,864 million cores

1.6 petabytes of memory

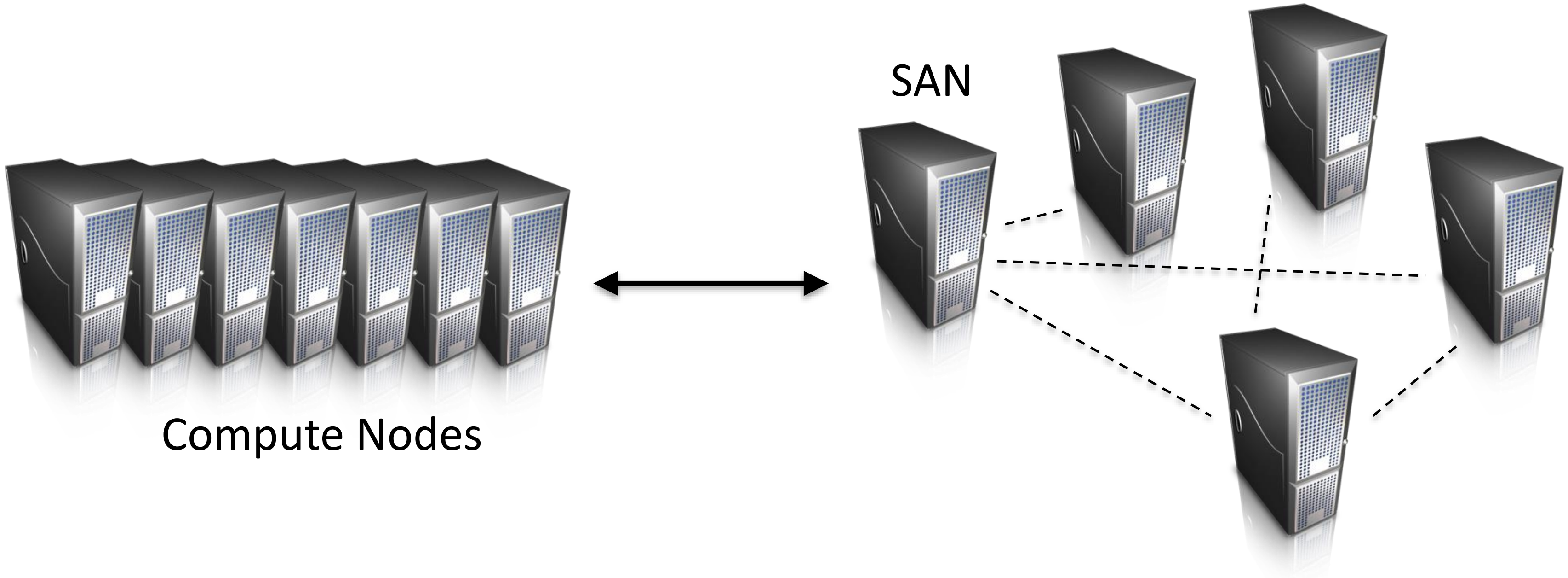
7.9 MWatts total power

Deployed in 2012, still #8 in TOP500 List (June 2018)


Sequoia
96 racks (12x8)
98,304 compute nodes
768 I/O nodes
BG/Q 5D Torus Fabric
QDR Infiniband
Ethernet
Management Ethernet
Login Nodes (32)
Login Nodes LAC (2)
Service Nodes
SCF 10 GbE
Lustre QDR IB SAN
Expansion to other SCF IB clusters
Lustre MDS & OSS Nodes
To other SCF clusters, file systems, HPSS, etc.
1.6 PB RAM
55 PB ZFS

Source: LLNL

Compute-Intensive vs. Data-Intensive



Why does this make sense for compute-intensive tasks?

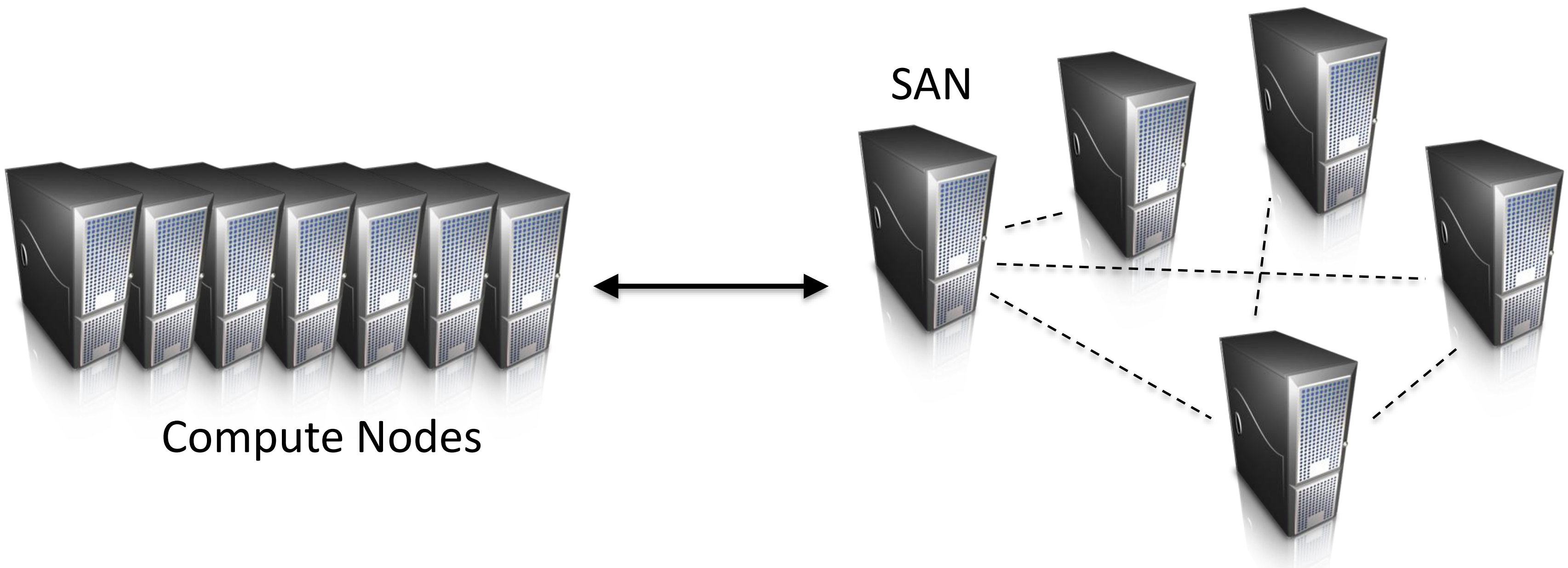
What's the issue for data-intensive tasks?

What's the solution?

Don't move data to workers… move workers to the data!

Key idea: co-locate storage and compute

Start up worker on nodes that hold the data



What's the solution?

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Start up worker on nodes that hold the data

We need a distributed file system for managing this

GFS (Google File System) for Google's MapReduce

HDFS (Hadoop Distributed File System) for Hadoop

GFS: Assumptions

Commodity hardware over "exotic" hardware

Scale "out", not "up"

High component failure rates

Inexpensive commodity components fail all the time

"Modest" number of huge files

Multi-gigabyte files are common, if not encouraged

Files are write-once, mostly appended to

Logs are a common case

Large streaming reads over random access

Design for high sustained throughput over low latency

GFS: Design Decisions

Files stored as chunks

Fixed size (64MB)

Reliability through replication

Each chunk replicated across 3+ chunkservers

Single master to coordinate access and hold metadata

Simple centralized management

No data caching

Little benefit for streaming reads over large datasets

Simplify the API: not POSIX!

Push many issues onto the client (e.g., data layout)

HDFS = GFS clone (same basic ideas)

From GFS to HDFS

Terminology differences:

GFS master = Hadoop namenode

GFS chunkservers = Hadoop datanodes

Implementation differences:

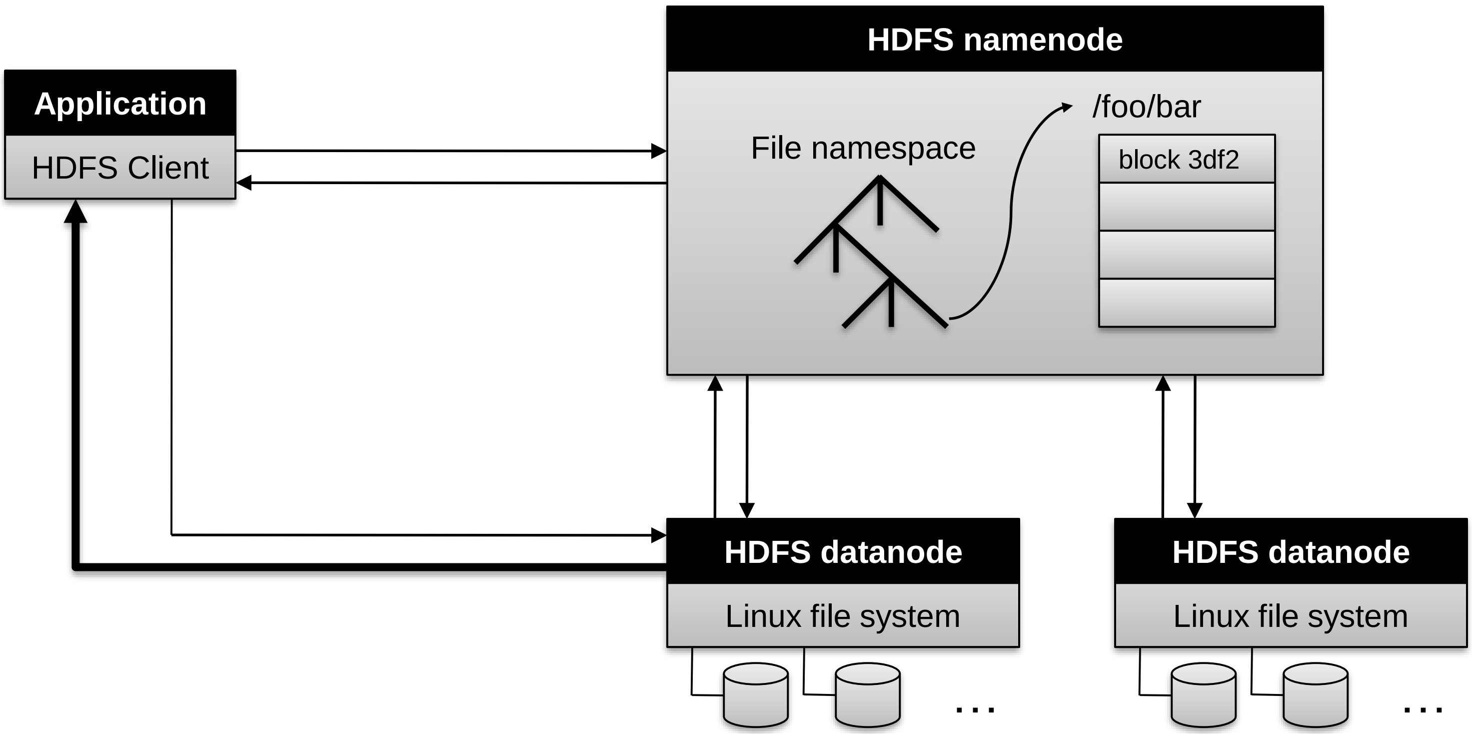
Different consistency model for file appends

Implementation language

Performance

For the most part, we'll use Hadoop terminology…

HDFS Architecture



Adapted from (Ghemawat et al., SOSP 2003)

Namenode Responsibilities

Managing the file system namespace

Holds file/directory structure, file-to-block mapping, metadata (ownership, access permissions, etc.)

Coordinating file operations

Directs clients to datanodes for reads and writes

No data is moved through the namenode

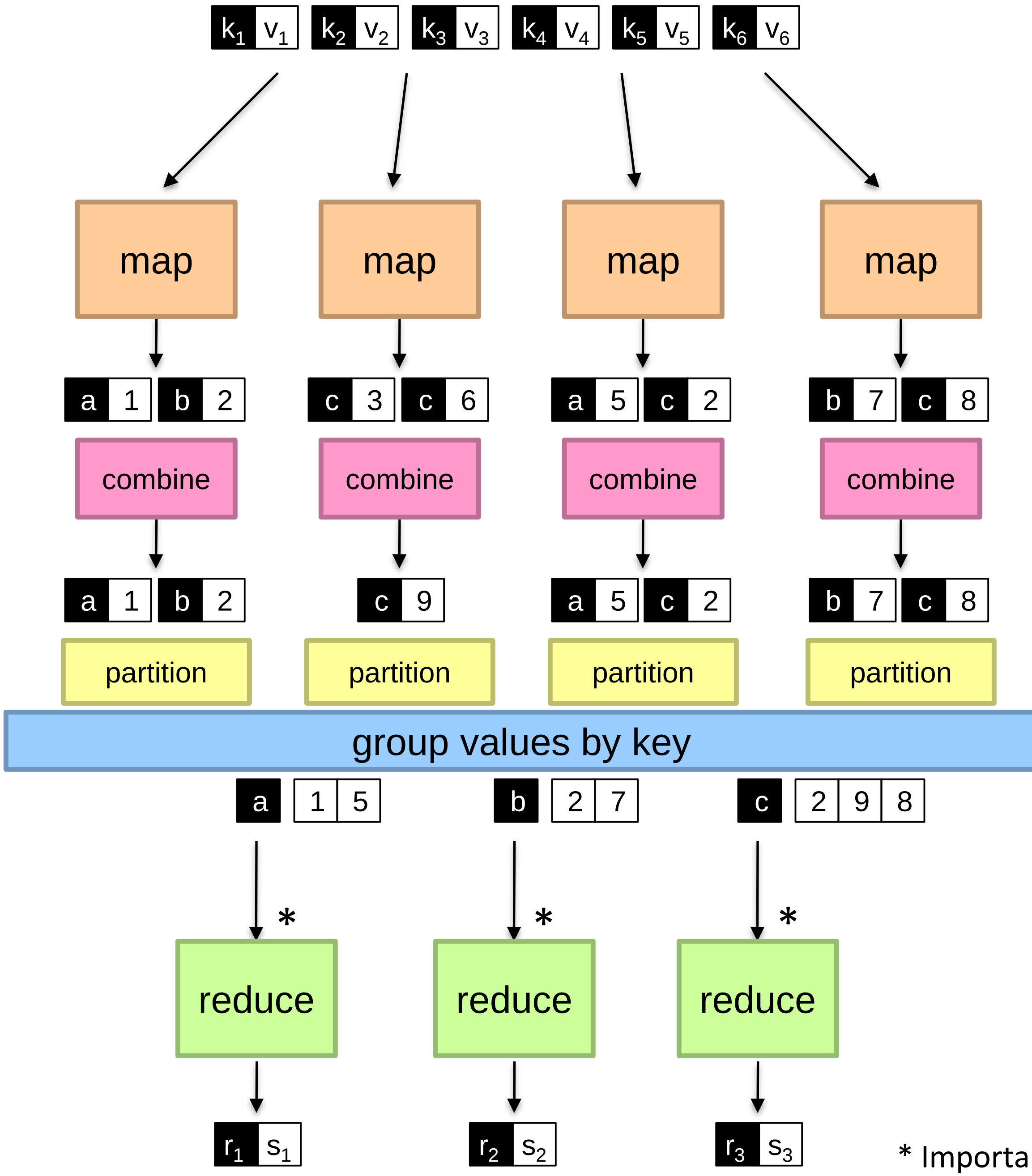
Maintaining overall health

Periodic communication with the datanodes

Block re-replication and rebalancing

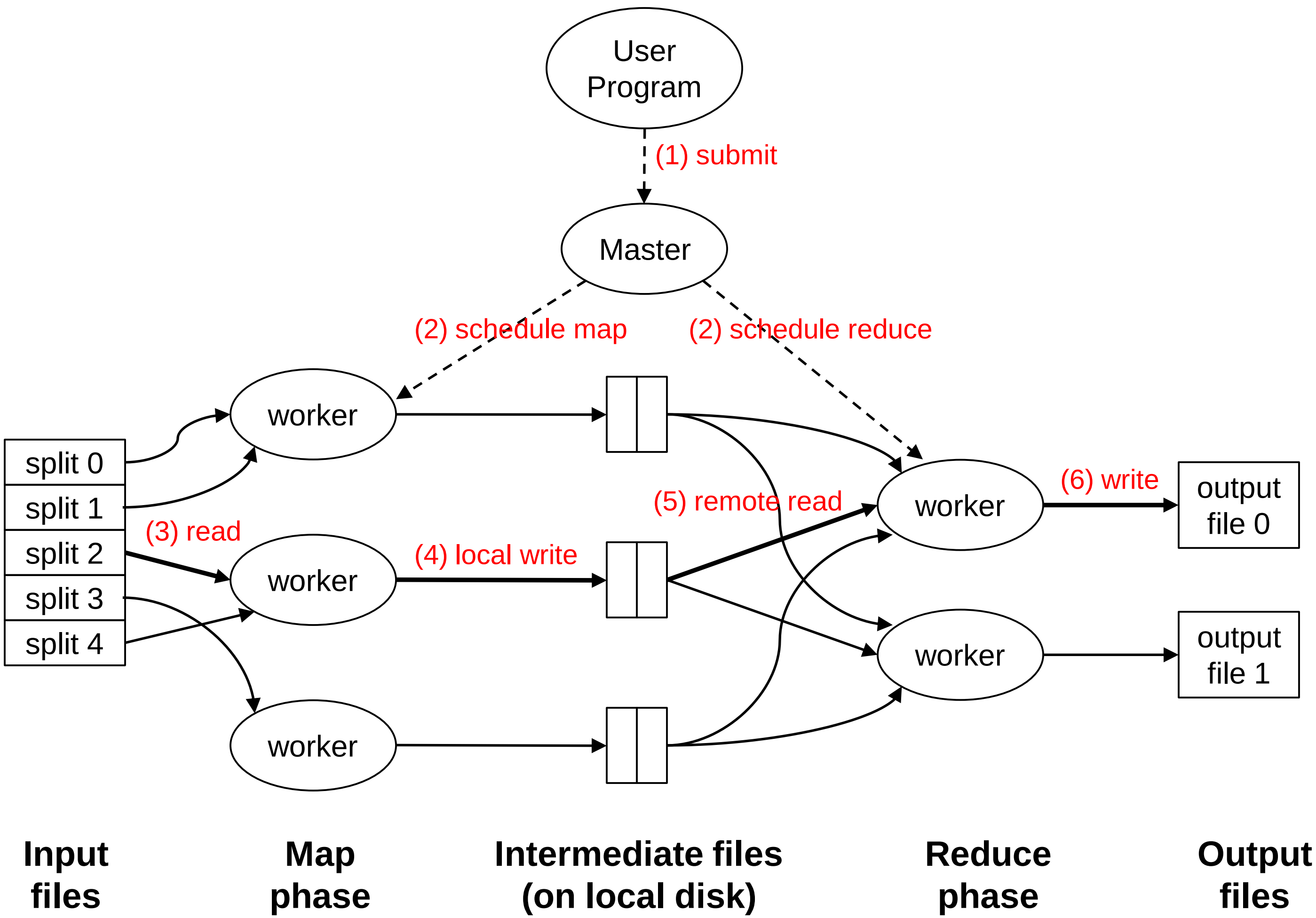
Garbage collection

Logical View

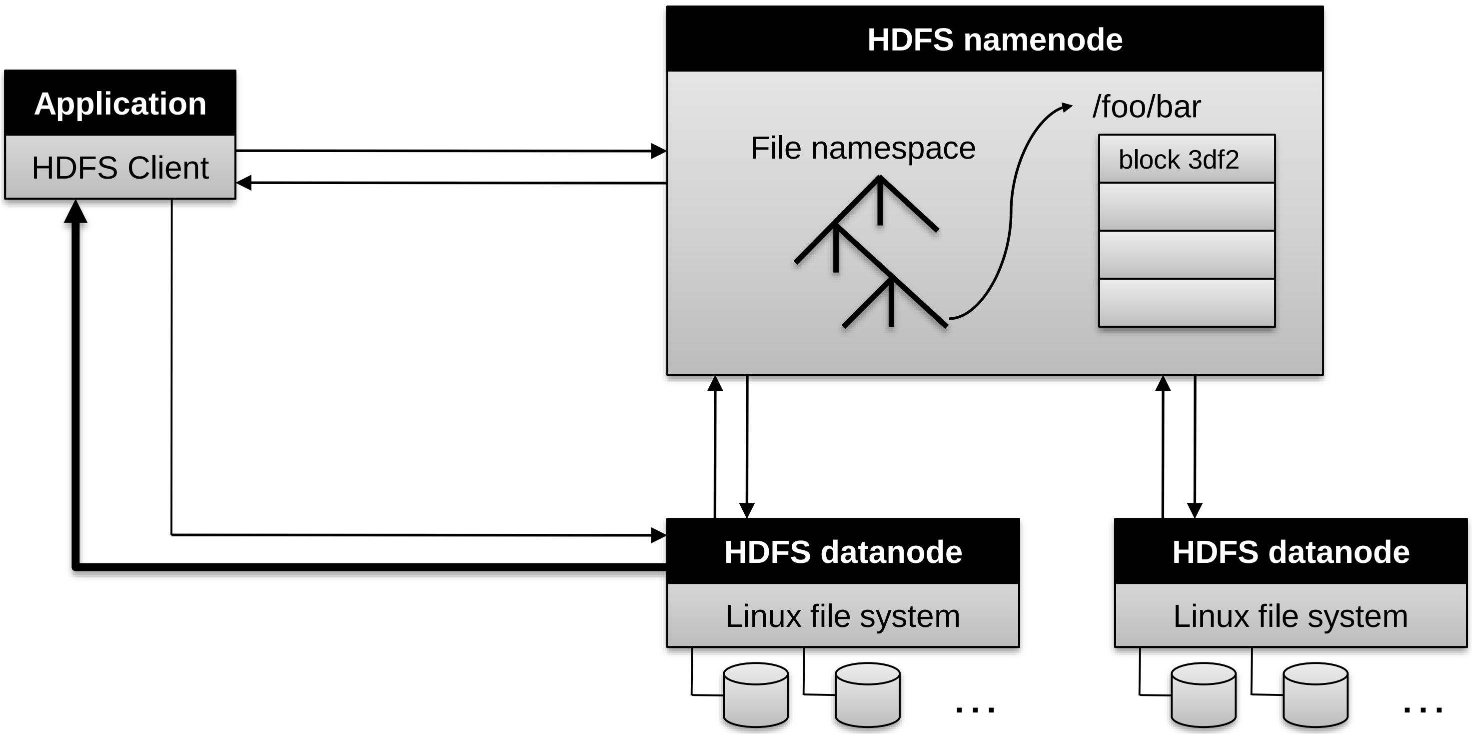


* Important detail: reducers process keys in sorted order

Physical View

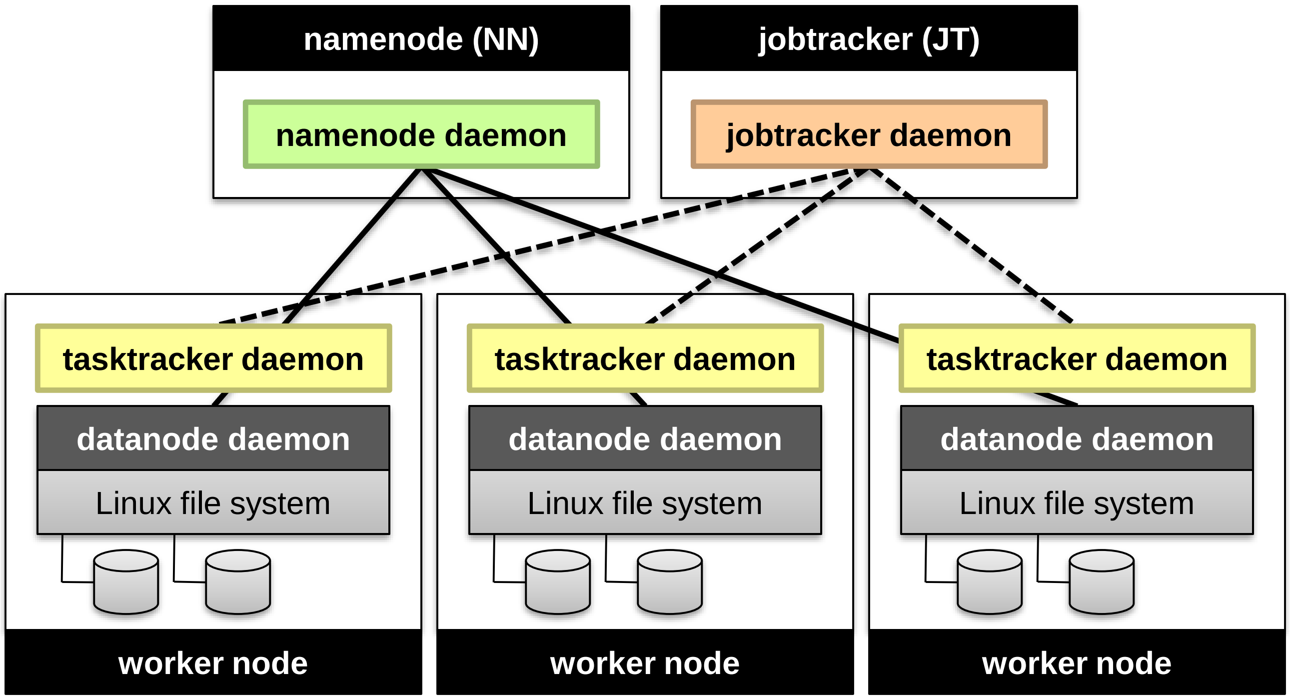


Adapted from (Dean and Ghemawat, OSDI 2004)



Adapted from (Ghemawat et al., SOSP 2003)

Putting everything together…



Basic Cluster Components *

Namenode (NN)

Master for HDFS

Jobtracker (JT)

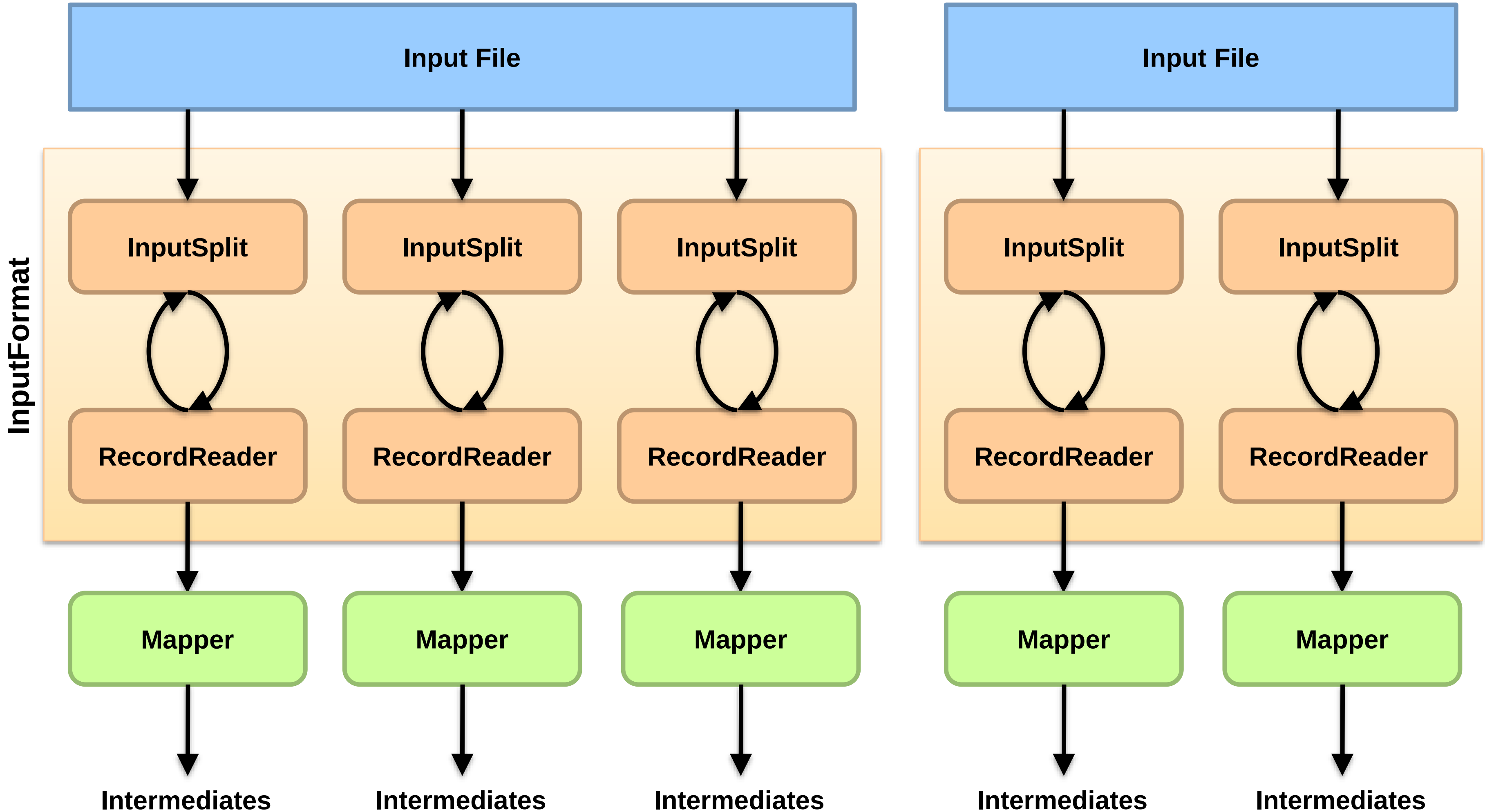
Coordinator for MapReduce jobs

On *each* of the worker machines:

Tasktracker (TT): contains multiple task slots

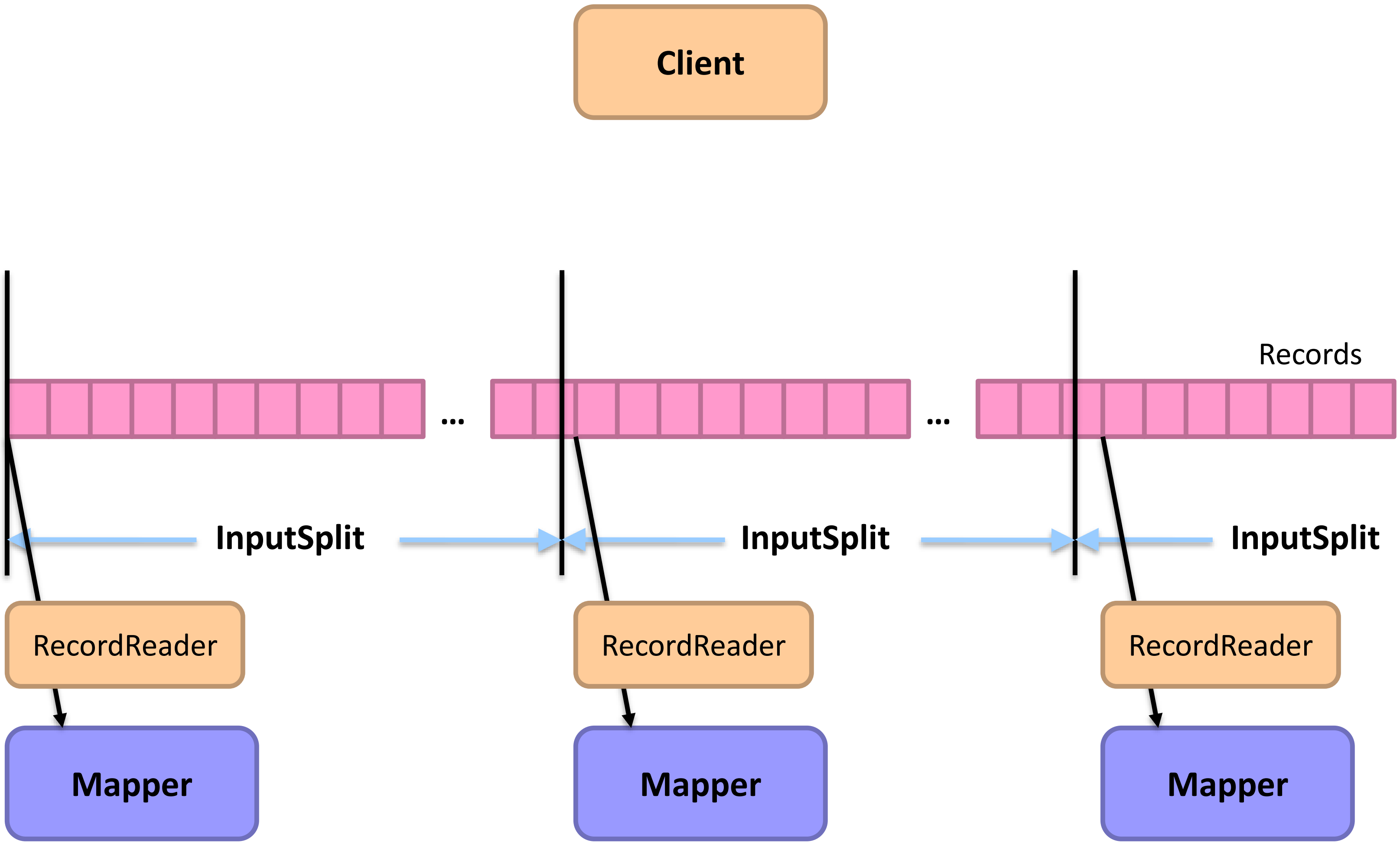
Datanode (DN): serves HDFS data blocks

* Not quite… leaving aside YARN for now



What are these input split?

Source: redrawn from a slide by Cloduera, cc-licensed



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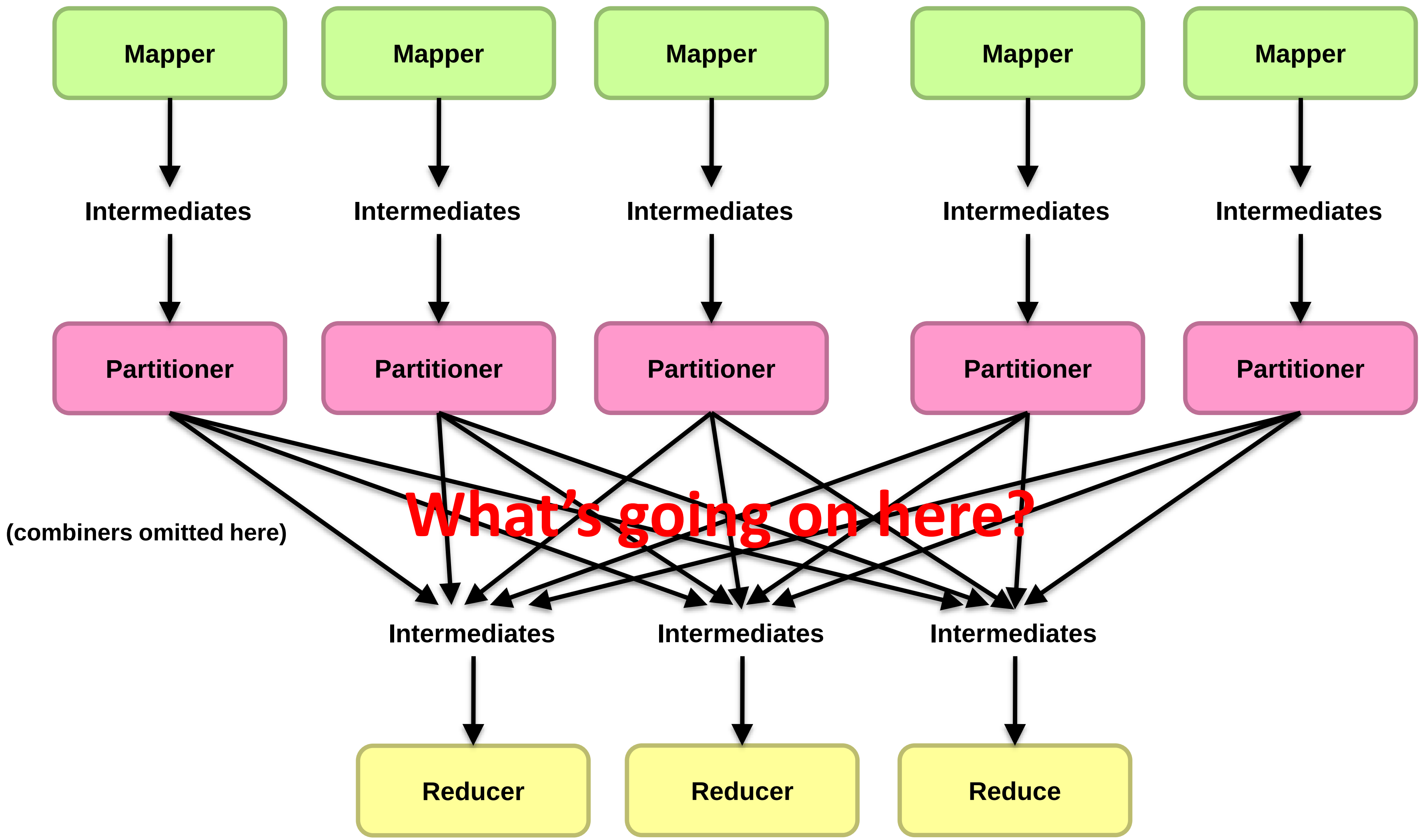


Source: redrawn from a slide by Cloduera, cc-licensed

Distributed Group By in MapReduce

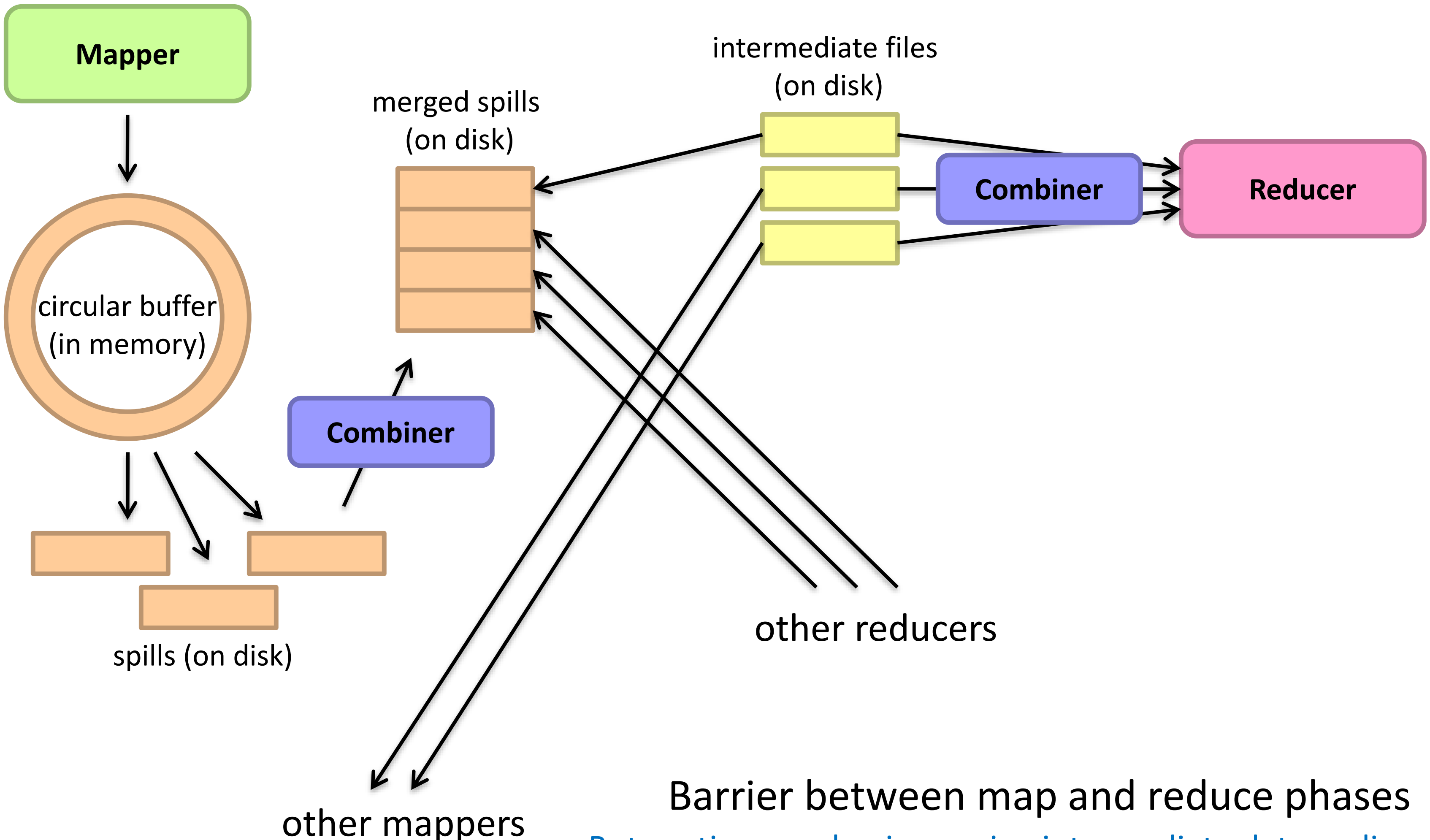
Map side

Map outputs are buffered in memory in a circular buffer
When buffer reaches threshold, contents are “spilled” to disk
Spills are merged into a single, partitioned file (sorted within each partition)
Combiner runs during the merges

Reduce side

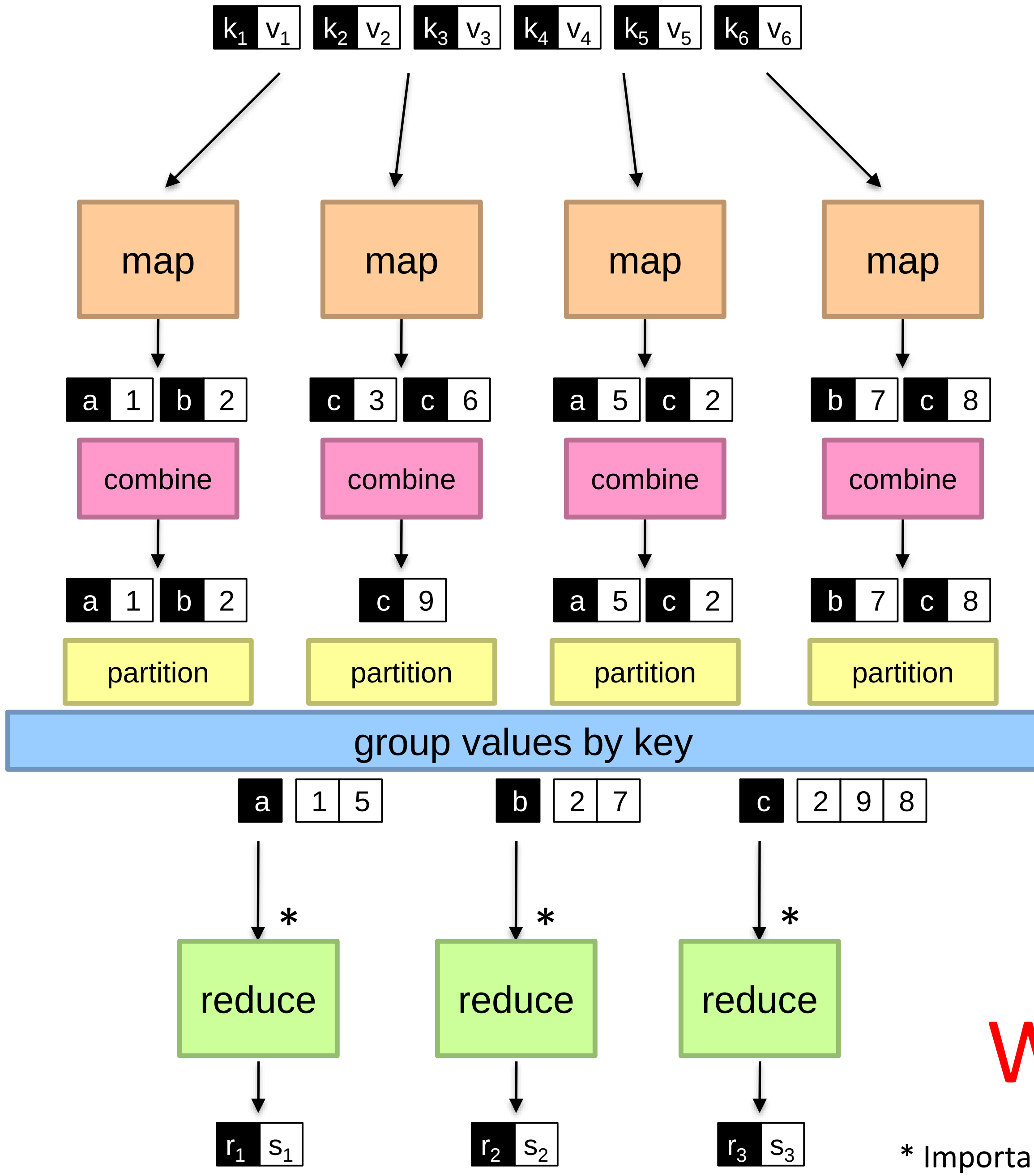
First, map outputs are copied over to reducer machine
“Sort” is a multi-pass merge of map outputs (happens in memory and on disk)
Combiner runs during the merges
Final merge pass goes directly into reducer

Distributed Group By in MapReduce



Barrier between map and reduce phases

But runtime can begin copying intermediate data earlier



Why?

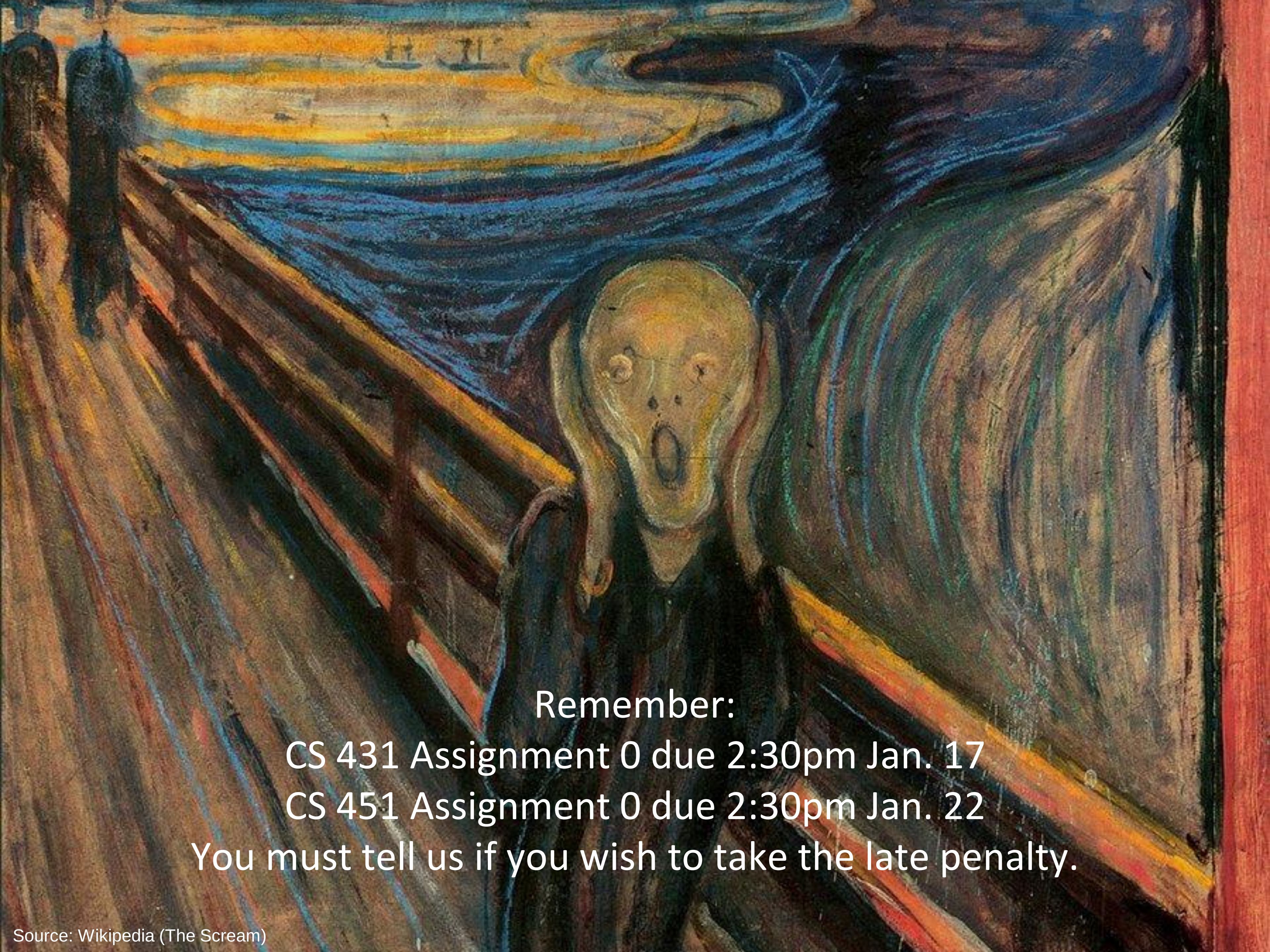
* Important detail: reducers process keys in sorted order

Law of Leaky Abstractions

All non-trivial abstractions, to some degree, are leaky.

Joel Spolsky

Remember logical vs. physical?



Remember:

CS 431 Assignment 0 due 2:30pm Jan. 17

CS 451 Assignment 0 due 2:30pm Jan. 22

You must tell us if you wish to take the late penalty.

Source: Wikipedia (The Scream)