# Big Data, Cloud Computing, and Map-Reduce

Session 1: Introduction to MapReduce

**Based on Slides from:**
**http://lintool.github.io/UMD-courses/bigdata-2015-Spring/**

**and**
**http://www.mmds.org/**

- We will use the book:

"Data-Intensive Text Processing with MapReduce"

by Jimmy Lin and Chris Dyer

(provided in Piazza and on-line)

- We will also concentrate on Hadoop version of MapReduce

# Cloud Computing and Big data

- Computing on “big data”
- Focus on applications and algorithm design
- MapReduce… and beyond

Google™
processes 20 PB a day (2008)
crawls 20B web pages a day (2012)

JPMorganChase
150 PB on 50k+ servers
running 15k apps (6/2011)

ebay®
>10 PB data, 75B DB calls
per day (6/2012)

INTERNET ARCHIVE
Wayback Machine: 240B web
pages archived, 5 PB (1/2013)

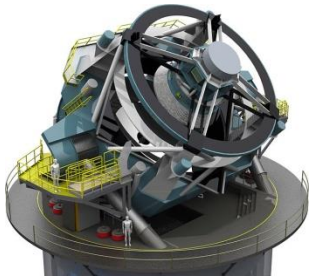
>100 PB of user data +
500 TB/day (8/2012)

facebook

LHC: ~15 PB a year

CERN

amazon web services™
S3: 449B objects, peak 290k
request/second (7/2011)
1T objects (6/2012)



LSST: 6-10 PB a year
(~2015)


SKA: 0.3 – 1.5 EB
per year (~2020)

# How much data?

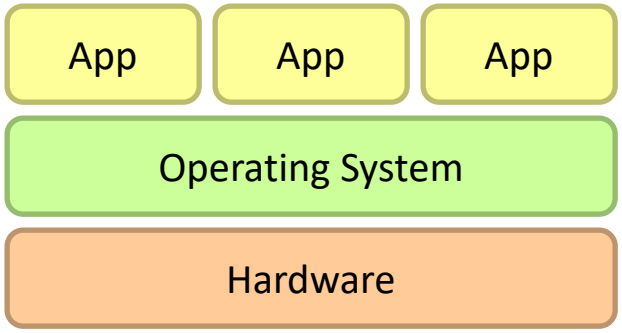
# Cloud Computing

- 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

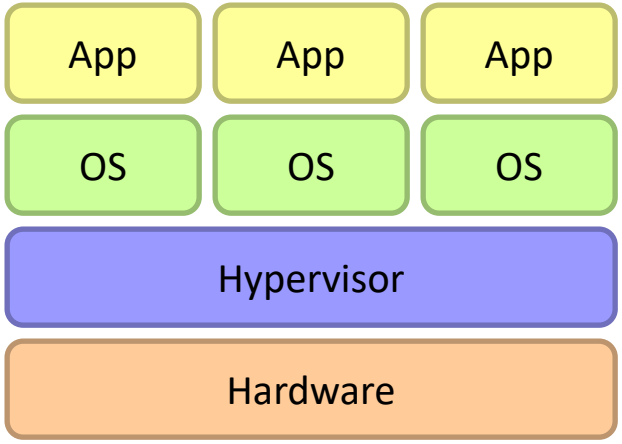
# Utility Computing

- What?
  - Computing resources as a metered service (“pay as you go”)
  - Ability to dynamically provision virtual machines
- 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

# Enabling Technology: Virtualization




Traditional Stack

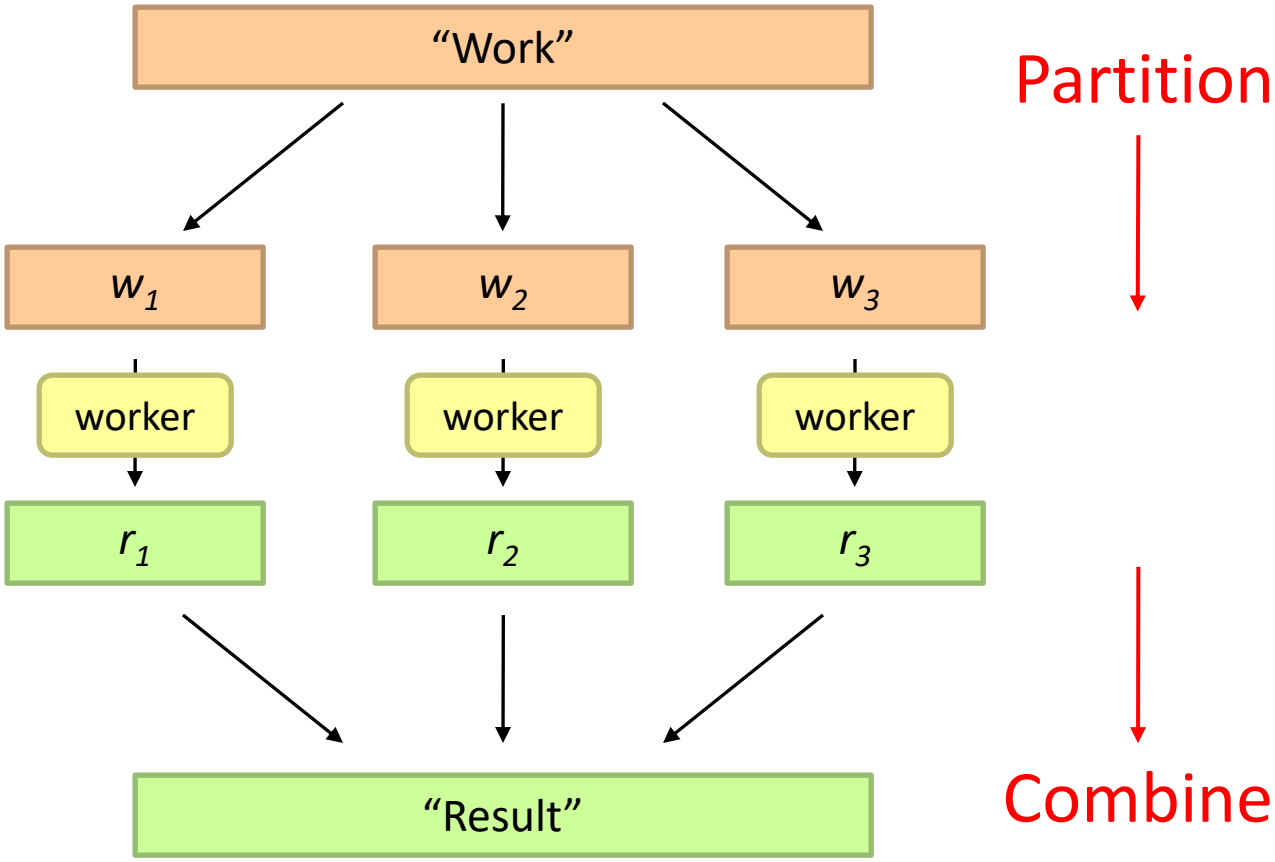



Virtualized Stack

# Everything as a Service

- Utility computing = Infrastructure as a Service (IaaS)
  - Why buy machines when you can rent cycles?
  - Examples: Amazon's EC2, Rackspace
- Platform as a Service (PaaS)
  - Give me nice API and take care of the maintenance, upgrades, …
  - Example: Google App Engine
- Software as a Service (SaaS)
  - Just run it for me!
  - Example: Gmail, Salesforce

# Divide and Conquer



# Parallelization Challenges

- How do we assign work units to workers?
- What if we have more work units than workers?
- What if workers need to share partial results?
- How do we aggregate partial results?
- How do we know all the workers have finished?
- What if workers die?

What's the common theme of all of these problems?

# Common Theme?

- Parallelization problems arise from:
  - Communication between workers (e.g., to exchange state)
  - Access to shared resources (e.g., data)
- Thus, we need a synchronization mechanism

# Managing Multiple Workers

- Difficult because
  - We don't know the order in which workers run
  - We don't know when workers interrupt each other
  - We don't know when workers need to communicate partial results
  - We don't know the order in which workers access shared data
- Thus, we need:
  - Semaphores (lock, unlock)
  - Conditional variables (wait, notify, broadcast)
  - Barriers
- Still, lots of problems:
  - Deadlock, livelock, race conditions...
  - Dining philosophers, sleeping barbers, cigarette smokers...
- Moral of the story: be careful!

# Where the rubber meets the road

- Concurrency is difficult to reason about
- Concurrency is even more difficult to reason about
  - At the scale of datacenters and across datacenters
  - In the presence of failures
  - In terms of multiple interacting services
- Not to mention debugging…
- The reality:
  - Lots of one-off solutions, custom code
  - Write you own dedicated library, then program with it
  - Burden on the programmer to explicitly manage everything

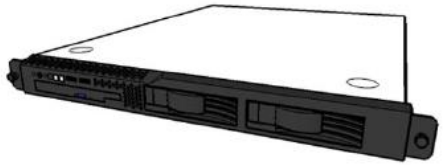

Source: Google

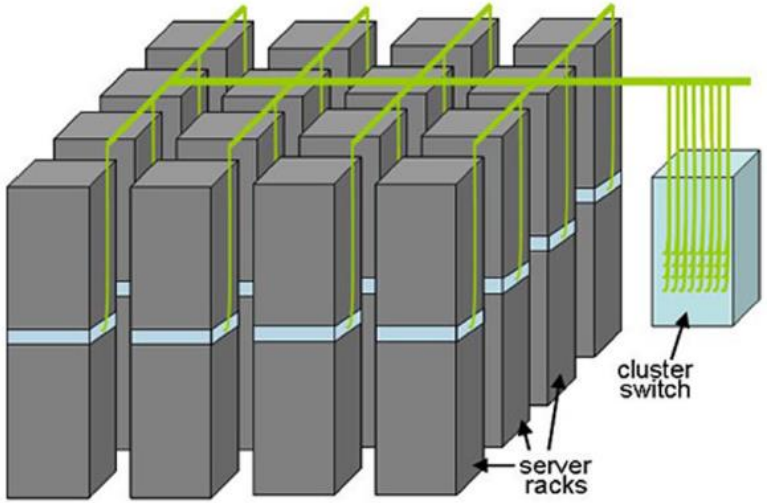
# What's the point?

- It's all about the right level of abstraction
  - Moving beyond the von Neumann architecture
  - We need better programming models
- Hide system-level details from the developers
  - No more race conditions, lock contention, etc.
- Separating the *what* from *how*
  - Developer specifies the computation that needs to be performed
  - Execution framework ("runtime") handles actual execution

**The datacenter *is* the computer!**

# Building Blocks

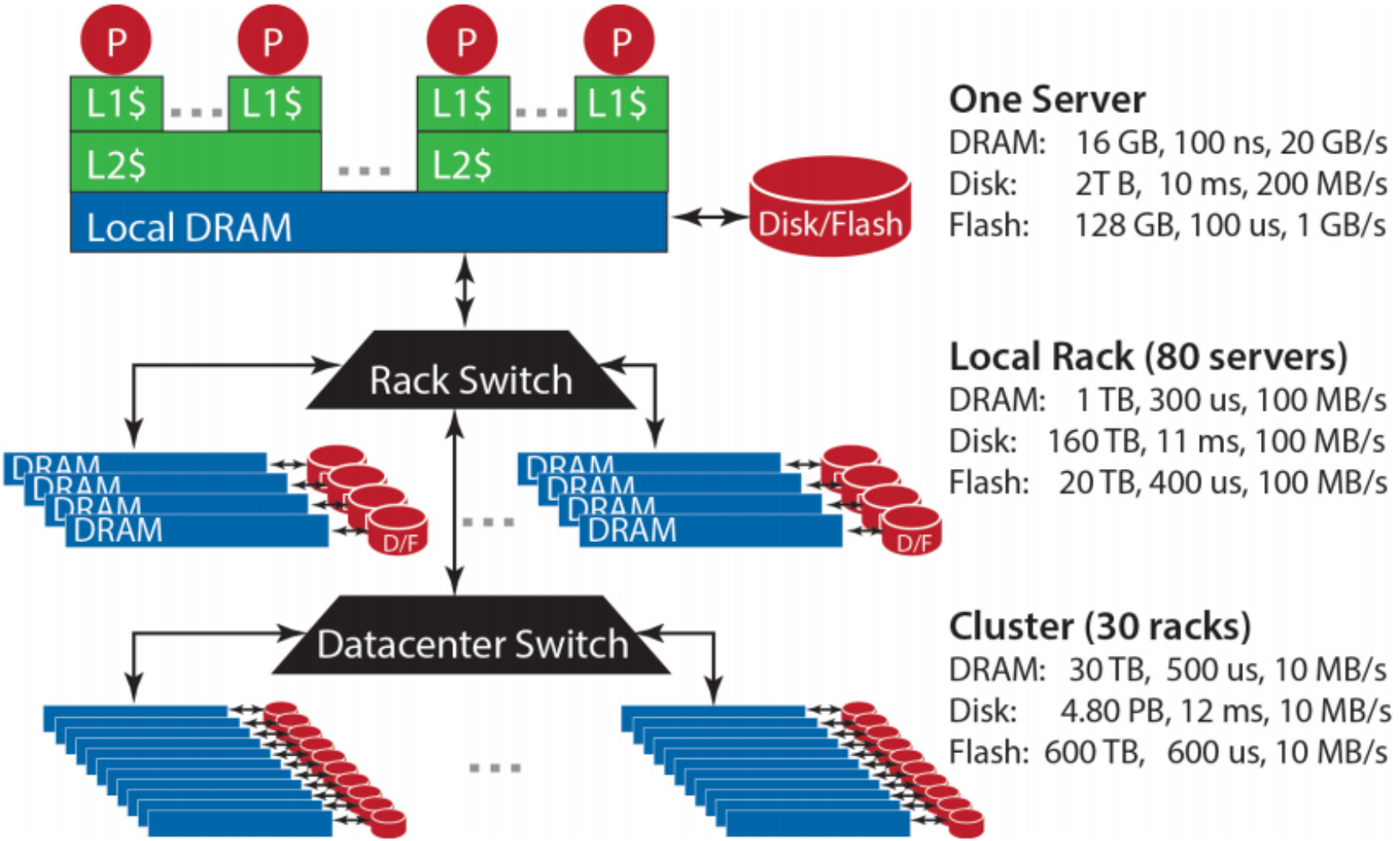





Source: Barroso and Urs Hölzle (2009)

Source: Google

# Storage Hierarchy



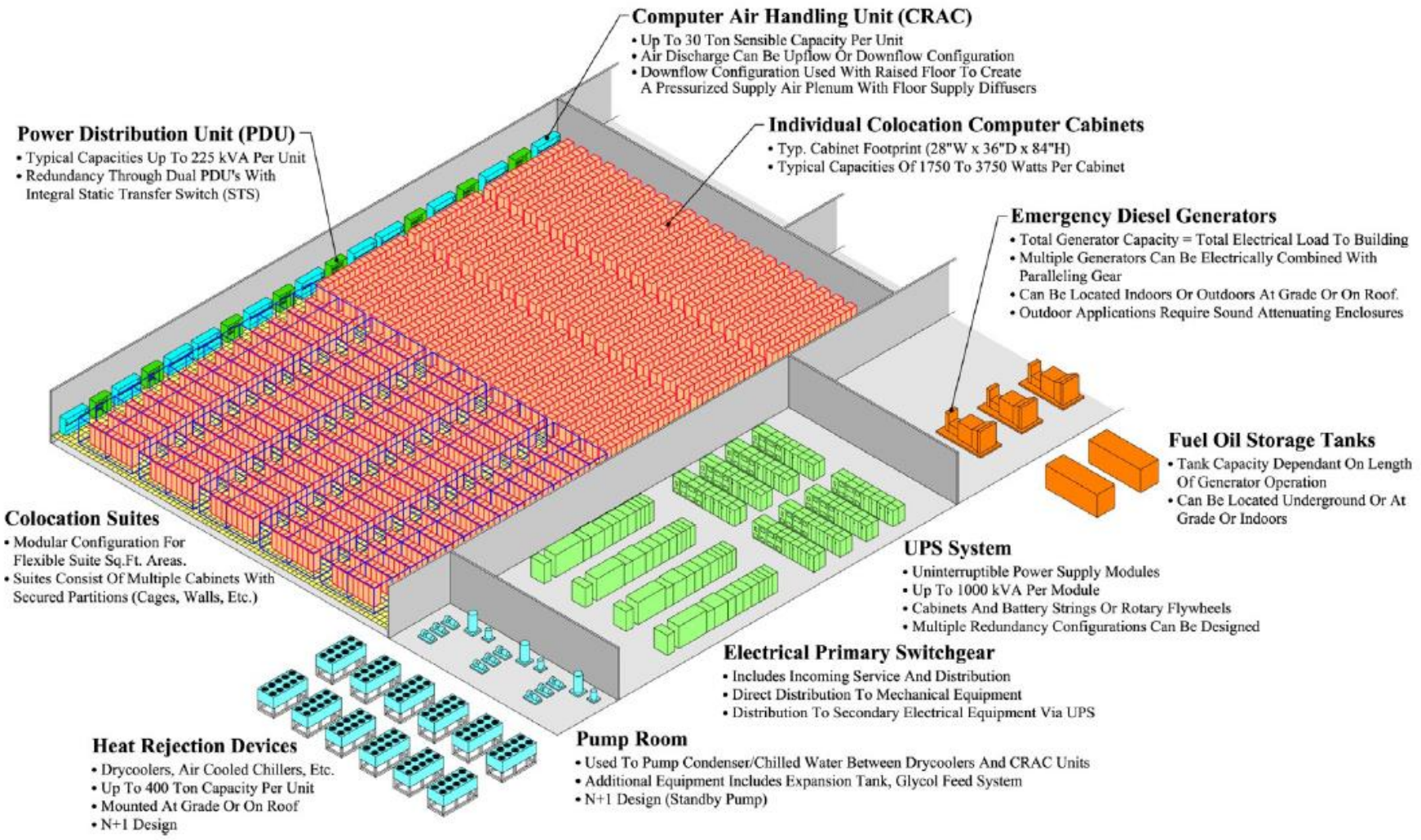

**One Server**
DRAM: 16 GB, 100 ns, 20 GB/s
Disk: 2T B, 10 ms, 200 MB/s
Flash: 128 GB, 100 us, 1 GB/s

**Local Rack (80 servers)**
DRAM: 1 TB, 300 us, 100 MB/s
Disk: 160 TB, 11 ms, 100 MB/s
Flash: 20 TB, 400 us, 100 MB/s

**Cluster (30 racks)**
DRAM: 30 TB, 500 us, 10 MB/s
Disk: 4.80 PB, 12 ms, 10 MB/s
Flash: 600 TB, 600 us, 10 MB/s

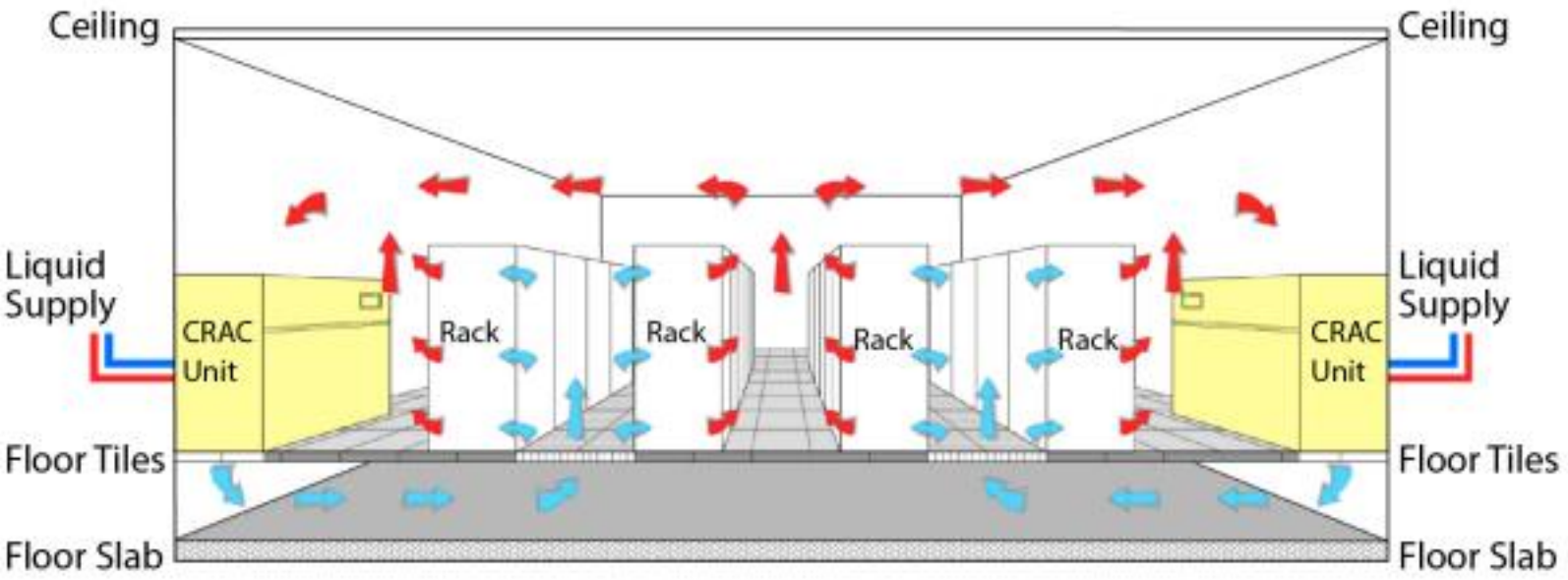
Source: Barroso and Urs Hölzle (2013)

# Anatomy of a Datacenter




Source: Barroso and Urs Hölzle (2013)

# Anatomy of a Datacenter




Source: Barroso and Urs Hölzle (2013)

# “Big Ideas”

- Scale “out”, not “up”
  - Limits of SMP and large shared-memory machines
- Move processing to the data
  - Cluster have limited bandwidth
- Process data sequentially, avoid random access
  - Seeks are expensive, disk throughput is reasonable
- Seamless scalability
  - From the mythical man-month to the tradable machine-hour


Source: Google

# Typical Big Data Problem

- Iterate over a large number of records
- Extract something of interest from each
- Shuffle and sort intermediate results
- Aggregate intermediate results
- Generate final output

Map

Reduce

**Key idea: provide a functional abstraction for these two operations**

(Dean and Ghemawat, OSDI 2004)

# MapReduce

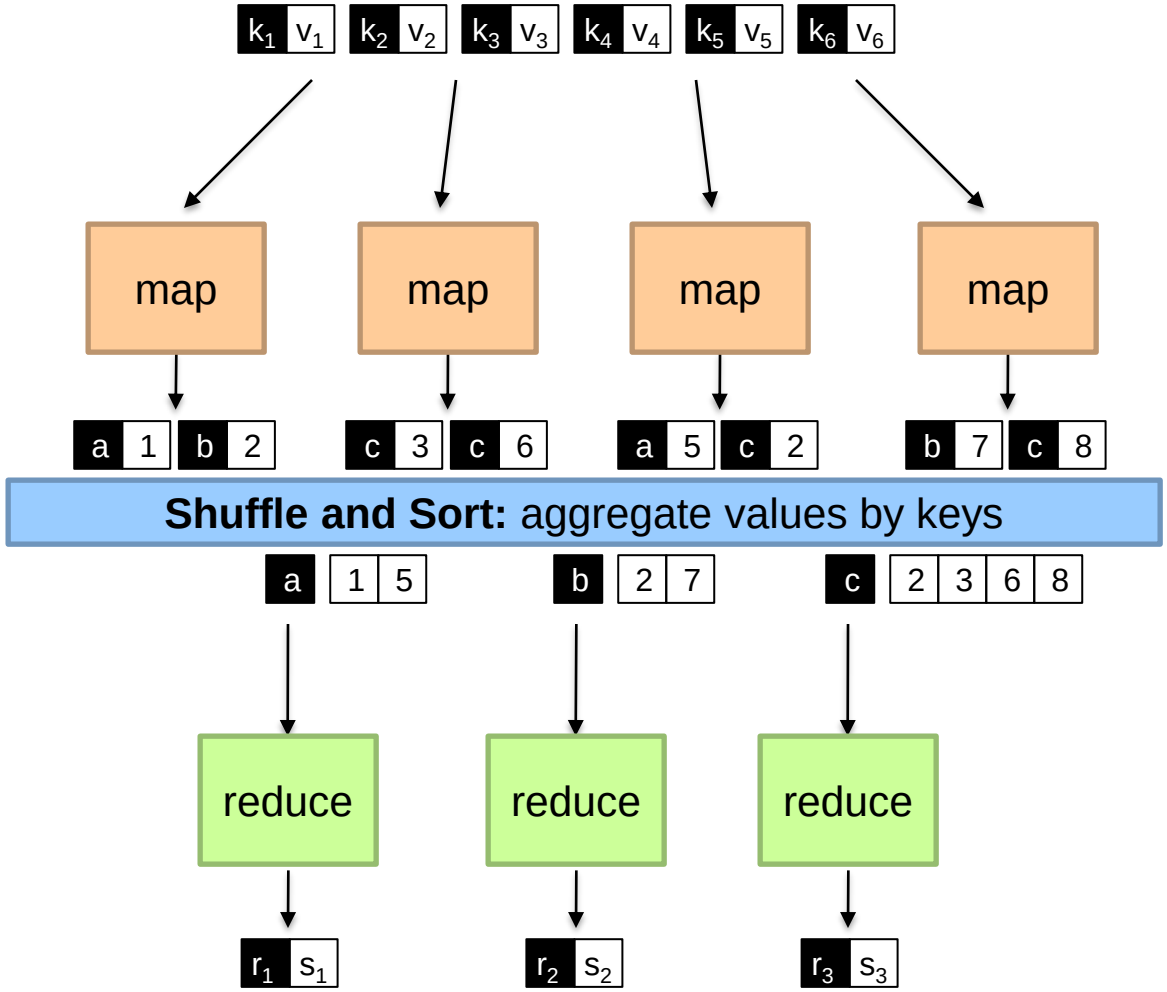
- Programmers specify two functions:

  **map** $(k_1, v_1) \rightarrow [<k_2, v_2>]$

  **reduce** $(k_2, [v_2]) \rightarrow [<k_3, v_3>]$

  - All values with the same key are sent to the same reducer

- The execution framework handles everything else…


k1 v1
k2 v2
k3 v3
k4 v4
k5 v5
k6 v6
map
map
map
map
a 1
b 2
c 3
c 6
a 5
c 2
b 7
c 8
Shuffle and Sort: aggregate values by keys
a 1 5
b 2 7
c 2 3 6 8
reduce
reduce
reduce
r1 s1
r2 s2
r3 s3

# MapReduce

- Programmers specify two functions:

  **map** (k, v) → <k', v'>*

  **reduce** (k', v') → <k', v'>*

  - All values with the same key are sent to the same reducer
- The execution framework handles everything else…

**What's "everything else"?**

# MapReduce “Runtime”

- Handles scheduling
  - Assigns workers to map and reduce tasks
- Handles “data distribution”
  - Moves processes to data
- Handles synchronization
  - Gathers, sorts, and shuffles intermediate data
- Handles errors and faults
  - Detects worker failures and restarts
- Everything happens on top of a distributed FS (later)

# MapReduce

- Programmers specify two functions:

  **map** (k, v) → <k', v'>*

  **reduce** (k', v') → <k', v'>*

  - All values with the same key are reduced together

- The execution framework handles everything else…

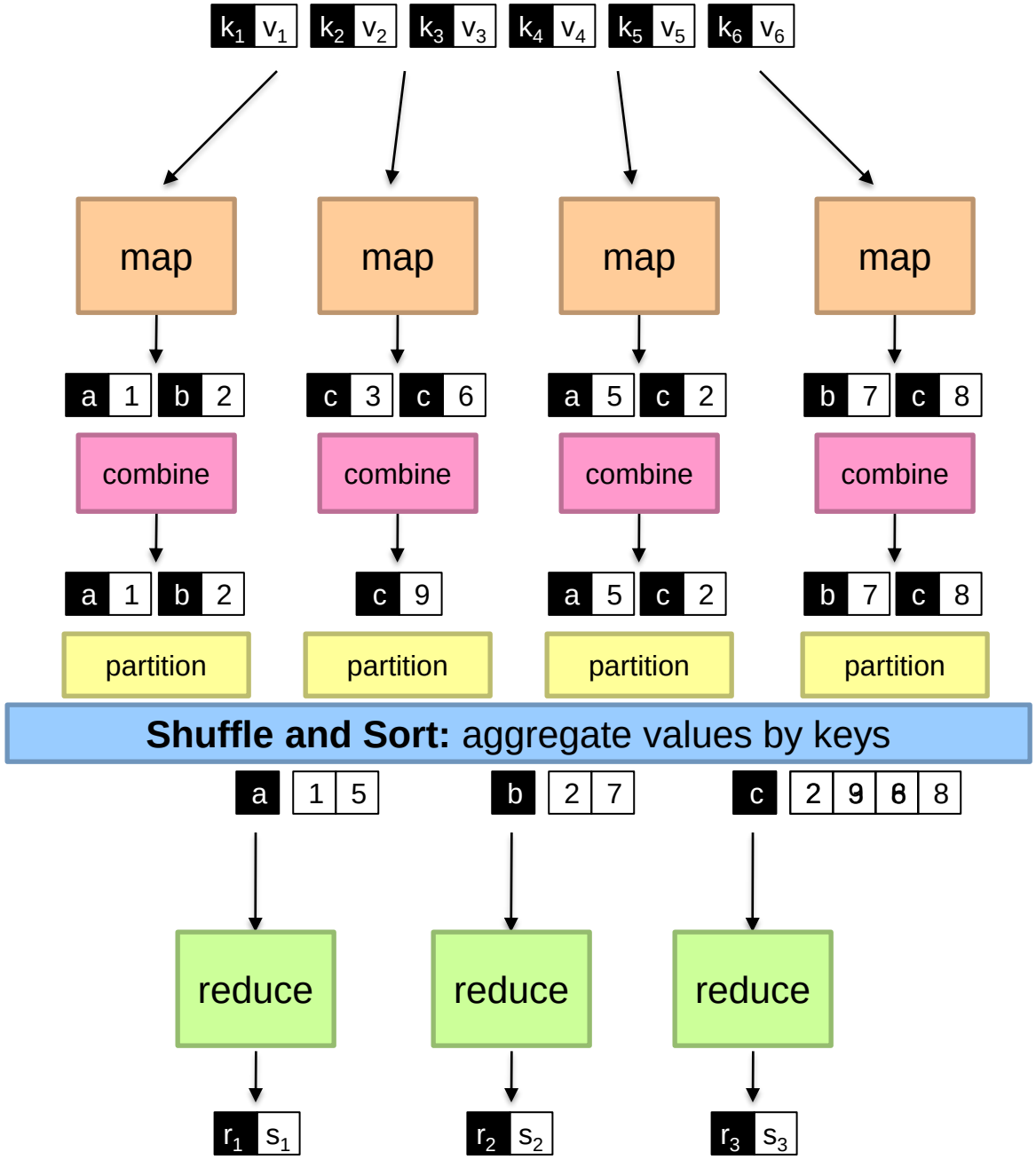
- Not quite…usually, programmers also specify:

  **partition** (k', number of partitions) → partition for k'

  - Often a simple hash of the key, e.g., hash(k') mod n
  - Divides up key space for parallel reduce operations

  **combine** (k', v') → <k', v'>*

  - Mini-reducers that run in memory after the map phase
  - Used as an optimization to reduce network traffic


k1 v1
k2 v2
k3 v3
k4 v4
k5 v5
k6 v6
map
map
map
map
a 1 b 2
c 3 c 6
a 5 c 2
b 7 c 8
combine
combine
combine
combine
a 1 b 2
c 9
a 5 c 2
b 7 c 8
partition
partition
partition
partition
Shuffle and Sort: aggregate values by keys
a 1 5
b 2 7
c 2 9 6 8
reduce
reduce
reduce
r1 s1
r2 s2
r3 s3

# Two more details…

- Barrier between map and reduce phases
  - But we can begin copying intermediate data earlier
- Keys arrive at each reducer in sorted order
  - No enforced ordering *across* reducers

# “Hello World”: Word Count

```
Map(String docid, String text):
    for each word w in text:
        Emit(w, 1);

Reduce(String term, Iterator<Int> values):
    int sum = 0;
    for each v in values:
        sum += v;
        Emit(term, value);
```

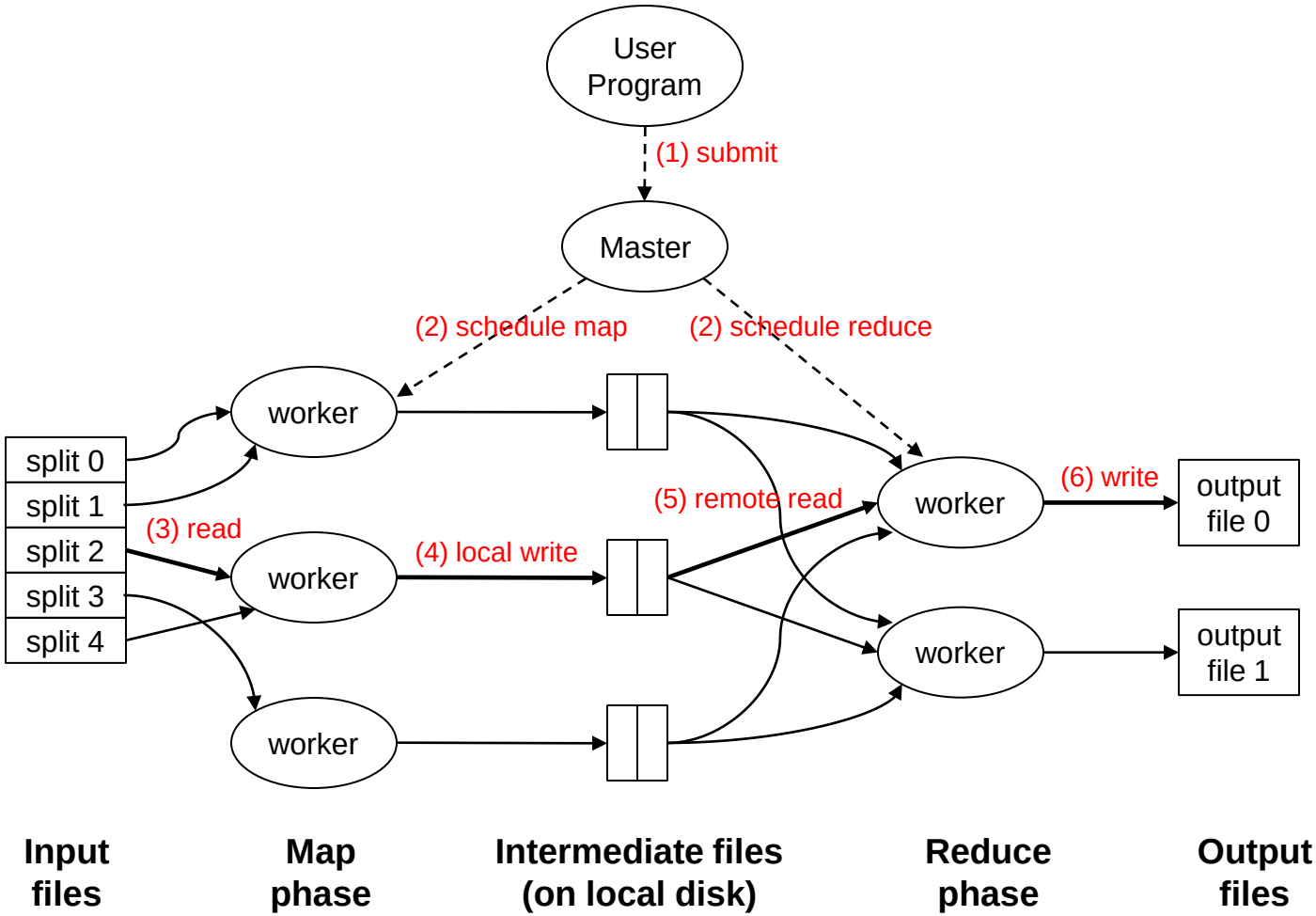
# MapReduce can refer to…

- The programming model
- The execution framework (aka “runtime”)
- The specific implementation

**Usage is usually clear from context!**

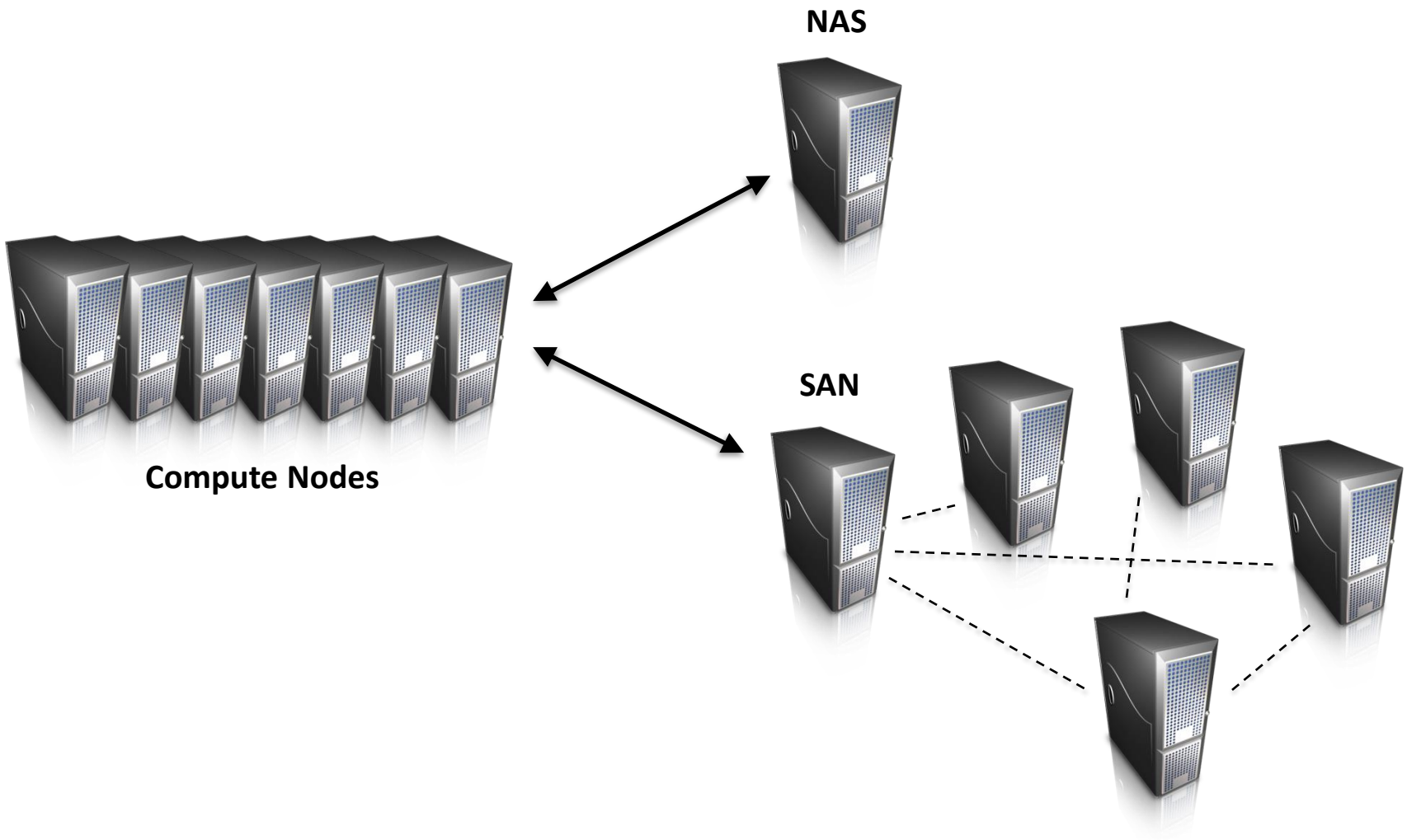
# MapReduce Implementations

- Google has a proprietary implementation in C++
  - Bindings in Java, Python
- Hadoop is an open-source implementation in Java
  - Development led by Yahoo, now an Apache project
  - Used in production at Yahoo, Facebook, Twitter, LinkedIn, Netflix, …
  - The *de facto* big data processing platform
  - Rapidly expanding software ecosystem
- Lots of custom research implementations
  - For GPUs, cell processors, etc.




Adapted from (Dean and Ghemawat, OSDI 2004)

# How do we get data to the workers?



# Distributed File System

- Don't move data to workers… move workers to the data!
  - Store data on the local disks of nodes in the cluster
  - Start up the workers on the node that has the data local
- Why?
  - Not enough RAM to hold all the data in memory
  - Disk access is slow, but disk throughput is reasonable
- A distributed file system is the answer
  - 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
  - Perhaps concurrently
- Large streaming reads over random access
  - 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, keep metadata
  - Simple centralized management
- No data caching
  - Little benefit due to large datasets, streaming reads
- Simplify the API
  - Push some of the issues onto the client (e.g., data layout)

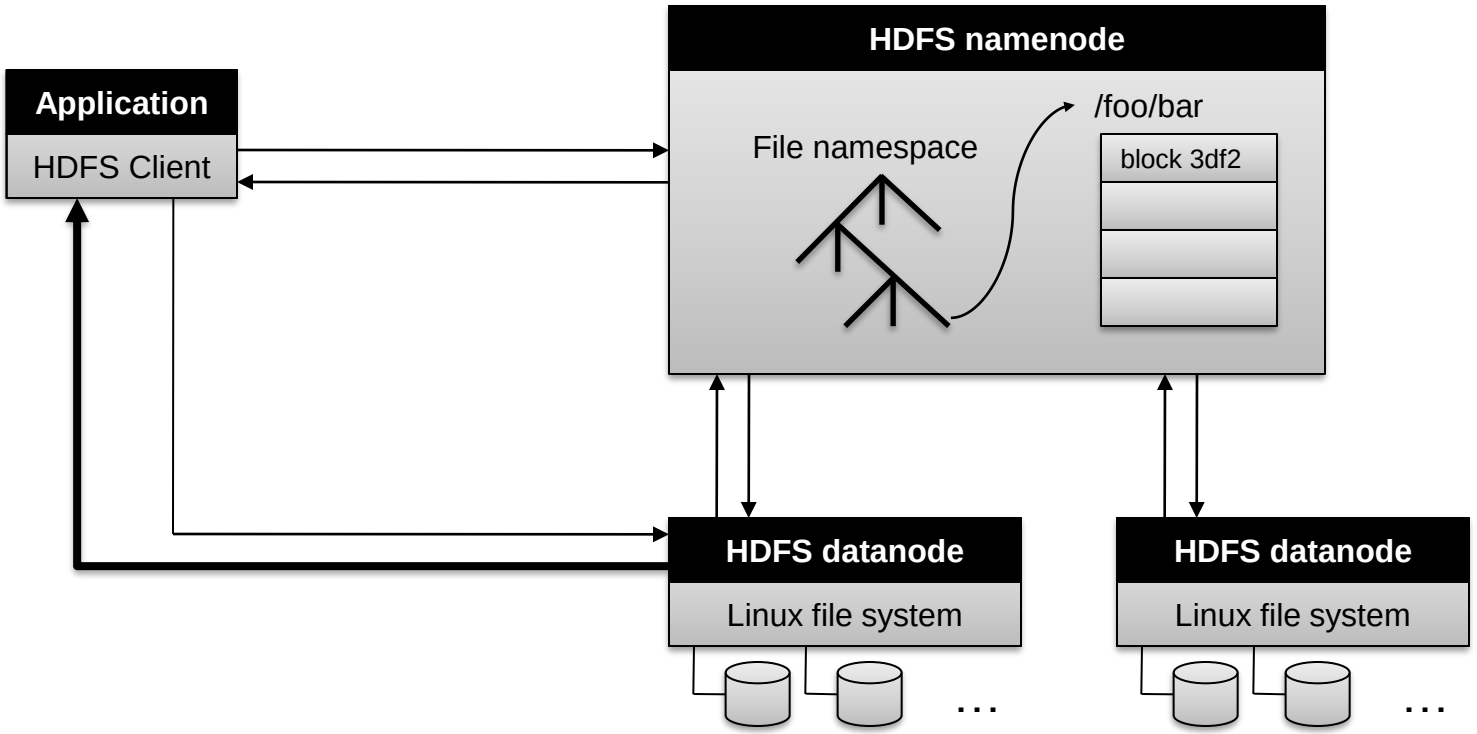
**HDFS = GFS clone (same basic ideas)**

# From GFS to HDFS

- Terminology differences:
  - GFS master = Hadoop namenode
  - GFS chunkservers = Hadoop datanodes
- Differences:
  - Different consistency model for file appends
  - Implementation
  - 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, metadata, file-to-block mapping, 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

# Putting everything together…