Data-Intensive Information Processing Applications — Session #1

Introduction to MapReduce

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What is this course about?

- Data-intensive information processing
- Large-data ("web-scale") problems
- Focus on applications
- MapReduce… and beyond
  - Hbase
  - Hive
  - Pig
  - (and possibly more)

What is MapReduce?

- Programming model for expressing distributed computations at a massive scale
- Execution framework for organizing and performing such computations
- Open-source implementation called Hadoop

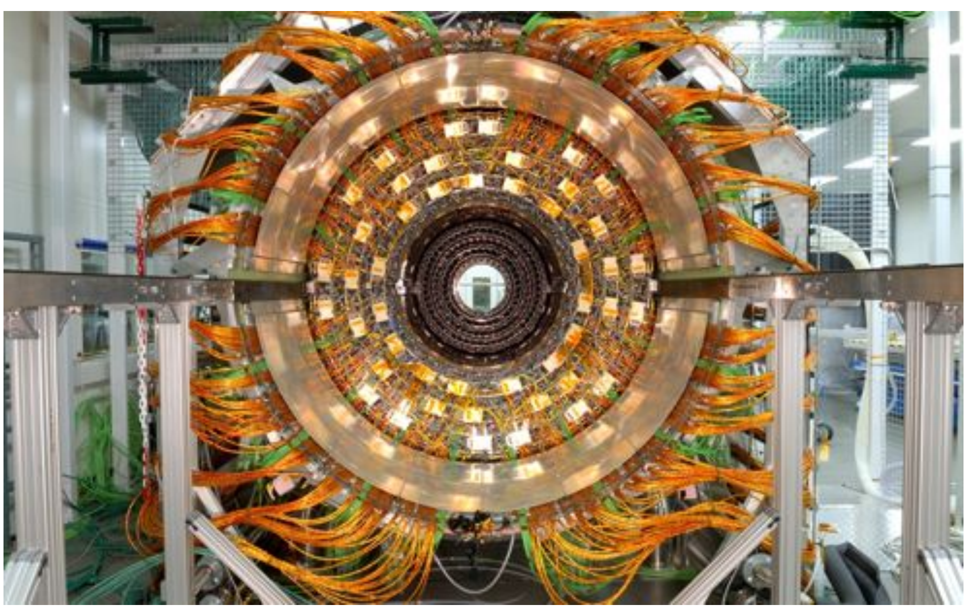
Why large data?

Source: Wikipedia (Everest)

How much data?

- Google processes 20 PB a day (2008)
- Wayback Machine has 3 PB + 100 TB/month (3/2009)
- Facebook has 2.5 PB of user data + 15 TB/day (4/2009)
- eBay has 6.5 PB of user data + 50 TB/day (5/2009)
- CERN's LHC will generate 15 PB a year (??)

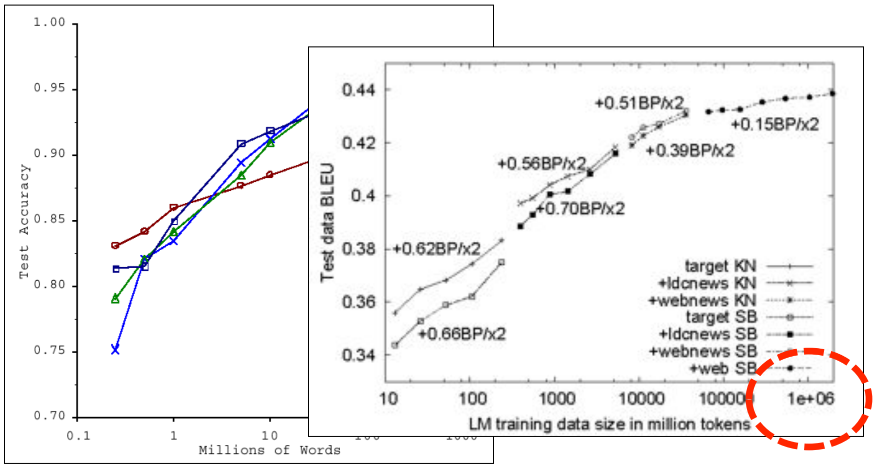
Maximilien Brice, © CERN



Maximilien Brice, © CERN

No data like more data!

s/knowledge/data/g;



How do we get here if we're not Google?

(Banko and Brill, ACL 2001)
(Brants et al., EMNLP 2007)

What to do with more data?

- Answering factoid questions
  - Pattern matching on the Web
  - Works amazingly well

Who shot Abraham Lincoln? → X shot Abraham Lincoln

- Learning relations
  - Start with seed instances
  - Search for patterns on the Web
  - Using patterns to find more instances

Wolfgang Amadeus Mozart (1756 - 1791)
Einstein was born in 1879

Birthday-of(Mozart, 1756)
Birthday-of(Einstein, 1879)

PERSON (DATE –
PERSON was born in DATE

(Brill et al., TREC 2001; Lin, ACM TOIS 2007)
(Agichtein and Gravano, DL 2000; Ravichandran and Hovy, ACL 2002; …)

The best thing since sliced bread?

- Before clouds…
  - Grids
  - Vector supercomputers
  - …
- Cloud computing means many different things:
  - Large-data processing
  - 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
  - AJAX as the de facto standard (for better or worse)
  - Examples: Facebook, YouTube, Gmail, …
- “The network is the computer”: take two
  - User data is stored “in the clouds”
  - Rise of the netbook, smartphones, etc.
  - Browser *is* the OS

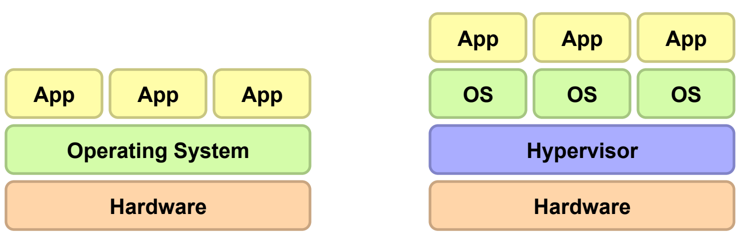
Source: Wikipedia (Electricity meter)

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

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

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

Who cares?

- Ready-made large-data problems
  - Lots of user-generated content
  - Even more user behavior data
  - Examples: Facebook friend suggestions, Google ad placement, Netflix movie suggestions
  - Business intelligence: gather everything in a data warehouse and run analytics to generate insight
- Utility computing
  - Provision Hadoop clusters on-demand in the cloud
  - Lower barrier to entry for tackling large-data problem
  - Commoditization and democratization of large-data capabilities

Course Administrivia

Course Pre-requisites

- Strong Java programming
  - But this course is *not* about programming: we'll expect you to pick up Hadoop (quickly) along the way
  - Focus on "thinking at scale" and algorithm design
- Solid knowledge of
  - Probability and statistics
  - Computer architecture
- No previous experience necessary in
  - MapReduce
  - Parallel and distributed programming
- If you're not in INFM, no problem (e-mail me)
- Audits: Must do homework, no exams – project optional

What’s in store

- Time and effort
- New was of thinking about computing
- Resources outside the class
- Uncertainty, unpredictability, etc. that comes with bleeding edge software
- Access to cool resources
- Learning a hot, in-demand skill
- Interesting, big problems

Course components

- Textbooks
- Components of the final grade:
  - Assignments
  - Midterm and final exams
  - Final project (of your choice, in groups of ~3)
  - Class participation
- Late policy
  - Everybody gets four free late days
  - This covers “traditional” excuses
    - “Too busy”
    - “It took longer than I thought it would take”
    - “It was harder than I initially thought”
    - “My dog ate my homework” and modern variants thereof

Cloud Resources

- Hadoop on your local machine
- Hadoop in a virtual machine on your local machine
- Hadoop on the Google/IBM cluster

Important Aside

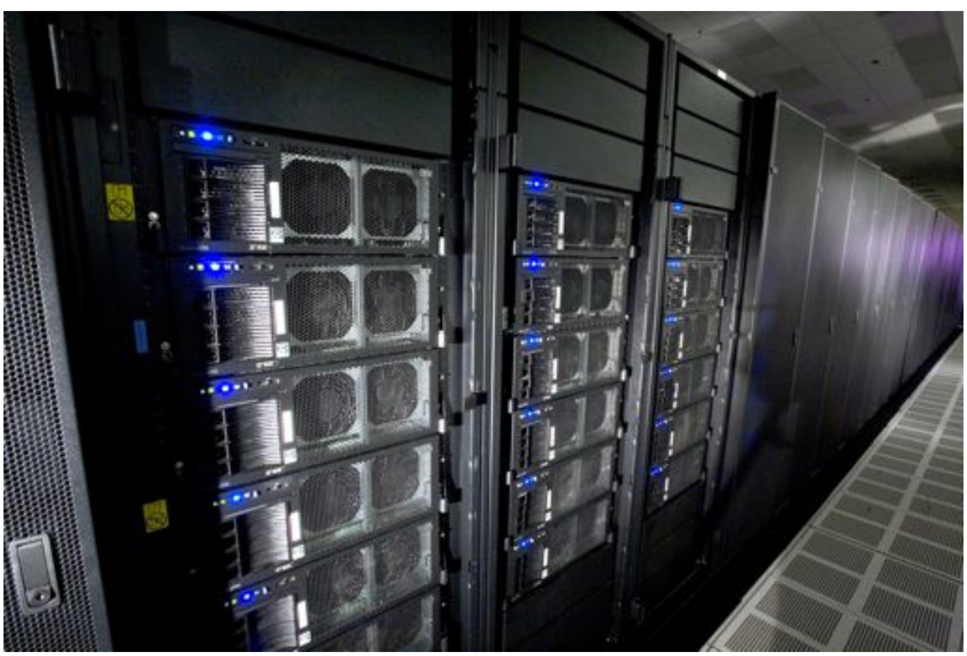
- Usage agreement for Google/IBM cluster
- Stay tuned for more details over email…

Source: Wikipedia (Japanese rock garden)

Hadoop Zen

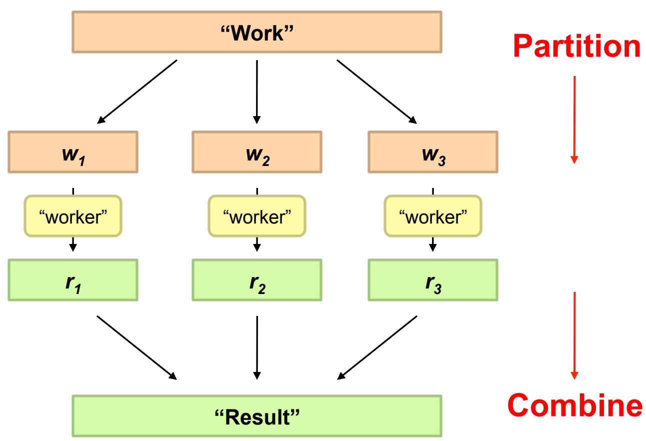
- This is bleeding edge technology (= immature!)
  - Bugs, undocumented features, inexplicable behavior
  - Data loss(!)
- Don’t get frustrated (take a deep breath)…
  - Those W$*#T@F! moments
- Be patient…
  - We will inevitably encounter “situations” along the way
- Be flexible…
  - We will have to be creative in workarounds
- Be constructive…
  - Tell me how I can make everyone’s experience better

How do we scale up?



Source: Wikipedia (IBM Roadrunner)

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 is 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

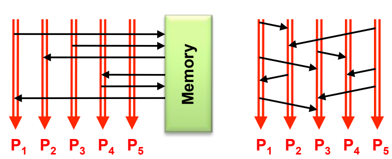

Source: Ricardo Guimarães Herrmann

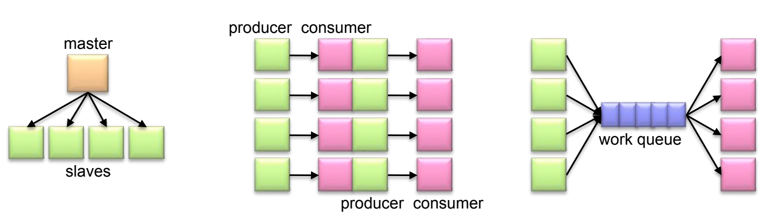
Managing Multiple Workers

- 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 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!

Current Tools

- Programming models
  - Shared memory (pthreads)
  - Message passing (MPI)
- Design Patterns
  - Master-slaves
  - Producer-consumer flows
  - Shared work queues

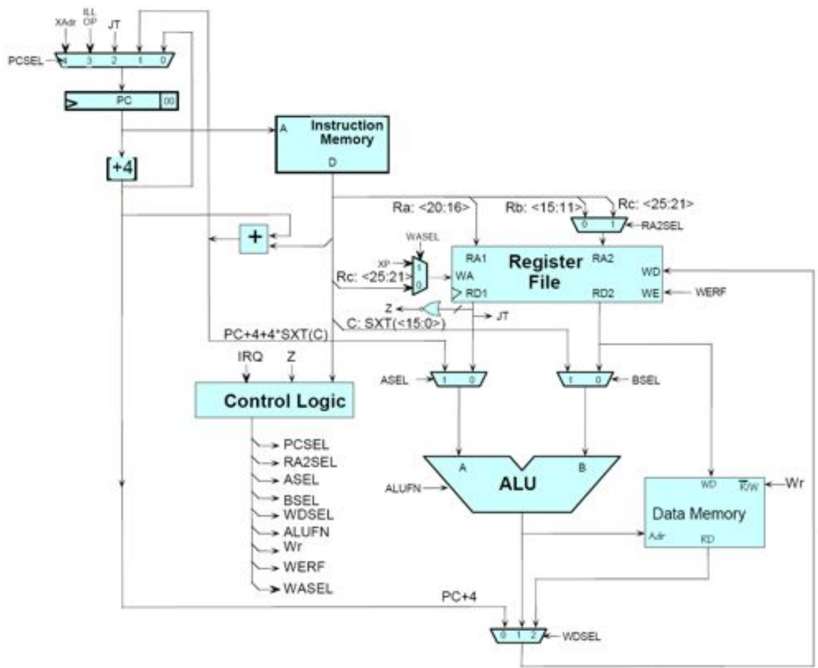




Where the rubber meets the road

- Concurrency is difficult to reason about
- Concurrency is even more difficult to reason about
  - At the scale of datacenters (even 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: Wikipedia (Flat Tire)



Source: MIT Open Courseware

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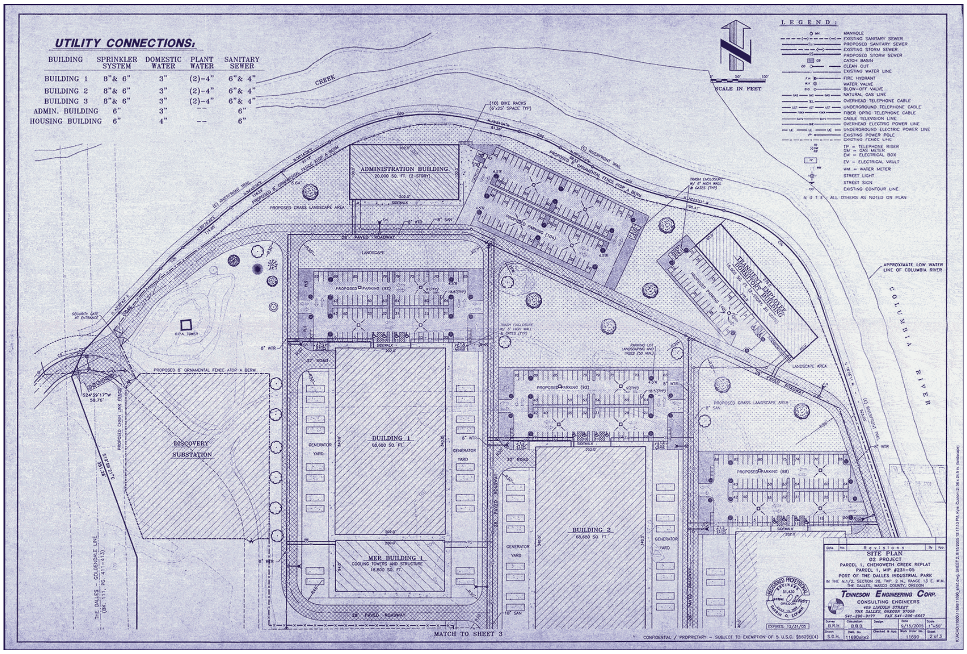


Source: Harper's (Feb, 2008)

What's the point?

- It's all about the right level of abstraction
  - The von Neumann architecture has served us well, but is no longer appropriate for the multi-core/cluster environment
- 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!

"Big Ideas"

- Scale "out", not "up"
  - Limits of SMP and large shared-memory machines
- Move processing to the data
  - Even the best clusters 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

MapReduce

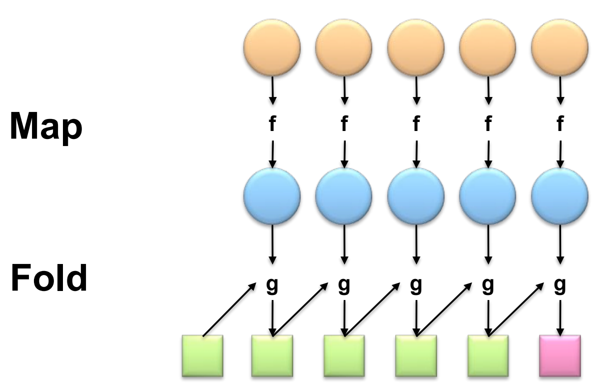
Typical Large-Data Problem

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

Key idea: provide a functional abstraction for these two operations

(Dean and Ghemawat, OSDI 2004)

Roots in Functional Programming



Roots in Functional Programming

```
Jordan-Boyd-Grabers-MacBook-Pro:~ jbg$ clisp
  i i i i i i i       ooooo    o        ooooooo   ooooo   ooooo
  I I I I I I I      8     8   8           8     8     o  8    8
  I  \ `+' /  I      8         8           8     8        8    8
   \  `-+-'  /       8         8           8      ooooo   8oooo
    `-__|__-'        8         8           8           8  8
        |            8     o   8           8     o     8  8
  ------+------       ooooo    8oooooo  ooo8ooo   ooooo   8

Welcome to GNU CLISP 2.48 (2009-07-28) <http://clisp.cons.org/>

Copyright (c) Bruno Haible, Michael Stoll 1992, 1993
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Copyright (c) Bruno Haible, Pierpaolo Bernardi, Sam Steingold 1998
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Type :h and hit Enter for context help.

[1]> (mapcar (lambda (x) (* x x)) (list 1 2 3 4 5))
(1 4 9 16 25)
[2]> (reduce '+ (list 1 2 3 4 5))
15
[3]> (reduce '+ (mapcar (lambda (x) (* x x)) (list 1 2 3 4 5)))
55
[4]> 
```

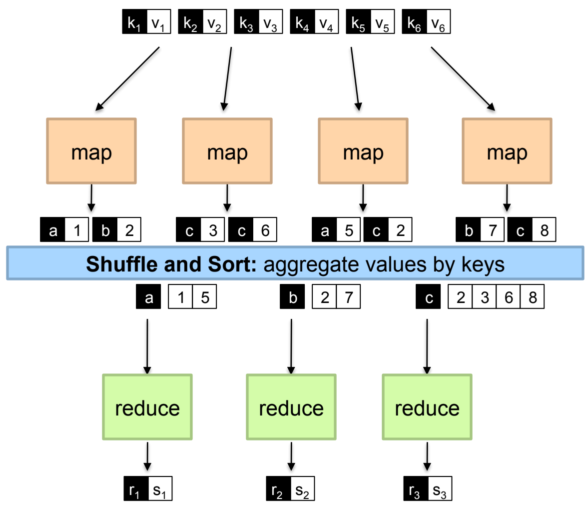
MapReduce

- 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…



MapReduce

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- 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)

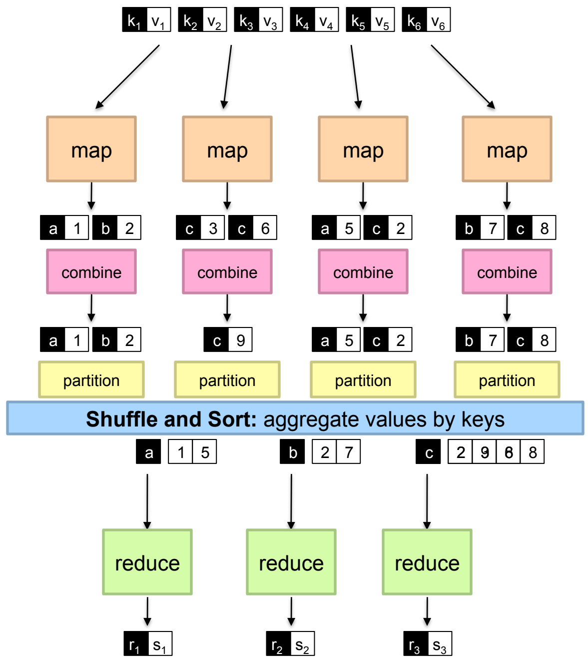
MapReduce

- 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



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);
```

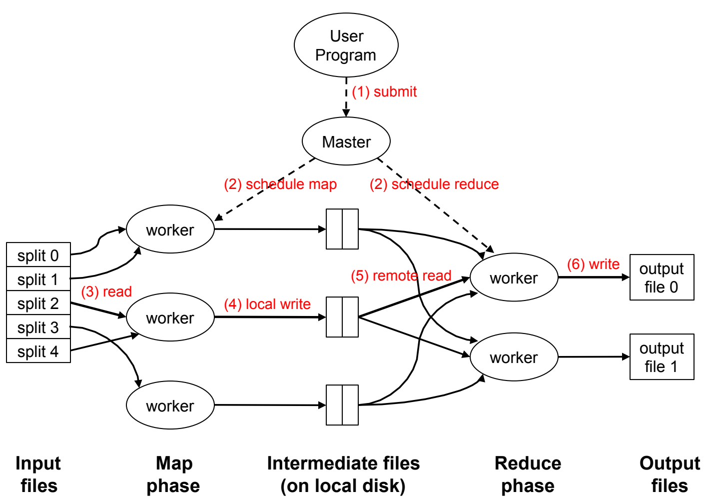
MapReduce can refer to…

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

Usage is usually clear from context!

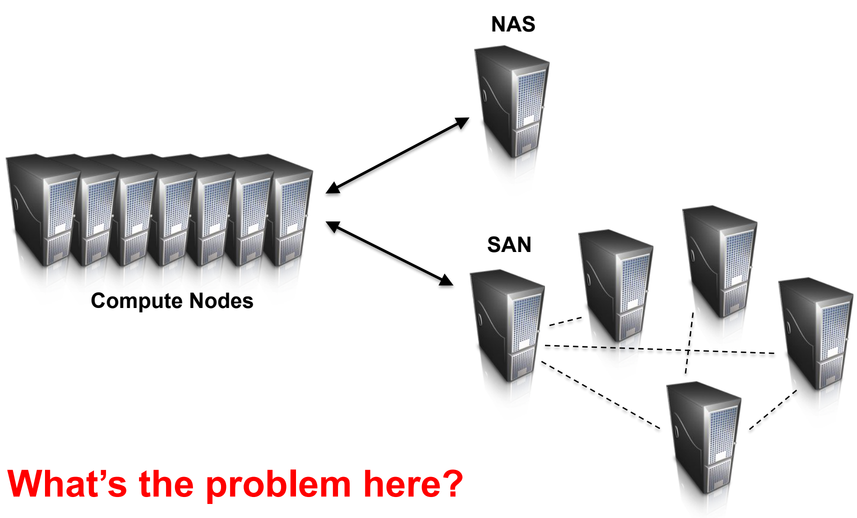
MapReduce Implementations

- Google has a proprietary implementation in C++
  - Bindings in Java, Python
- Hadoop is an open-source implementation in Java
  - Development led by Yahoo, used in production
  - Now an Apache project
  - 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?



What's the problem here?

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 slides adapted from material by (Ghemawat et al., SOSP 2003)

GFS: Design Decisions

- Files stored as chunks
  - Fixed size (64MB) – avoid little files!
- 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)

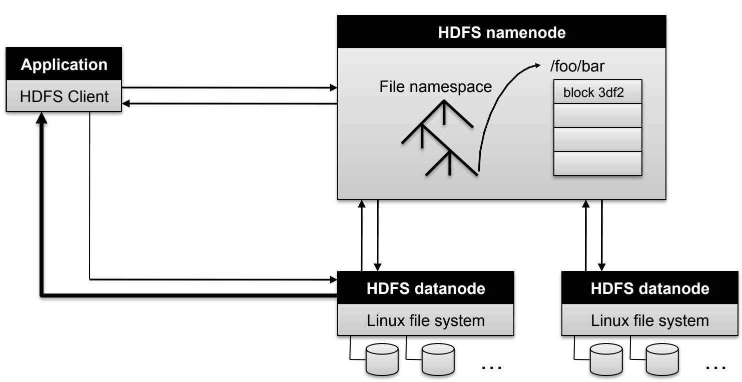
HDFS = GFS clone (same basic ideas)

From GFS to HDFS

- Terminology differences:
  - GFS master = Hadoop namenode
  - GFS chunkservers = Hadoop datanodes
- Functional differences:
  - No file appends in HDFS (planned feature)
  - HDFS performance is (likely) slower

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

HDFS Architecture

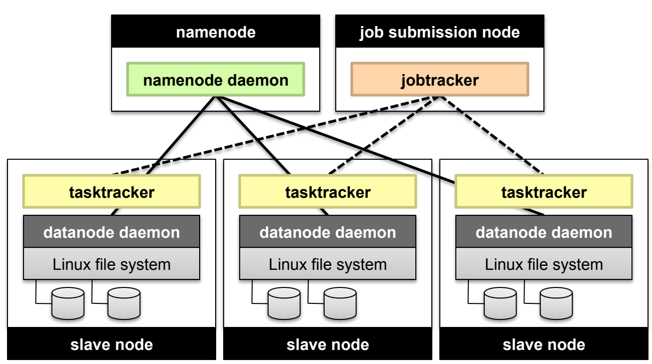


Adapted from (Ghemawat et al., SOSP 2003)

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…



Recap

- Why large data?
- Cloud computing and MapReduce
- Large-data processing: “big ideas”
- What is MapReduce?
- Importance of the underlying distributed file system