

Data-Intensive Information Processing Applications — Session #1

Introduction to MapReduce



Jimmy Lin
University of Maryland

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What is this course about?

- Data-intensive information processing
- Large-data (“web-scale”) problems
- Focus on applications
- MapReduce... and beyond

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?



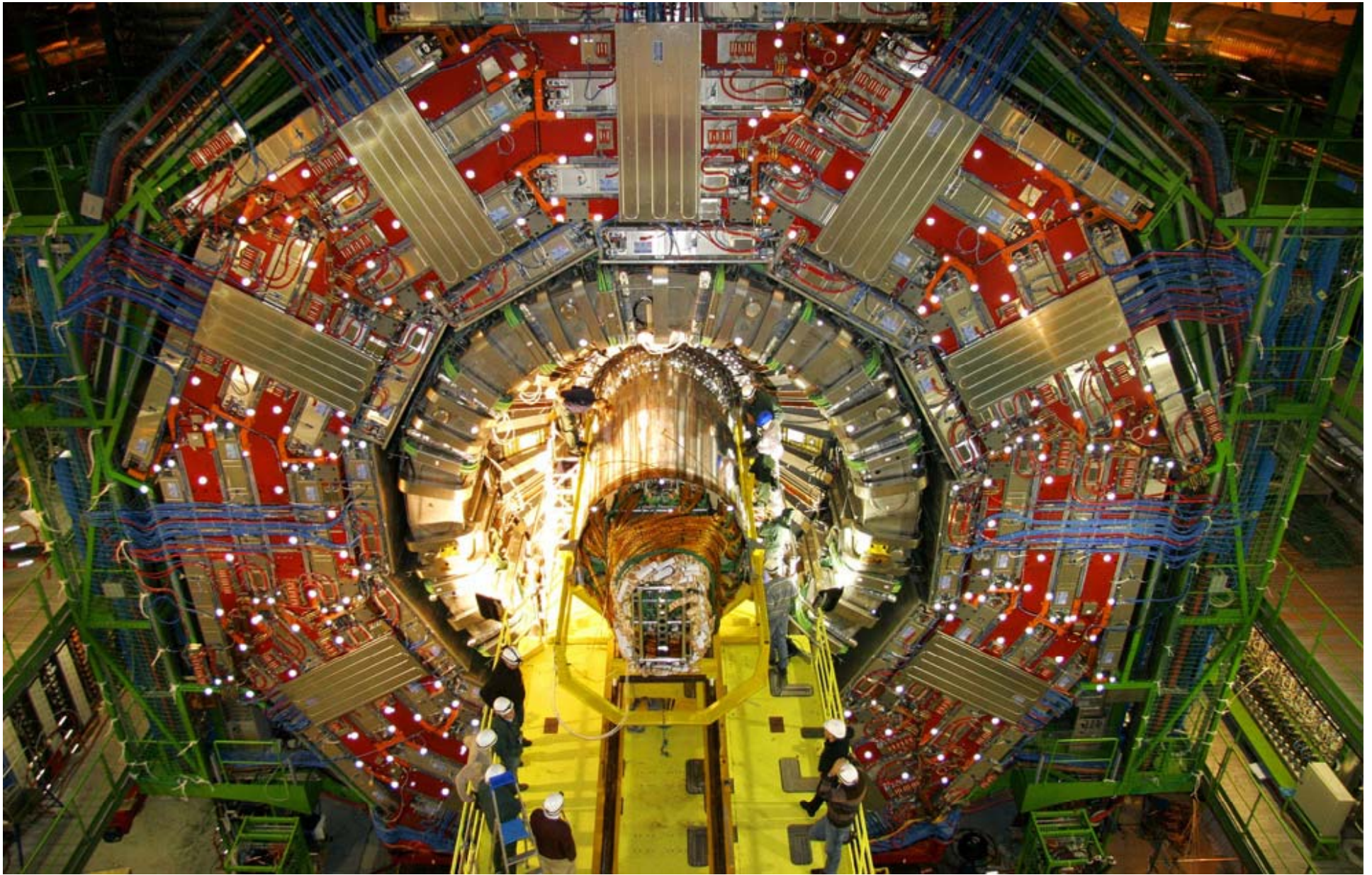
Source: Wikipedia (Everest)

How much data?

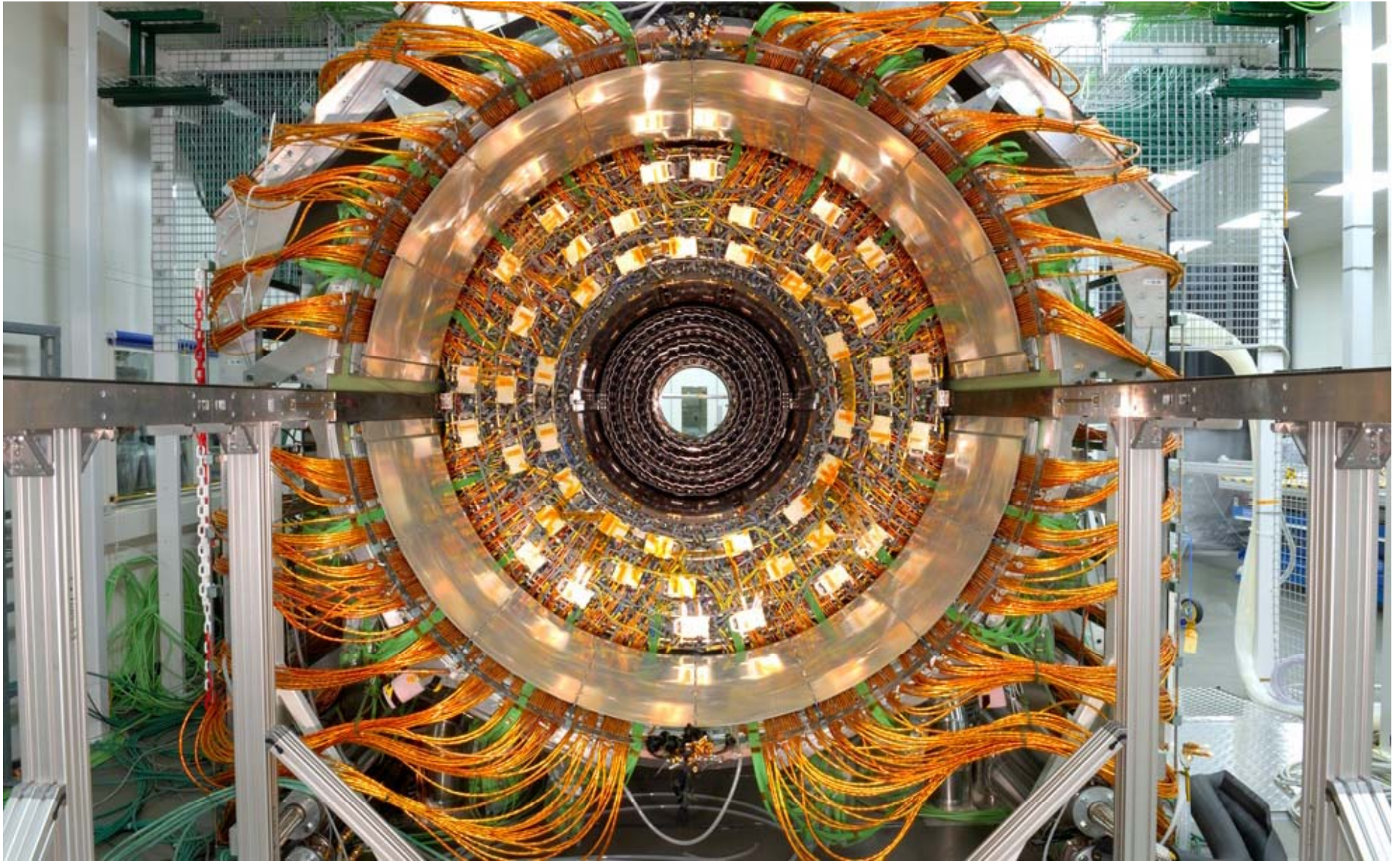
- Google processes 20 PB a day (2008)
- Wayback Machine has 3 PB + 100 TB/month (3/2009)
- Facebook has 2.5 PB of user data + 15 TB/day (4/2009)
- eBay has 6.5 PB of user data + 50 TB/day (5/2009)
- CERN's LHC will generate 15 PB a year (??)



640K ought to be enough for anybody.



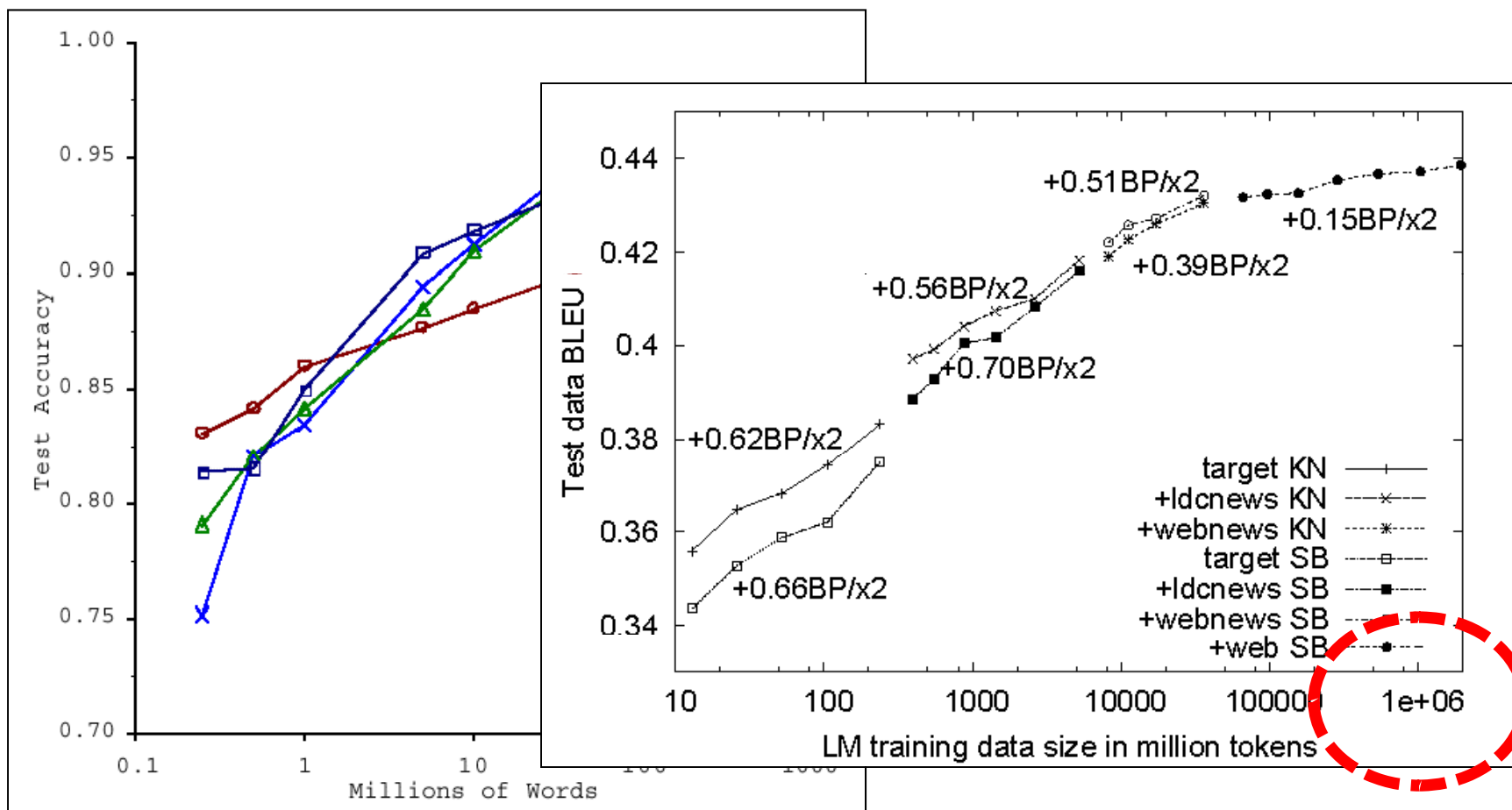
Maximilien Brice, © CERN



Maximilien Brice, © CERN

No data like more data!

s/knowledge/data/g;



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

What to do with more data?

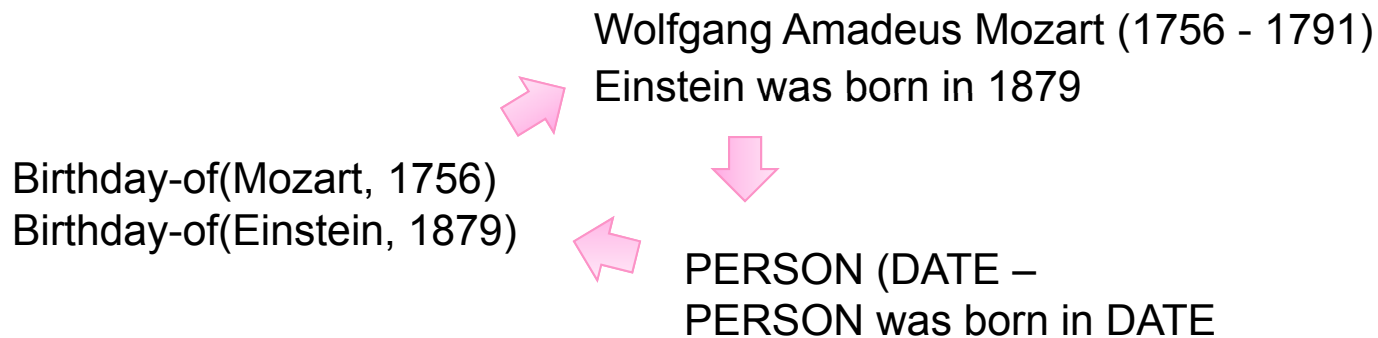
- Answering factoid questions

- 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



A large, dark, billowing cloud dominates the center of the frame, set against a bright blue sky. The cloud has a textured, almost smoky appearance. The text "What is cloud computing?" is overlaid in a clean, white, sans-serif font across the middle of the cloud.

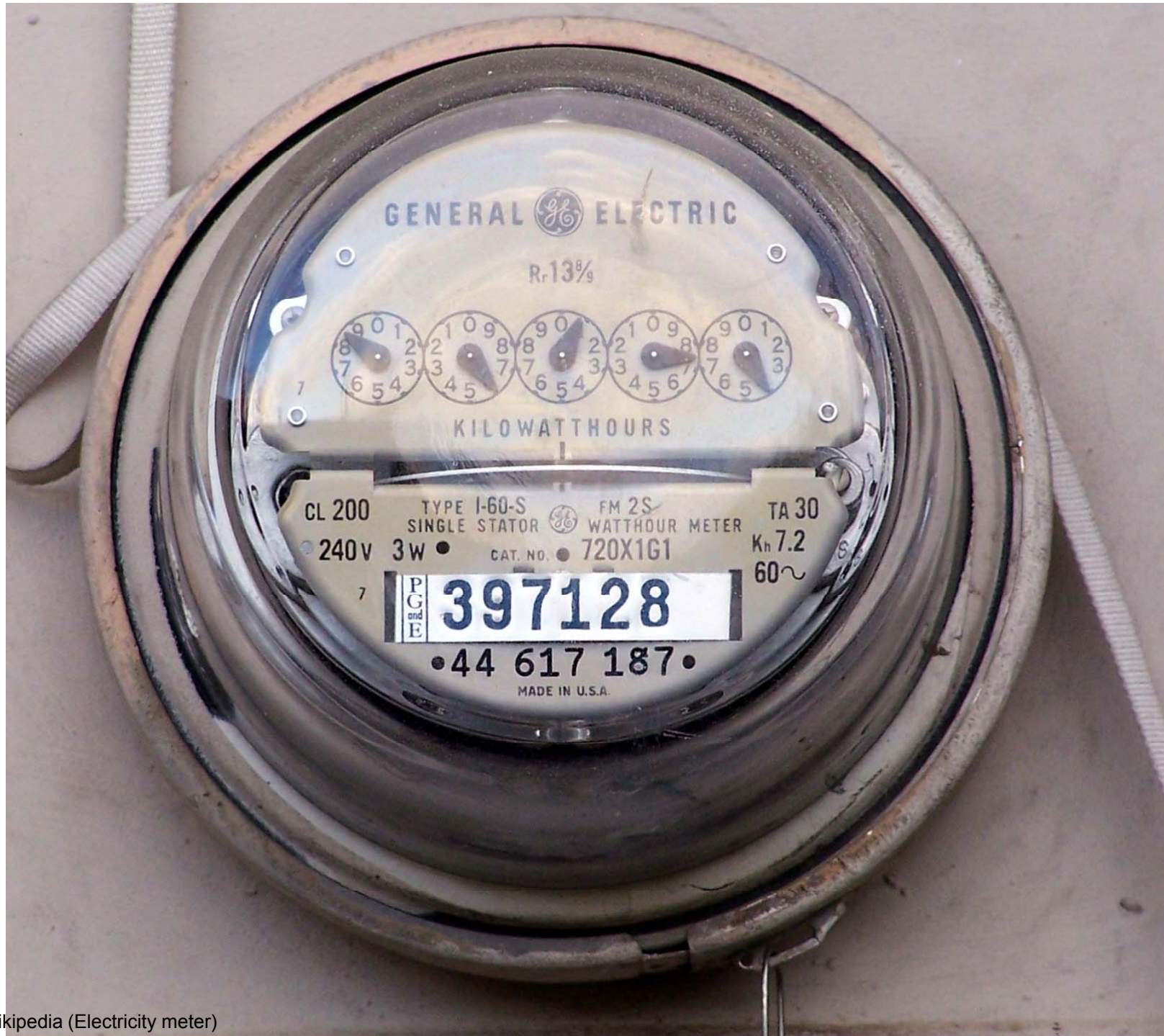
What is cloud computing?

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)

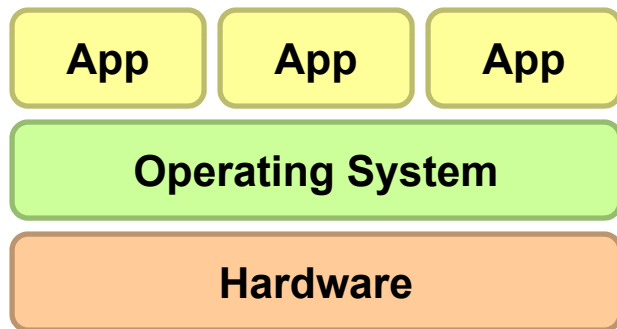
Utility Computing

- 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

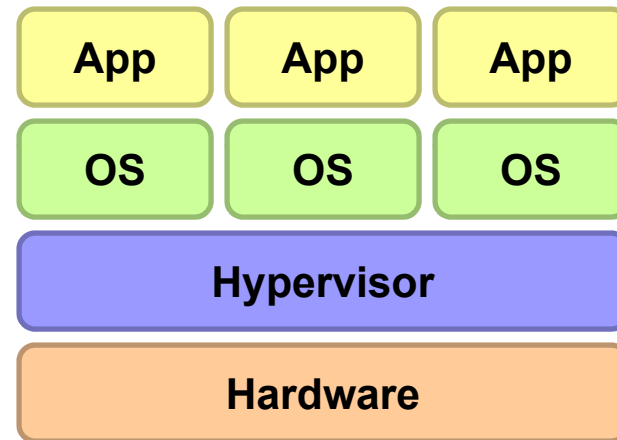
I think there is a world market for about five computers.



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
 - 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

This course is not for you...

- If you're not genuinely interested in the topic
- If you can't put in the time
- If you're not ready to do a lot of work
- If you're not open to thinking about computing in new ways
- If you can't cope with the uncertainty, unpredictability, etc. that comes with bleeding edge software

Otherwise, this will be a richly rewarding course!

Course components

- Textbooks
- Components of the final grade:
 - Assignments (important, but not worth much)
 - Midterm and final exams
 - Final project (of your choice, in groups of ~3)
 - Class participation
- I am unlikely to accept the following 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 in the clouds with Amazon EC2
- Hadoop on the Google/IBM cluster

Important Aside

- Usage agreement for EC2
- Usage agreement for Google/IBM cluster
- Stay tuned for more details over email...



Source: Wikipedia (Japanese rock garden)

Hadoop Zen

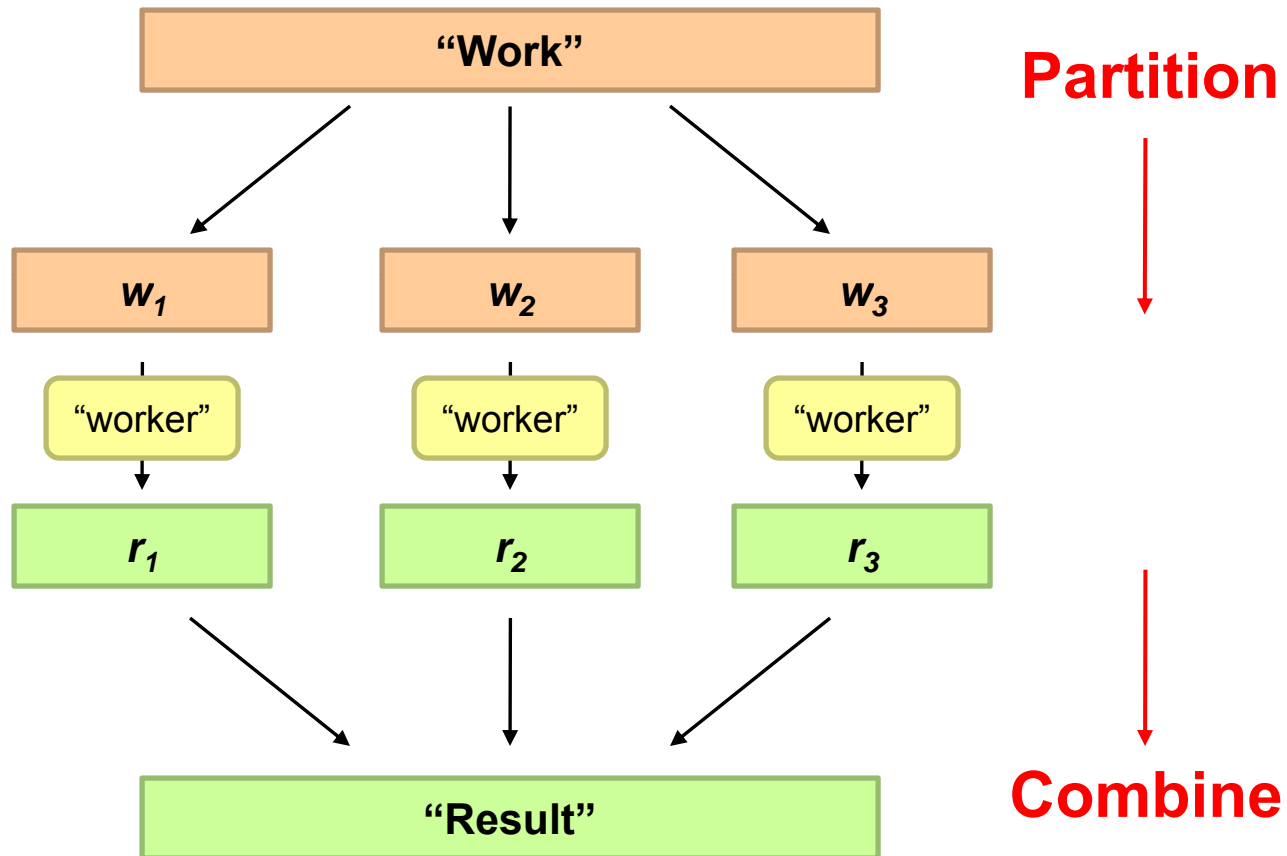
- This is bleeding edge technology (= immature!)
 - Bugs, undocumented features, inexplicable behavior
 - Data loss(!)
- Don't get frustrated (take a deep breath)...
 - Those W\$*#T@F! moments
- Be patient...
 - We will inevitably encounter “situations” along the way
- Be flexible...
 - We will have 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!

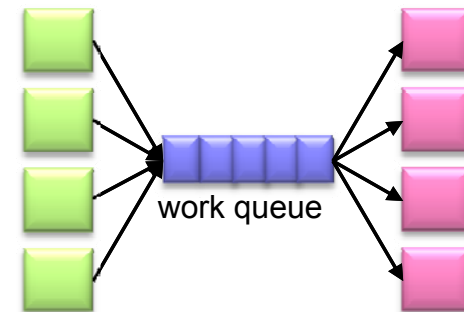
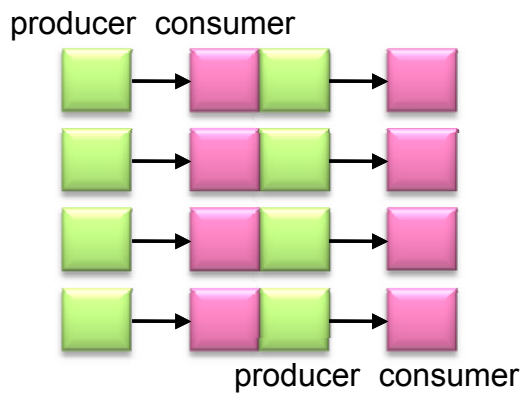
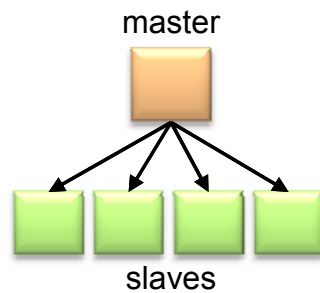
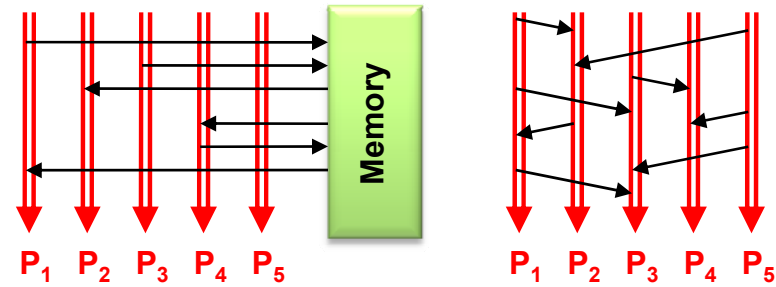
Current Tools

- Programming models

- Shared memory (pthreads)
- Message passing (MPI)

- Design Patterns

- Master-slaves
- Producer-consumer flows
- Shared work queues

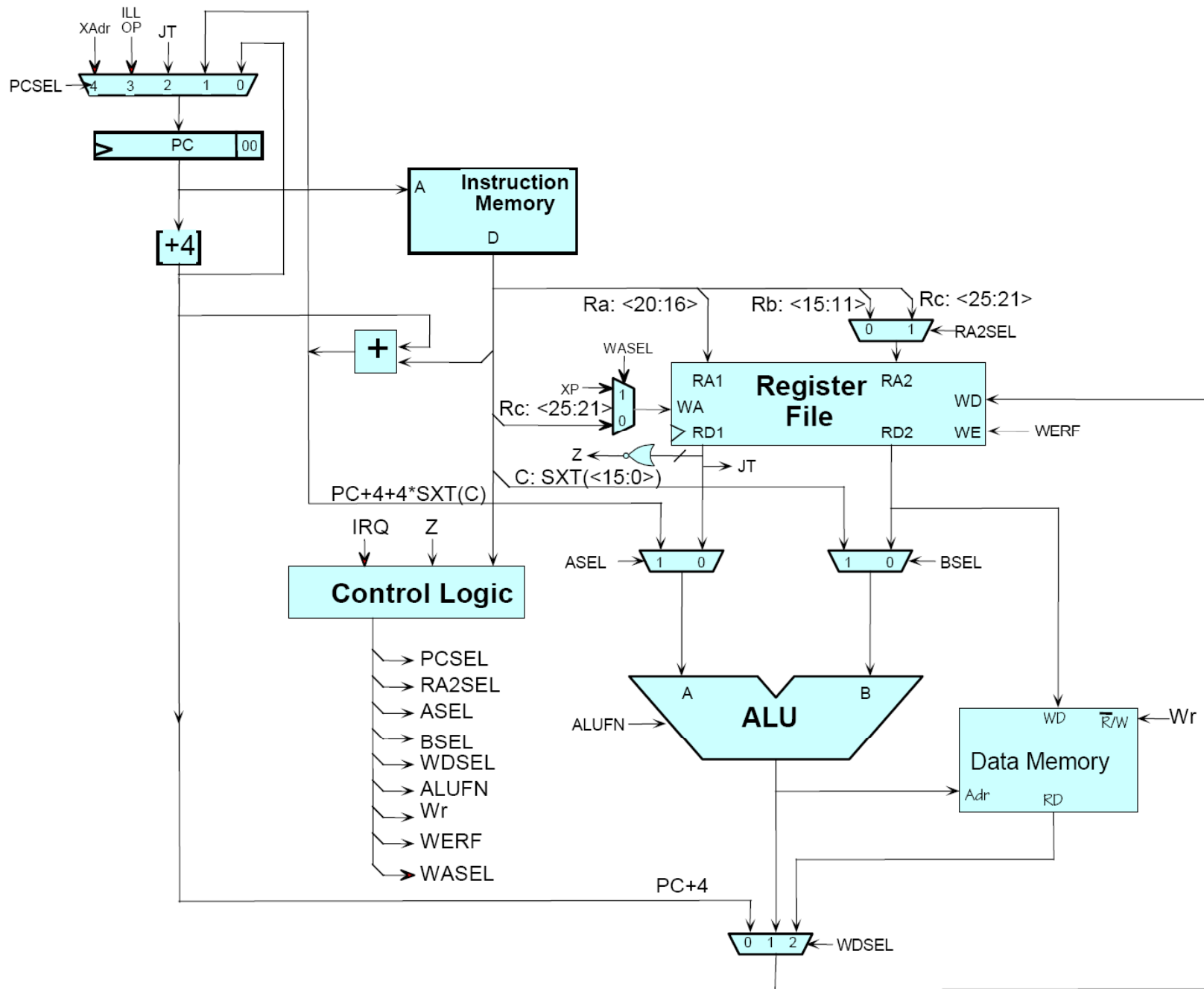


Where the rubber meets the road

- 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)





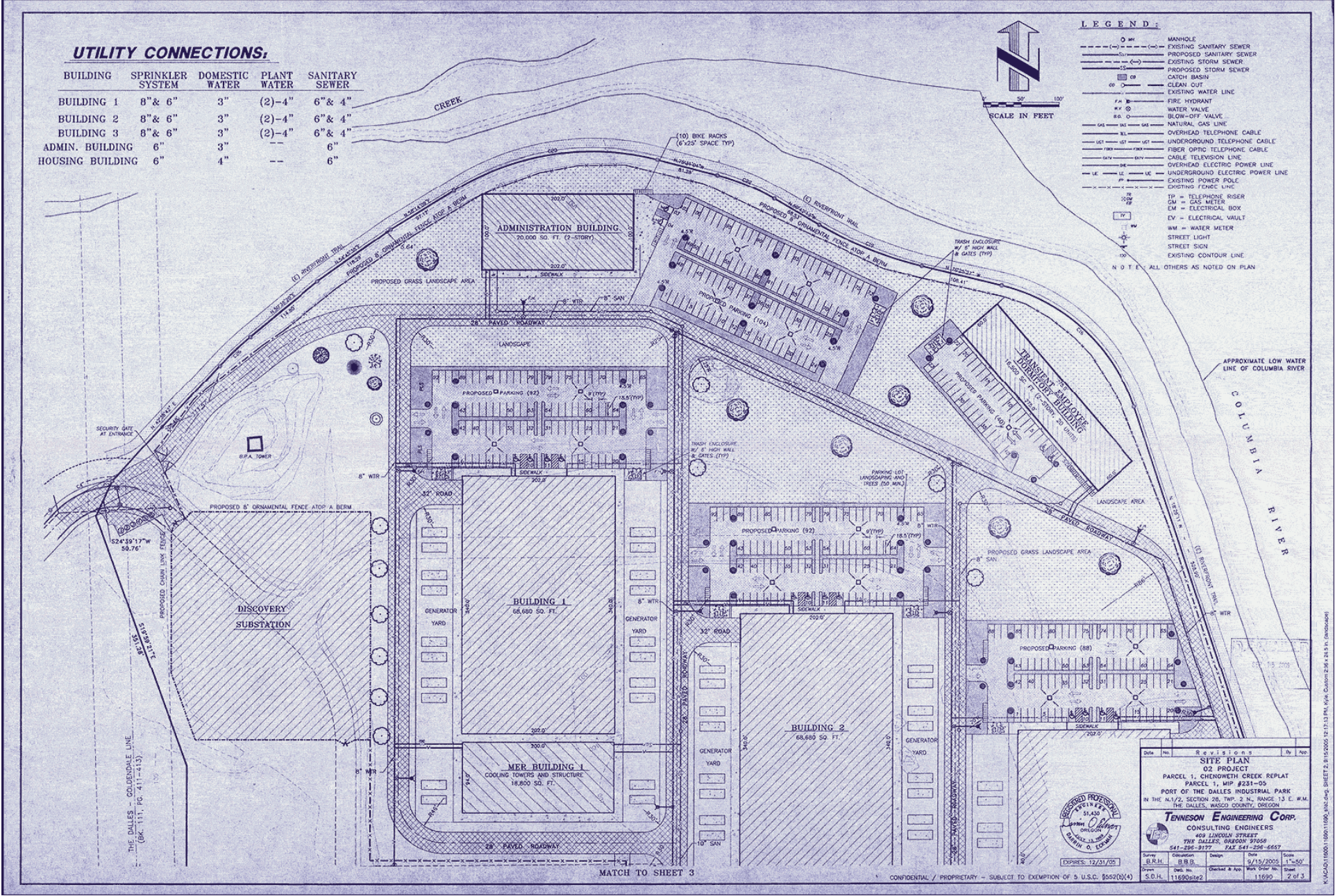
Source: MIT Open Courseware

UTILITY CONNECTIONS:

BUILDING	SPRINKLER SYSTEM	DOMESTIC WATER	PLANT WATER	SANITARY SEWER
BUILDING 1	8" & 6"	3"	(2)-4"	6" & 4"
BUILDING 2	8" & 6"	3"	(2)-4"	6" & 4"
BUILDING 3	8" & 6"	3"	(2)-4"	6" & 4"
ADMIN. BUILDING	6"	3"	--	6"
HOUSING BUILDING	6"	4"	--	6"

LEGEND:

- MH = MANHOLE
- (---) --- = EXISTING SANITARY SEWER
- (---) --- = PROPOSED SANITARY SEWER
- (---) --- = EXISTING STORM SEWER
- (---) --- = PROPOSED STORM SEWER
- (---) --- = CATCH BASIN
- = CLEAN OUT
- = EXISTING WATER LINE
- = FIRE HYDRANT
- = WATER VALVE
- = BLOW-OFF VALVE
- = NATURAL GAS LINE
- = OVERHEAD TELEPHONE CABLE
- = UNDERGROUND TELEPHONE CABLE
- = FIBER OPTIC TELEPHONE CABLE
- = CABLE TELEVISION LINE
- = OVERHEAD ELECTRIC POWER LINE
- = UNDERGROUND ELECTRIC POWER LINE
- = EXISTING POWER POLE
- = EXISTING FENCE LINE
- TP = TELEPHONE RISER
- GM = GAS METER
- EM = ELECTRICAL BOX
- EV = ELECTRICAL VAULT
- WM = WATER METER
- SL = STREET LIGHT
- SS = STREET SIGN
- = EXISTING CONTOUR LINE
- NOTE: ALL OTHERS AS NOTED ON PLAN



Date	No.	Revisions	By	App.
		02 PROJECT		
		SITE PLAN		
		PARCEL 1, CHENOWETH CREEK REPLAY		
		PARCEL 1, MIP #231-05		
		PORT OF THE DALLES INDUSTRIAL PARK		
		IN THE N. 1/2, SECTION 26, TWP. 2 N., RANGE 13 E. W.M.		
		THE DALLES, WAGDO COUNTY, OREGON		
TENNESON ENGINEERING CORP.				
CONSULTING ENGINEERS				
409 LINCOLN STREET				
780 DALLES, OREGON 97058				
541-296-2177 FAX 541-296-6657				
Survey	Collection	Design	Date	Sheet
E.R.H.	B.B.B.		9/15/2005	1 of 50
Drawn	Checked & App.	Work Order No.		Sheet
S.O.H.		11690		2 of 3

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
 - 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

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**

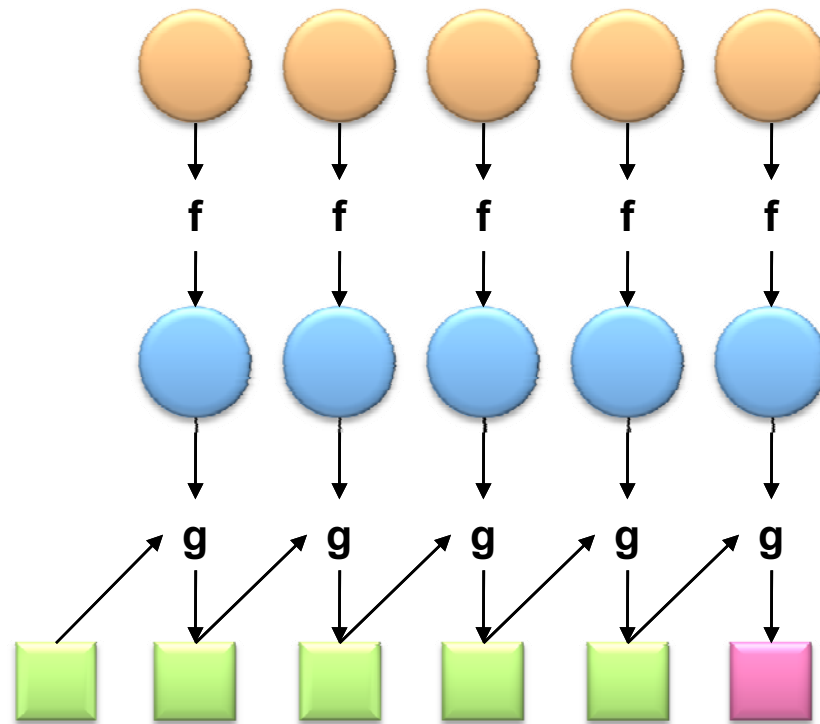
- Generate final output

Key idea: provide a functional abstraction for these two operations

Roots in Functional Programming

Map

Fold



MapReduce

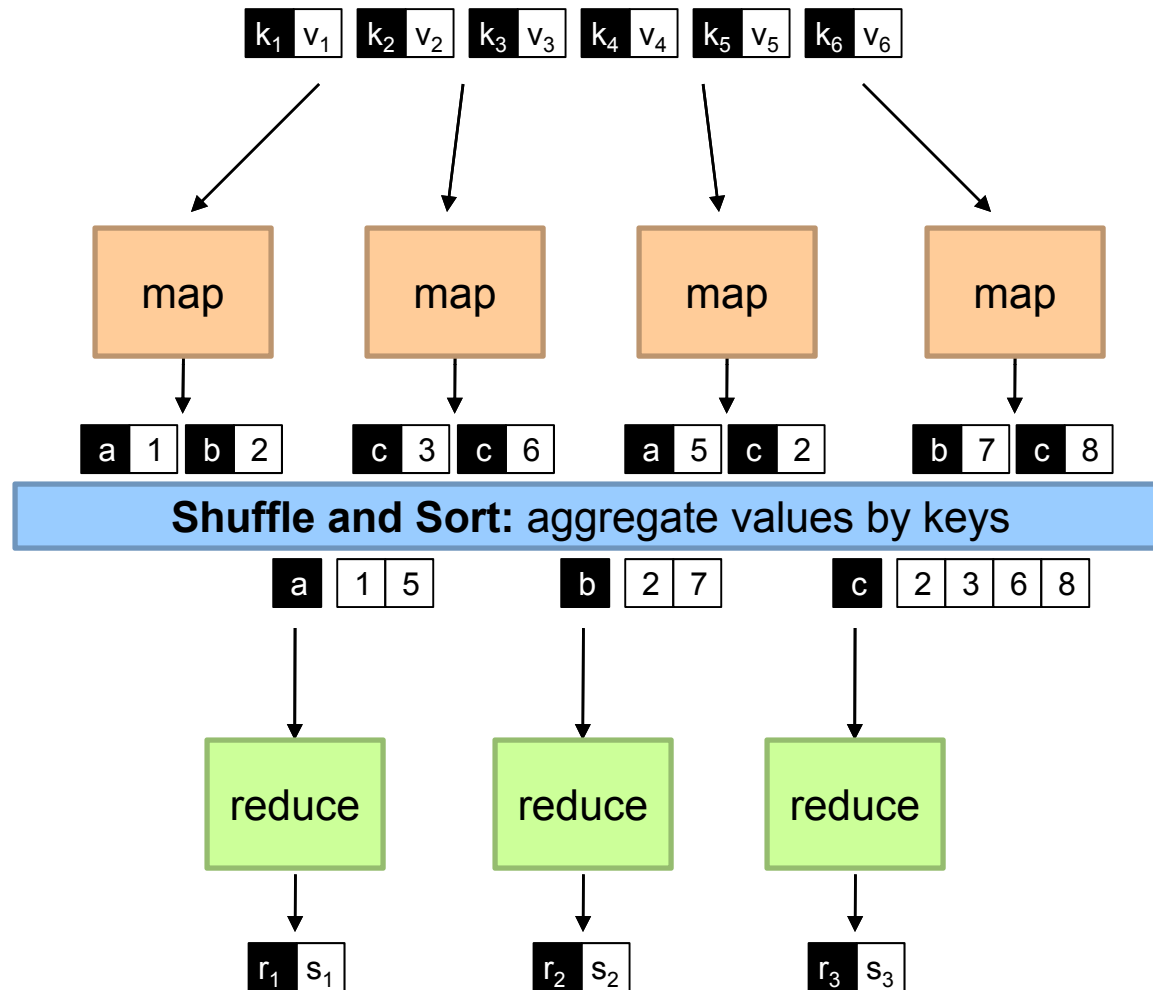
- Programmers specify two functions:

map $(k, v) \rightarrow \langle k', v' \rangle^*$

reduce $(k', v') \rightarrow \langle k', v' \rangle^*$

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

- The execution framework handles everything else...



MapReduce

- Programmers specify two functions:
 - map** $(k, v) \rightarrow \langle k', v' \rangle^*$
 - reduce** $(k', v') \rightarrow \langle k', v' \rangle^*$
 - All values with the same key are sent to the same reducer
- The execution framework handles everything else...

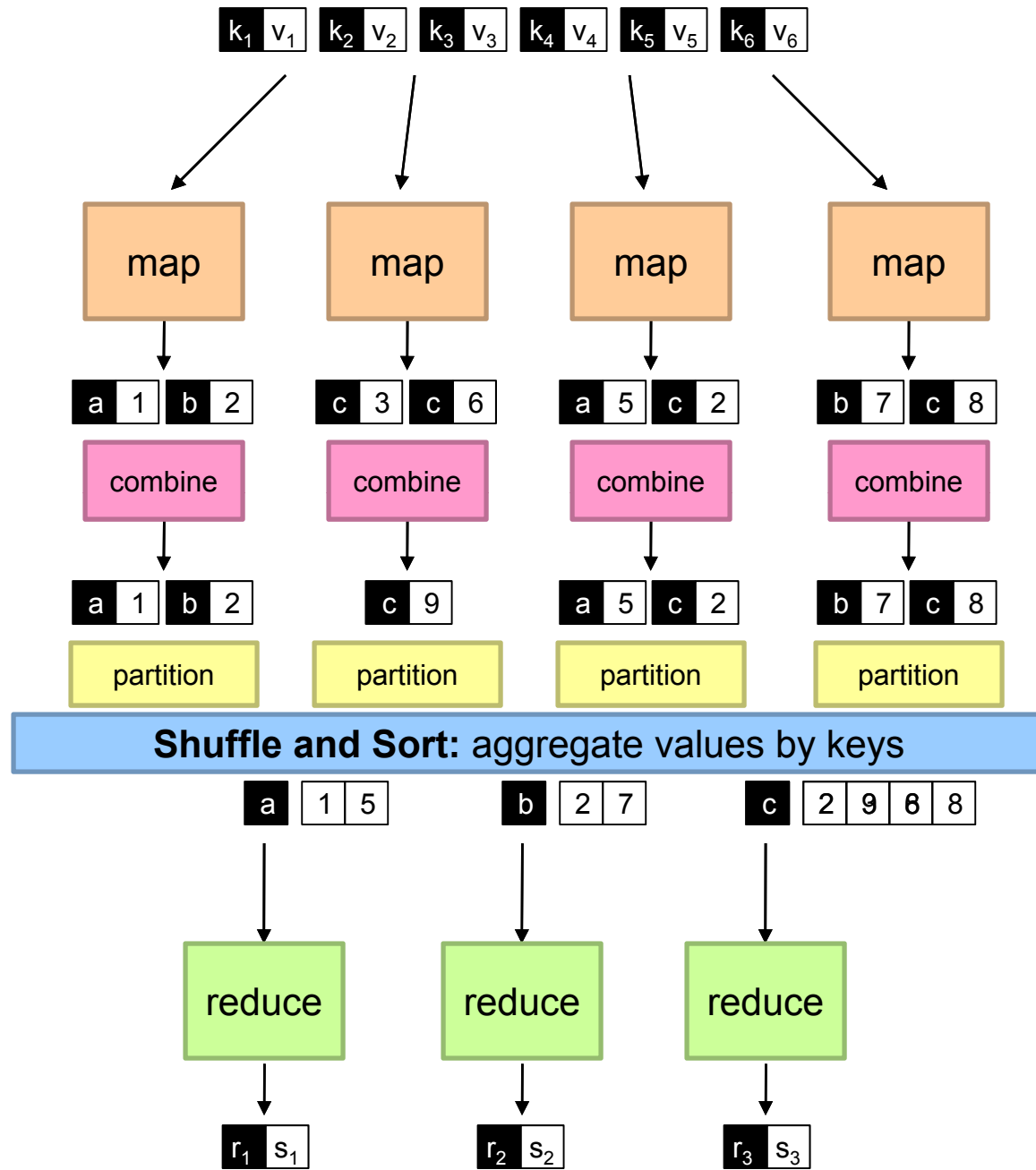
What's “everything else”?

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** $(k, v) \rightarrow \langle k', v' \rangle^*$
 - reduce** $(k', v') \rightarrow \langle k', v' \rangle^*$
 - All values with the same key are reduced together
- The execution framework handles everything else...
- Not quite...usually, programmers also specify:
 - partition** $(k', \text{number of partitions}) \rightarrow \text{partition for } k'$
 - Often a simple hash of the key, e.g., $\text{hash}(k') \bmod n$
 - Divides up key space for parallel reduce operations
 - combine** $(k', v') \rightarrow \langle k', v' \rangle^*$
 - 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);

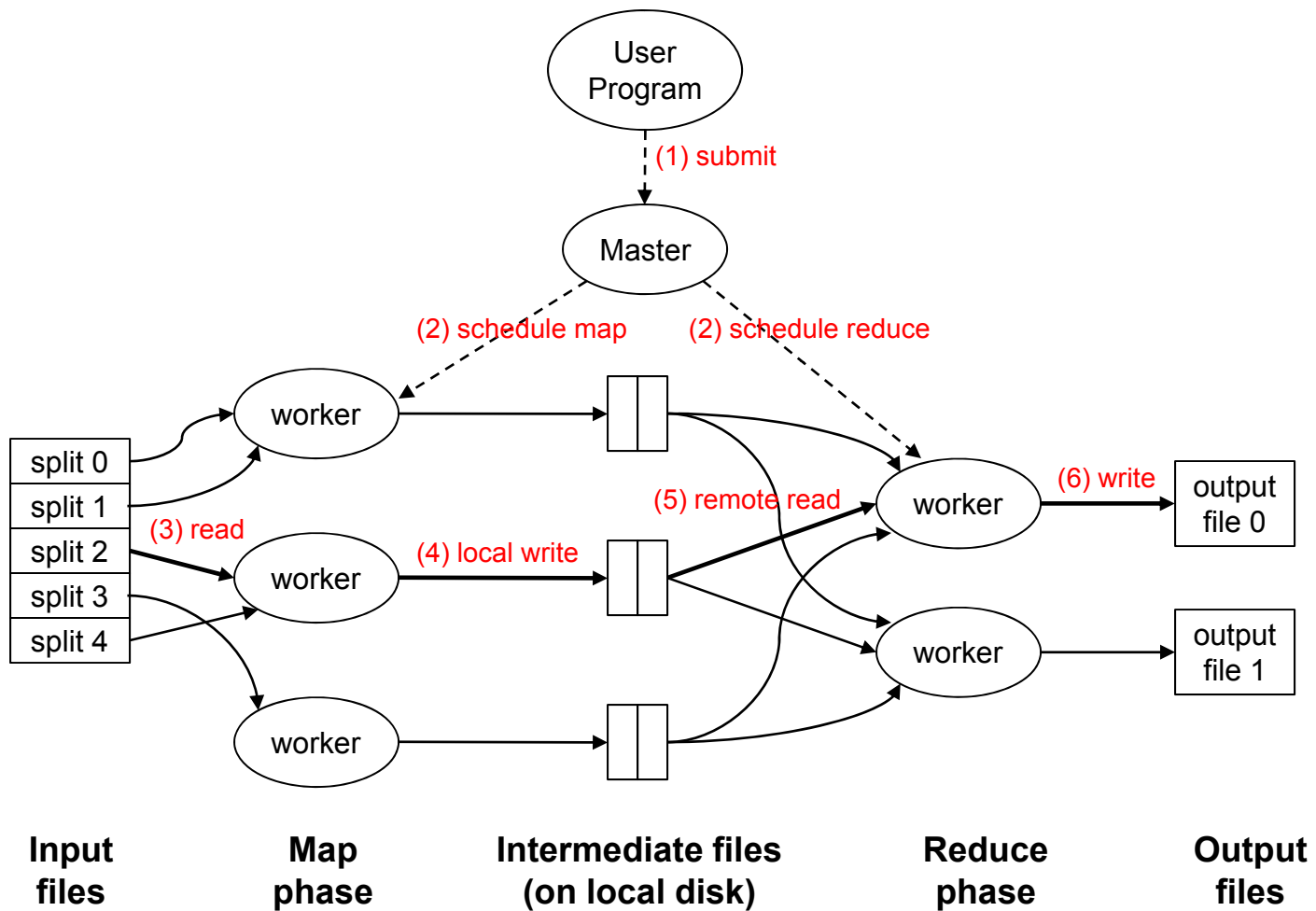
MapReduce can refer to...

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

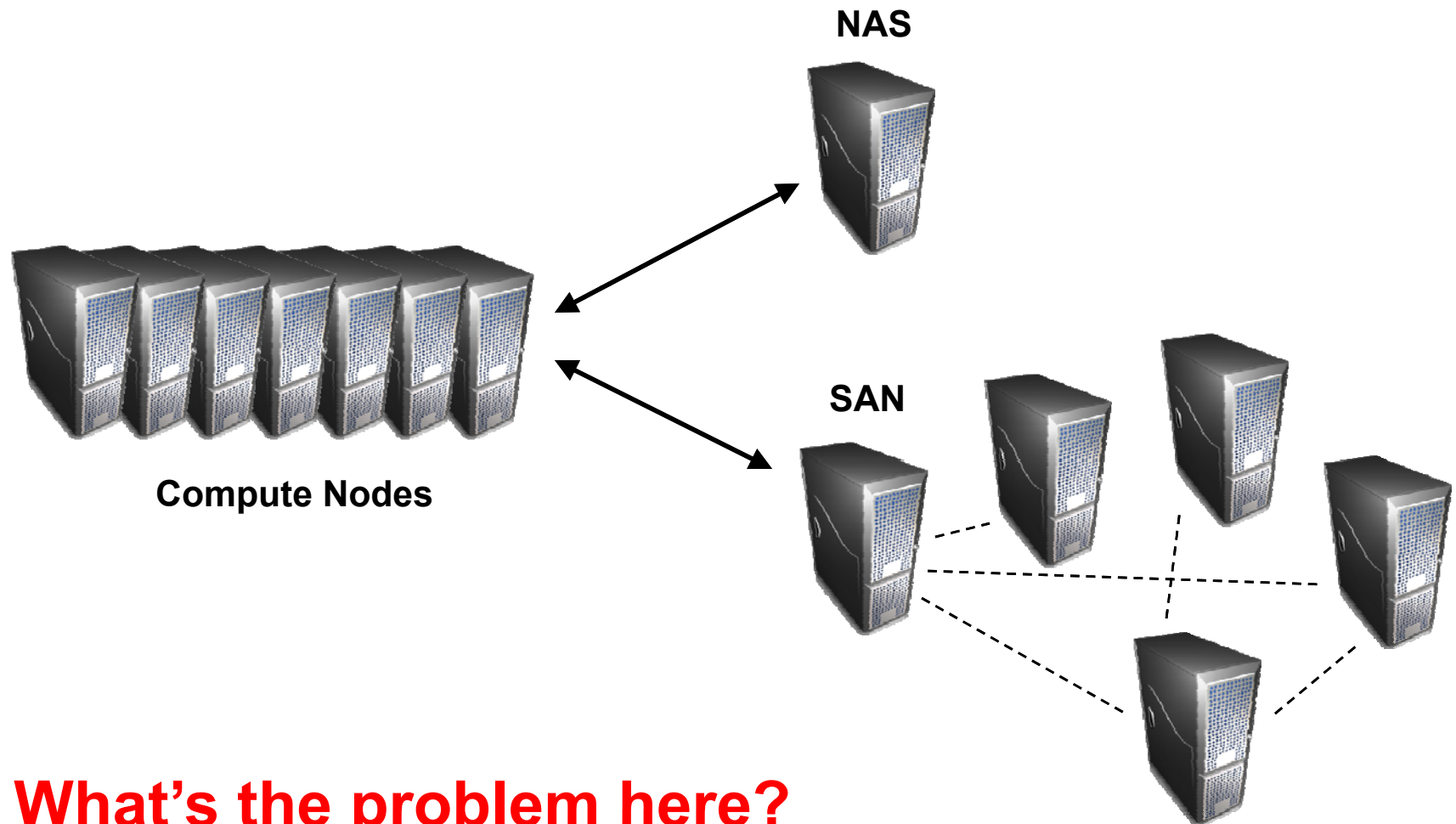
Usage is usually clear from context!

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.



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: 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)

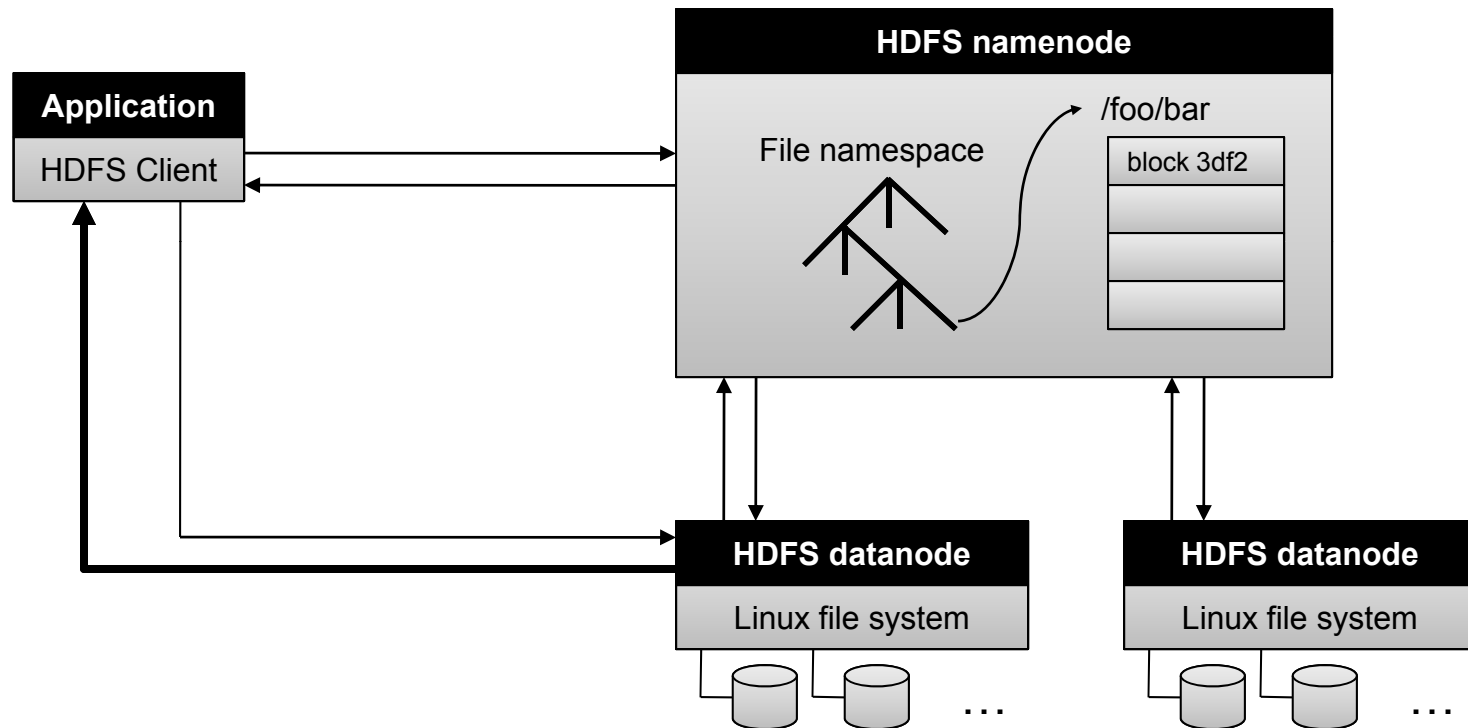
HDFS = GFS clone (same basic ideas)

From GFS to HDFS

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

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

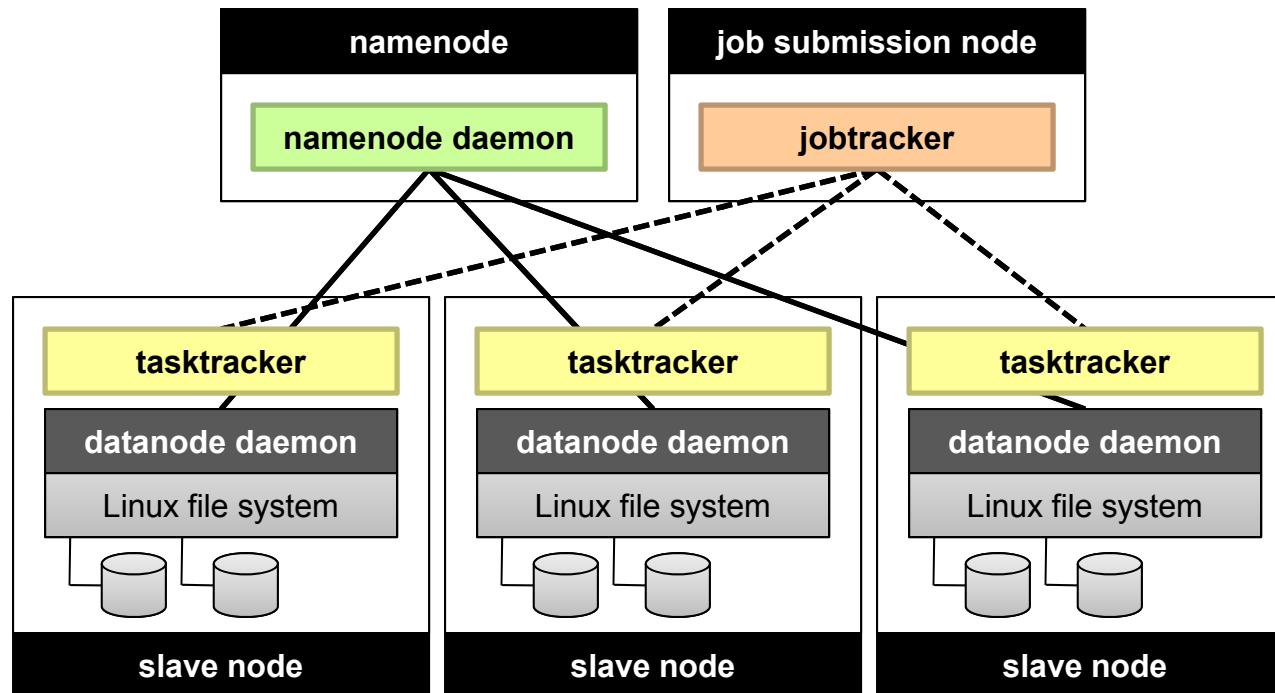
HDFS Architecture



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

A tropical beach scene at sunset. The sky is filled with scattered, small clouds that are illuminated from below, giving them a warm orange and yellow glow against a deep blue twilight sky. The sun is low on the horizon, creating a bright orange glow. In the foreground, the silhouettes of palm trees and other tropical vegetation are visible against the bright horizon. The beach is dark, and a few people can be seen walking along the shore. The water is calm, reflecting the colors of the sky.

Questions?

Photo credit: Jimmy Lin