Introduction to Clouds and MapReduce

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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
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

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

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
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?

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 (??)
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

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

PERSON (DATE – PERSON was born in DATE)

How do we scale up?

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

**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 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
What’s then is needed?

- 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

Typical Large-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

Key idea: provide a functional abstraction for these two operations

(Dean and Ghemawat, OSDI 2004)
MapReduce

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

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: 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)

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