Warehouse Scale Computing
But First, A Review/Redo of MOESI

• Goal is "Cache Coherence": All systems have the same view of memory
• Slides stolen from Morgan...
Each CPU has its own cache(s).

All CPU's communicate with each other and memory through a bus.

Let's go through an example to motivate why we need cache coherence!

One bank of memory is shared by all CPU's.
Can I get the data at 0xC0FFEE?
I don’t have that...
Can I have the data at 0xCOFFEE?
CPU 1
  └── Cache

CPU 2
  └── Cache

CPU 3
  └── Cache

Bus

Response

Memory
Hmm, I should remember that!

0x0FFFE = False
CPU 1
Cache

Here’s your data!

CPU 2
Cache

CPU 3
Cache

Bus

Memory

0xC0FFEE = False
CPU 1

Can I have the data at 0xC0FFEE?

CPU 2

CPU 3

Cache

Cache

Cache

Bus

Memory

0xC0FFEE = False
0xC0FFEE = False
Set 0xC0FFEE to True!

0xC0FFEE = True

0xC0FFEE = False
Hmm… These can’t both be true! What happened?

0xCOFFEE = True

0xCOFFEE = False
What happened?!

- Two CPU’s on a bus (communication device!) both read the same data; each processor got a copy of the data and stored it in their cache.
- Then, one CPU performed a write; their cache is up to date, but the other processor has stale data (and it doesn’t know its data is stale!)
- Things to think about:
  - How do we communicate when one processor changes the state of shared data?
  - Does every processor action cause data to change state?
  - Who should be responsible for providing the updated data?
  - What happens to memory while all of this is happening?
Basic Requirements: Keeping state & MSI

• Because we have multiple caches, we might have multiple copies of a piece of data floating around in our system (eg. the value of 0xC0FFEE in our previous example).

• We’ll need some way to track the status of these copies; do they match what we have in memory? (dirty, or “modified”), do other processors have a copy? Is that copy up to date or stale?

• We’ll keep state on a block-by-block basis; remember caches pull data in “blocksize” chunks, so all data within one block should have the same state.

• We already have "Valid" and "Dirty", so let's add an additional couple of bits for state
Additional Enhancements:

• We want to use write-back caches
  • A write-through cache design uses significantly more memory

• We want to minimize writes overall
  • So "write-back" even in the case of shared cache blocks!
    Helps reduce the cost of coherency misses

• We can communicate by broadcasting requests
  • Shout to all other processors
Idea Behind States

• **M**: Modified
  • I have the only copy, and can write, and its dirty
  • If this gets evicted, I need to flush the entry

• **O**: Owned
  • I have the *official* copy, and can write, and its dirty
  • When writing, I have to tell everyone else I'm writing (and it now turns Exclusive)

• **E**: Exclusive
  • I have the *only* copy

• **S**: Shared
  • I have a copy and can read away...

• **I**: Invalid (duh)
Can I get the data at 0xC0FFEE?

Valid | Dirty | State
0     | 0     | 1

0xC0FFEE = ???
I don’t have that...

Valid  Dirty  State
0       0     1

Valid  Dirty  State
0       0     1

0xC0FFEE = ???

0xC0FFEE = ???
Can I have the data at 0xC0FFEE?

CPU 1

Cache

CPU 2

Cache

CPU 3

Cache

Bus

Memory

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<th>State</th>
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0xC0FFEE = False

0xC0FFEE = ???
CPU 1

Cache

I don’t have that... (read)

CPU 2

Cache

CPU 3

Cache

Bus

Request & Response

Memory

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</table>

0xC0FFEE = False

0xC0FFEE = False
Set 0xC0FFEE to True!

Valid | Dirty | State
--- | --- | ---
1 | 0 | S

Valid | Dirty | State
--- | --- | ---
? | 0 | ?

0xC0FFEE = True

0xC0FFEE = False?
Psst! I’m changing the 0xC0FFEE block, write!

<table>
<thead>
<tr>
<th>Valid</th>
<th>Dirty</th>
<th>State</th>
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<tbody>
<tr>
<td>1</td>
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<td>M</td>
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<thead>
<tr>
<th>Valid</th>
<th>Dirty</th>
<th>State</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>I</td>
</tr>
</tbody>
</table>

0xC0FFEE = True

0xC0FFEE = ???
Can I get 0xC0FFEE again?

<table>
<thead>
<tr>
<th>Valid</th>
<th>Dirty</th>
<th>State</th>
</tr>
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<tbody>
<tr>
<td>1</td>
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<table>
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<tr>
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<th>Dirty</th>
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<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>I</td>
</tr>
</tbody>
</table>

0xC0FFEE = True

0xC0FFEE = ???
CPU 1

Cache

CPU 2

Cache

CPU 3

Cache

Bus

Memory

Valid  Dirty  State
1       1      O

Valid  Dirty  State
1       0      S

Yay! Consistent state!

0xC0FFEE = True

0xC0FFEE = True
## The Bits Needed

<table>
<thead>
<tr>
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<th>Dirty</th>
<th>Shared</th>
<th>State</th>
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</thead>
<tbody>
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<td>0</td>
<td>1</td>
<td>1</td>
<td>Invalid</td>
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<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>Exclusive</td>
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<tr>
<td>1</td>
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<td>1</td>
<td>Shared</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
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</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>Owned</td>
</tr>
</tbody>
</table>
Clicker Question:
Exam?

- A: 😄
- B: 😐
- C: 😭
- D: 😡
- E: %
Administrivia

- Proj 4 deadline moved to Wednesday, 4/17
  - We recommend completing lab 11 if you feel behind on project-scope material
  - The discussion worksheets on TLP and DLP are also helpful
  - Take advantage of OH this week to avoid the rush M/T/W
- Expect grades sometime next week, regrades after; grading is happening over the weekend.
- Refrain from discussing the exam on piazza til this weekend
- If you are frustrated with aspects of the exam, don't blame your TA, blame me!
Agenda

• Warehouse-Scale Computing
• Cloud Computing
• Request-Level Parallelism (RLP)
• Map-Reduce Data Parallelism
• And, in Conclusion …
Agenda

- Warehouse-Scale Computing
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Google’s WSCs

Ex: In Oregon
WSC Architecture

1U Server:
8 cores, 16 GiB DRAM, 4x1 TB disk

Rack:
40-80 servers, Local Ethernet (1-10Gbps) switch (30$/1Gbps/server)

Array (aka cluster):
16-32 racks, Expensive switch (10X bandwidth → 100x cost)
WSC Storage Hierarchy

1U Server:
DRAM: 16GB, 100ns, 20GB/s
Disk: 2TB, 10ms, 200MB/s

Rack (80 servers):
DRAM: 1TB, 300µs, 100MB/s
Disk: 160TB, 11ms, 100MB/s

Array (30 racks):
DRAM: 30TB, 500µs, 10MB/s
Disk: 4.80PB, 12ms,
Google Server Internals
Take a walk through a Google data center
Power Usage Effectiveness

- Energy efficiency
- Primary concern in the design of WSC
- Important component of the total cost of ownership

Power Usage Effectiveness (PUE):

\[
\text{PUE} = \frac{\text{Total Building Power}}{\text{IT equipment Power}}
\]

- Power efficiency measure for WSC
- Not considering efficiency of servers, networking
- Perfection = 1.0
- Google WSC’s PUE = 1.2
Power Usage Effectiveness

Datacenter

Total Power In

Infrastructure

Air Conditioning, Power Distribution, UPS, …

IT Equipment

Servers, Storage, Networks

PUE = Total Power/IT Power

PUE = 2.5
Cheating on Cooling

• Normally cooling the air requires big air-conditioning units
  • These suck a lot of power and still consume a lot of water
    • Evaporation of water to dissipate the energy

• Cheat #1: Heat-exchange to a water source
  • Locate your data center on a river or the ocean
  • Heat up water rather than air

• Cheat #2: Just have things open to the air!
  • Ups the failure rate, but if the power savings exceed the costs incurred by additional machines dying, 🌧️
Energy Proportionality

“The Case for Energy-Proportional Computing,”
Luiz André Barroso, Urs Hölzle,
*IEEE Computer*
December 2007

It is surprisingly hard to achieve high levels of utilization of typical servers (and your home PC or laptop is even worse)

Figure 1. Average CPU utilization of more than 5,000 servers during a six-month period. Servers are rarely completely idle and seldom operate near their maximum utilization, instead operating most of the time at between 10 and 50 percent of their maximum.
Energy-Proportional Computing


Energy Efficiency = Utilization/Power

Figure 2. Server power usage and energy efficiency at varying utilization levels, from idle to peak performance. Even an energy-efficient server still consumes about half its full power when doing virtually no work.
Energy Proportionality

“The Case for Energy-Proportional Computing,”
Luiz André Barroso, Urs Hölzle,
IEEE Computer
December 2007

Energy Efficiency = Utilization/Power

Figure 4. Power usage and energy efficiency in a more energy-proportional server. This server has a power efficiency of more than 80 percent of its peak value for utilizations of 30 percent and above, with efficiency remaining above 50 percent for utilization levels as low as 10 percent.
Agenda

- Warehouse Scale Computing
- Cloud Computing
- Request Level Parallelism (RLP)
- Map-Reduce Data Parallelism
- And, in Conclusion …
Cloud Distinguished by …

- Shared platform with illusion of isolation
  - Collocation with other tenants
  - Exploits technology of VMs and hypervisors (next lectures!)
  - At best “fair” allocation of resources, but not true isolation

- Attraction of low-cost cycles
  - Economies of scale driving move to consolidation
  - Statistical multiplexing to achieve high utilization/efficiency of resources

- Elastic service
  - Pay for what you need, get more when you need it
  - But no performance guarantees: assumes uncorrelated demand for resources
Cloud Services

- **SaaS**: deliver apps over Internet, eliminating need to install/run on customer's computers, simplifying maintenance and support
  - E.g., Google Docs, Win Apps in the Cloud
- **PaaS**: deliver computing “stack” as a service, using cloud infrastructure to implement apps. Deploy apps without cost/complexity of buying and managing underlying layers
  - E.g., Hadoop on EC2, Apache Spark on GCP
- **IaaS**: Rather than purchasing servers, software, data center space or net equipment, clients buy resources as an outsourced service. Billed on utility basis. Amount of resources consumed/cost reflect level of activity
  - E.g., Amazon Elastic Compute Cloud, Google Compute Platform
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Request-Level Parallelism (RLP)

• Hundreds of thousands of requests per second
• Popular Internet services like web search, social networking, …
• Such requests are largely independent
  • Often involve read-mostly databases
  • Rarely involve read-write sharing or synchronization across requests
• Computation easily partitioned across different requests and even within a request
• Can often "load balance" just at the DNS level:
  Just tell different people to use a different computer
Google Query-Serving Architecture
Web Search Result

About 1,560,000 results (0.75 seconds)

Nicholas Weaver (@ncweaver) · Twitter
https://twitter.com/ncweaver

It is @Popehat's tale, entitled "Short My Taint Team" twitter.com/Popehat/sta...

The writers for 2018 are just getting lazy. A Clinton Foundation supporter? twitter.com/nytmike/sta...

Legal twitter: Hypothetical question. The President committed a state crime before inauguration. While in office can the President be indicted by a state for his crime?

1 hour ago · Twitter
14 hours ago · Twitter
14 hours ago · Twitter

Nicholas Weaver · Berkeley
https://www.icsi.berkeley.edu/~nweaver/

Sep 26, 2012 - Short Bio. I received a B.A. in Astrophysics and Computer Science in 1995, and my Ph.D. in Computer Science in 2003 from the University of California at Berkeley. Although my dissertation was on novel FPGA architectures, I also was highly interested in Computer Security, including postulating the
Anatomy of a Web Search (1/3)

- Google “Nicholas Weaver”
  1. Direct request to “closest” Google Warehouse-Scale Computer
  2. Front-end load balancer directs request to one of many clusters of servers within WSC
  3. Within cluster, select one of many Google Web Servers (GWS) to handle the request and compose the response pages
  4. GWS communicates with Index Servers to find documents that contain the search words, “Nicholas”, “Weaver”, uses location of search as well as user information
  5. Send information about this search to the node in charge of tracking nweaver@gmail.com
  6. Return document list with associated relevance score
Anatomy of a Web Search (2/3)

• In parallel,
  • Ad system: if anyone has bothered to advertise for me
  • Customization based on my account
• Use docids (document IDs) to access indexed documents to get snippets of stuff
• Compose the page
  • Result document extracts (with keyword in context) ordered by relevance score
  • Sponsored links (along the top) and advertisements (along the sides)
Anatomy of a Web Search (3/3)

- Implementation strategy
  - Randomly distribute the entries
  - Make many copies of data (aka “replicas”) 
  - Load balance requests across replicas
- **Redundant copies** of indices and documents
  - Breaks up hot spots, e.g., “Justin Bieber”
  - Increases opportunities for *request-level parallelism*
  - Makes the system more *tolerant of failures*
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Data-Level Parallelism (DLP)

• SIMD
  • Supports data-level parallelism in a single machine
  • Additional instructions & hardware (e.g., AVX)
e.g., Matrix multiplication in memory

• DLP on WSC
  • Supports data-level parallelism across *multiple machines*
  • MapReduce & scalable file systems
Problem Statement

• How process large amounts of raw data (crawled documents, request logs, …) every day to compute derived data (inverted indices, page popularity, …) when computation conceptually simple but input data large and distributed across 100s to 1000s of servers so that finish in reasonable time?

• Challenge: Parallelize computation, distribute data, tolerate faults without obscuring simple computation with complex code to deal with issues
Solution: MapReduce

- Simple data-parallel *programming model* and *implementation* for processing large datasets
- Users specify the computation in terms of
  - a *map* function, and
  - a *reduce* function
- Underlying runtime system
  - Automatically *parallelize* the computation across large scale clusters of machines
  - *Handles* machine *failure*
  - *Schedule* inter-machine communication to make efficient use of the networks
Inspiration: Map & Reduce Functions, ex: Python

Calculate: \[ \sum_{n=1}^{4} n^2 \]

A = [1, 2, 3, 4]

```python
def square(x):
    return x * x

def sum(x, y):
    return x + y

reduce(sum, map(square, A))
```

Divide and Conquer!
MapReduce Programming Model

- **Map:** \((\text{in\_key}, \text{in\_value}) \rightarrow \text{list(interm\_key, interm\_val)})\

\[
\text{map}(\text{in\_key}, \text{in\_val}): \\
\quad \text{// DO WORK HERE} \\
\quad \text{emit(interm\_key, interm\_val)}
\]

- Slice data into “shards” or “splits” and distribute to workers
- Compute set of intermediate key/value pairs

- **Reduce:** \((\text{interm\_key}, \text{list(interm\_value)}) \rightarrow \text{list(out\_value)})\

\[
\text{reduce}(\text{interm\_key}, \text{list(interm\_val))}: \\
\quad \text{// DO WORK HERE} \\
\quad \text{emit(out\_key, out\_val)}
\]

- Combines all intermediate values for a particular key
- Produces a set of merged output values (usually just one)
MapReduce Execution

Fine granularity tasks: many more map tasks than machines

Bucket sort to get same keys together

2000 servers => ≈ 200,000 Map Tasks, ≈ 5,000 Reduce tasks
MapReduce Word Count Example

Distribute

that that is is that that is not is not is that it it is

Map 1

Map 2

Map 3

Map 4

Shuffle

is 1,1,1,1,1,1
it 1,1

Reduce

is 6; it 2

Collect

is 6; it 2; not 2; that 5

Local Sort

is 6; it 2; not 2; that 5

Distribute

that that is is that that is not is not is that it it is

Map 1

Map 2

Map 3

Map 4

Shuffle

is 1,1,1,1,1,1
it 1,1

Reduce

is 6; it 2

Collect

is 6; it 2; not 2; that 5

Local Sort
User-written Map function reads the document data and parses the words. For each word, it writes the (key, value) pair of (word, 1). The word is treated as the intermediate key and the associated value of 1 means that we saw the word once.

Map phase: (doc name, doc contents) \rightarrow \text{list(word, count)}

// "I do I learn" \rightarrow \[ ("I", 1), ("do", 1), ("I", 1), ("learn", 1) \]

map(key, value):
  for each word w in value:
    emit(w, 1)
Intermediate data is then sorted by MapReduce by keys and the user’s *Reduce* function is called for each unique key. In this case, Reduce is called with a list of a "1" for each occurrence of the word that was parsed from the document. The function adds them up to generate a total word count for that word.

*Reduce* phase: \((\text{word}, \text{list(counts)}) \rightarrow (\text{word}, \text{count}_\text{sum})\)

```python
// ("I", [1,1]) → ("I",2)
reduce(key, values):
    result = 0
    for each v in values:
        result += v
    emit(key, result)
```
The Combiner (Optional)

• One missing piece for our first example:
  • Many times, the output of a single mapper can be “compressed” to save on bandwidth and to distribute work (usually more map tasks than reduce tasks)
  • To implement this, we have the combiner:

```java
combiner(interm_key, list(interm_val)):
  // DO WORK (usually like reducer)
  emit(interm_key2, interm_val2)
```
Our Final Execution Sequence

- **Map** – Apply operations to all input key, val
- **Combine** – Apply reducer operation, but distributed across map tasks
- **Reduce** – Combine all values of a key to produce desired output
MapReduce Processing Example: Count Word Occurrences

• Pseudo Code: for each word in input, generate \(<key=word, value=1>\)
• Reduce sums all counts emitted for a particular word across all mappers

```java
map(String input_key, String input_value):
    // input_key: document name
    // input_value: document contents
    for each word w in input_value:
        EmitIntermediate(w, "1"); // Produce count of words
reduce(String output_key, Iterator intermediate_values):
    // output_key: a word
    // intermediate_values: a list of counts
    int result = 0;
    for each v in intermediate_values:
        result += ParseInt(v); // get integer from key-value
    Emit(output_key, result);
```
MapReduce Word Count Example (with Combiner)

Distribute

Map 1
- is 1
- that 1

Map 2
- is 1
- that 1

Map 3
- is 1
- is 2
- not 2
- not 1

Map 4
- is 1
- is 2
- it 2
- that 1

Shuffle

Reduce
- is 1,1,2,2
- it 2
- Reduce
- is 6; it 2

Reduce
- that 2,2,1
- not 2
- not 2; that 5

Collect

is 6; it 2; not 2; that 5
Shuffle phase
1. MR 1st splits the input files into $M$ "splits" then starts many copies of program on servers

Shuffle phase
MapReduce Processing

2. One copy—the master—is special. The rest are workers. The master picks idle workers and assigns each 1 of M map tasks or 1 of R reduce tasks.

Shuffle phase
3. A map worker reads the input split. It parses key/value pairs of the input data and passes each pair to the user-defined map function.

(The intermediate key/value pairs produced by the map function are buffered in memory)
4. Periodically, the buffered pairs are written to local disk, partitioned into $R$ regions by the partitioning function.
5. When a reduce worker has read all intermediate data for its partition, it bucket sorts using intermediate keys so that occurrences of same keys are grouped together. (The sorting is needed because typically many different keys map to the same reduce task.)
6. Reduce worker iterates over sorted intermediate data and for each unique intermediate key, it passes key and corresponding set of values to the user’s reduce function.

The output of the reduce function is appended to a final output file for this reduce partition.
7. When all map tasks and reduce tasks have been completed, the master wakes up the user program. The MapReduce call in user program returns the output of MR in R output files (1 per reduce task, with file names specified by user); often passed into another MR job so don’t concatenate.

Shuffle phase
Big Data Frameworks: Hadoop & Spark

- **Apache Hadoop**
  - Open-source MapReduce Framework
  - Hadoop Distributed File System (HDFS)
  - MapReduce Java APIs

- **Apache Spark**
  - Fast and general engine for large-scale data processing.
  - Originally developed in the AMP lab at UC Berkeley
  - Running on HDFS
  - Provides Java, Scala, Python APIs for
    - Database
    - Machine learning
    - Graph algorithm
public static void main(String[] args) throws IOException {
    JobConf conf = new JobConf(WordCount.class);
    conf.setJobName("wordcount");
    conf.setOutputKeyClass(Text.class);
    conf.setOutputValueClass(IntWritable.class);
    conf.setMapperClass(WCMapper.class);
    conf.setReducerClass(WCReducer.class);
    conf.setInputPath(new Path(args[0]));
    conf.setOutputPath(new Path(args[1]));
    JobClient.runJob(conf);
}

public class WCMapper extends MapReduceBase implements Mapper {
    private static final IntWritable ONE = new IntWritable(1);
    public void map(WritableComparable key, Writable value,
                    OutputCollector output,
                    Reporter reporter) throws IOException {
        String tokenizer = new StringTokenizer(\n            value.toString());
        while (tokenizer.hasMoreTokens()) {
            output.collect(new Text(tokenizer.nextToken()), ONE);
        }
    }
}

public class WCReducer extends MapReduceBase implements Reducer {
    public void reduce(WritableComparable key, Iterator values,
                        OutputCollector output,
                        Reporter reporter) throws IOException {
        int sum = 0;
        while (values.hasNext()) {
            sum += ((IntWritable) values.next()).get();
        }
        output.collect(key, new IntWritable(sum));
    }
}
// RDD: primary abstraction of a distributed collection of items

file = sc.textFile("hdfs://...")

// Two kinds of operations:
// **Actions**: RDD -> Value
// **Transformations**: RDD -> RDD
// e.g. flatMap, Map, reduceByKey

file.flatMap(lambda line: line.split())
  .map(lambda word: (word, 1))
  .reduceByKey(lambda a, b: a + b)

See [http://spark.apache.org/examples.html](http://spark.apache.org/examples.html)
MapReduce Processing Time Line

- Master assigns map + reduce tasks to “worker” servers
- As soon as a map task finishes, worker server can be assigned a new map or reduce task
- Data shuffle begins as soon as a given Map finishes
- Reduce task begins as soon as all data shuffles finish
- To tolerate faults, reassign task if a worker server “dies”
Show MapReduce Job Running

- ~41 minutes total
- ~29 minutes for Map tasks & Shuffle tasks
- ~12 minutes for Reduce tasks
- 1707 worker servers used
- Map (Green) tasks: read 0.8 TB, write 0.5 TB
- Shuffle (Red) tasks: read 0.5 TB, write 0.5 TB
- Reduce (Blue) tasks: read 0.5 TB, write 0.5 TB
MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 00 min 18 sec
323 workers; 0 deaths

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<tr>
<th>Type</th>
<th>Shards</th>
<th>Done</th>
<th>Active</th>
<th>Input(MB)</th>
<th>Done(MB)</th>
<th>Output(MB)</th>
</tr>
</thead>
<tbody>
<tr>
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MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 05 min 07 sec
1707 workers; 1 deaths

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Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 10 min 18 sec
1707 workers; 1 deaths

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Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 15 min 31 sec
1707 workers; 1 deaths

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Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 29 min 45 sec
1707 workers; 1 deaths

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MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 31 min 34 sec
1707 workers, 1 deaths

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MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 33 min 22 sec
1707 workers; 1 deaths

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MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 35 min 08 sec
1707 workers; 1 deaths

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MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 37 min 01 sec
1707 workers, 1 deaths

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MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 38 min 56 sec
1707 workers; 1 deaths

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Berkeley EECS
MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 40 min 43 sec
1707 workers; 1 deaths

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Critical Limitations...

- This only works for specific classes of problems
  - Need parallel compute over data and parallel reduction steps
- Spark can be even more limited
  - Hadoop at least allows some more flexibility
- **HUGE** overhead!
  - Hadoop Distributed File System: 3x+ redundant storage
  - Lots of startup and control overhead:
    So unless you have multiple-terabytes of data, don't bother!
- For many cases, you are better served throwing a Big F-n Database
  machine at the problem
  - Gazillion cores, a TON of memory, and a lot of SSD running Postgres or Oracle
And, in Conclusion ...

- Warehouse-Scale Computers (WSCs)
  - New class of computers
  - Scalability, energy efficiency, high failure rate
- Cloud Computing
  - Benefits of WSC computing for third parties
  - “Elastic” pay as you go resource allocation
- Request-Level Parallelism
  - High request volume, each largely independent of other
  - Use replication for better request throughput, availability
- MapReduce Data Parallelism
  - **Map**: Divide large data set into pieces for independent parallel processing
  - **Reduce**: Combine and process intermediate results to obtain final result
  - Hadoop, Spark