The MapReduce Paradigm

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with most slides shamelessly stolen from Jeff Dean and Yonatan Zunger

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Do We Need It?

If distributed computing is so hard, do we really need to do it?

Yes: Otherwise some problems are too big.

Example: 20+ billion web pages x 20KB = 400+ terabytes

• One computer can read 30-35 MB/sec from disk
  ~four months to read the web
• ~1,000 hard drives just to store the web
• Even more to do something with the data
Yes, We Do

Good news: same problem with 1000 machines, < 3 hours

Bad news: programming work

• communication and coordination
• recovering from machine failure (all the time!)
• status reporting
• debugging
• optimization
• locality

Bad news II: repeat for every problem you want to solve

How can we make this easier?
MapReduce

A simple programming model that applies to many large-scale computing problems

Hide messy details in MapReduce runtime library:

• automatic parallelization
• load balancing
• network and disk transfer optimization
• handling of machine failures
• robustness
• improvements to core library benefit all users of library!
Typical problem solved by MapReduce

Read a lot of data
**Map**: extract something you care about from each record
Shuffle and Sort
**Reduce**: aggregate, summarize, filter, or transform
Write the results

Outline stays the same,
**Map and Reduce** change to fit the problem
MapReduce Paradigm

Basic data type: the key-value pair (k,v).

For example, key = URL, value = HTML of the web page.

Programmer specifies two primary methods:

- **Map:** \((k, v) \mapsto (k_1, v_1), (k_2, v_2), (k_3, v_3), ..., (k_n, v_n)\)

- **Reduce:** \((k', <v'_1, v'_2, ..., v'_n)> \mapsto (k', v''_1), (k', v''_2), ..., (k', v''_n)\)

All \(v'\) with same \(k'\) are reduced together.

(Remember the invisible “Shuffle and Sort” step.)
**Example: Word Frequencies in Web Pages**

*A typical exercise for a new Google engineer in his or her first week*

Input: files with one document per record

**Specify a map function that takes a key/value pair**
- key = document URL
- value = document contents

**Output of map function is (potentially many) key/value pairs.**
In our case, output (word, “1”) once per word in the document

```
“document1”, “to be or not to be”
```

```
“to”, “1”
“be”, “1”
“or”, “1”
...
```
Example: Word Frequencies in Web Pages

MapReduce library gathers together all pairs with the same key (shuffle/sort)

Specify a *reduce* function that combines the values for a key
In our case, compute the sum

<table>
<thead>
<tr>
<th>Key</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>&quot;be&quot;</td>
<td>&quot;1&quot;, &quot;1&quot;</td>
</tr>
<tr>
<td>&quot;not&quot;</td>
<td>&quot;1&quot;</td>
</tr>
<tr>
<td>&quot;or&quot;</td>
<td>&quot;1&quot;</td>
</tr>
<tr>
<td>&quot;to&quot;</td>
<td>&quot;1&quot;, &quot;1&quot;</td>
</tr>
</tbody>
</table>

Output of reduce (usually 0 or 1 value) paired with key and saved

"be", "2"
"not", "1"
"or", "1"
"to", "2"
Under the hood: Scheduling

One master, many workers

- Input data split into $M$ map tasks (typically 64 MB in size)
- Reduce phase partitioned into $R$ reduce tasks (= # of output files)
- Tasks are assigned to workers dynamically
- Reasonable numbers inside Google: $M=200,000$; $R=4,000$; workers=2,000

Master assigns each map task to a free worker

- Considers locality of data to worker when assigning task
- Worker reads task input (often from local disk!)
- Worker produces $R$ local files containing intermediate (k,v) pairs

Master assigns each reduce task to a free worker

- Worker reads intermediate (k,v) pairs from map workers
- Worker sorts & applies user’s Reduce op to produce the output
- User may specify Partition: which intermediate keys to which Reducers
MapReduce

Input data

Master

Partitioned output

Map

Shuffle

Reduce

Map

Shuffle

Reduce

Map

Shuffle

Reduce

Map
MapReduce: Granularity

Fine granularity tasks: many more map tasks than machines

- Minimizes time for fault recovery
- Can pipeline shuffling with map execution
- Better dynamic load balancing

<table>
<thead>
<tr>
<th>Process</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>User Program</td>
<td>MapReduce()</td>
</tr>
<tr>
<td>Master</td>
<td>... wait...</td>
</tr>
<tr>
<td>Worker 1</td>
<td>Assign tasks to worker machines...</td>
</tr>
<tr>
<td>Worker 2</td>
<td>Map 2</td>
</tr>
<tr>
<td>Worker 3</td>
<td>Map 1</td>
</tr>
<tr>
<td>Worker 4</td>
<td>Read 1.1</td>
</tr>
<tr>
<td></td>
<td>Read 2.1</td>
</tr>
</tbody>
</table>
MapReduce: Fault Tolerance via Re-Execution

Worker failure:
• Detect failure via periodic heartbeats
• Re-execute completed and in-progress map tasks
• Re-execute in-progress reduce tasks
• Task completion committed through master

Master failure:
• State is checkpointed to replicated file system
• New master recovers & continues

Very Robust: lost 1600 of 1800 machines once, but finished fine
MapReduce: A Leaky Abstraction

MR insulates you from many concerns, but not all of them.

- Don't overload one reducer
- Don't leak memory, even a little!
- Static and global variables probably don't do what you expect
  (They can sometimes be useful, though!)
- Mappers might get rerun -- maybe on different data!
  
  Careful with side-effects: must be atomic, idempotent.

  Different reducers might see different versions!