## MapReduce: Programming in the Very Large

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### "The datacenter is the computer"



## Google versus Hadoop vs MR

- Google published the MapReduce paper in 2004.
- Doug Cutting had been working on an Open Source MapReduce. Linked up with Yahoo! to scale it up.
- Has taken off and become very popular
- Other MapReduce implementations also exist

## Indexing

- 1: Some Words Other: 2,3
- 2: Some other words Some: 1, 2
- 3: Other words Words: 1,2,3

Note that Index is **sorted** by key. Helpful for quick lookup of approximate matches



## Performance Numbers

- Biggest production Hadoop clusters are ~4000 nodes
- Facebook has 100 PB in Hadoop
- Best MapReduce-like system (TritonSort from UCSD) can sort 900 GB/minute on a 52-node, 800-disk cluster.

## **Distributed Implementation**



## A modern software stack





## The flow of information



## Slots, Tasks, and Attempts

• A **job** is split into **tasks**. Each **task** includes many calls to map() or reduce()



- Workers are long-running processes that are assigned tasks
- Multiple workers can be assigned the same task; these are termed separate attempts.

## Size and Failures

- Suppose you have a cluster of a thousand servers. How long between failures?
- How long for one machine to fail?
  - Intuition: machines fail once a year or two?
  - Depending on model, perhaps 5% of high-end hard disks fail each year (Schroder, FAST '07). A server might have ten hard disks.
- So for a thousand machines, we would expect failures more than once a day

## Handling Failures



Shuffle/Sort

Reduce

## Failures aren't absolute

- Some failures make nodes slow
- Reduces can't start until ALL maps finish



Bad!

ОК

## Fix: speculation

- Multiple tries at same task; pick first to finish
- Subtlety in deciding which tasks to try to speculatively execute



## Types for Map + Reduce functions

• Map:

('K1 \* 'V1 → ('K2 \* 'V2) bag) -> ('K1 \* 'V1) bag -> ('K2 \* 'V2) bag

• Reduce:

('K2 \* ('V2 list) → ('K3 \* 'V3) bag) -> 'K2 \* ('V2 list) bag -> ('K3 \* 'V3) bag

#### Indexing

Map: (DocID \* word bag)  $\rightarrow$  (word \* DocID) bag Reduce: (word \* DocID list)  $\rightarrow$  (word \* DocID) bags

#### The Java versions

interface Mapper<K1,V1,K2,V2> {
 public void map (K1 key,
 V1 val,
 OutputCollector<K2, V2> output);

#### The Java versions

interface Reducer<K2,V2,K3,V3> {
 public void reduce(K2 key,
 Iterator<V2> values,
 OutputCollector<K3, V3> output);

## Image to Text

- Can use MapReduce for simple parallelization.
- Imagine we have code to convert an image to text. How do we convert a million scanned images of book pages?
- Can just wrap the conversion routine in our Map() method; reduce is identity
- The embarrassingly parallel becomes trivial; real power of framework is in harder parallel problems.



## Word count?

- Similar to indexing except we only want counts, not locations
- Map: (DocID, String list) -> ?
- Reduce:
  - .... -> (String, int)

## Word count?

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- Map: (DocID, String list) -> (String, \_ ) bag
- Reduce:
   (String, \_ list) -> (String, int)

## Word count?

- Similar to indexing except we only want counts, not locations
- Map:

(DocID, string list) -> (string, unit) bag emit (w, ()) for each word w in list

• Reduce:

(string, unit list) -> (string, int)
emit length of list

## Map in Java

class WordCountMap implements Map {
 public void map (DocID key,
 List<String> val,
 OutputCollector<String, Integer> output) {

for (String s: val)
 output.collect(s, 1)

### Reduce in Java

```
class WordCountReduce {
  public void reduce(String key,
   Iterator<Integer> vals,
   OutputCollector<String, Integer> output) {
```

```
int count = 0;
for (int v: vals)
    count += 1;
output.collect(key, count)
}
```

#### Map + Reduce, and Combine functions

• Map:

('K1 \* 'V1)  $\rightarrow$  ('K2 \* 'V2) bag

- Reduce:
   ('K2 \* 'V2 list) → ('K3 \* 'V3) bag
- Combine
   ('K2 \* 'V2 list) → ('K2 \* 'V2) bag

## Reduce / Combine in Java

```
class WordCountReduce {
  public void reduce(String key,
   Iterator<Integer> vals,
   OutputCollector<String, Integer> output) {
```

```
int count = 0;
for (int v: vals)
    count += v;
output.collect(key, count)
}
```

## Word Count with Combine

Almost the same functional code, different configuration

conf.setOutputKeyClass(String.class); conf.setOutputValueClass(IntWritable.class); conf.setMapperClass(WordCountMap.class); conf.setReducerClass(WordCountReduce.class);

conf.setCombinerClass(WordCountReduce.class);

## A hypothetical....

HashMap<String, Integer> counts =
 new HashMap<String, Integer>();

public void map (DocID key, List<String> val, OutputCollector<String, Integer> output) {

```
for (String s: val) {
   count = 1;
   if (counts.contains(s))
      count += counts.get(s);
   counts.put(s, count);
  }
```

A: Correct program

**B: Compiler Error** 

C: Program produces wrong answer

# PageRank: measuring how much a webpage matters



- Model: user is clicking around randomly.
- With probability k, will start over at random; else follows a [random] link off current page.
- Matrix M encodes probabilities of transition from page p to page q
- $Pr[on page] = \mathbf{M} \cdot \mathbf{e}_p$

### PageRank: The link matrix



	Α	B	С
A	0	1	1
В	0	0	1
С	0	0	0

## The Stable State

- Distribution has a stationary point where
   v = M v (v is an eigenvector)
- Can solve by iteration:  $v_{k+1} = \mathbf{M} \cdot v_k$
- We can compute this as a MapReduce job

## Defining the types

• Class PageInfo;

}

- Class LinksInfo extends PageInfo {
   List<DocID> links;
   }
- Class Increment extends PageInfo { double inWeight;

## The logic

```
Reduce(DocID key, Iterator<PageInfo> vals,
OutputCollector<DocID, PageInfo> output {
  double total score = 0;
  LinksInfo info;
  for ( PageInfo i: vals) {
    if (i instanceof LinksInfo) {
       info = (LinksInfo) vals.next();
      output.collect(key, info)
     } else
       total score += ((Increment) i).inWeight;
   }
  double s = total score / info.links.size()
  for (DocID out: links.links)
    output.collect(key, Increment(s))
```

#### Iterative Jobs are common...





## Joins

Name	ZIP Code	ZIP code	State
John Doe	08540	08540	NJ
		14850	NY
Richard Roe	20037	20037	DC

Name	ZIP	State	
	Code		
John Doe	08540	NJ	
Richard Roe	20037	DC	

### Joins with MapReduce

Name		ZIP Code		ZIP code	State
John Do	e	08540		08540	NJ
Richard		20037		14850	NY
Roe				20037	DC

- If one table is small, just keep it in memory at every location and join in the Map method
- Can also join on Reduce side
  - Can emit whole contents of both tables in Map.
  - Use "join column" as sort key, then join in reduce().
- Higher-level languages help. (Pig, Hive, etc)

## Joins with MR, continued

- Class TableCell [could be int, string, etc]
- Class RowWithSource

```
map(NullWritable inKey, TableRow val ...){
    int fileId = getInputFileNumber();
    int joinCol = config.get("join_column_" +
    fileId);
    TableCell c = val.get(joinCol);
    RowWithSource v2 = new RowWithSource(val, fileId);
    output.collect(c, v2);
}
```

## Joins with MR, continued

Initialize joinCol1 and joinCol2 [class members] somewhere

```
reduce(TableCell key, Iterator <RowWithSource> values ...){
  List<RowWithSource> src1 = new List<RowWithSource> ();
  List<RowWithSource> src2 = new List<RowWithSource> ();
```

```
for (RowWithSource r: values)
  if (r.src == "1")
    src1.append(r);
  else
    src2.append(r);

for (RowWithSource r1: src1)
  for (RowWithSource r2: src2) {
    TableRow res = join(r1, r2, joinCol1, joinCol2);
    output.collect(null, res);
  }
```

## Observations

- Code is basically doing nested-loops over all pairs of rows which match on the join key.
- This doesn't require materializing the whole set of results, but does materialize the sets of inputs on each side.
- This code would be a lot easier with product types (e.g. Pair<A,B>)

#### What I work on



MapReduce is the Wrong Thing if the data is spread out: need more optimization to reduce wide-area transfer costs

## Deeper pipes for more locality



## Take-aways

- Big data needs specialized tools to process.
- Higher-order functions help manage complexity.
- Determinism and the absence of side-effects make parallelism and failure recovery simpler.
- If you have complicated functionality, consider building a language

## For more information

- Hadoop is public and open source.
- See http://hadoop.apache.org for information.
- Amazon's EC2 will let you run stuff at large scale for low (and incremental) costs.