HaLoop: Efficient Iterative Data Processing On Large Clusters

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QuickTime and a decompressor are needed to see this picture.



http://escience.washington.edu/

http://isg.ics.uci.edu

JCIRVINE

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Outline

- Motivation
- Caching & scheduling
- Fault-tolerance
- Programming model
- Related work
- Conclusion
- Cloud Computing Projects in UCI

Motivation

- MapReduce can't express recursion/iteration
- Lots of interesting programs need loops
 - graph algorithms
 - clustering
 - machine learning
 - recursive queries (CTEs, datalog, WITH clause)
- Dominant solution: Use a driver program outside of MapReduce
- Hypothesis: making MapReduce loop-aware affords optimization
 - lays a foundation for scalable implementations of recursive languages

Example 1: PageRank

Rank Table R_0		Linkage Table <i>L</i>			
url	rank				
www.a.com	1.0	url_src	url_dest		
www.b.com	1.0	www.a.com	www.b.com		R_{i+1}
www.c.com	1.0	www.a.com	www.c.com		
www.d.com	1.0	www.c.com	www.a.com	π(uri_	dest, $\gamma_{url_{dest}}$ SUM(rank))
www.e.com	1.0	www.e.com	www.c.com		Î
	1.0	www.d.com	www.b.com	P rank -	P rankly COUNT(url doct)
Rank Table R_3		www.c.com	www.e.com	n _i .i alik –	R _i .iank/γ _{url} coon (un_uest)
url	rank	www.e.com	www.c.com		
www.a.com	2.13	www.a.com	www.d.com	R _i .u	rl = L.url_src
www.b.com	3.89				
www.c.com	2.60			► R _i	► L
www.d.com	2.60				
www.e.com	2.13				

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PageRank Implementation on MapReduce

Join & compute rank



What's the problem?



L and Count are loop invariants, but

- 1. They are loaded on each iteration
- 2. They are shuffled on each iteration
- 3. Also, fixpoint evaluated as a separate MapReduce job per iteration

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Example 2: Transitive Closure



(semi-naïve evaluation)

Find all transitive friends of Eric

 R_0 {Eric, Eric}

 $R_1 \quad \{ \text{Eric, Elisa} \}$

 R_2 {Eric, Tom Eric, Harry}

 $R_3 \{\}$

Transitive Closure on MapReduce



What's the problem?



Friend is loop invariant, but

- 1. Friend is loaded on each iteration
- 2. Friend is shuffled on each iteration

Example 3: k-means

k_i = k centroids at iteration i



What's the problem?



P is loop invariant, but

1. *P* is loaded on each iteration

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Push loops into MapReduce!

- Architecture
- Cache loop-invariant data
- Scheduling
- Fault-tolerance
- Programming Model

HaLoop Architecture



Inter-iteration caching



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RI: Reducer Input Cache

- Provides:
 - Access to loop invariant data without map/shuffle
- Data:
 - Reducer function
- Assumes:
 - 1. Static partitioning (implies: no new nodes)
 - 2. Deterministic mapper implementation
- PageRank
 - Avoid loading and shuffling the web graph at every iteration
- Transitive Closure
 - Avoid loading and shuffling the friends graph at every iteration
- K-means
 - No help



Reducer Input Cache Benefit



Friends-of-friends query Billion Triples Dataset (120GB) 90 small instances on EC2

Overall run time

Reducer Input Cache Benefit



Friends-of-Friends query Billion Triples Dataset (120GB) 90 small instances on EC2



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Reducer Input Cache Benefit



Friends-of-friends query

Billion Triples Dataset (120GB)

90 small instances on EC2



RO: Reducer Output Cache

- Provides:
 - Distributed access to output of previous iterations
- Used By:
 - Fixpoint evaluation
- Assumes:
 - 1. Partitioning constant across iterations
 - 2. Reducer output key functionally determines Reducer input key

PageRank

- Allows distributed fixpoint evaluation
- Obviates extra MapReduce job
- Transitive Closure
 - No help
- K-means
 - No help



Reducer Output Cache Benefit



MI: Mapper Input Cache

- Provides:
 - Access to non-local mapper input on later iterations
- Data for:
 - Map function
- Assumes:
 - 1. Mapper input does not change
- PageRank
 - No help
- Transitive Closure
 - No help
- K-means
 - Avoids non-local data reads on iterations > 0



Mapper Input Cache Benefit



5% non-local data reads; ~5% improvement

However, Facebook has 70% non-local data reads!!

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Loop-aware Task Scheduling

Inpu Glo	ut: Node node, int iteration bal variable: HashMap <node, list<parition="">> last, HashMaph<node, List<partition>> current</partition></node, </node,>					
1:	if (iteration ==0) {					
2:	Partition part = StandardMapReduceSchedule(hode);					
3:	current.add(node, part);					
4:	}else{					
5:	if (node.hasFullLoad()) {					
6:	Node substitution = findNearbyNode(node)					
7:	last.get(substitution).addAll(last.remove(node)),nd a substitution					
8:	return;					
9:	}					
10:	if (last.get(node).size()>0) {					
11:	Partition part = last.get(nose).get(0);					
12:	schedule(part, node); Iteration-local					
13:	current.get(node).add(part); Schedule					
14:	list.remove(part);					
15:	}					
16:	}					
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Fault-tolerance (task failures)



Fault-tolerance (node failures)



node failure

Task re-execution



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Programming Model

- Mapper/reducer stay the same!
- Touch points
 - Input/Output: for each <iteration, step>
 - Cache filter: which tuple to cache?
 - Distance function: optional
- Nested job containing child jobs as loop body
- Minimize extra programming efforts

Related Work: Twister [Ekanayake HPDC 2010]

- Pipelining mapper/reducer
- Termination condition evaluated by main()

```
13. while(!complete){
```

- 14. monitor = driver.runMapReduceBCast(cData);
- 15. monitor.monitorTillCompletion();

In Detail: PageRank (Twister)

```
while (!complete) {
         // start the pagerank map reduce process
         monitor = driver.runMapReduceBCast(new
               BytesValue(tmpCompressedDvd.getBytes()));
run MR
         monitor.monitorTillCompletion();
         // get the result of process
         newCompressedDvd = ((PageRankCombiner)
               driver.getCurrentCombiner()).getResults();
         // decompress the compressed pagerank values
         newDvd = decompress(newCompressedDvd);
                                                   O(N) in the size
         tmpDvd = decompress(tmpCompressedDvd);
                                                  of the graph
         totalError = getError(tmpDvd, newDvd);
            get the difference between new and old pagerank values
         if (totalError < tolerance) {</pre>
term.
           complete = true;
cond.
         tmpCompressedDvd = newCompressedDvd;
       }
```

Related Work: Spark [Zaharia HotCloud 2010]

Reduction output collected at driver program

 "...does not currently support a grouped reduce operation as in MapReduce"

```
val spark = new SparkContext(<Mesos master>) all output sent
var count = spark.accumulator(0) to driver.
for (i <- spark.parallelize(1 to 10000, 10)) {
 val x = Math.random * 2 - 1
 val y = Math.random * 2 - 1
 if (x*x + y*y < 1) count += 1
}
println("Pi is roughly " + 4 * count.value / 10000.0)
```

Related Work: Pregel [Malewicz SIGMOD 2010]

- Graphs only
 - clustering: k-means, canopy, DBScan
- Assumes each vertex has access to outgoing edges
- So an edge representation ...

Edge(from, to)

requires offline preprocessing

perhaps using MapReduce

Related Work: BOOM [Alvaro EuroSys 10]

- Distributed computing based on Overlog (Datalog + temporal logic + more)
- Recursion supported naturally
 - app: API-compliant implementation of MR

Conclusions

- Relatively simple changes to MapReduce/Hadoop can support iterative/recursive programs
 - TaskTracker (Cache management)
 - Scheduler (Cache awareness)
 - Programming model (multi-step loop bodies, cache control)

Optimizations

- Caching reducer input realizes the largest gain
- Good to eliminate extra MapReduce step for termination checks
- Mapper input cache benefit inconclusive; need a busier cluster
- Future Work
 - Iteration & Recursion on top of Hyracks core!

Hyracks [Borkar et al., ICDE'11]

- Partitioned-Parallel Platform for data-intensive computing
 - Flexible (DAGs, location constraints)
 - Extensible ("micro-kernel" core, online-aggregation plugin (VLDB'11), B-tree plugin, R-tree plugin, Dataflow plugin...), an iteration/recursion plugin?

Jobs

- Dataflow DAG of operators and connectors
- Can set location constraints
- Can use a library of operators: joins, group-by, sort and so on

V.s. "competitors"

- V.s. Hadoop: more flexible model and less pressimistic
- V.s. Dryad: support data as first class citizens

