Revisiting the MapReduce Paradigm: an R-Specific View

Norm Matloff and Alex Rumbaugh
University of California at Davis

UCB R Group
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Visual Summary
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My view: Plain Old R can work better in many situations
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My view: Plain Old R can work better in many situations
Overview

• When I was here one year ago, I speculated that Hadoop would start to lose popularity sometime in the future.
• Too slow.
• Not many ops.
• That time seems to have begun.
• E.g. see The Hadoop Honeymoon Is Over, http://smartdatacollective.com/martynjones/318406/hadoop-honeymoon-over
• There is a new kid on the block, Spark, with an R interface, SparkR, a big improvement
• But I will argue that for us R users, the utility of either Hadoop or SparkR is much more limited than many people realize.
• And I will present an alternative.
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- Most famous example: Hadoop.
What’s Wrong with Hadoop

- SLOW. Like an elephant. :-)
- Input to code must come from disk, output must be written to disk.
- Awful for iterative algorithms.
- Sort phase (shuffle) is performed even if one’s algorithm doesn’t need it.
- Difficult to install/configure. Not everyone is a systems expert. Even worse when also need to install R interface.
- Map and reduce ops too low-level. “Build a house from matchsticks.”
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What Hadoop Gets Right

- Distributed file system (HDFS).
- "Move the computation to the data," rather than vice versa.
- Thus reduce time-consuming network communication time.
- Redundancy/fault tolerance, very important if have a huge cluster.
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Spark

- Extended map/reduce paradigm.
- Cacheability of intermediate results, i.e. no costly writes to disk.
- Lazy computation: programmer's several specified ops automatically combined into faster coalesced code.
- Shuffle often avoided.
- Runs on top of HDFS or other DFS, so retain "move the computation to the data" philosophy.
- Typically way faster than Hadoop.
- Has various high-level ops, not just map and reduce.
- Elegant, sophisticated fault-tolerance mechanism.
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Drawbacks to Spark

• Still have installation/configuration headaches, even worse than Hadoop.
  Ditto for SparkR.
• High-level ops are abstract, steep learning curve. (Where have we heard that before?)
• Not clear that SparkR has much advantage over Plain Old R (POR).
  See next slide.
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What’s in It for R Users?

• Granted, Hadoop/Spark have automatic fault tolerance, and an efficient sort, both important.
• But many apps don’t need a sort, and many Hadoop users have small clusters (Hadoop Wiki, https://wiki.apache.org/hadoop/PoweredBy).
• So, POR seems preferable for many users.
• No Java/database/configuration issues.
• No need to learn new abstractions.
• No forced shuffle.
• POR at least as expressive as SparkR, and already familiar.
• We’ve developed Snowdoop as an alternative:
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- Retains the DFS philosophy.
- Includes a distributed sort; could be optimized.
- So simple, it’s embarrassing, tough to call it a “package.”
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Word Count
Word Count

# prep: use SD filesplit(), load SD at nodes

# ndigs is number of digists in file suffix

fullwordcount <- function(cls, basename, ndigs) {
  counts <- clusterCall(cls, wordcensus, basename, ndigs)
  addlistssum <- function(lst1, lst2)
    addlists(lst1, lst2, sum)  # SD
  Reduce(addlistssum, counts)
}

wordcensus <- function(basename, ndigs) {
  fname <- filechunkname(basename, ndigs)  # SD
  words <- scan(fname, what="")
  tapply(words, words, length, simplify=FALSE)
}
Word Count, cont’d.
Word Count, cont’d.

Test:
Word Count, cont’d.

Test:

```r
library(partools)
c <- makeCluster(2)
setClusterInfo(c) # SD
clusterEvalQ(c, library(partools))
filesplit(c, "x") # SD
fullwordcount(c, "x", 1) # SD
```
Output
> fullwordcount(cls,"x",1)
$ a
[1] 2
$ chuck
[1] 2
$ Could
[1] 2
$ How
[1] 1
$ much
[1] 1
$ wood
[1] 1
$ woodchuck
[1] 2
$ If
[1] 1
$ 'Wood?'
[1] 1
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Snowdoop vs. Hadoop Speed

Disclaimer: No serious experiments done yet, just some small, very preliminary simulations.

k-Means Clustering:
• Antonio, author of the R-Hadoop interface rmr, told me that the k-Means example is “just an example,” not claimed to be fast.
• Our simulations (though not for large $n$, only $10^5$) indicate that Snowdoop is about 100X faster than Hadoop.
• Same simulations show Snowdoop gives about a 50% speedup over R’s serial kmeans() function, with 5 nodes.

Note: kmeans() is written in C, not R.

sorting:
• This should be Hadoop’s forte.
• Yet we are finding Snowdoop 2X faster.
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• None of the apps in MLlib, Spark's machine learning (aka statistics) library uses sorting.
• A BARUG speaker from Spark said that they haven't compared timings to non-MapReduce platforms.
• With both Hadoop and Spark, is it really a matter of "It's not important how well the dog could walk on his hind legs, but that he could do it at all"?
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Obtaining Snowdoop

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