Parallel Computation in R: What We Want, and How We (Might) Get It

Norm Matloff
University of California at Davis

Keynote Address
useR! 2017
Brussels, 6 July, 2017

Shameless Promotion

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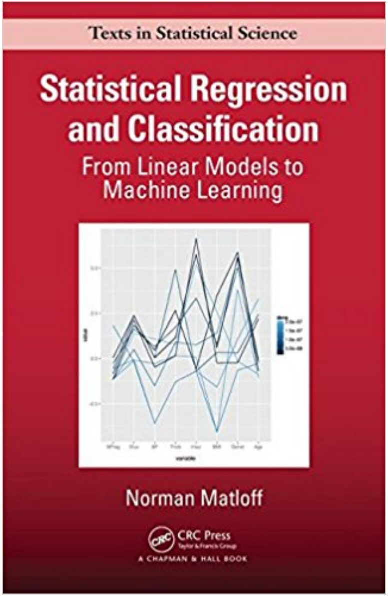

Out July 28!

(A longheld plan — decades — now finally got around to it.)

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Result: Users believe,

> *"I've got the hardware and I've got the data need — so I should be all set to do parallel computation in R on the data."*

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    - Serialization.

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- Parameters to tweak for the experts or the daring.

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- After getting burned by disappointing performance, some will be emboldened to learn the subtleties.
- Painless parallel computation is not possible.

Example: Matrix-Vector Multiplication

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- Naive use of **foreach** package likely quite slow; scatter-gather overhead a substantial proportion of the overall time.

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- Compute-intensive nonparametric: Graph algorithms.
- Run-of-the-mill aggregation: Group-by-and-find-means op.
- Tougher aggregation: Credit card fraud detection.

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- Useful in some apps.
- Available in **partools** package (NM, C. Fitzgerald), **github.com/matloff**.

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  - Newer methodology, e.g. ML, random graphs etc.
  - UseRs may have become fairly good programmers, but lack systems knowledge.

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- **Bottom line:** For most Use Cases, use one of the following
    - SA
    - Distributed computation, esp. using "Leave it there" concept.

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- MapReduce not well-suited to most of the above Use Cases.
- Highly elaborate Spark machinery violates the transparency requirement.
- On the other hand, the distributed file system approach of Hadoop/Spark is good for useRs too.

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  My personal side comment: Not clear whether, say, PCA, has much accuracy or usefulness at the truly Big Data scale, including for sparse matrices.

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I contend that very few useRs, even those who need parallel computation, need to guard against node failure.

The Principle of "Leave It There"

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  - (c) Manager collects (gathers) and combines the results.
- **But NO, avoid step (c) as much as possible.**

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Note too: The last step can be done in parallel too, with SA.

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Comparing Just a Few Packages

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pkg	flexibility	high-level ops
partools	high	few
ddR	medium	medium
multidplyr	low	more

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- might as well distribute a persistent version of the data, i.e. have **distributed files.**
- Like Hadoop/Spark, but without the complex machinery.
- Our **partools** package includes various functions for managing distributed files

Distributed Files in partools

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- File **x** spread across **x.001**, **x.002** etc.
- **filesplit():** Make distributed file from monolithic one.
- **fileread():** If node **i** does **fileread(x,d)**, then **x.i** will be read into the variable **d**.
- **filesave():** Saves distributed data to distributed file.
- Etc.

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- Say have distributed file **xy**, physically stored in files **xy.001**, **xy.002** etc.
- Say we have written functions (not shown) **NAtoMean** and **deleteOuts**, to handle missing values and remove outliers, as mentioned before. The functions have been given to the workers

"Leave It There" Example (cont'd.)

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```
# do NA removal at each worker,
# on the worker's chunk of xy
clusterEvalQ(cls,xy <- apply(xy,2,NAtoMean))
# do the outlier removal at each worker,
# on the worker's chunk of xy
clusterEvalQ(cls,xy <- apply(xy,2,deleteOuts))

# use Software Alchemy to perform linear regression,
# returning just the coefficients in this case
calm(cls,'y ~ .,data=xy')$tht
```

What Is Happening

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We are saying, At each worker node, do

```
xy ← apply(xy,2,NAtoMean))
```

which means, each node does the **apply** op *on its portion of* **xy**.

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- *If change data or create new data, save in distributed file form too! Use* **partools::filesave***.*

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  - **quantile()**
- Very easy to make your own SA functions.

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Say have distributed list, 2 compoments. From one, manager node receives

```
list(a=3,b=8)
```

and from the other

```
list(a=5,b=1,c=12)
```

The functions "adds" them, producing (non-distributed)

```
list(a=8,b=9,c=12)
```

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- Could do in other packages, not just **partools**.

Ready for the dissent. :-)