Parallel R, Revisited

Norm Matloff
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UseR! 2012
Vanderbilt University, June, 2012

URL for these slides:
`http://heather.cs.ucdavis.edu/user2012.pdf` (repeated on final slide)

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New York Times, Feb. 11, 2012

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NEWS ANALYSIS

The Age of Big Data

By STEVE LOHR
Published: February 11, 2012 | 82 Comments

GOOD with numbers? Fascinated by data? The sound you hear is opportunity knocking.

Enlarge This Image

Mo Zhou was snapped up by I.B.M. last summer, as a freshly minted Yale M.B.A., to join the technology company's fast-growing ranks of data consultants. They help businesses make sense of an explosion of data — Web traffic and social network comments, as well as software and sensors that monitor

SAS Web page

SAS Web page

NEWS / sascom MAGAZINE

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Big data: big challenges, big opportunities

An expert panel discusses how organizations can capitalize on big data to generate new ideas, build new markets and expand existing ones

Participating in a panel discussion at the recent Ideas Economy conference put on by The Economist, SAS Chief Executive Officer Jim Goodnight and other high-tech execs discussed so-called "big data" and the challenges and opportunities companies face in dealing with the ever-growing data deluge.

Oracle Web page

Oracle Web page

The term big data draws a lot of attention, but behind the hype there's a simple story. For decades, companies have been making business decisions based on transactional data stored in relational databases. Beyond that critical data, however, is a potential treasure trove of less structured data: weblogs, social media, email, sensors, and photographs that can be mined for useful information.

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Oracle, cont'd.

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Oracle, cont'd.

But Oracle rocks! :-)

Oracle, cont'd.

But Oracle rocks! :-)

Oracle R Enterprise

Integrates the Open-Source Statistical Environment R with Oracle Database 11*g*
Oracle R Enterprise allows analysts and statisticians to run existing R applications and use the R client directly a
Oracle Database 11*g*—vastly increasing scalability, performance and security. The combination of Oracle Databa
delivers an enterprise-ready, deeply integrated environment for advanced analytics. Users can also use analytic
where they can analyze data and develop R scripts for deployment while results stay managed inside Oracle Da

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- Mainly useful on "embarrassingly parallel" (EP) problems—those dividable into subproblems that need little or no intercommunication.
- What about non-EP apps?

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- Copy-on-write: Writing to one vector element sometimes causes copying entire vector.

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Challenges, cont'd.

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  - uncertainty abounds—so which way should R go?

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  - Thrust is C++ package for high-level operations, e.g. sort, search, prefix scan.
  - Thrust builds to multiple backends, including GPU and multicore.
  - So, **Rth** is a tool for easily parallelizing many R operations, usable on both GPU and multicore.

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- Key point:

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- Old, old idea in parallel processing: Break data into chunks, work on each chunk, then combine results.
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- New approach: Exploit the statistical properties.
- Key point: Calculate a **statistically equivalent** quantity that lends itself to EP computation.

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- Bonus: Automatic generation of standard errors (that you didn't have before).

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- Break into r chunks of n/r data points each.
- For i = 1,...,r calculate $\widehat{\theta}$ on chunk i, yielding $\tilde{\theta}_i$.
- Average all those chunked values:

$$\overline{\theta} = \frac{1}{r} \sum_{i=1}^{r} \tilde{\theta}_i$$

R Code (Snow)

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```
wrapper <- function(cls,z,probpars,sfrndmz=F) {
   if (!is.matrix(z)) z <- matrix(z,ncol=1)
   n <- probpars$n
   if (rndmz) z <- z[sample(1:n,n,replace=F),]
   nnodes <- length(cls) obslist <- list()
   chunksize <- n / nnodes
   for (i in 1:nnodes) {
      firstobs <- 1 + (i-1) * chunksize
      lastobs <- firstobs + chunksize - 1
      if (lastobs == n) lastobs <- n
      obslist[[i]] <- z[firstobs:lastobs,]
   }
   thts <- clusterApply(cls,obslist,sf)
   tht <- do.call("+",thts)
   tht / nnodes
}
```

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- But the computation of $\overline{\theta}$ is EP even if $\widehat{\theta}$ is non-EP.
- Alchemy! Non-EP $\rightarrow$ EP.

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- Uniprocessing case: Run time is $rO(n^c/r^c)$, i.e. $O(n^c/r^{c-1})$. So, if $c > 1$ NEP2EP gives a speedup with no parallelism!

NEP2EP Timing Experiments

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- num. cores = 2,4,8,16,24,32; sometimes better beyond 32, probably due to cache/VM effects
- procedures tried:
    - Kendall's τ
    - quantile regression
    - nonparametric hazard function est.
    - log-concave density est.
    - linear regression (random x)

Kendall's τ

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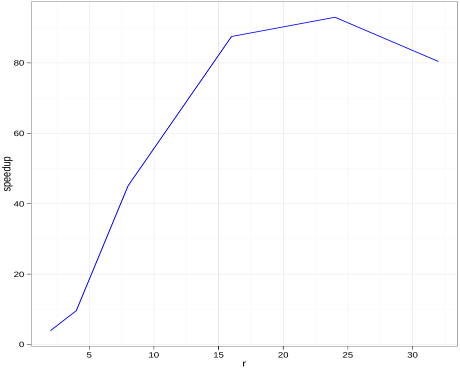
n = 10000

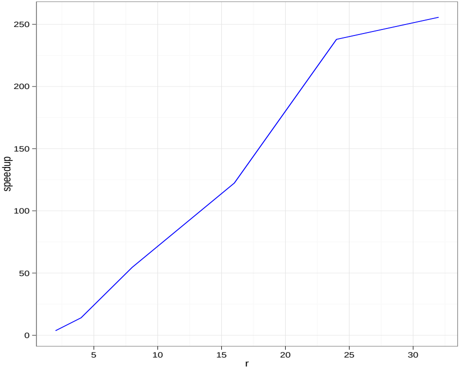


3.92X speedup at 2 threads
93.97X speedup at 24 threads

Kendall's τ, cont'd.

Kendall's τ, cont'd.

n = 25000



3.36X speedup at 2 threads 255.67X speedup at 32 threads

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Quantile Regression

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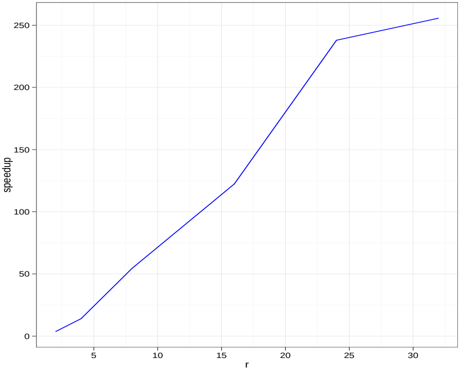
Quantile Regression

n = 10000, p = 10



0.86X speedup at 2 threads
1.16X speedup at 8 threads

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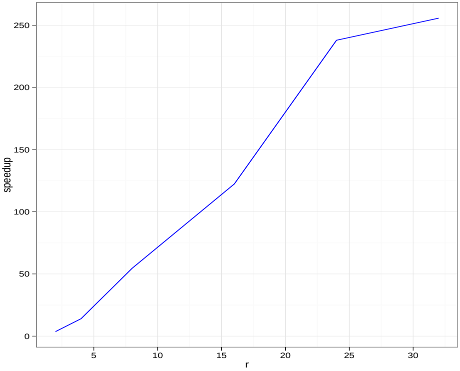
Quantile Regression

Quantile Regression

n = 10000, p = 25



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Hazard Function Estimation

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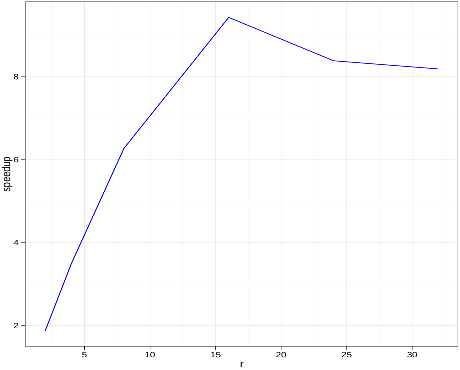
n = 25000, p = 0.2 (proportion missing); estimate quantiles 0.2, 0.4, 0.6, 0.8

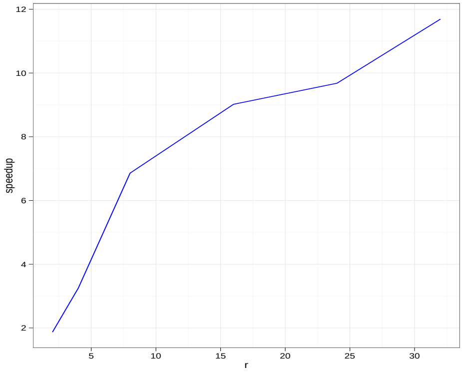


1.87X speedup at 2 threads
9.43X speedup at 16 threads

Hazard Function Estimation

Hazard Function Estimation

n = 50000, p = 0.02 (proportion missing)



1.87X speedup at 2 threads
11.69X speedup at 32 threads

Log Concave Density Estimation

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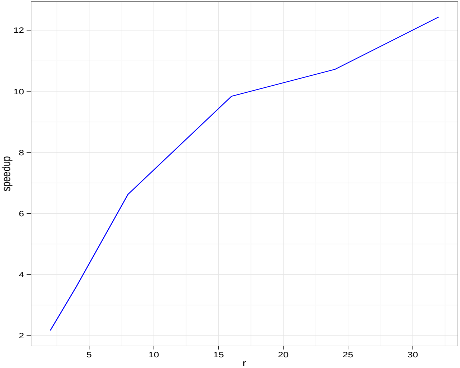
n = 200000



2.17X speedup at 2 threads
12.43X speedup at 32 threads

Linear Regression

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n = 50000, p = 50; should expect less here, $O(n, p^3)$

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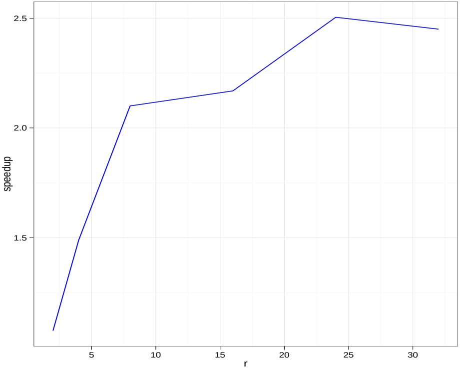

0.90X speedup at 2 threads 1.97X speedup at 32 threads

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Linear Regression

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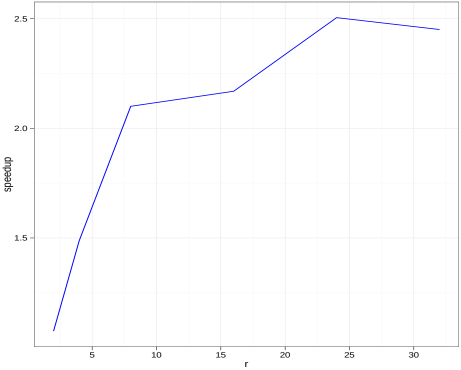
Linear Regression

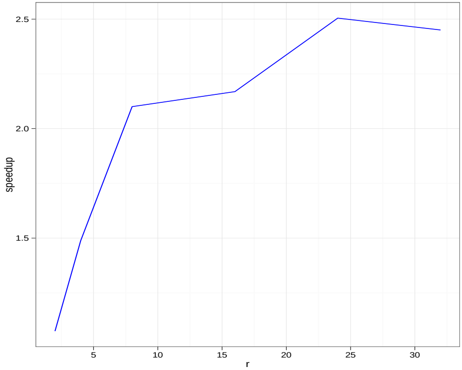
n = 50000, p = 100



1.08X speedup at 2 threads
2.50X speedup at 24 threads

Linear Regression

n = 50000, p = 100



1.08X speedup at 2 threads
2.50X speedup at 24 threads

Put in context: Seligman (2010) found GPU provides speedup only if $r > 1000$.

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- One can prove that NEP2EP works asymptotically, i.e. gives the same statistical accuracy as the original estimatator. Is that large-n requirement an issue?
- No, not an issue: Since we're talking about settings where parallel computing is needed, we're working with large samples by definition—the large n is the reason we need parallel computing!
- NEP2EP gives essentially the same values as the original.

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Accuracy

Accuracy

Absolute differences, r = 16:

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Accuracy

Absolute differences, r = 16:

app.	prob. size	rel. diff.
Kendall	n = 1000	0.005849463
quant. reg.	n = 10000, p = 10	0.001274819
haz. ftn.	n = 25000, p = 0.2	0.007422595
log conc. dens.	n = 25000	0.0003593208
lin. reg.	n = 50000, p = 100	0.0001207394

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Rth

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Motivations:

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- Nice to have the same parallel code work on multicore and GPU systems. PGP—Pretty Good Parallelism.
- Nice to have code for high-level operations available (sort, search, prefix scan, etc.).
- Hopefully make it (somewhat) easy for users to write their own parallel code.

Some Existing Possibilities

Some Existing Possibilities

These work on both multicore and GPUs:

- OpenCL: Extension of C.
- Magma: Matrix routines.
- OpenACC: Like OpenMP for GPUs.

But OpenCL and OpenACC do not provide high-level ops, and Magma is narrow.

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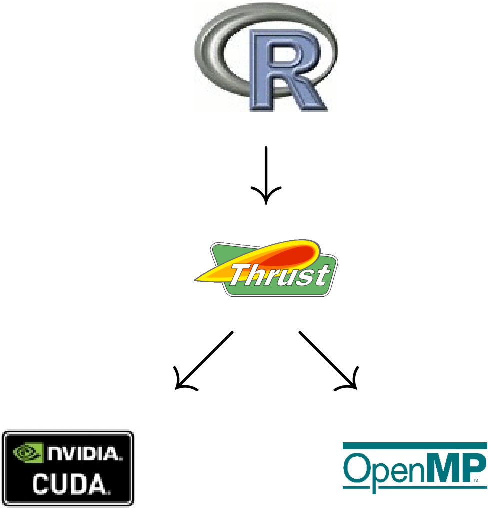
Rth

Rth



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What is Thrust?

- C++ package, modeled on STL.
- Can compile to either GPU or multicore backend.
- Provides high-level operations, e.g. sort, search, prefix scan, foreach, reduction, etc.

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Example: sorting

Example: sorting

R interface code:

```
rthsort <- function(x) {
   dyn.load("rthsort.so")
   n <- length(x)
   tmp <- .C("rthsort",as.double(x),
      as.integer(n),tmpres=double(n))
   return(tmp$tmpres)
}
```

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}
```

Sorting 10000000 numbers: R 4.78 sec, **Rth** 1.52sec.

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sorting, cont'd.

sorting, cont'd.

Thrust code:

```
#include <thrust/host_vector.h>
#include <thrust/device_vector.h>
#include <thrust/sort.h>

void rthsort(double *x, int *nx, double *xout)
{  int n = *nx;
   // set up device vector and copy x to it
   thrust::device_vector<double> dx(x,x+n);
   // sort, then copy back to x
   thrust::sort(dx.begin(), dx.end());
   thrust::copy(dx.begin(), dx.end(),xout);
}
```

General Pattern

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Sort example was straight wrapper. What about other cases?

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- Put together the appropriate Thrust ops.

General Pattern

Sort example was straight wrapper. What about other cases?

- Put together the appropriate Thrust ops.
- For most Thrust ops, write app-specific function to be called.

Example: convolution

Example: convolution

Thrust code:

```
void rthconv(double *x, int *nx,
   double *y, int *ny, double *z)
{  int nxx = *nx, nyy = *ny, nzz = nxx + nyy −
   thrust::device_vector<double> dx(x,x+nxx);
   ...
   thrust::counting_iterator<int> seqb(0);
   thrust::counting_iterator<int> seqe = seqb -
   thrust::for_each(seqb,seqe,do1i(dx.begin(),
      dy.begin(),dz.begin(),nxx,nyy));
   thrust::copy(dz.begin(), dz.end(),z);
}
```

Key line:

```
thrust::for_each(seqb,seqe,do1i(dx.begin(),...
```

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convolution, cont'd.

convolution, cont'd.

User supplies "foreach" function, in the form of a

```
struct do1i  {  // "do 1 i"
...
   __device__
   void operator()(const int i)
   {  int j;  // handle 1 i in i,j loop
      int rpi = rndperm[i];
      double xdi = xd[rpi];
      for (j = 0; j < ny; j++)
         zd[rpi+j] += xdi * yd[ny-j-1];
   }
};
```

convolution, cont'd.

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   }
};
```

A callable struct.

Performance

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- **Rth**'s **rthconv()** orders of magnitude faster than R's **convolve()**.

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Performance

- **Rth**'s **rthconv()** orders of magnitude faster than R's **convolve()**.
- Not fair to R's **convolve()**; latter written in C, but works via FFTs, slow.
- Also: R's **convolve()** runs out of space on problems than **rthconv()** can handle (multcore).

Kendall's Tau

Kendall's Tau

```
void rthkendall(float *xy,int *nxy,float *tau)
{  int i,n = *nxy, n2 = 2*n,totcount;
   thrust::counting_iterator<int> seqa(0);
   thrust::counting_iterator<int>
      seqb =  seqa + n - 1;
   doubvec dxy(xy,xy+n2);
   intvec tmp(n-1);
   thrust::transform(seqa,seqb,tmp.begin(),
      calcgti(dxy,n));
   totcount=thrust::reduce(tmp.begin(),tmp.end(
   *tau = totcount / (0.5*n*(n-1));
}
```

Key calls: **transform(), reduce()**; can combine using transform iterator

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- Not implemented yet.

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- Easy version: Specific numerical indices.

Example: submatrix ops, select()

- Not implemented yet.
- Easy version: Specific numerical indices.
- More elaborate: Dynamic parse of user R expression, sent off to Thrust code.

Some Thrust Ops

Some Thrust Ops

- sort, search
- reduce, min/max
- permute (e.g. for matrix transpose)
- partition, prefix scan
- foreach, transform, copyif
- set ops
- more are being added

Summary

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- “Software alchemy” parallelizes i.i.d. stat apps, any platform. Often get superlinear speedup.
- **Rth** provides a way to easily parallelize many other opps.

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Misc.

Misc.

URLs:

- these slides: http://heather.cs.ucdavis.edu/user2012.pdf
- my online book on parallel programming: http://heather.cs.ucdavis.edu/~matloff/158/PLN/ParProcBook.pdf
- **Rth**: http://heather.cs.ucdavis.edu/~matloff/rth.html

thanks to:

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- Prof. Bill Hsu (use of fast GPUs)
- the audience :-)