

Elevating R to Supercomputers

Drew Schmidt

National Institute for Computational Sciences
University of Tennessee, Knoxville

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The pbdR Core Team

Wei-Chen Chen¹

George Ostrouchov^{1,2}

Pragneshkumar Patel²

Drew Schmidt²



Support

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2 Benchmarks

3 Challenges

Why R?

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- 1 Because.

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- 1 Because.
- 2 R community has growing data size problem.
- 3 HPC community has growing need for data analytics.

Elevating R to Supercomputers

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- 1 Existing code.

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- 2 Syntax.

Elevating R to Supercomputers

- 1 Existing code.
- 2 Syntax.
- 3 **Philosophy.**

Programming with Big Data in R (pbdR)

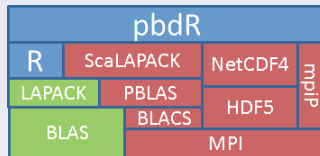
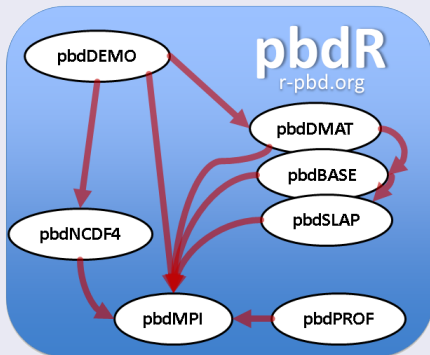
Productivity, Portability, Performance



- *Free^a* R packages.
- Bridging high-performance C with high-productivity of R
- Distributed data details implicitly managed.
- Methods have syntax *identical* to R.

^aMPL, BSD, and GPL licensed

pbdR Packages



pbdMPI vs Rmpi: API

pbdMPI vs Rmpi: API

Reduction Operations

Rmpi

```
1 # int
2 mpi.allreduce(x, type=1)
3 # double
4 mpi.allreduce(x, type=2)
```

pbdMPI

```
1 allreduce(x)
```

pbdMPI vs Rmpi: API

Reduction Operations

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pbdMPI

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1 allreduce(x)
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Types in R

```
1 > is.integer(1)
2 [1] FALSE
3 > is.integer(2)
4 [1] FALSE
5 > is.integer(1:2)
6 [1] TRUE
```


pbdMPI vs Rmpi: Performance

Table: Runtimes (seconds) for $10,000 \times 10,000$ allgather with **Rmpi** and **pbdMPI**.

Cores	Rmpi	pbdMPI	Speedup
32	24.6	6.7	3.67
64	25.2	7.1	3.55
128	22.3	7.2	3.10
256	22.4	7.1	3.15

pbdR Example Syntax

```
1 x <- x[-1, 2:5]
2 x <- log(abs(x) + 1)
3 xtx <- t(x) %*% x
4 ans <- svd(solve(xtx))
```

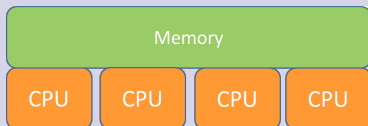
Look familiar?

The above runs on 1 core with R or 10,000 cores with pbdR

Shared and Distributed Memory Machines

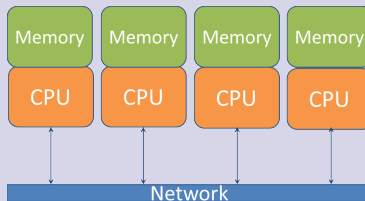
Shared Memory

Direct access to read/change memory (one node)



Distributed

No direct access to read/change memory.



Shared and Distributed Memory Machines

Shared Memory Machines

Thousands of cores



Nautilus, University of Tennessee
1024 cores
4 TB RAM

Distributed Memory Machines

Hundreds of thousands of cores



Kraken, University of Tennessee
112,896 cores
147 TB RAM

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- 2 1 core = 1 MPI process.
- 3 No tuning for data distribution.

Benchmark Data

- 1 Random normal $N(100, 10000)$.

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- 3 Three sets: 500, 1000, and 2000 columns.

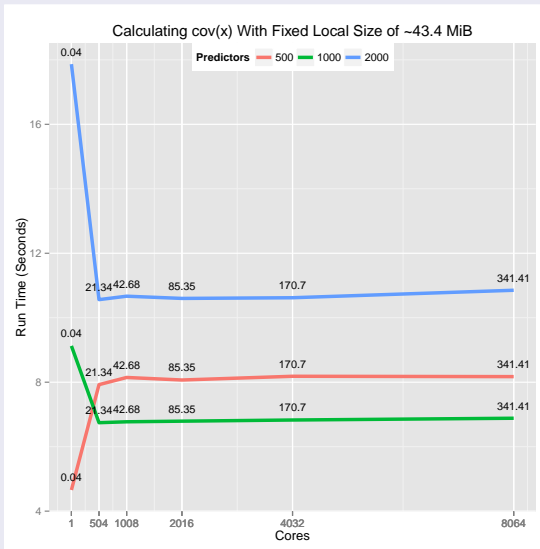
Benchmark Data

- 1 Random normal $N(100, 10000)$.
- 2 Local problem size of $\approx 43.4 \text{ MiB}$.
- 3 Three sets: 500, 1000, and 2000 columns.
- 4 Several runs at different core sizes within each set.

Covariance Code

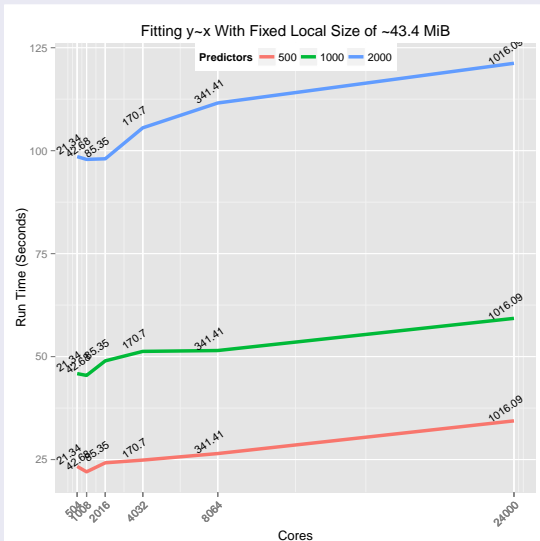
```
1 x <- ddmatrix("rnorm", nrow=n, ncol=p, mean=mean, sd=sd)
2
3 cov.x <- cov(x)
```

cov()



Linear Model Code

```
1 x <- ddmatrix("rnorm", nrow=n, ncol=p, mean=mean, sd=sd)
2 beta_true <- ddmatrix("runif", nrow=p, ncol=1)
3
4 y <- x %*% beta_true
5
6 beta_est <- lm.fit(x=x, y=y)$coefficients
```

`lm.fit()`

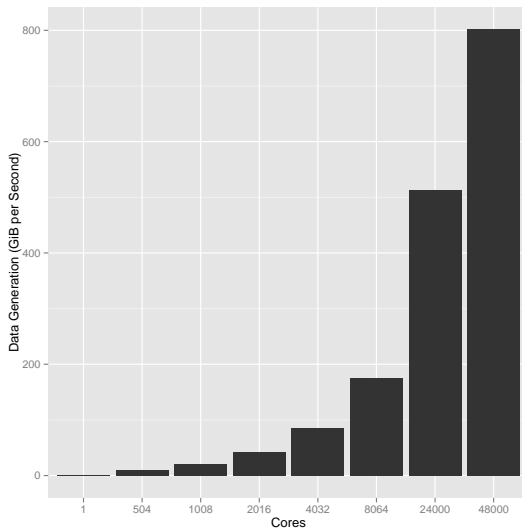
But wait! There's more...

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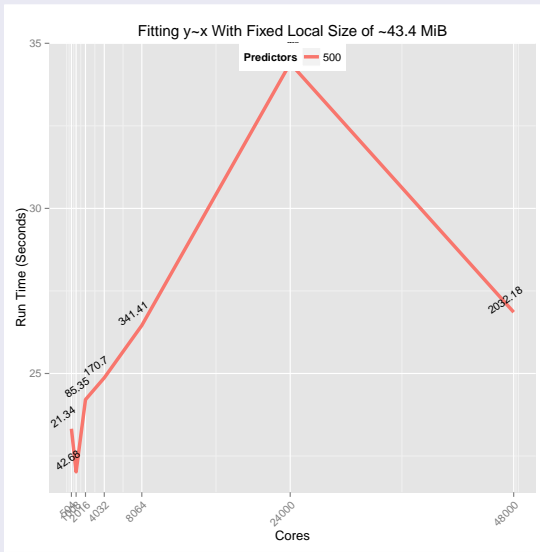
Anything worth doing is worth overdoing.

— Mick Jagger

Data Generation



```
lm.fit()
```



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Challenges

- Perceptions.
 - "R? Isn't that slow?"* – HPC people
 - "HPC? Isn't that hard?"* – R people

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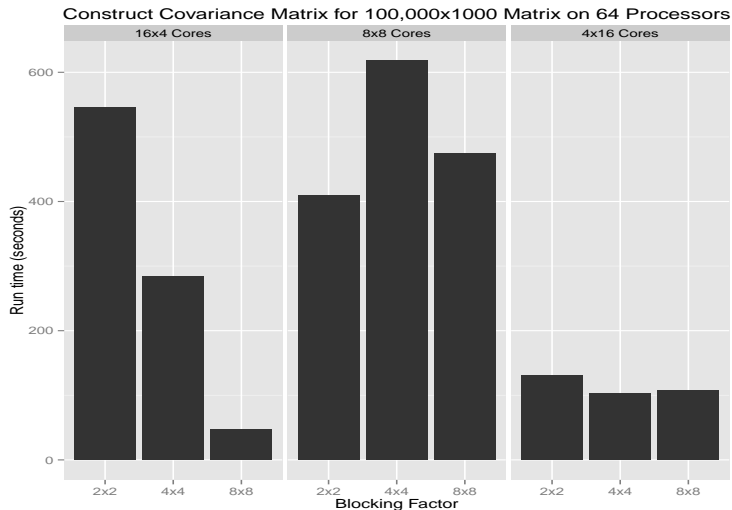
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- Perceptions.
 - “*R? Isn’t that slow?*” – HPC people
 - “*HPC? Isn’t that hard?*” – R people
- Package loading.
- Profiling.
- Data distribution and performance.

Covariance Revisited: Distributed Data Parameter Calibration



Thanks for coming!

Questions?

<http://r-pbd.org/>