Some new developments for the R engine

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Introduction

- R is a language for data analysis and graphics.
- Originally developed by Ross Ihaka and Robert Gentleman at University of Auckland, New Zealand.
- Now developed and maintained by a distributed group of 20 people.
- R is based on the S language developed by John Chambers and others at Bell Labs.
- R is widely used in the field of statistics and beyond, especially in university environments.
- R has become the primary framework for developing and making available new statistical methodology.
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- New large vector support.
- Fine-grained parallelization of vector and matrix operations.
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Large Vector Support

- *Big Data* is a hot topic in this session.
- Some categories:
  - fit into memory
  - fit on one machine's disk storage
  - require multiple machines to store
- Smaller large data sets can be handled by standard methods if enough memory is available.
- Very large data sets require specialized methods and algorithms.
- R should be able to handle smaller large data problems on machines with enough memory.

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Large Vector Support
Initial Objectives

- Through R 2.15.1 the total number of elements in a vector cannot exceed $2^{31} - 1 = 2,147,483,647$
- This limit represents the largest possible 32-bit signed integer.
- For numeric (double precision) data this means the largest possible vector is about 16 GB.
- This is fairly large, but is becoming an issue with larger data sets with many variables on 64-bit platforms.
- We need a way to raise this limit that meets several goals:
  - avoid having to rewrite too much of R itself
  - avoid requiring package authors to rewrite too much C code
  - avoid having existing compiled C code fail if possible
  - allow incrementally adding support for procedures where it makes sense
- For now, keep $2^{31} - 1$ limit on matrix rows and columns.

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- C level changes:
  - Preserve existing memory layout
  - Use special marker in length field to identify long vectors
  - LENGTH accessor (returning int) signals an error for long vectors
  - Long vector aware code uses XLENGTH to return R_xlen_t.
- R code should not need to be changed:
  - double precision indices can be used for subsetting
  - length will return double for long vectors
  - .C and .Fortran will signal errors for long vectors.
- A document describing how to add long vector support to a package should be available soon.

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- A number of internal functions now support long vectors.
- Some statistical functions with long vector support:
    - random number generators
    - mean
    - sort
    - fivenum
    - lm.fit
    - glm.fit
- The function dist can handle more than 2^{16} observations by returning a long vector result.
- Many matrix and array functions already support large arrays:
    - colSums, colMeans
    - rowSums, rowMeans

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- Converting existing methods to support large vectors is fairly straight forward, however:
  - more numerically stable algorithms may be needed
  - faster/parallel algorithms may be needed
  - the ability to interrupt computations may become important
  - statistical usefulness may not scale to larger data
- The size where these issues become relevant is likely much lower!
- Future work will consider
  - whether to add a separate 64-bit integer type, or change the basic R integer type to 64 bits
  - possibly adding 8 and 16 bit integer types
  - arithmetic and overflow issues that these raise
  - whether to allow numbers of rows and columns in matrices to exceed $2^{31} - 1$ as well

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Parallelizing Vector and Matrix Operations

- Most modern computers feature two or more processor cores.
- It is expected that tens of cores will be available soon.
- Two ways to take advantage of multiple cores:
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    - packages snow, multicore, parallel.
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- Good performance of the synchronization barrier is critical for fine-grained parallelization.
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- We are using a pthreads-based implementation using atomic integer operations for synchronization during the spin wait.
- We expect to make an interface to this framework available to package authors as well.
- Care is needed to make sure that all functions called from worker threads are thread-safe.
- Some things that are not thread-safe:
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  - signaling warnings and errors
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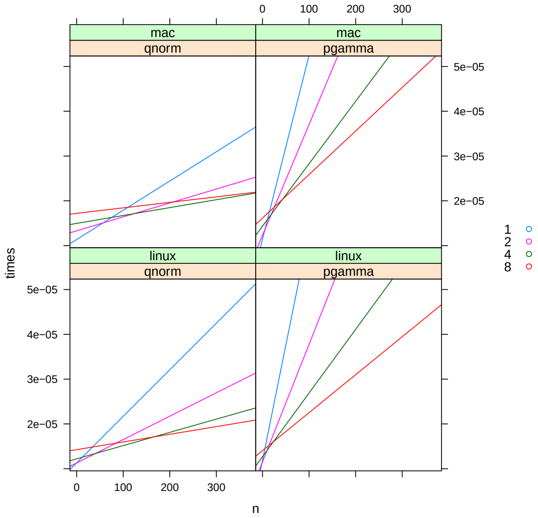

mac
qnorm
mac
pgamma
linux
qnorm
linux
pgamma
0
100
200
300
5e−05
4e−05
3e−05
2e−05
times
n
1
2
4
8

Some observations:

- Times are roughly linear in vector length.
- Intercepts on a given platform are roughly the same for all functions.
- Relative slopes of functions seem roughly independent of OS/architecture.

A simple calibration strategy:

- Compute relative slopes once, or average across several setups.
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The appropriate time to run calibration code is still open.

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- An experimental package pnmath0 that parallelizes many basic vectorized math functions is available at

  `http://www.stat.uiowa.edu/~luke/R/experimental/`
- The functions colSums and dist in the current R distribution can run in parallel but do not by default.
- Hopefully more will be included in the R distribution before too long.
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Parallelizing Vectorized Operations
Some Notes

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  - special instructions for most SPECIALs, many BUILTINs
  - inlining simple .Internal calls: e.g.

    ```
    dnorm(y, 2, 3)
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    is replaced by

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Byte Code Compilation
A Simple Example

R Code

```
f <- function(x) {
    s <- 0.0
    for (y in x)
        s <- s + y
    s
}
```

VM Assembly Code

```
    LDCONST 0.0
    SETVAR s
    POP
    GETVAR x
    STARTFOR y L2
L1: GETVAR s
    GETVAR y
    ADD
    SETVAR s
    POP
    STEPFOR L1
L2: ENDFOR
    POP
    GETVAR s
    RETURN
```

Timings for some simple benchmarks on an `x86_64` Ubuntu laptop:

Benchmark	*Interp.*	*Comp.*	*Speedup*	*Exper.*	*Speedup*
`p1`	32.19	7.98	4.0	1.47	21.9
`sum`	6.72	1.86	3.6	0.59	11.4
`conv`	14.48	4.30	3.4	0.81	17.9
`rem`	56.82	23.68	2.4	4.77	11.9

Interp., *Comp.* are for the current released version of R

Exper.: experimental version using

- separate instructions for vector, matrix indexing
- typed stack to avoid allocating intermediate scalar values

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- An alternative approach might use a register-based design.
- Some additional optimizations currently being explored:
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  Some promising preliminary results are available.
- Other possible directions include
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