Some Developments for the R Engine

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November 10, 2011
**Introduction**

- R is a language for data analysis and graphics.
- 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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- Taking advantage of multiple cores for
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The standard R evaluation mechanism
- parses code into a parse tree when the code is read
- evaluates code by interpreting the parse trees.

Most low level languages (e.g. C, FORTRAN) compile their source code to native machine code.

Some intermediate level languages (e.g. Java, C#) and many scripting languages (e.g. Perl, Python) compile to a simpler language called byte code.
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Byte code is the machine code for a *virtual machine*.

Virtual machine code can then be interpreted by a simpler, more efficient interpreter.

Virtual machines, and their machine code, are usually specific to the languages they are designed to support.

Various strategies for further compiling byte code to native machine code are also sometimes used.
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The first release of the compiler occurred with R 2.13.0 this spring.
Some improvements in the virtual machine interpreter were released with R 2.14.0 this fall.
The current compiler and virtual machine produce good improvements in a number of cases.
Better results should be possible with some improvements to the virtual machine and are currently being explored.
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The compiler can be called explicitly to compile single functions or files of code:

- `cmpfun` compiles a function
- `cmpfile` compiles a file to be loaded by `loadcmp`

It is also possible to have package code compiled when a package is installed.

- Use `--byte-compile` when installing, or specify the ByteCompile option in the DESCRIPTION file.
- R 2.14.0 by default compiles R code in all base and recommended packages.

Alternatively, the compiler can be used in a JIT mode where

- functions are compiled on first use
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- constant folding
- special instructions for most SPECIALs, many BUILTINs
- inlining simple .Internal calls: e.g.
  \[ \text{dnorm}(y, 2, 3) \]
  is replaced by
  \[ .\text{Internal}(\text{dnorm}(y, \text{mean} = 2, \text{sd} = 3, \text{log} = \text{FALSE})) \]
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A Simple Example

**R Code**

```r
f <- function(x) {
  s <- 0.0
  for (y in x)
    s <- s + y
  s
}
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**VM Assembly Code**

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LDCONST 0.0
SETVAR s
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GETVAR x
STARTFOR y L2
  L1: GETVAR s
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Some Performance Results

Timings for some simple benchmarks on an x86_64 Ubuntu laptop:

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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.

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Most modern computers feature two or more processor cores. It is expected that tens of cores will soon be common. A common question:

*How can I make R use more than one core for my computation?*

There are many easy answers. But this is the wrong question. The right question:

*How can we take advantage of having more than one core to get our computations to run faster?*

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Parallelizing Vector and Matrix Operations

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- **Explicit parallelization:**
  - Uses some form of annotation to specify parallelism
  - Packages `snow`, ` multicore`, `parallel`.

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  - Automatic, no user action needed

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- Run two worker threads.
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• Reality is a bit different:

![Diagram showing sequential and parallel operations with overlapping workloads.]

• There is
  - synchronization overhead
  - sequential code and use of shared resources (memory, bus, ...)
  - uneven workload

• Parallelizing will only pay off if $n$ is large enough.
  - For some functions, e.g. qbeta, $n \approx 10$ may be large enough.
  - For some, e.g. qnorm, $n \approx 1000$ is needed.
  - For basic arithmetic operations $n \approx 30000$ may be needed.

• Careful tuning to ensure improvement will be needed.

• Some aspects will depend on architecture and OS.
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\begin{align*}
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Parallelizing Vectorized Operations

Some Experimental Results

- qnorm, Linux/AMD/x86_64
- pgamma, Linux/AMD/x86_64
- qnorm, Mac OS X/Intel/i386
- pgamma, Mac OS X/Intel/i386
Some observations:

- Times are roughly linear in vector length.
- Intercepts on a given platform are roughly the same for all functions.
- If the slope for $P$ processors is $s_P$, then at least for $P = 2$ and $P = 4$,
  \[ s_P \approx s_1 / P \]

- Relative slopes of functions seem roughly independent of OS/architecture.

A simple calibration strategy:

- Compute relative slopes once, or average across several setups.
- For each OS/architecture combination compute the intercepts.

The appropriate time to run calibration code is still open.
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One possibility: using raw pthreads

Better choice: use Open MP

Open MP consists of

- compiler directives (#pragma statements in C)
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Most commercial compilers support Open MP.

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default(shared) private(i) reduction(&&:naflag)
for (i = 0; i < n; i++) {
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Steps in converting to Open MP:
- check f is thread-safe; modify if not
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- R memory allocation
- signaling warnings and errors
- user interrupt checking
- creating internationalized messages (calls to `gettext`)

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Functions in `nmath` that have not been parallelized yet:
- Bessel functions (partially done)
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Availability

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- This requires a version of gcc that
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- Very preliminary results for colSums on an 8-core Linux machine:

<table>
<thead>
<tr>
<th>size</th>
<th>time</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.5e−05</td>
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Some issues to consider:

- Again using too many processor cores for small problems can slow the computation down.
- `colSums` can be parallelized by rows or columns:
  - Handling groups of columns in parallel produces identical results to a sequential version.
  - Handling groups of rows in parallel changes numerical results slightly (floating point addition is not associative).
- `rowSums` is slightly more complex since locality of reference (column major storage) need to be taken into account.
- A number of other basic operations can be handled similarly.
- Simple uses of `apply` and `sweep` might also be handled along these lines.
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Using a Parallel BLAS

• Most core linear algebra calculations use the Basic Linear Algebra Subroutines library (BLAS).

• R has supported using a custom BLAS implementation for some time.

• Both Intel and AMD provide sequential and threaded accelerated BLAS implementations.

• Atlas and Goto’s BLAS also come in sequential and threaded versions.

• Very preliminary testing suggests that the Intel threaded BLAS works well for small and large matrices.

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*Big Data* is a hot topic in the popular and trade press.

Some categories:
- fit into memory
- fit on one machines disk storage
- require multiple machines to store

Smaller large data sets can be handled by standard methods if enough memory is available.

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Currently 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.
- Can this limit be raised without breaking too much existing R code and requiring the rewriting of too much C code?
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The R memory manager is easy enough to change.

Finding all the other places in the C code implementing R where `int` would need to be changed to a wider type, and making sure it is not changed where it should not be, is hard.

External code used by R is also a problem, in particular the BLAS.
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Some Possible Directions

- A possible strategy:
  - Change length fields in internal headers to support longer vectors.
  - Change standard field accessors to signal an error if long vectors are used.
  - Add new accessors that allow long vectors.
  - Gradually introduce long vector support into the R internals.
- The initial header change will require recompiling all C code but no further code changes.
- After the header change, support for large vectors can be introduced incrementally in R itself and in packages.
- It may eventually be necessary to introduce a long integer data type or change the integer type from 32 to 64 bits.
- It may also be sufficient to store larger integers as double precision floating point numbers.
- If the integer representation is changed, a possible direction to explore is whether smaller integer types could be added (one byte and two byte, for example).
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If successful, the header changes may occur within the next few weeks.
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