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Interpreter Internals: Unearthing Buried Treasure with CXXR

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Outline

The CXXR Project

The aim of the CXXR project[1] is progressively to reengineer the fundamental parts of the R interpreter from C into C++, with the intention that:

- Full functionality of the standard R distribution is preserved;
- The behaviour of R code is unaffected (unless it probes into the interpreter internals);
- No change to the existing interfaces for calling out from R to other languages (`.C`, `.Fortran`. `.Call` and `.External`).
- No change to the main APIs (`R.h` and `S.h`) for calling into R. However, a broader API is made available to external C++ code.

Work started in May 2007, shadowing R-2.5.1; the current release shadows R-2.12.1, and an upgrade to 2.13.1 is in progress.

We'll refer to the standard R interpreter as **CR**.

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Why Do This?

The broad mission of CXXR is to make the R interpreter more accessible to developers and researchers.

This is being achieved by various means, including:

- Improving the internal documentation;
- Tightening up the internal encapsulation boundaries within the interpreter;
- Moving to an object-oriented structure, thus reflecting a programming approach with which students are increasingly familiar.
- Expressing internal algorithms at a higher level of abstraction, and making them available to external code through the CXXR API.

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How R Objects are Implemented in CR

In CR, all R objects (as listed by the R command `objects()`) are implemented using a C 'union'. This is a way of telling the C compiler that a particular memory address may hold any one of several distinct datatypes: in this case 23 types, corresponding to the different types of R object.

This has several disadvantages:

- The compiler doesn't know which of the 23 types is occupying a particular union block. Consequently all type checking must be done at run-time; the possibilities of compile-time type checking are not exploited.
- Debugging at the C level is difficult.
- Introducing a new type of R object means modifying a data definition at the very heart of the interpreter.

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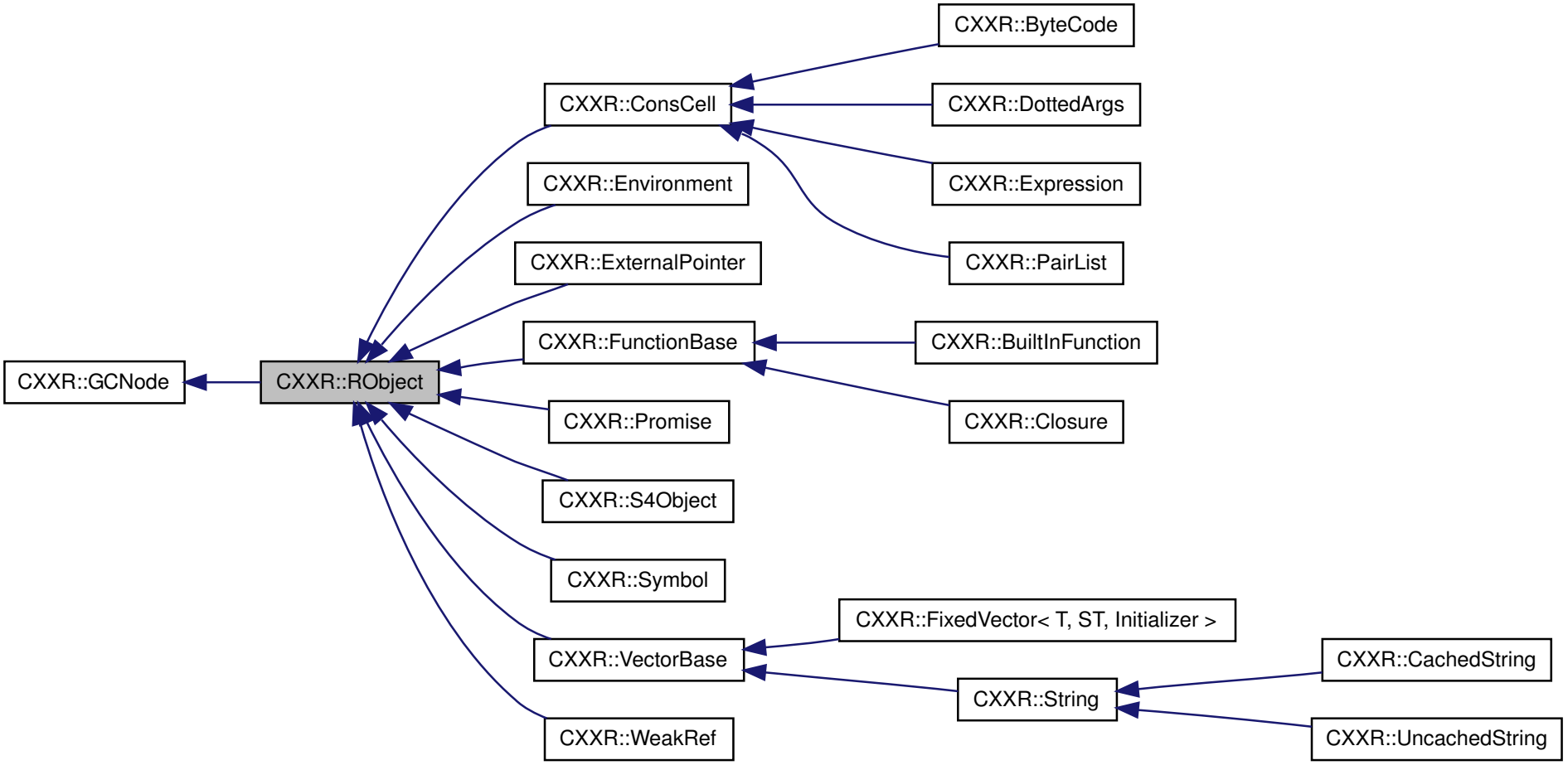
The `RObject` Class Hierarchy

In CXXR, the various sorts of R objects are implemented using a C++ class inheritance hierarchy rooted at `RObject`:



(Based on a diagram produced by Doxygen.)

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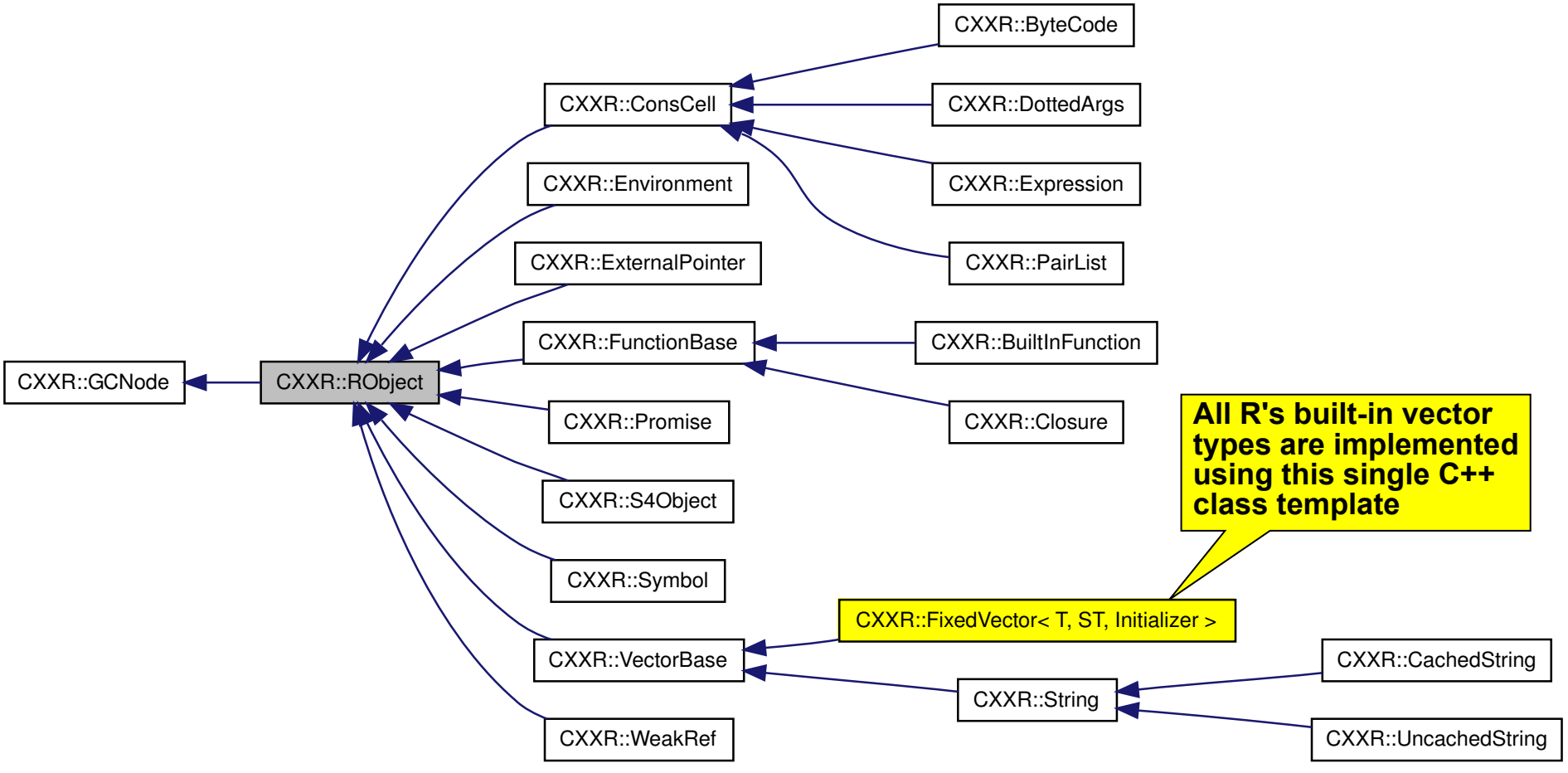

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The `RObject` Class Hierarchy
Objectives

- As far as possible, move all program code relating to a particular datatype into one place.
- Use C++'s public/protected/private mechanism to conceal implementational details and to defend class invariants.
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Extending the Class Hierarchy: Example

Introducing arbitrarily large integers

Suppose we wanted to write a package adding to R the capability of handling arbitrarily large integers, drawing on the GNU Multiple Precision Library at gmplib.org.

In fact there already is such a package: the **GMP** package by Antoine Lucas *et al.* which does this and much more . . .

. . . however the purpose of this example is to show how CXXR makes this task relatively straightforward. We'll call our nascent package **MyGMP**.

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Adding NA to what the GNU library provides

The GNU MP library defines a C++ class `mpz_class` to represent an arbitrarily large integer.

But an attractive characteristic of R is its ability to flag individual data points as 'not available': `NA`. As it stands `mpz_class` does not have this capability.

Fortunately, in CXXR we can put this right essentially in one line of C++ code:

```
namespace MyGMP {
    typedef CXXR::NAAugment<mpz_class> BigInt;
}
```

This type definition gives us a new C++ class which can represent an arbitrarily large integer or '`NA`'. This is set up in such a way that CXXR's generic algorithms can detect and handle `NA`s with little or no attention from the package writer.

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Vectors of `BigInt`s

So far we can represent an individual `BigInt`. But of course R works primarily with **vectors** (or matrices or higher dimensional arrays). We can introduce vectors/matrices/array of `BigInt`s into CXXR essentially with one further line of C++ code:

```
namespace MyGMP {
    typedef CXXR::FixedVector<BigInt,
                              CXXSXP,
                              ApplyBigIntClass> BigIntVector;
}
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`BigIntVector`s have now joined the `RObject` class hierarchy alongside the built-in data vector types. We can now assign `BigIntVector`s to R variables, and facilities such as garbage collection, copy management, dimensioning and so on are automatically in place.

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Binary Operations in R

Consider a binary operation on R vectors:

```
vr <- v1*v2
```

Basically this involves determining each element of the result by applying the binary operation to the corresponding elements of the two operands, so for example vr[1] is set to v1[1]*v2[1].

But there are complications. For example:

- If either operand element is NA, the corresponding result element must be set to NA.
- If the operands are of unequal length, the elements of the shorter operand are reused in rotation. But give a warning if its length is not a submultiple of that of the longer operand.
- Attributes (e.g. element names) of the result must be inferred somehow from the corresponding attributes of the operands.
- Further complications if the operands are matrices or higher dimensional arrays.

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Generic Algorithm for R Binary Functions

CXXR defines a **generic algorithm** (based on the C++ class template `CXXR::VectorOps::BinaryFunction`) for implementing R binary functions, and makes it available to package C++ code via the CXXR API.

To use this algorithm the package writer need only specify:

- The elementwise operation to be performed (ignoring NA), e.g. the multiplication operation defined for `mpz_class` by the GNU MP library.
- The two operands.
- The type of vector (or other vector-like container) to be produced as the result.
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Extending the Class Hierarchy: Example

Multiplying vectors/arrays of arbitrarily large integers

Package R code:

```
`*.BigInt` <- function(vl, vr) {
  .Call("MyGMP_multiply", as.bigint(vl), as.bigint(vr))
}
```

Package C++ code:

```
extern "C" {
    BigIntVector* MyGMP_multiply(const BigIntVector* vl,
                                 const BigIntVector* vr)
    {
        using namespace CXXR::VectorOps;
        return
            BinaryFunction<GeneralBinaryAttributeCopier,
                           std::multiplies<mpz_class> >()
            .apply<BigIntVector>(vl, vr);
    }
}
```

Extending the Class Hierarchy: Example

Computing factorials

With very little programming at the package level, we are already in a position to calculate some largish factorials:

```
> f <- as.bigint(c(1:20, NA))
> for (i in 3:21) f[i] <- f[i]*f[i-1]
> f
 [1] "1"                    "2"                    "6"
 [4] "24"                   "120"                  "720"
 [7] "5040"                 "40320"                "362880"
[10] "3628800"              "39916800"             "479001600"
[13] "6227020800"           "87178291200"          "1307674368000"
[16] "20922789888000"       "355687428096000"      "6402373705728000"
[19] "121645100408832000"   "2432902008176640000"  NA
```

Subscripting in R

R is renowned for the power of its subscripting operations.

The *R Language Definition* document devotes over four of its 51 pages to describing subscripting facilities. . . and even that doesn't tell the whole story.

The CR interpreter includes about 2000 C-language statements to implement these facilities.

But this C code is effectively 'locked up' for two related reasons:

- it isn't made available via a documented API,
- it is hard-wired around CR's built-in data types.

This code is **buried treasure**—it is not, as it stands, suitable for providing subscripting facilities for our `BigIntVector`s.

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CXXR::Subscripting Class Reference

Services to support R subscripting operations. More...

`#include <Subscripting.hpp>`

List of all members.

Classes

struct	**DimIndexer**

Static Public Member Functions

template<class VL , class VR > static VL *	**arraySubassign** (VL *lhs, const **ListVector** *indices, const VR *rhs) Assign to selected elements of an R matrix or array.
template<class VL , class VR > static VL *	**arraySubassign** (VL *lhs, const **PairList** *subscripts, const VR *rhs) Assign to selected elements of an R matrix or array.
template<class V > static V *	**arraySubset** (const V *v, const **ListVector** *indices, bool drop) Extract a subset from an R matrix or array.
template<class V > static V *	**arraySubset** (const V *v, const **PairList** *subscripts, bool drop) Extract a subset from an R matrix or array.
static std::pair< const **IntVector** *, std::size_t >	**canonicalize** (const **IntVector** *raw_indices, std::size_t range_size) Obtain canonical index vector from an IntVector.
static std::pair< const **IntVector** *, std::size_t >	**canonicalize** (const **LogicalVector** *raw_indices, std::size_t range_size) Obtain canonical index vector from a LogicalVector.
static std::pair< const **IntVector** *, std::size_t >	**canonicalize** (const **RObject** *raw_indices, std::size_t range_size, const **StringVector** *range_names)
static std::pair< const **IntVector** *, std::size_t >	**canonicalize** (const **StringVector** *raw_indices, std::size_t range_size, const **StringVector** *range_names) Obtain canonical index vector from an StringVector.

CXXR's `Subscripting` Class

CXXR's `Subscripting` class aims to encapsulate R's subscripting facilities within a number of generic algorithms.

These algorithms abstract away from:

- The type of the elements of the R vector/matrix/array. (`BigInt`s work just fine!)
- The data structure used to implement the vector/matrix/array itself. This opens the door to using the algorithms with packed data (e.g. A/T/G/C DNA bases), or with vector structures for large datasets which hold data on disk (in the style of the `ff` package).

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Extending the Class Hierarchy: Example

Subassignment: `[<-`

Package R code:

```
`[<-.BigInt` <- function(v, ..., value) {
  .External("MyGMP_bigintsubassign", v, as.bigint(value), ...)
}
```

Package C++ code:

```
extern "C" {
    BigIntVector* MyGMP_bigintsubassign(const PairList* args)
    {
        args = args->tail();
        BigIntVector* lhs
            = SEXP_downcast<BigIntVector*>(args->car());
        args = args->tail();
        const BigIntVector* rhs
            = SEXP_downcast<const BigIntVector*>(args->car());
        args = args->tail();
        return Subscripting::subassign(lhs, args, rhs);
    }
}
```

In the Pipeline: Serialization

At the moment there is no provision for `BigIntVector`s to be saved at the end of an R session, and subsequently restored.

Work is in progress on a new (CXXR-specific) approach to serialization of R objects, with the intention that there will be an easy-to-use framework for package writers to have objects of package-supplied C++ classes (such as `BigIntVector`) serialized/deserialized along with other session data.

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Summary

CXXR aims to open up the R interpreter to developers. In particular:

- Objects visible to R are implemented using a C++ class hierarchy which developers can easily extend.
- Key algorithms embodying R functionality are being rewritten at a higher level of abstraction and published via the CXXR API.

Summary

CXXR aims to open up the R interpreter to developers. In particular:

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Functionality Now in CXXR Core

- Memory allocation and garbage collection.
- `SEXPREC` union replaced by an extensible class hierarchy rooted at class `RObject`.
- Environments (i.e. variable→object mappings), with hooks to support provenance tracking.
- Expression evaluation. (S3 method despatch partially refactored; S4 despatch not yet refactored.)
- Contexts and indirect flows of control (with some loose ends).
- Unary and binary function despatch. `[`-subscripting.
- Object duplication is now handled by C++ copy constructors. (In an experimental development branch, object duplication is managed automatically, removing the need for `NAMED()` and `SET_NAMED()`.)

Conway's 'Game of Life'

CPU time for 100 iterations over a square matrix with wraparound (toroidal topology):

Grid size	**CR (secs)**	**CXXR (secs)**
32×32	0·047	0·053
64×64	0·168	0·191
128×128	0·686	0·743
256×256	3·084	3·004
512×512	33·402	14·239
1024×1024	144·386	60·128

The tests were carried out on a 2.8 GHz Pentium 4 with 1 MB L2 cache, comparing R-2.12.1 with CXXR 0.35-2.12.1.

CRAN Packages Tested

for useR! 2010 paper

Paper at useR! 2010 explored the compatibility of CXXR with 50 key packages from CRAN: those on which the largest number of other CRAN packages depend.

abind	gdata	MEMSS	RColorBrewer	scatterplot3d
akima	gee	mix	rgl	slam
ape	gtools	mlbench	rlecuyer	snow
biglm	kernlab	mlmRev	Rmpi	sp
bitops	leaps	multicore	robustbase	SparseM
car	lme4	mvtnorm	RODBC	timeDate
coda	logspline	numDeriv	rpvm	timeSeries
DBI	mapproj	nws	rsprng	tkrPlot
e1071	maps	quantreg	RSQLite	tripack
fBasics	mclust	randomForest	RUnit	xtable

Package versions were those current on 2010-05-05.

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bitops	leaps	multicore	robustbase	SparseM
car	lme4	mvtnorm	RODBC	timeDate
coda	logspline	numDeriv	rpvm	timeSeries
DBI	mapproj	ncdf	rpart	tkrPlot
e1071	maps	quadprog	RSQLite	tripack
fBasics	mclust	randomForest	RUnit	xtable

Apart from fixing latent bugs, only three lines of package code needed to be modified for all the tests included in the packages to pass.

All these changes were in package C code, never R code.

Package versions were those current on 2010-05-05.

Creating a `BigIntVector`

The R function `bigint` defined below creates a zero-filled vector of bigints of a specified length:

Package R code:

```
bigint <- function(length) {
    .Call("MyGMP_makebigint", as.integer(length))
}
```

Package C++ code:

```
extern "C" {
    BigIntVector* MyGMP_makebigint(const IntVector* arg)
    {
        if (arg->size() == 0)
            Rf_error(_("invalid '%s' argument"), "length");
        int sz = (*arg)[0];
        if (sz < 0)
            Rf_error(_("invalid '%s' argument"), "length");
        return CXXR_NEW(BigIntVector(sz, BigInt(long(0))));
    }
}
```