CXXR: An Ideas Hatchery for Future R Development

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Outline

1 CXXR
2 The RObject Extensible Class Hierarchy
3 Provenance Tracking and Serialization
4 Conclusion
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.

\(^1\)www.cs.kent.ac.uk/projects/cxxr
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Why Do This?

An initial motivation was to be able to introduce provenance-tracking facilities into CXXR: more on this later.

But CXXR has a broader mission: 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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- 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.
Written as far as possible in idiomatic C++, making free use of the C++ standard library, and some use of the peer-reviewed Boost libraries.

Contained in the C++ namespace CXXR.

Interfaces thoroughly documented using doxygen.

As far as possible self-contained: avoids calls into the outer layers.
The aim is that existing R packages should work with CXXR with minimal alteration, usually none at all. This is achieved by leaving the primary interfaces unchanged.
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.

<table>
<thead>
<tr>
<th>abind</th>
<th>gdata</th>
<th>MEMSS</th>
<th>RColorBrewer</th>
<th>scatterplot3d</th>
</tr>
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C files from CR adapted as necessary to work with the core.

With some exceptions, these C files have been redesignated as C++.
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2. The RObject Extensible Class Hierarchy
3. Provenance Tracking and Serialization
4. Conclusion
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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.
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- 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**

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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:

```cpp
define 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 `NAS` with little or no attention from the package writer.
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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 `BigInts` into CXXR essentially with one further line of C++ code:

```c++
namespace MyGMP {
    typedef CXXR::FixedVector<BigInt,
                              CXXSXP,
                              ApplyBigIntClass> BigIntVector;
}
```

`BigIntVectors` have now joined the `RObject` class hierarchy alongside the built-in data vector types. We can now assign `BigIntVectors` to R variables, and facilities such as garbage collection, copy management, dimensioning and so on are automatically in place.
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Consider a binary operation on R vectors:

```r
v_r <- v_1 * v_2
```

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 \( v_r[1] \) is set to \( v_1[1] * v_2[1] \).

But there are complications. For example:

- If either operand element is \( \text{NA} \), the corresponding result element must be set to \( \text{NA} \).
- 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.
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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, 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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With very little programming at the package level, we are already in a position to calculate some largish factorials:

```r
> f <- as.bigint(c(1:20, NA))
> for (i in 3:21) f[i] <- f[i]*f[i-1]
> f

[1] "1" "2" "6" "24" "120" "720" "5040" "362880" "3991680" "479001600"
[10] "1307674368000" "20922789888000" "355687428096000" "4790016000000"
[19] "121645100408832000" "2432902008176640000" NA
```
R is renowned for the power of its subscripting operations.

```r
> mx

<table>
<thead>
<tr>
<th>Country</th>
<th>Latest</th>
<th>Qtr 2011</th>
<th>Qtr 2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>Austria</td>
<td>3.9</td>
<td>3.6</td>
<td>2.7</td>
</tr>
<tr>
<td>Belgium</td>
<td>3.0</td>
<td>4.3</td>
<td>2.3</td>
</tr>
<tr>
<td>France</td>
<td>2.2</td>
<td>3.8</td>
<td>2.1</td>
</tr>
<tr>
<td>Germany</td>
<td>5.4</td>
<td>6.1</td>
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<tr>
<td>Greece</td>
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(GDP growth, *The Economist*, 2011-07-09)
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On the right are some examples of subscripting the R matrix above.

```r
> mx[c("France", "Germany"), -2]

<table>
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<tbody>
<tr>
<td>France</td>
<td>2.2  2.1  1.7</td>
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> mx[, 3]

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> mx[, 3, drop=FALSE]

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(GDP growth, The Economist, 2011-07-09)

On the right are some examples of subscripting the R matrix above.

```r
> mx[, "2012"] <- mx[, "2012"] + 0.5
> mx

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Subscripting expressions may also appear on the left-hand side of an assignment.
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.

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CXXR::Subscribing Class Reference

Services to support R subscripting operations. More...

#include <Subscribing.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 LogicalVector *, std::size_t > canonicalize (const LogicalVector *raw_indices, std::size_t range_size)
Obtain canonical index vector from a LogicalVector.

static std::pair< const RObject *, std::size_t range_size, const StringVector *range_names>
canonicalize (const RObject *raw_indices, std::size_t range_size, const StringVector *range_names)
Obtain canonical index vector from an RObject.
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. (*BigInts 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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Tracking Provenance During Data Analysis

Have you ever returned to a data analysis after a gap of months (or maybe years) and asked yourself such questions as the following?

- How exactly was this data object, or that model, derived from the original data?
- What data points were discarded, and how were they identified as being suspect?
- One of the datasets that went into the original analysis is now known to have been corrupt. Which results does this invalidate?

In other words, you are interested in interrogating the provenance of data objects, models, etc. This is a topic of increasing importance in information science.
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One of the pioneer provenance-aware applications was S, with its AUDIT facility: the classic paper *Auditing of Data Analyses*\(^2\) by Becker and Chambers is widely cited in the provenance-awareness literature.

An S session would maintain an **audit file**, recording all the top-level commands issued in this and previous sessions within the workspace, and identifying the data objects read and modified by the commands. This audit file could then be analysed using a separate tool, S AUDIT.

Chris Silles has been exploring the possibility of introducing such a facility into R, building on CXXR . . . but with the difference that provenance information can be interrogated directly from within an R session.

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Consider this example R command session:

```r
> one <- 1
> two <- c("deux", "zwei")
> two <- one + one
> three <- 3
> square <- function(x) x*x
> four <- square(two)
> five <- four + 1
> nine <- square(three)
> rm(two, five)
```
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Querying the provenance of an R object (strictly, an R binding):

```r
> provenance(nine)

$command
nine <- square(three)

$symbol
nine

$timestamp
[1] "01/07/11 15:50:43.497459"

$parents
[1] "square" "three"

$children
NULL
Consider this example R command session:

```r
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> two <- c("deux", "zwei")
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> five <- four + 1
> nine <- square(three)
> rm(two, five)
```

Querying the full pedigree of an R object:

```r
> pedigree(four)
one <- 1
two <- one + one
square <- function(x) x*x
four <- square(two)
```
Although having provenance information available during a single R session is useful, its real value arises when a data analysis (perhaps carried out by someone else) is resumed after a lapse of time.

This means that it is essential that provenance information is saved at the end of a session along with the data objects to which it relates.

This has led us to look more generally at serialization and deserialization within CXXR: the process by which a set of R objects is rendered into a form suitable for saving in a file, and subsequently restored.
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Delegate to each C++ class responsibility for serializing/deserializing objects of that class (instead of having a monolithic `serialize()` function as in CR).

Provide for provenance information to be serialized/deserialized automatically alongside the data to which it relates.

Provide 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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Serialization/Deserialization Objectives

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Outline

1. CXXR
2. The RObject Extensible Class Hierarchy
3. Provenance Tracking and Serialization
4. Conclusion
CXXR is offered as a workbench for you to try your own ideas out.

But volunteers to assist in the development of CXXR itself are also welcome. A conspicuous gap is a Windows port of CXXR: until now it has been tested only on Linux and (to a lesser extent) on MacOS X.
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 $\rightarrow$ object mappings), with hooks to support provenance tracking.
- Expression evaluation. (S3 method dispatch partially refactored; S4 dispatch not yet refactored.)
- Contexts and indirect flows of control (with some loose ends).
- Unary and binary function generics. [-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):

<table>
<thead>
<tr>
<th>Grid size</th>
<th>CR (secs)</th>
<th>CXXR (secs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>32 × 32</td>
<td>0.047</td>
<td>0.053</td>
</tr>
<tr>
<td>64 × 64</td>
<td>0.168</td>
<td>0.191</td>
</tr>
<tr>
<td>128 × 128</td>
<td>0.686</td>
<td>0.743</td>
</tr>
<tr>
<td>256 × 256</td>
<td>3.084</td>
<td>3.004</td>
</tr>
<tr>
<td>512 × 512</td>
<td>33.402</td>
<td>14.239</td>
</tr>
<tr>
<td>1024 × 1024</td>
<td>144.386</td>
<td>60.128</td>
</tr>
</tbody>
</table>

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.
Extending the Class Hierarchy: Example
Multiplying vectors/arrays of arbitrarily large integers

Package R code:

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

Package C++ code:

```cpp
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
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);
  }
}
```