Extending and Embedding R with C++

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Debian & R

Tutorial preceding
R/Finance 2010
Chicago, IL, USA
April 16, 2010
Preliminaries

- We assume a recent version of R so that
  \[\text{install.packages(c("Rcpp","RInside","inline"))}\]
  gets us current versions of the packages.
- All examples shown should work 'as is' on Linux, OS X and Windows provided a complete R development environment.
- The *R Installation and Administration* manual is an excellent start if you need to address the preceding point.
- In particular, one must use the same compilers used to build R in order to extend or embed the R engine.
- However, there is a known issue with the current RInside / Rcpp on Windows; but releases 0.2.1 and 0.7.1 do work.
Oh, and about the initial title ...

Extending and Embedding \textit{R} with C++ for Fun and Profit

Outline

1. Extending R
   - Why?
   - The standard API
   - Inline

2. Rcpp
   - Overview
   - New API
   - Examples

3. Rcpp Usage Examples
   - RInside
   - Others

4. Summary
   - Key points
   - Resources
Chambers (2008) opens chapter 11 (Interfaces I: Using C and Fortran) with these words:

Since the core of R is in fact a program written in the C language, it’s not surprising that the most direct interface to non-R software is for code written in C, or directly callable from C. All the same, including additional C code is a serious step, with some added dangers and often a substantial amount of programming and debugging required. You should have a good reason.
Chambers (2008) then proceeds with this rough map of the road ahead:

**Against:**
- It’s more work
- Bugs will bite
- Potential platform dependency
- Less readable software

**In Favor:**
- New and trusted computations
- Speed
- Object references

So is the deck stacked against us?
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R offers several functions to access compiled code: we focus on `.C` and `.Call` here. (*R Extensions*, sections 5.2 and 5.9; *Software for Data Analysis*).

The canonical example is the convolution function:

```c
void convolve(double *a, int *na, double *b, 
               int *nb, double *ab)
{
    int i, j, nab = *na + *nb - 1;

    for(i = 0; i < nab; i++)
        ab[i] = 0.0;

    for(i = 0; i < *na; i++)
        for(j = 0; j < *nb; j++)
            ab[i + j] += a[i] * b[j];
}
```
Compiled Code: The Basics cont.

The convolution function is called from R by

```r
conv <- function(a, b)
  .C("convolve",
      as.double(a),
      as.integer(length(a)),
      as.double(b),
      as.integer(length(b)),
      ab = double(length(a) + length(b) - 1))$ab
```

As stated in the manual, one must take care to coerce all the arguments to the correct R storage mode before calling `.C` as mistakes in matching the types can lead to wrong results or hard-to-catch errors.
Example 1: Running the convolution code via `.C`
All these files are at http://dirk.eddelbuettel.com/code/rcppTut

- Turn the C source file into a dynamic library using
  ```
  R CMD SHLIB convolve.C.c
  ```

- Load it inside an R script or session using
  ```
  dyn.load("convolve.C.so")
  ```

- Use it via the `.C()` interface as shown on previous slide

- All together in a helper file `convolve.C.sh`
  ```
  #!/bin/sh

  R CMD SHLIB convolve.C.c

  cat convolve.C.call.R | R --no-save
Using `.Call`, the example becomes

```c
#include <R.h>
#include <Rdefines.h>

extern "C" SEXP convolve2(SEXP a, SEXP b)
{
  int i, j, na, nb, nab;
  double *xa, *xb, *xab;
  SEXP ab;

  PROTECT(a = AS_NUMERIC(a));
  PROTECT(b = AS_NUMERIC(b));
  na = LENGTH(a); nb = LENGTH(b); nab = na + nb - 1;
  PROTECT(ab = NEW_NUMERIC(nab));
  xa = NUMERIC_POINTER(a); xb = NUMERIC_POINTER(b);
  xab = NUMERIC_POINTER(ab);

  for(i = 0; i < nab; i++) xab[i] = 0.0;
  for(i = 0; i < na; i++)
    for(j = 0; j < nb; j++) xab[i + j] += xa[i] * xb[j];
  UNPROTECT(3);
  return(ab);
}
```
Now the call simplifies to just the function name and the vector arguments—all other handling is done at the C/C++ level:

```r
conv <- function(a, b) .Call("convolve2", a, b)
```

In summary, we see that

- there are different entry points
- using different calling conventions
- leading to code that may need to do more work at the lower level.
Example 2: Running the convolution code via `.Call`

- Turn the C source file into a dynamic library using
  ```
  R CMD SHLIB convolve.Call.c
  ```

- Load it inside an R script or session using
  ```
  dyn.load("convolve.Call.so")
  ```

- Use it via the `.Call()` interface as shown previously

- All together in a helper file `convolve.Call.sh`
  ```
  #!/bin/sh

  R CMD SHLIB convolve.Call.c

  cat convolve.Call.call.R | R --no-save
  ```
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inline is a package by Oleg Sklyar et al that provides the function cfunction which can wrap Fortran, C or C++ code.

```r
## A simple Fortran example

code <- "
  integer i
  do 1 i=1, n(1)
    1 x(i) = x(i)**3
  
" 
cubefn <- cfunction(signature(n="integer", x="numeric"),
                     code, convention=".Fortran")

x <- as.numeric(1:10)
n <- as.integer(10)
cubefn(n, x)$x
```

cfunction takes care of compiling, linking, loading, ... by placing the resulting dynamically-loadable object code in the per-session temporary directory used by R.
Example 3: Convolution via `.C` with inline

Using the file `convolve.C.inline.R`

```r
require(inline)

code <- "int i, j, nab = *na + *nb - 1;

    for (i = 0; i < nab; i++)
        ab[i] = 0.0;

    for (i = 0; i < *na; i++) {
        for (j = 0; j < *nb; j++)
            ab[i + j] += a[i] * b[j];
    }
"

fun <- cfunction(signature(a="numeric", na="numeric",
                            b="numeric", nb="numeric",
                            ab="numeric"),
                 code, language="C", convention=".C")

fun(1:10, 10, 10:1, 10, numeric(19))$ab
```
Example 4: Convolution via `.Call` with inline

Using the file `convolve.Call.inline.R`

```r
require(inline)

code <- "
  int i, j, na, nb, nab;
  double *xa, *xb, *xab;
  SEXP ab;

  PROTECT(a = AS_NUMERIC(a)); PROTECT(b = AS_NUMERIC(b));
  na = LENGTH(a); nb = LENGTH(b); nab = na + nb - 1;
  PROTECT(ab = NEW_NUMERIC(nab));

  xa = NUMERIC_POINTER(a); xb = NUMERIC_POINTER(b);
  xab = NUMERIC_POINTER(ab);
  for (i = 0; i < nab; i++) xab[i] = 0.0;

  for (i = 0; i < na; i++)
    for (j = 0; j < nb; j++)
      xab[i + j] += xa[i] * xb[j];

  UNPROTECT(3);
  return(ab);
"

fun <- cfunction(signature(a="numeric", b="numeric"),
    code, language="C")

fun(1:10, 10:1)
```
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In a nutshell:

- **Rcpp** makes it easier to interface C++ and R code.

- Using the `.Call` interface, we can use features of the C++ language to automate the tedious bits of the macro-based C-level interface to R.

- One major advantage of using `.Call` is that richer R objects (vectors, matrices, lists, ... in fact most SEXP types incl functions, environments etc) can be passed directly between R and C++ without the need for explicit passing of dimension arguments.

- By using the C++ class layers, we do not need to manipulate the SEXP objects using any of the old-school C macros.

- `inline` eases usage, development and testing.
Example 5: Convolution using classic Rcpp

Using the file `convolve.Call.Rcpp.classic.R`

```r
require(inline)

code <-'
RcppVector<double> xa(a);
RcppVector<double> xb(b);

int nab = xa.size() + xb.size() - 1;
RcppVector<double> xab(nab);
for (int i = 0; i < nab; i++) xab(i) = 0.0;

for (int i = 0; i < xa.size(); i++)
  for (int j = 0; j < xb.size(); j++)
    xab(i + j) += xa(i) * xb(j);

RcppResultSet rs;
rs.add("ab", xab);
return rs.getReturnList();
'

fun <- cfunction(signature(a="numeric", b="numeric"),
     code, Rcpp=TRUE)
fun(1:10, 10:1)
```
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Rcpp was significantly extended over the last few months to permit more natural expressions. Consider this comparison between the R API and the new Rcpp API:

```
1 SEXP ab;
2 PROTECT(ab = allocVector(STRSXP, 2));
3 SET_STRING_ELT(ab, 0, mkChar("foo"));
4 SET_STRING_ELT(ab, 1, mkChar("bar"));
5 UNPROTECT(1);
```

```
1 CharacterVector ab(2);
2 ab[0] = "foo";
3 ab[1] = "bar";
```

Data types, including STL containers and iterators, can be nested and other niceties. Implicit converters allow us to combine types:

```
1 std::vector<double> vec;
2 [...]  
3 List x(3);
4 x[0] = vec;
5 x[1] = "some text";
6 x[2] = 42;
```

```
// With Rcpp 0.7.11 or later we can do:
1 std::vector<double> vec;
2 [...]  
3 List x = List::create(vec,  
4 "some text",  
5 42);
```
In R, functional programming is easy:

```r
R> data(faithful); lapply(faithful, summary)

$eruptions
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.60   2.16    4.00  3.49    4.45   5.10

$waiting 
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
 43.0   58.0    76.0  70.9    82.0   96.0
```

We can do that in C++ as well and pass the R function down to the data that we let the STL iterate over:

```cpp
src <- function (signature(data="list", fun = "function"), src, Rcpp = TRUE) {
  Rcpp::Function f(fun);
  Rcpp::List output(input.size());
  std::transform(input.begin(), input.end(), output.begin(), f);
  output.names() = input.names();
  return output;
}
cpp_lapply <- cfunction(signature(data="list", fun = "function"), src, Rcpp = TRUE)
```
Automatic catching and conversion of C++ exceptions:

```r
R> library(Rcpp); library(inline)
R> cpp <- 'Rcpp::NumericVector x(xs); // automatic conversion from SEXP
R> for (int i=0; i<x.size(); i++) {
R>   if (x[i] < 0)
R>     throw std::range_error("Non-negative values required");
R>   x[i] = log(x[i]);
R> }
R> return x; // automatic conversion to SEXP
'
R> fun <- cfunction(signature(xs="numeric"), cpp, Rcpp=TRUE)
R> fun( seq(2, 5) )

[1] 0.6931 1.0986 1.3863 1.6094

R> fun( seq(5, -2) )
Error in fun(seq(5, -2)) : Non-negative values required
R> fun( LETTERS[1:5] )
Error in fun(LETTERS[1:5]) : not compatible with INTSXP
R>
```
Example 6: Convolution using new Rcpp

Using the file `convolve.Call.Rcpp.new.R`

```r
require(inline)

code <- '
  Rcpp::NumericVector xa(a); // automatic conversion from SEXP
  Rcpp::NumericVector xb(b);

  int n_xa = xa.size();
  int n_xb = xb.size();
  int nab = n_xa + n_xb - 1;

  Rcpp::NumericVector xab(nab);

  for (int i = 0; i < n_xa; i++)
    for (int j = 0; j < n_xb; j++)
      xab[i + j] += xa[i] * xb[j];

  return xab; // automatic conversion to SEXP
',

fun <- cfunction(signature(a="numeric", b="numeric"),
  code, Rcpp=TRUE)

fun(1:10, 10:1)
```
In a recently-submitted paper, the following table summarises the performance of convolution examples:

<table>
<thead>
<tr>
<th>Implementation</th>
<th>Time in millisec</th>
<th>Relative to R API</th>
</tr>
</thead>
<tbody>
<tr>
<td>R API (as benchmark)</td>
<td>32</td>
<td></td>
</tr>
<tr>
<td>RcppVector&lt;double&gt;</td>
<td>354</td>
<td>11.1</td>
</tr>
<tr>
<td>NumericVector::operator[]</td>
<td>52</td>
<td>1.6</td>
</tr>
<tr>
<td>NumericVector::begin</td>
<td>33</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Table 1: Performance for convolution example

We averaged 1000 replications with two 100-element vectors – see examples/ConvolveBenchmarks/ in Rcpp for details.
Regression is a key component of many studies. In simulations, we often want to run a very large number of regressions.

R has `lm()` as the general purposes function. It is very powerful and returns a rich object—but it is not *lightweight*.

For this purpose, R has `lm.fit()`. But, this does not provide all relevant auxiliary data as e.g. the standard error of the estimate.

For the most recent *Introduction to High-Performance Computing with R* tutorial, I had written a hybrid R/C/C++ solution using the GNU GSL.

We complement this with a new C++ implementation around the Armadillo linear algebra classes.
Linear regression via GSL: lmGSL()

See the directory Rcpp/examples/FastLM

```r
lmGSL <- function() {
  src <- 'RcppVectorView<double> Yr(Ysexp);
  RcppMatrixView<double> Xr(Xsexp);

  int i, j, n = Xr.dim1(), k = Xr.dim2();
  double chi2;

  gsl_matrix *X = gsl_matrix_alloc(n, k);
  gsl_vector *y = gsl_vector_alloc(n);
  gsl_vector *c = gsl_vector_alloc(k);
  gsl_matrix *cov = gsl_matrix_alloc(k, k);

  for (i = 0; i < n; i++) {
    for (j = 0; j < k; j++) {
      gsl_matrix_set(X, i, j, Xr(i, j));
    }
    gsl_vector_set(y, i, Yr(i));
  }

  gsl_multifit_linear_workspace *wk =
    gsl_multifit_linear_alloc(n, k);
  gsl_multifit_linear(X, y, c, cov, &chi2, wk);
  gsl_multifit_linear_free (wk);
  RcppVector<double> StdErr(k);
  RcppVector<double> Coef(k);

  for (i = 0; i < k; i++) {
    Coef(i) = gsl_vector_get(c, i);
    StdErr(i) =
      sqrt(gsl_matrix_get(cov, i, i));
  }

  gsl_matrix_free (X);
  gsl_vector_free (y);
  gsl_vector_free (c);
  gsl_matrix_free (cov);

  RcppResultSet rs;
  rs.add("coef", Coef);
  rs.add("stderr", StdErr);

  return = rs.getReturnValue();
}
```

```c
for (i = 0; i < n; i++) {
  Coef(i) = gsl_vector_get(c, i);
  StdErr(i) =
    sqrt(gsl_matrix_get(cov, i, i));
}
```

gsl_matrix_free (X);

gsl_vector_free (y);
gsl_vector_free (c);
gsl_matrix_free (cov);

RcppResultSet rs;
rs.add("coef", Coef);
rs.add("stderr", StdErr);

return = rs.getReturnValue();
```
Linear regression via Armadillo: lmArmadillo example

Also see the directory Rcpp/examples/FastLM

```r
lmArmadillo <- function() {
  src <- '
  Rcpp::NumericVector yr(Ysexp);
  Rcpp::NumericVector Xr(Xsexp);  // actually an n x k matrix
  std::vector<int> dims = Xr.attr("dim");
  int n = dims[0], k = dims[1];
  arma::mat X(Xr.begin(), n, k, false);  // use advanced armadillo constructors
  arma::colvec y(yr.begin(), yr.size());
  arma::colvec coef = solve(X, y);  // model fit
  arma::colvec resid = y - X*coef;  // to comp. std.errr of the coefficients
  arma::mat covmat = trans(resid)*resid/(n-k) * arma::inv(arma::trans(X)*X);

  Rcpp::NumericVector coefr(k), stderrestr(k);
  for (int i=0; i<k; i++) {
    coefr[i] = coef[i];  // this would not be needed but we only
    stderrestr[i] = sqrt(covmat(i,i));  // have Rcpp.h here
  }

  return Rcpp::List::create( Rcpp::Named("coefficients", coefr),  // Rcpp 0.7.11
                            Rcpp::Named("stderr", stderrestr));
}

## turn into a function that R can call
fun <- cfunction(signature(Ysexp="numeric", Xsexp="numeric"),
  src, includes="#include <armadillo>", Rcpp=TRUE,
  cppargs="-I/usr/include", libargs="-larmadillo")
```
Linear regression via Armadillo: RcppArmadillo

See `fastLm` in the RcppArmadillo package

`fastLm` in the new RcppArmadillo does even better:

```cpp
#include <RcppArmadillo.h>

extern "C" SEXP fastLm(SEXP ys, SEXP Xs)
{
    Rcpp::NumericVector yr(ys);  // creates Rcpp vector from SEXP
    Rcpp::NumericMatrix Xr(Xs);  // creates Rcpp matrix from SEXP
    int n = Xr.nrow(), k = Xr.ncol();

    arma::mat X(Xr.begin(), n, k, false);  // reuses memory and avoids extra copy
    arma::colvec y(yr.begin(), yr.size(), false);

    arma::colvec coef = arma::solve(X, y);    // fit model y ~ X
    arma::colvec resid = y - X*coef;          // residuals

    double sig2 = arma::as_scalar(arma::trans(resid)*resid/(n-k));  // std.err est
    arma::colvec sdest = arma::sqrt(sig2*arma::diagvec(arma::inv(arma::trans(X)*X)));

    return Rcpp::List::create(  // requires Rcpp 0.7.11
        Rcpp::Named("coefficients") = coef,
        Rcpp::Named("stderr") = sdest
    );
}
```
Rcpp Example: Regression timings

Comparison of R and linear model fit routines

The small `longley` example exhibits less variability between methods, but the larger data set shows the gains more clearly.

For the small data set, all three appear to improve similarly on `lm`.

Source: Our calculations, see `examples/FastLM/` in Rcpp.
Comparison of R and linear model fit routines

By dividing the `lm` time by the respective times, we obtain the ’possible gains’ from switching.

One caveat, measurements depends critically on the size of the data as well as the cpu and libraries that are used.

Source: Our calculations, see examples/FastLM/ in Rcpp.
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Jeff Horner’s work on RApache lead to joint work in littler, a scripting / cmdline front-end. As it embeds R and simply ’feeds’ the REPL loop, the next step was to embed R in proper C++ classes: RInside.

```cpp
#include <RInside.h> // for the embedded R via RInside

int main(int argc, char *argv[]) {
    RInside R(argc, argv); // create an embedded R instance
    R["txt"] = "Hello, world!\n"; // assign a char* (string) to 'txt'
    R.parseEvalQ("cat(txt)"); // eval the init string, ignoring any returns
    exit(0);
}
```
Another simple example
See RInside/standard/rinside_sample8.cpp (in SVN, older version in pkg)

This example shows some of the new assignment and converter code:

```cpp
#include <RInside.h> // for the embedded R via RInside

int main(int argc, char *argv[]) {
    RInside R(argc, argv); // create an embedded R instance
    R["x"] = 10;
    R["y"] = 20;
    R.parseEvalQ("z <- x + y");
    int sum = R["z"];
    std::cout << "10 + 20 = " << sum << std::endl;
    exit(0);
}
```
A finance example

See the file `RInside/standard/rinside_sample4.cpp (edited)`

```cpp
#include <RInside.h> // for the embedded R via RInside
#include <iomanip>

int main(int argc, char *argv[]) {
  RInside R(argc, argv); // create an embedded R instance
  SEXP ans;
  R.parseEvalQ("suppressMessages(library(fPortfolio))");
  txt = "lppData <- 100 * LPP2005.RET[, 1:6];"
    "ewSpec <- portfolioSpec(); nAssets <- ncol(lppData); ";
  R.parseEval(txt, ans); // prepare problem
  const double dvec[6] = { 0.1, 0.1, 0.1, 0.1, 0.3, 0.3 }; // weights
  const std::vector<double> w(dvec, &dvec[6]);
  R.assign(w, "weightsvec"); // assign STL vec to R's 'weightsvec'
  
  R.parseEvalQ("setWeights(ewSpec) <- weightsvec");
  txt = "ewPortfolio <- feasiblePortfolio(data = lppData, spec = ewSpec,"
    "constraints = \"LongOnly\")";
    "print(ewPortfolio);
    "vec <- getCovRiskBudgets(ewPortfolio@portfolio)"
  ans = R.parseEval(txt); // assign covRiskBudget weights to ans
  Rcpp::NumericVector V(ans); // convert SEXP variable to an RcppVector
  ans = R.parseEval("names(vec)"); // assign columns names to ans
  Rcpp::CharacterVector n(ans);

  for (int i=0; i<names.size(); i++) {
    std::cout << std::setw(16) << n[i] << "\t" << std::setw(11) << V[i] << "\n";
  }
  exit(0);
}
```

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Extending and Embedding R with C++ @ R/Finance 2010
And another *parallel* example

See the file `RInside/mpi/rinside_mpi_sample2.cpp`

```plaintext
// MPI C++ API version of file contributed by Jianping Hua

#include <mpi.h>    // mpi header
#include <RInside.h> // for the embedded R via RInside

int main(int argc, char *argv[]) {
    MPI::Init(argc, argv);  // mpi initialization
    int myrank = MPI::COMM_WORLD.Get_rank();  // obtain current node rank
    int nodesize = MPI::COMM_WORLD.Get_size(); // obtain total nodes running.

    RInside R(argc, argv);  // create an embedded R instance

    std::stringstream txt;
    txt << "Hello from node " << myrank
        << " of " << nodesize << " nodes!" << std::endl;
    R.assign(txt.str(), "txt");  // assign string to R variable 'txt'

    std::string evalstr = "cat(txt)"; // show node information
    R.parseEvalQ(evalstr);  // eval the string, ign. any returns

    MPI::Finalize();  // mpi finalization

    exit(0);
}
```
C++ programs compute, gather or aggregate raw data.
Data is saved and analysed before a new 'run' is launched.
With **RInside** we now skip a step:
- collect data in a vector or matrix
- pass data to **R** — easy thanks to **Rcpp** wrappers
- pass one or more short 'scripts' as strings to **R** to evaluate
- pass data back to C++ programm — easy thanks to **Rcpp** converters
- resume main execution based on new results

A number of simple examples ship with **RInside**
- *nine* different examples in `examples/standard`
- *four* different examples in `examples/mpi`
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RInside uses Rcpp for object transfer and more
RcppArmadillo (which contains fastLM())
RcppExamples is a ’this is how you can do it’ stanza
RProtoBuf is what got Romain and me here, it may get rewritten to take more advantage of Rcpp
RQuantLib is where Rcpp orginally started
highlight is Romain’s first re-use of Rcpp
mvabund, sdcTable, bifactorial, minqa are truly external users which are all on CRAN
upcoming: pcaMethods (BioC), phylobase, possibly lme4
Your package here next?
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   - RInside
   - Others

4. Summary
   - Key points
   - Resources
This tutorial has tried to show you that

- While the deck way be stacked against you (when adding C/C++ to R), you can still pick where to play
- R can be extended in many ways; we focus on something that allows us write extensions
  - that are efficient: we want speed and features
  - that correspond to the R object model
  - that also allow us to embed R inside C++
- And all this while retaining 'high-level' STL-alike semantics, templates and other goodies in C++
- Using C++ abstractions wisely can keep the code both clean and readable – yet very efficient
Outline

1. Extending R
   - Why?
   - The standard API
   - Inline

2. Rcpp
   - Overview
   - New API
   - Examples

3. Rcpp Usage Examples
   - RInside
   - Others

4. Summary
   - Key points
   - Resources
Some pointers

- http://cran.r-project.org/package=Rcpp
- http://r-forge.r-project.org/projects/rcpp/
- and likewise for RInside, RProtoBuf and more.
Thank you!