Seamless R Extensions using Rcpp and RInside

Dirk Eddelbuettel
Debian & R

Joint work with Romain François

Presentation on March 30, 2010 to
UCLA Department of Statistics (3pm)
Los Angeles R Users Group (6pm)
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
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Motivation

Chambers (2008) opens chapter 11 (Interfaces I: Using C and Fortran) with these words:
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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.
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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. \((R \text{ Extensions}, \text{ sections 5.2 and 5.9}; \ Software \ for \ Data \ Analysis)\).
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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];
}
```
The convolution function is called from R by

\[ \text{convolve}(a, b) \]

As stated in the manual, one must take care to coerce all the arguments to the correct R storage mode before calling \text{C} as mistakes in matching the types can lead to wrong results or hard-to-catch errors.
The convolution function is called from R by

```
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.
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```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)
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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.
Extending R

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2. Others

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Extending R Rcpp Examples Summary

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```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
```
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```r
## A simple Fortran example

code <- 
  "
in t e g e r i 
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" 

cubefn <- cfunction ( signature ( n = "integer" , x = "numeric" ) ,
  code , convention = " . Fortran " )

x <- as.numeric ( 1 : 1 0 )
n <- as.integer ( 1 0 )
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.
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- **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.**
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- **inline** eases usage, development and testing.
Rcpp example

The convolution example can be rewritten in the 'Classic API':

```c++
#include <Rcpp.h>

RcppExport SEXP convolve_cpp(SEXP a, SEXP b) {
  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.getRReturnList();
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Seamless R Extensions using Rcpp + RInside
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:

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Functional programming in both languages

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

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 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 elements we let the STL iterate over:

```
src <- 'Rcpp::List input(data);
    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 )
```
Exception handling

Automatic catching and conversion of C++ exceptions:

```r
library(Rcpp); library(inline)

Rcpp::NumericVector x(xs);  // automatic conversion from SEXP
for (int i=0; i<x.size(); i++) {
  if (x[i] < 0)
    throw std::range_error("Non-negative values required");
  x[i] = log(x[i]);
}
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])
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  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
}
```
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Table 1: Performance for convolution example

We averaged 1000 replications with two 100-element vectors – see examples/ConvolveBenchmarks/ in Rcpp for details.
Another Speed Comparison Example

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For this purpose, R has \texttt{lm.fit()}. But, this does not provide all relevant auxiliary data as \textit{e.g.} the standard error of the estimate.
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For the most recent \textit{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()

```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.getReturnList();
}
```

---

**Note:**

- For use with Debian/Ubuntu, the function signature and `cppargs` include paths should be adjusted.
- The function can handle arguments that are `numeric` types.

---

**About the Example:**

This example demonstrates how to perform linear regression using the GNU Scientific Library (GSL) from Rcpp. The function `lmGSL()` takes two arguments, `Ysexp` and `Xsexp`, representing the dependent and independent variables, respectively. It allocates matrices and vectors for the data, performs the regression, and returns the coefficients and standard errors of the regression coefficients. The code utilizes Rcpp for seamless integration between R and C++.
Linear regression via Armadillo: lmArmadillo example

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

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

  ## 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**

**fastLm in the new RcppArmadillo** does even better:

```c++
#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
  );
}
```

Dirk Eddelbuettel

Seamless R Extensions using Rcpp + RInside
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.
Another Rcpp example (cont.)

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 depend 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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   - Examples

3. Rcpp Usage Examples
   - RInside
   - Others

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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.
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

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

```c
#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);
}
```
And another parallel example

```cpp
#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  // node information
       << " 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);
}
```
RInside workflow

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- A number of simple examples ship with RInside
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- 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
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- [dirk.eddelbuettel.com/code/rcpp.html](http://dirk.eddelbuettel.com/code/rcpp.html)
- [cran.r-project.org/package=Rcpp](http://cran.r-project.org/package=Rcpp)
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- and likewise for RInside, RProtoBuf and more.
The end

Thank you!