Seamless R Extensions using Rcpp and RInside

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Debian & R

Joint work with Romain François

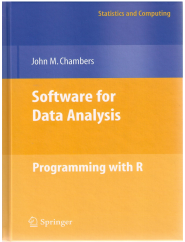
Presentation on March 30, 2010 to
UCLA Department of Statistics (3pm)
Los Angeles R Users Group (6pm)

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

Outline

Motivation



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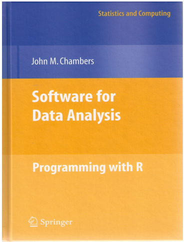

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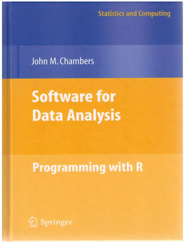

Chambers. *Software for Data Analysis: Programming with R.* Springer, 2008

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.*

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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 Extensions*, sections 5.2 and 5.9; *Software for Data Analysis*).

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The canonical example is the convolution function:

```
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.

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```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.

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```
#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);
}
```

Compiled Code: The Basics cont.

Now the call simplifies to just the function name and the vector arguments—all other handling is done at the C/C++ level:

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conv <- function(a, b) .Call("convolve2", a, b)
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- using different calling conventions
- leading to code that may need to do more work at the lower level.

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## 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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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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- 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.

Rcpp example

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#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.getReturnList();
}
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[...]
List x(3);
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[...]
List x(3);
x[0] = vec;
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x[2] = 42;
```

```
// With Rcpp 0.7.11 or later we can do:
std::vector<double> vec;
[...]
List x = List::create(vec,
                      "some text",
                      42);
```

Functional programming in both languages

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```
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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```

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:

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```
R> library(Rcpp); library(inline)
R> cpp <- '
+     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] )

Error in fun(LETTERS[1:5]) : not compatible with INTSXP

R>
```

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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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Implementation	Time in millisec	Relative to R API
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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.

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- 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()

```
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();
  '

  ## turn into a function that R can call
  ## args redundant on Debian/Ubuntu
  fun <-
    cfunction(signature(Ysexp="numeric",
      Xsexp="numeric"), src,
      includes=
        "#include <gsl/gsl_multifit.h>",
      Rcpp=TRUE,
      cppargs="-I/usr/include",
      libargs="-lgsl -lgslcblas")
}
```

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), stderrestr(k);
    for (int i=0; i<k; i++) {               // with RcppArmadillo template converters
        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

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

```
#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();

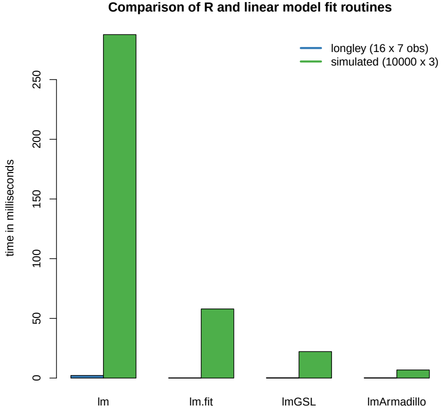
  arma::mat X(Xr.begin(), n, k, false);     // reuses memory and avoids extra copy
  arma::colvec y(yr.begin(), yr.size(), false);

  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

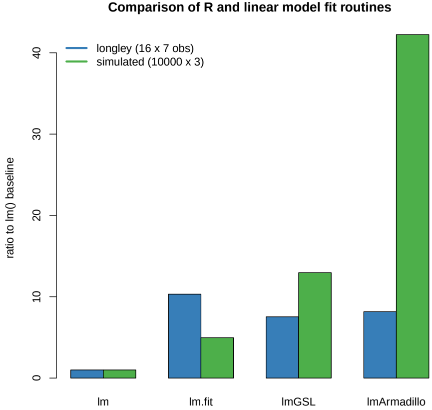


The small `longley` example exhibits less variability between methods, but the larger data set shows the gains more clearly.

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.)



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.

Outline

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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`.

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```
#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:

```
#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

```
// 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             // 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);
}
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- A number of simple examples ship with `RInside`

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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  - 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

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Some pointers

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- and likewise for RInside, RProtoBuf and more.

The end

Thank you!