The Rcpp Package

An Introduction

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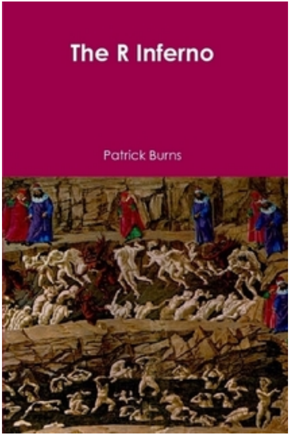
Table of Contents

Table of Contents

Entering the R Inferno

Lasciate ogne speranza, voi ch'iterate



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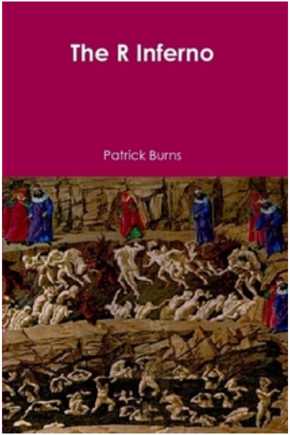

R is both an interactive environment for *data analysis, modeling and visualization* and a language designed to support these tasks.

Most people use R to understand data, few have formal training in software development. Focus on functionality and extensibility, speed is often neglected.

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Vectorization may help, *if you do it properly*.

Using the C Interface

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Long, error-prone and we still cannot use classes and the `STL`!

Table of Contents

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A Simple Example: The Old Way

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

int fibonacci(const int x) {
  if (x == 0) return(0);
  if (x == 1) return(1);
  return fibonacci(x - 1) + fibonacci(x - 2);
}

extern "C" SEXP fibWrapper(SEXP xs) {
  int x = Rcpp::as<int>(xs);
  int fib = fibonacci(x);
  return (Rcpp::wrap(fib));
}
```

↓

```
[gsarti@antergos ~]$ R CMD SHLIB fibo.c
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> dyn.load("fibo.so")
    .Call("fibonacci", as.integer(5))
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## Using a pure C++ function to allow recursive
## calls thanks to C++ identifier.
txt <- '
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fiboRcpp <- cxxfunction(signature(xs="int"),
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Still using `as` an `wrap` functions from the original `C API` through the `inline` package, still not intuitive enough.

A Simple Example: The Modern Way

```
// Inside fibo.cpp
#include <Rcpp.h>
using namespace Rcpp;

// [[Rcpp::export]]
int fibonacci1(const int x) {
  if (x == 0) return(0);
  if (x == 1) return(1);
  return fibonacci(x - 1) + fibonacci(x - 2);
}

// [[Rcpp::export]]
int fibonacci2(const int x) {
  if (x < 2) return x;
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// Inside the R file calling fibonacci
sourceCpp("fibo.cpp")
fibonacci1(20)
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Run-time performance of the recursive Fibonacci examples

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A caching mechanism ensures a single compilation of the code.

Table of Contents

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`SEXP` objects should be considered opaque, i.e. should be accessed only by macros provided by the `R API`. In this sense `Rcpp API` provides an higher level of abstraction

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We can think of an `RObject` as wrapper around the `SEXP` structure (In fact, the `SEXP` is indeed the only data member of an `RObject`)

The main idea is that all the functions that directly access the `SEXP` object are implemented in this class, this gives the user a much more transparent way to interact with `R` internals.

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- Numeric Vector: corresponds to the basic `R` type of a numeric vector and can hold real-valued floating-point variables.
- Integer Vector: Provides a natural mapping from and to the standard `R` integer vectors.

Other Vector Classes

Other common used vector classes are:

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Another useful feature of the vector family is the the presence of already implemented iterators, which gives full compatibility with the `C++` STL methods.

Named and List

The Named class is an helper class used for setting the key side of key/value pairs. It corresponds to R's c() map construct.

```
Rcpp::NumericVector x =
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The Generic Vector class is the equivalent of the `List` type in R. It can contain objects of different types, including other generic vectors. Because of its flexibility it is commonly used to parameter exchanges in either directions.

Function and Dataframe

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The Dataframe class is, much like its `R` counterpart, implemented as lists constrained to have elements of the same length. However, while `R` dataframes can *recycle*, i.e. elements of the shorter columns can be repeated until a valid `Dataframe` structure is obtained, this is not possible in `Rcpp` dataframes and will raise an exception.

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Namespaces are implemented using environments, and environment enable the use of *closures* as the standard for functions in R.

The R Object Oriented System

There are three main object systems in R:

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- S4 are just S3 objects with more formalism. They have a rigorous definition of attributes and inheritance, and have helper functions for defining generics and methods.
- RC implements message-passing object orientation. RC objects are also mutable: they dont use Rs usual copy-on-modify semantics, but are modified in place.

S4 and RC

The `Rcpp S4` class allows access and modification of `S4` objects attributes, allowing to test if an `RObject` is a `S4`. Nevertheless, it is a good practice to manipulate the object and isolate the interesting attributes directly in `R`, and then carry out the computations in `Rcpp` using simpler types.

The `Rcpp RC` class provides a natural interface for `R RC` classes. It is mostly used for mutable data-structures, particularly those that deal with graphics and stream of data. However, `RC` is not a common data-type and it is not firmly established in the community.

Table of Contents

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- basic math functions: `abs()`, `log()`, `sin()`, ...

Rcpp Sugar

Rcpp provides a lot of syntactic sugar expressions to ensure that C++ functions work very similarly to their R equivalents. Rcpp sugar makes possible to write efficient C++ code that looks almost identical to its R equivalent.

- arithmetic and logical vectorized operators: $+, *, -, /$, pow, $<, <=, >, >=, ==, != , !$
- logical summary functions: `any()`, `all()`
- scalar summaries: `mean()`, `min()`, `max()`, `sum()`, `sd()`, ...
- vector views: `head()`, `tail()`, `rep_len()`, ...
- basic math functions: `abs()`, `log()`, `sin()`, ...
- distributions: `runif()`, `dnorm()`, ...

Rcpp Sugar: An Example

```r
piR <-function(N)
{
  x <-runif(N)
  y <-runif(N)
  d <-sqrt(x^2+y^2)
  return(4*sum(d <=1.0) /N)
}
```

Rcpp Sugar: An Example

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  x <-runif(N)
  y <-runif(N)
  d <-sqrt(x^2+y^2)
  return(4*sum(d <=1.0) /N)
}
```

```cpp
double piSugar(const int N)
{
  NumericVector x = runif(N);
  NumericVector y = runif(N);
  NumericVector d = sqrt(x*x + y*y);
  return 4.0* sum(d <=1.0) / N;
}
```

Rcpp Sugar: An Example

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{
  x <-runif(N)
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```cpp
double piSugar(const int N)
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  NumericVector x = runif(N);
  NumericVector y = runif(N);
  NumericVector d = sqrt(x*x + y*y);
  return 4.0* sum(d <=1.0) / N;
}
```

The only difference is the type declaration and the missing operator ^ in C++.

Rcpp Sugar: Performances

Table 8.1 Run-time performance of *Rcpp sugar* compared to R and manually optimized C++

R expression	Runs	Manual	Sugar	R
`any(x * y < 0)`	5,000	0.00027	0.00069	6.8914
`ifelse(x<y, x*x, -(y*y))`	500	1.28566	1.52103	13.8829
`ifelse(x<y, x*x, -(y*y))` (noNA)	500	0.41462	1.14434	13.8537
`sapply(x, square)`	500	0.16721	0.19224	115.4236

Sugar functions don't always perform like hand-written ones in `C++` (for now!)

Exposing C++ Classes to R

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- Thanks to the macro `RCPP_MODULE`, that `Rcpp` provides.

Exposing C++ Classes to R

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- Unlike functions, it does not exist an attribute shortcut for classes
- Anyway, it's possible to avoid writing tedious operational code. How?
- Thanks to the macro `RCPP_MODULE`, that `Rcpp` provides.
- It can be used also for exposing functions.

Exposing C++ Classes: An Example

```
using namespace Rcpp;
class Uniform {
public:
    Uniform(double min_, double max_) : min(min_), max(max_) {}

    NumericVector draw(int n) const {
        RNGScope scope;
        return runif( n, min, max );
    }

    double min, max;
};

double uniformRange( Uniform* w) {
    return w->max - w->min;
}
```

Exposing C++ classes: An Example

We just have to choose a name for the module, and declare a name for every class member.

```
RCPP_MODULE(unif_module) {

    class_<Uniform>( "Uniform" )

    .constructor<double,double>()

    .field( "min", &Uniform::min )
    .field( "max", &Uniform::max )

    .method( "draw", &Uniform::draw )
    .method( "range", &uniformRange )
    ;

}
```

Exposing C++ classes: An Example

After compiling the .cpp file as a dynamic library, we load the module in R, and now it's ready to be used like a class.

exposing_classes_3.png

Extending Rcpp

Many packages are available to extend base `Rcpp` functionalities:

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- `RcppEigen`: Interface to the `Eigen` library, a library suited for dealing with matrix decomposition and sparse matrices.

Extending Rcpp

Many packages are available to extend base `Rcpp` functionalities:

- `Rinside`: Embedded `R` in `C++` applications.
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- `RcppEigen`: Interface to the `Eigen` library, a library suited for dealing with matrix decomposition and sparse matrices.

RcppArmadillo: An Example

```
#include<RcppArmadillo.h>

// [[Rcpp::depends(RcppArmadillo)]]

//[[Rcpp::export]]
arma::vec getEigenValues(arma::mat M)
  {
  return arma::eig_sym(M);
  }
```

RcppArmadillo: An Example

```cpp
#include<RcppArmadillo.h>

// [[Rcpp::depends(RcppArmadillo)]]

//[[Rcpp::export]]
arma::vec getEigenValues(arma::mat M)
  {
  return arma::eig_sym(M);
  }
```

```r
> sourceCpp("armadilloExample.cpp")
> X <-matrix(rnorm(4*4), 4, 4)
> Z <- X %*%t(X)
> getEigenValues(Z)
          [,1]
[1,] 0.1033663
[2,] 1.5578299
[3,] 3.0959708
[4,] 8.4696693
```

RcppArmadillo: An Example

```cpp
#include<RcppArmadillo.h>

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```

Notice that using attributes it is possible to declare dependencies on other packages.

Table of Contents

Bootstrap

Definition

Bootstrapping is a type of resampling where large numbers of smaller samples of the same size are repeatedly drawn, with replacement, from a single original sample.

In order to show a possible use case of `Rcpp` in statistics, we will write a function that computes the means and the standard deviations for a set of B samples bootstrapped from an original data set of size n.

Since the process is iterative by definition, we expect a `for` loop in the implementation, which can possibly be optimized by `Rcpp`.

Bootstrap, The R way

```r
bootstrap_r <- function(ds, B = 1000)
 {
  # Preallocate storage for statistics
  boot_stat <- matrix(NA, nrow = B, ncol = 2)

  n <- length(ds)

  # Perform bootstrap
  for(i in seq_len(B))
  {
    # Sample initial data
    gen_data <- ds[ sample(n, n, replace=TRUE) ]

    # Calculate sample data mean and SD
    boot_stat[i,] <- c(mean(gen_data), sd(gen_data))
  }

  # Return bootstrap result
  return(boot_stat)
}
```

Bootstrap, The C++ way

```cpp
#include <Rcpp.h>
using namespace Rcpp;

// [[Rcpp::export]]
Rcpp::NumericMatrix bootstrap_cpp(Rcpp::NumericVector ds, const int B = 1000)
{
  // Preallocate storage for statistics
  Rcpp::NumericMatrix boot_stat(B, 2);

  int n = ds.size();

  // Perform bootstrap
  for(int i = 0; i < B; i++)
  {
    // Sample initial data
    Rcpp::NumericVector gen_data = ds[ floor(Rcpp::runif(n, 0, n)) ];

    boot_stat(i, 0) = mean(gen_data); // sample mean
    boot_stat(i, 1) = sd(gen_data); // sample std dev
  }

  // Return bootstrap results
  return boot_stat;
}
```

Bootstrap Performances

```r
library(Rcpp)
library(rbenchmark)
library(inline)

B <- 10^4
N <- 100
data <- rnorm(n = N, 2, 4) + rnorm(n = N,3,1)

sourceCpp("bootCpp.cpp")
benchmark(r = bootstrap_r(data,B), cpp = bootstrap_cpp(data, B), replications = 10)
```

```
> benchmark(r = bootstrap_r(data,B), cpp = bootstrap_cpp(data, B), replications = 10)
  test replications elapsed relative user.self sys.self user.child sys.child
2  cpp           10   0.305    1.000     0.305        0          0         0
1    r           10   3.032    9.941     3.033        0          0         0
>
```

Our Rcpp approach is almost ten times faster!

Table of Contents

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