Introduction to Rcpp

Dirk Eddelbuettel

Invited Seminar, King Abdullah University of Science and Technology (KAUST), Saudi Arabia

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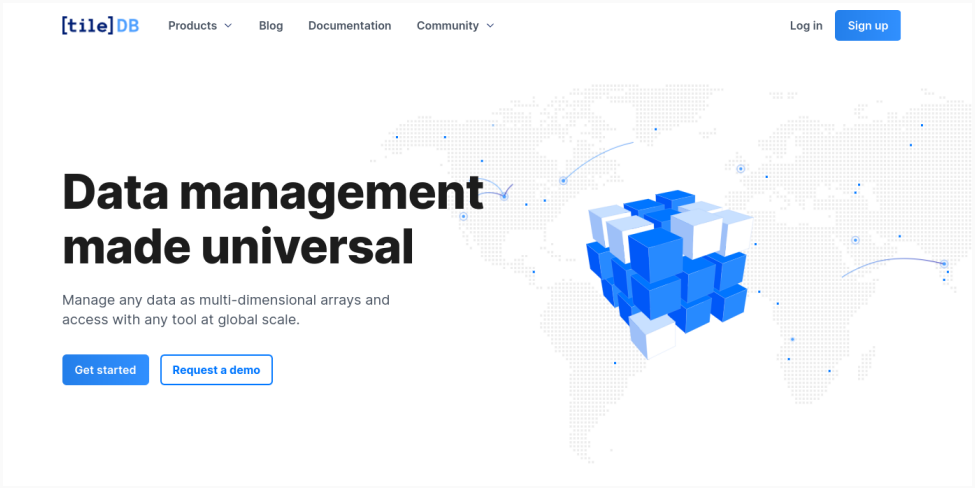
ILLINOIS

https://dirk.eddelbuettel.com/papers/kaust_rcppIntro_nov2022.pdf

Who am I ?

My day job



And we are hiring!

My other jobs

Academic

- (Adjunct) Clinical Professor, University of Illinois
  - developed and teaching Data Science Programming Methods class

Open Source

- Debian developer since 1995, currently maintaining about 185 packages
- R package author since 2002, author or maintainer of over 60 CRAN packages
- R Foundation Board Member, JSS Associate Editor
- Rocker Project co-founder: Docker for R, including official 'r-base' image

Introduction to Rcpp

Very Broad Outline

Overview

- Why ?
- How ?

Introduction: Why?

So why Rcpp?

Three key reasons

- Speed and Performance are key reasons
- We also can do some things you could not do before
- And it is easy (or 'easier') to extend R this way

Simple Example

R Version of 'is this number odd or even'

```
isOdd_r <- function(num = 10L) {
   result = (num %% 2L == 1L)
   return(result)
}
isOdd_r(42L)
```

```
## [1] FALSE
```

Simple Example (cont.)

C++ Version of 'is this number odd or even'

```cpp
bool isOdd_cpp(int num = 10) {
    bool result = (num % 2 == 1);
    return result;
}
```

Free-standing code, not yet executable, may need `Makefile`, ...

Simple Example (cont.)

Rcpp Version of 'is this number odd or even'

```
Rcpp::cppFunction("
bool isOdd_cpp(int num = 10) {
   bool result = (num % 2 == 1);
   return result;
}")
isOdd_cpp(42L)
```

```
## [1] FALSE
```

Simple Example (cont.)

In R

```
##
isOdd_r <- function(n=10L) {
   res = (n %% 2L == 1L)
   return(res)
}
isOdd_r(42L)
```

```
## [1] FALSE
```

In C++ via Rcpp

```
Rcpp::cppFunction("
bool isOdd_cpp(int n=10) {
   bool res = (n % 2 == 1);
   return res;
}")
isOdd_cpp(42L)
```

```
## [1] FALSE
```

Second Example: VAR(1)

Let's consider a very simple VAR(1) system of k variables.

For $k = 2$:

$$X_t = X_{t-1}B + E_t$$

where X_t is a row vector of length 2,
B is a 2 by 2 matrix and
E_t is a row of the error matrix of 2 columns.

Second Example: VAR(1)

In R code, given both the coefficient and error matrices (revealing k and n):

```
rSim <- function(B,E) {
    X <- matrix(0,nrow(E), ncol(E))
    for (r in 2:nrow(E)) {
        X[r,] = X[r-1, ] %*% B + E[r, ]
    }
    return(X)
}
```

Second Example: VAR(1)

```
library(Rcpp)
cppFunction('arma::mat cppSim(arma::mat B, arma::mat E) {
    int m = E.n_rows;
    int n = E.n_cols;
    arma::mat X(m,n);
    X.row(0) = arma::zeros<arma::mat>(1,n);
    for (int r=1; r<m; r++) {
        X.row(r) = X.row(r-1) * B + E.row(r);
    }
    return X;
}', depends="RcppArmadillo")
```

Second Example: VAR(1)

```
library(rbenchmark)
a <- matrix(c(0.5,0.1,0.1,0.5),nrow=2)
e <- matrix(rnorm(10000),ncol=2)
benchmark(cppSim(a,e), rSim(a,e), order="relative")[,1:4]
```

```
##           test replications elapsed relative
## 1 cppSim(a, e)          100   0.011    1.000
## 2   rSim(a, e)          100   0.691   62.818
```

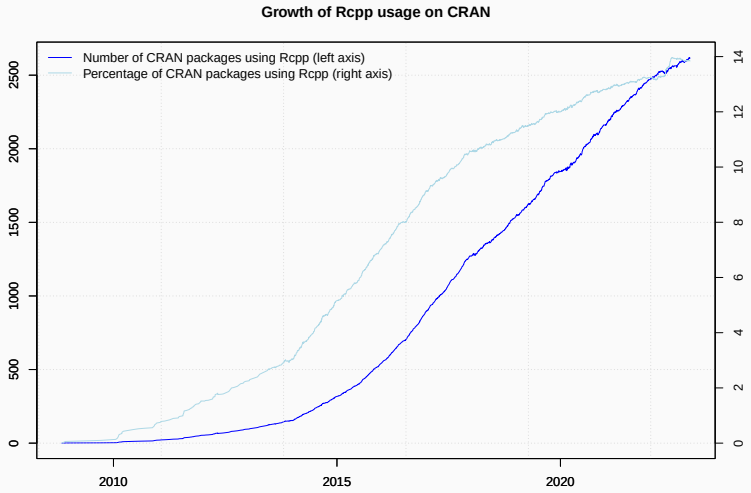
So when do we use Rcpp?

New things: Easy access to C/C++ libraries

- Sometimes speed is not the only reason
- C & C++ provide numerous libraries + APIs we may want to use
- Easy to provide access to as Rcpp eases data transfer

An Aside

Growth



Data current as of November 27, 2022.

Users on Core Repositories

Rcpp is currently used by

- 2616 CRAN packages
- 252 BioConductor packages
- an unknown (but “large”) number of GitHub projects

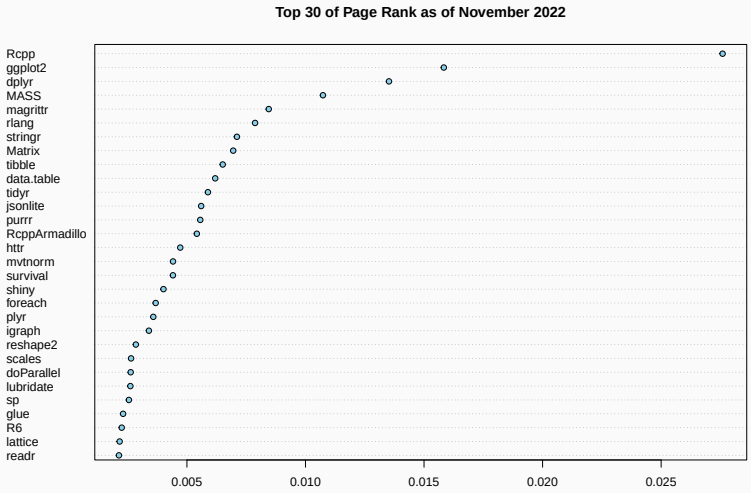
Pagerank

```
suppressMessages(library(utils))
library(pagerank)   # cf github.com/andrie/pagerank

cran <- "https://cran.r-project.org"
pr <- compute_pagerank(cran)
round(100*pr[1:5], 3)
```

```
##     Rcpp  ggplot2    dplyr     MASS magrittr
##    2.764    1.584    1.353    1.073    0.844
```

Pagerank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scales
doParallel
lubridate
sp
glue
R6
lattice
readr
0.005
0.010
0.015
0.020
0.025

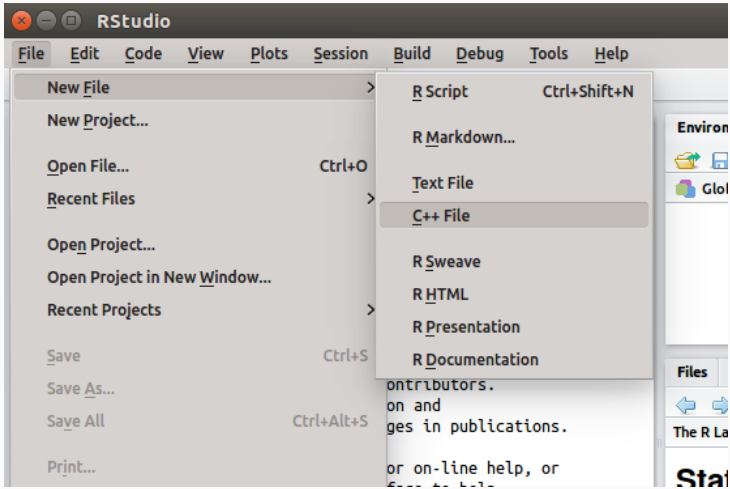
Percentage of Compiled Packages

```
db <- tools::CRAN_package_db()   # added in R 3.4.0
db <- db[!duplicated(db[,1]),]   # rows: nb of pkgs,
nTot <- nrow(db)                 # cols: different attributes
nRcpp <- length(tools::dependsOnPkgs("Rcpp",recursive=FALSE, installed=db))
nCompiled <- table(db[, "NeedsCompilation"])["yes"]
propRcpp <- nRcpp / nCompiled * 100
data.frame(tot=nTot, totRcpp = nRcpp, totCompiled = nCompiled,
           RcppPctOfCompiled = propRcpp)
```

```
##     tot totRcpp totCompiled RcppPctOfCompiled
## 1 18898    2616        4456           58.7074
```

Introduction: How?

Jumping Right In: Via RStudio



A First Example: Cont'ed

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

// This is a simple example of exporting a C++ function to R. You can source this function into
// an R session using the Rcpp::sourceCpp function (or via the Source button on the editor toolbar).

// [[Rcpp::export]]
NumericVector timesTwo(NumericVector x) {
  return x * 2;
}

// You can include R code blocks in C++ files processed with sourceCpp (useful for testing and
// development). The R code will be automatically  run after the compilation.

/*** R
timesTwo(42)
*/
```

A First Example: Cont'ed

So what just happened?

- We defined a very simple C++ function
- It operates on a numeric vector argument
- We ask Rcpp to 'source it' for us:
  - Behind the scenes Rcpp creates a wrapper
  - Rcpp then compiles, links, and loads the wrapper
- The function becomes available in R under the same name as the C++ function

Another Example: Focus on Speed

Consider a function defined as

$$f(n) \quad \text{such that} \quad \begin{cases} n & \text{when } n < 2 \\ f(n-1) + f(n-2) & \text{when } n \geq 2 \end{cases}$$

R implementation and use:

```
f <- function(n) {
    if (n < 2) return(n)
    return(f(n-1) + f(n-2))
}

## Using it on first 11 arguments
sapply(0:10, f)
```

```
##  [1]  0  1  1  2  3  5  8 13 21 34 55
```

An Introductory Example: Timing R Implementation

Timing:

```
library(rbenchmark)
benchmark(f(10), f(15), f(20))[,1:4]
```

```
##    test replications elapsed relative
## 1 f(10)          100   0.008    1.000
## 2 f(15)          100   0.098   12.250
## 3 f(20)          100   1.141  142.625
```

An Introductory Example: C++ Implementation

C(++) Code

```
int g(int n) {
    if (n < 2) return(n);
    return(g(n-1) + g(n-2));
}
```

Deployed as

```
Rcpp::cppFunction('int g(int n) {
   if (n < 2) return(n);
   return(g(n-1) + g(n-2));
}')
## Using it on first 11 arguments
sapply(0:10, g)
```

```
##  [1]  0  1  1  2  3  5  8 13 21 34 55
```

An Introductory Example: Comparing timing

Timing:

```
library(rbenchmark)
benchmark(f(20), g(20))[,1:4]
```

```
##    test replications elapsed relative
## 1 f(20)          100   1.172      586
## 2 g(20)          100   0.002        1
```

A nice gain of a few orders of magnitude.

Some Background

R Type mapping

Standard R types (integer, numeric, list, function, ... and compound objects) are mapped to corresponding C++ types using extensive template meta-programming – it just works:

```
library(Rcpp)
cppFunction("NumericVector la(NumericVector x){
  return log(abs(x));
}")
la(seq(-5, 5, by=2))
```

Also note: vectorized C++! `log(abs())` on vectors as R would.

STL Type mapping

Use of `std::vector<double>` and STL algorithms:

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

inline double f(double x) { return ::log(::fabs(x)); }

// [[Rcpp::export]]
std::vector<double> logabs2(std::vector<double> x) {
  std::transform(x.begin(), x.end(), x.begin(),  f);
  return x;
}
```

Not vectorized but `std::transform()` 'sweeps' `f()` across.

STL Type mapping

Used via

```
library(Rcpp)
sourceCpp("code/logabs2.cpp")
logabs2(seq(-5, 5, by=2))
```

Type mapping is seamless

Simple outer product of a col. vector (using RcppArmadillo):

```
library(Rcpp)
cppFunction("arma::mat v(arma::colvec a) { return a*a.t(); }",
            depends="RcppArmadillo")
v(1:3)
```

```
##      [,1] [,2] [,3]
## [1,]    1    2    3
## [2,]    2    4    6
## [3,]    3    6    9
```

Uses implicit conversion via `as<>` and `wrap` – cf vignette Rcpp-extending.

We can simplify the `log(abs(...))` example further:

```
#include <Rcpp.h>
// [[Rcpp::plugins(cpp11)]]

using namespace Rcpp;

// [[Rcpp::export]]
std::vector<double> logabs3(std::vector<double> x) {
   std::transform(x.begin(), x.end(), x.begin(), [](double x) {
                    return ::log(::fabs(x));
                  } );
   return x;
}
```

Sugar

Syntactic 'sugar': Simulating π in R

Draw (x, y), compute distance to origin. Do so repeatedly, and ratio of points below one to number N of simulations will approach $\pi/4$ as we fill the area of 1/4 of the unit circle.

```
piR <- function(N) {
    x <- runif(N)
    y <- runif(N)
    d <- sqrt(x^2 + y^2)
    return(4 * sum(d <= 1.0) / N)
}
set.seed(5)
sapply(10^(3:6), piR)
```

```
## [1] 3.15600 3.15520 3.13900 3.14101
```

Syntactic 'sugar': Simulating π in C++

Rcpp sugar enables us to write C++ code that is almost as compact.

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

// [[Rcpp::export]]
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;
}
```

The code is essentially identical.

Syntactic 'sugar': Simulating π

And by using the same RNG, so are the results.

```
library(Rcpp)
sourceCpp("code/piSugar.cpp")
set.seed(42); a <- piR(1.0e7)
set.seed(42); b <- piSugar(1.0e7)
identical(a,b)
```

```
## [1] TRUE
```

```
print(c(a,b), digits=7)
```

```
## [1] 3.140899 3.140899
```

Syntactic 'sugar': Simulating π

The performance is close with a small gain for C++ as R is already vectorised:

```
library(rbenchmark)
sourceCpp("code/piSugar.cpp")
benchmark(piR(1.0e6), piSugar(1.0e6))[,1:4]
```

```
##             test replications elapsed relative
## 1     piR(1e+06)          100   4.630    2.844
## 2 piSugar(1e+06)          100   1.628    1.000
```

How to: Main Usage Patterns

Basic Usage: evalCpp()

`evalCpp()` evaluates one C++ expression. Includes and dependencies can be declared.

This allows us to quickly check C++ constructs.

```
library(Rcpp)
evalCpp("2 + 2")      # simple test
```

```
## [1] 4
```

```
evalCpp("std::numeric_limits<double>::max()")
```

```
## [1] 1.79769e+308
```

Basic Usage: cppFunction()

`cppFunction()` creates, compiles and links a C++ file, and creates an R function to access it.

```
cppFunction("
    int exampleCpp11() {
        auto x = 10;
        return x;
}", plugins=c("cpp11"))
exampleCpp11()  # same identifier as C++ function
```

Basic Usage: sourceCpp()

`sourceCpp()` is the actual workhorse behind `evalCpp()` and `cppFunction()`. It is described in more detail in the package vignette Rcpp-attributes.

`sourceCpp()` builds on and extends `cxxfunction()` from package inline, but provides even more ease-of-use, control and helpers – freeing us from boilerplate scaffolding.

A key feature are the plugins and dependency options: other packages can provide a plugin to supply require compile-time parameters (cf RcppArmadillo, RcppEigen, RcppGSL).

Basic Usage: Packages

Package are *the* standard unit of R code organization.

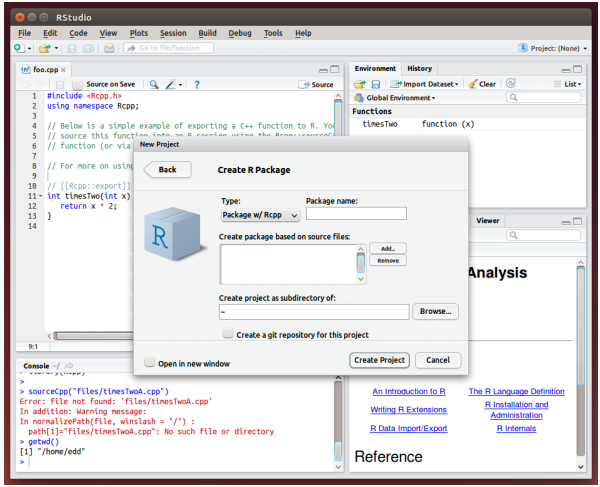
Creating packages with Rcpp is easy; an empty one to work from can be created by `Rcpp.package.skeleton()`

The vignette Rcpp-packages has fuller details.

As of November 2022, there are 2616 CRAN and 252 BioConductor packages which use Rcpp all offering working, tested, and reviewed examples.

Packages and Rcpp

Best way to organize R code with Rcpp is via a package:



`Rcpp.package.skeleton()` and its derivatives as e.g. `RcppArmadillo.package.skeleton()` create working packages.

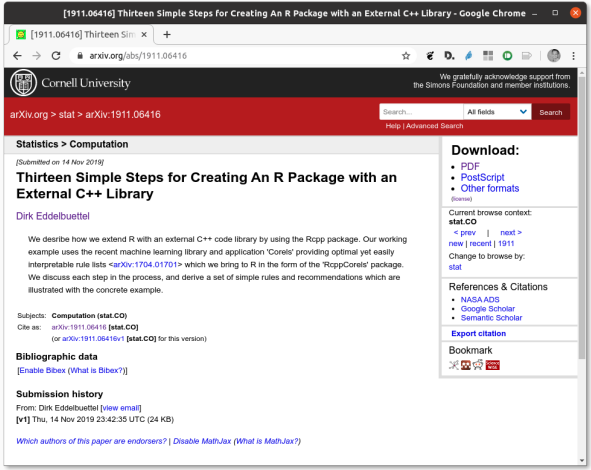
```
// another simple example: outer product of a vector, returning a matrix
// [[Rcpp::export]]
arma::mat rcpparma_outerproduct(const arma::colvec & x) {
    arma::mat m = x * x.t();
    return m;
}

// and the inner product returns a scalar
// [[Rcpp::export]]
double rcpparma_innerproduct(const arma::colvec & x) {
    double v = arma::as_scalar(x.t() * x);
    return v;
}
```

Two (or three) ways to link to external libraries

- *Full copies:* Do what mlpack does and embed a full copy; larger build time, harder to update, self-contained
- *With linking of libraries:* Do what *e.g.* RcppGSL does and use hooks in the package startup to store compiler and linker flags which are passed to environment variables
- *With C++ template headers only:* Do what RcppArmadillo and other do and just point to the headers

More details in extra vignettes.



Rcpp vignette and arXiv paper

(But there are alternatives approaches as *e.g.* ships packages with static libraries other packages can link against. This is however uncommon on CRAN.)

Big Picture

Should you use Rcpp? Or not?

Choice is yours

- Code generation helps remove build-cycle tedious and repetitive boilerplate
- The interfaces are shorter and simpler, and more R like
  - recall the `is_odd` function earlier
- Using the pllain C API to R is of course *perfectly fine*
- But (in our view) this requires more work
  - more manual steps for type conversion to/from R
  - additional steps for the required memory protection
  - all of which is error prone

Compare

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

SEXP convolve2(SEXP a, SEXP b) {
    int na, nb, nab;
    double *xa, *xb, *xab;
    SEXP ab;

    a = PROTECT(coerceVector(a, REALSXP));
    b = PROTECT(coerceVector(b, REALSXP));
    na = length(a);
    nb = length(b);
    nab = na + nb - 1;
    ab = PROTECT(allocVector(REALSXP, nab));
    xa = REAL(a);
    xb = REAL(b);
    xab = REAL(ab);
    for(int i = 0; i < nab; i++)
        xab[i] = 0.0;
    for(int i = 0; i < na; i++)
        for(int j = 0; j < nb; j++)
            xab[i + j] += xa[i] * xb[j];
    UNPROTECT(3);
    return ab;
}
```

```c
#include <Rcpp.h>

// [[Rcpp::export]]
Rcpp::NumericVector convolve2cpp(Rcpp::NumericVector a,
                                 Rcpp::NumericVector b) {
    int na = a.length(),
        nb = b.length();
    Rcpp::NumericVector ab(na + nb - 1);
    for (int i = 0; i < na; i++)
        for (int j = 0; j < nb; j++)
            ab[i + j] += a[i] * b[j];
    return(ab);
}
```

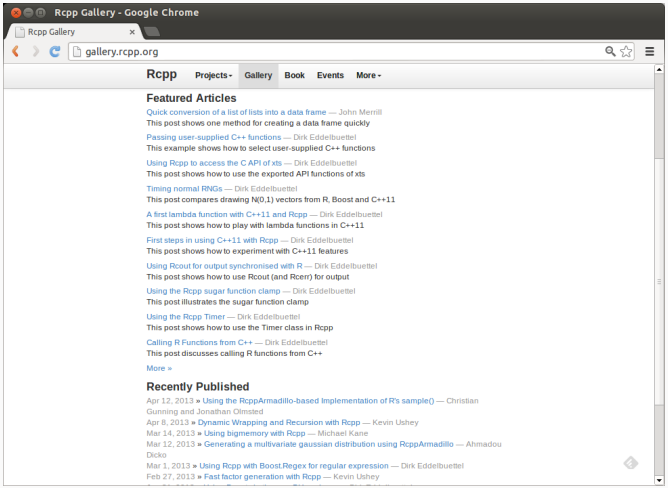
You always have a choice between the code (from Section 5.10.1 of *Writing R Extensions*) on the left, or the equivalent Rcpp code on the right.

More

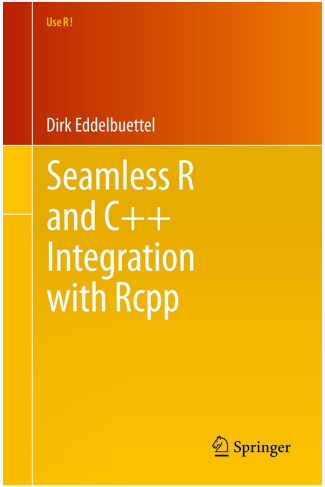
Rcpp Resources

- The package comes with nine pdf vignettes, and help pages.
- The introductory vignettes are now published (Rcpp and RcppEigen in *J Stat Software*, RcppArmadillo in *Comp Stat & Data Anlys*, Rcpp again in *TAS*)
- The rcpp-devel list is *the* recommended resource: helpful, and low volume.
- StackOverflow has by now several thousand posts (and is *searchable*)
- And a number of blog posts introduce/discuss features.

Rcpp Gallery



The Rcpp book



On sale since June 2013.

Thank you!

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