Extending R with C++

Motivation and Examples

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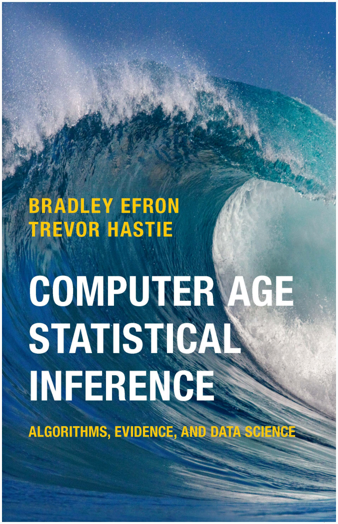
26 May 2017

Invited Keynote
R à Québec 2017
Université Laval
Québec, QC, Canada

Motivation



Almost all topics in twenty-first-century statistics are now computer-dependent [...]

Here and in all our examples we are employing the language R, itself one of the key developments in computer-based statistical methodology.

Efron and Hastie, 2016,
pages xv and 6 (footnote 3)

Computational Statistics in Practice

- Statistics is now computational (Efron & Hastie, 2016)
- Within (computational) statistics, reigning tool is R
- Given R, Rcpp key for two angles:
    - *Performance* always matters, ease of use a sweetspot
    - *"Extending R"* (Chambers, 2016)

About Me

Brief Bio

- PhD, MA Econometrics; MSc Ind.Eng. (Comp.Sci./OR)
- Finance Quant for 20 years
- Open Source for 22 years
  - Debian developer
  - R package author / contributor
  - R Foundation Board member
  - R Consortium ISC member
- JSS Associate Editor

Rcpp: Introduction via Tweets

Research Consulting
@iqssrtc

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Using #Rcpp to leverage the speed of c++ with the ease and clarity of R. Thanks, @eddelbuettel

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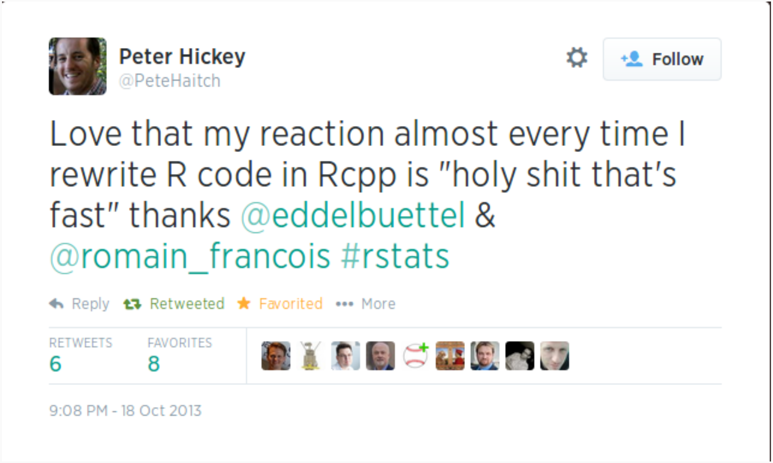
Peter Hickey
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Love that my reaction almost every time I rewrite R code in Rcpp is "holy shit that's fast" thanks @eddelbuettel & @romain_francois #rstats
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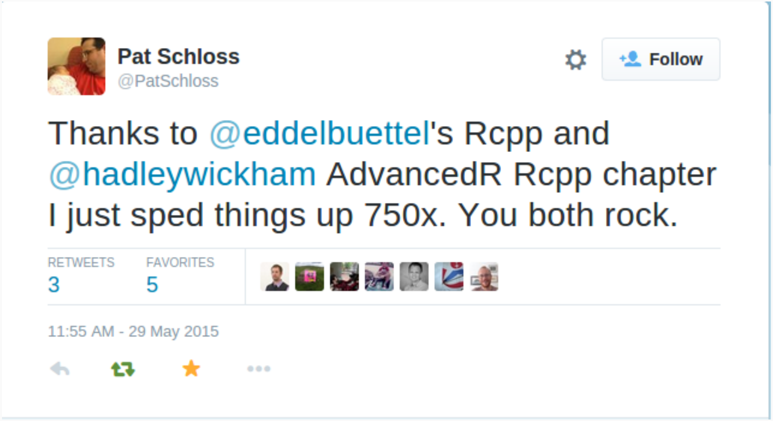
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Thanks to @eddelbuettel's Rcpp and @hadleywickham AdvancedR Rcpp chapter I just sped things up 750x. You both rock.
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@romain_francois
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@kwbroman
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@eddelbuettel @romain_francois Have I emphasized how much I ❤ #Rcpp?
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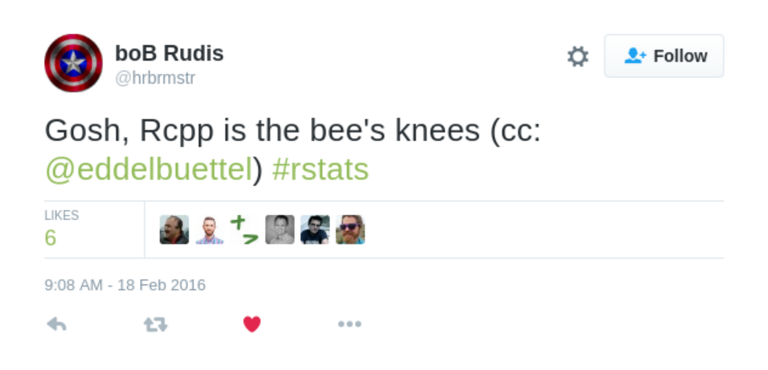
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@hrbrmstr
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Gosh, Rcpp is the bee's knees (cc: @eddelbuettel) #rstats
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Colin Gillespie
@csgillespie

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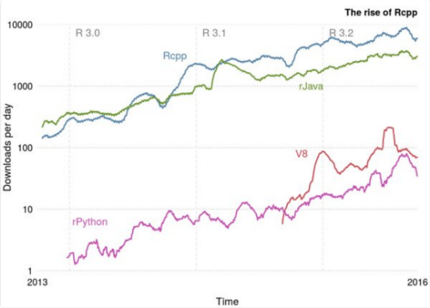
The rise of Rcpp #rstats



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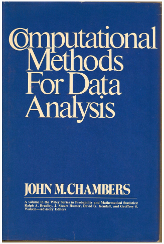
Dirk Eddelbuettel @eddelbuettel · Oct 25

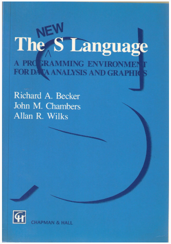
"It's easier to make an error if I am not using Rcpp"
-- @GaborCsardi , right now in the (wicked) R Hub presentation

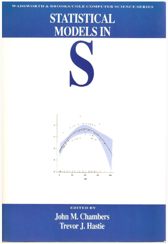
11

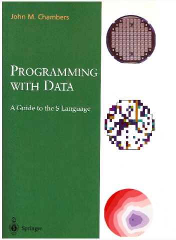
Extending R

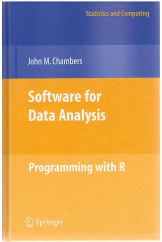
WHY R? : *PROGRAMMING WITH DATA* FROM 1977 TO 2016

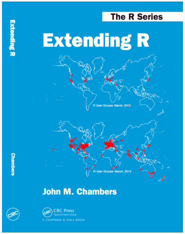










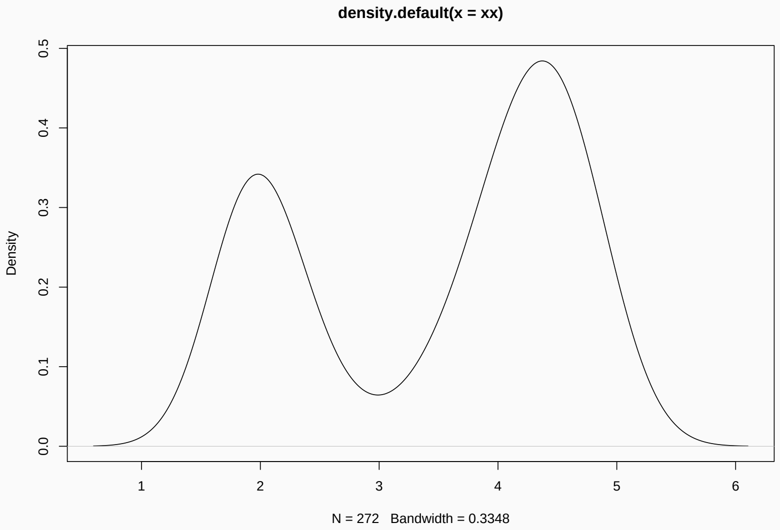


Thanks to John Chambers for high-resolution cover images. The publication years are, respectively, 1977, 1988, 1992, 1998, 2008 and 2016.

A Simple Example

```
xx <- faithful[,"eruptions"]
fit <- density(xx)
plot(fit)
```

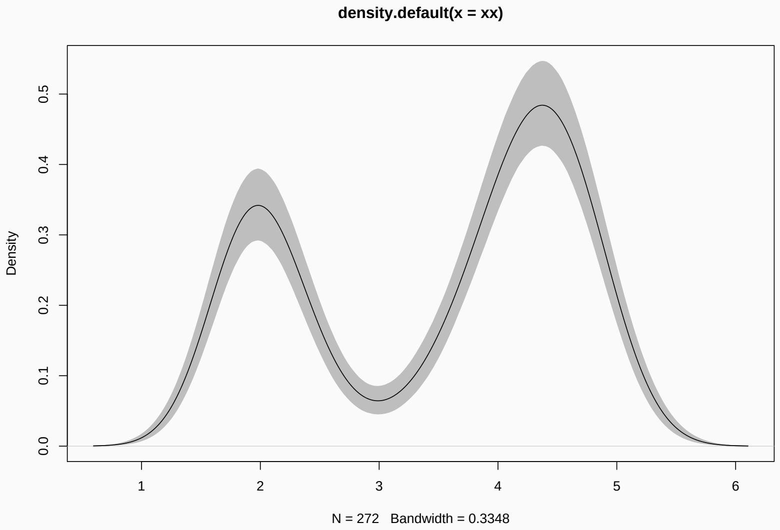
A Simple Example



A Simple Example - Refined

```
xx <- faithful[,"eruptions"]
fit1 <- density(xx)
fit2 <- replicate(10000, {
    x <- sample(xx,replace=TRUE);
    density(x, from=min(fit1$x), to=max(fit1$x))$y
})
fit3 <- apply(fit2, 1, quantile,c(0.025,0.975))
plot(fit1, ylim=range(fit3))
polygon(c(fit1$x,rev(fit1$x)), c(fit3[1,],rev(fit3[2,])),
    col='grey', border=F)
lines(fit1)
```

A Simple Example - Refined



So Why R?

R enables us to

- work interactively
- explore and visualize data
- access, retrieve and/or generate data
- summarize and report into pdf, html, ...

making it the key language for statistical computing, and a preferred environment for many data analysts.

So Why R?

R has always been extensible via

- C via a bare-bones interface described in *Writing R Extensions*
- Fortran which is also used internally by R
- Java via `rJava` by Simon Urbanek
- C++ but essentially at the bare-bones level of C

So while *in theory* this always worked – it was tedious *in practice*

Why Extend R?

Chambers (2008), opens Chapter 11 *Interfaces I: Using C and Fortran*:

> *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.*

Why Extend R?

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Why Extend R?

Chambers 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

Why Extend R?

The *Why?* boils down to:

- speed: Often a good enough reason for us … and a focus for us in this workshop.
- new things: We can bind to libraries and tools that would otherwise be unavailable in R
- references: Chambers quote from 2008 foreshadowed the work on *Reference Classes* now in R and built upon via Rcpp Modules, Rcpp Classes (and also RcppR6)

And Why C++?

- Asking Google leads to tens of million of hits.
- Wikipedia: *C++ is a statically typed, free-form, multi-paradigm, compiled, general-purpose, powerful programming language*
- C++ is industrial-strength, vendor-independent, widely-used, and *still evolving*
- In science & research, one of the most frequently-used languages: If there is something you want to use / connect to, it probably has a C/C++ API
- As a widely used language it also has good tool support (debuggers, profilers, code analysis)

Why C++?

Scott Meyers: *View C++ as a federation of languages*

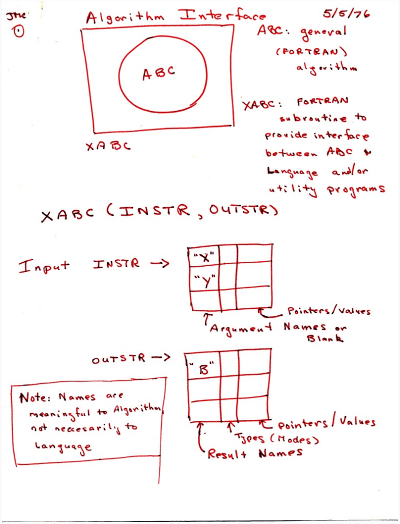
- *C* provides a rich inheritance and interoperability as Unix, Windows, ... are all build on C.
- *Object-Oriented C++* (maybe just to provide endless discussions about exactly what OO is or should be)
- *Templated C++* which is mighty powerful; template meta programming unequalled in other languages.
- *The Standard Template Library* (STL) is a specific template library which is powerful but has its own conventions.
- *C++11* and C++14 (and beyond) add enough to be called a fifth language.

NB: Meyers original list of four languages appeared years before C++11.

Why C++?

- Mature yet current
- Strong performance focus:
  - *You don't pay for what you don't use*
  - *Leave no room for another language between the machine level and C++*
- Yet also powerfully abstract and high-level
- C++11 + C++14 are a big deal giving us new language features
- While there are complexities, Rcpp users are mostly shielded

Interface Vision


JMC
1
Algorithm Interface
5/5/76
ABC
ABC: general (FORTRAN) algorithm
XABC: FORTRAN subroutine to provide interface between ABC & Language and/or utility programs
XABC
XABC (INSTR, OUTSTR)
Input INSTR →
"X"
"Y"
Argument Names or Blank
Pointers/Values
OUTSTR →
"B"
Result Names
Types (Modes)
Pointers/Values
Note: Names are meaningful to Algorithm, not neccesarily to Language

Interface Vision

R offers us the best of both worlds:

- Compiled code with
  - Access to proven libraries and algorithms in C/C++/Fortran
  - Extremely high performance (in both serial and parallel modes)
- Interpreted code with
  - A high-level language made for *Programming with Data*
  - An interactive workflow for data analysis
  - Support for rapid prototyping, research, and experimentation

Why Rcpp?

- Easy to learn as it really does not have to be that complicated – we will see numerous few examples
- Easy to use as it avoids build and OS system complexities thanks to the R infrastrucure
- Expressive as it allows for *vectorised* C++ using *Rcpp Sugar*
- Seamless access to all R objects: vector, matrix, list, S3/S4/RefClass, Environment, Function, …
- Speed gains for a variety of tasks Rcpp excels precisely where R struggles: loops, function calls, …
- Extensions greatly facilitates access to external libraries using eg *Rcpp modules*

Speed

Speed Example (due to StackOverflow)

Consider a function defined as

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

Speed Example in R

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
```

Speed Example Timed

Timing:

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

```
##     test replications elapsed relative
## 1 f(10)          100   0.010      1.0
## 2 f(15)          100   0.080      8.0
## 3 f(20)          100   0.796     79.6
```

Speed Example in C / C++

A C or C++ solution can be equally simple

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

But how do we call it from R?

Speed Example in C / C++

But Rcpp makes this *much* easier:

```
Rcpp::cppFunction("int g(int n) {
   if (n < 2) return(n);
   return(g(n-1) + g(n-2)); }")
sapply(0:10, g)
```

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

Timing:

```
Rcpp::cppFunction("int g(int n) {
   if (n < 2) return(n);
   return(g(n-1) + g(n-2)); }")
library(rbenchmark)
benchmark(f(25), g(25), order="relative")[,1:4]
```

```
##    test replications elapsed relative
## 2 g(25)          100   0.030    1.000
## 1 f(25)          100   9.022  300.733
```

A nice gain of a few orders of magnitude.

Another Angle on Speed

Run-time performance is just one example.

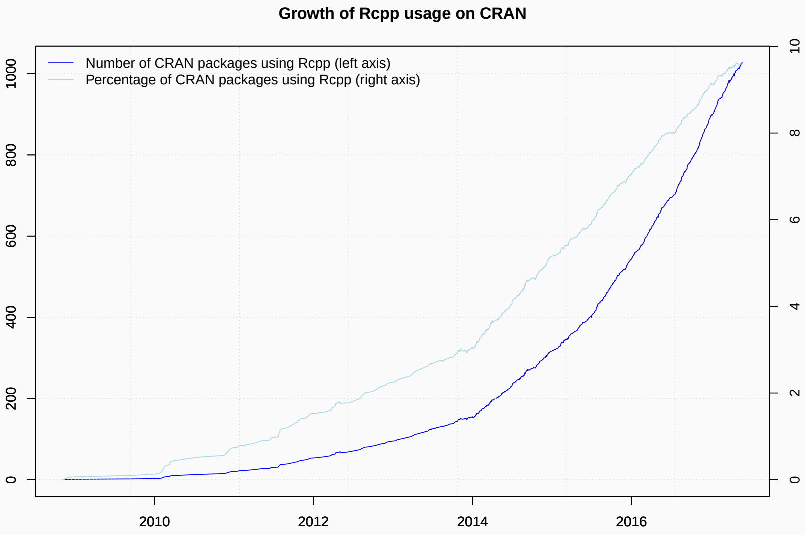
Time to code is another metric.

We feel quite strongly that helps you code more succinctly, leading to fewer bugs and faster development.

A good environment helps. RStudio integrates R and C++ development quite nicely (eg the compiler error message parsing is very helpful) and also helps with package building.

Empirics

Growth



Data current as of May 25, 2017.

Pagerank

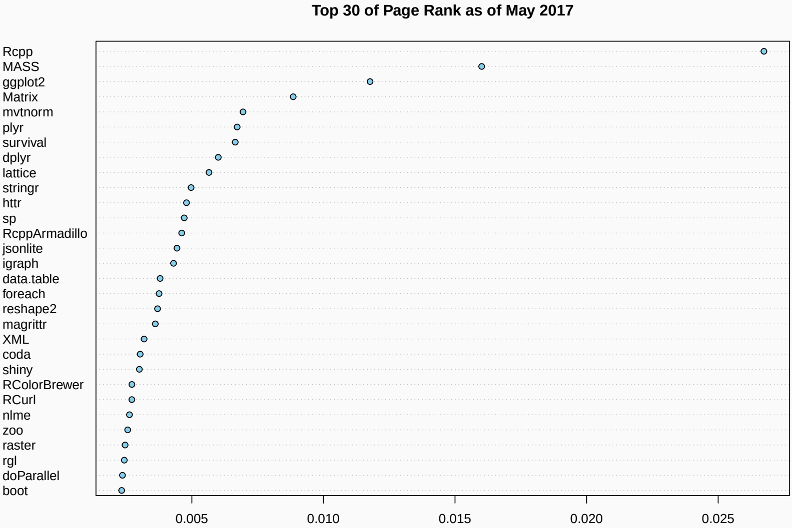
```r
library(pagerank)  # github.com/andrie/pagerank

cran <- "http://cloud.r-project.org"

pr <- compute_pagerank(cran)
round(100*pr[1:5], 3)
```

```
##    Rcpp    MASS ggplot2  Matrix mvtnorm
##   2.674   1.601   1.177   0.885   0.694
```

Pagerank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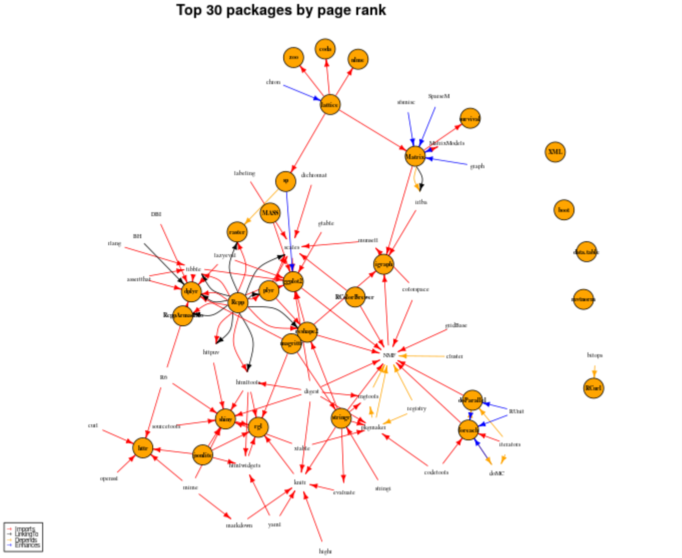
lattice
stringr
httr
sp
RcppArmadillo
jsonlite
igraph
data.table
foreach
reshape2
magrittr
XML
coda
shiny
RColorBrewer
RCurl
nlme
zoo
raster
rgl
doParallel
boot
0.005
0.010
0.015
0.020
0.025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boot
DBI
MASS
gtable
raster
BH
rlang
munsell
scales
lazyeval
igraph
data.table
tibble
assertthat
ggplot2
dplyr
plyr
Rcpp
RColorBrewer
colorspace
mvtnorm
RcppArmadillo
reshape2
gridBase
magrittr
NMF
cluster
bitops
httpuv
R6
htmltools
digest
RCurl
pkgtools
registry
doParallel
RUnit
curl
sourcetools
shiny
rgl
stringr
pkgmaker
foreach
httr
mime
xtable
iterators
openssl
jsonlite
htmlwidgets
knitr
evaluate
stringi
codetools
doMC
markdown
yaml
highr
Imports
LinkingTo
Depends
Enhances

CRAN Proportion

```r
db <- tools::CRAN_package_db()   # R 3.4.0 or later
dim(db)
```

```
## [1] 10685    65
```

```r
## all Rcpp reverse depends
(c(n_rcpp <- length(tools::dependsOnPkgs("Rcpp", recursive=FALSE,
                                         installed=db)),
   n_compiled <- table(db[, "NeedsCompilation"])[["yes"]]))
```

```
## [1] 1028 2857
```

```r
## Rcpp percentage of packages with compiled code
n_rcpp / n_compiled
```

```
## [1] 0.359818
```

Well-known packages using Rcpp

- Amelia by G King et al
- lme4 by D Bates, M Maechler et al
- forecast by R Hyndman et al
- RStan by A Gelman et al
- plyr,dplyr,roxygen2,readxl,readr,... by H Wickham et al
- httpuv by J Cheng / RStudio
- MTS by R Tsay

Rcpp: A Better C API for R

The R API

In a nutshell:

- R is a C program, and C programs can be extended
- R exposes an API with C functions and MACROS
- R also supports C++ out of the box with `.cpp` extension
- R provides several calling conventions:
  - `.C()` provides the first interface, is fairly limited, and discouraged
  - `.Call()` provides access to R objects at the C level
  - `.External()` and `.Fortran()` exist but can be ignored
- We will use `.Call()` exclusively

The .Call Interface

At the C level, everything is a `SEXP`, and every `.Call()` access uses this interface pattern:

```
SEXP foo(SEXP x1, SEXP x2){
...
}
```

which can be called from R via

```
.Call("foo", var1, var2)
```

Note that we need to compile, and link, and load, this manually in wasy which are OS-dependent.

Example: Convolution

```
#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;
}
```

Example: Convolution

```cpp
#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);
}
```

Types Overview: RObject

- The `RObject` can be thought of as a basic class behind many of the key classes in the `Rcpp` API.
- `RObject` (and our core classes) provide a thin wrapper around `SEXP` objects
- This is sometimes called a *proxy object* as we do not copy the R object.
- `RObject` manages the life cycle, the object is protected from garbage collection while in scope—so we do not have to do memory management.
- Core classes define several member common functions common to all objects (e.g. `isS4()`, `attributeNames`, ...); classes then add their specific member functions.

Overview of Classes: Comparison

Rcpp class	R `typeof`
`Integer(Vector|Matrix)`	`integer` vectors and matrices
`Numeric(Vector|Matrix)`	`numeric` ...
`Logical(Vector|Matrix)`	`logical` ...
`Character(Vector|Matrix)`	`character` ...
`Raw(Vector|Matrix)`	`raw` ...
`Complex(Vector|Matrix)`	`complex` ...
`List`	`list` (aka generic vectors) ...
`Expression(Vector|Matrix)`	`expression` ...
`Environment`	`environment`
`Function`	`function`
`XPtr`	`externalptr`
`Language`	`language`
`S4`	`S4`
...	...

Overview of key vector / matrix classes

- `IntegerVector` vectors of type `integer`
- `NumericVector` vectors of type `numeric`
- `RawVector` vectors of type `raw`
- `LogicalVector` vectors of type `logical`
- `CharacterVector` vectors of type `character`
- `GenericVector` generic vectors implementing `list` types

Common core functions for Vectors and Matrices

Key operations for all vectors, styled after STL operations:

- `operator()` access elements via `()`
- `operator[]` access elements via `[]`
- `length()` also aliased to `size()`
- `fill(u)` fills vector with value of `u`
- `begin()` pointer to beginning of vector, for iterators
- `end()` pointer to one past end of vector
- `push_back(x)` insert `x` at end, grows vector
- `push_front(x)` insert `x` at beginning, grows vector
- `insert(i, x)` insert `x` at position *i*, grows vector
- `erase(i)` remove element at position *i*, shrinks vector

Basic Usage

Basic Usage: evalCpp()

`evalCpp()` evaluates a single 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] 1.797693e+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
```

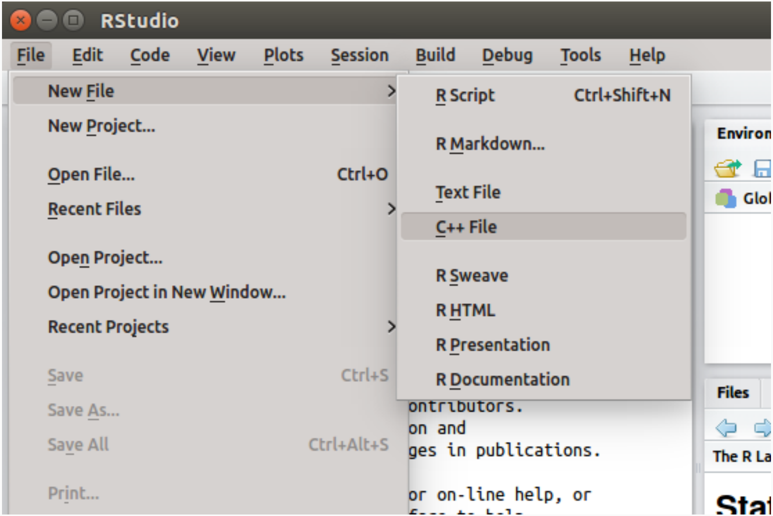
Basic Usage: sourceCpp()

`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 Uage: RStudio



Basic Uage: RStudio (Cont'ed)

The following file gets created:

```
#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)
*/
```

So what just happened?

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

Basic Usage: Packages

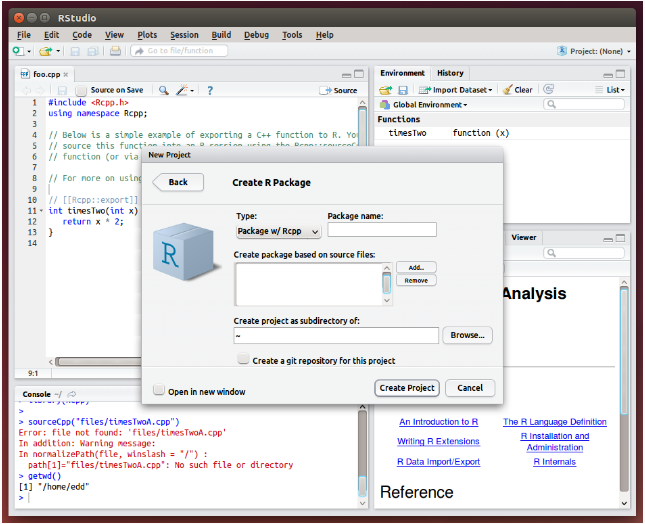
Package are *the* standard unit of R code organization.

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 May 26, 2017, there are 1030 packages on CRAN which use Rcpp, and a further 91 on BioConductor — with working, tested, and reviewed examples.

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



Packages and Rcpp

`Rcpp.package.skeleton()` and its derivatives. 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 RcppMLPACK (v1) does and embed a full copy; larger build time, harder to update, self-contained
- With linking of libraries: Do what RcppGSL or RcppMLPACK (v2) do 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.

Sugar Example

Syntactic 'sugar': Simulating π in R

Draw (x, y), compute dist d to origin. Repeat. Ratio of points with $\sum I(d \leq 1)/N$ goes to $\pi/4$ as we fill the 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] 3.156000 3.155200 3.139000 3.141008
```

Syntactic 'sugar': Simulating π in C++

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

```cpp
#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
```

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   6.828    1.986
## 2 piSugar(1e+06)          100   3.438    1.000
```

Takeaways

- We can prototype in R to derive a first solution
- We can then rewrite performance-critical parts
- Key R functions are often available in C++ via Rcpp Sugar
- Random Number Simulation will work on identical streams

Other Examples

Cumulative Sum: vector-cumulative-sum

A basic looped version:

```
#include <Rcpp.h>
#include <numeric>      // for std::partial_sum
using namespace Rcpp;

// [[Rcpp::export]]
NumericVector cumsum1(NumericVector x){
    double acc = 0;     // init an accumulator variable

    NumericVector res(x.size());  // init result vector

    for(int i = 0; i < x.size(); i++){
         acc += x[i];
         res[i] = acc;
    }
    return res;
}
```

Cumulative Sum: vector-cumulative-sum

An STL variant:

```cpp
// [[Rcpp::export]]
NumericVector cumsum2(NumericVector x){
    // initialize the result vector
    NumericVector res(x.size());
    std::partial_sum(x.begin(), x.end(), res.begin());
    return res;
}
```

Cumulative Sum: `vector-cumulative-sum`

Or just Rcpp sugar:

```
// [[Rcpp::export]]
NumericVector cumsum_sug(NumericVector x){
    return cumsum(x);  // compute + return result vector
}
```

Of course, all results are the same.

R Function Call from C++: `r-function-from-c++`

```cpp
#include <Rcpp.h>

using namespace Rcpp;

// [[Rcpp::export]]
NumericVector callFunction(NumericVector x,
                           Function f) {
    NumericVector res = f(x);
    return res;
}

/*** R
callFunction(x, fivenum)
*/
```

Using Boost via BH: using-boost-with-bh

```
// [[Rcpp::depends(BH)]]
#include <Rcpp.h>

// One include file from Boost
#include <boost/date_time/gregorian/gregorian_types.hpp>

using namespace boost::gregorian;

// [[Rcpp::export]]
Rcpp::Date getIMMDate(int mon, int year) {
    // compute third Wednesday of given month / year
    date d = nth_day_of_the_week_in_month(
                        nth_day_of_the_week_in_month::third,
                        Wednesday, mon).get_date(year);
    date::ymd_type ymd = d.year_month_day();
    return Rcpp::wrap(Rcpp::Date(ymd.year, ymd.month, ymd.day));
}
```

USING BOOST VIA BH: using-boost-with-bh

```
#include <Rcpp.h>
#include <boost/foreach.hpp>
using namespace Rcpp;
// [[Rcpp::depends(BH)]]

// the C-style upper-case macro name is a bit ugly
#define foreach BOOST_FOREACH

// [[Rcpp::export]]
NumericVector square( NumericVector x ) {
  // elem is a reference to each element in x
  // we can re-assign to these elements as well
  foreach( double& elem, x ) {
    elem = elem*elem;
  }
  return x;
}
```

C++11 now has something similar in a smarter `for` loop.

Vector Subsetting: subsetting

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

// [[Rcpp::export]]
NumericVector positives(NumericVector x) {
    return x[x > 0];
}

// [[Rcpp::export]]
List first_three(List x) {
    IntegerVector idx = IntegerVector::create(0, 1, 2);
    return x[idx];
}

// [[Rcpp::export]]
List with_names(List x, CharacterVector y) {
    return x[y];
}
```

Armadillo Eigenvalues: armadillo-eigenvalues

```
#include <RcppArmadillo.h>

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

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

ARMADILLO EIGENVALUES: armadillo-eigenvalues

```
sourceCpp("code/armaeigen.cpp")

set.seed(42)
X <- matrix(rnorm(4*4), 4, 4)
Z <- X %*% t(X)
getEigenValues(Z)
```

```
##             [,1]
## [1,]  0.3318872
## [2,]  1.6855884
## [3,]  2.4099205
## [4,] 14.2100108
```

```
# R gets the same results (in reverse)
# and also returns the eigenvectors.
```

Create xts from in C++: creating-xts-from-c++

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

NumericVector createXts(int sv, int ev) {
    IntegerVector ind = seq(sv, ev);     // values

    NumericVector dv(ind);               // date(time)s == reals
    dv = dv * 86400;                     // scaled to days
    dv.attr("tzone")    = "UTC";         // index has attributes
    dv.attr("tclass")   = "Date";

    NumericVector xv(ind);               // data has same index
    xv.attr("dim")         = IntegerVector::create(ev-sv+1,1);
    xv.attr("index")       = dv;
    CharacterVector cls = CharacterVector::create("xts","zoo");
    xv.attr("class")       = cls;
    xv.attr(".indexCLASS") = "Date";
    // ... some more attributes ...

    return xv;
}
```

RcppMLPACK: K-Means Example

```cpp
#include "RcppMLPACK.h"

using namespace mlpack::kmeans;
using namespace Rcpp;

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

// [[Rcpp::export]]
List cppKmeans(const arma::mat& data, const int& clusters) {

    arma::Col<size_t> assignments;
    KMeans<> k;     // Initialize with the default arguments.
    k.Cluster(data, clusters, assignments);

    return List::create(Named("clusters") = clusters,
                        Named("result")   = assignments);
}
```

Timing

Table 1: Benchmarking result

test	replications	elapsed	relative	user.self	sys.self
mlKmeans(t(wine), 3)	100	0.028	1.000	0.028	0.000
kmeans(wine, 3)	100	0.947	33.821	0.484	0.424

Table taken ‘as is’ from RcppMLPACK vignette.

RcppMLPACK: Nearest Neighbors Example

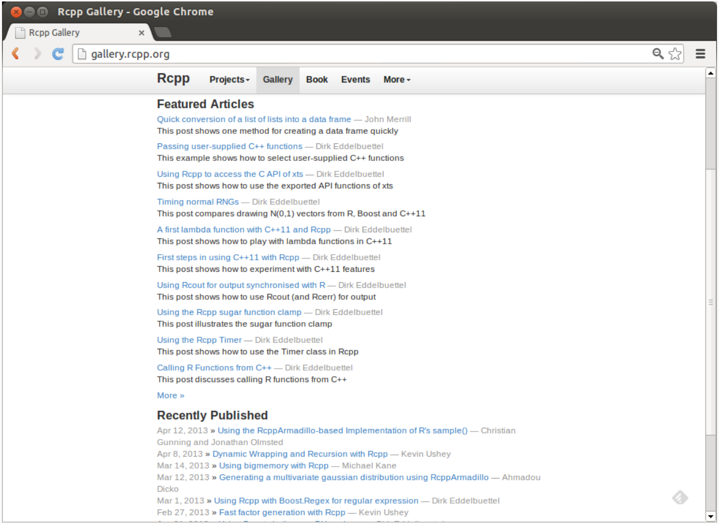
```
#include "RcppMLPACK.h"

using namespace Rcpp;
using namespace mlpack;          using namespace mlpack::neighbor;
using namespace mlpack::metric;   using namespace mlpack::tree;

// [[Rcpp::depends(RcppMLPACK)]]
// [[Rcpp::export]]
List nn(const arma::mat& data, const int k) {
    // using a test from MLPACK 1.0.10 file src/mlpack/tests/allknn_test.cpp
    CoverTree<LMetric<2>, FirstPointIsRoot,
              NeighborSearchStat<NearestNeighborSort> > tree =
        CoverTree<LMetric<2>, FirstPointIsRoot,
                  NeighborSearchStat<NearestNeighborSort> >(data);

    NeighborSearch<NearestNeighborSort, LMetric<2>,
                   CoverTree<LMetric<2>, FirstPointIsRoot,
                             NeighborSearchStat<NearestNeighborSort> > >
        coverTreeSearch(&tree, data, true);

    arma::Mat<size_t> coverTreeNeighbors;
    arma::mat coverTreeDistances;
    coverTreeSearch.Search(k, coverTreeNeighbors, coverTreeDistances);

    return List::create(Named("clusters") = coverTreeNeighbors,
                        Named("result")   = coverTreeDistances);

}
```

More

Documentation

- The package comes with eight pdf vignettes, and numerous help pages.
- The introductory vignettes are now published (Rcpp and RcppEigen in *J Stat Software*, RcppArmadillo in *Comp Stat & Data Anlys*)
- The rcpp-devel list is *the* recommended resource, generally very helpful, and fairly low volume.
- StackOverflow has a large collection of posts too.
- And a number of blog posts introduce/discuss features.

Rcpp Gallery



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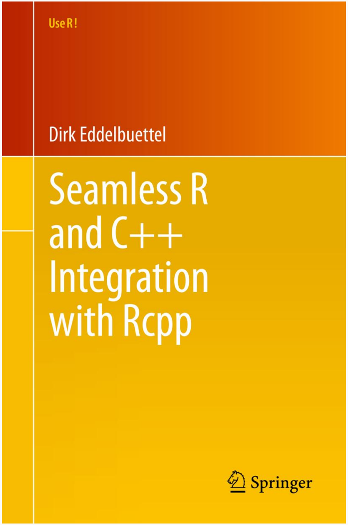

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Concluding

Summary

Key Themes

- Statistics largely computational
- R is a key ingredient
- Rcpp is a performant and expressive API extension
- Extending R is a key feature
    - Programming is (often) multi-lingual
    - Extending to other systems / languages natural
- Important to teach more than just single language

Merci!

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