A Hands-on Introduction to Rcpp

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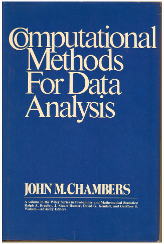
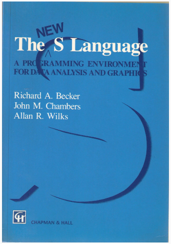
Overview

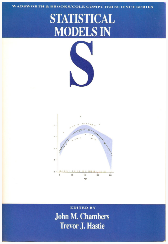
Outline

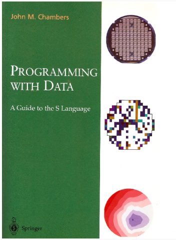
- Motivation
- (Very Brief) C++ Basics
- Getting Started
- Rcpp and the R API
- Applications
- Examples
- Packaging

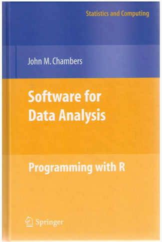
Motivation

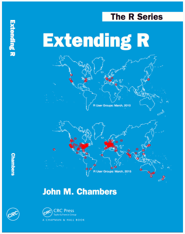








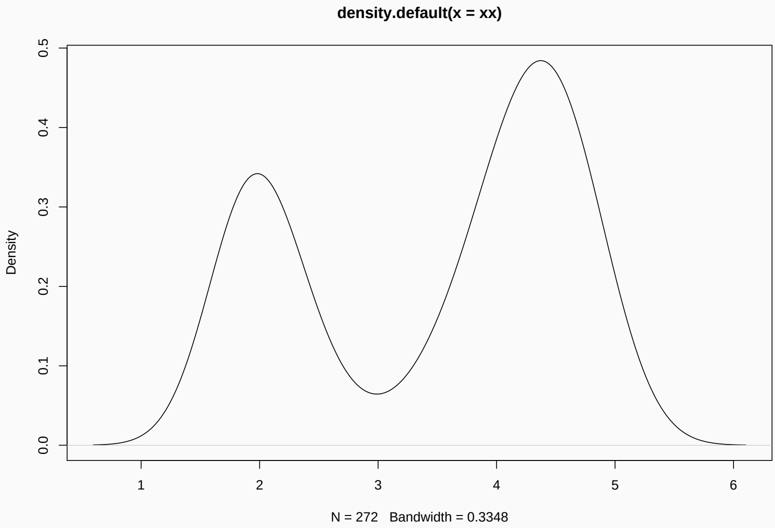




Thanks to John Chambers for sending me high-resolution scans of the covers of his books.

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

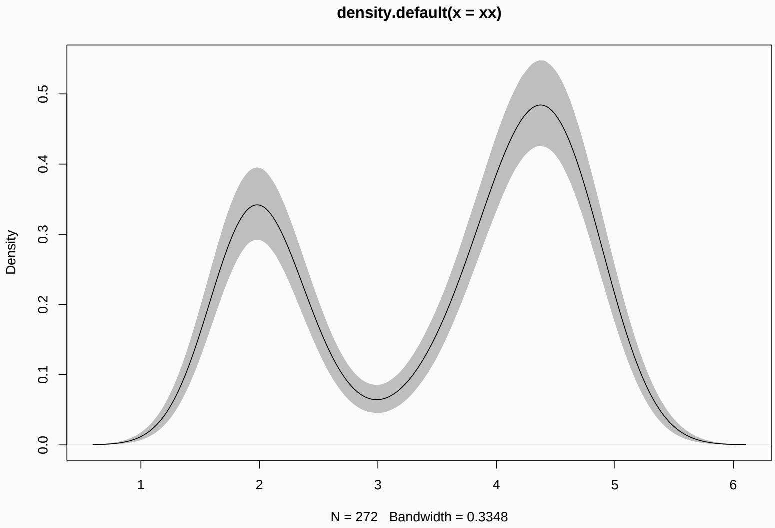
A Simple Example



A Simple Example - Refined

```r
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*

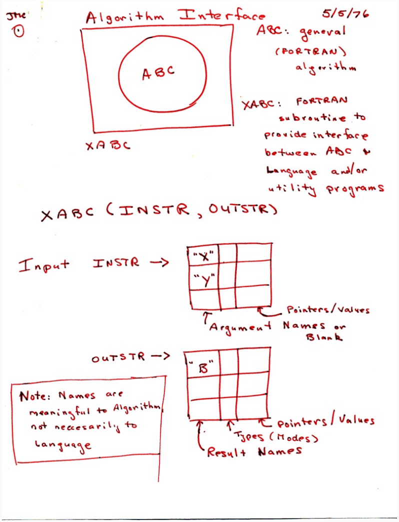
- *C* provides a rich inheritance and interoperability as Unix, Windows, ... are all build on C.
- *Object-Oriented C++* (maybe just to provide endless discussions about exactly what OO is or should be)
- *Templated C++* which is mighty powerful; template meta programming unequalled in other languages.
- *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 is a big deal giving us new language features
- While there are complexities, Rcpp users are mostly shielded

Interface Vision (Bell Labs, May 1976)



Thanks to John Chambers for a scanned copy of this sketch.

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
  - An accessible 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
- 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 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:

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

```
##     test replications elapsed relative
## 1 f(10)          100   0.020      1.0
## 2 f(15)          100   0.222     11.1
## 3 f(20)          100   2.490    124.5
```

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?

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
```

Speed Example Comparing R and C++

Timing:

```r
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   0.066    1.000
## 1 f(25)          100  28.379  429.985
```

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.

(Very Brief) C++ Basics

Programming with C++

- C++ Basics
- Debugging
- Best Practices

and then on to Rcpp itself

Compiled not Interpreted

Need to compile and link

```
#include <cstdio>

int main(void) {
    printf("Hello, world!\n");
    return 0;
}
```

Or streams output rather than `printf`

```cpp
#include <iostream>

int main(void) {
    std::cout << "Hello, world!" << std::endl;
    return 0;
}
```

`g++ -o` will compile and link

We will now look at an examples with explicit linking.

Compiled not Interpreted

```
#include <cstdio>

#define MATHLIB_STANDALONE
#include <Rmath.h>

int main(void) {
    printf("N(0,1) 95th percentile %9.8f\n",
           qnorm(0.95, 0.0, 1.0, 1, 0));
}
```

Compiled not Interpreted

We may need to supply:

- *header location* via `-I`,
- *library location* via `-L`,
- *library* via `-llibraryname`

```
g++ -I/usr/include -c qnorm_rmath.cpp
g++ -o qnorm_rmath qnorm_rmath.o -L/usr/lib -lRmath
```

Statically Typed

- R is dynamically typed: `x <- 3.14; x <- "foo"` is valid.
- In C++, each variable must be declared before first use.
- Common types are `int` and `long` (possibly with `unsigned`), `float` and `double`, `bool`, as well as `char`.
- No standard string type, though `std::string` is close.
- All these variables types are scalars which is fundamentally different from R where everything is a vector.
- `class` (and `struct`) allow creation of composite types; classes add behaviour to data to form `objects`.
- Variables need to be declared, cannot change

C++ is a Better C

- control structures similar to what R offers: `for`, `while`, `if`, `switch`
- functions are similar too but note the difference in positional-only matching, also same function name but different arguments allowed in C++
- pointers and memory management: very different, but lots of issues people had with C can be avoided via STL (which is something Rcpp promotes too)
- sometimes still useful to know what a pointer is ...

Object-Oriented

This is a second key feature of C++, and it does it differently from S3 and S4.

```
struct Date {
    unsigned int year;
    unsigned int month;
    unsigned int day
};

struct Person {
    char firstname[20];
    char lastname[20];
    struct Date birthday;
    unsigned long id;
};
```

Object-Oriented

Object-orientation in the C++ sense matches data with code operating on it:

```
class Date {
private:
    unsigned int year
    unsigned int month;
    unsigned int date;
public:
    void setDate(int y, int m, int d);
    int getDay();
    int getMonth();
    int getYear();
}
```

Generic Programming and the STL

The STL promotes *generic* programming.

For example, the sequence container types `vector`, `deque`, and `list` all support

- `push_back()` to insert at the end;
- `pop_back()` to remove from the front;
- `begin()` returning an iterator to the first element;
- `end()` returning an iterator to just after the last element;
- `size()` for the number of elements;

but only `list` has `push_front()` and `pop_front()`.

Other useful containers: `set`, `multiset`, `map` and `multimap`.

Traversal of containers can be achieved via *iterators* which require suitable member functions `begin()` and `end()`:

```
std::vector<double>::const_iterator si;
for (si=s.begin(); si != s.end(); si++)
    std::cout << *si << std::endl;
```

Another key STL part are *algorithms*:

```
double sum = accumulate(s.begin(), s.end(), 0);
```

Some other STL algorithms are

- `find` finds the first element equal to the supplied value
- `count` counts the number of matching elements
- `transform` applies a supplied function to each element
- `for_each` sweeps over all elements, does not alter
- `inner_product` inner product of two vectors

Template Programming

Template programming provides a 'language within C++': code gets evaluated during compilation.

One of the simplest template examples is

```
template <typename T>
const T& min(const T& x, const T& y) {
    return y < x ? y : x;
}
```

This can now be used to compute the minimum between two `int` variables, or `double`, or in fact any *admissible type* providing an `operator<()` for less-than comparison.

Another template example is a class squaring its argument:

```
template <typename T>
class square : public std::unary_function<T,T> {
public:
    T operator()(T t) const {
        return t*t;
    }
};
```

which can be used along with STL algorithms:

```
transform(x.begin(), x.end(), square);
```

Further Reading

Books by Meyers are excellent

I also like the (free) C++ Annotations

C++ FAQ

Resources on StackOverflow such as

- general info and its links, eg
- booklist

Debugging

Some tips:

- Generally painful, old-school `printf()` still pervasive
- Debuggers go along with compilers: `gdb` for `gcc` and `g++`; `lldb` for the clang / llvm family
- Extra tools such as `valgrind` helpful for memory debugging
- "Sanitizer" (ASAN/UBSAN) in newer versions of `g++` and `clang++`

Some Tips

- Version control: highly recommended to become familiar with `git` or `svn`
- Editor: *in the long-run*, recommended to learn productivity tricks for one editor: emacs, vi, eclipse, RStudio, ...

Getting Started with Rcpp

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
```

`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
```

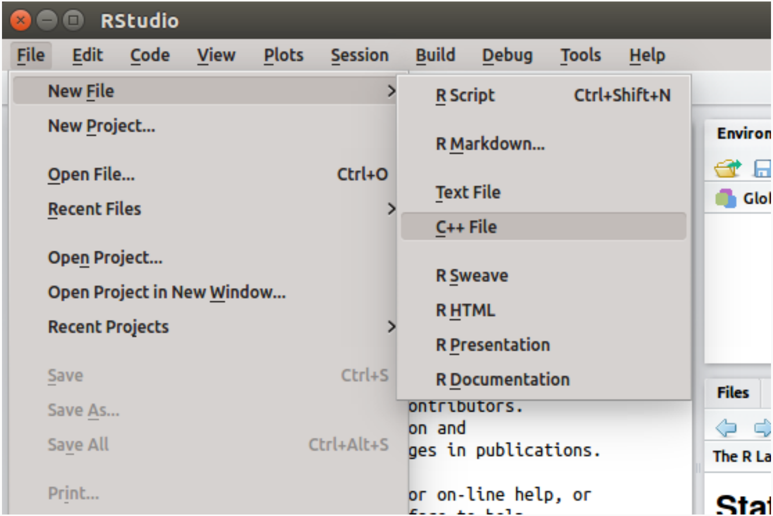
Basic Usage: sourceCpp()

`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)
*/
```

Basic Uage: RStudio (Cont'ed)

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

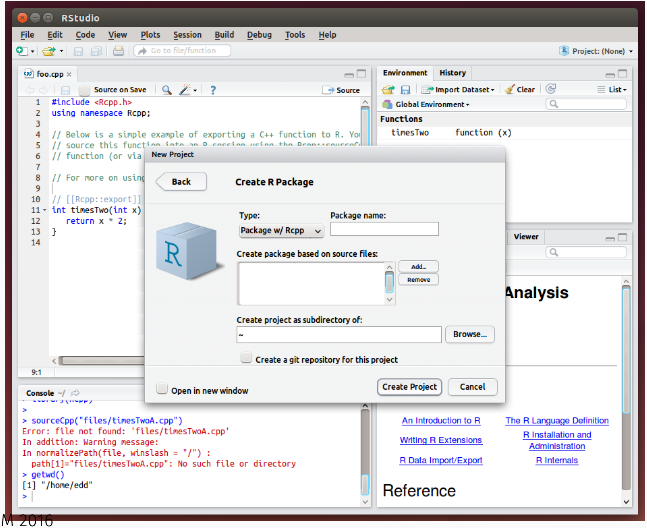
Package are *the* standard unit of R code organization.

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 July 2016, there are almost 700 packages on CRAN which use Rcpp, and a further 72 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 ways to link to external libraries

- *With linking of libraries:* Do what RcppGSL does and use hooks in the package startup to store compiler and linker flags, pass 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: A Better C API for R

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

```
#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

IntegerVector: A first example

A simpler version of `prod()` for integer vectors:

```
#include <Rcpp.h>

// [[Rcpp::export]]
int intVec1a(Rcpp::IntegerVector vec) {
    int prod = 1;
    for (int i=0; i<vec.size(); i++) {
        prod *= vec[i];
    }
    return prod;
}
```

We can also do this for STL vector types:

```
#include <Rcpp.h>

// [[Rcpp::export]]
int intVec1b(std::vector<int> vec) {
    int prod = 1;
    for (unsigned int i=0; i<vec.size(); i++) {
        prod *= vec[i];
    }
    return prod;
}
```

IntegerVector: Loopless

Loopless for `Rcpp::IntegerVector`:

```
#include <Rcpp.h>

// [[Rcpp::export]]
int intVec2a(Rcpp::IntegerVector vec) {
    int prod =
        std::accumulate(vec.begin(),
                        vec.end(), 1,
                        std::multiplies<int>());
    return prod;
}
```

IntegerVector: Loopless

Loopless for STL's `std::vector<int>`:

```
#include <Rcpp.h>

// [[Rcpp::export]]
int intVec2b(std::vector<int> vec) {
    int prod =
        std::accumulate(vec.begin(),
                        vec.end(), 1,
                        std::multiplies<int>());
    return prod;
}
```

This example generalizes sum of squares by supplying an exponentiation argument:

```
#include <Rcpp.h>

// [[Rcpp::export]]
double numVecEx1(Rcpp::NumericVector vec,
                 double p = 2.0) {
    double sum = 0.0;
    for (int i=0; i<vec.size(); i++) {
        sum += pow(vec[i], p);
    }
    return sum;
}
```

NumericVector: A Second Example

A second example alters a numeric vector:

```cpp
#include <Rcpp.h>

// [[Rcpp::export]]
NumericVector f(NumericVector m) {
    m(0) = 0;
    return m;
}
```

NumericVector: A Second Example

Calling the last example with an integer vector:

```r
Rcpp::sourceCpp("code/numVecEx3.cpp")

x <- 1:3          # same as c(1L, 2L, 3L)
print(data.frame(x=x, fx=f(x)), row.names=FALSE)
```

```
##  x fx
##  1  0
##  2  2
##  3  3
```

Calling the last example with a numeric vector:

```r
x <- c(1.0, 2.0, 3.0)
print(data.frame(x=x, fx=f(x)), row.names=FALSE)
```

```
##  x fx
##  0  0
##  2  2
##  3  3
```

We pass `x` as a `SEXP` which is a pointer.

Use `Rcpp::clone()` for deep copy.

Constructors

```
SEXP x;
NumericVector y(x);     // from a SEXP

// cloning (deep copy)
NumericVector z = clone(y);

// of a given size (all elements set to 0.0)
NumericVector y(10);

// ... specifying the value
NumericVector y(10, 2.0);

// with given elements
NumericVector y = NumericVector::create(1.0, 2.0);
```

`NumericMatrix` is a specialisation of `NumericVector` with a dimension attribute:

```
#include <Rcpp.h>

// [[Rcpp::export]]
Rcpp::NumericMatrix takeRoot(Rcpp::NumericMatrix mm) {
    Rcpp::NumericMatrix m =
                Rcpp::clone<Rcpp::NumericMatrix>(mm);
    std::transform(m.begin(), m.end(),
                   m.begin(), ::sqrt);
    return m;
}
```

```r
Rcpp::sourceCpp("code/numMatEx1.cpp")
takeRoot( matrix((1:9)*1.0, 3, 3) );
```

```
##          [,1]     [,2]     [,3]
## [1,] 1.000000 2.000000 2.645751
## [2,] 1.414214 2.236068 2.828427
## [3,] 1.732051 2.449490 3.000000
```

Armadillo Matrix Algebra

We prefer Armadillo for math though – more later.

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

#include <RcppArmadillo.h>

// [[Rcpp::export]]
Rcpp::List armafun(arma::mat m1) {
    arma::mat m2 = m1 + m1;
    arma::mat m3 = m1 * 2;
    return Rcpp::List::create(m1, m2);
}
```

Other Vector Types

Quick List:

- `LogicalVector` very similar to `IntegerVector`: two possible values of a logical, or boolean, type – plus `NA`.
- `CharacterVector` can be used for vectors of character vectors ("strings").
- `RawVector` can be used for vectors of raw strings (used eg in serialization).
- `Named` can be used to assign named elements in a vector, similar to R construct `a <- c(foo=3.14, bar=42)`.
- `List` (aka `GenericVector`) is the catch-all, different-types-allowed container, more below.

`List` types can be used to receive (named) values to R. As lists can be nested, each element type is allowed.

```
double someFunction(Rcpp::List params) {
    std::string method =
        Rcpp::as<std::string>(params["method"]);
    double tolerance =
        Rcpp::as<double>(params["tolerance"]);
    Rcpp::NumericVector startvalues =
        params["startvalues"];

    // ... more code here ...
```

GenericVector

Similarly, `List` types can return multiple values to R.

```
return
Rcpp::List::create(Rcpp::Named("method", method),
                   Rcpp::Named("tolerance", tolerance),
                   Rcpp::Named("iterations", iterations),
                   Rcpp::Named("parameters", parameters));
```

`DataFrame` can receive and return values.

```
Rcpp::IntegerVector v =
    Rcpp::IntegerVector::create(1,2,3);
std::vector<std::string> s =
    { "a", "b", "c" };                  // C++11
return Rcpp::DataFrame::create(Rcpp::Named("a") = v,
                               Rcpp::Named("b") = s);
```

But because a `data.frame` is a (internally) a list of vectors, not as easy to subset by rows as in R.

Functions

The `Function` class can access R functions we pass in:

```
#include <Rcpp.h>

// [[Rcpp::export]]

SEXP fun(Rcpp::Function f, SEXP x) {
    return f(x);
}
```

Functions

```r
sourceCpp("code/functionEx1.cpp")
fun(sort, sample(1:5, 10, TRUE))
```

```
##  [1] 1 1 2 3 4 5 5 5 5 5
```

```r
fun(sort, sample(LETTERS[1:5], 10, TRUE))
```

```
##  [1] "A" "A" "B" "C" "C" "D" "D" "E" "E" "E"
```

We can also instantiate functions directly:

```cpp
#include <Rcpp.h>

// [[Rcpp::export]]
Rcpp::NumericVector fun() {
    Rcpp::Function rt("rt");
    return rt(3, 4);
}
```

Functions

```r
sourceCpp("code/functionEx2.cpp")
set.seed(42)
fun()
```

```
## [1]  2.057339  0.100706 -0.075780
```

```r
set.seed(42)
rt(3, 4)
```

```
## [1]  2.057339  0.100706 -0.075780
```

Environments

```
#include <Rcpp.h>

// [[Rcpp::export]]
Rcpp::NumericVector fun() {
    Rcpp::Environment stats("package:stats");
    Rcpp::Function rt = stats["rt"];
    return rt(3, Rcpp::Named("df", 4));
}
```

Environments

```r
sourceCpp("code/environmentEx1.cpp")
set.seed(42)
fun()
```

```
## [1]  2.057339  0.100706 -0.075780
```

```r
set.seed(42)
rt(3, 4)
```

```
## [1]  2.057339  0.100706 -0.075780
```

S4

S4 objects can be accessed as well as created.

```
#include <Rcpp.h>

// [[Rcpp::export]]
Rcpp::S4 fun(Rcpp::S4 x) {
    x.slot("x") = 42;
    return x;
}
```

S4

```r
library(methods); sourceCpp("code/s4ex1.cpp")
setClass("S4ex", contains="character",
         representation(x="numeric"))
x <- new("S4ex", "bla", x=10);  x
```

```
## An object of class "S4ex"
## [1] "bla"
## Slot "x":
## [1] 10
```

```r
fun(x)
```

```
## An object of class "S4ex"
## [1] "bla"
## Slot "x":
## [1] 42
```

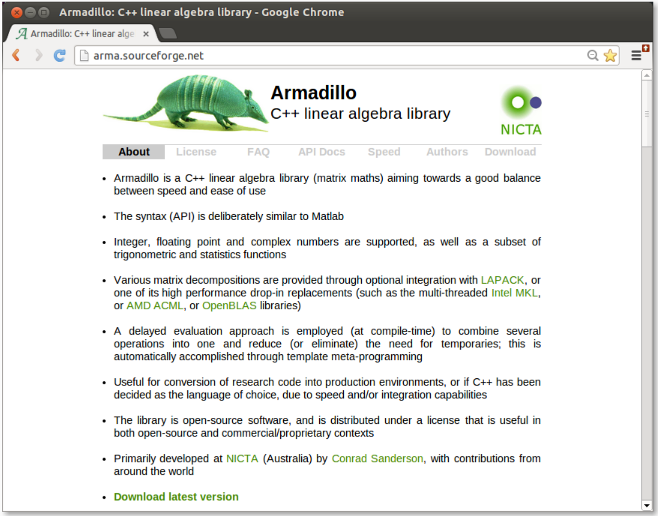
Applications

Overview

As of July 2016, almost 700 packages on CRAN use Rcpp

Single biggest “application” is RcppArmadillo for linear algebra

Armadillo


Armadillo: C++ linear algebra library - Google Chrome
Armadillo: C++ linear alge
arma.sourceforge.net
Armadillo
C++ linear algebra library
NICTA
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Speed
Authors
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Armadillo is a C++ linear algebra library (matrix maths) aiming towards a good balance between speed and ease of use
The syntax (API) is deliberately similar to Matlab
Integer, floating point and complex numbers are supported, as well as a subset of trigonometric and statistics functions
Various matrix decompositions are provided through optional integration with LAPACK, or one of its high performance drop-in replacements (such as the multi-threaded Intel MKL, or AMD ACML, or OpenBLAS libraries)
A delayed evaluation approach is employed (at compile-time) to combine several operations into one and reduce (or eliminate) the need for temporaries; this is automatically accomplished through template meta-programming
Useful for conversion of research code into production environments, or if C++ has been decided as the language of choice, due to speed and/or integration capabilities
The library is open-source software, and is distributed under a license that is useful in both open-source and commercial/proprietary contexts
Primarily developed at NICTA (Australia) by Conrad Sanderson, with contributions from around the world
Download latest version

What is Armadillo?

- Armadillo is a C++ linear algebra library (matrix maths) aiming towards a good balance between speed and ease of use.
- The syntax is deliberately similar to Matlab.
- Integer, floating point and complex numbers are supported.
- A delayed evaluation approach is employed (at compile-time) to combine several operations into one and reduce (or eliminate) the need for temporaries.
- Useful for conversion of research code into production environments, or if C++ has been decided as the language of choice, due to speed and/or integration capabilities.

Armadillo Highlights

- Provides integer, floating point and complex vectors, matrices and fields (3d) with all the common operations.
- Very good documentation and examples
    - website,
    - technical report (Sanderson, 2010)
    - CSDA paper (Sanderson and Eddelbuettel, 2014)
    - JOSS paper (Sanderson and Curtin, 2016).
- Modern code, building on / extending earlier matrix libraries.
- Responsive and active maintainer, frequent updates.
- Used eg by MLPACK, see Curtin et al (JMLR, 2013).

RcppArmadillo Highlights

- Template-only builds—no linking, and available whereever R and a compiler work (but Rcpp is needed)
- Easy to use, just add `LinkingTo: RcppArmadillo, Rcpp` to `DESCRIPTION` (i.e. no added cost beyond Rcpp)
- Really easy from R via Rcpp and automatic converters
- Frequently updated, widely used

Example: Eigen values

```cpp
#include <RcppArmadillo.h>

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

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

Example: Eigen values

```r
Rcpp::sourceCpp("code/arma_eigenvalues.cpp")
M <- cbind(c(1,-1), c(-1,1))
getEigenValues(M)
```

```
##      [,1]
## [1,]    0
## [2,]    2
```

```r
eigen(M)$values
```

```
## [1] 2 0
```

Example: Vector products

```cpp
#include <RcppArmadillo.h>

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

// 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;
}
```

Faster Linear Model with FastLm

- Implementations of `fastLm()` have been a staple during development of Rcpp
- First version was in response to a question by Ivo Welch on r-help.
- Request was for a fast function to estimate parameters – and their standard errors – from a linear model,
- It used GSL functions to estimate $\hat{\beta}$ as well as its standard errors $\hat{\sigma}$ – as `lm.fit()` in R only returns the former.
- It has since been reimplemented for RcppArmadillo and RcppEigen

Initial FastLm

```
#include <RcppArmadillo.h>

extern "C" SEXP fastLm(SEXP Xs, SEXP ys) {

  try {
    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, avoids extra copy
    arma::colvec y(yr.begin(), yr.size(), false);

    arma::colvec coef = arma::solve(X, y);      // fit model y ~ X
    arma::colvec res  = y - X*coef;             // residuals
    double s2 = std::inner_product(res.begin(), res.end(), res.begin(), 0.0)/(n - k);
    arma::colvec std_err =                      // std.errors of coefficients
        arma::sqrt(s2*arma::diagvec(arma::pinv(arma::trans(X)*X)));

    return Rcpp::List::create(Rcpp::Named("coefficients") = coef,
                              Rcpp::Named("stderr")       = std_err,
                              Rcpp::Named("df.residual")  = n - k   );
  } catch( std::exception &ex ) {
    forward_exception_to_r( ex );
  } catch(...) {
    ::Rf_error( "c++ exception (unknown reason)" );
  }
  return R_NilValue; // -Wall
}
```

Newer Version

```
// [[Rcpp::depends(RcppArmadillo)]]
#include <RcppArmadillo.h>
using namespace Rcpp;
using namespace arma;

// [[Rcpp::export]]
List fastLm(NumericVector yr, NumericMatrix Xr) {
   int n = Xr.nrow(), k = Xr.ncol();
   mat X(Xr.begin(), n, k, false);
   colvec y(yr.begin(), yr.size(), false);

   colvec coef = solve(X, y);
   colvec resid = y - X*coef;

   double sig2 = as_scalar(trans(resid)*resid/(n-k));
   colvec stderrest = sqrt(sig2 * diagvec( inv(trans(X)*X)) );

   return List::create(Named("coefficients") = coef,
                       Named("stderr")       = stderrest,
                       Named("df.residual")  = n - k    );
}
```

```
// [[Rcpp::depends(RcppArmadillo)]]
#include <RcppArmadillo.h>
using namespace Rcpp;
using namespace arma;

// [[Rcpp::export]]
List fastLm(const arma::mat& X, const arma::colvec& y) {
   int n = X.n_rows, k = X.n_cols;

   colvec coef = solve(X, y);
   colvec resid = y - X*coef;

   double sig2 = as_scalar(trans(resid)*resid/(n-k));
   colvec stderrest = sqrt(sig2 * diagvec( inv(trans(X)*X)) );

   return List::create(Named("coefficients") = coef,
                       Named("stderr")       = stderrest,
                       Named("df.residual")  = n - k   );
}
```

Interface Changes

```
arma::colvec y = Rcpp::as<arma::colvec>(ys);
arma::mat X = Rcpp::as<arma::mat>(Xs);
```

Convenient, yet incurs an additional copy. Next variant uses two steps, but only a pointer to objects is copied:

```
Rcpp::NumericVector yr(ys);
Rcpp::NumericMatrix Xr(Xs);
int n = Xr.nrow(), k = Xr.ncol();
arma::mat X(Xr.begin(), n, k, false);
arma::colvec y(yr.begin(), yr.size(), false);
```

Better if performance is a concern. But now RcppArmadillo has efficient `const references` too.

Benchmark

```
edd@don:~$ Rscript ~/git/rcpparmadillo/inst/examples/fastLm.r
                       test replications relative elapsed
3         fLmConstRef(X, y)         5000    1.000   0.245
2         fLmTwoCasts(X, y)         5000    1.045   0.256
4             fLmSEXP(X, y)         5000    1.094   0.268
1          fLmOneCast(X, y)         5000    1.098   0.269
6   fastLmPureDotCall(X, y)         5000    1.118   0.274
8              lm.fit(X, y)         5000    1.673   0.410
5          fastLmPure(X, y)         5000    1.763   0.432
7 fastLm(frm, data = trees)         5000   30.612   7.500
9     lm(frm, data = trees)         5000   30.796   7.545
## continued below
```

Benchmark

```
## continued from above
                      test replications relative elapsed
2        fLmTwoCasts(X, y)        50000    1.000   2.327
3            fLmSEXP(X, y)        50000    1.049   2.442
4        fLmConstRef(X, y)        50000    1.050   2.444
1         fLmOneCast(X, y)        50000    1.150   2.677
6 fastLmPureDotCall(X, y)        50000    1.342   3.123
5         fastLmPure(X, y)        50000    1.988   4.627
7             lm.fit(X, y)        50000    2.141   4.982
edd@don:~$
```

VAR(1) in R

Simulating a VAR(1) system of k variables:

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

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

We use $k = 2$ for this example.

VAR(1) in R

```r
## parameter and error terms used throughout
a <- matrix(c(0.5,0.1,0.1,0.5),nrow=2)
e <- matrix(rnorm(10000),ncol=2)

## Let's start with the R version
rSim <- function(coeff, errors) {
    simdata <- matrix(0, nrow(errors), ncol(errors))
    for (row in 2:nrow(errors)) {
        simdata[row,] = coeff %*% simdata[(row-1),] +
            errors[row,]
    }
    return(simdata)
}
rData <- rSim(a, e)                     # generated by R
```

VAR(1) IN C++

```
arma::mat rcppSim(const arma::mat& coeff,
                  const arma::mat& errors) {
    int m = errors.n_rows;
    int n = errors.n_cols;
    arma::mat simdata(m,n);
    simdata.row(0) = arma::zeros<arma::mat>(1,n);
    for (int row=1; row<m; row++) {
        simdata.row(row) = simdata.row(row-1) * coeff +
            errors.row(row);
    }
    return simdata;
}
```

Benchmark

```r
library(rbenchmark)
Rcpp::sourceCpp("code/arma_var1.cpp")
```

```
##
## R> a <- matrix(c(0.5, 0.1, 0.1, 0.5), 2, 2)
##
## R> e <- matrix(rnorm(10000), ncol = 2)
##
## R> head(rcppSim(a, e))
##            [,1]      [,2]
## [1,]  0.0000000 0.0000000
## [2,]  0.8915759 1.1792437
## [3,]  0.3858789 1.0815238
## [4,]  2.0054965 1.0828000
## [5,] -0.1754779 0.9469223
## [6,] -0.4886083 1.0468917
```

```r
benchmark(rSim(a,e), rcppSim(a, e))[,1:4]
```

```
##            test replications elapsed relative
## 2 rcppSim(a, e)          100   0.019    1.000
## 1    rSim(a, e)          100   2.624  138.105
```

The position of an object is estimated based on past values of 6×1 state vectors X and Y for position, V_X and V_Y for speed, and A_X and A_Y for acceleration.

Position updates as a function of the speed

$$X = X_0 + V_X dt \quad \text{and} \quad Y = Y_0 + V_Y dt,$$

which is updated as a function of the (unobserved) acceleration:

$$V_x = V_{X,0} + A_X dt \quad \text{and} \quad V_y = V_{Y,0} + A_Y dt.$$

MATLAB CODE: kalmanfilter.m

```
% Copyright 2010 The MathWorks, Inc.
function y = kalmanfilter(z)
  dt=1;
  % Initialize state transition matrix
  A=[ 1 0 dt 0 0 0; 0 1 0 dt 0 0;...  % [x ], [y ]
      0 0 1 0 dt 0; 0 0 0 1 0 dt;...  % [Vx], [Vy]
      0 0 0 0 1 0 ; 0 0 0 0 0 1 ];    % [Ax], [Ay]
  H = [ 1 0 0 0 0 0; 0 1 0 0 0 0 ];   % Init. measuremnt mat
  Q = eye(6);
  R = 1000 * eye(2);
  persistent x_est p_est              % Init. state cond.
  if isempty(x_est)
    x_est = zeros(6, 1);              % x_est=[x,y,Vx,Vy,Ax,Ay]'
    p_est = zeros(6, 6);
  end

  x_prd = A * x_est;                  % Predicted state and covariance
  p_prd = A * p_est * A' + Q;

  S = H * p_prd' * H' + R;            % Estimation
  B = H * p_prd';
  klm_gain = (S \ B)';

  % Estimated state and covariance
  x_est = x_prd + klm_gain * (z - H * x_prd);
  p_est = p_prd - klm_gain * H * p_prd;
  y = H * x_est;                      % Compute the estimated measurements
end                                   % of the function
```

MATLAB CODE: kalmanM.m WITH LOOP

```
function Y = kalmanM(pos)
  dt=1;
  %% Initialize state transition matrix
  A=[ 1 0 dt 0 0 0;...     % [x  ]
      0 1 0 dt 0 0;...     % [y  ]
      0 0 1 0 dt 0;...     % [Vx]
      0 0 0 1 0 dt;...     % [Vy]
      0 0 0 0 1 0 ;...     % [Ax]
      0 0 0 0 0 1 ];       % [Ay]
  H = [ 1 0 0 0 0 0; 0 1 0 0 0 0 ];    % Initialize measurement matrix
  Q = eye(6);
  R = 1000 * eye(2);
  x_est = zeros(6, 1);                 % x_est=[x,y,Vx,Vy,Ax,Ay]'
  p_est = zeros(6, 6);
  numPts = size(pos,1);
  Y = zeros(numPts, 2);
  for idx = 1:numPts
    z = pos(idx, :)';
    x_prd = A * x_est;                 % Predicted state and covariance
    p_prd = A * p_est * A' + Q;
    S = H * p_prd' * H' + R;           % Estimation
    B = H * p_prd';
    klm_gain = (S \ B)';
    x_est = x_prd + klm_gain * (z - H * x_prd);  % Estimated state and covariance
    p_est = p_prd - klm_gain * H * p_prd;
    Y(idx, :) = H * x_est;             % Compute the estimated measurements
  end
end   % of the function
```

Now in R

```
FirstKalmanR <- function(pos) {
    kalmanfilter <- function(z) {
        dt <- 1
        A <- matrix(c( 1, 0, dt, 0, 0, 0, 0, 1, 0, dt, 0, 0,  # x,  y
                      0, 0, 1, 0, dt, 0, 0, 0, 0, 1, 0, dt,  # Vx, Vy
                      0, 0, 0, 0, 1,  0, 0, 0, 0, 0, 0,  1), # Ax, Ay
                    6, 6, byrow=TRUE)
        H <- matrix( c(1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0),
                    2, 6, byrow=TRUE)
        Q <- diag(6)
        R <- 1000 * diag(2)
        xprd <- A %*% xest          # predicted state and covriance
        pprd <- A %*% pest %*% t(A) + Q
        S <- H %*% t(pprd) %*% t(H) + R     # estimation
        B <- H %*% t(pprd)
        kalmangain <- t(solve(S, B))
        ## estimated state and covariance, assign to vars in parent env
        xest <<- xprd + kalmangain %*% (z - H %*% xprd)
        pest <<- pprd - kalmangain %*% H %*% pprd
        y <- H %*% xest                     # compute the estimated measurements
    }
    xest <- matrix(0, 6, 1)
    pest <- matrix(0, 6, 6)
    N <- nrow(pos)
    y <- matrix(NA, N, 2)
    for (i in 1:N) y[i,] <- kalmanfilter(t(pos[i,,drop=FALSE]))
    invisible(y)
}
```

Improved in R

```
KalmanR <- function(pos) {
    kalmanfilter <- function(z) {
        xprd <- A %*% xest                        # predicted state and covariance
        pprd <- A %*% pest %*% t(A) + Q
        S <- H %*% t(pprd) %*% t(H) + R           # estimation
        B <- H %*% t(pprd)
        kalmangain <- t(solve(S, B))
        xest <<- xprd + kalmangain %*% (z - H %*% xprd)    # est. state and covariance
        pest <<- pprd - kalmangain %*% H %*% pprd          # ass. to vars in parent env
        y <- H %*% xest                           # compute the estimated measurements
    }
    dt <- 1
    A <- matrix( c( 1, 0, dt, 0, 0, 0,  # x
                   0, 1, 0, dt, 0, 0,   # y
                   0, 0, 1, 0, dt, 0,   # Vx
                   0, 0, 0, 1, 0, dt,   # Vy
                   0, 0, 0, 0, 1,  0,   # Ax
                   0, 0, 0, 0, 0,  1),  # Ay
                6, 6, byrow=TRUE)
    H <- matrix( c(1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0), 2, 6, byrow=TRUE)
    Q <- diag(6)
    R <- 1000 * diag(2)
    N <- nrow(pos)
    Y <- matrix(NA, N, 2)
    xest <- matrix(0, 6, 1)
    pest <- matrix(0, 6, 6)
    for (i in 1:N) Y[i,] <- kalmanfilter(t(pos[i,,drop=FALSE]))
    invisible(Y)
}
```

And now in C++

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

#include <RcppArmadillo.h>

using namespace arma;

class Kalman {
private:
    mat A, H, Q, R, xest, pest;
    double dt;

public:
    // constructor, sets up data structures
    Kalman() : dt(1.0) {
        A.eye(6,6);
        A(0,2) = A(1,3) = A(2,4) = A(3,5) = dt;
        H.zeros(2,6);
        H(0,0) = H(1,1) = 1.0;
        Q.eye(6,6);
        R = 1000 * eye(2,2);
        xest.zeros(6,1);
        pest.zeros(6,6);
    }

   // cont. below
```

And now in C++

```
// continued
    // sole member function: estimate model
    mat estimate(const mat & Z) {
       unsigned int n = Z.n_rows, k = Z.n_cols;
       mat Y = zeros(n, k);
       mat xprd, pprd, S, B, kalmangain;
       colvec z, y;

       for (unsigned int i = 0; i<n; i++) {
           z = Z.row(i).t();
           // predicted state and covariance
           xprd = A * xest;
           pprd = A * pest * A.t() + Q;
           // estimation
           S = H * pprd.t() * H.t() + R;
           B = H * pprd.t();
           kalmangain = (solve(S, B)).t();
           // estimated state and covariance
           xest = xprd + kalmangain * (z - H * xprd);
           pest = pprd - kalmangain * H * pprd;
           // compute the estimated measurements
           y = H * xest;
           Y.row(i) = y.t();
       }
       return Y;
    }
};
```

And the call:

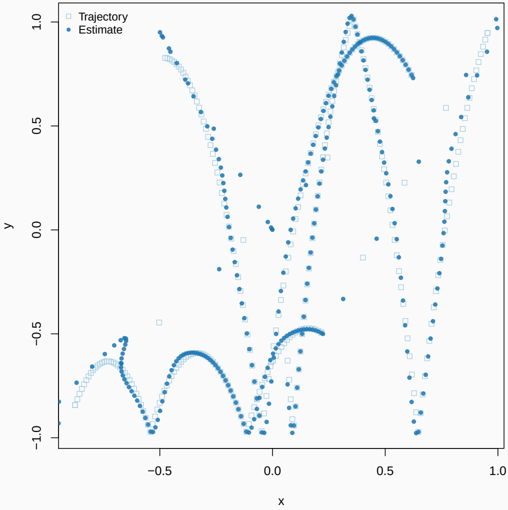
```cpp
// [[Rcpp::export]]
mat KalmanCpp(mat Z) {
  Kalman K;
  mat Y = K.estimate(Z);
  return Y;
}
```

Benchmark

```r
library(rbenchmark)
Rcpp::sourceCpp("code/kalman.cpp")
source("code/kalman.R")
p <- as.matrix(read.table("code/pos.txt",
                          header=FALSE,
                          col.names=c("x","y")))
benchmark(KalmanR(p), FirstKalmanR(p), KalmanCpp(p),
          order="relative", replications=500)[,1:4]
```

```
##              test replications elapsed relative
## 3    KalmanCpp(p)          500  11.445    1.000
## 1      KalmanR(p)          500  23.513    2.054
## 2 FirstKalmanR(p)          500  30.627    2.676
```

Reproduced Figure



RcppGSL

- RcppGSL is a convenience wrapper for accessing the GNU GSL, particularly for vector and matrix functions.
- Given that the GSL is a C library, we need to
    - do memory management and free objects (or let C++ do it for us as in recent versions of RcppGSL)
    - arrange for the GSL libraries to be found
- RcppGSL may still be a convenient tool for programmers more familiar with C than C++ wanting to deploy GSL algorithms.

GSL Vector Norm Example (old)

```
#include <RcppGSL.h>
#include <gsl/gsl_matrix.h>
#include <gsl/gsl_blas.h>

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

// [[Rcpp::export]]
Rcpp::NumericVector colNorm_old(Rcpp::NumericMatrix NM) {
    // this conversion involves an allocation
    RcppGSL::matrix<double> M = Rcpp::as< RcppGSL::matrix<double> >(NM);
    int k = M.ncol();
    Rcpp::NumericVector n(k);            // to store results
    for (int j = 0; j < k; j++) {
        RcppGSL::vector_view<double> colview = gsl_matrix_column (M, j);
        n[j] = gsl_blas_dnrm2(colview);
    }
    M.free();
    return n;                            // return vector
}
```

GSL Vector Norm Example (new)

```cpp
#include <RcppGSL.h>
#include <gsl/gsl_matrix.h>
#include <gsl/gsl_blas.h>

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

// newest version using typedefs and const &

// [[Rcpp::export]]
Rcpp::NumericVector colNorm(const RcppGSL::Matrix & G) {
    int k = G.ncol();
    Rcpp::NumericVector n(k);           // to store results
    for (int j = 0; j < k; j++) {
        RcppGSL::VectorView colview = gsl_matrix_const_column (G, j);
        n[j] = gsl_blas_dnrm2(colview);
    }
    return n;                           // return vector
}
```

GSL Vector Norm Example

```r
Rcpp::sourceCpp("code/gslNorm.cpp")
set.seed(42)
M <- matrix(rnorm(25), 5, 5)
colNorm(M)                                  # via GSL
```

```
## [1] 1.701241 2.526438 2.992635 3.903917 2.892030
```

```r
apply(M, 2, function(x) sqrt(sum(x^2)))   # via R
```

```
## [1] 1.701241 2.526438 2.992635 3.903917 2.892030
```

GSL bSpline Example

- The example comes from Section 39.7 of the GSL Reference manual, and constructs a data set from the curve $y(x) = \cos(x)\exp(-x/10)$ on the interval $[0, 15]$ with added Gaussian noise — which is then fit via linear least squares using a cubic B-spline basis functions with uniform breakpoints.
- Obviously all this could be done in R too as R can both generate data, and fit models including (B-)splines. But the point to be made here is that we can very easily translate a given GSL program (thanks to RcppGSL), and get it into R with ease thanks to Rcpp and Rcpp attributes.

GSL bSpline Example: C++ (1/5)

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

#include <gsl/gsl_bspline.h>
#include <gsl/gsl_multifit.h>
#include <gsl/gsl_rng.h>
#include <gsl/gsl_randist.h>
#include <gsl/gsl_statistics.h>

const int N = 200;                              // number of data points to fit
const int NCOEFFS = 12;                         // number of fit coefficients
const int NBREAK = (NCOEFFS - 2);               // ncoeffs + 2 - k = ncoeffs - 2 as k = 4

// [[Rcpp::export]]
Rcpp::List genData() {
    const size_t n = N;
    size_t i;
    RcppGSL::Vector w(n), x(n), y(n);

    gsl_rng_env_setup();
    gsl_rng *r = gsl_rng_alloc(gsl_rng_default);

    // ...
```

GSL bSpline Example: C++ (2/5)

```
    for (i = 0; i < n; ++i) {      // this is the data to be fitted
        double xi = (15.0 / (N - 1)) * i;
        double yi = cos(xi) * exp(-0.1 * xi);

        double sigma = 0.1 * yi;
        double dy = gsl_ran_gaussian(r, sigma);
        yi += dy;

        x[i] = xi;
        y[i] = yi;
        w[i] = 1.0 / (sigma * sigma);
    }

    gsl_rng_free(r);
    return Rcpp::DataFrame::create(Rcpp::Named("x") = x,
                                   Rcpp::Named("y") = y,
                                   Rcpp::Named("w") = w);
}
```

GSL bSpline Example: C++ (3/5)

```
// [[Rcpp::export]]
Rcpp::List fitData(Rcpp::DataFrame D) {
    const size_t ncoeffs = NCOEFFS;
    const size_t nbreak = NBREAK;
    const size_t n = N;
    size_t i, j;

    RcppGSL::Vector y = D["y"];     // access columns by name,
    RcppGSL::Vector x = D["x"];     // assigning to GSL vectors
    RcppGSL::Vector w = D["w"];

    gsl_bspline_workspace *bw;
    RcppGSL::Vector B(ncoeffs);
    RcppGSL::Vector c(ncoeffs);
    RcppGSL::Matrix X(n, ncoeffs);
    RcppGSL::Matrix cov(ncoeffs, ncoeffs);
    gsl_multifit_linear_workspace *mw;
    double chisq, Rsq, dof, tss;

    bw = gsl_bspline_alloc(4, nbreak);      // allocate a cubic bspline workspace (k = 4)
    mw = gsl_multifit_linear_alloc(n, ncoeffs);

    gsl_bspline_knots_uniform(0.0, 15.0, bw);   // use uniform breakpoints on [0, 15]
```

GSL bSpline Example: C++ (4/5)

```
for (i = 0; i < n; ++i) {           // construct the fit matrix X
    double xi = x[i];

    gsl_bspline_eval(xi, B, bw);        // compute B_j(xi) for all j

    for (j = 0; j < ncoeffs; ++j) {     // fill in row i of X
        double Bj = B[j];
        X(i,j) = Bj;
    }
}

gsl_multifit_wlinear(X, w, y, c, cov, &chisq, mw);  // do the fit

dof = n - ncoeffs;
tss = gsl_stats_wtss(w->data, 1, y->data, 1, y->size);
Rsq = 1.0 - chisq / tss;
```

GSL bSpline Example: C++ (5/5)

```
    Rcpp::NumericVector FX(151), FY(151);   // output the smoothed curve
    double xi, yi, yerr;
    for (xi = 0.0, i=0; xi < 15.0; xi += 0.1, i++) {
        gsl_bspline_eval(xi, B, bw);
        gsl_multifit_linear_est(B, c, cov, &yi, &yerr);
        FX[i] = xi;
        FY[i] = yi;
    }

    gsl_bspline_free(bw);
    gsl_multifit_linear_free(mw);

    return Rcpp::List::create(Rcpp::Named("X") = FX,
                              Rcpp::Named("Y") = FY,
                              Rcpp::Named("chisqdof") = Rcpp::wrap(chisq/dof),
                              Rcpp::Named("rsq") = Rcpp::wrap(Rsq));
}
```

GSL bSpline Example

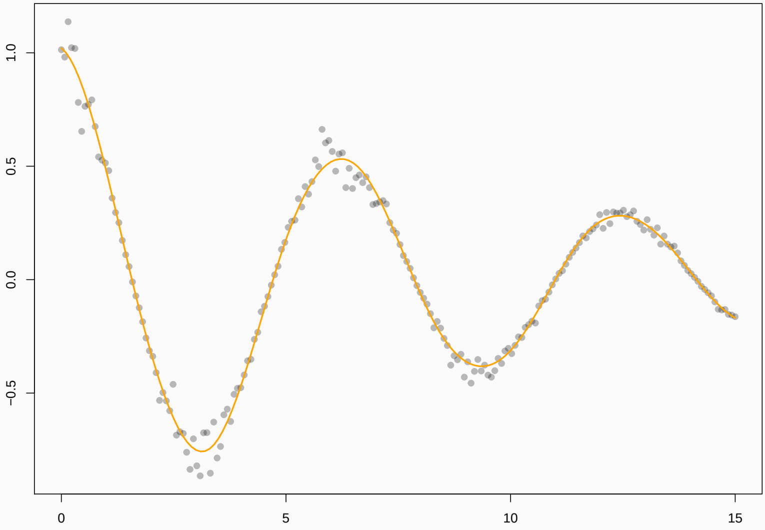
```r
Rcpp::sourceCpp("bSpline.cpp")

dat <- genData()                    # generate the data
fit <- fitData(dat)                 # fit the model

X <- fit[["X"]]                     # extract vectors
Y <- fit[["Y"]]

par(mar=c(3,3,1,1))
plot(dat[,"x"], dat[,"y"], pch=19, col="#00000044")
lines(X, Y, col="orange", lwd=2)
```

GSL bSpline Example



Examples from the Rcpp Gallery

Overview

- The *Rcpp Gallery* at `http://gallery.rcpp.org` provides over one hundred ready-to-run and documented examples.
- It is built on a blog-alike backend in a repository hosted at GitHub.
- You can clone the repository, or just download examples one-by-one.

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 var
    NumericVector res(x.size());  // init result vector
    for (int i = 0; i < x.size(); i++){
         acc += x[i];
         res[i] = acc;
    }
    return res;
}
```

An STL variant:

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

// [[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/

Sugar:

```
// [[Rcpp::export]]
NumericVector cumsum3(NumericVector x) {
    return cumsum(x);  // compute + return result
}
```

Calling an R Function: r-function-from-c++/

```
#include <Rcpp.h>

using namespace Rcpp;

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

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];
}
```

Vector Subsetting: armadillo-subsetting/

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

// [[Rcpp::export]]
arma::mat matrixSubset(arma::mat M) {
    // logical conditionL where is transpose larger?
    arma::umat a = trans(M) > M;
    arma::mat  N = arma::conv_to<arma::mat>::from(a);
    return N;
}

// [[Rcpp::export]]
arma::vec matrixSubset2(arma::mat M) {
    arma::mat Z = M * M.t();
    arma::vec v = Z.elem( arma::find( Z >= 100 ) );
    return v;
}
```

Boost via BH: a-first-boost-example/

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

// [[Rcpp::export]]
int computeGCD(int a, int b) {
    return boost::math::gcd(a, b);
}

// [[Rcpp::export]]
int computeLCM(int a, int b) {
    return boost::math::lcm(a, b);
}
```

Boost via BH: a-second-boost-example/

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

// [[Rcpp::export]]
std::vector<double> lexicalCast(std::vector<std::string> v) {
    std::vector<double> res(v.size());
    for (int i=0; i<v.size(); i++) {
        try {
            res[i] = lexical_cast<double>(v[i]);
        } catch(bad_lexical_cast &) {
            res[i] = NA_REAL;
        }
    }
    return res;
}
// R> lexicalCast(c("1.23", ".4", "1000", "foo", "42", "pi/4")(
// [1]    1.23    0.40 1000.00      NA   42.00      NA
```

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::Date(ymd.year, ymd.month, ymd.day);
}
```

Boost via BH: boost-regular-expressions/

NB: Use `Sys.setenv("PKG_LIBS"="-lboost_regex")`

```
// boost.org/doc/libs/1_53_0/libs/regex/example/snippets/credit_card_example.cpp
#include <Rcpp.h>
#include <string>
#include <boost/regex.hpp>

bool validate_card_format(const std::string& s) {
    static const boost::regex e("(\\d{4}[- ]){3}\\d{4}");
    return boost::regex_match(s, e);
}

// [[Rcpp::export]]
std::vector<bool> regexDemo(std::vector<std::string> s) {
    int n = s.size();
    std::vector<bool> v(n);
    for (int i=0; i<n; i++)
        v[i]  = validate_card_format(s[i]);
    return v;
}
```

Plugin support in Rcpp

```r
# setup plugins environment
.plugins <- new.env()
# built-in C++11 plugin
.plugins[["cpp11"]] <- function() {
    if (getRversion() >= "3.1")
        list(env = list(USE_CXX1X = "yes"))
    else if (.Platform$OS.type == "windows")
        list(env = list(PKG_CXXFLAGS = "-std=c++0x"))
    else
        list(env = list(PKG_CXXFLAGS ="-std=c++11"))
}
# built-in OpenMP++11 plugin
.plugins[["openmp"]] <- function() {
    list(env = list(PKG_CXXFLAGS="-fopenmp", PKG_LIBS="-fopenmp"))
}

# register a plugin
registerPlugin <- function(name, plugin) {
    .plugins[[name]] <- plugin
}
```

C++11 AUTO: first-steps-with-C++11/

```cpp
#include <Rcpp.h>

// Enable C++11 via this plugin
// [[Rcpp::plugins("cpp11")]]

// [[Rcpp::export]]
int useAuto() {
    auto val = 42;      // val will be of type int
    return val;
}
```

```
#include <Rcpp.h>

// [[Rcpp::plugins("cpp11")]]

// [[Rcpp::export]]
std::vector<std::string> useInitLists() {
    std::vector<std::string> vec =
        {"larry", "curly", "moe"};
    return vec;
}
```

C++11 RANGE: first-steps-with-C++11/

```
#include <Rcpp.h>

// [[Rcpp::plugins("cpp11")]]

// [[Rcpp::export]]
int simpleProd(std::vector<int> vec) {
    int prod = 1;
    for (int &x : vec) {          // loop over all values of vec
       prod *= x;                 // access each elem., comp. prod
    }
    return prod;
}
```

C++11 LAMBDA: simple-lambda-func-c++11/

```
#include <Rcpp.h>

// [[Rcpp::plugins("cpp11")]]

// [[Rcpp::export]]
std::vector<double>
transformEx(const std::vector<double>& x) {
    std::vector<double> y(x.size());
    std::transform(x.begin(), x.end(), y.begin(),
                   [](double x) { return x*x; } );
    return y;
}
```

OpenMP: using-rcppprogress/

We start we with (somewhat boring/made-up) slow double-loop:

```
#include <Rcpp.h>

// [[Rcpp::export]]
double long_computation(int nb) {
    double sum = 0;
    for (int i = 0; i < nb; ++i) {
        for (int j = 0; j < nb; ++j) {
            sum += R::dlnorm(i+j, 0.0, 1.0, 0);
        }
    }
    return sum + nb;
}
```

OpenMP: using-rcppprogress/

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

// [[Rcpp::export]]
double long_computation_omp(int nb, int threads=1) {
#ifdef _OPENMP
    if (threads > 0) omp_set_num_threads( threads );
    REprintf("Number of threads=%i\n", omp_get_max_threads());
#endif

    double sum = 0;
#pragma omp parallel for schedule(dynamic)
    for (int i = 0; i < nb; ++i) {
        double thread_sum = 0;
        for (int j = 0; j < nb; ++j) {
            thread_sum += R::dlnorm(i+j, 0.0, 1.0, 0);
        }
        sum += thread_sum;
    }
    return sum + nb;
}
```

OpenMP: using-rcppprogress/

Even on my laptop gains can be seen:

```
R> sourceCpp("code/openmpEx.cpp")
R> system.time(long_computation(1e4))
   user  system elapsed
 22.436   0.000  22.432
R> system.time(long_computation_omp(1e4,4))
Number of threads=4
   user  system elapsed
 25.432   0.076   7.046
R>
```

Packaging

R Packages

- This is an important topic in R programming
- Organising code in packages maybe *the* single most helpful step
- Core topic in R Programming / Advanced R courses
- Penn 2014 workshop had 90 minutes on this

R Packages

- `package.skeleton()` helpful as it creates a stanza
- `package.skeleton()` not helpful as it creates a stanza that does not pass `R CMD check` cleanly
- I wrote pkgKitten to provide `kitten()` which creates *packages that purr*
- Rcpp (and RcppArmadillo, RcppEigen) all have their own versions of `package.skeleton()`
- They can use `kitten()` if pkgKitten is installed
- Alternative: `devtools::create()` if you don't mind Hadleyverse dependency
- Also: RStudio File -> New Project -> New Directory -> R Package; and toggle 'R Package' to 'R Package w/ Rcpp'

Case Study: RcppAnnoy

- Uses only one C++ header (one plus header for Windows)

```
edd@don:~/git/rcppannoy$ tree inst/include/
inst/include/
├── annoylib.h
└── mman.h

0 directories, 2 files
edd@don:~/git/rcppannoy$ tree src/
src/
├── annoy.cpp
└── Makevars

0 directories, 2 files
edd@don:~/git/rcppannoy$
```

RcppAnnoy: src/Makevars

- One include indirection to the header file

```
## We want C++11 as it gets us 'long long' as well
CXX_STD = CXX11

PKG_CPPFLAGS = -I../inst/include/
```

RcppAnnoy: `src/annoy.cpp`

- Implemented as Rcpp Modules (not discussed today)
- Wraps around templated C++ class for either
    - Angular distance, or
    - Euclidian distance
- Package interesting as upstream C++ core used with Python by upstream

RcppAnnoy

```
edd@don:~$ tree git/rcppannoy/
git/rcppannoy/
├── ChangeLog
├── cleanup
├── demo
│   ├── 00Index
│   └── simpleExample.R
├── DESCRIPTION
├── inst
│   ├── include
│   │   ├── annoylib.h
│   │   └── mman.h
│   └── tests
│       ├── data
│       │   └── test.tree
│       ├── runit.angular.R
│       ├── runit.euclidean.R
│       └── runit.index.R
├── man
│   └── RcppAnnoy-package.Rd
├── NAMESPACE
├── R
│   └── annoy.R
├── rcppannoy.Rproj
├── README.md
├── src
│   ├── annoy.cpp
│   └── Makevars
└── tests
    └── runUnitTests.R

9 directories, 19 files
edd@don:~$
```

Plus a few additional files for tests and documentation.

- Uses one C++ header and one C++ source file from CNPy

```
edd@don:~/git/rcppcnpy$ tree src/
src/
├── cnpy.cpp           # from CNPy
├── cnpy.h             # from CNPy
├── cnpyMod.cpp        # our wrapper
├── Makevars           # add -lz (from R) and C++11
└── Makevars.win       # ditto

0 directories, 5 files
edd@don:~/git/rcppcnpy$
```

RcppCNPy

- For this package no other customization is needed
- Simply add the two source files
- Code integration done via Rcpp Modules (which we won't cover today)
- Here we just need one linker flag (supplied by R)

RcppCNPy: `src/Makevars`

One linker flag (and a compiler option for `long long`)

```
## We need the compression library
PKG_LIBS = -lz

## We want C++11 as it gets us 'long long' as well
CXX_STD = CXX11
```

```
edd@don:~$ tree git/rcppcnpy/
git/rcppcnpy/
├── ChangeLog
├── cleanup
├── demo
│   ├── 00Index
│   └── timings.R
├── DESCRIPTION
├── inst
│   ├── cnpy-LICENSE
│   ├── NEWS.Rd
│   └── THANKS
├── LICENSE
├── man
│   └── RcppCNPy-package.Rd
├── NAMESPACE
├── R
│   └── cnpy.R
├── rcppcnpy.Rproj
├── README.md
├── src
│   ├── cnpy.cpp
│   ├── cnpy.h
│   ├── cnpyMod.cpp
│   ├── Makevars
│   └── Makevars.win
├── tests
│   ├── createFiles.py
│   ├── fmat.npy
│   ├── fmat.npy.gz
│   ├── fvec.npy
│   ├── imat.npy
│   ├── ivec.npy
│   ├── loadFiles.py
│   ├── loadFiles.R
│   ├── loadFiles.Rout.save
│   ├── saveAndLoad.R
│   └── saveAndLoad.Rout.save
└── vignettes
    ├── RcppCNPy-intro.pdf
    └── RcppCNPy-intro.Rnw

7 directories, 32 files
edd@don:~$
```

More test files, more documentation files make this look more "busy" – but still a simple package.

RcppAPT

- A somewhat experimental package which only builds on Ubuntu or Debian
- Interface a system library we can assume to be present on those systems – but not on OS X, Windows or even other Linux systems

RcppAPT: `src/Makevars`

- Very simple

```
PKG_LIBS = -lapt-pkg
```

RcppAPT

```
edd@don:~$ tree git/rcppapt/
git/rcppapt/
├── ChangeLog
├── cleanup
├── configure
├── DESCRIPTION
├── inst
│   └── TODO.md
├── man
│   ├── getPackages.Rd
│   ├── hasPackages.Rd
│   └── rcppapt-package.Rd
├── NAMESPACE
├── R
│   └── RcppExports.R
├── README.md
└── src
    ├── getPackages.cpp
    ├── hasPackage.cpp
    ├── Makevars
    └── RcppExports.cpp

4 directories, 15 files
edd@don:~$
```

Very simple: a few functions wrapping code from ‘libapt‘ library.

- Recent package by Baptiste Auguie with some help from me
- Wrapper around some complex-valued error functions by Steven Johnson
- Upstream ships a single header and a single C++ file –> just place in `src/`
- Usage pretty easy: loop over elements of argument vector and call respective function to build return vector

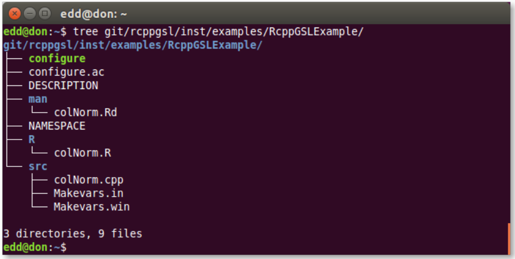
RcppFaddeeva

```cpp
//' @title Faddeeva family of error functions of the complex variable
//' @description the Faddeeva function
//' @param z complex vector
//' @param relerr double, requested error
//' @return complex vector
//' @describeIn wrap compute w(z) = exp(-z^2) erfc(-iz)
//' @family wrapper
//' @examples
//' Faddeeva_w(1:10 + 1i)
//' @export
// [[Rcpp::export]]
std::vector< std::complex<double> >
             Faddeeva_w(const std::vector< std::complex<double> >& z,
                        double relerr=0) {
  int N = z.size();
  std::vector< std::complex<double> > result(N);
  for(int i=0; i<N; i++)  result[i] = Faddeeva::w(z[i], relerr);
  return result;
}
```

RcppGSLExample

- This package is included in the RcppGSL package and part of the test environment
- It implements the same column norm example we looked at earlier.

RcppGSLExample



Simple package against library which we test for (`configure`) and set environment variable for (`src/Makevars.win`)

Change 'R-only' package to 'R and Rcpp' package

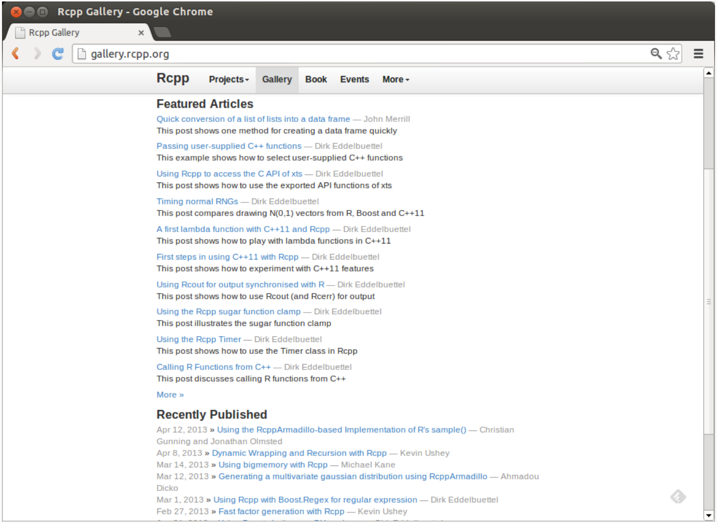
- No full example here
- Fairly easy to do manually:
    - Add `LinkingTo: Rcpp` to `DESCRIPTION`
    - Also add `Imports: Rcpp` to `DESCRIPTION`
    - Add `importFrom(Rcpp, "evalCpp")` to `NAMESPACE`
    - Add `useDynLib(yourPackageName)` to `NAMESPACE`
- Add some C++ code in `src/`
- Remember to run `compileAttributes()` each time you add (or change!) a C++ intrface

The End

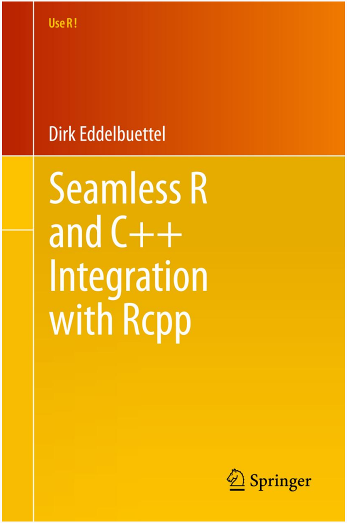
Documentation

- The package comes with nine pdf vignettes, and numerous help pages.
- The introductory vignettes are now published (for Rcpp and RcppEigen in *J Stat Software*, for RcppArmadillo in *Comp Stat & Data Anlys*)
- The rcpp-devel list is *the* recommended resource, generally very helpful, and fairly low volume.
- StackOverflow has over 1100 posts on Rcpp too.
- And a number of blog posts introduce/discuss features.

Rcpp Gallery



The Rcpp book



Thank You!

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