Rcpp

An Example-Driven Hands-on Introduction

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INTRODUCTION
Brief Overview

- Preliminary: Motivation
- Part I: How To Get Started, Some Background
- Part II: Using Rcpp with Packages
- Part III: A Worked Rcpp Package Example
- Part IV: A Worked ‘Faster Application’ Example
- Part V: Lots More (Small) Examples
- Brief Conclusion
- Appendix: C++ Refresher
Motivation: R for Programming with Data


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

xx <- faithful[, "eruptions"]
fit <- density(xx)
plot(fit)
A Simple Example

density.default(x = xx)

N = 272   Bandwidth = 0.3348
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)
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.
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*
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.*
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.*
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
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 the new *Reference Classes* now in R and built upon via Rcpp Modules, Rcpp Classes (and also RcppR6)
Why C++?

- Asking Google leads to about 52 million 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)
Scott Meyers: View C++ as a federation of languages

- C provides a rich inheritance and interoperability as Unix, Windows, ... are all built 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 metaprogramming 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
Algorithm Interface

ABC: general (FORTRAN) algorithm

XABC: FORTRAN subroutine to provide interface between ABC and/or language and/or utility programs

XABC(INSTR,OUTSTR)

Input INSTR →

"X" "Y"

Pointers/Values

Argument Names or Blank

5/5/76
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 – we will see numerous few examples
· *Easy to use* as it avoids build and OS system complexities thanks to the R infrastructure
· *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*
Part I: Getting Started
RStudio makes starting very easy:
The following file gets created:

```cpp
#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
A First Example: Cont’ed

Try it:

・ Save the file as, say, timesTwo.cpp
・ You could a temporary directory, or a projects directory, or your desktop (keep it simple)
・ Then at the R prompt:

```r
## simple
timesTwo(21)
## more interesting
timesTwo(c(1,2,3,44,101))
```
Building on the previous example, build a function `adder` that adds two vectors.

- hint: as we will see later, `+` is vectorised

What other features might such a function need?
One solution:

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

// [[Rcpp::export]]
NumericVector adder(NumericVector x,
                    NumericVector y) {
    NumericVector z = x + y;
    return z;
}
```
cppFunction() creates, compiles and links a C++ file, and creates an R function to access it.

cppFunction("int times2(int x) { return 2*x; }")
times2(21)  # same identifier as C++ function
cppFunction Exercise

Create a function or two using cppFunction() supplying an argument string with the code.

Experiment.

Use e.g. IntegerVector and/or NumericVector.
One solution:

```cpp
cppFunction('double myrange(NumericVector(x)) {
    return max(x) - min(x);
}
')
```

Linebreaks above purely stylistic. String can be multiline too, use `paste()` etc pp.
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
```  

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

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

```r
## [1] 1.797693e+308
```
Consider a function defined as

\[ F(n) \text{ such that } \begin{cases} 
  n & \text{when } n < 2 \\
  F(n - 1) + F(n - 2) & \text{when } n \geq 2
\end{cases} \]
R implementation and use:

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

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

## [1]  0  1  1  2  3  5  8 13 21 34 55
An Introductory Example: Timing R Implementation

Timing:

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

```
## test  replications elapsed relative
## 1    F(10)      100 0.019 1.000
## 2    F(15)      100 0.198 10.421
## 3    F(20)      100 2.208 116.211
```
int G(int n) {
    if (n < 2) return(n);
    return(G(n-1) + G(n-2));
}

deployed as

Rcpp::cppFunction('int G(int n) {
    if (n < 2) return(n);
    return(G(n-1) + G(n-2));
}')

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

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

```r
library(rbenchmark)
benchmark(F(25), G(25))[,1:4]
```

```r
## test replications elapsed relative
## 1 F(25) 100 24.496 510.333
## 2 G(25) 100 0.048 1.000
```

A nice gain of a few orders of magnitude.
Copy one or two of the Fibonacci solutions and excercise.

Install the `rbenchmark` or `microbenchmark` package and play with timings.
Everything uses this interface

```
SEXP .Call(SEXP a, SEXP b, SEXP c, ...)
```

which is explained in *Writing R Extensions*.

But we **never** have to deal with `.Call()` function, or the SEXP types.
Standard R types (integer, numeric, list, function, ... and compound objects) are mapped to corresponding C++ types using extensive template meta-programming – it just works:

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

As we saw before: vectorized C++!
Use of `std::vector<double>` and STL algorithms:

```cpp
#include <Rcpp.h>

using namespace Rcpp;

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

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

```r
library(Rcpp)
sourceCpp("code/logabs2.cpp")
logabs2(seq(-5, 5, by=2))
```
Outer product of a column vector (via RcppArmadillo):

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

Uses implicit conversion – see vignette Rcpp-extending.

In C++ source files use the attribute:

```c
// [[Rcpp::depends(RcppArmadillo)]]
```
We can simplify the $\log(\text{abs}(\ldots))$ example further:

```cpp
#include <Rcpp.h>

using namespace Rcpp;

std::vector<double> logabs3(std::vector<double> x) {
    std::transform(x.begin(), x.end(), x.begin(),
        [](double x) {
            return ::log(::fabs(x));
        });
    return x;
}
```
Part II: Rcpp and Packages
Basic Usage: Packages

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

They allow us to bundle

- code
- (optional) documentation
- (optional) data
- (optional) tests

and made development, versioning, sharing, ... easy thanks to the R infrastructure.
As of early November 2015, there are

- 503 packages on CRAN which use Rcpp,
- a further 70 on BioConductor,
- an unknown number on GitHub

So well over 500 packages on the official, tested repositories – all with working, tested, and reviewed examples.
Creating packages with Rcpp is easy!

Rcpp.package.skeleton() creates an empty package.

The vignette Rcpp-packages has fuller details.
Or just use RStudio (similar to Rcpp.package.skeleton())
These files are created by `Rcpp.package.skeleton()`.

We will examine some of the files. Using the RStudio feature is very similar. You can use either.
Package: samplePackage
Type: Package
Title: What the package does (short line)
Version: 1.0
Date: 2015-09-06
Author: Your Name
Maintainer: Your Name <your@email.com>
Description: More about what it does (maybe more than one line)
License: GPL (>= 2)
Imports: Rcpp (>= 0.12.0.5)
LinkingTo: Rcpp

Here the last two lines are key: we import Rcpp and link to it.
Packages and Rcpp Files: NAMESPACE

```r
useDynLib(samplePackage)
exportPattern("^[[:alpha:]]+")
importFrom(Rcpp, evalCpp)
```

This ensures that

- we load the code in this package
- export all (public) identifiers
- load a function from Rcpp (to ensure Rcpp gets imported)
#include <Rcpp.h>

using namespace Rcpp;

// [[Rcpp::export]]
List rcpp_hello_world() {
  CharacterVector x =
    CharacterVector::create("foo", "bar");
  NumericVector y =
    NumericVector::create(0.0, 1.0);
  List z = List::create(x, y);
  return z;
}
These files are *auto-generated* by the function `compileAttributes()`. Whenever we change the “interface” from our C++ function (that is exported to R) we need to re-run `compileAttributes()` – which RStudio automates.
Exercise: Package

Build and load the package.
Check the package.
Add a (C++) function to the package.
Packages: Rcpp and RcppArmadillo

Create packages via Rcpp.package.skeleton() and RcppArmadillo.package.skeleton():

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

// another simple example: outer product of a vector, returns 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;
}
```
#include <RcppArmadillo.h>

using namespace Rcpp;

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

    arma::colvec coef = arma::solve(X, y);  // fit model y ~ X
    arma::colvec res = y - X*coef;         // residuals

    // std.errors of coefficients
    double s2 =
        std::inner_product(res.begin(), res.end(), res.begin(), 0.0)/(n - k);

    arma::colvec std_err =
        arma::sqrt(s2 * arma::diagvec(arma::pinv(arma::trans(X)*X)));

    return List::create(_["coefficients"] = coef,
                         _["stderr"] = std_err,
                         _["df.residual"] = n - k);
}
RcppEigen has its fans, notably lme4.

RcppGSL was just updated, allows easy access to the GSL.

And your favourite package here as it is easy to write plugins, and even easier to just build against a library.
Part III: RcppZiggurat
Random numbers play an ever increasing role as simulations are so widely used.

R contains several high-quality generators.

Other languages, however, also have fast ones.
In 2000, Marsaglia and Tsang introduced Ziggurat: a new and fast generator for $N(0, 1)$ draws.

In 2005, Leong, Zhang et al improved one aspect. This is the version we use.

These were however done only for 32 bit machines.

Our RcppZiggurat package improves on that aspect, compares multiple implementations and provides a new easy-to-use version.
From the Marsaglia and Tsang (2000) version:

```c
#include <math.h>
static unsigned long jz, jsr=123456789;

#define SHR3 (jz=jsr, jsr^=(jsr<<13), jsr^=(jsr>>17), jsr^=(jsr<<5), jz+jsr)
#define UNI (.5 + (signed) SHR3*.2328306e-9)
#define IUNI SHR3

static long hz;
static unsigned long iz, kn[128], ke[256];
static float wn[128], fn[128], we[256], fe[256];

#define RNOR (hz=SHR3, iz=hz&127, (fabs(hz)<kn[iz])? hz*wn[iz] : nfix())
```

A handful of (global) variables and a handful of macros.

Plus a setup function and the nfix() tail fix.
From the Leong et al (2005) version:

```c
#define MWC ((znew<<16)+wnew )
#define SHR3 (jz=jsr, jsr^=(jsr<<13), jsr^=(jsr>>17), jsr^=(jsr<<5),jz+jsr)
#define CONG (jcong=69069*jcong+1234567)
#define KISS ((MWC^CONG)+SHR3)

#define RNOR (hz=KISS, iz=hz&127, (fabs(hz)<kn[iz]) ? hz*wn[iz] : nfix())
```

Five macros, plus the same two functions.
Macros.

Not exactly *de rigeur* any more.

Maybe once defensible for performance but notorious for possible side-effects.
class ZigguratLZLLV : public Zigg {
public:
    ZigguratLZLLV(uint32_t seed=123456789) :
        jsr(123456789), z(362436069), w(521288629), jcong(380116160) {
        setup();
        setSeed(seed);
    }
    inline double norm(void) { return RNOR; }
    void setSeed(const uint32_t jsrseed) { /* ... */ }
    uint32_t getSeed() { /* ... */ }
private:
    uint32_t jz, jsr, z, w, jcong;
    int32_t hz;
    uint32_t iz, kn[128];
    double wn[128], fn[128];
    void setup(void) { /* ... */ }
    inline double nfix(void) { /* ... */ }
};
This allows us

- keep all state variables private
- import and export only the seed
- but still have access to the trusted code
- and use only headers not requiring linking.

See the RcppZiggurat package, and its vignette, for much, much more detail.
We maintain a catch-all repository `samplecode` on GitHub.

It contains a subdirectory `earl-2015-09` with a complete package `UseZiggurat`. 
The package contains (essentially) two source files, and an entry in DESCRIPTION about where to find the required resources.

Via LinkingTo: RcppZiggurat, we tell R to let us access the header files of the named package.

This is sufficient as the design from the previous section can be implemented in headers only.
This function calls the ZigguratLZLLV generator – our implementation of the 2005 JSS paper “gold standard”.

```cpp
#include <Rcpp.h>
#include <ZigguratLZLLV.h>

static Ziggurat::LZLLV::ZigguratLZLLV z;

// [[Rcpp::export]]
bool setZigguratSeed(const int seed) {
    z.setSeed(seed);
    return true;
}

// [[Rcpp::export]]
Rcpp::NumericVector callZiggurat(int n) {
    Rcpp::NumericVector X(n);
    for (int i=0; i<n; i++) X(i) = z.norm();  // Ziggurat draw
    return X;
}
```
For comparison, we call `rnorm` from R (via its Rcpp variant)

```cpp
#include <Rcpp.h>

// [[Rcpp::export]]
Rcpp::NumericVector callrnorm(int n) {
    // have to call set.seed at the R level ...
    return Rcpp::rnorm(n);
}
```

Here the seed setting is done from R rather than via an argument...
Code from demo/zigguratVsR.R

```r
library(UseZiggurat)
library(microbenchmark)

seed <- 12345
n <- 1e5
N <- 100

set.seed(seed)
setZigguratSeed(seed)

res <- microbenchmark(callZiggurat(n), callrnorm(n), rnorm(n), times = N)
```
### Microbenchmark result:

```markdown
## Unit: milliseconds

<table>
<thead>
<tr>
<th>expr</th>
<th>min</th>
<th>lq</th>
<th>mean</th>
<th>median</th>
<th>uq</th>
<th>max</th>
<th>neval</th>
<th>cld</th>
</tr>
</thead>
<tbody>
<tr>
<td>callZiggurat(n)</td>
<td>1.439</td>
<td>1.466</td>
<td>1.524</td>
<td>1.474</td>
<td>1.480</td>
<td>3.216</td>
<td>100</td>
<td>a</td>
</tr>
<tr>
<td>callrnorm(n)</td>
<td>7.465</td>
<td>7.497</td>
<td>7.626</td>
<td>7.509</td>
<td>7.522</td>
<td>9.225</td>
<td>100</td>
<td>b</td>
</tr>
</tbody>
</table>
```

Comparison

callZiggurat(n)  
callrnorm(n)  
rnorm(n)

Time [milliseconds]

72/127
Part IV: RcppRedis
Previous Status

- We have a lot of data circulating at work
- Market prices, positions, risk estimates, profit/loss, ...
- The used to be displayed in a one-off ‘display grid’
- But no history, and no plots
Easy R Fix

- Use Redis to cache data
- Redis is simple, well-established, widely used
- Excellent R package rredis by Bryan Lewis
- Use Shiny to access Redis and create ‘dashboards’
- We need to be fast enough to keep users engaged
- Goal is ~ 250 msec (in-line with web UI research)
What does Redis do?

- Essentially a very fast and lightweight key/value store:
  - After \texttt{SET key value}
  - Do \texttt{GET key} to retrieve value

- APIs for multiple languages: C/C++, Python, Java, ...

- Can also store lists, sets, ...

- Can be coaxed to provide simple columnar data store

- Basic access: store strings, retrieve strings
What is wrong with that?

- String conversion ‘expensive’ when done repeatedly for a few thousand points
- Do string conversion in compiled code – RcppRedis
- A step better: R serialization and deserialization using RApiSerialize
library(Quandl)
Quandl.api_key(yourAPIkeyhere)  # register, obtain key; anon possible too
sp <- Quandl("CHRIS/CME_SP1" , type="xts")
saveRDS(sp, file="data/quandl-sp1.rds")  # longer series
es <- Quandl("CHRIS/CME_ES1" , type="xts")
saveRDS(es, file="data/quandl-es1.rds")  # more active
head(sp, 3)
TIME SERIES DASHBOARD: MONTHLY PLOT

SP

Apr 1982 / Oct 2015

2000
1800
1600
1400
1200
1000
800
600
400
200
200
400
600
800
1000
1200
1400
1600
1800
2000

200
400
600
800
1000
1200
1400
1600
1800
2000

Setter: Version 1 via rredis

```r
insertXtsR <- function(x, key) {
  xm <- coredata(x)
  xi <- as.integer(index(x))
  for (i in seq_len(nrow(xm))) {
    dat <- unname(c(xi[i], xm[i, , drop=TRUE]))
    redisRPush(key, dat)
  }
  invisible(NULL)
}
```
getter: Base Version via rredis

```r
def get_xtsR <- function(key) {
    n <- as.integer(redisLLen(key))
    vals <- redisLRange(key, 0, n)
    m <- length(vals)
    mat <- matrix(NA, n, 8)
    dat <- rep(NA, n)
    for (i in 1:n) {
        z <- vals[[i]]
        dat[i] <- z[1]
        mat[i, ] <- z[-1]
    }
    x <- xts(mat, order.by=as.Date(dat, origin="1970-01-01"))
    colnames(x) <- colnams
    x
}
```
getter: Rcpp version 1

```r
getXtsRcpp1 <- function(key) {
  n <- as.integer(redis$llen(key))
  vals <- redis$lrange(key, 0, n)
  m <- length(vals)
  mat <- matrix(NA, n, 8)
  dat <- rep(NA, n)
  for (i in 1:n) {
    z <- vals[[i]]
    dat[i] <- z[1]
    mat[i, ] <- z[-1]
  }
  x <- xts(mat, order.by=as.Date(dat, origin="1970-01-01"))
  colnames(x) <- colnams
  x
}
```
Getter: Rcpp Version 2

getXtsRcpp2 <- function(key) {
  mat <- redis$\texttt{listToMatrix}(redis$\texttt{lrange}(key, 0, -1))
  x <- \texttt{xts}(mat[, -1], \texttt{order.by=as.Date(mat[, 1], origin="1970-01-01")))
  colnames(x) <- colnams
  x
}
Timings

```r
key <- "quandl:cme:sp1"
res <- benchmark(getXtsR(key),
                  getXtsRcpp1(key),
                  getXtsRcpp2(key),
                  order="relative", replications=25)[,1:4]
print(res)
```

```
## test  replicatons elapsed relative
## 3 getXtsRcpp2(key) 25 0.608  1.000
## 2 getXtsRcpp1(key) 25 1.768  2.908
## 1 getXtsR(key) 25 29.063 47.801
```
Can we do better?

- Yes: Redis also offers a binary type
- We grab each data row as a vector
- Pointer plus length a common form of expression
New Rcpp Function: R Side

```
insertXtsRcpp <- function(x, key) {
    xm <- coredata(x)
    xi <- as.numeric(index(x))
    dat <- unname(cbind(xi, xm))
    for (i in seq_len(nrow(xm))) {
        redis$listRPush(key, dat[i,])
    }
    invisible(NULL)
}
```
New Rcpp Function: Setter

```cpp
// redis "append to list" -- without R serialization
std::string listRPush(std::string key, Rcpp::NumericVector x) {

    // uses binary protocol, see hiredis docs
    redisReply *reply =
        static_cast<redisReply*>(redisCommand(prc_, "RPUSH %s %b",
            key.c_str(),
            x.begin(), x.size()*szdb));

    std::string res = "";
    freeReplyObject(reply);
    return(res);
}
```
// redis "get from list from start to end" -- without R serialization
Rcpp::List listRange(std::string key, int start, int end) {
    redisReply *reply =
        static_cast<redisReply*>(redisCommand(prc_, "LRANGE %s %d %d", 
                                            key.c_str(), start, end));

    checkReplyType(reply, replyArray_t); // ensure we got array
    unsigned int len = reply->elements;
    Rcpp::List x(len);
    for (unsigned int i = 0; i < len; i++) {
        checkReplyType(reply->element[i], replyString_t); // ensure binary
        int nc = reply->element[i]->len;
        Rcpp::NumericVector v(nc/szdb);
        memcpy(v.begin(), reply->element[i]->str, nc);
        x[i] = v;
    }
    freeReplyObject(reply);
    return(x);
}
Use This Way

getXtsRcpp3 <- function(key) {
  mat <- redis$\text{listToMatrix}\left(redis$\text{listRange}\left(key, 0, -1\right)\right)
  x <- \text{xts}\left(mat[, -1], \text{order.by}=\text{as.Date}\left(mat[, 1], \text{origin}="1970-01-01"\right)\right)
  colnames(x) <- colnams
  x
}

key2 <- "quandl:cme:sp1:rcpp"
res2 <- benchmark(getXtsR(key),
                  getXtsRcpp1(key),
                  getXtsRcpp2(key),
                  getXtsRcpp3(key2),
                  order="relative", replications=25)[,1:4]
print(res2)

## test             replications elapsed relative
## 4 getXtsRcpp3(key2)     25    0.364    1.000
## 3 getXtsRcpp2(key)     25    0.582    1.599
## 2 getXtsRcpp1(key)     25    1.747    4.799
## 1      getXtsR(key)     25   29.481   80.992
Status

- Not so bad: ~ 80-fold increase for RcppRedis over rredis
- Inner retrievals (outside of xts creation) about 100 times faster
- 25 retrieval in 364 msec is clearly ‘good enough’
- Limitation: Storing small binary vectors not elegant
- Possible fix: MessagePack
- Alternative to ‘binary JSON’ and alternative
- Easy to use API
Simple MessagePack buffer creation, then sending MessagePack buffer as binary load.

```cpp
typedef msgpack::type::tuple<double, int, int, int> msg_t;

msgpack::sbuffer buffer;
msg_t m(v[0], (int)v[1], (int)v[2], (int)v[3]);       // fill the message type
msgpack::pack(buffer, m);                            // and pack it

replynew =
    static_cast<redisReply*>(redisCommand(d, "RPUSH %s %b",
                        key.c_str(),
                        buffer.data(), buffer.size()));

freeReplyObject(replynew);
```
Conclusion

- Simple things remain simple
- Memory allocation, loops, conversions, ... faster in C++
- Yet easily accessible from R
- Leverage R strength (e.g., shiny) by overcoming bottlenecks
- Leads to *Seamless Integration of R and C++* for accelerated modeling
Part V: Further Examples
A basic looped version:

```cpp
#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;
}
```
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;
}
```
Or just Rcpp sugar:

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

Of course, all results are the same.
#include <Rcpp.h>

using namespace Rcpp;

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

/*** R
  callFunction(x, fivenum)
callFunction(x, summary)
*/
// [[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));
}
```
#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.
#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];
}
#include <Rcpp.h>

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

// [[Rcpp::export]]
arma::vec getEigenValues(arma::mat M) {
    return arma::eig_sym(M);
}
Rcpp::sourceCpp("code/armaeigen.cpp")

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

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

# R gets the same results (in reverse)
# and also returns the eigenvectors.
#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;
}
The End
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 a fair number of posts too.

And a number of blog posts introduce/discuss features.
Thank You!

dirk@eddelbuettel.com

http://dirk.eddelbuettel.com/presentations/
Programming with C++

- C++ Basics
- Debugging
- Best Practices

and then on to Rcpp itself
Need to compile and link

```c
#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.
```c
#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));
}
```
We may need to supply:

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

```bash
g++ -I/usr/include -c qnorm_rmath.cpp
```
```bash
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 ...
This is a second key feature of C++, and it does it differently from S3 and S4.

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

```cpp
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();
};
```
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():

```cpp
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*:

```cpp
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 provides a ‘language within C++’: code gets evaluated during compilation.

One of the simplest template examples is

```cpp
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:

```cpp
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:

```cpp
transform(x.begin(), x.end(), square);
```
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
Made using

- TeXlive 20141024
- Beamer with mtheme
- Pandoc 1.12.4.2
- R 3.2.2
- rmarkdown 0.8.1
- Emacs 24.4
- Ubuntu 15.04