Rcpp Workshop
Part IV: Applications

Dr. Dirk Eddelbuettel
edd@debian.org
dirk.eddelbuettel@R-Project.org

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Outline

The first example
examples/standard/rinside_sample0.cpp

We have seen this first example in part I:

```
#include <RInside.h>                    // embedded R via RInside

int main(int argc, char *argv[]) {

    RInside R(argc, argv);              // create embedded R inst.

    R["txt"] = "Hello, world!\n";       // assign  to 'txt' in R

    R.parseEvalQ("cat(txt)");           // eval string, ignore result

    exit(0);
}
```

Assign a variable, evaluate an expression—easy!

RInside in a nutshell

Key aspects:

- RInside uses the embedding API of R
- An instance of R is launched by the RInside constructor
- It behaves just like a regular R process
- We submit commands as C++ strings which are parsed and evaluated
- Rcpp is to easily get data in and out from the enclosing C++ program.

A second example: part one

examples/standard/rinside_sample1.cpp

```
#include <RInside.h>          // for the embedded R via RInside

Rcpp::NumericMatrix createMatrix(const int n) {
    Rcpp::NumericMatrix M(n,n);
    for (int i=0; i<n; i++) {
        for (int j=0; j<n; j++) {
            M(i,j) = i*10 + j;
        }
    }
    return(M);
}
```

A second example: part two

examples/standard/rinside_sample1.cpp

```
int main(int argc, char *argv[]) {
  RInside R(argc, argv);    // create an embedded R instance

  const int mdim = 4;        // let the matrices be 4 by 4; create, fill
  R["M"] = createMatrix(mdim);   // assign data Matrix to R's 'M' var

  std::string str =
    "cat('Running ls()\n'); print(ls()); "
    "cat('Showing M\n'); print(M); "
    "cat('Showing colSums()\n'); Z <- colSums(M); "
    "print(Z); Z";                        // returns Z
  Rcpp::NumericVector v = R.parseEval(str); // eval, assign
  // now show vector on stdout
  exit(0);
}
```

Other example files provide similar R snippets and interchange.

A third example: Calling R plot functions

examples/standard/rinside_sample11.cpp

```
#include <RInside.h>                    // embedded R via RInside

int main(int argc, char *argv[]) {

  RInside R(argc, argv);                // create an embedded R instance

  // evaluate an R expression with curve()
  std::string cmd = "tmpf <- tempfile('curve');  "
    "png(tmpf); curve(x^2, -10, 10, 200); "
    "dev.off(); tmpf";
  // by running parseEval, we get filename back
  std::string tmpfile = R.parseEval(cmd);

  std::cout << "Could use plot in " << tmpfile << std::endl;
  unlink(tmpfile.c_str());   // cleaning up

  // alternatively, by forcing a display we can plot to screen
  cmd = "x11(); curve(x^2, -10, 10, 200); Sys.sleep(30);";
  R.parseEvalQ(cmd);

  exit(0);
}
```

A fourth example: Using Rcpp modules

examples/standard/rinside_module_sample0.cpp

```
#include <RInside.h>                    // for the embedded R via RInside
// a c++ function we wish to expose to R
const char* hello( std::string who ){
    std::string result( "hello " ) ;
    result += who ;
    return result.c_str() ;
}
RCPP_MODULE(bling){
    using namespace Rcpp ;
    function( "hello", &hello );
}
int main(int argc, char *argv[]) {
    // create an embedded R instance -- and load Rcpp so that modules work
    RInside R(argc, argv, true);
    // load the bling module
    R["bling"] = LOAD_RCPP_MODULE(bling) ;
    // call it and display the result
    std::string result = R.parseEval("bling$hello('world')") ;
    std::cout << "bling$hello('world') = '" << result << "'"
              << std::endl ;
    exit(0);
}
```

Other RInside standard examples

Besides ex0, ex1 and ex11

A quick overview:

- ex2 loads an Rmetrics library and access data
- ex3 run regressions in R, uses coefs and names in C++
- ex4 runs a small portfolio optimisation under risk budgets
- ex5 creates an environment and tests for it
- ex6 illustrations direct data access in R
- ex7 shows `as<>()` conversions from `parseEval()`
- ex8 is another simple bi-directional data access example
- ex9 makes a C++ function accessible to the embedded R
- ex10 creates and alters lists between R and C++
- ex12 uses `sample()` from C++

Outline

Parallel Computing with RInside

R is famously single-threaded.

High-performance Computing with R frequently resorts to fine-grained (**multicore**, **doSMP**) or coarse-grained (**Rmpi**, **pvm**, ...) parallelism. R spawns and controls other jobs.

Jianping Hua suggested to embed R via RInside in MPI applications.

Now we can use the standard and well understood MPI paradigm to launch multiple R instances, each of which is indepedent of the others.

A first example

examples/standard/rinside_sample2.cpp

```
#include <mpi.h>       // mpi header
#include <RInside.h> // for the embedded R via RInside

int main(int argc, char *argv[]) {

  MPI::Init(argc, argv);                          // mpi initialization
  int myrank = MPI::COMM_WORLD.Get_rank();        // current node rank
  int nodesize = MPI::COMM_WORLD.Get_size();      // total nodes running.

  RInside R(argc, argv);                          // embedded R instance

  std::stringstream txt;
  txt << "Hello from node " << myrank              // node information
      << " of " << nodesize << " nodes!" << std::endl;

  R["txt"] = txt.str();                           // assign to R var 'txt'
  R.parseEvalQ("cat(txt)");                       // eval, ignore returns

  MPI::Finalize();                                // mpi finalization
  exit(0);
}
```

A first example: Output

`examples/standard/rinside_sample2.cpp`

```
edd@max:/tmp$ orterun -n 8 ./rinside_mpi_sample2
Hello from node 5 of 8 nodes!
Hello from node 7 of 8 nodes!
Hello from node 1 of 8 nodes!
Hello from node 0 of 8 nodes!
Hello from node 2 of 8 nodes!
Hello from node 3 of 8 nodes!
Hello from node 4 of 8 nodes!
Hello from node 6 of 8 nodes!
edd@max:/tmp$
```

This uses Open MPI just locally, other hosts can be added via `-H node1,node2,node3`.

The other example(s) shows how to gather simulation results from MPI nodes.

Outline

Application example: Qt
RInside `examples/qt/`

The question is sometimes asked how to embed **RInside** in a larger program.

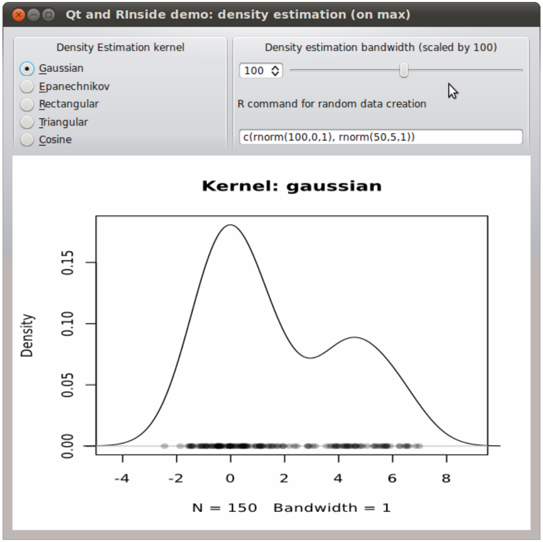
We just added a new example using **Qt**:

```
#include <QApplication>
#include "qtdensity.h"

int main(int argc, char *argv[])
{
    RInside R(argc, argv);       // create an embedded R instance

    QApplication app(argc, argv);
    QtDensity qtdensity(R);     // pass R inst. by reference
    return app.exec();
}
```

Application example: Qt density slider
RInside `examples/qt/`


Qt and RInside demo: density estimation (on max)
Density Estimation kernel
Gaussian
Epanechnikov
Rectangular
Triangular
Cosine
Density estimation bandwidth (scaled by 100)
100
R command for random data creation
Kernel: gaussian
Density
0.00
0.05
0.10
0.15
-4
-2
0
2
4
6
8
N = 150 Bandwidth = 1

(•) Gaussian

`c(rnorm(100,0,1), rnorm(50,5,1))`

This uses standard **Qt** / GUI paradigms of

- radio buttons
- sliders
- textentry

all of which send values to the R process which provides an SVG (or PNG as fallback) image that is plotted.

Application example: Qt density slider
RInside `examples/qt/`

The actual code is pretty standard **Qt** / GUI programming (and too verbose to be shown here).

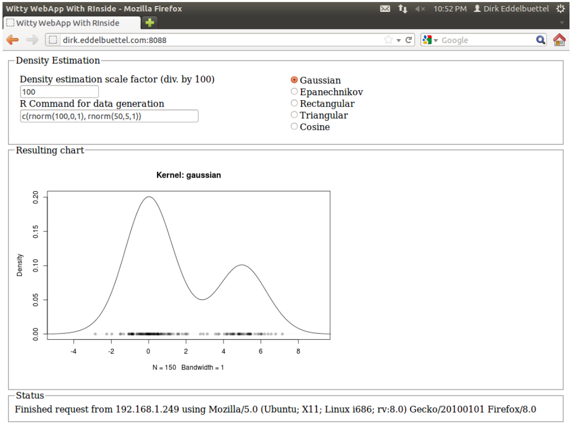
The `qtdensity.pro` file is interesting as it maps the entries in the `Makefile` (discussed in the next section) to the **Qt** standards.

It may need an update for OS X—we have not tried that yet.

Outline

Application example: Wt
RInside `examples/wt/`

Given the desktop application with **Qt**, the question arises how to deliver something similar “over the web” — and **Wt** helps.



Density Estimation

Density estimation scale factor (div. by 100)
100

R Command for data generation
c(rnorm(100,0,1), rnorm(50,5,1))

[✓ Gaussian]
Epanechnikov
Rectangular
Triangular
Cosine

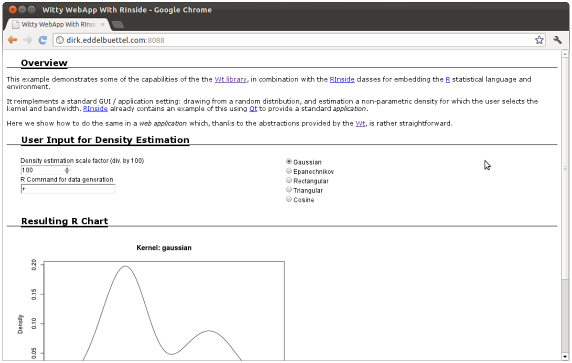
Resulting chart

Status
Finished request from 192.168.1.249 using Mozilla/5.0 (Ubuntu; X11; Linux i686; rv:8.0) Gecko/20100101 Firefox/8.0

Wt is similar to **Qt** so the code needs only a few changes.
Wt takes care of all browser / app interactions and determines the most featureful deployment.

Application example: Wt

RInside `examples/wt/`



Witty WebApp With RInside - Google Chrome

dirk.eddelbuettel.com:8088

Overview

This example demonstrates some of the capabilities of the the Wt library, in combination with the RInside classes for embedding the R statistical language and environment.

It reimplements a standard GUI / application setting: drawing from a random distribution, and estimation a non-parametric density for which the user selects the kernel and bandwidth. RInside already contains an example of this using Qt to provide a standard *application*.

Here we show how to do the same in a *web application* which, thanks to the abstractions provided by the Wt, is rather straightforward.

User Input for Density Estimation

Density estimation scale factor (div. by 100)
100
R Command for data generation
+

[✓ Gaussian] Epanechnikov Rectangular Triangular Cosine

Resulting R Chart

Wt can also be “dressed up” with simple CSS styling (and the text displayed comes from an external XML file, further separating content and presentation).

Outline

Building with RInside

RInside needs headers and libraries from several projects as it

embeds R itself	so we need R headers and libraries
uses Rcpp	so we need Rcpp headers and libraries
RInside itself	so we also need RInside headers and libraries

Building with RInside

Use the Makefile in `examples/standard`

The `Makefile` is set-up to create an binary for example example file supplied. It uses

R CMD config to query all of `-cppflags`, `-ldflags`, `BLAS_LIBS` and `LAPACK_LIBS`

Rscript to query `Rcpp:::CxxFlags` and `Rcpp:::LdFlags`

Rscript to query `RInside:::CxxFlags` and `RInside:::LdFlags`

The `qtdensity.pro` file does the equivalent for **Qt**.

Building with RInside

```
## comment out if you need a different version of R, and set R_HOME
R_HOME :=          $(shell R RHOME)
sources :=         $(wildcard *.cpp)
programs :=        $(sources:.cpp=)

## include headers and libraries for R
RCPPFLAGS :=    $(shell $(R_HOME)/bin/R CMD config --cppflags)
RLDFLAGS :=     $(shell $(R_HOME)/bin/R CMD config --ldflags)
RBLAS :=        $(shell $(R_HOME)/bin/R CMD config BLAS_LIBS)
RLAPACK :=      $(shell $(R_HOME)/bin/R CMD config LAPACK_LIBS)
## if you need to set an rpath to R itself, also uncomment
#RRPATH :=        -Wl,-rpath,$(R_HOME)/lib

## include headers and libraries for Rcpp interface classes
RCPPINCL :=     $(shell echo 'Rcpp:::CxxFlags()' | $(R_HOME)/bin/R --vanilla --slave)
RCPPLIBS :=     $(shell echo 'Rcpp:::LdFlags()'  | $(R_HOME)/bin/R --vanilla --slave)

## include headers and libraries for RInside embedding classes
RINSIDEINCL := $(shell echo 'RInside:::CxxFlags()'|$(R_HOME)/bin/R --vanilla --slave)
RINSIDELIBS := $(shell echo 'RInside:::LdFlags()' |$(R_HOME)/bin/R --vanilla --slave)

## compiler etc settings used in default make rules
CXX :=             $(shell $(R_HOME)/bin/R CMD config CXX)
CPPFLAGS :=        -Wall $(shell $(R_HOME)/bin/R CMD config CPPFLAGS)
CXXFLAGS :=        $(RCPPFLAGS) $(RCPPINCL) $(RINSIDEINCL)
CXXFLAGS +=        $(shell $(R_HOME)/bin/R CMD config CXXFLAGS)
LDLIBS :=          $(RLDFLAGS) $(RRPATH) $(RBLAS) $(RLAPACK) $(RCPPLIBS) $(RINSIDELIBS)

all:              $(programs)
                   @test -x /usr/bin/strip && strip $^
```

Outline

Armadillo

From `arma.sf.net` and slightly edited

What is Armadillo?

Armadillo is a C++ linear algebra library aiming towards a good balance between speed and ease of use. Integer, floating point and complex numbers are supported, as well as a subset of trigonometric and statistics functions. Various matrix decompositions are provided.

A delayed evaluation approach is employed (during compile time) to combine several operations into one and reduce (or eliminate) the need for temporaries. This is accomplished through recursive templates and template meta-programming.

This library is useful 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 at website `http://arma.sf.net`, and a recent technical report (Sanderson, 2010).
- Modern code, building upon and extending from earlier matrix libraries.
- Responsive and active maintainer, frequent updates.

RcppArmadillo highlights

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

Outline

Complete file for fastLM

RcppArmadillo `src/fastLm.cpp`

```
#include <RcppArmadillo.h>

extern "C" SEXP fastLm(SEXP ys, SEXP Xs) {
  try {
    arma::colvec y = Rcpp::as<arma::colvec>(ys);  // direct to arma
    arma::mat X    = Rcpp::as<arma::mat>(Xs);
    int df = X.n_rows - X.n_cols;
    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)/df;        // std.errors of coefs
    arma::colvec std_err = arma::sqrt(s2 *
                   arma::diagvec(arma::pinv(arma::trans(X)*X)));
    return Rcpp::List::create(Rcpp::Named("coefsficients")=coef,
                              Rcpp::Named("stderr") = std_err,
                              Rcpp::Named("df")     = df);
  } catch( std::exception &ex ) {
      forward_exception_to_r( ex );
  } catch(...) {
      ::Rf_error( "c++ exception (unknown reason)" );
  }
  return R_NilValue; // -Wall
}
```

Core part of fastLM

RcppArmadillo `src/fastLm.cpp`

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

int df = X.n_rows - X.n_cols;

arma::colvec coef = arma::solve(X, y);       // fit y ~ X

arma::colvec res  = y - X*coef;              // residuals

double s2 = std::inner_product(res.begin(), res.end(),
                res.begin(), 0.0)/df;        // std.err coefs

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

return Rcpp::List::create(Rcpp::Named("df") = df,
              Rcpp::Named("stderr") = std_err,
              Rcpp::Named("coefficients")     = coef);
```

Easy transfer from (and to) R

RcppArmadillo `src/fastLm.cpp`

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

int df = X.n_rows - X.n_cols;

arma::colvec coef = arma::solve(X, y);          // fit y ~ X

arma::colvec res  = y - X*coef;                 // residuals

double s2 = std::inner_product(res.begin(), res.end(),
                  res.begin(), 0.0)/df;         // std.err coefs

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

return Rcpp::List::create(Rcpp::Named("df") = df,
              Rcpp::Named("stderr") = std_err,
              Rcpp::Named("coefficients")    = coef);
```

Easy linear algebra via Armadillo

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

int df = X.n_rows - X.n_cols;

arma::colvec coef = arma::solve(X, y);        // fit y ∼ X

arma::colvec res  = y - X*coef;               // residuals

double s2 = std::inner_product(res.begin(), res.end(),
                  res.begin(), 0.0)/df;       // std.err coefs

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

return Rcpp::List::create(Rcpp::Named("df") = df,
              Rcpp::Named("stderr") = std_err,
              Rcpp::Named("coefficients")     = coef);
```

One note on direct casting with Armadillo

The code as just shown:

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

is very convenient, but does incur an additional copy of each object. A lighter variant uses two steps in which only a pointer to the object 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);
```

If performance is a concern, the latter approach may be preferable.

Performance comparison

Running the script included in the **RcppArmadillo** package:

```
edd@max:~/svn/rcpp/pkg/RcppArmadillo/inst/examples$ r fastLm.r
Loading required package: methods
                       test replications  relative elapsed
1            fLmOneCast(X, y)         5000  1.000000   0.170
2           fLmTwoCasts(X, y)         5000  1.029412   0.175
4     fastLmPureDotCall(X, y)         5000  1.211765   0.206
3            fastLmPure(X, y)         5000  2.235294   0.380
6                lm.fit(X, y)         5000  3.911765   0.665
5 fastLm(frm, data = trees)         5000 40.488235   6.883
7     lm(frm, data = trees)         5000 53.735294   9.135
edd@max:~/svn/rcpp/pkg/RcppArmadillo/inst/examples$
```

NB: This includes a minor change in SVN and not yet in the released package.

Outline

Example: VAR(1) Simulation

`examples/part4/varSimulation.r`

Lance Bachmeier started this example for his graduate students: Simulate a VAR(1) model row by row:

```
R> ## parameter and error terms used throughout
R> a <- matrix(c(0.5,0.1,0.1,0.5),nrow=2)
R> e <- matrix(rnorm(10000),ncol=2)
R> ## Let's start with the R version
R> 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)
+ }
R> rData <- rSim(a, e)                          # generated by R
```

Example: VAR(1) Simulation – Compiled R

examples/part4/varSimulation.r

With R 2.13.0, we can also compile the R function:

```
R> ## Now let's load the R compiler (requires R 2.13 or later)
R> suppressMessages(require(compiler))
R> compRsim <- cmpfun(rSim)
R> compRData <- compRsim(a,e)                     # gen. by R 'compiled'
R> stopifnot(all.equal(rData, compRData))   # checking results
```

Example: VAR(1) Simulation – RcppArmadillo

`examples/part4/varSimulation.r`

```
R> ## Now load 'inline' to compile C++ code on the fly
R> suppressMessages(require(inline))
R> code <- '
+    arma::mat coeff = Rcpp::as<arma::mat>(a);
+    arma::mat errors = Rcpp::as<arma::mat>(e);
+    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) *
+                          trans(coeff)+errors.row(row);
+    }
+    return Rcpp::wrap(simdata);
+ '
R> ## create the compiled function
R> rcppSim <- cxxfunction(signature(a="numeric",e="numeric"),
+                          code,plugin="RcppArmadillo")
R> rcppData <- rcppSim(a,e)                        # generated by C++ code
R> stopifnot(all.equal(rData, rcppData))          # checking results
```

Example: VAR(1) Simulation – RcppArmadillo

examples/part4/varSimulation.r

```
R> ## now load the rbenchmark package and compare all three
R> suppressMessages(library(rbenchmark))
R> res <- benchmark(rcppSim(a,e),
+                  rSim(a,e),
+                  compRsim(a,e),
+                  columns=c("test", "replications",
+                            "elapsed", "relative"),
+                  order="relative")
R> print(res)
            test replications elapsed relative
1  rcppSim(a, e)          100   0.038   1.0000
3 compRsim(a, e)          100   2.011  52.9211
2     rSim(a, e)          100   4.148 109.1579
R>
```

So more than fifty times faster than byte-compiled R and more than hundred times faster than R code.

Example: VAR(1) Simulation – RcppArmadillo

`examples/part4/varSimulation.r`

```
R> ## now load the rbenchmark package and compare all three
R> suppressMessages(library(rbenchmark))
R> res <- benchmark(rcppSim(a,e),
+                  rSim(a,e),
+                  compRsim(a,e),
+                  columns=c("test", "replications",
+                            "elapsed", "relative"),
+                  order="relative")
R> print(res)
            test replications elapsed relative
1  rcppSim(a, e)          100   0.038   1.0000
3 compRsim(a, e)          100   2.011  52.9211
2     rSim(a, e)          100   4.148 109.1579
R>
```

Outline

Kalman Filter

The Mathworks has a nice example[1] of a classic 'object tracking' problem showing gains from going from Matlab code to compiled C code.
The example is short:

```
% Copyright 2010 The MathWorks, Inc.
function y = kalmanfilter(z)
% #codegen
    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 ];
    Q = eye(6);
    R = 1000 * eye(2);
    persistent x_est p_est
    if isempty(x_est)
        x_est = zeros(6, 1);
        p_est = zeros(6, 6);
    end
    % Predicted state and covariance
    x_prd = A * x_est;
    p_prd = A * p_est * A' + Q;
    % Estimation
    S = H * p_prd' * H' + R;
    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;
    % Compute the estimated measurements
    y = H * x_est;
end                % of the function
```

[1] http://www.mathworks.com/products/matlab-coder/demos.html?file=/products/demos/shipping/coder/coderdemo_kalman_filter.html

Kalman Filter: In R

Easy enough – first naive solution

```r
FirstKalmanR <- function(pos) {

  kf <- function(z) {
    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)

    ## predicted state and covriance
    xprd <- A %*% xest
    pprd <- A %*% pest %*% t(A) + Q

     ## estimation
    S <- H %*% t(pprd) %*% t(H) + R
    B <- H %*% t(pprd)
    ##   kalmangain <- (S \ B)'
    kg <- t(solve(S, B))

    ## est. state and cov, assign to vars in parent env
    xest <<- xprd + kg %*% (z-H%*%xprd)
    pest <<- pprd - kg %*% H %*% pprd

    ## compute the estimated measurements
    y <- H %*% xest
  }

  xest <- matrix(0, 6, 1)
  pest <- matrix(0, 6, 6)

  for (i in 1:N) {
     y[i,] <- kf(t(pos[i,,drop=FALSE]))
  }

  invisible(y)
}
```

Kalman Filter: In R

Easy enough – with some minor refactoring

```
KalmanR <- function(pos) {

  kf <- function(z) {
    ## predicted state and covriance
    xprd <- A %*% xest
    pprd <- A %*% pest %*% t(A) + Q

    ## estimation
    S <- H %*% t(pprd) %*% t(H) + R
    B <- H %*% t(pprd)
    ##   kg <- (S \ B)'
    kg <- t(solve(S, B))

    ## estimated state and covariance
    ## assigned to vars in parent env
    xest <<- xprd + kg %*% (z-H%*%xprd)
    pest <<- pprd - kg %*% H %*% pprd

    ## compute the estimated measurements
    y <- H %*% xest
  }
  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,] <- kf(t(pos[i,,drop=FALSE]))
  }
  invisible(y)
}
```

Kalman Filter: In C++

Using a simple class

```cpp
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);
  }

  // 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);

    for (unsigned int i = 0; i<n; i++) {
      colvec z = Z.row(i).t();

      // predicted state and covriance
      mat xprd = A * xest;
      mat pprd = A * pest * A.t() + Q;

      // estimation
      mat S = H * pprd.t() * H.t() + R;
      mat B = H * pprd.t();
      mat kg = trans(solve(S, B));

      // estimated state and covariance
      xest = xprd + kg * (z - H * xprd);
      pest = pprd - kg * H * pprd;

      // compute the estimated measurements
      colvec y = H * xest;
      Y.row(i) = y.t();
    }
    return Y;
  }
};
```

Kalman Filter in C++

Trivial to use from R

Given the code from the previous slide in a text variable `kalmanClass`, we just do this

```
kalmanSrc <- '
  mat Z = as<mat>(ZS);        // passed from R
  Kalman K;
  mat Y = K.estimate(Z);
  return wrap(Y);
'

KalmanCpp <- cxxfunction(signature(ZS="numeric"),
                         body=kalmanSrc,
                         include=kalmanClass,
                         plugin="RcppArmadillo")
```

Kalman Filter: Performance

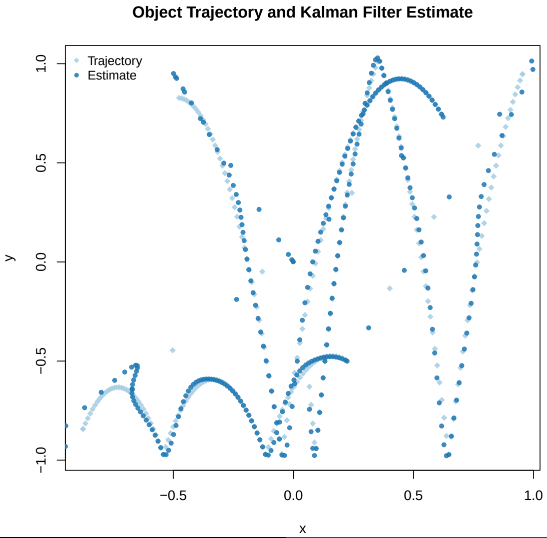
Quite satisfactory relative to R

Even byte-compiled 'better' R version is 66 times slower:

```
R> FirstKalmanRC <- cmpfun(FirstKalmanR)
R> KalmanRC <- cmpfun(KalmanR)
R>
R> stopifnot(identical(KalmanR(pos), KalmanRC(pos)),
+           all.equal(KalmanR(pos), KalmanCpp(pos)),
+           identical(FirstKalmanR(pos), FirstKalmanRC(pos)),
+           all.equal(KalmanR(pos), FirstKalmanR(pos)))
R>
R> res <- benchmark(KalmanR(pos), KalmanRC(pos),
+                  FirstKalmanR(pos), FirstKalmanRC(pos),
+                  KalmanCpp(pos),
+                  columns = c("test", "replications",
+                              "elapsed", "relative"),
+                  order="relative",
+                  replications=100)
R>
R> print(res)
               test replications elapsed relative
5    KalmanCpp(pos)          100   0.087   1.0000
2     KalmanRC(pos)          100   5.774  66.3678
1      KalmanR(pos)          100   6.448  74.1149
4 FirstKalmanRC(pos)         100   8.153  93.7126
3  FirstKalmanR(pos)         100   8.901 102.3103
```

Kalman Filter: Figure

Last but not least we can redo the plot as well



Outline

RcppEigen

RcppEigen wraps the Eigen library for linear algebra.

Eigen is similar to Armadillo, and very highly optimised—by internal routines replacing even the BLAS for performance.

Eigen is also offering a more complete API than Armadillo (but I prefer to work with the simpler Armadillo, most of the time).

RcppEigen is written mostly by Doug Bates who needs sparse matrix support for his C++ rewrite of **lme4** (e.g. **lme4eigen**).

Eigen can be faster than Armadillo. Andreas Alfons' CRAN package **robustHD** (using Armadillo) with a drop-in replacement **sparseLTSEigen** sees gain of 1/4 to 1/3.

However, Eigen is not always available on all platforms as there can be issues with older compilers (eg on OS X).

Outline

RcppEigen's fastLm
Slightly simplified / shortened

```
const MMatrixXd        X(as<MMatrixXd>(Xs));
const MVectorXd        y(as<MVectorXd>(ys));
Index                  n = X.rows(), p = X.cols();
lm                   ans = do_lm(X, y, ::Rf_asInteger(type));
NumericVector       coef = wrap(ans.coef());
List            dimnames = NumericMatrix(Xs).attr("dimnames");
VectorXd           resid = y - ans.fitted();
double                s2 = resid.squaredNorm()/ans.df();
PermutationType     Pmat = PermutationType(p);
Pmat.indices()           = ans.perm();
VectorXd              dd = Pmat * ans.unsc().diagonal();
ArrayXd               se = (dd.array() * s2).sqrt();
return List::create(_["coefficients"]  = coef,
                    _["se"]            = se,
                    _["rank"]          = ans.rank(),
                    _["df.residual"]   = ans.df(),
                    _["perm"]          = ans.perm(),
                    _["residuals"]     = resid,
                    _["s2"]            = s2,
                    _["fitted.values"] = ans.fitted(),
                    _["unsc"]          = ans.unsc());
```

RcppEigen's fastLm (cont.)
The lm alternatives

Doug defines a base class `lm` from which the following classes derive:

- LLt (standard Cholesky decomposition)
- LDLt (robust Cholesky decompostion with pivoting)
- SymmEigen (standard Eigen-decomposition)
- QR (standard QR decomposition)
- ColPivQR (Householder rank-revealing QR decomposition with column-pivoting)
- SVD (standard SVD decomposition)

The example file `lmBenchmark.R` in the package runs through these.

RcppEigen's fastLm (cont.)

The benchmark results

```
lm benchmark for n = 100000 and p = 40: nrep = 20
       test   relative elapsed user.self sys.self
3      LDLt   1.000000   0.911      0.91     0.00
7       LLt   1.000000   0.911      0.91     0.00
5   SymmEig   2.833150   2.581      2.17     0.40
6        QR   5.050494   4.601      4.17     0.41
2 ColPivQR    5.102086   4.648      4.20     0.43
8      arma   6.837541   6.229      6.00     0.00
1    lm.fit   9.189901   8.372      7.12     1.14
4       SVD  32.183315  29.319     28.44     0.76
9       GSL 113.680571 103.563    102.42     0.53
```

This improves significantly over the Armadillo-based solution.

One last remark on the fastLm routines

Doug sometimes reminds us about the occassional fine differences between *statistical* numerical analysis and standard numerical analysis.

Pivoting schemes are a good example. R uses a custom decomposition (with pivoting) inside of `lm()` which makes it both robust and precise, particularly for rank-deficient matrices.

The example for `fastLm` in both **RcppArmadillo** and **RcppEigen** provides an illustration.

If you are *really* sure your data is well-behaved, then using a faster (non-pivoting) scheme as in **RcppArmadillo**

Outline

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
- arrange for the GSL linker to be found

RcppGSL may still be a convenient tool for programmers more familiar with C than C++ wanting to deploy GSL algorithms.

Outline

Vector norm example—*c.f.* GSL manual

`examples/part4/gslNorm.cpp`

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

extern "C" SEXP colNorm(SEXP sM) {
  try {
    RcppGSL::matrix<double> M = sM;        // SEXP to gsl data structure
    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
  } catch( std::exception &ex ) {
    forward_exception_to_r( ex );
  } catch(...) {
    ::Rf_error( "c++ exception (unknown reason)" );
  }
  return R_NilValue; // -Wall
}
```

Core part of example

`examples/part4/gslNorm.cpp`

```
RcppGSL::matrix<double> M = sM;        // SEXP to GSL data
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
```

Core part of example

Using standard GSL functions: `examples/part4/gslNorm.cpp`

```
RcppGSL::matrix<double> M = sM;          // SEXP to GSL data
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
```

Outline

Gibbs Sampler Example

Darren Wilkinson wrote a couple of blog posts illustrating the performance of different implementations (C, Java, Python, ...) for a simple MCMC Gibbs sampler of this bivariate density::

$$f(x,y) = kx^2 \exp(-xy^2 - y^2 + 2y - 4x)$$

with conditional distributions

$$\begin{aligned} f(x|y) &\sim \text{Gamma}(3, y^2+4) \\ f(y|x) &\sim N\left(\frac{1}{1+x}, \frac{1}{2(1+x)}\right) \end{aligned}$$

i.e. we need repeated RNG draws from both a Gamma and a Gaussian distribution.

Outline

Gibbs Sampler Example

Sanjog Misra then sent me working R and C++ versions which I extended. In R we use:

```
Rgibbs <- function(N,thin) {
    mat <- matrix(0,ncol=2,nrow=N)
    x <- 0
    y <- 0
    for (i in 1:N) {
        for (j in 1:thin) {
            x <- rgamma(1,3,y*y+4)
            y <- rnorm(1,1/(x+1),1/sqrt(2*(x+1)))
        }
        mat[i,] <- c(x,y)
    }
    mat
}
```

Outline

Gibbs Sampler Example (cont.)

The C++ version using **Rcpp** closely resembles the R version::

```
gibbscode <- '
  // n and thin are SEXPs which the Rcpp::as function maps to C++ vars
  int N   = as<int>(n);
  int thn = as<int>(thin);
  int i,j;
  NumericMatrix mat(N, 2);
  RNGScope scope;           // Initialize Random number generator
  double x=0, y=0;
  for (i=0; i<N; i++) {
    for (j=0; j<thn; j++) {
      x = ::Rf_rgamma(3.0,1.0/(y*y+4));
      y = ::Rf_rnorm(1.0/(x+1),1.0/sqrt(2*x+2));
    }
    mat(i,0) = x;
    mat(i,1) = y;
  }
  return mat;              // Return to R
'
```

Gibbs Sampler Example (cont.)

We compile the C++ function:

```
# Compile and Load
RcppGibbs <- cxxfunction(signature(n="int",
                                   thin = "int"),
                         gibbscode, plugin="Rcpp")
```

Outline

Gibbs Sampler Example (cont.)

We also create a similar variant using the GSL's random number generators (as in Darren's example):

```
gslgibbscode <- '
  int N = as<int>(ns);
  int thin = as<int>(thns);
  int i, j;
  gsl_rng *r = gsl_rng_alloc(gsl_rng_mt19937);
  double x=0, y=0;
  NumericMatrix mat(N, 2);
  for (i=0; i<N; i++) {
    for (j=0; j<thin; j++) {
      x = gsl_ran_gamma(r,3.0,1.0/(y*y+4));
      y = 1.0/(x+1)+gsl_ran_gaussian(r,1.0/sqrt(2*x+2));
    }
    mat(i,0) = x;
    mat(i,1) = y;
  }
  gsl_rng_free(r);
  return mat;           // Return to R
'
```

Gibbs Sampler Example (cont.)

We compile the GSL / C function:

```
gslgibbsincl <- '
  #include <gsl/gsl_rng.h>
  #include <gsl/gsl_randist.h>

  using namespace Rcpp;  // just to be explicit
'

## Compile and Load
GSLGibbs <- cxxfunction(signature(ns="int",
                                  thns = "int"),
                        body=gslgibbscode,
                        includes=gslgibbsincl,
                        plugin="RcppGSL")
```

Outline

Gibbs Sampler Example (cont.)

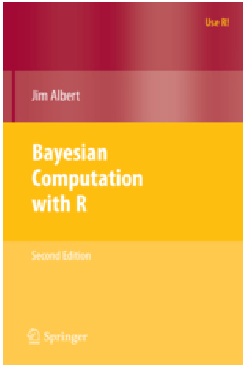
The result show a dramatic gain from the two compiled version relative to the R version, and the byte-compiled R version:

```
                 test repl. elapsed  relative user.self sys.self
4   GSLGibbs(N, thn)    10   7.918  1.000000      7.87     0.00
3 RcppGibbs(N, thn)    10  12.300  1.553423     12.25     0.00
2    RCgibbs(N, thn)    10 306.349 38.690200    305.07     0.11
1     Rgibbs(N, thn)    10 412.467 52.092321    410.76     0.18
```

The gain of the **GSL** version relative to the **Rcpp** is due almost entirely to a much faster RNG for the gamma distribution as shown by `timeRNGs.R`.

Outline

Accelerating Monte Carlo



Albert. *Bayesian Computation with R*, 2nd ed. Springer, 2009

Albert introduces simulations with a simple example in the first chapter.

We will study this example and translate it to R using RcppArmadillo (and Rcpp).

The idea is to, for a given level α, and sizes *n* and *m*, draw a number *N* of samples at these sizes, compoute a *t*-statistic and record if the test statistic exceeds the theoretical critical value given the parameters.

This allows us to study the impact of varying α, *N* or *M* — as well as varying parameters or even families of the random vectors.

Restating the problem

- With two samples $x_1, \ldots, x_m$ and $y_1, \ldots, y_n$ we can test

$$H_0 : \mu_x = \mu_y$$

- With sample means $\bar{X}$ and $\bar{Y}$, and s_x and $_y$ as respective standard deviations, the standard test is

$$T = \frac{\bar{X} - \bar{Y}}{s_P \sqrt{1/m + 1/n}}$$

whew s_p is the pooled standard deviation

$$s_p = \sqrt{\frac{(m-1)s_x^2 + (n-1)s_y^2}{m+n-2}}$$

Restating the problem

- Under H_0, we have $T \sim t(m+n-2)$ provided that
  - x_i and $x+i$ are NID
  - the standard deviations of populations x and y are equal.
- For a given level α, we can reject H if

$$|T| \geq t_{n+m-2,\alpha/2}$$

- But happens when we have
  - unequal population variances, or
  - non-normal distributions?
- Simulations can tell us.

Outline

Basic R version

Core function: `examples/part4/montecarlo.r`

```
## Section 1.3.3
## simulation algorithm for normal populations
sim1_3_3_R <- function() {
    alpha <- .1; m <- 10; n <- 10  # sets alpha, m, n
    N <- 10000                     # sets nb of sims
    n.reject <- 0                  # number of rejections
    crit <- qt(1-alpha/2,n+m-2)
    for (i in 1:N) {
        x <- rnorm(m,mean=0,sd=1)  # simulates xs from population 1
        y <- rnorm(n,mean=0,sd=1)  # simulates ys from population 2
        t.stat <- tstatistic(x,y)  # computes the t statistic
        if (abs(t.stat)>crit)
            n.reject=n.reject+1    # reject if |t| exceeds critical pt
    }
    true.sig.level <- n.reject/N   # est. is proportion of rejections
}
```

Basic R version

Helper function for *t*-statistic: `examples/part4/montecarlo.r`

```r
## helper function
tstatistic <- function(x,y) {
    m <- length(x)
    n <- length(y)
    sp <- sqrt(((m-1)*sd(x)^2 + (n-1)*sd(y)^2) / (m+n-2))
    t.stat <- (mean(x) - mean(y)) / (sp*sqrt(1/m + 1/n))
    return(t.stat)
}
```

Outline

RcppArmadillo version

Main function: `examples/part4/montecarlo.r`

```
sim1_3_3_arma <- cxxfunction(, plugin="RcppArmadillo",
                             inc=tstat_arma, body='
  RNGScope scope;        // properly deal with RNGs
  double alpha = 0.1;
  int m = 10, n = 10;    // sets alpha, m, n
  int N = 10000;         // sets the number of sims
  double n_reject = 0;   // counter of num. of rejects
  double crit = ::Rf_qt(1.0-alpha/2.0, n+m-2.0,true,false);
  for (int i=0; i<N; i++)  {
    NumericVector x = rnorm(m, 0, 1);     // sim xs from pop 1
    NumericVector y = rnorm(n, 0, 1);     // sim ys from pop 2
    double t_stat = tstatistic(Rcpp::as<arma::vec>(x),
                               Rcpp::as<arma::vec>(y));
    if (fabs(t_stat) > crit)
      n_reject++;              // reject if |t| exceeds critical pt
  }
  double true_sig_level = 1.0*n_reject / N;  // est. prop rejects
  return(wrap(true_sig_level));
')
```

RcppArmadillo version

Helper function for *t*-statistic: : `examples/part4/montecarlo.r`

```
tstat_arma <- '
 double tstatistic(const NumericVector &x,
                   const NumericVector &y) {
   int m = x.size();
   int n = y.size();
   double sp = sqrt( ( (m-1.0)*pow(sd(x),2) +
                    (n-1)*pow(sd(y),2) ) / (m+n-2.0) );
   double t_stat = (mean(x)-mean(y))/(sp*sqrt(1.0/m+1.0/n));
   return(t_stat);
 }
'
```

Outline

Rcpp version—using sugar functions mean, sd, ...

Main function: examples/part4/montecarlo.r

```
sim1_3_3_rcpp <- cxxfunction(, plugin="Rcpp",
                              inc=tstat_rcpp, body='
  RNGScope scope;       // properly deal with RNG settings
  double alpha = 0.1;
  int m = 10, n = 10;   // sets alpha, m, n
  int N = 10000;        // sets the number of simulations
  double n_reject = 0;  // counter of num. of rejections
  double crit = ::Rf_qt(1.0-alpha/2.0, n+m-2.0, true, false);
  for (int i=0; i<N; i++)  {
    NumericVector x = rnorm(m, 0, 1);    // sim xs from pop 1
    NumericVector y = rnorm(n, 0, 1);    // sim ys from pop 2
    double t_stat = tstatistic(x, y);
    if (fabs(t_stat) > crit)
      n_reject++;           // reject if |t| exceeds critical pt
  }
  double true_sig_level = 1.0*n_reject / N;  // est. prop rejects
  return(wrap(true_sig_level));
')
```

Rcpp version—using SVN version with `mean`, `sd`, ...

Helper function: `examples/part4/montecarlo.r`

```
tstat_rcpp <- '
 double tstatistic(const NumericVector &x,
                   const NumericVector &y) {
   int m = x.size();
   int n = y.size();
   double sp = sqrt( ( (m-1.0)*pow(sd(x),2) +
                   (n-1)*pow(sd(y),2) ) / (m+n-2.0) );
   double t_stat = (mean(x)-mean(y))/(sp*sqrt(1.0/m+1.0/n));
   return(t_stat);
 }
'
```

Outline

Benchmark results

examples/part4/montecarlo.r

```
R> library(rbenchmark)
R> res <- benchmark(sim1_3_3_R(),
+                  sim1_3_3_Rcomp(),
+                  sim1_3_3_arma(),
+                  sim1_3_3_rcpp(),
+                  columns=c("test", "replications",
+                            "elapsed", "relative",
+                            "user.self"),
+                  order="relative")
R> res
              test replications elapsed relative user.self
3  sim1_3_3_arma()          100   2.118  1.00000      2.12
4  sim1_3_3_rcpp()          100   2.192  1.03494      2.19
1     sim1_3_3_R()          100 153.772 72.60246    153.70
2 sim1_3_3_Rcomp()          100 154.251 72.82861    154.19
R>
```

Benchmark results

```
R> res
              test replications elapsed relative user.self
3  sim1_3_3_arma()          100   2.118  1.00000      2.12
4  sim1_3_3_rcpp()          100   2.192  1.03494      2.19
1     sim1_3_3_R()          100 153.772 72.60246    153.70
2 sim1_3_3_Rcomp()          100 154.251 72.82861    154.19
R>
```

In this example, the R compiler does not help at all. The difference between **RcppArmadillo** and **Rcpp** is neglible.

Suggestions (by Albert): replace *n*, *m*, standard deviations of Normal RNG, replace Nornal RNG, ... which, thanks to **Rcpp** and 'Rcpp sugar' is a snap.

Simulation results

`examples/part4/montecarlo.r`

Albert reports this table:

Populations	True Sign. Level
Normal pop. with equal spreads	0.0986
Normal pop. with unequal spreads	0.1127
$t(4)$ distr. with equal spreads	0.0968
Expon. pop. with equal spreads	0.1019
Normal + exp. pop. with unequal spreads	0.1563

Table: True significance level of t-test computed by simulation; standard error of each estimate is approximately 0.003.

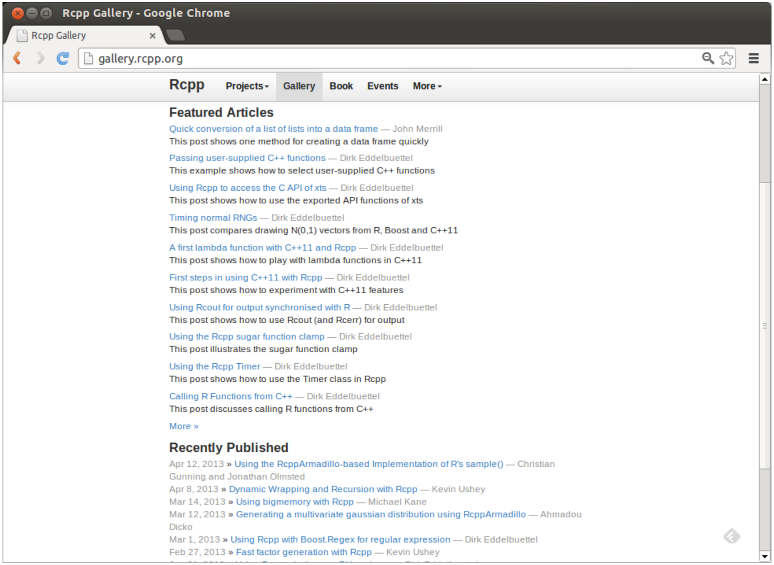
Our simulations are $\approx$ 70-times faster, so we can increase the number of simulation by 100 and reduce the standard error to $\sqrt{0.1 \times 0.9/1,000,000} = 0.0003$.

That's it, folks!

Want to learn more ?

- The **Rcpp** package has eight pdf vignettes, and numerous help pages; other packages tend to have vignettes as well.
- Several 'intro' vignettes have now been published: *J Stat Software, 2011 and 2013* for **Rcpp** (2011) and **RcppEigen** (2013); *Comp. Stat. & Data Anal.* for **RcppArmadillo** (2013).
- The rcpp-devel list is *the* recommended resource, generally very helpful, and fairly low volume.
- By now StackOverflow has a fair number of posts too.
- And a number of blog posts introduce/discuss features.

Rcpp Gallery



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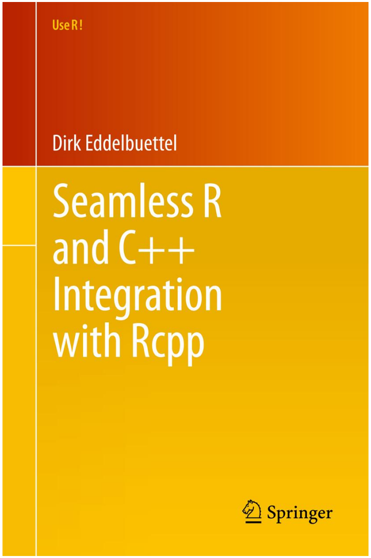

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