

RcppArmadillo: Accelerating R with C++ Linear Algebra

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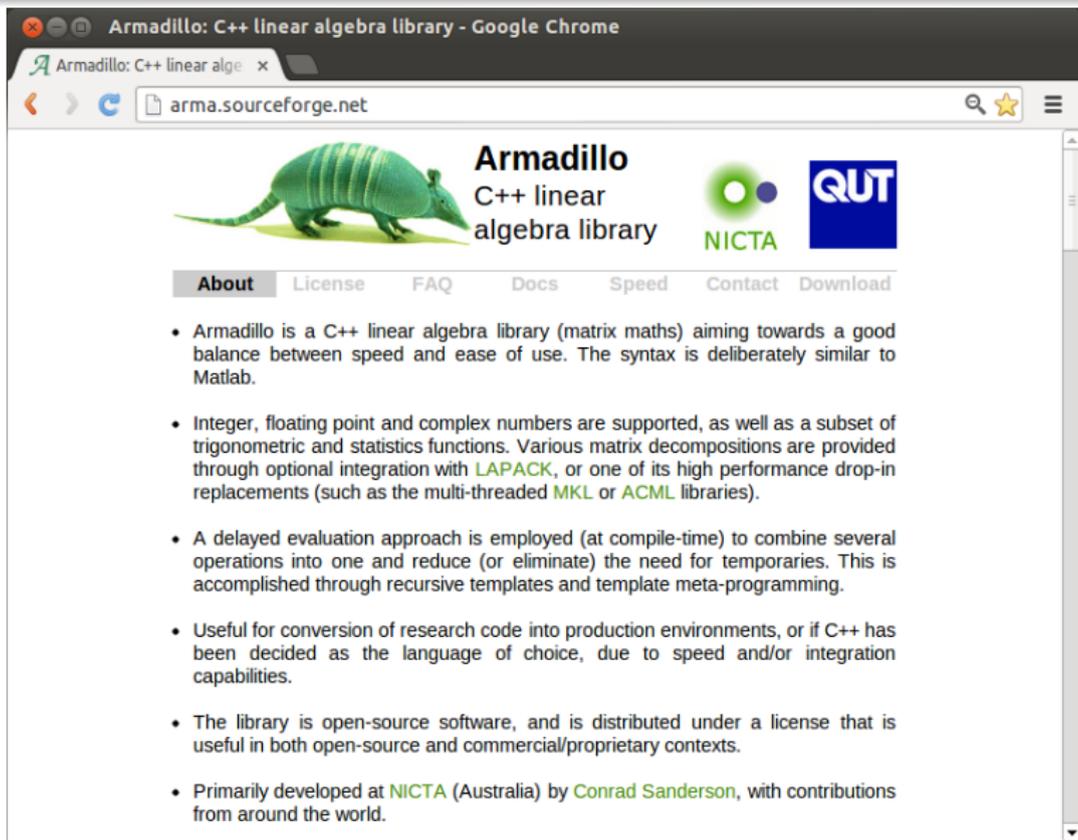
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University of Illinois at Chicago
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Outline

- 1 Intro
- 2 Examples
- 3 Case Study: Kalman Filter
- 4 End

Armadillo



Armadillo: C++ linear algebra library - Google Chrome

Armadillo: C++ linear algebra x

arma.sourceforge.net



Armadillo

C++ linear algebra library



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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 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 [MKL](#) or [ACML](#) 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 accomplished through recursive templates and 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.

What is Armadillo?

From `arma.sf.net` and slightly edited

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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 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 [...]*

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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 **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 wherever 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**
- Frequently updated, easy to use

Well-know packages using Rcpp / RcppArmadillo

To name just a few:

- [Amelia](#) by Gary King et al: Multiple Imputation from cross-section, time-series or both;
- [forecast](#) by Rob Hyndman et al: Time-series forecasting including state space and automated ARIMA modeling;
- [rugarch](#) by Alexios Ghalanos: Sophisticated financial time series models;
- [gRbase](#) by Søren Højsgaard: Graphical modeling

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Armadillo Eigenvalues

See <http://gallery.rcpp.org/articles/armadillo-eigenvalues/>

```
#include <RcppArmadillo.h>

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

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

Armadillo Eigenvalues

See <http://gallery.rcpp.org/articles/armadillo-eigenvalues/>

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

##           [,1]
## [1,]  0.3319
## [2,]  1.6856
## [3,]  2.4099
## [4,] 14.2100

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

Multivariate Normal RNG Draw

See

<http://gallery.rcpp.org/articles/simulate-multivariate-normal/>

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

using namespace Rcpp;

// [[Rcpp::export]]
arma::mat mvrnormArma(int n, arma::vec mu,
                      arma::mat sigma) {
    int ncols = sigma.n_cols;
    arma::mat Y = arma::randn(n, ncols);
    return arma::repmat(mu, 1, n).t() +
           Y * arma::chol(sigma);
}
```

Complete file for fastLM

RcppArmadillo src/fastLm.cpp

```

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

    arma::colvec coef = arma::solve(X, y); // fit model  $y \sim X$ 
    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
}

```

fastLm using Armadillo

Edited version of RcppArmadillo's `src/fastLm.cpp`

```

// [[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 );
}

```

fastLm using Armadillo

Edited version of RcppArmadillo's `src/fastLm.cpp`

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

// [[Rcpp::export]]
List fastLm2(colvec y, mat X) {
  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 );
}
```

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.

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Kalman Filter

The Mathworks site has a nice and short example of a classic 'object tracking' problem.

% 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 ; 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

Kalman Filter: In R

Easy enough – first naive solution

```

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 covariance
    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 covariance
    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

```
// [[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) = dt;
        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 func.: 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, kg;
    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();
        kg = (solve(S, B)).t();
        // estimated state and covariance
        xest = xprd + kg * (z - H * xprd);
        pest = pprd - kg * H * pprd;
        // compute estimated measurements
        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, we just add

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

Kalman Filter: Performance

Quite satisfactory relative to R

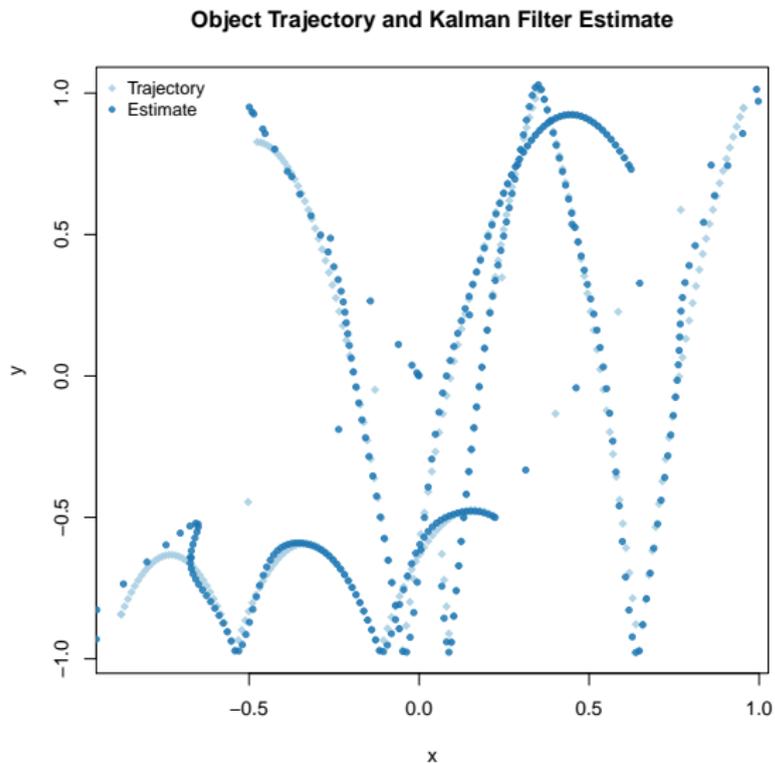
Even byte-compiled 'better' Rversion is 66 times slower:

```
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



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RcppArmadillo Paper

ScienceDirect.com - Computational Statistics & Data Analysis - RcppArmadillo: Accelerating R with

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RcppArmadillo: Accelerating R with high-performance C++ linear algebra

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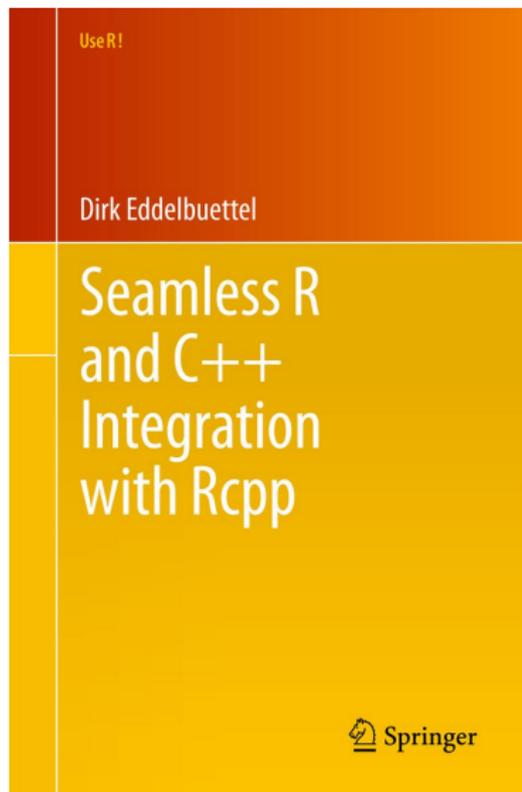
<http://dx.doi.org/10.1016/j.csda.2013.02.005>, [How to Cite or Link Using DOI](#)

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