



High Performance Functions With Rcpp

(make R coding faster with the integration of
C++)

About

This presentation is created by Farheen Nilofer (<https://in.linkedin.com/pub/farheen-nilofer/a5/5b9/58a>) as part of the internship requirements at DecisionStats.org.

I would like to thank Mr. Ajay Ohri (<https://in.linkedin.com/in/ajayohri>) and Miss Sunakshi for their invaluable help and guidance.

Get Code here:

https://github.com/Farheen2302/RCPD_Code

Introduction

The usage and implementation of [Rcpp package of R](#) have been detailed in these slides.

Convert a R function to a [Rcpp function](#) which is the integration of both C++ and R to make R coding many folds [faster](#) than the usual speed of [execution](#).

Every functionality is explained through many examples to make understand how the integration is done.

Prerequisites:

Languages:

1. Basics of C++ or C (both will work, you can go for it <http://www.learncpp.com/> or <http://www.cplusplus.com/>)
2. Basics of R (You can join 4 hours of R course at [DataCamp](#))

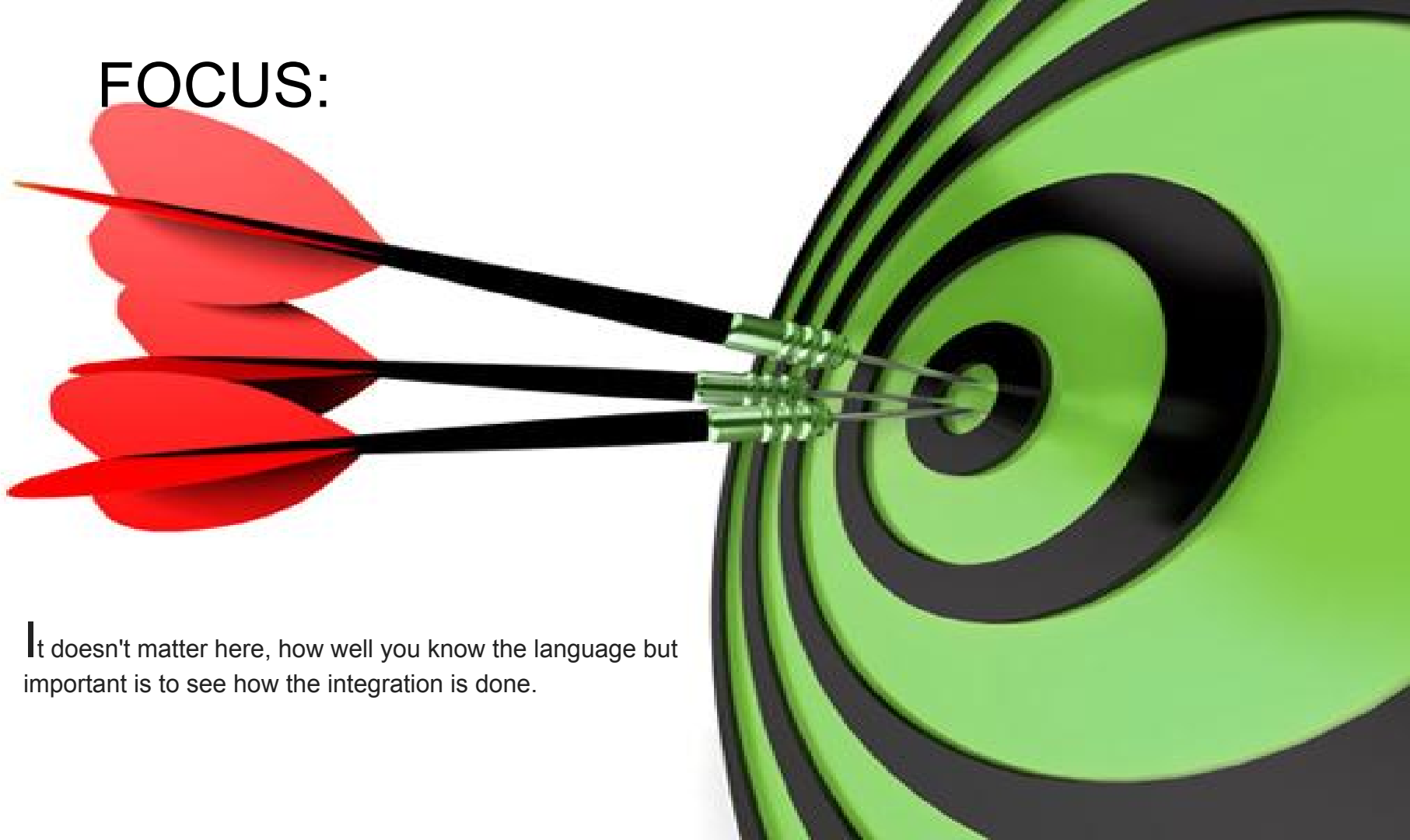
Tools:

R or better RStudio

You'll also need a working C++ compiler. To get it:

- On Windows, install [Rtools](#).
- On Mac, install Xcode from the app store.
- On Linux, `sudo apt-get install r-base-dev` or similar.

FOCUS:



It doesn't matter here, how well you know the language but important is to see how the integration is done.

What is Rcpp?

Rcpp is a package in R.

-tool written by Dirk E and Romain Francois

Rcpp makes it very easy to [integrate your R code with C++](#).

Rcpp provides easy ,clean and approachable API that will ultimately give you high performance code

link - <http://www.rcpp.org/>

Why we need Rcpp?

- code is just not fast enough.

- to improve the performance in R.

- **Rcpp package** help in integrating C++ with R and that help in making the code **faster**.

sources- <http://adv-r.had.co.nz/Rcpp.html>

Bottlenecks of R handled by C++

-problems of [Data Structures and Algorithms](#) the R doesn't support .

C++ has **STL**(Standard Template Library) to implement efficiently many data structures.

- Recursive functions or calling a function a million times are hardest time for R code to execute .

- [overhead of a function in C++ is much lower than R.](#)

-C++ makes it easy for loops to vectorise code easily whose subsequent iteration depend on previous ones.

What will be covered through these slides?

Using sourceCpp: sourceCpp() is a function of R to load files from the disk. sourceCpp() is Rcpp function -an extension of R source() to load C++ files in R.

Attributes and Classes: Attributes and classes to be used with Rcpp.

Missing Values: deal with R's missing values through C++.

Rcpp Sugar: avoid loops in C++ and write vectorized code (what is syntactic sugar- explain more)

The STL(Standard Template Library): use data structures and algorithms from STL,built in C++.

Examples: implemented examples to enhance the performance.

Putting Rcpp package:How to put C++ in R package.

Learning More: Many references to further learning is provided here.

1. Getting started with C++

When you run the below code, Rcpp will compile the C++ code and construct a R function that connect to the compiled C++ function.

What is compile?

Compile is a process to convert a high level language to a machine code that computer's processor uses.

How to run?

```
1 > library("Rcpp")
2 > cppFunction('int add(int a, int b, int c)
3 {
4   int sum = a + b + c; return sum;
5 }')
6 > add(4,5,6)
7 [1] 15
```

How to code in Rcpp?

This is the [example](#) to show how to go through the process of conversion.

R Code:

```
1 Rcode:
2 > oneR <-function()1L
3 > oneR()
4 [1] 1
```

C++ code:

Syntax of C++ code:

<http://www.cplusplus.com/doc/tutorial/functions/>

```
int oneR()
{
    return 1;
}
```

How to code in Rcpp?

- include the whole compiled C++ program inside the parenthesis of **cppFunction()** within quotes `' '` in the R console and hit enter.
- Nothing will happen on no error.
- Now call the function name as you do for R function call.

=====>

C++ implementation.

```
1  
2 > cppFunction('int oneR(){ return 1;}')  
3 > oneR()  
4 [1] 1|
```

How C++ functions different from R

Observe the above R and C++ code:

- Syntax to C++ looks alike of R -no assignment operator C++
- declare the type of output to be returned by the C++ function. In the above code the function returned 'int'.
- The **classes** for types of R vectors are **NumericVectors**, **IntegerVectors**, **CharacterVectors** and **LogicalVectors**
- **Scalars and Vectors** are different. The scalar equivalent of **numeric**, **integer** and **character** and **logical vectors** are **double**, **int** **String** and **bool**.
- use explicit **return statement** to return a value from the function.
- statement in C++ is terminated by **';'** .

2.Convert R functions to C++ equivalent.

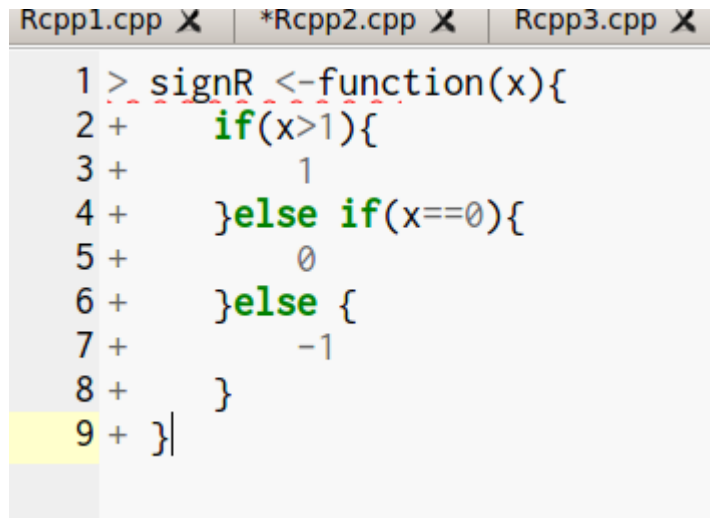
There are four different ways:

- Scalar input and scalar output
- Vector input and scalar output
- Vector input and vector output
- Matrix input and vector output

Scalar Input and Scalar Output

R code:

This simple R code and look at its C++ implementation in the next slide.



The screenshot shows a code editor with three tabs: Rcpp1.cpp, *Rcpp2.cpp, and Rcpp3.cpp. The active tab is Rcpp1.cpp, which contains the following C++ code:

```
1 > signR <-function(x){  
2 +   if(x>1){  
3 +       1  
4 +   }else if(x==0){  
5 +       0  
6 +   }else {  
7 +       -1  
8 +   }  
9 + }
```

Scalar Input and Scalar Output(cont..)

C++ code:

-C++ representation of above R code.

```
1 int signR(int x){  
2     if(x>0)  
3         return 1;  
4     else if(x==0)  
5         return 0;  
6     else  
7         return -1;  
8 }  
9
```


Scalar Input and Scalar Output(cont..)

If statement of C++ is same as

If statement of R

```
1 > cppFunction('int signR(int x){  
2 +   if(x>0)  
3 +     return 1;  
4 +   else if(x==0)  
5 +     return 0;  
6 +   else  
7 +     return -1;  
8 + }')  
9 > signR(0)  
10 [1] 0
```

Vector Input and Scalar Output(cont..)

R code:

```
1 > sum<- function(x){total <- 0
2 +   for(i in seq_along(x)){
3 +     total <-total + x[i]
4 +   }
5 +   total
6 + }
7 > sum(x)
8 [1] 15
```

Vector Input and Scalar Output

The cost of loops in C++ is very less

Rcpp:

```
1 > cppFunction('double sum(NumericVector x){  
2 +   double total = 0;  
3 +   int i=0;  
4 +   int len = x.size();  
5 +   for(i=0;i<len;i++)  
6 +   {  
7 +     total = total + x[i];  
8 +   }  
9 +   return total;  
10 + }')  
11 > x <- c(1,2,3,4,5)  
12 > sum(x)  
13 [1] 15
```

Some more difference between C++ and R.

C++ version is similar but bit different as in

- 1.C++ methods are called with a **full stop** as here done for calling 'size()'
- 2.'for' loop has a different syntax
- 3.In C++ vector **indices** start at '0', this is very common source of bug while converting R function to C++
- 4.Use '=' instead '<-'.

‘microbenchmark’ to compare the speed

```
install.packages("microbenchmark")
```

‘microbenchmark’ function from a package XC in R used to check the **execution speed** of our programs.

import ‘microbenchmark’ function through the command:

```
library(microbenchmark)
```

`system.time()` and `Rbenchmark()` also do the same.

```
1 > x <- runif(1e3)
2 > microbenchmark(
3 +   sum(x),
4 +   sumC(x),
5 +   sumR(x)
6 + )|
```

-minimum time taken by a C++ program is 4.272 and for the max value ,the least time 27.209

1 Unit: microseconds

2	expr	min	lq	mean	median	uq	max	neval	cld
3	sum(x)	630.703	668.2985	749.5731	699.4740	758.6200	2394.989	100	b
4	sumC(x)	4.272	5.0755	6.7247	6.3455	7.1195	27.209	100	a
5	sumR(x)	628.073	662.5360	715.4215	689.3375	763.9115	878.244	100	b

Vector Input Vector Output

R code:

```
pdistR <- function(x, ys){  
  sqrt((x - ys) ^ 2)  
}
```

Rcpp Code:

```
1 C Code:  
2 cppFunction('NumericVector pdistC(double x, NumericVector ys)  
3 + {  
4 +   int n = ys.size();  
5 +   NumericVector out(n);  
6 +   for(int i = 0; i < n ; i++) {  
7 +     out[i]=sqrt(pow(x - ys[i],2.0));  
8 +   }  
9 +   return out;  
10 + }')  
11 > pdistC(x,ys)  
12 [1] 1 2 3
```

Vector Input Vector Output(cont..)

We create a new numeric vector of length n with a constructor: `NumericVector out(n)`. Another useful way of making a vector is to copy an existing one:

```
NumericVector zs = clone(ys).
```

In C++ there is `pow()` to calculate power.

R code take 8 ms to execute and your C++ code takes 4ms but took 10mins time to write a C++.

What do you think is it worth it??

Yes ! When it comes calling same function a [million times](#) .

Matrix Input Vector output

Matrix could have equivalents like

NumericVector, IntegerVector,

CharacterVector, LogicalVector

Rcpp Code:=====>

```
1 > library("Rcpp")
2 > #Matrix input and Vector Output
3 > cppFunction('NumericVector rowsumC(NumericMatrix x) {
4 +     int row = x.nrow();
5 +     int col = x.ncol();
6 +     int i=0,j=0,total=0;
7 +     NumericVector out(col);
8 +     for(i = 0; i < row ; i++) {
9 +         total =0;
10 +         for(j = 0 ; j < col ; j++) {
11 +             total = total + x(i, j);
12 +         }
13 +         out[i] = total;
14 +     }
15 +     return out;}' )
16 >
17 |
```

DESCRIPTION:

There are two methods `nrow` and `ncol` for getting number of rows and number of columns.

```
1
2 > mat = matrix(c(1,2,3,4,5,6,7,8,9), nrow=3,ncol=3)
3 > rowsumC(mat)
4 [1] 12 15 18
5 > mat
6      [,1] [,2] [,3]
7 [1,]    1    4    7
8 [2,]    2    5    8
9 [3,]    3    6    9
10 >
```

From Inline to Stand-alone

Its tiresome to write code inside the function `cppFunction()`.

Are you too?

Can't we have some other method to do so?

Using `sourceCpp()`

The method we have earlier used was the [inline method](#).

Sometimes when you need some sort of code immediately because in real word everything is so fast the we need to keep everything ready.

Using sourceCpp() (cont..)

There comes [Stand alone functions](#). In this we need to already define the function and use it whenever required without the overhead of writing immediately.

How to do that?

Ans- You need to add only two three lines of code to your C++ function and compile the function whenever needed using `sourceCpp()` function from your R console.

Using sourceCpp() (cont..)

Make sure to save your Rcpp file as `.cpp` extension

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

And keep in mind that there is a 'gap' between `//` and `[[Rcpp::export]]`

```
// [[Rcpp::export]]
```

Using sourceCpp() (cont..)

Write Rcpp code in different file.

```
Rcpp1.cpp X
1 #include <Rcpp.h>
2 using namespace Rcpp;
3 // [[Rcpp::export]]
4 double mean(NumericVector x)
5 {
6     int n = x.size();
7     double total = 0.0;
8     for(int i = 0; i < n ; i++)
9     {
10         total += x[i];
11     }
12     return total/n;
13 }
```

How to compile standalone function

To compile your code, use function 'sourceCpp()' from R console, as shown below.

```
>
>
> sourceCpp('/home/farheen/Desktop/Rcpp_16_6/Rcpp1.cpp')
> x<-c(1,2,3,4,5,6,7)
> mean(x)
[1] 4
> |
```

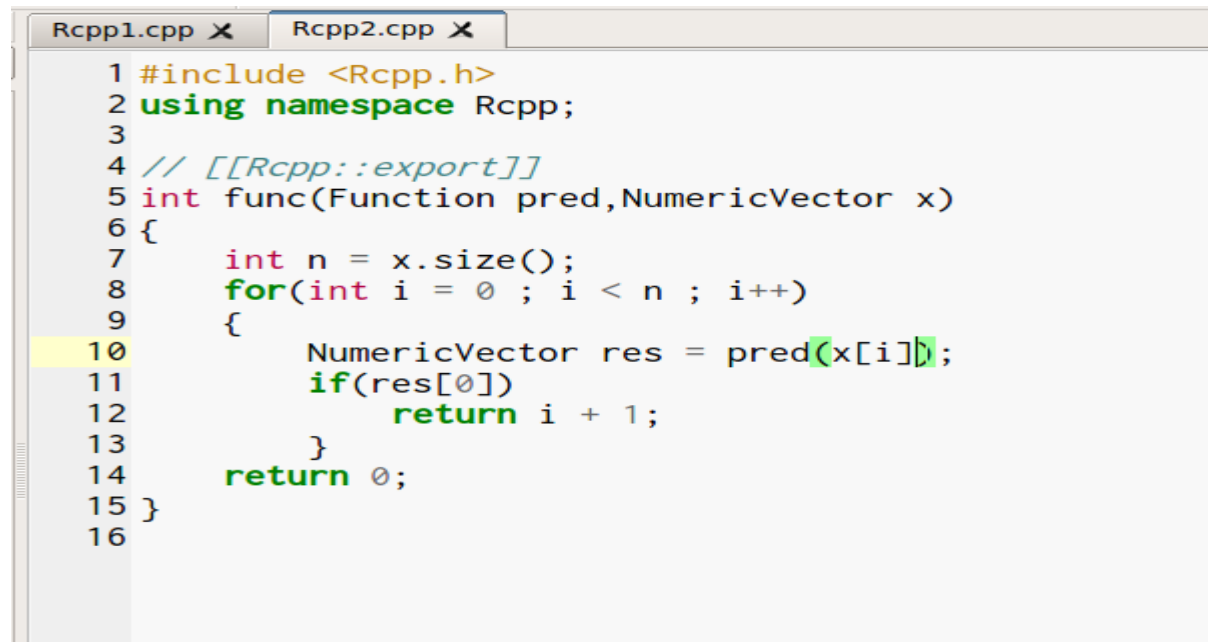
Note : You can see in the above image that C++ code is much faster than R's in built mean function.

```
> microbenchmark(mean(x),meanC(x))
Unit: microseconds
  expr    min      lq    mean  median      uq    max neval cld
mean(x) 341.788 342.275 343.4937 342.759 343.4055 367.799   100   b
meanC(x) 170.391 170.828 172.0789 171.764 172.2225 191.828   100   a
>
```

Example 1:

How to pass function as
argument?

=====>>

A screenshot of a C++ code editor with two tabs: 'Rcpp1.cpp' and 'Rcpp2.cpp'. The 'Rcpp2.cpp' tab is active, showing the following code:

```
1 #include <Rcpp.h>
2 using namespace Rcpp;
3
4 // [[Rcpp::export]]
5 int func(Function pred, NumericVector x)
6 {
7     int n = x.size();
8     for(int i = 0 ; i < n ; i++)
9     {
10         NumericVector res = pred(x[i]);
11         if(res[0])
12             return i + 1;
13     }
14     return 0;
15 }
16
```

```
> sourceCpp('/home/farheen/Desktop/Rcpp_16_6/Rcpp2.cpp')
> x <-c(0,0,1,1,0)
> func(sign,x)
[1] 3
```


Example 2:

```
Rcpp1.cpp X *Rcpp2.cpp X Rcpp3.cpp X
1 #include <Rcpp.h>
2 using namespace Rcpp;
3
4 // [[Rcpp::export]]
5 NumericVector mini(NumericVector x, NumericVector y)
6 {
7     int n = std::max(x.size(),y.size());
8     NumericVector x1 = rep_len(x, n);
9     NumericVector y1 = rep_len(y, n);
10    NumericVector out(n);
11    for(int i = 0 ; i < n ; i++)
12    {
13        out[i] = std::min(x1[i], y1[i]);
14    }
15    return out;
16 }
```

```
> sourceCpp('/home/farheen/Desktop/Rcpp_16_6/Rcpp3.cpp')
> x1 <- c(1,2,3,4,5,5)
> y1 <- c(1,24,3,1,3,4,5,6)
> mini(x1,y1)
[1] 1 2 3 1 3 4 1 2
> |
```

More practice.....

Someone here who want more brushing can also try ..

`all()`, `cumprod()`, `cummin()`, `cummax()`, `diff()`, `range`, `var` and for prior knowledge visit [wikipedia](https://en.wikipedia.org/).

3.Attributes and other classes

NumericVector,IntegerVector,LogicalVector,CharcterVector are Vector classes.

Scalar classes like int,double,bool,String and same for matrices like IntegerMatrix,NumericMatrix,LogicalMatrix and CharacterMatrix.

As we know all R objects have attributes.And these attributes can be set ,removed or modified using a 'attr()'

`attr(x,"dim")<- c(2,5)`

We will see '`::class()`' which allows us to create R vector using C++ scalar values.

```
1 > attr(x,"dim")<-c(2,5)
2 > x
3      [,1] [,2] [,3] [,4] [,5]
4 [1,]    1    3    5    7    9
5 [2,]    2    4    6    8   10
```

Attributes and other classes(cont...)

Now see how we used `::create()` to create a R `vector` from C++ `scalar`

```
1 #include <Rcpp.h>
2 using namespace Rcpp;
3 // [[Rcpp::export]]
4 NumericVector attrbs()
5 {
6     NumericVector out = NumericVector::create(1,2,3);
7     out.names()=CharacterVector::create('a','b','c');
8     out.attr("my-attr")="My_attributes";
9     out.attr("class")="my-class";
10
11     return out;
12 }
13
```

Attributes and other classes(cont...)

Output.:compiled stand alone function.

Checkout attributes,

```
1 sourceCpp( '/home/farheen/Desktop/Rcpp_16_6/Rcpp4.cpp' )
2 >
3 > attrbs()
4 abc\x9e*\004   bc\x9e*\004   c\x9e*\004
5               1             2             3
6 attr(,"my-attr")
7 [1] "My_attributes"
8 attr(,"class")
9 [1] "my-class"
10 |
```

List and DataFrames(**as()**,**lm()**,**inherit()**,**stop()**)

List and DataFrames one of the most important features in R.

-will see how to extract component from the list using **as()** and convert them into C++ equivalents.

Note **lm()**, **inherit()** and **stop()**.

List and DataFrames(cont..)

Look at as(),
how it converts
R objects'
component to C++

```
1 #include <Rcpp.h>
2
3 using namespace Rcpp;
4 // [[Rcpp::export]]
5 double mpe(List mod)
6 {
7     if(!mod.inherits("lm"))
8         stop("Only linear model accepted");
9
10    NumericVector resid = as<NumericVector>(mod["residuals"]);
11    NumericVector fitted = as<NumericVector>(mod["fitted.values"]);
12    int n = resid.size();
13    double err = 0;
14    for(int i = 0 ; i < n ; i++)
15    {
16        err += resid[i]/(resid[i]+fitted[i]);
17    }
18    return err/n;
19 }
```

List and DataFrames(cont..)

Check out the output ,the **errrrrr!**

```
1 > sourceCpp('/home/farheen/Desktop/Rcpp_16_6/Rcpp5.cpp')
2 >
3 > mod <- lm(mpg ~ wt,data = mtcars)
4 > mpg(mod)
5 Error: could not find function "mpg"
6 > mpe(mod)
7 [1] -0.01541615
8
```


Why R function in Rcpp code?

Calling a R function could be very useful.

1. For parameter [initialization](#).
2. Access a custom [data summary](#). To recode Huh! Overhead!
3. Calling a [plotting](#) routine. Tedious help, right?

Calling a R function would be [overhead](#) too.

Its slower than C++ equivalent and even [slower](#) than R code.

Warning: Do it when it make sense, not because its available.

Why R function in Rcpp code?

Here is the simple Rcpp code to demonstrate how to call R function from C++ code.

```
1 #include <Rcpp.h>
2 using namespace Rcpp;
3 // [[Rcpp::export]]
4
5 NumericVector CallRfunc(NumericVector x,Function f)
6 {
7     NumericVector res = f(x);
8     return res;
9 }
```

Why R function in Rcpp code?(_{cont..})

Look at the output ,it is similar to R function output below.

```
1 > x <- rnorm(1e5)
2 > CallRfunc(x, func)
3 [1] 1.077731
4 [1] 0.6233562
5 [1] 0.06276959
6 [1] 1.491707
7 [1] -0.1173361
```

Why R function in Rcpp code?(_{cont..})

This is the R function which is called
by 'CallRfunc()' above

```
1 func <-function(x) {  
2 +   i <- 0  
3 +   y <- 5  
4 +   for(i in seq(y)) {  
5 +     print (x[i])  
6 +   }  
7 + }  
8 >  
9 > func(x)  
10 [1] 0.6233562  
11 [1] 0.06276959  
12 [1] 1.491707  
13 [1] -0.1173361  
14 [1] -0.6419487  
15 >
```

Why R function in Rcpp code?(_{cont..})

There are classes for many more specialised language object.

Environment, ComplexVector, RawVector, DottPair, Language, Promise, Symbol, WeakReference and so on.

4.Missing Values

How to deal with missing values in Rcpp?

Lets find out!

We need to get two things.

1.How R's missing values behaves in C++ `Scalar(int ,double..)`.

2.How to get and set Missing values in `Vector(NumericVector,..)`.

Scalars

R's missing values are first coerced in C++ and then back to R vector.

```
1 #include <Rcpp.h>
2 using namespace Rcpp;
3
4 // [[Rcpp::export]]
5
6 List scal_mis()
7 {
8     int int_s=NA_INTEGER;
9     String chr_s=NA_STRING;
10    bool lgl_s = NA_LOGICAL;
11    double num_s = NA_REAL;
12
13    return List::create(int_s,chr_s,lgl_s,num_s);
14 }
```

Scalars(cont..)

With the exception
of bool, things
are pretty good
here.

```
1 > sourceCpp('/home/farheen/Desktop/Rcpp_16_6/Rcpp7.cpp')
2 > scal_mis()
3 [[1]]
4 [1] NA
5
6 [[2]]
7 [1] NA
8
9 [[3]]
10 [1] TRUE
11
12 [[4]]
13 [1] NA
```


Integers

With Integers ,we store missing values as smallest values

As C++ don't know the this special behaviour ,playing with it gives an incorrect value.

`evalCpp {Rcpp}`

Evaluates a C++ expression. This creates a C++ function using [cppFunction](#) and calls it to get the result

```
> evalCpp('NA_INTEGER + 1')  
[1] -2147483647  
>
```

Doubles

With doubles , ignore the missing values and work with R's **NaN**(Not A NUMBER)

It is R's NA is special type of NaA.It has characterstic that if it is involved in **logical expression** it gives **FALSE**.

With LOGICAL EXPRESSION=>

```
> evalCpp("NaN == 1")  
[1] FALSE  
> evalCpp("NaN < 1")  
[1] FALSE  
> evalCpp("NaN > 1")  
[1] FALSE  
> evalCpp("NaN == NaN")  
[1] FALSE  
>
```

Doubles(cont...)

With Boolean Values

Here NAN acts as a TRUE value

```
-  
> evalCpp("NAN && TRUE")  
[1] TRUE  
> evalCpp("NAN && FALSE")  
[1] FALSE  
> evalCpp("NAN || TRUE")  
[1] TRUE  
> evalCpp("NAN || FALSE")  
[1] TRUE  
>
```

Doubles(cont...)

In context with [Numeric Values](#) NA are propagated.

Look at the output ...

all **NANs**.

```
<
>
> evalCpp("NAN + 1")
[1] NaN
> evalCpp("NAN - 1")
[1] NaN
> evalCpp("NAN / 1")
[1] NaN
> evalCpp("NAN * 1")
[1] NaN
> |
```

String

String is Scalar string ,itself introduced by Rcpp.

String knows how to deal with missing values.

Boolean

One thing to note here is that C++ have only two value TRUE and FALSE while

R's logical Vector have three values TRUE, FALSE and NA.

VECTOR

-Missing values specific to the type of Vector like

```
1 #include <Rcpp.h>
2 using namespace Rcpp;
3
4 // [[Rcpp::export]]
5 List missing_values() {
6     return List::create(
7         NumericVector::create(NA_REAL),
8         IntegerVector::create(NA_INTEGER),
9         LogicalVector::create(NA_LOGICAL),
10        CharacterVector::create(NA_STRING));
11 }
```

VECTOR(cont...)

missing values.

```
1 > sourceCpp("/home/farheen/Desktop/Rcpp_16_6/Rcpp9.cpp")
2 > missing_values()
3 [[1]]
4 [1] NA
5
6 [[2]]
7 [1] NA
8
9 [[3]]
10 [1] NA
11
12 [[4]]
13 [1] NA
14
```

Each element in the list is of specific type.

```
1 > str(missing_values())
2 List of 4
3 $ : num NA
4 $ : int NA
5 $ : logi NA
6 $ : chr NA
```

VECTOR(cont...)

In this function you can see
each item in the
vector need to be check .

```
1 #include <Rcpp.h>
2 using namespace Rcpp;
3 // [[Rcpp::export]]
4 LogicalVector is_naC(NumericVector x)
5 {
6     int n = x.size();
7     LogicalVector out(n);
8
9     for(int i = 0 ; i < n ; i++)
10     {
11         out[i] = NumericVector::is_na(x[i]);
12     }
13
14     return out;
15 }
```


VECTOR(cont...)

Each element is specified if it is NA or not through logical Values.

```
1 > sourceCpp('/home/farheen/Desktop/Rcpp_16_6/Rcpp10.cpp')
2 > is_naC(x)
3 [1] FALSE FALSE FALSE TRUE FALSE FALSE TRUE FALSE
4 > |
```

5.Rcpp Sugar

Rcpp provide lot of Syntactic Sugar to ensure C++ function work very similar to their R equivalent.

Sugar functions can be roughly broken down into

- logical summary functions
- arithmetic and logical operators
- vector views
- other useful functions]

Lets begin

Rcpp Sugar(cont...)

ARITHMETIC AND LOGICAL OPERATORS:

All basic arithmetic and logical operators are vectorised as: +, *, -, /, pow, <, <=, >, >=, ==, !=, !.

Use sugar as following:

R function implementing pdistR

Now we could sugar to considerably simplify the code

```
1 pdistR <- function(x, ys) {  
2   sqrt((x - ys) ^ 2)  
3 }  
4  
5 > x <- c(1,23,4,5)  
6 > ys <- 3  
7 > pdistR(x, ys)  
8 [1] 2 20 1 2
```

Rcpp Sugar(cont...)

Sugar implementation in C++

Without sugar we need to use **loop**

```
1 #include <Rcpp.h>
2 using namespace Rcpp;
3
4 // [[Rcpp::export]]
5 NumericVector pdistC(NumericVector x, double ys)
6 {
7     return sqrt(pow((x - ys),2));
8 }
```

Rcpp Sugar(cont...)

LOGICAL SUMMARY FUNCTION

Use sugar to write an efficient function .

Sugar function like `any()`, `all()` , `is.na()` are very efficient .

This will do the same amount of work regardless
of the position of the missing values.

Proved in below microbench program

```
any_naR <- function(x) any(is.na(x))  
|  
> any_naR(x)  
[1] FALSE  
> x  
[1] 1 23 4 5  
>
```

Rcpp Sugar(cont...)

Sugar
implementation in
C++

Below microbench()
shows the execution of
both R and C++ code

```
1 #include <Rcpp.h>
2 using namespace Rcpp;
3
4 // [[Rcpp::export]]
5 bool any_naC(NumericVector x) {
6   return is_true(any(is_na(x)));
7 }
8
9 > sourceCpp('/home/farheen/Desktop/Rcpp_16_6/Rcpp14.cpp')
10 > any_naC(x)
11 [1] FALSE
12 > x
13 [1] 3
14 > x <- c(1,2,3,4,5,6,NA,34)
15 > any_naC(x)
16 [1] TRUE
17 >
```

Rcpp Sugar(cont...)

Changing the position of missing values.

```
1 > any_naR = function(x) any(is.na(x))
2 > x0 <- runif(1e5)
3 > x1 <- c(x0, NA)
4 > x2 <- c(NA, x0)
5 >
6 > microbenchmark(
7 +   any_naR(x0), any_naC(x0),
8 +   any_naR(x1), any_naC(x1),
9 +   any_naR(x2), any_naC(x2)
10 + )
```

Rcpp Sugar(cont...)

-execution time of each program have hardly any effect on the execution time of R code due to missing value place.

```
1 Unit: microseconds
2      expr      min      lq      mean      median      uq      max neval cld
3 any_naR(x0) 895.445 1013.2000 1054.2477 1046.034 1051.2110 2911.458   100  b
4 any_naC(x0) 2008.266 2011.9745 2019.3772 2016.564 2022.3300 2142.938   100  c
5 any_naR(x1) 895.095 1036.7700 1128.7003 1046.463 1053.0965 2926.561   100  b
6 any_naC(x1) 2007.986 2011.4295 2018.4665 2016.497 2023.3060 2058.282   100  c
7 any_naR(x2) 560.791  671.4505  818.6814  714.271  719.8905 2745.007   100 ab
8 any_naC(x2)   3.034   3.9560  369.9380    5.326   6.9315 36387.571   100  a
9 >
```


Rcpp Sugar(cont...)

VECTOR VIEW

There are many functions which Sugar provide to view the vector.

`head()`, `tail()`, `rep_each()`, `rep_len()`, `rev()`, `seq_along()`, and `seq_len()`.

In R these would all produce [copies of the vector](#), but in Rcpp they simply [point to the existing vector](#) which makes them efficient.

There's grab bag of sugar functions.

- Math functions: `abs()`, `acos()`, `asin()`, `atan()`, `beta()`, `ceil()`, `ceiling()`, `choose()`, `cos()`, `cosh()`, `digamma()`, `exp()`, `expm1()`, `factorial()`, `floor()`, `gamma()`, `lbeta()`, `lchoose()`, `lfactorial()`, `lgamma()`, `log()`, `log10()`, `log1p()`, `pentagamma()`, `psigamma()`, `round()`, `signif()`, `sin()`, `sinh()`, `sqrt()`, `tan()`, `tanh()`, `tetragamma()`, `trigamma()`, `trunc()`.
- Scalar summaries: `mean()`, `min()`, `max()`, `sum()`, `sd()`, and (for vectors) `var()`.
- Vector summaries: `cumsum()`, `diff()`, `pmin()`, and `pmax()`.
- Finding values: `match()`, `self_match()`, `which_max()`, `which_min()`.
- Dealing with duplicates: `duplicated()`, `unique()`.
- `d/q/p/r` for all standard distributions.

Finally, `noNA(x)` asserts that the vector `x` does not contain any missing values.

6.The STL(Standard Library Templates)

The real strength of C++ is when you use [STL](#) for algorithm and Data Structure.

If you need an algorithm or data structure that isn't implemented in STL, a good place to look is [boost](#).

Iterators are used heavily in STL .Many function either accept or return iterators.

They are the next step up from basic loops, [abstracting away the details of the underlying data structure](#)

The STL(cont...)

Using ITERATORS

Iterators are used heavily in STL .
Many function either
accept or return iterators.

They are the next step up from
basic loops,
abstracting away the
details of the underlying
data structure

```
1 #include <Rcpp.h>
2 using namespace Rcpp;
3 // [[Rcpp::export]]
4 double sum4(NumericVector x)
5 {
6     double total = 0.0;
7     NumericVector::iterator it;
8     for(it = x.begin() ; it != x.end(); ++it)
9     {
10         if(NumericVector::is_na(*it) == FALSE)
11         {
12             total += *it;
13         }
14     }
15     return total;
16 }
17 }
```

The STL(cont...)

```
1 > sourceCpp('/home/farheen/Desktop/Rcpp_16_6/Rcpp16.cpp')
2 > sum4(x)
3 [1] 55
4 > x
5 [1] 1 2 3 4 5 6 NA 34
6 >
```

The STL(cont...)

Iterators also allow us to use the C++ equivalents of the apply family of functions. For example, we could again rewrite sum() to use the `accumulate()` function.

Note: Third argument to
accumulate gives
the initial value
determines the data type.
(here 'double')

```
1
2 #include <Rcpp.h>
3
4 using namespace Rcpp;
5 // [[Rcpp::export]]
6 double sum4(NumericVector x)
7 {
8     return std::accumulate(x.begin(), x.end(), 0.0);
9 }
10
11
12 > sourceCpp('/home/farheen/Desktop/Rcpp_16_6/Rcpp17.cpp')
13 > sum4(x)
14 [1] 18
```

The STL(cont...)

ALGORITHMS

The `<algorithm>` header provides large number of algorithms that work with iterators. A good reference is available at <http://www.cplusplus.com/reference/algorithm/>.

Here we are implementing basic Rcpp version of `findInterval()`

Where two vector are inputs and
output is there upper bound.

The STL(cont...)

```
1 #include <Rcpp.h>
2
3 using namespace Rcpp;
4 // [[Rcpp::export]]
5
6 IntegerVector findInterval2(NumericVector a, NumericVector y)
7 {
8     IntegerVector out(a.size());
9     NumericVector::iterator it, pos;
10    IntegerVector::iterator out_it;
11
12    for(it = a.begin(), out_it = out.begin(); it != a.end(); ++it, ++out_it)
13    {
14        pos = std::upper_bound(y.begin(), y.end(), *it);
15        *out_it = std::distance(y.begin(), pos);
16    }
17    return out;
18 }
```

The STL(cont...)

Look at the output.

Upper bound position of the items in x are searched in the vector y.

It's generally better to use algorithms from the STL than hand rolled loops.

STL algorithms are **efficient**, well **tested** and these Standard algorithm makes the code **readable** and more **maintainable**.

```
1 > x <- c(34,56,78)
2 > findInterval2(x,y)
3 [1] 4 5 6
4 > x <- c(34,21,78)
5 > findInterval2(x,y)
6 [1] 4 3 6
7 > y
8 [1] 4 5 6 34 56 67
9 > x
10 [1] 34 21 78
11 > x <- c(21,34,78)
12 > findInterval2(x,y)
13 [1] 3 4 6
```


The STL(cont...)

Data Structures

The STL provides a large set of data structures: `array`, `bitset`, `list`, `forward_list`, `map`, `multimap`, `multiset`, `priority_queue`, `queue`, `dequeue`, `set`, `stack`, `unordered_map`, `unordered_set`, `unordered_multimap`, `unordered_multiset`, and `vector`.

The most important of these data structures are the `vector`, the `unordered_set`, and the `unordered_map`.

A good reference for STL data structures is <http://www.cplusplus.com/reference/stl/> — I recommend you keep it open while working with the STL.

Rcpp knows how to convert from many STL data structures to their R equivalents

The STL(_{cont...}): Vectors

Data Structures

An STL vector is very similar to an R vector but more efficient.

Vectors are templated i.e you need to specify their type while creating. `vector<int>`, `vector<bool>`, `vector<double>`, `vector<String>`.

`standard [] notation` : to access element in the vector

`.push_back()`: to add new element at the end of the vector.

`.reserve()` : to allocate sufficient storage.

More methods of a vector are described at <http://www.cplusplus.com/reference/vector/vector/>.

The STL(cont...) Data Structures

Look at the
two vector
declared and
there type.

```
1 #include <Rcpp.h>
2 using namespace Rcpp;
3
4 // [[Rcpp::export]]
5 List rleC(NumericVector x) {
6     std::vector<int> lengths;
7     std::vector<double> values;
8
9     // Initialise first value
10    int i = 0;
11    double prev = x[0];
12    values.push_back(prev);
13    lengths.push_back(1);
14
15    NumericVector::iterator it;
16    for(it = x.begin() + 1; it != x.end(); ++it) {
17        if (prev == *it) {
18            lengths[i]++;
19        } else {
20            values.push_back(*it);
21            lengths.push_back(1);
22
23            i++;
24            prev = *it;
25        }
26    }
27
28    return List::create(
29        _["lengths"] = lengths,
30        _["values"] = values
31    );
32 }
```

The STL(_{cont...}):Sets

Set maintain a unique set of values.

C++ provides both `ordered (std :: set)` and unordered sets (`std :: unordered_set`).

Unordered set are efficient than ordered sets.

Like vectors sets are also templated ,you need to specify the type. `unordered_set<int>`, `unordered_set<bool>`, etc.

For more details visit <http://www.cplusplus.com/reference/set/set/> and http://www.cplusplus.com/reference/unordered_set/unordered_set/.

Note : The use of `seen.insert(x[i]).second`. `insert()` returns a pair, the .first value is an iterator that points to element and the .second value is a boolean that's true if the value was a new addition to the set.

The STL_(cont...):Sets

Note that the ordered sets are only available in C++ 11.

Therefore you need to use cpp11 plugig.

// [Rcpp::plugins(cpp11)]

```
1 // [[Rcpp::plugins(cpp11)]]
2 #include <Rcpp.h>
3 #include <unordered_set>
4 using namespace Rcpp;
5
6 // [[Rcpp::export]]
7 LogicalVector duplicatedC(IntegerVector x) {
8     std::unordered_set<int> seen;
9     int n = x.size();
10    LogicalVector out(n);
11
12    for (int i = 0; i < n; ++i) {
13        out[i] = !seen.insert(x[i]).second;
14    }
15
16    return out;
17 }
```

The STL(_{cont...}):Map

It is useful for functions like `table()` or `match()` that need to look up the value ,instead of storing presence and absence it can store the additional data.

There are ordered (`std::map`) and unordered (`std::unordered_map`).

Map is templated ,you need to specify the type like `map<int, double>` ,`unordered_map<double, int>`.

The STL(_{cont...}):Sets

Unordered maps are only
available in C++ 11

```
1 #include <Rcpp.h>
2
3 using namespace Rcpp;
4 // [[Rcpp::export]]
5 std::map<double, int> tableC(NumericVector x)
6 {
7     std::map<double, int> counts;
8     int n = x.size();
9
10    for(int i = 0 ; i < n; i++)
11    {
12        counts[x[i]]++;
13    }
14    return counts;
15 }
```

The STL(cont...):Sets

output table:

```
1 > sourceCpp('/home/farheen/Desktop/Rcpp_16_6/Rcpp21.cpp')
2 > tableC(x)
3 1 2 3 4 5 6 7
4 3 2 3 3 2 4 1
5 > x
6 [1] 1 1 1 2 2 3 3 3 4 4 4 5 5 6 6 6 6 7
7 >
8 > y
9 [1] 4 5 6 34 56 67
10 > tableC(y)
11 4 5 6 34 56 67
12 1 1 1 1 1 1
```


7. Case Studies

Two case-studies to give you a reason to replace your R code with Rcpp.

1. Gibbs Sampler

2. R vectorisation vs C++ vectorisation

GIBBS SAMPLER:

The R and C++ code shown below is very similar (it only took a few minutes to convert the R version to the C++ version), but runs about 20 times faster on my computer.

Case Studies(cont...):GIBBS SAMPLER

R CODE:

```
gibbs_r <- function(N, thin) {  
  mat <- matrix(nrow = N, ncol = 2)  
  x <- 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  
}
```

```
> gibbs_r(5,5)  
      [,1]      [,2]  
[1,] 0.4385219 -0.2793711  
[2,] 0.2961570  1.4575477  
[3,] 1.3773151  0.2997856  
[4,] 0.9273027  0.1845081  
[5,] 0.2673503  1.2651604
```

Case Studies(_{cont...}): GIBBS SAMPLER

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

// [[Rcpp::export]]
NumericMatrix gibbs_cpp(int N, int thin)
{
    NumericMatrix mat(N,2);
    double x = 0, y=0;
    for(int i = 0; i < N; i++)
    {
        for(int j = 0; j < thin; j++)
        {
            x = rgamma(1,3,1/(y * y + 4))[0];
            y = rnorm(1,1/(x+1),1 / sqrt(2 * (x + 1)))[0];
        }
        mat(i,0) = x;
        mat(i,1) = y;
    }
    return(mat);
}
```

RCP CODE:

```
> gibbs_cpp(5,5)
      [,1]      [,2]
[1,] 1.1301489 0.1162286
[2,] 1.4336608 -0.0830889
[3,] 1.1651273 0.3415322
[4,] 0.5975518 0.1269640
[5,] 1.1521344 0.2927905
```

Case Studies(_{cont...}): GIBBS SAMPLER

Rcpp program is 20 times faster than the R code.

Check this-

min: 298/15 ~20

max: 702.240/40.028 ~17.54~`20

```
> library("microbenchmark", lib.loc="~/R/x86_64-pc-linux-gnu-library/3.2")
> microbenchmark(gibbs_r(5,5),gibbs_cpp(5,5))
Unit: microseconds
      expr      min       lq      mean    median      uq      max  neval  cld
gibbs_r(5, 5) 298.761 340.136 366.61687 365.643 377.5000 702.240   100    b
gibbs_cpp(5, 5) 15.252  18.705  21.85202  20.429  22.8265  40.028   100    a
> |
```

Case Studies: R VECTORIZATION VS C++ VECTORIZATION

-adapted from [“Rcpp is smoking fast for agent-based models in data frames”](#).

-predict the model response from three different inputs.

R code:

```
vaccR1 <- function(age, female, ily) {  
  p <- 0.25 + 0.3 * 1 / (1 - exp(0.04 * age)) + 0.1 * ily  
  p <- p * if (female) 1.25 else 0.75  
  p <- max(0, p)  
  p <- min(1, p)  
  p  
}  
  
vaccR2 <- function(age, female, ily) {  
  n <- length(age)  
  out <- numeric(n)  
  for (i in seq_len(n)) {  
    out[i] <- vaccR1(age[i], female[i], ily[i])  
  }  
  out  
}
```

Case Studies: R VECTORIZATION VS C++ VECTORIZATION(cont...)

R Code:(no loop in it)

```
ivaccR <- function(age,female,ily) {  
  p <- 0.25 + 0.3* 1/(1 - exp(0.04 * age)) +0.1*ily  
  p <- p* ifelse(female,1.25,0.75)  
  p<- pmax(0, p)  
  p <= pmin(0, p)  
  p  
}
```

Case Studies: R VECTORIZATION VS C++

VECTORIZATION(cont...)

Rcpp Code:

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

double vaccCpp(double age, bool female, bool ily)
{
    double p = .25 + .3 * 1/(1 - exp(0.04 * age)) + 0.1 * ily;
    p = p * (female ? 1.25 : 0.75);
    p = std::max(p, 0.0);
    p = std::min(p, 1.0);
    return p;
}

// [[Rcpp::export]]
NumericVector vaccRcpp(NumericVector age, LogicalVector female, LogicalVector ily) {
    int n = age.size();
    NumericVector out(n);
    for(int i = 0; i < n; i++)
    {
        out[i] = vaccCpp(age[i], female[i], ily[i]);
    }
    return out;
}
```

Case Studies: R VECTORIZATION VS C++

VECTORIZATION(cont...)

Vectorising in R gives a huge speedup.

```
> stopifnot(  
+   all.equal(vaccR2(age, female, ily), vaccR(age, female, ily)),  
+   all.equal(vaccR2(age, female, ily), vaccRcpp(age, female, ily))  
+ )  
>
```

create 11 vectors

Performance (~10x)
with the C++ loop

```
> microbenchmark(  
+   vacc1 = vaccR2(age, female, ily),  
+   vacc2 = vaccR(age, female, ily),  
+   vacc3 = vaccRcpp(age, female, ily)  
+ )
```

create only 1 vector.

Unit: microseconds

expr	min	lq	mean	median	uq	max	neval	cld
vacc1	7185.416	7381.747	9321.43999	7803.5265	8481.8995	21924.882	100	b
vacc2	448.927	461.346	496.60289	490.2125	514.2535	722.571	100	a
vacc3	57.047	58.542	67.37255	63.7660	69.1335	110.152	100	a

```
> |
```


8.USING RCPP IN PACKAGE

C++ code can also be bundles in packages instead of using sourceCpp().

BENEFITS:

- user can use C++ code without development tools
- R package build system automatically handle multiple source file and their dependencies.
- provide additional infrastructure

To include Rcpp to the existing package you put your C++ files in the src/ directory and modify/create the following configuration files:

- In DESCRIPTION add:

LinkingTo: Rcpp

Imports: Rcpp

- Make sure your NAMESPACE includes:

```
useDynLib(mypackage)
```

```
importFrom(Rcpp, sourceCpp)
```

USING RCPP IN PACKAGE(cont...)

- To generate a new Rcpp package that includes a simple “hello world” function you can use `Rcpp.package.skeleton()`:

```
Rcpp.package.skeleton("NewPackage", attributes = TRUE)
```

- To generate a package based on C++ files that you’ve been using with `sourceCpp()`, use the `cpp_files` parameter:

```
Rcpp.package.skeleton("NewPackage", example_code = FALSE,  
  cpp_files = c("convolve.cpp"))
```

Before building package you need to run `Rcpp::compileAttributes()`

- scans the C++ files for `Rcpp::export` attributes
- generates the code required to make the functions available in R

Re-run `Rcpp::compileAttributes()` whenever function is added.

For more details see [vignette\("Rcpp-package"\)](#)

LEARNING MORE

Rcpp book

[vignette\("Rcpp-package"\)](#)

[vignette\("Rcpp-modules"\)](#)

[vignette\("Rcpp-quickref"\)](#)

Rcpp homepage

Dirk's Rcpp page

Learning C++:

Effective C++ and *Effective STL* by Scott Meyers

C++ Annotations

Algorithm Libraries

Algorithm Design Manual

Introduction to Algorithms

online textbook

coursera course

Thank You

You can get the whole code :https://github.com/Farheen2302/RCPP_Code

Any questions?

Contact us at

info@decisionstats.org

farheenfnilofer@gmail.com