

High performance R with Rcpp

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Benjamin Skinner

R is really powerful, but for some tasks can be very slow. As data get larger and scripts require more complex algorithms and demanding tasks, even small bits of sluggishness become huge in the aggregate. Compiled languages such as C and C++ can be much faster than R, but require greater programming skill. While learning a compiled language is useful for many researchers, the upfront time needed to learn is often too steep for any given project.

Fortunately, the Rcpp¹ package bridges the gap between the two worlds. While there is a bit of a learning curve for Rcpp, which is based on C++, much R code can be, with few modifications, adjusted to become Rcpp code and run much faster for complex tasks.

This module will give one example of such a speed up. In my own research, I've computed the Great Circle ("as the crow flies") distance² between colleges and various geographic centroids many times using either the Haversine³ or Vincenty⁴ formula. But with over 7,500 colleges and universities in the United States, measuring the distance from each county centroid (around 3,000) became slow enough. Doing the same for all census tracts (around 70,000) and census block groups (over 200,000) was almost impossible. With small modifications to base R formula functions, however, I was able to convert them to compiled Rcpp function which run much, much faster.

```
## -----  
## libraries  
## -----  
library(tidyverse)  
  
## — Attaching packages ————— tidyverse 1.3.1 —  
  
## ✓ ggplot2 3.3.5      ✓ purrr   0.3.4  
## ✓ tibble  3.1.6      ✓ dplyr   1.0.8  
## ✓ tidyr   1.2.0      ✓ stringr 1.4.0  
## ✓ readr   2.1.2      ✓ forcats 0.5.1  
  
## — Conflicts ————— tidyverse_conflicts() —  
## ✖ dplyr::filter() masks stats::filter()  
## ✖ dplyr::lag()     masks stats::lag()  
  
library(Rcpp)  
library(microbenchmark)
```

And as always, we are working in the `./scripts` subdirectory.

```
## -----  
## directory paths  
## -----
```

¹<https://CRAN.R-project.org/package=Rcpp>

²https://en.wikipedia.org/wiki/Great-circle_distance

³https://en.wikipedia.org/wiki/Haversine_formula

⁴https://en.wikipedia.org/wiki/Vincenty%27s_formulae

```
## assume we're running this script from the ./scripts subdirectory
dat_dir <- file.path(".", "data")
rcpp_dir <- file.path(dat_dir, "rcpp")
```

Read in data

This module uses two data frames. The first has the names and locations of all colleges with a physical campus in 2015. The second has the locations of every census block group in the United States from the 2010 Census.

```
## -----
## input data
## -----

## assume we're running this script from the ./scripts subdirectory
df_col <- readRDS(file.path(rcpp_dir, "collegeloc.RDS"))
df_cbg <- readRDS(file.path(rcpp_dir, "cblocks.RDS"))
```

College locations

Here's a quick peek at the college location data (around 7,600 institutions).

```
## college locations
df_col
```

```
## # A tibble: 7,647 × 5
##   unitid instnm                fips5  lon  lat
##   <int> <chr>                <chr> <dbl> <dbl>
## 1 100654 Alabama A & M University 01089 -86.6 34.8
## 2 100663 University of Alabama at Birmingham 01073 -86.8 33.5
## 3 100690 Amridge University      01101 -86.2 32.4
## 4 100706 University of Alabama in Huntsville 01089 -86.6 34.7
## 5 100724 Alabama State University 01101 -86.3 32.4
## 6 100733 University of Alabama System Office 01125 -87.5 33.2
## 7 100751 The University of Alabama 01125 -87.5 33.2
## 8 100760 Central Alabama Community College 01123 -85.9 32.9
## 9 100812 Athens State University 01083 -87.0 34.8
## 10 100830 Auburn University at Montgomery 01101 -86.2 32.4
## # ... with 7,637 more rows
```

Census block group locations

And here's the census block group location data (around 217,000 block groups).

```
## census block group locations
df_cbg
```

```
## # A tibble: 217,740 × 4
##   fips11      pop  lon  lat
##   <chr>    <int> <dbl> <dbl>
## 1 010010201001    698 -86.5 32.5
## 2 010010201002   1214 -86.5 32.5
## 3 010010202001   1003 -86.5 32.5
## 4 010010202002   1167 -86.5 32.5
## 5 010010203001   2549 -86.5 32.5
```

```
## 6 010010203002 824 -86.5 32.5
## 7 010010204001 944 -86.4 32.5
## 8 010010204002 1937 -86.4 32.5
## 9 010010204003 935 -86.4 32.5
## 10 010010204004 570 -86.4 32.5
## # ... with 217,730 more rows
```

Compute great circle distance with Haversine

The Haversine formula⁵ is a fairly straightforward trigonometric problem. Since the coordinates in the data are in latitude and longitude and the formula requires radians, a quick helper function `deg_to_rad()` is used to make the conversion.

```
## convert degrees to radians
deg_to_rad <- function(degree) {
  m_pi <- 3.141592653589793238462643383280
  return(degree * m_pi / 180)
}

## compute Haversine distance between two points
dist_haversine <- function(xlon, xlat, ylon, ylat) {

  ## radius of Earth in meters
  e_r <- 6378137

  ## return 0 if same point
  if (xlon == ylon & xlat == ylat) { return(0) }

  ## convert degrees to radians
  xlon = deg_to_rad(xlon)
  xlat = deg_to_rad(xlat)
  ylon = deg_to_rad(ylon)
  ylat = deg_to_rad(ylat)

  ## haversine distance formula
  d1 <- sin((ylat - xlat) / 2)
  d2 <- sin((ylon - xlon) / 2)

  return(2 * e_r * asin(sqrt(d1^2 + cos(xlat) * cos(ylat) * d2^2)))
}
```

With the formula, we can compute the distance in meters between the first census block group and the first college in the data set pretty quickly.

```
## store first census block group point (x) and first college point (y)
xlon <- df_cbg[[1, "lon"]]
xlat <- df_cbg[[1, "lat"]]
ylon <- df_col[[1, "lon"]]
ylat <- df_col[[1, "lat"]]

## test single distance function
d <- dist_haversine(xlon, xlat, ylon, ylat)
```

⁵https://en.wikipedia.org/wiki/Haversine_formula#The_haversine_formula

```
## show  
d
```

```
## [1] 258212.3
```

Quick exercise Find the coordinates of two places you know the distance between pretty well (say, your hometown and where you live now or your first college or the nearest big city). Compute the distance and compare to Google's driving distance. It should be shorter (crows fly very straight), but similar. You may want to convert the meters to kilometers or miles. As always Google is your friend for all these steps.

Many to many distance matrix

Now that we have a core function, let's write a larger function that can take many input points, many output points, and compute the distances between them.

```
## compute many to many distances and return matrix  
dist_mtom <- function(xlon,      # vector of starting longitudes  
                      xlat,      # vector of starting latitudes  
                      ylon,      # vector of ending longitudes  
                      ylat,      # vector of ending latitudes  
                      x_names,   # vector of starting point names  
                      y_names) { # vector of ending point names  
  
  ## init output matrix (n X k)  
  n <- length(xlon)  
  k <- length(ylon)  
  mat <- matrix(NA, n, k)  
  
  ## double loop through each set of points to get all combinations  
  for(i in 1:n) {  
    for(j in 1:k) {  
      ## compute distance using core function  
      mat[i,j] <- dist_haversine(xlon[i], xlat[i], ylon[j], ylat[j])  
    }  
  }  
  
  ## add row and column names  
  rownames(mat) <- x_names  
  colnames(mat) <- y_names  
  return(mat)  
}
```

Let's test it with a subset of ten starting points.

```
## test matrix (limit to only 10 starting points)  
distmat <- dist_mtom(df_cbg$lon[1:10], df_cbg$lat[1:10],  
                    df_col$lon, df_col$lat,  
                    df_cbg$fips11[1:10], df_col$unitid)  
  
## show  
distmat[1:5,1:5]
```

```
##           100654   100663   100690   100706   100724
## 010010201001 258212.3 119349.8 31495.73 251754.3 21138.09
## 010010201002 256255.2 117447.3 32284.61 249798.4 22263.60
## 010010202001 256775.4 118210.3 31047.25 250348.1 21059.86
## 010010202002 258084.9 119554.9 30210.67 251665.2 20017.60
## 010010203001 256958.5 118703.3 29758.10 250567.0 19905.92
```

Quick exercise *Can you find the minimum distance for each starting point? What's the name of the nearest end point?*

Nearest end point

Rather than return a full matrix of distances that we then need to evaluate to find the shortest distance, let's write a new function, `dist_min()`, that will take two vectors of points again, but only return the closest point in the second group, with distance, for each point in the first group.

```
## compute and return minimum distance along with name
dist_min <- function(xlon,      # vector of starting longitudes
                    xlat,      # vector of starting latitudes
                    ylon,      # vector of ending longitudes
                    ylat,      # vector of ending latitudes
                    x_names,    # vector of starting point names
                    y_names) {  # vector of ending point names

  ## NB: Lengths: x coords == x names && y coords == y_names
  n <- length(xlon)
  k <- length(ylon)
  minvec_name <- vector('character', n)
  minvec_meter <- vector('numeric', n)

  ## init temporary vector for distances between one x and all ys
  tmp <- vector('numeric', k)

  ## give tmp names of y vector
  names(tmp) <- y_names

  ## loop through each set of starting points
  for(i in 1:n) {
    for(j in 1:k) {
      tmp[j] <- dist_haversine(xlon[i], xlat[i], ylon[j], ylat[j])
    }

    ## add to output matrix
    minvec_name[i] <- names(which.min(tmp))
    minvec_meter[i] <- min(tmp)
  }

  return(data.frame('fips11' = x_names,
                    'unitid' = minvec_name,
                    'meters' = minvec_meter,
                    stringsAsFactors = FALSE))
}
```

Let's test it out.

```
## test matrix (limit to only 10 starting points)
mindf <- dist_min(df_cbg$lon[1:10], df_cbg$lat[1:10],
                 df_col$lon, df_col$lat,
                 df_cbg$fips11[1:10], df_col$unitid)
```

```
## show
```

```
mindf
```

```
##           fips11 unitid  meters
## 1  010010201001 101471 15785.88
## 2  010010201002 101471 14228.69
## 3  010010202001 101471 13949.21
## 4  010010202002 101471 14870.35
## 5  010010203001 101471 13362.81
## 6  010010203002 101471 14389.79
## 7  010010204001 101471 12704.73
## 8  010010204002 101471 13270.80
## 9  010010204003 101471 14102.44
## 10 010010204004 101471 14756.51
```

Quick exercise How long will it take to find the closest college to each census block group? Use `system.time()` and extrapolate to make a best guess.

Rcpp

These worked well, but we only did 10 starting points. We need to find it for over 200,000 starting points. What we need is to convert the base R functions into Rcpp functions.

Below, the full script, `dist_func.cpp`, is discussed in pieces.

Front matter

The head of an Rcpp script is like an R script in that this is place to `#include` other header files. This is akin to having `library(...)` in an R script. At the very least, an Rcpp script needs to include it's own header files, `Rcpp.h`.

Next, we define preprocessor replacements. In the process of compiling the script, that is, turning the Rcpp code that's human readable into machine-readable byte code, the preprocessor first runs through the script. One job is to replace any `#define` directive with the value it has been given. In our code, that means that anywhere in the script that `e_r` is found, `6378137.0` literally replaces it.

Finally, we load the Rcpp namespace with `using namespace Rcpp;`. This means that we don't have to keep repeating `Rcpp::<...>` before every function we want. Sometimes, it's better to do it the long way, especially if you are using functions from multiple libraries that may overlap, but we're okay doing it this way this time.

```
// header files to include
#include <Rcpp.h>

// preprocessor replacements
#define e_r 6378137.0
#define m_pi 3.141592653589793238462643383280
```

```
// use Rcpp namespace to avoid Rcpp::<...> repetition
using namespace Rcpp;
```

Utility functions

First, we have the two utility functions to convert degrees to radians and to compute the Haversine distance between two points. A few things to note right away:

- Rcpp comments use `//` or `/* ... */`
- Lines must end in a semi-colon, `;`
- Variables are strongly typed⁶

When a language is strongly typed, the user must tell the compiler the variable type, like `double`, `int`, etc. R will guess what you want and change on fly. This is a nice interactive feature, but is part of what makes R slow sometimes. By strongly typing a variable, the computer knows right away what you want and doesn't waste time or memory making adjustments.

A few other things to notice:

- `doubles` should end in a `.` or `.0`, otherwise they are assumed to be integers; dividing by integers can have weird outcomes so unless you are REALLY sure you want an integer, a floating point number like a `double` is probably what you want (see `degree * m_pi / 180.0`)
- The variable type before the function name tells the compiler what form the function output will take
- Function arguments must also be typed

Finally, for the function to be available to you as a user, you must put `// [[Rcpp::export]]` just before it.

```
// convert degrees to radians
// [[Rcpp::export]]
double deg_to_rad_rcpp(double degree) {
    return(degree * m_pi / 180.0);
}

// compute Haversine distance between two points
// [[Rcpp::export]]
double dist_haversine_rcpp(double xlon,
                           double xlat,
                           double ylon,
                           double ylat) {

    // return 0 if same point
    if (xlon == ylon && xlat == ylat) return 0.0;

    // convert degrees to radians
    xlon = deg_to_rad_rcpp(xlon);
    xlat = deg_to_rad_rcpp(xlat);
    ylon = deg_to_rad_rcpp(ylon);
    ylat = deg_to_rad_rcpp(ylat);

    // haversine distance formula
    double d1 = sin((ylat - xlat) / 2.0);
```

⁶https://en.wikipedia.org/wiki/Strong_and_weak_typing

```
double d2 = sin((ylon - xlon) / 2.0);
return 2.0 * e_r * asin(sqrt(d1*d1 + cos(xlat) * cos(ylat) * d2*d2));
}
```

Many to many distance matrix

Moving to the main functions, notice that base R function has been changed only slightly. For the most part, the difference is that variables, argument, and function return must be typed.

A few other differences to note:

- the length of a vector is measured with `.size()`
- loops in C++ take the form `(; ;)`, which works as “start `i` as 0, check if `i` is less than the number of starting points, `n`, add 1 to `i`, then run the loop; if the check fails, skip the loop.

```
// compute many to many distances and return matrix
// [[Rcpp::export]]
NumericMatrix dist_mtom_rcpp(NumericVector xlon,
                             NumericVector xlat,
                             NumericVector ylon,
                             NumericVector ylat,
                             CharacterVector x_names,
                             CharacterVector y_names) {

    // init output matrix (x X y)
    int n = xlon.size();
    int k = ylon.size();
    NumericMatrix distmat(n,k);

    // double loop through each set of points to get all combinations
    for(int i = 0; i < n; i++) {
        for(int j = 0; j < k; j++) {
            distmat(i,j) = dist_haversine_rcpp(xlon[i],xlat[i],ylon[j],ylat[j]);
        }
    }
    // add row and column names
    rownames(distmat) = x_names;
    colnames(distmat) = y_names;
    return distmat;
}
```

Nearest end point

Again the Rcpp version of this script is almost identical to the base R version, just with variable typing added. Since we’re returning a data frame (Rcpp version: `DataFrame`), we have to create it with `DataFrame::create()` as we return it.

```
// compute and return minimum distance along with name
// [[Rcpp::export]]
DataFrame dist_min_rcpp(NumericVector xlon,
                        NumericVector xlat,
                        NumericVector ylon,
                        NumericVector ylat,
                        CharacterVector x_names,
```



```

        CharacterVector y_names) {

  // init output matrix (x X 3)
  int n = xlon.size();
  int k = ylon.size();
  CharacterVector minvec_name(n);
  NumericVector minvec_meter(n);
  NumericVector tmp(k);

  // loop through each set of starting points
  for(int i = 0; i < n; i++) {
    for(int j = 0; j < k; j++) {
      tmp[j] = dist_haversine_rcpp(xlon[i],xlat[i],yлон[j],yлат[j]);
    }
    // add to output matrix
    minvec_name[i] = y_names[which_min(tmp)];
    minvec_meter[i] = min(tmp);
  }

  // return created data frame
  return DataFrame::create(Named("fips11" = x_names,
                                Named("unitid" = minvec_name,
                                Named("meters" = minvec_meter,
                                _["stringsAsFactors"] = false);
}

```

Source the Rcpp file

To compile the Rcpp scripts and have the functions available to us in our R script or session, we need to read in the script with `sourceCpp()`. This works much like regular `source()` works, except for Rcpp files. We'll add the argument `rebuild = TRUE` so that if need to go back and adjust the source code during a session, it will be rebuilt when we call `sourceCpp()` again.

Compiling code can take a while. In essence, we're trading some time now for faster speed down the road. This is why compiled code isn't great for interactive coding sessions or for small tasks. But our code isn't complex and compiles rather quickly.

```

## source Rcpp code
sourceCpp('../scripts/dist_func.cpp', rebuild = TRUE)

```

Quick comparisons

Now that we have both versions of our distance measuring functions, we should compare the time it takes both to run. But first, let's make sure that they give the same results.

Single distance

```

d_Rcpp <- dist_haversine_rcpp(xlon, xlat, yлон, yлат)

## show
d_Rcpp

## [1] 258212.3

```

```
## compare
identical(d, d_Rcpp)
```

```
## [1] TRUE
```

For one point, our `dist_haversine()` and `dist_haversine_rcpp()` give the same result.

Many to many

Next, we'll compare our many to many matrix, making sure we get the same values.

```
distmat_Rcpp <- dist_mtom_rcpp(df_cbg$lon[1:10],
                              df_cbg$lat[1:10],
                              df_col$lon,
                              df_col$lat,
                              df_cbg$fips11[1:10],
                              df_col$unitid)
```

```
## show
distmat_Rcpp[1:5,1:5]
```

```
##           100654  100663  100690  100706  100724
## 010010201001 258212.3 119349.8 31495.73 251754.3 21138.09
## 010010201002 256255.2 117447.3 32284.61 249798.4 22263.60
## 010010202001 256775.4 118210.3 31047.25 250348.1 21059.86
## 010010202002 258084.9 119554.9 30210.67 251665.2 20017.60
## 010010203001 256958.5 118703.3 29758.10 250567.0 19905.92
```

```
## compare
all.equal(distmat, distmat_Rcpp)
```

```
## [1] TRUE
```

Again, we get the same values (within some very very small floating point rounding error).

Minimum distances

Finally, we'll compare the minimum distance function.

```
mindf_Rcpp <- dist_min_rcpp(df_cbg$lon[1:10],
                            df_cbg$lat[1:10],
                            df_col$lon,
                            df_col$lat,
                            df_cbg$fips11[1:10],
                            df_col$unitid)
```

```
## show
mindf_Rcpp
```

```
##           fips11 unitid  meters
## 1  010010201001 101471 15785.88
## 2  010010201002 101471 14228.69
## 3  010010202001 101471 13949.21
## 4  010010202002 101471 14870.35
## 5  010010203001 101471 13362.81
## 6  010010203002 101471 14389.79
## 7  010010204001 101471 12704.73
## 8  010010204002 101471 13270.80
```

```
## 9 010010204003 101471 14102.44
## 10 010010204004 101471 14756.51
```

```
## compare
all.equal(mindf, mindf_Rcpp)
```

```
## [1] TRUE
```

And once more, the same results. We're now ready to compare speeds!

Benchmarks

To compare really small differences in time, we'll use the `microbenchmark`⁷ package. Aside from being accurate at small time scales, it makes comparisons based on multiple runs and can plot the differences using the `autoplot()` function.

First, we'll compare the core `dist_haversine*()` functions.

```
## use microbenchmark to compare
tm_single <- microbenchmark(base_R = dist_haversine(xlon, xlat, ylon, ylat),
                             Rcpp = dist_haversine_rcpp(xlon, xlat, ylon, ylat),
                             times = 1000L)

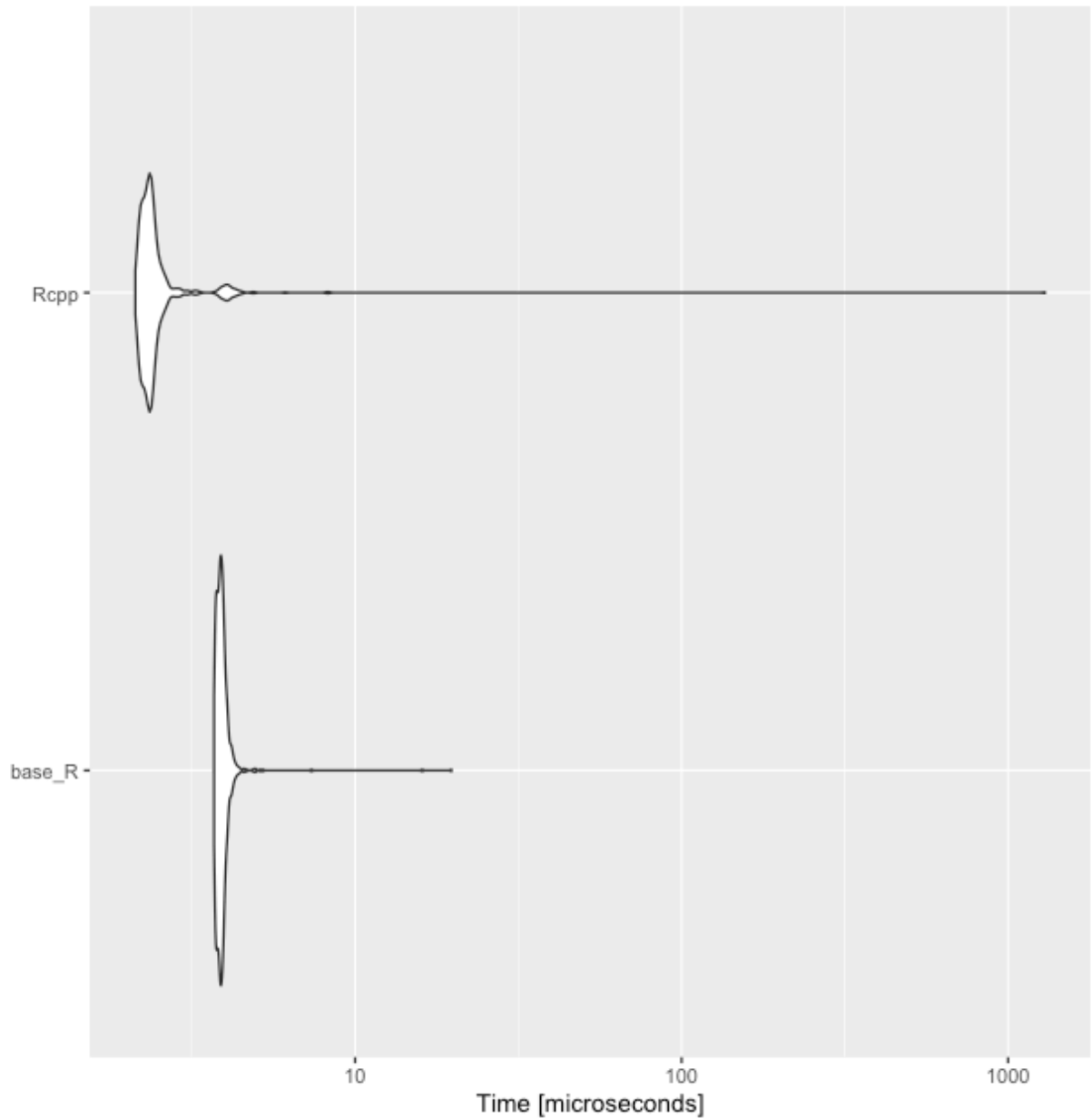
## results
tm_single
```

```
## Unit: microseconds
##      expr    min      lq    mean median      uq      max neval
## base_R 3.699 3.7935 3.930386 3.878 3.9615 19.746 1000
## Rcpp 2.123 2.2520 3.765456 2.346 2.4400 1298.082 1000
```

```
## plot
autoplot(tm_single)
```

Coordinate system already present. Adding new coordinate system, which will replace the existing one.

⁷<https://CRAN.R-project.org/package=microbenchmark>



Comparing `dist_haversine()` with `dist_haversine_rcpp()`, the compiled version isn't that much faster. Considering we're on the scale of microseconds, it *really* isn't that much faster.

time for base R to do many to many with 100 starting points

```
system.time(dist_mtom(df_cbg$lon[1:100],
  df_cbg$lat[1:100],
  df_col$lon,
  df_col$lat,
  df_cbg$fips11[1:100],
  df_col$unitid))
```

```
##    user  system elapsed
##  3.268   0.016   3.289
```

```
## ...and now Rcpp version
```

```
system.time(dist_mtom_rcpp(df_cbg$lon[1:100],  
                           df_cbg$lat[1:100],  
                           df_col$lon,  
                           df_col$lat,  
                           df_cbg$fips11[1:100],  
                           df_col$unitid))
```

```
##    user  system elapsed  
## 0.043   0.000   0.043
```

```
## compare just 10 many to many
```

```
tm_mtom <- microbenchmark(base_R = dist_mtom(df_cbg$lon[1:10],  
                                              df_cbg$lat[1:10],  
                                              df_col$lon,  
                                              df_col$lat,  
                                              df_cbg$fips11[1:10],  
                                              df_col$unitid),  
                          Rcpp = dist_mtom_rcpp(df_cbg$lon[1:10],  
                                                df_cbg$lat[1:10],  
                                                df_col$lon,  
                                                df_col$lat,  
                                                df_cbg$fips11[1:10],  
                                                df_col$unitid),  
                          times = 100L)
```

```
## results
```

```
tm_mtom
```

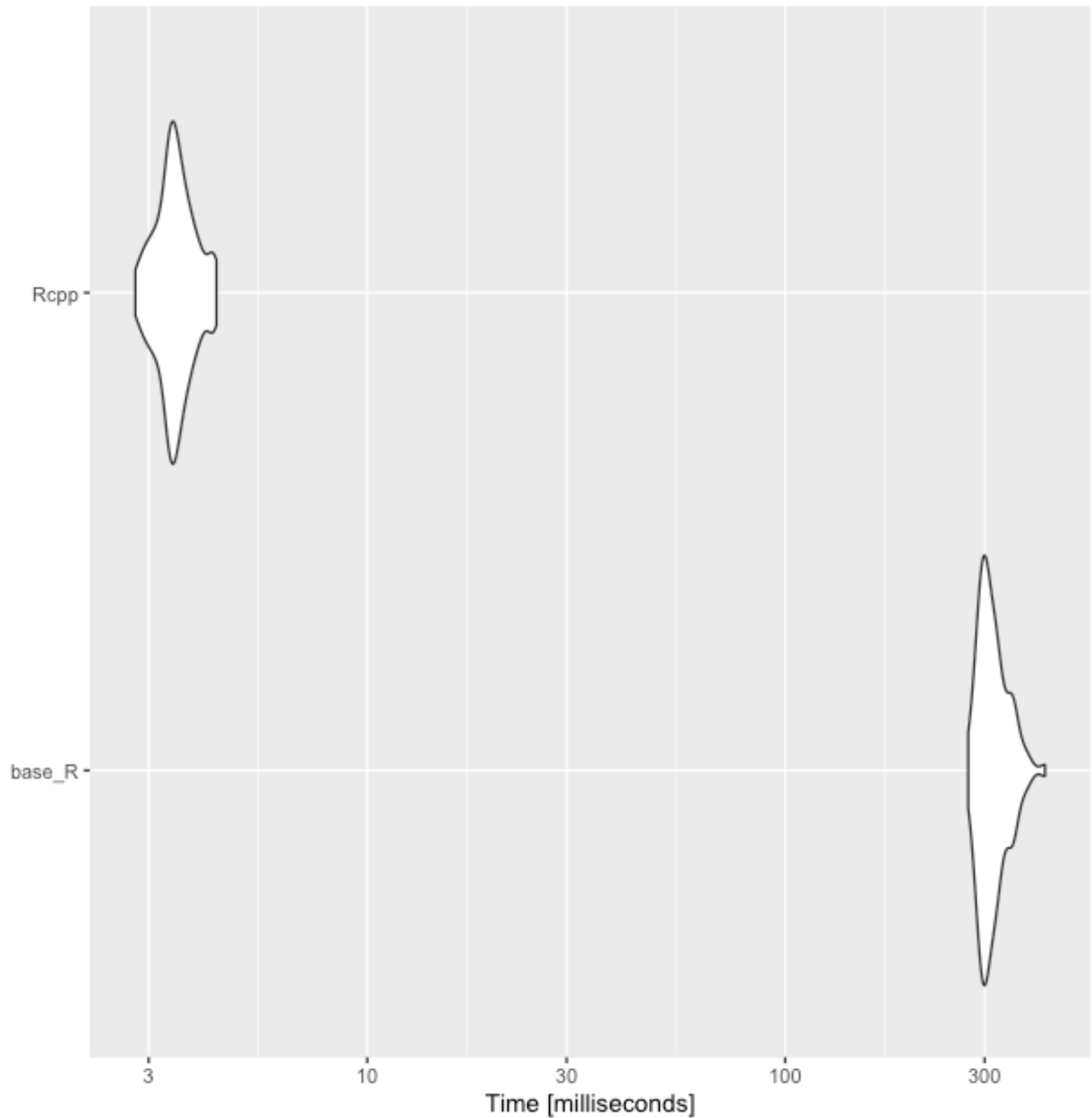
```
## Unit: milliseconds
```

```
##   expr      min       lq      mean    median      uq      max neval  
## base_R 273.980696 295.398724 314.543961 307.280900 327.221216 418.548440   100  
##   Rcpp   2.787054   3.293997   3.497548   3.445647   3.706862   4.356926   100
```

```
## plot
```

```
autoplot(tm_mtom)
```

```
## Coordinate system already present. Adding new coordinate system, which will replace the existing one.
```



Where we start to see speed improvements in the main function. The compiled version of the many to many function is nearly two orders of magnitude faster!

time for base R to do many to many with 100 starting points

```
system.time(dist_min(df_cbg$lon[1:100],
                    df_cbg$lat[1:100],
                    df_col$lon,
                    df_col$lat,
                    df_cbg$fips11[1:100],
                    df_col$unitid))
```

```
##    user  system elapsed
##  3.384   0.017   3.409
```

```
## ...and now Rcpp version
```

```
system.time(dist_min_rcpp(df_cbg$lon[1:100],  
                           df_cbg$lat[1:100],  
                           df_col$lon,  
                           df_col$lat,  
                           df_cbg$fips11[1:100],  
                           df_col$unitid))
```

```
##    user  system elapsed  
## 0.047   0.000   0.047
```

```
## compare just 10 min
```

```
tm_min <- microbenchmark(base_R = dist_min(df_cbg$lon[1:10],  
                                           df_cbg$lat[1:10],  
                                           df_col$lon,  
                                           df_col$lat,  
                                           df_cbg$fips11[1:10],  
                                           df_col$unitid),  
                         Rcpp = dist_min_rcpp(df_cbg$lon[1:10],  
                                              df_cbg$lat[1:10],  
                                              df_col$lon,  
                                              df_col$lat,  
                                              df_cbg$fips11[1:10],  
                                              df_col$unitid),  
                         times = 100)
```

```
## results
```

```
tm_min
```

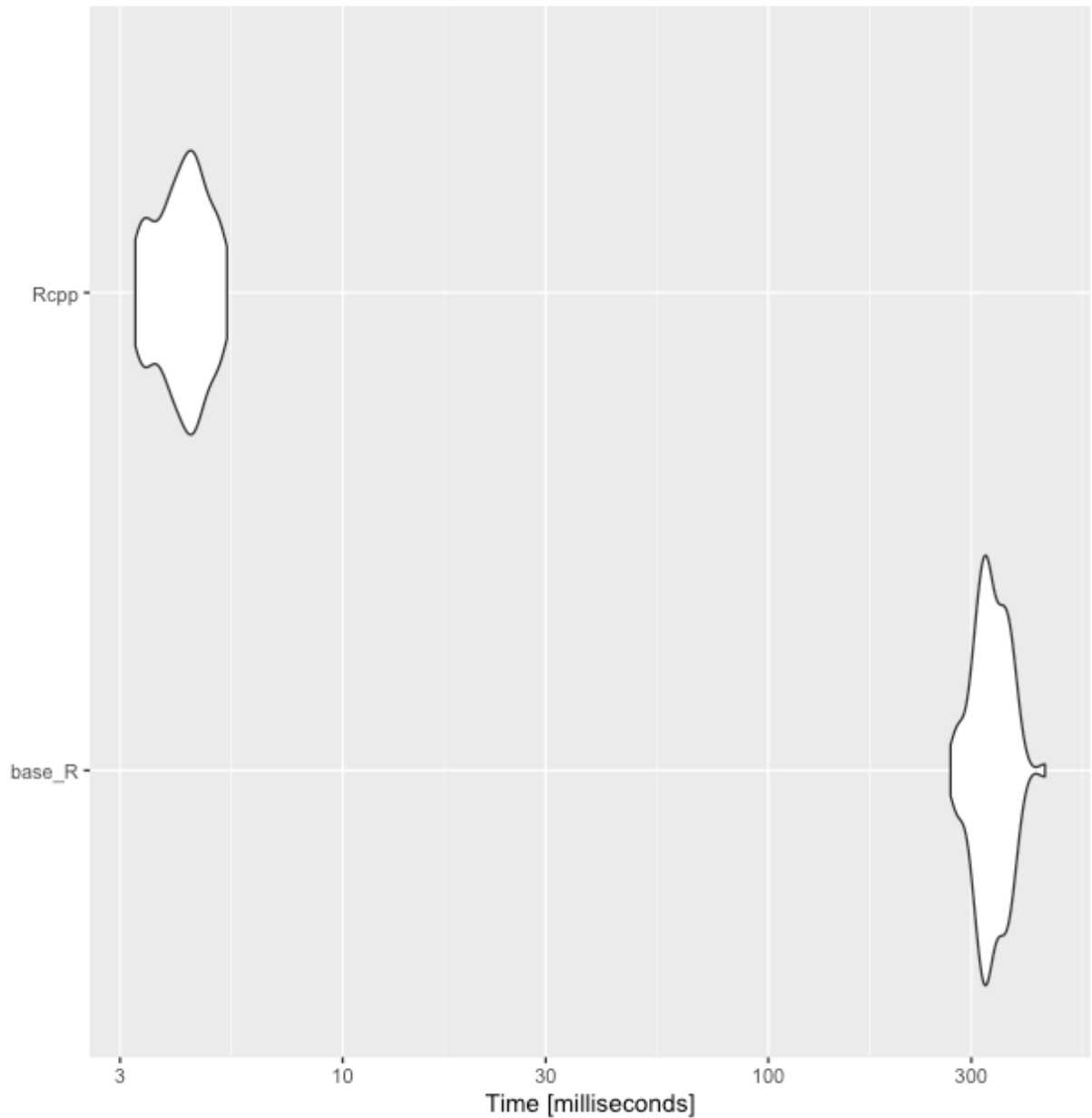
```
## Unit: milliseconds
```

```
##   expr      min       lq     mean   median      uq      max neval  
## base_R 268.082908 314.57547 335.109324 330.789767 358.781368 447.022916   100  
##   Rcpp   3.258531   3.82731   4.241349   4.297058   4.633562   5.347481   100
```

```
## plot
```

```
autoplot(tm_min)
```

```
## Coordinate system already present. Adding new coordinate system, which will replace the existing one.
```



Similarly, the compiled minimum distance function is much faster than the base R function.

In this case as well as the former, we should note that we aren't comparing fully optimized versions of either function. That said, while it's possible that the base R functions could be sped up, neither is likely to come close to matching the speed of the compiled Rcpp versions.

Full run for Rcpp version

Throughout, we've been running the functions on a reduced starting data set. But how long does it take to find the nearest college to each census block? Let's find out!

```
## find minimum
system.time(full_min <- dist_min_rcpp(df_cbg$lon,
                                     df_cbg$lat,
```



```
df_col$lon,
df_col$lat,
df_cbg$fips11,
df_col$unitid))
```

```
## user system elapsed
## 69.135 0.084 69.300
```

```
## show
```

```
full_min %>% tibble()
```

```
## # A tibble: 217,740 × 3
## fips11 unitid meters
## <chr> <chr> <dbl>
## 1 010010201001 101471 15786.
## 2 010010201002 101471 14229.
## 3 010010202001 101471 13949.
## 4 010010202002 101471 14870.
## 5 010010203001 101471 13363.
## 6 010010203002 101471 14390.
## 7 010010204001 101471 12705.
## 8 010010204002 101471 13271.
## 9 010010204003 101471 14102.
## 10 010010204004 101471 14757.
## # ... with 217,730 more rows
```

Just a little over a minute (on my laptop) to compute 217,000 by 7,700 distances, finding and storing the minimally distance college along with its distance!

Not-so quick exercise Below is a function that computes the great circle distance using Vincenty's formula⁸. It's more accurate than the haversine version, but can be much more computationally intensive. Try to convert the base R function into an Rcpp function. You'll need to start a new script and then use `sourceCpp()` to read it in and test. Once you've got, substitute the respective Vincenty formula functions into the `dist_min_*` functions and compare times.

A few things to keep in mind:

1. You'll need to declare your variables and types (lots of **double**); don't forget that double numbers need a decimal, otherwise C++ thinks they are integers.
2. Don't forget your semi-colon line endings!
3. `abs()` in C++ is `fabs()`
4. Remember: `a^2 = a * a`

```
## base R distance function using Vincenty formula
```

```
dist_vincenty <- function(xlon,
                           xlat,
                           ylon,
                           ylat) {

  ## return 0 if same point
  if (xlon == ylon && xlat == ylat) { return(0) }

  ## convert degrees to radians
  xlon <- deg_to_rad(xlon)
  xlat <- deg_to_rad(xlat)
```

```

ylon <- deg_to_rad(ylon)
ylat <- deg_to_rad(ylat)
## -----
## https://en.wikipedia.org/wiki/Vincenty%27s\_formulae
## -----
## some constants
a <- 6378137
f <- 1 / 298.257223563
b <- (1 - f) * a
U1 <- atan((1 - f) * tan(xlat))
U2 <- atan((1 - f) * tan(ylat))
sinU1 <- sin(U1)
sinU2 <- sin(U2)
cosU1 <- cos(U1)
cosU2 <- cos(U2)
L <- ylon - xlon
lambda <- L                                # initial value
## set up loop
iters <- 100                                # no more than 100 loops
tol <- 1.0e-12                               # tolerance level
again <- TRUE
## while loop...
while (again) {
  ## sin sigma
  sinLambda <- sin(lambda)
  cosLambda <- cos(lambda)
  p1 <- cosU2 * sinLambda
  p2 <- cosU1 * sinU2 - sinU1 * cosU2 * cosLambda
  sinsig <- sqrt(p1^2 + p2^2)
  ## cos sigma
  cossig <- sinU1 * sinU2 + cosU1 * cosU2 * cosLambda
  ## plain ol' sigma
  sigma <- atan2(sinsig, cossig)
  ## sin alpha
  sina <- cosU1 * cosU2 * sinLambda / sinsig
  ## cos^2 alpha
  cos2a <- 1 - (sina * sina)
  ## cos 2*sigma_m
  cos2sigm <- cossig - 2 * sinU1 * sinU2 / cos2a
  ## C
  C <- f / 16 * cos2a * (4 + f * (4 - 3 * cos2a))
  ## store old lambda
  lambdaOld <- lambda
  ## update lambda
  lambda <- L + (1 - C) * f * sina *
    (sigma + C * sinsig * (cos2sigm + C * cossig *
      (-1 + 2 * cos2sigm^2)))
  ## subtract from iteration total
  iters <- iters - 1
  ## go again if lambda diff is > tolerance and still have iterations
  again <- (abs(lambda - lambdaOld) > tol && iters > 0)
}
## if iteration count runs out, stop and send message

```

```

if (iters == 0) {
  stop("Failed to converge!", call. = FALSE)
}
else {
  ## u^2
  Usq <- cos2a * (a^2 - b^2) / (b^2)
  ## A
  A <- 1 + Usq / 16384 * (4096 + Usq * (-768 + Usq * (320 - 175 * Usq)))
  ## B
  B <- Usq / 1024 * (256 + Usq * (-128 + Usq * (74 - 47 * Usq)))
  ## delta sigma
  dsigma <- B * sinsig *
    (cos2sigm + B / 4 *
      (cossig * (-1 + 2 * cos2sigm^2)
        - B / 6 * cos2sigm * (-3 + 4 * sinsig^2)
        * (-3 + 4 * cos2sigm^2)))
  ## return the distance
  return(b * A * (sigma - dsigma))
}
}

```