# Computational Skills for Biostatistics I: Lecture 10

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# Advantages of R

#### R is great for many things

- Data analysis
- Statistical inference
- Statistics and statistics packages

# R is not a universal language

#### Different fields use different languages

Physics: Matlab/Python

Geology: Python

Applied math: Matlab/Java

Computational biology: Python/R

# R is not a universal language

#### Many statisticians don't use R

- Julia: great for large mixed models
- Python: image analysis, spatiotemporal modeling, anything with maps
- ► C++: Large sampling algorithms (common in Bayesian statistics)
- ► Java: non-Euclidean metric spaces
  - My PhD dissertation code was in Java

# Other languages

#### Why use another language?

- Inertia
- Speed
- ► Field standard
- Portability
- ► Ease of use

## Today's focus

#### Learning objectives

- ▶ Understand when you may want to write in C++
- ▶ See the infrastructure for interfacing R and C++
- Grasp the basic syntax of python

It is not possible to learn a new language in a single lecture; it is possible to get a feel for a new language

# Programming speed: R and C++

- ► There is a relatively easy way to use C++ "under the hood" of R
  - ▶ Package Rcpp
- ▶ This allows users to interface with your R package as usual...
- but with the potential for significant speed ups

#### Rcpp: example

```
Rcpp::sourceCpp("t_test_cpp.cpp")
set.seed(1)
x1 <- rnorm(30); x2 <- rnorm(50)
t_test_cpp(x1, x2)
## [1] -0.1796436</pre>
```

#### Rcpp: example

```
#include <Rcpp.h>
using namespace Rcpp;
// [[Rcpp::export]]
double t test cpp(NumericVector x1, NumericVector x2) {
    int n1 = x1.size():
    int n2 = x2.size():
    // Generate numerator and denominator
    double nume = mean(x1) - mean(x2);
    double denom = sqrt(var(x1)/n1 + var(x2)/n2);
    return nume/denom;
```

#### Rcpp: steps

- 1. Write code in C++
  - Preceed your function with // [[Rcpp::export]]
- 2. Compile your C++ code using Rcpp::sourceCpp()
- 3. Refer to your C++ function in R

#### C++

- ► C++ is a compiled language:

  Rcpp::sourceCpp("t\_test\_cpp.cpp") turns the program into machine-readable code
  - ▶ This results in highly efficient execution
- ► C++ is strongly-typed: the type of variable needs to be declared before its first use to allow for memory allocation

```
double t_test_cpp(NumericVector x1, NumericVector x2) {
   int n1 = x1.size();
   int n2 = x2.size();
   double nume = mean(x1) - mean(x2);
   double denom = sqrt(var(x1)/n1 + var(x2)/n2)
}
```

# Rcpp

- More recent versions of Rcpp include "syntactic sugar"
- Functionality for easy-to-use R functions
- ▶ i.e. C++ is not vectorized, but certain Rcpp functions are
  - e.g., implementations of sapply, pnorm, ifelse, vectorised addition/pointwise multiplication
  - http:
    //dirk.eddelbuettel.com/code/rcpp/Rcpp-sugar.pdf

## Rcpp: when not to bother

▶ Many operations in R are already backed by C/C++/Fortran, so are already fast

```
total <- 0
x <- rnorm(100)
y <- rnorm(100)
for (i in 1:10) {
  total <- total + x[i]*y[i]
}</pre>
x %*% y
```

```
## [,1]
## [1,] 1.699336
```

## Rcpp: when to bother

- ► Tasks that cannot be vectorised in R can typically be sped up in C++
  - Loops that you can't get rid of
- Iterative procedures where the next step depends on the current step
- Examples
  - Gradient descent
  - Expectation maximisation
  - Markov chains

## Rcpp: considerations

- ▶ Always prototype in R, then translate
  - when starting out, assume nothing about syntax!
- Expect more difficulty debugging
- ▶ It is also possible to do with C instead of C++
  - ▶ It's much harder and benefits are limited

## Rcpp: considerations

- ► You will need
  - ▶ R (>= 3.1)
  - Rcpp
  - ► A C++ compiler
    - ▶ Windows: Install Rtools
    - ► Mac: Install XCode (takes a lot of memory)

# How to learn a programming language

#### Good advice for any programming language

- Get something minimal working first
- Adapt examples
- Use Google liberally
- ▶ "c++ mean of vector"

## **TODO**

► Mauricio example

# Moving further beyond R

In your career as a statistician/data scientist, you will probably need some familiarity with python

- Collaborating on projects, especially interdisciplinary
- ▶ If you work with spatial data/image analysis, it may be worth learning to program in python
- Significantly easier to read/learn if you know R

Python and R are arguably the two most dominant languages for data scientists. R is often preferred by statisticians, and python is often preferred by computer scientists.

# Python

- Often faster than R
  - ► Typically in the same settings that C++ are preferable to R, python will beat R too
  - Often faster for IO and loops
- Large online community
- Modules extend base functionality
  - Similar to R packages
  - numpy, scipy, pandas, scikit-learn
- ► Great for
  - convex optimisation
  - ML libraries (though TensorFlow/keras now runs from R)

Both python and R are C under the hood, so it's not always worth switching.

## Language comparison

Gibbs sampler in various languages (revisited) by Darren Wilkinson (Newcastle)

► R: 1.0

▶ Python: 1.86

▶ PyPy: 14

▶ Java: 38

► C: 54

## Language comparison

The Python code ran  $[\sim 2x]$  faster than R. To me, that is **not really** worth worrying too much about. Differences in coding style and speed-up tricks can make much bigger differences than this... C was the fastest, and this is the reason that most of my MCMC code development has been traditionally done in C. It was around 60 times faster than R. This difference is worth worrying about, and can make the difference between an MCMC code being practical to run or not.

# Python: modules, assignment, loops

#### Some example Python code

```
import numpy as np
x = np.zeros(shape = (11, 2))
x[:, 1] = np.linspace(start = 0, stop = 10, num=11)
x
x[:, 0] = x[:, 1] / 3 + 1
x
for i in range(11):
    x[i, 1] = x[i, 1] + 1
x
```

## Python: Syntax

- ▶ Indentation/spacing is very important
  - Use either spaces or tabs
  - Spacing determines the grouping of operations, e.g., levels of loops
- ▶ Indexing starts at 0, not 1
  - First element in a array is number 0

# Python: matrix algebra

```
import numpy as np
A = np.array([[1, 2, 3], [4, 5, 6]])
A.T # transpose of A
np.transpose(A) # transpose of A
b1 = np.array([0.5, 1, 2])
b1
b2 = np.reshape(b1, (3, 1))
b2
A.dot(b2)
np.matmul(A, b2)
```

# Python: data analysis

```
import pandas as pd
dt = pd.read_csv('../lecture2/colon_cancer.csv')
dt['Tissue']
```

## Python scripts; on clusters

- ► You can execute a python script on the command line by running /usr/local/bin/python2.7 myscript.py
  - (or the equivalent for your installation location)
  - or python2.7 myscript.py if it's in your PATH
- You can execute a python script via a shell script (useful for the clusters)

# Python on the cluster

With the script you want to run in my\_script.py and with header #!/usr/local/bin/python2.7, you would have call\_script.sh as

```
#!/bin/sh
/usr/local/bin/python2.7 my_script.py
```

and submit\_sim.sh as

```
#!/bin/sh
qsub -t 1-22
  -cwd -e Trashfiles/ -o Trashfiles/
  -q s-normal.q
  -M name@uw.edu -m e call_script.sh
```

## Python: scripting

- Alternative to RStudio: Spyder
- Alternative to RMarkdown: Jupyter Notebooks
  - ▶ Easy install: conda install ipython jupyter
  - Awesome tutorial: https://hub.mybinder.org/user/ ipython-ipython-in-depth-6w6758qo/notebooks/ binder/Index.ipynb

## Python: Versions

- Python 2.7 and Python 3.3 are the most common
- Python 2.x is the legacy version
  - ▶ Better libraries, documentation
  - Default distribution for Unix
- Python 3.x is the present and future (from the Wiki)
- Moving forward, new features will be in Python 3 but not added to Python 2

# You can add the following your CV/R'esum'e

#### Skills/Software

- Proficient: R
  - Data analysis: tidyverse (dplyr, tibble, stringr, readr, tidyr), magrittr,

#### othersfromotherclasses

- Reporting: ggplot2, RMarkdown, knitr
- ▶ Performance: Rcpp, benchmarking, debugging, vectorisation
- Development: R package creation and maintenance, simulator, RStudio
- ► Familiar: git, unix, bash, Python, C++, distributed/cluster systems, optimisation algorithms

# Coming up

- ► Homework 10: final homework due next Wednesday
  - A final exercise with tidyverse
  - Basic use of Rcpp
  - Basic use of python
- Best of luck with your continuing education as a programmer and data analyst