# How To Make Your Code Faster

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#### Content

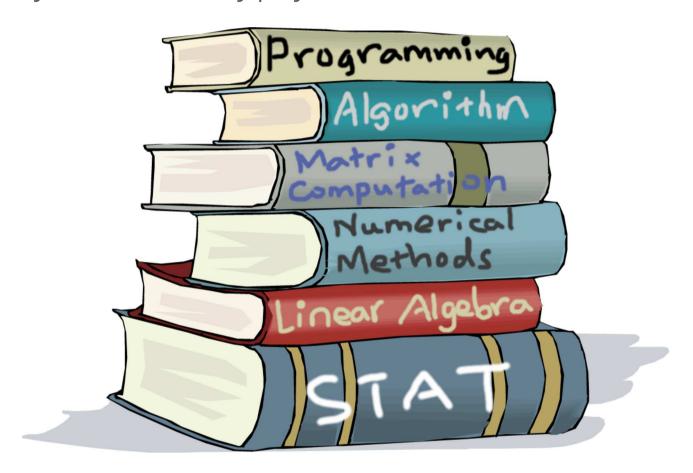
- · Why Is My Code So Slow?
- Approaches To Accelerating
- Remarks

#### How You Do Research

- · You design a model
- · You write the code
- · You run the code
- You wait
- You wait
- · You wait...

## Why Is My Code So Slow?

There are many factors that may play a role...



#### Possible Reasons

- Is the algorithm efficient?
- Are the software/libraries good enough?
- Is the programming language used appropriate for the problem?

## Approaches To Accelerating

- · Better designed algorithm
- High performance software and libraries
- More efficient languages

# Why Algorithm Matters

## **Example: Regression**

$$\hat{y} = X(X'X)^{-1}X'y$$

Algorithm 1: Direct translation

```
reg1 = function(x, y)
{
     x %*% solve(t(x) %*% x) %*% t(x) %*% y
}
```

· Algorithm 2: From right to left

```
reg2 = function(x, y)
{
     x %*% (solve(t(x) %*% x) %*% (t(x) %*% y))
}
```

## Regression Example cont.

· Algorithm 3: No explicit matrix inverse, special matrix structure

```
reg3 = function(x, y)
{
    x %*% solve(crossprod(x), crossprod(x, y))
}
```

#### Benchmark

```
test replications elapsed relative
1 reg1(x, y) 10 18.33 6.891
2 reg2(x, y) 10 3.93 1.477
3 reg3(x, y) 10 2.66 1.000
```

#### **Golden Rules**

- Low dimension first in matrix multiplication
- · Use crossprod(x, y) for X'y
- · Use  $\operatorname{crossprod}(\mathbf{x})$  for X'X
- · Use solve(A, b) for  $A^{-1}b$

## **Example: PCA**

- · Calculating the first k PC's of a data matrix X
- · Algorithm 1:
  - Form covariance matrix V = Cov(X)
  - Calculate eigen decomposition  $V=\Gamma\Lambda\Gamma'$
  - Extract the first k columns of  $\Gamma$  (the loadings)
  - Compute PC scores  $S=X\Gamma_k$
- Implemented in R function princomp()

#### PCA Example cont.

- · Algorithm 2:
  - Subtract column means from X to get centered matrix  $X_c$
  - Partial SVD on  $X_c \colon\! X_c o U_k D_k V_k'$
  - Compute PC scores  $S=X_cV_k$

```
library(rARPACK) ## For svds()
pca2 = function(x, k)
{
    xc = scale(x, center = TRUE, scale = FALSE)
    decomp = svds(xc, k, nu = 0, nv = k)
    xc %*% decomp$v
}
```

#### Benchmark

#### **Golden Rules**

- Do not compute what is unnecessary
- · Sometimes this can be hard

# Software/Libraries

#### Libraries To Use

- Even for the same algorithm, different software/libraries may provide different performance
- Switching to highly optimized libraries is usually easy
- Sometimes you can even keep the code unchanged and gain performance improvements for free!

## Linear Algebra: BLAS vs OpenBLAS

- · R uses a library called **BLAS** to do many linear algebra computation
- For example matrix-matrix product
- OpenBLAS is a highly optimized version of BLAS
- You can simply replace the BLAS contained in R by OpenBLAS

#### Benchmark

```
set.seed(123)
x = matrix(rnorm(2000^2), 2000)
system.time(crossprod(x))
```

Using original BLAS

```
user system elapsed 3.95 0.00 3.95
```

Using OpenBLAS with 4 threads

```
user system elapsed 0.76 0.00 0.20
```

## Reading Data: readr

- The readr package provides alternatives to read.table() and read.csv()
- Functions read\_delim() and read\_csv()
- Usually 5x to 10x faster

#### Benchmark

- Kaggle competition data (<a href="https://www.kaggle.com/c/homesite-quote-conversion/data">https://www.kaggle.com/c/homesite-quote-conversion/data</a>)
- Training set: 197 MB, 260753 observations, 299 variables

```
library(readr)
system.time(read.csv("train.csv")) ## Base R

user system elapsed
27.24  0.81  28.07

system.time(read_csv("train.csv")) ## readr

user system elapsed
4.77  0.27  5.03
```

## Working With Data Frames: dplyr

- · One of the most useful tools in R for data pre-processing and summarization
- Very efficient, no for loops
- · Hundreds of documents on web
- An introduction

### Summarizing Matrices: matrixStats

- Functions operating on rows and columns of matrices
- · Sums and means (in base R), variances, medians, ranks, order statistics, etc.
- Usually 5x to 10x faster than apply()

#### Benchmark

## Fitting Least Squares Regression: RcppEigen

- · Using the high performance C++ library Eigen for linear algebra
- Efficient algorithm (Cholesky decomposition)

#### Benchmark

```
test replications elapsed relative 3 fastLmPure(x, y, method = 2) 10 0.68 1.000 1 lm.fit(x, y) 10 3.81 5.603 2 reg3(x, y) 10 2.71 3.985
```

# Languages

#### When R Is Still Slow...

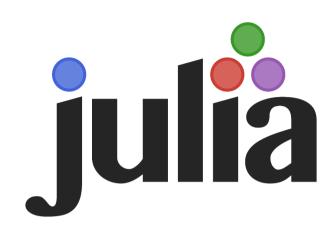
- Monte Carlo methods, iterative methods, nested loops, etc.
- You always have the freedom to switch to other languages
- May be a bit hard to learn in the beginning, but deserves
- My recommendations: C++ and Julia

#### **C**++



- Extremely hard to master
- But NOT hard to get started
- Nice and convenient interface to R (Rcpp)
- · Learning a small subset of C++ can make a big difference

## Julia



- Extremely easy to learn
- Syntax similar to R and Matlab
- Fast, really fast
- · You will love it

## **Example: Gibbs Sampling**

Example from Darren Wilkinson's Blog

$$f(x,y) \propto x^2 \exp\{-xy^2 - y^2 + 2y - 4x\}$$

- ·  $X|Y \sim rac{1}{y^2+4}Gamma(3)$
- ·  $Y|X \sim N\left(rac{1}{1+x},rac{1}{2(1+x)}
  ight)$

#### R Code

```
gibbs = function(N, thin)
{
   iter = 1:N
      xvec = numeric(N)
   yvec = numeric(N)
   x = 0
   y = 0
   for(i in 1:N)
   {
      for(j in 1:thin)
      {
            x = rgamma(1, shape = 3, scale = 1 / (y * y + 4))
            y = rnorm(1, 1 / (x + 1), 1 / sqrt(2 * x + 2))
      }
      xvec[i] = x
      yvec[i] = y
   }
   data.frame(Iter = iter, x = xvec, y = yvec)
}
```

## C++ Code With Rcpp

```
#include <Rcpp.h>
using namespace Rcpp;
// [[Rcpp::export]]
DataFrame gibbs rcpp(int N, int thin) {
    IntegerVector iter(N);
   for(int i = 0; i < N; i++)</pre>
        iter[i] = i + 1;
   NumericVector xvec(N);
   NumericVector yvec(N);
    double x = 0.0, y = 0.0;
   for(int i = 0; i < N; i++) {</pre>
        for(int j = 0; j < thin; j++) {</pre>
            x = R::rgamma(3.0, 1.0 / (y * y + 4.0));
            y = R::rnorm(1.0 / (x + 1.0), 1.0 / std::sqrt(2.0 * x + 2.0));
        xvec[i] = x;
        yvec[i] = y;
    return DataFrame::create(Named("Iter") = iter, Named("x") = xvec, Named("y") = yvec);
```

### Julia Code

```
using Distributions
using DataFrames
function gibbs_jl(N, thin)
   iter = 1:N
   xvec = zeros(N)
   yvec = zeros(N)
   x = 0.0
   y = 0.0
   for i = 1:N
       for j = 1:N
           x = rand(Gamma(3.0, 1.0 / (y * y + 4.0)))
           y = rand(Normal(1.0 / (x + 1.0), 1.0 / sqrt(2.0 * x + 2.0)))
       end
       xvec[i] = x
       yvec[i] = y
   end
   DataFrame(Iter = iter, x = xvec, y = yvec)
end
```

#### Benchmark - R and C++

```
set.seed(123)
system.time(res_r <- gibbs(1000, 1000))</pre>
  user system elapsed
   5.17
        0.00 5.17
set.seed(123)
system.time(res_rcpp <- gibbs_rcpp(1000, 1000))</pre>
  user system elapsed
  0.20
         0.00 0.21
identical(res_r, res_rcpp)
[1] TRUE
```

## Benchmark - Julia

```
srand(123)
@elapsed res_jl = gibbs_jl(1000, 1000)
```

0.098107808

## Plots - R and Julia

· R

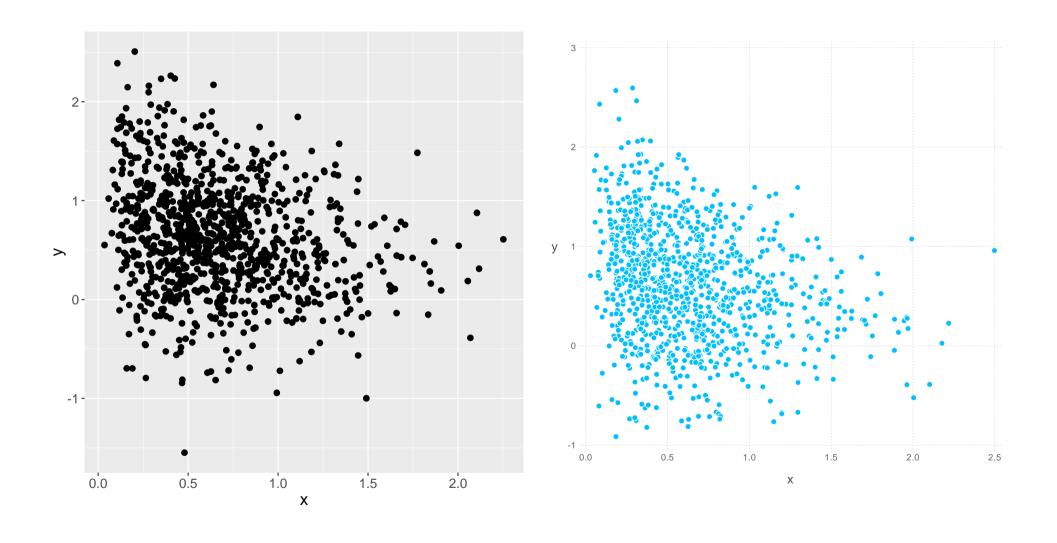
```
library(ggplot2)
ggplot(res, aes(x = x, y = y)) + geom_point()
```

Julia

```
using Gadfly

draw(SVG("gibbs_jl.svg", 6inch, 6inch),
    plot(res_jl, x = "x", y = "y", Geom.point))
```

# Plots - R and Julia



# Final Remarks

## Some Thoughts

- · When we compute for a model...
- First think of a good algorithm
- · Then try to use well-developed software and libraries
- · If still insufficient, try to learn and use other languages
  - It is not as hard as you thought

Q & A

# Thanks!