

APPLIED STATISTICAL PROGRAMMING

CODE PROFILING

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You will learn

- what code profiling is,
- what call stacks are,
- how to read flame graphs,
- the basics of *data.table()*

Code profiling

Code profiling is a way to measure storage and time complexity of a program with respect to its instruction set.

Answers questions like

1. How frequently is a method called?
2. How many times is a method called?
3. How much memory is allocated?
4. When does garbage collection happen?

How do I make my R code faster?

→ How long does it take to run?

```
# 400k rows, 150 columns
data <- as.data.frame(
  matrix(rnorm(4e5*150, mean=5),
    ncol=150))

normCols <- function(d){
  # Get column means
  means <- apply(d,2,mean)

  # De-mean each column
  for (i in seq_along(means)){
    d[,i] <- d[,i] - means[i]
  }
}

data_demeaned <- normCols(data)
```

```
# system.time isn't very informative
system.time({

  normCols <- function(d){
    # Get column means
    means <- apply(d,2,mean)

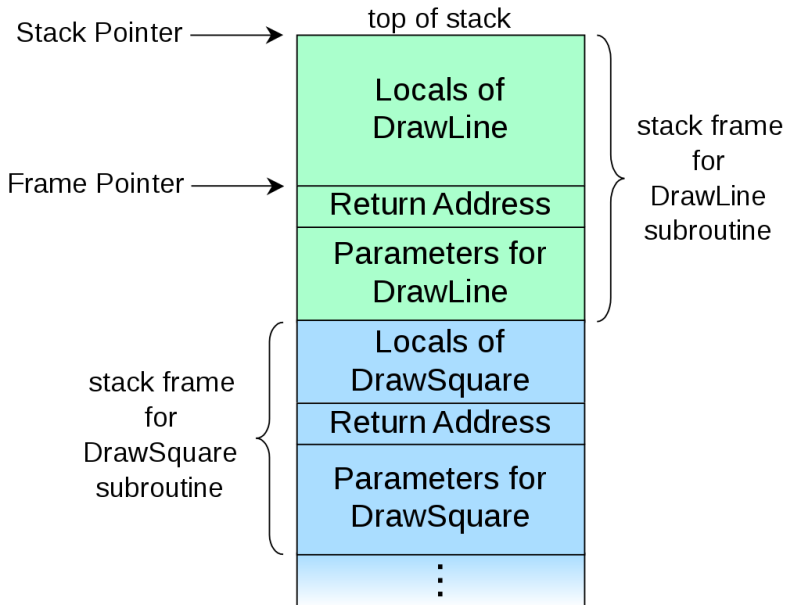
    # De-mean each column
    for (i in seq_along(means)){
      d[,i] <- d[,i] - means[i]
    }
  }
  data_demeaned <- normCols(data)

})
```

How do I make my R code faster?

—→ What parts of the code slow things down?

THE PARTS OF THE CODE: CALL STACKS



```
install.packages("profvis")  
library(profvis)  
  
profvis({  
  data(diamonds, package = "ggplot2")  
  
  plot(price ~ carat, data = diamonds)  
  m <- lm(price ~ carat, data = diamonds)  
  abline(m, col = "red")  
})
```

```
profvis({  
  
  normCols <- function(d){  
    # Get column means  
    means <- apply(d,2,mean)  
    # De-mean each column  
    for (i in seq_along(means)){  
      d[,i] <- d[,i] - means[i]  
    }  
  }  
  normCols(data)  
  
})
```

```
# Four ways to get column means  
profvis({  
  means <- apply(data, 2, mean)  
  means <- colMeans(data)  
  means <- lapply(data, mean)  
  means <- vapply(data, mean, numeric(1))  
})
```

```
# Profile using vapply instead
profvis({
  means <- vapply(data, mean, numeric(1))

  for (i in seq_along(means)){
    data[,i] <- data[,i] - means[i]
  }
})
```

ANOTHER EXAMPLE: QR DECOMPOSITION

```
gramschmidt <- function(x) {  
  x <- as.matrix(x)  
  n <- ncol(x)  
  m <- nrow(x)  
  q <- matrix(0, m, n)  
  r <- matrix(0, n, n)  
  for (j in 1:n) {  
    v = x[,j]  
    if (j > 1) {  
      for (i in 1:(j-1)) {  
        r[i,j] <- t(q[,i]) %*% x[,j]  
        v <- v - r[i,j] * q[,i]  
      }  
    }  
    r[j,j] <- sqrt(sum(v^2))  
    q[,j] <- v / r[j,j]  
  }  
  return(list('Q'=q, 'R'=r)) }
```

```
profvis({  
  set.seed(1234)  
  n <- 1000  
  M <- matrix(rnorm(n*n, mean=5), ncol=n)  
  QR <- gramschmidt(M)  
})
```

DETAILED `gramschmidt()` PROFILE

```
profvis({  
  n <- 1000  
  M <- matrix(rnorm(n**2, mean=5), ncol=n)  
  m <- nrow(M)  
  q <- matrix(0, m, n)  
  r <- matrix(0, n, n)  
  for (j in 1:n) {  
    v = M[,j]  
    if (j > 1) {  
      for (i in 1:(j-1)) {  
        r[i,j] <- t(q[,i]) %*% M[,j]  
        v <- v - r[i,j] * q[,i]  
      }  
    }  
    r[j,j] <- sqrt(sum(v^2))  
    q[,j] <- v / r[j,j]  
  } })
```


The algorithm for *gramschmidt()* is not numerically stable.
Instead use:

- Householder transforms (dense matrices)
- Givens rotations (sparse matrices)

Code profiling doesn't help with choosing the better implementation.

data.table

The benefits of *data.table*:

- subset rows,
- select and compute on columns, and
- perform aggregations by group

```
install.packages("data.table")
library(data.table)
input <- if (file.exists("flights14.csv")) {
  "flights14.csv"
} else {
  "https://raw.githubusercontent.com
  /Rdatatable/data.table/master/vignettes/
  flights14.csv"
}
flights <- fread(input)
flights
dim(flights)
```

*# Suppose DT is your data table that you fread in
DT[i, j, by]*

*# R: i j by
#SQL: where | order by select | update group by*

EXAMPLE: SUBSETTING

```
# Get all the flights with "JFK"  
# as the origin airport  
# in the month of June.  
ans1 <- flights[origin == "JFK" & month == 6L]  
head(ans1)  
  
# Get the first two rows from flights.  
ans2 <- flights[1:2]  
ans2
```

EXAMPLE: SELECTING

```
# Sort flights first by column origin  
# in ascending order,  
# and then by dest in descending order:
```

```
ans3 <- flights[order(origin, -dest)]  
head(ans3)
```

```
# Advanced computations  
# How many trips have had total delay < 0?
```

```
ans4 <- flights[,sum((arr_delay + dep_delay) < 0)]  
ans4
```

EXAMPLE: SELECTING

```
# Calculate the average arrival and  
# departure delay for all flights with "JFK"  
# as the origin airport in the month of June.
```

```
ans5 <- flights[origin == "JFK" & month == 6L,  
                .(m_arr = mean(arr_delay),  
                  m_dep = mean(dep_delay))]
```

```
ans5
```


EXAMPLE: SELECTING

```
# Get a vector
```

```
dat1 = flights[ , origin]
```

```
# Get a data table
```

```
dat2 = flights[ , .(origin)]
```

```
# Get multiple variables
```

```
dat3 = flights[, .(origin, year, month, hour)]
```

Run the R code that implements your EM algorithm from last in class activity, and continue working on the *Rcpp* implementation.

Include the resulting *.profvis* profile of your code with your in EM algorithm in class activity submission on Wednesday, April 20.

Click this [link](#) to go to the references.



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REFERENCES

Shaw, R. S. (2007). Example layout of a call stack showing stack frames and frame pointer. Retrieved April 17, 2022 from [*https://commons.wikimedia.org/wiki/File:Call_stack_layout.svg*](https://commons.wikimedia.org/wiki/File:Call_stack_layout.svg).