Big Data Analytics

Lecture 3:

Computation and Memory Part II

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11/03/2021

Updates

Schedule update

1. Introduction: Big Data, Data Economy. Walkowiak (2016): Chapter 1.
2. Computation and Memory in Applied Econometrics.
3. Computation and Memory in Applied Econometrics II.
4. Advanced R Programming. Wickham (2019): Chapters 2, 3, 17,23, 24.
5. Import, Cleaning and Transformation of Big Data. Walkowiak (2016): Chapter 3: p. 74-118.
6. Aggregation and Visualization. Walkowiak (2016): Chapter 3: p. 118-127; Wickham et al.(2015); Schwabish (2014).
7. Data Storage, Databases Interaction with R. Walkowiak (2016): Chapter 5.
8. Cloud Computing: Introduction/Overview, Distributed Systems, Walkowiak (2016): Chapter 4.
9. Applied Econometrics with Spark; Machine Learning and GPUs.
10. Project Presentations.
11. Project Presentations; Q&A.

Build groups for group examination

- Teams of 2-3.
- See Canvas Announcement.
- All team members must have a GitHub account.

Group examination: take-home exercises

- Analysis of (big) dataset in R.
- Report in R Markdown.
- Conceptual questions.
- Collaborate, hand-in, feedback via GitHub.

Group projects:

- A simple empirical research question.
- A large (>2GB) data set (of your choice).
    - Get inspired here and here
- Implement analysis in R.
- Present results in 6-7 minutes.
    - R-markdown (ioslides/shiny) or R presentation.
- Q&A, Feedback

Group projects:

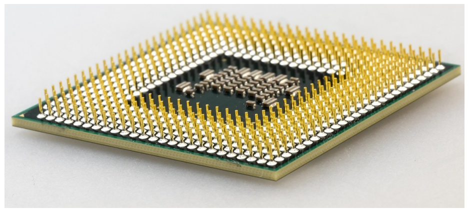
- Send short **disposition** to ulrich.matter@unisg.ch by end of March.
    - Data set (short description/link)
    - Research question
    - Idea for analysis (statistical approach)
- Have slides ready

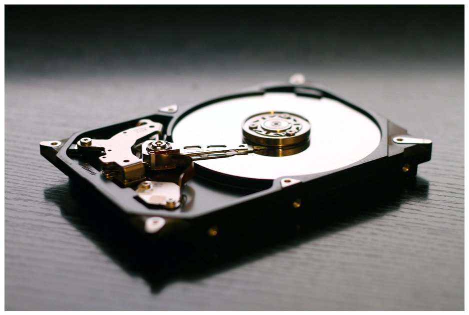
Goals for today

1. Understand basics of how to control resource allocation in R.
2. Know the basics of parallel computing in R.
3. Know the basics of efficient memory allocation and virtual memory (in data analytics context).

Recap of Week 2

Components of a computing environment





Components of a computing environment

Why should we care?

Big Data (Analytics)

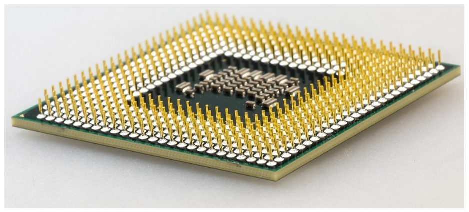
- Find an efficient (fast) statistical procedure. (Uluru vs OLS example)
- Need to understand how to **make best use of the available resources**, given a specific data analysis task.
  - CPU: Parallel processing (use all cores available)
  - RAM: Efficient memory allocation and usage
  - RAM + Mass Storage: Virtual memory, efficient swapping

Computation and Memory (Part II)

Efficient Use of Resources

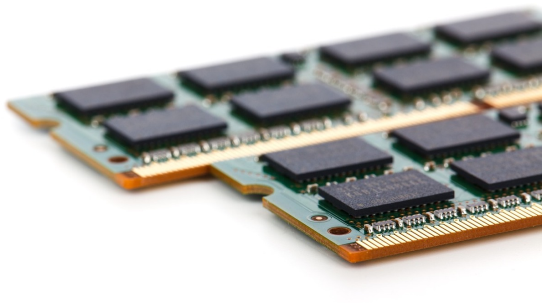
1) Parallel processing: CPU/core

- A CPU on any modern computer has several **cores**.
- The OS usually assigns automatically which tasks/processes should run on which core.
- We can explicitly instruct the computer to dedicate N cores to a specific computational task: **parallel processing**.



2) Memory allocation: RAM

- Standard computation procedures happen in-memory: data needs to be loaded into RAM.
- Default lower-level procedures to allocate memory might not be optimal for large data sets.
- We can explicitly use faster memory allocation procedures for a specific big data task.



3) Beyond RAM: virtual memory

- What if we run out of RAM?
- The OS deals with this by using part of the hard disk as **virtual memory**.
- By explicitly instructing the computer how to use **virtual memory for specific big data tasks**, we can speed things up.

Case study: Parallel processing

We start with importing the data into R.

```r
url <- "https://vincentarelbundock.github.io/Rdatasets/csv/carData/MplsStops.csv"
stopdata <- data.table::fread(url) # skipNul avoids running into encoding issues with this data set
```

Case study: Parallel processing

First, let’s remove observations with missing entries (`NA`) and code our main explanatory variable and the dependent variable.

```
# remove incomplete obs
stopdata <- na.omit(stopdata)
# code dependent var
stopdata$vsearch <- 0
stopdata$vsearch[stopdata$vehicleSearch=="YES"] <- 1
# code explanatory var
stopdata$white <- 0
stopdata$white[stopdata$race=="White"] <- 1
```

Case study: Parallel processing

We specify our baseline model as follows.

```
model <- vsearch ~ white + factor(policePrecinct)
```

Case study: Parallel processing

And estimate the linear probability model via OLS (the `lm` function).

```
fit <- lm(model, stopdata)
summary(fit)
```

```
##
## Call:
## lm(formula = model, data = stopdata)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.13937 -0.06329 -0.05473 -0.04227  0.97729
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)              0.054733   0.005154  10.619  < 2e-16 ***
## white                   -0.019553   0.004465  -4.380 1.19e-05 ***
## factor(policePrecinct)2  0.008556   0.006757   1.266   0.2054
## factor(policePrecinct)3  0.003409   0.006483   0.526   0.5990
## factor(policePrecinct)4  0.084639   0.006232  13.582  < 2e-16 ***
## factor(policePrecinct)5 -0.012465   0.006371  -1.956   0.0504 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.254 on 19078 degrees of freedom
```

Case study: Parallel processing

Compute bootstrap clustered standard errors.

```r
# load packages
library(data.table)
# set the 'seed' for random numbers (makes the example reproducible)
set.seed(2)

# set number of bootstrap iterations
B <- 10
# get selection of precincts
precincts <- unique(stopdata$policePrecinct)
# container for coefficients
boot_coefs <- matrix(NA, nrow = B, ncol = 2)
# draw bootstrap samples, estimate model for each sample
for (i in 1:B) {

     # draw sample of precincts (cluster level)
     precincts_i <- sample(precincts, size = 5, replace = TRUE)
     # get observations
     bs_i <- lapply(precincts_i, function(x) stopdata[stopdata$policePrecinct==x,])
     bs_i <- rbindlist(bs_i)

     # estimate model and record coefficients
     boot_coefs[i,] <- coef(lm(model, bs_i))[1:2] # ignore FE-coefficients
}
```

Case study: Parallel processing

Finally, let's compute SE_{boot}.

```
se_boot <- apply(boot_coefs,
                 MARGIN = 2,
                 FUN = sd)
se_boot
```

```
## [1] 0.004042725 0.004689611
```

Case study: Parallel processing

Parallel implementation…

```
# install.packages("doSNOW", "parallel")
# load packages for parallel processing
library(doSNOW)
# set the 'seed' for random numbers (makes the example reproducible)
set.seed(2)

# get the number of cores available
ncores <- parallel::detectCores()
# set cores for parallel processing
ctemp <- makeCluster(ncores) #
registerDoSNOW(ctemp)


# set number of bootstrap iterations
B <- 10
# get selection of precincts
precincts <- unique(stopdata$policePrecinct)
# container for coefficients
boot_coefs <- matrix(NA, nrow = B, ncol = 2)

# bootstrapping in parallel
boot_coefs <-
     foreach(i = 1:B, .combine = rbind, .packages="data.table") %dopar% {

          # draw sample of precincts (cluster level)
```

Case study: Parallel processing

As a last step, we compute again SE_{boot}.

```
se_boot <- apply(boot_coefs,
                 MARGIN = 2,
                 FUN = sd)
se_boot
```

```
## (Intercept)       white
## 0.004375874 0.005805687
```

Case study: Memory allocation

```r
#################################################################
# Big Data Statistics: Flights data import and preparation
#
# U. Matter, January 2019
#################################################################

# SET UP -----------------

# fix variables
DATA_PATH <- "../data/flights.csv"

# DATA IMPORT ----------------
flights <- read.csv(DATA_PATH)

# DATA PREPARATION --------
flights <- flights[,-1:-3]
```

Case study: Memory allocation

Inspect the memory usage.

```
# SET UP -----------------

# fix variables
DATA_PATH <- "../data/flights.csv"
# load packages
library(pryr)


# check how much memory is used by R (overall)
mem_used()
```

```
## 1.08 GB
```

```
# check the change in memory due to each step

# DATA IMPORT ----------------
mem_change(flights <- read.csv(DATA_PATH))
```

```
## 611 kB
```

```
# DATA PREPARATION --------
flights <- flights[,-1:-3]
```

Case study: Memory allocation

‘Collect the garbage’…

```
gc()
```

```
##             used  (Mb) gc trigger   (Mb)  max used   (Mb)
## Ncells   1063431  56.8    1757805   93.9   1757805   93.9
## Vcells 127595415 973.5  213343868 1627.7 211038278 1610.1
```

Case study: Memory allocation

Alternative approach (via memory mapping).

```
# load packages
library(data.table)

# DATA IMPORT ----------------
flights <- fread(DATA_PATH, verbose = TRUE)
```

```
##   OpenMP version (_OPENMP)       201511
##   omp_get_num_procs()            12
##   R_DATATABLE_NUM_PROCS_PERCENT  unset (default 50)
##   R_DATATABLE_NUM_THREADS        unset
##   R_DATATABLE_THROTTLE           unset (default 1024)
##   omp_get_thread_limit()         2147483647
##   omp_get_max_threads()          12
##   OMP_THREAD_LIMIT               unset
##   OMP_NUM_THREADS                unset
##   RestoreAfterFork               true
##   data.table is using 6 threads with throttle==1024. See ?setDTthreads.
## Input contains no \n. Taking this to be a filename to open
## [01] Check arguments
##   Using 6 threads (omp_get_max_threads()=12, nth=6)
##   NAstrings = [<<NA>>]
##   None of the NAstrings look like numbers.
##   show progress = 0
##   0/1 column will be read as integer
```

Case study: Memory allocation

Alternative approach (via memory mapping).

```r
# SET UP -----------------

# fix variables
DATA_PATH <- "../data/flights.csv"
# load packages
library(pryr)
library(data.table)

# housekeeping
flights <- NULL
gc()
```

```
##             used  (Mb) gc trigger   (Mb)  max used   (Mb)
## Ncells   1052467  56.3    1757805   93.9   1757805   93.9
## Vcells 124429667 949.4  213343868 1627.7 211038278 1610.1
```

```r
# check the change in memory due to each step

# DATA IMPORT ----------------
mem_change(flights <- fread(DATA_PATH))
```

```
## 35.8 MB
```

Insight from analyzing methods conceptually

- Methods for big data analytics come with an **‘overhead’**
    - Additional ‘preparatory’ steps.
    - Only faster than traditional methods if data set has a certain size!

Insight from analyzing methods conceptually

- Methods for big data analytics come with an **‘overhead’**
  - Additional ‘preparatory’ steps.
  - Only faster than traditional methods if data set has a certain size!
- Examples:
  - Parallel processing: Distribute data/task, combine afterwards.
  - `fread`: Memory maps data before actually reading it into RAM.

Beyond memory

- RAM is not sufficient to handle the amount of data to be analyzed…
- What to do?

Beyond memory

- RAM is not sufficient to handle the amount of data to be analyzed…
- **What to do?**
- Scale up by using parts of the available Mass Storage (hard-disk) as **virtual memory**

Out-of-memory strategies

- Chunked data files on disk
- Memory-mapped files and shared memory

Out-of-memory strategies

- Chunked data files on disk: `ff`-package
- Memory-mapped files and shared memory: `bigmemory`-package

Chunking data with the `ff`-package

Preparations

```
# SET UP --------------

# install.packages(c("ff", "ffbase"))
# load packages
library(ff)
library(ffbase)
library(pryr)

# create directory for ff chunks, and assign directory to ff
system("mkdir ffdf")
options(fftempdir = "ffdf")
```

Chunking data with the `ff`-package

Import data, inspect change in RAM.

```
##             used  (Mb) gc trigger   (Mb)  max used   (Mb)
## Ncells   1086709  58.1    1757805   93.9   1757805   93.9
## Vcells 128919936 983.6  213343868 1627.7 211038278 1610.1
```

```
mem_change(
flights <-
     read.table.ffdf(file="../data/flights.csv",
                     sep=",",
                     VERBOSE=TRUE,
                     header=TRUE,
                     next.rows=100000,
                     colClasses=NA)
)
```

```
## read.table.ffdf 1..100000 (100000)  csv-read=0.34sec ffdf-write=0.043sec
## read.table.ffdf 100001..200000 (100000)  csv-read=0.361sec ffdf-write=0.04sec
## read.table.ffdf 200001..300000 (100000)  csv-read=0.366sec ffdf-write=0.03sec
## read.table.ffdf 300001..336776 (36776)  csv-read=0.14sec ffdf-write=0.016sec
##  csv-read=1.207sec  ffdf-write=0.129sec  TOTAL=1.336sec
```

```
## -30 MB
```

Chunking data with the `ff`-package

Inspect file chunks on disk and data structure in R environment.

```r
# show the files in the directory keeping the chunks
list.files("ffdf")
```

```
##   [1] "clone1664b7fbd953f.ff" "clone1664b9b8cca9.ff"  "clone1e7014c0a1cd8.ff"
##   [4] "clone1e7015a4f712e.ff" "clone2aea22211d9e1.ff" "clone2aea2360c6703.ff"
##   [7] "clone2aea2566ab42d.ff" "clone2aea25e1c1f75.ff" "clone2d49618dbfbf6.ff"
##  [10] "clone2d4965ee3349a.ff" "clone2d49664b07745.ff" "clone2d49672b82b88.ff"
##  [13] "clone308112a4ca401.ff" "clone308113d044b7c.ff" "clone308113d22fb5f.ff"
##  [16] "clone3081149714ed4.ff" "clone399cd5627eb1f.ff" "clone399cd72c6506d.ff"
##  [19] "clone399cd78f6c4e6.ff" "clone399cd8b1f075.ff"  "clone3c3ef1e38eca1.ff"
##  [22] "clone3c3ef4ac46441.ff" "clone3c3ef514956e9.ff" "clone3c3efcb5fb24.ff"
##  [25] "ff1664b222c38f0.ff"    "ff1664b4d23ee78.ff"    "ff1664b4d7f1e3e.ff"
##  [28] "ff1e7011754e092.ff"    "ff1e7011a76d5a6.ff"    "ff1e7017084631e.ff"
##  [31] "ff2aea22c3703b9.ff"    "ff2aea2664ee33.ff"     "ff2aea26b164ce7.ff"
##  [34] "ff2d49627cd458.ff"     "ff2d49631ca5a34.ff"    "ff2d4964237cc21.ff"
##  [37] "ff30811207897c4.ff"    "ff308115699c1a.ff"     "ff30811b3430e.ff"
##  [40] "ff399cd1a2ffc0e.ff"    "ff399cd1e963877.ff"    "ff399cd5477c29.ff"
##  [43] "ff3c3ef17300293.ff"    "ff3c3ef2229a09b.ff"    "ff3c3ef765d6fb7.ff"
##  [46] "ffdf1664b11f63957.ff"  "ffdf1664b12d379a7.ff"  "ffdf1664b16a5a516.ff"
##  [49] "ffdf1664b16cc8da8.ff"  "ffdf1664b16d72904.ff"  "ffdf1664b178a08cd.ff"
##  [52] "ffdf1664b17c18654.ff"  "ffdf1664b23c24fe0.ff"  "ffdf1664b24c84c7c.ff"
##  [55] "ffdf1664b25a0763c.ff"  "ffdf1664b2663b0d0.ff"  "ffdf1664b283091fe.ff"
##  [58] "ffdf1664b2b44b5a4.ff"  "ffdf1664b2c262d7d.ff"  "ffdf1664b2cd1a62.ff"
##  [61] "ffdf1664b2e3a4c4e.ff"  "ffdf1664b2ed055dd.ff"  "ffdf1664b3054a5d7.ff"
```

Memory mapping with **bigmemory**

Preparations

```
# SET UP ----------------

# load packages
library(bigmemory)
library(biganalytics)
```

Memory mapping with `bigmemory`

Import data, inspect change in RAM.

```r
# import the data
flights <- read.big.matrix("../data/flights.csv",
                     type="integer",
                     header=TRUE,
                     backingfile="flights.bin",
                     descriptorfile="flights.desc")
```

Memory mapping with **bigmemory**

Inspect the imported data.

```
summary(flights)
```

```
##                       min          max         mean           NAs
## year          2013.000000  2013.000000  2013.000000      0.000000
## month            1.000000    12.000000     6.548510      0.000000
## day              1.000000    31.000000    15.710787      0.000000
## dep_time         1.000000  2400.000000  1349.109947   8255.000000
## sched_dep_time 106.000000  2359.000000  1344.254840      0.000000
## dep_delay      -43.000000  1301.000000    12.639070   8255.000000
## arr_time         1.000000  2400.000000  1502.054999   8713.000000
## sched_arr_time   1.000000  2359.000000  1536.380220      0.000000
## arr_delay      -86.000000  1272.000000     6.895377   9430.000000
## carrier          9.000000     9.000000     9.000000 318316.000000
## flight           1.000000  8500.000000  1971.923620      0.000000
## tailnum                                             336776.000000
## origin                                              336776.000000
## dest                                                336776.000000
## air_time        20.000000   695.000000   150.686460   9430.000000
## distance        17.000000  4983.000000  1039.912604      0.000000
## hour             1.000000    23.000000    13.180247      0.000000
## minute           0.000000    59.000000    26.230100      0.000000
## time_hour     2013.000000  2014.000000  2013.000261      0.000000
```

Memory mapping with `bigmemory`

Inspect the object loaded into the R environment.

```
flights
```

```
## An object of class "big.matrix"
## Slot "address":
## <pointer: 0x5608c09d84d0>
```

Memory mapping with `bigmemory`

- `backingfile`: The cache for the imported file (holds the raw data on disk).
- `descriptorfile`: Metadata describing the imported data set (also on disk).

Memory mapping with bigmemory

Understanding the role of `backingfile` and `descriptorfile`.

First, import a large data set without a backing-file:

```
# import data and check time needed
system.time(
     flights1 <- read.big.matrix("../data/flights.csv",
                                 header = TRUE,
                                 sep = ",",
                                 type = "integer")
)
```

```
##    user  system elapsed
##   1.022   0.013   1.034
```

```
# import data and check memory used
mem_change(
     flights1 <- read.big.matrix("../data/flights.csv",
                                 header = TRUE,
                                 sep = ",",
                                 type = "integer")
)
```

```
## 736 B
```

Memory mapping with bigmemory

Understanding the role of `backingfile` and `descriptorfile`.

Second, import the same data set with a backing-file:

```
# import data and check time needed
system.time(
     flights2 <- read.big.matrix("../data/flights.csv",
                                 header = TRUE,
                                 sep = ",",
                                 type = "integer",
                                 backingfile = "flights2.bin",
                                 descriptorfile = "flights2.desc"
                                 )
)
```

```
##    user  system elapsed
##   1.023   0.028   1.051
```

```
# import data and check memory used
mem_change(
     flights2 <- read.big.matrix("../data/flights.csv",
                                 header = TRUE,
                                 sep = ",",
                                 type = "integer",
                                 backingfile = "flights2.bin",
```

Memory mapping with `bigmemory`

Understanding the role of `backingfile` and `descriptorfile`.

Third, re-import the same data set with a backing-file.

```
# remove the loaded file
rm(flights2)

# 'load' it via the backing-file
system.time(flights2 <- attach.big.matrix("flights2.desc"))
```

```
##    user  system elapsed 
##   0.000   0.000   0.001
```

```
flights2
```

```
## An object of class "big.matrix"
## Slot "address":
## <pointer: 0x5608bf6f3930>
```

References